Untitled

March 11, 2019

```
In [64]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         from pprint import pprint
         from sklearn.model_selection import train_test_split, KFold
         from sklearn.metrics import confusion_matrix, accuracy_score, f1_score, precision_score
         %matplotlib inline
```

0.1 Class Lasso:

Lasso (least absolute shrinkage and selection operator; is a regression analysis method that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the statistical model it produces. Lasso regression performs L1 regularization, i.e. it adds a factor of sum of absolute value of coefficients in the optimization objective. Thus, lasso regression optimizes the following:

$$L\{X, Y, \theta\} = \frac{1}{2*m}\Big[\sum_{k=1}^{m}(Y - X(\theta))^2 + \lambda\|\theta\|_1\Big]$$

where λ is regularization parameter. - Class is callable and will calculate lasso regularization term on calling. - It has grad function which will calculate the gradient of lasso regularization term.

0.2 Class Ridge:

Ridge Regression is a remedial measure taken to alleviate multicollinearity amongst regression predictor variables in a model. Often predictor variables used in a regression are highly correlated. When they are, the regression coefficient of any one variable depend on which other predictor variables are included in the model, and which ones are left out. ridge regression performs L2 regularization, i.e. it adds a factor of sum of square of **L2** norm of coefficients in the optimization objective. Thus, ridge regression optimizes the following:

$$L\{X, Y, \theta\} = \frac{1}{2*m}\Big[\sum_{k=1}^{m}(Y - X(\theta))^2 + \lambda\|\theta\|_2^2\Big]$$

where λ is regularization parameter. - Class is callable and will calculate ridge regularization term on calling. - It has grad function which will calculate the gradient of ridge regularization term.

```python
In [41]: class lasso:
             def __init__(self, lambd):
                 self.lambd = lambd

             def __call__(self, w):
                 return 0.5 * self.lambd * np.linalg.norm(w)

             def grad(self, w):
                 return self.lambd * w


         class ridge:
             def __init__(self, lambd):
                 self.lambd = lambd

             def __call__(self, w):
                 return self.lambd * np.sum(np.abs(w))

             def grad(self, w):
                 return self.lambd * np.sign(w)
```

```python
In [42]: class LinearRegression:
             def __init__(self,
                          alpha=0.01,
                          iterariton=10000,
                          regularization="Ridge",
                          lambd=0):
                 self.alpha = alpha
                 self.iterariton = iterariton
                 self.theta_history = []
                 if regularization == "Ridge":
                     self.regularization = ridge(lambd)
                 else:
                     self.regularization = lasso(lambd)

             def cost_function(self, X, y, add = True):
                 regularization_param = 0
                 if add:
                     regularization_param = self.regularization(self.theta)
                 return (np.sum(np.power(((X @ self.theta.T) - y), 2)) +
                         regularization_param) / (2 * len(X))

             def standardize(self, X):
                 X_standardized = (X - self.mean) / self.var
                 return X_standardized

             def gradient_Descent(self, train_X, train_y):
                 self.cost = np.zeros(self.iterariton)
```

```
        m = len(train_X)
        for i in range(self.iterariton):
            grad = np.sum(
                train_X * (train_X @ self.theta.T - train_y),
                axis=0) + self.regularization.grad(self.theta)
            grad = grad * self.alpha / m
            self.theta = self.theta - grad
            self.cost[i] = self.cost_function(train_X, train_y)
            self.theta_history.append(self.theta.flatten())

    def train(self, train_X, train_y):
        self.mean, self.var = train_X.mean(), train_X.std()
        train_X = self.standardize(train_X)
        train_X = train_X.values
        ones = np.ones([train_X.shape[0], 1])
        train_X = np.concatenate((ones, train_X), axis=1)
        train_y = train_y.values
        limit = np.sqrt(1 / train_X.shape[1])
        self.theta = np.random.uniform(-limit, limit, (1, train_X.shape[1]))
        self.gradient_Descent(train_X, train_y)
        return self.cost_function(train_X, train_y, False)

    def predict(self, test_X):
        test_X = self.standardize(test_X)
        test_X = test_X.values
        ones = np.ones([test_X.shape[0], 1])
        test_X = np.concatenate((ones, test_X), axis=1)
        return test_X @ self.theta.T

    def error(self, y_pred, y_true):
        return (np.sum(np.square(y_pred - y_true))) / (2 * len(y_pred))

    def plot_wieghts_vs_iterations(self):
        plt.style.use('fivethirtyeight')
        weights = np.array(self.theta_history).T
        for i, w in enumerate(weights):
            plt.plot([i for i in range(1, self.iterariton + 1)],
                     w,
                     '-',
                     linewidth=1,
                     label="w" + str(i))
        plt.legend(bbox_to_anchor=(1.04, 1), loc="upper left")
        plt.show()
```

In [43]:
```
Admission_data = pd.read_csv('AdmissionDataset/data.csv')
```

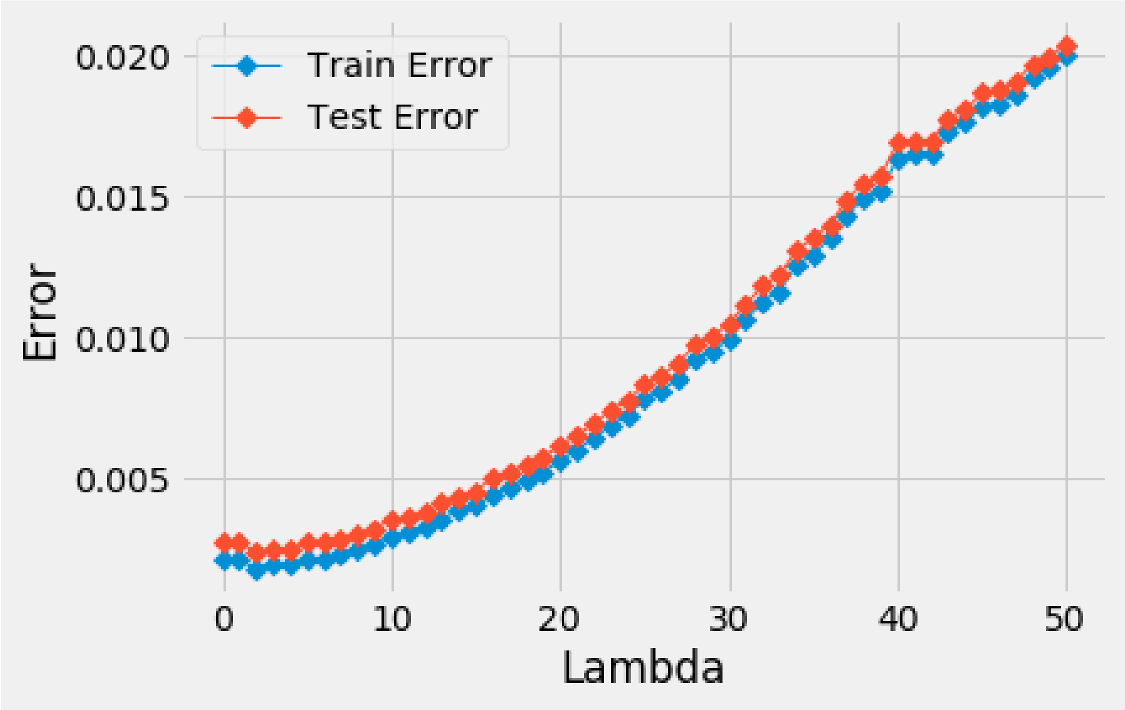
In [44]:
```
Admission_X = Admission_data.drop(['Serial No.', 'Chance of Admit '], axis=1)
Admission_y = Admission_data[['Chance of Admit ']]
```

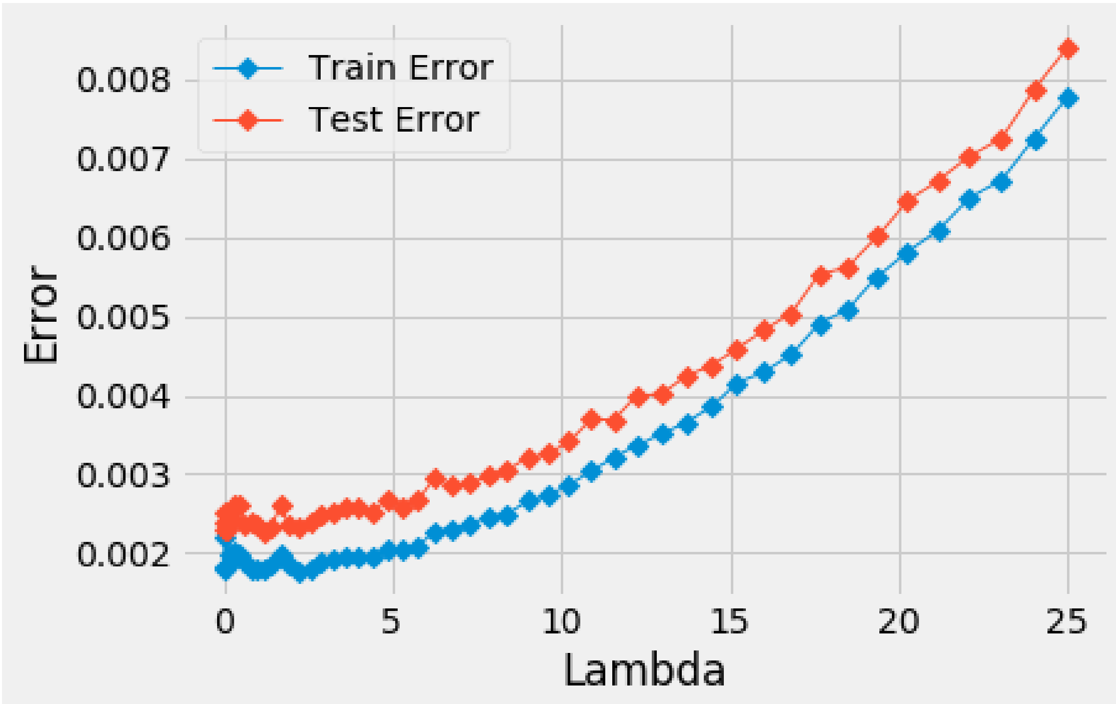
```
Admission_train_X, Admission_test_X, Admission_train_y, Admission_test_y = train_test_s
    Admission_X, Admission_y, random_state=4843548)
```

1 Part1

```
In [45]: lambdas = [(i**2) * 0.01 for i in range(0, 51)]
         def plot(lambdas):
             train_error = []
             test_error = []
             for lambd in lambdas:
                 LR = LinearRegression(lambd=lambd)
                 train_error.append(LR.train(Admission_train_X, Admission_train_y))
                 predicted_y = LR.predict(Admission_test_X)
                 test_error.append(LR.error(predicted_y, Admission_test_y.values))
             plt.style.use('fivethirtyeight')
             plt.plot(lambdas, train_error, '-D', linewidth=1, label="Train Error")
             plt.plot(lambdas, test_error, '-D', linewidth=1, label="Test Error")
             plt.legend(loc="best")
             plt.xlabel('Lambda')
             plt.ylabel("Error")
             plt.show()
```

```
In [46]: lambdas = [i for i in range(0, 51)]
         plot(lambdas)
         lambdas = [(i**2) * 0.01 for i in range(0, 51)]
         plot(lambdas)
```





1.1 Observations:

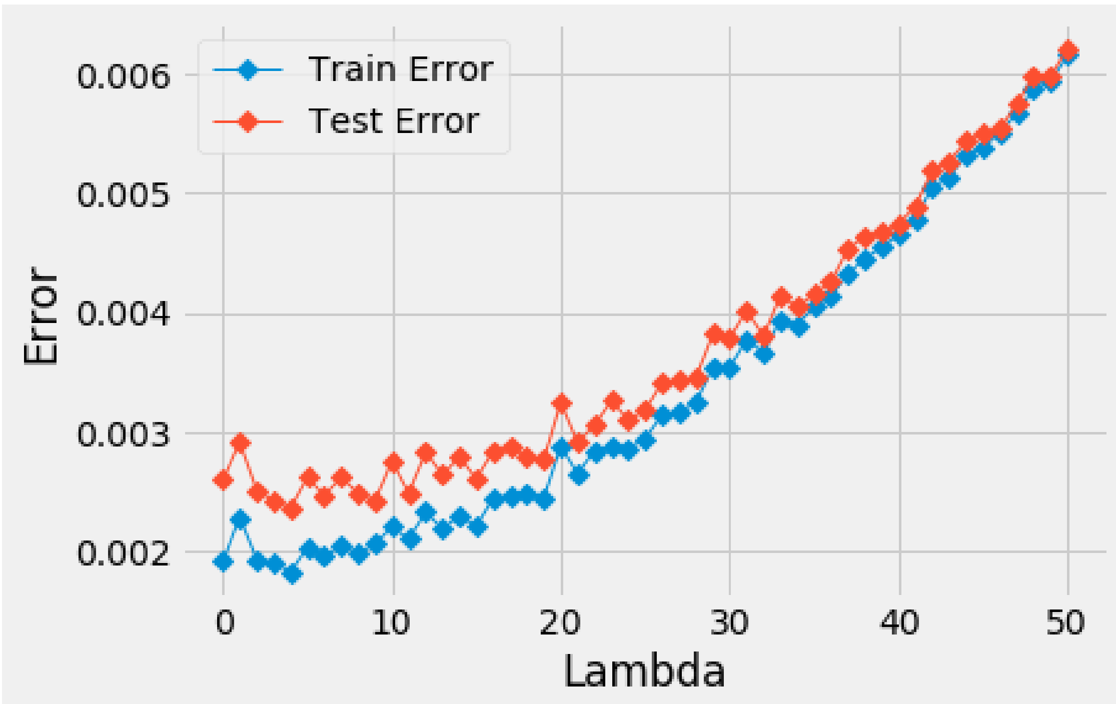
- The curve is smoothly increasing.
- Both training and testing errors are increasing.
- The curve is smooth also for very small values of lambda.
- Test error is getting become larger and larger than train error.

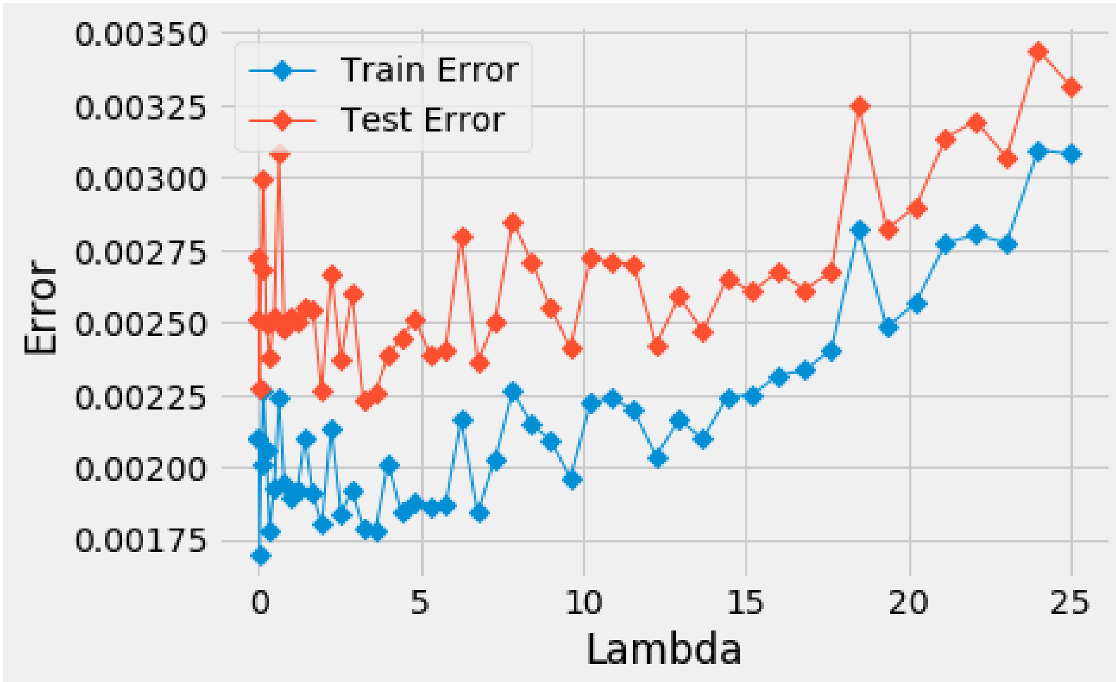
2 Part 2

```
In [47]: def plot(lambdas):
             train_error = []
             test_error = []
             for lambd in lambdas:
                 LR = LinearRegression(regularization="Lasso", lambd=lambd)
                 train_error.append(LR.train(Admission_train_X, Admission_train_y))
                 predicted_y = LR.predict(Admission_test_X)
                 test_error.append(LR.error(predicted_y, Admission_test_y.values))
             plt.xlabel("Lambda")
             plt.ylabel("Error")
             plt.style.use('fivethirtyeight')
             plt.plot(lambdas, train_error, '-D', linewidth=1, label="Train Error")
```

```
        plt.plot(lambdas, test_error, '-D', linewidth=1, label="Test Error")
        plt.legend(loc="best")
        plt.show()
```

```
In [48]: lambdas = [i for i in range(0, 51)]
         plot(lambdas)
         lambdas = [(i**2) * 0.01 for i in range(0, 51)]
         plot(lambdas)
```





2.1 Observations:

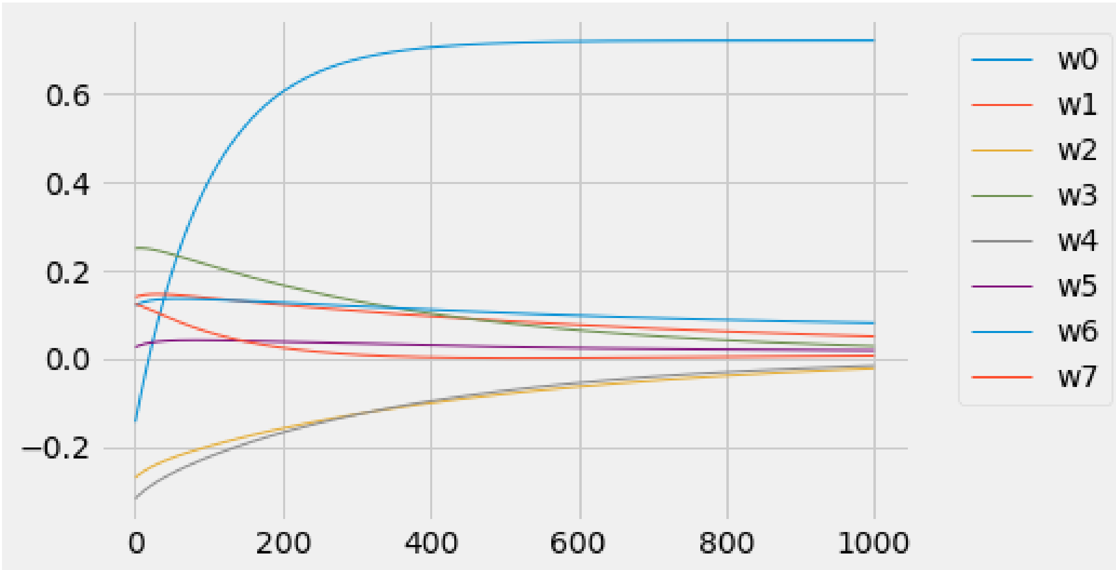
- The curve is smoothly increasing.
- Both training and testing errors are increasing.
- The curve is non smooth for very small values of lambda.
- Test error is getting become larger and larger than train error.

