Data Analysis Assignment Number Three - Bootstraps and Salaries

In [1]:
```
import pandas as pd
import seaborn as sns
import numpy as np
from matplotlib import pyplot as plt
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning) #Was added beca
                                                                # indexing floa
df = pd.read_csv('ds_salaries.csv')
```

Note : as the code cells are large and so are some of the visualization there are a lot of buffers to prevent clippings in the PDF format

Part One - Data Field salaries Dataset

Preprocessing the Dataset

Before we begin answering the questions in this assignment in order to avoid misjudgments, we should analyze the dataset we are working with.

What is the shape of the data set:

In [2]:
```
#Print the dataframe dimensions in an implicit manner.
print(f'The data set has {df.shape[0]} rows and {df.shape[1]} columns.')
```

```
The data set has 1565 rows and 6 columns.
```

Are there any missing values in our dataset?

In [3]:
```
#Check if there are any null elements in the dataframe.
df.isna().sum()
```

Out[3]:
```
experience_level    0
employment_type     0
job_title           0
salary_in_usd       0
remote_ratio        0
company_size        0
dtype: int64
```

It appears the dataset doesn't contain any anomalies such as missing data so it should be "safe" to operate on it without pre-processing it.

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Question One

Based on a survey that had been carried out on feburary 2023, the ratio of americans who entirely work from home is 35%. Under the assumption that this variable had also been measured amongst the "Data" workers in the US and had been found to be similiar:

Does the csv (data file) represent well the population of the "Data" workers? Or does it countain a sub representation for workers that work entirely from home?

Test the claim using the variable remote_ratio with a siginificane level of 0.05 .

Subquestion 1

State the null hypothesis and the alternative hypothesis.

Let p be the precentage of workers that work entirely from home.

$$H_0 : p = 35\%$$
$$H_1 : p \neq 35\%$$

Subquestion 2

What is the test statistic?

The test statistic in this question would be the ratio of data related field employees that work from home in our dataframe.

In [4]:
```
#Calculate the ratio of data related field employees
prob_remote_in_data = len(df[df.remote_ratio == "fully remote"])/df.shape[0]
prob_remote_in_data_rounded = round(prob_remote_in_data*100,3)
print(f'Our test statistic value is {prob_remote_in_data_rounded}% of employee
```

```
Our test statistic value is 32.46% of employees that work completely remote.
```

Subquestion 3

Write code that test the hypothesis using simulation. Write explanations for your code.

In [5]:
```
'''Similar to the dice roll simulations create a simulation under the null hyp
   employment_type would be the types we are intersted in
   prob_for_type would be the probability for every type
   sampling_size would be the size ouf or simulations which match our sample
   prob_remote_in_data is our real probability
    '''
employment_type = ["fully remote","not fully remote"]
prob_for_type = [0.35,0.65]
sampling_size = df.shape[0]
prob_remote_in_data = len(df[df.remote_ratio == "fully remote"])/df.shape[0]
```

In [6]:
```
def single_mean_simulation(types,prob_for_type,size,desired_type):
    '''This function creates a single simulation under the null hypothesis and
       we have in our sample
       returns a ratio describing the percentage of desired type count in our
    new_simulated_sample = np.random.choice(employment_type, p=prob_for_type,
    count = 0
    for i in range(size):
        if new_simulated_sample[i] == desired_type:
            count += 1
    return count/size
```

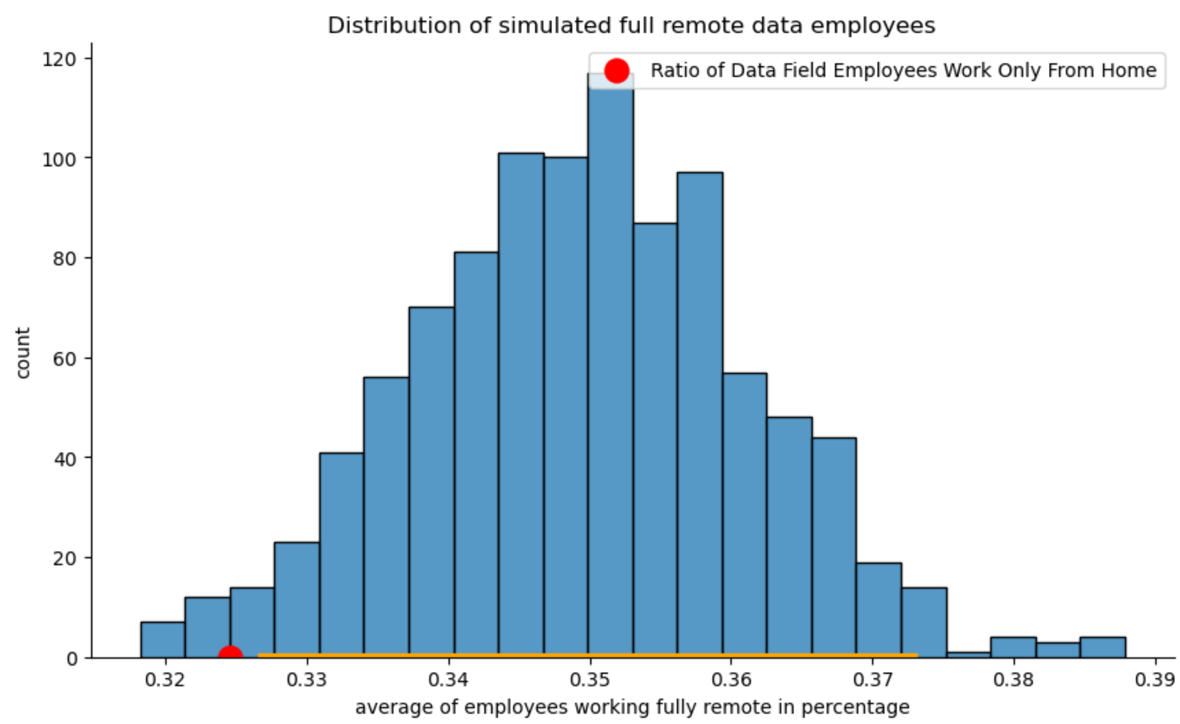
In [7]:
```
def mean_simulation(types , prob_for_type, num_replications, original_sample_s
    '''This is a wrapper function for single_mean_simulation , calls it num_re
      times and puts them all in an array
      returns an array of percentage of desired in simulations'''

    simulated_means = np.empty(num_replications)
    for i in range(num_replications):
        simulated_means[i] = single_mean_simulation(types,prob_for_type,origin


    return simulated_means
```

