Module 6: Data types and tidy data

Tidy data

Let's do some tidy exercise first. This is one of the non-tidy dataset assembled by Hadley Wickham (check out here (https://github.com/tidyverse/tidyr/tree/master/vignettes) for more datasets, explanation, and R code).

Let's take a look at this small dataset: https://raw.githubusercontent.com/tidyverse/tidyr/master/vignettes/pew.csv (https://raw.githubusercontent.com/tidyverse/tidyr/master/vignettes/pew.csv)

In [1]:
```
import pandas as pd
print(pd.__version__)
```

```
0.23.4
```

In [2]:
```
pew_df = pd.read_csv('https://raw.githubusercontent.com/tidyverse/tidyr/master/vignette
s/pew.csv')
pew_df
```

Out[2]:

	religion	<$10k	$10-20k	$20-30k	$30-40k	$40-50k	$50-75k	$75-100k	$100-150k	>150k	Don't know/refused
0	Agnostic	27	34	60	81	76	137	122	109	84	96
1	Atheist	12	27	37	52	35	70	73	59	74	76
2	Buddhist	27	21	30	34	33	58	62	39	53	54
3	Catholic	418	617	732	670	638	1116	949	792	633	1489
4	Don’t know/refused	15	14	15	11	10	35	21	17	18	116
5	Evangelical Prot	575	869	1064	982	881	1486	949	723	414	1529
6	Hindu	1	9	7	9	11	34	47	48	54	37
7	Historically Black Prot	228	244	236	238	197	223	131	81	78	339
8	Jehovah's Witness	20	27	24	24	21	30	15	11	6	37
9	Jewish	19	19	25	25	30	95	69	87	151	162
10	Mainline Prot	289	495	619	655	651	1107	939	753	634	1328
11	Mormon	29	40	48	51	56	112	85	49	42	69
12	Muslim	6	7	9	10	9	23	16	8	6	22
13	Orthodox	13	17	23	32	32	47	38	42	46	73
14	Other Christian	9	7	11	13	13	14	18	14	12	18
15	Other Faiths	20	33	40	46	49	63	46	40	41	71
16	Other World Religions	5	2	3	4	2	7	3	4	4	8
17	Unaffiliated	217	299	374	365	341	528	407	321	258	597

This dataset is about the relationships between income and religion, assembled from a research by the Pew Research Center. You can read more details here (https://github.com/tidyverse/tidyr/blob/master/vignettes/tidy-data.Rmd#column-headers-are-values-not-variable-names). Is this dataset tidy or not? Why?

Yes, many of the columns are values, not variable names. How should we fix it?

Pandas provides a convenient function called melt (http://pandas.pydata.org/pandas-docs/stable/generated/pandas.melt.html). You specify the `id_vars` that are variable columns, and `value_vars` that are value columns, and provide the name for the variable as well as the name for the values.

Q: so please go ahead and tidy it up! I'd suggest to use the variable name "income" and value name "frequency"

In [3]:
```
# TODO: put your code here
pew_tidy_df =pd.melt(pew_df, id_vars=['religion'],
                     value_vars=['<$10k','$10-20k','$20-30k', '$30-40k', '$40-50k', '$50
-75k', '$75-100k','$100-150k','>150k','Don\'t know/refused'],
                     var_name='income',
                     value_name='frequency')
```

If you were successful, you'll have something like this:

In [4]:
```
pew_tidy_df.sample(10)
```

Out[4]:

	religion	income	frequency
3	Catholic	<$10k	418
143	Unaffiliated	$100-150k	321
121	Orthodox	$75-100k	38
2	Buddhist	<$10k	27
5	Evangelical Prot	<$10k	575
134	Jehovah's Witness	$100-150k	11
158	Other Christian	>150k	12
124	Other World Religions	$75-100k	3
151	Historically Black Prot	>150k	78
19	Atheist	$10-20k	27

Data types

Let's talk about data types briefly. Understanding data types is not only important for choosing the right visualizations, but also important for efficient computing and storage of data. You may not have thought about how pandas represent data in memory. A Pandas `Dataframe` is essentially a bunch of `Series`, and those `Series` are essentially `numpy` arrays. An array may contain a fixed-length items such as integers or variable length items such as strings. Putting some efforts to think about the correct data type can potentially save a lot of memory as well as time.

A nice example would be the categorical data type. If you have a variable that only has several possible values, it's essentially a categorical data. Take a look at the `income` variable.

In [5]:
```
pew_tidy_df.income.value_counts()
```

Out[5]:
```
$100-150k             18
$50-75k               18
$75-100k              18
>150k                 18
<$10k                 18
$10-20k               18
$40-50k               18
$30-40k               18
Don't know/refused    18
$20-30k               18
Name: income, dtype: int64
```

These were the column names in the original messy data. The value can take only one of these income ranges and thus it is a categorical data. What is the data type that pandas use to store this column?

In [6]:
```
pew_tidy_df.income.dtype
```

Out[6]:
```
dtype('O')
```

The `O` means that it is an object data type, which does not have a fixed size like integer or float. The series contains a sort of pointer to the actual text objects. You can actually inspect the amount of memory used by the dataset.

In [7]:
```
pew_tidy_df.memory_usage()
```

Out[7]:
```
Index          80
religion     1440
income       1440
frequency    1440
dtype: int64
```

In [8]:
```
pew_tidy_df.memory_usage(deep=True)
```

Out[8]:
```
Index           80
religion     12780
income       14940
frequency     1440
dtype: int64
```

What's going on with the `deep=True` option? When you don't specify `deep=True`, the memory usage method just tells you the amount of memory used by the numpy arrays in the pandas dataframe. When you pass `deep=True`, it tells you the total amount of memory by including the memory used by all the text objects. So, the `religion` and `income` columns occupies almost ten times of memory than the `frequency` column, which is simply an array of integers.

In [9]:
```
pew_tidy_df.frequency.dtype
```

Out[9]:
```
dtype('int64')
```

Is there any way to save up the memory? Note that there are only 10 categories in the income variable. That means we just need 10 numbers to represent the categories! Of course we need to store the names of each category, but that's just one-time cost. The simplest way to convert a column is using `astype` method.

In [10]:
```
income_categorical_series = pew_tidy_df.income.astype('category')
# you can do pew_tidy_df.income = pew_tidy_df.income.astype('category')
```

Now, this series has the `CategoricalDtype` dtype.

In [11]:
```
income_categorical_series.dtype
```

Out[11]:
```
CategoricalDtype(categories=['$10-20k', '$100-150k', '$20-30k', '$30-40k', '$40-50k',
                  '$50-75k', '$75-100k', '<$10k', '>150k',
                  'Don't know/refused'],
                 ordered=False)
```

How much memory do we use?

In [12]:
```
income_categorical_series.memory_usage(deep=True)
```

Out[12]:
```
1410
```

In [13]:
```
pew_tidy_df.income.memory_usage(deep=True)
```

Out[13]:
```
15020
```

We have reduced the memory usage by almost 10 fold! Not only that, because now the values are just numbers, it will be much faster to match, filter, manipulate. If your dataset is huge, this can save up a lot of space and time.

If the categories have ordering, you can specify the ordering too.

In [14]:
```
from pandas.api.types import CategoricalDtype
```

In [15]:
```
income_type = CategoricalDtype(
    categories=['Don\'t know/refused', '<$10k', '$10-20k', '$20-30k', '$30-40k','$40-50
k', '$50-75k', '$75-100k', '$100-150k', '>150k'],
    ordered=True)
income_type
```

Out[15]:
```
CategoricalDtype(categories=['Don't know/refused', '<$10k', '$10-20k', '$20-30k',
                  '$30-40k', '$40-50k', '$50-75k', '$75-100k', '$100-150k',
                  '>150k'],
                 ordered=True)
```

In [16]:
```
pew_tidy_df.income.astype(income_type).dtype
```

Out[16]:
```
CategoricalDtype(categories=['Don't know/refused', '<$10k', '$10-20k', '$20-30k',
                  '$30-40k', '$40-50k', '$50-75k', '$75-100k', '$100-150k',
                  '>150k'],
                 ordered=True)
```

This data type now allows you to compare and sort based on the ordering.

Q: ok, now convert both religion and income columns of `pew_tidy_df` as categorical dtype (in place) and show that `pew_tidy_df` now uses much less memory

In [17]:
```
# Convert income to income_type category
pew_tidy_df.income = pew_tidy_df.income.astype(income_type)
# show memory usage
pew_tidy_df.income.memory_usage(deep=True)
```

Out[17]:
```
1230
```

In [18]:
```
#Find unique values for religion
religion_list=pew_tidy_df.religion.unique()
religion_list
```

Out[18]:
```
array(['Agnostic', 'Atheist', 'Buddhist', 'Catholic',
       'Don’t know/refused', 'Evangelical Prot', 'Hindu',
       'Historically Black Prot', "Jehovah's Witness", 'Jewish',
       'Mainline Prot', 'Mormon', 'Muslim', 'Orthodox', 'Other Christian',
       'Other Faiths', 'Other World Religions', 'Unaffiliated'],
      dtype=object)
```

In [19]:
```
#create religion_type
religion_type=CategoricalDtype(categories=religion_list, ordered= True)
religion_type
```

Out[19]:
```
CategoricalDtype(categories=['Agnostic', 'Atheist', 'Buddhist', 'Catholic',
                  'Don’t know/refused', 'Evangelical Prot', 'Hindu',
                  'Historically Black Prot', 'Jehovah's Witness', 'Jewish',
                  'Mainline Prot', 'Mormon', 'Muslim', 'Orthodox',
                  'Other Christian', 'Other Faiths', 'Other World Religions',
                  'Unaffiliated'],
                 ordered=True)
```

In [20]:
```
# Convert religion to religion_type category
pew_tidy_df.religion = pew_tidy_df.religion.astype(religion_type)
# show memory usage
pew_tidy_df.religion.memory_usage(deep=True)
```

Out[20]:
```
2199
```

If you want to know more

- Jean-Nicholas Hould: Tidy Data in Python (http://www.jeannicholashould.com/tidy-data-in-python.html)
- Stephen Simmons | Pandas from the Inside (https://www.youtube.com/watch?v=CowlcrtSyME)
- Data school: How do I make my pandas DataFrame smaller and faster? (https://www.youtube.com/watch?v=wDYDYGyN_cw)

In [25]:
```
import altair as alt
alt.renderers.enable('notebook')
```

Out[25]:
```
RendererRegistry.enable('notebook')
```

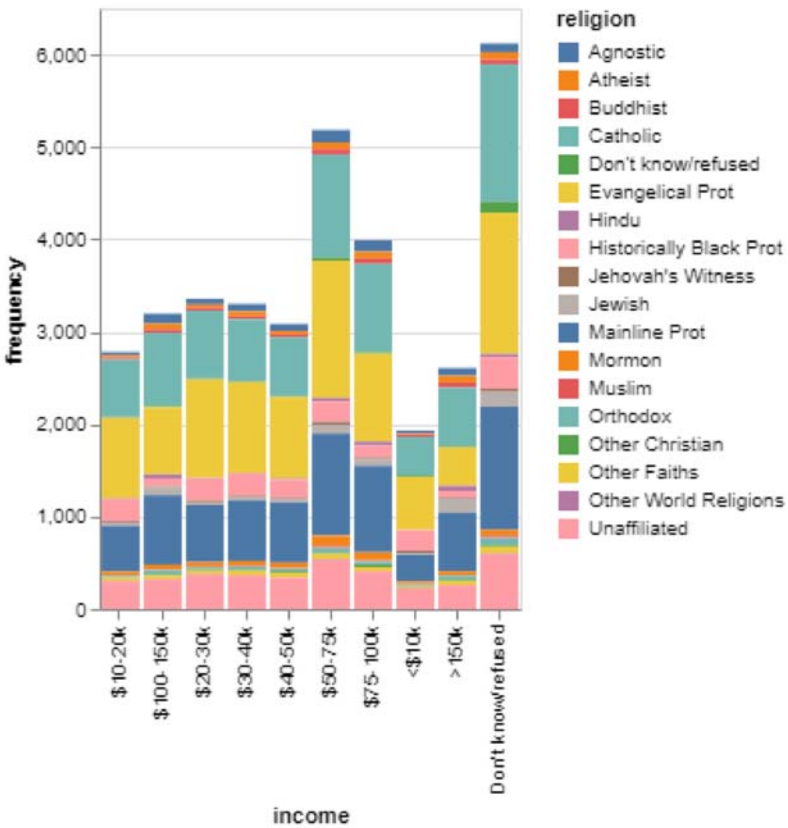
In [26]:
```
chart = alt.Chart(pew_tidy_df)
```

In [27]:
```
source = pew_tidy_df

alt.Chart(source).mark_bar().encode(
    x='income',
    y='frequency',
    color='religion'
)
```

<vega.vegalite.VegaLite at 0x1642adc61d0>

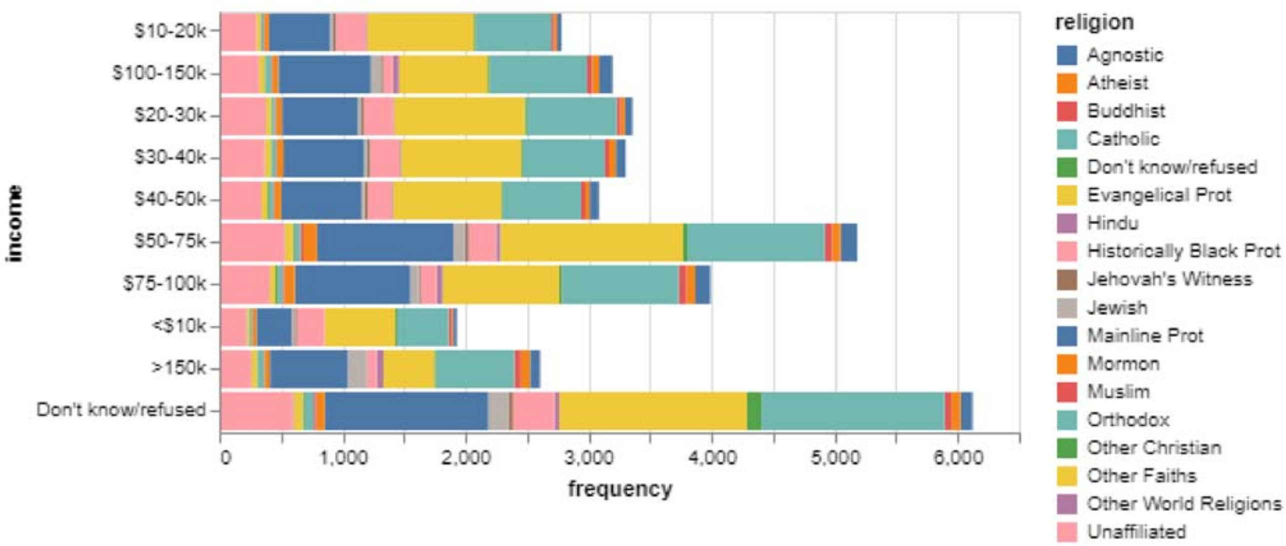
Out[27]:



In [28]:
```
alt.Chart(source).mark_bar().encode(
    y='income',
    x='frequency',
    color='religion'
)
```

```
<vega.vegalite.VegaLite at 0x1642adc6160>
```

Out[28]:



In [29]:
```
alt.Chart(source).mark_bar().encode(
    y='income',
    x='frequency',
    color='religion'
).save('m06_results_yezeret_helen_1.html')
```