tfjp9lroj

April 9, 2024

0.0.1 C. Using minimum support = 0.01 and minimum confidence threshold = 0.1, 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/)

[3]:
```
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules

DATA_FILE = "Grocery_Items_61.csv"
MIN_SUPPORT_THRESHOLD = 0.01
MIN_CONFIDENCE_THRESHOLD = 0.1

def load_preprocess_data(file_path):
    raw_data = pd.read_csv(file_path)
    processed_data = raw_data.apply(lambda row: row.dropna().tolist(), axis=1).
↪tolist()
    return processed_data

def encode_transaction_data(processed_data):
    encoder = TransactionEncoder()
    encoded_array = encoder.fit(processed_data).transform(processed_data)
    onehot_encoded_dataframe = pd.DataFrame(encoded_array, columns=encoder.
↪columns_)
    return onehot_encoded_dataframe

def find_itemsets_with_min_support(onehot_encoded_df, support_threshold):
    frequent_itemsets = apriori(onehot_encoded_df,␣
↪min_support=support_threshold, use_colnames=True)
    return frequent_itemsets

def derive_association_rules(frequent_itemsets, confidence_threshold):
    rules = association_rules(frequent_itemsets, metric="confidence",␣
↪min_threshold=confidence_threshold)
    return rules

def perform_grocery_analysis(file_path, support_threshold,␣
↪confidence_threshold):
```

```
    processed_data = load_preprocess_data(file_path)
    onehot_encoded_df = encode_transaction_data(processed_data)
    frequent_itemsets = find_itemsets_with_min_support(onehot_encoded_df,␣
 ↪support_threshold)
    association_rules = derive_association_rules(frequent_itemsets,␣
 ↪confidence_threshold)
    return onehot_encoded_df, frequent_itemsets, association_rules

encoded_df, itemsets, rules = perform_grocery_analysis(DATA_FILE,␣
 ↪MIN_SUPPORT_THRESHOLD, MIN_CONFIDENCE_THRESHOLD)
print(encoded_df)
print(itemsets)
rules
```

```
      Instant food products  UHT-milk  abrasive cleaner  artif. sweetener  \
0                     False     False             False             False
1                     False     False             False             False
2                     False     False             False             False
3                     False     False             False             False
4                     False     False             False             False
…                       …        …                …                 …
7995                  False     False             False             False
7996                  False     False             False             False
7997                  False     False             False             False
7998                  False     False             False             False
7999                  False     False             False             False

      baby cosmetics   bags  baking powder  bathroom cleaner   beef  berries  \
0              False  False          False             False  False     True
1              False  False          False             False  False    False
2              False  False          False             False  False    False
3              False  False          False             False  False    False
4              False  False          False             False  False    False
…                …     …             …                 …     …       …
7995           False  False          False             False  False    False
7996           False  False          False             False  False    False
7997           False  False          False             False  False    False
7998           False  False          False             False  False    False
7999           False  False          False             False  False    False

      …  turkey  vinegar  waffles  whipped/sour cream  whisky  white bread  \
0     …   False    False    False               False   False        False
1     …   False    False    False               False   False        False
2     …   False    False    False               False   False        False
3     …   False    False    False               False   False        False
4     …   False    False    False               False   False        False
…   …     …       …        …                  …       …           …
```

```
7995  …   False    False    False              False   False          False
7996  …   False    False    False              False   False          False
7997  …   False    False    False              False   False          False
7998  …   False    False    False               True   False          False
7999  …   False    False    False              False   False          False

      white wine  whole milk  yogurt  zwieback
0          False       False   False     False
1          False       False   False     False
2          False        True   False     False
3          False        True   False     False
4          False       False   False     False
…            …         …   …       …
7995       False       False   False     False
7996       False       False   False     False
7997       False       False   False     False
7998       False        True   False     False
7999       False       False   False     False

[8000 rows x 166 columns]
     support                    itemsets
0   0.020125                  (UHT-milk)
1   0.034875                      (beef)
2   0.020875                   (berries)
3   0.018125                 (beverages)
4   0.043750              (bottled beer)
..       …                         …
64  0.010500  (other vegetables, rolls/buns)
65  0.015625  (whole milk, other vegetables)
66  0.013500        (whole milk, rolls/buns)
67  0.011250              (whole milk, soda)
68  0.010125            (whole milk, yogurt)

[69 rows x 2 columns]
```

[3]:
```
          antecedents         consequents  antecedent support  \
0        (whole milk)  (other vegetables)            0.155875
1  (other vegetables)        (whole milk)            0.122500
2        (rolls/buns)        (whole milk)            0.107625
3              (soda)        (whole milk)            0.097375
4            (yogurt)        (whole milk)            0.086250

   consequent support   support  confidence      lift  leverage  conviction  \
0            0.122500  0.015625    0.100241  0.818290 -0.003470    0.975261
1            0.155875  0.015625    0.127551  0.818290 -0.003470    0.967535
2            0.155875  0.013500    0.125436  0.804719 -0.003276    0.965195
3            0.155875  0.011250    0.115533  0.741188 -0.003928    0.954388
```

```
4            0.155875  0.010125    0.117391  0.753112 -0.003319    0.956398

   zhangs_metric
0      -0.208275
1      -0.201954
2      -0.213798
3      -0.278944
4      -0.264039
```

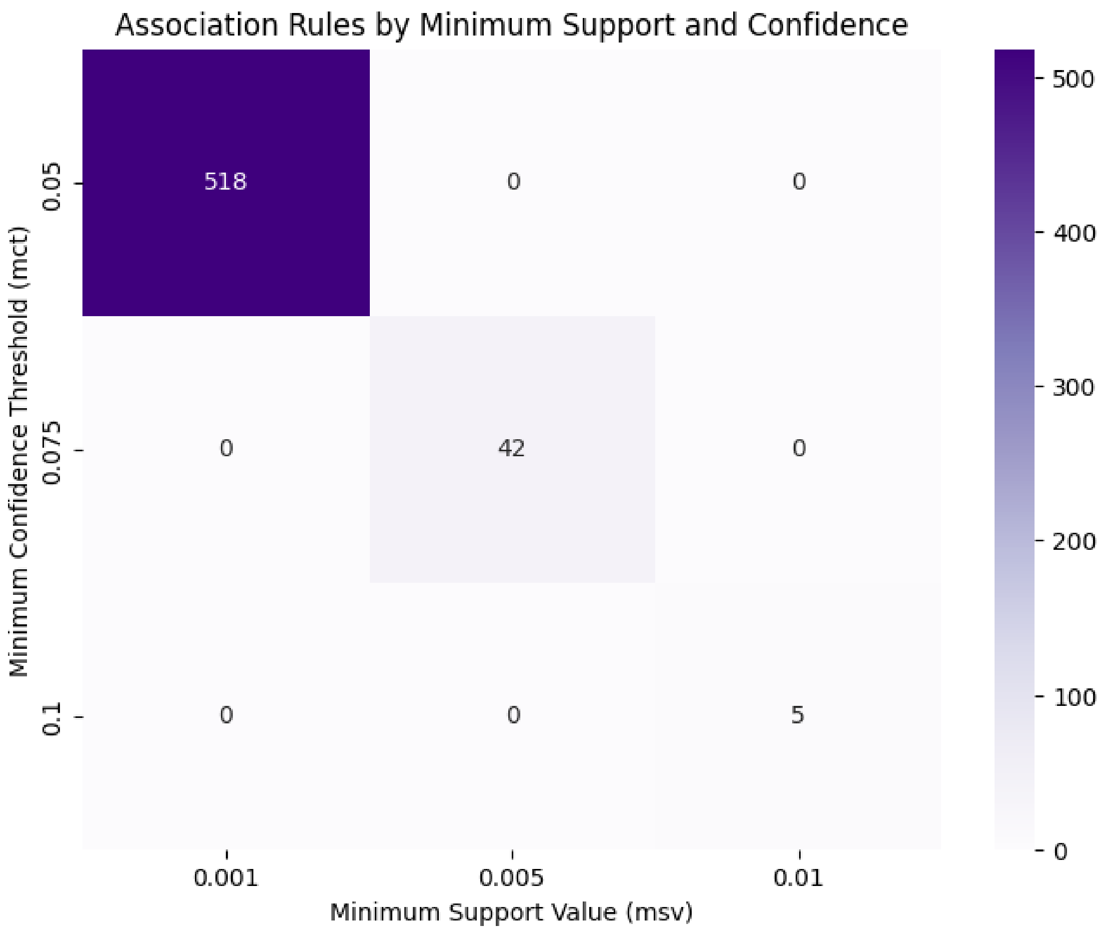
0.0.2 what are the association rules you can extract from your dataset?

- While whole milk turns up, the odds of having other vegetable items in the basket is 8.182%.
- When other vegetables are bought, there's an 8.182% chance that whole milk is also in the basket.
- Other products such as rolls or buns, as well as whole milk with probability of 8.041% will be imported too.
- Soda is bought with whole milk with a 7.411% likelihood.
- Yogurt tends to be bought together with whole milk with a 7.531% chance.

0.0.3 d. 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. (2.5 points)

[5]:
```python
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from mlxtend.frequent_patterns import apriori, association_rules

MIN_SUPPORT_VALUES = [0.001, 0.005, 0.01]
MIN_CONFIDENCE_VALUES = [0.05, 0.075, 0.1]
PAIRS = list(zip(MIN_SUPPORT_VALUES, MIN_CONFIDENCE_VALUES))

def generate_association_rules(transactions, pairs):
    rule_counts_matrix = np.zeros((len(pairs), len(pairs)))

    for idx, (support, confidence) in enumerate(pairs):
        frequent_itemsets = apriori(transactions, min_support=support,␣
 ↪use_colnames=True)
        rules = association_rules(frequent_itemsets, metric="confidence",␣
 ↪min_threshold=confidence)
        rule_counts_matrix[idx, idx] = len(rules)
```

```
    return rule_counts_matrix

def plot_rules_heatmap(rule_counts, support_values, confidence_values):
    plt.figure(figsize=(8, 6))
    sns.heatmap(rule_counts, annot=True, fmt=".0f", cmap="Purples",
                xticklabels=support_values, yticklabels=confidence_values)
    plt.title("Association Rules by Minimum Support and Confidence")
    plt.xlabel("Minimum Support Value (msv)")
    plt.ylabel("Minimum Confidence Threshold (mct)")
    plt.show()

rule_counts_matrix = generate_association_rules(encoded_df, PAIRS)
plot_rules_heatmap(rule_counts_matrix, MIN_SUPPORT_VALUES,
 ↪MIN_CONFIDENCE_VALUES)
```



0.0.4 e. Split the dataset into 50:50 (i.e., 2 equal subsets) and extract association rules for each data subset for minimum support = 0.005 and minimum confident threshold = 0.075. Show the association rules for both sets. Which association rules appeared in both sets (note that there could be none)? (1 point)

[6]:
```python
import pandas as pd
from sklearn.model_selection import train_test_split
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules


TEST_SPLIT_RATIO = 0.5
RANDOM_SEED = 40
MIN_SUPPORT_THRESHOLD = 0.005
MIN_CONFIDENCE_THRESHOLD = 0.075

def split_dataset(dataframe, test_ratio, seed):
    return train_test_split(dataframe, test_size=test_ratio, random_state=seed)

def find_association_rules(data, support, confidence):
    transaction_encoder = TransactionEncoder()
    data_encoded = transaction_encoder.fit(data).transform(data)
    df_encoded = pd.DataFrame(data_encoded, columns=transaction_encoder.
 ↪columns_)
    frequent_itemsets = apriori(df_encoded, min_support=support,␣
 ↪use_colnames=True)
    rules = association_rules(frequent_itemsets, metric="confidence",␣
 ↪min_threshold=confidence)
    return rules

def merge_rule_sets(rules1, rules2):
    return pd.merge(rules1, rules2, on=list(rules1.columns), how='outer')


data_set1, data_set2 = split_dataset(encoded_df, TEST_SPLIT_RATIO, RANDOM_SEED)

rules_set1 = find_association_rules(data_set1, MIN_SUPPORT_THRESHOLD,␣
 ↪MIN_CONFIDENCE_THRESHOLD)
rules_set2 = find_association_rules(data_set2, MIN_SUPPORT_THRESHOLD,␣
 ↪MIN_CONFIDENCE_THRESHOLD)
```

[8]:
```python
print("Rule set 1\n")
print(rules_set1)

print("Rule set 2\n")
print(rules_set2)
```

```
Rule set 1

    antecedents   consequents  antecedent support  consequent support  \
0           (a)           ( )             0.02575             0.02450
1           ( )           (a)             0.02450             0.02575
2           (b)           ( )             0.00975             0.02450
3           ( )           (b)             0.02450             0.00975
4           (c)           ( )             0.02000             0.02450
…           …             …                   …                  …
5259        (e)  (t, c, a, l)             0.02925             0.00550
5260        (t)  (a, c, l, e)             0.01925             0.00650
5261        (c)  (t, a, l, e)             0.02000             0.00625
5262        (a)  (t, c, l, e)             0.02575             0.00550
5263        (l)  (t, c, a, e)             0.01525             0.00625

      support  confidence       lift  leverage  conviction  zhangs_metric
0     0.01750    0.679612  27.739251  0.016869    3.044742       0.989428
1     0.01750    0.714286  27.739251  0.016869    3.409875       0.988160
2     0.00725    0.743590  30.350602  0.007011    3.804450       0.976573
3     0.00725    0.295918  30.350602  0.007011    1.406442       0.991340
4     0.01550    0.775000  31.632653  0.015010    4.335556       0.988150
…       …          …          …         …          …             …
5259  0.00500    0.170940  31.080031  0.004839    1.199552       0.996987
5260  0.00500    0.259740  39.960040  0.004875    1.342096       0.994112
5261  0.00500    0.250000  40.000000  0.004875    1.325000       0.994898
5262  0.00500    0.194175  35.304501  0.004858    1.234139       0.997357
5263  0.00500    0.327869  52.459016  0.004905    1.478506       0.996128

[5264 rows x 10 columns]
Rule set 2

    antecedents   consequents  antecedent support  consequent support  \
0           (a)           ( )             0.02575             0.02450
1           ( )           (a)             0.02450             0.02575
2           (b)           ( )             0.00975             0.02450
3           ( )           (b)             0.02450             0.00975
4           (c)           ( )             0.02000             0.02450
…           …             …                   …                  …
5259        (e)  (t, c, a, l)             0.02925             0.00550
5260        (t)  (a, c, l, e)             0.01925             0.00650
5261        (c)  (t, a, l, e)             0.02000             0.00625
5262        (a)  (t, c, l, e)             0.02575             0.00550
5263        (l)  (t, c, a, e)             0.01525             0.00625

      support  confidence       lift  leverage  conviction  zhangs_metric
0     0.01750    0.679612  27.739251  0.016869    3.044742       0.989428
1     0.01750    0.714286  27.739251  0.016869    3.409875       0.988160
2     0.00725    0.743590  30.350602  0.007011    3.804450       0.976573
```

```
3     0.00725    0.295918  30.350602  0.007011     1.406442        0.991340
4     0.01550    0.775000  31.632653  0.015010     4.335556        0.988150
…       …          …          …         …            …               …
5259  0.00500    0.170940  31.080031  0.004839     1.199552        0.996987
5260  0.00500    0.259740  39.960040  0.004875     1.342096        0.994112
5261  0.00500    0.250000  40.000000  0.004875     1.325000        0.994898
5262  0.00500    0.194175  35.304501  0.004858     1.234139        0.997357
5263  0.00500    0.327869  52.459016  0.004905     1.478506        0.996128

[5264 rows x 10 columns]
```

[9]:

```
combined_rules = merge_rule_sets(rules_set1, rules_set2)
combined_rules
```

[9]:

```
        antecedents consequents  antecedent support  consequent support  \
0               (a)         ( )             0.02575             0.02450
1               (a)   (t, l, e)             0.02575             0.00750
2               (a)   (s, l, e)             0.02575             0.00775
3               (a)   (l, r, e)             0.02575             0.00775
4               (a)   (t, i, e)             0.02575             0.00725
…                …        …                    …                  …
5259         (r, n)      ( , i)             0.01150             0.01500
5260         (r, n)   (s,  , e)             0.01150             0.01325
5261         (r, n)   ( , i, e)             0.01150             0.01250
5262         (r, n)   (a,  , e)             0.01150             0.01400
5263   (s,  , r, n)         (e)             0.00600             0.02925

      support  confidence       lift  leverage  conviction  zhangs_metric
0     0.01750    0.679612  27.739251  0.016869    3.044742       0.989428
1     0.00625    0.242718  32.362460  0.006057    1.310609       0.994714
2     0.00600    0.233010  30.065769  0.005800    1.293693       0.992291
3     0.00625    0.242718  31.318509  0.006050    1.310279       0.993657
4     0.00500    0.194175  26.782725  0.004813    1.231967       0.988106
…       …          …          …         …           …              …
5259  0.00600    0.521739  34.782609  0.005828    2.059545       0.982549
5260  0.00500    0.434783  32.813782  0.004848    1.745788       0.980804
5261  0.00525    0.456522  36.521739  0.005106    1.817000       0.983934
5262  0.00550    0.478261  34.161491  0.005339    1.889833       0.982021
5263  0.00500    0.833333  28.490028  0.004824    5.824500       0.970724

[5264 rows x 10 columns]
```

0.0.5 2. [ImageClassification using CNN]Constructa4-class classification model using a convolutional neural network with the following simple architecture (2 point)

- i 1Convolutional Layer with 8 3×3 filters.
- ii 1 max pooling with 2×2 pool size
- iii Flatten the Tensor

- iv 1 hidden layer with 16 nodes for fully connected neural network
- v Output layer has 4 nodes (since 4 classes) using 'softmax' activation function.

[12]:
```
import numpy as np
from keras.utils import to_categorical
from PIL import Image
import os
from sklearn.model_selection import train_test_split

myDogBreeds = [
    "n02099712-Labrador_retriever",
    "n02110185-Siberian_husky",
    "n02113799-standard_poodle",
    "n02113186-Cardigan"
]

def get_images_base_directory():
    base_directory = os.getcwd()
    return os.path.join(base_directory, 'images')

def load_and_label_images(directory, breed_idx, target_img_size):
    images = []
    labels = []

    for image_filename in os.listdir(directory):
        full_image_path = os.path.join(directory, image_filename)
        with Image.open(full_image_path) as image:
            resized_image = image.convert('RGB').resize(target_img_size)
            images.append(np.array(resized_image))
            labels.append(breed_idx)

    return images, labels

def normalize_and_encode_images(images, labels, total_breeds):
    normalized_images = np.array(images, dtype=np.float32) / 255.0
    one_hot_encoded_labels = to_categorical(labels, num_classes=total_breeds)

    return normalized_images, one_hot_encoded_labels

def create_image_dataset(breeds, directory, img_size):
    dataset_images = []
    dataset_labels = []

    for idx, breed in enumerate(breeds):
        breed_path = os.path.join(directory, breed)
        if breed in os.listdir(directory):
            images, labels = load_and_label_images(breed_path, idx, img_size)
```

```
            dataset_images.extend(images)
            dataset_labels.extend(labels)

    return normalize_and_encode_images(dataset_images, dataset_labels,␣
 ↪len(breeds))

images_directory = get_images_base_directory()
target_image_size = (128, 128)
final_dataset, final_labels = create_image_dataset(myDogBreeds,␣
 ↪images_directory, target_image_size)

# Split the dataset
X_train, X_val, y_train, y_val = train_test_split(final_dataset, final_labels,␣
 ↪test_size=0.20, random_state=40)
```

[ ]:

```

```

[21]:

```
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras import Sequential
from sklearn.model_selection import train_test_split

def create_and_train_cnn(num_filters, kernel_size, input_shape, num_classes,␣
 ↪X_train, y_train, X_val, y_val, epochs, batch_size):
    model = Sequential([
        Conv2D(num_filters, kernel_size=kernel_size, activation='relu',␣
 ↪input_shape=input_shape),
        MaxPooling2D(pool_size=(2, 2)),
        Flatten(),
        Dense(16, activation='relu'),
        Dense(num_classes, activation='softmax')
    ])
    model.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

    history = model.fit(X_train, y_train, epochs=epochs, batch_size=batch_size,␣
 ↪validation_data=(X_val, y_val))
    return history


def plot_learning_curves(histories, num_epochs):
    for label, history in histories.items():
        plt.plot(history.history['accuracy'], label=f'{label} training␣
 ↪accuracy')
```

```
        plt.plot(history.history['val_accuracy'], label=f'{label} validation␣
↪accuracy')

        plt.title('Training and Validation Accuracy')
        plt.xlabel('Epochs')
        plt.ylabel('Accuracy')
        plt.legend()
        plt.show()


input_shape = (128, 128, 3)
num_classes = 4
epochs = 20
batch_size = 32

filters_options = [4, 8, 16]
histories = {}

for num_filters in filters_options:
    histories[f'Filters {num_filters}'] = create_and_train_cnn(
        num_filters, (3, 3), input_shape, num_classes, X_train, y_train, X_val,␣
↪y_val, epochs, batch_size
    )

plot_learning_curves(histories, epochs)
```

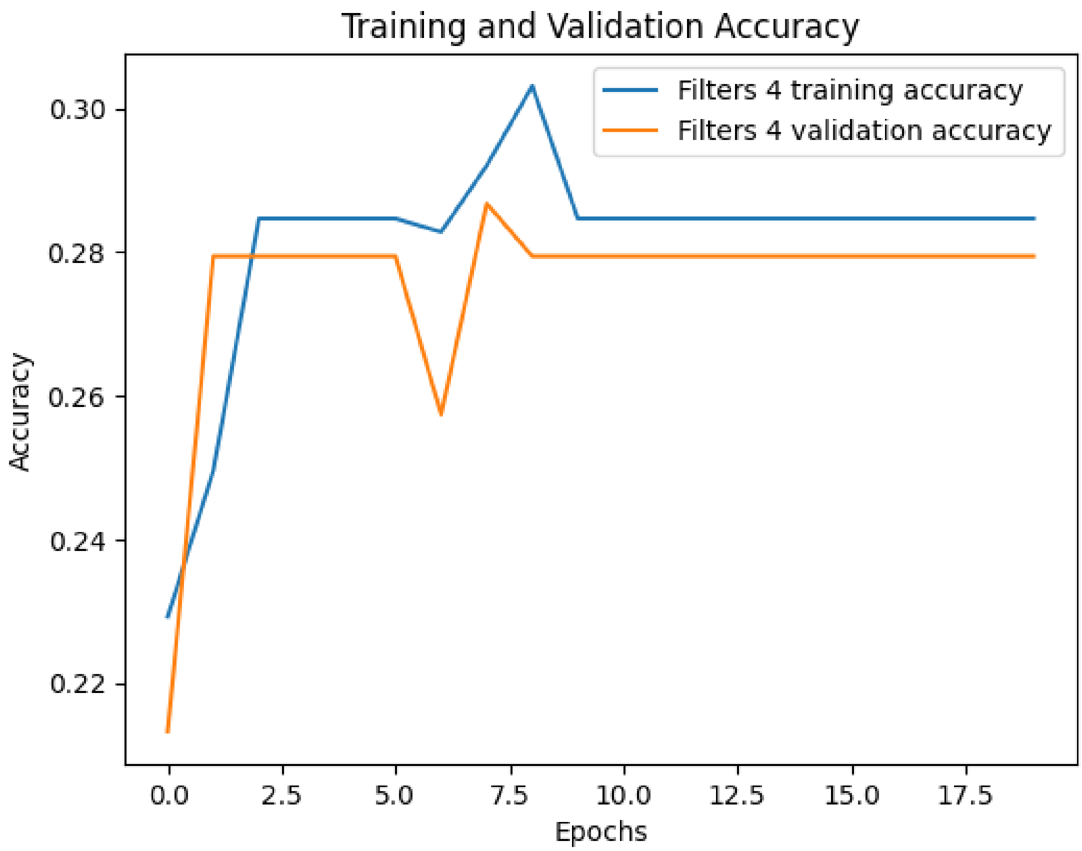
```
Epoch 1/20
17/17            1s 18ms/step -
accuracy: 0.2203 - loss: 1.4757 - val_accuracy: 0.2132 - val_loss: 1.3864
Epoch 2/20
17/17            0s 11ms/step -
accuracy: 0.2187 - loss: 1.3864 - val_accuracy: 0.2794 - val_loss: 1.3859
Epoch 3/20
17/17            0s 11ms/step -
accuracy: 0.2756 - loss: 1.3858 - val_accuracy: 0.2794 - val_loss: 1.3856
Epoch 4/20
17/17            0s 11ms/step -
accuracy: 0.2679 - loss: 1.3857 - val_accuracy: 0.2794 - val_loss: 1.3853
Epoch 5/20
17/17            0s 12ms/step -
accuracy: 0.2922 - loss: 1.3850 - val_accuracy: 0.2794 - val_loss: 1.3849
Epoch 6/20
17/17            0s 11ms/step -
accuracy: 0.2808 - loss: 1.3849 - val_accuracy: 0.2794 - val_loss: 1.3847
Epoch 7/20
17/17            0s 10ms/step -
accuracy: 0.2946 - loss: 1.3837 - val_accuracy: 0.2574 - val_loss: 1.3988
```

