In [1]:
```
import numpy as np
import pandas as pd
from sklearn import preprocessing
from tensorflow import keras
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras import optimizers
import keras.utils as ker
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from keras.layers import Dense, InputLayer, Flatten, Dropout
import tensorflow as tf
from sklearn.metrics import classification_report, confusion_matrix, accuracy_
score, roc_auc_score, roc_curve, precision_score, recall_score, accuracy_score
, f1_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.utils import resample
```

```
Using TensorFlow backend.
```

In [2]:
```
## Read data from csv file 'student-mat.csv'
math_data = pd.read_csv('encoded_math_data.csv')
```

In [3]:
```
## Encoding Schools
list_of_schools = []
for i in math_data['school']:
    if i == 'GP':
        school = 1
    else:
        school = 0
    list_of_schools.append(school)

math_data['school'] = list_of_schools
```

In [4]:
```
## One-hot encoding binary variables.
school_one_hot = ker.to_categorical(math_data['school']).tolist()
sex_one_hot = ker.to_categorical(math_data['sex']).tolist()
address_one_hot = ker.to_categorical(math_data['address']).tolist()
pstatus_one_hot = ker.to_categorical(math_data['Pstatus']).tolist()
fedu_one_hot = ker.to_categorical(math_data['Fedu']).tolist()
medu_one_hot = ker.to_categorical(math_data['Medu']).tolist()
schoolsup_one_hot = ker.to_categorical(math_data['schoolsup']).tolist()
famsup_one_hot = ker.to_categorical(math_data['famsup']).tolist()
paid_one_hot = ker.to_categorical(math_data['paid']).tolist()
activities_one_hot = ker.to_categorical(math_data['activities']).tolist()
nursery_one_hot = ker.to_categorical(math_data['nursery']).tolist()
higher_one_hot = ker.to_categorical(math_data['higher']).tolist()
internet_one_hot = ker.to_categorical(math_data['internet']).tolist()
romantic_one_hot = ker.to_categorical(math_data['romantic']).tolist()

## Adding one-hot vectors to df
math_data['school_one_hot'] = school_one_hot
math_data['sex_one_hot'] = sex_one_hot
math_data['address_one_hot'] = address_one_hot
math_data['pstatus_one_hot'] = pstatus_one_hot
math_data['fedu_one_hot'] = fedu_one_hot
math_data['medu_one_hot'] = medu_one_hot
math_data['schoolsup_one_hot'] = schoolsup_one_hot
math_data['famsup_one_hot'] = famsup_one_hot
math_data['paid_one_hot'] = paid_one_hot
math_data['activities_one_hot'] = activities_one_hot
math_data['nursery_one_hot'] = nursery_one_hot
math_data['higher_one_hot'] = higher_one_hot
math_data['internet_one_hot'] = internet_one_hot
math_data['romantic_one_hot'] = romantic_one_hot
```

In [5]:
```
# Creating a new binary variable - 1 if student failed first grading period
previous_grade_list = []
for i in math_data['M1']:
    if i < 9.5: # Fail
        label = 1
    else: # Pass
        label = 0
    previous_grade_list.append(label)
math_data['previous_pass_fail'] = previous_grade_list
```

In [6]:
```
## Creating labels - Pass(0) or Fail(1)
list_of_labels = []
for i in math_data['M3']:
    if i < 9.5: # Fail
        label = 1
    else: # Pass
        label = 0
    list_of_labels.append(label)
math_data['label'] = list_of_labels
```

In [7]:
```
math_data['label'].value_counts()
```

Out[7]:
```
0    265
1    130
Name: label, dtype: int64
```

In [8]:
```
## Upsample the minority class to deal with the skewed dataset.
math_data_maj = math_data[math_data['label']==0]
math_data_min = math_data[math_data['label']==1]
math_data_min_upsampled = resample(math_data_min, replace=True, n_samples=265)
math_data_balanced = pd.concat([math_data_maj, math_data_min_upsampled])
math_data_balanced['label'].value_counts()
```

Out[8]:
```
1    265
0    265
Name: label, dtype: int64
```

In [9]:
```
math_data_balanced = math_data_balanced.reset_index(drop=True)
```

In [10]:
```
balanced_math_data = math_data_balanced.drop(math_data_balanced.columns[[0]], axis=1)
```

In [11]:
```
## Creating input vector (X)
X = []
for i in range(0, len(balanced_math_data)):
    x = []
#    x.append(balanced_math_data['age'][i])
    x.append(balanced_math_data['Medu'][i])
    x.append(balanced_math_data['Fedu'][i])
#    x.append(balanced_math_data['both_parents_college'][i])
#    x.append(balanced_math_data['studytime'][i])
#    x.append(balanced_math_data['famrel'][i])
#    x.append(balanced_math_data['freetime'][i])
    x.append(balanced_math_data['goout'][i])
    x.append(balanced_math_data['Dalc'][i])
    x.append(balanced_math_data['Walc'][i])
#    x.append(balanced_math_data['health'][i])
#    x.append(balanced_math_data['m_absences'][i])
    x.append(balanced_math_data['failures'][i])

#    x.extend(balanced_math_data['sex_one_hot'][i])
#    x.extend(balanced_math_data['address_one_hot'][i])
#    x.extend(balanced_math_data['pstatus_one_hot'][i])
#    x.extend(balanced_math_data['schoolsup_one_hot'][i])
#    x.extend(balanced_math_data['famsup_one_hot'][i])
    x.extend(balanced_math_data['paid_one_hot'][i])
#    x.extend(balanced_math_data['activities_one_hot'][i])
#    x.extend(balanced_math_data['nursery_one_hot'][i])
#    x.extend(balanced_math_data['school_one_hot'][i])
    x.extend(balanced_math_data['higher_one_hot'][i])
    x.extend(balanced_math_data['internet_one_hot'][i])
    x.extend(balanced_math_data['romantic_one_hot'][i])
    x.append(balanced_math_data['previous_pass_fail'][i])
    x.append(balanced_math_data['M1'][i])
    X.append(x)
```

In [12]:
```
Y = np.array(balanced_math_data['label'])
X = np.array(X)
```

In [47]:
```
## split dataset into train-test.
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.25, stra
tify=Y)
```

In [14]:
```
X.shape[1:]
```

Out[14]:
```
(16,)
```

In [15]:
```
X_train[0]
```

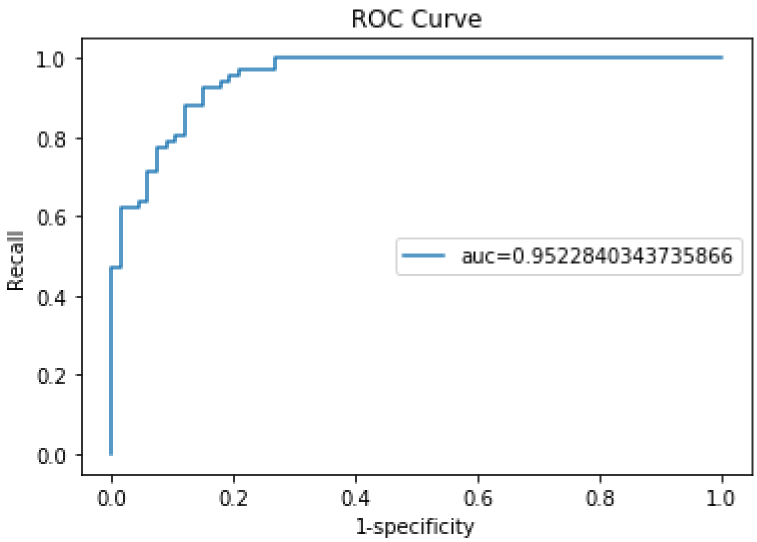
Out[15]:
```
array([ 3.,  2.,  2.,  1.,  1.,  0.,  0.,  1.,  0.,  1.,  0.,  1.,  1.,
        0.,  0., 14.])
```

