Principles and Techniques of Data Science

Data 100

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Welcome

This text offers supplementary resources to accompany lectures presented in the Summer 2023 iteration of the UC Berkeley course Data 100: Principles and Techniques of Data Science, taught by Bella Crouch and Dominic Liu.

New notes will be added each week to accompany live lectures. See the full calendar of lectures on the course website.

If you spot any typos or would like to suggest changes, let us know! **Email**: data100.instructors@berkeley.edu

1 Introduction

> **Note**
>
> - Acquaint yourself with the overarching goals of Data 100
> - Understand the stages of the data science lifecycle

Data science is an interdisciplinary field with a variety of applications. The field is rapidly evolving; many of the key technical underpinnings in modern-day data science were only popularized during the 21st century.

A true mastery of data science requires a deep theoretical understanding and strong grasp of domain expertise. This course will help you build on the former – specifically, the foundation of your technical knowledge. To do so, we've organized concepts in Data 100 around the **data science lifecycle**: an iterative process that encompasses the various statistical and computational building blocks of data science.

1.1 Data Science Lifecycle

The data science lifecycle is a high-level overview of the data science workflow. It's a cycle of stages that a data scientist should explore as they conduct a thorough analysis of a data-driven problem.

There are many variations of the key ideas present in the data science lifecycle. In Data 100, we visualize the stages of the lifecycle using a flow diagram. Notice how there are two entry points.

1.1.1 Ask a Question

Whether by curiosity or necessity, data scientists will constantly ask questions. For example, in the business world, data scientists may be interested in predicting the profit generated by a certain investment. In the field of medicine, they may ask whether some patients are more likely than others to benefit from a treatment.

Posing questions is one of the primary ways the data science lifecycle begins. It helps to fully define the question. Here are some things you should ask yourself before framing a question.

- What do we want to know?
  - A question that is too ambiguous may lead to confusion.
- What problems are we trying to solve?
  - The goal of asking a question should be clear in order to justify your efforts to stakeholders.
- What are the hypotheses we want to test?
  - This gives a clear perspective from which to analyze final results.
- What are the metrics for our success?
  - This gives a clear point to know when to finish the project.

1.1.2 Obtain Data

The second entry point to the lifecycle is by obtaining data. A careful analysis of any problem requires the use of data. Sometimes, data may be readily available to us; other times, we may have to embark on a process to collect it. When doing so, it is crucial to ask the following:

- What data do we have and what data do we need?
  - Define the units of the data (people, cities, points in time, etc.) and what features to measure.
- How will we sample more data?
  - Scrape the web, collect manually, etc.
- Is our data representative of the population we want to study?
  - If our data is not representative of our population of interest, then we can come to incorrect conclusions.

Key procedures: *data acquisition*, *data cleaning*

1.1.3 Understand the Data

Raw data itself is not inherently useful. It's impossible to discern all the patterns and relationships between variables without carefully investigating them. Therefore, translating pure data to actionable insights is a key job of a data scientist. For example, we may choose to ask:

- How is our data organized and what does it contain?

  - Knowing what the data says about the world helps us better understand the world.
- Do we have relevant data?
  - If the data we have collected is not useful to the question at hand, then we must collected more data.
- What are the biases, anomalies, or other issues with the data?
  - These can lead to many false conclusions if ignored, so data scientists must always be aware of these issues.
- How do we transform the data to enable effective analysis?
  - Data is not always easy to interpret at first glance, so a data scientist should reveal these hidden insights.

Key procedures: *exploratory data analysis*, *data visualization*.

1.1.4 Understand the World

After observing the patterns in our data, we can begin answering our question. This may require that we predict a quantity (machine learning) or measure the effect of some treatment (inference).

From here, we may choose to report our results, or possibly conduct more analysis. We may not be satisfied by our findings, or, our initial exploration may have brought up new questions that require a new data.

- What does the data say about the world?
  - Given our models, the data will lead us to certain conclusions about the real world.
- Does it answer our questions or accurately solve the problem?
  - If our model and data cannot accomplish our goals, then we must reform our question, model, or both.
- How robust are our conclusions and can we trust the predictions?
  - Inaccurate models can lead to untrue conclusions.

Key procedures: *model creation*, *prediction*, *inference*.

1.2 Conclusion

The data science lifecycle is meant to be a set of general guidelines rather than a hard list of requirements. In our journey exploring the lifecycle in Data 100, we'll cover the underlying theory and technologies used in data science. It is our hope that, by the end of the course, you start to see yourself as a data scientist.

With that, let's begin by introducing one of the most important tools in exploratory data analysis: `pandas`.

2 Pandas I

> **Note**
>
> - Build familiarity with basic `pandas` syntax
> - Learn key data structures: DataFrames, Series, and Indices
> - Understand methods for extracting data: `.loc`, `.iloc`, and `[ ]`

In this sequence of lectures, we will dive right into things by having you explore and manipulate real-world data. To do so, we'll introduce `pandas`, a popular Python library for interacting with **tabular data**.

2.1 Tabular Data

Data scientists work with data stored in a variety of formats. The primary focus of this class is in understanding *tabular data* —- data that is stored in a table.

Tabular data is one of the most common systems that data scientists use to organize data. This is in large part due to the simplicity and flexibility of tables. Tables allow us to represent each **observation**, or instance of collecting data from an individual, as its own row. We can record distinct characteristics, or **features**, of each observation in separate columns.

To see this in action, we'll explore the `elections` dataset, which stores information about political candidates who ran for president of the United States in various years.

```python
import pandas as pd
pd.read_csv("data/elections.csv")
```

	Year	Candidate	Party	Popular vote	Result	%
0	1824	Andrew Jackson	Democratic-Republican	151271	loss	57.210122
1	1824	John Quincy Adams	Democratic-Republican	113142	win	42.789878
2	1828	Andrew Jackson	Democratic	642806	win	56.203927
3	1828	John Quincy Adams	National Republican	500897	loss	43.796073
4	1832	Andrew Jackson	Democratic	702735	win	54.574789
5	1832	Henry Clay	National Republican	484205	loss	37.603628
6	1832	William Wirt	Anti-Masonic	100715	loss	7.821583
7	1836	Hugh Lawson White	Whig	146109	loss	10.005985
8	1836	Martin Van Buren	Democratic	763291	win	52.272472
9	1836	William Henry Harrison	Whig	550816	loss	37.721543
10	1840	Martin Van Buren	Democratic	1128854	loss	46.948787
11	1840	William Henry Harrison	Whig	1275583	win	53.051213
12	1844	Henry Clay	Whig	1300004	loss	49.250523
13	1844	James Polk	Democratic	1339570	win	50.749477
14	1848	Lewis Cass	Democratic	1223460	loss	42.552229
15	1848	Martin Van Buren	Free Soil	291501	loss	10.138474
16	1848	Zachary Taylor	Whig	1360235	win	47.309296
17	1852	Franklin Pierce	Democratic	1605943	win	51.013168
18	1852	John P. Hale	Free Soil	155210	loss	4.930283
19	1852	Winfield Scott	Whig	1386942	loss	44.056548
20	1856	James Buchanan	Democratic	1835140	win	45.306080
21	1856	John C. Frémont	Republican	1342345	loss	33.139919
22	1856	Millard Fillmore	American	873053	loss	21.554001
23	1860	Abraham Lincoln	Republican	1855993	win	39.699408
24	1860	John Bell	Constitutional Union	590901	loss	12.639283
25	1860	John C. Breckinridge	Southern Democratic	848019	loss	18.138998
26	1860	Stephen A. Douglas	Northern Democratic	1380202	loss	29.522311
27	1864	Abraham Lincoln	National Union	2211317	win	54.951512
28	1864	George B. McClellan	Democratic	1812807	loss	45.048488
29	1868	Horatio Seymour	Democratic	2708744	loss	47.334695
30	1868	Ulysses Grant	Republican	3013790	win	52.665305
31	1872	Horace Greeley	Liberal Republican	2834761	loss	44.071406
32	1872	Ulysses Grant	Republican	3597439	win	55.928594
33	1876	Rutherford Hayes	Republican	4034142	win	48.471624
34	1876	Samuel J. Tilden	Democratic	4288546	loss	51.528376
35	1880	James B. Weaver	Greenback	308649	loss	3.352344
36	1880	James Garfield	Republican	4453337	win	48.369234
37	1880	Winfield Scott Hancock	Democratic	4444976	loss	48.278422
38	1884	Benjamin Butler	Anti-Monopoly	134294	loss	1.335838
39	1884	Grover Cleveland	Democratic	4914482	win	48.884933
40	1884	James G. Blaine	Republican	4856905	loss	48.312208
41	1884	John St. John	Prohibition	147482	loss	1.467021
42	1888	Alson Streeter	Union Labor	146602	loss	1.288861
43	1888	Benjamin Harrison	Republican	5443633	win	47.858041
44	1888	Clinton B. Fisk	Prohibition	249819	loss	2.196299
45	1888	Grover Cleveland	Democratic	5534488	loss	48.656799
46	1892	Benjamin Harrison	Republican	5176108	loss	42.984101
47	1892	Grover Cleveland	Democratic	5553898	win	46.121393
48	1892	James B. Weaver	Populist	1041028	loss	8.645038
49	1892	John Bidwell	Prohibition	270879	loss	2.249468
50	1896	John M. Palmer	National Democratic	134645	loss	0.969566
51	1896	Joshua Levering	Prohibition	131312	loss	0.945565

In the `elections` dataset, each row represents one instance of a candidate running for president in a particular year. For example, the first row represents Andrew Jackson running for president in the year 1824. Each column represents one characteristic piece of information about each presidential candidate. For example, the column named "Result" stores whether or not the candidate won the electon.

Your work in Data 8 helped you grow very familiar with using and interpreting data stored in a tabular format. Back then, you used the `Table` class of the `datascience` library, a special programming library specifically for Data 8 students.

In Data 100, we will be working with the programming library `pandas`, which is generally accepted in the data science community as the industry- and academia-standard tool for manipulating tabular data (as well as the inspiration for Petey, our panda bear mascot).

2.2 DataFrames, Series, and Indices

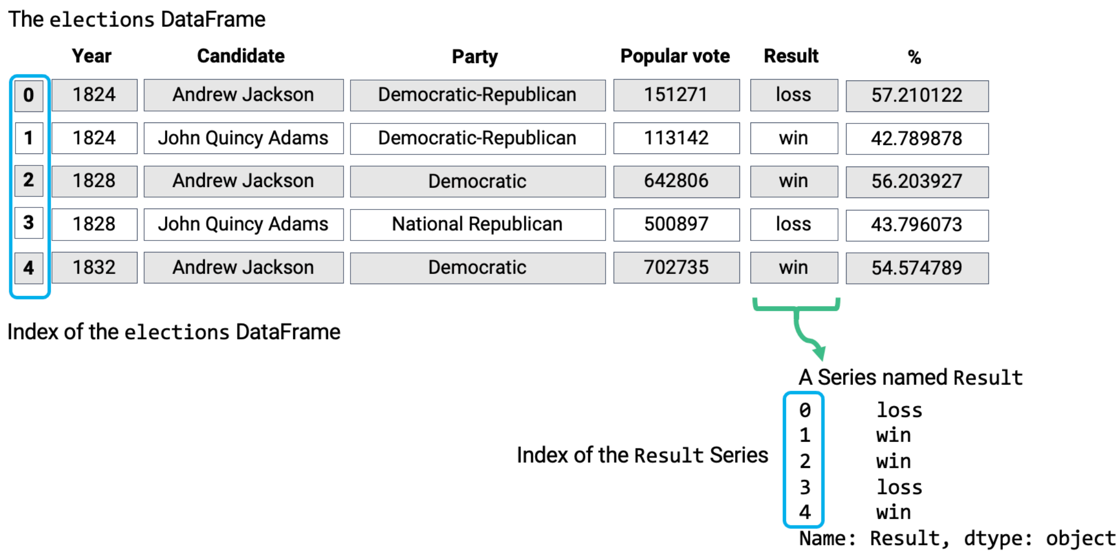
To begin our studies in `pandas`, we must first import the library into our Python environment. This will allow us to use `pandas` data structures and methods in our code.

```
# `pd` is the conventional alias for Pandas, as `np` is for NumPy
import pandas as pd
```

There are three fundamental data structures in `pandas`:

1. **Series**: 1D labeled array data; best thought of as columnar data
2. **DataFrame**: 2D tabular data with rows and columns
3. **Index**: A sequence of row/column labels

DataFrames, Series, and Indices can be represented visually in the following diagram, which considers the first few rows of the `elections` dataset.



Notice how the **DataFrame** is a two-dimensional object – it contains both rows and columns. The **Series** above is a singular column of this DataFrame, namely, the `Result` column. Both contain an **Index**, or a shared list of row labels (here, the integers from 0 to 4, inclusive).

2.2.1 Series

A Series represents a column of a DataFrame; more generally, it can be any 1-dimensional array-like object containing values of the same type with associated data labels, called its index. In the cell below, we create a Series named `s`.

```
s = pd.Series([-1, 10, 2])
s
```

	0
0	-1
1	10
2	2

```
s.values # Data contained within the Series
```

```
array([-1, 10,  2])
```

```
s.index # The Index of the Series
```

```
RangeIndex(start=0, stop=3, step=1)
```

By default, the Index of a Series is a sequential list of integers beginning from 0. Optionally, a manually-specified list of desired indices can be passed to the `index` argument.

```
s = pd.Series([-1, 10, 2], index = ["a", "b", "c"])
s
```

	0
a	-1
b	10
c	2

Indices can also be changed after initialization.

```
s.index = ["first", "second", "third"]
s
```

	0
first	-1
second	10
third	2

2.2.1.1 Selection in Series

Much like when working with NumPy arrays, we can select a single value or a set of values from a Series. There are 3 primary methods of selecting data.

1. A single index label
2. A list of index labels
3. A filtering condition

To demonstrate this, let's define the Series `ser`.

```
ser = pd.Series([4, -2, 0, 6], index = ["a", "b", "c", "d"])
ser
```

	0
a	4
b	-2
c	0
d	6

2.2.1.1.1 A Single Index Label

```
ser["a"] # We return the value stored at the Index label "a"
```

```
4
```

2.2.1.1.2 A List of Index Labels

```
ser[["a", "c"]] # We return a *Series* of the values stored at labels "a" and "c"
```

	0
a	4
c	0

2.2.1.1.3 A Filtering Condition

Perhaps the most interesting (and useful) method of selecting data from a Series is with a filtering condition.

