Titanic Tutorial

Part 1 : Graphics Analysis

Part 2 : Feature Reduction (Extraction/Selection)

Part 3 : Filling in Missing Values

Part 1 : Graphics Analysis

In [41]:
```
import pandas as pd
import yellowbrick

import warnings
warnings.filterwarnings("ignore")
```

In [42]:
```
#Step 1:  Load data into a dataframe
addr = "Data/train.csv"
data = pd.read_csv(addr)
```

In [43]:
```
# Step 2:  check the dimension of the table
print("The dimension of the table is: ", data.shape)
```

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

In [44]:
```
#Step 3:  Look at the data
print(data.head(5))
```

```
   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
```

In [45]:
```
#Step 5:  what type of variables are in the table
print("Describe Data")
print(data.describe())
```

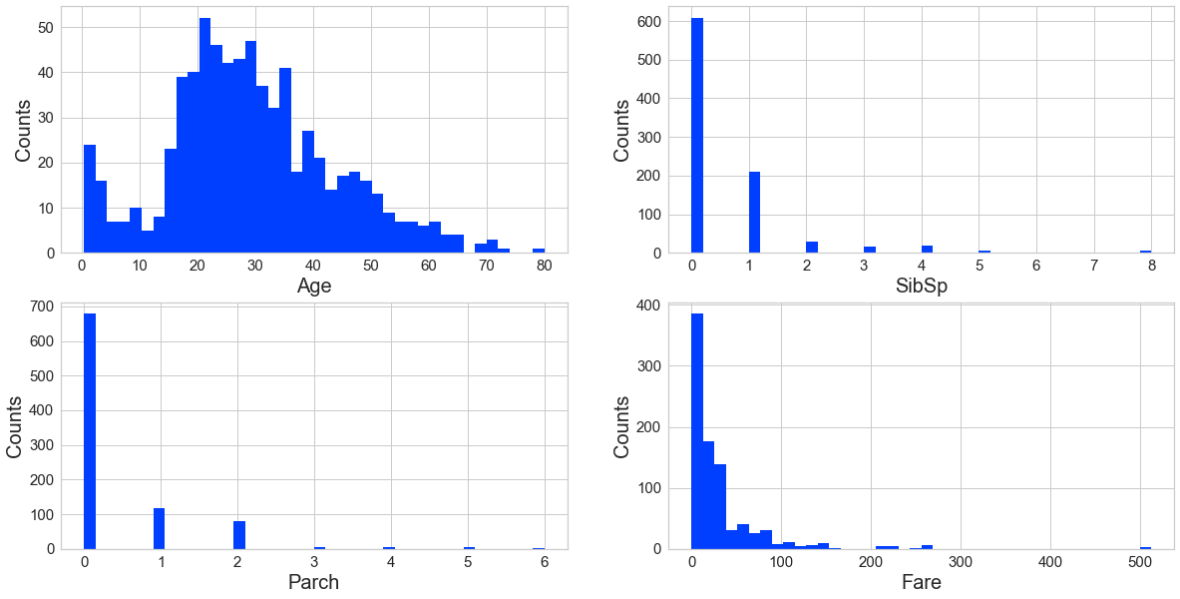
```
Describe Data
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    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
```

In [46]:
```
print("Summarized Data")
print(data.describe(include=['O']))
```

```
Summarized Data
                                                      Name   Sex Ticket Ca
bin  \
count                                                  891   891    891
204
unique                                                 891     2    681
147
top     Angle, Mrs. William A (Florence "Mary" Agnes H...  male   1601
G6
freq                                                     1   577      7
4

       Embarked
count       889
unique        3
top           S
freq        644
```

