HW3: Occupation Dataset

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Introduction:

Special thanks to: https://github.com/guipsamora (https://github.com/guipsamora) for sharing his datasets, materials, and questions.

- https://github.com/justmarkham (https://github.com/justmarkham) for sharing the dataset and materials.

In [1]:
```
### Step 0a. Import the necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:
```
### Step 0b. Import the dataset from this address. https://raw.githubuse
rcontent.com/justmarkham/DAT8/master/data/u.user
### Step 0c. Assign it to a variable called users and use the 'user_id'
 as index
users = pd.read_csv('https://raw.githubusercontent.com/justmarkham/DAT8/
master/data/u.user',
                    sep='|', index_col='user_id')
```

In [3]:
```
# Step 1. See the first 5 entries
users.head()
```

Out[3]:

user_id	age	gender	occupation	zip_code
1	24	M	technician	85711
2	53	F	other	94043
3	23	M	writer	32067
4	24	M	technician	43537
5	33	F	other	15213

In [4]:
```
# Step 2. How many observations and columns are in the data?
print(users.shape)
```

```
(943, 4)
```

In [5]:
```
# Step 3. How many different occupations there are in this dataset?
len(users.loc[:,'occupation'].unique())
```

Out[5]:
```
21
```

In [6]:
```
# Step 4. What is the most frequent occupation?
users.occupation.value_counts().idxmax()
```

Out[6]:
```
'student'
```

In [7]:
```
# Step 5. Discover what is the mean age per occupation.
# Sort the results and find the 3 occupations with the lowest mean age a
nd the 3 with the highest
users['age'].groupby(users['occupation']).mean().sort_values().head(3)
```

Out[7]:
```
occupation
student          22.081633
none             26.555556
entertainment    29.222222
Name: age, dtype: float64
```

In [8]:
```
users['age'].groupby(users['occupation']).mean().sort_values().tail(3)
```

Out[8]:
```
occupation
educator    42.010526
doctor      43.571429
retired     63.071429
Name: age, dtype: float64
```

In [9]:
```
# Step 6. Find the proportion of males by occupation and sort it from th
e most to the least
result = users[users['gender']=='M']['gender'].groupby(users['occupatio
n']).count()/(users['gender'].groupby(users['occupation']).count())*100
result.sort_values(ascending = False)
```

Out[9]:
```
occupation
doctor           100.000000
engineer          97.014925
technician        96.296296
retired           92.857143
programmer        90.909091
executive         90.625000
scientist         90.322581
entertainment     88.888889
lawyer            83.333333
salesman          75.000000
educator          72.631579
student           69.387755
other             65.714286
marketing         61.538462
writer            57.777778
none              55.555556
administrator     54.430380
artist            53.571429
librarian         43.137255
healthcare        31.250000
homemaker         14.285714
Name: gender, dtype: float64
```

In [10]:
```
# Step 7. For each occupation, calculate the minimum and maximum ages
# See groupby and agg() to perform multiple aggregate functions at once
users['age'].groupby(users['occupation']).agg(['min', 'max'])
```

Out[10]:

occupation	min	max
administrator	21	70
artist	19	48
doctor	28	64
educator	23	63
engineer	22	70
entertainment	15	50
executive	22	69
healthcare	22	62
homemaker	20	50
lawyer	21	53
librarian	23	69
marketing	24	55
none	11	55
other	13	64
programmer	20	63
retired	51	73
salesman	18	66
scientist	23	55
student	7	42
technician	21	55
writer	18	60

In [11]:
```
# Step 8. For each combination of occupation and gender, calculate the mean age.
# Arrange the results in a table so each row is an occupation, and you have a
# column of the average male age and another column with the average female age.
# Sort the resulting table by Female mean age from least to greatest
users['age'].groupby([users['occupation'], users['gender']]).mean().unstack().sort_values(by = 'F')
```

Out[11]:

gender	F	M
occupation		
student	20.750000	22.669118
salesman	27.000000	38.555556
scientist	28.333333	36.321429
engineer	29.500000	36.600000
artist	30.307692	32.333333
entertainment	31.000000	29.000000
programmer	32.166667	33.216667
homemaker	34.166667	23.000000
other	35.472222	34.028986
none	36.500000	18.600000
marketing	37.200000	37.875000
writer	37.631579	35.346154
technician	38.000000	32.961538
educator	39.115385	43.101449
lawyer	39.500000	36.200000
healthcare	39.818182	45.400000
librarian	40.000000	40.000000
administrator	40.638889	37.162791
executive	44.000000	38.172414
retired	70.000000	62.538462
doctor	NaN	43.571429

In [12]:
```
# Step 9. For each occupation find the count of women and men
# Arrange the results in a table so each row is an occupation, similar t
o above
users['gender'].groupby([users['occupation'], users['gender']]).count().
unstack()
```

Out[12]:

gender	F	M
occupation		
administrator	36.0	43.0
artist	13.0	15.0
doctor	NaN	7.0
educator	26.0	69.0
engineer	2.0	65.0
entertainment	2.0	16.0
executive	3.0	29.0
healthcare	11.0	5.0
homemaker	6.0	1.0
lawyer	2.0	10.0
librarian	29.0	22.0
marketing	10.0	16.0
none	4.0	5.0
other	36.0	69.0
programmer	6.0	60.0
retired	1.0	13.0
salesman	3.0	9.0
scientist	3.0	28.0
student	60.0	136.0
technician	1.0	26.0
writer	19.0	26.0

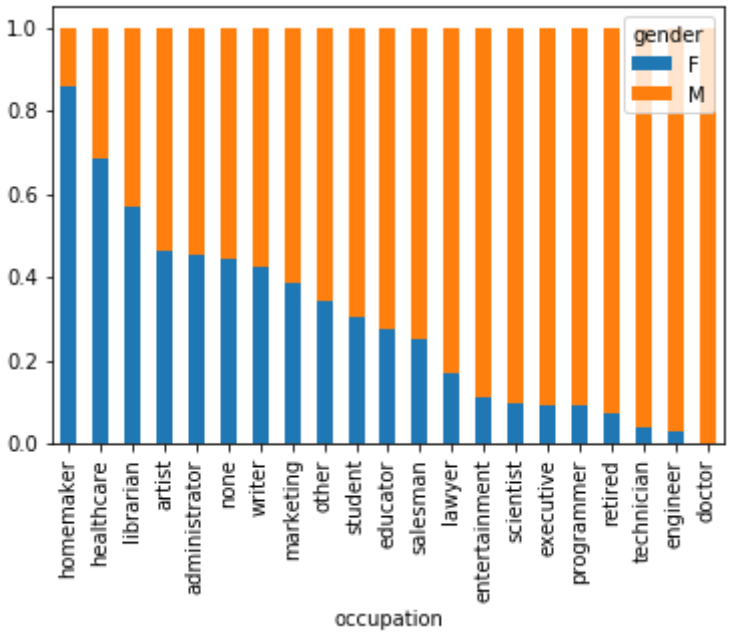
In [13]:
```
# Step 10. Turn the counts above into proportions. e.g administrator 0.4
55696 0.544304
# Arrange results in increasing order of proportion men
totalUsers = users['gender'].groupby(users['occupation']).count()
result = users['gender'].groupby([users['occupation'], users['gender']])
.count()/totalUsers
step10 = result.unstack().sort_values(by = 'M')
step10
```

Out[13]:

gender	F	M
occupation		
homemaker	0.857143	0.142857
healthcare	0.687500	0.312500
librarian	0.568627	0.431373
artist	0.464286	0.535714
administrator	0.455696	0.544304
none	0.444444	0.555556
writer	0.422222	0.577778
marketing	0.384615	0.615385
other	0.342857	0.657143
student	0.306122	0.693878
educator	0.273684	0.726316
salesman	0.250000	0.750000
lawyer	0.166667	0.833333
entertainment	0.111111	0.888889
scientist	0.096774	0.903226
executive	0.093750	0.906250
programmer	0.090909	0.909091
retired	0.071429	0.928571
technician	0.037037	0.962963
engineer	0.029851	0.970149
doctor	NaN	1.000000

In [14]:
```
# Create a stacked barchart showing the results above
step10.plot.bar(stacked = True)
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x11e5b4c50>



In [15]:
```
# Extract the first digit of each zip code
# and create a new column called 'region' that maps the
# first digit of the zip to new values using this dictionary:
d = {'0': 'New England',
'1': 'Mid-Atlantic',
'2': 'Central East Coast',
'3': 'The South',
'4': 'Midwest',
'5': 'Northern Great Plains',
'6': 'Central Great Plains',
'7': 'Southern Central',
'8': 'Mountain Desert',
'9': 'West Coast'}

# print the first 5 rows of the result
```

In [16]:
```
users['region'] = users.zip_code.str[0].map(d)
users.head()
```

Out[16]:

user_id	age	gender	occupation	zip_code	region
1	24	M	technician	85711	Mountain Desert
2	53	F	other	94043	West Coast
3	23	M	writer	32067	The South
4	24	M	technician	43537	Midwest
5	33	F	other	15213	Mid-Atlantic

In [17]:
```
# for the occuptation 'retired', find the mean age of each region
users[users['occupation']=='retired']['age'].groupby(users['region']).mean()
```

Out[17]:
```
region
Central East Coast       60.0
Central Great Plains     59.5
Mid-Atlantic             60.0
Midwest                  69.0
New England              65.0
Northern Great Plains    61.0
The South                73.0
West Coast               60.5
Name: age, dtype: float64
```