

- A Series is a data structure in Pandas that holds an array of information along with a named index.
- The named index differentiates this from a simple NumPy array.
- Formal Definition: One-dimensional ndarray with axis labels



NumPy array has numeric index

Index	Data
0	1776
1	1867
2	1821





• Pandas Series adds on a labeled index

Labeled Index	Data
USA	1776
CANADA	1867
MEXICO	1821



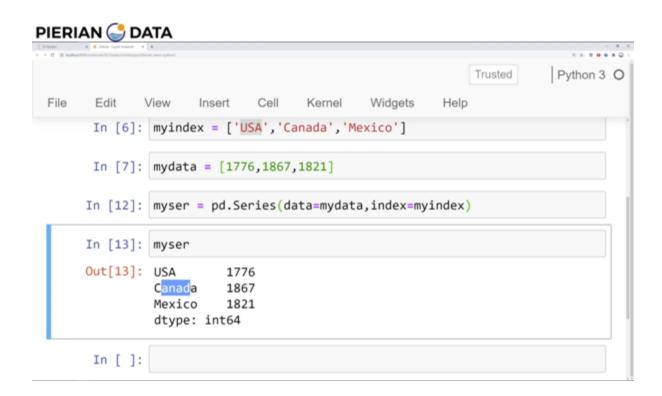


Data is still numerically organized

Numeric Index	Labeled Index	Data
0	USA	1776
1	CANADA	1867
2	MEXICO	1821



- Let's explore the various ways to create a Pandas Series object.
- We'll also learn about some key properties and operations.
- Later on we will learn how to combine
 Series with a shared index to create a tabular data structure called a DataFrame.





- When reading in missing values, pandas will display them as NaN values.
- There are also newer specialized null pandas values such as pd.NaT to imply the value missing should be a timestamp.

PIERIAN 🍪 DATA

Not a number , not a timestamp



- Options for Missing Data
 - o Keep it
 - o Remove it
 - o Replace it
 - Note, there is never 100% correct approach that applies to all circumstances, it all depends on the exact situation you encounter!



- Keeping the missing data
 - o PROS:
 - Easiest to do
 - Does not manipulate or change the true data
 - O CONS:
 - Many methods do not support NaN
 - Often there are reasonable guesses





- Keeping the missing data
 - o PROS:
 - Easiest to do
 - Does not manipulate or change the true data
 - o CONS:
 - Many methods do not support NaN
 - Often there are reasonable guesses



- Dropping or Removing the missing data
 - o PROS:
 - Easy to do.
 - Can be based on rules.
 - o CONS:
 - Potential to lose a lot of data or useful information.
 - Limits trained models for future data.





- Removing or Dropping missing data
 - Dropping a Row
 - Makes sense when a lot of info is missing

	Year	Pop	GDP	Area
USA	1776	NAN	NAN	NAN
CANADA	1867	38	1.7	3.86
MEXICO	1821	126	1.22	0.76





- Removing or Dropping missing data
 - Dropping a Row
 - Clearly this data point as a row should probably be dropped

	Year	Pop	GDP	Area
USA	1776	NAN	NAN	NAN
CANADA	1867	38	1.7	3.86
MEXICO	1821	126	1.22	0.76





- Removing or Dropping missing data
 - Dropping a Column
 - Good choice if every row is missing that particular feature

	Year	Pop	GDP	Area
USA	1776	328	20.5	NAN
CANADA	1867	38	1.7	NAN
MEXICO	1821	126	1.22	0.76





- Filling in the missing data
 - o PROS:
 - Potential to save a lot of data for use in training a model
 - o CONS:
 - Hardest to do and somewhat arbitrary
 - Potential to lead to false conclusions





- Filling in missing data
 - Fill with same value
 - Good choice if NaN was a placeholder

	Year	Pop	GDP	Carriers
USA	1776	328	20.5	11
CANADA	1867	38	1.7	NAN
MEXICO	1821	126	1.22	NAN





- Filling in missing data
 - o Fill with same value
 - Here NAN can be filled in with zero

	Year	Pop	GDP	Carriers
USA	1776	328	20.5	11
CANADA	1867	38	1.7	0
MEXICO	1821	126	1.22	0





- Filling in missing data
 - o Fill with interpolated or estimated value
 - Much harder and requires reasonable assumptions

	Year	Pop	GDP	Perct
USA	1776	328	20.5	75%
CANADA	1867	38	1.7	NAN
MEXICO	1821	126	1.22	25%





- Filling in missing data
 - o Fill with interpolated or estimated value
 - Much harder and requires reasonable assumptions

	Year	Pop	GDP	Perct	
USA	1776	328	20.5	75%	h
CANADA	1867	38	1.7	50%	۲(
MEXICO	1821	126	1.22	25%	V





- Let's explore the code syntax in pandas for dealing with missing values.
- Later on in the course we will have a deeper discussion on trying to decide between keep,remove, and replace options.





- Often the data you need exists in two separate sources, fortunately, Pandas makes it easy to combine these together.
- The simplest combination is if both sources are already in the same format, then a concatenation through the pd.concat() call is all that is needed.





 Concatenation is simply "pasting" the two DataFrames together, by columns:

	Year	Pop			GDP	Perct
USA	1776	328		USA	20.5	75%
CANADA	1867	38	←	CANADA	1.7	NAN
MEXICO	1821	126		MEXICO	1.22	25%





 Concatenation is simply "pasting" the two DataFrames together, by columns:

	Year	Pop	←→		GDP	Perct
USA	1776	328		USA	20.5	75%
CANADA	1867	38		CANADA	1.7	NAN
MEXICO	1821	126		MEXICO	1.22	25%





 Concatenation is simply "pasting" the two DataFrames together, by rows:

Р
5
7
Р
2
6





- Often DataFrames are not in the exact same order or format, meaning we can not simply concatenate them together.
- In this case, we need to merge the DataFrames.
- This is analogous to a JOIN command in SQL.



- The .merge() method takes in a key argument labeled how
- There are 3 main ways of merging tables together using the how parameter:
 - Inner
 - Outer
 - Left or Right



 The main idea behind the argument is to decide how to deal with information only present in one of the joined tables.





- Let's imagine a simple example.
- Our company is holding a conference for people in the movie rental industry.
- We'll have people register online beforehand and then login the day of the conference.





After the conference we have these tables

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





 The respective id columns indicate what order they registered or logged in on site.

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





 (e.g. There is only one person in the company named "Andrew")

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





 To help you keep track, Registrations names' first letters go A,B,C,D

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





 First we need to decide on what column to merge together.

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





 The on column should be a primary identifier, meaning unique per row.

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





 The on column should also be present in both tables being merged.

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





 Since we assume names are unique here, will we merge on= "name".

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





 Next we need to decide how to merge the tables on the name column.

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





• With how="inner" the result will be the set of records that match in both tables.

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





 With how= "inner" the result will be the set of records that match in both tables.

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie
4	David

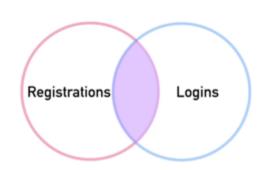
LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





Merges are often shown as a Venn diagram pd.merge(registrations,logins,how='inner',on='name')

REGISTRATIONS	
reg_id	name
1	Andrew
2	Bob
3	Charlie



LOGINS		
log_id name		
1	Xavier	
2	Andrew	
3	Yolanda	
4	Bob	



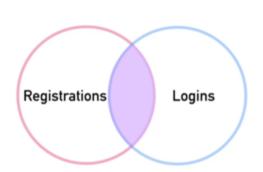


David

pd.merge(registrations,logins,how='inner',on='name')

REGISTRATIONS			
reg_id name			
1 Andrev			
2	Bob		
3	Charlie		
4 David			





LOGINS	
log_id name	
1	Xavier
2	Andrew
3	Yolanda
4	Bob



pd.merge(registrations,logins,how='inner',on='name')

REGISTRATIONS		
reg_id name		
1 Andrew		
2	Bob	
3	Charlie	
4 David		

RESULTS		
reg_id	log_id	
1	Andrew	2
2	Bob	4

LOGINS	
log_id	name
1	Xavier
2	Andrew
3	Yolanda
4	Bob





- Now that we understand an "inner" merge, let's explore "left" versus "right" merge conditions.
- Note! Order of the tables passed in as arguments does matter here!





Let's explore an **how= "left"** condition with our two example tables.

REGISTRATIONS		
reg_id name		
1	Andrew	
2	Bob	
3	Charlie	
4	David	

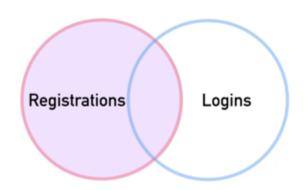
LOGINS		
log_id name		
1	Xavier	
2	Andrew	
3	Yolanda	
4	Bob	





pd.merge(registrations,logins,how='left',on='name')

REGISTRATIONS		
reg_id name		
1 Andrev		
2	Bob	
3	Charlie	
4 David		



LOGINS		
log_id name		
1 Xavier		
2	Andrew	
3	Yolanda	
4 Bob		





pd.merge(registrations,logins,how='left',on='name')

REGISTRATIONS		
reg_id name		
1	Andrew	
2	Bob	
3	Charlie	
4 David		



RESULTS		
reg_id	name	log_id
1	Andrew	2
2	Bob	4
3	Charlie	NaN
4	David	NaN

LOGINS					
log_id name					
1	Xavier				
2	Andrew				
3	Yolanda				
4 Bob					



pd.merge(registrations,logins,how='right',on='name')

REGISTRATIONS					
reg_id name					
1 Andrew					
2	Bob Charlie				
3					
4 David					

RESULTS				
reg_id	log_id			
1 Andrew		2		
2 Bob		4		
NaN	Xavier	1		
NaN	Yolanda	3		

LOGINS					
log_id name					
1 Xavier					
2	Andrew				
3 Yolanda					
4	Bob				





 Setting how= "outer" allows us to include everything present in both tables.





 But we have names that only appear in one table!

REGISTRATIONS					
reg_id name					
1	Andrew				
2	Bob				
3	Charlie				
4	David				

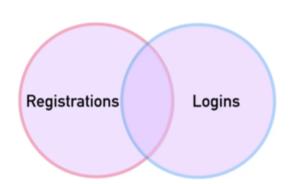
LOGINS					
log_id name					
1	Xavier				
2	Andrew				
3	Yolanda				
4 Bob					





pd.merge(registrations,logins,how='outer',on='name')

REGISTRATIONS					
reg_id name					
1	Andrew				
2	Bob				
3	Charlie				
4 David					



LOGINS					
log_id name					
1	Xavier				
2	Andrew				
3	Yolanda				
4	Bob				



pd.merge(registrations,logins,how='outer',on='name')

REGISTRATIONS						
reg_id name						
1 Andrew						
2	Bob					
3	Charlie					
4 David						

RESULTS				
reg_id	name	log_id		
1	Andrew	2		
2	Bob	4		
3	Charlie	NaN		
4	David	NaN		
NaN	Xavier	1		
NaN	Yolanda	3		

LOGINS					
log_id name					
1	Xavier				
2	Andrew				
3	Yolanda				
4 Bob					



- Often text data needs to be cleaned or manipulated for processing.
- While we can always use a custom apply() function for these tasks, pandas comes with many built-in string method calls.
- Let's learn how to use them!



- Basic Python has a datetime object containing date and time information.
- Pandas allows us to easily extract information from a datetime object to use feature engineering.





- For example, we may have recent timestamped sales data.
- Pandas will allow us to extract information from the timestamp, such as:
 - Day of the Week
 - Weekend vs Weekday
 - AM vs PM



- Pandas can read in data from a wide variety of sources and has excellent online documentation!
- In this series of lectures we will cover some of the most popular ways to read in datasets.



Note!

- You need to know the exact directory location and correct file name.
- You may need passwords or permissions for certain data inputs (e.g. a SQL database password).





- Final Note:
 - It's almost impossible for us to help with datasets outside the course, since they could be incorrectly formatted, in the wrong location, or have a different name.



- Video Lectures:
 - CSV Files
 - HTML Tables
 - Excel Files
 - SQL Databases





- Websites display tabular information through the use of HTML tables tags:
- Pandas has the ability to automatically convert these HTML tables into a DataFrame.



- Important Notes!
 - Not every table in a website is available through HTML tables.
 - Some websites may block your computer from scraping the HTML of the site through pandas.
 - It may be more efficient to use an API.





- Let's work through an example of grabbing all the tables from a Wikipedia Article and then cleaning and organizing the information to get a DataFrame.
- Output to an HTML table is also very useful to display tables on a website!



- Pandas treats an Excel Workbook as a dictionary, with the key being the sheet name and the value being the DataFrame representing the sheet itself.
- Note! Using pandas with Excel requires additional libraries!
- Let's explore how this works!





- Pandas can read and write to various SQL engines through the use of a driver and the sqlalchemy python library.
- So how does this work?





- Step 1:
 - Figure out what SQL Engine you are connecting to, for just a few examples:
 - PostgreSQL
 - MySQL
 - MS SQL Server



- Step 2:
 - Install the appropriate Python driver library (Most likely requires a Google Search):
 - PostgreSQL psycopg2
 - MySQL pymysql
 - MS SQL Server pyodbc





- Step 3:
 - Use the sqlalchemy library to connect to your SQL database with the driver:
 - docs.sqlalchemy.org/en/13/dialects/index.html



- Step 4:
 - Use the sqlalchemy driver connection with pandas read_sql method
 - Pandas can read in entire tables as a DataFrame or actual parse a SQL query through the connection:
 - SELECT * FROM table;





- Important Note!
 - Use your skills in information lookup to easily find many online resources regarding examples for all of the major SQL engines, for example:
 - Google Search: Oracle SQL + pandas



 For our example, we'll use SQLite since it comes with Python and we can easily create a temporary database inside of your RAM.





- Pivot tables allow you to reorganize data, refactoring cells based on columns and a new index.
- This is best shown visually...





 A DataFrame with repeated values can be pivoted for a reorganization and clarity

	df				ат.р		mns='bar es='baz'		
	foo	bar	baz	Z00	ь	ar	A	В	С
0	one	Α	1	х					_
1	one	В	2	у	10	00			
2	one	С	3	z	,				
3	two	Α	4	q	o	ne	1	2	3
4	two	В	5	W					
5	two	С	6	t	tv	wo	4	5	6





- You should first go through this checklist before running a pivot():
 - What question are you trying to answer?
 - What would a dataframe that answers the question look like? Does it need a pivot()
 - What do you want the resulting pivot to look like?