# Analyzing Categorical Data

In this project, we'll be working with categorical data and will be using a subset of data from the following data set: (https://www.kaggle.com/datasets/norc/general-social-survey?select=gss.csv).

After cleaning the data, we will use some visualizations tools. We also had used statsmodels for a special type of categorical plot.

In [3]:
```
# Import packages
import pandas as pd
import numpy as np
import plotly.express as px
import matplotlib.pyplot as plt
from statsmodels.graphics.mosaicplot import mosaic

# Read in csv as a DataFrame and preview it
df = pd.read_csv("/Users/antoniogondim/Downloads/gss_sub.csv")
df
```

Out[3]:

| | year | id | labor_status | self_employed | marital_status | n_siblings | age | high_scho |
|---|---|---|---|---|---|---|---|---|
| **0** | 1972.0 | 1.0 | WORKING FULLTIME | SOMEONE ELSE | NEVER MARRIED | 3.0 | 23.0 | 16 |
| **1** | 1972.0 | 2.0 | RETIRED | SOMEONE ELSE | MARRIED | 4.0 | 70.0 | 10 |
| **2** | 1972.0 | 3.0 | WORKING PARTTIME | SOMEONE ELSE | MARRIED | 5.0 | 48.0 | 12 |
| **3** | 1972.0 | 4.0 | WORKING FULLTIME | SOMEONE ELSE | MARRIED | 5.0 | 27.0 | 1 |
| **4** | 1972.0 | 5.0 | KEEPING HOUSE | SOMEONE ELSE | MARRIED | 2.0 | 61.0 | 12 |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **59594** | 2014.0 | 2539.0 | KEEPING HOUSE | SOMEONE ELSE | WIDOWED | 6.0 | 89.0 | 14 |
| **59595** | 2014.0 | 2540.0 | WORKING FULLTIME | SOMEONE ELSE | DIVORCED | 3.0 | 56.0 | 12 |
| **59596** | 2014.0 | 2541.0 | WORKING FULLTIME | SOMEONE ELSE | NEVER MARRIED | 5.0 | 24.0 | 14 |
| **59597** | 2014.0 | 2542.0 | WORKING FULLTIME | SOMEONE ELSE | NEVER MARRIED | 2.0 | 27.0 | 13 |
| **59598** | 2014.0 | 2543.0 | WORKING PARTTIME | SOMEONE ELSE | WIDOWED | 2.0 | 71.0 | 12 |

59599 rows × 16 columns

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59599 entries, 0 to 59598
Data columns (total 16 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   year                   59599 non-null  float64
 1   id                     59599 non-null  float64
 2   labor_status           59583 non-null  object 
 3   self_employed          59306 non-null  object 
 4   marital_status         59575 non-null  object 
 5   n_siblings             56682 non-null  float64
 6   age                    59599 non-null  float64
 7   high_school            59440 non-null  float64
 8   degree                 59464 non-null  object 
 9   political_affiliation  59257 non-null  object 
 10  environment            59388 non-null  object 
 11  law_enforcement        59378 non-null  object 
 12  drugs                  59380 non-null  object 
 13  space_exploration      59596 non-null  object 
 14  inequality             1532 non-null   float64
 15  household_size         59599 non-null  float64
dtypes: float64(7), object(9)
memory usage: 7.3+ MB
```

In [5]:

```
df=df.drop('inequality', axis=1)
#Too many null values at this column
df.isnull().sum()
```

Out[5]:

```
year                        0
id                          0
labor_status               16
self_employed             293
marital_status             24
n_siblings               2917
age                         0
high_school               159
degree                    135
political_affiliation     342
environment               211
law_enforcement           221
drugs                     219
space_exploration           3
household_size              0
dtype: int64
```

In [6]:

```
df['n_siblings'].value_counts()
```

Out[6]:
```
 2.0     10717
 1.0      9602
 3.0      9109
 4.0      6705
 5.0      4860
 6.0      3688
 7.0      3168
 8.0      2075
 9.0      1536
-1.0      1518
 10.0     1066
 11.0      826
 12.0      550
 13.0      370
 14.0      213
 15.0      144
 99.0      111
 16.0      105
 98.0       57
 17.0       48
 21.0       46
 18.0       41
 20.0       29
 19.0       25
 22.0       15
 23.0       14
 25.0        6
 27.0        6
 26.0        6
 31.0        6
 24.0        5
 30.0        4
 33.0        2
 32.0        2
 29.0        2
 68.0        1
 35.0        1
 34.0        1
 37.0        1
 55.0        1
Name: n_siblings, dtype: int64
```

In [7]:
```
df.n_siblings.replace(np.nan,int(2.0), inplace=True)
```

In [8]:
```
df.shape
```

Out[8]:
```
(59599, 15)
```

In [9]:
```
df=df.dropna()
df.shape
```

Out[9]:
```
(58439, 15)
```

Above we see that our DataFrame contains `float64` column (numerical data), as well as a number of `object` columns, i.e object data types contain strings.

df.describe() method with the `include` parameter to select a particular DataType (in this case `"O"`). This returns the count, number of unique values, the mode, and frequency of the mode for each column having object as data type.

In [10]:
```
df.describe(include="O")
```

Out[10]:

| | labor_status | self_employed | marital_status | degree | political_affiliation | environment |
|---|---|---|---|---|---|---|
| **count** | 58439 | 58439 | 58439 | 58439 | 58439 | 58439 |
| **unique** | 8 | 4 | 5 | 6 | 9 | 5 |
| **top** | WORKING FULLTIME | SOMEONE ELSE | MARRIED | HIGH SCHOOL | NOT STR DEMOCRAT | IAP |
| **freq** | 28960 | 48809 | 31376 | 30124 | 12272 | 37576 |

In [11]:
```
df["environment"].value_counts()
```

Out[11]:
```
IAP             37576
TOO LITTLE      12971
ABOUT RIGHT      5351
TOO MUCH         1660
DK                881
Name: environment, dtype: int64
```

# Manipulating categorical data

- The categorical variable type can be useful, especially here:
  - It is possible to specify a precise order to the categories when the default order may be incorrect (e.g., via alphabetical).
  - Can be compatible with other Python libraries.

Let's take our existing categorical variables and convert them from strings to categories. Here, we use `.select_dtypes()` to return only object columns, and with a dictionary set their type to be a category.

In [13]:
```
# Create a dictionary of column and data type mappings
conversion_dict = {k: "category" for k in df.select_dtypes(include="object").co

# Convert our DataFrame and check the data types
df = df.astype(conversion_dict)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 58439 entries, 0 to 59598
Data columns (total 15 columns):
 #   Column                 Non-Null Count  Dtype   
---  ------                 --------------  -----   
 0   year                   58439 non-null  float64 
 1   id                     58439 non-null  float64 
 2   labor_status           58439 non-null  category
 3   self_employed          58439 non-null  category
 4   marital_status         58439 non-null  category
 5   n_siblings             58439 non-null  float64 
 6   age                    58439 non-null  float64 
 7   high_school            58439 non-null  float64 
 8   degree                 58439 non-null  category
 9   political_affiliation  58439 non-null  category
 10  environment            58439 non-null  category
 11  law_enforcement        58439 non-null  category
 12  drugs                  58439 non-null  category
 13  space_exploration      58439 non-null  category
 14  household_size         58439 non-null  float64 
dtypes: category(9), float64(6)
memory usage: 3.6 MB
```

Already we can see that the memory usage of the DataFrame has been halved from 7 mb to about 4 mb, optmizing the data.

## Cleaning up the `labor_status` column

To analyze the relationship between employment and attitudes over time, we need to clean up the `labor_status` column. We can preview the existing categories using `.categories`.

In [14]:
```
df["labor_status"].values
```

Out[14]:
```
['WORKING FULLTIME', 'RETIRED', 'WORKING PARTTIME', 'WORKING FULLTIME', 'KEEPI
NG HOUSE', ..., 'KEEPING HOUSE', 'WORKING FULLTIME', 'WORKING FULLTIME', 'WORK
ING FULLTIME', 'WORKING PARTTIME']
Length: 58439
Categories (8, object): ['KEEPING HOUSE', 'OTHER', 'RETIRED', 'SCHOOL', 'TEMP
NOT WORKING', 'UNEMPL, LAID OFF', 'WORKING FULLTIME', 'WORKING PARTTIME']
```

In [15]:
```
df["labor_status"].value_counts()
```

Out[15]:
```
WORKING FULLTIME    28960
KEEPING HOUSE        9478
RETIRED              7861
WORKING PARTTIME     6012
UNEMPL, LAID OFF     1920
SCHOOL               1807
TEMP NOT WORKING     1240
OTHER                1161
Name: labor_status, dtype: int64
```

Let's collapse some of these categories. The easiest way to do this is to replace the values inside the column using a dictionary, and then reset the data type back to a category.

In [16]:
```
# Create a dictionary of categories to collapse
new_labor_status = {"UNEMPL, LAID OFF": "UNEMPLOYED",
                    "TEMP NOT WORKING": "UNEMPLOYED",
                    "WORKING FULLTIME": "EMPLOYED",
                    "WORKING PARTTIME": "EMPLOYED"
                   }

