# MLPRegressor\_v1\_stage\_3

November 25, 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,u chean_absolute_error, mean_squared_error from statsmodels.tools.eval_measures import stde
```

#### 1.1 Read the etl info results

#### 1.2 Read the dataset

```
[]: df = pd.read_csv('../../dataset_clean/PlatteRiverWeir_features_v1_clean.csv')
df

[]: SensorTime CaptureTime Stage Discharge grayMean \
0 2012-06-09 13:15:00 2012-06-09T13:09:07 2.99 916.0 97.405096
```

```
1
       2012-06-09 13:15:00
                             2012-06-09T13:10:29
                                                     2.99
                                                               916.0
                                                                      104.066757
2
       2012-06-09 13:45:00
                             2012-06-09T13:44:01
                                                     2.96
                                                               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
42054
       2019-10-11 09:00:00
                             2019-10-11T08:59:53
                                                     2.54
                                                               434.0
                                                                       82.872720
42055
       2019-10-11 10:00:00
                                                     2.54
                                                               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
                                                               434.0
                                                                        98.738399
                                                     2.54
                        hMean
                                  hSigma
                                                            hMean0
                                                                     entropyMean1
       graySigma
                                            grayMean0
0
       39.623303
                   105.368375
                               41.572939
                                            97.084576
                                                        106.047217
                                                                         0.092532
1
       40.179745
                   112.399458
                               41.795584
                                           105.668610
                                                        114.886049
                                                                         0.090279
2
                               42.145582
       40.533218
                   114.021526
                                           106.786307
                                                        116.053131
                                                                         0.090561
3
       41.752678
                   112.612830
                               43.575351
                                           107.674299
                                                        117.005027
                                                                         0.095616
4
       44.442097
                   114.839424
                               46.302008
                                           114.858589
                                                        124.519271
                                                                         0.101601
42054
       57.702652
                    87.260572
                               61.485334
                                            43.737485
                                                         46.616662
                                                                         0.120668
                                            46.268458
42055
       55.840861
                    94.175906
                               59.006132
                                                         49.716207
                                                                         0.113951
42056
       54.355753
                   100.534577
                               56.921028
                                            49.841325
                                                         53.984763
                                                                         0.110346
                                            53.912185
42057
       52.787629
                   102.891159
                               55.083532
                                                         58.857575
                                                                         0.112571
42058
       52.025453
                   105.292067
                               53.994155
                                            59.611803
                                                         65.697745
                                                                         0.110247
       entropySigma1
                                   WwRawLineMean
                                                   WwRawLineSigma
                           hMean1
0
            0.632319
                       169.963345
                                         0.000000
                                                          0.00000
1
            0.620077
                       175.220945
                                         0.000000
                                                          0.000000
2
            0.620853
                       179.554842
                                         0.00000
                                                          0.00000
3
            0.651642
                       180.921521
                                         0.000000
                                                          0.00000
4
                                                          0.00000
            0.688024
                       183.131779
                                         0.00000
42054
            0.824195
                       126.181417
                                     38385.370066
                                                      15952.029728
42055
            0.783437
                       131.754200
                                     40162.989292
                                                      15467.708856
42056
            0.766074
                       138.014068
                                     42095.946590
                                                      16770.357949
42057
            0.777376
                       146.470365
                                     45345.490954
                                                      17498.432849
42058
            0.760248
                       156.957374
                                     47877.870782
                                                      19963.166359
       WwCurveLineMean
                         WwCurveLineSigma
0
              0.00000
                                  0.000000
1
              0.00000
                                  0.000000
2
              0.000000
                                  0.000000
3
              0.000000
                                  0.000000
4
                                  0.00000
              0.000000
                             16444.401209
42054
          37550.894823
          39397.339095
                             16009.008049
42055
42056
          41350.006568
                             17489.374617
```

```
42057
               44553.920296
                                 18268.294896
     42058
               47280.270559
                                 20559.358767
     [42059 rows x 17 columns]
[]: df['SensorTime'] = pd.to_datetime(df['SensorTime'])
     df['Year'] = df['SensorTime'].dt.year
[]: df.dtypes
[]: SensorTime
                         datetime64[ns]
     CaptureTime
                                 object
                                float64
     Stage
    Discharge
                                float64
     grayMean
                                float64
    graySigma
                                float64
    hMean
                                float64
    hSigma
                                float64
                                float64
    grayMean0
    hMean0
                                float64
     entropyMean1
                                float64
     entropySigma1
                                float64
    hMean1
                                float64
     WwRawLineMean
                                float64
    WwRawLineSigma
                                float64
    WwCurveLineMean
                                float64
     WwCurveLineSigma
                                float64
     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)]</pre>
     df_train = df_train.iloc[np.random.permutation(len(df_train))]
     df_test = df[(df.Year >= 2018) & (df.Year <= 2019)]</pre>
[]: 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)
```

### 1.4 Train model

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

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV 2/5] END clf_activation=tanh, clf_alpha=0.095,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.135 total time=
                                                                     35.4s
[CV 3/5] END clf_activation=tanh, clf_alpha=0.095,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.136 total time=
                                                                     37.2s
[CV 1/5] END clf_activation=tanh, clf_alpha=0.095,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.137 total time=
                                                                     42.7s
[CV 4/5] END clf_activation=tanh, clf_alpha=0.095,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.150 total time=
                                                                     34.4s
[CV 5/5] END clf_activation=tanh, clf_alpha=0.095,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.131 total time=
[CV 2/5] END clf__activation=tanh, clf__alpha=0.019000000000000003,
clf hidden layer sizes=(256, 256, 128, 128, 64);, score=-0.132 total time=
[CV 3/5] END clf__activation=tanh, clf__alpha=0.019000000000000003,
clf_hidden_layer_sizes=(256, 256, 128, 128, 64);, score=-0.147 total time=
2.0min
[CV 1/5] END clf_activation=tanh, clf_alpha=0.019000000000000003,
clf_hidden_layer_sizes=(256, 256, 128, 128, 64);, score=-0.134 total time=
2.9min
```

```
[CV 4/5] END clf_activation=tanh, clf_alpha=0.019000000000000003,
clf_hidden_layer_sizes=(256, 256, 128, 128, 64);, score=-0.149 total time=
3.2min
[CV 5/5] END clf__activation=tanh, clf__alpha=0.019000000000000003,
clf_hidden_layer_sizes=(256, 256, 128, 128, 64);, score=-0.136 total time=
3.5min
[CV 1/5] END clf_activation=tanh, clf_alpha=0.064,
clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.133 total time= 4.1min
[CV 3/5] END clf_activation=tanh, clf_alpha=0.064,
clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.129 total time= 4.4min
[CV 2/5] END clf_activation=tanh, clf_alpha=0.064,
clf_hidden layer_sizes=(512, 256, 128, 128);, score=-0.123 total time= 5.0min
clf_hidden_layer_sizes=(512, 256);, score=-0.137 total time= 3.3min
[CV 5/5] END clf_activation=tanh, clf_alpha=0.064,
clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.133 total time= 4.8min
clf_hidden_layer_sizes=(512, 256);, score=-0.129 total time= 3.9min
[CV 1/5] END clf_activation=tanh, clf_alpha=0.005,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.135 total time= 1.1min
clf_hidden_layer_sizes=(512, 256);, score=-0.134 total time= 4.6min
[CV 2/5] END clf_activation=tanh, clf_alpha=0.005,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.116 total time=
                                                        47.6s
[CV 3/5] END clf_activation=tanh, clf_alpha=0.005,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.116 total time= 55.7s
[CV 4/5] END clf_activation=tanh, clf_alpha=0.064,
clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.141 total time= 5.9min
[CV 4/5] END clf_activation=tanh, clf_alpha=0.005,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.133 total time=
[CV 5/5] END clf_activation=tanh, clf_alpha=0.005,
clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.128 total time=
clf_hidden_layer_sizes=(512, 256);, score=-0.140 total time= 3.8min
clf_hidden_layer_sizes=(512, 256);, score=-0.129 total time= 3.3min
[CV 4/5] END clf__activation=tanh, clf__alpha=0.0140000000000000000,
clf_hidden_layer_sizes=(512, 256);, score=-0.134 total time= 3.4min
clf_hidden_layer_sizes=(512, 256);, score=-0.126 total time= 4.0min
[CV 3/5] END clf_activation=tanh, clf_alpha=0.035,
clf_hidden_layer_sizes=(512, 256);, score=-0.138 total time= 3.4min
clf_hidden_layer_sizes=(512, 256);, score=-0.125 total time= 4.9min
clf_hidden_layer_sizes=(512, 256);, score=-0.130 total time= 4.8min
[CV 2/5] END clf_activation=tanh, clf_alpha=0.035,
clf_hidden_layer_sizes=(512, 256);, score=-0.134 total time= 3.9min
```

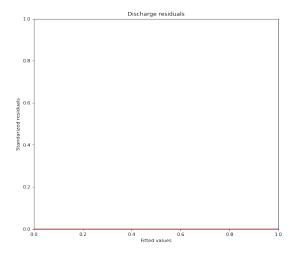
```
[CV 1/5] END clf_activation=tanh, clf_alpha=0.035,
    clf_hidden_layer_sizes=(512, 256);, score=-0.139 total time= 4.6min
    [CV 1/5] END clf__activation=tanh, clf__alpha=0.0140000000000000000,
    clf_hidden_layer_sizes=(512, 256);, score=-0.129 total time= 5.9min
    [CV 1/5] END clf activation=relu, clf alpha=0.079,
    clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.137 total time=
    [CV 2/5] END clf_activation=relu, clf_alpha=0.079,
    clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.122 total time= 54.5s
    [CV 4/5] END clf_activation=tanh, clf_alpha=0.035,
    clf_hidden_layer_sizes=(512, 256);, score=-0.140 total time= 4.5min
    [CV 5/5] END clf_activation=tanh, clf_alpha=0.035,
    clf_hidden_layer_sizes=(512, 256);, score=-0.134 total time= 3.7min
    [CV 3/5] END clf_activation=relu, clf_alpha=0.079,
    clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.125 total time=
    [CV 4/5] END clf_activation=relu, clf_alpha=0.079,
    clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.129 total time=
                                                                         28.5s
    [CV 5/5] END clf_activation=relu, clf_alpha=0.079,
    clf_hidden_layer_sizes=(128, 64, 64, 32);, score=-0.121 total time= 58.5s
    [CV 3/5] END clf_activation=relu, clf_alpha=0.098,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.124 total time= 4.4min
    [CV 4/5] END clf_activation=relu, clf_alpha=0.098,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.128 total time= 5.4min
    [CV 5/5] END clf_activation=relu, clf_alpha=0.098,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.130 total time= 5.2min
    [CV 1/5] END clf_activation=relu, clf_alpha=0.098,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.130 total time= 5.8min
    [CV 2/5] END clf_activation=relu, clf_alpha=0.098,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.120 total time= 6.1min
    [CV 4/5] END clf_activation=tanh, clf_alpha=0.068,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.148 total time= 3.1min
    [CV 1/5] END clf_activation=tanh, clf_alpha=0.068,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.131 total time= 3.9min
    [CV 3/5] END clf_activation=tanh, clf_alpha=0.068,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.130 total time= 3.4min
    [CV 2/5] END clf activation=tanh, clf alpha=0.068,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.121 total time= 4.8min
    [CV 5/5] END clf_activation=tanh, clf_alpha=0.068,
    clf_hidden_layer_sizes=(512, 256, 128, 128);, score=-0.130 total time= 3.1min
[]: 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,
```

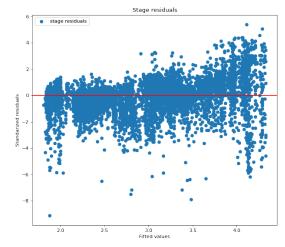
```
0.01, 0.011, 0.012, 0.013, 0.014, 0.015, 0.016, 0.017, 0.018,
           0.019, 0.02, 0.021, 0.022, 0.023, 0.024...
           0.064, 0.065, 0.066, 0.067, 0.068, 0.069, 0.07, 0.071, 0.072,
           0.073, 0.074, 0.075, 0.076, 0.077, 0.078, 0.079, 0.08, 0.081,
           0.082, 0.083, 0.084, 0.085, 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
[]: -0.12564252541286405
[]: clf.best params
[]: {'clf_hidden_layer_sizes': (128, 64, 64, 32),
      'clf__alpha': 0.005,
      'clf activation': 'tanh'}
    1.5 Test model
[]: clf.score(X_test, y_test)
[]: -0.2048234530139613
[]: 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: 0.47553643717104777
    mse: 0.2048234530139613
    rmse: 0.4525742513819818
    mae: 0.2871773460912934
```

mape: 0.10087996276424001

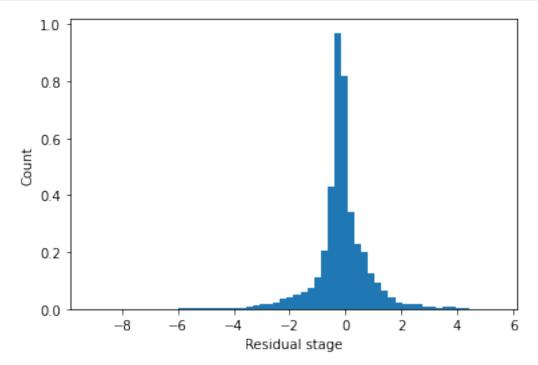
Error estandar: 0.44767144126579655

```
[]: 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])
     figure, ax = plt.subplots(ncols=2, figsize=(20, 8), dpi=80)
     ax[1].scatter(y_real_stage, residual_stage / residual_stage.std(), label="stage_u
     →residuals")
     \#ax[0].scatter(y\_real\_discharge, residual\_discharge / residual\_discharge.std(), 
     → label="discharge residuals")
     ax[1].axhline(y=0.0, color='r', linestyle='-')
     ax[0].axhline(y=0.0, color='r', linestyle='-')
     ax[1].set_title("Stage residuals")
     ax[0].set_title("Discharge residuals")
     ax[1].set_xlabel("Fitted values")
     ax[0].set xlabel("Fitted values")
     ax[1].set_ylabel("Standarized residuals")
     ax[0].set_ylabel("Standarized residuals")
     plt.legend()
     plt.show()
```





```
[]: 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')

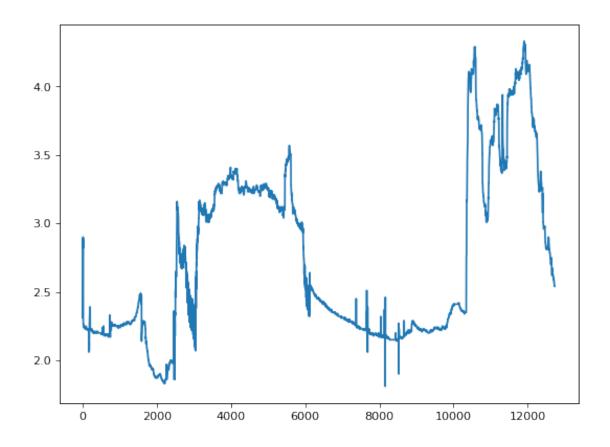
plt.xlabel('Residual discharge');

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 0x7fc114f04eb0>]



```
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")
ax[0].legend()
ax[1].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.

