Blending search queries with social media data to improve forecasts of economic indicators

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The forecasting of political, economic, and public health indicators using internet activity has demonstrated mixed results. For example, while some measures of explicitly surveyed public opinion correlate well with social media proxies, the opportunity for profitable investment strategies to be driven solely by sentiment extracted from social media appears to have expired. Nevertheless, the internet's space of potentially predictive input signals is combinatorially vast and will continue to invite careful exploration. Here, we combine unemployment related search data from Google Trends with economic language on Twitter to attempt to nowcast and forecast: 1. State and national unemployment claims for the US, and 2. Consumer confidence in G7 countries. Building off of a recently developed search-query-based model, we show that incorporating Twitter data improves forecasting of unemployment claims, while the original method remains marginally better at nowcasting. Enriching the input signal with temporal statistical features (e.g., moving average and rate of change) further reduces errors, and improves the predictive utility of the proposed method when applied to other economic indices, such as consumer confidence.

I. INTRODUCTION

Macroeconomic time series play a significant role in investment analysis [1], government budget planning [2], and economic forecasting [3, 4]. Many business stakeholders make decisions based on the projected outputs generated by statistical models of related economic time series. As a result, there is a vast literature on time series modeling of economic indicators, ranging in complexity from linear to nonlinear [5], univariate to multivariate [4], to deep learning [6].

Among all economic measures, leading indicators comprise the subset that usually, but not always, change before the economy as a whole changes [7, 8]. For example, weekly unemployment insurance claims data¹ are used in current economic analysis of unemployment trends both nationally and in each state [7]. Specifically, initial claims measure emerging unemployment and continued claims measure the number of persons claiming unemployment benefits for at least a week. As another example, the *consumer confidence index* (CCI) provides an indication of future household consumption and savings [7]. CCI is based upon survey responses regarding expected financial health, sentiment about the general economic situation, unemployment, and capacity to save. The Organization for Economic Co-operation and Development (OECD) regularly provides updates of these and related indices on a monthly basis for multiple countries².

Complementing these traditional measures of economic activity and outlook, alternative internet trace data have gained increasing attention in both the academic literature and the data science industry over the past several years. The volume, velocity, and variety of data reflecting individual attitudes and opinions available online is hard to fathom. For example, Google Trends³ provides access to an anonymous and aggregated but largely unfiltered sample of actual search requests. This allows us to infer public interest in most topics at geographic scales from city to state to country. Researchers have been utilizing such data in epidemiology [9], biology [10] and electronic health records (EHR) [11], among others. Similarly, social media data has also been extensively investigated in research on ecological economics [12], emotional indicators in slang [13], and sociotechnical time series [14, 15].

There are several existing statistical and time series models that can be used for time series forecasting. For example, Scott et. al. [16, 17] propose to use Bayesian Structural Time Series (BSTS) to predict economic variables. De Livera et. al. [18] introduce two forecasting methods, BATS and TBATS, which use exponential smoothing and are based on innovations in state-space modeling. Recently, Yi et. al. [19] proposed a novel statistical model, the Penalized Regression with Inferred Seasonality Module (PRISM), to forecast US unemployment claims based on Google Trends data. PRISM employs a time series seasonal decomposition and related Google Trends search data as features. Li et. al. use

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¹ https://www.dol.gov/

² https://data.oecd.org/

³ https://trends.google.com/trends/

LASSO [20-22] to make predictions with lead times spanning from the present (known as *future zero* or *nowcast-ing*) to three weeks into the future for US unemployment claims data.

Motivated by the recent work of Li et. al., in the present study we introduce a generalized version of their model called GPRISM (generalized PRISM). To be more concrete, our contribution in this paper is threefold: First, we propose a general modeling framework that incorporates flexible time series operators as predictors [23]. Second, we leverage the frequency of economic language appearing on Twitter in the modeling task. Unlike Google Trends data, which is normalized so as to make relative comparisons between separate terms problematic, raw Twitter data allows for proper statistical estimates of phrase popularity. Inclusion of Twitter data also extends the available training period beyond five years. Finally, we expand the use case to a more granular level (US States), which could help potential stakeholders with more fine grained unemployment information. We also apply our GPRISM model to the aforementioned consumer confidence indicator (CCI). In brief, our results suggest that the proposed model outperforms the original in most cases, suggesting that blending social media and search queries can improve the predictive utility of each signal alone.

The paper is structured as follows. Section II describes the data used in this work. Section III demonstrates the details of the proposed GPRISM model, describing how the features are created and how the model is trained. Numerical results on US and state level unemployment claim data, together with the CCI use case are discussed in section IV, followed with conclusions in section V.

We adopt the following notation throughout the paper. Time series (indexed by t) are denoted by boldface letters, e.g., \mathbf{y}_t . The Euclidean norm of a p dimensional vector $\vec{v} \in \mathbb{R}^p$ is denoted by $\|\vec{v}\|_2$. The ℓ_1 norm of a vector \vec{v} is denoted by $\|\vec{v}\|_1$. \mathbb{R} is the set of real numbers. **Z** is the set of integers. $\mathscr{L}[\cdot]$ is the time series operator (that maps one time series to another time series). \mathbb{R}^n_k is the n dimensional space $\{0\}^k \times \mathbb{R}^{n-k}$ with the first k dimensions populated by degenerated single value spaces (to represent the transient part of the discrete series).

II. DATA DESCRIPTION

Two main classes of economic time series are considered: US and state level unemployment initial claims data, and country level consumer confidence indicators. Each is described in detail below.

A. Unemployment claims

An initial unemployment claim is filed by an individual after separation from an employer. The claim requests a determination of basic eligibility for the Unemployment Insurance program. It is generally known as one of the leading indicators for the economy. The time series data for national unemployment statistics [19] can be obtained directly from Federal Reserve Economic Data (FRED)⁴. Figure 1 shows the unemployment initial claim data from 2011 to 2019. In addition, state level unemployment claim data is available directly from the Employment & Training Administration (United States Department of Labor)⁵, which is the original source of this data set.

B. Consumer confidence index

The Consumer Confidence Index (CCI) provides a proxy for future household consumption and savings, based upon survey responses regarding expected financial outlook, sentiment about the broader economy, unemployment, and capability of savings. Data for the largest economies including G7 countries can be obtained from the OECD website⁶. Figure 2 plots the available CCI data for the 60 year period ending in 2020.

C. Google Trends

The Google Trends website⁷ provides real-time internet search data. The weekly relative popularity of search query terms is available via an API, with the score being normalized to a number between 0 and 100. The site can also return other query terms that are most highly correlated with the search term. Here, following Yi et. al., we adopt the top 25 search terms that are most related to "unemployment"" [19]. The detailed terms are provided in Appendix.

D. Twitter

Social media data reflecting the frequency of specific economic terms is obtained from the Storywrangling project [15], an open source API offering day scale phrase popularity going back to 2009.⁸ Storywrangler collects a random 10% of all public messages using Twitter's Decahose API, and parses tweets into daily frequencies of words, 2-word phrases, and three word expressions, i.e. n-grams with n = 1, 2, 3.

⁴ https://fred.stlouisfed.org/series/ICNSA

⁵ https://oui.doleta.gov/unemploy/claims_arch.asp

 $^{^{6}}$ data.oecd.org/leadind/consumer-confidence-index-cci.htm

⁷ www.google.com/trends

⁸ https://storywrangling.org/



FIG. 1. Weekly unemployment initial claim data (2011 to 2019) collected and aggregated to the national level by the US Department of Labor from each state's unemployment insurance program office. This is a vital and frequently leveraged macroeconomic indicator. However, the data is reported with a one week delay, and thus there is a strong need to predict the current unemployment rate, i.e. nowcast.



FIG. 2. Monthly Consumer Confidence Index from OECD. An indicator above 100 signals a boost in the consumers' confidence towards the future economic situation, as a consequence of which they are less prone to save, and more inclined to spend money on major purchases in the next 12 months. Values below 100 indicate a pessimistic attitude towards future developments in the economy, possibly resulting in a tendency to save more and consume less. The lines represent the CCI index for the corresponding country or super-nations Germany (DEU), France (FRA), the United Kingdom (GBR), Italy (ITA), Japan (JPN), the European area (EA19, representing 19 countries); OECD total (OECD), and OECD Europe (OECDE).

