Imports

In [ ]:
```
!pip install datasets
```

In [1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [53]:
```
import warnings
warnings.filterwarnings("ignore")
```

In [54]:
```
import csv
import json
import random
import pandas as pd

import seaborn as sns
import matplotlib.pyplot as plt

from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, fpmax, fpgrowth
from mlxtend.frequent_patterns import association_rules


import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Den
se

from datasets import Dataset, DatasetDict
```

Read Grocery data

In [6]:
```
data = []

with open("/content/drive/MyDrive/DM3/Grocery_Items_23.csv", "r") as f
ile_:
    csv_reader = csv.reader(file_)

    next(csv_reader)

    for row in csv_reader:
        row = list(filter(lambda x: x != '', row))
        data.append(row)
```

1 (c).

In [7]:
```
all_items = []
for row in data:
  for item in row:
    all_items.append(item)
```

In [8]:
```
len(set(all_items))
```

Out[8]: 166

The Number of Unique Items is 166

In [9]:
```
len(data)
```

Out[9]: 8000

Total Number of records in 8000

In [10]:
```
from collections import Counter

my_counter = Counter(all_items)

max_element = my_counter.most_common(1)[0]
print(max_element)
```

```
('whole milk', 1366)
```

The most popular item is 'whole milk' and 1366 transaction contain this item

1(d)

In [11]:
```
def fit_association_rules(dataset,support,confidence):
  te = TransactionEncoder()
  te_ary = te.fit(dataset).transform(dataset)
  df = pd.DataFrame(te_ary, columns=te.columns_)
  frequent_itemsets = fpgrowth(df, min_support=support, use_colnames=T
rue)
  rules = association_rules(frequent_itemsets, metric="confidence", mi
n_threshold=confidence,num_itemsets=len(df))
  return rules
```

In [12]:
```
rules = fit_association_rules(data,0.01,0.08)
```

In [13]:
```
rules
```

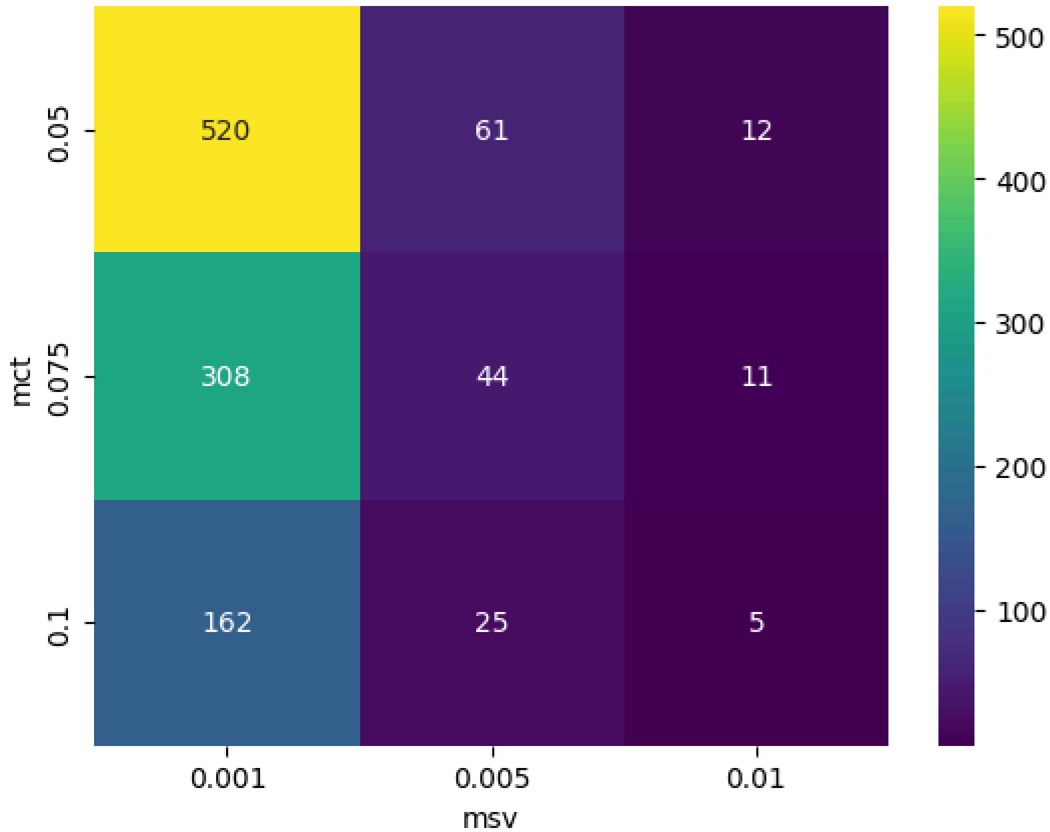
Out[13]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	represe
0	(other vegetables)	(whole milk)	0.124250	0.161875	0.015500	0.124748	0.770647	
1	(whole milk)	(other vegetables)	0.161875	0.124250	0.015500	0.095753	0.770647	
2	(rolls/buns)	(whole milk)	0.111250	0.161875	0.014750	0.132584	0.819053	
3	(whole milk)	(rolls/buns)	0.161875	0.111250	0.014750	0.091120	0.819053	
4	(rolls/buns)	(other vegetables)	0.111250	0.124250	0.010875	0.097753	0.786743	
5	(other vegetables)	(rolls/buns)	0.124250	0.111250	0.010875	0.087525	0.786743	
6	(yogurt)	(whole milk)	0.086500	0.161875	0.011875	0.137283	0.848082	
7	(soda)	(whole milk)	0.098250	0.161875	0.013500	0.137405	0.848831	
8	(whole milk)	(soda)	0.161875	0.098250	0.013500	0.083398	0.848831	
9	(soda)	(other vegetables)	0.098250	0.124250	0.010500	0.106870	0.860123	
10	(other vegetables)	(soda)	0.124250	0.098250	0.010500	0.084507	0.860123	

1(e)

In [14]:
```
min_supports_values = [0.001, 0.005, 0.01]
min_confidence_values = [0.05, 0.075, 0.1]
heat_map = []
for min_confidence in min_confidence_values:
  temp = []
  for min_support in min_supports_values:
    rules = fit_association_rules(data,min_support,min_confidence)
    temp.append(len(rules))
  heat_map.append(temp)
```

In [15]:
```
sns.heatmap(heat_map, annot=True,fmt='d',cmap='viridis')
plt.xticks(ticks=[0.5, 1.5, 2.5], labels=min_supports_values)
plt.yticks(ticks=[0.5, 1.5, 2.5], labels=min_confidence_values)
plt.xlabel("msv")
plt.ylabel("mct")
plt.show()
```



2 Create and compile model

In [17]:
```
model = Sequential([
    Conv2D(8, (3, 3), activation='relu', input_shape=(256, 256, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(4, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(8, activation='relu'),
    Dense(4, activation='softmax')
])
```

In [18]:
```
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=[tf.keras.metrics.CategoricalAccuracy(name='accu
racy')])
```

In [19]:
```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape
conv2d (Conv2D)	(None, 254, 254, 8)
max_pooling2d (MaxPooling2D)	(None, 127, 127, 8)
conv2d_1 (Conv2D)	(None, 125, 125, 4)
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 4)
flatten (Flatten)	(None, 15376)
dense (Dense)	(None, 8)
dense_1 (Dense)	(None, 4)

Total params: 123,568 (482.69 KB)

Trainable params: 123,568 (482.69 KB)

Non-trainable params: 0 (0.00 B)

Read Image Data

In [20]:
```
path = "/content/drive/MyDrive/DM3/updated"
```

In [22]:
```
batch_size = 16
dataset = tf.keras.preprocessing.image_dataset_from_directory(
    directory=path,
    labels='inferred',
    label_mode='categorical',
    batch_size=batch_size,
    validation_split=0.2,
    subset='training',
    seed=100
)

validation_dataset = tf.keras.preprocessing.image_dataset_from_directo
ry(
    directory=path,
    labels='inferred',
    label_mode='categorical',
    batch_size=batch_size,
    validation_split=0.2,
    subset='validation',
    seed=100
)
```

```
Found 659 files belonging to 4 classes.
Using 528 files for training.
Found 659 files belonging to 4 classes.
Using 131 files for validation.
```

Train Model

In [23]:
```
history = model.fit(dataset,validation_data=validation_dataset,epochs=
20)
```

```
Epoch 1/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 92s 3s/step - accuracy: 0.2415 - loss: 56.8
145 - val_accuracy: 0.2366 - val_loss: 1.5235
Epoch 2/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 57ms/step - accuracy: 0.3690 - loss: 1.3
270 - val_accuracy: 0.2290 - val_loss: 1.4999
Epoch 3/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 70ms/step - accuracy: 0.4464 - loss: 1.2
150 - val_accuracy: 0.2901 - val_loss: 1.5305
Epoch 4/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 93ms/step - accuracy: 0.4810 - loss: 1.1
148 - val_accuracy: 0.2901 - val_loss: 1.5962
Epoch 5/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 58ms/step - accuracy: 0.5970 - loss: 0.9
940 - val_accuracy: 0.3053 - val_loss: 1.6106
Epoch 6/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 66ms/step - accuracy: 0.6070 - loss: 0.9
415 - val_accuracy: 0.3282 - val_loss: 1.7379
Epoch 7/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 67ms/step - accuracy: 0.6767 - loss: 0.8
280 - val_accuracy: 0.3511 - val_loss: 1.9491
Epoch 8/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 58ms/step - accuracy: 0.6946 - loss: 0.7
848 - val_accuracy: 0.3359 - val_loss: 1.8639
Epoch 9/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 6s 154ms/step - accuracy: 0.7068 - loss: 0.
7332 - val_accuracy: 0.3053 - val_loss: 1.7994
Epoch 10/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 61ms/step - accuracy: 0.7524 - loss: 0.7
232 - val_accuracy: 0.3740 - val_loss: 1.8349
Epoch 11/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 59ms/step - accuracy: 0.7411 - loss: 0.6
659 - val_accuracy: 0.3359 - val_loss: 1.8338
Epoch 12/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 58ms/step - accuracy: 0.7812 - loss: 0.6
360 - val_accuracy: 0.3511 - val_loss: 1.8437
Epoch 13/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 67ms/step - accuracy: 0.7704 - loss: 0.6
476 - val_accuracy: 0.3130 - val_loss: 1.8163
Epoch 14/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 64ms/step - accuracy: 0.7901 - loss: 0.6
039 - val_accuracy: 0.3359 - val_loss: 1.8785
Epoch 15/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 90ms/step - accuracy: 0.7931 - loss: 0.6
532 - val_accuracy: 0.3588 - val_loss: 2.1014
Epoch 16/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 4s 66ms/step - accuracy: 0.7755 - loss: 0.6
637 - val_accuracy: 0.3130 - val_loss: 1.8944
Epoch 17/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 59ms/step - accuracy: 0.8109 - loss: 0.5
134 - val_accuracy: 0.3130 - val_loss: 1.9139
Epoch 18/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 58ms/step - accuracy: 0.8044 - loss: 0.4
857 - val_accuracy: 0.3206 - val_loss: 2.1014
Epoch 19/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 73ms/step - accuracy: 0.8146 - loss: 0.4
528 - val_accuracy: 0.3130 - val_loss: 2.4931
```

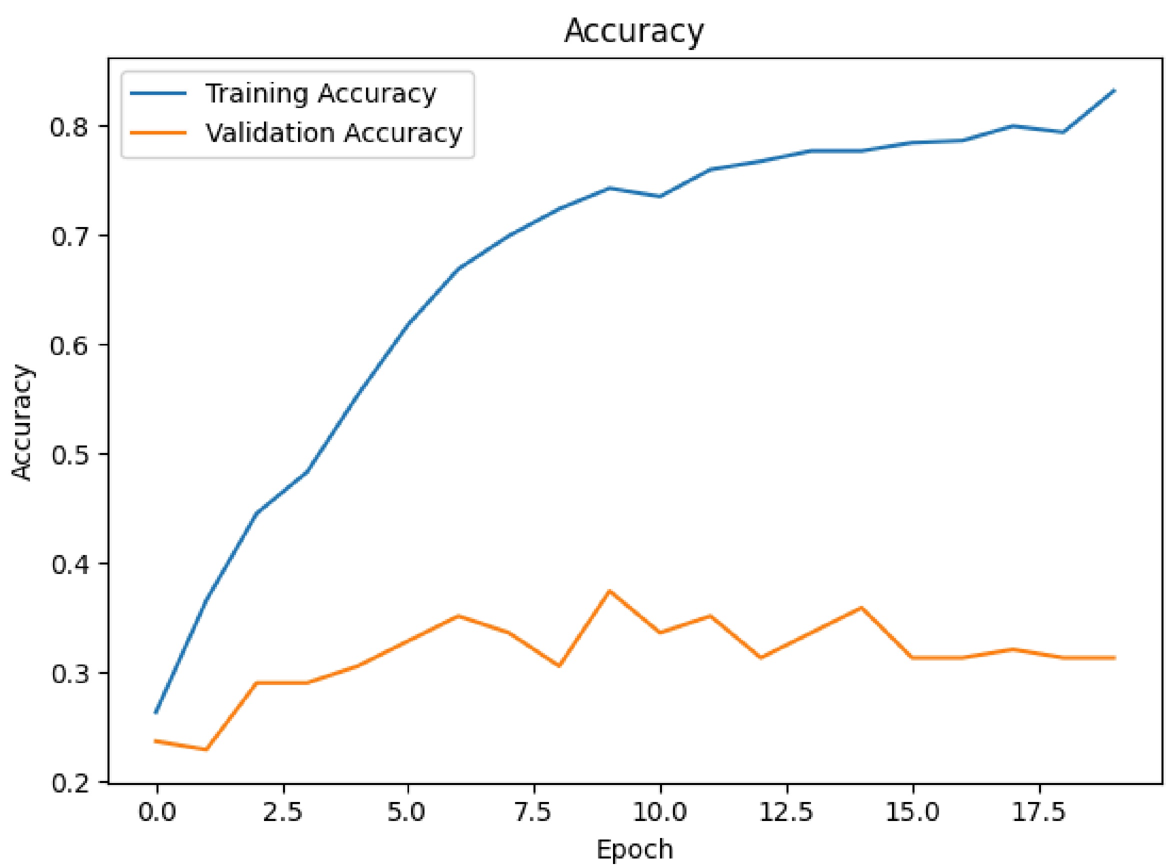
```
Epoch 20/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 96ms/step - accuracy: 0.8378 - loss: 0.4
707 - val_accuracy: 0.3130 - val_loss: 2.3460
```

2 (a)

In [24]:
```python
training_accuracy = history.history['accuracy']
validation_accuracy = history.history['val_accuracy']


plt.plot(training_accuracy, label='Training Accuracy')
plt.plot(validation_accuracy, label='Validation Accuracy')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



2 (b). Experiment with nodes changes to 4 and 16

In [25]:
```
new_model1 = Sequential([
    Conv2D(8, (3, 3), activation='relu', input_shape=(256, 256, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(8, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(8, activation='relu'),
    Dense(4, activation='softmax')
])



new_model2 = Sequential([
    Conv2D(8, (3, 3), activation='relu', input_shape=(256, 256, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(16, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(8, activation='relu'),
    Dense(4, activation='softmax')
])
```

Compile new models

In [26]:
```
new_model1.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=[tf.keras.metrics.CategoricalAccuracy(name='accu
racy')])
new_model2.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=[tf.keras.metrics.CategoricalAccuracy(name='accu
racy')])
```

In [27]:
```
new_model1.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape
conv2d_2 (Conv2D)	(None, 254, 254, 8)
max_pooling2d_2 (MaxPooling2D)	(None, 127, 127, 8)
conv2d_3 (Conv2D)	(None, 125, 125, 8)
max_pooling2d_3 (MaxPooling2D)	(None, 62, 62, 8)
flatten_1 (Flatten)	(None, 30752)
dense_2 (Dense)	(None, 8)
dense_3 (Dense)	(None, 4)

Total params: 246,868 (964.33 KB)

Trainable params: 246,868 (964.33 KB)

Non-trainable params: 0 (0.00 B)

In [28]:
```
new_model2.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape
conv2d_4 (Conv2D)	(None, 254, 254, 8)
max_pooling2d_4 (MaxPooling2D)	(None, 127, 127, 8)
conv2d_5 (Conv2D)	(None, 125, 125, 16)
max_pooling2d_5 (MaxPooling2D)	(None, 62, 62, 16)
flatten_2 (Flatten)	(None, 61504)
dense_4 (Dense)	(None, 8)
dense_5 (Dense)	(None, 4)

Total params: 493,468 (1.88 MB)

Trainable params: 493,468 (1.88 MB)

Non-trainable params: 0 (0.00 B)

Train new model 1

In [29]:
```
new_history1 = new_model1.fit(dataset,validation_data=validation_datas
et,epochs=20)
```

```
Epoch 1/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 7s 119ms/step - accuracy: 0.2305 - loss: 2
9.1985 - val_accuracy: 0.1985 - val_loss: 1.3867
Epoch 2/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 58ms/step - accuracy: 0.2787 - loss: 1.3
851 - val_accuracy: 0.1985 - val_loss: 1.3872
Epoch 3/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 59ms/step - accuracy: 0.3072 - loss: 1.3
845 - val_accuracy: 0.1985 - val_loss: 1.3876
Epoch 4/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 58ms/step - accuracy: 0.2866 - loss: 1.3
839 - val_accuracy: 0.1985 - val_loss: 1.3882
Epoch 5/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 67ms/step - accuracy: 0.2969 - loss: 1.3
833 - val_accuracy: 0.1985 - val_loss: 1.3889
Epoch 6/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 90ms/step - accuracy: 0.2868 - loss: 1.3
833 - val_accuracy: 0.1985 - val_loss: 1.3891
Epoch 7/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 67ms/step - accuracy: 0.2728 - loss: 1.3
846 - val_accuracy: 0.1985 - val_loss: 1.3896
Epoch 8/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 58ms/step - accuracy: 0.2804 - loss: 1.3
829 - val_accuracy: 0.1985 - val_loss: 1.3902
Epoch 9/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 58ms/step - accuracy: 0.2996 - loss: 1.3
803 - val_accuracy: 0.1985 - val_loss: 1.3908
Epoch 10/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 58ms/step - accuracy: 0.2972 - loss: 1.3
809 - val_accuracy: 0.1985 - val_loss: 1.3912
Epoch 11/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 85ms/step - accuracy: 0.2816 - loss: 1.3
814 - val_accuracy: 0.1985 - val_loss: 1.3916
Epoch 12/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 81ms/step - accuracy: 0.2927 - loss: 1.3
788 - val_accuracy: 0.1985 - val_loss: 1.3920
Epoch 13/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 4s 61ms/step - accuracy: 0.2894 - loss: 1.3
816 - val_accuracy: 0.1985 - val_loss: 1.3925
Epoch 14/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 63ms/step - accuracy: 0.2929 - loss: 1.3
810 - val_accuracy: 0.1985 - val_loss: 1.3928
Epoch 15/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 70ms/step - accuracy: 0.2928 - loss: 1.3
802 - val_accuracy: 0.1985 - val_loss: 1.3932
Epoch 16/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 89ms/step - accuracy: 0.2744 - loss: 1.3
831 - val_accuracy: 0.1985 - val_loss: 1.3935
Epoch 17/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 81ms/step - accuracy: 0.2871 - loss: 1.3
821 - val_accuracy: 0.1985 - val_loss: 1.3937
Epoch 18/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 68ms/step - accuracy: 0.2869 - loss: 1.3
838 - val_accuracy: 0.1985 - val_loss: 1.3943
Epoch 19/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 65ms/step - accuracy: 0.2756 - loss: 1.3
829 - val_accuracy: 0.1985 - val_loss: 1.3944
```

```
Epoch 20/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 61ms/step - accuracy: 0.2776 - loss: 1.3
842 - val_accuracy: 0.1985 - val_loss: 1.3947
```

Train New Model 2

In [30]:
```
new_history2 = new_model2.fit(dataset,validation_data=validation_datas
et,epochs=20)
```

```
Epoch 1/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 6s 98ms/step - accuracy: 0.3036 - loss: 20.
8716 - val_accuracy: 0.2977 - val_loss: 1.3860
Epoch 2/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 4s 102ms/step - accuracy: 0.2478 - loss: 1.
3862 - val_accuracy: 0.2977 - val_loss: 1.3861
Epoch 3/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 4s 110ms/step - accuracy: 0.2472 - loss: 1.
3858 - val_accuracy: 0.2977 - val_loss: 1.3865
Epoch 4/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 70ms/step - accuracy: 0.2636 - loss: 1.3
853 - val_accuracy: 0.2977 - val_loss: 1.3867
Epoch 5/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 62ms/step - accuracy: 0.2317 - loss: 1.3
857 - val_accuracy: 0.1985 - val_loss: 1.3873
Epoch 6/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 63ms/step - accuracy: 0.2860 - loss: 1.3
840 - val_accuracy: 0.1985 - val_loss: 1.3877
Epoch 7/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 69ms/step - accuracy: 0.2882 - loss: 1.3
826 - val_accuracy: 0.1985 - val_loss: 1.3882
Epoch 8/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 75ms/step - accuracy: 0.2933 - loss: 1.3
835 - val_accuracy: 0.1985 - val_loss: 1.3888
Epoch 9/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 90ms/step - accuracy: 0.2663 - loss: 1.3
858 - val_accuracy: 0.1985 - val_loss: 1.3891
Epoch 10/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 4s 62ms/step - accuracy: 0.2762 - loss: 1.3
831 - val_accuracy: 0.1985 - val_loss: 1.3897
Epoch 11/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 61ms/step - accuracy: 0.2883 - loss: 1.3
812 - val_accuracy: 0.1985 - val_loss: 1.3902
Epoch 12/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 61ms/step - accuracy: 0.2666 - loss: 1.3
837 - val_accuracy: 0.1985 - val_loss: 1.3907
Epoch 13/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 78ms/step - accuracy: 0.2605 - loss: 1.3
847 - val_accuracy: 0.1985 - val_loss: 1.3908
Epoch 14/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 88ms/step - accuracy: 0.2706 - loss: 1.3
821 - val_accuracy: 0.1985 - val_loss: 1.3915
Epoch 15/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 60ms/step - accuracy: 0.2976 - loss: 1.3
786 - val_accuracy: 0.1985 - val_loss: 1.3918
Epoch 16/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 69ms/step - accuracy: 0.2799 - loss: 1.3
826 - val_accuracy: 0.1985 - val_loss: 1.3923
Epoch 17/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 67ms/step - accuracy: 0.2816 - loss: 1.3
836 - val_accuracy: 0.1985 - val_loss: 1.3927
Epoch 18/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 2s 69ms/step - accuracy: 0.2697 - loss: 1.3
846 - val_accuracy: 0.1985 - val_loss: 1.3929
Epoch 19/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 82ms/step - accuracy: 0.2793 - loss: 1.3
815 - val_accuracy: 0.1985 - val_loss: 1.3932
```

```
Epoch 20/20
33/33 ━━━━━━━━━━━━━━━━━━━━ 3s 86ms/step - accuracy: 0.2881 - loss: 1.3
811 - val_accuracy: 0.1985 - val_loss: 1.3935
```

2 (c)

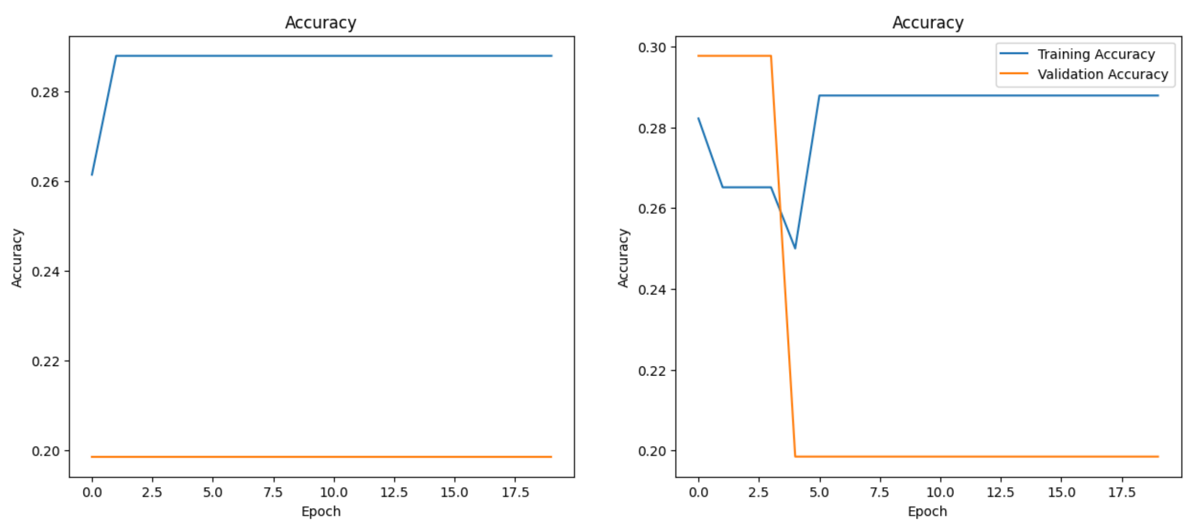
In [31]:
```python
training_accuracy1 = new_history1.history['accuracy']
validation_accuracy1 = new_history1.history['val_accuracy']

training_accuracy2 = new_history2.history['accuracy']
validation_accuracy2 = new_history2.history['val_accuracy']

fig,axes = plt.subplots(1,2,figsize=(15,6))
axes[0].plot(training_accuracy1, label='Training Accuracy')
axes[0].plot(validation_accuracy1, label='Validation Accuracy')
axes[0].set_title('Accuracy')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Accuracy')

axes[1].plot(training_accuracy2, label='Training Accuracy')
axes[1].plot(validation_accuracy2, label='Validation Accuracy')
axes[1].set_title('Accuracy')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('Accuracy')
plt.legend()

plt.show()
```



2 (d)

1. The initial model appears to suffer from overfitting. While the training accuracy increased to 84%, the validation accuracy remained below 25%.
2. In the experiment model 1 and model 2 suffers from undefitting , as persistently low accuracies across both training and validation sets.

3

In [33]:
```
def load_data(file_path):
    with open(file_path, 'r') as f:
        data = [json.loads(line) for line in f]
    return data
```

In [34]:
```
train_data = load_data("/content/drive/MyDrive/DM3/student_23/train.js
on")
val_data = load_data("/content/drive/MyDrive/DM3/student_23/validatio
n.json")
test_data = load_data("/content/drive/MyDrive/DM3/student_23/test.jso
n")
```

In [36]:
```
dataset = DatasetDict({
    "train": Dataset.from_list(train_data),
    "validation": Dataset.from_list(val_data),
    "test": Dataset.from_list(test_data)
})

dataset.save_to_disk("sem_eval_dataset")
```

In [37]:
```
labels = [label for label in dataset['train'].features.keys() if label
not in ['ID', 'Tweet']]
id2label = {idx:label for idx, label in enumerate(labels)}
label2id = {label:idx for idx, label in enumerate(labels)}
labels
```

Out[37]:
```
['anger',
 'anticipation',
 'disgust',
 'fear',
 'joy',
 'love',
 'optimism',
 'pessimism',
 'sadness',
 'surprise',
 'trust']
```

In [38]:
```
from transformers import AutoTokenizer
import numpy as np

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

def preprocess_data(examples):
  text = examples["Tweet"]
  encoding = tokenizer(text, padding="max_length", truncation=True, ma
x_length=128)
  labels_batch = {k: examples[k] for k in examples.keys() if k in labe
ls}
  labels_matrix = np.zeros((len(text), len(labels)))
  for idx, label in enumerate(labels):
    labels_matrix[:, idx] = labels_batch[label]

  encoding["labels"] = labels_matrix.tolist()

  return encoding
```

In [39]:
```
encoded_dataset = dataset.map(preprocess_data, batched=True, remove_co
lumns=dataset['train'].column_names)
```

In [40]:
```
encoded_dataset.set_format("torch")
```

In [41]:
```
from transformers import AutoModelForSequenceClassification

model = AutoModelForSequenceClassification.from_pretrained("bert-base-
uncased",
                                                           problem_typ
e="multi_label_classification",
                                                           num_labels=
len(labels),
                                                           id2label=id
2label,
                                                           label2id=la
bel2id)
```

```
Some weights of BertForSequenceClassification were not initialized fro
m 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.
```

In [42]:
```
batch_size = 8
metric_name = "f1"
```

In [43]:
```
from transformers import TrainingArguments, Trainer

args = TrainingArguments(
    f"bert-finetuned-sem_eval-english",
    evaluation_strategy = "epoch",
    save_strategy = "epoch",
    learning_rate=2e-5,
    per_device_train_batch_size=batch_size,
    per_device_eval_batch_size=batch_size,
    num_train_epochs=5,
    weight_decay=0.01,
    load_best_model_at_end=True,
    metric_for_best_model=metric_name,
)
```

In [44]:
```
from sklearn.metrics import f1_score, roc_auc_score, accuracy_score
from transformers import EvalPrediction
import torch

def multi_label_metrics(predictions, labels, threshold=0.5):
    sigmoid = torch.nn.Sigmoid()
    probs = sigmoid(torch.Tensor(predictions))
    y_pred = np.zeros(probs.shape)
    y_pred[np.where(probs >= threshold)] = 1
    y_true = labels
    f1_micro_average = f1_score(y_true=y_true, y_pred=y_pred, average
='micro')
    roc_auc = roc_auc_score(y_true, y_pred, average = 'micro')
    accuracy = accuracy_score(y_true, y_pred)
    metrics = {'f1': f1_micro_average,
               'roc_auc': roc_auc,
               'accuracy': accuracy}
    return metrics

def compute_metrics(p: EvalPrediction):
    preds = p.predictions[0] if isinstance(p.predictions,
            tuple) else p.predictions
    result = multi_label_metrics(
        predictions=preds,
        labels=p.label_ids)
    return result
```

In [45]:
```
outputs = model(input_ids=encoded_dataset['train']['input_ids'][0].uns
queeze(0), labels=encoded_dataset['train'][0]['labels'].unsqueeze(0))
outputs
```

```
We strongly recommend passing in an `attention_mask` since your input_
ids may be padded. See https://huggingface.co/docs/transformers/troubl
eshooting#incorrect-output-when-padding-tokens-arent-masked.
```

Out[45]:
```
SequenceClassifierOutput(loss=tensor(0.6401, grad_fn=<BinaryCrossEntro
pyWithLogitsBackward0>), logits=tensor([[ 0.7788, -0.0009,  0.4671,
0.0596, -0.2869, -0.1744, -0.3475,  0.1844,
          0.2262, -0.1921,  0.0752]], grad_fn=<AddmmBackward0>), hidde
n_states=None, attentions=None)
```

In [46]:
```
trainer = Trainer(
    model,
    args,
    train_dataset=encoded_dataset["train"],
    eval_dataset=encoded_dataset["validation"],
    tokenizer=tokenizer,
    compute_metrics=compute_metrics
)
```

In [47]:
```
trainer.train()
```

```
wandb: WARNING The `run_name` is currently set to the same value as `TrainingArguments.output_dir`. If this was not intended, please specify a different run name by setting the `TrainingArguments.run_name` parameter.
wandb: Using wandb-core as the SDK backend.  Please refer to https://wandb.me/wandb-core for more information.


wandb: Logging into wandb.ai. (Learn how to deploy a W&B server locally: https://wandb.me/wandb-server)
wandb: You can find your API key in your browser here: https://wandb.ai/authorize
wandb: Paste an API key from your profile and hit enter, or press ctrl+c to quit:

 ..........

wandb: ERROR API key must be 40 characters long, yours was 25


wandb: Appending key for api.wandb.ai to your netrc file: /root/.netrc
```

Tracking run with wandb version 0.18.7

Run data is saved locally in `/content/wandb/run-20241129_220424-u04sy97i`

Syncing run **[bert-finetuned-sem_eval-english (https://wandb.ai/patels78-rowan-university/huggingface/runs/u04sy97i)](https://wandb.ai/patels78-rowan-university/huggingface/runs/u04sy97i)** to [Weights & Biases (https://wandb.ai/patels78-rowan-university/huggingface)](https://wandb.ai/patels78-rowan-university/huggingface) ([docs (https://wandb.me/developer-guide)](https://wandb.me/developer-guide))

View project at [https://wandb.ai/patels78-rowan-university/huggingface (https://wandb.ai/patels78-rowan-university/huggingface)](https://wandb.ai/patels78-rowan-university/huggingface)

View run at [https://wandb.ai/patels78-rowan-university/huggingface/runs/u04sy97i (https://wandb.ai/patels78-rowan-university/huggingface/runs/u04sy97i)](https://wandb.ai/patels78-rowan-university/huggingface/runs/u04sy97i)

[1875/1875 07:33, Epoch 5/5]

Epoch	Training Loss	Validation Loss	F1	Roc Auc	Accuracy
1	No log	0.354214	0.617700	0.736169	0.192500
2	0.407500	0.327928	0.643457	0.750446	0.220000
3	0.296000	0.322414	0.681406	0.778505	0.247500
4	0.246800	0.320954	0.663578	0.765654	0.220000
5	0.246800	0.320341	0.692521	0.788160	0.250000

Out[47]:
```
TrainOutput(global_step=1875, training_loss=0.29769027099609374, metrics={'train_runtime': 519.0228, 'train_samples_per_second': 28.9, 'train_steps_per_second': 3.613, 'total_flos': 986746187520000.0, 'train_loss': 0.29769027099609374, 'epoch': 5.0})
```

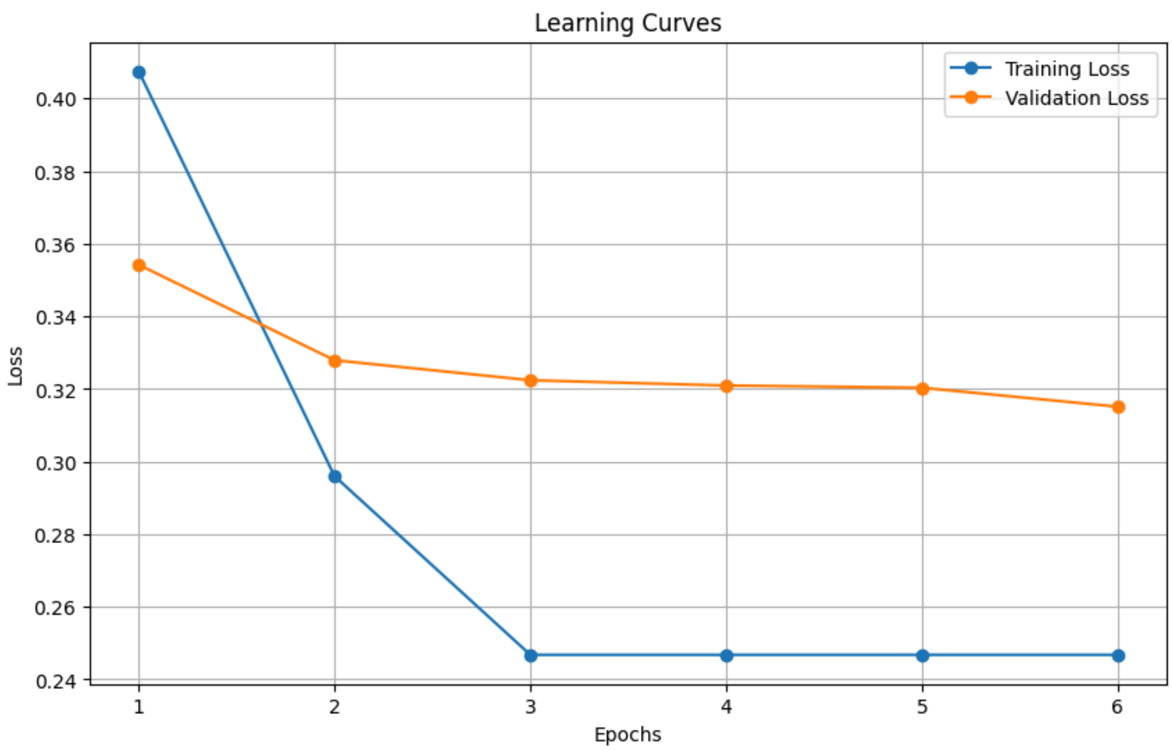
In [48]:
```
test_results = trainer.evaluate(encoded_dataset["test"])
print("Test Results:", test_results)
```

[188/188 00:10]

```
Test Results: {'eval_loss': 0.31512686610221863, 'eval_f1': 0.68299319
72789116, 'eval_roc_auc': 0.7830501218682399, 'eval_accuracy': 0.27133
33333333333, 'eval_runtime': 10.7438, 'eval_samples_per_second': 139.6
16, 'eval_steps_per_second': 17.499, 'epoch': 5.0}
```

In [52]:
```
train_losses = [log["loss"] for log in trainer.state.log_history if "l
oss" in log]
train_losses += [train_losses[-1]]*3
val_losses = [log["eval_loss"] for log in trainer.state.log_history if
"eval_loss" in log]

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



In [50]:
```
from sklearn.metrics import accuracy_score
import numpy as np

predictions = trainer.predict(encoded_dataset["test"])
preds_logits = predictions.predictions
true_labels = predictions.label_ids

sigmoid = torch.nn.Sigmoid()
probs = sigmoid(torch.Tensor(preds_logits)).numpy()

threshold = 0.5
binary_preds = (probs >= threshold).astype(int)

def exact_match_accuracy(predictions, labels):
    return np.mean(np.all(predictions == labels, axis=1))

def at_least_one_match_accuracy(predictions, labels):
  acc=0
  for i,j in zip(binary_preds,true_labels):
    for(a,b) in zip(i,j):
      if((a==b) and a == 1):
        acc +=1
        break
  return acc/len(predictions)

exact_match_acc = exact_match_accuracy(binary_preds, true_labels)
at_least_one_match_acc = at_least_one_match_accuracy(binary_preds, true_labels)

print(f"Exact Match Accuracy: {exact_match_acc * 100:.2f}%")
print(f"At Least One Match Accuracy: {at_least_one_match_acc * 100:.2f}%")
```

```
Exact Match Accuracy: 27.13%
At Least One Match Accuracy: 85.87%
```