Ousiometrics:
The essence of meaning aligns with a power-danger-structure framework instead of valence-arousal-dominance

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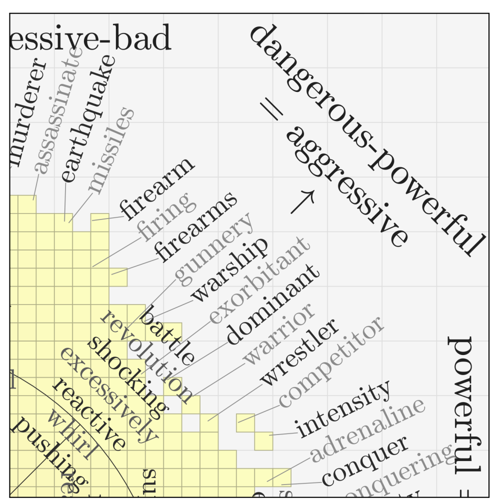
Logline:

We show that the essential meaning conveyed by individual words is best represented by a compass-like plane described by interrelated differentials of bad-good, weak-powerful, gentle-aggressive, and safe-dangerous, joined with a third dimension of structured-unstructured (GPADS).

We uncover a linguistic 'safety bias' by examining how words are used in large-scale, diverse corpora.

We find the power-danger-structure framework to be naturally aligned with token usage in real corpora as well as with seemingly disparate frameworks.

We construct and demonstrate the use of an 'ousiometer' for measuring time series of essential meaning.



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Abstract:

From work emerging through the middle of the 20th century, the essence of meaning has become generally accepted as being well captured by the three orthogonal dimensions of evaluation, potency, and activation (EPA). Recast in psychology as valence, arousal, and dominance (VAD), these essential dimensions have become the cornerstone of sentiment analysis across many fields.

By re-examining first types and then tokens for the English language, and through the use of automatically annotated histograms—'ousiograms'—we find here that:

1. The essence of meaning conveyed by words is not aligned with VAD but is best described by a power-danger-structure (PDS) orthogonal framework spanned by the semantic differentials of weak vs. powerful, safe vs. dangerous, and structured vs. unstructured.

2. The primary plane of the PDS framework is consistent with a circumplex-type model with the intercardinal axes forming a goodness-aggression-structure (GAS) framework with axes bad vs. good and gentle vs. aggressive, and both frameworks can be combined as GPADS.

3. Analysis of a disparate collection of large-scale English language corpora—literature, news, Wikipedia, talk radio, and social media—shows that natural language exhibits a systematic bias toward safe, low-danger words.

4. The Pollyanna principle's positivity bias in communication is, in fact, a one-dimensional projection of an underlying safety bias.

We demonstrate remarkable agreement between the PDS framework and (1) the circumplex model of affect; and (2) a data-driven determination of archetypes in fiction stories whose primary dimensions are fools vs. heros, angels vs. demons, and traditionlists vs. adventurers. Finally, we use our findings to construct a prototype 'ousiometer', a distant-reading instrument that measures essential meaning in large-scale texts.

Keywords:

meaning; essential meaning; ousiometrics; ousiometry; ousiograms; language; words; semantic differentials; Osgood; best-worst scaling; essential meaning frameworks; VAD; GAS; PDS; GPAD; GPADS; valence; arousal; dominance; goodness; aggression; power; danger; structure; emotion; mental states; lexical instruments; hedonometrics; computational humanities; stories; archetypes; archetypometrics; telegnomics

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1 Introduction

As encoded by human language, meaning spans a high dimensional semantic space that is continually expanding and evolving, bearing complex hierarchical and networked structures [1–3]. In attempting to understand any quantified complex system, a most basic step is to apply a method of dimensional reduction. If we distill meaning to its essence, boiling off all higher dimensions of meaning—the focus of our work here—do we find fundamental dimensions of meaning space that are interpretable and, moreover, reliably experienced, conceptualized, and conveyed by people [4–10]?

The short answer is yes—Osgood et al.'s methods [6] (see below) have proved to be successful and the Osgood framework has come to be widely used across many fields. But as we will show, Osgood's framework does not fully hold up to a modern computational analysis using large-scale datasets and new methodologies.

Here, we define 'ousiometrics' to be the quantitative study of the essential meaningful components of an entity, however represented and perceived. Used in philosophical and theological settings, the word 'ousia' comes from Ancient Greek οὐσία and is the etymological root of the word 'essence' whose more modern usage is our intended reference.

Introducing the terminology of ousiometrics in particular helps us distinguish from general fields which study meaning such as semantics or semiotics. And for framing purposes, being able to thematically name specialized tools and instruments will be helpful in the presentation of our work. In particular, we will develop and explore a series of 'ousiograms' which are annotated representations of two dimensional slices of meaning space.

For our purposes here, and in the tradition of Osgood et al. [5, 6] and the many who have followed [9–19], our measurement of essential meaning will rest on—and is constrained by—the map presented by language.

1.1 How the measurement of essential meaning has been operationalized

To help explain the purpose of our paper—why our approach to ousiometrics is warranted—we outline the relevant history of measuring essential meaning, and describe the longstanding problematic aspects of experiment design and measurement instruments.

The quantitative measurement of the essence of meaning was primarily developed by researchers in the middle of the 1900s, particularly by Osgood and colleagues, with their foundational work published in the 1950s [5, 6]. The majority of ensuing research [7, 8, 13] has been built around human evaluation of words or phrases using the instrument of the semantic differential [5, 6, 20]. In a typical study, surveyed participants are asked to rate individual words on Likert scales with endpoints described by 'bipolar adjectival pairs' (BAPs) such as {soft ⇔ hard}, {rough ⇔ smooth}, and {cold ⇔ hot}. Throughout, we will indicate semantic differentials as per the examples of the preceding sentence, bracketing and connecting bipolar adjectival pairs with the symbol ⇔. The measurement of essential meaning is thus operationalized via surveys which ask people to respond to isolated words and phrases, given some semantic differential and some scale.

Modern support for semantic differentials comes from findings that large language models (LLMs) encode semantic axes consistent with human judgment. Grand et al. [21] demonstrate that "semantic projection"—mapping embeddings onto differential axes like size, age, and wealth—recovers feature-level conceptual knowledge. Zhou and Bhatia [22] and Wang et al. [23] show that modern LLMs align well with human semantic judgments and feature norms. Li et al. [24] and Park et al. [25] further validate emergent and hierarchical structures in contextual embeddings.

Each semantic differential is considered a dimension (an axis) in a potentially high dimensional space, and researchers then apply some variant of factor analysis to the average scores, such as principal component analysis (PCA) or singular value decomposition (SVD), or more sophisticated methods [26–30]. In general, factor analysis determines a set of dimensions that are linear combinations of the study's semantic differentials, which must then be interpreted. As we detail below, we are able to use basic SVD and it is in the interpretation step that we develop a new systematic methodology.

Based on a range of studies, Osgood *et al.* [6] identified three orthogonal dimensions for the essence of meaning. In order of variance explained for the studies at the time, the three dimensions were dubbed:
1. Evaluation (e.g., {positive ⇔ negative}),
2. Potency (e.g., {dominant ⇔ submissive}), and
3. Activity (e.g., {active ⇔ passive}).

Though the 'EPA' framework has been challenged in various ways [9, 31, 32], as have semantic differentials themselves [9, 19], researchers were increasingly drawn to take the EPA framework as a ground truth when carrying out new studies [13, 15, 19].

In the focused context of studying emotion, a theoretical concept of a three dimensional representation of emotion goes back to (at least) Wundt in the late 1800s [33, 34]. For emotion, the EPA dimensions were re-ordered and recast by Mehrhabian and Russell as: 1. Pleasure (Valence), 2. Arousal, and 3. Dominance (PAD or

VAD) [11, 12]. To make clear that this was the authors' intention, from the summary of Ref. [12]:

> "Semantic differential studies, in particular, have shown that human judgments of diverse samples of stimuli can be characterized in terms of three dimensions: evaluation, activity, and potency. We have termed the corresponding emotional responses pleasure, arousal, and dominance."

Subsequent work has tended to use the term valence instead of pleasure, and we will follow the VAD nomenclature.

The VAD framework has seen extensive application across diverse disciplines. In psychology [35, 36], neuroscience [37, 38], and natural language processing (NLP) [39, 40], VAD provides dimensional models to capture affective meaning. Other areas include sentiment analysis [41, 42], emotion detection [43, 44], marketing [45, 46], human-computer interaction [47, 48], and education [49, 50].

Now, while VAD was intended to be a scoped version of EPA, the two frameworks have been conflated. Generally, VAD has become the framework presented in studies, even when essential meaning, rather than emotion, has been the focus [13, 15, 19]. Elsewhere, the original connection between VAD and EPA has been overlooked or considered broken, leading to re-analyses about whether or not the match between EPA and VAD holds at all [51].

Nevertheless, to be consistent with the direction taken by the literature, we will refer to VAD rather than the more general EPA going forward.

1.2 The major problems with measuring essential meaning

We describe a set of problems that we contend have thwarted the full development of ousiometry over time.

1. Scale:
Given that the EPA framework was developed before and during the 1950s, the foundational studies were limited in size, both in lexicon analyzed and the number of participants surveyed. For example, as part of the research that led to the EPA framework, Osgood *et al.* [6]report on a study of 20 concept nouns evaluated on 50 semantic differentials by 100 undergraduates. Published in 1980, Russell's circumplex model of affect (which we examine later in Sec. 4.1) was based on the scoring of 28 words and phrases [9]. The Affective Norms for English Words (ANEW) study of the late 1990s moved the lexicon size up to 1,034, but with VAD as the accepted fundamental framework, and still using surveys of undergraduates. In work carried out around 2010 involving two of the present authors, an order of magnitude jump to over 10,000 English words was conducted online through Amazon's Mechanical Turk with 50 evaluations per word along the single semantic differential of valence interpreted as happiness (discussed further below) [14]. This data set, labMT (language assessment by Mechanical Turk), was later expanded to 10 languages, each with over 10,000 words scored online by participants around the world [52]. Crucially, and in contrast to the ANEW word lists, the labMT words analyzed were chosen according to frequency of usage (again, discussed further below). In 2013, Warriner *et al.* [15] published scores for close to 14,000 English with VAD scores. Finally, in 2018, Mohammad produced what will be the basis of our analysis here, the NRC VAD lexicon: Over 20,000 English words and phrases with VAD scores [19].

So, it is only in the last 15 years that studied lexicons have begun to represent the scale of human vocabularies. We are consequently now well placed to perform the necessary work of re-examining the findings of the field's foundational research.

2. The focus on types alone and not tokens:
We use the standard type-token language for describing entities [53]: Type refers to an entity's class (or species) while token refers to an entity itself as an instance of that class. Beyond language, the type-token distinction appears across all complex systems with heavy-tailed distributions of component frequencies. Perhaps in settings not involving words and texts, the problems with studying only types would be more apparent. For example, in determining some overall measure of a forest, we would not want to assign equal weight to the most common and the most rare species. Here, we will study both lexicons (types) and large-scale texts (tokens), gaining separate results from both.

Almost all essential meaning studies have been at the level of types, each word or concept given equal weighting. However, we must consider the weight of types in a text according to the frequency of their corresponding tokens [53]. Only then can we make defensible observations about a whole space of communication. The ANEW study [13], for example, is based on 1,034 expert chosen words which proved to be a poor fit for natural language [54]. By contrast, with careful consideration of word usage, we were able to show that the Polyanna Principle [55] manifests a linguistic positivity bias across 24 corpora spanning 10 languages [52].

3. The use of Likert scales for semantic differentials:
The use of a Likert scale for evaluations of semantic differentials has long been standard practice. Relatively

recently, best-worst scaling has been suggested to be a more robust instrument than the Likert scale, as well as a far more efficient one [56]. To our great benefit, Mohammad's survey of over 20,000 words and phrases preferentially uses best-worst scaling, finding appreciable improvement in split-half reliabilities over studies using Likert scales.

4. Limitations of factor analysis for a large number of categorical dimensions:
While tables of factor analysis weightings can be exhaustively informative for small-scale studies, we will not be able to make much sense of point clouds of tens of thousands of unlabeled words in two or three dimensions. Here, we will show how a kind of automatically annotated histogram—an ousiogram—coupled with ranked word lists provides an instrument that will help us explore, describe, and support our assessments of the dimensions of essential meaning.

5. The misalignment between expert-chosen, end-point descriptors and dimensions of essential meaning:
We come to a critical problem with any essential meaning study that starts from a presumption of the EPA/VAD framework. We go back to basics and outline the four step experimental process that has been used to extract essential dimensions of meaning in the first place:

i. Participants are asked to rate a set of N_{types} types (e.g., words, images) using a set of $N_{\text{differentials}}$ semantic differentials defined by bipolar adjectival pairs. Some examples from Osgood *et al.*'s 50 semantic differentials for the study mentioned above include {large ⇔ small}, {clean ⇔ dirty}, {brave ⇔ cowardly}, {bass ⇔ treble}, and {near ⇔ far} (p. 43 in Ref. [6]).

ii. Some variant of factor analysis (e.g., PCA, SVD) is then employed to obtain an ordered set of dimensions that are linear combinations of the semantic differential dimensions.

iii. Researchers interpret the main dimensions and ascribe them with both descriptive names (e.g., 'evaluation') and, crucially, sets of 'end-point descriptors' (e.g., happiness, pleasure, contentedness for high valence and unhappiness, annoyance, negativeness for low valence). These new semantic differentials are not then described by simple bipolar adjectival pairs but rather clusters of words and phrases at each end.

iv. Researchers reduce the meaning space to 2 or 3 of the most prominent dimensions (e.g., by variance explained through singular values).

With ousiometric dimensions so determined (e.g., EPA), researchers then move on to new studies using only a modified version of step I:

i. Participants are asked to rate a set of N_{types} types along 2 or 3 expert-chosen dimensions that are defined by expert-identified sets of end-point descriptors.

As such, there is then no assurance that the expert-identified end-point descriptors will be construed by participants in a way that imposes the expert-defined dimensions.

Indeed, we observe that across many studies, raters have been presented with end-point descriptors that render the three VAD dimensions with problematic imprecision [6, 9, 13, 19, 51]. For example, for the ANEW study, valence was described to participants as a {happy ⇔ unhappy} scale as follows (emphasis added):

> "At one extreme of [this {happy ⇔ unhappy}] scale, you are **happy, pleased, satisfied, contented, hopeful**. ... The other end of the scale is when you feel completely **unhappy, annoyed, unsatisfied, melancholic, despaired, or bored**."

The meaning captured by both ends is broad, the numbers of descriptors differ, and the word 'bored' clearly overlaps with the dimension of arousal.

For the NRC VAD lexicon, raters were guided by end-point descriptors ('paradigm terms') which were taken from Refs. [6], [9], and [13]. We list all descriptors for the six end-points used in Ref. [19] in Tab. 1. As for the ANEW study, we see the end-points for each dimension combine to create coarse semantic limits. For example, for low arousal, there is clear semantic separation between 'sluggishness' and 'calmness', as there is for 'weak' and 'guided' for low dominance.

Our remedy is simple: Always carry out steps 1–4 above even when attempting to impose a minimal ousiometric framework. Factor analysis will then accommodate a reasonable lack of exactness in how dimensions are prescribed. And if we find that the VAD framework is in fact perfectly prescribable, we will have done the work needed to make this clear.

6. Presuming that the VAD framework does capture essential meaning and that the three dimensions are orthogonal:
As we have observed, Osgood *et al.*'s [6] EPA/VAD framework has become generally accepted as valid. However, modern, large-scale VAD evaluations of words and phrases have increasingly pointed toward the VAD

VAD end-points	Paradigm words and phrases presented to raters
highest valence	happiness, pleasure, positiveness, satisfaction, contentedness, hopefulness
lowest valence	unhappiness, annoyance, negativeness, dissatisfaction, melancholy, despair
highest arousal	arousal, activeness, stimulation, frenzy, jitteriness, alertness
lowest arousal	unarousal, passiveness, relaxation, calmness, sluggishness, dullness, sleepiness
highest dominance	dominant, in control of the situation, powerful, influential, important, autonomous
lowest dominance	submissive, controlled by outside factors, weak, influenced, cared-for, guided

Table 1: End-point descriptors used in Ref. [19] for the survey leading to the NRC VAD lexicon. As for many studies presuming an orthogonal VAD framework, the end-points are semantically broad and imprecise.

framework being non-orthogonal. Leaving aside problematic sampling of words, the ANEW study [13] found evidence that arousal was mildly positively correlated with the magnitude of valence. The near 14,000 lemma VAD study of Warriner *et al.* [15] found correlations between the three VAD dimensions, the strongest being between valence and dominance with $r_{\mathbf{Va},\mathbf{Dm}} \simeq 0.72$ (Pearson's correlation), which prompted the authors to call into question the orthogonality of the VAD framework.

Most recently, using best-worst scaling for the NRC VAD lexicon, Mohammad [19] found a somewhat weaker correlation of $r_{\mathbf{Va},\mathbf{Dm}} \simeq 0.49$, and then asserted that valence and dominance were only "slightly correlated", a view with which we do not agree. In reference to the valence-dominance correlation in the Warriner *et al.* study [15], Mohammad stated:

> "Given that the split-half reliability score for their dominance annotations is only 0.77, the high V–D correlations raises the suspicion whether annotators sufficiently understood the difference between dominance and valence."

So the suggestion here is that the problem is not that the VAD framework is not orthogonal, but that participants failed to grasp the definitions of dimensions.

Our position, per problem 5 above, is that imposing VAD dimensions experimentally through end-point descriptors is a difficult task and that factor analysis is always required. And in challenging the VAD framework, we will show that these observed correlations are real and understandable, and ultimately lead to a revised framework we will identify to be power-danger-structure (PDS).

We note that we do not use the expanded NRC VAD lexicon described in Ref. [57] as the lexicon merges words scored with best-worst scaling and traditional Likert scale.

1.3 Roadmap for the paper

We first describe the data sets we analyze and explore in Sec. 2. We make the key distinction between text corpora that are type-based (i.e., lexicons) or token-based (written or recorded expression) [53].

Through a series of integrated figures, we then demonstrate our four main findings: 1. The framework of valence-arousal-dominance (VAD) is far from being an orthogonal system [15], and this failure is due to the difficulties of constructing semantic differentials for essential dimensions of meaning (Secs. 3.1 and 3.2); 2. A goodness-aggression-structure (GAS) framework and a power-danger-structure (PDS) framework both provide two alternative, interpretable, and interconnected orthogonal systems that agree with earlier circumplex formulations, and which we will combine as a goodness-power-aggression-danger-structure (GPADS) framework (Secs. 3.4, 3.5, and 3.6); and 3. Only the power-danger-structure framework aligns with the essential meaning patterns of real corpora when we properly account for frequency of usage by considering tokens; and 4. Diverse, large-scale text corpora present a systematic, low-danger 'safety bias' (Sec. 3.8).

With the GAS, PDS, and GPADS frameworks established, we identify remarkable congruences in two other areas which are far removed from how people respond to isolated words: 1. The influential circumplex model of affect [9] (Sec. 4.1); and 2. Archetypometrics—the data driven determination of fictional character archetypes [58, 59] (Sec. 4.2).

We share ousiometric word scores for all frameworks, additional figures, and scripts on Gitlab and/or in the Supplementary Materials.

We summarize our results and offer thoughts on future work in Sec. 6.

2 Description of data sets

We build our findings in two stages using two distinct kinds of word lists: 1. Types: A lexicon for the English language (each word is of equal importance), and 2. Tokens: Frequency-rank distributions [60] for large-scale corpora (words are ranked by frequency of usage with most used word having rank 1; words with tied frequency are given an average of corresponding ranks if they were not tied). In general, observations made solely by examining a lexicon (the level of types) will be given a stringent test when confronted by real-world word usage (the level of tokens).

The type stage: As indicated in the introduction, we use the NRC VAD lexicon comprising around 20,000 words and terms [19]. The lexicon was compiled from a variety of sources and largely contains lower-case, latin-character words along with some 2-, 3-, and 4-grams (an n-gram is a phrase made up of n-terms). Proper nouns and function words have generally been excluded. Some words are evidently hashtag constructions from social media (with the hashtag removed). The lexicon is a union of existing lexicons, some of which were expert-compiled (e.g., the ANEW study [13]) and others based on frequency of usage. While the presence of expert-compiled lexicons is not ideal, we will see that the coverage of real corpora is sufficient for the purposes of our work here.

For each term in the NRC VAD lexicon, scores within the VAD framework [11, 12] were assessed by survey using best-worst scaling [56]. Terms were presented in groups of four and participants were asked to rank the highest and lowest according to one of the three VAD dimensions (see Ref. [19] for full details). Each term's score is in the interval [0,1]. To accommodate singular value decomposition, we remove the mean from each dimension, which by the nature of best-worst scaling is $\frac{1}{2}$. We thus shift the VAD scores from [0,1] to [$-\frac{1}{2}$,$+\frac{1}{2}$].

The token stage: With findings from studying the NRC VAD lexicon, we then analyze seven corpora—where frequency of word usage now matters—which vary broadly in kind, formality, scale, and historical time frame.

1. English Fiction (1900–2019) from the Google Books project, with each book contributing words equally, and then each year's size-rank distribution weighted equally [61, 62];
2. Jane Austen's six novels with all books merged, sourced from the Gutenberg Project, http://www.gutenberg.org.
3. The majority of Arthur Conan Doyle's Sherlock Holmes stories with all stories merged, (4 novels and 44 short stories taken from https://sherlock-holm.es/, missing the 12 short stories contained in "The Case-Book of Sherlock Holmes");
4. The New York Times (1987–2007) Frequency-rank distributions merged without reweighting across all years [63];
5. Wikipedia (English language, 2019/03 snapshot) [64];
6. RadioTalk (transcriptions of talk radio broadcasts in the US, 2018/10–2019/03) [65];
7. Twitter (approximately 10% of all tweets identified as English in 2020—including retweets—with each day's frequency-rank distribution contributing equally) [66].

3 Analysis, Results, and Discussion

3.1 Ousiograms

Complex systems are often manifested from a set of distinct, named entities—types—whose frequencies of occurrence as interacting tokens roughly obey a heavy-tailed distribution, and whose characteristics reside in some high dimensional space [60, 67–70]. Language is a canonical example with words as types and meanings as one of their characteristics. One approach to better understanding such high dimensional complex systems, is thorough dimensional reduction where we maintain the set of all types but seek to distill the characteristics of these types down to an essential few.

To inform and help validate our analysis, we will use 'ousiograms'. We define an ousiogram as a systematically and informatively annotated two-dimensional histogram for two essential quantities of a complex system's component entities. The entities represented in ousiograms may be either types or tokens [53], with types contributing equally while a token's contribution would be proportional to the frequency of that token's appearance within a given system.

In Fig. 1, we present an ousiogram for valence **Va** and dominance **Dm** for the NRC VAD lexicon [19]. We use valence and dominance as an example to demonstrate the non-orthogonality of the VAD framework with best-worst scaling. In Figs. S1–S9 in the Supplementary Materials, we provide the corresponding **Va-Ar** and **Ar-Dm** large-scale ousiograms. For our main analysis, we present smaller versions of these ousiograms in Figs. 2A–C, which we discuss below in Sec. 3.4.

We first briefly describe the ousiogram in Fig. 1 (see the Figure's caption for more detail), and then contend with the non-orthogonality of the VAD framework.

As a guide, we label the cardinal directions for valence **Va** and dominance **Dm** by the standard (if problematic)

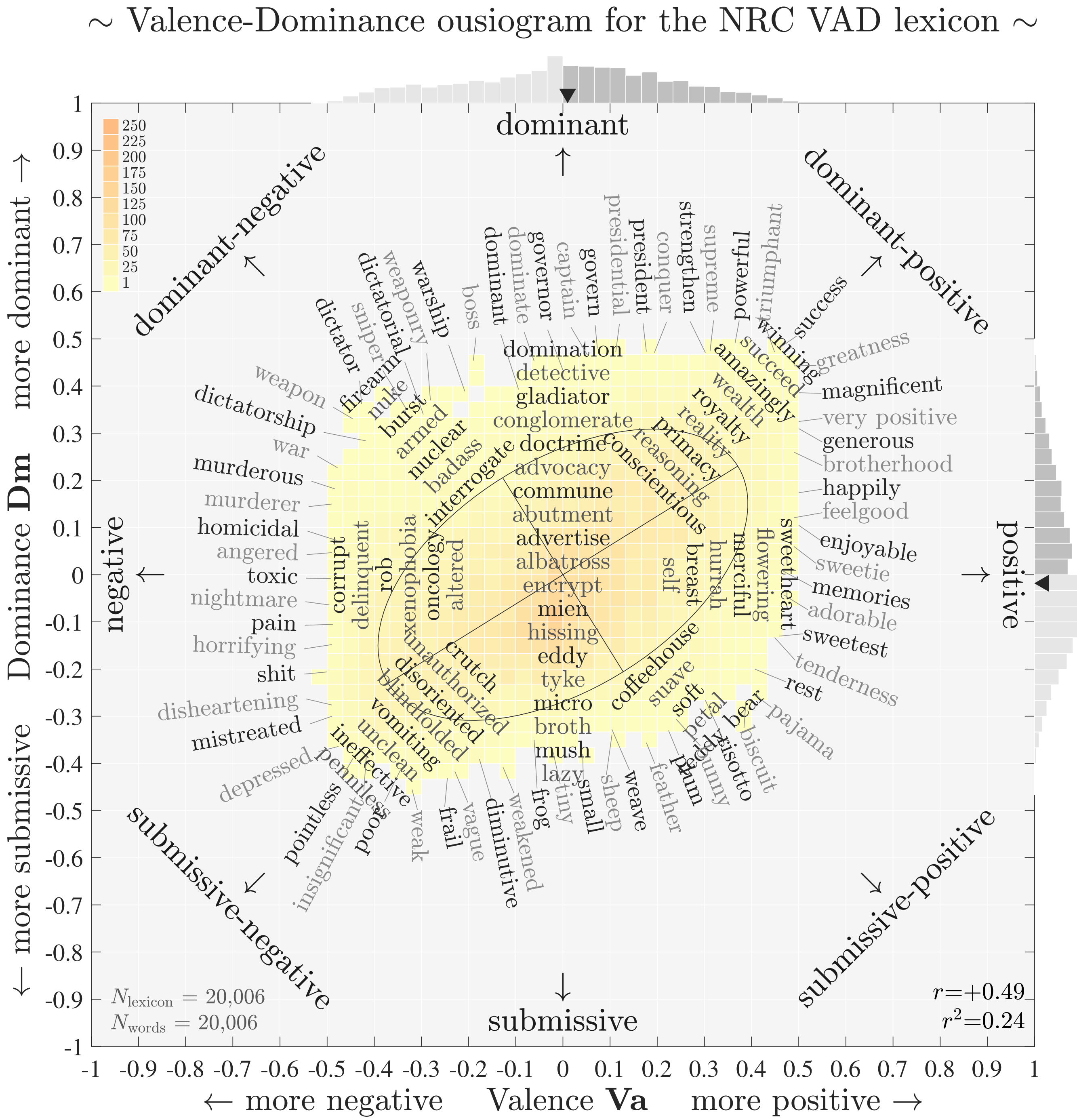

Figure 1: Valence-dominance 'ousiogram' for the NRC VAD lexicon of around 20,000 words scored within the valence-arousal-dominance (VAD) framework [11, 12] using best-worst scaling [19, 56]. Ousiograms are annotated two-dimensional histograms of two essential dimensions describing any collection of labeled entities. Here, we arrange words according to their valence-dominance scores, collapsing the third dimension of arousal. We use a bin width of 1/30, and we have shifted all **Va**, **Ar**, and **Dm** scores from [0,1] to [$-\frac{1}{2}$,$+\frac{1}{2}$]. To enable comparisons, we use limits of [-1,1] throughout the paper. We plot marginal distributions of **Va** and **Dm** along the top and right sides, with darker gray indicating positive values, and solid dark triangles locating the medians of **Va** and **Dm**. The ellipse represents the axes determined by singular value decomposition (SVD) acting on the **Va-Dm** plane, and shows a strong departure from the **Va** and **Dm** axes. We label words around the edge of the **Va-Dm** distribution aligned with normals to the distribution's convex hull, and add example words at internal locations along the main axes and the two diagonals. Upon inspection, the words shown are reasonably located according to their essential values of **Va** and **Dm**. Notes: See Figs. S1 and S3 in the Supplementary Materials for large-scale ousiograms of **Va-Ar** and **Ar-Dm**. Labeled words are not restricted in their value of the third dimension, arousal **Ar**, which may vary unevenly. Alternating shades of gray are for readability. For these larger ousiograms, we automatically label the four cardinal and inter-cardinal directions with their endpoint adjective (e.g, 'dominant-positive' in the northeast corner).

bipolar adjectival pairs anchoring the semantic differentials {negative ⇔ positive} and {submissive ⇔ dominant}. The intercardinal directions are then combinations of these adjectives (e.g., submissive-positive). We label all other ousiograms in the same fashion with appropriate bipolar adjectival pairs.

Given that we have shifted the VAD scores to lie in [-$\frac{1}{2}$,+$\frac{1}{2}$], the two dimensional histogram of Fig. 1 shows that the NRC VAD lexicon accesses much of the available **Va-Dm** plane. The marginal distributions at the top and right show that both valence and dominance are well dispersed, with dominance exhibiting some minor asymmetry. The dark triangles indicate the medians for each marginal.

We show words using two kinds of annotations: At the extremes of the histogram's boundary and internally along the cardinal and intercardinal axes. (See Ref. [15] for scatter plots with perimeter annotations.) For words on the boundary, we automatically construct and segment a convex hull for the histogram, determine normals to each segment, and annotate the closest word. Internally, we find words closest to points along the eight outgoing lines. We leave the third dimension aside (here, arousal **Ar**). Both the bin width for the underlying histogram and the spacing of annotations are tunable, and we avoid annotating a word more than once.

Ousiograms will have two main benefits for us. First, they give us a way to check that words line up with prescribed axes. Second, and crucially for our later work here, when we move to a potential new framework, ousiograms will help us to interpret the underlying axes.

In the first sense of acting as a check, the ousiogram of Fig. 1 shows that word ratings performed by the survey participants in Ref [19] are reasonably sensible. Travelling around the histogram's boundary, we see how the essential meaning of words incrementally changes. Starting in the 'dominant-positive' direction (upper right), we see 'triumphant', 'success', and 'greatness'. As we move clockwise going down the right side of the boundary, the annotated words become softer while remaining pleasant: 'generous' to 'memories' to 'pajama'. Moving left along the bottom boundary, positive gives way to negative, and we reach the extreme of negative-submissive: 'feather' to 'weakened' to 'pointless'. Moving up the left side, we see a string of negative words which grow in strength, partly because of the scope of dominance: 'depressed', 'nightmare', 'murderous', 'dictator'. Returning across the top of the ousiogram, we move through martial, leadership, and power terms that gradually lessen in violence: 'weaponry', 'dominate', 'president', 'powerful', and back to 'success'.

Internally, each of the eight directions leading out from the center also reflect changes in the strength of essential meaning. For the full negative-submissive to dominant-positive axis, for example, we track from 'penniless', 'vomiting', 'disoriented', and 'crutch,' up through to 'conscientious', 'qualifying', 'amazingly', and 'success'.

The words 'encrypt' and 'albatross' are neutral in the **Va-Dm** plane, and are worth reflecting on. These are certainly meaningful words. And as for all words, these examples could take on a strong meaning in the right context. An albatross for sailors is a dire omen whereas an albatross in golf is a rare, extraordinary success. But raters are asked to compare the essential meaning of words based on the perceived meaning in isolation, which is to say, in the context of the rater's knowledge of the word.

3.2 The Valence-Arousal-Dominance (VAD) framework is not orthogonal

We turn now to the issue of orthogonality, a longstanding point of contention for the EPA and VAD frameworks [6, 9, 11, 12, 15, 19]. For the NRC VAD lexicon, we find that the VAD dimensions as interpreted by raters are not close to being orthogonal. We observe that standard correlation coefficients for the three pairs of VAD variables are

$$r_{\mathbf{Va},\mathbf{Ar}} \simeq -0.27,\ r_{\mathbf{Ar},\mathbf{Dm}} \simeq 0.30,\ \text{and}\ r_{\mathbf{Va},\mathbf{Dm}} \simeq 0.49, \quad (1)$$

where the corresponding p-values are computed to be essentially 0. If the VAD framework were orthogonal, these three correlation coefficients should be statistically indistinguishable from 0.

We note that the linkages between the VAD dimensions are not simple, with valence and arousal being anticorrelated with the other two pairs being positively correlated.

For a visual guide, and one that we will use throughout the paper, the ellipse in Fig. 1 represents the coordinate system uncovered by singular value decomposition (SVD) [71] in the **Va-Dm** plane (we ignore **Ar** for this example calculation). The ellipse is clearly off axis. For the equivalent ellipses for the **Va-Ar** and **Ar-Dm** planes, see the ousiograms in Figs. 2A and C as well as in Supplementary Materials.

Now, given that we do not see orthogonality for the VAD framework for the largest lexicon ever studied coupled with a markedly improved rating system, we are compelled to investigate why VAD (equivalently EPA) fails as an orthogonal framework and what alternate framework might be revealed in doing so.

The root cause of confusion lies in the difficulty of ascribing stable and meaningful end-point descriptors for VAD (and EPA) variables. As was true for Osgood *et al.*'s work that led to the EPA framework [6], from the start in developing the VAD framework [11, 12], Mehrabian and Russell were concerned with both orthogonality and finding suitable end-point descriptors. As explored in Ref. [51], researchers have continued to use a varying array of end-point descriptors for EPA and VAD, including the same researchers over time [9, 13, 19].

Problematically, and as we noted in the introduction, some end-point descriptors have the effect of correlating different dimensions. For example, in the ANEW study of Ref. [13], the negative valence end-point was presented to participants as a state of feeling “completely unhappy, annoyed, unsatisfied, melancholic, despaired, or bored.” The last descriptor ‘bored’ evidently would be elicited at the low end-point of the arousal dimension which itself was framed as “completely relaxed, calm, sluggish, dull, sleepy, or unaroused.”

For the NRC VAD lexicon we study here [19], the end-points were described by 6 or 7 words or phrases, unavoidably broadening them away from being sharply defined (Tab. 1). For example, the words ‘happiness’ and ‘hopefulness’ are used for high valence, ‘unhappiness’ and ‘despair’ for low valence, ‘activeness’ and ‘frenzy’ for high arousal, and ‘relaxation’ and ‘sluggishness’ for low arousal (see Tab. 1 for all descriptors). There is a gap in meaning between all of these pairs of words, and how participants might perform at rating or ranking words is not a priori clear.

A further complication is that the names of the dimensions themselves do not track well within the VAD framework. While not strictly necessary that they do so, if the name of dimension is a word with a common meaning, then raters may be guided away from an intended direction in meaning space. For example, the word ‘arousal’ is itself high on arousal (**Ar**=0.44) but also registers on the valence and dominance dimensions **Va**=0.29, **Dm**=0.23. And while the word ‘dominance’ scores strongly in dominance and neutrally for valence, it does pick up in the arousal dimension with (**Va**,**Ar**,**Dm**) = (0.04,0.28,0.34). By contrast, ‘valence’ is sufficiently rare—it is not part of the NRC VAD lexicon—that it does not color how it is defined for the measurement of emotion. We are of course not suggesting that there is a simple solution to such ousiometric nomenclature issues—we are after all using words to define words as well as kinds of meanings of words.

While we have critiqued how end-point descriptors have been used, we are not saying such an approach is invalid. Rather, we point out that: 1. The EPA dimensions were originally outputs of relatively small studies involving numerous semantic differentials, and 2. The attempt to then make these dimensions controlled inputs to new studies is an entirely different exercise.

In sum, the NRC VAD lexicon, the output of Ref. [19]’s study, does not align with the VAD framework, even though the VAD framework was the intended input.

To move forward, we observe that for any essence-of-meaning study, if participants are guided by some well constructed set of end-point descriptors, then we can always compare and re-consider how well these descriptors perform. Moreover, we must allow that a distinct framework may emerge over time as far larger and more sophisticated studies are carried out. We are effectively maintaining the approach of the founding experiments, allowing the outcomes to remain informative and be potentially corrective.

3.3 Additional analytic processes for the level of types

For the following sections, we complement our analysis of the results of SVD with four pieces in the Supplementary Materials:

- Sec. S1: Large-scale ousiograms in Figs. S1–S9.
- Sec. S2: Explorations of synousionyms and antousionyms, words that are similar or opposite in terms of essential meaning.
- Sec. S3: An ‘MRI’ of meaning space rendered as a flipbook in Figs. S10–S28.
- Sec. S4: Lists of the top 20 words ranked by component size along the 13 axes of a 3×3 cube that is aligned with the SVD dimensions. See Figs. S29–S41. Each axis is a semantic differential, making for 26 end point cubes (the neutral center cube brings the total to 27=3×3). Words are ordered by component size with the restriction that their vector representations lie within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$ around a given axis. We present the full cube below in Sec. 3.7 and Fig. 4.

3.4 Assessing the failure of the Valence-Arousal-Dominance (VAD) framework

In the present and following two sections, we show how the NRC VAD lexicon affords two possible alternate and mutually consistent frameworks: Goodness-Aggression-Structure (GAS) and Power-Danger-Structure (PDS). The steps of our analysis are represented by the rows of Fig. 2, which we explain as follows.

We first note that for the NRC VAD lexicon, the overall contributions to variance explained by the three VAD

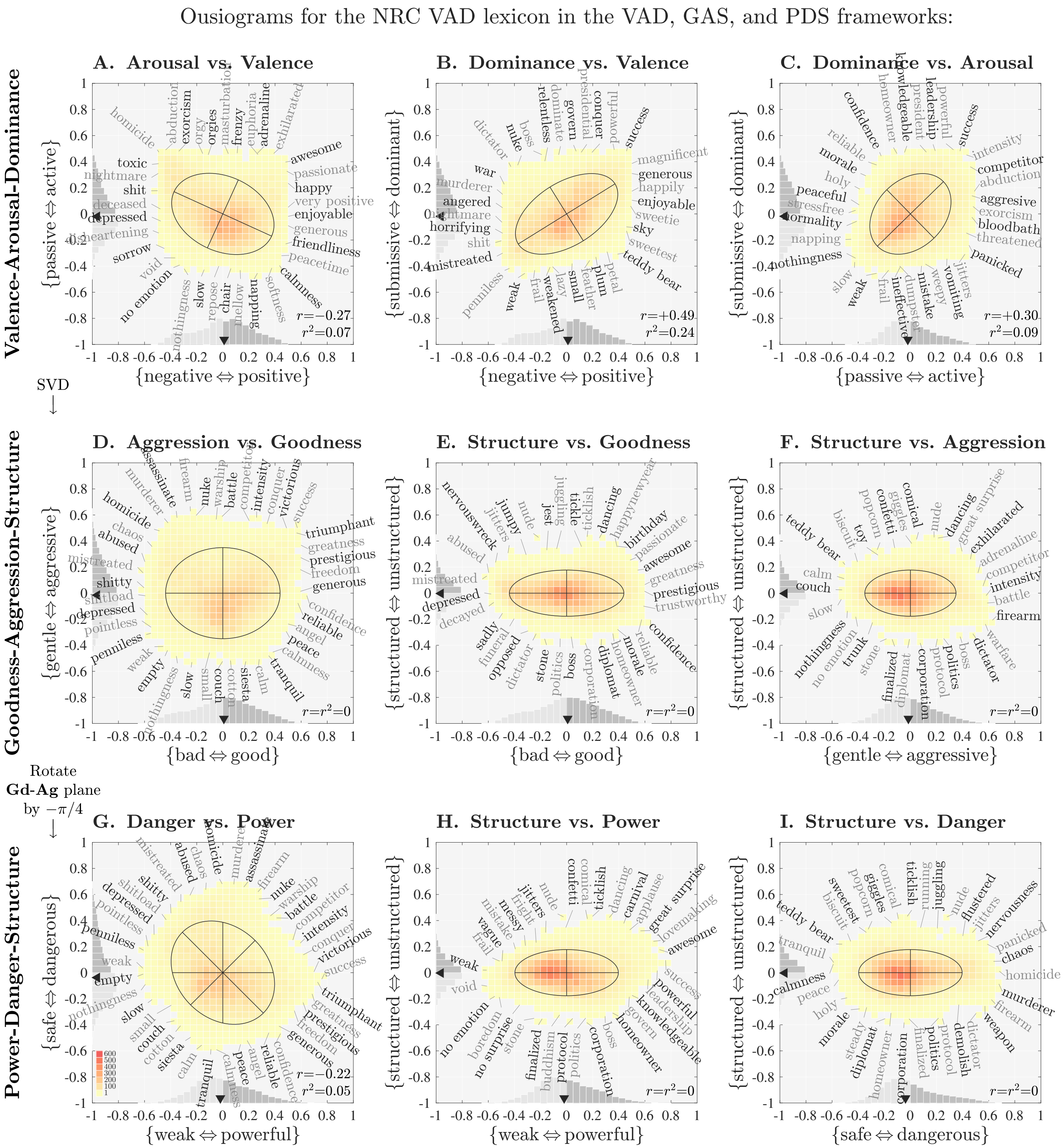

Figure 2: Ousiograms showing the analytic sequence moving from the valence-arousal-dominance (VAD) framework (top row) to the goodness-aggression-structure (GAS) and power-danger-structure (PDS) frameworks (second and third rows). **Row 1, panels A, B, and C:** Ousiograms for the three pairs of variables **Va**, **Ar**, and **Dm** for $\sim$ 20,000 words in the VAD NRC lexicon [19] (panel B corresponds to Fig. 1). We determine the ellipses by using singular value decomposition (SVD) in each plane, ignoring the third dimension. The ill fit of the VAD framework is apparent for the misalignments of ellipse axes. Word annotations along the edges of the nine pairwise distributions, coupled with ranked words lists by component size (Figs. S29 to S33), enable interpretation of the new frameworks of GAS and PDS. **Row 2, panels D, E, and F:** We perform SVD on the full matrix formed by the **Va**, **Ar**, and **Dm** scores, and identify goodness **Gd**, aggression **Ag**, and structure **St**, with the first two dimensions accounting for over 90% of explained variance **Row 3, panels G, H, and I:** Rotating the goodness-aggression plane by $-\pi/4$, we uncover a framework with {weak ⇔ powerful} and {safe ⇔ dangerous}. The GA and PD dimensions interlink to form an interpretable circumplex model GPADS. See Fig. 3 for a larger, more detailed power-danger ousiogram. As any lexicon reflects only the possible but not the used language (types versus tokens), whether or not the VAD, GAS, or PDS frameworks are sensible must be tested by considering real corpora. See Sec. 3.4 and Eqs. 2 and 4 for interpretation of the VAD, GAS, and PDS relationships.

dimensions of meaning are approximately 44.4%, 28.0%, and 27.6%. Valence is clearly the leading dimension with arousal and dominance balanced.

To determine the uncorrelated orthogonal dimensions for the NRC VAD lexicon, we perform singular value decomposition (SVD) on the 3 by 20,006 matrix $\mathbb{A}$ of average VAD scores ($\mathbb{A} = \mathbb{U}\Sigma\mathbb{V}^{\mathrm{T}}$). We find singular values $\sigma_1 \simeq 34.1$, $\sigma_2 \simeq 27.2$, and $\sigma_3 \simeq 13.8$, which correspond to explained variances of 55.6%, 35.3%, and 9.1%. The first two dimensions now explain 90.9% as opposed to 72.4% explained by **Va** and **Ar**.

The point cloud of VAD scores is thus a non-axis-aligned ellipsoid, strongly flattened in one dimension. In Fig. 2, the first row of ousiograms show projected histograms of the ellipsoid in VAD space for each pair of dimensions (Fig. 2B corresponds to Fig. 1). The SVD ellipses in all three projections demonstrate the correlations in Eq. (1) above.

As for all ousiograms, the word annotations help us understand how raters have responded to the end-point descriptors. Here, these annotations may be diagnostic (VAD) or illuminating (GAS and PDS, below). For VAD, we have already considered **Va-Dm** ousiogram's annotation (Fig. 2B), finding them to be sensible, and we see that annotations for the other dimension pairs are similarly interpretable within the VAD framework (Figs. 2A and C).

3.5 The Goodness-Aggression-Structure (GAS) framework

Moving to the the middle row of panels (Figs. 2D–F), we show ousiograms for word scores represented by the orthogonal basis determined by SVD acting on the VAD word scores. By construction, all three SVD ellipses are now aligned with the underlying axes.

Upon considering the annotated words, along with the ranked word lists in Figs. S30, S32, and S33, we interpret these three new essence-of-meaning dimensions to be goodness **Gd**, aggression **Ag**, and structure **St**. (For annotations internal to each histogram, see the larger ousiograms in Supplementary Materials.)

To arrive at the goodness dimension, we look to words on the left and right side of the ousiogram in Fig. 2D. On the left, we see 'shitty', 'penniless', 'mistreated', and 'abused'; and on the right, 'reliable', 'confidence', 'freedom', and 'triumphant'.

Words at the bottom and top of the same ousiogram in Fig. 2D are connected in essential meaning by their signifying of low and high aggression: 'slow', 'couch', 'siesta', and 'calm', versus 'assassinate', 'battle', 'competitor', and 'conquer'.

Finally, we distill the vertical dimension in the ousiograms of Figs. 2E and 2F as structure. We choose the alignment of the third dimension to be {structured ⇔ unstructured}, moving upwards. At the bottom of these ousiograms, we have words connoting organization, rigidity, and systematic form: 'stone', 'protocol', 'corporation', 'dictator', and 'diplomat'. At the top, we see terms that convey lack of structure: 'jest', 'confetti', 'dancing', 'popcorn', and 'great surprise'. To support the choice of orientation for the structure axis, we make a thermodynamic analogy where rigid organization is akin to a zero temperature frozen state, and a growing lack of structure corresponds to increasing temperature. We also see that {serious ⇔ playful} and {predictable ⇔ unpredictable} differentials are subsets of the more general {structured ⇔ unstructured} differential. Broadly speaking, we view the third dimension of essential meaning {structured ⇔ unstructured} as encoding evolvability.

For purposes of clarity of argument, we have sought to choose valid but distinct names for the three dimensions in GAS to distinguish them from VAD (or EPA). We acknowledge that valence, evaluation, and goodness are conceptually similar as are activity, arousal, and aggression. And as we discuss below, in the realm of emotion, valence is often taken to be analogous to a {happiness ⇔ sadness} dimension [13, 72].

The linear transformation between VAD and GAS obtained from SVD is:

$$\begin{bmatrix} \mathbf{Gd} \\ \mathbf{Ag} \\ \mathbf{St} \end{bmatrix} \simeq \begin{bmatrix} +0.86 & -0.15 & +0.48 \\ -0.16 & +0.83 & +0.54 \\ +0.48 & +0.55 & -0.69 \end{bmatrix} \begin{bmatrix} \mathbf{Va} \\ \mathbf{Ar} \\ \mathbf{Dm} \end{bmatrix}. \quad (2)$$

In moving to the GAS framework, we have goodness most connected with valence (+0.86) and dominance (+0.48), with a minor negative linkage to arousal (−0.15). Aggression is most connected with arousal (+0.83) and also, like goodness, with dominance (+0.54), but is somewhat at odds with valence (−0.16). And what we have identified as an increasing lack of structure corresponds roughly equally to increases in valence and arousal (+0.48 and +0.55) while increasing dominance points in the direction of more structure (−0.69).

We can now see that what separates the GAS framework from the VAD framework (or EPA framework) is that the dominance (or potency) dimension lies within the goodness-aggression plane. That is, the three conceptual dimensions of VAD are in fact collapsed into the two dimensions of goodness and aggression, with a new third and less important dimension of structure being revealed.

When dominance is near zero, Eq. (2) shows that goodness and aggression approximate valence and arousal. However, the correlations between valence and dominance as well as arousal and dominance mean that dominance increasing in magnitude will move goodness-aggression away from valence-arousal.

Returning to the ousiogram in Fig. 2D, we see that the four intercardinal axes carry distinguishable essential meanings, interpolating between the {good ⇔ bad} and {high-aggression ⇔ low-aggression} axes.

The diagonal axis running from 'weak' and 'empty' to 'success' and 'triumphant' is a {weak ⇔ powerful} axis, while the orthogonal diagonal axis traveling from 'calmness' and 'peace' to 'murderer' and 'homicide' is, we argue, a {safe ⇔ dangerous} axis.

3.6 The Power-Danger-Structure (PDS) framework

For reasons we explain below, we are drawn to consider {weak ⇔ powerful} and {safe ⇔ dangerous} as an alternate essence-of-meaning axes, which we achieve in the third row of ousiograms in Fig. 2 by a simple clockwise rotation of the **Gd-Ag** plane by $-\pi/4$. We call this rotation of the GAS framework the Power-Danger-Structure (PDS) framework, and we will then also consider a combined framework: GPADS.

At this stage, we do not view either GAS or PDS to be correct but rather complementary, interrelated frameworks. Even though we of course only need two basis vectors to describe two dimensions, viewing word scores in the combined GPADS framework is valuable.

Expressed as a simple linear transformations, we have

$$\begin{bmatrix} \mathbf{Pw} \\ \mathbf{Dg} \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} \mathbf{Gd} \\ \mathbf{Ag} \end{bmatrix}. \tag{3}$$

We supply a more detailed power-danger ousiogram in Fig. 3. When later considering large-scale corpora, we will see that the PDS framework rather than GAS conforms to real word usage (tokens instead of types). But we first must explore its characteristics for the unamplified NRC VAD lexicon.

In the PDS framework, the variance explained is now evenly divided between power and danger (45.5% each) while structure's contribution remains the same. Further, the words with the largest magnitude are now aligned with the positive axes of power and danger. For the largest overall magnitude word 'success', the PDS coordinates are $(\mathbf{Pw}, \mathbf{Dg}, \mathbf{St}) = (0.76, -0.05, 0.10)$. For 'murderer', $(\mathbf{Pw}, \mathbf{Dg}, \mathbf{St}) = (0.08, 0.68, -0.09)$. Of the top 20 words by vector magnitude, 12 are strongly aligned with the power direction and 8 with the danger direction (see Figs. S29 and S31). However, we suffer one drawback as we have reintroduced a non-zero correlation, $r = -0.22$, as indicated by the rotated ellipse in Fig. 2G and Fig. 3.

The rotated and internal annotations in the power-danger ousiogram in Fig. 3, are now in line with our interpretation of the two axes being {weak ⇔ powerful} and {safe ⇔ dangerous}. The horizontal axis, for example, runs from 'void', 'nothingness', and 'empty' to 'powerful', 'success', and 'almighty'. We find high danger in 'earthquake', 'suicidebombing', and 'toxic', and safety in 'serenity', 'softness', and 'tranquil'.

As for the valence-dominance ousiogram in Fig. 1, traveling around the boundary of the power-danger ousiogram loops us through an ousiometrically sensible sequence of terms. Moving upwards and around from 'triumphant', words take on increasingly violent connotations, while moving down, success begins to ebb while peaceful aspects build.

Crucially, and as we have described, the GAS and PDS frameworks form GPADS, a kind of circumplex model. We list the four axes in the primary plane in order from danger at the top of the PD plane, moving clockwise by $\pi/4$ through aggression, power, and goodness.

Each of the four directions in GA and PD are mutually intelligible by their adjacent directions in the alternate framework. For example, powerful is aggressive-good, dangerous is aggressive-bad, good is safe-powerful ('wisdom' and 'generous'), bad is dangerous-weak ('deceased' and 'bankruptcy'), and gentle is weak-safe.

Combining SVD and the $-\pi/4$ rotation, we have the linear transformation connecting the VAD and PDS frameworks:

$$\begin{bmatrix} \mathbf{Pw} \\ \mathbf{Dg} \\ \mathbf{St} \end{bmatrix} \simeq \begin{bmatrix} +0.50 & +0.48 & +0.72 \\ -0.72 & +0.69 & +0.04 \\ +0.48 & +0.55 & -0.69 \end{bmatrix} \begin{bmatrix} \mathbf{Va} \\ \mathbf{Ar} \\ \mathbf{Dm} \end{bmatrix}. \tag{4}$$

We see that power is roughly a direct sum of valence, arousal, and dominance (+0.50, +0.48, and +0.72). Danger is a near equally weighted linear combination of negative valence and positive arousal (−0.72 and +0.69), and has little connection to dominance (+0.04). Structure's connection to VAD remains the same as in Eq. (2) since we have rotated a plane orthogonal to its axis.

We have thus determined that the VAD framework was effectively interpreted as strongly correlated by participants in the NRC VAD lexicon study of Ref. [19]. We also now have two complementary frameworks in GAS in PDS that are potential candidates for a fundamental minimal representation of essential meaning.

