DATA ANALYTICS - TASK 1 REPORT

1. Introduction

This report provides a comprehensive analysis of the NBA Draft Combine measurements dataset. The goal is to uncover key insights and relationships between various physical attributes of players over different years.

2. Methodology

Data Loading and Exploration:

- **Loading the dataset**: The dataset was loaded into a pandas dataframe.
- **Exploration**: Basic exploration techniques such as displaying the first few rows (head), getting an overview of the dataframe (info), and generating descriptive statistics (describe) were used.

Year-Wise Comparison:

- The dataset was grouped by the Year column, and the mean values of all numeric columns were calculated for each year.

Data Visualization:

- A heatmap was used to visualize the correlation matrix of year-wise averages.
- Scatter plots were created to analyze relationships between key attributes, such as height and wingspan, and standing reach and vertical leap

3. Data Analysis

Loading and Exploring the Dataset:

```
df = pd.read_csv('C:/Users/Dell/OneDrive/Desktop/VervaBridge Tasks/achou-nba-draft-combine-measurements/nba_draft_combine_all_years.csv')

print(df.head())

print(df.info())

print(df.describe())
```

- The dataset contains multiple measurements of players over several years.
- **df.info()**: Revealed the presence of numeric and non-numeric columns, including null values in certain attributes.

- **df.describe()**: Provided statistical summaries such as mean, standard deviation, and percentiles for numeric columns.

Year-Wise Comparison:

```
numeric_cols = df.select_dtypes(include='number').columns

df_yearwise = df.groupby('Year')[numeric_cols].mean()

print(df_yearwise.head())
```

- The dataframe was grouped by year, and the mean of each numeric attribute was calculated for each year.
- This grouping helped in understanding the evolution of player measurements over the years.

Correlation Matrix Visualization:

```
plt.figure(figsize=(10, 6))

sns.heatmap(df_yearwise.corr(), annot=True)

plt.title('Correlation Matrix of Year-Wise Averages')

plt.show()
```

- The heatmap revealed correlations between different measurements on a year-wise average basis.
- For example, strong correlations were observed between attributes such as height, wingspan, and standing reach.

Relationship between Height and Wingspan:

```
sns.scatterplot(x='Height (No Shoes)', y='Wingspan', data=df)

plt.title('Relationship between Height and Wingspan')

plt.show()
```

- The scatter plot showed a positive relationship between a player's height (without shoes) and their wingspan.
- Taller players tend to have longer wingspans, which is an expected and logical outcome.

Relationship between Standing Reach and Vertical Leap:

```
sns.scatterplot(x='Standing reach', y='Vertical (Max)', data=df)
```

```
plt.title('Relationship between Standing Reach and Vertical Leap')

plt.show()
```

- The scatter plot showed the relationship between standing reach and maximum vertical leap.
- Insights into how standing reach might affect a player's jumping ability were observed.

4. Key Insights

1. **Evolution of Player Measurements:**
   - Over the years, there has been a notable change in the average physical measurements of players, reflecting evolving player profiles and training regimens.
2. **Correlations between Attributes:**
   - Height, wingspan, and standing reach show strong correlations, indicating that taller players generally have longer wingspans and higher standing reaches.
3. **Height vs. Wingspan:**
   - There is a clear positive relationship between height and wingspan, suggesting that wingspan increases with height.
4. **Standing Reach vs. Vertical Leap:**
   - Players with greater standing reach do not necessarily have higher vertical leaps, indicating that jumping ability is influenced by factors beyond just standing reach.

5. Recommendations

1. **Player Selection:**
   - Teams can use these insights to better assess player potential based on physical measurements, especially when it comes to positions requiring specific physical attributes.
2. **Training Focus:**
   - Training programs can be tailored to improve attributes that are less correlated with inherent physical traits, such as vertical leap, to enhance overall player performance.
3. **Future Data Collection:**

- Continue collecting detailed combine measurements to track trends and changes in player profiles over time. This will help in maintaining a comprehensive database for future analyses.

4. **Further Research:**

    - Investigate other factors influencing vertical leap and other performance metrics, such as strength, agility, and conditioning, to gain a holistic understanding of player capabilities.