Lab 1: Dartboard Statistics Part 2

Start with our imports

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy
```

First we grab our data

```
dartboard_data = pd.read_csv("combined_dart_strikes.csv")
my_data = pd.read_csv("Shahid_Sovereign_dartboard.csv")
my_strikes = my_data["Dart Strike"].to_numpy()
dart_strikes = dartboard_data["Dart strike"].to_numpy()
dartboard_data.head()
```

	Dart strike
0	-12
1	-10
2	-8
3	-5
4	0

Create a function to calculate the mean and std of an array

```
def mean(arr):
    return sum(arr)/len(arr)

def std(arr):
    return np.sqrt((sum((arr - mean(arr))**2))/(len(arr)-1))
```

Get the mean and std

```
print("Numpy Data")
print(f"""My Data:
  mean: {my_strikes.mean():.4f}
  std: {my_strikes.std():.4f}
  std_uncertainty: {my_strikes.std()/np.sqrt(len(my_strikes)):.4f}

Class Data:
  mean: {dart_strikes.mean():.4f}
  std: {dart_strikes.std():.4f}
  std_uncertainty: {dart_strikes.std()/np.sqrt(len(dart_strikes)):.4f}""")
```

```
Numpy Data
My Data:
  mean: 1.4467
  std: 5.1479
  std_uncertainty: 0.4203

Class Data:
  mean: 0.3419
  std: 6.4152
  std_uncertainty: 0.0682
```

```
print("My Data")
print(f"""My Data:
  mean: {mean(my_strikes):.4f}
  std: {std(my_strikes):.4f}
  std_uncertainty: {std(my_strikes)/np.sqrt(len(my_strikes)):.4f}

Class Data:
  mean: {mean(dart_strikes):.4f}
  std: {std(dart_strikes):.4f}
  std_uncertainty: {std(dart_strikes)/np.sqrt(len(dart_strikes)):.4f}""")
```

```
My Data
My Data:
  mean: 1.4467
  std: 5.1651
  std_uncertainty: 0.4217
```

```
Class Data:
  mean: 0.3419
  std: 6.4156
  std_uncertainty: 0.0682
```

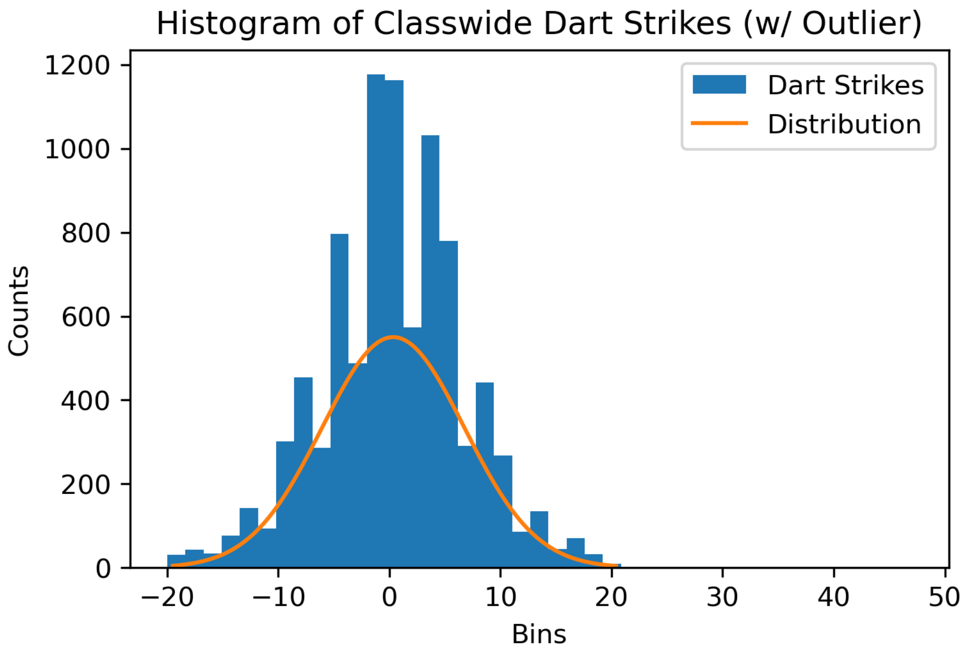
Define a function for the distribution

```
def N(x, mean, std):
  return 1/(std*np.sqrt(2*np.pi)) * np.exp(-((x-mean)**2)/(2*std**2))

# Normal distribution of counts
# total_num_events*N(x,mean,std)
```

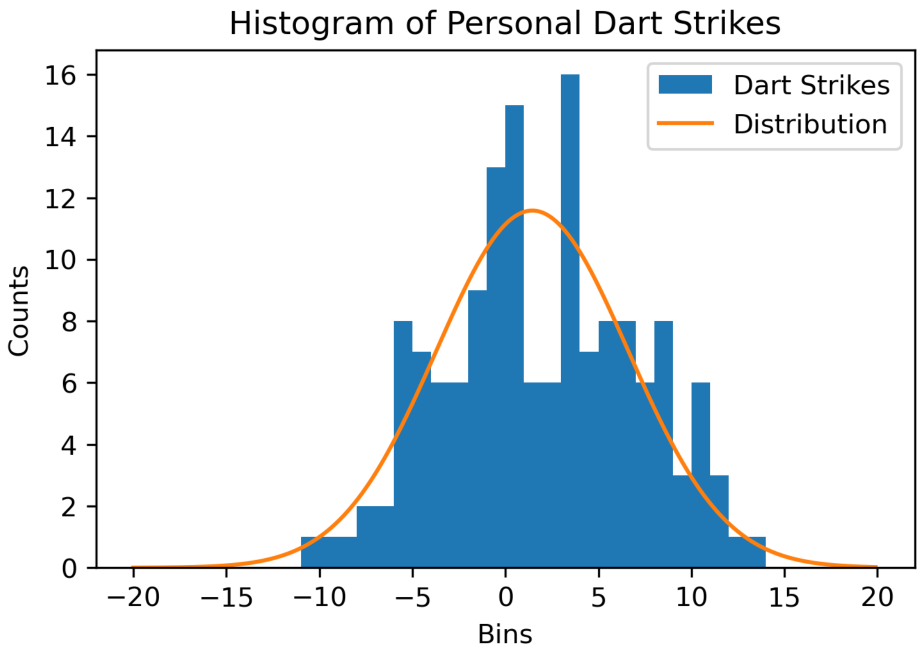
Plot the class wide histogram

```
X = np.arange(-20,20, 0.1)+0.5
plt.figure()
plt.title("Histogram of Classwide Dart Strikes (w/ Outlier)")
plt.xlabel("Bins")
plt.ylabel("Counts")
plt.hist(dart_strikes, bins=41, label="Dart Strikes")
plt.plot(X, len(dart_strikes)*N(X, mean(dart_strikes), std(dart_strikes)), label="Distributi
plt.legend()
plt.show()
```



Plot my histogram

```
X = np.arange(-20,20, 0.1)
plt.figure()
plt.title("Histogram of Personal Dart Strikes")
plt.xlabel("Bins")
plt.ylabel("Counts")
plt.hist(my_strikes, np.arange(-20,21, 1), range=(-20,20), label="Dart Strikes")
plt.plot(X, len(my_strikes)*N(X, mean(my_strikes), std(my_strikes)), label="Distribution")
plt.legend()
plt.show()
```



Check for outliers

```
np.sort(dart_strikes)[-5:]
```

```
array([20, 20, 20, 20, 47])
```

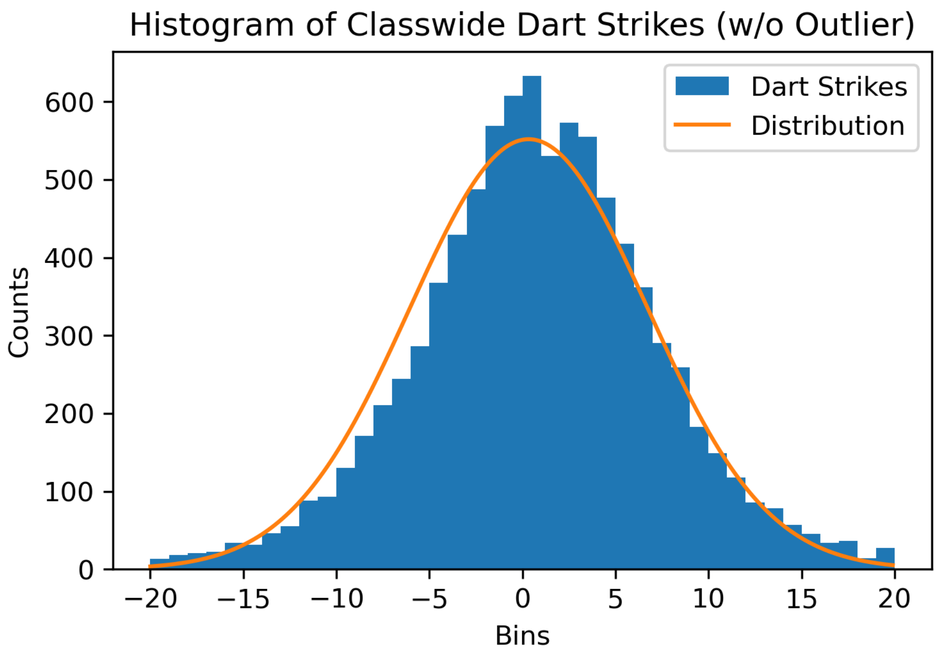
We should not have this outlier since it is beyond our bins, so we scap the one bad datapoint, and recalculate the mean and std

```
fixed_strikes = dart_strikes[dart_strikes <= 20]
print(f"""Fixed Strikes:
  mean: {mean(fixed_strikes):.4f}
  std: {std(fixed_strikes):.4f}
  std_uncertainty: {std(fixed_strikes)/np.sqrt(len(fixed_strikes)):.4f}""")
```

```
Fixed Strikes:
  mean: 0.3366
  std: 6.3967
  std_uncertainty: 0.0680
```

Now we Plot without outliers

```
X = np.arange(-20,20, 0.1)
plt.figure()
plt.title("Histogram of Classwide Dart Strikes (w/o Outlier)")
plt.xlabel("Bins")
plt.ylabel("Counts")
plt.hist(fixed_strikes, np.arange(-20,21, 1), label="Dart Strikes")
plt.plot(X, len(fixed_strikes)*N(X, mean(fixed_strikes), std(fixed_strikes)), label="Distribu
plt.legend()
plt.show()
```



Get the bins and counts in the bins

```
class_bins, class_counts = np.unique(fixed_strikes, return_counts=True)
my_bins, my_counts = np.unique(my_strikes, return_counts=True)


# Ignore bins that have no counts as they will skew the results of the fit
class_expected = len(fixed_strikes)*N(class_bins, fixed_strikes.mean(), fixed_strikes.std())
my_expected = len(my_strikes)*N(my_bins, mean(my_strikes), std(my_strikes))
```

Perform a chi^2 test on each dataset

```
# Class Wide
chi2_stat, p_value = scipy.stats.chisquare(class_counts, f_exp=class_expected, sum_check=Fals
#chi2_stat = np.sum((class_counts - class_expected)**2 / class_expected)
#p_value = scipy.stats.chi2.cdf(chi2_stat, df=len(class_bins)-3)
print(f"""Class Stats:
  #-counts: {len(class_counts)}
  #-bins: {len(class_bins)}
  Chi-square statistic: {chi2_stat}
  P-value: {p_value}""")

# Personal
chi2_stat, p_value = scipy.stats.chisquare(my_counts, f_exp=my_expected, sum_check=False)
#chi2_stat = np.sum((my_counts - my_expected)**2 / my_expected)
#p_value = scipy.stats.chi2.sf(chi2_stat, df=len(my_bins)-3)
print(f"""\nMy Stats:
  #-counts: {len(my_counts)}
  #-bins: {len(my_bins)}
  Chi-square statistic: {chi2_stat}
  P-value: {p_value}""")
```

```
Class Stats:
  #-counts: 41
  #-bins: 41
  Chi-square statistic: 198.46991860479906
  P-value: 7.004836864456655e-23

My Stats:
  #-counts: 25
  #-bins: 25
  Chi-square statistic: 21.775709049958802
  P-value: 0.592651908460754
```

The class p-value is astronomically small, which means we reject our null hypothesis that the data follows a normal distribution. This is mainly due to the fac that the χ^2 test is far too sensitive for large sample sizes whereas our data is larger larger than a typical significance level of 0.05 meaning it doesnt reject the null hypothesis and is normally distributed according to our null hypothesis.