house_prices2

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1 Predicting house prices (part 2)

We try to improve prediction of house prices based on [Erdoğan Seref's](#) German housing dataset from [www.immobilienscout24.de](#) published at [www.kaggle.com](#) under a [Attribution-NonCommercial-ShareAlike 4.0 International License](#).

We load preprocessed data and adjust data types.

```
[1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import sklearn.linear_model as linear_model
import sklearn.metrics as metrics
import sklearn.model_selection as model_selection
import sklearn.preprocessing as preprocessing
import sklearn.pipeline as pipeline

data_path = 'house_prices2/'

[2]: data = pd.read_csv(data_path + 'german_housing_preprocessed.csv', index_col=0)

data['Type'] = data['Type'].astype('category')
data['Condition'] = data['Condition'].astype('category')
data['Garage_type'] = data['Garage_type'].astype('category')

data['Condition'].cat.reorder_categories(['first occupation',
                                          'first occupation after_
↳ refurbishment',
                                          'maintained',
                                          'renovated',
                                          'modernized',
                                          'refurbished',
```

```
'fixer-upper',
'dilapidated'], inplace=True)
```

```
[3]: data.head()
```

```
[3]:
```

	Price	Type	Living_space	Lot	Rooms	Bathrooms	\
0	13.118355	Multiple dwelling	4.663439	5.433722	5.5	1.0	
2	13.526494	Farmhouse	5.093075	4.406719	5.0	2.0	
3	12.464583	Farmhouse	4.941642	6.701960	4.0	2.0	
8	12.804909	Duplex	5.424950	6.880384	10.0	4.0	
10	14.375126	Mid-terrace house	5.347108	7.286192	6.0	2.0	

	Floors	Year_built	Year_renovated	Condition	State	\
0	2.0	2.772589	2.772589	modernized	Baden-Württemberg	
2	4.0	2.079442	2.079442	dilapidated	Baden-Württemberg	
3	2.0	4.795791	3.044522	fixer-upper	Baden-Württemberg	
8	2.0	5.356586	1.791759	modernized	Baden-Württemberg	
10	3.0	4.406719	1.945910	modernized	Baden-Württemberg	

	City	Place	Garages	Garage_type
0	Bodenseekreis	Bermatingen	2.0	Outside parking lot
2	Esslingen (Kreis)	Ostfildern	1.0	Garage
3	Waldshut (Kreis)	Bonndorf im Schwarzwald	1.0	Garage
8	Enzkreis	Neuenbürg	8.0	Outside parking lot
10	Stuttgart	Schönberg	2.0	Garage

1.1 More data

Results obtained from linear regression showed that input variables do not suffice to explain the targets. Thus, we should add more input variables. When preprocessing the data we dropped several columns. Keeping them could increase prediction quality slightly, but there were several good reasons to drop those columns. The main reason were lots of missing values in those columns.

A far better idea is to collect additional data. What features of a house influence the selling price? Of course its location! Up to now we did not use location information at all, but we have location information available. There are columns **State**, **City**, **Place**. But city names do not help. We need something like proximity to big cities or nice landscape. Adding a layer of abstraction we might ask for the demand for houses and the wealth of potential buyers. So we should head out for statistical information about local real estate markets and about economic power of different regions in Germany.

Everything we need is publicly available at www.regionalstatistik.de provided by *Statistische Ämter des Bundes und der Länder* under the license [Datenlizenz Deutschland – Namensnennung – Version 2.0](#). Clicking here and there we find two interesting tables: * [annual income per inhabitant](#) * [prices for construction ground](#)

From those tables we may compile a [table with 4 columns](#) (region id, region name, income, ground prices).

