

Data Prep & Exploration Checklist

This is a non-exhaustive checklist that can help you structure your analysis on Jupyter Notebook.

Step 1	: Import & Observe	
	Import necessary libraries	<pre>import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns</pre>
	Set notebook options	<pre># show all dataframe columns pd.set_option('display.max_columns', None) # set matplotlib global settings eg. figsize plt.rcParams['figure.figsize'] = (8.0, 6.0)</pre>
	Import your data (set delimiter and index column if applicable)	<pre># import data df_full = pd.read_csv('data.csv', sep=';', index_col=0) # check the first few rows of your dataframe df_full.head()</pre>
	Check the dimensions of your dataframe	df_full.shape
	Checkpoint #1: Make a copy of your dataset and remove any unecessary columns (you might come back to this later as you start analysing the columns)	<pre>df = df_full.drop(columns=['B', 'C']).copy()</pre>
	Get a first overview of your dataset (look out for data types, missing values, column names and row range)	df.info()
Step 2	l: Format & Validate	
	Check the output of df.info(). Does each column have the data type you would expect? If not, reformat column	<pre># some useful functions (click for more on string functions) df['col'].str.split() df['col'].str.replace() df['col'].astype()</pre>
	Format date columns	<pre># click to read more on how to specify date formats pd.to_datetime(df['date_col'], format='%Y%m%d')</pre>
	Check for suspicious values / outliers (Eg. what is the count? is the max value too far away from 75th percentile? Are there any negative values where there shouldn't be?)	<pre>df.describe()</pre>
	Create subsets for categorical / numerical variables to make your analysis easier	<pre># categorical variables df_cat = df.select_dtypes(include='object').copy() # numerical variables df_num = df.select_dtypes(include=['int','float']).copy()</pre>
	Check how many unique values are in each categorical column	<pre># count number of unique values per column df_cat.nunique()</pre>
	For variables with a small number of unique values, check value counts for consistency (eg. ideally you don't want a gender column to have values "M", "F", "Male", "Female")	<pre># check actual count df["categorical_col"].value_counts() # check proportion df["categorical_col"].value_counts(normalize=True) * 100</pre>
Step 3	: Check for duplication	
	Check for duplicated rows	<pre># check how many rows are duplicated df.duplicated().sum() # observe duplicated rows (understand why duplication occurs) df[df.duplicated(keep=False)]</pre>
	Check for duplicated columns (sometimes columns with different names might have the same values)	<pre>df.T.duplicated() # if data is too large you can just check the first few rows df.head(100).T.duplicated()</pre>
	Check that ID column does not contain duplicates (and if it does, understand why)	df['ID'].nunique() / len(df)
	Decide on duplication handling strategy (keep vs remove)	<pre># drop duplicates and keep the first occurence df.drop_duplicates(keep='First')</pre>

Step 4:	Check for missing values		
		<pre># to check number of missing values df.isna().sum()</pre>	
	Check for missing data	# to check proportion of missing values	
		df.isna().mean() * 100	
	Are the second of		
	Visualize missing data - Check if missing values coincide across columns	<pre>sns.heatmap(df.isnull(),</pre>	
	- Sort by date and plot, do missing values occure before/after a certain	<pre>yticklabels=False, cbar=False)</pre>	
	date?		
		# to drop missing values	
	Decide on missing data handling strategy (imputation vs deletion)	df.dropna()	
	Because of missing data nariating strategy (impartation vs desertion)	<pre># to impute missing values eg. using mean df.filna(df['co'l.mean()])</pre>	
		# create a copy to use for the rest of your analysis	
	Checkpoint #2: Reset index, make a copy of your final clean dataframe and save it as a csy	<pre>df_final = df.reset_index(drop=True).copy() # save a csv so that you can quickly import it next time</pre>	
	and save it as a csv	df_final.to_csv('data_final.csv')	
Step 5	i: Visualize data		
	Univariate visualizations	<pre># categorical: which category has the most/least observations? sns.countplot(df, x="categorical col")</pre>	
		<pre># numerical: what distribution do you observe? sns.histplot(df, x="numerical col")</pre>	
		<pre>sns.boxplot(df, x="numerical_col")</pre>	
		# create scatterplots for all numerical variable combinations	
	Multivariate visualizations	<pre>sns.pairplot(df_num) # visualize correlations between numerical columns</pre>	
		<pre>sns.heatmap(df_num.corr())</pre>	
		<pre># check how distribution varies by different categories sns.violinplot(data=df, x="cat1", y="num", hue="cat2")</pre>	
		<pre>sns.boxplot(data=df, x="cat1", y="num", hue="cat2")</pre>	
	Save your visualizations	<pre># make sure to give your file a meaningful name plt.savefig('sales by quarter.png', dpi=200)</pre>	
		pic.saverig(sales_by_quarter.phg , upi-200)	
Step 6	: Clean up notebook		
	Remove any redundant / unused cells (or put them in an appendix)		
	Make sure your notebook is well structured with clear sections defined by headings and subheadings		
	Add a notebook introduction/executive summary at the beginning		
	Make sure you have communicated your insights clearly (don't leave any plots or findings without explanations)		
	Finally, reset your kernel and check that your notebook runs from top to bottom with no errors		