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May 28, 2025

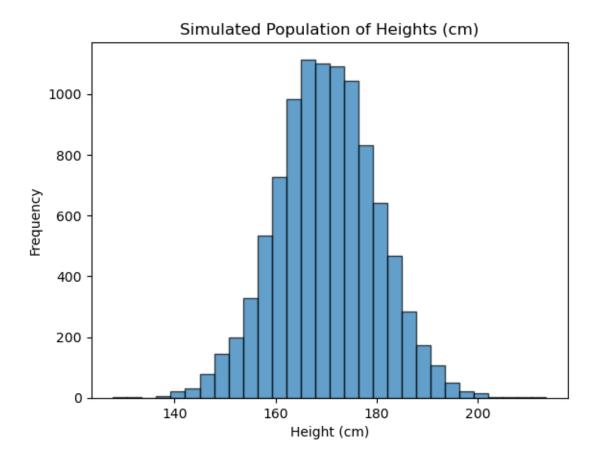
```
[9]: import numpy as np
  import matplotlib.pyplot as plt

[10]: np.random.seed(420)

[13]: #To simulate population
  population = np.random.normal(loc = 170, scale = 10, size = 10000)

[14]: plt.hist(population, bins = 30, edgecolor = 'black', alpha = 0.7)
    plt.title("Simulated Population of Heights (cm)")
    plt.xlabel("Height (cm)")
    plt.ylabel("Frequency")

    plt.show()
```



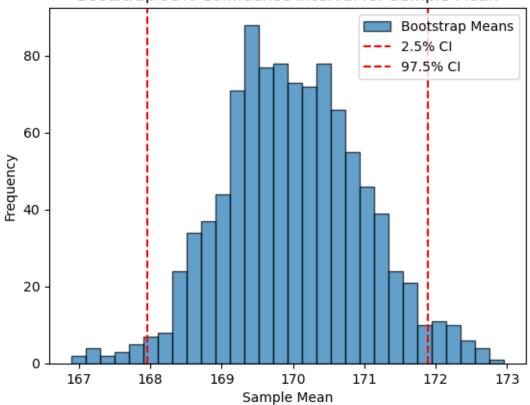
[24]: #Store means from bootstrap

```
# Add CI boundaries
plt.axvline(lower, color = 'red', linestyle = '--', label = '2.5% CI')
plt.axvline(upper, color = 'red', linestyle = '--', label = '97.5% CI')

# Decorate plot
plt.title("Bootstrap 95% Confidence Interval for Sample Mean")
plt.xlabel("Sample Mean")
plt.ylabel("Frequency")

plt.legend()
plt.show()
```

Bootstrap 95% Confidence Interval for Sample Mean



```
[26]: # Taking a single sample
sample = np.random.choice(population, size = 100, replace = False)

# Sample stats
sample_mean = np.mean(sample)
```

```
sample_std = np.std(sample, ddof=1) # ddof = Delta Degree of Freedom, sample_\( \)
\( \sigma \) means that use ddof = 1, it's a theorem.

\( n = \len(\) sample)
\( z = 1.96 \) # 95% confidence, derive from standard normal distribution where P(-1. \)
\( \sigma \) 96 < Z < 1.96) = 0.95. You don't really need to calculate this, just look up_\( \sigma \)
\( \sigma \) the chart.

# Confidence interval formula
\( \text{ci_lower} = \text{sample_mean} - z * (\) (\) (\) sample_\( \text{std} / \) np.sqrt(n))
\( \text{ci_upper} = \text{sample_mean} + z * (\) (\) (\) (\) (\( \) formula): [\( \) (\( \) ci_\) upper: .2f\\( \) ]")</pre>
```

95% CI (formula): [167.81, 172.08]