# Producing Visualization using Income Census Dataset

SUBMITTED BY:

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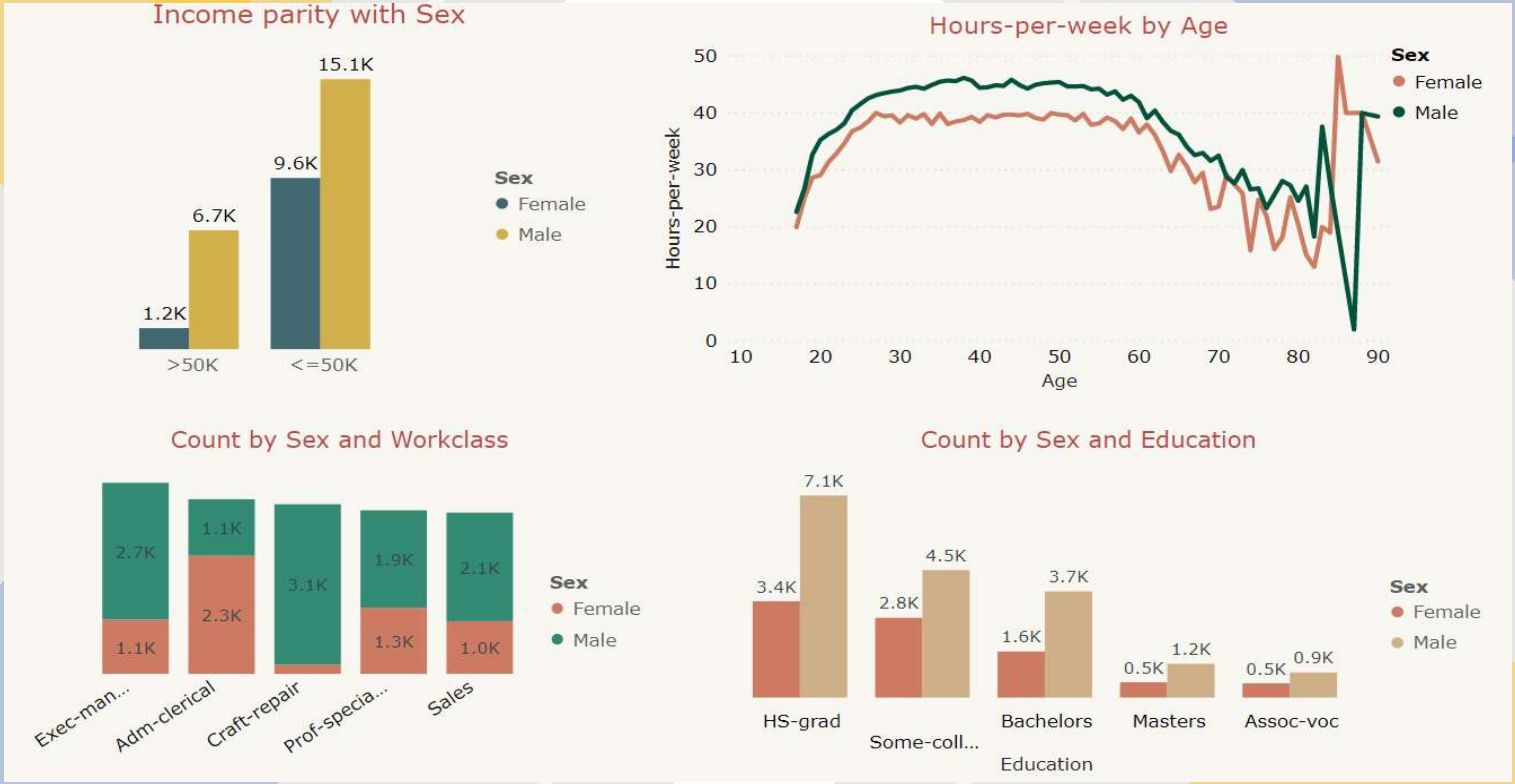
# Questions we are trying to answer using the Income Census Dataset

- **Who is earning more… Male or Female ?**
- **Why are they earning more?**
- **Who is working for a greater number of hours ?**
- **What are the top earning Occupation ?**
- **Female Representation in these Occupations ?**

# Visualization of the Dashboard



# Data Description

Machine Learning Repository

### Data Set Information:

Extraction was done by Barry Becker from the 1994 Census database. A set of reasonably clean records was extracted using the following conditions: ((AAGE>16) && (AGI>100) && (AFNLWGT>1)&& (HRSWK>0))

Prediction task is to determine whether a person makes over 50K a year.

### Attribute Information:

Listing of attributes:

>50K, <=50K.

age: continuous.
workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
fnlwgt: continuous.
education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
education-num: continuous.
marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
sex: Female, Male.
capital-gain: continuous.
capital-loss: continuous.
hours-per-week: continuous.
native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

The Census Income dataset consists of 16 columns and 16384 Rows

# Data Cleaning Part 1…

In [28]:
```python
import pandas as pd
import numpy as np
```

In [29]:
```python
#Load data set
df= pd.read_csv(r'C:\Users\garvi\OneDrive\Documents\Durham college\College Logo\income_evaluation - Copy.csv')
df.head(30)
```

Dropping the columns

Out[29]:

| | age | workclass | fnlwgt | education | education-num | marital-status | occupation | relationship | race | sex | capital-gain | capital-loss | hours-per-week | native-country | income |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 39 | State-gov | 77516 | Bachelors | 13 | Never-married | Adm-clerical | Not-in-family | White | Male | 2174 | 0 | 40 | United-States | <=50K |
| 1 | 50 | Self-emp-not-inc | 83311 | Bachelors | 13 | Married-civ-spouse | Exec-managerial | Husband | White | Male | 0 | 0 | 13 | United-States | <=50K |
| 2 | 38 | Private | 215646 | HS-grad | 9 | Divorced | Handlers-cleaners | Not-in-family | White | Male | 0 | 0 | 40 | United-States | <=50K |
| 3 | 53 | Private | 234721 | 11th | 7 | Married-civ-spouse | Handlers-cleaners | Husband | Black | Male | 0 | 0 | 40 | United-States | <=50K |
| 4 | 28 | Private | 338409 | Bachelors | 13 | Married-civ-spouse | Prof-specialty | Wife | Black | Female | 0 | 0 | 40 | Cuba | <=50K |
| 5 | 37 | Private | 284582 | Masters | 14 | Married-civ-spouse | Exec-managerial | Wife | White | Female | 0 | 0 | 40 | United-States | <=50K |
| 6 | 49 | Private | 160187 | 9th | 5 | Married-spouse-absent | Other-service | Not-in-family | Black | Female | 0 | 0 | 16 | Jamaica | <=50K |
| 7 | 52 | Self-emp-not-inc | 209642 | HS-grad | 9 | Married-civ-spouse | Exec-managerial | Husband | White | Male | 0 | 0 | 45 | United-States | >50K |
| 8 | 31 | Private | 45781 | Masters | 14 | Never- | Prof- | Not-in-family | White | Female | 14084 | 0 | 50 | United- | >50K |

# …Data Cleaning Part 1

In [30]:

```
#Dropping columns from the dataframe
df= df.drop([' education-num', ' capital-gain', ' capital-loss',' fnlwgt'], axis=1)
df.head(30)
```

Out[30]:

| | age | workclass | education | marital-status | occupation | relationship | race | sex | hours-per-week | native-country | income |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 39 | State-gov | Bachelors | Never-married | Adm-clerical | Not-in-family | White | Male | 40 | United-States | <=50K |
| 1 | 50 | Self-emp-not-inc | Bachelors | Married-civ-spouse | Exec-managerial | Husband | White | Male | 13 | United-States | <=50K |
| 2 | 38 | Private | HS-grad | Divorced | Handlers-cleaners | Not-in-family | White | Male | 40 | United-States | <=50K |
| 3 | 53 | Private | 11th | Married-civ-spouse | Handlers-cleaners | Husband | Black | Male | 40 | United-States | <=50K |
| 4 | 28 | Private | Bachelors | Married-civ-spouse | Prof-specialty | Wife | Black | Female | 40 | Cuba | <=50K |
| 5 | 37 | Private | Masters | Married-civ-spouse | Exec-managerial | Wife | White | Female | 40 | United-States | <=50K |
| 6 | 49 | Private | 9th | Married-spouse-absent | Other-service | Not-in-family | Black | Female | 16 | Jamaica | <=50K |
| 7 | 52 | Self-emp-not-inc | HS-grad | Married-civ-spouse | Exec-managerial | Husband | White | Male | 45 | United-States | >50K |
| 8 | 31 | Private | Masters | Never-married | Prof-specialty | Not-in-family | White | Female | 50 | United-States | >50K |
| 9 | 42 | Private | Bachelors | Married-civ-spouse | Exec-managerial | Husband | White | Male | 40 | United-States | >50K |
| 10 | 37 | Private | Some-college | Married-civ-spouse | Exec-managerial | Husband | Black | Male | 80 | United-States | >50K |
| 11 | 30 | State-gov | Bachelors | Married-civ-spouse | Prof-specialty | Husband | Asian-Pac-Islander | Male | 40 | India | >50K |
| 12 | 23 | Private | Bachelors | Never-married | Adm-clerical | Own-child | White | Female | 30 | United-States | <=50K |

Dropped the columns

# Data Cleaning Part 2

| | age | workclass | education | marital-status | occupation | relationship | race | sex | hours-per-week | native-country | income |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 27 | 54 | ? | Some-college | Married-civ-spouse | ? | Husband | Asian-Pac-Islander | Male | 60 | South | >50K |
| 28 | 39 | Private | HS-grad | Divorced | Exec-managerial | Not-in-family | White | Male | 80 | United-States | <=50K |
| 29 | 49 | Private | HS-grad | Married-civ-spouse | Craft-repair | Husband | White | Male | 40 | United-States | <=50K |

In [31]:
```
df.isnull().sum()
```
Out[31]:
```
age               0
 workclass        0
 education        0
 marital-status   0
 occupation       0
 relationship     0
 race             0
 sex              0
 hours-per-week   0
 native-country   0
 income           0
dtype: int64
```

Checking for the Null values and replacing '?' with 'Unknown'

In [32]:
```
#replacing '?' with Unknown:
df[' workclass'].replace(' ?', ' Unknown',inplace=True)
df[' occupation'].replace(' ?', ' Unknown',inplace=True)
df[' native-country'].replace(' ?', ' Unknown',inplace=True)
```

In [26]:
```
df.head(30)
```
Out[26]:

| | age | workclass | education | marital-status | occupation | relationship | race | sex | hours-per-week | native-country | income |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 39 | State-gov | Bachelors | Never-married | Adm-clerical | Not-in-family | White | Male | 40 | United-States | <=50K |

# ...Data Cleaning Part 2

Replaced the '?' with 'Unknown'

In [32]:
```python
#replacing '?' with Unknown:
df[' workclass'].replace(' ?', ' Unknown',inplace=True)
df[' occupation'].replace(' ?', ' Unknown',inplace=True)
df[' native-country'].replace(' ?', ' Unknown',inplace=True)
```

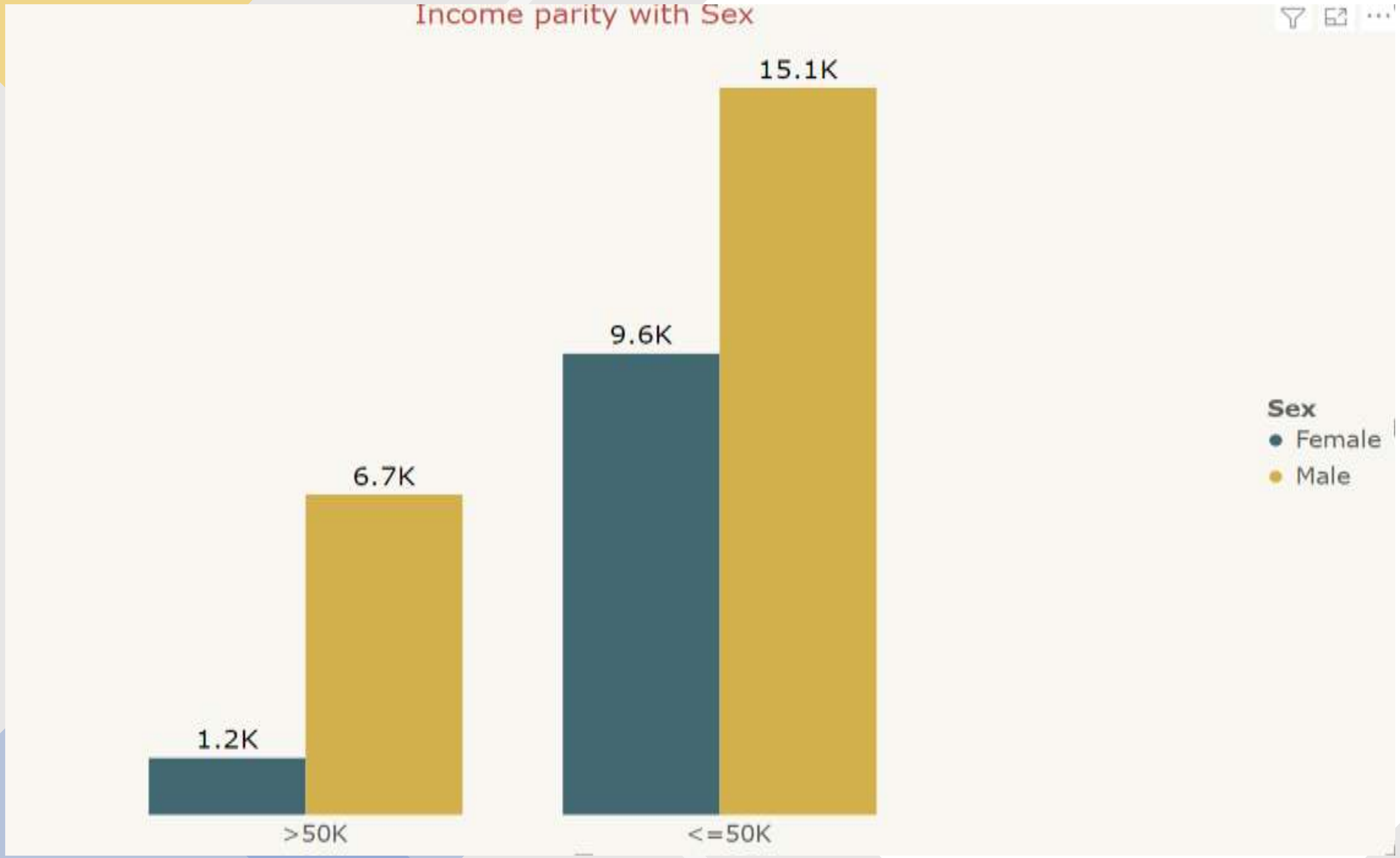
In [26]:
```python
df.head(30)
```

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | inspct | | | | | | |
| **18** | 38 | Private | 11th | Married-civ-spouse | Sales | Husband | White | Male | 50 | United-States | <=50K |
| **19** | 43 | Self-emp-not-inc | Masters | Divorced | Exec-managerial | Unmarried | White | Female | 45 | United-States | >50K |
| **20** | 40 | Private | Doctorate | Married-civ-spouse | Prof-specialty | Husband | White | Male | 60 | United-States | >50K |
| **21** | 54 | Private | HS-grad | Separated | Other-service | Unmarried | Black | Female | 20 | United-States | <=50K |
| **22** | 35 | Federal-gov | 9th | Married-civ-spouse | Farming-fishing | Husband | Black | Male | 40 | United-States | <=50K |
| **23** | 43 | Private | 11th | Married-civ-spouse | Transport-moving | Husband | White | Male | 40 | United-States | <=50K |
| **24** | 59 | Private | HS-grad | Divorced | Tech-support | Unmarried | White | Female | 40 | United-States | <=50K |
| **25** | 56 | Local-gov | Bachelors | Married-civ-spouse | Tech-support | Husband | White | Male | 40 | United-States | >50K |
| **26** | 19 | Private | HS-grad | Never-married | Craft-repair | Own-child | White | Male | 40 | United-States | <=50K |
| **27** | 54 | Unknown | Some-college | Married-civ-spouse | Unknown | Husband | Asian-Pac-Islander | Male | 60 | South | >50K |
| **28** | 39 | Private | HS-grad | Divorced | Exec-managerial | Not-in-family | White | Male | 80 | United-States | <=50K |

In [39]:
```python
#Saving our cleaned file as CSV
df.to_csv(r'C:\Users\garvi\OneDrive\Documents\Durham college\College Logo\income_evaluation - Cleaned_Copy.csv', index=False)
```

In [ ]:

# Who is earning more….?

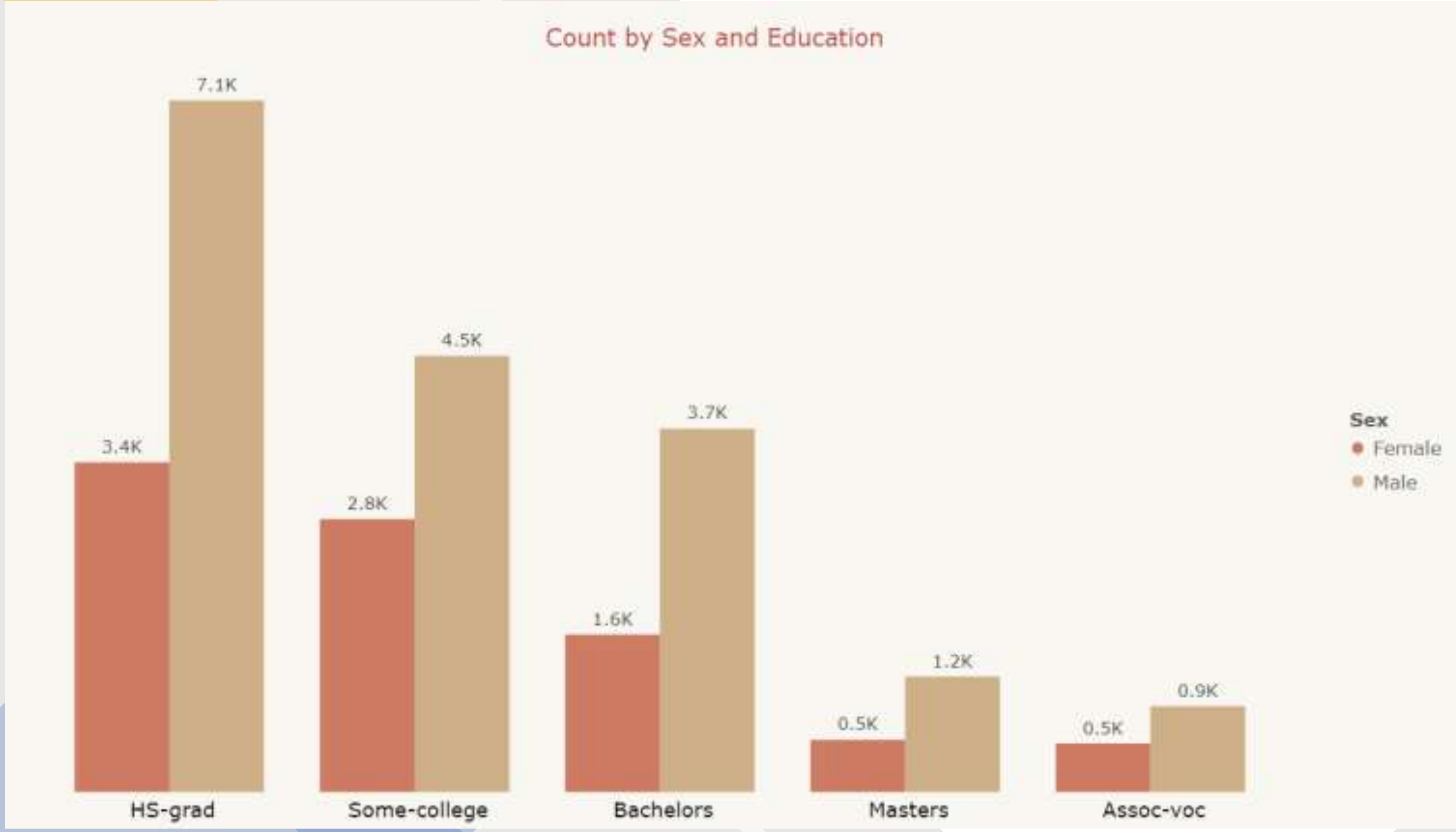



## Inferences from the chart

- A clustered column chart is used for this visualization. The **Income category is at X axis** and the **count** of the **Males** and **Females** on **Y axis**.

- It can be inferred from the chart that number of **Males earning more than $50k** is almost **five times** the number of **Females**.
- **Men** are **more likely** to **earn more** than **$50K**