We emphasize that at this stage, we do not know if the VAD, GAS, or PDS frameworks—or indeed none of

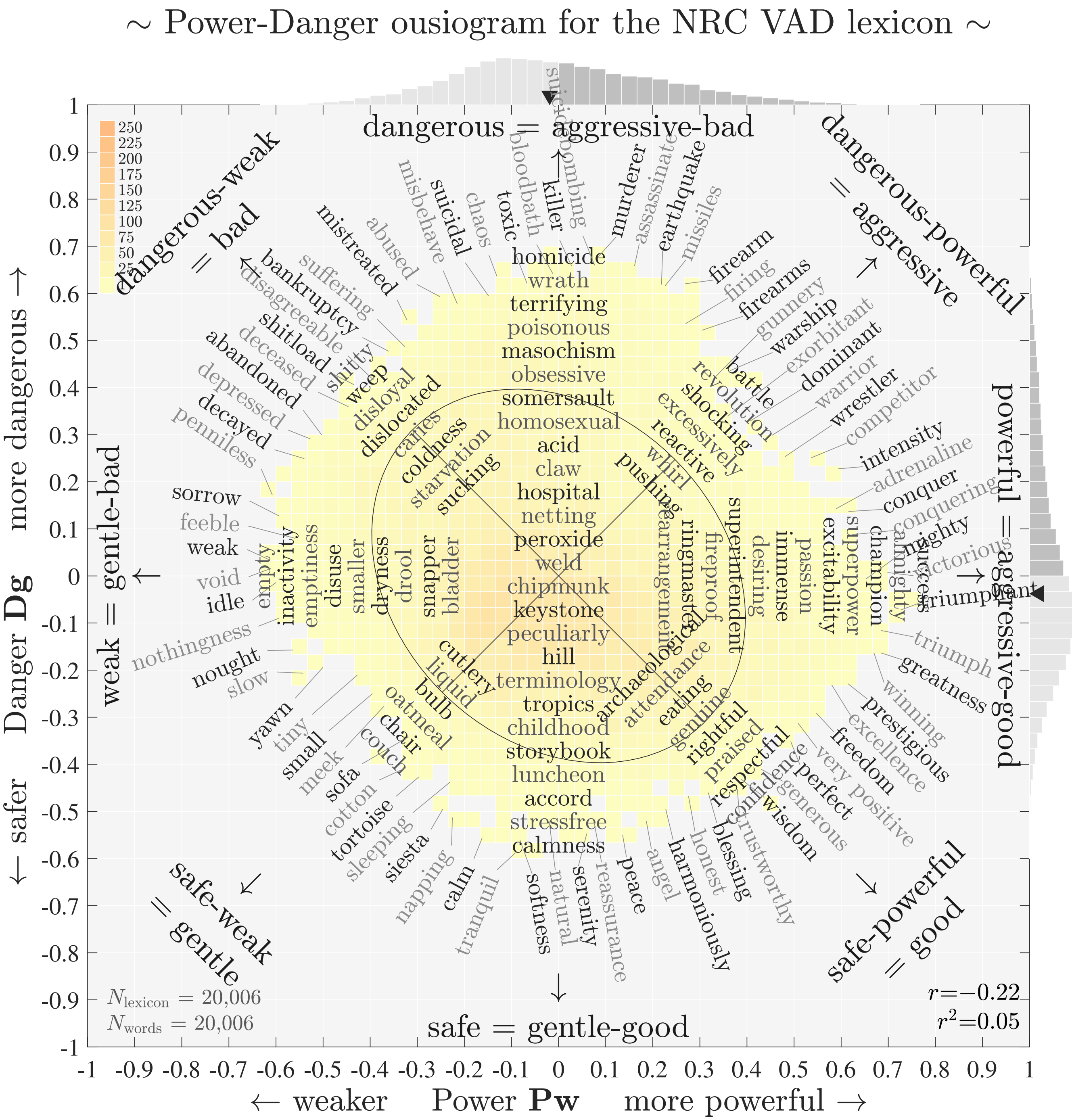

Figure 3: Power-danger ousiogram for the NRC VAD lexicon [19] for the PDS framework, an expanded version of Fig. 2G with internal annotations. The diagonal endpoints match the axis endpoints for the GAS framework: safe-powerful ∼ good, dangerous-weak ∼ bad, powerful-dangerous ∼ aggressive, and safe-weak ∼ gentle. PDS and GAS interpolate between each other in the primary plane which can be viewed as a kind of circumplex model, GPADS [9], which can be viewed as a cube model (see Fig. 4). Both power and danger reach further into positive values than negative with $-0.612 \leq \mathbf{Pw} \leq 0.758$ and $-0.591 \leq \mathbf{Dg} \leq 0.681$. The modes and the medians indicate a slight safe-weak tendency for the meanings of words in the NRC VAD lexicon (medians: -0.019 and -0.038, dark triangles), which is cautioned as an observation preliminary to later measurements where, in accounting for frequency of usage, we find a bias towards safety in real corpora (see Figs. 5 and 6). In the Supplementary Materials, we provide larger ousiograms with internal labels for all corpora and all three frameworks (for the NRC VAD lexicon examples, we use the same color map across all figures).

them—may be suitable when confronted with real word usage when we consider tokens instead of types. What we do have is a circumplex-like model in GPADS which contains two clear orthogonal frameworks.

3.7 A cube model of meaning for the Goodness-Power-Aggression-Danger-Structure (GPADS) framework

In Fig. 4, we combine all of our framework identifications in a unified GPADS cube model of essential meaning.

The middle primary plane shows the four interconnected axes of GAS and PDS: GPAD. In anticipation of our later findings, we have aligned the cube within the PDS framework, though it could be readily rotated to align with GAS.

The cube model is complementary to the map-like ousiograms in Fig. 3 and Figs. S1–S9 and is also informed by and connected with lists of ranked words in Figs. S29–S41.

For the word lists, we show the top 20 words by component size for each of the 13 cube axes, 9 of which connect the structured and unstructured levels. Three axes connect face cubes, six connect edge cubes, and four connect corner cubes. To avoid overlap we restrict words to cones around axes of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$. For example, Fig. S39 shows the top 20 words for unstructured-gentle vs. structured-aggressive, which is the axis connecting the corner cubes in the front top left and back lower right.

For each cube (except the neutral one), we show three adjectives that capture the words associated with that cube and their location within the GPADS framework. The adjectives are in some cases words directly taken from the relevant list but more usually are general descriptors.

3.8 The linguistic 'safety bias' of disparate large-scale, corpora

Having established the GAS and PDS frameworks as alternatives to VAD, we turn to real, large-scale corpora. By intent, we have so far only considered the essential meaning of words and terms in the NRC VAD lexicon—the level of types.

We now aim to incorporate frequency of usage of words—tokens—for a collection of well-defined corpora. We can only do so sensibly within each structured corpus—we cannot meaningfully combine, for example, the New York Times and Twitter.

For an initial example corpus, we investigate the ousiometric content of 1-grams used in English fiction from 1900–2020 per the Google Books project [61]. We note that we have earlier argued and demonstrated that the Google Books project generates problematic corpora in that 1. Each book is in principle counted once (popularity is not measured) and that 2. For all English books combined, the corpus is clouded by a growing preponderance of scientific literature [62]. To use the framing of types and tokens for the former point, the books are themselves types, containing n-grams as tokens, but we do not have the books as tokens by knowing, for example, numbers of copies sold. Nevertheless, for our purposes here, the relatively-science-free 2019 English fiction corpus provides a raw large-scale body of text to examine.

We generate ousiograms in the same fashion as before, but we now weight words by their frequency of usage. The NRC VAD lexicon acts as a lexical lens on the frequency-rank distribution—we only take word counts for those words we have VAD/GAS/PDS scores for. In Fig. 5, we reprise the analytic sequence of Fig. 2 for words used in English fiction.

Whereas for the NRC VAD lexicon, the histograms were relatively uniform, we now see uneven distributions. For the VAD row, we see the distributions are not aligned with the underlying axes of the VAD framework (Figs. 5A–C). The main ousiogram for goodness-aggression (Fig. 5D) still does not align well, showing an off-axis bias towards goodness and low aggression, the former being a linguistic signature of the Pollyanna principle [52, 55, 73]. We discuss both biases further below. The goodness-structure and aggression-structure ousiograms (Figs. 5E and F) show biases towards goodness and low aggression that appear more aligned.

It is in the PDS framework (Figs. 5G–I), that we see robust agreement between ousiograms and the underlying axes. In the main power-danger ousiogram (Fig. 5G), the histogram shows a definitive bias towards safe, low-danger words. As shown by the marginal on the left axis, the danger distribution is skewed strongly towards safer words, and the median danger score is well below 0. By contrast, power presents a symmetric marginal distribution with a median slightly above 0. The power-structure ousiogram shows a general spread (Fig. 5H) while the danger-structure ousiogram again shows a clear safety bias (Fig. 5I).

In Fig. 6, we expand our analysis to show power-danger ousiograms for six more corpora: The novels of Jane Austen, a subset of Arthur Conan Doyle's Sherlock Holmes stories, the New York Times, Wikipedia, transcriptions of talk radio in the US, and Twitter (see Sec. 2 for details). These corpora vary widely in size and kind: written versus spoken, news, literature, formal and

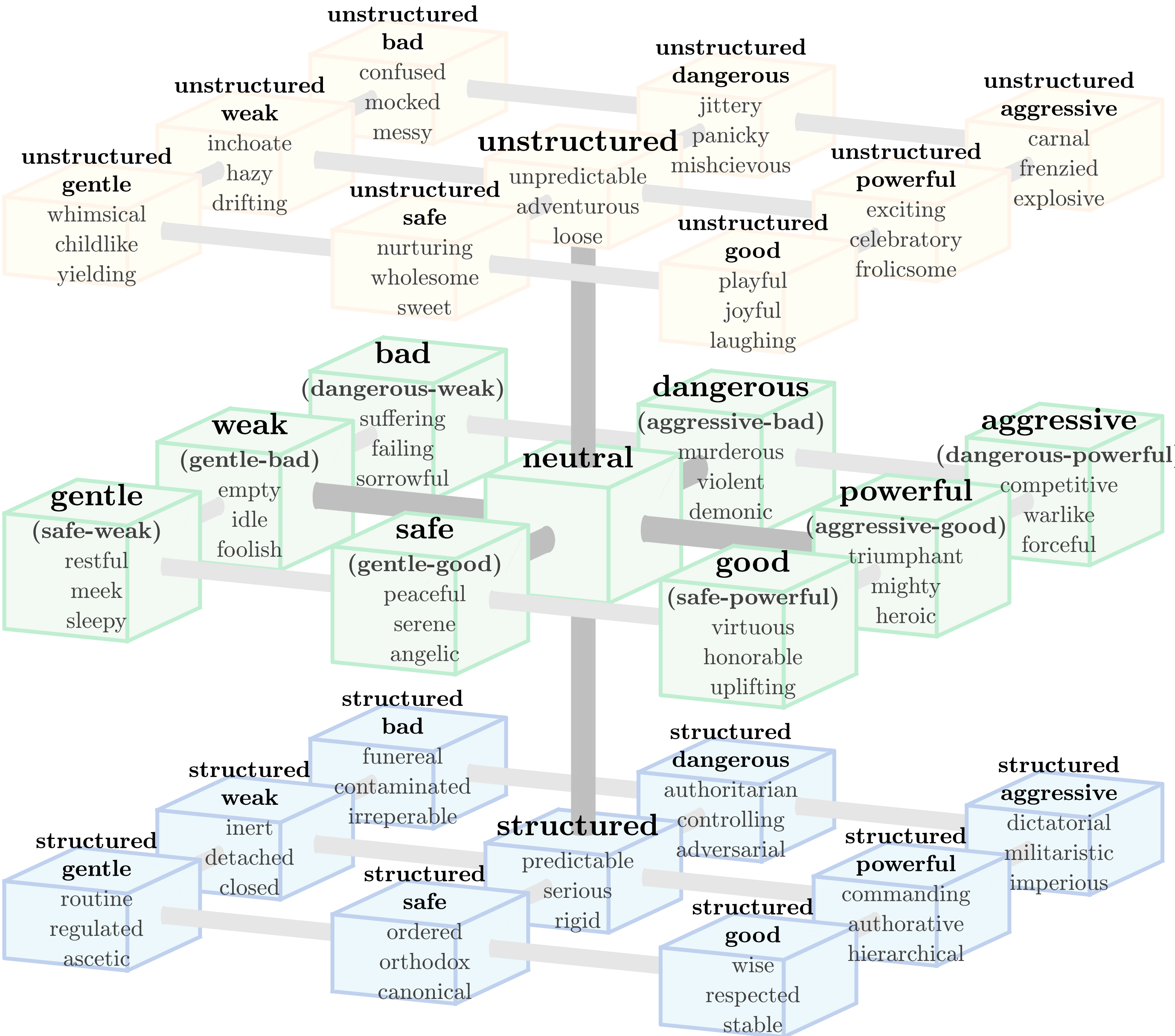

Figure 4: An exploded cube representing the GPADS framework. In Figs. S29–S41 in the Supplementary Materials, we provide complementary lists of 20 words for each end of the 13 cube axes. Words are ranked by component size conditioned on sufficient alignment. Each of these paired lists indicates a differential with a small version of the exploded cube depicted. The example words on each block are a mixture of words on these lists and adjectives which capture a category. For the cube, blue represents structure (cold, low temperature, rigid) and yellow represents lack of structure (warm, high temperature, loose), while block thickness qualitatively indicates variance explained.

informal, bearing social amplification or not (e.g., the inclusion of retweets from Twitter encodes one form of echoing, but the other corpora carry no such equivalent signature of popularity). For each corpus, we provide the full analytic sequence in the manner of Figs. 2 and 5 in Figs. S42–S47.

The power-danger ousiograms for these six distinct corpora in Fig. 6 all present the same safety bias for words as we saw for English fiction in Fig. 5G. While varying in detail as they must, the six histograms in Fig. 6 all show a weight toward words below the horizontal {weak ⇔ powerful} axis, and the danger marginals on the left axes of all ousiograms are skewed toward safety. There is no such bias for the power dimension, though median power is at or above zero in all cases.

We emphasize again that our initial determination of the PDS framework was performed only at the level of types, using the NRC VAD lexicon. In these subsequent tests with real corpora, we have found that our hypothesized ousiometric PDS framework has been borne out to be fundamental.

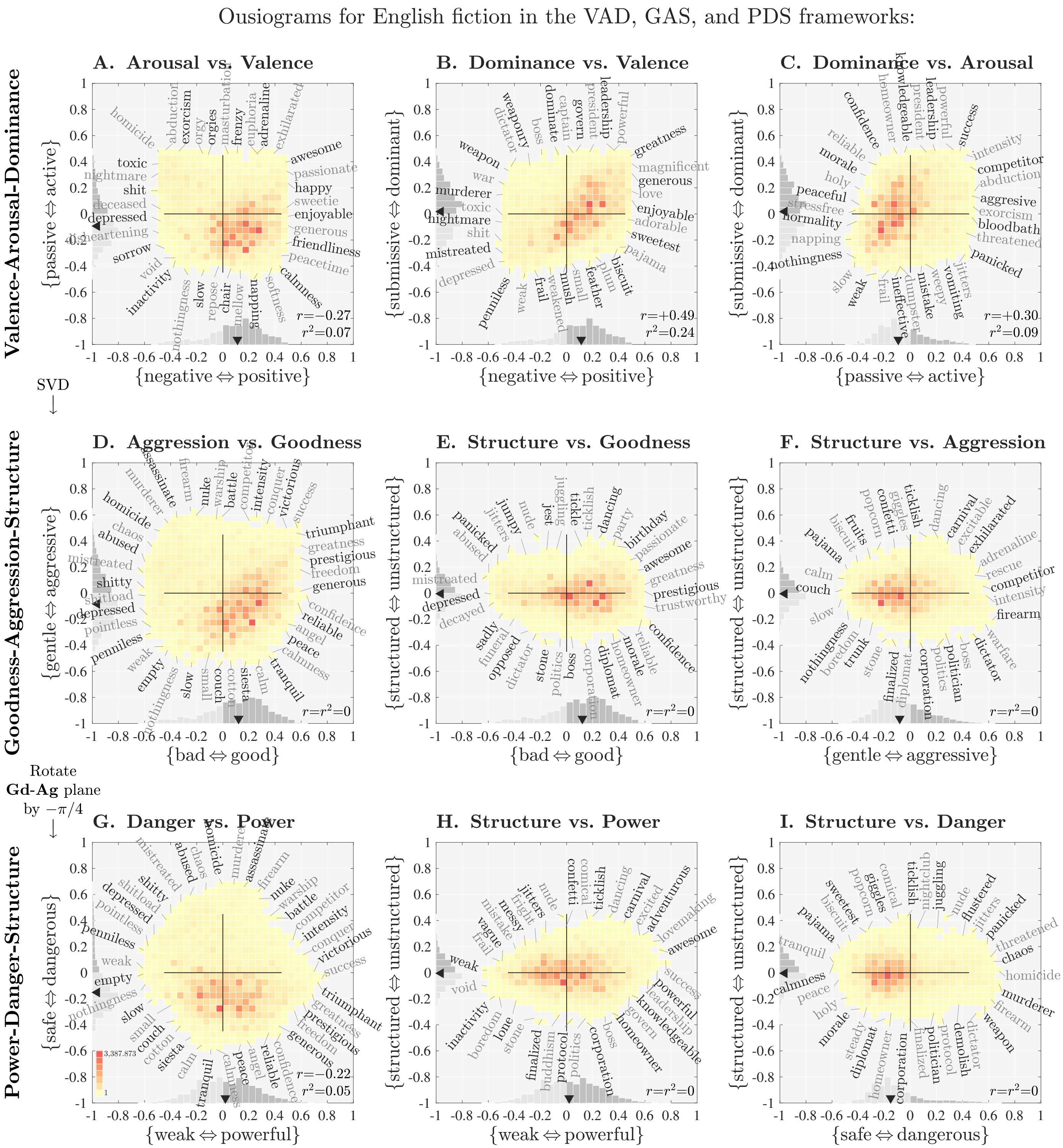

Figure 5: Ousiograms for English fiction (1900–2019) arranged in the same analytic sequence format as Fig. 2. We now allow each word's contribution to be its overall frequency of usage within a given corpus. We form a single frequency-rank distribution [60] for the entire corpus by equally weighting each year's frequency-rank distribution [61, 62]. The sequence indicates that: 1. Overall, the Google Books English fiction corpus is best aligned with the PDS framework, and that 2. Expressed language exhibits a 'safety bias', a generalization of the Pollyanna principle [52, 55, 73]. **Row 1, panels A, B, and C:** In the VAD framework, the histograms are clearly misaligned with the main axes. **Row 2, panels D, E, and F:** The histograms are again poorly aligned with the main axes of **Gd**, **Ag**, and **St**. The marginal distributions for Goodness and Aggression in panel D show an apparent 'goodness bias' and a 'low-aggression bias'. The goodness bias is an instantiation of the the Pollyanna principle for language [52, 55]. **Row 3, panels G, H, and I:** Rotation to the power-danger framework shows that words used in English fiction conform to a safety bias with the preponderance of words falling on the safe side of the power-danger plane (panel G). Both the goodness and aggression biases in panel D are revealed to be one dimensional projections of an underlying safety bias. Words are distributed broadly in the power-structure plane (panel H) and are on the safe side of the danger-structure plane (panel I).

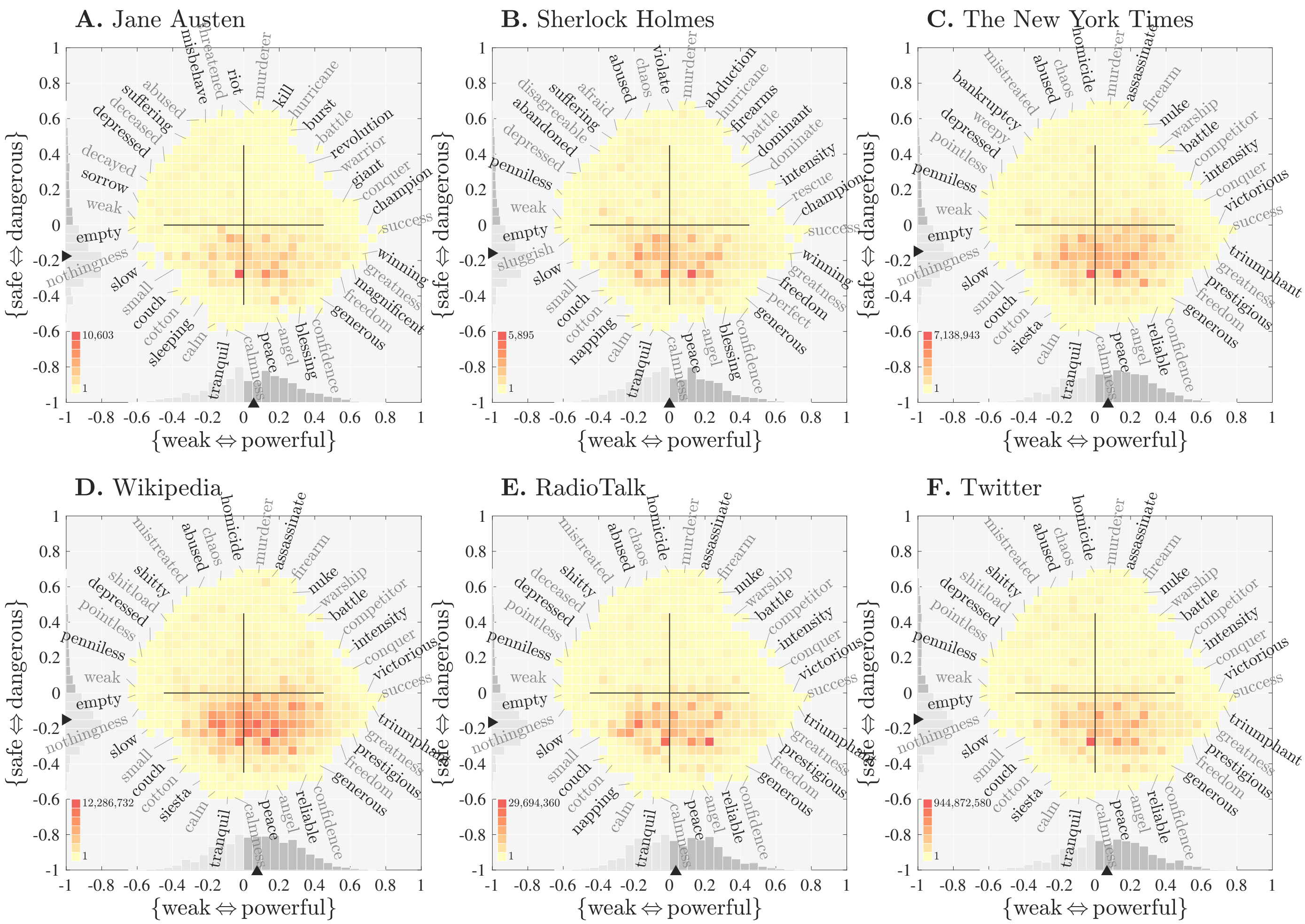

Figure 6: Ousiograms for power-danger space for six corpora of varying type and scale: **A.** Jane Austen's novels; **B.** Arthur Conan Doyle's Sherlock Holmes novels and short stories; **C.** The New York Times (1987–2007) [63]; **D.** Wikipedia (March, 2019) [64]; **E.** Talk radio transcripts (2018/10–2019/03) [65]; and **F.** Twitter (approximately 10% of all English tweets in 2020, with each day weighted equally) [66, 74]. Words of the six corpora all strongly canvass power-danger space with a marked bias towards safe. Jane Austen's novels, the New York Times, and Wikipedia are all author-side corpora in that their frequency-rank distributions do not incorporate popularity of books, sections, or entries. By contrast, Twitter incorporates a reader-side measure of popularity through amplification by retweets. Each ousiogram's color map is linearly normalized to the highest count bin, and the maximum bin count is indicated at the top of each color bar. The highest count bin in panels A, C, and F is due to the word 'be' (**Pw**=-0.001, **Dg**=-0.300). See Sec. 2 for description of data sets. For the six corpora here, we provide the full VAD-GAS-PDS analytic sequence of Figs. 2 and 5 in Figs. S42, S43, S44, S45, S46, and S47.

4 Congruences

4.1 Russell's circumplex model of emotion

We consider Russell's highly cited circumplex model of affect [9], in light of the GPADS framework. We find general accordance with one region of disagreement being in the aggressive direction (the dangerous-powerful quadrant).

Affective states are representations of emotional states, and may be external (e.g., facial expressions) or internal (conscious awareness). In linking to essential meaning, in 1952, Schlosberg [75] was one of the first to suggest that emotion—as conveyed by facial expressions—could be well represented by two dimensions, suggesting {pleasantness ⇔ unpleasantness} and {attention ⇔ rejection}. Two years later, Schlosberg then posited a third dimension of level of activation while also asserting that "the field [of emotion] is chaotic" [76]. Certain emotions would seem to readily connect with locations in the power-danger framework. Fear is a particular response to danger, contentment is a possible state in a safe environment, and so on. We examine such connections carefully below.

We consider Russell's original, unrevised model because of its historical and continued importance to the field [31, 32, 77, 78] as well as the challenge delivered by such a distinct kind of study. Indeed, the approximate

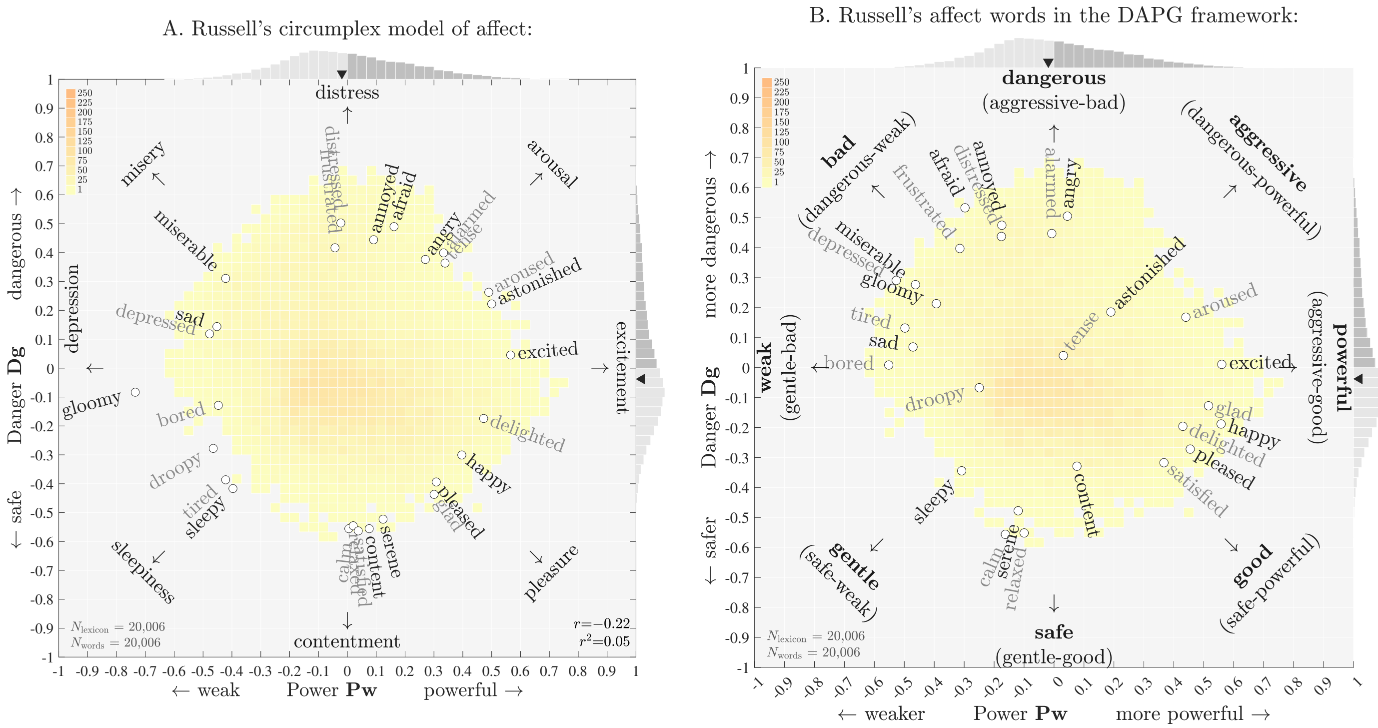

Figure 7: Comparison of Russell's circumplex model of affect [9] with the GPAD framework. The two frameworks show impressive agreement given how differently words were scored in Refs. [9] and [19]. **A.** Reconstruction of the circumplex model scores for 27 affect words for the first survey presented in Fig. 2 in Ref. [9]. We obtained data for 27 of 28 terms by visual inspection of Fig. 2 in [9], omitting the 2-gram 'at ease'. To enable comparison, we rotate Russell's scores by $-\pi/4$, and also underlie both plots with the power-danger histogram per Fig. 3. The comparison is nevertheless with the GPAD framework, and the PD alignment is for consistency. Leaving angles unchanged, we uniformly rescale the magnitude of scores for the 27 affect words in the circumplex model to give an approximate fit to the power-danger scale—only angles and relative magnitudes may be sensibly compared. **B.** Locations in the power-danger plane for the 27 affect words of Ref. [9], all of which are also found in the NRC VAD lexicon. We indicate the full GPAD framework with directions.

agreement between the studies of Russell and Mohammad is remarkable given the differences between them: Era (late 1970s versus late 2010s), subjects (undergraduate students at the University of British Columbia versus online crowdsourcing), assessment type (various in Ref. [9] versus best-worst scaling), scale (28 versus $\sim$ 20,000 terms), and framing (the specific of affect versus the general of essential meaning).

Building on earlier work [75, 79], Russell asserted that eight fundamental affect concepts could be arranged as compass points on a circle (see Fig. 1 in Ref. [9]). As we indicate in Fig. 7A, starting from pointing upwards and stepping around clockwise, these concepts are distress ($\sim$ danger), arousal ($\sim$ aggression), excitement ($\sim$ power), pleasure ($\sim$ goodness), contentment ($\sim$ safety), sleepiness ($\sim$ gentleness), depression ($\sim$ weakness), and misery ($\sim$ badness). In line with the VAD framework, Russell took the underlying horizontal and vertical dimensions to be {pleasure $\Leftrightarrow$ displeasure} and {arousal $\Leftrightarrow$ sleepiness}, aligning in the GPAD frameworks {goodness $\Leftrightarrow$ badness} and {aggression $\Leftrightarrow$ gentleness} The alignment with the GAS framework notwithstanding, we have facilitated comparison with the GPAD framework, by rotating Russell's framework by $-\pi/4$.

Russell then carried out a series of varying types of surveys on perceptions of 28 affect terms (e.g., 'afraid', 'glad', 'serene', 'bored'). In Fig. 7A, we show the locations of 27 words according to the results presented in Fig. 2 of Ref. [9] (we exclude the 2-gram 'at ease'). In Fig. 7B, we show the same words located by their power-danger scores.

In general, we see that words in the circumplex and GPAD frameworks are reasonably well aligned. A number of words show strong congruence across the two studies, including 'sleepy', 'excited', 'aroused', and 'miserable'. Angles of affect words are generally similar with a maximum discrepancy of around $\pi/4$. For example, 'tired' is in the direction of gentle in the circumplex model and weak in GPAD framework ('sleepy' aligns with gentle in both, and the added hue of danger for 'tired' in the GPAD framework is sensible). Apart from 'tense' and to a lesser extent 'astonished' and 'droopy', affect words register strong power-danger magnitudes, and are consequently located around an approximate circle.

The word that most stands out as differing between the two studies is 'tense'. On top of the major distinctions between the studies listed above, without the context of working with a small set of emotion-themed words, participants in the NRC VAD study would be more likely to interpret words and phrases by their most general, dominant meaning. While many of the affect words have clear meanings that are emotional (e.g., 'miserable'), the word 'tense' might not be as strongly construed as 'stressed'. Over four decades, we might also expect meanings of some words to shift somewhat. And in any case, the four surveys in Russell only show rough agreement with each other (see Figs. 2–5 in Ref. [9]).

4.2 Fictional characters

In separate work—archetypometrics—we have carried out extensive analysis of a dataset of 2000 characters from 341 popular stories from literature, movies, and television which have over 70 million ratings across 464 semantic differential traits [58, 59]. As per our methodology here, we performed SVD on the 464×2000 matrix and then generated a suite of ousiograms and ranked lists for both essential trait and character space. Here, we focus on a few core elements of essential trait space.

In Fig. 8, we show an ousiogram for the first two singular dimensions of essential trait space, and in Tab. 2, we list the top 15 traits for the first three dimensions.

Remarkably, the PDS framework is aligned with the first three dimensions of archetype space. We emphasize that we again kept the factor analysis simple, and that we did not perform any rotations or further manipulations.

We have named the archetype pairs of the first three dimensions {Fool ⇔ Hero}, {Angel ⇔ Demon}, and {Traditionalist ⇔ Adventurer}. For even more agreement, we find that in the GPADS framework, the words 'foolish', 'heroic', 'angelic', and 'demonic' are all located in strong alignment with their corresponding archetypes in essential trait space. We have included these words as descriptors in the meaning cube in Fig. 4.

These archetype names are of course general names which may register variably. We further define them by distilling the dominant traits into four pairs of semantic differentials each. For {Fool ⇔ Hero}, we have {weak ⇔ powerful}, {incompetent ⇔ capable}, {lazy ⇔ purposeful}, and {stupid ⇔ intelligent}; for {Angel ⇔ Demon}, we have {safe ⇔ dangerous}, {pure ⇔ depraved}, {virtuous ⇔ corrupt}, and {humble ⇔ arrogant}; and for {Traditionalist ⇔ Adventurer}, we have {serious ⇔ playful}, {predictable ⇔ unpredictable}, {humorless ⇔ funny}, and {uncreative ⇔ creative}.

One differential that might first appear at odds with our framework is {villainous ⇔ heroic} which is aligned with {bad ⇔ good}. However, the differential correctly interpolates between the directions of {**demon**} (villain) and {**hero**} which are not opposites but rather at right angles to each other. That is, {villainous ⇔ heroic} ∼ {weak ⇔ powerful} - {safe ⇔ dangerous} = {bad ⇔ good}.

Finally, for a circumplex model of archetypes that is aligned with the GPAD framework, and as indicated in Fig. 8, we suggest (moving around the circle starting at the top): Demons (dangerous), Dominators (aggressive), Heroes (powerful), Paragons (good), Angels (safe), Innocents (or Lambs) (gentle), Fools (weak), and Wretches (bad).

5 Ousiometer

We construct an elementary 'ousiometer', a lexical instrument for measuring the average essential meaning of large-scale texts. We take a similar approach to that of our hedonometer [14, 52, 80–83]. We view the ousiometer and hedonometer as example 'telegnomic' lexical instruments capable of remotely sensing meaning, knowledge, and stories.

We use M to represent one of the essential meaning dimensions within a specified ousiometric framework. For a simple ousiometer, we compute the average meaning score $M_{\text{avg}}(\Omega)$ for a text Ω in the following way. We consider only the 1-grams of the NRC VAD lexicon, leaving aside n-grams for $n \geq 2$ for possible future improvements. For any given text Ω, we apply a 'lexical lens' $\mathcal{L}$, a simple operator that filters the text's 1-grams, returning the subset 1-gram lexicon that intersects with the NRC VAD 1-gram lexicon. We denote the lensed text as $\mathcal{L}(\Omega)$. We write the resultant lensed lexicon as $R_{\mathcal{L}(\Omega)}$, further specifying this set to be a list of 1-grams ordered by descending frequency of usage f_τ within $\mathcal{L}(\Omega)$. For each 1-gram τ in the lensed lexicon $R_{\mathcal{L}(\Omega)}$, we then straightforwardly determine τ's normalized frequency as $p_\tau = f_\tau / \sum_{\tau'} f_{\tau'}$.

In general, given a lexical lens $\mathcal{L}$, the average ousiometric score of a text Ω is:

$$M_{\text{avg}}(\Omega; \mathcal{L}) = \sum_{\tau \in R_{\mathcal{L}(\Omega)}} p_\tau M_\tau, \tag{5}$$

where M_τ is the average ousiometric score for the 1-gram τ derived from the NRC VAD lexicon scores [19].

As an example, in Fig. 9, we show ousiometric trajectory and time series for Victor Hugo's "Les Misérables." In doing so, we are continuing the development of our earlier computational work on the measurement of emotional arcs in stories, famously ventured by Kurt Vonnegut [52, 82, 84, 85].

The main plot is an ousiometric trajectory of "Les Misérables" in the GPAD framework, oriented in the PD

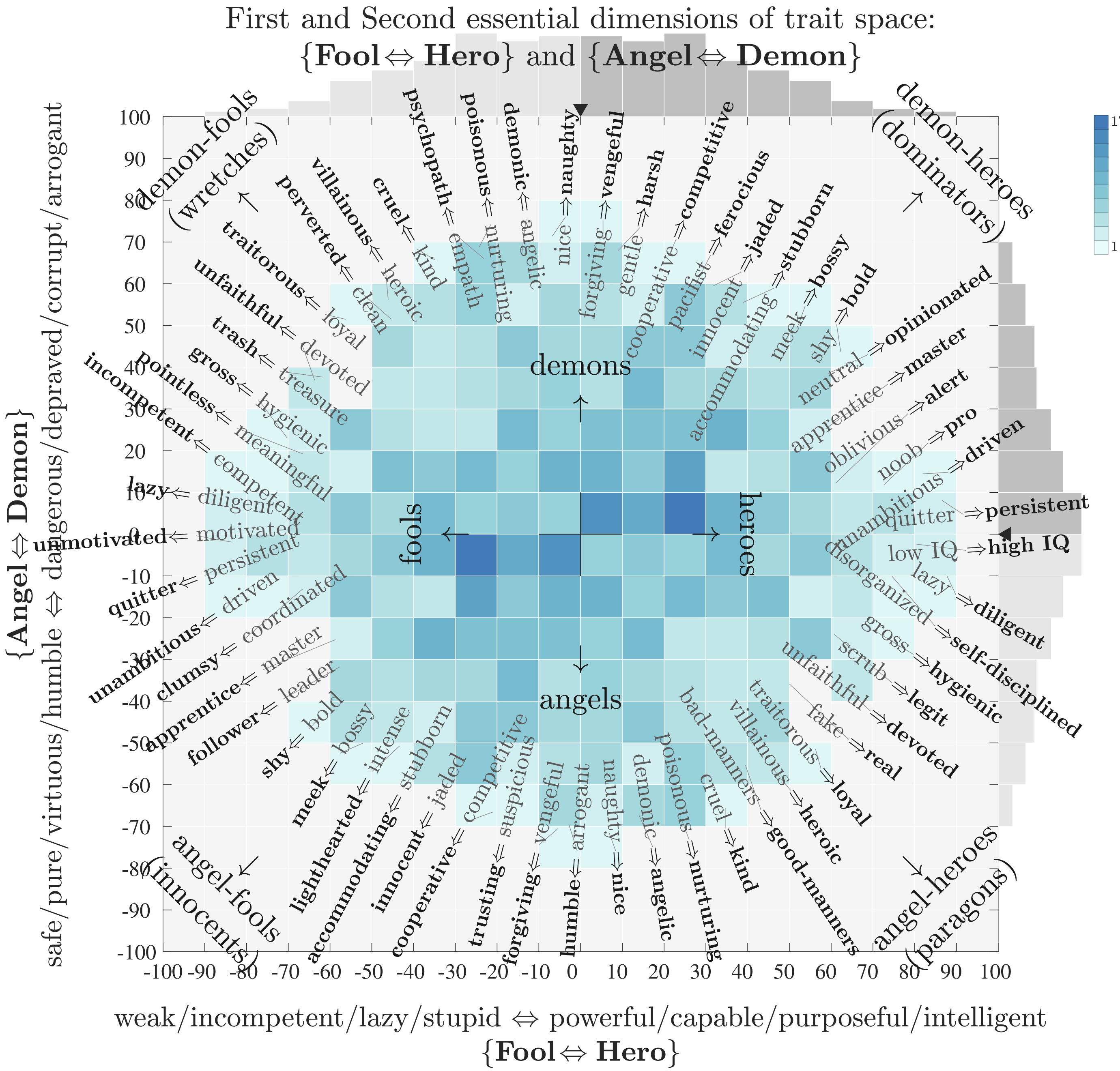

Figure 8: Ousiogram for the first two singular dimensions of essential trait space based on 2000 fictional characters evaluated across 464 traits each. We observe a clear congruence between the GPADS framework and the primary archetypes of fictional characters. Compare with Tab. 2 which lists the top ranked traits for the first three dimensions. The first three dimensions of essential trait space align with PDS as {Fool ⇔ Hero} for {weak ⇔ powerful}, {Angel ⇔ Demon} for {safe ⇔ dangerous}, and {Traditionalist ⇔ Adventurer} for {structured ⇔ unstructured}. Because the orientation of each trait's semantic differentials was arbitrary, we duplicated all semantic differentials with their bipolar adjectival pairs swapped. Hence, the traits and their reverse appear on opposite sides of the ousiogram. See Ref. [58] for a full exploration of archetype space with analysis that shows the first six singular dimensions rise to the level of identifiable archetypes.

Essential trait dimension 1 {Fool ⇔ Hero} ∼ {weak ⇔ powerful}	Essential trait dimension 2 {Angel ⇔ Demon} ∼ {safe ⇔ dangerous}	Essential trait dimension 3 {Traditionalist ⇔ Adventurer} ∼ {structured ⇔ unstructured}
1.{lazy ⇔ diligent}	1.{nice ⇔ naughty}	1.{scheduled ⇔ spontaneous}
2.{quitter ⇔ persistent}	2.{forgiving ⇔ vengeful}	2.{stick-in-the-mud ⇔ adventurous}
3.{unmotivated ⇔ motivated}	3.{humble ⇔ arrogant}	3.{uncreative ⇔ open to new experiences}
4.{unambitious ⇔ driven}	4.{nurturing ⇔ poisonous}	4.{serious ⇔ bold}
5.{incompetent ⇔ competent}	5.{gentle ⇔ harsh}	5.{monotone ⇔ expressive}
6.{low IQ ⇔ high IQ}	6.{angelic ⇔ demonic}	6.{lifeless ⇔ spirited}
7.{absentminded ⇔ focused}	7.{warm ⇔ quarrelsome}	7.{corporate ⇔ freelance}
8.{helpless ⇔ resourceful}	8.{cooperative ⇔ competitive}	8.{geriatric ⇔ vibrant}
9.{unobservant ⇔ perceptive}	9.{empath ⇔ psychopath}	9.{serious ⇔ playful}
10.{slacker ⇔ workaholic}	10.{kind ⇔ cruel}	10.{stoic ⇔ expressive}
11.{disorganized ⇔ self-disciplined}	11.{wholesome ⇔ salacious}	11.{shy ⇔ playful}
12.{noob ⇔ pro}	12.{altruistic ⇔ selfish}	12.{humorless ⇔ funny}
13.{slugabed ⇔ go-getter}	13.{sweet ⇔ bitter}	13.{deliberate ⇔ spontaneous}
14.{underachiever ⇔ overachiever}	14.{respectful ⇔ rude}	14.{orderly ⇔ chaotic}
15.{gross ⇔ hygienic}	15.{pure ⇔ debased}	15.{withdrawn ⇔ outgoing}

Table 2: The leading trait composition for the three primary dimensions of archetype space [58]. Traits are ranked by component size in each dimension. Compare with the ousiogram in Fig. 8 for the first two dimensions.

plane. To the right, we display ousiometric time series for the GAS framework which interlocks with the same for the PDS framework running along the bottom. The colors indicate 10 narrative reading time blocks, as measured by 1-grams, and help show the ousiometric trajectories path in time.

We observe that the {bad ⇔ good} time series is of similar form to what we found using our hedonometer [82]. In Fig. S73, we show a screenshot for the happiness time series for "Les Misérables" taken from our interactive story viewer at https://hedonometer.org. The agreement is satisfactory given that the hedonometer and ousiometer instruments are built on two distinct word lists using different evaluations (Likert vs. best-worst scaling). An interactive visualization based on Fig. 9 would be a natural next step.

In Figs. S48–S72 in the Supplementary Materials, we supply a flipbook which traces out the GPADS time series over 25 epochs.

A full analysis of our ousiometric time series for "Les Misérables" is well beyond the scope of our present work, and we reserve it for future exploration. Our purpose here is simply to show that we can readily build an ousiometer for large-scale texts.

In connected work on the ousiometrics of literature [85], we have used empirical mode decomposition on ousiometric time series to find that longer books are structured more like concatenations of shorter texts, revealing characteristic fluctuations in power and danger.

Finally, in the Supplementary Materials, we provide another example use of an ousiometer for streaming text: A retrospective analysis of Twitter for 2020/01 to 2021/01 inclusive (Sec. S8 and Fig. S74).

6 Concluding remarks

The mismeasurement of meaning: The quantitative measurement of essential meaning—ousiometrics—has been properly engaged as a scientific challenge for close to a century. Based on semantic differentials, the three dimensional orthogonal framework of evaluation-potency-activation (EPA) due to Osgood *et al.* [6] has effectively remained the leading conceptual framework, if not always by direct reference. Research into the specific context of affect saw EPA adapted as valence-arousal-dominance (VAD) [11, 12]. The VAD formalism has become widespread and not limited to studies of emotion, even being used for general essential meaning studies instead of EPA [13, 19].

We have shown that $\sim$ 20,000 terms evaluated by best-worst scaling in the VAD framework fails to reproduce the orthogonal VAD framework itself. We have contended that this cannot be explained away by participants misunderstanding bipolar adjectival pairs used to define VAD dimensions. Rather, we have argued that a longstanding problem for ousiometrics has been the difficulty of ascribing bipolar adjectival pairs to accurately characterize dimensions derived from participants' assessments of a larger set of semantic differentials [51]. As is, researchers tend to provide sets of bipolar adjectival pairs for fundamental dimensions, making them overly blunt instruments that have more likelihood of being correlated (see Tab. 1). Even after exploring antonyms and antousionyms (Sec. S2), we continue to see this

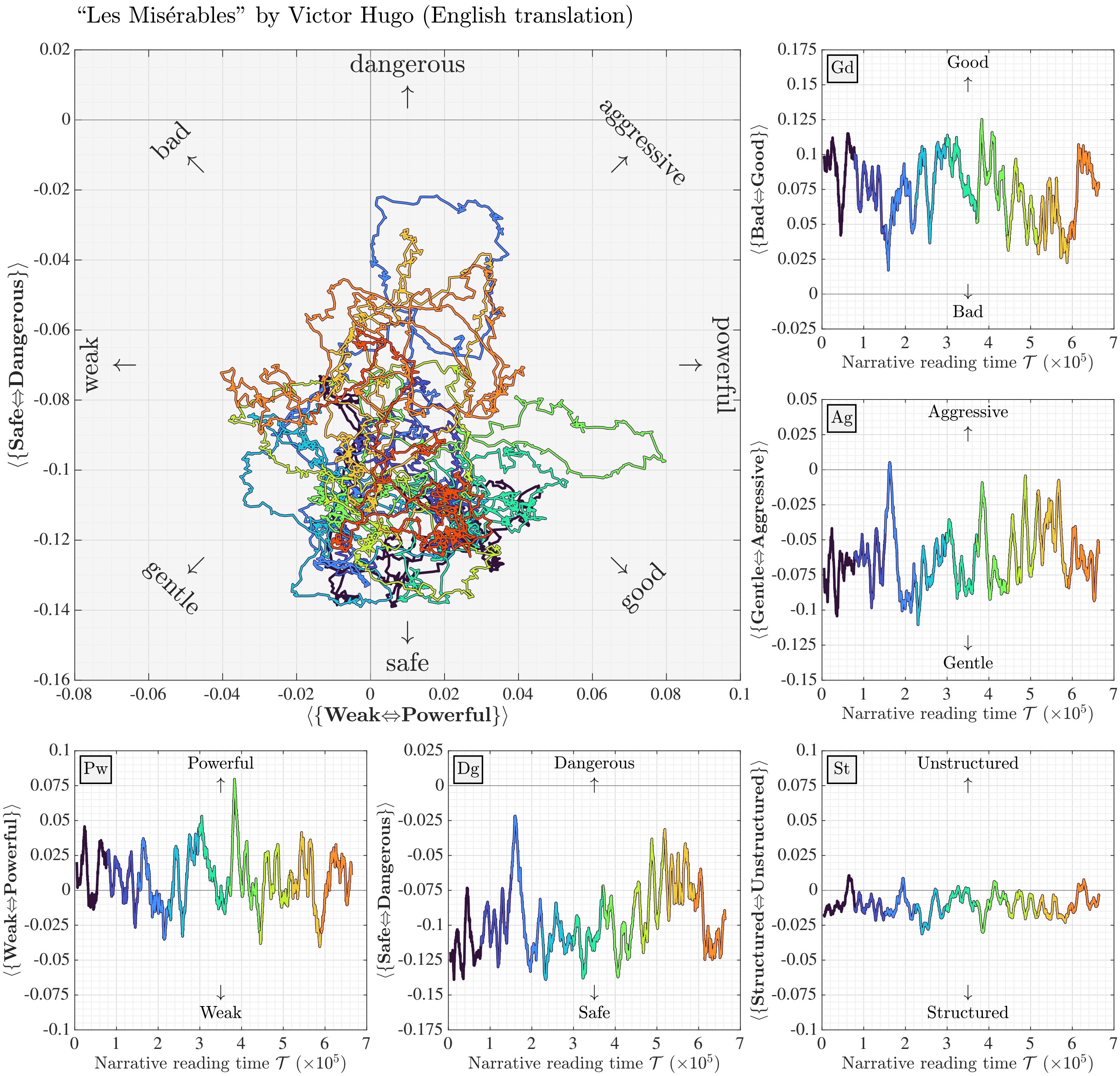

Figure 9: The ousiometer as a telegnomic lexical instrument for literature: Example ousiometric time series for Victor Hugo's Les Misérables. Main plot: Ousiometric trajectory of the novel in the PD plane with the GPAD framework indicated. The five individual time series comprise the GPADS framework. We break the timeline into 10 equal epochs and align the colors on all time series, including that of the trajectory in the PD plane. Narrative reading time $\mathcal{T}$ is in terms of 1-grams which includes numbers, punctuation, and other non-word elements. All vertical ranges for the time series are the same (0.20), and are shifted as needed. As expected per variance explained, the first four time series of the GPADS framework show similar variation while Structure is muted. Smoothing is at 10,000 1-grams with steps of 100 1-grams. See the accompanying flipbook in Figs. S48–S72 in the Supplementary Materials.

dimension characterization problem as unavoidable.

We recommend that ousiometric studies start from a larger set—on the order of 20 to 50—of simple bipolar adjectival pairs and always perform dimensional reduction. Standardizing such a set of clear bipolar adjectival pairs would be of great value to the field, and our advice is independent of which instrument is employed to rate semantic differentials (Likert scale, best-worst scaling, etc.). (Likert scales may have less inter-rater reliability than best-worst scaling but do allow datasets to be extended with independent studies.) Such studies will be more expensive but will be far more robust. Using ousiograms, which provide richly informative visualizations, the extracted dimensions can then be examined and identified. For lexicons sufficiently rich in types and corpora-matching in terms of tokens, we expect that the axes of {weak ⇔ powerful} and {safe ⇔ dangerous} will emerge.

Automatically annotated histograms like our ousiograms could be used in any sphere to compare two variables measured for a collection of categorical entities (e.g., crime rates and median house prices for cities in the US).

The GAS, PDS, and GPADS frameworks: Here, we have found that essential meaning does not conform to VAD but is instead well captured by the two mutually interpretable coordinate systems spanned by the broad semantic differentials {bad ⇔ good} and {gentle ⇔ aggressive} (GAS), and {weak ⇔ powerful} and {safe ⇔ dangerous} (PDS). Both share the dimension of essential meaning—{structured ⇔ unstructured}—which we may interpret as the dimension of evolution. We have argued in particular that the primary two dimensional plane, which accounts for over 90% of variance explained for types, can be viewed as a kind of circumplex model giving us GPADS. We note that one of the 50 semantic differentials used by Osgood et al. [6] in their foundational work was {safe ⇔ dangerous}. We now understand that the dimension Activation in the EPA framework was an error. All dimensions have an intensity level signified by vector magnitude.

The safety bias of communication: Our finding of a safety bias in diverse written and spoken language generalizes our earlier work which revealed a positivity bias [52, 73]—a linguistic instantiation of the Pollyanna Principle [55]. In the GAS framework we have defined here, the positivity bias is a goodness bias. We have also found a complementary linguistic low-aggression bias in the GAS framework (see Fig. 5D).

We now understand that the linguistic goodness bias and the linguistic low-aggression bias are shadows of an underlying linguistic safety bias—projections of points in the 2-d **Pw-Dg** plane onto the orthogonal 1-d diagonal axes of goodness and aggression. The one dimensional map is not the two-dimensional territory.

Because of the safety bias, congruences with other spaces like fictional archetypes, and the behavior of our prototype ousiometer, we have demonstrated that the PDS framework is the most minimal, well-aligned description of essential meaning. This does not however lead us to discarding the GAS framework as the GPADS circumplex framework affords richer, more immediately informative analyses than either alone.

7 Code, data, and other materials

The GPADS framework data, scripts, and documentation reside on Gitlab at https://gitlab.com/petersheridandodds/ousiometry. The GPADS dataset is also on Zenodo [86].

We also provide a range of supporting material at the paper's Online Appendices: compstorylab.org/ousiometry/.

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References

[1] G. Lakoff and M. Johnson. *Metaphors We Live By*. University of Chicago Press, Chicago, IL, 1980.

[2] G. A. Miller. WordNet: A lexical database for English. *Communications of the ACM*, 38:39–41, 1995.

[3] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. Distributed representations of words and phrases and their compositionality. In *Advances in Neural Information Processing Systems*, pages 3111–3119, 2013.

[4] C. E. Osgood. The nature and measurement of meaning. *Psychological Bulletin*, 49(3):197–237, 1952.

[5] L. M. Solomon. A factorial study of complex auditory stimuli (passive sonar sounds). *Unpublished Doctoral Dissertation, University of Illinois*, 1954.

[6] C. Osgood, G. Suci, and P. Tannenbaum. *The Measurement of Meaning*. University of Illinois, Urbana, IL, 1957.

[7] C. E. Osgood. On the whys and wherefores of E, P, and A. *Journal of Personality and Social Psychology*, 12:194, 1969.

[8] C. E. Osgood, W. H. May, M. S. Miron, and M. S. Miron. *Cross-cultural Universals of Affective Meaning*. University of Illinois Press, 1975.

[9] J. A. Russell. A circumplex model of affect. *Journal of Personality and Social Psychology*, 39:1161, 1980.

[10] J. A. Russell. Core affect and the psychological construction of emotion. *Psychological Review*, 110:145–172, 2003.

[11] A. Mehrabian and J. A. Russell. *An Approach to Environmental Psychology*. MIT Press, 1974.

[12] A. Mehrabian and J. A. Russell. The basic emotional impact of environments. *Perceptual and Motor Skills*, 38:283–301, 1974.

[13] M. M. Bradley and P. J. Lang. Affective norms for English words (ANEW): Stimuli, instruction manual and affective ratings. Technical report c-1, University of Florida, Gainesville, FL, 1999.

[14] P. S. Dodds, K. D. Harris, I. M. Kloumann, C. A. Bliss, and C. M. Danforth. Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter. *PLoS ONE*, 6:e26752, 2011.

[15] A. B. Warriner, V. Kuperman, and M. Brysbaert. Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behav. Res. Methods*, 45, 2013.

[16] A. B. Warriner and V. Kuperman. Affective biases in English are bi-dimensional. *Cognition & Emotion*, 2014. Published online October 14, 2014; http://dx.doi.org/10.1080/02699931.2014.968098.

