Superheroes

Motivation

There are thousands of superheroes in the superhero world and each superhero has their unique set of abilities, backstory and personality. This can make it overwhelming for someone who is just entering this world and it would be helpful if the user can get personalized superhero recommendations to explore those superheroes which resonate strongly with him.

1.0: Load Dataset

In [1]:

```python
# Imports
import pandas as pd
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import KFold
from copy import copy
import numpy as np
from sklearn.metrics import accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt
import os
import plotly.graph_objs as go
import plotly.offline as py
import plotly.express as px
import plotly.io as pio
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.ensemble import RandomForestRegressor
from sklearn import tree
from sklearn.metrics import r2_score
import re
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from collections import defaultdict
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import MinMaxScaler

sns.set()
```

In [2]:

```python
# Ignore warning messages
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```python
# Load dataset
df_supes = pd.read_csv('superheroes_nlp_dataset.csv')
df_supes.head()
```

Out[3]:

	name	real_name	full_name	overall_score	history_text	powers_text	intelligence_sco
0	3-D Man	Delroy Garrett, Jr.	Delroy Garrett, Jr.	6	Delroy Garrett, Jr. grew up to become a track ...	NaN	
1	514A (Gotham)	Bruce Wayne	NaN	10	He was one of the many prisoners of Indian Hil...	NaN	1
2	A-Bomb	Richard Milhouse Jones	Richard Milhouse Jones	20	Richard "Rick" Jones was orphaned at a young ...	On rare occasions, and through unusual circu...	
3	Aa	Aa	NaN	12	Aa is one of the more passive members of the P...	NaN	
4	Aaron Cash	Aaron Cash	Aaron Cash	5	Aaron Cash is the head of security at Arkham A...	NaN	

5 rows × 81 columns

In [4]:
```python
df_supes.columns
```

Out[4]:
```
Index(['name', 'real_name', 'full_name', 'overall_score', 'history_text',
       'powers_text', 'intelligence_score', 'strength_score', 'speed_scor
e',
       'durability_score', 'power_score', 'combat_score', 'superpowers',
       'alter_egos', 'aliases', 'place_of_birth', 'first_appearance',
       'creator', 'alignment', 'occupation', 'base', 'teams', 'relative
s',
       'gender', 'type_race', 'height', 'weight', 'eye_color', 'hair_colo
r',
       'skin_color', 'img', 'has_electrokinesis', 'has_energy_construct
s',
       'has_mind_control_resistance', 'has_matter_manipulation',
       'has_telepathy_resistance', 'has_mind_control', 'has_enhanced_hear
ing',
       'has_dimensional_travel', 'has_element_control', 'has_size_changin
g',
       'has_fire_resistance', 'has_fire_control', 'has_dexterity',
       'has_reality_warping', 'has_illusions', 'has_energy_beams',
       'has_peak_human_condition', 'has_shapeshifting', 'has_heat_resista
nce',
       'has_jump', 'has_self-sustenance', 'has_energy_absorption',
       'has_cold_resistance', 'has_magic', 'has_telekinesis',
       'has_toxin_and_disease_resistance', 'has_telepathy', 'has_regenera
tion',
       'has_immortality', 'has_teleportation', 'has_force_fields',
       'has_energy_manipulation', 'has_endurance', 'has_longevity',
       'has_weapon-based_powers', 'has_energy_blasts', 'has_enhanced_sens
es',
       'has_invulnerability', 'has_stealth', 'has_marksmanship', 'has_fli
ght',
       'has_accelerated_healing', 'has_weapons_master', 'has_intelligenc
e',
       'has_reflexes', 'has_super_speed', 'has_durability', 'has_stamin
a',
       'has_agility', 'has_super_strength'],
      dtype='object')
```

1.2: Data Cleaning

In [5]:
```python
# Dropping columns not required
df_supes = df_supes.drop(['real_name', 'full_name', 'alter_egos', 'aliases
                          'first_appearance', 'occupation', 'base', 'relati
                          'gender', 'type_race', 'height', 'weight', 'eye_c
                          'skin_color', 'img'], axis=1)
```

In [6]:
```python
df_supes.isna().sum()
```

Out[6]:
```
name                    2
overall_score           0
history_text           90
powers_text           364
intelligence_score      0
                     ...
has_super_speed        67
has_durability         67
has_stamina            67
has_agility            67
has_super_strength     67
Length: 64, dtype: int64
```

In [7]:
```python
# Cleaning up data by assigning "Unknown" to NaN strings
df_supes['name'] = df_supes['name'].replace(np.nan, 'Unknown')
df_supes['powers_text'] = df_supes['powers_text'].replace(np.nan, 'Unknown
df_supes['history_text'] = df_supes['history_text'].replace(np.nan, 'Unkno
df_supes['creator'] = df_supes['creator'].replace(np.nan, 'Unknown')
df_supes['alignment'] = df_supes['alignment'].replace(np.nan, 'Unknown')
```

In [8]:
```python
# Replacing special characters with NaN values
df_supes['overall_score'].replace(r'^\s*$', np.nan, regex=True, inplace=Tr
df_supes['overall_score'].replace('∞', np.nan, inplace=True)
df_supes['overall_score'].replace('-', np.nan, inplace=True)
```

In [9]:
```python
# Dropping superheroes with NaN values for superpowers
df_supes = df_supes.dropna()
```

In [10]:
```python
df_supes.isna().sum()
```

Out[10]:
```
name                  0
overall_score         0
history_text          0
powers_text           0
intelligence_score    0
                     ..
has_super_speed       0
has_durability        0
has_stamina           0
has_agility           0
has_super_strength    0
Length: 64, dtype: int64
```

In [11]:
```python
# Resetting the index column
df_supes = df_supes.reset_index(drop=True)
```

In [12]:

```
df_supes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1316 entries, 0 to 1315
Data columns (total 64 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   name                             1316 non-null   object 
 1   overall_score                    1316 non-null   object 
 2   history_text                     1316 non-null   object 
 3   powers_text                      1316 non-null   object 
 4   intelligence_score               1316 non-null   int64  
 5   strength_score                   1316 non-null   int64  
 6   speed_score                      1316 non-null   int64  
 7   durability_score                 1316 non-null   int64  
 8   power_score                      1316 non-null   int64  
 9   combat_score                     1316 non-null   int64  
 10  superpowers                      1316 non-null   object 
 11  creator                          1316 non-null   object 
 12  alignment                        1316 non-null   object 
 13  teams                            1316 non-null   object 
 14  has_electrokinesis               1316 non-null   float64
 15  has_energy_constructs            1316 non-null   float64
 16  has_mind_control_resistance      1316 non-null   float64
 17  has_matter_manipulation          1316 non-null   float64
 18  has_telepathy_resistance         1316 non-null   float64
 19  has_mind_control                 1316 non-null   float64
 20  has_enhanced_hearing             1316 non-null   float64
 21  has_dimensional_travel           1316 non-null   float64
 22  has_element_control              1316 non-null   float64
 23  has_size_changing                1316 non-null   float64
 24  has_fire_resistance              1316 non-null   float64
 25  has_fire_control                 1316 non-null   float64
 26  has_dexterity                    1316 non-null   float64
 27  has_reality_warping              1316 non-null   float64
 28  has_illusions                    1316 non-null   float64
 29  has_energy_beams                 1316 non-null   float64
 30  has_peak_human_condition         1316 non-null   float64
 31  has_shapeshifting                1316 non-null   float64
 32  has_heat_resistance              1316 non-null   float64
 33  has_jump                         1316 non-null   float64
 34  has_self-sustenance              1316 non-null   float64
 35  has_energy_absorption            1316 non-null   float64
 36  has_cold_resistance              1316 non-null   float64
 37  has_magic                        1316 non-null   float64
 38  has_telekinesis                  1316 non-null   float64
 39  has_toxin_and_disease_resistance 1316 non-null   float64
 40  has_telepathy                    1316 non-null   float64
 41  has_regeneration                 1316 non-null   float64
 42  has_immortality                  1316 non-null   float64
 43  has_teleportation                1316 non-null   float64
 44  has_force_fields                 1316 non-null   float64
 45  has_energy_manipulation          1316 non-null   float64
 46  has_endurance                    1316 non-null   float64
 47  has_longevity                    1316 non-null   float64
 48  has_weapon-based_powers          1316 non-null   float64
 49  has_energy_blasts                1316 non-null   float64
 50  has_enhanced_senses              1316 non-null   float64
 51  has_invulnerability              1316 non-null   float64
```

```
 52  has_stealth                        1316 non-null   float64
 53  has_marksmanship                   1316 non-null   float64
 54  has_flight                         1316 non-null   float64
 55  has_accelerated_healing            1316 non-null   float64
 56  has_weapons_master                 1316 non-null   float64
 57  has_intelligence                   1316 non-null   float64
 58  has_reflexes                       1316 non-null   float64
 59  has_super_speed                    1316 non-null   float64
 60  has_durability                     1316 non-null   float64
 61  has_stamina                        1316 non-null   float64
 62  has_agility                        1316 non-null   float64
 63  has_super_strength                 1316 non-null   float64
dtypes: float64(50), int64(6), object(8)
memory usage: 658.1+ KB
```

Data Exploration

Total Power Column

In [13]:

```
# Summing up all the powers of each superhero
df_supes['all_powers'] = df_supes.sum(axis=1)
```

Creating Smaller DataFrames

In [14]:

```
# Creating a smaller DataFrame for data visualization purposes
df_merge = df_supes[['name', 'creator', 'alignment', 'all_powers']]
df_merge
```

Out[14]:

	name	creator	alignment	all_powers
0	3-D Man	Marvel Comics	Good	347.0
1	514A (Gotham)	DC Comics	Unknown	338.0
2	A-Bomb	Marvel Comics	Good	562.0
3	Aa	DC Comics	Good	392.0
4	Aaron Cash	DC Comics	Good	237.0
...	...	...	...	...
1311	Zatanna	DC Comics	Good	313.0
1312	Zero	Capcom	Good	585.0
1313	Zoom (New 52)	DC Comics	Bad	514.0
1314	Zoom	DC Comics	Bad	346.0
1315	Zzzax	Marvel Comics	Bad	432.0

1316 rows × 4 columns

In [15]:
```
# Making DataFrame of superheroes of comic book creators
comic_supes = df_merge[df_merge['creator'].str.contains('Comics')==True]
comic_supes
```