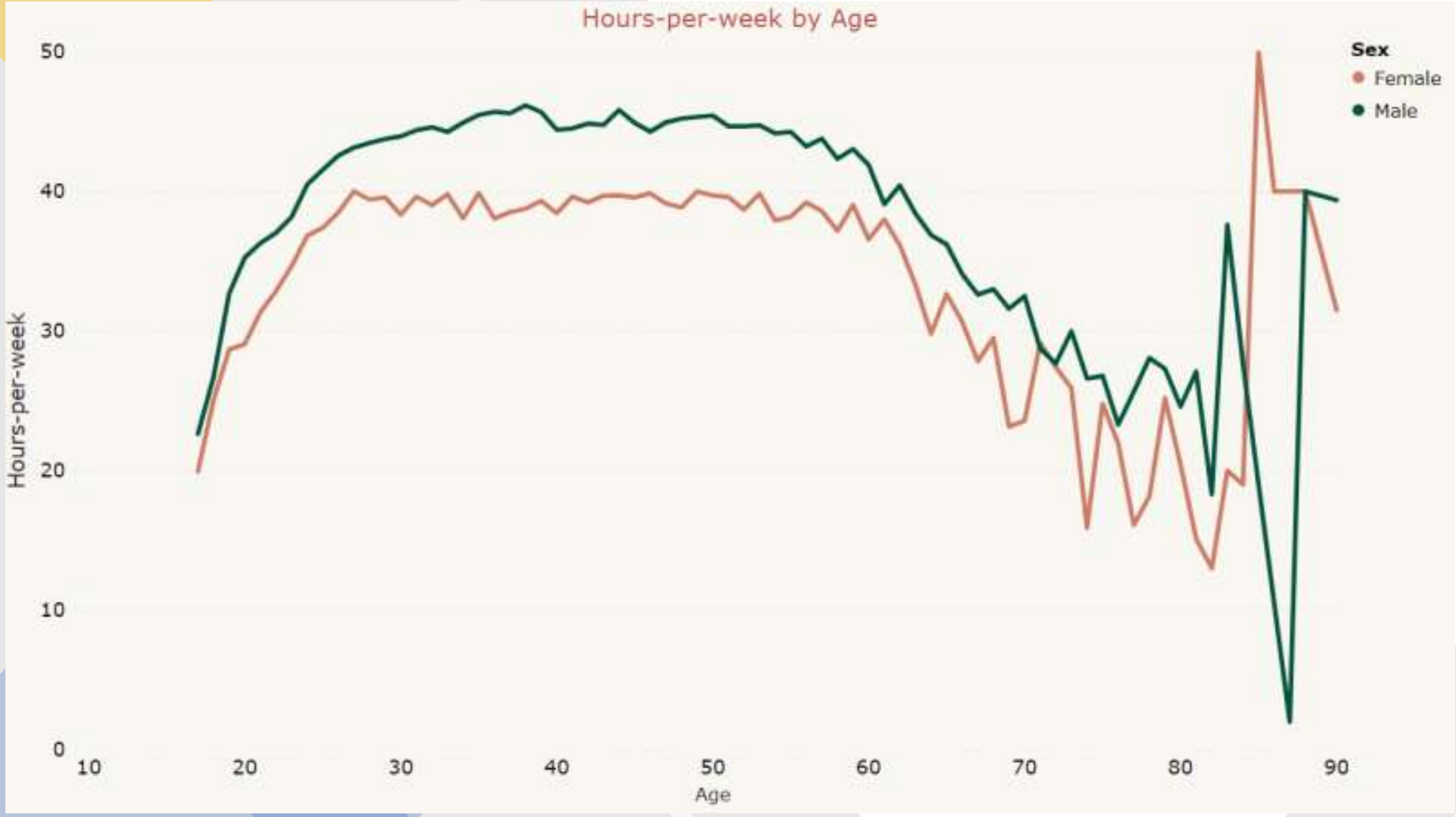
# Why are they earning more…. ?




## Inferences from the chart

- A Stacked Column Chart has been used to show the **count of people (Y axis)** based on the level of **Education** (X axis) attained by them.
- The visual shows that more Men are likely to attain a certain level of education as compared to their female counterpart.
- No surprises here as to why Men are earning more than females. Since men are more educated than females they are better paid off for their job and are earning handsomely.

# Who is working for a  greater number of hours....?

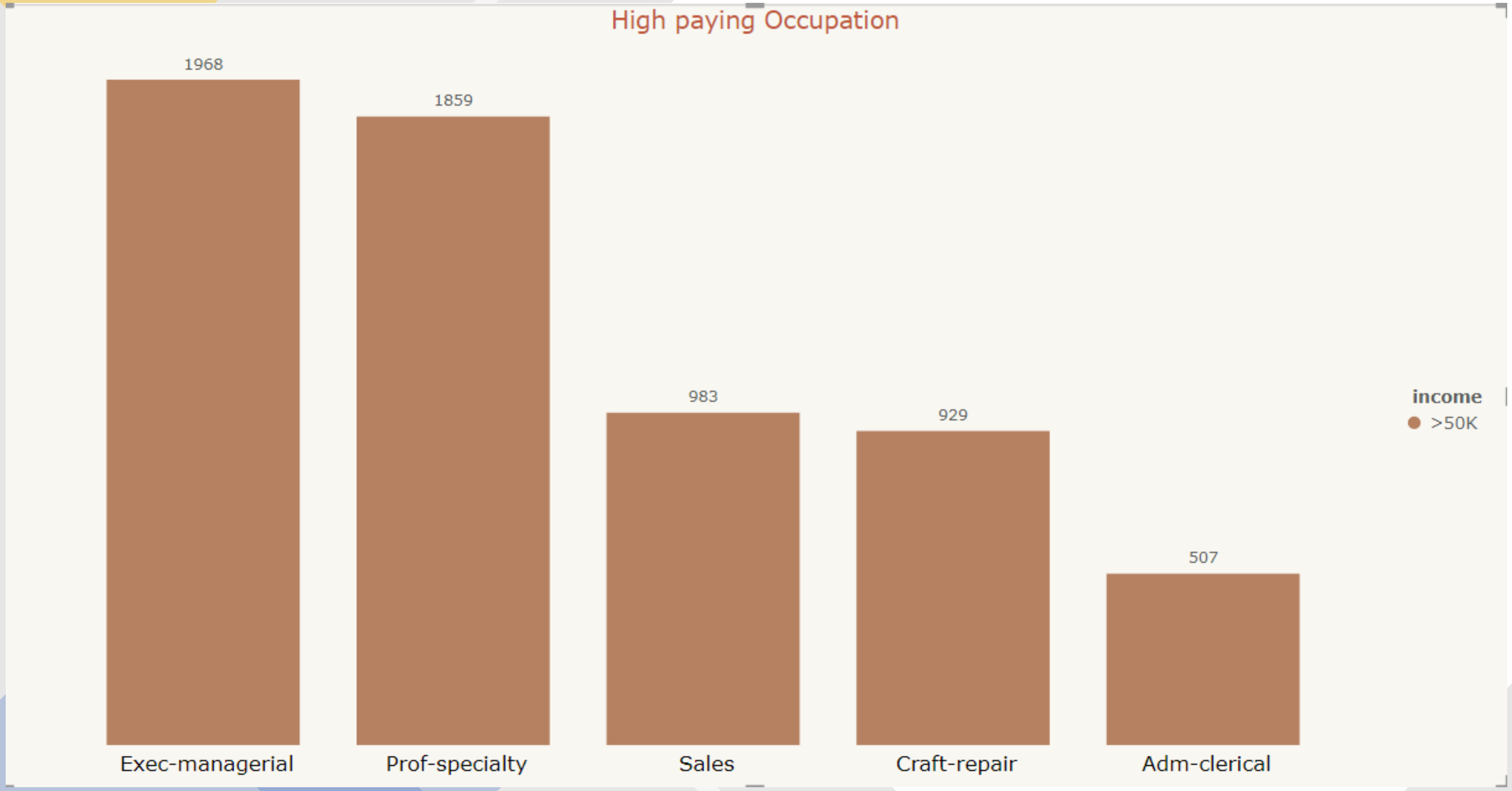



## Inferences from the chart

- A line chart has been used to establish the relation between **Hours per week (Y axis)** spent by an individual **(Sex as legend)** and their **Age (X axis).**

- We can see that **Males** put in **more no. of hours** than Females for almost all Ages. This trend continues **till age 85**, after which **females have worked more**. In the age range from **85-88, females** have **outperformed** the males, thereafter which males again worked for more no of hours. Overall, we can say **Males have put more number of hours working than Females.**

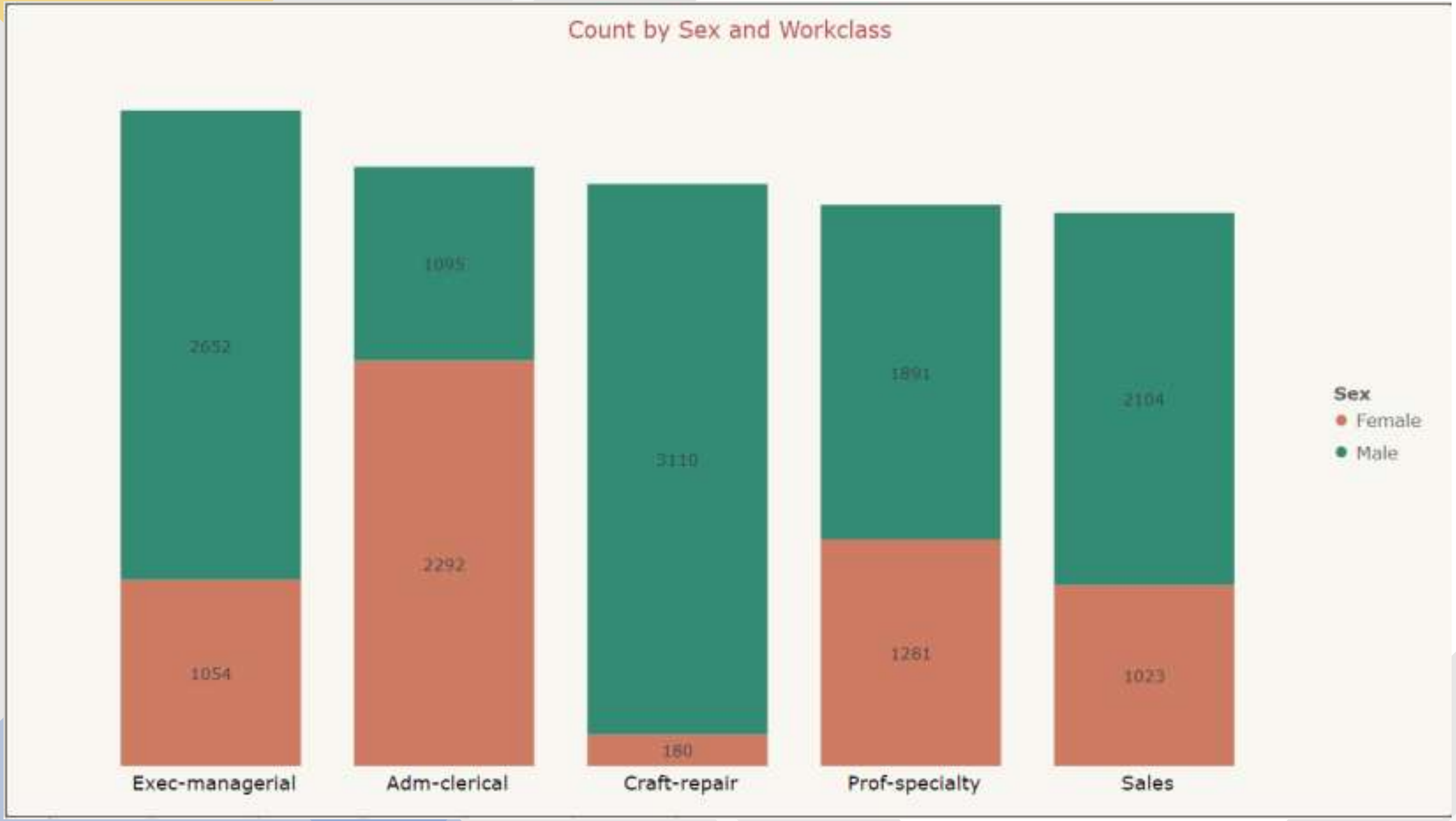
# What are the high paying Occupations….?




## Inferences from the chart

- A Clustered Column Chart is used for this visualization. Type of **Occupation** is in **(X axis)** and **Count of people** under that occupation is in **(Y axis).**
- This chart presents the **number of people employed in occupations which are paying more than $50k.**
- It can be seen from the chart that **Exec-managerial** is the **highest paying** occupation with **1968** professionals working in it, followed by **Prof-specialty** with **1859** and last is **Adm-clerical** with **507** professionals employed in the same occupation.

# Female representation in these Occupations….?




**Inferences from the chart**

- A Stacked column chart is used for this visualization. The Occupation is in X axis and Count of people is in Y axis. It is further filtered by the gender of these people.
- The chart represents the **Highest paying occupation** with **Female representation**. The **number of females** in any occupation (highest paying occupation) are **less** compared to their male counter parts **except the Adm-clerical job** where females have out played males.
- Since **less females take up** the **highest paying** occupation, we can easily understand why **they are getting paid less** compared to males.

# Conclusions

According to the Income Census data it can be concluded that **Males earn more than Females**, this can be attributed to the following facts:

- Males are **more educated** as compared to their counter parts for any level of education.
- They can devote **more hours at work** as compared to women.
- Males have **more opportunities** to work in highest paying Professions, whereas, Females have less representation in these Occupations.

# Video Link

Please find the link below to my YouTube channel for the Interactive Video presentation:

https://youtu.be/V9tgT2PcVfY

# References

- The Census Income dataset has been taken from: UCI machine learning repository.

- *Data Link:* [*https://archive.ics.uci.edu/ml/datasets/census+income*](https://archive.ics.uci.edu/ml/datasets/census+income)

# Thank You