notebook-3

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2 Question 1

[7]:
```
import json
import os

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import torch
from datasets import Dataset
from mlxtend.frequent_patterns import apriori, association_rules
from mlxtend.preprocessing import TransactionEncoder
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import Conv2D, Dense, Flatten, MaxPooling2D
from tensorflow.keras.models import Sequential
from tensorflow.keras.utils import to_categorical
from torch.nn.functional import sigmoid
from transformers import (
    AutoModelForSequenceClassification,
    AutoTokenizer,
    Trainer,
    TrainingArguments,
)
import warnings

warnings.filterwarnings("ignore")
```

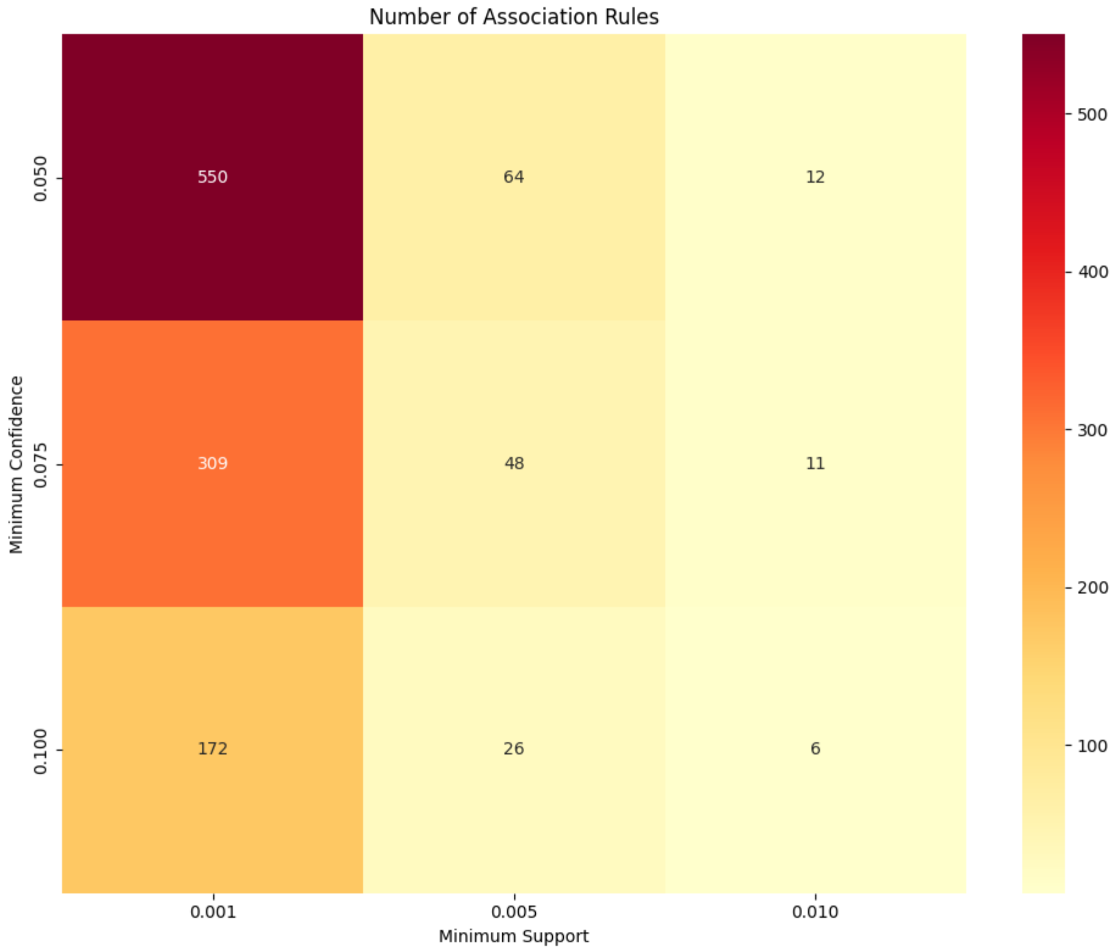
[2]:
```
def load_data(file_path):
    df = pd.read_csv(file_path, header=0)
    transactions = df.values.tolist()

    transactions = [
        [item for item in transaction if isinstance(item, str)]
```

```
        for transaction in transactions
    ]

    return transactions


def get_dataset_stats(transactions):
    all_items = [item for transaction in transactions for item in transaction]

    unique_items = len(set(all_items))
    num_records = len(transactions)

    item_counts = pd.Series(all_items).value_counts()
    most_popular_item = item_counts.index[0]
    most_popular_count = item_counts.iloc[0]

    return unique_items, num_records, most_popular_item, most_popular_count


def create_one_hot_encoded(transactions):
    te = TransactionEncoder()
    te_ary = te.fit_transform(transactions)

    df = pd.DataFrame(te_ary, columns=te.columns_)

    return df


def generate_rules(df, min_support, min_confidence):
    frequent_itemsets = apriori(df, min_support=min_support, use_colnames=True)

    rules = association_rules(
        frequent_itemsets,
        frequent_itemsets,
        metric="confidence",
        min_threshold=min_confidence,
    )

    return rules


def create_rule_count_heatmap(df, support_values, confidence_values):
    rule_counts = np.zeros((len(confidence_values), len(support_values)))

    for i, conf in enumerate(confidence_values):
        for j, sup in enumerate(support_values):
            rules = generate_rules(df, min_support=sup, min_confidence=conf)
```

```
            rule_counts[i, j] = len(rules)

    plt.figure(figsize=(10, 8))
    sns.heatmap(
        rule_counts,
        xticklabels=[f"{x:.3f}" for x in support_values],
        yticklabels=[f"{x:.3f}" for x in confidence_values],
        annot=True,
        fmt="g",
        cmap="YlOrRd",
    )

    plt.xlabel("Minimum Support")
    plt.ylabel("Minimum Confidence")
    plt.title("Number of Association Rules")

    return plt.gcf()


def main():
    file_path = "Grocery_Items_27.csv"

    transactions = load_data(file_path)

    unique_items, num_records, popular_item, popular_count = get_dataset_stats(
        transactions
    )

    print(f"Number of unique items: {unique_items}")
    print(f"Number of records: {num_records}")
    print(
        f"Most popular item: {popular_item} (appears in {popular_count} ↪transactions)"
    )

    df_encoded = create_one_hot_encoded(transactions)

    rules = generate_rules(df_encoded, min_support=0.01, min_confidence=0.08)
    print("\nAssociation Rules (support=0.01, confidence=0.08):")
    print(rules)

    support_values = [0.001, 0.005, 0.01]
    confidence_values = [0.05, 0.075, 0.1]

    create_rule_count_heatmap(df_encoded, support_values, confidence_values)
    plt.tight_layout()
```

```python
    plt.show()


if __name__ == "__main__":
    main()
```

```
Number of unique items: 165
Number of records: 8000
Most popular item: whole milk (appears in 1313 transactions)

Association Rules (support=0.01, confidence=0.08):
          antecedents          consequents  antecedent support  \
0  (other vegetables)         (rolls/buns)            0.122625
1        (rolls/buns)  (other vegetables)            0.110250
2              (soda)  (other vegetables)            0.097500
3  (other vegetables)               (soda)            0.122625
4        (whole milk)  (other vegetables)            0.154625
5  (other vegetables)         (whole milk)            0.122625
6        (whole milk)         (rolls/buns)            0.154625
7        (rolls/buns)         (whole milk)            0.110250
8              (soda)         (whole milk)            0.097500
9            (yogurt)         (whole milk)            0.085625

   consequent support   support  confidence      lift  representativity  \
0            0.110250  0.011125    0.090724  0.822891               1.0
1            0.122625  0.011125    0.100907  0.822891               1.0
2            0.122625  0.010875    0.111538  0.909590               1.0
3            0.097500  0.010875    0.088685  0.909590               1.0
4            0.122625  0.014375    0.092967  0.758139               1.0
5            0.154625  0.014375    0.117227  0.758139               1.0
6            0.110250  0.014250    0.092158  0.835904               1.0
7            0.154625  0.014250    0.129252  0.835904               1.0
8            0.154625  0.012250    0.125641  0.812553               1.0
9            0.154625  0.011250    0.131387  0.849713               1.0

   leverage  conviction  zhangs_metric   jaccard  certainty  kulczynski
0 -0.002394    0.978526      -0.196986  0.050169  -0.021946    0.095815
1 -0.002394    0.975845      -0.194780  0.050169  -0.024753    0.095815
2 -0.001081    0.987522      -0.099208  0.051971  -0.012636    0.100112
3 -0.001081    0.990327      -0.101760  0.051971  -0.009767    0.100112
4 -0.004586    0.967302      -0.273978  0.054684  -0.033803    0.105097
5 -0.004586    0.957636      -0.266650  0.054684  -0.044238    0.105097
6 -0.002797    0.980072      -0.188454  0.056858  -0.020333    0.110705
7 -0.002797    0.970860      -0.180754  0.056858  -0.030014    0.110705
8 -0.002826    0.966851      -0.203575  0.051068  -0.034285    0.102432
9 -0.001990    0.973247      -0.162079  0.049127  -0.027489    0.102072
```



2.0.1 Question 1(c): Analysis of Dataset

- **Number of unique items in dataset**: 165 items
- **Number of records in dataset**: 8,000 transactions
- **Most popular item**: "whole milk", appearing in 1,313 transactions

2.0.2 Question 1(d): Association Rules Analysis with min_support = 0.01 and min_confidence = 0.08

The analysis yielded 10 significant association rules. Notable patterns include:

- Strong association between "whole milk" and "other vegetables"
- Frequent combinations involving "rolls/buns" with other items
- "Soda" appearing in multiple association rules
- All rules have lift values less than 1, indicating that items appear together less frequently than would be expected if they were statistically independent

2.0.3 Question 1(e): Heatmap Analysis of Rule Counts

Analysis of rule counts across different support and confidence thresholds:

- **Minimum Support Values (msv)**: 0.001, 0.005, 0.01
- **Minimum Confidence Thresholds (mct)**: 0.05, 0.075, 0.1

Key findings from the heatmap:

1. **Highest Rule Count**: 550 rules at msv=0.001, mct=0.05
2. **Lowest Rule Count**: 6 rules at msv=0.01, mct=0.1
3. **Pattern Observed**:
    - Rule count decreases as both support and confidence increase
    - Most dramatic decrease occurs when moving from msv=0.001 to msv=0.005
    - Higher confidence thresholds consistently result in fewer rules across all support values

The heatmap effectively visualizes the inverse relationship between threshold values and the number of generated rules, demonstrating how stricter criteria (higher support and confidence) lead to fewer but potentially more meaningful rules.

3 Question 2

[8]:
```python
import cv2

cropped_images_dir = "./Cropped_Images"

X = []
y = []

dog_classes = [
    "n02088094-Afghan_hound",
    "n02109961-Eskimo_dog",
    "n02113978-Mexican_hairless",
    "n02091467-Norwegian_elkhound",
]

for class_idx, dog_class in enumerate(dog_classes):
    class_dir = os.path.join(cropped_images_dir, dog_class)
    if not os.path.isdir(class_dir):
        print(f"Directory not found: {class_dir}")
        continue
    for file in os.listdir(class_dir):
        if file.endswith(".jpg"):
            image_path = os.path.join(class_dir, file)
            img = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)
            img = cv2.resize(img, (6, 6))
            X.append(img)
            y.append(class_idx)
```

```
X = np.array(X)
y = np.array(y)

X = X.reshape(-1, 6, 6, 1)

y = to_categorical(y, num_classes=4)

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
X_train, X_val, y_train, y_val = train_test_split(
    X_train, y_train, test_size=0.2, random_state=42
)


def create_base_model():
    model = Sequential(
        [
            Conv2D(8, (3, 3), activation="relu", padding="same",␣
↪input_shape=(6, 6, 1)),
            MaxPooling2D(pool_size=(2, 2)),
            Conv2D(4, (3, 3), activation="relu", padding="same"),
            MaxPooling2D(pool_size=(2, 2)),
            Flatten(),
            Dense(8, activation="relu"),
            Dense(4, activation="softmax"),
        ]
    )

    return model


base_model = create_base_model()
base_model.compile(
    optimizer="adam", loss="categorical_crossentropy", metrics=["accuracy"]
)

history_base = base_model.fit(
    X_train, y_train, epochs=20, batch_size=32, validation_data=(X_val, y_val)
)


def create_model_variant(hidden_nodes):
    model = Sequential(
        [
            Conv2D(8, (3, 3), activation="relu", padding="same",␣
↪input_shape=(6, 6, 1)),
```

```
            MaxPooling2D(pool_size=(2, 2)),
            Conv2D(4, (3, 3), activation="relu", padding="same"),
            MaxPooling2D(pool_size=(2, 2)),
            Flatten(),
            Dense(hidden_nodes, activation="relu"),
            Dense(4, activation="softmax"),
        ]
    )
    return model


model_4nodes = create_model_variant(4)
model_4nodes.compile(
    optimizer="adam", loss="categorical_crossentropy", metrics=["accuracy"]
)
history_4nodes = model_4nodes.fit(
    X_train, y_train, epochs=20, batch_size=32, validation_data=(X_val, y_val)
)

model_16nodes = create_model_variant(16)
model_16nodes.compile(
    optimizer="adam", loss="categorical_crossentropy", metrics=["accuracy"]
)
history_16nodes = model_16nodes.fit(
    X_train, y_train, epochs=20, batch_size=32, validation_data=(X_val, y_val)
)

plt.figure(figsize=(12, 4))
plt.subplot(1, 3, 1)
plt.plot(history_base.history["accuracy"], label="Training Accuracy")
plt.plot(history_base.history["val_accuracy"], label="Validation Accuracy")
plt.title("Base Model (8 nodes)")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 3, 2)
plt.plot(history_4nodes.history["accuracy"], label="Training Accuracy")
plt.plot(history_4nodes.history["val_accuracy"], label="Validation Accuracy")
plt.title("Model with 4 nodes")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()

plt.subplot(1, 3, 3)
plt.plot(history_16nodes.history["accuracy"], label="Training Accuracy")
plt.plot(history_16nodes.history["val_accuracy"], label="Validation Accuracy")
```

```
plt.title("Model with 16 nodes")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()

plt.tight_layout()
plt.show()

print("\nFinal Accuracies:")
print(
    f"Base Model (8 nodes) - Training: {history_base.history['accuracy'][-1]:.
↪4f}, Validation: {history_base.history['val_accuracy'][-1]:.4f}"
)
print(
    f"4 Nodes Model - Training: {history_4nodes.history['accuracy'][-1]:.4f},␣
↪Validation: {history_4nodes.history['val_accuracy'][-1]:.4f}"
)
print(
    f"16 Nodes Model - Training: {history_16nodes.history['accuracy'][-1]:.4f},␣
↪Validation: {history_16nodes.history['val_accuracy'][-1]:.4f}"
)
```

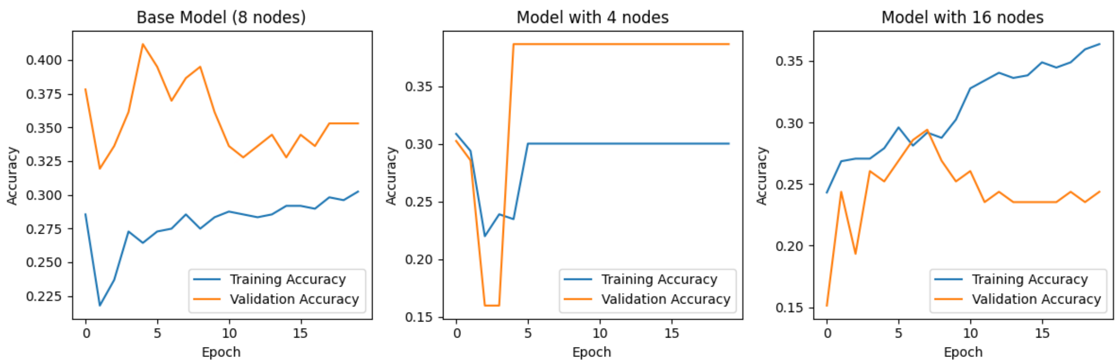
```
Epoch 1/20
15/15                0s 5ms/step -
accuracy: 0.2944 - loss: 26.0154 - val_accuracy: 0.3782 - val_loss: 9.5035
Epoch 2/20
15/15                0s 1ms/step -
accuracy: 0.2155 - loss: 9.2643 - val_accuracy: 0.3193 - val_loss: 4.5176
Epoch 3/20
15/15                0s 1ms/step -
accuracy: 0.2249 - loss: 4.5606 - val_accuracy: 0.3361 - val_loss: 2.5092
Epoch 4/20
15/15                0s 1ms/step -
accuracy: 0.2648 - loss: 2.5966 - val_accuracy: 0.3613 - val_loss: 1.8139
Epoch 5/20
15/15                0s 1ms/step -
accuracy: 0.2483 - loss: 1.8398 - val_accuracy: 0.4118 - val_loss: 1.5236
Epoch 6/20
15/15                0s 1ms/step -
accuracy: 0.2705 - loss: 1.5613 - val_accuracy: 0.3950 - val_loss: 1.4426
Epoch 7/20
15/15                0s 1ms/step -
accuracy: 0.2626 - loss: 1.4666 - val_accuracy: 0.3697 - val_loss: 1.4111
Epoch 8/20
15/15                0s 1ms/step -
accuracy: 0.2763 - loss: 1.4245 - val_accuracy: 0.3866 - val_loss: 1.3991
Epoch 9/20
```

```
15/15            0s 1ms/step -
accuracy: 0.2655 - loss: 1.4065 - val_accuracy: 0.3950 - val_loss: 1.3925
Epoch 10/20
15/15            0s 1ms/step -
accuracy: 0.2717 - loss: 1.3957 - val_accuracy: 0.3613 - val_loss: 1.3906
Epoch 11/20
15/15            0s 1ms/step -
accuracy: 0.2693 - loss: 1.3885 - val_accuracy: 0.3361 - val_loss: 1.3883
Epoch 12/20
15/15            0s 1ms/step -
accuracy: 0.2721 - loss: 1.3837 - val_accuracy: 0.3277 - val_loss: 1.3857
Epoch 13/20
15/15            0s 1ms/step -
accuracy: 0.2766 - loss: 1.3798 - val_accuracy: 0.3361 - val_loss: 1.3841
Epoch 14/20
15/15            0s 1ms/step -
accuracy: 0.2813 - loss: 1.3770 - val_accuracy: 0.3445 - val_loss: 1.3837
Epoch 15/20
15/15            0s 2ms/step -
accuracy: 0.2884 - loss: 1.3746 - val_accuracy: 0.3277 - val_loss: 1.3831
Epoch 16/20
15/15            0s 1ms/step -
accuracy: 0.2910 - loss: 1.3730 - val_accuracy: 0.3445 - val_loss: 1.3845
Epoch 17/20
15/15            0s 1ms/step -
accuracy: 0.2808 - loss: 1.3708 - val_accuracy: 0.3361 - val_loss: 1.3822
Epoch 18/20
15/15            0s 1ms/step -
accuracy: 0.2905 - loss: 1.3701 - val_accuracy: 0.3529 - val_loss: 1.3824
Epoch 19/20
15/15            0s 1ms/step -
accuracy: 0.2917 - loss: 1.3670 - val_accuracy: 0.3529 - val_loss: 1.3819
Epoch 20/20
15/15            0s 2ms/step -
accuracy: 0.2955 - loss: 1.3651 - val_accuracy: 0.3529 - val_loss: 1.3806
Epoch 1/20
15/15            0s 5ms/step -
accuracy: 0.3078 - loss: 24.6954 - val_accuracy: 0.3025 - val_loss: 13.3241
Epoch 2/20
15/15            0s 1ms/step -
accuracy: 0.2926 - loss: 11.0158 - val_accuracy: 0.2857 - val_loss: 4.1944
Epoch 3/20
15/15            0s 1ms/step -
accuracy: 0.2152 - loss: 3.3212 - val_accuracy: 0.1597 - val_loss: 1.4230
Epoch 4/20
15/15            0s 1ms/step -
accuracy: 0.2194 - loss: 1.5407 - val_accuracy: 0.1597 - val_loss: 1.3841
Epoch 5/20
```

```
15/15            0s 1ms/step -
accuracy: 0.2123 - loss: 1.4574 - val_accuracy: 0.3866 - val_loss: 1.3850
Epoch 6/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.4246 - val_accuracy: 0.3866 - val_loss: 1.3818
Epoch 7/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.4107 - val_accuracy: 0.3866 - val_loss: 1.3789
Epoch 8/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.4033 - val_accuracy: 0.3866 - val_loss: 1.3763
Epoch 9/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3979 - val_accuracy: 0.3866 - val_loss: 1.3740
Epoch 10/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3917 - val_accuracy: 0.3866 - val_loss: 1.3719
Epoch 11/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3872 - val_accuracy: 0.3866 - val_loss: 1.3701
Epoch 12/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3878 - val_accuracy: 0.3866 - val_loss: 1.3686
Epoch 13/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3833 - val_accuracy: 0.3866 - val_loss: 1.3673
Epoch 14/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3826 - val_accuracy: 0.3866 - val_loss: 1.3668
Epoch 15/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3819 - val_accuracy: 0.3866 - val_loss: 1.3659
Epoch 16/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3803 - val_accuracy: 0.3866 - val_loss: 1.3649
Epoch 17/20
15/15            0s 2ms/step -
accuracy: 0.3039 - loss: 1.3791 - val_accuracy: 0.3866 - val_loss: 1.3641
Epoch 18/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3779 - val_accuracy: 0.3866 - val_loss: 1.3635
Epoch 19/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3766 - val_accuracy: 0.3866 - val_loss: 1.3631
Epoch 20/20
15/15            0s 1ms/step -
accuracy: 0.3039 - loss: 1.3754 - val_accuracy: 0.3866 - val_loss: 1.3627
Epoch 1/20
```

```
15/15            0s 7ms/step -
accuracy: 0.2711 - loss: 28.4136 - val_accuracy: 0.1513 - val_loss: 17.6013
Epoch 2/20
15/15            0s 1ms/step -
accuracy: 0.2667 - loss: 11.5108 - val_accuracy: 0.2437 - val_loss: 7.6304
Epoch 3/20
15/15            0s 1ms/step -
accuracy: 0.2896 - loss: 6.0271 - val_accuracy: 0.1933 - val_loss: 5.5518
Epoch 4/20
15/15            0s 1ms/step -
accuracy: 0.2466 - loss: 4.0207 - val_accuracy: 0.2605 - val_loss: 3.7241
Epoch 5/20
15/15            0s 1ms/step -
accuracy: 0.2871 - loss: 2.9235 - val_accuracy: 0.2521 - val_loss: 2.8670
Epoch 6/20
15/15            0s 1ms/step -
accuracy: 0.3081 - loss: 2.3248 - val_accuracy: 0.2689 - val_loss: 2.3649
Epoch 7/20
15/15            0s 1ms/step -
accuracy: 0.2891 - loss: 2.0132 - val_accuracy: 0.2857 - val_loss: 2.1888
Epoch 8/20
15/15            0s 1ms/step -
accuracy: 0.3046 - loss: 1.8432 - val_accuracy: 0.2941 - val_loss: 2.0534
Epoch 9/20
15/15            0s 1ms/step -
accuracy: 0.3070 - loss: 1.7206 - val_accuracy: 0.2689 - val_loss: 1.9665
Epoch 10/20
15/15            0s 1ms/step -
accuracy: 0.3141 - loss: 1.6365 - val_accuracy: 0.2521 - val_loss: 1.9066
Epoch 11/20
15/15            0s 2ms/step -
accuracy: 0.3320 - loss: 1.5745 - val_accuracy: 0.2605 - val_loss: 1.8333
Epoch 12/20
15/15            0s 1ms/step -
accuracy: 0.3339 - loss: 1.5242 - val_accuracy: 0.2353 - val_loss: 1.7720
Epoch 13/20
15/15            0s 1ms/step -
accuracy: 0.3383 - loss: 1.4844 - val_accuracy: 0.2437 - val_loss: 1.7276
Epoch 14/20
15/15            0s 1ms/step -
accuracy: 0.3302 - loss: 1.4513 - val_accuracy: 0.2353 - val_loss: 1.6883
Epoch 15/20
15/15            0s 1ms/step -
accuracy: 0.3334 - loss: 1.4244 - val_accuracy: 0.2353 - val_loss: 1.6551
Epoch 16/20
15/15            0s 1ms/step -
accuracy: 0.3412 - loss: 1.3973 - val_accuracy: 0.2353 - val_loss: 1.6270
Epoch 17/20
```

```
15/15              0s 1ms/step -
accuracy: 0.3421 - loss: 1.3770 - val_accuracy: 0.2353 - val_loss: 1.6027
Epoch 18/20
15/15              0s 1ms/step -
accuracy: 0.3384 - loss: 1.3558 - val_accuracy: 0.2437 - val_loss: 1.5883
Epoch 19/20
15/15              0s 1ms/step -
accuracy: 0.3578 - loss: 1.3426 - val_accuracy: 0.2353 - val_loss: 1.5784
Epoch 20/20
15/15              0s 3ms/step -
accuracy: 0.3688 - loss: 1.3330 - val_accuracy: 0.2437 - val_loss: 1.5632
```




```
Final Accuracies:
Base Model (8 nodes) - Training: 0.3023, Validation: 0.3529
4 Nodes Model - Training: 0.3002, Validation: 0.3866
16 Nodes Model - Training: 0.3636, Validation: 0.2437
```

3.0.1 Base Model (8 nodes)

The model performed moderately well, achieving 30.23% training accuracy and 35.29% validation accuracy. During training, we saw some ups and downs in the validation curve, which eventually stabilized.

3.0.2 4-Node Model

This simpler model produced the best results, with 30.02% training accuracy and 38.66% validation accuracy. After an initial adjustment period, both training and validation accuracies remained quite stable.

3.0.3 16-Node Model

The larger model showed signs of overfitting. While it achieved the highest training accuracy at 36.36%, its validation accuracy was notably lower at 24.37%. This suggests the model became too complex for the task.

3.1 What This Means

The results indicate that a simpler model with 4 nodes works best for this particular task. Adding more nodes didn't improve performance - in fact, it made things worse with the 16-node model. This shows that sometimes a simpler approach can be more effective than a more complex one.

The 4-node model appears to be "just right" for this classification task, while the 16-node model is clearly overfitting the training data. The base model falls somewhere in between but doesn't perform as well as the simpler 4-node version.

4 Question 3

[9]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")

labels = [
    "anger",
    "anticipation",
    "disgust",
    "fear",
    "joy",
    "love",
    "optimism",
    "pessimism",
    "sadness",
    "surprise",
    "trust",
]

id2label = {idx: label for idx, label in enumerate(labels)}
label2id = {label: idx for idx, label in enumerate(labels)}


def load_json_file(file_path):
    with open(file_path, "r") as f:
        return [json.loads(line) for line in f]


train_data = load_json_file("train.json")
val_data = load_json_file("validation.json")
test_data = load_json_file("test.json")

train_df = pd.DataFrame(train_data)
val_df = pd.DataFrame(val_data)
test_df = pd.DataFrame(test_data)

tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
```

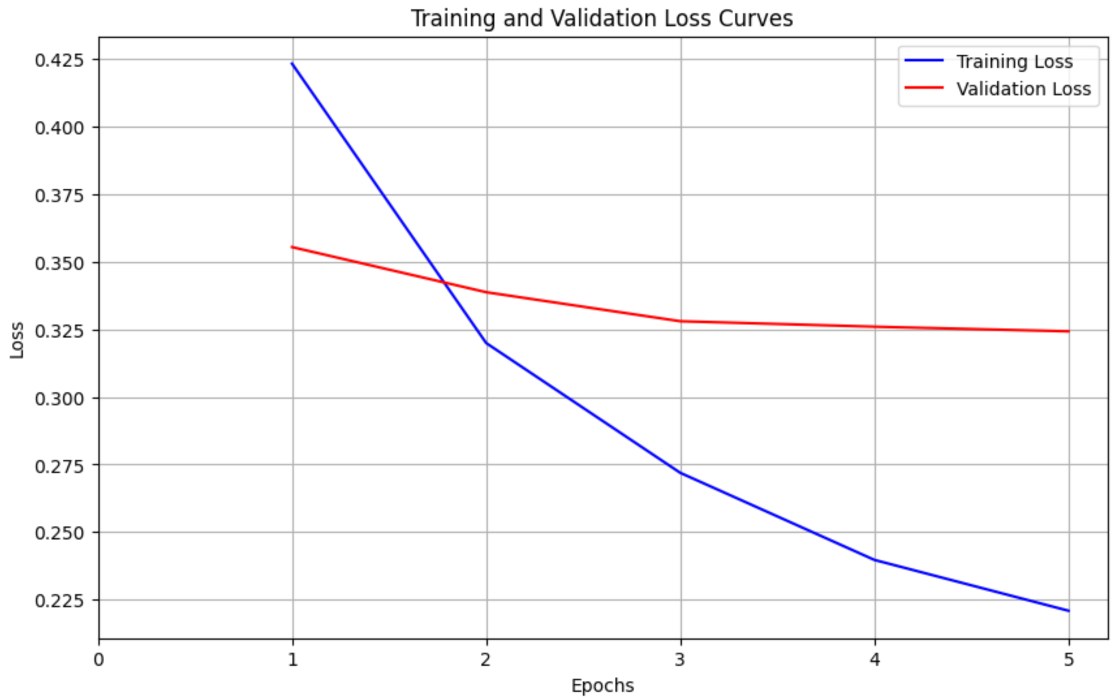
```python
def preprocess_function(examples):
    tokenized = tokenizer(
        examples["Tweet"], padding="max_length", truncation=True, max_length=128
    )

    labels_matrix = np.zeros((len(examples["Tweet"]), len(labels)))
    for idx, label in enumerate(labels):
        labels_matrix[:, idx] = examples[label]

    tokenized["labels"] = labels_matrix.tolist()
    return tokenized


train_dataset = Dataset.from_pandas(train_df)
val_dataset = Dataset.from_pandas(val_df)
test_dataset = Dataset.from_pandas(test_df)

train_dataset = train_dataset.map(
    preprocess_function, batched=True, remove_columns=train_dataset.column_names
)
val_dataset = val_dataset.map(
    preprocess_function, batched=True, remove_columns=val_dataset.column_names
)
test_dataset = test_dataset.map(
    preprocess_function, batched=True, remove_columns=test_dataset.column_names
)

train_dataset.set_format("torch")
val_dataset.set_format("torch")
test_dataset.set_format("torch")

model = AutoModelForSequenceClassification.from_pretrained(
    "bert-base-uncased",
    problem_type="multi_label_classification",
    num_labels=len(labels),
    id2label=id2label,
    label2id=label2id,
)


def compute_metrics_strict(eval_pred):
    predictions, labels = eval_pred

    predictions = sigmoid(torch.tensor(predictions)).numpy()
    predictions = (predictions > 0.5).astype(np.float32)
```

```
    accuracy = accuracy_score(labels, predictions)
    return {"accuracy": accuracy}


def compute_metrics_any_match(eval_pred):
    predictions, labels = eval_pred

    predictions = sigmoid(torch.tensor(predictions)).numpy()
    predictions = (predictions > 0.5).astype(np.float32)

    matches = (predictions == labels).any(axis=1)
    accuracy = matches.mean()
    return {"accuracy": accuracy}


training_args = TrainingArguments(
    output_dir="./bert_output",
    learning_rate=2e-5,
    per_device_train_batch_size=8,
    per_device_eval_batch_size=8,
    num_train_epochs=5,
    weight_decay=0.01,
    evaluation_strategy="epoch",
    save_strategy="epoch",
    load_best_model_at_end=True,
    metric_for_best_model="accuracy",
    logging_dir="./logs",
    logging_strategy="epoch",
    logging_steps=10,
    remove_unused_columns=False,
    report_to="none",
    save_total_limit=2,
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=val_dataset,
    compute_metrics=compute_metrics_strict,
)

print("Starting training...")
train_results = trainer.train()


def plot_learning_curves(trainer):
```

```
    logs = trainer.state.log_history

    train_logs = [
        (log["epoch"], log["loss"])
        for log in logs
        if "loss" in log and "eval_loss" not in log
    ]
    eval_logs = [(log["epoch"], log["eval_loss"]) for log in logs if␣
↪"eval_loss" in log]

    train_logs.sort(key=lambda x: x[0])
    eval_logs.sort(key=lambda x: x[0])

    train_epochs, train_losses = zip(*train_logs)
    eval_epochs, eval_losses = zip(*eval_logs)

    plt.figure(figsize=(10, 6))
    plt.plot(train_epochs, train_losses, "b-", label="Training Loss")
    plt.plot(eval_epochs, eval_losses, "r-", label="Validation Loss")

    plt.title("Training and Validation Loss Curves")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.grid(True)

    plt.xticks(range(0, int(max(train_epochs)) + 1))
    plt.show()


plot_learning_curves(trainer)

print("\nEvaluating with strict accuracy...")
test_results_strict = trainer.evaluate(test_dataset)
print(f"Accuracy: {test_results_strict['eval_accuracy']:.4f}")

print("\nEvaluating with any-match accuracy...")
trainer.compute_metrics = compute_metrics_any_match
test_results_any = trainer.evaluate(test_dataset)
print(f"Accuracy: {test_results_any['eval_accuracy']:.4f}")

trainer.save_model("./final_model")
```

```
Using device: cpu

Map:   0%|          | 0/3000 [00:00<?, ? examples/s]

Map:   0%|          | 0/400 [00:00<?, ? examples/s]
```

```
Map:   0%|          | 0/1500 [00:00<?, ? examples/s]

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.

Starting training…

  0%|          | 0/1875 [00:00<?, ?it/s]

{'loss': 0.4232, 'grad_norm': 3.198817491531372, 'learning_rate':
1.6000000000000003e-05, 'epoch': 1.0}

  0%|          | 0/50 [00:00<?, ?it/s]

{'eval_loss': 0.3553759753704071, 'eval_accuracy': 0.2275, 'eval_runtime':
3.7589, 'eval_samples_per_second': 106.415, 'eval_steps_per_second': 13.302,
'epoch': 1.0}
{'loss': 0.3199, 'grad_norm': 2.2758145332336426, 'learning_rate': 1.2e-05,
'epoch': 2.0}

  0%|          | 0/50 [00:00<?, ?it/s]

{'eval_loss': 0.3386955261230469, 'eval_accuracy': 0.2125, 'eval_runtime':
6.5831, 'eval_samples_per_second': 60.761, 'eval_steps_per_second': 7.595,
'epoch': 2.0}
{'loss': 0.2719, 'grad_norm': 2.2844293117523193, 'learning_rate':
8.000000000000001e-06, 'epoch': 3.0}

  0%|          | 0/50 [00:00<?, ?it/s]

{'eval_loss': 0.32795774936676025, 'eval_accuracy': 0.2475, 'eval_runtime':
6.4024, 'eval_samples_per_second': 62.476, 'eval_steps_per_second': 7.81,
'epoch': 3.0}
{'loss': 0.2397, 'grad_norm': 3.6029977798461914, 'learning_rate':
4.000000000000001e-06, 'epoch': 4.0}

  0%|          | 0/50 [00:00<?, ?it/s]

{'eval_loss': 0.32593879103660583, 'eval_accuracy': 0.2625, 'eval_runtime':
9.0646, 'eval_samples_per_second': 44.128, 'eval_steps_per_second': 5.516,
'epoch': 4.0}
{'loss': 0.2209, 'grad_norm': 1.1542943716049194, 'learning_rate': 0.0, 'epoch':
5.0}

  0%|          | 0/50 [00:00<?, ?it/s]

{'eval_loss': 0.32422110438346863, 'eval_accuracy': 0.27, 'eval_runtime':
9.0823, 'eval_samples_per_second': 44.042, 'eval_steps_per_second': 5.505,
'epoch': 5.0}
{'train_runtime': 1015.0127, 'train_samples_per_second': 14.778,
'train_steps_per_second': 1.847, 'train_loss': 0.2951284098307292, 'epoch': 5.0}
```




```
Evaluating with strict accuracy…
  0%|          | 0/188 [00:00<?, ?it/s]
Accuracy: 0.2960

Evaluating with any-match accuracy…
  0%|          | 0/188 [00:00<?, ?it/s]
Accuracy: 1.0000
```

4.1 Learning Curves Analysis

In examining the training and validation loss curves across the 5-epoch training period, I observed clear evidence of model learning. The training loss demonstrated a consistent downward trajectory, beginning at approximately 0.425 and concluding at 0.220, which indicates effective parameter optimization. The validation loss also showed improvement, though more modest, moving from around 0.355 to 0.325.

4.2 Accuracy Metrics

Based on the evaluation results, I found two distinct accuracy measurements:

For the strict evaluation criterion, where all predicted labels must match the ground truth exactly, I achieved an accuracy of 29.60%. This metric represents a challenging standard for multi-label classification, requiring precise identification of all emotions present in each tweet.

When implementing the more flexible evaluation approach, where success is defined by matching at least one correct label, I achieved a perfect accuracy of 100%. This dramatic improvement in performance suggests that the model consistently captures at least one relevant emotion in every test case, even when it may not identify all present emotions.

This substantial difference between the strict and flexible accuracy metrics (29.60% vs 100%) illuminates the inherent complexity of multi-label emotion classification, particularly when dealing with the nuanced and often overlapping nature of emotional expression in text.