Out[15]:

	name	creator	alignment	all_powers
0	3-D Man	Marvel Comics	Good	347.0
1	514A (Gotham)	DC Comics	Unknown	338.0
2	A-Bomb	Marvel Comics	Good	562.0
3	Aa	DC Comics	Good	392.0
4	Aaron Cash	DC Comics	Good	237.0
...	...	...	...	...
1309	Yukio (FOX)	Marvel Comics	Good	324.0
1311	Zatanna	DC Comics	Good	313.0
1313	Zoom (New 52)	DC Comics	Bad	514.0
1314	Zoom	DC Comics	Bad	346.0
1315	Zzzax	Marvel Comics	Bad	432.0

1007 rows × 4 columns

In [16]:
```
comic_pivot = comic_supes.pivot_table(values='all_powers', index='creator'
comic_pivot = comic_pivot.replace(np.nan, 0)
comic_pivot
```

Out[16]:

alignment	Bad	Good	Neutral	Unknown
creator				
DC Comics	406.846667	393.148649	398.725000	396.142857
Dark Horse Comics	427.750000	366.777778	394.000000	0.000000
Icon Comics	192.000000	218.666667	0.000000	0.000000
Image Comics	567.500000	527.833333	0.000000	0.000000
Marvel Comics	381.172619	370.339041	446.222222	393.244444

In [17]:
```python
score_data = df_supes[['intelligence_score','strength_score','speed_score'
score_data.head()
```

Out[17]:

	intelligence_score	strength_score	speed_score	durability_score	power_score	combat_s
0	85	30	60	60	40	
1	100	20	30	50	35	
2	80	100	80	100	100	
3	80	50	55	45	100	
4	80	10	25	40	30	

Creating Pivot Tables

In [18]:
```python
# Making a pivot table showing the mean superpower value by creator and al
supes_pivot = df_supes.pivot_table(values=['intelligence_score', 'strength
                                   'power_score', 'combat_score'], index='creato
supes_pivot = supes_pivot.replace(np.nan, 0)
supes_pivot.head()
```

Out[18]:

	combat_score				durability_score				intelligence_	
alignment	**Bad**	**Good**	**Neutral**	**Unknown**	**Bad**	**Good**	**Neutral**	**Unknown**	**Bad**	**G**
creator										
ABC Studios	0.0	12.5	0.0	0.0	0.0	27.5	0.0	0.0	0.0	
Blizzard Entertainment	0.0	0.0	0.0	100.0	0.0	0.0	0.0	55.0	0.0	
Capcom	100.0	90.0	100.0	100.0	50.0	100.0	95.0	90.0	100.0	
Cartoon Network	0.0	40.0	80.0	0.0	0.0	40.0	55.0	0.0	0.0	
Clive Barker	25.0	50.0	0.0	0.0	80.0	100.0	0.0	0.0	90.0	

5 rows × 24 columns

In [19]:

```
# Making a pivot table with the smaller DataFrame
merge_pivot = df_merge.pivot_table(values='all_powers', index='creator', c
merge_pivot = merge_pivot.replace(np.nan, 0)
merge_pivot.head()
```

Out[19]:

alignment	Bad	Good	Neutral	Unknown
creator				
ABC Studios	0.0	194.25	0.0	0.0
Blizzard Entertainment	0.0	0.00	0.0	407.0
Capcom	475.0	585.50	570.0	570.0
Cartoon Network	0.0	255.00	380.0	0.0
Clive Barker	352.0	386.00	0.0	0.0

2.0: Data Visualization

In [20]:

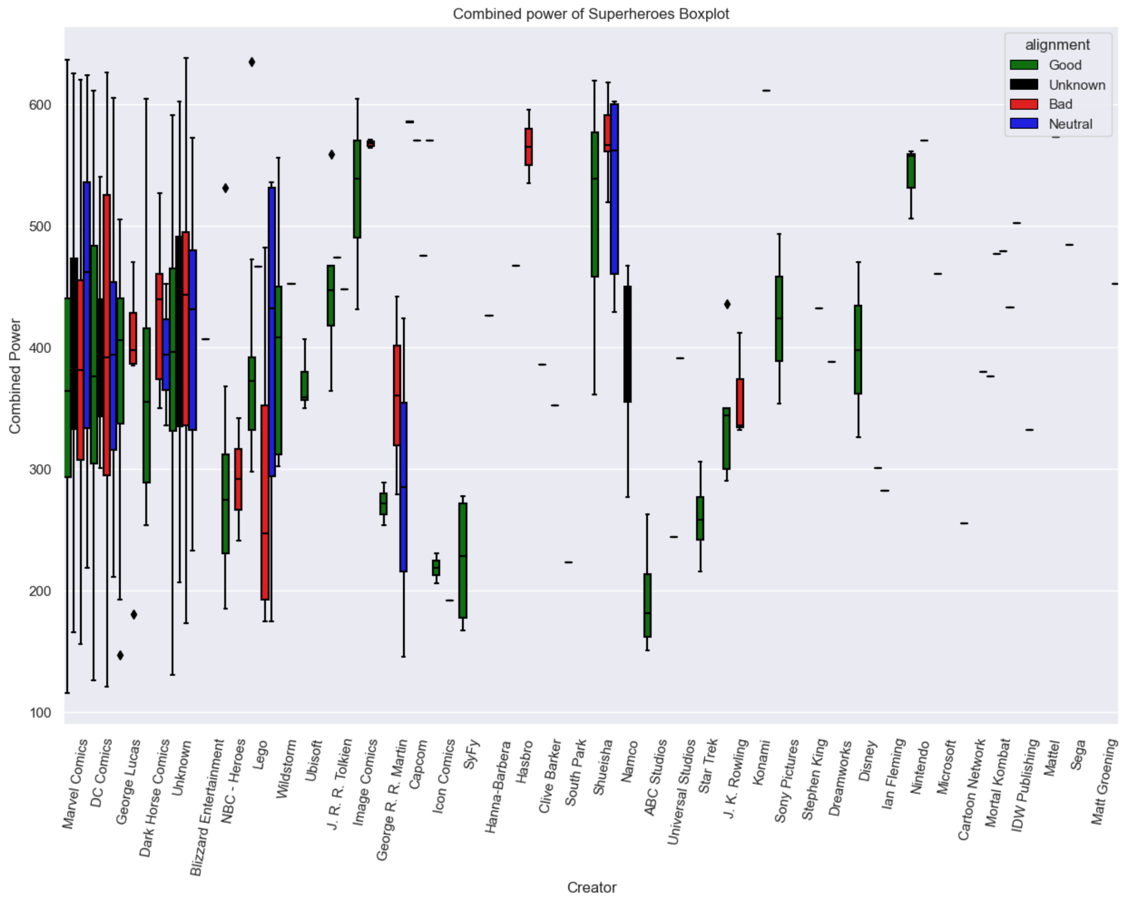
```
# Define absolute path for saving figures
save_path = os.path.abspath('Charts')
```

In [21]:

```python
# Stripplot to show relationship between creator and combined power of sup
plt.figure(figsize=(15, 10))
plt.xticks(rotation=80)
sns.stripplot(data=df_merge, x='creator', y='all_powers', hue='alignment',

# Save figure
plt.savefig(save_path + '/Stripp_Powers_Creators.jpg')
```

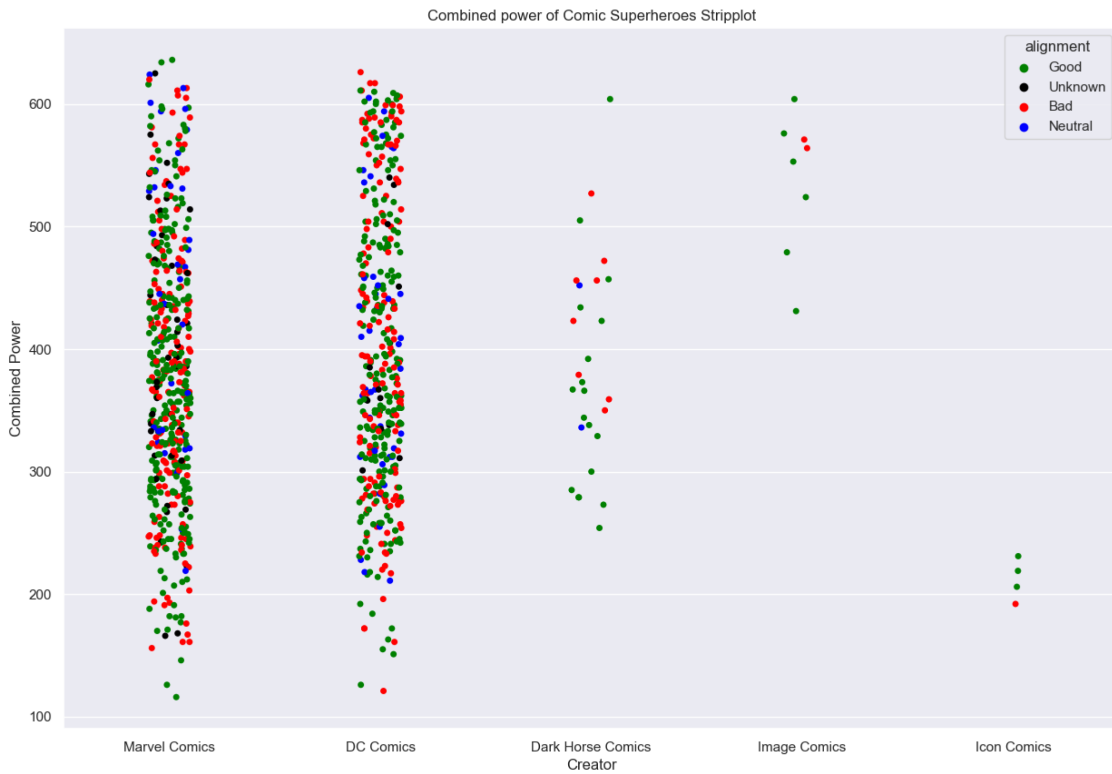
In [22]:

```python
# Boxplot to show relationship between creator and combined power of super
plt.figure(figsize=(15,10))
plt.xticks(rotation=80)
sns.boxplot(df_merge, x='creator', y='all_powers', hue='alignment', palett

# Save figure
plt.savefig(save_path + '/Box_Powers_Creators.jpg')
```



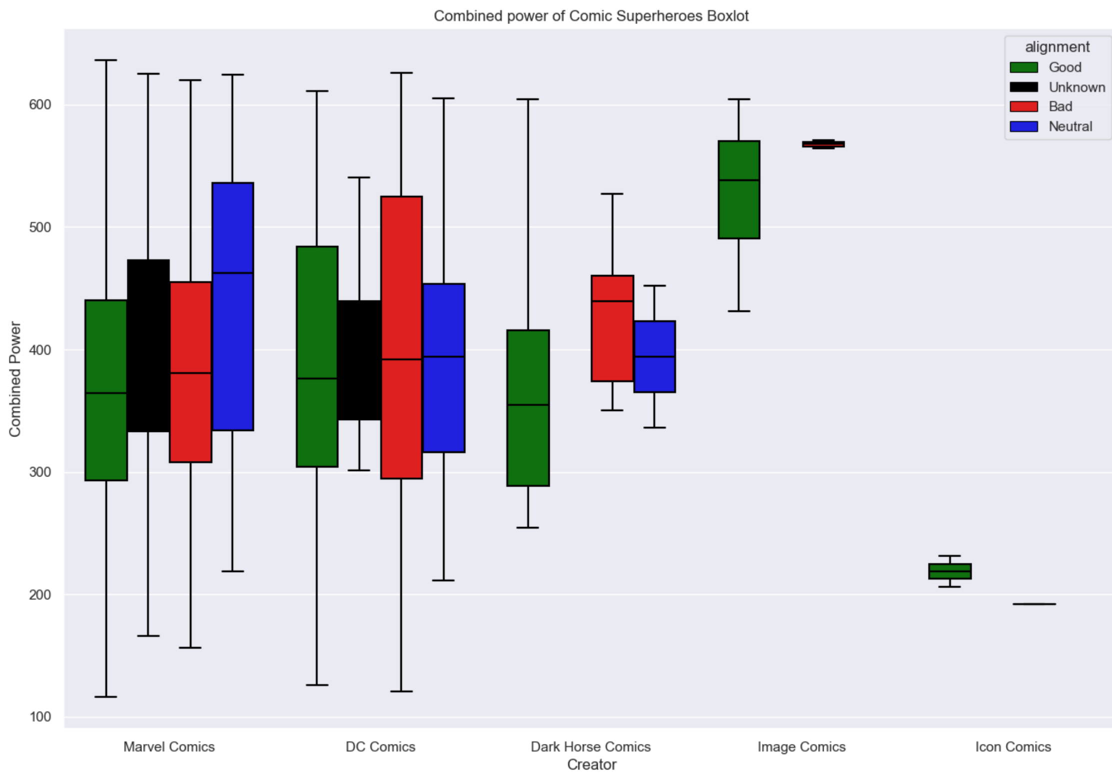
In [23]:

```
# Stripplot to show relationship between comic book creators and combined
plt.figure(figsize=(15, 10))
sns.stripplot(data=comic_supes, x='creator', y='all_powers', hue='alignmen

# Save figure
plt.savefig(save_path + '/Stripp_Powers_Comic_Creators.jpg')
```



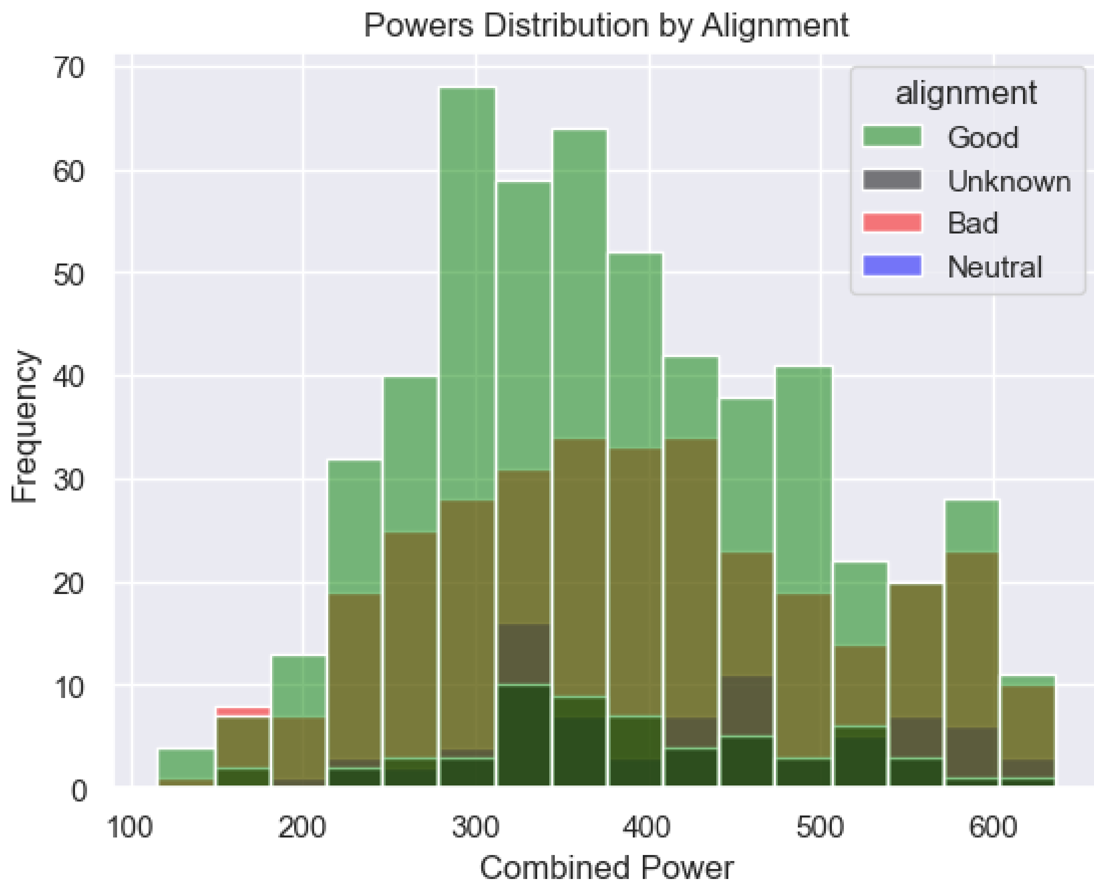
In [24]:

```
# Boxplot to show relationship between comic book creators and combined po
plt.figure(figsize=(15, 10))
sns.boxplot(data=comic_supes, x='creator', y='all_powers', hue='alignment'

plt.savefig(save_path + '/Box_Powers_Comic_Creators.jpg')
```



In [25]:

```
# Histplot to show the power distribution by alignment
sns.histplot(data=comic_supes, x='all_powers', hue='alignment',
             palette=['green', 'black', 'red', 'blue']).set(title='Powers
plt.savefig(save_path + '/Hist_Powers_Alignment.jpg')
```

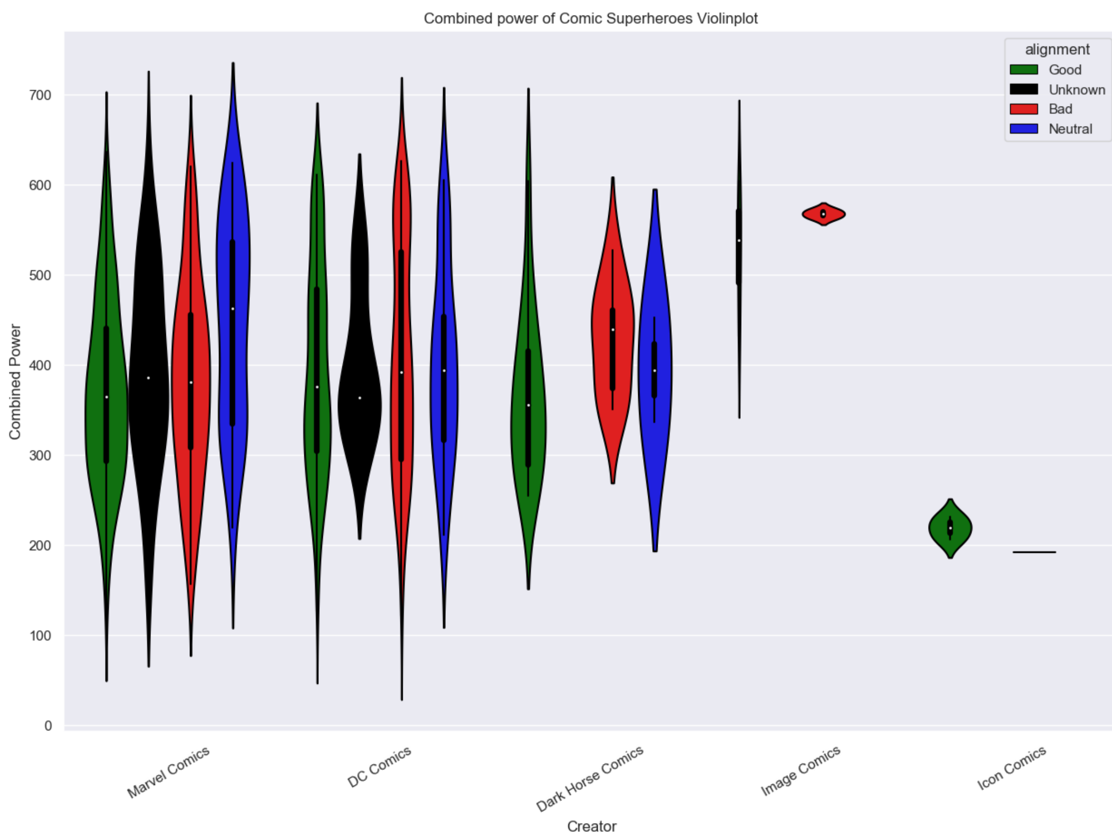


In [26]:

```
# Displot to show the power distribution by alignment
sns.displot(comic_supes, x='all_powers',hue='alignment',
                palette=['green', 'black', 'red', 'blue'], kind="kde", multip
plt.savefig(save_path + '/Dis_Powers_Alignment.jpg')
```

In [27]:

```
fig, ax = plt.subplots(figsize=(15, 10))
sns.violinplot(data=comic_supes, x="creator", y="all_powers", hue="alignme

plt.xticks(rotation=30)

# Save figure
plt.savefig(save_path + "/Violinplot_Powers.jpg")
```

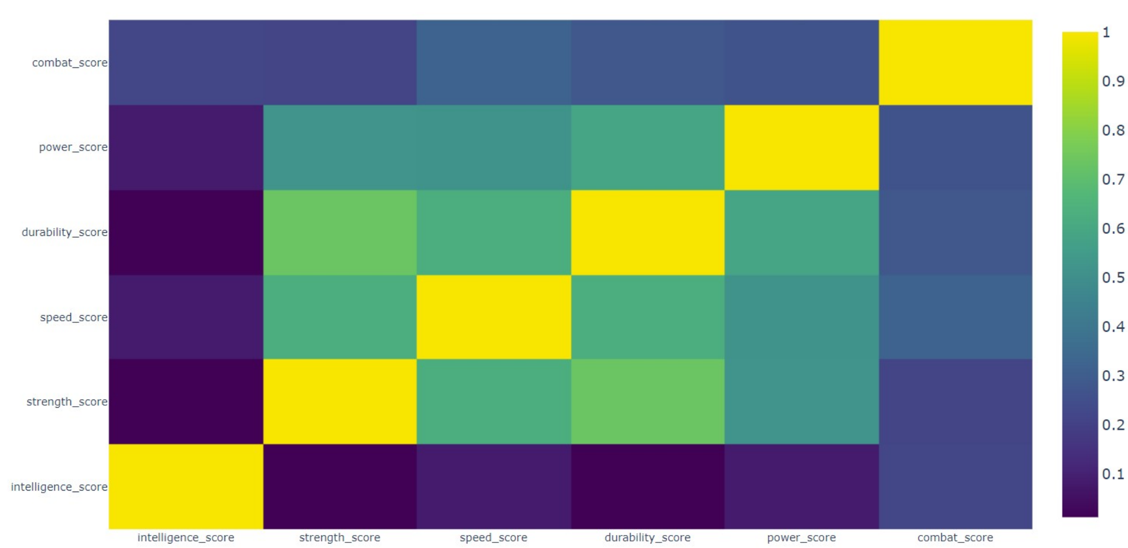


In [28]:

```
def correlation_plot():
    #correlation
    correlation = score_data.corr()
    #tick labels
    matrix_cols = correlation.columns.tolist()
    #convert to array
    corr_array  = np.array(correlation)
    trace = go.Heatmap(z = corr_array,
                       x = matrix_cols,
                       y = matrix_cols,
                       colorscale='Viridis',
                       colorbar   = dict(),)

    layout = go.Layout(dict(title = 'Correlation Matrix for variables',
                            #autosize = False,
                            #height   = 1400,
                            #width    = 1600,
                            margin   = dict(r = 0 ,l = 100,
                                            t = 0,b = 100,
                                          ),
                            yaxis    = dict(tickfont = dict(size = 9)),
                            xaxis    = dict(tickfont = dict(size = 9)),
                           )
                      )
    fig = go.Figure(data = [trace],layout = layout)
    py.iplot(fig)
```

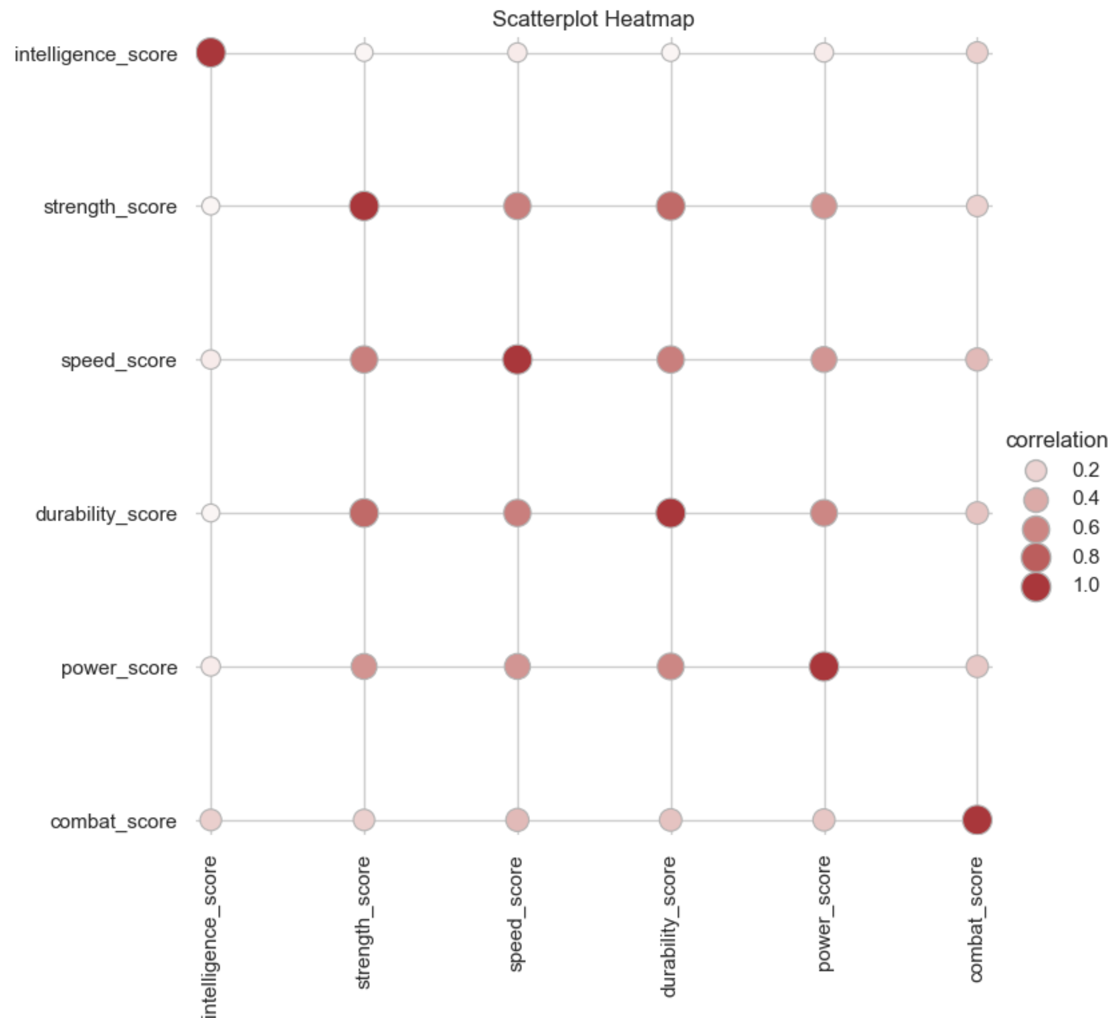
In [29]:

```
# Heatmap to show correlation of scores between different powers
# correlation_plot()
```



In [30]:

```python
sns.set_theme(style="whitegrid")

df_heat = df_supes.loc[:, ['intelligence_score','strength_score','speed_sc

# df_heat.columns = df_heat.columns.map("-".join)

# Compute a correlation matrix and convert to long-form
corr_mat = df_heat.corr().stack().reset_index(name="correlation")

# Draw each cell as a scatter point with varying size and color
g = sns.relplot(
    data=corr_mat,
    x="level_0", y="level_1", hue="correlation", size="correlation",
    palette="vlag", hue_norm=(-1, 1), edgecolor=".7",
    height=8, sizes=(50, 250), size_norm=(-.2, .8),
)

# Tweak the figure to finalize
g.set(xlabel="", ylabel="", aspect="equal")
g.despine(left=True, bottom=True)
g.ax.margins(.02)
for label in g.ax.get_xticklabels():
    label.set_rotation(90)
for artist in g.legend.legendHandles:
    artist.set_edgecolor(".7")
plt.title("Scatterplot Heatmap")

# Save figure
plt.savefig(save_path + "/Scatterplot_Heatmap_Scores.jpg")
```



3.0: Sentiment Analysis

In [31]:

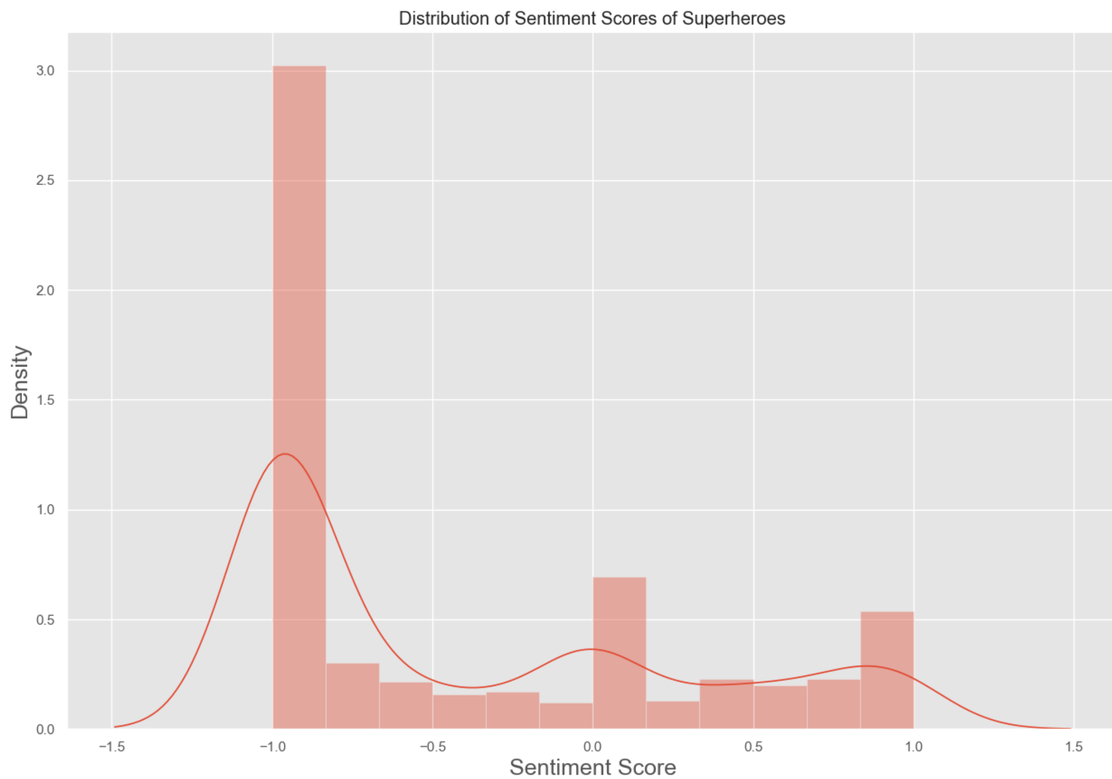
```
#implement the sentiment score analyzer
analyzer = SentimentIntensityAnalyzer()

scores_dict = dict()

# The history description of superheroes is used to calculate the sentimen
df_supes['sentiment_score'] = df_supes['history_text'].apply(lambda x: ana
scores_dict = df_supes.set_index('name')['sentiment_score'].to_dict()
```

In [32]:

```
scores_list = list(scores_dict.values())
scores_list = [float(score) for score in scores_list]
```

In [33]:

```
plt.style.use('ggplot')
fig, ax = plt.subplots()
fig.set_size_inches(15, 10)
colors = ['#FFD700', '#7EC0EE']

# Visualizing the sentiment score distribution
sns.set_context("paper", font_scale=1.5)
f = sns.distplot(scores_list, kde=True);
f.set_xlabel("Sentiment Score",fontsize=18)
f.set_ylabel("Density",fontsize=18)
f.set_title('Distribution of Sentiment Scores of Superheroes')
plt.savefig(save_path + '/Sentiment_Distribution.jpg')
```



4.0: Dimensionality Reduction (PCA)

In [34]:

```
# Perform PCA with quantative features to group
x_feat_list = ['intelligence_score','strength_score','speed_score','durabi
x_vals = df_supes.loc[:,x_feat_list].values
```

In [35]:

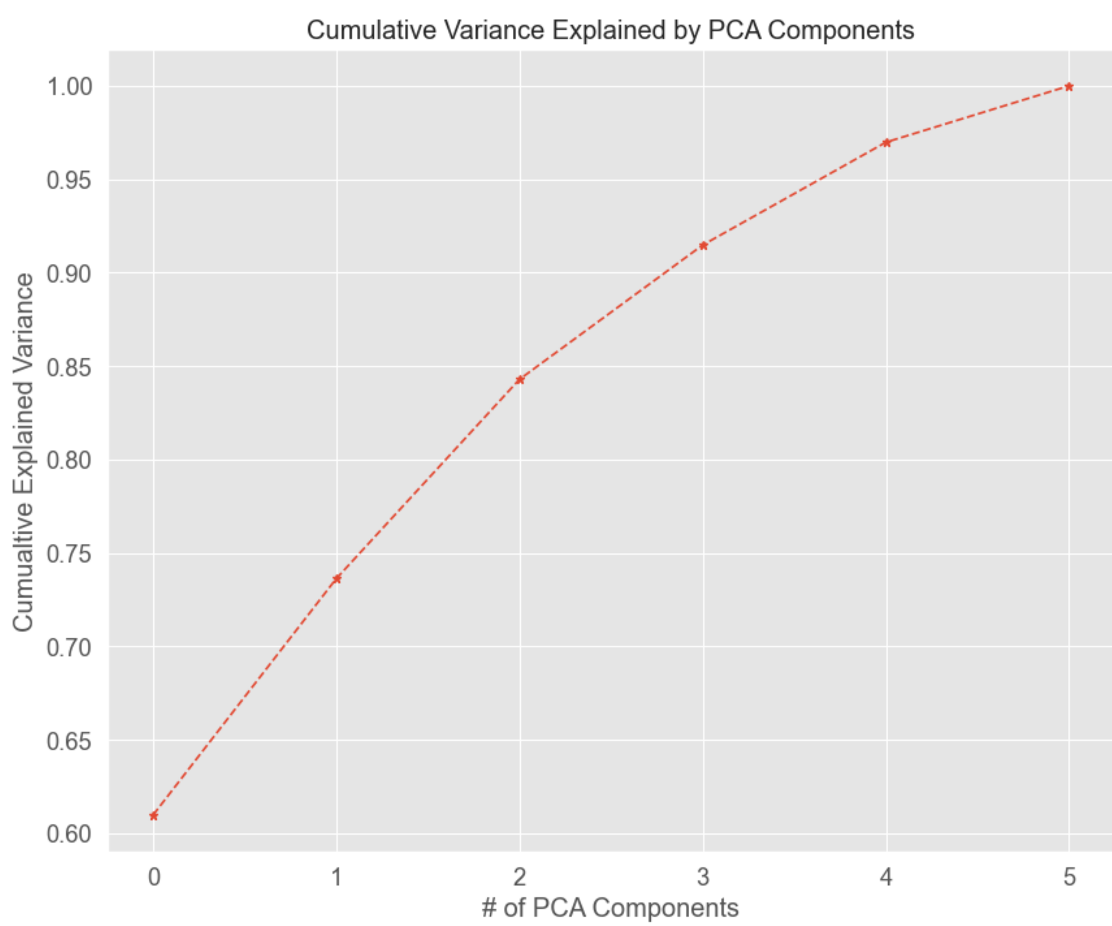
```
# Use PCA to fit and transform the features
pca = PCA()
pca.fit_transform(x_vals)
```

Out[35]:

```
array([[ 17.43096248,   7.29645172, -22.81358134,  16.07210554,
        -11.81131793,  -1.16763795],
       [ 37.75548557, -19.66816555, -32.62216199, -13.42685929,
         -6.79972641, -12.04467552],
       [-80.25115701,  14.67137859,  -3.42360011,  -4.03704219,
          2.71364046,   4.95530049],
       ...,
       [-47.0685847 , -15.67940003,   5.6198202 ,  34.75294793,
          0.3892916 ,  -6.70221852],
       [  8.01728314,   2.55427371,  42.7677209 ,  71.74503242,
         11.98556258,   9.8877171 ],
       [-49.19431455,  40.83155648,   3.17306584,   9.110265  ,
        -12.96484911,  34.34807012]])
```

In [36]:

```
# Plot to figure out how many components to use in actual PCA model
plt.figure(figsize = (10,8))
plt.plot(range(0,6), pca.explained_variance_ratio_.cumsum(), marker = "*",
plt.title("Cumulative Variance Explained by PCA Components")
plt.xlabel('# of PCA Components')
plt.ylabel('Cumualtive Explained Variance');

# Save figure
plt.savefig(save_path + '/CumVariancePCA_LINE.jpg')
```

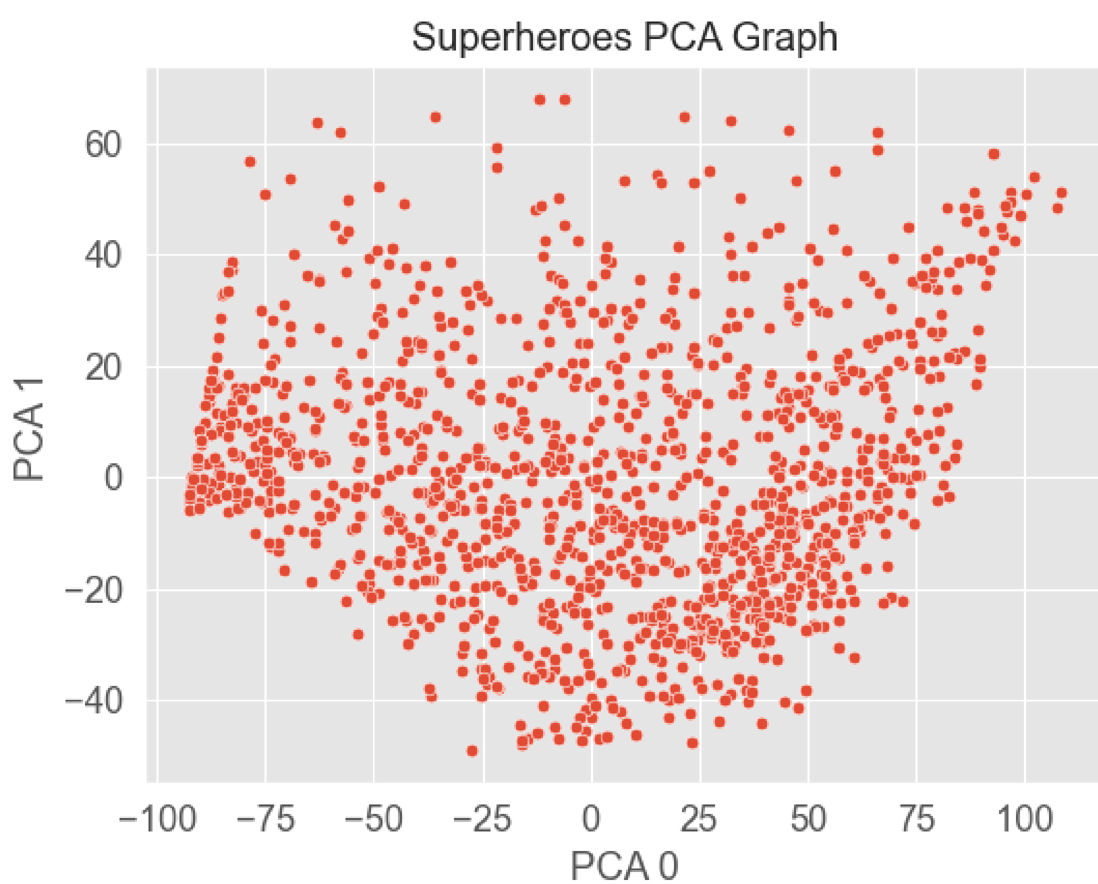


PCA Analysis

We can see from the cumulative explained variance graph above that after 3 components, there is a marginal increase in the percent of variance explained. Thus, to optimize the PCA model, we will use n_components = 3

In [37]:
```
pca = PCA(n_components=3, whiten=False)
x_pca = pca.fit_transform(x_vals)

# add features back into PCAdataframe (for plotting PCA)
df_supes['PCA 0'] = x_pca[:, 0]
df_supes['PCA 1'] = x_pca[:, 1]
```

In [38]:
```
# Seaborn scatter plot for display
sns.scatterplot(data=df_supes, x="PCA 0", y="PCA 1").set(title='Superheroe

# Save fig
plt.savefig(save_path + '/PCAPlot_SCT.jpg')
```



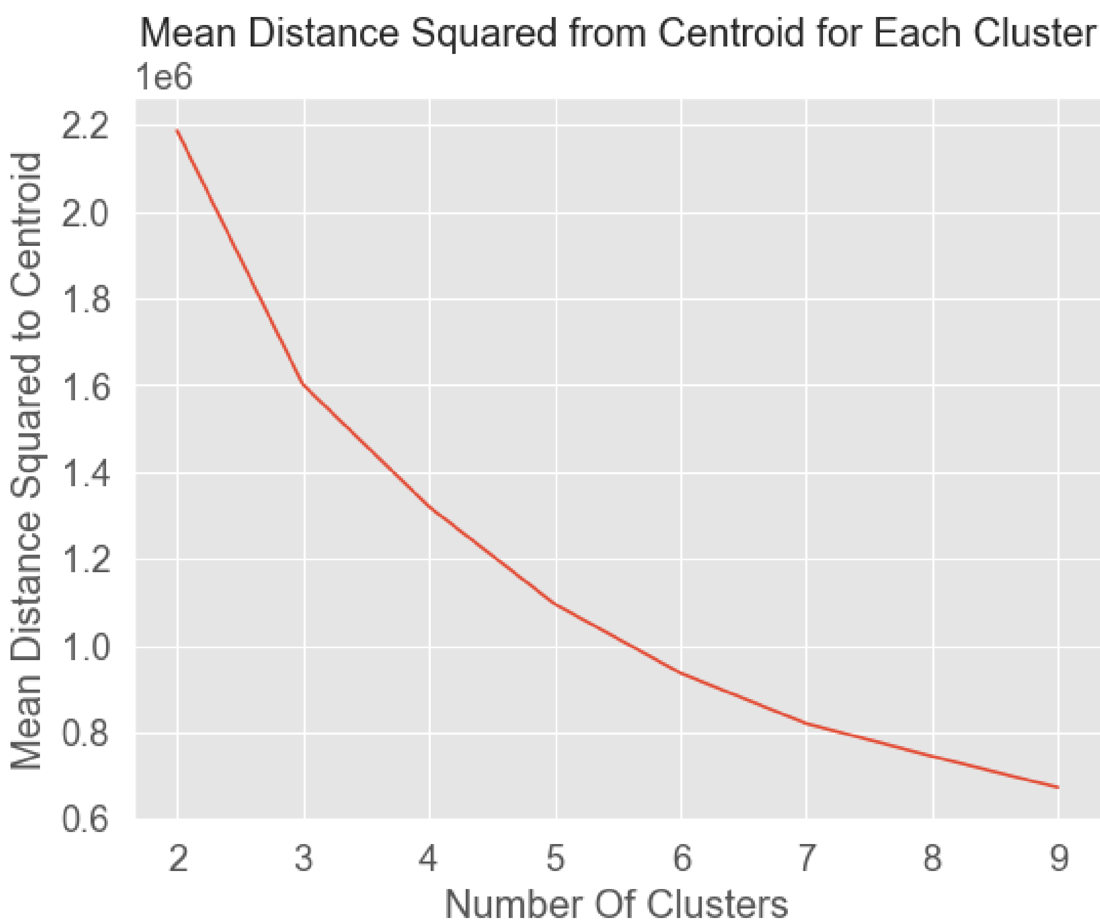
5.0: Machine Learning

5.0.1: K-Means Clustering

General Clustering

In [39]:
```
# Optimize number of clusters
mean_d_dict = dict()
for n_clusters in range(2, 10):
    kmeans = KMeans(n_clusters=n_clusters)
    kmeans.fit(x_pca)
    y = kmeans.predict(x_pca)

    # compute & store mean distance
    mean_d = -kmeans.score(x_pca)
    mean_d_dict[n_clusters] = mean_d
```

In [40]:
```
# Graph mean distance to centroid to find the optimal n-value
plt.plot(mean_d_dict.keys(), mean_d_dict.values())
plt.xlabel('Number Of Clusters')
plt.ylabel('Mean Distance Squared to Centroid');
plt.title('Mean Distance Squared from Centroid for Each Cluster');

# Save fig
plt.savefig(save_path + '/MeanD2Clusters_LINE.jpg')
```



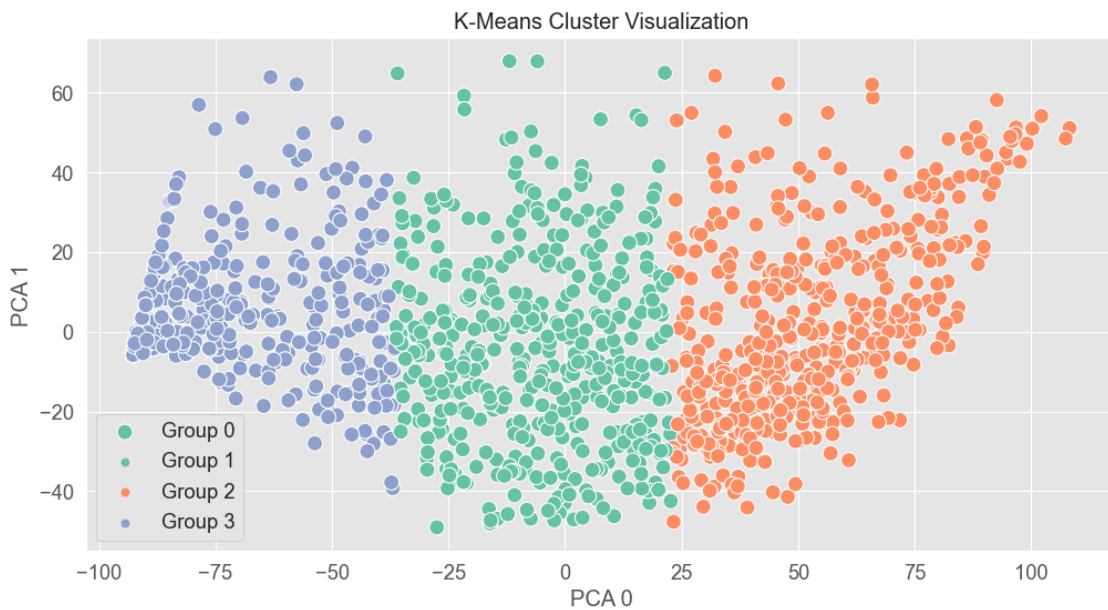
We can see from the above graph comparing the mean distance squared from the centroid for each cluster decreases as the number of clusters increases. To optimize the K-Means Cluster algorithm, we must select the cluster at which the next decrease is marginal compared to the previous ones. However, there is no clear elbow in the graph above so no k will optimize our algorithm.

In [41]:

```
# X values are the features given in PCA y-axis
x = df_supes['PCA 0'].values.reshape(-1,1)

# Fit in KMeans algorithm
kmeans = KMeans(n_clusters=3)
kmeans.fit_transform(x)
y = kmeans.predict(x)
```

In [42]:

```
sns.scatterplot(data=df_supes, x='PCA 0', y='PCA 1', s=100, hue=y, palette
plt.gcf().set_size_inches(12, 6)
plt.title('K-Means Cluster Visualization')
plt.legend([f"Group {i}" for i in range(0,6)])

# Save figure
plt.savefig(save_path + '/ClusterChart_SCT.jpg')
```



Clustering Similar Superheroes

In [43]:

```
x_feat_list = ['intelligence_score','strength_score','speed_score','durabi

df_supes_similar = pd.DataFrame()

for feature in x_feat_list:
    df_supes_similar[f'{feature}'] = df_supes[feature] / df_supes[feature]

df_supes_similar.var()
```

Out[43]:

```
intelligence_score    1.0
strength_score        1.0
speed_score           1.0
durability_score      1.0
power_score           1.0
combat_score          1.0
sentiment_score       1.0
dtype: float64
```

In [44]:

```
# Perform PCA on popular superheroes data
pca_popular = PCA(n_components=3, whiten=False)
x_pca_popular = pca_popular.fit_transform(df_supes_similar[x_feat_list])

# Add principal components back into dataframe
df_supes['PCA 0'] = x_pca_popular[:, 0]
df_supes['PCA 1'] = x_pca_popular[:, 1]
```

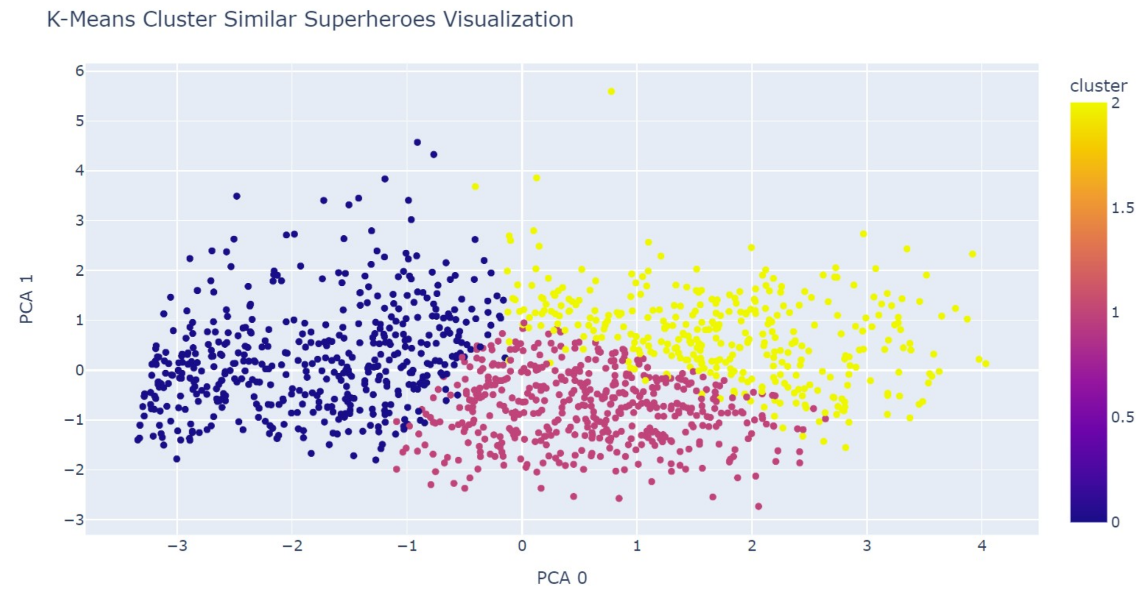
In [45]:

```
# Optimize number of clusters for popular superheroes
mean_d_dict = dict()
for n_clusters in range(2, 10):
    kmeans = KMeans(n_clusters=n_clusters)
    kmeans.fit(x_pca_popular)
    y = kmeans.predict(x_pca_popular)

    # Compute & Store mean distance
    mean_d = -kmeans.score(x_pca_popular)
    mean_d_dict[n_clusters] = mean_d
```

In [46]:

```
# Perform K-Means clustering on principal components
kmeans = KMeans(n_clusters=3)
df_supes['cluster'] = kmeans.fit_predict(x_pca_popular)
```

In [47]:
```python
# Create scatterplot using Plotly Express
# fig = px.scatter(df_supes, x='PCA 0', y='PCA 1', color='cluster', hover_
# fig.update_layout(title='K-Means Cluster Similar Superheroes Visualizati
#                   legend=dict(yanchor="top", y=0.99, xanchor="left", x
# fig.show()
```



4.0.2: Classification

Data Splitting & Model Training

In [48]:
```python
comic_supes = df_supes[df_supes['creator'].str.contains('Comics')==True]
```

In [49]:
```python
# We divide each feature by the standard deviation
df_supes_scaled = pd.DataFrame()
for feature in ['intelligence_score','strength_score','speed_score','durab
    df_supes_scaled[f'{feature}'] = comic_supes[feature] / comic_supes[fea

df_supes_scaled.var()
```

Out[49]:
```
intelligence_score    1.0
strength_score        1.0
speed_score           1.0
durability_score      1.0
power_score           1.0
combat_score          1.0
dtype: float64
```

KFold Cross Validation

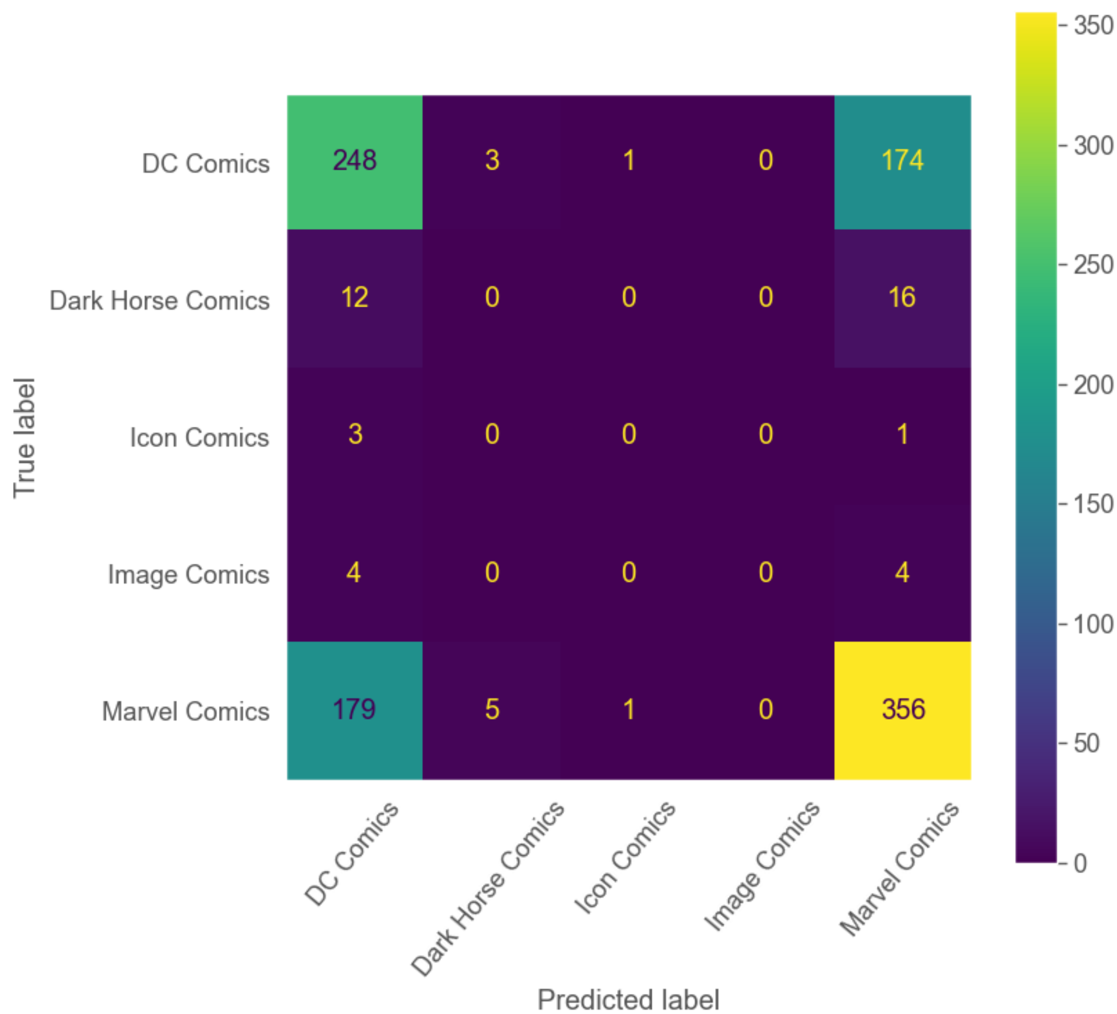
In [50]:

```
k = 3

x_feat_list = ['intelligence_score','strength_score','speed_score','durabi

y_feat = 'creator'

x = df_supes_scaled.loc[:, x_feat_list].values
y_true = comic_supes.loc[:, y_feat].values

# initializing a knn_classifier
knn_classifier = KNeighborsClassifier(n_neighbors=k)

n_splits = 10

# construction of kfold object
kfold = StratifiedKFold(n_splits=n_splits, shuffle=True)

# allocate an empty array to store predictions in
y_pred = copy(y_true)

for train_idx, test_idx in kfold.split(x, y_true):
    # build arrays which correspond to x, y train /test
    x_test = x[test_idx, :]
    x_train = x[train_idx, :]
    y_true_train = y_true[train_idx]

    # fit happens "inplace", we modify the internal state of knn_classifie
    knn_classifier.fit(x_train, y_true_train)

    # estimate each bean's class
    y_pred[test_idx] = knn_classifier.predict(x_test)
```

Confusion Matrix

In [51]:

```
# The confusion matrix is made
conf_mat = confusion_matrix(y_true=y_true, y_pred=y_pred)

# The confusion matrix display is made
conf_mat_disp = ConfusionMatrixDisplay(conf_mat, display_labels=np.unique(

conf_mat_disp.plot()
plt.gcf().set_size_inches(8, 8)
plt.grid(False)
plt.xticks(rotation=50)
# Save figure
plt.savefig(save_path + '/ConfMat.jpg')
```



In [52]:

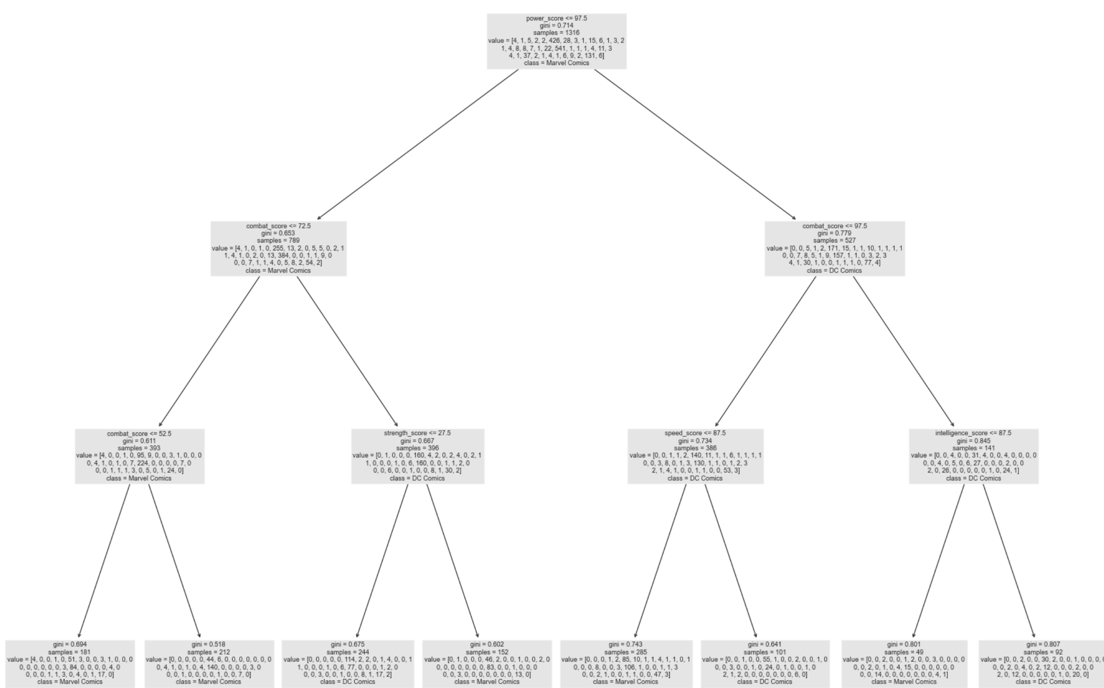
```
# Computing the accuracy score of the confusion matrix
print("The accuracy of the model is " + str(round(accuracy_score(y_true, y
```

```
The accuracy of the model is 60.0%
```

4.0.3: Decision Tree Regressor

In [53]:

```
max_depth = 3
x_feat_list = ['intelligence_score', 'strength_score', 'speed_score', 'dur

#extracting data from dataframe
x = df_supes.loc[:, x_feat_list].values
y = df_supes.loc[:, 'creator'].values

#build decision tree classifier
dec_tree_clf = tree.DecisionTreeClassifier(max_depth=max_depth)

# fit data
dec_tree_clf.fit(x, y)

# initialize empty figure (plot_tree sets text size to fill given figure
# if we resize figure afterwards text size remains too small)
plt.figure()
plt.gcf().set_size_inches(20, 15)

# 'plot' decision tree
tree.plot_tree(dec_tree_clf,
               feature_names=x_feat_list,
               class_names=dec_tree_clf.classes_);
```



4.0.4: Random Forest Regressor

In [54]:

```
x_feat_list =  ['intelligence_score', 'strength_score', 'speed_score', 'du

#extracting data from dataframe
x = df_supes.loc[:, x_feat_list].values
y = df_supes.loc[:, 'overall_score'].values

n_splits = 10

#build Random Forest Regressor
randomforest_rg = RandomForestRegressor()

# construction of kfold object
skfold = KFold(n_splits=n_splits, shuffle=True)

# allocate an empty array to store predictions in
y_pred = np.empty_like(y)

for train_idx, test_idx in skfold.split(x, y):
    #get training data
    x_train = x[train_idx, :]
    y_train = y[train_idx]

    #get test data
    x_test = x[test_idx, :]

    # fit data
    randomforest_rg = randomforest_rg.fit(x_train, y_train)

    # estimate on test data
    y_pred[test_idx] = randomforest_rg.predict(x_test)

#compute r2 score
r2 = r2_score(y_true=y, y_pred=y_pred)
r2
```

