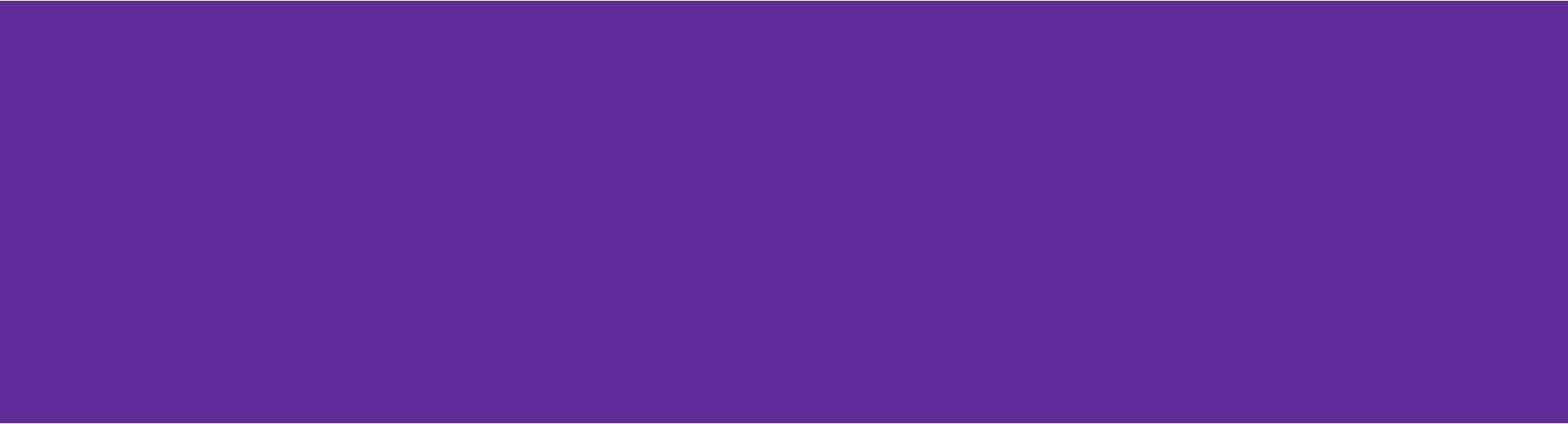


# **Analysis of the US Census Bureau's Annual Business Survey**

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Walter



# Initial Questions

- What is the average salary of employees by state?
- What percentage of workers are male and what percentage are female? How does that compare to the number of male versus female owners?
- What technologies are mostly used by employer firms?
- What is the salary range for jobs that require varying levels of use of software-based technology?
- In which industries are individuals who work with Artificial Intelligence likely to earn the highest salaries?
- What is the educational background of business owners? Does more education make it more likely for you to own a business?

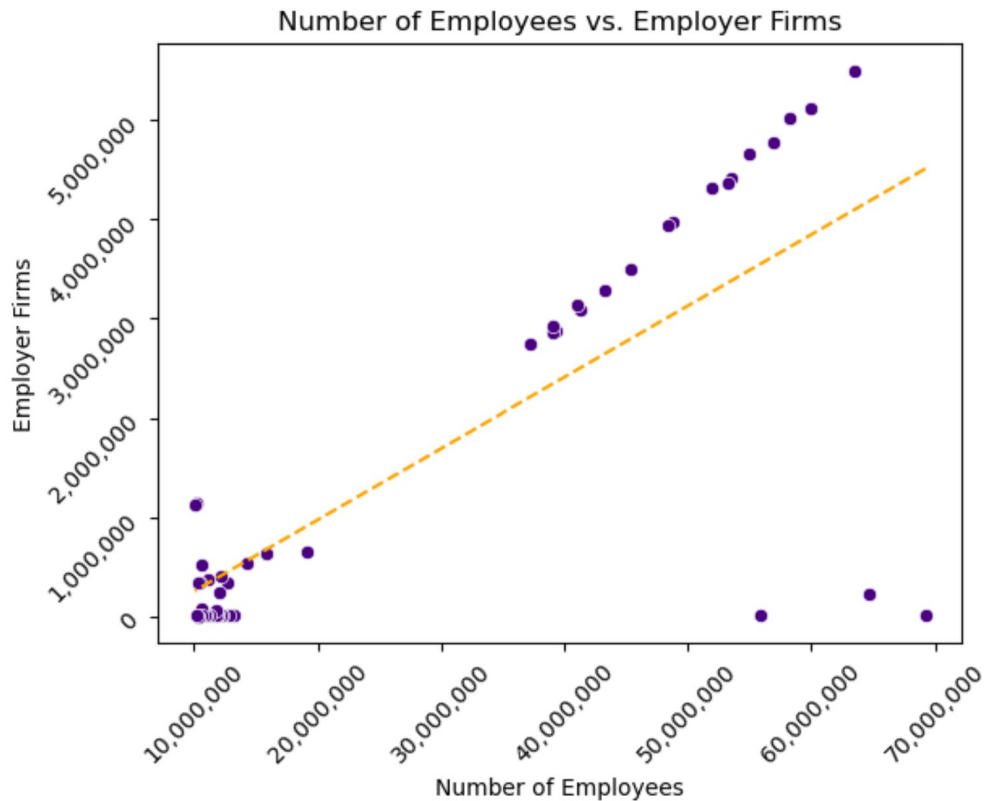
# ETL Steps

- Each dataset was loaded in and the first row was removed (Duplicate header row).
- The index of each row was then reset and previous index was removed.
- Multiple columns in the dataframe were renamed to make the purpose of the columns clearer.
- The data types of the numeric columns were changed from object to either an integer or a float.
- Removed nulls and flagged data.

# Company Summary



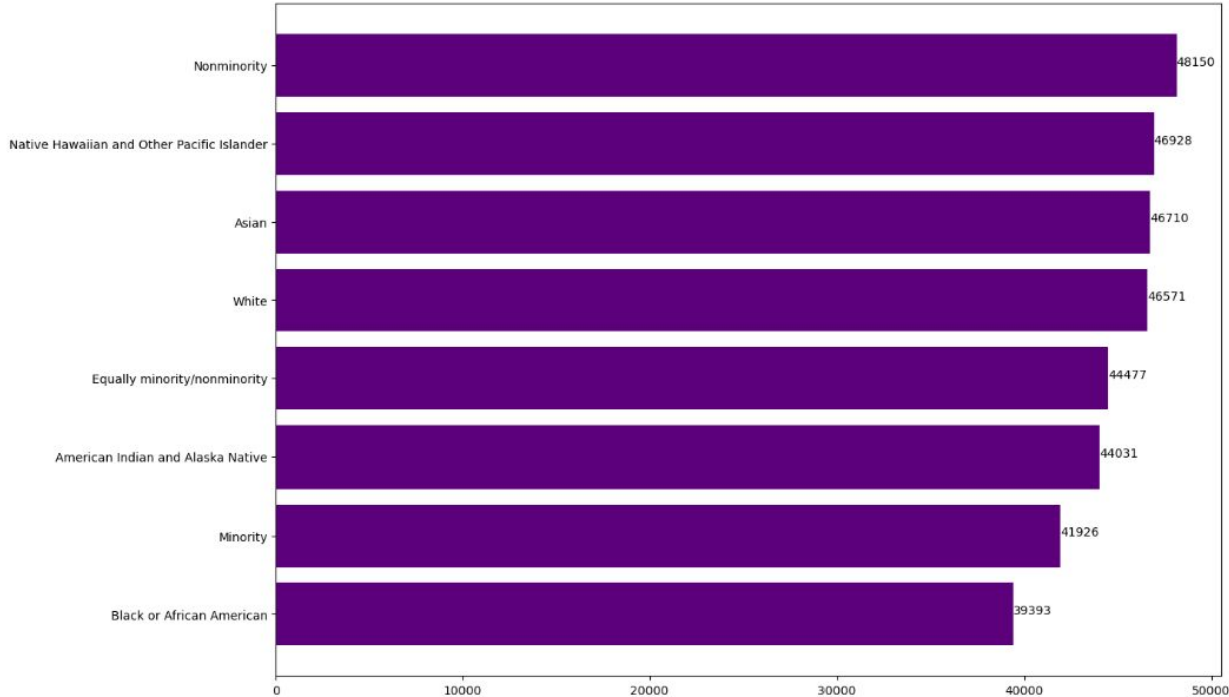
# Employee Count and Employer Firms



View the correlation between number of employees and the number of employer firms.

- Top 50 companies were used in this visualization.
- One outlier removed from the dataset.
- Correlation of the graph is  $\approx 0.7792$ .
- Correlation not visible with smaller companies, clear trend with the mid-large sized companies.
- Employer firms all  $> 0$ , no company in the top 50 has none, some way smaller than others (lowest = 4000).

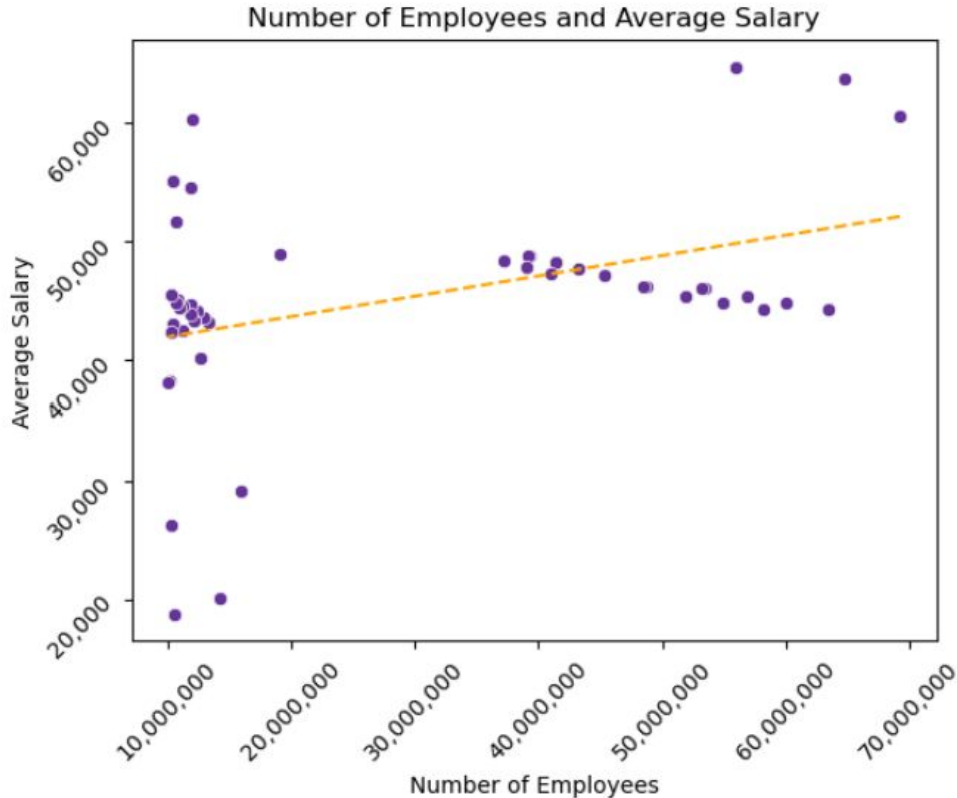
# Average Salary Compared to Race



Bar Chart of average employee salary based on race

- Average salary was calculated by the annual payroll / number of employees \* 100.
- Average Salary column's mean was taken and grouped by race.
- Total, classifiable, nonclassifiable columns were taken out of the visual.

# Average Salary and Number of Employees



Correlation between size of companies and average payroll

- Top 50 companies by size were also used in this visualization.
- Smaller companies had no correlation to the average salary.
- Mid-Large sized companies showed a decline in the average salary as the company size grew.
- Misleading trendline and correlation due to the companies with under 20,000,000 employees.

# Code snippets

1. Creating DataFrame with top 50 companies by employee count

a. `top50 = df.sort_values(by = 'EMP', ascending=False)[:50]`

2. Checking the correlation of scatter plots

a. `correlation = df['EMP'].corr(df['FIRMPDEMP'])`

b. `correlation = df['EMP'].corr(df['Average_Salary'])`

3. Creating an Average Salary column

a. `df['Average_Salary'] = (df['PAYANN']/df['EMP'])*1000`

4. Rounding the Average Salary column then calculating the mean grouped by race.

a. `df["Average_Salary_Rounded"] = df["Average_Salary"].round(0)`

b. `df = df.groupby("RACE_GROUP_LABEL")["Average_Salary"].mean()`



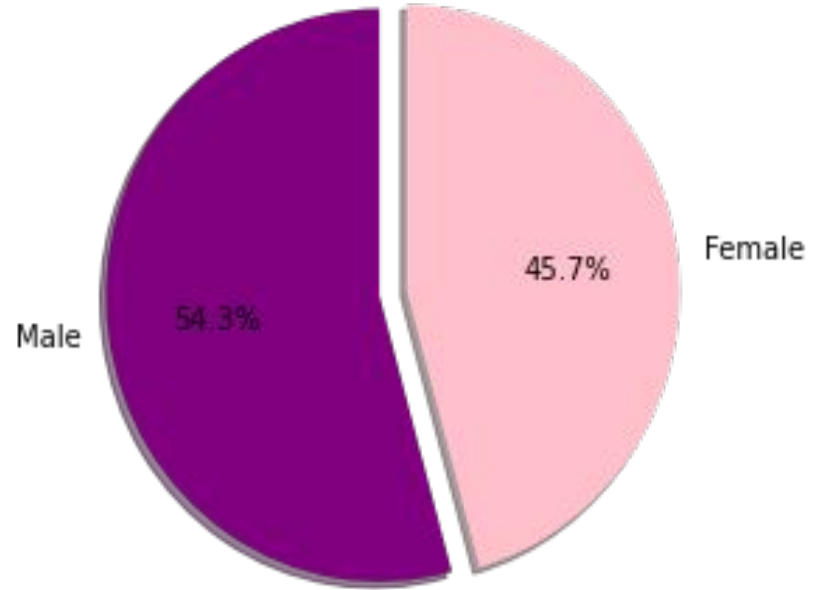
# Characteristics of Businesses



## Question: Percentage of male and female employees.

Steps to generate visual:

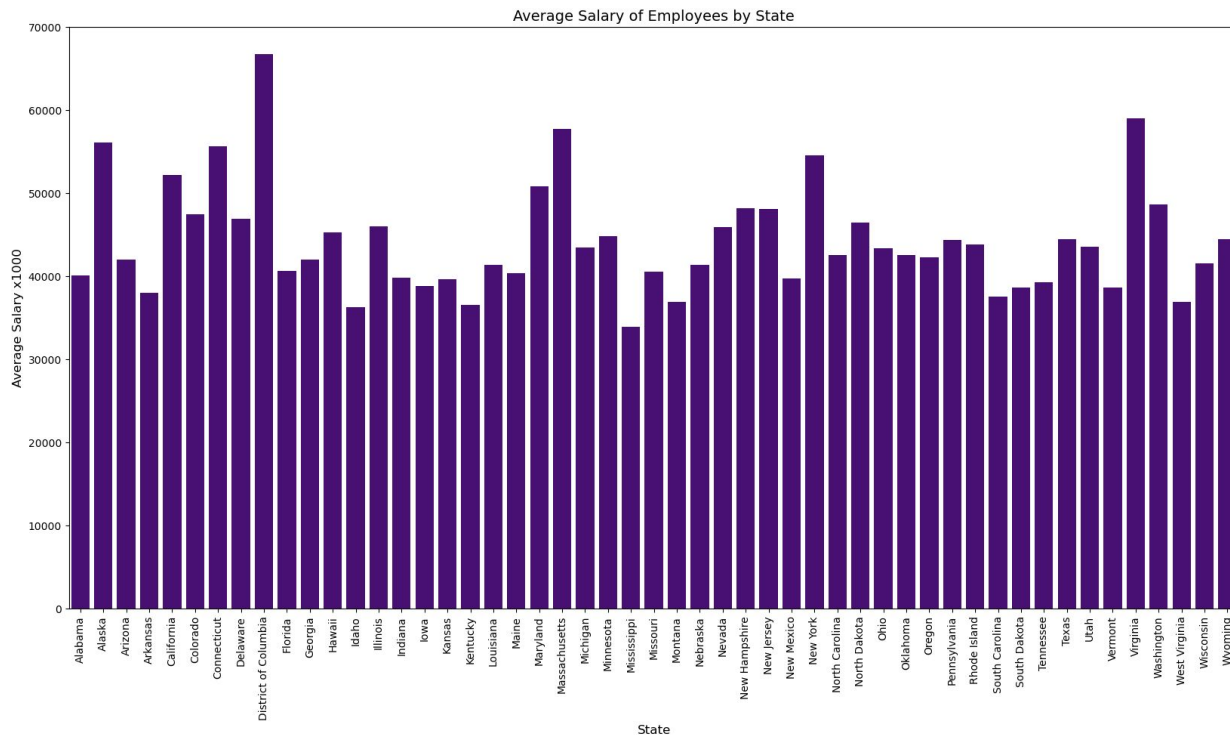
- Group the number of workers.
- Determine the count of workers for each gender:
  - $\text{Total\_gender\_count} = \text{Total} - (\text{Classifiable} + \text{Unclassifiable})$
  - $\text{Male\_count} = \text{Male} + \text{Equally male/female}$
  - $\text{Female\_count} = \text{Female} + \text{Equally male/female}$
- Calculate percentages:
  - $\text{Percent\_male} = (\text{Male\_count} / \text{Total\_gender\_count}) * 100$
  - $\text{Percent\_female} = (\text{Female\_count} / \text{Total\_gender\_count}) * 100$
- Plot as Pie chart



## Question: Average Salary of Employees per state

Steps to generate visual:

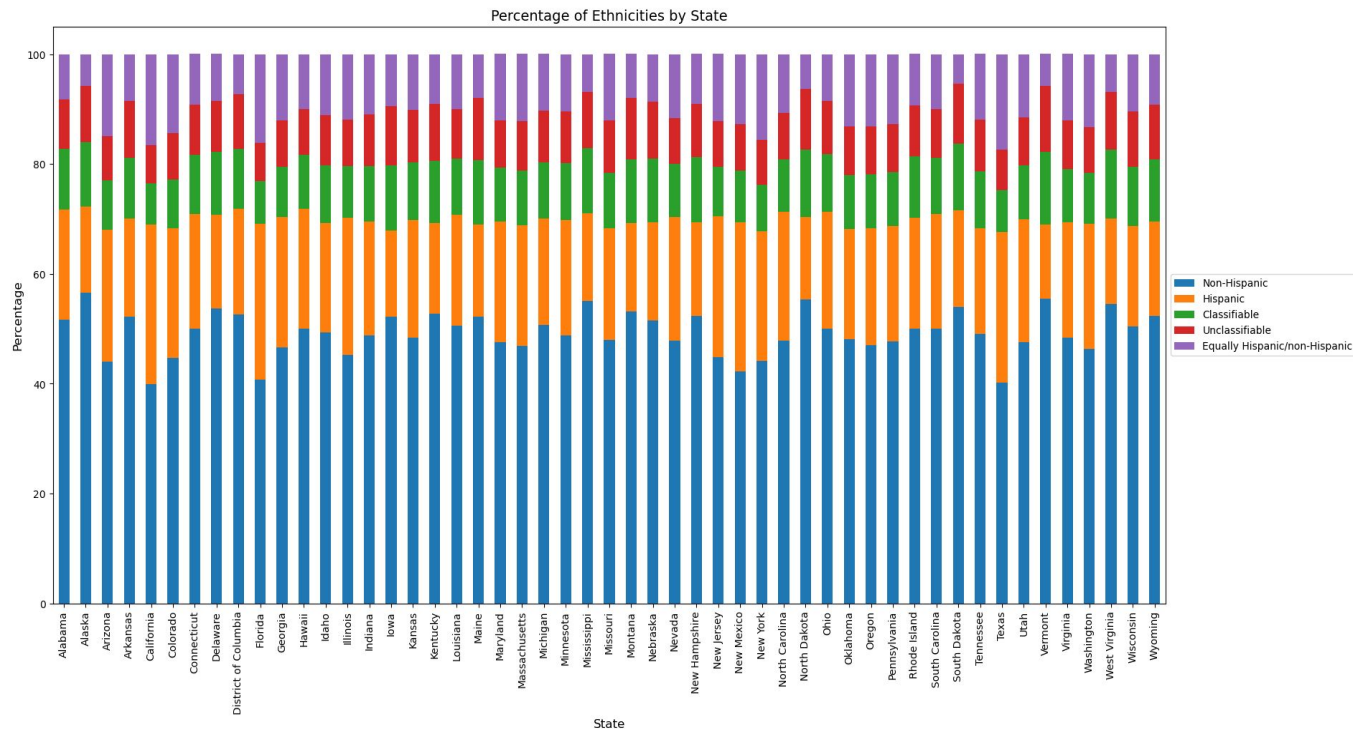
- API call on the business summary data table.
- Group salary values and states.
- Take the average of the salary values for each state.



# Question: For each state, what percentage of workers belong to each ethnicity?

Steps to generate visual:

- Drop the native “total” value from data set.
- Group by state name and ethnicity group label.
- Calculate new total ethnicity value for each state.
- Calculate the percentage of each ethnicity by dividing each ethnicities count by the total value for each state.
- Plot the resulting data on stacked bar chart.

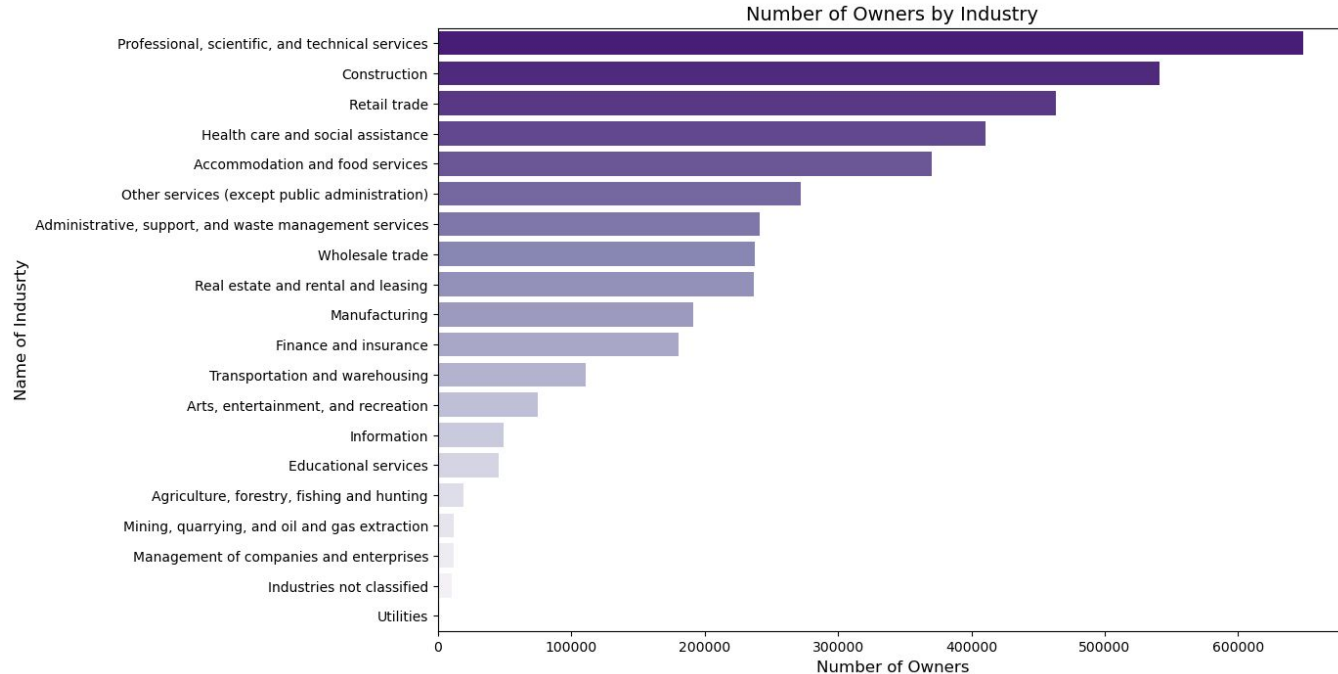


# Characteristics of Business Owners



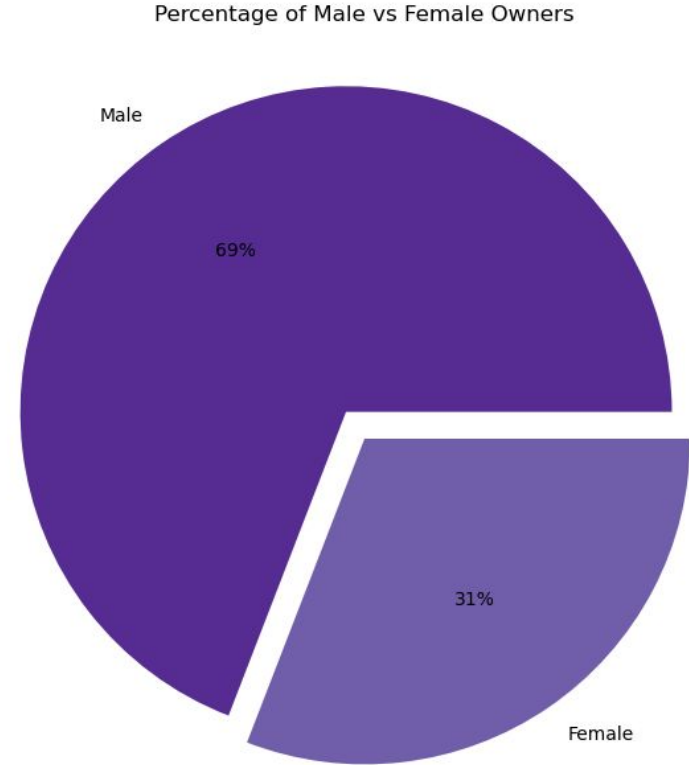
# What is the breakdown of number of owners by industry?

- Filtered down to focus on each individual industry
- Used group by and sum to get the totals
- Sorted values so the bars would be in descending order
- Difficult to draw conclusions from the graph since the largest industry includes a wide array of businesses



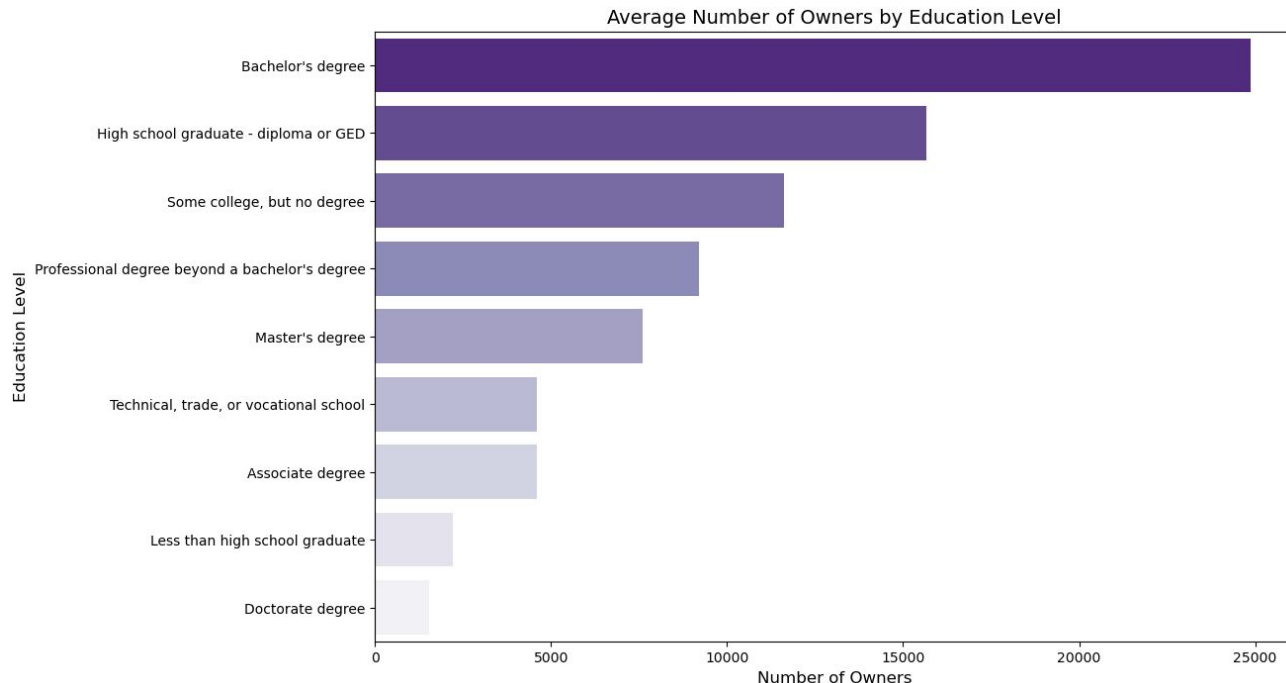
# Is there are a large difference between the percentage of male versus female business owners?

- Filtered again to focus on the data for male vs female business owners
- You can immediately see that the difference is much larger than the one between the percentage of male vs female employees
- Used explode so that the pieces of the pie would pop out



# What is the educational background of business owners?

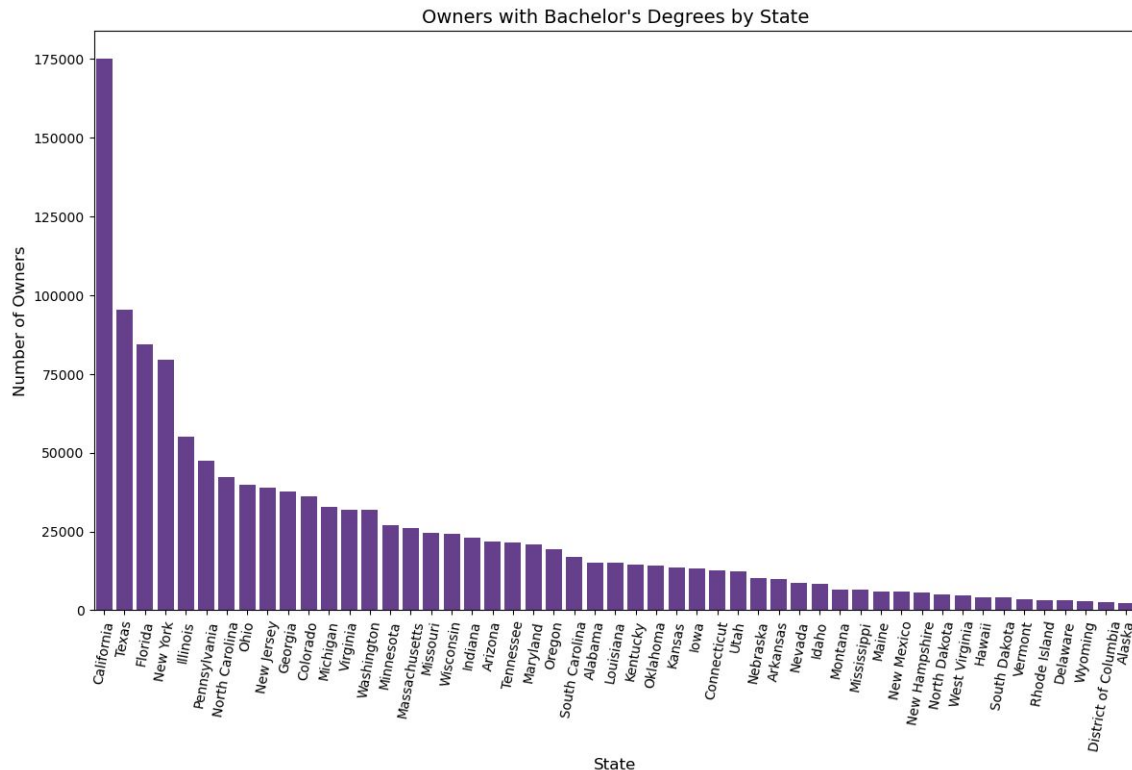
- Did another request to get data at the state level
- Used group by and the mean function to get the combined average for each education level





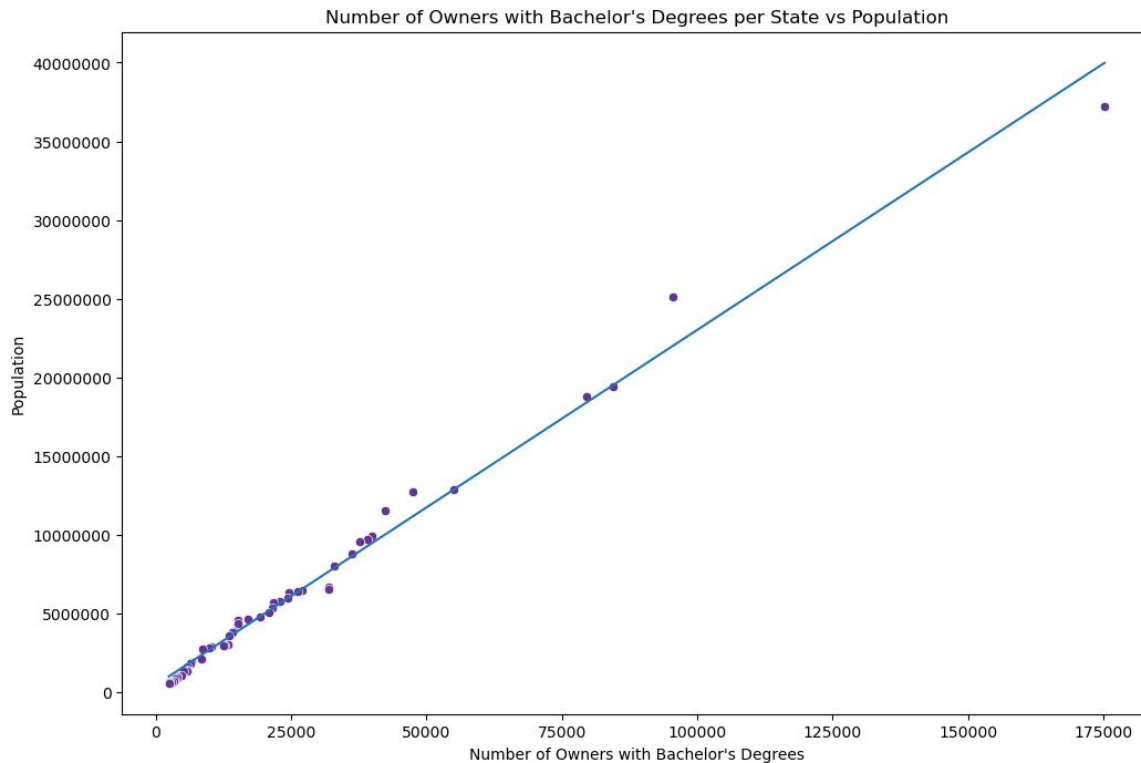
# Is there a difference in number of owners with Bachelor's degrees at the state level?

- Wanted to see if there was a difference in the number of owners with Bachelor's degrees per state
- At first glance it looks like there is a large difference, but...



# Comparing data from the previous graph to US Census population data

- When the data from the last slide is compared to state population, there is an r value of .99
- Tip: To get graph values out of scientific notation use “ticklabel\_format (style = ‘plain’)”



# **Technology Characteristics of Businesses**



**1. Dropped rows where *NAICS2017\_LABEL* equals *Total for all sectors***

```
indexNA = techuses[(techuses['NAICS2017_LABEL'] == 'Total for all sectors')].index  
techuses.drop(indexNA , inplace=True)
```

**2. To easily obtain the different levels of use for each particular technology, split column *Tech Use* into two columns named *Technology Used* and *Level of Use***

```
techuses[['Technology Used','Level of Use']] = techuses['Tech Use'].str.split(':', expand=True)  
techuses= techuses.drop(['Tech Use'], axis=1)
```

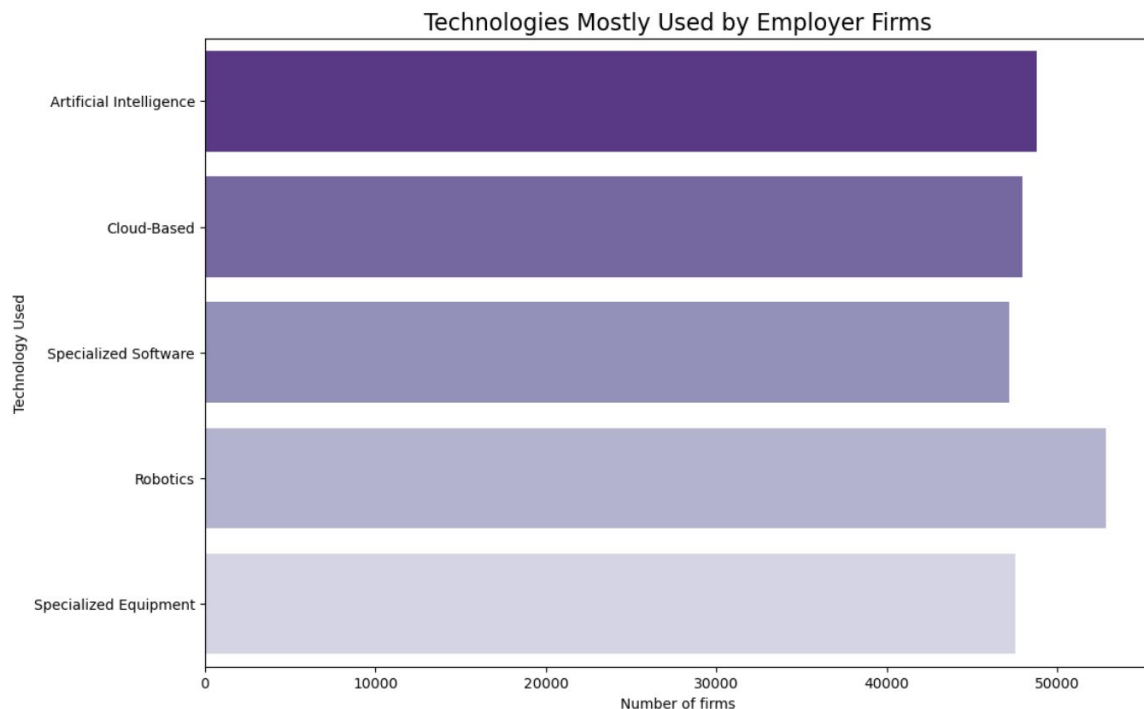
**3. Exclude rows using the `~isin()` method.**

```
techuses= techuses.loc[~techuses['Level of Use'].isin(['Total use','Total Reporting','Don't know'])]
```

**4. Calculated the Average Salary**

```
techuses['Average Salary']= (techuses['Annual Payroll']/techuses['Number of  
Employees'])*1000
```

# What technologies are mostly used by employer firms?

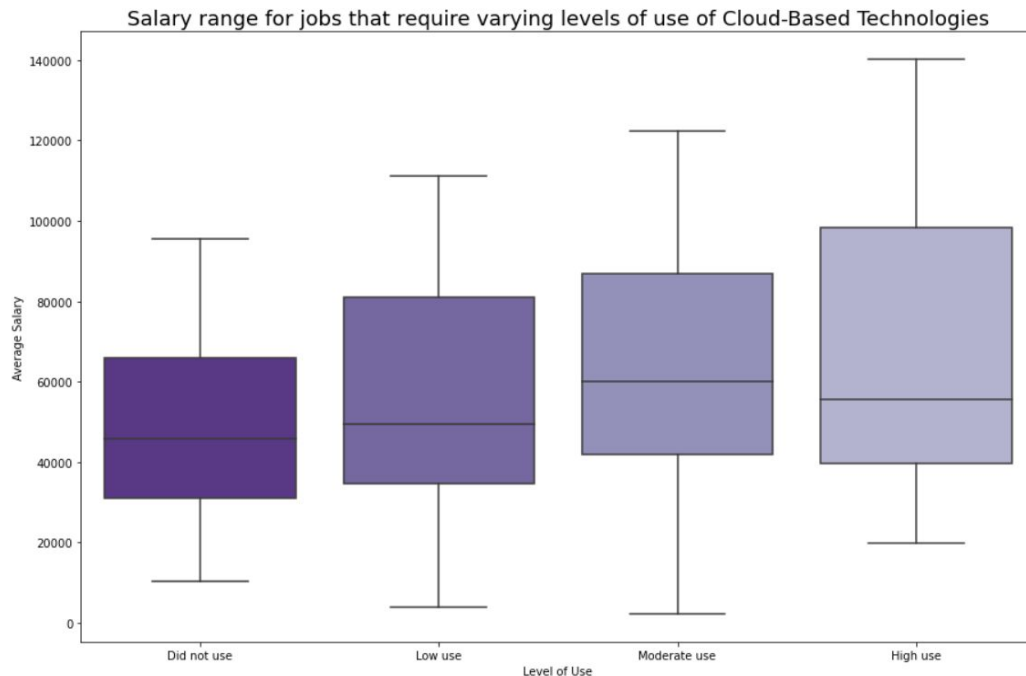


- We created a new DataFrame called `firmtech` that includes relevant columns from the `techuse` dataframe.
- Used `firmtech` as the data for our barplot.
- *Set confidence interval to None.*

```
sns.barplot(y= firmtech['Technology Used'], x=firmtech['Number of firms'], data=firmtech,  
ci=None);
```

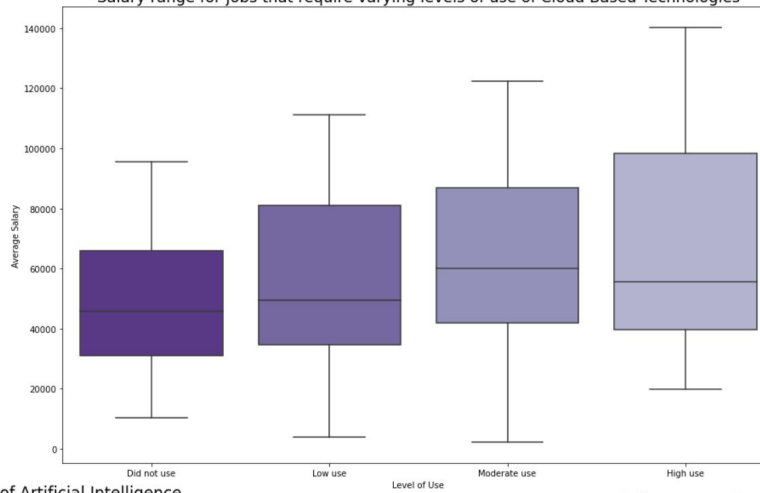
# What is the salary range for jobs that require varying levels of use of software-based technology?

- Created new data frames for each technology, called ai, cloud, and software, respectively.
- Removed rows that are flagged as S or D in the PAYANN\_F column.
- *Manually set the order according to the level of use with 'order='*

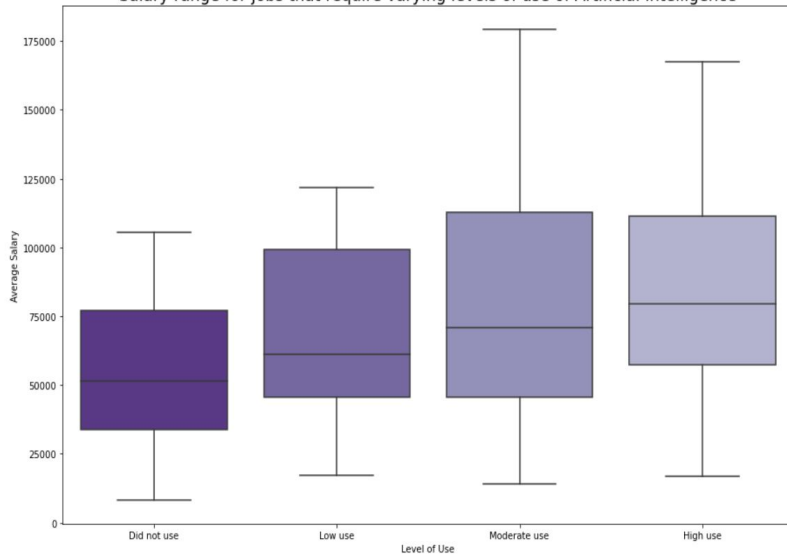


```
software_plot= sns.boxplot(x='Level of Use', y='Average Salary', data=software, order=['Did not use', 'Low use', 'Moderate use', 'High use'])
```

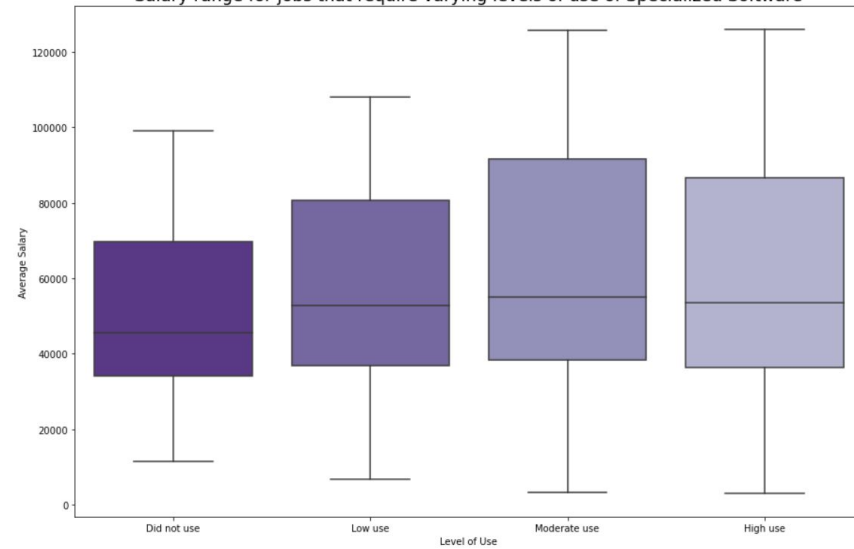
Salary range for jobs that require varying levels of use of Cloud-Based Technologies



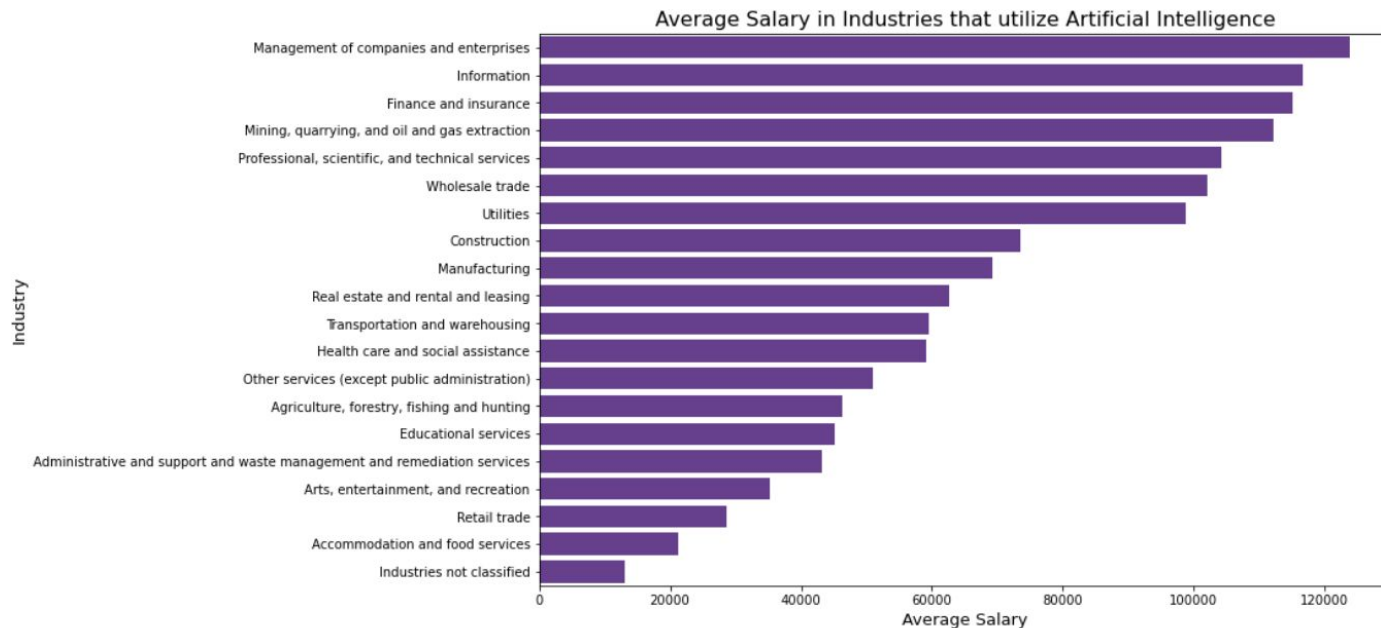
Salary range for jobs that require varying levels of use of Artificial Intelligence



Salary range for jobs that require varying levels of use of Specialized Software



# In which industries are individuals who work with Artificial Intelligence likely to earn the highest salaries?



- We grouped the Technology Used, Industry, and aggregated Average Salary into a new dataframe called `group_tech`.
- Created a numpy array called `ai_industry` that contains the unique values for Industry from the `ai` DataFrame and sorted it.
- Created a new DataFrame called `Payroll_ai` by transposing a list of the `group_tech` and `ai_industry` data.



# Code snippets

```
software= techuses[techuses['Technology Used'] == 'Specialized Software']  
ai= techuses[techuses['Technology Used']== 'Artificial Intelligence']  
cloud= techuses[techuses['Technology Used'] == 'Cloud-Based']
```

```
group_tech= ai.groupby(['Technology Used','Industry'])['Average Salary'].mean()  
ai_industry= ai['Industry'].unique()  
ai_industry.sort()  
Payroll_ai= (pd.DataFrame([list(group_tech),ai_industry])).T
```

**THANK YOU**

**ANY QUESTIONS**