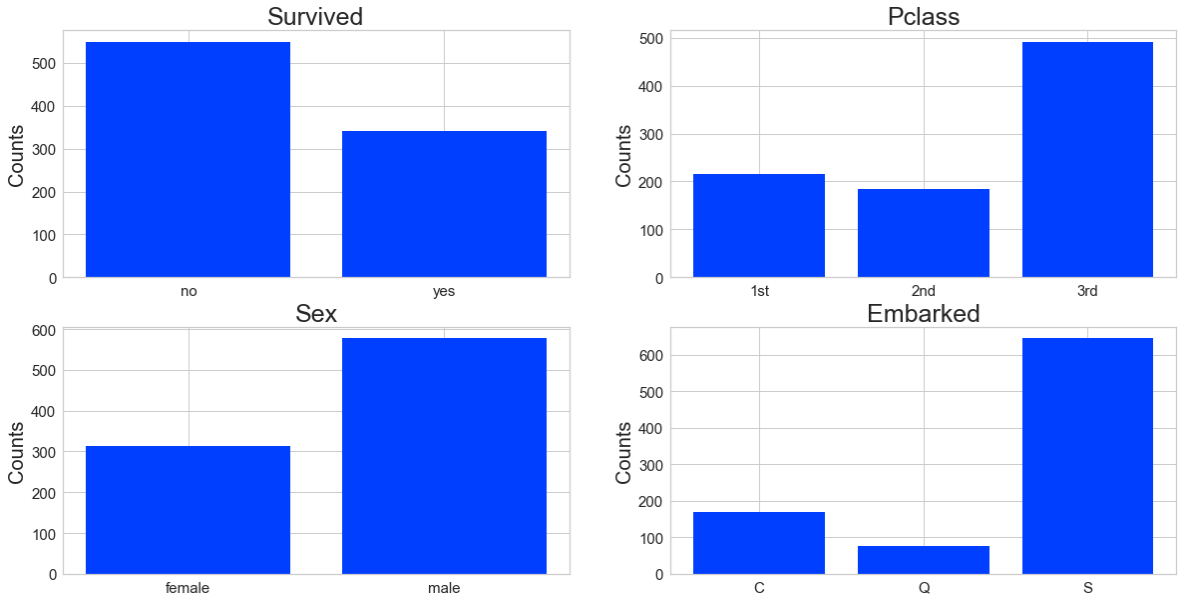
In [47]:
```
#Step 6: import visulization packages
import matplotlib.pyplot as plt
```

In [48]:
```
# set up the figure size
plt.rcParams['figure.figsize'] = (20, 10)

# make subplots
fig, axes = plt.subplots(nrows = 2, ncols = 2)

# Specify the features of interest
num_features = ['Age', 'SibSp', 'Parch', 'Fare']
xaxes = num_features
yaxes = ['Counts', 'Counts', 'Counts', 'Counts']

# draw histograms
axes = axes.ravel()
for idx, ax in enumerate(axes):
    ax.hist(data[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()
```



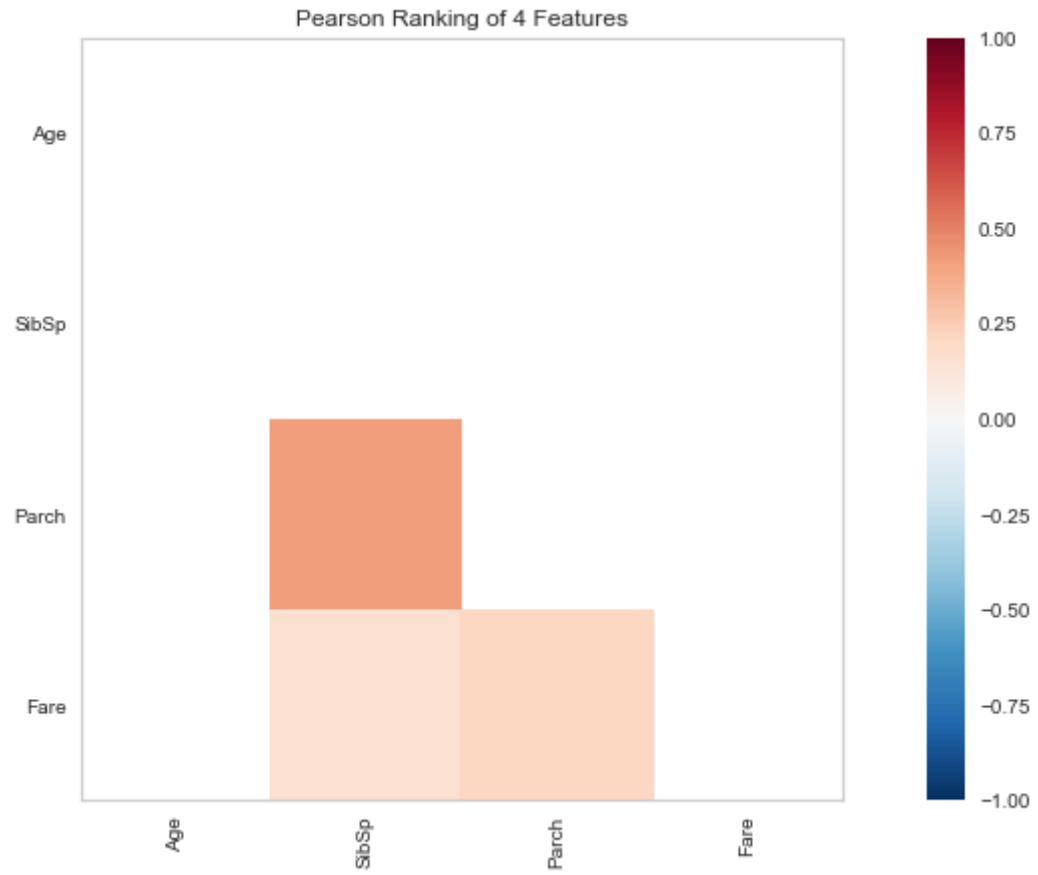
In [49]:

```
#7:  Barcharts: set up the figure size
%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 = data.replace({'Survived': {1: 'yes', 0: 'no'}}).groupby('Sur
vived').size().reset_index(name='Counts')['Survived']
Y_Survived = data.replace({'Survived': {1: 'yes', 0: 'no'}}).groupby('Sur
vived').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 = data.replace({'Pclass': {1: '1st', 2: '2nd', 3: '3rd'}}).group
by('Pclass').size().reset_index(name='Counts')['Pclass']
Y_Pclass = data.replace({'Pclass': {1: '1st', 2: '2nd', 3: '3rd'}}).group
by('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 = data.groupby('Sex').size().reset_index(name='Counts')['Sex']
Y_Sex = data.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 = data.groupby('Embarked').size().reset_index(name='Counts')[
'Embarked']
Y_Embarked = data.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()
```

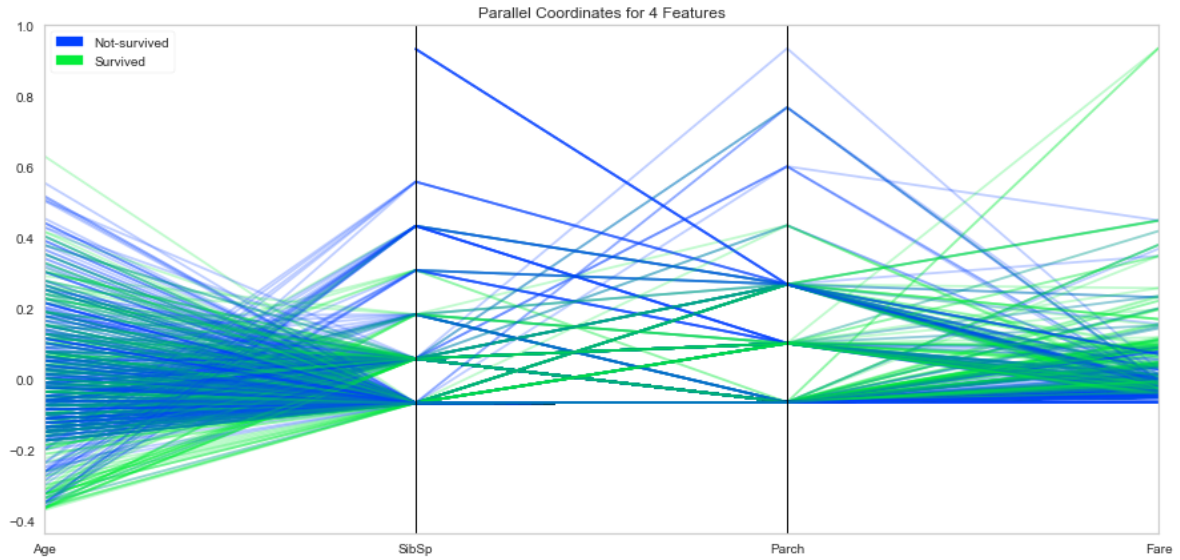

Survived
Counts
0
100
200
300
400
500
no
yes
Pclass
Counts
0
100
200
300
400
500
1st
2nd
3rd
Sex
Counts
0
100
200
300
400
500
600
female
male
Embarked
Counts
0
100
200
300
400
500
600
C
Q
S

