

Predicting Future Sales

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Agenda

- 1. Overview
- 2. Critique of Other Competition Submissions
- 3. Our Solution
- 4. Final Prediction



Overview

Objective: Predict total sales (quantity) for every product and store in the next month (November 2015)

Dataset: includes 6 csv files from 1C company (Russian software company)

• items:

1	Α	В	C
1	item_name	item_id	item_category_id
2	ĐĐ¡Đ¢Đ~ ĐĐĐ′ĐĐ–Đ″Đ•ĐĐ~Đ~ (ĐŸĐ)ĐĐ	0	40
3	Professional Edition Full [PC, ЦĐ,фрĐ	1	76
4)' Ð>Đ£Đ§ĐĐ¥ Đ¡Đ>ĐĐ'Đ« (UNV)	2	40
5	"ĐžĐ>Đ£Đ'ĐĐ¯ Đ'ĐžĐ>ĐĐ (Univ)	3	40
6)šĐžĐ ОБКР(Đ¡Đ¢Đ•ĐšĐ›Đž)	4	40
7	œĐ•Đ Đ~ĐšĐĐĐ¡ĐšĐ~Đ• ГРĐФФĐ~£	5	40

<u>item_categories</u>:

1	Α	В	
1	item_category_name	item_category_id	
2	PC - Đ"Đ°Ñ€Đ½Đ¸Ñ,Ñfры/ĐаÑfÑ^Đ½Đ¸ĐºĐ¸	0	
3	ÐкÑÐμÑÑÑfарÑ∢ - PS2	1	
4	ÐкÑÐμÑÑÑfарÑ∢ - PS3	2	
5	ÐкÑÐμÑÑÑfарÑ∢ - PS4	3	
6	ÐкÑÐμÑÑÑfарÑ∢ - PSP	4	
7	ÐĐºÑĐμÑÑĥfĐ°Ñ€Ñ< - PSVita	5	

• shops:

	A	В
1	shop_name	shop_id
2	уÑ,ÑĐº ĐžÑ€Đ´Đ¶Đ¾Đ½Đ¸ĐºĐ¸Đ´Đ∙Đμ, 56 Ñ"Ñŧ	0
3	Ñ,ÑĐº Đ¢Đ¦ "ЦĐμĐ½Ñ,Ñ€Đ°Đ»ÑŒĐ½Ñ‹Đ¹" Ñ"I	1
4	ĐĐ´Ñ‹Đ³ĐμÑ Đ¢Đ¦ "ĐœĐμĐ³Đ°"	2
5	Ñ^иÑа Đ¢Đ Đš "ĐžĐºÑ,ÑĐ±Ñ€ÑŒ-ĐšĐ¸Đ½Đ¾	3
6	Đ¾Đ»Đ¶ÑĐºĐ¸Đ¹ Đ¢Đ¦ "Đ′Đ¾Đ»Đ³Đ° ĐœĐ¾Đ»Đ	4
7)′Đ¾Đ»Đ¾Đ³Đ´Đ° Đ¢Đ Đ¦ "ĐœĐ°Ñ€Đ¼Đμлад	5



Overview

• sales-train: training set

	Α	В	C	D	E	F
1	date	date_block_num	shop_id	item_id	item_price	item_cnt_day
2	02.01.2013	0	59	22154	999	1
3	03.01.2013	0	25	2552	899	1
4	05.01.2013	0	25	2552	899	-1
5	06.01.2013	0	25	2554	1709.05	1
6	15.01.2013	0	25	2555	1099	1
7	10.01.2013	0	25	2564	349	1

• test: test set

	Α	В	С
1	ID	shop_id	item_id
2	0	5	5037
3	1	5	5320
4	2	5	5233
5	3	5	5232
6	4	5	5268
7	5	5	5039

• <u>sample</u>: sample submission file in the correct format

	Α	В
1	ID	item_cnt_month
2	0	0.5
3	1	0.5
4	2	0.5
5	3	0.5
6	4	0.5
7	5	0.5
8	6	0.5
9	7	0.5
10	8	0.5
11	9	0.5
12	10	0.5
13	11	0.5
14	12	0.5



Critique of Other Competition Submissions

Random Forest

- Pros:
 - Suitable for large dataset
 - Easy data preparation comparing to other algorithms
- Cons:
 - Did not tune the hyperparameter
 - Computationally intense when number of trees is big
 - Will cause overfitting when noise is large
 - Lower output accuracy because it cannot guarantee the best tree
- RMSE: 2.0182

```
#Random forest regressor model building
from sklearn.ensemble import RandomForestRegressor

RF_model = RandomForestRegressor()
RF_model.fit(X_prepared, y)
```



Critique of Other Competition Submissions

LightGBM (Light Gradient Boosting Machine)

- Pros:
 - Faster training speed, Light GBM uses a histogram-based algorithm i.e it buckets continuous feature values into discrete bins which fasten the training procedure
 - Replaces continuous values to discrete bins which results in lower memory usage
- Cons:
 - Light GBM split the tree leaf-wise which can lead to overfitting as it produces much complex trees
 - Did not do cross validation for hyperparameters
- RMSE: 0.9610

```
evals_result = {}
gbm = lgb.train(
    params,
    lgb_train,
    num_boost_round=3000,
    valid_sets=(lgb_train, lgb_eval),
    feature_name = feature_name,
    #categorical_feature = categorical_features,
    verbose_eval=5,
    evals_result = evals_result,
    early_stopping_rounds = 10)
```



Our Solution

XGBoost: eXtreme Gradient Boosting--"ALL in One" algorithm

As a popular supervised-learning algorithm, XGBoost uses decision trees as base learners; combining many weak learners to make a strong learner to speed up and increase the performance of gradient boosted decision trees

- Regularization
- Parallel Processing
- Handling Missing Values
- Effective Tree Pruning

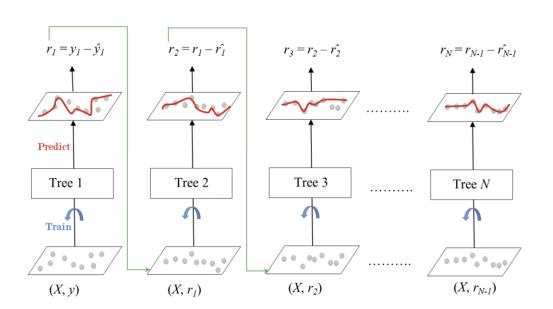


Our Solution

How does

XGBoost

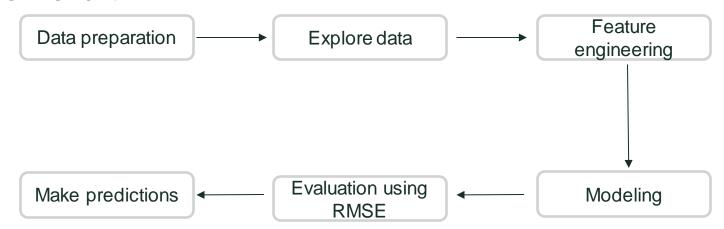
work?





Our Solution

Flow chart





Final Prediction

Performance: RMSE=0.877

Final prediction results:

ID	item_cnt_month
33050	0.01800462
32455	0.003886187
35412	0.019796828
32228	0.020295562
35385	0
32229	0.073716491
33048	0.007104043
32454	0
32446	0.036807135
33047	0.215048745
31748	0.042575739
33046	0.073391959
32370	0.073716491
34153	0.073716491
33045	0.027066618
30784	0.031092696
34150	0.073716491
31880	0.036855627
32286	0.121237382
30785	0.008510824
33044	0.015567578
32371	0.004501749

