Using Variable Length Google Search Volume Time-Series to Predict Natural Gas Prices with LSTMs

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Abstract

The ability to accurately project the price of commodities is one of the most useful applications of deep learning. It finds use from hedge funds seeking to maximize profit to public administrations modelling the outcomes of different policies. In the typical year, these algorithms are quite successful, at least more so than their human counterparts. However, these models have almost always failed to predict drastic economic downturns such as the crash of oil in 2020 or the now expected crashes of Bitcoin. It's critical to everyone that we can prepare for sudden events that can drastically alter the markets. Building off of the work of Tang et al. [12], we use historical commodity prices along with Google search trends and news report sentimentatlity to hopefully achieve better commodity price predictions both in normal and abnormal times. In order to accomplish this task, we will use stacked LSTMs and BiLSTMs and perform a Bayesian search over the models hyperparameters. We will compare our results with those from similar papers.

1. Introduction

The price fluctuation of good and stocks are often difficult to predict due to the numerous amounts of variables that play an important role of the price function. While there exists research that reflects on those expected variables [9]. Additionally, the research conducted which compares multiple results comprised from other researchers and their unique test leading to their results [10]. The importance of being able to accurately predict the price of commodities is vital to creating plans to aid those in need. The more accurate our forecasting ability is, the better prepared we can hope to be in uncertain times. It would allow emergency services and first responders to allocate enough supplies in the event of unpredictable events that could cause server damage to our infrastructure. However, there has been minimal research on the price fluctuation of goods and stocks due to external events, such as war, pandemics, or environmental catastrophes. While reports have been brought up that show certain effects of specific tragedies, such as the COVID-19 pandemic report [6]. The rate that prices fluctuate of goods and stocks during times of crisis and compared to other times of crisis could potentially help uncover areas which are most impacted. Including opportunities for potential preventive measures to attempt to thwart a severe effect.

The source code for our project can be found at https://www.github.org/Nragis/cs4263-project.

2. Related Work

Our work builds off of a sequence of papers, all working on the NYMEX natural gas prices dataset.

In their paper, Su et al., 2019 [11] present the application of four different machine learning algorithms including Gaussian process regression (GPR), gradient boosting machines (GBM), support vector machines (SVN) and artificial neural networks (ANN) for the monthly prediction of natural gas spot prices.

Building off of the work of Su et al., Ali, 2020 [2] and Ali et al., 2021 [3] test out two more algorithms, LSBoost and a deep neural network (DNN) respectively. Both of these models, specifically the DNN far outperformed the four models proposed by [11].

Finally, Tang et al, 2019 [12] takes an alternative improvement on the work of [11]. In their paper, they use a similar shallow ANN model, but they significantly improve the data used by using sentiment analyzed yahoo finance articles and daily google search volume for "Natural Gas". In a direct self-comparison, they found that the model given the google search volume history far outperformed the model with only historical prices data and the model that also had sentiment analyzed yahoo finance articles. Finally, Tang et al.'s work was on the four futures prices rather than the spot price.

3. Proposed Approach

In this paper, we combine the methods used in the papers above along with a few additions to produce a model that can accurately predict Natural Gas futures prices a day into the future. We will combine the data improvements of [12] and the model improvements of [3] to produce results far outperforming either work. In addition, we will make improvements on top of both papers in both categories.

We will utilize variable time-length time series features to predict fixed time-length labels. Our features will span all the prior data that we have, rather than being restricted by a time-window. To help us predict futures prices, we will include historical natural gas futures and spot prices. Additionally, we will use google search volumes for terms we chose related to "Natural Gas" in order to demonstrate public interest in a topic over time.

Finally, we will use LSTMs rather than simple feed forward perceptrons to perform a more powerful analysis on the time-series features. Following these LSTMs, we will have a dense feed forward network to process the output of the LSTM layers.

