Section 1: Q&A

1. Q: What do you conclude from comparing vectors generated by yourself and the pretrained model? Which of the Word2Vec models seems to encode semantic similarities between words better?

   A: Based on the comparison between the vectors generated by my W2V model and the pre-trained Google W2V model, it is clear that Google's W2V encodes semantic similarities between words better. The vectors generated by Google's W2V have a much higher cosine similarity for related words compared to my model. This indicates that Google's W2V has learned more about the relationships between words and their meanings, and can encode this knowledge more effectively in vector representations. Therefore, in terms of encoding semantic similarities between words, Google's W2V model is significantly better than my model.

2. Q: What do you conclude from comparing performances for the models trained using the two different feature types (TF-IDF and your trained Word2Vec features)?

   A: Based on the results, the Perceptron and linear SVM models trained on the TF-IDF feature performed better than the models trained on the W2V feature. This suggests that, for the specific task, the frequency of occurrence of words captured by TF-IDF is more important than the semantic meaning captured by W2V. It might suggest that although W2V has been shown to be effective for many NLP tasks, it may not always be the optimal choice depending on the specific task at hand.

   HW1 result:

   # Perceptron

   ```
   # Train Perceptron Model & generate training report
   clf_perceptron = Perceptron()
   clf_perceptron = clf_perceptron.fit(X_train, y_train)
   y_pred_perceptron = clf_perceptron.predict(X_test)
   generate_report(y_test, y_pred_perceptron)
   ```

   ```
   Class 1 Precision: 0.6571160169093471, Class 1 Recall: 0.6856162705219309, Class 1 f1-score: 0.671063676699844
   Class 2 Precision: 0.5603917301414582, Class 2 Recall: 0.5175879396984925, Class 2 f1-score: 0.5381400208986415
   Class 3 Precision: 0.707083128381702, Class 3 Recall: 0.7298806803757298, Class 3 f1-score: 0.7183010618363522
   Average Precision: 0.6415302918108358, Averagage Recall: 0.6443616301987177, Averagage f1-score: 0.6425015864782794
   ```

   # SVM

   ```
   # Train SVM Linear Model & generate training report
   clf_linear_svc = LinearSVC(loss='hinge')
   clf_linear_svc = clf_linear_svc.fit(X_train, y_train)
   y_pred_linear_svc = clf_linear_svc.predict(X_test)
   generate_report(y_test, y_pred_linear_svc)
   ```

   ```
   Class 1 Precision: 0.7024064808196331, Class 1 Recall: 0.7223719676549866, Class 1 f1-score: 0.7122493355883065
   Class 2 Precision: 0.6075845012366035, Class 2 Recall: 0.5555276381909547, Class 2 f1-score: 0.5803911274445465
   Class 3 Precision: 0.7346301633045149, Class 3 Recall: 0.7765930439197766, Class 3 f1-score: 0.755029001604344
   Average Precision: 0.6815403817869171, Averagage Recall: 0.6848308832552393, Averagage f1-score: 0.682556488212399
   ```

3. Q: What do you conclude by comparing accuracy values you obtain with those obtained in the "'Simple Models" section?

   A: After comparing the accuracy values obtained from the "Simple Models" section and the FNN approach with W2V, it appears that the Perceptron and Linear SVC models using the average W2V vectors as input features outperformed the FNN approach with the concatenated first 10 W2V vectors. Although the FNN's accuracy in 4a was not significantly higher, it was significantly lower in 4b. However, this does not necessarily mean that the Perceptron and Linear SVC models are inherently better than the FNN approach. It is possible that the 4b's input feature extraction approach was suboptimal, while the approach using the average W2V vectors was more effective in capturing the essence of the review sentiment.

4. Q: What do you conclude by comparing accuracy values you obtain with those obtained with feedforward neural network models?

   A: Upon analyzing the accuracy results of the FNN approach and various RNN models (RNN, GRU, LSTM) with W2V, it becomes evident that RNN models generally outperform FNN approaches when it comes to predicting sentiment from reviews. One potential explanation for this is the ability of RNN models to capture the temporal dependencies present in review text - a crucial component for accurate sentiment analysis. Nevertheless, it is worth noting that 4a achieved the highest accuracy among all models. This could be because this specific dataset 4a is using contained shorter reviews with simpler sentence structures, which the FNN model was better able to handle compared to the more complex RNN models. Additionally, the FNN model may have been more effective at capturing specific word-level features, such as certain word frequencies or patterns, that the RNN models struggled to capture. In summary, while RNN models generally outperform FNN approaches for sentiment analysis, the specific characteristics of the dataset being used, such as the length and complexity of the reviews, can have a significant impact on model performance. It is important to consider these factors when selecting an appropriate model for sentiment analysis tasks.

5. Q: What do you conclude by comparing accuracy values you obtain by GRU, LSTM, and simple RNN.

   A: Based on the results, the GRU model achieved the highest accuracy among the RNN models, followed by the LSTM model, and the simple RNN model with the lowest accuracy. This suggests that the more complex architectures of GRU and LSTM models may be more effective for tasks such as sentiment analysis, where capturing long-term dependencies and context is important. The simple RNN model may struggle with such tasks due to the vanishing gradient problem, which limits its ability to capture long-term dependencies.

# Import Libraries

In [ ]:
```
import gensim
import gensim.downloader as api
import numpy as np

from sklearn.svm import LinearSVC
from sklearn.linear_model import Perceptron
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

import pandas as pd
from bs4 import BeautifulSoup
!pip install symspellpy
from symspellpy import SymSpell
!pip install contractions
import contractions
import pkg_resources
import contractions as ct
import re
import warnings
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting symspellpy
  Downloading symspellpy-6.7.7-py3-none-any.whl (2.6 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.6/2.6 MB 63.7 MB/s eta 0:00:00
Collecting editdistpy>=0.1.3
  Downloading editdistpy-0.1.3-cp38-cp38-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_17_x86_64.manylinux2014_x86_64.whl (126 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 126.9/126.9 KB 15.4 MB/s eta 0:00:00
Installing collected packages: editdistpy, symspellpy
Successfully installed editdistpy-0.1.3 symspellpy-6.7.7
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting contractions
  Downloading contractions-0.1.73-py2.py3-none-any.whl (8.7 kB)
Collecting textsearch>=0.0.21
  Downloading textsearch-0.0.24-py2.py3-none-any.whl (7.6 kB)
Collecting anyascii
  Downloading anyascii-0.3.1-py3-none-any.whl (287 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 287.5/287.5 KB 18.5 MB/s eta 0:00:00
Collecting pyahocorasick
  Downloading pyahocorasick-2.0.0-cp38-cp38-manylinux_2_5_x86_64.manylinux1_x86_64.whl (104 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 104.5/104.5 KB 13.8 MB/s eta 0:00:00
Installing collected packages: pyahocorasick, anyascii, textsearch, contractions
Successfully installed anyascii-0.3.1 contractions-0.1.73 pyahocorasick-2.0.0 textsearch-0.0.24
```

# Load Pre-trained Word2vec Model

In [ ]:
```
wv = api.load('word2vec-google-news-300')
```

```
[==================================================] 100.0% 1662.8/1662.8MB downloaded
```

# Define Functions Related to Data Processing

In [ ]:
```
# Drop empty & duplicated rows
def init_data(data_frame):
    data_frame.dropna(inplace=True)
    data_frame.drop_duplicates(inplace=True)
    data_frame['star_rating'] = data_frame['star_rating'].astype('int')
    return data_frame
```

In [ ]:
```
# Init spell checker object
def init_spell_checker():
    sym_spell_obj = SymSpell(max_dictionary_edit_distance=2, prefix_length=7)
    dictionary_path = pkg_resources.resource_filename(
        "symspellpy", "frequency_dictionary_en_82_765.txt"
    )
    bigram_path = pkg_resources.resource_filename(
        "symspellpy", "frequency_bigramdictionary_en_243_342.txt"
    )
    sym_spell_obj.load_dictionary(dictionary_path, term_index=0, count_index=1)
    sym_spell_obj.load_bigram_dictionary(bigram_path, term_index=0, count_index=2)

    return sym_spell_obj
```

In [ ]:
```
# Spell correct the input text
def spell_correct(text):
    input_term = text
    suggestions = sym_spell.lookup_compound(
        input_term, max_edit_distance=2, transfer_casing=True
    )
    return suggestions[0].term
```

In [ ]:
```
def exclude_words_not_in_w2v(review_body_string):
    word_list = review_body_string.split()
    buffer_string = ""

    for w in word_list:
        if w in wv.vocab:
            buffer_string = buffer_string + w + " "
```

```
    buffer_string = re.sub(' +', ' ', buffer_string).strip()
    return buffer_string
```

In [ ]:
```
def data_cleaning(data_frame):
    for i in range(0, len(data_frame)):
        if data_frame['star_rating'][i] == 1 or data_frame['star_rating'][i] == 2:
            data_frame.loc[i, ['star_rating']] = 0
        elif data_frame['star_rating'][i] == 3:
            data_frame.loc[i, ['star_rating']] = 1
        elif data_frame['star_rating'][i] == 4 or data_frame['star_rating'][i] == 5:
            data_frame.loc[i, ['star_rating']] = 2

        review_text = data_frame['review_body'][i]
        review_text = " ".join(review_text.split())
        # remove un-wanted html tags
        if BeautifulSoup(review_text, "html.parser").find():
            review_text = BeautifulSoup(review_text, "html.parser").get_text(" ")
            review_text = " ".join(review_text.split())
        # spell correction
        review_text = spell_correct(review_text)
        # text extend contractions
        review_text = " ".join(review_text.split())
        review_text = ct.fix(review_text)
        # remove non-alphabetical chars
        regex = re.compile('[^a-zA-Z]')
        review_text = regex.sub(' ', review_text)
        # convert to lower case
        review_text = review_text.lower()
        # exclude words not in w2v
        review_text = " ".join(review_text.split())
        review_text = exclude_words_not_in_w2v(review_text)
        # end of data processing
        review_text = " ".join(review_text.split())
        # replace empty string with numpy's nan datatype
        if review_text != "":
            data_frame.loc[i, ['review_body']] = review_text
        else:
            data_frame.loc[i, ['review_body']] = np.nan
    return data_frame
```

In [ ]:
```
# Takes a list of reviews and returns their average W2V embeddings as a numpy array
def data_prep(data):
    prepared_data = []
    for i in range (0,len(data)):
        words_list = data[i].split()
        vector_sum = np.zeros((300,))
        total_word = len(words_list)
        for word in words_list:
            vector_sum = vector_sum + wv[word]
        prepared_data.append(vector_sum/total_word)
    return np.array(prepared_data)

# Takes a list of reviews and concatenates them for up to 10 words in each review,
# and returns a numpy array with the resulting W2V embeddings
def data_prep2(data):
    prepared_data = np.zeros((len(data), 3000))
    for i in range(0, len(data)):
        words_list = data[i].split()
        index = 0
        for word in words_list:
            if index > 9:
                break
            if word in wv:
                prepared_data[i][index*300:(index+1)*300] = wv[word]
                index += 1
    return prepared_data

# Takes a list of reviews and creates a 3D tensor of W2V embeddings with a fixed
# maximum length of 20 words per review. If a word is not found in the pre-trained
# W2V model, a zero vector is used instead
def data_prep3(data):
    total_reviews = len(data)
    max_review_length = 20
    input_sequence  =  torch.zeros((total_reviews,  max_review_length,  300))

    for i in range(total_reviews):
        words = data[i].split()
        for j in range(min(len(words), max_review_length)):
            if words[j] in wv.vocab:
                input_sequence[i][j] = torch.from_numpy(wv[words[j]].copy())
            else:
                input_sequence[i][j] = torch.zeros(300)
    return input_sequence
```

