HW4: Occupation Dataset

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Introduction:

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

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

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

In [2]:
```
### I believe the following data set is from the US in the 1950s.
### Gender proportions and ages are thus reflective of that era.
### Import the dataset from this address. https://raw.githubusercontent.com/justmarkha
### 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.
                      sep='|', index_col='user_id')
```

In [3]:
```
# Problem 1. See the first 10 entries. (done for you)
users.head(10)
```

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
6	42	M	executive	98101
7	57	M	administrator	91344
8	36	M	administrator	05201
9	29	M	student	01002
10	53	M	lawyer	90703

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

Out[4]:
```
(943, 4)
```

There are `943` observations and `4` columns.

In [5]:
```
# Problem 3. How many different occupations are there in this dataset?
users["occupation"].describe()
```

Out[5]:
```
count         943
unique         21
top       student
freq          196
Name: occupation, dtype: object
```

There are `21` different occupations.

In [6]:
```
# Problem 4. What is the most frequent occupation?
users["occupation"].describe()
```

Out[6]:
```
count         943
unique         21
top       student
freq          196
Name: occupation, dtype: object
```

`Student` is the most frequent occupation.

In [7]:
```
# Problem 5. Discover what is the mean age per occupation.
# Sort the results and find the 3 occupations with the lowest mean age and the 3 with
mean_age_per_occupation = users.groupby("occupation")["age"].mean().sort_values()
print(mean_age_per_occupation)
```

```
occupation
student          22.081633
none             26.555556
entertainment    29.222222
artist           31.392857
homemaker        32.571429
programmer       33.121212
technician       33.148148
other            34.523810
scientist        35.548387
salesman         35.666667
writer           36.311111
engineer         36.388060
lawyer           36.750000
marketing        37.615385
executive        38.718750
administrator    38.746835
librarian        40.000000
healthcare       41.562500
educator         42.010526
doctor           43.571429
retired          63.071429
Name: age, dtype: float64
```

In [8]:
```
print(mean_age_per_occupation.head(3))
```

```
occupation
student          22.081633
none             26.555556
entertainment    29.222222
Name: age, dtype: float64
```

`Student`, `None`, and `Entertainment` have the lowest mean age.

In [9]:
```
print(mean_age_per_occupation.tail(3))
```

```
occupation
educator    42.010526
doctor      43.571429
retired     63.071429
Name: age, dtype: float64
```

`Educator`, `Doctor`, and `Retired` have the highest mean age.

In [10]:
```
# Problem 6. Find the proportion of males by occupation and sort it from the most to t
prop_males_by_pop = users.groupby("occupation")["gender"].value_counts(normalize = Tru
prop_males_by_pop = prop_males_by_pop[:, "M"]
prop_males_by_pop.sort_values(ascending = False)
```

Out[10]:
```
occupation
doctor           1.000000
engineer         0.970149
technician       0.962963
retired          0.928571
programmer       0.909091
executive        0.906250
scientist        0.903226
entertainment    0.888889
lawyer           0.833333
salesman         0.750000
educator         0.726316
student          0.693878
other            0.657143
marketing        0.615385
writer           0.577778
none             0.555556
administrator    0.544304
artist           0.535714
librarian        0.431373
healthcare       0.312500
homemaker        0.142857
Name: proportion, dtype: float64
```

In [11]:
```
# Problem 7. For each occupation, calculate the minimum and maximum ages
# See groupby and agg() to perform multiple aggregate functions at once
users.groupby("occupation")["age"].agg(["min", "max"])
```

Out[11]:

	min	max
occupation		
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 [12]:

```
# Problem 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.groupby(["occupation", "gender"])["age"].mean().unstack().sort_values(by = "F")
```

Out[12]:

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 [13]:

```
# Problem 9. For each occupation find the count of women and men
# Arrange the results in a table so each row is an occupation, similar to above
users.groupby("occupation")["gender"].value_counts().unstack()
```

Out[13]:

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 [14]:

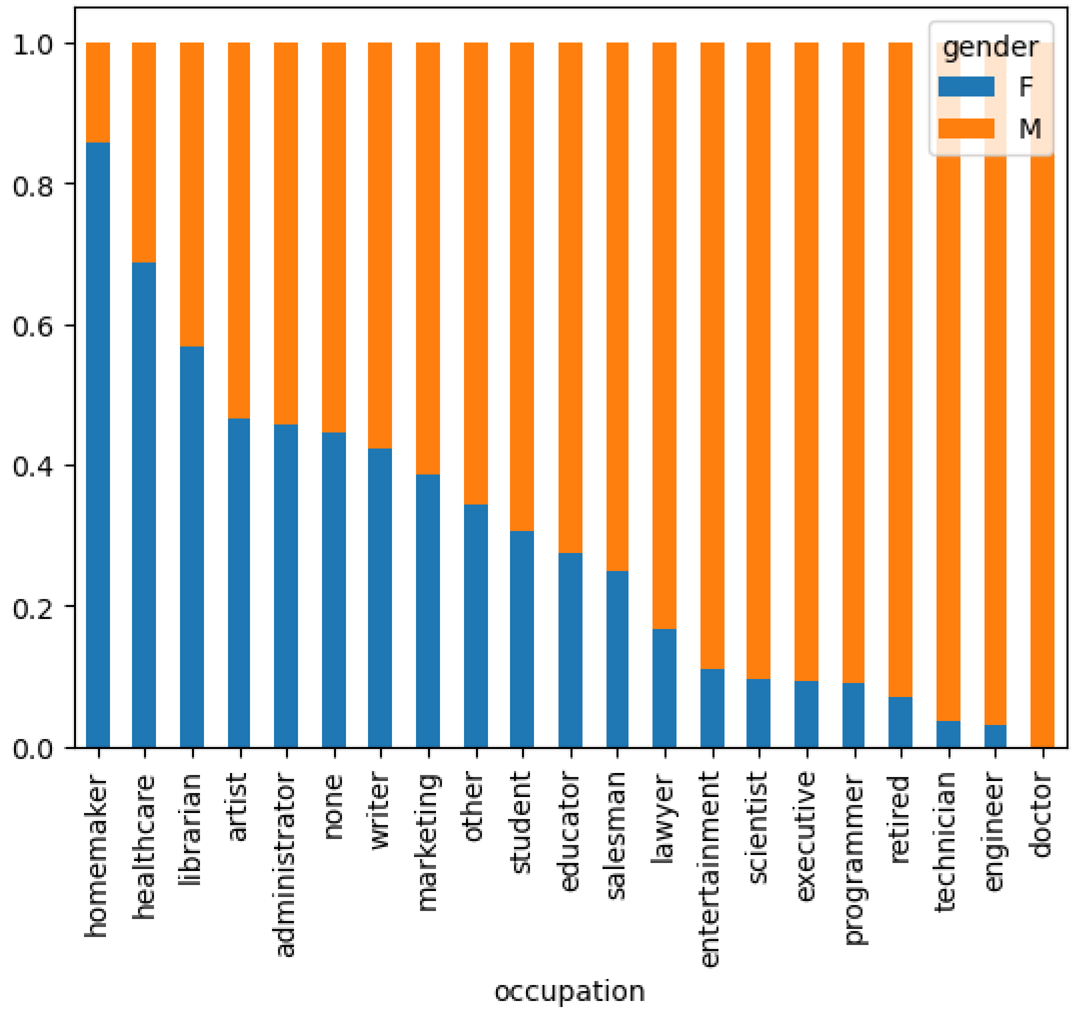
```
# Problem 10. Turn the counts above into proportions. e.g administrator 0.455696 0.544
# Arrange results in increasing order of proportion men
prop_gender_by_occupation = users.groupby("occupation")["gender"].value_counts(normali
prop_gender_by_occupation
```

Out[14]:

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 [15]:

```
# Create a stacked barchart showing the results above
prop_gender_by_occupation.plot.bar(stacked = True)
plt.show()
```



In [16]:

```
# 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
# Postal codes that begin with a letter are actually Canadian but are missing the last
```

In [17]:

```
users["region"] = users["zip_code"].apply(lambda zipcode: zipcode[0])
users["region"] = users["region"].apply(lambda zipcode: "Canada" if zipcode.isalpha()
users["region"].head()
```

Out[17]:
```
user_id
1    Mountain Desert
2         West Coast
3          The South
4            Midwest
5       Mid-Atlantic
Name: region, dtype: object
```

In [18]:
```
# For the occupation 'retired', find the mean age of each region
users_retired = users[["age", "region"]][users["occupation"] == "retired"]
users_retired.groupby("region")["age"].mean()
```

Out[18]:
```
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
```