SPRAWOZDANIE

Zajęcia: Nauka o danych I

Prowadzący: prof. dr hab. Vasyl Martsenyuk

Laboratorium Nr 6 Data 7.12.2024 Temat: „Analiza danych z wykorzystaniem narzędzi do regresji "	Tomasz Pietrzyk Informatyka II stopień, niestacjonarne, 1semestr, gr.1a

1. Polecenie:

1. W Pythonie, R oraz KNIME porównaj wyniki regresji liniowej, Ridge, sieci neuronowych na tym samym zbiorze danych.

2. Zbadaj wpływ zmiennych objaśniających na predykcję (np. analiza ważności cech w Ridge).

3. Wykonaj analizę reszt dla modelu regresji liniowej:

-Sprawdź założenie normalności błędów,

- Zbadaj autokorelację reszt (np. test Durbin-Watson w Pythonie lub R).

4. Porównaj jakość modeli przy użyciu danych o różnych skalach (np. znormalizowanych i oryginalnych).

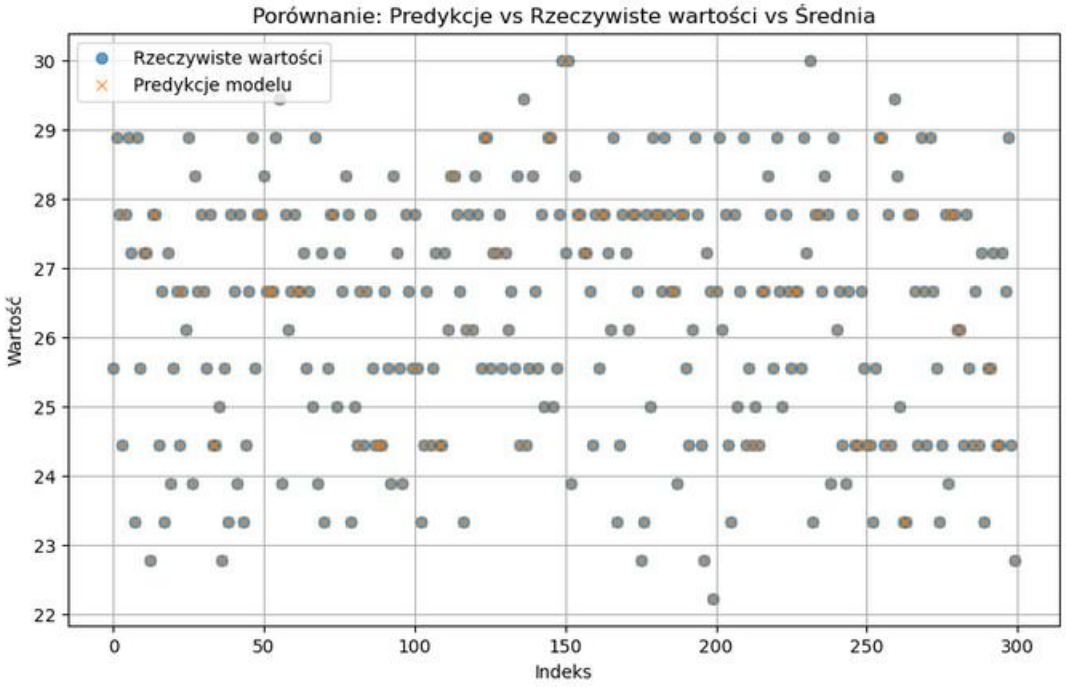
2. Opis programu opracowanego (kody źródłowe, rzuty ekranu)

GitHub: https://github.com/TomekPietrzyk/NOD_I_2024_NS.git

```python
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

data = pd.read_csv('Summary of Weather.csv')
data = data.head(1500)
df = data.select_dtypes(include=['float'])
df.info()
df= df.dropna(axis=1, how='all')
df = df.fillna(0)
df.info()
X = df.drop('MeanTemp', axis=1)
y = df['MeanTemp']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

lr = LinearRegression()
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)
print("R^2:", r2_score(y_test, y_pred_lr))

# Tworzenie wykresu rzeczywistych wartości vs. predykcje vs. średnia
plt.figure(figsize=(10, 6))

# Rzeczywiste wartości
plt.plot(y_test.values, label="Rzeczywiste wartości", marker='o', linestyle='', alpha=0.7)

# Predykcje modelu
plt.plot(y_pred_lr, label="Predykcje modelu", marker='x', linestyle='', alpha=0.7)


# Dodanie tytułów i legendy
plt.title("Porównanie: Predykcje vs Rzeczywiste wartości vs Średnia")
plt.xlabel("Indeks")
plt.ylabel("Wartość")
plt.legend()
plt.grid(True)

# Wyświetlenie wykresu
plt.show()
```

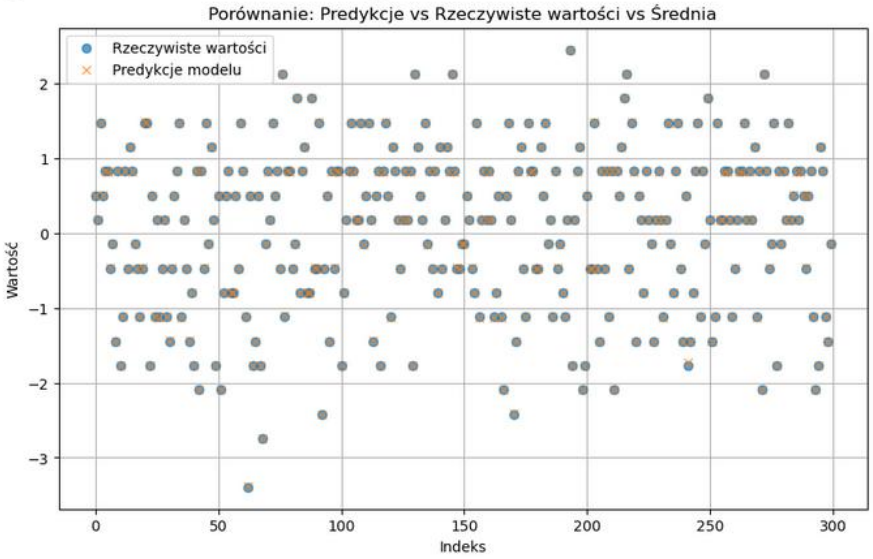
```
C:\Users\Tomasz 2115\AppData\Local\Temp\ipykernel_26652\1473849838.py:6: DtypeWarning: Columns (7,8,18,25) have mixed types. Specify dtype option on import or set low_memory=
False.
  data = pd.read_csv('Summary of Weather.csv')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1500 entries, 0 to 1499
Data columns (total 20 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   WindGustSpd  0 non-null      float64
 1   MaxTemp      1500 non-null   float64
 2   MinTemp      1500 non-null   float64
 3   MeanTemp     1500 non-null   float64
 4   DR           0 non-null      float64
 5   SPD          0 non-null      float64
 6   MAX          1500 non-null   float64
 7   MIN          1500 non-null   float64
 8   MEA          1500 non-null   float64
 9   SND          0 non-null      float64
 10  FT           0 non-null      float64
 11  FB           0 non-null      float64
 12  FTI          0 non-null      float64
 13  ITH          0 non-null      float64
 14  PGT          0 non-null      float64
 15  SD3          0 non-null      float64
 16  RHX          0 non-null      float64
 17  RHN          0 non-null      float64
 18  RVG          0 non-null      float64
 19  WTE          0 non-null      float64
dtypes: float64(20)
memory usage: 234.5 KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1500 entries, 0 to 1499
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   MaxTemp   1500 non-null   float64
 1   MinTemp   1500 non-null   float64
 2   MeanTemp  1500 non-null   float64
 3   MAX       1500 non-null   float64
 4   MIN       1500 non-null   float64
 5   MEA       1500 non-null   float64
dtypes: float64(6)
memory usage: 70.4 KB
```

```
R^2: 1.0
```

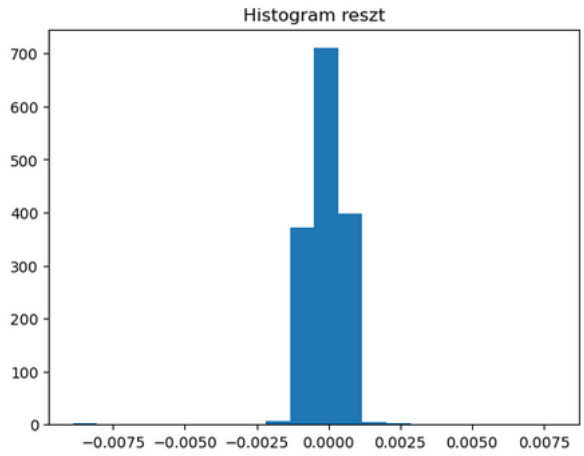

Porównanie: Predykcje vs Rzeczywiste wartości vs Średnia
Rzeczywiste wartości
Predykcje modelu
Wartość
Indeks
30
29
28
27
26
25
24
23
22
0
50
100
150
200
250
300

[147]:
```
from sklearn.linear_model import Ridge

ridge = Ridge(alpha=1.0)
ridge.fit(X,y)
y_pred_lr = ridge.predict(X_test)
print("R^2:", r2_score(y_test, y_pred_lr))


feature_importance = abs(ridge.coef_)
print(feature_importance)

# Tworzenie wykresu rzeczywistych wartości vs. predykcje vs. średnia
plt.figure(figsize=(10, 6))

# Rzeczywiste wartości
plt.plot(y_test, label="Rzeczywiste wartości", marker='o', linestyle='', alpha=0.7)

# Predykcje modelu
plt.plot(y_pred_lr, label="Predykcje modelu", marker='x', linestyle='', alpha=0.7)


# Dodanie tytułów i legendy
plt.title("Porównanie: Predykcje vs Rzeczywiste wartości vs Średnia")
plt.xlabel("Indeks")
plt.ylabel("Wartość")
plt.legend()
plt.grid(True)
```

```
R^2: 0.9999838644646152
[[0.00987952 0.00537644 0.00987952 0.00537644 0.97346472]]
```



[115]:
```
from scipy.stats import shapiro
import matplotlib.pyplot as plt
import numpy as np

# Oblicz reszty
residuals = y - ridge.predict(X)

# Histogram reszt
plt.hist(residuals, bins=20)
plt.title("Histogram reszt")
plt.show()

# Test Shapiro-Wilka
stat, p = shapiro(residuals)
print("Statystyka Shapiro-Wilka:", stat, "P-wartość:", p)
```




```
Statystyka Shapiro-Wilka: 0.7113724089868779 P-wartość: 5.384588757016430e-45
```

[117]:
```
from statsmodels.stats.stattools import durbin_watson

# Test Durbin-Watsona
dw_stat = durbin_watson(residuals)
print("Statystyka Durbin-Watsona:", dw_stat)
```

```
Statystyka Durbin-Watsona: 1.8504902607143376
```

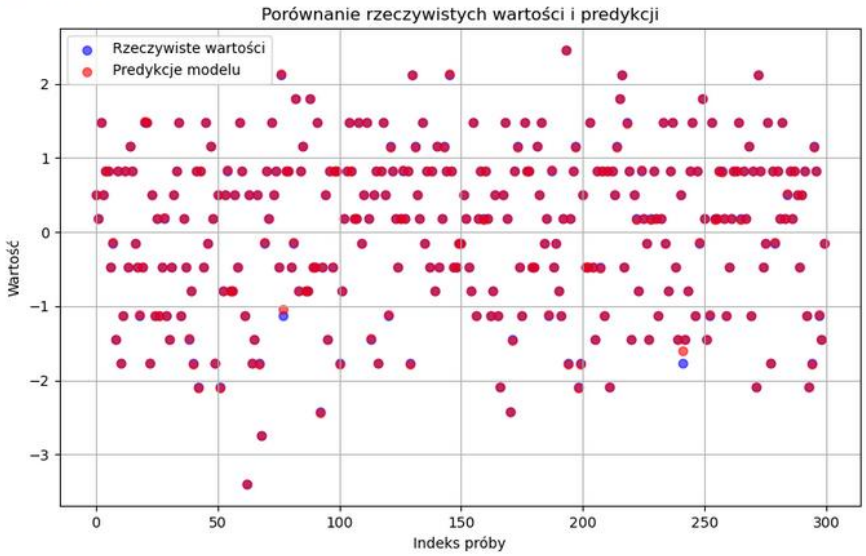
[123]:
```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.datasets import make_regression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.utils import plot_model

import numpy as np

print(y)
print(X)


y = np.array(y)

# Normalizacja danych
scaler_X = StandardScaler()
scaler_y = StandardScaler()
X = scaler_X.fit_transform(X)
y = scaler_y.fit_transform(y.reshape(-1, 1))

# Podział na zbiory treningowy i testowy
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Budowa sieci neuronowej
model = Sequential([
    Dense(64, activation='relu', input_shape=(X.shape[1],)),
    Dense(32, activation='relu'),
    Dense(1)  # Warstwa wyjściowa dla regresji
])

# Kompilacja modelu
model.compile(optimizer='adam', loss='mse', metrics=['mae'])


# Wizualizacja struktury sieci
plot_model(model, to_file='model_visualization.png', show_shapes=True, show_layer_names=True)

# Trenowanie modelu
history = model.fit(X_train, y_train, validation_split=0.2, epochs=25, batch_size=32)

# Ocena modelu
loss, mae = model.evaluate(X_test, y_test)
print("Średni błąd absolutny (MAE):", mae)

# Przewidywanie
y_pred = scaler_y.inverse_transform(model.predict(X_test))


# Oblicz współczynnik R²
r2 = r2_score(y_test, y_pred)
print(f"Współczynnik R²: {r2:.4f}")
```

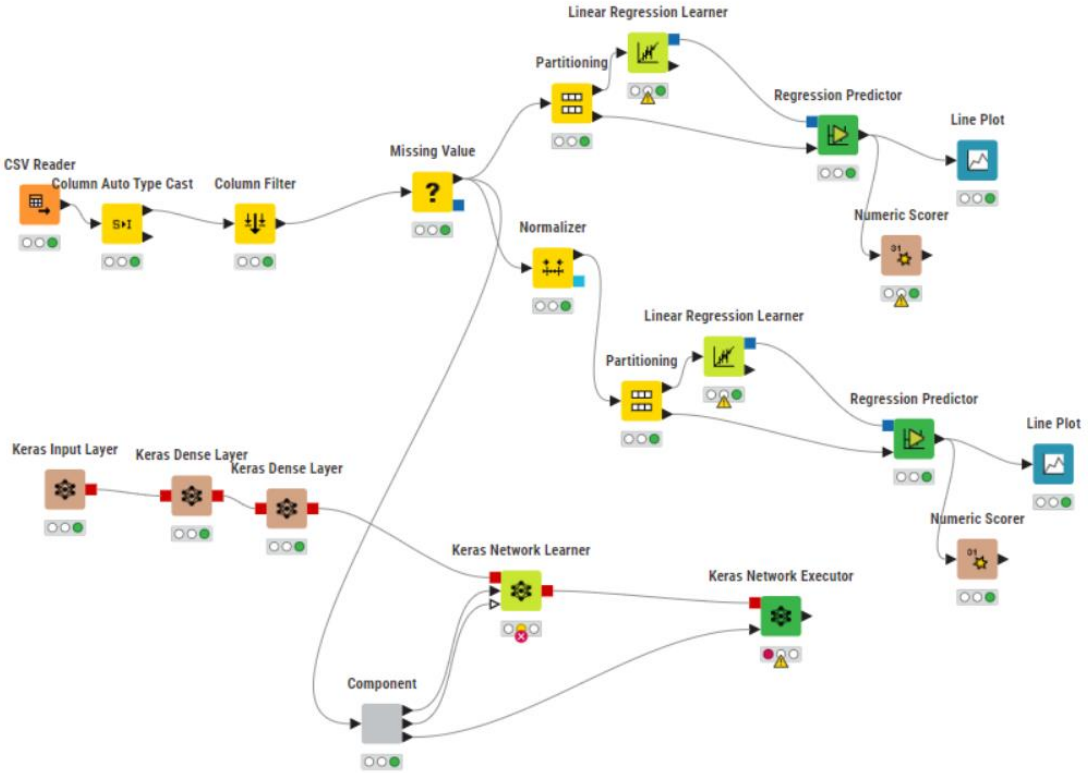
```
[[-1.44555898]
 [-0.47146263]
 [-1.1208602 ]
 ...
 [ 0.17793493]
 [-0.47146263]
 [ 0.17793493]]
[[-1.74483174 -0.34010157 -1.74483174 -0.34010156 -1.44555898]
 [-0.44228648 -0.73343413 -0.44228648 -0.73343414 -0.47146263]
 [-1.52774087 -0.34010157 -1.52774087 -0.34010156 -1.1208602 ]
 ...
 [-0.2251956   0.83989615 -0.2251956   0.83989615  0.17793493]
 [-1.09355911  0.44656358 -1.09355911  0.44656358 -0.47146263]
 [-0.44228648  0.83989615 -0.44228648  0.83989615  0.17793493]]
You must install pydot (`pip install pydot`) for `plot_model` to work.
Epoch 1/25
C:\Users\Tomasz 2115\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequ
ential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
30/30 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - loss: 0.8824 - mae: 0.7466 - val_loss: 0.0599 - val_mae: 0.1691
Epoch 2/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0372 - mae: 0.1342 - val_loss: 0.0159 - val_mae: 0.0962
Epoch 3/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0168 - mae: 0.0934 - val_loss: 0.0126 - val_mae: 0.0847
Epoch 4/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0129 - mae: 0.0821 - val_loss: 0.0109 - val_mae: 0.0778
Epoch 5/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0103 - mae: 0.0731 - val_loss: 0.0100 - val_mae: 0.0738
Epoch 6/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.0082 - mae: 0.0661 - val_loss: 0.0080 - val_mae: 0.0646
Epoch 7/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0065 - mae: 0.0589 - val_loss: 0.0066 - val_mae: 0.0572
Epoch 8/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0076 - mae: 0.0555 - val_loss: 0.0052 - val_mae: 0.0515
Epoch 9/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0036 - mae: 0.0443 - val_loss: 0.0038 - val_mae: 0.0421
Epoch 10/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0034 - mae: 0.0388 - val_loss: 0.0026 - val_mae: 0.0327
Epoch 11/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.0013 - mae: 0.0284 - val_loss: 0.0019 - val_mae: 0.0259
Epoch 12/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 9.7432e-04 - mae: 0.0231 - val_loss: 0.0013 - val_mae: 0.0200
Epoch 13/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 5.8115e-04 - mae: 0.0175 - val_loss: 0.0010 - val_mae: 0.0171
Epoch 14/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 4.8617e-04 - mae: 0.0157 - val_loss: 8.0866e-04 - val_mae: 0.0144
Epoch 15/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 4.2890e-04 - mae: 0.0134 - val_loss: 6.4758e-04 - val_mae: 0.0125
Epoch 16/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 2.6706e-04 - mae: 0.0116 - val_loss: 5.3209e-04 - val_mae: 0.0115
Epoch 17/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 2.1359e-04 - mae: 0.0100 - val_loss: 4.6720e-04 - val_mae: 0.0105
Epoch 18/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 1.8618e-04 - mae: 0.0094 - val_loss: 4.1819e-04 - val_mae: 0.0096
Epoch 19/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 2.2092e-04 - mae: 0.0089 - val_loss: 3.9168e-04 - val_mae: 0.0094
Epoch 20/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.4366e-04 - mae: 0.0078 - val_loss: 3.7474e-04 - val_mae: 0.0092
Epoch 21/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.0902e-04 - mae: 0.0073 - val_loss: 3.3928e-04 - val_mae: 0.0088
Epoch 22/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.0440e-04 - mae: 0.0069 - val_loss: 3.4191e-04 - val_mae: 0.0086
Epoch 23/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.2023e-04 - mae: 0.0071 - val_loss: 2.8636e-04 - val_mae: 0.0073
Epoch 24/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 8.6704e-05 - mae: 0.0062 - val_loss: 2.8367e-04 - val_mae: 0.0071
Epoch 25/25
30/30 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.0565e-04 - mae: 0.0065 - val_loss: 2.6345e-04 - val_mae: 0.0070
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.8628e-04 - mae: 0.0072
Średni błąd absolutny (MAE): 0.007117715664207935
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
Współczynnik R²: 0.9998
```

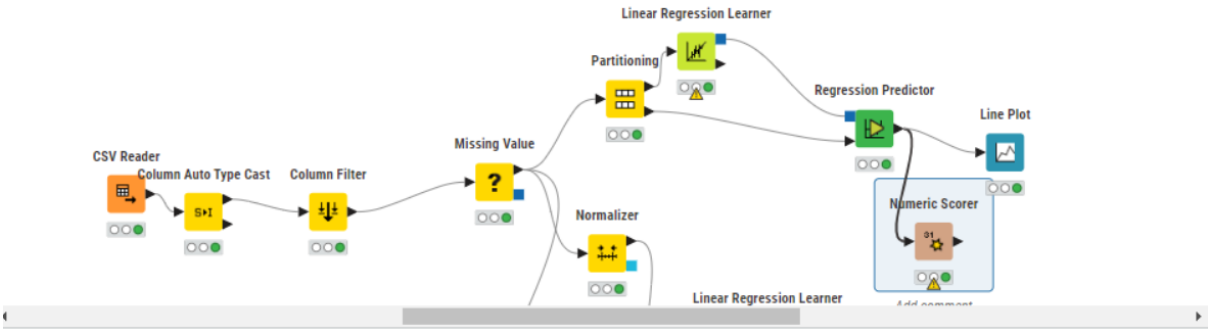
[133]:

```
# Obliczenie współczynnika R²
r2 = r2_score(y_test, y_pred)
print(f"Średni błąd absolutny (MAE): {mae}")
print(f"Współczynnik R²: {r2:.4f}")

# Wizualizacja wyników
plt.figure(figsize=(10, 6))
plt.scatter(range(len(y_test)), y_test, label='Rzeczywiste wartości', color='blue', alpha=0.6)
plt.scatter(range(len(y_pred)), y_pred, label='Predykcje modelu', color='red', alpha=0.6)

plt.title('Porównanie rzeczywistych wartości i predykcji')
plt.xlabel('Indeks próby')
plt.ylabel('Wartość')
plt.legend()
plt.grid(True)
plt.show()
```

```
Średni błąd absolutny (MAE): 0.00376130221411585 8
Współczynnik R²: 0.9999
```



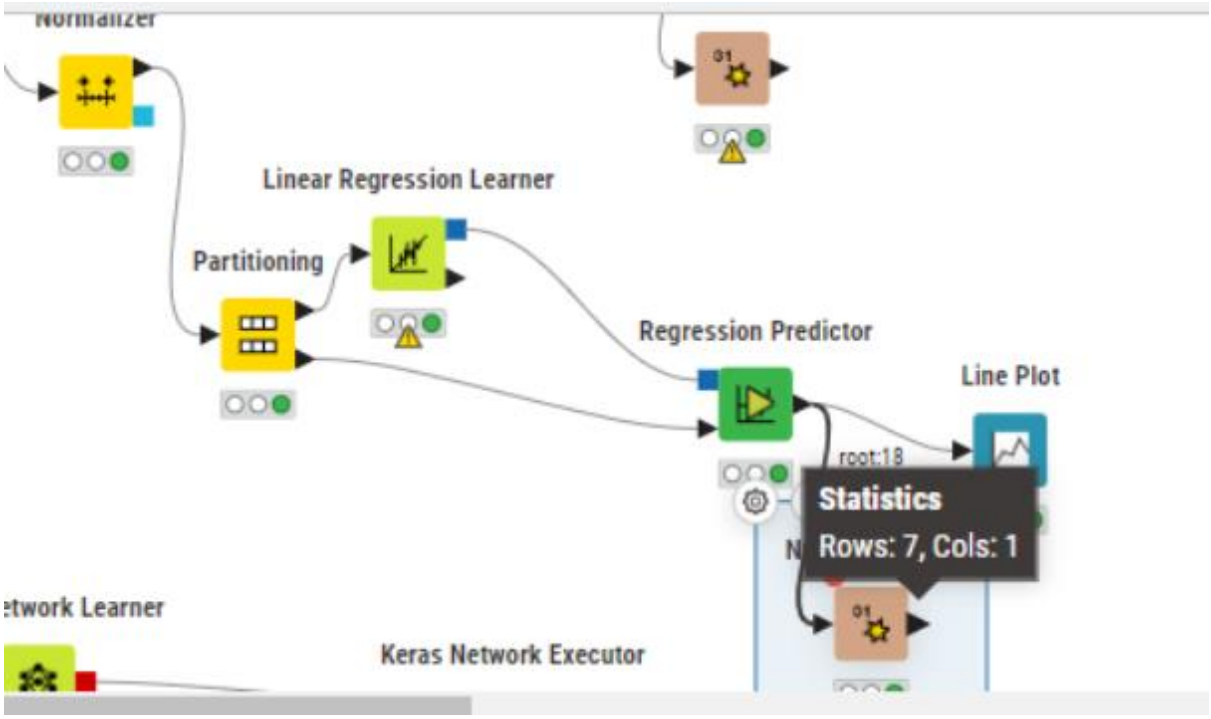




▶ 1: Statistics Flow Variables

Rows: 7 | Columns: 1 Table | Statistics

#	RowID	Prediction (MeanTemp) *Number (double)*
1	R^2	0.998
2	mea...	0.056
3	mea...	0.122
4	root ...	0.35
5	mea...	-0.004
6	mea...	NaN
7	adju...	0.998



3. Wnioski

Wszystkie algorytmy wykazały wyoki wskaźnik detekcji R^2 co ciekawe po normalizacji danych predykcja osiągnęła niższą wartość niż przed predykcją prawdopodobnie dlatego, że data set est uzależniony od Min Max najbardziej i normalizacja zmienjsza ich „wagę” przy predykcji.