2.2 Part 3:

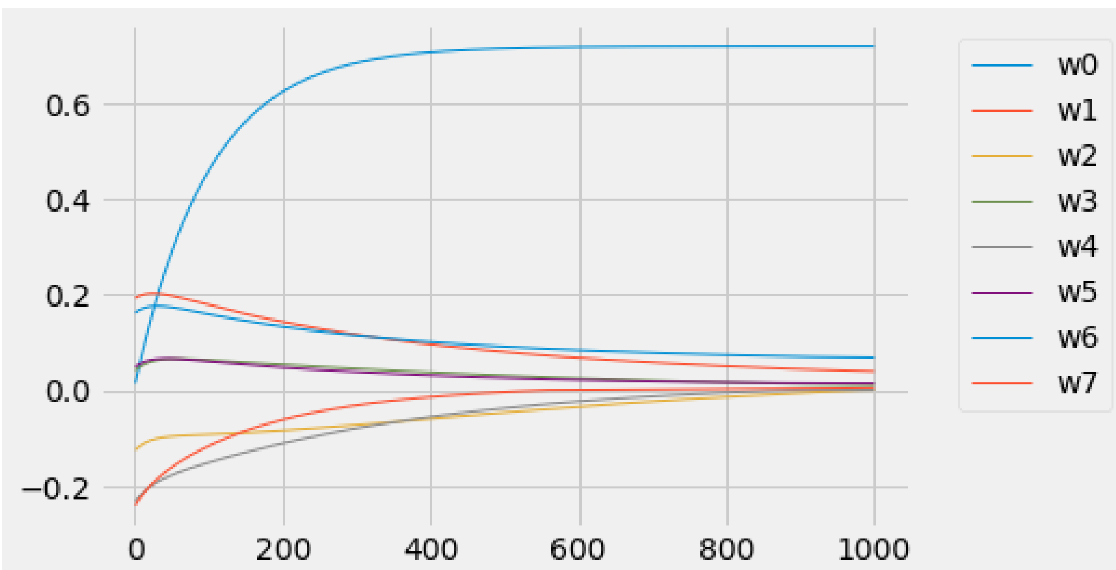
- For small values of lambda test error is higher than train error.
- As Lambda increases the test error tends towards train error.
- The difference between two is becoming almost 0.
- The smaller error for lower lambdas signify low bias.
- However the difference between two errors is high i.e. high variance.
- The samller difference in train and test error signifies low variance.
- The value of error is very high thus representing high bias.
- We want to find an value of lambda such that the magnitude of error is less as well as the difference between two is also less.
- Thus its a tradeoff between bias and variance. The plot help us in finding the right lambda

2.3 Part 4:

```
In [49]: LR = LinearRegression(regularization="Lasso", lambd=1)
         train_error = LR.train(Admission_train_X, Admission_train_y)
         LR.plot_wieghts_vs_iterations()
```



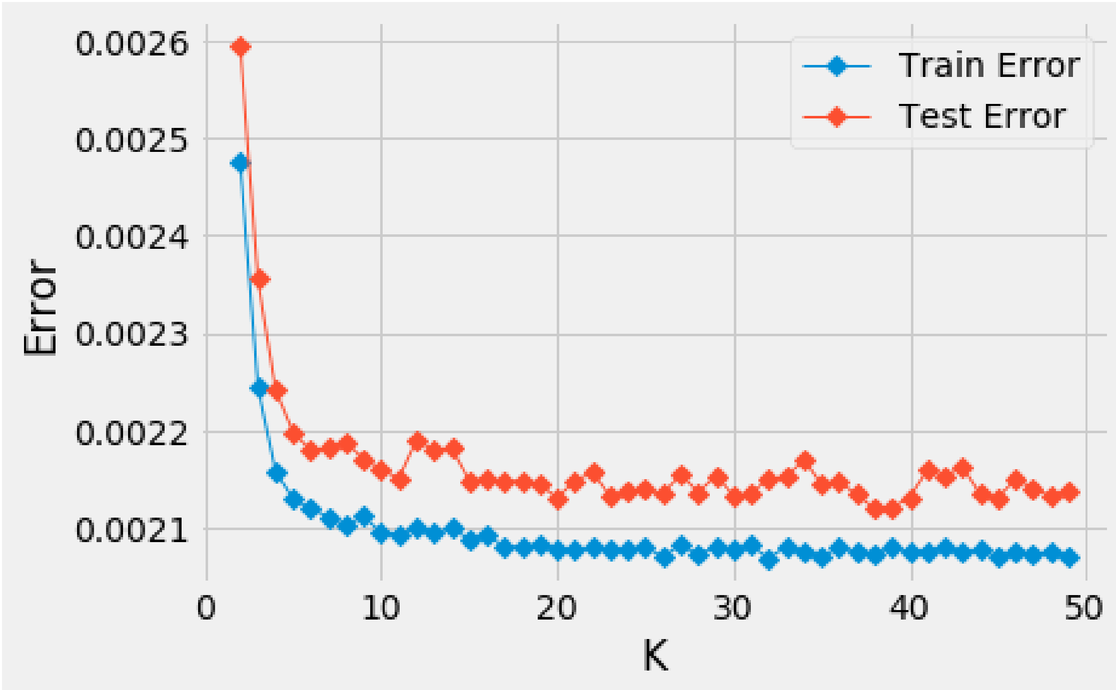

```
In [50]: LR = LinearRegression(lambd=1)
         train_error = LR.train(Admission_train_X, Admission_train_y)
         LR.plot_wieghts_vs_iterations()
```



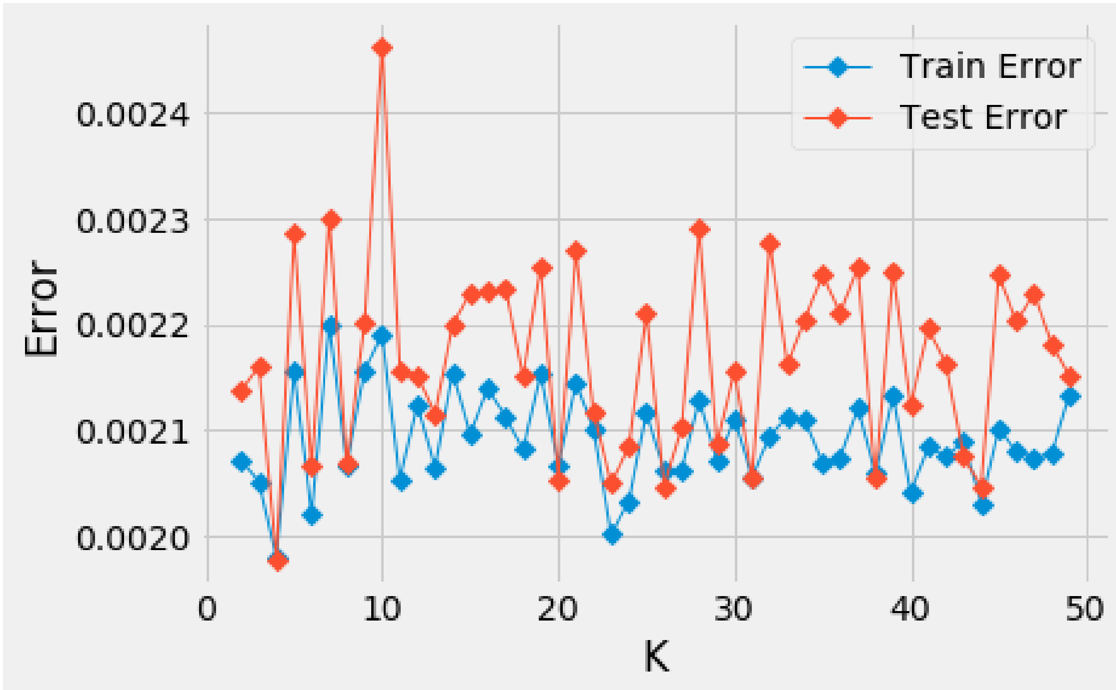
2.4 Observations:

- Most of the weights are becoming zero with increasing iterations.
- The result is mostly because of one parameter that is w0.
- Ridge wieghts are fater converging towards 0.

```
In [65]: def K_fold_cross_validation(X,
                                     y,
                                     alpha=0.01,
                                     iterariton=1000,
                                     regularization="Ridge",
                                     lambd=5,
                                     K=10):
             LR = LinearRegression(
                 alpha=alpha,
                 iterariton=iterariton,
                 regularization=regularization,
                 lambd=lambd)
             rkf = KFold(n_splits=K, random_state=None)
             train_error = []
             test_error = []
             for train_index, test_index in rkf.split(X):
                 #          display(train_index, test_index)
                 train_X, test_X = X.iloc[train_index], X.iloc[test_index]
                 train_y, test_y = y.iloc[train_index], y.iloc[test_index]
                 train_error.append(LR.train(train_X, train_y))
                 predicted_y = LR.predict(test_X)
                 test_error.append(LR.error(predicted_y, test_y.values))


         #      train_error = np.array(train_error)
         #      test_error = np.array(test_error)

             return np.mean(train_error), np.mean(test_error)

In [58]: ks = [i for i in range(2, 50)]
         train_errors = []
         test_errors = []
         for k in ks:
             train_error, test_error = K_fold_cross_validation(
                 Admission_X, Admission_y, K=k)
             train_errors.append(train_error)
             test_errors.append(test_error)

In [59]: plt.xlabel("K")
         plt.ylabel("Error")
         plt.style.use('fivethirtyeight')
         plt.plot(ks, train_errors, '-D', linewidth=1, label="Train Error")
         plt.plot(ks, test_errors, '-D', linewidth=1, label="Test Error")
         plt.legend(loc="best")
         plt.show()
```




```
In [68]: ks = [i for i in range(2, 50)]
         train_errors = []
         test_errors = []
         for k in ks:
             train_error, test_error = K_fold_cross_validation(
                 Admission_X, Admission_y, regularization="Lasso",K=k)
             train_errors.append(train_error)
             test_errors.append(test_error)

         plt.xlabel("K")
         plt.ylabel("Error")
         plt.style.use('fivethirtyeight')
         plt.plot(ks, train_errors, '-D', linewidth=1, label="Train Error")
         plt.plot(ks, test_errors, '-D', linewidth=1, label="Test Error")
         plt.legend(loc="best")
         plt.show()
```



2.5 Observations:

- For Ridge As K is increasing the the error is getting constant.
- However using Repeated KFold the error is very smooth.
- But using normal KFold the error hs some incosistencies.
- Lasso regularization is not producing smooth results.
- After a certain value of K increasing doesnot provide new insights.

In [62]:
```
def leave_one_out(X,
                  y,
                  alpha=0.01,
                  iterariton=1000,
                  regularization="Ridge",
                  lambd=0):
    return K_fold_cross_validation(
        X,
        y,
        alpha=alpha,
        iterariton=iterariton,
        regularization=regularization,
        lambd=lambd,
        K=len(X))
```

In [63]:
```
leave_one_out(Admission_X, Admission_y)
```

Out[63]:
```
(0.0021230744084915288, 0.002209313418042245)
```