First, we apply a boolean condition to the Series. This create **a new Series of boolean values**.

```
ser > 0 # Filter condition: select all elements greater than 0
```

	0
a	True
b	False
c	False
d	True

We then use this boolean condition to index into our original Series. `pandas` will select only the entries in the original Series that satisfy the condition.

```python
ser[ser > 0]
```

	0
a	4
d	6

2.2.2 DataFrames

In Data 8, you represented tabular data using the `Table` class of the `datascience` library. In Data 100, we'll be using the `DataFrame` class of the `pandas` library.

With our new understanding of `pandas` in hand, let's return to the `elections` dataset from before. Now, we recognize that it is represented as a `pandas` DataFrame.

```python
import pandas as pd

elections = pd.read_csv("data/elections.csv")
elections
```

	Year	Candidate	Party	Popular vote	Result	%
0	1824	Andrew Jackson	Democratic-Republican	151271	loss	57.210122
1	1824	John Quincy Adams	Democratic-Republican	113142	win	42.789878
2	1828	Andrew Jackson	Democratic	642806	win	56.203927
3	1828	John Quincy Adams	National Republican	500897	loss	43.796073
4	1832	Andrew Jackson	Democratic	702735	win	54.574789
5	1832	Henry Clay	National Republican	484205	loss	37.603628
6	1832	William Wirt	Anti-Masonic	100715	loss	7.821583
7	1836	Hugh Lawson White	Whig	146109	loss	10.005985
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14	1848	Lewis Cass	Democratic	1223460	loss	42.552229
15	1848	Martin Van Buren	Free Soil	291501	loss	10.138474
16	1848	Zachary Taylor	Whig	1360235	win	47.309296
17	1852	Franklin Pierce	Democratic	1605943	win	51.013168
18	1852	John P. Hale	Free Soil	155210	loss	4.930283
19	1852	Winfield Scott	Whig	1386942	loss	44.056548
20	1856	James Buchanan	Democratic	1835140	win	45.306080
21	1856	John C. Frémont	Republican	1342345	loss	33.139919
22	1856	Millard Fillmore	American	873053	loss	21.554001
23	1860	Abraham Lincoln	Republican	1855993	win	39.699408
24	1860	John Bell	Constitutional Union	590901	loss	12.639283
25	1860	John C. Breckinridge	Southern Democratic	848019	loss	18.138998
26	1860	Stephen A. Douglas	Northern Democratic	1380202	loss	29.522311
27	1864	Abraham Lincoln	National Union	2211317	win	54.951512
28	1864	George B. McClellan	Democratic	1812807	loss	45.048488
29	1868	Horatio Seymour	Democratic	2708744	loss	47.334695
30	1868	Ulysses Grant	Republican	3013790	win	52.665305
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39	1884	Grover Cleveland	Democratic	4914482	win	48.884933
40	1884	James G. Blaine	Republican	4856905	loss	48.312208
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48	1892	James B. Weaver	Populist	1041028	loss	8.645038
49	1892	John Bidwell	Prohibition	270879	loss	2.249468
50	1896	John M. Palmer	National Democratic	134645	loss	0.969566
51	1896	Joshua Levering	Prohibition	131312	loss	0.945565

Let's dissect the code above.

1. We first import the `pandas` library into our Python environment, using the alias `pd`. `import pandas as pd`
2. There are a number of ways to read data into a DataFrame. In Data 100, our datasets are typically stored in a CSV (comma-seperated values) file format. We can import a CSV file into a DataFrame by passing the data path as an argument to the following `pandas` function. `pd.read_csv("data/elections.csv")`

This code stores our DataFrame object in the `elections` variable. We see that our `elections` DataFrame has 182 rows and 6 columns (`Year`, `Candidate`, `Party`, `Popular Vote`, `Result`, `%`). Each row represents a single record – in our example, a presedential candidate from some particular year. Each column represents a single attribute, or feature of the record.

In the example above, we constructed a DataFrame object using data from a CSV file. As we'll explore in the next section, we can also create a DataFrame with data of our own.

2.2.2.1 Creating a DataFrame

There are many ways to create a DataFrame. Here, we will cover the most popular approaches.

1. Using a list and column names
2. From a dictionary
3. From a Series

2.2.2.1.1 Using a List and Column Names

Consider the following examples. The first code cell creates a DataFrame with a single column `Numbers`. The second creates a DataFrame with the columns `Numbers` and `Description`. Notice how a 2D list of values is required to initialize the second DataFrame – each nested list represents a single row of data.

```
df_list_1 = pd.DataFrame([1, 2, 3], columns=["Numbers"])
df_list_1
```

	Numbers
0	1
1	2
2	3

```
df_list_2 = pd.DataFrame([[1, "one"], [2, "two"]], columns = ["Number", "Description"])
df_list_2
```

	Number	Description
0	1	one
1	2	two

2.2.2.1.2 From a Dictionary

A second (and more common) way to create a DataFrame is with a dictionary. The dictionary keys represent the column names, and the dictionary values represent the column values.

```
df_dict = pd.DataFrame({"Fruit": ["Strawberry", "Orange"], "Price": [5.49, 3.99]})
df_dict
```

	Fruit	Price
0	Strawberry	5.49
1	Orange	3.99

2.2.2.1.3 From a Series

Earlier, we noted that a Series is usually thought of as a column in a DataFrame. It follows then, that a DataFrame is equivalent to a collection of Series, which all share the same index.

In fact, we can initialize a DataFrame by merging two or more Series.

```
# Notice how our indices, or row labels, are the same

s_a = pd.Series(["a1", "a2", "a3"], index = ["r1", "r2", "r3"])
s_b = pd.Series(["b1", "b2", "b3"], index = ["r1", "r2", "r3"])

pd.DataFrame({"A-column": s_a, "B-column": s_b})
```

	A-column	B-column
r1	a1	b1
r2	a2	b2
r3	a3	b3

2.2.3 Indices

The major takeaway: we can think of a **DataFrame** as a collection of **Series** that all share the same **Index**.

On a more technical note, an Index doesn't have to be an integer, nor does it have to be unique. For example, we can set the index of the `elections` Dataframe to be the name of presidential candidates.

```python
# This sets the index to be the "Candidate" column
elections.set_index("Candidate", inplace=True)
elections.index
```

```
Index(['Andrew Jackson', 'John Quincy Adams', 'Andrew Jackson',
       'John Quincy Adams', 'Andrew Jackson', 'Henry Clay', 'William Wirt',
       'Hugh Lawson White', 'Martin Van Buren', 'William Henry Harrison',
       ...
       'Darrell Castle', 'Donald Trump', 'Evan McMullin', 'Gary Johnson',
       'Hillary Clinton', 'Jill Stein', 'Joseph Biden', 'Donald Trump',
       'Jo Jorgensen', 'Howard Hawkins'],
      dtype='object', name='Candidate', length=182)
```

And, if we'd like, we can revert the index back to the default list of integers.

```python
# This resets the index to be the default list of integers
elections.reset_index(inplace=True)
elections.index
```

```
RangeIndex(start=0, stop=182, step=1)
```

2.3 Slicing in DataFrames

Now that we've learned how to create DataFrames, let's dive more deeply into their capabilities.

The API (application programming interface) for the DataFrame class is enormous. In this section, we'll discuss several methods of the DataFrame API that allow us to extract subsets of data.

The simplest way to manipulate a DataFrame is to extract a subset of rows and columns, known as **slicing**. We will do so with four primary methods of the DataFrame class:

1. `.head` and `.tail`
2. `.loc`
3. `.iloc`
4. `[]`

2.3.1 Extracting data with `.head` and `.tail`

The simplest scenario in which we want to extract data is when we simply want to select the first or last few rows of the DataFrame.

To extract the first `n` rows of a DataFrame `df`, we use the syntax `df.head(n)`.

```
# Extract the first 5 rows of the DataFrame
elections.head(5)
```

	Candidate	Year	Party	Popular vote	Result	%
0	Andrew Jackson	1824	Democratic-Republican	151271	loss	57.210122
1	John Quincy Adams	1824	Democratic-Republican	113142	win	42.789878
2	Andrew Jackson	1828	Democratic	642806	win	56.203927
3	John Quincy Adams	1828	National Republican	500897	loss	43.796073
4	Andrew Jackson	1832	Democratic	702735	win	54.574789

Similarly, calling `df.tail(n)` allows us to extract the last `n` rows of the DataFrame.

```
# Extract the last 5 rows of the DataFrame
elections.tail(5)
```

	Candidate	Year	Party	Popular vote	Result	%
177	Jill Stein	2016	Green	1457226	loss	1.073699
178	Joseph Biden	2020	Democratic	81268924	win	51.311515
179	Donald Trump	2020	Republican	74216154	loss	46.858542
180	Jo Jorgensen	2020	Libertarian	1865724	loss	1.177979
181	Howard Hawkins	2020	Green	405035	loss	0.255731

2.3.2 Indexing with .loc

The `.loc` operator selects rows and columns in a DataFrame by their row and column label(s), respectively. The **row labels** (commonly referred to as the **indices**) are the bold text on the far *left* of a DataFrame, while the **column labels** are the column names found at the *top* of a DataFrame.

To grab data with `.loc`, we must specify the row and column label(s) where the data exists. The row labels are the first argument to the `.loc` function; the column labels are the second. For example, we can select the the row labeled `0` and the column labeled `Candidate` from the `elections` DataFrame.

```
elections.loc[0, 'Candidate']
```

```
'Andrew Jackson'
```

To select *multiple* rows and columns, we can use Python slice notation. Here, we select the rows from labels `0` to `3` and the columns from labels `"Year"` to `"Popular vote"`.

```
elections.loc[0:3, 'Year':'Popular vote']
```

	Year	Party	Popular vote
0	1824	Democratic-Republican	151271
1	1824	Democratic-Republican	113142
2	1828	Democratic	642806
3	1828	National Republican	500897

Suppose that instead, we wanted *every* column value for the first four rows in the `elections` DataFrame. The shorthand `:` is useful for this.

```
elections.loc[0:3, :]
```

	Candidate	Year	Party	Popular vote	Result	%
0	Andrew Jackson	1824	Democratic-Republican	151271	loss	57.210122
1	John Quincy Adams	1824	Democratic-Republican	113142	win	42.789878
2	Andrew Jackson	1828	Democratic	642806	win	56.203927
3	John Quincy Adams	1828	National Republican	500897	loss	43.796073

There are a couple of things we should note. Firstly, unlike conventional Python, Pandas allows us to slice string values (in our example, the column labels). Secondly, slicing with `.loc` is *inclusive*. Notice how our resulting DataFrame includes every row and column between and including the slice labels we specified.

Equivalently, we can use a list to obtain multiple rows and columns in our `elections` DataFrame.

```
elections.loc[[0, 1, 2, 3], ['Year', 'Candidate', 'Party', 'Popular vote']]
```

	Year	Candidate	Party	Popular vote
0	1824	Andrew Jackson	Democratic-Republican	151271
1	1824	John Quincy Adams	Democratic-Republican	113142
2	1828	Andrew Jackson	Democratic	642806
3	1828	John Quincy Adams	National Republican	500897

Lastly, we can interchange list and slicing notation.

```
elections.loc[[0, 1, 2, 3], :]
```

	Candidate	Year	Party	Popular vote	Result	%
0	Andrew Jackson	1824	Democratic-Republican	151271	loss	57.210122
1	John Quincy Adams	1824	Democratic-Republican	113142	win	42.789878
2	Andrew Jackson	1828	Democratic	642806	win	56.203927
3	John Quincy Adams	1828	National Republican	500897	loss	43.796073

2.3.3 Indexing with .iloc

Slicing with `.iloc` works similarly to `.loc`, however, `.iloc` uses the *index positions* of rows and columns rather the labels (think to yourself: **l**oc uses **l**abels; **i**loc uses **i**ndices). The arguments to the `.iloc` function also behave similarly -– single values, lists, indices, and any combination of these are permitted.

Let's begin reproducing our results from above. We'll begin by selecting for the first presidential candidate in our `elections` DataFrame:

```
# elections.loc[0, "Candidate"] - Previous approach
elections.iloc[0, 1]
```

```
1824
```

Notice how the first argument to both `.loc` and `.iloc` are the same. This is because the row with a label of 0 is conveniently in the 0^{th} index (equivalently, the first position) of the `elections` DataFrame. Generally, this is true of any DataFrame where the row labels are incremented in ascending order from 0.

However, when we select the first four rows and columns using `.iloc`, we notice something.

```
# elections.loc[0:3, 'Year':'Popular vote'] - Previous approach
elections.iloc[0:4, 0:4]
```

	Candidate	Year	Party	Popular vote
0	Andrew Jackson	1824	Democratic-Republican	151271
1	John Quincy Adams	1824	Democratic-Republican	113142
2	Andrew Jackson	1828	Democratic	642806
3	John Quincy Adams	1828	National Republican	500897

Slicing is no longer inclusive in `.iloc` -– it's *exclusive*. In other words, the right-end of a slice is not included when using `.iloc`. This is one of the subtleties of `pandas` syntax; you will get used to it with practice.

List behavior works just as expected.

```
#elections.loc[[0, 1, 2, 3], ['Year', 'Candidate', 'Party', 'Popular vote']] - Previous Ap
elections.iloc[[0, 1, 2, 3], [0, 1, 2, 3]]
```

	Candidate	Year	Party	Popular vote
0	Andrew Jackson	1824	Democratic-Republican	151271
1	John Quincy Adams	1824	Democratic-Republican	113142
2	Andrew Jackson	1828	Democratic	642806
3	John Quincy Adams	1828	National Republican	500897

This discussion begs the question: when should we use `.loc` vs `.iloc`? In most cases, `.loc` is generally safer to use. You can imagine `.iloc` may return incorrect values when applied to a dataset where the ordering of data can change.

2.3.4 Indexing with []

The `[]` selection operator is the most baffling of all, yet the most commonly used. It only takes a single argument, which may be one of the following:

1. A slice of row numbers
2. A list of column labels
3. A single column label

That is, `[]` is *context dependent*. Let's see some examples.

