FLIPOO PRESETANTION REPORT

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Abstract. This report mainly explain, analyse and solve the problem of predicting the future sales with the database which is given. And the report contains five parts. The first part decribe the problem, interpret the data and evaluation criteria. Moreover,the report do some data processing, which includes filter duplicate data and others. Third, select some features to construct feature matrix. Then, experiment and analyze the performance of the lightgbm model based on experimental result. The last one is conclusion.

Contents

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1991 *Mathematics Subject Classification.* Artificial Intelligence.
Key words and phrases. Machine Learning, Data Mining, ...

1. Introduction

1.1. **Describe the Problem.** This is a problem with time-series prediction. Many information are given about daily sales data.The raw dataset contains train set with 2935849 samples and 214200 unlabeled samples as test set. Through the train data, predict total sales for every product and store in the next month.

1.2. **Interpret the Data.** Here's the data in the dataset.

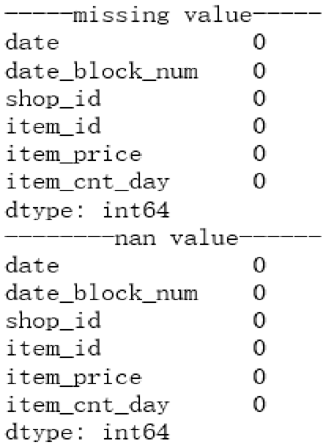
Table 1:Data

Name	Description	Attribute
sales_train.csv	Training set(data from January 2013 to October 2015)	date,date_block_num, shop_id,item_id, item_price,item_cnt_day
test.csv	Test set(Predict sale in November 2015)	ID,shop_id,item_id
items.csv	Supplementary information of products	item_name, item_id, item_category_id
shops.csv	Supplementary information of shops	shops_name, shops_id
item_categories.csv	Supplementary information of item categories	item_categories_name, item_categories_id
sample_submission.csv	Format of submission	ID,item_cnt_month

1.3. **Evaluation Criteria.** Before experiment, determine the evaluation methods to assess the model performance is very important, usually it has the RMSE methods to evaluate.

2. Data Processing

2.1. **Missing Value and NaN Value.** There are no missing value and none value.



```
-----missing value-----
date              0
date_block_num    0
shop_id           0
item_id           0
item_price        0
item_cnt_day      0
dtype: int64
--------nan value------
date              0
date_block_num    0
shop_id           0
item_id           0
item_price        0
item_cnt_day      0
dtype: int64
```

Figure 1. Missing Value and NaN Value

2.2. **Outliers and Duplicate Data.** Filter duplicate data, outliers and data with price less than zero.

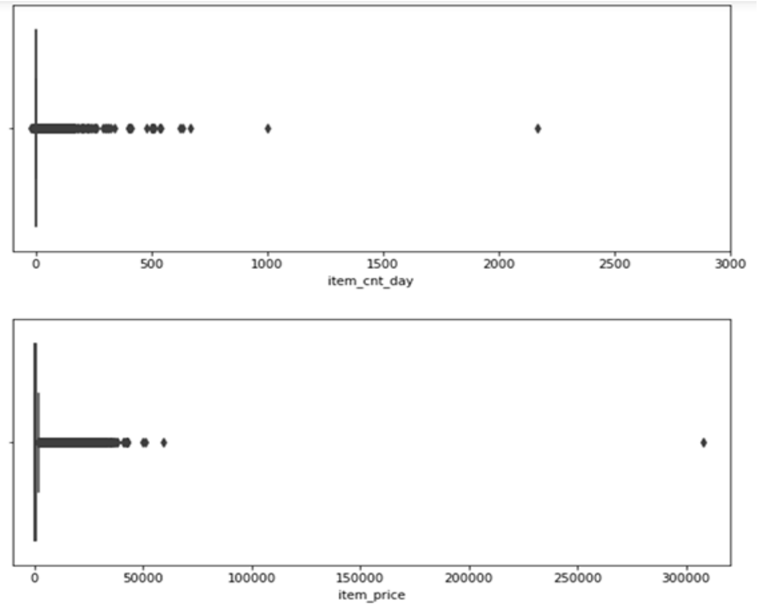


Figure 2. Outliers Data

2.3. **Process Shops Set.** Some shops have same shop name and different shop ID, such as ID of 39 and 40,10 and 11,0 and 57, 58 and 1. Then fliter the test set and modify the shop ID based on the test. On the other hand, the report analyses shops name and finds the name can be divided into three parts: shop's city,shop's type and the shop's name. Encoding shops information is able to reduce memory usage and find a connection with sales.

2.4. **Process Items Set.** Some items have same item name and different item ID, such as ID of 2514 and 2558,2968 and 2970,5061 and 5063, 14537 and 14539,19465 and 19475,19579 and 19581 . Then fliter the test set and modify the item ID based on the test.

2.5. **Process Categories Set.** Analyses categories name and finds the name can be divided into two parts: category's type-category's subtype. Encoding shops information is able to reduce memory usage and find a connection with sales.

2.6. **Sales Analysis.** Figure3 shows that total sales every month are decreased over time. This reason probably is shops and items are decreased. By analyzing the data, there are many discontinued items in figure4 and these shops are closed:closed shops:0,1,8,11,13,17,23,27,29,30,32,33,40,43,51,54.

3. Feature Selection

3.1. **Data Feature.** Data Feature mainly includes the features that analysing in the previous chapters, such as shop id and various codes. The specific features are shown below.

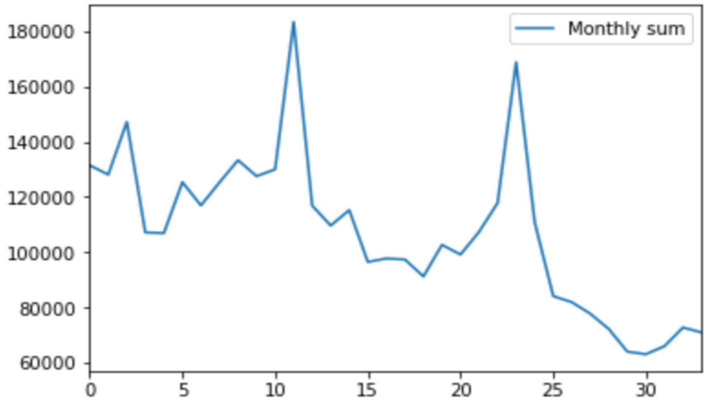
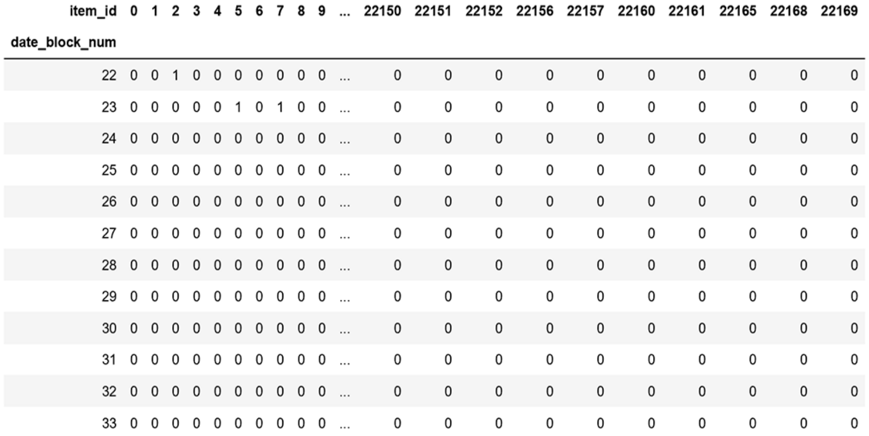


FIGURE 3. Total Sales Over Time



item_id	0	1	2	3	4	5	6	7	8	9	...	22150	22151	22152	22156	22157	22160	22161	22165	22168	22169
date_block_num																					
22	0	0	1	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	1	0	1	0	0	...	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
30	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

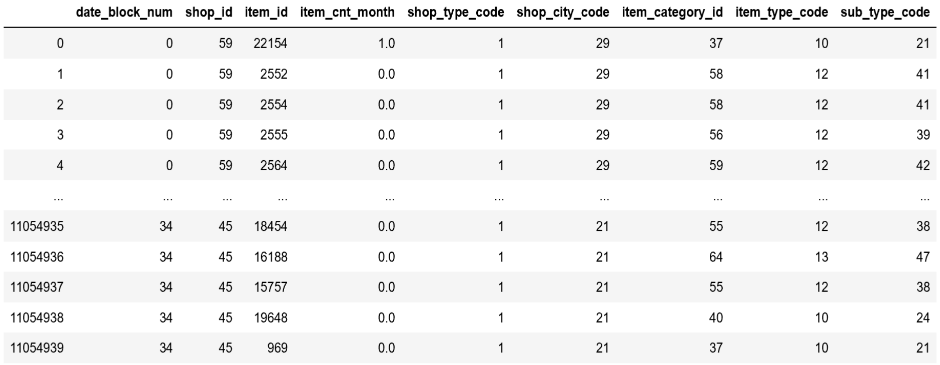
FIGURE 4. Discontinued Products

3.2. **Monthly Sales Feature.**

- average monthly sales of items
- average monthly sales of shops
- average monthly sales of categories
- average monthly sales of types and subtypes
- average monthly sales of shop's city-item
- average monthly sales of shop's type-item

3.3. **Historical Feature.** From figure3 and materials searched in the Internet, historical month delays are set with 1,2,3,6 and 12, and the historical features are below. Finally, first 12 months records and NAN records should be deleted.

- monthly sales of items
- average monthly sales of shops
- average monthly sales of items



	date_block_num	shop_id	item_id	item_cnt_month	shop_type_code	shop_city_code	item_category_id	item_type_code	sub_type_code
0	0	59	22154	1.0	1	29	37	10	21
1	0	59	2552	0.0	1	29	58	12	41
2	0	59	2554	0.0	1	29	58	12	41
3	0	59	2555	0.0	1	29	56	12	39
4	0	59	2564	0.0	1	29	59	12	42
...	...	...	...	...	...	...	...	...	...
11054935	34	45	18454	0.0	1	21	55	12	38
11054936	34	45	16188	0.0	1	21	64	13	47
11054937	34	45	15757	0.0	1	21	55	12	38
11054938	34	45	19648	0.0	1	21	40	10	24
11054939	34	45	969	0.0	1	21	37	10	21

Figure 5. Data Feature

- average monthly sales of categories
- average monthly sales of types and subtypes
- average monthly sales of shop's city-item
- average monthly sales of shop's type-item

4. Experiment and Analysis

Using lightgbm to predict the sales. And in the final database, change zero to closed shops and discontinued items.
In the midterm report, XGBoost is used to predict the sales. And in the final report, Lightgbm is used to predict the sales. Because Lightgbm has the faster speed and higher accuracy than XGBoost.
XGBoost [1] is to establish K regression trees so that the predicted value of the tree group is as close as possible to the true value (accuracy) and has the greatest generalization ability. From a mathematical point of view, this is a functional optimization, multi-target. Lightgbm[2] is a distributed gradient promotion framework based on decision tree algorithm. Lightgbm is designed to provide a data science tool with high efficiency, low memory consumption, high accuracy, supporting parallel and large-scale data processing The final score is 1.04885 and get the middle rank.
Figure6 shows the feature importance of sales.
The result:

- score:0.93740
- rank:3027/873

5. Conclusions

- Exploratory data analysis and data processing is very important for the competition. Exploratory data analysis help to have a certain understanding of the overall appearance of the data, which will help later modeling and analysis. And data processing includes dealing with missing data and outliers, processing datasets and others.
- The most important thing is feature engineering. In the midterm report, several features are selected and some information in database is not used.

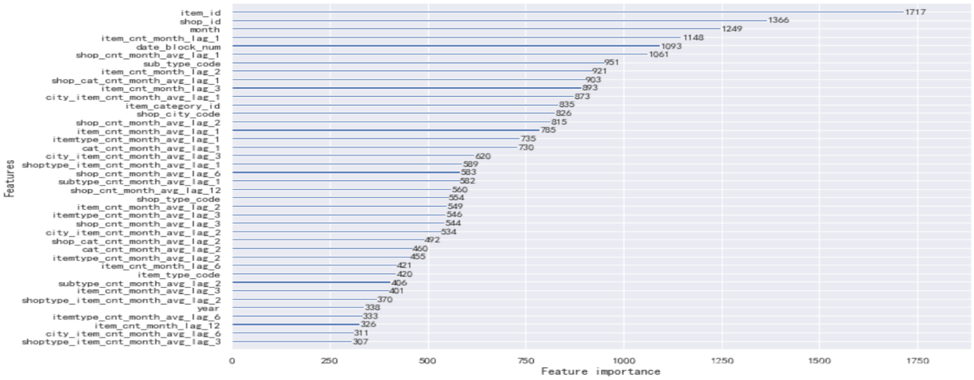


Figure 6. Feature Importance

And in this report, more features are selected, such as historical features and monthly sales feature.

- Compare to midterm presentation, RMSE decreased from 1.04885 to 0.93740. The reason mainly is more features and different modeling. In the figure of feature importance and monthly sales, some historical feature play an important role. And lightgbm model's and xgboost model's result have a marginal difference, but processing speed of lightgbm model is faster.

References

[1] Gleb Beliakov, Simon James, and Gang Li. Learning choquet-integral-based metrics for semisupervised clustering. *Fuzzy Systems, IEEE Transactions on*, 19(3):562–574, 2011.

[2] Y. Zhang Wang, Dehua and Y. Zhao. Lightgbm: An effective mirna classification method in breast cancer patients. *the 2017 International Conference.*, 2017.