02_Model

September 24, 2020

1 flats-in-cracow machine learning

1.1 Imports

[1]:
```
from datetime import datetime
from distutils.dir_util import copy_tree
from pathlib import Path

import joblib
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

from matplotlib.ticker import MaxNLocator
from pylab import rcParams
from sklearn.compose import ColumnTransformer, TransformedTargetRegressor
from sklearn.dummy import DummyRegressor
from sklearn.ensemble import (GradientBoostingRegressor, RandomForestRegressor,
                              VotingRegressor)
from sklearn.impute import KNNImputer
from sklearn.metrics import (mean_absolute_error, mean_squared_error,
                             mean_squared_log_error)
from sklearn.model_selection import GridSearchCV, train_test_split, KFold
from sklearn.neural_network import MLPRegressor
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
```

1.2 Setup

[2]:
```
# Create directory for images
Path("img").mkdir(parents=True, exist_ok=True)

# Set default figure size
rcParams['figure.figsize'] = (4, 4)

# Tell pandas how to display floats
pd.options.display.float_format = "{:,.2f}".format
```

1.3 Data loading

[3]:
```python
path = '../flats-data/cleaned_data.csv'
```

[4]:
```python
data = pd.read_csv(path, lineterminator='\n')
```

[5]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4102 entries, 0 to 4101
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   District   4102 non-null   object
 1   Amount     4102 non-null   int64
 2   Seller     4102 non-null   object
 3   Area       4102 non-null   int64
 4   Rooms      4102 non-null   int64
 5   Bathrooms  4102 non-null   int64
 6   Parking    4102 non-null   object
 7   Garden     4102 non-null   bool
 8   Balcony    4102 non-null   bool
 9   Terrace    4102 non-null   bool
 10  Floor      4102 non-null   bool
 11  New        4102 non-null   bool
 12  Estate     4102 non-null   bool
 13  Townhouse  4102 non-null   bool
 14  Apartment  4102 non-null   bool
 15  Land       4102 non-null   bool
 16  Studio     4102 non-null   bool
dtypes: bool(10), int64(4), object(3)
memory usage: 264.5+ KB
```

[6]:
```python
data.head()
```

[6]:
```
    District   Amount   Seller  Area  Rooms  Bathrooms     Parking  Garden  \
0   biezanow   439082  realtor    56      3          1     covered    True
1   podgorze   845000  realtor   132      5          2  no parking   False
2   podgorze   360000  realtor    41      2          1  no parking   False
3  krowodrza  1190000  realtor    81      3          1  no parking    True
4    debniki   990000  realtor    93      4          2      street   False

   Balcony  Terrace  Floor    New  Estate  Townhouse  Apartment   Land  Studio
0     True    False   True   True   False      False       True   True   False
1    False     True  False  False   False      False       True  False   False
2     True    False  False  False   False      False      False  False   False
3    False     True   True   True   False      False       True   True   False
```

```
4    False    False  False  False   False      False      False  False   False
```

1.4 Feature engineering

The next step is to engineer features. We add columns describing the `Total Rooms` in the property, ratio of `Area to Rooms` and so on.

[7]:
```
data['Log Area'] = np.round(np.log(data['Area']), 2)
data['Bool Sum'] = data.select_dtypes(bool).sum(axis=1)
# Avoid division by zero
data['Area to Bool Sum'] = round(data['Area'] / (data.select_dtypes(bool).
 ↪sum(axis=1) + 1), 2)
data['Rooms to Bool Sum'] = round(data['Rooms'] / (data.select_dtypes(bool).
 ↪sum(axis=1) + 1), 2)
data['Rooms to Bathrooms' ] = round(data['Rooms'] / data['Bathrooms'], 2)
data['Total Rooms'] = round(data['Rooms'] + data['Bathrooms'], 2)
data['Area to Rooms'] = round(data['Area'] / data['Rooms'], 2)
data['Area to Bathrooms'] = round(data['Area'] / data['Rooms'], 2)
data['Area to Total Rooms'] = round(data['Area'] / data['Total Rooms'], 2)
```

1.5 Data split

We decide to use 80% of the data to train the model and 20% to check performance. We make sure to remove the `Amount` column from the training data since this is our target and remove duplicates before training.

[8]:
```
print(len(data))
data = data.drop_duplicates()
print(len(data))
```

```
4102
3586
```

[9]:
```
X = data.drop(['Amount'], axis=1)
y = data['Amount']

split = train_test_split(X, y, train_size=.8,
                         random_state=123)

X_train, X_test, y_train, y_test = split
```

1.6 Models

Next step is to create the models and associated piplines. We apply one hot encoding to categorical features and use the `ColumnTransformer` parameter `passthrough` to allow the rest of the columns to remain unchanged.

