Winning Solution of Kaggle Algorithmic Trading Challenge

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Outline

Overview

- Kaggle Algorithm Trading Challenge was organized by the Capital Markets Cooperative Research Center (CMCRC - www.cmcrc.com) in Macquarie University, Sydney, Australia.
- The timeline is from Nov 11, 2011 to Jan 8, 2012.
- Winning prize is cash $8,000 and consideration for entry to the CMCRC PhD program.
- The winning team goes to Ildefons Magrans de Abril and Masashi Sugiyama de Abril and Sugiyama (2013), two engineer researchers in Tokyo Institute of Technology, Japan.

Introduction

- The competition was to predict the short term response following large liquidity shocks.
- A liquidity shock is defined as any trade that changes the best bid or ask price.
- Liquidity shocks occur when a large (series of small) trade consumes all available volume of best offer.
- This kind of model can be used to optimize execution strategies of large transactions.
- Following a liquidity shock the spread may be temporarily widened, and/or result in permanent price shifts.

Training & Testing Dataset

- The training dataset consists of 754,018 samples of trade and quote data observations before and after a liquidity shock.
- There are 102 different securities of the London Stock Exchange (LSE) included.
- The liquidity shock takes place at time interval 51, i.e., time interval 1-50 are pre-liquidity and time interval 52-100 are post liquidity.
- The test dataset consists of 50000 samples similar to the training dataset but without the post-liquidity shock observations.

Training & Testing Dataset (Cont'd)

- Further variables
  - security id (*security_id*)
  - indicator of buyer or seller (*initiator*)
  - the volume-weighted average price causing the liquidity shock (*trade_vwap*)
  - the total size of the trade causing the liquidity shock (*trade_volume*)
- The test dataset consists of 50,000 samples similar to the training dataset but without post-liquidity-shock observations (i.e. time interval 51-100).
- The goodness of fit is measured by root-mean-square error (RMSE).

$$\textbf{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

Outline

Time Interval Partitioning Algorithm

- Recall that we are to predict post-shock observations in time interval 51-100.
- Intuitively, prediction power/signal decays as time goes forward.
- Therefore we should not use the same model for each time interval. However, we may risk overfitting if we specify one model for each interval.
- We are to divide the 50 time intervals into several subgroups within each of which one model is applied.

Time Interval Partitioning Algorithm (Cont'd)

- Greedy algorithm is applied for time interval partitioning.

Algorithm 1 Time interval partitioning algorithm

$b \leftarrow e \leftarrow 52$; $P \leftarrow$ NULL; $i \leftarrow 1$
while $b < 100$ **do**
    $C_i \leftarrow$ NULL; $e \leftarrow b +$ length(C_i); bestError$\leftarrow \infty$
    repeat
        $C_i \leftarrow$ createTimeInterval(b,e)
        $C_{all} \leftarrow$ createTimeInterval$(e$+1,100)
        error$\leftarrow$ evaluateModel(P, C_i, C_{all})
        if bestError $>$ error **then**
            bestError$\leftarrow$ error
        end if
        $e \leftarrow e + 1$
    until bestError$\neq$ error
    addTimeInterval(P, C_i)
    $i \leftarrow i + 1$; $b \leftarrow e$
end while

Time Interval Partitioning Algorithm (Cont'd)

- Time interval 52-100 are divided into K sub-groups. And thus K sub-models are fitted.
- Let $C_i \subseteq \{52, 53, ..., 100\}$ be the i'th subgroup. Then the prediction model is:

$$M_{\text{bid}(t)} = \sum_{i=1}^{K} \delta_{t,C_i} M_{\text{bid},i}(t),$$

$$M_{\text{ask}(t)} = \sum_{i=1}^{K} \delta_{t,C_i} M_{\text{ask},i}(t).$$

where $t \in \{52, 53, ..., 100\}$, and $M_{\text{bid}(t)}/M_{\text{ask}(t)}$ is the sub-model to be fitted, and

$$\delta_{t,C_i} = \begin{cases} 1 & \text{if} \quad t \in C_i, \\ 0 & \text{otherwise.} \end{cases}$$

Outline

Feature Engineering

- *Price Features*
  - exponential moving average (EMA) of the last n bid/ask prices
  - the price rises/drops of the last n bid/ask prices
- *Liquidity Features*
  - The *depth* of the order book
- *Spread Features*
  - exponential moving average (EMA) of the last n bid-ask spreads
- *Arrival Rate Features*
  - the number of quotes/trades during the last n time intervals.

Feature Selection

- Feature selection is based on the *feature importance* ranking in Random Forest.
- A selection algorithm similar to the *backward-forward* algorithm in linear regression is implemented.

Algorithm 2 Feature selection algorithm

```
1:  Train a single piece model using all S features
2:  Compute model performance against the test set
3:  Rank features importance (RF importance method)
4:  for each subset size S_i=S, S − 1, . . . , 1 : do
5:      Retrain the model with only S_i most important features
6:      Re-compute individual variable importance and re-rank
7:      Fit the model to S_f features and rank individual features
8:  end for
9:  Determine which S_i yielded the smallest RMSE. Call this S_f
10: repeat
11:     Choose a set of semantically similar features from S_f
12:     Select the feature with less rank not selected before
13:     Evaluate the model performance
14:     If smaller RMSE, then remove the feature
15: until no improvement
16: repeat
17:     Choose a feature set among the already removed in Steps 1)-9) considering only
        those semantically orthogonal with the already selected in Steps 1)-15)
18:     If smaller RMSE, then we add the feature to S_f
19: until no improvement
```

Outline

Model Approach

- Gradient Boosting Machines and Random Forest are implement separately for this project (Back then Xgboost was not developed yet).
- A 4-fold cross validation with a 75%-25% proportion for training and testing respectively is used.
- The optimized Gradient Boosting Machine and Random Forest models delivered respectively and average cross-validated RMSE of 1.163 and 1.156.

- See the evolution of public and private scores in the following plot:

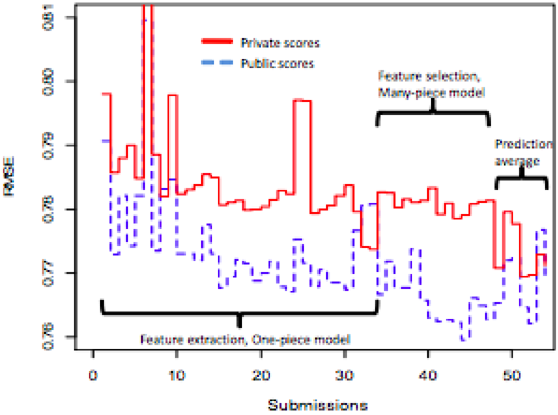

Figure: Evolution of public (dashed line) and private (solid line) scores. Feature construction, selection, partitioning and final prediction average were performed sequentially as indicated in the plot.

References I

de Abril, I. M. and Sugiyama, M. (2013). Winning the kaggle algorithmic trading challenge with the composition of many models and feature engineering, *IEICE Transactions on Information and Systems* (3): 742–745.