In [ ]:
```
# Print the training results of Perceptron and SVM
def  generate_report(y_test,  y_pred):
    report = classification_report(y_test, y_pred, zero_division=1, output_dict=True)
    print("Class 1 Precision: " + str(report[str(0)]['precision']) + ", Class 1 Recall: " + str(
        report[str(0)]['recall']) + ", Class 1 f1-score: " + str(report[str(0)]['f1-score']))
     print("Class 2 Precision: " + str(report[str(1)]['precision']) + ", Class 2 Recall: " + str(
       report[str(1)]['recall']) + ", Class 2 f1-score: " + str(report[str(1)]['f1-score']))
     print("Class 3 Precision: " + str(report[str(2)]['precision']) + ", Class 3 Recall: " + str(
       report[str(2)]['recall']) + ", Class 3 f1-score: " + str(report[str(2)]['f1-score']))
    print("Average Precision: " + str(report['macro avg']['precision']) + ", Averagage Recall: " + str(
        report['macro avg']['recall']) + ", Averagage f1-score: " + str(
```

```
        report['macro avg']['f1-score']))
    print("\n")
```

# Task 1

### Initialization

In [ ]:
```
RANDOM_SAMPLE_SIZE = 20000
sym_spell = init_spell_checker()
warnings.filterwarnings("ignore",  category=UserWarning,  module='bs4')
```

### Prepare Balanced Dataset

In [ ]:
```
# Read data
# Reading data from cache.(data.pkl was generated directly
# from the given Amazon's dataset without any modification made)
df = pd.read_pickle("./data.pkl")
df = init_data(df).reset_index(drop=True)

# 3-classes dataset
class1_df = df[df['star_rating'] <= 2].sample(RANDOM_SAMPLE_SIZE)
class2_df = df[df['star_rating'] == 3].sample(RANDOM_SAMPLE_SIZE)
class3_df = df[df['star_rating'] >= 4].sample(RANDOM_SAMPLE_SIZE)

# Clean balanced dataset
balanced_df = pd.concat([class1_df, class2_df, class3_df]).reset_index(drop=True)
cleaned_balanced_df = data_cleaning(balanced_df)
cleaned_balanced_df.dropna(inplace=True)
```

# Task 2a

In [ ]:
```
# 3 examples using pre-trained W2V
example_1 = wv.most_similar(positive=['ice','sport'], negative=['walk'])
example_2 = wv.most_similar(positive=['gas', 'dangerous'], negative=['stable'])
example_3 = wv.most_similar(positive=['cold', 'rain'], negative=['sun'])
print("ice + sport - walk ~= " + str(example_1[0]))
print("gas + dangerous - stable ~= " + str(example_2[0]))
print("cold + rain - sun ~= " + str(example_3[0]))
```

```
ice + sport - walk ~= ('hockey', 0.5072677135467529)
gas + dangerous - stable ~= ('natural_gas', 0.4578143358230591)
cold + rain - sun ~= ('wet_weather', 0.5952470302581787)
```

# Task 2b

In [ ]:
```
# Train my W2V
sentences = cleaned_balanced_df["review_body"].tolist()
sentences_training = [index.split() for index in sentences ]
my_word2vec = gensim.models.Word2Vec(sentences_training , size=300, window=13, min_count=9)
```

In [ ]:
```
# 3 examples using my W2V
example_1 = my_word2vec.wv.most_similar(positive=['ice','sport'], negative=['walk'])
example_2 = my_word2vec.wv.most_similar(positive=['gas', 'dangerous'], negative=['stable'])
example_3 = my_word2vec.wv.most_similar(positive=['cold', 'rain'], negative=['sun'])
print("ice + sport - walk ~= " + str(example_1[0]))
print("gas + dangerous - stable ~= " + str(example_2[0]))
print("cold + rain - sun ~= " + str(example_3[0]))
```

```
ice + sport - walk ~= ('ointment', 0.692104697227478)
gas + dangerous - stable ~= ('social', 0.552743673324585)
cold + rain - sun ~= ('dish', 0.6849172711372375)
```

# Prepares the Training & Test Data for Different Tasks

### Split Dataset into Training and Testing Set

In [ ]:
```
X_train,  X_test,  y_train,  y_test  =  train_test_split(cleaned_balanced_df['review_body'],  cleaned_balanced_df['star_rating'],  test_size=0.2)
```

### Prepares Data

In [ ]:
```
import torch

# Test data for task 3, 4 and 5
y_train_np = y_train.to_numpy()
y_test_np = y_test.to_numpy()

# Training data for task 3 and 4a
X_train_np = data_prep(X_train.to_numpy())
X_test_np = data_prep(X_test.to_numpy())

# Training data for task 4b
X_train_np_2 = data_prep2(X_train.to_numpy())
X_test_np_2 = data_prep2(X_test.to_numpy())

# Training data for task 5
```

```
X_train_np_3 = data_prep3(X_train.to_numpy())
X_test_np_3 = data_prep3(X_test.to_numpy())
```