[17] A. B. Warriner, D. I. Shore, L. A. Schmidt, C. L. Imbault, and V. Kuperman. Sliding into happiness: A new tool for measuring affective responses to words. *Canadian Journal of Experimental Psychology/Revue Canadienne de Psychologie Expérimentale*, 71:71, 2017.

[18] S. M. Mohammad. Word affect intensities. In *Proceedings of the 11th Edition of the Language Resources and Evaluation Conference (LREC-2018)*, Miyazaki, Japan, 2018.

[19] S. M. Mohammad. Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 English words. In *Proceedings of The Annual Conference of the Association for Computational Linguistics (ACL)*, Melbourne, Australia, 2018.

[20] T. F. Karwoski and H. S. Odbert. Color-music. *Psychological Monographs*, 50:i, 1938.

[21] G. Grand, I. A. Blank, F. Pereira, and E. Fedorenko. Semantic projection recovers rich human knowledge of multiple object features from word embeddings. *Nature Human Behaviour*, 6(7):975–987, 2022.

[22] S. Zhou and S. Bhatia. Semantic structure in large language models aligns with human judgments. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, 2023.

[23] S. Wang, J.-W. van de Meent, and A. Lingnau. Conceptual organization in humans and deep language models: A study using semantic feature norms and natural language. *Cognition*, 223:105021, 2022.

[24] X. Li, Y. Zhang, D. Khashabi, and D. Roth. Measuring emergent semantic axes in foundation models. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2022.

[25] C. Park, S. Zhang, V. Shwartz, and N. A. Smith. Measuring and discovering hierarchical lexical structure in contextual embeddings. *Transactions of the Association for Computational Linguistics*, 11:1–17, 2023.

[26] L. L. Thurstone. Multiple factor analysis. *Psychological Review*, 38(5):406–427, 1931.

[27] K. G. J"oreskog. A general approach to confirmatory maximum likelihood factor analysis. *Psychometrika*, 34(2):183–202, 1969.

[28] L. R. Fabrigar, D. T. Wegener, R. C. MacCallum, and E. J. Strahan. Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, 4(3):272–299, 1999.

[29] L. L. Visinescu and N. Evangelopoulos. Orthogonal rotations in latent semantic analysis: An empirical study. *Decision Support Systems*, 62:131–143, June 2014.

[30] R. I. Jennrich. A simple general method for oblique rotation. *Psychometrika*, 67(1):7–19, March 2002.

[31] L. Feldman Barrett and J. A. Russell. The structure of current affect: Controversies and emerging consensus. *Current Directions in Psychological Science*, 8:10–14, 1999.

[32] M. Yik, J. A. Russell, and J. H. Steiger. A 12-point circumplex structure of core affect. *Emotion*, 11:705, 2011.

[33] W. M. Wundt. *Grundriss der Psychologie*. Kröner, 1922.

[34] R. Reisenzein. Wundt's three-dimensional theory of emotion. *Poznan Studies in the Philosophy of the Sciences and the Humanities*, 75:219–250, 2000.

[35] A. B. Warriner, V. Kuperman, and M. Brysbaert. Norms of valence, arousal, and dominance for 13,915 english lemmas. *Behavior Research Methods*, 45(4):1191–1207, 2013.

[36] M. M. Bradley and P. J. Lang. Measuring emotion: The self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry*, 25(1):49–59, 1994.

[37] S. Gannouni, A. Aledaily, K. Belwafi, and H. Aboalsamh. Adaptive emotion detection using the valence-arousal-dominance model and eeg brain rhythmic activity changes in relevant brain lobes. *IEEE Access*, 8:67444–67455, 2020.

[38] P. J. Lang, M. M. Bradley, and B. N. Cuthbert. International affective picture system (iaps): Technical manual and affective ratings. Technical report, NIMH Center for the Study of Emotion and Attention, 1997.

[39] R. Takanami and M. El-Haj. Unifying emotion analysis datasets using valence arousal dominance (vad). In *Proceedings of the 1st Workshop on Language Data Challenges*, 2023.

[40] S. M. Mohammad. Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 english words. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics*, pages 174–184, 2018.

[41] M. V. Mäntylä, B. Adams, G. Destefanis, D. Graziotin, and M. Ortu. Mining valence, arousal, and dominance: Possibilities for detecting burnout and productivity? *arXiv preprint arXiv:1603.04287*, 2016.

[42] S. M. Mohammad. NRC VAD Lexicon v2: Norms for valence, arousal, and dominance for over 55,000 English terms, 2025. arXiv preprint.

[43] K.-H. Yang, T. Zhang, and S. Ananiadou. Disentangled variational autoencoder for emotion recognition in conversations. *IEEE Transactions on Affective Computing*, 2023.

[44] S. Park, J. Kim, S. Ye, J. Jeon, and A. Oh. Dimensional emotion detection from categorical emotion. *arXiv preprint arXiv:1911.02499*, 2019.

[45] A. Mehrabian and J. A. Russell. *An approach to environmental psychology.* MIT Press, 1974.

[46] P. J. Lang, M. K. Greenwald, M. M. Bradley, and A. O. Hamm. Looking at pictures: Affective, facial, visceral, and behavioral reactions. *Psychophysiology*, 30(3):261–273, 1993.

[47] G. K. Verma and U. S. Tiwary. Affect representation and recognition in 3d continuous valence–arousal–dominance space. *Multimedia Tools and Applications*, 76(20):21615–21645, 2014.

[48] M. Ortu, G. Destefanis, and B. Adams. Mining valence, arousal, and dominance: Possibilities for detecting burnout and productivity? *arXiv preprint arXiv:1603.04287*, 2016.

[49] Y. Wang, L. Zhang, X. Chen, and Y. Liu. The role of emotion in an experimental learning intervention. *Journal of Educational Psychology*, 114(3):456–472, 2022.

[50] Z. Guendil, Z. Lachiri, and C. Maaoui. Computational framework for emotional vad prediction using eeg signals. *Journal of Ambient Intelligence and Humanized Computing*, 8(4):593–605, 2017.

[51] I. Bakker, T. Van Der Voordt, P. Vink, and J. De Boon. Pleasure, arousal, dominance: Mehrabian and Russell revisited. *Current Psychology*, 33:405–421, 2014.

[52] P. S. Dodds, E. M. Clark, S. Desu, M. R. Frank, A. J. Reagan, J. R. Williams, L. Mitchell, K. D. Harris, I. M. Kloumann, J. P. Bagrow, K. Megerdoomian, M. T. McMahon, B. F. Tivnan, and C. M. Danforth. Human language reveals a universal positivity bias. *Proc. Natl. Acad. Sci.*, 112(8):2389–2394, 2015. Available online at http://www.pnas.org/content/112/8/2389.

[53] G. Herdan. *Type-Token Mathematics: A Textbook of Mathematical Linguistics*. Mouton, The Hague, Netherlands, 1960.

[54] A. J. Reagan, B. F. Tivnan, J. R. Williams, C. M. Danforth, and P. S. Dodds. Sentiment analysis methods for understanding large-scale texts: A case for using continuum-scored words and word shift graphs. *EPJ Data Science*, 6, 2017.

[55] J. Boucher and C. E. Osgood. The Pollyanna hypothesis. *Journal of Verbal Learning and Verbal Behavior*, 8(1):1–8, 1969.

[56] J. J. Louviere, T. N. Flynn, and A. A. J. Marley. *Best-worst scaling: Theory, methods and applications*. Cambridge University Press, 2015.

[57] S. M. Mohammad. Nrc vad lexicon v2: Norms for valence, arousal, and dominance for over 55k english terms, 2025.

[58] P. S. Dodds, J. W. Zimmerman, C. G. Beauregard, A. M. A. Fehr, M. I. Fudolig, T. R. Tangherlini, and C. M. Danforth. Archetypometrics, a Pragmateia: Empirical determination of the fundamental archetypes of fictional characters, 2025. Working paper, Zenodo, https://doi.org/10.5281/zenodo.17117974.

[59] P. S. Dodds. Archetypometrics dataset, 2025. Zenodo Dataset, https://doi.org/10.5281/zenodo.16953724.

[60] G. K. Zipf. *Human Behaviour and the Principle of Least-Effort*. Addison-Wesley, Cambridge, MA, 1949.

[61] J.-B. Michel, Y. K. Shen, A. P. Aiden, A. Veres, M. K. Gray, The Google Books Team, J. P. Pickett, D. Hoiberg, D. Clancy, P. Norvig, J. Orwant, S. Pinker, M. A. Nowak, and E. A. Lieberman. Quantitative analysis of culture using millions of digitized books. *Science Magazine*, 331:176–182, 2011.

[62] E. A. Pechenick, C. M. Danforth, and P. S. Dodds. Characterizing the Google Books corpus: Strong limits to inferences of socio-cultural and linguistic evolution. *PLoS ONE*, 10:e0137041, 2015.

[63] E. Sandhaus. The New York Times Annotated Corpus. Linguistic Data Consortium, Philadelphia, 2008. Available online at: https://doi.org/10.35111/77ba-9x74.

[64] I. Semenov. Wikipedia word frequency, 2019. https://github.com/IlyaSemenov/wikipedia-word-frequency, accessed 2021/04/02.

[65] D. Beeferman, W. Brannon, and D. Roy. RadioTalk: A large-scale corpus of talk radio transcripts. *arXiv preprint arXiv:1907.07073*, 2019.

[66] T. Alshaabi, J. L. Adams, M. V. Arnold, J. R. Minot, D. R. Dewhurst, A. J. Reagan, C. M. Danforth, and P. S. Dodds. Storywrangler: A massive exploratorium for sociolinguistic, cultural, socioeconomic, and political timelines using Twitter. *Science Advances*, 7:eabe6534, 2021.

[67] H. A. Simon. On a class of skew distribution functions. *Biometrika*, 42:425–440, 1955.

[68] J. R. Williams, P. R. Lessard, S. Desu, E. M. Clark, J. P. Bagrow, C. M. Danforth, and P. S. Dodds. Zipf's law holds for phrases, not words. *Nature Scientific Reports*, 5:12209, 2015.

[69] M. E. J. Newman. Power laws, Pareto distributions and Zipf's law. *Contemporary Physics*, 46:323–351, 2005.

[70] P. S. Dodds, J. R. Minot, M. V. Arnold, T. Alshaabi, J. L. Adams, D. R. Dewhurst, T. J. Gray, M. R. Frank, A. J. Reagan, and C. M. Danforth. Allotaxonometry and rank-turbulence divergence: A universal instrument for comparing complex systems. *EPJ Data Science*, 12(37):1–42, 2023. arXiv version: https://arxiv.org/abs/2002.09770.

[71] G. Strang. *Introduction to Linear Algebra*. Cambridge Wellesley Press, Wellesley, MA, 4th edition, 2009.

[72] P. S. Dodds and C. M. Danforth. Measuring the happiness of large-scale written expression: Songs, blogs, and presidents. *Journal of Happiness Studies*, 11(4):441–456, 2009.

[73] I. M. Kloumann, C. M. Danforth, K. D. Harris, C. A. Bliss, and P. S. Dodds. Positivity of the English language. *PLoS ONE*, 7:e29484, 2012.

[74] T. Alshaabi, D. R. Dewhurst, J. R. Minot, M. V. Arnold, J. L. Adams, C. M. Danforth, and P. S. Dodds. The growing amplification of social media: Measuring temporal and social contagion dynamics for over 150 languages on Twitter for 2009–2020. *EPJ Data Science*, 10:15, 2021.

[75] H. Schlosberg. The description of facial expressions in terms of two dimensions. *Journal of Experimental Psychology*, 44:229, 1952.

[76] H. Schlosberg. Three dimensions of emotion. *Psychological Review*, 61:81–88, 1954.

[77] J. A. Russell. How shall an emotion be called? In R. Plutchik and H. R. Conte, editors, *Circumplex Models of Personality and Emotions*, pages 205–220. American Psychological Association, 1997.

[78] L. Feldman Barrett and J. A. Russell. Independence and bipolarity in the structure of current affect. *Journal of Personality and Social Psychology*, 74:967, 1998.

[79] S. Fillenbaum. *Structures in the subjective lexicon*. Academic Press, 1971.

[80] F. Y. Edgeworth. *Mathematical Physics: An Essay into the Application of Mathematics to Moral Sciences*. Kegan Paul, London, UK, 1881.

[81] P. S. Dodds and C. M. Danforth. Measuring the happiness of large-scale written expression: songs, blogs, and presidents. *Journal of Happiness Studies*, 2009. doi:10.1007/s10902-009-9150-9.

[82] A. J. Reagan, L. Mitchell, C. M. Danforth, and P. S. Dodds. The emotional arcs of stories are dominated by six basic shapes. *EPJ Data Science*, 5:31, 2016. Available at https://arxiv.org/abs/1606.06820.

[83] R. J. Gallagher, M. R. Frank, L. Mitchell, A. J. Schwartz, A. J. Reagan, C. M. Danforth, and P. S. Dodds. Generalized word shift graphs: A method for visualizing and explaining pairwise comparisons between texts. *EPJ Data Science*, 10:4, 2021. Available online at https://arxiv.org/abs/2008.02250.

[84] Kurt Vonnegut on the shapes of stories, 2010. https://www.youtube.com/watch?v=oP3c1h8v2ZQ, accessed May 15, 2014.

[85] M. I. Fudolig, T. Alshaabi, K. Cramer, , C. M. Danforth, and P. S. Dodds. A decomposition of book structure through ousiometric fluctuations in cumulative word-time. *Nature Humanities and Social Sciences Communications*, 10:187, 2023. Available online at https://arxiv.org/abs/2208.09496.

[86] P. S. Dodds. Essential meaning word scores for ousiometric framework of Goodness-Power-Aggression-Danger-Structure (GPADS), 2026. Zenodo Dataset, https://doi.org/10.5281/zenodo.15784610.

[87] P. S. Dodds, J. R. Minot, M. V. Arnold, T. Alshaabi, J. L. Adams, A. J. Reagan, and C. M. Danforth. Computational timeline reconstruction of the stories surrounding Trump: Story turbulence, narrative control, and collective chronopathy. *PLOS ONE*, page e0260592, 2021. https://arxiv.org/abs/2008.07301.

[88] T. Alshaabi, M. V. Arnold, J. R. Minot, J. L. Adams, D. R. Dewhurst, A. J. Reagan, R. Muhamad, C. M. Danforth, and P. S. Dodds. How the world's collective attention is being paid to a pandemic: COVID-19 related n-gram time series for 24 languages on Twitter. *PLOS ONE*, 16:e0244476, 2021. Available online at https://arxiv.org/abs/2003.12614.

[89] H. Wu, R. J. Gallagher, T. Alshaabi, J. L. Adams, J. R. Minot, M. V. Arnold, B. Foucault Welles, R. Harp, P. S. Dodds, and C. M. Danforth. Say Their Names: Resurgence in the collective attention toward Black victims of fatal police violence following the death of George Floyd, 2021. Available online at https://arxiv.org/abs/2106.10281.

[90] G. Miller. Social Scientists wade into the Tweet stream. *Science*, 333:1814–1815, 2011.

[91] A. Bermingham and A. Smeaton. On using Twitter to monitor political sentiment and predict election results. In *Proceedings of the Workshop on Sentiment Analysis where AI meets Psychology (SAAIP 2011)*, pages 2–10, Chiang Mai, Thailand, Nov. 2011. Asian Federation of Natural Language Processing.

[92] D. Gayo-Avello. I wanted to predict elections with Twitter and all i got was this lousy paper: A balanced survey on election prediction using Twitter data. *Communications of the ACM*, 55(11):89–96, 2012.

[93] A. Jungherr and P. Jürgens. Forecasting the pulse: How deviations from regular patterns in online data can identify offline phenomena. *Internet Research*, 23(5):589–607, 2013.

Supplementary Material for "Ousiometrics: The essence of meaning aligns with a power-danger-structure framework instead of valence-arousal-dominance."

Note: The supplementary material is best viewed in single page mode rather than continuous scroll.

In particular, these sequences of figures are aligned so that their sections function as flipbooks:

- Sec. S1: Large ousiograms for the VAD, GAS, and PDS frameworks: Figs. S1–S9.
- Sec. S3: 'MRI' slices of GPAD plane with Structure **St** varying: S10–S28.
- Sec. S4: Tables of words with largest components in GPADS framework for semantic differentials in cube model: Figs. S29–S41.
- Sec. S5: Analytic sequence demonstrating the safety bias for six distinct corpora: Figs. S42–S47.
- Sec. S6: Epoch sequence of ousiometric time series for Victor Hugo's "Les Misérables": Figs. S48–S72.

S1 Large ousiograms for VAD, GAS, and PDS

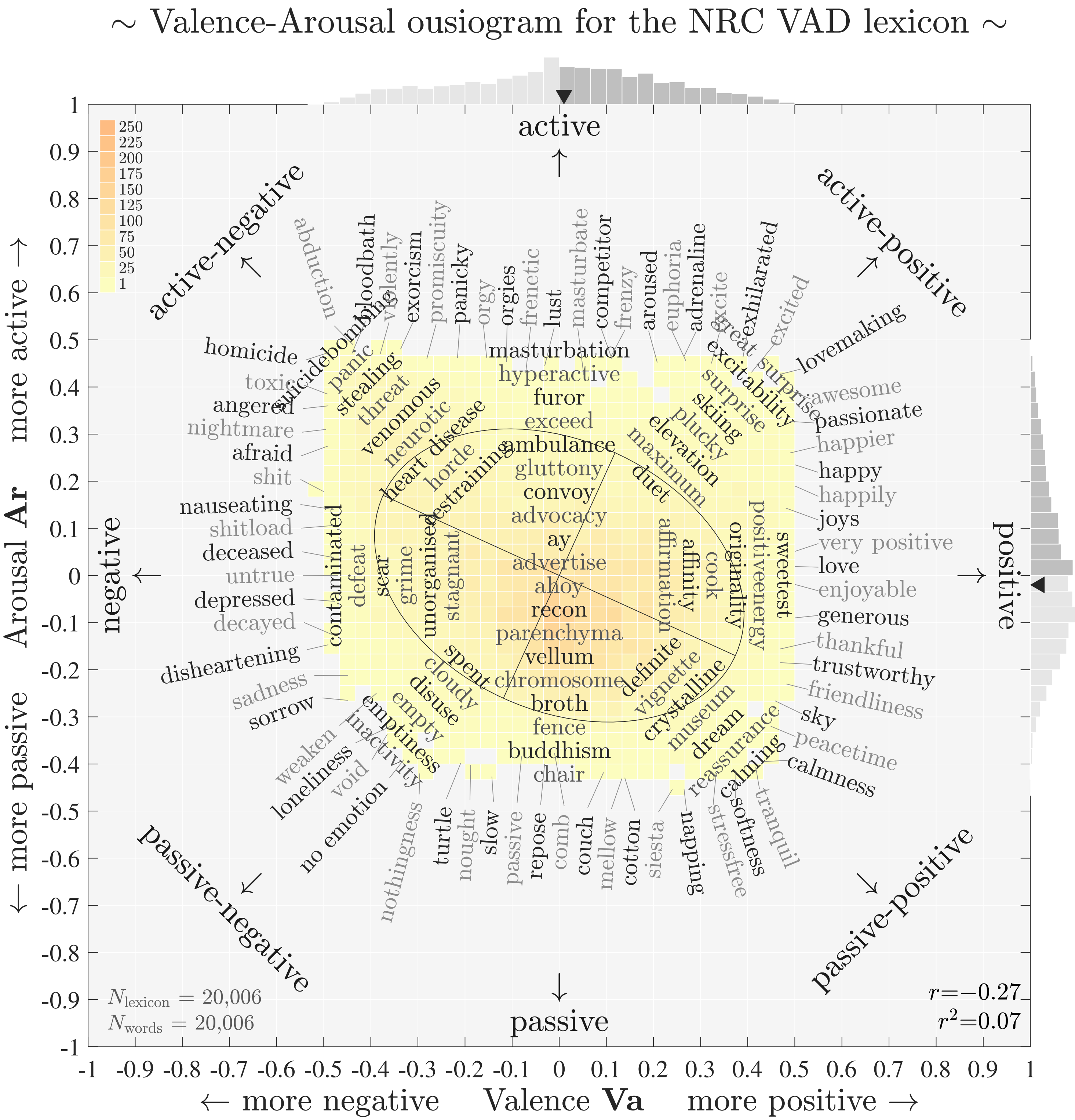


Figure S1: Ousiogram for arousal vs. valence in the VAD framework.

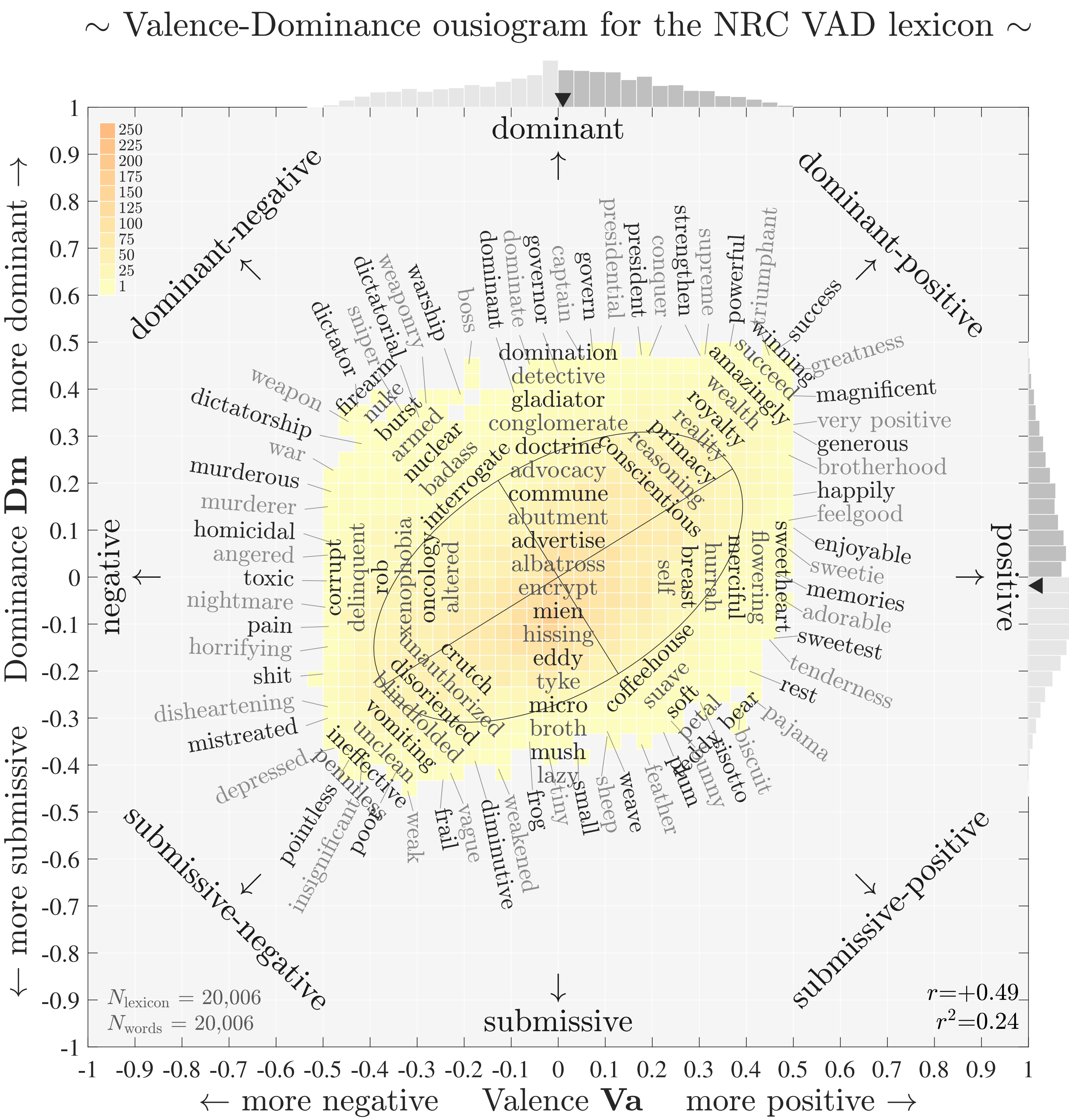


Figure S2: Ousiogram for dominance vs. valence in the VAD framework. Matches Fig. 1 in the main paper.

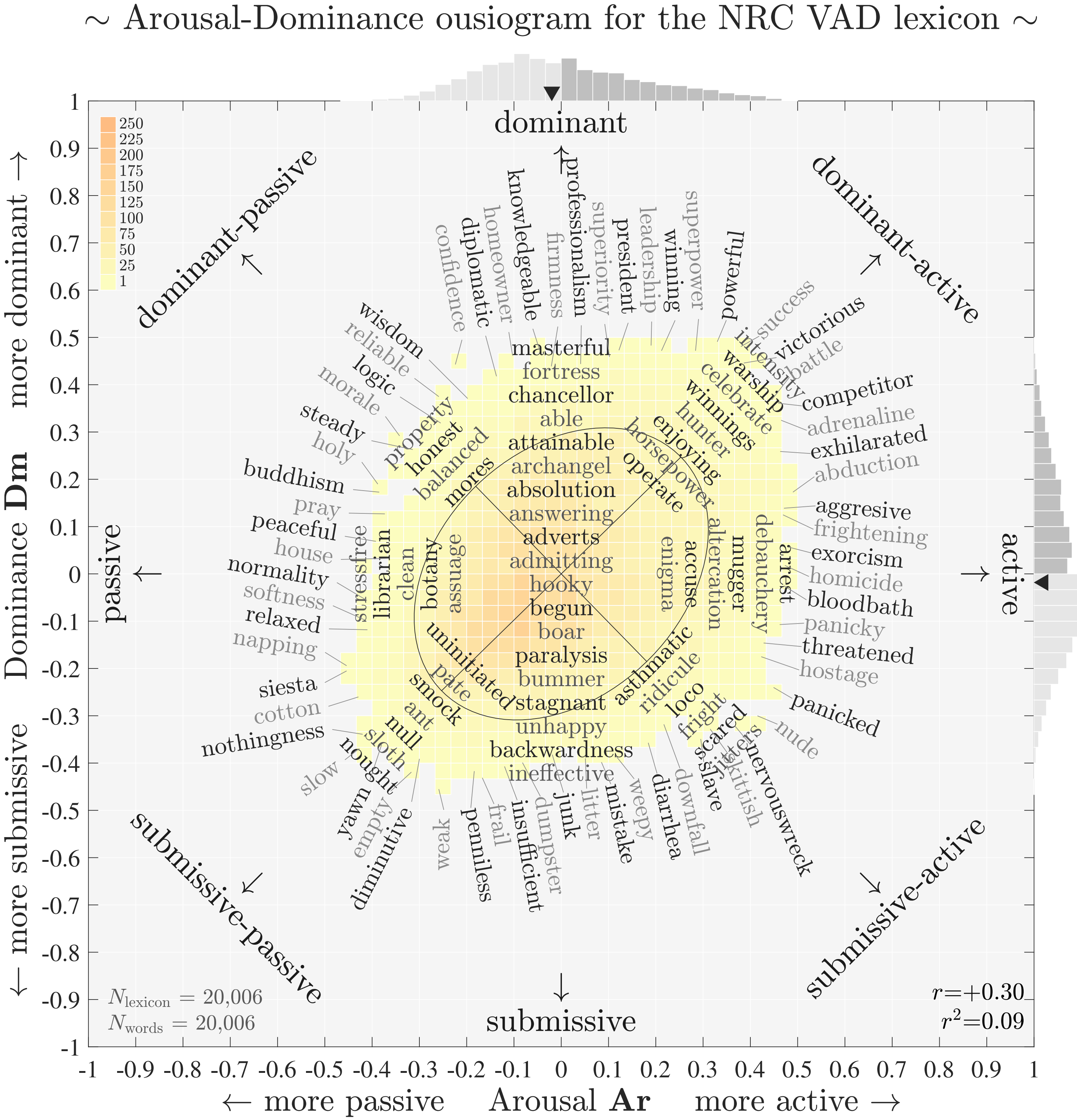


Figure S3: Ousiogram for arousal vs. dominance in the VAD framework.

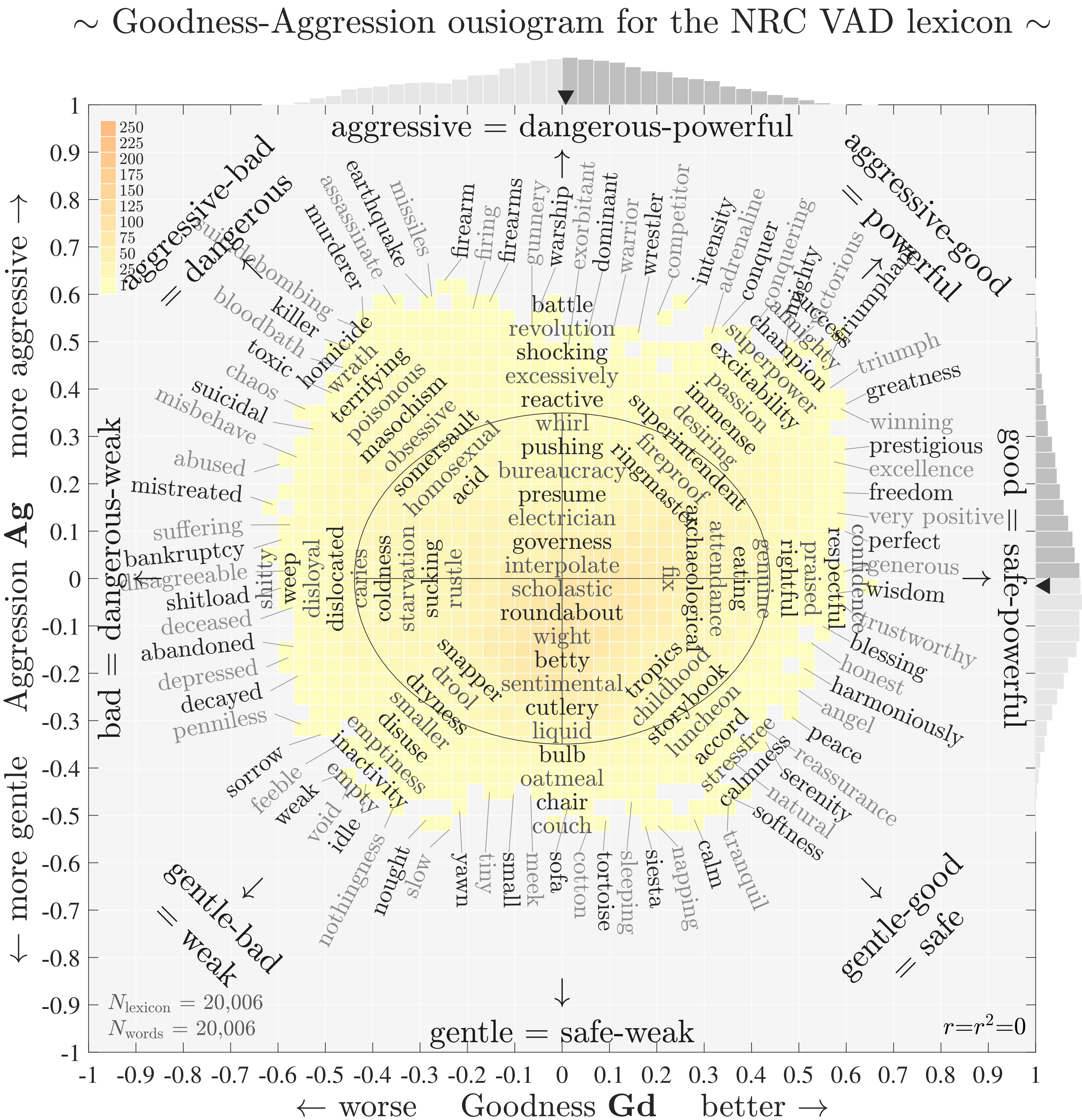


Figure S4: Ousiogram for aggression vs. goodness in the GAS framework.

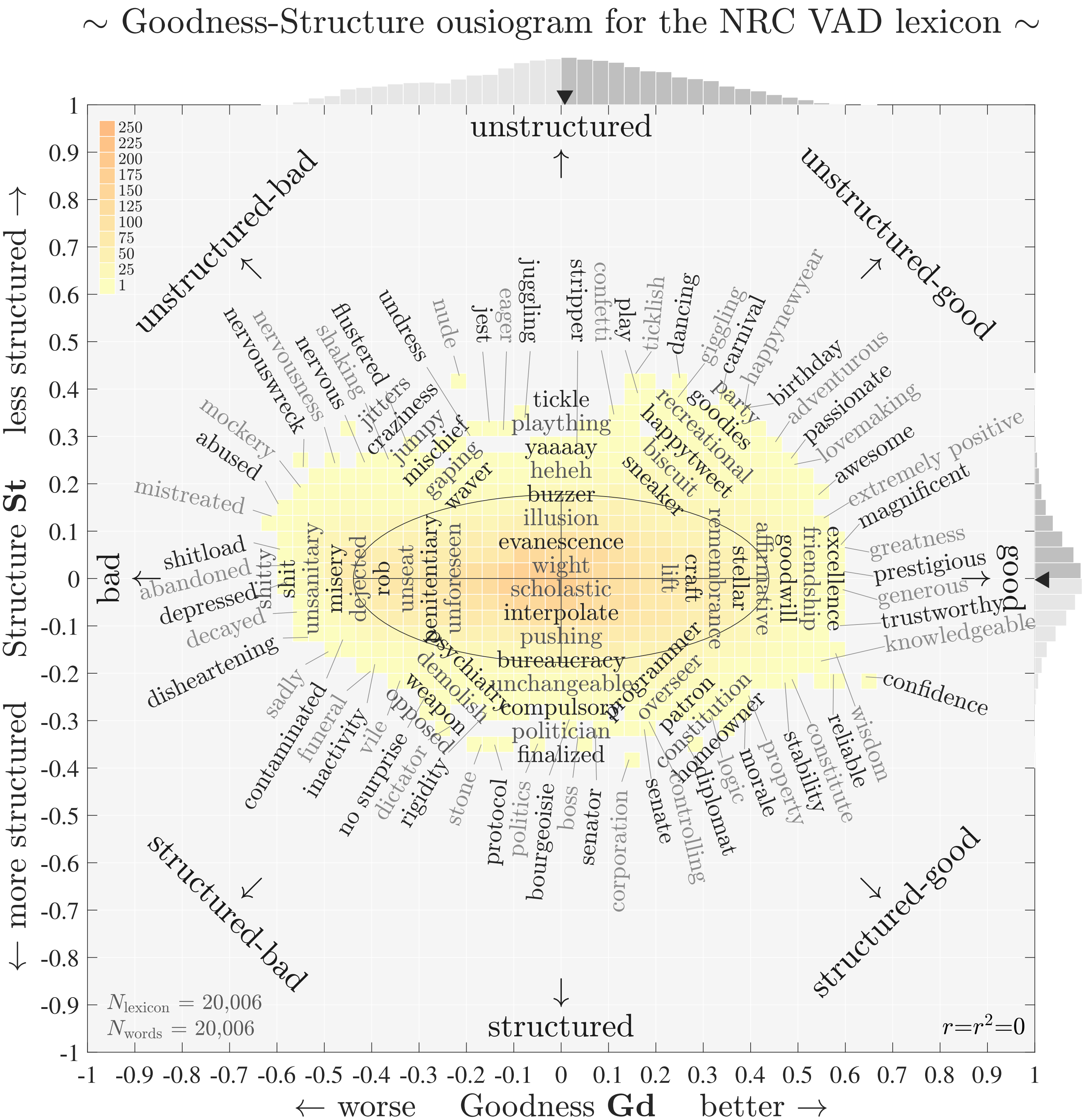


Figure S5: Ousiogram for structure vs. goodness in the GAS framework.

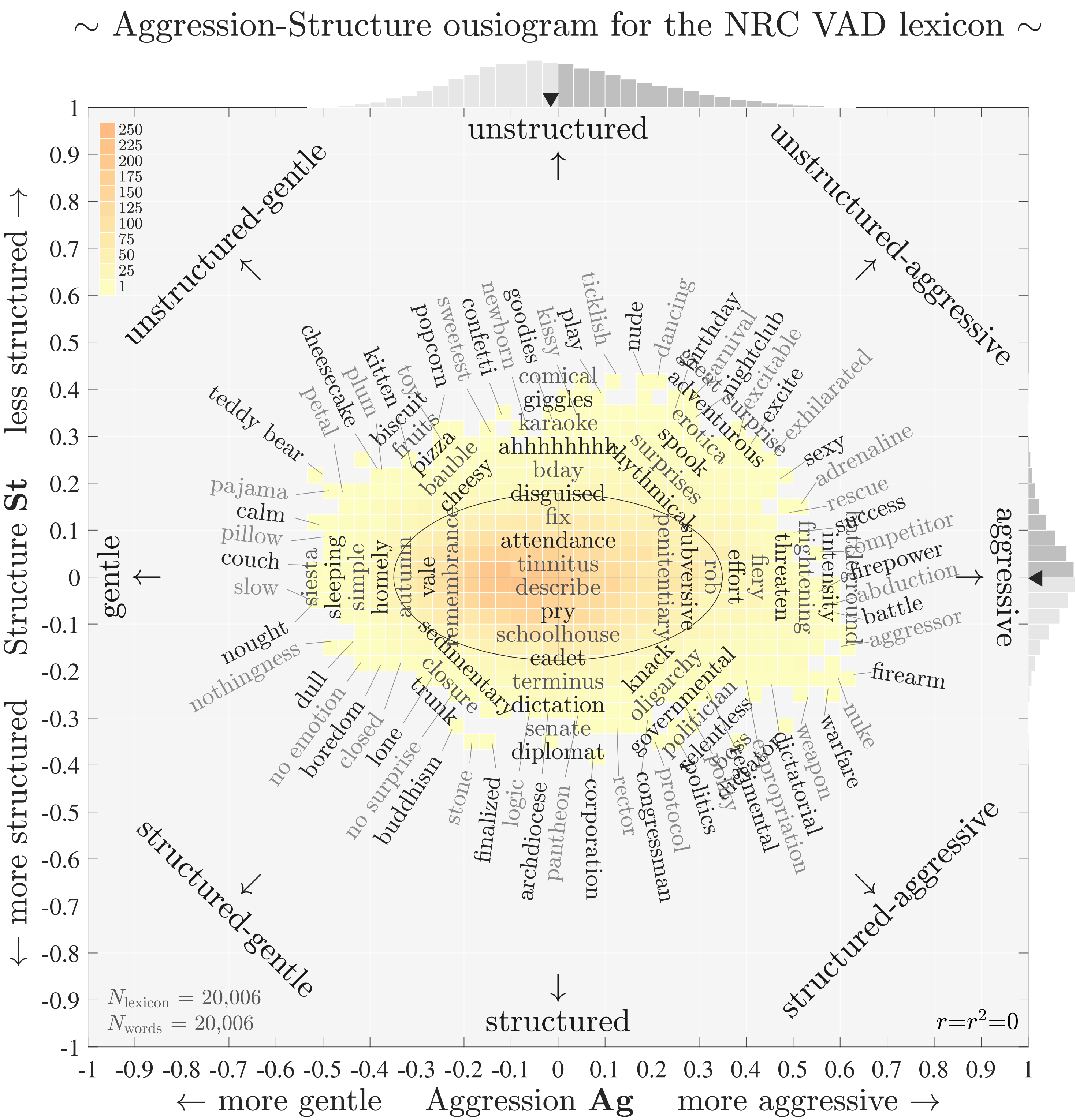


Figure S6: Ousiogram for structure vs. aggression in the GAS framework.

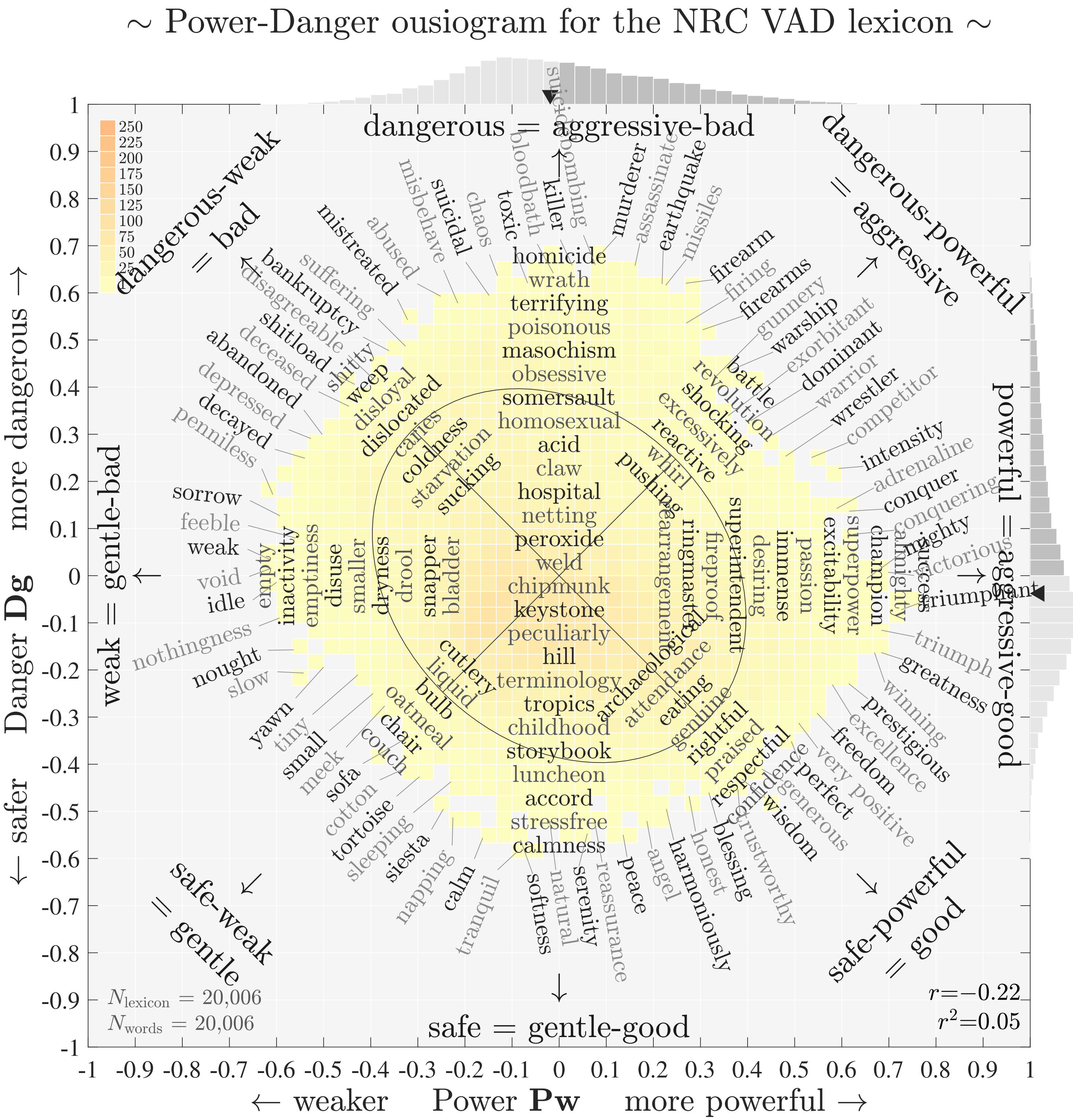


Figure S7: Ousiogram for danger vs. power in the PDS framework. Matches Fig. 3 in the main paper.

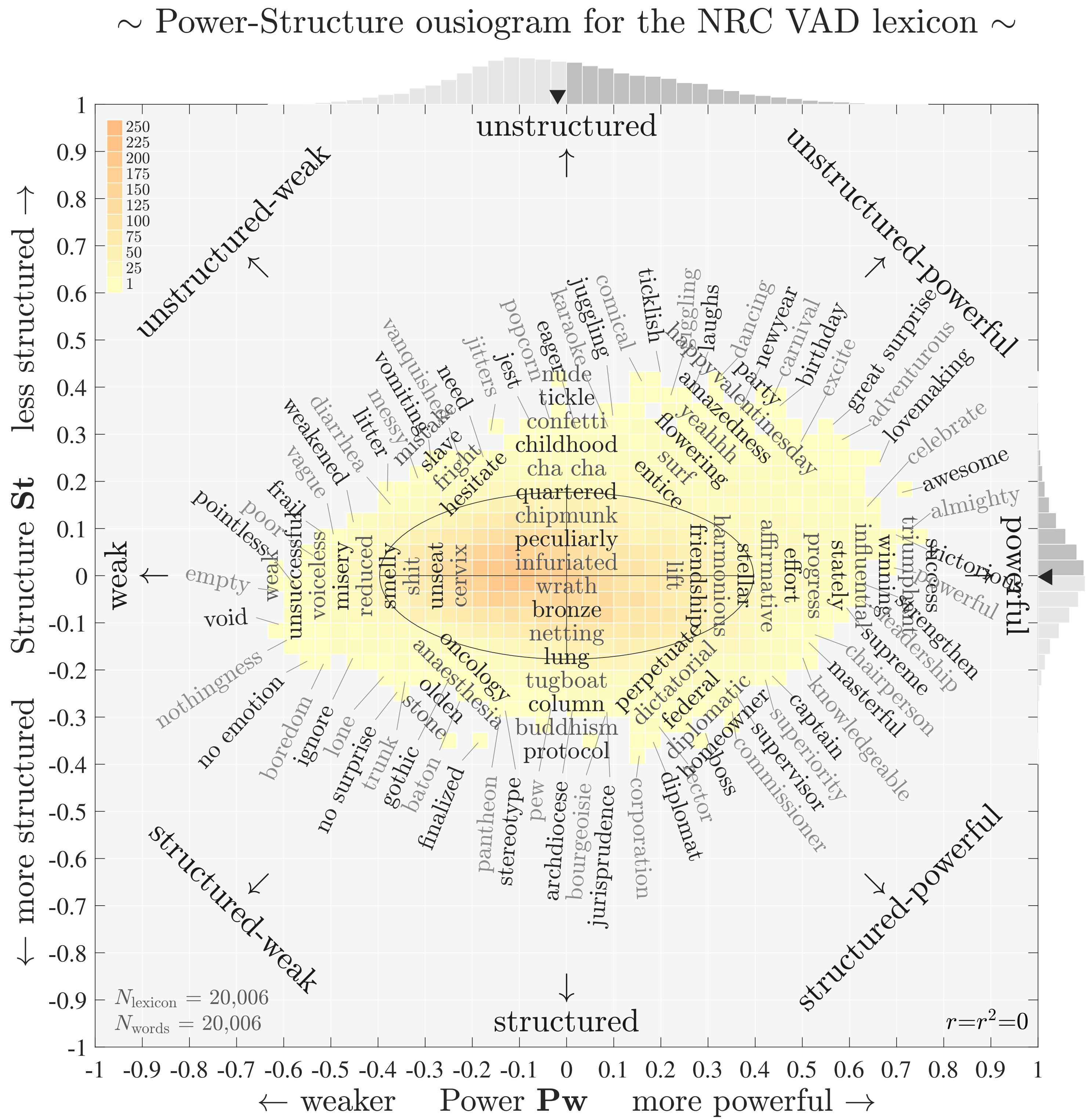


Figure S8: Ousiogram for structure vs. power in the PDS framework.

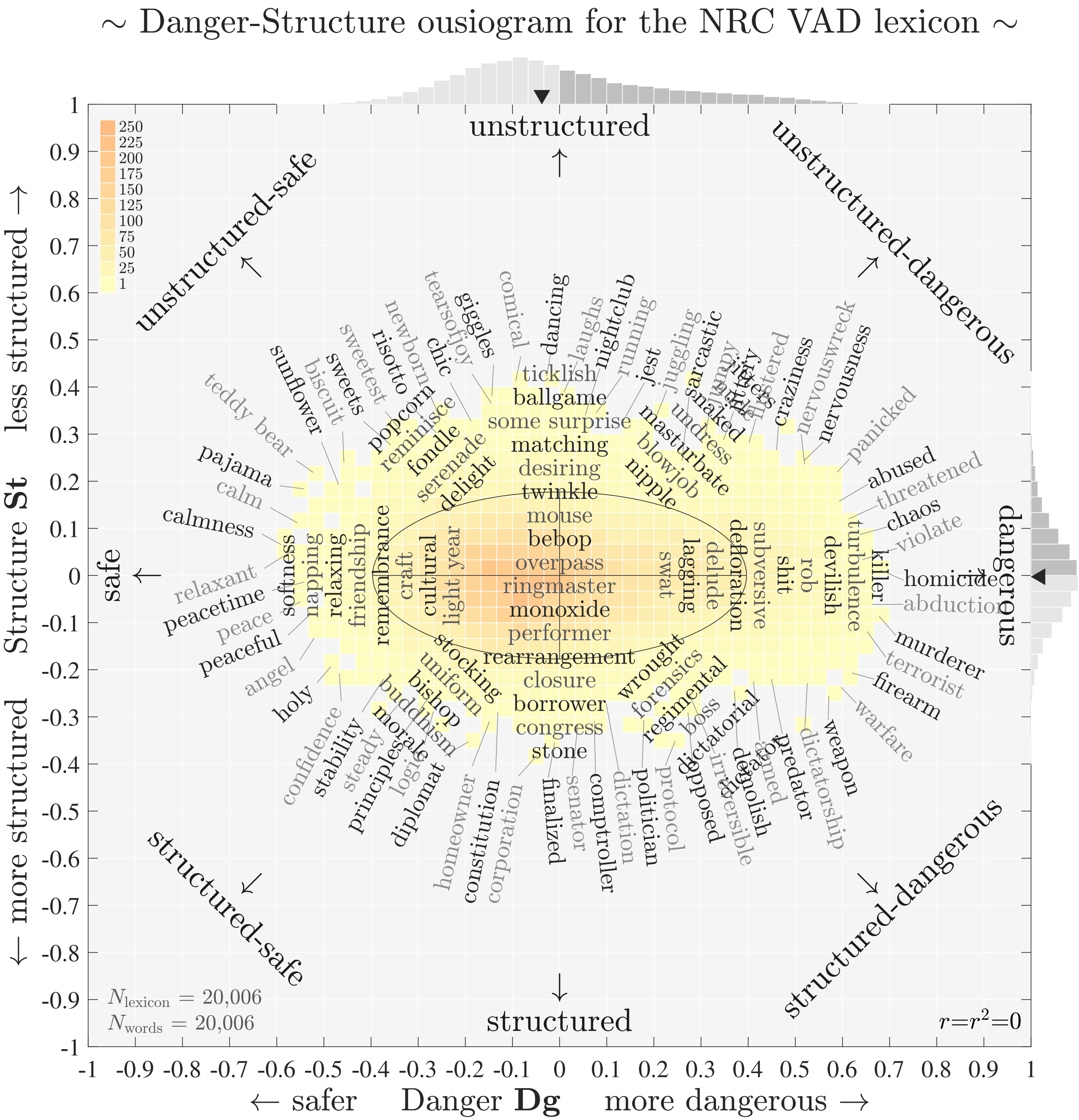


Figure S9: Ousiogram for structure vs. danger in the PDS framework.

S2 Synousionyms and antousionyms, and the problems with prescribing ousiometric axes through end-point descriptors

Which words and terms match in terms of essence of meaning? We define synousionym and antousionym as the ousiometric equivalents of synonym and antonym.

To determine a word's synousionyms, we find the words closest in PDS-space (the specific framework does not matter). For antousionyms, we find words closest to the negated point in PDS-space ($-\mathbf{Pw}, -\mathbf{Dg}, -\mathbf{St}$) (we could equivalently use GAS).

Distilling words to their essential meaning may affect synonym and antonym pairs in opposite ways. Words that are not synonyms may be synousionyms, while words that are antonyms may not be anousionyms.

For example, the word 'failure', $(\mathbf{Pw}, \mathbf{Dg}, \mathbf{St})$ = (-0.39, 0.28, 0.13), is not the antousionym of 'success', $(\mathbf{Pw}, \mathbf{Dg}, \mathbf{St})$ = (0.76, -0.05, 0.09). Within the NRC VAD lexicon, the closest antousionym for 'success' is 'empty', $(\mathbf{Pw}, \mathbf{Dg}, \mathbf{St})$ = (-0.61, -0.01, -0.03). In Tab. S1, we show the closest four synousionyms as well as five antousionyms for the words 'wisdom', 'success', 'volcanic', and 'homicide'. These words are examples of four extreme points of the power-danger ousiogram: safe-powerful, powerful, dangerous-powerful, and dangerous.

In Sec. 3.2, we noted that choosing names of ousiometric dimensions may be problematic, going beyond the issues of end-point descriptors. For one example, the word 'goodness' has the following VAD, GAS, and PDS scores: (0.47, -0.18, 0.21), (0.54, -0.11, -0.02), and (0.30, -0.45, -0.02). We see that 'goodness' has a non-neutral low aggression component and is not purely aligned with the Goodness axis. The five closest synousionyms of 'goodness' are 'thankful', 'friendship', 'motherly', 'hope', and 'graciously' while the five top antousionyms of 'goodness' are 'frustrating', 'cadaver', 'displease', 'shameful', and 'disrespectful'. The antonym 'badness' is not a close antousionym of 'goodness' with VAD, GAS, and PDS scores of (-0.406, 0.323, -0.037), (-0.417, 0.311, 0.008), and (-0.075, 0.515, 0.008). Within the PDS framework, while 'badness' is aligned with the danger axis, 'goodness' is in the safe-powerful quadrant. Some close synousionyms for 'badness' are 'rabid', 'shatter', and 'tremor' and for antousionyms, we find 'comfortable', 'homestead', and 'peacetime'.

A further complication for determining end-point descriptors is that due to the asymmetric, point coverage of essential meaning space, the closest antousionym may not be reflexive. For example, 'chaos' has PDS scores (-0.13, 0.67, 0.09). The closest antousionym for 'chaos' is 'angel' (0.19, -0.52, -0.13) whose closest antousionym is 'shattered' (-0.19, 0.49, 0.11).

These observations again point to the difficulties of prescribing dimensions for participants in surveys. The solution is to see end-point descriptors as guides only and to always examine how participants responded using SVD.

For the PDS framework, 'powerful' and 'dangerous' align well with the end-points of their respective axes with PDS scores of (0.70, -0.02, 0.02) and (0.09, 0.66, 0.10). The word 'weak' similarly aligns well with the negative power axis with PDS scores of (-0.61, 0.03, 0.02). And 'powerful' and 'weak' are both antonyms and close antousionyms of each other.

