KNN

Regression based on k-nearest neighbors.

The target is predicted by local interpolation of the targets associated of the nearest neighbors in the training set.

One thing to note KNN wont require any transformation so we are opting power transformation here!

In [ ]:

```
# lets import some 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.neighbors import KNeighborsRegressor


from sklearn.metrics import mean_absolute_error, r2_score

from joblib import load,dump
```

In [ ]:

```
# 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	LONGITUD
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

	DISTRICT	UPAZILA	STATION_ID	STATION_NAME	DATE	RAIN_FALL(mm)	LATITUDE	LONGITUDI
3	Bandarban	Lama	CL317	Lama	04-jan-2017	0.0	21.81	92.1
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
```

In [ ]:

```
X.shape, y.shape
```

Out[ ]:

```
((1826, 1), (1826, 1))
```

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
)
```

Model Building

Initialize our CV

In [ ]:

```
kflod = KFold(n_splits=5,shuffle=True, random_state=17)
```

Initialize the KNN model with default parameters

- n_neighbors: 5
- weights: uniform
- algorithm: auto
- leaf_size: 30
- p: 2 (power parameter of Minkowski metric)
- metric: minkowski
- metric_params: None

In [ ]:

```
knn =  KNeighborsRegressor(n_jobs=-1)
```

As usual, lets first check our CV scores with the default parameters!

In [ ]:

```
results = cross_val_score(
    knn,
    X_train,
    y_train,
    cv=kflod,
```

```
    scoring='neg_mean_absolute_error'
)
-results.mean()
```

Out[ ]: 0.4486728767123287

Note:

- This is better than our linear models!

Checking for train-test accuracy

In [ ]:
```
knn.fit(X_train,y_train)
```

Out[ ]: KNeighborsRegressor(n_jobs=-1)

In [ ]:
```
# accuracy on the train set
knn_pred = knn.predict(X_train)
mean_absolute_error(y_train,knn_pred)
```

Out[ ]: 0.3863758904109589

In [ ]:
```
# accuracy on the test set
knn_pred = knn.predict(X_test)
mean_absolute_error(y_test,knn_pred)
```

Out[ ]: 0.4345224043715846

Learning Curve

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

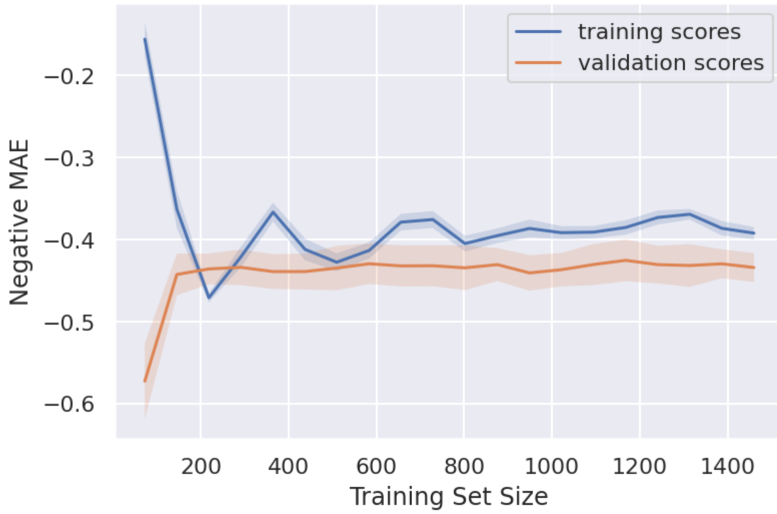
In [ ]:
```
# Helper function
alphas = np.logspace(-2, 0, 20)
def plot_with_err(x, data, **kwargs):
    mu, std = data.mean(1), data.std(1)
    lines = plt.plot(x, mu, "-", **kwargs)
    plt.fill_between(
        x,
        mu - std,
        mu + std,
        edgecolor="none",
        facecolor=lines[0].get_color(),
        alpha=0.2,
    )
```

In [ ]:
```
def plot_learning_curve():
    train_sizes = np.linspace(0.05,1,20)
    N_train, val_train, val_test = learning_curve(
        knn,X,y, train_sizes=train_sizes,cv=kflod,scoring='neg_mean_absolute_err
    )
    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:

- From this we conlude, adding more data to this stage, wont help us to improve the model!

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,
    y=y_train,
    param_name=param,
    param_range=param_grid,
    cv=kflod,
    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);
```

- **Number of Neighbors**

In [ ]:

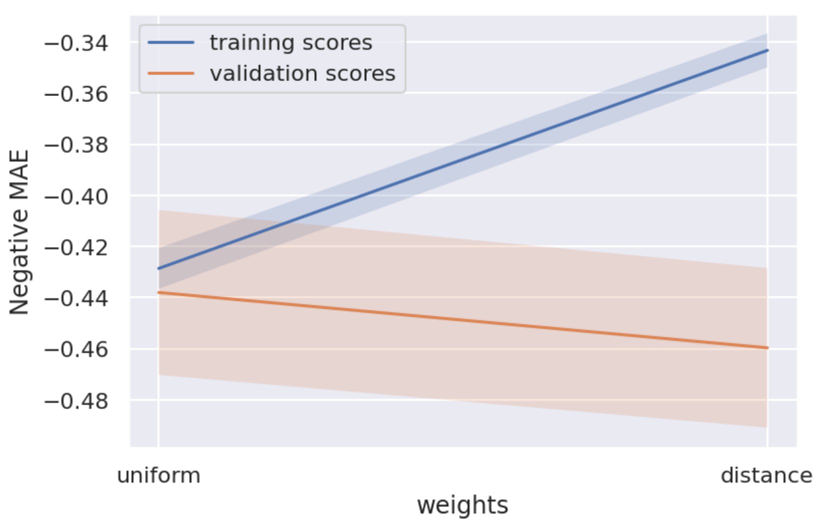
```
plot_validation_curve([5, 10, 15, 20, 30, 50, 75, 100],'n_neighbors',knn)
```

from figure its clear that the optimal range for number of neighbors is between 40 to 60

- **weights**

In [ ]:

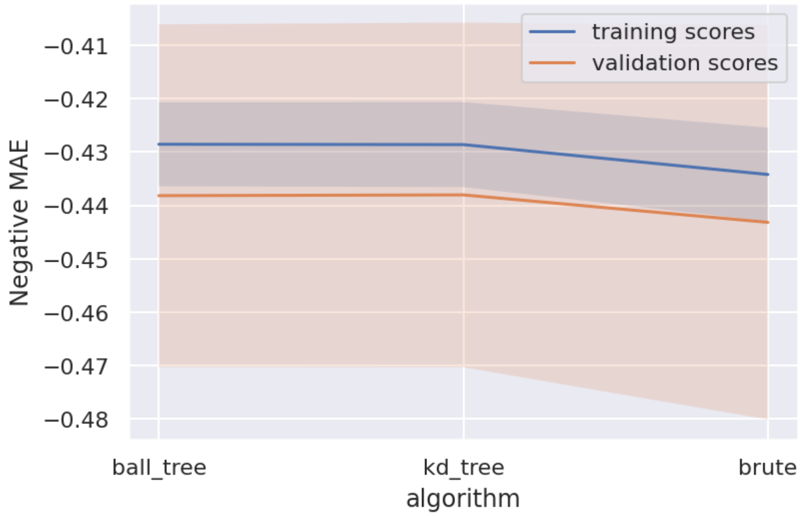
```
knn = KNeighborsRegressor(n_neighbors=45,n_jobs=-1)
plot_validation_curve(['uniform','distance'],'weights',knn)
```



There will be higher variance in the model if we use distance as our weights!

- **algorithm**

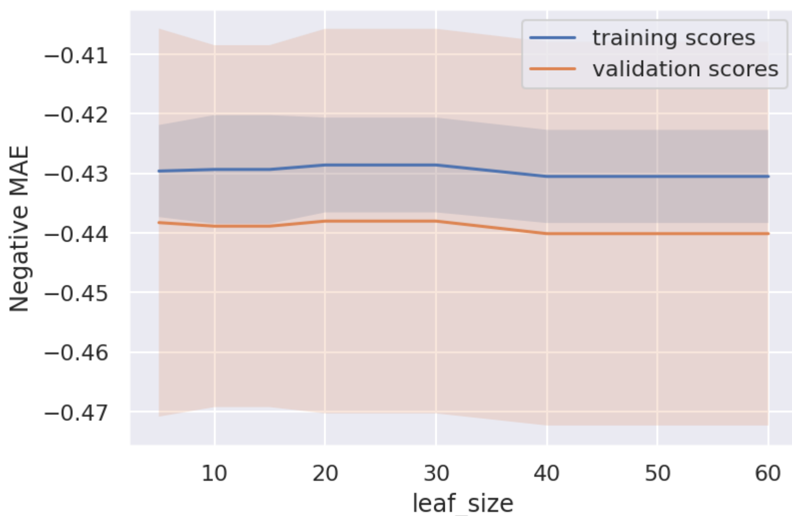
In [ ]:
```
plot_validation_curve(['ball_tree','kd_tree','brute'],'algorithm',knn)
```



there's no significant distance in algorithms

- **leaf size**

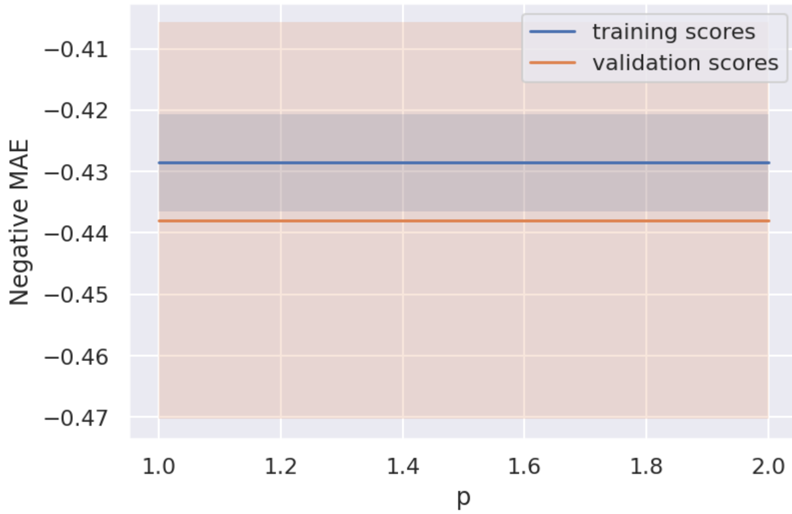
In [ ]:
```
knn = KNeighborsRegressor(n_neighbors=45,algorithm='kd_tree',n_jobs=-1)
plot_validation_curve([5,10,15,20,30,40,50,60],'leaf_size',knn)
```



No siginficant difference here too

- **p**

In [ ]:
```
plot_validation_curve([1,2],'p',knn)
```



doesnt matter which norm we use!

Hyper Parameter Tuning

Based on the knowledge of the validation curves we plotted lets do the hyperparameter tuning of KNN in order to find the best model!

In [ ]:

```
knn_params = {
    'n_neighbors':[40,45,50,55,60],
    'algorithm': ['ball_tree','kd_tree'],
    'weights':['uniform','distacne']
}
knn = KNeighborsRegressor(n_jobs=-1)
gcv = GridSearchCV(knn,knn_params,n_jobs=-1,cv=kflod,verbose=1,\
    scoring='neg_mean_absolute_error')
```

In [ ]:

```
# training the model
gcv.fit(X_train,y_train)
```

Out[ ]:

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
GridSearchCV(cv=KFold(n_splits=5, random_state=17, shuffle=True),
             estimator=KNeighborsRegressor(n_jobs=-1), n_jobs=-1,
             param_grid={'algorithm': ['ball_tree', 'kd_tree'],
                         'n_neighbors': [40, 45, 50, 55, 60],
                         'weights': ['uniform', 'distacne']},
             scoring='neg_mean_absolute_error', verbose=1)
```

In [ ]:

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

Out[ ]:

```
-0.4377368493150685
```

In [ ]:

```
# the best estimator
gcv.best_estimator_
```

Out[ ]:

```
KNeighborsRegressor(algorithm='ball_tree', n_jobs=-1, n_neighbors=50)
```

In [ ]:

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

Out[ ]:

```
{'algorithm': 'ball_tree', 'n_neighbors': 50, 'weights': 'uniform'}
```

Lets check the train-test accuracy of our best estimator

In [ ]:

```
# accuracy on train set
knn_pred = gcv.best_estimator_.predict(X_train)
mean_absolute_error(y_train,knn_pred)
```

Out[ ]:

```
0.42500967123287675
```

In [ ]:

```
# accuracy on the test set
knn_pred = gcv.best_estimator_.predict(X_test)
mean_absolute_error(y_test,knn_pred)
```

Out[ ]:

```
0.422436174863388
```

Final Note

- Theres little to none overfitting occuring here
- we have significantly increase the accuracy of our model to .42 meters!

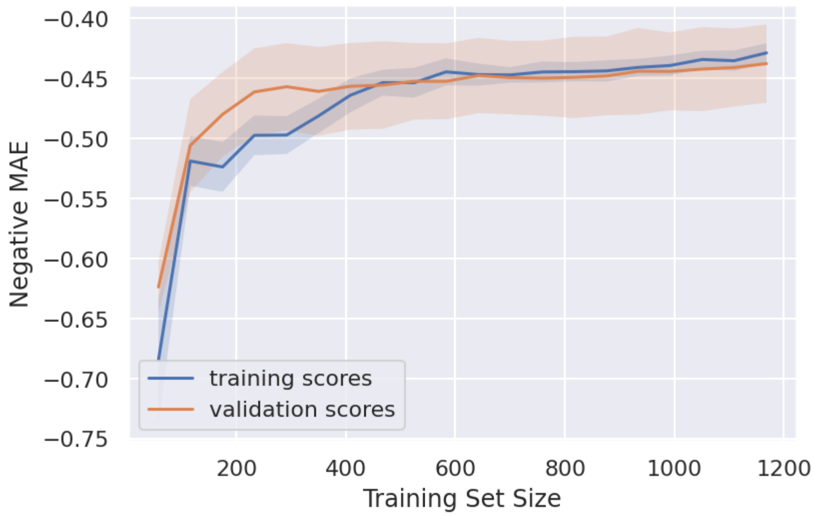
Learning Curve

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,y_train, \
        train_sizes=train_sizes,cv=kflod,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 the model

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

Out[ ]:
```
['./Saved Model/knn.joblib']
```