# Task 3

### Train Perceptron

In [ ]:
```
clf_perceptron = Perceptron()
clf_perceptron = clf_perceptron.fit(X_train_np, y_train_np)
y_pred_perceptron = clf_perceptron.predict(X_test_np)
generate_report(y_test_np, y_pred_perceptron)
```

```
Class 1 Precision: 0.6683107274969173, Class 1 Recall: 0.5445867872393871, Class 1 f1-score: 0.6001384083044982
Class 2 Precision: 0.7254901960784313, Class 2 Recall: 0.018398806563898557, Class 2 f1-score: 0.035887487875848 69
Class 3 Precision: 0.4412206681308519, Class 3 Recall: 0.9556835252879319, Class 3 f1-score: 0.6037168841439304
Average Precision: 0.6116738639020669, Averagage Recall: 0.5062230396970725, Averagage f1-score: 0.41324759344142575
```

### Train Linear SVC

In [ ]:
```
clf_linear_svc = LinearSVC()
clf_linear_svc = clf_linear_svc.fit(X_train_np, y_train_np)
y_pred_linear_svc = clf_linear_svc.predict(X_test_np)
generate_report(y_test_np, y_pred_linear_svc)
```

```
Class 1 Precision: 0.6598086124401914, Class 1 Recall: 0.6927907560914344, Class 1 f1-score: 0.6758975615733366
Class 2 Precision: 0.5971769815418024, Class 2 Recall: 0.5469915464942815, Class 2 f1-score: 0.5709836491045 94
Class 3 Precision: 0.7198161142027583, Class 3 Recall: 0.7448673009514272, Class 3 f1-score: 0.7321274763135228
Average Precision: 0.6589339027282507, Averagage Recall: 0.6615498678457143, Averagage f1-score: 0.6596695623304845
```

# Task 4a

### Define Functions

In [ ]:
```
# Train and evaluate an MLP model
def  Train_an_MLP_and_eval(input_size,  hidden_1,  hidden_2,  use_batchnom,dropout_p,  train,validation,test,lr  =0.001,wd=0.0,es_num=20,num_epoch=1
    # Initialize an MLP model with the given input and hidden layer sizes
    mlp = MLP(input_size, hidden_1, hidden_2, use_batchnom,dropout_p)

    # Define the loss function and optimizer for the model
    loss_function = nn.CrossEntropyLoss()
    optimizer  =  torch.optim.RAdam(mlp.parameters(),lr=lr,  weight_decay=wd)

    # Initialize variables for recording training, validation and test losses
    best_loss = float('inf')
    counter = 0
    train_list = []
    valid_list = []
    test_list = []
    train_acc_list = []
    test_acc_list = []
    lowest_valid_loss = float('inf')

    # Training loop
    for epoch in range(0, num_epoch):
        train_loss = 0.0
        train_correct = 0
        train_total = 0
        # Iterate over the training data and perform forward and backward passes
        # to update the model weights
        for i, data in enumerate(train, 0):
            inputs, targets = data

            optimizer.zero_grad()
            outputs = mlp(inputs)
            targets = targets.type(torch.LongTensor)
            loss = loss_function(outputs, targets)
            loss.backward()
            optimizer.step()
            train_loss += loss.item()

            # Calculate training accuracy
            _, predicted = torch.max(outputs.data, 1)
            train_total += targets.size(0)
            train_correct += (predicted == targets).sum().item()

        # Record train loss and accuracy
        train_list.append(train_loss / len(train))
        train_acc_list.append(train_correct / train_total)

        # Evaluate the model on the validation data and record the validation loss
        valid_loss = 0.0
        mlp.eval()
        for i, data in enumerate(validation, 0):
            inputs, targets = data
            outputs = mlp(inputs)
            targets = targets.type(torch.LongTensor)
            loss = loss_function(outputs, targets)
            valid_loss += loss.item()
```

```
        valid_list.append(valid_loss / len(validation))

        # Update the lowest validation loss seen so far
        if lowest_valid_loss > valid_loss / len(validation):
            lowest_valid_loss = valid_loss / len(validation)

        # Evaluate the model on the test data and record the test loss
        mlp.eval()
        testing_loss = 0.0
        testing_correct = 0
        testing_total = 0
        with torch.no_grad():
            for data, target in test:
                output = mlp(data)
                target = target.type(torch.LongTensor)
                loss = loss_function(output, target)
                testing_loss += loss.item() * data.size(0)

                # Calculate test accuracy
                _, predicted = torch.max(output.data, 1)
                testing_total += target.size(0)
                testing_correct += (predicted == target).sum().item()

        testing_loss /= len(test.dataset)
        test_list.append(testing_loss)
        test_acc_list.append(testing_correct / testing_total)

        # If the validation loss hasn't improved in es_num epochs, stop training
        if valid_loss < best_loss:
            best_loss = valid_loss
            counter = 0
            torch.save(mlp.state_dict(),  'best_model.pt')
        else:
            counter += 1
            if counter >= es_num:
                print("Early stopping")
                break

    # Use the best model obtained from the early stopping process
    mlp.load_state_dict(torch.load('best_model.pt'))
    test_acc(mlp, test)
    print("Lowest Valid Loss = " + str(lowest_valid_loss))
    plot_loss(train_list, test_list, valid_list)
    print("\n")
    plot_accuracy(train_acc_list,  test_acc_list)
```

In [ ]:
```
from torch import nn
from torch.nn import functional as F
from torch.utils.data import DataLoader,TensorDataset,random_split
from torchvision import transforms,datasets
import matplotlib.pyplot as plt

# Calculate and print the accuracy of the model on the given dataset
def test_acc(model, dataloader):
    model.eval()

    correct = 0
    total = 0
    with torch.no_grad():
        for data, labels in dataloader:
            outputs = model(data)
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()
    accuracy = 100 * correct / total
    print('Test accuracy: {:.16f}%'.format(accuracy))

# Plot the training, validation, and test losses
def plot_loss(train_loss, test_loss, val_loss):
    epochs = len(train_loss)
    x = range(epochs)

    plt.plot(x, train_loss, label='Training Loss')
    plt.plot(x, test_loss, label='Testing Loss')
    plt.plot(x, val_loss, label='Validation Loss')

    plt.xlabel('Epoch')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()

# Plot the training and testing accuracy
def plot_accuracy(train_acc_list, test_acc_list):
    plt.plot(train_acc_list, label='Training Accuracy')
    plt.plot(test_acc_list, label='Testing Accuracy')
    plt.legend()
    plt.title('Training and Testing Accuracy')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy')
    plt.show()
```

### Setup Dataloaders for Task 4a and 4b

In [ ]:
```
# use GPU if available, otherwise use CPU
device = "cuda" if torch.cuda.is_available() else "cpu"
print(f"Using {device} device")
```

```python
#####   Dataloaders for task 4a #####
BATCH_SIZE = 64
X_train_tensor = torch.Tensor(X_train_np)
X_test_tensor = torch.Tensor(X_test_np)
y_train_tensor = torch.Tensor(y_train_np)
y_test_tensor = torch.Tensor(y_test_np)

train_dataset = TensorDataset(X_train_tensor,y_train_tensor)
test_dataset = TensorDataset(X_test_tensor,y_test_tensor)

train_dataset, validation_dataset = random_split(train_dataset,[0.9,0.1])

train_dataloader = DataLoader(train_dataset, batch_size=BATCH_SIZE, shuffle=True)
test_dataloader = DataLoader(test_dataset, batch_size=BATCH_SIZE, shuffle=True)
validation_dataloader = DataLoader(validation_dataset, batch_size=BATCH_SIZE, shuffle=True)

#####   Dataloaders for task 4b #####
BATCH_SIZE_2 = 32

X_train_tensor_2 = torch.Tensor(X_train_np_2.astype('float32'))
X_test_tensor_2  = torch.Tensor(X_test_np_2.astype('float32'))

train_dataset_2 = TensorDataset(X_train_tensor_2,y_train_tensor)
test_dataset_2 = TensorDataset(X_test_tensor_2,y_test_tensor)

train_dataset_2,  validation_dataset_2  =  random_split(train_dataset_2,[0.9,0.1])

train_dataloader_2 = DataLoader(train_dataset_2, batch_size=BATCH_SIZE_2, shuffle=True)
test_dataloader_2 = DataLoader(test_dataset_2, batch_size=BATCH_SIZE_2, shuffle=True)
validation_dataloader_2= DataLoader(validation_dataset_2, batch_size=BATCH_SIZE_2, shuffle=True)
```

```
Using cuda device
```

### MLP constructor

In [ ]:

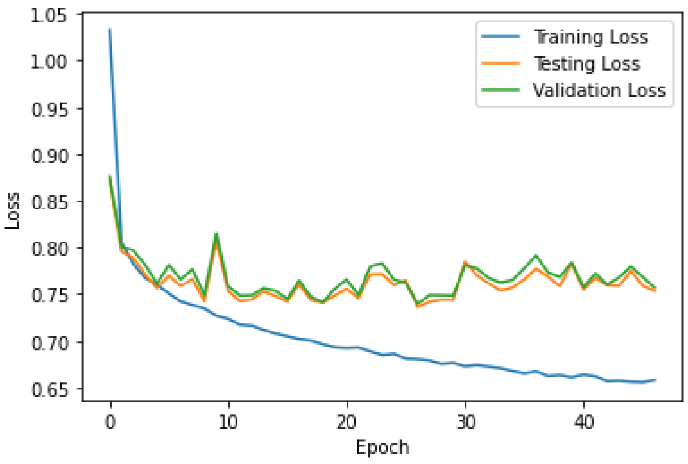
```python
class MLP(nn.Module):
    def __init__(self, input_size, hidden_1, hidden_2, use_batchnorm, dropout_p=0.0, output_size=3):
        super().__init__()

        # Create a sequence of layers
        self.layers = nn.Sequential(
            # Flatten the input tensor
            nn.Flatten(),
            # Fully connected layer
            nn.Linear(input_size, hidden_1),
            # Add batch normalization if True
            nn.BatchNorm1d(hidden_1) if use_batchnorm else nn.Identity(),
            # Apply ReLU activation function
            nn.ReLU(),
            # Apply dropout with probability dropout_p
            nn.Dropout(dropout_p),
            # Fully connected layer
            nn.Linear(hidden_1,  hidden_2),
            # Add batch normalization if True
            nn.BatchNorm1d(hidden_2) if use_batchnorm else nn.Identity(),
            # Apply ReLU activation function
            nn.ReLU(),
            # Apply dropout with probability dropout_p
            nn.Dropout(dropout_p),
            # Fully connected layer
            nn.Linear(hidden_2,  output_size)
        )

    def forward(self, x):
        return self.layers(x)
```

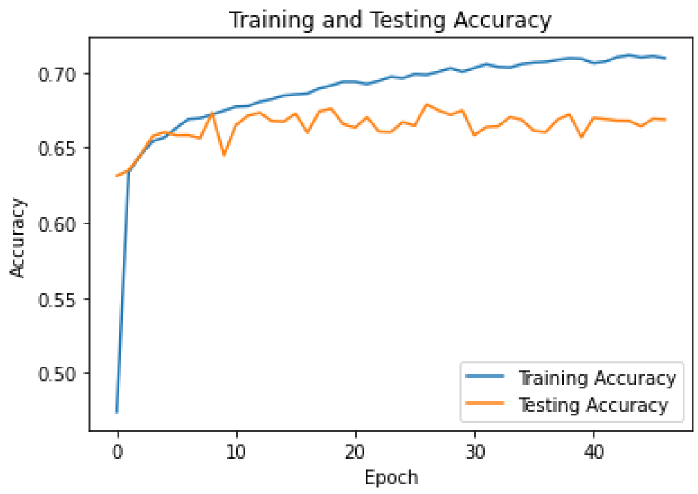
### Train MLP 4a

In [ ]:

```python
Train_an_MLP_and_eval(300,100,10,True,0.5,train_dataloader,validation_dataloader,test_dataloader,wd=0.001)
```

```
Early stopping
Test accuracy: 67.8669667416854168%
Lowest Valid Loss = 0.7396570483843485
```

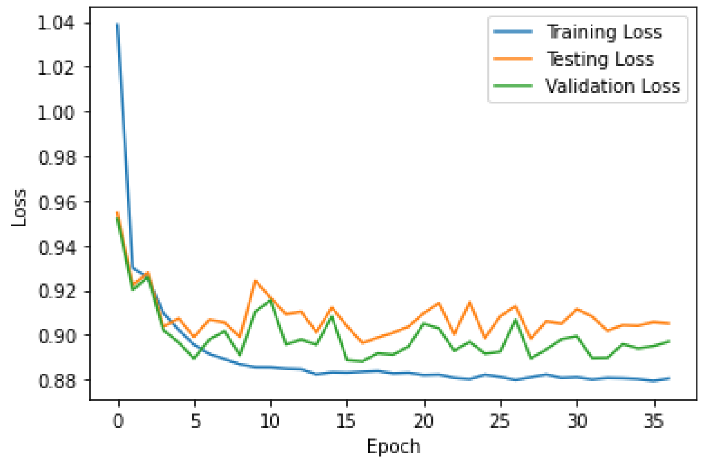





### Train MLP 4b

In [ ]:
```
Train_an_MLP_and_eval(3000,100,10,True,0.5,train_dataloader_2,validation_dataloader_2,test_dataloader_2,wd  =  0.01)
```

```
Early stopping
Test accuracy: 56.9809118946403288%
Lowest Valid Loss = 0.8882299156983694
```





# Task 5

### Constructors for RNN, GRU, and LSTM

In [ ]:
```
class RNN(nn.Module):
    def __init__(self, input_size, hid_dim, output_dim):
        super().__init__()
        # A bidirectional RNN should be better for Amazon reviews
        self.rnn = nn.RNN(input_size, hid_dim, batch_first=True, bidirectional=True)
        # Define a linear layer to generate the final output from the concatenated hidden state
        self.fc = nn.Linear(hid_dim * 2, output_dim)

    def forward(self, x):
        output, hidden = self.rnn(x)
        # The RNN returns a tensor with shape (num_layers * num_directions, batch_size, hidden_size)
        # In this case, we only want the last hidden state of both directions, which is why -2 and -1 is used
        last_hidden_fw = hidden[-2, :, :]
        last_hidden_bw = hidden[-1, :, :]
        # Concatenate the last hidden states along the second dimension
        hidden_concat = torch.cat([last_hidden_fw, last_hidden_bw], dim=1)
        out = self.fc(hidden_concat)
        return out


class GRU(nn.Module):
    def __init__(self, input_size, hid_dim, output_dim):
        super().__init__()
        # A bidirectional RNN should be better for Amazon reviews
        self.gru = nn.GRU(input_size, hid_dim, batch_first=True, bidirectional=True)
        # Define a linear layer to generate the final output from the concatenated hidden state
        self.fc = nn.Linear(hid_dim * 2, output_dim)

    def forward(self, x):
        output, hidden = self.gru(x)
        # The GRU also returns a tensor with shape (num_layers * num_directions, batch_size, hidden_size)
```

```
        # However, in this case, the first dimension corresponds to the different gates in the GRU
        # To get the last hidden state of both directions, we use 0 and 1
        last_hidden_fw = hidden[0, :, :]
        last_hidden_bw = hidden[1, :, :]
        # Concatenate the last hidden states along the second dimension
        hidden_concat = torch.cat([last_hidden_fw, last_hidden_bw], dim=1)
        out = self.fc(hidden_concat)
        return out

class LSTM(nn.Module):
    def _init_(self, input_size, hid_dim, output_dim):
        super()._init_()
        # A bidirectional RNN should be better for Amazon reviews
        self.lstm = nn.LSTM(input_size, hid_dim, batch_first=True, bidirectional=True)
        self.fc = nn.Linear(hid_dim * 2, output_dim)

    def forward(self, x):
        output, (hidden, cell) = self.lstm(x)
        # The LSTM also returns a tuple containing the hidden state and the cell state
        # We only want the last hidden state of both directions, which is why -2 and -1 is used
        last_hidden_fw = hidden[-2, :, :]
        last_hidden_bw = hidden[-1, :, :]
        # Concatenate the last hidden states along the second dimension
        hidden_concat = torch.cat([last_hidden_fw, last_hidden_bw], dim=1)
        out = self.fc(hidden_concat)
        return out
```

### Function to Train a RNN

In [ ]:
```
def Train_a_RNN_and_eval(model_abbrv,input_size, hidden_1, output_size ,train, validation, test, num_epochs=100):
    if model_abbrv == "rnn":
        model = RNN(input_size, hidden_1, output_size)
    elif model_abbrv == "gru":
        model = GRU(input_size,  hidden_1,  output_size)
    elif model_abbrv == "lstm":
        model = LSTM(input_size, hidden_1, output_size)

    optimizer = torch.optim.RAdam(model.parameters())
    loss_function = nn.CrossEntropyLoss()
    best_loss = float('inf')
    counter = 0
    train_list = []
    valid_list = []
    test_list = []
    train_acc_list = []
    test_acc_list = []
    lowest_valid_loss = float('inf')

    for epoch in range(num_epochs):
        train_loss = 0.0
        train_total = 0
        train_correct = 0
        for i, batch in enumerate(train, 0):
            inputs, targets = batch
            optimizer.zero_grad()
            outputs = model(inputs)
            targets = targets.type(torch.LongTensor)
            loss = loss_function(outputs, targets)
            loss.backward()
            optimizer.step()
            train_loss += loss.item()

            # Calculate training accuracy
            _, predicted = torch.max(outputs.data, 1)
            train_total += targets.size(0)
            train_correct += (predicted == targets).sum().item()

        # record train loss and accuracy
        train_list.append(train_loss / len(train))
        train_acc_list.append(train_correct / train_total)

        # record validation loss
        valid_loss = 0.0
        model.eval()
        for i, data in enumerate(validation, 0):
            inputs, targets = data
            outputs = model(inputs)
            targets = targets.type(torch.LongTensor)
            loss = loss_function(outputs, targets)
            valid_loss += loss.item()
        valid_list.append(valid_loss  /  len(validation))

        # update lowest validation loss
        if lowest_valid_loss > valid_loss / len(validation):
            lowest_valid_loss = valid_loss / len(validation)

         # record test loss
        model.eval()
        testing_loss = 0.0
        testing_total = 0.0
        testing_correct = 0.0
        with torch.no_grad():
            for data, target in test:
                output = model(data)
                target = target.type(torch.LongTensor)
                loss = loss_function(output, target)
```

```
                testing_loss += loss.item() * data.size(0)

                # Calculate test accuracy
                _, predicted = torch.max(output.data, 1)
                testing_total += target.size(0)
                testing_correct += (predicted == target).sum().item()

        testing_loss /= len(test.dataset)
        test_list.append(testing_loss)
        test_acc_list.append(testing_correct / testing_total)

        # early stopping
        if valid_loss < best_loss:
            best_loss = valid_loss
            counter = 0
            torch.save(model.state_dict(),  'best_model.pt')
        else:
            counter += 1
            if counter >= 20:
                print("Early stopping")
                break

    # Use the best model obtained from the early stopping process
    model.load_state_dict(torch.load('best_model.pt'))
    test_acc(model, test)
    print("Lowest Valid Loss = " + str(lowest_valid_loss))
    plot_loss(train_list, test_list, valid_list)
    print("\n")
    plot_accuracy(train_acc_list,  test_acc_list)
```

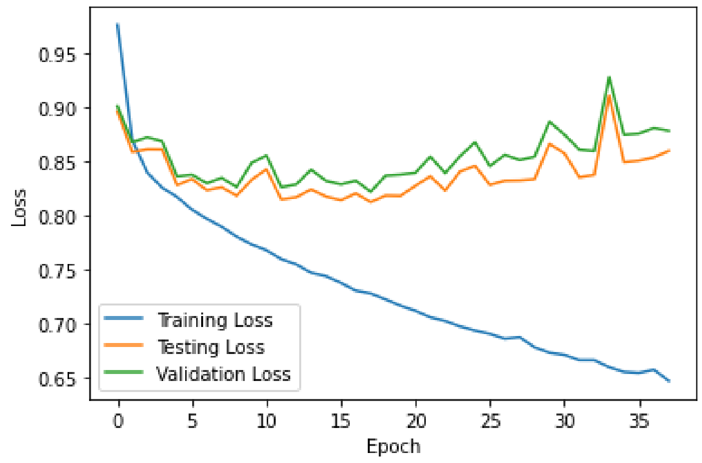
### Setup Dataloaders for Task 5

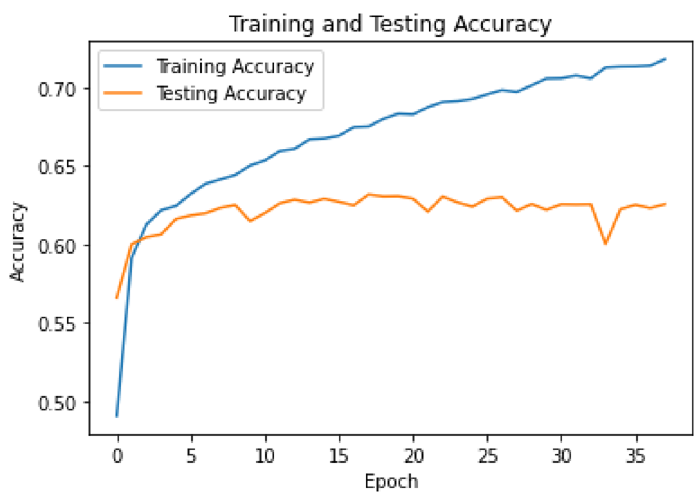
In [ ]:
```
BATCH_SIZE_3 = 32

X_train_tensor_3 = torch.Tensor(X_train_np_3).to(dtype=torch.float32)
X_test_tensor_3  = torch.Tensor(X_test_np_3).to(dtype=torch.float32)

train_dataset_3 = TensorDataset(X_train_tensor_3, y_train_tensor)
test_dataset_3 = TensorDataset(X_test_tensor_3, y_test_tensor)

train_dataset_3, validation_dataset_3 = random_split(train_dataset_3, [0.9, 0.1])

train_dataloader_3 = DataLoader(train_dataset_3, batch_size=BATCH_SIZE_3, shuffle=True)
test_dataloader_3 = DataLoader(test_dataset_3, batch_size=BATCH_SIZE_3, shuffle=True)
validation_dataloader_3  = DataLoader(validation_dataset_3,  batch_size=BATCH_SIZE_3,  shuffle=True)
```

### Task 5a

In [ ]:
```
Train_a_RNN_and_eval("rnn",300,  20,  3,  train_dataloader_3,  validation_dataloader_3,  test_dataloader_3)
```

```
Early stopping
Test accuracy: 63.1741268650495940%
Lowest Valid Loss = 0.8216418268283209
```

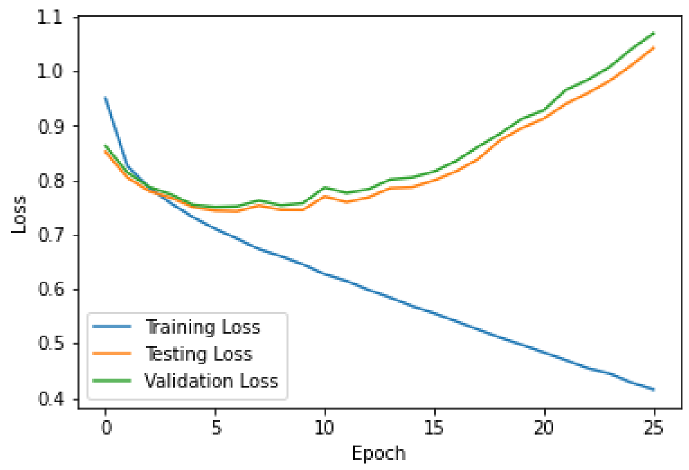


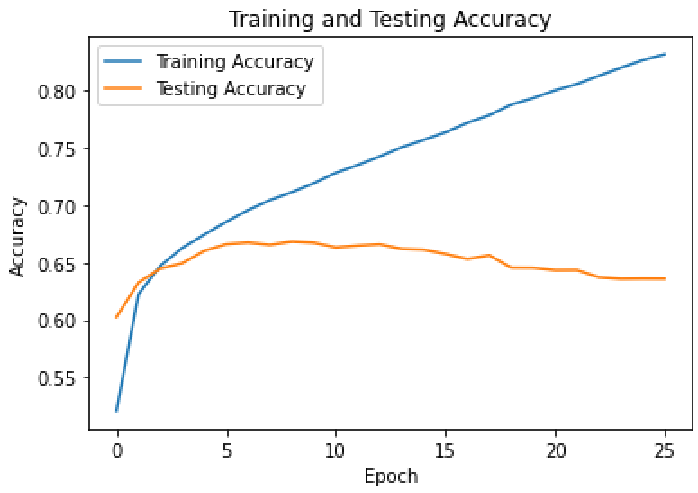




### Task 5b

In [ ]:
```
Train_a_RNN_and_eval("gru",300,  20,  3,  train_dataloader_3,  validation_dataloader_3,  test_dataloader_3)
```

```
Early stopping
Test accuracy: 66.5999833291656245%
Lowest Valid Loss = 0.7504309892654419
```

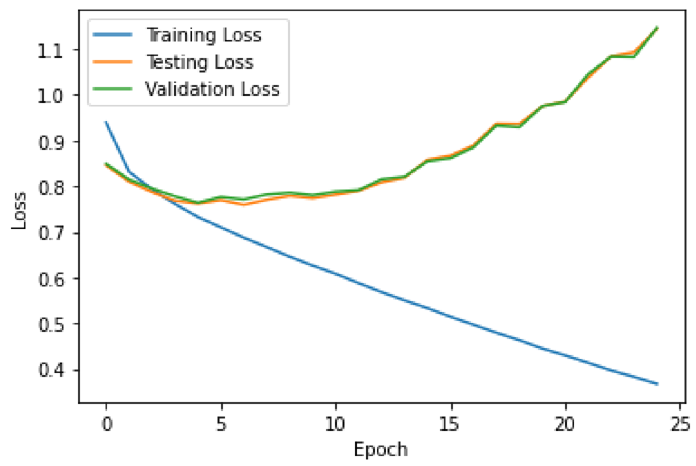


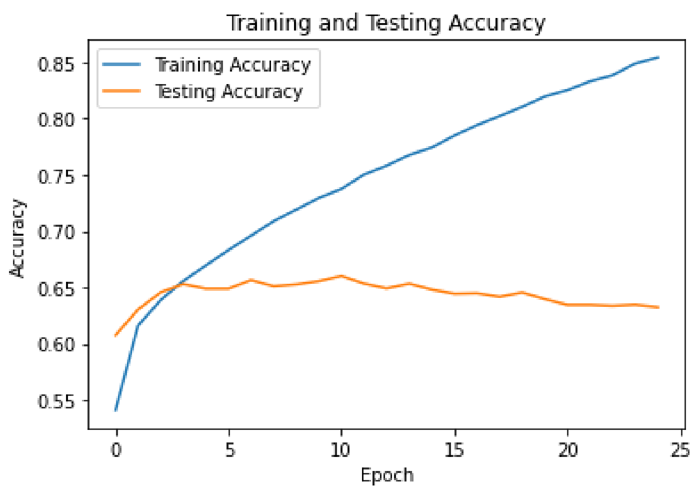




### Task 5c

In [ ]:
```
Train_a_RNN_and_eval("lstm",300,  20,  3,  train_dataloader_3,  validation_dataloader_3,  test_dataloader_3)
```

```
Early stopping
Test accuracy: 64.8828873885137938%
Lowest Valid Loss = 0.7637279011805852
```




Che Wei Wu