Outline

1. Loading Data

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import cyrtranslit
```

```
from sklearn import preprocessing, model_selection, metrics, feature_selection, ensemble, linear_model, cross_decomposition, feature_extraction, decomposition, compose,neural_network
import lightgbm as lgb
from scipy import stats
import time
from sklearn.externals import joblib
import pickle
import os

import tensorflow as tf
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPooling2D
from keras.layers import LSTM, Input, TimeDistributed
from keras.models import Model
from keras.optimizers import RMSprop

# Import the backend
from keras import backend as K

color = sns.color_palette()
%matplotlib inline
```

```
Using TensorFlow backend.
```

```
train = pd.read_csv('../train.csv.zip',compression='zip',parse_dates=['activation_date'])
test = pd.read_csv('../test.csv.zip',compression='zip',parse_dates=['activation_date'])
```

2. Exploratory Data Analysis

Back to Outline

Summary

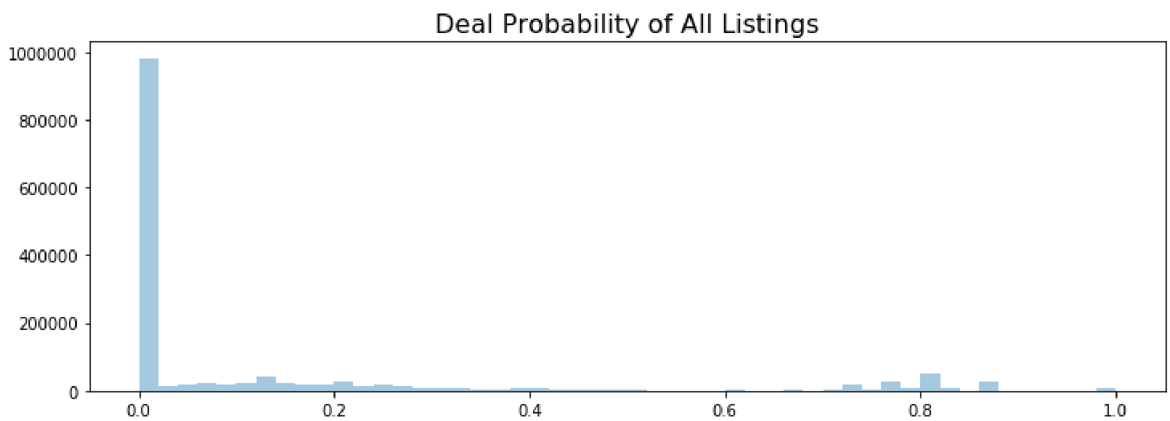
- Data is big.
- It’s in Russian with Cyrillic alphabet.
- Outcome variable is very non-normal. There’s three distinct groups. (Zero Range, Lower Range, Upper Range)
- Titles and descriptions offer endless NLP opportunities.
- Plenty of categorical data to binarize.

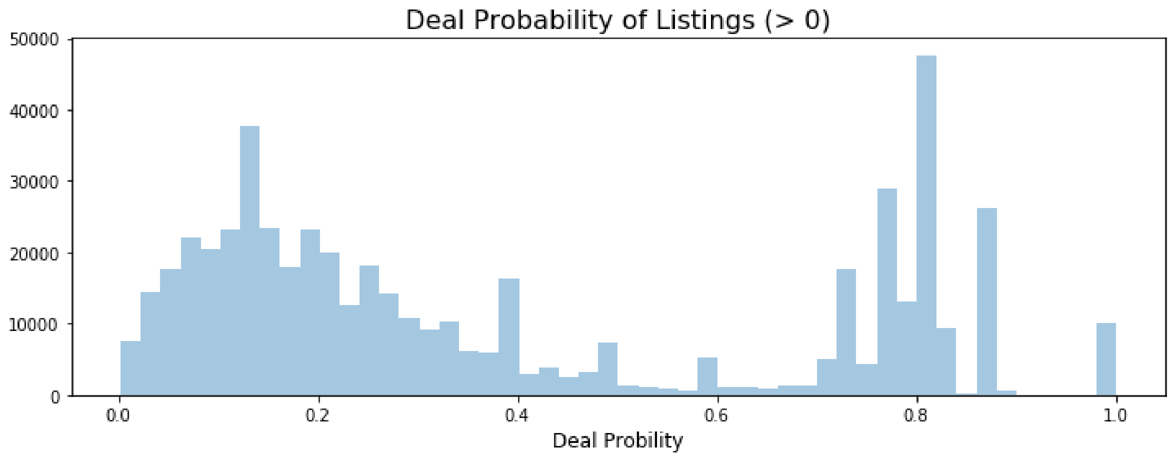
2.1. Distribution of Target

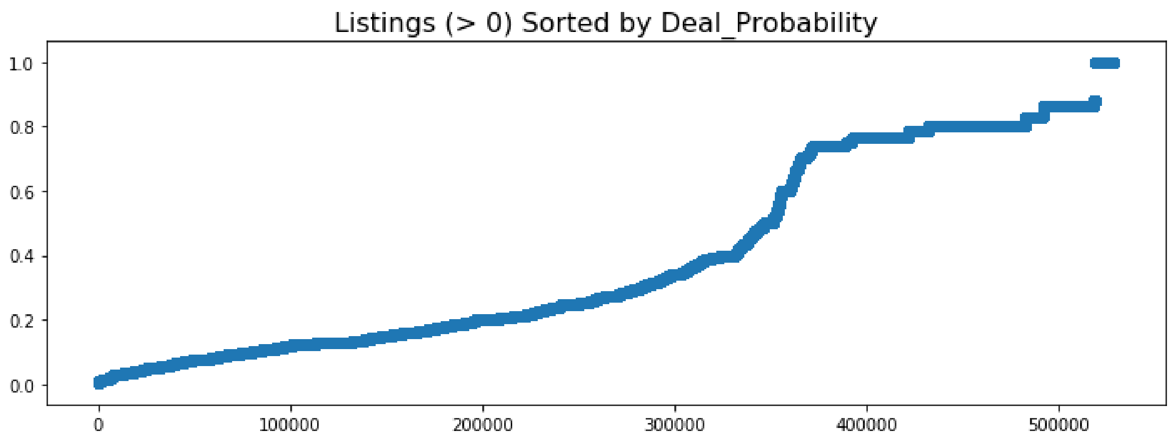
Back to Outline

> There's about a million listings with zero demand, and a much smaller number with varying chance of selling.

```python
# Define deal probabilities and those over zero
probs = train["deal_probability"].values
probs_no0 = probs[probs>0]

# Plot probability histogram
plt.figure(figsize=(12,4))
sns.distplot(probs, kde=False)
plt.title("Deal Probability of All Listings", fontsize=16)
plt.show()

# Probabilities > 0 hist
plt.figure(figsize=(12,4))
sns.distplot(probs_no0, kde=False)
plt.xlabel('Deal Probility', fontsize=12)
plt.title("Deal Probability of Listings (> 0)", fontsize=16)
plt.show()

# Scatter of sorted probs
plt.figure(figsize=(12,4))
plt.scatter(range(probs_no0.shape[0]), np.sort(probs_no0))
plt.title("Listings (> 0) Sorted by Deal_Probability", fontsize=16)
plt.show()
```







2.2. Distribution of Demand by Region

Back to Outline

First let's translate the regions from Russian using the `cyrtranslit` package. Then visualize the distribution of each region.

```
# Get unique regions in cyrilic
cyrilic_regs = train.region.unique().tolist()
# Get unique translations
latin_regs = [cyrtranslit.to_latin(reg,'ru') for reg in cyrilic_regs]

# Put regions in a dictionary
reg_dict = {}
for cyr, lat in zip(cyrilic_regs,latin_regs):
    reg_dict[cyr]=lat

# Create a translated list of each region in the dataset
en_list = []
for reg in train.region:
    en_list.append(reg_dict[reg])

# Add english list as column
train['region_en'] = en_list
```

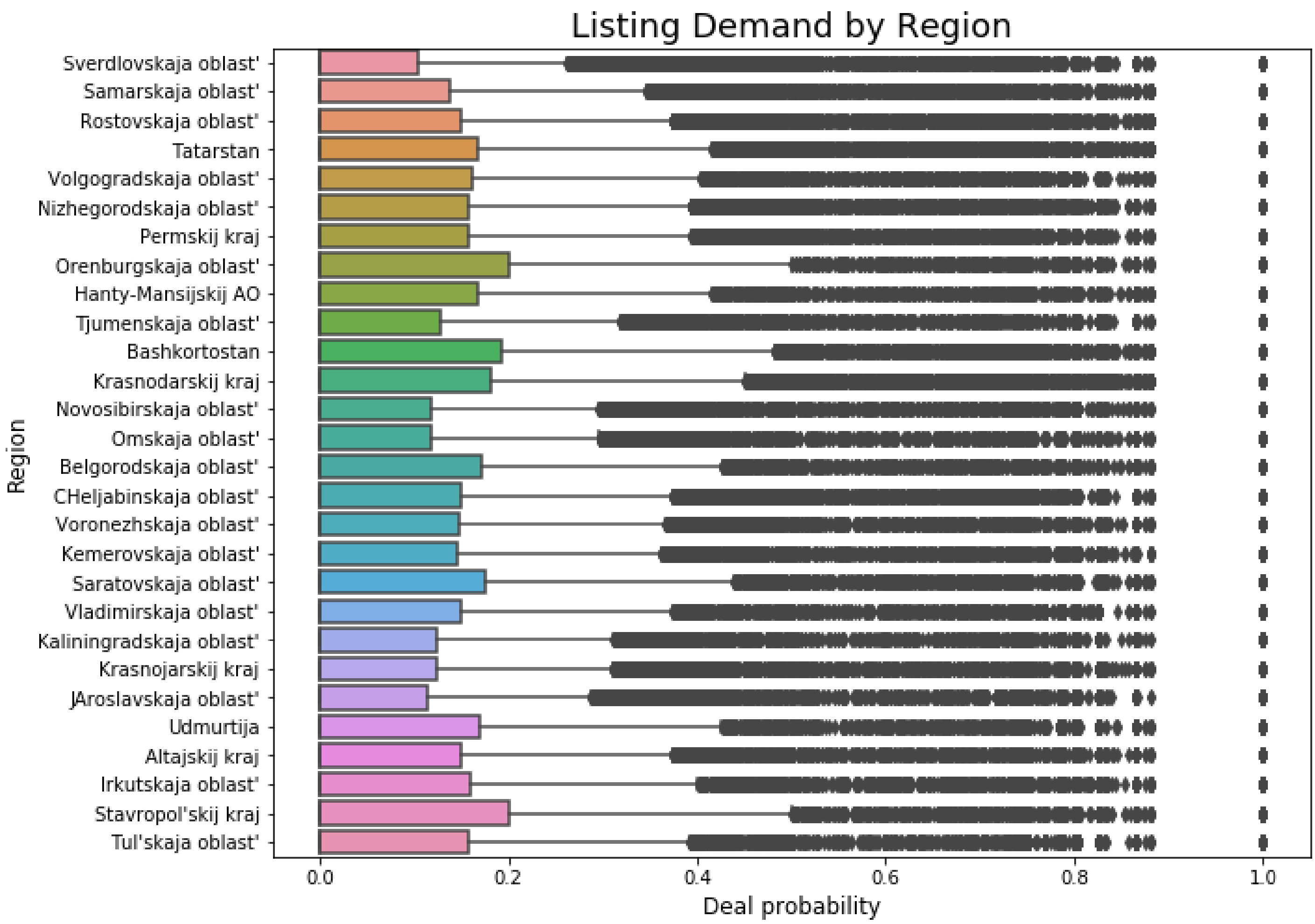
```
print('Translation of Russian Regions')
pd.DataFrame(latin_regs[:10],index=cyrilic_regs[:10],columns=
['Translations'])
```

```
Translation of Russian Regions
```

	Translations
Свердловская область	Sverdlovskaja oblast'
Самарская область	Samarskaja oblast'
Ростовская область	Rostovskaja oblast'
Татарстан	Tatarstan
Волгоградская область	Volgogradskaja oblast'
Нижегородская область	Nizhegorodskaja oblast'
Пермский край	Permskij kraj
Оренбургская область	Orenburgskaja oblast'
Ханты-Мансийский АО	Hanty-Mansijskij AO
Тюменская область	Tjumenskaja oblast'

- There is a tremendous amount of outliers. Not surprising due to the large size of the data.
- Anything with over 50% chances of selling is an outlier. Based on regional data, expecting a sale is an exception rather than the norm.

```
# Boxplots by Region
plt.figure(figsize=(10,8))
sns.boxplot(x="deal_probability", y="region_en", data=train)
plt.xlabel('Deal probability', fontsize=12)
plt.ylabel('Region', fontsize=12)
plt.title("Listing Demand by Region",fontsize=18)
plt.show()
```



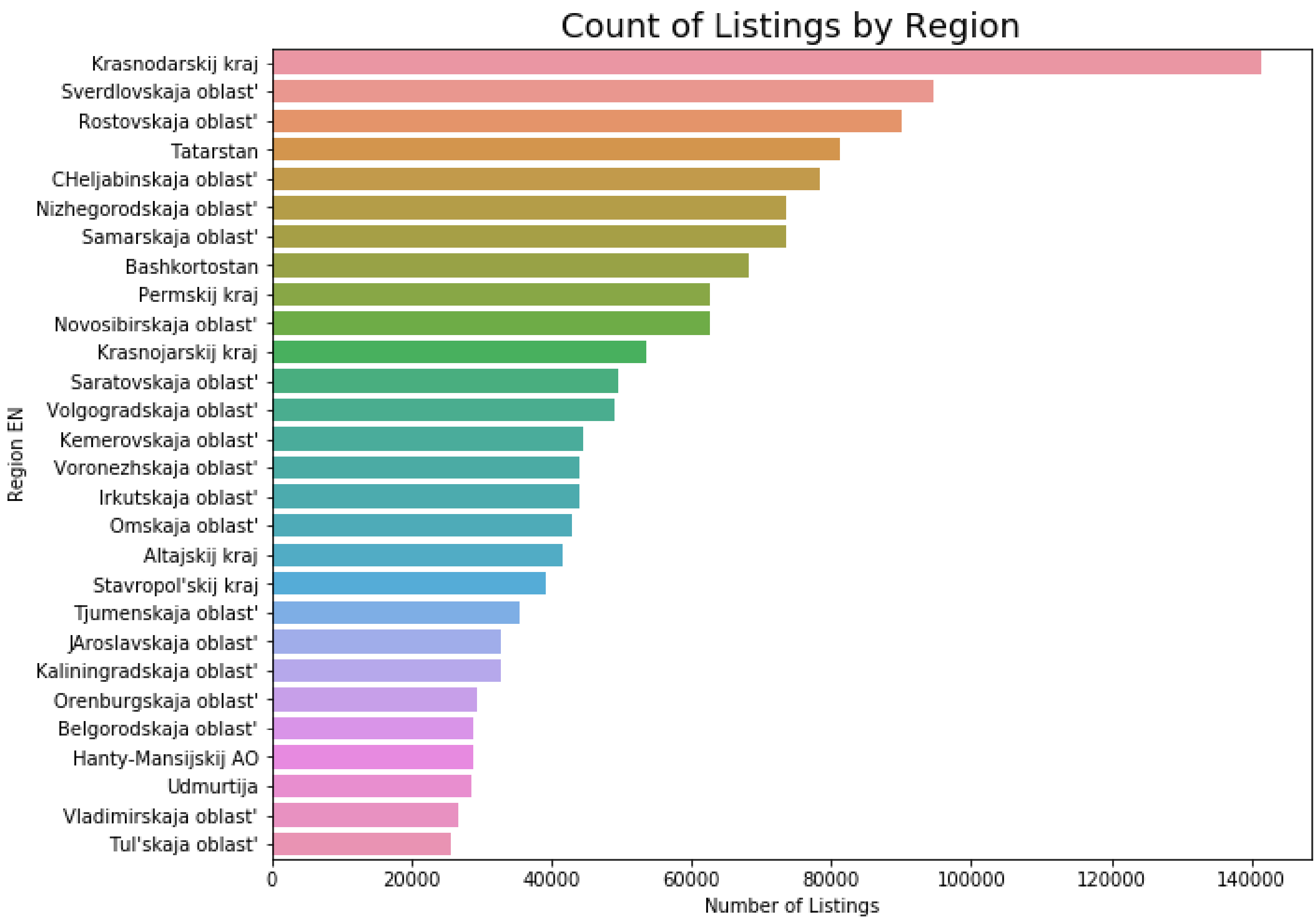
Percentage of Listings per Region

```python
# Get region group counts, sort and divide by N of listings
region_perc =
train.groupby('region_en').count().item_id.sort_values(ascending=False)/len(train)

# Top 5 regions
print('Percentage of Listings in Top Regions\n')
print(np.round(region_perc*100,2)[:5])
```

```
Percentage of Listings in Top Regions

region_en
Krasnodarskij kraj        9.41
Sverdlovskaja oblast'     6.28
Rostovskaja oblast'       5.99
Tatarstan                 5.41
CHeljabinskaja oblast'    5.21
Name: item_id, dtype: float64
```

Count of Listings by Region

```python
# Visualize sorted listing counts by region
plt.figure(figsize=(10,8))
sns.countplot(data=train,y='region_en',order=region_perc.keys())
plt.title('Count of Listings by Region',fontsize=18)
plt.ylabel('Region EN')
plt.xlabel('Number of Listings')
plt.show()
```



2.3. Deal Probability by City

Back to Outine

```python
# Get unique cities in cyrilic
cyrilic_cits = train.city.unique().tolist()
# Get unique translations
latin_cits = [cyrtranslit.to_latin(cit,'ru') for cit in cyrilic_cits]

# Put regions in a dictionary
cit_dict = {}
for cyr, lat in zip(cyrilic_cits,latin_cits):
    cit_dict[cyr]=lat

# Create a translated list of each region in the dataset
en_list = []
for cit in train.city:
```

```
    en_list.append(cit_dict[cit])

# Add english list as column
train['city_en'] = en_list

print('Translation of Russian Cities (First 10)')
pd.DataFrame(latin_cits[:10],index=cyrilic_cits[:10],columns=['Translations'])
```

```
Translation of Russian Cities (First 10)
```

	Translations
Екатеринбург	Ekaterinburg
Самара	Samara
Ростов-на-Дону	Rostov-na-Donu
Набережные Челны	Naberezhnye CHelny
Волгоград	Volgograd
Чистополь	CHistopol'
Нижний Новгород	Nizhnij Novgorod
Пермь	Perm'
Оренбург	Orenburg
Ханты-Мансийск	Hanty-Mansijsk

Percentage of Listings per City

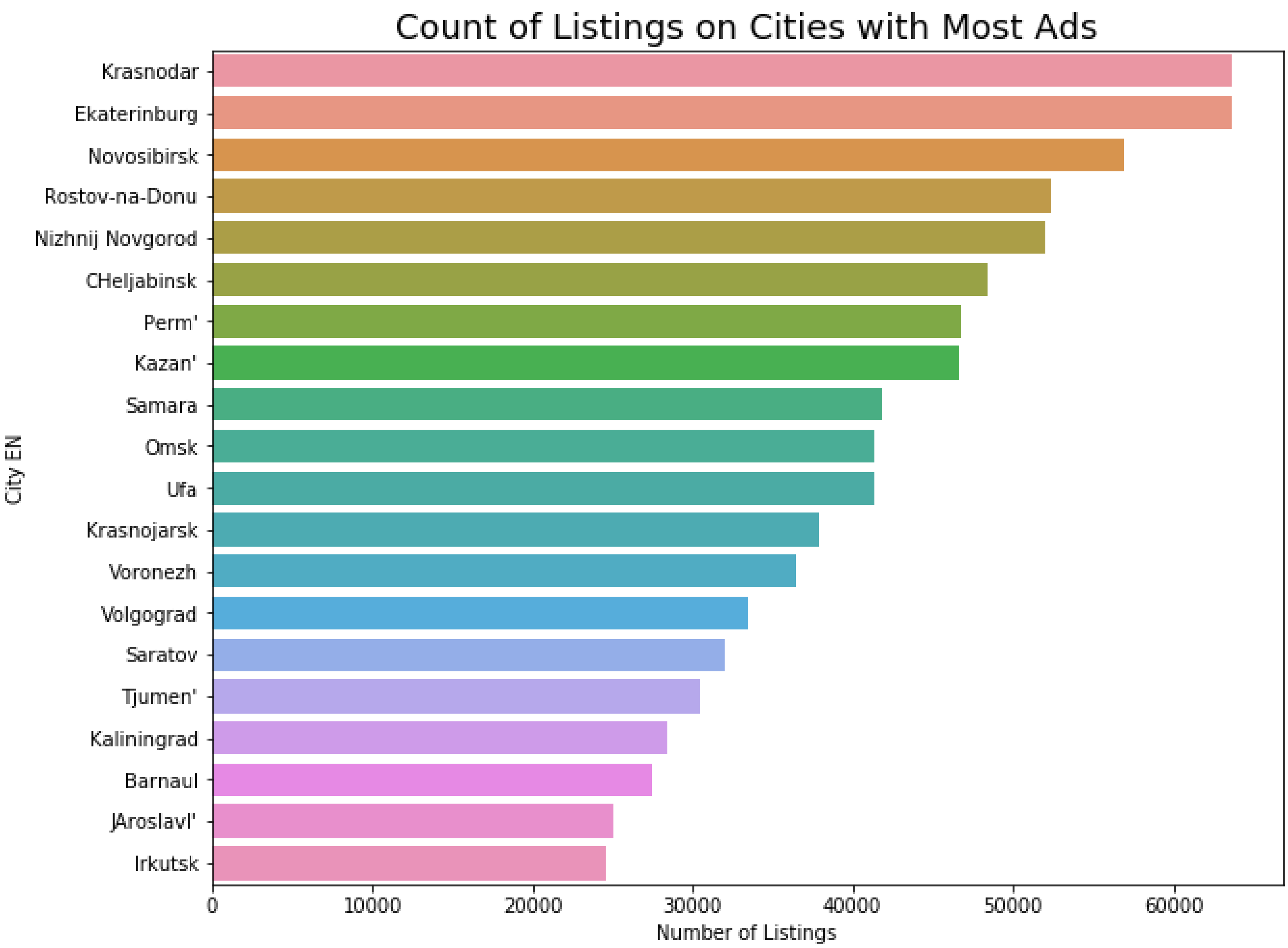
```
# Get city group counts, sort and divide by N of listings
city_perc = train.groupby('city_en').count().item_id.sort_values(ascending=False)/len(train)

# Top cities
print('Percentage of Listings in Top Cities\n')
print(np.round(city_perc*100,2)[:10])

```

```
Percentage of Listings in Top Cities

city_en
Krasnodar           4.23
Ekaterinburg        4.23
Novosibirsk         3.79
Rostov-na-Donu      3.48
Nizhnij Novgorod    3.46
CHeljabinsk         3.22
```

```
Perm'               3.11
Kazan'              3.10
Samara              2.79
Omsk                2.75
Name: item_id, dtype: float64
```

Count of Listings by City

```python
top20_cities = city_perc[:20].keys()

plot_data = train[train['city_en'].isin(top20_cities)]

# Visualize sorted listing counts by region
plt.figure(figsize=(10,8))
sns.countplot(data=plot_data,y='city_en',order=top20_cities)
plt.title('Count of Listings on Cities with Most Ads',fontsize=18)
plt.ylabel('City EN')
plt.xlabel('Number of Listings')
plt.show()
```



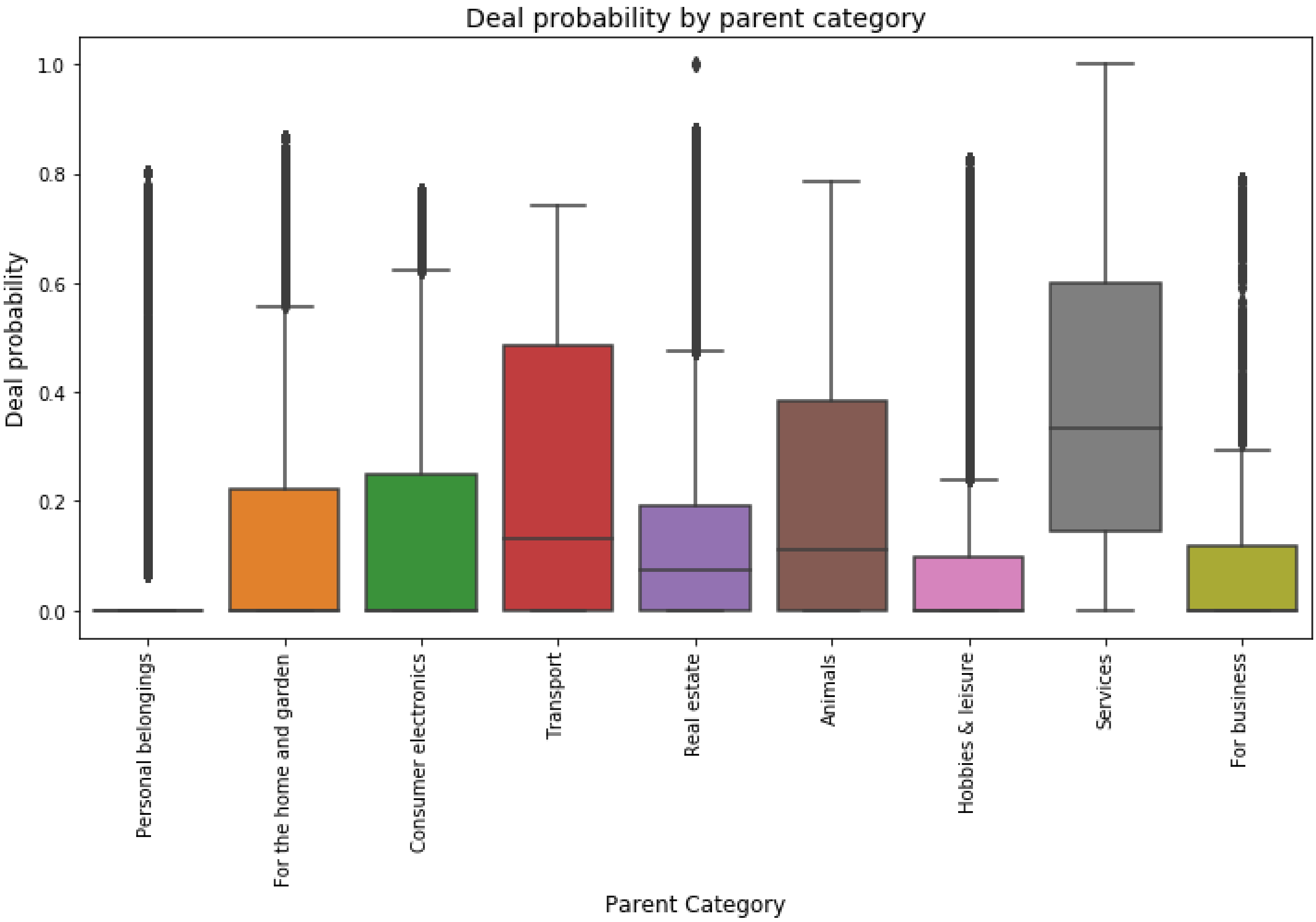
2.4. Deal Probability by Parent Category

Back to Outline

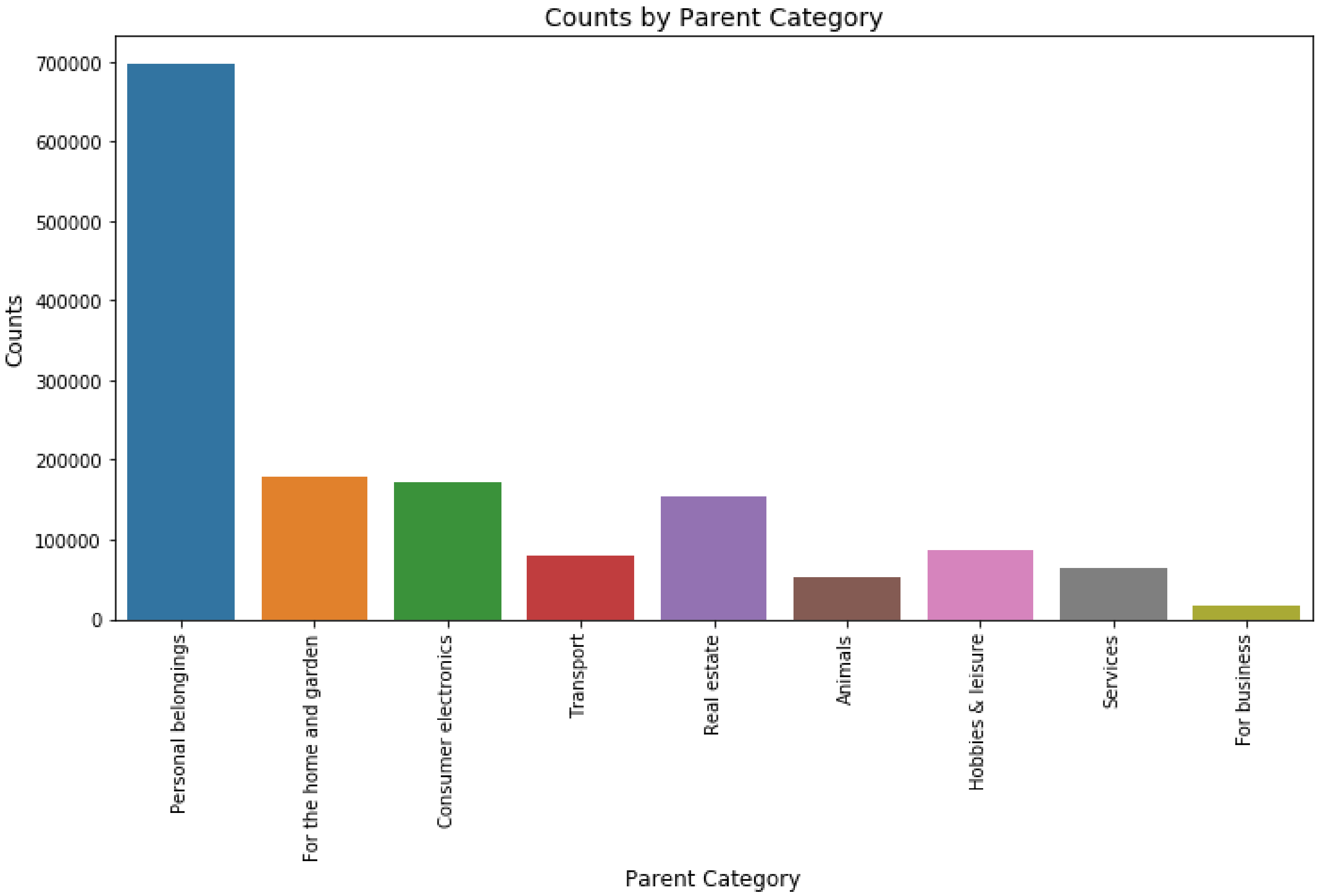
```python
from io import StringIO
```

```
temp_data = StringIO("""
parent_category_name,parent_category_name_en
Личные вещи,Personal belongings
Для дома и дачи,For the home and garden
Бытовая электроника,Consumer electronics
Недвижимость,Real estate
Хобби и отдых,Hobbies & leisure
Транспорт,Transport
Услуги,Services
Животные,Animals
Для бизнеса,For business
""")

temp_df = pd.read_csv(temp_data)
train = pd.merge(train, temp_df, on="parent_category_name", how="left")
test = pd.merge(test, temp_df, on="parent_category_name", how="left")
```

```
plt.figure(figsize=(12,6))
sns.boxplot(x="parent_category_name_en", y="deal_probability", data=train)
plt.ylabel('Deal probability', fontsize=12)
plt.xlabel('Parent Category', fontsize=12)
plt.title("Deal probability by parent category", fontsize=14)
plt.xticks(rotation='vertical')
plt.show()

plt.figure(figsize=(12,6))
sns.countplot(x="parent_category_name_en",data=train)
plt.ylabel('Counts', fontsize=12)
plt.xlabel('Parent Category', fontsize=12)
plt.title("Counts by Parent Category", fontsize=14)
plt.xticks(rotation='vertical')
plt.show()
```



Deal probability by parent category
Deal probability
1.0
0.8
0.6
0.4
0.2
0.0
Personal belongings
For the home and garden
Consumer electronics
Transport
Real estate
Animals
Hobbies & leisure
Services
For business
Parent Category

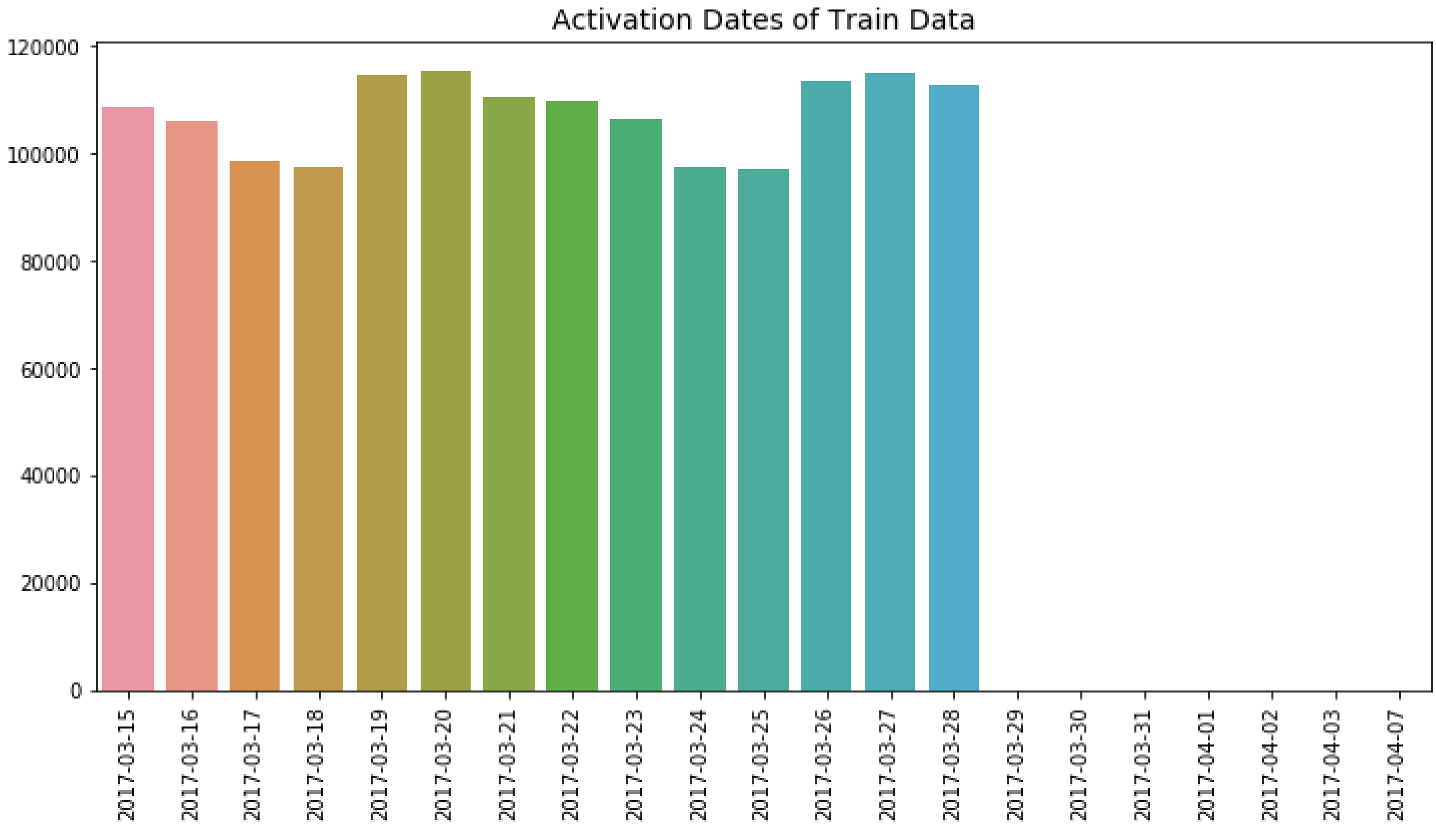


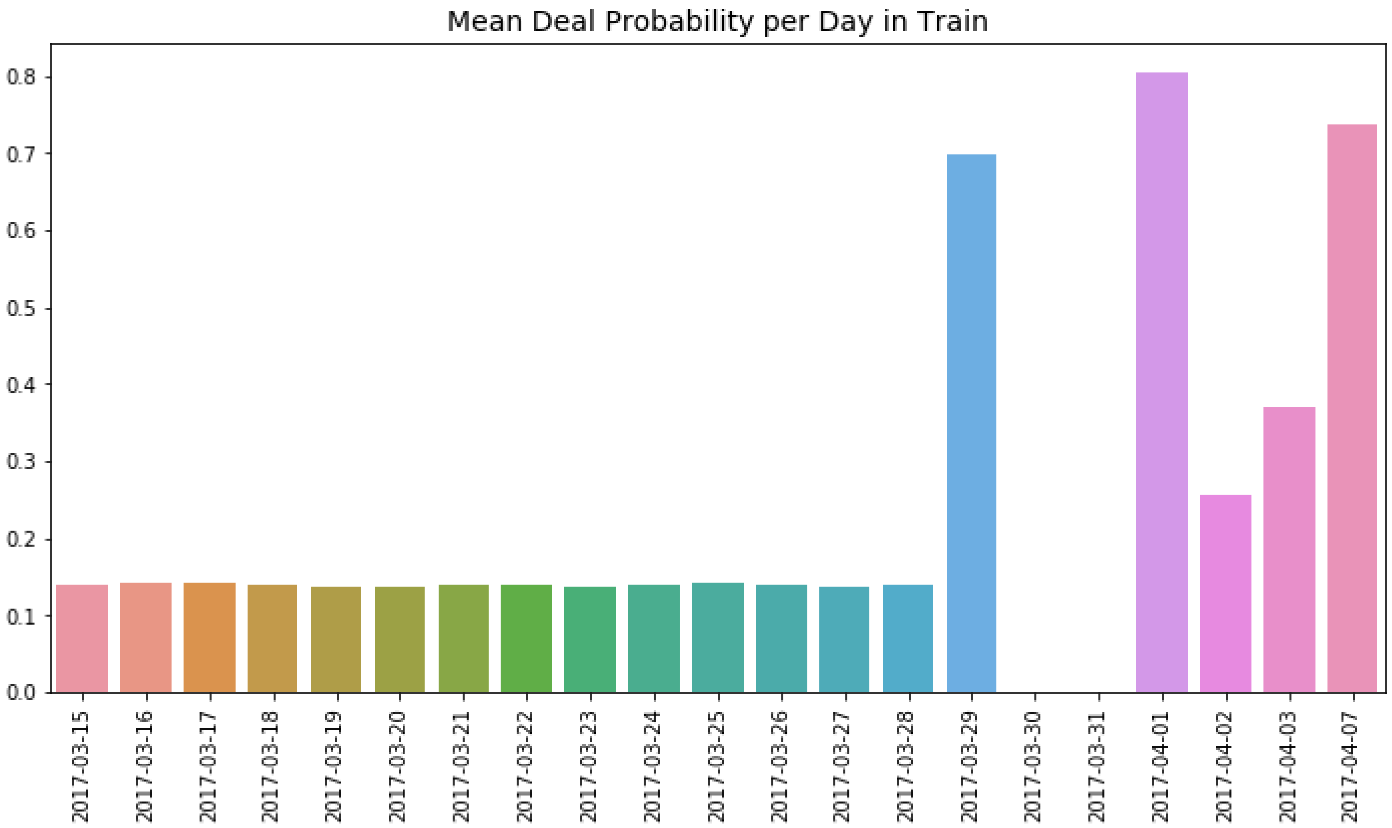
2.5. Activation Date and Deal Probability

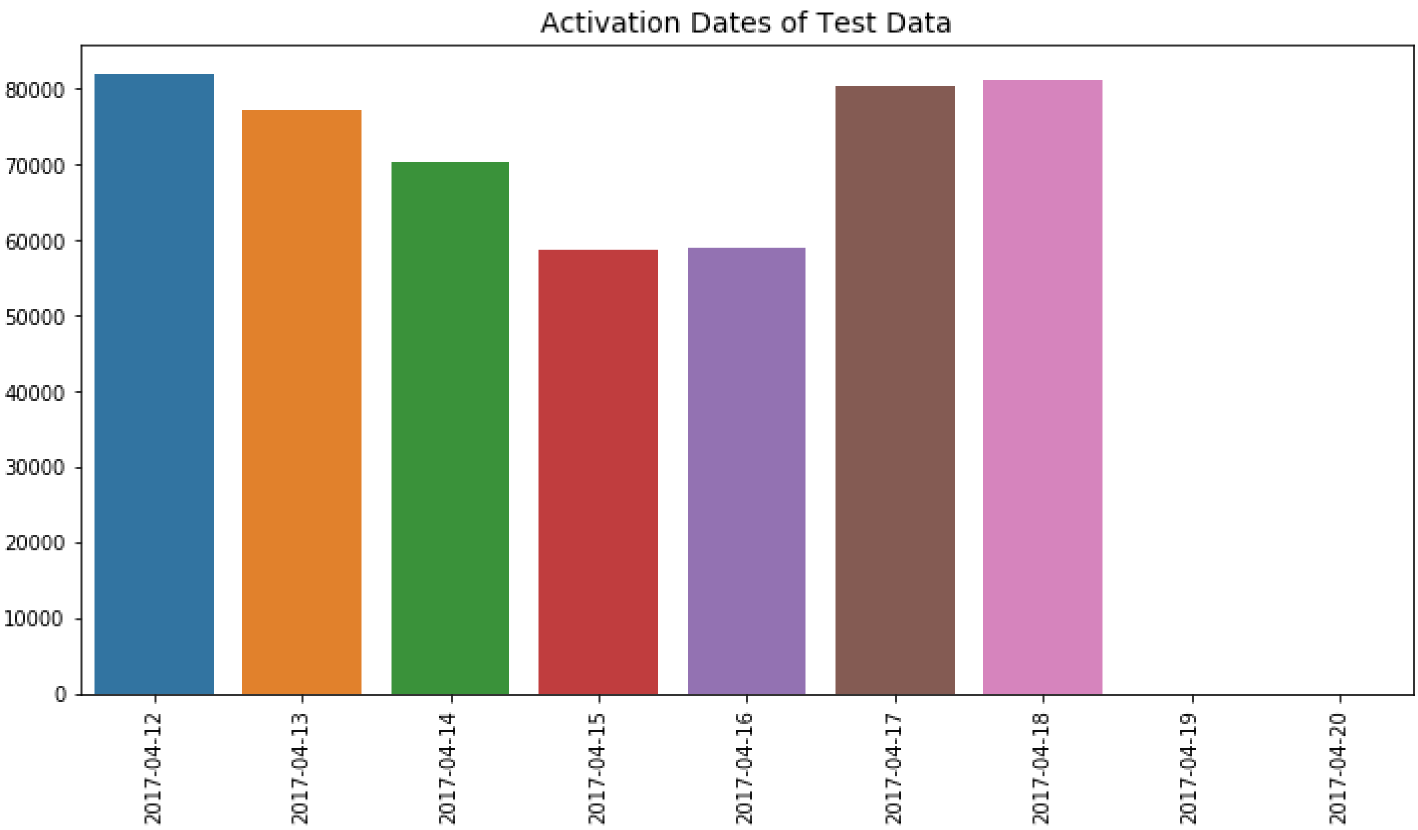
Back to Outline

```
srs = train.activation_date.value_counts().sort_index()

plt.figure(figsize=(12,6))
sns.barplot(x=srs.index.date,y=srs.values)
plt.xticks(rotation=90)
plt.title('Activation Dates of Train Data',fontsize=14)
plt.show()

srs = train.groupby('activation_date')['deal_probability'].mean()

plt.figure(figsize=(12,6))
sns.barplot(x=srs.index.date,y=srs.values)
plt.xticks(rotation=90)
plt.title('Mean Deal Probability per Day in Train',fontsize=14)
plt.show()

srs = test.activation_date.value_counts().sort_index()

plt.figure(figsize=(12,6))
sns.barplot(x=srs.index.date,y=srs.values)
plt.xticks(rotation=90)
```

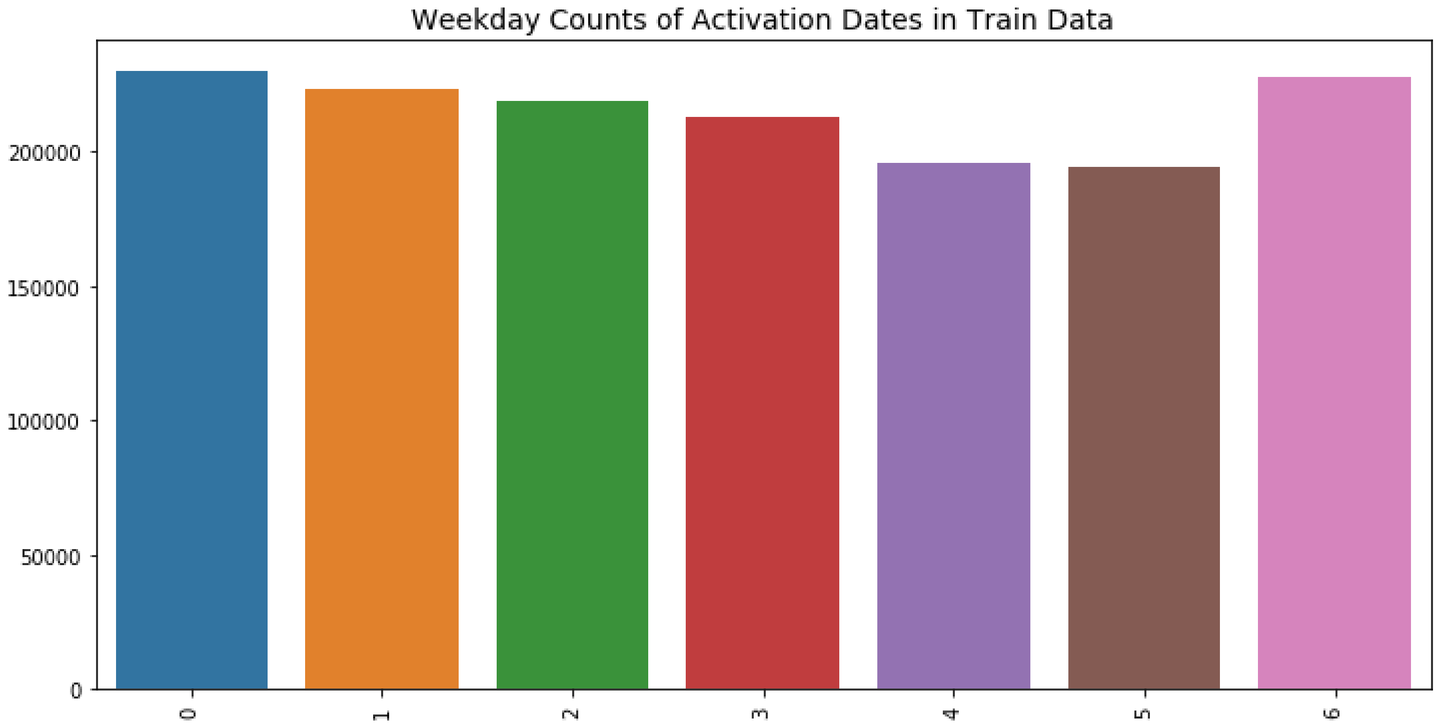
```
plt.title('Activation Dates of Test Data',fontsize=14)
plt.show()


```

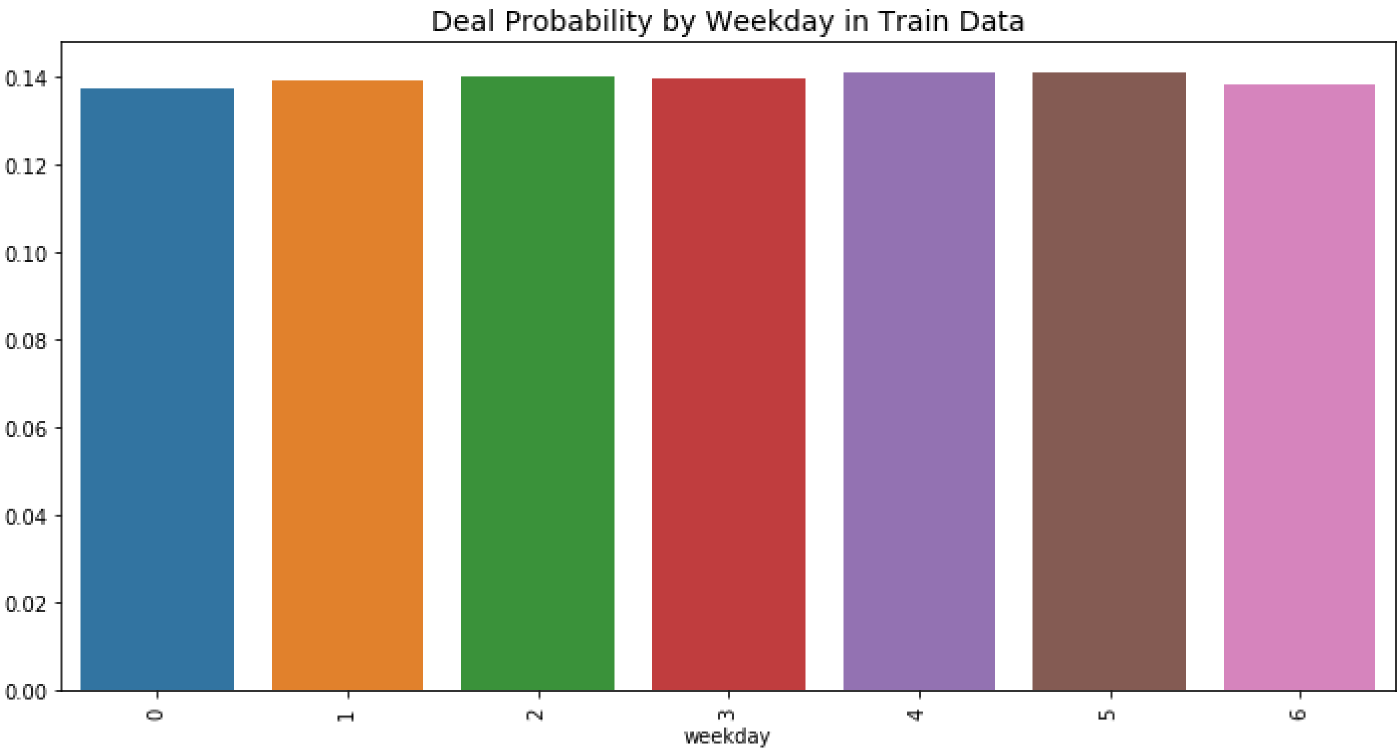







```
srs = train.activation_date.dt.weekday.value_counts().sort_index()

plt.figure(figsize=(12,6))
sns.barplot(x=srs.index,y=srs.values)
plt.xticks(rotation=90)
plt.title('Weekday Counts of Activation Dates in Train Data',fontsize=14)
plt.show()

train['weekday'] = train.activation_date.dt.weekday
srs = train.groupby('weekday').deal_probability.mean()

plt.figure(figsize=(12,6))
sns.barplot(x=srs.index,y=srs.values)
plt.xticks(rotation=90)
plt.title('Deal Probability by Weekday in Train Data',fontsize=14)
plt.show()
```



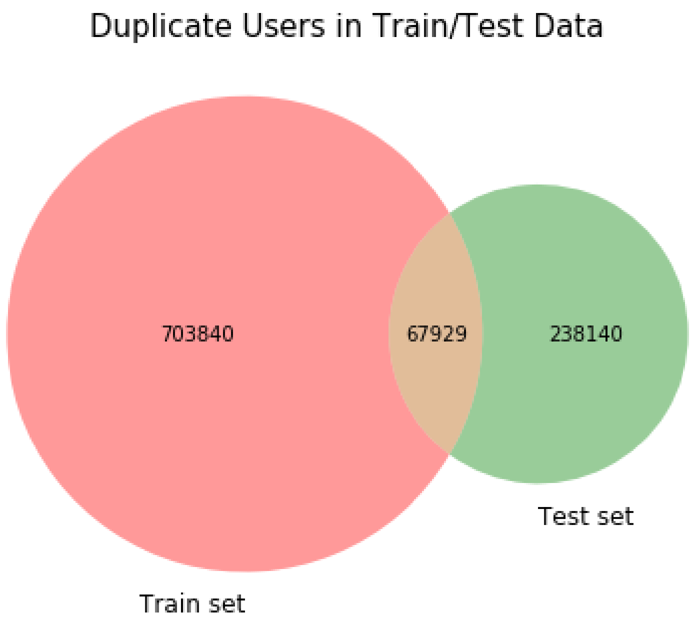


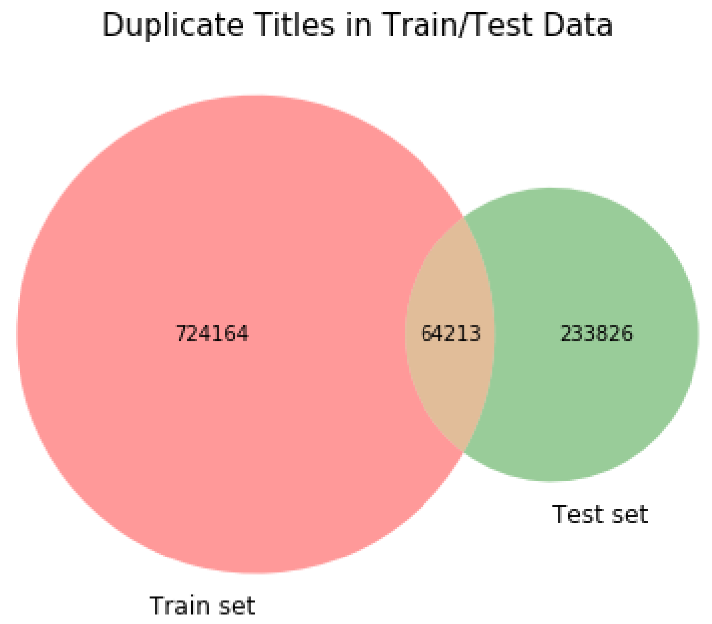
2.6. Duplicates in Train and Test

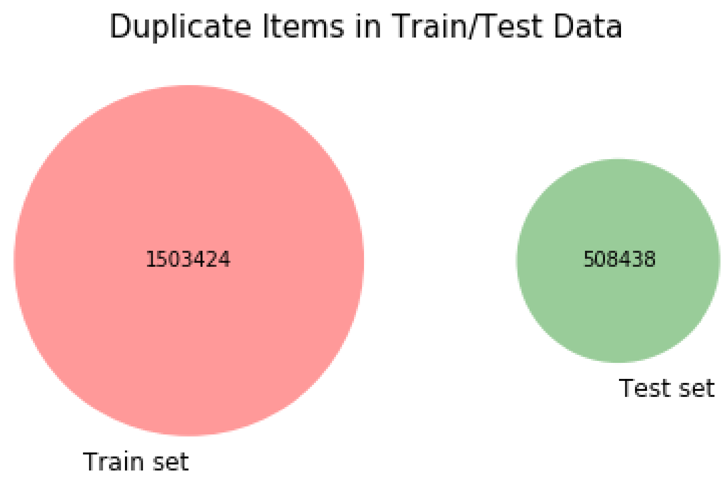
Back to Outline

```
from matplotlib_venn import venn2

plt.figure(figsize=(7,6))
venn2([set(train.user_id), set(test.user_id)], set_labels = ('Train set', 'Test set')
)
```

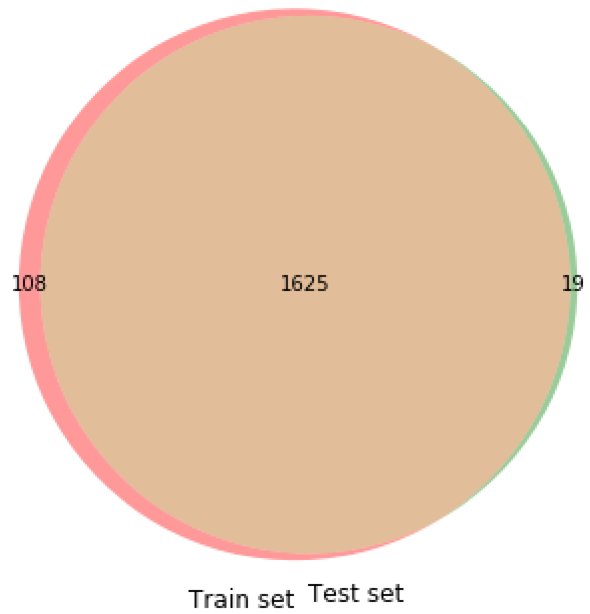
```
plt.title("Duplicate Users in Train/Test Data", fontsize=15)
plt.show()

plt.figure(figsize=(7,6))
venn2([set(train.title), set(test.title)], set_labels = ('Train set', 'Test set') )
plt.title("Duplicate Titles in Train/Test Data", fontsize=15)
plt.show()

plt.figure(figsize=(7,6))
venn2([set(train.item_id), set(test.item_id)], set_labels = ('Train set', 'Test set') )
plt.title("Duplicate Items in Train/Test Data", fontsize=15)
plt.show()

plt.figure(figsize=(7,6))
venn2([set(train.city), set(test.city)], set_labels = ('Train set', 'Test set') )
plt.title("Duplicate Cities in Train/Test Data", fontsize=15)
plt.show()

plt.figure(figsize=(7,6))
venn2([set(train.param_1), set(test.param_1)], set_labels = ('Train set', 'Test set') )
plt.title("Duplicate Param_1 Values in Train/Test Data", fontsize=15)
plt.show()
```



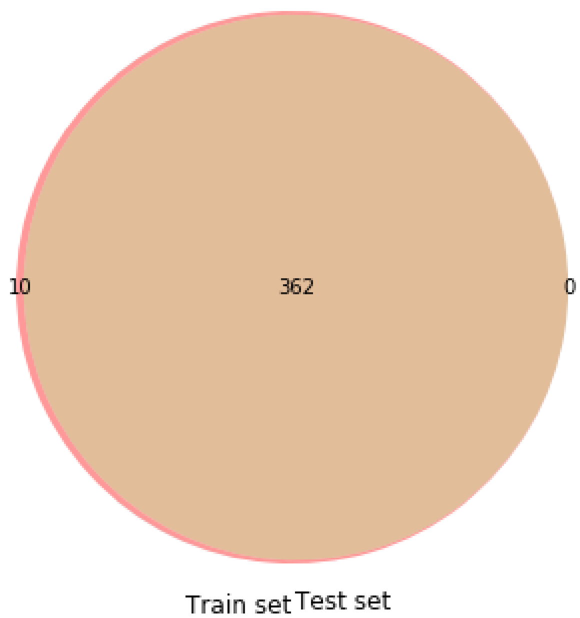

Duplicate Titles in Train/Test Data
724164
64213
233826
Test set
Train set


Duplicate Items in Train/Test Data
1503424
508438
Test set
Train set

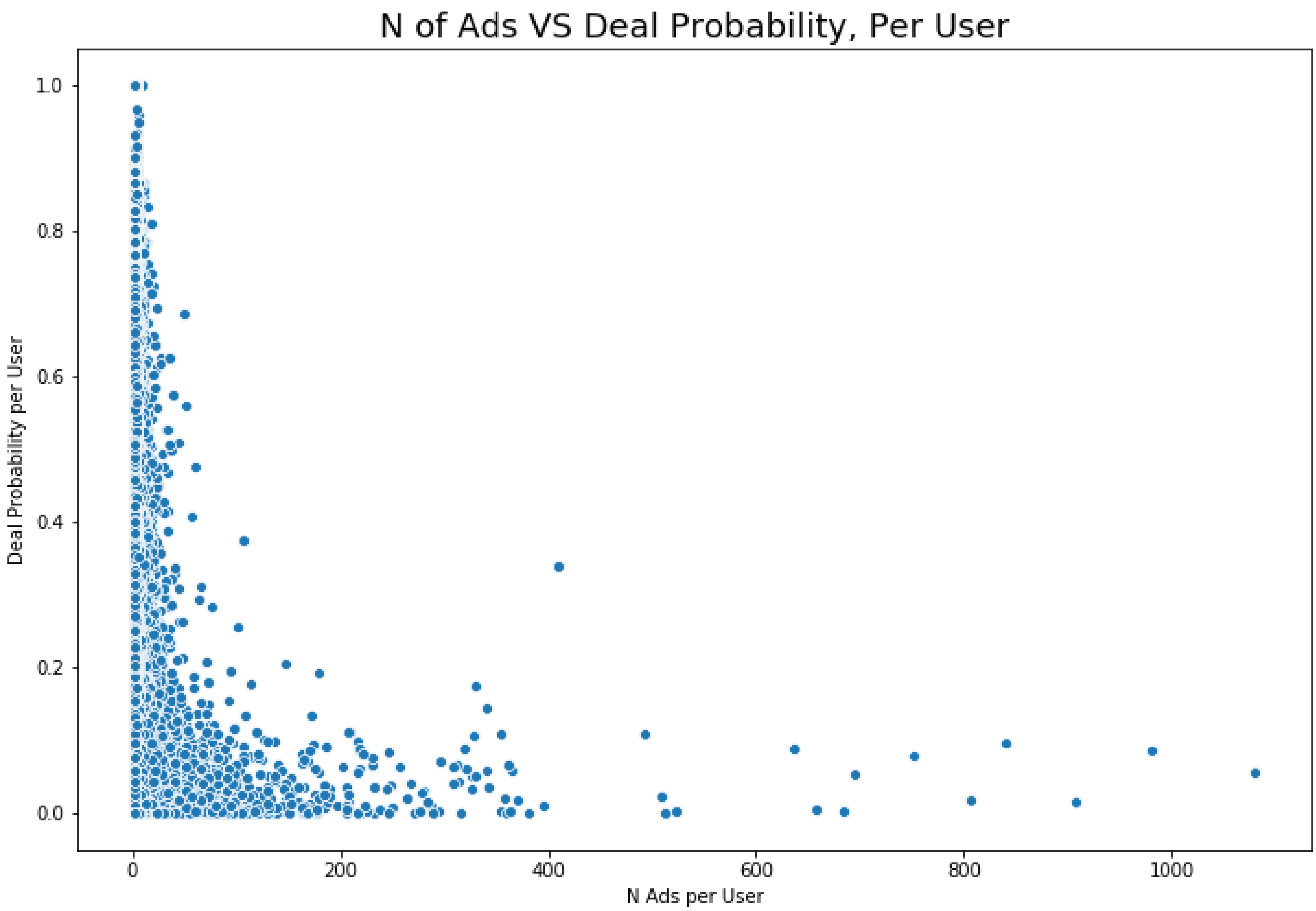
Duplicate Cities in Train/Test Data



Duplicate Param_1 Values in Train/Test Data



```python
user_prob = train.groupby('user_id').deal_probability.mean().sort_index()

user_items = train.user_id.value_counts().sort_index()

plt.figure(figsize=(12,8))
sns.scatterplot(user_items,user_prob)
plt.xlabel('N Ads per User')
plt.ylabel('Deal Probability per User')
plt.title('N of Ads VS Deal Probability, Per User',fontsize=18)
plt.show()
```



3. Pipeline

Back to Outline

```python
# Load and describe engineered features
train_features = pd.DataFrame(index=train.index)
test_features = pd.DataFrame(index=test.index)
```

3.1. Cross-Decomposition of TF-IDF Vectors with BiGrams

This process consists of extracting term frequency vectors using the text in each ad as a document. Tokens for unigrams and bigrams will be included in this stage. Lastly, the resulting matrix will be reduced to the smallest number of components that retain all potential predictive power. Perform onto both titles and descriptions and retain separate components for each.

```
path = 'feature_engineering/1.tfidf_ngrams/feature_dumps/'
print('Loading and joining feature sets:...')
for file in os.listdir(path):
    print(file)
    if file[:4] == 'test':
        test_features = test_features.join(joblib.load(path+file))
    else:
        train_features = train_features.join(joblib.load(path+file))
```

```
Loading and joining feature sets:...
train_descr_idfngram.sav
train_title_idfngram.sav
test_descr_idfngram.sav
test_title_idfngram.sav
```

3.2. Discretized Vector Cross-Decomposition

This consists of splitting the dependent variable into discrete ranges and creating a vocabulary for each range. Then vectorize and cross-decompose each vocabulary independently. Resulting components for each vocabulary will reflect the presence of terms common in a certain discrete range of target.

```
path = 'feature_engineering/2.discrete-decomp/feature_dumps/'
print('Loading and joining feature sets:...')
for file in os.listdir(path):
    print(file)
    if file[:4] == 'test':
        test_features = test_features.join(joblib.load(path+file))
    else:
        train_features = train_features.join(joblib.load(path+file))
```

```
Loading and joining feature sets:...
test_title_zeroidf.sav
test_title_lowcnt.sav
train_title_zeroidf.sav
train_title_lowcnt.sav
test_title_lowidf.sav
test_title_zerocnt.sav
train_title_zerocnt.sav
train_title_upidf.sav
train_title_upcnt.sav
train_title_lowidf.sav
test_title_upcnt.sav
test_title_upidf.sav
```

3.3. Discretized Vector Sums

Similar to previous procedure, vocabularies are created for discrete ranges of target. However instead of decomposing the vectors of those vocabularies, you simply sum their frequencies along the row axis of the term frequency matrix. This results in a single variable for each vocabulary, which represents the aggregate frequency of a vocabulary's terms per ad.

```
path = 'feature_engineering/3.vector-sums/feature_dumps/'
print('Loading and joining feature sets:...')
for file in os.listdir(path):
    print(file)
    if file[:4] == 'test':
        test_features = test_features.join(pd.read_pickle(path+file,compression='zip'))
    else:
        train_features = train_features.join(pd.read_pickle(path+file,compression='zip'))
```

```
Loading and joining feature sets:...
test_sums.pkl
train_sums.pkl
```

3.4. Sentiment Analysis

An NLP library called `polyglot` offers multi-language tools, such as Sentiment-Analysis and Named-Entity-Recognition in Russian.

```
path = 'feature_engineering/4.sentiment/feature_dumps/'
print('Loading and joining feature sets:...')
for file in os.listdir(path):
    print(file)
    if file[:4] == 'test':
        test_features = test_features.join(joblib.load(path+file))
    else:
        train_features = train_features.join(joblib.load(path+file))
```

```
Loading and joining feature sets:...
test_title_polarity.sav
train_title_polarity.sav
```

3.5. Categorical Features

3.5.1 Binary CountVectorizer

Several categorical variables in this data have thousands of unique values which would increase the dimensional space unreasonably if binarizing in dense format. A binary `CountVectorizer` does the heavy lifting of populating dummy counts in sparse format, and `PLSR` reduces the numerous columns to a few core components.

3.5.2. Target-Sorted Label Encodings

Additionally, a label encoder of each feature is made with particular considerations. Normally, label encoding isn't recommended for machine learning because the algorithm will interpret the code numbers as meaningful information. However, encodings can convey useful information if categorical values are sorted by their mean outcome value. This way, each label's code will represent an approximation of the target outcome.

```python
path = 'feature_engineering/5.categorical/feature_dumps/'
print('Loading and joining feature sets:...')
for file in os.listdir(path):
    print(file)
    if file[:4] == 'test':
        test_features = test_features.join(joblib.load(path+file))
    else:
        train_features = train_features.join(joblib.load(path+file))
```

```
Loading and joining feature sets:...
train_categorical.sav
test_categorical.sav
```

```python
path = 'feature_engineering/5.categorical/feature_dumps_encoder/'
print('Loading and joining feature sets:...')
for file in os.listdir(path):
    print(file)
    if file[:4] == 'test':
        test_features = test_features.join(joblib.load(path+file))
    else:
        train_features = train_features.join(joblib.load(path+file))
```

```
Loading and joining feature sets:...
train_codes.sav
test_codes.sav
```

```python
dummies = train[['parent_category_name_en','user_type']]
dummies = pd.get_dummies(dummies)

train_features = train_features.join(dummies)

dummies = test[['parent_category_name_en','user_type']]
dummies = pd.get_dummies(dummies)

test_features = test_features.join(dummies)
```

3.6. Other Features

- Imputations
- Missing Indicators
- Day-of-Week dummies.

```python
path = 'feature_engineering/6.other/feature_dumps/'
print('Loading and joining feature sets:...')
for file in os.listdir(path):
    print(file)
    if file[:4] == 'test':
        test_features = test_features.join(joblib.load(path+file))
    else:
        train_features = train_features.join(joblib.load(path+file))
```

```
Loading and joining feature sets:...
train_othfeat.sav
test_othfeat.sa
```

3.7. Scaling Features

```python
train_features = joblib.load('feature_dumps/train_features.sav')
test_features = joblib.load('feature_dumps/test_features.sav')
```

```python
both = train_features.append(test_features,sort=False).reset_index(drop=True)
```

```python
scaler = preprocessing.RobustScaler()
```

```python
scaler.fit(both)
```

```
RobustScaler(copy=True, quantile_range=(25.0, 75.0), with_centering=True,
       with_scaling=True)
```

4. Evaluation

[Back to Outline](#)

- Evaluation and comparison of multiple models via robust analysis of residuals and error.

```python
train_scale = joblib.load('feature_dumps/train_scale.sav')
test_scale = joblib.load('feature_dumps/test_scale.sav')
```

```python
def rmse(y,pred):
    return metrics.mean_squared_error(y,pred)**0.5

score = metrics.make_scorer(rmse)
linear = linear_model.LinearRegression()
```

4.0. Baseline Linear Regression

```
preds = pd.DataFrame()
```

```
y = train.deal_probability
X_dev,X_val,y_dev,y_val = model_selection.train_test_split(train_scale,y)
```

```
# Baseline cv with linear regression
cv = model_selection.cross_val_score(
    X=X_dev,y=y_dev,estimator=linear,
    cv=10,scoring=score
)
```

```
print('CV Scores:\n',cv)
print('Mean CV score:\n',cv.mean())
```

```
CV Scores:
 [0.2164809  0.21699175 0.21778808 0.21968502 0.21857161 0.21801418
 0.21727649 0.21810469 0.21669987 0.21771957]
Mean CV score:
 0.217733215497144
```

```
linear = linear.fit(X_dev,y_dev)
```

```
pred = linear.predict(X_val)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
print('RMSE without modification:',metrics.mean_squared_error(y_val,pred)**0.5)
pred[pred>1] = 1
pred[pred<0] = 0
print('RMSE fit-to-range:',metrics.mean_squared_error(y_val,pred)**0.5)
preds['lr'] = pred
```

```
Less than zero: 17953
Over one: 246
RMSE without modification: 0.2178849636631909
RMSE fit-to-range: 0.21752330734164146
```

```
pred = linear.predict(test_scale)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
```

```
Less than zero: 12597
Over one: 163
```

```python
sub = pd.DataFrame({'item_id':test.item_id,'deal_probability':pred})

sub.loc[sub.deal_probability>1,'deal_probability'] = 1
sub.loc[sub.deal_probability<0,'deal_probability'] = 0

sub.to_csv('predictions/sub_lr.csv',index=False)
```

```
!kaggle competitions submit -c avito-demand-prediction -f predictions/sub_lr.csv -m "Message"
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /home/user/.kaggle/kaggle.json'
100%|████████████████████████████████████████| 15.7M/15.7M [00:29<00:00, 556kB/s]
Successfully submitted to Avito Demand Prediction Challenge
```

Private Score: 0.24664

Public Score: 0.24229

4.1. PLSR 50 Components

Back to Outline

```python
plsr = cross_decomposition.PLSRegression(n_components=50)
plsr.fit(X_dev,y_dev)
```

```
PLSRegression(copy=True, max_iter=500, n_components=50, scale=True, tol=1e-06)
```

```python
pred = plsr.predict(X_val)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
print('RMSE without modification:',metrics.mean_squared_error(y_val,pred)**0.5)
pred[pred>1] = 1
pred[pred<0] = 0
print('RMSE fit-to-range:',metrics.mean_squared_error(y_val,pred)**0.5)
preds['plsr50'] = pred
```

```
Less than zero: [17953]
Over one: [247]
RMSE without modification: 0.21789044528359755
RMSE fit-to-range: 0.21752825004059145
```

```
pred = plsr.predict(test_scale)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
```

```
Less than zero: [12702]
Over one: [163]
```

```
pred = [p[0] for p in pred]
sub = pd.DataFrame({'item_id':test.item_id,'deal_probability':pred})

sub.loc[sub.deal_probability>1,'deal_probability'] = 1
sub.loc[sub.deal_probability<0,'deal_probability'] = 0

sub.to_csv('predictions/sub_plsr50.csv',index=False)
```

```
!kaggle competitions submit -c avito-demand-prediction -f predictions/sub_plsr50.csv -m "Message"
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /home/user/.kaggle/kaggle.json'
100%|██████████████████████████████████████████| 15.7M/15.7M [00:29<00:00, 557kB/s]
Successfully submitted to Avito Demand Prediction Challenge
```

Private Score: 0.24661

Public Score: 0.24226

```
train_plsr50 = plsr.transform(train_scale)
test_plsr50 = plsr.transform(test_scale)
```

4.2. Light Gradient Boosting

Back to Outline

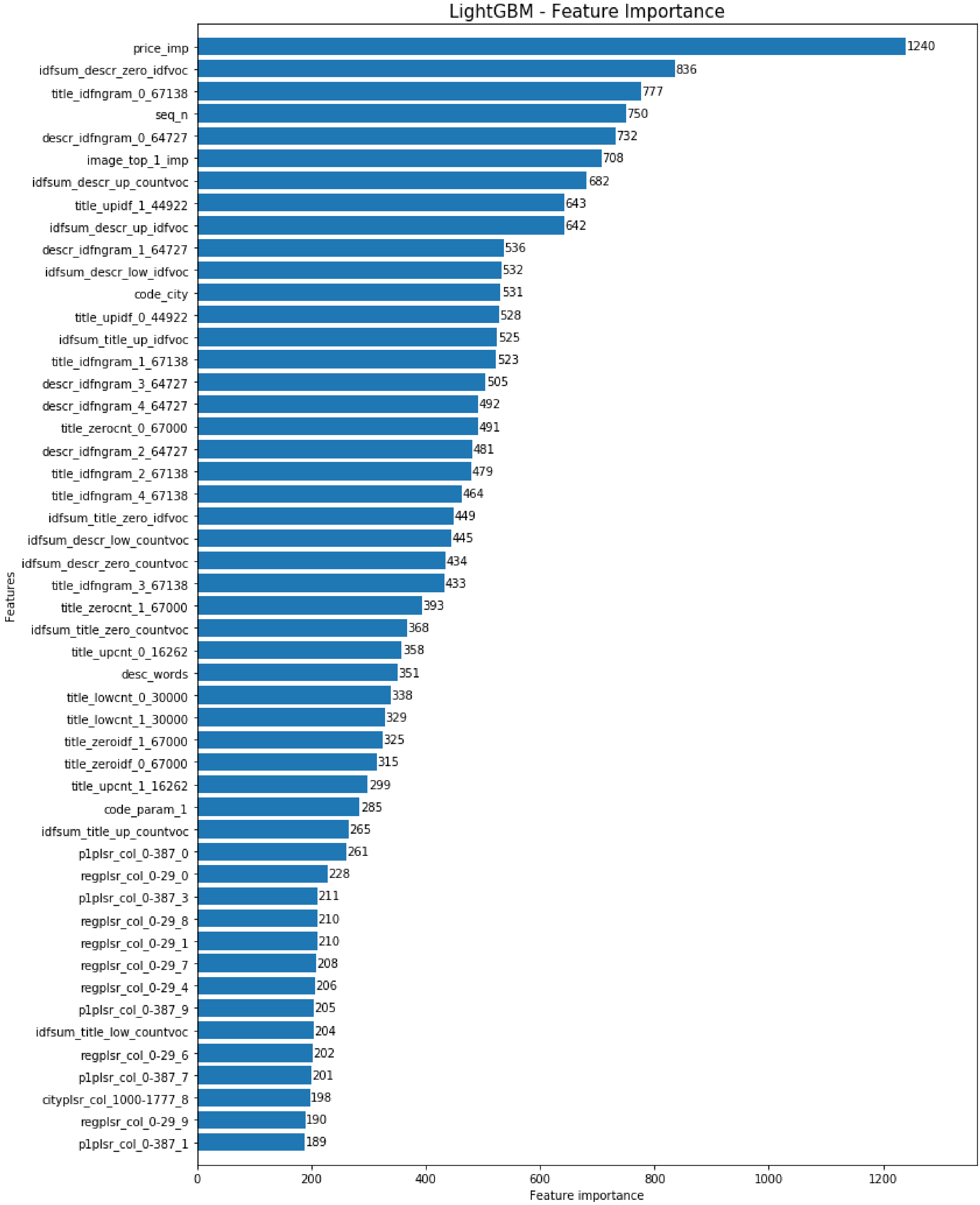
```
params = {
        "objective" : "regression",
        "metric" : "rmse",
        "num_leaves" : 30,
        "learning_rate" : 0.1,
        "bagging_fraction" : 0.7,
        "feature_fraction" : 0.7,
        "bagging_frequency" : 5,
        "bagging_seed" : 2342,
```

```
        "verbosity" : -1
    }

lgtrain = lgb.Dataset(X_dev, label=y_dev)
lgval = lgb.Dataset(X_val, label=y_val)
evals_result = {}

gb = lgb.train(params, lgtrain, 1000, valid_sets=[lgval],
               early_stopping_rounds=100, verbose_eval=20,
               evals_result=evals_result)
```

```
Training until validation scores don't improve for 100 rounds.
[20]    valid_0's rmse: 0.214165
[40]    valid_0's rmse: 0.210232
[60]    valid_0's rmse: 0.208477
[80]    valid_0's rmse: 0.207474
[100]   valid_0's rmse: 0.206755
[120]   valid_0's rmse: 0.206255
[140]   valid_0's rmse: 0.205848
[160]   valid_0's rmse: 0.205525
[180]   valid_0's rmse: 0.20528
[200]   valid_0's rmse: 0.205048
[220]   valid_0's rmse: 0.204862
[240]   valid_0's rmse: 0.20471
[260]   valid_0's rmse: 0.204591
[280]   valid_0's rmse: 0.204482
[300]   valid_0's rmse: 0.20438
[320]   valid_0's rmse: 0.2043
[340]   valid_0's rmse: 0.204212
[360]   valid_0's rmse: 0.204124
[380]   valid_0's rmse: 0.204032
[400]   valid_0's rmse: 0.203959
[420]   valid_0's rmse: 0.203919
[440]   valid_0's rmse: 0.203838
[460]   valid_0's rmse: 0.203796
[480]   valid_0's rmse: 0.20375
[500]   valid_0's rmse: 0.203702
[520]   valid_0's rmse: 0.203649
[540]   valid_0's rmse: 0.20362
[560]   valid_0's rmse: 0.203575
[580]   valid_0's rmse: 0.203512
[600]   valid_0's rmse: 0.203477
[620]   valid_0's rmse: 0.203442
[640]   valid_0's rmse: 0.203418
[660]   valid_0's rmse: 0.203381
[680]   valid_0's rmse: 0.203348
[700]   valid_0's rmse: 0.203299
[720]   valid_0's rmse: 0.203272
[740]   valid_0's rmse: 0.203259
[760]   valid_0's rmse: 0.203234
[780]   valid_0's rmse: 0.203218
[800]   valid_0's rmse: 0.203195
[820]   valid_0's rmse: 0.203176
```

```
[840]   valid_0's rmse: 0.203156
[860]   valid_0's rmse: 0.203136
[880]   valid_0's rmse: 0.203109
[900]   valid_0's rmse: 0.203081
[920]   valid_0's rmse: 0.203049
[940]   valid_0's rmse: 0.20304
[960]   valid_0's rmse: 0.203008
[980]   valid_0's rmse: 0.20299
[1000]  valid_0's rmse: 0.202964
Did not meet early stopping. Best iteration is:
[1000]  valid_0's rmse: 0.202964
```

```
fig, ax = plt.subplots(figsize=(12,18))
lgb.plot_importance(gb, max_num_features=50, height=0.8, ax=ax)
ax.grid(False)
plt.title("LightGBM - Feature Importance", fontsize=15)
plt.show()
```


LightGBM - Feature Importance
Features
Feature importance
price_imp 1240
idfsum_descr_zero_idfvoc 836
title_idfngram_0_67138 777
seq_n 750
descr_idfngram_0_64727 732
image_top_1_imp 708
idfsum_descr_up_countvoc 682
title_upidf_1_44922 643
idfsum_descr_up_idfvoc 642
descr_idfngram_1_64727 536
idfsum_descr_low_idfvoc 532
code_city 531
title_upidf_0_44922 528
idfsum_title_up_idfvoc 525
title_idfngram_1_67138 523
descr_idfngram_3_64727 505
descr_idfngram_4_64727 492
title_zerocnt_0_67000 491
descr_idfngram_2_64727 481
title_idfngram_2_67138 479
title_idfngram_4_67138 464
idfsum_title_zero_idfvoc 449
idfsum_descr_low_countvoc 445
idfsum_descr_zero_countvoc 434
title_idfngram_3_67138 433
title_zerocnt_1_67000 393
idfsum_title_zero_countvoc 368
title_upcnt_0_16262 358
desc_words 351
title_lowcnt_0_30000 338
title_lowcnt_1_30000 329
title_zeroidf_1_67000 325
title_zeroidf_0_67000 315
title_upcnt_1_16262 299
code_param_1 285
idfsum_title_up_countvoc 265
p1plsr_col_0-387_0 261
regplsr_col_0-29_0 228
p1plsr_col_0-387_3 211
regplsr_col_0-29_8 210
regplsr_col_0-29_1 210
regplsr_col_0-29_7 208
regplsr_col_0-29_4 206
p1plsr_col_0-387_9 205
idfsum_title_low_countvoc 204
regplsr_col_0-29_6 202
p1plsr_col_0-387_7 201
cityplsr_col_1000-1777_8 198
regplsr_col_0-29_9 190
p1plsr_col_0-387_1 189
0
200
400
600
800
1000
1200

```
pred = gb.predict(X_val, num_iteration=gb.best_iteration)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
print('RMSE without modification:',metrics.mean_squared_error(y_val,pred)**0.5)
pred[pred>1] = 1
pred[pred<0] = 0
print('RMSE fit-to-range:',metrics.mean_squared_error(y_val,pred)**0.5)
preds['gb'] = pred
```

```
Less than zero: 12674
Over one: 139
RMSE without modification: 0.20283926728961743
RMSE fit-to-range: 0.20276590248215942
```

```
pred = gb.predict(test_scale, num_iteration=gb.best_iteration)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
```

```
Less than zero: 16640
Over one: 26
```

```
sub = pd.DataFrame({'item_id':test.item_id,'deal_probability':pred})

sub.loc[sub.deal_probability>1,'deal_probability'] = 1
sub.loc[sub.deal_probability<0,'deal_probability'] = 0

sub.to_csv('predictions/sub_gb.csv',index=False)
```

```
!kaggle competitions submit -c avito-demand-prediction -f predictions/sub_gb.csv -m "Message"
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /home/user/.kaggle/kaggle.json'
100%|██████████████████████████████████████| 15.7M/15.7M [00:20<00:00, 791kB/s]
Successfully submitted to Avito Demand Prediction Challenge
```

Private Score: 0.24261
Public Score: 0.23856

4.3. LGB with PLSR 50 Components

[Back to Outline](#)

preds = joblib.load('feature_dumps/preds.sav') train_plsr50 = joblib.load('feature_dumps/train_plsr50.sav') test_plsr50 = joblib.load('feature_dumps/test_plsr50.sav')

```
params = {
        "objective" : "regression",
        "metric" : "rmse",
        "num_leaves" : 30,
        "learning_rate" : 0.1,
        "bagging_fraction" : 0.7,
        "feature_fraction" : 0.7,
        "bagging_frequency" : 5,
        "bagging_seed" : 2342,
        "verbosity" : -1
    }

lgtrain = lgb.Dataset(X_dev, label=y_dev)
lgval = lgb.Dataset(X_val, label=y_val)
evals_result = {}

gb = lgb.train(params, lgtrain, 1000, valid_sets=[lgval],
               early_stopping_rounds=100, verbose_eval=20,
               evals_result=evals_result)
```

```
Training until validation scores don't improve for 100 rounds.
[20]	valid_0's rmse: 0.216184
[40]	valid_0's rmse: 0.213355
[60]	valid_0's rmse: 0.212656
[80]	valid_0's rmse: 0.212232
[100]	valid_0's rmse: 0.212004
[120]	valid_0's rmse: 0.211837
[140]	valid_0's rmse: 0.211719
[160]	valid_0's rmse: 0.211625
[180]	valid_0's rmse: 0.211549
[200]	valid_0's rmse: 0.211446
[220]	valid_0's rmse: 0.21136
[240]	valid_0's rmse: 0.211308
[260]	valid_0's rmse: 0.211228
[280]	valid_0's rmse: 0.211167
[300]	valid_0's rmse: 0.211116
[320]	valid_0's rmse: 0.211073
[340]	valid_0's rmse: 0.211042
[360]	valid_0's rmse: 0.210998
[380]	valid_0's rmse: 0.210972
[400]	valid_0's rmse: 0.21095
[420]	valid_0's rmse: 0.21093
[440]	valid_0's rmse: 0.210885
[460]	valid_0's rmse: 0.210848
[480]	valid_0's rmse: 0.210811
[500]	valid_0's rmse: 0.210783
[520]	valid_0's rmse: 0.210758
[540]	valid_0's rmse: 0.21074
[560]	valid_0's rmse: 0.210708
[580]	valid_0's rmse: 0.210696
```

```
[600]   valid_0's rmse: 0.210675
[620]   valid_0's rmse: 0.210657
[640]   valid_0's rmse: 0.210635
[660]   valid_0's rmse: 0.210606
[680]   valid_0's rmse: 0.210583
[700]   valid_0's rmse: 0.210565
[720]   valid_0's rmse: 0.210558
[740]   valid_0's rmse: 0.21054
[760]   valid_0's rmse: 0.210525
[780]   valid_0's rmse: 0.210518
[800]   valid_0's rmse: 0.210499
[820]   valid_0's rmse: 0.210491
[840]   valid_0's rmse: 0.210483
[860]   valid_0's rmse: 0.210474
[880]   valid_0's rmse: 0.210475
[900]   valid_0's rmse: 0.210453
[920]   valid_0's rmse: 0.210449
[940]   valid_0's rmse: 0.210443
[960]   valid_0's rmse: 0.210436
[980]   valid_0's rmse: 0.210428
[1000]  valid_0's rmse: 0.210428
Did not meet early stopping. Best iteration is:
[994]   valid_0's rmse: 0.210425
```

```
pred = gb.predict(X_val, num_iteration=gb.best_iteration)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
print('RMSE without modification:',metrics.mean_squared_error(y_val,pred)**0.5)
pred[pred>1] = 1
pred[pred<0] = 0
print('RMSE fit-to-range:',metrics.mean_squared_error(y_val,pred)**0.5)
preds['gb_plsr50'] = pred
```

```
Less than zero: 4996
Over one: 50
RMSE without modification: 0.21042460691349882
RMSE fit-to-range: 0.2104147368480157
```

```
pred = gb.predict(test_plsr50)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
```

```
Less than zero: 4541
Over one: 14
```

```
sub = pd.DataFrame({'item_id':test.item_id,'deal_probability':pred})

sub.loc[sub.deal_probability>1,'deal_probability'] = 1
sub.loc[sub.deal_probability<0,'deal_probability'] = 0

sub.to_csv('predictions/sub_gb_plsr50.csv',index=False)
```

```
!kaggle competitions submit -c avito-demand-prediction -f predictions/sub_gb_plsr50.csv -m "Message"
```

Private Score: 0.24795

Public Score: 0.24364

4.4. Feature Selection

Back to Outline

```
def rmse(y,pred):
    return metrics.mean_squared_error(y,pred)**0.5

score = metrics.make_scorer(rmse)
linear = linear_model.LinearRegression()
```

```
results = pd.DataFrame(index=['Importances','CoefLasso','CoefRidge','FRegression'],columns=['Score','Selector'])
```

```
n_features = 30
data = train_scale
model = linear_model.LinearRegression()
```

```
# Score of SelectFromModel on Tree-based feature importances
selector1 = feature_selection.SelectFromModel(
    ensemble.ExtraTreesRegressor(),
    threshold=-np.inf,
    max_features=n_features)

# Undersample dataset to reduce time
index = np.random.choice(len(train),size=int(4e5))
selector1.fit(data.iloc[index],train.iloc[index].deal_probability)
selection = data.iloc[:,selector1.get_support()]

# Score of these features
cv = model_selection.cross_val_score(model,selection,y,cv=5,scoring=score)
print('CV Scores:',cv)
print('Selection by Tree Importances:',np.mean(cv))
results.loc['Importances','Score'] = np.mean(cv)
results.loc['Importances','Selector']=selector1
```

```
/home/user/anaconda3/lib/python3.7/site-packages/sklearn/ensemble/forest.py:246: FutureWarning: The default value of n_estimators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

```
CV Scores: [0.21981017 0.22058937 0.21954811 0.22004812 0.22781175]
Mean CV Score: 0.2215615026676442
```

```
# Score of SelectFromModel from Lasso coefs
selector2 = feature_selection.SelectFromModel(
    linear_model.Lasso(),
    threshold=-np.inf,
    max_features=n_features)
selector2.fit(data,train.deal_probability)
selection = data.iloc[:,selector2.get_support()]

# Score of these features
cv = model_selection.cross_val_score(model,selection,y,cv=5,scoring=score)
print('CV Scores:',cv)
print('Selection by Lasso Coefs:',np.mean(cv))
results.loc['CoefLasso','Score'] = np.mean(cv)
results.loc['CoefLasso','Selector']=selector2
```

```
CV Scores: [0.22494939 0.22541752 0.224815   0.22524057 0.23888665]
Selection by Coefs: 0.22786182658485582
```

```
# Score of SelectKBest from f_regression
selector3 = feature_selection.SelectKBest(
    feature_selection.f_regression,
    k=n_features)
selector3.fit(data,train.deal_probability)
selection = data.iloc[:,selector3.get_support()]
# Score of these features
cv = model_selection.cross_val_score(model,selection,y,cv=5,scoring=score)
print('CV Scores:',cv)
print('Selection by f_regression:',np.mean(cv))
results.loc['FRegression','Score'] = np.mean(cv)
results.loc['FRegression','Selector']=selector3
```

```
CV Scores: [0.21925924 0.22004998 0.21892292 0.21950854 0.21973396]
Selection by f_regression: 0.21949492619756367
```

```
# Score of SelectFromModel from Ridge coefs
selector4 = feature_selection.SelectFromModel(
```

```
    linear_model.Ridge(),
    threshold=-np.inf,
    max_features=n_features)
selector4.fit(data,train.deal_probability)
selection = data.iloc[:,selector4.get_support()]

# Score of these features
cv = model_selection.cross_val_score(model,selection,y,cv=5,scoring=score)
print('CV Scores:',cv)
print('Selection by Ridge Coefs:',np.mean(cv))
results.loc['CoefRidge','Score'] = np.mean(cv)
results.loc['CoefRidge','Selector']=selector4
```

```
CV Scores: [0.21923302 0.21989553 0.21890318 0.21946869 0.2197511 ]
Selection by Ridge Coefs: 0.2194503027900982
```

```
display(results.sort_values(by='Score',ascending=True))
best = results.sort_values(by='Score',ascending=True).iloc[0,1]
```

	Score	Selector
CoefRidge	0.21945	SelectFromModel(estimator=Ridge(alpha=1.0, cop...
FRegression	0.219495	SelectKBest(k=30, score_func=<function f_regre...
Importances	0.221562	SelectFromModel(estimator=ExtraTreesRegressor(...
CoefLasso	0.227862	SelectFromModel(estimator=Lasso(alpha=1.0, cop...

```
# Keep the best features
train_sel30 = train_scale.loc[:,best.get_support()]
test_sel30 = test_scale.loc[:,best.get_support()]
```

```
joblib.dump(train_sel30,'feature_dumps/train_sel30.sav')
joblib.dump(test_sel30,'feature_dumps/test_sel30.sav')
```

4.5. LGB with 30 Ridge Features

Back to Outline

preds = joblib.load('feature_dumps/preds.sav')

train_plsr50 = joblib.load('feature_dumps/train_plsr50.sav') test_plsr50 = joblib.load('feature_dumps/test_plsr50.sav')

```
params = {
```

```
        "objective" : "regression",
        "metric" : "rmse",
        "num_leaves" : 30,
        "learning_rate" : 0.1,
        "bagging_fraction" : 0.7,
        "feature_fraction" : 0.7,
        "bagging_frequency" : 5,
        "bagging_seed" : 2342,
        "verbosity" : -1
    }

lgtrain = lgb.Dataset(X_dev, label=y_dev)
lgval = lgb.Dataset(X_val, label=y_val)
evals_result = {}

gb = lgb.train(params, lgtrain, 1000, valid_sets=[lgval],
               early_stopping_rounds=100, verbose_eval=20,
               evals_result=evals_result)
```

```
Training until validation scores don't improve for 100 rounds.
[20]    valid_0's rmse: 0.217496
[40]    valid_0's rmse: 0.214649
[60]    valid_0's rmse: 0.213806
[80]    valid_0's rmse: 0.213349
[100]   valid_0's rmse: 0.213057
[120]   valid_0's rmse: 0.212834
[140]   valid_0's rmse: 0.212662
[160]   valid_0's rmse: 0.212531
[180]   valid_0's rmse: 0.212428
[200]   valid_0's rmse: 0.212326
[220]   valid_0's rmse: 0.212237
[240]   valid_0's rmse: 0.212158
[260]   valid_0's rmse: 0.212099
[280]   valid_0's rmse: 0.212044
[300]   valid_0's rmse: 0.211999
[320]   valid_0's rmse: 0.211952
[340]   valid_0's rmse: 0.21191
[360]   valid_0's rmse: 0.211871
[380]   valid_0's rmse: 0.211835
[400]   valid_0's rmse: 0.211789
[420]   valid_0's rmse: 0.211757
[440]   valid_0's rmse: 0.211718
[460]   valid_0's rmse: 0.211703
[480]   valid_0's rmse: 0.211689
[500]   valid_0's rmse: 0.211662
[520]   valid_0's rmse: 0.211644
[540]   valid_0's rmse: 0.211635
[560]   valid_0's rmse: 0.211613
[580]   valid_0's rmse: 0.211593
[600]   valid_0's rmse: 0.211576
[620]   valid_0's rmse: 0.211555
[640]   valid_0's rmse: 0.211521
[660]   valid_0's rmse: 0.211512
```

```
[680]   valid_0's rmse: 0.211506
[700]   valid_0's rmse: 0.211491
[720]   valid_0's rmse: 0.211487
[740]   valid_0's rmse: 0.211476
[760]   valid_0's rmse: 0.21146
[780]   valid_0's rmse: 0.211449
[800]   valid_0's rmse: 0.211446
[820]   valid_0's rmse: 0.211436
[840]   valid_0's rmse: 0.211426
[860]   valid_0's rmse: 0.211428
[880]   valid_0's rmse: 0.211414
[900]   valid_0's rmse: 0.211404
[920]   valid_0's rmse: 0.211395
[940]   valid_0's rmse: 0.211389
[960]   valid_0's rmse: 0.211373
[980]   valid_0's rmse: 0.211372
[1000]  valid_0's rmse: 0.211368
Did not meet early stopping. Best iteration is:
[998]   valid_0's rmse: 0.211368
```

```
pred = gb.predict(X_val, num_iteration=gb.best_iteration)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
print('RMSE without modification:',metrics.mean_squared_error(y_val,pred)**0.5)
pred[pred>1] = 1
pred[pred<0] = 0
print('RMSE fit-to-range:',metrics.mean_squared_error(y_val,pred)**0.5)
preds['gb_sel30'] = pred
```

```
Less than zero: 5962
Over one: 49
RMSE without modification: 0.21136754065569408
RMSE fit-to-range: 0.21135017334460043
```

```
pred = gb.predict(test_sel30)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
```

```
Less than zero: 4939
Over one: 22
```

```
sub = pd.DataFrame({'item_id':test.item_id,'deal_probability':pred})

sub.loc[sub.deal_probability>1,'deal_probability'] = 1
sub.loc[sub.deal_probability<0,'deal_probability'] = 0

sub.to_csv('predictions/sub_gb_sel30.csv',index=False)
```

```
!kaggle competitions submit -c avito-demand-prediction -f predictions/sub_gb_sel30.csv
-m "Message"
```

Private Score: 0.24551

Public Score: 0.24135

4.6. Optimal N Features

Back to Outline

```
train_scale = joblib.load('feature_dumps/train_scale.sav')
test_scale = joblib.load('feature_dumps/test_scale.sav')

def rmse(y,pred):
    return metrics.mean_squared_error(y,pred)**0.5

score = metrics.make_scorer(rmse)

y = train.deal_probability
X_dev,X_val,y_dev,y_val = model_selection.train_test_split(train_scale,y)
```

```
n_features = np.arange(15,41,2).tolist()
data = train_scale
selector = feature_selection.SelectFromModel(
    linear_model.Ridge(),
    threshold=-np.inf)
model = linear_model.LinearRegression()
```

```
results = pd.DataFrame(columns=['Score'])
```

```
for n in n_features:
    selector.max_features = n
    selector.fit(data,y)
    selection = data.iloc[:,selector.get_support()]
    # Score of these features
    cv = model_selection.cross_val_score(model,selection,y,cv=5,scoring=score)
    print('n_features:',n)
    print('CV Scores:',cv)
    print('Mean CV Score:',np.mean(cv))
    results.loc[n,'Score'] = np.mean(cv)
```

```
n_features: 15
```

```
CV Scores: [0.2214024  0.22209101 0.22094013 0.22155788 0.22183177]
Mean CV Score: 0.22156463741803306
n_features: 17
CV Scores: [0.22100592 0.22173035 0.22052086 0.2211415  0.22143075]
Mean CV Score: 0.22116587668869325
n_features: 19
CV Scores: [0.22083071 0.22159906 0.2204022  0.22099091 0.22127407]
Mean CV Score: 0.22101939035838733
n_features: 21
CV Scores: [0.22041142 0.22113124 0.2200198  0.22056364 0.22084657]
Mean CV Score: 0.2205945303982421
n_features: 23
CV Scores: [0.21976962 0.22047235 0.21944153 0.21997114 0.22030295]
Mean CV Score: 0.21999151556366475
n_features: 25
CV Scores: [0.21946033 0.220143   0.21910807 0.21969886 0.22000164]
Mean CV Score: 0.2196823801454494
n_features: 27
CV Scores: [0.21935752 0.22001905 0.21901719 0.21959855 0.21987588]
Mean CV Score: 0.21957363990238027
n_features: 29
CV Scores: [0.219244   0.21990291 0.21890315 0.21946918 0.21975633]
Mean CV Score: 0.2194551130733152
n_features: 31
CV Scores: [0.21922796 0.21989394 0.21890329 0.21946472 0.21974498]
Mean CV Score: 0.2194469787959578
n_features: 33
CV Scores: [0.21909725 0.21974639 0.21874192 0.21930899 0.21957575]
Mean CV Score: 0.21929405938767052
n_features: 35
CV Scores: [0.21870135 0.21940735 0.2183705  0.21890897 0.21913743]
Mean CV Score: 0.2189051192649462
n_features: 37
CV Scores: [0.21866231 0.21936372 0.21832554 0.2188617  0.21909518]
Mean CV Score: 0.21886169117350002
n_features: 39
CV Scores: [0.21839662 0.21912002 0.21806015 0.21860995 0.21885036]
Mean CV Score: 0.21860741846370296
```

```
n_features = np.arange(42,81,5).tolist()
data = train_scale
selector = feature_selection.SelectFromModel(
    linear_model.Ridge(),
    threshold=-np.inf)
model = linear_model.LinearRegression()
```

```
for n in n_features:
    selector.max_features = n
    selector.fit(data,y)
    selection = data.iloc[:,selector.get_support()]
    # Score of these features
    cv = model_selection.cross_val_score(model,selection,y,cv=5,scoring=score)
    print('n_features:',n)
    print('CV Scores:',cv)
    print('Mean CV Score:',np.mean(cv))
    results.loc[n,'Score'] = np.mean(cv)
```

```
n_features: 42
CV Scores: [0.21829902 0.21901327 0.21796659 0.21854189 0.21874101]
Mean CV Score: 0.21851235449796982
n_features: 47
CV Scores: [0.21815648 0.21885869 0.21780344 0.21836326 0.21858112]
Mean CV Score: 0.2183525972046391
n_features: 52
CV Scores: [0.21781718 0.21858665 0.21753391 0.2180219  0.21831257]
Mean CV Score: 0.21805444311090497
n_features: 57
CV Scores: [0.21767949 0.2184194  0.21738006 0.21788763 0.21818195]
Mean CV Score: 0.21790970823055159
n_features: 62
CV Scores: [0.21758837 0.21832427 0.21729401 0.21781125 0.21810756]
Mean CV Score: 0.21782509519951762
n_features: 67
CV Scores: [0.21755824 0.21828864 0.21725398 0.21777762 0.2180867 ]
Mean CV Score: 0.21779303464336142
n_features: 72
CV Scores: [0.21744609 0.21814406 0.21712654 0.21764411 0.21795778]
Mean CV Score: 0.21766371694471878
n_features: 77
CV Scores: [0.21740361 0.21811641 0.21709358 0.21761114 0.21792684]
Mean CV Score: 0.2176303186024358
```

4.7. PLSR by Original Feature

Back to Outline

```
train_plsrbyf = pd.DataFrame(index=train.index)
test_plsrbyf= pd.DataFrame(index=test.index)
```

Title

```
f = 'title'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in
train_scale.columns.tolist()])]]
```

```
n_comp = 5
plsr = cross_decomposition.PLSRegression(n_components=n_comp)
plsr.fit(train_scale[cols],y)
train_plsr = pd.DataFrame(plsr.transform(train_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
test_plsr = pd.DataFrame(plsr.transform(test_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
```

```
cv = model_selection.cross_val_score(model,train_plsr,y,cv=5,scoring=score)
```

```
print(cv)
print(np.mean(cv))
```

```
[0.22706459 0.22759629 0.22707199 0.22745858 0.22764216]
0.22736672196238264
```

```
train_plsrbyf = train_plsrbyf.join(train_plsr)
```

```
test_plsrbyf = test_plsrbyf.join(test_plsr)
```

Description

```
f = 'desc'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in train_scale.columns.tolist()])]]
```

```
n_comp = 5
plsr = cross_decomposition.PLSRegression(n_components=n_comp)
plsr.fit(train_scale[cols],y)
train_plsr = pd.DataFrame(plsr.transform(train_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
test_plsr = pd.DataFrame(plsr.transform(test_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
```

```
cv = model_selection.cross_val_score(model,train_plsr,y,cv=5,scoring=score)
```

```
print(cv)
print(np.mean(cv))
```

```
[0.22920629 0.22972656 0.22875886 0.2294567  0.22963888]
0.2293574579086925
```

```
train_plsrbyf = train_plsrbyf.join(train_plsr)
```

```
test_plsrbyf = test_plsrbyf.join(test_plsr)
```

Param_1

```
f = 'p1'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in train_scale.columns.tolist()])]]
```

```
n_comp = 5
plsr = cross_decomposition.PLSRegression(n_components=n_comp)
plsr.fit(train_scale[cols],y)
train_plsr = pd.DataFrame(plsr.transform(train_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
test_plsr = pd.DataFrame(plsr.transform(test_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
```

```
cv = model_selection.cross_val_score(model,train_plsr,y,cv=5,scoring=score)
```

```
print(cv)
print(np.mean(cv))
```

```
[0.23890726 0.23882191 0.23851118 0.23926176 0.23933843]
0.23896810819187678
```

```
train_plsrbyf = train_plsrbyf.join(train_plsr)
```

```
test_plsrbyf = test_plsrbyf.join(test_plsr)
```

Param_2

```
f = 'p2'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in train_scale.columns.tolist()])]]
```

```
n_comp = 5
plsr = cross_decomposition.PLSRegression(n_components=n_comp)
plsr.fit(train_scale[cols],y)
train_plsr = pd.DataFrame(plsr.transform(train_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
test_plsr = pd.DataFrame(plsr.transform(test_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
```

```
cv = model_selection.cross_val_score(model,train_plsr,y,cv=5,scoring=score)
```

```
print(cv)
print(np.mean(cv))
```

```
[0.24378045 0.24348772 0.24340874 0.2440492  0.2441572 ]
0.24377666270113338
```

```
train_plsrbyf = train_plsrbyf.join(train_plsr)
```

```
test_plsrbyf = test_plsrbyf.join(test_plsr)
```

Param_3

```
f = 'p3'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in train_scale.columns.tolist()])]]
```

```
n_comp = 5
plsr = cross_decomposition.PLSRegression(n_components=n_comp)
plsr.fit(train_scale[cols],y)
train_plsr = pd.DataFrame(plsr.transform(train_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
test_plsr = pd.DataFrame(plsr.transform(test_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
```

```
cv = model_selection.cross_val_score(model,train_plsr,y,cv=5,scoring=score)
```

```
print(cv)
print(np.mean(cv))
```

```
[0.25166324 0.25154532 0.25108586 0.25199132 0.25212277]
0.25168170236853965
```

```
train_plsrbyf = train_plsrbyf.join(train_plsr)
```

```
test_plsrbyf = test_plsrbyf.join(test_plsr)
```

Region

```
f = 'reg'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in train_scale.columns.tolist()])]]
```

```
n_comp = 5
plsr = cross_decomposition.PLSRegression(n_components=n_comp)
plsr.fit(train_scale[cols],y)
train_plsr = pd.DataFrame(plsr.transform(train_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
test_plsr = pd.DataFrame(plsr.transform(test_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
```

```
cv = model_selection.cross_val_score(model,train_plsr,y,cv=5,scoring=score)
```

```
print(cv)
print(np.mean(cv))
```

```
[0.2598769  0.25964108 0.25932434 0.26040616 0.2603358 ]
0.2599168552462979
```

```
train_plsrbyf = train_plsrbyf.join(train_plsr)
```

```
test_plsrbyf = test_plsrbyf.join(test_plsr)
```

City

```
f = 'city'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in train_scale.columns.tolist()])]]
```

```
n_comp = 5
plsr = cross_decomposition.PLSRegression(n_components=n_comp)
plsr.fit(train_scale[cols],y)
train_plsr = pd.DataFrame(plsr.transform(train_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
test_plsr = pd.DataFrame(plsr.transform(test_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
```

```
cv = model_selection.cross_val_score(model,train_plsr,y,cv=5,scoring=score)
```

```
print(cv)
print(np.mean(cv))
```

```
[0.25947971 0.25915577 0.25885413 0.25989806 0.25988651]
0.25945483436315697
```

```
train_plsrbyf = train_plsrbyf.join(train_plsr)
```

```
test_plsrbyf = test_plsrbyf.join(test_plsr)
```

Category Name

```
f = 'catnam'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in train_scale.columns.tolist()])]]
```

```
n_comp = 5
plsr = cross_decomposition.PLSRegression(n_components=n_comp)
plsr.fit(train_scale[cols],y)
train_plsr = pd.DataFrame(plsr.transform(train_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
test_plsr = pd.DataFrame(plsr.transform(test_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
```

```
cv = model_selection.cross_val_score(model,train_plsr,y,cv=5,scoring=score)
```

```
print(cv)
print(np.mean(cv))
```

```
[0.2436163  0.24350094 0.24312993 0.24371419 0.24399855]
0.2435919807121306
```

```
train_plsrbyf = train_plsrbyf.join(train_plsr)
```

```
test_plsrbyf = test_plsrbyf.join(test_plsr)
```

Parent

```
f = 'parent'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in train_scale.columns.tolist()])]]
```

```
n_comp = 5
plsr = cross_decomposition.PLSRegression(n_components=n_comp)
plsr.fit(train_scale[cols],y)
train_plsr = pd.DataFrame(plsr.transform(train_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
test_plsr = pd.DataFrame(plsr.transform(test_scale[cols]),columns=['{}_{}'.format(f,i) for i in np.arange(n_comp)])
```

```
cv = model_selection.cross_val_score(model,train_plsr,y,cv=5,scoring=score)
```

```
print(cv)
print(np.mean(cv))
```

```
[0.24758108 0.24736126 0.24718824 0.24770739 0.2479346 ]
0.2475545146993571
```

```
train_plsrbyf = train_plsrbyf.join(train_plsr)
```

```
test_plsrbyf = test_plsrbyf.join(test_plsr)
```

Encoders

```
f = 'code'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in
train_scale.columns.tolist()])]]
```

```
cv = model_selection.cross_val_score(model,train_scale[cols],y,cv=5,scoring=score)
```

```
cv
```

```
array([0.23900483, 0.23894502, 0.23858882, 0.23932502, 0.23946458])
```

```
train_plsrbyf = train_plsrbyf.join(train_scale[cols])
```

```
test_plsrbyf = test_plsrbyf.join(test_scale[cols])
```

Misses

```
f = 'miss'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in
train_scale.columns.tolist()])]]
```

```
cv = model_selection.cross_val_score(model,train_scale[cols],y,cv=5,scoring=score)
```

```
cv
```

```
array([0.25628223, 0.25591782, 0.25567995, 0.25666355, 0.25671415])
```

```
train_plsrbyf = train_plsrbyf.join(train_scale[cols])
```

```
test_plsrbyf = test_plsrbyf.join(test_scale[cols])
```

User Types

```
f = 'type'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in
train_scale.columns.tolist()])]]
```

```
cv = model_selection.cross_val_score(model,train_scale[cols],y,cv=5,scoring=score)
```

```
cv
```

```
array([0.259206  , 0.25890883, 0.25865925, 0.25973767, 0.25965589])
```

```
train_plsrbyf = train_plsrbyf.join(train_scale[cols])
```

```
test_plsrbyf = test_plsrbyf.join(test_scale[cols])
```

Days

```
f = 'day'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in
train_scale.columns.tolist()])]]
```

```
cv = model_selection.cross_val_score(model,train_scale[cols],y,cv=5,scoring=score)
```

```
cv
```

```
array([0.26005697, 0.25978067, 0.25946028, 0.26059606, 0.26049315])
```

```
train_plsrbyf = train_plsrbyf.join(train_scale[cols])
```

```
test_plsrbyf = test_plsrbyf.join(test_scale[cols])
```

Imputations

```python
f = 'imp'
cols = train_scale.columns[[arg[0] for arg in np.argwhere([f in col for col in train_scale.columns.tolist()])]]
```

```python
cv = model_selection.cross_val_score(model,train_scale[cols],y,cv=5,scoring=score)
```

```python
cv
```

```
array([0.25578898, 0.25550334, 0.25520081, 0.25636177, 0.30268639])
```

```python
train_plsrbyf = train_plsrbyf.join(train_scale[cols])
```

```python
test_plsrbyf = test_plsrbyf.join(test_scale[cols])
```

Seq_n

```python
train_plsrbyf = train_plsrbyf.join(train_scale.seq_n)
```

```python
test_plsrbyf = test_plsrbyf.join(test_scale.seq_n)
```

```python
cv = model_selection.cross_val_score(model,train_plsrbyf,y,cv=5,scoring=score)
```

```python
cv
```

```
array([0.21842824, 0.219155  , 0.21820018, 0.21869518, 0.21909233])
```

```python
joblib.dump(train_plsrbyf,'feature_dumps/train_plsrbyf.sav')
```

```
['feature_dumps/train_plsrbyf.sav']
```

```python
joblib.dump(test_plsrbyf,'feature_dumps/test_plsrbyf.sav')
```

```
['feature_dumps/test_plsrbyf.sav']
```

4.8. LGB with PLSR by Original Feature

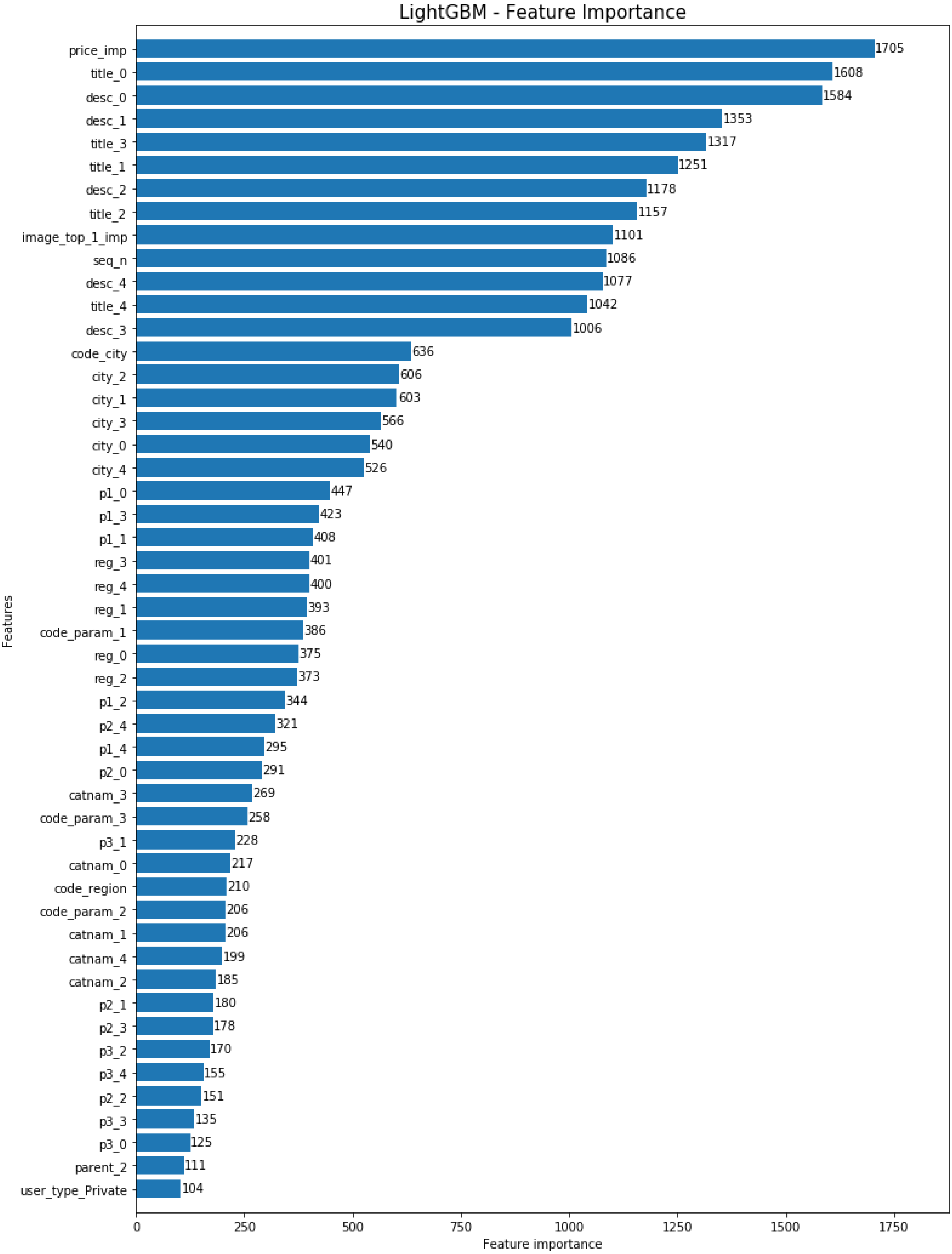
Back to Outline

```
params = {
        "objective" : "regression",
        "metric" : "rmse",
        "num_leaves" : 30,
        "learning_rate" : 0.1,
        "bagging_fraction" : 0.7,
        "feature_fraction" : 0.7,
        "bagging_frequency" : 5,
        "bagging_seed" : 2342,
        "verbosity" : -1
    }

lgtrain = lgb.Dataset(X_dev, label=y_dev)
lgval = lgb.Dataset(X_val, label=y_val)
evals_result = {}

gb = lgb.train(params, lgtrain, 1000, valid_sets=[lgval],
               early_stopping_rounds=100, verbose_eval=20,
               evals_result=evals_result)
```

```
Training until validation scores don't improve for 100 rounds.
[20]	valid_0's rmse: 0.215517
[40]	valid_0's rmse: 0.21169
[60]	valid_0's rmse: 0.210382
[80]	valid_0's rmse: 0.209627
[100]	valid_0's rmse: 0.209132
[120]	valid_0's rmse: 0.20878
[140]	valid_0's rmse: 0.208521
[160]	valid_0's rmse: 0.208332
[180]	valid_0's rmse: 0.208156
[200]	valid_0's rmse: 0.208005
[220]	valid_0's rmse: 0.207872
[240]	valid_0's rmse: 0.207739
[260]	valid_0's rmse: 0.207636
[280]	valid_0's rmse: 0.207534
[300]	valid_0's rmse: 0.207445
[320]	valid_0's rmse: 0.207354
[340]	valid_0's rmse: 0.207287
[360]	valid_0's rmse: 0.207218
[380]	valid_0's rmse: 0.207147
[400]	valid_0's rmse: 0.207067
[420]	valid_0's rmse: 0.207019
[440]	valid_0's rmse: 0.20697
[460]	valid_0's rmse: 0.206927
[480]	valid_0's rmse: 0.206889
```

```
[500]	valid_0's rmse: 0.206848
[520]	valid_0's rmse: 0.20681
[540]	valid_0's rmse: 0.206754
[560]	valid_0's rmse: 0.206718
[580]	valid_0's rmse: 0.206688
[600]	valid_0's rmse: 0.206637
[620]	valid_0's rmse: 0.206589
[640]	valid_0's rmse: 0.206551
[660]	valid_0's rmse: 0.206527
[680]	valid_0's rmse: 0.206494
[700]	valid_0's rmse: 0.20646
[720]	valid_0's rmse: 0.206429
[740]	valid_0's rmse: 0.206406
[760]	valid_0's rmse: 0.206389
[780]	valid_0's rmse: 0.206374
[800]	valid_0's rmse: 0.20635
[820]	valid_0's rmse: 0.206323
[840]	valid_0's rmse: 0.206309
[860]	valid_0's rmse: 0.206295
[880]	valid_0's rmse: 0.206278
[900]	valid_0's rmse: 0.206255
[920]	valid_0's rmse: 0.206232
[940]	valid_0's rmse: 0.206222
[960]	valid_0's rmse: 0.206205
[980]	valid_0's rmse: 0.206178
[1000]	valid_0's rmse: 0.206158
Did not meet early stopping. Best iteration is:
[1000]	valid_0's rmse: 0.206158
```

```
fig, ax = plt.subplots(figsize=(12,18))
lgb.plot_importance(gb, max_num_features=50, height=0.8, ax=ax)
ax.grid(False)
plt.title("LightGBM - Feature Importance", fontsize=15)
plt.show()
```


LightGBM - Feature Importance
Features
Feature importance
price_imp 1705
title_0 1608
desc_0 1584
desc_1 1353
title_3 1317
title_1 1251
desc_2 1178
title_2 1157
image_top_1_imp 1101
seq_n 1086
desc_4 1077
title_4 1042
desc_3 1006
code_city 636
city_2 606
city_1 603
city_3 566
city_0 540
city_4 526
p1_0 447
p1_3 423
p1_1 408
reg_3 401
reg_4 400
reg_1 393
code_param_1 386
reg_0 375
reg_2 373
p1_2 344
p2_4 321
p1_4 295
p2_0 291
catnam_3 269
code_param_3 258
p3_1 228
catnam_0 217
code_region 210
code_param_2 206
catnam_1 206
catnam_4 199
catnam_2 185
p2_1 180
p2_3 178
p3_2 170
p3_4 155
p2_2 151
p3_3 135
p3_0 125
parent_2 111
user_type_Private 104
0
250
500
750
1000
1250
1500
1750

```
pred = gb.predict(X_val, num_iteration=gb.best_iteration)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
print('RMSE without modification:',metrics.mean_squared_error(y_val,pred)**0.5)
pred[pred>1] = 1
pred[pred<0] = 0
print('RMSE fit-to-range:',metrics.mean_squared_error(y_val,pred)**0.5)
preds['gb_plsrbyf'] = pred
```

```
Less than zero: 8101
Over one: 53
RMSE without modification: 0.20615780720704704
RMSE fit-to-range: 0.20612838300391242
```

```
pred = gb.predict(test_plsrbyf)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
```

```
Less than zero: 13258
Over one: 21
```

```
sub = pd.DataFrame({'item_id':test.item_id,'deal_probability':pred})

sub.loc[sub.deal_probability>1,'deal_probability'] = 1
sub.loc[sub.deal_probability<0,'deal_probability'] = 0

sub.to_csv('predictions/sub_gb_plsrbyf.csv',index=False)
```

```
!kaggle competitions submit -c avito-demand-prediction -f predictions/sub_gb_plsrbyf.csv -m "Message"
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /home/user/.kaggle/kaggle.json'
100%|██████████████████████████████| 15.8M/15.8M [00:16<00:00, 1.02MB/s]
Successfully submitted to Avito Demand Prediction Challenge
```

Private Score: 0.24004

Public Score: 0.23596

4.9. Multi Layer Perceptron

Back to Outline

```
mlp = neural_network.MLPRegressor(verbose=True,
                                  hidden_layer_sizes=(64,1),
                                  n_iter_no_change=10,
                                  tol=0.0001,
                                  learning_rate_init=0.1,
                                 )
```

```
mlp.fit(X_dev,y_dev)
```

```
Iteration 1, loss = 0.03414127
Iteration 2, loss = 0.03412936
Iteration 3, loss = 0.03412152
Iteration 4, loss = 0.03412905
Iteration 5, loss = 0.03412075
Iteration 6, loss = 0.03409799
Iteration 7, loss = 0.03412794
Iteration 8, loss = 0.03412402
Iteration 9, loss = 0.03412227
Iteration 10, loss = 0.03412462
Iteration 11, loss = 0.03411990
Iteration 12, loss = 0.03411259
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs.
Stopping.
```

```
MLPRegressor(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.9,
       beta_2=0.999, early_stopping=False, epsilon=1e-08,
       hidden_layer_sizes=(64, 1), learning_rate='constant',
       learning_rate_init=0.1, max_iter=200, momentum=0.9,
       n_iter_no_change=10, nesterovs_momentum=True, power_t=0.5,
       random_state=None, shuffle=True, solver='adam', tol=0.0001,
       validation_fraction=0.1, verbose=True, warm_start=False)
```

```
pred = mlp.predict(X_val)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
print('RMSE without modification:',metrics.mean_squared_error(y_val,pred)**0.5)
pred[pred>1] = 1
pred[pred<0] = 0
print('RMSE fit-to-range:',metrics.mean_squared_error(y_val,pred)**0.5)
preds['mlp_plsrbyf'] = pred
```

```
Less than zero: 0
Over one: 0
RMSE without modification: 0.2603847814321052
RMSE fit-to-range: 0.2603847814321052
```

```
pred = mlp.predict(test_plsrbyf)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
```

```
Less than zero: 0
Over one: 0
```

```
sub = pd.DataFrame({'item_id':test.item_id,'deal_probability':pred})

sub.loc[sub.deal_probability>1,'deal_probability'] = 1
sub.loc[sub.deal_probability<0,'deal_probability'] = 0

sub.to_csv('predictions/sub_mlp_plsrbyf.csv',index=False)
```

```
!kaggle competitions submit -c avito-demand-prediction -f predictions/sub_mlp_plsrbyf.csv -m "Message"
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /home/user/.kaggle/kaggle.json'
100%|██████████| 16.0M/16.0M [00:16<00:00, 1.01MB/s]
Successfully submitted to Avito Demand Prediction Challenge
```

Private Score: 0.27107

Public Score: 0.26633

4.10. Keras

Back to Outline

```
ker = Sequential()
ker.add(Dense(64, activation='relu', input_dim=72))
ker.add(Dense(1, activation='relu'))

ker.compile(loss='mean_squared_error',optimizer='adam',metrics=['accuracy'])
```

```
ker.fit(X_dev,y_dev,epochs=30,verbose=1)
```

```
WARNING:tensorflow:From /home/user/anaconda3/lib/python3.7/site-packages/tensorflow/python/ops/math_ops.py:3066: to_int32 (from tensorflow.python.ops.math_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/30
```

```
1127568/1127568 [==============================] - 34s 31us/step - loss: 0.0730 - acc: 0.6466
Epoch 2/30
1127568/1127568 [==============================] - 34s 30us/step - loss: 0.0455 - acc: 0.6480
Epoch 3/30
1127568/1127568 [==============================] - 35s 31us/step - loss: 0.0448 - acc: 0.6480
Epoch 4/30
1127568/1127568 [==============================] - 33s 29us/step - loss: 0.0447 - acc: 0.6479
Epoch 5/30
1127568/1127568 [==============================] - 37s 33us/step - loss: 0.0447 - acc: 0.6479
Epoch 6/30
1127568/1127568 [==============================] - 36s 32us/step - loss: 0.0446 - acc: 0.6479
Epoch 7/30
1127568/1127568 [==============================] - 41s 37us/step - loss: 0.0446 - acc: 0.6479
Epoch 8/30
1127568/1127568 [==============================] - 42s 37us/step - loss: 0.0445 - acc: 0.6479
Epoch 9/30
1127568/1127568 [==============================] - 45s 40us/step - loss: 0.1481 - acc: 0.6480
Epoch 10/30
1127568/1127568 [==============================] - 41s 36us/step - loss: 0.0445 - acc: 0.6480
Epoch 11/30
1127568/1127568 [==============================] - 32s 28us/step - loss: 0.0444 - acc: 0.6480
Epoch 12/30
1127568/1127568 [==============================] - 31s 28us/step - loss: 0.0445 - acc: 0.6480
Epoch 13/30
1127568/1127568 [==============================] - 42s 38us/step - loss: 0.0444 - acc: 0.6480
Epoch 14/30
1127568/1127568 [==============================] - 48s 43us/step - loss: 0.0444 - acc: 0.6480
Epoch 15/30
1127568/1127568 [==============================] - 30s 26us/step - loss: 0.0444 - acc: 0.6480
Epoch 16/30
1127568/1127568 [==============================] - 35s 31us/step - loss: 0.0444 - acc: 0.6480
Epoch 17/30
1127568/1127568 [==============================] - 27s 24us/step - loss: 0.0444 - acc: 0.6480
Epoch 18/30
1127568/1127568 [==============================] - 35s 31us/step - loss: 0.0443 - acc: 0.6481
Epoch 19/30
```

```
1127568/1127568 [==============================] - 42s 37us/step - loss: 0.0445 - acc: 0.6480
Epoch 20/30
1127568/1127568 [==============================] - 43s 38us/step - loss: 0.0443 - acc: 0.6480
Epoch 21/30
1127568/1127568 [==============================] - 37s 33us/step - loss: 0.0444 - acc: 0.6480
Epoch 22/30
1127568/1127568 [==============================] - 36s 32us/step - loss: 0.0445 - acc: 0.6480
Epoch 23/30
1127568/1127568 [==============================] - 38s 33us/step - loss: 0.0443 - acc: 0.6480
Epoch 24/30
1127568/1127568 [==============================] - 38s 34us/step - loss: 0.0443 - acc: 0.6480
Epoch 25/30
1127568/1127568 [==============================] - 39s 34us/step - loss: 0.0443 - acc: 0.6480
Epoch 26/30
1127568/1127568 [==============================] - 39s 35us/step - loss: 0.0444 - acc: 0.6480
Epoch 27/30
1127568/1127568 [==============================] - 38s 34us/step - loss: 0.0446 - acc: 0.6481
Epoch 28/30
1127568/1127568 [==============================] - 36s 32us/step - loss: 0.0446 - acc: 0.6480
Epoch 29/30
1127568/1127568 [==============================] - 37s 33us/step - loss: 0.0443 - acc: 0.6479
Epoch 30/30
1127568/1127568 [==============================] - 38s 34us/step - loss: 0.0445 - acc: 0.6480
```

```
pred = ker.predict(X_val)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
print('RMSE without modification:',metrics.mean_squared_error(y_val,pred)**0.5)
pred[pred>1] = 1
pred[pred<0] = 0
print('RMSE fit-to-range:',metrics.mean_squared_error(y_val,pred)**0.5)
preds['ker_plsrbyf'] = pred
```

```
Less than zero: [0]
Over one: [308]
RMSE without modification: 0.21108059545026234
RMSE fit-to-range: 0.21100376236913634
```

```
pred = ker.predict(test_plsrbyf)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
```

```
Less than zero: [0]
Over one: [227]
```

```
pred = [p[0] for p in pred]
sub = pd.DataFrame({'item_id':test.item_id,'deal_probability':pred})

sub.loc[sub.deal_probability>1,'deal_probability'] = 1
sub.loc[sub.deal_probability<0,'deal_probability'] = 0

sub.to_csv('predictions/sub_ker_plsrbyf.csv',index=False)
```

```
!kaggle competitions submit -c avito-demand-prediction -f predictions/sub_ker_plsrbyf.csv -m "Message"
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /home/user/.kaggle/kaggle.json'
100%|██████████████████████████████████████| 14.9M/14.9M [00:14<00:00, 1.07MB/s]
Successfully submitted to Avito Demand Prediction Challenge
```

Private Score: 0.24423

Public Score: 0.23975

4.11. RandomForestRegressor

Back to Outline

```
rf = ensemble.RandomForestRegressor(
    n_estimators=100,
    verbose=10,
    random_state=33
)
```

```
rf.fit(X_dev,y_dev)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
```

```
building tree 1 of 100
```

```
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   58.9s remaining:    0.0s
```

```
building tree 2 of 100
```

```
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:  2.0min remaining:    0.0s
```

```
building tree 3 of 100
```

```
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:  3.0min remaining:    0.0s
```

```
building tree 4 of 100
```

```
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:  4.1min remaining:    0.0s
```

```
building tree 5 of 100
```

```
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:  5.2min remaining:    0.0s
```

```
building tree 6 of 100
```

```
[Parallel(n_jobs=1)]: Done   6 out of   6 | elapsed:  6.1min remaining:    0.0s
```

```
building tree 7 of 100
```

```
[Parallel(n_jobs=1)]: Done   7 out of   7 | elapsed:  7.0min remaining:    0.0s
```

```
building tree 8 of 100
```

```
[Parallel(n_jobs=1)]: Done   8 out of   8 | elapsed:  8.0min remaining:    0.0s
```

```
building tree 9 of 100
```

```
[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed:  9.1min remaining:    0.0s
```

```
building tree 10 of 100
building tree 11 of 100
building tree 12 of 100
building tree 13 of 100
building tree 14 of 100
building tree 15 of 100
building tree 16 of 100
building tree 17 of 100
building tree 18 of 100
building tree 19 of 100
building tree 20 of 100
building tree 21 of 100
```

```
building tree 22 of 100
building tree 23 of 100
building tree 24 of 100
building tree 25 of 100
building tree 26 of 100
building tree 27 of 100
building tree 28 of 100
building tree 29 of 100
building tree 30 of 100
building tree 31 of 100
building tree 32 of 100
building tree 33 of 100
building tree 34 of 100
building tree 35 of 100
building tree 36 of 100
building tree 37 of 100
building tree 38 of 100
building tree 39 of 100
building tree 40 of 100
building tree 41 of 100
building tree 42 of 100
building tree 43 of 100
building tree 44 of 100
building tree 45 of 100
building tree 46 of 100
building tree 47 of 100
building tree 48 of 100
building tree 49 of 100
building tree 50 of 100
building tree 51 of 100
building tree 52 of 100
building tree 53 of 100
building tree 54 of 100
building tree 55 of 100
building tree 56 of 100
building tree 57 of 100
building tree 58 of 100
building tree 59 of 100
building tree 60 of 100
building tree 61 of 100
building tree 62 of 100
building tree 63 of 100
building tree 64 of 100
building tree 65 of 100
building tree 66 of 100
building tree 67 of 100
building tree 68 of 100
building tree 69 of 100
building tree 70 of 100
building tree 71 of 100
building tree 72 of 100
building tree 73 of 100
building tree 74 of 100
building tree 75 of 100
```

```
building tree 76 of 100
building tree 77 of 100
building tree 78 of 100
building tree 79 of 100
building tree 80 of 100
building tree 81 of 100
building tree 82 of 100
building tree 83 of 100
building tree 84 of 100
building tree 85 of 100
building tree 86 of 100
building tree 87 of 100
building tree 88 of 100
building tree 89 of 100
building tree 90 of 100
building tree 91 of 100
building tree 92 of 100
building tree 93 of 100
building tree 94 of 100
building tree 95 of 100
building tree 96 of 100
building tree 97 of 100
building tree 98 of 100
building tree 99 of 100
building tree 100 of 100
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed: 97.1min finished
```

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                      max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=None,
                      oob_score=False, random_state=33, verbose=10, warm_start=False)
```

```
pred = rf.predict(X_val)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
print('RMSE without modification:',metrics.mean_squared_error(y_val,pred)**0.5)
pred[pred>1] = 1
pred[pred<0] = 0
print('RMSE fit-to-range:',metrics.mean_squared_error(y_val,pred)**0.5)
preds['rf_plsrbyf'] = pred
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.3s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.5s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:    0.8s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:    1.1s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    1.3s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   6 out of   6 | elapsed:    1.6s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   7 out of   7 | elapsed:    1.9s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   8 out of   8 | elapsed:    2.1s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed:    2.4s remaining:    0.0s
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:   24.9s finished
```

```
Less than zero: 0
Over one: 0
RMSE without modification: 0.21064608123386366
RMSE fit-to-range: 0.21064608123386366
```

```
pred = rf.predict(test_plsrbyf)
print('Less than zero:',sum(pred<0))
print('Over one:',sum(pred>1))
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.3s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.7s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:    1.0s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:    1.3s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    1.6s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   6 out of   6 | elapsed:    1.9s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   7 out of   7 | elapsed:    2.2s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   8 out of   8 | elapsed:    2.6s remaining:    0.0s
[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed:    2.9s remaining:    0.0s
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:   30.2s finished
```

```
Less than zero: 0
Over one: 0
```

```
#pred = [p[0] for p in pred]
sub = pd.DataFrame({'item_id':test.item_id,'deal_probability':pred})

sub.loc[sub.deal_probability>1,'deal_probability'] = 1
sub.loc[sub.deal_probability<0,'deal_probability'] = 0

sub.to_csv('predictions/sub_rf_plsrbyf.csv',index=False)
```

```
!kaggle competitions submit -c avito-demand-prediction -f
predictions/sub_rf_plsrbyf.csv -m "Message"
```

```
Warning: Your Kaggle API key is readable by other users on this system! To fix this, you can run 'chmod 600 /home/user/.kaggle/kaggle.json'
100%|██████████████████████████████████████| 14.7M/14.7M [00:15<00:00, 994kB/s]
Successfully submitted to Avito Demand Prediction Challenge
```

Private Score: 0.24491

Public Score: 0.24088

4.12. Error Analysis

```
train_scale = joblib.load('feature_dumps/train_scale.sav')
test_scale = joblib.load('feature_dumps/test_scale.sav')
```

```
y = train.deal_probability
X_dev,X_val,y_dev,y_val = model_selection.train_test_split(train_scale,y)
```

```
params = {
        "objective" : "regression",
        "metric" : "rmse",
        "num_leaves" : 30,
        "learning_rate" : 0.1,
        "bagging_fraction" : 0.7,
        "feature_fraction" : 0.7,
        "bagging_frequency" : 5,
        "bagging_seed" : 2342,
        "verbosity" : -1
    }

lgtrain = lgb.Dataset(X_dev, label=y_dev)
lgval = lgb.Dataset(X_val, label=y_val)
evals_result = {}

gb = lgb.train(params, lgtrain, 1000, valid_sets=[lgval],
               early_stopping_rounds=100, verbose_eval=20,
               evals_result=evals_result)
```

```
Training until validation scores don't improve for 100 rounds.
[20]	valid_0's rmse: 0.214165
[40]	valid_0's rmse: 0.210232
[60]	valid_0's rmse: 0.208477
[80]	valid_0's rmse: 0.207474
[100]	valid_0's rmse: 0.206755
[120]	valid_0's rmse: 0.206255
[140]	valid_0's rmse: 0.205848
[160]	valid_0's rmse: 0.205525
[180]	valid_0's rmse: 0.20528
[200]	valid_0's rmse: 0.205048
[220]	valid_0's rmse: 0.204862
```

```
[240]   valid_0's rmse: 0.20471
[260]   valid_0's rmse: 0.204591
[280]   valid_0's rmse: 0.204482
[300]   valid_0's rmse: 0.20438
[320]   valid_0's rmse: 0.2043
[340]   valid_0's rmse: 0.204212
[360]   valid_0's rmse: 0.204124
[380]   valid_0's rmse: 0.204032
[400]   valid_0's rmse: 0.203959
[420]   valid_0's rmse: 0.203919
[440]   valid_0's rmse: 0.203838
[460]   valid_0's rmse: 0.203796
[480]   valid_0's rmse: 0.20375
[500]   valid_0's rmse: 0.203702
[520]   valid_0's rmse: 0.203649
[540]   valid_0's rmse: 0.20362
[560]   valid_0's rmse: 0.203575
[580]   valid_0's rmse: 0.203512
[600]   valid_0's rmse: 0.203477
[620]   valid_0's rmse: 0.203442
[640]   valid_0's rmse: 0.203418
[660]   valid_0's rmse: 0.203381
[680]   valid_0's rmse: 0.203348
[700]   valid_0's rmse: 0.203299
[720]   valid_0's rmse: 0.203272
[740]   valid_0's rmse: 0.203259
[760]   valid_0's rmse: 0.203234
[780]   valid_0's rmse: 0.203218
[800]   valid_0's rmse: 0.203195
[820]   valid_0's rmse: 0.203176
[840]   valid_0's rmse: 0.203156
[860]   valid_0's rmse: 0.203136
[880]   valid_0's rmse: 0.203109
[900]   valid_0's rmse: 0.203081
[920]   valid_0's rmse: 0.203049
[940]   valid_0's rmse: 0.20304
[960]   valid_0's rmse: 0.203008
[980]   valid_0's rmse: 0.20299
[1000]  valid_0's rmse: 0.202964
Did not meet early stopping. Best iteration is:
[1000]  valid_0's rmse: 0.202964
```

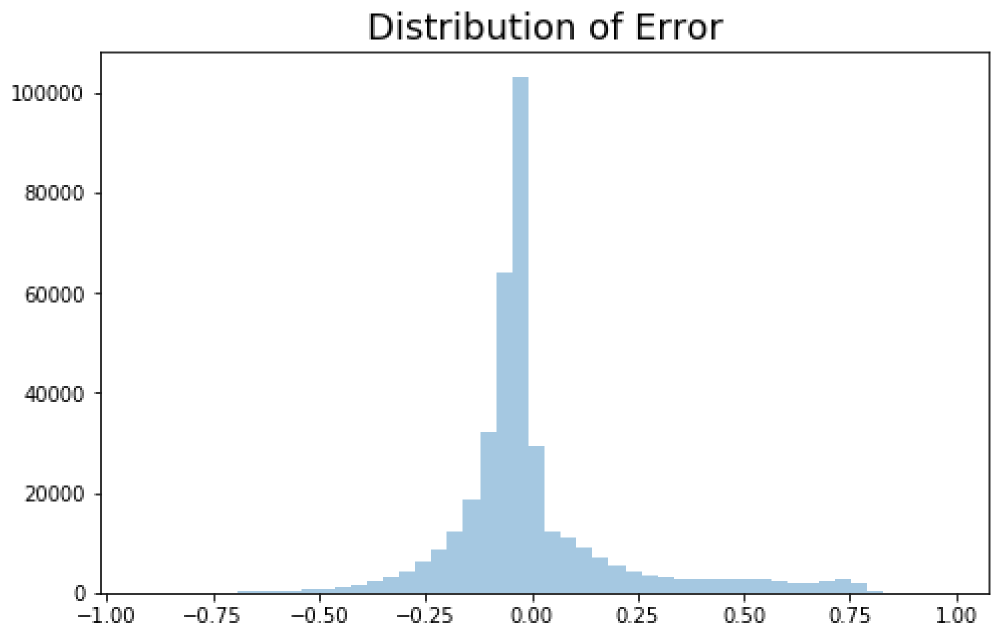
```python
pred = gb.predict(X_val, num_iteration=gb.best_iteration)
```

```python
residual = y_val - pred
```

```python
resdf = pd.DataFrame({'y':y_val,'pred':pred,'residual':residual})
```

```
plt.figure(figsize=(8,5))
sns.scatterplot(x='pred',y='residual',data=resdf)
plt.title('Scedasticity of Error',fontsize=18)
plt.show()
```


```
plt.figure(figsize=(8,5))
sns.distplot(residual.values,kde=False)
plt.title('Distribution of Error',fontsize=18)
plt.show()
```



5. Product

[Back to Outline]

Based on several comparisons, the above-described feature-engineering pipeline followed by LightGBM is the best approach at predicting the deal probability of an online ad.

Why it works?

It works due to the robustness and variety of feature-extraction and decomposition techniques. While feature extraction can generate a lot of data, this is only useful in a reduced dimensional space. Decomposing large CSR matrices produces predictively powerful components.

What problem it solves?

Online platforms for selling used goods rely on regular people selling their belongings online to achieve high-traffic. These sellers blindly sell their things with erroneous expectations and bad listing practices, thus becoming frustrated with online sales. Helping sellers understand the demand of their listings contributes in several ways: Informed sellers can optimize their listings for maximum deal probability and also optimize their choice of goods to sell, based on the deal probability of particular categories.

How will it work in production?

In a production environment this model would learn from the sales information of a historic time window in order to predict the deal probability of new ads. Necessary maintenance might involve adjusting some of the feature-engineering procedures to ensure they are capturing the most valuable information.