Lab9

May 7, 2024

1 Uczenie nadzorowane - predykcja

Import bibliotek

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score,␣
  ↪max_error
import xgboost as xgb
import math
import numpy as np
```

[2]:
```
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/housing/
  ↪housing.data"
names = ['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',␣
  ↪'TAX', 'PTRATIO', 'B', 'LSTAT', 'MEDV']
dataset = pd.read_csv(url, delim_whitespace=True, names=names)

display(dataset.head())
```

```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296.0
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242.0
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242.0
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222.0
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222.0

   PTRATIO       B  LSTAT  MEDV
0     15.3  396.90   4.98  24.0
1     17.8  396.90   9.14  21.6
2     17.8  392.83   4.03  34.7
3     18.7  394.63   2.94  33.4
4     18.7  396.90   5.33  36.2
```

1.1 EDA

[3]:
```
dataset.info()
dataset.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    int64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    int64
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

[3]:

	CRIM	ZN	INDUS	CHAS	NOX	RM \
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000

	AGE	DIS	RAD	TAX	PTRATIO	B \
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032
std	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864
min	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000
25%	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500
50%	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000
75%	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000
max	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000

LSTAT MEDV

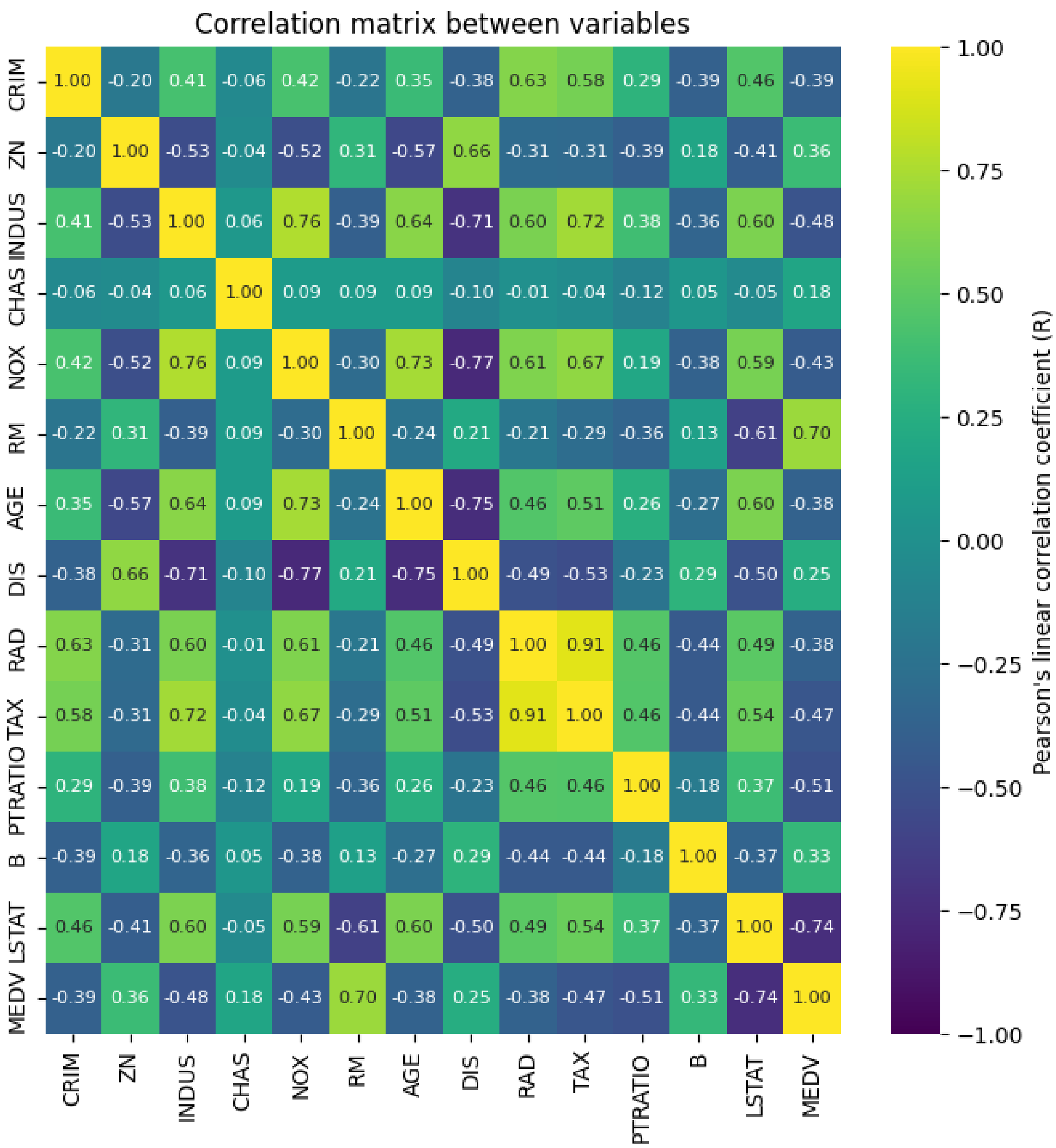
```
count  506.000000  506.000000
mean    12.653063   22.532806
std      7.141062    9.197104
min      1.730000    5.000000
25%      6.950000   17.025000
50%     11.360000   21.200000
75%     16.955000   25.000000
max     37.970000   50.000000
```

[4]:
```
print(dataset.isna().sum())
```

```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
MEDV       0
dtype: int64
```

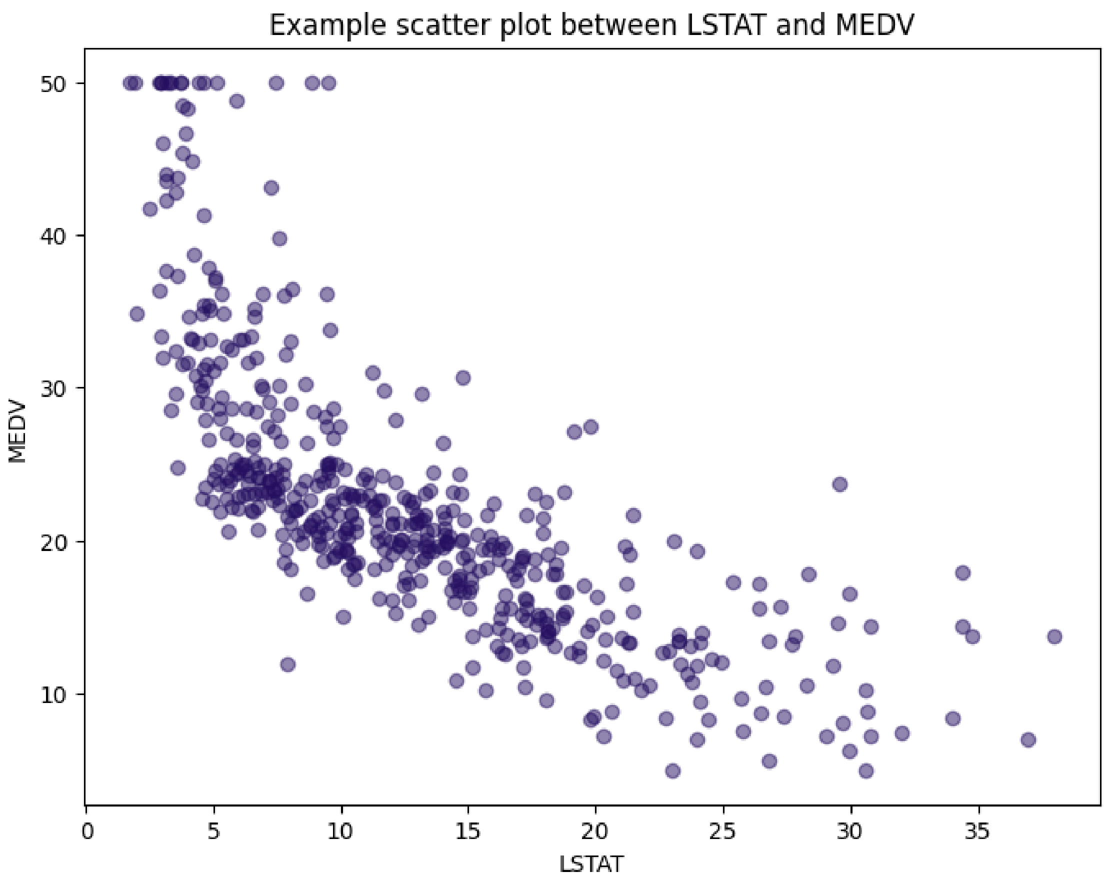
[5]:
```
plt.figure(figsize=(8, 8))
sns.heatmap(dataset.corr(), annot=True, annot_kws={"fontsize":8}, fmt=".2f",␣
 ↪cmap='viridis', vmin=-1, vmax=1, cbar_kws={'label': "Pearson's linear␣
 ↪correlation coefficient (R)"})
plt.title('Correlation matrix between variables')
```

[5]:
```
Text(0.5, 1.0, 'Correlation matrix between variables')
```



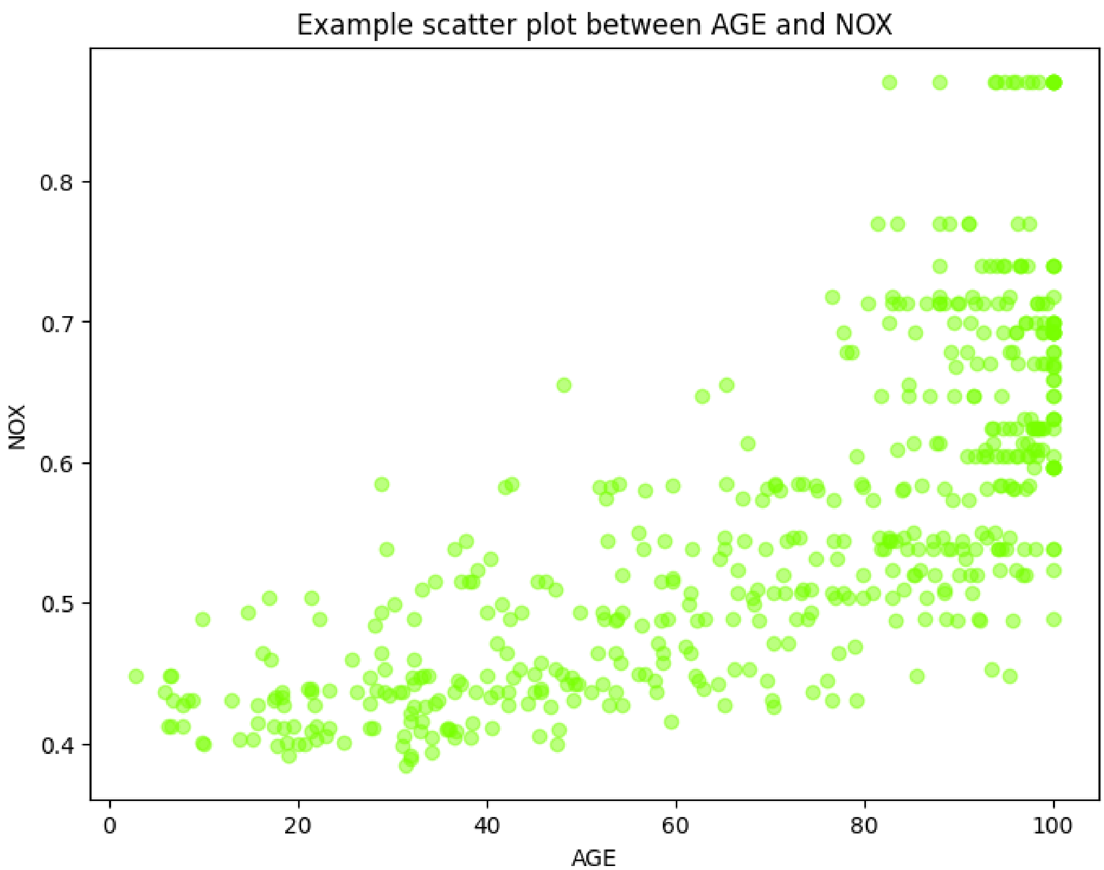
[6]:
```
plt.figure(figsize=(8,6))
plt.scatter(dataset['LSTAT'], dataset['MEDV'], color="#250F61", alpha=0.5)
plt.title("Example scatter plot between LSTAT and MEDV")
plt.xlabel("LSTAT")
plt.ylabel("MEDV")
```

[6]:
```
Text(0, 0.5, 'MEDV')
```



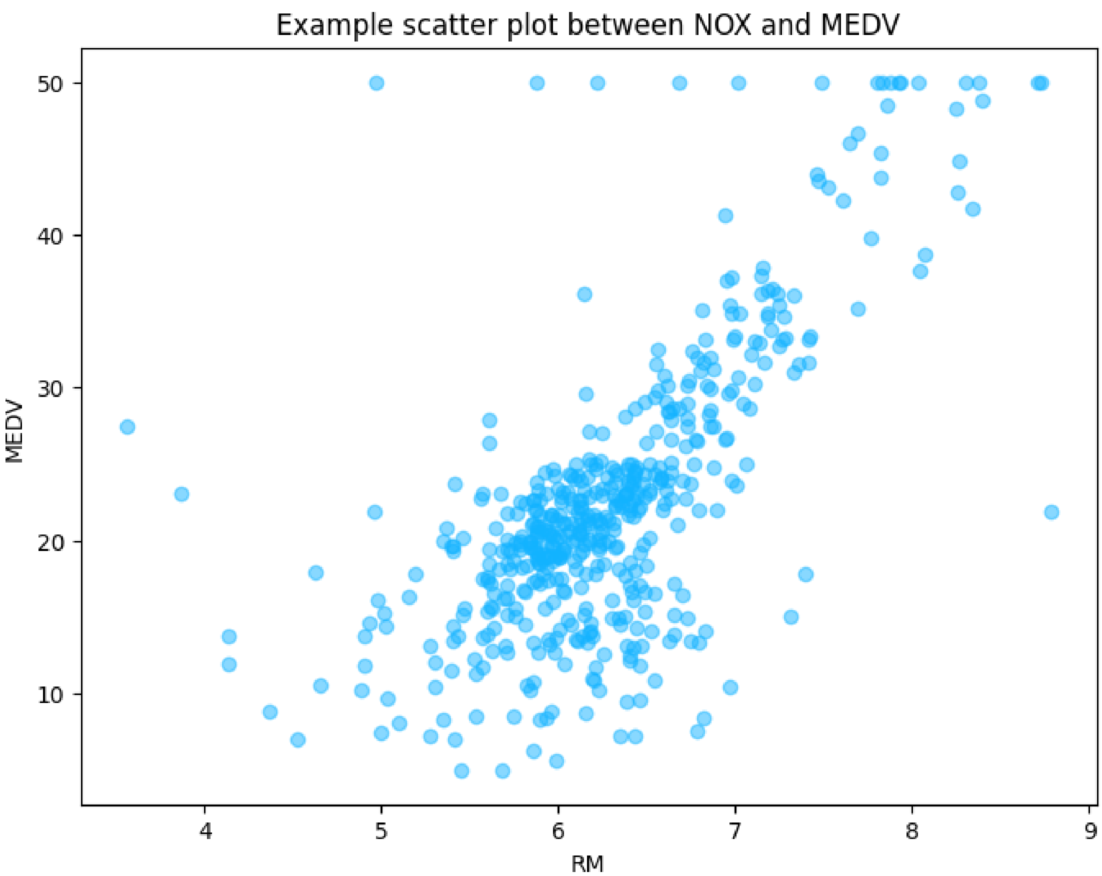
[7]:
```
plt.figure(figsize=(8, 6))
plt.scatter( dataset['AGE'], dataset['NOX'], color='#78FF00', alpha=0.5)
plt.title('Example scatter plot between AGE and NOX')
plt.xlabel('AGE')
plt.ylabel('NOX')
```

