Python for Data Analysts: A Step-by-Step Guide for Beginners

Step 1: Import Necessary Libraries	
	3
Step 2: Load Data	3
	3
From a CSV file on the desktop:	3
From the web:	3
Step 3: Convert CSV to DataFrame	3
Step 4: Remove Unneeded Columns	3
Step 5: Rename Column Headers	4
Step 6: Describe the Dataset	4
Step 7: Handle/Remove Null or N/A Values	4
Remove rows with null values:	4
Fill null values with a specific value:	4
Step 8: Merge Tables	4
# Merge on a common column (e.g., 'id')	4
Step 9: Change Data Types	4
Step 10: Perform Mathematical Calculations	4
# Example: Add a new column that is the sum of two existing columns	4
# Example: Calculate the mean of a column	4
Step 11: Create Visualizations	4
Line Chart	4
Bar Chart	5
Histogram	5
Seaborn Example (Bar Plot)	5
Additional Notes:	5
For filtering rows based on conditions:	5
For grouping data:	5
For saving the cleaned/processed data back to a file:	6
More Step Guides	6
1. Create Pivot Tables	6
2. Sort Data by a Column	6
3. Filter Rows Based on Multiple Conditions	6
0.1 filed New Based of Fractipes Conditions	
4. Apply Custom Functions to Columns	6
4. Apply Custom Functions to Columns	6
4. Apply Custom Functions to Columns 5. Cumulative Sum and Running Totals	6 6
4. Apply Custom Functions to Columns 5. Cumulative Sum and Running Totals 6. Detect and Remove Duplicates	6 6
4. Apply Custom Functions to Columns 5. Cumulative Sum and Running Totals 6. Detect and Remove Duplicates Find Duplicates:	6 6 6
4. Apply Custom Functions to Columns 5. Cumulative Sum and Running Totals 6. Detect and Remove Duplicates Find Duplicates: Remove Duplicates:	6 6 6 6
4. Apply Custom Functions to Columns 5. Cumulative Sum and Running Totals 6. Detect and Remove Duplicates Find Duplicates: Remove Duplicates: 7. Group and Aggregate	6 6 6 7
4. Apply Custom Functions to Columns 5. Cumulative Sum and Running Totals 6. Detect and Remove Duplicates Find Duplicates: Remove Duplicates: 7. Group and Aggregate 9. Generate Random Data	6 6 6 7 7
4. Apply Custom Functions to Columns 5. Cumulative Sum and Running Totals 6. Detect and Remove Duplicates Find Duplicates: Remove Duplicates: 7. Group and Aggregate 9. Generate Random Data 10. Normalize or Standardize Data	6 6 7 7

12. Split a Column into Multiple Columns	7
13. Create a Time Series Plot	7
14. Find Outliers Using IQR	8
15. Extract Text Patterns	8
16. Create Dummy Variables	8
17. Reshape Data (Melt and Pivot)	8
Melt (Wide to Long):	8
Pivot (Long to Wide):	8
18. Create a Box Plot	8
19. Rolling Window Calculations	8
20. Export Data to Excel	8
21. Split Data into Train and Test Sets	8
22. Aggregate Multiple Columns with Different Functions	9
23. Count Unique Values in a Column	9
24. Generate Pairplots with Seaborn	9
25. Perform String Manipulations	9
Convert to lowercase:	9
Check if a string contains a substring:	9
Other Common Visualizations	
1. Heatmap	9
Purpose : Visualize the correlation or relationship between variables	
2. Scatter Plot	
Purpose : Explore the relationship between two numerical variables	9
3. Stacked Bar Chart	
Purpose : Show proportions or parts of a whole over categories	
4. Bubble Chart	
Purpose : Visualize three variables with X, Y, and bubble size	
5. Pairplot	
Purpose: Explore pairwise relationships in a dataset	
6. Pie Chart	
Purpose: Show proportions of categories.	
7. Violin Plot	
Purpose : Visualize the distribution of data and its probability density	
8. Box Plot	
Purpose: Display data spread and detect outliers	
9. Histogram with KDE (Density Curve)	
Purpose: Show distribution of a single variable	
10. Treemap	
Purpose: Represent hierarchical data in a nested structure	
11. Word Cloud	
Purpose: Visualize the frequency of words in a dataset	
12. Area Chart	
Purpose: Show trends over time with emphasis on magnitude	
13. Donut Chart	12

Purpose: Pie chart variation with a center cut out	12
14. Facet Grid	12
Purpose: Visualize data subsets across multiple categories	12
15. Geospatial Heatmap	13
Purpose: Visualize geospatial data (e.g., latitude and longitude)	13
16. Regplot (Regression Line)	13
Purpose: Add a regression line to visualize the trend.	13
17. Time Series with Multiple Lines	13
Purpose: Show trends for multiple categories over time.	13
18. Population Pyramid	13
Purpose : Show age distribution split by gender (or similar categories)	13

Overview:

Python is an essential tool for data analysts, providing a powerful and flexible environment for data manipulation, analysis, and visualization. This step-by-step guide covers fundamental operations that every data analyst should master, from loading data to performing complex analyses and visualizations.

First Phase

Step 1: Import Necessary Libraries

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

Step 2: Load Data

From a CSV file on the desktop:

data = pd.read_csv(r'C:\path_to_your_file\filename.csv')

From the web:

url = 'https://example.com/filename.csv'

data = pd.read_csv(url)

Step 3: Convert CSV to DataFrame

The data object above is already a pandas DataFrame.

Step 4: Remove Unneeded Columns

 $columns_to_drop = \hbox{['column1', 'column2']} \ \# \ Replace \ with \ actual \ column \ names$

data = data.drop(columns=columns_to_drop)

Step 5: Rename Column Headers

```
new_column_names = {
   'old_column1': 'new_column1',
   'old_column2': 'new_column2'
}
data = data.rename(columns=new_column_names)
```

Step 6: Describe the Dataset

```
print(data.describe()) # Summary of numerical columns
print(data.info()) # General info, including null values
```

Step 7: Handle/Remove Null or N/A Values

Remove rows with null values:

```
data = data.dropna()
```

Fill null values with a specific value:

data['column_name'] = data['column_name'].fillna(0) # Replace with a default value

Step 8: Merge Tables

```
table1 = pd.read_csv('table1.csv')

table2 = pd.read_csv('table2.csv')

# Merge on a common column (e.g., 'id')

merged_data = pd.merge(table1, table2, on='id', how='inner') # Options: 'inner', 'outer', 'left', 'right'
```

Step 9: Change Data Types

```
data['column_name'] = data['column_name'].astype('int') # Convert to integer

data['date_column'] = pd.to_datetime(data['date_column']) # Convert to datetime
```

Step 10: Perform Mathematical Calculations

```
# Example: Add a new column that is the sum of two existing columns data['new_column'] = data['column1'] + data['column2']
```

```
# Example: Calculate the mean of a column
mean_value = data['column_name'].mean()
```

Step 11: Create Visualizations

Line Chart

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

```
Visit: bit.ly/360-analytics-insights
```

```
plt.plot(data['x_column'], data['y_column'], label='Line 1')
plt.title('Line Chart')
plt.xlabel('X-axis Label')
plt.ylabel('Y-axis Label')
plt.legend()
plt.show()
Bar Chart
plt.figure(figsize=(10, 6))
plt.bar(data['x_column'], data['y_column'], color='skyblue', label='Bar 1')
plt.title('Bar Chart')
plt.xlabel('X-axis Label')
plt.ylabel('Y-axis Label')
plt.legend()
plt.show()
Histogram
plt.figure(figsize=(10, 6))
plt.hist(data['column_name'], bins=20, color='green', alpha=0.7, label='Histogram')
plt.title('Histogram')
plt.xlabel('Value')
plt.ylabel('Frequency')
plt.legend()
plt.show()
Seaborn Example (Bar Plot)
plt.figure(figsize=(10, 6))
sns.barplot(x='x_column', y='y_column', data=data, palette='Blues')
plt.title('Seaborn Bar Chart')
plt.xlabel('X-axis Label')
plt.ylabel('Y-axis Label')
plt.show()
```

Additional Notes:

For **filtering rows** based on conditions:

 $filtered_data = data[data['column_name'] > 50] \ \# \ Example: Filter \ rows \ where \ column > 50$

For grouping data:

grouped_data = data.groupby('group_column')['value_column'].sum().reset_index()

data.to_csv(r'C:\path_to_save\processed_file.csv', index=False)

More Step Guides

1. Create Pivot Tables

```
pivot_table = data.pivot_table(
  values='value_column',
  index='index_column',
  columns='column_name',
  aggfunc='sum'
)
print(pivot_table)
```

2. Sort Data by a Column

```
sorted_data = data.sort_values(by='column_name', ascending=False)
print(sorted_data)
```

3. Filter Rows Based on Multiple Conditions

```
filtered_data = data[(data['column1'] > 50) & (data['column2'] == 'category')]
print(filtered_data)
```

4. Apply Custom Functions to Columns

```
def custom_function(x):
return x * 2 if x > 50 else x
```

data['new_column'] = data['existing_column'].apply(custom_function)

5. Cumulative Sum and Running Totals

data['cumulative_sum'] = data['value_column'].cumsum()

6. Detect and Remove Duplicates

```
Find Duplicates:
```

```
duplicates = data[data.duplicated()]
print(duplicates)

Remove Duplicates:
data = data.drop_duplicates()
```

7. Group and Aggregate

aggregated_data = data.groupby('group_column')['value_column'].agg(['sum', 'mean', 'min'])
print(aggregated_data)

8. Create a New Column Based on a Condition

data['new_column'] = np.where(data['column'] > 50, 'High', 'Low')

9. Generate Random Data

```
random_data = np.random.randint(0, 100, size=(10, 3))
random_df = pd.DataFrame(random_data, columns=['A', 'B', 'C'])
print(random_df)
```

10. Normalize or Standardize Data

Normalize (scale to range [0, 1]):

 $\label{eq:data['column']-data['column']-data['column'].min()) / (data['column'].max() - data['column'].min()) / (data['column'].min()) / (data['$

Standardize (convert to Z-scores):

data['standardized_column'] = (data['column'] - data['column'].mean()) / data['column'].std()

11. Correlation Matrix

```
correlation_matrix = data.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

12. Split a Column into Multiple Columns

 $data[['new_col1', 'new_col2']] = data['column_to_split'].str.split('_', expand=True)$

13. Create a Time Series Plot

```
data['date_column'] = pd.to_datetime(data['date_column'])
data.set_index('date_column', inplace=True)
data['value_column'].plot(figsize=(10, 6), title='Time Series Plot')
plt.xlabel('Date')
plt.ylabel('Value')
plt.show()
```

14. Find Outliers Using IQR

Q1 = data['column_name'].quantile(0.25)

Q3 = data['column_name'].quantile(0.75)

IQR = Q3 - Q1

outliers = data[(data['column_name'] < Q1 - 1.5 * IQR) | (data['column_name'] > Q3 + 1.5 * IQR)] print(outliers)

15. Extract Text Patterns

 $data['extracted_text'] = data['text_column'].str.extract(r'(\d{4})') \ \# \ Example: Extract \ 4-digit \ numbers$

16. Create Dummy Variables

data_with_dummies = pd.get_dummies(data, columns=['categorical_column'], drop_first=True)

17. Reshape Data (Melt and Pivot)

Melt (Wide to Long):

melted_data = pd.melt(data, id_vars=['id_column'], var_name='variable', value_name='value')
print(melted_data)

Pivot (Long to Wide):

pivoted_data = melted_data.pivot(index='id_column', columns='variable', values='value')
print(pivoted_data)

18. Create a Box Plot

sns.boxplot(x='categorical_column', y='numerical_column', data=data)
plt.title('Box Plot')
plt.show()

19. Rolling Window Calculations

data['rolling_mean'] = data['value_column'].rolling(window=3).mean()

20. Export Data to Excel

data.to_excel(r'C:\path_to_save\filename.xlsx', index=False)

21. Split Data into Train and Test Sets

from sklearn.model_selection import train_test_split

train, test = train_test_split(data, test_size=0.2, random_state=42)

22. Aggregate Multiple Columns with Different Functions

```
agg_data = data.groupby('group_column').agg({'col1': 'sum', 'col2': 'mean', 'col3': 'max'})
print(agg_data)
```

23. Count Unique Values in a Column

```
unique_counts = data['column_name'].nunique()
print(f"Number of unique values: {unique_counts}")
```

24. Generate Pairplots with Seaborn

```
sns.pairplot(data, hue='categorical_column', diag_kind='kde')
plt.title('Pairplot')
plt.show()
```

25. Perform String Manipulations

```
Convert to lowercase:
```

data['column'] = data['column'].str.lower()

Check if a string contains a substring:

data['contains_keyword'] = data['column'].str.contains('keyword')

Other Common Visualizations

1. Heatmap

```
Purpose: Visualize the correlation or relationship between variables.
plt.figure(figsize=(10, 6))
sns.heatmap(data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```

2. Scatter Plot

```
Purpose: Explore the relationship between two numerical variables.

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

sns.scatterplot(x='x_column', y='y_column', data=data, hue='category_column', style='category_column', palette='viridis')

plt.title('Scatter Plot')

plt.xlabel('X-axis Label')

plt.ylabel('Y-axis Label')

plt.show()
```

3. Stacked Bar Chart

```
Purpose: Show proportions or parts of a whole over categories.
```

```
data.groupby(['category', 'sub_category'])['value'].sum().unstack().plot(kind='bar', stacked=True, figsize=(10, 6))

plt.title('Stacked Bar Chart')

plt.xlabel('Category')

plt.ylabel('Value')

plt.legend(title='Sub-Category')

plt.show()
```

4. Bubble Chart

```
Purpose: Visualize three variables with X, Y, and bubble size.
```

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

plt.scatter(data['x_column'], data['y_column'], s=data['size_column'] * 100, alpha=0.5, c=data['color_column'], cmap='viridis')

plt.title('Bubble Chart')

plt.xlabel('X-axis Label')

plt.ylabel('Y-axis Label')

plt.colorbar(label='Color Metric')

plt.show()
```

5. Pairplot

```
Purpose: Explore pairwise relationships in a dataset.
```

```
sns.pairplot(data, hue='category_column', diag_kind='kde', palette='husl')
plt.suptitle('Pairplot', y=1.02)
plt.show()
```

6. Pie Chart

```
Purpose: Show proportions of categories.
```

```
data['category'].value_counts().plot.pie(
   autopct='%1.1f%%', figsize=(8, 8), startangle=90, colormap='viridis')
plt.title('Pie Chart')
plt.ylabel('') # Remove default y-label
plt.show()
```

7. Violin Plot

```
Purpose: Visualize the distribution of data and its probability density.
```

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

sns.violinplot(x='category_column', y='value_column', data=data, palette='Set2')

plt.title('Violin Plot')

plt.xlabel('Category')

plt.ylabel('Value')

plt.show()

8. Box Plot

```
Purpose: Display data spread and detect outliers.
plt.figure(figsize=(10, 6))
sns.boxplot(x='category_column', y='value_column', data=data, palette='Set3')
plt.title('Box Plot')
plt.xlabel('Category')
```

plt.show()

plt.ylabel('Value')

9. Histogram with KDE (Density Curve)

```
Purpose: Show distribution of a single variable.
```

```
plt.figure(figsize=(10, 6))
sns.histplot(data['value_column'], kde=True, bins=30, color='blue')
plt.title('Histogram with KDE')
plt.xlabel('Value')
plt.ylabel('Frequency')
plt.show()
```

10. Treemap

```
Purpose: Represent hierarchical data in a nested structure.
```

```
import squarify
sizes = data['value_column']
labels = data['category_column']

plt.figure(figsize=(10, 6))
squarify.plot(sizes=sizes, label=labels, alpha=0.8, color=sns.color_palette('Set2'))
plt.title('Treemap')
plt.axis('off')
plt.show()
```

11. Word Cloud

Purpose: Visualize the frequency of words in a dataset.

from wordcloud import WordCloud

```
text = ''.join(data['text_column'].dropna())

wordcloud = WordCloud(background_color='white', colormap='viridis').generate(text)

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

plt.imshow(wordcloud, interpolation='bilinear')

plt.axis('off')

plt.title('Word Cloud')

plt.show()
```

12. Area Chart

```
Purpose: Show trends over time with emphasis on magnitude.

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

plt.fill_between(data['x_column'], data['y_column'], color='skyblue', alpha=0.5)

plt.plot(data['x_column'], data['y_column'], color='Slateblue', alpha=0.8)

plt.title('Area Chart')

plt.xlabel('X-axis Label')

plt.ylabel('Y-axis Label')

plt.show()
```

13. Donut Chart

```
Purpose: Pie chart variation with a center cut out.
sizes = data['value_column']
labels = data['category_column']

plt.figure(figsize=(8, 8))
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90, pctdistance=0.85, colors=sns.color_palette('Set2'))
centre_circle = plt.Circle((0, 0), 0.70, fc='white')
plt.gca().add_artist(centre_circle)
plt.title('Donut Chart')
plt.show()
```

14. Facet Grid

```
Purpose: Visualize data subsets across multiple categories.
g = sns.FacetGrid(data, col='category_column', col_wrap=4, height=4)
g.map(plt.hist, 'value_column', bins=20, color='skyblue')
```

```
g.fig.suptitle('Facet Grid', y=1.02)
plt.show()
```

15. Geospatial Heatmap

```
Purpose: Visualize geospatial data (e.g., latitude and longitude).
```

import geopandas as gpd

from shapely.geometry import Point

```
geometry = [Point(xy) for xy in zip(data['longitude'], data['latitude'])]
geo_df = gpd.GeoDataFrame(data, geometry=geometry)

geo_df.plot(marker='o', color='red', markersize=10, figsize=(10, 8))
plt.title('Geospatial Heatmap')
plt.show()
```

16. Regplot (Regression Line)

```
Purpose: Add a regression line to visualize the trend.
```

```
plt.figure(figsize=(10, 6))
sns.regplot(x='x_column', y='y_column', data=data, color='teal', line_kws={"color": "red"})
plt.title('Regression Plot')
plt.xlabel('X-axis Label')
plt.ylabel('Y-axis Label')
plt.show()
```

17. Time Series with Multiple Lines

```
Purpose: Show trends for multiple categories over time.
```

```
plt.figure(figsize=(12, 6))

for label, group in data.groupby('category_column'):

    plt.plot(group['time_column'], group['value_column'], label=label)

plt.title('Time Series with Multiple Lines')

plt.xlabel('Time')

plt.ylabel('Value')

plt.legend(title='Category')

plt.show()
```

18. Population Pyramid

```
Purpose: Show age distribution split by gender (or similar categories).
male = data[data['gender'] == 'Male']['age'].value_counts().sort_index()
female = data[data['gender'] == 'Female']['age'].value_counts().sort_index()
```

```
plt.figure(figsize=(10, 6))
plt.barh(male.index, male.values, color='blue', label='Male')
plt.barh(female.index, -female.values, color='pink', label='Female')
plt.title('Population Pyramid')
plt.xlabel('Count')
plt.ylabel('Age')
plt.legend()
plt.show()
```