LECTURE 5

Pandas, Part III

Advanced Pandas (More on Grouping, Aggregation, Pivot Tables, and Merging)

Data Science, Fall 2023 @ Knowledge Stream

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Today's Roadmap

Lecture 5

- Pandas, Part III
  - Groupby Review
  - More on Groupby
  - Pivot Tables
  - Joining Tables
- EDA, Part I
  - Structure: Tabular Data
  - Granularity
  - Structure: Variable Types

Groupby Review

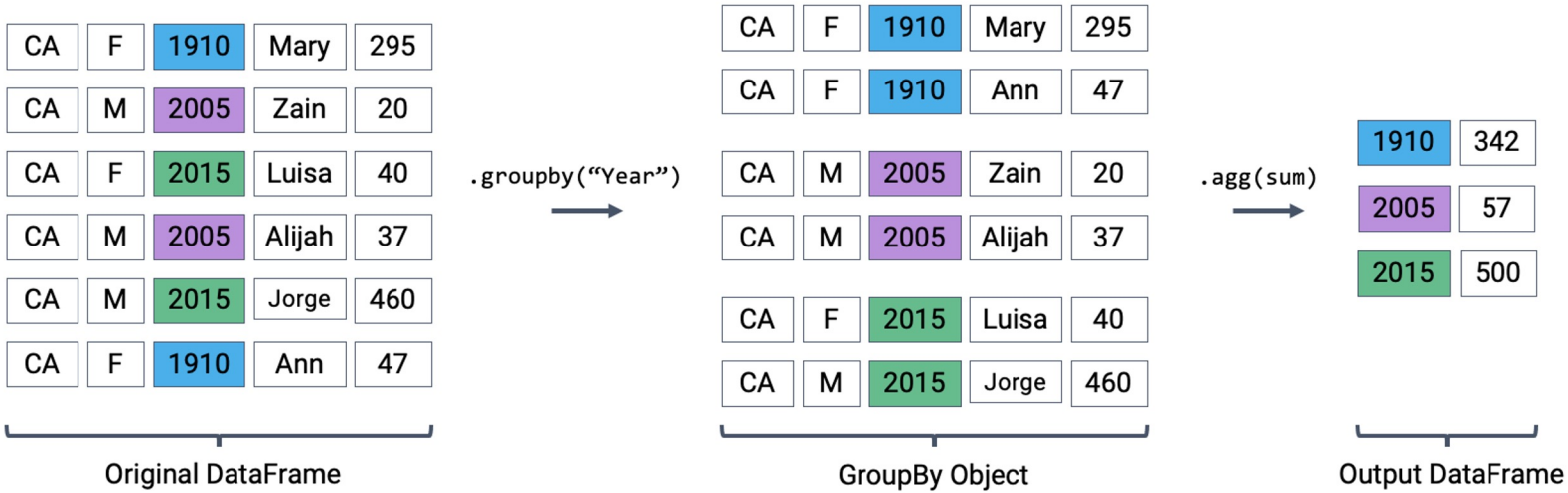
Lecture 5

- **Pandas, Part III**
  - **Groupby Review**
  - More on Groupby
  - Pivot Tables
  - Joining Tables
- EDA, Part I
  - Structure: Tabular Data
  - Granularity
  - Structure: Variable Types

Revisiting `groupby.agg`

```
dataframe.groupby(column_name).agg(aggregation_function)
```

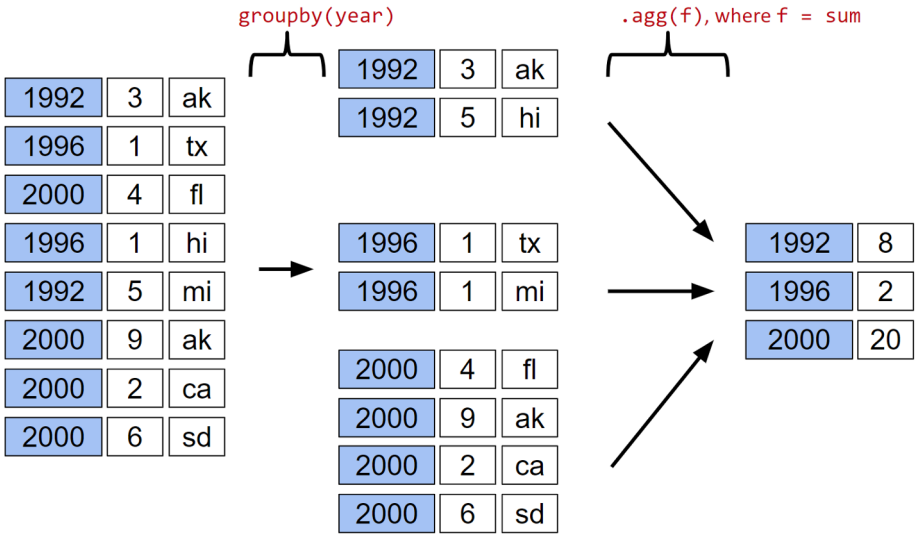
`babynames.groupby("Year")[["Count"]].agg(sum)` computes the total number of babies born in each year.



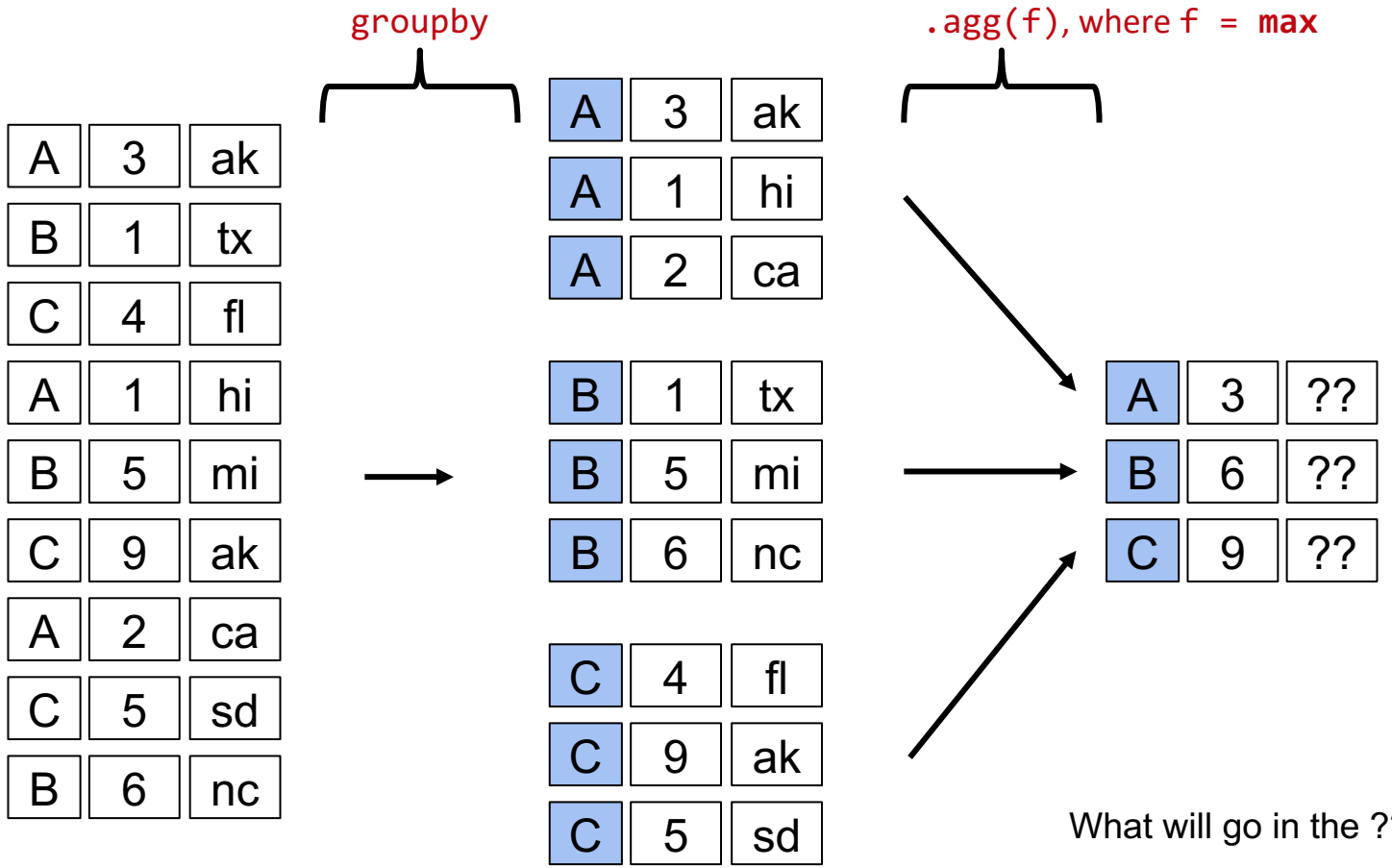
Revisiting `groupby.agg`

A **`groupby`** operation involves some combination of **splitting the object, applying a function**, and **combining the results**.

- So far, we've seen that `df.groupby("year").agg(sum)`:
  - **Split** `df` into sub-`DataFrame`s based on `year`.
  - **Apply** the `sum` function to each column of each sub-`DataFrame`.
  - **Combine** the results of `sum` into a single `DataFrame`, indexed by `year`.

