In [39]:

```
# import

from math import sqrt

import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, plot_confus
ion_matrix
from scipy.spatial import distance
```

In [40]:

```
# load dataset
df_train = pd.read_csv('train.csv')
df_test = pd.read_csv('test.csv')
```

Data Exploration

In [41]:

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [42]:

```
df_train.head()
```

Out[42]:

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

PassengerId	Survived	Pclass	Henry Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked

In [43]:

```
df_train.describe()
```

Out[43]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

- **Fare ranges between 0 - 512.3**
- **Pclass could be modeled as a categorical feature**

In [44]:

```
print(f"Pclass n of unique values: {df_train['Pclass'].nunique()}")
print(f"Pclass unique values:      {df_train['Pclass'].unique()}")
```

```
Pclass n of unique values: 3
Pclass unique values:      [3 1 2]
```

In [45]:

```
df_train['Pclass'] = df_train['Pclass'].map({1:'Upper', 2:'Middle', 3:'Lower'})
df_test['Pclass'] = df_test['Pclass'].map({1:'Upper', 2:'Middle', 3:'Lower'})
```

- **Pclass has 3 unique values (1: Upper Class, 2: Middle Class, 3: Lower Class)**
- **Translate it into a categorical feature**

In [46]:

```
df_train.select_dtypes(include = 'object').nunique()
```

Out[46]:

```
Pclass        3
Name        891
Sex           2
Ticket      681
Cabin       147
Embarked      3
dtype: int64
```

In [47]:

```
df_train['Embarked'] = df_train['Embarked'].map({'C':'Cherbourg', 'Q':'Queenstown', 'S':'Southam
pton'})
df_test['Embarked'] = df_test['Embarked'].map({'C':'Cherbourg', 'Q':'Queenstown', 'S':'Southampt
on'})
```

- **Sex is defined in the data documentary as female, male**
- **Embarked can be mapped according to data documentation (C = Cherbourg, Q = Queenstown, S = Southampton) for better readablity**

In [48]:

```
df_train['Name'].head()
```

Out[48]:

```
0                                Braund, Mr. Owen Harris
1    Cumings, Mrs. John Bradley (Florence Briggs Th...
2                                 Heikkinen, Miss. Laina
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)
4                               Allen, Mr. William Henry
Name: Name, dtype: object
```

In [49]:

```
df_train['Name'].duplicated().any()
```

Out[49]:

```
False
```

- **Name is mostly unstructured text**
- **There are no duplicates in the train set**
- **The title (Mr., Ms., etc) is contained in the name**

In [53]:

```
df_train.isnull().sum().sort_values(ascending = False)
```

Out[53]:

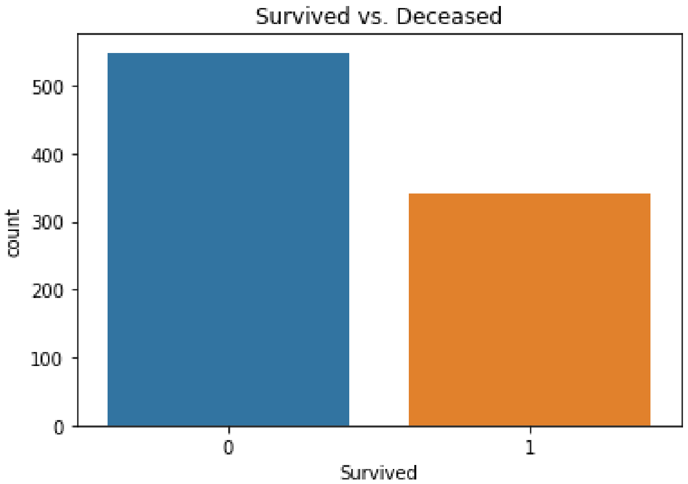
```
Cabin          687
Age            177
Embarked         2
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
SibSp            0
Parch            0
Ticket           0
Fare             0
dtype: int64
```

- **Cabin and Age have maximum NaN count**
- **Cabin should be removed in Pre Processing**
- **Age should be cleared in Pre Processing, as it important for model building**
- **Embarked should be cleared in Pre Processing**

Data Visualization

In [54]:

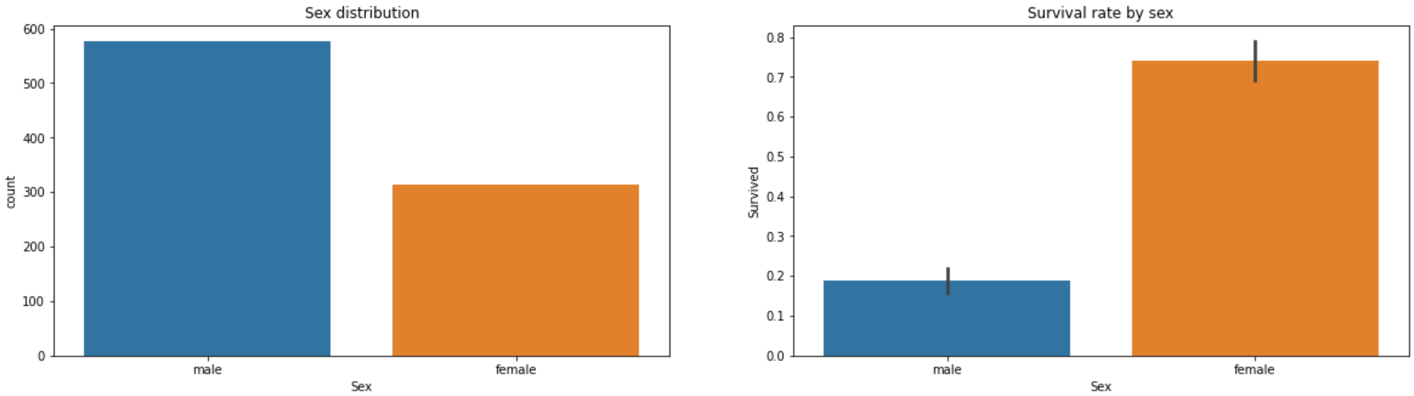
```
# survived
sns.countplot(x = df_train['Survived']).set_title('Survived vs. Deceased');
```



Over a third of the people survied

In [55]:

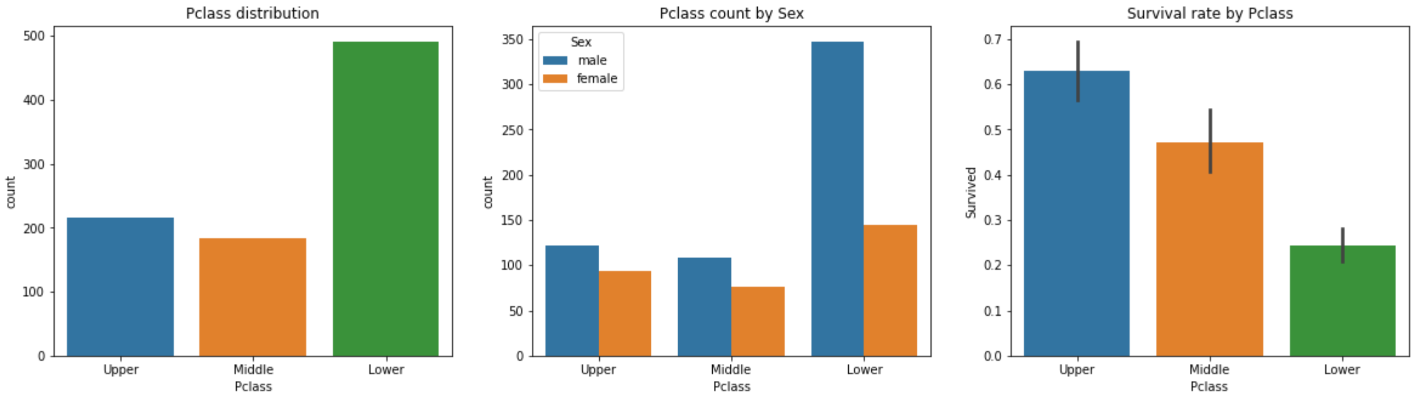
```
# Sex
fig, axes = plt.subplots(1, 2, figsize=(20, 5))

sns.countplot(ax = axes[0], x = df_train['Sex']).set_title('Sex distribution')
sns.barplot(ax = axes[1], data = df_train, x = "Sex", y = "Survived").set_title('Survival rate b
y sex');
```



- **Most travelers were male**
- **The survival rate for females is higher**

In [56]:

```
fig, axes = plt.subplots(1, 3, figsize=(20, 5))

pclass_order = ["Upper", "Middle", "Lower"]

sns.countplot(ax = axes[0], x = df_train['Pclass'], order = pclass_order).set_title('Pclass dist
ribution')
sns.countplot(ax = axes[1], data = df_train, x = 'Pclass', order = pclass_order, hue = 'Sex').se
t_title('Pclass count by Sex')
sns.barplot(ax = axes[2], data = df_train, x = "Pclass", y = "Survived", order = pclass_order).s
et_title('Survival rate by Pclass');
```

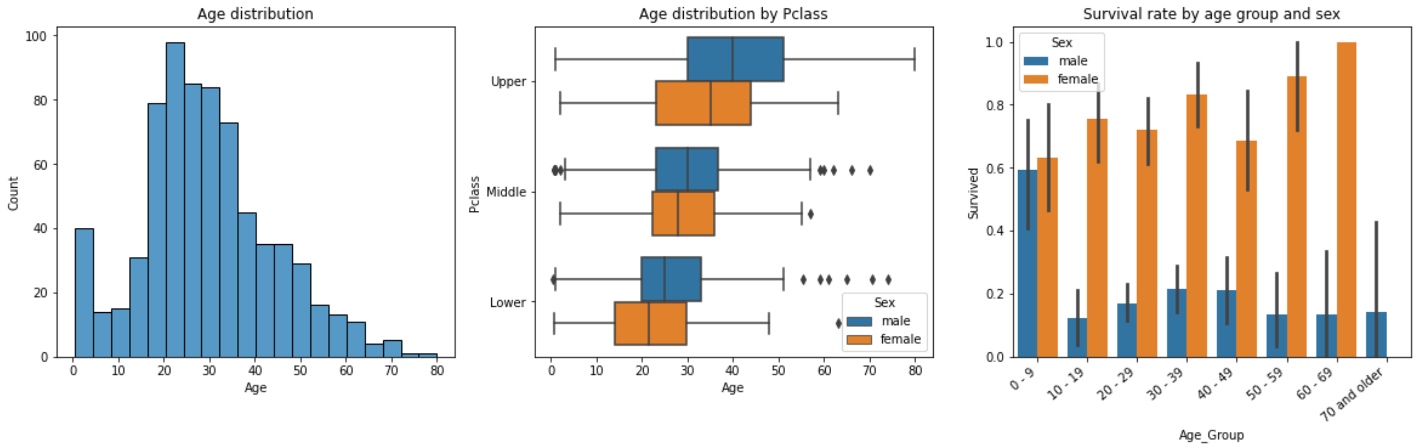


- **Most travelers were in the lower class**
- **Chance of survival grows with class**

In [57]:

```
# Age
fig, axes = plt.subplots(1, 3, figsize=(20, 5))

sns.histplot(ax = axes[0], data=df_train, x="Age").set_title('Age distribution')
sns.boxplot(ax = axes[1], data=df_train, x="Age", y="Pclass", hue='Sex', order=["Upper", "Middle
", "Lower"]).set_title('Age distribution by Pclass')

#Plot by age group

#Define age limit for groups and their labels
age_groups_thresholds = [0, 9, 19, 29, 39, 49, 59, 69, np.inf]
age_groups = ["0 - 9", "10 - 19", "20 - 29", "30 - 39", "40 - 49", "50 - 59", "60 - 69", "70 and
older"]

#Cut Age Series by thresholds and load into new feature
df_train["Age_Group"] = pd.cut(df_train['Age'], age_groups_thresholds, labels=age_groups)
```

```
sns.barplot(ax = axes[2], data=df_train, x="Age_Group", y="Survived", hue="Sex").set_title('Surv
ival rate by age group and sex')
axes[2].set_xticklabels(axes[2].get_xticklabels(), rotation = 40, ha="right");
```



- **The Age is normally distributed with a positive skew**
- **For males, children from 0 - 9 had the highest chance of surival**
- **Women in all age groups had high survival rate**
- **Women of old age had a higher survival rate than girls**

Data Pre-processing

- **Fill the missing Age values with their mean**
- **Fill the missing Embarked values with backward fill (gets the last avaiable value)**

In [60]:

```
#Train data
age_mean = df_train['Age'].mean()
df_train['Age'].fillna(round(age_mean),inplace=True)
df_train['Embarked'].fillna(method = 'bfill', inplace = True)
```

In [61]:

```
#Test data
age_mean_test = df_test['Age'].mean()
df_test['Age'].fillna(round(age_mean_test),inplace=True)
df_test['Embarked'].fillna(method = 'bfill', inplace = True)
```

Data normalization

- **Numeric data - standardize it by normalizing the min max to be inbetween 0 and 1**
- **Categorical data - One Hot Encoding**

In [62]:

```
#Scale all numeric features to 0 - 1
def scale(num_features):
    min_max_scaler = MinMaxScaler()
    num_features = min_max_scaler.fit_transform(num_features)
    return pd.DataFrame(num_features)

#One hot encode categorical features
def one_hot_encode(cat_features):
    one_hot_enc = OneHotEncoder(handle_unknown = 'ignore', sparse = False)
    cat_features_one_hot = pd.DataFrame(one_hot_enc.fit_transform(cat_features))
    return pd.DataFrame(cat_features_one_hot)

#Normalize data according to data type
def normalize_data(df):
    cat_features = df.select_dtypes(include = 'object')
    num_features = df.select_dtypes(exclude = 'object')

    cat_features = one_hot_encode(cat_features)
    num_features = scale(num_features)
```

```
    df = pd.concat([num_features, cat_features], axis = 1)
    return df.to_numpy()
```

Splitting the data into training and testing dataset

In [63]:

```
#Training
X = df_train[['Age', 'Fare', 'SibSp', 'Parch', 'Sex', 'Pclass', 'Embarked']]
X = normalize_data(X)

y = df_train['Survived'].to_numpy()

X_train, X_dev, y_train, y_dev = train_test_split(X, y, train_size = 0.8, test_size = 0.2, rando
m_state = 0)
```

In [64]:

```
#Testing
X_test = df_test[['Age', 'Fare', 'SibSp', 'Parch', 'Sex', 'Pclass', 'Embarked']]
X_test = normalize_data(X_test)
```

Model building

In [65]:

```
class KNearestNeighbourEstimatorVect():
    def __init__(self, k_):
        self.k_ = k_

    def fit(self, X, y):
        self.X_ = X
        self.y_ = y

    def predict(self, X):
        distances = distance.cdist(X, self.X_, 'euclidean')
        i_k_smallest = np.argpartition(distances, self.k_)[:,:self.k_]
        values = self.y_[i_k_smallest]
        predictions = np.average(values, axis=1) > 0.5
        return 1*predictions
```

In [66]:

```
m = len(y_train)

best_accuracy =  float('-inf')
best_k = -1
for k in range(1, m):
    knn_estimator = KNearestNeighbourEstimatorVect(k_ = k)
    knn_estimator.fit(X_train, y_train)
    y_pred = knn_estimator.predict(X_dev)
    accuracy = accuracy_score(y_dev, y_pred)

    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_k = k
        best_y_pred = y_pred

print(f'Best k: {best_k}')
print(f'Score:  {round(best_accuracy, 2)}')
```

```
Best k: 76
Score:  0.83
```

In [67]:

```
confusion_m = confusion_matrix(y_dev, best_y_pred)
confusion_m
```

Out[67]:

```
array([[108,   2],
       [ 28,  41]])
```

In [69]:

```
labels = ['True Negative','False Positive','False Negative','True Positive']
labels = np.asarray(labels).reshape(2,2)
sns.heatmap(confusion_m, annot = labels, fmt = '', cmap = 'Blues');
```