M5 Forecasting – Predicting Wallmart Sales

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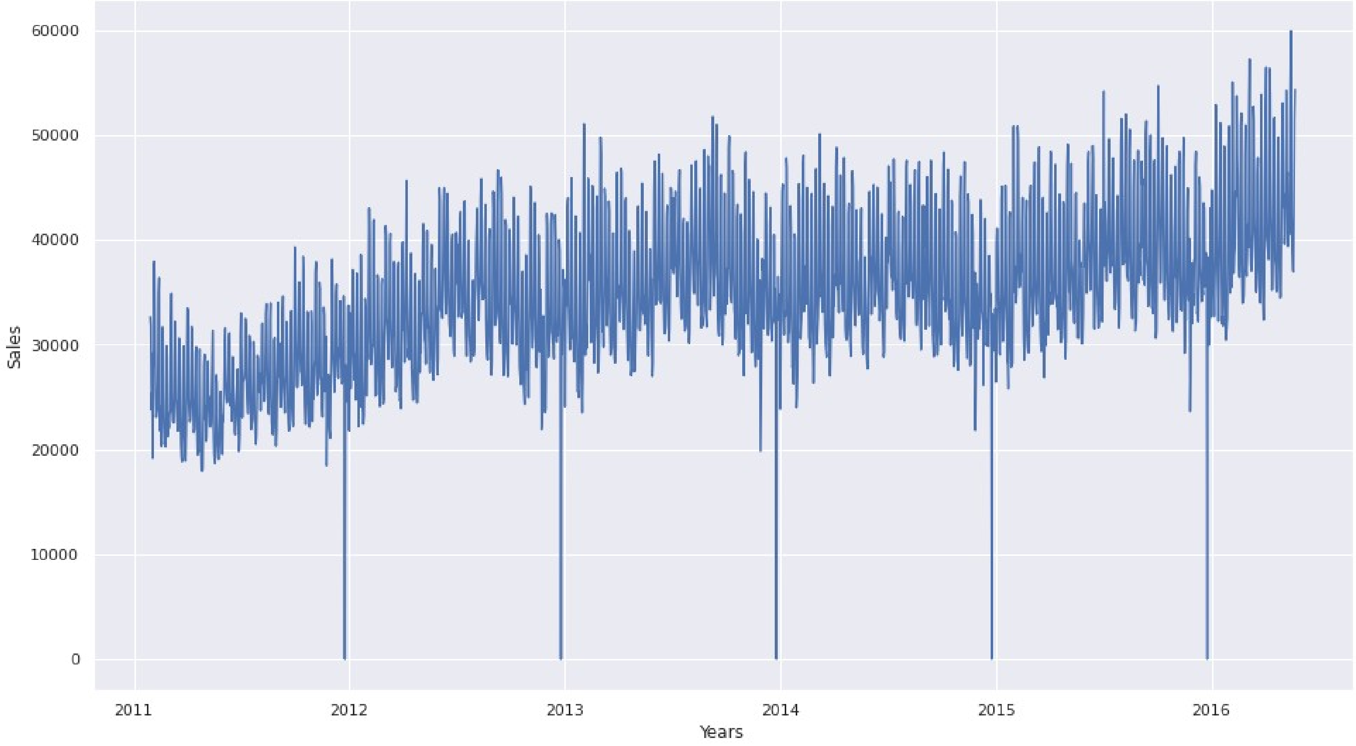
Problem and Target

The competition gives us the goal of predicting the amount of items sold in Wallmart stores. To make our prediction, we are provided with historical data of:

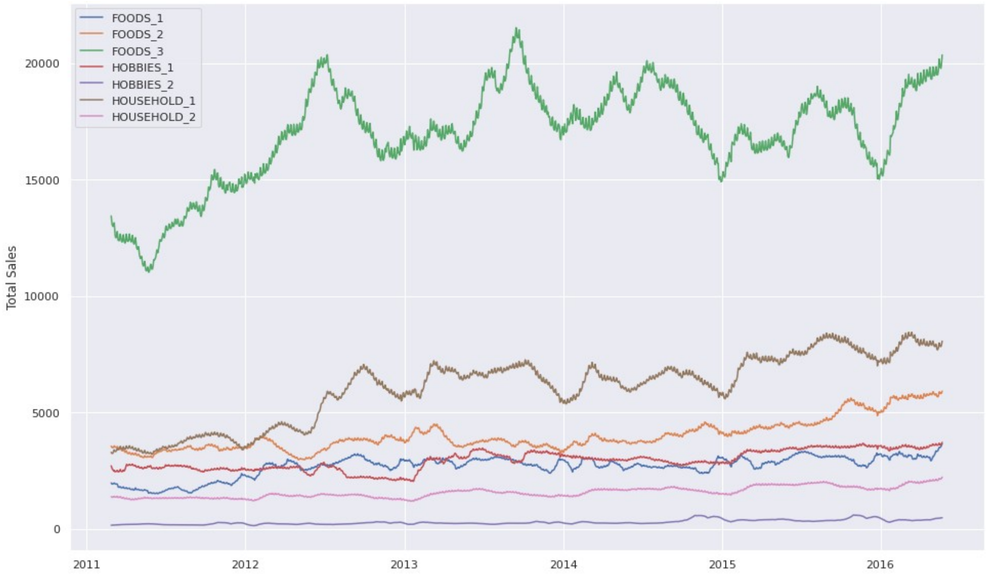
- Calendar data outlining any events, cultural, religious or othwerise
- Sales data of each product in each store on each day
- Product prices for each week

Dataset

- Sales fluctuate often
- Clear upwards trend
- A lot of noise
- Large amplitude



Breaking down the fluctuations



Sadly, even though the proportion of each product type is relatively stable with one noteable exception, our sales are still very unstable, even on a store basis. This means that the time component is crucial in our predictions.

Model Evaluation

- Given the competitive nature of the contest, we are only concerned with a single metric: the Weighted Root Mean Squared Scaled Error. This score determines the placings for the contest.

$$RMSSE = \sqrt{\frac{1}{h} \frac{\sum_{t=n+1}^{n+h} \left(Y_t - \widehat{Y}_t\right)^2}{\frac{1}{n-1} \sum_{t=2}^{n} \left(Y_t - Y_{t-1}\right)^2}}$$

$$WRMSSE = \sum_{i=1}^{42,840} w_i * RMSSE$$

Model 1 – Linear Regression

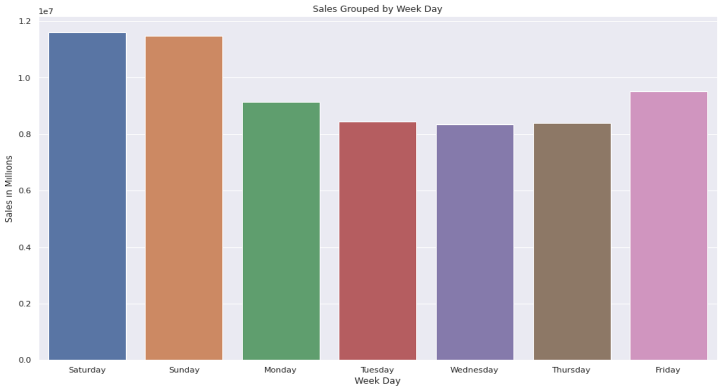
The idea behind this model is simple: we ignore the noise. Even though our data is very unstable, it showed a very clear and simple upwards trend.

```
rmse_train: 3.5637158109429197, rmse_test: 3.5780065258685196
```

Underwhelming. Could work for long term trends somewhat, but 28 days is far too small a timeframe for this kind of model.

Model 2 – Random Forest

Our hope is this model manages to identifiy events that simple sharp changes in our data. Like the impact of weekends.




```
rmse_train: 3.1610962650355, rmse_test: 3.248270722756284
```

… yeah no. Our data is too densely packed, and events are not impactful enough. This calls for a more sophisticated model.

Model 3 -LightGBM

- LGBM is a fantastic model for time series forecasting. It does however require proper tuning for great results. As such we will introduce two new special features: lags and rolling means.

```
train.columns
```

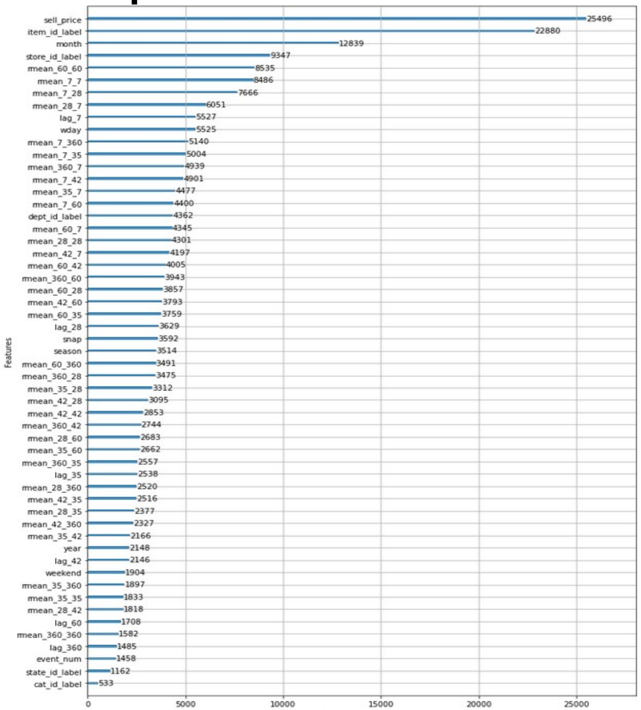
```
Index(['index', 'id', 'item_id', 'dept_id', 'cat_id', 'store_id', 'state_id',
       'wm_yr_wk', 'wday', 'month', 'year', 'items_sold', 'sell_price',
       'event_num', 'snap', 'weekend', 'season', 'item_id_label',
       'dept_id_label', 'cat_id_label', 'store_id_label', 'state_id_label',
       'lag_7', 'lag_28', 'lag_35', 'lag_42', 'lag_60', 'lag_360', 'rmean_7_7',
       'rmean_28_7', 'rmean_35_7', 'rmean_42_7', 'rmean_60_7', 'rmean_360_7',
       'rmean_7_28', 'rmean_28_28', 'rmean_35_28', 'rmean_42_28',
       'rmean_60_28', 'rmean_360_28', 'rmean_7_35', 'rmean_28_35',
       'rmean_35_35', 'rmean_42_35', 'rmean_60_35', 'rmean_360_35',
       'rmean_7_42', 'rmean_28_42', 'rmean_35_42', 'rmean_42_42',
       'rmean_60_42', 'rmean_360_42', 'rmean_7_60', 'rmean_28_60',
       'rmean_35_60', 'rmean_42_60', 'rmean_60_60', 'rmean_360_60',
       'rmean_7_360', 'rmean_28_360', 'rmean_35_360', 'rmean_42_360',
       'rmean_60_360', 'rmean_360_360'],
      dtype='object')
```

23385830 rows × 64 columns

Our train set is becoming gigantic.

Feature importance

Our model is very happy with the new features and incorporates a lot of them into our final predictions.



Final prediction

The model, unsurprisingly, vastly outperformed the other two:

- It incorporates specific time shifts very well (say week or month)
- Lags and rolling features work great for time series forecasting
- Cross validation was far more effective

```
rmse_train: 1.9160976387384971, rmse_test: 2.061217187706627
```

These values suggest that the model's prediction should be competitive on the competition leaderboard