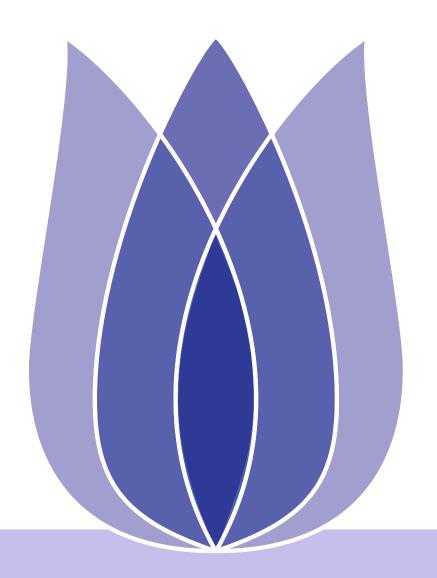
# FLIP(00) Final-term Presentation

Rongxin Xu Hunan University

29 November 2019



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## **Outline**

Problem Statement

Exploratory Data Analysis

Feature Engineering

Methods

Forecast Results

Conclusion

Problem Statement
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Problem Description

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# **Problem Statement**



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## **Problem Description**

Problem Statement

Problem Description

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This is a problem with time-series prediction. After a month of making scientific observations and taking careful measurements, can predict total sales for every product and store in the next month. 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.



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### **Data Set**

**Problem Statement** 

Problem Description

#### Data Set

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There are 6 data sets with a total of 11 attributes, the fllowings are the name and meaning of attributes.

### Data List

id an Id that represents a (Shop, Item) tuple within the test set.

**shop\_id** unique identifier of a shop.

item\_id unique identifier of a product.

item\_category\_id unique identifier of item category.

item\_cnt\_day percentage of soul in the creature.

item\_price current price of an item.

date in format dd/mm/yyyy.

date\_block\_num unique identifier of item category.

item\_name name of item.

**shop\_name** name of shop.

item\_category\_name name of item category.



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#### Exploratory Data Analysis

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# **Exploratory Data Analysis**



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## **Data Information**

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The following is the statistical result of each attribute in sales\_train.csv. There are 6 numerical variables, and no missing values. The data is very clean and complete, So let's start visual analysis.

	date_block_num	shop_id	item_id	item_price	item_cnt_day	item_category_id
count	2935849	2935849	2935849	2935849	2935849	2935849
mean	14.57	33	10197.23	890.62	1.24	40
$\operatorname{std}$	9.42	16.23	6324.3	1726.44	2.62	17.1
min	0	0	0	-1	-22	0
25%	7	22	4476	249	1	28
50%	14	31	9343	399	1	40
75%	23	47	15684	999	1	55
max	33	59	22169	307980	2169	83



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Use EDA to plot the distribution of the data, can observate the data intuitively and find the relation between the attribute values.

### Figures

- ♦ Histogrm
- **♦** Boxplot
- ◆ Scatterplot Plot
- ◆ Correllogram



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#### Data Visualization

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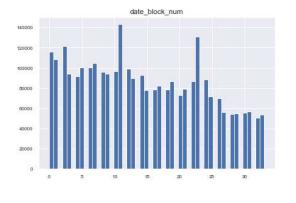
Methods

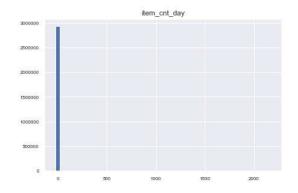
Forecast Results

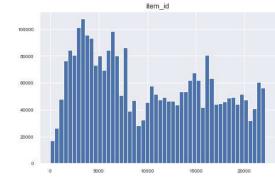
Conclusion



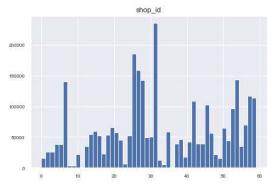
It seems that item\_id and shop\_id has a huge impact on sales and sales tend to decline with the date.













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#### Data Visualization

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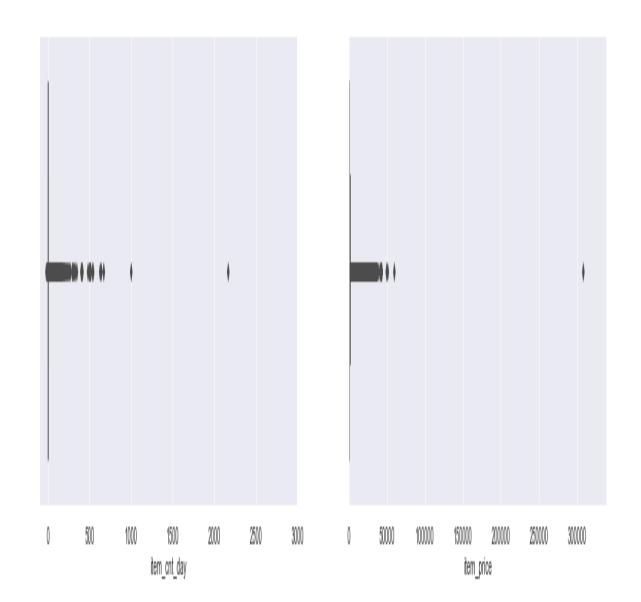
Methods

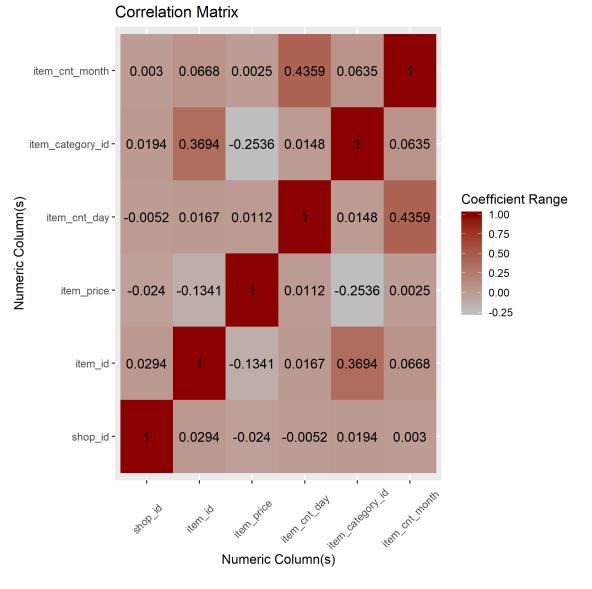
Forecast Results

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£xp

When analyzing the data, the boxplot can effectively help us identify the characteristics of the data: visually identify outliers in the dataset or determine the data dispersion and bias of the data set. We can see that the outliers are very small, so can be ignored.







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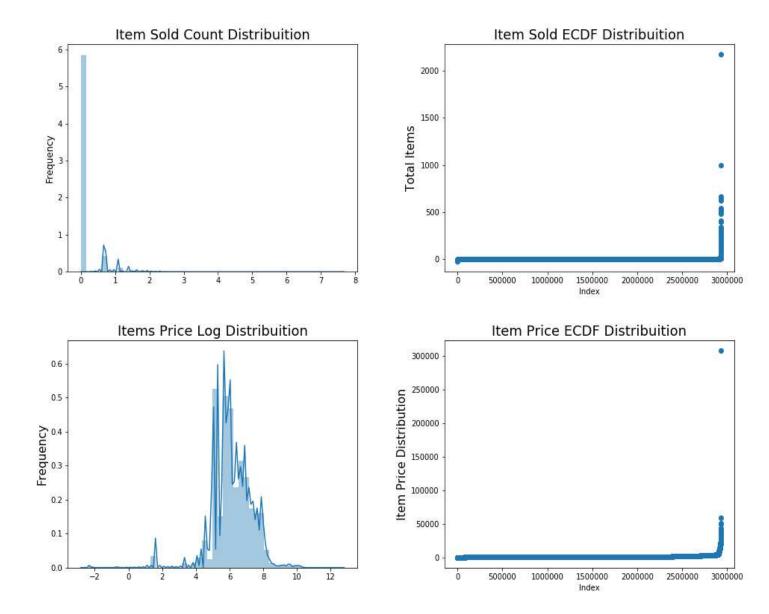
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It can be seen from the scatter plot that the daily sales volume of the product is mainly concentrated between 0 and 1, and the price of the product can also be concentrated.





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Exploratory Data Analysis

#### Feature Engineering

Features importance

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# Feature Engineering



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# Features importance

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Feature Engineering

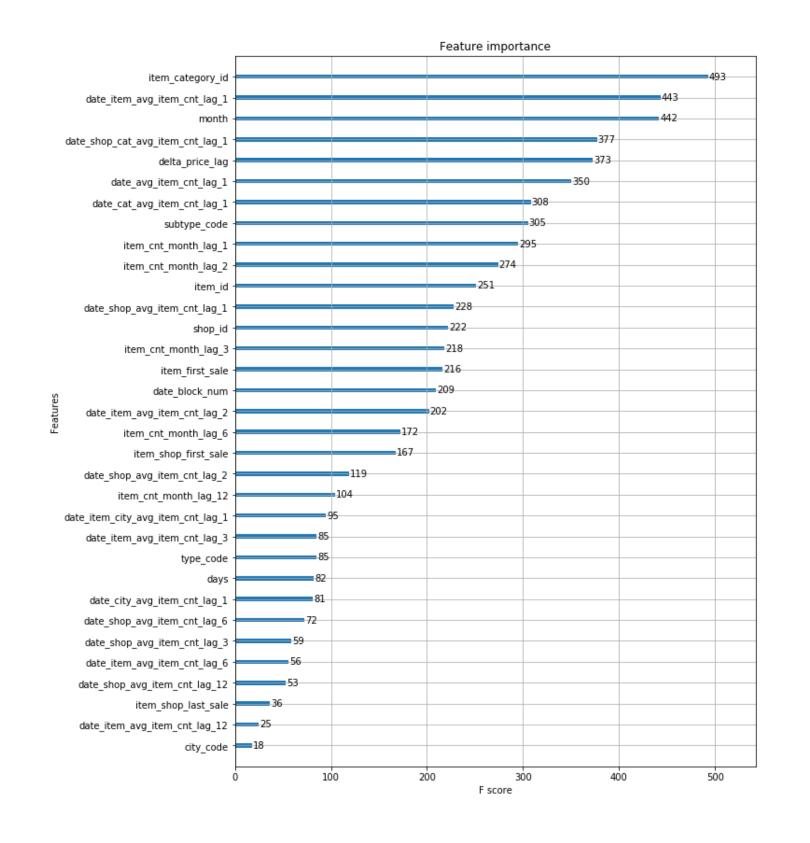
Features importance

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We take all of these features to form a new train datad.





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# Methods



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## **Ensembling**

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To combine the 1st level model predictions, I'll use a simple linear regression. As I'm only feeding the model with predictions I don't need a complex model.

- Base Models
  - ◆ RandomForest
  - ◆ XGBoost
  - ◆ LSTM
  - ♦ Linear regression
  - ♦ KNN
- Ensemble Model
  - Linear regression





## Route

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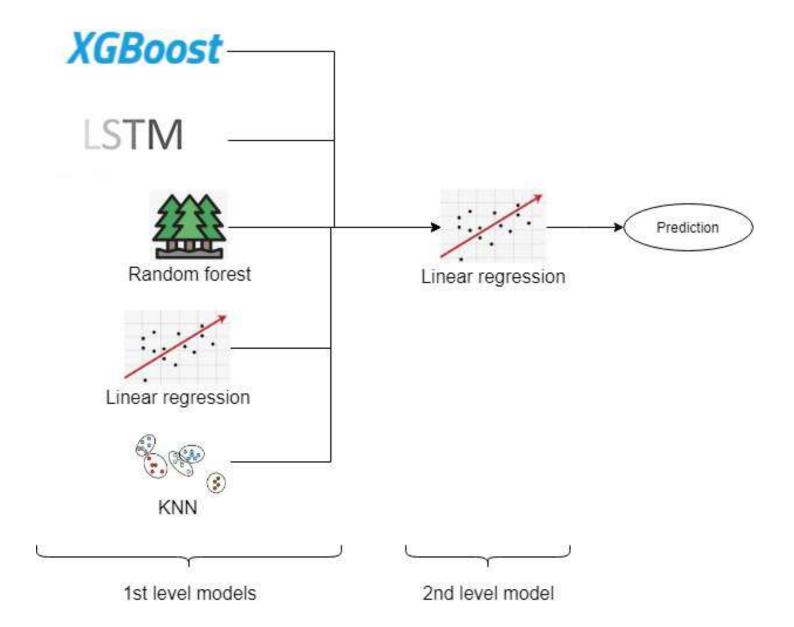
Ensembling

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Here is an image to help the understanding







Exploratory Data Analysis

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# **Forecast Results**



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# **Evaluation Methods**

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#### **Evaluation Methods**

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■ RMSE



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### **Forecast Results**

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**Evaluation Methods** 

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The following are the best Score in training of the base models.

Table 1: Best Score of the Base Models

	RandomForest	XGBoost	LSTM	Linear regression	KNN
Train rmse	0.8358	0.8327	0.9276	0.8572	0.6976
Validation rmse	0.8810	0.8959	0.6611	0.8806	0.8946

■ Ensemble model means using more than 1 model to finish the prediction. The train rmse is 0.764973649571408.



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# Conclusion



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### Conclusion

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Exploratory data analysis is very important for the competition, Discover the imperfections of the data and have a certain understanding of the overall appearance of the data, which will help later modeling and analysis.

The data that we have, needed processed in many cases. Data preprocessing includes deal with missing data and outliers, We must think carefully about the outliers, such as ignoring them.

The most important thing is feature engineering. We have to think carefully and deal with outliers, such as ignoring or deleting them.

There is no best model, only the best model. We should try as many models as possible to get the best prediction results.

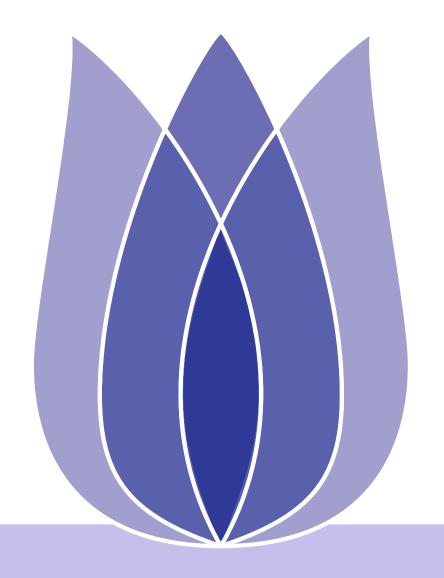
Feature engineering is very important and even plays a decisive role in this competition.

The Ensemble model may perform better than a single model when dealing with some complex problems.



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# Thank you & Question

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