```
[10]: categorical = list(X.select_dtypes('object').columns)
      continuous = list(X.select_dtypes('int64'))
      continuous += list(X.select_dtypes('float64'))
```

1.6.1 Baseline model

For comparison purposes we create a model to give base predictions.

```
[11]: dmr = DummyRegressor()

      dmr_ohe = Pipeline(
          steps=[('onehot', OneHotEncoder(handle_unknown='ignore'))]
      )

      dmr = Pipeline(steps = [('preprocessor', dmr_ohe),
                              ('regressor', dmr)])

      # dmr.fit(X_train, y_train)
```

1.6.2 Multi-layer Perceptron

For the neural network we apply the `MinMaxScaler` so that the continuous columns have values in $[0, 1]$ and then we apply `OneHotEncoder` to the categorical columns.

```
[12]: mlp = MLPRegressor(hidden_layer_sizes=(100, 100, 100),
                         max_iter=2*10**4,
                         random_state=123)

      mlp_ohe = Pipeline(
          steps=[('onehot', OneHotEncoder(handle_unknown='ignore'))]
      )

      mlp_scale = Pipeline(
          steps=[('scale', MinMaxScaler())]
      )

      mlp_pre = ColumnTransformer(
          transformers = [
              ('scale', mlp_scale, continuous),
              ('cat', mlp_ohe, categorical),
          ],
          remainder='passthrough'
      )

      mlp_trans = TransformedTargetRegressor(regressor=mlp,
                                             transformer=MinMaxScaler())
```

```
mlp = Pipeline(steps = [('preprocessor', mlp_pre),
                        ('transformer', mlp_trans)])

# mlp.fit(X_train, y_train)
```

1.6.3 Gradient Boosting Regressor

For the gradient booster we only apply `OneHotEncoder` to the categorical columns.

[13]:
```
gbr = GradientBoostingRegressor(random_state=123)

gbr_ohe = Pipeline(
    steps=[('onehot', OneHotEncoder(handle_unknown='ignore'))]
)

gbr_pre = ColumnTransformer(
    transformers = [
        ('cat', gbr_ohe, categorical)
    ],
    remainder='passthrough'
)

gbr = Pipeline(steps = [('preprocessor', gbr_pre),
                        ('regressor', gbr)])

# gbr.fit(X_train, y_train)
```

1.7 Parameter tuning

We set up the training process to conduct basic parameter tuning and cross validation.

[14]:
```
kf = KFold(n_splits=5, random_state=123, shuffle=True)
```

[15]:
```
gbr_grid = {'regressor__max_depth': [5, 10, 15],
            'regressor__n_estimators': [50, 100, 200, 300],
            'regressor__min_samples_split': [2, 4],
            'regressor__min_samples_leaf': [2, 4],
            'regressor__max_features': ['auto']}

gbr_gs = GridSearchCV(estimator=gbr,
                      param_grid=gbr_grid,
                      cv=kf,
                      n_jobs=8,
                      scoring='neg_root_mean_squared_error',
                      verbose=2)
```

[16]:

```
layers = [(100, 100, 100),
          (150, 200, 150),
          (200, 400, 200)]

mlp_grid = {'transformer__regressor__activation': ['relu'],
            'transformer__regressor__solver': ['adam'],
            'transformer__regressor__learning_rate': ['adaptive'],
            'transformer__regressor__learning_rate_init': [0.01, 0.001, 0.0001],
            'transformer__regressor__hidden_layer_sizes': layers}

mlp_gs = GridSearchCV(estimator=mlp,
                      param_grid=mlp_grid,
                      cv=kf,
                      n_jobs=8,
                      scoring='neg_root_mean_squared_error',
                      verbose=2)
```

1.8 Training

[17]:

```
dmr.fit(X_train, y_train)
```

[17]:

```
Pipeline(steps=[('preprocessor',
                 Pipeline(steps=[('onehot',
                                  OneHotEncoder(handle_unknown='ignore'))])),
                ('regressor', DummyRegressor())])
```

[18]:

```
mlp = mlp_gs.fit(X_train, y_train).best_estimator_
mlp
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
```

```
[Parallel(n_jobs=8)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  25 tasks      | elapsed:   18.6s
[Parallel(n_jobs=8)]: Done  45 out of  45 | elapsed:   47.5s finished
```

[18]:

```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('scale',
                                                  Pipeline(steps=[('scale',
MinMaxScaler())]),
                                                  ['Area', 'Rooms', 'Bathrooms',
                                                   'Bool Sum', 'Total Rooms',
                                                   'Log Area',
                                                   'Area to Bool Sum',
                                                   'Rooms to Bool Sum',
                                                   'Rooms to Bathrooms',
                                                   'Area to Rooms',
```

```
                                                               'Area to Bathrooms',
                                                               'Area to Total Rooms']),
                                                             ('cat',
                                                              Pipeline(steps=[('onehot',
OneHotEncoder(handle_unknown='ignore'))]),
                                                              ['District', 'Seller',
                                                               'Parking'])])),
                ('transformer',
TransformedTargetRegressor(regressor=MLPRegressor(hidden_layer_sizes=(150,
       200,
       150),
learning_rate='adaptive',
learning_rate_init=0.01,
max_iter=20000,
random_state=123),
                                            transformer=MinMaxScaler()))])
```

CV RMSE score for MLPRegressor:

[19]:
```python
print(round(abs(mlp_gs.best_score_)))
```

```
118596
```

[20]:
```python
gbr = gbr_gs.fit(X_train, y_train).best_estimator_
gbr
```

```
Fitting 5 folds for each of 48 candidates, totalling 240 fits
```

```
[Parallel(n_jobs=8)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  25 tasks      | elapsed:    7.8s
[Parallel(n_jobs=8)]: Done 146 tasks      | elapsed:  1.1min
[Parallel(n_jobs=8)]: Done 240 out of 240 | elapsed:  2.6min finished
```

[20]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('cat',
                                                  Pipeline(steps=[('onehot',
OneHotEncoder(handle_unknown='ignore'))]),
                                                  ['District', 'Seller',
                                                   'Parking'])])),
                ('regressor',
                 GradientBoostingRegressor(max_depth=5, max_features='auto',
                                           min_samples_leaf=2,
                                           random_state=123))])
```

CV RMSE score for GradientBoostingRegressor:

[21]:
```python
print(round(abs(gbr_gs.best_score_)))
```

121466

1.8.1 Voting Regressor

We create a VotingRegressor with uniform weights to be able to combine predictions of our models.

[22]:
```
vote = VotingRegressor(estimators=[['mlp', mlp], ['gbr', gbr]], n_jobs=8)
vote = vote.fit(X_train, y_train)
```

1.9 Model performance

We obtain predictions for the testing set and compare RMSE, MAE and MSLE scores of our models.

[23]:
```
def get_scores(regressor, X_test, y_true, verb=True):
    """
    Obtain RMSE, MAE and MSLE for test set.
    """

    y_pred = regressor.predict(X_test)

    rmse = mean_squared_error(y_pred=y_pred,
                              y_true=y_test,
                              squared=False)

    mae = mean_absolute_error(y_pred=y_pred,
                              y_true=y_test)

    msle = mean_squared_log_error(y_pred=y_pred,
                                  y_true=y_test)

    if verb:

        print(f'RMSE: {rmse:10.2f}')
        print(f'MAE:  {mae:10.2f}')
        print(f'MSLE: {msle:10.2f}')

    return (rmse, mae, msle)
```

1.9.1 Dummy

[24]:
```
dmr_score = get_scores(regressor=dmr,
                       X_test=X_test,
                       y_true=y_test)
```

```
RMSE:  220344.24
MAE:   163404.90
MSLE:       0.14
```

1.9.2 Multilayer Perceptrion

[25]:
```
mlp_score = get_scores(regressor=mlp,
                       X_test=X_test,
                       y_true=y_test)
```

```
RMSE:  120134.95
MAE:    78720.34
MSLE:       0.04
```

1.9.3 Gradient Boosting Regressor

[26]:
```
gbr_score = get_scores(regressor=gbr,
                       X_test=X_test,
                       y_true=y_test)
```

```
RMSE:  115726.26
MAE:    75875.53
MSLE:       0.03
```

1.9.4 Voting Regressor

[27]:
```
vote_score = get_scores(regressor=vote,
                        X_test=X_test,
                        y_true=y_test)
```

```
RMSE:  112840.52
MAE:    73245.76
MSLE:       0.03
```

1.9.5 Comparison

We are happy to see that the `VotingRegressor` outperforms the `DummyRegressor` model as well the `GradientBoostingRegressor` and the `MLPRegressor`.

[28]:
```
scores = [dmr_score,
          mlp_score,
          gbr_score,
          vote_score]

scores = pd.DataFrame(scores,
                      index=['DMR', 'MLP', 'GBR', 'VOTE'],
                      columns=['RMSE', 'MAE', 'MSLE'])

scores
```

[28]:

	RMSE	MAE	MSLE
DMR	220,344.24	163,404.90	0.14

```
MLP  120,134.95  78,720.34  0.04
GBR  115,726.26  75,875.53  0.03
VOTE 112,840.52  73,245.76  0.03
```

1.10 Visualizations

We produce a couple of plots the visually inspect the performance of our model. We use the test data set with the predicted `Amount` to produce the plots.

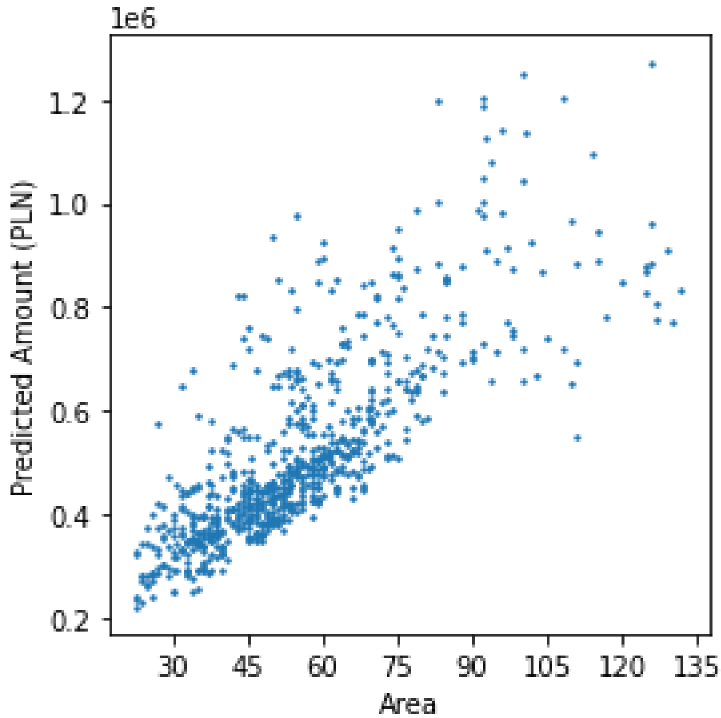
[29]:
```
cols = ['Amount', 'Predicted Amount',
        'District', 'Area', 'Total Rooms']

X_pred = X_test.copy()
X_pred.loc[:, 'Amount'] = y
X_pred.loc[:, 'Predicted Amount'] = vote.predict(X_test)
X_pred = X_pred.loc[:, cols]

X_pred.head()
```

[29]:

	Amount	Predicted Amount	District	Area	Total Rooms
2776	782000	849,866.16	stare miasto	59	3
3142	417000	401,471.17	pradnik czerwony	47	4
640	239000	281,984.44	pradnik czerwony	24	2
171	230000	347,420.45	podgorze	35	3
1209	889000	879,570.56	bronowice	125	6

