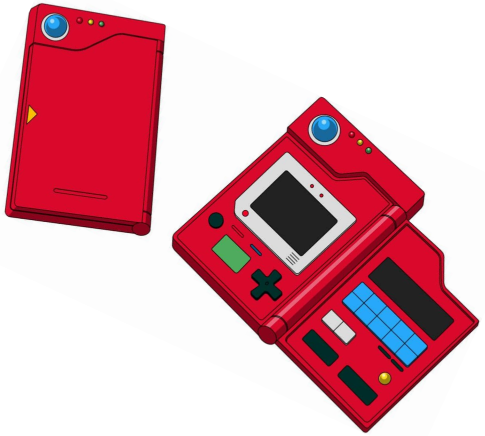
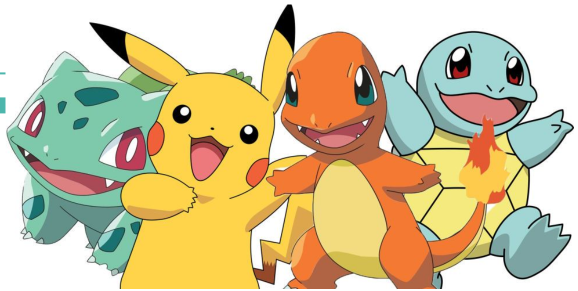


# Predicting Pokemon types with stats from over 721 Pokémon



# Background Info

- Nintendo released Pokemon Red & Green for Gameboy Japan in 1996
- Each Pokemon has a type and specific base stat that made it strong or weak against other Pokemon
- 150 Pokemon in Gen I, with 15 types
- 802 Pokemon in Gen VII  with 18 types
- Pokemon can have a primary and secondary type
- For this project, we will be looking at primary type only because with the combination possibilities, there are 146 type combinations

# Problem Statement and  Hypothesis

By looking at and comparing the pokemon base stats (including HP, attack, special attack, defense, special defense, and speed) can we accurately predict the pokemon's primary type.

There are a lot of pokemon out there, and it'd be cool to predict its strengths and weaknesses by looking at base stats.  I've been playing Pokemon since the original games came to USA in 1997, and still love it

- Note- we will only be looking at the game data.  This will not include the trading cards, Pokemon Go, or the animated series

# About the Data

- I found this data on Kaggle https://www.kaggle.com/abcsds/pokemon
- Most of the data was sourced from data found on Bublapedia, a Pokemon encyclopedia:http://bulbapedia.bulbagarden.net/wiki/Main_Page
- The data set contains information from Gen I to Gen VI, so I pulled my own testing data from Bulbapedia and used Pokemon from Gen VII as testing

# First Looks

There are 801 rows and 13 columns

```
In [18]: df.shape
Out[18]: (801, 13)
```

```
In [29]: df.head()
Out[29]:
```

| | Pokemon_Number | Name | Type_1 | Type_2 | Total | HP | Attack | Defense | Sp.Atk | Sp.Def | Speed | Generation | Legendary |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | Bulbasaur | Grass | Poison | 318 | 45 | 49 | 49 | 65 | 65 | 45 | 1 | False |
| **1** | 2 | Ivysaur | Grass | Poison | 405 | 60 | 62 | 63 | 80 | 80 | 60 | 1 | False |
| **2** | 3 | Venusaur | Grass | Poison | 525 | 80 | 82 | 83 | 100 | 100 | 80 | 1 | False |
| **3** | 3 | VenusaurMega Venusaur | Grass | Poison | 625 | 80 | 100 | 123 | 122 | 120 | 80 | 1 | False |
| **4** | 4 | Charmander | Fire | NaN | 309 | 39 | 52 | 43 | 60 | 50 | 65 | 1 | False |

# Looking at Pokemon Types

```
In [30]: df.Type_1.value_counts()

Out[30]: Water       112
         Normal       98
         Grass        70
         Bug          69
         Psychic      57
         Fire         52
         Electric     44
         Rock         44
         Ground       32
         Ghost        32
         Dragon       32
         Dark         31
         Poison       28
         Fighting     27
         Steel        27
         Ice          24
         Fairy        17
         Flying        4
         Name: Type_1, dtype: int64
```

# Graphing

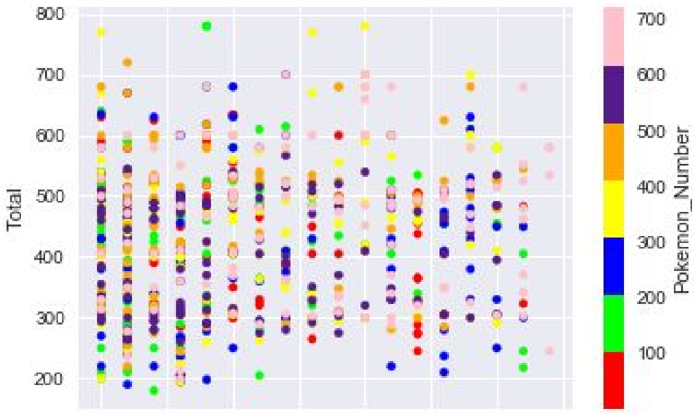
Renaming the types with a numeric value

```
In [34]: df['Type_1'] = df.Type_1.map({'Water':0, 'Normal':1, 'Grass':2, 'Bug':3, 'Psychic':4, 'Fire':5,
'Electric':6, 'Rock':7, 'Ground':8, 'Ghost':9, 'Dragon':10, 'Dark':11, 'Poison':12, 'Fighting':13,
'Steel':14, 'Ice':15, 'Fairy':16, 'Flying':17})
```

## Scatter Plot: X = Type_1, Y = Total (all stats added together) and c = Pokemon Number

```
Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x1187394d0>
```

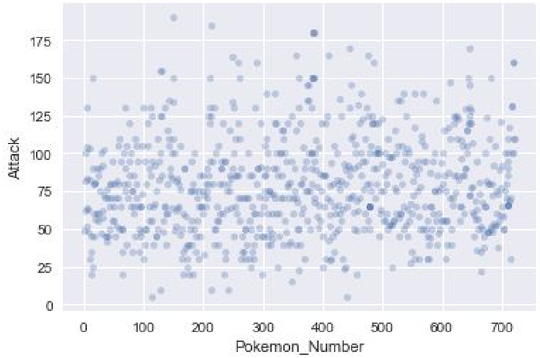
You can see the 18 columns for the different types. You can also see that there is a high range with the TOTAL metric



# Scatter Plots of Pokemon Stats

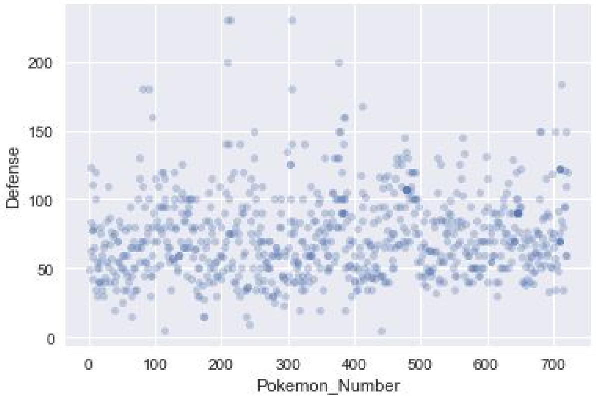
## Attack

```
In [50]: # add transparency
         df.plot(kind='scatter', x='Pokemon_Number', y='Attack', alpha=0.3)

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x11874b990>
```




## Defense

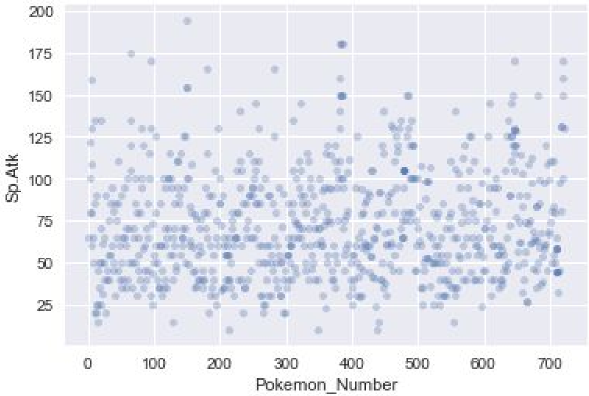
```
In [51]: df.plot(kind='scatter', x='Pokemon_Number', y='Defense', alpha=0.3)

Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x118dab490>
```



# Continued

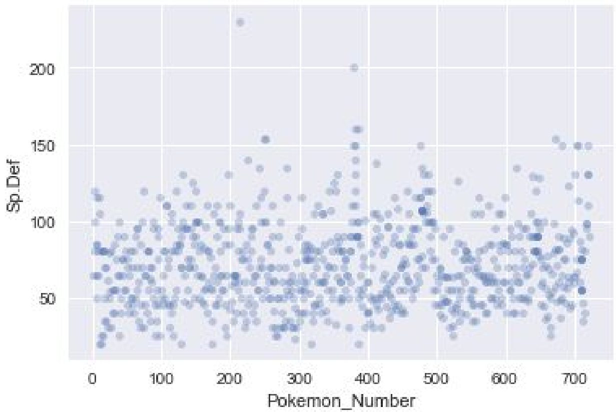
## Special Attack

```
In [54]: df.plot(kind='scatter', x='Pokemon_Number', y='Sp.Atk', alpha=0.3)

Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x1191dba90>
```




## Special Defense

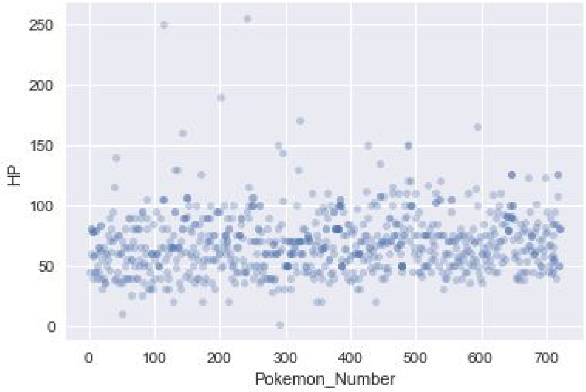
```
df.plot(kind='scatter', x='Pokemon_Number', y='Sp.Def', alpha=0.3)

<matplotlib.axes._subplots.AxesSubplot at 0x110b886d0>
```



# Continued

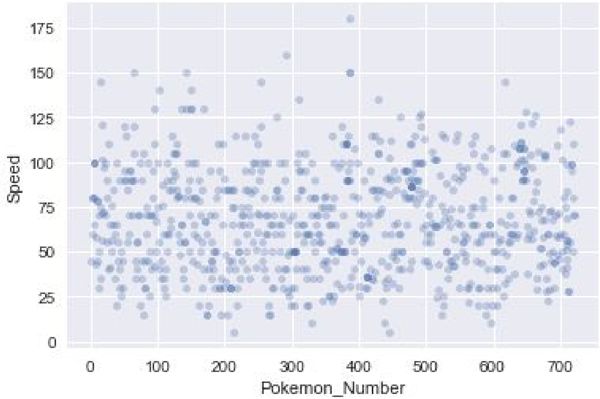
HP

```
In [52]: df.plot(kind='scatter', x='Pokemon_Number', y='HP', alpha=0.3)
Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x1191dba10>
```

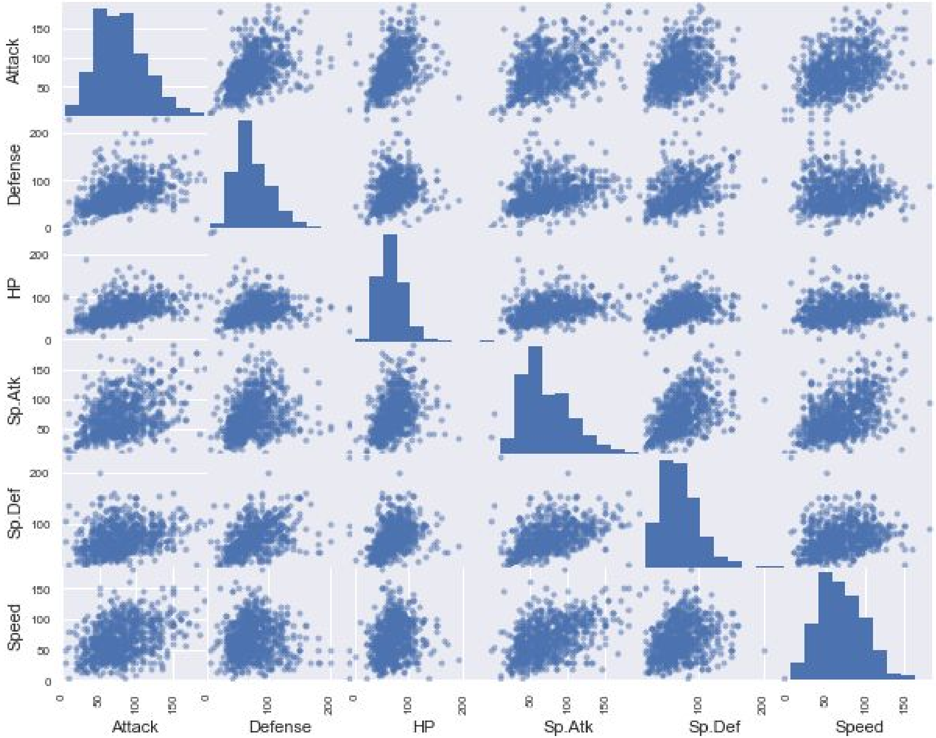



Speed

```
df.plot(kind='scatter', x='Pokemon_Number', y='Speed', alpha=0.3)
<matplotlib.axes._subplots.AxesSubplot at 0x110b926d0>
```



# Scatter Matrix



# KNN to predict Type based on Stats- Step 1

```
#Starting a KNN to see features versus type to determine strength in type1
# store feature matrix in "X"
feature_cols = ['Attack', 'Defense', 'HP', 'Sp.Atk', 'Sp.Def', 'Speed']
X = df[feature_cols]
print (X)
```

| | Attack | Defense | HP | Sp.Atk | Sp.Def | Speed |
|---|---|---|---|---|---|---|
| 0 | 49 | 49 | 45 | 65 | 65 | 45 |
| 1 | 62 | 63 | 60 | 80 | 80 | 60 |
| 2 | 82 | 83 | 80 | 100 | 100 | 80 |
| 3 | 100 | 123 | 80 | 122 | 120 | 80 |
| 4 | 52 | 43 | 39 | 60 | 50 | 65 |
| 5 | 64 | 58 | 58 | 80 | 65 | 80 |
| 6 | 84 | 78 | 78 | 109 | 85 | 100 |
| 7 | 130 | 111 | 78 | 130 | 85 | 100 |
| 8 | 104 | 78 | 78 | 159 | 115 | 100 |
| 9 | 48 | 65 | 44 | 50 | 64 | 43 |
| 10 | 63 | 80 | 59 | 65 | 80 | 58 |
| 11 | 83 | 100 | 79 | 85 | 105 | 78 |
| 12 | 103 | 120 | 79 | 135 | 115 | 78 |
| 13 | 30 | 35 | 45 | 20 | 20 | 45 |

Creating our features (X)

# Step 1 Continued...

Creating our response vector, y and checking types

```
# store response vector in "y"
y = df.Type_1
print(y)
```

```
0     2
1     2
2     2
3     2
4     5
5     5
6     5
7     5
8     5
9     0
10    0
```

```
# check X's type
print type(X)
print type(X.values)
```

```
<class 'pandas.core.frame.DataFrame'>
<type 'numpy.ndarray'>
```

```
# check X's shape (n = number of observations, p = number of features)
print X.shape
```

```
(800, 6)
```

```
# check y's shape (single dimension with length n)
print y.shape
```

```
(800,)
```

# Step 2. Import the Estimator

In this step, we're going to import KNN Classifier from Sklearn

```
#Step 2: Decide on the estimator you want to to use and import that class
from sklearn.neighbors import KNeighborsClassifier
```

# Step 3. Instantiate the estimator

```
#Step 3: "Instantiate" the "estimator"
knn = KNeighborsClassifier(n_neighbors=1)
type(knn)
```

```
sklearn.neighbors.classification.KNeighborsClassifier
```

```
print knn
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=1, p=2,
           weights='uniform')
```

# Step 4. Fit the Model

```
#Step 4: Fit the model with data (aka "model training")
knn.fit(X, y)
```

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=1, p=2,
           weights='uniform')
```

We're using stats from Generation I through Generation VI to fit the KNN model.  For our predictions, we'll use Pokemon stats from Gen VII

# Step 5. Use the model to predict the response for a new observation

```
#Step 5: Use the model to predict the response for a new observation
#this data only goes through Gen VI, using pkmn from VII to have knn predict type_1
#Grass: Fomantis num 753,
#Attack55,Defense35,HP40,Sp.Atk50,Sp.Def35,Speed35....looking for type #2 grass
#Electric: Xurkitree num 796
#Attack89,Defense71,HP 83,Sp.Atk173,Sp.Def71,Speed83....looking for type #6 electric
#Psychic: Necrozma num 800
#Attack107,Defense101,HP97,Sp.Atk127,Sp.Def89,Speed79....looking for type #4 psychic
new_observation = [[55, 35, 40, 50, 35, 35], [89, 71, 83, 173, 71, 83], [107, 101, 97, 127, 89, 79]]
knn.predict(new_observation)
```

Adding a new observation to see how it is classified

# Step 5 continued...

```
#adding a new pokemon- dragon type Jangmo-o num 782 - should be type 10
#adding water, Pyukumuku, num 771 should be type 0
X_new = [[55, 35, 40, 50, 35, 35], [89, 71, 83, 173, 71, 83], [107, 101, 97, 127, 89, 79], [55, 65, 45,
45, 45, 45], [60, 130, 55, 30, 130, 5]]
knn.predict(X_new)
```

```
array([3, 6, 5, 0, 9])
```

```
#predict probability
knn.predict_proba
```

```
<bound method KNeighborsClassifier.predict_proba of KNeighborsClassifier(algorithm='auto', leaf_size=30, m
etric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=1, p=2,
           weights='uniform')>
```

# Step 6. Evaluate Accuracy

```
#Step 6: Evaluate the error or accuracy of the model--measure accuracy/cross validation
# instantiate the model (using the value K=5)
knn = KNeighborsClassifier(n_neighbors=5)

# fit the model with data
knn.fit(X, y)

# predict the response for new observations
knn.predict(X_new)
```

```
array([1, 5, 5, 0, 7])
```

```
# calculate predicted probabilities of class membership
knn.predict_proba(X_new)
```

```
array([[ 0. ,  0.2,  0. ,  0.2,  0. ,  0. ,  0.2,  0. ,  0. ,  0. ,  0. ,
         0.2,  0.2,  0. ,  0. ,  0. ,  0. ,  0. ],
       [ 0. ,  0.2,  0. ,  0. ,  0. ,  0.4,  0.2,  0. ,  0. ,  0. ,  0. ,
         0.2,  0. ,  0. ,  0. ,  0. ,  0. ,  0. ],
       [ 0. ,  0. ,  0. ,  0. ,  0. ,  0.6,  0.2,  0. ,  0. ,  0. ,  0. ,
         0.2,  0. ,  0. ,  0. ,  0. ,  0. ,  0. ],
       [ 0.2,  0. ,  0.2,  0.2,  0. ,  0. ,  0. ,  0.2,  0. ,  0. ,  0. ,
         0.2,  0. ,  0. ,  0. ,  0. ,  0. ,  0. ],
       [ 0. ,  0. ,  0.2,  0. ,  0. ,  0. ,  0. ,  0.6,  0. ,  0.2,  0. ,
         0. ,  0. ,  0. ,  0. ,  0. ,  0. ,  0. ]])
```