Pokémon Analysis

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Overview

With the new Pokémon Scarlet and Violet's release just around the corner, the competitive Pokémon community are eager to get an edge over the other players by finding the strongest Pokémon. Using linear regression we can highlight two variables that affect the attack of a Pokémon.

Business Understanding

To get an edge over other players, the enthusiast players would like to predict the attack stats of the next generation Pokémon to see if they are worth using. However, the stats of a Pokémon is not the only variable to consider. Our model will not factor in the moves/skills, items or other game mechanics..

In [1]:
```
#import packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import scipy.stats as stats
import seaborn as sns

from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import MinMaxScaler
from sklearn import preprocessing
```

In [2]:
```
#read data from file
pokemon_df = pd.read_csv('data/Pokemon.csv')
```

Data Understanding

We have obtained the data from Kaggle which uses the Pokémon official site as well as community sites. The data is accurate as it has been extracted from the games. We can see each stat of a Pokémon as well as the name, type, generation and if the Pokémon is legendary or not.
After getting an idea of the data we are dealing with we can see the only null values are from type 2 which is accurate as not all Pokémon have a second type.

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

Out[3]:

	#	Name	Type 1	Type 2	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation
0	1	Bulbasaur	Grass	Poison	318	45	49	49	65	65	45	1
1	2	Ivysaur	Grass	Poison	405	60	62	63	80	80	60	1
2	3	Venusaur	Grass	Poison	525	80	82	83	100	100	80	1
3	3	VenusaurMega Venusaur	Grass	Poison	625	80	100	123	122	120	80	1
4	4	Charmander	Fire	NaN	309	39	52	43	60	50	65	1

In [4]:
```
pokemon_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 13 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   #           800 non-null    int64 
 1   Name        800 non-null    object
 2   Type 1      800 non-null    object
 3   Type 2      414 non-null    object
 4   Total       800 non-null    int64 
 5   HP          800 non-null    int64 
 6   Attack      800 non-null    int64 
 7   Defense     800 non-null    int64 
 8   Sp. Atk     800 non-null    int64 
 9   Sp. Def     800 non-null    int64 
 10  Speed       800 non-null    int64 
 11  Generation  800 non-null    int64 
 12  Legendary   800 non-null    bool  
dtypes: bool(1), int64(9), object(3)
memory usage: 75.9+ KB
```

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

Out[5]:

	#	Total	HP	Attack	Defense	Sp. Atk	Sp. Def
count	800.000000	800.00000	800.000000	800.000000	800.000000	800.000000	800.000000
mean	362.813750	435.10250	69.258750	79.001250	73.842500	72.820000	71.902500
std	208.343798	119.96304	25.534669	32.457366	31.183501	32.722294	27.828916
min	1.000000	180.00000	1.000000	5.000000	5.000000	10.000000	20.000000
25%	184.750000	330.00000	50.000000	55.000000	50.000000	49.750000	50.000000
50%	364.500000	450.00000	65.000000	75.000000	70.000000	65.000000	70.000000
75%	539.250000	515.00000	80.000000	100.000000	90.000000	95.000000	90.000000
max	721.000000	780.00000	255.000000	190.000000	230.000000	194.000000	230.000000

Checking the stats between legendary and non-legendary Pokémon we can see they are not too different with highest total stats for legendary is 780 and normal Pokémon highest is 700. Legendary has a larger mean as they don't have to evolve. We can keep legendary Pokémon in our analysis.

In [6]:
```
# check stats for non-legendary
```

```
pokemon_df.loc[pokemon_df['Legendary'] == True].describe()
```

Out[6]:

	#	Total	HP	Attack	Defense	Sp. Atk	Sp. Def
count	65.000000	65.000000	65.000000	65.000000	65.000000	65.000000	65.000000
mean	470.215385	637.384615	92.738462	116.676923	99.661538	122.184615	105.938462
std	173.651095	60.937389	21.722164	30.348037	28.255131	31.104608	28.827004
min	144.000000	580.000000	50.000000	50.000000	20.000000	50.000000	20.000000
25%	381.000000	580.000000	80.000000	100.000000	90.000000	100.000000	90.000000
50%	483.000000	600.000000	91.000000	110.000000	100.000000	120.000000	100.000000
75%	642.000000	680.000000	105.000000	131.000000	115.000000	150.000000	120.000000
max	721.000000	780.000000	150.000000	190.000000	200.000000	194.000000	200.000000

In [7]:
```
# check stats for non-legendary
pokemon_df.loc[pokemon_df['Legendary'] == False].describe()
```

Out[7]:

	#	Total	HP	Attack	Defense	Sp. Atk	Sp. Def
count	735.000000	735.000000	735.000000	735.000000	735.000000	735.000000	735.000000
mean	353.315646	417.213605	67.182313	75.669388	71.559184	68.454422	68.892517
std	208.590419	106.760417	24.808849	30.490153	30.408194	29.091705	25.669310
min	1.000000	180.000000	1.000000	5.000000	5.000000	10.000000	20.000000
25%	175.500000	324.000000	50.000000	54.500000	50.000000	45.000000	50.000000
50%	346.000000	425.000000	65.000000	72.000000	66.000000	65.000000	65.000000
75%	533.500000	498.000000	79.500000	95.000000	85.000000	85.000000	85.000000
max	715.000000	700.000000	255.000000	185.000000	230.000000	175.000000	230.000000

Other observations:

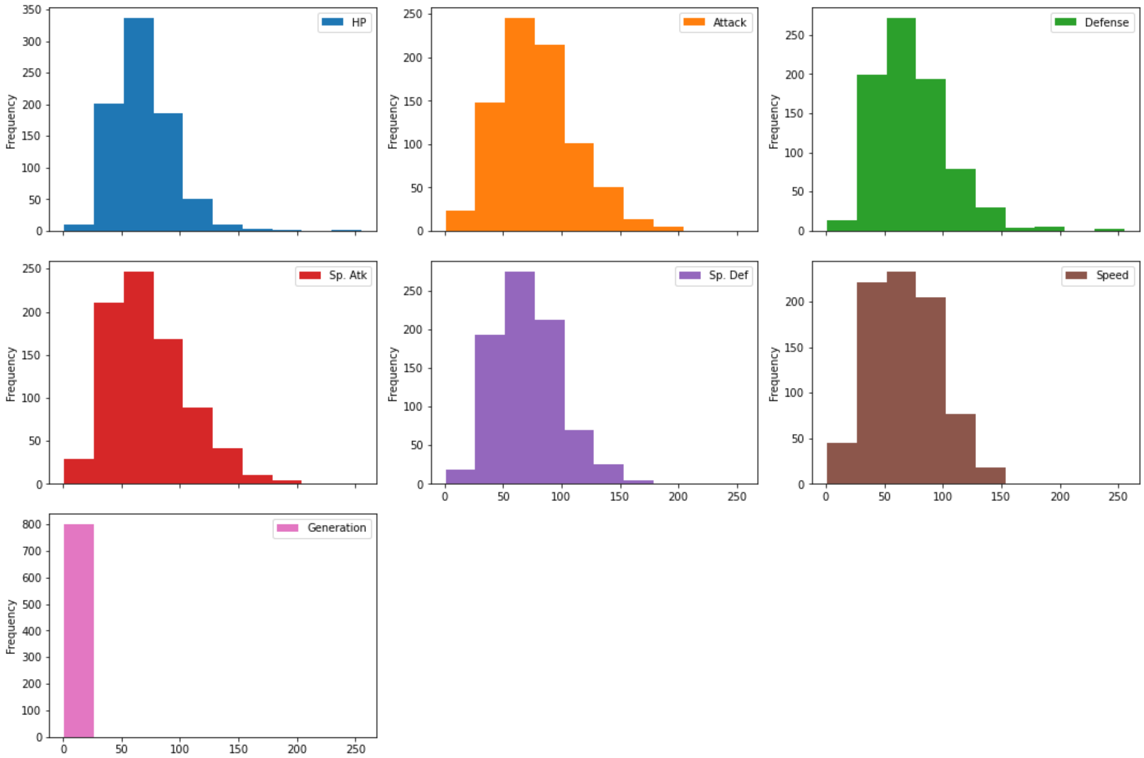
- There are a total of 18 unique Pokémon types.
- Histogram shows the data is slightly positively skewed.
- Hp, defence and special defence has some outliers we can remove

In [8]:
```
# number of unique types
unique = pokemon_df['Type 1'].unique()
print(unique)
len(unique)
```

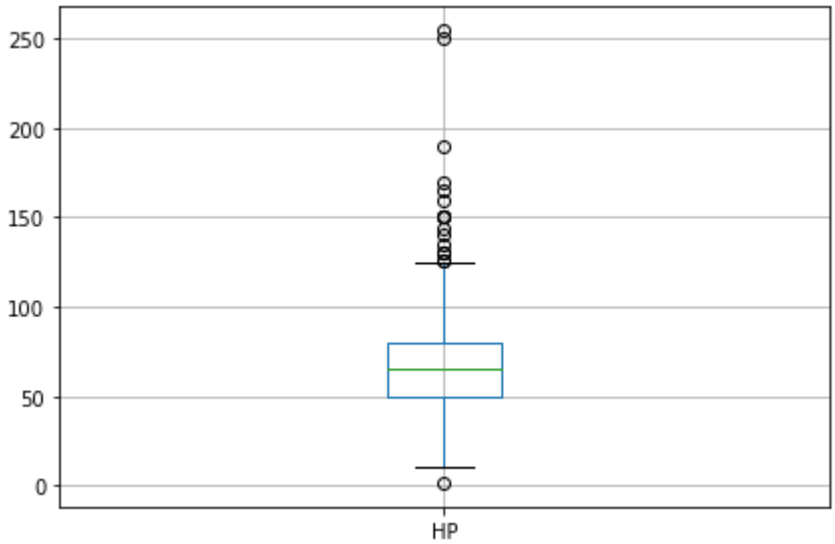
```
['Grass' 'Fire' 'Water' 'Bug' 'Normal' 'Poison' 'Electric' 'Ground'
 'Fairy' 'Fighting' 'Psychic' 'Rock' 'Ghost' 'Ice' 'Dragon' 'Dark' 'Steel'
 'Flying']
```

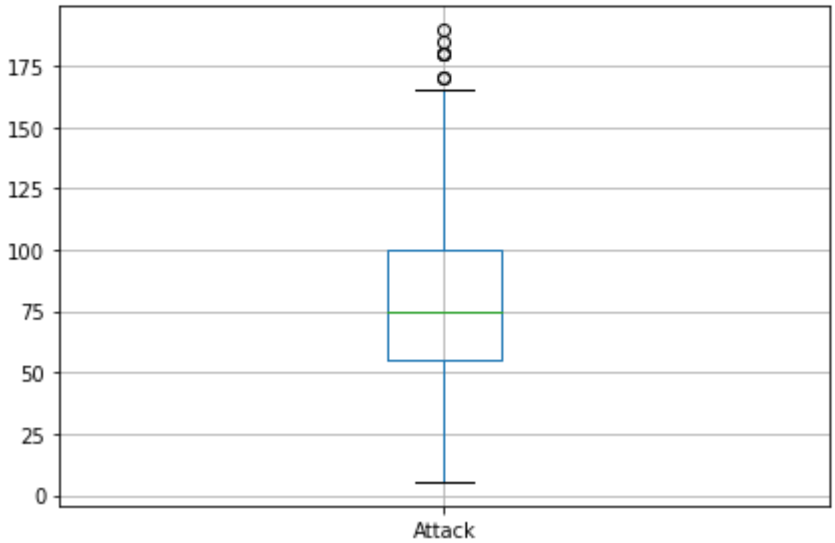
Out[8]: 18

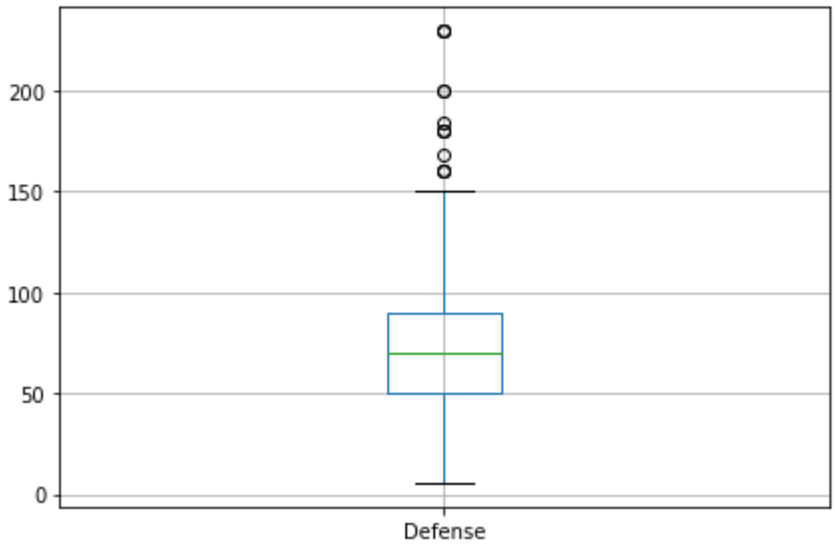
In [9]:
```
# We will be removing Total as that is all the stats added together.
pokemon_df.iloc[:,5:12].plot.hist(subplots = True, layout=(3,3), figsize=(1
plt.tight_layout()
plt.show()
```

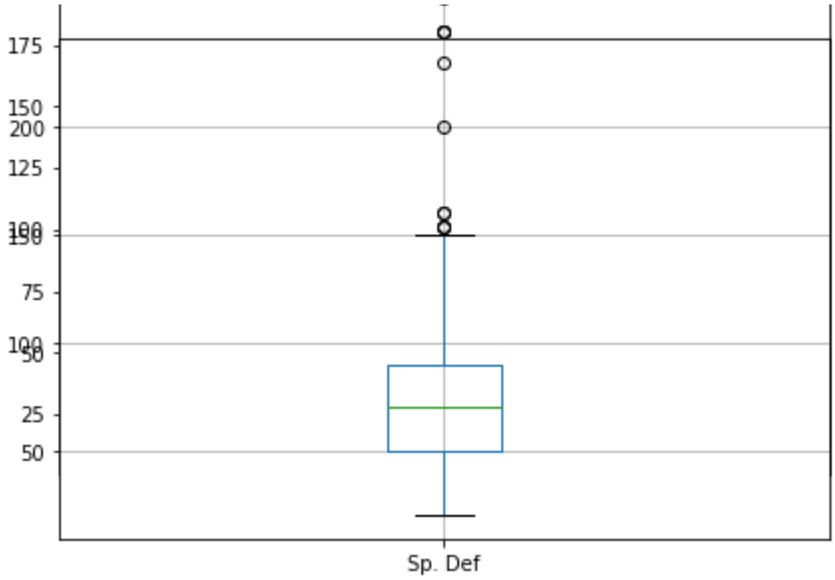


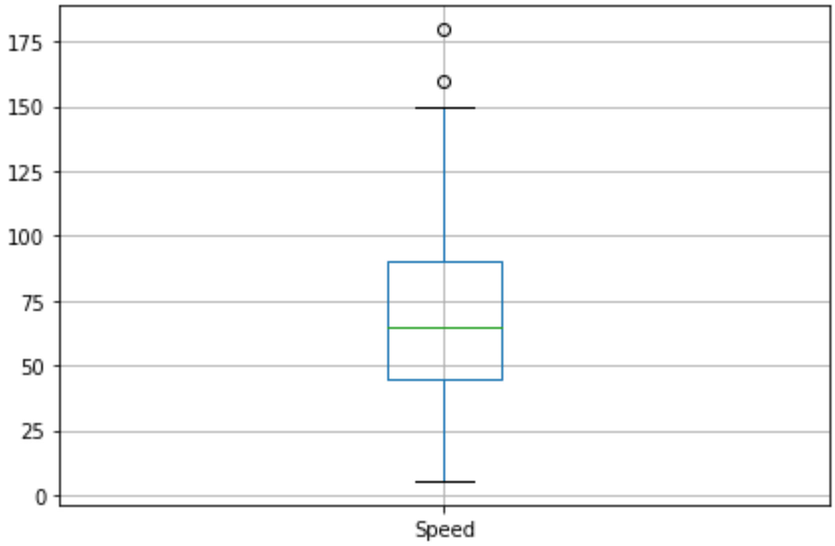
In [10]:
```
# box plots of stats
columns = pokemon_df.iloc[:,5:11].columns

for c in columns:
    pokemon_df[[c]].boxplot()
    plt.tight_layout()
    plt.show()
```











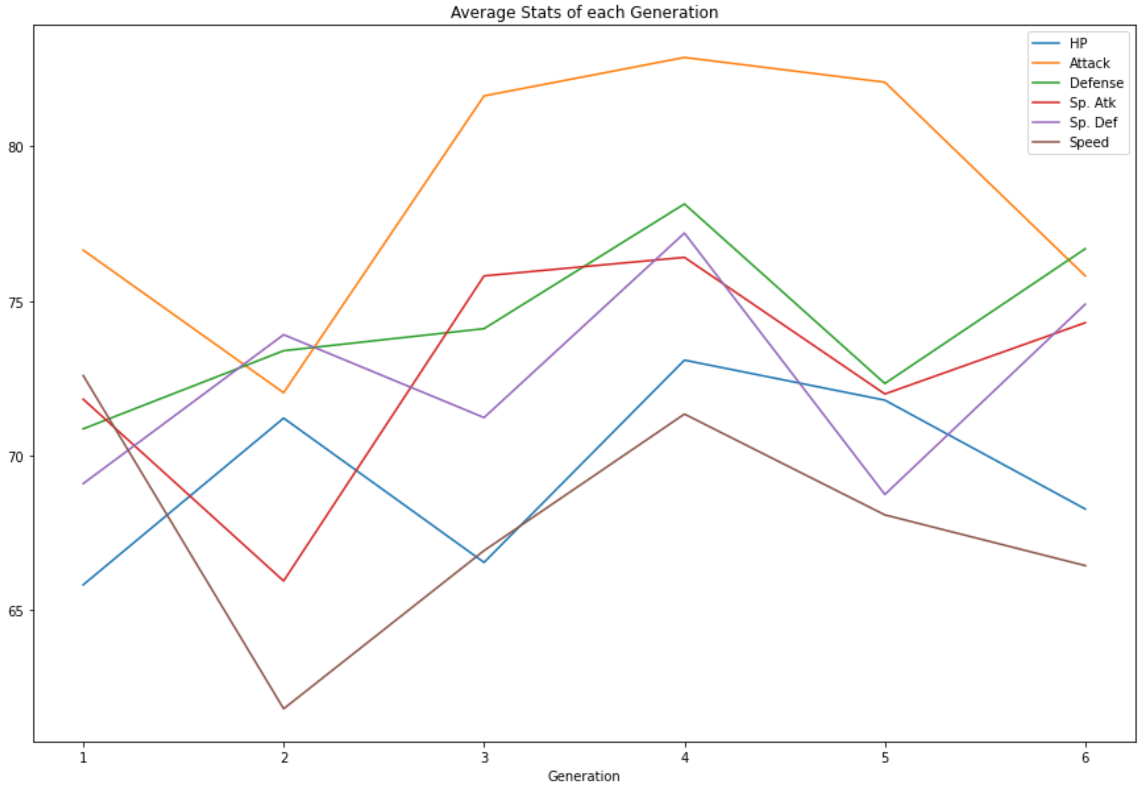
In [11]:

```
# outliers to remove
remove_pokemon1 = pokemon_df[pokemon_df['HP'] >= 200]
remove_pokemon2 =pokemon_df[pokemon_df['Defense'] >= 200]
remove_pokemon3 =pokemon_df[pokemon_df['Sp. Def'] >= 200]

remove_pokemon = pd.concat([remove_pokemon1, remove_pokemon2, remove_pokemoı
remove_pokemon
```

Out[11]:

	#	Name	Type 1	Type 2	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Gener
121	113	Chansey	Normal	NaN	450	250	5	5	35	105	50	
261	242	Blissey	Normal	NaN	540	255	10	10	75	135	55	
223	208	Steelix	Steel	Ground	510	75	85	200	55	65	30	
224	208	SteelixMega Steelix	Steel	Ground	610	75	125	230	55	95	30	
230	213	Shuckle	Bug	Rock	505	20	10	230	10	230	5	
333	306	AggronMega Aggron	Steel	NaN	630	70	140	230	60	80	50	
414	377	Regirock	Rock	NaN	580	80	100	200	50	100	50	
415	378	Regice	Ice	NaN	580	80	50	100	100	200	50	

In [12]:
```
# average stats for each generation
pokemon_stats = ['HP', 'Attack', 'Defense', 'Sp. Atk', 'Sp. Def', 'Speed']
pokemon_stats_by_generation = pokemon_df.groupby('Generation').mean()[pokem
pokemon_stats_by_generation.plot.line(figsize=(15,10), title='Average Stats
```



Data Preparation

We will start to go through the data and make changes that fit our needs like removing outliers, mega evolutions as that is part of a game mechanic and is not in every Pokémon game and other columns we don't need like the index number and name. Type 2 will be converted to **1** if it has a second type and **0** if they don't. Total will need to be removed as well because that is just the other stats added up.

In [13]:
```
pokemon_clean_df = pokemon_df.copy(deep=True)
pokemon_clean_df.head()
```

Out[13]:

	#	Name	Type 1	Type 2	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation
0	1	Bulbasaur	Grass	Poison	318	45	49	49	65	65	45	1
1	2	Ivysaur	Grass	Poison	405	60	62	63	80	80	60	1
2	3	Venusaur	Grass	Poison	525	80	82	83	100	100	80	1
3	3	VenusaurMega Venusaur	Grass	Poison	625	80	100	123	122	120	80	1
4	4	Charmander	Fire	NaN	309	39	52	43	60	50	65	1

In [14]:
```
# Remove outliers
pokemon_clean_df.drop(remove_pokemon['Name'].index, axis=0, inplace=True)
```

In [15]:
```
# remove mega evolutions
pokemon_clean_df.drop(pokemon_clean_df[pokemon_clean_df['Name'].str.contain
```

In [16]:
```
# New binary column for pokemon with second type
pokemon_clean_df['Has Type 2'] = np.where(pokemon_clean_df["Type 2"].isnull
pokemon_clean_df.head()
```

Out[16]:

	#	Name	Type 1	Type 2	Total	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation
0	1	Bulbasaur	Grass	Poison	318	45	49	49	65	65	45	1
1	2	Ivysaur	Grass	Poison	405	60	62	63	80	80	60	1
2	3	Venusaur	Grass	Poison	525	80	82	83	100	100	80	1
4	4	Charmander	Fire	NaN	309	39	52	43	60	50	65	1
5	5	Charmeleon	Fire	NaN	405	58	64	58	80	65	80	1

In [17]:
```
# remove pokedex number, name, type 2, total, legendary
pokemon_clean_df.drop(['#','Name','Type 2','Total','Legendary'], axis=1, in
pokemon_clean_df.reset_index(drop=True, inplace=True)
pokemon_clean_df.head()
```