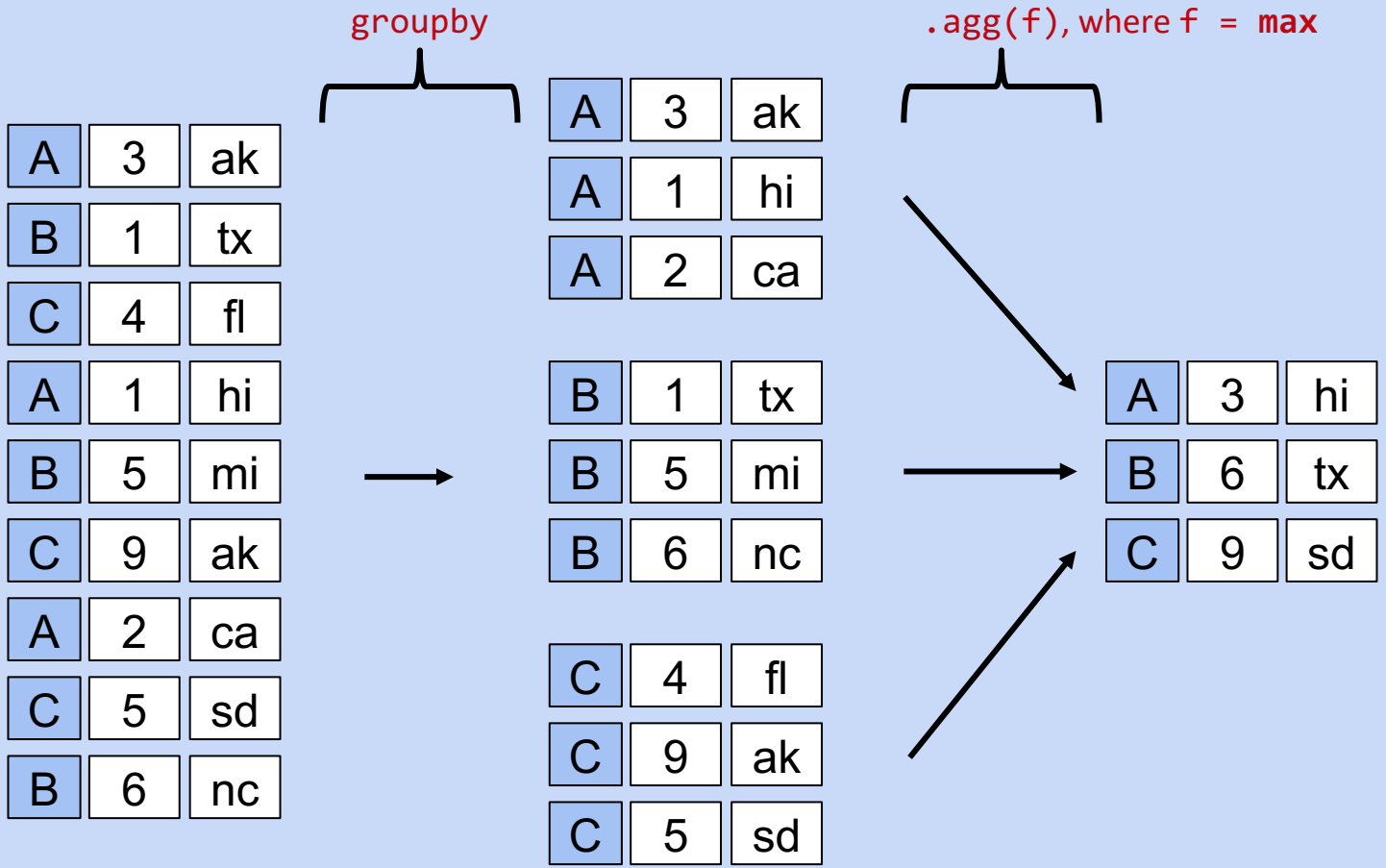


Groupby Review Question



What will go in the ??

Answer


groupby
.agg(f), where f = max
A 3 ak
B 1 tx
C 4 fl
A 1 hi
B 5 mi
C 9 ak
A 2 ca
C 5 sd
B 6 nc
A 3 ak
A 1 hi
A 2 ca
B 1 tx
B 5 mi
B 6 nc
C 4 fl
C 9 ak
C 5 sd
A 3 hi
B 6 tx
C 9 sd

Aggregation Functions

What goes inside of `.agg( )`?

- Any function that aggregates several values into one summary value
- Common examples:

In-Built Python Functions	`NumPy` Functions	In-Built `pandas` functions
`.agg(sum)`	`.agg(np.sum)`	`.agg("sum")`
`.agg(max)`	`.agg(np.max)`	`.agg("max")`
`.agg(min)`	`.agg(np.min)`	`.agg("min")`
	`.agg(np.mean)`	`.agg("mean")`
		`.agg("first")`
		`.agg("last")`

Some commonly-used aggregation functions can even be called directly, without the explicit use of `.agg( )`

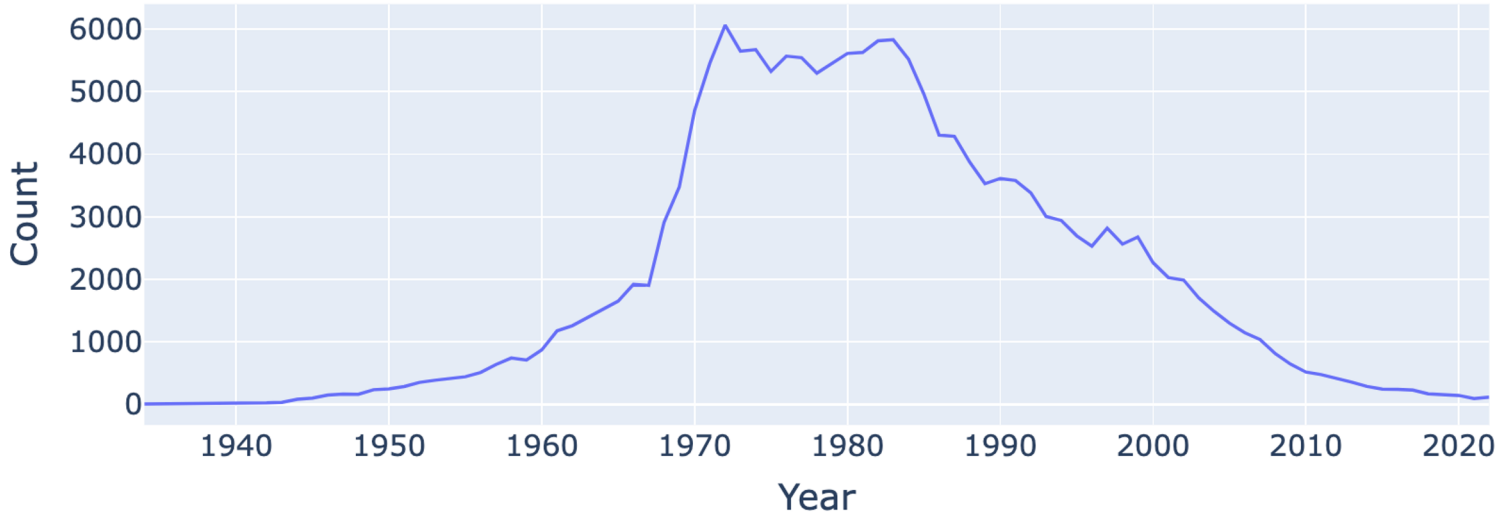
```
babynames.groupby("Year").mean()
```

Putting Things Into Practice

Goal: Find the baby name with sex "F" that has fallen in popularity the most in California.

```
f_babynames = babynames[babynames["Sex"] == "F"]
f_babynames = f_babynames.sort_values(["Year"])
jenn_counts_series = f_babynames[f_babynames["Name"] == "Jennifer"]["Count"]
```

Number of Jennifers Born in California Per Year.



What Is "Popularity"?

Goal: Find the baby name with sex "F" that has fallen in popularity the most in California.

How do we define "fallen in popularity?"

- Let's create a metric: "Ratio to Peak" (RTP).
- The RTP is the ratio of babies born with a given name in 2022 to the *maximum* number of babies born with that name in *any* year.

Example for "Jennifer":

- In 1972, we hit peak Jennifer. 6,065 Jennifers were born.
- In 2022, there were only 114 Jennifers.
- RTP is 114 / 6065 = 0.018796372629843364.

Calculating RTP

```
max_jenn = max(f_babynames[f_babynames["Name"] == "Jennifer"]["Count"])
```

```
6065
```

```
curr_jenn = f_babynames[f_babynames["Name"] == "Jennifer"]["Count"].iloc[-1]
```

```
114
```

Remember: `f_babynames` is sorted by year.
`.iloc[-1]` means "grab the latest year"

```
rtp = curr_jenn / max_jenn
```

```
0.018796372629843364
```

```
def ratio_to_peak(series):
    return series.iloc[-1] / max(series)
```

```
jenn_counts_ser = f_babynames[f_babynames["Name"] == "Jennifer"]["Count"]
ratio_to_peak(jenn_counts_ser)
```

```
0.018796372629843364
```

Renaming Columns After Grouping

By default, `.groupby` will not rename any aggregated columns (the column is still named "Count", even though it now represents the RTP.

For better readability, we may wish to rename "Count" to "Count RTP"

```
rtp_table = f_babynames.groupby("Name")[["Count"]].agg(ratio_to_peak)
rtp_table = rtp_table.rename(columns = {"Count": "Count RTP"})
```

Name	Count
Aadhini	1.000000
Aadhira	0.500000
Aadhya	0.660000
Aadya	0.586207
Aahana	0.269231
...	...

Name	Count RTP
Aadhini	1.000000
Aadhira	0.500000
Aadhya	0.660000
Aadya	0.586207
Aahana	0.269231
...	...

Some Data Science Payoff

By sorting `rtp_table` we can see the names whose popularity has decreased the most.

```
rtp_table.sort_values("Count RTP")
```

Name	Count RTP
Debra	0.001260
Debbie	0.002815
Carol	0.003180
Tammy	0.003249
Susan	0.003305
...	...
Fidelia	1.000000
Naveyah	1.000000
Finlee	1.000000
Roseline	1.000000
Aadhini	1.000000

13782 rows × 1 columns

Some Data Science Payoff

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Name	Count RTP
Debra	0.001260
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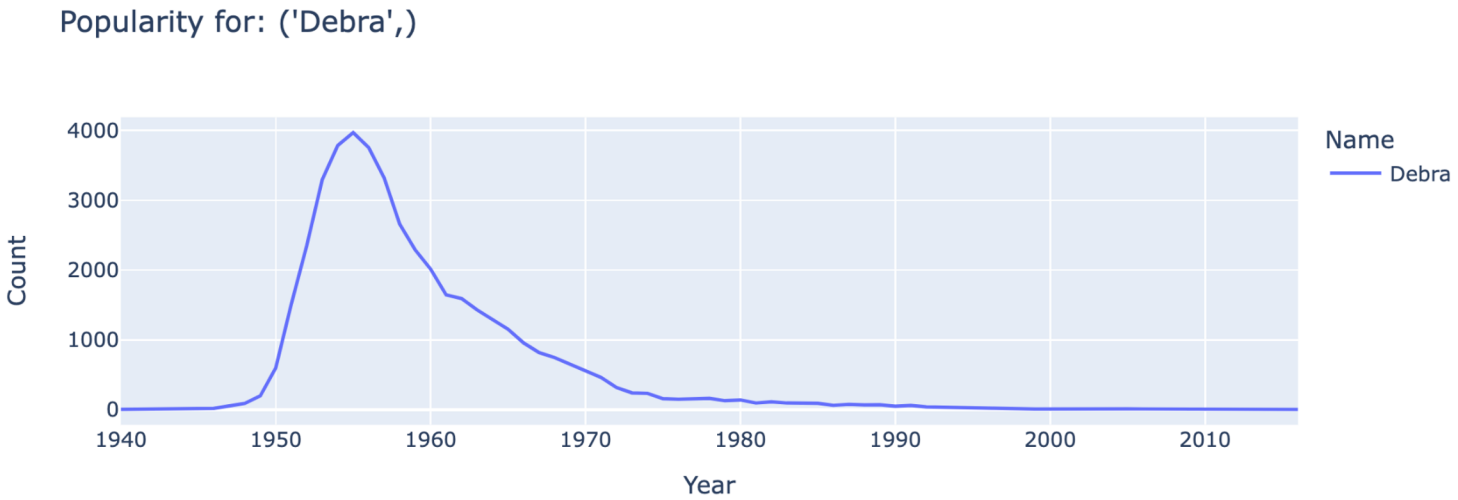
...	...
Fidelia	1.000000
Naveyah	1.000000
Finlee	1.000000
Roseline	1.000000
Aadhini	1.000000

13782 rows × 1 columns

```
px.line(f_babynames[f_babynames["Name"] == "Debra"],
                        x = "Year", y = "Count")
```



We'll learn about plotting in week 4.

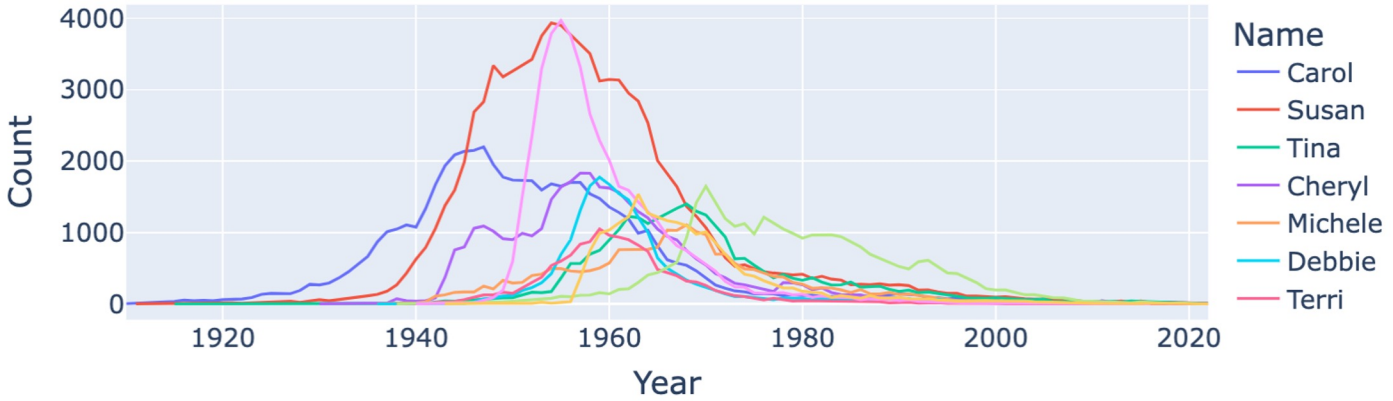
Some Data Science Payoff

We can get the list of the top 10 names and then plot popularity with::

```
top10 = rtp_table.sort_values("Count RTP").head(10).index
```

```
ndex(['Debra', 'Debbie', 'Carol', 'Tammy', 'Susan', 'Cheryl', 'Shannon',
       'Tina', 'Michele', 'Terri'],
      dtype='object', name='Name')
```

```
px.line(f_babynames[f_babynames["Name"].isin(top10)],
                          x = "Year", y = "Count", color = "Name")
```



Answer

Before, we saw that the code below generates the Count RTP for all female names.

```
babynames.groupby("Name")[["Count"]].agg(ratio_to_peak)
```

We use similar logic to compute the summed counts of all baby names.

```
babynames.groupby("Name")[["Count"]].agg(sum)
```

or

```
babynames.groupby("Name")[["Count"]].sum()
```

Name	Count
Aadan	18
Aadarsh	6
Aaden	647
Aadhav	27
Aadhini	6
...	...
Zymir	5
Zyon	133
Zyra	103
Zyrah	21
Zyrus	5

20437 rows × 1 columns

Answer

Now, we create groups for each *year*.

```
babynames.groupby("Year")[["Count"]].agg(sum)
```

or

```
babynames.groupby("Year")[["Count"]].sum()
```

or

```
babynames.groupby("Year").sum(numeric_only=True)
```

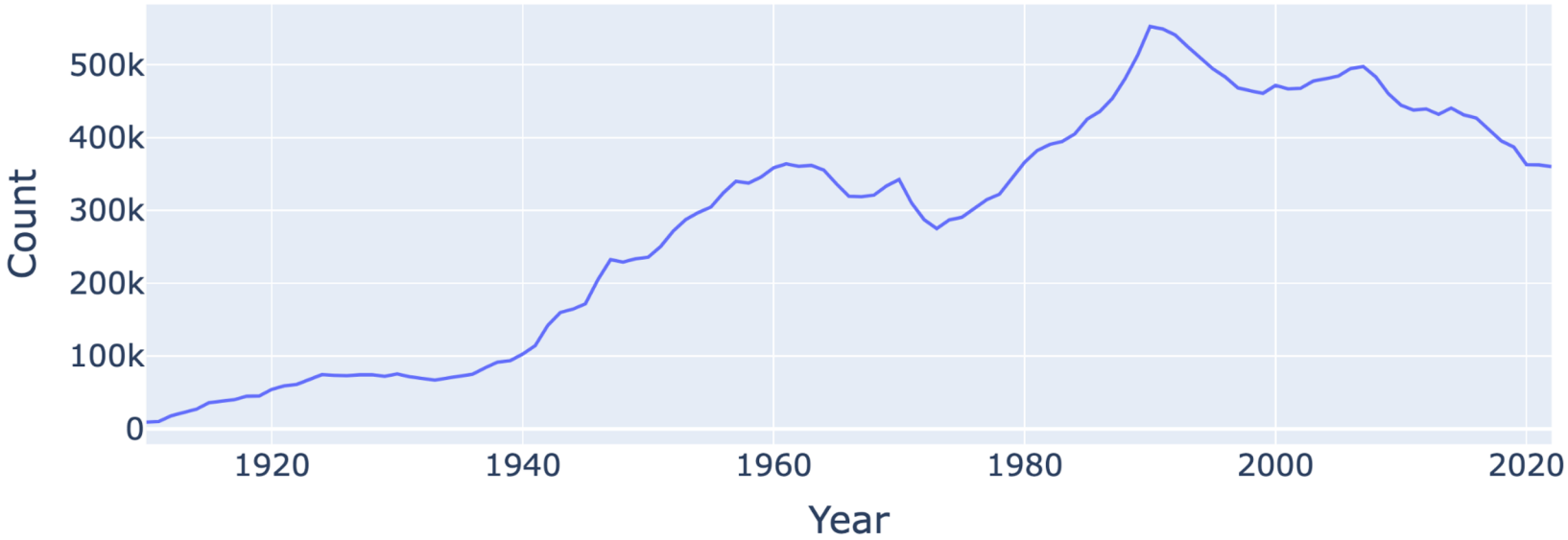
Year	Count
1910	9163
1911	9983
1912	17946
1913	22094
1914	26926
...	...
2018	395436
2019	386996
2020	362882
2021	362582
2022	360023

113 rows × 1 columns

Plotting Birth Counts

Plotting the `DataFrame` we just generated tells an interesting story.

```
puzzle2 = babynames.groupby("Year")[["Count"]].agg(sum)
px.line(puzzle2, y = "Count")
```



More on Groupby

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Raw `GroupBy` Objects and Other Methods

The result of a groupby operation applied to a DataFrame is a **`DataFrameGroupBy`** object.

- It is not a **`DataFrame`**!

```
grouped_by_year = elections.groupby("Year")
type(grouped_by_year)
```

```
pandas.core.groupby.generic.DataFrameGroupBy
```

Given a **`DataFrameGroupBy`** object, can use various functions to generate **`DataFrames`** (or **`Series`**). **`agg`** is only one choice:

```
df.groupby(col).mean()
df.groupby(col).sum()
df.groupby(col).min()
df.groupby(col).max()
```

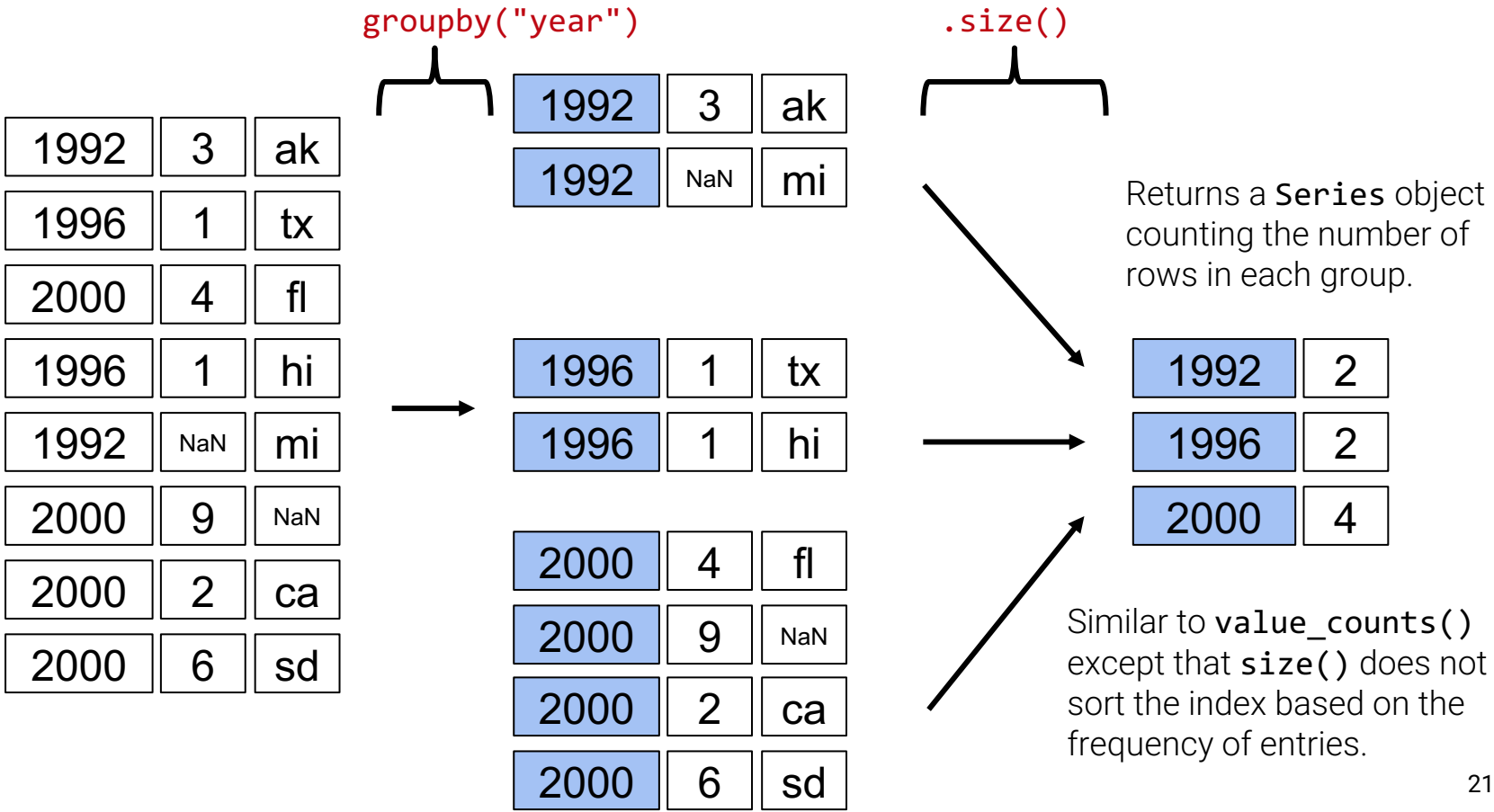
```
df.groupby(col).first()
df.groupby(col).last()
df.groupby(col).size()
df.groupby(col).count()
```

```
df.groupby(col).filter()
```