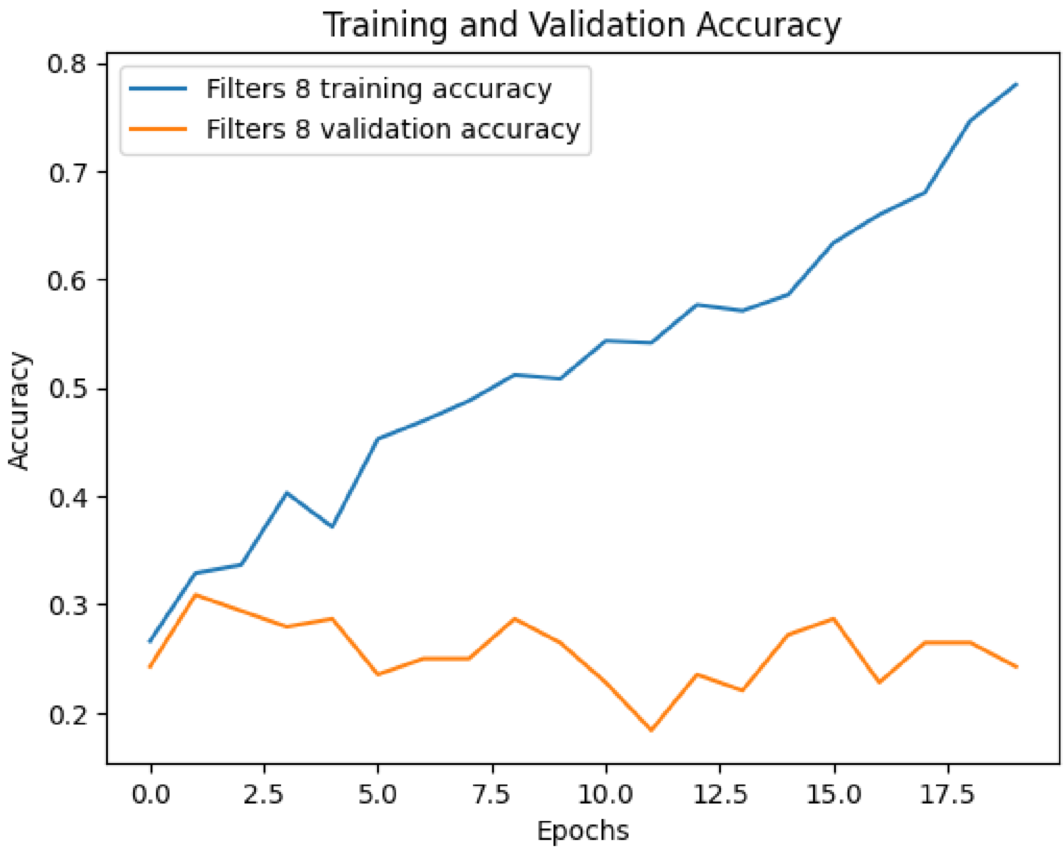
```
Epoch 8/20
17/17            0s 10ms/step -
accuracy: 0.2662 - loss: 1.3820 - val_accuracy: 0.2868 - val_loss: 1.3884
Epoch 9/20
17/17            0s 10ms/step -
accuracy: 0.2692 - loss: 1.3817 - val_accuracy: 0.2794 - val_loss: 1.3841
Epoch 10/20
17/17            0s 10ms/step -
accuracy: 0.2934 - loss: 1.3834 - val_accuracy: 0.2794 - val_loss: 1.3838
Epoch 11/20
17/17            0s 11ms/step -
accuracy: 0.2593 - loss: 1.3859 - val_accuracy: 0.2794 - val_loss: 1.3837
Epoch 12/20
17/17            0s 10ms/step -
accuracy: 0.2536 - loss: 1.3855 - val_accuracy: 0.2794 - val_loss: 1.3836
Epoch 13/20
17/17            0s 10ms/step -
accuracy: 0.2679 - loss: 1.3854 - val_accuracy: 0.2794 - val_loss: 1.3835
Epoch 14/20
17/17            0s 10ms/step -
accuracy: 0.2603 - loss: 1.3871 - val_accuracy: 0.2794 - val_loss: 1.3833
Epoch 15/20
17/17            0s 10ms/step -
accuracy: 0.2894 - loss: 1.3834 - val_accuracy: 0.2794 - val_loss: 1.3832
Epoch 16/20
17/17            0s 10ms/step -
accuracy: 0.2912 - loss: 1.3830 - val_accuracy: 0.2794 - val_loss: 1.3831
Epoch 17/20
17/17            0s 10ms/step -
accuracy: 0.2878 - loss: 1.3834 - val_accuracy: 0.2794 - val_loss: 1.3831
Epoch 18/20
17/17            0s 11ms/step -
accuracy: 0.2836 - loss: 1.3828 - val_accuracy: 0.2794 - val_loss: 1.3830
Epoch 19/20
17/17            0s 10ms/step -
accuracy: 0.2909 - loss: 1.3843 - val_accuracy: 0.2794 - val_loss: 1.3829
Epoch 20/20
17/17            0s 12ms/step -
accuracy: 0.2555 - loss: 1.3855 - val_accuracy: 0.2794 - val_loss: 1.3829
Epoch 1/20
17/17            1s 21ms/step -
accuracy: 0.2580 - loss: 2.5223 - val_accuracy: 0.2426 - val_loss: 1.3697
Epoch 2/20
17/17            0s 15ms/step -
accuracy: 0.3295 - loss: 1.3490 - val_accuracy: 0.3088 - val_loss: 1.3716
Epoch 3/20
17/17            0s 15ms/step -
accuracy: 0.3676 - loss: 1.2976 - val_accuracy: 0.2941 - val_loss: 1.3650
```

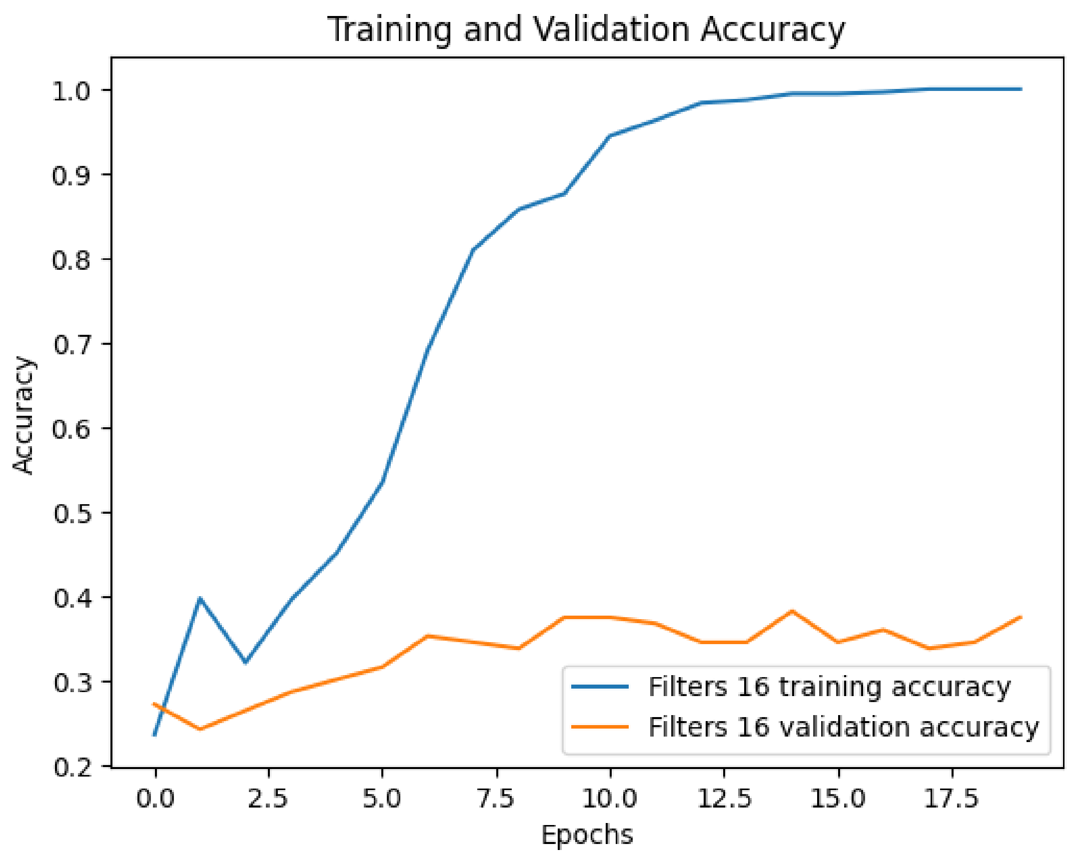
```
Epoch 4/20
17/17             0s 15ms/step -
accuracy: 0.3928 - loss: 1.2223 - val_accuracy: 0.2794 - val_loss: 1.4518
Epoch 5/20
17/17             0s 15ms/step -
accuracy: 0.3794 - loss: 1.2392 - val_accuracy: 0.2868 - val_loss: 1.3848
Epoch 6/20
17/17             0s 15ms/step -
accuracy: 0.4547 - loss: 1.1218 - val_accuracy: 0.2353 - val_loss: 1.4114
Epoch 7/20
17/17             0s 15ms/step -
accuracy: 0.4893 - loss: 1.0389 - val_accuracy: 0.2500 - val_loss: 1.4326
Epoch 8/20
17/17             0s 15ms/step -
accuracy: 0.4917 - loss: 1.0137 - val_accuracy: 0.2500 - val_loss: 1.4142
Epoch 9/20
17/17             0s 15ms/step -
accuracy: 0.5508 - loss: 0.9344 - val_accuracy: 0.2868 - val_loss: 1.4469
Epoch 10/20
17/17             0s 15ms/step -
accuracy: 0.5238 - loss: 0.9165 - val_accuracy: 0.2647 - val_loss: 1.4546
Epoch 11/20
17/17             0s 15ms/step -
accuracy: 0.5480 - loss: 0.8646 - val_accuracy: 0.2279 - val_loss: 1.4748
Epoch 12/20
17/17             0s 15ms/step -
accuracy: 0.5073 - loss: 0.8622 - val_accuracy: 0.1838 - val_loss: 1.6022
Epoch 13/20
17/17             0s 15ms/step -
accuracy: 0.5827 - loss: 0.8376 - val_accuracy: 0.2353 - val_loss: 1.5276
Epoch 14/20
17/17             0s 15ms/step -
accuracy: 0.5754 - loss: 0.8018 - val_accuracy: 0.2206 - val_loss: 1.5444
Epoch 15/20
17/17             0s 17ms/step -
accuracy: 0.5997 - loss: 0.7715 - val_accuracy: 0.2721 - val_loss: 1.5702
Epoch 16/20
17/17             0s 15ms/step -
accuracy: 0.5972 - loss: 0.7626 - val_accuracy: 0.2868 - val_loss: 1.6489
Epoch 17/20
17/17             0s 15ms/step -
accuracy: 0.6775 - loss: 0.7152 - val_accuracy: 0.2279 - val_loss: 1.6515
Epoch 18/20
17/17             0s 15ms/step -
accuracy: 0.6839 - loss: 0.7129 - val_accuracy: 0.2647 - val_loss: 1.6593
Epoch 19/20
17/17             0s 15ms/step -
accuracy: 0.7467 - loss: 0.6547 - val_accuracy: 0.2647 - val_loss: 1.7520
```

```
Epoch 20/20
17/17            0s 15ms/step -
accuracy: 0.7858 - loss: 0.6169 - val_accuracy: 0.2426 - val_loss: 1.7524
Epoch 1/20
17/17            2s 37ms/step -
accuracy: 0.2241 - loss: 1.8969 - val_accuracy: 0.2721 - val_loss: 1.3651
Epoch 2/20
17/17            1s 29ms/step -
accuracy: 0.3891 - loss: 1.3623 - val_accuracy: 0.2426 - val_loss: 1.3716
Epoch 3/20
17/17            1s 29ms/step -
accuracy: 0.3230 - loss: 1.3168 - val_accuracy: 0.2647 - val_loss: 1.3652
Epoch 4/20
17/17            1s 30ms/step -
accuracy: 0.3705 - loss: 1.2326 - val_accuracy: 0.2868 - val_loss: 1.3398
Epoch 5/20
17/17            1s 30ms/step -
accuracy: 0.4166 - loss: 1.1434 - val_accuracy: 0.3015 - val_loss: 1.3768
Epoch 6/20
17/17            1s 29ms/step -
accuracy: 0.4727 - loss: 1.0480 - val_accuracy: 0.3162 - val_loss: 1.3712
Epoch 7/20
17/17            1s 28ms/step -
accuracy: 0.6713 - loss: 0.8677 - val_accuracy: 0.3529 - val_loss: 1.3558
Epoch 8/20
17/17            1s 29ms/step -
accuracy: 0.8245 - loss: 0.6782 - val_accuracy: 0.3456 - val_loss: 1.4161
Epoch 9/20
17/17            1s 29ms/step -
accuracy: 0.8412 - loss: 0.6139 - val_accuracy: 0.3382 - val_loss: 1.4847
Epoch 10/20
17/17            1s 31ms/step -
accuracy: 0.8736 - loss: 0.4887 - val_accuracy: 0.3750 - val_loss: 1.4931
Epoch 11/20
17/17            1s 29ms/step -
accuracy: 0.9308 - loss: 0.3684 - val_accuracy: 0.3750 - val_loss: 1.6230
Epoch 12/20
17/17            1s 29ms/step -
accuracy: 0.9588 - loss: 0.2939 - val_accuracy: 0.3676 - val_loss: 1.5782
Epoch 13/20
17/17            1s 29ms/step -
accuracy: 0.9773 - loss: 0.2204 - val_accuracy: 0.3456 - val_loss: 1.6483
Epoch 14/20
17/17            1s 29ms/step -
accuracy: 0.9889 - loss: 0.1700 - val_accuracy: 0.3456 - val_loss: 1.7450
Epoch 15/20
17/17            1s 29ms/step -
accuracy: 0.9961 - loss: 0.1252 - val_accuracy: 0.3824 - val_loss: 1.7771
```

```
Epoch 16/20
17/17            1s 31ms/step -
accuracy: 0.9944 - loss: 0.1038 - val_accuracy: 0.3456 - val_loss: 1.8562
Epoch 17/20
17/17            1s 30ms/step -
accuracy: 0.9989 - loss: 0.0832 - val_accuracy: 0.3603 - val_loss: 1.9231
Epoch 18/20
17/17            1s 29ms/step -
accuracy: 1.0000 - loss: 0.0707 - val_accuracy: 0.3382 - val_loss: 1.9537
Epoch 19/20
17/17            1s 29ms/step -
accuracy: 1.0000 - loss: 0.0556 - val_accuracy: 0.3456 - val_loss: 2.0074
Epoch 20/20
17/17            1s 29ms/step -
accuracy: 1.0000 - loss: 0.0501 - val_accuracy: 0.3750 - val_loss: 2.1641
```




Training and Validation Accuracy
Filters 8 training accuracy
Filters 8 validation accuracy
Accuracy
Epochs
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5



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). Are there model overfit or underfit or just right?

Model with 4 Filters:

- This model shows the lowest accuracy among the three, both in training and validation.
- The proximity between the rates of training and validation accuracy show that the model does not tend to overfit; but the reverse, if it is underfitting.
- Underfitting is characterized by a model that is too simple to capture the underlying structure of the data. This model likely lacks the capacity to learn the features necessary for a higher accuracy.

Model with 8 Filters:

- There is an improvement in training accuracy compared to the model with 4 filters, indicating that increasing the capacity of the model helps in learning from the training data.
- Though the validation accuracy might go up, it might not grow at the same speed as the training mistakes are.This gap suggests the model may be starting to overfit, as it's learning features that are not generalizing well to the validation set.

- Learning specific to the training data is when the model generalizes the patterns seen there which are not present in the new data that the model has not seen before is called overfitting.

Model with 16 Filters:

- The model that has 16 filters has a considerable rise in the training accuracy to approach optimum levels, but this gap is quite notable as you get to the validation accuracy.
- The high training accuracy paired with the lower validation accuracy is a classic sign of overfitting. The model may have moved beyond the training data to a level where it inadvertently memorizes the noise and details that are not representative of the main trends in the data.

[ ]:

```

```