Corporación Favorita Grocery Sales Forecasting

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The Kaggle Competition

https://www.kaggle.com/c/favorita-grocery-sales-forecasting

The Challenge: grocery stores are always in a delicate dance with purchasing and sales forecasting. Predict a little over, and grocers are stuck with overstocked, perishable goods. Guess a little under, and popular items quickly sell out, leaving money on the table and customers fuming. The problem becomes more complex as retailers add new locations with unique needs, new products, ever transitioning seasonal tastes, and unpredictable product marketing.

The Goal: To build a model that more accurately forecasts product sales.

Evaluation

Submissions are evaluated on the Normalized Weighted Root Mean Squared Logarithmic Error (NWRMSLE), calculated as follows:

$$NWRMSLE = \sqrt{\frac{\sum_{i=1}^{n} w_i \left(\ln(\hat{y}_i + 1) - \ln(y_i + 1)\right)^2}{\sum_{i=1}^{n} w_i}}$$

This metric is suitable when predicting values across a large range of orders of magnitudes. It avoids penalizing large differences in prediction when both the predicted and the true number are large: predicting 5 when the true value is 50 is penalized more than predicting 500 when the true value is 545.

Data

holidays_events.csv: Holidays and Events, with metadata. 351 rows

items.csv: Item metadata, including family, class, and perishable. 4101 rows.

oil.csv: Daily oil price. Includes values during both the train and test data timeframe. (Ecuador is an oil-dependent country and it's economical health is highly vulnerable to shocks in oil prices.) 1219 rows.

stores.csv: Store metadata, including city, state, type, and cluster. 55 rows.

test.csv: Test data, with the date, store_nbr, item_nbr combinations that are to be predicted, along with the onpromotion information. 3,000,000 rows

train.csv: Training data, which includes the target unit_sales by date, store_nbr, and item_nbr and a unique id to label rows. 125,000,000 rows

transactions.csv: The count of sales transactions for each date, store_nbr combination. 83489 rows.

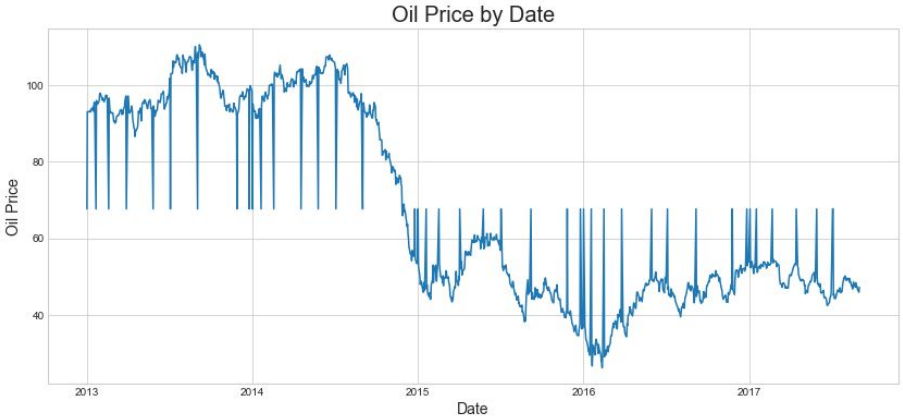
Data cleaning

merge item, store, oil

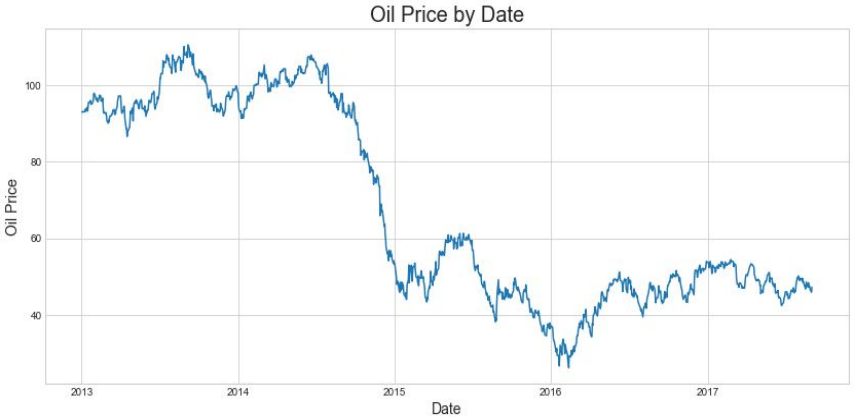
problem - missing oil data.

Visualization is important

oil price with fillna mean



oil price with fillna ffill



Feature engineering

mean_sales

payday

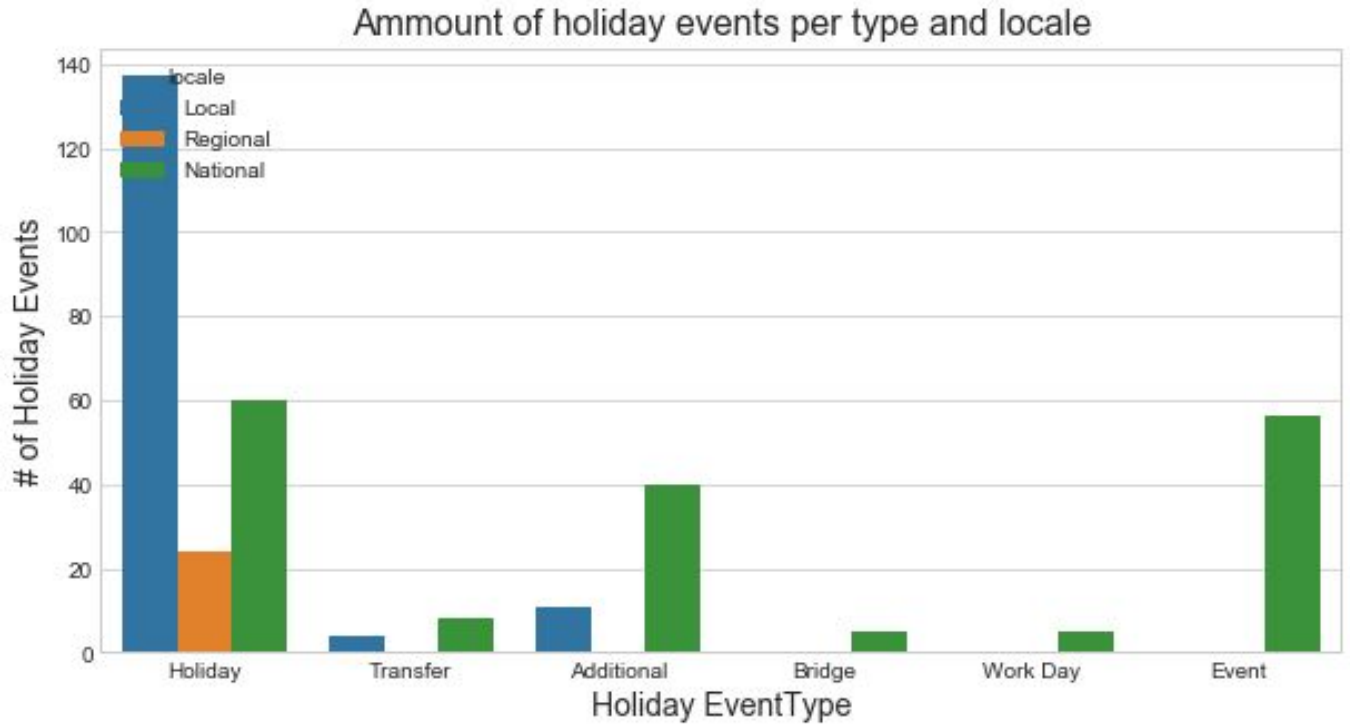
weekday

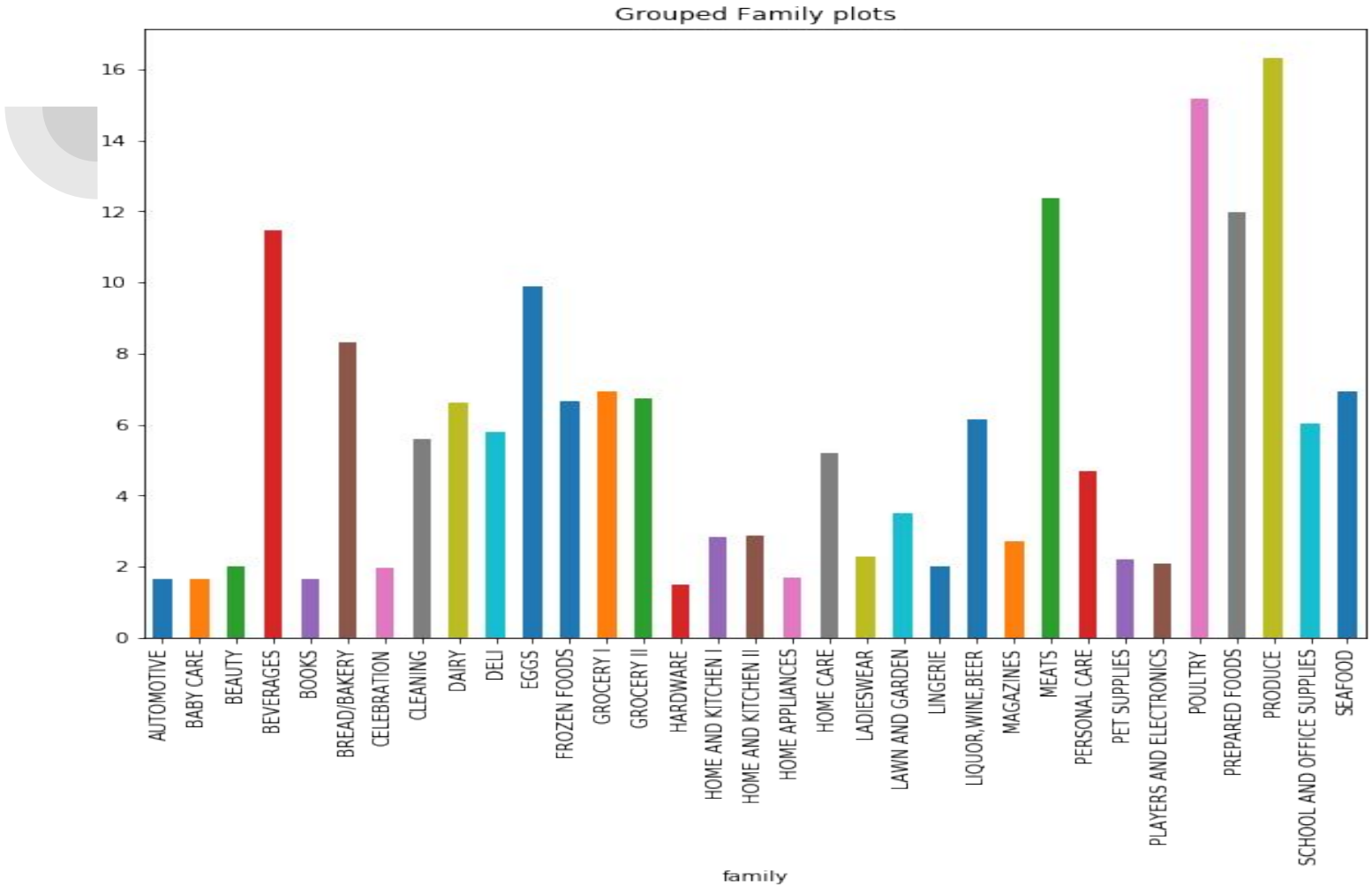
day

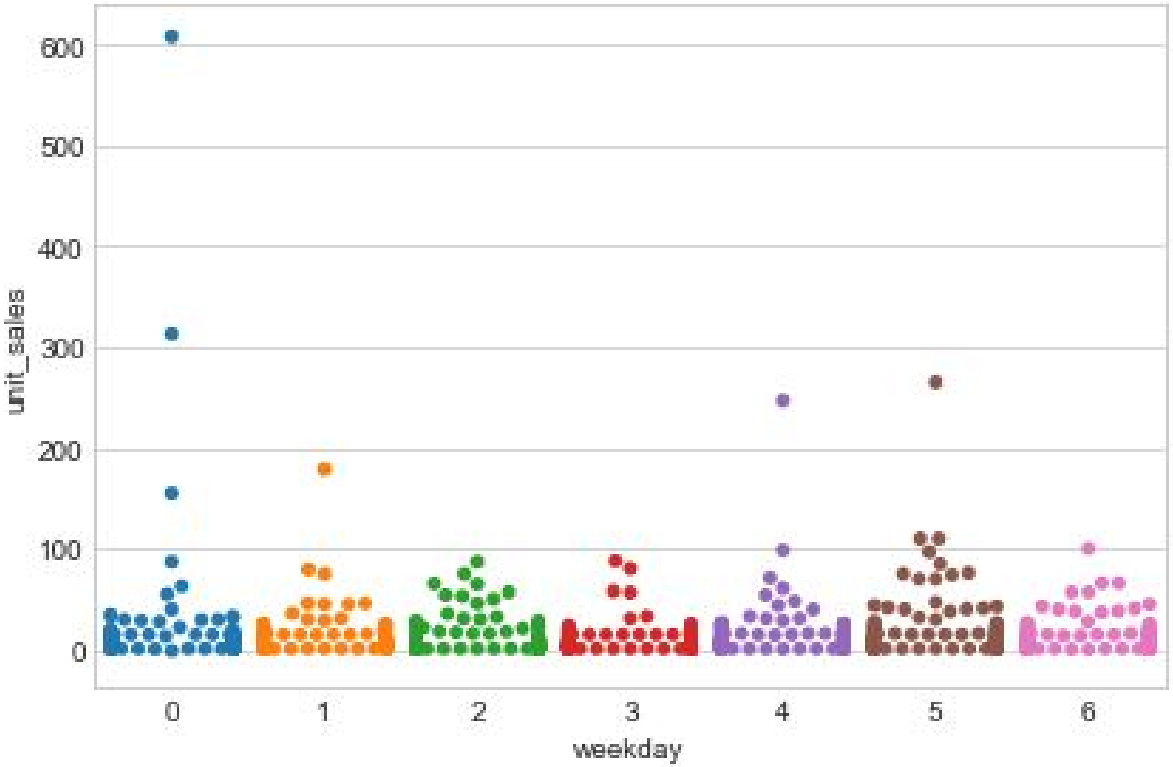
month

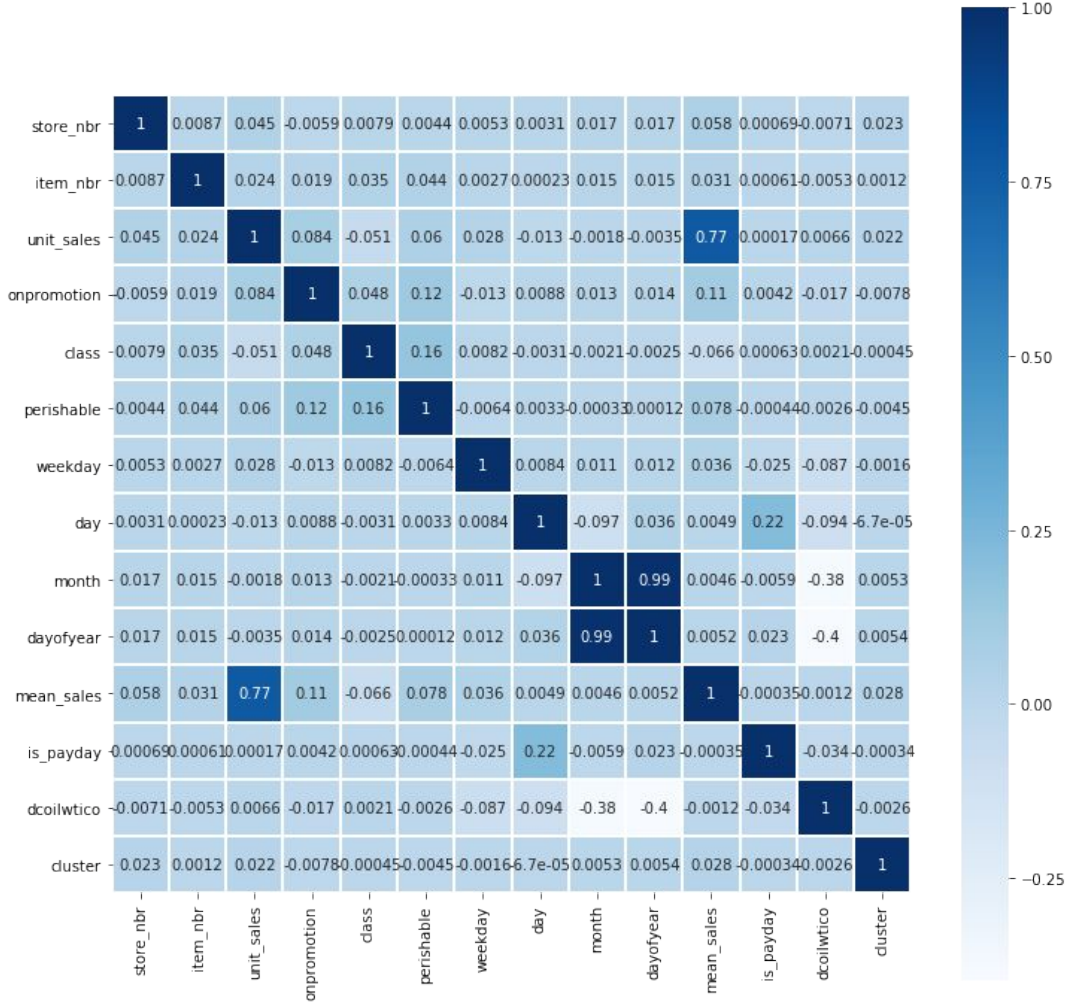
dayofyear

Exploratory data analysis




Grouped Family plots
16
14
12
10
8
6
4
2
0
AUTOMOTIVE
BABY CARE
BEAUTY
BEVERAGES
BOOKS
BREAD/BAKERY
CELEBRATION
CLEANING
DAIRY
DELI
EGGS
FROZEN FOODS
GROCERY I
GROCERY II
HARDWARE
HOME AND KITCHEN I
HOME AND KITCHEN II
HOME APPLIANCES
HOME CARE
LADIESWEAR
LAWN AND GARDEN
LINGERIE
LIQUOR,WINE,BEER
MAGAZINES
MEATS
PERSONAL CARE
PET SUPPLIES
PLAYERS AND ELECTRONICS
POULTRY
PREPARED FOODS
PRODUCE
SCHOOL AND OFFICE SUPPLIES
SEAFOOD
family


600
500
400
300
200
100
0
unit_sales
0
1
2
3
4
5
6
weekday


store_nbr 1 0.0087 0.045 -0.0059 0.0079 0.0044 0.0053 0.0031 0.017 0.017 0.058 0.00069 -0.0071 0.023
item_nbr 0.0087 1 0.024 0.019 0.035 0.044 0.0027 0.00023 0.015 0.015 0.031 0.00061 -0.0053 0.0012
unit_sales 0.045 0.024 1 0.084 -0.051 0.06 0.028 -0.013 -0.0018 -0.0035 0.77 0.00017 0.0066 0.022
onpromotion -0.0059 0.019 0.084 1 0.048 0.12 -0.013 0.0088 0.013 0.014 0.11 0.0042 -0.017 -0.0078
class 0.0079 0.035 -0.051 0.048 1 0.16 0.0082 -0.0031 -0.0021 -0.0025 -0.066 0.00063 0.0021 -0.00045
perishable 0.0044 0.044 0.06 0.12 0.16 1 -0.0064 0.0033 -0.00033 0.00012 0.078 -0.00044 -0.0026 -0.0045
weekday 0.0053 0.0027 0.028 -0.013 0.0082 -0.0064 1 0.0084 0.011 0.012 0.036 -0.025 -0.087 -0.0016
day 0.0031 0.00023 -0.013 0.0088 -0.0031 0.0033 0.0084 1 -0.097 0.036 0.0049 0.22 -0.094 -6.7e-05
month 0.017 0.015 -0.0018 0.013 -0.0021 -0.00033 0.011 -0.097 1 0.99 0.0046 -0.0059 -0.38 0.0053
dayofyear 0.017 0.015 -0.0035 0.014 -0.0025 0.00012 0.012 0.036 0.99 1 0.0052 0.023 -0.4 0.0054
mean_sales 0.058 0.031 0.77 0.11 -0.066 0.078 0.036 0.0049 0.0046 0.0052 1 -0.00035 -0.0012 0.028
is_payday -0.00069 0.00061 0.00017 0.0042 0.00063 0.00044 -0.025 0.22 -0.0059 0.023 -0.00035 1 -0.034 -0.00034
dcoilwtico -0.0071 -0.0053 0.0066 -0.017 0.0021 -0.0026 -0.087 -0.094 -0.38 -0.4 -0.0012 -0.034 1 -0.0026
cluster 0.023 0.0012 0.022 -0.0078 0.00045 -0.0045 -0.0016 -6.7e-05 0.0053 0.0054 0.028 -0.00034 -0.0026 1
store_nbr item_nbr unit_sales onpromotion class perishable weekday day month dayofyear mean_sales is_payday dcoilwtico cluster
1.00 0.75 0.50 0.25 0.00 −0.25

Data transformation

- Convert categorical data using one hot encoding then truncatedSVD to reduce dimension
  - family, city, state, type, weekday, day, month, cluster
- Scale mean_sales and oil price (dcoilwtico)
- item_id too large for one hot encoding, use mean encoding instead.

Stacking

A

X0	x1	x2	xn	y
0.17	0.25	0.93	0.79	1
0.35	0.61	0.93	0.57	0
0.44	0.59	0.56	0.46	0
0.37	0.43	0.74	0.28	1
0.96	0.07	0.57	0.01	1

B

X0	x1	x2	xn	y
0.89	0.72	0.50	0.66	0
0.58	0.71	0.92	0.27	1
0.10	0.35	0.27	0.37	0
0.47	0.68	0.30	0.98	0
0.39	0.53	0.59	0.18	1

C

X0	x1	x2	xn	y
0.29	0.77	0.05	0.09	?
0.38	0.66	0.42	0.91	?
0.72	0.66	0.92	0.11	?
0.70	0.37	0.91	0.17	?
0.59	0.98	0.93	0.65	?

Consider datasets A,B,C. Target variable (y) is known for A,B

Stacking

A

X0	x1	x2	xn	y
0.17	0.25	0.93	0.79	1
0.35	0.61	0.93	0.57	0
0.44	0.59	0.56	0.46	0
0.37	0.43	0.74	0.28	1
0.96	0.07	0.57	0.01	1

B

X0	x1	x2	xn	y
0.89	0.72	0.50	0.66	0
0.58	0.71	0.92	0.27	1
0.10	0.35	0.27	0.37	0
0.47	0.68	0.30	0.98	0
0.39	0.53	0.59	0.18	1

C

X0	x1	x2	xn	y
0.29	0.77	0.05	0.09	?
0.38	0.66	0.42	0.91	?
0.72	0.66	0.92	0.11	?
0.70	0.37	0.91	0.17	?
0.59	0.98	0.93	0.65	?

Train algorithm **0** on A and make predictions for B and C and save to **B1, C1**

B1

pred0
0.24
0.95
0.64
0.89
0.11

C1

pred0
0.50
0.62
0.22
0.90
0.20

Stacking

A

X0	x1	x2	xn	y
0.17	0.25	0.93	0.79	1
0.35	0.61	0.93	0.57	0
0.44	0.59	0.56	0.46	0
0.37	0.43	0.74	0.28	1
0.96	0.07	0.57	0.01	1

B

X0	x1	x2	xn	y
0.89	0.72	0.50	0.66	0
0.58	0.71	0.92	0.27	1
0.10	0.35	0.27	0.37	0
0.47	0.68	0.30	0.98	0
0.39	0.53	0.59	0.18	1

C

X0	x1	x2	xn	y
0.29	0.77	0.05	0.09	?
0.38	0.66	0.42	0.91	?
0.72	0.66	0.92	0.11	?
0.70	0.37	0.91	0.17	?
0.59	0.98	0.93	0.65	?

Train algorithm **0** on A and make predictions for B and C and save to **B1, C1**

Train algorithm **1** on A and make predictions for B and C and save to **B1, C1**

Train algorithm **2** on A and make predictions for B and C and save to **B1, C1**

B1

pred0	pred1	pred2	y
0.24	0.72	0.70	0
0.95	0.25	0.22	1
0.64	0.80	0.96	0
0.89	0.58	0.52	0
0.11	0.20	0.93	1

C1

pred0	pred1	pred2	y
0.50	0.50	0.39	?
0.62	0.59	0.46	?
0.22	0.31	0.54	?
0.90	0.47	0.09	?
0.20	0.09	0.61	?

Stacking

A

X0	x1	x2	xn	y
0.17	0.25	0.93	0.79	1
0.35	0.61	0.93	0.57	0
0.44	0.59	0.56	0.46	0
0.37	0.43	0.74	0.28	1
0.96	0.07	0.57	0.01	1

B

X0	x1	x2	xn	y
0.89	0.72	0.50	0.66	0
0.58	0.71	0.92	0.27	1
0.10	0.35	0.27	0.37	0
0.47	0.68	0.30	0.98	0
0.39	0.53	0.59	0.18	1

C

X0	x1	x2	xn	y
0.29	0.77	0.05	0.09	?
0.38	0.66	0.42	0.91	?
0.72	0.66	0.92	0.11	?
0.70	0.37	0.91	0.17	?
0.59	0.98	0.93	0.65	?

Train algorithm **0** on A and make predictions for B and C and save to **B1, C1**

Train algorithm **1** on A and make predictions for B and C and save to **B1, C1**

Train algorithm **2** on A and make predictions for B and C and save to **B1, C1**

B1

pred0	pred1	pred2	y
0.24	0.72	0.70	0
0.95	0.25	0.22	1
0.64	0.80	0.96	0
0.89	0.58	0.52	0
0.11	0.20	0.93	1

C1

pred0	pred1	pred2	y
0.50	0.50	0.39	?
0.62	0.59	0.46	?
0.22	0.31	0.54	?
0.90	0.47	0.09	?
0.20	0.09	0.61	?

Train algorithm **3** on B1 and make predictions for C1

Preds3
0.45
0.23
0.99
0.34
0.05

Conclusion

My model use XGBoost, Keras Regressor, Adaboast, RandomForestRegressor as first level of stacking with XGBoost on second level. resulting in .969, while the winning score is .509.

Looking at winning solutions feature engineering is very important.

Next step

- Try algorithms from winning solutions,
- Try time series algorithms