The descriptor 'safe' does not perform as cleanly however, as it connotes more-than-neutral power with PDS scores of (0.29, -0.41, -0.09). Antousionyms for 'dangerous' are 'relaxed', 'softness', 'calming', 'relaxant', and 'calmness'. (The closest antousionym for 'safe' is 'seasick'.) However semantic differentials also must divide a space into two halves, and {safe ⇔ dangerous} does this well when we consider words above and below the {weak ⇔ powerful} axis. We also feel 'safe' functions well conceptually as an end-point descriptor as it is an easily reached antonym of 'dangerous', if not also an antousionym.

We note that in developing our work, we entertained a number of alternative names for the PDS framework including Success, Stress, and Structure, and Power, Peril, and Play. Ultimately, both of these choices are limited as truly general ousiometric frameworks with success and play in particular eliciting people-centric themes. And in any case, while alliteration may appeal to some, the confusion of variables starting with the same letter would be problematic.

The full space of synousionyms and antousionyms can be explored using VAD, GAS, and PDS scores for all words and terms in the Supplementary Materials.

Safe-Powerful (Good) to Dangerous-Weak (Bad) axis:

Synousionyms	Valence	Arousal	Dominance	Goodness	Aggression	Structure	Power	Danger	Structure
Anchor: wisdom	0.430	-0.198	0.371	0.579	-0.031	-0.158	0.388	-0.432	-0.158
education	0.396	-0.225	0.340	0.539	-0.065	-0.167	0.336	-0.427	-0.167
healthy	0.438	-0.181	0.318	0.558	-0.047	-0.108	0.362	-0.428	-0.108
trustworthy	0.469	-0.185	0.324	0.589	-0.052	-0.100	0.379	-0.453	-0.100
reliable	0.412	-0.259	0.375	0.575	-0.076	-0.202	0.353	-0.460	-0.202
Antousionyms	Valence	Arousal	Dominance	Goodness	Aggression	Structure	Power	Danger	Structure
bullshit	-0.458	0.176	-0.317	-0.575	0.046	0.095	-0.373	0.439	0.095
shitty	-0.480	0.179	-0.337	-0.604	0.042	0.100	-0.397	0.456	0.100
nauseate	-0.438	0.160	-0.324	-0.558	0.026	0.101	-0.376	0.413	0.101
weeping	-0.418	0.188	-0.332	-0.549	0.042	0.131	-0.359	0.418	0.131
shame	-0.440	0.170	-0.345	-0.572	0.023	0.120	-0.388	0.421	0.120
diarrhea	-0.408	0.184	-0.357	-0.552	0.023	0.151	-0.374	0.407	0.151

Powerful (Aggressive-Good) to Weak (Gentle-Bad) axis:

Synousionyms	Valence	Arousal	Dominance	Goodness	Aggression	Structure	Power	Danger	Structure
Anchor: success	0.459	0.380	0.481	0.571	0.501	0.095	0.758	-0.050	0.095
almighty	0.438	0.374	0.458	0.543	0.487	0.098	0.728	-0.040	0.098
triumphant	0.449	0.337	0.472	0.565	0.462	0.073	0.726	-0.072	0.073
champion	0.390	0.380	0.445	0.494	0.492	0.087	0.698	-0.001	0.087
victorious	0.384	0.386	0.446	0.489	0.499	0.087	0.698	0.007	0.087
Antousionyms	Valence	Arousal	Dominance	Goodness	Aggression	Structure	Power	Danger	Structure
sorrow	-0.448	-0.265	-0.336	-0.509	-0.329	-0.127	-0.593	0.127	-0.127
tasteless	-0.354	-0.304	-0.352	-0.430	-0.385	-0.092	-0.576	0.032	-0.092
idle	-0.321	-0.333	-0.388	-0.414	-0.434	-0.068	-0.600	-0.014	-0.068
empty	-0.312	-0.317	-0.419	-0.424	-0.439	-0.033	-0.610	-0.011	-0.033
void	-0.365	-0.337	-0.370	-0.443	-0.420	-0.103	-0.611	0.016	-0.103

Dangerous-Powerful (Aggressive) to Safe-Weak (Gentle) axis:

Synousionyms	Valence	Arousal	Dominance	Goodness	Aggression	Structure	Power	Danger	Structure
Anchor: volcanic	-0.156	0.410	0.281	-0.061	0.515	-0.045	0.322	0.407	-0.045
shelling	-0.163	0.417	0.273	-0.072	0.518	-0.039	0.316	0.417	-0.039
artillery	-0.150	0.412	0.294	-0.050	0.523	-0.050	0.335	0.405	-0.050
wild	-0.188	0.422	0.250	-0.105	0.514	-0.032	0.289	0.438	-0.032
rifles	-0.163	0.364	0.265	-0.068	0.470	-0.062	0.284	0.380	-0.062
Antousionyms	Valence	Arousal	Dominance	Goodness	Aggression	Structure	Power	Danger	Structure
couch	0.094	-0.418	-0.302	-0.002	-0.524	0.025	-0.372	-0.369	0.025
mellow	0.133	-0.431	-0.235	0.066	-0.504	-0.009	-0.310	-0.403	-0.009
pillow	0.163	-0.372	-0.305	0.049	-0.498	0.085	-0.317	-0.387	0.085
tortoise	0.173	-0.422	-0.250	0.092	-0.511	0.025	-0.297	-0.427	0.025
quilt	0.143	-0.377	-0.274	0.048	-0.482	0.052	-0.307	-0.375	0.052
cotton	0.139	-0.429	-0.260	0.059	-0.517	0.012	-0.324	-0.407	0.012

Dangerous (Aggressive-Bad) to Safe (Gentle-Good) axis:

Synousionyms	Valence	Arousal	Dominance	Goodness	Aggression	Structure	Power	Danger	Structure
Anchor: homicide	-0.490	0.473	0.018	-0.485	0.478	0.011	-0.005	0.681	0.011
killer	-0.459	0.471	0.043	-0.446	0.485	0.008	0.028	0.658	0.008
psychopath	-0.460	0.443	0.036	-0.446	0.458	-0.003	0.009	0.640	-0.003
bloodshed	-0.452	0.442	0.025	-0.444	0.450	0.008	0.004	0.633	0.008
violate	-0.439	0.470	0.019	-0.440	0.468	0.033	0.020	0.642	0.033
Antousionyms	Valence	Arousal	Dominance	Goodness	Aggression	Structure	Power	Danger	Structure
natural	0.354	-0.382	-0.019	0.354	-0.382	-0.026	-0.020	-0.520	-0.026
tranquil	0.417	-0.406	-0.145	0.351	-0.480	0.078	-0.091	-0.588	0.078
softness	0.375	-0.414	-0.098	0.338	-0.455	0.021	-0.082	-0.561	0.021
serenity	0.400	-0.378	0.057	0.429	-0.345	-0.054	0.060	-0.547	-0.054
comfortable	0.427	-0.337	-0.027	0.406	-0.361	0.039	0.032	-0.542	0.039
calmness	0.434	-0.395	-0.106	0.383	-0.453	0.065	-0.049	-0.591	0.065

Table S1: Example synousionyms and antousionyms for the four axes of the GAS and PDS frameworks using four anchor words of 'wisdom', 'success', 'volcanic', and 'homicide', and with scores in the three frameworks of VAD, GAS, and PDS. See the linear transformations of Eq. (2) and Eq. (4) for how VAD connects with GAS and PDS.

S3 Flipbook 'MRIs' in power-danger-structure framework

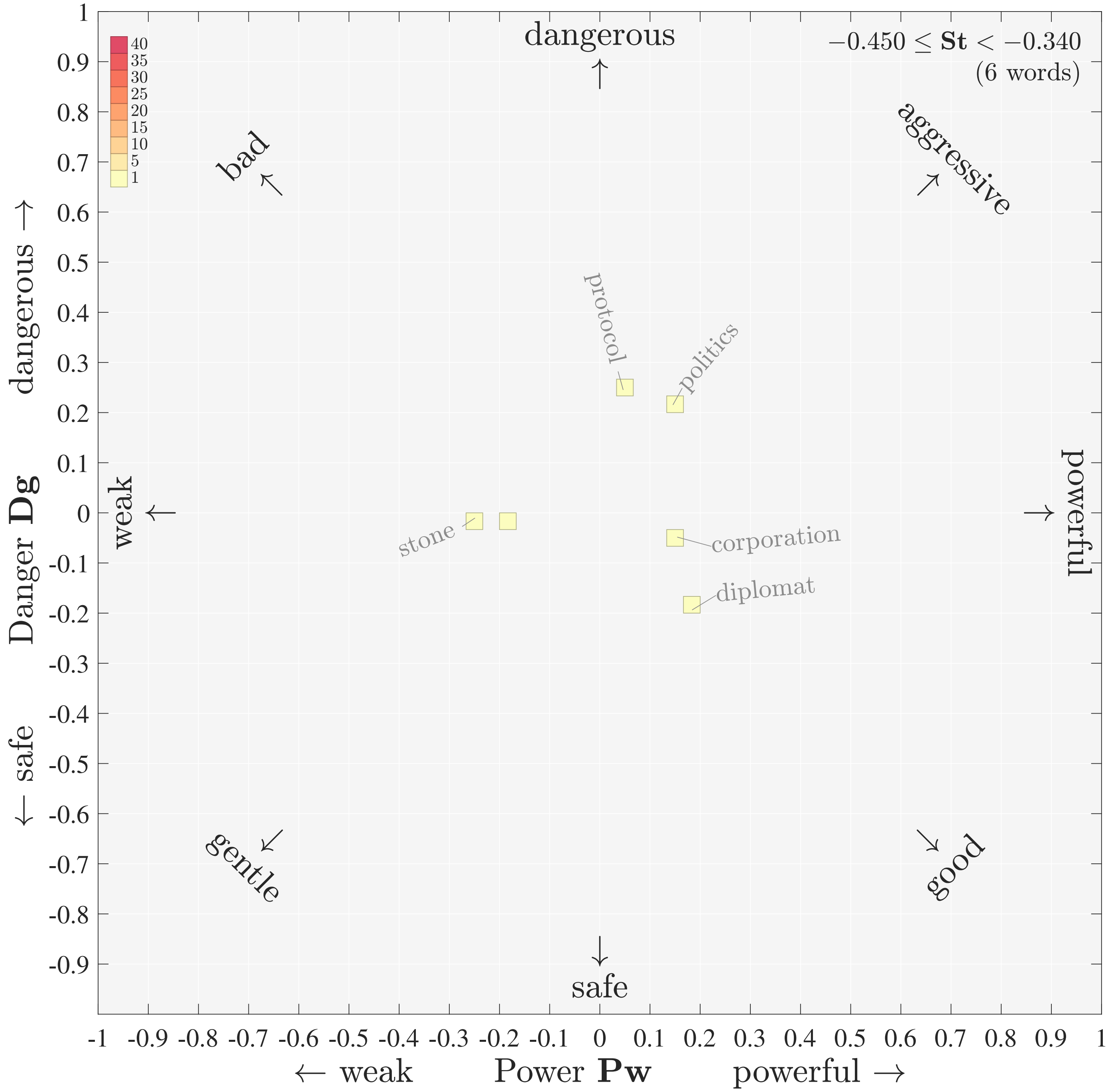


Figure S10: Ousiometric slice for power-danger plane with structure: $-0.450 \leq \mathbf{St} < -0.340$.

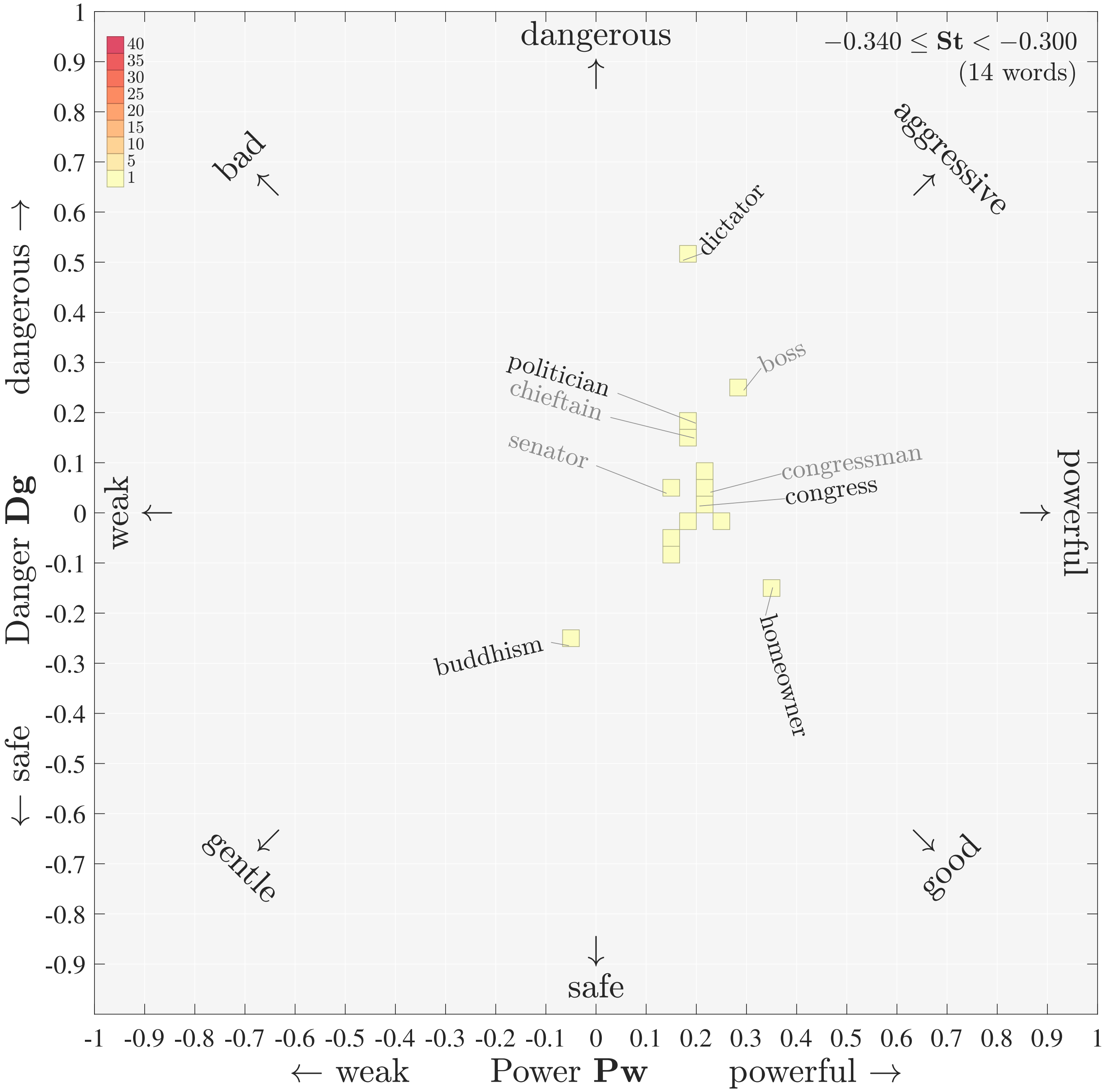


Figure S11: Ousiometric slice for power-danger plane with structure: $-0.340 \leq \mathbf{St} < -0.300$.

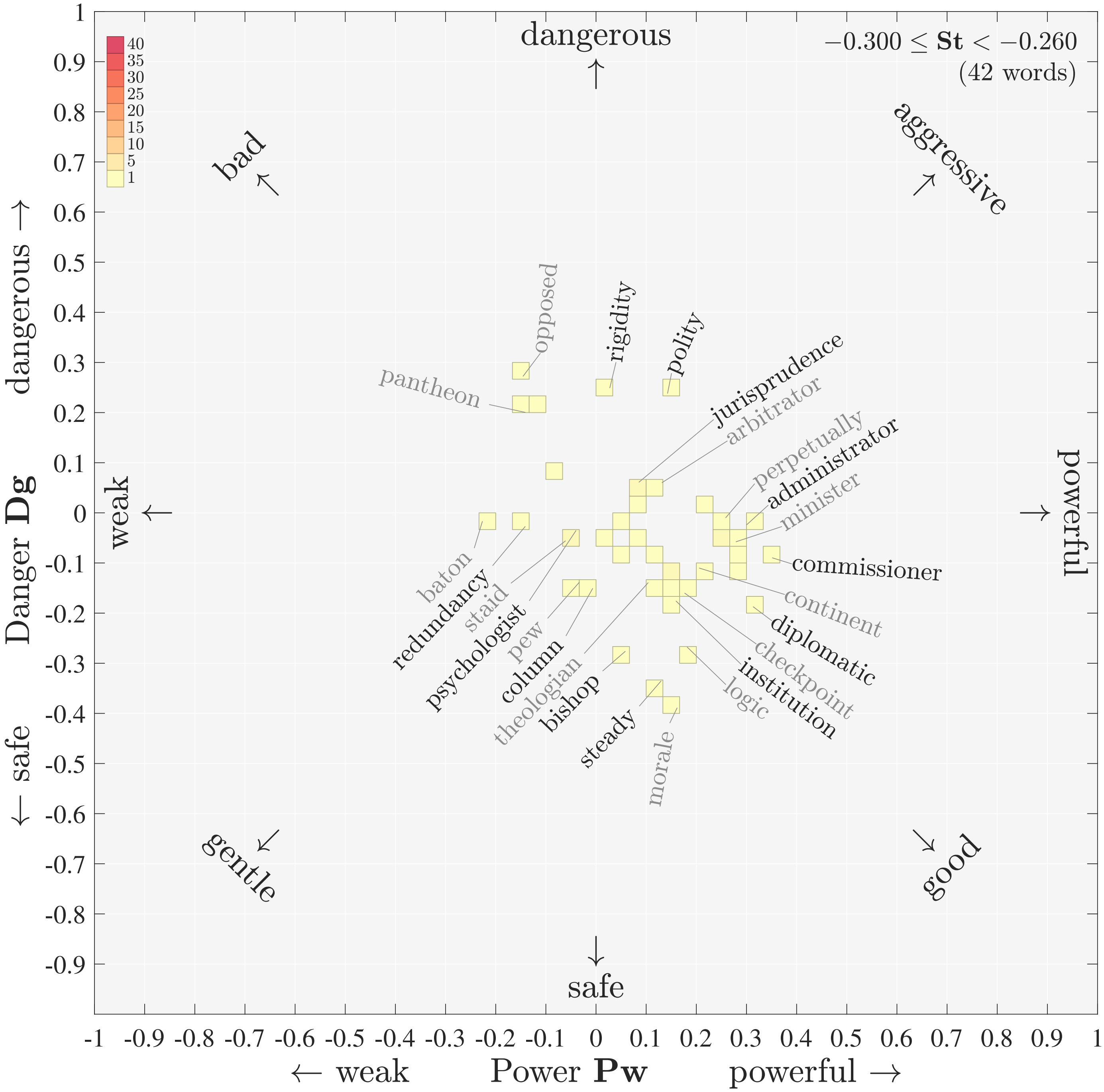


Figure S12: Ousiometric slice for power-danger plane with structure: $-0.300 \leq \mathbf{St} < -0.260$.

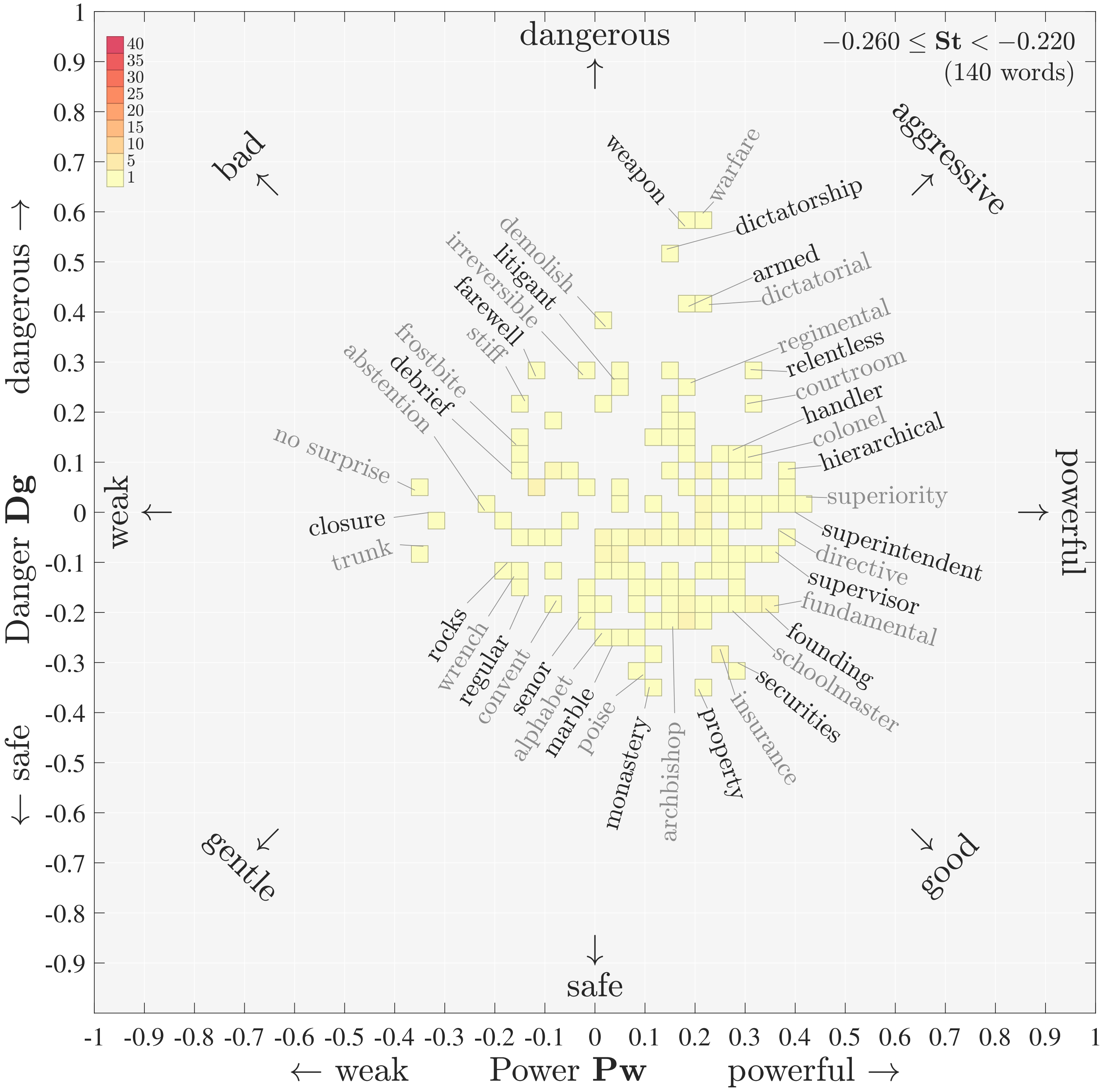


Figure S13: Ousiometric slice for power-danger plane with structure: $-0.260 \leq \mathbf{St} < -0.220$.

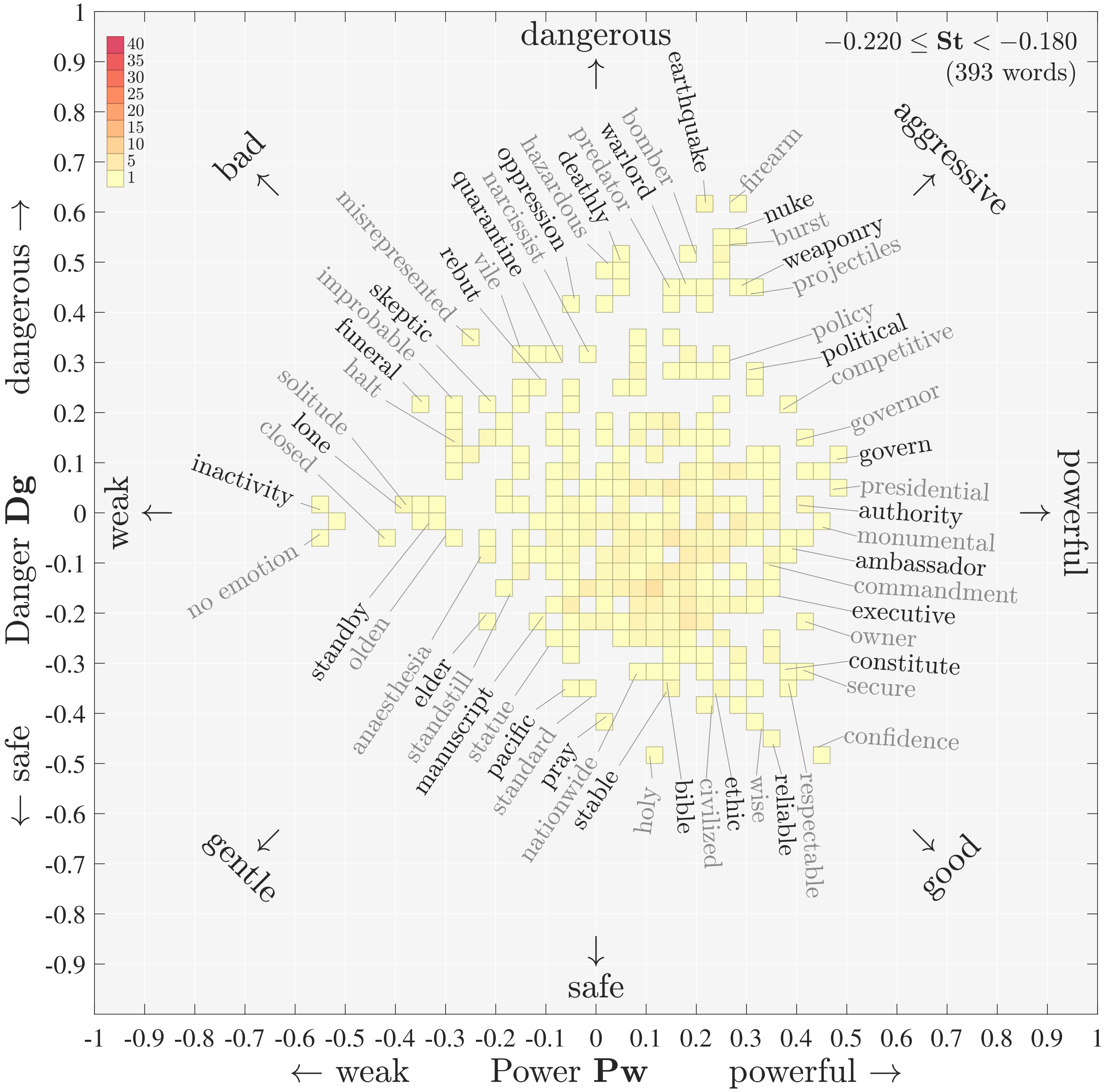


Figure S14: Ousiometric slice for power-danger plane with structure: $-0.220 \leq \mathbf{St} < -0.180$.

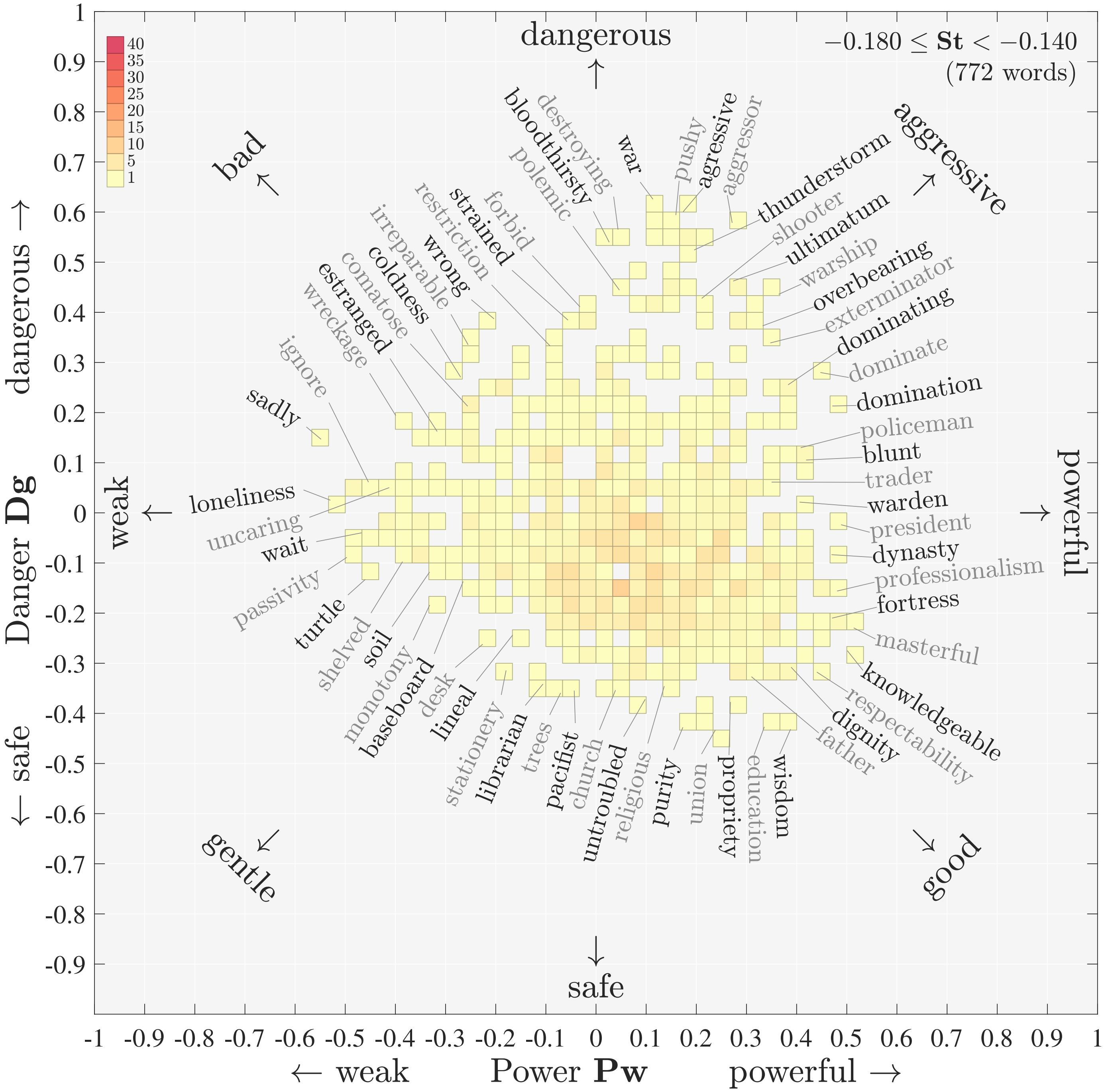


Figure S15: Ousiometric slice for power-danger plane with structure: $-0.180 \leq \mathbf{St} < -0.140$.

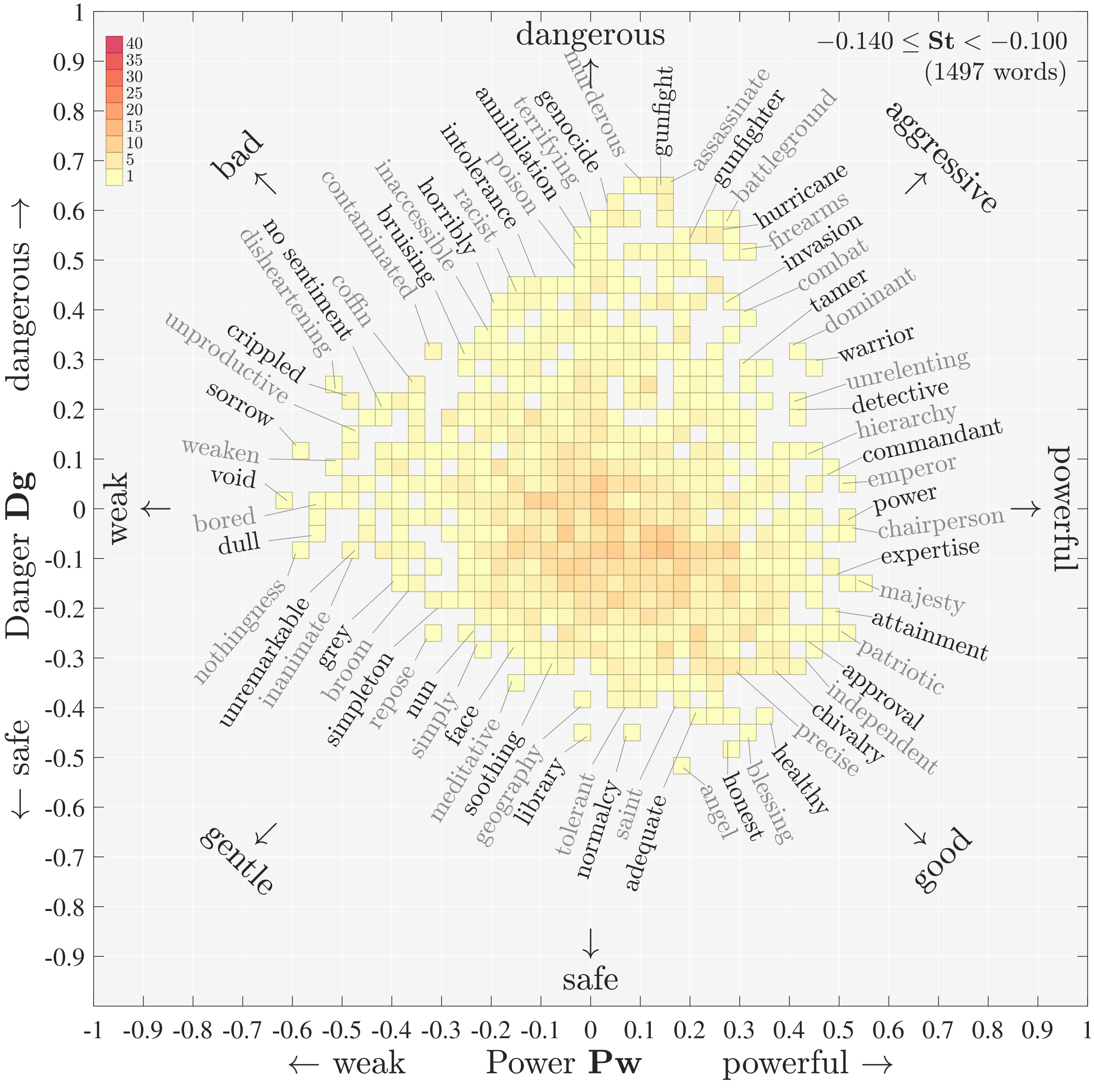


Figure S16: Ousiometric slice for power-danger plane with structure: $-0.140 \leq \mathbf{St} < -0.100$.

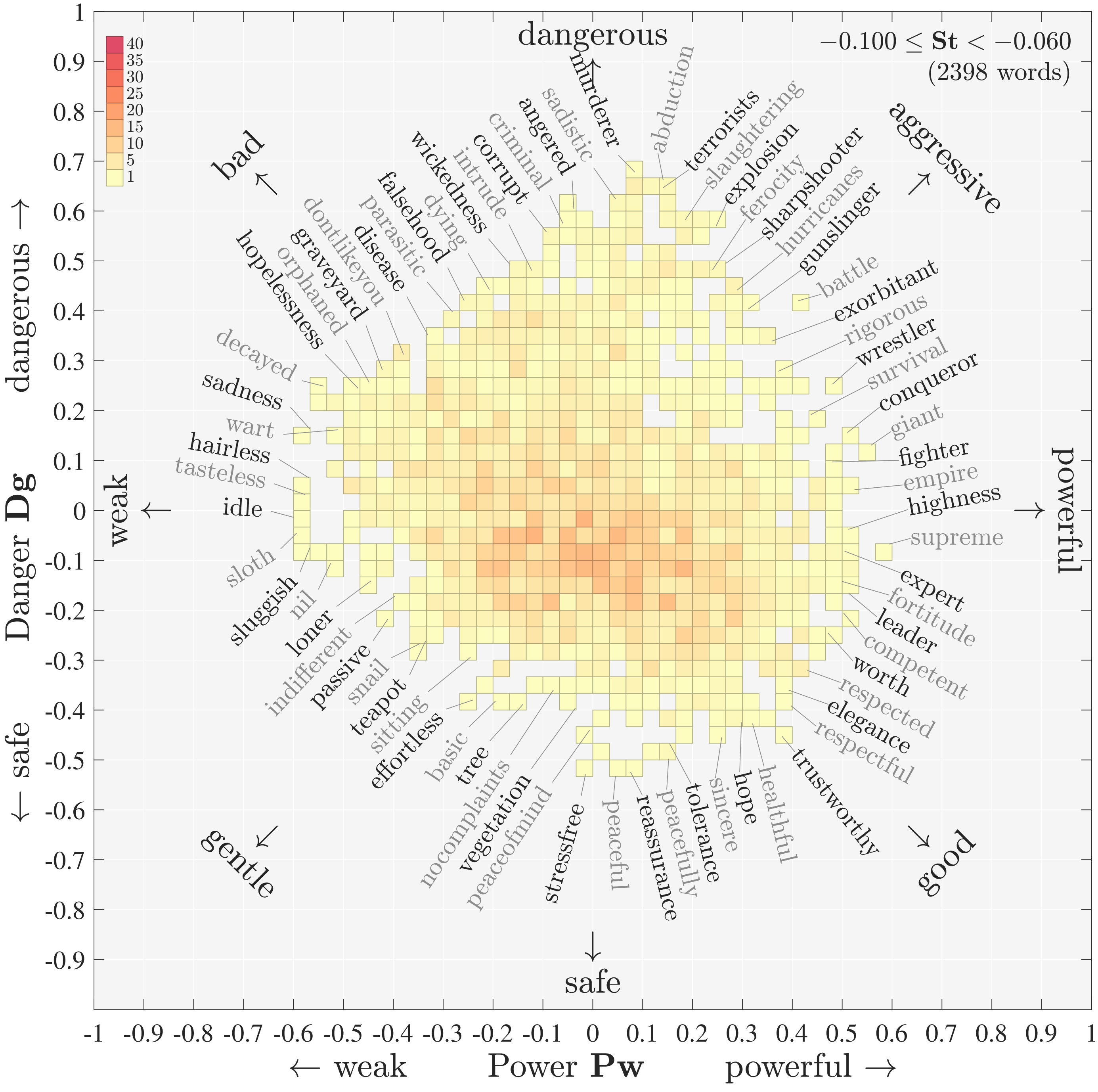


Figure S17: Ousiometric slice for power-danger plane with structure: $-0.100 \leq \mathbf{St} < -0.060$.

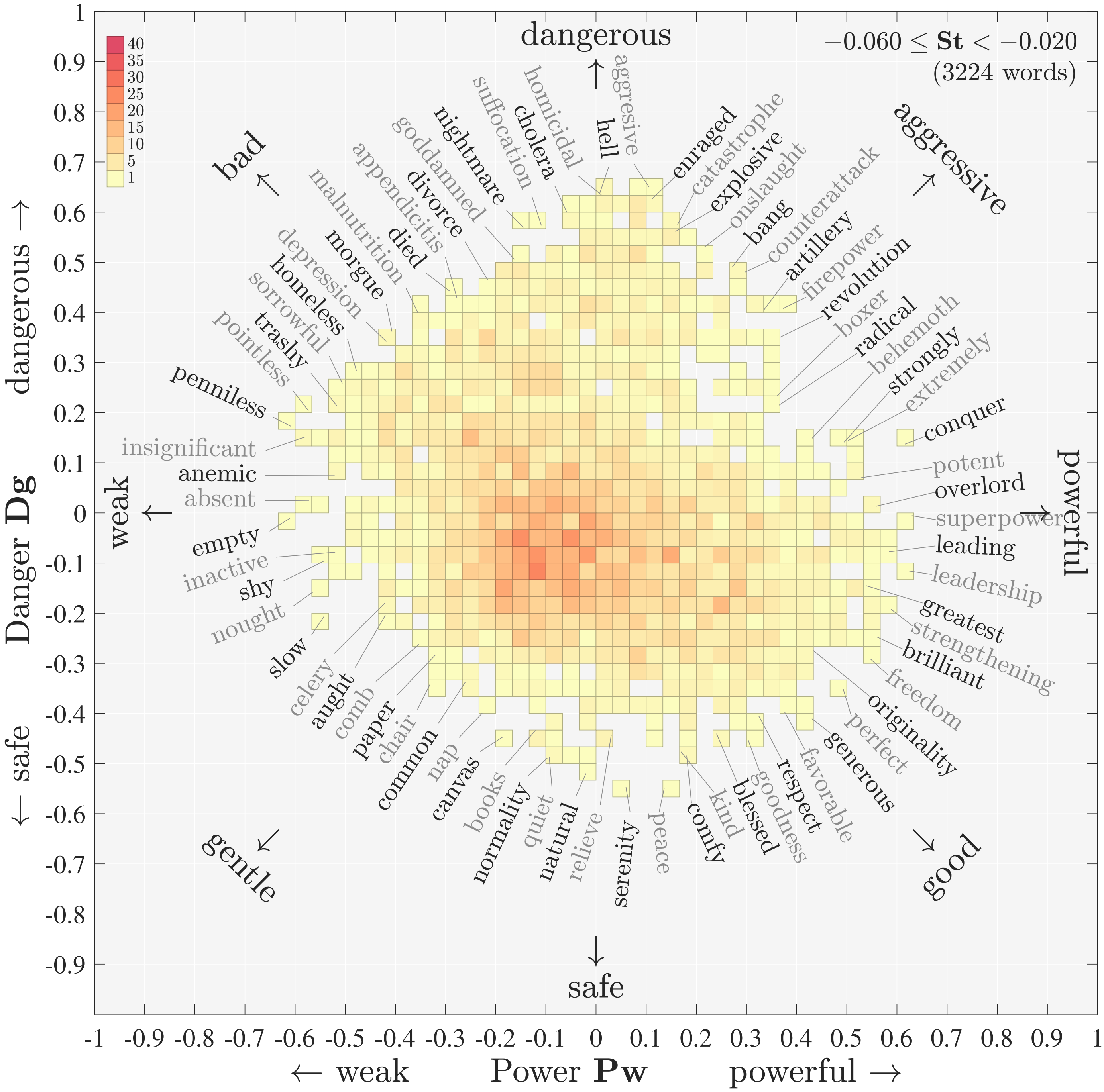


Figure S18: Ousiometric slice for power-danger plane with structure: $-0.060 \leq \mathbf{St} < -0.020$.

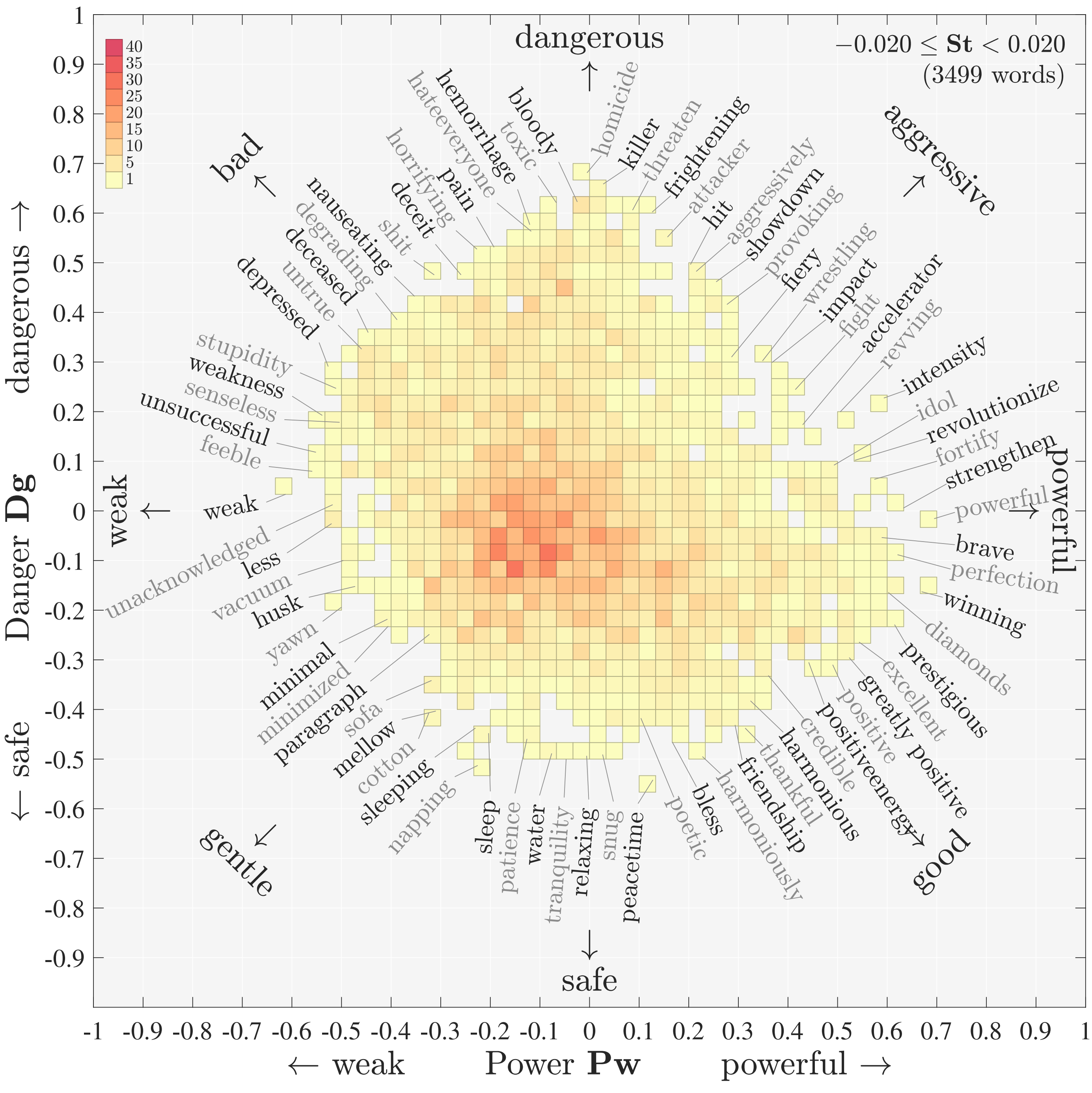


Figure S19: Ousiometric slice for power-danger plane with structure: $-0.020 \leq \mathbf{St} < 0.020$.

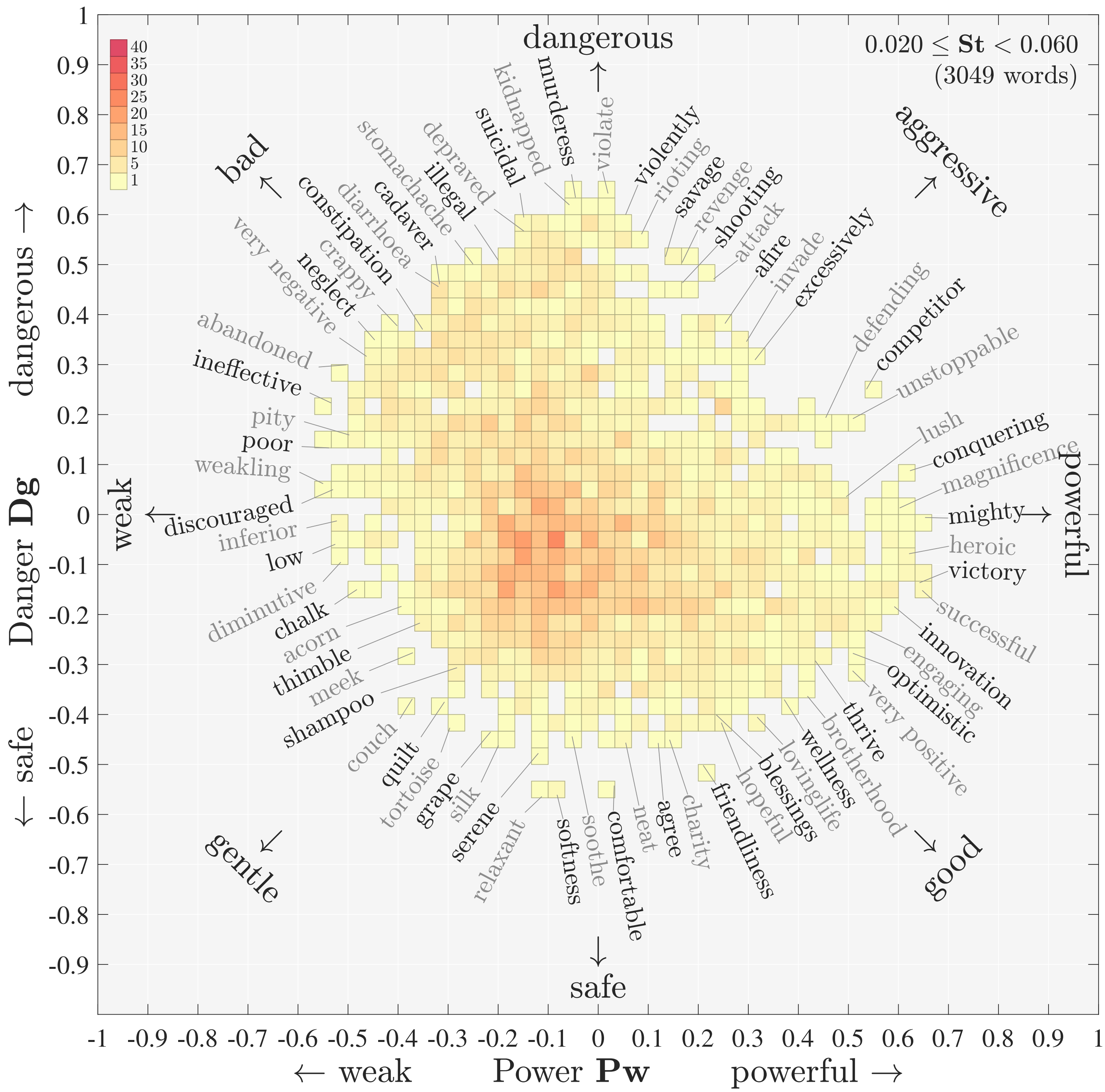


Figure S20: Ousiometric slice for power-danger plane with structure: $0.020 \leq \mathbf{St} < 0.060$.

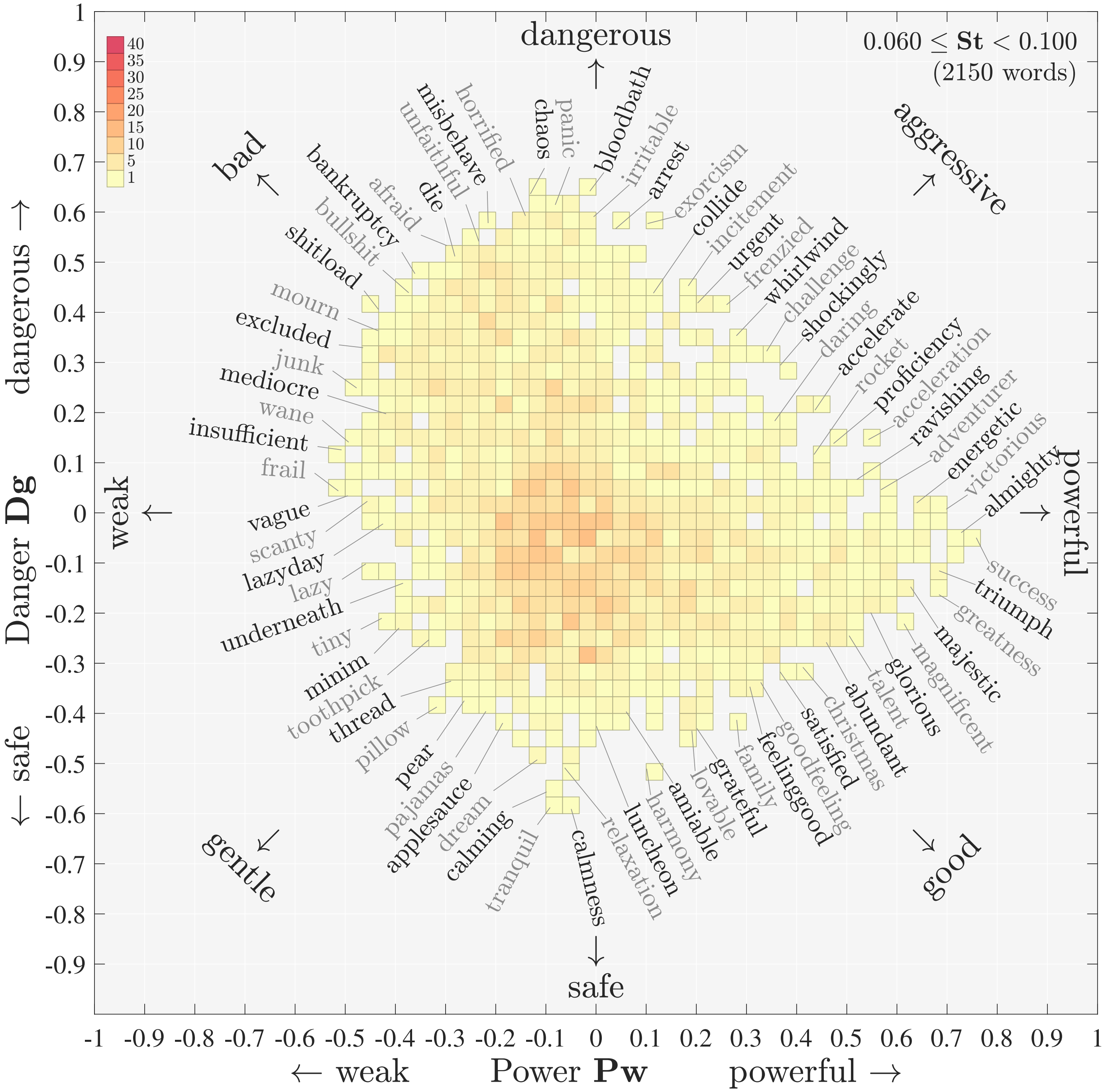


Figure S21: Ousiometric slice for power-danger plane with structure: $0.060 \leq \mathbf{St} < 0.100$.

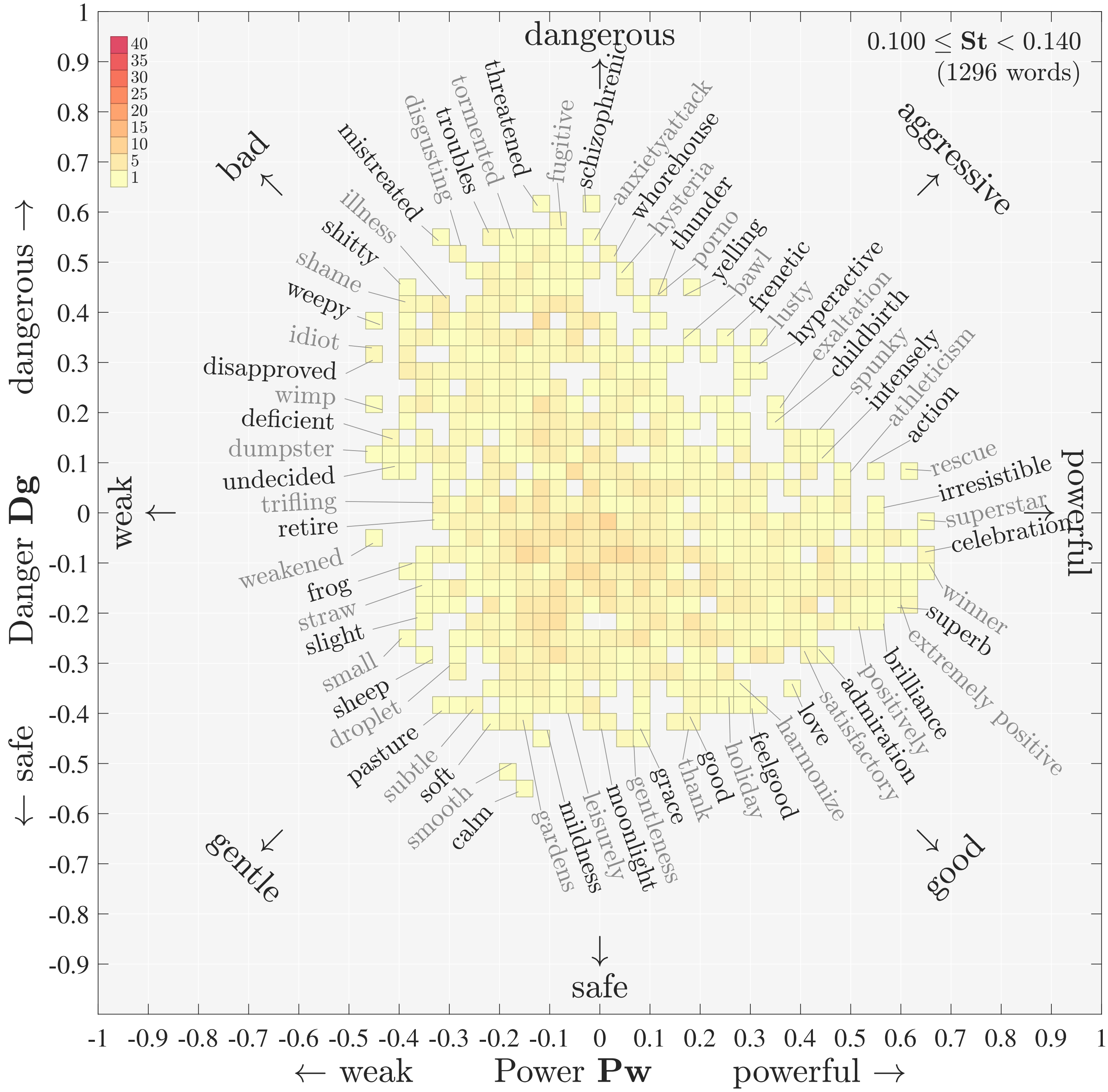


Figure S22: Ousiometric slice for power-danger plane with structure: $0.100 \leq \mathbf{St} < 0.140$.

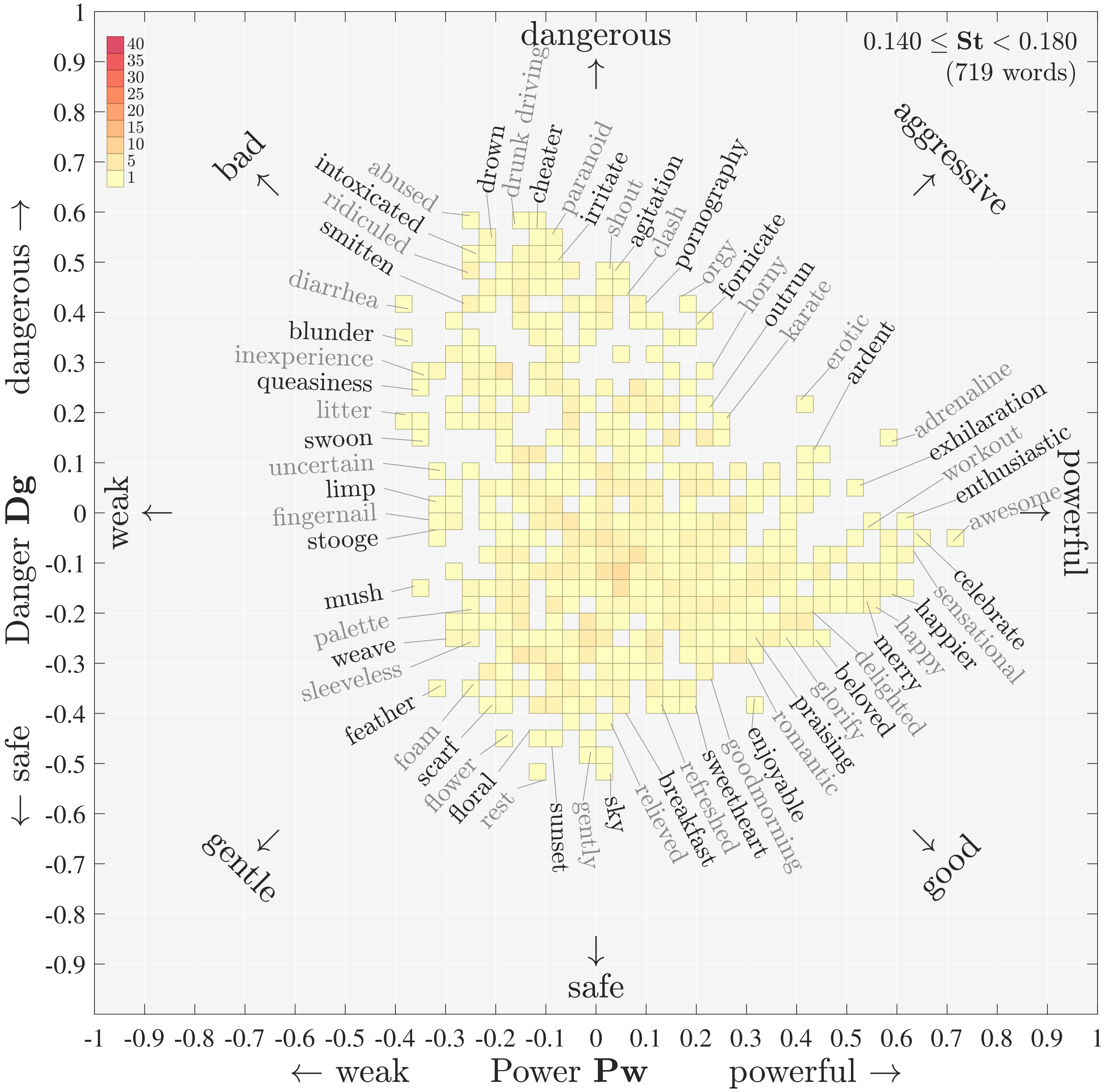


Figure S23: Ousiometric slice for power-danger plane with structure: $0.140 \leq \mathbf{St} < 0.180$.

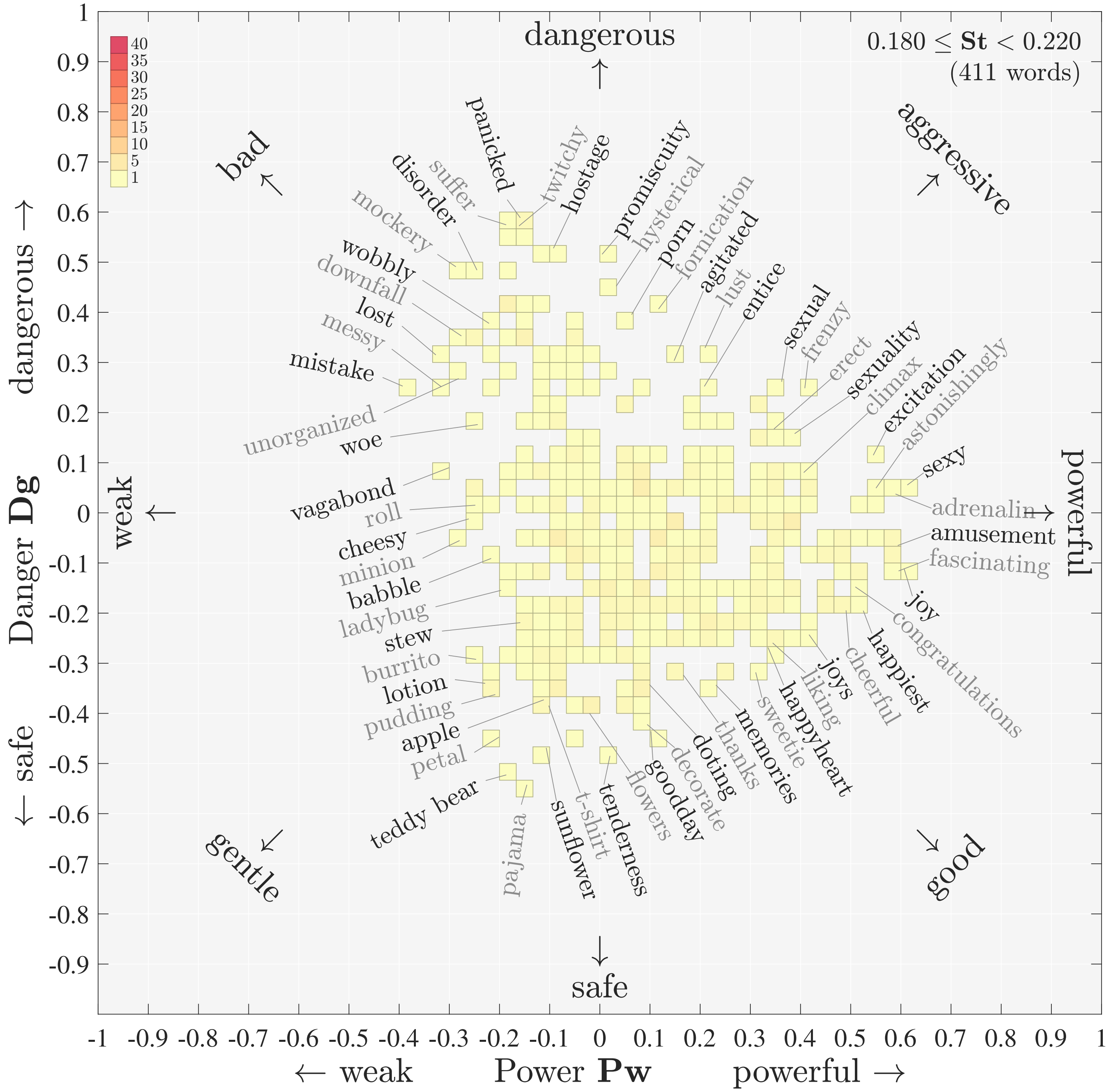


Figure S24: Ousiometric slice for power-danger plane with structure: $0.180 \leq \mathbf{St} < 0.220$.

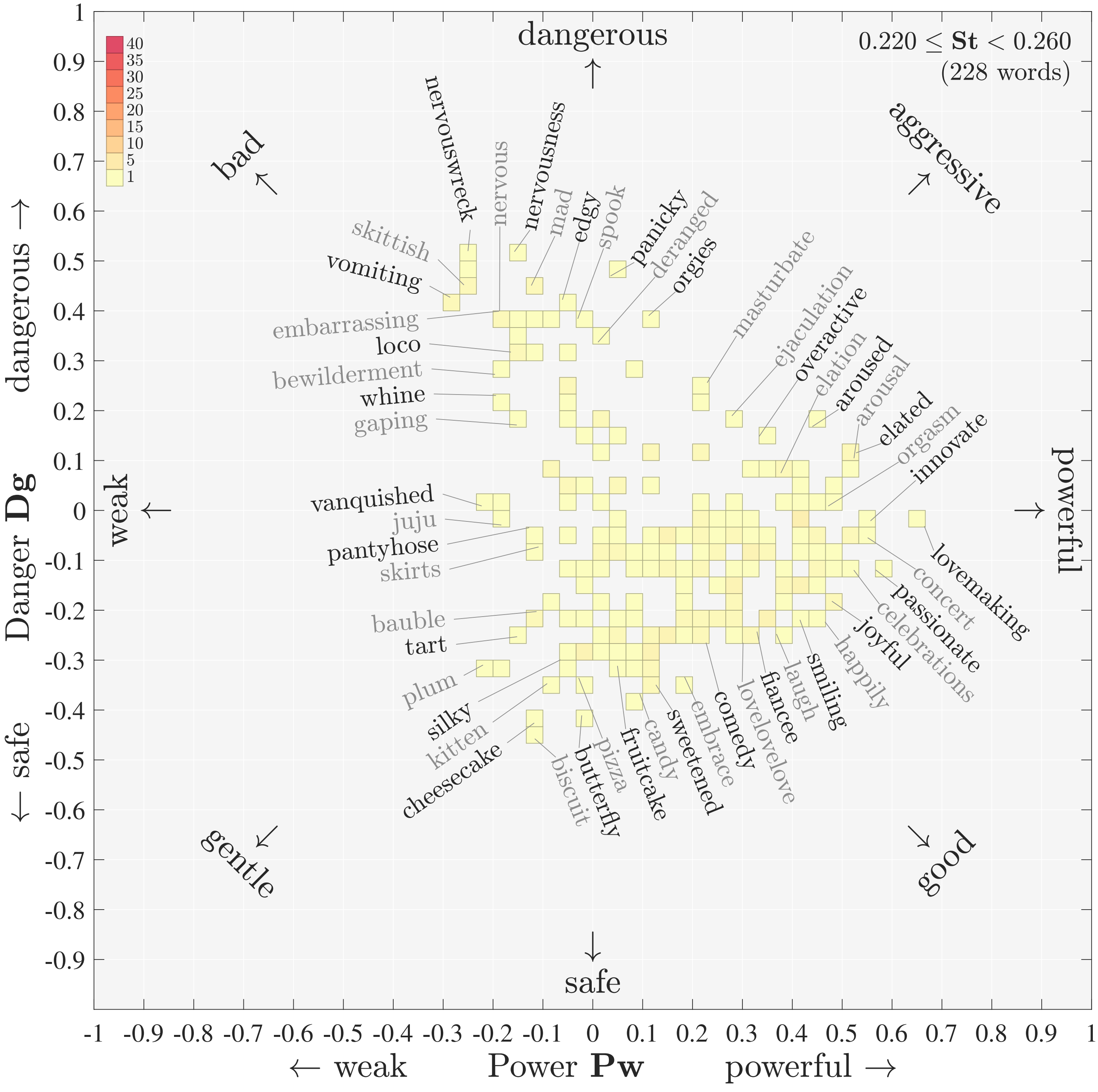


Figure S25: Ousiometric slice for power-danger plane with structure: $0.220 \leq \mathbf{St} < 0.260$.

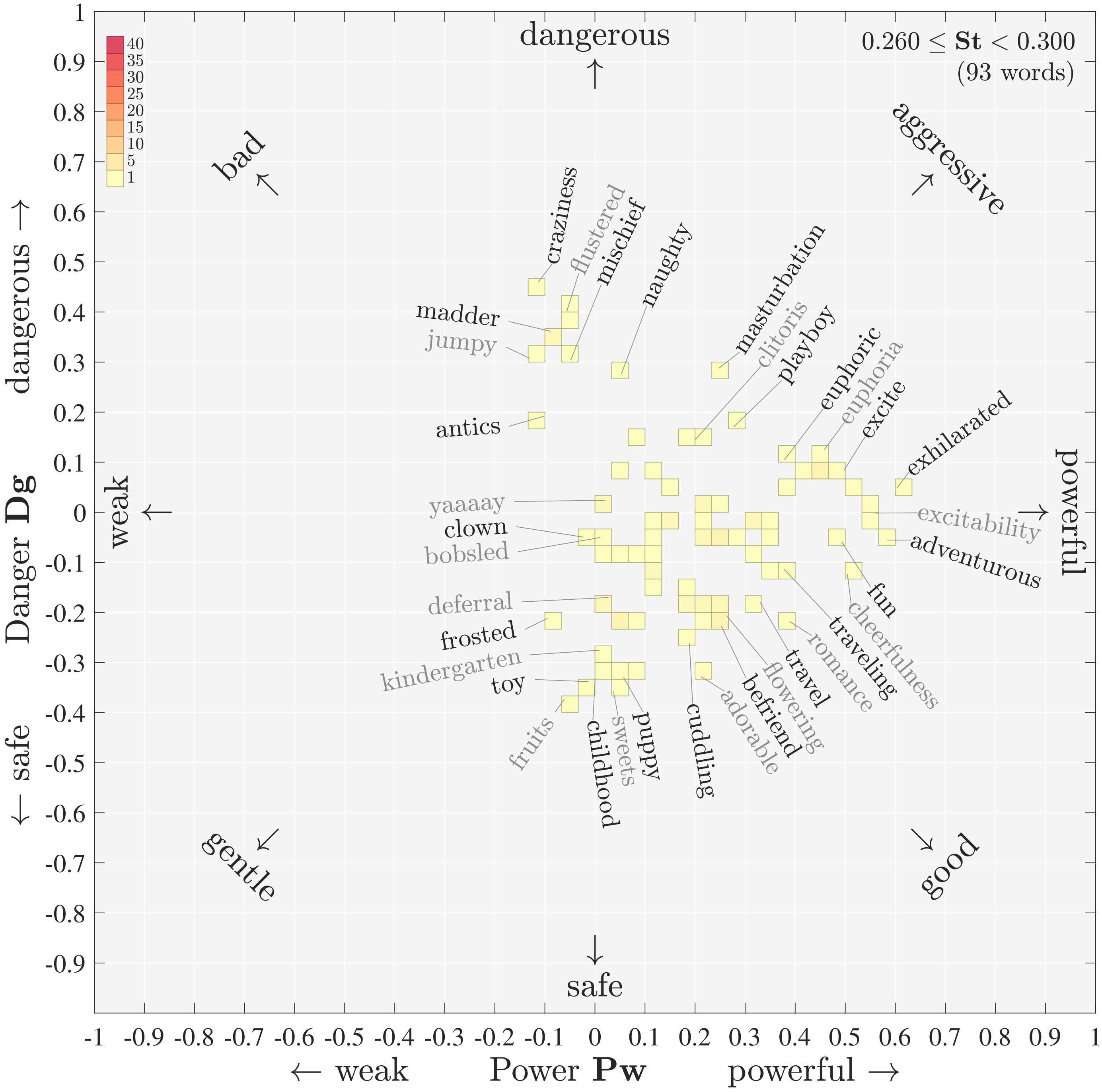


Figure S26: Ousiometric slice for power-danger plane with structure: $0.260 \leq \mathbf{St} < 0.300$.

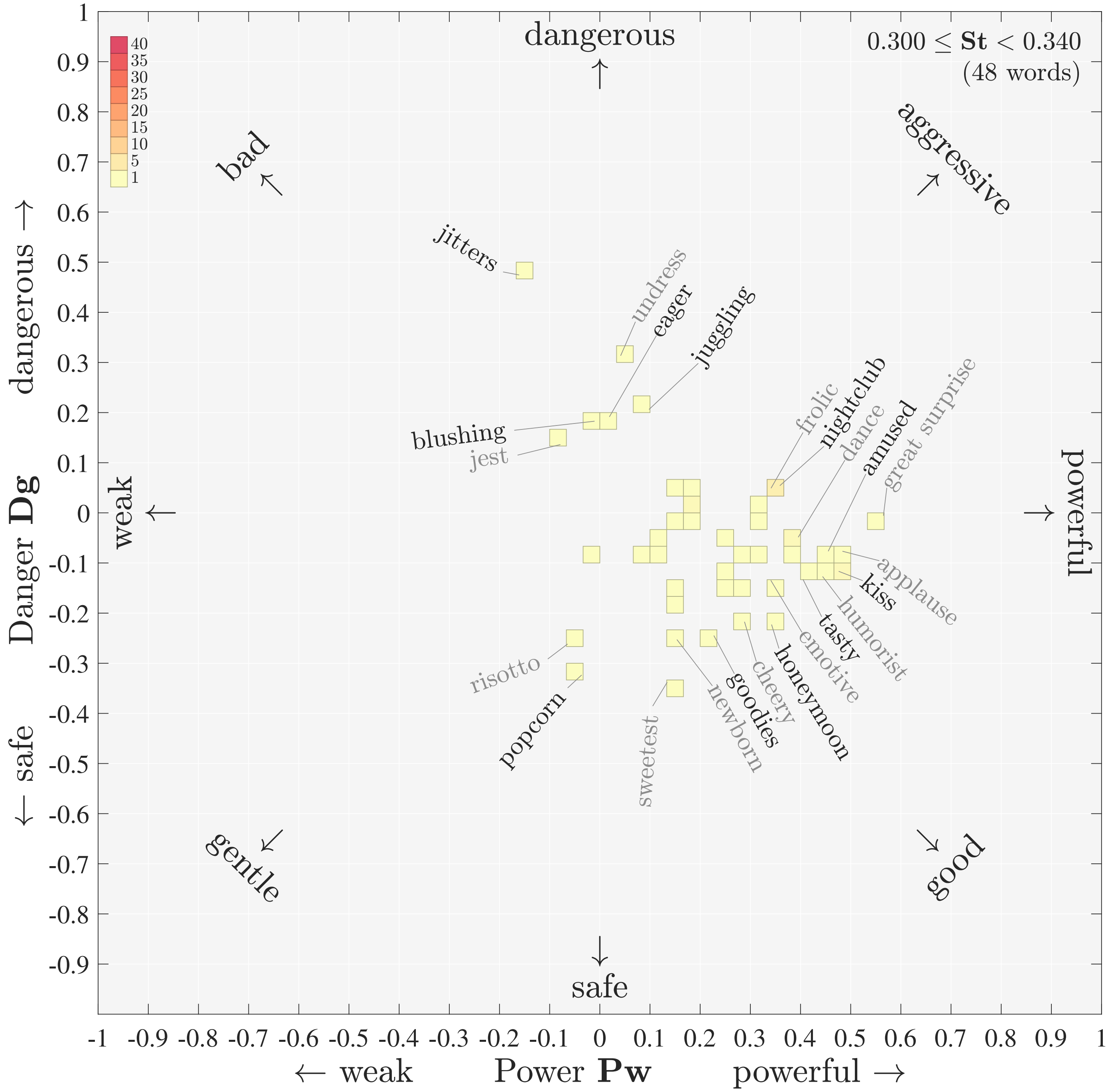


Figure S27: Ousiometric slice for power-danger plane with structure: $0.300 \leq \mathbf{St} < 0.340$.

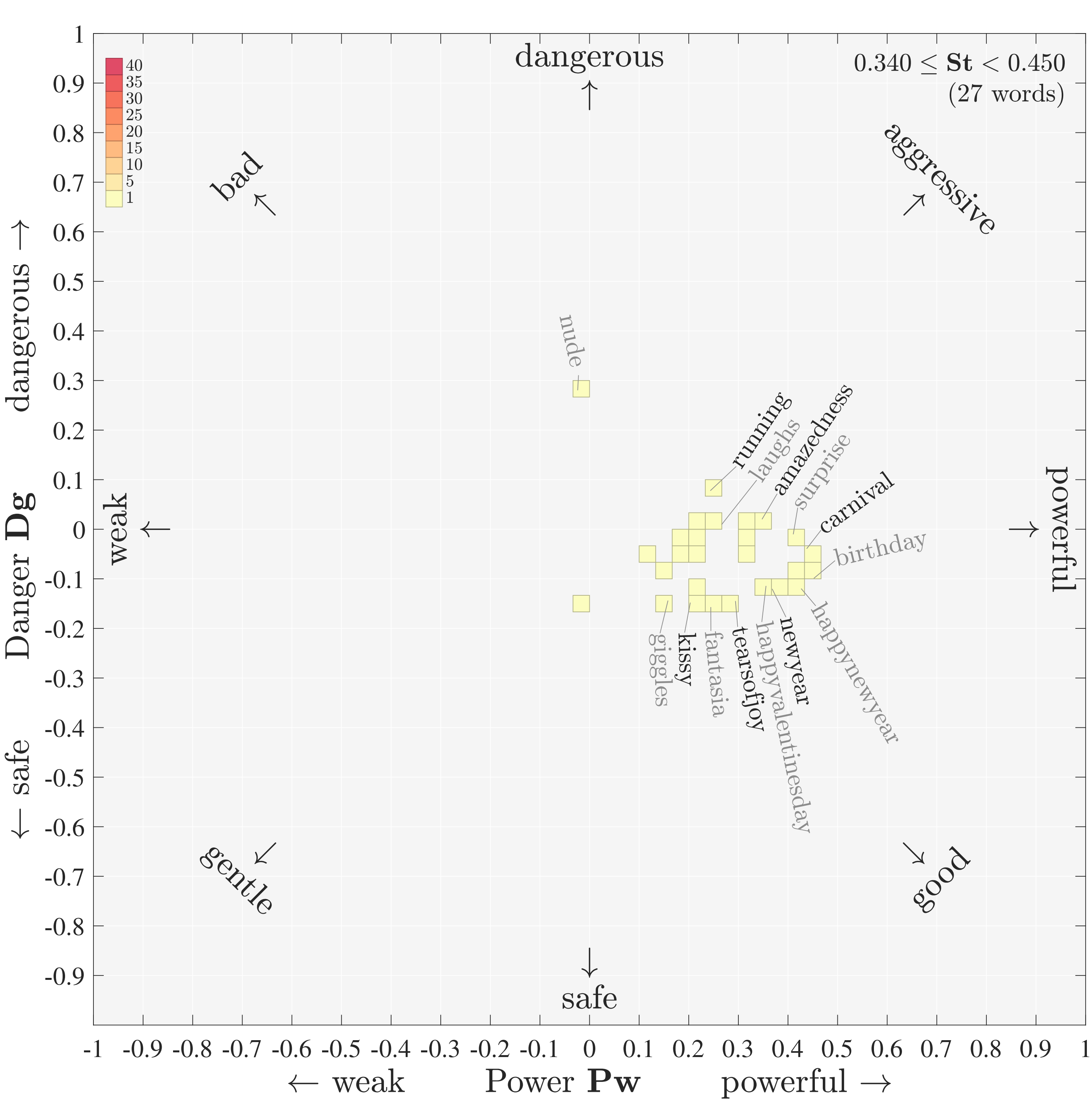
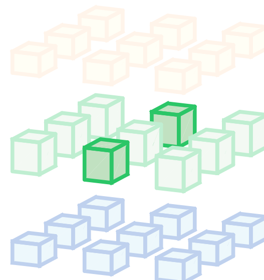


Figure S28: Ousiometric slice for power-danger plane with structure: $0.340 \leq \mathbf{St} < 0.450$.

S4 Tables for the 13 semantic differential pairs within cube-based ousiometric framework

safe ⇐  ⇒ **dangerous**

(gentle-good)
peaceful
serene
angelic

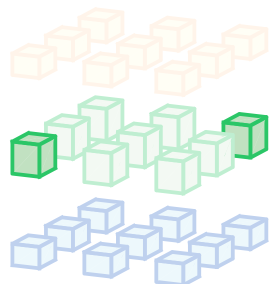
(aggressive-bad)
murderous
violent
demonic

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **calmness**	77.1	77.9	7.9	0.99	-0.05	-0.59	0.07
2. **tranquil**	76.7	78.3	11.6	0.98	-0.09	-0.59	0.08
3. **relaxant**	73.7	75.5	12.5	0.98	-0.11	-0.56	0.05
4. **softness**	73.2	74.1	8.6	0.99	-0.08	-0.56	0.02
5. **calming**	72.7	74.3	12.0	0.98	-0.10	-0.56	0.07
6. **relaxed**	72.0	73.3	10.8	0.98	-0.10	-0.55	0.03
7. **peace**	71.8	74.3	14.9	0.97	0.14	-0.55	-0.06
8. **serenity**	71.5	72.3	8.4	0.99	0.06	-0.55	-0.05
9. **comfortable**	70.8	71.1	5.3	1.00	0.03	-0.54	0.04
10. **peacetime**	70.8	72.7	13.3	0.97	0.13	-0.54	-0.01
11. **peaceful**	69.6	70.7	10.3	0.98	0.05	-0.53	-0.09
12. **stressfree**	69.1	70.1	9.7	0.99	-0.01	-0.53	-0.09
13. **reassurance**	68.5	70.1	12.5	0.98	0.08	-0.52	-0.09
14. **natural**	67.9	68.1	3.6	1.00	-0.02	-0.52	-0.03
15. **sky**	67.8	70.4	15.6	0.96	0.03	-0.52	0.14
16. **harmony**	66.7	68.4	13.0	0.97	0.10	-0.51	0.06
17. **relaxation**	66.4	67.6	10.9	0.98	-0.06	-0.51	0.08
18. **tranquility**	65.3	65.6	5.4	1.00	-0.05	-0.50	0.00
19. **relaxing**	64.4	64.5	0.7	1.00	-0.01	-0.49	-0.00
20. **teatime**	64.4	66.9	15.9	0.96	-0.11	-0.49	0.09

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **homicide**	89.0	89.0	179.0	-1.00	-0.01	0.68	0.01
2. **murderer**	88.5	89.9	169.9	-0.98	0.08	0.68	-0.09
3. **abduction**	86.5	88.8	166.9	-0.97	0.14	0.66	-0.06
4. **murderous**	86.3	88.6	166.8	-0.97	0.10	0.66	-0.12
5. **suicidebombing**	86.2	87.1	171.5	-0.99	0.08	0.66	-0.06
6. **killer**	86.0	86.1	177.5	-1.00	0.03	0.66	0.01
7. **dangerous**	85.9	87.6	168.8	-0.98	0.09	0.66	-0.10
8. **assassinate**	85.9	89.6	163.4	-0.96	0.16	0.66	-0.11
9. **terrorist**	85.1	87.4	166.8	-0.97	0.10	0.65	-0.12
10. **gunfight**	85.0	88.0	165.1	-0.97	0.14	0.65	-0.10
11. **gunshot**	85.0	87.1	167.4	-0.98	0.11	0.65	-0.09
12. **terrorism**	84.9	87.2	167.0	-0.97	0.13	0.65	-0.07
13. **aggresive**	84.8	86.2	169.8	-0.98	0.11	0.65	-0.05
14. **terrorists**	84.5	87.1	165.7	-0.97	0.14	0.65	-0.08
15. **tsunami**	84.3	86.7	166.4	-0.97	0.12	0.65	-0.10
16. **violate**	83.9	84.0	176.6	-1.00	0.02	0.64	0.03
17. **bloodbath**	83.8	84.2	174.2	-0.99	-0.01	0.64	0.06
18. **slaughter**	83.7	84.3	173.2	-0.99	0.07	0.64	-0.04
19. **psychopath**	83.5	83.5	179.2	-1.00	0.01	0.64	-0.00
20. **hell**	83.3	83.6	175.8	-1.00	0.01	0.64	-0.05

Figure S29: Words with largest components in safe and dangerous directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

gentle ⇐



⇒ **aggressive**

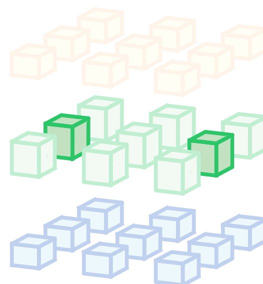
(safe-weak)
restful
meek
sleepy

(dangerous-powerful)
competitive
warlike
forceful

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **couch**	68.4	68.5	2.8	1.00	-0.37	-0.37	0.03
2. **cotton**	67.5	68.0	6.6	0.99	-0.32	-0.41	0.01
3. **tortoise**	66.8	67.9	10.6	0.98	-0.30	-0.43	0.03
4. **mellow**	65.9	66.4	7.5	0.99	-0.31	-0.40	-0.01
5. **pasture**	65.5	67.9	15.2	0.97	-0.31	-0.39	0.12
6. **pillow**	65.1	66.3	11.2	0.98	-0.32	-0.39	0.09
7. **lawn**	63.1	65.3	15.0	0.97	-0.30	-0.39	0.11
8. **quilt**	63.0	63.7	8.3	0.99	-0.31	-0.37	0.05
9. **chair**	62.2	62.5	5.3	1.00	-0.33	-0.34	-0.04
10. **sleeping**	61.6	64.5	17.3	0.95	-0.23	-0.44	0.00
11. **asleep**	61.6	61.8	4.8	1.00	-0.31	-0.36	-0.01
12. **sofa**	61.0	61.0	2.5	1.00	-0.32	-0.34	-0.01
13. **sleepy**	60.3	60.4	3.8	1.00	-0.31	-0.34	0.02
14. **meek**	59.7	60.5	9.2	0.99	-0.37	-0.28	0.03
15. **subtle**	59.5	62.4	17.6	0.95	-0.25	-0.39	0.11
16. **minimized**	58.9	61.1	15.4	0.96	-0.41	-0.23	-0.02
17. **pear**	58.9	60.6	13.7	0.97	-0.26	-0.37	0.08
18. **napkin**	58.5	60.4	14.3	0.97	-0.40	-0.24	-0.01
19. **teacup**	57.9	58.5	8.3	0.99	-0.27	-0.36	0.02
20. **sheep**	57.9	60.2	16.0	0.96	-0.33	-0.29	0.12

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **battle**	76.8	77.4	172.7	-0.99	0.41	0.42	-0.08
2. **warship**	73.9	76.9	163.9	-0.96	0.36	0.44	-0.15
3. **firepower**	72.1	72.3	175.7	-1.00	0.37	0.41	-0.03
4. **counterattack**	71.8	74.0	166.1	-0.97	0.30	0.48	-0.04
5. **bang**	70.5	73.4	163.7	-0.96	0.27	0.49	-0.03
6. **warrior**	69.4	72.2	163.9	-0.96	0.45	0.30	-0.11
7. **artillery**	68.3	68.9	172.4	-0.99	0.33	0.41	-0.05
8. **dominant**	67.9	70.1	165.5	-0.97	0.41	0.33	-0.12
9. **tornado**	67.8	70.9	162.8	-0.96	0.28	0.46	-0.09
10. **shelling**	67.6	68.5	171.1	-0.99	0.32	0.42	-0.04
11. **hurricanes**	67.4	69.7	165.4	-0.97	0.29	0.44	-0.08
12. **volcanic**	67.3	68.0	171.7	-0.99	0.32	0.41	-0.04
13. **wild**	67.1	68.6	167.9	-0.98	0.29	0.44	-0.03
14. **showdown**	66.2	68.9	163.8	-0.96	0.26	0.46	0.02
15. **revolution**	66.1	66.2	176.8	-1.00	0.37	0.35	-0.03
16. **gunslinger**	66.0	67.8	166.8	-0.97	0.31	0.40	-0.10
17. **fighting**	65.8	68.1	165.4	-0.97	0.29	0.43	-0.08
18. **explode**	65.4	68.2	163.8	-0.96	0.27	0.44	-0.08
19. **overbearing**	65.1	68.2	162.8	-0.96	0.33	0.37	-0.15
20. **combat**	65.0	67.8	163.3	-0.96	0.31	0.40	-0.14

Figure S30: Words with largest components in gentle and aggressive directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

weak ⇐  ⇒ **powerful**

(gentle-bad)
empty
idle
foolish

(aggressive-good)
triumphant
mighty
heroic

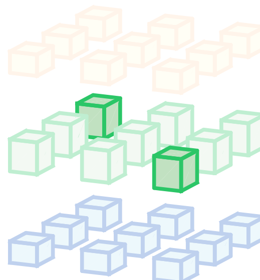
Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **weak**	80.0	80.2	3.6	1.00	-0.61	0.03	0.02
2. **void**	79.7	80.9	9.7	0.99	-0.61	0.02	-0.10
3. **empty**	79.7	79.8	3.3	1.00	-0.61	-0.01	-0.03
4. **penniless**	79.4	82.6	15.9	0.96	-0.61	0.17	-0.02
5. **idle**	78.3	78.9	6.6	0.99	-0.60	-0.01	-0.07
6. **sloth**	77.6	78.5	9.0	0.99	-0.59	-0.05	-0.08
7. **nothingness**	77.5	80.4	15.4	0.96	-0.59	-0.09	-0.14
8. **sorrow**	77.4	80.9	16.9	0.96	-0.59	0.13	-0.13
9. **insignificant**	75.7	78.4	15.1	0.97	-0.58	0.15	-0.04
10. **hopeless**	75.7	78.0	13.8	0.97	-0.58	0.14	-0.04
11. **tasteless**	75.3	76.3	9.6	0.99	-0.58	0.03	-0.09
12. **absent**	74.7	75.0	4.9	1.00	-0.57	0.03	-0.04
13. **hairless**	74.3	75.4	9.5	0.99	-0.57	0.07	-0.07
14. **sluggish**	74.0	75.8	12.3	0.98	-0.57	-0.07	-0.10
15. **nought**	73.6	76.7	16.2	0.96	-0.56	-0.16	-0.04
16. **dull**	73.4	75.9	14.6	0.97	-0.56	-0.05	-0.14
17. **unhelpful**	73.1	75.6	14.8	0.97	-0.56	0.15	-0.02
18. **boring**	73.0	73.2	4.4	1.00	-0.56	0.01	-0.04
19. **feeble**	73.0	73.8	8.3	0.99	-0.56	0.08	-0.01
20. **bored**	72.1	74.3	14.1	0.97	-0.55	0.01	-0.14

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **success**	99.0	100.0	171.9	-0.99	0.76	-0.05	0.10
2. **almighty**	95.1	96.1	171.7	-0.99	0.73	-0.04	0.10
3. **triumphant**	94.8	95.8	171.9	-0.99	0.73	-0.07	0.07
4. **awesome**	92.9	96.0	165.4	-0.97	0.71	-0.06	0.18
5. **victorious**	91.2	91.9	172.9	-0.99	0.70	0.01	0.09
6. **champion**	91.1	91.8	172.9	-0.99	0.70	-0.00	0.09
7. **powerful**	90.7	90.8	178.1	-1.00	0.69	-0.02	0.02
8. **triumph**	89.3	91.4	167.7	-0.98	0.68	-0.12	0.09
9. **greatness**	89.3	92.2	165.6	-0.97	0.68	-0.16	0.07
10. **superman**	87.8	89.4	169.3	-0.98	0.67	-0.10	0.08
11. **winning**	87.4	90.0	166.3	-0.97	0.67	-0.16	0.01
12. **richness**	86.4	87.2	172.3	-0.99	0.66	-0.04	0.08
13. **breathtaking**	86.4	87.8	169.4	-0.98	0.66	-0.10	0.08
14. **winner**	85.7	88.2	166.3	-0.97	0.66	-0.10	0.12
15. **mighty**	85.3	85.6	175.3	-1.00	0.65	-0.01	0.05
16. **invincible**	85.0	85.7	172.7	-0.99	0.65	-0.00	0.08
17. **celebration**	84.7	86.8	167.2	-0.98	0.65	-0.08	0.12
18. **successful**	84.6	87.0	166.5	-0.97	0.65	-0.15	0.04
19. **victory**	83.9	85.9	167.5	-0.98	0.64	-0.14	0.04
20. **succeed**	83.9	85.4	169.0	-0.98	0.64	-0.11	0.05

Figure S31: Words with largest components in weak and powerful directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

bad

(dangerous-weak)
suffering
failing
sorrowful

⇐  ⇒

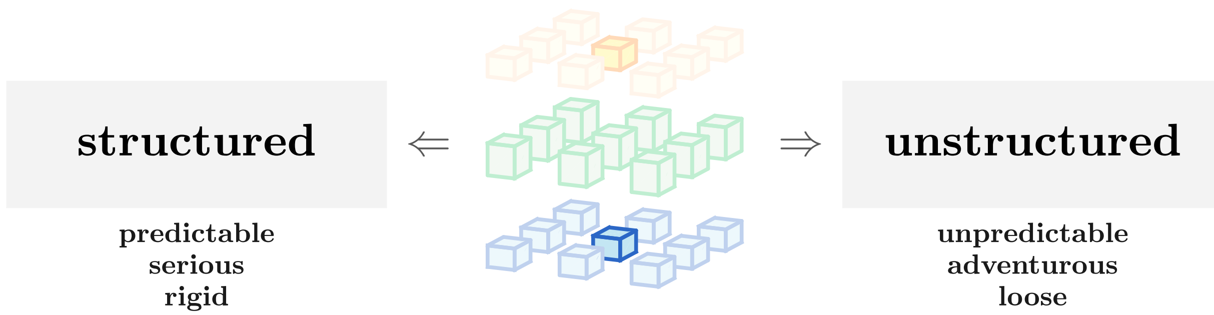
good

(safe-powerful)
virtuous
honorable
uplifting

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **shitty**	78.8	80.1	10.2	0.98	-0.40	0.46	0.10
2. **shitload**	77.5	78.0	6.2	0.99	-0.43	0.41	0.06
3. **bankruptcy**	77.4	78.7	10.5	0.98	-0.36	0.48	0.07
4. **depressed**	75.5	78.6	16.1	0.96	-0.53	0.29	-0.01
5. **weepy**	75.1	77.0	12.6	0.98	-0.44	0.38	0.12
6. **suffering**	75.1	77.1	13.2	0.97	-0.33	0.49	0.07
7. **bullshit**	75.0	76.3	10.5	0.98	-0.37	0.44	0.10
8. **disagreeable**	74.7	75.5	8.2	0.99	-0.39	0.42	0.08
9. **shame**	74.6	76.3	12.1	0.98	-0.39	0.42	0.12
10. **deceased**	74.4	74.8	6.2	0.99	-0.45	0.36	0.01
11. **abandoned**	74.1	76.5	14.5	0.97	-0.50	0.30	0.03
12. **weep**	73.9	74.7	8.5	0.99	-0.41	0.39	0.08
13. **mourn**	73.7	74.6	9.0	0.99	-0.43	0.36	0.07
14. **neglect**	73.5	74.2	8.2	0.99	-0.45	0.35	0.04
15. **excluded**	73.3	74.8	11.6	0.98	-0.46	0.33	0.06
16. **nauseate**	72.9	74.2	10.6	0.98	-0.38	0.41	0.10
17. **shit**	72.8	74.4	11.6	0.98	-0.31	0.48	-0.00
18. **untrue**	72.5	73.6	9.7	0.99	-0.46	0.33	-0.01
19. **nauseating**	72.5	72.9	6.1	0.99	-0.35	0.43	0.02
20. **idiot**	72.3	74.5	13.9	0.97	-0.45	0.33	0.11

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **perfect**	78.0	79.2	169.7	-0.98	0.49	-0.35	-0.04
2. **generous**	77.6	77.7	177.4	-1.00	0.43	-0.41	-0.02
3. **freedom**	77.5	81.1	162.8	-0.96	0.55	-0.29	-0.03
4. **trustworthy**	76.9	78.3	169.2	-0.98	0.38	-0.45	-0.10
5. **very positive**	75.8	78.2	166.0	-0.97	0.51	-0.31	0.04
6. **wisdom**	75.7	78.5	164.5	-0.96	0.39	-0.43	-0.16
7. **greatly positive**	75.6	78.5	164.4	-0.96	0.52	-0.30	-0.02
8. **honorable**	74.7	75.1	173.7	-0.99	0.43	-0.38	-0.05
9. **positivity**	74.1	77.2	163.5	-0.96	0.52	-0.28	-0.01
10. **positive**	73.9	75.8	167.2	-0.98	0.49	-0.31	-0.02
11. **guarantee**	73.0	74.0	170.5	-0.99	0.37	-0.42	-0.08
12. **healthy**	72.9	74.5	168.1	-0.98	0.36	-0.43	-0.11
13. **respectful**	72.8	73.3	173.6	-0.99	0.40	-0.39	-0.06
14. **optimistic**	72.6	76.0	162.9	-0.96	0.51	-0.28	0.05
15. **brotherhood**	72.2	72.5	174.3	-1.00	0.42	-0.36	0.04
16. **blessing**	71.8	75.0	163.4	-0.96	0.32	-0.46	-0.13
17. **favorable**	71.4	71.7	174.8	-1.00	0.38	-0.40	-0.05
18. **great trust**	71.2	73.6	165.0	-0.97	0.49	-0.28	-0.02
19. **goodness**	69.9	71.3	168.6	-0.98	0.30	-0.45	-0.02
20. **elegance**	69.5	70.4	171.1	-0.99	0.39	-0.36	-0.08

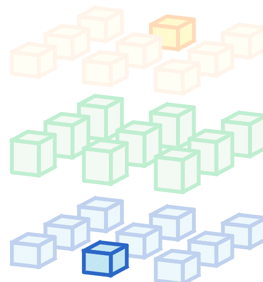
Figure S32: Words with largest components in bad and good directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.



Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **century**	37.8	38.6	11.3	0.98	0.05	-0.03	-0.29
2. **archdiocese**	37.3	37.8	8.7	0.99	0.01	-0.04	-0.29
3. **psychologist**	35.7	36.3	11.0	0.98	-0.04	-0.04	-0.27
4. **staid**	34.2	35.8	17.5	0.95	-0.06	-0.06	-0.26
5. **criterion**	34.1	35.7	16.9	0.96	0.08	0.02	-0.26
6. **metropolitan**	33.6	34.8	14.6	0.97	0.06	0.03	-0.26
7. **monastic**	32.9	34.4	16.8	0.96	0.01	-0.08	-0.25
8. **district**	30.6	31.8	16.1	0.96	0.00	-0.07	-0.23
9. **iron**	29.9	31.1	16.0	0.96	0.03	-0.06	-0.23
10. **coding**	29.7	30.8	15.0	0.97	0.02	-0.06	-0.23
11. **clinical**	29.0	30.3	16.8	0.96	-0.02	0.06	-0.22
12. **diction**	28.9	29.7	13.3	0.97	0.04	-0.04	-0.22
13. **feudal**	27.4	28.2	13.4	0.97	-0.05	0.01	-0.21
14. **conservatism**	27.1	27.3	5.8	0.99	-0.01	-0.02	-0.21
15. **utilitarian**	26.8	27.2	9.8	0.99	-0.00	-0.04	-0.21
16. **ground**	26.7	27.8	16.4	0.96	-0.05	-0.03	-0.20
17. **taxonomy**	26.2	26.7	11.3	0.98	-0.01	0.04	-0.20
18. **tense**	24.8	25.6	14.9	0.97	0.03	0.04	-0.19
19. **indenture**	24.7	25.0	8.7	0.99	0.01	-0.03	-0.19
20. **disinfect**	24.5	25.2	12.9	0.97	0.03	-0.03	-0.19

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **plaything**	40.3	42.0	163.7	-0.96	-0.01	-0.09	0.31
2. **joke**	37.1	38.7	163.8	-0.96	0.02	-0.08	0.28
3. **yaaaay**	36.1	36.3	173.4	-0.99	0.02	0.02	0.28
4. **drum**	34.4	34.9	170.9	-0.99	0.03	0.03	0.26
5. **clown**	34.3	35.1	168.2	-0.98	-0.02	-0.05	0.26
6. **bobsled**	34.2	34.9	168.9	-0.98	0.01	-0.05	0.26
7. **potpourri**	33.3	34.5	164.6	-0.96	-0.04	-0.06	0.25
8. **jump rope**	33.0	33.9	166.8	-0.97	0.06	-0.01	0.25
9. **laughable**	33.0	33.4	170.6	-0.99	-0.04	0.01	0.25
10. **ahhhhhhhh**	32.9	34.5	162.5	-0.95	-0.06	0.06	0.25
11. **weeeee**	32.7	34.0	163.7	-0.96	-0.06	0.04	0.25
12. **yaaay**	32.5	32.9	170.8	-0.99	0.00	-0.04	0.25
13. **fanciful**	31.8	33.2	163.2	-0.96	0.02	-0.07	0.24
14. **yayyyy**	31.4	32.8	163.7	-0.96	0.04	-0.06	0.24
15. **serpentine**	30.5	31.0	169.9	-0.98	-0.02	0.04	0.23
16. **yo-yo**	29.9	30.1	173.7	-0.99	0.00	0.03	0.23
17. **jamboree**	28.7	28.7	178.3	-1.00	0.00	0.01	0.22
18. **clowns**	28.4	29.7	162.6	-0.95	0.05	0.04	0.22
19. **yayy**	28.0	28.7	167.4	-0.98	0.01	-0.05	0.21
20. **cantina**	27.9	28.7	166.4	-0.97	0.04	-0.03	0.21

Figure S33: Words with largest components in structured and unstructured directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

structured safe ⇐  ⇒ **unstructured dangerous**

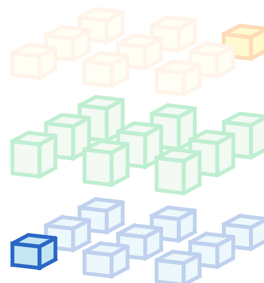
(structured-gentle-good)
ordered
orthodox
canonical

(unstructured-aggressive-bad)
jittery
panicky
mishcievous

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **buddhism**	54.4	55.1	9.3	0.99	-0.05	-0.27	-0.32
2. **bishop**	51.5	52.1	8.5	0.99	0.06	-0.28	-0.28
3. **pacific**	51.2	53.6	17.3	0.95	-0.06	-0.35	-0.20
4. **poise**	50.4	52.8	17.4	0.95	0.10	-0.32	-0.22
5. **conservatory**	46.3	48.5	17.4	0.95	0.11	-0.27	-0.23
6. **alphabet**	45.4	45.4	2.5	1.00	0.01	-0.24	-0.25
7. **marble**	45.1	45.5	7.7	0.99	0.03	-0.27	-0.22
8. **statue**	44.7	46.5	16.4	0.96	-0.09	-0.27	-0.22
9. **commonly**	44.4	46.2	16.2	0.96	-0.05	-0.30	-0.18
10. **headline**	43.5	44.9	14.4	0.97	0.07	-0.26	-0.21
11. **full**	42.4	43.7	14.1	0.97	0.08	-0.23	-0.23
12. **document**	41.7	42.2	8.5	0.99	0.04	-0.24	-0.21
13. **sector**	41.6	43.2	16.1	0.96	-0.05	-0.28	-0.17
14. **documentary**	41.2	42.6	14.8	0.97	-0.01	-0.28	-0.16
15. **senor**	40.6	40.8	5.8	0.99	-0.03	-0.21	-0.23
16. **uniform**	39.9	40.0	4.8	1.00	0.03	-0.22	-0.21
17. **therapeutic**	39.2	41.0	17.1	0.96	0.08	-0.24	-0.19
18. **habit**	39.1	40.9	16.8	0.96	-0.01	-0.28	-0.15
19. **storeroom**	38.8	39.5	10.3	0.98	-0.04	-0.23	-0.19
20. **unitary**	38.8	38.9	4.1	1.00	-0.01	-0.20	-0.22

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **nude**	65.4	66.9	167.9	-0.98	-0.02	0.28	0.43
2. **flustered**	63.0	64.4	168.1	-0.98	-0.06	0.40	0.28
3. **edgy**	61.6	64.2	163.5	-0.96	-0.06	0.42	0.24
4. **naked**	60.5	61.9	168.0	-0.98	-0.06	0.38	0.27
5. **jittery**	58.7	60.0	168.1	-0.98	-0.09	0.35	0.29
6. **spook**	58.7	60.1	167.6	-0.98	-0.03	0.38	0.25
7. **madder**	58.1	59.9	166.1	-0.97	-0.09	0.36	0.27
8. **bonkers**	57.2	59.5	164.1	-0.96	-0.09	0.37	0.25
9. **undress**	56.8	57.0	174.4	-1.00	0.04	0.31	0.30
10. **jumpy**	55.6	58.2	162.9	-0.96	-0.13	0.31	0.29
11. **deranged**	53.3	54.1	170.3	-0.99	0.01	0.34	0.24
12. **mischief**	53.1	53.6	172.4	-0.99	-0.05	0.30	0.27
13. **intrigue**	51.1	51.9	169.7	-0.98	-0.04	0.32	0.23
14. **naughty**	49.5	50.0	171.9	-0.99	0.05	0.28	0.26
15. **evacuate**	47.7	49.1	166.3	-0.97	-0.07	0.30	0.22
16. **anal**	47.7	49.6	163.8	-0.96	-0.06	0.32	0.20
17. **gambling**	47.1	48.0	168.4	-0.98	-0.03	0.30	0.21
18. **nudity**	46.7	48.1	166.1	-0.97	0.08	0.28	0.22
19. **eager**	46.7	48.1	166.1	-0.97	0.02	0.19	0.31
20. **sarcastic**	46.4	47.2	169.7	-0.98	-0.06	0.26	0.24

Figure S34: Words with largest components in structured-safe and unstructured-dangerous directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

structured gentle ⇐  ⇒ **unstructured aggressive**

(structured-safe-weak)
routine
regulated
ascetic

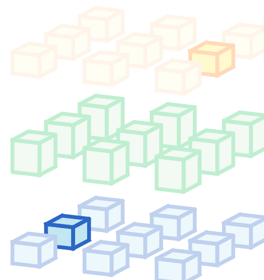
(unstructured-dangerous-powerful)
carnal
frenzied
explosive

