

HW#5

April 21, 2020

```
[1]: import warnings
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np
from plotnine import *

from sklearn.preprocessing import StandardScaler

from sklearn.cluster import AgglomerativeClustering

from sklearn.cluster import KMeans
from sklearn.mixture import GaussianMixture

from sklearn.metrics import silhouette_score

import scipy.cluster.hierarchy as sch
from matplotlib import pyplot as plt

%matplotlib inline
```

```
[2]: # Name: Name of each pokemon

# Type 1: Each pokemon has a type, this determines weakness/resistance to
↳ attacks

# Type 2: Some pokemon are dual type and have 2

# Total: sum of all stats that come after this, a general guide to how strong a
↳ pokemon is

# HP: hit points, or health, defines how much damage a pokemon can withstand
↳ before fainting

# Attack: the base modifier for normal attacks (eg. Scratch, Punch)
```

```
# Defense: the base damage resistance against normal attacks

# SP Atk: special attack, the base modifier for special attacks (e.g. fire_
→blast, bubble beam)

# SP Def: the base damage resistance against special attacks

# Speed: determines which pokemon attacks first each round
```

```
[3]: poke = pd.read_csv("https://raw.githubusercontent.com/cmparlettpelleriti/
→CPSC392ParlettPelleriti/master/Data/Pokemon.csv")
poke.head()
```

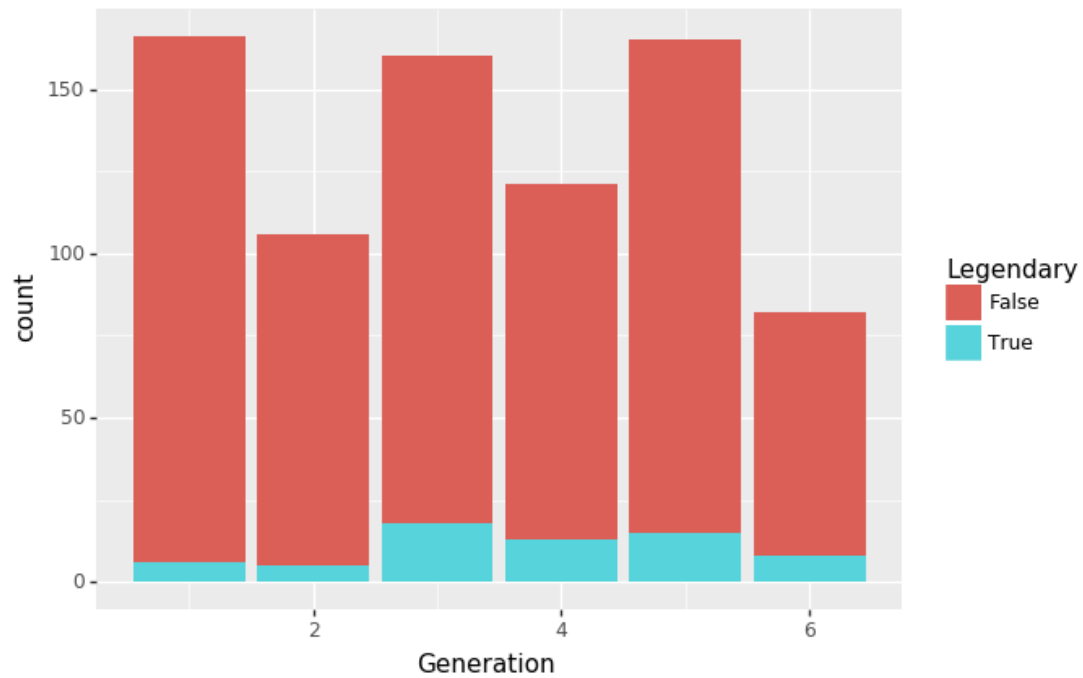
```
[3]:
```

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

	Sp. Def	Speed	Generation	Legendary
0	65	45	1	False
1	80	60	1	False
2	100	80	1	False
3	120	80	1	False
4	50	65	1	False

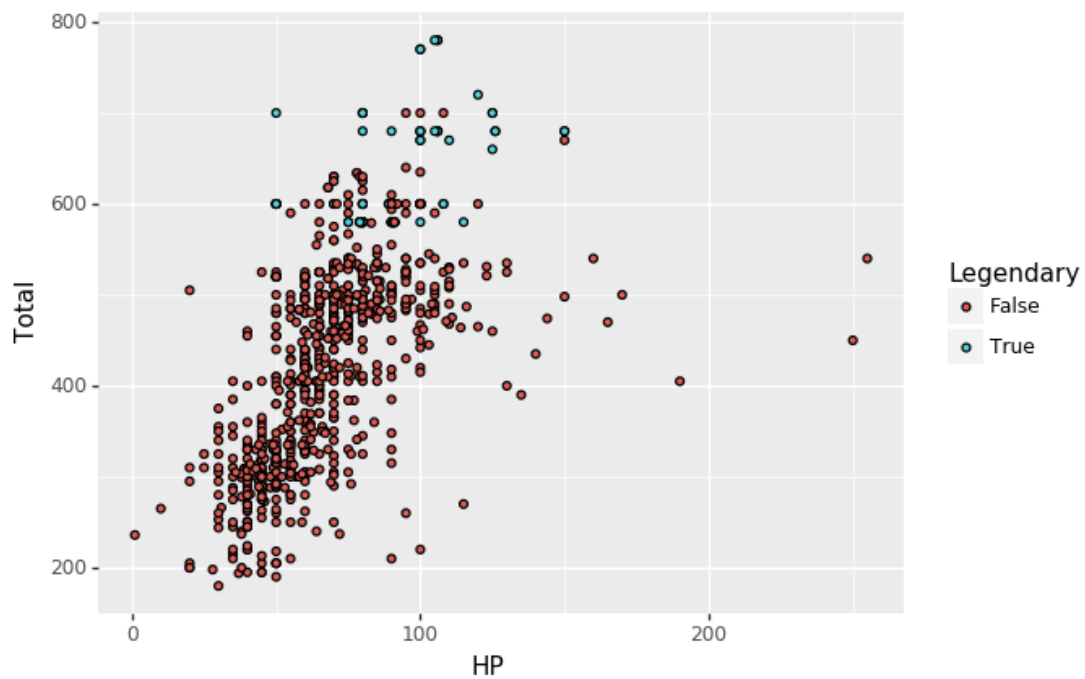
1 1. Explore Data

```
[4]: ggplot(poke, aes("Generation", fill = "Legendary")) + geom_bar()
```



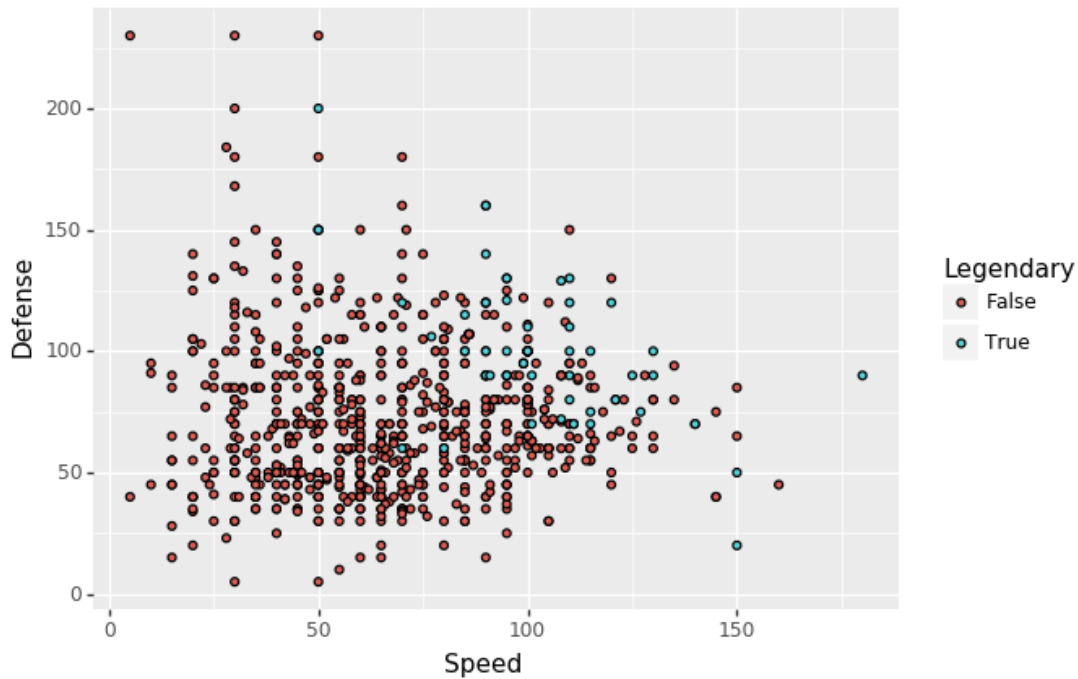
```
[4]: <ggplot: (317225441)>
```

```
[5]: ggplot(poke, aes("HP", "Total")) + geom_point(aes(fill = "Legendary"))
```



```
[5]: <ggplot: (316648725)>
```

```
[6]: ggplot(poke, aes("Speed", "Defense")) + geom_point(aes(fill = "Legendary"))
```



```
[6]: <ggplot: (317712945)>
```