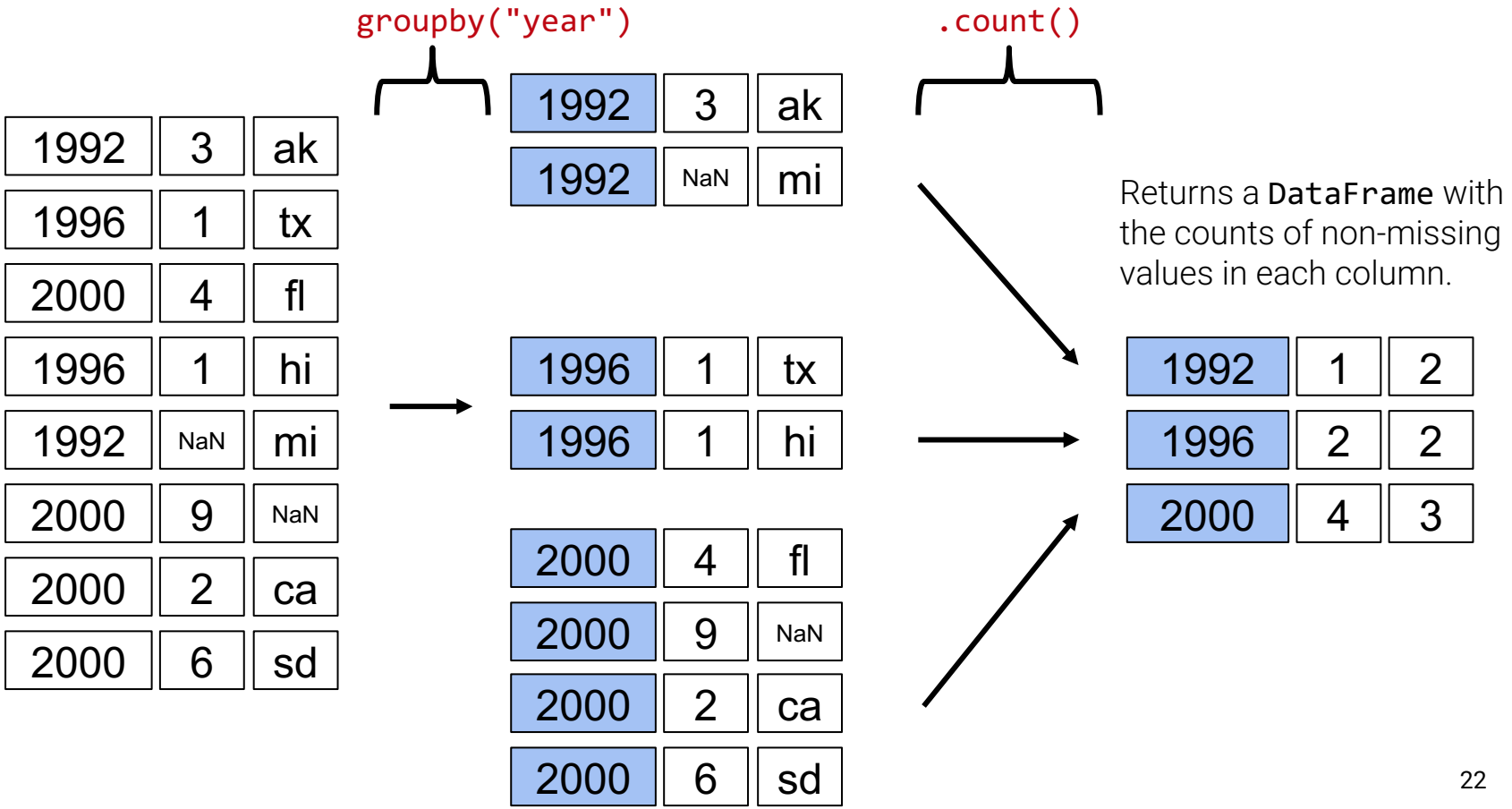
🤨What's the difference?

See https://pandas.pydata.org/docs/reference/groupby.html for a list of **`DataFrameGroupBy`** methods.

groupby.size() and groupby.count()



groupby.size() and groupby.count()

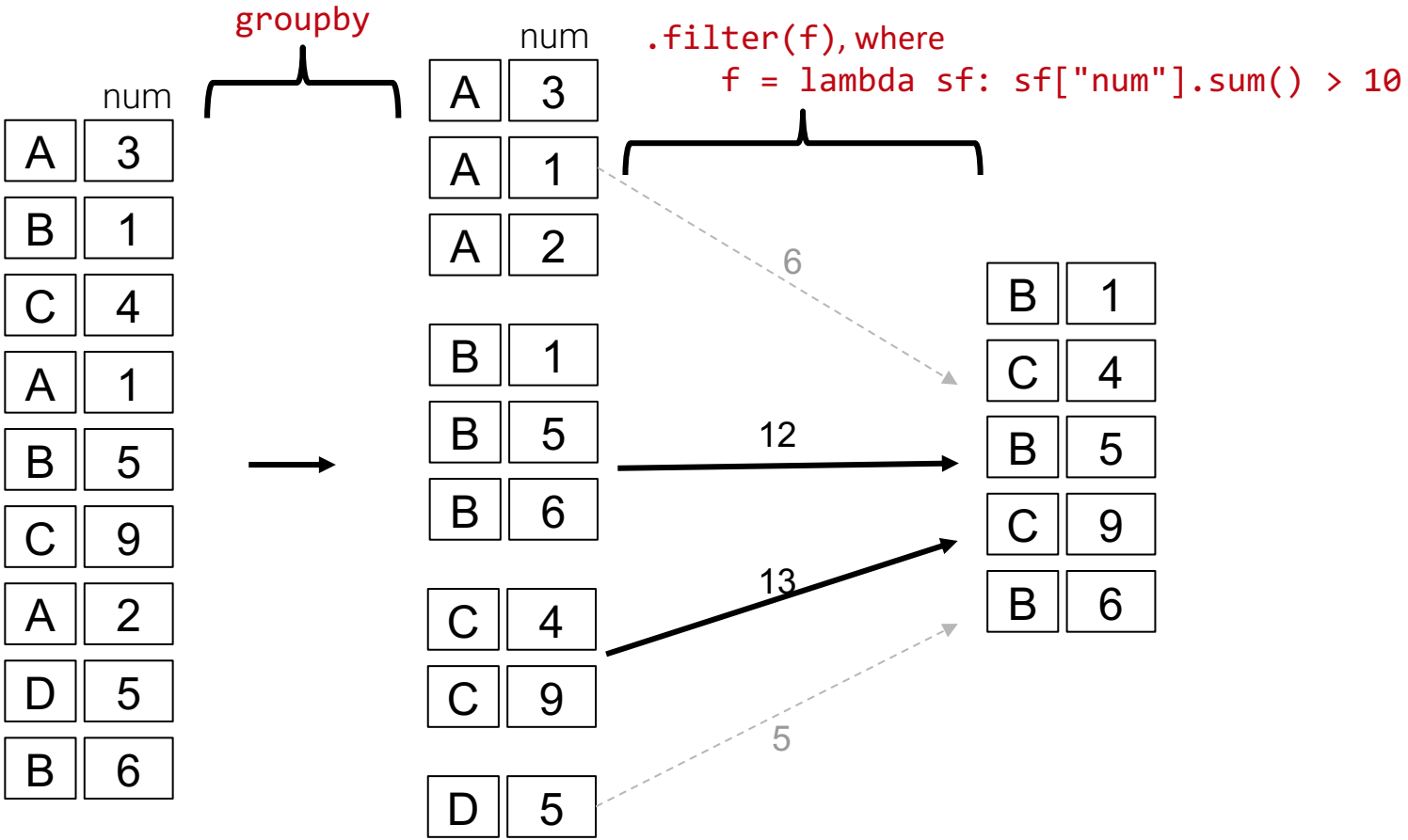


Filtering by Group

Another common use for groups is to filter data.

- `groupby.filter` takes an argument `func`.
- `func` is a function that:
  - Takes a `DataFrame` as input.
  - Returns either `True` or `False`.
- `filter` applies `func` to each group/sub-`DataFrame`:
  - If `func` returns **True** for a group, then all rows belonging to the group are **preserved**.
  - If `func` returns **False** for a group, then all rows belonging to that group are **filtered out**.
- Notes:
  - Filtering is done per group, not per row. Different from boolean filtering.
  - Unlike `agg()`, the column we grouped on does NOT become the index!

groupby.filter()



Filtering Elections Dataset

Going back to the `elections` dataset.

Let's keep only election year results where the max '%' is less than 45%.

```
elections.groupby("Year").filter(lambda sf: sf["%"].max() < 45)
```

	Year	Candidate	Party	Popular vote	Result	%
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
66	1912	Eugene V. Debs	Socialist	901551	loss	6.004354
67	1912	Eugene W. Chafin	Prohibition	208156	loss	1.386325
68	1912	Theodore Roosevelt	Progressive	4122721	loss	27.457433
69	1912	William Taft	Republican	3486242	loss	23.218466
70	1912	Woodrow Wilson	Democratic	6296284	win	41.933422
115	1968	George Wallace	American Independent	9901118	loss	13.571218

Puzzle: We want to know the **best election by each party**.

- Best election: The election with the highest % of votes.
- For example, Democrat's best election was in 1964, with candidate Lyndon Johnson winning 61.3% of votes.

Party	Year	Candidate	Popular vote	Result	%
American	1856	Millard Fillmore	873053	loss	21.554001
American Independent	1968	George Wallace	9901118	loss	13.571218
Anti-Masonic	1832	William Wirt	100715	loss	7.821583
Anti-Monopoly	1884	Benjamin Butler	134294	loss	1.335838
Citizens	1980	Barry Commoner	233052	loss	0.270182
Communist	1932	William Z. Foster	103307	loss	0.261069
Constitution	2008	Chuck Baldwin	199750	loss	0.152398
Constitutional Union	1860	John Bell	590901	loss	12.639283
Democratic	1964	Lyndon Johnson	43127041	win	61.344703

Attempt #1

Why does the table seem to claim that Woodrow Wilson won the presidency in 2020?

```
elections.groupby("Party").max().head(10)
```

Party	Year	Candidate	Popular vote	Result	%
American	1976	Thomas J. Anderson	873053	loss	21.554001
American Independent	1976	Lester Maddox	9901118	loss	13.571218
Anti-Masonic	1832	William Wirt	100715	loss	7.821583
Anti-Monopoly	1884	Benjamin Butler	134294	loss	1.335838
Citizens	1980	Barry Commoner	233052	loss	0.270182
Communist	1932	William Z. Foster	103307	loss	0.261069
Constitution	2016	Michael Peroutka	203091	loss	0.152398
Constitutional Union	1860	John Bell	590901	loss	12.639283
Democratic	2020	Woodrow Wilson	81268924	win	61.344703
Democratic-Republican	1824	John Quincy Adams	151271	win	57.210122

Problem with Attempt #1

Why does the table seem to claim that Woodrow Wilson won the presidency in 2020?

Every column is calculated independently! Among Democrats:

- Last year they ran: 2020.
- Alphabetically the latest candidate name: Woodrow Wilson.
- Highest % of vote: 61.34%.

```
elections.groupby("Party").max().head(10)
```

Party	Year	Candidate	Popular vote	Result	%
American	1976	Thomas J. Anderson	873053	loss	21.554001
American Independent	1976	Lester Maddox	9901118	loss	13.571218
Anti-Masonic	1832	William Wirt	100715	loss	7.821583
Anti-Monopoly	1884	Benjamin Butler	134294	loss	1.335838
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Constitutional Union	1860	John Bell	590901	loss	12.639283
Democratic	2020	Woodrow Wilson	81268924	win	61.344703
Democratic-Republican	1824	John Quincy Adams	151271	win	57.210122

Attempt #2: Motivation

- We want to preserve entire rows, so we need an aggregate function that does that.

Party	Year	Candidate	Popular vote	Result	%
American	1856	Millard Fillmore	873053	loss	21.554001
American Independent	1968	George Wallace	9901118	loss	13.571218
Anti-Masonic	1832	William Wirt	100715	loss	7.821583
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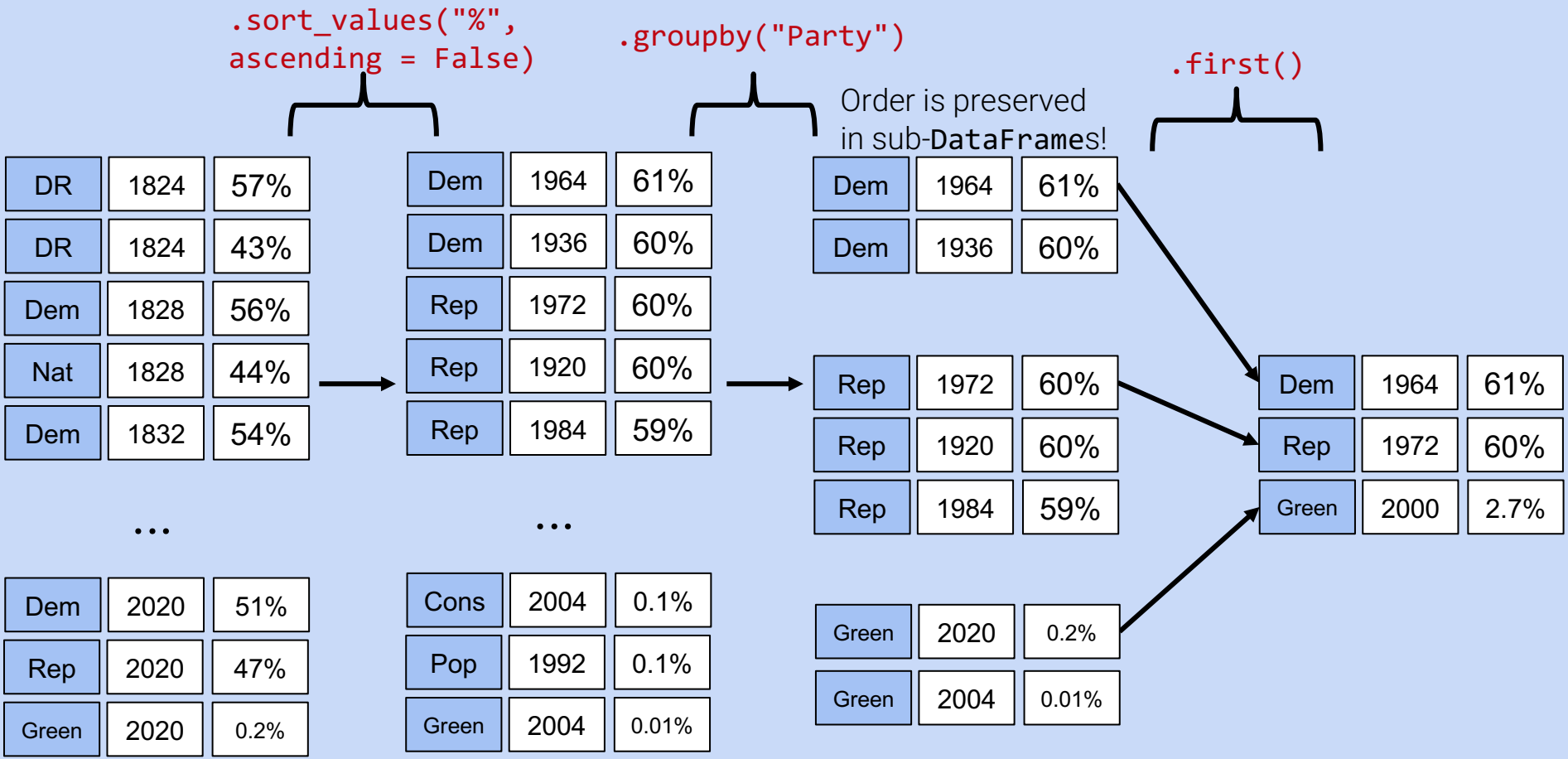
Democratic	1964	Lyndon Johnson	43127041	win	61.344703

Attempt #2: Solution



Attempt #2: Solution

- First sort the `DataFrame` so that rows are in descending order of `%`.
- Then group by Party and take the first item of each sub-`DataFrame`.
- Note: Lab will give you a chance to try this out if you didn't quite follow during lecture.

```
elections_sorted_by_percent = elections.sort_values("%", ascending=False)
elections_sorted_by_percent.groupby("Party").first()
```

	Year	Candidate	Party	Popular vote	Result	%
114	1964	Lyndon Johnson	Democratic	43127041	win	61.344703
91	1936	Franklin Roosevelt	Democratic	27752648	win	60.978107
120	1972	Richard Nixon	Republican	47168710	win	60.907806
79	1920	Warren Harding	Republican	16144093	win	60.574501
133	1984	Ronald Reagan	Republican	54455472	win	59.023326

`elections_sorted_by_percent`

Party	Year	Candidate	Popular vote	Result	%
American	1856	Millard Fillmore	873053	loss	21.554001
American Independent	1968	George Wallace	9901118	loss	13.571218
Anti-Masonic	1832	William Wirt	100715	loss	7.821583
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Constitutional Union	1860	John Bell	590901	loss	12.639283
Democratic	1964	Lyndon Johnson	43127041	win	61.344703

groupby Puzzle - Alternate Approaches

Using a **lambda** function

```
elections_sorted_by_percent = elections.sort_values("%", ascending=False)
elections_sorted_by_percent.groupby("Party").agg(lambda x : x.iloc[0])
```

Using **idxmax** function

```
best_per_party = elections.loc[elections.groupby("Party")["%"].idxmax()]
```

Using **drop_duplicates** function

```
best_per_party2 = elections.sort_values("%").drop_duplicates(["Party"], keep="last")
```

There's More Than One Way to Find the Best Result by Party

In `Pandas`, there's more than one way to get to the same answer.

- Each approach has different tradeoffs in terms of readability, performance, memory consumption, complexity, etc.
- Takes a very long time to understand these tradeoffs!
- If you find your current solution to be particularly convoluted or hard to read, maybe try finding another way!

More on `DataFrameGroupby` Object

We can look into **`DataFrameGroupby`** objects in following ways:

```
grouped_by_party = elections.groupby("Party")
grouped_by_party.groups
```

```
{'American': [22, 126], 'American Independent': [115, 119, 124], 'Anti-Masonic': [6], 'Anti-Monopoly': [38], 'Citiz
ens': [127], 'Communist': [89], 'Constitution': [160, 164, 172], 'Constitutional Union': [24], 'Democratic': [2, 4,
8, 10, 13, 14, 17, 20, 28, 29, 34, 37, 39, 45, 47, 52, 55, 57, 64, 70, 74, 77, 81, 83, 86, 91, 94, 97, 100, 105, 10
8, 111, 114, 116, 118, 123, 129, 134, 137, 140, 144, 151, 158, 162, 168, 176, 178], 'Democratic-Republican': [0,
1], 'Dixiecrat': [103], 'Farmer-Labor': [78], 'Free Soil': [15, 18], 'Green': [149, 155, 156, 165, 170, 177, 181],
'Greenback': [35], 'Independent': [121, 130, 143, 161, 167, 174], 'Liberal Republican': [31], 'Libertarian': [125,
128, 132, 138, 139, 146, 153, 159, 163, 169, 175, 180], 'National Democratic': [50], 'National Republican': [3, 5],
'National Union': [27], 'Natural Law': [148], 'New Alliance': [136], 'Northern Democratic': [26], 'Populist': [48,
61, 141], 'Progressive': [68, 82, 101, 107], 'Prohibition': [41, 44, 49, 51, 54, 59, 63, 67, 73, 75, 99], 'Reform':
[150, 154], 'Republican': [21, 23, 30, 32, 33, 36, 40, 43, 46, 53, 56, 60, 65, 69, 72, 79, 80, 84, 87, 90, 96, 98,
104, 106, 109, 112, 113, 117, 120, 122, 131, 133, 135, 142, 145, 152, 157, 166, 171, 173, 179], 'Socialist': [58, 6
2, 66, 71, 76, 85, 88, 92, 95, 102], 'Southern Democratic': [25], 'States' Rights': [110], 'Taxpayers': [147], 'Uni
on': [93], 'Union Labor': [42], 'Whig': [7, 9, 11, 12, 16, 19]}
```

```
grouped_by_party.get_group("Socialist")
```

	Year	Candidate	Party	Popular vote	Result	%
58	1904	Eugene V. Debs	Socialist	402810	loss	2.985897
62	1908	Eugene V. Debs	Socialist	420852	loss	2.850866
66	1912	Eugene V. Debs	Socialist	901551	loss	6.004354
71	1916	Allan L. Benson	Socialist	590524	loss	3.194193

Pivot Tables

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  - Granularity
  - Structure: Variable Types

Grouping by Multiple Columns

Suppose we want to build a table showing the total number of babies born of each Gender in each year. One way is to **groupby** *using both columns* of interest:

```
babynames.groupby(["Year", "Sex"])[["Count"]].agg(sum).head(6)
```

		Count
Year	**Sex**	
1910	**F**	5950
	M	3213
1911	**F**	6602
	M	3381
1912	**F**	9804
	M	8142

Note: Resulting `DataFrame` is multi-indexed. That is, its index has multiple dimensions. Will explore in a later lecture.

Pivot Tables

A more natural approach is to create a pivot table.

```
babynames_pivot = babynames.pivot_table(
    index = "Year",     # rows (turned into index)
    columns = "Sex",    # column values
    values = ["Count"], # field(s) to process in each group
    aggfunc = np.sum,   # group operation
)
babynames_pivot.head(6)
```

Sex	F	M
Year		
1910	5950	3213
1911	6602	3381
1912	9804	8142
1913	11860	10234
1914	13815	13111
1915	18643	17192

`groupby(["Year", "Sex"])` vs. `pivot_table`

The pivot table more naturally represents our data.

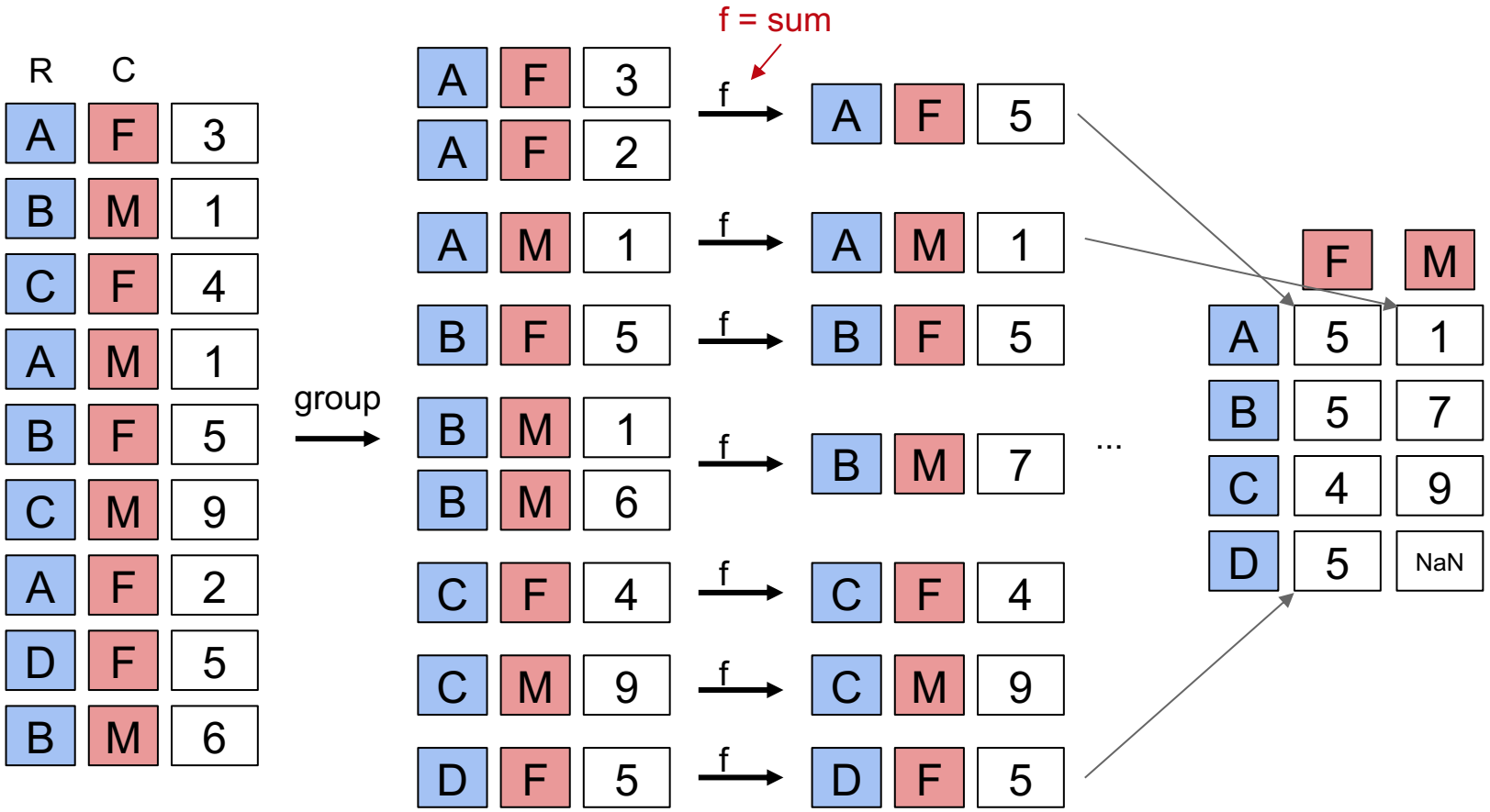
`groupby` output

		Count
Year	**Sex**	
1910	**F**	5950
	M	3213
1911	**F**	6602
	M	3381
1912	**F**	9804
	M	8142

`pivot_table` output

Sex	**F**	**M**
Year		
1910	5950	3213
1911	6602	3381
1912	9804	8142
1913	11860	10234
1914	13815	13111
1915	18643	17192

Pivot Table Mechanics



Pivot Tables with Multiple Values

We can include multiple values in our pivot tables.

```
babynames_pivot = babynames.pivot_table(
    index = "Year",     # rows (turned into index)
    columns = "Sex",    # column values
    values = ["Count", "Name"],
    aggfunc = np.max,   # group operation
)
babynames_pivot.head(6)
```

	Count		Name	
Sex	F	M	F	M
Year				
1910	295	237	Yvonne	William
1911	390	214	Zelma	Willis
1912	534	501	Yvonne	Woodrow
1913	584	614	Zelma	Yoshio
1914	773	769	Zelma	Yoshio
1915	998	1033	Zita	Yukio

Join Tables

Lecture 5

- **Pandas, Part III**
  - Groupby Review
  - More on Groupby
  - Pivot Tables
  - **Joining Tables**
- EDA, Part I
  - Structure: Tabular Data
  - Granularity
  - Structure: Variable Types

Joining Tables

Suppose want to know the popularity of presidential candidate's names in 2022.

- Example: Dwight Eisenhower's name Dwight is not popular today, with only 5 babies born with this name in California in 2022.

To solve this problem, we'll have to join tables.

Creating Table 1: Babynames in 2022

Let's set aside names in California from 2022 first:

```
babynames_2022 = babynames[babynames["Year"] == 2022]
babynames_2022
```

	State	Sex	Year	Name	Count
235835	CA	F	2022	Olivia	2178
235836	CA	F	2022	Emma	2080
235837	CA	F	2022	Camila	2046
235838	CA	F	2022	Mia	1882
235839	CA	F	2022	Sophia	1762
235840	CA	F	2022	Isabella	1733
235841	CA	F	2022	Luna	1516
235842	CA	F	2022	Sofia	1307
235843	CA	F	2022	Amelia	1289
235844	CA	F	2022	Gianna	1107

Creating Table 2: Presidents with First Names

To join our table, we'll also need to set aside the first names of each candidate.

```
elections["First Name"] = elections["Candidate"].str.split().str[0]
```

	Year	Candidate	Party	Popular vote	Result	%	First Name
0	1824	Andrew Jackson	Democratic-Republican	151271	loss	57.210122	Andrew
1	1824	John Quincy Adams	Democratic-Republican	113142	win	42.789878	John
2	1828	Andrew Jackson	Democratic	642806	win	56.203927	Andrew
3	1828	John Quincy Adams	National Republican	500897	loss	43.796073	John
4	1832	Andrew Jackson	Democratic	702735	win	54.574789	Andrew
...	...	...	...	...	...	...	...
177	2016	Jill Stein	Green	1457226	loss	1.073699	Jill
178	2020	Joseph Biden	Democratic	81268924	win	51.311515	Joseph
179	2020	Donald Trump	Republican	74216154	loss	46.858542	Donald
180	2020	Jo Jorgensen	Libertarian	1865724	loss	1.177979	Jo
181	2020	Howard Hawkins	Green	405035	loss	0.255731	Howard

182 rows × 7 columns

Joining Our Tables

```
merged = pd.merge(left = elections, right = babynames_2022,
                  left_on = "First Name", right_on = "Name")

merged = elections.merge(right = babynames_2022,
                  left_on = "First Name", right_on = "Name")
```

	Year_x	Candidate	Party	Popular vote	Result	%	First Name	State	Sex	Year_y	Name	Count
0	1824	Andrew Jackson	Democratic-Republican	151271	loss	57.210122	Andrew	CA	M	2022	Andrew	741
1	1828	Andrew Jackson	Democratic	642806	win	56.203927	Andrew	CA	M	2022	Andrew	741
2	1832	Andrew Jackson	Democratic	702735	win	54.574789	Andrew	CA	M	2022	Andrew	741
3	1824	John Quincy Adams	Democratic-Republican	113142	win	42.789878	John	CA	M	2022	John	490
4	1828	John Quincy Adams	National Republican	500897	loss	43.796073	John	CA	M	2022	John	490
...	...	...	...	...	...	...	...	...	...	...	...	...

Joining Our Tables: Four Options

1. inner_merged_df = pd.merge(left_df, right_df, on='key')
2. outer_merged_df = pd.merge(left_df, right_df, on='key', how='outer')
3. left_merged_df = pd.merge(left_df, right_df, on='key', how='left')
4. right_merged_df = pd.merge(left_df, right_df, on='key', how='right')

DataFrame 1

	ID	Age
0	2	25
1	3	30
2	4	28

DataFrame 2

	ID	Name
0	0	Bob
1	1	Alice
2	2	John

Joining Our Tables: Inner Merge

1. inner_merged_df = pd.merge(left_df, right_df, on='ID')

DataFrame 1

	ID	Name
0	1	Bob
1	2	Alice
2	3	John

DataFrame 2

	ID	Age
0	2	25
1	3	30
2	4	28

Inner merge

	ID	Name	Age
0	2	Alice	25
1	3	John	30

Joining Our Tables: Outer Merge

1. inner_merged_df = pd.merge(left_df, right_df=, on='ID', how='outer')

DataFrame 1

	ID	Name
0	1	Bob
1	2	Alice
2	3	John

DataFrame 2

	ID	Age
0	2	25
1	3	30
2	4	28

outer merge

	ID	Name	Age
0	1	Bob	NaN
1	2	Alice	25
2	3	John	30
4	4	NaN	28

Joining Our Tables: right Merge

1. inner_merged_df = pd.merge(left_df, right_df=, on='ID', how='right')

DataFrame 1

	ID	Name
0	1	Bob
1	2	Alice
2	3	John

DataFrame 2

	ID	Age
0	2	25
1	3	30
2	4	28

right merge

	ID	Name	Age
0	2	Alice	25
1	3	John	30
2	4	NaN	28

Joining Our Tables: left Merge

1. inner_merged_df = pd.merge(left_df, right_df=, on='ID', how='left')

DataFrame 1

	ID	Name
0	1	Bob
1	2	Alice
2	3	John

DataFrame 2

	ID	Age
0	2	25
1	3	30
2	4	28

left merge

	ID	Name	Age
0	1	Bob	NaN
1	2	Alice	25
2	3	John	30

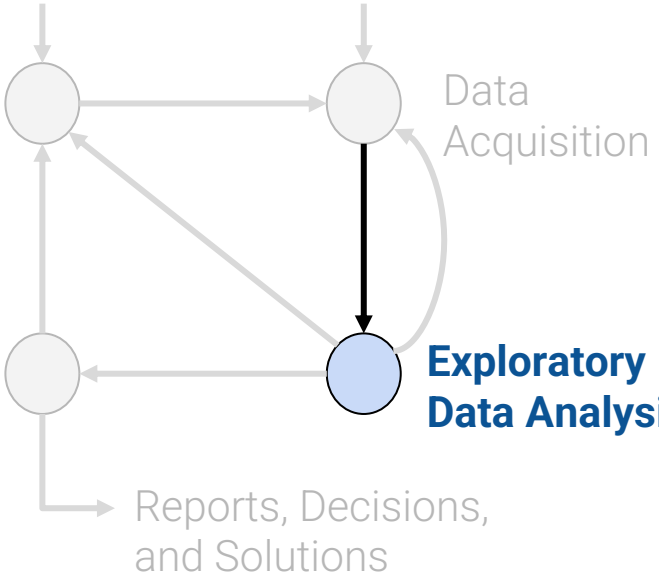
Data Wrangling and EDA, Part I

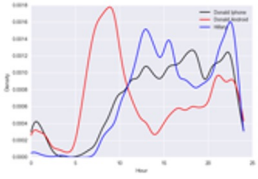
Exploratory Data Analysis and its role in the data science lifecycle

The Next Step

EDA Guiding Principles

Plan for First Few Weeks





(Weeks 1 and 2)

Exploring and Cleaning Tabular Data
From `datascience` to `pandas`

(Weeks 2 and 3)

Data Science in Practice
EDA, Data Cleaning, Text processing (regular expressions)

Structure: Tabular Data

Lecture 05

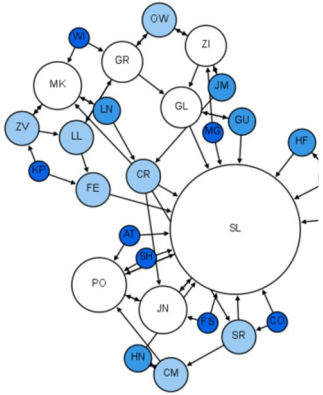
- Pandas, Part III
  - Groupby Review
  - More on Groupby
  - Pivot Tables
  - Joining Tables
- **EDA, Part I**
  - **Structure: Tabular Data**
  - Granularity
  - Structure: Variable Types

Rectangular and Non-rectangular Data

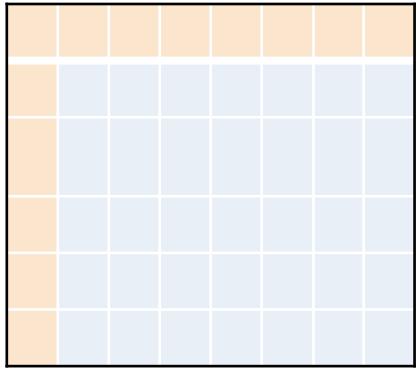
Data come in many different shapes.

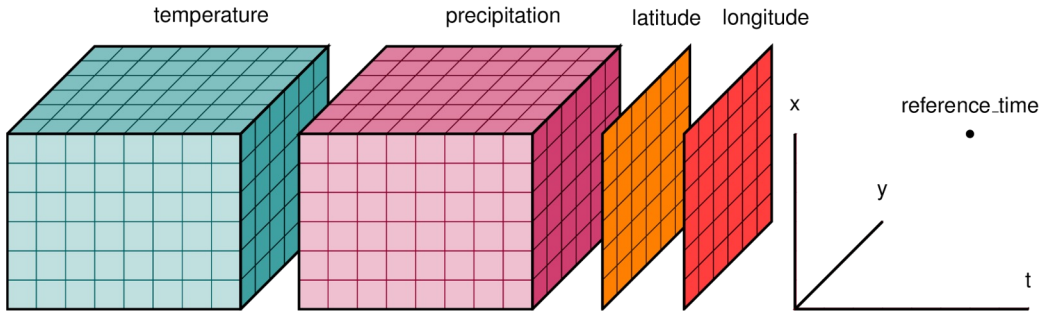
1723786

Non-rectangular data



Rectangular data



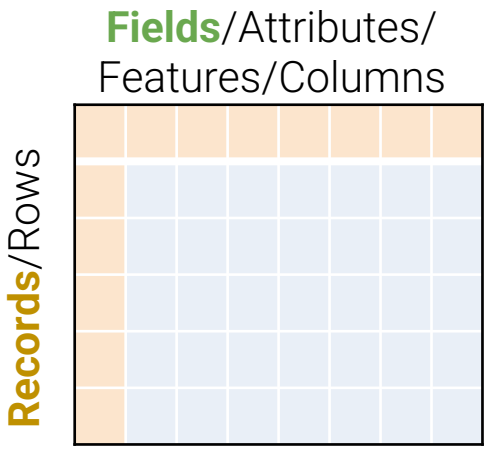


Rectangular Data

We often prefer rectangular data for data analysis (why?)

- Regular structures are easy manipulate and analyze
- A big part of data cleaning is about transforming data to be more rectangular

Two kinds of rectangular data: **Tables** and **Matrices**.



Tables (a.k.a. `DataFrames` in R/Python and relations in SQL)

- Named columns with different types
- Manipulated using data transformation languages (map, filter, group by, join, …)

Matrices

- Numeric data of the same type (float, int, etc.)
- Manipulated using linear algebra

What are the differences?
Why would you use one over the other?

Tuberculosis – United States, 2021

CDC Morbidity and Mortality Weekly Report (MMWR) 03/25/2022.

Summary

What is already known about this topic?

The number of reported U.S. tuberculosis (TB) cases decreased sharply in 2020, possibly related to multiple factors associated with the COVID-19 pandemic.

What is added by this report?

Reported TB incidence (cases per 100,000 persons) increased 9.4%, from 2.2 during 2020 to 2.4 during 2021 but was lower than incidence during 2019 (2.7). Increases occurred among both U.S.-born and non–U.S.-born persons.

What are the implications for public health practice?

Factors contributing to changes in reported TB during 2020–2021 likely include an actual reduction in TB incidence as well as delayed or missed TB diagnoses. Timely evaluation and treatment of TB and latent tuberculosis infection remain critical to achieving U.S. TB elimination.

What is **incidence**?
Why use it here?

How was "9.4% increase" computed?

Question: Can we **reproduce** these rates using government data?

Demo Slides

CSV: Comma-Separated Values

Tuberculosis in the US [CDC source].

CSV is a very common **tabular file format**.

- **Records** (rows) are delimited by a newline: `'\n'`, `"\r\n"`
- **Fields** (columns) are delimited by commas: `','`

Pandas: `pd.read_csv(header=...)`

Fields/Attributes/Features/Columns

Records/Rows		U.S. jurisdiction	TB cases 2019	...
	0	Total	8,900	...
	1	Alabama	87	...

Granularity

Lecture 04, Data 100 Fall 2023

- Pandas, Part III
  - Groupby Review
  - More on Groupby
  - Pivot Tables
  - Joining Tables
- **EDA, Part I**
  - Structure: Tabular Data
  - **Granularity**
  - Structure: Variable Types

Key Data Properties to Consider in EDA

(we'll come back to this)

Structure -- the "shape" of a data file

Granularity -- how fine/coarse is each datum

Scope -- how (in)complete is the data

Temporality -- how is the data situated in time

Faithfulness -- how well does the data capture "reality"

Granularity: How Fine/Coarse Is Each Datum?

What does each **record** represent?

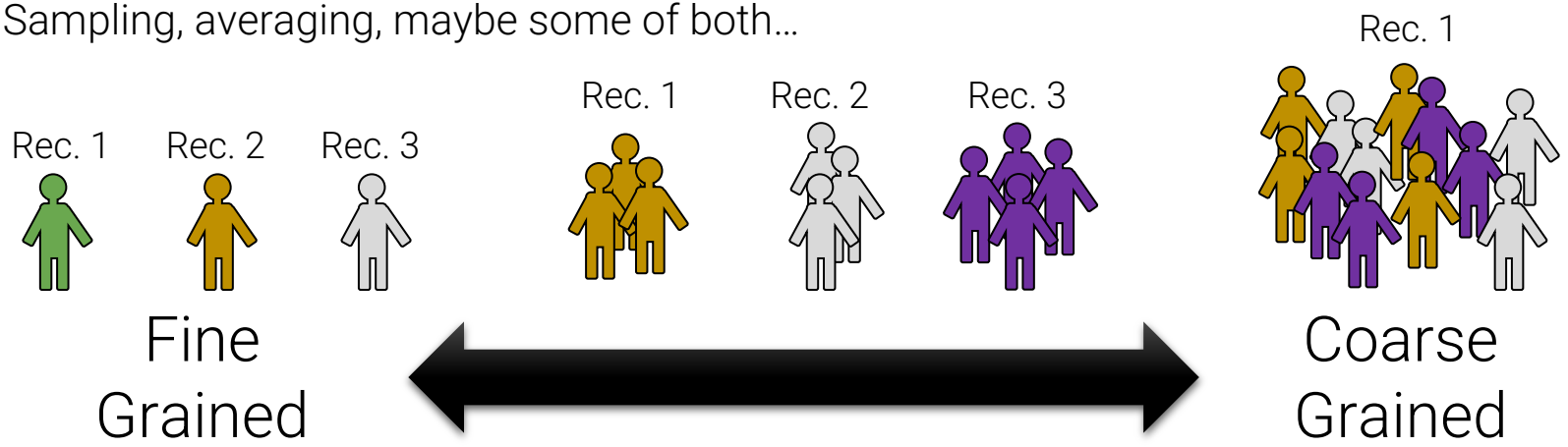
- Examples: a purchase, a person, a group of users

Do all records capture granularity at the same level?

- Some data will include summaries (aka **rollups**) as records.

If the data are **coarse**, how were the records aggregated?

- Sampling, averaging, maybe some of both…



To the demo!!

Structure: Variable Types

Lecture 04, Data 100 Fall 2023

- Pandas, Part III
  - Groupby Review
  - More on Groupby
  - Pivot Tables
  - Joining Tables
- **EDA, Part I**
  - Structure: Tabular Data
  - Granularity
  - **Structure: Variable Types**

(we're back to this)

Variable Type

Structure -- the "shape" of a data file

Granularity -- how fine/coarse is each datum

Scope -- how (in)complete is the data

Temporality -- how is the data situated in time

Faithfulness -- how well does the data capture "reality"

Variables Are Columns

Let's look at records with the same granularity.

What does each **column** represent?

A **variable** is a **measurement** of a particular concept.

The U.S. Jurisdiction **variable**

	U.S. jurisdiction	TB cases 2019	…
1	Alabama	87	…
2	Alaska	58	…
…	…	…	…

It has two common properties:

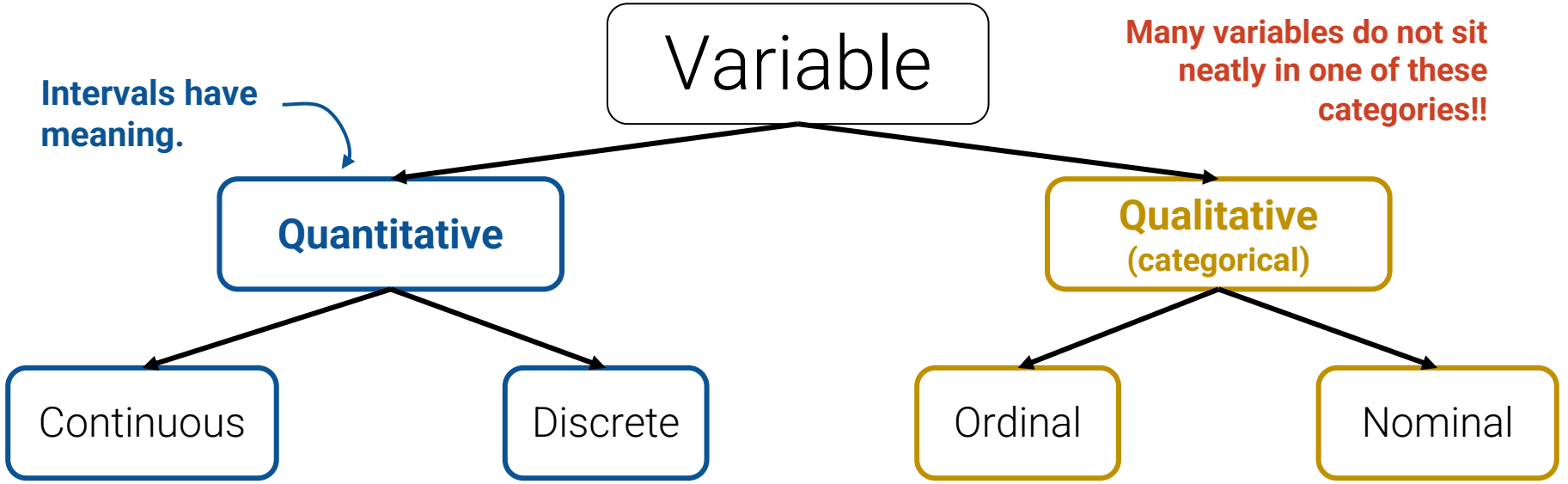
- **Datatype/Storage type**:
  How each variable value is stored in memory. `df[colname].dtype`
  - integer, floating point, boolean, object (string-like), etc.

  Affects which pandas functions you use.
- **Variable type/Feature type**:
  Conceptualized measurement of information (and therefore what values it can take on).
  - Use expert knowledge
  - Explore data itself
  - Consult data codebook (if it exists).

  Affects how you visualize and interpret the data.

⚠In this class, "variable types" are conceptual!!

Variable Feature Types



Could be measured to arbitrary precision.

Examples:
- Price
- Temperature

Finite possible values

Examples:
- Number of siblings
- Yrs of education

Categories w/ordered levels; no consistent meaning to difference

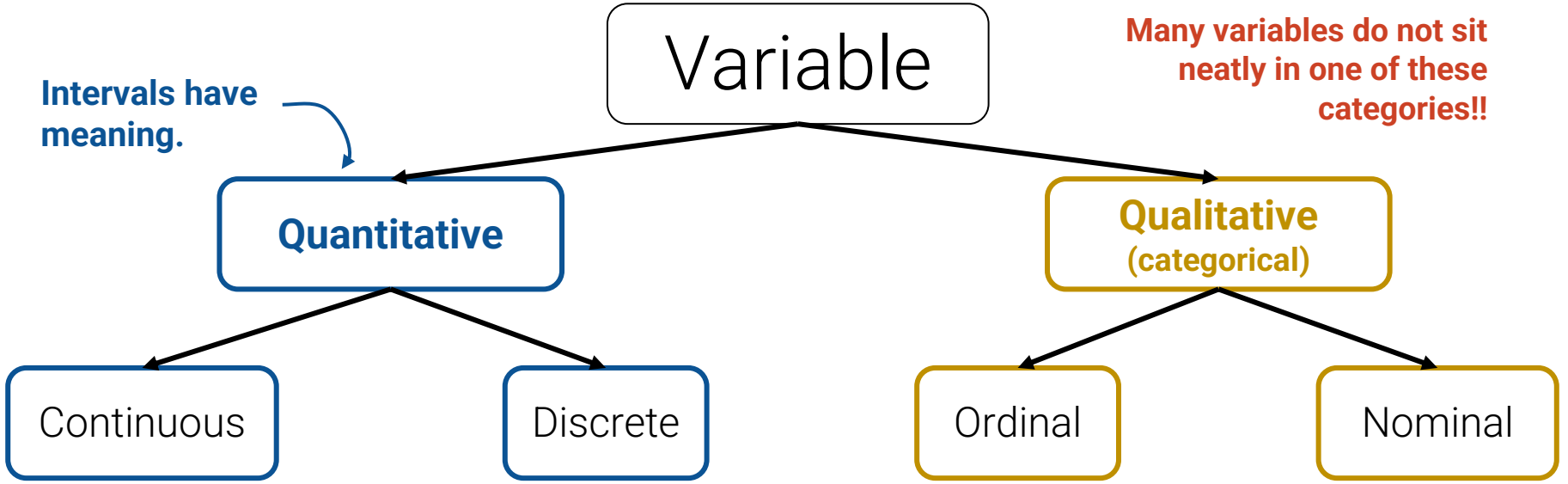
Examples:
- Preferences
- Level of education

Categories w/ no specific ordering.

Examples:
- Political Affiliation
- Cal ID number

Note that **qualitative variables** could have numeric levels; conversely, **quantitative variables** could be stored as strings!

Variable Feature Types



Could be measured to arbitrary precision.

Examples:
- Price
- Temperature

Finite possible values

Examples:
- Number of siblings
- Yrs of education

Categories w/ordered levels; no consistent meaning to difference

Examples:
- Preferences
- Level of education

Categories w/ no specific ordering.

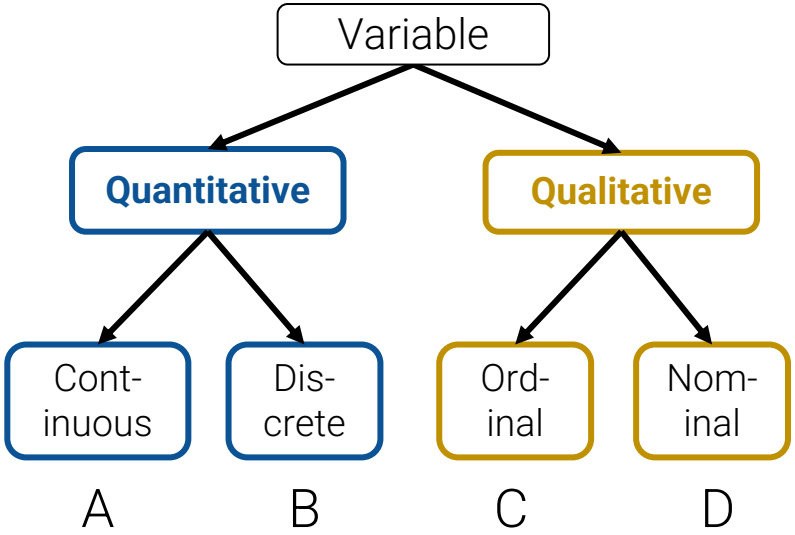
Examples:
- Political Affiliation
- Cal ID number

Note that **qualitative variables** could have numeric levels; conversely, **quantitative variables** could be stored as strings!

Variable Types

What is the feature type (i.e., variable type) of each variable?

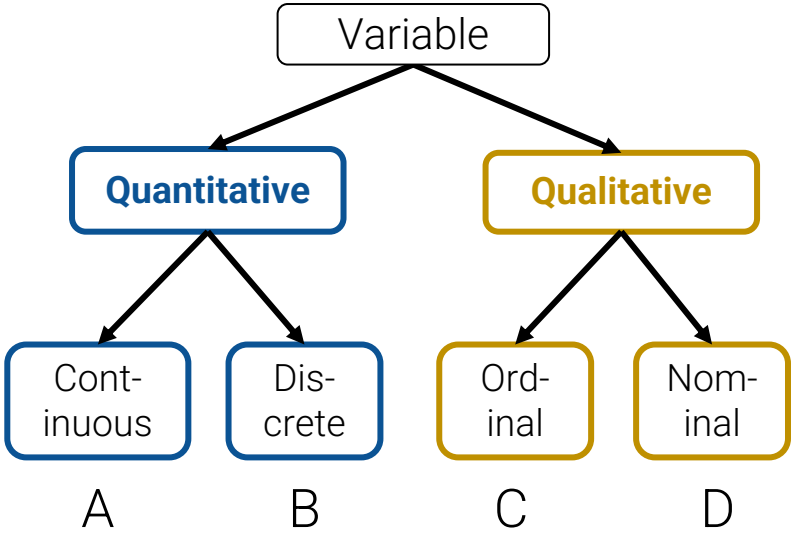
Q	Variable	Feature Type
1	CO_2 level (ppm)	
2	Number of siblings	
3	GPA	
4	Income bracket (low, med, high)	
5	Race/Ethnicity	
6	Number of years of education	
7	Yelp Rating	



Variable Types

What is the feature type of each variable?

Q	Variable	Feature Type
1	CO_2 level (ppm)	**A. Quantitative Cont.**
2	Number of siblings	**B. Quantitative Discrete**
3	GPA	**A. Quantitative Cont.**
4	Income bracket (low, med, high)	**C. Qualitative Ordinal**
5	Race/Ethnicity	**D. Qualitative Nominal**
6	Number of years of education	**B. Quantitative Discrete**
7	Yelp Rating	**C. Qualitative Ordinal**



Many of these examples show how "shaggy" these categories are!!
We will revisit variable types when we learn how to visualize variables.