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **desk**	47.4	48.8	13.7	0.97	-0.23	-0.26	-0.14
2. **elder**	46.0	46.1	3.6	1.00	-0.22	-0.20	-0.19
3. **nun**	45.7	47.3	15.0	0.97	-0.24	-0.25	-0.13
4. **notebook**	44.3	44.6	7.2	0.99	-0.23	-0.19	-0.17
5. **dune**	43.5	44.5	12.1	0.98	-0.24	-0.20	-0.14
6. **blueprint**	42.8	43.8	12.3	0.98	-0.22	-0.22	-0.13
7. **lineal**	42.3	43.3	12.2	0.98	-0.17	-0.24	-0.15
8. **baseboard**	41.5	43.5	17.5	0.95	-0.26	-0.14	-0.15
9. **regular**	41.2	42.3	13.3	0.97	-0.14	-0.17	-0.24
10. **sample**	40.3	41.4	13.6	0.97	-0.17	-0.23	-0.13
11. **point**	40.2	41.1	12.0	0.98	-0.20	-0.21	-0.12
12. **wrench**	40.2	41.6	15.2	0.97	-0.16	-0.13	-0.24
13. **standstill**	39.5	39.5	3.8	1.00	-0.17	-0.16	-0.19
14. **shingle**	39.1	40.9	17.4	0.95	-0.20	-0.22	-0.10
15. **neutrality**	39.1	39.7	10.3	0.98	-0.20	-0.18	-0.13
16. **monk**	38.6	39.1	9.6	0.99	-0.20	-0.18	-0.13
17. **ancient**	38.4	39.2	11.7	0.98	-0.22	-0.14	-0.15
18. **monogram**	38.2	39.2	12.7	0.98	-0.20	-0.19	-0.12
19. **march**	38.2	39.4	14.3	0.97	-0.14	-0.23	-0.14
20. **zen**	38.0	38.9	12.6	0.98	-0.19	-0.20	-0.11

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **sexual**	61.7	63.6	165.8	-0.97	0.36	0.26	0.19
2. **masturbation**	60.4	60.5	176.5	-1.00	0.25	0.29	0.27
3. **lust**	56.8	58.2	167.6	-0.98	0.21	0.33	0.21
4. **striptease**	56.6	58.1	167.1	-0.97	0.33	0.22	0.20
5. **masturbate**	56.0	56.1	177.0	-1.00	0.23	0.26	0.26
6. **playboy**	54.5	55.7	168.4	-0.98	0.28	0.17	0.27
7. **ejaculate**	53.7	55.2	166.8	-0.97	0.32	0.20	0.19
8. **ejaculation**	53.2	53.8	171.2	-0.99	0.28	0.19	0.24
9. **horny**	52.8	53.9	168.7	-0.98	0.23	0.29	0.18
10. **seduction**	51.4	53.4	164.3	-0.96	0.28	0.27	0.14
11. **entice**	50.5	50.7	174.7	-1.00	0.21	0.25	0.21
12. **jump**	50.1	52.4	163.0	-0.96	0.32	0.17	0.18
13. **vagina**	48.7	48.8	177.3	-1.00	0.20	0.22	0.23
14. **agitated**	48.2	50.4	162.8	-0.96	0.15	0.30	0.19
15. **stripper**	47.0	48.7	165.0	-0.97	0.19	0.15	0.28
16. **spirits**	46.6	47.0	173.2	-0.99	0.24	0.18	0.20
17. **clitoris**	46.6	48.0	165.8	-0.97	0.20	0.15	0.27
18. **bustling**	45.2	45.9	169.8	-0.98	0.18	0.25	0.17
19. **impulse**	45.1	46.9	164.2	-0.96	0.26	0.22	0.12
20. **karate**	44.7	46.0	166.3	-0.97	0.26	0.19	0.14

Figure S35: Words with largest components in structured-gentle and unstructured-aggressive directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

structured weak ⇐



⇒ **unstructured powerful**

(structured-gentle-bad)
inert
detached
closed

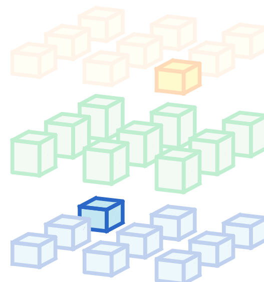
(unstructured-aggressive-good)
exciting
celebratory
frolicsome

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **no surprise**	56.0	57.3	12.0	0.98	-0.36	0.04	-0.25
2. **lone**	55.6	57.9	16.2	0.96	-0.39	0.01	-0.21
3. **stone**	55.3	56.1	9.7	0.99	-0.25	-0.01	-0.35
4. **trunk**	52.4	54.3	15.0	0.97	-0.34	-0.07	-0.22
5. **closure**	51.2	52.2	11.3	0.98	-0.33	-0.00	-0.22
6. **lethargic**	50.3	52.6	17.3	0.95	-0.35	0.03	-0.19
7. **finalized**	50.0	52.4	17.2	0.96	-0.19	-0.01	-0.35
8. **standby**	48.1	50.0	16.1	0.96	-0.33	-0.02	-0.19
9. **inactivate**	47.8	48.8	11.8	0.98	-0.31	0.00	-0.20
10. **olden**	46.8	47.9	12.3	0.98	-0.30	-0.04	-0.21
11. **unoccupied**	46.2	47.3	12.7	0.98	-0.31	-0.00	-0.19
12. **baton**	45.5	45.7	5.4	1.00	-0.23	-0.02	-0.27
13. **fragment**	43.7	45.7	17.2	0.96	-0.28	0.08	-0.19
14. **abstention**	42.9	43.0	3.0	1.00	-0.22	0.00	-0.24
15. **distance**	41.6	43.6	17.4	0.95	-0.28	0.06	-0.17
16. **anaesthesia**	40.3	42.0	16.1	0.96	-0.23	-0.09	-0.21
17. **celibacy**	39.0	39.1	3.8	1.00	-0.20	-0.01	-0.22
18. **grate**	38.9	40.7	16.8	0.96	-0.26	-0.05	-0.16
19. **delete**	38.1	39.7	16.2	0.96	-0.27	0.01	-0.15
20. **omit**	37.7	38.4	11.3	0.98	-0.23	-0.04	-0.18

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **great surprise**	81.8	84.9	164.6	-0.96	0.57	-0.01	0.32
2. **carnival**	75.3	75.7	174.3	-1.00	0.44	-0.04	0.38
3. **birthday**	75.0	76.6	168.3	-0.98	0.45	-0.10	0.36
4. **applause**	74.9	77.0	166.8	-0.97	0.48	-0.08	0.33
5. **amusing**	73.0	75.8	164.2	-0.96	0.48	-0.10	0.31
6. **amused**	72.9	74.4	168.4	-0.98	0.46	-0.08	0.33
7. **party**	72.6	73.7	170.3	-0.99	0.42	-0.09	0.37
8. **happynewyear**	72.2	74.2	166.8	-0.97	0.43	-0.12	0.36
9. **excite**	72.2	75.6	162.7	-0.95	0.50	0.08	0.28
10. **kiss**	72.1	75.4	163.0	-0.96	0.48	-0.12	0.30
11. **extreme surprise**	71.7	75.1	162.5	-0.95	0.50	0.07	0.28
12. **fun**	70.6	73.9	162.8	-0.96	0.49	-0.06	0.27
13. **surprise**	69.4	69.7	174.6	-1.00	0.41	-0.01	0.34
14. **dancing**	69.3	69.9	172.1	-0.99	0.33	-0.03	0.42
15. **excitable**	69.2	71.7	164.9	-0.97	0.45	0.09	0.30
16. **humorist**	69.0	72.2	163.0	-0.96	0.44	-0.13	0.30
17. **tasty**	68.6	71.0	165.0	-0.97	0.40	-0.13	0.34
18. **dance**	67.8	68.3	173.1	-0.99	0.40	-0.05	0.34
19. **ecstasy**	67.0	70.3	162.5	-0.95	0.46	0.08	0.26
20. **rollercoaster**	66.4	69.4	163.3	-0.96	0.46	0.07	0.26

Figure S36: Words with largest components in structured-weak and unstructured-powerful directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

structured bad ⇐



⇒ **unstructured good**

(structured-dangerous-weak)
funereal
contaminated
irreperable

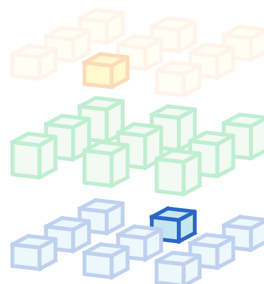
(unstructured-safe-powerful)
playful
joyful
laughing

Word	Comp. Size	Size	Angle	Cos.	**Pw**	**Dg**	**St**
1. **misrepresented**	58.2	60.0	14.2	0.97	-0.24	0.34	-0.19
2. **funeral**	57.7	59.6	14.6	0.97	-0.35	0.22	-0.20
3. **deletion**	56.0	57.4	13.0	0.97	-0.24	0.32	-0.18
4. **irreparable**	55.5	58.2	17.6	0.95	-0.26	0.34	-0.15
5. **improbable**	53.8	54.5	8.8	0.99	-0.29	0.23	-0.20
6. **opposed**	53.4	55.3	15.2	0.96	-0.15	0.27	-0.29
7. **coldness**	52.9	54.1	12.5	0.98	-0.27	0.27	-0.16
8. **bruising**	52.8	55.3	17.6	0.95	-0.25	0.31	-0.13
9. **vile**	52.5	55.1	17.6	0.95	-0.15	0.33	-0.22
10. **extinct**	49.9	52.0	16.3	0.96	-0.26	0.27	-0.13
11. **ineligible**	48.8	49.6	10.4	0.98	-0.27	0.17	-0.21
12. **skeptic**	48.3	48.3	1.8	1.00	-0.21	0.22	-0.21
13. **darkened**	48.3	48.7	7.9	0.99	-0.25	0.22	-0.17
14. **pantheon**	48.0	50.1	16.7	0.96	-0.14	0.20	-0.29
15. **annulment**	47.6	48.7	12.1	0.98	-0.27	0.16	-0.20
16. **farewell**	47.5	49.8	17.4	0.95	-0.12	0.27	-0.24
17. **comatose**	47.3	48.1	10.8	0.98	-0.26	0.21	-0.16
18. **deflect**	47.2	48.0	10.2	0.98	-0.20	0.26	-0.17
19. **stereotype**	46.8	48.9	17.2	0.96	-0.13	0.20	-0.29
20. **halt**	46.2	48.0	16.0	0.96	-0.28	0.14	-0.19

Word	Comp. Size	Size	Angle	Cos.	**Pw**	**Dg**	**St**
1. **smiling**	66.1	69.0	163.3	-0.96	0.42	-0.22	0.24
2. **romance**	66.0	68.0	166.2	-0.97	0.39	-0.22	0.27
3. **honeymoon**	65.8	66.8	170.2	-0.99	0.34	-0.22	0.31
4. **laugh**	65.0	66.2	168.7	-0.98	0.37	-0.25	0.25
5. **sweetie**	64.0	64.8	171.0	-0.99	0.31	-0.32	0.22
6. **laughter**	62.6	64.3	167.1	-0.97	0.37	-0.22	0.24
7. **scrumptious**	62.6	63.6	169.4	-0.98	0.35	-0.23	0.26
8. **fiancee**	62.0	62.6	171.9	-0.99	0.33	-0.24	0.25
9. **liking**	61.9	63.0	169.0	-0.98	0.34	-0.26	0.22
10. **cheery**	61.5	62.1	171.7	-0.99	0.29	-0.22	0.31
11. **goodies**	60.8	61.7	170.1	-0.99	0.23	-0.24	0.33
12. **adorable**	60.6	61.6	169.9	-0.98	0.21	-0.33	0.26
13. **loving**	60.1	62.9	163.1	-0.96	0.37	-0.24	0.18
14. **travel**	60.0	61.6	166.7	-0.97	0.33	-0.18	0.29
15. **lovee**	59.8	61.6	166.1	-0.97	0.35	-0.26	0.19
16. **hearts**	59.6	62.2	163.4	-0.96	0.36	-0.25	0.17
17. **lovelovelove**	59.4	59.9	173.0	-0.99	0.30	-0.27	0.22
18. **happyheart**	59.4	61.0	166.7	-0.97	0.34	-0.27	0.18
19. **memories**	59.0	60.5	167.2	-0.98	0.23	-0.34	0.21
20. **delicious**	58.4	60.2	166.0	-0.97	0.35	-0.20	0.22

Figure S37: Words with largest components in structured-bad and unstructured-good directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

unstructured safe ⇐



⇒ **structured dangerous**

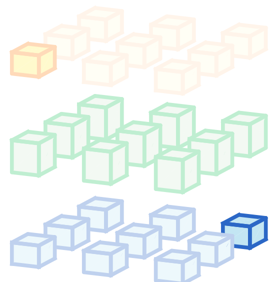
(unstructured-gentle-good)
nurturing
wholesome
sweet

(structured-aggressive-bad)
authoritarian
controlling
adversarial

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **popcorn**	60.6	60.8	4.5	1.00	-0.04	-0.32	0.33
2. **sweetest**	59.7	62.3	16.5	0.96	0.13	-0.34	0.31
3. **fruits**	58.7	60.1	12.4	0.98	-0.06	-0.37	0.26
4. **sweets**	58.6	59.3	8.7	0.99	0.04	-0.36	0.28
5. **butterfly**	58.4	61.0	16.9	0.96	-0.02	-0.41	0.22
6. **toy**	58.2	58.4	4.5	1.00	-0.01	-0.34	0.29
7. **puppy**	57.7	58.3	8.0	0.99	0.06	-0.33	0.30
8. **pet**	57.1	59.6	16.8	0.96	-0.04	-0.40	0.22
9. **candy**	56.6	59.0	16.5	0.96	0.09	-0.37	0.24
10. **childhood**	54.7	55.1	6.9	0.99	0.00	-0.33	0.26
11. **comic**	54.5	56.7	16.1	0.96	0.11	-0.33	0.25
12. **colors**	54.4	56.8	16.5	0.96	-0.00	-0.38	0.21
13. **reminisce**	54.1	55.6	13.3	0.97	0.10	-0.30	0.28
14. **decorative**	53.9	55.8	15.0	0.97	0.10	-0.33	0.26
15. **pizza**	53.8	54.6	9.4	0.99	-0.03	-0.34	0.25
16. **kitten**	53.4	55.7	16.7	0.96	-0.09	-0.35	0.23
17. **nursery**	52.5	54.9	16.9	0.96	0.07	-0.35	0.21
18. **pie**	52.4	54.1	14.3	0.97	0.05	-0.35	0.22
19. **risotto**	52.1	52.9	10.0	0.98	-0.06	-0.26	0.30
20. **fruitcake**	51.0	51.8	10.2	0.98	0.05	-0.31	0.24

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **demolish**	56.9	58.1	168.1	-0.98	0.02	0.37	-0.24
2. **protocol**	55.0	56.2	168.2	-0.98	0.05	0.25	-0.35
3. **rigidity**	49.2	49.4	174.4	-1.00	0.03	0.25	-0.28
4. **irreversible**	48.4	48.6	175.5	-1.00	-0.02	0.27	-0.25
5. **obligation**	46.8	47.8	168.5	-0.98	0.07	0.28	-0.23
6. **narcissist**	46.5	48.3	164.5	-0.96	-0.02	0.32	-0.18
7. **litigant**	45.4	45.9	172.3	-0.99	0.04	0.26	-0.23
8. **jailer**	44.6	46.7	162.7	-0.95	0.01	0.32	-0.17
9. **antagonist**	43.9	45.4	165.2	-0.97	0.07	0.28	-0.20
10. **judging**	43.5	45.3	163.9	-0.96	0.07	0.28	-0.19
11. **carnivorous**	42.3	43.7	165.8	-0.97	0.03	0.28	-0.17
12. **forensics**	42.1	42.2	176.6	-1.00	0.02	0.23	-0.23
13. **curfew**	41.1	42.9	163.1	-0.96	0.01	0.29	-0.15
14. **induce**	40.8	42.1	165.5	-0.97	0.06	0.26	-0.19
15. **python**	40.7	42.7	162.6	-0.95	0.00	0.29	-0.15
16. **penal**	40.7	41.6	167.9	-0.98	-0.03	0.26	-0.18
17. **cardiology**	40.6	41.6	168.0	-0.98	-0.05	0.25	-0.19
18. **critic**	40.1	41.5	165.1	-0.97	0.07	0.25	-0.18
19. **smug**	40.1	41.6	164.4	-0.96	-0.06	0.26	-0.18
20. **revocation**	39.8	41.2	164.8	-0.97	0.06	0.26	-0.17

Figure S38: Words with largest components in unstructured-safe and structured-dangerous directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

unstructured gentle	⇐		⇒	**structured aggressive**
(unstructured-safe-weak) **whimsical** **childlike** **yielding**				(structured-dangerous-powerful) **dictatorial** **militaristic** **imperious**

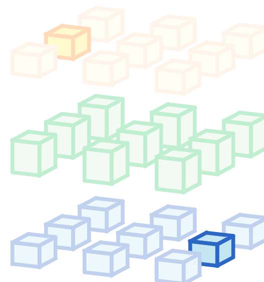
Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **feather**	62.2	64.4	15.3	0.96	-0.31	-0.34	0.17
2. **pudding**	57.5	60.0	16.9	0.96	-0.21	-0.36	0.19
3. **lotion**	57.3	59.1	14.0	0.97	-0.23	-0.34	0.19
4. **wig**	57.3	58.5	11.7	0.98	-0.23	-0.33	0.21
5. **plum**	57.2	57.9	9.1	0.99	-0.22	-0.31	0.23
6. **burrito**	56.3	56.8	7.9	0.99	-0.25	-0.29	0.21
7. **foam**	55.7	58.4	17.5	0.95	-0.24	-0.34	0.15
8. **puree**	54.6	56.7	15.8	0.96	-0.22	-0.33	0.17
9. **bunny**	54.5	55.7	11.8	0.98	-0.19	-0.31	0.23
10. **foaming**	52.9	55.3	16.8	0.96	-0.27	-0.30	0.13
11. **platter**	52.7	55.2	17.4	0.95	-0.23	-0.32	0.14
12. **weave**	52.5	54.4	15.1	0.97	-0.30	-0.25	0.15
13. **shoes**	52.2	53.5	12.3	0.98	-0.18	-0.30	0.21
14. **cream**	52.0	54.1	16.1	0.96	-0.22	-0.31	0.15
15. **crayon**	51.4	53.5	16.2	0.96	-0.29	-0.25	0.14
16. **butter**	50.4	51.4	10.9	0.98	-0.24	-0.26	0.16
17. **sleeveless**	50.1	51.1	11.4	0.98	-0.25	-0.26	0.16
18. **littlethings**	49.9	52.2	17.1	0.96	-0.16	-0.31	0.19
19. **froth**	49.5	50.9	13.1	0.97	-0.27	-0.24	0.15
20. **lego**	49.1	50.5	13.3	0.97	-0.27	-0.23	0.15

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **boss**	65.8	66.4	172.8	-0.99	0.29	0.24	-0.33
2. **dictatorial**	65.7	68.6	163.1	-0.96	0.23	0.41	-0.23
3. **exterminator**	65.0	67.4	164.6	-0.96	0.35	0.34	-0.18
4. **relentless**	63.2	63.5	174.2	-0.99	0.31	0.28	-0.24
5. **imperialist**	61.4	63.9	164.0	-0.96	0.27	0.37	-0.18
6. **army**	60.6	63.4	163.1	-0.96	0.37	0.26	-0.18
7. **political**	60.0	60.8	170.8	-0.99	0.31	0.29	-0.21
8. **cop**	58.7	60.6	165.4	-0.97	0.29	0.33	-0.17
9. **policy**	56.9	58.0	168.9	-0.98	0.27	0.30	-0.19
10. **courtroom**	56.5	57.2	171.2	-0.99	0.30	0.22	-0.23
11. **armada**	56.5	58.6	164.6	-0.96	0.34	0.25	-0.17
12. **military**	56.5	57.7	168.1	-0.98	0.32	0.24	-0.19
13. **commando**	54.0	54.8	170.5	-0.99	0.24	0.29	-0.19
14. **imposing**	53.4	55.1	165.9	-0.97	0.30	0.25	-0.16
15. **demanding**	53.2	55.5	163.4	-0.96	0.30	0.26	-0.14
16. **regimental**	52.2	52.6	172.9	-0.99	0.19	0.26	-0.24
17. **manipulate**	52.2	54.5	163.4	-0.96	0.17	0.33	-0.20
18. **claimant**	51.7	53.3	165.9	-0.97	0.18	0.31	-0.20
19. **politician**	51.6	53.1	166.2	-0.97	0.20	0.18	-0.31
20. **courts**	51.6	52.5	169.2	-0.98	0.26	0.25	-0.17

Figure S39: Words with largest components in unstructured-gentle and structured-aggressive directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

unstructured
weak

⇐



⇒

structured
powerful

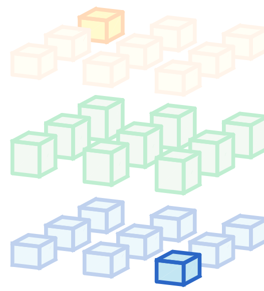
(unstructured-gentle-bad)
inchoate
hazy
drifting

(structured-aggressive-good)
commanding
authorative
hierarchical

Word	Comp. Size	Size	Angle	Cos.	**Pw**	**Dg**	**St**
1. **vagabond**	46.9	49.1	17.3	0.95	-0.30	0.09	0.21
2. **minion**	43.0	44.5	14.6	0.97	-0.28	-0.06	0.19
3. **roll**	42.9	43.1	4.7	1.00	-0.25	0.02	0.22
4. **vanquished**	42.5	42.5	2.4	1.00	-0.22	0.01	0.24
5. **cheesy**	41.8	42.3	9.1	0.99	-0.26	-0.01	0.19
6. **loopy**	40.0	40.8	10.7	0.98	-0.24	0.05	0.19
7. **underestimate**	40.0	42.0	17.6	0.95	-0.28	0.02	0.15
8. **vassal**	40.0	41.3	14.5	0.97	-0.25	0.06	0.18
9. **need**	39.6	40.4	11.4	0.98	-0.18	0.03	0.25
10. **dubious**	39.4	41.1	16.4	0.96	-0.27	0.04	0.16
11. **murmur**	39.4	39.7	7.2	0.99	-0.23	0.03	0.20
12. **juju**	38.4	38.9	8.8	0.99	-0.18	-0.03	0.23
13. **babble**	38.2	40.0	17.5	0.95	-0.22	-0.09	0.20
14. **hide**	37.0	37.8	11.6	0.98	-0.23	0.04	0.17
15. **leftover**	36.1	36.7	11.0	0.98	-0.23	-0.03	0.17
16. **scampi**	35.6	36.9	15.1	0.97	-0.21	-0.07	0.18
17. **hesitate**	35.4	36.0	10.7	0.98	-0.19	0.05	0.19
18. **shin**	35.2	35.6	8.3	0.99	-0.22	0.02	0.17
19. **ska**	33.8	35.2	15.9	0.96	-0.17	0.07	0.20
20. **ahhh**	33.8	34.9	14.3	0.97	-0.15	-0.04	0.22

Word	Comp. Size	Size	Angle	Cos.	**Pw**	**Dg**	**St**
1. **commissioner**	59.0	60.5	167.5	-0.98	0.35	-0.09	-0.29
2. **superintendent**	57.4	59.6	164.1	-0.96	0.40	0.00	-0.22
3. **supervisor**	56.8	58.6	165.9	-0.97	0.36	-0.08	-0.25
4. **business man**	55.9	58.1	164.2	-0.96	0.38	0.06	-0.23
5. **directive**	54.5	56.4	165.2	-0.97	0.37	-0.04	-0.22
6. **producer**	54.1	55.6	166.9	-0.97	0.36	0.02	-0.23
7. **governmental**	52.7	53.3	171.2	-0.99	0.32	0.03	-0.25
8. **administrator**	52.6	52.8	175.4	-1.00	0.30	-0.02	-0.27
9. **magistrate**	52.6	54.2	165.9	-0.97	0.36	-0.02	-0.21
10. **reformer**	52.5	54.2	165.4	-0.97	0.36	0.02	-0.21
11. **patriarch**	52.4	53.8	167.0	-0.97	0.31	-0.09	-0.26
12. **minister**	51.6	52.1	171.7	-0.99	0.28	-0.06	-0.28
13. **controlling**	50.5	50.9	173.6	-0.99	0.25	-0.02	-0.30
14. **warrants**	50.2	51.2	168.8	-0.98	0.27	-0.08	-0.27
15. **colonel**	50.2	52.6	162.7	-0.95	0.31	0.11	-0.24
16. **officer**	49.7	50.4	170.5	-0.99	0.26	-0.06	-0.28
17. **congressman**	49.2	50.0	169.7	-0.98	0.23	0.04	-0.30
18. **juridical**	49.1	49.6	171.9	-0.99	0.25	-0.05	-0.28
19. **patron**	48.7	49.9	167.3	-0.98	0.29	-0.08	-0.24
20. **legislator**	48.6	50.3	165.1	-0.97	0.31	0.08	-0.22

Figure S40: Words with largest components in unstructured-weak and structured-powerful directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

unstructured bad ⇐  ⇒ **structured good**

(unstructured-dangerous-weak)
confused
mocked
messy

(structured-safe-powerful)
wise
respected
stable

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **slave**	71.3	73.6	14.2	0.97	-0.28	0.43	0.24
2. **skittish**	71.1	74.5	17.3	0.95	-0.26	0.45	0.23
3. **vomiting**	70.7	73.2	15.2	0.97	-0.29	0.43	0.22
4. **lost**	62.5	64.1	12.9	0.97	-0.33	0.32	0.19
5. **downfall**	62.0	63.8	13.3	0.97	-0.28	0.35	0.19
6. **stifled**	60.1	61.4	12.0	0.98	-0.25	0.34	0.21
7. **mocked**	60.0	61.8	13.7	0.97	-0.23	0.36	0.21
8. **wobbly**	59.6	62.4	17.3	0.95	-0.22	0.38	0.19
9. **inexperience**	58.9	61.3	15.9	0.96	-0.34	0.27	0.16
10. **unsettled**	58.8	60.7	14.1	0.97	-0.31	0.30	0.17
11. **cockroach**	58.4	60.9	16.5	0.96	-0.30	0.33	0.15
12. **messy**	58.3	59.2	9.8	0.99	-0.32	0.25	0.21
13. **queasiness**	58.2	60.6	16.1	0.96	-0.35	0.24	0.17
14. **confused**	57.4	59.0	13.3	0.97	-0.30	0.29	0.17
15. **twit**	57.1	59.6	16.8	0.96	-0.30	0.31	0.15
16. **flee**	56.2	58.8	17.1	0.96	-0.16	0.34	0.25
17. **impotence**	56.2	58.9	17.3	0.95	-0.26	0.34	0.15
18. **unorganized**	56.2	56.8	8.6	0.99	-0.28	0.27	0.20
19. **shiver**	55.8	58.1	15.9	0.96	-0.18	0.34	0.21
20. **shaky**	55.4	56.8	12.7	0.98	-0.21	0.32	0.20

Word	Comp. Size	Size	Angle	Cos.	Pw	Dg	St
1. **confidence**	84.2	88.3	162.6	-0.95	0.44	-0.47	-0.21
2. **reliable**	76.6	80.2	162.6	-0.95	0.35	-0.46	-0.20
3. **wise**	72.7	75.7	163.9	-0.96	0.33	-0.43	-0.20
4. **secure**	68.9	72.0	163.0	-0.96	0.41	-0.31	-0.19
5. **respectable**	68.3	71.1	164.0	-0.96	0.38	-0.34	-0.18
6. **constitute**	68.0	69.7	167.3	-0.98	0.38	-0.31	-0.21
7. **stability**	67.0	68.4	168.0	-0.98	0.30	-0.37	-0.22
8. **autonomy**	64.7	65.9	169.2	-0.98	0.35	-0.29	-0.22
9. **educator**	64.4	66.5	165.4	-0.97	0.32	-0.35	-0.18
10. **soundness**	63.3	65.0	166.7	-0.97	0.36	-0.27	-0.20
11. **sacred**	63.2	66.3	162.4	-0.95	0.37	-0.31	-0.16
12. **parent**	62.8	64.9	165.2	-0.97	0.35	-0.31	-0.18
13. **maestro**	62.3	64.8	163.9	-0.96	0.34	-0.32	-0.16
14. **civilized**	62.3	64.7	164.3	-0.96	0.23	-0.38	-0.21
15. **propriety**	61.8	64.6	163.1	-0.96	0.27	-0.38	-0.17
16. **securities**	61.5	61.9	173.6	-0.99	0.29	-0.30	-0.23
17. **property**	60.8	62.4	167.1	-0.97	0.21	-0.35	-0.25
18. **father**	60.4	62.6	164.8	-0.96	0.31	-0.33	-0.16
19. **proprietary**	60.3	61.4	168.8	-0.98	0.26	-0.34	-0.21
20. **order**	59.8	61.1	168.1	-0.98	0.27	-0.33	-0.19

Figure S41: Words with largest components in unstructured-bad and structured-good directions, within a cone of half angle $\frac{1}{2}\frac{180}{\pi}\cos^{-1}(2/\sqrt{6}) \simeq 17.6°$.

S5 Ousiogram analysis sequences for real corpora

Ousiograms for Jane Austen’s novels in the VAD, GAS, and PDS frameworks:

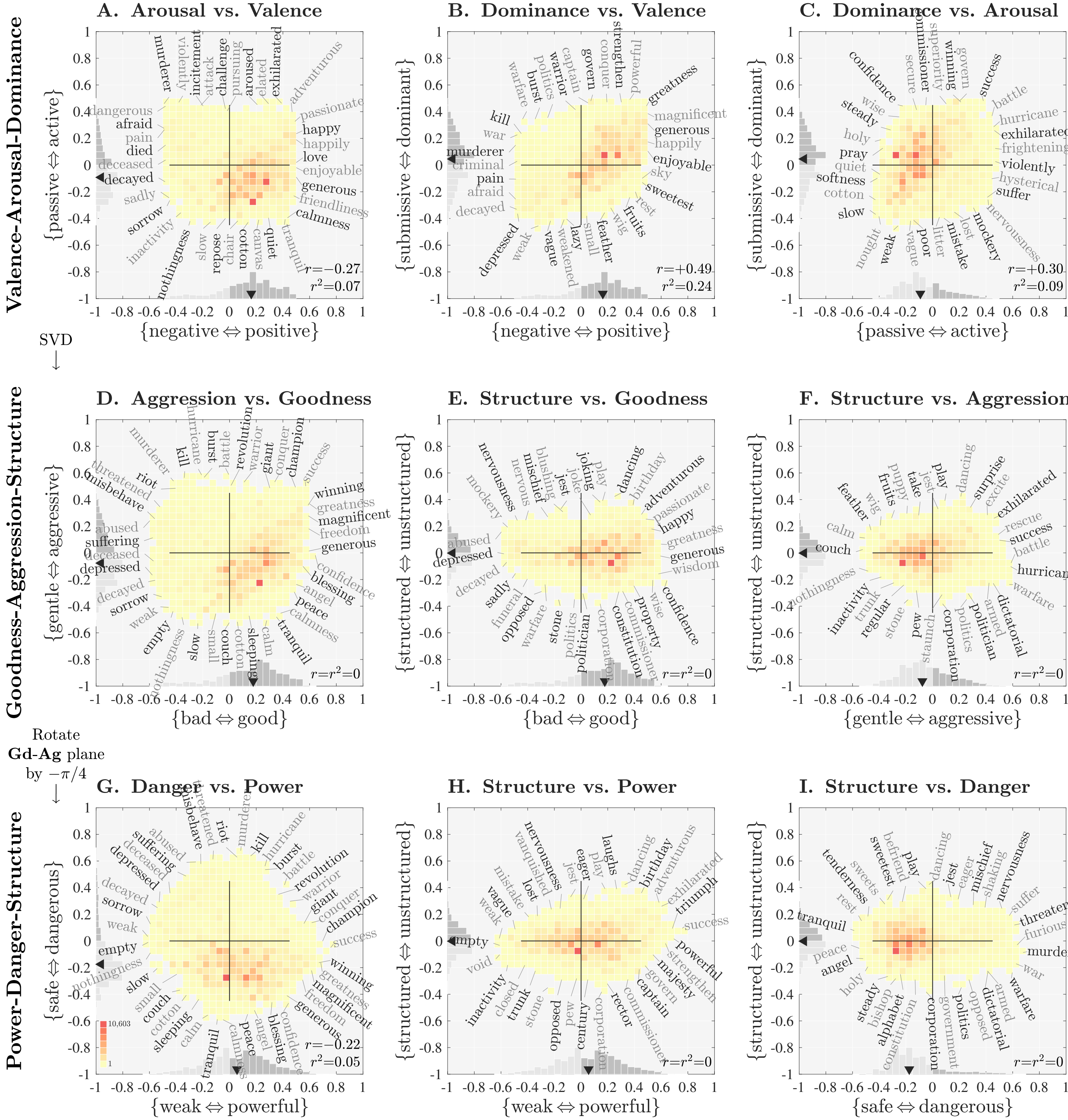


Figure S42: Ousiograms showing the VAD-GAS-PDS analytic sequence for Jane Austen’s novels: “Sense and Sensibility,” “Pride and Prejudice,” “Mansfield Park,” “Emma,” “Northanger Abbey,” and “Persuasion,” published in 1811–1818. We obtained all novels from the Gutenberg Project: http://www.gutenberg.org. The underlying Zipf distribution is built by merging all books and then constructing a word frequency distribution. Panel G corresponds to Fig. 6A.

Ousiograms for Sherlock Holmes in the VAD, GAS, and PDS frameworks:

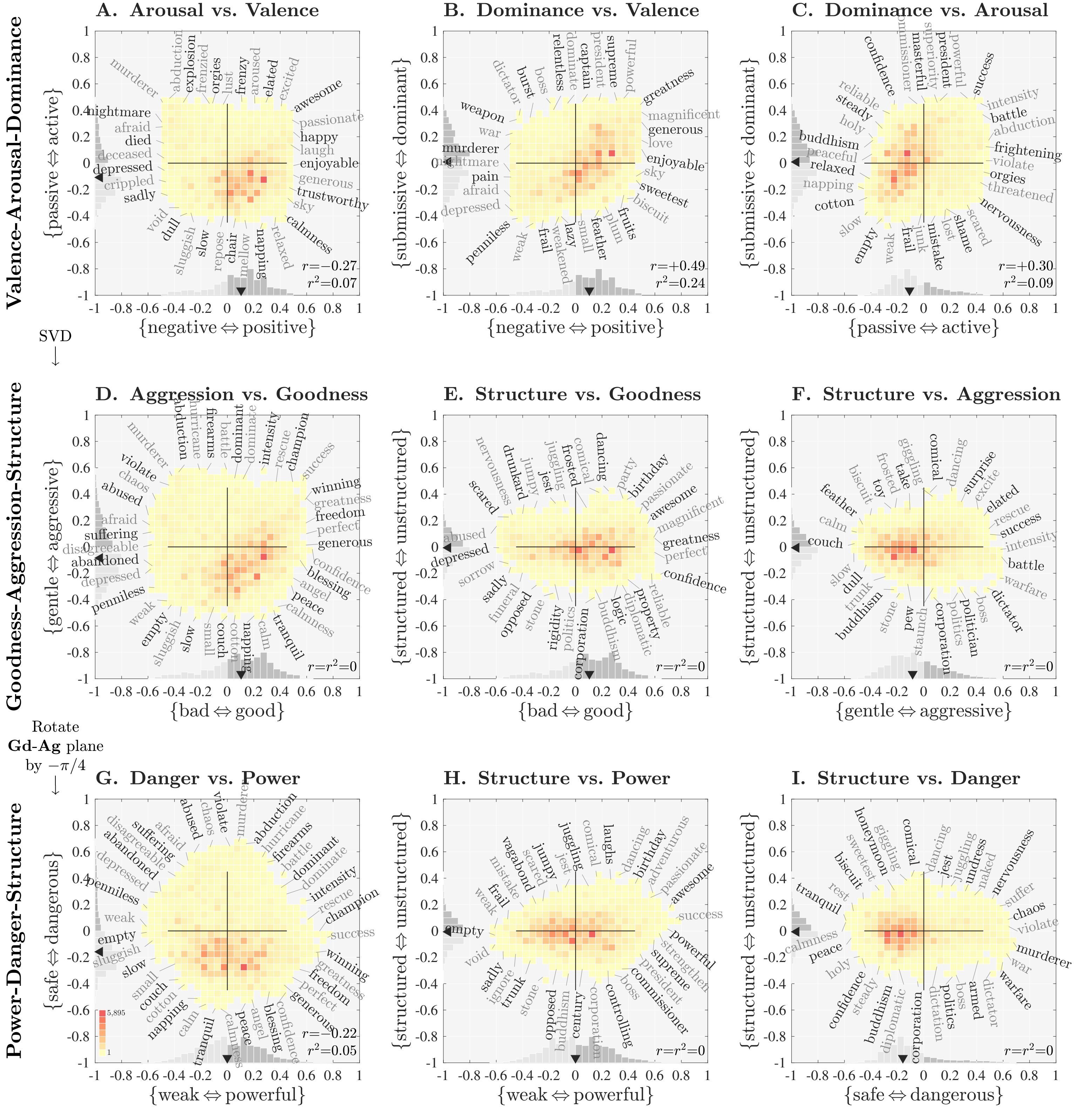


Figure S43: Ousiograms showing the VAD-GAS-PDS analytic sequence for Sir Arthur Conan Doyle's Sherlock Holmes novels and short stories. We obtained four novels and forty-four short stories from the complete Sherlock Holmes Canon https://sherlock-holm.es/ (due to copyright, twelve short stories contained in the "Case-Book of Sherlock Holmes" were not available from this source). The underlying Zipf distribution is built by merging all books and then constructing a word frequency distribution. Panel G corresponds to Fig. 6B.

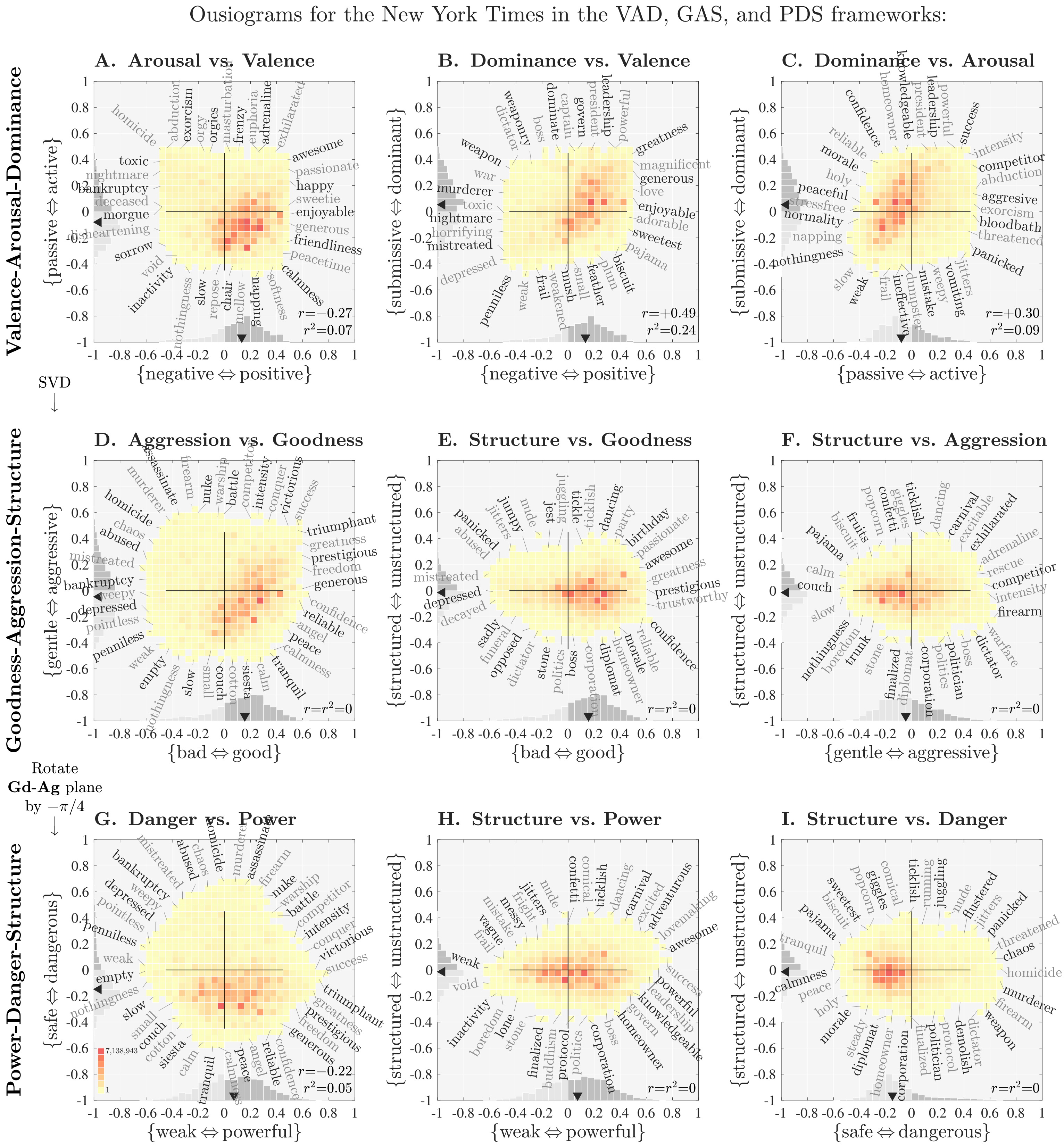


Figure S44: Ousiograms showing the VAD-GAS-PDS analytic sequence for the New York Times. The underlying Zipf distribution is built from a 1987–2007 annotated corpus [63]. Panel G corresponds to Fig. 6C.

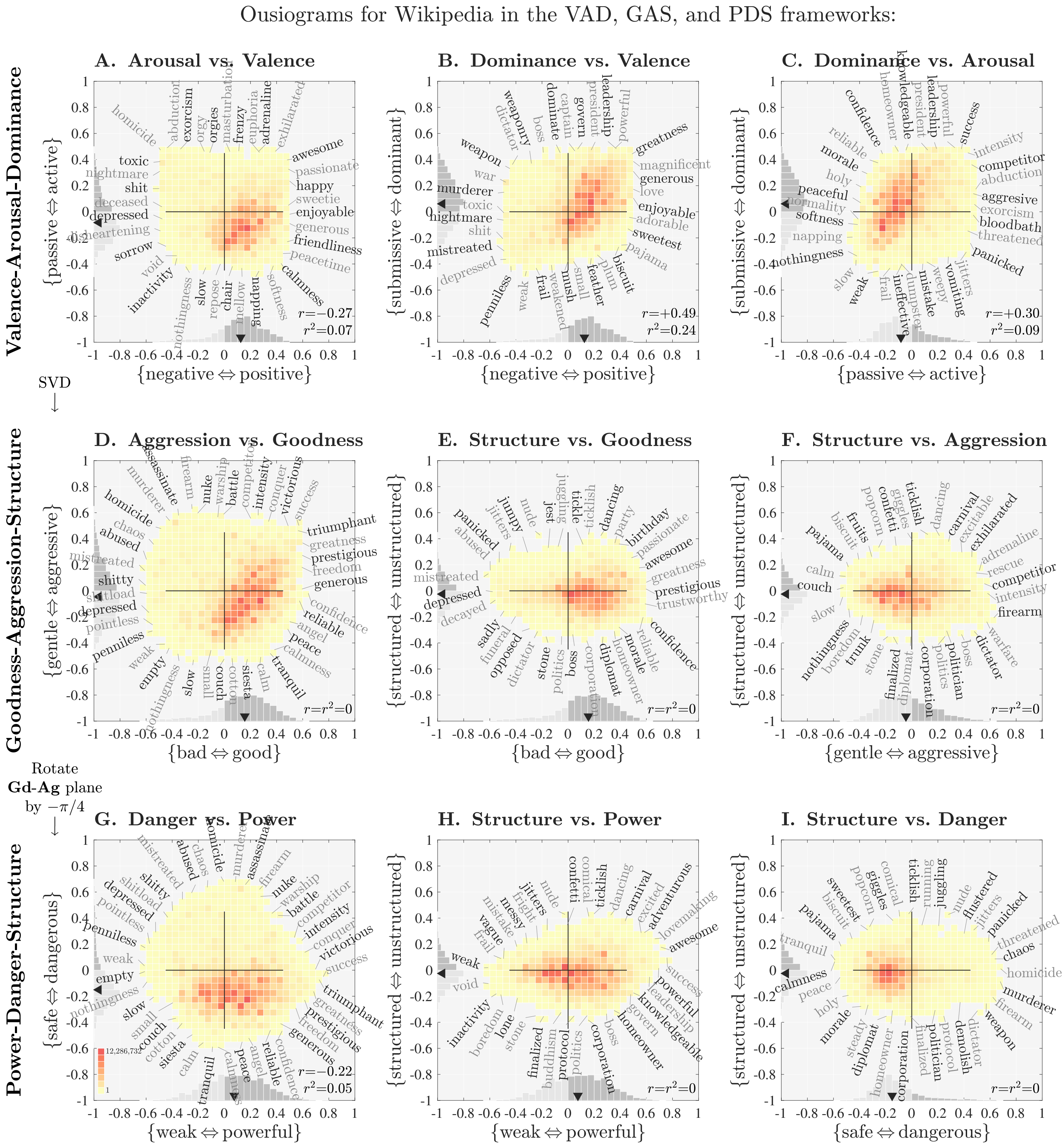


Figure S45: Ousiograms showing the VAD-GAS-PDS analytic sequence for Wikipedia. The underlying Zipf distribution is based on the March 2019 dump of the English Wikipedia [64]. Panel G corresponds to Fig. 6D.

Ousiograms for RadioTalk in the VAD, GAS, and PDS frameworks:

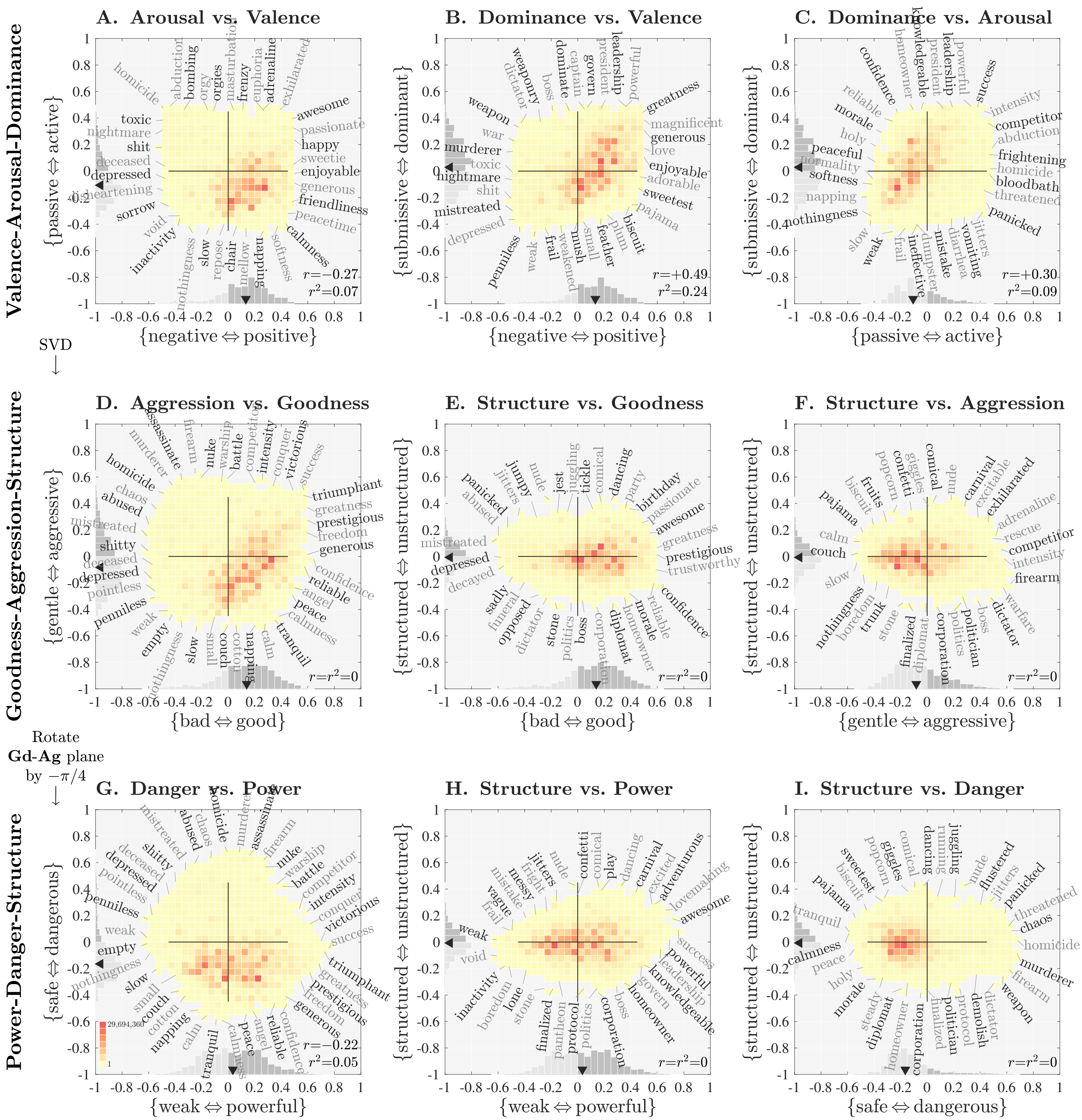


Figure S46: Ousiograms showing the VAD-GAS-PDS analytic sequence for the RadioTalk corpus. The underlying Zipf distribution automated transcriptions of talk radio in the US covering the time period 2018/10–2019/03) [65]. Panel G corresponds to Fig. 6E.

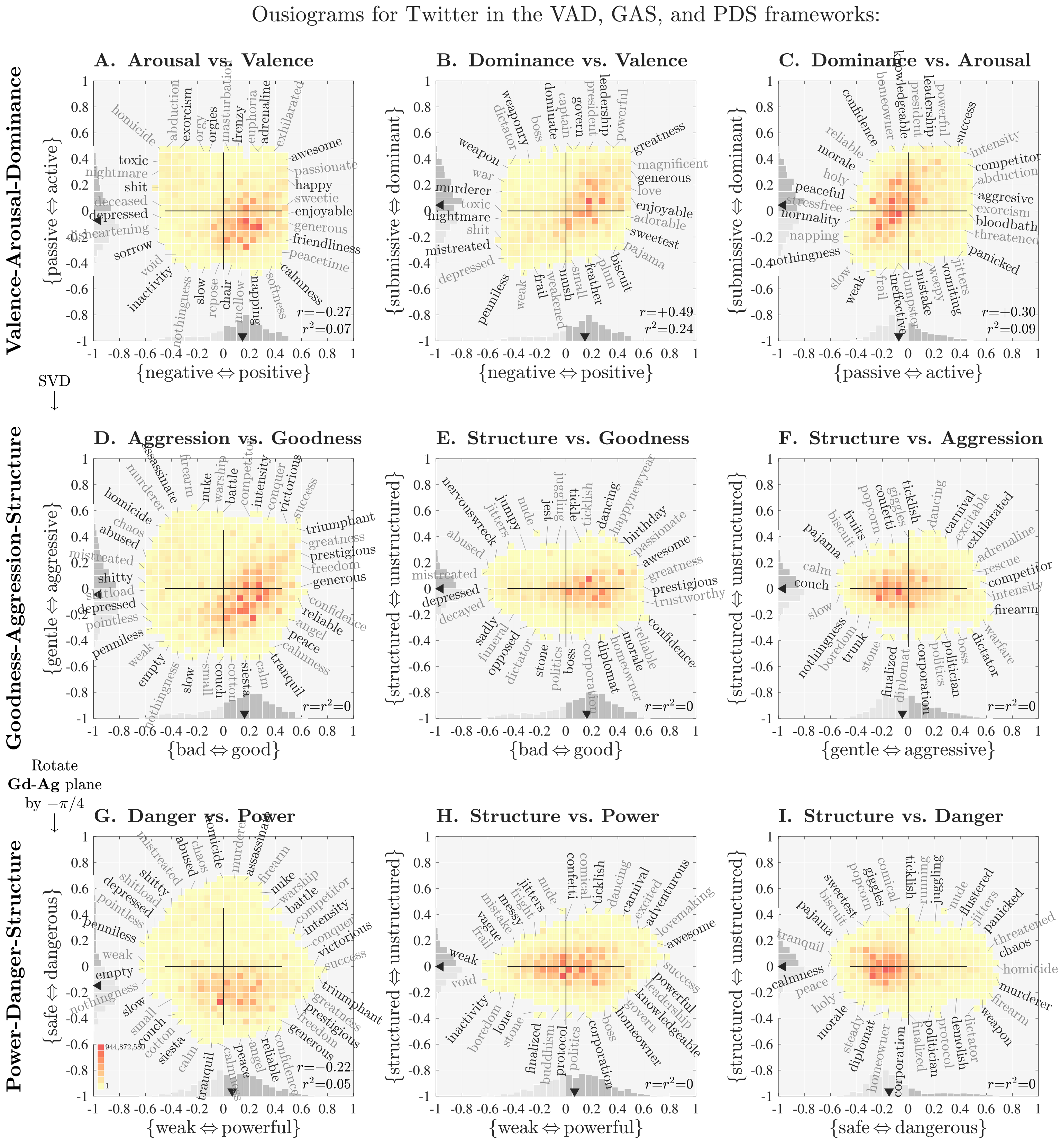


Figure S47: Ousiograms showing the VAD-GAS-PDS analytic sequence for Twitter. The underlying Zipf distribution is an equal weighting of day-scale Zipf distributions derived from approximately 10% of English tweets in 2020 [66]. In contrast to the Zipf distributions obtained from 'flat' corpora, the Zipf distribution for Twitter encodes a strong sense of popularity as social amplification is naturally included through retweets. Panel G corresponds to Fig. 6F.

S6 Ousiometric time series and trajectory for Les Misérables: Flipbook

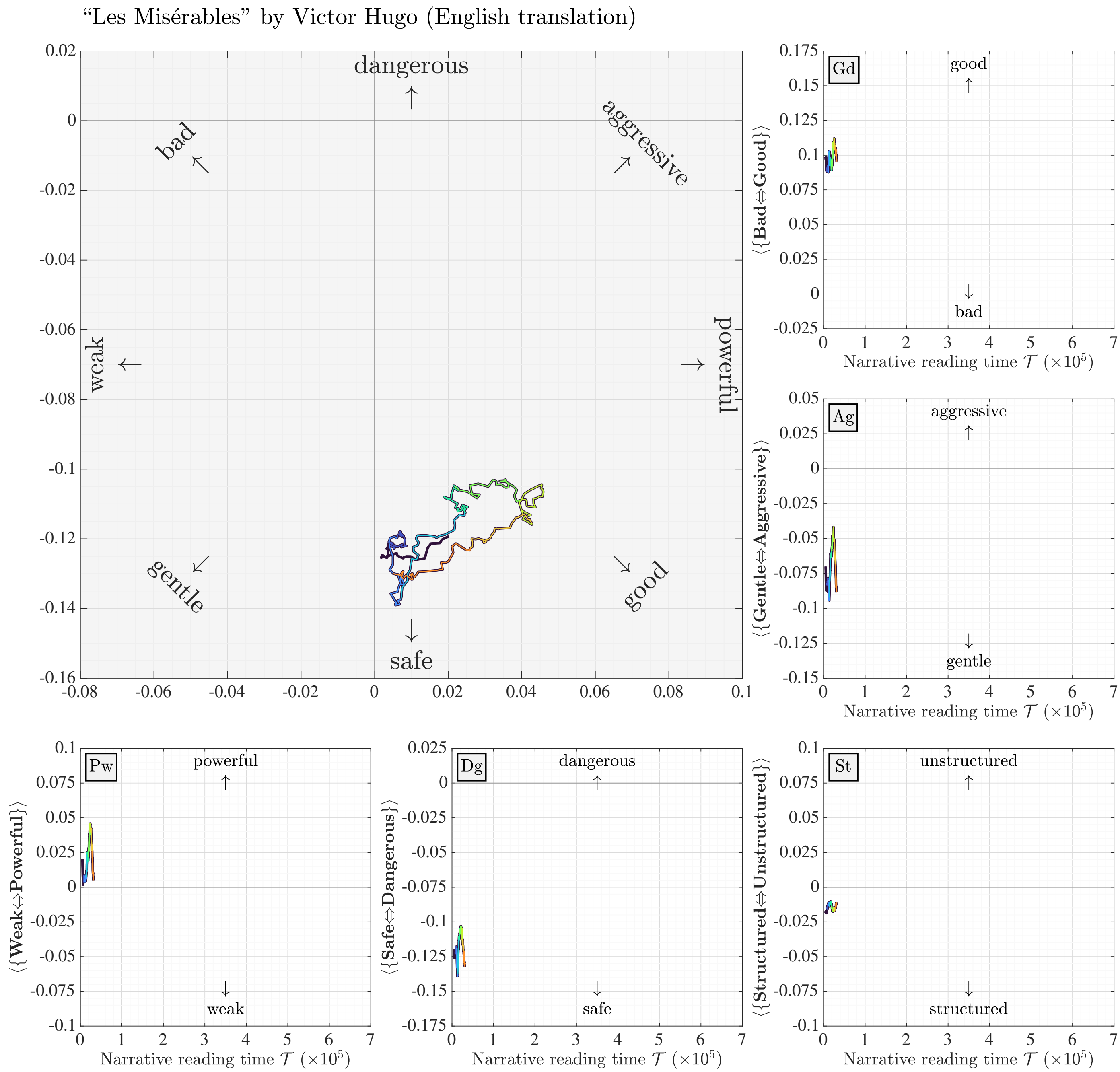


Figure S48: Epoch 1 of 25 in Victor Hugo’s “Les Misérables.”

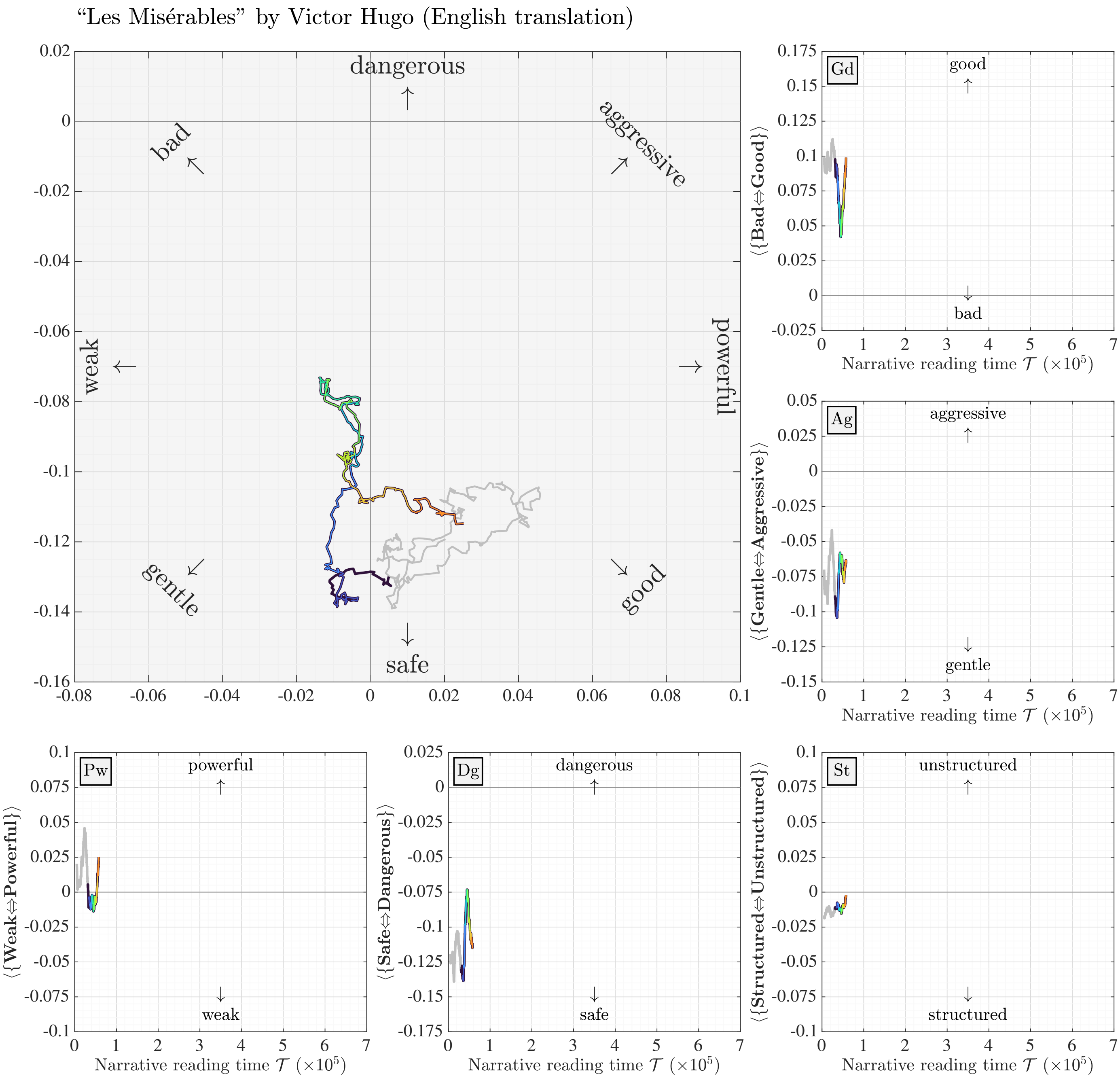


Figure S49: Epoch 2 of 25 in Victor Hugo's "Les Misérables."

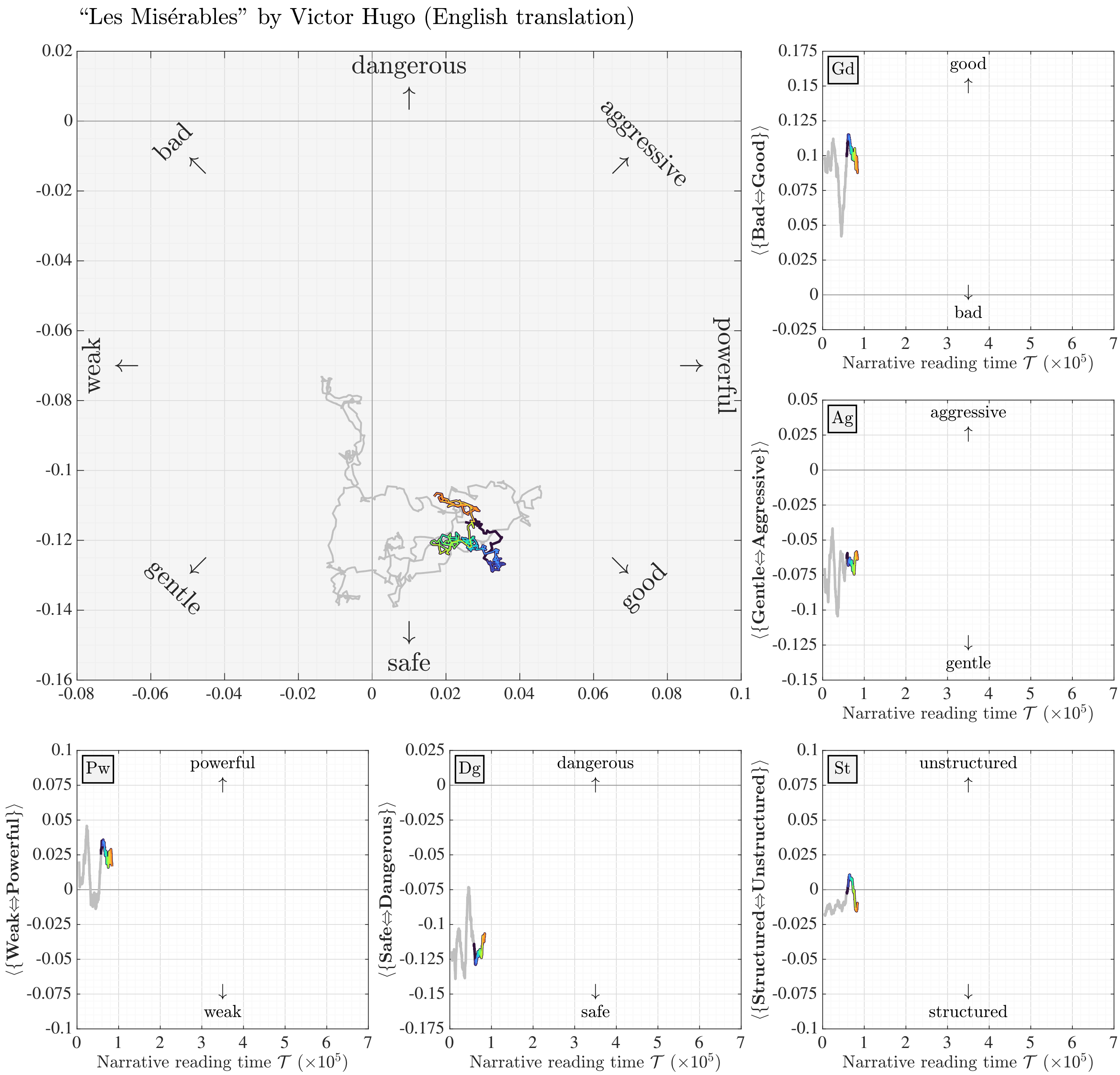


Figure S50: Epoch 3 of 25 in Victor Hugo's "Les Misérables."

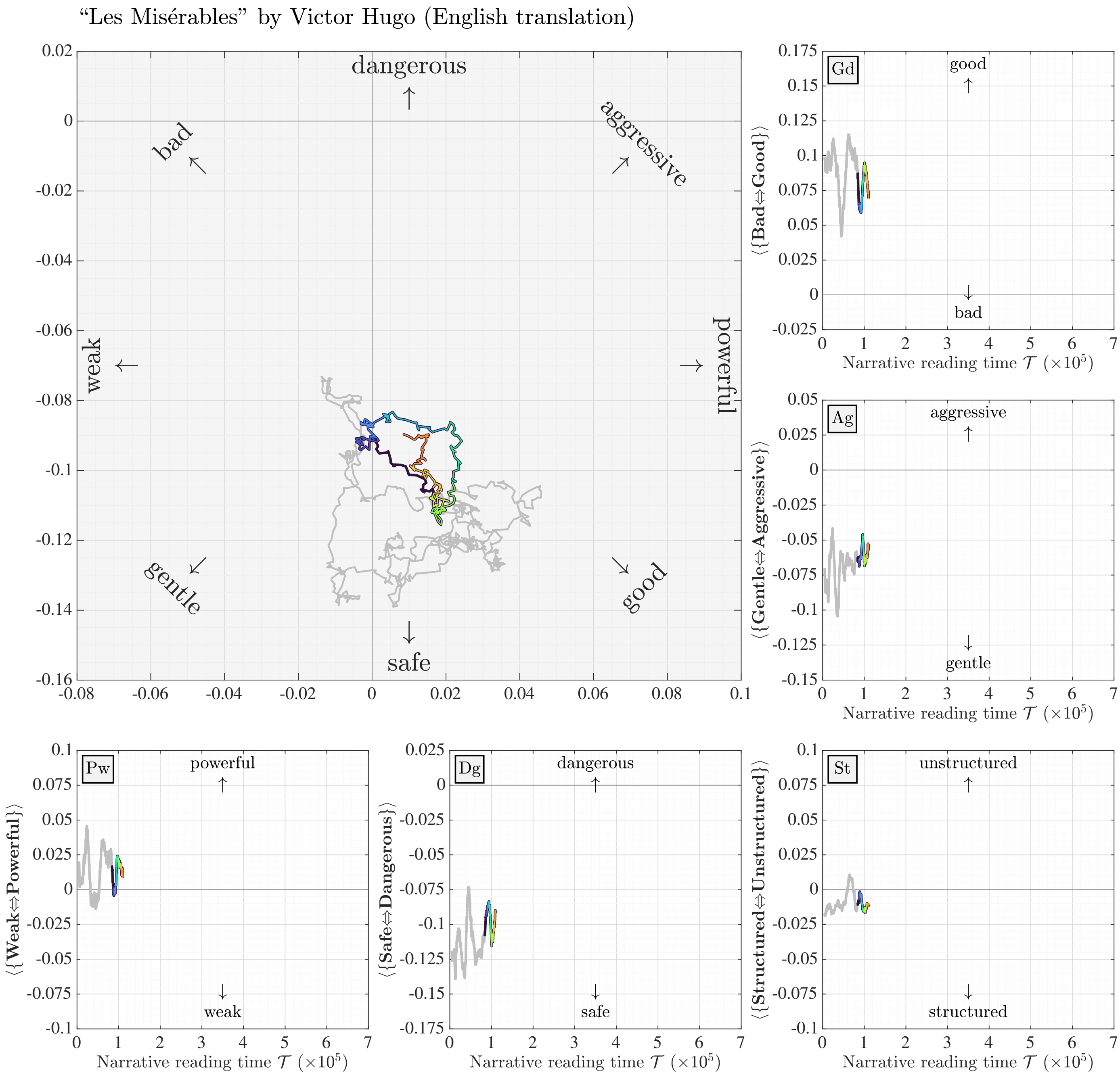


Figure S51: Epoch 4 of 25 in Victor Hugo's "Les Misérables."

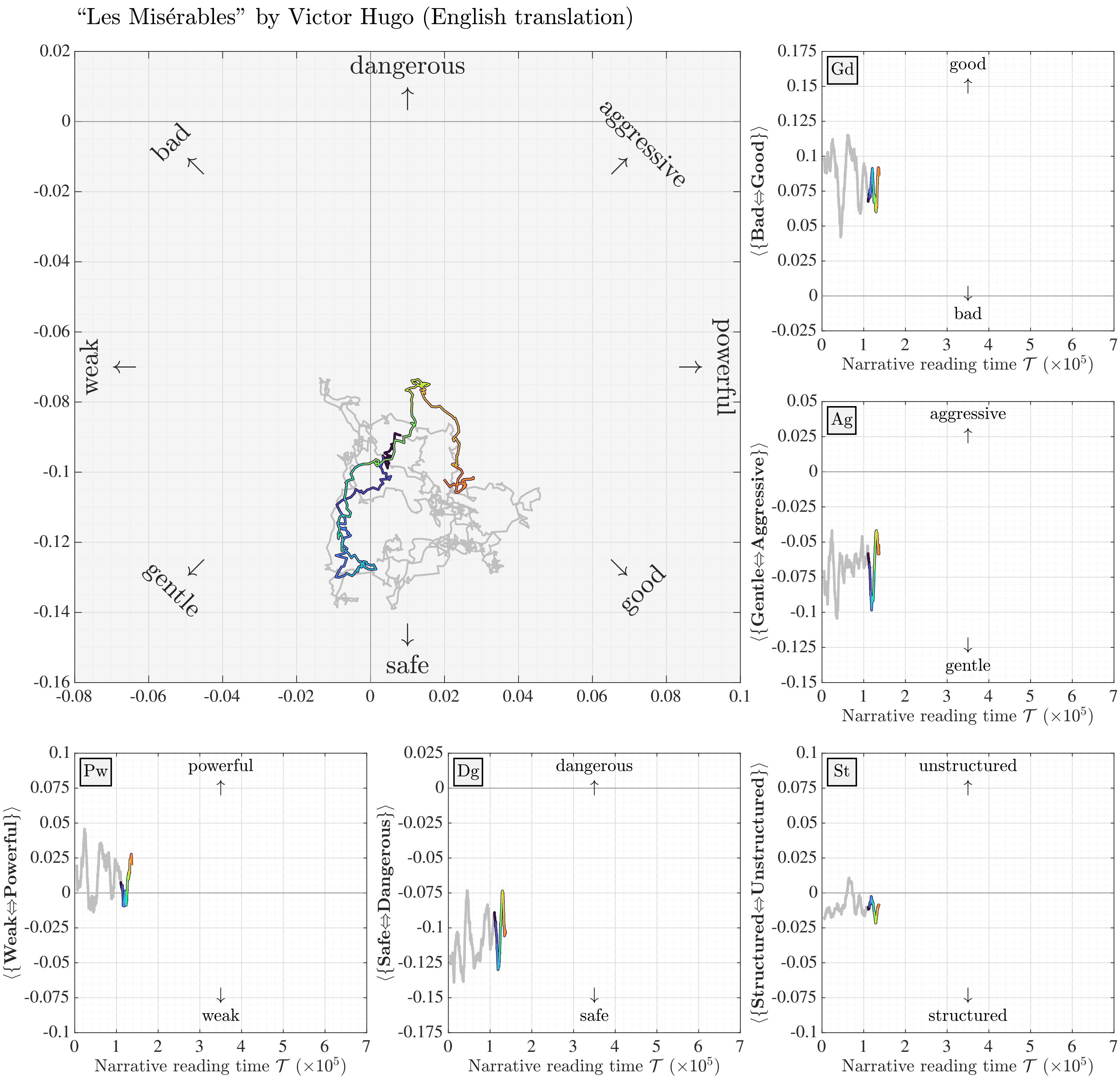


Figure S52: Epoch 5 of 25 in Victor Hugo's "Les Misérables."

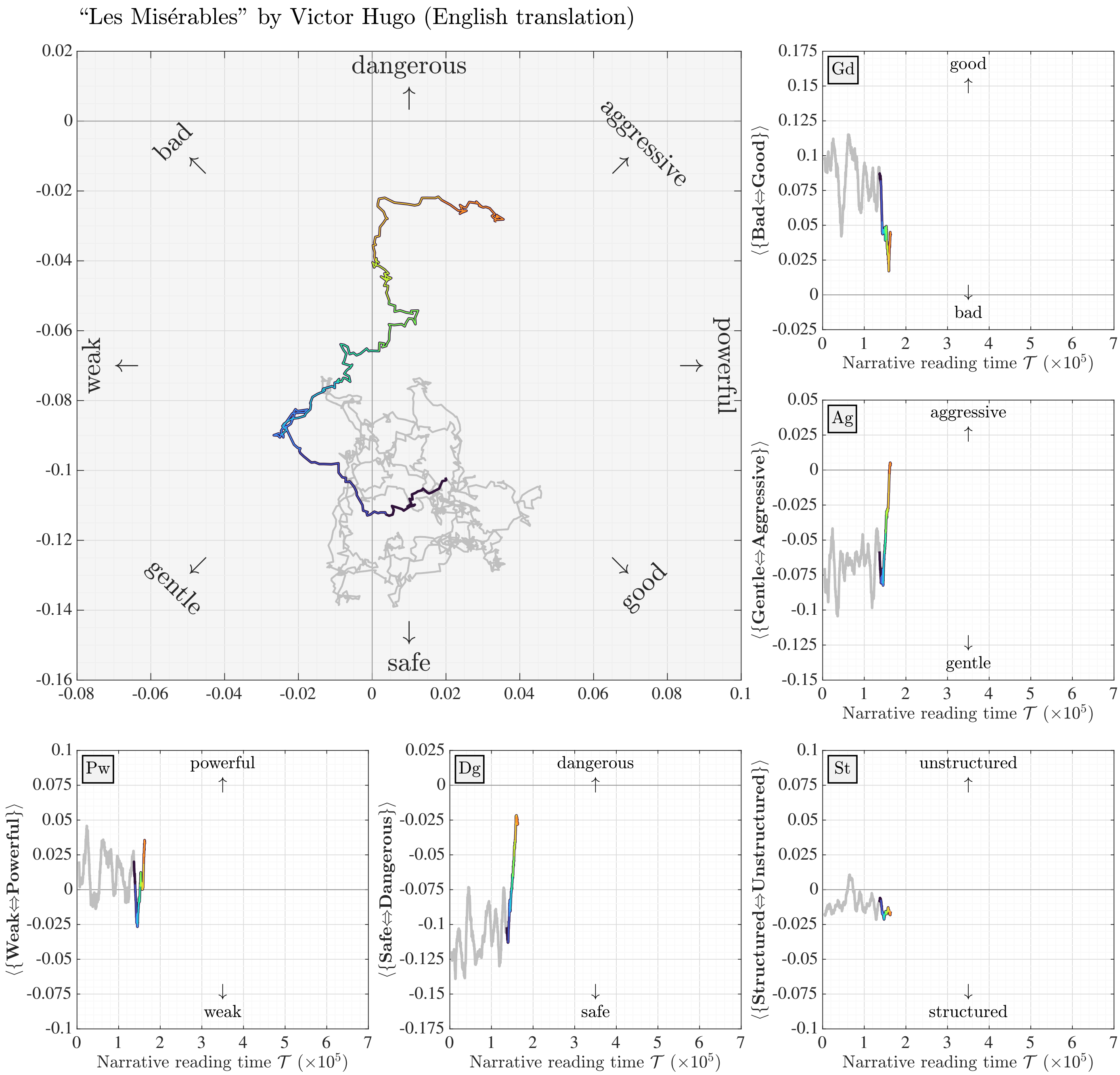


Figure S53: Epoch 6 of 25 in Victor Hugo's "Les Misérables."

"Les Misérables" by Victor Hugo (English translation)

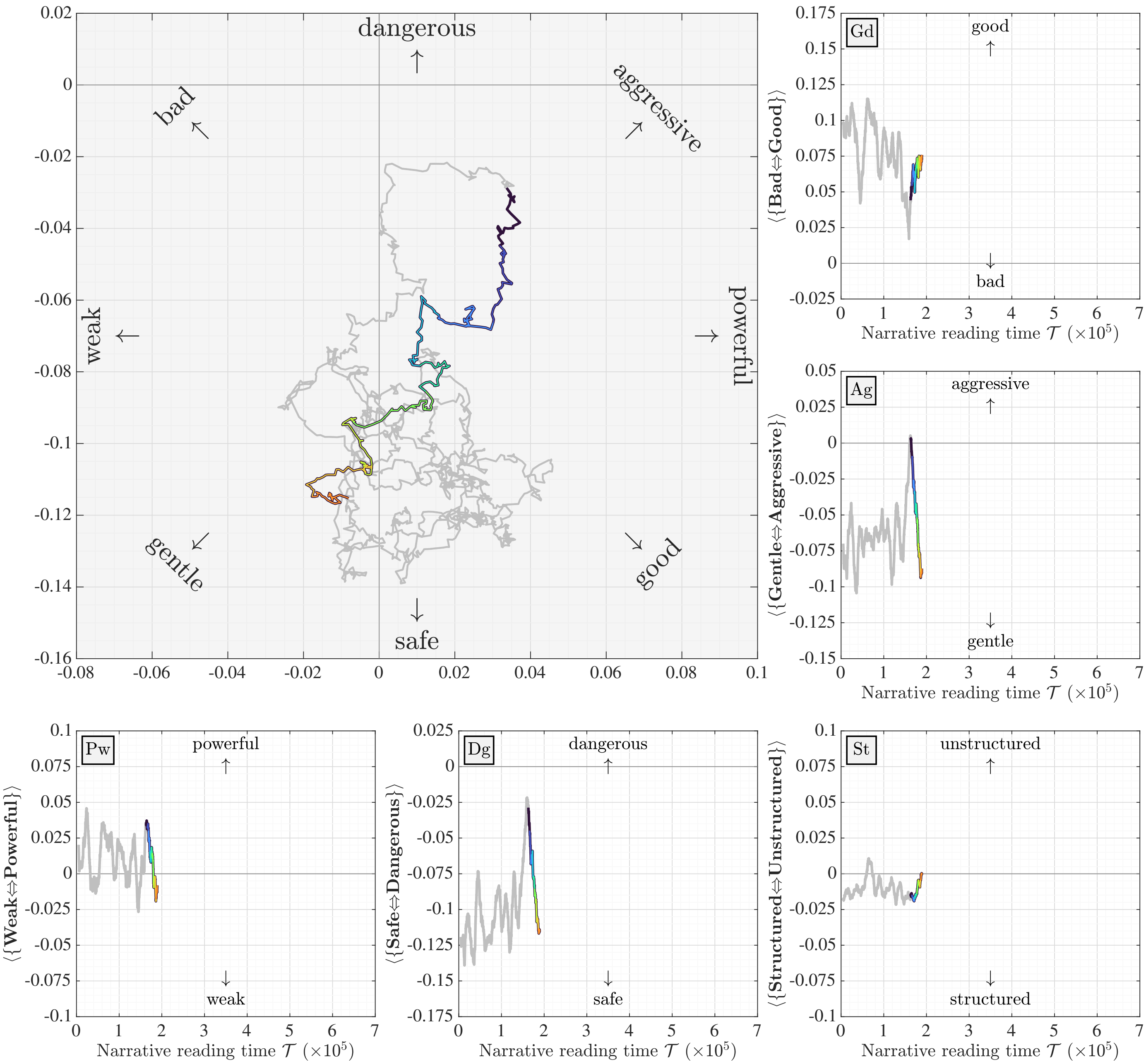


Figure S54: Epoch 7 of 25 in Victor Hugo's "Les Misérables."

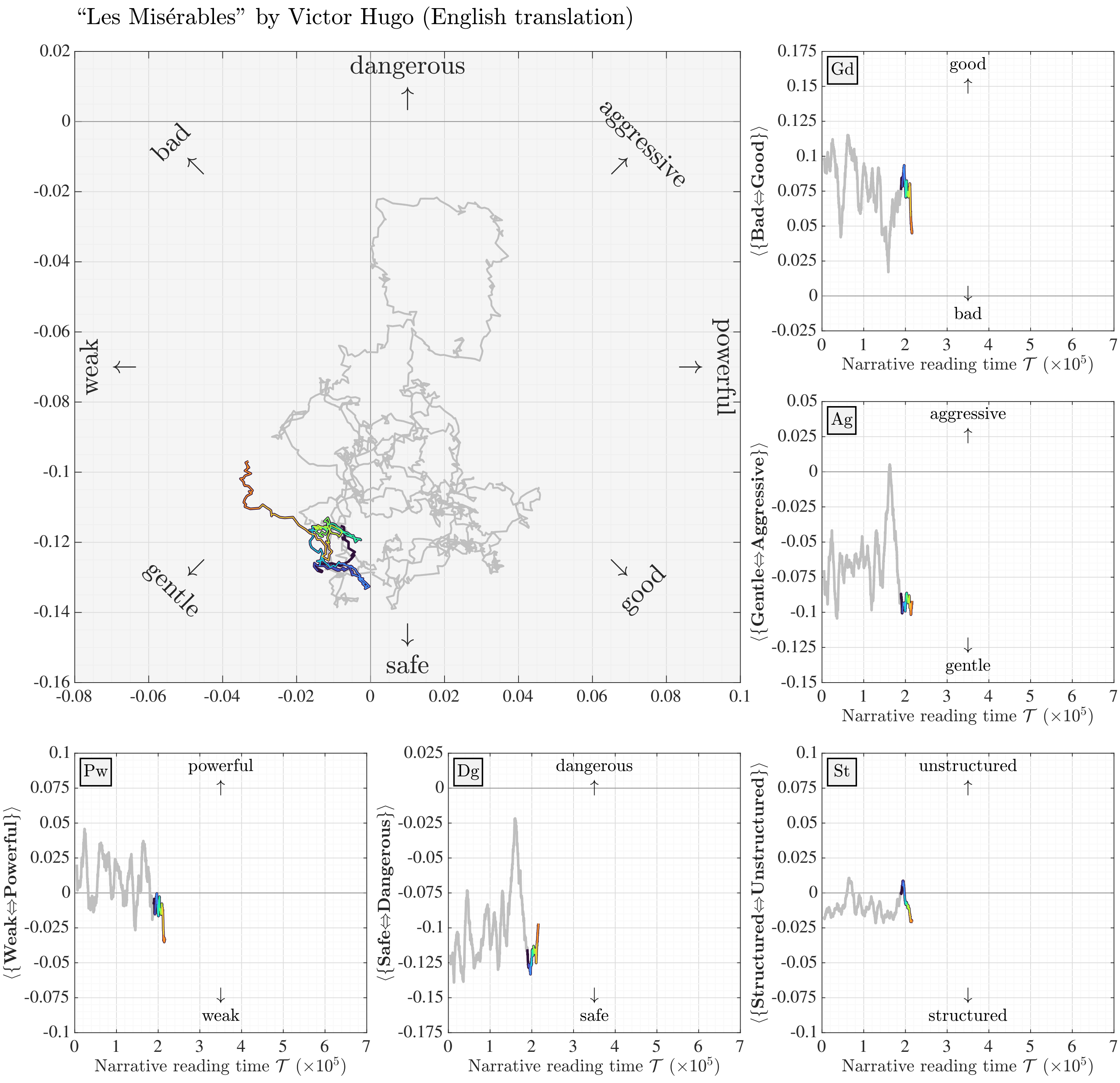


Figure S55: Epoch 8 of 25 in Victor Hugo's "Les Misérables."

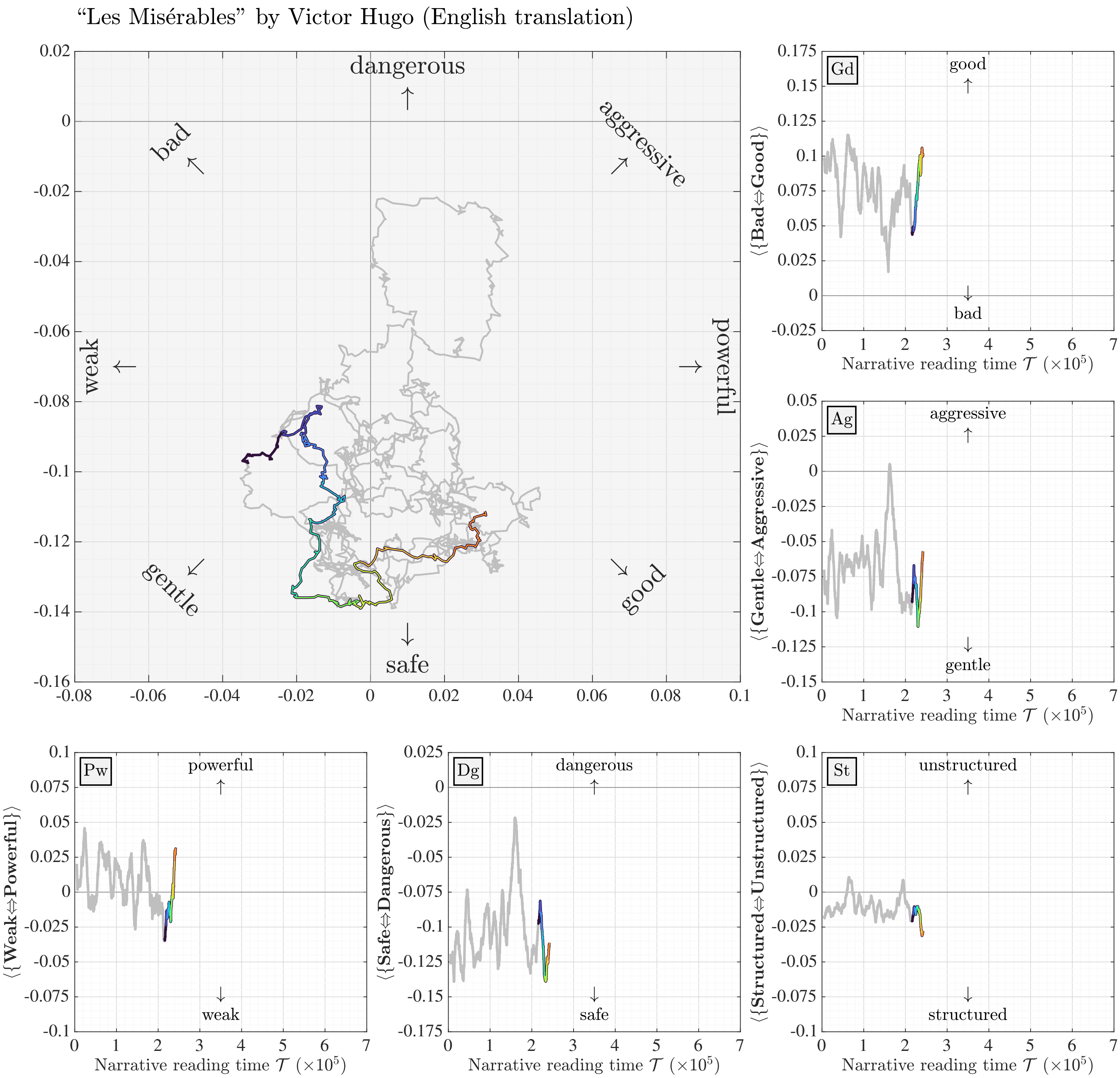


Figure S56: Epoch 9 of 25 in Victor Hugo's "Les Misérables."

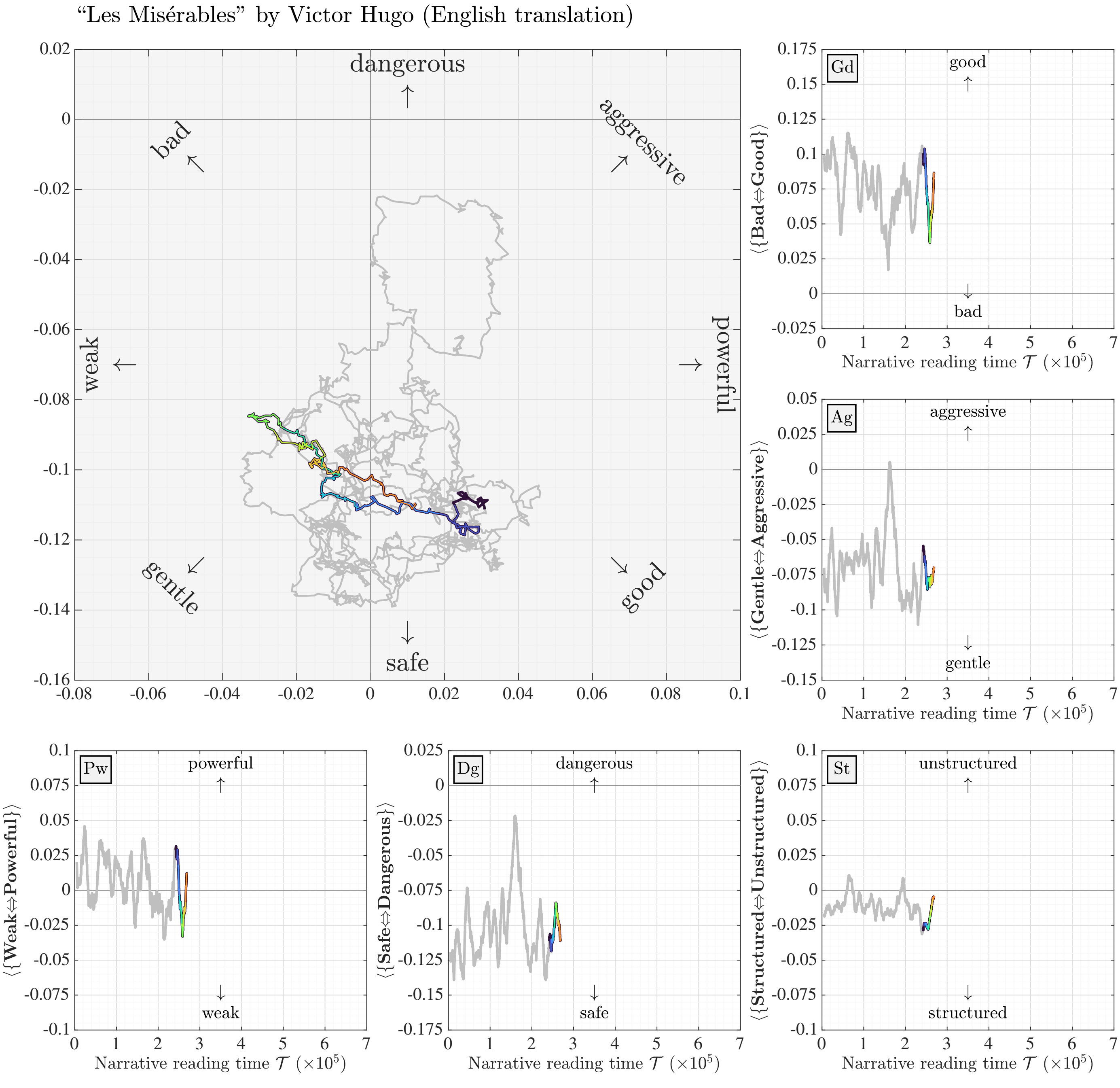


Figure S57: Epoch 10 of 25 in Victor Hugo's "Les Misérables."

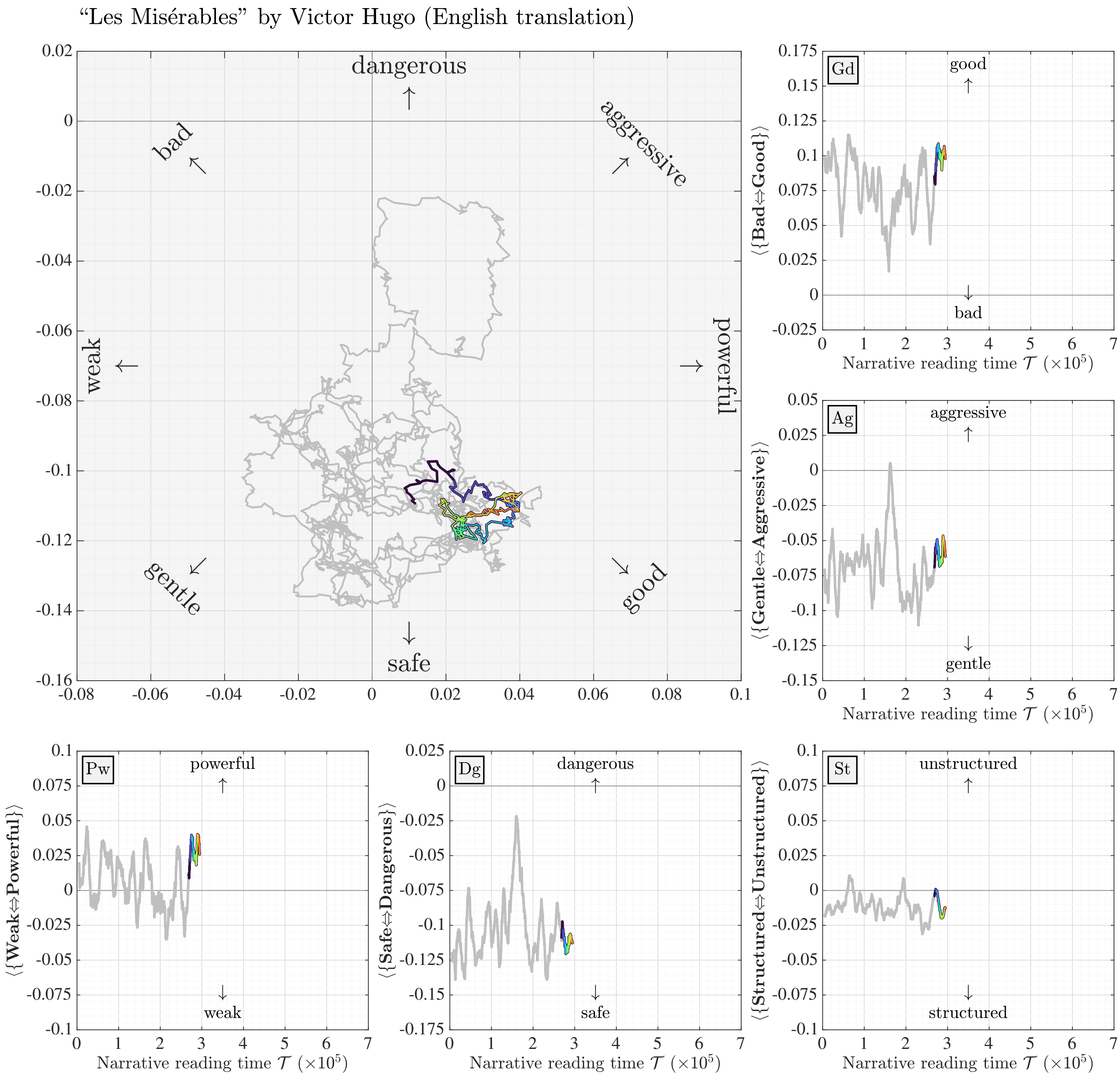


Figure S58: Epoch 11 of 25 in Victor Hugo's "Les Misérables."

“Les Misérables” by Victor Hugo (English translation)

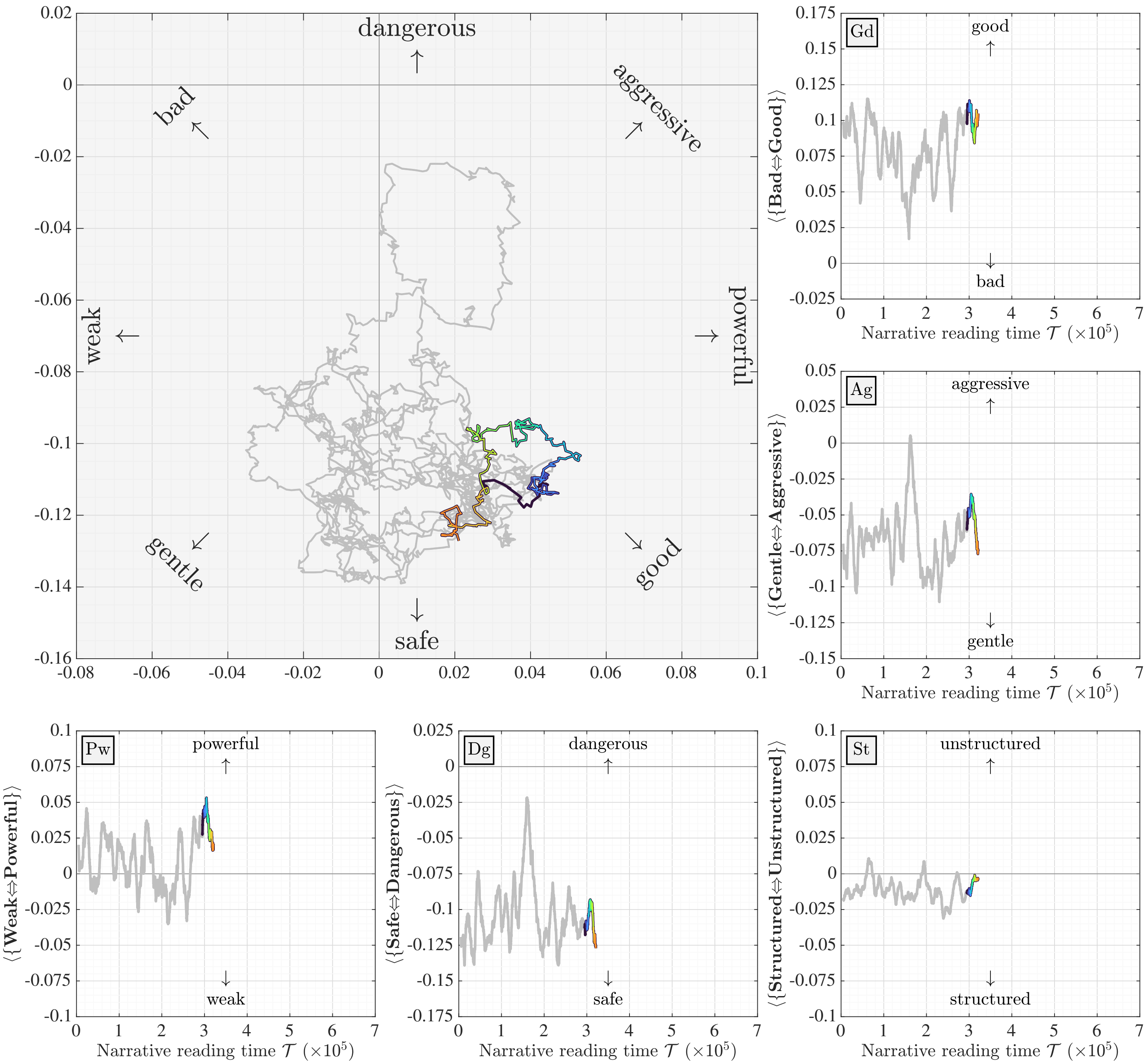


Figure S59: Epoch 12 of 25 in Victor Hugo’s “Les Misérables.”

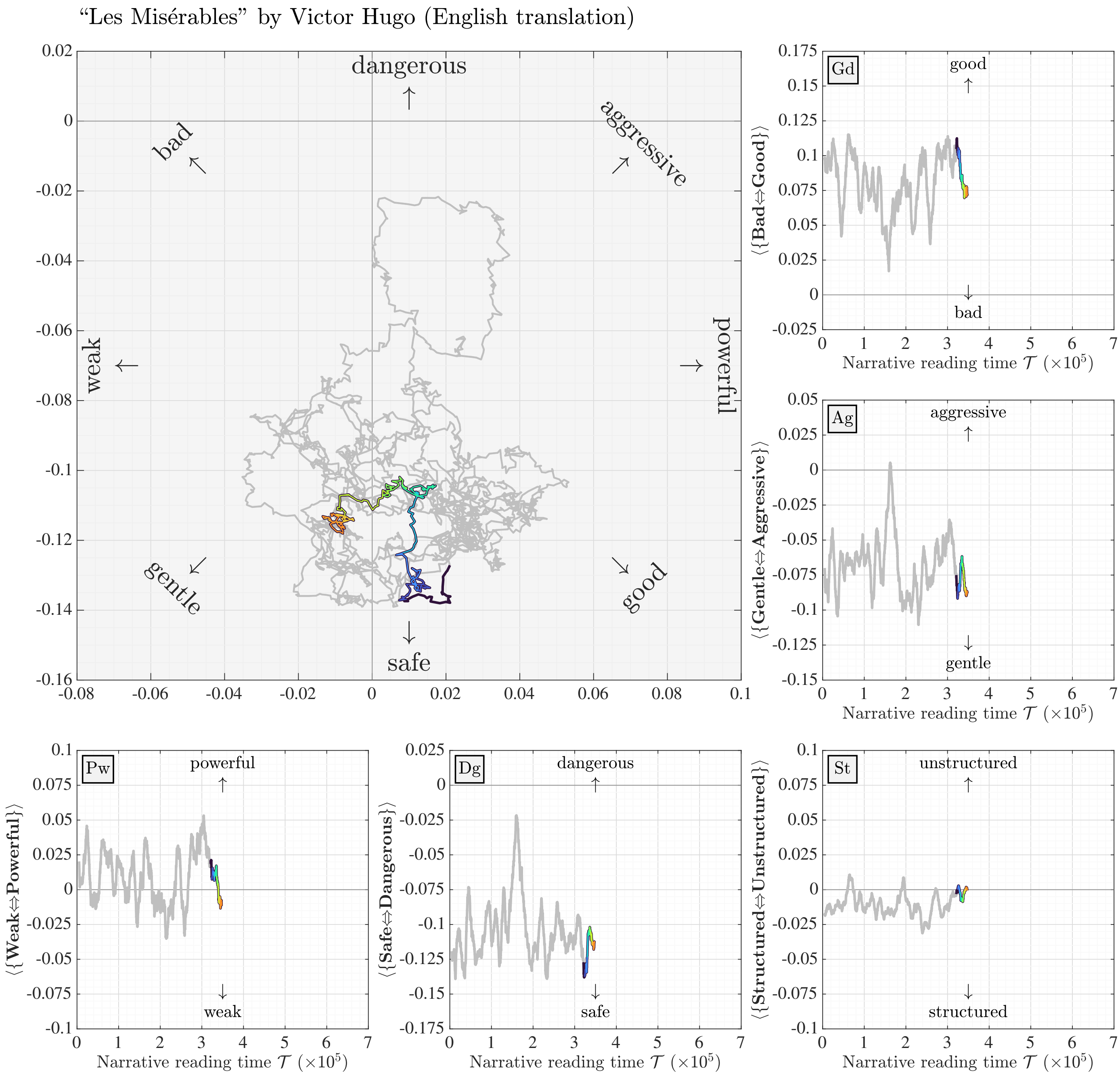


Figure S60: Epoch 13 of 25 in Victor Hugo's "Les Misérables."

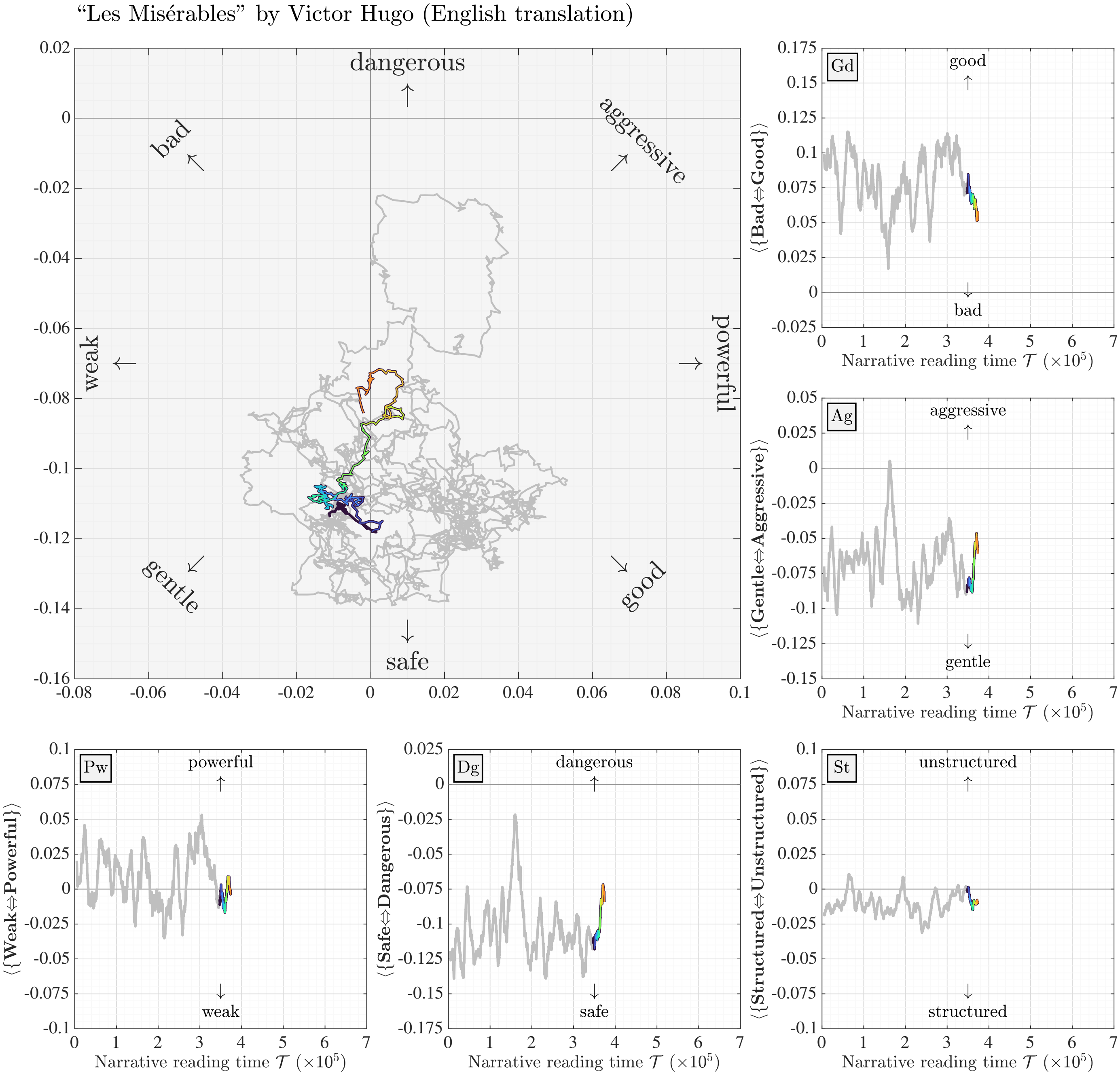


Figure S61: Epoch 14 of 25 in Victor Hugo's "Les Misérables."

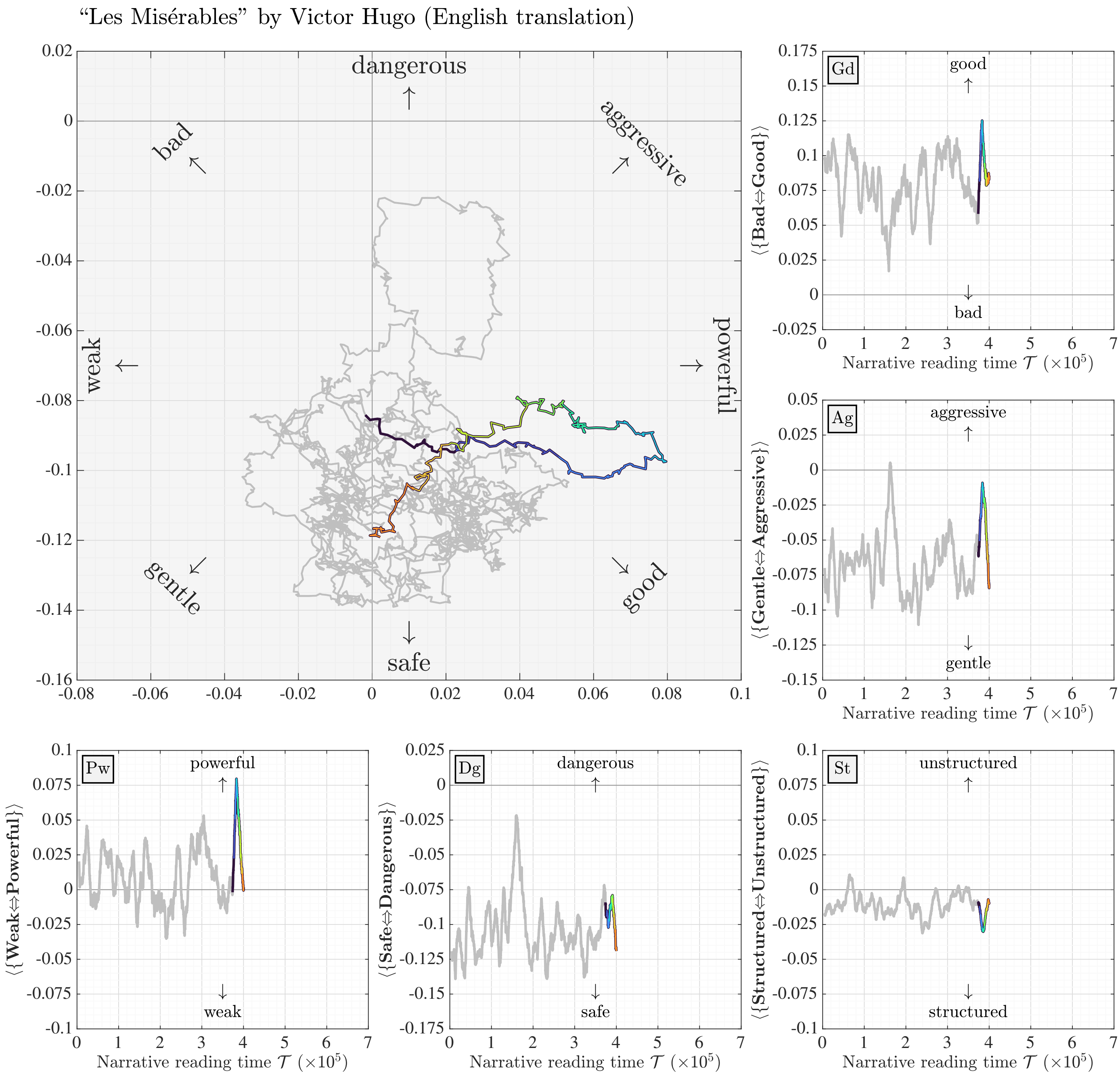


Figure S62: Epoch 15 of 25 in Victor Hugo's "Les Misérables."

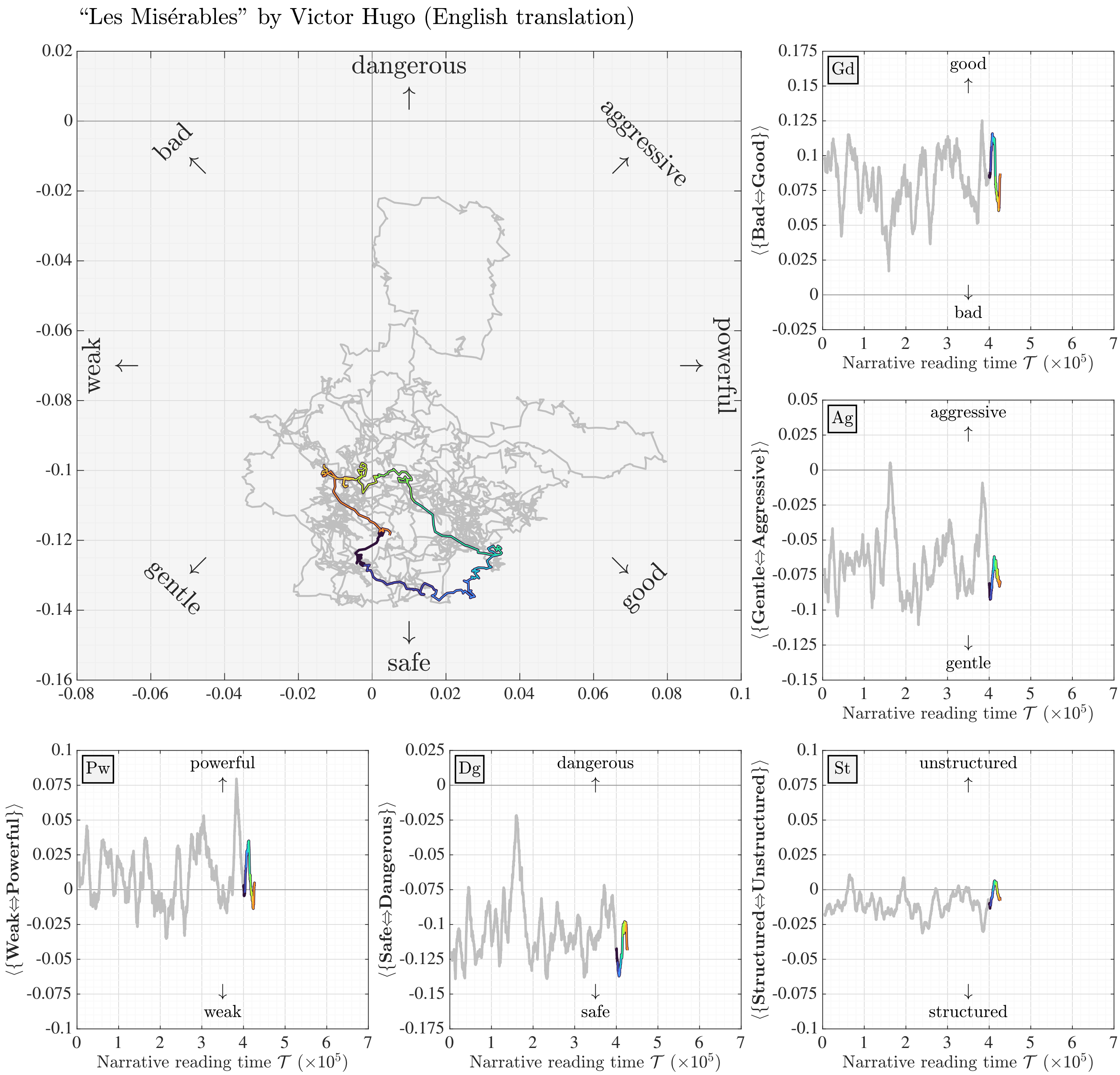


Figure S63: Epoch 16 of 25 in Victor Hugo's "Les Misérables."

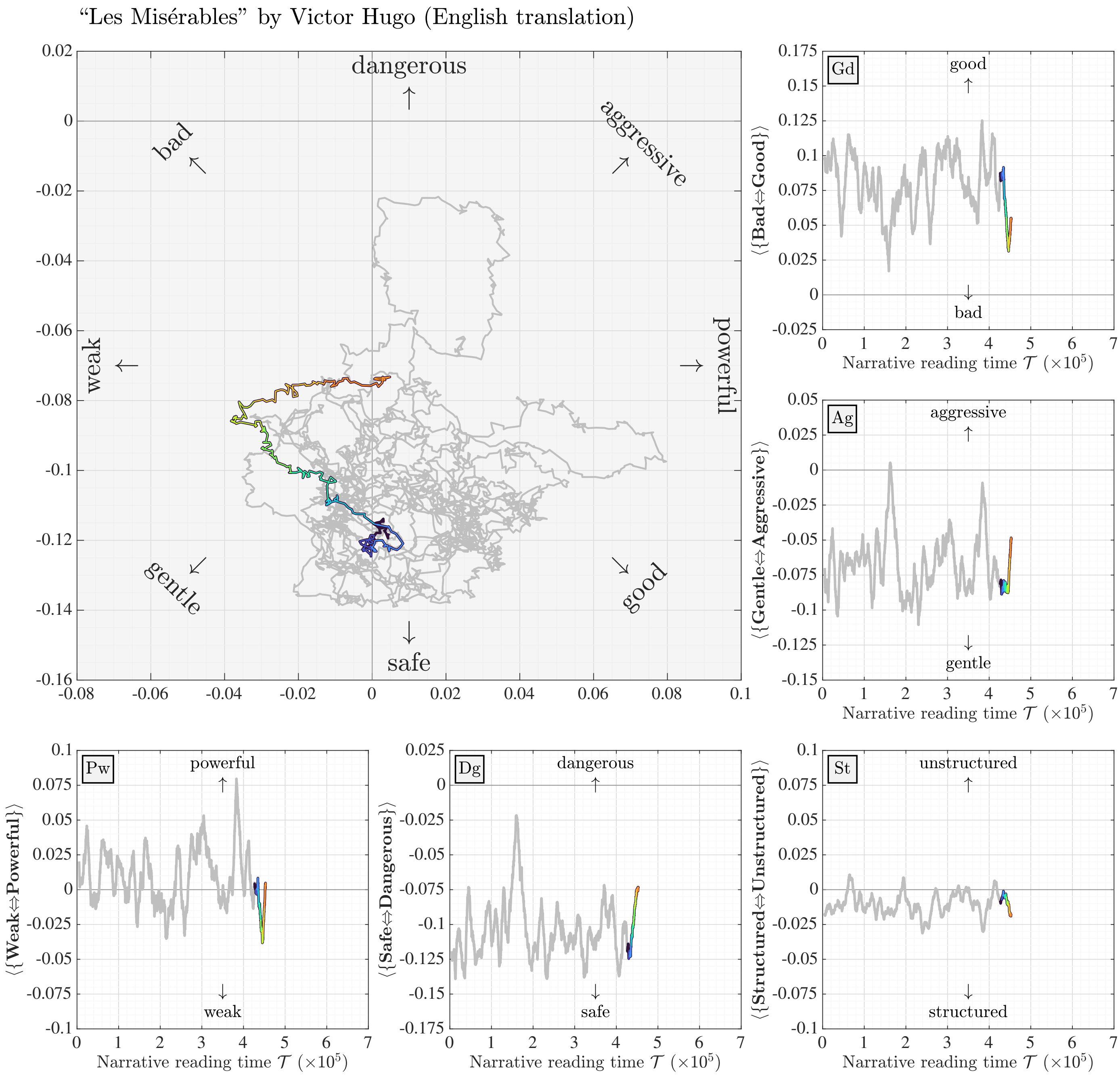


Figure S64: Epoch 17 of 25 in Victor Hugo’s “Les Misérables.”

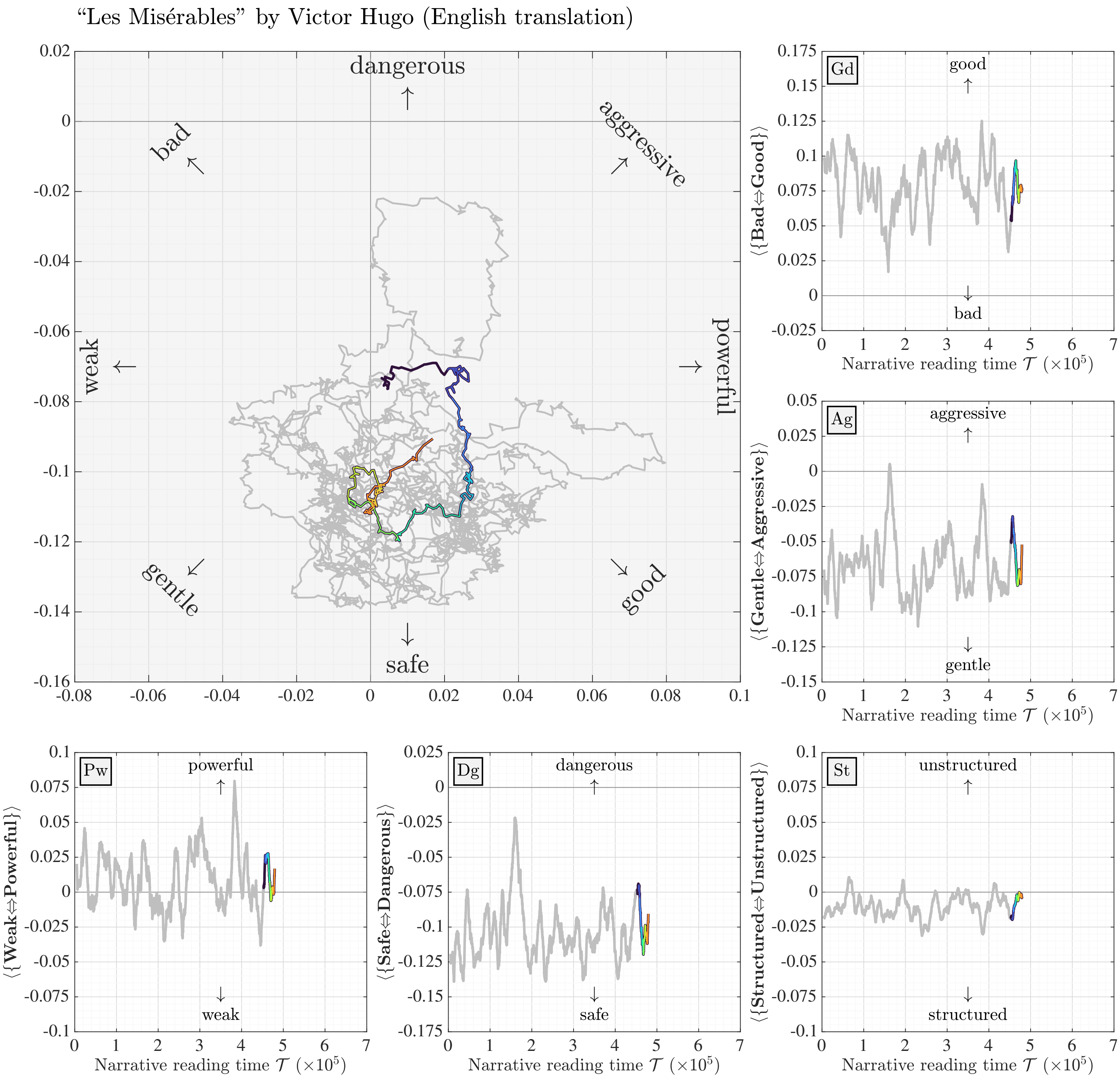


Figure S65: Epoch 18 of 25 in Victor Hugo's "Les Misérables."

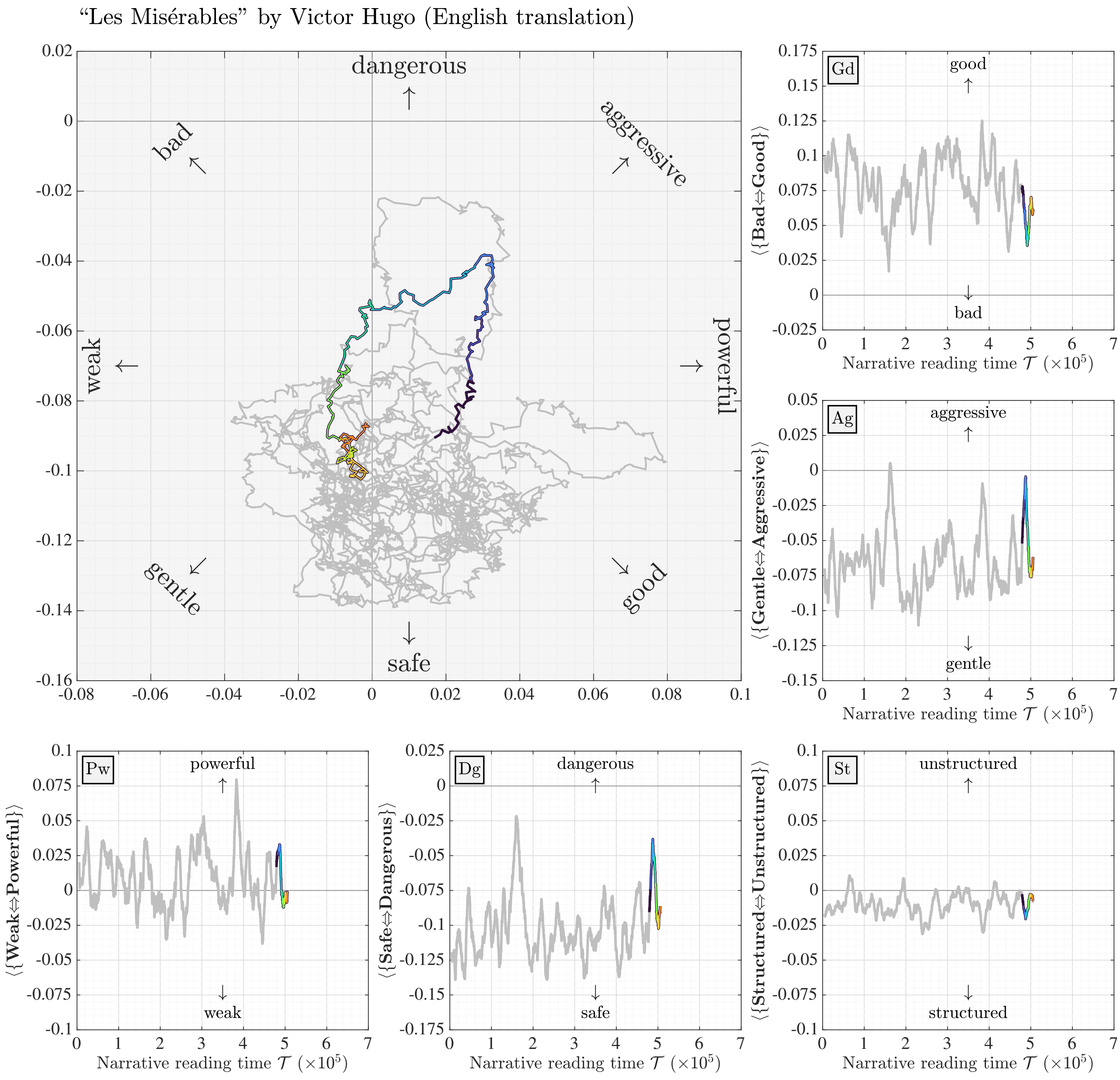


Figure S66: Epoch 19 of 25 in Victor Hugo’s “Les Misérables.”

"Les Misérables" by Victor Hugo (English translation)

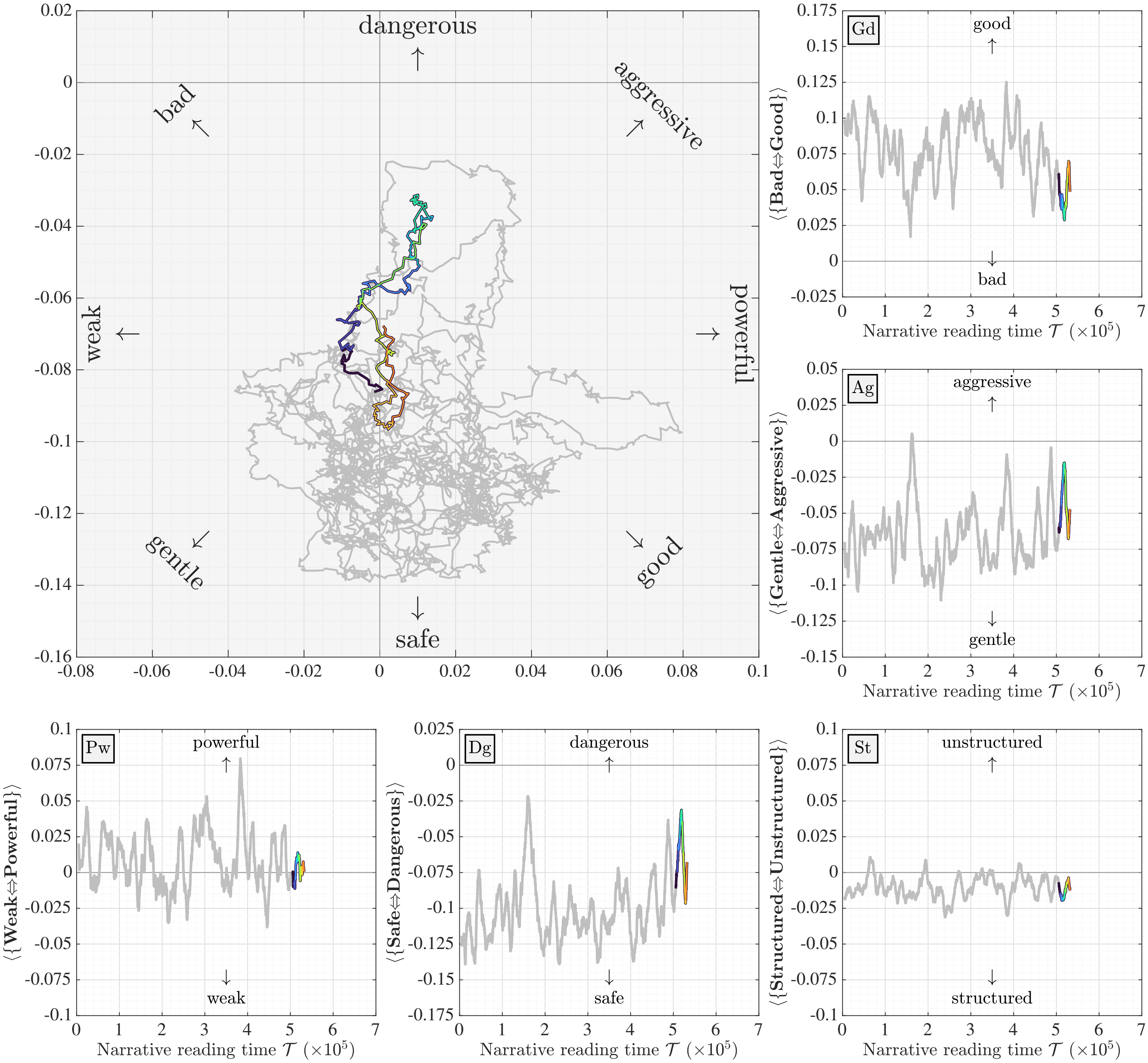


Figure S67: Epoch 20 of 25 in Victor Hugo's "Les Misérables."

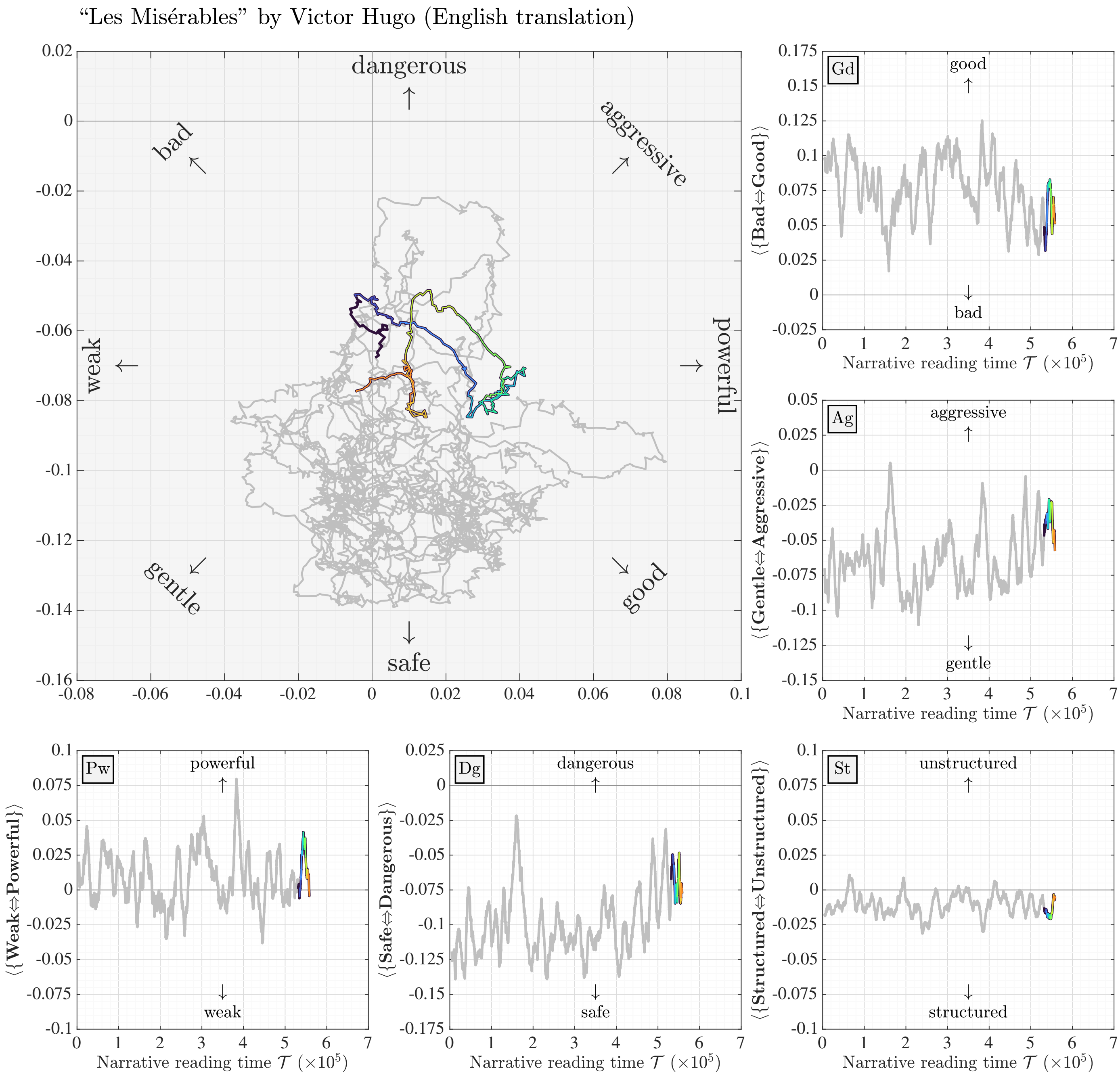


Figure S68: Epoch 21 of 25 in Victor Hugo's "Les Misérables."

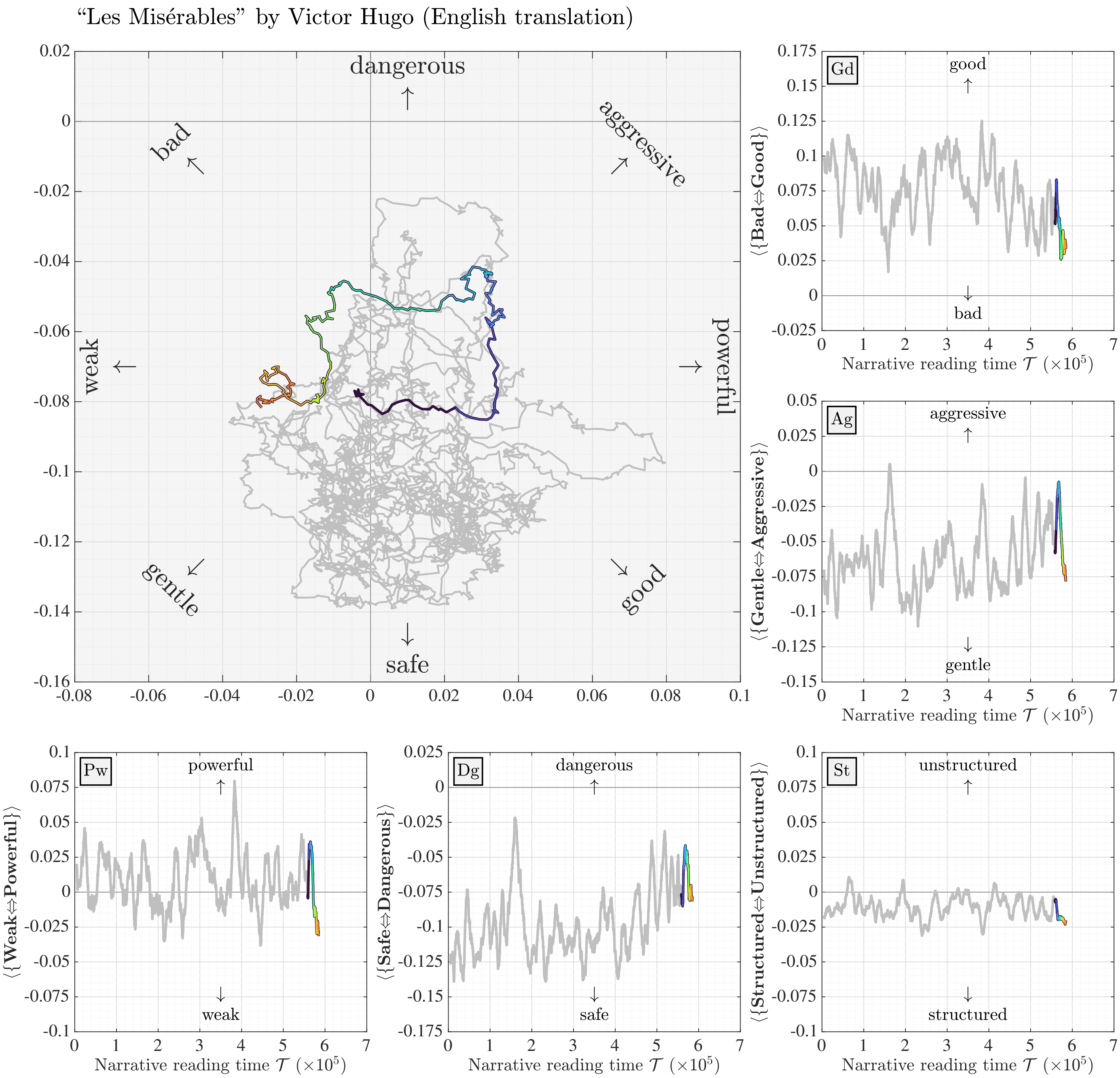


Figure S69: Epoch 22 of 25 in Victor Hugo's "Les Misérables."

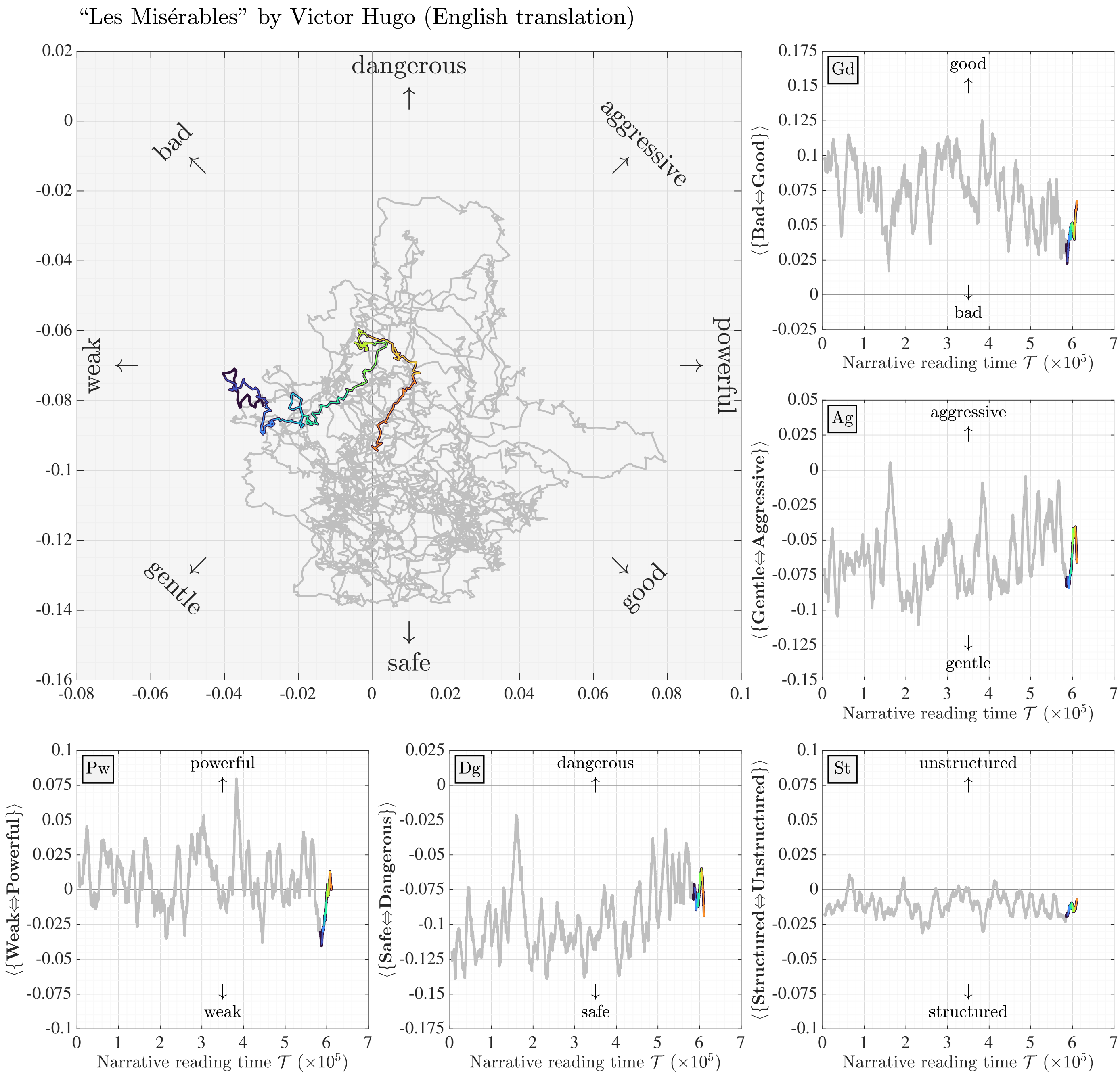


Figure S70: Epoch 23 of 25 in Victor Hugo's "Les Misérables."

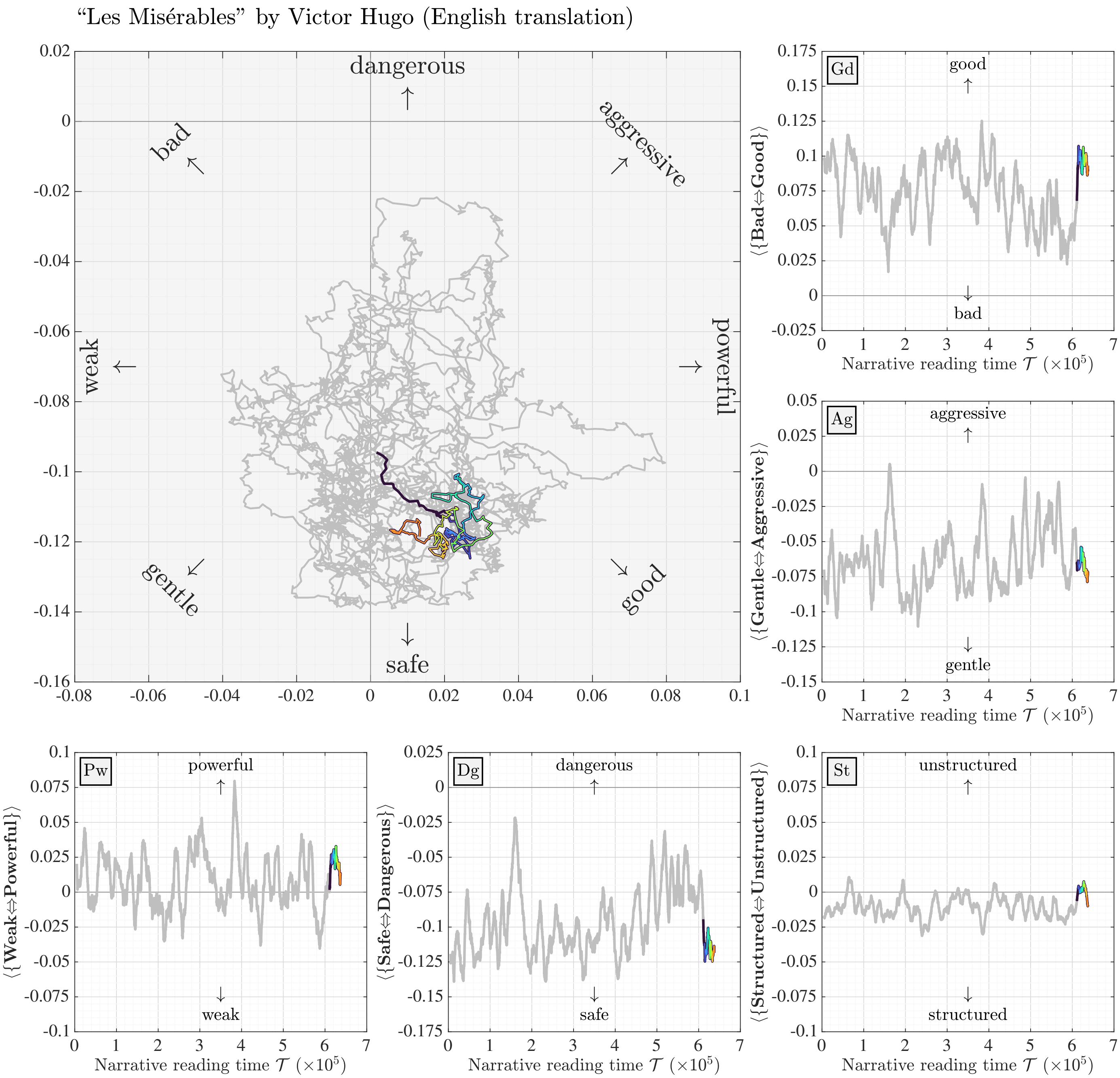


Figure S71: Epoch 24 of 25 in Victor Hugo's "Les Misérables."

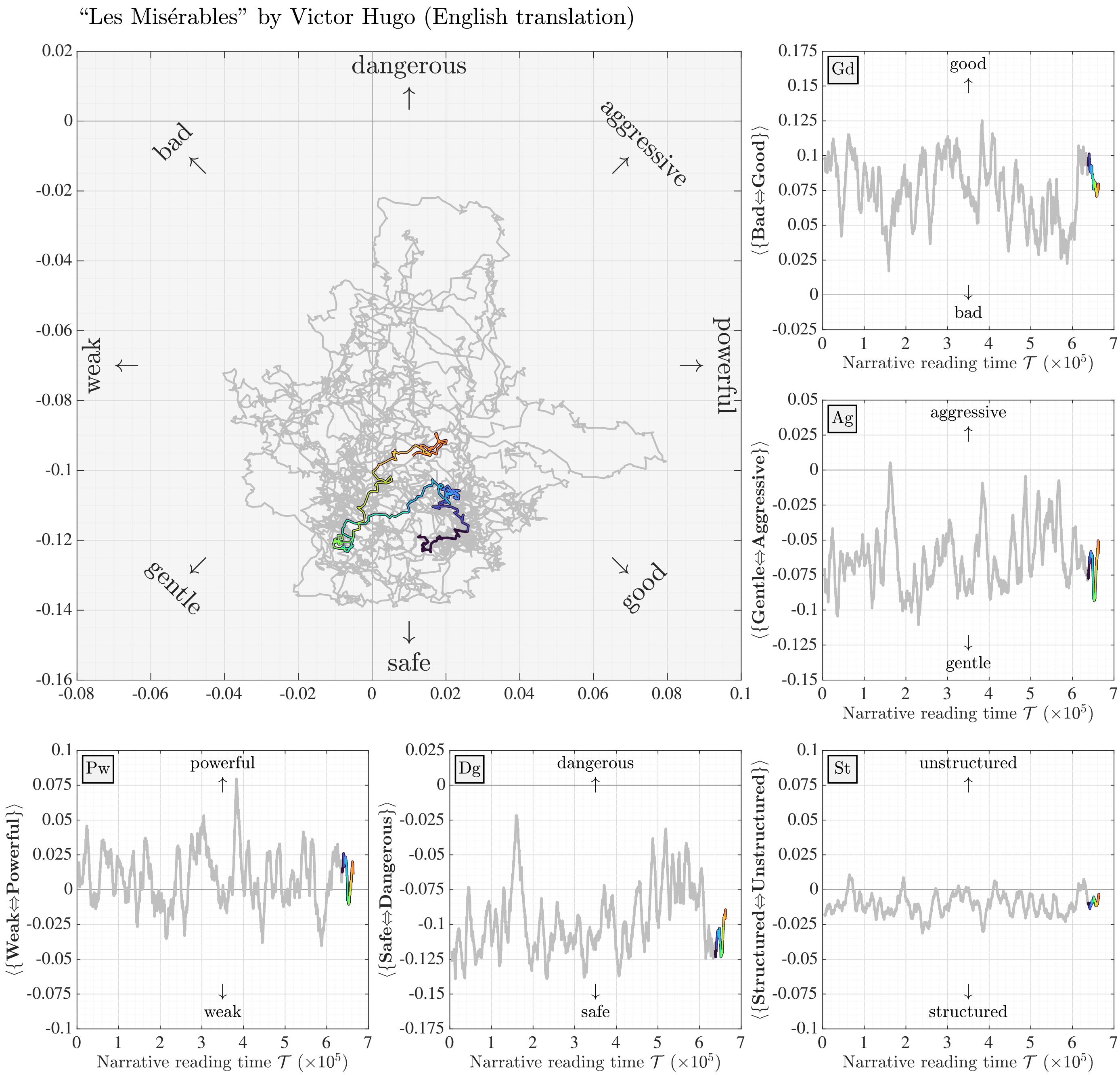


Figure S72: Epoch 25 of 25 in Victor Hugo's "Les Misérables."

S7 Hedonometer for Les Misérables

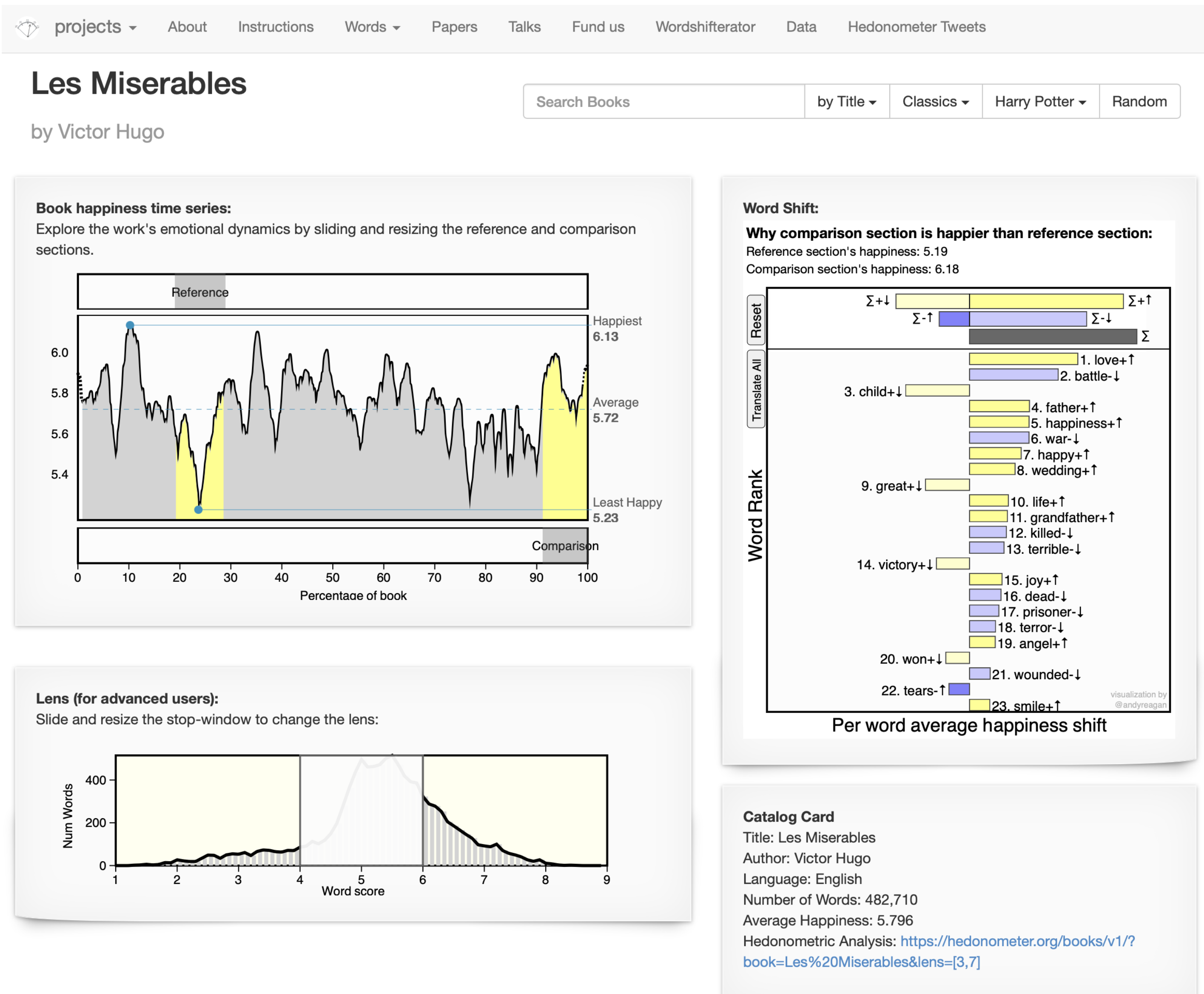


Figure S73: Hedonometric time series for Les Misérables showing a similar profile to the ousiometric {bad ⇔ good} time series in Fig. 9 in Sec. 5. Screenshot from interactive viewer at https://hedonometer.org based on Ref. [82].

S8 Ousiometer prototype for high frequency social media

For an example corpus, we assess English language Twitter [66, 74] for the historically turbulent time period 2020/01/01 to 2021/01/31 [87]. In Fig. S74, we show ousiometric time series for the three frameworks of VAD, GAS, and PDS. We explain how we compute these time series and then briefly discuss how they track specific historical events.

We now apply our prototype ousiometer to English language Twitter at a base resolution of 15 minutes [66, 74]. We use Eq. (5) to generate the ousiometric time series in Fig. S74. The three columns of Fig. S74 correspond to the VAD, GAS, and PDS frameworks. The rows from top to bottom move from the year scale of 2020 and the start of 2021, focusing in on the attack on the US Capitol by supporters of President Trump on 2021/01/06. The specific time frames are 13 months (2020/01/01 to 2021/01/31), 5 weeks (2020/12/19 to 2021/01/23), and 3 days (2021/01/05 to 2021/01/07). We overlay day-scale and hour-scale smoothing for the first two rows respectively.

Looking across all panels, we see the various ousiometric biases in the context of Twitter. Valence, dominance, goodness, and power all show positive biases, while arousal, aggression, and danger present negative averages. Structure is the only neutral dimension.

At the year scale in Figs. S74A–C, the three frameworks show evidence of major shocks, trends, and daily fluctuations, all to varying degrees. The two major events in the first half of 2020—those leading to long-lasting societal effects—were the global realization of the COVID-19 pandemic in mid March and the murder of George Floyd at the end of May and subsequent Black Lives Matter protests [88, 89]. A number of other events also stand out including the assassination of the Iranian general Soleimani by the US on 2020/01/03, which led to talk of war.

We only see the COVID-19-response shock in four dimensions—valence, goodness, power, and danger—while the shock of George Floyd's murder registers in all eight dimensions. The COVID-19 shock is muted in part because we are (understandably) missing key words in the NRC VAD lens such as 'coronavirus', and 'covid'. The word 'pandemic' points directly to danger with PDS scores (0.00,0.45,-0.03), as does 'virus' with (-0.04, 0.32, 0.06). As we discuss below, expanding the NRC VAD lexicon is an evidently needed step for improving the ousiometer.

Moving to the five weeks of the second row of Fig. S74, the main signal deviations are due to Christmas, New Year's Eve and Day, and the 2021/01/06 attack on the US Capitol. We also now see a daily cycle across all dimensions, reminiscent of what we found when measuring happiness (valence) on Twitter using the hedonometer [14, 90].

Finally, the time series in the bottom row of Fig. S74 show, in high temporal resolution, the collective shock expressed on Twitter in response to the attack on the US Capitol. For over roughly two hours starting after midday on 2021/01/06, we see the strongest shocks occur in valence (decreasing, Fig. S74G) and danger (increasing, Fig. S74I).

For the main dimensions of the orthogonal frameworks, GAS and PDS, it is danger **Dg** that is the real dimension of change. In the PDS framework, while danger rises, power **Pw** remains relatively constant throughout the attack. In the GAS framework, the time series for goodness and aggression mirror each other and are projections of the danger signal. We also observe an increase in more rigid and serious 1-grams, as the structure scores **St** drops through the attack.

While we have presented the GAS and PDS time series as distinct sets and notwithstanding that they are of course linear transformations of each other, we suggest that showing all five time series is of value. The eight cardinal and intercardinal points of the power-danger plane are all meaningful, and it is helpful to reflect on which one might be dominating. We are after all plotting time series that represent the harder-to-visualize trajectory of a curve in PDS space.

For a deeper analysis of all time series, and beyond the scope of the present paper, we would use word shift graphs [14, 52, 54, 72, 83] to illuminate which 1-grams drive changes in ousiometric scores.

We note that these instruments are not inherently predictive for social phenomena, but rather extract real-time signals of essential meaning from online text. Analysis of such signals in pursuit of prediction is itself a separate, massive, and fraught enterprise [91–93].

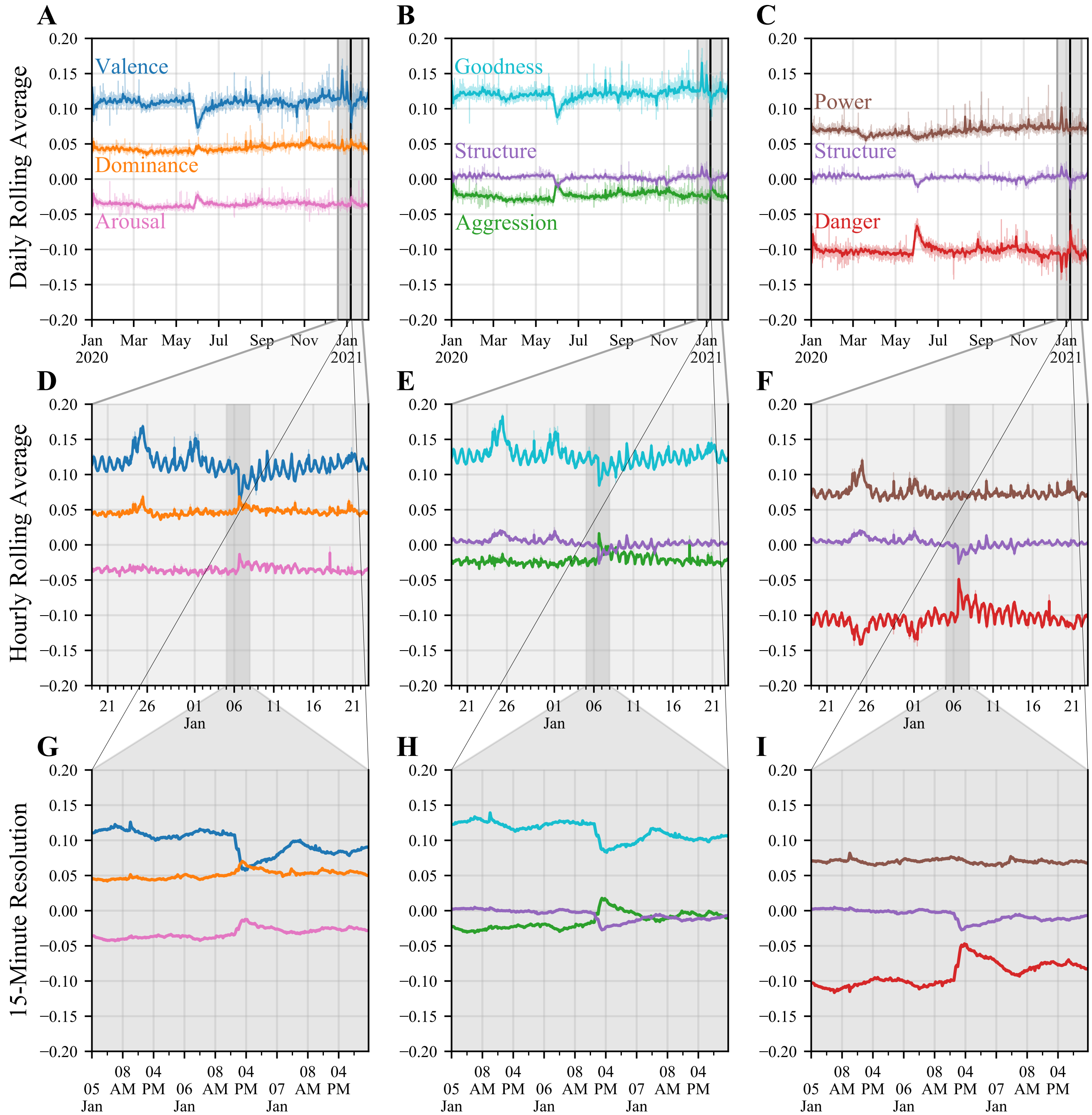


Figure S74: The ousiometer: Example essential meaning time series for Twitter, 2020/01–2021/01. The three columns correspond to average meaning scores for the frameworks of VAD, GAS, and PDS, computed per Eq. (5). The first row shows time series for the 13 months covering all of 2020 and January, 2021. The second and third rows focus in on the attack on the US Capitol on 2021/01/06 by supporters of President Trump. The scale for the second row is 5 weeks (2020/12/19 to 2021/01/23) and 3 days (2021/01/05 to 2021/01/07) for the third row. All underlying time series are 15 minute time scales with day-scale and hour-scale smoothing overlaid in the first and second rows. Major events with spikes and/or durable memory are the US's assassination of the Iranian general Soleimani, the COVID pandemic, George Floyd's murder, and events related to the 2020 US presidential election, including the attack on the US Capitol. Because dominance is relatively stable throughout, the GAS and PDS dimensions effectively vary as functions only of valence and arousal (see Eqs. 2 and 4). In particular, goodness and aggression track valence and arousal closely. For the 2021/01/06 attack, the danger time series spikes while power remains stable (panels F and I). Structure drops indicating increased seriousness. In total, even though only three are indepedent, power, danger, goodness, aggression, and structure are all valuable time series. Notes: We constructed the Twitter 1-gram corpus from approximately 10% of all English tweets [66, 74], with all 1-grams moved to lower case. We form a lexical lens $\mathcal{L}$ by taking 1-grams from the NRC VAD lexicon and adding a hashtag version of each 1-gram. As such, the ousiometer is not specifically tailored for Twitter during the time period covered. As we have done for the hedonometer [14, 88], our ousiometer could be readily improved by expanding the lexical lens to incorporate missing salient 1-grams.