# Assignment_8_2_Raghuwanshi_Prashant_DSC550

October 23, 2021

**Assignment: 8.2 Exercise: Model Evaluation and Selection**

**Name: Prashant Raghuwanshi**

**Date: 10/23/2021**

**Course: DSC550-T301 Data Mining (2221-1)**

**Case Study: Titanic Case Study Part 3**

[1]:
```
import pandas as pd
import yellowbrick
import matplotlib.pyplot as plt
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\deprecation.py:144:
FutureWarning: The sklearn.metrics.classification module is  deprecated in
version 0.22 and will be removed in version 0.24. The corresponding classes /
functions should instead be imported from sklearn.metrics. Anything that cannot
be imported from sklearn.metrics is now part of the private API.
  warnings.warn(message, FutureWarning)
```

[2]:
```
# 1.Load the data from the "train.csv" file into a DataFrame.
addr1 = "C:/Users/dell/Documents/Machine_learning_assigments/week-6/train.csv"
df_train = pd.read_csv(addr1)
```

[3]:
```
# 2.Display the dimensions of the file (so you’ll have a good idea the amount␣
↪of data you are working with.
print("The dimension of the table is: ", df_train.shape)
```

```
The dimension of the table is:  (891, 12)
```

[4]:
```
# 3.Display the first 5 rows of data so you can see the column headings and the␣
↪type of data for each column.
print(df_train.head(5))
# a.Notice that Survived is represented as a 1 or 0
# b.Notice that missing data is represented as "NaN"
# c.The Survived variable will be the "target" and the other variables will be␣
↪the "features"
```

```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[5]:
```
#4.        Think about some questions that might help you predict who will␣
 ↪survive:
# a.What do the variables look like? For example, are they numerical or␣
 ↪categorical data. If they are numerical, what are their distribution; if␣
 ↪they are categorical, how many are they in different categories?
# b.Are the numerical variables correlated?
# c.Are the distributions of numerical variables the same or different among␣
 ↪survived and not survived? Is the survival rate different for different␣
 ↪values? For example, were people more likely to survive if they were younger?
# d.Are there different survival rates in different categories? For example,␣
 ↪did more women survived than man?
```

[6]:
```
# target variable is categorical variable, some of the feature variable are␣
 ↪numeric
```

[7]:
```
#5.Look at summary information about your data (total, mean, min, max, freq,␣
 ↪unique, etc.)
print("\nDescribe Data\n")
print(df_train.describe())
```

```
Describe Data

       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
```

```
min      1.000000    0.000000    1.000000    0.420000    0.000000
25%    223.500000    0.000000    2.000000   20.125000    0.000000
50%    446.000000    0.000000    3.000000   28.000000    0.000000
75%    668.500000    1.000000    3.000000   38.000000    1.000000
max    891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

[8]:

```
print("\nSummarized Data\n")
print(df_train.describe(include=['O']))
```

```
Summarized Data

                                   Name   Sex  Ticket        Cabin Embarked
count                               891   891     891          204      889
unique                              891     2     681          147        3
top     Vande Velde, Mr. Johannes Joseph  male  347082  C23 C25 C27        S
freq                                  1   577       7            4      644
```

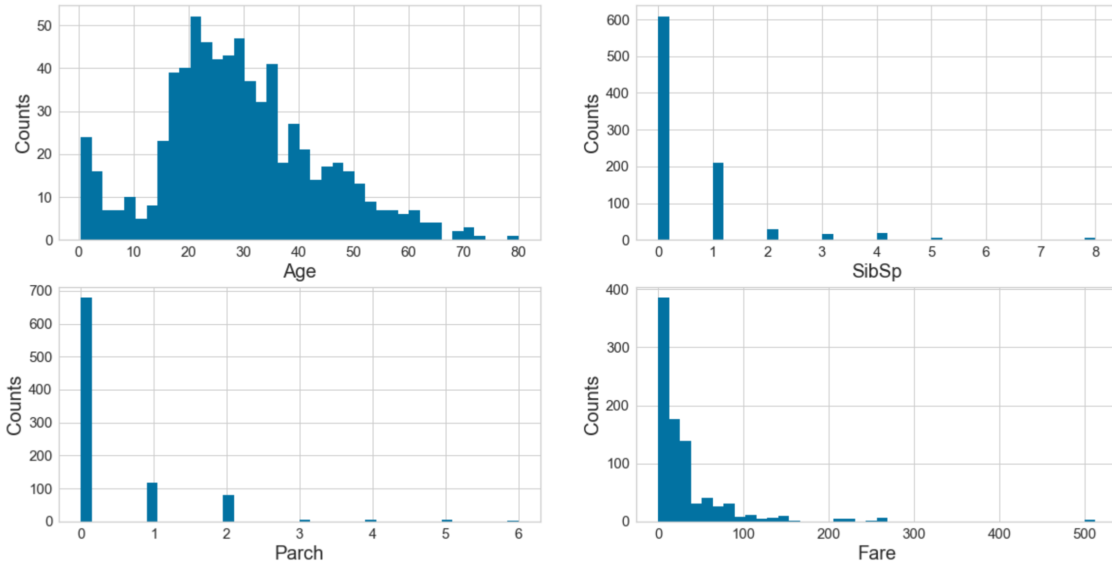
[9]:

```
#6.Make some histograms of your data ("A picture is worth a thousand words!")
#  a.Most of the passengers are around 20 to 30 years old and don't have␣
 ↪siblings or relatives with them.
#  b.A large amount of the tickets sold were less than $50. There are very few␣
 ↪tickets sold where the fare was over $500.

num_features = ['Age', 'SibSp', 'Parch', 'Fare']
xaxes = num_features
yaxes = ['Counts', 'Counts', 'Counts', 'Counts']
```