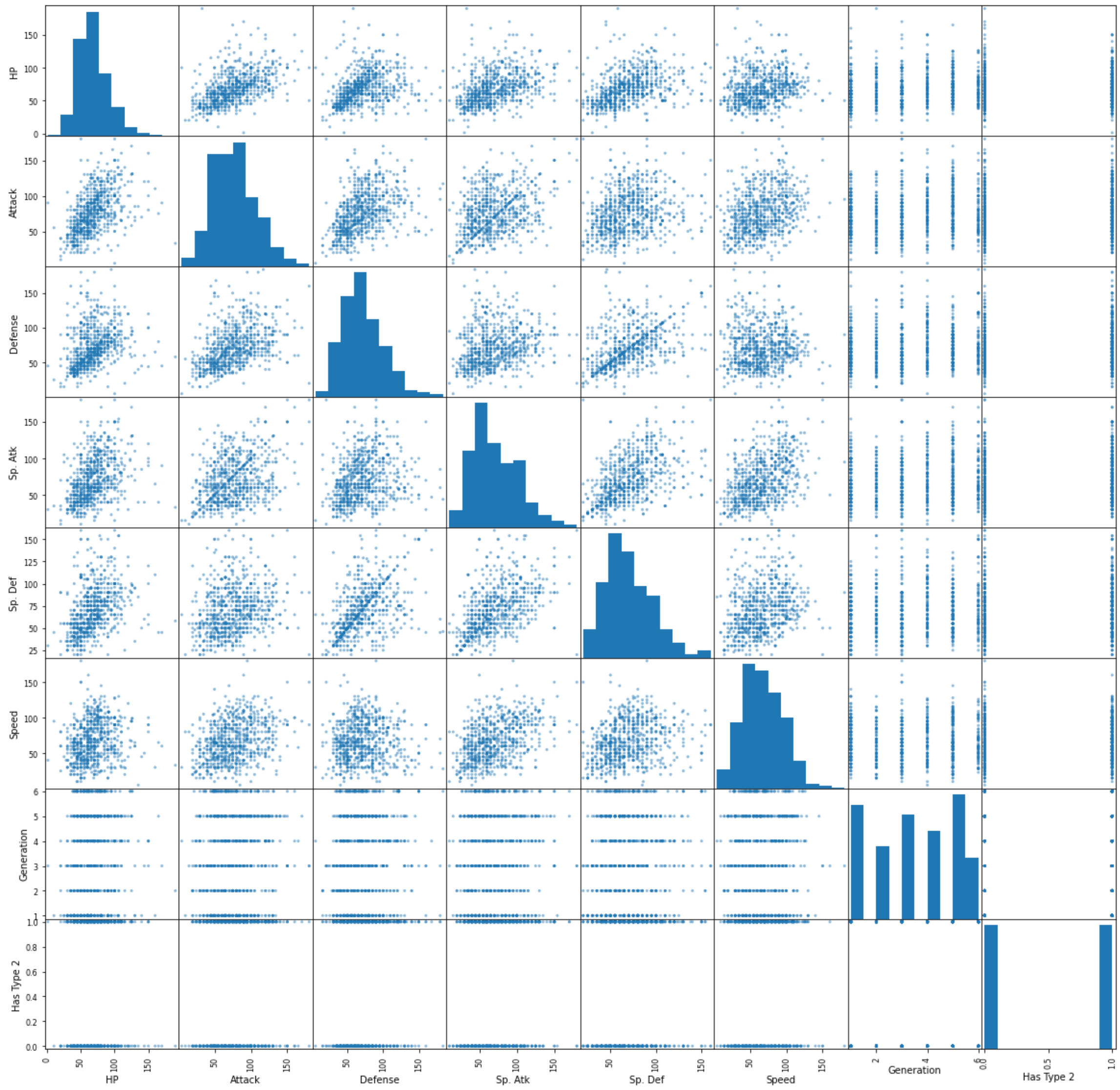
Out[17]:

	Type 1	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Has Type 2
0	Grass	45	49	49	65	65	45	1	1
1	Grass	60	62	63	80	80	60	1	1
2	Grass	80	82	83	100	100	80	1	1
3	Fire	39	52	43	60	50	65	1	0
4	Fire	58	64	58	80	65	80	1	0

Multicollinearity check

- No correlations over 0.75 with other predictors.
- HP and defence are highly correlated with our dependant variable attack

In [18]:
```
stat_predictors = pokemon_clean_df.iloc[:,1:9]
pd.plotting.scatter_matrix(stat_predictors, figsize  = [20, 20]);
plt.show()
```



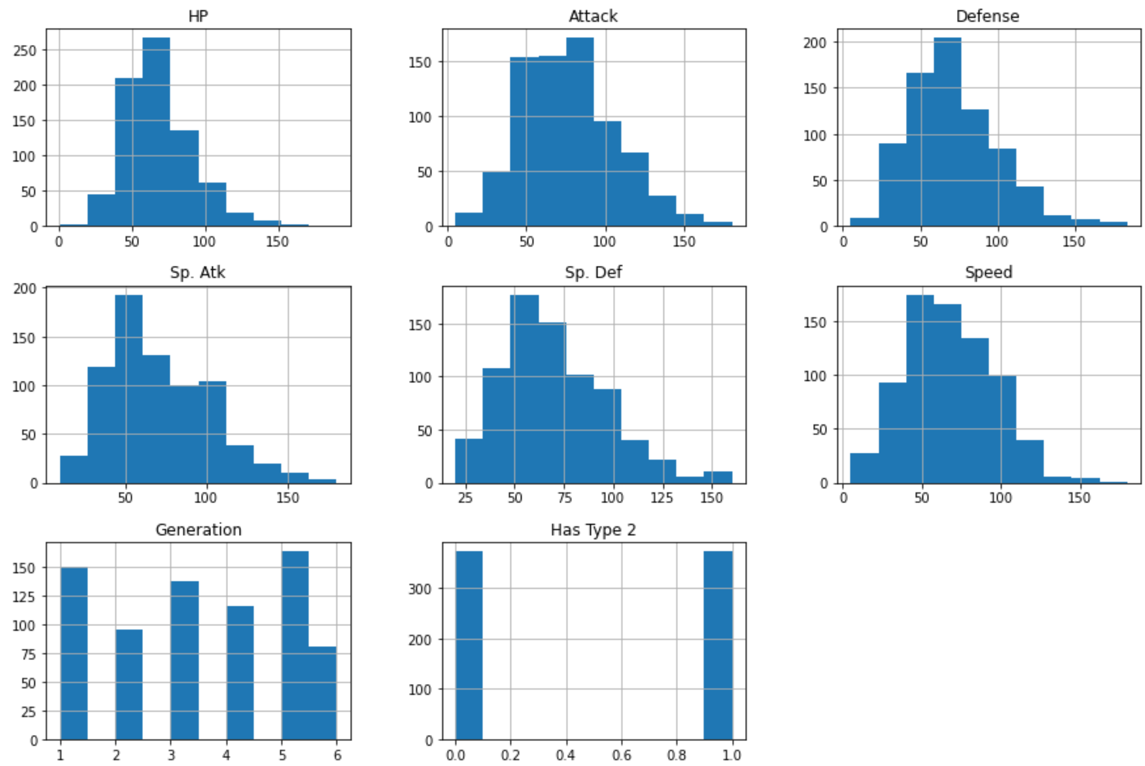
In [19]:
```
# none over 0.75
stat_predictors.corr().style.background_gradient(cmap='coolwarm')
```

Out[19]:

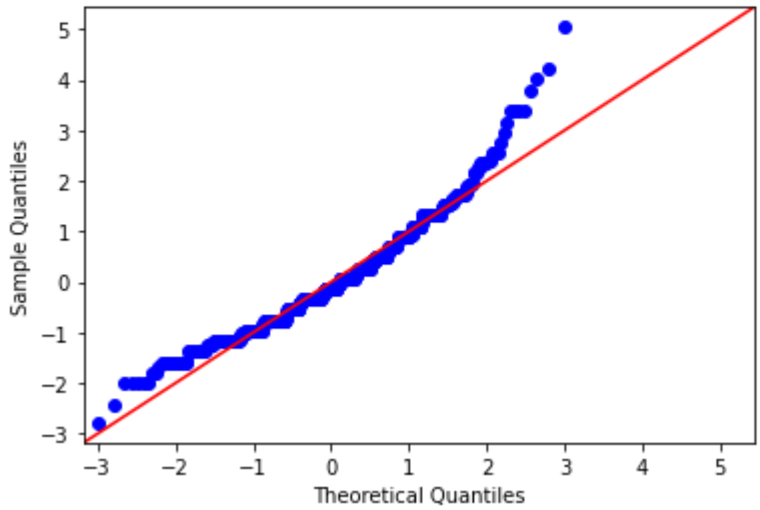
	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	Generation	Has Type 2
HP	1.000000	0.511040	0.318909	0.405698	0.393469	0.193413	0.106463	0.072524
Attack	0.511040	1.000000	0.436548	0.376459	0.253266	0.347043	0.099621	0.083202
Defense	0.318909	0.436548	1.000000	0.234861	0.503284	0.035755	0.095425	0.165694
Sp. Atk	0.405698	0.376459	0.234861	1.000000	0.529399	0.455270	0.086140	0.110084
Sp. Def	0.393469	0.253266	0.503284	0.529399	1.000000	0.276801	0.083481	0.111262
Speed	0.193413	0.347043	0.035755	0.455270	0.276801	1.000000	0.011523	0.063425
Generation	0.106463	0.099621	0.095425	0.086140	0.083481	0.011523	1.000000	0.071125
Has Type 2	0.072524	0.083202	0.165694	0.110084	0.111262	0.063425	0.071125	1.000000

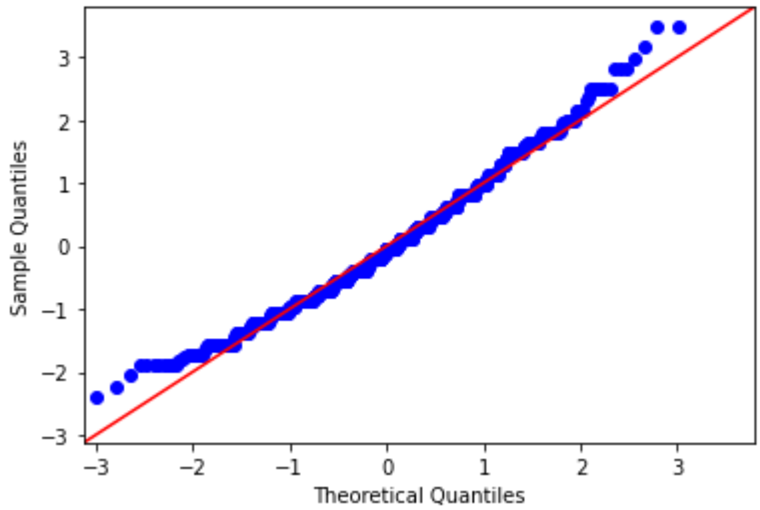
Normal distribution of data

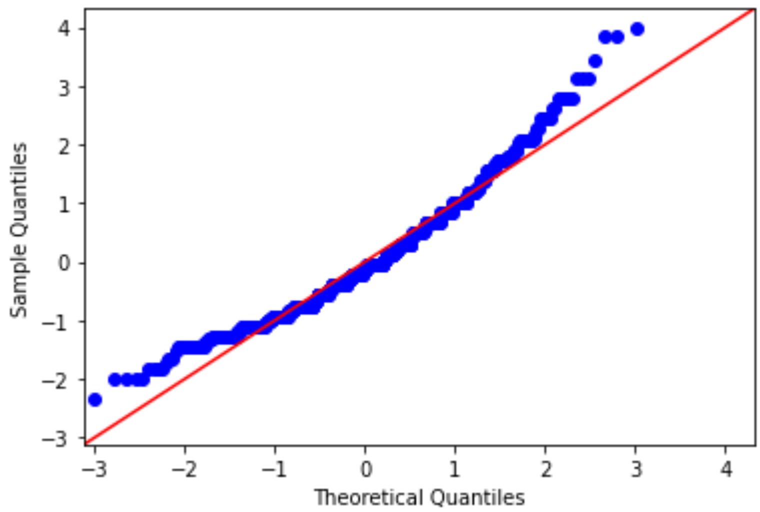
In [20]:
```
stat_predictors.hist(figsize=(15,10));
```

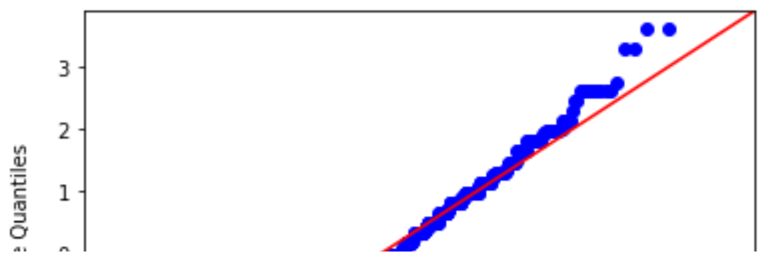


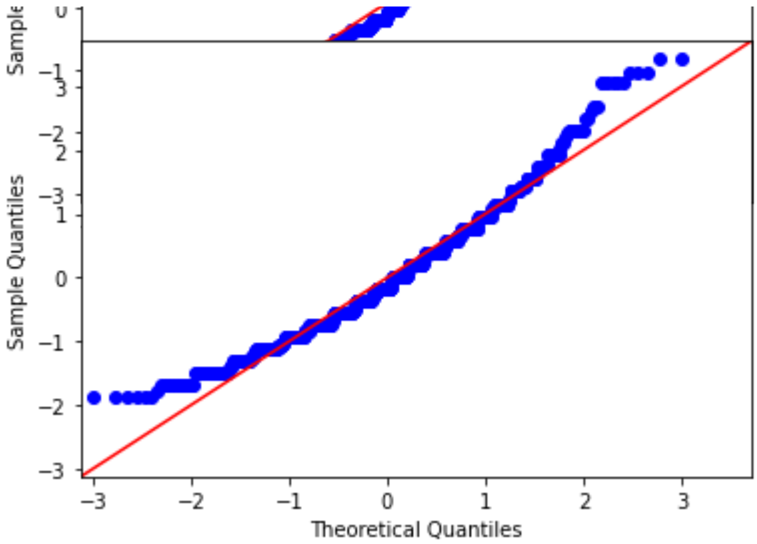
In [21]:
```
# QQ-Plots
columns = stat_predictors.columns
for c in columns:
    sm.graphics.qqplot(stat_predictors[c], dist=stats.norm, line='45', fit=
```

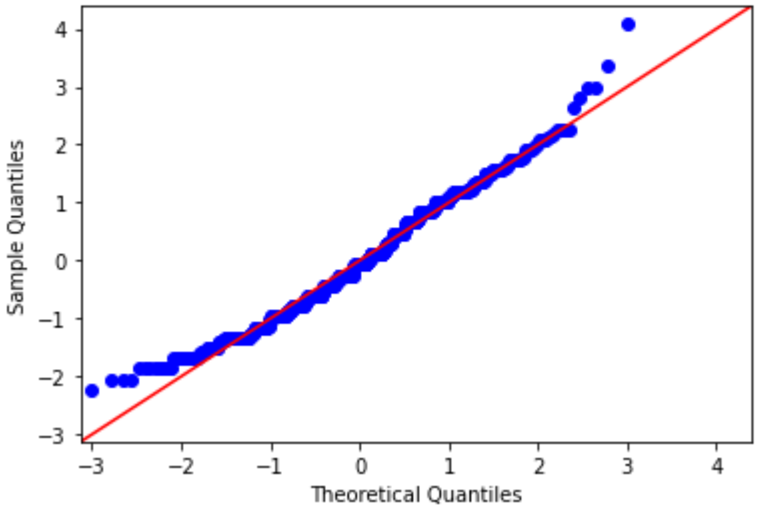


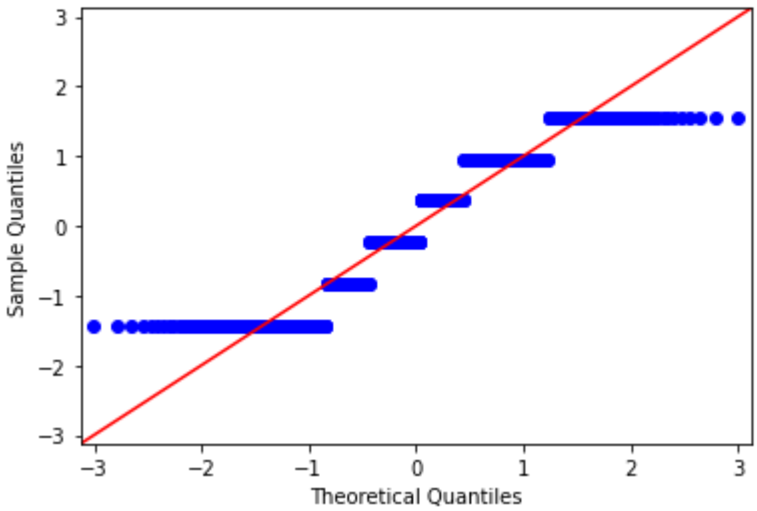


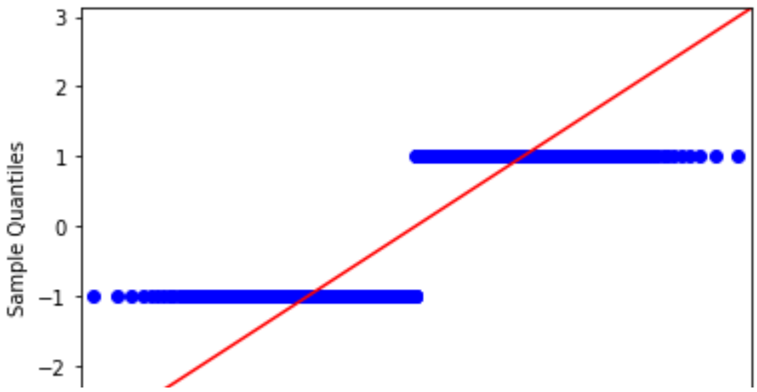


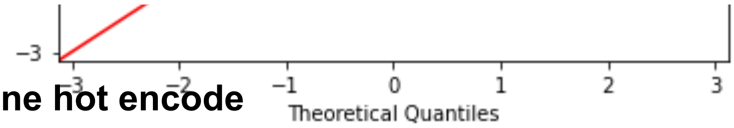



Sample Quantiles
Theoretical Quantiles


Sample Quantiles
Theoretical Quantiles


Sample Quantiles
Theoretical Quantiles


Sample Quantiles



One hot encode

For linear regression, categorical data should be transformed using one-hot encoding.

In [22]:
```
# dummy variables
type_dum = pd.get_dummies(pokemon_clean_df['Type 1'], prefix='type', drop_f
gen_dum = pd.get_dummies(pokemon_clean_df['Generation'], prefix='gen', drop_

# add dummy variables
pokemon_df = pd.concat([stat_predictors.iloc[:,0:6], stat_predictors['Has Ty
```

Modeling

In [23]:
```
dependent = pokemon_df['Attack']
predictors = pokemon_df.drop(['Attack'], axis=1)
```

Model 1

For the first model we use all the predictors that we think should be useful to our model. With an R-Squared value of 0.530 we can explain 53% of the variations of our model. There are quite a few predictors with a P-value over 0.05 which we can remove from our model.

In [24]:
```
#all predictors
predictors_int = sm.add_constant(predictors)
model = sm.OLS(dependent, predictors_int).fit()
model.summary()
```

Out[24]:

OLS Regression Results

Dep. Variable:	Attack	**R-squared:**	0.532
Model:	OLS	**Adj. R-squared:**	0.514
Method:	Least Squares	**F-statistic:**	29.07
Date:	Sat, 25 Jun 2022	**Prob (F-statistic):**	8.32e-99
Time:	20:30:23	**Log-Likelihood:**	-3300.2
No. Observations:	745	**AIC:**	6658.
Df Residuals:	716	**BIC:**	6792.
Df Model:	28		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	5.9300	4.108	1.444	0.149	-2.134	13.994
HP	0.4026	0.038	10.479	0.000	0.327	0.478
Defense	0.3526	0.036	9.898	0.000	0.283	0.423
Sp. Atk	0.2311	0.037	6.312	0.000	0.159	0.303
Sp. Def	-0.2350	0.040	-5.889	0.000	-0.313	-0.157
Speed	0.2666	0.033	8.184	0.000	0.203	0.331

Has Type 2	-2.7049	1.649	-1.640	0.101	-5.943	0.533
type_Dark	8.4933	4.755	1.786	0.074	-0.842	17.828
type_Dragon	17.0461	4.970	3.430	0.001	7.290	26.803
type_Electric	-10.0813	4.323	-2.332	0.020	-18.569	-1.594
type_Fairy	-7.8512	6.084	-1.290	0.197	-19.796	4.094
type_Fighting	23.9155	5.025	4.759	0.000	14.049	33.782
type_Fire	1.4326	4.133	0.347	0.729	-6.682	9.547
type_Flying	-11.1469	10.870	-1.025	0.305	-32.487	10.193
type_Ghost	-5.0243	4.706	-1.068	0.286	-14.264	4.215
type_Grass	-3.3612	3.719	-0.904	0.366	-10.663	3.941
type_Ground	14.5622	4.571	3.186	0.002	5.589	23.536
type_Ice	-5.2251	5.189	-1.007	0.314	-15.413	4.962
type_Normal	-0.0872	3.528	-0.025	0.980	-7.013	6.838
type_Poison	2.0323	4.790	0.424	0.672	-7.373	11.437
type_Psychic	-14.7508	4.146	-3.558	0.000	-22.890	-6.611
type_Rock	12.4584	4.313	2.889	0.004	3.992	20.925
type_Steel	3.5702	5.370	0.665	0.506	-6.973	14.114
type_Water	-6.1163	3.388	-1.805	0.071	-12.767	0.535
gen_2	-0.2169	2.787	-0.078	0.938	-5.689	5.255
gen_3	2.4176	2.507	0.964	0.335	-2.505	7.340
gen_4	1.8536	2.627	0.706	0.481	-3.305	7.012
gen_5	3.7170	2.435	1.526	0.127	-1.064	8.498
gen_6	-0.9092	3.030	-0.300	0.764	-6.859	5.041

Omnibus:	59.386	**Durbin-Watson:**	1.578
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	99.607
Skew:	0.556	**Prob(JB):**	2.35e-22
Kurtosis:	4.405	**Cond. No.**	2.67e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.67e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

In [25]:

```
# sort predictors by P-value

coefs = pd.DataFrame({
    'coef': model.params.values,
    'pvalue': round(model.pvalues, 2),
    'name': model.params.index
}).sort_values(by='pvalue', ascending=False)
coefs
```

Out[25]:

	coef	pvalue	name
type_Normal	-0.087166	0.98	type_Normal
gen_2	-0.216896	0.94	gen_2
gen_6	-0.909152	0.76	gen_6
type_Fire	1.432624	0.73	type_Fire
type_Poison	2.032252	0.67	type_Poison
type_Steel	3.570218	0.51	type_Steel
gen_4	1.853621	0.48	gen_4
type_Grass	-3.361231	0.37	type_Grass
gen_3	2.417649	0.34	gen_3
type_Ice	-5.225102	0.31	type_Ice
type_Flying	-11.146853	0.31	type_Flying
type_Ghost	-5.024296	0.29	type_Ghost
type_Fairy	-7.851161	0.20	type_Fairy
const	5.930004	0.15	const
gen_5	3.717003	0.13	gen_5
Has Type 2	-2.704934	0.10	Has Type 2
type_Water	-6.116295	0.07	type_Water
type_Dark	8.493269	0.07	type_Dark
type_Electric	-10.081291	0.02	type_Electric
Defense	0.352578	0.00	Defense
Sp. Atk	0.231100	0.00	Sp. Atk
Sp. Def	-0.234985	0.00	Sp. Def
type_Fighting	23.915477	0.00	type_Fighting
Speed	0.266608	0.00	Speed
type_Rock	12.458445	0.00	type_Rock
type_Dragon	17.046078	0.00	type_Dragon
type_Ground	14.562232	0.00	type_Ground
HP	0.402615	0.00	HP

In [26]:
```
# drop predictors with p-values over 0.05
drop_columns = coefs[coefs['pvalue'] > 0.05]['name'].values
drop_columns = drop_columns[drop_columns != 'const']
pokemon_df2 = pokemon_df.drop(drop_columns, axis=1)
predictors = pokemon_df2.drop(['Attack'], axis=1)
```

Model 2

After removing the high p-values we still have a few predictors that can be removed. We check our data for multicollinearity which there isn't. We also run a min max scaler so that the stats are all on the same scale. Recursive Feature Elimination helps us find the best predictors to remove.

In [27]:
```
#Removed high p-values
predictors_int = sm.add_constant(predictors)
model = sm.OLS(dependent, predictors_int).fit()
model.summary()
```

Out[27]:

OLS Regression Results

Dep. Variable:	Attack	**R-squared:**	0.514
Model:	OLS	**Adj. R-squared:**	0.507
Method:	Least Squares	**F-statistic:**	70.47
Date:	Sat, 25 Jun 2022	**Prob (F-statistic):**	4.97e-107
Time:	20:30:23	**Log-Likelihood:**	-3314.3
No. Observations:	745	**AIC:**	6653.
Df Residuals:	733	**BIC:**	6708.
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.9010	3.084	1.589	0.112	-1.154	10.956
HP	0.4053	0.037	10.963	0.000	0.333	0.478
Defense	0.3606	0.034	10.713	0.000	0.295	0.427
Sp. Atk	0.2121	0.035	6.144	0.000	0.144	0.280
Sp. Def	-0.2507	0.040	-6.336	0.000	-0.328	-0.173
Speed	0.2815	0.031	8.949	0.000	0.220	0.343
type_Dragon	19.4756	4.236	4.598	0.000	11.160	27.791
type_Electric	-7.8479	3.451	-2.274	0.023	-14.623	-1.073
type_Fighting	26.1335	4.322	6.047	0.000	17.649	34.618
type_Ground	16.1127	3.873	4.160	0.000	8.509	23.716
type_Psychic	-11.6910	3.143	-3.719	0.000	-17.862	-5.520
type_Rock	12.9333	3.559	3.634	0.000	5.947	19.920

Omnibus:	55.597	**Durbin-Watson:**	1.548
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	86.354
Skew:	0.553	**Prob(JB):**	1.77e-19
Kurtosis:	4.249	**Cond. No.**	942.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [28]:
```
pokemon_df2.corr().style.background_gradient(cmap='coolwarm')
```

Out[28]:

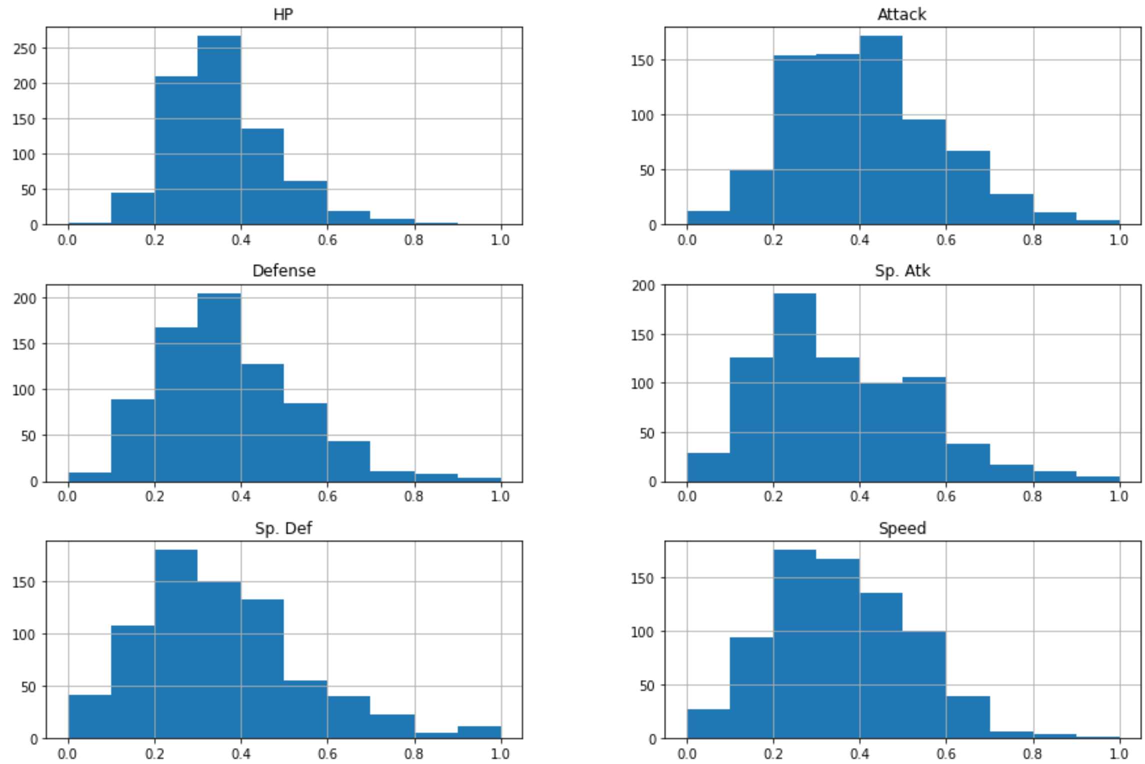
	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	type_Dragon
HP	1.000000	0.511040	0.318909	0.405698	0.393469	0.193413	0.105920

	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	type_Dragon
Attack	0.511040	1.000000	0.436548	0.376459	0.253266	0.347043	0.189920
Defense	0.318909	0.436548	1.000000	0.234861	0.503284	0.035755	0.060911
Sp. Atk	0.405698	0.376459	0.234861	1.000000	0.529399	0.455270	0.106504
Sp. Def	0.393469	0.253266	0.503284	0.529399	1.000000	0.276801	0.104303
Speed	0.193413	0.347043	0.035755	0.455270	0.276801	1.000000	0.077015
type_Dragon	0.105920	0.189920	0.060911	0.106504	0.104303	0.077015	1.000000
type_Electric	-0.094831	-0.065126	-0.054438	0.136066	0.029193	0.153181	-0.046480
type_Fighting	0.015720	0.116010	-0.046578	-0.134299	-0.041660	-0.026427	-0.035434
type_Ground	0.048938	0.139245	0.101679	-0.097248	-0.054864	-0.022223	-0.040286

Standardise data

In [29]:

```
# define min max scaler
scaler = MinMaxScaler()
# transform data
scaled = scaler.fit_transform(stat_predictors.iloc[:,0:6])
data = pd.DataFrame(scaled, columns=stat_predictors.iloc[:,0:6].columns)
data.hist(figsize=(15,10))
plt.show()
```



In [30]:

```
pokemon_df3 = pd.concat([data, predictors.iloc[:,5:11]], axis=1)
pokemon_df3
```

Out[30]:

	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	type_Dragon	type_Electric
0	0.232804	0.251429	0.245810	0.323529	0.321429	0.228571	0	0
1	0.312169	0.325714	0.324022	0.411765	0.428571	0.314286	0	0
2	0.417989	0.440000	0.435754	0.529412	0.571429	0.428571	0	0

	HP	Attack	Defense	Sp. Atk	Sp. Def	Speed	type_Dragon	type_Electric
3	0.201058	0.268571	0.212291	0.294118	0.214286	0.342857	0	0
4	0.301587	0.337143	0.296089	0.411765	0.321429	0.428571	0	0
...	...	...	...	...	...	...	...	...
740	0.566138	0.542857	0.648045	0.417647	0.535714	0.514286	1	0
741	0.259259	0.542857	0.810056	0.529412	0.928571	0.257143	0	0
742	0.417989	0.600000	0.307263	0.823529	0.785714	0.371429	0	0
743	0.417989	0.885714	0.307263	0.941176	0.785714	0.428571	0	0
744	0.417989	0.600000	0.642458	0.705882	0.500000	0.371429	0	0

RFE

Recursive Feature Elimination

In [31]:
```
rfe_df = pokemon_df3.copy(deep=True)
rfe_pred = rfe_df.drop('Attack',axis=1)
rfe_pred.head()
```

Out[31]:

	HP	Defense	Sp. Atk	Sp. Def	Speed	type_Dragon	type_Electric	type_Fightin
0	0.232804	0.245810	0.323529	0.321429	0.228571	0	0	
1	0.312169	0.324022	0.411765	0.428571	0.314286	0	0	
2	0.417989	0.435754	0.529412	0.571429	0.428571	0	0	
3	0.201058	0.212291	0.294118	0.214286	0.342857	0	0	
4	0.301587	0.296089	0.411765	0.321429	0.428571	0	0	

In [32]:
```
linreg = LinearRegression()
selector = RFE(linreg, n_features_to_select = 9)
selector = selector.fit(rfe_pred, rfe_df['Attack'])
print(list(zip(rfe_pred, selector.ranking_)))
```

```
[('HP', 1), ('Defense', 1), ('Sp. Atk', 1), ('Sp. Def', 1), ('Speed', 1),
('type_Dragon', 1), ('type_Electric', 3), ('type_Fighting', 1), ('type_Gro
und', 1), ('type_Psychic', 2), ('type_Rock', 1)]
```

In [33]:
```
# best 2 predictors
selector = RFE(linreg, n_features_to_select = 2)
selector = selector.fit(rfe_pred, rfe_df['Attack'])
print(list(zip(rfe_pred, selector.ranking_)))
```

```
[('HP', 1), ('Defense', 1), ('Sp. Atk', 4), ('Sp. Def', 3), ('Speed', 2),
('type_Dragon', 6), ('type_Electric', 10), ('type_Fighting', 5), ('type_Gr
ound', 7), ('type_Psychic', 9), ('type_Rock', 8)]
```

Model 3

With our final model we have an R-Squared value that can explain 50.3% of the variance in our model. All our predictors can be considered statistically significant as their P-Value is less than 0.05.
One of the assumptions for linear regression is that our data needs to have normal distribution. This can be seen with our QQ-Plot mostly falling on the red line. The skew value also reinforces this by being between -0.5 and 0.5.

Another assumption for linear regression is that the data needs to be homoscedastic which is represented in our residuals scatterplot not having a cone like shape or pattern.

In [34]:
```
dependent = rfe_df['Attack']
predictors = rfe_pred.drop(['type_Electric', 'type_Psychic'], axis=1)

predictors_int = sm.add_constant(predictors)
model = sm.OLS(dependent, predictors_int).fit()
model.summary()
```

Out[34]:

OLS Regression Results

Dep. Variable:	Attack	**R-squared:**	0.503
Model:	OLS	**Adj. R-squared:**	0.497
Method:	Least Squares	**F-statistic:**	82.53
Date:	Sat, 25 Jun 2022	**Prob (F-statistic):**	2.59e-105
Time:	20:30:24	**Log-Likelihood:**	524.89
No. Observations:	745	**AIC:**	-1030.
Df Residuals:	735	**BIC:**	-983.6
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0016	0.017	-0.095	0.925	-0.035	0.031
HP	0.4600	0.040	11.564	0.000	0.382	0.538
Defense	0.3848	0.035	11.137	0.000	0.317	0.453
Sp. Atk	0.1786	0.033	5.381	0.000	0.113	0.244
Sp. Def	-0.2138	0.032	-6.728	0.000	-0.276	-0.151
Speed	0.2749	0.032	8.697	0.000	0.213	0.337
type_Dragon	0.1215	0.024	4.994	0.000	0.074	0.169
type_Fighting	0.1536	0.025	6.160	0.000	0.105	0.203
type_Ground	0.0953	0.022	4.264	0.000	0.051	0.139
type_Rock	0.0782	0.021	3.813	0.000	0.038	0.118

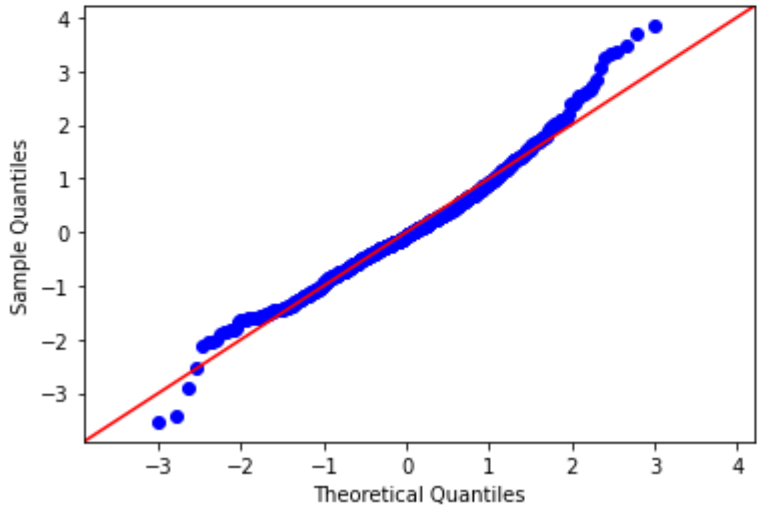
Omnibus:	40.719	**Durbin-Watson:**	1.551
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	57.851
Skew:	0.460	**Prob(JB):**	2.74e-13
Kurtosis:	4.008	**Cond. No.**	12.8

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

QQ-Plot

Mostly follows the red line indicating data is normally distributed

In [35]:
```
resid1 = model.resid
fig = sm.graphics.qqplot(resid1, dist=stats.norm, line='45', fit=True)
```

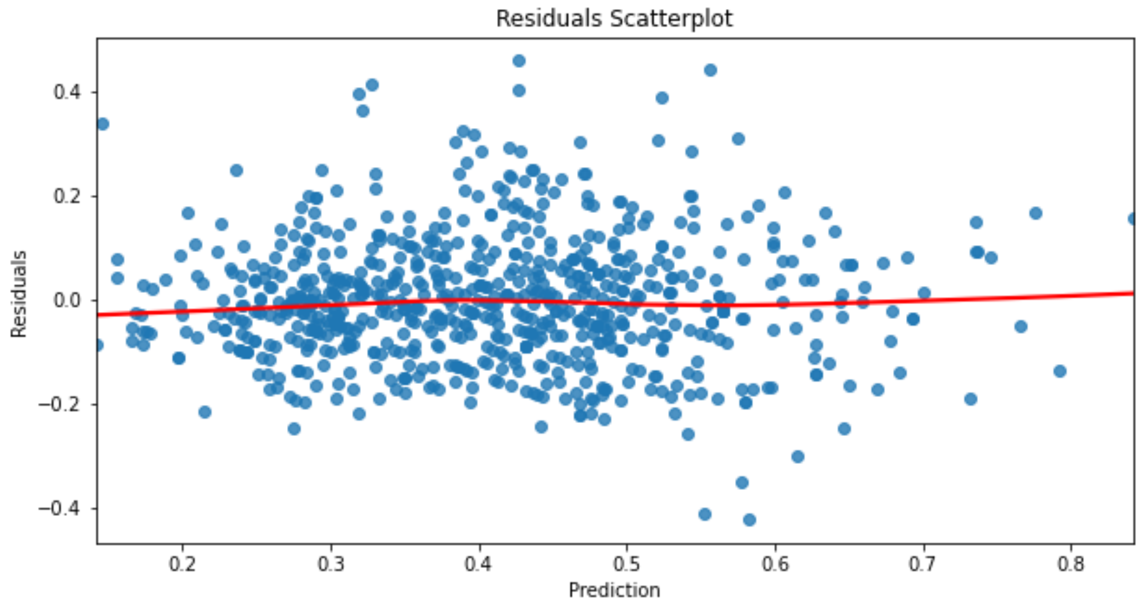


Homoscedasticity

Plots don't show a cone like pattern

In [36]:
```
plt.figure(figsize=(10,5))
sns.regplot(x=model.predict(), y=model.resid, lowess=True, line_kws={'color
plt.title('Residuals Scatterplot')
plt.xlabel('Prediction')
plt.ylabel('Residuals')
```

Out[36]:
```
Text(0, 0.5, 'Residuals')
```



Training

Training and test MSE is similar so we can expect the model to perform similarly on different data. Accuracy of the model is 50.14%

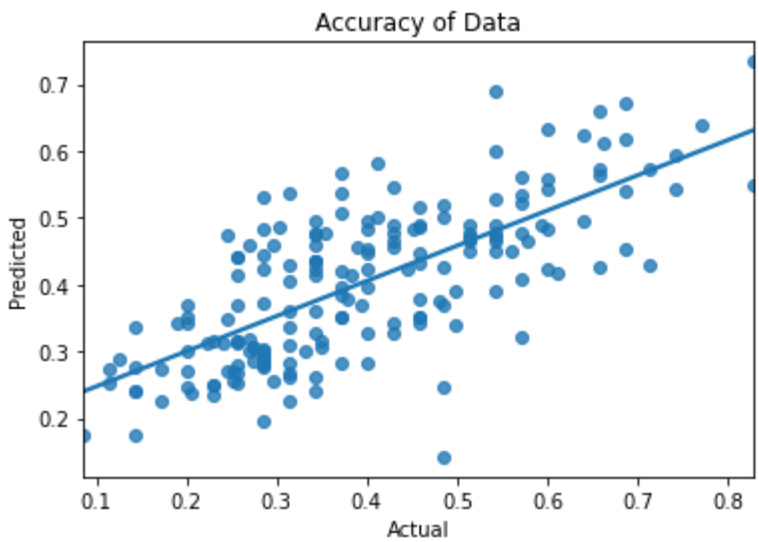
In [37]:
```
y = dependent
X = predictors
X_train, X_test, y_train, y_test = train_test_split(X, y)

linreg = LinearRegression()
linreg.fit(X_train, y_train)

y_hat_train = linreg.predict(X_train)
y_hat_test = linreg.predict(X_test)

train_mse = mean_squared_error(y_train, y_hat_train)
test_mse = mean_squared_error(y_test, y_hat_test)
print('Train Mean Squared Error:', train_mse)
print('Test Mean Squared Error:', test_mse)
```

```
Train Mean Squared Error: 0.015127276429836516
Test Mean Squared Error: 0.01200812854901391
```

In [38]:
```
Accuracy=r2_score(y_test,y_hat_test)*100
print(" Accuracy of the model is %.2f" %Accuracy)
```

```
 Accuracy of the model is 51.43
```

In [39]:
```
plot = sns.regplot(x=y_test,y=y_hat_test,ci=None).set(title='Accuracy of Da
```



Conclusion

The best 2 predictors for our model is HP and defence which is also highlighted from the correlation matrix. With an accuracy of 50% this model may not be enough to provide players with enough insight on the upcoming generation of Pokémon. Even if our model had high accuracy with predicting the attack of the new generation there are so many other factors to account for.
Having high attack doesn't mean it is a top tier Pokémon to use as the other stats like speed may be a lot lower meaning that Pokémon attacks second. There are also varying skills and other game mechanics that can change the outcome of a high attack Pokémon versus a low attack Pokémon.

In [ ]: