In [1]:

```
import numpy as np
import pandas as pd
import os
import datetime as dt
import matplotlib.pyplot as plt
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.linear_model import LinearRegression, Lasso
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import KFold, GridSearchCV
from xgboost import XGBRegressor
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
/Users/taras/opt/anaconda3/lib/python3.8/site-packages/xgboost/compat.
py:31: FutureWarning: pandas.Int64Index is deprecated and will be remo
ved from pandas in a future version. Use pandas.Index with the appropr
iate dtype instead.
  from pandas import MultiIndex, Int64Index
```

In [2]:

```
os.chdir('/Users/taras/Documents/mrsool/')
```

Read the data

In [3]:

```
train_data = pd.read_csv('train.csv')
test_data = pd.read_csv('test.csv')
```

In [4]:

```
train_data.columns
```

Out[4]:

```
Index(['creation_datetime', 'updated_at', 'age_less_than', 'num_apartm
ents',
       'num_bedrooms', 'floor_num', 'num_kitchens', 'closed',
       'commercial_or_residential', 'property_type', 'driver_room', 'd
uplex',
       'family_or_single', 'furnished', 'num_living_rooms', 'maid_roo
m',
       'price_per_meter', 'advertiser_type', 'pool', 'paid', 'price',
       'rent_period', 'num_rooms', 'area', 'street_direction', 'street
_width',
       'for_rent_or_sale', 'num_water_cycles', 'Latitude', 'Longitud
e',
       'region_name_en', 'nearest_city_name_en', 'district_name_en'],
      dtype='object')
```

In [5]:

```
train_data.head()
```

Out[5]:

	creation_datetime	updated_at	age_less_than	num_apartments	num_bedrooms	floor_num	n
0	2016-03-04 13:49:48	2016-06-02 07:07:34	0	1	4	0	
1	2016-02-21 23:35:44	2016-02-25 12:19:14	0	0	0	0	
2	2016-01-05 21:26:47	2016-03-05 18:25:43	0	0	5	0	
3	2016-02-04 09:29:46	2016-02-04 09:29:58	0	0	1	0	
4	2016-03-28 13:22:12	2016-05-31 16:37:40	4	0	3	2	

5 rows × 33 columns

Inappropriate data removal

In [6]:

```
train_data['floor_num'].value_counts()
```

Out[6]:

```
 0     59713
 1      9573
 2      7007
 3      3390
 4       136
 5        40
 20       22
 10       21
 6        16
 8        12
 7        10
 12        9
 9         7
 15        5
 17        3
-1         3
 14        2
 16        2
 13        2
 11        1
 18        1
Name: floor_num, dtype: int64
```

In [7]:

```
train_data.loc[train_data['floor_num'] == -1]
```

Out[7]:

	creation_datetime	updated_at	age_less_than	num_apartments	num_bedrooms	floor_nur
9602	2015-05-12 20:00:19	2015-05-14 08:38:18	2	0	0	-
42351	2015-05-12 19:58:43	2015-05-14 08:38:26	-1	0	0	-
56672	2015-04-29 16:51:01	2015-04-29 16:51:01	-1	0	3	-

3 rows × 33 columns

Looks like there are 3 records with very strange data. As it's a small amount and all of them are closed we can remove them.

In [8]:

```
train_data = train_data.loc[train_data['floor_num'] != -1]
test_data = test_data.loc[test_data['floor_num'] != -1]
```

Process data

Convert strings to datetimes.

Make variableas binary.

Translate Arabic to English.