In [8]:
```
simulated_means = mean_simulation(employment_type,prob_for_type,1000,sampling_
```

Subquestion 4

What is your conclusion? Present a numerative result as well as a graph depicting the test result

In [9]:
```
#Display the means of the simulations in a histogram plot with 95% CI and our
facetgrid_obj = sns.displot(simulated_means, stat='count',aspect = 1.75)
facetgrid_obj.axes[0, 0].scatter(prob_remote_in_data, 0, s=150, color='red')
facetgrid_obj.axes[0, 0].legend(['Ratio of Data Field Employees Work Only From
left_end = np.percentile(simulated_means, 2.5,method='higher')
right_end = np.percentile(simulated_means, 97.5,method='higher')
facetgrid_obj.axes[0, 0].hlines(y=0, xmin=left_end, xmax=right_end, colors='or
facetgrid_obj.set(title='Distribution of simulated full remote data employees'
plt.show(facetgrid_obj)
```



In [10]:
```
print(f'Using Confidence interval of confidence 95% our test statistic is {pro
```

```
Using Confidence interval of confidence 95% our test statistic is 32.46%
which is not within the confidence interval  [32.652% , 37.316%]
```

As the question demanded both numerical value and a graph representation we can see based on the graph that the mean of the dataset is not inside of the confidence interval therefore we will reject the null hypothesis. The dataset does not represent the salaries of people who work in the data field,under the assumption that on average 35% of data field related employees work entirely remotely.

Question Two

Background : **There is a claim that Data Scientists earn in average a salary that is equal to the salary that Data Engineers earn. Test the claim based on the given data, under the assumption that it represents well the "Data" field related jobs in the US**

Subquestion 1

State the null hypothesis and the alternative hypothesis

Let d denote the difference between the mean salary of data scientists and data engineers.

$$H_0 : d = 0$$
$$H_1 : d \neq 0$$

Subquestion 2

What is the test statistic?

The test statitistic is the difference between the mean salary of data scientists and data engineers in our dataset.

Subquestion 3

Write code that tests the hypothesis using confidence interval (with at aleast 5000 replications). Explain the code that you write.

In [11]:
```
#Calculate and print the amount of data scientists and data engineers in our d
data_scientist_count = df[df['job_title'] == "Data Scientist"].shape[0]
data_engineer_count =  df[df['job_title'] == "Data Engineer"].shape[0]
print("Before answering this question lets first figure out how many engineers
print(f'There are {data_scientist_count} Data Scientists in this data set.')
print(f'There are {data_engineer_count} Data Engineers in this data set.')
```

```
Before answering this question lets first figure out how many engineers we ha
ve of both types.
There are 315 Data Scientists in this data set.
There are 472 Data Engineers in this data set.
```

Next, we should filter out the dataset so we could more easily work on it.

In [12]:
```
#create a new dataframe filtering out the irrelevent job titles.
df_DE_DS = df[(df['job_title'] == "Data Scientist") | (df['job_title'] == "Dat
df_DE_DS.reset_index(inplace=True) #There's no need for this line but it's nic
df_DE_DS = df_DE_DS.drop(columns={'index'}) #Pandas refuses to allow inplace
```

The Dataset we are working on in this question:

In [13]:
```
#A simple visualization of our new Dataframe.
df_DE_DS
```

Out[13]:

	experience_level	employment_type	job_title	salary_in_usd	remote_ratio	company_size
0	SE	FT	Data Scientist	147100	hybrid	M
1	SE	FT	Data Scientist	90700	hybrid	M
2	SE	FT	Data Scientist	170000	hybrid	M
3	SE	FT	Data Scientist	150000	hybrid	M
4	SE	FT	Data Engineer	253200	hybrid	M
...	...	...	...	...	...	...
782	SE	FT	Data Engineer	182000	fully remote	M
783	MI	FT	Data Scientist	130000	hybrid	M
784	MI	FT	Data Scientist	90000	hybrid	M
785	EN	FT	Data Engineer	160000	hybrid	M
786	EN	FT	Data Engineer	135000	hybrid	M

787 rows × 6 columns

In [14]:
```
def diff_of_avgs(df, column_name, grouping_var):
    '''This function gets a df and calculates the difference of two means
    df is our dataframe
    column_name is our column of interest
    grouping_var would be the feature we would like to seperate by our two gro
    returns the difference between the two averages'''
    grpby_var = df.groupby(grouping_var) #creating a groupby object for our tw
    avgs = grpby_var[column_name].mean() #calculates the mean for each series
    return avgs[1] - avgs[0]

def bootstrap_mean_difference(original_sample, column_name, grouping_var, num_
    '''This function creates an array of means of bootstraps generated by sepe
    original_df would be the unaltered Dataframe
    alt_df would be the filtered dataframe
    column_of_interest would be the column we are interested to test
    bootstrap_count describes the amount of bootstraps
    sample_size would be the size of each sample we want to generate
    returns an array of differences between the means'''
    original_sample_size = original_sample.shape[0] # we need to replicate wit
    original_sample_cols_of_interest = original_sample[[column_name, grouping_
    bstrap_mean_diffs = np.empty(num_replications)
    for i in range(num_replications):
        bootstrap_sample = original_sample_cols_of_interest.sample(original_sa
        resampled_mean_diff = diff_of_avgs(bootstrap_sample, column_name, grou
        bstrap_mean_diffs[i] = resampled_mean_diff

    return bstrap_mean_diffs
```

In [15]:
```
#Create the bootstrap array
difference_in_salary = bootstrap_mean_difference(df_DE_DS , 'salary_in_usd','j
```

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Subquestion 4

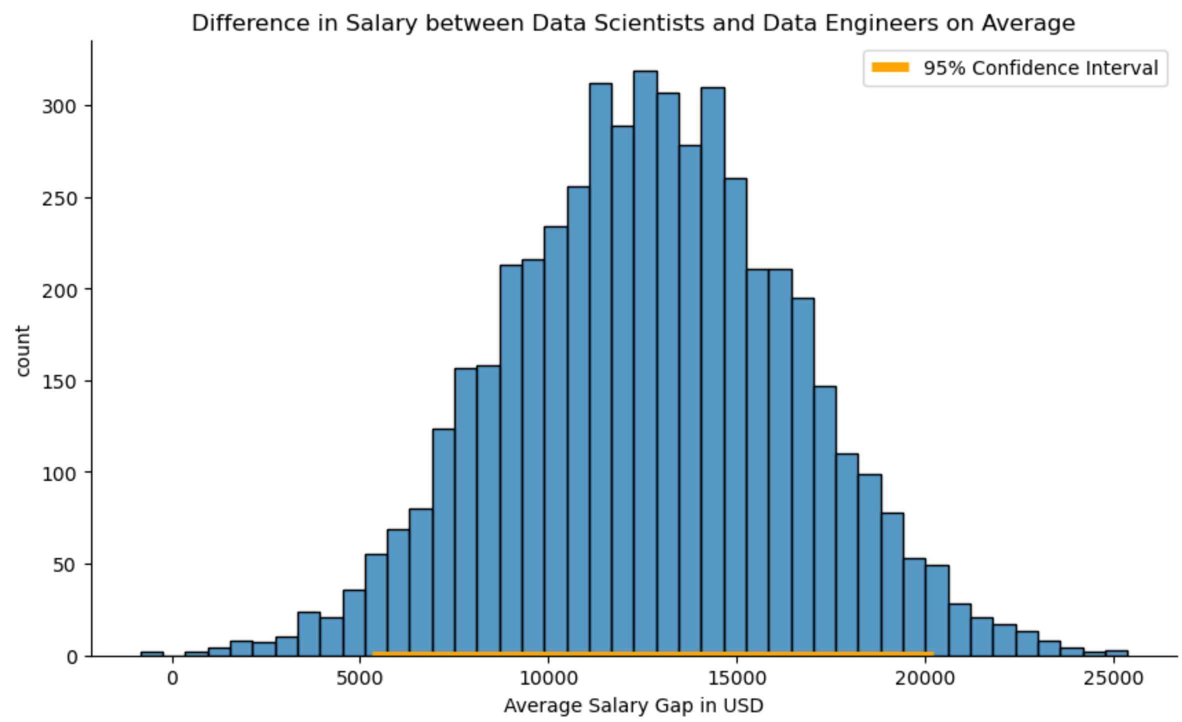
Find confidence intervals to the paramater values you found with confidence level of 0.99 and 0.95

For 95% confidence level:

In [16]:
```
#Display the histogram of our difference in salary means with a 95% CI
facetgrid_obj = sns.displot(difference_in_salary, stat='count',aspect = 1.75)
facetgrid_obj.set(title='Difference in Salary between Data Scientists and Data

left_end = np.percentile(difference_in_salary, 2.5,method='higher')
right_end = np.percentile(difference_in_salary, 97.5,method='higher')
facetgrid_obj.axes[0, 0].hlines(y=0, xmin=left_end, xmax=right_end, colors='or
facetgrid_obj.axes[0,0].legend(['95% Confidence Interval'])

plt.show(facetgrid_obj)
```



In [17]:
```
print(f'The Confidence Interval of 95% confidence is of range = [{round(left_e
```

```
The Confidence Interval of 95% confidence is of range = [5294.98$,20206.65$]
```

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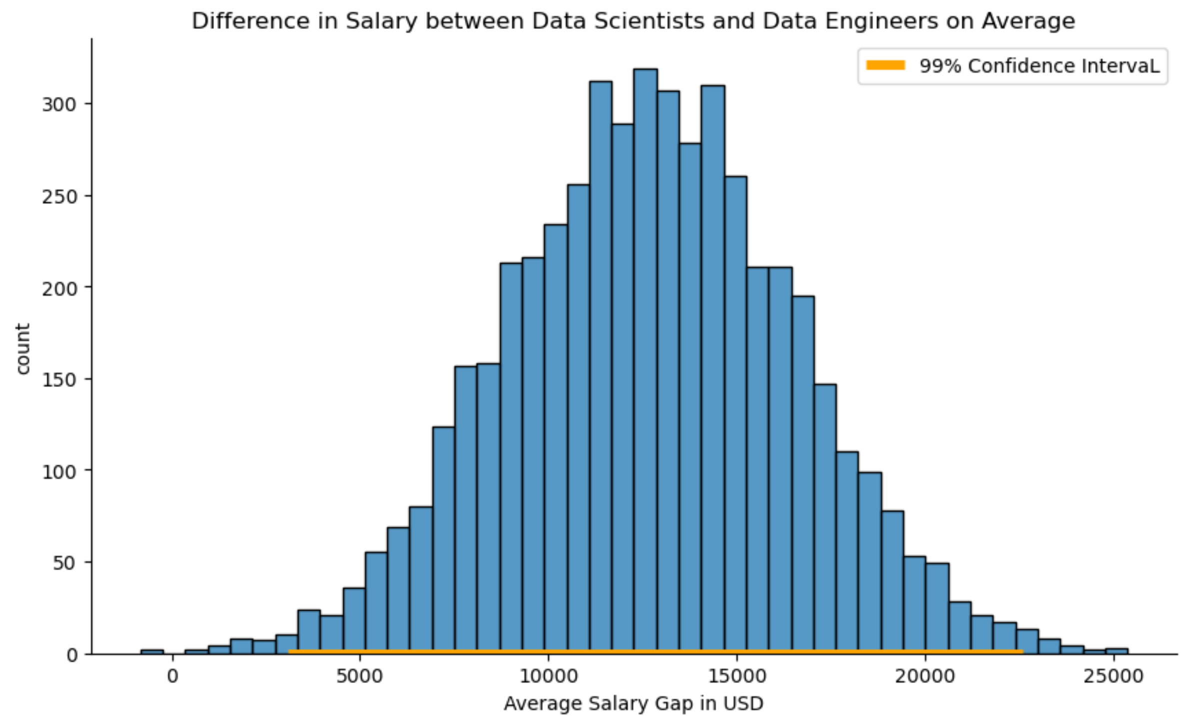
For 99% confidence level:

In [18]:
```
#Display the histogram of our difference in salary means with a 95% CI
facetgrid_obj = sns.displot(difference_in_salary, stat='count',aspect = 1.75)
facetgrid_obj.set(title='Difference in Salary between Data Scientists and Data
left_end = np.percentile(difference_in_salary, 0.5,method='higher')
right_end = np.percentile(difference_in_salary, 99.5,method='higher')
facetgrid_obj.axes[0, 0].hlines(y=0, xmin=left_end, xmax=right_end, colors='or
facetgrid_obj.axes[0, 0].legend(['99% Confidence IntervaL'])
plt.show(facetgrid_obj)
```



In [19]:
```
print(f'The Confidence Interval of 99% confidence is of range = [{round(left_e
```

```
The Confidence Interval of 99% confidence is of range = [3065.99$,22591.11$]
```

Subquestion 5

What is your conclusion? Present numerical values as well as graphs depicting the test' result for both of the mentioned confidence levels

It is clear that for both confidence levels our test statistic is not within our confidence interval therefore we should reject the null hypothesis data engineers and data scientists do not earn on average the same salary.

Question Three

Calculate the confidence interval of confidence 95% for mean salaries of workers in medium sized companies(M). Explain the code that you wrote and explicitly display the confidence interval.

As we did before we should first filter out the desired group, in this question it would be medium sized companies.

In [20]:
```
#Filter out our dataframe based on the requirement and reset the index.
df_M_size_comp = df[df['company_size'] == "M"]
df_M_size_comp.reset_index(inplace=True)
df_M_size_comp = df_M_size_comp.drop(columns={'index'})
```

The Dataset in this question:

In [21]:
```
#Print to give a sense of what dataframe we are working on.
df_M_size_comp
```

Out[21]:

	experience_level	employment_type	job_title	salary_in_usd	remote_ratio	company_size
0	SE	FT	Data Scientist	147100	hybrid	M
1	SE	FT	Data Scientist	90700	hybrid	M
2	SE	FT	Data Analyst	130000	fully remote	M
3	SE	FT	Data Analyst	100000	fully remote	M
4	SE	FT	Data Modeler	147100	hybrid	M
...	...	...	...	...	...	...
1496	MI	FT	Data Analyst	100000	hybrid	M
1497	MI	FT	Data Scientist	130000	hybrid	M
1498	MI	FT	Data Scientist	90000	hybrid	M
1499	EN	FT	Data Engineer	160000	hybrid	M
1500	EN	FT	Data Engineer	135000	hybrid	M

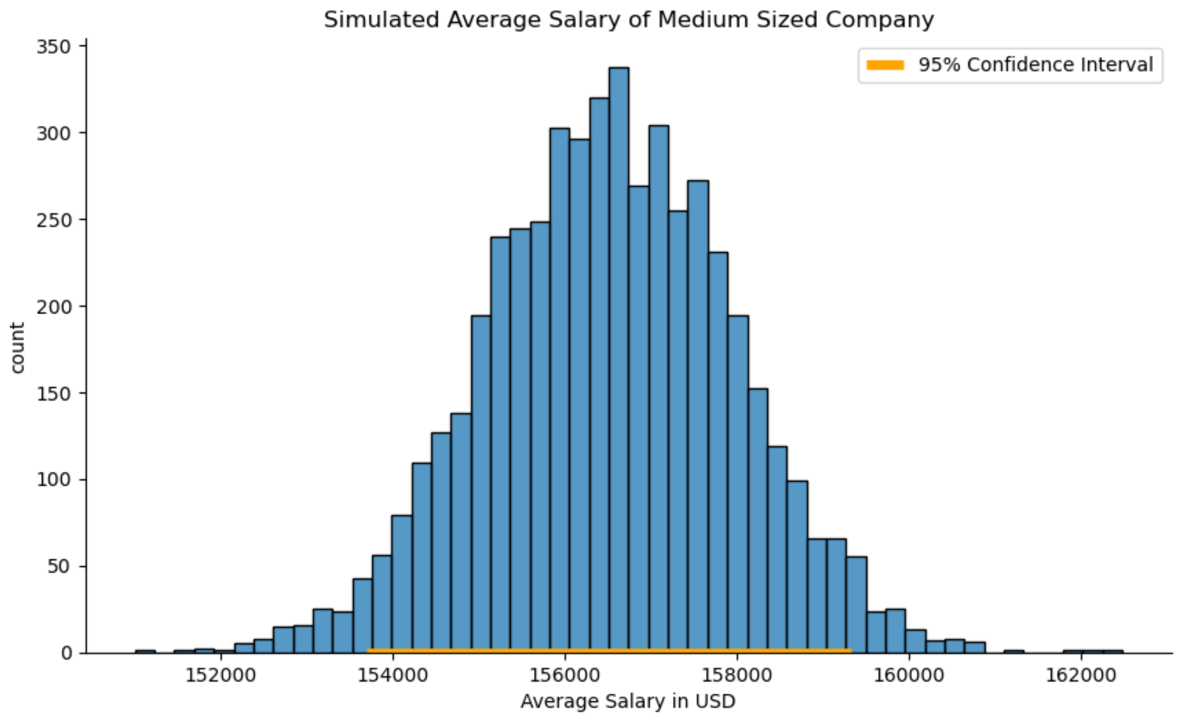
1501 rows × 6 columns

Because we are specifically told this dataset contains a sample that represents well to the real world companies of size M we should take it as a sample rather than generating a sample from it. If we generate a sample from it we would be creating a sample from a sample.

In [22]:
```
def bootstrap_mean(original_sample, column_name, num_replications):
    '''This funcion creates a bootstrap mean using a sample
       original_sample is the sample we use to create the bootstraps
       column_name is the name of the column we are intersted in
       num_replications would be the bootstrap count
    '''
    original_sample_size = original_sample.shape[0]
    original_sample_var_of_interest = original_sample[[column_name]]
    bstrap_means = np.empty(num_replications)
    for i in range(num_replications):
        bootstrap_sample = original_sample_var_of_interest.sample(original_sam
        resampled_mean = bootstrap_sample.mean()
        bstrap_means[i] = resampled_mean

    return bstrap_means
```

In [23]:
```
#Creates a single sample and generates a bootstrap of means in the image of th
sample = df_M_size_comp.sample(200,replace=True)
M_company_simulated_means =  bootstrap_mean(df_M_size_comp,"salary_in_usd",500
```

```
In [24]: #Display the sample in a histogram with a 95% CI.
facetgrid_obj = sns.displot(M_company_simulated_means, stat='count',aspect = 1
facetgrid_obj.set(title='Simulated Average Salary of Medium Sized Company', xl

left_end = np.percentile(M_company_simulated_means, 2.5,method='higher')
right_end = np.percentile(M_company_simulated_means, 97.5,method='higher')
facetgrid_obj.axes[0, 0].hlines(y=0, xmin=left_end, xmax=right_end, colors='or
facetgrid_obj.axes[0, 0].legend(['95% Confidence Interval'])

plt.show(facetgrid_obj)
```



The confidence interval for the Simulated Average Salary of Medium Sized Company Employees is:

```
In [25]: #Display the CI bounds.
print(f'The lower bound is: {round(left_end,3)} USD\nThe upper bound is: {roun
```

```
The lower bound is: 153704.423 USD
The upper bound is: 159330.48 USD
```

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Question Four

Background :A certain financial data analysis company would like to know what is the median that is being paid to workers in the data field. A new clumsy data analyst accidently deleted the data file. In order to find the median, he decided to create a sample and calculate its median using bootstraps. He found a file with data on employees in the data field in one of the e-mails that he recieved, without knowing that the people in the file are only employees that dont work from home completely (Hybrid). The employee picked 150 people at random from the file and asked them their salary. Since he promised a monetary compensation to those that responded, all of the people that recieved the e-mail replied back. Assume the data that was reported is true and exists in the original data file.

Subquestion 1

In order to test the chance the employee succeeded creating (from the sample of hybrid employees) confidence interval of 95% that contains the true median of the salary of all employees, run 100 simulations that sample 150 employees from the population of hybrid employees and calculates for each sample the confidence interval of confidence 95% of the median of their salary. Out of 100 confidence inervals how many of them

contains the true median of the employees that work in the "data field" as it can be calculated directly from the original data?

In [26]:
```
#Filter out the dataframe to have only hybrid type employees.
df_hybrid = df[df['remote_ratio'] == "hybrid"]
print(f'The filtered (hybrid) dataset the employee will sample from:')
df_hybrid
```

```
The filtered (hybrid) dataset the employee will sample from:
```

Out[26]:

	experience_level	employment_type	job_title	salary_in_usd	remote_ratio	company_size
2	SE	FT	Applied Scientist	222200	hybrid	L
3	SE	FT	Applied Scientist	136000	hybrid	L
4	SE	FT	Data Scientist	147100	hybrid	M
5	SE	FT	Data Scientist	90700	hybrid	M
8	EN	FT	Applied Scientist	213660	hybrid	L
...	...	...	...	...	...	...
1560	SE	FT	Machine Learning Engineer	134500	hybrid	L
1561	MI	FT	Data Scientist	130000	hybrid	M
1562	MI	FT	Data Scientist	90000	hybrid	M
1563	EN	FT	Data Engineer	160000	hybrid	M
1564	EN	FT	Data Engineer	135000	hybrid	M

1057 rows × 6 columns

In [27]:
```
#bootstrap method but with median as our statistic
def bootstrap_median(original_sample, column_name, num_replications):
    '''This function creates a bootstrap of medians of a certain column based
        original_sample is our original sample used to create the bootstrap
        column_name is our column we are interested in for the median
        num_replications would the bootstrap size
        returns an array of the bootstrap medians'''

    original_sample_size = original_sample.shape[0] # replicates with same siz
    original_sample_var_of_interest = original_sample[[column_name]] # filter
    bstrap_medians = np.empty(num_replications)
    for i in range(num_replications):
        bootstrap_sample = original_sample_var_of_interest.sample(original_sam
        resampled_median = np.percentile(bootstrap_sample,50 , method='higher'
        bstrap_medians[i] = resampled_median

    return bstrap_medians
```

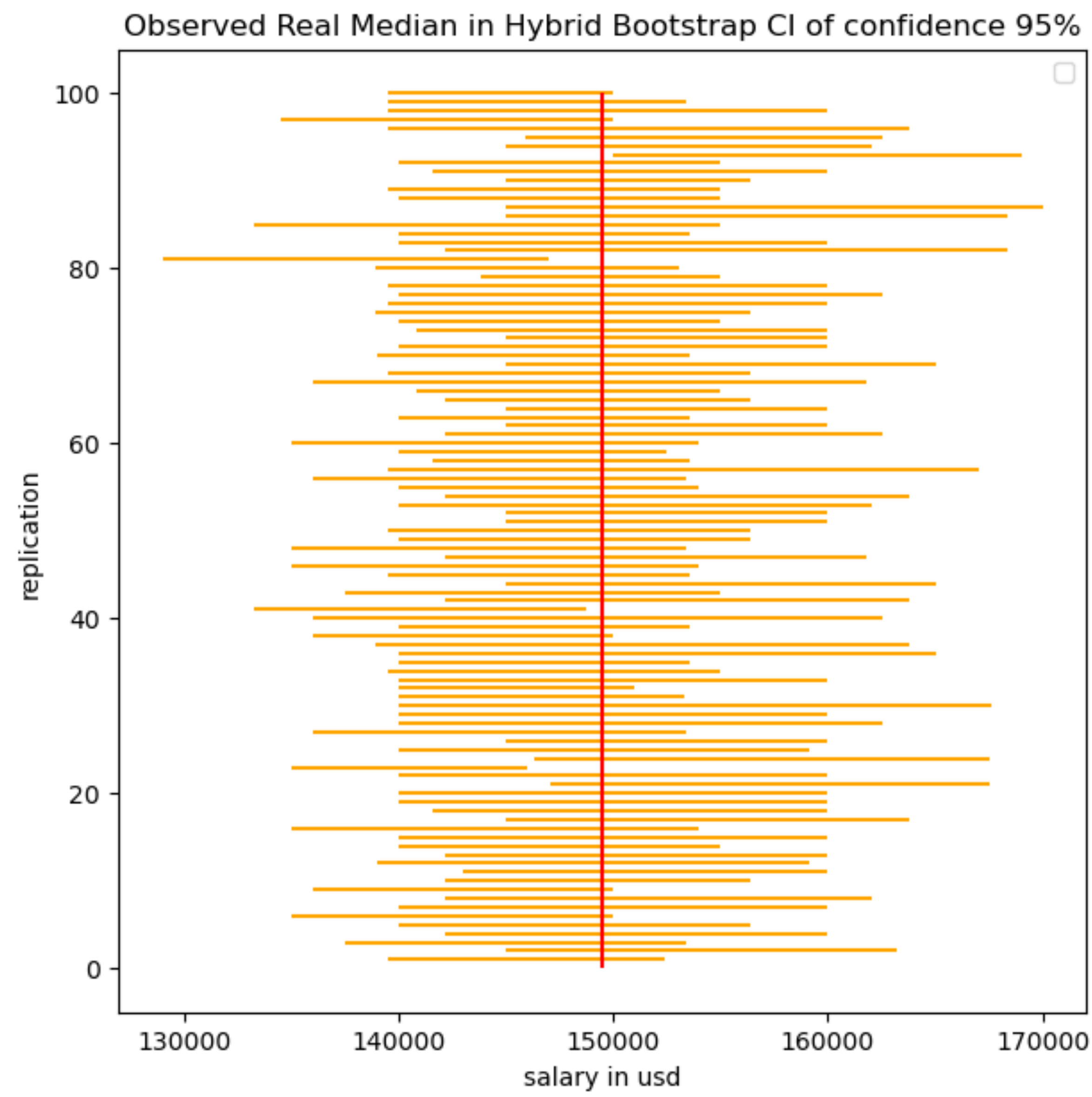
In [28]:
```
#calculate our real median that the analyst isn't able to access
observed_median = df['salary_in_usd'].median()
```

In [29]:
```
#check if the true value falls within the simulated confidence intervals
#using this method instead of packaging in functions in order to add an additi
'''This codebox contains code creates bootstraps calculates their CI of 95% co
    and checks if our observed median is in the interval

    num_of_btsp is the amount of our bootstrap simulations
    sample_size is the size of each sample
    left_ends is an array containing all the lower bounds of our CI
    right_ends is an array containing all the upper bounds of our CI
    medians_in_interval contains 1 if our median is between our bounds and 0 o

'''
left_ends = []
right_ends = []
medians_in_interval = []
num_of_btsp = 100
sample_size = 150
for i in range(num_of_btsp):
    sample = df_hybrid.sample(sample_size,replace=False)
    medians = bootstrap_median(sample, "salary_in_usd",5000)
    left = np.percentile(medians,2.5,method="higher")
    left_ends.append(left)
    right = np.percentile(medians,97.5,method="higher")
    right_ends.append(right)
    medians_in_interval.append((observed_median >= left) and (observed_median
```

In [30]:
```
print(f'In {np.count_nonzero(medians_in_interval)} out of {num_of_btsp} the ob
```

```
In 96 out of 100 the observed median was inside the interval of confidence le
vel 95%.
```

In [31]:
```
#Present a visualisation that depicts the amount of times the median was insid
fig = plt.figure(figsize=(7,7))
ax = plt.axes()
ax.legend(['Median'])
for i in np.arange(100):
    plt.hlines(i+1,left_ends[i],right_ends[i],colors='orange',linestyles='soli
plt.vlines(observed_median, ymin=0 , ymax=i+1, colors ='red') #creates a line
ax.set(xlabel='salary in usd',ylabel='replication',title="Observed Real Median
print('') #buffer to prevent ax text from appearing
```



Subquestion 2

The data analyst used a sample that wasn't taken at random from the same population that he is testing (but from another population). In spite of that, does the theoretical gurantee of the bootstrap method? Explain your reasoning.

The answer depends but in general: **No** , there is no theoretical gurantee of the bootstrap method if the sample that was taken is not from the same population that the data analyst is testing.

One of the guiding principles behind the bootstrap method is the assumption that the sample we drew represents the population we are testing. Assuming such an assumption (and other such as sufficently sized sample size) is true, we are able to indirectly draw infinetly from the original population. Which in turn, would let us find approximations about said population.

However, since the data analyst drew from a seperate population, there is no gurantee that the sample he drew represents in any form the "data related employees" , even if the data analyst drew from a subset of a data employees (as in any specific attribute) there is no gurantee it wont skew his results.

Side note : The chance the bootstrap does work is the case the second population happens to distribute similarly as the population he is testing. In regards to a specific statistic function, if the parameter is "relatively" close to the actual real parameter (A rather surprising example would

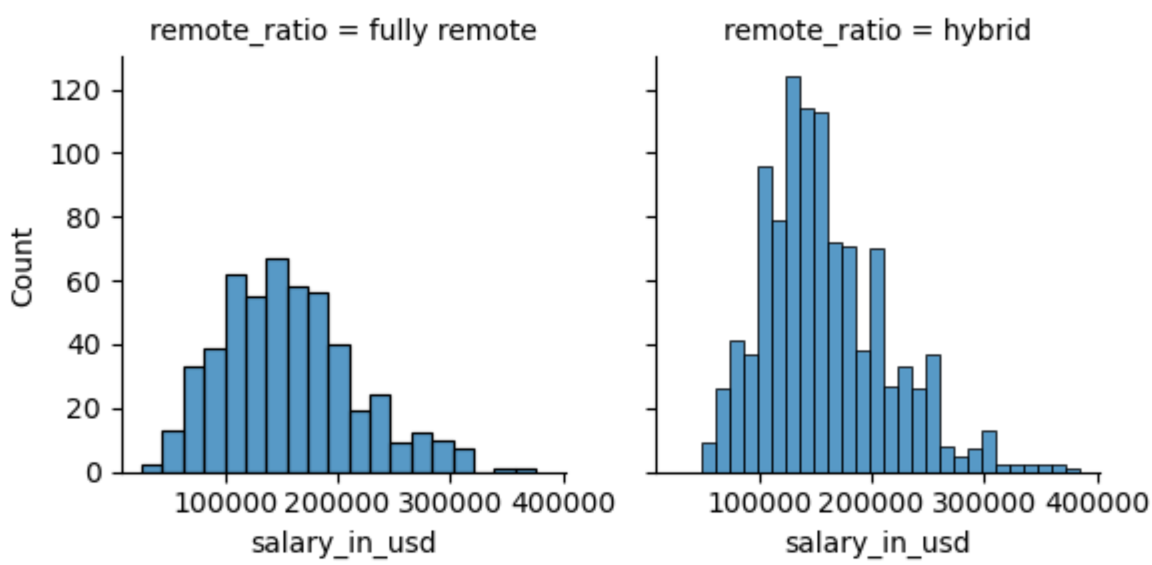
Subquestion 3

How would your answers change in Subquestion A and B if the data analysis company would like to know the quarter salary of the employees working in the field (as in , instead of calculating the median , the data analyst would calculate the first quarter of the salaries). Explain your reasoning.

Hint : Draw the distribution of salaries or their sum for two different employee groups.

In [32]:
```
#Seperates and draws two histograms for salary size per remote type.
salary_distribution = sns.FacetGrid(df,col="remote_ratio")
salary_distribution.map(sns.histplot, "salary_in_usd")
```

Out[32]: `<seaborn.axisgrid.FacetGrid at 0x21ae980ff10>`



In [33]:
```
#Print the first quarter of both employee types.
print(f'The first quarter of all employees is {np.percentile(df["salary_in_usd
print(f'The first quarter of hybrid employees is {np.percentile(df_hybrid["sal
```

```
The first quarter of all employees is 120000.
The first quarter of hybrid employees is 120000.
```

Claim : It seems both quarters are of the same value therefore even if we mix between the two group for the statistic quarter ONLY we should expect to see it the exact same amount of times in our bootstrap's CI as we would see it if we selected the correct group, the reason for that being is that as we create bootstraps of one group we would expect to see their statistic test in the bootstraps 95% of the time but as the values are identical this would mean the other group's statistic test would also show the exact amount of time.

As a demonstration let's test the idea out by creating bootstraps similar to question 4-1A.

In [34]:
```
#boostrap method but with quarter as the statistic
def bootstrap_quarter(original_sample, column_name, num_replications):
    '''This function creates a bootstrap of quarter of a certain column based
        original_sample is our original sample used to create the bootstrap
        column_name is our column we are interested in for the quarter
        num_replications would the bootstrap size
        returns an array of the bootstrap quarter'''

    original_sample_size = original_sample.shape[0]
    original_sample_var_of_interest = original_sample[[column_name]]
    bstrap_quarters = np.empty(num_replications)
    for i in range(num_replications):
        bootstrap_sample = original_sample_var_of_interest.sample(original_sam
        resampled_quarter = np.percentile(bootstrap_sample[column_name],25,met
        bstrap_quarters[i] = resampled_quarter

    return bstrap_quarters
```

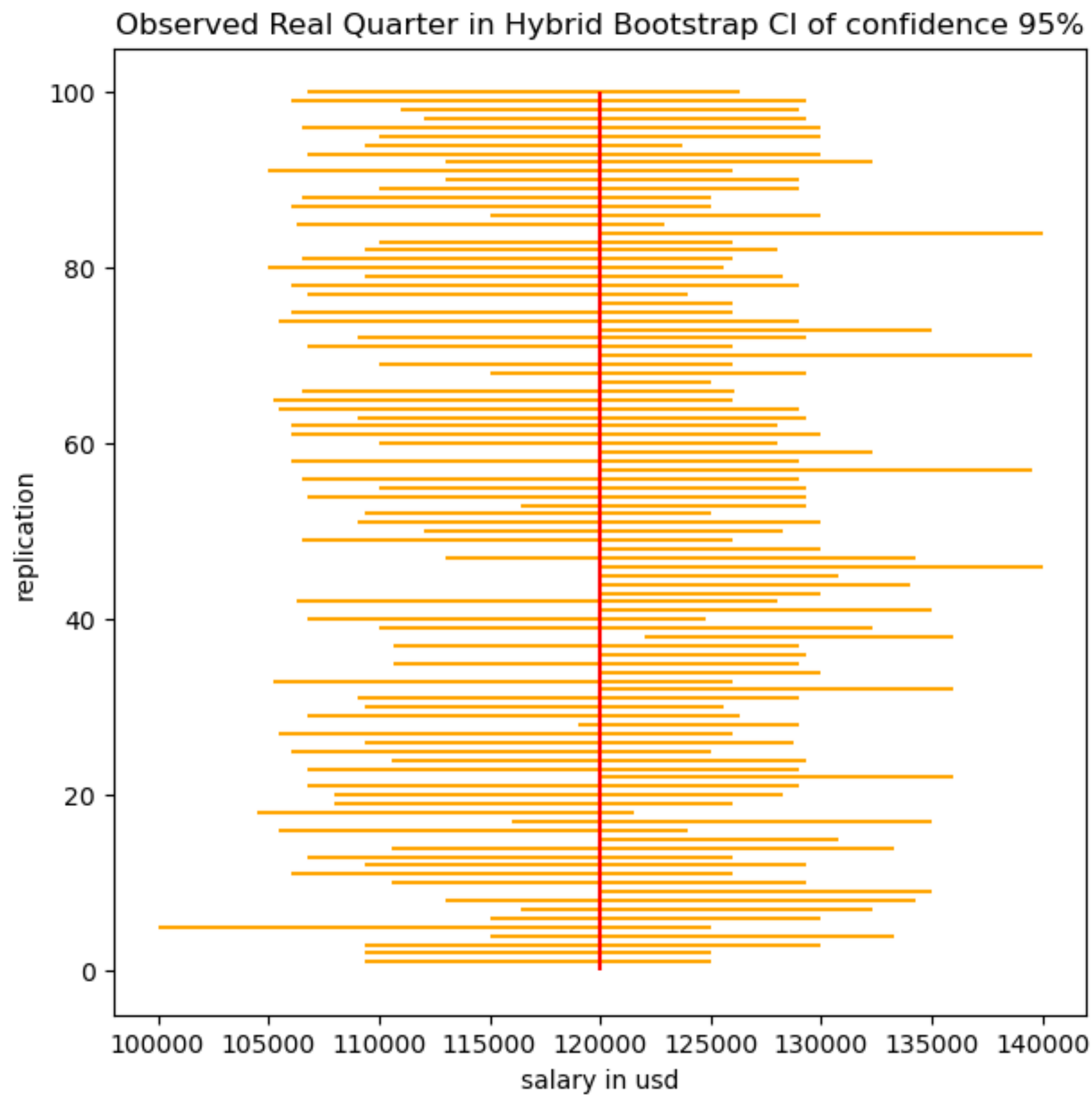
In [35]:
```
#calculate our real quarter that the analyst isn't able to access
observed_quarter = np.percentile(df['salary_in_usd'] , 25 , method = "higher")
```

In [36]:
```
#Generating 100 bootstraps with CI and static quarter of confidence 95% from h
#Much like subquestion 4-1A except we are using a different statistic - first
#Not paackaged into one function in order to use all 3 arrays for visualzation
'''This codebox contains code creates bootstraps calculates their CI of 95% co
    and checks if our observed quarter is in the interval

    num_of_btsp is the amount of our bootstrap simulations
    sample_size is the size of each sample
    left_ends is an array containing all the lower bounds of our CI
    right_ends is an array containing all the upper bounds of our CI
    medians_in_interval contains 1 if our quarter is between our bounds and 0

'''
left_ends = []
right_ends = []
quarters_in_interval = []
num_of_btsp = 100
sample_size = 150
for i in range(num_of_btsp):
    sample = df_hybrid.sample(sample_size,replace=False)
    quarters = bootstrap_quarter(sample, "salary_in_usd",5000)
    left = np.percentile(quarters,2.5,method="higher")
    left_ends.append(left)
    right = np.percentile(quarters,97.5,method="higher")
    right_ends.append(right)
    quarters_in_interval.append((observed_quarter >= left) and (observed_quart
```

In [37]:
```
print(f'In {np.count_nonzero(medians_in_interval)} out of {num_of_btsp} times
```

```
In 96 out of 100 times the observed quarter was inside the interval of CI 9
5%.
```

In [38]:
```
#Present a visualisation that depicts the amount of times the quarter was insi
fig = plt.figure(figsize=(7,7))
ax = plt.axes()
for i in np.arange(100):
    plt.hlines(i+1,left_ends[i],right_ends[i],colors='orange',linestyles='soli
plt.vlines(observed_quarter, ymin=0 , ymax=i+1, colors ='red') #creates a line
ax.set(xlabel='salary in usd',ylabel='replication',title="Observed Real Quarte
print('') #buffer to prevent ax text from appearing
```



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Part Two - Racism in the American Judiciary System

Question One

In 2~4 short sentences explain why it is problematic to use bootstraps to calculate confidence intervals using very small sample sizes.

As previously mentioned in Part 1 - Question 4 Subquestion 2 the theoretical background of bootstraps rely on large sample sizes picked at random in order to simulate the distribution of the population we are attempting to test. Using small sample sizes amplifies the variance / "noise" of the sample which in turn would hinder its ability to mimic the qualities our original unreachable population has.

Question Two

Background : **Researchers in the US examined the effect race has on judgets's death penalty verdict during trialing a person who had been accused of murder.**

The researchers have found there's a seems to be a difference whether or not the victim's race had been taken in cons570 consarieration or not. While considering the race of the victim, black convicts are sentenced the death penalty more often than white people. However, when not considering the race of the victim black people are sentenced the death penalty less than white people.

Subquestion 1

Which statistical phenomenon could explain the gap between the results whether we consider the race of the victim and when we do not?

The difference in the gap could be explained by the phenomenon **"Simpson's Paradox "**.

Simpson's Paradox is a paradox that claims that there could always be a new frame in which we could observe our data that would completely shift our conclusion.

For example, in this specific dataset:

Without including the race of the victim the conclusion we might reach would be "The judges are biased against black people"

However, when we do include the race of the victim it would appear that the judges are actually biased against white people.

Subquestion 2

Sub 1 of Subquestion 2

Which tendecy of the judges could explain the gap in the results?

Hint : Which scenario would more likely result a death sentence?

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There are a couple of factors that might bias a judge to verdict a death sentence in different proprotions to black and white people.

Background for the crime : It could be the case that whenever black people commit murder they do so for backgrounds that are far less heinous than their white counterpart(An example for this would be recent rise of white school shooters). As we assume the death verdict would be given if and only if there is concrete evidence to the crime and the crime is beyond reasonable of a doubt of malicious heinous intent, this would result in black people given the death sentence less often.

Racism : It could also be a simple fact that although the US is perceived to be racist against people of color, in reality they are racially biased against white people therefore white people are given the death sentence more often than their black counter-part.

Sub 2 of Subquestion 2

Which tendecy of the convicts could explain the gap in the results?

Hint : What is the relation between the race of the victim and the convicts race?

Based on the data presented when seperated to race it would appear that black people are sentenced to death more often than white people when they are convicted of murder. There are a few explanations that could explain these statistics.

Frequency : When looking at the chart it seems apparent that mixed race crimes murders are rather uncommon . When we compare the death verdict sentence rate per convict race per victim race it gives us the impression that black people are inpropertionally given the death sentence compared to white people. However, in reality it could be the case that because these cross racial murders are rather infrequent (when looking at the overall count) it could be the case that these exact murders were unique in some sort of a way that made the judge rule the way that he did.