[10]:

```
# set up the figure size
plt.rcParams['figure.figsize'] = (20, 10)
# make subplots
fig, axes = plt.subplots(nrows = 2, ncols = 2)
# draw histograms
axes = axes.ravel()
for idx, ax in enumerate(axes):
    ax.hist(df_train[num_features[idx]].dropna(), bins=40)
    ax.set_xlabel(xaxes[idx], fontsize=20)
    ax.set_ylabel(yaxes[idx], fontsize=20)
```

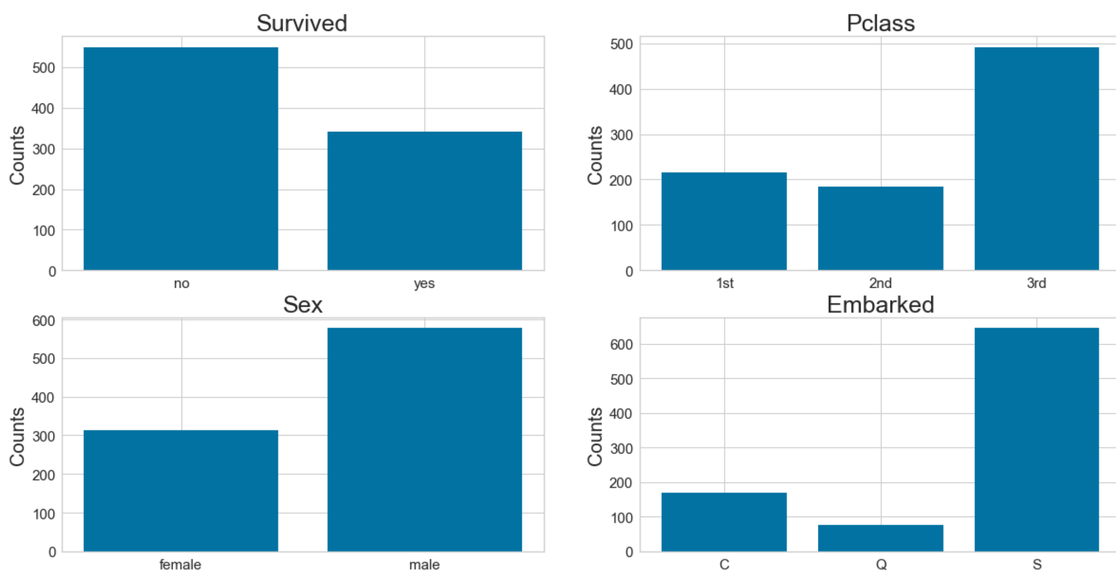
```
    ax.tick_params(axis='both', labelsize=15)
plt.show()
```




[11]:

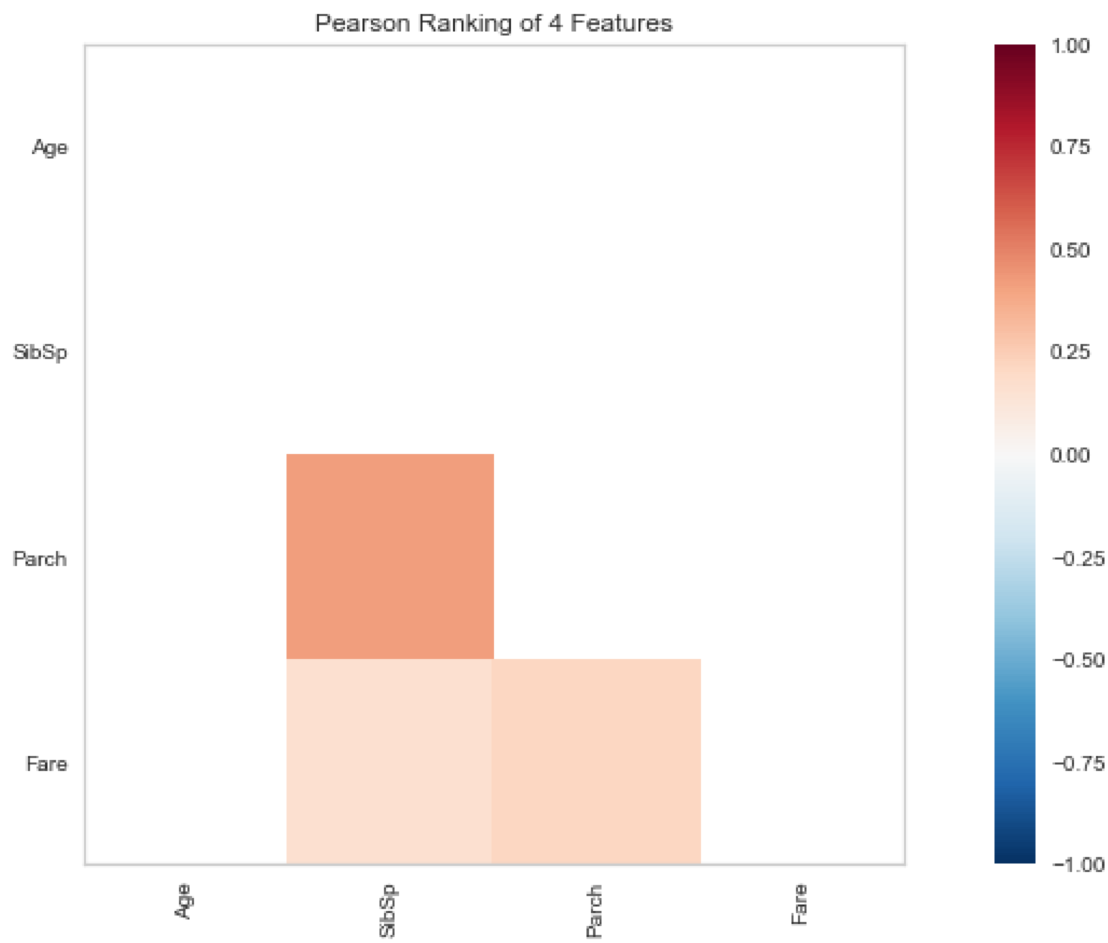
```
#7.Make some bar charts for variables with only a few options.
#a.Ticket and Cabin have more than 100 variables so don't do those!
#%matplotlib inline
plt.rcParams['figure.figsize'] = (20, 10)
# make subplots
fig, axes = plt.subplots(nrows = 2, ncols = 2)
# make the data read to feed into the visulizer
X_Survived = df_train.replace({'Survived': {1: 'yes', 0: 'no'}}).
 ↪groupby('Survived').size().reset_index(name='Counts')['Survived']
Y_Survived = df_train.replace({'Survived': {1: 'yes', 0: 'no'}}).
 ↪groupby('Survived').size().reset_index(name='Counts')['Counts']
# make the bar plot
axes[0, 0].bar(X_Survived, Y_Survived)
axes[0, 0].set_title('Survived', fontsize=25)
axes[0, 0].set_ylabel('Counts', fontsize=20)
axes[0, 0].tick_params(axis='both', labelsize=15)
# make the data read to feed into the visulizer
X_Pclass = df_train.replace({'Pclass': {1: '1st', 2: '2nd', 3: '3rd'}}).
 ↪groupby('Pclass').size().reset_index(name='Counts')['Pclass']
Y_Pclass = df_train.replace({'Pclass': {1: '1st', 2: '2nd', 3: '3rd'}}).
 ↪groupby('Pclass').size().reset_index(name='Counts')['Counts']
# make the bar plot
axes[0, 1].bar(X_Pclass, Y_Pclass)
axes[0, 1].set_title('Pclass', fontsize=25)
axes[0, 1].set_ylabel('Counts', fontsize=20)
```

```
axes[0, 1].tick_params(axis='both', labelsize=15)

# make the data read to feed into the visulizer
X_Sex = df_train.groupby('Sex').size().reset_index(name='Counts')['Sex']
Y_Sex = df_train.groupby('Sex').size().reset_index(name='Counts')['Counts']
# make the bar plot
axes[1, 0].bar(X_Sex, Y_Sex)
axes[1, 0].set_title('Sex', fontsize=25)
axes[1, 0].set_ylabel('Counts', fontsize=20)
axes[1, 0].tick_params(axis='both', labelsize=15)

# make the data read to feed into the visulizer
X_Embarked = df_train.groupby('Embarked').size().
 ↪reset_index(name='Counts')['Embarked']
Y_Embarked = df_train.groupby('Embarked').size().
 ↪reset_index(name='Counts')['Counts']
# make the bar plot
axes[1, 1].bar(X_Embarked, Y_Embarked)
axes[1, 1].set_title('Embarked', fontsize=25)
axes[1, 1].set_ylabel('Counts', fontsize=20)
axes[1, 1].tick_params(axis='both', labelsize=15)
#plt.show()
```




[12]:
```
#8.To see if the data is correlated, make some Pearson Ranking charts
#  b.The correlation between the variables is low (1 or -1 is high positive or␣
 ↪high negative, 0 is low or no correlation)
#    These results show there is "some" positive correlation but it's not a␣
 ↪high correlation.
```

```python
plt.rcParams['figure.figsize'] = (15, 7)

# import the package for visulization of the correlation
from yellowbrick.features import Rank2D

# extract the numpy arrays from the data frame
X = df_train[num_features].to_numpy()

# instantiate the visualizer with the Covariance ranking algorithm
visualizer = Rank2D(features=num_features, algorithm='pearson')
visualizer.fit(X)                # Fit the data to the visualizer
visualizer.transform(X)             # Transform the data
#  a.Notice that in my sample code, I have saved this png file.
visualizer.poof(outpath="d://pcoords1.png") # Draw/show/poof the data
#plt.show()
```



[13]:

```
#Use Parallel Coordinates visualization to compare the distributions of␣
↪numerical variables between passengers that survived and those that did not␣
↪survive.
#a. That’s a cool chart, isn’t it?!
# Compare variables against Survived and Not Survived
#set up the figure size
#%matplotlib inline
plt.rcParams['figure.figsize'] = (15, 7)
plt.rcParams['font.size'] = 50
```

[14]:

```
# setup the color for yellowbrick visulizer
from yellowbrick.style import set_palette
set_palette('sns_bright')
# import packages
from yellowbrick.features import ParallelCoordinates
```

[15]:

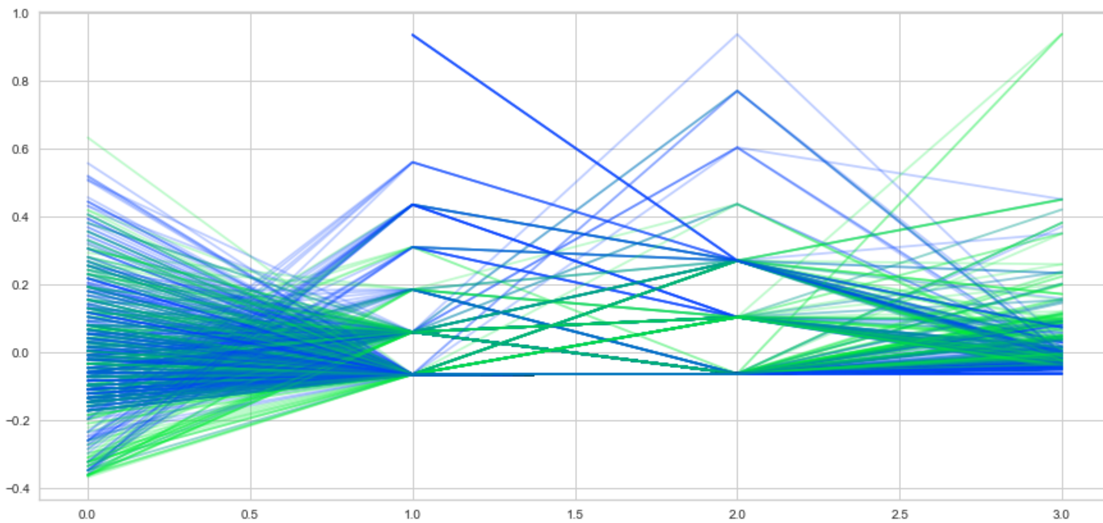
```
# Specify the features of interest and the classes of the target
classes = ['Not-survived', 'Survived']
num_features = ['Age', 'SibSp', 'Parch', 'Fare']
# copy data to a new dataframe
data_norm = df_train.copy()
```

[16]:

```
# normalize data to 0-1 range
for feature in num_features:
    data_norm[feature] = (df_train[feature] - df_train[feature].
↪mean(skipna=True)) / (df_train[feature].max(skipna=True) - df_train[feature].
↪min(skipna=True))
```

[17]:

```
# Extract the numpy arrays from the data frame
X = data_norm[num_features].to_numpy()
y = df_train.Survived.to_numpy()

# Instantiate the visualizer
visualizer = ParallelCoordinates(classes=classes, features=num_features)
visualizer.fit(X, y)      # Fit the data to the visualizer
visualizer.transform(X)   # Transform the data
#visualizer.poof(outpath="d://pcoords2.png") # Draw/show/poof the data
plt.show();
```



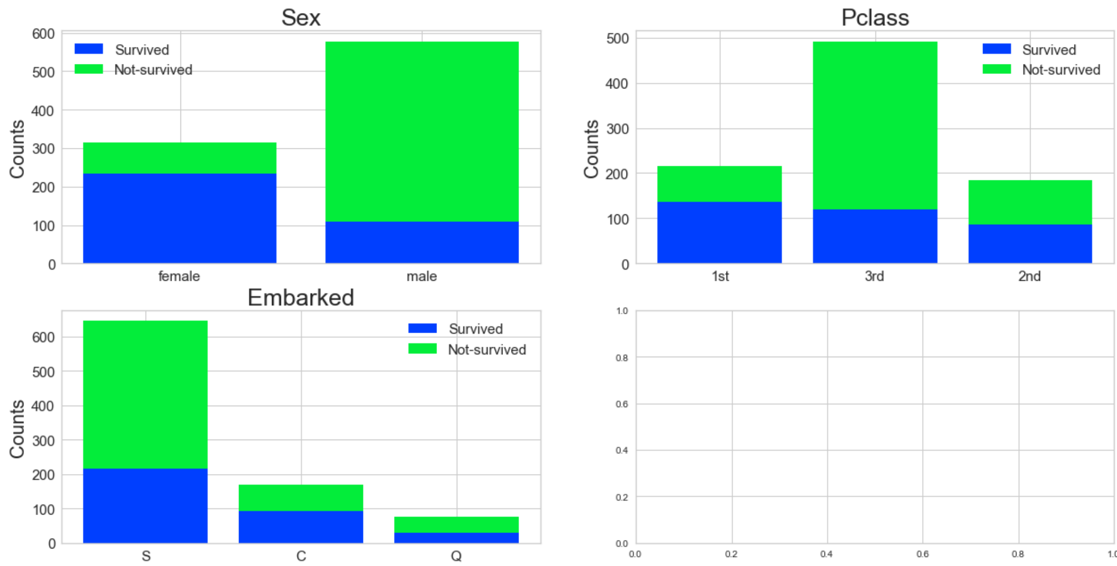

**Passengers traveling with siblings on the boat have a higher death rate**

**passengers who paid a higher fare had a higher survival rate.**

[18]:
```
#10.Use Stack Bar Charts to compare passengers who survived to passengers who␣
↪didn't survive based on the other variables.
# a.More females survived than men.  3rd Class Tickets had a lower survival␣
↪rate.
# Also, Embarkation from Southampton port had a lower survival rate.
plt.rcParams['figure.figsize'] = (20, 10)
# make subplots
fig, axes = plt.subplots(nrows = 2, ncols = 2)
# make the data read to feed into the visulizer
Sex_survived = df_train.replace({'Survived': {1: 'Survived', 0:␣
↪'Not-survived'}})[df_train['Survived']==1]['Sex'].value_counts()
Sex_not_survived = df_train.replace({'Survived': {1: 'Survived', 0:␣
↪'Not-survived'}})[df_train['Survived']==0]['Sex'].value_counts()
Sex_not_survived = Sex_not_survived.reindex(index = Sex_survived.index)
# make the bar plot
p1 = axes[0, 0].bar(Sex_survived.index, Sex_survived.values)
p2 = axes[0, 0].bar(Sex_not_survived.index, Sex_not_survived.values,␣
↪bottom=Sex_survived.values)
axes[0, 0].set_title('Sex', fontsize=25)
axes[0, 0].set_ylabel('Counts', fontsize=20)
axes[0, 0].tick_params(axis='both', labelsize=15)
axes[0, 0].legend((p1[0], p2[0]), ('Survived', 'Not-survived'), fontsize = 15)

# make the data read to feed into the visualizer
```

```
Pclass_survived = df_train.replace({'Survived': {1: 'Survived', 0:␣
↪'Not-survived'}}).replace({'Pclass': {1: '1st', 2: '2nd', 3:␣
↪'3rd'}})[df_train['Survived']==1]['Pclass'].value_counts()
Pclass_not_survived = df_train.replace({'Survived': {1: 'Survived', 0:␣
↪'Not-survived'}}).replace({'Pclass': {1: '1st', 2: '2nd', 3:␣
↪'3rd'}})[df_train['Survived']==0]['Pclass'].value_counts()
Pclass_not_survived = Pclass_not_survived.reindex(index = Pclass_survived.index)
# make the bar plot
p3 = axes[0, 1].bar(Pclass_survived.index, Pclass_survived.values)
p4 = axes[0, 1].bar(Pclass_not_survived.index, Pclass_not_survived.values,␣
↪bottom=Pclass_survived.values)
axes[0, 1].set_title('Pclass', fontsize=25)
axes[0, 1].set_ylabel('Counts', fontsize=20)
axes[0, 1].tick_params(axis='both', labelsize=15)
axes[0, 1].legend((p3[0], p4[0]), ('Survived', 'Not-survived'), fontsize = 15)

# make the data read to feed into the visualizer
Embarked_survived = df_train.replace({'Survived': {1: 'Survived', 0:␣
↪'Not-survived'}})[df_train['Survived']==1]['Embarked'].value_counts()
Embarked_not_survived = df_train.replace({'Survived': {1: 'Survived', 0:␣
↪'Not-survived'}})[df_train['Survived']==0]['Embarked'].value_counts()
Embarked_not_survived = Embarked_not_survived.reindex(index = Embarked_survived.
↪index)
# make the bar plot
p5 = axes[1, 0].bar(Embarked_survived.index, Embarked_survived.values)
p6 = axes[1, 0].bar(Embarked_not_survived.index, Embarked_not_survived.values,␣
↪bottom=Embarked_survived.values)
axes[1, 0].set_title('Embarked', fontsize=25)
axes[1, 0].set_ylabel('Counts', fontsize=20)
axes[1, 0].tick_params(axis='both', labelsize=15)
axes[1, 0].legend((p5[0], p6[0]), ('Survived', 'Not-survived'), fontsize = 15)
#plt.show()
```

[18]:
```
<matplotlib.legend.Legend at 0x245f52426a0>
```




[19]:
```
# 11.Some of my questions have been answered by seeing the charts but in some ways,
# looking at this much data has created even more questions.
# a.Now it's time to reduce some of the features so we can concentrate on the things that matter!
#   There features we will get rid of are:  "PassengerId", "Name", "Ticket" and "Cabin".
#   (ID doesn't really give us any useful data, Ticket and Cabin have too many variables.
#   Name might reflect that they are related but we're keeping the category about siblings (for now).
```

[20]:
```
# b.We can also fill in missing values.
# (Cabin has some missing values but we are dropping that feature.)
#  Age has some missing values so I'll fill in with the average age.
#  Embarked also has some missing so I'll the most common.
```

[21]:
```
#fill the missing age data with median value
def fill_na_median(df_train, inplace=True):
    return df_train.fillna(df_train.median(), inplace=inplace)

fill_na_median(df_train['Age'])

# check the result
print(df_train['Age'].describe())
```

```
count    891.000000
mean      29.361582
```

```
std       13.019697
min        0.420000
25%       22.000000
50%       28.000000
75%       35.000000
max       80.000000
Name: Age, dtype: float64
```

[22]:

```
# fill with the most represented value
def fill_na_most(df_train, inplace=True):
    return df_train.fillna('S', inplace=inplace)

fill_na_most(df_train['Embarked'])

# check the result
print(df_train['Embarked'].describe())
```

```
count     891
unique      3
top         S
freq      646
Name: Embarked, dtype: object
```

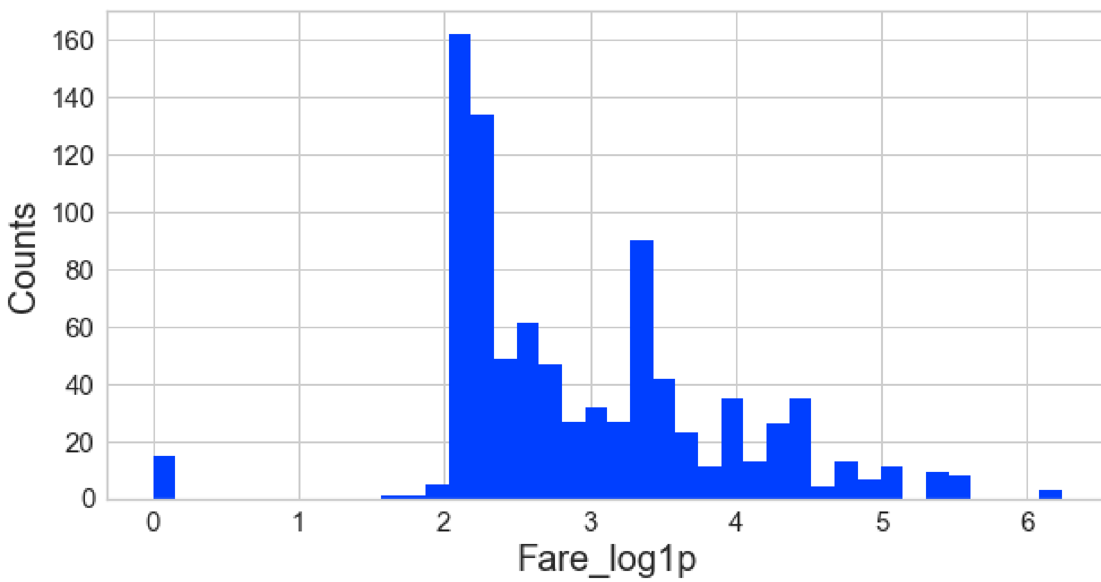
[23]:

```
# import package
import numpy as np

# log-transformation
def log_transformation(df_train):
    return df_train.apply(np.log1p)

df_train['Fare_log1p'] = log_transformation(df_train['Fare'])

# check the data
print(df_train.describe())
```

```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  891.000000  891.000000
mean    446.000000    0.383838    2.308642   29.361582    0.523008
std     257.353842    0.486592    0.836071   13.019697    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   22.000000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   35.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare  Fare_log1p
count  891.000000  891.000000  891.000000
mean     0.381594   32.204208    2.962246
std      0.806057   49.693429    0.969048
```

```
min      0.000000    0.000000    0.000000
25%      0.000000    7.910400    2.187218
50%      0.000000   14.454200    2.737881
75%      0.000000   31.000000    3.465736
max      6.000000  512.329200    6.240917
```

[24]:
```
#12 If you go back and look at the histograms of Fare, you'll see that it is␣
↪very skewed…many low cost fares, not very many high cost fares.
# Log Transformation is a good method to use on highly skewed data.
#check the distribution using histogram
# set up the figure size
#%matplotlib inline
plt.rcParams['figure.figsize'] = (10, 5)

plt.hist(df_train['Fare_log1p'], bins=40)
plt.xlabel('Fare_log1p', fontsize=20)
plt.ylabel('Counts', fontsize=20)
plt.tick_params(axis='both', labelsize=15)
#plt.show()
```




[25]:
```
# Convert your categorical data into numbers (Sex, PClass, Embark)
#Step 13 - convert categorical data to numbers
#get the categorical data
cat_features = ['Pclass', 'Sex', "Embarked"]
data_cat = df_train[cat_features]
```

[26]:
```
data_cat.head()
```

[26]:
```
  Pclass     Sex Embarked
0       3    male        S
1       1  female        C
2       3  female        S
3       1  female        S
4       3    male        S
```

[27]:
```
data_cat = data_cat.replace({'Pclass': {1: '1st', 2: '2nd', 3: '3rd'}})
```

[28]:
```
data_cat.head()
```

[28]:
```
  Pclass     Sex Embarked
0    3rd    male        S
1    1st  female        C
2    3rd  female        S
3    1st  female        S
4    3rd    male        S
```

[29]:
```
# One Hot Encoding
data_cat_dummies = pd.get_dummies(data_cat)
# check the data
print(data_cat_dummies.head(8))
```

```
   Pclass_1st  Pclass_2nd  Pclass_3rd  Sex_female  Sex_male  Embarked_C  \
0           0           0           1           0         1           0
1           1           0           0           1         0           1
2           0           0           1           1         0           0
3           1           0           0           1         0           0
4           0           0           1           0         1           0
5           0           0           1           0         1           0
6           1           0           0           0         1           0
7           0           0           1           0         1           0

   Embarked_Q  Embarked_S
0           0           1
1           0           0
2           0           1
3           0           1
4           0           1
5           1           0
6           0           1
7           0           1
```

CASE STUDY -3

[30]:
```
#Step 14 - create a whole features dataset that can be used for train and␣
 ↪validation data splitting
# here we will combine the numerical features and the dummie features together
```

```
features_model = ['Age', 'SibSp', 'Parch', 'Fare_log1p']
data_model_X = pd.concat([df_train[features_model], data_cat_dummies], axis=1)
```

[31]:
```
data_model_X.head()
```

[31]:
```
    Age  SibSp  Parch  Fare_log1p  Pclass_1st  Pclass_2nd  Pclass_3rd  \
0  22.0      1      0    2.110213           0           0           1
1  38.0      1      0    4.280593           1           0           0
2  26.0      0      0    2.188856           0           0           1
3  35.0      1      0    3.990834           1           0           0
4  35.0      0      0    2.202765           0           0           1

   Sex_female  Sex_male  Embarked_C  Embarked_Q  Embarked_S
0           0         1           0           0           1
1           1         0           1           0           0
2           1         0           0           0           1
3           1         0           0           0           1
4           0         1           0           0           1
```

[32]:
```
# create a whole target dataset that can be used for train and validation data␣
↪splitting
#data_model_y1 = df_train.replace({'Survived': {1: 'Survived', 0:␣
↪'Not_survived'}})['Survived']
data_model_y = df_train['Survived']
data_model_y.head()
```

[32]:
```
0    0
1    1
2    1
3    1
4    0
Name: Survived, dtype: int64
```

[34]:
```
# separate data into training and validation and check the details of the␣
↪datasets
# import packages
from sklearn.model_selection import train_test_split

# split the data
X_train, X_val, y_train, y_val = train_test_split(data_model_X, data_model_y,␣
↪test_size =0.3, random_state=11)

# number of samples in each set
print("No. of samples in training set: ", X_train.shape[0])
print("No. of samples in validation set:", X_val.shape[0])

# Survived and not-survived
```

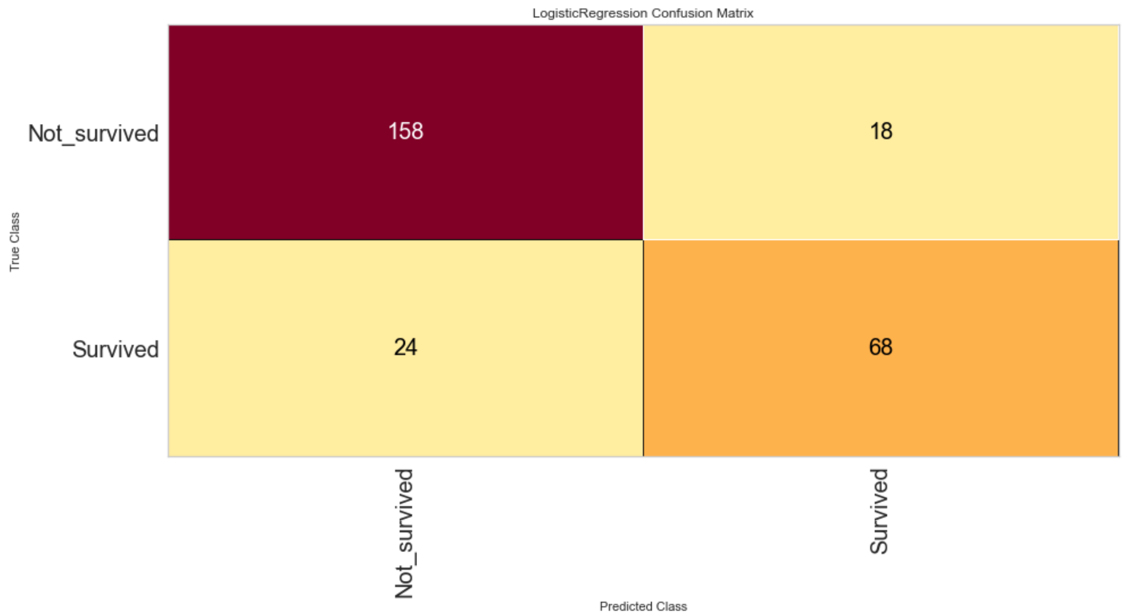
```
print('\n')
print('No. of survived and not-survived in the training set:')
print(y_train.value_counts())

print('\n')
print('No. of survived and not-survived in the validation set:')
print(y_val.value_counts())
```

```
No. of samples in training set:  623
No. of samples in validation set: 268


No. of survived and not-survived in the training set:
0    373
1    250
Name: Survived, dtype: int64


No. of survived and not-survived in the validation set:
0    176
1     92
Name: Survived, dtype: int64
```