In [16]:
```
## DNN model utilizing TF's Keras API
model = keras.models.Sequential()
model.add(keras.layers.InputLayer(input_shape=X.shape[1:]))
model.add(keras.layers.Dense(128, activation='sigmoid'))
model.add(keras.layers.Dense(128, activation='sigmoid'))
model.add(keras.layers.Dense(1, activation='sigmoid'))
model.compile(optimizer='adam',
              loss='binary_crossentropy')
model.summary()
model.fit(X_train, y_train, epochs=36, batch_size=1, validation_split=0.2)
Y_pred = model.predict_classes(X_test)

## Metrics -
print('\nPrecision score: {:.4f}'.format(precision_score(y_test, Y_pred)))
print('Recall score: {:.4f}'.format(recall_score(y_test, Y_pred)))
print('Accuracy score: {:.4f}'.format(accuracy_score(y_test, Y_pred)))
print('F1 score: {:.4f}'.format(f1_score(y_test, Y_pred)))

print('\nClassification accuracy report:')
print(classification_report(y_test, Y_pred))
print('\nConfusion matrix:')
print(confusion_matrix(y_test, Y_pred))

## Creating an ROC/AUC curve to visualize performance.
classification_probs = model.predict_proba(X_test)
classification_AUC = roc_auc_score(y_test, classification_probs)
print("\nAUC Index: {:.3f}".format(classification_AUC))
fpr, tpr, threshold = roc_curve(y_test,  classification_probs)
plt.plot(fpr,tpr,label="auc="+str(classification_AUC))
plt.legend(loc=5)
plt.ylabel('Recall')
plt.xlabel('1-specificity')
plt.title('ROC Curve')
plt.show()
```

```
WARNING:tensorflow:From /opt/conda/lib/python3.7/site-packages/tensorflow_cor
e/python/ops/resource_variable_ops.py:1628: calling BaseResourceVariable.__in
it__ (from tensorflow.python.ops.resource_variable_ops) with constraint is de
precated and will be removed in a future version.
Instructions for updating:
If using Keras pass *_constraint arguments to layers.
WARNING:tensorflow:From /opt/conda/lib/python3.7/site-packages/tensorflow_cor
e/python/ops/nn_impl.py:183: where (from tensorflow.python.ops.array_ops) is
deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 128)               2176
_________________________________________________________________
dense_1 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 129
=================================================================
Total params: 18,817
Trainable params: 18,817
Non-trainable params: 0
_________________________________________________________________
WARNING:tensorflow:From /opt/conda/lib/python3.7/site-packages/tensorflow_cor
e/python/keras/optimizer_v2/optimizer_v2.py:460: BaseResourceVariable.constra
int (from tensorflow.python.ops.resource_variable_ops) is deprecated and will
be removed in a future version.
Instructions for updating:
Apply a constraint manually following the optimizer update step.
Train on 317 samples, validate on 80 samples
Epoch 1/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.5627 - val
_loss: 0.4635
Epoch 2/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3852 - val
_loss: 0.4482
Epoch 3/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3370 - val
_loss: 0.5854
Epoch 4/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3440 - val
_loss: 0.4768
Epoch 5/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3426 - val
_loss: 0.4928
Epoch 6/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3334 - val
_loss: 0.4799
Epoch 7/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3312 - val
_loss: 0.4940
Epoch 8/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3316 - val
_loss: 0.4912
Epoch 9/36
```

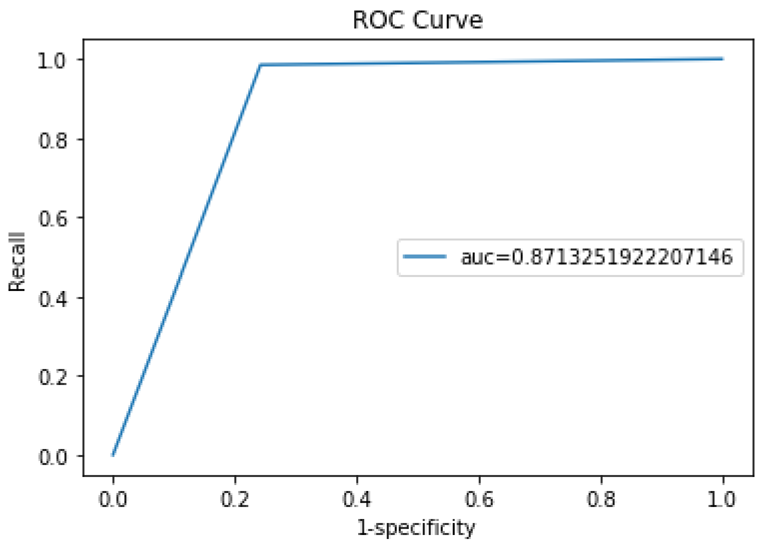
```
317/317 [==============================] - 1s 2ms/sample - loss: 0.3324 - val
_loss: 0.5050
Epoch 10/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3260 - val
_loss: 0.4934
Epoch 11/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3231 - val
_loss: 0.5045
Epoch 12/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3076 - val
_loss: 0.5042
Epoch 13/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3033 - val
_loss: 0.5136
Epoch 14/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3151 - val
_loss: 0.4786
Epoch 15/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3105 - val
_loss: 0.5101
Epoch 16/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2960 - val
_loss: 0.4789
Epoch 17/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3121 - val
_loss: 0.4739
Epoch 18/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3047 - val
_loss: 0.5283
Epoch 19/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3022 - val
_loss: 0.4994
Epoch 20/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3001 - val
_loss: 0.5151
Epoch 21/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2766 - val
_loss: 0.4916
Epoch 22/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2966 - val
_loss: 0.4903
Epoch 23/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2886 - val
_loss: 0.4862
Epoch 24/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2849 - val
_loss: 0.5587
Epoch 25/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.3142 - val
_loss: 0.4742
Epoch 26/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2890 - val
_loss: 0.4861
Epoch 27/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2829 - val
_loss: 0.4785
Epoch 28/36
```

```
317/317 [==============================] - 1s 2ms/sample - loss: 0.2870 - val
_loss: 0.4781
Epoch 29/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2876 - val
_loss: 0.5133
Epoch 30/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2795 - val
_loss: 0.4935
Epoch 31/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2866 - val
_loss: 0.4870
Epoch 32/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2685 - val
_loss: 0.4974
Epoch 33/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2769 - val
_loss: 0.4997
Epoch 34/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2849 - val
_loss: 0.4898
Epoch 35/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2666 - val
_loss: 0.5010
Epoch 36/36
317/317 [==============================] - 1s 2ms/sample - loss: 0.2727 - val
_loss: 0.4951

Precision score: 0.8267
Recall score: 0.9394
Accuracy score: 0.8722
F1 score: 0.8794

Classification accuracy report:
              precision    recall  f1-score   support

           0       0.93      0.81      0.86        67
           1       0.83      0.94      0.88        66

   micro avg       0.87      0.87      0.87       133
   macro avg       0.88      0.87      0.87       133
weighted avg       0.88      0.87      0.87       133


Confusion matrix:
[[54 13]
 [ 4 62]]

AUC Index: 0.952
```


ROC Curve
Recall
1-specificity
auc=0.9522840343735866
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0

In [27]:
```
## Tuning hyperparameters of tree - cross-validated grid-search over a paramet
er grid.
optimized_tree = DecisionTreeClassifier()
params = {"max_depth": range(1,10),
           "min_samples_split": range(2,10,1),
           "max_leaf_nodes": range(2,5)}

opt_tree = GridSearchCV(optimized_tree, params, cv=5) ##  folds in stratified
 k-fold.
opt_tree.fit(X_train,y_train)
print("Best Parameters:", opt_tree.best_params_)

## Grid Search Tree Metrics
grid_tree_y_pred = opt_tree.predict(X_test)
grid_tree_probs = opt_tree.predict_proba(X_test)
grid_tree_AUC = roc_auc_score(y_test, grid_tree_probs[:, 1])  ## Probability h
ere just like lecture notes.

print('\nPrecision score: {:.4f}'.format(precision_score(y_test, grid_tree_y_p
red)))
print('Recall score: {:.4f}'.format(recall_score(y_test, grid_tree_y_pred)))
print('Accuracy score: {:.4f}'.format(accuracy_score(y_test, grid_tree_y_pred
)))
print('F1 score: {:.4f}'.format(f1_score(y_test, grid_tree_y_pred)))

print("\nAUC Index:", grid_tree_AUC)
fpr, tpr, threshold = roc_curve(y_test,  grid_tree_probs[:, 1])
plt.plot(fpr,tpr,label="auc="+str(grid_tree_AUC))
plt.legend(loc=5)
plt.ylabel('Recall')
plt.xlabel('1-specificity')
plt.title('ROC Curve')
plt.show()
```

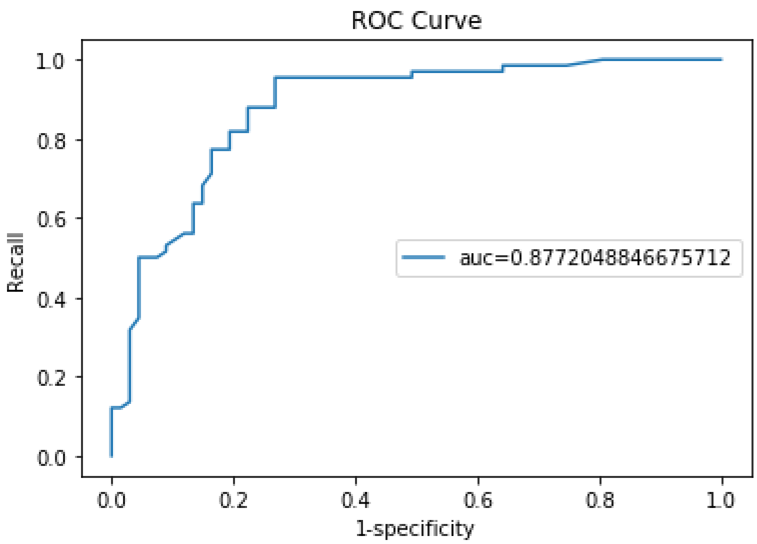
```
Best Parameters: {'max_depth': 1, 'max_leaf_nodes': 2, 'min_samples_split':
2}

Precision score: 0.8049
Recall score: 0.9851
Accuracy score: 0.8722
F1 score: 0.8859

AUC Index: 0.8713251922207146
```



In [38]:
```
## Random Forest - cross-validated grid-search over a parameter grid.
rf = RandomForestClassifier(n_estimators=100, n_jobs=-1, bootstrap=True)
params = {"max_depth": range(1,10),
           "min_samples_split": range(2,10,1),
           "max_leaf_nodes": range(2,5)}

opt_rf = GridSearchCV(rf, params)
opt_rf.fit(X_train,y_train)
print("Best Parameters:", opt_rf.best_params_)

rf_y_pred = opt_rf.predict(X_test)
rf_probs = opt_rf.predict_proba(X_test)

## Metrics
print('Precision score: {:.4f}'.format(precision_score(y_test,rf_y_pred)))
print('Recall score: {:.4f}'.format(recall_score(y_test,rf_y_pred)))
print('Accuracy score: {:.4f}'.format(accuracy_score(y_test,rf_y_pred)))
print('F1 score: {:.4f}'.format(f1_score(y_test,rf_y_pred)))

rf_AUC = roc_auc_score(y_test, rf_probs[:, 1])
print("\nAUC Index:", rf_AUC)
fpr, tpr, threshold = roc_curve(y_test,  rf_probs[:, 1])
plt.plot(fpr,tpr,label="auc="+str(rf_AUC))
plt.legend(loc=5)
plt.ylabel('Recall')
plt.xlabel('1-specificity')
plt.title('ROC Curve')
plt.show()
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/model_selection/_split.py:205
3: FutureWarning: You should specify a value for 'cv' instead of relying on t
he default value. The default value will change from 3 to 5 in version 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
Best Parameters: {'max_depth': 8, 'max_leaf_nodes': 2, 'min_samples_split':
2}
Precision score: 0.7733
Recall score: 0.8788
Accuracy score: 0.8120
F1 score: 0.8227

AUC Index: 0.8772048846675712
```



In [48]:
```
## Logistic Regression
log_regression = LogisticRegression().fit(X_train, y_train)
logistic_y_pred = log_regression.predict(X_test)
log_probs = log_regression.predict_proba(X_test)

## Metrics
print('Precision score: {:.4f}'.format(precision_score(y_test,logistic_y_pred
)))
print('Recall score: {:.4f}'.format(recall_score(y_test,logistic_y_pred)))
print('Accuracy score: {:.4f}'.format(accuracy_score(y_test,logistic_y_pred)))
print('F1 score: {:.4f}'.format(f1_score(y_test,logistic_y_pred)))

log_AUC = roc_auc_score(y_test, log_probs[:, 1])
print("\nAUC Index:", log_AUC)
fpr, tpr, threshold = roc_curve(y_test,  log_probs[:, 1])
plt.plot(fpr,tpr,label="auc="+str(log_AUC))
plt.legend(loc=5)
plt.ylabel('Recall')
plt.xlabel('1-specificity')
plt.title('ROC Curve')
plt.show()
```

```
Precision score: 0.8308
Recall score: 0.8182
Accuracy score: 0.8271
F1 score: 0.8244

AUC Index: 0.9122568973315243

/opt/conda/lib/python3.7/site-packages/sklearn/linear_model/logistic.py:433:
FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a s
olver to silence this warning.
  FutureWarning)
```