0.) Import and Clean data

```
In [1]:
          H
                 import pandas as pd
                 import matplotlib.pyplot as plt
               2
                 import numpy as np
                 from sklearn.linear model import LogisticRegression
In [2]:
                 from sklearn.tree import DecisionTreeClassifier
              3
                 from sklearn.ensemble import BaggingClassifier
                 from sklearn.datasets import make_classification
                 from sklearn.metrics import accuracy score
                 from sklearn.model selection import train test split
              7
                 from sklearn.preprocessing import StandardScaler
                 from sklearn.tree import plot tree
                 from sklearn.metrics import confusion matrix
             10
                 import seaborn as sns
             11 from sklearn.tree import DecisionTreeClassifier
                 from sklearn.ensemble import BaggingClassifier
             13 from sklearn.metrics import accuracy score
             14 from sklearn.preprocessing import StandardScaler
                 from sklearn.model selection import train test split
                 from sklearn.discriminant analysis import QuadraticDiscriminantAnalysi
                 df = pd.read csv("bank.csv", sep = ";")
In [3]:
                 df.head()
In [4]:
   Out[4]:
                                marital education default balance housing
                age
                                                                        loan
                                                                              contact day
              0
                 30
                     unemployed
                                married
                                          primary
                                                     no
                                                           1787
                                                                     no
                                                                          no
                                                                               cellular
                                                                                       19
              1
                 33
                        services married
                                       secondary
                                                    no
                                                           4789
                                                                    yes
                                                                         yes
                                                                               cellular
                                                                                       11
              2
                 35
                    management
                                 single
                                          tertiary
                                                           1350
                                                                               cellular
                                                                                       16
                                                    no
                                                                    yes
                                                                          no
              3
                    management married
                                          tertiary
                                                           1476
                                                                             unknown
                                                                                        3
                                                     no
                                                                    ves
                                                                         ves
                 59
                       blue-collar married secondary
                                                             0
                                                                             unknown
                                                                                       5
                                                                    yes
                                                     no
                                                                          no
In [5]:
                 df.columns
   Out[5]: Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housi
             ng',
                    'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pday
             s',
                     'previous', 'poutcome', 'y'],
                   dtype='object')
```

```
df = df.drop(["default", "pdays", "previous", "poutcome"], axis = 1)
In [6]:
          M
                  df = pd.get_dummies(df, columns = ["loan", "job", "marital", "housing",
               2
               3
                  df.head()
In [7]:
               1
    Out[7]:
                                                         job_blue-
                 age balance day duration
                                             y loan_yes
                                                                   job_entrepreneur job_housemaid
                                                             collar
                         1787
                                                                0
              0
                  30
                               19
                                        79 no
                                                      0
                                                                                 0
                                                                                               0
              1
                  33
                         4789
                                       220 no
                                                                0
                                                                                 0
                                                                                               0
                                11
                                                       1
              2
                  35
                         1350
                                                      0
                                                                0
                                                                                 0
                                                                                               0
                                16
                                       185 no
               3
                  30
                         1476
                                 3
                                       199 no
                                                                0
                                                                                 0
                                                                                               0
                                                                                 0
                                                                                               0
               4
                  59
                            0
                                 5
                                       226 no
                                                      0
                                                                1
              5 rows × 67 columns
In [8]:
                  y = pd.get_dummies(df["y"], drop_first = True)
          H
                  X = df.drop(["y"], axis = 1)
In [ ]:
          H
               1
In [9]:
                  obs = len(y)
          H
               1
                  plt.bar(["No","Yes"],[len(y[y.yes==0])/obs,len(y[y.yes==1])/obs])
               2
                  plt.ylabel("Percentage of Data")
                  plt.show()
                 0.8
              Percentage of Data
                 0.6
                 0.4
                 0.2
                 0.0
```

Yes

No

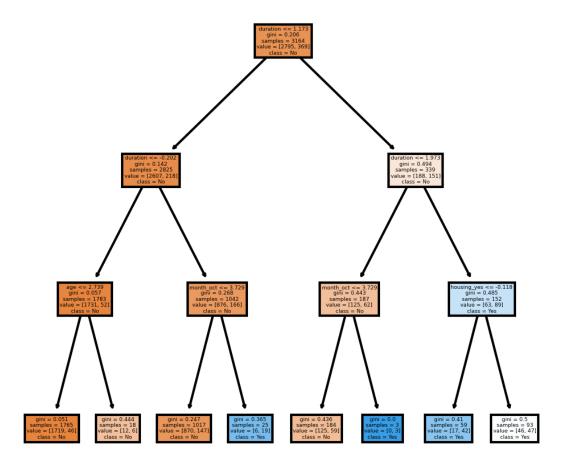
#1.) Based on the visualization above, use your expert opinion to transform the data based on what we learned this quarter

2.) Build and visualize a decision tree of Max Depth 3. Show the confusion matrix.

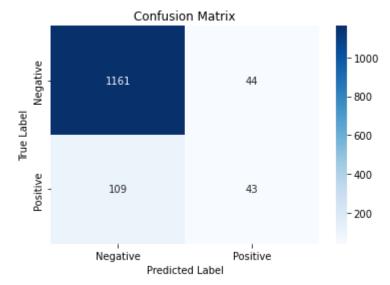
dtype: float64

```
In [13]:
                                                                    fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)
                                                                     plot tree(dtree, filled = True, feature names = X.columns, class names
                                                          2
                                                          3
                                                          4
                                                                     #fig.savefig('imagename.png')
                                                           5
               Out[13]: [Text(0.5, 0.875, 'duration <= 1.173\ngini = 0.206\nsamples = 3164\nvalue</pre>
                                                    = [2795, 369]\nclass = No'),
                                                       Text(0.25, 0.625, 'duration <= -0.202\ngini = 0.142\nsamples = 2825\nval
                                                    ue = [2607, 218] \setminus nclass = No'),
                                                       Text(0.125, 0.375, 'age <= 2.739 \cdot 10^{-2} = 0.057 \cdot 10^{-2} = 1783 \cdot 10
                                                    [1731, 52]\nclass = No'),
                                                       Text(0.0625, 0.125, 'gini = 0.051\nsamples = 1765\nvalue = [1719, 46]\nc
                                                    lass = No'),
                                                       Text(0.1875, 0.125, 'gini = 0.444\nsamples = 18\nvalue = [12, 6]\nclass
                                                    = No'),
                                                       Text(0.375, 0.375, 'month oct <= 3.729\ngini = 0.268\nsamples = 1042\nva
                                                    lue = [876, 166]\nclass = No'),
                                                       Text(0.3125, 0.125, 'gini = 0.247\nsamples = 1017\nvalue = [870, 147]\nc
                                                    lass = No'),
                                                       Text(0.4375, 0.125, 'gini = 0.365\nsamples = 25\nvalue = [6, 19]\nclass
                                                    = Yes'),
                                                       Text(0.75, 0.625, 'duration <= 1.973 \cdot 10^{-2} | Text(
                                                    = [188, 151]\nclass = No'),
                                                       Text(0.625, 0.375, 'month oct <= 3.729\ngini = 0.443\nsamples = 187\nval
                                                    ue = [125, 62]\nclass = No'),
                                                       Text(0.5625, 0.125, 'gini = 0.436\nsamples = 184\nvalue = [125, 59]\ncla
                                                    ss = No'),
                                                       Text(0.6875, 0.125, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]\nclass = Ye
                                                    s'),
                                                       Text(0.875, 0.375, 'housing_yes <= -0.118\ngini = 0.485\nsamples = 152\n
                                                    value = [63, 89]\nclass = Yes'),
                                                       Text(0.8125, 0.125, 'gini = 0.41\nsamples = 59\nvalue = [17, 42]\nclass
                                                    = Yes'),
                                                       Text(0.9375, 0.125, 'gini = 0.5\nsamples = 93\nvalue = [46, 47]\nclass =
```

Yes')]



1b.) Confusion matrix on out of sample data. Visualize and store as variable



3.) Use bagging on your descision tree

```
In [16]:
               1 \# X = X \text{ train}
                  # y = y_train
               3
                 # Create and fit bagging classifier
                  dtree = DecisionTreeClassifier(max depth=3)
                  bagging = BaggingClassifier(base_estimator=dtree, n_estimators=100, ma
               7
                  bagging.fit(X_train, y_train)
               8
               9
                 # Predict and evaluate
              10 y_pred = bagging.predict(X_test)
              11 | accuracy = accuracy_score(y_test, y_pred)
              12 print("Accuracy:", accuracy)
              13
```

C:\Users\parzu\anaconda3\lib\site-packages\sklearn\ensemble_bagging.py:7
19: DataConversionWarning: A column-vector y was passed when a 1d array w as expected. Please change the shape of y to (n_samples,), for example u sing ravel().

```
y = column_or_1d(y, warn=True)
```

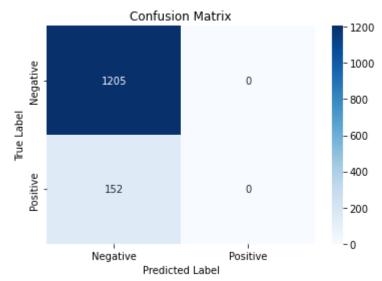
Accuracy: 0.887988209285188

C:\Users\parzu\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarni
ng: X does not have valid feature names, but BaggingClassifier was fitted
with feature names

warnings.warn(

C:\Users\parzu\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarni
ng: X does not have valid feature names, but BaggingClassifier was fitted
with feature names

warnings.warn(



4.) Boost your tree

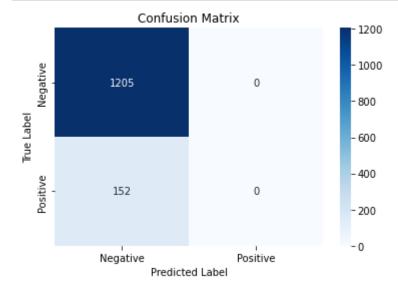
C:\Users\parzu\anaconda3\lib\site-packages\sklearn\utils\validation.py:99
3: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().

y = column_or_1d(y, warn=True)

C:\Users\parzu\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarni
ng: X does not have valid feature names, but AdaBoostClassifier was fitte
d with feature names

warnings.warn(

C:\Users\parzu\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarni
ng: X does not have valid feature names, but AdaBoostClassifier was fitte
d with feature names
warnings.warn(



Out[23]: 0.888

5.) Create a superlearner with at least 5 base learner models. Use a logistic reg for your metalearner. Interpret your coefficients and save your CM.

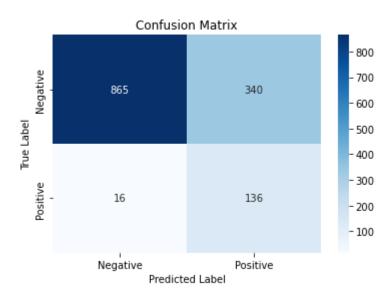
```
In [25]:
           H
                  from sklearn.linear model import LogisticRegression
                   from sklearn.ensemble import RandomForestClassifier
                3
                  ####IMPORT MORE BASE LEARNERS####
                4
                  from mlens.ensemble import SuperLearner
In [109]:
                  # # ### SET YOUR BASE LEARNERS
           H
                1
                2
                  # base estimaters = [
                3
                        LogisticRegression()
                4
                  # # ]
                5
                6
                  # # super_learner = SuperLearner ()
                7
                  # # super_learner.add(base_estimaters )
                8
                  # # ### FIT TO TRAINING DATA
               10 # # super_learner.fit(X_train, y_train)
               11 # # ### GET base predictions
               12
               13
                  # # base_predictions = super_learner.fit(X_train)
  In [ ]:
           H
                1
 In [26]:
                  from sklearn.linear_model import LogisticRegression
                  from sklearn.tree import DecisionTreeClassifier
                  from sklearn.ensemble import RandomForestClassifier, GradientBoosting(
                  from mlens.ensemble import SuperLearner
                5 from sklearn.metrics import confusion matrix
                6 | from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysi
                  from sklearn.svm import SVC
```

```
In [29]:
                  base estimators = [ RandomForestClassifier(random state=101), Gradient
                3
                  super learner = SuperLearner(folds=10, random state=42)
                  super learner.add(base estimators)
                  super_learner.fit(X_scaled, y_train)
                  base predictions = super learner.predict(X test)
                8
                return selt._tit(X, y)
              C:\Users\parzu\anaconda3\lib\site-packages\sklearn\neighbors\ classifi
              cation.py:198: DataConversionWarning: A column-vector y was passed whe
              n a 1d array was expected. Please change the shape of y to (n sample
              s,), for example using ravel().
                return self. fit(X, y)
              C:\Users\parzu\anaconda3\lib\site-packages\sklearn\neighbors\ classifi
              cation.py:198: DataConversionWarning: A column-vector y was passed whe
              n a 1d array was expected. Please change the shape of y to (n sample
              s,), for example using ravel().
                return self._fit(X, y)
              C:\Users\parzu\anaconda3\lib\site-packages\sklearn\neighbors\ classifi
              cation.py:198: DataConversionWarning: A column-vector y was passed whe
              n a 1d array was expected. Please change the shape of y to (n sample
              s,), for example using ravel().
                return self. fit(X, y)
              C:\Users\parzu\anaconda3\lib\site-packages\sklearn\utils\validation.p
              y:993: DataConversionWarning: A column-vector y was passed when a 1d a
              rray was expected. Please change the shape of y to (n samples, ), for
              example using ravel().
In [119]:
                  ### TRAIN YOUR METALEARNER
In [30]:
           H
                  # Preprocess X test
                  base predictions test = super learner.predict(X test)
                1 y train.values.reshape(len(y train),).shape
In [31]:
    Out[31]: (3164,)
In [32]:
                  base predictions
    Out[32]: array([[0., 0., 1., 0., 0.],
                     [0., 0., 1., 0., 0.],
                     [0., 0., 1., 0., 0.],
                     [0., 0., 1., 0., 0.],
                     [0., 0., 1., 0., 0.],
                     [0., 0., 1., 0., 0.]], dtype=float32)
```

```
In [34]:
               1 X scaled.shape
   Out[34]: (3164, 66)
                 X test.shape
In [35]:
   Out[35]: (1357, 66)
                 Log reg = LogisticRegression(fit intercept = False).fit(X scaled,y tra
In [36]:
                 y_pred = Log_reg.predict(X_test)
 In [ ]:
                 ### INTERPRET COEFFICIENTS
In [41]:
                 Log_reg.coef_
   Out[41]: array([[ 2.99482647e-02, -2.07906128e-02, 5.25933838e-02,
                      7.23533812e-01, -5.74514805e-02, -8.04015134e-02,
                     -5.42396930e-02, -1.36875158e-02, -3.83995673e-02,
                      3.60674360e-02, -1.61779931e-02, -3.71929050e-02,
                      2.50415602e-02, -4.36219942e-02, -6.79631027e-02,
                      1.06432242e-02, -7.97132721e-02, -4.15474785e-02,
                     -6.07221985e-02, 1.89421162e-02, -1.86813553e-01,
                     -6.73457975e-02, -3.66996359e-02, -1.10929490e-03,
                     -3.06184205e-02, -1.81181958e-02, -1.57524856e-02,
                     -1.77253008e-02, 1.63732997e-03, -2.19696958e-02,
                     -3.37525124e-03, -8.23646052e-03, -1.00219752e-03,
                     -9.34799995e-03, -7.44656399e-03, -9.33704216e-03,
                      9.92128396e-03, 9.27480760e-03, -1.23920699e-02,
                     -4.28404898e-02, 3.83989939e-03, -1.80772529e-02,
                     -9.99484937e-03, -3.81974867e-04, 5.32158876e-03,
                     -1.97283851e-02, 7.82176181e-04, 3.66060762e-03,
                      9.54145314e-03, 1.71400261e-03, 5.56776161e-03,
                      5.97370942e-03, -9.30571705e-02, 6.06659618e-02,
                      1.21674990e-03, -5.88368805e-02, -1.33298178e-01,
                      4.32922016e-02, 1.48996578e-01, -9.96601459e-02,
                     -9.39024136e-02, 2.39218625e-01, 7.58023383e-02,
                      2.01032260e-02, 7.36824974e-02, -2.70084716e-02]])
```

Each component of this array reflects the weight or coefficient of the related feature in the logistic regression model.

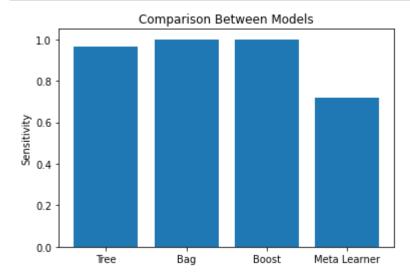
Metal Learner Accuracy: 0.737656595431098



6.) Create a bar chart comparing decision tree, bagged, boosted and super learner Sensitivities (Out of Sample)

Sensitivity: 0.7178423236514523 Specificity: 0.8947368421052632

```
In [52]:
                  sen_raw = cm_raw[0,0]/(cm_raw[0,0]+cm_raw[0,1])
               2
                  spec_raw = cm_raw[1,1]/(cm_raw[1,0]+cm_raw[1,1])
               3
               4
                 # Bagging
               5
                 sen_bag = cm_bag[0,0]/(cm_bag[0,0]+cm_bag[0,1])
                  spec_bag = cm_bag[1,1]/(cm_bag[1,0]+cm_bag[1,1])
               7
               8
                 # Boosting
               9
                 sen\_boost = cm\_boost[0,0]/(cm\_boost[0,0]+cm\_boost[0,1])
                 spec_boost = cm_boost[1,1]/(cm_boost[1,0]+cm_boost[1,1])
              10
              11
              12
                 # meta Learner
                 sen_SL = cm2[0,0]/(cm2[0,0]+cm2[0,1])
              13
                 spec_SL = cm2[1,1]/(cm2[1,0]+cm2[1,1])
```



```
In []: N 1

In []: N 1

In []: N 1

In []: N 1
```