CMPE 480 HOMEWORK 4 REPORT

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Information about Dataset

In the project I used the Loan Approval Classification Dataset from Kaggle. The dataset includes 13 features and 1 target variable. The target is a binary field, 0 stands for rejection of the loan and 1 stands for approval. Features include information about the person who made the loan offer such as age, gender, income, home ownership, credit score. Some of these fields are continuous fields however the model I implemented can handle only categorical data. Therefore, I had to encode these fields to 5 classes using the *qcut* function numpy in order to be able to run the model on the data.

Usage of 5-fold Cross-Validation

In order to apply hyperparameter tuning with cross-validation, I had to add parameters to the class. I tried to choose my parameters in a way that will reduce fallouts and added <code>max_depth</code> (limits the depth of the tree) and <code>min_samples_split</code> (minimum number of samples for a node to be allowed to get split). These parameters have default values which makes them uninfluential on the model. In implementation, I tried to keep my model as similar to the decision tree classifier of scikit-learn as possible so I named everything with the same names as the library.

I implemented cross-validation as a method under the *DecisionTree* class. The method accepts only *max_depth* and *min_samples_split* as parameters, else it raises error. If one or two of these parameters are not specified by the user it assigns them with the default value.

Then the method operates as follows:

- One combination of max depth and min samples split is chosen
- The data is split to 5 pieces of equal size.
- 1 of the pieces is named as the validation set and union of other 4 pieces is named the training set.
- Accuracy on the validation set is calculated.
- Step 3 and 4 are applied to other 4 pieces too.
- Average accuracy is calculated. If it is higher than the previous best *max_depth* and *min samples split* kept as the best parameters.
- All the steps above are applied to all parameter combinations.
- The method returns the best parameters

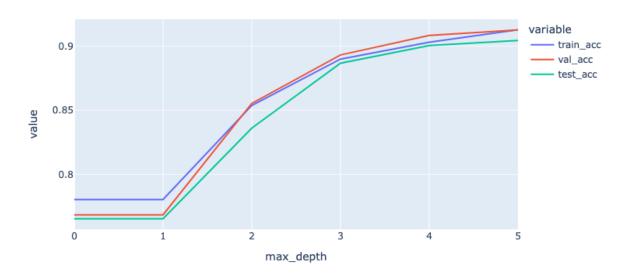
With the default values of the model, the accuracy on the test data was approximately 0.869. After applying hyperparameter tuning with cross-validation I reached the accuracy of 0.905 which is a valuable increase in these levels of accuracies and also I had a simpler model with maximum depth of 5 and minimum 60 samples for nodes which are split.

Note: Since the algorithm doesn't work fast with cross-validation, I firstly created a parameter grid with large differences between values then narrowed it down depending on the output. Therefore, in the source code you may see a narrow range of values.

Error Plots

In the optimum model, maximum depth is 5. Therefore, to see the improvement I created this plot using increasing values for *max depth* until reaching 5

Accuracy vs. Depth



Best Decision Tree

```
Leaf: predicts 0
Value = (59456.0, 76436.8]:
Split on feature: cb_person_cred_hist_length
Value = (76436.8, 103841.0]:
    Value = HOMEIMPROVEMENT:
Split on feature: person home ownership
Split on feature: person income
```

```
Value = (7999.999, 43081.8]:
   Value = (43081.8, 59456.0]:
   Value = (59456.0, 76436.8]:
   Value = (103841.0, 7200766.0]:
Value = EDUCATION:
Split on feature: person_income
   Value = (43081.8, 59456.0]:
   Value = (103841.0, 7200766.0]:
Value = HOMEIMPROVEMENT:
Split on feature: person_income
   Value = (59456.0, 76436.8]:
   Value = (76436.8, 103841.0]:
```

```
Leaf: predicts 1
Split on feature: person age
```

```
Value = (23.0, 25.0]:
Split on feature: person income
   Value = (43081.8, 59456.0]:
   Value = (59456.0, 76436.8]:
Value = PERSONAL:
Split on feature: person education
```

```
Split on feature: loan_intent
   Value = EDUCATION:
    Split on feature: person income
       Value = (76436.8, 103841.0]:
```

```
Value = (10000.0, 14520.2]:
Split on feature: person_age
Value = EDUCATION:
Split on feature: person_home_ownership
```

```
Leaf: predicts 0
Value = HOMEIMPROVEMENT:
   Value = (76436.8, 103841.0]:
   Value = (103841.0, 7200766.0]:
Split on feature: person_income
   Value = (59456.0, 76436.8]:
Split on feature: person home ownership
Split on feature: person_income
```

```
Value = (59456.0, 76436.8]:
       Value = (76436.8, 103841.0]:
       Value = (103841.0, 7200766.0]:
Split on feature: person income
       Value = EDUCATION:
       Value = PERSONAL:
    Value = (43081.8, 59456.0]:
    Split on feature: person_age
```

```
Leaf: predicts 0
   Value = EDUCATION:
   Value = HOMEIMPROVEMENT:
   Value = VENTURE:
Value = (103841.0, 7200766.0]:
   Value = HOMEIMPROVEMENT:
```

```
Value = (43081.8, 59456.0]:
   Value = DEBTCONSOLIDATION:
   Value = EDUCATION:
   Value = HOMEIMPROVEMENT:
Value = (59456.0, 76436.8]:
   Value = HOMEIMPROVEMENT:
   Value = PERSONAL:
Value = (76436.8, 103841.0]:
Split on feature: person home ownership
```

```
Leaf: predicts 0
Split on feature: person home ownership
       Value = EDUCATION:
       Value = HOMEIMPROVEMENT:
       Value = PERSONAL:
       Value = VENTURE:
   Split on feature: person age
    Value = DEBTCONSOLIDATION:
```

```
Value = (652.0, 676.0]:
Value = EDUCATION:
Split on feature: person_income
   Value = (43081.8, 59456.0]:
   Value = (59456.0, 76436.8]:
   Value = (76436.8, 103841.0]:
   Value = (59456.0, 76436.8]:
Split on feature: person home ownership
```

```
Leaf: predicts 0
Split on feature: person income
   Value = (43081.8, 59456.0]:
Value = DEBTCONSOLIDATION:
Split on feature: cb_person_cred_hist_length
Value = EDUCATION:
   Value = (43081.8, 59456.0]:
   Value = (59456.0, 76436.8]:
Split on feature: person income
```

```
Value = (43081.8, 59456.0]:
           Value = (59456.0, 76436.8]:
           Value = (76436.8, 103841.0]:
        Value = PERSONAL:
        Split on feature: person income
           Value = (43081.8, 59456.0]:
           Value = (76436.8, 103841.0]:
           Value = (103841.0, 7200766.0]:
        Split on feature: person_home_ownership
           Value = RENT:
Split on feature: loan_int_rate
```

```
Split on feature: loan_amnt
       Value = EDUCATION:
       Value = HOMEIMPROVEMENT:
       Value = VENTURE:
       Value = RENT:
   Value = (14520.2, 35000.0]:
```

```
Value = (591.0, 626.0]:
   Value = HOMEIMPROVEMENT:
   Value = DEBTCONSOLIDATION:
   Value = HOMEIMPROVEMENT:
   Value = PERSONAL:
Split on feature: person_gender
Split on feature: person_age
```

```
Leaf: predicts 0
Value = EDUCATION:
Value = PERSONAL:
Value = VENTURE:
Value = HOMEIMPROVEMENT:
```

```
Value = MEDICAL:
Value = PERSONAL:
Value = HOMEIMPROVEMENT:
Value = HOMEIMPROVEMENT:
Value = PERSONAL:
```

```
Leaf: predicts 1
Split on feature: cb person cred hist length
   Value = HOMEIMPROVEMENT:
   Value = PERSONAL:
```

```
Value = EDUCATION:
       Value = HOMEIMPROVEMENT:
Split on feature: person_home_ownership
       Value = DEBTCONSOLIDATION:
       Value = HOMEIMPROVEMENT:
       Value = PERSONAL:
       Value = DEBTCONSOLIDATION:
```

```
Split on feature: loan_int_rate
           Value = DEBTCONSOLIDATION:
           Value = HOMEIMPROVEMENT:
           Value = PERSONAL:
           Value = EDUCATION:
           Value = HOMEIMPROVEMENT:
```

```
Value = (14520.2, 35000.0]:
   Value = DEBTCONSOLIDATION:
   Value = EDUCATION:
   Value = HOMEIMPROVEMENT:
   Value = VENTURE:
   Value = DEBTCONSOLIDATION:
   Value = EDUCATION:
```

```
Leaf: predicts 0
   Value = VENTURE:
   Value = DEBTCONSOLIDATION:
   Value = HOMEIMPROVEMENT:
   Value = PERSONAL:
Split on feature: person income
   Value = (59456.0, 76436.8]:
   Value = DEBTCONSOLIDATION:
```

```
Value = PERSONAL:
   Value = VENTURE:
Split on feature: person_home_ownership
   Value = RENT:
   Value = DEBTCONSOLIDATION:
   Value = HOMEIMPROVEMENT:
   Value = PERSONAL:
   Value = HOMEIMPROVEMENT:
```

```
Leaf: predicts 1
Value = HOMEIMPROVEMENT:
Value = HOMEIMPROVEMENT:
Value = DEBTCONSOLIDATION:
Value = PERSONAL:
```

```
Value = HOMEIMPROVEMENT:
   Value = PERSONAL:
Value = DEBTCONSOLIDATION:
Split on feature: person_age
```

```
Leaf: predicts 0
Split on feature: person_income
   Value = (43081.8, 59456.0]:
   Value = (59456.0, 76436.8]:
Split on feature: person home ownership
   Value = (499.999, 4400.0]:
```

```
Value = (14520.2, 35000.0]:
Split on feature: person_home_ownership
   Value = MORTGAGE:
           Value = (14520.2, 35000.0]:
           Value = (59456.0, 76436.8]:
           Value = EDUCATION:
           Value = VENTURE:
        Split on feature: person_income
```

```
Leaf: predicts 1
Value = (76436.8, 103841.0]:
Value = (103841.0, 7200766.0]:
Value = HOMEIMPROVEMENT:
Value = PERSONAL:
```

```
Value = (14520.2, 35000.0]:
Value = RENT:
        Value = EDUCATION:
        Value = HOMEIMPROVEMENT:
        Value = PERSONAL:
    Split on feature: person_income
        Value = (43081.8, 59456.0]:
```

Source Code

```
import numpy as np
import pandas as pd
from sklearn.metrics import accuracy_score
from sklearn.model selection import train test split
class DecisionTree():
  def init (self, max depth: int = None, min samples split: int = 2):
      self.max_depth = max_depth if max_depth is not None else float('inf') #
maximum depth of the tree
      self.min_samples_split = min_samples_split # minimum number of samples
required to split an internal node
       # a recursive dictionary that represents the decision tree
       # has 4 keys: 'leaf', 'label', 'split_feature', 'children'
      # these 4 keys represent only the first node of the tree
       # other nodes are stored in the 'children' key recursively
      self. tree = None
  def str (self):
      if self._tree is None:
          return "Decision tree has not been fitted yet."
      return self._tree_to_str(self._tree, indent="")
  def tree to str(self, node, indent=""):
      if node['leaf']:
```

```
return f"{indent}Leaf: predicts {node['label']}\n"  # return the label
of the leaf node
       # if the node is not a leaf node, print the split feature and recursively
print the children
       s = f"{indent}Split on feature: {node['split_feature']}\n"
      for val, child node in node['children'].items():
           s += f"{indent}
                            Value = {val}:\n"
           s += self. tree to str(child node, indent + "
       return s
  def fit(self, X, y):
      self._tree = self._fit(X, y, depth=0)
  def fit(self, X, y, depth):
      # return a leaf node if the stopping criteria are met (base case)
      if len(np.unique(y)) == 1:
          return {
               'leaf': True,
               'label': y.iloc[0],
              'depth': depth
       # base case 2: if there are no features left to split on, return a leaf node
      if len(X.columns) == 0:
          return {
               'leaf': True,
               'label': y.value_counts().idxmax(),
               'depth': depth
       # base case 3: if the maximum depth is reached, return a leaf node
       if depth >= self.max depth:
          return {
               'leaf': True,
              'label': y.value_counts().idxmax(),
              'depth': depth
```

```
# base case 4: if the number of samples is less than the minimum samples
required to split, return a leaf node
       if len(y) < self.min samples split:</pre>
           return {
               'leaf': True,
               'label': y.value counts().idxmax(),
               'depth': depth
       current entropy = self._entropy(y) # calculate the entropy of the current
node
      best info gain = 0
      best_feature = None
      best X list = []
      best_y_list = []
       # iterate over all the features and find the one that gives the best
information gain
       for feature in X.columns:
           X_list, y_list = self._split_feature(X, y, feature)
           info gain = self. information gain(current entropy, y, y list)
          if info gain > best info gain:
              best_info_gain = info_gain
              best_feature = feature
              best_X_list = X_list
              best y list = y list
       # base case 5: if the best information gain is 0 (no improvement on the
model), return a leaf node
       if best info gain == 0:
           return {
               'leaf': True,
               'label': y.value counts().idxmax(),
               'depth': depth
       depth += 1 # increment the depth of the tree, since we are going to split
on a feature
       # create a node with the best feature to split on
       node = {
           'leaf': False,
           'split_feature': best_feature,
          'children': {},
```

```
'label': y.value_counts().idxmax(), # non-leaf nodes have labels as
well (most common label) as a fallout plan
           'depth': depth
       # recursively create the children of the node
       unique values = np.unique(X[best feature])
       for i, val in enumerate(unique values):
           child_subtree = self._fit(best_X_list[i], best_y_list[i], depth)
          node['children'][val] = child_subtree
       return node
  def predict(self, X):
       # apply the predict one function to each row of the dataframe
      predictions = []
       for , row in X.iterrows():
          predictions.append(self._predict_one(row))
       return pd.Series(predictions, index=X.index)
  def predict one(self, x):
       # traverse the tree until a leaf node is reached
       # while traversing go to the child node that corresponds to the value of the
       node = self. tree
       while not node['leaf']:
           split feature = node['split feature']
          val = x[split feature]
           try:
               node = node['children'][val]
has not seen before
           # in this case, return the most common label of the current node
           # label field of the non-leaf are used here
          except KeyError:
               return node['label']
       return node['label']
  def cross validation(self, X, y, params, cross val splits=5):
```

```
# assign defaults to parameters if they are not provided
       if not params['max depth']:
           params['max depth'] = [None]
       if not params['min_samples_split']:
           params['min samples split'] = [2]
       # check if the parameters are valid
      for key in params:
           if key not in ['max depth', 'min samples split']:
               raise ValueError(f"Invalid parameter: {key}")
      best accuracy = 0
      len val = len(X) // cross val splits
       # iterate over all the hyperparameters
       for max depth in params['max depth']:
           for min_samples_split in params['min_samples_split']:
               sum accuracy = 0
               self.max_depth = max_depth if max_depth is not None else
float('inf')
              self.min_samples_split = min_samples_split
               # iterate over all the cross validation splits
               for i in range(cross_val_splits):
                   # create the training and validation sets
                   X_train_cv = pd.concat([X.iloc[:i*len_val, :].copy(),
X.iloc[(i+1)*len val:, :].copy()])
                   X \text{ val} = X.iloc[i * len val: (i + 1) * len val]
                   y train cv = pd.concat([y train.iloc[:i*len val].copy(),
y train.iloc[(i+1)*len val:].copy()])
                   y val = y.iloc[i * len(y) // cross val splits: (i + 1) * len(y)
// cross val splits]
                   # fit the model and get the accuracy on the validation set
                   self.fit(X train cv, y train cv)
                   y pred cv = self.predict(X val)
                   sum_accuracy += accuracy_score(y_val, y_pred_cv)
               print(f"max_depth: {max_depth}, min_samples_split:
{min samples split}, accuracy: {sum accuracy / cross val splits}")
               # update the best hyperparameters if the current model is better
               if sum accuracy / cross val splits > best accuracy:
                   best_accuracy = sum_accuracy / cross_val_splits
                   best params = (max depth, min samples split)
```

```
print(f"Best accuracy: {best_accuracy}, Best params: {best params}")
       return best params
  def _entropy(self, y):
       # calculate the entropy of a node for a given variable
       classes = np.unique(y)
       entropy = 0
       for class in classes:
          nominator = (y == class_).sum()
          denominator = len(y)
          item = nominator / denominator
          entropy -= item * np.log2(item)
       return entropy
  def _information_gain(self, current_entropy, old_y, new_y_list = []):
       # calculate the information gain for a given entropy, variable and list of
       for y in new y list:
          current_entropy -= (len(y) / len(old_y)) * self._entropy(y)
       return current entropy
  def split feature(self, X, y, feature):
      X list = []
      y list = []
       for class_ in np.unique(X[feature]):
          mask = X[feature] == class
          X_list.append(X[mask].drop(columns=[feature])) # drop the feature
column to avoid using it again
          y_list.append(y[mask])
       return X list, y list
if __name__ == "__main__":
  df = pd.read csv('loan_data.csv')
   # convert the numerical values to categorical values
```

```
# apply this to the test data as well, so that the test data has the same
categories as the training data
  numerical classes = [
       'person_age',
       'person income',
       'person_emp_exp',
       'loan amnt',
       'loan int rate',
       'loan percent income',
       'cb person cred hist length',
       'credit score',
  for class in numerical classes:
       df[class_] = pd.qcut(df[class_], 5, duplicates='drop')
  X = df.drop('loan status', axis=1)
  y = df['loan_status']
  X train, X test, y train, y test = train test split(X, y, test size=0.1,
random_state=42)
  # apply cross validation to find the best hyperparameters
  dt = DecisionTree()
  params = {
       'max_depth': [2, 5, 7, 10, 12, None],
       'min_samples split': [200, 100, 50, 20, 10, 5, 2]
  best params = dt.cross validation(X train, y train, params)
  # create one more instance of the model with the best hyperparameters
  max depth, min samples split = best params
  dt = DecisionTree(max depth=max depth, min samples split=min samples split)
  with open('tree.txt', 'w') as f:
      f.write(str(dt))
  # fit the model and make predictions
  dt.fit(X train, y train)
  y_pred = dt.predict(X_test)
  # calculate the accuracy
  print(accuracy_score(y_test, y_pred))
```