# conf interval

#### November 3, 2022

# Confidence Intervals + Quick Reference to my fantastic CI tutorial + This code is based on this blog post

We are taking the data from Uniform distribution. According to the CLT. Means of any other distribution will follow a normal distribution. with std of  $\frac{\sigma}{\sqrt{n}}$  where n is the sample size an  $\sigma$  is the global std which usually is estimated by sample std. If we can say (based on CLT) that the sample emeans center around the global mean with std  $\frac{\sigma}{\sqrt{n}}$  then based on the characteristics of normal distribution we can also say that that 66 % percent of the means are +/- 1 std away from the global mean. ~95 % is ~2 std away from the global mean and ~99% means is 3 std away from global mean. Thus if we have the sample mean and based on the sample size and sample std the std for the sample means, we can now say with specific confidence an interval where the means should be located.

```
[]: import numpy as np
     from scipy.stats import t, norm
     import math
     import matplotlib.pyplot as plt
     from dataclasses import dataclass
     @dataclass
     class ConfidenceInterval:
         mean:float
         lower_bound:float
         upper_bound:float
         test_type:str
         extremum val:float
         def get_size(self)->float:
             return self.upper_bound-self.lower_bound
         def print_statistics(self):
             print(f"Median: {self.mean}")
             print(f"Min boundary {self.lower_bound}")
             print(f"Max boundary {self.upper_bound}")
             print(f"Width is {self.get_size()}" )
             print()
     def
      -calculate_confidence_interval(sample_mean,sample_std,sample_size,confidence,test_type)->Con
```

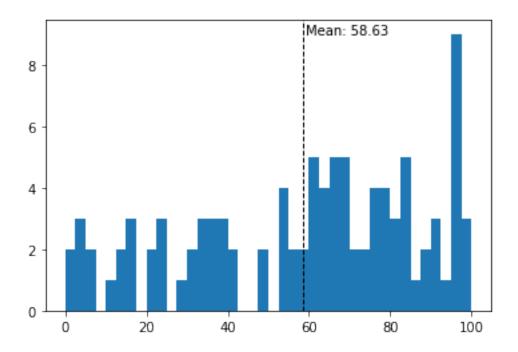
```
alpha=1-confidence
         # Only thing that is different for t and z confidence intervale is the \Box
      ⇔extremum value
         if test type == "t":
             degrees_of_freedom=sample_size-1
             extremum val=float(np.abs(t.ppf(alpha/2,degrees of freedom))) # t val - |
      →based on confidence we have chosen, how many standard distributions is the
      ⇔ci width. If Confidence is 95%, then std is ~2
         elif test_type == "z":
             extremum_val=float(np.abs(norm.ppf(alpha/2))) # z_val - based on_
      →confidence we have chosen, how many standard distributions is the ci width.
      →If Confidence is 95%, then std is ~2.
         else:
             raise Exception("Wrong test type provided")
         clt_based_std = sample_std / math.sqrt(sample_size) # The std for sample_u
      →means. Calculated based on CLT
         max_expected_difference = extremum_val * clt_based_std # std * (how many_
      ⇔stds based on chosen confidence interval size)
         return
      GonfidenceInterval(mean=sample_mean,lower_bound=sample_mean-max_expected_difference,upper_b
     def perform_comparison(sample_size:int=100, confidence:float=0.95):
         # Generate sample data from uniform distritubution on the range 0..100
         x = np.random.uniform(size=100)
         x_{positive} = x_{min}(x)
         x_scaled = x_positive/max(x_positive)*100
         x = x \text{ scaled}
         # Calculate confidence intervals based on both Normal distribution (Z val)_{\sqcup}
      →and t distribution (t val)
         ci_z=calculate_confidence_interval(sample_mean=x.mean(),sample_std=x.
      std(),sample_size=sample_size,confidence=confidence,test_type='z')
         ci_t=calculate_confidence_interval(sample_mean=x.mean(),sample_std=x.
      std(),sample_size=sample_size,confidence=confidence,test_type='t')
         return x, ci_z, ci_t
[]: sample_size=15
     confidence=0.95
     x, ci_z, ci_t = perform_comparison(sample_size=sample_size,confidence=0.95)
     print(f"Sample size: {sample size}, Sample std: {x.std()}, Confidence
      \hookrightarrow {confidence}, Max value {max(x)}, Min value: {min(x)}")
     # plt.text((m+s)*1.1, max_ylim*0.9, 'Mean+Std: {:.2f}'.format(m+s))
```

```
# plt.text((m-s)*1.1, max ylim*0.9, 'Mean+Std: {:.2f}'.format(m-s))
ci_z.print_statistics()
ci_t.print_statistics()
print(f"Differences in CI size ci_t-ci_z {ci_t.get_size()-ci_z.get_size()}")
# PLOT THE GENERATED DISTRIBUTION X
def plot default histogram(x,bins=40,start=0,end=100):
    counts, bins = np.histogram(x,bins=bins)
    plt.hist(bins[:-1],len(bins)-1,weights=counts,range=(start,end))
    plt.axvline(x.mean(), color='k', linestyle='dashed', linewidth=1)
    # plt.axvline(m+s, color='r', linestyle='dashed', linewidth=1)
    # plt.axvline(m-s, color='r', linestyle='dashed', linewidth=1)
    min_ylim, max_ylim = plt.ylim()
    plt.text(x.mean()*1.01, max_ylim*0.95, 'Mean: {:.2f}'.format(x.mean()))
plot_default_histogram(x)
Sample size: 15, Sample std: 28.635469814784415, Confidence 0.95, Max value
100.0, Min value: 0.0
```

100.0, Min value: 0.0 Median: 58.62569127706479 Min boundary 44.13441039605592 Max boundary 73.11697215807366 Width is 28.982561762017745

Median: 58.62569127706479 Min boundary 42.76789665960571 Max boundary 74.48348589452387 Width is 31.715589234918156

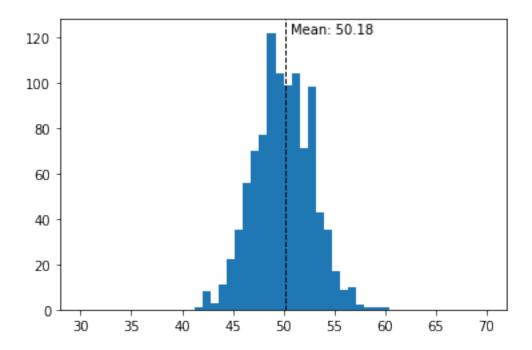
Differences in CI size ci\_t-ci\_z 2.7330274729004103



Now we perform this experiment 1000 times and see how the distribution of means will look like. E.g. we take the sample with size 100 and we do this 1000 times. Then we plot the means of these 1000 samples. Based on the Central Limit Theorem (CLT) this distribution should now have  $\sim$  global mean as the mean and the standard distribution  $\frac{\sigma}{\sqrt{n}}$  where  $\sigma$ = Global std and n is sample size for 1 sample. PS! In reality we almost always limit our experiment with taking 1 sample only. The current setup aims to showcase how CLT works and how this allows us to build Confidence Intervals, Hypothesis tests and all other good things.

```
[]: means = []
for i in range(1000):
    x, ci_z, ci_t = perform_comparison(sample_size=sample_size,confidence=0.95)
    means.append(x.mean())

means = np.asarray(means)
plot_default_histogram(means,bins=50,start=30,end=70)
```



Lets now take a few additional samples to show how we derive the confidence interval from 1 sample. Run this cell at least 5 times to see how the confidence intervals are generated for each sample ADDITIONAL SAMPLE 1 COMPARED TO MEAN

```
[]: def take_sample_and_show(means):
         x_sample, sample_ci_z, sample_ci_t = __

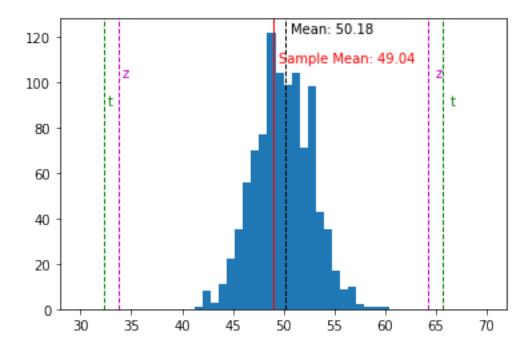
-perform_comparison(sample_size=sample_size,confidence=0.95)
         plot_default_histogram(means,bins=50,start=30,end=70)
         # ADD THE SAMPLE
         plt.axvline(x_sample.mean(), color='r', linewidth=1)
         min_ylim, max_ylim = plt.ylim()
         plt.text(x_sample.mean()*1.01,max_ylim*0.85, 'Sample Mean: {:.2f}'.
      →format(x_sample.mean()),color='r')
         print(f"Sample size: {len(x_sample)}, Sample std: {x_sample.std()},
      →Confidence {confidence}, Max value {max(x_sample)}, Min value:
      \rightarrow{min(x_sample)}")
         # PLOT CI INFOR FOR Z TESTS
         z_color='m'
         plt.axvline(sample_ci_z.upper_bound, color=z_color, linestyle='dashed',_u
      →linewidth=1)
         plt.axvline(sample_ci_z.lower_bound, color=z_color, linestyle='dashed',_
      →linewidth=1)
         plt.text(sample_ci_z.upper_bound*1.01, max_ylim*0.8, 'z',color=z_color)
```

```
plt.text(sample_ci_z.lower_bound*1.01, max_ylim*0.8, 'z',color=z_color)

# PLOT CI INFO FOR T TESTS

t_color='g'
plt.axvline(sample_ci_t.upper_bound, color=t_color, linestyle='dashed',u')
inewidth=1)
plt.axvline(sample_ci_t.lower_bound, color=t_color, linestyle='dashed',u')
inewidth=1)
plt.text(sample_ci_t.upper_bound*1.01, max_ylim*0.7, 't',color=t_color)
plt.text(sample_ci_t.lower_bound*1.01, max_ylim*0.7, 't',color=t_color)
take_sample_and_show(means)
```

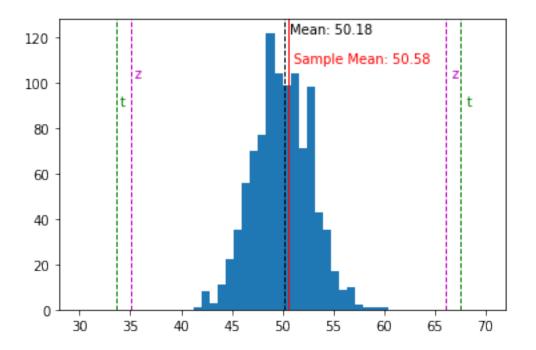
Sample size: 100, Sample std: 30.160875214238498, Confidence 0.95, Max value 100.0, Min value: 0.0



#### ADDITIONAL SAMPLE 2 COMPARED TO MEAN

#### []: take\_sample\_and\_show(means)

Sample size: 100, Sample std: 30.53389768088036, Confidence 0.95, Max value 100.0, Min value: 0.0



### ADDITIONAL SAMPLE 3 COMPARED TO MEAN

## []: take\_sample\_and\_show(means)

Sample size: 100, Sample std: 29.464664243459364, Confidence 0.95, Max value 100.0, Min value: 0.0

