# MLPRegressor v1 seg 2

November 24, 2022

# 1 MLPRegressor

```
import numpy as np import pandas as pd import matplotlib.pyplot as plt from sklearn.model_selection import train_test_split, RandomizedSearchCV from sklearn.preprocessing import StandardScaler from sklearn.pipeline import Pipeline from sklearn.neural_network import MLPRegressor from sklearn.feature_selection import SelectFromModel from sklearn.metrics import r2_score, mean_absolute_percentage_error,umean_absolute_error, mean_squared_error from statsmodels.tools.eval_measures import stde
```

## 1.1 Read the etl info results

## 1.2 Read the dataset

```
1
            2012-06-09 13:15:00
                                 2012-06-09T13:10:29
                                                       2.99
                                                                 916.0
                                                                        104.066757
     2
                                                       2.96
            2012-06-09 13:45:00
                                 2012-06-09T13:44:01
                                                                 873.0
                                                                        105.636831
     3
            2012-06-09 14:45:00
                                 2012-06-09T14:44:30
                                                       2.94
                                                                 846.0
                                                                        104.418949
     4
            2012-06-09 15:45:00
                                 2012-06-09T15:44:59
                                                       2.94
                                                                 846.0
                                                                        106.763541
           2019-10-11 09:00:00
     42054
                                 2019-10-11T08:59:53
                                                       2.54
                                                                 434.0
                                                                         82.872720
                                                       2.54
     42055
           2019-10-11 10:00:00
                                                                 434.0
                                 2019-10-11T09:59:52
                                                                         89.028383
     42056
           2019-10-11 11:00:00 2019-10-11T10:59:52
                                                       2.54
                                                                 434.0
                                                                         94.722097
            2019-10-11 12:00:00 2019-10-11T11:59:53
     42057
                                                       2.54
                                                                 434.0
                                                                         96.693270
     42058
           2019-10-11 12:45:00 2019-10-11T12:59:52
                                                       2.54
                                                                 434.0
                                                                         98.738399
                       entropyMean
                                    entropySigma
            graySigma
                                                       hMean
                                                                 hSigma \
     0
            39.623303
                          0.203417
                                        0.979825
                                                  105.368375
                                                              41.572939
                          0.206835
     1
            40.179745
                                        1.002624
                                                  112.399458
                                                              41.795584
     2
            40.533218
                          0.204756
                                        0.994246
                                                  114.021526
                                                              42.145582
     3
            41.752678
                          0.202428
                                        0.983170
                                                  112.612830
                                                              43.575351
     4
            44.442097
                          0.202661
                                        0.989625
                                                  114.839424
                                                              46.302008
     42054
            57.702652
                          0.221708
                                        1.076393
                                                   87.260572 61.485334
     42055
            55.840861
                                                   94.175906
                                                              59.006132
                          0.233168
                                        1.124774
     42056
           54.355753
                          0.240722
                                        1.151833
                                                  100.534577
                                                              56.921028
     42057
                          0.244789
                                                  102.891159
            52.787629
                                        1.171987
                                                              55.083532
     42058
           52.025453
                          0.252812
                                        1.213278
                                                  105.292067
                                                              53.994155
                          sSigma
                                                 vSigma
                 sMean
                                       vMean
     0
            124.520218 4.111846 132.405971
                                              14.983367
                                  133.070221
     1
            124.317679 4.270429
                                              15.334166
     2
                        4.310293 133.294541
            124.304621
                                              15.502448
                                  133.458381
     3
            124.369736
                        4.120586
                                              15.190064
     4
            124.283191 4.088480
                                  133.573595
                                              14.801143
     42054
           127.807813
                        2.564157
                                  124.073149
                                              13.757842
     42055
            127.336000
                        2.585121
                                  124.882812
                                              13.234735
     42056
            126.958768
                        2.774867
                                  126.145409
                                              13.408480
     42057
                        2.998683
                                  127.508063
            126.679956
                                              13.863205
     42058
            126.328075
                        3.258103
                                  128.788256
                                              14.353808
     [42059 rows x 14 columns]
[]: df['SensorTime'] = pd.to_datetime(df['SensorTime'])
     df['Year'] = df['SensorTime'].dt.year
[]: df.dtypes
[]: SensorTime
                     datetime64[ns]
     CaptureTime
                             object
     Stage
                            float64
```

```
Discharge
                            float64
                            float64
     grayMean
     graySigma
                            float64
     entropyMean
                            float64
     entropySigma
                            float64
    hMean
                            float64
    hSigma
                            float64
    sMean
                            float64
                            float64
     sSigma
    vMean
                            float64
                            float64
    vSigma
     Year
                               int64
     dtype: object
[]: df = df[(df.Stage > 0) & (df.Discharge > 0)]
```

#### 1.3 Divide dataset to X and Y

```
[]: np.random.seed(0)

df_train = df[(df.Year >= 2012) & (df.Year <= 2017)]

df_train = df_train.iloc[np.random.permutation(len(df_train))]

df_test = df[(df.Year >= 2018) & (df.Year <= 2019)]

[]: df_train = df_train.drop(columns=["Year", "SensorTime", "CaptureTime"])

df_test = df_test.drop(columns=["Year", "SensorTime", "CaptureTime"])

[]: y_train = df_train["Stage"]

X_train = df_train.drop(columns=["Stage", "Discharge"])

y_test = df_test["Stage"]

X_test = df_test.drop(columns=["Stage", "Discharge"])

[]: #X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, \( \rightarrow \) random_state=0)</pre>
```

#### 1.4 Train model

```
[]: pipeline = Pipeline([
          ('scaler', StandardScaler()),
          ('clf', MLPRegressor(shuffle=False, max_iter=2000))
])
```

```
#param_grid = {'clf__hidden_layer_sizes': [(10), (10, 20), (10, 5, 15), (20, \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \( \) \
```

#### []: clf.fit(X\_train, y\_train)

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV 3/5] END clf activation=tanh, clf alpha=0.095,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.247 total time=
[CV 1/5] END clf_activation=tanh, clf_alpha=0.095,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.244 total time=
                                                                     43.6s
[CV 2/5] END clf_activation=tanh, clf_alpha=0.095,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.241 total time=
                                                                     44.0s
[CV 4/5] END clf_activation=tanh, clf_alpha=0.095,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.245 total time=
                                                                     37.0s
[CV 5/5] END clf_activation=tanh, clf_alpha=0.095,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.228 total time=
[CV 3/5] END clf__activation=tanh, clf__alpha=0.019000000000000003,
clf_hidden_layer_sizes=(256, 256, 128, 128, 64);, score=-0.235 total time=
2.0min
[CV 4/5] END clf__activation=tanh, clf__alpha=0.019000000000000003,
clf_hidden_layer_sizes=(256, 256, 128, 128, 64);, score=-0.254 total time=
2.1min
[CV 5/5] END clf__activation=tanh, clf__alpha=0.019000000000000003,
clf_hidden_layer_sizes=(256, 256, 128, 128, 64);, score=-0.231 total time=
2.4min
[CV 2/5] END clf__activation=tanh, clf__alpha=0.019000000000000003,
clf_hidden_layer_sizes=(256, 256, 128, 128, 64);, score=-0.250 total time=
2.7min
[CV 1/5] END clf__activation=tanh, clf__alpha=0.019000000000000003,
clf_hidden_layer_sizes=(256, 256, 128, 128, 64);, score=-0.270 total time=
3.0min
[CV 1/5] END clf_activation=tanh, clf_alpha=0.064,
clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.222 total time= 6.4min
[CV 2/5] END clf_activation=tanh, clf_alpha=0.064,
clf hidden layer sizes=(512, 256, 128, 128);, score=-0.223 total time= 6.1min
[CV 3/5] END clf_activation=tanh, clf_alpha=0.064,
clf hidden layer sizes=(512, 256, 128, 128);, score=-0.237 total time= 6.0min
[CV 4/5] END clf_activation=tanh, clf_alpha=0.064,
```

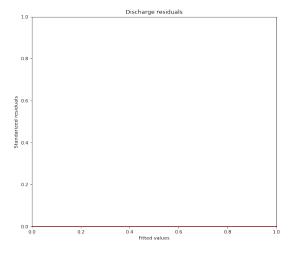
```
clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.238 total time= 5.9min
clf_hidden_layer_sizes=(512, 256);, score=-0.231 total time= 5.3min
[CV 5/5] END clf_activation=tanh, clf_alpha=0.064,
clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.234 total time= 6.1min
clf_hidden_layer_sizes=(512, 256);, score=-0.234 total time= 5.8min
clf_hidden_layer_sizes=(512, 256);, score=-0.232 total time= 5.4min
[CV 1/5] END clf_activation=tanh, clf_alpha=0.005,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.263 total time= 1.3min
[CV 2/5] END clf_activation=tanh, clf_alpha=0.005,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.259 total time= 1.3min
[CV 3/5] END clf_activation=tanh, clf_alpha=0.005,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.276 total time= 1.4min
[CV 4/5] END clf_activation=tanh, clf_alpha=0.005,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.266 total time= 1.3min
[CV 5/5] END clf_activation=tanh, clf_alpha=0.005,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.260 total time= 1.3min
clf_hidden_layer_sizes=(512, 256);, score=-0.241 total time= 4.2min
clf_hidden_layer_sizes=(512, 256);, score=-0.240 total time= 5.5min
[CV 1/5] END clf__activation=tanh, clf__alpha=0.0140000000000000000,
clf_hidden_layer_sizes=(512, 256);, score=-0.224 total time= 5.9min