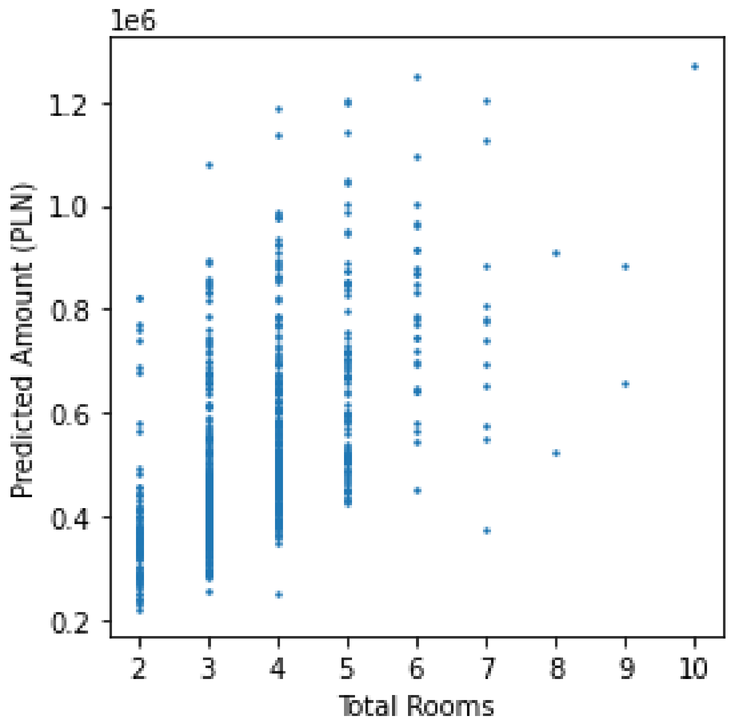
On our first visual it can be seen that there exists a fairly linear relationship between the `Predicted Amount` and the `Area` of the property.

[30]:
```
plt.scatter(X_pred['Area'], X_pred['Predicted Amount'], s=2)
plt.xlabel('Area')
plt.ylabel('Predicted Amount (PLN)')

ax = plt.gca()
ax.xaxis.set_major_locator(MaxNLocator(integer=True))

plt.tight_layout()
plt.savefig('img/area_vs_amount.png')
plt.show()
```



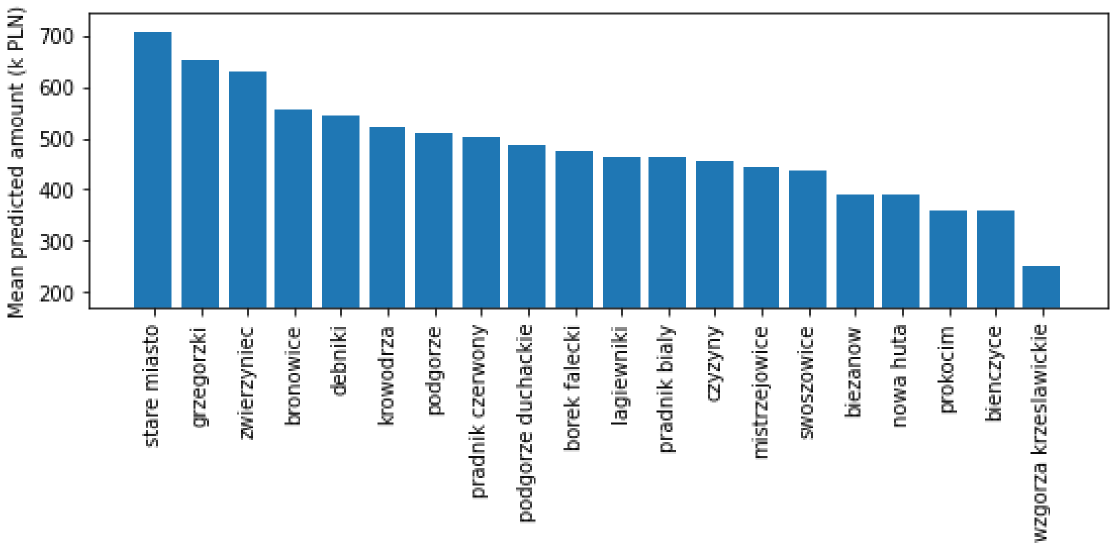
On the second visual it can bee seen, as expected the more `Total Rooms` in a `Property` the more it should cost.

[31]:
```
plt.scatter(X_pred['Total Rooms'], X_pred['Predicted Amount'], s=2)
plt.xlabel('Total Rooms')
plt.ylabel('Predicted Amount (PLN)')

ax = plt.gca()
ax.xaxis.set_major_locator(MaxNLocator(integer=True))

plt.tight_layout()
plt.show()
```



Next we want to check if the model distinguishes between districts. We group the data by `District` and calculate the mean of the predictions with the group. We produce a bar chart sorted from highest average to lowest. Clearly the model distinguishes between district that are near the city center (`stare miasto`, `zwierzyniec`) and those further away (`łagiewniki`, `bieżanów`).

[32]:
```
width = 1600
height = width/2
dpi = 200

X_grp = X_pred[['District', 'Predicted Amount']]
X_grp = X_grp.groupby('District', as_index=False).mean()
X_grp = X_grp.sort_values('Predicted Amount', ascending=False)

plt.figure(figsize=(width/dpi, height/dpi))

plt.bar(X_grp['District'], X_grp['Predicted Amount'] / 1000)

plt.ylabel('Mean predicted amount (k PLN)')
plt.ylim(X_grp['Predicted Amount'].min() * 0.67 / 1000, None)
plt.xticks(rotation=90)

plt.tight_layout()
plt.savefig('img/district_vs_avg_amount.png')
plt.show()
```



1.11 Getting predictions

Next we would like see how the model handles sets of arbitrary parameters. We write a function to transform inputs to desired format and obtain prediction from the model.

[33]:
```
def get_pred(district,
             seller,
             area,
             rooms,
             bathrooms,
             parking,
             garden,
             balcony,
             terrace,
             floor,
             new,
             estate,
             townhouse,
             apartment,
             land,
             studio):

    columns = ['District',
               'Seller',
               'Area',
               'Rooms',
               'Bathrooms',
               'Parking',
               'Garden',
```

```
           'Balcony',
           'Terrace',
           'Floor',
           'New',
           'Estate',
           'Townhouse',
           'Apartment',
           'Land',
           'Studio',
           'Log Area',
           'Bool Sum',
           'Area to Bool Sum',
           'Rooms to Bool Sum',
           'Rooms to Bathrooms',
           'Total Rooms',
           'Area to Rooms',
           'Area to Bathrooms',
           'Area to Total Rooms']

log_area = np.log(area)

all_bools = [garden,
             balcony,
             terrace,
             floor,
             new,
             estate,
             townhouse,
             apartment,
             land,
             studio]

bool_sum = sum(all_bools)
area_to_bool_sum = area / (bool_sum + 1)
rooms_to_bool_sum = rooms / (bool_sum + 1)
rooms_to_bathrooms = rooms / bathrooms
total_rooms = rooms + bathrooms
area_to_rooms = area / total_rooms
area_to_bathrooms = area / bathrooms
area_to_total_rooms = area / total_rooms

x = [district,
     seller,
     area,
     rooms,
     bathrooms,
     parking,
```

```
         garden,
         balcony,
         terrace,
         floor,
         new,
         estate,
         townhouse,
         apartment,
         land,
         studio,
         log_area,
         bool_sum,
         area_to_bool_sum,
         rooms_to_bool_sum,
         rooms_to_bathrooms,
         total_rooms,
         area_to_rooms,
         area_to_bathrooms,
         area_to_total_rooms]

    x = pd.DataFrame([x], columns=columns)
    x = float(vote.predict(x))

    return int(round(x, -3))
```

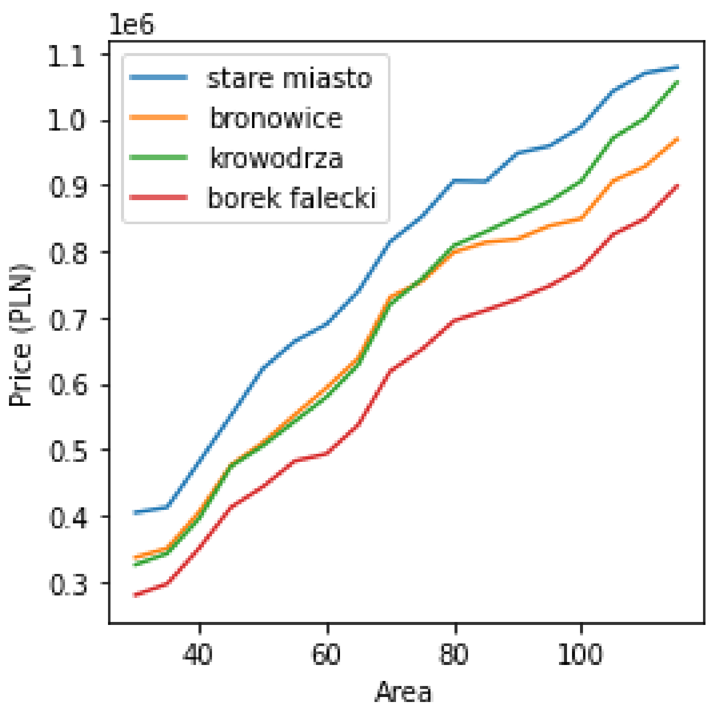
We create lists of inputs for the model to predict.

[34]:
```
areas = range(30, 120, 5)
rooms = range(1, 5)
districts = ['stare miasto',
             'bronowice',
             'krowodrza',
             'borek falecki']
```

Next we loop over lists of possible `Area`'s and `Room`'s and plot the outputs. First we check how the model reacts to different districts.

[35]:
```
plt.figure()

for d in districts:
    value = list()
    for a in areas:
        pred = get_pred(district=d,
         seller='realtor',
         area=a,
         rooms=2,
         bathrooms=1,
         parking='street',
```

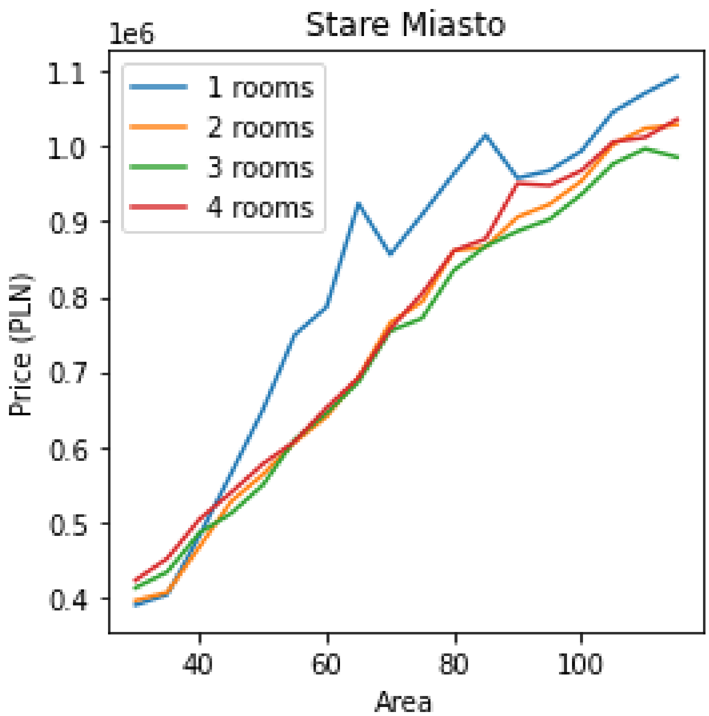
```
            garden=False,
            balcony=False,
            terrace=False,
            floor=False,
            new=True,
            estate=False,
            townhouse=True,
            apartment=False,
            land=False,
            studio=True)
          value.append(pred)
    plt.plot(areas, value, label=d)

plt.ylabel('Price (PLN)')
plt.xlabel('Area')
plt.legend(loc='best')
plt.savefig('img/area_vs_amount_by_district')
plt.show()
```



We do the same for different amounts of `Room`'s.

[36]:
```
plt.figure()

for r in rooms:
```

```
    value = list()
    for a in areas:
        pred = get_pred(district='stare miasto',
         seller='owner',
         area=a,
         rooms=r,
         bathrooms=1,
         parking='street',
         garden=False,
         balcony=True,
         terrace=False,
         floor=False,
         new=True,
         estate=False,
         townhouse=True,
         apartment=False,
         land=False,
         studio=True)
        value.append(pred)
    plt.plot(areas, value, label=f'{r} rooms')

plt.title('Stare Miasto')
plt.ylabel('Price (PLN)')
plt.xlabel('Area')
plt.legend(loc='best')
plt.savefig('img/area_vs_amount_by_rooms')
plt.show()
```



1.12 Final training

The last step is to fit the model to the entire dataset and save it for later use.

[37]:
```
start = datetime.now()

gbr.fit(X, y)
joblib.dump(gbr, f'../flats-model/gbr.joblib')

mlp.fit(X, y)
joblib.dump(mlp, f'../flats-model/mlp.joblib')

vote.fit(X, y)
joblib.dump(vote, f'../flats-model/vote.joblib')

end = datetime.now()

duration = (end - start).seconds

print(f'Full training took {int(duration)} seconds.')
```

```
Full training took 80 seconds.
```

[38]:
```python
# Copy files to portfolio
# fromDirectory = '.'
# toDirectory = '/home/dev/Github/data-science-portfolio/flats-in-cracow'
# copy_tree(fromDirectory, toDirectory)
```