Contributors

The following people contributed to the project.

1. Sandipto Sanyal (PGID 12010004)
2. Keelasevalpatti Sai Sabareesh (PGID 12010043)
3. Abhishek Gupta (PGID 12010020)

Document Format

This document uses the following formatting:

Texts marked in the following boxes are python code snippets to depict the calculation steps in code:

In [5]:
```
<some code here>
```

<Corresponding output here if applicable with appropriate graphs and tables>

Import necessary Libraries

In [1]:
```
from scipy.stats import norm, t
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
pd.options.display.max_columns = 20
pd.options.display.max_rows = 500
from statistics import stdev, mean
import warnings
warnings.filterwarnings("ignore")
import math
```

t- distribution Confidence Interval

The below method performs the following mathematical calculations for estimation of population mean from a given sample:

For a given confidence interval CI, sample standard deviation S, sample mean, and number of observations in the given sample,

- **If it is two sided:**

Sample mean($\overline{X}$) = Average of all the given samples/number of samples

Sample standard deviation(S_X) =

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2},$$

N = Number of samples

Degrees of freedom(df) = (n-1)

$S_{\overline{X}} = S_X/\sqrt{n}$

C.I = Given Class Interval

α = (1-C.I) = error that we are willing to tolerate

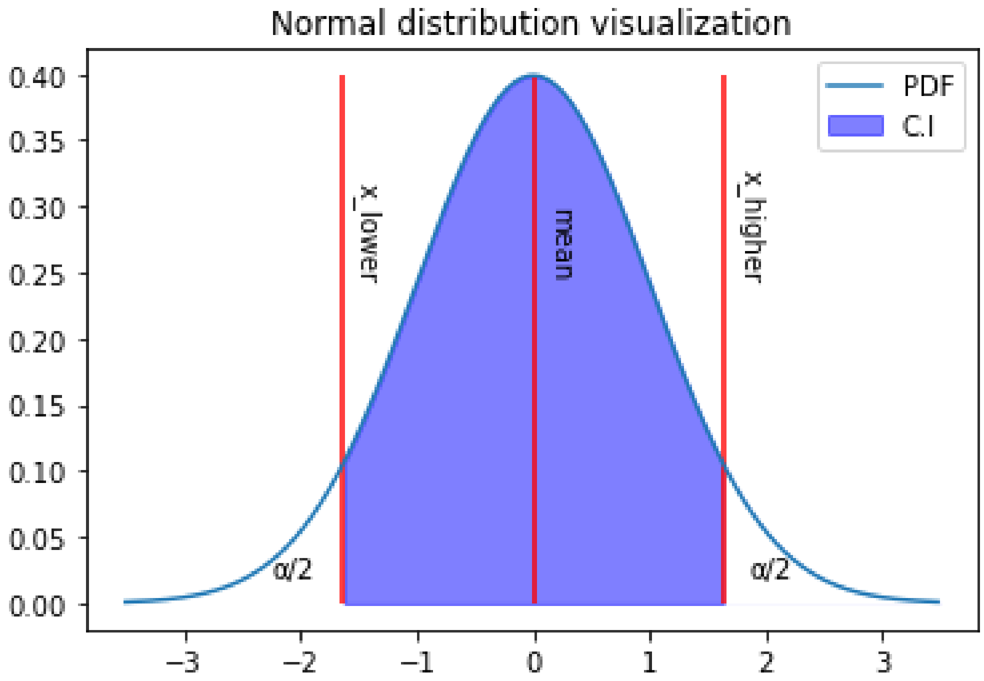
From the t-Table we get the t-value based on the given degrees of freedom and corresponding α

The C.I is as follows:

$P(\overline{X} - t_{(df,\, \alpha/2)} * S_{\overline{X}} \leq \mu \leq \overline{X} + t_{(df,\, \alpha/2)} * S_{\overline{X}}) = C.I.$

Note that $t_{(df,\, \alpha/2)}$ is actually the unsigned t value for given df and α.

Thus for a 2 sided confidence interval test the population mean is expected to lie within the given shaded region between x_higher and x_lower.



- **If it is upper one sided confidence interval:**

Sample mean($\overline{X}$) = Average of all the given samples/number of samples

Sample standard deviation(S_X) =

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2},$$

N = Number of samples
Degrees of freedom(df) = (n-1)

$\overline{S}_X = S_X/\sqrt{n}$

C.I = Given Class Interval

As it is one sided test we will have either left or right α given by

α = (1-C.I) = Error we are willing to tolerate

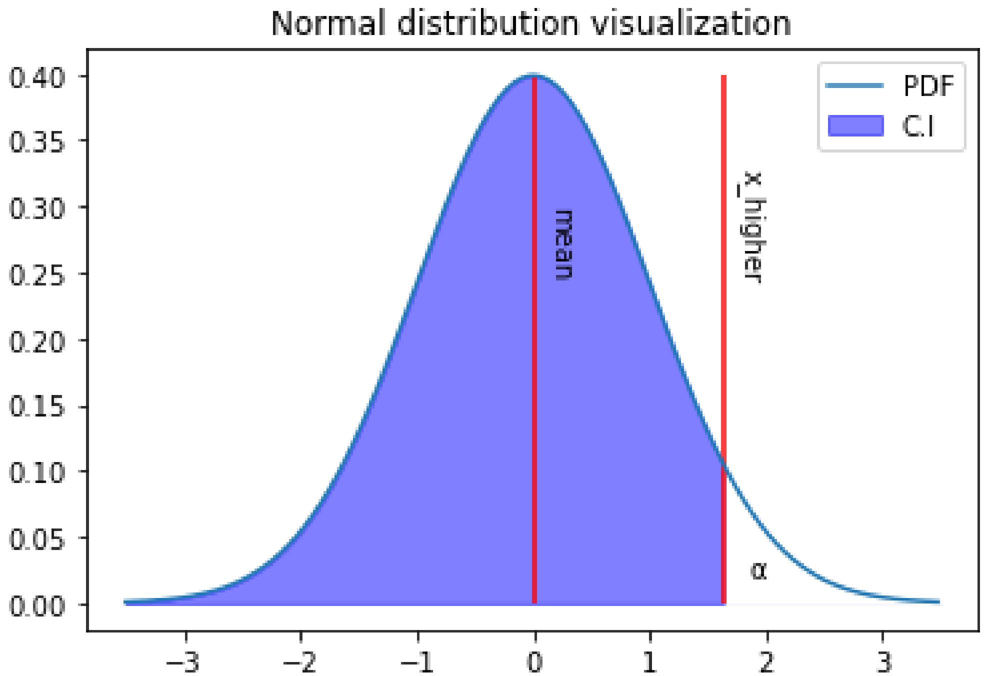
From the t-Table we get the t-value based on the given degrees of freedom and corresponding α

The C.I is as follows:

Lower Limit = -infinity

Upper Limit = $\overline{X} + t_{(df,\, \alpha)} * S_{\overline{X}}$.

Thus the population mean will be expected to lie in the shaded region < x_higher as below:



In [2]:
```
def t_ci(confidence_interval: float = 0.90,
            sample_std_dev: float = 1,
            number_of_samples:int = 2,
            mean: float = 0,
            two_sided: bool = True
            ):
    '''


    Parameters
    ----------
    confidence_interval : float, optional
        DESCRIPTION. The default is 0.90.
    sample_std_dev : float, optional
        DESCRIPTION. The default is 1.
    number_of_samples : int, optional
        DESCRIPTION. The default is 100.
    mean : float, optional
        DESCRIPTION. The default is 0.
    two_sided : bool, optional
        DESCRIPTION. The default is True.

    Returns
    -------
    TYPE
        DESCRIPTION.

    '''
    # declaring problem constants
    x_bar = mean
    n = number_of_samples # number of samples taken
    sigma = sample_std_dev # sample standard deviation
    sigma_x_bar = sigma/n**0.5 # std dev of sample means
    df = n-1 # degrees of freedom
    # get the probabilities of the tail areas
    if two_sided:
        prob_high  = (1+confidence_interval)/2
        prob_low  = (1-confidence_interval)/2
    else:
        prob_high  = confidence_interval
        prob_low  = 0
    # compute the value of x_lower and x_higher
```

```
    x_lower = t.ppf(prob_low,df,loc=x_bar,scale=sigma_x_bar)
 x_higher = t.ppf(prob_high,df,loc=x_bar,scale=sigma_x_bar)    return
 round(x_lower,3), round(x_higher,3)
```

Read the dataset

In [3]:
```
df = pd.read_csv(r'SA1_Group_17.csv', index_col='Index')
```

Get the numerical and non-numerical columns

A separate dataset has been prepared to list out the numerical and the categorical columns.

In [4]:
```
column_desc = pd.read_csv(r'Data description.csv') categorical_cols
 = column_desc.non_numeric_columns.dropna().tolist() numeric_cols =
 column_desc.numeric_columns.dropna().tolist()
```

View the dataset descriptive statistics of the numerical columns

Some Important points

- Though OPER_DUR_DD is expected to be a continuous variable it looks like the rows are missing various data eventhough unit was operational. It just don't make sense that OPER_DUR_MM is filled (meaning the unit was operational for given number of months) but don't have the data OPER_DUR_DD (duration of operation in days). So for the descriptive statistics we will omit this as of now.
- Other columns which are dropped because they are categorical in nature but were encoded. Getting descriptive statistics for categorical columns doesn't make sense. We will get distinct counts of them later.

In [5]:
```
print('Descriptive Statistics for the numerical columns')
display(df[numeric_cols].describe())
```

Descriptive Statistics for the numerical columns

	OPER_DUR_MM	MKT_VAL_FA	ORI_PURC_VAL_PM	EMP_TOTAL	GOP_Year3	VOE_Year3	NET_Year3
count	10000.000000	1.000000e+04	1.000000e+04	10000.000000	1.000000e+04	1.000000e+04	1.000000e+04
mean	10.559000	8.547566e+05	3.245659e+05	5.885900	9.259034e+07	2.855352e+04	1.200584e+06
std	2.111437	5.466470e+06	1.791879e+06	10.858502	9.081048e+09	1.225493e+06	8.056149e+06
min	0.000000	0.000000e+00	0.000000e+00	1.000000	0.000000e+00	0.000000e+00	-3.500000e+06
25%	10.000000	5.000000e+04	2.000000e+04	2.000000	4.666250e+04	0.000000e+00	5.700000e+04
50%	12.000000	1.500000e+05	5.045000e+04	3.000000	1.000000e+05	0.000000e+00	1.590000e+05
75%	12.000000	5.000000e+05	1.900000e+05	6.000000	3.800000e+05	0.000000e+00	5.112225e+05
max	12.000000	3.653958e+08	8.961474e+07	350.000000	9.081050e+11	9.430860e+07	4.269214e+08

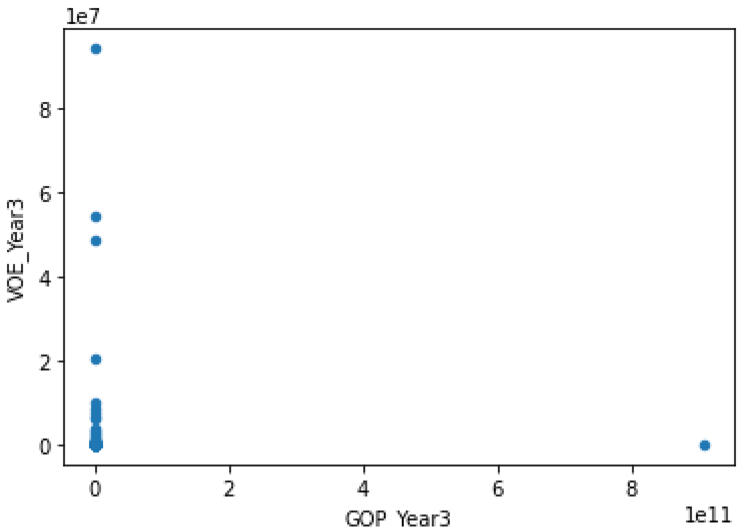
Inference: Two majorly important columns GOP_Year3 and VOE_Year3 contains outliers. This is evident from their difference between mean and median. Let's try to remove the data which is the outlier.

A quick view about the two columns containing outliers

Below we plot a scatter plot to visualize the presence of outliers in both the columns

In [6]:
```
df.plot.scatter('GOP_Year3','VOE_Year3')
```

Out[6]:



Inference: The single point on GOP_Year3 might going to be messing up with the whole statistical analysis. Let's remove them from the dataset

Find out the data which is an outlier

To perform this we eliminate the data which is > 3.5 standard deviations away from the mean for GOP_YEAR3 column.

In [7]:
```
def check_outlier(value,mean,sd):
  z = abs((value-mean)/sd)
  return z > 3.5
mean = df.GOP_Year3.mean()
sd = df.GOP_Year3.std()
df['GOP_Year3_is_outlier'] = df.GOP_Year3.apply(lambda row: check_outlier(row,mean,sd))
```

```
mean = df.VOE_Year3.mean()
sd = df.VOE_Year3.std()
df['VOE_Year3_is_outlier'] = df.VOE_Year3.apply(lambda row: check_outlier(row,mean,sd))
print('Number of outliers for GOP_Year3 outlier: {}'.format(len(df[df.GOP_Year3_is_outlier])))
print('Number of outliers for VOE_Year3 outlier: {}'.format(len(df[df.VOE_Year3_is_outlier])))
```

```
Number of outliers for GOP_Year3 outlier: 1
Number of outliers for VOE_Year3 outlier: 9
```

In [8]:

```
df_without_outliers = df[df.GOP_Year3_is_outlier==False]
df_without_outliers.GOP_Year3.describe()
```

Out[8]:

```
count     9.999000e+03
mean      1.780014e+06
std       1.715855e+07
min       0.000000e+00
25%       4.662500e+04
50%       1.000000e+05 75%
3.800000e+05 max
1.193961e+09
Name: GOP_Year3, dtype: float64
```

Inference: As expected from the graph above 1 data point is an outlier in GOP_Year3. We shall elliminate that. But there are 9 data points as outliers for VOE_Year3. Losing out 9 more data can be problematic. We shall keep them and move forward.

Question 1. The 95 percent confidence interval for the "Gross output – Year 3 (Rs)

To perform this we will construct a 2 sided 95% confidence interval by t-test

Calculations:

Since the population standard deviation(sigma) is not given, we are using t-distribution with sample standard deviation.

95% of C.I

From the given Dataset for GOP_Year3

Number of samples (n) = 10000

Sample mean($\overline{X}$) = Average of all the given samples/number of samples=($\overline{X}_1$+ $\overline{X}_2$+ $\overline{X}_3$+…….+$\overline{X}_{10000}$)/n = 1780013.5

Sample standard deviation(S_X) =

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2},$$

N = Number of samples= 10000,

$\overline{X}$ = 1780013.5

S_X=17158554.099

Degrees of freedom(df) = (n-1) = 9999

$\overline{S}_X$= $S_X/\sqrt{n}$ = 17158554.099/$\sqrt{10000}$ = 171585.541

C.I = 0.95

α = (1-C.I) = 0.05

The C.I is as follows:

$P(\overline{X} - t_{df}\ \alpha/2 * \overline{S}_x \le \mu \le \overline{X} + t_{df}\ \alpha/2 * \overline{S}_x) = 0.95$

From the t-Table we get the t-value as 1.962(t_{val}) for the df = 9999

$$t_{val} * \overline{S}_x = 336650.8314$$

<u>LL:</u>

$\overline{X} - t_{df}\ \alpha/2 * \overline{S}_X$ = 1443362.669

UL:

$\bar{X} + t_{df}\ \alpha/2 * \bar{S}_X = 2116664$

P(1443363≤ μ ≤ 2116664) = 0.95

Hence mean of gross output – year 3 lies between 1443363 and 2116664

In [9]:
```
confidence_interval = 0.95 sample_std_dev =
df_without_outliers.GOP_Year3.std() number_of_samples
= len(df_without_outliers.GOP_Year3) sample_mean =
df_without_outliers.GOP_Year3.mean()
lower, higher = t_ci(confidence_interval,sample_std_dev,number_of_samples,sample_mean)
print('Mean of Gross output - Year 3 of population is expected to lie between Rs. {} and Rs. {}'.format(lower
,higher))
```

```
Mean of Gross output - Year 3 of population is expected to lie between Rs. 1443654.578 and Rs. 2116372.612
```

Question 2: Defining metrics for performance of the units

We define the performance of the units as follows:

1. **op_per_asset = GOP_Year3/MKT_VAL_FA.**
   This metric is useful in determining how the units are performing on the basis of utilization of the fixed assets. As a basic understanding more the MKT_VAL_FA more should be GOP_Year3. If the ratio is low for any unit it means there might be a problem of under utilization of resources happening in that given unit. Also if the ratio is too high denotes the units are working with highly deprecated assets which can be a great risk sooner or later.

1. **op_per_employee: GOP_Year3/EMP_TOTAL**
   In these world of automation initiatives to increase productivitiy of business this metric is very useful. If the ratio is too low it means those units might potentially show redundancies in job roles. Employees of those units might be available to take up newer challenging roles which in turn will be increasing the business. Units showing too high value might be facing employee shortage problems.

Calculations:

To get the values of Metric op_per_asset Data = Individual value of 'GOP_Year3' / Individual value of 'MKT_VAL_FA'

For some rows in the data where the MKT_VAL_FA = 0 due to which we are getting inf values for op_per_asset This seems to be some sort of a data collection issue. To avoid this we filter the data to remove the inf values.

1285800		1500000	0.8572
49600		0	#DIV/0!
17000		30000	0.566666667

After removing those null values the op_per_asset Dataset has been set where Sample mean and Sample Standard deviation has been calculated.

Number of samples (n) = 9954

Sample mean($\overline{X}$) = Average of all the given samples/number of samples=$(\overline{X}_1+\overline{X}_2+\overline{X}_3+\ldots\ldots.+\overline{X}_{10000})/n$ = 2.39

Sample standard deviation(S_X) =

$$s=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i-\overline{x})^2}\,,$$

S_X = 12.030814

To get the values of Metric op_per_employee Data = Individual value of 'GOP_Year3' / Individual value of 'EMP_TOTAL'

Number of samples (n) = 9954

Sample mean($\overline{X}$) = Average of all the given samples/number of samples=$(\overline{X}_1+\overline{X}_2+\overline{X}_3+\ldots\ldots.+\overline{X}_{10000})/n$ = 147674.2

Sample standard deviation(S_X) =

$$s = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \overline{x})^2},$$

S_X = 967953.4

In [10]:
```
df_without_outliers['op_per_asset'] = df_without_outliers['GOP_Year3']/df_without_outliers['MKT_VAL_FA']
df_without_outliers['op_per_employee'] = df_without_outliers['GOP_Year3']/df_without_outliers['EMP_TOTAL']
print('Description of the two metrics')
display(df_without_outliers[['op_per_asset','op_per_employee']].describe())
```

```
Description of the two metrics
```

	op_per_asset	op_per_employee
count	9997.000000	9.999000e+03
mean	inf	1.479189e+05
std	NaN	9.660946e+05
min	0.000000	0.000000e+00
25%	0.450000	1.760000e+04
50%	0.900000	3.421429e+04
75%	1.790667	7.575000e+04
max	inf	7.595800e+07

Inference: It seems there are some rows in the data where the MKT_VAL_FA = 0 due to which we are getting inf values. This seems to be some sort of a data collection issue. To avoid this we filter the data to remove the inf values. Also there seems to be some missing values too.

In [11]:
```
import math filtered_df =
df_without_outliers[~df_without_outliers.op_per_asset.isna()] filtered_df =
df_without_outliers[df_without_outliers.op_per_asset != math.inf]
filtered_df[['op_per_asset','op_per_employee']].describe()
```

Out[11]:

	op_per_asset	op_per_employee
count	9952.000000	9.954000e+03

mean	2.395023	1.476742e+05
std	12.030814	9.679534e+05
min	0.000000	0.000000e+00
25%	0.450000	1.750075e+04
50%	0.891083	3.406559e+04
75%	1.762542	7.526600e+04
max	601.500000	7.595800e+07

Inference: This resulted in losing out around 40 data points from our sample. There can be a separate analysis how those 40 data points had MKT_VAL_FA = 0. But this is out of scope for this exercise.

Question 3: 99% confidence interval for the population mean of the above metrics

99% confidence interval for op_per_asset:

Since we have described that both low op_per_asset and high op_per_asset is a problem here, we will define two sided confidence interval for the given metric

Calculations:

The 2 Metrics defined by us in q2 are 'op_per_asset' and 'op_per_employee'

99% of C.I

For '**op_per_asset'**

Sample mean ($\overline{X}$)= 2.39

Sample standard deviation(S_X) = 12.03

Number of samples (n) = 9954

S_X = 12.03

Degrees of freedom(df) = n -1 = 9953

$\overline{S}_X$ = S_X/n*0.5 = 0.120584

α = (1-C.I) = 0.01

The C.I is as follows:

$$P(\bar{X} - t_{df}\ \alpha/2 * \bar{S}_x \leq \mu \leq \bar{X} + t_{df}\ \alpha/2 * \bar{S}_x) = 0.99$$

From the t-Table we get the t-value as 2.581(t_{val}) for the df = 9953

$$t_{val} * \bar{S}_X = 0.311227$$

<u>LL:</u>

$$\bar{X} - t_{df}\ \alpha/2 * \bar{S}_X = 2.078773$$

<u>UL:</u>

$$\bar{X} + t_{df}\ \alpha/2 * \bar{S}_X = 2.701227$$

$P(2.078773 \leq \mu \leq 2.701227) = 0.99$

Hence mean of Output Per Asset as of Year 3 lies between 2.078773 and 2.701227

In [12]:
```
confidence_interval = 0.99
sample_std_dev = filtered_df.op_per_asset.std()
number_of_samples = len(filtered_df.op_per_asset)
sample_mean = filtered_df.op_per_asset.mean()
two_sided = True
lower, higher = t_ci(confidence_interval,
                     sample_std_dev,
                     number_of_samples,
                     sample_mean,
                     two_sided
                    )
print('Mean of Output Per Asset as of Year 3 of population is expected to lie between {} and {}'.format(lower
,higher))
```

```
Mean of Output Per Asset as of Year 3 of population is expected to lie between 2.084 and 2.706
```

99% confidence interval for op_per_employee:

Since we have described that both low op_per_employee and high op_per_asset is a problem here, we will define two sided confidence interval for the given metric

Calculations:

For '**op_per_employee'**

Sample mean ($\overline{X}$)= 147674.169

Sample standard deviation(S_X) = 967953.394

Number of samples (n) = 9954

S_X = 967953.394

Degrees of freedom(df) = n -1 = 9953

$\overline{S}_X = S_X/n*0.5 =$

α = (1-C.I)/2 = 0.01

The C.I is as follows:

$$P(\overline{X} - t_{df}\ \alpha/2 * \overline{S}_x \leq \mu \leq \overline{X} + t_{df}\ \alpha/2 * \overline{S}_x) = 0.99$$

From the t-Table we get the t-value as 2.581(t_{val}) for the df = 9953

$$t_{val} * \overline{S}_X = 25041.79$$

LL:

$$\overline{X} - t_{df}\ \alpha/2 * \overline{S}_X = 122632.4$$

UL:

$$\overline{X} + t_{df}\ \alpha/2 * \overline{S}_X = 172716$$

$P(122632.4 \leq \mu \leq 172716) = 0.99$

Hence mean of Output Per Asset as of Year 3 lies between 122632.4 and 172716

In [13]:
```
confidence_interval = 0.99
sample_std_dev = filtered_df.op_per_employee.std()
number_of_samples = len(filtered_df.op_per_employee)
sample_mean = filtered_df.op_per_employee.mean()
two_sided = True
lower, higher = t_ci(confidence_interval,
                     sample_std_dev,
                     number_of_samples,
                     sample_mean,
                     two_sided
                    )
print('Mean of Gross Output Per Employee as of Year 3 of population is expected to lie between Rs.{} and Rs.{}'.format(lower,higher))
```

```
Mean of Gross Output Per Employee as of Year 3 of population is expected to lie between Rs.122679.005 and Rs.172669.334
```

Question 4

a. Probability that a firm selected at random is a SSSBE unit

Calculations:

Probability that a firm selected at random is a SSSBE unit

First we need to filter out only SSSBE Units under the ‘UNIT_TYPE’ Coulmn in the Filtered Dataset

We will filter out with the Label value ‘2’ that corresponds to only SSSBE Units

P_{SSSBE} = Number of only SSSBE units/Total number of units
= 2155/9954
= 0.216

Probability that a firm selected at random is a SSSBE unit = 0.216

In [14]:
```
# filter only SSSBE units
p = len(filtered_df[filtered_df.UNIT_TYPE==2])/len(filtered_df)
print(f'Probability = {round(p,3)}')
```

```
Probability = 0.216
```

b. Probability that a firm selected at random is GOOD in performance

We calculate this by checking if the values of the column op_per_asset > mean of the column op_per_asset

Calculations:

Probability that a firm selected at random is GOOD in performance

As mentioned in the question we need to first calculate the performance measure of first metric taken in q2 that is op_per_asset

As calculated in q2 mean of op_per_asset = 2.395023

To decide if the firm selected at random is good or not?
We calculate this by checking if the values of the column op_per_asset > mean of the column op_per_asset

We found out that there are 1779 number of units that are performing good

P_{good} = Number of good units/Total number of units
= 1779/9954
= 0.17872212

Probability that a firm selected at random is GOOD in performance = 0.17872212

In [15]:
```
mean_op_per_asset = filtered_df.op_per_asset.mean() filtered_df['good_in_performance'] =
filtered_df.op_per_asset.apply(lambda row: row > mean_op_per_asset) p =
len(filtered_df[filtered_df.good_in_performance==True])/len(filtered_df) print(f'Probability =
{round(p,10)}') print('Number of units performing good =
{}'.format(len(filtered_df[filtered_df.good_in_performance==True])))
```

```
Probability = 0.1787221218
Number of units performing good = 1779
```

c. Probability that a firm selected is a SSSBE Unit and ALSO GOOD in performance

Calculations:

Probability that a firm selected is a SSSBE Unit and ALSO GOOD in performance(P_{SSSBE})
Number of SSSBE units = 2155
Among these 2155 units we need to find out the units that are performing good
Number of units that are SSSBE and Good performance = 349
Total number of units = 9954

P_{SSSBE} = Number of units that are SSSBE and Good performance / Total number of units

= 349/9954

= 0.035

P_{SSSBE} = 0.035

In [16]:
```
n_sssbe_good_performance = len(filtered_df[(filtered_df.UNIT_TYPE==2) \
                                            &(filtered_df.good_in_performance==True) \
                                       ]) print('Probability that firm is SSSBE Unit and also a good
performer = {0:.3f}'.format(n_sssbe_good_performan ce/len(filtered_df)))
p_good_given_sssbe = n_sssbe_good_performance/len(filtered_df[(filtered_df.UNIT_TYPE==2)])
print('Conditional probability that a firm is Good given that its SSSBE:{}'.format(p_good_given_sssbe))
```

```
Probability that firm is SSSBE Unit and also a good performer = 0.035
Conditional probability that a firm is Good given that its SSSBE:0.16194895591647332
```

d. Conclusion about performance of SSSBE units

From calculation in 4c. we can see that only a mere 3.5% of our sample data comprise of performances from SSSBE units which are performing good. But to conclude whether SSSBE units performance are good or bad in compared to SSI we have to do a comparative study

Calculations:

Conclusion about performance of SSSBE units

We are comparing SSSBE units with SSI units to decide whether SSSBE units are performing good or bad

Probability that a firm selected is a SSI Unit and ALSO GOOD in performance(P_{SSI})

Number of SSI units = 7799

Among these 7799 units we need to find out the units that are performing good

Number of units that are SSI and Good performance = 1430

Total number of units = 9954

P_{SSI} = Number of units that are SSI and Good performance / Total number of units

= 1430/9954

= 0.14366

P_{SSI} = 0.14366.

In [17]:
```
n_ssi_good_performance = len(filtered_df[(filtered_df.UNIT_TYPE==1) \
                                          &(filtered_df.good_in_performance==True) \
                                     ]) print('Probability that firm is SSI Unit and also a good performer
= {0:.3f}'.format(n_ssi_good_performance/l en(filtered_df)))
p_good_given_ssi = n_ssi_good_performance/len(filtered_df[(filtered_df.UNIT_TYPE==1)])
print('Conditional probability that a firm is Good given that its SSI:{}'.format(p_good_given_ssi))
```

```
Probability that firm is SSI Unit and also a good performer = 0.144
Conditional probability that a firm is Good given that its SSI:0.18335684062059238
```

Inference: From the above calculations it is clear that:

1. A majority of good performer is SSI units and not SSSBE units in our sample.
2. If we see the conditional probability to understand if given that a firm is an SSSBE unit what is the probability that it will perform good < if given that a firm is SSI Unit what is the probability of being good performer.

Based on these above caclculations it is evident that performance of SSSBE unit is not good as compared to SSI Units.

5. Null Hypothesis test

Null hypothesis H_0: Population mean of VOE_Year3 ≥ 87,300

Alternate Hypothesis H_1: Population mean of VOE_Year3 < 87,300

We will setup a one sided confidence interval of 0.95

Since population standard deviation is not given to us we will use sample standard deviation and use t test

In [18]:
```
df_without_outliers.VOE_Year3.describe()
```

Out[18]:
```
count    9.999000e+03
mean     2.855638e+04
std      1.225555e+06
min      0.000000e+00
25%      0.000000e+00
```

```
50%      0.000000e+00 75%
0.000000e+00 max
9.430860e+07
Name: VOE_Year3, dtype: float64
```

In [19]:
```
confidence_interval = 0.95 sample_std_dev =
 df_without_outliers.VOE_Year3.std() number_of_samples
 = len(df_without_outliers.VOE_Year3) mean = 87300
 two_sided = False
 lower, higher = t_ci(confidence_interval,sample_std_dev,number_of_samples,mean,two_sided)
 sample_mean = df_without_outliers.VOE_Year3.mean()
 print('Sample Mean for Value of Exports for Year 3 is expected to lie between Rs. {} and Rs. {}'.format(lower
 ,higher))
 print(f'Does our sample mean falls within above range? Ans: {lower<=sample_mean<=higher} and the value
 {sample_me an}')
 print(f'The t value for sample mean:{t.cdf(sample_mean,df=number_of_samples-1,loc=mean,scale=sample_std_dev/n
 umber_of_samples**0.5)}')
```

```
Sample Mean for Value of Exports for Year 3 is expected to lie between Rs. -inf and Rs. 107461.457
Does our sample mean falls within above range? Ans: True and the value 28556.37683768377
The t value for sample mean:8.334157737807495e-07
```

Inference: It is evident that from the one sided t-test though the sample mean lies between the given ranges the P value is << 0.05. Hence we can surely reject the Null hypothesis that the population mean of VOE_Year3 ≥ 87300.

6. Special incentives for SSSBE or SSI or both

Explanation: Below we will define the success criteria as follows:

1. If unit is an SSSBE Unit its a success. We calculate the population proportion of its success rate.
2. If unit is an SSI Unit its a success. We calculate the population proportion of its success rate.

For the unit to get incentives the population proportion of it should be < 0.25

For the unit to get incentives the population proportion of it should be < 0.25

We have used statsmodels api library in python to estimate proportions .

`proportion_confint` function accepts three arguments number of successes, number of trials and alpha value and returns proportion.

α =0.1
Number of Trials = Total Count = 9954
Number of Successes = SSSBE Count = 2155

In [20]:
```
import statsmodels.api as sm
from statsmodels.stats.proportion import proportion_confint
```

In [21]:
```
confidence_interval = 0.99 sssbe_count =
len(filtered_df[filtered_df.UNIT_TYPE==2]) total_count
= len(filtered_df)


sssbe_pop_prop = proportion_confint(count=sssbe_count,    # Number of "successes"
                                   nobs=total_count,    # Number of trials
 alpha=(1 - confidence_interval))
print('Population proportion of SSSBE units is expected to lie within {} by confidence interval of {}'.format
(sssbe_pop_prop, confidence_interval))
```

```
Population proportion of SSSBE units is expected to lie within (0.2058626874239812, 0.22712907468170493) by c
onfidence interval of 0.99
```

In [22]:
```
confidence_interval = 0.99 sssbe_count =
len(filtered_df[filtered_df.UNIT_TYPE==1]) total_count
= len(filtered_df)

sssbe_pop_prop = proportion_confint(count=sssbe_count,    # Number of "successes"
                                   nobs=total_count,    # Number of trials
 alpha=(1 - confidence_interval))
print('Population proportion of SSI units is expected to lie within {} by confidence interval of {}'.format(s
ssbe_pop_prop, confidence_interval))
```

```
Population proportion of SSI units is expected to lie within (0.772870925318295, 0.7941373125760187) by confi
dence interval of 0.99
```

Inference: Since SSSBE Unit's population proportion is expected to be lying below 25% we would recommend these special incentives for SSSBE.

7. Contention that a larger proportion of SSSBEs are managed by men as compared to women

Explanation: For this we will estimate population proportion of SSSBE Units managed by Male. The column MAN_BY will be beneficial for this case.

1. We define success if a unit is managed by man.
2. We estimate the population proportion of SSSBE units to be managed by men from our sample by a set confidence interval.
3. If the estimated population proportion > 0.5 this contention will hold true.

α =0.1
Number of Trials = SSSBE Count = 2155
Number of Successes = Units managed by man = 2102.

In [23]:
```
# filter out only SSSBE Units
sssbe_df = df[df.UNIT_TYPE == 2]
sssbe_df.MAN_BY.value_counts()
```

Out[23]:
```
1    2102
2      55
Name: MAN_BY, dtype: int64
```

In [24]:
```
confidence_interval = 0.99 no_of_sssbe_units_managed_by_men =
len(sssbe_df[sssbe_df.MAN_BY == 1]) number_of_sssbe_units =
len(sssbe_df)
male_employee_pop_prop = proportion_confint(count=no_of_sssbe_units_managed_by_men,    # Number of "successe
s"
                                            nobs=number_of_sssbe_units,    # Number of trials
 alpha=(1 - confidence_interval))
print('Population proportion of SSSBE units being managed by men is expected to lie within {} by confidence i
nterval of {}'.format(sssbe_pop_prop, confidence_interval))
```

```
Population proportion of SSSBE units being managed by men is expected to lie within (0.772870925318295, 0.794
1373125760187) by confidence interval of 0.99
```

Inference: Thus we are 99% confident that the population proportion of SSSBE Units being managed by men lies much above 50%. Hence we are accepting the above contention.

8. Distribution of defined metrics

We have used histogram to identify the distribution of the metrics.
First metric is op_per_asset and second metric is op_per_employee.

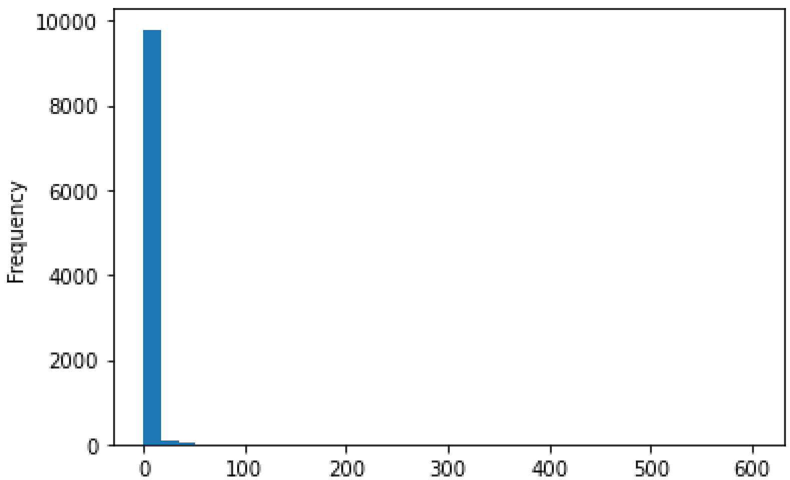
In [25]:
```
filtered_df[['op_per_asset','op_per_employee']].describe()
```

Out[25]:

	op_per_asset	op_per_employee
count	9952.000000	9.954000e+03
mean	2.395023	1.476742e+05
std	12.030814	9.679534e+05
min	0.000000	0.000000e+00
25%	0.450000	1.750075e+04
50%	0.891083	3.406559e+04
75%	1.762542	7.526600e+04
max	601.500000	7.595800e+07

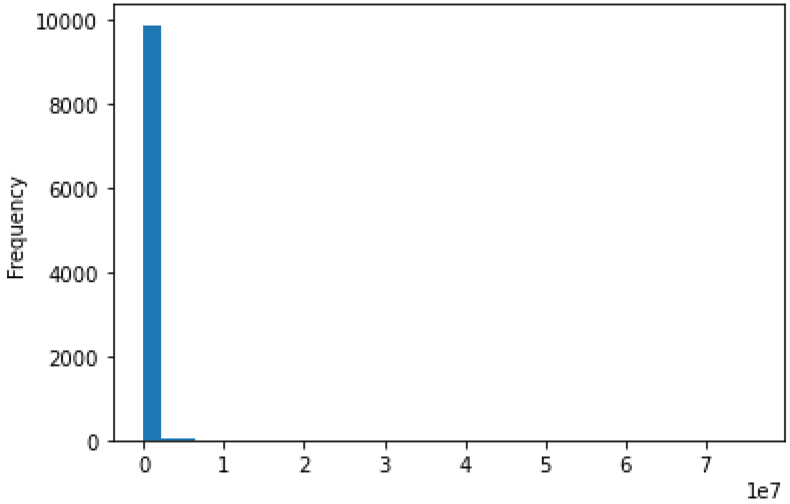
In [26]:
```
filtered_df['op_per_asset'].plot.hist(bins=35)
```

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x2880bb06f88>



In [27]:
```
filtered_df['op_per_employee'].plot.hist(bins=35)
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x2880bbd9a48>



Inference: The distributions of the metrics 'op_per_asset' and 'op_per_employee' are right skewed in nature. We can find the evidence from the above histograms and also the .describe() method here where it is seen that median << mean