SVR

Epsilon-Support Vector Regression.

The free parameters in the model are C and epsilon.

In [ ]:

```
# lets import the dependencies

import warnings
warnings.filterwarnings('ignore')

import matplotlib.pyplot as plt
%config InlineBackend.figure_format = 'retina'
plt.style.use('ggplot')
import pandas as pd
import numpy as np

import seaborn as sns
sns.set()

from sklearn.model_selection import train_test_split , KFold
from sklearn.model_selection import GridSearchCV, cross_val_score, learning_curv
from sklearn.model_selection import validation_curve

from sklearn.preprocessing import PowerTransformer

from sklearn.svm import SVR

from sklearn.metrics import mean_absolute_error, r2_score
from joblib import load,dump
```

In [ ]:

```
# loading the data
# loading our data
df = pd.read_csv("./Data/data.csv",sep=",")
df.drop(['Unnamed: 0'], axis=1, inplace=True) # There were some formatting issue
                                              # writing the csv
```

In [ ]:

```
df.head()
```

Out[ ]:

	DISTRICT	UPAZILA	STATION_ID	STATION_NAME	DATE	RAIN_FALL(mm)	LATITUDE	LONGITUDI
0	Bandarban	Lama	CL317	Lama	01-jan-2017	0.0	21.81	92.1
1	Bandarban	Lama	CL317	Lama	02-jan-2017	0.0	21.81	92.1
2	Bandarban	Lama	CL317	Lama	03-jan-2017	0.0	21.81	92.1
3	Bandarban	Lama	CL317	Lama	04-jan-2017	0.0	21.81	92.1

	DISTRICT	UPAZILA	STATION_ID	STATION_NAME	DATE	RAIN_FALL(mm)	LATITUDE	LONGITUDI
4	Bandarban	Lama	CL317	Lama	05-jan-2017	0.0	21.81	92.1

Defining our X and y

In [ ]:
```
X = df['RAIN_FALL(mm)'].values.reshape(-1,1) # input feature
y = df['WATER_LEVEL(m)'].values.reshape(-1,1) # target feature
```

making the train test split

In [ ]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X,y, test_size=0.2, random_state=17, shuffle=True
)
```

PreProcessing

Power Transformation

In [ ]:
```
pt  = PowerTransformer(method='box-cox')
X_train_transformed = pt.fit_transform(X_train+0.000001)
X_test_transformed = pt.transform(X_test+0.000001)
```

In [ ]:
```
pt.lambdas_
```

Out[ ]:
```
array([-0.10662485])
```

In [ ]:
```
y_train_transformed = pt.fit_transform(y_train+0.000001)
y_test_transformed = pt.transform(y_test+0.000001)
y_train_transformed = y_train_transformed.ravel()
y_test_transformed = y_test_transformed.ravel()
```

In [ ]:
```
pt.lambdas_
```

Out[ ]:
```
array([-5.34754941])
```

Model Building

Initialize our CV

In [ ]:
```
kfold = KFold(n_splits=5,shuffle=True,random_state=17)
```

Initialize Support Vector Regressor with default parameters:

- kernel: rbf
- tol : 1e-3

- C: 1
- epsilon: 0.1
- verbose:True
- max_iteration: -1

In [ ]:
```
svr = SVR()
```

CV Scores:

In [ ]:
```
results = cross_val_score(
    svr,
    X_train_transformed,
    y_train_transformed,
    cv=kfold,
    scoring='neg_mean_absolute_error'
)
-results.mean()
```

Out[ ]:
```
0.5760287054297919
```

Note:

- we got 0.44 in KNN

Train-test accuracy

In [ ]:
```
svr.fit(X_train_transformed,y_train_transformed)
```

Out[ ]:
```
SVR()
```

In [ ]:
```
# accuracy on the train set
pred = svr.predict(X_train_transformed)
mean_absolute_error(y_train_transformed,pred)
```

Out[ ]:
```
0.5751854260156385
```

In [ ]:
```
# accuracy on the test set
pred = svr.predict(X_test_transformed)
mean_absolute_error(y_test_transformed,pred)
```

Out[ ]:
```
0.570577574929561
```

Learning Curve

lets plot the learning curve to see how our dataset's size influence the model accuracy

In [ ]:
```
# Helper function
alphas = np.logspace(-2, 0, 20)
def plot_with_err(x, data, **kwargs):
    mu, std = data.mean(1), data.std(1)
    lines = plt.plot(x, mu, "-", **kwargs)
```

```
    plt.fill_between(
        x,
        mu - std,
        mu + std,
        edgecolor="none",
        facecolor=lines[0].get_color(),
        alpha=0.2,
    )
```

In [ ]:

```
def plot_learning_curve():
    train_sizes = np.linspace(0.05,1,20)
    N_train, val_train, val_test = learning_curve(
        svr,X_train_transformed,y_train_transformed, \
        train_sizes=train_sizes,cv=kfold,scoring='neg_mean_absolute_error'
    )
    plot_with_err(N_train, val_train, label="training scores")
    plot_with_err(N_train, val_test, label="validation scores")
    plt.xlabel("Training Set Size")
    plt.ylabel("Negative MAE")
    plt.legend()
    plt.grid(True);
```

In [ ]:

```
plot_learning_curve()
```

Note:

- its clear that training and validation curve converges, assuaring no variance problem in the data

Validation Curves

In [ ]:

```
# helper function
def plot_with_err(x, data, **kwargs):
    mu, std = data.mean(1), data.std(1)
    lines = plt.plot(x, mu, "-", **kwargs)
    plt.fill_between(
        x,
        mu - std,
        mu + std,
        edgecolor="none",
```

```
            facecolor=lines[0].get_color(),
            alpha=0.2,
        )
```

In [ ]:

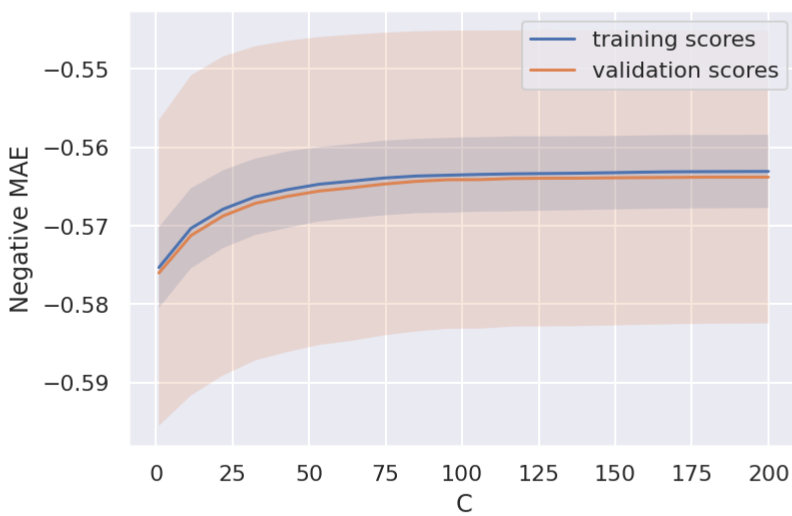
```
def plot_validation_curve(param_grid,param,estimator):
    val_train, val_test = validation_curve(
    estimator=estimator,
    X=X_train_transformed,
    y=y_train_transformed,
    param_name=param,
    param_range=param_grid,
    cv=kfold,
    scoring="neg_mean_absolute_error",
    n_jobs=-1
    )

    plot_with_err(param_grid, val_train, label="training scores")
    plot_with_err(param_grid, val_test, label="validation scores")
    plt.xlabel(param)
    plt.ylabel("Negative MAE")
    plt.legend()
    plt.grid(True);
```

- **C:** Regularization parameter. The strength of the regularization is inversely proportional to C. Must be strictly positive. The penalty is a squared l2 penalty.

In [ ]:

```
plot_validation_curve(np.linspace(1,200,20),'C',svr)
```



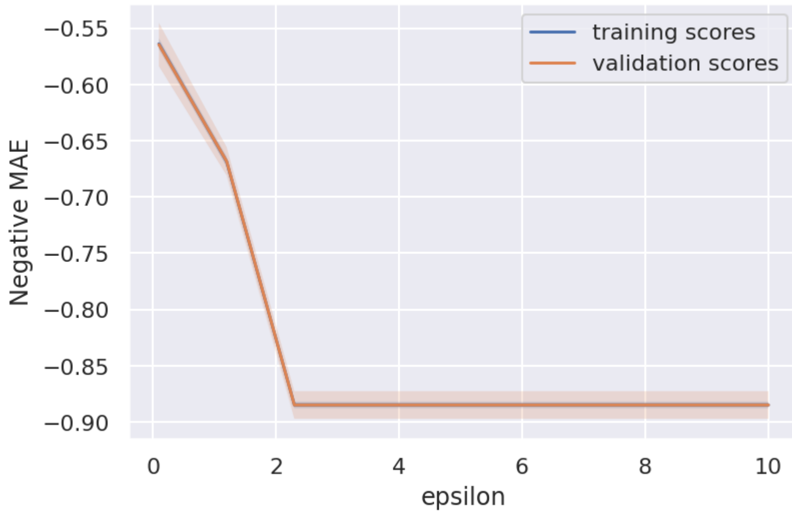
Note:

- After 75, there's no significant improvement

- **epsilon:** Epsilon in the epsilon-SVR model. It specifies the epsilon-tube within which no penalty is associated in the training loss function with points predicted within a distance epsilon from the actual value.

In [ ]:

```
svr = SVR(C=80)
plot_validation_curve(np.linspace(0.1,10,10),'epsilon',svr)
```



Hyper-Parameter Tuning:

In [ ]:

```
svr_params = {
    'C': np.linspace(1,200,20),
    'epsilon': np.linspace(0.01,10,10)
}
svr = SVR()
gcv = GridSearchCV(svr,svr_params,n_jobs=-1,cv=kfold,verbose=1,\
    scoring='neg_mean_absolute_error')
```

In [ ]:

```
# training the model
gcv.fit(X_train_transformed,y_train_transformed)
```

Out[ ]:

```
Fitting 5 folds for each of 200 candidates, totalling 1000 fits
GridSearchCV(cv=KFold(n_splits=5, random_state=17, shuffle=True),
             estimator=SVR(), n_jobs=-1,
             param_grid={'C': array([  1.        ,  11.47368421,  21.94736842,
32.42105263,
        42.89473684,  53.36842105,  63.84210526,  74.31578947,
        84.78947368,  95.26315789, 105.73684211, 116.21052632,
       126.68421053, 137.15789474, 147.63157895, 158.10526316,
       168.57894737, 179.05263158, 189.52631579, 200.        ]),
                         'epsilon': array([ 0.01,  1.12,  2.23,  3.34,  4.45,
5.56,  6.67,  7.78,  8.89,
       10.  ])},
             scoring='neg_mean_absolute_error', verbose=1)
```

In [ ]:

```
# the best score
gcv.best_score_
```

Out[ ]:

```
-0.5636756238996249
```

In [ ]:

```
# the best estimators parameters
gcv.best_params_
```

Out[ ]: {'C': 179.05263157894734, 'epsilon': 0.01}

In [ ]:
```
# Lets check the train test accuracy of our model
svr_pred = gcv.best_estimator_.predict(X_train_transformed)
mean_absolute_error(y_train_transformed,svr_pred)
```

Out[ ]: 0.5627343535124258

In [ ]:
```
# Lets check the test test accuracy of our model
svr_pred = gcv.best_estimator_.predict(X_test_transformed)
mean_absolute_error(y_test_transformed,svr_pred)
```

Out[ ]: 0.5623383600494728

Learning Curve

In [ ]:
```
def plot_learning_curve():
    train_sizes = np.linspace(0.05,1,20)
    N_train, val_train, val_test = learning_curve(
        gcv.best_estimator_,X_train_transformed,y_train_transformed, \
        train_sizes=train_sizes,cv=kfold,scoring='neg_mean_absolute_error'
    )
    plot_with_err(N_train, val_train, label="training scores")
    plot_with_err(N_train, val_test, label="validation scores")
    plt.xlabel("Training Set Size")
    plt.ylabel("Negative MAE")
    plt.legend()
    plt.grid(True);
```

In [ ]:
```
plot_learning_curve()
```

Saving Model

In [ ]:
```
dump(gcv.best_estimator_,'./Saved Model/svr.joblib')
```

Out[ ]: ['./Saved Model/svr.joblib']