# CARTE-Enbridge Bootcamp

#### Lab 1-1b

In this lab, we'll delve into:

- Working with NumPy and pandas
- Data Loading and Cleaning
- Basic Data Visualization

Let's get started!

# NumPy and Pandas

## NumPy

NumPy is a Python library that provides a variety of useful features for working with numerical data. The most important feature of NumPy is the **NumPy array**, a data structure that (as the name implies) is similar to a Python list, but provides additional features that make it useful for data science. Let's take a look at some of the advantages NumPy arrays have over Python lists:

- Ease of use: You can write small, concise, and intuitive mathematical expressions like X + 2 and X \* Y (where X and Y are arrays), and the operations will be performed element-wise (sometimes called vectorized).
   This means that unlike Python lists, you don't have to write loops in order to make simple mathematical operations!
- Performance: NumPy arrays are implemented in C under the hood, meaning that operations on large arrays can be orders of magnitude faster than operations on Python lists!
- Useful features: NumPy provides many convenience functions and methods for performing quick and accurate mathematical operations and conversions on your data. For example, you can compute the mean and standard deviation of an array using np.mean() and np.std(), respectively.
- **Broad applicability:** NumPy is the base of the entire Python data science ecosystem. Practically every data science library for Python leverages NumPy in some way, making it a crucial skill to master for data science.

#### Creating NumPy Arrays

There are a variety of ways to create NumPy arrays, but the easiest way is to convert an existing list using np.array(). Let's create a NumPy array from a

list of integers:

```
In [1]: import numpy as np # convention, np is the standard alias

my_list = [1, 2, 3, 4, 5]
 my_array = np.array(my_list)

print(my_array)
 print(my_array * 2)
 print(my_array.sum())

[1 2 3 4 5]
 [2 4 6 8 10]
 15
```

### **Pandas**

Pandas is a Python library that provides additional data structures and data manipulation methods that make working with data easier. The primary data structures in Pandas are **Series** and **DataFrames**. A **Series** is a one-dimensional array of data where each element is labeled with an index. A **DataFrame** is a tabular data structure comprised of rows and columns, similar to a spreadsheet, database table, or R's data.frame object. Pandas is one of the most popular data science libraries for Python, and will be used heavily in this course.

One of many convenient features of Pandas is that it can read in just about any tabular data - including CSVs, Excel spreadsheets, and SQL tables - and convert them to DataFrames. In this example, we will load a CSV from a URL (yes, it can download files too!) and convert it to a DataFrame:

```
In [2]: import pandas as pd

# Read in the CSV file
df = pd.read_csv(
    "https://raw.githubusercontent.com/pandas-dev/pandas/main/pandas/tests/i
)

# Display the first 5 rows of the DataFrame
df.head(5)
```

	Bank Name	City	ST	CERT	Acquiring Institution	Closing Date	Updated Date
0	Banks of Wisconsin d/b/a Bank of Kenosha	Kenosha	WI	35386	North Shore Bank, FSB	31-May- 13	31-May- 13
1	Central Arizona Bank	Scottsdale	ΑZ	34527	Western State Bank	14-May- 13	20-May- 13
2	Sunrise Bank	Valdosta	GA	58185	Synovus Bank	10-May- 13	21-May- 13
3	Pisgah Community Bank	Asheville	NC	58701	Capital Bank, N.A.	10-May- 13	14-May- 13
4	Douglas County Bank	Douglasville	GA	21649	Hamilton State Bank	26-Apr- 13	16-May- 13

We can do a lot of convenient things with Pandas DataFrames, such as:

• Group rows by their value in a particular column:

Out[2]:

```
In [3]: # Get a list of cities (in the City column), grouped by state (in the ST col
for state, cities in df.groupby("ST")["City"]:
    print(state)
    print(cities.values)
    print()
```

```
['Sylacauga' 'Birmingham' 'Birmingham' 'Fort Deposit' 'Irondale'
'Birmingham' 'Montgomery']
AR
['Batesville' 'Bentonville' 'Gravette']
ΑZ
['Scottsdale' 'Gold Canyon' 'Phoenix' 'Prescott' 'Scottsdale' 'Scottsdale'
 'Scottsdale' 'Mesa' 'Phoenix' 'Mesa' 'Phoenix' 'Flagstaff' 'Phoenix'
 'Gilbert' 'Phoenix']
CA
['Palm Desert' 'Nevada City' 'San Luis Obispo' 'Napa' 'Palm Springs'
 'Westminster' 'Woodland Hills' 'Sonoma' 'Solvang' 'Chico' 'Stockton'
 'Granite Bay' 'San Diego' 'San Rafael' 'Oakland' 'La Jolla' 'Los Angeles'
 'Santa Monica' 'La Jolla' 'San Clemente' 'San Francisco' 'San Francisco'
 'Los Angeles' 'San Diego' 'Bakersfield' 'Ventura' 'Temecula'
 'Rancho Cucamonga' 'Los Angeles' 'Irvine' 'Calabasas' 'Merced'
 'Culver City' 'Redlands' 'Pomona' 'Newport Beach' 'Los Angeles'
 'Newport Beach' 'Pasadena' 'Torrance']
CO
['Greenwood Village' 'Greeley' 'Windsor' 'Castle Rock' 'Louisville'
 'Denver' 'Pueblo' 'Greeley' 'Colorado Springs']
CT
['Stamford']
['Marianna' 'Orange Park' 'Lutz' 'Tamarac' 'Destin' 'Naples' 'Palatka'
 'North Lauderdale' 'Jacksonville' 'Belleview' 'Crestview' 'Clearwater'
 'Milton' 'Palm Beach' 'Sarasota' 'Apollo Beach' 'Port St. Lucie' 'Tampa'
 'Cocoa Beach' 'Brooksville' 'Winter Park' 'Port Orange' 'Orlando'
 'Coral Gables' 'Carrabelle' 'Tampa' 'Jacksonville' 'Crawfordville'
 'Ponte Vedra Beach' 'Bradenton' 'Ocala' 'Bartow' 'Panama City Beach'
 'Port Saint Joe' 'Lantana' 'Clewiston' 'Aventura' 'Miami' 'Englewood'
 'Tampa' 'Naples' 'Fort Lauderdale' 'Bonifay' 'Fort Pierce' 'Clermont'
 'Palatka' 'Key West' 'Orlando' 'Boca Raton' 'Marco Island' 'Immokalee'
 'Miami' 'Panama City' 'Miami' 'Fort Myers' 'Naples' 'Sarasota'
 'Bradenton' 'Naples' 'Venice' 'Sarasota' 'Jupiter'
 'Coral Gables' 'Cape Coral' 'Ocala' 'Bradenton' 'Bradenton' 'Tallahassee'
 'Boca Raton' 'Miami']
GA
['Valdosta' 'Douglasville' 'LaGrange' 'Braselton' 'Jasper' 'Woodstock'
 'Buford' 'Ailey' 'Marietta' 'Rock Spring' 'Doraville' 'Ellaville'
 'Stockbridge' 'Rockmart' 'Jonesboro' 'Decatur' 'Gray' 'Woodstock'
 'Cumming' 'Statesboro' 'Stockbridge' 'Atlanta' 'Clayton' 'Jackson'
 'Franklin' 'Macon' 'Valdosta' 'Dallas' 'East Ellijay' 'Cartersville'
 'Springfield' 'Clarkesville' 'Watkinsville' 'Roswell' 'McDonough'
 'Brunswick' 'Atlanta' 'McCaysville' 'Dawsonville' 'Vidalia' 'Tifton'
 'Barnesville' 'Gordon' 'Winder' 'Douglasville' 'Ellijay' 'Acworth'
 'Jasper' 'Savannah' 'Saint Marys' 'Cartersville' 'Carrollton' 'Hiawassee'
 'Ellijay' 'Duluth' 'Cornelia' 'Carrollton' 'Atlanta' 'Reidsville'
 'Norcross' 'Atlanta' 'Sparta' 'Lawrenceville' 'Atlanta' 'Newnan'
```

```
'Atlanta' 'Gray' 'Perry' 'Macon' 'Woodstock' 'Alpharetta' 'Suwanee'
 'Winder' 'Newnan' 'Villa Rica' 'Fayetteville' 'Atlanta' 'Kennesaw'
 'Atlanta' 'Stockbridge' 'Commerce' 'McDonough' 'Duluth' 'Jackson'
 'Loganville' 'Alpharetta' 'Alpharetta' 'Alpharetta' 'Atlanta']
ΗI
['Honolulu']
IΑ
['Johnston']
ID
['Ketchum']
ΙL
['Chicago' 'Princeton' 'Crete' 'Waukegan' 'Chicago' 'Shabbona' 'Wilmette'
 'Chicago' 'Hoffman Estates' 'Des Plaines' 'Aledo' 'Geneva' 'Shorewood'
 'Chicago' 'Western Springs' 'Wood Dale' 'St. Charles' 'Chicago' 'Maywood'
 'Chicago' 'Palos Heights' 'Chicago' 'Arcola' 'Elmwood Park' 'Naperville'
 'Peotone' 'Chicago' 'Chicago' 'Chicago' 'Rockford' 'Normal'
 'Orland Park' 'Antioch' 'Springfield' 'Aurora' 'Chicago' 'Lemont'
 'Westmont' 'Chicago' 'Rolling Meadows' 'Oak Forest' 'Harvey' 'Worth'
 'Danville' 'Elizabeth' 'Oregon' 'Winchester' 'Clinton' 'Lincolnwood'
 'Macomb' 'Champaign' 'Glenwood' 'Pittsfield' 'Berkeley' 'Eldred'
 'Chicago' 'Hinsdale' 'Metropolis']
['Shelbyville' 'Evansville' 'Columbus' 'Sioux City']
KS
['Leawood' 'Olathe' 'Overland Park' 'Olathe' 'Sylvan Grove'
'Overland Park' 'Anthony' 'Paola' 'Topeka']
['Lexington' 'Louisville']
['Lacombe' 'Covington' 'Cheneyville']
MA
['Lowell']
MD
['Gaithersburg' 'Cambridge' 'Randallstown' 'Baltimore' 'Baltimore'
'Germantown' 'Baltimore' 'Crofton']
['Dearborn' 'Mount Clemens' 'Hamtramck' 'Farmington Hills' 'Hastings'
'Plymouth' 'Port Huron' 'Sterling Heights' 'New Baltimore' 'Detroit'
'Warren' 'Farmington Hills' 'Northville' 'Shelby Township']
MN
['Andover' 'Bloomington' 'Maple Grove' 'Little Falls' 'Forest Lake'
 'Wyoming' 'Rosemount' 'Lino Lakes' 'New Prague' 'Saint Paul' 'Champlin'
 'Aurora' 'Hancock' 'Hallock' 'St. Stephen' 'Oakdale' 'Otsego'
 'Spring Grove' 'Woodbury' 'Forest Lake' 'Pine City' 'Staples']
```

```
MO
['Sunrise Beach' 'Sedalia' 'St. Louis' 'Glasgow' 'Ellington'
'Jefferson City' 'Chesterfield' 'Springfield' 'Butler' 'Creve Coeur'
'Leeton' 'St. Louis' 'Kansas City' 'Sugar Creek' 'Hume' 'Kansas City']
MS
['Carthage' 'Rosedale']
NC
['Asheville' 'Lenoir' 'Whiteville' 'Asheville' 'Asheville' 'Wilmington'
'Wilmington']
NE
['Omaha' 'Lincoln' 'Loup City']
NH
['Manchester']
NJ
['Fort Lee' 'Cranford' 'Cherry Hill' 'Elizabeth' 'Ridgewood' 'Newark']
MM
['Taos' 'Albuquerque' 'Santa Fe']
NV
['Las Vegas' 'Las Vegas' 'Reno' 'Las Vegas' 'Carson City' 'Las Vegas'
'Elko' 'Henderson' 'Henderson' 'Reno']
NY
['Port Chester' 'New York' 'New York' 'Williamsville' 'White Plains']
0H
['Milford' 'Parma' 'Cleveland' 'West Chester' 'Lakeview' 'Oakwood' 'Malta']
0K
['Kingfisher' 'Davis' 'Camargo' 'Blackwell' 'Altus']
['Eugene' 'Cave Junction' 'The Dalles' 'Prineville' 'Silverton'
'Beaverton'l
PA
['Berwyn' 'Boothwyn' 'Huntingdon Valley' 'Southampton' 'Bala Cynwyd'
'Pittsburgh' 'Pittsburgh' 'Philadelphia']
['Mayaguez' 'Hato Rey' 'San Juan']
SC
['Charleston' 'Pawleys Island' 'Columbia' 'Charleston' 'Easley'
'Kingstree' 'Spartanburg' 'Bluffton' 'Myrtle Beach']
SD
['Sioux Falls']
```

```
['Lynchburg' 'Knoxville' 'Franklin' 'Alamo']
['Plano' 'La Coste' 'Houston' 'Madisonville' 'Teague' 'Austin' 'Dallas'
 'Sanderson' 'Houston' 'Sierra Blanca']
UT
['Saint George' 'Draper' 'Ogden' 'Kaysville' 'Layton' 'Salt Lake City'
'Ephraim']
VA
['Norfolk' 'Richmond' 'Martinsville' 'Reston']
WA
['University Place' 'Colfax' 'Snohomish' 'Burlington' 'Tacoma' 'Shoreline'
 'Arlington' 'Longview' 'Seattle' 'Everett' 'Lynnwood' 'Tacoma'
 'Bainbridge Island' 'Seattle' 'Bellingham' 'Lacey' 'Bremerton'
 'Vancouver'l
WΙ
['Kenosha' 'Milwaukee' 'Cassville' 'Stoughton' 'Burlington' 'West Allis'
'Racine' 'Blanchardville']
WV
['Northfork']
WY
['Thermopolis']
```

• Filter rows based on a condition (or multiple conditions):

```
In [4]: # Get a list of all banks in California that were acquired by U.S. Bank N.A. df[(df["ST"] == "CA") \& (df["Acquiring Institution"] == "U.S. Bank N.A.")]
```

Out[4]:		Bank Name	City	ST	CERT	Acquiring Institution	Closing Date	Updated Date
	343	Pacific National Bank	San Francisco	CA	30006	U.S. Bank N.A.	30-Oct- 09	22-Aug-12
	344	California National Bank	Los Angeles	CA	34659	U.S. Bank N.A.	30-Oct- 09	5-Sep-12
	345	San Diego National Bank	San Diego	CA	23594	U.S. Bank N.A.	30-Oct- 09	22-Aug-12

And lastly for now,

• Sort rows by the values in one or more columns:

In [5]: # Sort the DataFrame by the Acquiring Institution column
df.sort\_values("Acquiring Institution", ascending=True)

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	Bank Name	City	ST	CERT	Acquiring Institution	Closing Date	Updated Date
76	<b>76</b> Old Harbor Clearwat Bank		FL	57537	1st United Bank	21-Oct- 11	8-Nov-12
162	The Bank of Miami, N.A.	Coral Gables	FL	19040	1st United Bank	17-Dec- 10	2-Nov-12
323	Republic Federal Bank, N.A.	Miami	FL	22846	1st United Bank	11-Dec- 09	5-Nov-12
131	The Bank of Commerce	Wood Dale	IL	34292	Advantage National Bank Group	25-Mar- 11	22-Jan-13
399	BankFirst	Sioux Falls	SD	34103	Alerus Financial, N.A.	17-Jul-09	20-Aug-12
187	North County Bank	Arlington	WA	35053	Whidbey Island Bank	24-Sep- 10	20-Aug-12
264	City Bank	Lynnwood	WA	21521	Whidbey Island Bank	16-Apr- 10	14-Sep-12
409	Mirae Bank	Los Angeles	CA	57332	Wilshire State Bank	26-Jun- 09	20-Aug-12
98	Virginia Business Bank	Richmond	VA	58283	Xenith Bank	29-Jul-11	9-Oct-12
8	First Federal Bank	Lexington	KY	29594	Your Community Bank	19-Apr- 13	23-Apr-13

 $506 \text{ rows} \times 7 \text{ columns}$ 

# **Data Cleaning**

Often when we're working with data, we'll find that it's not in the format we need it to be in. For example, we might find that some of the values are missing, or that some of the values are in the wrong format. In this section, we'll learn how to deal with some of these common issues.

### Missing Values

Missing values are values that are absent from the dataset. Missing values are common in real-world datasets for a variety of reasons, such as data not being collected properly or data being lost. Missing values are represented in Pandas

by either NaN or None. Let's take a look at how we can deal with missing values in Pandas.

```
In [6]: # Load the Titanic dataset
df = pd.read_csv(
        "https://raw.githubusercontent.com/datasciencedojo/datasets/master/titan
)

# Display the first 5 rows of the DataFrame
df.head(5)
```

Out[6]:	ut[6]: Passe		Survived	Pclass	Name	Sex	Age	SibSp	Parch	Tic
	0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	21
	1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17
	2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/ 3101
	3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113
	4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373 <sub>′</sub>

This is a famous dataset containing information about the passengers of the Titanic. We'll come back to it a few times in this course. For now, let's take a look at the Age column. We can see that some of the values are missing, and are represented by NaN . Let's count how many values are missing:

```
In [7]: # Display the number of missing values in the Age column
    missing_count = df["Age"].isna().sum()
    print(
         f"There are {missing_count} missing values in the Age column out of {ler
    )
```

There are 177 missing values in the Age column out of 891 total rows.

We can see that there are 177 missing values in the Age column. Later on, we'll learn how to deal with missing values, but for now, let's move on to another common data cleaning task: converting data to the right format.

#### Data Types

Data types are a way of telling the computer how to interpret the data in a column. For example, the Age column in the Titanic dataset is represented as floating-point numbers (i.e. numbers with decimal points). This makes sense, since a person's age can be represented as a decimal (e.g. 27.5 years old). However, the Survived column is represented as integers (i.e. whole numbers). This also makes sense, since a person can either survive (1) or not survive (0). Let's take a look at the data types of each column:

```
In [8]: df.dtypes
Out[8]: PassengerId
                          int64
        Survived
                          int64
        Pclass
                          int64
        Name
                         object
        Sex
                         object
        Age
                        float64
        SibSp
                          int64
        Parch
                         int64
        Ticket
                         object
        Fare
                        float64
        Cabin
                         object
        Embarked
                         object
        dtype: object
```

You may notice that a few of the columns are represented as object. This is Pandas's way of saying that it doesn't know what data type to use. In this case, it's because the values in those columns are strings, and Pandas doesn't know how to convert them to a numeric data type. Let's take a look at the Sex column:

```
In [9]: df["Sex"]
Out[9]: 0
                  male
         1
                female
         2
                female
         3
                female
         4
                  male
                 . . .
         886
                  male
         887
                female
         888
                female
         889
                  male
         890
                  male
         Name: Sex, Length: 891, dtype: object
```

While it might make sense for this column to contain male and female when a person is looking at it, when we're doing data science it's much easier for this column to contain a number. There are a few ways to do this, and we will look at some of the others later. For now, let's create a new column called is\_female

which has a value of True when the passenger is a female, and False otherwise:

In [10]: df["is\_female"] = df["Sex"] == "female"
 df.head(5)

Out[10]:		PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Tic
	0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	21
	1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female	38.0	1	0	PC 17
	2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/ 3101
	3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113
	4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373

If you look at the last column, you'll see that we have added our new column that only contains True or False. Why does this benefit us? For one thing, it allows us to easily do mathematical operations directly on the data. Let's say we want to count how many women were on the ship. If we try to take the sum of the Sex column, we get the following:

In [11]: df["Sex"].sum()

Out[11]:

'malefemalefemalefemalemalemalemalefemalefemalefemalefemalemalemalefema emalefemalefemalemalemalemalemalefemalefemalefemalefemalefemalefemalefema alefemalemalemalemalefemalemalefemalemalefemalemalemalemalemalemalemale alemalemalemalefemalemalefemalemalemalemalemalemalefemalemalefemale alemalefemalemalemalefemalefemalemalefemalemalemalemalemalefemale emalemalefemalemalemalemalefemalefemalemalemalemalemalefemalemalemalema lemale female male female male male female male female male male male female male male female male male female mefemalemalefemalefemalemalefemalefemalemalemalemalemalemalefemalemalema emalemalemalemalefemalefemalemalefemalemalefemalemalefemalemalemalemalemale femalefemalemalemalemalefemalefemalemalemalefemal alefemalefemalefemalefemalemalemalemalefemalemalemalemalefemalefemalema emalemalefemalefemalefemalemalemalemalemalefemalemalefemalefemalemale malefemalemalefemalefemalefemalefemalefemalefemalefemalefemalemalefemale alemalefemalefemalemalefemalefemalefemalefemalefemalefemalefemalefema lemalemalemalefemalemalefemalemalemalemalefemalemalemalemalefemalefemale efemalemalemalemalemalemalemalemalefemalefemalefemalefemalemalemalemalefema emalemalefemalefemalemalefemalemalemalefemalemalefemalemalemalemalefema lefemalemalefemalemalemalemalemalefemalemalefemalemalemalemalemalefem alemalemalefemalemalefemalefemalefemalemalefemalemalemalemalefemalemale malefemalefemalemalemalefemalefemalefemalefemalefemalefemalefemalemalemalef alefemalemalemalemalefemalemalemalefemalefemalefemalefemalemalemalema emalemalefemalefemalefemalefemalemalemalefemalemalemalemalemalemalemalemalemale emalemalefemalemalefemalemalefemalefemalefemalefemalefemalefemalemalemale alemalemalemalemalemalemalefemalefemalefemalefemalemalemalemalemalemalema efemalefemalemalemalefemalemalefemalefemalefemalefemalemalemalemalemalefe emalemalefemalefemalemalemalemalemalemalefemalefemalefemalemalefemalemalemale alefemalemalefemalemalemalefemalemalefemalemalefemalemalemalemalemalema lefemalefemalemalemalemalemalemalemalemalefemalefemalefemalefemalefemal emalemalemalemalemalefemalemalemalemalemalefemalemalemalemalemalefemale efemalemalefemalemalemalemalefemalemalefemalemalefemalemalefemalefemalefemalefemalefemalefemalefemalemalefemalemalefemalemalemalefemalemalefemalemalefemalemalefemalemalefemalemalefemalemalemalefemalemalefemalemalefemalemalefemalemalefemalemalefemalemalemalefemalemalefemalemalefemalemalefemalemalefemalemalefemalemalemalefemalemalefemalemalefemalemalefemalemalefemalemalefemalemalemalefemalefemalemalefemalefemalemalefem femalemalemalefemalemalemalefemalemalefemalemalemalemalemalemalefem alefemalemalemalemalefemalemalemalemalemalemalemalefemalemalemalema efemalefemalefemalefemalemalemalemalemalefemalemalefemalefemalefemalemale malemalefemalefemalemalefemalemalefemalemalefemalefemalemalemale'

Clearly that's totally useless! Let's try the same with our new is\_female column:

```
In [12]: df["is_female"].sum()
```

Out[12]: 314

Much more convenient! We can even calculate the percentage of passengers who were women in a single line now:

```
In [13]: df["is_female"].mean() * 100
```

Out[13]: 35.24130190796858

Another benefit is to do with how much storage our data takes up. Let's compare the memory usage of our two columns:

```
In [14]: memory_usage_sex = df["Sex"].memory_usage(deep=True)
    memory_usage_is_female = df["is_female"].memory_usage(deep=True)
    print(f"Sex column memory usage: {memory_usage_sex} bytes")
    print(f"is_female column memory usage: {memory_usage_is_female} bytes")
    print(f"Sex column uses {memory_usage_sex/memory_usage_is_female:.2f} times

Sex column memory usage: 55111 bytes
```

is\_female column memory usage: 1023 bytes Sex column uses 53.87 times more data

## **Data Visualization**

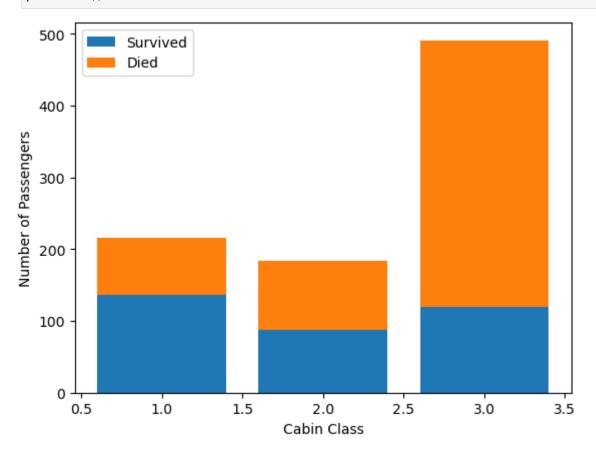
Data visualization turns complex datasets into easily digestible visuals, making it quicker to spot underlying patterns. Let's say we are interested in the relationship between cabin class and survival rate. We can use a bar chart to visualize this relationship:

```
In [15]: import matplotlib.pyplot as plt # Standard convention - matplotlib's pyplot
In [16]: # Get the number of survivors and fatalities for each cabin class
    survivors = df.groupby("Pclass")["Survived"].sum()
    fatalities = df.groupby("Pclass")["Survived"].count() - survivors

# Create a bar chart
    plt.bar(survivors.index, survivors.values, label="Survived")
    plt.bar(fatalities.index, fatalities.values, bottom=survivors.values, label=

# Add labels and a legend
    plt.xlabel("Cabin Class")
    plt.ylabel("Number of Passengers")
    plt.legend()
```

# Display the chart
plt.show()



Thanks to our visualization, we can easily see that the survival rate was highest for passengers in first class, and lowest for passengers in third class. We can also see that there were more fatalities than survivors in third class, but more survivors than fatalities in first and second class. This is just one example of how data visualization can help us understand our data.

# Optional Exercise: Data Visualization

In this exercise, you will create a visualization to answer the following question:

What was the survival rate by title?

We have provided the code to extract the title from each passenger's name, and to create a new column called Title containing the title for each passenger. You will need to create a visualization to answer the question above. You can use any type of visualization you like, but we recommend a bar chart or a pie chart.

```
In [18]: df[
             "Title"
         ].value counts() # You might notice the title Jonkheer - this is a Dutch ho
Out[18]: Title
         Mr
                     517
         Miss
                     182
                     125
         Mrs
                      40
         Master
         Dr
                       7
         Rev
                       6
         Col
                       2
                       2
         Mlle
                       2
         Major
                       1
         Ms
         Mme
                       1
         Don
                       1
         Lady
                       1
         Sir
                       1
         Capt
                       1
         Countess
                       1
         Jonkheer
                       1
         Name: count, dtype: int64
In [19]: # One possible answer - a bar chart
         survivors = df.groupby("Title")["Survived"].sum()
         fatalities = df.groupby("Title")["Survived"].count() - survivors
         plt.bar(survivors.index, survivors.values, label="Survived")
         plt.bar(fatalities.index, fatalities.values, bottom=survivors.values, label=
         plt.xlabel("Title")
         plt.xticks(rotation=45) # Rotates the x-axis labels by 45 degrees
         plt.ylabel("Number of Passengers")
         plt.legend()
         plt.show()
```