4. Data

4.1. Labels

To be able to compare directly with Tang et al. [12], we will use the same daily NYMEX natural gas futures prices from the US Energy Information Administration website (https://www.eia.gov/). These futures are for 1 month, 2 month, 3 month, and 4 month time periods. In alignment with Tang, we will be using data from these four contracts from January 2013 to June 2019. 1,638 records in total. Then, we will use simple linear interpolation to fill in any days without an entry like weekends or holidays. We end up with data from every day between January 2, 2013 to June 28, 2019, or 2,369 records total.

Finally, we take the logarithm of every data point to eliminate the exponential nature of financial data and standardize each column seperately using following equations for each element

$$x' = \frac{(x-\mu)}{\sigma} \tag{1}$$

Figure 1. Data descriptions of NYMEX futures prices from Jan 2, 2013 to June 28, 2019.

	Mean	Std Dev	Skew	Kurtosis
Futures 1	3.172	0.718	0.637	0.202
Futures 2	3.302	0.683	0.501	-0.405
Futures 3	3.232	0.660	0.461	-0.540
Futures 4	3.249	0.637	0.491	-0.492

where μ is the mean of the column and σ is the standard deviation.

Figure 2. Data descriptions of regularized NYMEX futures prices from Jan 2, 2013 to June 28, 2019

Regularized	Mean	Std Dev	Skew	Kurtosis
Futures 1	0	1.0	0.033	-0.087
Futures 2	0	1.0	0.026	-0.334
Futures 3	0	1.0	0.040	-0.475
Futures 4	0	1.0	0.091	-0.499

4.2. Features

4.2.1 NYMEX

We will be using historical data from the same NYMEX dataset mentioned above including the natural gas spot prices we did not use for our labels. However, we will nnow be using data ranging from January 5, 2004 to June 28, 2019, filling empty days using the same interpolation methods. We end up with 5,654 records of data, each with five points: one spot price and four futures prices. See Figure 3 for our graph of the NYMEX dataset.

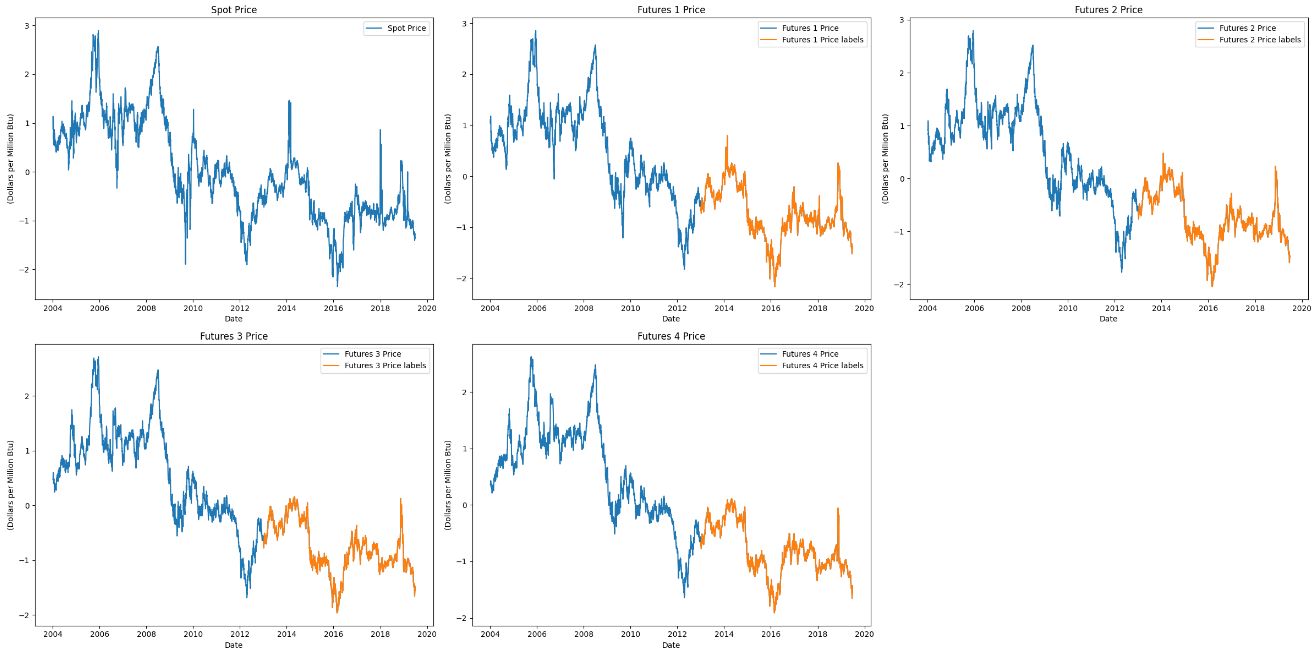
We then regularize the data exactly as we did to our label data.

4.2.2 Google Trends

We will be using Google Trends (https://trends.google.com/) as our source for Google search history data. In this paper, we will be using the daily search volume data of 14 different terms, including "Natural Gas" from January 5, 2004 to June 28, 2019. We end up with the same number of 5,654 records as we saw in our NYMEX features. However, for our google trends dataset, we have 14 columns, one for each search term. See Figure 4 for data descriptive statistics and Figure 5 for each series plotted (by the month).

Each column is not directly comparable with the other columns, and is only comparable with itself. For example, if "Natural Gas" has 23 for a day while "Recession" has a 73, this does not mean that "Recession" was searched more that day. This only means that "Recession" was searched

Figure 3. NYMEX Futures Prices from Jan 5, 2004 to June 28, 2019. Labels in orange and features in both blue and orange.



more on this day than a day where "Recession" is less than 73.

Figure 4. Data descriptions of daily Google search volume from Jan 5, 2004 to June 28, 2019.

	Mean	Std Dev	Skew	Kurtosis
Natural Gas	51.95	10.62	0.181	0.758
Oil	44.42	0.683	0.374	-0.898
Coal	24.19	0.660	0.368	0.276
Nuclear Power	5.662	4.064	7.544	135.1
Wind Power	20.34	13.15	1.396	2.496
Hydroelectric	15.68	12.59	0.852	0.424
Solar Power	35.28	12.69	0.676	0.697
Gold	40.15	13.01	-0.040	0.627
Silver	47.10	10.54	-0.224	0.176
Platinum	43.51	8.671	0.325	1.355
Copper	58.34	12.92	0.015	-0.237
Biofuel	12.82	12.15	1.762	4.112
Recession	5.728	6.258	3.348	16.91
CPI	20.55	11.41	1.031	1.893

4.3. Formatting Data

Instead of our features consisting of one or N days prior to the day we're trying to predict (our label) using a time-series window. We will be using variable length time series features spanning from the beginning of our dataset to the day immediately prior to our label. This allows us to have as much information as possible, given our datasets, for each prediction.

The input to our model will look like $(Batch, Time, Features)$ where $Batch$ is fixed at 16, $Time$ is variable, and $Feature$ is fixed at 19 (5 NYMEX and 14 Google).

The output of our model will be fixed however, looking like $(Batch, 1, Labels)$ where $Batch$ is 16, and $Labels$ is 4 (NYMEX Futures).

5. Metrics

In alignment with Tang, we will use mean absolute error (MAE) and root mean square error (RMSE) to compare results. Our goal is to minimize these values, indicating a more accurate regression.

$$MAE = \frac{1}{N}\sum_{i}^{N}|y_i - \hat{y_i}| \tag{2}$$

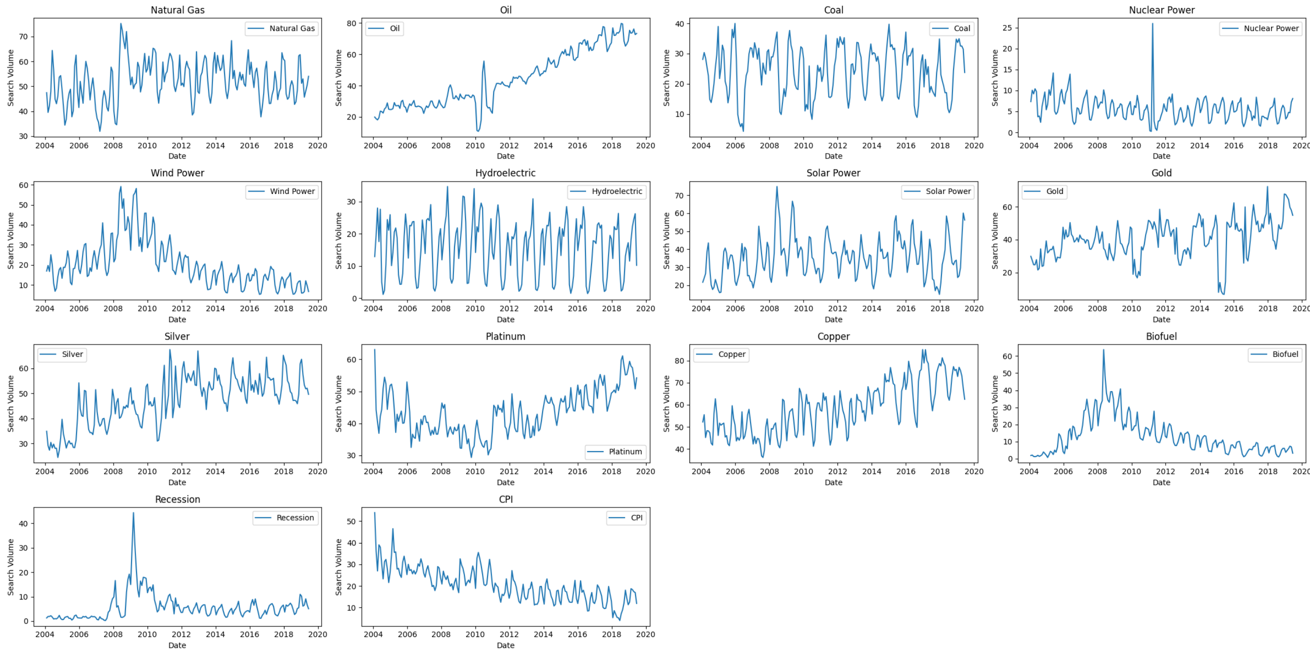
$$RMSE = \sqrt{\frac{1}{N}\sum_{i}^{N}(y_i - \hat{y_i})^2} \tag{3}$$

Where y_i and $\hat{y_i}$ are the real and predicted values respectively.

6. Results

We used Python3 for all of our code. We used Pytrends for scraping Google Trends data, and we use Pandas [8]

Figure 5. Monthly Google search volume from Jan 5, 2004 to June 28, 2019



for our data formatting and preprocessing stages of our research. Finally, we used Keras [4], and Tensorflow [1] for creating, training, and testing our models. Finally, we used Matplotlib [5] to create all of our plots.

We used a Tensorflow Dataset from generators rather than RaggedTensors to get variable time length tensors from our dataset and handle batching/shuffling. We also used 80% of the data for training, 10% for validation, and 10% for testing in order to help prevent under/overfitting and select the best model.

We experimented with both stacked LSTMs and stacked BiLSTMs followed by several layers of densely connected perceptrons, and finally an output layer with a Mean-Squared-Error loss function. To find the best model for our data, we performed a Bayesian hyperparameter optimization using Keras Tuner [7] over the hyperparameter dimensions listed in Figure 6). We ran this search for 50 trials, and let each model train for 50 epochs a piece.

The best hyperparameters we found are shown in Figure 7. Note the lack of layers. We will discuss this in Section 8.

After finding the optimal hyperparameters, we let the model train for a total of 250 epochs, and saved the model with the lowest validation loss. See Figure 9 to see the training and validation loss over training epochs.

After training, we then tested these models on the test dataset we set aside previously, and evaluated the MAE and RMSE as shown above. The results are in Figure 10

Figure 8 shows the predictions of our Stacked BiLSTM model overlayed on top of the correct labels. As you can see, our model is very close to exactly correct for most of the time-series. Differing on average only 0.026 standard deviations from the correct value.

Figure 6. Hyperparameter distrbutions searched for our models

Name	Type	Min	Max	Distribution(Step)
LSTM Layers	Int	1	5	Uniform(1)
LSTM Nodes	Int	32	256	Uniform(32)
Dense Layers	Int	1	3	Uniform(1)
Dense Nodes	Int	256	2048	Uniform(256)
Dropout Rate	Float	0	0.999	Uniform
Learning Rate	Float	1e-6	1e-1	Log
Beta_1	Float	0.8	0.999	Linear

Figure 7. Best hyperparamers found by search and overall training loss

Name	Stacked LSTM	Stacked BiLSTM
LSTM Layers	1	1
LSTM Nodes	256	32
Dense Layers	1	1
Dense Nodes	2048	2048
Dropout Rate	0.0	0.0
Learning Rate	3e-5	1e-2
Beta_1	0.8	0.8
Loss	0.004	0.004

Figure 8. Stacked BiLSTM 1-day NYMEX futures prices predictions compared with their true values

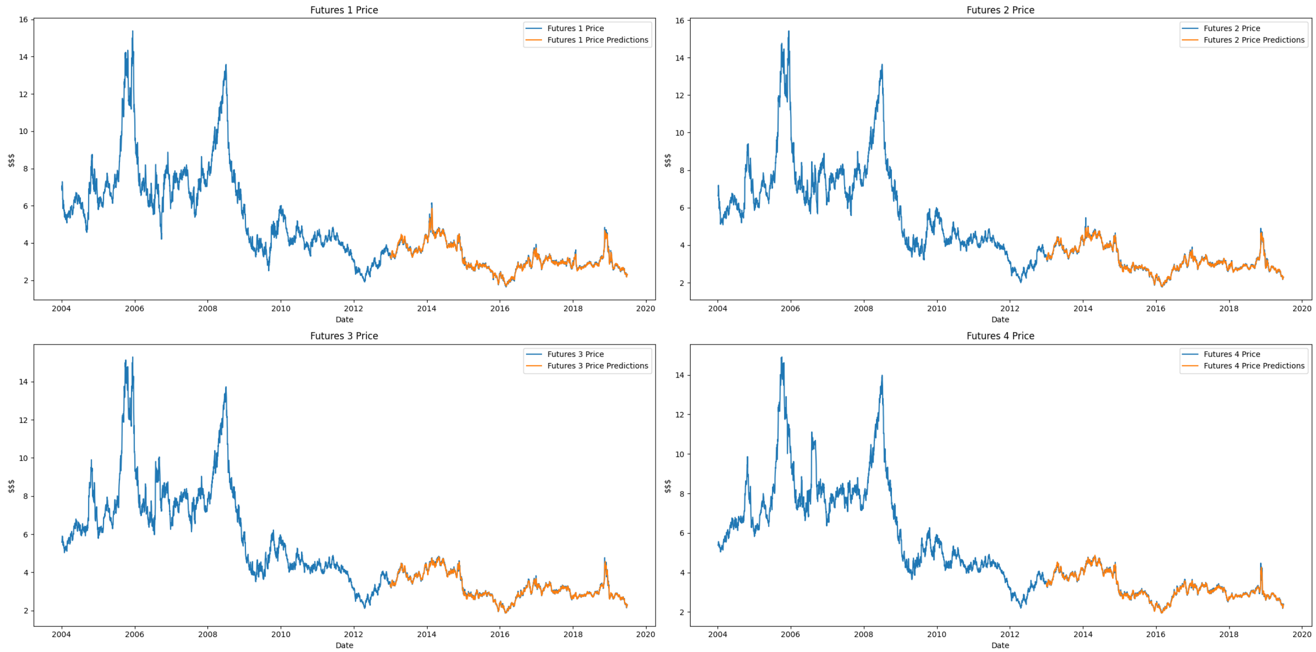


Figure 9. Training loss (blue) and validation loss (orange) over epochs trained of our Stacked BiLSTM model

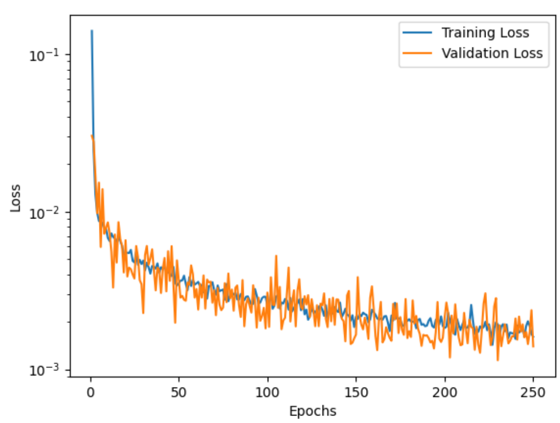


Figure 10. Comparison of Stacked LSTM to Stacked BiLSTM on predicting Natural Gas futures prices

Model	MAE	RMSE
Stacked LSTM	0.0326	0.0435
Stacked BiLSTM	0.0261	0.0335

7. Comparisons to Prior Work

We will be comparing our results with the results of the four other papers mentioned in Section 2: Su et al. [11]. Ali et al., 2020 [2], Ali et al., 2021 [3], and Tang et al. [12].

While, the first 4 all are predicting Natural Gas spot prices, Tang, like us, is predicting Natural Gas futures prices. Thus, since Tang is predicting 4 seperate data points, we must adjust their metrics accordingly: sum seperate MAEs for total MAE and square, sum, then root seperate RMSEs for total RMSE.

If we had more time, we would adapt out model to predict spot prices as well to directly compare to the first four papers better. However, since we do not, we will multiply each MAE by four and each RMSE by two since they were metrics on a single length vector, while our metrics are on a length four vector. We do this to simulate the model having four identically good outputs. This is not a perfect substitution by a long shot, but it allows us to compare our results more broadly.

Finally, we take the best model from each paper for predicting one day ahead. For this reason, we will only be comparing with our Stacked BiLSTM.

The adjusted metrics from each paper next to our own can be found in Figure 11.

As we can see above, our model performed much better than all the other models. We performed over twice as good as even the prior best model.

This improvement can likely be dually attributed to a

Figure 11. Comparison of Stacked LSTM to Stacked BiLSTM on predicting Natural Gas futures prices

Author	Model	MAE	RMSE
Su et al. [11]	ANN		1.4494
Ali et al., 2020 [2]	LSBoost		1.1398
Ali et al., 2021 [3]	DNN		0.4880
Tang et al., 2021 [12]	ANN	0.3663	0.2548
This Study	BiLSTM	0.0261	0.0355

stronger dataset, both from more google search terms, and from a variable time length feature, and to a stronger model, a stacked BiLSTM.

8. Conclusion and Future Work

While our model performed quite well, we have already identified many ways in which it could be easily improved.

First, our computation power was limited, likely resulting in our optimal lstm and dense depth being stunted below what they could be. We believe that with more computation time and power, a model with greater depth could outperform our model. This is supported by the fact that we didn't see even any overfitting in Figure 9.

Second, the sentiment analysis used in Tang et al. could be used in conjunction with google search volume to create an even more knowledgeable and hopefully superior model.

Third, a search could be performed over all the top search trends to find out which trends corrolate the strongest with the NYMEX prices. Alternatively, one could perform a dimensionality reduction on a larger search volume dataset to feed directly into the model.

Fourth, a seperate model could be created and trained for each of the labels (including spot price). This would allow the model to specialize more, and you could take the output of all 4 (or 5) of these models to get your overall output.

Finally, the ideas in this paper could be expanded to predict prices greater than one day in the future. Either, one could train a new model for each time delta they would like to predict (1 day, 2 days, 3 days...), or one could train a single model, and run a recursive calculation, concatentating the predictions for one day into the future onto the features, and feeding that new time series into the model to predict two days into the future.

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