TalkingData AdTracking Fraud Detection Challenge

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0. Overview

Description

TalkingData, China's largest independent big data service platform, covers over 70% of active mobile device s nationwide. They handle 3 billion clicks per day, of which 90% are potentially fraudulent. The goal of the competition is to create an algorithm that predicts whether a user will download an app after clicking a mobile app ad.

Evalution

Submissions are evaluated on area under the ROC curve between the predicted probability and the observed target.

0. overview

variables

- ip : ip address of click
- app : app id for marketing
- device : device type id of user mobile phone
- os : os version id of user mobile phone
- channel : channel id of mobile ad publisher
- click_time : timestamp of click (UTC)
- attributed_time : if user download the app for after clicking an ad, this is the time of the app download
- is_attributed : the target that is to be predicted, indicating the app was download

1. Data Exploration

Explore 100,000 data

- ip : 100000 non-null int64
- app : 100000 non-null int64
- device : 100000 non-null int64
- os : 100000 non-null int64
- channel : 100000 non-null int64
- click_time : 100000 non-null datetime64
- attributed_time : 227 non-null object
- is_attributed : 100000 non-null int64

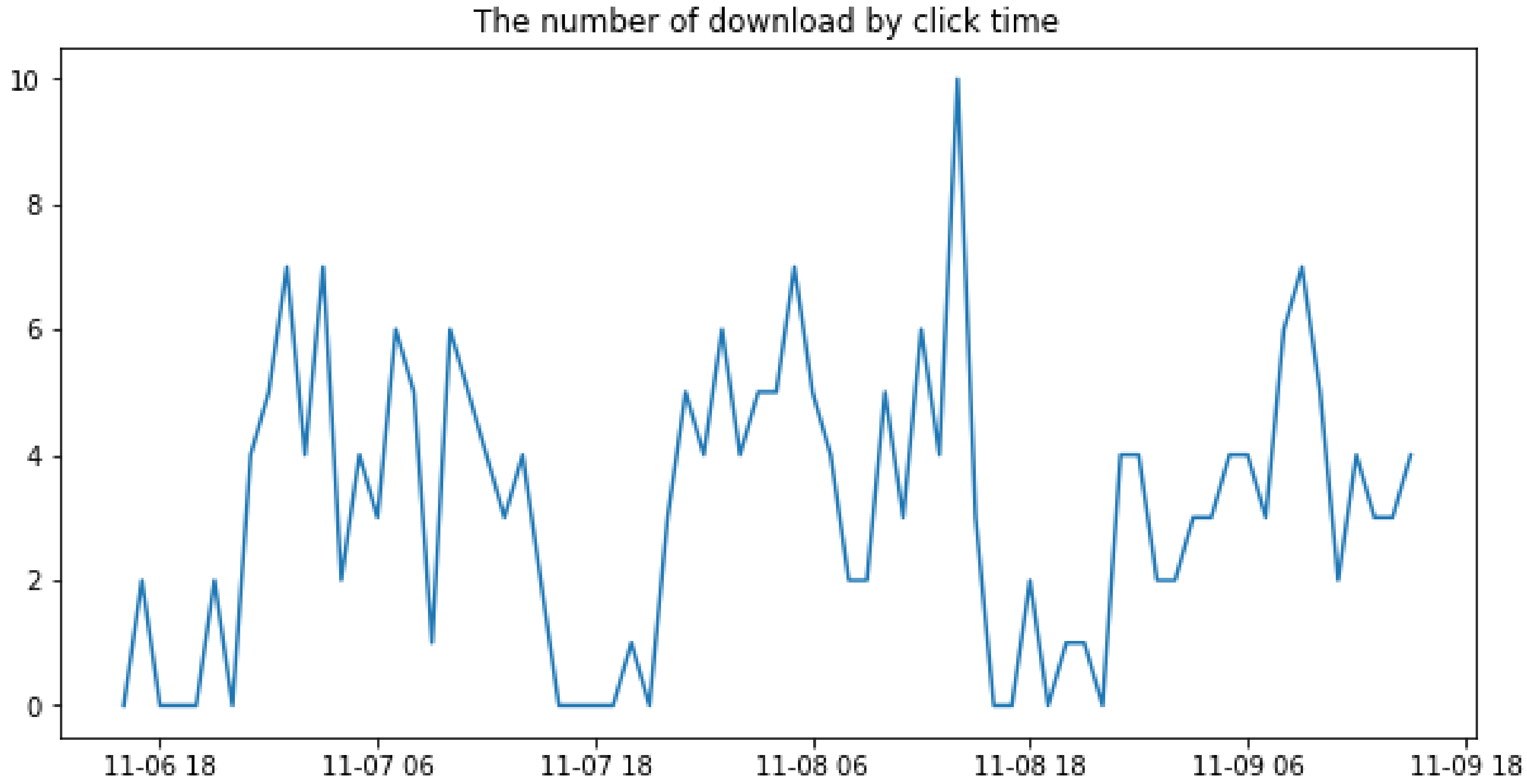
Check download frequency

- 0 : 99773
- 1 : 227

download proportion : 0.00227

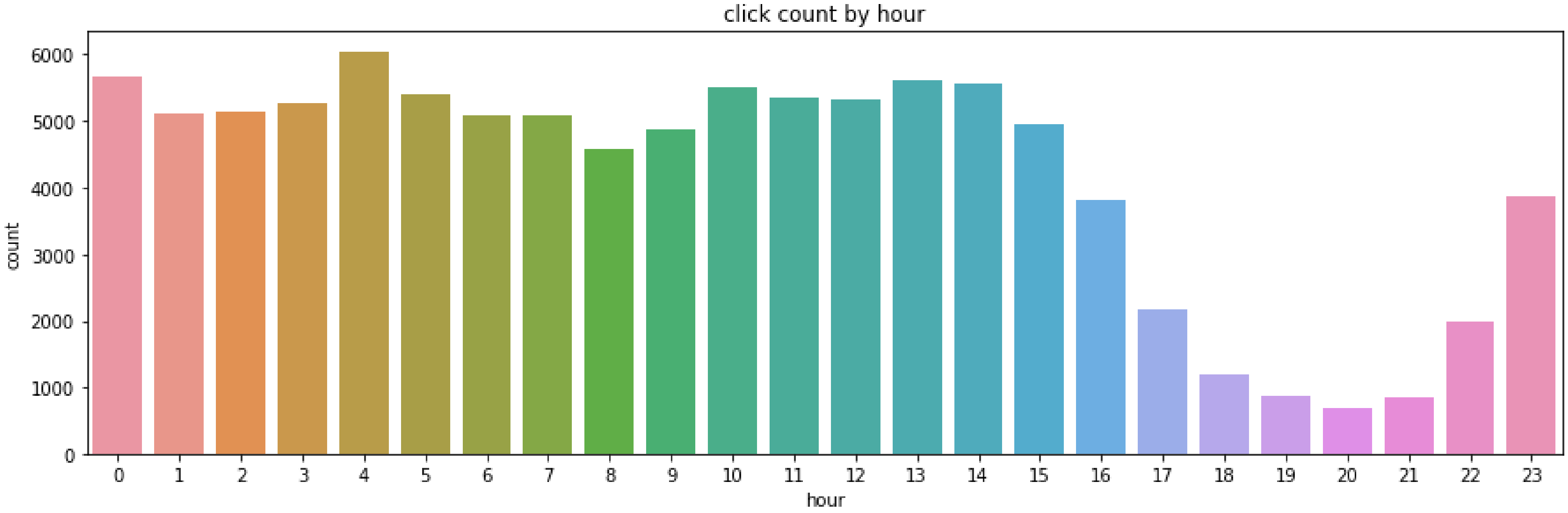
1. Data Exploration

Check the number of download by click time



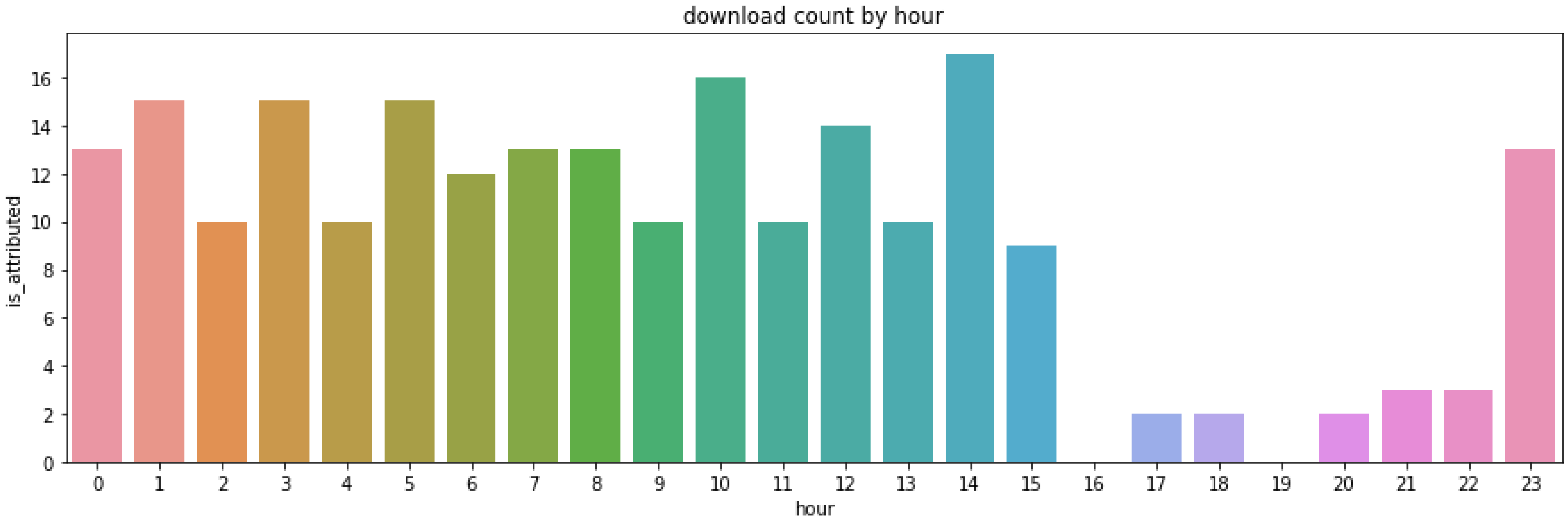
1. Data Exploration

Check click count per hour



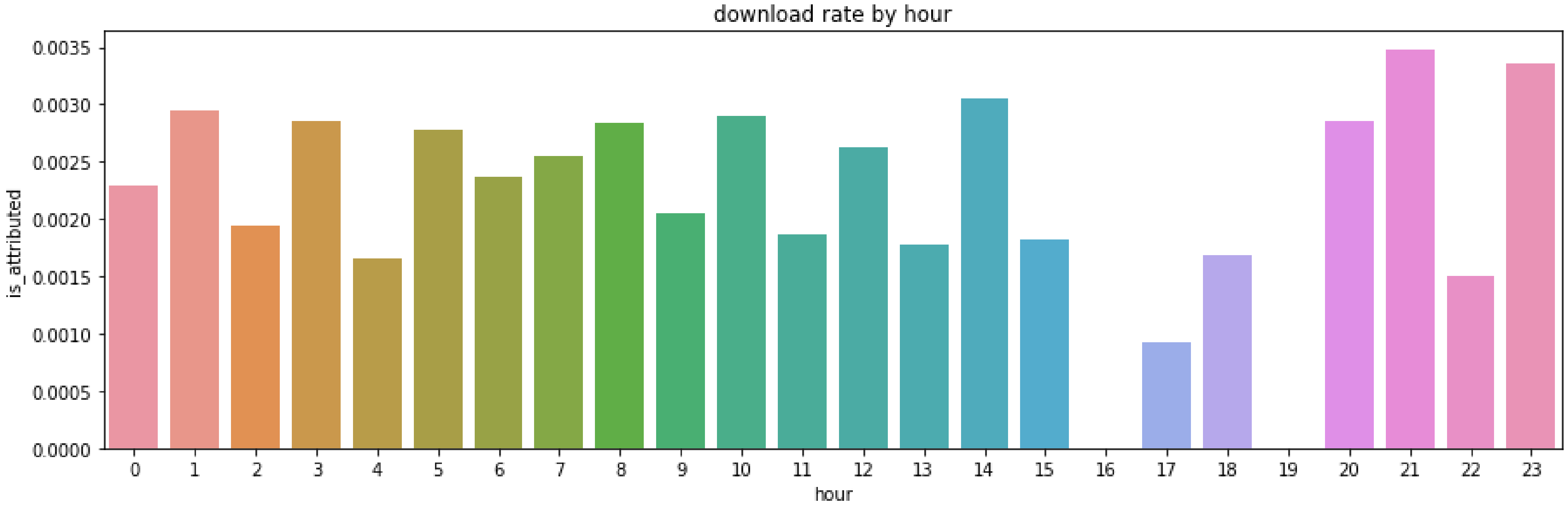
1. Data Exploration

Check download count per hour



1. Data Exploration

Check download rate per hour



1. Data Exploration

Check click count, download count, download rate (by app, device, os, channel)

Don't put the graph here because it is so large.

Please refer to the address below to view it.

https://github.com/MinPinSunHwa/Ad_Tracking_Project

1. Data Exploration

Check correlation

ip	: 0.053833
app	: 0.059722
device	: 0.001630
os	: 0.001630
channel	: -0.024133
hour	: -0.005629

Method1

2. Data Preprocessing

Train all data

preprocessing

Train sample data

preprocessing

Make derived variables

Create derived variables in each train all dataset and train sample dataset.

A total of 14 derived variables are created.

- hour : hour from click time

2. Data Preprocessing

Train all data

preprocessing

Train sample data

preprocessing

Make derived variables

: download proportion

- ip_attr_prop : # by ip
- app_attr_prop : # by app
- device_attr_prop : # by device
- os_attr_prop : # by os
- channel_attr_prop : # by channel
- hour_attr_prop : # by hour
- tot_attr_ptop : the sum of the above 6 variables

2. Data Preprocessing

Train all data

preprocessing

Train sample data

preprocessing

Make derived variables

: download proportion

- ip_hour_prop : # by ip and hour
- ip_app_prop : # by ip and app
- ip_channel_prop : # by ip and channel
- hour_app_prop : # by hour and app
- hour_channel_prop : # by hour and channel
- tot_vv_prop : the sum of the above 5 variables

2. Data Preprocessing

Train all data

preprocessing

Train sample data

preprocessing

Check correlation

- ip_attr_prop : 0.438892
- app_attr_prop : 0.444209
- device_attr_prop : 0.201987
- os_attr_prop : 0.226293
- channel_attr_prop : 0.389942
- hour_attr_prop : 0.008851
- tot_attr_ptop : 0.532482

2. Data Preprocessing

Train all data

preprocessing

Train sample data

preprocessing

Check correlation

ip_hour_prop	: 0.582208
ip_app_prop	: 0.755585
ip_channel_prop	: 0.715354
hour_app_prop	: 0.457047
hour_channel_prop	: 0.416602
tot_vv_prop	: 0.739013

2. Data Preprocessing

Preprocess test data

Based on train all dataset except ‘hour’ variable, 13 derived variables are created in the test dataset.

Because train all dataset is the most data, the value of the test dataset can be filled without as many blanks as possible, thus creating derived variables in the test dataset using train all dataset.

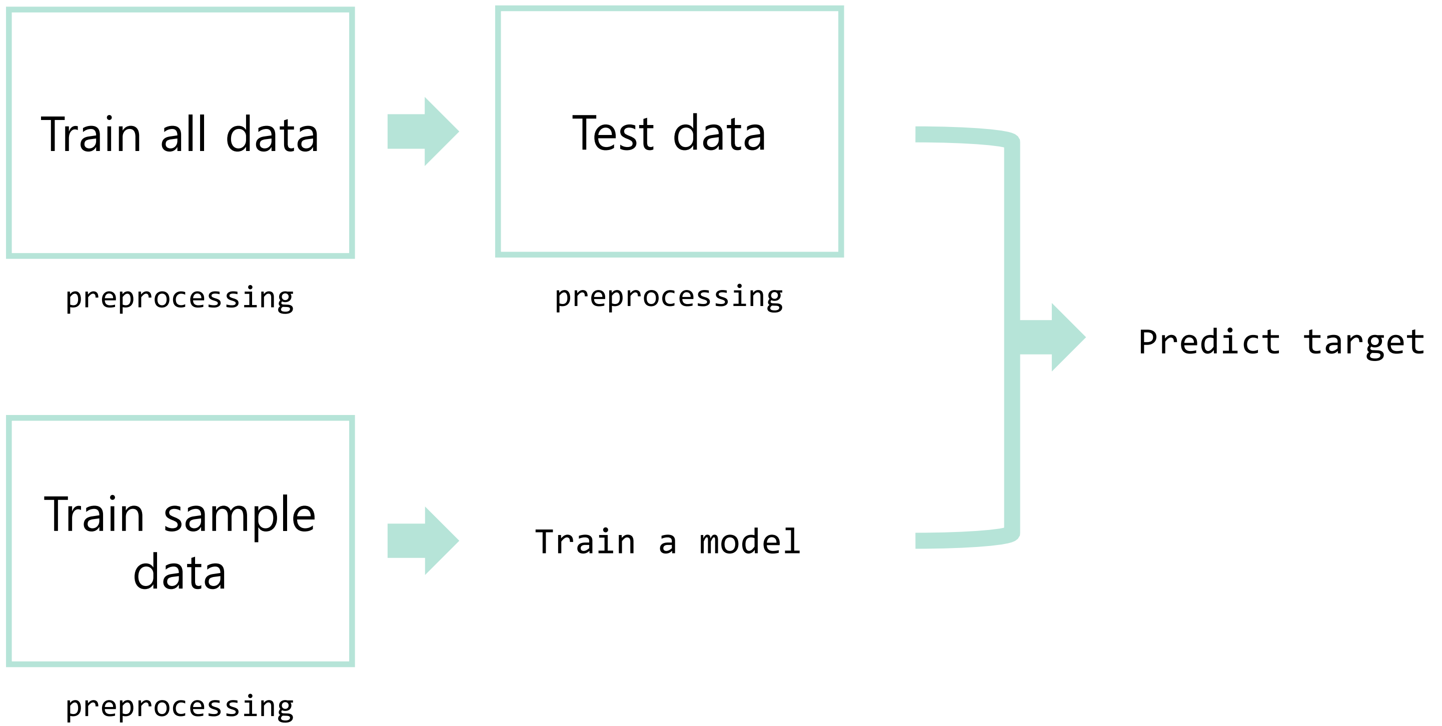
3. Target Variable Prediction

Create functions

Create functions prior to prediction of the target variable.

- check_data : To check data distribution
- examine_outlier : To check for values other then 0 and 1

3. Target Variable Prediction



3. Target Variable Prediction

Create features to use a model

- feat1 = ip_attr_prop, app_attr_prop, device_attr_prop, os_attr_prop, channel_attr_prop, hour_attr_prop, tot_attr_prop
- feat2 = ip_hour_prop, ip_app_prop, ip_channel_prop, hour_app_prop, hour_channel_prop, tot_vv_prop
- feat3 = feat1 + feat2
- feat4 = ip_attr_prop, app_attr_prop, channel_attr_prop, tot_attr_prop
- feat5 = feat4 + feat2
- feat6 = app_attr_prop, channel_attr_prop, hour_app_prop, hour_channel_prop

3. Target Variable Prediction

Predict target variable

- Linear Regression
- Ridge
- Logistic Regression
- Decision Tree
- Random Forest
- Gradient Boosting
- K-Nearest Neighbors
- Support Vector machines
- LightGBM

Skip because it takes too long

3. Target Variable Prediction

Predict target variable

- Linear Regression

	10m	20m	30m
feat1	0.9336475	0.3937085	0.9396936
feat2	0.7903207	0.7990348	0.8090254
feat3	0.6832881	0.6891693	0.6870306
feat4	0.9394377	0.9393066	0.9394337
feat5	0.6786381	0.6730954	0.6829231
feat6	0.9467690	0.9468087	0.9466697

✓ 10m, 20m, 30m : 10, 20, 30 million train data

✓ The value in table : kaggle score (AUC)

3. Target Variable Prediction

Predict target variable

- Logistic Regression

C	10m	20m	30m
0.01	$\boxed{0.9518560}$	0.9518226	0.9518260
0.1	0.9517896	0.9518113	0.9517822
1	0.9517904	0.9517846	0.9517540
10	0.9517882	0.9517830	0.9517553

- ✓ feature : feat6

3. Target Variable Prediction

Predict target variable

- Decision Tree

max_depth	10m	20m	30m
3	0.9039194	0.9039806	0.9040380
4	0.9068583	0.9065484	0.9067215
5	0.9379549	0.9245333	0.9310434

- ✓ feature : feat6

3. Target Variable Prediction

Predict target variable

- Random Forest

max_depth \ n_estimators	30	50	70
3	0.9117286	0.9325352	0.9325768
4	0.9446114	0.9444698	0.9481182
5	0.9511519	0.9506940	0.9506489

- ✓ feature : feat6
- ✓ sample : 10m
- ✓ max_features : 1

3. Target Variable Prediction

Predict target variable

- Gradient Boosting

max_depth \ n_estimators	30	50
3	0.9058254	0.9069254
4	0.9426463	0.9432340
5	0.9477711	$\boxed{0.9486383}$

- ✓ feature : feat6
- ✓ sample : 10m
- ✓ learning_rate : 0.01

3. Target Variable Prediction

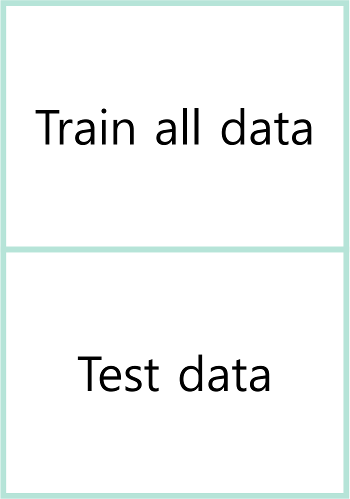
Predict target variable

- LightGBM

	10m	20m	30m
feat1	0.9426481	0.9411704	0.9398357
feat2	0.8694790	0.8232350	0.8775217
feat3	0.8694790	0.8467034	0.8577380
feat4	0.9410401	0.9413678	0.9411245
feat5	0.8921562	0.8471011	0.8415991
feat6	0.9514271	0.9528658	0.9526517

Method2

2. Data Preprocessing



merge

Make and fill a variable ‘is_attributed’ in test data

Make a variable ‘is_attributed’ in test data, then fill the variable with the proportion of download in train data

Merge train data and test data

Combine train data and test data to make derived variables together.

2. Data Preprocessing

Train all data

Test data

preprocessing

Make derived variables

Create 21 derived variables in merged dataset.

After preprocessing separate dataset, then extract a sample.

- 14 derived variables made in method1

2. Data Preprocessing

Train all data
Test data

preprocessing

Make derived variables

: download proportion among download

- ip_attr_tot_prop : # by ip
- app_attr_tot prop : # by app
- device_attr_tot_prop : # by device
- os_attr_tot_prop : # by os
- channel_attr_tot_prop : # by channel
- hour_attr_tot_prop : # by hour
- tot_attr_tot_ptop : the sum of the above 6 variables

2. Data Preprocessing

Train all data
Test data

preprocessing

Check correlation

ip_attr_prop	: 0.438472
app_attr_prop	: 0.442714
device_attr_prop	: 0.235278
os_attr_prop	: 0.226075
channel_attr_prop	: 0.389457
hour_attr_prop	: 0.007377
tot_attr_ptop	: 0.547662

2. Data Preprocessing

Train all data
Test data

preprocessing

Check correlation

- ip_attr_tot_prop : -0.003495
- app_attr_tot_prop : 0.235278
- device_attr_tot_prop : -0.044279
- os_attr_tot_prop : -0.001541
- channel_attr_tot_prop : 0.264980
- hour_attr_tot_prop : 0.007057
- tot_attr_tot_ptop : 0.026574

2. Data Preprocessing

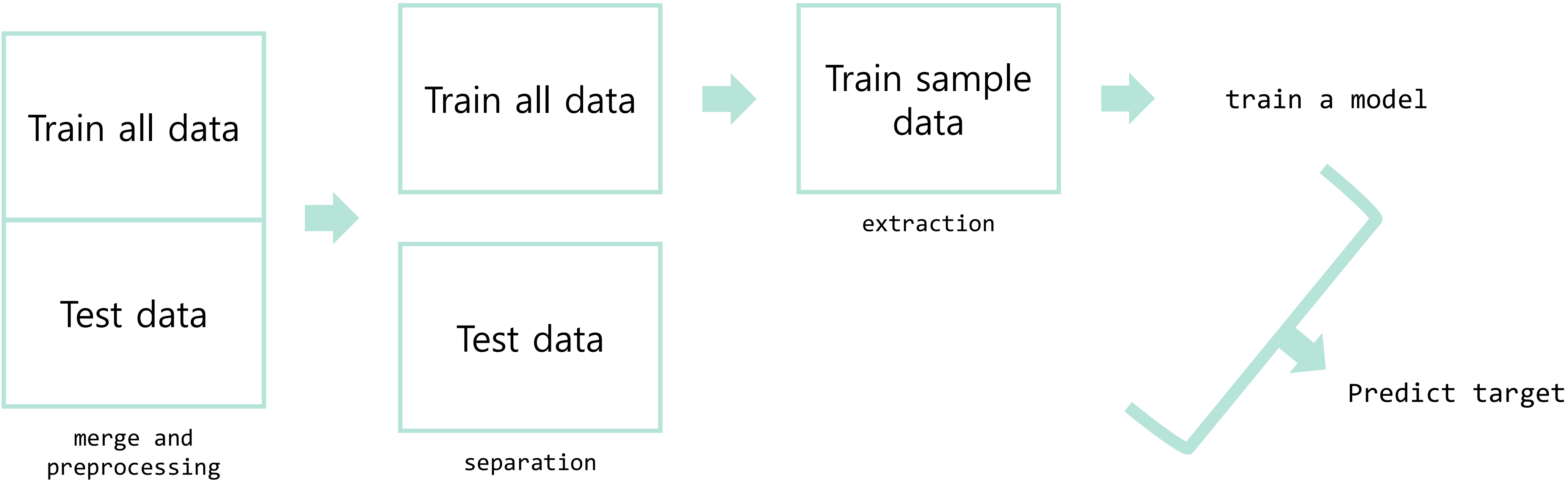
Train all data
Test data

preprocessing

Check correlation

- ip_hour_prop : 0.581782
- ip_app_prop : 0.753387
- ip_channel_prop : 0.713664
- hour_app_prop : 0.452420
- hour_channel_prop : 0.413714
- tot_vv_ptop : 0.739452

3. Target Variable Prediction



3. Target Variable Prediction

Create features to use a model

- feat1 = ip_attr_prop, app_attr_prop, device_attr_prop, os_attr_prop, channel_attr_prop, hour_attr_prop, tot_attr_prop
- feat2 = ip_hour_prop, ip_app_prop, ip_channel_prop, hour_app_prop, hour_channel_prop, tot_vv_prop
- feat3 = feat1 + feat2
- feat4 = ip_attr_prop, app_attr_prop, channel_attr_prop, tot_attr_prop
- feat5 = feat4 + feat2
- feat6 = feat5 + app_attr_tot_prop, channel_attr_tot_prop

3. Target Variable Prediction

Create features to use a model

- feat7 = app_attr_prop, channel_attr_prop, hour_app_prop, hour_channel_prop
- feat8 = feat7 + app_attr_tot_prop, channel_attr_tot_prop
- feat9 = app_attr_prop, device_attr_prop, os_attr_prop, channel_attr_prop, hour_attr_prop
- feat10 = feat9 + hour_app_prop, hour_channel_prop
- feat11 = feat10 + app_attr_tot_prop, channel_attr_tot_prop

3. Target Variable Prediction

Predict target variable

- LightGBM
- LightGBM : add categorical_feature (app, channel)
- Mean of the highest 3 scores

3. Target Variable Prediction

Predict target variable

- LightGBM

	40m
feat1	0.5688519
feat2	0.7514380
feat3	0.5293284
feat4	0.5320984
feat5	0.2968826
feat6	0.6316038

3. Target Variable Prediction

Predict target variable

- LightGBM

	10m	20m	30m	40m	50m
feat7	0.9509782	0.9519082	0.9505800	0.9509782	0.9520227
feat8	0.9538612	0.9527098	0.9525610	0.9532771	0.9525889
feat9	0.9572276	0.9550265	0.9568368	0.9532595	0.9556014
feat10	0.9501722	0.9504824	0.9508289	0.9524248	0.9516097
feat11	0.9544192	0.9564199	0.9538744	0.9536148	0.9525215

3. Target Variable Prediction

Predict target variable

- LightGBM : add categorical_feature

	10m	20m	30m	40m	50m
feat7	0.9536391	0.9541964	0.9543481		
feat8	0.9544556	0.9544834	0.9539668		
feat9	0.9592092	0.9591456	0.9594930	0.9569738	0.9585332
feat10	0.9579120	0.9571316	0.9572331	0.9565375	0.9558988
feat11	0.9576898	0.9583076	0.9570422	0.9567561	0.9542069

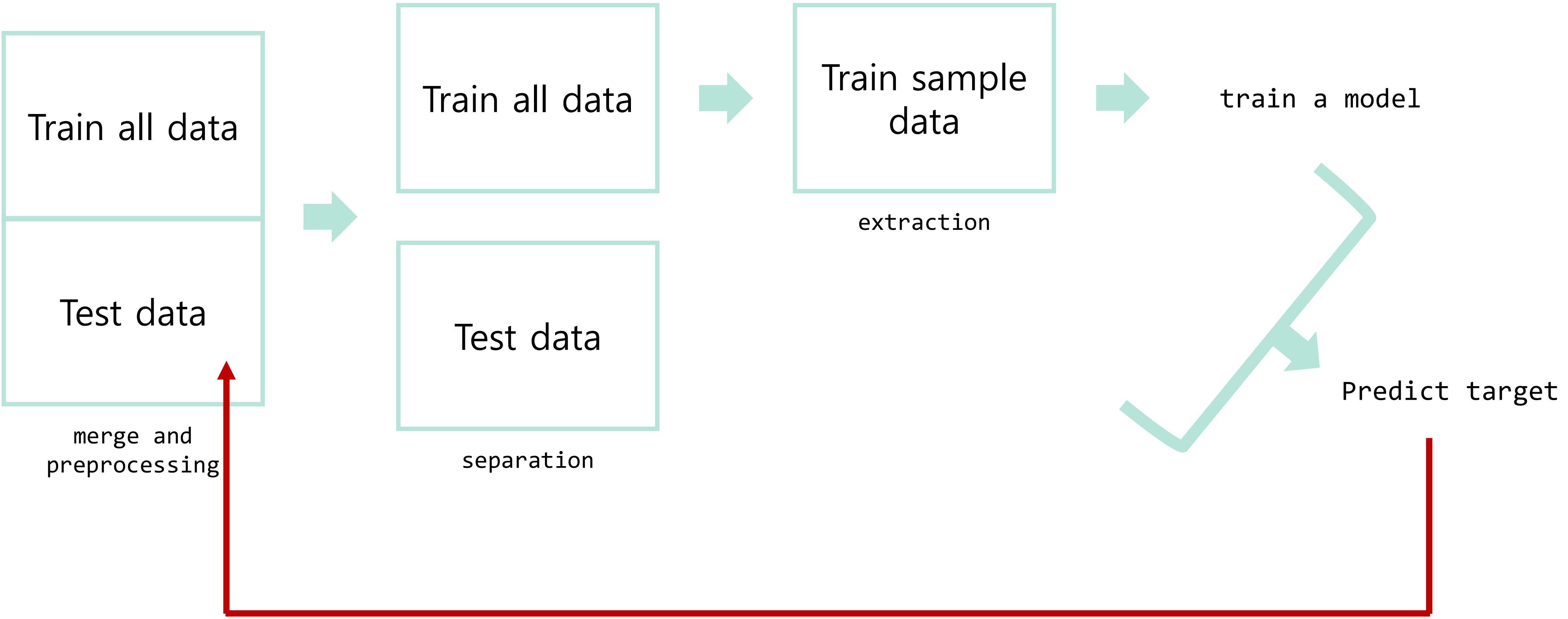
3. Target Variable Prediction

Predict target variable

- Mean of the highest 3 scores : 0.9601829

Method3

2. Data Preprocessing



Inserts the target variable predicted by the best score in method2 into the variable ‘is_attributed’ in test dataset.

2. Data Preprocessing

Train all data
Test data

preprocessing

Check correlation

- ip_attr_prop : 0.433923
- app_attr_prop : 0.415598
- device_attr_prop : 0.195802
- os_attr_prop : 0.217134
- channel_attr_prop : 0.361186
- hour_attr_prop : 0.001310
- tot_attr_ptop : 0.437112

2. Data Preprocessing

Train all data
Test data

preprocessing

Check correlation

- ip_attr_tot_prop : -0.004292
- app_attr_tot_prop : 0.058505
- device_attr_tot_prop : -0.047266
- os_attr_tot_prop : -0.007671
- channel_attr_tot_prop : 0.175313
- hour_attr_tot_prop : 0.001170
- tot_attr_tot_ptop : -0.013554

2. Data Preprocessing

Train all data
Test data

preprocessing

Check correlation

- ip_hour_prop : 0.565648
- ip_app_prop : 0.706752
- ip_channel_prop : 0.672597
- hour_app_prop : 0.394257
- hour_channel_prop : 0.352294
- tot_vv_ptop : 0.676771

3. Target Variable Prediction

Create features to use a model

- feat1 = ip_attr_prop, app_attr_prop, device_attr_prop, os_attr_prop, channel_attr_prop, hour_attr_prop, tot_attr_prop
- feat2 = ip_hour_prop, ip_app_prop, ip_channel_prop, hour_app_prop, hour_channel_prop, tot_vv_prop
- feat3 = feat1 + feat2
- feat4 = ip_attr_prop, app_attr_prop, channel_attr_prop, tot_attr_prop
- feat5 = feat4 + feat2
- feat6 = feat5 + app_attr_tot_prop, channel_attr_tot_prop

3. Target Variable Prediction

Create features to use a model

- feat7 = app_attr_prop, channel_attr_prop, hour_app_prop, hour_channel_prop
- feat8 = feat7 + app_attr_tot_prop, channel_attr_tot_prop
- feat9 = app_attr_prop, device_attr_prop, os_attr_prop, channel_attr_prop, hour_attr_prop
- feat10 = feat9 + hour_app_prop, hour_channel_prop
- feat11 = feat10 + app_attr_tot_prop, channel_attr_tot_prop

3. Target Variable Prediction

Predict target variable

- LightGBM
- Mean of the highest 3 scores
- Min or Max of the highest 3 scores

3. Target Variable Prediction

Predict target variable

- LightGBM

	10m	20m	30m	40m	50m
feat1	0.9583284	0.9593660	0.9603516	0.9594674	0.9602325
feat2	0.9475335				
feat3	0.9518953				
feat4	0.9539884				
feat5	0.9494600				
feat6	0.9495302				

- ✓ Add categorical_feature : app, channel
- ✓ max_depth : 3

3. Target Variable Prediction

Predict target variable

- LightGBM

	10m	20m	30m	40m	50m
feat7	0.9535959				
feat8	0.9538248				
feat9	0.9586031	0.9599000	0.9604426	0.9605254	0.9605942
feat10	0.9582457	0.9595100	0.9602716	0.9606479	0.9607716
feat11	0.9588514	0.9596459	0.9603991	0.9608608	0.9608304

- ✓ Add categorical_feature : app, channel
- ✓ max_depth : 3

3. Target Variable Prediction

Predict target variable

❖ LightGBM

	10m	20m	30m	40m	50m
feat1	0.9583113	0.9596961	0.9599524	0.9601369	0.9599524
feat2	0.9470242	0.9472043			
feat3	0.9549069	0.9521961			
feat4	0.9542260	0.9547919			
feat5	0.9493426	0.9494986			
feat6	0.9494255	0.9498724			

✓ Add categorical_feature : app, channel

✓ max_depth : 5

3. Target Variable Prediction

Predict target variable

- LightGBM

	10m	20m	30m	40m	50m
feat7	0.9541271	0.9546565			
feat8	0.9539828	0.9550807			
feat9	0.9588967	0.9600684	0.9605240	0.9610805	0.9612525
feat10	0.9587186	0.9595902	0.9603856	0.9609769	0.9613507
feat11	0.9585257	0.9599040	0.9608502	0.9612153	0.9612539

✓ Add categorical_feature : app, channel

✓ max_depth : 5

3. Target Variable Prediction

Predict target variable

- Mean of the highest 3 scores : 0.9614675
- Min or Max of the highest 3 scores : 0.9614597

4. Conclusion

Result

- Variables related to app and channel were important.
- The best score : 0.9614675

Realization

- It was more important to know which variables to use than which model to use.

Thank you.

GitHub : https://github.com/MinPinSunHwa/Ad_Tracking_Project