ASumbaraju_wk7_TitanicCaseStudyPart3

July 20, 2021

1 Titanic Tutorial Part 3

2 1.Graphics Analysis

3 2.Feature Reduction (Extraction/Selection)

4 3.Filling in Missing Values

5 4.Split_Train_Test

6 5.Model Selection and Evaluation

[1]:
```
import pandas as pd
import yellowbrick
```

[6]:
```
#Step 1:  Load data into a dataframe
addr1 = "C:\BU\DSC550\wk7\week-7/train.csv"
data = pd.read_csv(addr1)
```

[7]:
```
# 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)
```

[8]:
```
#Step 3:  Look at the data
data.head(5)
```

[8]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th…	female	38.0	1
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0
3	4	1	1				
4	5	0	3				

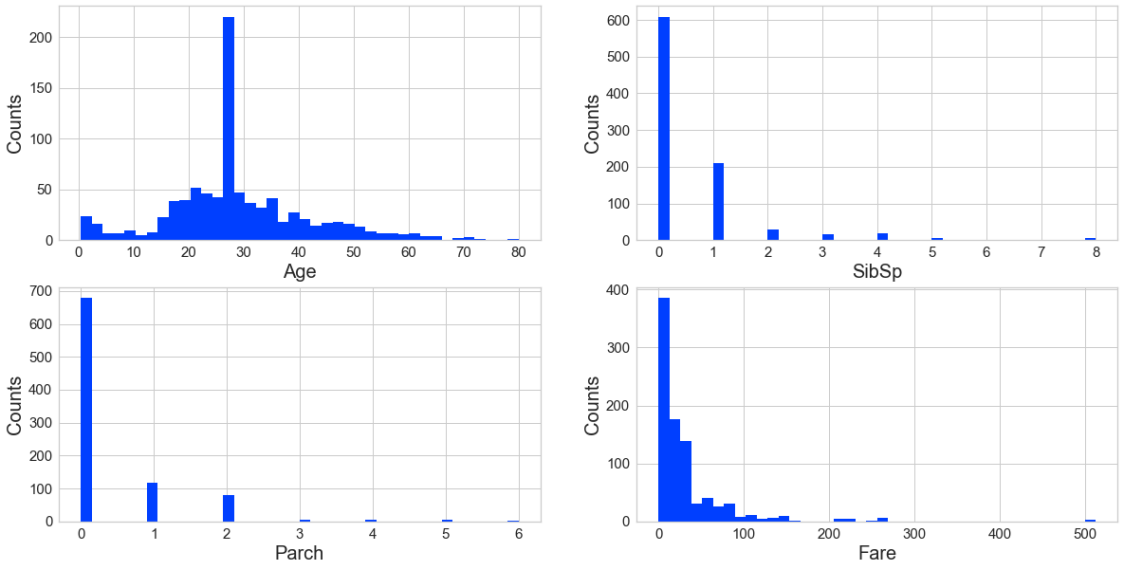
```
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   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
```

[9]:
```
#Step 5:  what type of variables are in the table
print("Describe Data")
print(data.describe())
print("Summarized Data")
print(data.describe(include=['O']))
```

```
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
Summarized Data
                          Name   Sex  Ticket        Cabin Embarked
count                      891   891     891          204      889
unique                     891     2     681          147        3
top     Rice, Master. Eugene  male  347082  C23 C25 C27        S
freq                         1   577       7            4      644
```