# Replace the values in the column and reset as a category
df["labor_status_clean"] = df["labor_status"].replace(new_labor_status).astype(
print(df.dtypes)
# Preview the new column
df["labor_status_clean"].value_counts()
```

```
year                      float64
id                        float64
labor_status             category
self_employed            category
marital_status           category
n_siblings                float64
age                       float64
high_school               float64
degree                   category
political_affiliation    category
environment              category
law_enforcement          category
drugs                    category
space_exploration        category
household_size            float64
labor_status_clean       category
dtype: object
```

Out[16]:
```
EMPLOYED         34972
KEEPING HOUSE     9478
RETIRED           7861
UNEMPLOYED        3160
SCHOOL            1807
OTHER             1161
Name: labor_status_clean, dtype: int64
```

## Reordering categories

In [17]:
```
df["environment"].values
```

Out[17]:
```
['IAP', 'IAP', 'IAP', 'IAP', 'IAP', ..., 'TOO LITTLE', 'TOO LITTLE', 'TOO LITT
LE', 'IAP', 'IAP']
Length: 58439
Categories (5, object): ['ABOUT RIGHT', 'DK', 'IAP', 'TOO LITTLE', 'TOO MUCH']
```

In [21]:
```
# Set the new order
new_order = ["TOO LITTLE", "ABOUT RIGHT", "TOO MUCH", "DK", "IAP"]
categories_to_remove = ["DK", "IAP"]

# Loop through each column
for col in ["environment", "law_enforcement", "drugs"]:
    # Reorder and remove the categories
    df[col + "_clean"] = df[col].cat.reorder_categories(new_order, ordered=True
    df[col + "_clean"] = df[col + "_clean"].cat.remove_categories(categories_tc

# Preview one of the columns' categories
df["environment_clean"].cat.categories
```

Out[21]:
```
Index(['TOO LITTLE', 'ABOUT RIGHT', 'TOO MUCH'], dtype='object')
```

Now let's also apply these steps to education level in one go: collapsing, removing, and reording.

In [22]:
```
df['degree'].values #let's reorder that and remove 'DK'
```

Out[22]:
```
['BACHELOR', 'LT HIGH SCHOOL', 'HIGH SCHOOL', 'BACHELOR', 'HIGH SCHOOL', ...,
'JUNIOR COLLEGE', 'HIGH SCHOOL', 'HIGH SCHOOL', 'HIGH SCHOOL', 'HIGH SCHOOL']
Length: 58439
Categories (6, object): ['BACHELOR', 'DK', 'GRADUATE', 'HIGH SCHOOL', 'JUNIOR
COLLEGE', 'LT HIGH SCHOOL']
```

In [23]:
```
# Define a dictionary to map old degree categories to new ones
new_degree = {"LT HIGH SCHOOL": "HIGH SCHOOL",
              "BACHELOR": "COLLEGE/UNIVERSITY",
              "GRADUATE": "COLLEGE/UNIVERSITY",
              "JUNIOR COLLEGE": "COLLEGE/UNIVERSITY"}

# Replace old degree categories with new ones and convert to categorical data t
df["degree_clean"] = df["degree"].replace(new_degree).astype("category")

# Remove "DK" category from degree_clean column
df["degree_clean"] = df["degree_clean"].cat.remove_categories(["DK"])

# Reorder degree_clean categories and set as ordered
df["degree_clean"] = df["degree_clean"].cat.reorder_categories(["HIGH SCHOOL",

# Preview the new column
df["degree_clean"].value_counts()
```

Out[23]:
```
HIGH SCHOOL           42756
COLLEGE/UNIVERSITY    15660
Name: degree_clean, dtype: int64
```

By `IntervalIndex` we set cutoff ranges for the `year`. We then use `pd.cut()` to cut our `year` column by these ranges, and set labels for each range.

In [27]:
```
decade_boundaries = [(1970, 1979),(1979,1989) , (1989, 1999), (1999, 2009), (20
# Set the bins and cut the DataFrame

bins = pd.IntervalIndex.from_tuples(decade_boundaries)#this method returns an a

decade_labels = {bins[0]:'1970s',
                 bins[1]: '1980s',
                 bins[2]:'1990s',
                 bins[3]:'2000s',
                bins[4]:'2010s'}


print(bins)
df["decade"] = pd.cut(df["year"], bins)#creates a new column based on the year
print(df['decade'].values, df['decade'].dtypes)

# Rename each of the intervals of decade_boundaries as the decades on decade_la
df['decade']=df["decade"].replace(decade_labels)#.astype('category')
```

```
# Preview the new column
df[['year','decade']]
```

```
IntervalIndex([(1970, 1979], (1979, 1989], (1989, 1999], (1999, 2009], (2009, 
2019]], dtype='interval[int64, right]')
[(1970, 1979], (1970, 1979], (1970, 1979], (1970, 1979], (1970, 1979], ..., (2
009, 2019], (2009, 2019], (2009, 2019], (2009, 2019], (2009, 2019]]
Length: 58439
Categories (5, interval[int64, right]): [(1970, 1979] < (1979, 1989] < (1989, 
1999] < (1999, 2009] < (2009, 2019]] category
```

Out[27]:

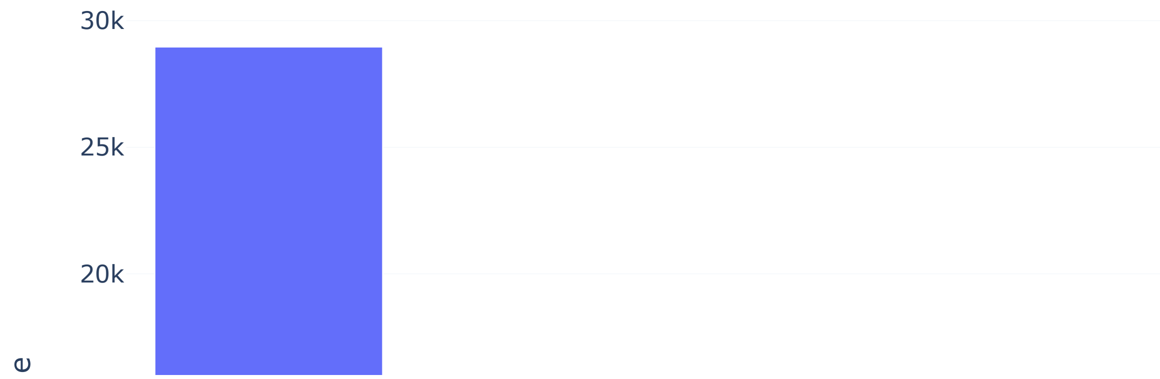
| | year | decade |
|---|---|---|
| **0** | 1972.0 | 1970s |
| **1** | 1972.0 | 1970s |
| **2** | 1972.0 | 1970s |
| **3** | 1972.0 | 1970s |
| **4** | 1972.0 | 1970s |
| **...** | ... | ... |
| **59594** | 2014.0 | 2010s |
| **59595** | 2014.0 | 2010s |
| **59596** | 2014.0 | 2010s |
| **59597** | 2014.0 | 2010s |
| **59598** | 2014.0 | 2010s |

58439 rows × 2 columns

# Visualization

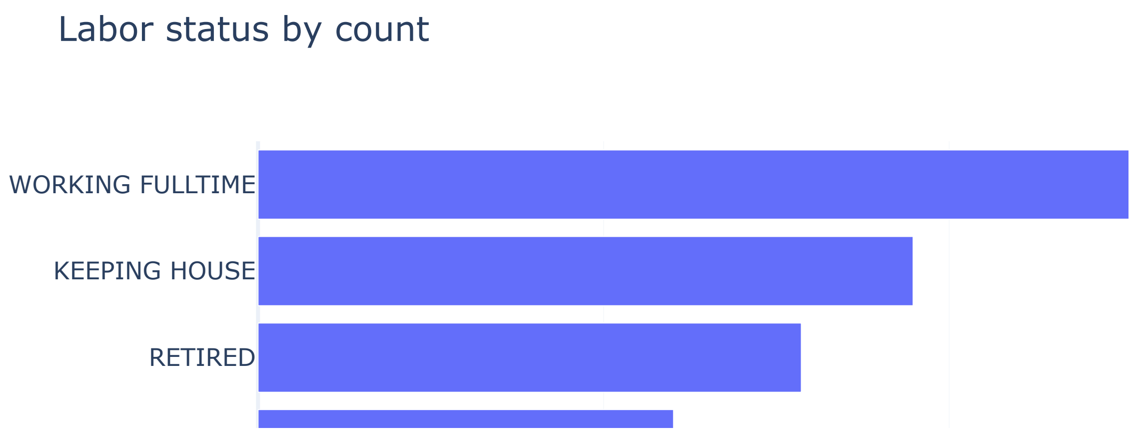
In [28]:

```
# Create a new figure object
fig = px.bar(df["labor_status"].value_counts(),
             template="plotly_white"
            )

# Hide the legend and show the plot
fig.update_layout(showlegend=False)
fig.show()
```




Let's change the orientation of the plot and add a title, for a better perspective.

In [96]:
```
# Create a new figure object
fig = px.bar(df["labor_status"].value_counts(ascending=True),
             template="plotly_white",
             orientation="h",
             title="Labor status by count"
            )

# Hide the legend and show the plot
fig.update_layout(showlegend=False)
fig.show()
```




## Bar charts

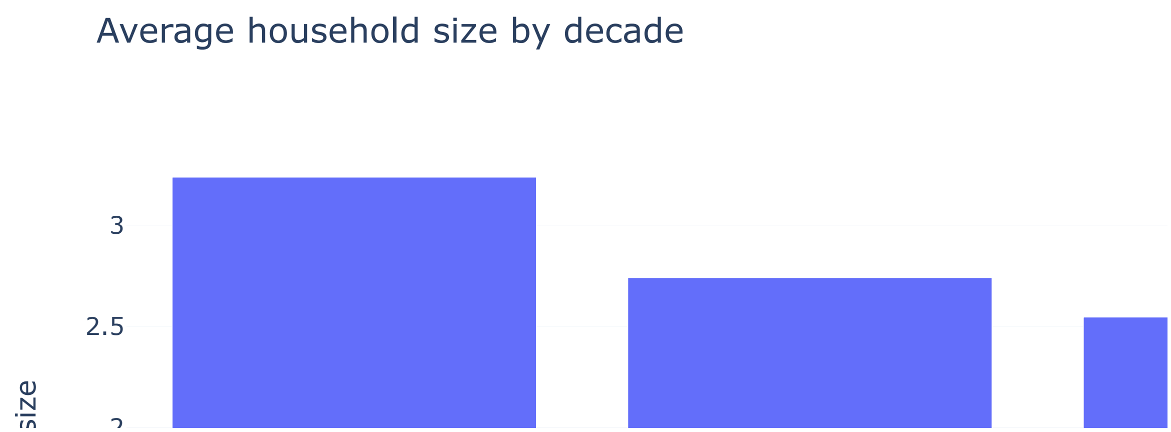
In [97]:
```
## Aggregate household size by year
household_by_decade = df.groupby("decade",as_index=False)["household_size"].mea
household_by_decade
```

Out[97]:

| | decade | household_size |
|---|---|---|
| 0 | 1970s | 3.238023 |
| 1 | 1980s | 2.741394 |
| 2 | 1990s | 2.546036 |
| 3 | 2000s | 2.464682 |
| 4 | 2010s | 2.411328 |

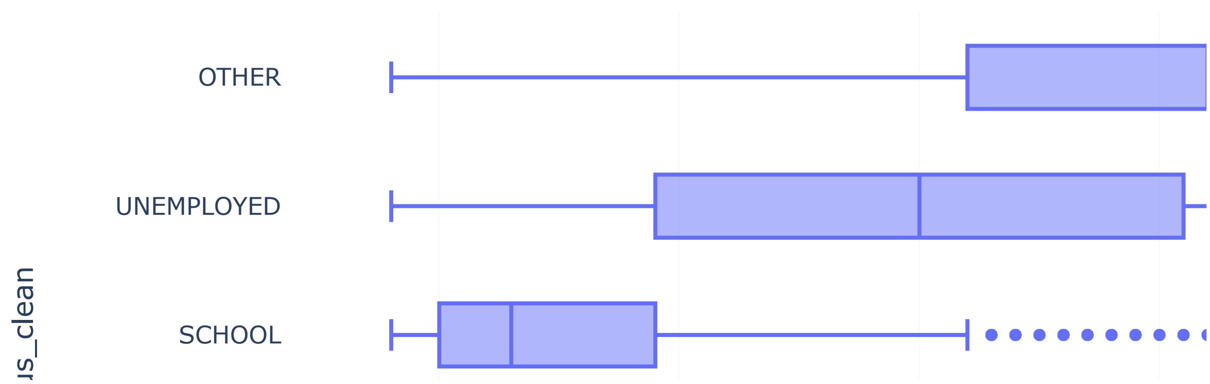
In [98]:
```
# Create a new figure object
fig = px.bar(household_by_decade,
             x="decade",
             y="household_size",
             template="plotly_white",
             title="Average household size by decade"
            )
```

```
fig.show()
```




## Boxplots

In [99]:
```
# Create a new figure object
fig = px.box(df,
             x="age",
             y="labor_status_clean",
             template="plotly_white"
            )

fig.show()
```




## Mosaic plots

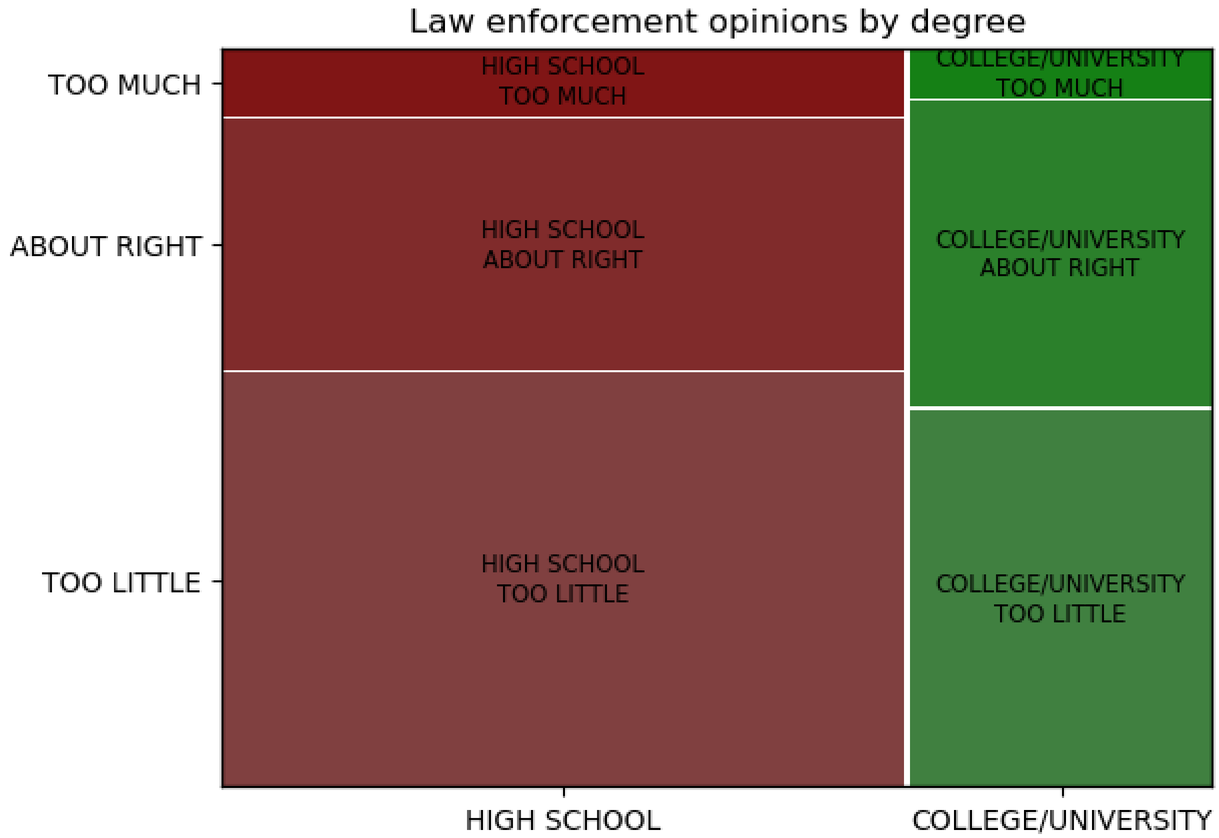
visualize the relationship between two categorical variables. One way to do this is a frequency table, which will give the counts across the different combinations of the two variables. create a frequency table using `pd.crosstab()`

In [100…
```
pd.crosstab(df["degree_clean"], df["law_enforcement_clean"])
```

Out[100]:

| law_enforcement_clean | TOO LITTLE | ABOUT RIGHT | TOO MUCH |
|---|---|---|---|
| **degree_clean** | | | |
| **HIGH SCHOOL** | 7937 | 4799 | 1309 |
| **COLLEGE/UNIVERSITY** | 3193 | 2598 | 422 |

In [101…
```
# Create a mosaic plot and show it
mosaic(df,
       ['degree_clean', 'law_enforcement_clean'],
       title='Law enforcement opinions by degree')

plt.show()
```




## Line charts

The final plot type we will cover is a line plot. Line plots often (but not always!) show the relationship between time and a numerical variable. Adding in a categorical variable can be a great way to enrich a line plot and provide other information.

Here, we use the `.value_counts()` method as an aggregation function, and use this in combination with a Plotly `line_plot()` to visualize the trend in marital statuses over the years.

In [102…

```
# Group the dataframe by year and marital status, and calculate the normalized
marital_rates = df.groupby(["year"], as_index=False)["marital_status"].value_cc

# Display the resulting DataFrame
marital_rates
```

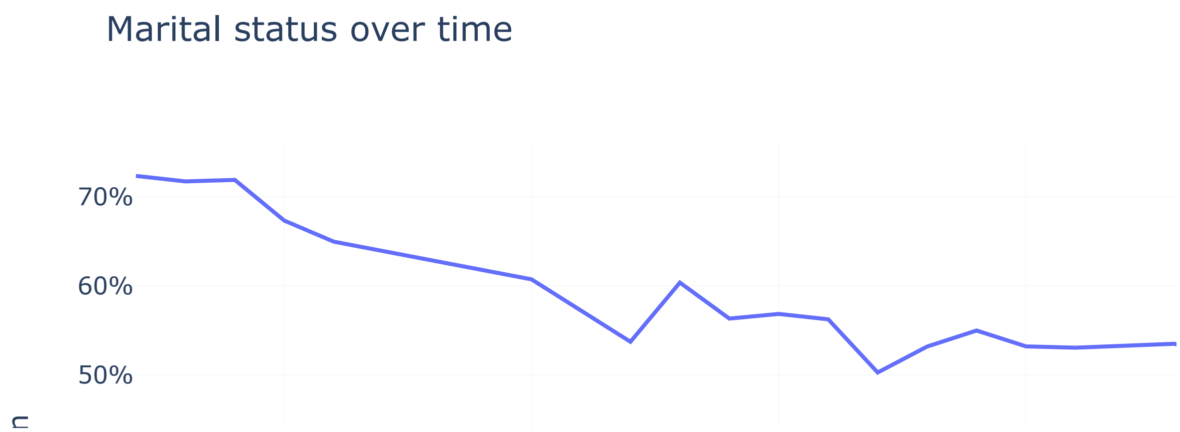
Out[102]:

| | year | marital_status | proportion |
|---|---|---|---|
| **0** | 1972.0 | MARRIED | 0.723391 |
| **1** | 1972.0 | NEVER MARRIED | 0.128744 |
| **2** | 1972.0 | WIDOWED | 0.084130 |
| **3** | 1972.0 | DIVORCED | 0.039516 |
| **4** | 1972.0 | SEPARATED | 0.024219 |
| **...** | ... | ... | ... |
| **145** | 2014.0 | MARRIED | 0.458918 |
| **146** | 2014.0 | NEVER MARRIED | 0.265331 |
| **147** | 2014.0 | DIVORCED | 0.163126 |
| **148** | 2014.0 | WIDOWED | 0.081363 |
| **149** | 2014.0 | SEPARATED | 0.031263 |

150 rows × 3 columns

In [103…

```
# Create a new figure object
fig = px.line(marital_rates,
              x="year",
              y="proportion",
              color="marital_status",
              template="plotly_white",
              title="Marital status over time"
             )

# Update the y-axis to show percentages
fig.update_yaxes(tickformat=".0%")

# Show the plot
fig.show()
```




In [ ]:

In [ ]: