Coding_output

April 28, 2025

```
[]: import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
    import plotly
[]: df = pd.read_csv('pokemon_data.csv')
[]: df_c = pd.DataFrame(
         # Removing duplicate rows
        df.drop_duplicates()
        # removing empty rows
         .dropna(how='all')
        # Removing specific columns
        .drop(columns=[])
        .reset_index(drop=True)
    )
    # Renaming column titles: replacing _ with spaces and capitalising each word
    df_c.columns = df_c.columns.str.replace('_', ' ').str.title()
    # Capitalising 'Id' and 'Hp' column title, saving changes
    df_c.rename(columns={'Id':'ID', 'Hp':'HP', 'Sp. Attack': 'Special Attack', 'Sp. |
      →Defense':'Special Defense'}, inplace=True)
     # Adding Total Weakness Column
    list_weaknesses = ['Normal Weakness', 'Fire Weakness', 'Water Weakness', |
      'Grass Weakness', 'Ice Weakness', 'Fighting Weakness', 'Poison Weakness',
         'Ground Weakness', 'Flying Weakness', 'Psychic Weakness', 'Bug Weakness',
         'Rock Weakness', 'Ghost Weakness', 'Dragon Weakness', 'Dark Weakness',
         'Steel Weakness', 'Fairy Weakness']
    df_c['Total Weakness'] = df_c[list_weaknesses].sum(axis=1)
[]: # Making dictionary to store dfs
    type_df_dict = {}
     # Go through each unique value in the Type 1 column
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```
for type_value in df_c['Type 1'].unique():
         # Filter the DataFrame for the rows same as current type
         type_df = df_c[df_c['Type 1'] == type_value]
         # Store the DataFrame in a dictionary with the type as the key
         type_df_dict[f"df_type_{type_value}"] = type_df
     type_df_names = list(type_df_dict.keys())
     print(type_df_names)
    ['df_type_Grass', 'df_type_Fire', 'df_type_Water', 'df_type_Bug',
    'df_type_Normal', 'df_type_Poison', 'df_type_Electric', 'df_type_Ground',
    'df_type_Fairy', 'df_type_Fighting', 'df_type_Psychic', 'df_type_Rock',
    'df_type_Ghost', 'df_type_Ice', 'df_type_Dragon', 'df_type_Dark',
    'df_type_Steel', 'df_type_Flying']
[]: all_stats_base = ['Base Stats', 'HP', 'Attack', 'Special Attack', 'Speed', |

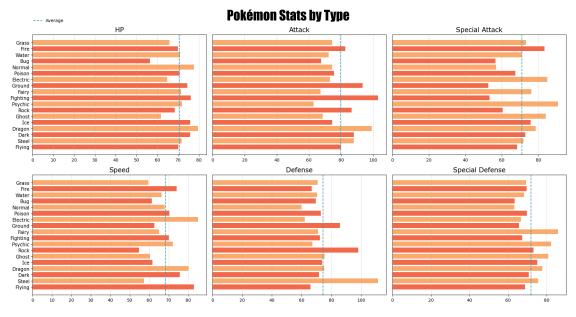
¬'Defense', 'Special Defense']

     type_df_mean_dict = {}
     # Go through each unique value in the Type 1 column
     for type_value in df_c['Type 1'].unique():
         # Filter the DataFrame for the rows same as current type
         type_df = df_c[df_c['Type 1'] == type_value]
         mean_values = type_df[all_stats_base].mean().round()
         # Create a new dataframe with the mean values
         mean_df = pd.DataFrame(mean_values).transpose() # Convert the Series to a_
      \hookrightarrow DataFrame
         mean_df['Type 1'] = type_value # Add the type as a column
         # Store the new mean dataframe in the dictionary
         type_df_mean_dict[f"df_type_{type_value}_mean"] = mean_df
     type_df_mean_names = list(type_df_mean_dict.keys())
     print(type_df_mean_names)
    ['df_type_Grass_mean', 'df_type_Fire_mean', 'df_type_Water_mean',
    'df_type_Bug_mean', 'df_type_Normal_mean', 'df_type_Poison_mean',
    'df_type_Electric_mean', 'df_type_Ground_mean', 'df_type_Fairy_mean',
    'df_type_Fighting_mean', 'df_type_Psychic_mean', 'df_type_Rock_mean',
    'df_type_Ghost_mean', 'df_type_Ice_mean', 'df_type_Dragon_mean',
    'df_type_Dark_mean', 'df_type_Steel_mean', 'df_type_Flying_mean']
```

```
[]: # Creating new dataframe using only columns needed
     df_stats = df_c[['HP', 'Attack', 'Special Attack', 'Defense', 'Special_
      ⇔Defense', 'Speed', 'Base Stats', 'Type 1']]
     type_order = df_stats['Type 1'].unique()
     # Group by 'Type 1' and calculate mean of all stats
     plot_df_stats = df_stats.groupby('Type 1').mean(numeric_only=True).reset_index()
     # Order by custom type order
     plot_df_ordered = plot_df_stats.set_index('Type 1').loc[type_order].
      →reset_index()
     # Stats setup
     all_stats = ['HP', 'Attack', 'Special Attack', 'Speed', 'Defense', 'Special_
      ⇔Defense']
     overall_averages = plot_df_stats[all_stats].mean()
[]: # Plotting parallel bar chart to compare stats across types of pokemon
     # importing Line2D to create line for legend
     from matplotlib.lines import Line2D
     # setting custom fonts
     impact_font = {'fontname':'Impact'}
     verdana_font = {'fontname': 'Verdana'}
     # Plot figure
     fig = plt.figure(figsize=(18, 18))
     # Adding title: chnaging font, size, and position
     fig.suptitle('Pokémon Stats by Type', **impact_font, size=30, y=0.76)
     # Create custom line for the legend
     avg_line = Line2D([0], [0], color='#419EAE', linestyle='--', linewidth=1.5,__
      →label='Average')
     # Add legend to plot
     fig.legend(handles=[avg_line], loc='upper right', fontsize=10, __
      ⇒bbox_to_anchor=(0.11, 0.75), frameon=False)
     # Plotting graphs for individual stats
     # Creating loop to plot all charts
     for i, stat in enumerate(all stats):
         row = 1 + i // 3
         col = i % 3
```

ax = plt.subplot2grid((4, 3), (row, col))

```
values = plot_df_ordered.set_index('Type 1')[stat]
    colours = ['#FAAA6D', '#F2684A']
   bar_colours = [colours[i % 2] for i in range(len(values))]
   # Customise charts
   ax.barh(type_order, values, color=bar_colours)
   ax.set_title(f'{stat}', fontsize=15, **verdana_font)
   ax.invert_yaxis()
   ax.grid(axis='x', linestyle='--', alpha=0.6)
   ax.axvline(overall_averages[stat], color='#419EAE', linestyle='--', u
 →linewidth=1.5)
    # For the first column in each row, show y-ticks with the Pokémon types
   if col == 0:
       ax.set_yticks(range(len(type_order)))
       ax.set_yticklabels(type_order, fontsize=11, **verdana_font)
    # For other columns, hide the y-ticks (type)
   else:
       ax.set_yticks([])
# Printing plot
plt.tight_layout()
plt.show()
```



```
summary_stats = df_c[all_stats_base].describe().round()
     summary_stats
[]:
           Base Stats
                            ΗP
                                Attack Special Attack
                                                         Speed Defense \
                1025.0 1025.0
                               1025.0
                                                1025.0 1025.0
                                                                 1025.0
     count
                 428.0
                          70.0
                                  78.0
                                                  70.0
                                                          67.0
                                                                   73.0
    mean
                                  30.0
     std
                 113.0
                          27.0
                                                  30.0
                                                          29.0
                                                                   29.0
                                   5.0
    min
                 175.0
                          1.0
                                                  10.0
                                                          5.0
                                                                    5.0
     25%
                 323.0
                          50.0
                                  55.0
                                                  47.0
                                                          45.0
                                                                   50.0
    50%
                 450.0
                          68.0
                                75.0
                                                  65.0
                                                          65.0
                                                                   70.0
    75%
                 508.0
                          85.0
                                 100.0
                                                  90.0
                                                          88.0
                                                                   90.0
    max
                 720.0
                         255.0
                                 181.0
                                                 173.0
                                                         200.0
                                                                  230.0
            Special Defense
                     1025.0
     count
    mean
                       70.0
    std
                       27.0
    min
                       20.0
    25%
                       50.0
    50%
                       67.0
     75%
                       86.0
                      230.0
    max
[]: import plotly.graph_objects as graph_objects
     from plotly.subplots import make_subplots
     import plotly.express as px
[]: import plotly.graph_objects as graph_objects
     from plotly.subplots import make subplots
     import plotly.express as px
[]: # customise pie chart colours
     pie_chart_colours = [
         '#E64556', # HP (dark pink)
         '#A2D7D5', # Attack (light teal)
         '#55A3AB', # Special Attack (dark teal)
         '#7D78A3',  # Speed (purple)
         '#FCC499', # Defense (ligh orange)
         '#FAAA6D'  # Special Defense (dark orange)
     ]
     # Number of rows and columns in the subplot grid
     n_types = len(type_df_mean_dict)
     # Adjusting to 3 columns
     n cols = 3
     # There are 18 types (18/3=6)
```

[]: # creating summary stats table and rounding

```
n_rows = 6
# Create subplot grid using Plotly
fig = make_subplots(
   rows=n_rows, cols=n_cols,
   subplot_titles=[type_name.replace("df_type_", "").replace("_mean", "") for_
specs=[[{'type': 'pie'}] * n_cols for _ in range(n_rows)]
# Loop through each DataFrame in type of mean dict and create a pie chart in \Box
 ⇔each subplot
for i, (type_name, type_df) in enumerate(type_df_mean_dict.items()):
    # Extract the the different stats
   stats = type_df[all_stats].values.flatten()
   # Create labels for the stats
   labels = all_stats
   # Calculate row and column for each pie chart
   row = i // n_cols + 1
   col = i \% n_cols + 1
   # Create the pie chart for the current type
   pie = graph_objects.Pie(
       labels=labels,
       values=stats,
       name=type_name.replace("df_type_", "").replace("_mean", ""),
       hole=0.3.
       marker=dict(colors=pie_chart_colours)
       )
   # Add the pie chart to the appropriate subplot
   fig.add trace(pie, row=row, col=col)
# Update the layout
fig.update_layout(
   title_text="Base Stats Composition by Pokémon Type",
   title_font=dict(
       family='Impact',
       color='#042C3B', #navy
       size=28
   ),
   height=2000,
   width=1000,
   title_x=0.5, # Center the title
   legend=dict(
```

```
# positioning legend
x=-0.08,
y=1.05,
# setting background colour of legend transparent
bgcolor='rgba(0,0,0,0)'
)

# Show the plot
fig.show()
```

```
[]: # Set up the subplot grid (2 rows x 3 columns)
     fig, axes = plt.subplots(2, 3, figsize=(18, 10))
     # Flatten so we can loop easily
     axes = axes.flatten()
     fig.suptitle('Impact of Individual Stats on Base Stats', **impact_font, __
      \Rightarrowsize=25, y=0.985)
     # Loop through each stat and plot on its own subplot
     for idx, stat in enumerate(all_stats):
         ax = axes[idx]
         # Scatter plot
         ax.scatter(df_c[stat], df_c['Base Stats'], alpha=0.5)
         # Calculate and add line of best fit
         m, b = np.polyfit(df_c[stat], df_c['Base Stats'], 1)
         ax.plot(df_c[stat], m * df_c[stat] + b, color='red')
         # Customise each subplot
         ax.set_xlabel(stat, fontsize=11, **verdana_font)
         ax.set_title(f'Impact of {stat} on Base Stats', fontsize=15, **verdana_font)
         ax.tick_params(axis='both', which='major', labelsize=9)
         y= df_c['Base Stats']
         y_pred= m * df_c[stat] + b
         # Calculate R2
         tss = np.sum((y - np.mean(y))**2)
         rss = np.sum((y - y_pred)**2)
         r_squared = 1 - (rss / tss)
         # Add title and R^2 value inside the plot
         ax.set_title(f'{stat} vs Base Stats', fontsize=12)
         ax.set_xlabel(stat, fontsize=10)
         ax.tick params(axis='both', which='major', labelsize=9)
```

P vs Base Stats | HP vs Base Stats | Special Attack vs Bas

```
[]: from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score
from sklearn.tree import DecisionTreeRegressor
```

```
[]: # 1. Define X and y
X = df_c[['Base Stats', 'Egg Cycles']]
y = df_c['Capturing Rate']

# 2. Train/test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, \( \text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\text{\tex
```

```
# 3. Random Forest Model
    model = RandomForestRegressor(n_estimators=200, random_state=67) # 100 trees_
     ⇔in the forest
    # 4. Fit the model
    model.fit(X_train, y_train)
    # 5. Predictions and score
    y_pred = model.predict(X_test)
    # 6. Evaluate
    print(f"R2 Score: {r2_score(y_test, y_pred)}")
    R<sup>2</sup> Score: 0.9611803650469675
[]: # 1. Define X and y
    X = df_c[['Base Stats', 'Capturing Rate', ]]
    y = df_c['Is Legendary']
    # 2. Train/test split
    →random_state=42)
    # 3. Random Forest Model
    model = RandomForestRegressor(n_estimators=200, random_state=67) # 100 trees_
     ⇔in the forest
    # 4. Fit the model
    model.fit(X_train, y_train)
    # 5. Predictions and score
    y_pred = model.predict(X_test)
    # 6. Evaluate
    print(f"R2 Score: {r2_score(y_test, y_pred)}")
    R<sup>2</sup> Score: 0.8356980469693582
[]: from causalinference import CausalModel
[]: model = CausalModel(
        Y=df_c['Base Stats'].values,
        D=df_c['Is Legendary'].values,
        X=df_c[['Total Weakness', 'Height Inches', 'Weight Pounds', 'Capturing Rate',
        'Egg Cycles', 'Gen'
        ]].values
```

```
model.est_via_ols()
model.est_via_matching()
# Visualizing the outcomes
plt.figure(figsize=(12, 6))
plt.suptitle('Effects of Legendary Status on Total Base Stats', fontsize=20, __
 →**impact_font)
plt.subplot(1, 2, 1)
plt.hist(df_c[df_c['Is Legendary'] == 0]['Base Stats'], alpha=0.5,__
 ⇔label='Control', color='#92D1B3')
plt.hist(df_c[df_c['Is Legendary'] == 1]['Base Stats'], alpha=0.5, label='Isu
 plt.title('Distribution of Outcomes')
plt.xlabel('Base Stats', **verdana_font)
plt.ylabel('Frequency', **verdana_font)
plt.legend(frameon=False)
plt.subplot(1, 2, 2)
treated_mean = df_c[df_c['Is Legendary'] == 1]['Base Stats'].mean()
control_mean = df_c[df_c['Is Legendary'] == 0]['Base Stats'].mean()
plt.bar(['Control', 'Is Legendary'], [control_mean, treated_mean], __
 ⇔color=['#92D1B3', '#B74555'])
plt.title('Average Base Stats by Group', **verdana_font)
plt.ylabel('Average Base Stats', **verdana_font)
plt.tight_layout()
plt.show()
```

Effects of Legendary Status on Total Base Stats

