Lecture 4
The Split-Apply-Combine Paradigm

Flight Delays

Which airline carriers are most likely to be delayed?

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Let's look at a data set of all domestic flights that departed from one of the New York City airports (JFK, LaGuardia, and Newark) on November 16, 2013.

```
import pandas as pd
data_dir = "https://datasci112.stanford.edu/data/"
df = pd.read_csv(data_dir + "flights_nyc_20131116.csv")
df
```

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df
```

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0	US	1895	EWR	CLT	-5.0
1	UA	1014	LGA	IAH	-3.0
2	AA	2243	JFK	MIA	2.0
3	UA	303	JFK	SFO	-8.0
4	US	795	LGA	PHL	-8.0
...	...	...	...	...	...
573	B6	745	JFK	PSE	-3.0
574	B6	839	JFK	BQN	0.0
575	UA	360	EWR	PBI	NaN
576	US	1946	EWR	CLT	NaN
577	US	2142	LGA	BOS	NaN

578 rows × 5 columns

Visualizing Delays

We already know how to visualize and summarize a quantitative variable like **dep_delay**.

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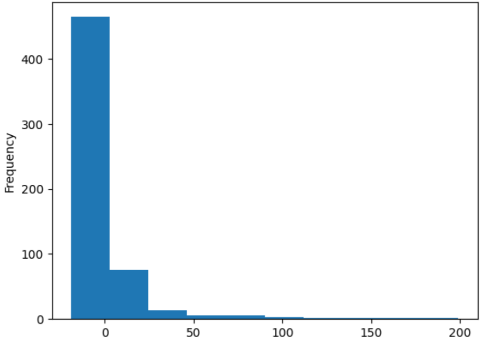

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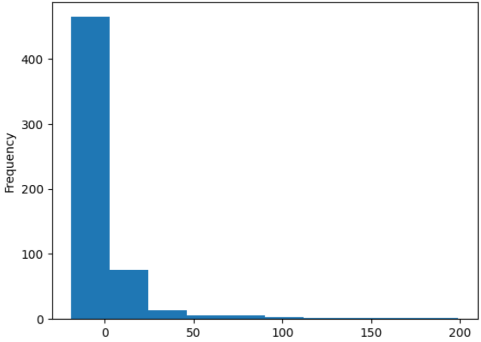

But how do we compare delays across different carriers?

1. Boolean Masking
2. The Split-Apply-Combine Paradigm
3. Visualizing Conditional Distributions

What do you think the following code will produce?

```
df["carrier"] == "UA"
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0      False
1      True
2      False
3      True
4      False
       ...
573    False
574    False
575     True
576    False
577    False
Name: carrier, Length: 578, dtype: bool
```

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0       False
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a Series of booleans

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indicates whether each flight was United or not

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another example of vectorization!

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What about the following?

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(df["carrier"] == "UA").sum()
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123

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Name: carrier, Length: 578, dtype: bool
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What about the following?

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(df["carrier"] == "UA").sum()
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```
123
```

the number of United flights that day

Boolean Series

How would you interpret the following?

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What You Need to Know about Booleans

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What You Need to Know about Booleans

- Applying a relational operator like `==`, `<`, `>`, and `!=` on a `Series` produces a `Series` of booleans, by vectorization.

Boolean Series

How would you interpret the following?

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What You Need to Know about Booleans

- Applying a relational operator like `==`, `<`, `>`, and `!=` on a `Series` produces a `Series` of booleans, by vectorization.
- Arithmetic operations can be performed on booleans in `Series`, treating `True` as 1 and `False` as 0.

Boolean Masks

A boolean `Series` can be passed as a key to a `DataFrame` to *mask* the data.

```
df[df["carrier"] == "UA"]
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8	UA	1187	LGA	ORD	-5.0
9	UA	258	EWR	MCO	-2.0
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...	...	...	...	...	...
537	UA	1631	EWR	IAH	-3.0
549	UA	1409	EWR	TPA	-1.0
552	UA	1071	EWR	BQN	5.0
562	UA	1066	EWR	BOS	-5.0
575	UA	360	EWR	PBI	NaN

123 rows × 5 columns

A Boolean mask acts as a “filter” to select data.

Boolean Masks

A boolean `Series` can be passed as a key to a `DataFrame` to *mask* the data.

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df[df["carrier"] == "UA"]
```

The index has changed!

	carrier	flight	origin	dest	dep_delay
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df[df["carrier"] == "UA"]["dep_delay"].mean()
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- Note that this is a summary of a conditional distribution of
- **dep_delay**:

  - $\text{mean}(\textbf{dep\_delay} | \textbf{carrier} = \text{UA})$.

1. Boolean Masking
2. The Split-Apply-Combine Paradigm
3. Visualizing Conditional Distributions

Another Exercise

To compare carriers, we need to summarize all the conditional distributions of **dep_delay** given **carrier**:

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for carrier in df["carrier"].unique():
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To compare carriers, we need to summarize all the conditional distributions of $\mathbf{dep\_delay}$ given $\mathbf{carrier}$:

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for carrier in df["carrier"].unique():
  print(carrier, df[df["carrier"] == carrier]["dep_delay"].mean())
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US -2.324324324324324
UA 5.590163934426229
AA -1.337837837837838
DL 3.295238095238095
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Problems with this Solution

- It is inconvenient (have to write a `for` loop over the possible values).

The code becomes long and repetitive, especially if there are many carriers.
You have to write a for-loop for each one every time → not practical.

Another Exercise

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Problems with this Solution

- It is inconvenient (have to write a `for` loop over the possible values).
- The values are not stored in a Pandas object for further analysis (e.g., visualization).

The Split-Apply-Combine Paradigm

This analysis fits into the **split-apply-combine paradigm** (Wickham, 2011).

	carrier	flight	origin	dest	dep_delay
0	US	1895	EWR	CLT	-5.0
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578 rows × 5 columns

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123 rows × 5 columns

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	carrier	flight	origin	dest	dep_delay
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533	DL	2454	JFK	DEN	-3.0
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544	DL	427	JFK	LAX	14.0
567	DL	985	JFK	BOS	106.0

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.mean()

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.mean()

5.590164

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105 rows × 5 columns

.mean()

3.295238

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split | apply | combine

key

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.mean() → 5.590164

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567	DL	985	JFK	BOS	106.0

105 rows × 5 columns

.mean() → 3.295238

```
carrier
AA    -1.337838
B6     1.537879
DL     3.295238
EV     1.247619
UA     5.590164
US    -2.324324
Name: dep_delay, dtype: float6
```

Split-Apply-Combine in Pandas

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The split-apply-combine paradigm is implemented in Pandas as the `.groupby()` method.

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```
df.groupby("carrier")["dep_delay"].mean()
```

groupby("carrier") → groups the DataFrame by each unique carrier.

["dep_delay"] → selects only the dep_delay column for each group.

The result is a GroupBy object, not actual calculations yet.

.mean()
average departure delay for each carrier.

Split-Apply-Combine in Pandas

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UA     5.590164
US    -2.324324
Name: dep_delay, dtype: float64
```

The values are in a Series for further analysis!

A Python Series is a one-dimensional labeled array capable of holding data of any type (integers, strings, floats, etc.). Each element has an index label, which allows easy access and alignment.
Key points:
One-dimensional (like a single column in a table).
Has values and index.Can be created from lists, dictionaries, or NumPy arrays.

Split-Apply-Combine in Pandas

For example, we could plot the mean delay for each carrier.

```
df.groupby("carrier")["dep_delay"].mean().plot.bar()
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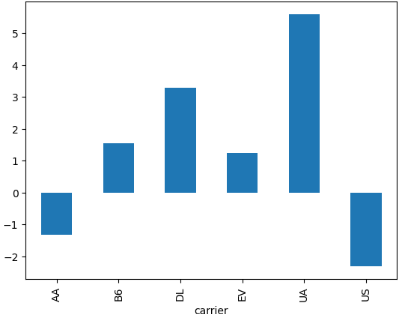

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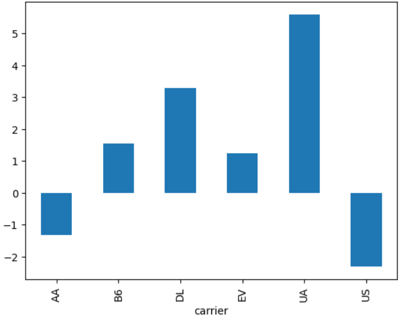

Notice that United Airlines had the longest average delay.

Splitting on Multiple Keys

What if we wanted to also split by the origin airport?

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df.groupby(["carrier", "origin"])["dep_delay"].mean()
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```

```
carrier  origin
AA       EWR       -3.375000
         JFK        1.771429
         LGA       -4.322581
B6       EWR       -0.823529
         JFK       -0.836735
         LGA       17.588235
DL       EWR       19.222222
         JFK        4.980000
         LGA       -1.652174
EV       EWR        1.483146
         JFK        0.000000
         LGA       -0.083333
UA       EWR        7.525773
         JFK        1.909091
         LGA       -4.928571
US       EWR       -5.000000
         JFK        5.400000
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         JFK        5.400000
         LGA       -5.312500
Name: dep_delay, dtype: float64
```

⟶

```
.unstack("origin")
```

origin	EWR	JFK	LGA
carrier			
AA	-3.375000	1.771429	-4.322581
B6	-0.823529	-0.836735	17.588235
DL	19.222222	4.980000	-1.652174
EV	1.483146	0.000000	-0.083333
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Crosstab

Splitting on Multiple Keys

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→

```
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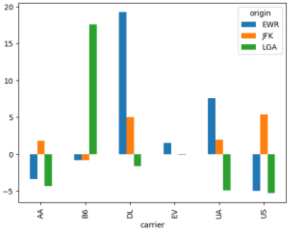
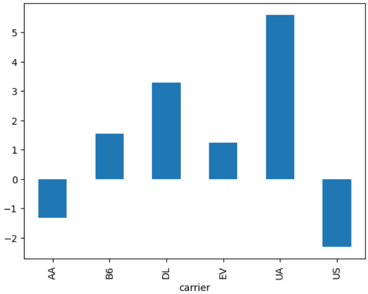
US	-5.000000	5.400000	-5.312500

```
.plot.bar()
```



ird

```
ax = (df.
      groupby("carrier")
      ["dep_delay"].mean().
      plot.bar())
```




```
ax = (df.
      groupby(["carrier", "origin"])
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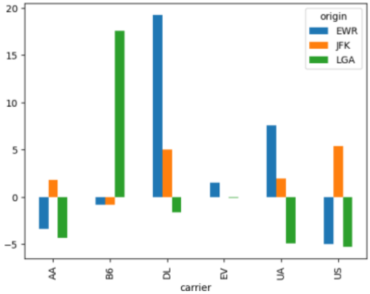
      unstack("origin").
      plot.bar())
```



Notice Anything Weird?

```
ax = (df.
      groupby("carrier")
      ["dep_delay"].mean().
      plot.bar())
ax.set_ylim(-6, 20)
```

```
ax = (df.
      groupby(["carrier", "origin"])
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      plot.bar())
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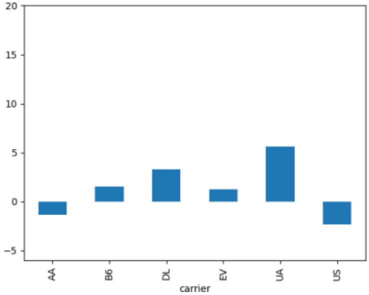

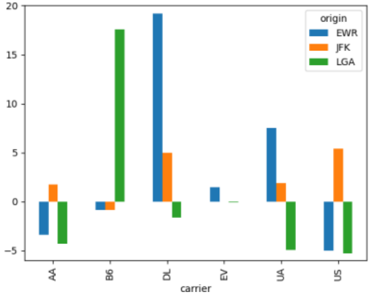

Summary / Weird Points
Negative delays → some flights departed earlier than scheduled.
Extremely high delays → certain carrier–origin combinations have averages far above the norm.
Distribution imbalance → some carriers show values that are very different compared to others.

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```
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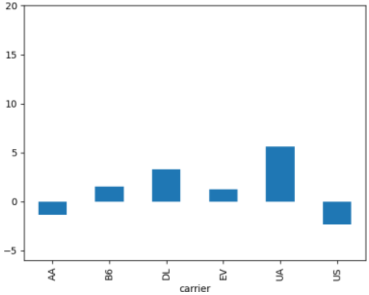

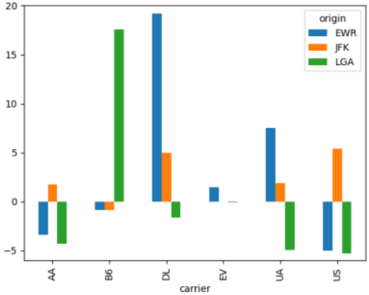

Let's investigate in a Colab!

1. Boolean Masking

2. The Split-Apply-Combine Paradigm

3. Visualizing Conditional Distributions

Comparing Distributions

It is possible to use `.groupby()` with all kinds of operations.

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axes[0].set_xlabel("Departure Delay")
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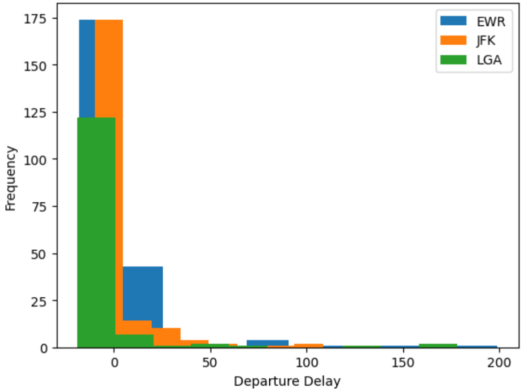

Comparing Distributions

To prevent *overplotting*, we set the opacity parameter `alpha`.

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```
axes = df.groupby("origin")["dep_delay"].plot.hist(legend=True,
                                                    alpha=0.4)
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```

Comparing Distributions

To prevent *overplotting*, we set the opacity parameter `alpha`.

```
axes = df.groupby("origin")["dep_delay"].plot.hist(legend=True,
                                                   alpha=0.4)
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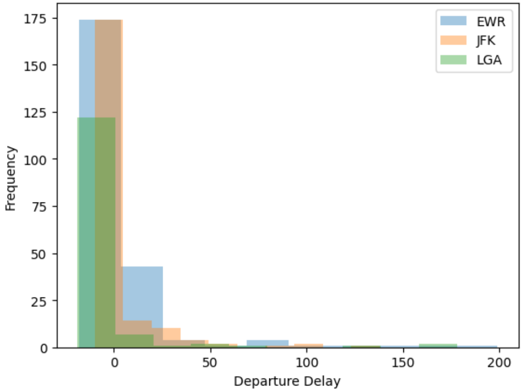
```



Comparing Distributions

Density histograms visualize the conditional distribution $\mathbf{dep\_delay} \mid \mathbf{carrier}$ directly, allowing for easy comparison.

Comparing Distributions

Density histograms visualize the conditional distribution **dep_delay | carrier** directly, allowing for easy comparison.

```
axes = df.groupby("origin")["dep_delay"].plot.hist(legend=True,
                                                   alpha=0.4,
                                                   density=True)
axes[0].set_xlabel("Departure Delay")
```

Comparing Distributions

Density histograms visualize the conditional distribution **dep_delay | carrier** directly, allowing for easy comparison.

```
axes = df.groupby("origin")["dep_delay"].plot.hist(legend=True,
                                                    alpha=0.4,
                                                    density=True)
axes[0].set_xlabel("Departure Delay")
```