Out[54]:

```
0.30304208907401153
```

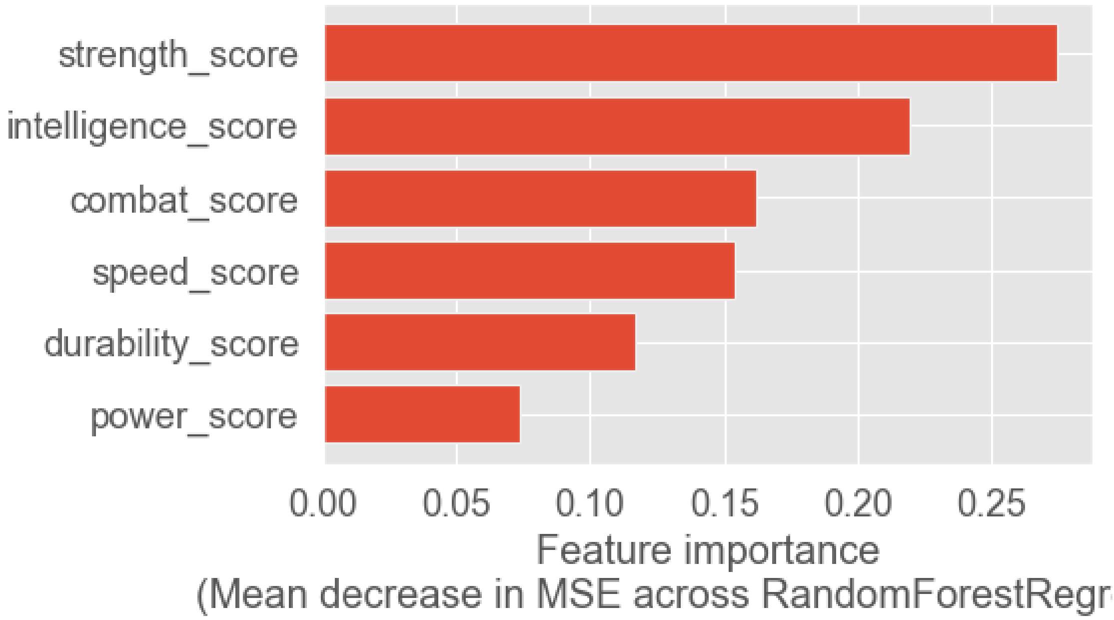
In [55]:
```python
x_feat_list =  ['intelligence_score', 'strength_score', 'speed_score', 'du

#eextracting data from dataframe
x = df_supes.loc[:, x_feat_list].values
y = df_supes.loc[:, 'overall_score'].values

#construct regressor
rf_rg = RandomForestRegressor(n_estimators=100)

#fit data
rf_rg.fit(x, y)
```

Out[55]:
```
▾ RandomForestRegressor
RandomForestRegressor()
```

In [56]:
```python
def plot_feat_import(feat_list, feat_import, sort=True, limit=None):
    """ plots feature importances in a horizontal bar chart

    Args:
        feat_list (list): str names of features
        feat_import (np.array): feature importances (mean gini reduce)
        sort (bool): if True, sorts features in decreasing importance
            from top to bottom of plot
        limit (int): if passed, limits the number of features shown
            to this value
    """

    if sort:
        # sort features in decreasing importance
        idx = np.argsort(feat_import).astype(int)
        feat_list = [feat_list[_idx] for _idx in idx]
        feat_import = feat_import[idx]

    if limit is not None:
        # limit to the first limit feature
        feat_list = feat_list[:limit]
        feat_import = feat_import[:limit]

    # plot and label feature importance
    plt.barh(feat_list, feat_import)
    plt.gcf().set_size_inches(5, len(feat_list) / 2)
    plt.xlabel('Feature importance\n(Mean decrease in MSE across RandomFor
```

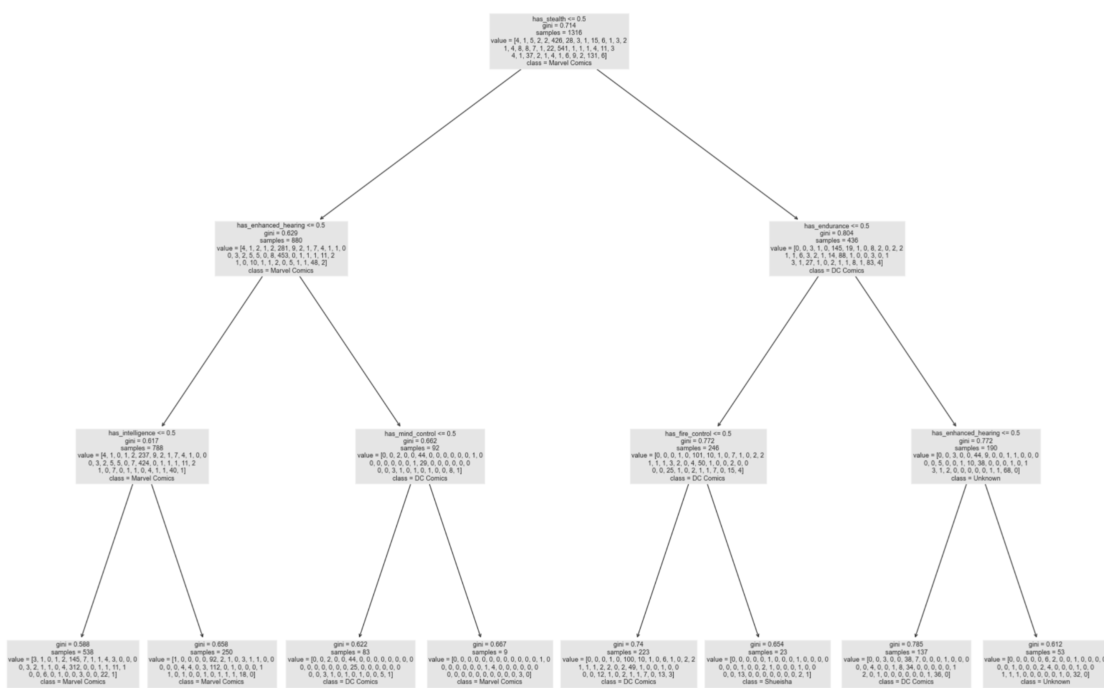
In [57]:

```
#plot the feature importance graph
plot_feat_import(x_feat_list, rf_rg.feature_importances_)
```



In [58]:

```python
max_depth = 3
x_feat_list = ['has_mind_control', 'has_enhanced_hearing', 'has_element_co
               'has_self-sustenance', 'has_energy_absorption', 'has_magic'
               'has_energy_manipulation', 'has_endurance', 'has_weapon-bas
               'has_weapons_master', 'has_intelligence','has_reflexes', 'h

#extracting data from dataframe
x = df_supes.loc[:, x_feat_list].values
y = df_supes.loc[:, 'creator'].values

#build decision tree classifier
dec_tree_clf = tree.DecisionTreeClassifier(max_depth=max_depth)

# fit data
dec_tree_clf.fit(x, y)

# initialize empty figure (plot_tree sets text size to fill given figure
# if we resize figure afterwards text size remains too small)
plt.figure()
plt.gcf().set_size_inches(20, 15)

# 'plot' decision tree
tree.plot_tree(dec_tree_clf,
               feature_names=x_feat_list,
               class_names=dec_tree_clf.classes_);
```



5.0: Recommendation System

In [59]:

```python
def get_scores(name, idx):
    """
    Function that retrieves a dictionary of scores for a superhero based o

    Args:
        name (str): The name of the superhero to retrieve scores for.
        idx (int): The index of the superhero in the dataframe.

    Returns:
        score_dict (dict): A dictionary of scores for the superhero with t
    """
    score_dict = {}
    for col in num_cols:
        score_dict[col] = df_supes.loc[idx, col]
    return score_dict
```

In [60]:

```
# Define the columns to include in the recommendation system
text_cols = ["powers_text", "history_text", "creator", "alignment"]

num_cols = ["intelligence_score", "strength_score", "speed_score", "durabi
            'has_fire_control', 'has_reality_warping', 'has_energy_beams',
               'has_self-sustenance', 'has_energy_absorption', 'has_magic'
               'has_energy_manipulation', 'has_endurance', 'has_weapon-bas
               'has_weapons_master', 'has_intelligence','has_reflexes', 'h

# Initialize the scaler
scaler = MinMaxScaler()

# Normalize the values in num_cols
df_supes[num_cols] = scaler.fit_transform(df_supes[num_cols])

# Concatenate the text and numerical columns
df_supes["combined_text"] = df_supes[text_cols].apply(lambda x: " ".join(x


# Fit TfidfVectorizer to the combined text column
tfidf = TfidfVectorizer()
tfidf_matrix = tfidf.fit_transform(df_supes["combined_text"])

# Compute the cosine similarity matrix
cosine_sim = cosine_similarity(tfidf_matrix)

def get_recommendations(name, tolerance, cosine_sim=cosine_sim):
    """
    Function that recommends similar superheroes based on the numerical sc

    Args:
        name (str): The name of the superhero to get recommendations for.
        tolerance (float): The tolerance for similarity between the scores
        cosine_sim (numpy.ndarray): The cosine similarity matrix to use fo

    Returns:
        pandas.Series: A pandas Series containing the names of the recomme
    """
    idx = df_supes[df_supes["name"] == name].index[0]
    score_dict = get_scores(name, idx)
    sim_scores = list(enumerate(cosine_sim[idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:4]
    superhero_indices = [i[0] for i in sim_scores]

    # Filter by similar numerical scores
    similar_indices = []
    for i in superhero_indices:
        similar = True
        for col, value in score_dict.items():
            if not (value - tolerance <= df_supes.loc[i, col] <= value + t
                similar = False
                break
        if similar:
            similar_indices.append(i)
```

```python
    return df_supes["name"].iloc[similar_indices]
```

In [61]:

```python
# Get recommendations for a specific superhero
get_recommendations("Spider-Man (Raimi Trilogy)", tolerance=1)
```

Out[61]:

```
517    Harry Osborn (Raimi Trilogy)
494                 Green Goblin II
917                  Peter Petrelli
Name: name, dtype: object
```