[7]:
```
Text(0, 0.5, 'NOX')
```



[8]:
```
plt.figure(figsize=(8, 6))
plt.scatter( dataset['RM'], dataset['MEDV'], color='#12B3FF', alpha=0.5)
plt.title('Example scatter plot between NOX and MEDV')
plt.xlabel('RM')
plt.ylabel('MEDV')
```

[8]: Text(0, 0.5, 'MEDV')



Do wykresów punktowych wybrane zostały takie połączenia kolumn, dla których współczynnik korelacji Pearsona był jednym z większych. Oprócz tych zestawień widać wysoką współliniowość na przykład pomiędzy zmiennymi NOX i INDUS, DIS i INDUS, AGE czy AGE i DIS.

1.2 Podział zbioru danych

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

X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2,␣
↪random_state=42)
display(y_train)
display(y_test)
```

```
477    12.0
15     19.9
332    19.4
423    13.4
19     18.2
       …
```

```
106    19.5
270    21.1
348    24.5
435    13.4
102    18.6
Name: MEDV, Length: 404, dtype: float64

173    23.6
274    32.4
491    13.6
72     22.8
452    16.1
       …
412    17.9
436     9.6
411    17.2
86     22.5
75     21.4
Name: MEDV, Length: 102, dtype: float64
```

1.3 Modele regresji

[10]:
```
lr = LinearRegression()
lr.fit(X_train, y_train)

# XGBoost Gradientowe wzmacnianie drzew
xg_reg = xgb.XGBRegressor(objective='reg:squarederror', colsample_bytree=0.3,␣
 ↪learning_rate=0.1,
                          max_depth=5, alpha=10, n_estimators=10)
xg_reg.fit(X_train,y_train)
```

[10]:
```
XGBRegressor(alpha=10, base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=0.3, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=5, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=10, n_jobs=None,
             num_parallel_tree=None, …)
```

1.4 Dobór parametrów

[11]:
```
params = {'learning_rate' : [0.01, 0.1, 0.3], 'max_depth': [3, 5, 7],␣
↪'n_estimators': [50, 100, 200]}

xg_reg = xgb.XGBRegressor(objective='reg:squarederror', colsample_bytree=0.3)

grid = GridSearchCV(estimator=xg_reg, param_grid=params, cv=5,␣
↪scoring='neg_mean_squared_error')
grid.fit(X_train, y_train)

print("Best score: %f using params: %s" % (grid.best_score_, grid.best_params_))
```

```
Best score: -13.743169 using params: {'learning_rate': 0.1, 'max_depth': 3,
'n_estimators': 200}
```

[12]:
```
# Tworze model z najlepszymi parametrami
xg_reg = xgb.XGBRegressor(objective='reg:squarederror', colsample_bytree=0.3, ␣
↪alpha=10, **grid.best_params_)
xg_reg.fit(X_train,y_train)
```

[12]:
```
XGBRegressor(alpha=10, base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=0.3, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=3, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=200, n_jobs=None,
             num_parallel_tree=None, …)
```

[13]:
```
#Regresja liniowa

y_pred_lr = lr.predict(X_test)
print('Linear Regression - MSE: ', mean_squared_error(y_test, y_pred_lr))
print('Linear Regression - MAE: ', mean_absolute_error(y_test, y_pred_lr))
print('Linear Regression - R2: ', r2_score(y_test, y_pred_lr))
print('Linear Regression - MAXError: ', max_error(y_test, y_pred_lr), "\n")

y_pred_xg = xg_reg.predict(X_test)
print('XGBoost - MSE: ', mean_squared_error(y_test, y_pred_xg))
print('XGBoost - MAE: ', mean_absolute_error(y_test, y_pred_xg))
print('XGBoost - R2: ', r2_score(y_test, y_pred_xg))
print('XGBoost - MAXError: ', max_error(y_test, y_pred_xg))
```

```
Linear Regression - MSE:  24.291119474973478
```

```
Linear Regression - MAE:  3.189091965887837
Linear Regression - R2:  0.6687594935356326
Linear Regression - MAXError:  25.260428393480645

XGBoost - MSE:  8.300848313048355
XGBoost - MAE:  1.885623426063388
XGBoost - R2:  0.8868073082374468
XGBoost - MAXError:  17.506866455078125
```

Na podstawie powyższych wyników można spekulować, że model XGBoost jest lepiej dopasowany do danych

2 Założenia dla regresji liniowej

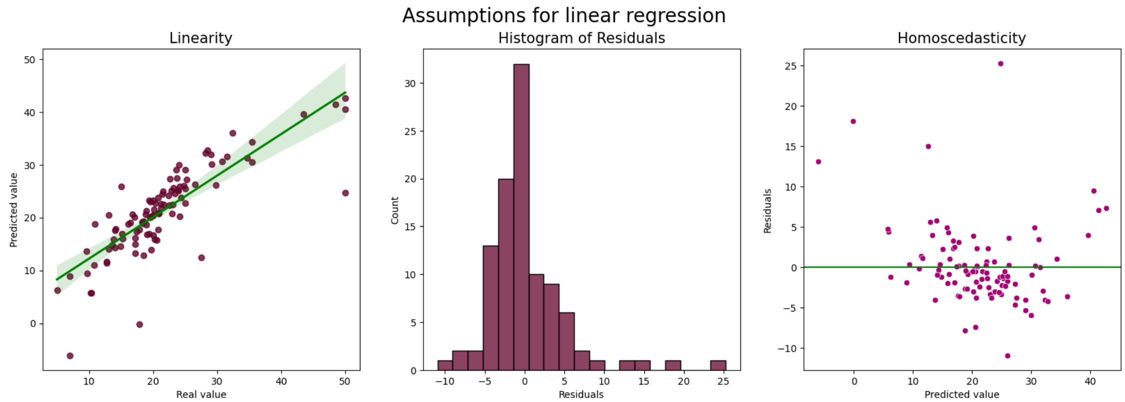
2.0.1 1. liniowa zależność

[14]:
```
fig, ax = plt.subplots(1, 3, figsize=(20, 6))
fig.suptitle("Assumptions for linear regression", fontsize=20)
MEDV = pd.DataFrame({"Real":y_test,"Predicted":y_pred_lr})
sns.regplot(data=MEDV,x="Real",y="Predicted", ax=ax[0], color="#63042c",␣
 ↪line_kws=dict(color="g"))
ax[0].set_xlabel("Real value")
ax[0].set_ylabel("Predicted value")
ax[0].set_title("Linearity", fontsize=15)

residuals_lr = y_test - y_pred_lr
sns.histplot(residuals_lr, ax=ax[1], color="#63042c")
ax[1].set_xlabel("Residuals")
ax[1].set_title("Histogram of Residuals", fontsize=15)

sns.scatterplot(x=y_pred_lr, y=residuals_lr, color='#a30373', ax=ax[2])
ax[2].set_title("Homoscedasticity", fontsize=15)
ax[2].axhline(y=0, c="green")
ax[2].set_xlabel("Predicted value")
ax[2].set_ylabel("Residuals")
```

[14]:
```
Text(0, 0.5, 'Residuals')
```



[14]:

1. Wykres liniowy wygląda względnie dobrze, pojawiają się wartości odstające. Pomimo to, na podstawie wcześniej stworzonego wykresu macierzy korelacji trzeba stwierdzić, że dla pewnych cech np. PTRATIO lub CHAS współczynnik korelacji liniowej Pearsona jest niski. To założenie nie jest spełnione.
2. Rozkład reszt jest prawostronnie asymetryczny, skośny. Ciężko byłoby go określić jako normalny. To założenie również nie jest spełnione.
3. Punkty na wykresie prezentującym homoskedastyczność nie są skupione wokół linii. Można zauważyć sporo wartości odstających.