III. MODEL DESCRIPTION

In this section, we give a brief overview of the time series prediction model PRISM [19], and then describe the details of our proposed generalization (GPRISM). Our main goal is to make predictions of future values of the time series $\{\mathbf{y}_t\}$ using past values of both $\{\mathbf{y}_t\}$, and exogenous time series $\{\mathbf{x}_t\}$.

Depending on the application, $\{\mathbf{y}_t\}$ may experience delay or administrative lag due to the time required to process paperwork. For example, unemployment claim



FIG. 3. Feature creation step with time series operators. For a given time series \mathbf{y}_t and a function $f_{k,\theta}(\cdot)$ with parameters k and θ , we can create a new time series $\tilde{\mathbf{y}}_t$ as a new feature. At each time point in \mathbf{y}_t , the previous k elements (red bar) are transformed with $f_{k,\theta}(\cdot)$ into a new value (red dot), which will be the new feature at the corresponding time point. This process is repeated, say for the blue bar and blue dot, to get the whole feature $\tilde{\mathbf{y}}_t$.



FIG. 4. Step 1: feature creation with time series operators. For a given function f_{θ} , we can create a new feature (red, feature 1) with the aforementioned process by applying f_{θ} on the original time series. Similarly, with additional types of functions (say $\tilde{f}_{\tilde{\theta}}$), we can repeatedly create multiple features (until the p^{th} feature). The whole data matrix can be calculated in this fashion with enough historical data. In the end, we can choose the desired time period as our final modeling data matrix $\mathbf{X}_{n \times p}$.

data $\{\mathbf{y}_t\}$ is usually unavailable at time t, but estimates are released publicly weeks later. Based on the information $\{\mathbf{y}_i\}_{i=1}^{t-1}$, we may also want to perform a nowcast or real-time prediction in addition to the future forecasts, e.g., two weeks ahead. However, this does not affect the general mathematical formulation of the time series model⁹.

The first step of the PRISM model is to apply a seasonal decomposition on the previous fixed window of length M. Specifically, at time t we decompose the time series $\{\mathbf{y}_i\}_{i=t-M}^{t-1}$ as follow:

$$\{\mathbf{y}_i\}_{i=t-M}^{t-1} \xrightarrow{\text{seasonal decomposition}} \{\gamma_{i,t}, z_{i,t}\}_{i=t-M}^{t-1}.$$
 (1)

In this expression, $\{\gamma_{i,t}\}_{i=t-M}^{t-1}$ is the estimated seasonal component from the decomposition, while $\{z_{i,t}\}_{i=t-M}^{t-1}$ represents the remaining contributions including trends and noise. Note that for a given time t, 2M additional data points are generated by this process. The second step is to train the model with penalized regression using the linear model:

$$\mathbf{y}_{t+l} = \mu_y^{(l)} + \sum_{j=1}^K \alpha_j^{(l)} \mathbf{z}_{t-j,t} + \sum_{j=1}^K \delta_j^{(l)} \gamma_{t-j,t} + \sum_{i=1}^q \beta_i^{(l)} \mathbf{x}_{i,t}.$$
(2)

Here, K is how many lagged historical decomposed data points we want to use, and α, δ, β are fitted coefficients for the non-seasonal, seasonal and exogenous features. Note that for each prediction length l, we train a different model. As a result, coefficients are labeled with (l) to indicate separate model predictions at time t. The penalization terms with l_1 penalty for the coefficients are added to the objective function, as for the normal LAS-SO model¹⁰. We also note that the time resolution (for a single time step) in our applications are weekly for the unemployment claims and monthly for the consumer confidence index.

 $^{^9}$ Note that we can always shift the time series to meet the application need, as long as future information is not used to train the model.

¹⁰ which can be trained with the glmnet package in \mathbf{R} .



FIG. 5. Step 2: model training for the one step ahead prediction task. With the modeling data matrix $\mathbf{X}_{n \times p}$, we can create our training/testing and predictor/features pairs on a rolling/walk forward basis. At a given time point, the original time series is shifted ahead with desired steps depending on the need, and the most recent n_t data until the last time point with the p features are selected as the training data, while features from the current time point are used to make the prediction as test set. The model is always updated as new data arrives.