clf_hidden_layer_sizes=(512, 256);, score=-0.235 total time= 5.6min
[CV 1/5] END clf_activation=tanh, clf_alpha=0.035,
clf_hidden_layer_sizes=(512, 256);, score=-0.236 total time= 5.2min
clf_hidden_layer_sizes=(512, 256);, score=-0.234 total time= 5.5min
clf_hidden_layer_sizes=(512, 256);, score=-0.226 total time= 6.4min
clf hidden layer sizes=(512, 256);, score=-0.224 total time= 6.2min
[CV 2/5] END clf_activation=tanh, clf_alpha=0.035,
clf_hidden_layer_sizes=(512, 256);, score=-0.240 total time= 5.3min
[CV 3/5] END clf_activation=tanh, clf_alpha=0.035,
clf_hidden_layer_sizes=(512, 256);, score=-0.235 total time= 5.1min
[CV 1/5] END clf_activation=relu, clf_alpha=0.098,
clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.225 total time= 3.9min
[CV 1/5] END clf_activation=relu, clf_alpha=0.079,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.219 total time= 49.3s
[CV 4/5] END clf_activation=tanh, clf_alpha=0.035,
clf_hidden_layer_sizes=(512, 256);, score=-0.250 total time= 4.7min
[CV 5/5] END clf_activation=tanh, clf_alpha=0.035,
clf_hidden_layer_sizes=(512, 256);, score=-0.238 total time= 4.9min
[CV 2/5] END clf_activation=relu, clf_alpha=0.079,
```

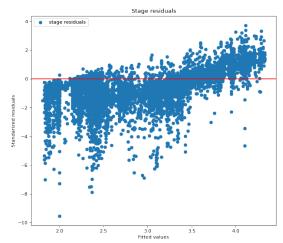
```
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.225 total time=
    [CV 3/5] END clf_activation=relu, clf_alpha=0.079,
    clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.252 total time=
                                                                          54.4s
    [CV 5/5] END clf_activation=relu, clf_alpha=0.079,
    clf hidden layer sizes=(128, 64, 64, 32);, score=-0.218 total time=
    [CV 4/5] END clf_activation=relu, clf_alpha=0.079,
    clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.226 total time=
    [CV 2/5] END clf_activation=relu, clf_alpha=0.098,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.209 total time= 5.6min
    [CV 4/5] END clf_activation=relu, clf_alpha=0.098,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.223 total time= 5.6min
    [CV 3/5] END clf_activation=relu, clf_alpha=0.098,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.246 total time= 6.0min
    [CV 3/5] END clf_activation=tanh, clf_alpha=0.068,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.236 total time= 4.2min
    [CV 5/5] END clf_activation=relu, clf_alpha=0.098,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.202 total time= 7.1min
    [CV 1/5] END clf_activation=tanh, clf_alpha=0.068,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.223 total time= 4.6min
    [CV 2/5] END clf activation=tanh, clf alpha=0.068,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.223 total time= 4.7min
    [CV 4/5] END clf_activation=tanh, clf_alpha=0.068,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.242 total time= 4.4min
    [CV 5/5] END clf_activation=tanh, clf_alpha=0.068,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.230 total time= 4.0min
[]: RandomizedSearchCV(estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                                  ('clf',
                                                  MLPRegressor(max_iter=2000,
                                                               shuffle=False))]),
                       n_jobs=8,
                       param_distributions={'clf_activation': ['tanh', 'relu'],
                                             'clf_alpha': array([0.001, 0.002,
    0.003, 0.004, 0.005, 0.006, 0.007, 0.008, 0.009,
           0.01, 0.011, 0.012, 0.013, 0.014, 0.015, 0.016, 0.017, 0.018,
           0.019, 0.02 , 0.021, 0.022, 0.023, 0.024...
           0.064, 0.065, 0.066, 0.067, 0.068, 0.069, 0.07, 0.071, 0.072,
           0.073, 0.074, 0.075, 0.076, 0.077, 0.078, 0.079, 0.08, 0.081,
           0.082, 0.083, 0.084, 0.085, 0.086, 0.087, 0.088, 0.089, 0.09,
           0.091, 0.092, 0.093, 0.094, 0.095, 0.096, 0.097, 0.098, 0.099]),
                                             'clf_hidden_layer_sizes': [(256, 256,
                                                                         128, 128,
                                                                         64),
                                                                        (512, 256),
                                                                        (128, 64,
                                                                         64, 32),
                                                                        (512, 256,
```

```
128,
128)]},
```

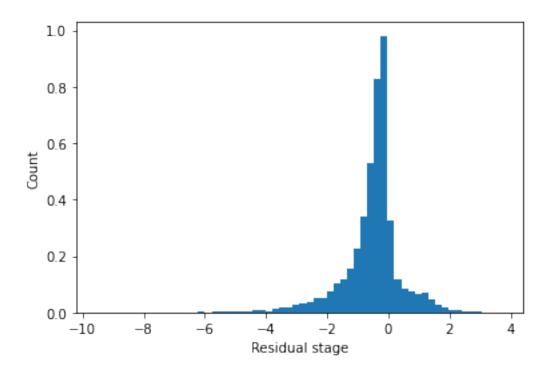
scoring='neg\_mean\_squared\_error', verbose=3)

```
[]: clf.best_score_
[]: -0.22091953882505555
[]: clf.best params
[]: {'clf_hidden_layer_sizes': (512, 256, 128, 128),
      'clf alpha': 0.098,
      'clf__activation': 'relu'}
    1.5 Test model
[]: clf.score(X_test, y_test)
[]: -0.4255222840231655
[]: y_pred = clf.predict(X_test)
[]: print("R^2: ", r2_score(y_test, y_pred))
    print("mse: ", mean_squared_error(y_test, y_pred))
    print("rmse: ", mean squared error(y test, y pred, squared=False))
    print("mae: ", mean_absolute_error(y_test, y_pred))
    print("mape: ", mean_absolute_percentage_error(y_test, y_pred))
    print("Error estandar: ", stde(y_test.squeeze(),
          y_pred.squeeze(), ddof=2))
    R^2: -0.08957704724707871
    mse: 0.4255222840231655
    rmse: 0.6523206910892567
    mae: 0.43109842602881954
    mape: 0.16322167249582156
    Error estandar: 0.581351761528604
[]: residuals = y_test - y_pred
    residuals_std = residuals/residuals.std()
    y_real_stage = y_test
    residual_stage = residuals
    #y_real_discharge = np.array([i[-1] for i in y_test])
    \#residual\_discharge = np.array([i[-1] for i in residuals])
```





```
[]: plt.hist(residual_stage / residual_stage.std(), density=True, bins = 60)
   plt.ylabel('Count')
   plt.xlabel('Residual stage');
   plt.show()
```



```
[]: """plt.hist(residual_discharge / residual_discharge.std(), density=True, bins =

→60)

plt.ylabel('Count')

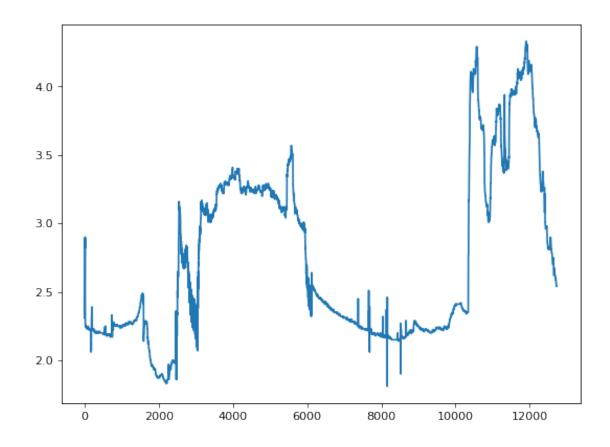
plt.xlabel('Residual discharge');

plt.show()"""
```

[]: "plt.hist(residual\_discharge / residual\_discharge.std(), density=True, bins =
60)\nplt.ylabel('Count')\nplt.xlabel('Residual discharge');\nplt.show()"

```
[]: plt.figure(figsize=(8, 6), dpi=80)
plt.plot(np.arange(len(y_test)), y_test, label="Stage real")
```

[]: [<matplotlib.lines.Line2D at 0x7f0d54aef700>]



```
[]: figure, ax = plt.subplots(ncols=2, figsize=(20, 8), dpi=80)

ax[0].plot(np.arange(len(y_test)), y_test, label="Stage real")
ax[0].plot(np.arange(len(y_test)), y_pred, label="Stage pred")

ax[0].set_title("Stage predictions")
ax[1].set_title("Discharge predictions")

ax[1].set_ylabel("Values")
ax[0].set_ylabel("Values")
ax[1].set_xlabel("Time")

plt.legend()
plt.show()
```

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.

