

# Airfoil\_Self\_Noise Data Set

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.

Lets get started!

## Loading the data

```
In [1]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

```
In [4]: df = pd.read_csv('airfoil_self_noise.dat', sep='\t', names=['freq', 'angle',
'chord', 'velocity', 'displacement', 'pressure'])
```

```
In [5]: df.head()
```

Out[5]:

	freq	angle	chord	velocity	displacement	pressure
0	800	0.0	0.3048	71.3	0.002663	126.201
1	1000	0.0	0.3048	71.3	0.002663	125.201
2	1250	0.0	0.3048	71.3	0.002663	125.951
3	1600	0.0	0.3048	71.3	0.002663	127.591
4	2000	0.0	0.3048	71.3	0.002663	127.461

## Data Check

Check if any kind of data processing required

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1503 entries, 0 to 1502
Data columns (total 6 columns):
freq          1503 non-null int64
angle         1503 non-null float64
chord         1503 non-null float64
velocity      1503 non-null float64
displacement  1503 non-null float64
pressure      1503 non-null float64
dtypes: float64(5), int64(1)
memory usage: 70.5 KB
```

In [7]: `df.describe()`

Out[7]:

	freq	angle	chord	velocity	displacement	pressure
<b>count</b>	1503.000000	1503.000000	1503.000000	1503.000000	1503.000000	1503.000000
<b>mean</b>	2886.380572	6.782302	0.136548	50.860745	0.011140	124.835943
<b>std</b>	3152.573137	5.918128	0.093541	15.572784	0.013150	6.898657
<b>min</b>	200.000000	0.000000	0.025400	31.700000	0.000401	103.380000
<b>25%</b>	800.000000	2.000000	0.050800	39.600000	0.002535	120.191000
<b>50%</b>	1600.000000	5.400000	0.101600	39.600000	0.004957	125.721000
<b>75%</b>	4000.000000	9.900000	0.228600	71.300000	0.015576	129.995500
<b>max</b>	20000.000000	22.200000	0.304800	71.300000	0.058411	140.987000

In [9]: `df.isnull().T.any().T.any()`

Out[9]: False

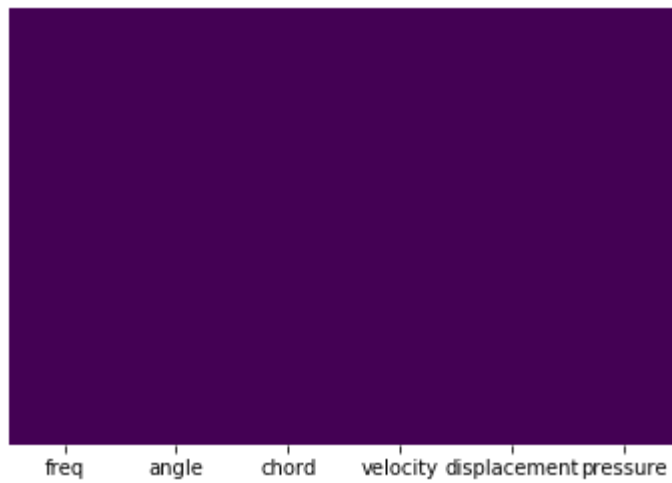
In [11]: `df.isnull().sum()`

```
Out[11]: freq          0
angle            0
chord            0
velocity         0
displacement     0
pressure         0
dtype: int64
```

## Exploratory Data Analysis

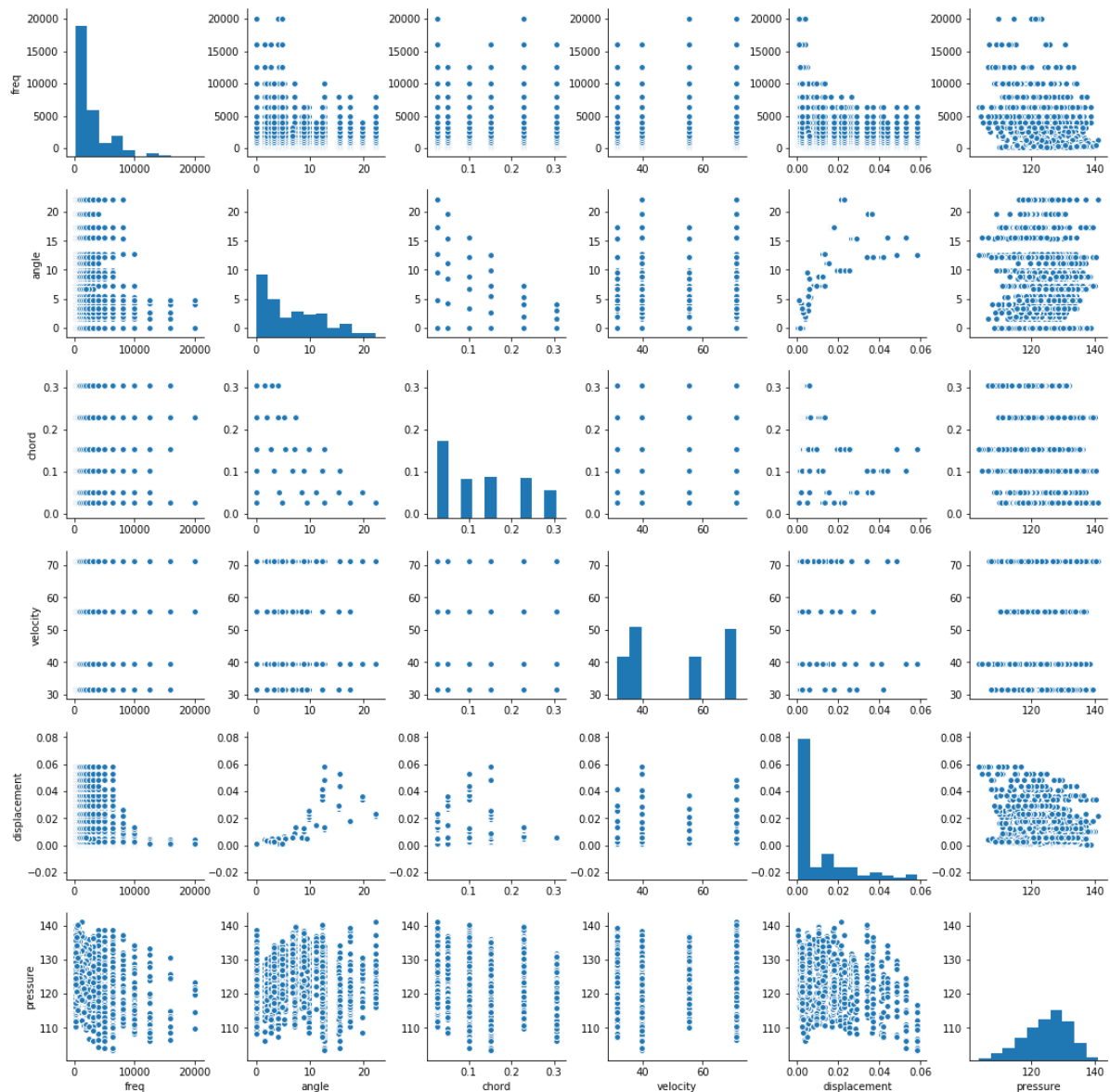
```
In [12]: sns.heatmap(df.isnull(), cbar=False, cmap='viridis', yticklabels=False)
```

```
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0xc3d6470>
```



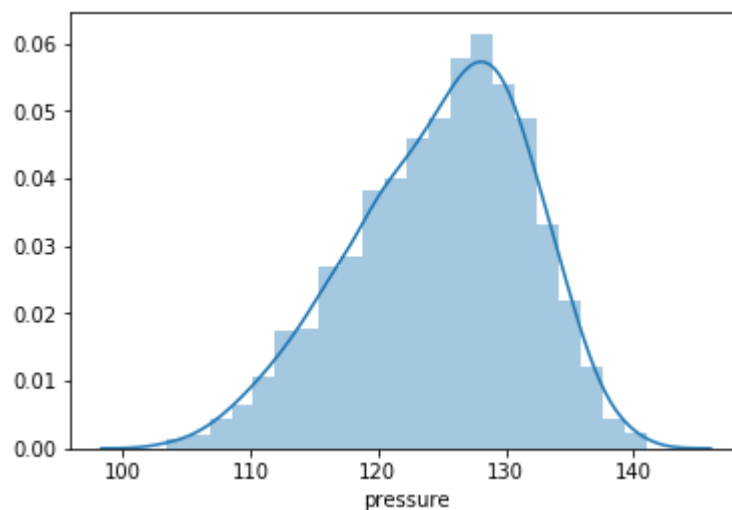
```
In [13]: sns.pairplot(df)
```

```
Out[13]: <seaborn.axisgrid.PairGrid at 0xc01f4e0>
```



```
In [14]: sns.distplot(df.pressure)
```

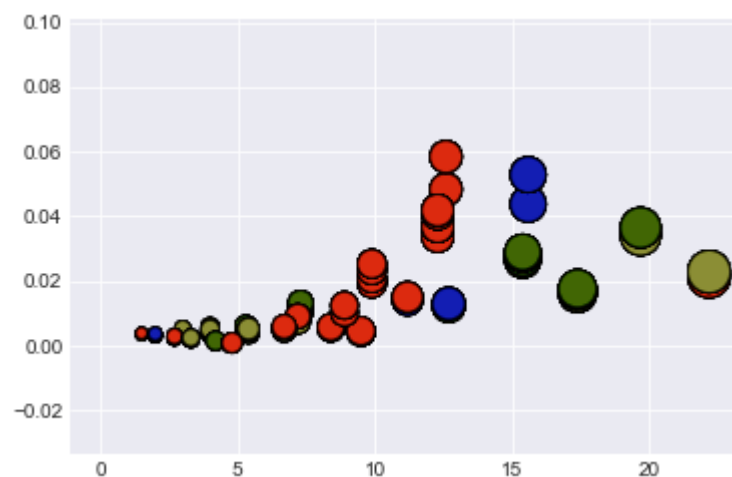
```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0xda4ed30>
```



**Here No Linear Relationship is to be found. Hence Linear Regression may not be the right model for this dataset. However, just for the sake of practicing, we will go forward and apply linear regression on this model.**

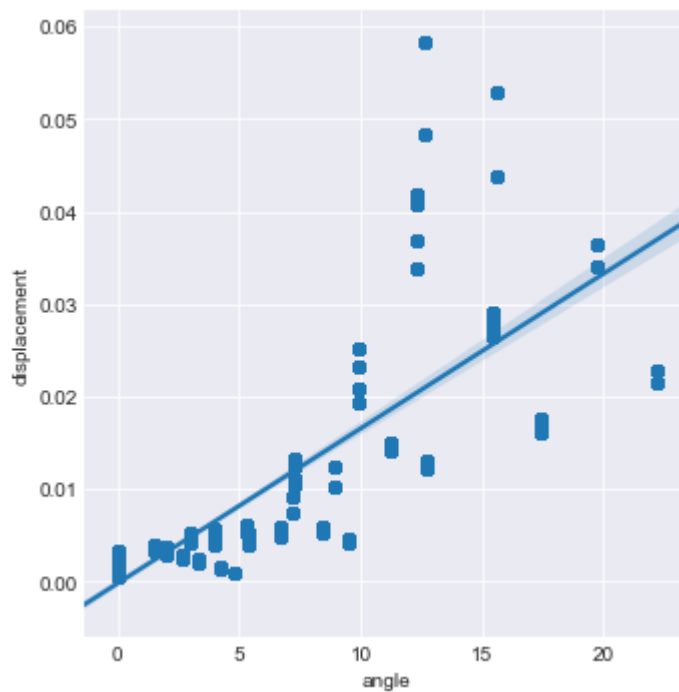
```
In [28]: plt.style.use('seaborn-darkgrid')
plt.scatter(df['angle'], df['displacement'], alpha=0.7, marker='o', s=df.angle*
20, c=['r', 'g', 'b', 'y'], edgecolors='black')
```

```
Out[28]: <matplotlib.collections.PathCollection at 0x104c15f8>
```



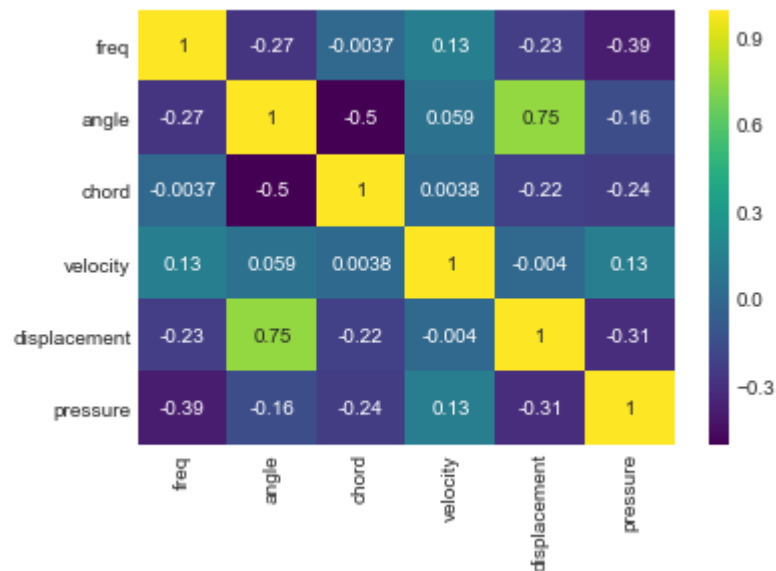
```
In [42]: sns.lmplot(x='angle', y='displacement', data=df)
```

```
Out[42]: <seaborn.axisgrid.FacetGrid at 0x114576d8>
```



```
In [43]: sns.heatmap(df.corr(), annot=True, cmap='viridis')
```

```
Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x11234d68>
```



## Training and Testing Data

Now that we've explored the data a bit, let's go ahead and split the data into training and testing sets.

```
In [29]: from sklearn.model_selection import train_test_split
```

```
In [30]: X_train, X_test, y_train, y_test = train_test_split(df.drop('pressure',axis=1), df['pressure'], test_size=0.3, random_state=101)
```

## Training the Model

Now its time to train our model on our training data!

**Import LinearRegression from sklearn.linear\_model**

```
In [31]: from sklearn.linear_model import LinearRegression
```

```
In [32]: lm = LinearRegression()
```

```
In [33]: lm.fit(X_train, y_train)
```

```
Out[33]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)
```

## Predicting the Variables

```
In [34]: pred = lm.predict(X_test)
```

## Evaluating the Model

**Now evaluating the model with r2 score and coefficients and errors**

**R2 Score**

```
In [35]: from sklearn import metrics
```

```
In [37]: print(metrics.r2_score(y_test, pred))
```

```
0.545250154543
```

**Coefficients**

```
In [38]: coefficients = pd.DataFrame(lm.coef_, index=df.columns[:-1], columns=['Coefficients'])
```

In [39]: `coefficients`

Out[39]:

	Coefficients
<b>freq</b>	-0.001208
<b>angle</b>	-0.421277
<b>chord</b>	-35.949614
<b>velocity</b>	0.093341
<b>displacement</b>	-147.089444

### Interpreting the coefficients:

- Holding all other features fixed, 1 unit increase in frequency is associated with **decrease of 0.001208 unit pressure**.
- Holding all other features fixed, 1 unit increase in angle is associate with **decrease of 0.421277 unit pressure**
- Holding all other features fixed, 1 unit increase in chord is associated with **decrease of 35.949614 unit pressure**
- Holding all other features fixed, 1 unit increase in velocity is associated with **increase of 0.093341 unit pressure**
- Holding all other features fixed, 1 unit increase in displace is associated with **decrease of 147.089 unit pressure**

### Calculating Errors

```
In [40]: print("MAE: ", metrics.mean_absolute_error(y_test, pred))
print("MSE: ", metrics.mean_squared_error(y_test, pred))
print("RMSE: ", np.sqrt(metrics.mean_squared_error(y_test, pred)))
```

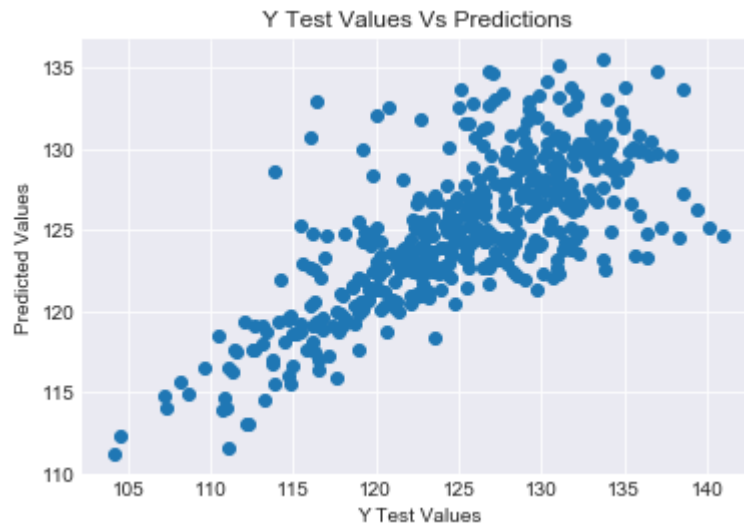
```
MAE:  3.51034617723
MSE:  21.2130571577
RMSE:  4.60576347175
```

### Plotting the Test Values Vs Predicted Values



```
In [44]: plt.title('Y Test Values Vs Predictions')
plt.xlabel('Y Test Values')
plt.ylabel('Predicted Values')
plt.scatter(y_test, pred)
```

Out[44]: <matplotlib.collections.PathCollection at 0x1147d240>



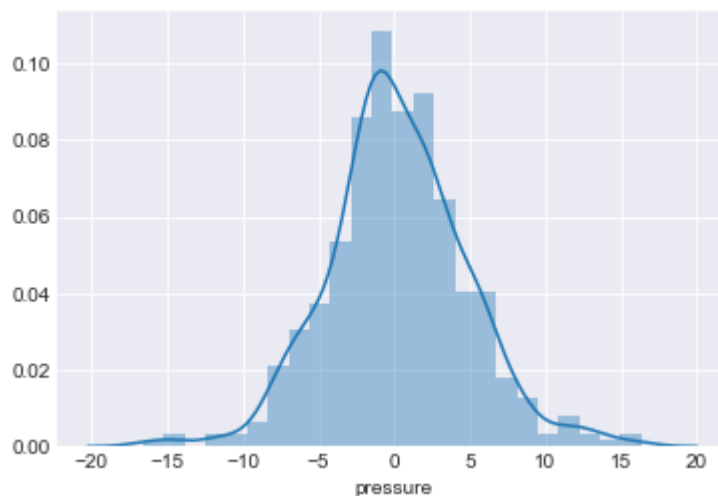
## Residuals

You should have gotten a model with an OK OK fit. Let's quickly explore the residuals to make sure everything was okay with our data.

**Plot a histogram of the residuals and make sure it looks normally distributed. Use either seaborn distplot, or just plt.hist().**

```
In [46]: sns.distplot((y_test-pred))
```

Out[46]: <matplotlib.axes.\_subplots.AxesSubplot at 0x11720400>



**The residuals looks normally distributed**