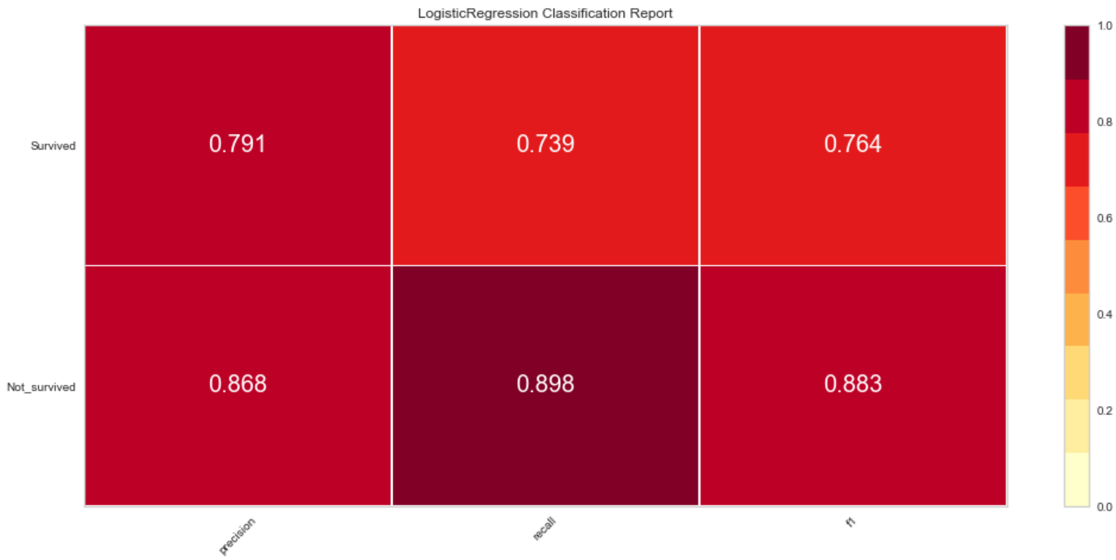
[38]:
```
# Step 15 - Eval Metrics
from sklearn.linear_model import LogisticRegression

from yellowbrick.classifier import ConfusionMatrix
from yellowbrick.classifier import ClassificationReport
from yellowbrick.classifier import ROCAUC
# ROC and AUC
# Instantiate the classification model
model = LogisticRegression(solver='liblinear')
#The ConfusionMatrix visualizer taxes a model
classes = ['Not_survived','Survived']
cm = ConfusionMatrix(model, classes=classes, label_encoder={0: "Not_survived",␣
 ↪1: "Survived"}, percent=False)

#Fit fits the passed model. This is unnecessary if you pass the visualizer a␣
 ↪pre-fitted model
cm.fit(X_train, y_train)

#To create the ConfusionMatrix, we need some test data. Score runs predict() on␣
 ↪the data
#and then creates the confusion_matrix from scikit learn.
cm.score(X_val, y_val)

# change fontsize of the labels in the figure
```

```
for label in cm.ax.texts:
    label.set_size(20)

#How did we do?
cm.poof()
```

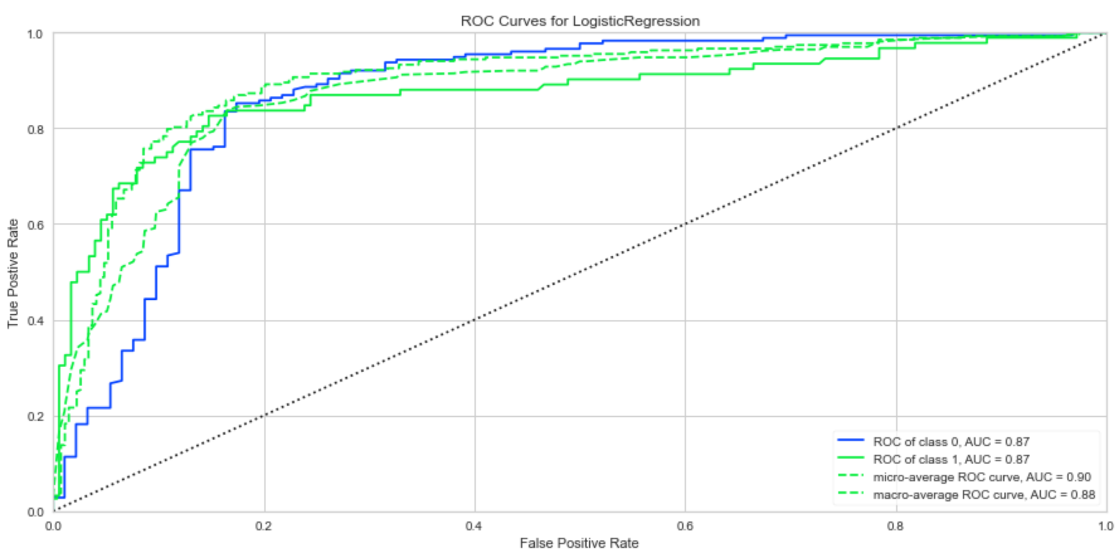
```
C:\ProgramData\Anaconda3\lib\site-
packages\sklearn\metrics\_classification.py:191: FutureWarning: elementwise
comparison failed; returning scalar instead, but in the future will perform
elementwise comparison
  >>> y_true = [0, 1, 2, 3]
```




[39]:
```
# Step 15 - Eval Metrics
# Precision, Recall, and F1 Score
# set the size of the figure and the font size
#%matplotlib inline
plt.rcParams['figure.figsize'] = (15, 7)
plt.rcParams['font.size'] = 20

# Instantiate the visualizer
visualizer = ClassificationReport(model, classes=classes)

visualizer.fit(X_train, y_train)  # Fit the training data to the visualizer
visualizer.score(X_val, y_val)  # Evaluate the model on the test data
g = visualizer.poof()
```




[40]:
```
# ROC and AUC
#Instantiate the visualizer
visualizer = ROCAUC(model, pos_label = 1)
visualizer.fit(X_train, y_train)  # Fit the training data to the visualizer
visualizer.score(X_val, y_val)  # Evaluate the model on the test data
g = visualizer.poof()
```




[ ]: