Lab 5: Introducing Classification

Objectives:

- To gain hands-on experience classifying small dataset
- To implement concepts related to Decision Tree classifier (i.e. Entropy, Information Gain), along with using existing libraries.

```
In [ ]: # # Run this cell if you use Colab
# from google.colab import drive
# drive.mount('/content/drive')
```

Code it yourself

10 <=30 medium

11 31-40 medium

>40 medium

high

12 31-40

```
In [2]: import pandas as pd

# Read the data
df = pd.read_csv('./sources/toy_data.csv')
df
```

	df					
Out[2]:		age	income	student	credit rating	buys computer
	0	<=30	high	no	fair	no
	1	<=30	high	no	excellent	no
	2	31-40	high	no	fair	yes
	3	>40	medium	no	fair	yes
	4	>40	low	yes	fair	yes
	5	>40	low	yes	excellent	no
	6	31-40	low	yes	excellent	yes
	7	<=30	medium	no	fair	no
	8	<=30	low	yes	fair	yes
	9	>40	medium	yes	fair	yes

yes

no

yes

no

```
In [3]: print(df.info())
```

yes

yes

yes

no

excellent

excellent

excellent

fair

TODO: Write functions to compute Gain and Entropy, as discussed in the lecture.

```
In [4]: import numpy as np
In [5]: def EntropyCalc(df):
             total_count = df['yes'] + df['no']
             prob_yes = df['yes'] / total_count
             prob_no = df['no'] / total_count
             entropy = 0
             if ( prob_yes > 0 ) :
                 entropy -= prob_yes * np.log2(prob_yes)
             if ( prob_no > 0 ) :
                 entropy -= prob_no * np.log2(prob_no)
             return entropy
In [6]: def Weighted_EntropyCalc(df , total_target_count):
             total_count = df['yes'] + df['no']
             weighted_ratio = total_count / total_target_count
             entropy = df['Entropy']
             return weighted_ratio * entropy
In [7]: #Target Entropy
         target_df = df['buys computer'].value_counts()
         target_entropy = EntropyCalc(target_df)
         target_entropy
Out[7]: np.float64(0.9402859586706311)
In [16]: def compute_information_gain(df, attribute, target, target_entropy, entropy_func, weight
             attr_df = df.groupby(attribute)[target].value_counts().unstack(fill_value=0).reset_i
             for i in range(len(attr_df)):
                 attr_df.loc[i, 'Entropy'] = entropy_func(attr_df.loc[i])
                 attr_df.loc[i, 'Weighted'] = weighted_entropy_func(attr_df.loc[i], len(df))
             return target_entropy - attr_df['Weighted'].sum()
         age_ig = compute_information_gain(df, 'age', 'buys computer', target_entropy, EntropyCal
In [17]:
         income_ig = compute_information_gain(df, 'income', 'buys computer', target_entropy, Entr
         student_ig = compute_information_gain(df, 'student', 'buys computer', target_entropy, En
```

credit_rating_ig = compute_information_gain(df, 'credit rating', 'buys computer', target

```
print(f'Information Gain of "age" >> {age_ig}')
 print(f'Information Gain of "income" >> {income_ig}')
 print(f'Information Gain of "student" >> {student_ig}')
 print(f'Information Gain of "credit rating" >> {credit_rating_ig}')
Information Gain of "age" >> 0.24674981977443933
Information Gain of "income" >> 0.02922256565895487
Information Gain of "student" >> 0.15183550136234159
Information Gain of "credit rating" >> 0.04812703040826949
```

Using Libraries

Now that you know how to compute these values by yourselfs, now let's use some libraries.

Steps:

- Split the Data → Divide dataset into training (80%) and testing (20%).
- Train the Model → Fit a Decision Tree using the training data.
- Test the Model → Use the trained model to predict on test data.
- Evaluate Performance → Compare predictions with actual values (e.g., Accuracy Score).

Prepare features and labels.

```
In [12]: # Features
         features = df.drop('buys computer', axis=1)
         features
         # Alternatively, you can use this:
         # features = df.iloc[:, :-1]
```

Out[12]:

	age	income	student	credit rating
0	<=30	high	no	fair
1	<=30	high	no	excellent
2	31-40	high	no	fair
3	>40	medium	no	fair
4	>40	low	yes	fair
5	>40	low	yes	excellent
6	31-40	low	yes	excellent
7	<=30	medium	no	fair
8	<=30	low	yes	fair
9	>40	medium	yes	fair
10	<=30	medium	yes	excellent
11	31-40	medium	no	excellent
12	31-40	high	yes	fair
13	>40	medium	no	excellent

```
In [13]: # Labels (or Target)
         labels = df['buys computer']
         labels
         # # Alternatively, you can use this:
         # labels = df.iloc[:, [-1]]
Out[13]: 0
                no
         1
                no
         2
               yes
         3
               yes
         4
              yes
         5
               no
         6
               yes
         7
               no
         8
              yes
         9
              yes
         10
               yes
         11
              yes
         12
               yes
         13
               no
         Name: buys computer, dtype: object
In [14]: import pandas as pd
         import matplotlib.pyplot as plt
         from sklearn.model_selection import train_test_split
         from sklearn.tree import DecisionTreeClassifier, plot_tree
In [15]: # 1. Load the dataset
         X = features.values # Features
         y = labels.values # Target Labels
         # 2. Split the dataset into training (80%) and testing (20%)
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
         # 3. Create and train a Decision Tree model with entropy criterion
         clf = DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=42)
         clf.fit(X_train, y_train)
```

```
ValueError
                                          Traceback (most recent call last)
Cell In[15], line 10
      8 # 3. Create and train a Decision Tree model with entropy criterion
      9 clf = DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=42)
---> 10 clf.fit(X_train, y_train)
File c:\Users\Feen_Phoorin\AppData\Local\Programs\Python\Python313\Lib\site-packages\skle
arn\base.py:1389, in _fit_context.<locals>.decorator.<locals>.wrapper(estimator, *args, *
*kwargs)
  1382
            estimator._validate_params()
  1384 with config_context(
  1385
           skip_parameter_validation=(
  1386
                prefer_skip_nested_validation or global_skip_validation
  1387
  1388 ):
-> 1389
            return fit_method(estimator, *args, **kwargs)
File c:\Users\Feen_Phoorin\AppData\Local\Programs\Python\Python313\Lib\site-packages\skle
arn\tree\_classes.py:1024, in DecisionTreeClassifier.fit(self, X, y, sample_weight, check
_input)
   993 @_fit_context(prefer_skip_nested_validation=True)
   994 def fit(self, X, y, sample_weight=None, check_input=True):
   995
            """Build a decision tree classifier from the training set (X, y).
   996
   997
            Parameters
   (\ldots)
  1021
                Fitted estimator.
  1022
-> 1024
            super()._fit(
  1025
               Χ,
  1026
  1027
                sample_weight=sample_weight,
  1028
                check_input=check_input,
  1029
  1030
            return self
File c:\Users\Feen Phoorin\AppData\Local\Programs\Python\Python313\Lib\site-packages\skle
arn\tree\_classes.py:252, in BaseDecisionTree._fit(self, X, y, sample_weight, check_inpu
t, missing values in feature mask)
   248 check X params = dict(
    249
            dtype=DTYPE, accept_sparse="csc", ensure_all_finite=False
    250 )
    251 check_y_params = dict(ensure_2d=False, dtype=None)
--> 252 X, y = validate data(
           self, X, y, validate_separately=(check_X_params, check_y_params)
   253
    254 )
   256 missing_values_in_feature_mask = (
   257     self._compute_missing_values_in_feature_mask(X)
   258 )
   259 if issparse(X):
File c:\Users\Feen Phoorin\AppData\Local\Programs\Python\Python313\Lib\site-packages\skle
arn\utils\validation.py:2956, in validate_data(_estimator, X, y, reset, validate_separate
ly, skip_check_array, **check_params)
   2954 if "estimator" not in check_X_params:
            check_X_params = {**default_check_params, **check_X_params}
-> 2956 X = check array(X, input name="X", **check X params)
   2957 if "estimator" not in check_y_params:
            check_y_params = {**default_check_params, **check_y_params}
File c:\Users\Feen Phoorin\AppData\Local\Programs\Python\Python313\Lib\site-packages\skle
arn\utils\validation.py:1055, in check_array(array, accept_sparse, accept_large_sparse, d
```

```
type, order, copy, force_writeable, force_all_finite, ensure_all_finite, ensure_non_negat
ive, ensure_2d, allow_nd, ensure_min_samples, ensure_min_features, estimator, input_name)
  1053
               array = xp.astype(array, dtype, copy=False)
  1054
-> 1055
                array = _asarray_with_order(array, order=order, dtype=dtype, xp=xp)
  1056 except ComplexWarning as complex_warning:
  1057 raise ValueError(
  1058
                "Complex data not supported\n{}\n".format(array)
   1059
           ) from complex_warning
File c:\Users\Feen_Phoorin\AppData\Local\Programs\Python\Python313\Lib\site-packages\skle
arn\utils\_array_api.py:839, in _asarray_with_order(array, dtype, order, copy, xp, devic
e)
    837
           array = numpy.array(array, order=order, dtype=dtype)
           array = numpy.asarray(array, order=order, dtype=dtype)
--> 839
    841 # At this point array is a NumPy ndarray. We convert it to an array
   842 # container that is consistent with the input's namespace.
   843 return xp.asarray(array)
ValueError: could not convert string to float: '31-40'
```

There's an error:

ValueError: could not convert string to float: '31-40'

```
In [18]: from sklearn.preprocessing import LabelEncoder

# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Apply Label Encoding for all categorical columns

df['age'] = label_encoder.fit_transform(df['age'])

df['income'] = label_encoder.fit_transform(df['income'])

df['student'] = label_encoder.fit_transform(df['student'])

df['credit rating'] = label_encoder.fit_transform(df['credit rating'])

df['buys computer'] = label_encoder.fit_transform(df['buys computer'])

# Display the encoded DataFrame

print(df)
```

```
age income student credit rating buys computer
а
     1
             0
                     0
                                    1
                                                  0
1
     1
             0
                     0
                                    0
                                                  0
2
     0
             0
                     0
                                    1
                                                  1
3
     2
             2
                     0
                                    1
                                                  1
4
     2
           1
                     1
                                    1
                                                  1
5
     2
             1
                                    0
                                                  0
                     1
6
     0
             1
                     1
                                    0
                                                  1
7
     1
             2
                     0
                                   1
                                                  0
8
     1
            1
                     1
                                   1
                                                  1
9
     2
            2
                     1
                                    1
                                                  1
10
     1
             2
                     1
                                    0
                                                  1
             2
                     0
                                    0
11
     0
                                                  1
12
             0
                     1
                                    1
                                                  1
13
     2
             2
                     a
                                    0
                                                  0
```

Let's check out an updated dataframe.

```
In [19]: df
```

19]:		age	income	student	credit rating	buys computer	
	0	1	0	0	1	0	
	1	1	0	0	0	0	
	2	0	0	0	1	1	
	3	2	2	0	1	1	
	4	2	1	1	1	1	
	5	2	1	1	0	0	
	6	0	1	1	0	1	
	7	1	2	0	1	0	
	8	1	1	1	1	1	
	9	2	2	1	1	1	
1	0	1	2	1	0	1	
1	1	0	2	0	0	1	
1	12	0	0	1	1	1	
1	13	2	2	0	0	0	
: # X	2. (_tr	Spli ain, Cred = Ded	it the do X_test, ate and cisionTr	y_train <i>train a l</i> eeClassi	nto training y_test = tr Decision Tree Fier(criterio	model with ent	ing (20%) (X, y, test_size=0.2, random_ tropy criterion ax_depth=3, random_state=42)
	lf.	fit()	(_train,	y_train)		
]: 🔻	V				DecisionTre	eClassifier	Ú (?)
D	eci	sion	TreeCla	ssifier(criterion='e	entropy', max_	depth=3, random_state=42)
			train.sh test.sha				
	1, 4 , 4)						
N	Now we're going build the Decision Tree Classifier						
]: f	rom	skle	earn.tre	e import	DecisionTree	Classifier	

clf = DecisionTreeClassifier(criterion='entropy', random_state=42) # Using 'entropy' as

Initialize the Decision Tree classifier

Train the model

clf.fit(X_train, y_train)

```
# Predict on the test set
y_pred = clf.predict(X_test)
```

And evaluate our model.

```
In [24]: from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")

# Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion Matrix
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

Accuracy: 1.00

Classification Report:

support	f1-score	recall	precision	
1	1.00	1.00	1.00	0
2	1.00	1.00	1.00	1
3	1.00			accuracy
3	1.00	1.00	1.00	macro avg
3	1.00	1.00	1.00	weighted avg

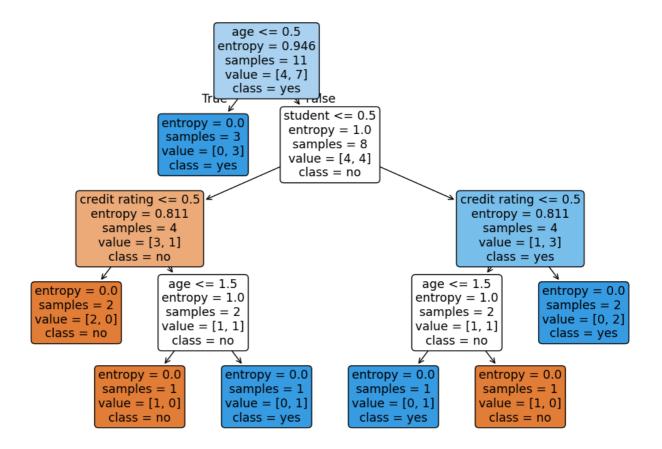
Confusion Matrix:

[[1 0] [0 2]]

And visualize our tree!

```
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

# Plot the decision tree
plt.figure(figsize=(12, 8))
plot_tree(clf, filled=True, feature_names=X.columns, class_names=['no', 'yes'], rounded=
plt.show()
```



Put them all together.

```
In [26]:
         import pandas as pd
         from sklearn.preprocessing import LabelEncoder
         from sklearn.model_selection import train_test_split
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
         import matplotlib.pyplot as plt
         from sklearn.tree import plot_tree
         # data
         data = pd.read_csv('sources/toy_data.csv')
         df = pd.DataFrame(data)
         # Encode categorical columns using LabelEncoder
         label encoder = LabelEncoder()
         df['age'] = label_encoder.fit_transform(df['age'])
         df['income'] = label_encoder.fit_transform(df['income'])
         df['student'] = label encoder.fit transform(df['student'])
         df['credit rating'] = label encoder.fit transform(df['credit rating'])
         df['buys computer'] = label_encoder.fit_transform(df['buys computer'])
         # Separate features (X) and target (y)
         X = df.drop('buys computer', axis=1)
         y = df['buys computer']
         # Split the dataset into training and test sets (80% train, 20% test)
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
         # Initialize the Decision Tree classifier
         clf = DecisionTreeClassifier(criterion='entropy', random state=42)
         # Train the model
         clf.fit(X_train, y_train)
```

```
# Predict on the test set
 y_pred = clf.predict(X_test)
 # Calculate accuracy
 accuracy = accuracy_score(y_test, y_pred)
 print(f"Accuracy: {accuracy:.2f}")
 # Classification report
 print("Classification Report:")
 print(classification_report(y_test, y_pred))
 # Confusion Matrix
 print("Confusion Matrix:")
 print(confusion_matrix(y_test, y_pred))
 # Plot the decision tree
 plt.figure(figsize=(12, 8))
 plot_tree(clf, filled=True, feature_names=X.columns, class_names=['no', 'yes'], rounded=
 plt.show()
Accuracy: 1.00
Classification Report:
               precision
                             recall f1-score
                                                  support
            0
                     1.00
                                1.00
                                           1.00
                                                         1
            1
                     1.00
                                           1.00
                                                         2
                                1.00
                                           1.00
                                                         3
    accuracy
                    1.00
                                1.00
                                           1.00
                                                         3
   macro avg
                                                         3
weighted avg
                    1.00
                                1.00
                                           1.00
Confusion Matrix:
[[1 0]
 [0 2]]
                                 age <= 0.5
                               entropy = 0.946
                                samples = 11
                                value = [4, 7]
                                 class = yes
                                           <del>ਪੂ ਜ਼</del>dlse
                                          student <= 0.5
                       entropy = 0.0
                                          entropy = 1.0
                       samples = 3
                                           samples = 8
                       value = [0, 3]
                                          value = [4, 4]
                        class = yes
                                            class = no
          credit rating <= 0.5
                                                                     credit rating <= 0.5
            entropy = 0.811
                                                                       entropy = 0.811
             samples = 4
                                                                        samples = 4
             value = [3, 1]
                                                                        value = [1, 3]
                                                                         class = yes
              class = no
                       age <= 1.5
                                                               age <= 1.5
   entropy = 0.0
                                                                                  entropy = 0.0
                       entropy = 1.0
                                                              entropy = 1.0
   samples = 2
                                                                                  samples = 2
                                                              samples = 2
                       samples = 2
   value = [2, 0]
                                                                                  value = [0, 2]
                       value = [1, 1]
                                                              value = [1, 1]
    class = no
                                                                                  class = yes
                        class = no
                                                               class = no
             entropy = 0.0
                                entropy = 0.0
                                                    entropy = 0.0
                                                                        entropy = 0.0
                                                                        samples = 1
             samples = 1
                                 samples = 1
                                                    samples = 1
             value = [1, 0]
                                value = [0, 1]
                                                    value = [0, 1]
                                                                        value = [1, 0]
              class = no
                                 class = yes
                                                     class = yes
                                                                         class = no
```

Is the output tree the same as what you calculated yourself? Explain in your own words why they are the same or different.

Ans: The entropy and information gain are not the same since the model use only 80% of the dataset (11 samples), while hand calculated use 100 % of the dataset (14 samples)

Another example, another dataset -- Iris

```
In [27]: from sklearn.datasets import load_iris
         # 1. Load the Iris dataset
         iris = load_iris()
         X = iris.data # Features
         y = iris.target # Target labels
         # 2. Split the dataset into training (80%) and testing (20%)
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
         # 3. Create and train a Decision Tree model with entropy criterion
         clf = DecisionTreeClassifier(criterion='entropy', max_depth=3, random_state=42)
         clf.fit(X_train, y_train)
         # 4. Make predictions on the test set
         y_pred = clf.predict(X_test)
         # 5. Evaluate the model
         accuracy = accuracy_score(y_test, y_pred)
         print(f"Model Accuracy: {accuracy:.2f}")
         # 6. Visualize the Decision Tree
         plt.figure(figsize=(10, 6))
         plot_tree(clf, filled=True, feature_names=iris.feature_names, class_names=iris.target_na
         plt.show()
```

Model Accuracy: 1.00

