In [1]:
```
#Processamento e Análise em Big Data
#Tarefa 05
#Grupo 03
#20/04/2021
```

In [2]:
```
import pandas as pd
from pyspark.sql import functions as F
from pyspark.ml.feature import PCA
from pyspark.ml.feature import StringIndexer, VectorAssembler
from pyspark.ml import Pipeline
from pyspark.sql.functions import col
```

Análise Descritiva

In [56]:
```
data_ = spark.read.csv('pima_indian_diabetes.csv', header=True)
```

In [4]:
```
data_.limit(5).toPandas()
```

Out[4]:

	n_pregnant	plasma_glucose_concentration	blood_pressure	triceps_skinfold_thickness	2hours
0	6	148	72	35	
1	1	85	66	29	
2	8	183	64	0	
3	1	89	66	23	
4	0	137	40	35	

Checando o Schema do Dataframe

In [5]:
```
data_.printSchema()
```

```
root
 |-- n_pregnant: string (nullable = true)
 |-- plasma_glucose_concentration: string (nullable = true)
 |-- blood_pressure: string (nullable = true)
 |-- triceps_skinfold_thickness: string (nullable = true)
 |-- 2hours_serum_insulin: string (nullable = true)
 |-- body_mass_index: string (nullable = true)
 |-- diabtes_pedigree_function: string (nullable = true)
 |-- age: string (nullable = true)
 |-- class: string (nullable = true)
```

Vamos converter os valores string para int e float

In [57]:
```
num_cols = ['n_pregnant', 'class', 'age']
for col in num_cols:
    data_ = data_.withColumn(col, data_[col].cast('int'))

num_cols = ['plasma_glucose_concentration', 'blood_pressure','triceps_skinfold
_thickness',
            '2hours_serum_insulin','body_mass_index', 'diabetes_pedigree_functi
on' ]
for col in num_cols:
    data_ = data_.withColumn(col, data_[col].cast('float'))


data_.printSchema()
```

```
root
 |-- n_pregnant: integer (nullable = true)
 |-- plasma_glucose_concentration: float (nullable = true)
 |-- blood_pressure: float (nullable = true)
 |-- triceps_skinfold_thickness: float (nullable = true)
 |-- 2hours_serum_insulin: float (nullable = true)
 |-- body_mass_index: float (nullable = true)
 |-- diabetes_pedigree_function: float (nullable = true)
 |-- age: integer (nullable = true)
 |-- class: integer (nullable = true)
```

copiando Dataframe

In [7]:
```
schema = data_.schema
X_pd = data_.toPandas()
data_model = spark.createDataFrame(X_pd,schema=schema)
del X_pd
data_model.printSchema()
```

```
root
 |-- n_pregnant: integer (nullable = true)
 |-- plasma_glucose_concentration: float (nullable = true)
 |-- blood_pressure: float (nullable = true)
 |-- triceps_skinfold_thickness: float (nullable = true)
 |-- 2hours_serum_insulin: float (nullable = true)
 |-- body_mass_index: float (nullable = true)
 |-- diabetes_pedigree_function: float (nullable = true)
 |-- age: integer (nullable = true)
 |-- class: integer (nullable = true)
```

Colunas presentes no Dataframe

In [8]:
```
for column in data_.limit(5).toPandas().columns:
    print(column)
```

```
n_pregnant
plasma_glucose_concentration
blood_pressure
triceps_skinfold_thickness
2hours_serum_insulin
body_mass_index
diabtes_pedigree_function
age
class
```

> *n_pregnant - Número de vezes que engravidou*
>
> *plasma_glucose_concentration - Concentração de glicose plasmática a 2 horas em um teste oral de tolerância à glicose*
>
> *blood_pressure - Pressão arterial diastólica (mm Hg)*
>
> *triceps_skinfold_thickness - Espessura da dobra da pele do tríceps (mm)*
>
> *2hours_serum_insulin - Insulina sérica de 2 horas (mu U / ml)*
>
> *body_mass_index - Índice de massa corporal (peso em kg / (altura em m) ^ 2)*
>
> *diabtes_pedigree_function - valores que medem a tendência ao desenvolvimento de diabetes com base nas relações genéticas do indivíduo*
>
> *age - Idade*
>
> *class - Presença ou não de diabetes*

Vamos ver as estatísticas das variáveis

In [9]:
```
data_.summary().toPandas().T
```

Out[9]:

	0	1	2	3	4	
summary	count	mean	stddev	min	25%	50
n_pregnant	768	3.8450520833333335	3.3695780626988	0	1	
plasma_glucose_concentration	768	120.89453125	31.97261819513622	0.0	99.0	117
blood_pressure	768	69.10546875	19.355807170644777	0.0	62.0	72
triceps_skinfold_thickness	768	20.536458333333332	15.952217567727642	0.0	0.0	23
2hours_serum_insulin	768	79.79947916666667	115.24400235133803	0.0	0.0	29
body_mass_index	768	31.99257813890775	7.884160293010772	0.0	27.3	32
diabetes_pedigree_function	768	0.4718763029280429	0.3313285967924436	0.078	0.243	0.37
age	768	33.240885416666664	11.760231540678689	21	24	2
class	768	0.3489583333333333	0.476951377242799	0	0	

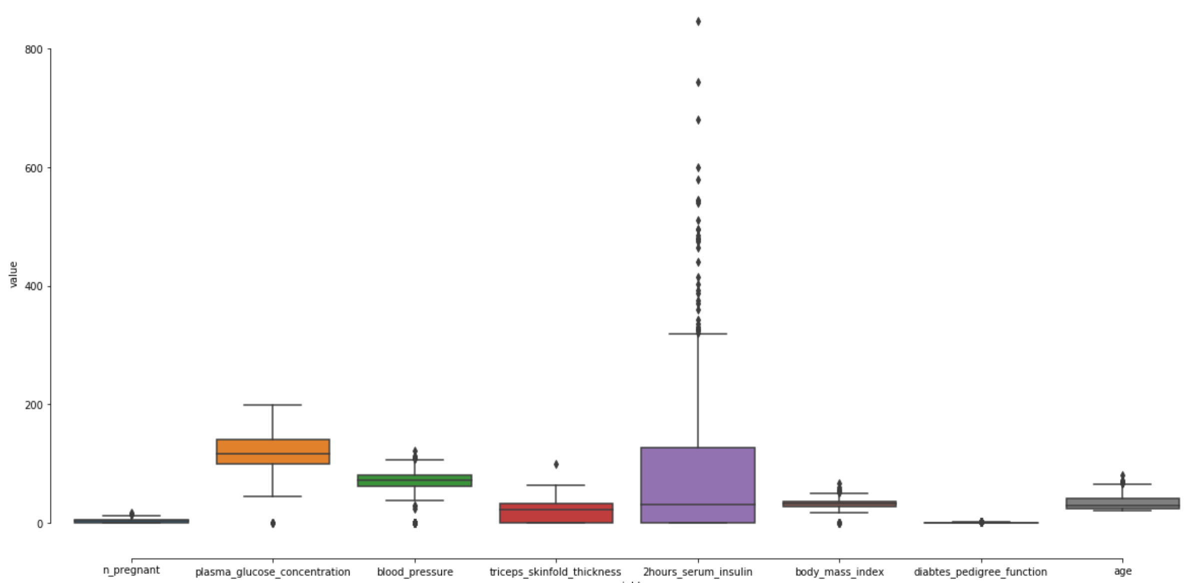
Vamos plotar Boxplots das vatiáveis para ter uma visão geral de dimensão e distribuição dos dados

In [58]:
```
import matplotlib.pyplot as plt
import seaborn as sns


plt.rcParams['figure.figsize']=(20,10)
tips = sns.load_dataset("tips")

sns.boxplot(x="variable", y="value", data=pd.melt(data_.toPandas().drop(['clas
s'], axis=1)))


sns.despine(offset=10, trim=True)
```

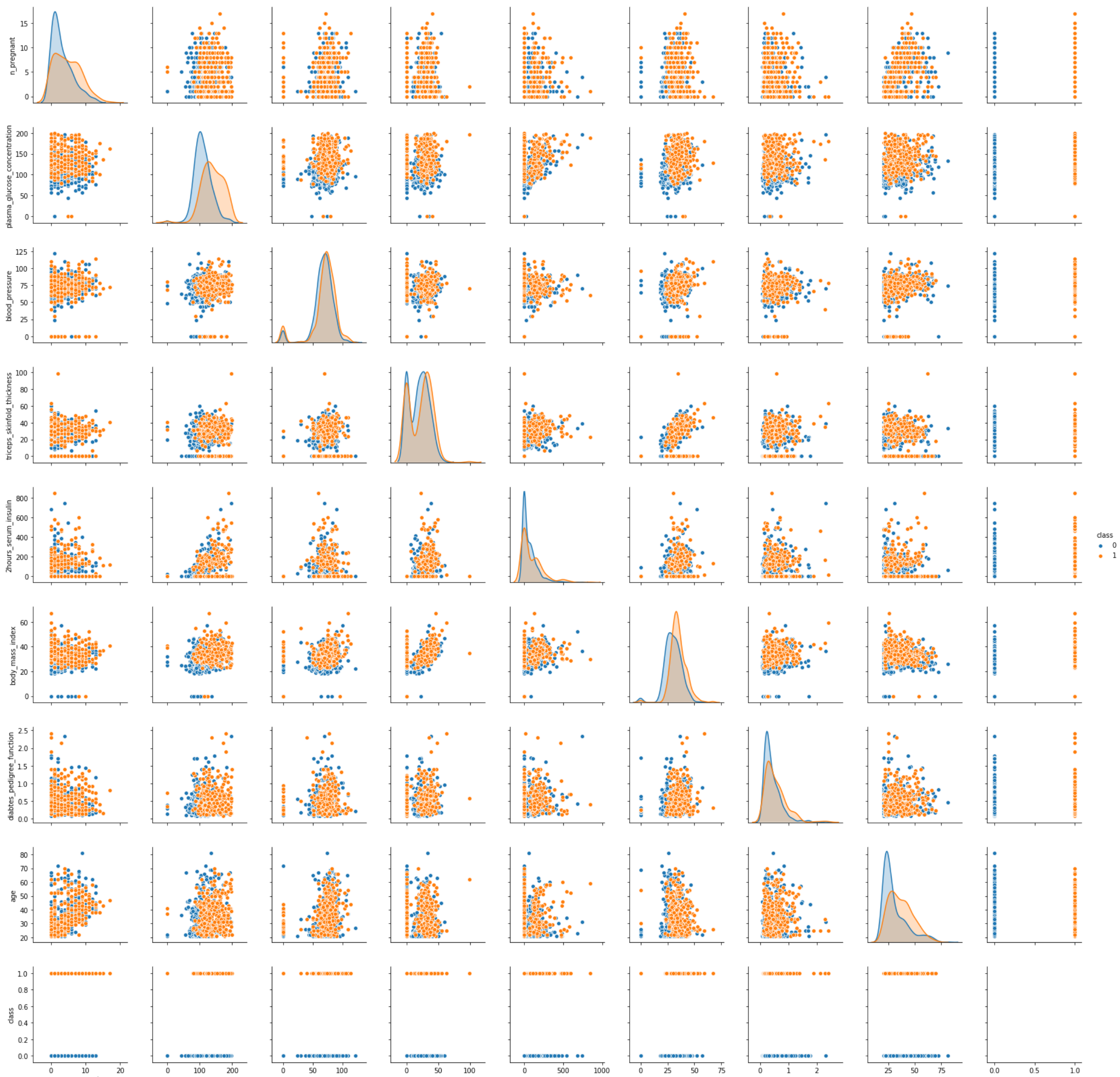


> *No gráfico acima fica evidente que algumas variáveis apresentam bastantes outliers, o que pode impactar na performance dos modelos de Machine learning*
>
> *Futuramente iremos tratá-los a fim de verificar o quanto esses outliers interferem no modelo*

Vamos plotar uma Scatterplot Matrix para ver se conseguimos enxergar relações entre as variáveis, assim como se existe alguma Decision Boundery aparente aos nossos olhos

In [11]:
```
sns.pairplot(data_.toPandas(), hue="class");
```

```
/home/matheus/anaconda3/lib/python3.7/site-packages/statsmodels/nonparametri
c/kde.py:487: RuntimeWarning: invalid value encountered in true_divide
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
/home/matheus/anaconda3/lib/python3.7/site-packages/statsmodels/nonparametri
c/kdetools.py:34: RuntimeWarning: invalid value encountered in double_scalars
  FAC1 = 2*(np.pi*bw/RANGE)**2
```



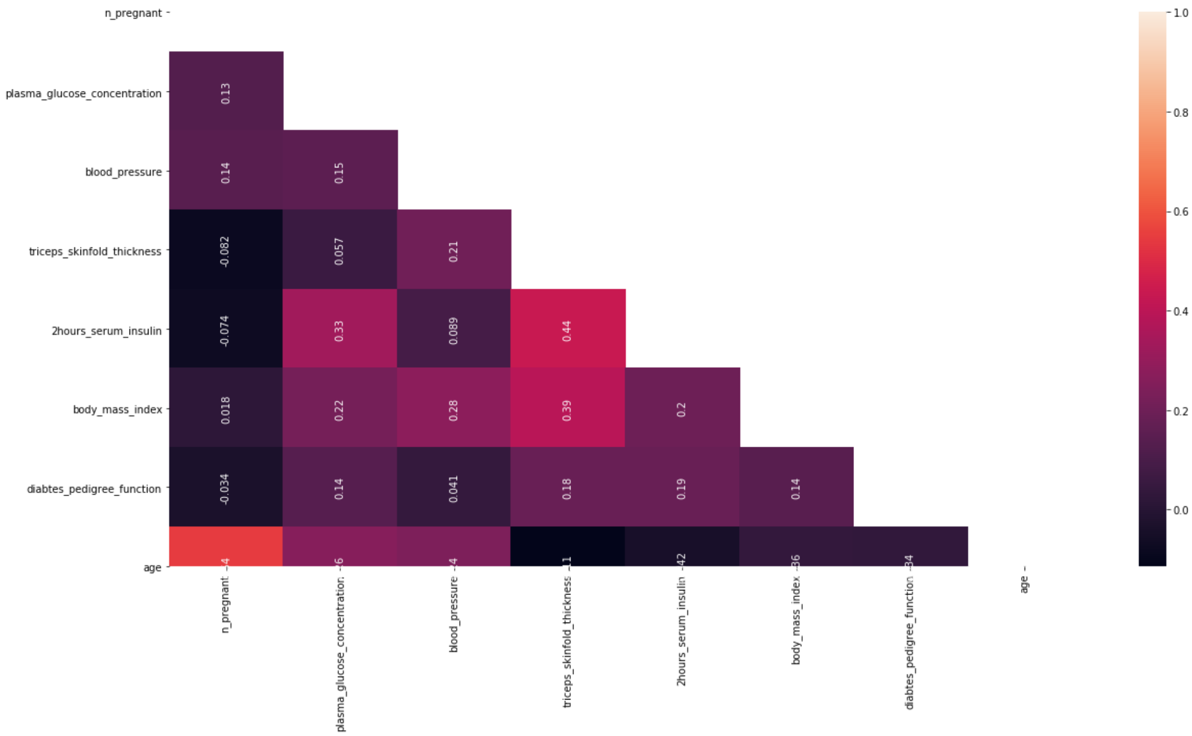
Notas: > > >

Agora que já tivemos um insight visual, vamos mensurar numericalmente o qual forte são as relações entre essas variáveis usando a matrix de correlação

In [59]:
```
import numpy as np

data_corr = data_.toPandas().drop(['class'], axis=1).corr()

mask = np.triu(data_corr)
sns.heatmap(data_corr, annot=True, mask=mask,annot_kws={'rotation': 90});
```



In [ ]:

Dentre as variáveis independentes do modelo "n_pregnant" é a única que aparenta ter um comportamento discreto. Abaixo iremos explorar ela um pouco

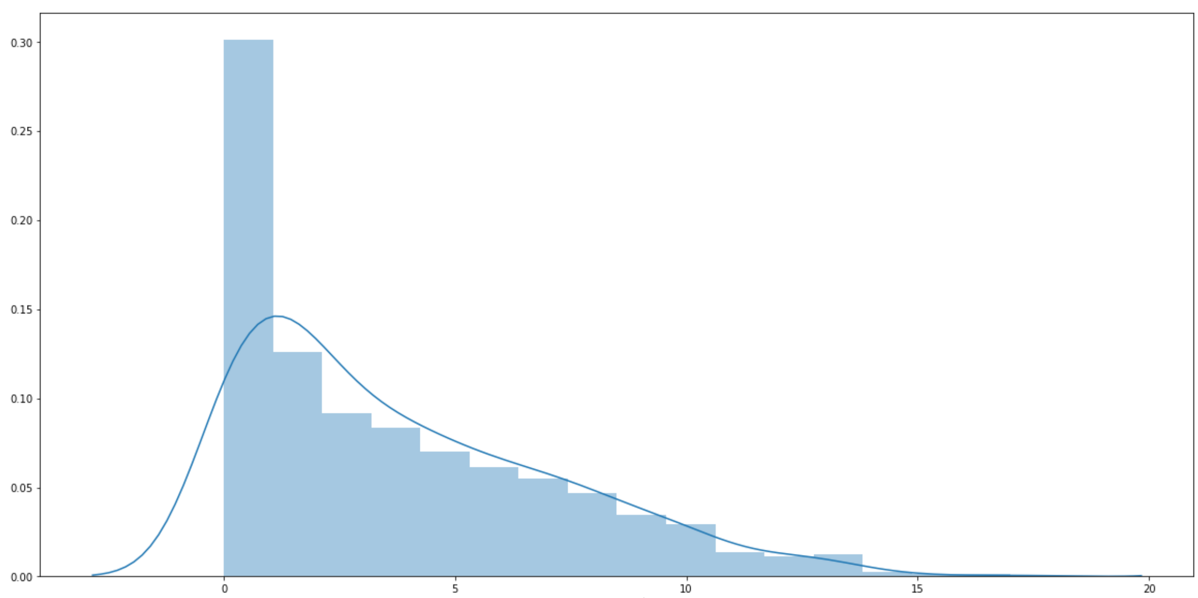
Valores únicos e sua ocorrência:

In [13]:
```
data_.groupby('n_pregnant').count().toPandas().sort_values(by='count', ascending=False)
```

Out[13]:

	n_pregnant	count
1	1	135
16	0	111
15	2	103
4	3	75
9	4	68
5	5	57
3	6	50
11	7	45
10	8	38
7	9	28
12	10	24
13	11	11
2	13	10
0	12	9
14	14	2
6	15	1
8	17	1

In [60]:
```
sns.distplot(data_.toPandas()["n_pregnant"]);
```



In [ ]:

Vamos fazer um teste de normalidade

In [15]:
```
from scipy import stats

x = data_.select('n_pregnant').toPandas()['n_pregnant']

k2, p = stats.normaltest(x)
alpha = 1e-3
print("p = {:g}".format(p))

if p < alpha:
      print("The null hypothesis can be rejected")
else:
      print("The null hypothesis cannot be rejected")
```

```
p = 3.91429e-18
The null hypothesis can be rejected
```

O teste rejeitou a hipotese nula, consequentemente a coluna "n_pregnant" não apresenta uma curva normal

Criando os modelos ML

Antes de começar o preprocessamento do Dataframe vamos treinar um modelo sem e verificar as metricas com os dados crus a fim de criar um benchmark

In [16]:
```
stages = []

label_stringIdx = StringIndexer(inputCol = 'class', outputCol = 'label')
stages += [label_stringIdx]
assemblerInputs = ['n_pregnant', 'age','plasma_glucose_concentration', 'blood_pressure','triceps_skinfold_thickness',
            '2hours_serum_insulin','body_mass_index', 'diabtes_pedigree_function']

assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
stages += [assembler]
```

In [17]:
```
cols = data_.columns

pipeline = Pipeline(stages = stages)
pipelineModel = pipeline.fit(data_)
data_ = pipelineModel.transform(data_)
selectedCols = ['label', 'features'] + cols
data_ = data_.select(selectedCols)
data_.printSchema()
```

```
root
 |-- label: double (nullable = false)
 |-- features: vector (nullable = true)
 |-- n_pregnant: integer (nullable = true)
 |-- plasma_glucose_concentration: float (nullable = true)
 |-- blood_pressure: float (nullable = true)
 |-- triceps_skinfold_thickness: float (nullable = true)
 |-- 2hours_serum_insulin: float (nullable = true)
 |-- body_mass_index: float (nullable = true)
 |-- diabtes_pedigree_function: float (nullable = true)
 |-- age: integer (nullable = true)
 |-- class: integer (nullable = true)
```

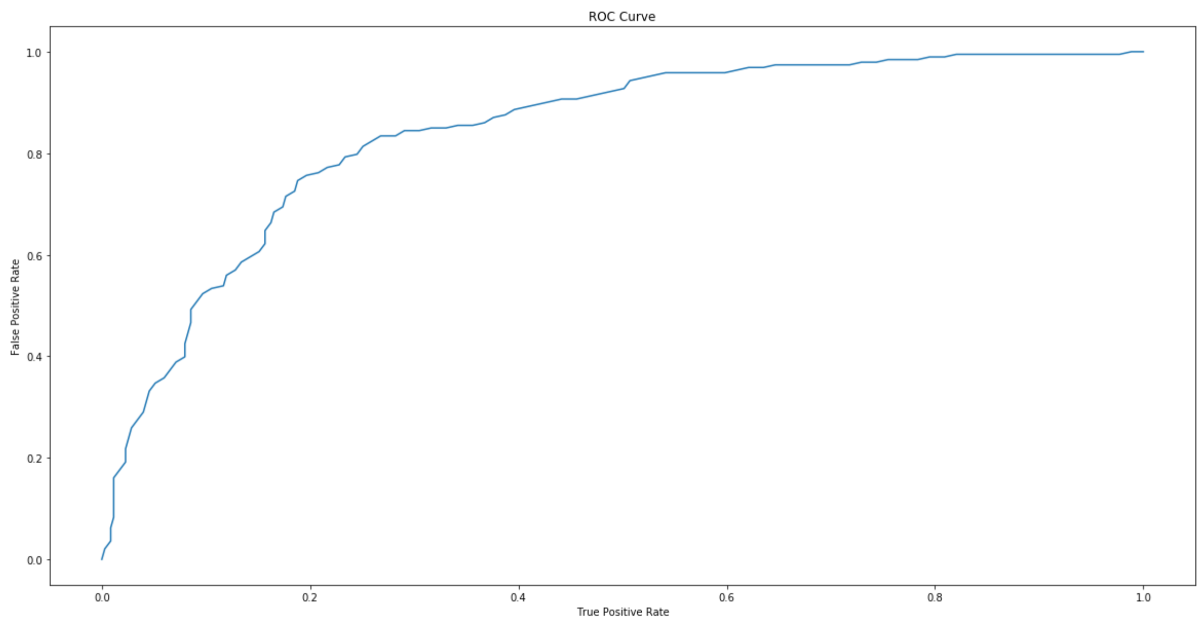
In [18]:
```
# Preparando pros modelos
train, test = data_.randomSplit([0.7, 0.3], seed = 2019)
print("Training Dataset Count: " + str(train.count()))
print("Test Dataset Count: " + str(test.count()))
```

```
Training Dataset Count: 544
Test Dataset Count: 224
```

Logistic Regression Model

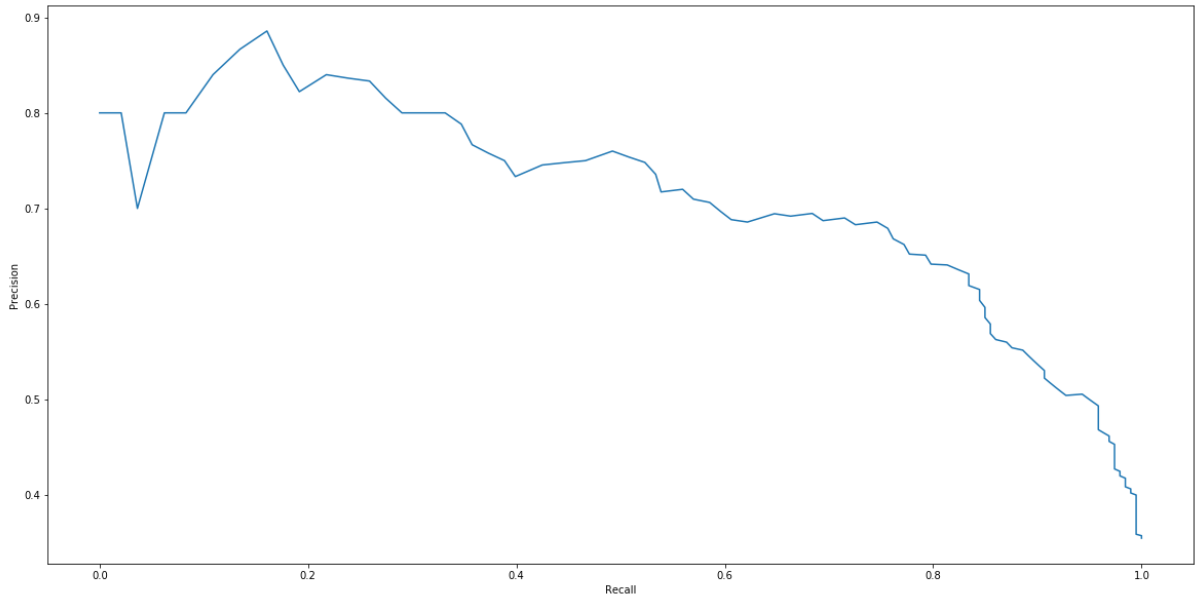
In [62]:
```
from pyspark.ml.classification import LogisticRegression
lr = LogisticRegression(featuresCol = 'features', labelCol = 'label', maxIter=
10)
lrModel = lr.fit(train)

trainingSummary = lrModel.summary
roc = trainingSummary.roc.toPandas()
plt.plot(roc['FPR'],roc['TPR'])
plt.ylabel('False Positive Rate')
plt.xlabel('True Positive Rate')
plt.title('ROC Curve')
plt.show()
print('Training set areaUnderROC: ' + str(trainingSummary.areaUnderROC))
```




```
Training set areaUnderROC: 0.8412677324594429
```

In [63]:
```
pr = trainingSummary.pr.toPandas()
plt.plot(pr['recall'],pr['precision'])
plt.ylabel('Precision')
plt.xlabel('Recall')
plt.show()
```



In [21]:
```
from pyspark.ml.evaluation import BinaryClassificationEvaluator

predictions = lrModel.transform(test)
evaluator = BinaryClassificationEvaluator()
print('Test Area Under ROC', evaluator.evaluate(predictions))
```

```
Test Area Under ROC 0.8171812080536911
```

Decision Tree Classifier

In [22]:
```
from pyspark.ml.classification import DecisionTreeClassifier

dt = DecisionTreeClassifier(featuresCol = 'features', labelCol = 'label', maxD
epth = 3)
dtModel = dt.fit(train)
predictions = dtModel.transform(test)
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions, {evaluator
.metricName: "areaUnderROC"})))
```

```
Test Area Under ROC: 0.720268456375839
```

Random Forest Classifier

In [23]:
```
from pyspark.ml.classification import RandomForestClassifier

rf = RandomForestClassifier(featuresCol = 'features', labelCol = 'label')
rfModel = rf.fit(train)
predictions = rfModel.transform(test)
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions, {evaluator
.metricName: "areaUnderROC"})))
```

```
Test Area Under ROC: 0.8136912751677854
```

Gradient-Boosted Tree Classifier

In [24]:
```
from pyspark.ml.classification import GBTClassifier

gbt = GBTClassifier(maxIter=10)
gbtModel = gbt.fit(train)
predictions = gbtModel.transform(test)
evaluator = BinaryClassificationEvaluator()
print("Test Area Under ROC: " + str(evaluator.evaluate(predictions, {evaluator
.metricName: "areaUnderROC"})))
```

```
Test Area Under ROC: 0.7434004474272928
```

Gradient-Boosted Tree Classifier + Cross Validator + Grid Search

In [25]:
```
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator
paramGrid = (ParamGridBuilder()
             .addGrid(gbt.maxDepth, [2, 4, 6])
             .addGrid(gbt.maxBins, [20, 60])
             .addGrid(gbt.maxIter, [10, 20])
             .build())
cv = CrossValidator(estimator=gbt, estimatorParamMaps=paramGrid, evaluator=eva
luator, numFolds=5)
# Run cross validations.  This can take about 6 minutes since it is training o
ver 20 trees!
cvModel = cv.fit(train)
predictions = cvModel.transform(test)
evaluator.evaluate(predictions)
```

Out[25]:
```
0.8207606263982102
```

Nosso Benchmark

> *Logistic Regression Model - Area Under ROC 0.8171812080536911*
>
> *Decision Tree Classifier - Area Under ROC: 0.720268456375839*
>
> *Random Forest Classifier - Area Under ROC: 0.8136912751677854*
>
> *Gradient-Boosted Tree Classifier - Area Under ROC: 0.7434004474272928*
>
> *Gradient-Boosted Tree Classifier + Cross Validator + Grid Search - Area Under ROC:0.8207606263982102*

Criando nosso modelo

Vamos desenvolver algumas funções de processamento, treinamento e teste, para que em seguida possamos rodar todas possibilidades de modelos, considerando varios tipos de processamento difernetes
Funções de processamento:

In [26]:
```
from pyspark.ml.classification import RandomForestClassifier
from pyspark.ml.classification import GBTClassifier
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml.classification import MultilayerPerceptronClassifier
from pyspark.ml.tuning import ParamGridBuilder, CrossValidator
from pyspark.ml.evaluation import BinaryClassificationEvaluator
from pyspark.mllib.evaluation import BinaryClassificationMetrics
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.feature import MinMaxScaler, StandardScaler
from pyspark.ml import Pipeline
from pyspark.sql import functions as f
```

> *Remover outliers*

In [44]:
```
# outliers_parameters = [False,'StdDev']

def remove_outliers(df, outliers_type):
    if outliers_type == 'StdDev':
        data = df.where(df.body_mass_index  > 10.0)
        data = data.where(data.triceps_skinfold_thickness  > 0)
        data = data.where(data['2hours_serum_insulin']  > 0 )
        data = data.where( data['2hours_serum_insulin']  < 350)
        return data

    else:
        return df
```

Fazer amostragem nas classes - balanceamento

In [28]:
```
#  sample_parameters = [False, True]

def balance_dataframe(df, sample_type):
    if sample_type == True:
        lenght = []
        sample_list = []
        lenght.append(df.filter(df['class'] == 1).count())
        lenght.append(df.filter(df['class'] == 0).count())
        sample_size = min(lenght)
        sample_list.extend(df.filter(df['class'] == 1).rdd.takeSample(False, s
ample_size, seed=0))
        sample_list.extend(df.filter(df['class'] == 0).rdd.takeSample(False, s
ample_size, seed=0))

        data = sqlContext.createDataFrame(sample_list)
        return data
    else:
        return df
```

Remover agrupamento de duplicados remanecentes

In [29]:
```
# remove_distinct_parameters = [False,['n_pregnant','2hours_serum_insulin', 'a
ge', 'class'],[ 'age', 'class']]

def remove_dinstinct(df, remove_distinct_type):
    if remove_distinct_type == False:
        return df
    else:
        data = df.drop_duplicates(subset=remove_distinct_type)
        return data
```

Normalizar valores - MinMax / Standalizer

In [30]:
```
# normalization_parameters = [False,'MinMax', 'Standalizer']


def normalize_dataframe(df, normalization_type):


    columns_to_scale = []
    stages = []

    for column in df.columns:
        if column == "class": continue
        columns_to_scale.append(column)

    if normalization_type == 'MinMax':


        label_stringIdx = StringIndexer(inputCol = 'class', outputCol = 'labe
l')
        stages += [label_stringIdx]
        pipeline = Pipeline(stages = stages)
        pipelineModel = pipeline.fit(df)
        df_result = pipelineModel.transform(df)

        assemblers = VectorAssembler(inputCols=columns_to_scale, outputCol="fe
atures_preprocessing")
        vector = assemblers.transform(df_result)
        standard_scaler = MinMaxScaler(inputCol="features_preprocessing", outp
utCol="features")
        train = standard_scaler.fit(vector).transform(vector)
        return train

    elif normalization_type == 'Standalizer':

        label_stringIdx = StringIndexer(inputCol = 'class', outputCol = 'labe
l')
        stages += [label_stringIdx]
        pipeline = Pipeline(stages = stages)
        pipelineModel = pipeline.fit(df)
        df_result = pipelineModel.transform(df)

        assemblers = VectorAssembler(inputCols=columns_to_scale, outputCol="fe
atures_preprocessing")
        vector = assemblers.transform(df_result)
        standard_scaler = StandardScaler(inputCol="features_preprocessing", ou
tputCol="features")
        train = standard_scaler.fit(vector).transform(vector)
        return train

    else:

        label_stringIdx = StringIndexer(inputCol = 'class', outputCol = 'labe
l')
        stages += [label_stringIdx]

        assembler = VectorAssembler(inputCols=columns_to_scale, outputCol="fea
tures")
```

```
        stages += [assembler]

        cols = df.columns

        pipeline = Pipeline(stages = stages)
        pipelineModel = pipeline.fit(df)
        df_result = pipelineModel.transform(df)
        selectedCols = ['label', 'features'] + cols
        df_result = df_result.select(selectedCols)
        return df_result
```

Modelos:

In [46]:
```
def apply_Logistic_Regression_Model(df):

    train, test = df.randomSplit([0.8, 0.2], seed = 2019)

    #tocar esssa linha
    model = LogisticRegression(featuresCol = 'features', labelCol = 'label', m
axIter=10)

    evaluator = BinaryClassificationEvaluator()

     # Create ParamGrid for Cross Validation
    paramGrid = (ParamGridBuilder()
             .addGrid(model.regParam,[0.02])
             .addGrid(model.elasticNetParam,[0.2])
             .build())

        # Create 5-fold CrossValidator
    cv = CrossValidator(estimator = model,
                        estimatorParamMaps = paramGrid,
                        evaluator = evaluator,
                        numFolds = 5)
    # Run cross validations.
    cvModel = cv.fit(train)


    # Use test set here so we can measure the accuracy of our model on new dat
a
    predictions = cvModel.transform(test)

    # cvModel uses the best model found from the Cross Validation
    # Evaluate best model
    acc = evaluator.evaluate(predictions)
    auc = BinaryClassificationMetrics(predictions['label','prediction'].rdd).a
reaUnderROC
    print('Accuracy:', acc)
    print('AUC:',auc)
    return acc, auc
```

In [47]:
```
def apply_Decision_Tree_Model(df):
    train, test = df.randomSplit([0.8, 0.2], seed = 2019)

    #tocar esssa linha
    model = DecisionTreeClassifier(featuresCol = 'features', labelCol = 'labe
l')

    evaluator = BinaryClassificationEvaluator()

     # Create ParamGrid for Cross Validation
    paramGrid = (ParamGridBuilder()
                 .addGrid(model.maxDepth, [2, 20])
                 .addGrid(model.maxBins, [10, 40])
                 .build())

        # Create 5-fold CrossValidator
    cv = CrossValidator(estimator = model,
                        estimatorParamMaps = paramGrid,
                        evaluator = evaluator,
                        numFolds = 5)
    # Run cross validations.
    cvModel = cv.fit(train)


    # Use test set here so we can measure the accuracy of our model on new dat
a
    predictions = cvModel.transform(test)

    # cvModel uses the best model found from the Cross Validation
    # Evaluate best model
    acc = evaluator.evaluate(predictions)
    auc = BinaryClassificationMetrics(predictions['label','prediction'].rdd).a
reaUnderROC
    print('Accuracy:', acc)
    print('AUC:',auc)
    return acc, auc
```

In [48]:
```
def apply_Random_Forest_Model(df):

    train, test = df.randomSplit([0.8, 0.2], seed = 2019)
    # Create an initial RandomForest model.
    model = RandomForestClassifier(labelCol="label", featuresCol="features")
    # Evaluate model
    evaluator = BinaryClassificationEvaluator()
    # Create ParamGrid for Cross Validation
    paramGrid = (ParamGridBuilder()
             .addGrid(model.maxDepth, [2 ])
             .addGrid(model.maxBins, [10,])
             .addGrid(model.numTrees, [5])
             .build())

    # Create 5-fold CrossValidator
    cv = CrossValidator(estimator = model,
                      estimatorParamMaps = paramGrid,
                      evaluator = evaluator,
                      numFolds = 5)
    # Run cross validations.
    cvModel = cv.fit(train)


    # Use test set here so we can measure the accuracy of our model on new dat
a
    predictions = cvModel.transform(test)

    # cvModel uses the best model found from the Cross Validation
    # Evaluate best model
    acc = evaluator.evaluate(predictions)
    auc = BinaryClassificationMetrics(predictions['label','prediction'].rdd).a
reaUnderROC
    print('Accuracy:', acc)
    print('AUC:', auc)
    return acc, auc
```

In [49]:
```
def apply_Gradient_BoostedT_Model(df):

    train, test = df.randomSplit([0.8, 0.2], seed = 2019)

    #tocar esssa linha
    model = GBTClassifier(featuresCol = 'features', labelCol = 'label', maxIte
r=10 )

    evaluator = BinaryClassificationEvaluator()

     # Create ParamGrid for Cross Validation
    paramGrid = (ParamGridBuilder()
             .addGrid(model.maxDepth, [2, ])
             .addGrid(model.maxBins, [20])
             .addGrid(model.maxIter, [10])
             .build())

        # Create 5-fold CrossValidator
    cv = CrossValidator(estimator = model,
                        estimatorParamMaps = paramGrid,
                        evaluator = evaluator,
                        numFolds = 5)
    # Run cross validations.
    cvModel = cv.fit(train)


    # Use test set here so we can measure the accuracy of our model on new dat
a
    predictions = cvModel.transform(test)

    # cvModel uses the best model found from the Cross Validation
    # Evaluate best model
    acc = evaluator.evaluate(predictions)
    auc = BinaryClassificationMetrics(predictions['label','prediction'].rdd).a
reaUnderROC
    print('Accuracy:', acc)
    print('AUC:',auc)
    return acc, auc
```

In [50]:
```
def apply_MultiLayer_Perceptron(df):
    train, test = df.randomSplit([0.8, 0.2], seed = 2019)

    model = MultilayerPerceptronClassifier(featuresCol = 'features', labelCol
= 'label')
    evaluator = BinaryClassificationEvaluator()
    paramGrid = (ParamGridBuilder()
        .addGrid(model.maxIter,[10, 20])
        .addGrid(model.stepSize ,[0.03, 0.01])
        .addGrid(model.solver ,['l-bfgs', 'gd'])
        .addGrid(model.layers, [[8, 12, 2], [8, 5, 2], [8, 5, 4, 2]])
        .build())

        # Create 5-fold CrossValidator
    cv = CrossValidator(estimator = model, estimatorParamMaps = paramGrid, eva
luator = evaluator, numFolds = 5)
    # Run cross validations.
    cvModel = cv.fit(train)


    # Use test set here so we can measure the accuracy of our model on new dat
a
    predictions = cvModel.transform(test)

    # cvModel uses the best model found from the Cross Validation
    # Evaluate best model
    acc = f
    evaluator.evaluate(predictions)
    auc = BinaryClassificationMetrics(predictions['label','prediction'].rdd).a
reaUnderROC
    print('Accuracy:', acc)
    print('AUC:',auc)
    return acc, auc
```

Ordem que as funções devem rodar

> *data = removeoutliers(data, outliers_tag)*
>
> *data = balance_dataframe(data, sample_tag)*
>
> *data = remove_dinstinct(data, remove_distinct_tag)*
>
> *data = normalize_dataframe(data, normalization_tag)*
>
> *apply_Logistic_Regression_Model(data)*

No codigo a baixo iremos fazer um loop entre todos metodos de processamento de modelos de machine learnin para encontrar qual o melhor pipeline de processamento/modelo para nosso conjunto de dados

In [51]:
```
from datetime import datetime
start = datetime.now()

# models = ["MLP","GBT","RDF","DCT","LGR"]


outliers_parameters = [False,'StdDev','DropCol']
sample_parameters = [False, True]
remove_distinct_parameters = [False,['n_pregnant','2hours_serum_insulin', 'ag
e', 'class'],[ 'age', 'class']]
normalization_parameters = [False,'MinMax', 'Standalizer']
models = ["RDF","LGR","GBT"]

result = []

for model in models:
    for outliers_tag in outliers_parameters:
        for sample_tag in sample_parameters:
            for remove_distinct_tag in remove_distinct_parameters:
                for normalization_tag in normalization_parameters:

                    dic = {}

                    data = remove_outliers(data_model, outliers_tag)
                    data = balance_dataframe(data, sample_tag)
                    data = remove_dinstinct(data, remove_distinct_tag)
                    data = normalize_dataframe(data, normalization_tag)

                    print(model)
                    if model == "MLP":
                        acc, auc = apply_MultiLayer_Perceptron(data)

                    elif model == "GBT":
                       acc, auc = apply_Gradient_BoostedT_Model(data)

                    elif model == "RDF":
                        acc, auc = apply_Random_Forest_Model(data)

                    elif model == "DCT":
                        acc, auc = apply_Decision_Tree_Model(data)

                    elif model == "LGR":
                        acc, auc = apply_Logistic_Regression_Model(data)

                    print(" ")
                    dic["Model Name"] = model
                    dic["outliers_tag"] = outliers_tag
                    dic["sample_tag"] = sample_tag
                    dic["remove_distinct_tag"] = remove_distinct_tag
                    dic["normalization_tag"] = normalization_tag
                    dic["Acuracia"] = acc
                    dic["AUC"] = auc
                    result.append(dic)


df = pd.DataFrame(result)
```

```
df = df.sort_values(by=['AUC'], ascending=False)

stop = datetime.now()
print('Time: ', stop - start)
```

```
RDF
Accuracy: 0.8453608247422681
AUC: 0.7697368421052632

RDF
Accuracy: 0.7912234042553192
AUC: 0.6758209822725951

RDF
Accuracy: 0.7912234042553192
AUC: 0.6758209822725951

RDF
Accuracy: 0.7703488372093023
AUC: 0.7881578947368422

RDF
Accuracy: 0.8031666666666665
AUC: 0.8331043956043955

RDF
Accuracy: 0.8031666666666665
AUC: 0.8331043956043955

RDF
Accuracy: 0.6212121212121212
AUC: 0.5833333333333334

RDF
Accuracy: 0.6262626262626262
AUC: 0.5625

RDF
Accuracy: 0.6262626262626262
AUC: 0.5625

RDF
Accuracy: 0.8359113712374582
AUC: 0.7317124735729387

RDF
Accuracy: 0.8292224080267557
AUC: 0.7609427609427609

RDF
Accuracy: 0.8292224080267557
AUC: 0.7609427609427609

RDF
Accuracy: 0.7361793611793612
AUC: 0.6512422360248447

RDF
Accuracy: 0.7751842751842751
AUC: 0.711111111111111

RDF
```

```
Accuracy: 0.7751842751842751
AUC: 0.711111111111111

RDF
Accuracy: 0.8
AUC: 0.775

RDF
Accuracy: 0.9861111111111112
AUC: 0.875

RDF
Accuracy: 0.9861111111111112
AUC: 0.875

RDF
Accuracy: 0.8771991555242786
AUC: 0.7384615384615384

RDF
Accuracy: 0.8496428571428571
AUC: 0.8082706766917294

RDF
Accuracy: 0.8496428571428571
AUC: 0.8082706766917294

RDF
Accuracy: 0.8968750000000001
AUC: 0.8875

RDF
Accuracy: 0.950625
AUC: 0.962962962962963

RDF
Accuracy: 0.950625
AUC: 0.962962962962963

RDF
Accuracy: 0.44696969696969696
AUC: 0.38636363636363635

RDF
Accuracy: 0.5857142857142856
AUC: 0.5347222222222222

RDF
Accuracy: 0.5857142857142856
AUC: 0.5347222222222222

RDF
Accuracy: 0.7391304347826086
AUC: 0.735

RDF
Accuracy: 0.8063241106719368
```

```
AUC: 0.7685185185185186

RDF
Accuracy: 0.8063241106719368
AUC: 0.7685185185185186

RDF
Accuracy: 0.8527667984189723
AUC: 0.7559288537549407

RDF
Accuracy: 0.8241106719367588
AUC: 0.8003952569169962

RDF
Accuracy: 0.8241106719367588
AUC: 0.8003952569169962

RDF
Accuracy: 0.8
AUC: 0.8125

RDF
Accuracy: 0.6666666666666666
AUC: 0.7857142857142857

RDF
Accuracy: 0.6666666666666666
AUC: 0.7857142857142857

RDF
Accuracy: 0.8453608247422681
AUC: 0.7697368421052632

RDF
Accuracy: 0.7912234042553192
AUC: 0.6758209822725951

RDF
Accuracy: 0.7912234042553192
AUC: 0.6758209822725951

RDF
Accuracy: 0.7703488372093023
AUC: 0.7881578947368422

RDF
Accuracy: 0.8031666666666665
AUC: 0.8331043956043955

RDF
Accuracy: 0.8031666666666665
AUC: 0.8331043956043955

RDF
Accuracy: 0.6212121212121212
AUC: 0.5833333333333334
```

```
RDF
Accuracy: 0.6262626262626262
AUC: 0.5625

RDF
Accuracy: 0.6262626262626262
AUC: 0.5625

RDF
Accuracy: 0.8359113712374582
AUC: 0.7317124735729387

RDF
Accuracy: 0.8292224080267557
AUC: 0.7609427609427609

RDF
Accuracy: 0.8292224080267557
AUC: 0.7609427609427609

RDF
Accuracy: 0.7361793611793612
AUC: 0.6512422360248447

RDF
Accuracy: 0.7751842751842751
AUC: 0.711111111111111

RDF
Accuracy: 0.7751842751842751
AUC: 0.711111111111111

RDF
Accuracy: 0.8
AUC: 0.775

RDF
Accuracy: 0.9861111111111112
AUC: 0.875

RDF
Accuracy: 0.9861111111111112
AUC: 0.875

LGR
Accuracy: 0.7993127147766323
AUC: 0.7573049987925623

LGR
Accuracy: 0.7429078014184399
AUC: 0.6794871794871794

LGR
Accuracy: 0.6914893617021277
AUC: 0.6462201591511936
```

```
LGR
Accuracy: 0.721576227390181
AUC: 0.8214285714285714

LGR
Accuracy: 0.7693333333333339
AUC: 0.717391304347826

LGR
Accuracy: 0.7403333333333332
AUC: 0.7083333333333334

LGR
Accuracy: 0.5858585858585857
AUC: 0.6499999999999999

LGR
Accuracy: 0.6565656565656565
AUC: 0.5625

LGR
Accuracy: 0.6363636363636364
AUC: 0.6499999999999999

LGR
Accuracy: 0.7391304347826085
AUC: 0.6599468320779797

LGR
Accuracy: 0.8189799331103679
AUC: 0.7541806020066888

LGR
Accuracy: 0.774247491638796
AUC: 0.7234800838574424

LGR
Accuracy: 0.6480343980343977
AUC: 0.5785984848484848

LGR
Accuracy: 0.6689189189189189
AUC: 0.6328029375764993

LGR
Accuracy: 0.6744471744471747
AUC: 0.5872015915119363

LGR
Accuracy: 0.5714285714285714
AUC: 0.4318181818181819

LGR
Accuracy: 0.6805555555555556
AUC: 0.5357142857142857

LGR
```

```
Accuracy: 0.7361111111111113
AUC: 0.5833333333333334

LGR
Accuracy: 0.7424349049964815
AUC: 0.6825396825396826

LGR
Accuracy: 0.7864285714285715
AUC: 0.7564935064935066

LGR
Accuracy: 0.7228571428571428
AUC: 0.7000000000000001

LGR
Accuracy: 0.7962500000000005
AUC: 0.7639225181598064

LGR
Accuracy: 0.89
AUC: 0.9166666666666667

LGR
Accuracy: 0.8700000000000003
AUC: 0.825

LGR
Accuracy: 0.7575757575757576
AUC: 0.6083333333333334

LGR
Accuracy: 0.8999999999999999
AUC: 0.7285714285714286

LGR
Accuracy: 0.8428571428571427
AUC: 0.7285714285714286

LGR
Accuracy: 0.6996047430830039
AUC: 0.7150000000000001

LGR
Accuracy: 0.7312252964426879
AUC: 0.7601214574898786

LGR
Accuracy: 0.7154150197628459
AUC: 0.6887351778656127

LGR
Accuracy: 0.7272727272727273
AUC: 0.66699604743083

LGR
Accuracy: 0.6818181818181819
```

```
AUC: 0.67

LGR
Accuracy: 0.6897233201581028
AUC: 0.67

LGR
Accuracy: 0.48
AUC: 0.2222222222222222

LGR
Accuracy: 0.625
AUC: 0.75

LGR
Accuracy: 0.45833333333333326
AUC: 0.0

LGR
Accuracy: 0.7993127147766323
AUC: 0.7573049987925623

LGR
Accuracy: 0.7429078014184399
AUC: 0.6794871794871794

LGR
Accuracy: 0.6914893617021277
AUC: 0.6462201591511936

LGR
Accuracy: 0.721576227390181
AUC: 0.8214285714285714

LGR
Accuracy: 0.7693333333333339
AUC: 0.717391304347826

LGR
Accuracy: 0.7403333333333332
AUC: 0.7083333333333334

LGR
Accuracy: 0.5858585858585857
AUC: 0.6499999999999999

LGR
Accuracy: 0.6565656565656565
AUC: 0.5625

LGR
Accuracy: 0.6363636363636364
AUC: 0.6499999999999999

LGR
Accuracy: 0.7391304347826085
AUC: 0.6599468320779797
```

LGR
Accuracy: 0.8189799331103679
AUC: 0.7541806020066888

LGR
Accuracy: 0.774247491638796
AUC: 0.7234800838574424

LGR
Accuracy: 0.6480343980343977
AUC: 0.5785984848484848

LGR
Accuracy: 0.6689189189189189
AUC: 0.6328029375764993

LGR
Accuracy: 0.6744471744471747
AUC: 0.5872015915119363

LGR
Accuracy: 0.5714285714285714
AUC: 0.4318181818181819

LGR
Accuracy: 0.6805555555555556
AUC: 0.5357142857142857

LGR
Accuracy: 0.7361111111111113
AUC: 0.5833333333333334

GBT
Accuracy: 0.8324169530355098
AUC: 0.7327127659574468

GBT
Accuracy: 0.8262411347517731
AUC: 0.6997549019607843

GBT
Accuracy: 0.8257978723404256
AUC: 0.6997549019607843

GBT
Accuracy: 0.8338178294573643
AUC: 0.7282608695652174

GBT
Accuracy: 0.8443333333333333
AUC: 0.8219533275713051

GBT
Accuracy: 0.8443333333333333
AUC: 0.8219533275713051

```
GBT
Accuracy: 0.6565656565656566
AUC: 0.696969696969697

GBT
Accuracy: 0.7828282828282829
AUC: 0.75

GBT
Accuracy: 0.7828282828282829
AUC: 0.75

GBT
Accuracy: 0.8520066889632106
AUC: 0.7670004171881519

GBT
Accuracy: 0.8808528428093647
AUC: 0.7874426366291197

GBT
Accuracy: 0.8808528428093647
AUC: 0.7874426366291197

GBT
Accuracy: 0.7733415233415232
AUC: 0.7361111111111112

GBT
Accuracy: 0.7733415233415232
AUC: 0.7361111111111112

GBT
Accuracy: 0.7571428571428571
AUC: 0.7571428571428572

GBT
Accuracy: 0.9305555555555555
AUC: 0.9090909090909091

GBT
Accuracy: 0.9305555555555555
AUC: 0.9090909090909091

GBT
Accuracy: 0.8662913441238564
AUC: 0.8712121212121212

GBT
Accuracy: 0.8492857142857142
AUC: 0.75

GBT
Accuracy: 0.8485714285714286
AUC: 0.75

GBT
```

```
Accuracy: 0.8706250000000001
AUC: 0.8101903695408734

GBT
Accuracy: 0.9012500000000004
AUC: 0.8607843137254902

GBT
Accuracy: 0.9012500000000004
AUC: 0.8607843137254902

GBT
Accuracy: 0.7272727272727273
AUC: 0.6439393939393939

GBT
Accuracy: 0.8785714285714286
AUC: 0.7916666666666667

GBT
Accuracy: 0.8785714285714286
AUC: 0.7916666666666667

GBT
Accuracy: 0.7885375494071146
AUC: 0.7351190476190477

GBT
Accuracy: 0.7658102766798419
AUC: 0.6887351778656127

GBT
Accuracy: 0.7658102766798419
AUC: 0.6887351778656127

GBT
Accuracy: 0.8448616600790514
AUC: 0.7559523809523809

GBT
Accuracy: 0.8043478260869567
AUC: 0.7114624505928854

GBT
Accuracy: 0.8043478260869567
AUC: 0.7114624505928854

GBT
Accuracy: 0.6799999999999999
AUC: 0.8125

GBT
Accuracy: 0.625
AUC: 0.625

GBT
Accuracy: 0.625
```

```
AUC: 0.625

GBT
Accuracy: 0.8324169530355098
AUC: 0.7327127659574468

GBT
Accuracy: 0.8262411347517731
AUC: 0.6997549019607843

GBT
Accuracy: 0.8257978723404256
AUC: 0.6997549019607843

GBT
Accuracy: 0.8338178294573643
AUC: 0.7282608695652174

GBT
Accuracy: 0.8443333333333333
AUC: 0.8219533275713051

GBT
Accuracy: 0.8443333333333333
AUC: 0.8219533275713051

GBT
Accuracy: 0.6565656565656566
AUC: 0.696969696969697

GBT
Accuracy: 0.7828282828282829
AUC: 0.75

GBT
Accuracy: 0.7828282828282829
AUC: 0.75

GBT
Accuracy: 0.8520066889632106
AUC: 0.7670004171881519

GBT
Accuracy: 0.8808528428093647
AUC: 0.7874426366291197

GBT
Accuracy: 0.8808528428093647
AUC: 0.7874426366291197

GBT
Accuracy: 0.7699631449631451
AUC: 0.7014742014742015

GBT
Accuracy: 0.7733415233415232
AUC: 0.7361111111111112
```

```
GBT
Accuracy: 0.7733415233415232
AUC: 0.7361111111111112

GBT
Accuracy: 0.7571428571428571
AUC: 0.7571428571428572

GBT
Accuracy: 0.9305555555555555
AUC: 0.9090909090909091

GBT
Accuracy: 0.9305555555555555
AUC: 0.9090909090909091

Time:  2:51:16.107462
```

In [54]:
```
df.head(15)
```

Out[54]:

	Model Name	outliers_tag	sample_tag	remove_distinct_tag	normalization_tag	Acuracia	AUC
22	RDF	StdDev	False	[n_pregnant, 2hours_serum_insulin, age, class]	MinMax	0.950625	0.96296
23	RDF	StdDev	False	[n_pregnant, 2hours_serum_insulin, age, class]	Standalizer	0.950625	0.96296
76	LGR	StdDev	False	[n_pregnant, 2hours_serum_insulin, age, class]	MinMax	0.890000	0.91666
124	GBT	False	True	[age, class]	MinMax	0.930556	0.90909
125	GBT	False	True	[age, class]	Standalizer	0.930556	0.90909
161	GBT	DropCol	True	[age, class]	Standalizer	0.930556	0.90909
160	GBT	DropCol	True	[age, class]	MinMax	0.930556	0.90909
21	RDF	StdDev	False	[n_pregnant, 2hours_serum_insulin, age, class]	False	0.896875	0.88750
52	RDF	DropCol	True	[age, class]	MinMax	0.986111	0.87500
53	RDF	DropCol	True	[age, class]	Standalizer	0.986111	0.87500
16	RDF	False	True	[age, class]	MinMax	0.986111	0.87500
17	RDF	False	True	[age, class]	Standalizer	0.986111	0.87500
126	GBT	StdDev	False	False	False	0.866291	0.87121
131	GBT	StdDev	False	[n_pregnant, 2hours_serum_insulin, age, class]	Standalizer	0.901250	0.86078
130	GBT	StdDev	False	[n_pregnant, 2hours_serum_insulin, age, class]	MinMax	0.901250	0.86078