The difficult part is matching region names in German housing data set with region names in the region table. Here is some code doing the job:

```
[4]: # remove rows with missing location information
data = data.dropna(subset=('State', 'City'))

# reindex to remove gaps in the index
#data.index = data.index.reindex(range(0, len(data)))[0]
data.index = pd.RangeIndex(0, len(data))
```

```
[5]: regions = pd.read_csv(data_path + 'regions.csv')

regions.head(5)
```

```
[5]:      id      region  income  prices
0      0      Deutschland    22623   137.67
1      1  Schleswig-Holstein    22864    85.30
2    1001  Flensburg, Kreisfreie Stadt    19296    85.30
3    1002  Kiel, Landeshauptstadt, Kreisfreie Stadt    19263    85.30
4    1003  Lübeck, Hansestadt, Kreisfreie Stadt    20363   110.84
```

```
[6]: data['city_short'] = data['City'].str.replace(' (Kreis)', '', regex=False)
data['region_idx'] = 0

for (idx, city_short) in enumerate(data['city_short']):
    find_results = regions['region'].str.find(str(city_short))
    if not (find_results > -1).any():
        #print(city_short)
        if data.loc[idx, 'State'] == 'Hamburg':
            find_results = regions['region'].str.find('Hamburg')
            data.loc[idx, 'region_idx'] = regions.index[find_results > -1][-1]
        elif data.loc[idx, 'State'] == 'Bremen':
            find_results = regions['region'].str.find('Bremen')
            data.loc[idx, 'region_idx'] = regions.index[find_results > -1][-1]
        elif data.loc[idx, 'State'] == 'Berlin':
            district = city_short.split('(')[-1][0:-1]
            if district == 'Weißensee':
                district = 'Pankow'
            if district == 'Prenzlauer Berg':
                district = 'Pankow'
            if district == 'Hohenschönhausen':
                district = 'Lichtenberg'
            if district == 'Wedding':
                district = 'Berlin-Mitte'
            find_results = regions['region'].str.find(district)
            #print('***', city_short, ':', district, '-->',
            ↪regions['Region'][find_results > -1])
            data.loc[idx, 'region_idx'] = regions.index[find_results > -1][-1]
```

```

elif city_short == 'Neuss (Rhein-Kreis)':
    find_results = regions['region'].str.find('Neuss')
    data.loc[idx, 'region_idx'] = regions.index[find_results > -1][-1]
elif city_short == 'Sankt Wendel':
    find_results = regions['region'].str.find('Wendel')
    data.loc[idx, 'region_idx'] = regions.index[find_results > -1][-1]
elif city_short == 'Stadtverband Saarbrücken':
    find_results = regions['region'].str.find('Saarbrücken,
↳Regionalverband')
    data.loc[idx, 'region_idx'] = regions.index[find_results > -1][-1]
elif city_short.split()[1] in ('in', 'im', 'an', 'am'):
    if city_short.split()[0] == 'Neustadt':
        find_results = regions['region'].str.find(city_short.
↳split()[-1])
    else:
        find_results = regions['region'].str.find(city_short.split()[0])
        #print('***', city_short, '-->', regions.loc[find_results > -1,
↳'Region'])
    data.loc[idx, 'region_idx'] = regions.index[find_results > -1][-1]
else:
    print('NOT FOUND:', city_short)

else:
    # take last match (smallest region)
    data.loc[idx, 'region_idx'] = regions.index[find_results > -1][-1]

```

```

[7]: data['Region_id'] = regions.loc[data['region_idx'], 'id'].values
data['Income'] = regions.loc[data['region_idx'], 'income'].values
data['Land_prices'] = regions.loc[data['region_idx'], 'prices'].values

```

```

[8]: data = data.drop(columns=['city_short', 'region_idx'])

```

```

[9]: data.head(5)

```

```

[9]:
      Price      Type  Living_space      Lot  Rooms  Bathrooms  \
0  13.118355  Multiple dwelling    4.663439  5.433722    5.5        1.0
1  13.526494      Farmhouse    5.093075  4.406719    5.0        2.0
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      Floors  Year_built  Year_renovated  Condition      State  \
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1        4.0    2.079442    2.079442  dilapidated  Baden-Württemberg
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```

	City	Place	Garages	Garage_type \
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2	Waldshut (Kreis)	Bonndorf im Schwarzwald	1.0	Garage
3	Enzkreis	Neuenbürg	8.0	Outside parking lot
4	Stuttgart	Schönberg	2.0	Garage

	Region_id	Income	Land_prices
0	8435	26548	172.95
1	8116	25449	387.06
2	8337	25304	111.64
3	8236	25496	192.18
4	8111	25559	1500.34

```
[10]: data.to_csv(data_path + 'german_housing_extended.csv')
```

1.2 Linear regression

Now we do linear regression as before, but with two additional columns.

```
[11]: data['Condition_codes'] = data['Condition'].cat.codes
data = pd.get_dummies(data, columns=['Type', 'Garage_type'], drop_first=True)
```

```
[12]: y = data['Price'].to_numpy()
X = data.drop(columns=['Price', 'Condition', 'State', 'City', 'Place',
↳ 'Region_id']).to_numpy()

print(X.shape, y.shape)
```

```
(4763, 23) (4763,)
```

```
[13]: X_train, X_test, y_train, y_test = model_selection.train_test_split(X, y,
↳ test_size=0.2)

print(y_train.size, y_test.size)
```

```
3810 953
```

```
[14]: steps = [('poly', preprocessing.PolynomialFeatures()),
               ('ridge', linear_model.Ridge())]

pipe = pipeline.Pipeline(steps)

param_grid = {'poly__degree': [1, 2, 3],
              'ridge__alpha': [0] + [2 ** k for k in range(5, 15)]}

gs = model_selection.GridSearchCV(pipe, param_grid=param_grid,
```

```

scoring='neg_mean_squared_error', n_jobs=-1,
cv=5)

gs.fit(X_train, y_train)
best_params = gs.best_params_

/home/jef19jdw/anaconda3/envs/ds_lecture/lib/python3.7/site-
packages/sklearn/linear_model/_ridge.py:148: LinAlgWarning: Ill-conditioned
matrix (rcond=5.73552e-18): result may not be accurate.
  overwrite_a=True).T

```

1.3 Evaluation

Now the interesting part. Do we see an increase in prediction quality?

```

[15]: print(best_params)

pipe.set_params(**best_params)
pipe.fit(X_train, y_train)

y_test_pred = pipe.predict(X_test)

{'poly__degree': 2, 'ridge__alpha': 512}

/home/jef19jdw/anaconda3/envs/ds_lecture/lib/python3.7/site-
packages/sklearn/linear_model/_ridge.py:148: LinAlgWarning: Ill-conditioned
matrix (rcond=5.73552e-18): result may not be accurate.
  overwrite_a=True).T

```

```

[16]: rmse = np.sqrt(metrics.mean_squared_error(y_test, y_test_pred))
sigma = np.std(y_test)
print('RMSE:', rmse)
print('standard deviation:', sigma)
print('ratio:', rmse / sigma)

```

```

RMSE: 0.4248066771021125
standard deviation: 0.801578549021144
ratio: 0.5299626313863683

```

```

[17]: fig, ax = plt.subplots()
ax.plot(y_test, y_test_pred, 'or', markersize=3)
ax.plot([9, 17], [9, 17], '-b')
ax.set_xlabel('true targets')
ax.set_ylabel('predictions')
ax.set_aspect('equal')
plt.show()

```

Looks much better!

1.4 Feature importance

With a trained model we may look at feature importances to see which features have high influence on the selling price.

```
[18]: import sklearn.inspection as inspection
```

```
[19]: result = inspection.permutation_importance(pipe, X, y, n_jobs=-1)
```

```
[20]: cols = data.drop(columns=['Price', 'Condition', 'State', 'City', 'Place', '
    ↳ 'Region_id']).columns
    imp = pd.Series(result.importances_mean, index=cols)
    imp = imp.sort_values(ascending=False)
    imp
```

```
[20]: Land_prices      0.372617
    Living_space      0.362034
    Year_built        0.174309
    Lot               0.068924
    Income            0.057952
    Rooms             0.031420
    Type_Villa        0.015153
    Bathrooms         0.014141
```

Type_Duplex	0.013529
Year_renovated	0.010670
Garage_type_Outside parking lot	0.009923
Type_Corner house	0.008855
Floors	0.007275
Condition_codes	0.007134
Type_Mid-terrace house	0.005969
Garages	0.004720
Garage_type_Garage	0.003324
Type_Multiple dwelling	0.002968
Type_Single dwelling	0.002767
Type_Farmhouse	0.001868
Type_Special property	0.001690
Garage_type_Underground parking lot	0.001336
Type_Residential property	0.000284
dtype: float64	

[]: