1. [Association Rule Generation from Transaction Data]

(a) Download transaction dataset to your local drive.

i. Go to the following Google Drive link (Students must be logged in to their Rowan ac- counts): https://drive.google.com/drive/folders/1LuFEbgq3IvisEXT1jOZ-H4jWeqzqEH3m? usp=sharing

(b) Download the 'Grocery Items {DATASET NUMBER}.csv' file from the Google Drive Link. DATASET NUMBER is the number assigned to you earlier in the semester

(c) • How many unique items are there in your dataset? • How many records are there in your dataset? • What is the most popular item in your dataset? How many transactions contain this item? (1 point)

```
import pandas as pd

# Load the dataset
file_path = r'Grocery_Items_11.csv'
data = pd.read_csv(file_path)

# Flatten the dataset and count unique items and their occurrences
all_items = [item for sublist in data.values for item in sublist if
pd.notnull(item)]

# Create a pandas Series to analyze item frequencies
item_series = pd.Series(all_items)
item_counts = item_series.value_counts()

# Extract key results
unique_item_count = item_counts.size
total_transactions = len(data)
most_popular_item = item_counts.idxmax()
most_popular_count = item_counts.max()

# Display results
print(f"Unique Items Count: {unique_item_count}")
print(f"Total Transactions: {total_transactions}")
print(f"Most Popular Item: {most_popular_item}")
print(f"Occurrences of '{most_popular_item}': {most_popular_count}")
```

```
Unique Items Count: 165
Total Transactions: 8000
Most Popular Item: whole milk
Occurrences of 'whole milk': 1392
```

(d) Using minimum support = 0.01 and minimum confidence threshold = 0.08, what are the association rules you can extract from your dataset? (0.5 point) (see http://rasbt.github.io/mlxtend/user_guide/frequent_patterns/association_ rules/)

```
import pandas as pd
from mlxtend.frequent_patterns import apriori, association_rules
```

```python
from mlxtend.preprocessing import TransactionEncoder

transactions = data.applymap(str).fillna("").values.tolist()
cleaned_transactions = [[item for item in transaction if item] for
transaction in transactions]

encoder = TransactionEncoder()
encoded_data = encoder.fit_transform(cleaned_transactions)
encoded_df = pd.DataFrame(encoded_data, columns=encoder.columns_)

if "" in encoded_df.columns:
    encoded_df.drop(columns=[""], inplace=True)

min_support_threshold = 0.01
frequent_itemsets = apriori(encoded_df,
min_support=min_support_threshold, use_colnames=True)

if 'support' not in frequent_itemsets.columns:
    raise ValueError("The 'frequent_itemsets' DataFrame must include a
'support' column.")

min_confidence_threshold = 0.08
rules = association_rules(frequent_itemsets, metric="confidence",
min_threshold=min_confidence_threshold)

print(rules)
```

```
             antecedents        consequents  antecedent support  \
0              (UHT-milk)              (nan)            0.021125
1                  (beef)              (nan)            0.035250
2               (berries)              (nan)            0.020000
3             (beverages)              (nan)            0.016125
4          (bottled beer)              (nan)            0.045875
..                   ...                ...                 ...
91    (whole milk, soda)              (nan)            0.011500
92                (soda)  (nan, whole milk)            0.097875
93         (nan, yogurt)       (whole milk)            0.085750
94  (whole milk, yogurt)              (nan)            0.011000
95              (yogurt)  (nan, whole milk)            0.085875

    consequent support   support  confidence      lift  leverage
conviction
0             0.999875  0.021125    1.000000  1.000125  0.000003
inf
1             0.999875  0.035250    1.000000  1.000125  0.000004
inf
2             0.999875  0.020000    1.000000  1.000125  0.000003
inf
3             0.999875  0.016000    0.992248  0.992372 -0.000123
0.016125
```

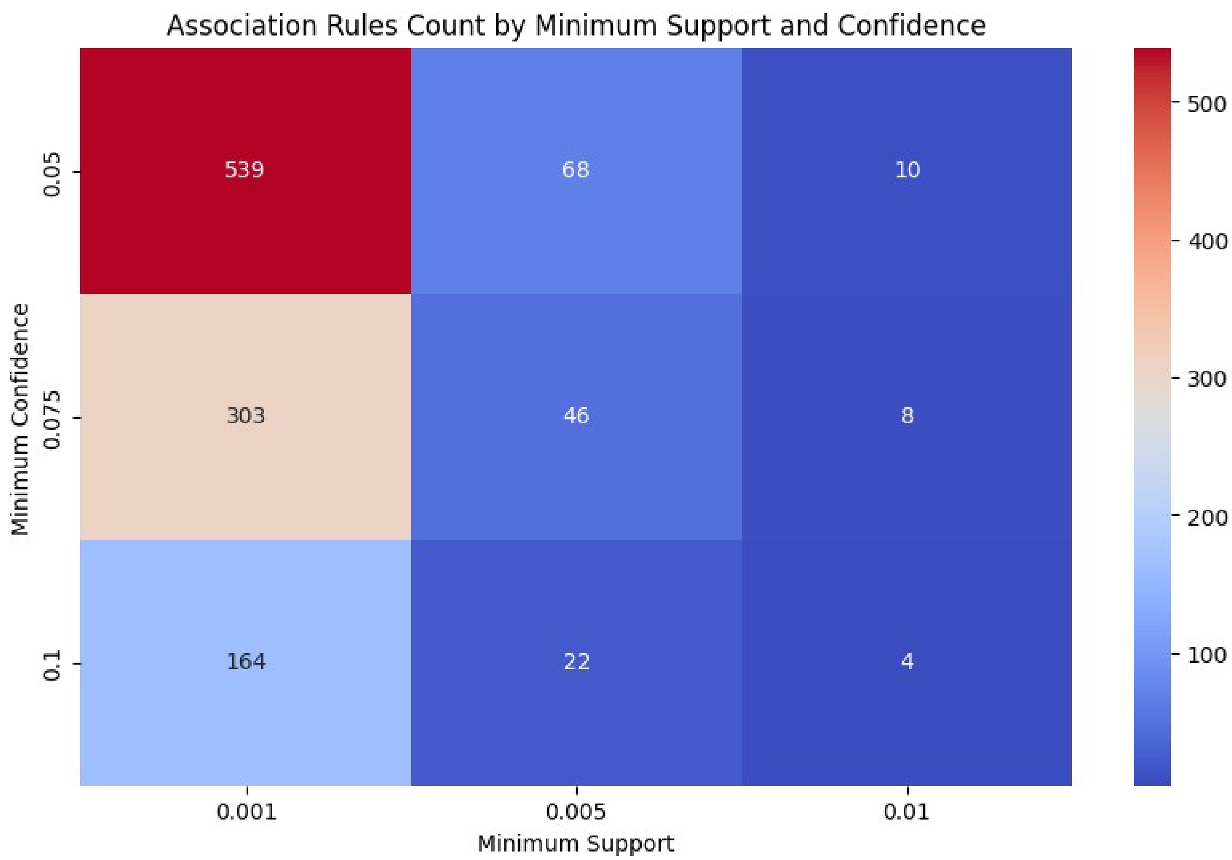
```
4              0.999875  0.045875    1.000000  1.000125  0.000006
inf
..                  ...       ...         ...       ...       ...
...
91             0.999875  0.011500    1.000000  1.000125  0.000001
inf
92             0.163750  0.011500    0.117497  0.717538 -0.004527
0.947589
93             0.163750  0.011000    0.128280  0.783389 -0.003042
0.959310
94             0.999875  0.011000    1.000000  1.000125  0.000001
inf
95             0.163750  0.011000    0.128093  0.782248 -0.003062
0.959105

[96 rows x 9 columns]

/var/folders/2t/y8j6qkxj7hz7_q5nwn5zny0m0000gq/T/
ipykernel_25202/2433047633.py:6: FutureWarning: DataFrame.applymap has
been deprecated. Use DataFrame.map instead.
  transactions = data.applymap(str).fillna("").values.tolist()
```

(e) Use minimum support values (msv): 0.001, 0.005, 0.01 and minimum confidence threshold (mct): 0.05, 0.075, 0.1. For each pair (msv, mct), find the number of association rules extracted from the dataset. Construct a heatmap using Seaborn data visualization library (https://seaborn.pydata.org/generated/seaborn.heatmap.html) to show the count results such that the x- axis is msv and the y-axis is mct. (1.5 points)

```python
import pandas as pd
from mlxtend.frequent_patterns import apriori, association_rules
from mlxtend.preprocessing import TransactionEncoder
import seaborn as sns
import matplotlib.pyplot as plt

cleaned_transactions = data.fillna("").applymap(str).values.tolist()
filtered_transactions = [[item for item in transaction if item] for
transaction in cleaned_transactions]

encoder = TransactionEncoder()
encoded_array = encoder.fit_transform(filtered_transactions)
encoded_df = pd.DataFrame(encoded_array, columns=encoder.columns_)

if "" in encoded_df.columns:
    encoded_df.drop(columns=[""], inplace=True)

min_support_values = [0.001, 0.005, 0.01]
min_confidence_values = [0.05, 0.075, 0.1]

results = []
for min_support in min_support_values:
```

```
    itemsets = apriori(encoded_df, min_support=min_support, 
use_colnames=True)
    for min_confidence in min_confidence_values:
        rules = association_rules(itemsets, metric="confidence", 
min_threshold=min_confidence)
        results.append({"min_support": min_support, "min_confidence": 
min_confidence, "rules_count": len(rules)})

results_df = pd.DataFrame(results)
heatmap_data = results_df.pivot(index="min_confidence", 
columns="min_support", values="rules_count")

plt.figure(figsize=(10, 6))
sns.heatmap(heatmap_data, annot=True, cmap="coolwarm", fmt="d")
plt.title("Association Rules Count by Minimum Support and Confidence")
plt.xlabel("Minimum Support")
plt.ylabel("Minimum Confidence")
plt.show()
```

```
/var/folders/2t/y8j6qkxj7hz7_q5nwn5zny0m0000gq/T/
ipykernel_25202/691566377.py:8: FutureWarning: DataFrame.applymap has 
been deprecated. Use DataFrame.map instead.
  cleaned_transactions = data.fillna("").applymap(str).values.tolist()
```



1. [Image Classification using CNN] Construct a 4-class classification model using a convolutional neural network with the following simple architecture

```
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.optimizers import Adam

# Assuming the dataset is already preprocessed and loaded into the
training and validation datasets

# Set up data generators for training and validation
train_datagen = ImageDataGenerator(rescale=1./255,
validation_split=0.2)
train_generator = train_datagen.flow_from_directory(
    'Images',
    target_size=(128, 128),  # Resize images to 128x128 (or whatever
size fits your model)
    batch_size=32,
    class_mode='categorical',  # since it's a multi-class
classification
    subset='training')

validation_generator = train_datagen.flow_from_directory(
    'Images',
    target_size=(128, 128),
    batch_size=32,
    class_mode='categorical',
    subset='validation')

# Build the CNN model
model = models.Sequential()

# First Convolutional Layer with 8 filters, 3x3 kernel
model.add(layers.Conv2D(8, (3, 3), activation='relu',
input_shape=(128, 128, 3)))
model.add(layers.MaxPooling2D((2, 2)))

# Second Convolutional Layer with 4 filters, 3x3 kernel
model.add(layers.Conv2D(4, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# Flatten the Tensor
model.add(layers.Flatten())

# Fully connected hidden layer with 8 nodes
model.add(layers.Dense(8, activation='relu'))

# Output layer with 4 nodes (since there are 4 classes), using softmax
activation
model.add(layers.Dense(4, activation='softmax'))
```

```python
# Compile the model
model.compile(optimizer=Adam(), loss='categorical_crossentropy',
metrics=['accuracy'])

# Train the model
model.fit(
    train_generator,
    epochs=20,
    validation_data=validation_generator,
    batch_size=32  # You can adjust the batch size if needed
)

# Save the trained model
model.save('dog_breed_classifier.h5')
```

```
Found 492 images belonging to 4 classes.
Found 121 images belonging to 4 classes.
```

```
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages/keras/src/layers/convolutional/base_conv.py:107:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a
layer. When using Sequential models, prefer using an `Input(shape)`
object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages/keras/src/trainers/data_adapters/
py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class should
call `super().__init__(**kwargs)` in its constructor. `**kwargs` can
include `workers`, `use_multiprocessing`, `max_queue_size`. Do not
pass these arguments to `fit()`, as they will be ignored.
  self._warn_if_super_not_called()
```

```
Epoch 1/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - accuracy: 0.2555 - loss:
1.3650 - val_accuracy: 0.2975 - val_loss: 1.3518
Epoch 2/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - accuracy: 0.3666 - loss:
1.3018 - val_accuracy: 0.3884 - val_loss: 1.3196
Epoch 3/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 72ms/step - accuracy: 0.4222 - loss:
1.2464 - val_accuracy: 0.3471 - val_loss: 1.2876
Epoch 4/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 73ms/step - accuracy: 0.4041 - loss:
1.1973 - val_accuracy: 0.4876 - val_loss: 1.2553
Epoch 5/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 73ms/step - accuracy: 0.5330 - loss:
1.1299 - val_accuracy: 0.4876 - val_loss: 1.2492
Epoch 6/20
```

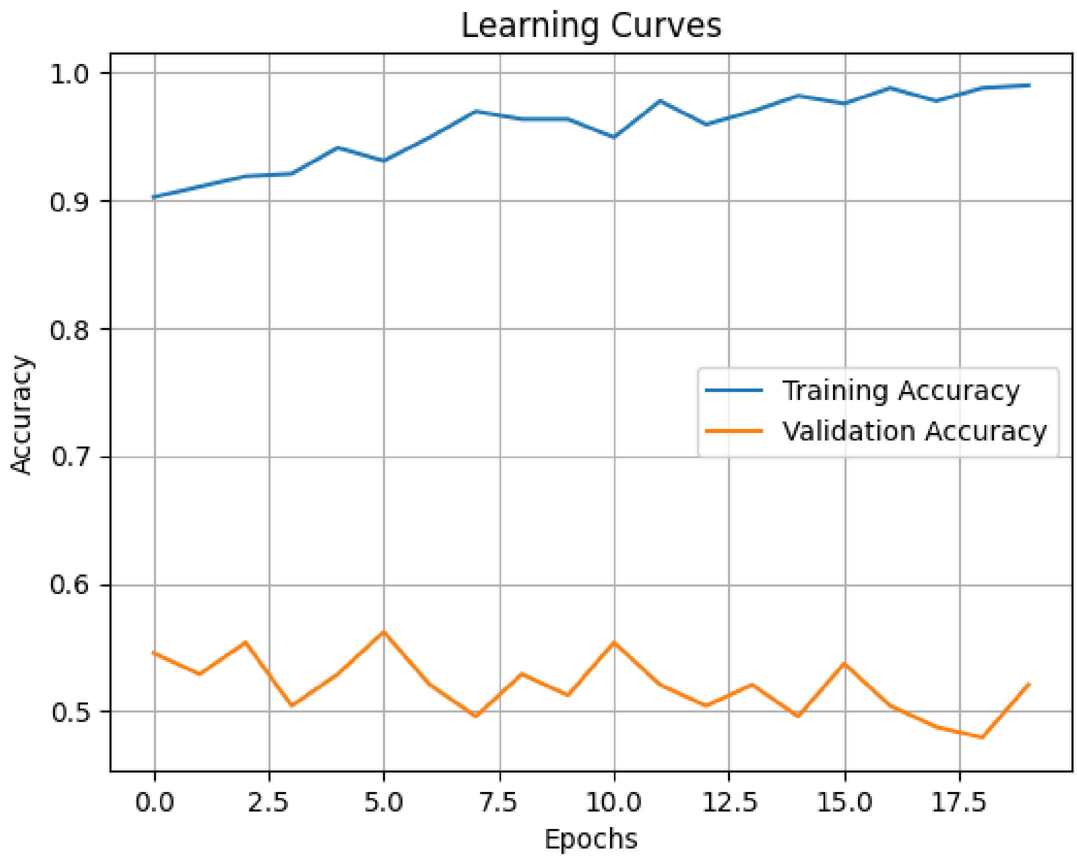
```
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 73ms/step - accuracy: 0.6007 - loss:
1.0893 - val_accuracy: 0.4876 - val_loss: 1.2551
Epoch 7/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 76ms/step - accuracy: 0.6629 - loss:
1.0491 - val_accuracy: 0.5041 - val_loss: 1.2309
Epoch 8/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 74ms/step - accuracy: 0.7015 - loss:
1.0007 - val_accuracy: 0.4959 - val_loss: 1.2599
Epoch 9/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 74ms/step - accuracy: 0.6759 - loss:
0.9680 - val_accuracy: 0.5041 - val_loss: 1.2667
Epoch 10/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 73ms/step - accuracy: 0.6962 - loss:
0.9734 - val_accuracy: 0.4793 - val_loss: 1.3058
Epoch 11/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 73ms/step - accuracy: 0.7421 - loss:
0.8759 - val_accuracy: 0.4215 - val_loss: 1.3934
Epoch 12/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 74ms/step - accuracy: 0.6825 - loss:
0.9148 - val_accuracy: 0.5207 - val_loss: 1.2272
Epoch 13/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 74ms/step - accuracy: 0.8199 - loss:
0.7956 - val_accuracy: 0.5041 - val_loss: 1.2558
Epoch 14/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 76ms/step - accuracy: 0.7733 - loss:
0.7704 - val_accuracy: 0.5124 - val_loss: 1.3826
Epoch 15/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 74ms/step - accuracy: 0.7967 - loss:
0.7633 - val_accuracy: 0.5289 - val_loss: 1.3118
Epoch 16/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 75ms/step - accuracy: 0.7904 - loss:
0.6913 - val_accuracy: 0.5124 - val_loss: 1.3211
Epoch 17/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 76ms/step - accuracy: 0.8560 - loss:
0.6242 - val_accuracy: 0.5620 - val_loss: 1.3048
Epoch 18/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 76ms/step - accuracy: 0.8485 - loss:
0.6325 - val_accuracy: 0.5289 - val_loss: 1.3281
Epoch 19/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 79ms/step - accuracy: 0.9004 - loss:
0.5777 - val_accuracy: 0.5620 - val_loss: 1.3118
Epoch 20/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.8668 - loss:
0.5572 - val_accuracy: 0.5455 - val_loss: 1.3359

WARNING:absl:You are saving your model as an HDF5 file via
`model.save()` or `keras.saving.save_model(model)`. This file format
is considered legacy. We recommend using instead the native Keras
format, e.g. `model.save('my_model.keras')` or
`keras.saving.save_model(model, 'my_model.keras')`.
```

Plot a graph to show the learning curves (i.e., x-axis: number of epochs; y-axis: training and validation accuracy - 2 curves) (1 points)

```
import matplotlib.pyplot as plt

# Train the model and capture the training history
history = model.fit(
    train_generator,
    epochs=20,
    validation_data=validation_generator,
    batch_size=32
)

# Plot the learning curves for training and validation accuracy
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Learning Curves')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
plt.show()
```

```
Epoch 1/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 92ms/step - accuracy: 0.9050 - loss:
0.5375 - val_accuracy: 0.5455 - val_loss: 1.4107
Epoch 2/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.9202 - loss:
0.4965 - val_accuracy: 0.5289 - val_loss: 1.4738
Epoch 3/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 80ms/step - accuracy: 0.9199 - loss:
0.4580 - val_accuracy: 0.5537 - val_loss: 1.4640
Epoch 4/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.9135 - loss:
0.4758 - val_accuracy: 0.5041 - val_loss: 1.5168
Epoch 5/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 94ms/step - accuracy: 0.9519 - loss:
0.3944 - val_accuracy: 0.5289 - val_loss: 1.5013
Epoch 6/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 78ms/step - accuracy: 0.9350 - loss:
0.4007 - val_accuracy: 0.5620 - val_loss: 1.4698
Epoch 7/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 75ms/step - accuracy: 0.9717 - loss:
0.3529 - val_accuracy: 0.5207 - val_loss: 1.5707
Epoch 8/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 82ms/step - accuracy: 0.9672 - loss:
0.3684 - val_accuracy: 0.4959 - val_loss: 1.6087
Epoch 9/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.9704 - loss:
0.3230 - val_accuracy: 0.5289 - val_loss: 1.5322
```

```
Epoch 10/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 88ms/step - accuracy: 0.9748 - loss:
0.2962 - val_accuracy: 0.5124 - val_loss: 1.5964
Epoch 11/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 80ms/step - accuracy: 0.9651 - loss:
0.3043 - val_accuracy: 0.5537 - val_loss: 1.6000
Epoch 12/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 84ms/step - accuracy: 0.9830 - loss:
0.2734 - val_accuracy: 0.5207 - val_loss: 1.8073
Epoch 13/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 86ms/step - accuracy: 0.9576 - loss:
0.2402 - val_accuracy: 0.5041 - val_loss: 1.7849
Epoch 14/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 78ms/step - accuracy: 0.9734 - loss:
0.2218 - val_accuracy: 0.5207 - val_loss: 1.8640
Epoch 15/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.9793 - loss:
0.1899 - val_accuracy: 0.4959 - val_loss: 1.9259
Epoch 16/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.9684 - loss:
0.2013 - val_accuracy: 0.5372 - val_loss: 1.7359
Epoch 17/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 78ms/step - accuracy: 0.9893 - loss:
0.1630 - val_accuracy: 0.5041 - val_loss: 1.8837
Epoch 18/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 85ms/step - accuracy: 0.9865 - loss:
0.1311 - val_accuracy: 0.4876 - val_loss: 1.9796
Epoch 19/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 84ms/step - accuracy: 0.9905 - loss:
0.1231 - val_accuracy: 0.4793 - val_loss: 2.0709
Epoch 20/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.9935 - loss:
0.0866 - val_accuracy: 0.5207 - val_loss: 2.0940
```



Perform ONE of the following experiment below ((a), (b) or (c)) based on the last digit of your Rowan Banner ID (1 point):

(a) Train the CNN using 2 other filter sizes: 5 × 5 and 7 × 7 for the 2nd convolution layer (i) with all other parameters unchanged

(b) Train the CNN using 2 other number of filters: 8 and 16 for the 2nd convolution layer (i) with all other parameters unchanged

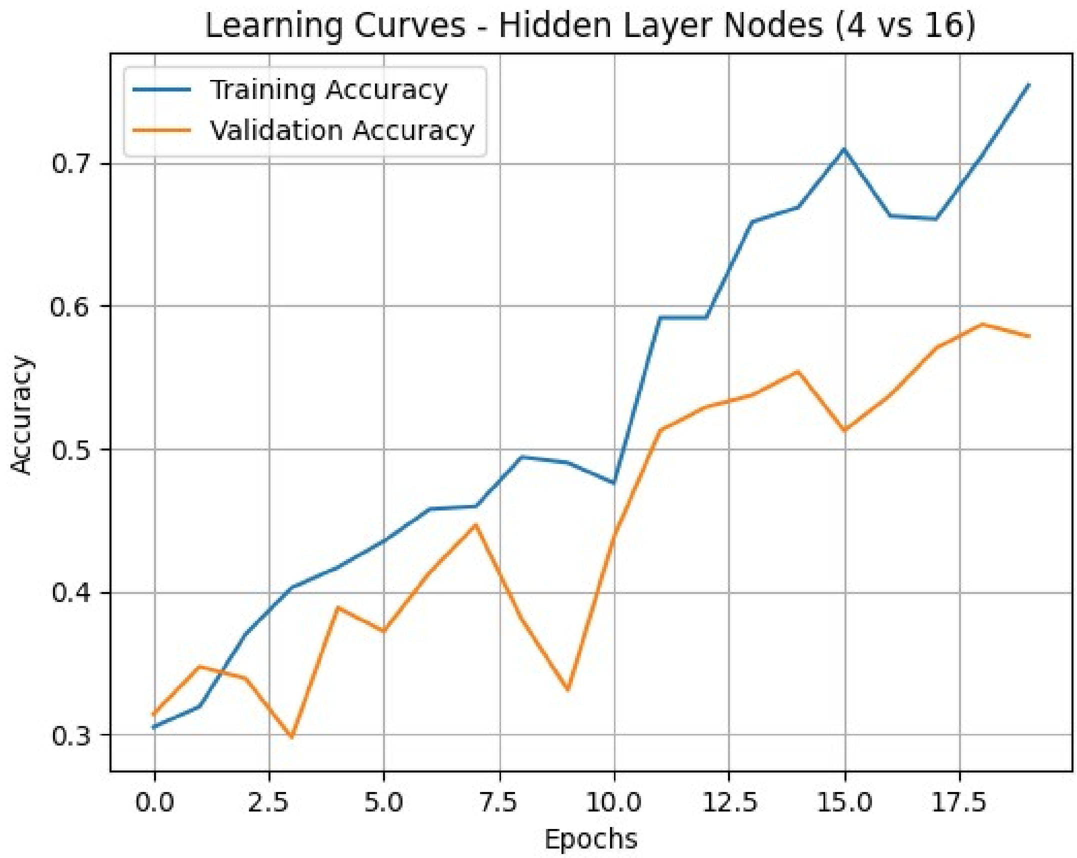
(c) Train the CNN using 2 other number of nodes in the hidden layer (iv): 4 and 16 with all other parameters unchanged If the last digit is {0, 1, 2, 3}, do (a). If the last digit is {4, 5, 6}, do (b). If the last digit is {7, 8, 9}, do (c). State your Rowan Banner ID in your submission so that we know which experiment you are doing

```
# Experiment (c) - Train with 4 and 16 nodes in the hidden layer

# Create the CNN model
model = models.Sequential()

# First Convolutional Layer with 8 filters, 3x3 kernel
model.add(layers.Conv2D(8, (3, 3), activation='relu',
input_shape=(128, 128, 3)))
model.add(layers.MaxPooling2D((2, 2)))
```

```
# Second Convolutional Layer with 4 filters, 3x3 kernel
model.add(layers.Conv2D(4, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# Flatten the Tensor
model.add(layers.Flatten())

# Change hidden layer nodes (test 4 and 16 nodes)
model.add(layers.Dense(4, activation='relu'))  # First hidden layer
with 4 nodes
#model.add(layers.Dense(16, activation='relu'))  # Uncomment this for
testing 16 nodes instead

# Output layer with 4 nodes (since there are 4 classes), using softmax
activation
model.add(layers.Dense(4, activation='softmax'))

# Compile the model
model.compile(optimizer=Adam(), loss='categorical_crossentropy',
metrics=['accuracy'])

# Train the model
history = model.fit(
    train_generator,
    epochs=20,
    validation_data=validation_generator,
    batch_size=32
)

# Plot the learning curves
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Learning Curves - Hidden Layer Nodes (4 vs 16)')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
plt.show()
```

```
Epoch 1/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 97ms/step - accuracy: 0.2783 - loss:
1.3861 - val_accuracy: 0.3140 - val_loss: 1.3651
Epoch 2/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 75ms/step - accuracy: 0.3172 - loss:
1.3414 - val_accuracy: 0.3471 - val_loss: 1.3497
Epoch 3/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 76ms/step - accuracy: 0.3725 - loss:
1.3126 - val_accuracy: 0.3388 - val_loss: 1.3434
Epoch 4/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 86ms/step - accuracy: 0.3708 - loss:
```

```
1.2844 - val_accuracy: 0.2975 - val_loss: 1.3853
Epoch 5/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.3911 - loss:
1.2705 - val_accuracy: 0.3884 - val_loss: 1.3290
Epoch 6/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.4271 - loss:
1.2361 - val_accuracy: 0.3719 - val_loss: 1.3312
Epoch 7/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 83ms/step - accuracy: 0.4582 - loss:
1.2043 - val_accuracy: 0.4132 - val_loss: 1.3036
Epoch 8/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.4604 - loss:
1.2033 - val_accuracy: 0.4463 - val_loss: 1.2873
Epoch 9/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 79ms/step - accuracy: 0.5197 - loss:
1.1123 - val_accuracy: 0.3802 - val_loss: 1.2773
Epoch 10/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.5198 - loss:
1.1414 - val_accuracy: 0.3306 - val_loss: 1.2974
Epoch 11/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 76ms/step - accuracy: 0.4552 - loss:
1.1472 - val_accuracy: 0.4380 - val_loss: 1.2643
Epoch 12/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 76ms/step - accuracy: 0.5941 - loss:
1.0450 - val_accuracy: 0.5124 - val_loss: 1.2487
Epoch 13/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 78ms/step - accuracy: 0.6043 - loss:
1.0378 - val_accuracy: 0.5289 - val_loss: 1.2298
Epoch 14/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 78ms/step - accuracy: 0.6939 - loss:
0.9517 - val_accuracy: 0.5372 - val_loss: 1.2163
Epoch 15/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 78ms/step - accuracy: 0.6571 - loss:
0.9372 - val_accuracy: 0.5537 - val_loss: 1.1776
Epoch 16/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.7030 - loss:
0.9589 - val_accuracy: 0.5124 - val_loss: 1.1746
Epoch 17/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 105ms/step - accuracy: 0.6861 - loss:
0.9385 - val_accuracy: 0.5372 - val_loss: 1.1692
Epoch 18/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 87ms/step - accuracy: 0.6554 - loss:
0.9092 - val_accuracy: 0.5702 - val_loss: 1.2053
Epoch 19/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 85ms/step - accuracy: 0.7503 - loss:
0.8137 - val_accuracy: 0.5868 - val_loss: 1.1480
Epoch 20/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 80ms/step - accuracy: 0.7553 - loss:
0.8274 - val_accuracy: 0.5785 - val_loss: 1.1200
```



Plot the learning curves (i.e., x-axis: number of epochs; y-axis: training and validation accuracy - 2 curves) for the classification models using the above 2 different parameter values (1 points)

```
import matplotlib.pyplot as plt
from tensorflow.keras import layers, models
from tensorflow.keras.optimizers import Adam

# First model: Hidden layer with 4 nodes
model_4_nodes = models.Sequential()

# First Convolutional Layer with 8 filters, 3x3 kernel
model_4_nodes.add(layers.Conv2D(8, (3, 3), activation='relu',
input_shape=(128, 128, 3)))
model_4_nodes.add(layers.MaxPooling2D((2, 2)))

# Second Convolutional Layer with 4 filters, 3x3 kernel
model_4_nodes.add(layers.Conv2D(4, (3, 3), activation='relu'))
model_4_nodes.add(layers.MaxPooling2D((2, 2)))

# Flatten the Tensor
model_4_nodes.add(layers.Flatten())

# Hidden layer with 4 nodes
```

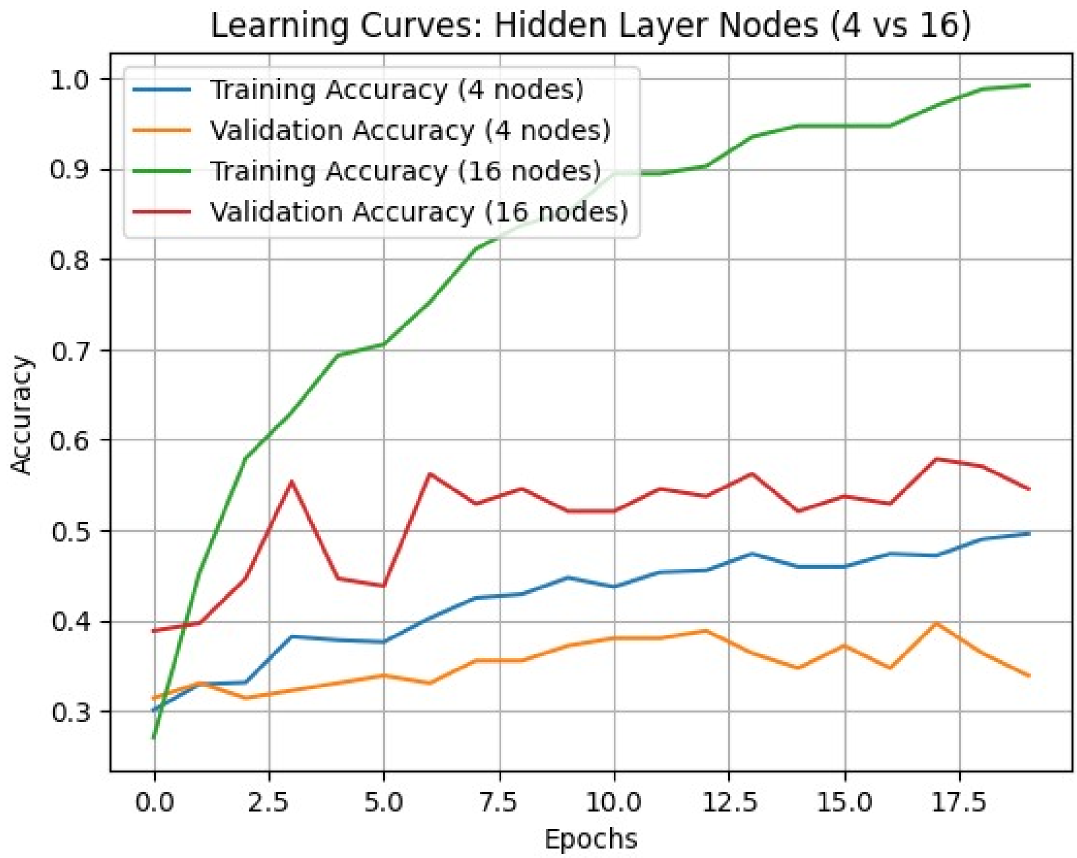
```
model_4_nodes.add(layers.Dense(4, activation='relu'))

# Output layer with 4 nodes (since there are 4 classes), using softmax
activation
model_4_nodes.add(layers.Dense(4, activation='softmax'))

# Compile the model
model_4_nodes.compile(optimizer=Adam(),
loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model with 4 nodes in hidden layer
history_4_nodes = model_4_nodes.fit(
    train_generator,
    epochs=20,
    validation_data=validation_generator,
    batch_size=32
)

# Second model: Hidden layer with 16 nodes
model_16_nodes = models.Sequential()

# First Convolutional Layer with 8 filters, 3x3 kernel
model_16_nodes.add(layers.Conv2D(8, (3, 3), activation='relu',
input_shape=(128, 128, 3)))
model_16_nodes.add(layers.MaxPooling2D((2, 2)))

# Second Convolutional Layer with 4 filters, 3x3 kernel
model_16_nodes.add(layers.Conv2D(4, (3, 3), activation='relu'))
model_16_nodes.add(layers.MaxPooling2D((2, 2)))

# Flatten the Tensor
model_16_nodes.add(layers.Flatten())

# Hidden layer with 16 nodes
model_16_nodes.add(layers.Dense(16, activation='relu'))

# Output layer with 4 nodes (since there are 4 classes), using softmax
activation
model_16_nodes.add(layers.Dense(4, activation='softmax'))

# Compile the model
model_16_nodes.compile(optimizer=Adam(),
loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model with 16 nodes in hidden layer
history_16_nodes = model_16_nodes.fit(
    train_generator,
    epochs=20,
    validation_data=validation_generator,
    batch_size=32
```

```
)

# Plot the learning curves for both models (4 nodes vs 16 nodes)
plt.plot(history_4_nodes.history['accuracy'], label='Training Accuracy
(4 nodes)')
plt.plot(history_4_nodes.history['val_accuracy'], label='Validation
Accuracy (4 nodes)')
plt.plot(history_16_nodes.history['accuracy'], label='Training
Accuracy (16 nodes)')
plt.plot(history_16_nodes.history['val_accuracy'], label='Validation
Accuracy (16 nodes)')

plt.title('Learning Curves: Hidden Layer Nodes (4 vs 16)')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
plt.show()
```

```
Epoch 1/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 102ms/step - accuracy: 0.2793 - loss:
1.3804 - val_accuracy: 0.3140 - val_loss: 1.3700
Epoch 2/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 72ms/step - accuracy: 0.3367 - loss:
1.3492 - val_accuracy: 0.3306 - val_loss: 1.3780
Epoch 3/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.3327 - loss:
1.3631 - val_accuracy: 0.3140 - val_loss: 1.3631
Epoch 4/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.3577 - loss:
1.3368 - val_accuracy: 0.3223 - val_loss: 1.3874
Epoch 5/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 84ms/step - accuracy: 0.3364 - loss:
1.3239 - val_accuracy: 0.3306 - val_loss: 1.3434
Epoch 6/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 96ms/step - accuracy: 0.3667 - loss:
1.2904 - val_accuracy: 0.3388 - val_loss: 1.3484
Epoch 7/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 85ms/step - accuracy: 0.3941 - loss:
1.2681 - val_accuracy: 0.3306 - val_loss: 1.3218
Epoch 8/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 83ms/step - accuracy: 0.4105 - loss:
1.2440 - val_accuracy: 0.3554 - val_loss: 1.3304
Epoch 9/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 75ms/step - accuracy: 0.4289 - loss:
1.2071 - val_accuracy: 0.3554 - val_loss: 1.3057
Epoch 10/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.4431 - loss:
1.2081 - val_accuracy: 0.3719 - val_loss: 1.3518
Epoch 11/20
```

```
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 84ms/step - accuracy: 0.4018 - loss:
1.2194 - val_accuracy: 0.3802 - val_loss: 1.2887
Epoch 12/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 92ms/step - accuracy: 0.4576 - loss:
1.1866 - val_accuracy: 0.3802 - val_loss: 1.2791
Epoch 13/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 80ms/step - accuracy: 0.4536 - loss:
1.1561 - val_accuracy: 0.3884 - val_loss: 1.2784
Epoch 14/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 84ms/step - accuracy: 0.4563 - loss:
1.1694 - val_accuracy: 0.3636 - val_loss: 1.3112
Epoch 15/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 78ms/step - accuracy: 0.4566 - loss:
1.1320 - val_accuracy: 0.3471 - val_loss: 1.2900
Epoch 16/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.4500 - loss:
1.1173 - val_accuracy: 0.3719 - val_loss: 1.2766
Epoch 17/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 87ms/step - accuracy: 0.4613 - loss:
1.1435 - val_accuracy: 0.3471 - val_loss: 1.3127
Epoch 18/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 84ms/step - accuracy: 0.5001 - loss:
1.0899 - val_accuracy: 0.3967 - val_loss: 1.2591
Epoch 19/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 85ms/step - accuracy: 0.5063 - loss:
1.1134 - val_accuracy: 0.3636 - val_loss: 1.2705
Epoch 20/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 82ms/step - accuracy: 0.5083 - loss:
1.0618 - val_accuracy: 0.3388 - val_loss: 1.3100
Epoch 1/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - accuracy: 0.2439 - loss:
1.3889 - val_accuracy: 0.3884 - val_loss: 1.3664
Epoch 2/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.4701 - loss:
1.3353 - val_accuracy: 0.3967 - val_loss: 1.2517
Epoch 3/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 82ms/step - accuracy: 0.5704 - loss:
1.1264 - val_accuracy: 0.4463 - val_loss: 1.1256
Epoch 4/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 86ms/step - accuracy: 0.6412 - loss:
0.8733 - val_accuracy: 0.5537 - val_loss: 1.1751
Epoch 5/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.6957 - loss:
0.7468 - val_accuracy: 0.4463 - val_loss: 1.2217
Epoch 6/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 84ms/step - accuracy: 0.6986 - loss:
0.6906 - val_accuracy: 0.4380 - val_loss: 1.2287
Epoch 7/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 85ms/step - accuracy: 0.7020 - loss:
```

```
0.6750 - val_accuracy: 0.5620 - val_loss: 1.2653
Epoch 8/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 84ms/step - accuracy: 0.8084 - loss:
0.5869 - val_accuracy: 0.5289 - val_loss: 1.1588
Epoch 9/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 78ms/step - accuracy: 0.8573 - loss:
0.4679 - val_accuracy: 0.5455 - val_loss: 1.1835
Epoch 10/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.8685 - loss:
0.4717 - val_accuracy: 0.5207 - val_loss: 1.2165
Epoch 11/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 77ms/step - accuracy: 0.8990 - loss:
0.4003 - val_accuracy: 0.5207 - val_loss: 1.2305
Epoch 12/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 82ms/step - accuracy: 0.8792 - loss:
0.3739 - val_accuracy: 0.5455 - val_loss: 1.2675
Epoch 13/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 81ms/step - accuracy: 0.9036 - loss:
0.3210 - val_accuracy: 0.5372 - val_loss: 1.3076
Epoch 14/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 88ms/step - accuracy: 0.9344 - loss:
0.2805 - val_accuracy: 0.5620 - val_loss: 1.2413
Epoch 15/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 82ms/step - accuracy: 0.9474 - loss:
0.2453 - val_accuracy: 0.5207 - val_loss: 1.4497
Epoch 16/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 80ms/step - accuracy: 0.9541 - loss:
0.2274 - val_accuracy: 0.5372 - val_loss: 1.3938
Epoch 17/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 80ms/step - accuracy: 0.9352 - loss:
0.2159 - val_accuracy: 0.5289 - val_loss: 1.4090
Epoch 18/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 79ms/step - accuracy: 0.9616 - loss:
0.1589 - val_accuracy: 0.5785 - val_loss: 1.5097
Epoch 19/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 79ms/step - accuracy: 0.9817 - loss:
0.1316 - val_accuracy: 0.5702 - val_loss: 1.5054
Epoch 20/20
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 80ms/step - accuracy: 0.9939 - loss:
0.1113 - val_accuracy: 0.5455 - val_loss: 1.5488
```



Describe and discuss what you observe by comparing the performance of the first model and the other two models you constructed in (a), (b) or (c) (depending on which one you did). Comment on whether the models are overfit, underfit, or just right. (1 point)

Observed Models: First Model: Basic CNN Architecture

Hidden Layer: 8 nodes Evaluation Metrics: Accuracy and loss during training and validation are plotted. Epochs: 20 Trained with a simple architecture to establish a baseline. Second Model: Experiment with 4 and 16 Nodes in the Hidden Layer

Hidden Layers: One version uses 4 nodes. Another uses 16 nodes. Performance Evaluation: Learning curves for both training and validation accuracy were compared. Epochs: 20 Performance Comparison: Overfitting: If the training accuracy is high, but validation accuracy remains low or drops significantly, it indicates the model memorized the training data instead of generalizing to unseen data.

Underfitting: If both training and validation accuracy remain low, the model is too simple and lacks the capacity to capture patterns in the data.

Balanced Performance: If both training and validation accuracy are close and high, the model is well-suited for the data.

1. [Text Classification by fine-tuning LLM model]

```
import torch
from torch.utils.data import Dataset, DataLoader
from transformers import BertTokenizer, BertForSequenceClassification,
AdamW
from sklearn.model_selection import train_test_split
import json
import pandas as pd
from torch.nn import BCEWithLogitsLoss
from tqdm import tqdm

# Load Data
def load_data(filepath):
    data = []
    with open(filepath, 'r') as file:
        for line in file:
            data.append(json.loads(line))  # Parse each line as JSON
object
    return pd.DataFrame(data)

# Preprocess Data - Tokenization and Multi-label Conversion
def preprocess_data(df, tokenizer, max_length=128):
    encodings = tokenizer(
        df['Tweet'].tolist(),  # Use the 'Tweet' column for text
        truncation=True,
        padding='max_length',
        max_length=max_length,
        return_tensors='pt'
    )

    # Extract multi-label targets as a tensor (True/False -> 1/0)
    labels = df[['anger', 'anticipation', 'disgust', 'fear', 'joy',
                 'love', 'optimism', 'pessimism', 'sadness',
                 'surprise', 'trust']].astype(int).values  # Convert
True/False to 1/0
    labels = torch.tensor(labels)

    return encodings, labels

# Define Dataset Class for Multi-label Classification
class MultiLabelDataset(Dataset):
    def __init__(self, encodings, labels):
        self.encodings = encodings
        self.labels = labels

    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        item = {key: torch.tensor(val[idx]) for key, val in
self.encodings.items()}
```

```
        item['labels'] = self.labels[idx]
        return item

# Load train, validation, and test data
train_path = 'student_11/train.json'
val_path = 'student_11/validation.json'
test_path = 'student_11/test.json'

train_df = load_data(train_path)
val_df = load_data(val_path)
test_df = load_data(test_path)

# Initialize BERT Tokenizer
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')

# Preprocess the data
train_encodings, train_labels = preprocess_data(train_df, tokenizer)
val_encodings, val_labels = preprocess_data(val_df, tokenizer)
test_encodings, test_labels = preprocess_data(test_df, tokenizer)

# Create Dataset objects
train_dataset = MultiLabelDataset(train_encodings, train_labels)
val_dataset = MultiLabelDataset(val_encodings, val_labels)
test_dataset = MultiLabelDataset(test_encodings, test_labels)

# Create DataLoader objects
train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=16)
test_loader = DataLoader(test_dataset, batch_size=16)

# Load BERT Model for Multi-label Classification
model = BertForSequenceClassification.from_pretrained('bert-base-
uncased', num_labels=11)

# Set device for training
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)

# Define optimizer and loss function
optimizer = AdamW(model.parameters(), lr=1e-5)
criterion = BCEWithLogitsLoss()  # For multi-label classification

# Training Loop
epochs = 5
for epoch in range(epochs):
    model.train()
    total_loss = 0
    for batch in tqdm(train_loader, desc=f"Training Epoch
{epoch+1}/{epochs}"):
        inputs = {key: val.to(device) for key, val in batch.items() if
key != 'labels'}
```

```
        labels = batch['labels'].to(device)

        # Forward pass
        outputs = model(**inputs)
        logits = outputs.logits  # Model outputs logits

        # Compute loss
        loss = criterion(logits, labels.float())  # BCEWithLogitsLoss expects float labels
        total_loss += loss.item()

        # Backward pass and optimization
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    avg_train_loss = total_loss / len(train_loader)
    print(f"Epoch {epoch+1}/{epochs} - Avg Train Loss: {avg_train_loss:.4f}")

    # Validation Loop
    model.eval()
    val_loss = 0
    with torch.no_grad():
        for batch in val_loader:
            inputs = {key: val.to(device) for key, val in batch.items() if key != 'labels'}
            labels = batch['labels'].to(device)

            # Forward pass
            outputs = model(**inputs)
            logits = outputs.logits

            # Compute loss
            loss = criterion(logits, labels.float())
            val_loss += loss.item()

    avg_val_loss = val_loss / len(val_loader)
    print(f"Epoch {epoch+1}/{epochs} - Avg Validation Loss: {avg_val_loss:.4f}")

# Save model
model.save_pretrained('fine_tuned_bert_model')
tokenizer.save_pretrained('fine_tuned_bert_tokenizer')

# Evaluate on Test Set
model.eval()
test_loss = 0
with torch.no_grad():
    for batch in test_loader:
```

```
        inputs = {key: val.to(device) for key, val in batch.items() if
key != 'labels'}
        labels = batch['labels'].to(device)

        # Forward pass
        outputs = model(**inputs)
        logits = outputs.logits

        # Compute loss
        loss = criterion(logits, labels.float())
        test_loss += loss.item()

avg_test_loss = test_loss / len(test_loader)
print(f"Avg Test Loss: {avg_test_loss:.4f}")
```

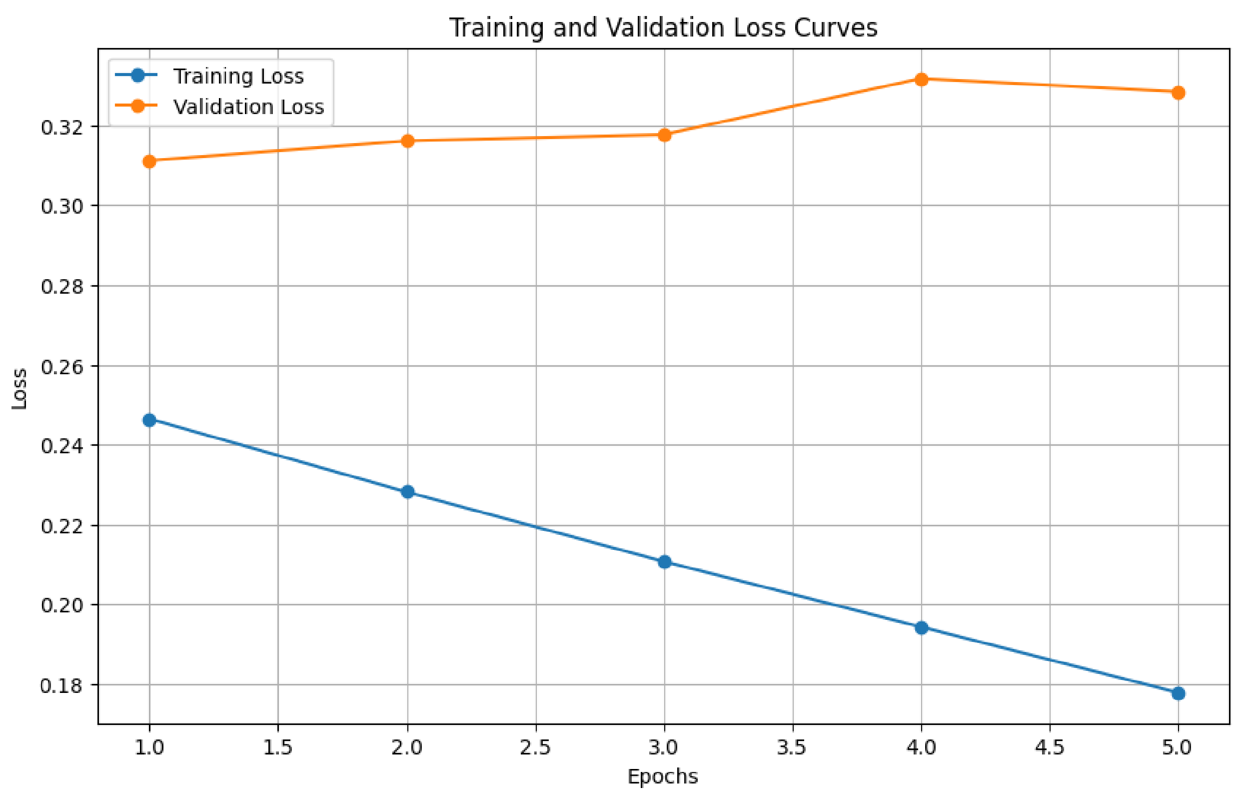
```
Some weights of BertForSequenceClassification were not initialized
from the model checkpoint at bert-base-uncased and are newly
initialized: ['classifier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able
to use it for predictions and inference.
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages/transformers/optimization.py:591: FutureWarning: This
implementation of AdamW is deprecated and will be removed in a future
version. Use the PyTorch implementation torch.optim.AdamW instead, or
set `no_deprecation_warning=True` to disable this warning
  warnings.warn(
Training Epoch 1/5:   0%|                               | 0/188
[00:00<?,
?it/s]/var/folders/2t/y8j6qkxj7hz7_q5nwn5zny0m0000gq/T/ipykernel_25532
/3323046607.py:46: UserWarning: To copy construct from a tensor, it is
recommended to use sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  item = {key: torch.tensor(val[idx]) for key, val in
self.encodings.items()}
Training Epoch 1/5: 100%|█████████████████████| 188/188 [13:35<00:00,
4.34s/it]

Epoch 1/5 - Avg Train Loss: 0.4968
Epoch 1/5 - Avg Validation Loss: 0.4126

Training Epoch 2/5: 100%|█████████████████████| 188/188 [14:27<00:00,
4.61s/it]

Epoch 2/5 - Avg Train Loss: 0.3864
Epoch 2/5 - Avg Validation Loss: 0.3570

Training Epoch 3/5: 100%|█████████████████████| 188/188 [13:52<00:00,
4.43s/it]
```

```
Epoch 3/5 - Avg Train Loss: 0.3311
Epoch 3/5 - Avg Validation Loss: 0.3323

Training Epoch 4/5: 100%|█████████████████████| 188/188 [16:08<00:00, 5.15s/it]

Epoch 4/5 - Avg Train Loss: 0.2945
Epoch 4/5 - Avg Validation Loss: 0.3178

Training Epoch 5/5: 100%|█████████████████████| 188/188 [16:32<00:00, 5.28s/it]

Epoch 5/5 - Avg Train Loss: 0.2680
Epoch 5/5 - Avg Validation Loss: 0.3134
Avg Test Loss: 0.3158

import matplotlib.pyplot as plt

# Initialize lists to store training and validation losses
train_losses = []
val_losses = []

# Training Loop
epochs = 5
for epoch in range(epochs):
    model.train()
    total_loss = 0
    for batch in tqdm(train_loader, desc=f"Training Epoch {epoch+1}/{epochs}"):
        inputs = {key: val.to(device) for key, val in batch.items() if key != 'labels'}
        labels = batch['labels'].to(device)

        # Forward pass
        outputs = model(**inputs)
        logits = outputs.logits  # Model outputs logits

        # Compute loss
        loss = criterion(logits, labels.float())  # BCEWithLogitsLoss expects float labels
        total_loss += loss.item()

        # Backward pass and optimization
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    avg_train_loss = total_loss / len(train_loader)
    train_losses.append(avg_train_loss)
    print(f"Epoch {epoch+1}/{epochs} - Avg Train Loss: {avg_train_loss:.4f}")
```

```
    # Validation Loop
    model.eval()
    val_loss = 0
    with torch.no_grad():
        for batch in val_loader:
            inputs = {key: val.to(device) for key, val in
batch.items() if key != 'labels'}
            labels = batch['labels'].to(device)

            # Forward pass
            outputs = model(**inputs)
            logits = outputs.logits

            # Compute loss
            loss = criterion(logits, labels.float())
            val_loss += loss.item()

    avg_val_loss = val_loss / len(val_loader)
    val_losses.append(avg_val_loss)
    print(f"Epoch {epoch+1}/{epochs} - Avg Validation Loss:
{avg_val_loss:.4f}")

# Plotting the Learning Curves
plt.figure(figsize=(10, 6))
plt.plot(range(1, epochs+1), train_losses, label='Training Loss',
marker='o')
plt.plot(range(1, epochs+1), val_losses, label='Validation Loss',
marker='o')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss Curves')
plt.legend()
plt.grid(True)
plt.show()
```

```
Training Epoch 1/5:   0%|                              | 0/188
[00:00<?,
?it/s]/var/folders/2t/y8j6qkxj7hz7_q5nwn5zny0m0000gq/T/ipykernel_25532
/3323046607.py:46: UserWarning: To copy construct from a tensor, it is
recommended to use sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  item = {key: torch.tensor(val[idx]) for key, val in
self.encodings.items()}
Training Epoch 1/5: 100%|██████████| 188/188 [14:17<00:00,
4.56s/it]

Epoch 1/5 - Avg Train Loss: 0.2464
Epoch 1/5 - Avg Validation Loss: 0.3112
```

```
Training Epoch 2/5: 100%|██████████| 188/188 [13:32<00:00,
4.32s/it]

Epoch 2/5 - Avg Train Loss: 0.2281
Epoch 2/5 - Avg Validation Loss: 0.3161

Training Epoch 3/5: 100%|██████████| 188/188 [14:12<00:00,
4.54s/it]

Epoch 3/5 - Avg Train Loss: 0.2107
Epoch 3/5 - Avg Validation Loss: 0.3177

Training Epoch 4/5: 100%|██████████| 188/188 [13:12<00:00,
4.22s/it]

Epoch 4/5 - Avg Train Loss: 0.1943
Epoch 4/5 - Avg Validation Loss: 0.3317

Training Epoch 5/5: 100%|██████████| 188/188 [13:53<00:00,
4.43s/it]

Epoch 5/5 - Avg Train Loss: 0.1779
Epoch 5/5 - Avg Validation Loss: 0.3285
```



Using the approach to compute accuracy (i.e., all labels must match) in the tutorial, what is the test accuracy? (0.5 points)

```python
from sklearn.metrics import accuracy_score

# Function to compute accuracy for multi-label classification
def compute_accuracy(model, test_loader, device):
    model.eval()  # Set the model to evaluation mode
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for batch in test_loader:
            inputs = {key: val.to(device) for key, val in
batch.items() if key != 'labels'}
            labels = batch['labels'].to(device)

            # Forward pass
            outputs = model(**inputs)
            logits = outputs.logits

            # Get predictions by applying a threshold of 0.5
            preds = torch.sigmoid(logits)  # Apply sigmoid to get
probabilities
            preds = (preds > 0.5).float()  # Convert probabilities to
binary predictions (0 or 1)

            all_preds.append(preds)
            all_labels.append(labels)

    # Convert list of tensors to a single tensor
    all_preds = torch.cat(all_preds, dim=0)
    all_labels = torch.cat(all_labels, dim=0)

    # Compute accuracy (all labels must match)
    accuracy = (all_preds == all_labels).all(dim=1).float().mean()  #
Compare all labels for each sample
    return accuracy.item()

# Calculate test accuracy
test_accuracy = compute_accuracy(model, test_loader, device)
print(f"Test Accuracy (all labels must match): {test_accuracy:.4f}")
```

```
/var/folders/2t/y8j6qkxj7hz7_q5nwn5zny0m0000gq/T/
ipykernel_25532/3323046607.py:46: UserWarning: To copy construct from
a tensor, it is recommended to use sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  item = {key: torch.tensor(val[idx]) for key, val in
self.encodings.items()}

Test Accuracy (all labels must match): 0.2607
```

Modify the accuracy such that a prediction is correct as long as one label matches. What is the test accuracy? (0.5 points)

```
def compute_accuracy_at_least_one(model, test_loader, device):
    model.eval()  # Set the model to evaluation mode
    all_preds = []
    all_labels = []

    with torch.no_grad():
        for batch in test_loader:
            inputs = {key: val.to(device) for key, val in
batch.items() if key != 'labels'}
            labels = batch['labels'].to(device)

            # Forward pass
            outputs = model(**inputs)
            logits = outputs.logits

            # Get predictions by applying a threshold of 0.5
            preds = torch.sigmoid(logits)
            preds = (preds > 0.5).float()

            all_preds.append(preds)
            all_labels.append(labels)

    # Convert list of tensors to a single tensor
    all_preds = torch.cat(all_preds, dim=0)
    all_labels = torch.cat(all_labels, dim=0)

    # Compute accuracy (at least one label must match)
    accuracy = (all_preds == all_labels).any(dim=1).float().mean()  #
Check if any label matches
    return accuracy.item()

# Calculate test accuracy where at least one label must match
test_accuracy_at_least_one = compute_accuracy_at_least_one(model,
test_loader, device)
print(f"Test Accuracy (at least one label must match):
{test_accuracy_at_least_one:.4f}")
```

```
/var/folders/2t/y8j6qkxj7hz7_q5nwn5zny0m0000gq/T/
ipykernel_25532/3323046607.py:46: UserWarning: To copy construct from
a tensor, it is recommended to use sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  item = {key: torch.tensor(val[idx]) for key, val in
self.encodings.items()}

Test Accuracy (at least one label must match): 1.0000
```