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- Reference: https://mesonet.agron.iastate.edu/request/download.phtml?network=CT_ASOS

Data Preparation

```
#load file
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.moun
```

```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore")
from sklearn.model_selection import train_test_split
```

```
#load airport weather dataset
df_airport_weather = pd.read_csv("/content/drive/My Drive/Data Science with Python Spring2020
df_airport_weather.shape
```

```
(9122, 31)
```

```
#subset the data
df_subset=df_airport_weather[['station','valid','lon','lat','tmpf','dwpf','sknt','relh','drct
df_subset
```

	station	valid	lon	lat	tmpf	dwpf	sknt	relh	drct	p01i	alt
0	BDL	1/1/2019 0:00	-72.6825	41.9381	M	M	5	M	110	0.01	30.1
1	BDL	1/1/2019 0:05	-72.6825	41.9381	M	M	4	M	120	0.01	30.1
2	BDL	1/1/2019 0:10	-72.6825	41.9381	M	M	4	M	110	0.02	30.1
3	BDL	1/1/2019 0:15	-72.6825	41.9381	M	M	3	M	110	0.03	30.1
4	BDL	1/1/2019 0:20	-72.6825	41.9381	M	M	3	M	100	0.04	30.1
...	...	...	...	...	...	...	...	...	...	...	..
9117	BDL	1/30/2019 23:40	-72.6825	41.9381	M	M	18	M	260	M	29.8
9118	BDL	1/30/2019 23:45	-72.6825	41.9381	M	M	19	M	260	M	29.8
9119	BDL	1/30/2019 23:50	-72.6825	41.9381	M	M	23	M	260	M	29.8
9120	BDL	1/30/2019 23:51	-72.6825	41.9381	16	5	23	61.23	270	T	29.8
9121	BDL	1/30/2019 23:55	-72.6825	41.9381	M	M	19	M	260	M	29.8

9122 rows × 13 columns

Data Preprocessing

```
#Cleaning up the tmpf, sknt and dwpf columns ‘M’/'T' counts as NA values
df_subset=df_subset.replace('M',np.nan)
df_subset=df_subset.replace('T',np.nan)
df_subset.isna
```

```
<bound method DataFrame.isna of      station            valid      lon      lat  ...  p0
0        BDL    1/1/2019 0:00 -72.6825  41.9381  ...  0.01  30.17     NaN  NaN
1        BDL    1/1/2019 0:05 -72.6825  41.9381  ...  0.01  30.16     NaN  NaN
2        BDL    1/1/2019 0:10 -72.6825  41.9381  ...  0.02  30.16     NaN  NaN
3        BDL    1/1/2019 0:15 -72.6825  41.9381  ...  0.03  30.16     NaN  NaN
4        BDL    1/1/2019 0:20 -72.6825  41.9381  ...  0.04  30.15     NaN  NaN
...      ...              ...      ...      ...  ...   ...    ...     ...  ...
9117     BDL  1/30/2019 23:40 -72.6825  41.9381  ...   NaN  29.87     NaN  NaN
9118     BDL  1/30/2019 23:45 -72.6825  41.9381  ...   NaN  29.88     NaN  NaN
9119     BDL  1/30/2019 23:50 -72.6825  41.9381  ...   NaN  29.89     NaN  NaN
9120     BDL  1/30/2019 23:51 -72.6825  41.9381  ...   NaN  29.89  1012.3   31
9121     BDL  1/30/2019 23:55 -72.6825  41.9381  ...   NaN  29.89     NaN  NaN

[9122 rows x 13 columns]>
```

```
#Droping all NA rows
df_subset = df_subset.dropna()
df_subset
```

	station	valid	lon	lat	tmpf	dwpf	sknt	relh	drct	p01i	alt
207	BDL	1/1/2019 15:51	-72.6825	41.9381	53.1	41	17	63.38	320	0	29.6
220	BDL	1/1/2019 16:51	-72.6825	41.9381	51.1	33.1	19	49.98	310	0	29.7
232	BDL	1/1/2019 17:51	-72.6825	41.9381	48.9	30.9	20	49.63	310	0	29.7
244	BDL	1/1/2019 18:51	-72.6825	41.9381	46	30	17	53.37	330	0	29.8
255	BDL	1/1/2019 19:51	-72.6825	41.9381	43	28.9	27	57.21	300	0	29.8
...	...	...	...	...	...	...	...	...	...	...	..
8141	BDL	1/27/2019 19:51	-72.6825	41.9381	44.1	27	14	50.73	190	0	29.
8297	BDL	1/28/2019 7:51	-72.6825	41.9381	24.1	10	13	54.36	340	0	30.0
8950	BDL	1/30/2019 10:51	-72.6825	41.9381	25	15.1	13	65.58	330	0	29.
9053	BDL	1/30/2019 18:51	-72.6825	41.9381	27	7	14	42.11	230	0	29.7
9077	BDL	1/30/2019 20:51	-72.6825	41.9381	28	7	8	40.41	190	0	29.7

