predict_airfoil_self_nose

April 16, 2019

1 SCS3253 Machine Learning Project

2 Group I

3 ** Investigating Predictive Modeling for Airfoil Self-Noise **

Submitted by :
* Amarendra Sabat * Claudinei Daitx * Suwei (Stream) Qi

- **Instruction**
- The NASA data set comprises different size NACA 0012 airfoils at various wind tunnel speeds and angles of attack.
- The span of the airfoil and the observer position were the same in all of the experiments.
- The NASA data set was obtained from a series of aerodynamic and acoustic tests of two and three-dimensional airfoil blade sections conducted in an anechoic wind tunnel.
- Relevant Papers:
  - T.F. Brooks, D.S. Pope, and A.M. Marcolini. Airfoil self-noise and prediction. Technical report, NASA RP-1218, July 1989.
  - K. Lau. A neural networks approach for aerofoil noise prediction. Masterâs thesis, Department of Aeronautics. Imperial College of Science, Technology and Medicine (London, United Kingdom), 2006.
  - R. Lopez. Neural Networks for Variational Problems in Engineering. PhD Thesis, Technical University of Catalonia, 2008.
- Citation :
- Dua, D. and Graff, C. (2019). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science.

Link: Airfoil Self-Noise Data Set
##1. Import Python libraries

```
In [0]: import os
        import warnings
        import pandas as pd
        import seaborn as sns
        import numpy as np

        # To plot pretty figures
        %matplotlib inline
        import matplotlib
        import matplotlib.pyplot as plt
        from IPython.core.display import HTML, display

        # Machine learn packages
        import tensorflow as tf
        from sklearn.pipeline import Pipeline
        from sklearn.model_selection import train_test_split
        from sklearn.model_selection import GridSearchCV
        from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet, BayesianR
        from sklearn.svm import SVR
        from sklearn.preprocessing import StandardScaler, QuantileTransformer, MaxAbsScaler
        from sklearn.decomposition import PCA
        from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
        from mpl_toolkits.mplot3d import Axes3D
        from tensorflow import keras

        # Remove all warnings in this notebook
        warnings.filterwarnings('ignore')
        tf.logging.set_verbosity(tf.logging.ERROR)

        # Same random seed state
        np.random.seed(42)
        random_state=42
```

3.1 2. Load airfloil dataset

3.1.1 2.1 Attribute Information

1. Frequency (Hertzs)
2. Angle of attack (degrees)
3. Chord length (meters)
4. Free-stream velocity (meters per second)
5. Suction side displacement thickness (meters)

The only output is: 6. Scaled sound pressure level (decibels)

```
In [0]: url_file = 'https://archive.ics.uci.edu/ml/machine-learning-databases/00291/airfoil_se
        columns = ['frequency',
                   'angle_of_attack',
                   'chord_length',
```

```
               'free_stream_velocity',
               'suction_side_displacement_thickness',
               'scaled_sound_pressure_level']

features = ['frequency','angle_of_attack',
            'chord_length',
            'free_stream_velocity',
            'suction_side_displacement_thickness']

airfoil_dataset = pd.read_csv(url_file, sep='\t', header=None, names=columns)
```

In [3]:
```
airfoil_dataset.head()
```

Out[3]:
```
   frequency  angle_of_attack  chord_length  free_stream_velocity  \
0        800              0.0        0.3048                  71.3
1       1000              0.0        0.3048                  71.3
2       1250              0.0        0.3048                  71.3
3       1600              0.0        0.3048                  71.3
4       2000              0.0        0.3048                  71.3

   suction_side_displacement_thickness  scaled_sound_pressure_level
0                             0.002663                      126.201
1                             0.002663                      125.201
2                             0.002663                      125.951
3                             0.002663                      127.591
4                             0.002663                      127.461
```

In [4]:
```
airfoil_dataset.tail()
```

Out[4]:
```
      frequency  angle_of_attack  chord_length  free_stream_velocity  \
1498       2500             15.6        0.1016                  39.6
1499       3150             15.6        0.1016                  39.6
1500       4000             15.6        0.1016                  39.6
1501       5000             15.6        0.1016                  39.6
1502       6300             15.6        0.1016                  39.6

      suction_side_displacement_thickness  scaled_sound_pressure_level
1498                             0.052849                      110.264
1499                             0.052849                      109.254
1500                             0.052849                      106.604
1501                             0.052849                      106.224
1502                             0.052849                      104.204
```

In [5]:
```
airfoil_dataset.describe()
```

Out[5]:
```
         frequency  angle_of_attack  chord_length  free_stream_velocity  \
count  1503.000000      1503.000000   1503.000000           1503.000000
mean   2886.380572         6.782302      0.136548             50.860745
std    3152.573137         5.918128      0.093541             15.572784
```

```
min       200.000000        0.000000      0.025400               31.700000
25%       800.000000        2.000000      0.050800               39.600000
50%      1600.000000        5.400000      0.101600               39.600000
75%      4000.000000        9.900000      0.228600               71.300000
max     20000.000000       22.200000      0.304800               71.300000

       suction_side_displacement_thickness  scaled_sound_pressure_level
count                          1503.000000                  1503.000000
mean                              0.011140                   124.835943
std                               0.013150                     6.898657
min                               0.000401                   103.380000
25%                               0.002535                   120.191000
50%                               0.004957                   125.721000
75%                               0.015576                   129.995500
max                               0.058411                   140.987000
```

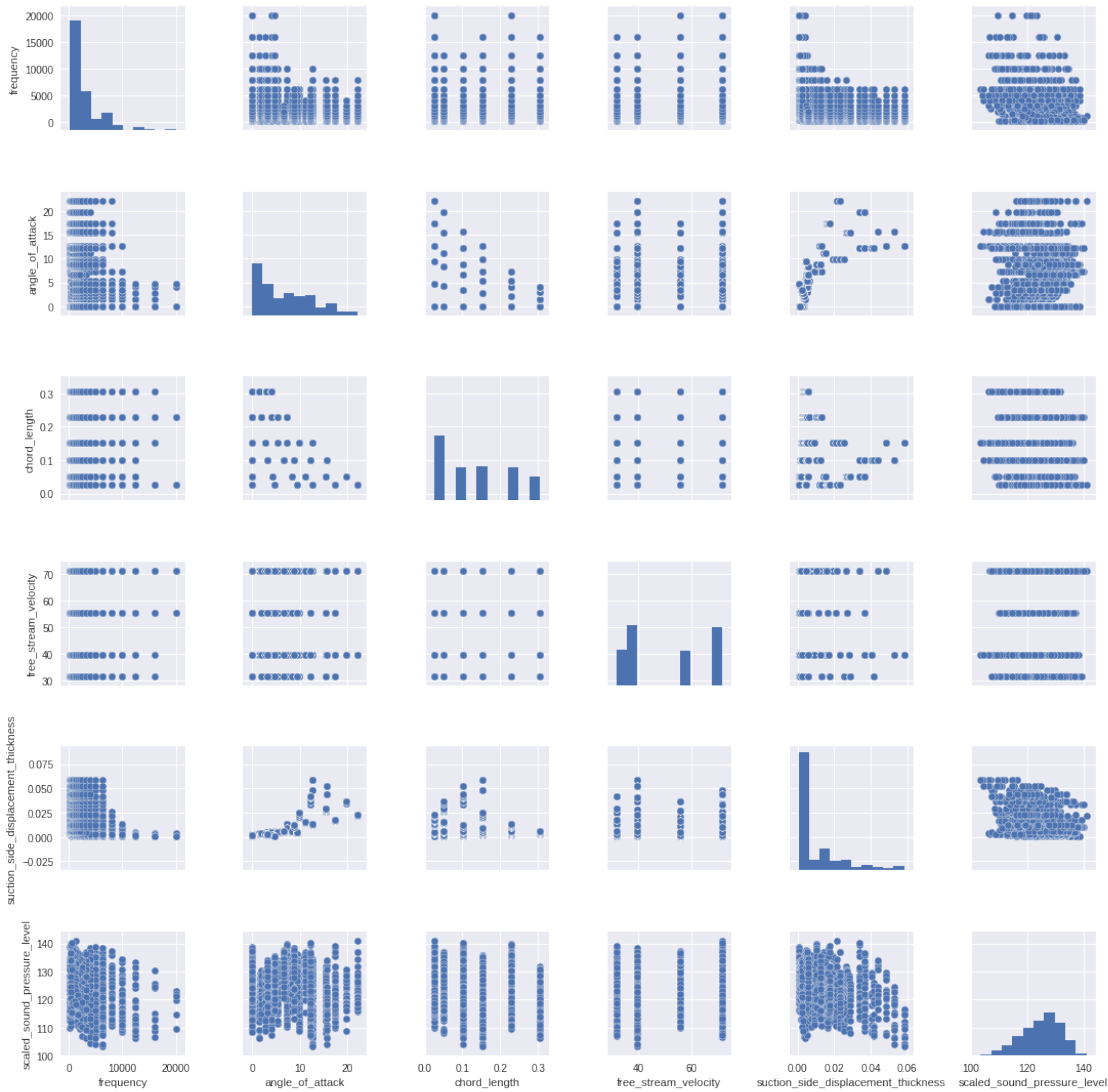
In [6]:
```
airfoil_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1503 entries, 0 to 1502
Data columns (total 6 columns):
frequency                              1503 non-null int64
angle_of_attack                        1503 non-null float64
chord_length                           1503 non-null float64
free_stream_velocity                   1503 non-null float64
suction_side_displacement_thickness    1503 non-null float64
scaled_sound_pressure_level            1503 non-null float64
dtypes: float64(5), int64(1)
memory usage: 70.5 KB
```

3.1.2 2.2 Insights

In [7]:
```
airfoil_plot = airfoil_dataset.copy()
sns.pairplot(airfoil_plot)
```

Out[7]:
```
<seaborn.axisgrid.PairGrid at 0x7f2659096320>
```



- There are only four free stream velocities.
  - 31.7 m/s
  - 39.6 m/s
  - 55.5 m/s
  - 71.3 m/s

In [8]:
```
airfoil_plot["free_stream_velocity"].value_counts()
```

Out[8]:
```
39.6    480
71.3    465
31.7    281
55.5    277
Name: free_stream_velocity, dtype: int64
```

- There are six chord lengths:
  - 2.5 cm
  - 5 cm
  - 10 cm
  - 15 cm
  - 22 cm
  - 30 cm

In [9]:
```
airfoil_plot["chord_length"].value_counts()
```

Out[9]:
```
0.0254    278
0.1524    271
0.2286    266
0.1016    263
0.0508    237
0.3048    188
Name: chord_length, dtype: int64
```

3.2 3. Examine dimensions in a graphic

You can use this concept to reduce the number of features in your dataset without having to lose much information and keep or improve the model's performance. In this case, you can see two different dimensionality reductions PCA and T-SNE and, it shows that this dataset is non-linear.

3.2.1 3.1 Split features and targets

In this section, I will split the original dataset in two new datasets:

1. Features: all columns except the target column
2. Target: only the target column

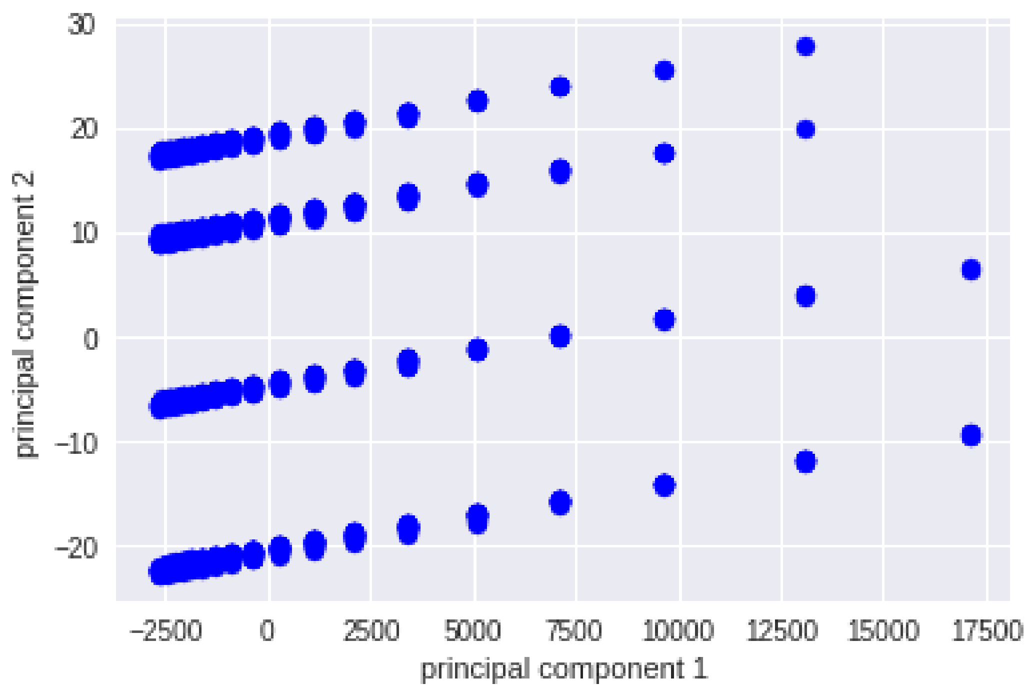
In [0]:
```
train_data = airfoil_dataset.copy()
train_set = train_data.drop("scaled_sound_pressure_level", axis = 1)
train_labels = train_data["scaled_sound_pressure_level"].copy()
```

3.2.2 3.2 Visualization using PCA

Using PCA is possible to see this dataset is non-linear and I can not get good results if I use a linear model such as Linear Regression.

In [11]:
```
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(train_set)
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2'])

finalDf = pd.concat([principalDf, train_labels], axis = 1)

fig = plt.figure()
ax = fig.add_subplot(1,1,1)
```

```
ax.scatter(finalDf['principal component 1'], finalDf['principal component 2'], c='b',

ax.set_xlabel('principal component 1')
ax.set_ylabel('principal component 2')


plt.show()
```

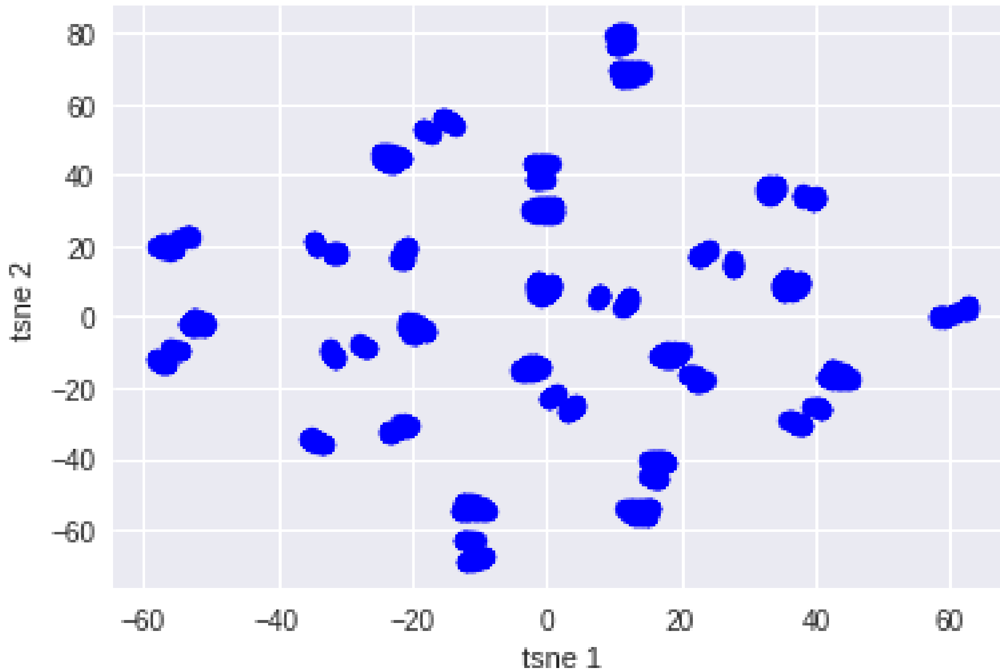


3.2.3 3.3 Visualization using t-SNE

Using T-SNE you can see in this dataset all the clusters and detect that you need a non-linear model to get the best results for the prediction.

```
In [12]: from sklearn.manifold import TSNE
         import time
         time_start = time.time()

         data_tsne = TSNE(random_state=random_state).fit_transform(train_set)

         fig = plt.figure()
         ax = fig.add_subplot(1,1,1)

         ax.scatter(data_tsne[:,0], data_tsne[:,1],  c='b', marker='o')
```

```
ax.set_xlabel('tsne 1')
ax.set_ylabel('tsne 2')


plt.show()
```



3.3 Choosing my model

3.3.1 4.1 Feature Engine

For this scenario I'm using three feature engines:

- Quantile transformer: This method transforms the features to follow a uniform or a normal distribution. This method is good when you work with non-linear datasets
- Max Abs scaler: Scale each feature by its maximum absolute value.
- Standard scaler: Standardize features by removing the mean and scaling to unit variance.

```
In [0]: train_set = QuantileTransformer(random_state=0).fit_transform(train_set)
        train_set = MaxAbsScaler().fit_transform(train_set)
        train_set = StandardScaler().fit_transform(train_set)
```

```
In [0]: X_train, X_test, y_train, y_test = train_test_split(train_set,
                                                            train_labels,
                                                            test_size=0.2)
```

```
In [0]: def show_table(data):
            html = ['<link rel=\"stylesheet\" href=\"https://www.w3schools.com/w3css/4/w3.css\"
                    "<table class=\"w3-table-all\"> ",
                    '<tr>',
                    '<th>Model</th>',
                    '<th>R2 score</th>',
                    '<th>MSE score</th>',
                    '</tr>']
            for row in data:
                key, r2, mse = row
                html.append("<tr>")
                html.append("<td>{0}</td>".format(key))
                html.append("<td>{0}</td>".format(r2))
                html.append("<td>{0}</td>".format(mse))
                html.append("</tr>")

            html.append("</table>")
            return html

        def plot_history(history):
            hist = pd.DataFrame(history.history)
            hist['epoch'] = history.epoch

            plt.figure()
            plt.xlabel('Epoch')
            plt.ylabel('Mean Abs Error [scaled_sound_pressure_level]')
            plt.plot(hist['epoch'], hist['mean_absolute_error'],
                   label='Train Error')
            plt.plot(hist['epoch'], hist['val_mean_absolute_error'],
                   label = 'Val Error')
            plt.ylim([0,20])
            plt.legend()

            plt.figure()
            plt.xlabel('Epoch')
            plt.ylabel('Mean Square Error [$scaled_sound_pressure_level^2$]')
            plt.plot(hist['epoch'], hist['mean_squared_error'],
                   label='Train Error')
            plt.plot(hist['epoch'], hist['val_mean_squared_error'],
                   label = 'Val Error')
            plt.ylim([0,40])
            plt.legend()
            plt.show()
```

3.3.2 Machine learning models

I have the class ModelEstimator to train and predict all models. In this case, I am using linear and non-linear models to see the difference between them.

```
In [0]: class ModelEstimator():
            def __init__(self, models, parameters):
                self.models = models
                self.parameters = parameters

            def fit(self, X_train, X_test, y_train, y_test, cv=3, refit=True):
                results = []
                for key, model in self.models.items():
                    current_parameter = self.parameters.get(key, {})
                    gs = GridSearchCV(model,
                                      current_parameter,
                                      cv=cv,
                                      scoring=None,
                                      refit=refit,
                                      return_train_score=True)
                    gs.fit(X_train, y_train)
                    y_predict = gs.predict(X_test)

                    results.append((key, r2_score(y_test, y_predict), mean_squared_error(y_tes

                return results
```

Now I am choosing a few models and parameters to test and get the best result for each model. In this case I do not need to choose a specific parameter because the ModelEstimator class is using GridSearchCV to decide the best estimator for each model.

```
In [0]: models_to_train = {
                'LinearRegression': LinearRegression(),
                'Ridge': Ridge(),
                'Lasso': Lasso(),
                'ElasticNet': ElasticNet(),
                'BayesianRidge': BayesianRidge(compute_score=True),
                'SVR': SVR()
            }

        parameters_to_train = {
            'LinearRegression': {'fit_intercept': [True, False], 'normalize': [True, False]},
            'Ridge': {'alpha': [0.1, 1.0, 10.0]},
            'Lasso': {'alpha': [0.1, 1.0, 10.0]},
            'ElasticNet': {'alpha': [0.1, 1.0, 10.0], 'l1_ratio': [0, 0.1, 0.5, 1, 10, 100]},
            'BayesianRidge': {},
            'SVR': {'kernel': ['linear', 'poly', 'rbf', 'sigmoid'], 'gamma': ['auto', 'scale']
        }

        train_estimator = ModelEstimator(models_to_train, parameters_to_train)
        results = train_estimator.fit(X_train, X_test, y_train, y_test, cv=5)
```

3.3.3 4.3 Neural network

Another approach is to use neural networks to find best results. In this case, I am using five hidden layers and Ridge (L2) for the regularization.

In [0]:
```
model_activation = tf.nn.relu
model_kernel = keras.regularizers.l2(0.01)
layer_unit = 64


model = keras.Sequential([
    keras.layers.Flatten(input_shape=[5]),

    keras.layers.Dense(layer_unit,
                       activation=model_activation,
                       kernel_regularizer=model_kernel),

    keras.layers.Dense(layer_unit,
                       activation=model_activation,
                       kernel_regularizer=model_kernel),

    keras.layers.Dense(layer_unit,
                       activation=model_activation,
                       kernel_regularizer=model_kernel),

    keras.layers.Dense(layer_unit,
                       activation=model_activation,
                       kernel_regularizer=model_kernel),

    keras.layers.Dense(1)
])


model.compile(loss='mean_squared_error',
              optimizer='adam',
              metrics=['mean_absolute_error', 'mean_squared_error'])

early_stop = keras.callbacks.EarlyStopping(monitor='val_loss',patience=10)

history  = model.fit(X_train, y_train, epochs=500, validation_split = 0.2, verbose=0)

y_pred = model.predict(X_test).flatten()

results.append(('Neural network', r2_score(y_test, y_pred), mean_squared_error(y_test,
```

3.4 Results

- Using linear regressions such as LinearRegression the best model has an accuracy of nearby 45%.

- Using non-linear regressions such as SVR the best model has an accuracy of nearby 79%. It is 34% more than linear models.
- Using a neural network the accuracy is around 88%. It is around 10% more than SVR.

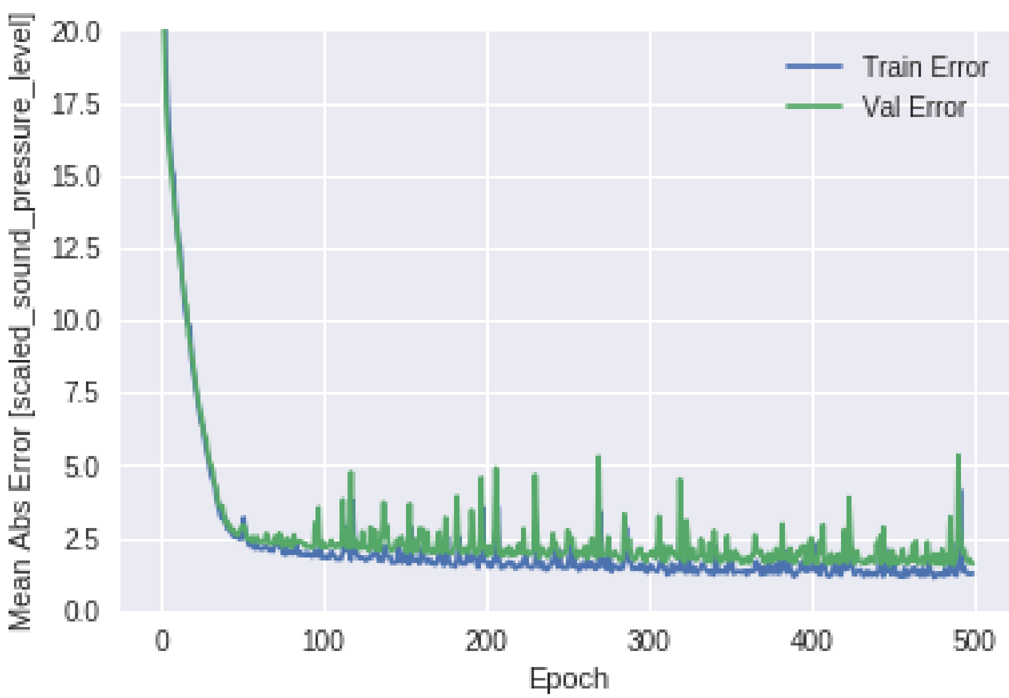
For this dataset using a neural network, you can get the best result but, it does not mean the SVR not fit well. It means for this dataset and this amount of data (1503 rows) a neural network fits better than an SVR model.

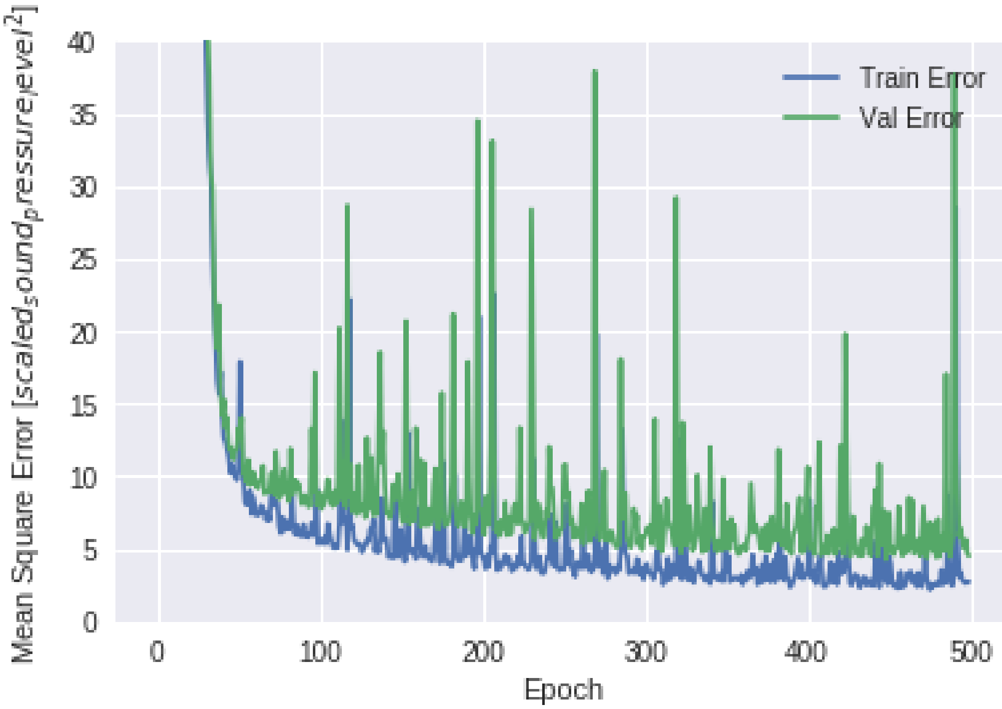
```
In [19]: html_results = show_table(results)
         display(HTML(''.join(html_results)))
```

```
<IPython.core.display.HTML object>
```

In these graphs you can see the best result, for this scenario is using Neural network.

```
In [20]: plot_history(history)
```




Mean Square Error [$scaled_sound_pressure_level^2$]
Epoch
Train Error
Val Error
0
5
10
15
20
25
30
35
40
0
100
200
300
400
500