I'm gonna start with the Regularized linear models as my benchmark estimators! Models to be implemented in this notebook:

- Ridge Regression
- Lasso Regression
- Elastic

But first lets import some dependencies and our data

In [ ]:

```
# importing 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, learning_curve
from sklearn.model_selection import GridSearchCV, cross_val_score

from sklearn.linear_model import Ridge, Lasso, ElasticNet

from sklearn.preprocessing import PowerTransformer

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	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

	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

Lets make our X and y respectively

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 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
)
```

Power Transform (Box-Cox)

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)
```

In [ ]:

```
pt.lambdas_
```

Out[ ]:

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

Model Building

Ridge Regression

Linear least squares with l2 regularization.

lets now initialize our CV and model with default parameters provided by sklearn!

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

lets check our CV scores with default parameters

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

Out[ ]:
```
0.605630841351809
```

Lets check for train test accuracy now

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

Out[ ]:
```
Ridge(random_state=17)
```

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

Out[ ]:
```
0.6055762485546179
```

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

Out[ ]:
```
0.6011885371212594
```

Learning Curve

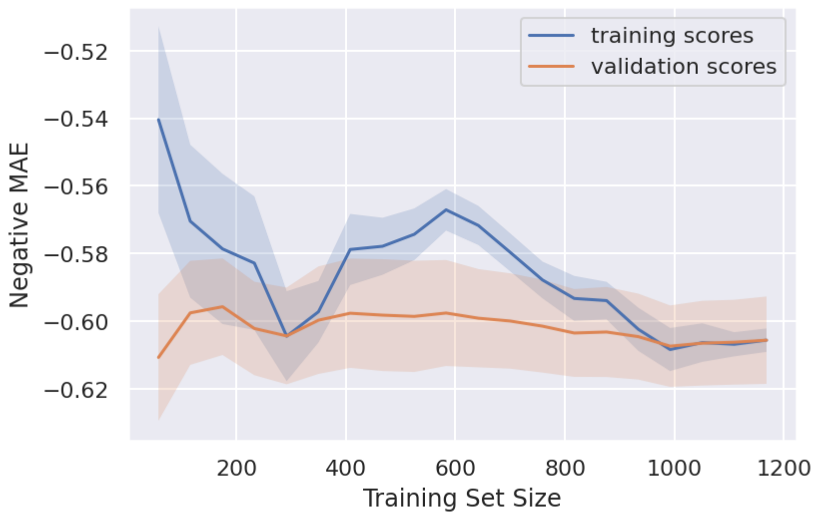
In [ ]:
```
# Helper function
alphas = np.logspace(-2, 0, 20)
def plot_with_err(x, data, **kwargs):
    mu, std = data.mean(1), data.std(1)
    lines = plt.plot(x, mu, "-", **kwargs)
    plt.fill_between(
        x,
        mu - std,
        mu + std,
        edgecolor="none",
        facecolor=lines[0].get_color(),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

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

```python
    train_sizes = np.linspace(0.05,1,20)
    N_train, val_train, val_test = learning_curve(
        ridge_regression,X_train_transformed,y_train_transformed, train_sizes=tr
    )
    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 [ ]:

```python
plot_learning_curve()
```



Note:

- Theres seems like no variance problem, thus tuning the hyperparameter alpha wont do much good here! So lets move onto LASSO!
- by MAE 0.6 means that, on average model is 0.6 meter wrong on predicting the correct value of water level!

Saving the Model

In [ ]:

```python
dump(ridge_regression,'./Saved Model/RidgeRegression.joblib')
```

Out[ ]:

```
['./Saved Model/RidgeRegression.joblib']
```

Lasso Regression

Linear Model trained with L1 prior as regularizer (aka the Lasso).

In [ ]:

```python
kflod = KFold(n_splits=5,shuffle=True, random_state=17)
lasso_regression = Lasso(random_state=17, max_iter=10000)
```

In [ ]:

```python
results = cross_val_score(
    lasso_regression,
    X_train_transformed,
```

```
    y_train_transformed,
    cv=kflod,
    scoring='neg_mean_absolute_error'
)
-results.mean()
```

Out[ ]: 0.8732801748385459

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

Out[ ]: Lasso(max_iter=10000, random_state=17)

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

Out[ ]: 0.8729811451213172

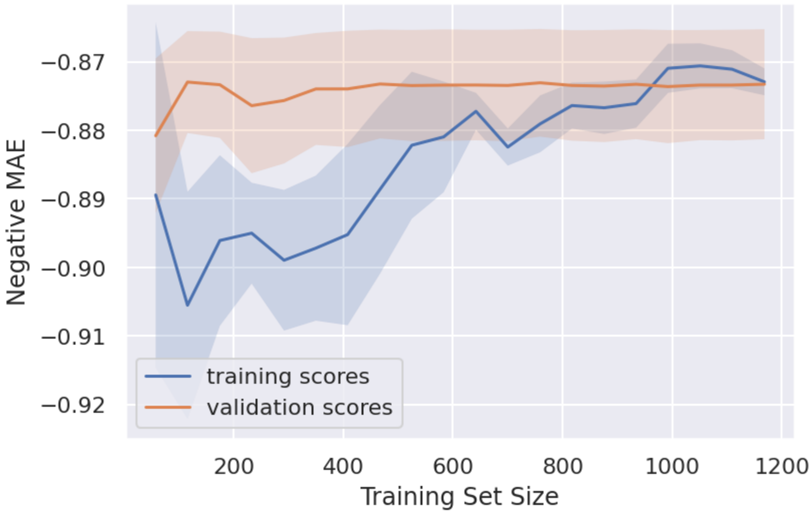
In [ ]:
```
# accuracy on the test set
lasso_pred = lasso_regression.predict(X_test_transformed)
mean_absolute_error(y_test_transformed,lasso_pred)
```

Out[ ]: 0.8666496419855901

Learning Curve

In [ ]:
```
def plot_learning_curve():
    train_sizes = np.linspace(0.05,1,20)
    N_train, val_train, val_test = learning_curve(
        lasso_regression,X_train_transformed,y_train_transformed, train_sizes=tr
    )
    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(lasso_regression,'./Saved Model/LassoRegression.joblib')
```

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