Machine Learning Engineer Nanodegree

Capstone Proposal

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Proposal

Domain Background

Demand predictions in supply chain managagemnt (SCM) and logistics have historically been a constant pressure to make them more precise (Thomas & Griffin, 1996). The reason for this is due to the fact that inaccurate forecasting results in either too low supply to fulfill the current market demand, or too much, which in turn results in increased holding costs from inventory. Common ways to predict demand in SCM have been statistical models such as the ARIMA model (Jaipuria & Mahapatra, 2014). Academic articles have tested and noted that more advanced neural networks does not show a statistically significant improvement over traditional statistical models such as Moving Average and ARIMA (Shukla & Jharkharia, 2011).

The key area of interest is: As an organisation grow larger, the more vital the precision in these predicitons become. Therefore, we will explore the possibility to utilise Machine Learning algorithms to predict the demand of certain products, in order for the SCM-team to make better planning for instance purchasing product components for an upcoming season.

Problem Statement

The problem organisations SCM-departments face is that inaccurate forecasting for future demand cost organisations a lot of either missed sales or increased costs due to handling and storage of inventory (Thomas & Griffin, 1996). Therefore, we will test the hypothesis of comapring classic and more common statistical demand forecasting models to the more recent neural networks and machine learning algorithms, to assess if they produce better results. This will be used for predicting the department-wide sales for each store for the following year given our dataset of 45 retail stores. With this set-up, we can see that it is quantifiable, measurable and replicable.

Datasets and Inputs

We will use the dataset provided by Manjeet Singh on Kaggle.com "Retail Data Analytics Historical sales data from 45 stores" link. We are provided with historical sales data for 45 stores located in different regions - each store contains a number of departments. The company also runs several promotional markdown events throughout the year. These markdowns precede prominent holidays, the four largest of which are the Super Bowl, Labor Day, Thanksgiving, and Christmas. The weeks including these holidays are weighted five times higher in the evaluation than non-holiday weeks.

In the dataset we find three separate files: Features, Sales and Stores

1. Features data set.csv

Contains data related to the store, department, and regional activity for the given dates.

- Store - the store number
- Date - the week
- Temperature - average temperature in the region
- Fuel_Price - cost of fuel in the region
- MarkDown1-5 - anonymized data related to promotional markdowns. MarkDown data is only available after * Nov 2011, and is not available for all stores all the time. Any missing value is marked with an NA
- CPI - the consumer price index
- Unemployment - the unemployment rate
- IsHoliday - whether the week is a special holiday week
- Sales

2. sales data-set.csv

Historical sales data, which covers to 2010-02-05 to 2012-11-01. Within this tab you will find the following fields:

- Store - the store number
- Dept - the department number
- Date - the week
- Weekly_Sales - sales for the given department in the given store
- IsHoliday - whether the week is a special holiday week

3. stores data-set.csv

Anonymized information about the 45 stores, indicating the type and size of store.

- The store number (anonomised)
- Type
- Size

Size of total dataset

The different files containts the following amount of data: * Features data set.csv - 182 rows, 12 columns * sales data-set.csv - 143 rows, 5 columns * Stores data-

set.csv - 45 rows, 3 columns

How will we work with these files

From my inital analysis, we will try to at least merge the features and sales data-set to find potentially find ways to utilise the data to improve our forecast. Some dates seems to be missing for the sales data vs the features data, but we will address that as we move on with the analysis to find the best forecast method.

Solution Statement

How we would solve this problem is to test the hypothesis of Neural Networks providing a better prediction compared to classical statistical models, such as the moving average. We will do this through analysing the historical patterns in combination with the added features mentioned to predict how tomorrows demand will look like.

Benchmark Model

The initial benchmark model will be a moving average model as it is a simple and computationally inexpensive model and/or potentially the ARIMA model (Shukla & Jharkharia, 2011), and use that prediction score as a benchmark when we compare it to our machine learning algortihm.

Evaluation Metrics

Ways to evalute the different models could include 1-3 of the following statistical measures of how accurate a forecast system is;

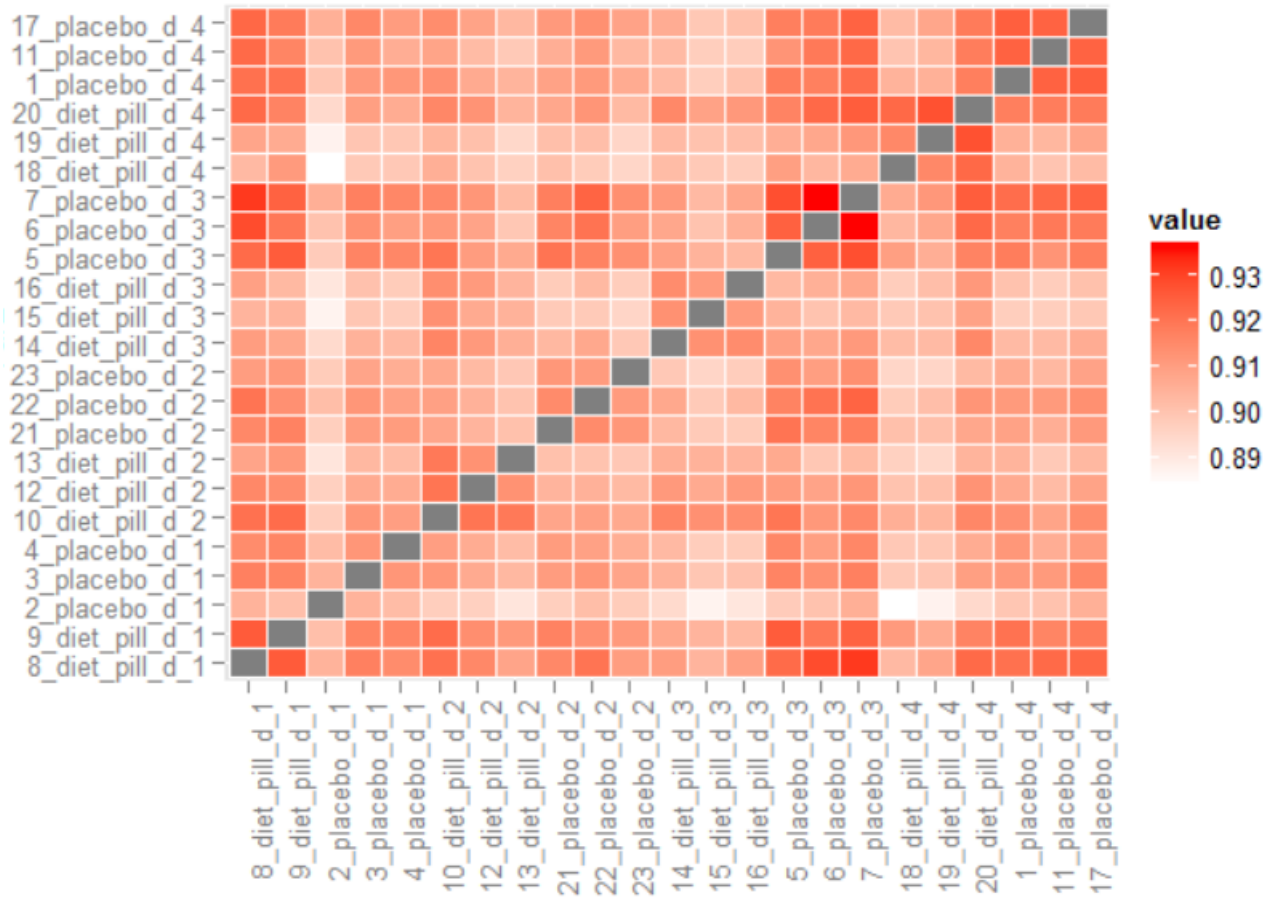
- mean squared error (MSE) - measures the average of the squares of the errors
- Root Mean Squared Error (RMSE) - the square root of the variance, known as the standard error
- Mean Absolute Percentage Error (MAPE) - measures the average of the absolute mean percentage error between the forecast and the actual demand for a specific time

Mean squared error	$\mathrm{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2$
Root mean squared error	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$
Mean absolute error	$\mathrm{MAE} = \frac{1}{n}\sum_{t=1}^{n} \lvert e_t \rvert$
Mean absolute percentage error	$\mathrm{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n} \left\lvert \frac{e_t}{y_t} \right\rvert$

All of which will help us to assess which models are providing us with the better demand forecast model. The smaller the number is (closer to 0), the better.

Project Design

1. To start we will set up a notebook instance and set up the training, validation and test data.
2. Then we will proceed to visualise the data to get a better grip of what it looks like and how the different categorical data could be helping in the predictive demand forecasting model. In this part, we will include a correlation heat map, to understand how the data affect each other. Similar to the one attached:



3. Then we will build our models -- In this case it seems fitting to test it with a moving average and a neural network to find some good predictions for the sales of the company.
4. Then compare the scores -- Comparing the different models form step 3, might be other considered when we get into the data if needed.
5. Finalise the results in a summary of what each model gave and what some notes in regards to the use of each model.

Before submitting your proposal, ask yourself. . .

- Does the proposal you have written follow a well-organized structure similar to that of the project template? **Answer**: Yes.
- Is each section (particularly **Solution Statement** and **Project Design**) written in a clear, concise and specific fashion? Are there any ambiguous terms or phrases that need clarification? **Answer:** Yes
- Would the intended audience of your project be able to understand your proposal?
- Have you properly proofread your proposal to assure there are minimal grammatical and spelling mistakes?
- Are all the resources used for this project correctly cited and referenced? **Answer:** Yes

References

Jaipuria, S., & Mahapatra, S. S. (2014). An improved demand forecasting method to reduce bullwhip effect in supply chains. Expert Systems with Applications, 41(5), 2395–2408. https://doi.org/10.1016/j.eswa.2013.09.038

Shukla, M., & Jharkharia, S. (2011). ARIMA models to forecast demand in fresh supply chains. International Journal of Operational Research, 11(1), 1. https://doi.org/10.1504/ijor.2011.040325

Thomas, D. J., & Griffin, P. M. (1996). Coordinated supply chain management. European Journal of Operational Research, 94(1), 1–15. https://doi.org/10.1016/0377-2217(96)00098-7