Can we predict fire with weather data?

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Abstract

Contents

1 Introduction

The weather has literally been the hot topic of discussion in recent times. One aspect of weather data is that, when it is combined with other data sets, it can be used to predict varied different aspects related to the society. For example, one particular aspect could be how does traffic conditions change based on the

weather in a particular city or if there is a correlation between crime rates and weather conditions. In this project, we are trying to address a more important issue of predicting wildfires in different cities based on weather conditions. Since the future weather data is readily available these days, a good model would help predict these wildfires in advance and take necessary precautions to completely avoid it. This would help avoid human and wildlife loss. It would also help contain the impact of these wildfires on the environment which increases the content of poisonous gases in the environment, making the nearby uninhabitable.

Wildfires are growing in frequency and intensity by the day. The 2019 wildfire season of California has more than 6800 fires recorded by the US Forest Service and approximately 250000 acres of burnt land. These wildfires could be the result of foul human activities but there has been a lot of speculation on the high correlation of these fires with the weather. Climate change is not only making the fire season longer but on average much more intense. The idea is to use the model to predict these fires in advance, thereby reducing such incidents.

2 EDA

2.1 Covariates

To build our final dataset, we wrote a python script to get the geographical coordinate (latitude and longitude) of all cities and built tables with missing information about fires. Then, we went through the database with information about fires and filled in the fire indicator in the tables using the coordinates obtained in the previous step.

The features that we have in our final dataset are:

Table 1: Features

Covariate	Type	Description
Humidity	Real	Humidity at a given hour
Pressure	Real	Air Pressure at a given hour
Temperature	Real	Air temperature at a given hour
Weather Description	Categorical	Description of weather at a given time, e.g. “sky is ckear”
WindDirection	Real	Wind direction in degrees at a given time, North being 0°, clock-wise being positive direction
WindSpeed	Real	Wind speed at a given time

Table 2: Response

Response	Type	Description
Fire	Boolean	Whether there’s a fire at a given hour

2.2 Basic Statistics

The size of the dataset in the Fires table is: $18,800,465 \times 39$, the size of the weather table is: $1,629,108 \times 10$ and the size of the final table is: $1,629,108 \times 11$. The following figures help illustrate what the final dataset looks like:

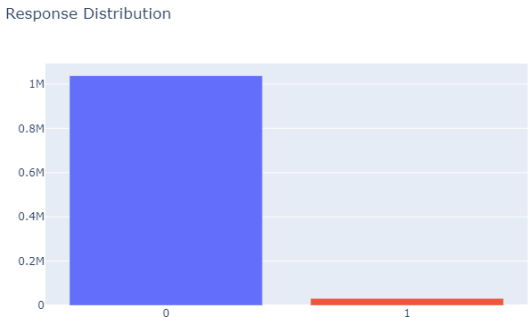

Figure 1: Response Distribution

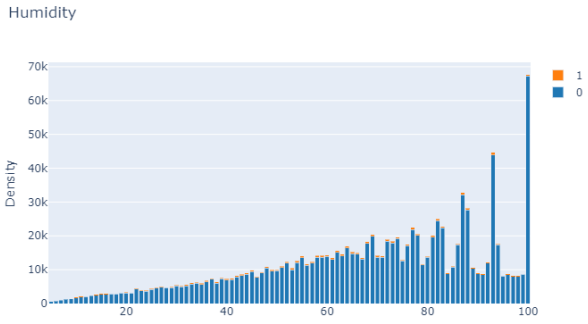

Figure 2: Histogram of Humidity

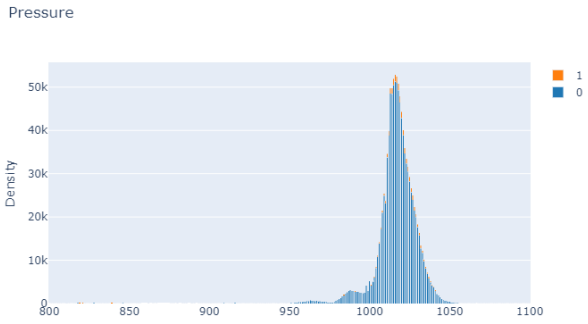

Figure 3: Histogram of Pressure

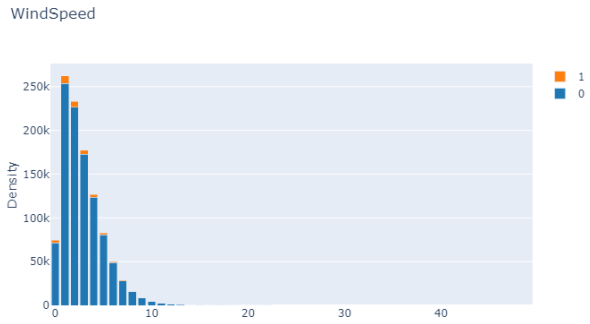

Figure 4: Histogram of Wind Speed

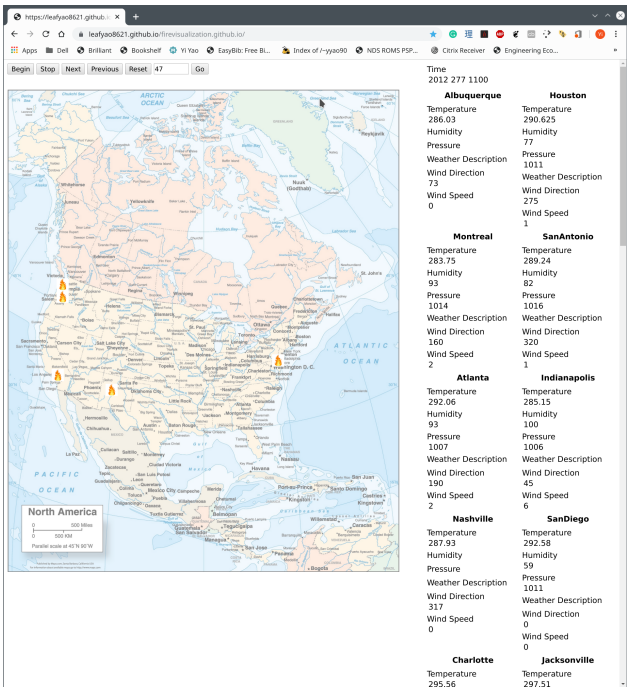

Figure 5: Screenshot from Visualization Tool

3 Brief Description of Algorithms and Definitions Used

3.1 XGBoost

XGBoost is an implementation of gradient boosted decision trees designed for speed and performance.Boosting is an ensemble technique where new models are added to correct the errors made by existing models. Models are added sequentially until no further improvements can be made. A popular example is the AdaBoost algorithm that weights data points that are hard to predict. Gradient boosting is an approach where new models are created that predict the residuals or errors of prior models and then added together to make the final prediction. It is called gradient boosting because it uses a gradient descent algorithm to minimize the loss when adding new models.

3.2 SVM

A support-vector machine constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks like outliers detection.[3] Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin, the lower the generalization error of the classifier.

3.3 Decision Trees

A decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements.

3.4 DBScan

DBSCAN - Density-Based Spatial Clustering of Applications with Noise. DBScan finds core samples of high density and expands clusters from them. It is good for data which contains clusters of similar density.

3.5 Balanced Accuracy

The balanced accuracy in binary and multiclass classification problems to deal with imbalanced datasets. It is defined as the average of recall obtained on each class.

4 Model Building and Accuracy Tuning

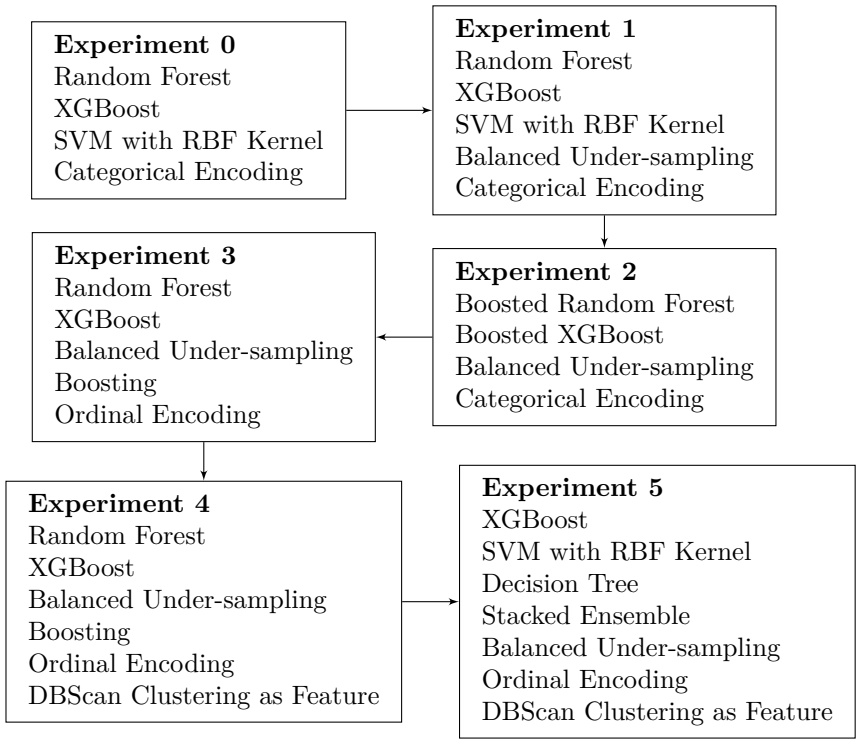

Figure 6: Flowchart of Experiments

4.1 Preliminary Analysis

4.1.1 Experiment 0 - Primitive Model Fitting

First, we fit XGBoost, Random Forest and SVM by using the entire dataset and found the accuracy to be quite low. The low accuracy could be because of the model overfitting. There are, afterall, 1M negative samples and roughly 25k positive samples.

4.1.2 Experiment 1 - Under-sampling

Recognizing the unbalanced nature of our dataset, we created a balanced training data set by combining all the positive samples with a random subset of all the negative samples. Using this balanced training data set, we fit XGBoost, Random Forest and SVM with RBF kernel. We observed a significant improvement in test accuracy in the XGBoost and Random Forest models; however, we have not observed any significant improvement in the SVM models.

Table 3: NewYork

Classifier	Meta Parameter	Training	Test
	n_estimators	bal_acc	bal_acc
XGBClassifier	99	0.6709	0.6778
RandomForestClassifier	81	0.7192	0.7144

4.2 Accurarcy Tuning

4.2.1 Experiment 2 - Boosting Models Fitted with Balanced Sub-samples

Having the possibility of underfitting due to under-sampling in mind, we have experimented with boosting to increase accuracy. By keeping all the positive samples and randomly resampling negative samples equal to the number of positive samples, we have kept the balance of the training data set while making better use of the data set we have available.

4.2.2 Experiment 3 - Clusters of Many-hot Encoding

Having observed some order in the covariate "Weather Description", we have experimented with many-hot encoding for ordinal variables. Since an overall could not be established by the team, we have turned to many-hot encoding on 3 clusters of levels and one-hot encoding on the remaining levels. As for models, we continued to use the boosted algorithms in the previous experiment.

4.2.3 Experiment 4 - DBScan Clustering as Feature

We have also experimented adding one-hot encoded output of an unsupervised clustering algorithm, DBScan as covariates to the dataset to be fitted with supervised models.

4.2.4 Experiment 5 - Stacked Ensemble

In this experiment, we explore feature engineering through the addition of two features, one which is to use the weather types as oridinal features and another one by grouping them using DBScan Algorithm and using their groups as features. We utilize the power of ensemble learning where we combine various weak learners in order to make better predictions. The algorithms that we picked are SVMs with RBF Kernel, Decision

trees and XGBoost. These were identified to perform poorly with the original dataset fed as a whole. Here is what we found.

5 Conclusion

Overall, our objective was to be able to predict fires given weather data. Our accuracy depended upon the methods we picked to push the accuracy up. We identify that we hit the information "roof" when it comes to how well we could predict the fire. Some other interesting observations are as follows:

* The XGBoost algorithm when fed with one round of undersampling with the no. of estimators higher than 25 seemed to have learned all the information available.
* The stacked ensemble algorithm performed the best for the cities shown in this report. It's interesting to note that although weak learners do not capture complex information, when we differ the way they capture that information, we see that they perform well collectively without having to weigh it in the final prediction.
* The information roof that we clearly hit which may indicate that we needed more real features that inherently affect the prediction. That may be the error that we seem not able to avoid.
* And to address the elephant in the room, Could we predict the recent fires in California? **Answer**
* This project may be a weapon of math destruction because

References

[1] Brodersen, K. H., Ong, C. S., Stephan, K. E., and Buhmann, J. M. The balanced accuracy and its posterior distribution.

[2] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. Scikit-learn: Machine learning in python. *Journal of Machine Learning Research 12* (2011), 2825–2830.