In [9]:

```
duplex_vals = {
    "ليست دوبلكس" : 0,
    "دوبلكس":1,
}

closed_vals = {
    "مغلق" : 'closed',
    "متاح": 'open',
    "غير منشور": 'not published',
}

com_res_vals = {
    "غير محدد" : 'undefined',
    "سكني": 'residental',
    "تجاري": 'commercial',
    "كلاهما": 'both',
    "4": 'undefined',
    "5": 'undefined',
    "6": 'undefined',
    "7": 'undefined',
}

property_vals = {
    "فيلا" : 'villa',
    "شقة": 'appartment',
    "أرض": 'land',
    "عمارة": 'architecture',
    "دور": 'floor',
    "استراحة": 'lounge',
    "محل": 'shop',
    "بيت": 'house',
    "مكتب تجاري": 'commercial office',
    "مستودع": 'storehouse',
    "مزرعة": 'farm',
    "مخيم": 'camp',
    "قصر": 'castle',
    "غرفة": 'appartment',
}

driver_vals = {
    "لا يوجد غرفة سائق" : 0,
    "غرفة سائق":1,
}

family_vals = {
    "عزاب" : 0,
    "عوائل":1,
}

furnished_vals = {
    "لا يوجد اثاث" : 0,
    "مؤثثة":1,
}

maid_room_vals = {
    "لا يوجد غرفة خادمة" : 0,
    "غرفة خادمة":1,
}
```

```
market_vals = {
    "0" : "مالك",
    "1" : "مسوق",
}

pool_vals = {
    "0" : "لا يوجد مسبح",
    "1" : "مسبح",
}

paid_vals = {
    "0" : "مجاني",
    "1" : "مدفوع",
}

rent_period_vals = {
    "غير محدد" : 'undefined',
    "سنوي": 'annual',
    "يومي": 'daily',
    "شهري": 'monthly',
    "4": 'undefined',
    "5": 'undefined',
    "6": 'undefined',
}

street_direction_vals = {
    "غير محدد" : 'undefined',
    "شمال": 'north',
    "جنوب": 'south',
    "شرق": 'east',
    "غرب": 'west',
    "شمال شرقي": 'northeast',
    "جنوب شرقي": 'southeast',
    "جنوب غربي": 'southwest',
    "شمال غربي": 'northwest',
    "3 شوارع": 'undefined',
    "4 شوارع": 'undefined',
}

rent_sale_vals = {
    "0" : "للبيع",
    "1" :"للإيجار",
}
```

In [10]:

```
def process(df):
    """
    Translate to english (or make variables binary if it is possible).
    """
    for date_col in ['creation_datetime', 'updated_at']:
        df[date_col] = pd.to_datetime(df[date_col], format='%Y-%m-%d %H:%M:%S')

    df['duplex'] = df['duplex'].map(lambda x: duplex_vals.get(x, 0))
    df['closed'] = df['closed'].map(lambda x: closed_vals.get(x, 'closed'))
    df['commercial_or_residential'] = df['commercial_or_residential'].map(lambda x:
    df['property_type'] = df['property_type'].map(lambda x: property_vals.get(x, 'vi
    df['driver_room'] = df['driver_room'].map(lambda x: driver_vals.get(x, 0))
    df['family'] = df['family_or_single'].map(lambda x: family_vals.get(x, 0))
    df['furnished'] = df['furnished'].map(lambda x: furnished_vals.get(x, 0))
    df['maid_room'] = df['maid_room'].map(lambda x: maid_room_vals.get(x, 0))
    df['is_market_adv'] = df['advertiser_type'].map(lambda x: market_vals.get(x, 1))
    df['pool'] = df['pool'].map(lambda x: pool_vals.get(x, 0))
    df['paid'] = df['paid'].map(lambda x: paid_vals.get(x, 0))
    df['rent_period'] = df['rent_period'].map(lambda x: rent_period_vals.get(x, 'unc
    df['street_direction'] = df['street_direction'].map(lambda x: street_direction_v
    df['for_rent'] = df['for_rent_or_sale'].map(lambda x: rent_sale_vals.get(x, 0))

    df.drop(columns=['family_or_single', 'advertiser_type', 'for_rent_or_sale'], inp

    return df
```

In [11]:

```
train_data = process(df=train_data)
test_data = process(df=test_data)
```

Let's look on the data

In [12]:

```
train_data.head()
```

Out[12]:

	creation_datetime	updated_at	age_less_than	num_apartments	num_bedrooms	floor_num	nu
0	2016-03-04 13:49:48	2016-06-02 07:07:34	0	1	4	0	
1	2016-02-21 23:35:44	2016-02-25 12:19:14	0	0	0	0	
2	2016-01-05 21:26:47	2016-03-05 18:25:43	0	0	5	0	
3	2016-02-04 09:29:46	2016-02-04 09:29:58	0	0	1	0	
4	2016-03-28 13:22:12	2016-05-31 16:37:40	4	0	3	2	

5 rows × 33 columns

Which proper types present in our data?

In [13]:

```
train_data['property_type'].value_counts()
```

Out[13]:

```
villa               27345
appartment          19731
land                16872
architecture         5022
floor                4203
lounge               2767
shop                 2057
house                 724
commercial office     654
storehouse            301
farm                  239
camp                   55
castle                  2
Name: property_type, dtype: int64
```

Our company operates with buildings and lands (land, farm and camp). Buildings and lands have different characteristics and it should be taken into account in our analysis. Almost 80% of ads related to buildings.

There are opened and closed advertisements

In [14]:

```
train_data['closed'].value_counts()
```

Out[14]:

```
closed          59396
open            20570
not published       6
Name: closed, dtype: int64
```

There are only 6 non-published ads so we can handle them as opened.

In [15]:

```
def add_open_and_land_features(df):
    df['is_land'] = df['property_type'].map(lambda x: 1 if x in ('land', 'farm', 'ca
    df['is_opened'] = df['closed'].map(lambda x: 0 if x == 'closed' else 1)
    df.drop(columns=['closed'], inplace=True)

    return df
```

In [16]:

```
train_data = add_open_and_land_features(df=train_data)
test_data = add_open_and_land_features(df=test_data)
```

In [17]:

```
# Save data for analysis
train_data.to_csv('data.csv', index=False)
```

In [ ]:

```

```

In [18]:

```
# As discussed in analysis, are most popular items are villas for sale, appartments
# Each of them need separate models. I will make a simple model for villas for sale.
```

Preprocessing

In [19]:

```
def preprocess(df, is_train=True):
    df = df.loc[df['property_type'] == 'villa']
    df = df.loc[df['for_rent'] == 0]
    df = df.loc[df['rent_period'] == 'undefined']

    df.drop(columns=['property_type', 'for_rent'], inplace=True)

    # We will use `district_name_en` as geofraphical feature, so we can remove other
    df.drop(columns=['region_name_en', 'nearest_city_name_en', 'Latitude', 'Longituc

    # Remove other non-meaningful features
    df.drop(columns=['paid', 'is_land', 'commercial_or_residential', 'rent_period',
                     'creation_datetime', 'floor_num', 'num_rooms', 'price_p

    # last possible price update to take into account inflation (in reality we can c
    df['days_since_last_update'] = (df['updated_at'].max() - df['updated_at']).map(l
    df.drop(columns=['updated_at'], inplace=True)

    # Trim outliers in appartments values
    df['num_apartments'] = df['num_apartments'].map(lambda x: x if x <= 5 else 5)

    # There is strange that there are no bedrooms
    df['num_bedrooms'] = df['num_bedrooms'].map(lambda x: x if x > 0 else 1)

    # Handle outliers at area column (can be done more precisely)
    df['area'] = df['area'].map(lambda x: x if x > 200 else 200)
    df['area'] = df['area'].map(lambda x: x if x < 5000 else 5000)

    if is_train:
        # Remove low price values (they are likely to be dor a rent, not for sale)
        df = df.loc[df['price'] > 500000]

        # Also prices with values more then RAI 250 mln looks abnormal
        df = df.loc[df['price'] <= 50000000]

    return df
```

In [20]:

```
train_data = preprocess(df=train_data)
test_data = preprocess(df=test_data, is_train=False)
```

In [21]:

```
all_districts = train_data['district_name_en'].value_counts()
keep_districts = list(all_districts.loc[all_districts > 200].index)
```

In [22]:

```
# In real model it is better to group near small populated districts. But here we wi
train_data['district_name_en'] = train_data['district_name_en'].map(lambda x: x if x
test_data['district_name_en'] = test_data['district_name_en'].map(lambda x: x if x i
```

In [23]:

```
encoder = OneHotEncoder(drop='first', handle_unknown='ignore')
encoder.fit(train_data[['district_name_en', 'street_direction']])
```

Out[23]:

```
OneHotEncoder(drop='first', handle_unknown='ignore')
```

In [ ]:

In [24]:

```
encodings_train = encoder.transform(train_data[['district_name_en', 'street_directic
for x in range(encodings_train.shape[1]):
    train_data[f'encoding_{x}'] = encodings_train[:, x].astype(int)

train_data.drop(columns=['district_name_en', 'street_direction'], inplace=True)
```

In [25]:

```
encodings_test = encoder.transform(test_data[['district_name_en', 'street_direction'
for x in range(encodings_test.shape[1]):
    test_data[f'encoding_{x}'] = encodings_test[:, x].astype(int)

test_data.drop(columns=['district_name_en', 'street_direction'], inplace=True)
```

In [ ]:

In [26]:

```
train_x = train_data.drop(columns='price')
train_y = train_data['price']
```

Algorithm selection

In [27]:

```
kfold = KFold(n_splits=5, shuffle=True)
res = pd.DataFrame()
for train_ix, valid_ix in kfold.split(train_x):
    train_df = train_x.iloc[train_ix]
    train_target = train_y.iloc[train_ix]
    valid_df = train_x.iloc[valid_ix]
    valid_target = train_y.iloc[valid_ix]

    model = LinearRegression()
    model.fit(train_df, train_target)
    predictions = model.predict(valid_df)

    iter_res = pd.DataFrame(predictions)
    iter_res.columns = ['prediction']
    iter_res.index = valid_target.index
    iter_res['real'] = valid_target
    res = res.append(iter_res)
```

In [28]:

```
# Linear Regression
mean_absolute_error(iter_res['real'], iter_res['prediction'])
```

Out[28]:

```
691318.855218209
```

In [29]:

```
kfold = KFold(n_splits=5, shuffle=True)
res = pd.DataFrame()
for train_ix, valid_ix in kfold.split(train_x):
    train_df = train_x.iloc[train_ix]
    train_target = train_y.iloc[train_ix]
    valid_df = train_x.iloc[valid_ix]
    valid_target = train_y.iloc[valid_ix]

    model = Lasso(alpha=0.1)
    model.fit(train_df, train_target)
    predictions = model.predict(valid_df)

    iter_res = pd.DataFrame(predictions)
    iter_res.columns = ['prediction']
    iter_res.index = valid_target.index
    iter_res['real'] = valid_target
    res = res.append(iter_res)
```

In [30]:

```
# Lasso Regression
mean_absolute_error(iter_res['real'], iter_res['prediction'])
```

Out[30]:

```
713236.3592156691
```

In [31]:

```
kfold = KFold(n_splits=5, shuffle=True)
res = pd.DataFrame()
for train_ix, valid_ix in kfold.split(train_x):
    train_df = train_x.iloc[train_ix]
    train_target = train_y.iloc[train_ix]
    valid_df = train_x.iloc[valid_ix]
    valid_target = train_y.iloc[valid_ix]

    model = RandomForestRegressor(n_estimators=100)
    model.fit(train_df, train_target)
    predictions = model.predict(valid_df)

    iter_res = pd.DataFrame(predictions)
    iter_res.columns = ['prediction']
    iter_res.index = valid_target.index
    iter_res['real'] = valid_target
    res = res.append(iter_res)
```

In [32]:

```
# RandomForest Regression
mean_absolute_error(iter_res['real'], iter_res['prediction'])
```

Out[32]:

```
502010.1183576915
```

In [33]:

```
kfold = KFold(n_splits=5, shuffle=True)
res = pd.DataFrame()
for train_ix, valid_ix in kfold.split(train_x):
    train_df = train_x.iloc[train_ix]
    train_target = train_y.iloc[train_ix]
    valid_df = train_x.iloc[valid_ix]
    valid_target = train_y.iloc[valid_ix]

    xgb_model = XGBRegressor(
        gamma=0,
        learning_rate=0.07,
        max_depth=8,
        min_child_weight=1.5,
        n_estimators=100,
        reg_alpha=0.75,
        reg_lambda=0.5,
        subsample=0.8,
        seed=42,
    )
    xgb_model.fit(train_df, train_target)
    predictions = xgb_model.predict(valid_df)

    iter_res = pd.DataFrame(predictions)
    iter_res.columns = ['prediction']
    iter_res.index = valid_target.index
    iter_res['real'] = valid_target
    res = res.append(iter_res)
```

In [34]:

```
# XGBoost Regression
mean_absolute_error(iter_res['real'], iter_res['prediction'])
```

Out[34]:

```
523341.0801633384
```

In [35]:

```
# Looks like xgboost the best choise. Also there is sense to try catboost. The reaso
# categorical features and mentioned algorithm handle them well.
```

Parameters tuning

In [36]:

```



#for tuning parameters
#parameters_for_testing = {
#    'gamma':[0,0.03,0.1,0.3],
#    'min_child_weight':[1.5,6,10],
#    'learning_rate':[0.1,0.07],
#    'max_depth':[3,5, 8],
#    'n_estimators':[100],
#    'reg_alpha':[1e-5, 1e-2,  0.75],
#    'reg_lambda':[1e-5, 1e-2, 0.45],
#    'subsample':[0.6,0.8]
#}


#xgb_model = XGBRegressor(learning_rate =0.1, n_estimators=100, max_depth=5,
#     min_child_weight=1, gamma=0, subsample=0.8, colsample_bytree=0.8, nthread=6, s

#gsearch1 = GridSearchCV(estimator = xgb_model, param_grid = parameters_for_testing,
#gsearch1.fit(train_x,train_y)
#print (gsearch1.grid_scores_)
#print('best params')
#print (gsearch1.best_params_)
#print('best score')
#print (gsearch1.best_score_)
```

In [ ]:

```

```

In [37]:

```
kfold = KFold(n_splits=5, shuffle=True)
res = pd.DataFrame()
for train_ix, valid_ix in kfold.split(train_x):
    train_df = train_x.iloc[train_ix]
    train_target = train_y.iloc[train_ix]
    valid_df = train_x.iloc[valid_ix]
    valid_target = train_y.iloc[valid_ix]

    xgb_model = XGBRegressor(gamma=0,
        learning_rate=0.07,
        max_depth=8,
        min_child_weight=1.5,
        n_estimators=1000,
        reg_alpha=0.75,
        reg_lambda=0.45,
        subsample=0.8,
        seed=42,
    )
    xgb_model.fit(train_df, train_target)
    predictions = xgb_model.predict(valid_df)

    iter_res = pd.DataFrame(predictions)
    iter_res.columns = ['prediction']
    iter_res.index = valid_target.index
    iter_res['real'] = valid_target
    res = res.append(iter_res)
```

In [38]:

```
mean_absolute_error(iter_res['real'], iter_res['prediction'])
```

Out[38]:

```
567975.985853728
```

In [39]:

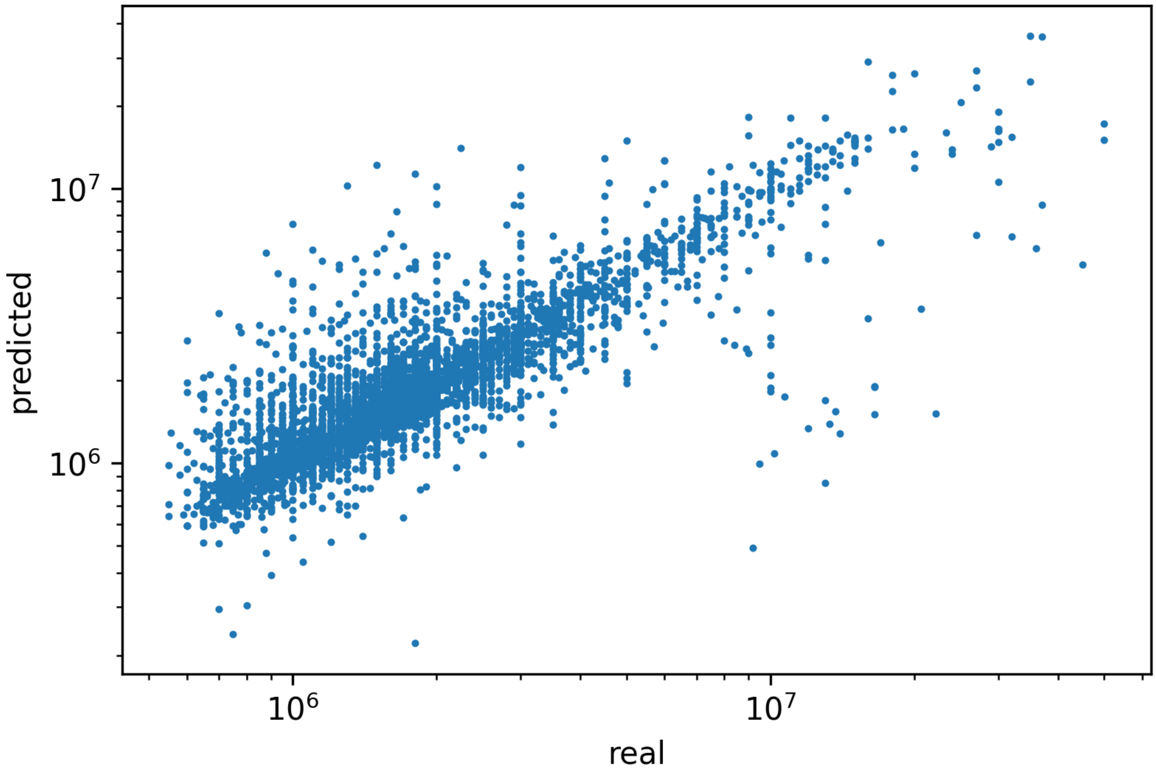
```
from sklearn.metrics import r2_score
r2_score(iter_res['real'], iter_res['prediction'])
```

Out[39]:

```
0.6309933706442425
```

In [40]:

```
fig = plt.figure(dpi=300)
ax = fig.add_subplot(1, 1, 1)
ax.scatter(iter_res['real'], iter_res['prediction'], s=2)
ax.set_xscale('log')
ax.set_yscale('log')
ax.set_xlabel('real')
ax.set_ylabel('predicted')
fig.show()
```



There is a group of outliers below the main trend. Looks like their price is enormous. We need deeper investigation to get whether we should remove them. In case this data is really incorrect then we should reeducate model without such data.

In [41]:

```
best_xgb_model = XGBRegressor(gamma=0,
                  learning_rate=0.07,
                  max_depth=8,
                  min_child_weight=1.5,
                  n_estimators=100,
                  reg_alpha=0.75,
                  reg_lambda=0.45,
                  subsample=0.8,
                  seed=42)
best_xgb_model.fit(train_x, train_y)
```

Out[41]:

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-
1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.07, max_delta_step=0, max_depth=8,
             min_child_weight=1.5, missing=nan, monotone_constraints
='()',
             n_estimators=100, n_jobs=16, num_parallel_tree=1, random_
state=42,
             reg_alpha=0.75, reg_lambda=0.45, scale_pos_weight=1, seed
=42,
             subsample=0.8, tree_method='exact', validate_parameters=
1,
             verbosity=None)
```

In [42]:

```
predicted_prices = best_xgb_model.predict(test_data)
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]:

```

```

In [ ]:

```

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In [ ]:

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In [ ]:

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In [ ]:

```

```