A. GPRISM

To generalized PRISM so that it can incorporate additional temporal information and predictive signals, we start by defining a time series operator.

Definition III.1 (infinite version) Assume $\mathbf{y}_t \in \mathbb{R}^{\mathbf{Z}}$ is an infinite time series and define a function $f_{k,\theta}(\cdot)$: $\mathbb{R}^k \to \mathbb{R}$, where k is the window size and θ is the parameter set. $f_{k,\theta}(\cdot)$ induces a **time series operator** $\mathscr{L}^{f_{k,\theta}}[\cdot]: \mathbb{R}^{\mathbf{Z}} \to \mathbb{R}^{\mathbf{Z}}$ that maps \mathbf{y}_t to $\tilde{\mathbf{y}}_t \in \mathbb{R}^{\mathbf{Z}}$ s.t.

$$\tilde{\mathbf{y}}_i = f_{k,\theta}(\mathbf{y}_{(i-k+1):i}) \tag{3}$$

i.e. $\tilde{\mathbf{y}}_t = \mathscr{L}^{f_{k,\theta}}[\mathbf{y}]_t.$

In practice, time series observations are finite. As long as we have enough historical data, we can ignore the first transient part of the discrete series¹¹.

Definition III.2 (finite version) Assume $\mathbf{y}_t \in \mathbb{R}^n$ is a finite time series with length n and define a function $f_{k,\theta}(\cdot) : \mathbb{R}^k \to \mathbb{R}$, where k is the window size and θ is the parameter set. $f_{k,\theta}(\cdot)$ induces a **time series operator** $\mathscr{L}^{f_{k,\theta}}[\cdot] : \mathbb{R}^n \to \mathbb{R}^n_{k-1}$ that maps \mathbf{y}_t to $\tilde{\mathbf{y}}_t \in \mathbb{R}^n_{k-1}$ s.t.

$$\tilde{\mathbf{y}}_i = f_{k,\theta}(\mathbf{y}_{(i-k+1):i}) \tag{4}$$

for $i \geq k$ and $\tilde{\mathbf{y}}_i = 0$ (or other dummy placeholder) for i < k, *i.e.* $\tilde{\mathbf{y}}_t = \mathscr{L}^{f_{k,\theta}}[\mathbf{y}]_t$.

Note that the window size k can also be viewed as a parameter for the function $f(\cdot)$. Since it is a common parameter for most of the operators, we separate it from θ , which can vary depending on the operator type. One can create specific operators depending on the nature of the task, below are some examples of those we commonly use.

Example III.3 (smoothing) Let $\mathbf{x} \in \mathbb{R}^k$. Arguably the easiest information one can extract from a time series would be the moving average, e.g.

$$f_k(\mathbf{x}) = \frac{1}{k} \sum_{i=1}^k x_i.$$
 (5)

Remark III.4 Based on the nature of the data, one should be careful about whether the last several days of information are appropriate as features. For example, in the unemployment claim application, real-time t information is not available. Thus, when crafting the function f, one should be aware of this issue to avoid look ahead bias, *i.e.*

$$f_k(\mathbf{x}) = \frac{1}{k-1} \sum_{i=1}^{k-1} x_i.$$
 (6)

and similar for other operators.

Example III.5 (stabilization) Let $\mathbf{x} \in \mathbb{R}^k$. One way to extract time series information from historical data is by measuring its rate of change from baseline. This operation can be generated with the following function:

$$f_k(\mathbf{x}) = \frac{x_k - x_1}{x_1}.\tag{7}$$

Example III.6 (seasonal decomposition) Let $\mathbf{x} \in \mathbb{R}^k$ and SD represent a seasonal decomposition. This process results in γ (and z) of the input time series with the original length, e.g., k. Let $f_{k,j}$ be the function that only takes the j^{th} element of the decomposition results:

$$f_{k,j}(\mathbf{x}) = \mathsf{SD}(\mathbf{x})_j. \tag{8}$$

Thus, a series of functions $\{f_{k,j}\}_{j=1}^{M}$ defines the desired features in PRISM.

¹¹ This can be as short as length k-1, where k is the window size



FIG. 6. The state level unemployment initial claim results for the nowcast task. The x-axis is the years and the y-axis is the prediction MAE results in thousands. Three models are compared here: the original model (blue), the model with additional moving average and rate of change features (red), and the model with additional features together with the Twitter data.

Furthermore, indicators from traditional technical analysis in finance [24] can also be viewed as examples of time series operators. We now move on to a discussion about how to utilize these operators to engineer features and train the model. original time series using a window length of k (blue strip in the first axis) using the desired value (blue circle) as a label. For the next time point, we repeat this process for the red strip and red circle, and so on.

B. Feature creation

For simplicity, let us first focus on the case in which we only have one function/operator f/\mathscr{L} for a series \mathbf{y}_t . Assuming we have enough historical data, Figure 3 suggests that by applying f repeatedly on a rolling basis over time, a second time series $\tilde{\mathbf{y}}_t$ can be generated with $\tilde{\mathbf{y}}_t = \mathscr{L}[\mathbf{y}_t]$ as a new feature that incorporates previous temporal information defined with f.

For example, at time $t = t_1$, our goal is to create a new feature for $t = t_1$ (blue circle in the second axis) using the original timeseries \mathbf{y}_t . We learn the function f on the This process can be applied with arbitrary type/number (p) of time series operators. Then, as is shown in Figure 4, p new features can be generated based on the original time series. For example, the solid blue and red arrows represent the process we described above for one function f. With a separate function \tilde{f} (dashed arrows), another feature can be created in the same fashion. By trimming the initial transient period data, we arrive at the final data matrix $\mathbf{X}_{n \times p}^{\top}$, with sample size n and dimension p.

C. Model training

With the data matrix in place (including the corresponding exogenous data if needed), we can proceed to train the model on a rolling/walk forward basis. Figure 5 illustrates how to use historical data up to time point t to train the model, and make *l*-step predictions (in the figure, l = 1). For example, at time t = i, the task is to predict the next original time point t = i + 1 using the features at t = i. So this pair of data becomes our testing set. On the other hand, we use all the data available up to time t = i - 1 (for the features) to train the model.

D. Evaluation Metrics

Prediction results are evaluated in the test region using the root mean squared error (RMSE)

$$RMSE(\hat{\mathbf{y}}_t, \mathbf{y}_t) = \frac{1}{\sqrt{n_{\text{test}}}} \|\hat{\mathbf{y}}_t - \mathbf{y}_t\|_2, \qquad (9)$$

and mean absolute error (MAE)

$$MAE(\hat{\mathbf{y}}_t, \mathbf{y}_t) = \frac{1}{n_{\text{test}}} \|\hat{\mathbf{y}}_t - \mathbf{y}_t\|_1, \qquad (10)$$

IV. RESULTS

Having described the data and model, we now provide the numerical results associated with the model performance on the aforementioned data sets.

A. Unemployment claim and social media data

In the unemployment claim task, we first present the performance of our GPRISM model on national US data before refining the experiments to the individual state level. We download statistics on relative popularity for the key words suggested by prior work on Google Trends [19] and further filter out *n*-grams with a high missing data rate. (See the Appendix for a reference table of terms). For Twitter data, we use frequencies associated with the terms unemployed, unemployment, and unemployment rate.

The four time ranges considered in this experiment are 2010-2014, 2012-2016, 2014-2018 and 2016-2020. These ranges are necessitated by one notable drawback of Google Trends data, namely that it is transformed using a different normalization factor in every five year range [19]. We compare the performance of four models at prediction tasks associated with these data sets. First, we evaluate the PRISM model without Google Trends data (original). Second, we deploy the GPRISM model, where the moving average and rate of change features are included but without Twitter data (MR). Third, we implement the PRISM model with Google Trends data included (original/G). Finally, we test the GPRISM model which uses the moving average and rate of change features as well as Twitter data (MR/T).

Table I shows the RMSE results for four different prediction tasks, i.e., *i* weeks into the future for i = 0, 1, 2, 3, where i = 0 corresponds to a nowcast. Performance for the models without social media data are shown in the first two columns (lowest RMSE marked with asterisk), while the models with the social media data appear in the last two columns (having the lowest RMSE marked with asterisk). The overall lowest RMSE models are bold faced. As we can see from the results, the proposed GPRISM model outperforms the original model in most cases except for the nowcast, which suggests that the Google Trend data may be more suitable for instantaneous estimates, while the Twitter data may provide more insights on a longer time horizon. One potential mechanism at play is that individuals searching for information about unemployment, or searching for a new job, do so privately on Google, while Twitter is the platform to publicly express fear about losing a job in the near future. Similar conclusion can be drawn from the MAE result, which is provided in Appendix.

In addition to the US national level, we also train and test the model for results at the level of individual states. We expect that this refined spatial scale will be of great interest for economic and business practitioners to make more accurate decisions. Figure 6 presents the MAE of the nowcast model applied on multiple states from 2016 to 2019. The PRISM model is shown in blue (original), while the GPRISM model with the moving average and rate of change features is shown in red (MR), while the GPRISM model with additional Twitter data is shown in green (MR/T).

All models perform worse on the nowcast task in all states for 2017, and best in 2019. The three models exhibit similar performance for 2016 and 2017, but GPRISM improves upon PRISM performance for 2018 and 2019. For lead times 1-3 weeks into the future, model performances degrade as expected, but the prediction tasks have respectively similar results when looking across the three models. We provide the 3 week prediction results in the Appendix.

B. Consumer Confidence Index (CCI)

We apply our model to another leading economic indicator by forecasting the monthly Consumer Confidence Index from 2010 to 2020. We consider CCI data for large economies, France, Germany, Italy, Japan, the United Kingdom and the United States (G7 countries except Canada which does not have data directly available on the OECD website), as well as several intergovernmental organizations like EA19 Euro area (19 countries, EU19), G7(G-7), OECD - Europe (OECDE) and OECD - Total (OECD).

task	dates	original	MR	original/G	MR/T
nowcast	2010-2014	28058	*25262	*21046	25252
	2012-2016	*16318	18156	18359	*18202
	2014-2018	15985	*15343	*14127	15410
	2016-2020	15083	*14013	*13821	14151
pred.1	2010-2014	28756	*25697	25932	*25455
	2012-2016	*16740	18101	19439	*18085
	2014-2018	16014	*15215	15755	*15141
	2016-2020	14725	*13905	14264	*13891
pred.2	2010-2014	29194	*26479	26944	*26470
	2012-2016	*16386	16715	18733	*16680
	2014-2018	15852	*15213	15452	*14987
	2016-2020	15125	*13909	14487	*14132
pred.3	2010-2014	29900	*26934	27159	*27109
	2012-2016	*15897	16706	18057	*16379
	2014-2018	16364	*15409	15814	*15700
	2016-2020	15246	*14178	14918	*13705

TABLE I. The RMSE for the US level unemployment claim results. Four tasks are considered here, i.e. nowcast, future one, two, three weeks ahead prediction with four time ranges (2010-2014, 2012-2016, 2014-2018, and 2016-2020). Moreover, four models are compared here in the last columns, the original model (original), the model with additional moving average and rate of change features (MR), the original model with the Google Trends data (original/G) and the MR model with the Twitter data (MR/T). The first two models do not use the exogenous features, while the last two models use social media features. For each of the simulation scenario (row), the smallest error among the four models is in bold face, while the smaller one among the two models (for either without social media models, and with social media models) is denoted with an asterisk.

Figure 7 presents the RMSE results for the one month ahead prediction task. The blue dots correspond to the RMSE for the PRISM model, and the red dots correspond to the RMSE for the GPRISM model by adding the moving average and rate of change features. Our results demonstrate that the proposed GPRISM model yields a lower RMSE.

V. CONCLUDING REMARKS

In this paper, we have proposed a general and flexible time series modeling framework with a focus on nowcasting and short term predictions for important economic indicators. The framework allows the user to incorporate temporal information derived from historical time series data with various kinds of time series operators, as well as external auxiliary data. Moreover, the user is able to utilize different machine learning models from the resulting data matrix, which expands possibilities for improv-



FIG. 7. Errors for the Consumer Confidence Index prediction task across different global indices. Two models are compared here, the original PRISM model (blue) and the model with additional moving average and rate of change features GPRISM (red). The x-axis is the RMSE with the same unit as in Figure 2, and the y-axis delineates the countries and super-nations.

enhance the model performance, possibly because relative frequency information is available unlike the Google Trends data. A pair of important use cases forecasting leading economic indicators demonstrate the preferred model results, which should be of great practical interests for economic decision makers.