125 rows × 13 columns

```
#Converting date using proper format
df_subset.dtypes
df_subset['valid']= pd.to_datetime(df_subset['valid'])
df_subset['valid']
```

```
207    2019-01-01 15:51:00
220    2019-01-01 16:51:00
232    2019-01-01 17:51:00
244    2019-01-01 18:51:00
255    2019-01-01 19:51:00
               ...
8141   2019-01-27 19:51:00
8297   2019-01-28 07:51:00
8950   2019-01-30 10:51:00
9053   2019-01-30 18:51:00
9077   2019-01-30 20:51:00
Name: valid, Length: 125, dtype: datetime64[ns]
```

```
#Creating columns for MONTH, DAY and YEAR
df_subset['day'] = pd.to_datetime(df_subset['valid']).dt.day
df_subset['month'] = pd.to_datetime(df_subset['valid']).dt.month
df_subset['year'] = pd.to_datetime(df_subset['valid']).dt.year
df_subset
```

	station	valid	lon	lat	tmpf	dwpf	sknt	relh	drct	p01i	alti	ms
207	BDL	2019-01-01 15:51:00	-72.6825	41.9381	53.1	41	17	63.38	320	0	29.68	1005
220	BDL	2019-01-01 16:51:00	-72.6825	41.9381	51.1	33.1	19	49.98	310	0	29.74	1007
232	BDL	2019-01-01 17:51:00	-72.6825	41.9381	48.9	30.9	20	49.63	310	0	29.77	1008
244	BDL	2019-01-01 18:51:00	-72.6825	41.9381	46	30	17	53.37	330	0	29.81	1009
255	BDL	2019-01-01 19:51:00	-72.6825	41.9381	43	28.9	27	57.21	300	0	29.88	1011
...	...	...	...	...	...	...	...	...	...	...	...	...

```
#Creating a new column called MonthDay in "MM-DD" format
df_subset['MonthDay'] = df_subset['month'].map(str) + '-' +  df_subset['day'].map(str)
df_subset
```

	station	valid	lon	lat	tmpf	dwpf	sknt	relh	drct	p01i	alti	ms
207	BDL	2019-01-01 15:51:00	-72.6825	41.9381	53.1	41	17	63.38	320	0	29.68	1005
220	BDL	2019-01-01 16:51:00	-72.6825	41.9381	51.1	33.1	19	49.98	310	0	29.74	1007
232	BDL	2019-01-01 17:51:00	-72.6825	41.9381	48.9	30.9	20	49.63	310	0	29.77	1008
244	BDL	2019-01-01 18:51:00	-72.6825	41.9381	46	30	17	53.37	330	0	29.81	1009
255	BDL	2019-01-01 19:51:00	-72.6825	41.9381	43	28.9	27	57.21	300	0	29.88	1011
...	...	...	...	...	...	...	...	...	...	...	...	...

Data Recoding

```
# Creating a binary flag column for rows/observations that are cold (below 32 degF)
#If below 32 degF, call it “COLD”;
#otherwise, call it “HOT”
df_subset['tmpf'] = df_subset['tmpf'].astype(float)
df_subset['tmpf_b'] = df_subset['tmpf'].apply(lambda x:'COLD' if x < 32 else 'HOT')
df_subset['tmpf_b']
```

```
207      HOT
220      HOT
232      HOT
244      HOT
255      HOT
        ...
8141     HOT
8297    COLD
8950    COLD
9053    COLD
9077    COLD
Name: tmpf_b, Length: 125, dtype: object
```

```
#Creating a binary flag column for rows/observations are windy.
#If above 20 miles per hour, call it “WINDY”,
#otherwise call it “CALM”
df_subset['sknt'] = df_subset['sknt'].astype(float)
df_subset['sknt_mph'] = df_subset['sknt']*1.15078   #converting knots to miles per hour
df_subset['sknt_b'] = df_subset['sknt_mph'].apply(lambda x:'CALM' if x < 20 else 'WINDY')
df_subset['sknt_b']
```

```
207      CALM
220     WINDY
232     WINDY
244      CALM
255     WINDY
        ...
8141     CALM
8297     CALM
8950     CALM
9053     CALM
9077     CALM
Name: sknt_b, Length: 125, dtype: object
```

Aggregation

```
#show the counts of each weather type.
freq_table = pd.crosstab(index=df_subset['sknt_b'], columns=df_subset['tmpf_b'])
freq_table
```

tmpf_b	COLD	HOT
sknt_b		
CALM	56	44
WINDY	18	7

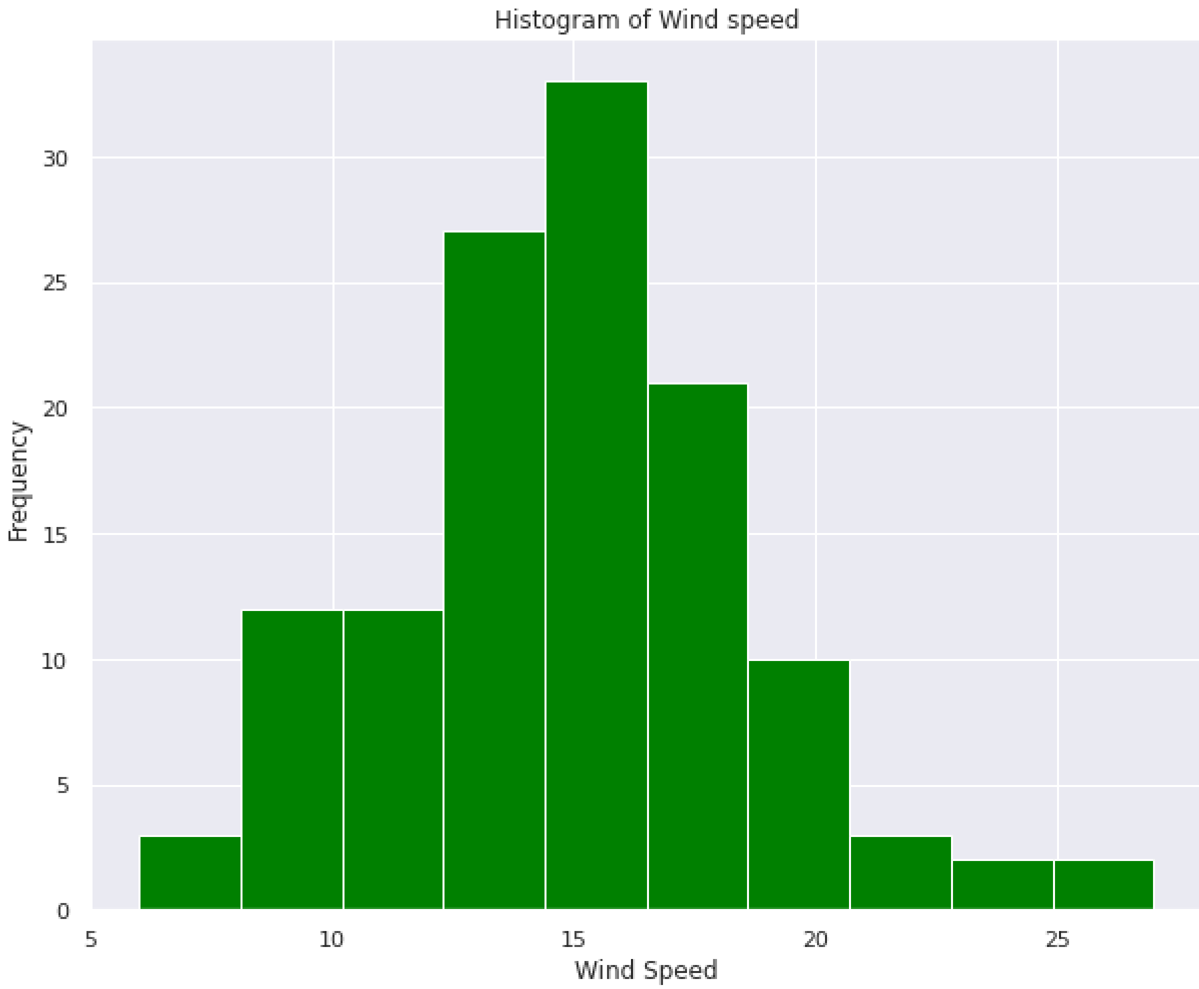
```
#A table that shows the average wind speed and average temperature per day.
df_avg=df_subset.groupby(['day','month','year']).agg({'tmpf':'mean','sknt':'mean'})
df_avg
```

			tmpf	sknt
day	month	year		
1	1	2019	44.862500	17.875000
2	1	2019	37.000000	10.000000
3	1	2019	41.666667	15.666667
4	1	2019	39.000000	10.000000
6	1	2019	39.040000	14.800000
7	1	2019	25.683333	13.833333
9	1	2019	38.828571	15.142857
10	1	2019	30.176471	16.000000
11	1	2019	22.700000	13.900000
12	1	2019	17.380000	11.400000
17	1	2019	29.050000	13.000000
20	1	2019	18.550000	15.500000
21	1	2019	0.526316	16.684211
22	1	2019	6.655556	14.333333
24	1	2019	50.620000	14.800000
25	1	2019	34.033333	15.888889
26	1	2019	29.450000	9.000000
27	1	2019	42.700000	13.666667
28	1	2019	24.100000	13.000000
30	1	2019	26.666667	11.666667

Data Visualization

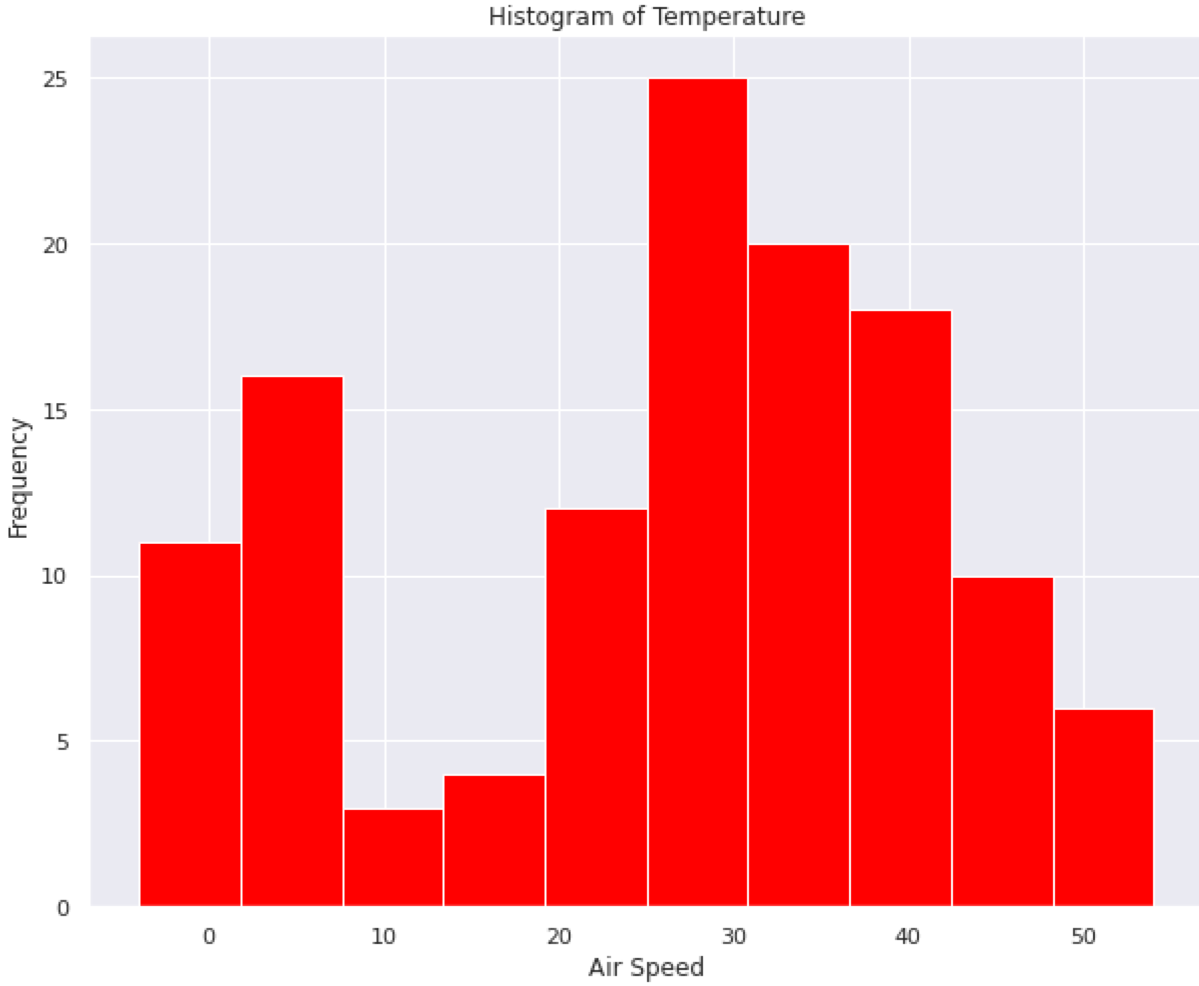
```
#histogram plot of the wind speed
import matplotlib.pyplot as plt
df_subset.hist('sknt', color='green')
plt.title("Histogram of Wind speed")
plt.xlabel('Wind Speed')
plt.ylabel('Frequency')
```

```
Text(0, 0.5, 'Frequency')
```



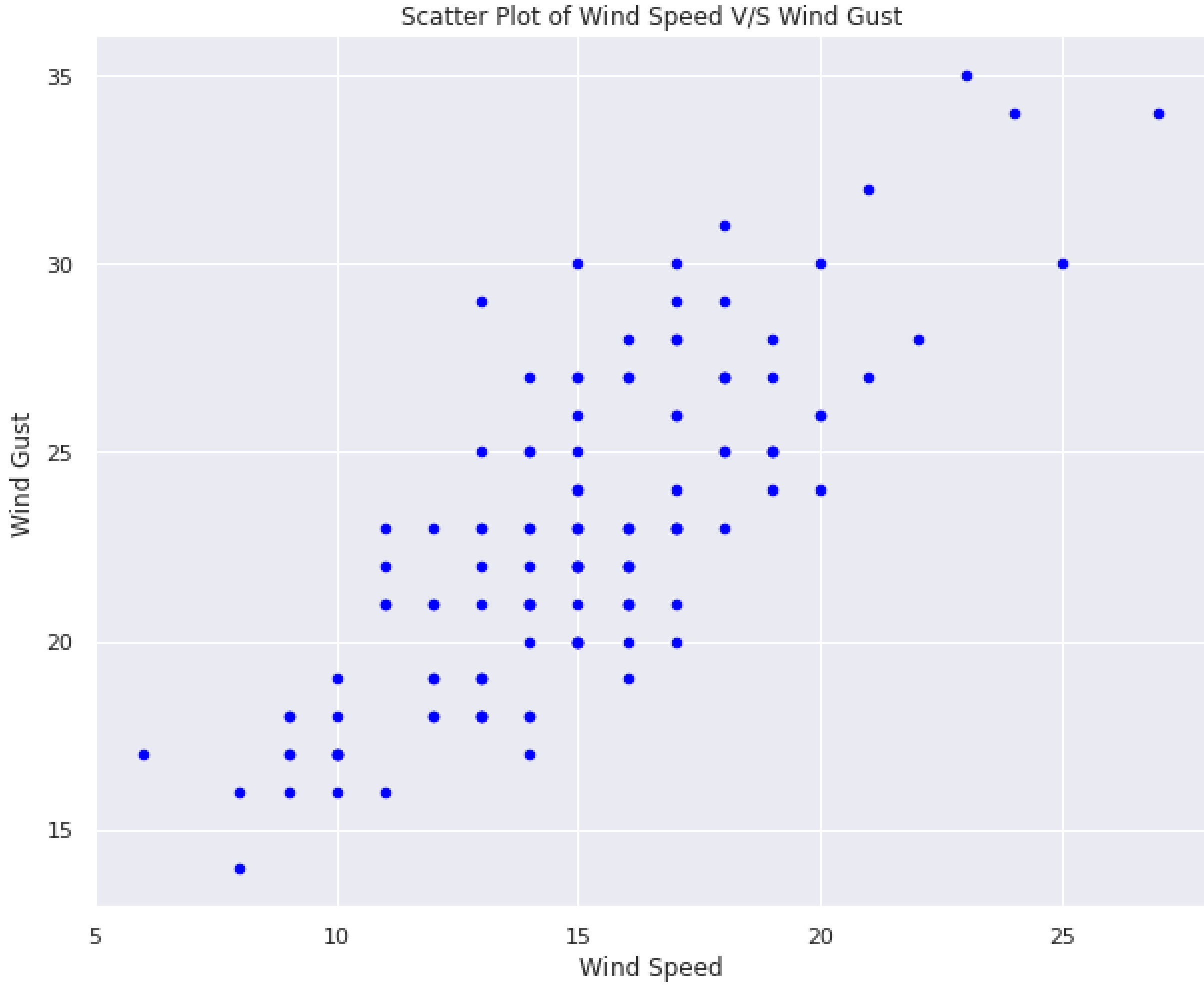

```
# a histogram plot of the temperature column
import matplotlib.pyplot as plt
df_subset.hist('tmpf', color='red')
plt.title("Histogram of Temperature")
plt.xlabel('Air Speed')
plt.ylabel('Frequency')
```

```
Text(0, 0.5, 'Frequency')
```




```
#a scatter plot of the wind speed V/S wind gust column
df_subset['gust'] = df_subset['gust'].astype(float)
df_subset.plot.scatter(x='sknt',
                      y='gust',
                      c='Blue')
plt.title("Scatter Plot of Wind Speed V/S Wind Gust")
plt.xlabel("Wind Speed")
plt.ylabel("Wind Gust")
```

```
Text(0, 0.5, 'Wind Gust')
```




```
#Line plot of the sknt, tmpf and dwpf (as a 3 panel plot), each having a different color.
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

# specify dimensions of plot
sns.set(rc={'figure.figsize':(10,8)})

#3 rows and 1 columns
fig, ax = plt.subplots(3,1)

#line plot for Wind Speed
ax[0].plot(df_subset.sknt,color='green')
ax[0].set_title("Line Plot of Wind Speed")
ax[0].set_xlabel('wind speed')


#line plot for Air Temperature
ax[1].plot(df_subset.tmpf,color='yellow')
ax[1].set_title("Line Plot of Air Temperature")
ax[1].set_xlabel('Air Temperature')
```

```
#line plot for Dew Point Temperature
ax[2].plot(df_subset.dwpf,color='red')
ax[2].set_title("Line Plot of Dew Point Temperature")
ax[2].set_xlabel('Dew Point Temperature')

fig.tight_layout()
plt.show()
```


```
Y_aw = df_subset['gust']
X_aw = df_subset[['tmpf','dwpf','sknt','relh','drct','p01i','alti','mslp']]
X_aw[['dwpf','relh','drct','p01i','alti','mslp']]= X_aw[['dwpf','relh','drct','p01i','alti','
X_aw.dtypes
```

```
tmpf    float64
dwpf    float64
sknt    float64
relh    float64
drct    float64
p01i    float64
alti    float64
mslp    float64
dtype: object
```

Polynomial Features

```
# Create polynomial features (and interactions).
from sklearn.preprocessing import PolynomialFeatures

# specify the degree of the poly fit
# the higher the degree, the weirder the fit!
# includes INTERACTIONS and Polynomials... lots of variables here...
poly_features = PolynomialFeatures(degree=2)

# transforms the existing features to higher degree features.
X_poly = poly_features.fit_transform(X_aw)
X_poly = np.nan_to_num(X_poly)
tmp_trans = pd.DataFrame(X_poly)

print("Original Data")
print(X_aw.head()) #13 columns
print("##########################")
#tmp_trans= pd.DataFrame(np.nan_to_num(tmp_trans))
print("Poly Features")
print(tmp_trans.head()) #105 columns
tmp_trans.shape
```

Original Data

Log Features

```
# Create log features
import numpy as np
tmp_log_a = np.log(X_aw)
tmp_log_a[np.isneginf(tmp_log_a)] = 0    #recode -inf to 0...
tmp_log = pd.DataFrame(tmp_log_a)
tmp_log = tmp_log.fillna(0)
print(tmp_log.shape) # same number of columns, but they've changed.
tmp_log
```

(125, 8)

	tmpf	dwpf	sknt	relh	drct	p01i	alti	mslp
207	3.972177	3.713572	2.833213	4.149148	5.768321	0.0	3.390473	6.912942
220	3.933784	3.499533	2.944439	3.911623	5.736572	0.0	3.392493	6.915029
232	3.889777	3.430756	2.995732	3.904595	5.736572	0.0	3.393501	6.915823
244	3.828641	3.401197	2.833213	3.977249	5.799093	0.0	3.394844	6.917111
255	3.761200	3.363842	3.295837	4.046729	5.703782	0.0	3.397189	6.919585
...	...	...	...	...	...	...	...	...
8141	3.786460	3.295837	2.639057	3.926517	5.247024	0.0	3.397858	6.920375
8297	3.182212	2.302585	2.564949	3.995629	5.828946	0.0	3.403195	6.925595
8950	3.218876	2.714695	2.564949	4.183271	5.799093	0.0	3.394508	6.917210
9053	3.295837	1.945910	2.639057	3.740285	5.438079	0.0	3.393501	6.916021
9077	3.332205	1.945910	2.079442	3.699077	5.247024	0.0	3.392157	6.914532

125 rows × 8 columns

Concatenate log and polynomial features

```
# smoosh the two dataframes together
# reset index of tables
#X_aw.reset_index(inplace=True,drop=True)   #drop not to make additional column for index
tmp_trans.reset_index(inplace=True,drop=True)
tmp_log.reset_index(inplace=True,drop=True)

#Join these two datasets together with the original variables.
df_resultant = pd.concat([tmp_trans,tmp_log], axis=1)

# look at how many more columns there are
```

```
df_resultant.shape
```

```
(125, 53)
```

```
#check missing values
df_resultant
missing_values = df_resultant.isnull().sum(axis=0)
missing_values
```

```
0       0
1       0
2       0
3       0
4       0
5       0
6       0
7       0
8       0
9       0
10      0
11      0
12      0
13      0
14      0
15      0
16      0
17      0
18      0
19      0
20      0
21      0
22      0
23      0
24      0
25      0
26      0
27      0
28      0
29      0
30      0
31      0
32      0
33      0
34      0
35      0
36      0
37      0
38      0
39      0
40      0
41      0
42      0
43      0
44      0
tmpf    0
dwpf    0
sknt    0
relh    0
drct    0
p01i    0
alti    0
mslp    0
dtype: int64
```

```
# Shuffle the data, then do an 80/20 split on the data
```

```
Y_aw.reset_index(inplace=True,drop=True)
X_train ,X_test, y_train, y_test = train_test_split(df_resultant, Y_aw, test_size=0.2, random

# ensure the split worked - checked how many rows there are!
print('X_train', X_train.shape,'y_train', y_train.shape)
print('X_test ', X_test.shape, 'y_test ', y_test.shape)
```

```
X_train (100, 53) y_train (100,)
X_test  (25, 53) y_test  (25,)
```

Linear Regression

```
#Linear Regression
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error

# fit the training data to Linear Regression
LR_model = LinearRegression() # specifies an empty model
LR_model.fit(X_train, y_train)
# predicting on training data-set
y_train_predict = LR_model.predict(X_train)
# predicting on test data-set
y_test_predict = LR_model.predict(X_test)
df_linear_reg_pred = pd.DataFrame(y_test_predict)
df_linear_reg_pred

# the Linear regression model results
score_test = LR_model.score(X_test, y_test)
mae_test = mean_absolute_error(y_test,y_test_predict)
print("R2:{0:.4f}, MAE:{1:.2f}".format(score_test, mae_test))
```

```
R2:-0.2335, MAE:3.38
```

Lasso Regression

```
#Fitting an lasso on your concatenated dataset (the polynomial features and
#interactions, and the log features)
#with varying alpha values (0.01, 0.1, 1, 10, 100, 1000),
#observing model best fit in terms of R2 and MAE
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_absolute_error

df_model_results = []

alphas = [0.01, 0.1, 1, 10, 100, 1000]        # this is essentially alpha values

# the Lasso on Training data set
```

```
for a in alphas:
  model = Lasso(alpha=a).fit(X_train, y_train)
  score_train = model.score(X_train, y_train)
  pred_y = model.predict(X_train)
  mae = mean_absolute_error(y_train,pred_y)

# the Lasso on Test data set
  score_test = model.score(X_test, y_test)
  pred_y_test = model.predict(X_test)
  mae_test = mean_absolute_error(y_test,pred_y_test)

#Show results in a table for training and validation results.
  df_model_results.append([a, score_train, score_test, mae, mae_test])
df_model_results = pd.DataFrame(data=df_model_results, columns=['Alpha', 'Training R2', 'Test
print(df_model_results)
```

```
     Alpha  Training R2   Test R2  Training MAE  Test MAE
0     0.01     0.708028  0.738219      1.876754  1.630231
1     0.10     0.702573  0.747352      1.912473  1.628341
2     1.00     0.698641  0.748369      1.921989  1.615872
3    10.00     0.690043  0.758812      1.973353  1.573544
4   100.00     0.659944  0.756681      2.110637  1.479246
5  1000.00     0.622187  0.703419      2.245159  1.758379
```

Ridge Regression

```
#Fitting an ridge on your concatenated dataset (the polynomial features and
#interactions, and the log features)
#with varying alpha values (0.01, 0.1, 1, 10, 100, 1000),
#observing model best fit in terms of R2 and MAE
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_absolute_error

df_model_results = []

alphas = [0.01, 0.1, 1, 10, 100, 1000]        # this is essentially alpha values

# the ridge on Training data set
for a in alphas:
  model = Lasso(alpha=a).fit(X_train, y_train)
  score_train = model.score(X_train, y_train)
  pred_y = model.predict(X_train)
  mae = mean_absolute_error(y_train,pred_y)

# the Lasso on Test data set
  score_test = model.score(X_test, y_test)
  pred_y_test = model.predict(X_test)
  mae_test = mean_absolute_error(y_test,pred_y_test)

#Show results in a table for training and validation results.
```

```
  df_model_results.append([a, score_train, score_test, mae, mae_test])
df_model_results = pd.DataFrame(data=df_model_results, columns=['Alpha', 'Training R2', 'Test
print(df_model_results)
```

```
     Alpha  Training R2   Test R2  Training MAE  Test MAE
0     0.01     0.708028  0.738219      1.876754  1.630231
1     0.10     0.702573  0.747352      1.912473  1.628341
2     1.00     0.698641  0.748369      1.921989  1.615872
3    10.00     0.690043  0.758812      1.973353  1.573544
4   100.00     0.659944  0.756681      2.110637  1.479246
5  1000.00     0.622187  0.703419      2.245159  1.758379
```

ElasticNet Regression

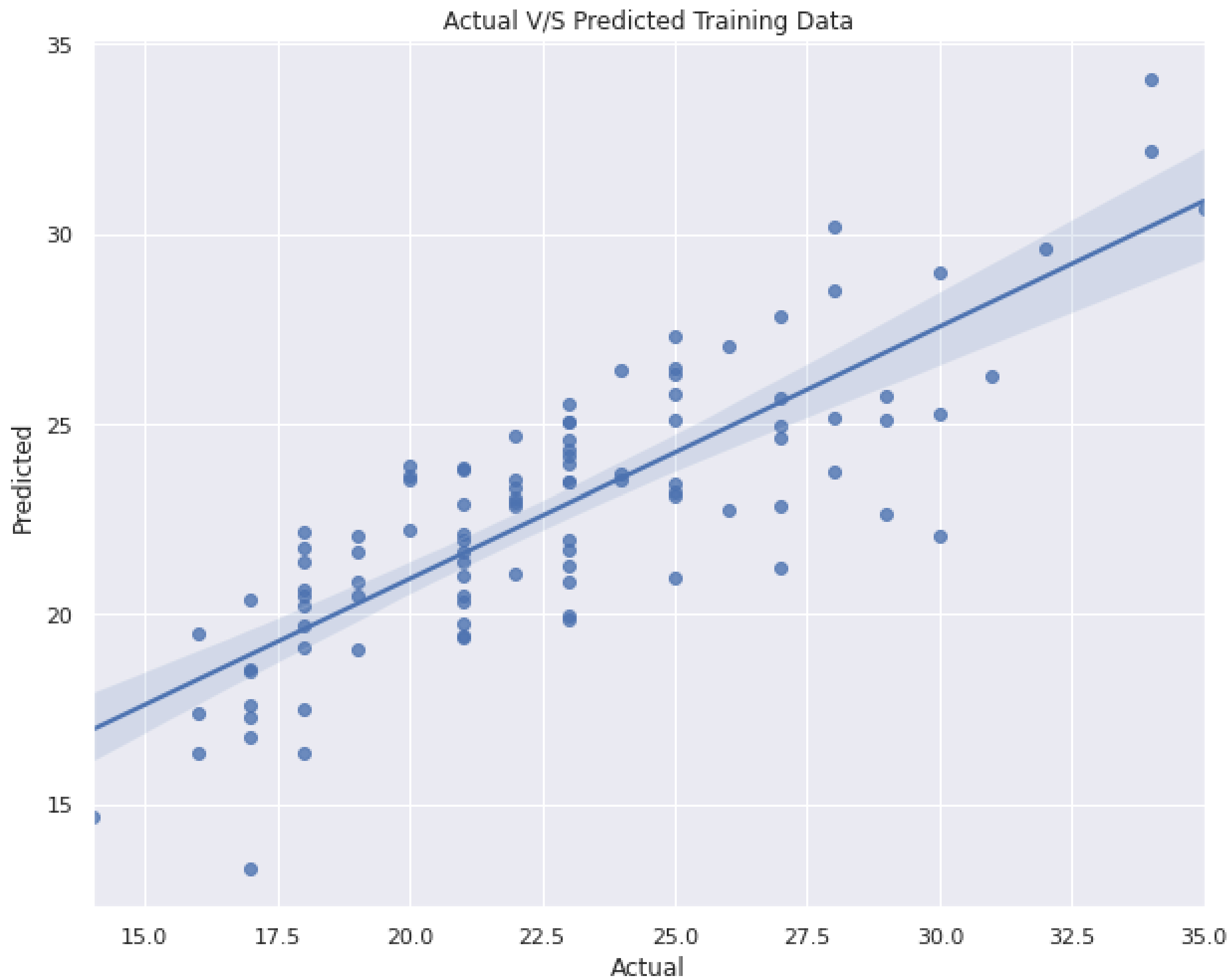
```
#Fitting an elasticNet on your concatenated dataset (the polynomial features and
#interactions, and the log features)
#with varying alpha values (0.01, 0.1, 1, 10, 100, 1000), observing model best fit in terms o
from sklearn.linear_model import ElasticNet
from sklearn.metrics import mean_absolute_error

df_model_results = []

alphas = [0.01, 0.1, 1, 10, 100, 1000]        # this is essentially alpha values

# the ElasticNet on Training data set
for a in alphas:
  model = ElasticNet(alpha=a).fit(X_train, y_train)
  score_train = model.score(X_train, y_train)
  pred_y = model.predict(X_train)
  mae = mean_absolute_error(y_train,pred_y)

# the ElasticNet on Test data set
  score_test = model.score(X_test, y_test)
  pred_y_test = model.predict(X_test)
  mae_test = mean_absolute_error(y_test,pred_y_test)

#Show results in a table for training and validation results.
  df_model_results.append([a, score_train, score_test, mae, mae_test])
df_model_results = pd.DataFrame(data=df_model_results, columns=['Alpha', 'Training R2', 'Test
print(df_model_results)
```

```
     Alpha  Training R2   Test R2  Training MAE  Test MAE
0     0.01     0.707933  0.737560      1.877783  1.630985
1     0.10     0.702803  0.747741      1.911686  1.626407
2     1.00     0.699798  0.746914      1.916014  1.623505
3    10.00     0.692084  0.754303      1.957291  1.586926
4   100.00     0.676581  0.775164      2.033666  1.464900
5  1000.00     0.626251  0.693646      2.235905  1.776960
```

```
#Scatterplot of actual vs. predicted for your best fitting model.
```

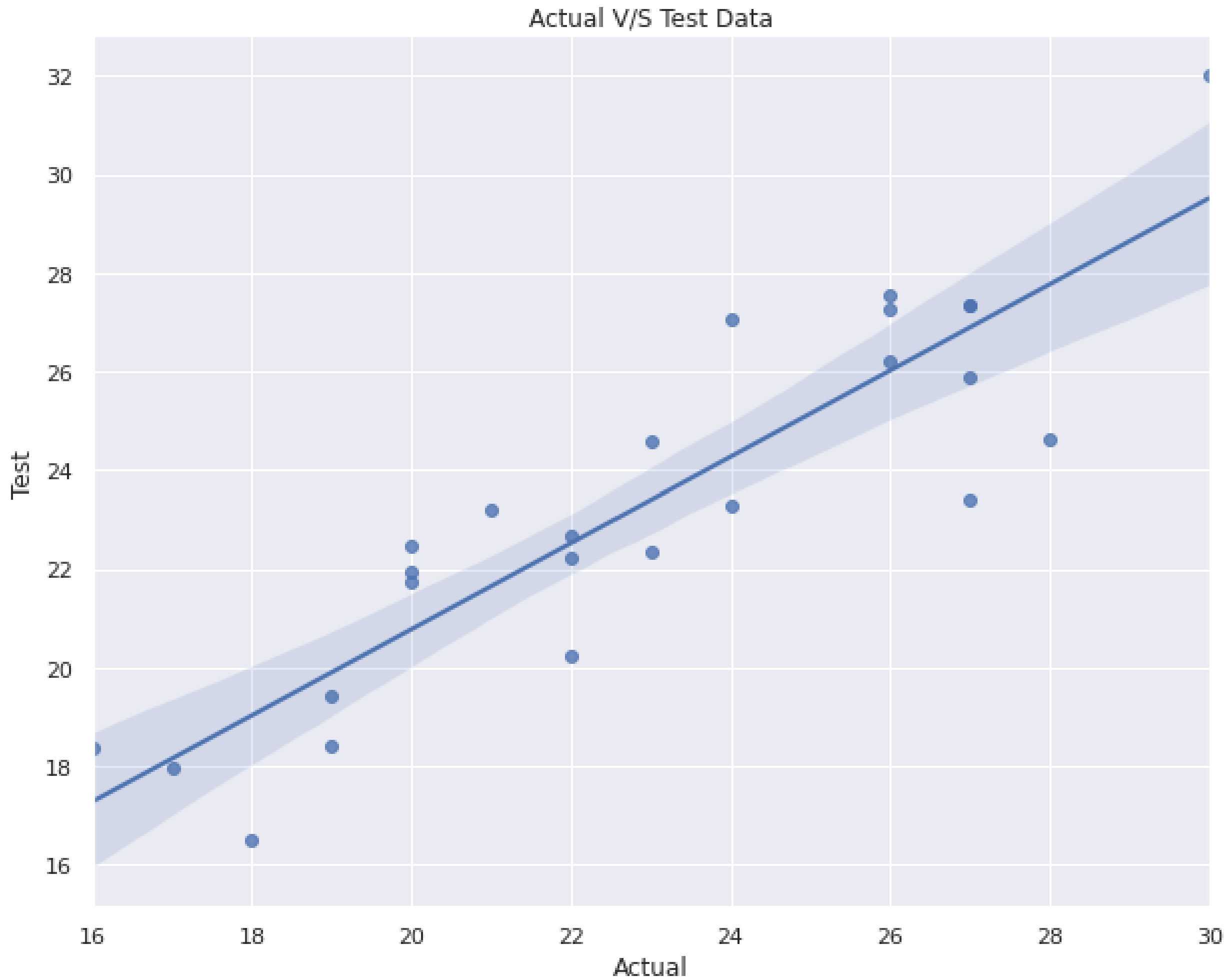
```
import seaborn
model = ElasticNet(alpha=100.00).fit(X_train, y_train)
score_train = model.score(X_train, y_train)
pred_y = model.predict(X_train)
seaborn.regplot(y_train,pred_y)
plt.title("Actual V/S Predicted Training Data")
plt.xlabel("Actual")
plt.ylabel("Predicted")
```

```
Text(0, 0.5, 'Predicted')
```




```
#Scatterplot of actual vs. test for your best fitting model.
score_test = model.score(X_test, y_test)
pred_y_test = model.predict(X_test)
mae_test = mean_absolute_error(y_test,pred_y_test)
seaborn.regplot(y_test,pred_y_test)
plt.title("Actual V/S Test Data")
plt.xlabel("Actual")
plt.ylabel("Test")
```

```
Text(0, 0.5, 'Test')
```



Baseline ElsticNet Regression

```
#After doing the same on the smaller original dataset it was observed that
#all the feature engineering helped enhance model accuracy
X_aw.reset_index(inplace=True,drop=True)   #drop not to make additional column for index
X_train_subset ,X_test_subset, Y_train_subset, Y_test_subset = train_test_split(X_aw, Y_aw, t

# ensure the split worked - checked how many rows there are!
print('X_train', X_train_subset.shape,'y_train', Y_train_subset.shape)
print('X_test ', X_test_subset.shape, 'y_test ', X_test_subset.shape)
```

```
X_train (100, 8) y_train (100,)
X_test  (25, 8) y_test  (25, 8)
```

```
alphas = [0.01, 0.1, 1, 10, 100, 1000]

df_model_results_s = []
```

```
# the ElasticNet on original dataset
# training dataset
for a in alphas:
  model = ElasticNet(alpha=a).fit(X_train_subset, Y_train_subset)
  score_train = model.score(X_train_subset, Y_train_subset)
  pred_y_simple_train = model.predict(X_train_subset)
  mae = mean_absolute_error(Y_train_subset,pred_y_simple_train)
  score_test = model.score(X_test_subset, Y_test_subset)
  pred_y_simple_test = model.predict(X_test_subset)
  mae_test = mean_absolute_error(Y_test_subset,pred_y_simple_test)


#Show results in a table for training and validation results.
  df_model_results_s.append([a, score_train, score_test, mae, mae_test])
df_model_results_s = pd.DataFrame(data=df_model_results_s, columns=['Alpha', 'Training R2', '
print(df_model_results_s)
```

```
     Alpha  Training R2   Test R2  Training MAE  Test MAE
0     0.01     0.640694  0.672966      2.201683  1.804642
1     0.10     0.638061  0.680525      2.202587  1.793387
2     1.00     0.623941  0.702218      2.240013  1.760866
3    10.00     0.413763  0.525454      2.701517  2.230617
4   100.00     0.000000 -0.003528      3.480000  3.170400
5  1000.00     0.000000 -0.003528      3.480000  3.170400
```