I see that most of the legendary pokemons are equipped with the best attacks and defenses which makes sense.

2 2. K-means model

```
[7]: features = ["Legendary", "HP", "Total", "Speed", "Attack", "Defense"]
X = poke[features]

z = StandardScaler()
X[features] = z.fit_transform(X)

km = KMeans(n_clusters = 5)

km.fit(X)

membership = km.predict(X)
```

```
X["cluster"] = membership

silhouette_score(X, membership)
```

[7]: 0.45044341226229606

which features did you use and why? - I used “Legendary”, “HP”, “Total”, “Speed”, “Attack”, and “Defense” to member the pokemon because I felt theses were important variables to identify pokemon

did you standardize your variables? why or why not? - yes I did because not all variables were not measured on the same scale.

which k works best? what metrics did you use to determine this? - I ran the model several times with different k values and found that between 4 and 5 n_clusters was the best amount for maximizing our silhouette score

3. Gaussian Mixture model

```
[8]: features = ["Legendary", "HP", "Total", "Speed", "Attack", "Defense"]
```

```
X = poke[features]
z = StandardScaler()
X[features] = z.fit_transform(X)
Xdf = X

n_components = [2,3,4,5,6]

sils = []
for n in n_components:
    gmm = GaussianMixture(n_components = n)
    gmm.fit(X)
    colName = str(n) + "assign"
    clusters = gmm.predict(X)

    Xdf[colName] = clusters

    sils.append(silhouette_score(X, clusters))

print(sils)
```

```
[0.5029335973278094, 0.5061383802739656, 0.4911189789750171, 0.5033830610048823,
0.5392913667951059]
```

which features did you use and why? - I used “Legendary”, “HP”, “Total”, “Speed”, “Attack”, and “Defense” to member the pokemon because I felt theses were important variables to identify pokemon

did you standardize your variables? why or why not? - yes I did because not all variables were not measured on the same scale.

which number of components works best? what metrics did you use to determine this? - After running the model for 2,3,4,5,and 6 num pf components, the silhouette score showed that 5 components was the ideal amount of components.

4 4. Hierarchical model

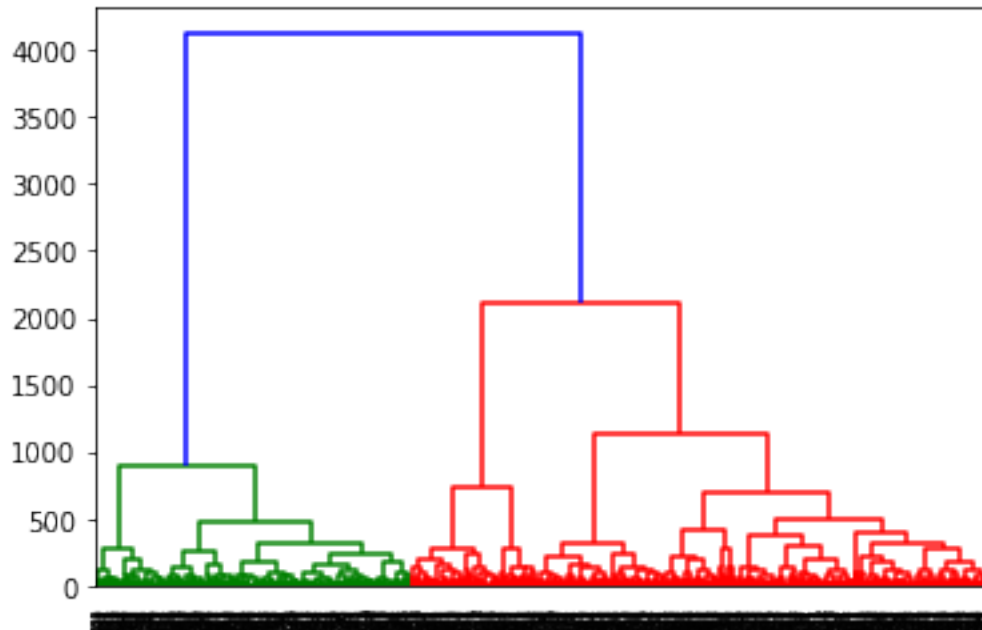
```
[9]: features = ["Legendary", "HP", "Total", "Speed", "Attack", "Defense"]

X = poke[features]

hac = AgglomerativeClustering(affinity = "euclidean",
                             linkage = "ward")

hac.fit(X)

dendro = sch.dendrogram(sch.linkage(X, method='ward'))
```



```
[10]: hac = AgglomerativeClustering(n_clusters =2,
                                    affinity = "euclidean",
                                    linkage = "ward")

hac.fit(X)
```

```
[10]: AgglomerativeClustering(affinity='euclidean', compute_full_tree='auto',
                               connectivity=None, distance_threshold=None,
                               linkage='ward', memory=None, n_clusters=2)
```

```
[11]: membership = hac.labels_
      membership
```

```
[11]: array([1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1,
            0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0,
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            0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0,
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            1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0,
            0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0,
            0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1,
            0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0,
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            0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1,
            0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1,
            0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
            0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
            0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0,
            1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0,
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            1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0,
            0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0,
            0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
            0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0,
            1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0,
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            0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0,
            1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0,
            1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0,
            0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0,
            0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0,
            0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0,
            1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0,
            0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0,
            0, 0, 0, 0, 0, 0, 0, 0])
```

```
[12]: silhouette_score(X, membership)
```

[12]: 0.5002392714696835

which features did you use and why? - I used “Legendary”, “HP”, “Total”, “Speed”, “Attack”, and “Defense” to member the pokemon because I felt theses were important variables to identify pokemon

did you standardize your variables? why or why not? - yes I did because not all variables were not measured on the same scale.

which number of clusters works best? what metrics did you use to determine this? - I used 2 clusters because it produced the best silhouette score, also this amount of clusters is the least computationally expensive.

5 5. Compare the results from each model

Were the clusters created by each method similar? - Yes I would say the models were very similar.

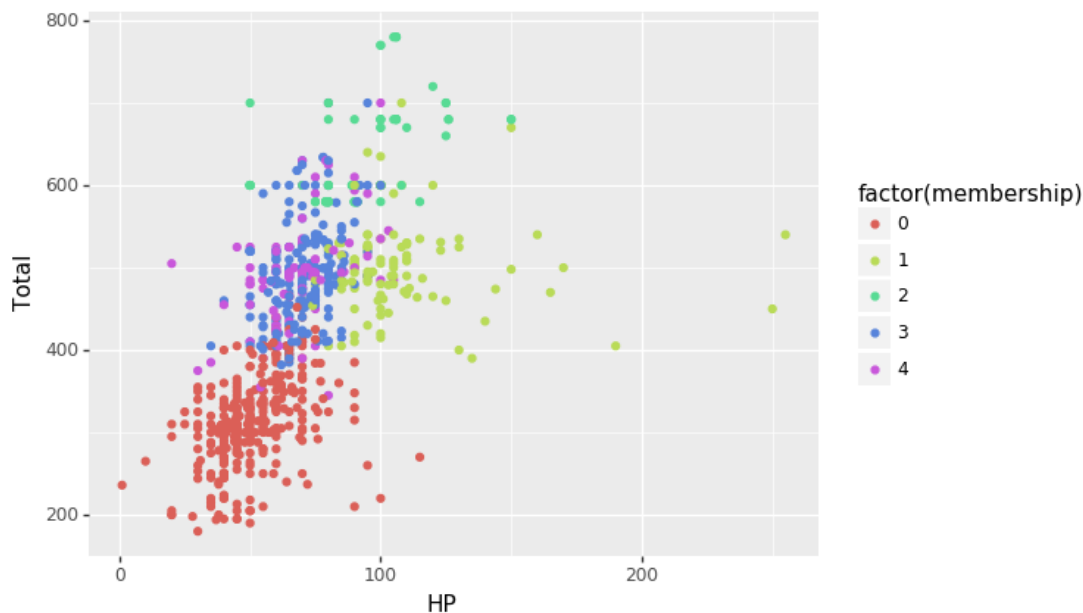
Describe the clusters from each method (in other words, are the mean values for features different between clusters? - I did not see a huge differencnt in the mean values between clusters

How would you describe each cluster to someone who hasn't seen the data before? e.g. “This cluster is very fast, and has a low attack....etc”) - I would describe these clusters by saying which were closer to legendary or not.

6 GGLOT Per Method

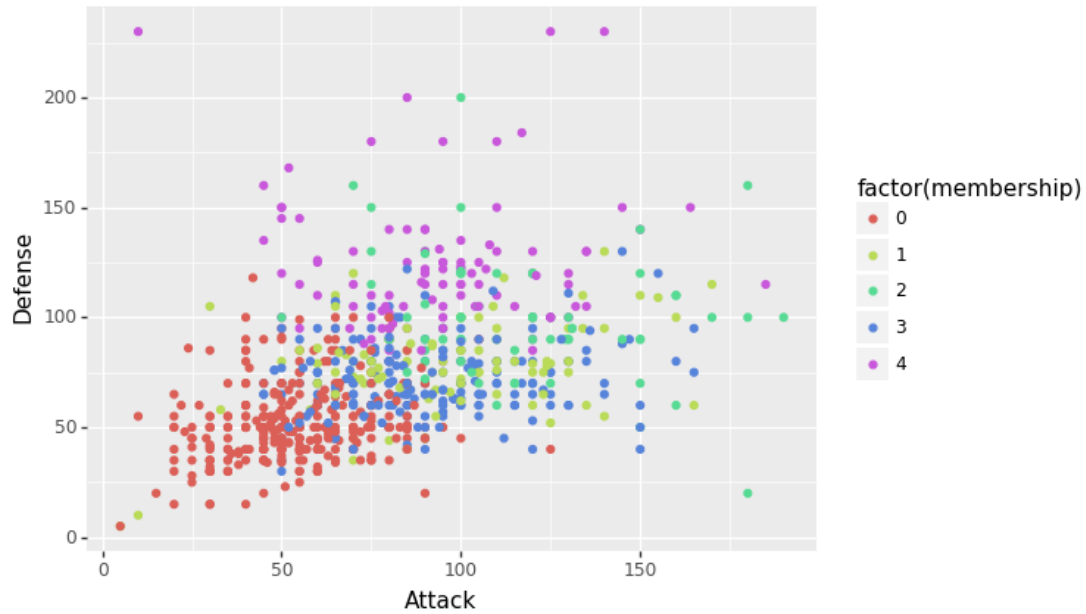
7 K-means model

```
[13]: (ggplot(X, aes("HP", "Total", color = "factor(membership)")) + geom_point())
```




```
[13]: <ggplot: (317687565)>
```

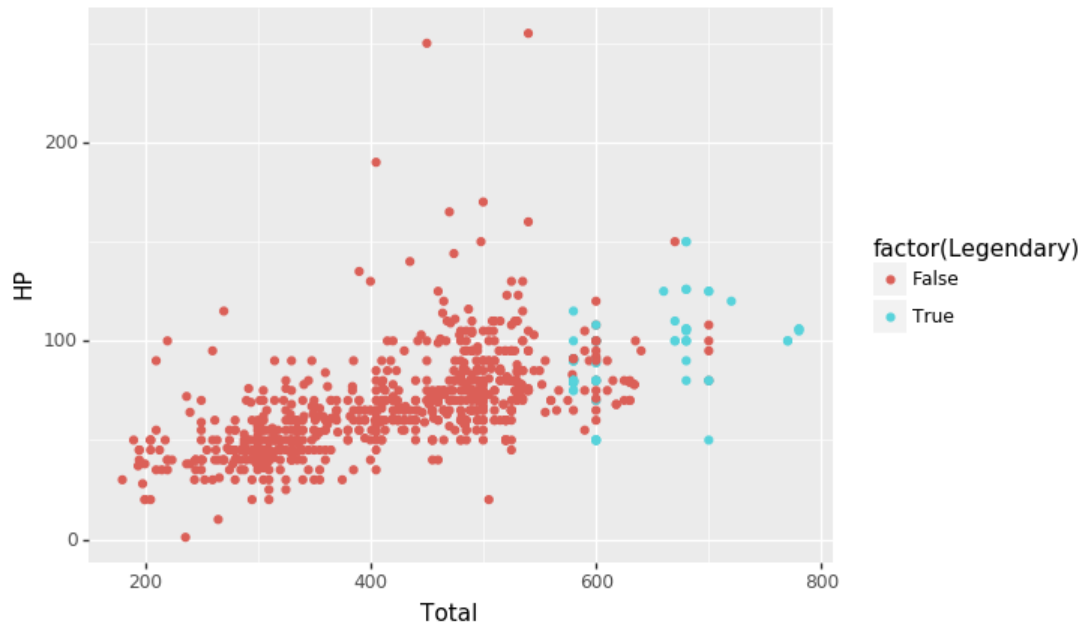
```
[14]: (ggplot(X, aes("Attack", "Defense", color = "factor(membership)")) +  
  ↪ geom_point())
```



```
[14]: <ggplot: (316658233)>
```

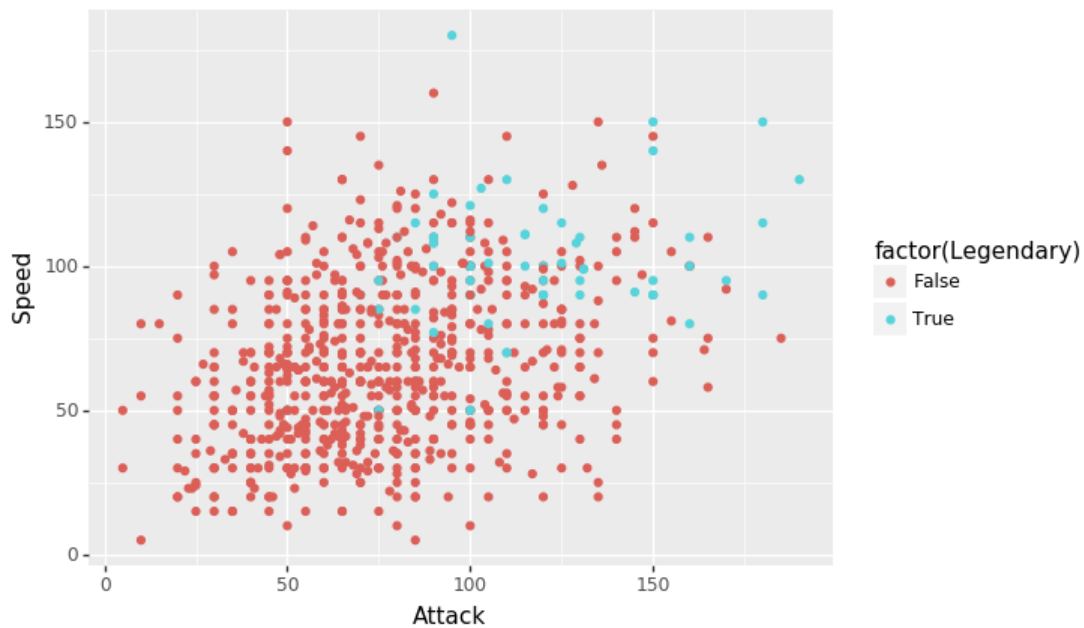
8 Gaussian Mixture model

```
[18]: (ggplot(X, aes("Total", "HP", color = "factor(Legendary)")) + geom_point())
```



[18]: <ggplot: (320273381)>

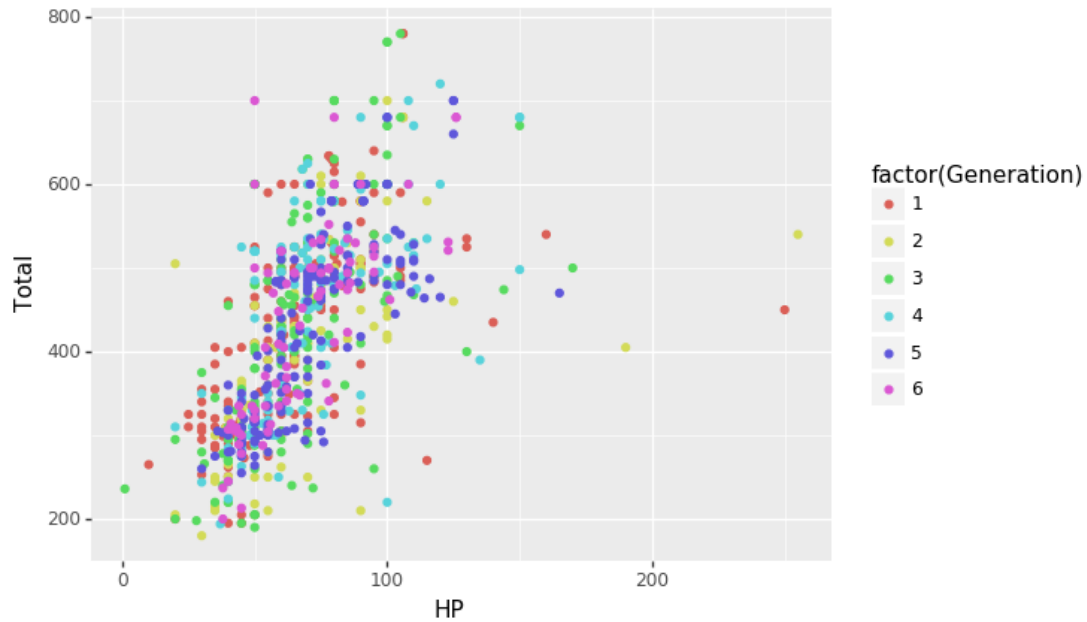
[19]: (ggplot(X, aes("Attack","Speed", color = "factor(Legendary)")) + geom_point())



[19]: <ggplot: (320297417)>

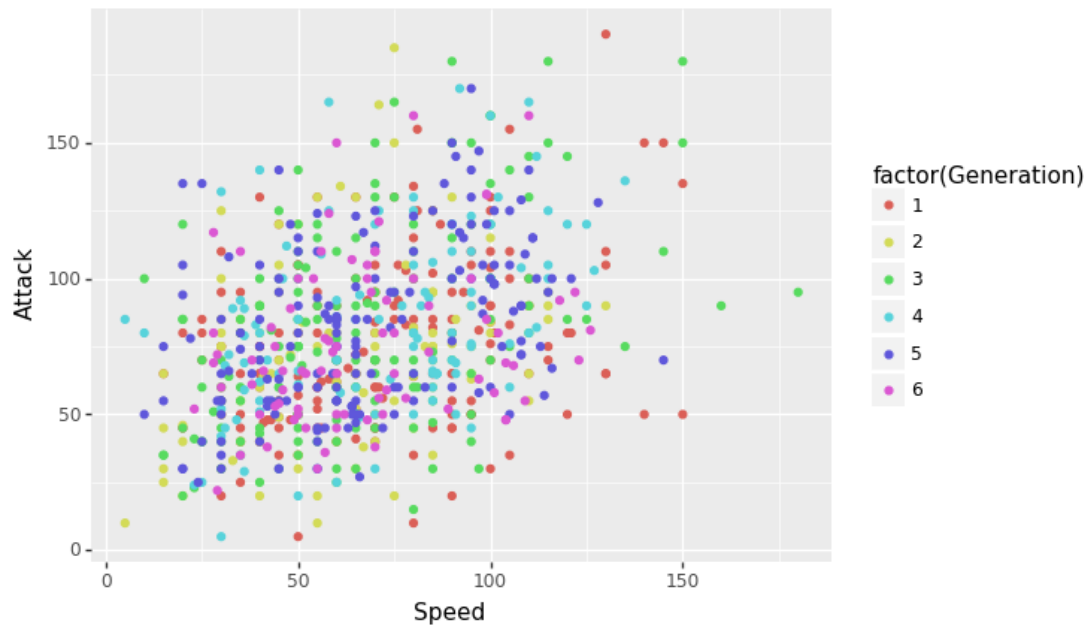
9 Hierarchical model

```
[20]: (ggplot(poke, aes("HP", "Total")) + geom_point(aes(color =  
  ↪ "factor(Generation)")))
```



```
[20]: <ggplot: (320173553)>
```

```
[21]: (ggplot(poke, aes("Speed", "Attack")) + geom_point(aes(color =  
  ↪ "factor(Generation)")))
```



```
[21]: <ggplot: (320297577)>
```

```
[ ]:
```

```
[ ]:
```