2.3.4.1 A slice of row numbers

Say we wanted the first four rows of our `elections` DataFrame.

```
elections[0:4]
```

	Candidate	Year	Party	Popular vote	Result	%
0	Andrew Jackson	1824	Democratic-Republican	151271	loss	57.210122
1	John Quincy Adams	1824	Democratic-Republican	113142	win	42.789878
2	Andrew Jackson	1828	Democratic	642806	win	56.203927
3	John Quincy Adams	1828	National Republican	500897	loss	43.796073

2.3.4.2 A list of column labels

Suppose we now want the first four columns.

```
elections[["Year", "Candidate", "Party", "Popular vote"]]
```

	Year	Candidate	Party	Popular vote
0	1824	Andrew Jackson	Democratic-Republican	151271
1	1824	John Quincy Adams	Democratic-Republican	113142
2	1828	Andrew Jackson	Democratic	642806
3	1828	John Quincy Adams	National Republican	500897
4	1832	Andrew Jackson	Democratic	702735
5	1832	Henry Clay	National Republican	484205
6	1832	William Wirt	Anti-Masonic	100715
7	1836	Hugh Lawson White	Whig	146109
8	1836	Martin Van Buren	Democratic	763291
9	1836	William Henry Harrison	Whig	550816
10	1840	Martin Van Buren	Democratic	1128854
11	1840	William Henry Harrison	Whig	1275583
12	1844	Henry Clay	Whig	1300004
13	1844	James Polk	Democratic	1339570
14	1848	Lewis Cass	Democratic	1223460
15	1848	Martin Van Buren	Free Soil	291501
16	1848	Zachary Taylor	Whig	1360235
17	1852	Franklin Pierce	Democratic	1605943
18	1852	John P. Hale	Free Soil	155210
19	1852	Winfield Scott	Whig	1386942
20	1856	James Buchanan	Democratic	1835140
21	1856	John C. Frémont	Republican	1342345
22	1856	Millard Fillmore	American	873053
23	1860	Abraham Lincoln	Republican	1855993
24	1860	John Bell	Constitutional Union	590901
25	1860	John C. Breckinridge	Southern Democratic	848019
26	1860	Stephen A. Douglas	Northern Democratic	1380202
27	1864	Abraham Lincoln	National Union	2211317
28	1864	George B. McClellan	Democratic	1812807
29	1868	Horatio Seymour	Democratic	2708744
30	1868	Ulysses Grant	Republican	3013790
31	1872	Horace Greeley	Liberal Republican	2834761
32	1872	Ulysses Grant	Republican	3597439
33	1876	Rutherford Hayes	Republican	4034142
34	1876	Samuel J. Tilden	Democratic	4288546
35	1880	James B. Weaver	Greenback	308649
36	1880	James Garfield	Republican	4453337
37	1880	Winfield Scott Hancock	Democratic	4444976
38	1884	Benjamin Butler	Anti-Monopoly	134294
39	1884	Grover Cleveland	Democratic	4914482
40	1884	James G. Blaine	Republican	4856905
41	1884	John St. John	Prohibition	147482
42	1888	Alson Streeter	Union Labor	146602
43	1888	Benjamin Harrison	Republican	5443633
44	1888	Clinton B. Fisk	Prohibition	249819
45	1888	Grover Cleveland	Democratic	5534488
46	1892	Benjamin Harrison	Republican	5176108
47	1892	Grover Cleveland	Democratic	5553898
48	1892	James B. Weaver	Populist	1041028
49	1892	John Bidwell	Prohibition	270879
50	1896	John M. Palmer	National Democratic	134645
51	1896	Joshua Levering	Prohibition	131312

2.3.4.3 A single column label

Lastly, `[ ]` allows us to extract only the `Candidate` column.

```
elections["Candidate"]
```

	Candidate
0	Andrew Jackson
1	John Quincy Adams
2	Andrew Jackson
3	John Quincy Adams
4	Andrew Jackson
5	Henry Clay
6	William Wirt
7	Hugh Lawson White
8	Martin Van Buren
9	William Henry Harrison
10	Martin Van Buren
11	William Henry Harrison
12	Henry Clay
13	James Polk
14	Lewis Cass
15	Martin Van Buren
16	Zachary Taylor
17	Franklin Pierce
18	John P. Hale
19	Winfield Scott
20	James Buchanan
21	John C. Frémont
22	Millard Fillmore
23	Abraham Lincoln
24	John Bell
25	John C. Breckinridge
26	Stephen A. Douglas
27	Abraham Lincoln
28	George B. McClellan
29	Horatio Seymour
30	Ulysses Grant
31	Horace Greeley
32	Ulysses Grant
33	Rutherford Hayes
34	Samuel J. Tilden
35	James B. Weaver
36	James Garfield
37	Winfield Scott Hancock
38	Benjamin Butler
39	Grover Cleveland
40	James G. Blaine
41	John St. John
42	Alson Streeter
43	Benjamin Harrison
44	Clinton B. Fisk
45	Grover Cleveland
46	Benjamin Harrison
47	Grover Cleveland
48	James B. Weaver
49	John Bidwell
50	John M. Palmer
51	Joshua Levering

The output is a Series! In this course, we'll become very comfortable with `[]`, especially for selecting columns. In practice, `[]` is much more common than `.loc`.

2.4 Parting Note

The `pandas` library is enormous and contains many useful functions. Here is a link to documentation. We certainly don't expect you to memorize each and every method of the library.

The introductory Data 100 `pandas` lectures will provide a high-level view of the key data structures and methods that will form the foundation of your `pandas` knowledge. A goal of this course is to help you build your familiarity with the real-world programming practice of…Googling! Answers to your questions can be found in documentation, Stack Overflow, etc. Being able to search for, read, and implement documentation is an important life skill for any data scientist.

With that, let's move on to Pandas II.

3 Pandas II

Note

- Build familiarity with advanced `pandas` syntax
- Extract data from a DataFrame using conditional selection
- Recognize situations where aggregation is useful and identify the correct technique for performing an aggregation

Last time, we introduced the `pandas` library as a toolkit for processing data. We learned the DataFrame and Series data structures, familiarized ourselves with the basic syntax for manipulating tabular data, and began writing our first lines of `pandas` code.

In this lecture, we'll start to dive into some advanced `pandas` syntax. You may find it helpful to follow along with a notebook of your own as we walk through these new pieces of code.

We'll start by loading the `babynames` dataset.

```python
import pandas as pd
import numpy as np
import urllib.request
import os.path
import zipfile

data_url = "https://www.ssa.gov/oact/babynames/state/namesbystate.zip"
local_filename = "babynamesbystate.zip"
if not os.path.exists(local_filename): # if the data exists don't download again
    with urllib.request.urlopen(data_url) as resp, open(local_filename, 'wb') as f:
        f.write(resp.read())

zf = zipfile.ZipFile(local_filename, 'r')

ca_name = 'CA.TXT'
field_names = ['State', 'Sex', 'Year', 'Name', 'Count']
with zf.open(ca_name) as fh:
    babynames = pd.read_csv(fh, header=None, names=field_names)
```

```
babynames.head()
```

	State	Sex	Year	Name	Count
0	CA	F	1910	Mary	295
1	CA	F	1910	Helen	239
2	CA	F	1910	Dorothy	220
3	CA	F	1910	Margaret	163
4	CA	F	1910	Frances	134

3.1 Conditional Selection

Conditional selection allows us to select a subset of rows in a DataFrame if they follow some specified condition.

To understand how to use conditional selection, we must look at another possible input of the `.loc` and `[]` methods – a boolean array, which is simply an array where each element is either `True` or `False`. This boolean array must have a length equal to the number of rows in the DataFrame. It will return all rows in the position of a corresponding True value in the array.

To see this in action, let's select all even-indexed rows in the first 10 rows of our DataFrame.

```
# Ask yourself: why is :9 is the correct slice to select the first 10 rows?
babynames_first_10_rows = babynames.loc[:9, :]

# Notice how we have exactly 10 elements in our boolean array argument
babynames_first_10_rows[[True, False, True, False, True, False, True, False, True, False]]
```

	State	Sex	Year	Name	Count
0	CA	F	1910	Mary	295
2	CA	F	1910	Dorothy	220
4	CA	F	1910	Frances	134
6	CA	F	1910	Evelyn	126
8	CA	F	1910	Virginia	101

We can perform a similar operation using `.loc`.

```
babynames_first_10_rows.loc[[True, False, True, False, True, False, True, False, True, Fal
```

	State	Sex	Year	Name	Count
0	CA	F	1910	Mary	295
2	CA	F	1910	Dorothy	220
4	CA	F	1910	Frances	134
6	CA	F	1910	Evelyn	126
8	CA	F	1910	Virginia	101

These techniques worked well in this example, but you can imagine how tedious it might be to list out `True`s and `False`s for every row in a larger DataFrame. To make things easier, we can instead provide a logical condition as an input to `.loc` or `[]` that returns a boolean array with the necessary length.

For example, to return all names associated with `F` sex:

```
# First, use a logical condition to generate a boolean array
logical_operator = (babynames["Sex"] == "F")

# Then, use this boolean array to filter the DataFrame
babynames[logical_operator].head()
```

	State	Sex	Year	Name	Count
0	CA	F	1910	Mary	295
1	CA	F	1910	Helen	239
2	CA	F	1910	Dorothy	220
3	CA	F	1910	Margaret	163
4	CA	F	1910	Frances	134

Here, `logical_operator` evaluates to a Series of boolean values with length 400762.

```
print("There are a total of {} values in 'logical_operator'".format(len(logical_operator))
```

```
There are a total of 400762 values in 'logical_operator'
```

Rows starting at row 0 and ending at row 235790 evaluate to `True` and are thus returned in the DataFrame.

```
print("The 0th item in this 'logical_operator' is: {}".format(logical_operator.iloc[0]))
print("The 235790th item in this 'logical_operator' is: {}".format(logical_operator.iloc[2
print("The 235791th item in this 'logical_operator' is: {}".format(logical_operator.iloc[2
```

```
The 0th item in this 'logical_operator' is: True
The 235790th item in this 'logical_operator' is: True
The 235791th item in this 'logical_operator' is: False
```

Passing a Series as an argument to `babynames[]` has the same affect as using a boolean array. In fact, the `[]` selection operator can take a boolean Series, array, and list as arguments. These three are used interchangeably thoughout the course.

We can also use `.loc` to achieve similar results.

```
babynames.loc[babynames["Sex"] == "F"].head()
```

	State	Sex	Year	Name	Count
0	CA	F	1910	Mary	295
1	CA	F	1910	Helen	239
2	CA	F	1910	Dorothy	220
3	CA	F	1910	Margaret	163
4	CA	F	1910	Frances	134

Boolean conditions can be combined using various operators that allow us to filter results by multiple conditions. Some examples include the `&` (and) operator and the `|` (or) operator.

Note: When combining multiple conditions with logical operators, be sure to surround each condition with a set of parenthesis `()`. If you forget, your code will throw an error.

For example, if we want to return data on all females born before the 21st century, we can write:

```
babynames[(babynames["Sex"] == "F") & (babynames["Year"] < 2000)].head()
```

	State	Sex	Year	Name	Count
0	CA	F	1910	Mary	295
1	CA	F	1910	Helen	239
2	CA	F	1910	Dorothy	220
3	CA	F	1910	Margaret	163
4	CA	F	1910	Frances	134

Boolean array selection is a useful tool, but can lead to overly verbose code for complex conditions. `Pandas` provide many alternatives:

```
(
    babynames[(babynames["Name"] == "Bella") |
```

```
                (babynames["Name"] == "Alex") |
                (babynames["Name"] == "Ani") |
                (babynames["Name"] == "Lisa")]
).head()
# Note: The parentheses surrounding the code make it possible to break the code on to mult
```

	State	Sex	Year	Name	Count
6289	CA	F	1923	Bella	5
7512	CA	F	1925	Bella	8
12368	CA	F	1932	Lisa	5
14741	CA	F	1936	Lisa	8
17084	CA	F	1939	Lisa	5

The `.isin` function can be used to filter dataframes. The method helps in selecting rows with having a particular (or multiple) value in a particular column.

```
names = ["Bella", "Alex", "Ani", "Lisa"]
babynames[babynames["Name"].isin(names)].head()
```

	State	Sex	Year	Name	Count
6289	CA	F	1923	Bella	5
7512	CA	F	1925	Bella	8
12368	CA	F	1932	Lisa	5
14741	CA	F	1936	Lisa	8
17084	CA	F	1939	Lisa	5

The function `str.startswith` can be used to define a filter based on string values in a `Series` object.

```
babynames[babynames["Name"].str.startswith("N")].head()
```

	State	Sex	Year	Name	Count
76	CA	F	1910	Norma	23
83	CA	F	1910	Nellie	20
127	CA	F	1910	Nina	11
198	CA	F	1910	Nora	6
310	CA	F	1911	Nellie	23

3.2 Handy Utility Functions

`pandas` contains an extensive library of functions that can help shorten the process of setting and getting information from its data structures. In the following section, we will give overviews of each of the main utility functions that will help us in Data 100.

- `Numpy` and built-in function support
- `.shape`
- `.size`
- `.describe()`
- `.sample()`
- `.value_counts()`
- `.unique()`
- `.sort_values()`

3.2.1 `Numpy`

```
bella_counts = babynames[babynames["Name"] == "Bella"]["Count"]
```

```
# Average number of babies named Bella each year
np.mean(bella_counts)
```

```
270.1860465116279
```

```
# Max number of babies named Bella born on a given year
max(bella_counts)
```

```
902
```

3.2.2 `.shape` and `.size`

`.shape` and `.size` are attributes of Series and DataFrames that measure the "amount" of data stored in the structure. Calling `.shape` returns a tuple containing the number of rows and columns present in the DataFrame or Series. `.size` is used to find the total number of elements in a structure, equivalent to the number of rows times the number of columns.

Many functions strictly require the dimensions of the arguments along certain axes to match. Calling these dimension-finding functions is much faster than counting all of the items by hand.

```
babynames.shape
```

```
(400762, 5)
```

```
babynames.size
```

```
2003810
```

3.2.3 `.describe()`

If many statistics are required from a DataFrame (minimum value, maximum value, mean value, etc.), then `.describe()` can be used to compute all of them at once.

```
babynames.describe()
```

	Year	Count
count	400762.000000	400762.000000
mean	1985.131287	79.953781
std	26.821004	295.414618
min	1910.000000	5.000000
25%	1968.000000	7.000000
50%	1991.000000	13.000000
75%	2007.000000	38.000000
max	2021.000000	8262.000000

A different set of statistics will be reported if `.describe()` is called on a Series.

```
babynames["Sex"].describe()
```

	Sex
count	400762
unique	2
top	F
freq	235791

3.2.4 `.sample()`

As we will see later in the semester, random processes are at the heart of many data science techniques (for example, train-test splits, bootstrapping, and cross-validation). `.sample()` lets us quickly select random entries (a row if called from a DataFrame, or a value if called from a Series).

```
babynames.sample()
```

	State	Sex	Year	Name	Count
140322	CA	F	1997	Parisa	11

```
babynames.sample(5).iloc[:, 2:]
```

	Year	Name	Count
8258	1926	Conchita	7
109116	1989	Diana	1212
192703	2010	Eveny	6
113913	1990	Ilana	20
109929	1989	Emerald	34

```
babynames[babynames["Year"] == 2000].sample(4, replace = True).iloc[:, 2:]
```

	Year	Name	Count
150329	2000	Sunny	21
338738	2000	Noah	1391
152407	2000	Dejanique	5
339377	2000	Hudson	30

3.2.5 `.value_counts()`

When we want to know the distribution of the items in a Series (for example, what items are most/least common), we use `.value-counts()` to get a breakdown of the unique *values* and their *counts*. In the example below, we can determine the name with the most years in which at least one person has taken that name by counting the number of times each name appears in the `"Name"` column of `babynames`.

```
babynames["Name"].value_counts().head()
```

	Name
Jean	221
Francis	219
Guadalupe	216
Jessie	215
Marion	213

3.2.6 `.unique()`

If we have a Series with many repeated values, then `.unique()` can be used to identify only the *unique* values. Here we can get a list of all the names in `babynames`.

Exercise: what function can we call on the Series below to get the number of unique names?

```python
babynames["Name"].unique()
```

```
array(['Mary', 'Helen', 'Dorothy', ..., 'Zyire', 'Zylo', 'Zyrus'],
      dtype=object)
```

3.2.7 `.sort_values()`

Ordering a DataFrame can be useful for isolating extreme values. For example, the first 5 entries of a row sorted in descending order (that is, from highest to lowest) are the largest 5 values. `.sort_values` allows us to order a DataFrame or Series by a specified rule. For DataFrames, we must specify the column by which we want to compare the rows and the function will return such rows. We can choose to either receive the rows in `ascending` order (default) or `descending` order.

```python
babynames.sort_values(by = "Count", ascending=False).head()
```

	State	Sex	Year	Name	Count
263272	CA	M	1956	Michael	8262
264297	CA	M	1957	Michael	8250
313644	CA	M	1990	Michael	8247
278109	CA	M	1969	Michael	8244
279405	CA	M	1970	Michael	8197

We do not need to explicitly specify the column used for sorting when calling `.value_counts()` on a Series. We can still specify the ordering paradigm – that is, whether values are sorted in ascending or descending order.

```
babynames["Name"].sort_values(ascending=True).head()
```

	Name
380256	Aadan
362255	Aadan
365374	Aadan
394460	Aadarsh
366561	Aaden

3.2.7.1 Sorting With a Custom Key

Using `.sort_values` can be useful in many situations, but it many not cover all use cases. This is because `pandas` automatically sorts values in order according to numeric value (for number data) or alphabetical order (for string data). The following code finds the top 5 most popular names in California in 2021.

```
# Sort names by count in year 2021
# Recall that `.head(5)` displays the first five rows in the DataFrame
babynames[babynames["Year"] == 2021].sort_values("Count", ascending=False).head()
```

	State	Sex	Year	Name	Count
397909	CA	M	2021	Noah	2591
397910	CA	M	2021	Liam	2469
232145	CA	F	2021	Olivia	2395
232146	CA	F	2021	Emma	2171
397911	CA	M	2021	Mateo	2108

This offers us a lot of functionality, but what if we need to sort by some other metric? For example, what if we wanted to find the longest names in the DataFrame?

We can do this by specifying the `key` parameter of `.sort_values`. The `key` parameter is assigned to a function of our choice. This function is then applied to each value in the specified column. `pandas` will, finally, sort the DataFrame by the values outputted by the function.

```
# Here, a lambda function is applied to find the length of each value, `x`, in the "Name"
babynames.sort_values("Name", key=lambda x: x.str.len(), ascending=False).head(5)
```

	State	Sex	Year	Name	Count
313143	CA	M	1989	Franciscojavier	6
333732	CA	M	1997	Ryanchristopher	5
330421	CA	M	1996	Franciscojavier	8
323615	CA	M	1993	Johnchristopher	5
310235	CA	M	1988	Franciscojavier	10

3.3 Adding and Removing Columns

To add a new column to a DataFrame, we use a syntax similar to that used when accessing an existing column. Specify the name of the new column by writing `dataframe["new_column"]`, then assign this to a Series or Array containing the values that will populate this column.

```
# Add a column named "name_lengths" that includes the length of each name
babynames["name_lengths"] = babynames["Name"].str.len()
babynames.head(5)
```

	State	Sex	Year	Name	Count	name_lengths
0	CA	F	1910	Mary	295	4
1	CA	F	1910	Helen	239	5
2	CA	F	1910	Dorothy	220	7
3	CA	F	1910	Margaret	163	8
4	CA	F	1910	Frances	134	7

```
# Sort by the temporary column
babynames = babynames.sort_values(by = "name_lengths", ascending=False)
babynames.head()
```

	State	Sex	Year	Name	Count	name_lengths
313143	CA	M	1989	Franciscojavier	6	15
333732	CA	M	1997	Ryanchristopher	5	15
330421	CA	M	1996	Franciscojavier	8	15
323615	CA	M	1993	Johnchristopher	5	15
310235	CA	M	1988	Franciscojavier	10	15

In the example above, we made use of an in-built function given to us by the `str` accessor for getting the length of names. Then we used `name_length` column to sort the dataframe. What if we had wanted to generate the values in our new column using a function of our own making?

We can do this using the Series `.map` method. `.map` takes in a function as input, and will apply this function to each value of a Series.

For example, say we wanted to find the number of occurrences of the sequence "dr" or "ea" in each name.

```
# First, define a function to count the number of times "dr" or "ea" appear in each name
def dr_ea_count(string):
    return string.count("dr") + string.count("ea")

# Then, use `map` to apply `dr_ea_count` to each name in the "Name" column
babynames["dr_ea_count"] = babynames["Name"].map(dr_ea_count)

# Sort the DataFrame by the new "dr_ea_count" column so we can see our handiwork
babynames.sort_values(by = "dr_ea_count", ascending = False).head(5)
```

	State	Sex	Year	Name	Count	name_lengths	dr_ea_count
101969	CA	F	1986	Deandrea	6	8	3
304390	CA	M	1985	Deandrea	6	8	3
131022	CA	F	1994	Leandrea	5	8	3
115950	CA	F	1990	Deandrea	5	8	3
108723	CA	F	1988	Deandrea	5	8	3

If we want to remove a column or row of a DataFrame, we can call the `.drop` method. Use the `axis` parameter to specify whether a column or row should be dropped. Unless otherwise specified, `pandas` will assume that we are dropping a row by default.

```
# Drop our "dr_ea_count" and "length" columns from the DataFrame
babynames = babynames.drop(["dr_ea_count", "name_lengths"], axis="columns")
babynames.head(5)
```

	State	Sex	Year	Name	Count
313143	CA	M	1989	Franciscojavier	6
333732	CA	M	1997	Ryanchristopher	5
330421	CA	M	1996	Franciscojavier	8
323615	CA	M	1993	Johnchristopher	5
310235	CA	M	1988	Franciscojavier	10

Notice that we reassigned `babynames` to the result of `babynames.drop(...)`. This is a subtle, but important point: `pandas` table operations **do not occur in-place**. Calling `dataframe.drop(...)` will output a *copy* of `dataframe` with the row/column of interest removed, without modifying the original `dataframe` table.

In other words, if we simply call:

```
# This creates a copy of `babynames` and removes the row with label 3...
babynames.drop(3, axis="rows")

# ...but the original `babynames` is unchanged!
# Notice that the row with label 3 is still present
babynames.head(5)
```

	State	Sex	Year	Name	Count
313143	CA	M	1989	Franciscojavier	6
333732	CA	M	1997	Ryanchristopher	5
330421	CA	M	1996	Franciscojavier	8
323615	CA	M	1993	Johnchristopher	5
310235	CA	M	1988	Franciscojavier	10

3.4 Aggregating Data with GroupBy

Up until this point, we have been working with individual rows of DataFrames. As data scientists, we often wish to investigate trends across a larger *subset* of our data. For example, we may want to compute some summary statistic (the mean, median, sum, etc.) for a group of rows in our DataFrame. To do this, we'll use `pandas` `GroupBy` objects.

Let's say we wanted to aggregate all rows in `babynames` for a given year.

```
babynames.groupby("Year")
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7fd1582fb6a0>
```

What does this strange output mean? Calling `.groupby` has generated a `GroupBy` object. You can imagine this as a set of "mini" sub-DataFrames, where each subframe contains all of the rows from `babynames` that correspond to a particular year.

The diagram below shows a simplified view of `babynames` to help illustrate this idea.

We can't work with a `GroupBy` object directly – that is why you saw that strange output earlier, rather than a standard view of a DataFrame. To actually manipulate values within these "mini" DataFrames, we'll need to call an *aggregation method*. This is a method that tells `pandas` how to aggregate the values within the `GroupBy` object. Once the aggregation is applied, `pandas` will return a normal (now grouped) DataFrame.

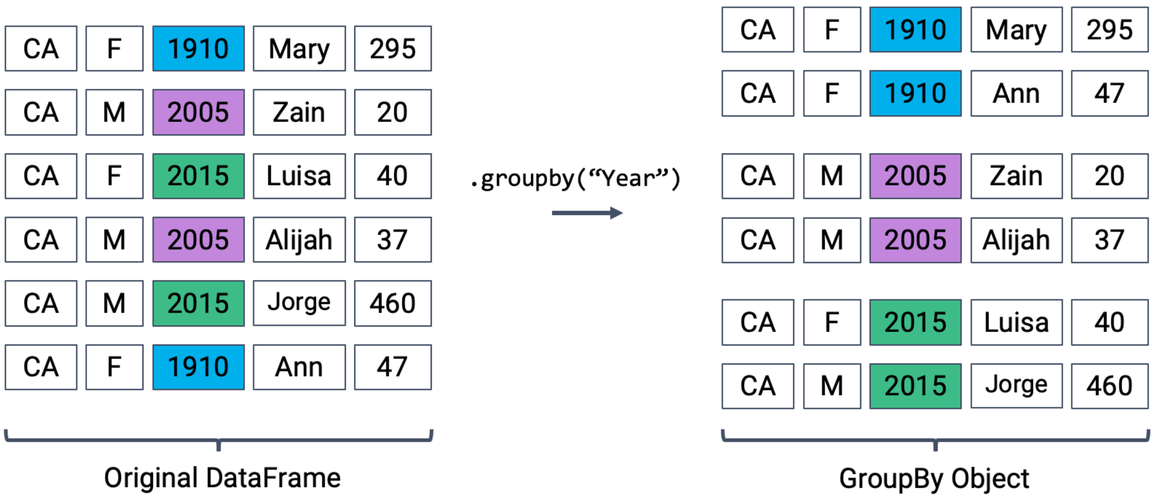

Figure 3.1: Creating a GroupBy object

The first aggregation method we'll consider is `.agg`. The `.agg` method takes in a function as its argument; this function is then applied to each column of a "mini" grouped DataFrame. We end up with a new DataFrame with one aggregated row per subframe. Let's see this in action by finding the `sum` of all counts for each year in `babynames` – this is equivalent to finding the number of babies born in each year.

```
babynames.groupby("Year").agg(sum).head(5)
```

	Count
Year	
1910	9163
1911	9983
1912	17946
1913	22094
1914	26926

We can relate this back to the diagram we used above. Remember that the diagram uses a simplified version of `babynames`, which is why we see smaller values for the summed counts.

Calling `.agg` has condensed each subframe back into a single row. This gives us our final output: a DataFrame that is now indexed by `"Year"`, with a single row for each unique year in the original `babynames` DataFrame.

You may be wondering: where did the `"State"`, `"Sex"`, and `"Name"` columns go? Logically, it doesn't make sense to `sum` the string data in these columns (how would we add "Mary" + "Ann"?). Because of this, `pandas` will simply omit these columns when it performs the

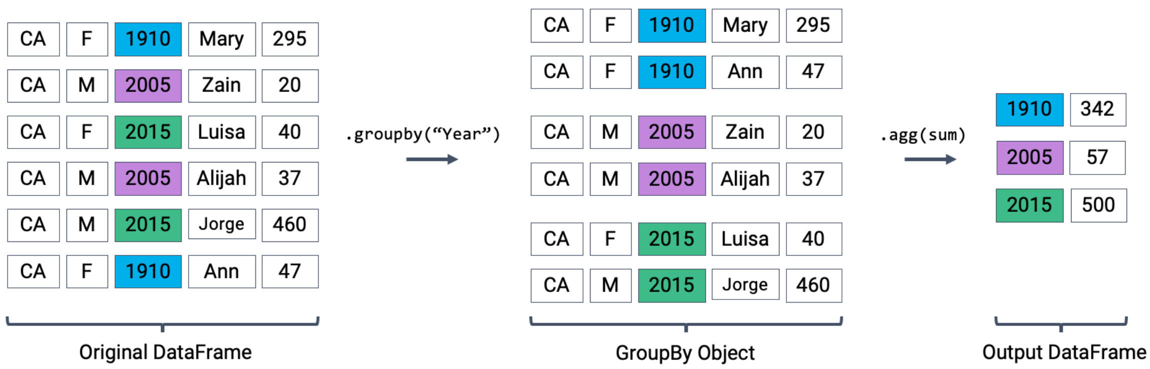

Figure 3.2: Performing an aggregation

aggregation on the DataFrame. Since this happens implicitly, without the user specifying that these columns should be ignored, it's easy to run into troubling situations where columns are removed without the programmer noticing. It is better coding practice to select *only* the columns we care about before performing the aggregation.

```
# Same result, but now we explicitly tell Pandas to only consider the "Count" column when
babynames.groupby("Year")[["Count"]].agg(sum).head(5)
```

	Count
Year	
1910	9163
1911	9983
1912	17946
1913	22094
1914	26926

3.4.1 Parting note

Manipulating `DataFrames` is a skill that is not mastered in just one day. Due to the flexibility of `pandas`, there are many different ways to get from a point A to a point B. We recommend trying multiple different ways to solve the same problem to gain even more practice and reach that point of mastery sooner.

Next, we will start digging deeper into the mechanics behind grouping data.