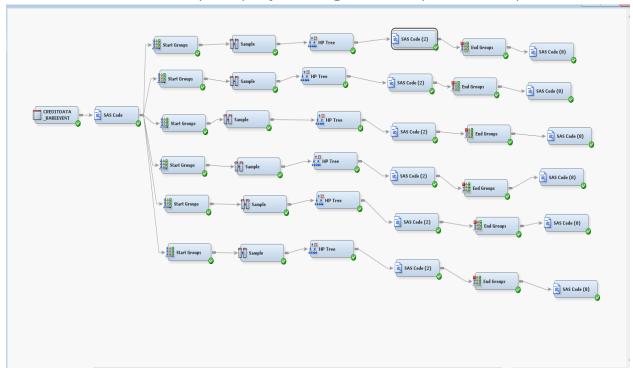
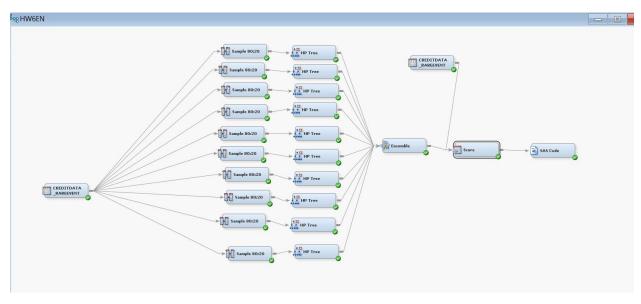
SAS solution

1. A screen shot of your project diagrams, step 1 and step 2





2. A screen shot or listing of SAS Code used inside one loop and all nodes outside the loop. Should be 3 screenshots.

SAS code 1

```
%let fprate = 1.00;
   %let fnrate = 0.15;
   Proc Datasets library=MyScores kill;
SAS code 2
   %let temp=myscores.temp50;
   %let score=myscores.score50;
   data &temp;
   RETAIN FP FN NBad NGood FPCost FNCost;
   KEEP N F Score Sensitivity Specificity MISSCLASS MISC FN NBad
      FP NGood FNR FPR TPR TNR FPCost FNCost Loss;
   set &EM IMPORT DATA END=EOF;
   if N EQ 1 then do;
      FN = 0;
      FP = 0;
      NBad = 0;
      NGood = 0;
      FPCost = 0;
      FNCost = 0;
   end;
   if Compare(Good_Bad, "bad", "i") EQ 0 then NBad = NBad + 1;
if Compare(Good_Bad, "good", "i") EQ 0 then NGood = Ngood + 1;
   if Compare(Good_Bad, I_Good_Bad, "i") NE 0 AND
      Compare(Good_Bad, "bad", "i") EQ 0 THEN DO;
            FP = FP + 1;
            FPCost = FPCost + &FPRate * AMOUNT;
   END;
   if Compare(Good_Bad, I_Good_Bad, "i") NE 0 AND
      Compare(Good_Bad, "good", "i") EQ 0 THEN DO;
            FN = FN + 1;
            FNCost = FNCost + &FNRate * AMOUNT;
   END;
   if EOF Then do;
      N = N;
      MissClass = FP + FN;
      FNR = FN / NGood;
      FPR = FP / Nbad;
      Misc = MissClass / N;
          = NGood - FN;
      TP
      TN = NBad - FP;
      TPR = TP / NGood;
      TNR = TN / NBad;
      Sensitivity = (TP)/(TP+FN);
      Specificity = (TN)/(TN+FP);
      F Score = 2*TP/(2*TP + FP + FN);
```

```
/*Adjust for size of "good" cases */
      FNCost = (10000/NGood) * FNCost;
   /*No adjustment needed for bad cases since
     all 500 of them are included in every
     sample */
      Loss = FPCost + FNCost ;
      output :
   end;
   proc append base= &score data= &temp;
   run;
SAS CODE 3
   %let p=50;
   proc means data=myscores.score&p;
   run;
SAS Code 4
  %let FPRate=1.0;
  %let FNRate=0.15;
   data mylib.score15;
   RETAIN FP FN NBad NGood FPCost FNCost;
   KEEP N F Score Sensitivity Specificity MISSCLASS MISC FN NBad
      FP NGood FNR FPR TPR TNR FPCost FNCost Loss;
   set &EM IMPORT SCORE END=EOF;
   if _N_ EQ 1 then do;
      FN = 0;
      FP = 0;
      NBad = 0;
     NGood = 0;
      FPCost = 0;
      FNCost = 0;
   end;
   if Compare(Good_Bad, "bad", "i") EQ 0 then NBad = NBad + 1;
   if Compare(Good_Bad, "good", "i") EQ 0 then NGood = Ngood + 1;
   if Compare(Good_Bad, EM_CLASSIFICATION, "i") NE 0 AND
      Compare(Good_Bad, "bad", "i") EQ 0 THEN DO;
           FP = FP + 1;
           FPCost = FPCost + &FPRate * AMOUNT;
   END;
   if Compare(Good_Bad, EM_CLASSIFICATION, "i") NE 0 AND
      Compare(Good_Bad, "good", "i") EQ 0 THEN DO;
            FN = FN + 1;
           FNCost = FNCost + &FNRate * AMOUNT;
   END;
   if EOF Then do;
      N = N;
     MissClass = FP + FN;
      FNR = FN / NGood;
      FPR = FP / Nbad;
     Misc = MissClass / N;
      TP = NGood - FN;
```

```
TN = NBad - FP;
TPR = TP / NGood;
TNR = TN / NBad;
Sensitivity = (TP)/(TP+FN);
Specificity = (TN)/(TN+FP);
F_Score = 2*TP/(2*TP + FP + FN);
/* no need to adjust FP cost because this is scoring the entire dataset */
Loss = FPCost + FNCost;
output;
end;
proc means data=mylib.score15;
run;
```

3. A table showing average loss and MISC for each ratio

Ratio	Loss	MISC
50:50	1500830.50	0.192
60:40	1139443.10	0.179
70:30	994540.50	0.162
75:25	792165.10	0.132
<mark>80:20</mark>	<mark>746225.90</mark>	<mark>0.083</mark>
85:15	792044.98	0.112

Chose the 80:20 ratio

4. A description of the total loss and MISC for the ensemble model calculated from the entire dataset, not the smaller ratio dataset.

Variable	N	Mean	Std Dev	Minimum	Maximum
FP	1	205.0000000		205.0000000	205.0000000
FN	1	59.0000000		59.0000000	59.0000000
NBad	1	500.0000000		500.0000000	500.0000000
NGood	1	10000.00		10000.00	10000.00
FPCost	1	541125.00		541125.00	541125.00
FNCost	1	89398.95		89398.95	89398.95
N	1	10500.00		10500.00	10500.00
MissClass	1	264.0000000		264.0000000	264.0000000
FNR	1	0.0059000		0.0059000	0.0059000
FPR	1	0.4100000		0.4100000	0.4100000
Misc	1	0.0251429		0.0251429	0.0251429
TPR	1	0.9941000		0.9941000	0.9941000
TNR	1	0.5900000		0.5900000	0.5900000
Sensitivity	1	0.9941000		0.9941000	0.9941000
Specificity	1	0.5900000		0.5900000	0.5900000
F Score	1	0.9868957		0.9868957	0.9868957
Loss	1	630523.95		630523.95	630523.95

