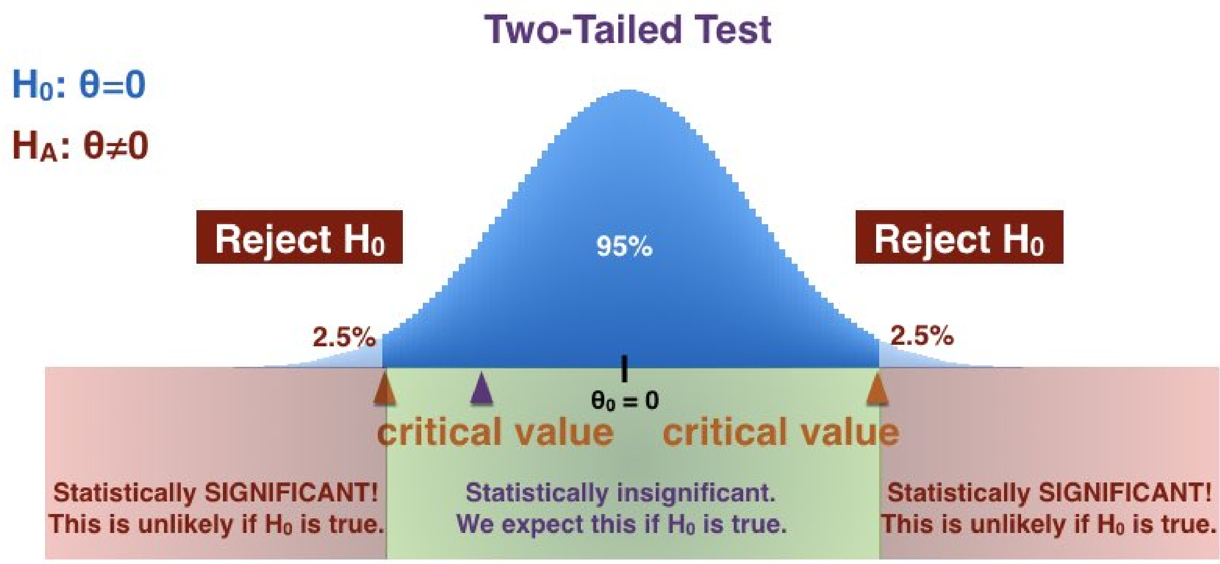
Hypothesis Testing



Hypothesis testing is the process of using statistics to determine the probability that a specific hypothesis is true. It formulates 2 hypothesis.

> - **Null Hypothesis (H_0) :** proposes the observations are a results of pure chance and there is no relationship and difference between 2 or more groups.
> - **Alternative Hypothesis (H_a) :** states the sample observations are influenced by non- random cause and there is some realtionship and difference between 2 or more groups.

significance level (α) : The significance level (denoted by the Greek letter α) is the probability threshold that determines when you reject the null hypothesis. Often, researchers choose a significant level of 0.01, 0.05, or 0.10, but any value between 0 and 1 can be used. Setting the significant level α = 0.01 means that there is a 1% chance that you will accept your alternative hypothesis when your null hypothesis is actually true.

For our example, we will set a significant level of α = 0.05.

Importing necessary Package

In [1]:
```
from pyforest import *

import statsmodels.stats.api as sm
from scipy import stats
from scipy.stats import shapiro, anderson, pearsonr, ttest_ind, mannwhitneyu
```

Loading Dataset

In [2]:
```python
df = pd.read_csv('titanic_train.csv')
df.head()
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Eml
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	

In [3]:
```python
new_df = df[['Age','Fare','Survived']].dropna()
new_df.head()
```

Out[3]:

	Age	Fare	Survived
0	22.0	7.2500	0
1	38.0	71.2833	1
2	26.0	7.9250	1
3	35.0	53.1000	1
4	35.0	8.0500	0

In [4]:
```python
len(new_df)
```

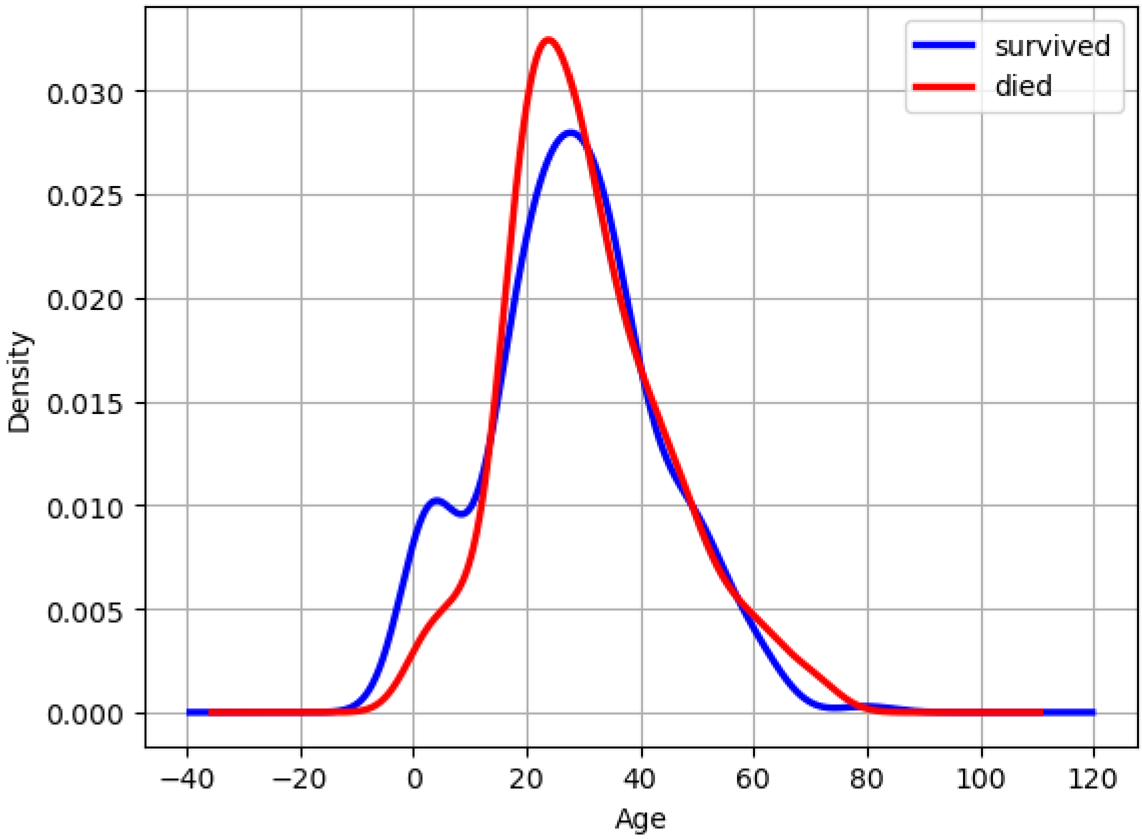
Out[4]: 714

In [5]:
```python
survived = new_df[new_df.Survived == 1]
died = new_df[new_df.Survived == 0]
```

Visualizing Age Distribution:

In [6]:
```
survived['Age'].plot(kind='kde', color='blue',lw=2.5, grid= True)
died['Age'].plot(kind='kde', color='red',lw=2.5, grid= True)
plt.legend(['survived','died'])
plt.xlabel('Age')
```

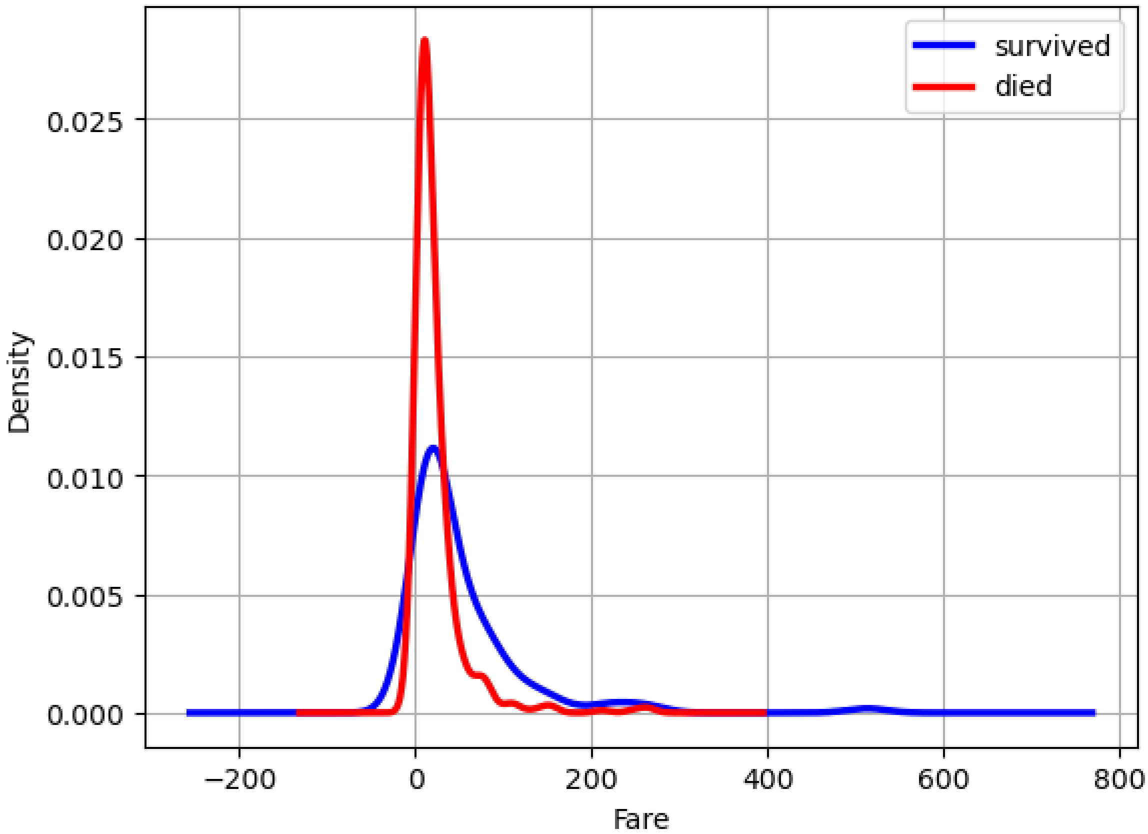
Out[6]: `Text(0.5, 0, 'Age')`



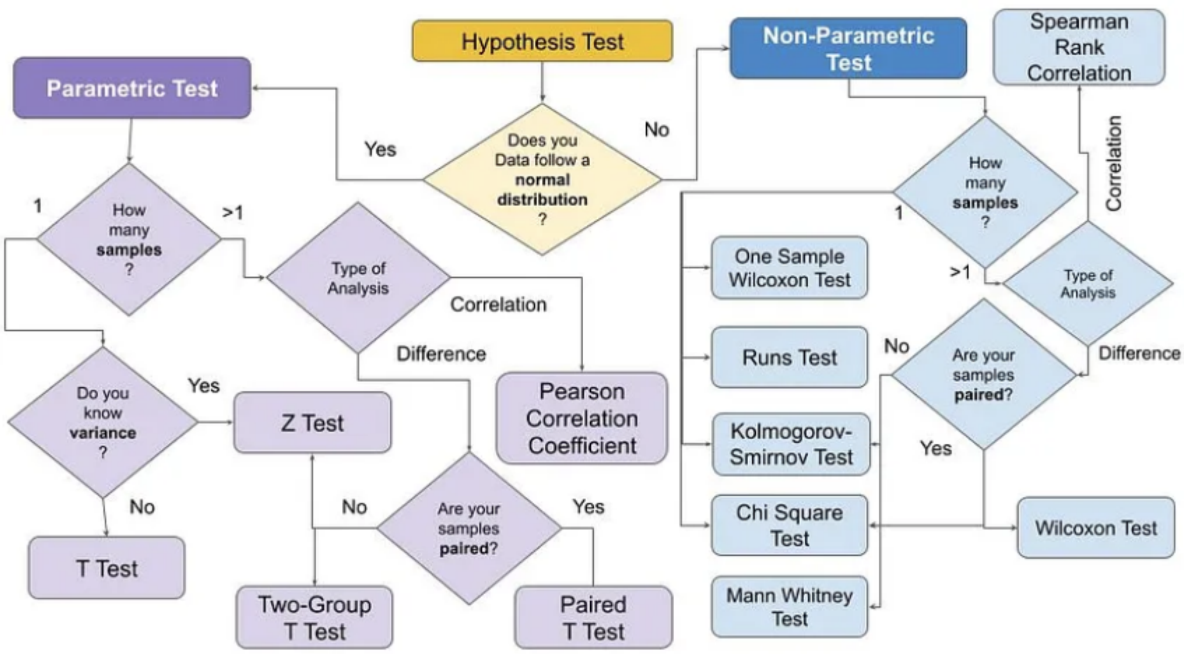
Visualizing Fare Distribution:

In [7]:
```
survived['Fare'].plot(kind='kde', color='blue',lw=2.5, grid= True,)
died['Fare'].plot(kind='kde', color='red',lw=2.5, grid= True)
plt.legend(['survived','died'])
plt.xlabel('Fare')
```

Out[7]: Text(0.5, 0, 'Fare')



Hypothesis Test to understand



Variable Distribution Type Tests (Gaussian)

- Shapiro-Wilk Test
- D'Agostino's K^2 Test
- Anderson-Darling Test

Step:1 Normality Check

1. Shapiro Test

The Shapiro-Wilk test is a statistical test used to assess whether a given sample comes from a normally distributed population. It tests the null hypothesis that a sample is drawn from a normal distribution. The test is sensitive to deviations from normality in the tails of the distribution.

Here's a general overview of how the test works:

- **Null Hypothesis (H0):** The data follows a normal distribution.
- **Alternative Hypothesis (Ha):** The data does not follow a normal distribution.

The test statistic is calculated from the sample data, and a p-value is obtained. The p-value represents the probability of observing a test statistic as extreme as the one computed from the sample, assuming the null hypothesis is true.

If the p-value is less than the chosen significance level (commonly 0.05), the null hypothesis is rejected, suggesting that the data does not follow a normal distribution. If the p-value is greater than the significance level, there is insufficient evidence to reject the null hypothesis, and it is assumed that the data follows a normal distribution.

In [8]:
```
# Shapiro Test for Age from Survived and died passenger
```

In [9]:
```
stat, p_value =shapiro(survived.Age)
print(p_value)
```

```
0.0014263729099184275
```

In [10]:
```
stat, p_value =shapiro(died.Age)
print(p_value)
```

```
7.816021252438077e-08
```

In [11]:
```
# Shapiro Test for Fare from Survived and died passenger
```

In [12]:
```
stat, p_value =shapiro(survived.Fare)
print(p_value)
```

```
2.963307919251319e-25
```

In [13]:
```
stat, p_value =shapiro(died.Fare)
print(p_value)
```

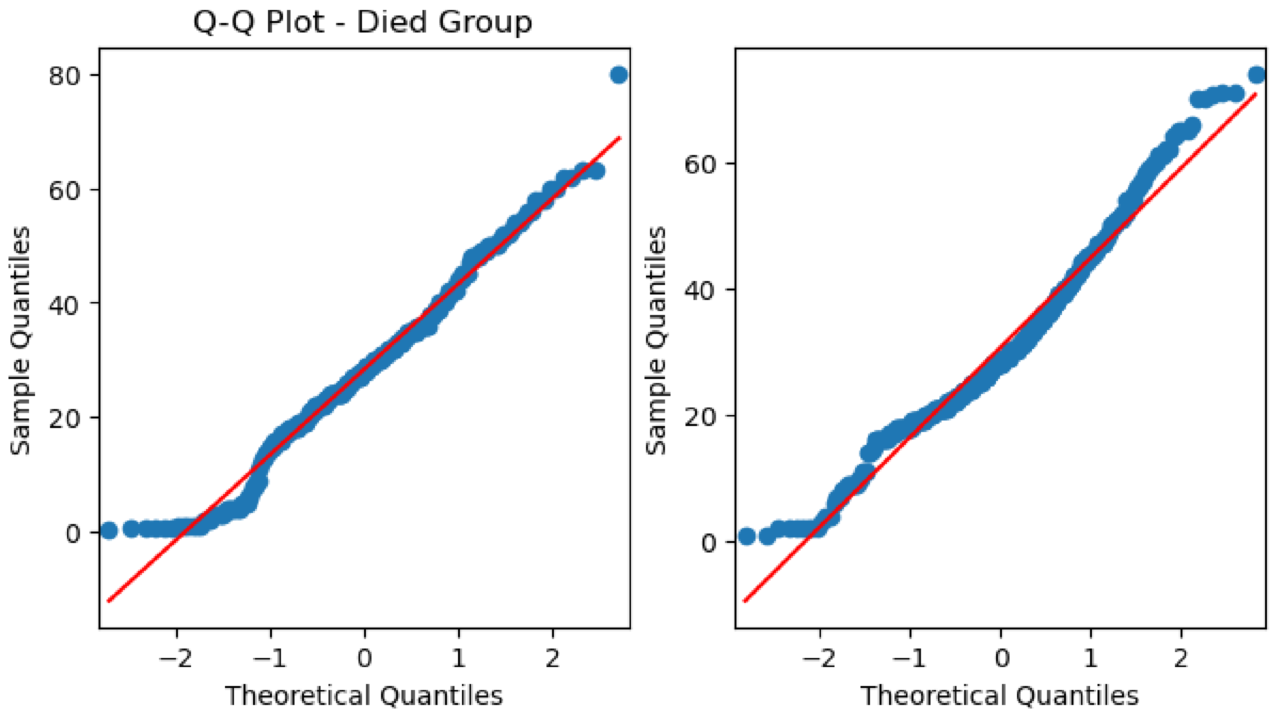
```
3.4173530956723984e-32
```

Both Age and Fare have p value < 0.05

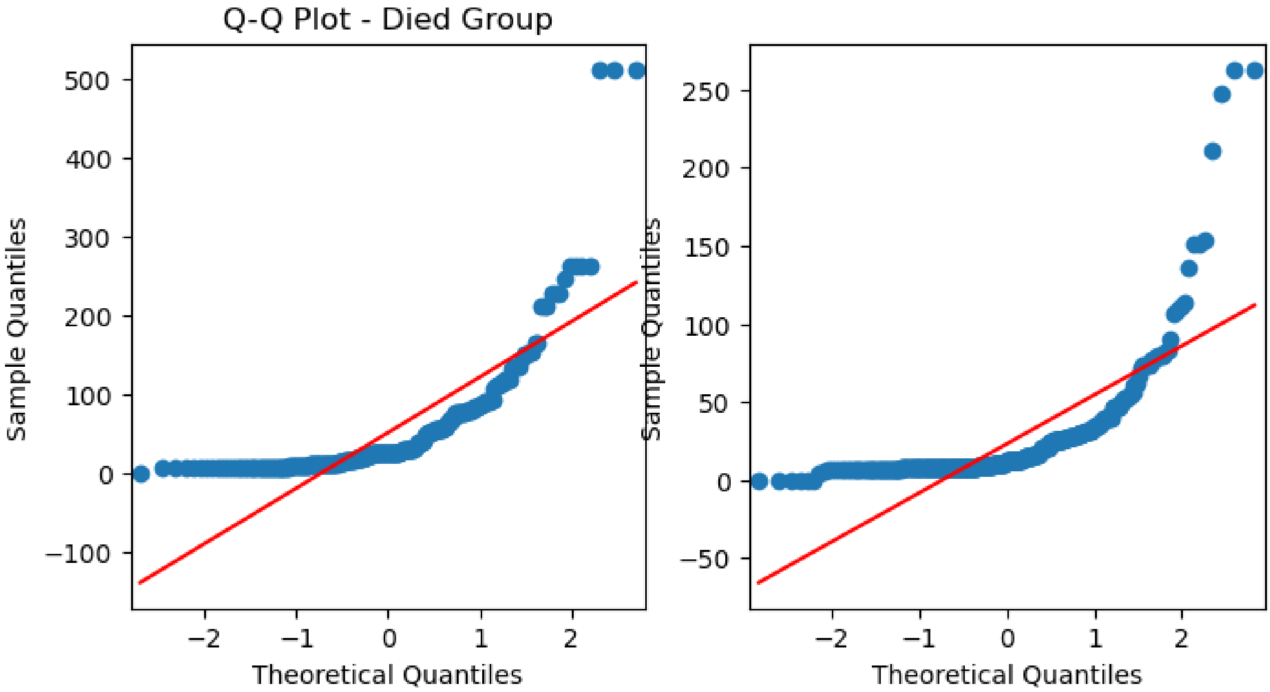
=> Weak evidence against normally distributed data and null hypothesis is rejected.

2. Visual Normality Checks (Q-Q Plot)

In [15]:
```
from statsmodels.graphics.gofplots import qqplot
fig, axs =plt.subplots(1,2,figsize=(8,4))

qqplot(survived.Age, line='s', ax=axs[0])
axs[0].set_title('Q-Q Plot - Survived Group')

qqplot(died.Age, line='s', ax=axs[1])
axs[0].set_title('Q-Q Plot - Died Group')

plt.show()
```



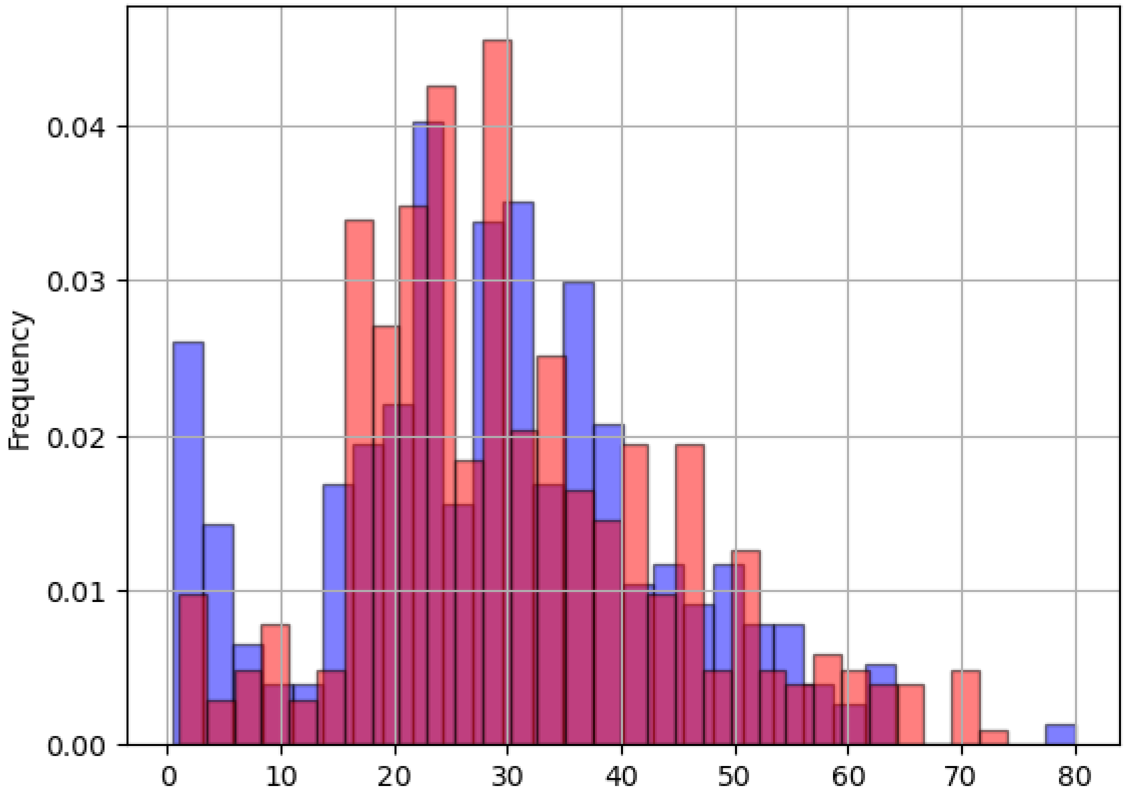
In [16]:
```
fig, axs =plt.subplots(1,2,figsize=(8,4))

qqplot(survived.Fare, line='s', ax=axs[0])
axs[0].set_title('Q-Q Plot - Survived Group')

qqplot(died.Fare, line='s', ax=axs[1])
axs[0].set_title('Q-Q Plot - Died Group')

plt.show()
```



3. Visual Normality Checks (Histogram)

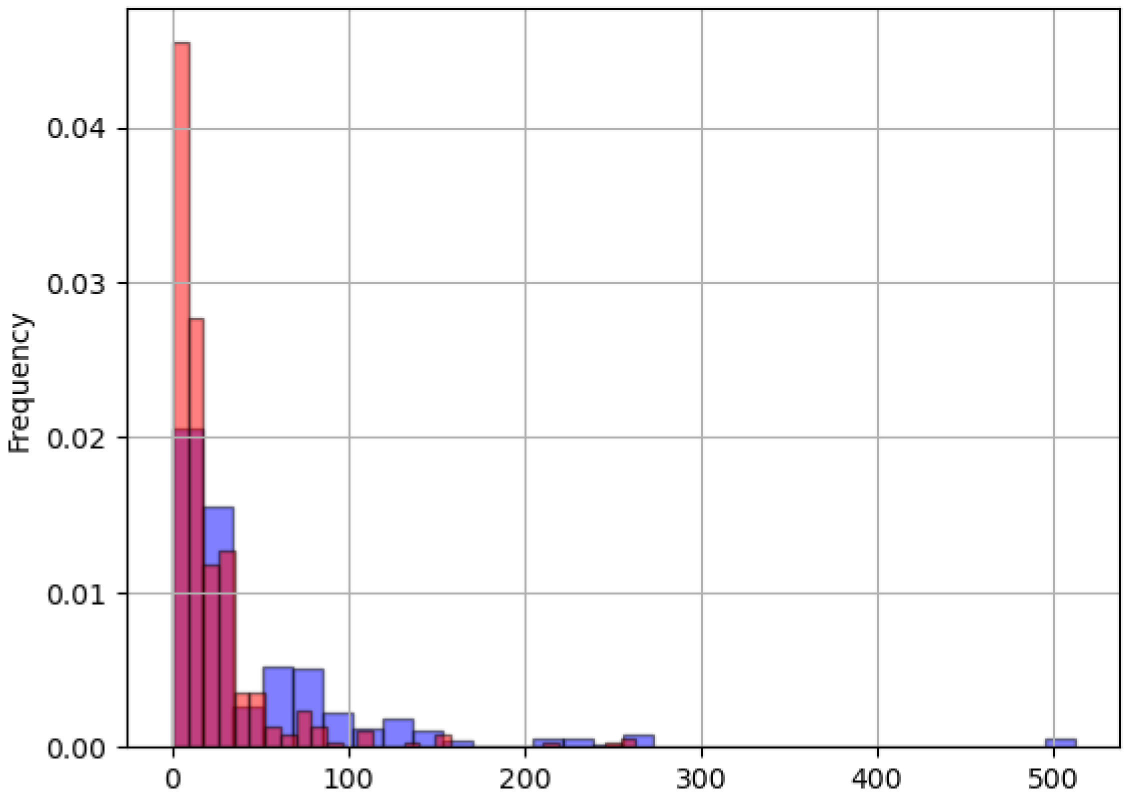
In [17]:
```
survived['Age'].plot(kind='hist', bins=30, grid= True,density=True, edgecolor='black'
died['Age'].plot(kind='hist', bins=30, grid= True,density=True, edgecolor='black' ,cc
```

Out[17]: <Axes: ylabel='Frequency'>



In [18]:
```
survived['Fare'].plot(kind='hist', bins=30, grid= True,density=True, edgecolor='black
died['Fare'].plot(kind='hist', bins=30, grid= True,density=True, edgecolor='black' ,c
```

Out[18]: <Axes: ylabel='Frequency'>



Step-2 :Parametric and non-parametric test

If Data Is normally distributed:

> Use Parametric Statistical Methods : t-Test, z- test, ANOVA -test

Else:

> Use Nonparametric Statistical Methods : Mann-Whiney U-Test

- Independent Samples T-Test

- **Scenario:** You have two independent groups, and each data point in one group is not related to the data points in the other group. Interpretation

> - H0: the means of the samples are equal.
> - H1: the means of the samples are unequal.

- Mann-Whitney U-Test

- **Scenario:**

    > - H0: the distributions of both samples are equal.
    > - H1: the distributions of both samples are not equal.

Man-Whitney U-Test

In [23]:
```
# def ttest(var1, var2, alpha = 0.05):
#     t_stat, p_value = stats.ttest_ind(var1, var2)
#     if p_value < alpha:
#         return (f'p-value :{p_value} < {alpha} ', 'Null Hypothesis is rejected.')
#     else:
#         return (f'p-value :{p_value} >= {alpha}', 'Null Hypothesis is not rejected'

# def survived_vs_died_ttest(df, col, alpha =0.05):
#     survive =df[df.Survived==1][col]
#     die = df[df.Survived==0][col]
#     return ttest(survive, die, alpha)

def utest(var1, var2, alpha = 0.05):
    t_stat, p_value = stats.mannwhitneyu(var1, var2)
    if p_value < alpha:
        return (f'p-value :{p_value} < {alpha} ', 'Null Hypothesis is rejected.')
    else:
        return (f'p-value :{p_value} >= {alpha}', 'Null Hypothesis is not rejected')

def survived_vs_died(df, col, alpha =0.05):
    survive =df[df.Survived==1][col]
    die = df[df.Survived==0][col]
    return utest(survive, die, alpha)
```

In [24]:
```
sample_df = new_df.sample(200)
sample_df
```

Out[24]:

	Age	Fare	Survived
294	24.00	7.8958	0
357	38.00	13.0000	0
231	29.00	7.7750	0
831	0.83	18.7500	1
102	21.00	77.2875	0
...	...	...	...
736	48.00	34.3750	0
462	47.00	38.5000	0
761	41.00	7.1250	0
393	23.00	113.2750	1
816	23.00	7.9250	0

200 rows × 3 columns

Hypothesis Test for 'Fare'

- **Null Hypothesis :** There is no difference in Fare between those who survived and those who died.
- **Alternate Hypothesis :** There is significan difference in Fare between those who survived and those who died.

In [26]:
```
survived_vs_died(sample_df, 'Fare' )
```

Out[26]:
```
('p-value :3.4425202375655015e-11 < 0.05 ', 'Null Hypothesis is rejected.')
```

Interpretation:

The null hypothesis (that there is no difference in Fare between those who survived and those who died) is rejected. There is evidence to suggest a significant difference in Fare for passengers who survived compared to those who did not survive.

In [27]:
```
survived_vs_died(sample_df, 'Age' )
```

Out[27]:
```
('p-value :0.003532314735075274 < 0.05 ', 'Null Hypothesis is rejected.')
```

Interpretation:

The null hypothesis (that there is no difference in Age between survived and died passengers) is rejected. There is evidence to suggest a significant difference in Age for passengers who survived compared to those who did not survive.

- https://machinelearningmastery.com/statistical-hypothesis-tests/ (https://machinelearningmastery.com/statistical-hypothesis-tests/)
- https://machinelearningmastery.com/statistical-hypothesis-tests-in-python-cheat-sheet/ (https://machinelearningmastery.com/statistical-hypothesis-tests-in-python-cheat-sheet/)