

LiBerTY – Store Sales Forecast with Machine Learning

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November 2022

Abstract

LiBerTY is an ensemble regression engine to predict the store sales given past sales figures. It employed a variety of robust and general data analysis and machine learning techniques to achieve good result within a short amount of time, competitive to existing best-known result while being robust and generally applicable to other problems.

Introduction¹

The ability to predict the sales of a variety of stores is highly sought out in supply chain logistics, as it finds applications in increasing customer satisfaction and reducing food waste. We are proposing use of multiple Supervised Learning methods to predict the sales of stores based on time series dataset of Corporación Favorita, an Ecuador based grocery retailer. Ecuador is a country whose economy is strongly dependent on the oil and fluctuates with the price of oil.

Our work focused on a dataset from an ongoing Kaggle competition [1], “Store Sales – Time Series Forecasting”. The dataset includes multiple csv sheets of time series data. We will try to evaluate the different aspects that might impact the sales in a store like Holiday seasons, Oil prices and historical sales data across all stores.

We plan on using different Supervised Learning models to predict the prices and then evaluate which of those

models give out the best results. Supervised learning approach works best in this case, as we have huge time series data of both input and the output parameters mentioned above. We applied several transformation and optimization to improve the data quality in preparation for the optimization. To seek the best store sales prediction, We have evaluated several models including linear regression, Gradient Boost (XGBoost), Light GBM, Random Forest, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM). We found XGBoost to be the best- performing individual method, and focused on hyper-parameter tuning via grid search. We further employed ensemble prediction to further improve our results, achieving a notable RMSLE score of 0.425 within our compressed project time-frame.

Related Work²

The store-sales prediction problem can be directly formulated as a multivariate multiple time-series regression problems. Prior to the modern age of machine learning, Auto-Regressive Moving Average (ARMA) was one of the most well-known technique, first proposed by [2] in his Ph.D thesis, and later popularized by Box and Jenkins [3], according to Wikipedia [4]. ARMA provides a succinct description of a (weakly) stationary stochastic process in terms of two variables, one for the auto-regression (AR), and the second for the moving average (MA). ARIMA, where “I” stands for Integrated and “S” stands for seasonal, are variants of ARMA appropriate for cases when data show evidence of non-stationarity, such as a long-term upward trend, and seasonality.

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¹Suhas’s section

²Hardy’s section, and others

Random forest, first proposed by Ho [5] in 2008, is a well-established technique that relies on an ensemble learning method for classification or regression based on a collection of decision trees at training time. For regression tasks, usually the average prediction of the individual trees is taken, thereby correcting the tendency of individual trees to overfit to their training set.

XGBoost [6], first released in 2016, is a popular open-source software library which provides a gradient boosting decision tree (GBDT) framework for a plethora of program languages.

LightGBM [7] is a gradient boosting decision tree (GBDT) developed by Microsoft with the explicit goal of speeding up the training process of conventional GBDT by up to 20X while achieving almost the same accuracy. The huge runtime efficiency makes it a popular GBDT technique in recent years.

- Support Vector Machine(SVM) /Support Vector Regression (SVR)
- Long Short-Term Memory (LSTM)

Data Preparation³

Our main dataset contained the daily sales figures of 54 stores of Corporación Favorita, from January 1st, 2013 to August 15th, 2017, except Christmas Days when the stores were all closed. We are also given the locations (city and state) of each store. There are a total of 33 different product families, from *Automobile* to *Seafood*. Note that not all stores sell all products. Moreover, there were some stores that opened only after the data collection has begun, and sometimes the sales figures of certain stores were missing over a few months. All stores in the dataset were still in business as of August 15th, 2017. After properly dealing with missing data, Christmas, and stores that were yet to open, we would have a dataset made of $(\#days) \times (\#stores) \times (\#families) = 1688 \times 54 \times 33 = 3008016$ numbers. We were also given the daily oil price over the same period of time, as well as the dates of the regional or national holidays.

³Hardy's section

These information could have a tremendous impact on the accuracy of our prediction, and hence must be considered.

Our job is to predict the sales figures for each store between August 16th, 2017 and August 31st, 2017, inclusive.

The preprocessing of data will include checking for missing values and if found, imputing them so that no data is disregarded. We have also checked for frequency distribution of data elements as part of Data exploration. We have calculated and plotted correlation mapping to establish the correlations between different input and output parameters such as holiday events, oil prices, transactions per store type, dates of salary, natural calamities etc.

Experimental Setup⁴

Talk about the experimental setup, including how to

Part I⁵

- Linear regression
- XGBoost
- LightGBM
- Grid search technique to improve XGBoost performance

Part II⁶

- LSTM, architecture, slightly different flow

Part III⁷

- Ensemble approach. You can quote this [8]
- Final result
- Visualization

⁴Hardy's section

⁵Loukya's section

⁶Cody's section

⁷Suhas's section

Discussion⁸

- Possible enhancements

Conclusions⁹

In this work, we have presented LiBerTY, an ensemble regression engine that successfully predicts the store sales, which successfully employed a variety of data engineering and machine learning techniques.

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⁸TBD

⁹Hardy