Python Solution

```
from AdvancedAnalytics import ReplaceImputeEncode,calculate
from sklearn.tree import DecisionTreeClassifier
import math
import pandas as pd
import numpy as np
from imblearn.under_sampling import RandomUnderSampler
credit xlsx="CreditData RareEvent.xlsx"
credit_df = pd.read_excel(credit_xlsx)
attribute map = {
'age':['I',(1, 120),[0,0]],
'amount':['I',(0, 20000),[0,0]],
'duration':['I',(1,100),[0,0]],
'checking':['N',(1, 2, 3, 4),[0,0]],
'coapp':['N',(1,2,3),[0,0]],
'depends':['B',(1,2),[0,0]],
'employed':['N',(1,2,3,4,5),[0,0]],
'existcr':['N',(1,2,3,4),[0,0]],
'foreign':['B',(1,2),[0,0]],
'good_bad':['B',('bad', 'good'),[0,0]],
'history':['N',(0,1,2,3,4),[0,0]],
'housing':['N',(1, 2, 3), [0,0]],
'installp':['N',(1,2,3,4),[0,0]],
'job':['N',(1,2,3,4),[0,0]],
'marital':['N',(1,2,3,4),[0,0]],
```

```
'other':['N',(1,2,3),[0,0]],
'property':['N',(1,2,3,4),[0,0]],
'resident':['N',(1,2,3,4),[0,0]],
'savings':['N',(1,2,3,4,5),[0,0]],
'telephon':['B',(1,2),[0,0]] }
#Using RIE to replace and impute missing values and enocde attributes
rie = ReplaceImputeEncode(data map=attribute map,nominal encoding='one-hot',
                                                                interval_scale='std', drop=True, display=True)
encoded credit = rie.fit transform(credit df)
y = np.asarray(encoded_credit['good_bad']) # The target is not scaled or
imputed
X = np.asarray(encoded_credit.drop('good_bad',axis=1))
#Calculate potential loss for FP and FN
fp cost = np.array(credit df['amount'])
fn_cost = np.array(0.15 * credit_df['amount'])
#Create the ratio list for max:min
ratio = ['50:50','60:40','70:30','75:25','80:20','85:15']
rus ratio =
({0:500,1:500},{0:500,1:750},{0:500,1:1167},{0:500,1:1500},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:500,1:2000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:5000},{0:50
500,1:2833})
#Set up 10 random sample with different random seed
np.random.seed(12345)
\max \ \text{seed} = 2^{**}10 - 1
rand val = np.random.randint(1, high=max seed, size=10)
best ratio = 0
min loss = 1e64
best decTree =0
#Get the Best Tree Depth which minimize the loss
for k in range(len(rus ratio)):
          min loss d = 1e64
          best depth = 0
          print("\nDecesion Tree using " + ratio[k] + " RUS")
          for j in range(2,21):
                   d = j #Tree depth
                   fn_loss = np.zeros(len(rand_val))
                   fp_loss = np.zeros(len(rand_val))
                   misc = np.zeros(len(rand val))
                   for i in range(len(rand_val)):
```

```
rus =
RandomUnderSampler(ratio=rus_ratio[k], random_state=rand_val[i],
                                      return indices=False,replacement=False)
            X_rus, y_rus = rus.fit_sample(X, y)
            dtc = DecisionTreeClassifier(criterion='gini', max depth=d,
                              min_samples_split=5, min_samples_leaf=5)
            dtc.fit(X_rus,y_rus)
            loss, conf_mat = calculate.binary_loss(y, dtc.predict(X),
                                                     fp cost, fn cost,
display=False)
            fn_loss[i] = loss[0]
            fp_loss[i] = loss[1]
            misc[i] = (conf mat[1] + conf mat[2])/y.shape[0]
        avg_misc = np.average(misc) #Avg Missclassificaition rate
        t loss = fp loss+fn loss #Total Loss
        avg_loss = np.average(t_loss) #Avg Loss
        if avg loss < min loss d: #Get the least loss among the tree depth
            min loss d = avg loss
            se loss d = np.std(t loss)/math.sqrt(len(rand val))
            best_depth = d
            misc d = avg misc
            fn avg loss = np.average(fn loss)
            fp_avg_loss = np.average(fp_loss)
    if min_loss_d < min_loss:# Get the best ratio and the best depth tree</pre>
        min loss = min loss d
        se_loss = se_loss_d
        best ratio = k
        best decTree = best depth
    print("{:.<23s}{:d}".format("Best Depth", best_depth))</pre>
    print("{:.<23s}{:12.4f}".format("Misclassification Rate",misc_d))</pre>
    print("{:.<23s} ${:10,.0f}".format("False Negative Loss",fn_avg_loss))</pre>
    print("{:.<23s} ${:10,.0f}".format("False Positive Loss",fp_avg_loss))</pre>
    print("{:.<23s} ${:10,.0f}{:5s}${:<,.0f}".format("Total Loss",</pre>
          min_loss_d, " +/- ", se_loss_d))
print("")
print("{:.<23s}{:>12s}".format("Best RUS Ratio", ratio[best_ratio]))
print("{:.<23s}{:d}".format("Best Depth", best decTree))</pre>
print("{:.<23s} ${:10,.0f}{:5s}${:<,.0f}".format("Lowest Loss", \</pre>
min_loss, " +/-", se_loss))
#Ensemble Modelling
n obs = len(y)
n_rand = 100 # No of random samples to be selected out of the best
ratio(85:15)
predicted prob = np.zeros((n obs,n rand))
```

```
avg prob = np.zeros(n obs)
predicted_prob = np.zeros((n_obs,n_rand))
avg prob = np.zeros(n obs)
# Setup 100 random number seeds
np.random.seed(12345)
\max \ \text{seed} = 2^{**}20 - 1
rand_value = np.random.randint(1, high=max_seed, size=n_rand)
# Model 100 random samples- each with a Best ratio, which in our case is
85:15
for i in range(len(rand value)):
    rus = RandomUnderSampler(ratio=rus_ratio[best_ratio],
random state=rand value[i],
                             return_indices=False, replacement=False)
    X rus, y rus = rus.fit sample(X, y)
    dtc = DecisionTreeClassifier(criterion='gini', max_depth=best_decTree,
                             min samples split=5, min samples leaf=5)
    dtc.fit(X rus,y rus)
    predicted prob[0:n obs, i] = dtc.predict proba(X)[0:n obs, 0]
for i in range(n obs):
    avg_prob[i] = np.mean(predicted_prob[i,0:n_rand])
# Set y_pred equal to the predicted classification
y_pred = avg_prob[0:n_obs] < 0.5
y_pred.astype(np.int)
# Calculate loss from using the ensemble predictions
print("\nEnsemble Estimates based on averaging",len(rand_value), "Models")
loss, conf mat = calculate.binary loss(y, y pred, fp cost, fn cost)
```

PYTHON RESULTS

```
Decesion Tree using 50:50 RUS

Best Depth............16

Misclassification Rate. 0.2294

False Negative Loss.... $ 1,235,474

False Positive Loss.... $ 127,819

Total Loss............ $ 1,363,293 +/- $33,292

Decesion Tree using 60:40 RUS

Best Depth.............20
```

Misclassification Rate. 0.1613
False Negative Loss.... \$ 886,420
False Positive Loss.... \$ 164,850

Total Loss...... \$ 1,051,271 +/- \$23,579

Decesion Tree using 70:30 RUS

Best Depth.....19

Misclassification Rate. 0.0984
False Negative Loss.... \$ 521,994
False Positive Loss.... \$ 209,416

Total Loss...... \$ 731,410 +/- \$23,112

Decesion Tree using 75:25 RUS

Best Depth.....20

Misclassification Rate. 0.0801
False Negative Loss.... \$ 393,880
False Positive Loss.... \$ 208,579
Total Loss

Total Loss...... \$ 602,460 +/- \$16,842

Decesion Tree using 80:20 RUS

Best Depth.....17

Misclassification Rate. 0.0602
False Negative Loss.... \$ 302,752
False Positive Loss.... \$ 210,330

Total Loss...... \$ 513,082 +/- \$16,155

Decesion Tree using 85:15 RUS

Best Depth.....18

Misclassification Rate. 0.0394
False Negative Loss.... \$ 179,630
False Positive Loss.... \$ 260,525

Total Loss......\$ 440,155 +/- \$13,332

Best RUS Ratio....... 85:15

Best Depth.....18

Lowest Loss...... \$ 440,155 +/- \$13,332

Ensemble Estimates based on averaging 100 Models