In [51]:

```
#Step 8: Pearson Ranking
#set up the figure size
%matplotlib inline
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 = data[num_features].values

# 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
visualizer.poof(outpath="images/pcoords1.png") # Draw/show/poof the data
plt.show()
```

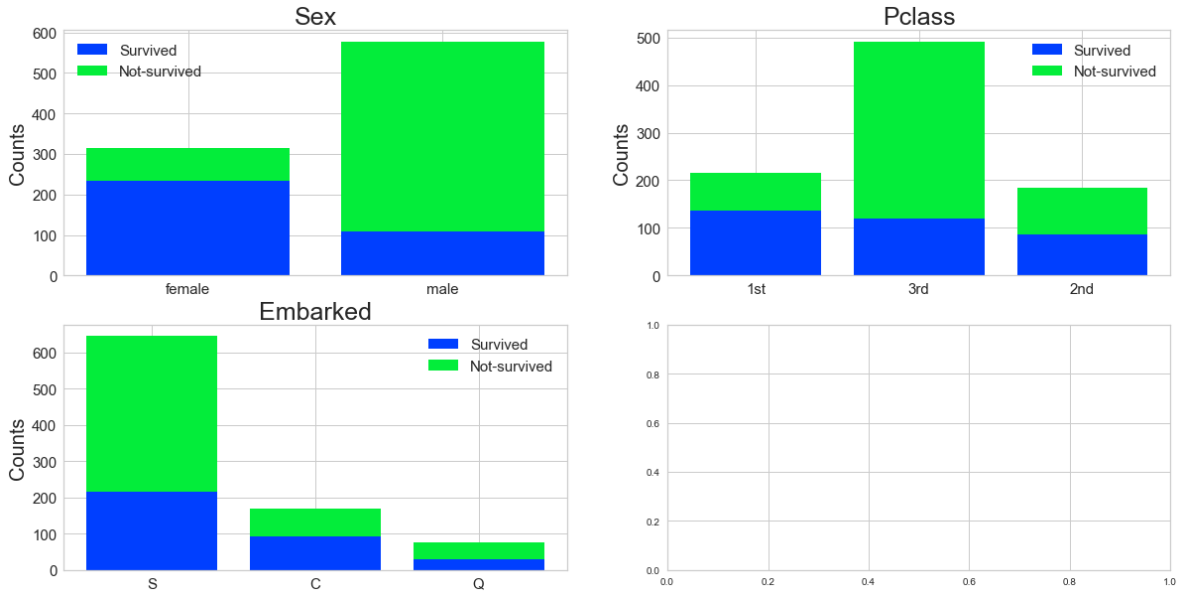


In [52]:
```
# Step 9:  Compare variables against Survived and Not Survived
#set up the figure size
%matplotlib inline
plt.rcParams['figure.figsize'] = (15, 7)
plt.rcParams['font.size'] = 50

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

# import packages
from yellowbrick.features import ParallelCoordinates
# 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 = data.copy()
# normalize data to 0-1 range
for feature in num_features:
    data_norm[feature] = (data[feature] - data[feature].mean(skipna=True
)) / (data[feature].max(skipna=True) - data[feature].min(skipna=True))

# Extract the numpy arrays from the data frame
X = data_norm[num_features].values
y = data.Survived.values

# 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="images/pcoords2.png") # Draw/show/poof the data
plt.show();
```



In [53]:
```
# Step 10 - stacked bar charts to compare survived/not survived
#set up the figure size
%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
Sex_survived = data.replace({'Survived': {1: 'Survived', 0: 'Not-survive
d'}})[data['Survived']==1]['Sex'].value_counts()
Sex_not_survived = data.replace({'Survived': {1: 'Survived', 0: 'Not-surv
ived'}})[data['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, bott
om=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 = data.replace({'Survived': {1: 'Survived', 0: 'Not-survi
ved'}}).replace({'Pclass': {1: '1st', 2: '2nd', 3: '3rd'}})[data['Survive
d']==1]['Pclass'].value_counts()
Pclass_not_survived = data.replace({'Survived': {1: 'Survived', 0: 'Not-s
urvived'}}).replace({'Pclass': {1: '1st', 2: '2nd', 3: '3rd'}})[data['Sur
vived']==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 visulizer
Embarked_survived = data.replace({'Survived': {1: 'Survived', 0: 'Not-sur
vived'}})[data['Survived']==1]['Embarked'].value_counts()
Embarked_not_survived = data.replace({'Survived': {1: 'Survived', 0: 'Not
-survived'}})[data['Survived']==0]['Embarked'].value_counts()
Embarked_not_survived = Embarked_not_survived.reindex(index = Embarked_su
rvived.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.va
lues, 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)

# Nothing to show in [1,1]
plt.show()
```



Part 2 : Feature Reduction (Extraction/Selection)

In [54]:
```
# Load Libraries and data
import pandas as pd
import yellowbrick

import warnings
warnings.filterwarnings("ignore")

#Step 1:  Load data into a dataframe
addr = "Data/train.csv"
data = pd.read_csv(addr)
data.shape
```

Out[54]:
```
(891, 12)
```

In [55]:
```
print(data['Age'].describe())
```

```
count    714.000000
mean      29.699118
std       14.526497
min        0.420000
25%       20.125000
50%       28.000000
75%       38.000000
max       80.000000
Name: Age, dtype: float64
```

In [56]:
```
data['Age'].median()
```

Out[56]:
```
28.0
```

In [57]:
```
# How many Nan's in Age Column?
data.isnull()['Age'].sum()
```

Out[57]:
```
177
```

In [58]:
```
#Show it.
data['Age']
```

Out[58]:
```
0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
       ...
886    27.0
887    19.0
888     NaN
889    26.0
890    32.0
Name: Age, Length: 891, dtype: float64
```

In [59]:
```
data['Age'][data['Age'] == 28].count()
```

Out[59]:
```
25
```

In [60]:
```
# Step 11 - fill in missing values and eliminate features
#fill the missing age data with median value
def fill_na_median(data, inplace):
    """
        This function calculate the median of the input data which comes
 in as a pandas series.
    """
    return data.fillna(round(data.median()), inplace=inplace)
```

In [61]:
```
# Apply the nfunction
fill_na_median(data['Age'],inplace=True)
print(data['Age'])
```

```
0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
       ...
886    27.0
887    19.0
888    28.0
889    26.0
890    32.0
Name: Age, Length: 891, dtype: float64
```

In [62]:
```
# check the result
print(data['Age'].describe())
#replacing NaNs with mean decreased the mean from 29.699 to 29.361
```

```
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
```

In [63]:
```
# How many Nan's in Age Column?
if (data.isnull()['Age'].sum() == 0):
    print("All NaN's are replace with mean value.")
else:
    print("Looks line removing NaN's didn't work!")
```

```
All NaN's are replace with mean value.
```

In [64]:
```
# After replacing NaN's, total number of people age 28 changed from 25 to
202(25 + 177 NaNs)
data['Age'][data['Age'] == 28].count()
```

Out[64]:
```
202
```

In [65]:
```
# fill with the most represented value
def fill_na_most(data, inplace=True):
    """
        This function Replaces NaN's with letter 'S'.
    """
    return data.fillna('S', inplace=inplace)
```

In [66]:
```
print(data['Embarked'])
```

```
0      S
1      C
2      S
3      S
4      S
      ..
886    S
887    S
888    S
889    C
890    Q
Name: Embarked, Length: 891, dtype: object
```

In [67]:
```
fill_na_most(data['Embarked'])

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

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

In [68]:
```
# import package
import numpy as np

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

In [69]:
```
print(data['Fare'])
```

```
0       7.2500
1      71.2833
2       7.9250
3      53.1000
4       8.0500
        ...
886    13.0000
887    30.0000
888    23.4500
889    30.0000
890     7.7500
Name: Fare, Length: 891, dtype: float64
```

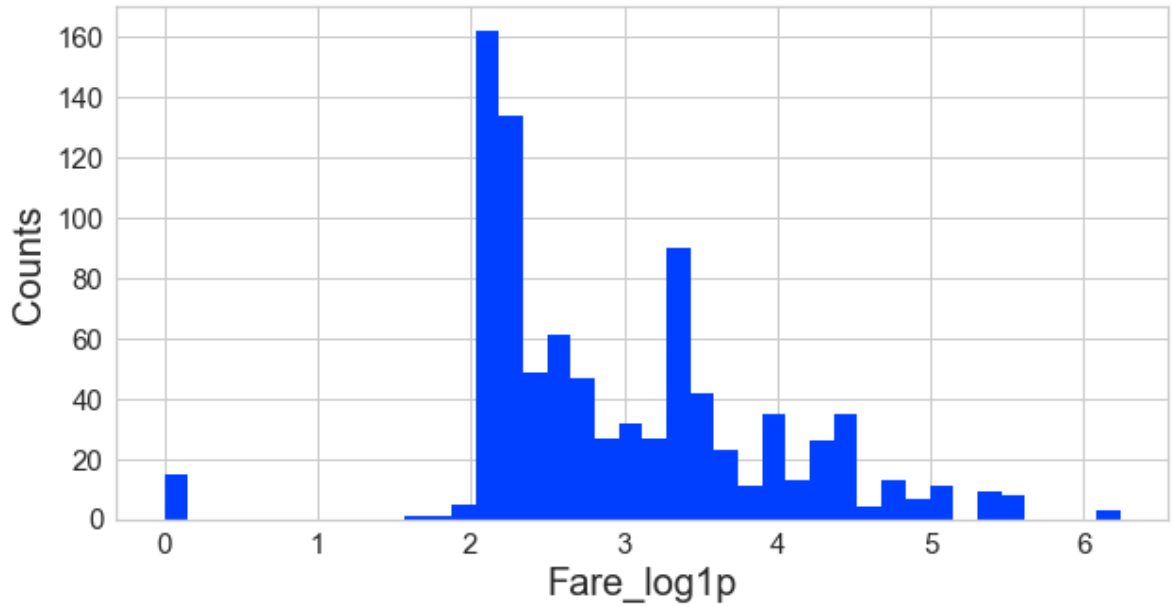
In [70]:
```
# The new column is
data['Fare_log1p'] = log_transformation(data['Fare'])

# check the data
print(data.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
```

In [71]:
```
print(data[['Fare','Fare_log1p']])
```

```
        Fare  Fare_log1p
0     7.2500    2.110213
1    71.2833    4.280593
2     7.9250    2.188856
3    53.1000    3.990834
4     8.0500    2.202765
..       ...         ...
886  13.0000    2.639057
887  30.0000    3.433987
888  23.4500    3.196630
889  30.0000    3.433987
890   7.7500    2.169054

[891 rows x 2 columns]
```

In [72]:
```
#Step 12 - adjust skewed data (fare)
#check the distribution using histogram
# set up the figure size
%matplotlib inline
plt.rcParams['figure.figsize'] = (10, 5)

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



In [73]:
```
#Step 13 - convert categorical data to numbers
#get the categorical data
cat_features = ['Pclass', 'Sex', "Embarked"]
data_cat = data[cat_features]
data_cat = data_cat.replace({'Pclass': {1: '1st', 2: '2nd', 3: '3rd'}})
# 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
```

Part 3 : Filling in Missing Values

In [74]:
```
import pandas as pd
import yellowbrick

import warnings
warnings.filterwarnings("ignore")
```

In [75]:
```
#Titanic Tutorial Part 3
#Graphics Analysis
#Feature Reduction (Extraction/Selection)
#Filling in Missing Values
#Split_Train_Test
#Model Selection and Evaluation
```

In [81]:
```
#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 tog
ether
features_model = ['Age', 'SibSp', 'Parch', 'Fare_log1p']
data_model_X = pd.concat([data[features_model], data_cat_dummies], axis=1
)
print("data_model_X",type( data_model_X))
# create a whole target dataset that can be used for train and validation
data splitting
data_model_y = data.replace({'Survived': {1: 'Survived', 0: 'Not_survive
d'}})['Survived']
print(type(data_model_y))
# 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_mode
l_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())
```

```
data_model_X <class 'pandas.core.frame.DataFrame'>
<class 'pandas.core.series.Series'>
No. of samples in training set:  623
No. of samples in validation set: 268


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


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

In [ ]:
```
type(y_train)
```

In [78]:
```
# 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

# Instantiate the classification model
model = LogisticRegression()

#The ConfusionMatrix visualizer taxes a model
classes = ['Not_survived','Survived']
cm = ConfusionMatrix(model, classes=classes, percent=False)

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

#To create the ConfusionMatrix, we need some test data. Score runs predic
t() 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()

# 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 visualiz
er
visualizer.score(X_val, y_val)  # Evaluate the model on the test data
g = visualizer.poof()

# ROC and AUC
#Instantiate the visualizer
visualizer = ROCAUC(model)

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

Out[78]:
```
pandas.core.series.Series
```

In [77]:

```
# Step 15 - Eval Metrics
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```
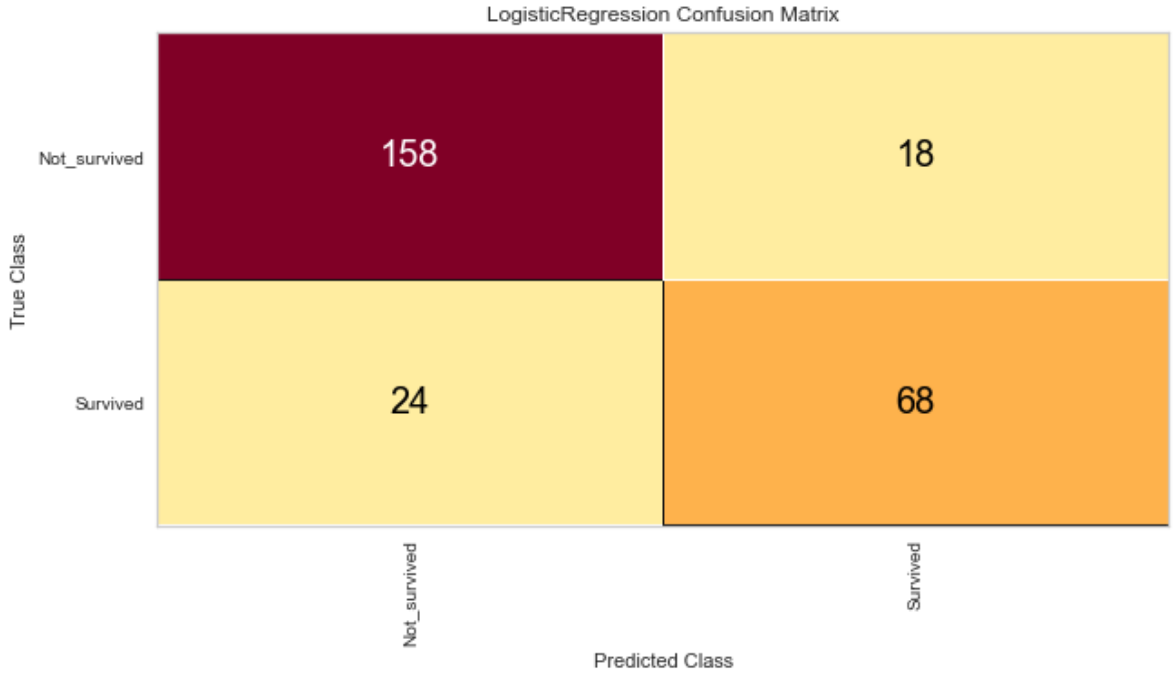
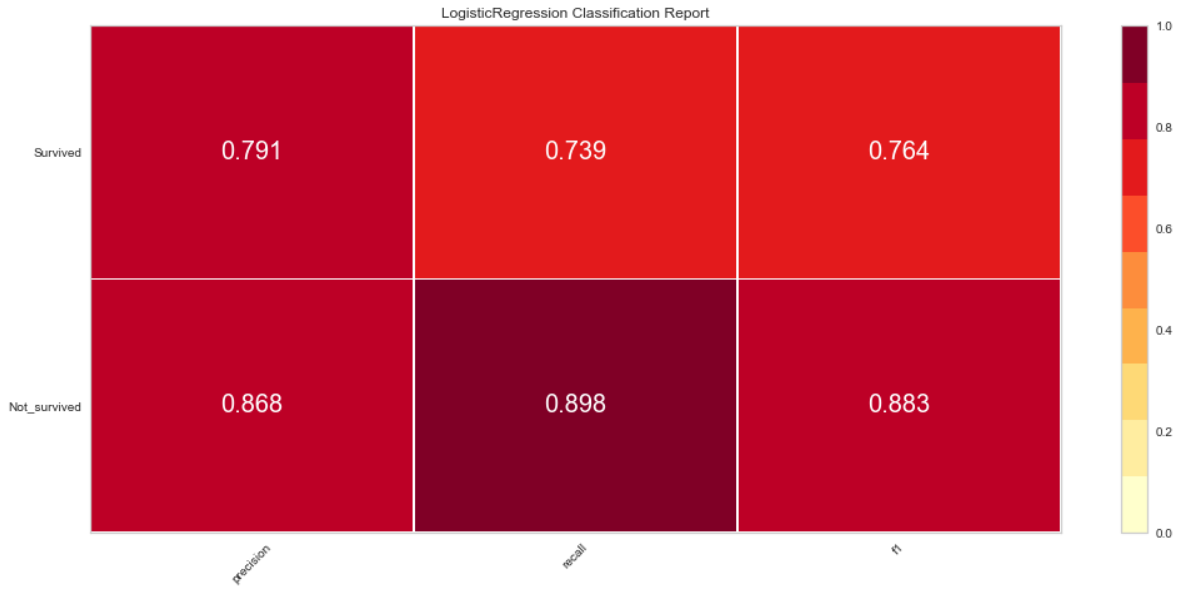
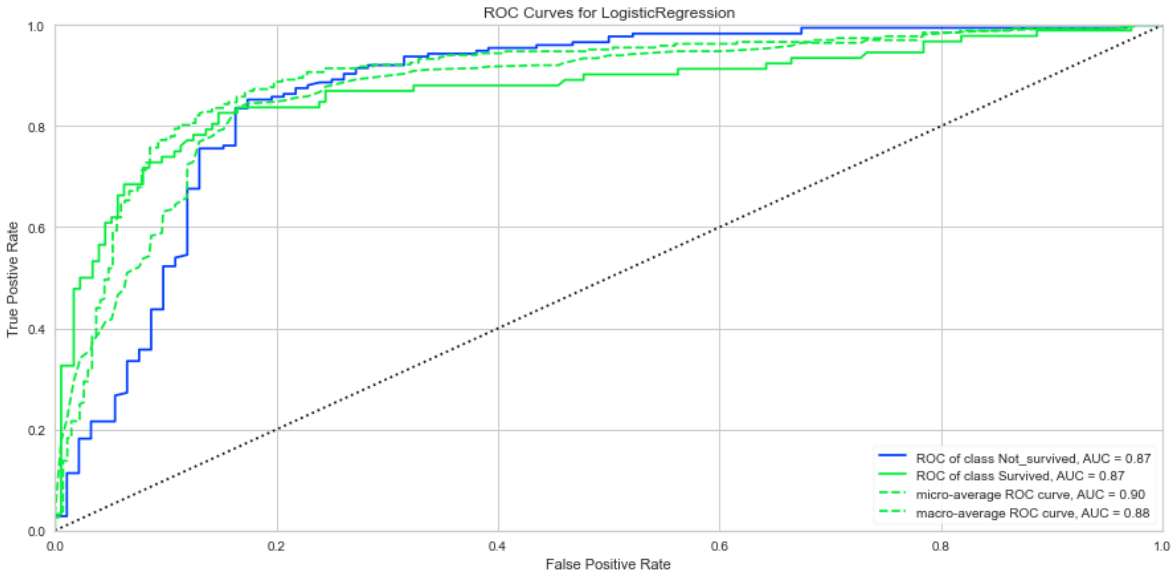


LogisticRegression Confusion Matrix
Not_survived
Survived
True Class
158
18
24
68
Not_survived
Survived
Predicted Class


LogisticRegression Classification Report
Survived
Not_survived
0.791
0.739
0.764
0.868
0.898
0.883
precision
recall
f1
1.0
0.8
0.6
0.4
0.2
0.0


ROC Curves for LogisticRegression
True Postive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC of class Not_survived, AUC = 0.87
ROC of class Survived, AUC = 0.87
micro-average ROC curve, AUC = 0.90
macro-average ROC curve, AUC = 0.88

In [ ]: