## Course introduction

**WORKING WITH CATEGORICAL DATA IN PYTHON** 



Kasey Jones
Research Data Scientist



## What does it mean to be "categorical"?

#### Categorical

- Finite number of groups (or categories)
- These categories are usually fixed or known (eye color, hair color, etc.)
- Known as qualitative data

#### Numerical

- Known as quantitative data
- Expressed using a numerical value
- Is usually a measurement (height, weight, IQ, etc.)

#### Ordinal vs. nominal variables

#### Ordinal

Categorical variables that have a natural order

Strongly Disagree Disagree Neutral Agree Strongly Agree

1 2 3 4 5

#### Nominal

Categorical variables that cannot be placed into a natural order

Blue Green Red Yellow Purple

#### Our first dataset

```
adult.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
    Column
                     Non-Null Count Dtype
                     32561 non-null int64
    Age
    Workclass
                     32561 non-null
                                     object
    fnlgwt
                     32561 non-null int64
    Education
                     32561 non-null object
    Education Num
                     32561 non-null int64
                     32561 non-null object
    Marital Status
```

<sup>&</sup>lt;sup>1</sup> https://www.kaggle.com/uciml/adult-census-income



### Using describe

```
adult["Marital Status"].describe()
```

```
count 32561
unique 7
top Married-civ-spouse
freq 14976
Name: Marital Status, dtype: object
```

## Using value counts

adult["Marital Status"].value\_counts()

```
Married-civ-spouse 14976
Never-married 10683
Divorced 4443
Separated 1025
Widowed 993
Married-spouse-absent 418
Married-AF-spouse 23
Name: Marital Status, dtype: int64
```



## Using value counts with normalize

```
adult["Marital Status"].value_counts(normalize=True)
```

```
Married-civ-spouse 0.459937

Never-married 0.328092

Divorced 0.136452

Separated 0.031479

Widowed 0.030497

Married-spouse-absent 0.012837

Married-AF-spouse 0.000706

Name: Marital Status, dtype: float64
```

## Knowledge check

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## Categorical data in pandas

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#### dtypes: object

```
adult = pd.read_csv("data/adult.csv")
adult.dtypes
```

```
Age
                    int64
Workclass
                   object
fnlgwt
                    int64
Education
                   object
Education Num
                    int64
Marital Status
                   object
Occupation
                   object
Relationship
                   object
```

## dtypes: categorical

#### Default dtype:

```
adult["Marital Status"].dtype
```

```
dtype('0')
```

#### Set as categorical:

```
adult["Marital Status"] = adult["Marital Status"].astype("category")
adult["Marital Status"].dtype
```

```
CategoricalDtype(categories=[' Divorced', ' Married-AF-spouse',
' Married-civ-spouse', ' Married-spouse-absent', ' Never-married',
' Separated', ' Widowed'], ordered=False)
```



#### Creating a categorical Series

```
my_data = ["A", "A", "C", "B", "C", "A"]

my_series1 = pd.Series(my_data, dtype="category")
print(my_series1)

0     A
1     A
```

```
1 A
2 C
...
dtype: category
Categories (3, object): [A, B, C]
```

## Creating a categorical Series

```
my_data = ["A", "A", "C", "B", "C", "A"]
my_series2 = pd.Categorical(my_data, categories=["C", "B", "A"], ordered=True)
my_series2
```

```
[A, A, C, B, C, A]
Categories (3, object): [C < B < A]
```

### Why do we use categorical: memory

Memory saver:

```
adult = pd.read_csv("data/adult.csv")
adult["Marital Status"].nbytes
```

#### 260488

```
adult["Marital Status"] = adult["Marital Status"].astype("category")
adult["Marital Status"].nbytes
```

32617

## Specify dtypes when reading data

1. Create a dictionary:

```
adult_dtypes = {"Marital Status": "category"}
```

2. Set the dtype parameter:

```
adult = pd.read_csv("data/adult.csv", dtype=adult_dtypes)
```

3. Check the dtype:

```
adult["Marital Status"].dtype
```

```
CategoricalDtype(categories=[' Divorced', ' Married-AF-spouse',
..., ' Widowed'], ordered=False)
```

## pandas category practice

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## Grouping data by category in pandas

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## The basics of .groupby(): splitting data

```
adult = pd.read_csv("data/adult.csv")
adult1 = adult[adult["Above/Below 50k"] == " <=50K"]
adult2 = adult[adult["Above/Below 50k"] == " >50K"]
```

is replaced by

```
groupby_object = adult.groupby(by=["Above/Below 50k"])
```

## The basics of .groupby(): apply a function

```
groupby_object = adult.groupby(by=["Above/Below 50k"])
```

#### Apply a function:

```
groupby_object.mean()
```

```
Age fnlgwt Education Num Capital Gain ...

Above/Below 50k
<=50K 36.783738 190340.86517 9.595065 148.752468 ...

>50K 44.249841 188005.00000 11.611657 4006.142456 ...
```

#### One liner:

```
adult.groupby(by=["Above/Below 50k"]).mean()
```



### Specifying columns

Option 1: only runs .sum() on two columns.

```
adult.groupby(by=["Above/Below 50k"])['Age', 'Education Num'].sum()
```

```
Age Education Num
Above/Below 50k
<=50K 909294 237190
>50K 346963 91047
```

Option 2: runs .sum() on all numeric columns and then subsets.

```
adult.groupby(by=["Above/Below 50k"]).sum()[['Age', 'Education Num']]
```

Option 1 is preferred - especially when using large datasets



## Groupby multiple columns

```
adult.groupby(by=["Above/Below 50k", "Marital Status"]).size()
```

Above/Below 50k	Marital Status	
<=50K	Divorced	3980
	Married-AF-spouse	13
	Married-civ-spouse	8284
	Married-spouse-absent	384
	Never-married	10192
	Separated	959
	Widowed	908
>50K	Divorced	463
	Married-AF-spouse	10 < Only 10 records
	Married-civ-spouse	6692
•••		



# Practice using .group()

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