IBM DATA ANALYST CAPSTONE PROJECT

CAPSTONE PROJECT : "TECHNOLOGY TREND ANALYSIS"

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INTRODUCTION

In fufillment of the IBM Data Analyst Professional Certificate, and completing a Caspstone Project, I'm working as a Data Analyst recently hired by a global IT and business consulting services firm that is known for their expertise in IT solutions and their team of highly experienced IT consultants.

In order to keep pace with changing technologies and remain competitive, my organization regularly analyzes data to help identify future skill requirements. As a Data Analyst, I will be assisting with this initiative, and have been tasked with collecting data from various sources and identifying trends for this year's report on emerging skills.

Firstly, I will begin by scraping internet web sites. And also collect the top programming skills that are most in demand from a Stack Overflow Developer 2019 Survey.

Once this is completed, data will be made ready for analysis using data wrangling techniques and then applying statistical techniques to analyze the data. Analyzing the data and identify insights and trends may include the following:

*What are the top programming languages in demand?

*What are the top database skills in demand?

*What are the popular IDEs?

After analyzing the data, I'll bring all of my information together by using IBM Cognos Analytics to create a dashboard. And finally, share my findings in a PowerPoint presentation.

DATA COLLECTION

In [1]:
```
# Import Required Libraries
import requests
import pandas as pd
```

Collecting Data Using Webscrapping

Extract information from the website below. The data to scrape contains the name of the Programming Language and Average Annual Salary

In [2]:
```
# This url contains the data to scrape
url = "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-DA0321EN
```

In [3]:
```
# Import the required libraries

from bs4 import BeautifulSoup # this module helps in web scrapping.
import requests  # this module helps us to download a web page
```

In [4]:
```
# Get the contents of the webpage in text format and store in a variable called data
data  = requests.get(url).text
```

In [5]:
```
# Create a soup object
soup = BeautifulSoup(data,"html5lib")
```

In [6]:
```
# Scrape the Language name and annual average salary.

table = soup.find('table') # in html table is represented by the tag <table>
data = []
for row in table.find_all('tr'):
    col = row.find_all('td')
    lang_name = col[1].getText()
    avg_salary = col[3].getText()
    data.append([lang_name, avg_salary])
data
```

Out[6]:
```
[['Language', 'Average Annual Salary'],
 ['Python', '$114,383'],
 ['Java', '$101,013'],
 ['R', '$92,037'],
 ['Javascript', '$110,981'],
 ['Swift', '$130,801'],
 ['C++', '$113,865'],
 ['C#', '$88,726'],
 ['PHP', '$84,727'],
 ['SQL', '$84,793'],
 ['Go', '$94,082']]
```

In [7]:
```
# Save the scrapped data into a file named popular-languages.csv

import pandas as pd
df=pd.DataFrame(data)#.set_index("Language name")
new_header = df.iloc[0]
df = df[1:]
df.columns = new_header
df = df.reset_index(drop=True)
df
```

Out[7]:

	Language	Average Annual Salary
0	Python	$114,383
1	Java	$101,013
2	R	$92,037
3	Javascript	$110,981
4	Swift	$130,801
5	C++	$113,865
6	C#	$88,726
7	PHP	$84,727
8	SQL	$84,793
9	Go	$94,082

In [8]:
```
df.to_csv('popular-languages.csv')
```

Survey Datasets Exploration

In [9]:
```
dataset_url = "https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-
```

In [10]:
```
# Load the data available at dataset_url into a dataframe.
df = pd.read_csv(dataset_url)
```

In [11]:
```
# Explore the Dataset.
df.head()    #The head displays the top 5 rows and columns from your dataset.
```

Out[11]:

	Respondent	MainBranch	Hobbyist	OpenSourcer	OpenSource	Employment	Country	Student	Ed
0	4	I am a developer by profession	No	Never	The quality of OSS and closed source software ...	Employed full-time	United States	No	Bachelor's d (BA, BS,
1	9	I am a developer by profession	Yes	Once a month or more often	The quality of OSS and closed source software ...	Employed full-time	New Zealand	No	college/uni study w ear
2	13	I am a developer by profession	Yes	Less than once a month but more than once per ...	OSS is, on average, of HIGHER quality than pro...	Employed full-time	United States	No	Master's d (MA, MS, M MBA
3	16	I am a developer by profession	Yes	Never	The quality of OSS and closed source software ...	Employed full-time	United Kingdom	No	Master's d (MA, MS, M MBA
4	17	I am a developer by profession	Yes	Less than once a month but more than once per ...	The quality of OSS and closed source software ...	Employed full-time	Australia	No	Bachelor's d (BA, BS,

5 rows × 85 columns

In [12]:
```
# Number of Rows
df.shape[0]
```

Out[12]: 11552

In [13]:
```
# Number of Columns
df.shape[1]
```

Out[13]: 85

In [14]:
```
# Data types for each column
df.dtypes
```

Out[14]:
```
Respondent       int64
MainBranch      object
Hobbyist        object
OpenSourcer     object
OpenSource      object
                 ...
Sexuality       object
Ethnicity       object
Dependents      object
SurveyLength    object
SurveyEase      object
Length: 85, dtype: object
```

In [15]:
```
# Mean Age of Survey Participant
df["Age"].mean()
```

Out[15]: 30.77239449133718

In [16]:
```
# Number of unique countries in the Country column
df["Country"].nunique()
```

Out[16]: 135

DATA WRANGLING

Data wrangling or data munging is the process of removing errors and combining complex data sets to make them more accessible and easier to analyze. Here we will identify and remove duplicate rows, find and impute missing values and normalize the data.

Finding and Removing Duplicate Data

In [17]:
```
# Finding duplicates (how many duplicate rows exist in the dataframe.)
df.duplicated(keep='first').sum()
```

Out[17]: 154

In [18]:
```
# Removing duplicates
df.drop_duplicates(ignore_index=True, inplace=True)
```

In [19]:
```
# Verify if duplicates were actually dropped.
df.duplicated(keep='first').sum()
```

Out[19]: 0

In [20]:
```
df.shape
```

Out[20]: (11398, 85)

Finding and Imputing Missing Values

In [21]:
```
# Finding Missing values (Lets find the missing values for all columns.)
df.isnull().sum()
```

Out[21]:
```
Respondent        0
MainBranch        0
Hobbyist          0
OpenSourcer       0
OpenSource       81
               ...
Sexuality       542
Ethnicity       675
Dependents      140
SurveyLength     19
SurveyEase       14
Length: 85, dtype: int64
```

In [22]:
```
# Number of rows missing in the column "WorkLoc"
df["WorkLoc"].isnull().sum()
```

Out[22]: 32

In [23]:
```
# Number of rows missing in the column "EdLevel"
df["EdLevel"].isnull().sum()
```

Out[23]: 112

In [24]:
```
# Number of rows missing in the column "Country"
df["Country"].isnull().sum()
```

Out[24]: 0

In [25]:
```
# Imputing missing values (Lets find the value counts for the column WorkLoc)
df["WorkLoc"].value_counts()
```

Out[25]:
```
Office                                            6806
Home                                              3589
Other place, such as a coworking space or cafe     971
Name: WorkLoc, dtype: int64
```

Identify the value that is most frequent (majority) in the WorkLoc column. The majority value here is 'Office'. Then Impute (replace) all the empty rows in the column WorkLoc with the value that you have identified as majority.

In [26]:
```
df["WorkLoc"].fillna(value="Office",inplace=True)
```

After imputation there should ideally not be any empty rows in the WorkLoc column. Verify if imputing was successful.

In [27]:
```
df["WorkLoc"].value_counts()
```

Out[27]:
```
Office                                            6838
Home                                              3589
Other place, such as a coworking space or cafe     971
Name: WorkLoc, dtype: int64
```

In [28]:
```
df["WorkLoc"].isnull().sum()
```

Out[28]: 0

Normalizing Data

There are two columns in the dataset that talk about compensation.

One is "CompFreq". This column shows how often a developer is paid (Yearly, Monthly, Weekly).

The other is "CompTotal". This column talks about how much the developer is paid per Year, Month, or Week depending upon his/her "CompFreq".

This makes it difficult to compare the total compensation of the developers.

We will create a new column called 'NormalizedAnnualCompensation' which contains the 'Annual Compensation' irrespective of the 'CompFreq'.

Once this column is ready, it makes comparison of salaries easy.

In [29]:
```
#Various categories in the column 'CompFreq'
df["CompFreq"].unique()
```

Out[29]: array(['Yearly', 'Monthly', 'Weekly', nan], dtype=object)

Create a new column named 'NormalizedAnnualCompensation'

In [30]:
```
df["CompFreq"].replace(to_replace="Yearly",value=1,inplace=True)
df["CompFreq"].replace(to_replace="Monthly",value=12,inplace=True)
df["CompFreq"].replace(to_replace="Weekly",value=52,inplace=True)
```

In [31]:
```
df["CompFreq"].unique()
```

Out[31]: array([1., 12., 52., nan])

In [32]:
```
df["CompFreq"].value_counts()
```

Out[32]:
```
1.0     6073
12.0    4788
52.0     331
Name: CompFreq, dtype: int64
```

In [33]:
```
df['NormalizedAnnualCompensation'] = df["CompTotal"] * df["CompFreq"]
df
```

Out[33]:

	Respondent	MainBranch	Hobbyist	OpenSourcer	OpenSource	Employment	Country	Student
0	4	I am a developer by profession	No	Never	The quality of OSS and closed source software ...	Employed full-time	United States	No
1	9	I am a developer by profession	Yes	Once a month or more often	The quality of OSS and closed source software ...	Employed full-time	New Zealand	No
2	13	I am a developer by profession	Yes	Less than once a month but more than once per ...	OSS is, on average, of HIGHER quality than pro...	Employed full-time	United States	No
3	16	I am a developer by profession	Yes	Never	The quality of OSS and closed source software ...	Employed full-time	United Kingdom	No
4	17	I am a developer by profession	Yes	Less than once a month but more than once per ...	The quality of OSS and closed source software ...	Employed full-time	Australia	No
...	...	...	...	...	...	...	...	...
11393	25136	I am a developer by profession	Yes	Never	OSS is, on average, of HIGHER quality than pro...	Employed full-time	United States	No
11394	25137	I am a developer by profession	Yes	Never	The quality of OSS and closed source software ...	Employed full-time	Poland	No
11395	25138	I am a developer by profession	Yes	Less than once per year	The quality of OSS and closed source software ...	Employed full-time	United States	No
11396	25141	I am a developer by profession	Yes	Less than once a month but more than once per ...	OSS is, on average, of LOWER quality than prop...	Employed full-time	Switzerland	No
11397	25142	I am a developer by profession	Yes	Less than once a month but more than once per ...	OSS is, on average, of HIGHER quality than pro...	Employed full-time	United Kingdom	No

11398 rows × 86 columns

In [34]:
```
df["Respondent"].nunique()
```

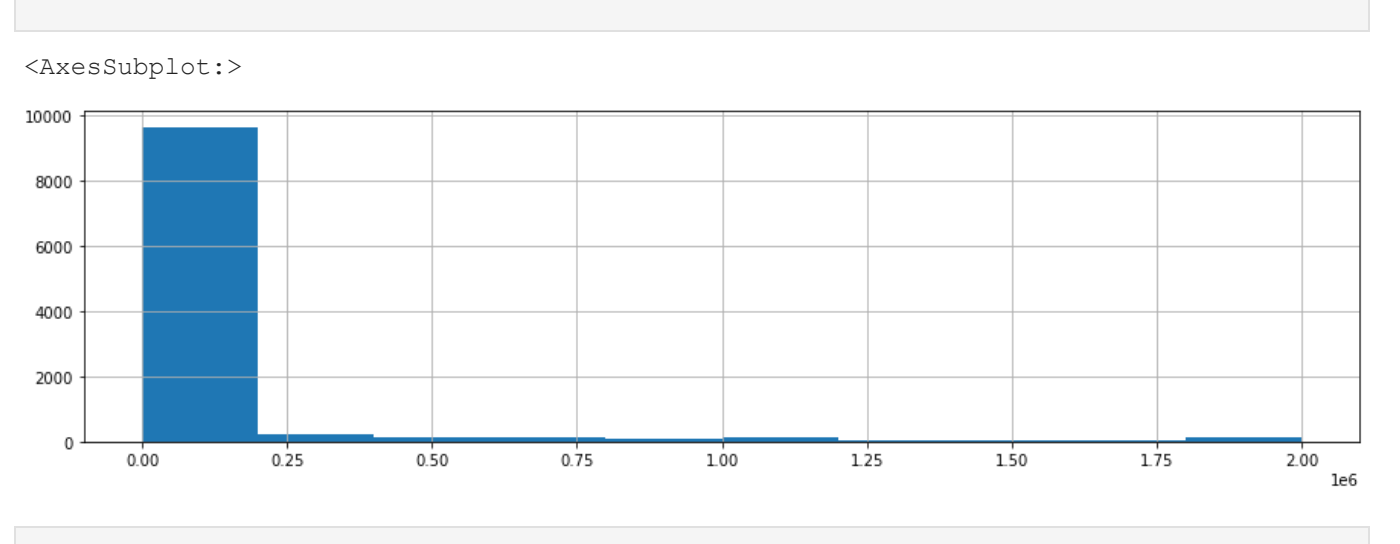
Out[34]: 11398

In [35]:
```
df["ConvertedComp"].describe()
```

Out[35]:
```
count    1.058200e+04
mean     1.315967e+05
std      2.947865e+05
min      0.000000e+00
25%      2.686800e+04
50%      5.774500e+04
75%      1.000000e+05
max      2.000000e+06
Name: ConvertedComp, dtype: float64
```

In [36]:
```
df["ConvertedComp"].hist(figsize=(15,4))
```

Out[36]: <AxesSubplot:>



In [37]:
```
df['NormalizedAnnualCompensation'].median()
```

Out[37]: 100000.0

In [38]:
```
df.to_csv("M2_DW.csv",index=False)
```

EXPLORATORY DATA ANALYSIS

In this exploratory data analysis. we will find out the distribution of data, presence of outliers and also determine the correlation between different columns in the dataset.

Analyzing the data distribution

In [39]:
```
df = pd.read_csv("https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/I
```

The column ConvertedComp contains Salary converted to annual USD salaries using the exchange rate on 2019-02-01.

This assumes 12 working months and 50 working weeks.

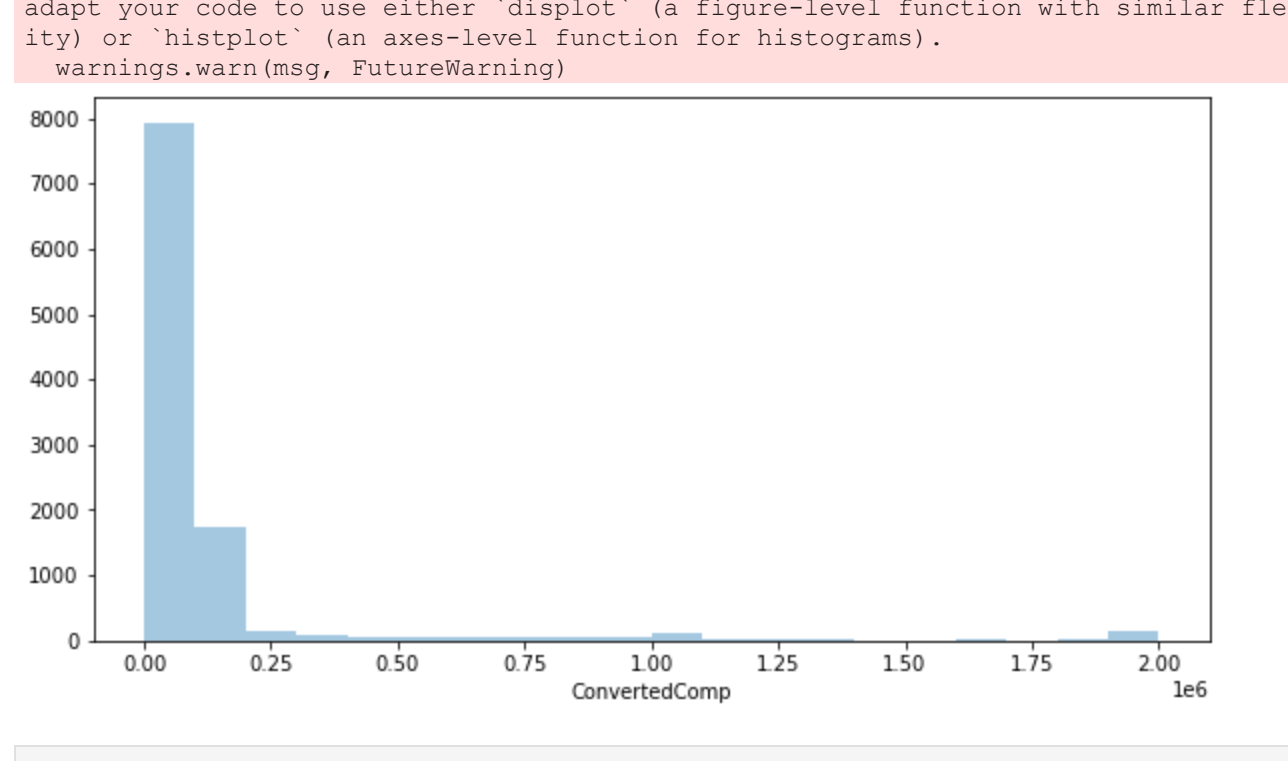
Lets plot the distribution curve for the column ConvertedComp.

In [40]:
```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Plot the histogram for the column ConvertedComp

In [41]:
```
plt.figure(figsize=(10,5))
sns.distplot(a=df["ConvertedComp"],bins=20,kde=False)
plt.show()
```

```
C:\Users\chrix\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarnin
g: `distplot` is a deprecated function and will be removed in a future version. Please
adapt your code to use either `displot` (a figure-level function with similar flexibil
ity) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [42]:
```
# Median of the column ConvertedComp
df["ConvertedComp"].median()
```

Out[42]: 57745.0

In [43]:
```
# Mean of the column ConvertedComp
df["Age"].median()
```

Out[43]: 29.0

In [44]:
```
# Gender Value Count
df["Gender"].value_counts()
```

Out[44]:
```
Man                                                            10480
Woman                                                            731
Non-binary, genderqueer, or gender non-conforming                 63
Man;Non-binary, genderqueer, or gender non-conforming             26
Woman;Non-binary, genderqueer, or gender non-conforming           14
Woman;Man                                                          9
Woman;Man;Non-binary, genderqueer, or gender non-conforming        2
Name: Gender, dtype: int64
```

In [45]:
```
# Median ConvertedComp of responders identified themselves only as a Man
woman = df[df["Gender"] == "Man"]
woman["ConvertedComp"].median()
```

Out[45]: 57744.0

In [46]:
```
# Median ConvertedComp of responders identified themselves only as a Woman
woman = df[df["Gender"] == "Woman"]
woman["ConvertedComp"].median()
```

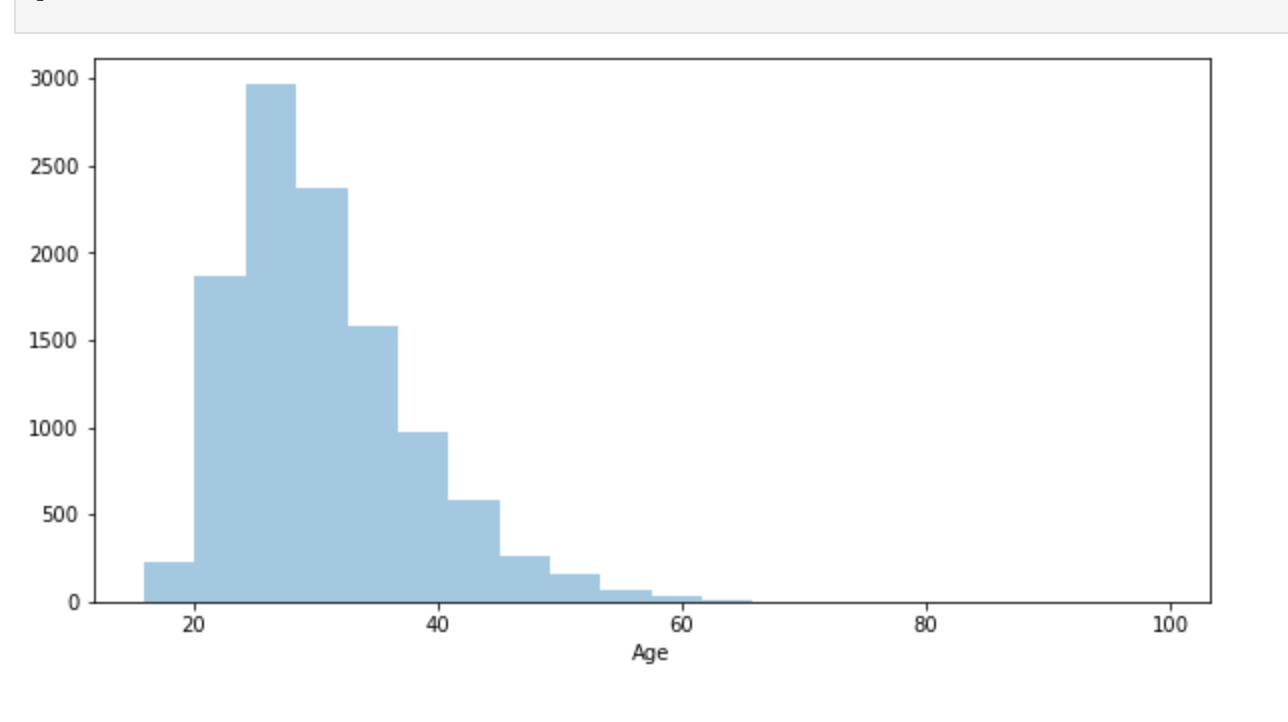
Out[46]: 57708.0

In [47]:
```
# Summary for the column Age
df["Age"].describe()
```

Out[47]:
```
count    11111.000000
mean        30.778895
std          7.393686
min         16.000000
25%         25.000000
50%         29.000000
75%         35.000000
max         99.000000
Name: Age, dtype: float64
```

Lets plot a histogram of the column Age.

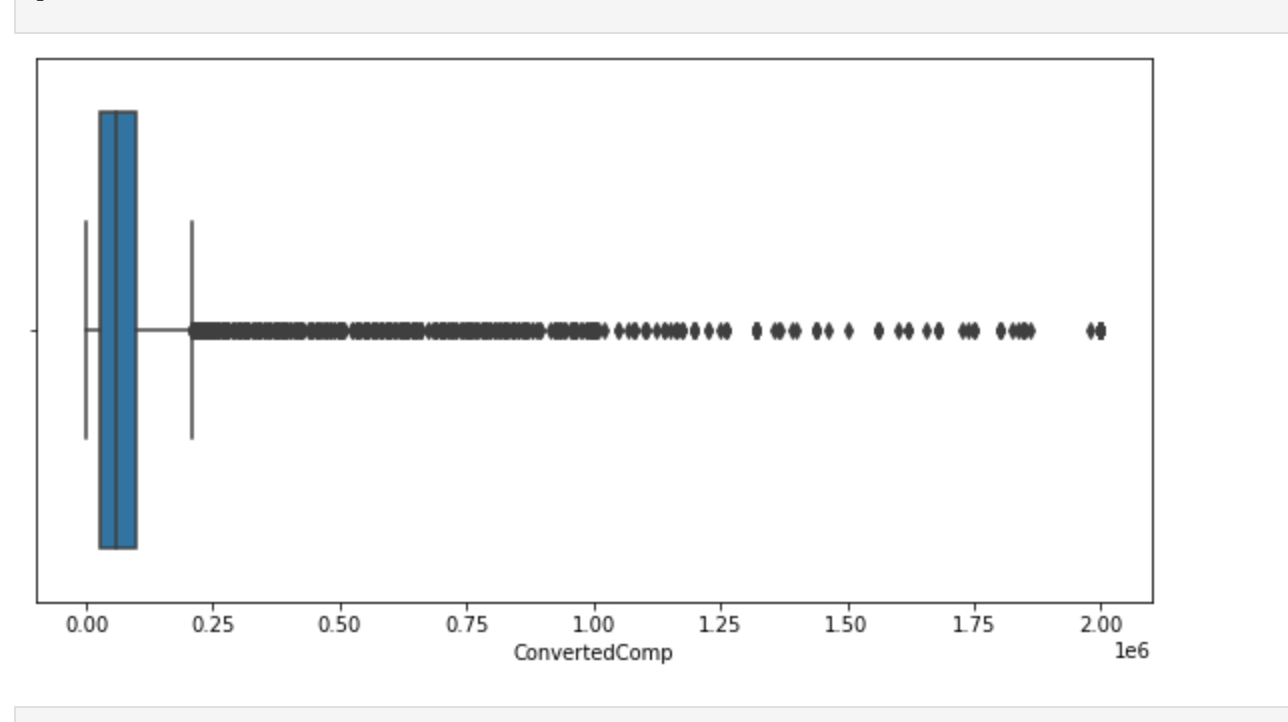
In [48]:
```
plt.figure(figsize=(10,5))
sns.distplot(a=df["Age"],bins=20,kde=False)
plt.show()
```



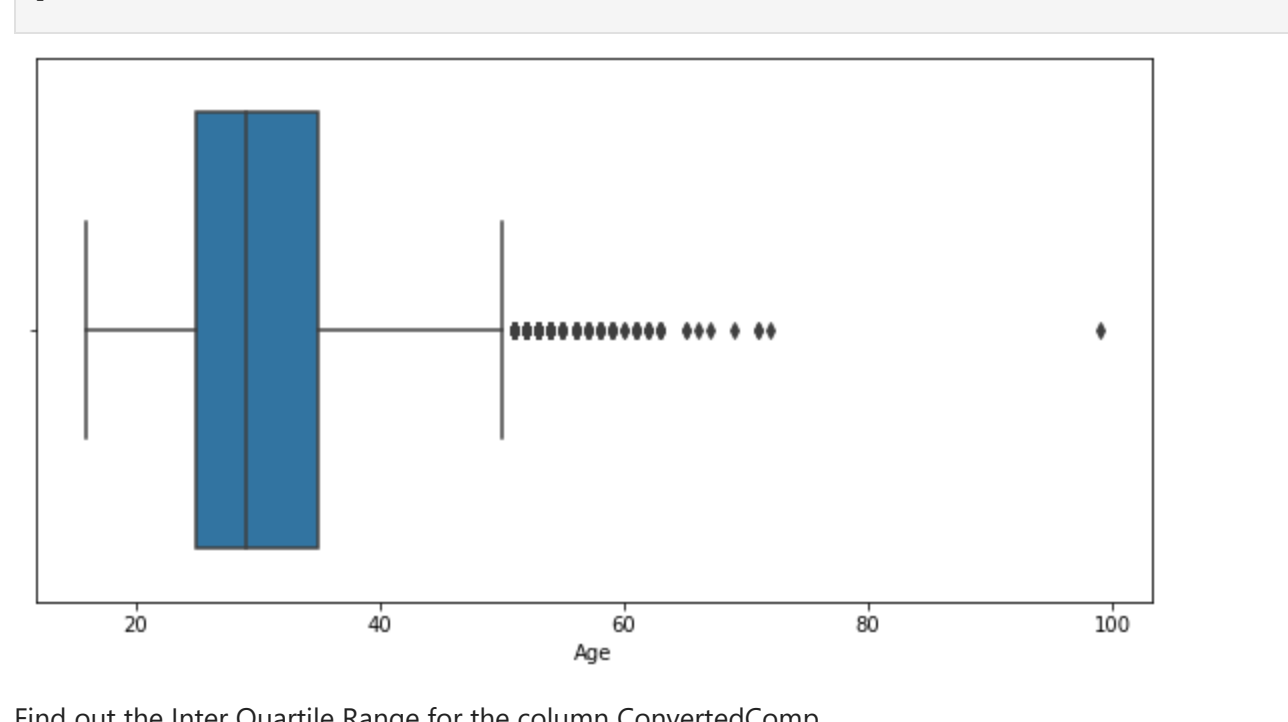
Identifying and removing outliers

Find out if outliers exist in the column ConvertedComp using a box plot

In [49]:
```
plt.figure(figsize=(10,5))
sns.boxplot(x=df.ConvertedComp, data=df)
plt.show()
```



In [50]:
```
plt.figure(figsize=(10,5))
sns.boxplot(x=df.Age, data=df)
plt.show()
```



Find out the Inter Quartile Range for the column ConvertedComp.

In [51]:
```
df["ConvertedComp"].describe()
```

Out[51]:
```
count    1.058200e+04
mean     1.315967e+05
std      2.947865e+05
min      0.000000e+00
25%      2.686800e+04
50%      5.774500e+04
75%      1.000000e+05
max      2.000000e+06
Name: ConvertedComp, dtype: float64
```

In [52]:
```
# Median Converted Comp before removing outliers
df["ConvertedComp"].median()
```

Out[52]: 57745.0

In [53]:
```
# Inter Quartile Range for the column ConvertedComp

1.000000e+05 - 2.686800e+04
```

Out[53]: 73132.0

Find out the upper and lower bounds.

In [54]:
```
Q1 = df["ConvertedComp"].quantile(0.25)
Q3 = df["ConvertedComp"].quantile(0.75)
IQR = Q3 - Q1
print(IQR)
```

```
73132.0
```

Identify how many outliers are there in the ConvertedComp column.

In [55]:
```
outliers = (df["ConvertedComp"] < (Q1 - 1.5 * IQR)) | (df["ConvertedComp"] > (Q3 + 1.5
outliers.value_counts()
```

Out[55]:
```
False    10519
True       879
Name: ConvertedComp, dtype: int64
```

Create a new dataframe by removing the outliers from the ConvertedComp column.

In [56]:
```
less = (df["ConvertedComp"] < (Q1 - 1.5 * IQR))
less.value_counts()
```

Out[56]:
```
False    11398
Name: ConvertedComp, dtype: int64
```

In [57]:
```
more = (df["ConvertedComp"] > (Q3 + 1.5 * IQR))
more.value_counts()
```

Out[57]:
```
False    10519
True       879
Name: ConvertedComp, dtype: int64
```

In [58]:
```
RemoveConvertedcomp = df[~(df["ConvertedComp"] > (Q3 + 1.5 * IQR))]
RemoveConvertedcomp.head()
```

Out[58]:

	Respondent	MainBranch	Hobbyist	OpenSourcer	OpenSource	Employment	Country	Student	Ed
0	4	I am a developer by profession	No	Never	The quality of OSS and closed source software ...	Employed full-time	United States	No	Bachelor's d (BA, BS, E
1	9	I am a developer by profession	Yes	Once a month or more often	The quality of OSS and closed source software ...	Employed full-time	New Zealand	No	college/univ study w earr
2	13	I am a developer by profession	Yes	Less than once a month but more than once per ...	OSS is, on average, of HIGHER quality than pro...	Employed full-time	United States	No	Master's d (MA, MS, M MBA
4	17	I am a developer by profession	Yes	Less than once a month but more than once per ...	The quality of OSS and closed source software ...	Employed full-time	Australia	No	Bachelor's d (BA, BS, E
5	19	I am a developer by profession	Yes	Never	The quality of OSS and closed source software ...	Employed full-time	Brazil	No	college/univ study w earr

5 rows × 85 columns

In [59]:
```
# Median Converted Comp after removing outliers
RemoveConvertedcomp["ConvertedComp"].median()
```

Out[59]: 52704.0

In [60]:
```
# Mean Converted Comp after removing outliers
RemoveConvertedcomp["ConvertedComp"].mean()
```

Out[60]: 59883.20838915799

Correlation

Lets find the correlation between Age and all other numerical columns

In [61]:
```
df.corr()
```

Out[61]:

	Respondent	CompTotal	ConvertedComp	WorkWeekHrs	CodeRevHrs	Age
Respondent	1.000000	-0.013490	0.002181	-0.015314	0.004621	0.004041
CompTotal	-0.013490	1.000000	0.001037	0.003510	0.007063	0.006970
ConvertedComp	0.002181	0.001037	1.000000	0.021143	-0.033865	0.105386
WorkWeekHrs	-0.015314	0.003510	0.021143	1.000000	0.026517	0.036518
CodeRevHrs	0.004621	0.007063	-0.033865	0.026517	1.000000	-0.020469
Age	0.004041	0.006970	0.105386	0.036518	-0.020469	1.000000

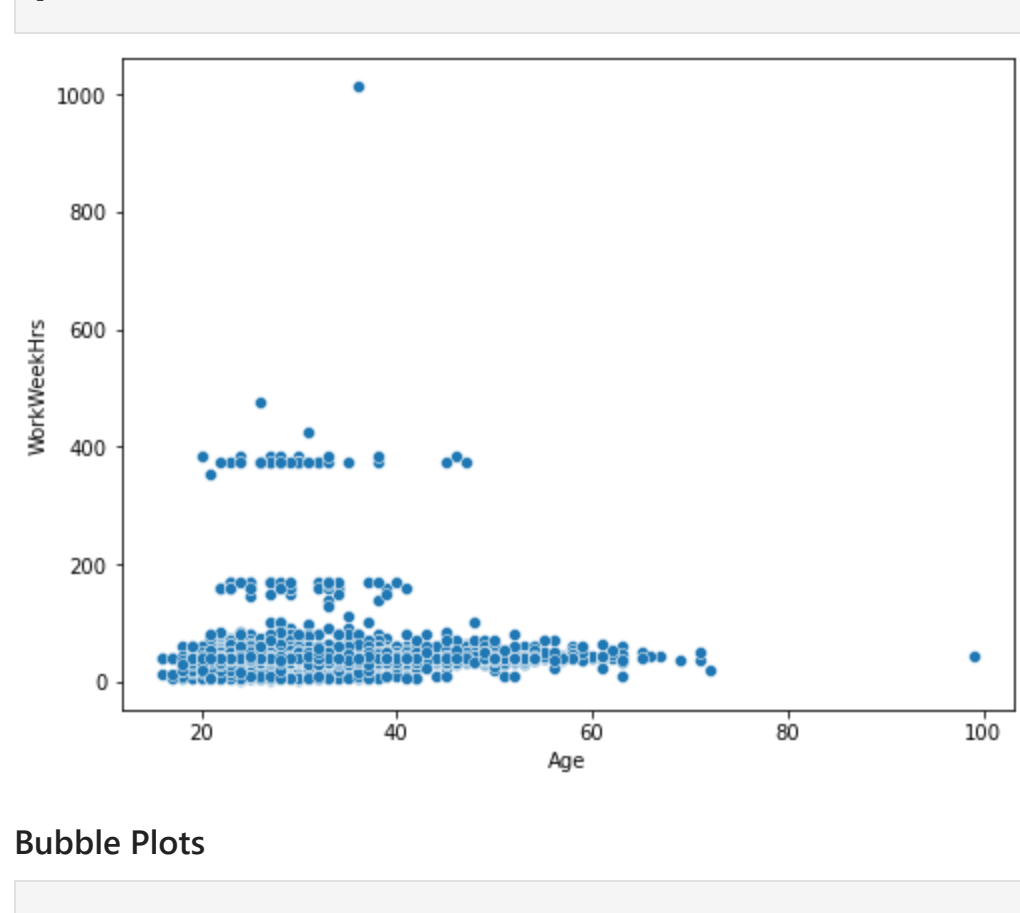
DATA VISUALIZATION

Visualizing relationships in data

Scatter Plots

In [62]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(x='Age', y='WorkWeekHrs', data=df)

plt.show()
```

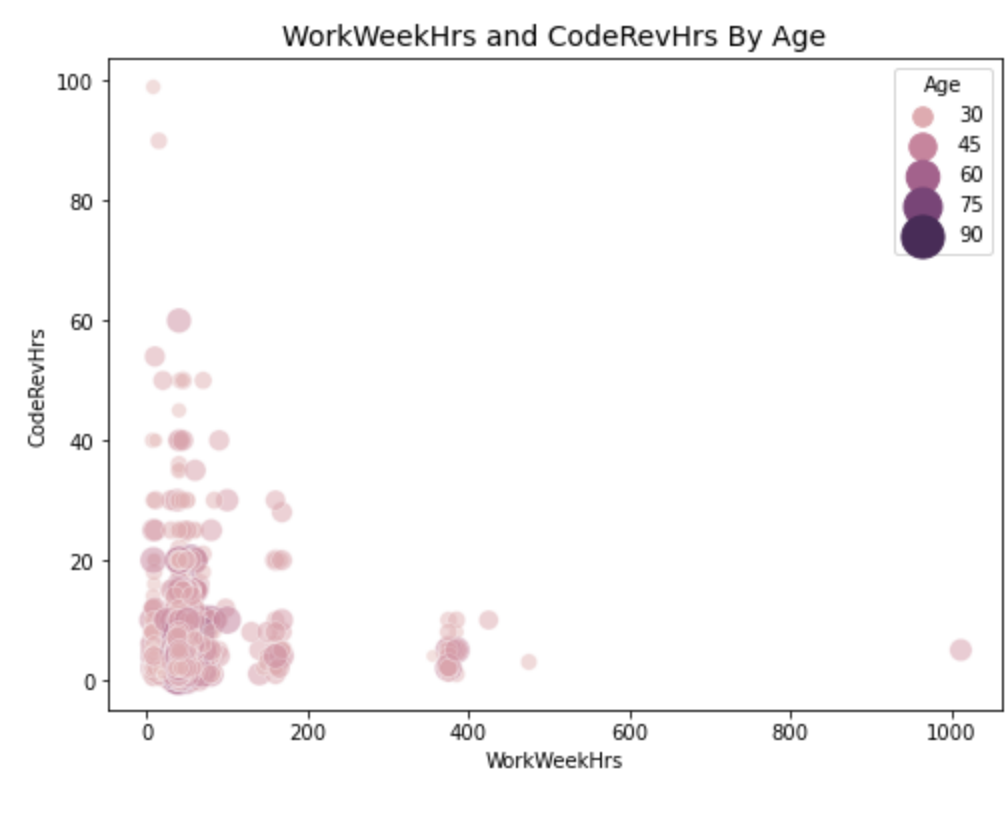


Bubble Plots

In [63]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(data=df, x='WorkWeekHrs', y='CodeRevHrs', size='Age', hue='Age', alpha

plt.title('WorkWeekHrs and CodeRevHrs By Age', size=14)
plt.xlabel('WorkWeekHrs', size=10)
plt.ylabel('CodeRevHrs', size=10)

plt.show()
```



PRESENTATION OF FINDINGS

The story of the project analysis is presented on a PowerPoint template. Click on the link below to view presentation

https://1drv.ms/p/s!ApEXLB-uX7f6gZsrceiaIJp9VLjQpg?e=l0bb2n