uczenie_nadzorowane

May 13, 2025

[10]:
```
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd
import xgboost as xgb
```

1 Wczytanie danych

[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)
```

```
/tmp/ipykernel_6362/3994773014.py:3: FutureWarning: The 'delim_whitespace'
keyword in pd.read_csv is deprecated and will be removed in a future version.
Use ``sep='\s+'`` instead
  dataset = pd.read_csv(url, delim_whitespace=True, names=names)
```

2 EDA

[21]:
```
df = dataset
print("Podstawowe informacje o zbiorze:")
display(df.info())

print("\nStatystyki opisowe:")
print(df.describe())

print("\nLiczba brakujących wartości w każdej kolumnie:")
display(df.isnull().sum())
```

```
Podstawowe informacje o zbiorze:
<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
```

```
None
```

```
Statystyki opisowe:
             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
```

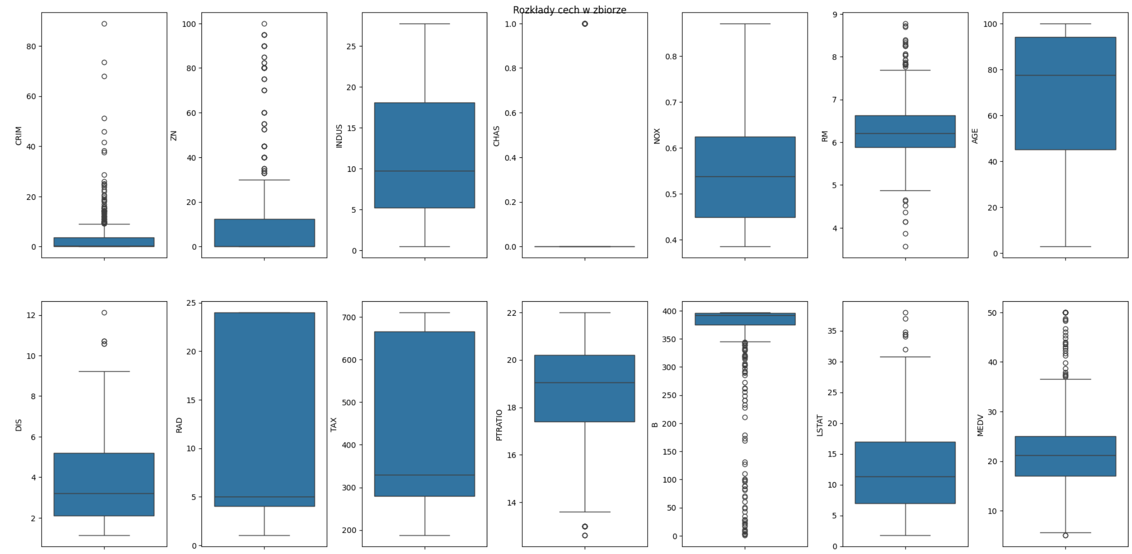
```
mean    12.653063   22.532806
std      7.141062    9.197104
min      1.730000    5.000000
25%      6.950000   17.025000
50%     11.360000   21.200000
75%     16.955000   25.000000
max     37.970000   50.000000
```

```
Liczba brakujących wartości w każdej kolumnie:
```

```
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
```

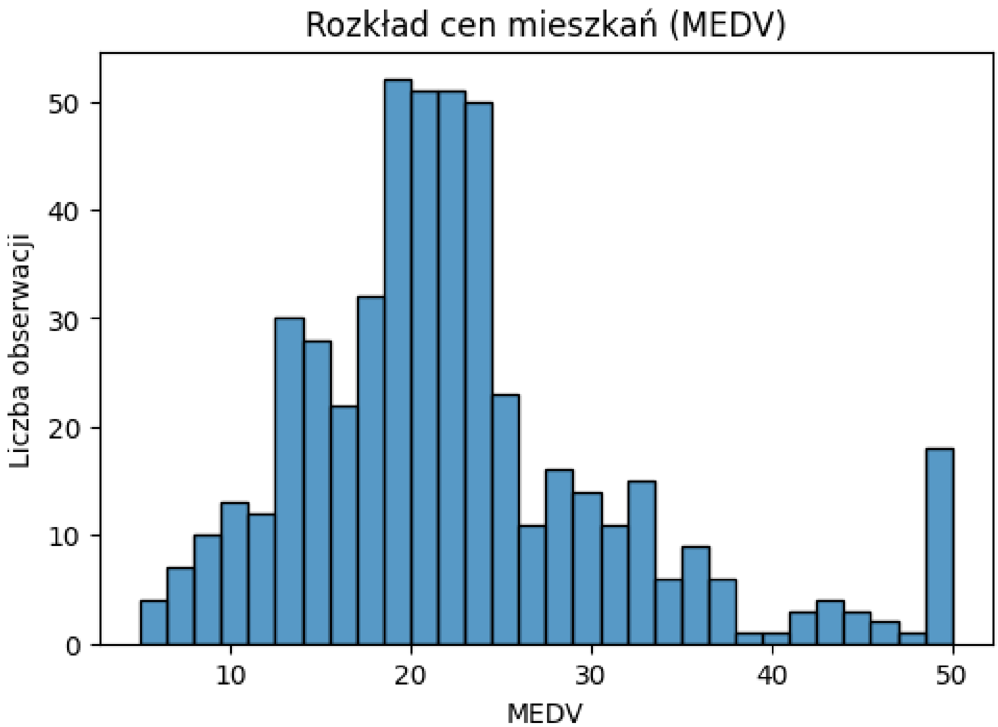
2.1 Rozkład cech w zbiorze

[18]:
```
fig, axs = plt.subplots(ncols=7, nrows=2, figsize=(20, 10))
index = 0
axs = axs.flatten()
for i,j in df.items():
    sns.boxplot(y=i, data=df, ax=axs[index])
    index += 1
plt.suptitle('Rozkłady cech w zbiorze ')
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=5.0)
```



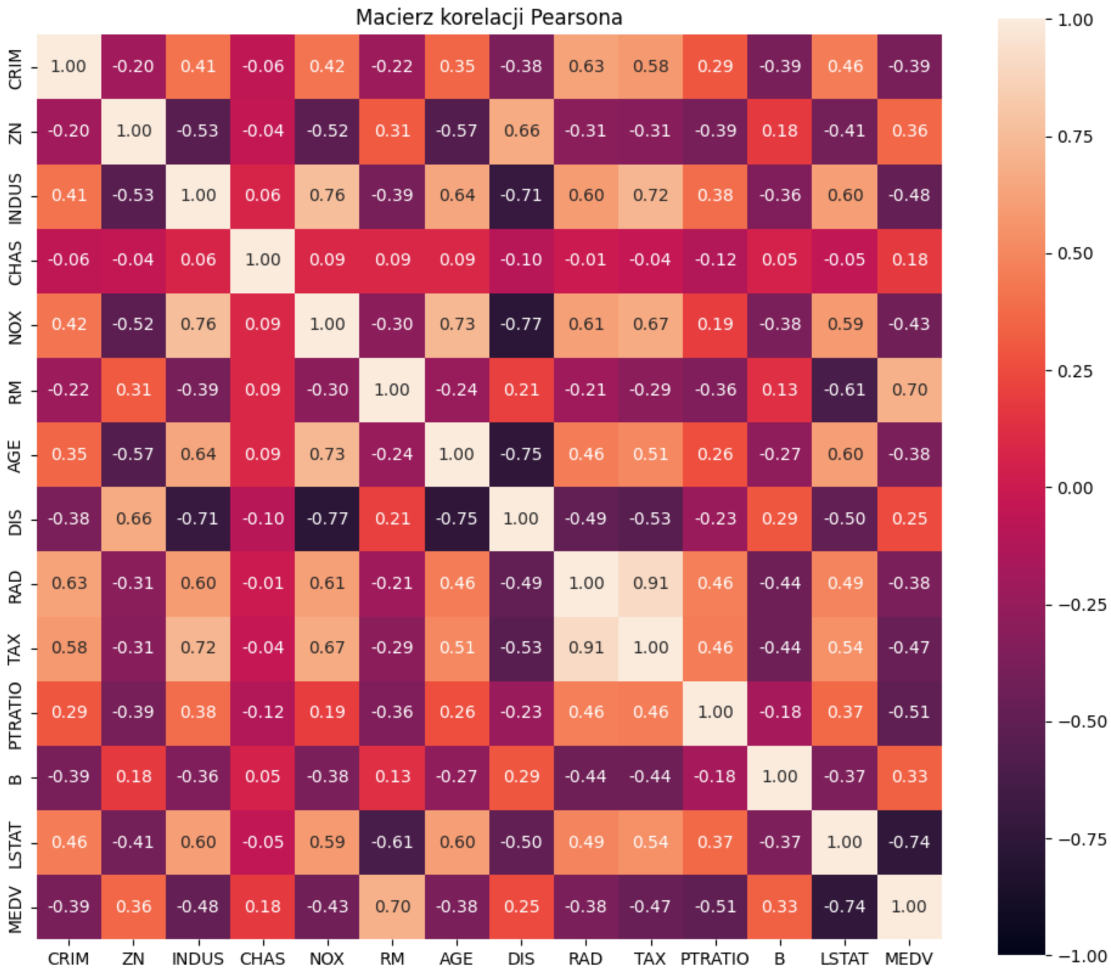
2.1.1 Rozkład MEDV

[ ]:
```
plt.figure(figsize=(6, 4))
sns.histplot(df['MEDV'], bins=30)
plt.title('Rozkład cen mieszkań (MEDV)')
plt.xlabel('MEDV')
plt.ylabel('Liczba obserwacji')
plt.show()
```



2.2 Sprawdzenie współliniowości

[13]:
```
plt.figure(figsize=(12, 10))
correlation_matrix = df.corr()
sns.heatmap(correlation_matrix, annot=True, fmt='.2f', square=True, vmin=-1,␣
↪vmax=1)
plt.title('Macierz korelacji Pearsona')
plt.show()
```



[14]:
```python
print("\nPary zmiennych o wysokiej korelacji (|r| > 0.75):")
high_corr = correlation_matrix.abs().unstack().sort_values(ascending=False)
high_corr = high_corr[high_corr < 1]
display(high_corr[high_corr > 0.75])
```

```
Pary zmiennych o wysokiej korelacji (|r| > 0.75):

RAD    TAX      0.910228
TAX    RAD      0.910228
DIS    NOX      0.769230
NOX    DIS      0.769230
INDUS  NOX      0.763651
NOX    INDUS    0.763651
dtype: float64
```

[19]:
```python
# Opcjonalnie: Współczynnik VIF (Variance Inflation Factor) do analizy␣
↪współliniowości
from statsmodels.stats.outliers_influence import variance_inflation_factor

X = df.drop('MEDV', axis=1)
vif_data = pd.DataFrame()
vif_data['feature'] = X.columns
vif_data['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.
↪shape[1])]
print("\nWspółczynniki VIF:")
print(vif_data.sort_values(by='VIF', ascending=False))
```

```
Współczynniki VIF:
    feature        VIF
10  PTRATIO  85.029547
5        RM  77.948283
4       NOX  73.894947
9       TAX  61.227274
6       AGE  21.386850
11        B  20.104943
8       RAD  15.167725
7       DIS  14.699652
2     INDUS  14.485758
12    LSTAT  11.102025
1        ZN   2.844013
0      CRIM   2.100373
3      CHAS   1.152952
```

3 Podział na zbiór treningowy i testowy

[23]:
```python
# Podział zbioru danych
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)
```

4 Badanie modeli

[24]:
```python
# Regresja Liniowa
lr = LinearRegression()
lr.fit(X_train, y_train)

# XGBoost
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)
```

[24]:
```
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,
             feature_weights=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, …)
```

5 GridSearchCV dla XGBoost

[26]:
```
# GridSearchCV dla XGBoost
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: %.2f using params: %s" % (grid.best_score_, grid.
 ↪best_params_))
```

```
Best score: -13.74 using params: {'learning_rate': 0.1, 'max_depth': 3,
'n_estimators': 200}
```

6 Test vs Train

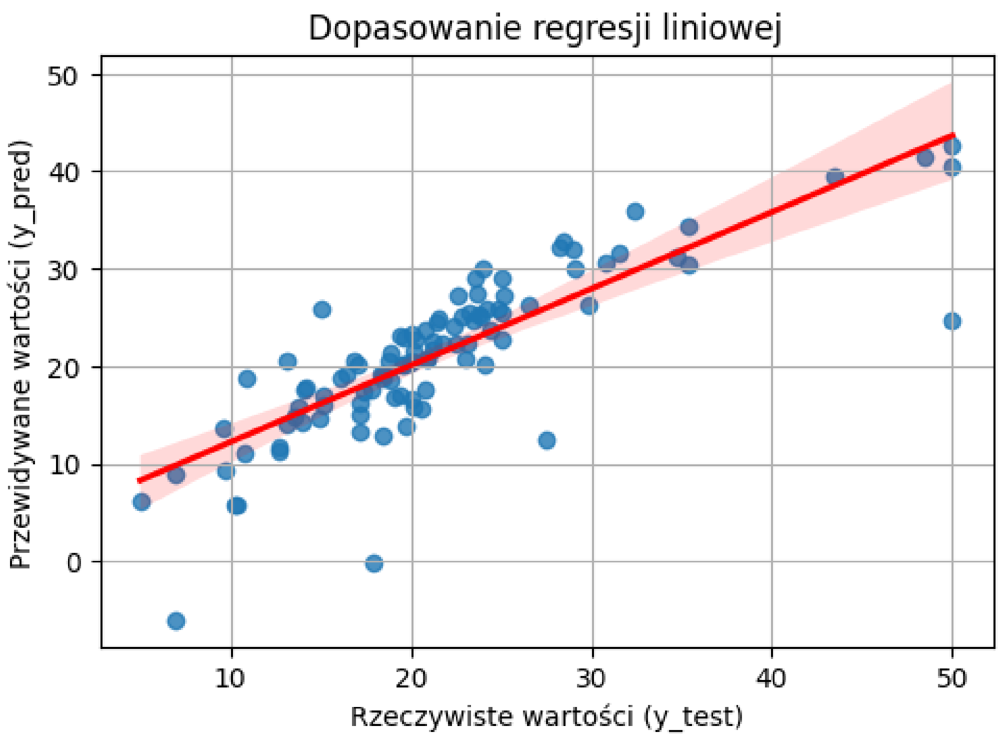
[25]:
```
# Ewaluacja modeli

# 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))

# XGBoost
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))
```

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

```
Linear Regression - MAE:  3.189091965887837
Linear Regression - R2:  0.6687594935356326
XGBoost - MSE:  40.061291602494165
XGBoost - MAE:  4.234852414972642
XGBoost - R2:  0.4537130108927857
```

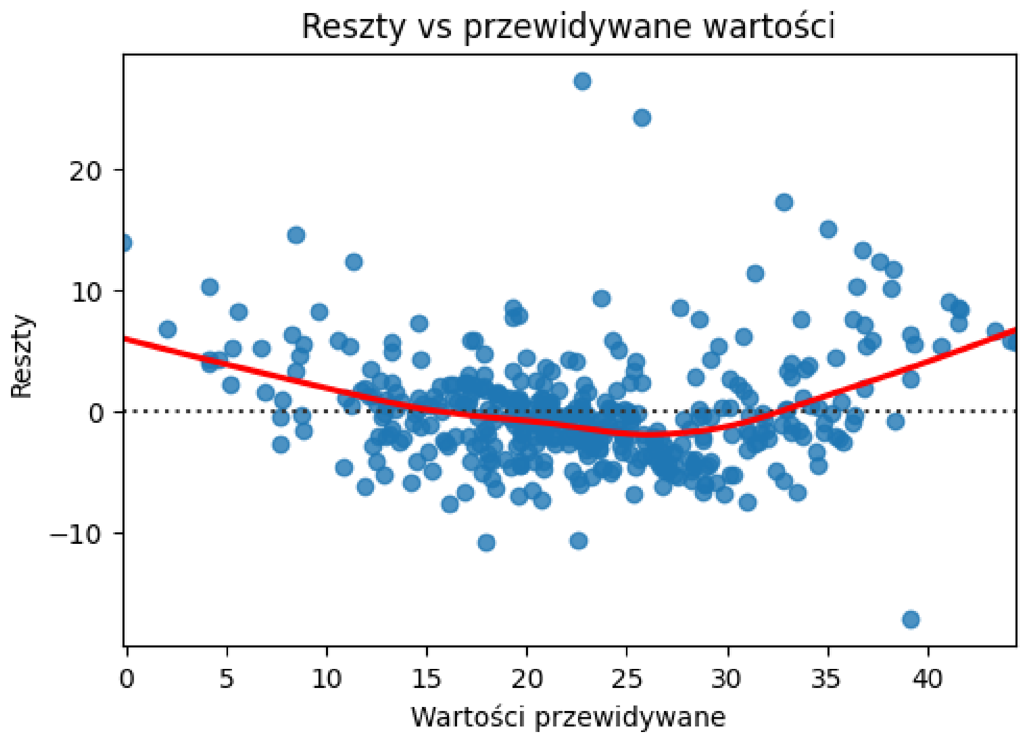
7 Założenia Regresji Liniowej

[43]:
```python
plt.figure(figsize=(6, 4))
sns.regplot(x=y_test, y=y_pred_lr, line_kws={"color": "red"})
plt.xlabel("Rzeczywiste wartości (y_test)")
plt.ylabel("Przewidywane wartości (y_pred)")
plt.title("Dopasowanie regresji liniowej")
plt.grid()
plt.show()
```

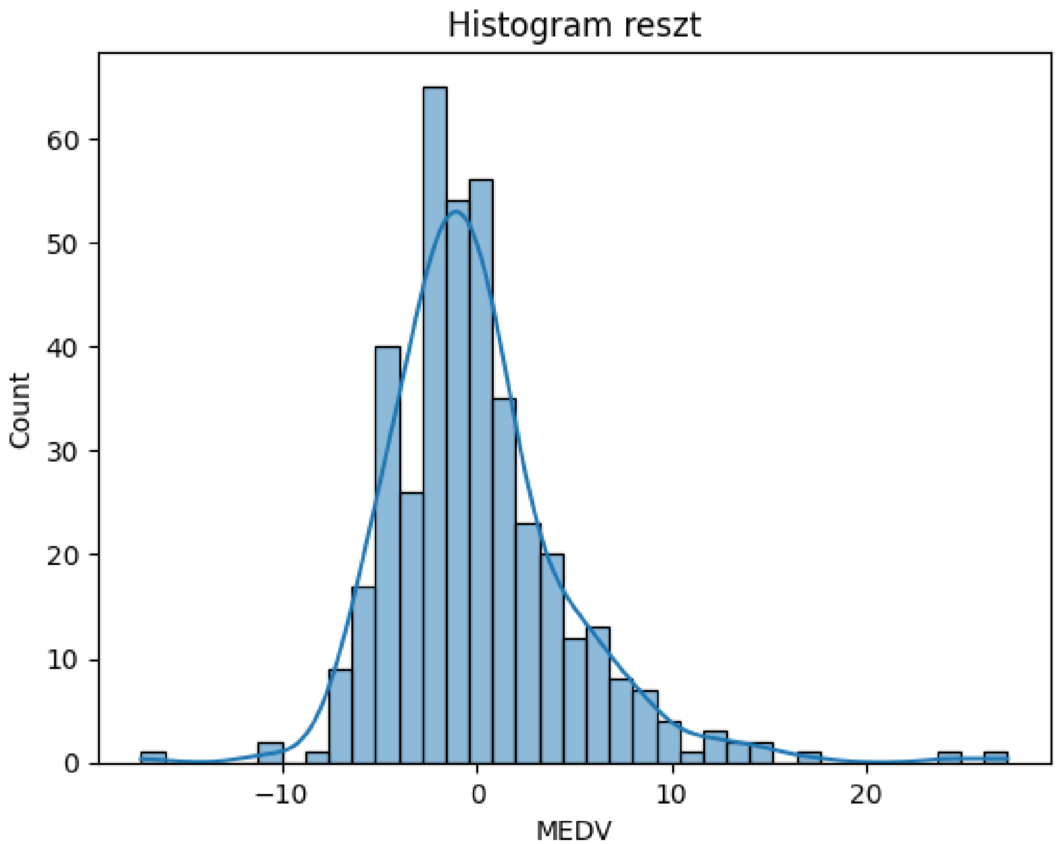


[42]:
```python
y_train_pred = lr.predict(X_train)
residuals = y_train - y_train_pred

plt.figure(figsize=(6, 4))
sns.residplot(x=y_train_pred, y=residuals, lowess=True, line_kws={'color':␣
 ↪'red'})
```

```
plt.xlabel('Wartości przewidywane')
plt.ylabel('Reszty')
plt.title('Reszty vs przewidywane wartości')
plt.show()
```



[ ]:
```
sns.histplot(residuals, kde=True)
plt.title("Histogram reszt")
plt.show()
```



7.1 Regresja liniowa nie spełnia założeń, ponieważ:

- Na wykresie widać, że residua mają różne rozproszenie (przy skrajnych wartościach są bardziej rozrzucone). To znaczy, że ich rozrzut nie jest taki sam w całym zakresie, a w regresji liniowej powinien być stały.
- Histogram reszt jest lekko przekrzywiony (prawoskośny), więc nie przypomina rozkładu normalnego, jak powinien.