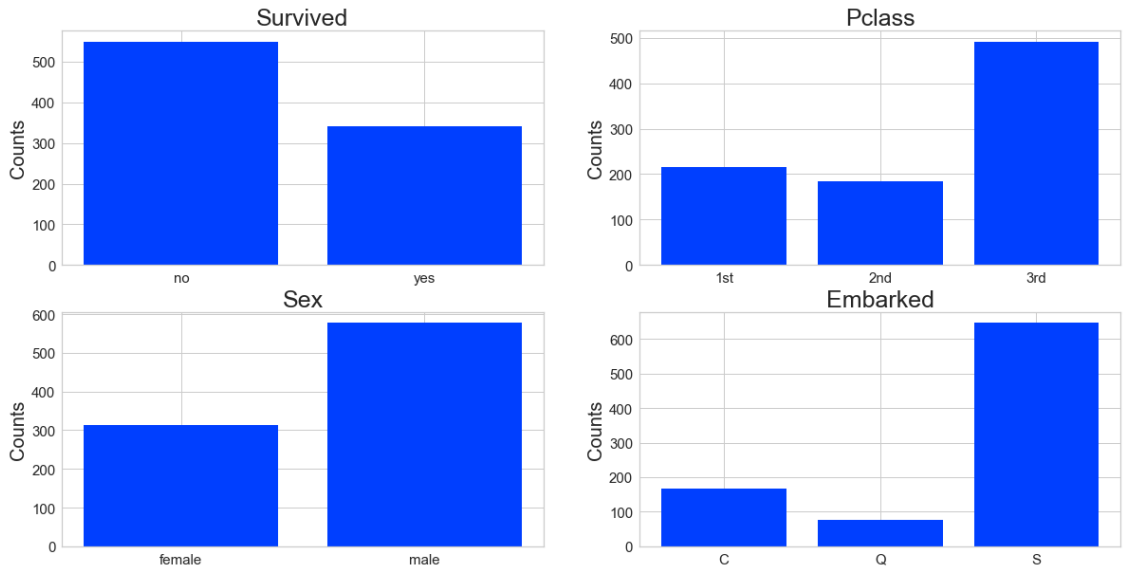
[33]:
```
#Step 6: import visulization packages
import matplotlib.pyplot as plt

# 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()
```



[34]:
```
#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('Survived').size().reset_index(name='Counts')['Survived']
```

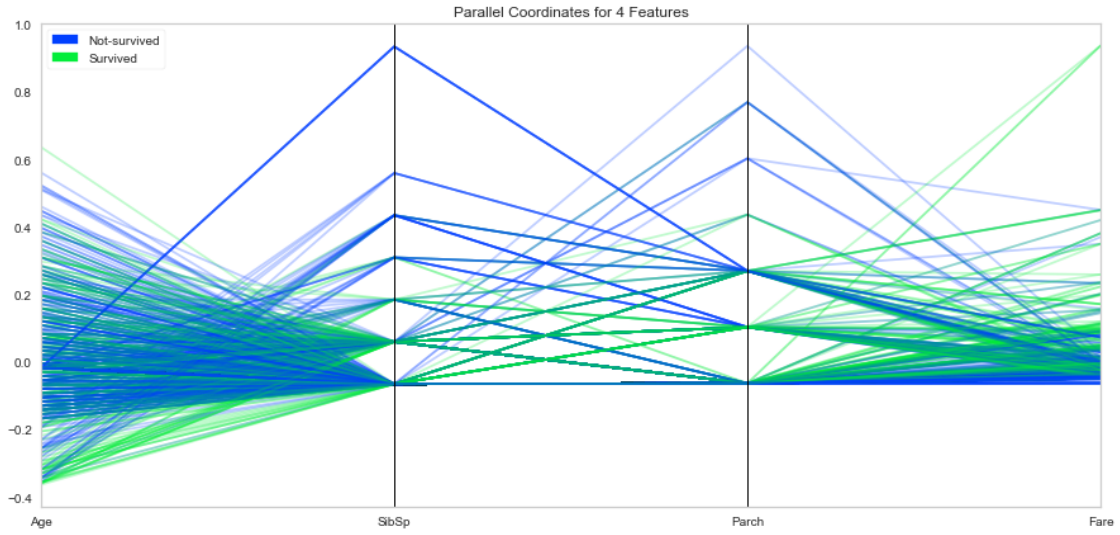
```
Y_Survived = data.replace({'Survived': {1: 'yes', 0: 'no'}}).
 ↪groupby('Survived').size().reset_index(name='Counts')['Counts']
# make the bar plot
axes[0, 0].bar(X_Survived, Y_Survived)
axes[0, 0].set_title('Survived', fontsize=25)
axes[0, 0].set_ylabel('Counts', fontsize=20)
axes[0, 0].tick_params(axis='both', labelsize=15)

# make the data read to feed into the visulizer
X_Pclass = data.replace({'Pclass': {1: '1st', 2: '2nd', 3: '3rd'}}).
 ↪groupby('Pclass').size().reset_index(name='Counts')['Pclass']
Y_Pclass = data.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 = 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()
```



[36]:
```
#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
import numpy as np
X = np.asmatrix(data[num_features])

# 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="C:\BU\DSC550\wk7\images/pcoords1.png") # Draw/show/
 ↪poof the data
plt.show()
```

[37]:
```
# 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
```

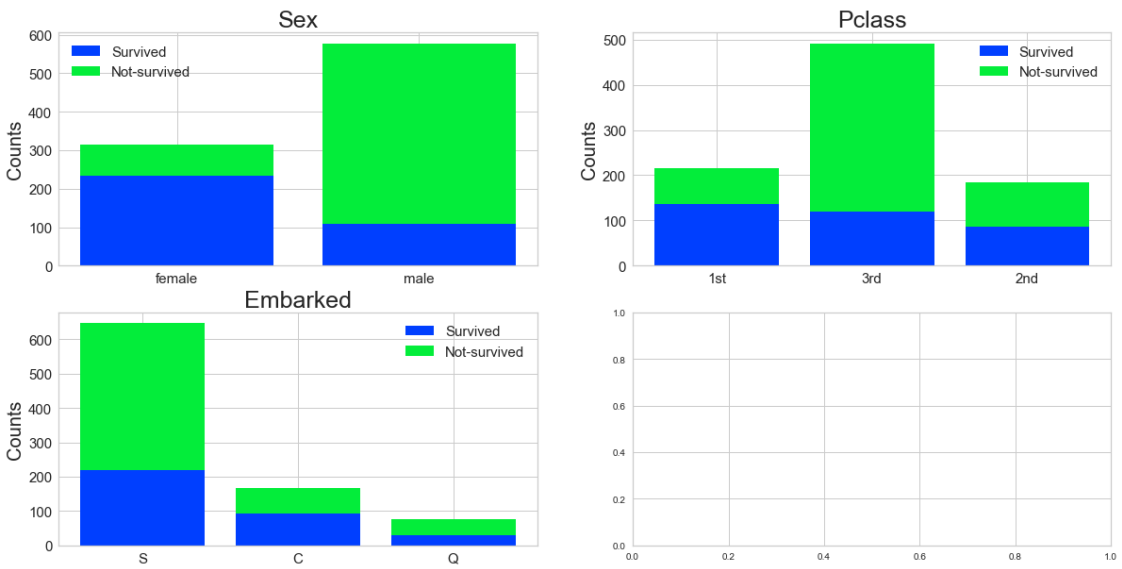
```
data_norm = data.copy()
# normalize data to 0-1 range
for feature in num_features:
    data_norm[feature] = (data[feature] - data[feature].mean(skipna=True)) /␣
 ↪(data[feature].max(skipna=True) - data[feature].min(skipna=True))

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

# Instantiate the visualizer
# 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="C:\BU\DSC550\wk7\images/pcoords2.png") # Draw/show/
 ↪poof the data
plt.show();
```



[38]:
```
# 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-survived'}})[data['Survived']==1]['Sex'].value_counts()
Sex_not_survived = data.replace({'Survived': {1: 'Survived', 0:␣
 ↪'Not-survived'}})[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,␣
 ↪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 visulizer
Pclass_survived = data.replace({'Survived': {1: 'Survived', 0:␣
 ↪'Not-survived'}}).replace({'Pclass': {1: '1st', 2: '2nd', 3:␣
 ↪'3rd'}})[data['Survived']==1]['Pclass'].value_counts()
Pclass_not_survived = data.replace({'Survived': {1: 'Survived', 0:␣
 ↪'Not-survived'}}).replace({'Pclass': {1: '1st', 2: '2nd', 3:␣
 ↪'3rd'}})[data['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 visulizer
Embarked_survived = data.replace({'Survived': {1: 'Survived', 0:␣
 ↪'Not-survived'}})[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_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()
```



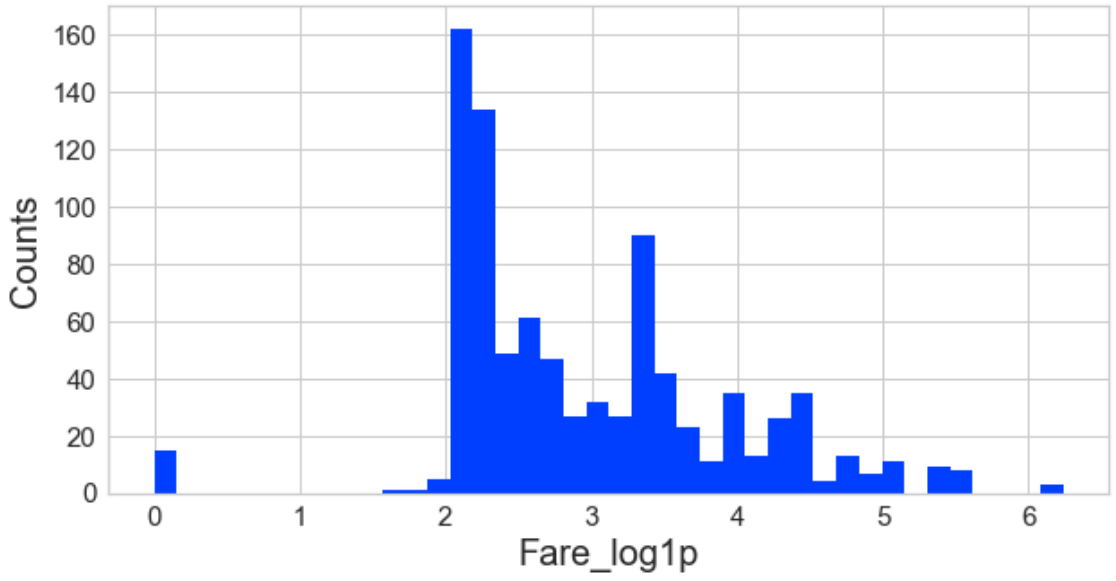
[39]:
```
# Step 11 - fill in missing values and eliminate features
#fill the missing age data with median value
def fill_na_median(data, inplace=True):
    return data.fillna(data.median(), inplace=inplace)

fill_na_median(data['Age'])

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

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

fill_na_most(data['Embarked'])

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

# import package
import numpy as np

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

```
data['Fare_log1p'] = log_transformation(data['Fare'])

# check the data
print(data.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
count     891
unique      3
top         S
freq      646
Name: Embarked, dtype: object
       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
```

[40]:
```
#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()
```



[41]:
```
#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
```

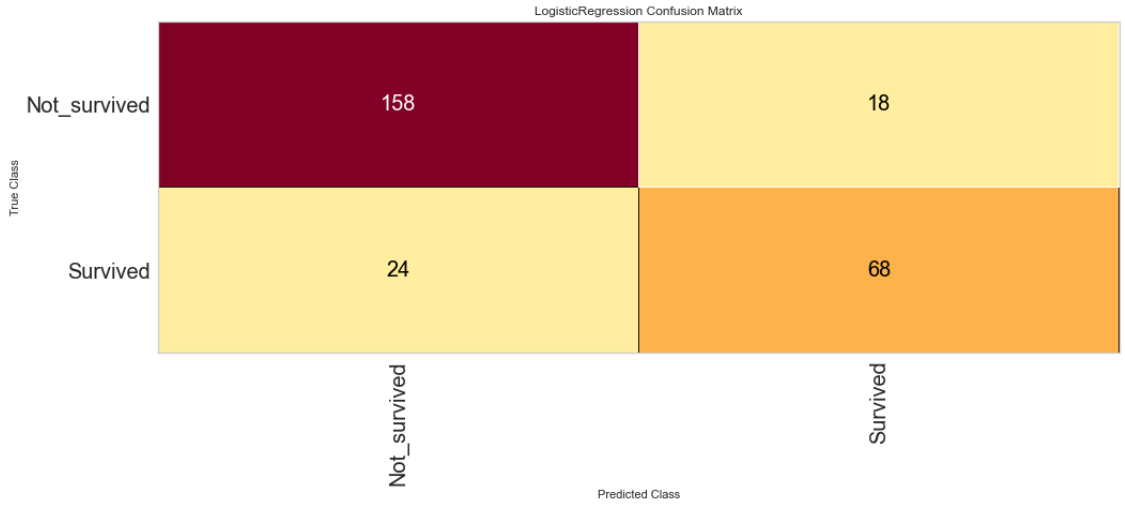
[91]:
```
#Step 14 - create a whole features dataset that can be used for train and␣
 ↪validation data splitting
# here we will combine the numerical features and the dummie features together
features_model = ['Age', 'SibSp', 'Parch', 'Fare_log1p']
data_model_X = pd.concat([data[features_model], data_cat_dummies], axis=1)

# create a whole target dataset that can be used for train and validation data␣
 ↪splitting
data_model_y = data.Survived
# 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
```

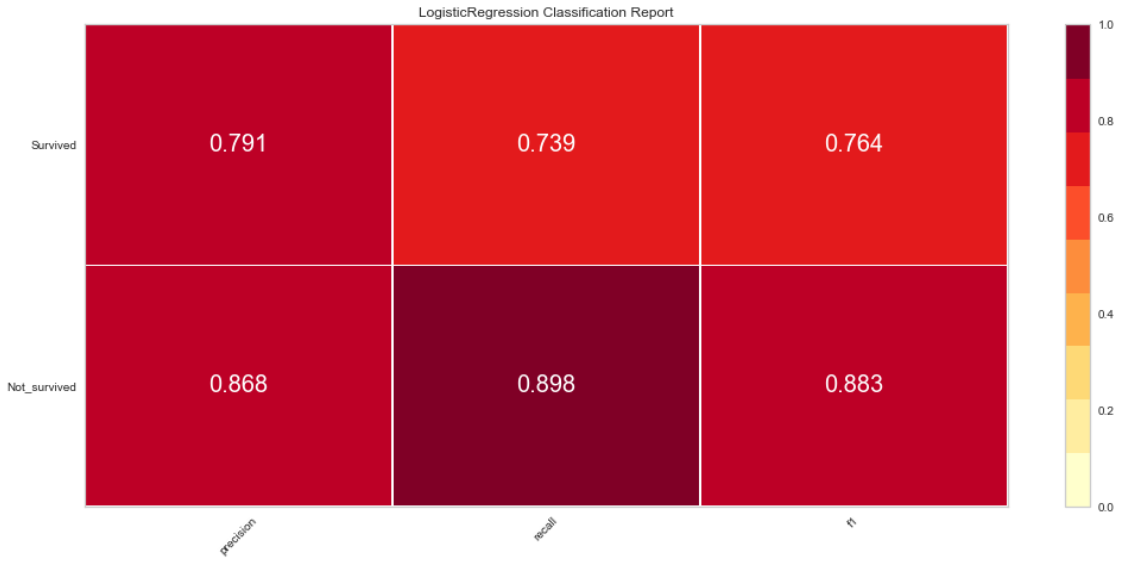
```
No. of survived and not-survived in the validation set:
0    176
1     92
Name: Survived, dtype: int64
```

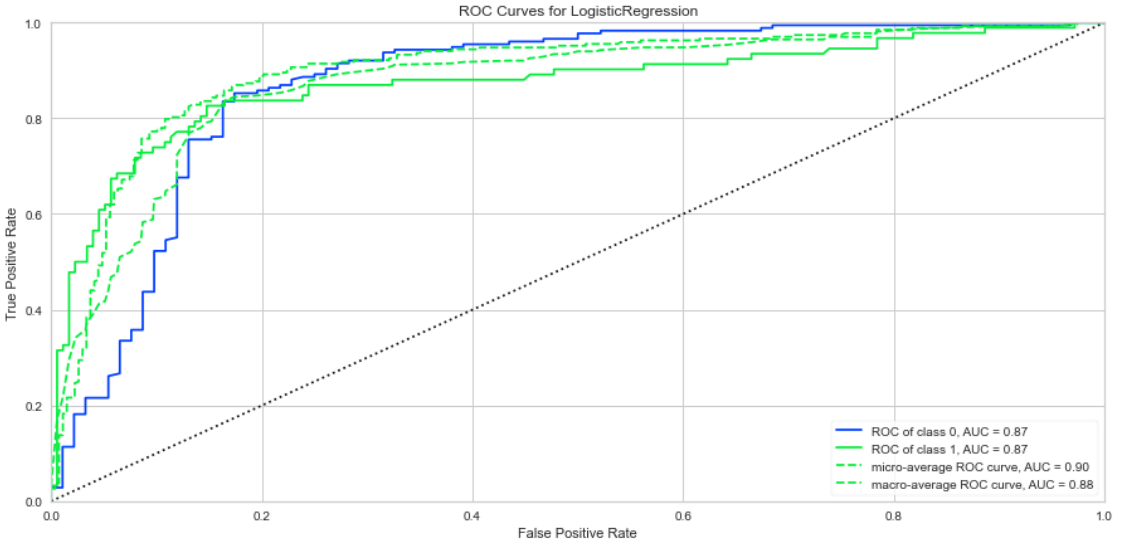
[92]:
```
# Step 15 - Eval Metrics
from sklearn.linear_model import LogisticRegression

from yellowbrick.classifier import ConfusionMatrix
from yellowbrick.classifier import ClassificationReport
from yellowbrick.classifier import ROCAUC
```

[93]:
```
import warnings
warnings.filterwarnings("ignore")

# 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 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()
plt.show()
```



[94]:
```
# 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()

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

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()
```


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 Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC of class 0, AUC = 0.87
ROC of class 1, AUC = 0.87
micro-average ROC curve, AUC = 0.90
macro-average ROC curve, AUC = 0.88

[ ]: