Recommendation System and Retail Investors' Trading Behavior

Yueyang Liu

yueyl@stanford.edu

Introduction

Literature on attention and its asset pricing implications suggests that retail traders pay attention to stocks that appear in the media and that they tend to buy attention-grabbing stocks. Stock recommendations on the TV show Mad Money and Wall $treet Week have proven to catch people's attention and create price pressure on the stocks recommended.[1] [2].

We conjecture that due to limited attention, individual traders will trade stocks on their attention lists most of the time, and we uncovered the attention span of individual traders by analyzing the historical trading data of household investment accounts.

Data

The data is a collection of over 3M historical trading records of accounts opened by 78,000 US households over the period 1991 to 1996, provided by a brokerage firm. Each trading record contains account number, security traded, buy/sell action, and amount proceeded. Below is histogram on the number of trading records of over 110,000 accounts after we preprocessed the data.

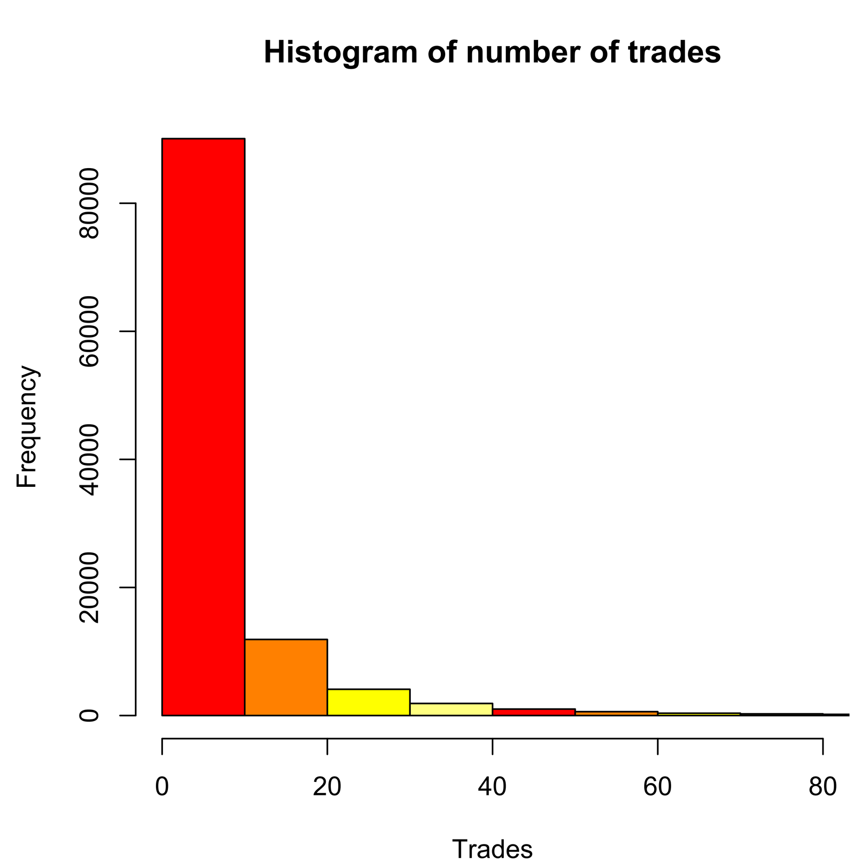

Figure 1: Data Visualization

Data Preprocessing & Feature Selection

We first preprocessed the data:

- Removed records with incomplete information.
- Disregarded selling records.

We then divided the data into 60% training set, 20% dev set, and 20%test set. We used k-fold cross validation with k =4.

The feature we selected is the proportion of net purchase of a target stock in total net purchase:

$$R_{ij} = 1 + 4\frac{\Sigma_k Q_{ij}^{(k)}}{\Sigma_{j,k} Q_{ij}^{(k)}},$$

where $Q_{ij}^{(k)}$ is the net purchase of stock j by individual i on the k-th trading record. We call R_{ij} the rating of stock j given by individual i.

Methods

The baseline algorithm

The baseline algorithm predicts a trader's trading behavior based on his historical trading pattern:

$$\hat{R}_{ij} = R_{ij}^t = 1 + 4\frac{\Sigma_k Q_{ij}^{(k)}}{\Sigma_{j,k} Q_{ij}^{(k)}}.$$

Co-clustering

$$\hat{R}_{ij} = \bar{C_{ij}} + \mu_i - \bar{C_i} + \mu_j - \bar{C_j}$$

K-nearest neighbors

$$\hat{R}_{ij} = \frac{\Sigma_x sim(x,i) R_{xj}}{\Sigma_x sim(x,i)}$$

Slope1 algorithm

$$\hat{R}_{ij} = \mu_i + \frac{1}{|R_j(i)|} \sum_{k \in R_j(i)} d(j,k),$$

where $R_j(i)$ is a collection of securities rated by i that has common buyer(s) with j, and $d(j,k)$ is the average difference in ratings.

The SVD algorithm

$$\hat{R}_{ij} = \mu + \alpha_i + \beta_j + u_j^T v_i,$$

Results

We used four different metrics to measure the performance of the five aforementioned algorithms. We ignored accounts with less than k (=0, 5, 10) trading records. We selected the best performing model, the SVD model, and performed error analysis on the test set subsequently. The results are displayed in a single table:

	Absolute Difference	Squared Error Loss	Correlation	Off-list Purchase Freq
Baseline x 5	0.9255563	2.22274	0.2646485	66.25618%
Baseline x 10	0.9273742	2.236623	0.2658816	66.32099%
SVD x 5	0.6712376	6.96842	0.3006886	8.487923%
SVD x 10	0.6647289	1.689458	0.5782379	8.318833%
SVD x 10 on Test	0.6539475	1.703746	0.5791437	8.338271%
KNN	0.7224191	121.8325	0.07668223	9.576529%
Slope1 x 10	0.6504646	3.781545	0.3654226	1.263692%
Co-clustering x 10	0.788613	1.757612	0.4962717	42.70668%

Figure 2: Results

Performance of slope1 and co-clustering on dev set, and that of SVD algorithm on test set is shown below:

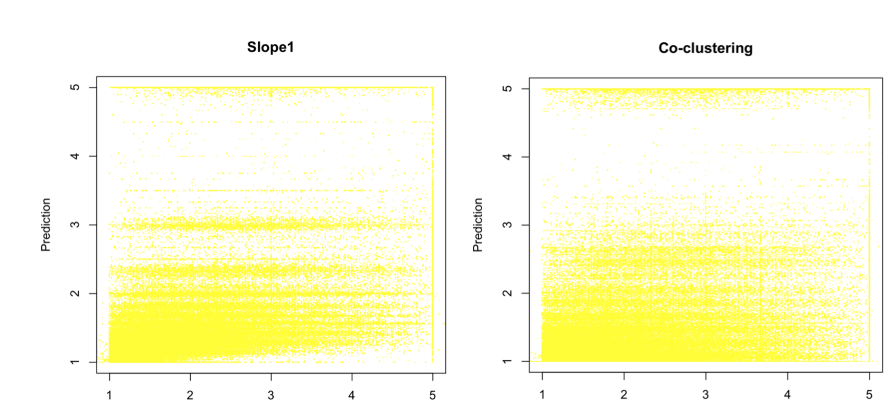

Figure 3: Performance

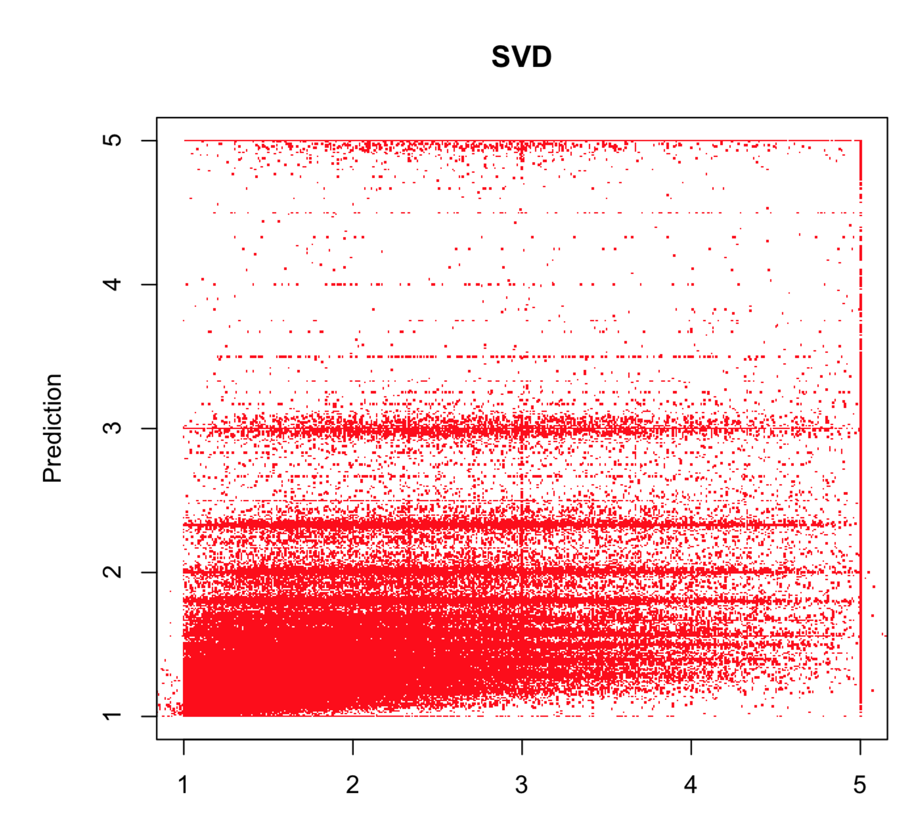

Figure 4: Performance

Discussion

We have successfully uncovered retail traders' attention lists and identified unexpected trading with limited data. As we expected, SVD algorithm performs the best on data with accounts of less than 10 trading records removed. With minimal data, we observe both actual ratings of 5 and predicted ratings of 5. We also observe that in support of our hypothesis, unexpected trading on the bottom right corner of the plots is a small selection of trading records. Utilizing machine learning, we are opening up new directions of research in behavioral finance in detecting abnormal trading behaviors and giving insights on asset pricing dynamics and policy making.

Future Directions

- Construct a probabilistic model of how individuals trade.
- Improve the current algorithms (feature selection; accounts with minimal trading records; demographic data).
- Use trading actions on listed securities and off-list securities to predict stock price movements.
- Detect illegal trading.

References

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