Future directions and applications of this work are vast. As one natural extension, model performance out to improve using multivariate time series. We believe inter correlations between the target variables/series can also provide additional information for the prediction task, and can be exploited as temporal features with time series operators. The model can also be further generalized to panel data case, or applied to spatiotemporal applications. With additional data from the spatial/instance level dimension, one can increase the resolution of model predictions.

Another natural extension would enable a data-driven selection of words on social media which are found to correlate with economic activity [14]. While a small set of economically themed terms were used in the present study, there is potential improvement available if, for example, proxies for fear about losing one's job is found to correlate with future job loss.

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unemployment	unemployment benefits	unemployment rate	
unemployment office	pa unemployment	claim unemployment	
ny unemployment	nys unemployment	ohio unemployment	
unemployment florida	unemployment extension	texas unemployment	
nj unemployment	unemployment number	file unemployment	
unemployment insurance	california unemployment	unemployed	
unemployment oregon	new york unemployment	indiana unemployment	
unemployment washington	unemployment wisconsin	unemployment online	
unemployment login			

In this part, we provide the terms that is used in the Google Trends data set. Twenty five terms, which are listed in Table S1, are used as additional features in the US level unemployment prediction model with Google trends [19].

TABLE S1. Top 25 search query terms related to "unemployment" that is used in the Google Trends data.

1. US unemployment MAE

Table S2 shows the results in MAE for four different prediction tasks: nowcast, prediction for future i weeks with i = 1, 2, 3. The models without the exogenous social media data are the first two columns (having the lowest MAE marked with asterisk), while the models with the social media data are the last two columns (having the lowest MAE marked with asterisk). The overall lowest MAE are in bold face. As we can see from the results, the proposed model outperforms the origin model in most cases.

Appendix B: State level unemployment MAE

Figure S1 presents the MAE of the models applied on multiples states from 2016 to 2019 for the 3 weeks prediction. The original PRISM model is in red (original), while the GPRISM model by adding moving average and rate of change features is in green (add), while the GPRISM model with additional Twitter data is in blue (add twitter). As we can see from Figure 6, the GPRISM model has relatively lower MAE in most of the cases.

task	dates	original	MR	original/G	MR/T
nowcast	2010-2014	23158	*21071	*16914	21185
	2012-2016	*12140	13158	13419	*13114
	2014-2018	13086	*11922	*11088	11965
	2016-2020	11247	*10083	10616	*10076
pred.1	2010-2014	23758	*21463	21634	*21380
	2012-2016	*12506	12931	14482	*13025
	2014-2018	13235	*11935	12937	*11645
	2016-2020	10862	*10327	10332	*10212
pred.2	2010-2014	24021	*22144	22642	*22028
	2012-2016	*12399	12693	14323	*12588
	2014-2018	13035	*11875	12636	*11769
	2016-2020	10965	*10218	10558	*10456
pred.3	2010-2014	24904	*22767	23169	*22998
	2012-2016	*11941	12690	14486	*12419
	2014-2018	13599	*12320	13288	*12654
	2016-2020	10579	*10333	10615	*9924

TABLE S2. The MAE for the US level unemployment claim results. Four tasks are considered here, i.e. nowcast, future one, two, three weeks ahead prediction with four time ranges (2010-2014, 2012-2016, 2014-2018, and 2016-2020). Moreover, four models are compared here in the last columns, the original model (original), the model with additional moving average and rate of change features (MR), the original model with the Google Trends data (original/G) and the MR model with the Twitter data (MR/T). The first two models do not use the exogenous features, while the last two models use social media features. For each of the simulation scenario (row), the smallest error among the four models is in bold face, while the smaller one among the two models (for either without social media models, and with social media models) is denoted with an asterisk.



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FIG. S1. The state level unemployment initial claim results for the future three-week prediction task. The x-axis is the years and the y-axis is the prediction RMSE results in thousands. Three models are compared here: the original model (blue), the model with additional moving average and rate of change features (red), and the model with additional features together with the Twitter data.