In [2]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
from scipy.stats import sem, t
import seaborn as sns
import scipy.stats as stats
import statsmodels.api as sm

import os
```

In [4]:

```
df = pd.read_csv('D:/AnitaRJ/DATA SCIENCE/Anita_DSAI_Practicals/loans_income.csv')
df.head()
```

Out[4]:

	x
0	67000
1	52000
2	100000
3	78762
4	37041

The Bootstrap Definition of Bootstrap

One easy and effective way to estimate the sampling distributions of a statistic, or of model parameters, is to draw additional samples,with replacement, from the sample itself and recalculate the statistic or model for each resample. This procedure is called the bootstrap. Why Do We Use The Bootstrap

The bootstrap is used for sample size determination; experiment with different values for n to see how the sampling distribution is affected. The Algorithm For A Bootstrap

```
Draw a sample value, record, replace it.
Repeat n times.
Record the mean of the n resampled values.
Repeat steps 1-3 R times.
Use the R result to:

        Calculate their standard deviation.
        Produce a histogram or a boxplot.
        Find a confidence interval.
```

An Example of Using The Bootstrap

In [5]:

```
loans_income = np.array(pd.read_csv("D:/AnitaRJ/DATA SCIENCE/Anita_DSAI_Practicals/loans_income.csv"))
loans_income[:5]
```

Out[5]:

```
array([[ 67000],
       [ 52000],
       [100000],
       [ 78762],
       [ 37041]], dtype=int64)
```

In [6]:

```
# Making a flat list from list of lists
loans_income = np.array([item for sublist in loans_income for item in sublist])
```

In [7]:

```
def bootstrap(l,R):
    n = len(loans_income)
    # Number of Bootstrap Samples
    means_of_boot_samples = []
    for reps in range(R):
        #Steps 1,2
        boot_sample = np.random.choice(loans_income, size = n)
        #Step 3
        means_of_boot_samples.append(round(np.mean(boot_sample), 3))
    return means_of_boot_samples

bootstrap(loans_income, 5)
```

Out[7]:

```
[68771.86, 68691.891, 68733.206, 68497.226, 68643.668]
```

Now as we have a means of bootstrap samples we can estimate:

A. Their standard deviation (this estimates sample mean standard error)

In [8]:

```
np.std(bootstrap(loans_income, 100))
```

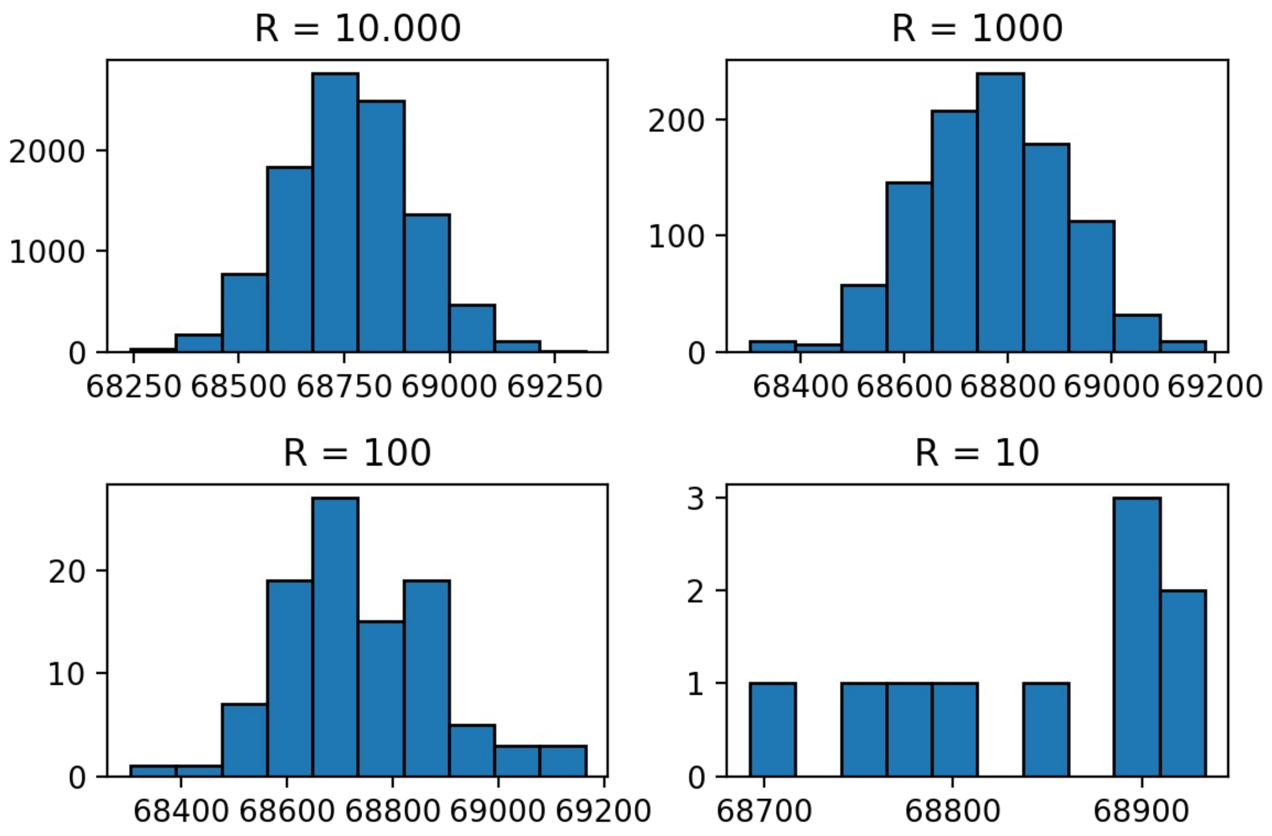
Out[8]:

```
116.49938191429958
```

Produce a histogram or boxplot

In [9]:

```
plt.figure(dpi = 200)

plt.subplot(221)
plt.title("R = 10.000")
plt.hist(bootstrap(loans_income, 10000), edgecolor = 'k')

plt.subplot(222)
plt.title("R = 1000")
plt.hist(bootstrap(loans_income, 1000), edgecolor = 'k')

plt.subplot(223)
plt.title("R = 100")
plt.hist(bootstrap(loans_income, 100), edgecolor = 'k')

plt.subplot(224)
plt.title("R = 10")
plt.hist(bootstrap(loans_income, 10), edgecolor = 'k')

plt.tight_layout()
```



As we can see distribution of 10000 means is more compact and bell-shaped than the distribution with smaller amount of means. This phenomenon is termed as central limit theorem.

Find a confidence interval.

In [10]:

```
data = bootstrap(loans_income, 1000)
lower_lim, upper_lim = np.percentile(data, 2.5), np.percentile(data, 95)
print("Lower Limit: ", lower_lim)
print("Upper Limit: ", upper_lim)
```

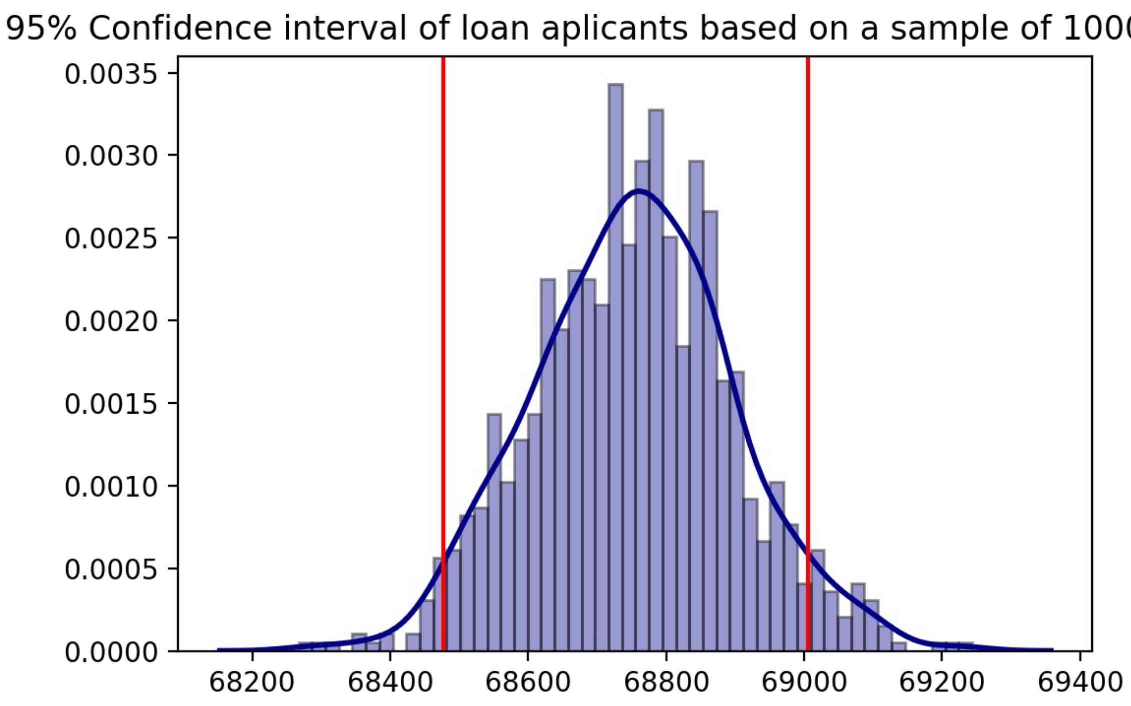
```
Lower Limit:  68476.5669
Upper Limit:  69005.8885
```

In [11]:

```
plt.figure(dpi = 200)
plt.title("95% Confidence interval of loan aplicants based on a sample of 1000 means")

sns.distplot(bootstrap(loans_income, 1000), hist=True, kde=True,
             color = 'darkblue', bins = 50,
             hist_kws={'edgecolor':'black'},
             kde_kws={'linewidth': 2})

plt.axvline(x=lower_lim,color='red')
plt.axvline(x=upper_lim,color='red')
```

Out[11]:

```
<matplotlib.lines.Line2D at 0x2081a4d8908>
```



In [ ]: