Lecture 2
Relationships between Categorical Variables

1 Review

2 Two (or More) Categorical Variables

3 Proportions and Probabilities

4 Joint and Conditional Distributions

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2 Two (or More) Categorical Variables

3 Proportions and Probabilities

4 Joint and Conditional Distributions

Types of Data

Type	On Disk	In Python
tabular		

Types of Data

Type	On Disk	In Python
tabular	CSV	

Types of Data

Type	On Disk	In Python
tabular	CSV	DataFrame

Types of Data

Type	On Disk	In Python
tabular	CSV	DataFrame
hierarchical		

Types of Data

Type	On Disk	In Python
tabular	CSV	DataFrame
hierarchical	JSON	

Types of Data

Type	On Disk	In Python
tabular	CSV	DataFrame
hierarchical	JSON	dict

```
{
  "name": "Alice",
  "age": 28,
  "married": false,
  "children": null,
  "scores": [90, 85, 88],
  "address": {
    "city": "London",
    "zip": 12345
  }
}
```

Types of Data

Type	On Disk	In Python
tabular	CSV	`DataFrame`
hierarchical	JSON	`dict`
textual		

Types of Data

Type	On Disk	In Python
tabular	CSV	`DataFrame`
hierarchical	JSON	`dict`
textual	plaintext	

Types of Data

Type	On Disk	In Python
tabular	CSV	`DataFrame`
hierarchical	JSON	`dict`
textual	plaintext	`string`

Types of Data

Type	On Disk	In Python
tabular	CSV	DataFrame
~~hierarchical~~	~~JSON~~	~~dict~~
textual	plaintext	string
geospatial	???	???

```
{
  "type": "Feature",
  "geometry": {
    "type": "Point",
    "coordinates": [-0.1276, 51.5072]
  },
  "properties": {
    "name": "London",
    "country": "United Kingdom",
    "population": "8,982,000"
  }
}
```

- **Vector data:** `.shp`, `.geojson`, `.kml`, `.gpx`, `.gpkg`
- **Raster data:** `.tif`, `.img`, `.asc`
- **Databases / Mixed:** `.gdb`, `.gpkg`

Example for geojson file.

Types of Variables

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

`pd.read_json("file.json")` or `json.load()`

pandas / json

Types of Variables

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

	name	pclass	survived	sex	age	sibsp	parch	ticket	fare	cabin	embarked	boat	body	home.dest
0	Allen, Miss. Elisabeth Walton	1	1	female	29.0000	0	0	24160	211.3375	B5	S	2	NaN	St Louis, MO
1	Allison, Master. Hudson Trevor	1	1	male	0.9167	1	2	113781	151.5500	C22 C26	S	11	NaN	Montreal, PQ / Chesterville, ON
2	Allison, Miss. Helen Loraine	1	0	female	2.0000	1	2	113781	151.5500	C22 C26	S	NaN	NaN	Montreal, PQ / Chesterville, ON
3	Allison, Mr. Hudson Joshua Creighton	1	0	male	30.0000	1	2	113781	151.5500	C22 C26	S	NaN	135.0	Montreal, PQ / Chesterville, ON
4	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	1	0	female	25.0000	1	2	113781	151.5500	C22 C26	S	NaN	NaN	Montreal, PQ / Chesterville, ON
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1304	Zabour, Miss. Hileni	3	0	female	14.5000	1	0	2665	14.4542	NaN	C	NaN	328.0	NaN
1305	Zabour, Miss. Thamine	3	0	female	NaN	1	0	2665	14.4542	NaN	C	NaN	NaN	NaN
1306	Zakarian, Mr. Mapriededer	3	0	male	26.5000	0	0	2656	7.2250	NaN	C	NaN	304.0	NaN
1307	Zakarian, Mr. Ortin	3	0	male	27.0000	0	0	2670	7.2250	NaN	C	NaN	NaN	NaN
1308	Zimmerman, Mr. Leo	3	0	male	29.0000	0	0	315082	7.8750	NaN	S	NaN	NaN	NaN

1309 rows × 14 columns

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variables

observational units

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...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
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1309 rows × 14 columns

quantitative variables

categorical variables

One Categorical Variable

To *summarize* a categorical variable, we report the **counts** of each possible category.

```
df["pclass"].value_counts().sort_index()
```

```
1    323
2    277
3    709
Name: pclass, dtype: int64
```

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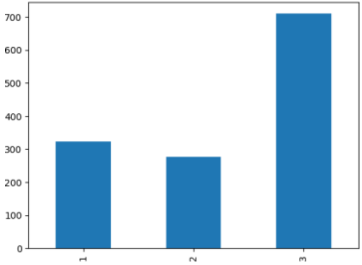
3     709
Name: pclass, dtype: int64
```

To *visualize* a categorical variable, we make a **bar plot**.

```
df["pclass"].value_counts().sort_index().plot.bar()
```



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Selecting Columns

Note that we selected a single column by passing the column name as a key to the DataFrame.

```
df["pclass"]
```

```
0       1
1       1
2       1
       ..
1306    3
1307    3
1308    3
Name: pclass, Length: 1309, dtype: int64
```

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df["pclass"]
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0        1
1        1
2        1
        ..
1306     3
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The result is a one-dimensional `pandas` object called a `Series`.

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df[["pclass", "survived"]]
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0       1
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Name: pclass, Length: 1309, dtype: int64
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```
df[["pclass", "survived"]]
```

	pclass	survived
0	1	1
1	1	1
2	1	0
3	1	0
4	1	0
...	...	...
1304	3	0
1305	3	0
1306	3	0
1307	3	0
1308	3	0

1309 rows × 2 columns

The result is two-dimensional, another smaller DataFrame.

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df["pclass"]
```

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0       1
1       1
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Name: pclass, Length: 1309, dtype: int64
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```
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```

	pclass	survived
0	1	1
1	1	1
2	1	0
3	1	0
4	1	0
...	...	...
1304	3	0
1305	3	0
1306	3	0
1307	3	0
1308	3	0

1309 rows × 2 columns

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How do we make sense of multiple variables at once?

Summarizing Multiple Categorical Variables

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```
pclass  survived
3       0           528
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3       1           181
2       0           158
1       0           123
2       1           119
dtype: int64
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pclass  survived
3       0           528
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1       0           123
2       1           119
dtype: int64
```

Note that the result is a `Series`, with a multi-level index, one for each variable!

Summarizing Multiple Categorical Variables

```
pclass    survived
3         0           528
1         1           200
3         1           181
2         0           158
1         0           123
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Let's make this information easier to read by arranging one variable along the rows and the other along the columns.

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```
(df[["pclass", "survived"]].value_counts().
 unstack())
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survived	0	1
pclass		
1	123	200
2	158	119
3	528	181

Summarizing Multiple Categorical Variables

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This representation is called a **two-way table** or a **crosstab** (short for "cross-tabulation").

Visualizing Multiple Categorical Variables

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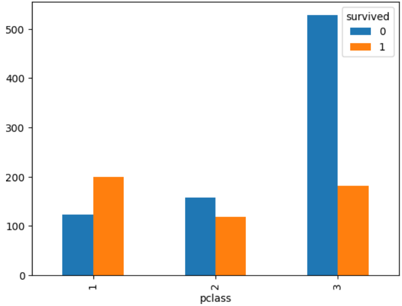

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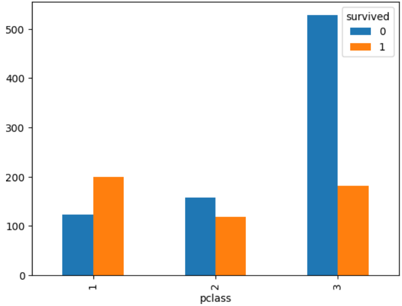

This is called a **grouped bar plot**.

Marginal Counts

How do we recover the counts for each individual variable from a crosstab?

```
crosstab = df[["pclass", "survived"]].value_counts().unstack()
crosstab
```

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We could sum over the columns (across each row) to obtain the counts for **pclass**...

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crosstab.sum(axis="columns")
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...or sum over the rows (down each column) to obtain the counts for **survived**.

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```

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survived
0     809
1     500
dtype:  int64
```

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Notice that the values in a distribution add up to 1.0!

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- One interpretation is as a **probability**.
- “If we were to pick a passenger on the Titanic at random, the probability that they are in 3rd class is 0.541635.”

- We notate this as
  - $P(\text{3rd class}) = 0.541635$
- or, if we want to be explicit about the variable and the category,
  - $P(\textbf{pclass} = 3) = 0.541635$

Vectorization

Let's take a closer look at the code for calculating the proportions.

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Vectors in pandas work like vectors in math!

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Math Review

To multiply a vector

$$\vec{v} = (v_1, v_2, \ldots, v_n)$$

by a scalar (a.k.a. number) a,

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by a scalar (a.k.a. number) a,

$$a\vec{v} = (av_1, av_2, \ldots, av_n),$$

we multiply each component of the vector by a.

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2 Two (or More) Categorical Variables

3 Proportions and Probabilities

4 Joint and Conditional Distributions

Joint Distributions

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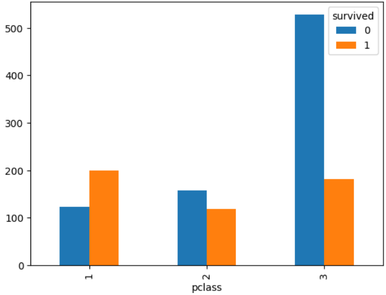
Notice that the values in the joint distribution also sum to 1.0!

Visualizing Joint Distributions



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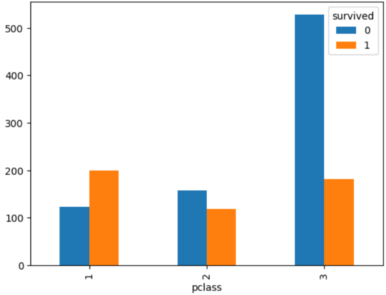

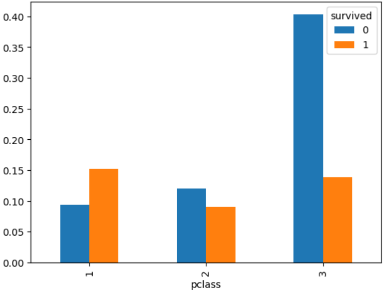

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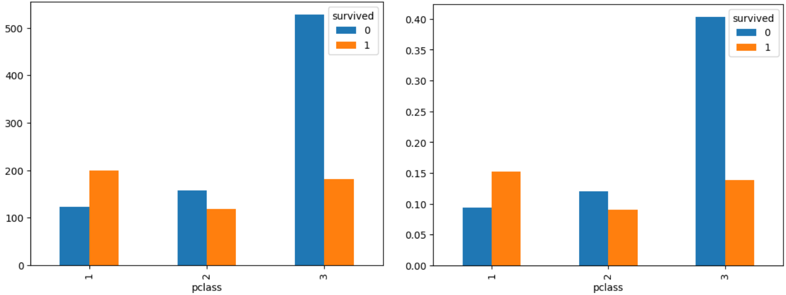

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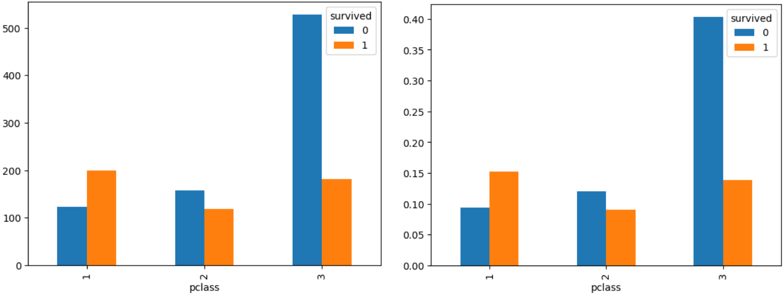

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To appreciate the power of proportions, we need to look at conditional distributions.

Conditional Distributions

To compare survival across the classes, we should normalize by the total in each class.

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These are the **conditional distributions** of `survived` given `pclass`.

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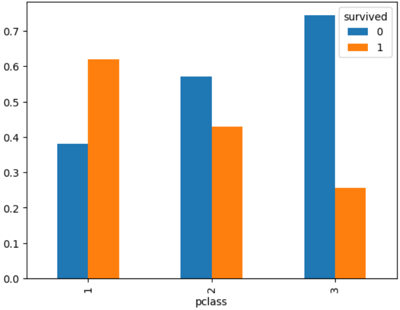

Visualizing Conditional Distributions

To visualize a conditional distribution, we could make a grouped bar plot...

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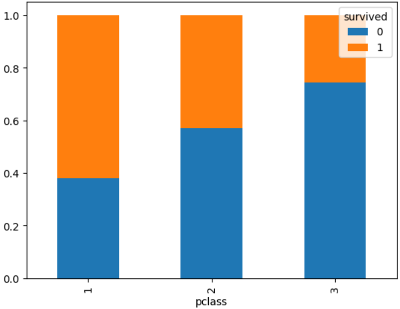
(crosstab.divide(pclass_marginal, axis="rows").
 plot.bar(stacked=True))
```



...but it is better to make a **stacked bar plot**.

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