Pre processing data

In [1]:
```
#!pip install pandas
import pandas as pd
import csv
```

Changing the delimiter from ',' to ';'

In [2]:
```
with open('data.csv', 'r') as input_file, open('data_all.csv', 'w', newline='') as output_file:
    writer = csv.writer(output_file, delimiter=';')
    for line in input_file:
        line = line.strip()

        last_comma = line.rfind(',')

        if last_comma != -1:
            row = [line[:last_comma], line[last_comma + 1:]]

        writer.writerow(row)
```

Importing the data

In [3]:
```
data_all = pd.read_csv('data_all.csv', sep=';')
data_all.describe()
```

Out[3]:

	ticket_description	expert_id
count	400	400
unique	40	10
top	Les permissions des rôles d'utilisateur ne fon...	expert_8
freq	16	53

Normalizing characters (because of invalid characters in french data)

In [4]:
```
import unicodedata

def normalize_chars(text):
    if isinstance(text, str):
        normalized = unicodedata.normalize('NFKD', text)
        no_diacritics = ''.join(char for char in normalized if not unicodedata.combining(char))
        return no_diacritics
    return text

data_all['ticket_description'] = data_all['ticket_description'].apply(normalize_chars)

data_all.to_csv('data_all_normalized.csv', sep=';', index=False)
```

Check for null values

In [5]:
```
data_all.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 2 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   ticket_description  400 non-null    object
 1   expert_id           400 non-null    object
dtypes: object(2)
memory usage: 6.4+ KB
```

Check validity of values

In [6]:
```
import re

def check_row(row):
    c1 = len(row['ticket_description'].strip()) > 0
    c2 = bool(re.match(r'^expert_\d+$', row['expert_id']))
    return c1 and c2

data_all_cleaned = data_all[data_all.apply(check_row, axis=1)]

data_all = data_all_cleaned.reset_index(drop=True)

data_all.describe()
```

Out[6]:

	ticket_description	expert_id
count	400	400
unique	40	10
top	Les permissions des roles d'utilisateur ne fon...	expert_8
freq	16	53

Change the label type from string to integer (out of simplicity, since expert ids are integers)

In [7]:
```
for i,row in data_all.iterrows():
    data_all.at[i, 'expert_id'] = int(data_all.at[i, 'expert_id'].split('_')[1])
data_all.head()
```

Out[7]:

	ticket_description	expert_id
0	Data not syncing with the cloud.	6
1	System reports inaccurate metrics.	4
2	Payment gateway timeout error.	5
3	Permissions issue for user roles.	0
4	Integration with third-party API fails.	5

Splitting the data into english and french parts

In [8]:
```
num_eng = 200

data_eng = data_all.iloc[:num_eng]
data_fr = data_all.iloc[num_eng:]

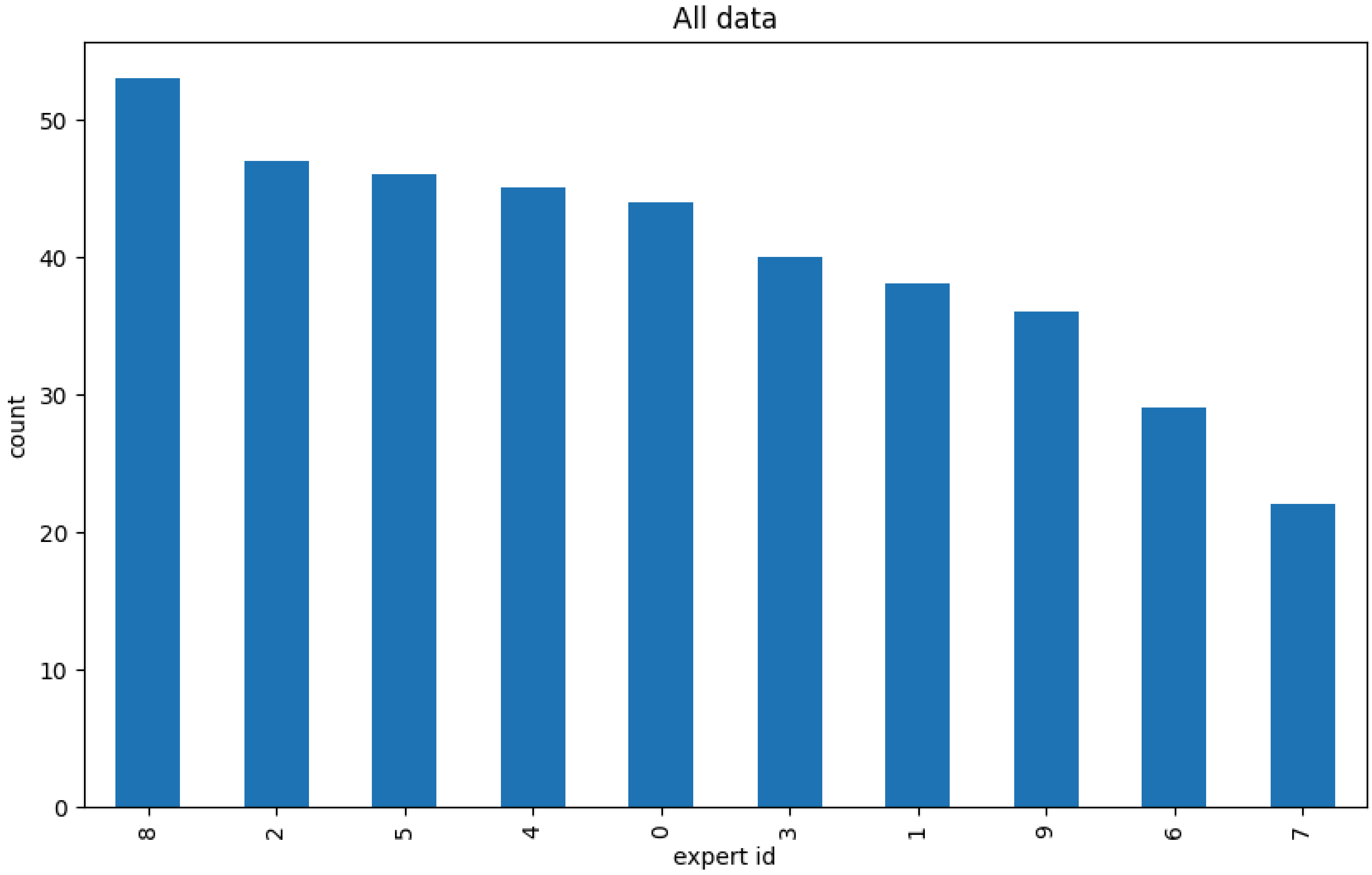
data_eng.to_csv('data_1_eng.csv', sep=';', index=False)
data_fr.to_csv('data_1_fr.csv', sep=';', index=False)
```

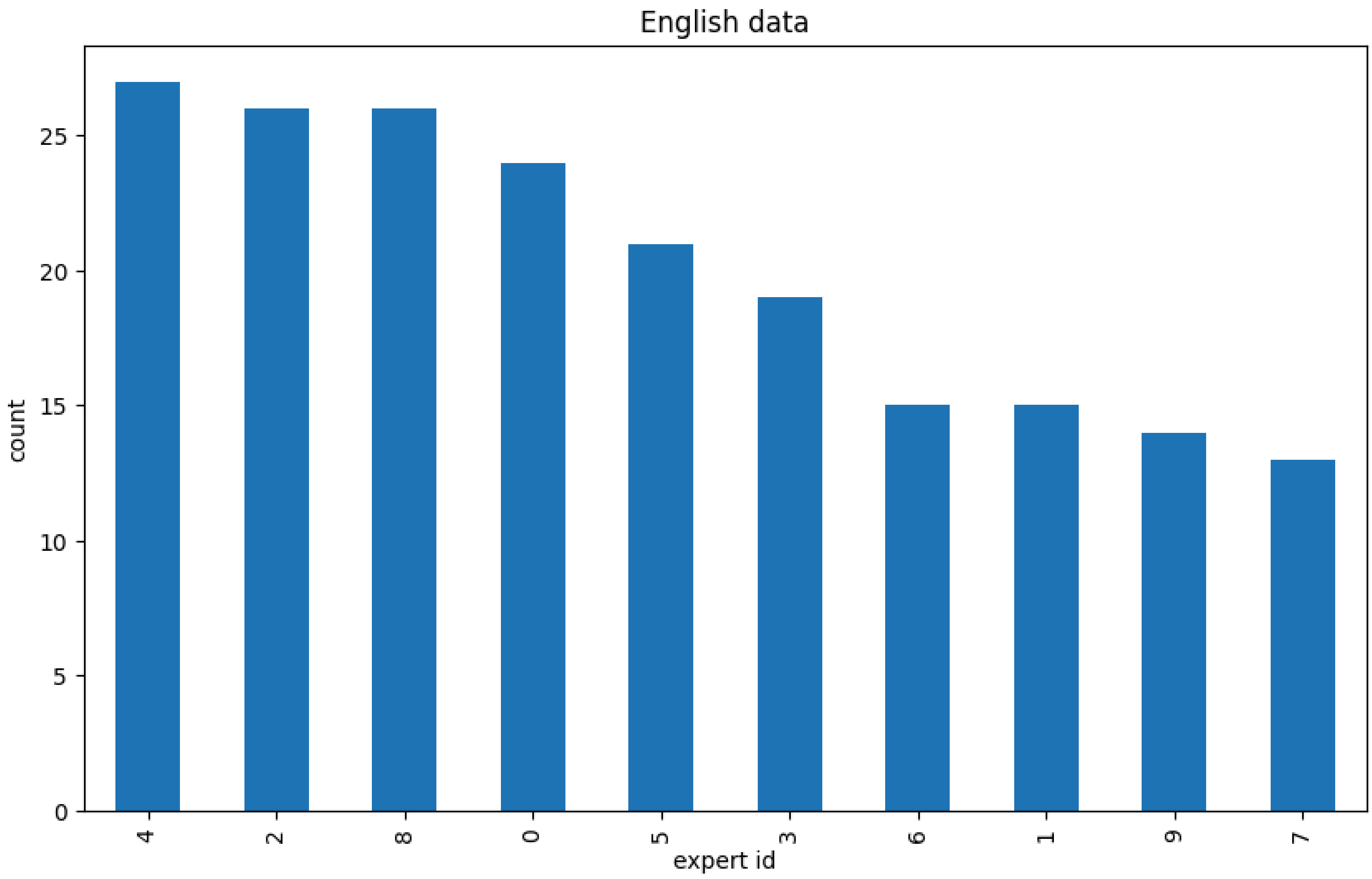
Analyzing the distribution

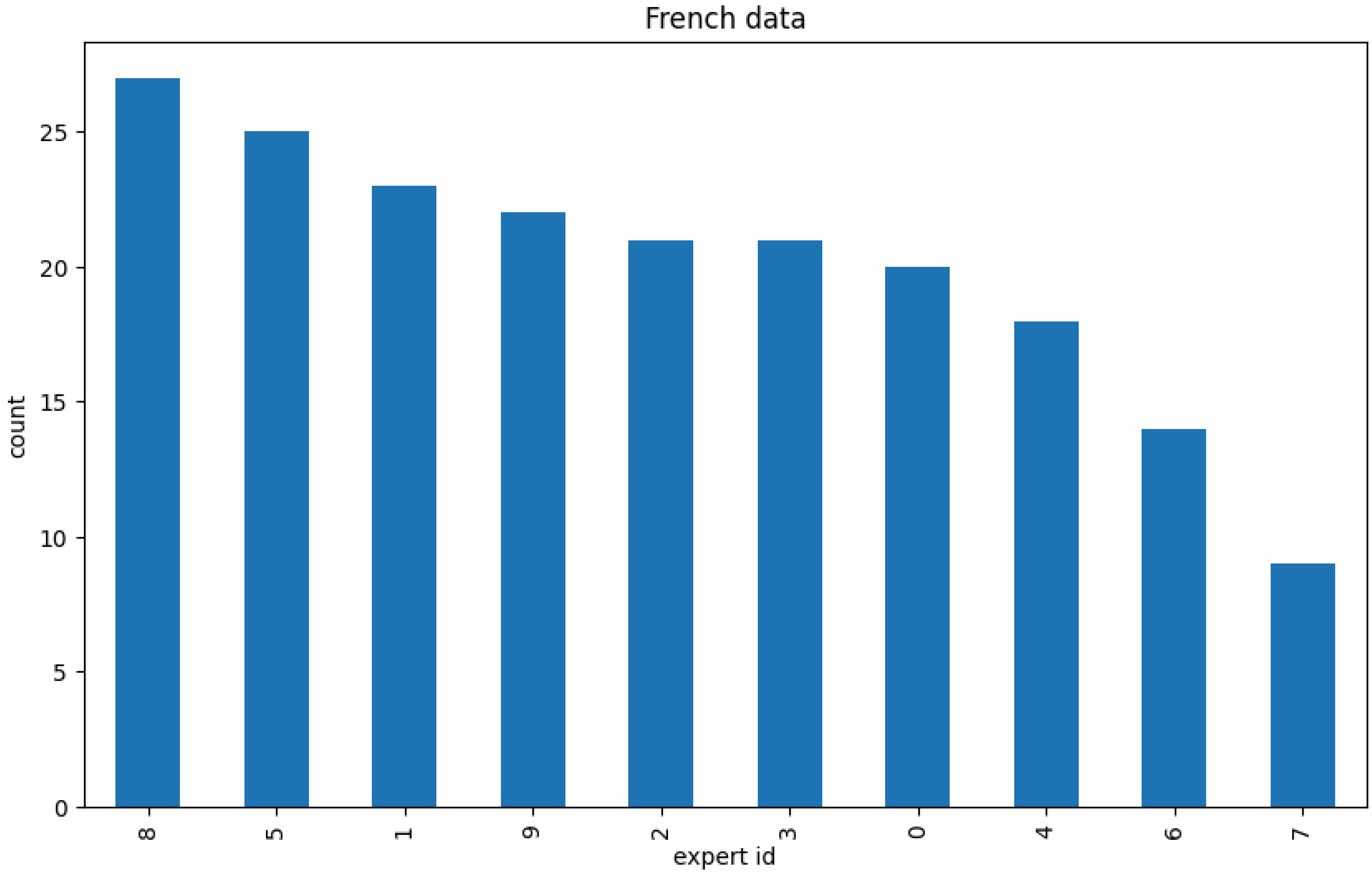
In [9]:
```
#!pip install matplotlib
import matplotlib.pyplot as plt

distributions = [
    (data_all['expert_id'].value_counts(), 'All data'),
    (data_eng['expert_id'].value_counts(), 'English data'),
    (data_fr['expert_id'].value_counts(), 'French data')
]

for dist, title in distributions:
    dist.plot(kind='bar', figsize=(10, 6))
    plt.title(title)
    plt.xlabel('expert id')
    plt.ylabel('count')
    plt.show()
```


All data
count
50
40
30
20
10
0
8
2
5
4
0
3
1
9
6
7
expert id


English data
count
25
20
15
10
5
0
4
2
8
0
5
3
6
1
9
7
expert id



There is a significance difference in distribution between the highest and the lowest frequent classes, but overall, the data is not highly imbalanced

APPROACH 1: Removing the duplicates

In the first approach, this task was concidered to be a multi-class classification problem where each sentance belongs to only one label. Therefore, the duplicates represent redundant data which can influence overfitting and that's why we remove it

In [10]:
```
data_1_all = data_all.drop_duplicates()
data_1_eng = data_eng.drop_duplicates()
data_1_fr = data_fr.drop_duplicates()
print(data_1_all.describe())
print(data_1_eng.describe())
print(data_1_fr.describe())
```

```
                                      ticket_description  expert_id
count                                                250        250
unique                                                40         10
top     Le planificateur n'execute pas les taches prog...          0
freq                                                   9         30
                      ticket_description  expert_id
count                                124        124
unique                                20         10
top     Application fails to save settings.          0
freq                                   8         16
                                      ticket_description  expert_id
count                                                126        126
unique                                                20         10
top     Le systeme genere des metriques inexactes dans...          8
freq                                                   9         16
```

APPROACH 2: Soft label encoding

In the second approach, this task is concidered to be a multi-label classification problem, where sentances do not belong to exclusively one class. Sentances can be completed by different experts and all of the provided data is useful. Instead of having multiple sentances with single labels, we group the sentances and assign labels of the all experts that were assigned to each sentance. This is label encoding, but instead of it being binary, we use soft labels where values are not 1s and 0s, but are actually float values in range [0,1], indicating the frequency of assigned experts

In [11]:
```
def encode_labels(data):
    result_rows = []

    # iterating through unique sentances
    for ticket_description in data['ticket_description'].unique():
        # filtering rows
        filtered_rows = data[data['ticket_description'] == ticket_description]

        # calculating the expert frequency
        frequency = filtered_rows['expert_id'].value_counts(normalize=True).reindex(range(num_classes), fill_value=0)
        expert_ids_str = ','.join(map(lambda x: f"{x:.3f}", frequency.values))

        # appending the results
        result_rows.append({
```

```
            'ticket_description': ticket_description,
            'expert_ids': expert_ids_str
        })

    return pd.DataFrame(result_rows)

num_classes = data_all['expert_id'].nunique()

data_2_all = encode_labels(data_all)
data_2_eng = encode_labels(data_eng)
data_2_fr = encode_labels(data_fr)

data_2_eng.to_csv('data_2_all.csv', sep=';', index=False)
data_2_eng.to_csv('data_2_eng.csv', sep=';', index=False)
data_2_fr.to_csv('data_2_fr.csv', sep=';', index=False)
```

First model: Traditional vectorization with Naive Bayes and Logistic Legression

The traditional model was initially done with the first approach: multi-class classification, while the second advanced model was done also with the second apporach of multi-label classification

Data splitting

Since the first approach is mutli-class classification, we will perform the classical splitting of data into train, valid and test sets. Since we do not have a lot of data and we would like to evaluate all of the classes (experts), we will make sure to have at least one instance of each class in all three data splits. Since input data is not large, we will manually make sure to have the right ratio of splits (we cannot count on creating splits by comparing ratios to a random number)

In [12]:
```
import random
import numpy as np
from sklearn.model_selection import train_test_split

def assign_train_valid_test_split(df, class_column, train_ratio=0.8, valid_ratio=0.1, test_ratio=0.1, random_seed=None):
    # checking the sum of all ratios
    assert (train_ratio + valid_ratio + test_ratio) == 1.0

    # creating dataframes for splits
    train_data = pd.DataFrame()
    valid_data = pd.DataFrame()
    test_data = pd.DataFrame()

    # iterating through all the classes and grouping rows
    for class_label, group in df.groupby(class_column):
        # shuffling the group
        group = group.sample(frac=1, random_state=random_seed).reset_index(drop=True)

        # calculating the sizes
        train_size = int(len(group) * train_ratio)
        valid_size = int(len(group) * valid_ratio)

        # make sure to have at least one instance in each split
        train_size = max(train_size, 1)
        valid_size = max(valid_size, 1)
        test_size = max(len(group) - train_size - valid_size, 1)

        # adjust sizes
        while train_size + valid_size + test_size > len(group):
            if train_size > valid_size and train_size > test_size:
                train_size -= 1
            elif valid_size > test_size:
                valid_size -= 1
            else:
                test_size -= 1

        # splitting the group
        train_split = group[:train_size]
        valid_split = group[train_size:train_size + valid_size]
        test_split = group[train_size + valid_size:]

        # appending the data
        train_data = pd.concat([train_data, train_split], ignore_index=True)
        valid_data = pd.concat([valid_data, valid_split], ignore_index=True)
        test_data = pd.concat([test_data, test_split], ignore_index=True)

    # shuffling final splits
    train_data = train_data.sample(frac=1, random_state=random_seed).reset_index(drop=True)
    valid_data = valid_data.sample(frac=1, random_state=random_seed).reset_index(drop=True)
    test_data = test_data.sample(frac=1, random_state=random_seed).reset_index(drop=True)

    # adding a split column
    train_data['split'] = 'train'
    valid_data['split'] = 'valid'
```

```
    test_data['split'] = 'test'

    # combine all splits into a single dataframe for simplicity
    final_df = pd.concat([train_data, valid_data, test_data], ignore_index=True)

    return final_df

data_all = assign_train_valid_test_split(data_all, random_seed=1, class_column='expert_id')
data_eng = assign_train_valid_test_split(data_eng, random_seed=1, class_column='expert_id')
data_fr = assign_train_valid_test_split(data_fr, random_seed=1, class_column='expert_id')
```

Inspecting to make sure the ratios are approapriate

In [13]:
```
print(data_all.value_counts('split', normalize=True))
print(data_eng.value_counts('split', normalize=True))
print(data_fr.value_counts('split', normalize=True))
```

```
split
train    0.7900
test     0.1225
valid    0.0875
Name: proportion, dtype: float64
split
train    0.780
test     0.145
valid    0.075
Name: proportion, dtype: float64
split
train    0.780
test     0.135
valid    0.085
Name: proportion, dtype: float64
```

Making sure all of the classes are present in all three splits

In [14]:
```
print(len(data_eng[data_eng['split']=='train'].expert_id.unique()))
print(len(data_eng[data_eng['split']=='valid'].expert_id.unique()))
print(len(data_eng[data_eng['split']=='test'].expert_id.unique()))

print(len(data_all[data_all['split']=='train'].expert_id.unique()))
print(len(data_all[data_all['split']=='valid'].expert_id.unique()))
print(len(data_all[data_all['split']=='test'].expert_id.unique()))
```

```
10
10
10
10
10
10
```

In the second approach, since the sentances are grouped and unique, if we split the data into training, valid and test sets, a significant part of the data would not used in the training and therefore not learned on, which we want to avoid since we do not have a lot of data. Instead of splitting, we will use nested k fold cross validation to make sure we use all of the unique data during training and evaluating the model

Vectorizing

In [15]:
```
#!pip install scikit-learn
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
```

Since the chosen models Naive Bayes and Logistic Regression require numerical features, we use a simple and effiicent TF-IDF vectorization to convert sentances into numbers, by measuering words importance in sentances and their uniquenes across all sentances

In [16]:
```
def get_tfidf_vectors_and_labels(df, vectorizer, split="train", include_valid=False):
    # in case we want to use valid split for training or testing
    if include_valid:
        combined_data = df[df.split.isin([split, "valid"])]
    else:
        combined_data = df[df.split == split]
    # fitting the vectorizer
    if split == "train":
        vectorizer.fit(combined_data['ticket_description'])
    # transforming sentances into numbers
    vectors = vectorizer.transform(combined_data['ticket_description'])
    # attaching the labels
    labels = combined_data['expert_id']

    return vectors.toarray(), labels.to_numpy(dtype=int), vectorizer
```

Training

The training and predicting is performed with either Naive Bayes or Logistic Regression. The models are similar in complexity, where Naive Bayes chooses the class based on probabilites of words belonging to that class, while logistci regression learns the words contributions to sentance's class

In [17]:
```
from sklearn.metrics import f1_score, classification_report

def do_tfidf_prediction(df, max_features, model='Naive Bayes'):
    # initializing vectorizer with given number of features
    vectorizer = TfidfVectorizer(max_features=max_features)
    # getting the numerical transformations
    # here, because of model's simplicity and small data, we will include valid split into training
    vectors_train, labels_train, vectorizer = get_tfidf_vectors_and_labels(df, split="train", vectorizer=vectorizer, include_v
    vectors_test, labels_test, _ = get_tfidf_vectors_and_labels(df, split="test", vectorizer=vectorizer)

    # training naive bayes or logistic regression model
    if model == 'Naive Bayes':
        classifier = MultinomialNB().fit(vectors_train, labels_train)
    else:
        classifier = LogisticRegression().fit(vectors_train, labels_train)

    # predictions
    predicted_train = classifier.predict(vectors_train)
    predicted_test = classifier.predict(vectors_test)

    # overall f1 scores, macro since classes are not exactly evenly distributed
    f1_train = f1_score(labels_train, predicted_train, average='macro')
    f1_test = f1_score(labels_test, predicted_test, average='macro')

    return f1_train, f1_test, vectorizer, classifier
```

Inspecting results for a fixed size of max_features

In [18]:
```
f1_train, f1_test, _, _ = do_tfidf_prediction(data_all, max_features = 10)
f1_train, f1_test
```

Out[18]:
```
(0.11772011123907462, 0.03305322128851541)
```

Evaluating

Trying out different number of max_features and plotting their train and test f1 scores. It's performed with both models on three different datasets: english only, french only and all combined

In [19]:
```
datasets = {
    "data_all": data_all,
    "data_eng": data_eng,
    "data_fr": data_fr
}

# setting different colours for datasets
colors = {
    "data_all": ("blue", "lightblue"),
    "data_eng": ("green", "lightgreen"),
    "data_fr": ("red", "lightcoral")
}

max_features_list = [2, 4, 6, 8, 16, 32, 64, 128, 256]

models = ['Naive Bayes', 'Logistic Regression']

for model_name in models:

    plt.figure(figsize=(10, 6))

    # iterating through datasets
    for dataset_name, dataset in datasets.items():

        f1_scores_train = []
        f1_scores_test = []

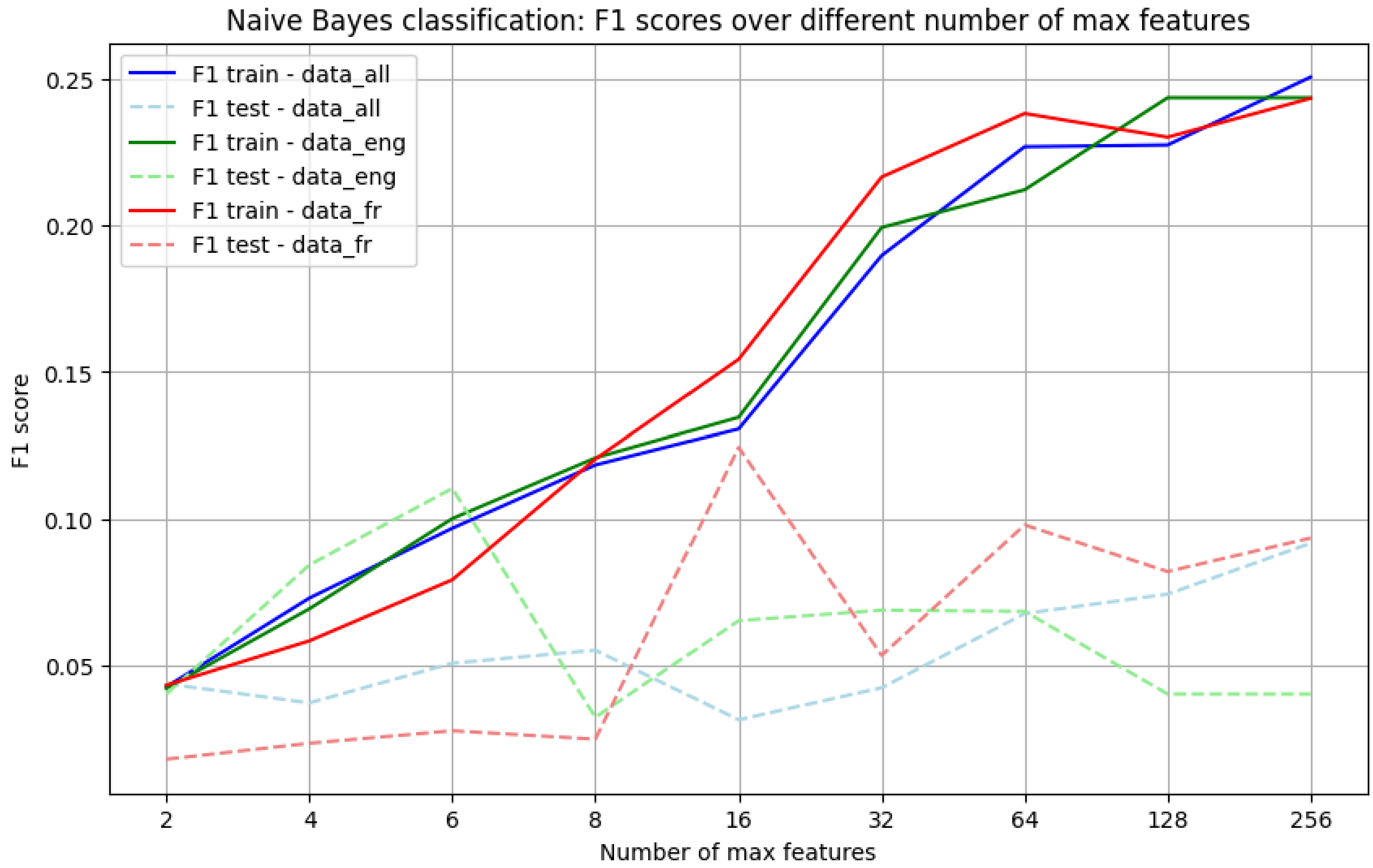
        # calculating the f1 scores
        for max_features in max_features_list:
            f1_train, f1_test, _, _ = do_tfidf_prediction(dataset, max_features=max_features, model=model_name)
            f1_scores_train.append(f1_train)
            f1_scores_test.append(f1_test)

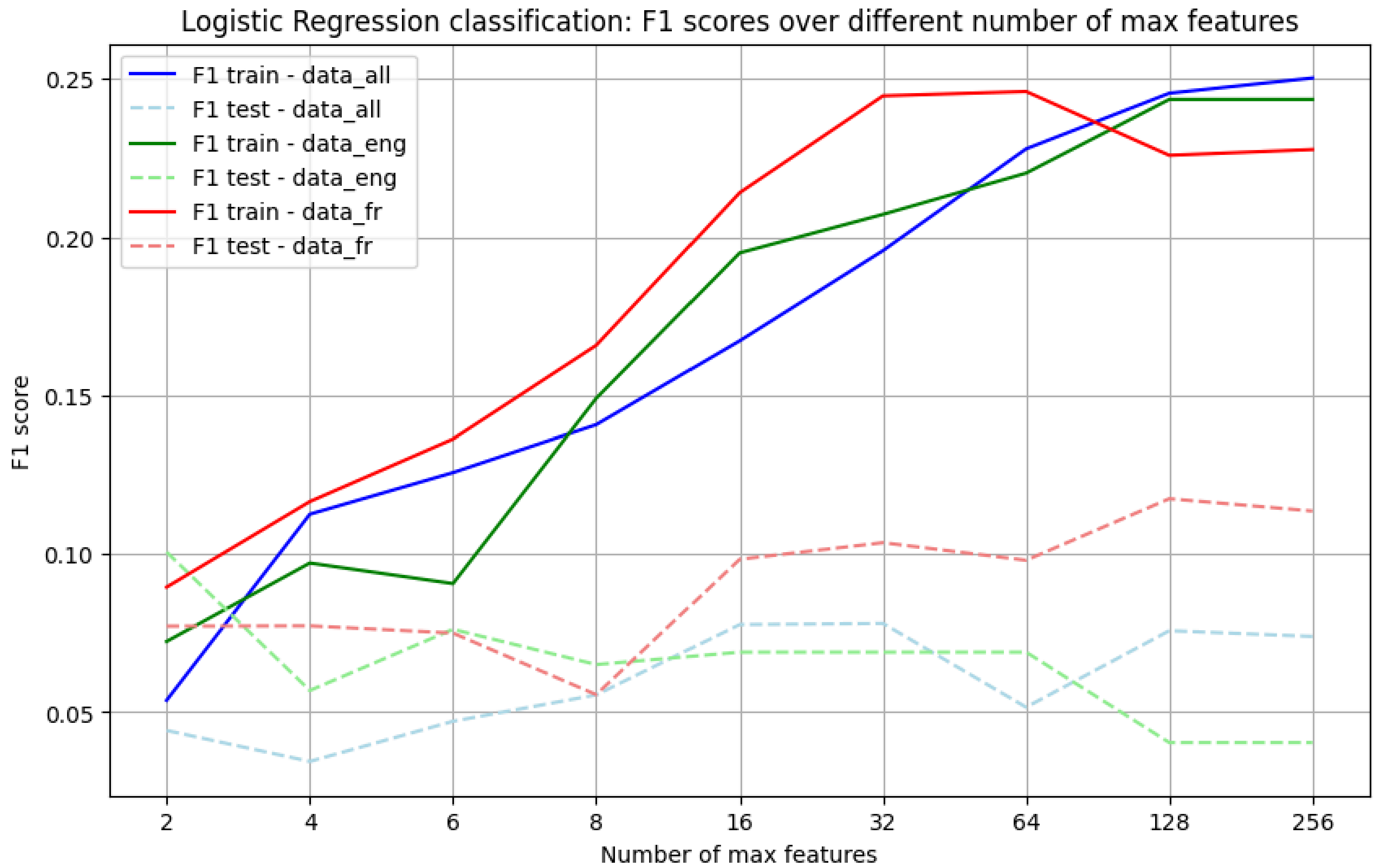
        # plotting train and test scores
        plt.plot(
            np.arange(len(max_features_list)),
            f1_scores_train,
            label=f"F1 train - {dataset_name}",
            color=colors[dataset_name][0]
        )
        plt.plot(
            np.arange(len(max_features_list)),
            f1_scores_test,
            label=f"F1 test - {dataset_name}",
            color=colors[dataset_name][1],
            linestyle="dashed"
```

```
    )

plt.xticks(np.arange(len(max_features_list)), max_features_list)
plt.xlabel("Number of max features")
plt.ylabel("F1 score")
plt.title(f"{model_name} classification: F1 scores over different number of max features")
plt.legend()
plt.grid(True)

plt.show()
```





Inference

Since the goal of this task is to return top three experts for a sentence in inference, we will convert the predictions into probabilites and return top three of them

In [20]:
```
def inference_vect(classifier, input_sentence, vectorizer, k=3):
    # vectorizing the input sentance
    input_vector = vectorizer.transform([input_sentence]).toarray()

    # predicting probabilities for all calsses
```

```
    if hasattr(classifier, "predict_proba"):
        probs = classifier.predict_proba(input_vector).squeeze()
    else:
        raise ValueError("The provided classifier does not support probability prediction.")

    # getting top k predictions
    top_k_indices = np.argsort(probs)[-k:][::-1]
    top_k_classes = [f"class_{i}" for i in top_k_indices]
    top_k_probs = probs[top_k_indices]

    return top_k_classes, top_k_probs
```

Passing a new sentance to the Naive Bayes model with both english and french data, and 256 max features

In [21]:
```
_, _, vectorizer, classifier = do_tfidf_prediction(data_all, max_features = 256, model='Naive Bayes')

inference_vect(classifier, 'Memory limit exceeded.', vectorizer, k=3)
```

Out[21]:
```
(['class_5', 'class_0', 'class_6'],
 array([0.1311454 , 0.1305303 , 0.12289652]))
```

Conclusion: The multi-class classification approach, where same sentances are assigned different classes, definitely affects the performanse. On top of that, the data set is too small to produce high quality results, specially after removing the duplicates. The large number of classes is also making it harder to learn patterns. The limited data size leads to overfitting on the training set, and poor generalization on the test set. The results are generally poor and similar for all three datasets.

Second model: BERT

BERT is one of the most popular large language models, famous for its fine tuned usages, amongst which is classification of text. For this task, we are using a pret trained version of BERT, called DistilBERT. This model is smaller in size and faster, and is suitable for the small dataset we are using.

This model is used for both approaches: multi-class classification, and the multi-label classification, with slightly different cofigurations. Here we are focusing on two different subsets: the english only data and the combined both languages data

For the first approach, we split the data into train, valid and test sets, while the second approach will use nested k fold cross validation

In [22]:
```
x_train_all = data_all[data_all.split=='train']['ticket_description'].values
y_train_all = data_all[data_all.split=='train']['expert_id'].values
x_valid_all = data_all[data_all.split=='valid']['ticket_description'].values
y_valid_all = data_all[data_all.split=='valid']['expert_id'].values
x_test_all = data_all[data_all.split=='test']['ticket_description'].values
y_test_all = data_all[data_all.split=='test']['expert_id'].values


x_train_eng = data_eng[data_eng.split=='train']['ticket_description'].values
y_train_eng = data_eng[data_eng.split=='train']['expert_id'].values
x_valid_eng = data_eng[data_eng.split=='valid']['ticket_description'].values
y_valid_eng = data_eng[data_eng.split=='valid']['expert_id'].values
x_test_eng = data_eng[data_eng.split=='test']['ticket_description'].values
y_test_eng = data_eng[data_eng.split=='test']['expert_id'].values
```

Tokenizer

Since BERT is a tranformer architecture, it requires the input text to be tokenized. Here we are introducing two different tokenizers, one for english data and the other one for multilingual, becasue of the presence of french language. MAX_LEN is calculated in order to use less than default 512 tokens, for efficiency, since the sentances in our data are much small than that

In [23]:
```
#!pip install transformersa
from transformers import DistilBertTokenizer

MAX_LEN = 0

tokenizer_eng = DistilBertTokenizer.from_pretrained('distilbert-base-uncased', padding=True, truncation=True)
tokenizer_all = DistilBertTokenizer.from_pretrained('distilbert-base-multilingual-cased', padding=True, truncation=True)

# combining all data to find the max tokens size
all_data = np.concatenate((x_train_all, x_valid_all, x_test_all))

# calculating the max tokens length and inspecting the tokenizer output
for i in range(len(all_data)):
    if len(tokenizer_eng(all_data[i])['input_ids']) > MAX_LEN:
        MAX_LEN = len(tokenizer_eng(all_data[i])['input_ids'])
    if i == 0:
        # tokenize sentences
        tokenizer_out = tokenizer_eng(all_data[i])
        # convert numerical tokens to alphabetical tokens
```

```
        encoded_tok = tokenizer_eng.convert_ids_to_tokens(tokenizer_out.input_ids)
        # decode tokens back to string
        decoded = tokenizer_eng.decode(tokenizer_out.input_ids)
        print(tokenizer_out)
        print('\n')
        print(encoded_tok, '\n')
        print('\n')
        print(decoded, '\n')
        print('\n')
        print('---------------- \n')

# multiplied by 2, to allow twice longter sentances in inference
MAX_LEN = MAX_LEN * 2
MAX_LEN
```

```
C:\Users\David\AppData\Local\Programs\Python\Python311\Lib\site-packages\tqdm\auto.py:21: TqdmWarning: IProgress not found. Ple
ase update jupyter and ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
{'input_ids': [101, 2543, 9628, 5991, 4646, 4026, 1012, 102], 'attention_mask': [1, 1, 1, 1, 1, 1, 1, 1]}


['[CLS]', 'fire', '##wall', 'blocks', 'application', 'traffic', '.', '[SEP]']



[CLS] firewall blocks application traffic. [SEP]



----------------
```

Out[23]: 72

Custom dataset

Creating a custom dataset class which will be used by other tools during training and evaluating

In [24]:

```
#!pip3 install torch torchvision torchaudio
import torch
from torch.utils.data import Dataset

class MyDataset(Dataset):
    def __init__(self, sentences, labels, tokenizer, max_len, soft_labels=False):
        self.sentences = sentences
        # Can be either hard or soft labels
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_len = max_len
        self.soft_labels = soft_labels

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

    def __getitem__(self, item):
        # returns sentance and its label(s)
        sentence = str(self.sentences[item])
        label = self.labels[item]

        # tokenize the sentence
        tokenizer_out = self.tokenizer(
            sentence,
            add_special_tokens=True,
            max_length=self.max_len,
            return_token_type_ids=False,
            padding='max_length',
            return_attention_mask=True,
            return_tensors='pt',
            truncation=True
        )

        # handle soft labels for second approach
        if self.soft_labels:
            # convert the soft labels into right format
            label_tensor = torch.tensor(
                list(map(float, label.split(','))), dtype=torch.float
            )
        else:
            # convert the hard labels
            label_tensor = torch.tensor(label, dtype=torch.long)

        # return a dictionary of outputs
        return {
            'input_ids': tokenizer_out['input_ids'].flatten(),
            'attention_mask': tokenizer_out['attention_mask'].flatten(),
            'label': label_tensor
```

```
        }


# for first approach
train_dataset_all = MyDataset(x_train_all, y_train_all, tokenizer_all, MAX_LEN)
valid_dataset_all = MyDataset(x_valid_all, y_valid_all, tokenizer_all, MAX_LEN)
test_dataset_all = MyDataset(x_test_all, y_test_all, tokenizer_all, MAX_LEN)

train_dataset_eng = MyDataset(x_train_eng, y_train_eng, tokenizer_eng, MAX_LEN)
valid_dataset_eng = MyDataset(x_valid_eng, y_valid_eng, tokenizer_eng, MAX_LEN)
test_dataset_eng = MyDataset(x_test_eng, y_test_eng, tokenizer_eng, MAX_LEN)

# for second approach
dataset_2_all = MyDataset(
    data_2_all['ticket_description'].values,
    data_2_all['expert_ids'].values,
    tokenizer_all,
    MAX_LEN,
    soft_labels=True
)
dataset_2_eng = MyDataset(
    data_2_eng['ticket_description'].values,
    data_2_eng['expert_ids'].values,
    tokenizer_eng,
    MAX_LEN,
    soft_labels=True
)
```

Inspect the output shape of the dataset

In [25]:
```
train_dataset_all[0]
```

Out[25]:
```
{'input_ids': tensor([  101, 16011, 33743, 47352, 19800, 26482,   119,   102,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0]),
 'attention_mask': tensor([1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
         0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]),
 'label': tensor(4)}
```

Building the model

Importing the models

In [26]:
```
from transformers import DistilBertModel

PRE_TRAINED_MODEL_NAME_ENG = 'distilbert-base-uncased'
PRE_TRAINED_MODEL_NAME_ALL = 'distilbert-base-multilingual-cased'


distil_bert_eng = DistilBertModel.from_pretrained(PRE_TRAINED_MODEL_NAME_ENG)
distil_bert_all = DistilBertModel.from_pretrained(PRE_TRAINED_MODEL_NAME_ALL)
print(distil_bert_eng)
print(distil_bert_all)
```

```
DistilBertModel(
  (embeddings): Embeddings(
    (word_embeddings): Embedding(30522, 768, padding_idx=0)
    (position_embeddings): Embedding(512, 768)
    (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
    (dropout): Dropout(p=0.1, inplace=False)
  )
  (transformer): Transformer(
    (layer): ModuleList(
      (0-5): 6 x TransformerBlock(
        (attention): DistilBertSdpaAttention(
          (dropout): Dropout(p=0.1, inplace=False)
          (q_lin): Linear(in_features=768, out_features=768, bias=True)
          (k_lin): Linear(in_features=768, out_features=768, bias=True)
          (v_lin): Linear(in_features=768, out_features=768, bias=True)
          (out_lin): Linear(in_features=768, out_features=768, bias=True)
        )
        (sa_layer_norm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
        (ffn): FFN(
          (dropout): Dropout(p=0.1, inplace=False)
          (lin1): Linear(in_features=768, out_features=3072, bias=True)
          (lin2): Linear(in_features=3072, out_features=768, bias=True)
          (activation): GELUActivation()
        )
        (output_layer_norm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      )
    )
  )
)
DistilBertModel(
  (embeddings): Embeddings(
    (word_embeddings): Embedding(119547, 768, padding_idx=0)
    (position_embeddings): Embedding(512, 768)
    (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
    (dropout): Dropout(p=0.1, inplace=False)
  )
  (transformer): Transformer(
    (layer): ModuleList(
      (0-5): 6 x TransformerBlock(
        (attention): DistilBertSdpaAttention(
          (dropout): Dropout(p=0.1, inplace=False)
          (q_lin): Linear(in_features=768, out_features=768, bias=True)
          (k_lin): Linear(in_features=768, out_features=768, bias=True)
          (v_lin): Linear(in_features=768, out_features=768, bias=True)
          (out_lin): Linear(in_features=768, out_features=768, bias=True)
        )
        (sa_layer_norm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
        (ffn): FFN(
          (dropout): Dropout(p=0.1, inplace=False)
          (lin1): Linear(in_features=768, out_features=3072, bias=True)
          (lin2): Linear(in_features=3072, out_features=768, bias=True)
          (activation): GELUActivation()
        )
        (output_layer_norm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      )
    )
  )
)
```

Inspecting output and shape of the model

In [27]:
```
first_sample = train_dataset_eng[0]
hidden_state = distil_bert_eng(first_sample['input_ids'].unsqueeze(0), attention_mask=first_sample['attention_mask'].unsqueeze
hidden_state[0].shape
```

Out[27]:
```
torch.Size([1, 72, 768])
```

Building the classifier

The pretrained BERT model is used as a parent class for our custom class which represents the fine tuned model. In order to perform classifications, we need to create an output layer which will continue on the output of the parent model encoder. We put a simple linear layer which acts as a classifier, by transforming the dimensions of the encoder's output to the number of unique classes in this task. These outputs are raw logits and are later transformed into probabilities when calculating the losses. Dropout of 10% is used on the encoder's output for regularization. The loss functions differ for the two approaches. The soft labeled approach is using KL Divergence Loss, whcih is comparing the probability distributions of true and predicted labels, while the first approach is using Cross Entropy Loss on the predicted hard labels of the batch and the true ones. The encoder output we are using here is contained in the 0th token, which represents the special CLS token in the transformer architecture and it contains information such as the sentiment of the sentance

In [28]:
```
from transformers import DistilBertPreTrainedModel, DistilBertConfig

# used for freezing the model parameters during fine tuning
FREEZE_PRETRAINED_MODEL = True

class DistilBertForSentimentClassification(DistilBertPreTrainedModel):
    def __init__(self, pretrained_model_name, config, num_labels, freeze_encoder=False, soft_labels=False):
        super().__init__(config)
        self.num_labels = num_labels
```

```
        self.soft_labels = soft_labels
        # iload a pretrained DistilBERT model as encoder
        self.encoder = DistilBertModel.from_pretrained(pretrained_model_name)
        # freeze the parameters
        if freeze_encoder:
            for param in self.encoder.parameters():
                param.requires_grad = False

        # classifier layer
        self.classifier = torch.nn.Linear(
            in_features=config.dim, out_features=self.num_labels, bias=True
        )
        # usage of small dropout for regularization
        self.dropout = torch.nn.Dropout(p=0.1)

    def forward(
        self,
        input_ids=None,
        attention_mask=None,
        head_mask=None,
        inputs_embeds=None,
        labels=None,
        output_attentions=None,
        output_hidden_states=None,
    ):
        # encoding a batch of sequences
        encoder_output = self.encoder(
            input_ids=input_ids,
            attention_mask=attention_mask,
            head_mask=head_mask,
            inputs_embeds=inputs_embeds,
            output_attentions=output_attentions,
            output_hidden_states=output_hidden_states,
        )
        # extract the hidden state from the output
        hidden_state = encoder_output[0] # (bs, seq_len, dim)
        # only select the encoding corresponding to the first token (CLS)
        pooled_output = hidden_state[:, 0]  # (bs, dim)
        # apply dropout
        pooled_output = self.dropout(pooled_output)  # (bs, dim)
        # feed into the classifier
        logits = self.classifier(pooled_output)  # (bs, num_labels)

        outputs = (logits,) + encoder_output[1:]

        # compute loss
        if labels is not None:
            if self.soft_labels:
                # use KLDivLoss for soft labels
                loss_function = torch.nn.KLDivLoss(reduction="batchmean")
                logits = torch.nn.functional.log_softmax(logits, dim=-1)
                loss = loss_function(logits, labels)
            else:
                # use CrossEntropyLoss for hard labels
                loss_function = torch.nn.CrossEntropyLoss()
                loss = loss_function(logits, labels)
            outputs = (loss,) + outputs

        return outputs  # (loss), logits, (hidden_states), (attentions)



classes = data_all.expert_id.unique().tolist()

# create the models

# first approach
model_eng_only = DistilBertForSentimentClassification(
    pretrained_model_name=PRE_TRAINED_MODEL_NAME_ENG,
    config=distil_bert_eng.config,
    num_labels=len(classes),
    freeze_encoder = FREEZE_PRETRAINED_MODEL
)

model_all = DistilBertForSentimentClassification(
    pretrained_model_name=PRE_TRAINED_MODEL_NAME_ALL,
    config=distil_bert_all.config,
    num_labels=len(classes),
    freeze_encoder = FREEZE_PRETRAINED_MODEL
)
```

Choosing the device for training

In [29]:
```
if torch.cuda.is_available():
    print('GPU will be used.')
    device = torch.device('cuda')
else:
```

```
    device = torch.device('cpu')
    print('CPU will be used.')
```

```
CPU will be used.
```

Training and evaluation

First approach

We are using the Trainer class to handle the training of the model. We are initializing it for both datasets: english only and combined. Parameters such as learning rate, batch size, number of epochs and weight decay are defined here. The binary evaluation metrics are also passed to the Trainer: accuracy, precision, recall and f1 are also passed to the Trainer class for evaluation.

In [30]:
```
from transformers import Trainer, TrainingArguments
from sklearn.metrics import precision_recall_fscore_support, accuracy_score

def compute_metrics(pred):
    labels = pred.label_ids
    preds = pred.predictions.argmax(-1)
    precision, recall, f1, _ = precision_recall_fscore_support(labels, preds, zero_division=0)
    acc = accuracy_score(labels, preds)
    return {
        'accuracy': acc,
        'f1': f1.tolist(),
        'precision': precision.tolist(),
        'recall': recall.tolist()
    }

training_args = TrainingArguments(
    output_dir='./results',
    logging_dir='./logs',
    logging_first_step=True,
    logging_steps=20,
    num_train_epochs=16,
    per_device_train_batch_size=8,
    per_device_eval_batch_size=8,
    eval_strategy="epoch",
    learning_rate=1e-4,
    weight_decay=0.01
)

trainer_eng_only = Trainer(
    model=model_eng_only,
    args=training_args,
    train_dataset=train_dataset_eng,
    eval_dataset=valid_dataset_eng,
    compute_metrics=compute_metrics
)
trainer_all = Trainer(
    model=model_all,
    args=training_args,
    train_dataset=train_dataset_all,
    eval_dataset=valid_dataset_all,
    compute_metrics=compute_metrics
)
```

Execution of training

In [31]:
```
trainer_eng_only.train()
trainer_all.train()
```

[320/320 00:49, Epoch 16/16]

Epoch	Training Loss	Validation Loss	Accuracy	F1	Precision	Recall
1	2.314600	2.342511	0.133333	[0.0, 0.0, 0.0, 0.3333333333333333, 0.0, 0.2857142857142857, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 0.2, 0.0, 0.2, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 1.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.0]
2	2.293400	2.325679	0.066667	[0.0, 0.0, 0.0, 0.3333333333333333, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 0.2, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 1.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]
3	2.259400	2.315276	0.000000	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]
4	2.287100	2.310107	0.066667	[0.0, 0.0, 0.0, 0.0, 0.18181818181818182, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.1111111111111111, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.0, 0.0]
5	2.271100	2.309044	0.133333	[0.0, 0.0, 0.0, 0.0, 0.18181818181818182, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.1111111111111111, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0]
6	2.248100	2.306098	0.066667	[0.0, 0.0, 0.0, 0.0, 0.2222222222222222, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.14285714285714285, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.0, 0.0]
7	2.245100	2.304898	0.133333	[0.0, 0.0, 0.0, 0.0, 0.18181818181818182, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.1111111111111111, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0]
8	2.237500	2.303114	0.133333	[0.0, 0.0, 0.0, 0.0, 0.2222222222222222, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.14285714285714285, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0]
9	2.247900	2.301908	0.133333	[0.0, 0.0, 0.0, 0.0, 0.2222222222222222, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.14285714285714285, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0]
10	2.237600	2.301284	0.133333	[0.0, 0.0, 0.0, 0.0, 0.2222222222222222, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.14285714285714285, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0]
11	2.255200	2.301351	0.133333	[0.0, 0.0, 0.0, 0.0, 0.18181818181818182, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.1111111111111111, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0]
12	2.238100	2.300346	0.133333	[0.0, 0.0, 0.0, 0.0, 0.2222222222222222, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.14285714285714285, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0]
13	2.237200	2.299312	0.066667	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.5, 0.0]
14	2.242000	2.299373	0.133333	[0.0, 0.0, 0.0, 0.0, 0.2222222222222222, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.14285714285714285, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0]
15	2.245100	2.299217	0.133333	[0.0, 0.0, 0.0, 0.0, 0.2222222222222222, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.14285714285714285, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0]
16	2.228700	2.299080	0.133333	[0.0, 0.0, 0.0, 0.0, 0.2222222222222222, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.14285714285714285, 0.0, 0.0, 0.0, 0.5, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.0, 0.5, 0.0]

[640/640 01:44, Epoch 16/16]

Epoch	Training Loss	Validation Loss	Accuracy	F1	Precision	Recall
1	2.295500	2.300529	0.171429	[0.0, 0.0, 0.0, 0.32, 0.2222222222222222, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 0.19047619047619047, 0.14285714285714285, 0.0, 0.0, 0.0, 0.0, 0.0]	[0.0, 0.0, 0.0, 1.0, 0.5, 0.0, 0.0, 0.0, 0.0, 0.0]
2	2.301500	2.287256	0.200000	[0.0, 0.0, 0.0, 0.2, 0.3333333333333333, 0.4444444444444444, 0.0, 0.0, 0.13333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.16666666666666666, 0.21428571428571427, 0.4, 0.0, 0.0, 0.1, 0.0]	[0.0, 0.0, 0.0, 0.25, 0.75, 0.5, 0.0, 0.0, 0.2, 0.0]
3	2.272700	2.281674	0.171429	[0.0, 0.0, 0.0, 0.2, 0.36363636363636365, 0.4, 0.0, 0.0, 0.10526315789473684, 0.0]	[0.0, 0.0, 0.0, 0.16666666666666666, 0.2857142857142857, 0.3333333333333333, 0.0, 0.0, 0.07142857142857142, 0.0]	[0.0, 0.0, 0.0, 0.25, 0.5, 0.5, 0.0, 0.0, 0.2, 0.0]
4	2.246300	2.277365	0.171429	[0.0, 0.0, 0.0, 0.2857142857142857, 0.2857142857142857, 0.4, 0.0, 0.0, 0.10526315789473684, 0.0]	[0.0, 0.0, 0.0, 0.3333333333333333, 0.2, 0.3333333333333333, 0.0, 0.0, 0.07142857142857142, 0.0]	[0.0, 0.0, 0.0, 0.25, 0.5, 0.5, 0.0, 0.0, 0.2, 0.0]
5	2.251300	2.275478	0.200000	[0.0, 0.0, 0.0, 0.2857142857142857, 0.5, 0.4, 0.0, 0.0, 0.19047619047619047, 0.0]	[0.0, 0.0, 0.0, 0.3333333333333333, 0.5, 0.3333333333333333, 0.0, 0.0, 0.125, 0.0]	[0.0, 0.0, 0.0, 0.25, 0.5, 0.5, 0.0, 0.0, 0.4, 0.0]
6	2.264400	2.274962	0.085714	[0.0, 0.0, 0.0, 0.2857142857142857, 0.0, 0.25, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.3333333333333333, 0.0, 0.25, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.25, 0.0, 0.25, 0.0, 0.0, 0.2, 0.0]
7	2.298800	2.273968	0.085714	[0.0, 0.0, 0.0, 0.2857142857142857, 0.0, 0.25, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.3333333333333333, 0.0, 0.25, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.25, 0.0, 0.25, 0.0, 0.0, 0.2, 0.0]
8	2.257200	2.274157	0.057143	[0.0, 0.0, 0.0, 0.0, 0.0, 0.25, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.25, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.25, 0.0, 0.0, 0.2, 0.0]
9	2.270900	2.273896	0.085714	[0.0, 0.0, 0.0, 0.2857142857142857, 0.0, 0.25, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.3333333333333333, 0.0, 0.25, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.25, 0.0, 0.25, 0.0, 0.0, 0.2, 0.0]
10	2.264100	2.273124	0.085714	[0.0, 0.0, 0.0, 0.0, 0.0, 0.36363636363636365, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.2857142857142857, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.2, 0.0]
11	2.248100	2.272781	0.085714	[0.0, 0.0, 0.0, 0.0, 0.0, 0.36363636363636365, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.2857142857142857, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.2, 0.0]
12	2.277200	2.272537	0.085714	[0.0, 0.0, 0.0, 0.0, 0.0, 0.36363636363636365, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.2857142857142857, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.0, 0.5, 0.0, 0.0, 0.2, 0.0]
13	2.249200	2.272375	0.142857	[0.0, 0.0, 0.0, 0.0, 0.5, 0.36363636363636365, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.2857142857142857, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.5, 0.0, 0.0, 0.2, 0.0]
14	2.269600	2.272310	0.142857	[0.0, 0.0, 0.0, 0.0, 0.5, 0.36363636363636365, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.2857142857142857, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.5, 0.0, 0.0, 0.2, 0.0]
15	2.266300	2.272475	0.142857	[0.0, 0.0, 0.0, 0.0, 0.5, 0.36363636363636365, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.2857142857142857, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.5, 0.0, 0.0, 0.2, 0.0]
16	2.271600	2.272498	0.142857	[0.0, 0.0, 0.0, 0.0, 0.5, 0.36363636363636365, 0.0, 0.0, 0.11764705882352941, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.2857142857142857, 0.0, 0.0, 0.08333333333333333, 0.0]	[0.0, 0.0, 0.0, 0.0, 0.5, 0.5, 0.0, 0.0, 0.2, 0.0]

Out[31]:
```
TrainOutput(global_step=640, training_loss=2.267172926664352 3, metrics={'train_runtime': 104.6262, 'train_samples_per_secon
d': 48.324, 'train_steps_per_second': 6.117, 'total_flos': 92907791271936.0, 'train_loss': 2.2671729266643523, 'epoch': 16.
0})
```

Plotting of the training and validation losses

In [32]:
```
def plot_losses(trainers, labels, colors):
    plt.figure(figsize=(10, 6))

    for trainer, label, color in zip(trainers, labels, colors):
        # extract the log history
        log_history = trainer.state.log_history

        # filter train losses
        train_losses = [
            entry['loss'] for entry in log_history
            if 'loss' in entry and 'epoch' in entry
        ]
        # filter valid losses
        eval_losses = [
            entry['eval_loss'] for entry in log_history
            if 'eval_loss' in entry
        ]

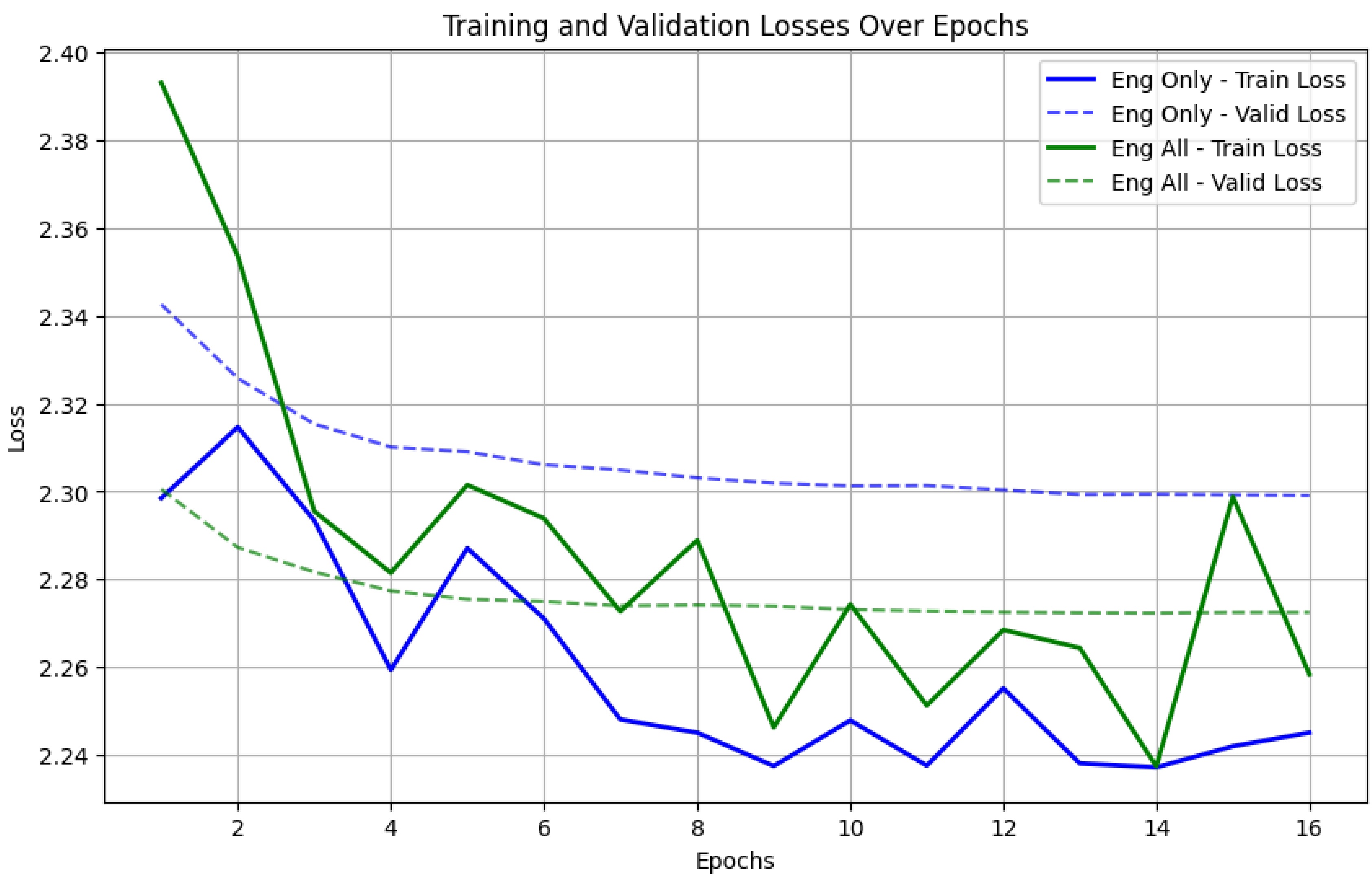
        # make sure the lengths match
        min_length = min(len(train_losses), len(eval_losses))
        train_losses = train_losses[:min_length]
        eval_losses = eval_losses[:min_length]

        # x axis for epochs
        epochs = range(1, min_length + 1)

        plt.plot(epochs, train_losses, label=f"{label} - Train Loss", color=color, linewidth=2)
        plt.plot(epochs, eval_losses, label=f"{label} - Valid Loss", color=color, linestyle='dashed', alpha=0.7)

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


plot_losses(
    trainers=[trainer_eng_only, trainer_all],
    labels=["Eng Only", "Eng All", "All"],
    colors=["blue", "green", "red"]
)
```



The training and validation losses are similar for both english only and both language models. The loss values are high and indicate poor performance, which can be the result of several factors, such as the size of the data, hyper parameters and also the possibly wrnong apporach of multi-class classification. The losses are lowering, showing that the model is improving over time. The flunctiations are much bigger in the training loss, which is the consencuence of updating parameters after each batch and adjusting to its data. The english only model showed to be slightly better, even though its using less data, possibly becasue it contains only one language. The overall performance for both models is poor, which is also reflected by the output evaluation metrics for each epoch. This can potentially be improved by fine tuning the learning rate, number of epochs, batch sizes and weight decay hyper parameters

Evaluation

Predicting the labels for the test set

In [33]:
```
test_results_eng_only = trainer_eng_only.predict(test_dataset=test_dataset_eng)
test_results_all = trainer_all.predict(test_dataset=test_dataset_all)
```

Plotting the f1 scores of the test results per class

In [34]:
```
import numpy as np
import matplotlib.pyplot as plt

f1_scores_eng_only = test_results_eng_only.metrics["test_f1"]
f1_scores_all = test_results_all.metrics["test_f1"]

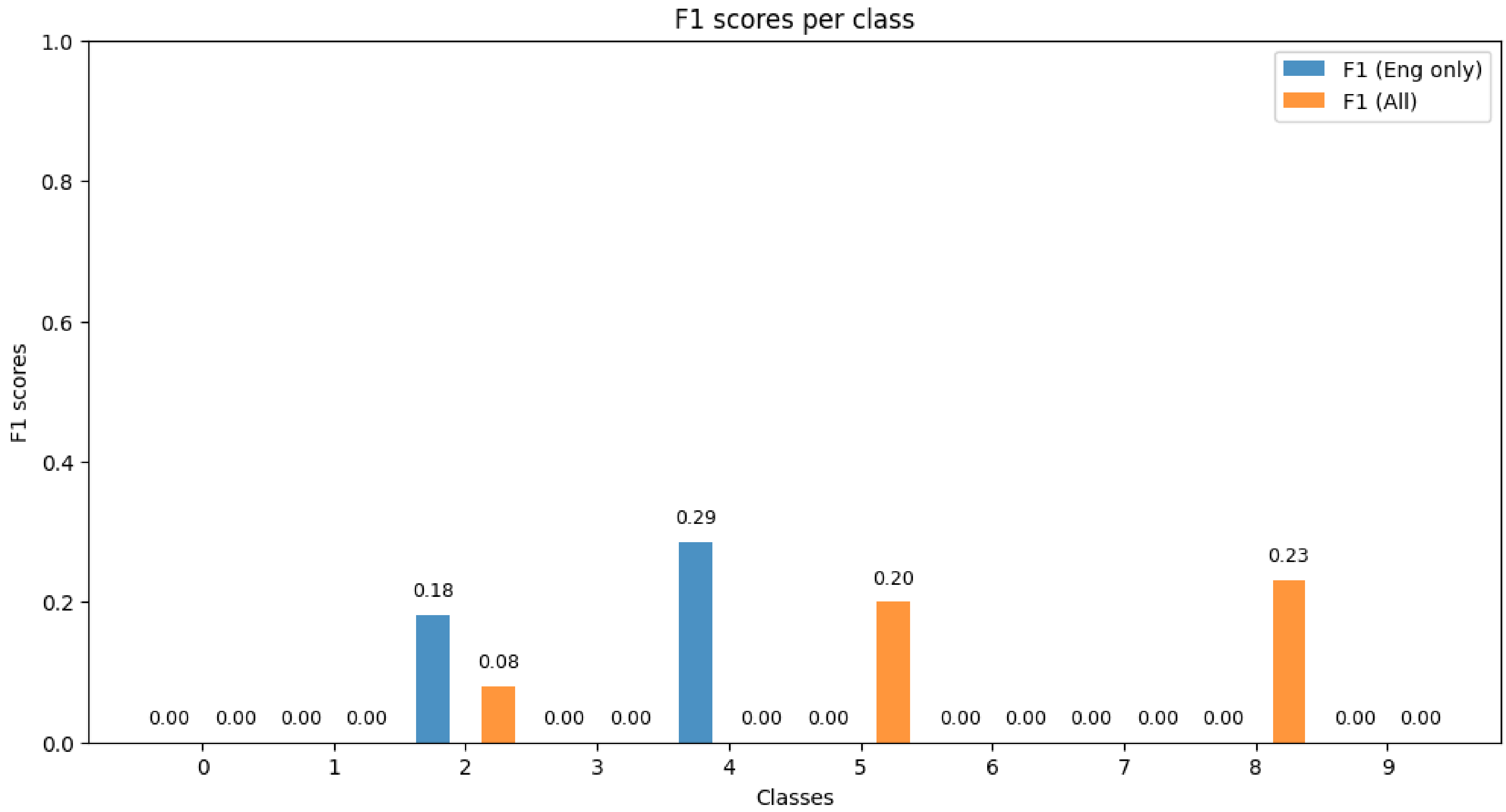
# x axis for classes
x = np.arange(num_classes)
width = 0.25

# plotting the scores
plt.figure(figsize=(12, 6))
bars_eng_only = plt.bar(x - width, f1_scores_eng_only, width, label='F1 (Eng only)', alpha=0.8)
bars_all = plt.bar(x + width, f1_scores_all, width, label='F1 (All)', alpha=0.8)

plt.xlabel('Classes')
plt.ylabel('F1 scores')
plt.title('F1 scores per class')
plt.ylim(0, 1)
plt.xticks(ticks=x, labels=range(num_classes))
plt.legend()

for bars in [bars_eng_only, bars_all]:
        for bar in bars:
                height = bar.get_height()
                plt.text(
                    bar.get_x() + bar.get_width() / 2,
                    height + 0.02,
                    f'{height:.2f}',
                    ha='center',
                    va='bottom',
                    fontsize=9
        )

plt.show()
```



The produced per class f1 scores are very sparse, showing results for only few classes. This is due to the fact that the model has poor performance but also that test set is small and the number of classes which had correct prediction is also small. All of the classes with scores of 0 have not been predicted correctly even once. One observation is that the class for expert_8 had a high score, and is also the most distributed class in the data set, which creates the possibility that the model was slightly more biased for this class

Second approach training

In the second approach, we are not using classical train,valid,test splits of the data and therefore will not use the Trainer class as in the first approach. We will create our own implemnetation of the training algorithm following the nested k fold cross validation approach. The goal of this is to use the most out of our limited data, since we grouped all of the input sentences by their uniqueness and we want to make sure we use all of them in the training as well as in the evaluating of the model. The precision metric used here is precision@k, which is comparing the rankings of class probabilities in predictions and true labels. This is used to give insight in the performance based on the goal of this task, which is predicting top three experts.

In [35]:
```
from sklearn.model_selection import KFold
from sklearn.metrics import log_loss
import numpy as np
import torch
from torch.utils.data import Subset, DataLoader

def precision_at_k(preds, labels, k):
    # getting indices of top k probabilities
    top_k_preds = np.argsort(preds, axis=-1)[:, -k:]
    top_k_labels = np.argsort(labels, axis=-1)[:, -k:]

    precision = 0

    # iterating through indices
    for i, (pred_indices, true_indices) in enumerate(zip(top_k_preds, top_k_labels)):
        # create rank mapping for true indices
        true_ranks = {idx: rank for rank, idx in enumerate(reversed(true_indices))}

        matched = 0
        for rank, pred_idx in enumerate(reversed(pred_indices)):  # Reverse for highest rank (closest to the top)
            # concider correctly predicted top k indices
            if pred_idx in true_indices:
                # penalize by the difference in rank
                rank_penalty = 1 / (abs(true_ranks[pred_idx] - rank) + 1)
                matched += rank_penalty

        # normalize the values
        precision += matched / k

    # return the average
    return precision / len(preds)

def nested_k_fold_training(outer_split, inner_split, model_constructor, dataset, learning_rate, weight_decay, num_epochs):
    # create outer k fold splits
    outer_kf = KFold(n_splits=outer_split, shuffle=True, random_state=1)

    results = []
    precisions = []

    # outer folds, where data is split into train_val and test parts
    for outer_fold, (train_val_idx, test_idx) in enumerate(outer_kf.split(dataset)):

        print(f"Outer Fold {outer_fold + 1}")

        # always start with a new model in outer fold
        model = model_constructor()

        # split the data for inner fold and test evaluation
        train_val_dataset = Subset(dataset, train_val_idx)
        test_dataset = Subset(dataset, test_idx)

        # create inner k fold splits
        inner_kf = KFold(n_splits=inner_split, shuffle=True, random_state=1)

        # keep track of the best model to return
        best_model = None
        best_score = float('inf')

        # inner folds, where data is split into train and valid parts
        for inner_fold, (train_idx, val_idx) in enumerate(inner_kf.split(train_val_dataset)):

            print(f"  Inner Fold {inner_fold + 1}")

            # split the data for training and validation
            train_dataset = Subset(train_val_dataset, train_idx)
            val_dataset = Subset(train_val_dataset, val_idx)

            train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)
            val_loader = DataLoader(val_dataset, batch_size=8)

            optimizer = torch.optim.AdamW(model.parameters(), lr=learning_rate, weight_decay=weight_decay)

            # training loop
            model.train()
            for epoch in range(num_epochs):
                train_loss = 0
                for batch in train_loader:
                    optimizer.zero_grad()
                    # pass data to model and get outputs
                    outputs = model(
```

```
                    input_ids=batch['input_ids'],
                    attention_mask=batch['attention_mask'],
                    labels=batch['label']
                )
                # get the loss
                loss = outputs[0]
                train_loss += loss.item()
                # backpropagation
                loss.backward()
                optimizer.step()

            avg_train_loss = train_loss / len(train_loader)
            print(f"Epoch {epoch+1}/{num_epochs}, Train Loss: {avg_train_loss:.4f}")

        # validation loop
        model.eval()
        val_loss = 0
        val_preds, val_labels = [], []

        # disable parameter updating
        with torch.no_grad():
            for batch in val_loader:
                # pass data to model and get outputs
                outputs = model(
                    input_ids=batch['input_ids'],
                    attention_mask=batch['attention_mask'],
                    labels=batch['label']
                )
                # get the loss
                loss = outputs[0]
                val_loss += loss.item()
                # get the logits for precision calculation
                logits = outputs[1]
                # apply softmax to get log probabilities
                log_probs = torch.nn.functional.log_softmax(logits, dim=-1)

                # collect predictions and labels for precision calculation
                val_preds.append(log_probs.exp().cpu().numpy())
                val_labels.append(batch['label'].cpu().numpy())

        # average the validation loss
        val_loss /= len(val_loader)
        # convert to right format
        val_preds = np.vstack(val_preds)
        val_labels = np.vstack(val_labels)
        # calculate precision
        prec_at_k = precision_at_k(val_preds, val_labels, k=3)
        print(f"    Validation Loss: {val_loss:.4f}, Precision@K: {prec_at_k:.4f}")

        # keep track of the best model
        if val_loss < best_score:
            best_score = val_loss
            best_model = model

    # evaluate the model on outer fold test data
    test_loader = DataLoader(test_dataset, batch_size=8)
    test_loss = 0
    test_preds, test_labels = [], []
    # disable parameter updating
    with torch.no_grad():
        for batch in test_loader:
            # pass data to model and get outputs
            outputs = best_model(
                input_ids=batch['input_ids'],
                attention_mask=batch['attention_mask'],
                labels=batch['label']
            )
            # get the loss
            loss = outputs[0]
            test_loss += loss.item()
             # get the logits for precision calculation
            logits = outputs[1]
            # apply softmax to get log probabilities
            log_probs = torch.nn.functional.log_softmax(logits, dim=-1)
            # collect predictions and labels for precision calculation
            test_preds.append(log_probs.exp().cpu().numpy())
            test_labels.append(batch['label'].cpu().numpy())

    # average the test loss
    test_loss /= len(test_loader)
    # convert to right format
    test_preds = np.vstack(test_preds)
    test_labels = np.vstack(test_labels)
    # calculate precision
    prec_at_k = precision_at_k(test_preds, test_labels, k=3)
    precisions.append(prec_at_k)
    print(f"  Test Loss (Outer Fold {outer_fold + 1}): {test_loss:.4f}, Precision@K: {prec_at_k:.4f}")
```

```
        results.append(test_loss)

    # final evaluation
    average_test_loss = np.mean(results)
    print(f"Average Test Loss: {average_test_loss:.4f}")
    average_prec_at_k = np.mean(precisions)
    print(f"Average Precision@K: {average_prec_at_k:.4f}")

    return best_model
```

In [36]:
```
# used to create a new instance of model for nested k fold cross validation
def model_constructor(pretrained_model_name, config, num_labels, freeze_encoder, soft_labels):
    return DistilBertForSentimentClassification(
        pretrained_model_name=pretrained_model_name,
        config=config,
        num_labels=num_labels,
        freeze_encoder=freeze_encoder,
        soft_labels=soft_labels
    )
```

Initialization of models and training

In [37]:
```
model_2_trained_eng = nested_k_fold_training(
    outer_split=5,
    inner_split=5,
    model_constructor=lambda: model_constructor(
        pretrained_model_name=PRE_TRAINED_MODEL_NAME_ENG,
        config=distil_bert_eng.config,
        num_labels=len(classes),
        freeze_encoder=True,
        soft_labels=True
    ),
    dataset=dataset_2_eng,
    learning_rate=1e-4,
    num_epochs=16,
    weight_decay=0.01
)
```

```
Outer Fold 1
  Inner Fold 1
Epoch 1/16, Train Loss: 0.6443
Epoch 2/16, Train Loss: 0.6502
Epoch 3/16, Train Loss: 0.6021
Epoch 4/16, Train Loss: 0.6422
Epoch 5/16, Train Loss: 0.6105
Epoch 6/16, Train Loss: 0.6119
Epoch 7/16, Train Loss: 0.6034
Epoch 8/16, Train Loss: 0.5852
Epoch 9/16, Train Loss: 0.5802
Epoch 10/16, Train Loss: 0.6033
Epoch 11/16, Train Loss: 0.5573
Epoch 12/16, Train Loss: 0.5509
Epoch 13/16, Train Loss: 0.5616
Epoch 14/16, Train Loss: 0.5531
Epoch 15/16, Train Loss: 0.5631
Epoch 16/16, Train Loss: 0.5324
    Validation Loss: 0.4985, Precision@K: 0.2222
  Inner Fold 2
Epoch 1/16, Train Loss: 0.5276
Epoch 2/16, Train Loss: 0.5280
Epoch 3/16, Train Loss: 0.5351
Epoch 4/16, Train Loss: 0.5126
Epoch 5/16, Train Loss: 0.5132
Epoch 6/16, Train Loss: 0.5445
Epoch 7/16, Train Loss: 0.5051
Epoch 8/16, Train Loss: 0.5147
Epoch 9/16, Train Loss: 0.5063
Epoch 10/16, Train Loss: 0.4908
Epoch 11/16, Train Loss: 0.5093
Epoch 12/16, Train Loss: 0.5160
Epoch 13/16, Train Loss: 0.4530
Epoch 14/16, Train Loss: 0.4681
Epoch 15/16, Train Loss: 0.4924
Epoch 16/16, Train Loss: 0.4859
    Validation Loss: 0.6492, Precision@K: 0.1481
  Inner Fold 3
Epoch 1/16, Train Loss: 0.4974
Epoch 2/16, Train Loss: 0.4724
Epoch 3/16, Train Loss: 0.4958
Epoch 4/16, Train Loss: 0.4739
Epoch 5/16, Train Loss: 0.5070
Epoch 6/16, Train Loss: 0.4628
Epoch 7/16, Train Loss: 0.4874
Epoch 8/16, Train Loss: 0.4996
Epoch 9/16, Train Loss: 0.4574
Epoch 10/16, Train Loss: 0.4524
Epoch 11/16, Train Loss: 0.4654
Epoch 12/16, Train Loss: 0.4840
Epoch 13/16, Train Loss: 0.4603
Epoch 14/16, Train Loss: 0.4637
Epoch 15/16, Train Loss: 0.4500
Epoch 16/16, Train Loss: 0.4587
    Validation Loss: 0.6677, Precision@K: 0.1667
  Inner Fold 4
Epoch 1/16, Train Loss: 0.5110
Epoch 2/16, Train Loss: 0.5142
Epoch 3/16, Train Loss: 0.5105
Epoch 4/16, Train Loss: 0.4984
Epoch 5/16, Train Loss: 0.4915
Epoch 6/16, Train Loss: 0.5198
Epoch 7/16, Train Loss: 0.4944
Epoch 8/16, Train Loss: 0.4935
Epoch 9/16, Train Loss: 0.5003
Epoch 10/16, Train Loss: 0.4802
Epoch 11/16, Train Loss: 0.4897
Epoch 12/16, Train Loss: 0.4803
Epoch 13/16, Train Loss: 0.4784
Epoch 14/16, Train Loss: 0.4769
Epoch 15/16, Train Loss: 0.4727
Epoch 16/16, Train Loss: 0.4474
    Validation Loss: 0.4975, Precision@K: 0.1481
  Inner Fold 5
Epoch 1/16, Train Loss: 0.4883
Epoch 2/16, Train Loss: 0.5053
Epoch 3/16, Train Loss: 0.4854
Epoch 4/16, Train Loss: 0.4891
Epoch 5/16, Train Loss: 0.5060
Epoch 6/16, Train Loss: 0.5109
Epoch 7/16, Train Loss: 0.4753
Epoch 8/16, Train Loss: 0.4755
Epoch 9/16, Train Loss: 0.4642
Epoch 10/16, Train Loss: 0.4931
Epoch 11/16, Train Loss: 0.4793
Epoch 12/16, Train Loss: 0.4688
Epoch 13/16, Train Loss: 0.4782
```

```
Epoch 14/16, Train Loss: 0.4626
Epoch 15/16, Train Loss: 0.4712
Epoch 16/16, Train Loss: 0.4473
    Validation Loss: 0.4003, Precision@K: 0.3333
  Test Loss (Outer Fold 1): 0.6512, Precision@K: 0.2361
Outer Fold 2
  Inner Fold 1
Epoch 1/16, Train Loss: 0.6335
Epoch 2/16, Train Loss: 0.6200
Epoch 3/16, Train Loss: 0.5970
Epoch 4/16, Train Loss: 0.6179
Epoch 5/16, Train Loss: 0.6221
Epoch 6/16, Train Loss: 0.5613
Epoch 7/16, Train Loss: 0.5784
Epoch 8/16, Train Loss: 0.5590
Epoch 9/16, Train Loss: 0.5842
Epoch 10/16, Train Loss: 0.5702
Epoch 11/16, Train Loss: 0.5587
Epoch 12/16, Train Loss: 0.5740
Epoch 13/16, Train Loss: 0.5602
Epoch 14/16, Train Loss: 0.5248
Epoch 15/16, Train Loss: 0.5010
Epoch 16/16, Train Loss: 0.5608
    Validation Loss: 0.8048, Precision@K: 0.0000
  Inner Fold 2
Epoch 1/16, Train Loss: 0.6644
Epoch 2/16, Train Loss: 0.6354
Epoch 3/16, Train Loss: 0.6344
Epoch 4/16, Train Loss: 0.6277
Epoch 5/16, Train Loss: 0.6213
Epoch 6/16, Train Loss: 0.6166
Epoch 7/16, Train Loss: 0.6248
Epoch 8/16, Train Loss: 0.6116
Epoch 9/16, Train Loss: 0.6146
Epoch 10/16, Train Loss: 0.6289
Epoch 11/16, Train Loss: 0.6242
Epoch 12/16, Train Loss: 0.6173
Epoch 13/16, Train Loss: 0.6302
Epoch 14/16, Train Loss: 0.6045
Epoch 15/16, Train Loss: 0.6047
Epoch 16/16, Train Loss: 0.6143
    Validation Loss: 0.3974, Precision@K: 0.2037
  Inner Fold 3
Epoch 1/16, Train Loss: 0.5449
Epoch 2/16, Train Loss: 0.5349
Epoch 3/16, Train Loss: 0.5237
Epoch 4/16, Train Loss: 0.5506
Epoch 5/16, Train Loss: 0.5307
Epoch 6/16, Train Loss: 0.5167
Epoch 7/16, Train Loss: 0.5612
Epoch 8/16, Train Loss: 0.5261
Epoch 9/16, Train Loss: 0.5501
Epoch 10/16, Train Loss: 0.4986
Epoch 11/16, Train Loss: 0.5301
Epoch 12/16, Train Loss: 0.5337
Epoch 13/16, Train Loss: 0.5182
Epoch 14/16, Train Loss: 0.5253
Epoch 15/16, Train Loss: 0.5286
Epoch 16/16, Train Loss: 0.5173
    Validation Loss: 0.6518, Precision@K: 0.2222
  Inner Fold 4
Epoch 1/16, Train Loss: 0.5809
Epoch 2/16, Train Loss: 0.5559
Epoch 3/16, Train Loss: 0.5358
Epoch 4/16, Train Loss: 0.5675
Epoch 5/16, Train Loss: 0.5542
Epoch 6/16, Train Loss: 0.5280
Epoch 7/16, Train Loss: 0.5660
Epoch 8/16, Train Loss: 0.5475
Epoch 9/16, Train Loss: 0.5559
Epoch 10/16, Train Loss: 0.5303
Epoch 11/16, Train Loss: 0.5358
Epoch 12/16, Train Loss: 0.5375
Epoch 13/16, Train Loss: 0.5307
Epoch 14/16, Train Loss: 0.5329
Epoch 15/16, Train Loss: 0.5292
Epoch 16/16, Train Loss: 0.5271
    Validation Loss: 0.4744, Precision@K: 0.6667
  Inner Fold 5
Epoch 1/16, Train Loss: 0.5158
Epoch 2/16, Train Loss: 0.5297
Epoch 3/16, Train Loss: 0.5514
Epoch 4/16, Train Loss: 0.5347
Epoch 5/16, Train Loss: 0.5037
Epoch 6/16, Train Loss: 0.5301
Epoch 7/16, Train Loss: 0.5224
Epoch 8/16, Train Loss: 0.5122
```

```
Epoch 9/16, Train Loss: 0.4986
Epoch 10/16, Train Loss: 0.5355
Epoch 11/16, Train Loss: 0.5261
Epoch 12/16, Train Loss: 0.5350
Epoch 13/16, Train Loss: 0.5150
Epoch 14/16, Train Loss: 0.5254
Epoch 15/16, Train Loss: 0.5056
Epoch 16/16, Train Loss: 0.5068
    Validation Loss: 0.4821, Precision@K: 0.2778
  Test Loss (Outer Fold 2): 0.4552, Precision@K: 0.1389
Outer Fold 3
  Inner Fold 1
Epoch 1/16, Train Loss: 0.5689
Epoch 2/16, Train Loss: 0.6111
Epoch 3/16, Train Loss: 0.5880
Epoch 4/16, Train Loss: 0.5730
Epoch 5/16, Train Loss: 0.6423
Epoch 6/16, Train Loss: 0.5746
Epoch 7/16, Train Loss: 0.5764
Epoch 8/16, Train Loss: 0.5849
Epoch 9/16, Train Loss: 0.5760
Epoch 10/16, Train Loss: 0.5753
Epoch 11/16, Train Loss: 0.5787
Epoch 12/16, Train Loss: 0.5637
Epoch 13/16, Train Loss: 0.5559
Epoch 14/16, Train Loss: 0.5455
Epoch 15/16, Train Loss: 0.5637
Epoch 16/16, Train Loss: 0.5364
    Validation Loss: 0.5020, Precision@K: 0.2778
  Inner Fold 2
Epoch 1/16, Train Loss: 0.5379
Epoch 2/16, Train Loss: 0.5401
Epoch 3/16, Train Loss: 0.5363
Epoch 4/16, Train Loss: 0.5380
Epoch 5/16, Train Loss: 0.4934
Epoch 6/16, Train Loss: 0.5125
Epoch 7/16, Train Loss: 0.5351
Epoch 8/16, Train Loss: 0.5078
Epoch 9/16, Train Loss: 0.5184
Epoch 10/16, Train Loss: 0.5088
Epoch 11/16, Train Loss: 0.5011
Epoch 12/16, Train Loss: 0.4923
Epoch 13/16, Train Loss: 0.5387
Epoch 14/16, Train Loss: 0.5157
Epoch 15/16, Train Loss: 0.5054
Epoch 16/16, Train Loss: 0.5082
    Validation Loss: 0.5375, Precision@K: 0.1111
  Inner Fold 3
Epoch 1/16, Train Loss: 0.5101
Epoch 2/16, Train Loss: 0.5106
Epoch 3/16, Train Loss: 0.4746
Epoch 4/16, Train Loss: 0.4569
Epoch 5/16, Train Loss: 0.4586
Epoch 6/16, Train Loss: 0.4547
Epoch 7/16, Train Loss: 0.4899
Epoch 8/16, Train Loss: 0.4752
Epoch 9/16, Train Loss: 0.4561
Epoch 10/16, Train Loss: 0.4555
Epoch 11/16, Train Loss: 0.4772
Epoch 12/16, Train Loss: 0.4580
Epoch 13/16, Train Loss: 0.4829
Epoch 14/16, Train Loss: 0.4625
Epoch 15/16, Train Loss: 0.4566
Epoch 16/16, Train Loss: 0.4563
    Validation Loss: 0.6484, Precision@K: 0.1852
  Inner Fold 4
Epoch 1/16, Train Loss: 0.4811
Epoch 2/16, Train Loss: 0.4970
Epoch 3/16, Train Loss: 0.4993
Epoch 4/16, Train Loss: 0.5024
Epoch 5/16, Train Loss: 0.4831
Epoch 6/16, Train Loss: 0.4895
Epoch 7/16, Train Loss: 0.5187
Epoch 8/16, Train Loss: 0.4821
Epoch 9/16, Train Loss: 0.4675
Epoch 10/16, Train Loss: 0.4849
Epoch 11/16, Train Loss: 0.4704
Epoch 12/16, Train Loss: 0.4721
Epoch 13/16, Train Loss: 0.4436
Epoch 14/16, Train Loss: 0.4717
Epoch 15/16, Train Loss: 0.4818
Epoch 16/16, Train Loss: 0.4928
    Validation Loss: 0.4796, Precision@K: 0.3333
  Inner Fold 5
Epoch 1/16, Train Loss: 0.4982
Epoch 2/16, Train Loss: 0.4788
Epoch 3/16, Train Loss: 0.4849
```

```
Epoch 4/16, Train Loss: 0.5107
Epoch 5/16, Train Loss: 0.4636
Epoch 6/16, Train Loss: 0.4770
Epoch 7/16, Train Loss: 0.4828
Epoch 8/16, Train Loss: 0.4459
Epoch 9/16, Train Loss: 0.4639
Epoch 10/16, Train Loss: 0.4444
Epoch 11/16, Train Loss: 0.4462
Epoch 12/16, Train Loss: 0.4574
Epoch 13/16, Train Loss: 0.4499
Epoch 14/16, Train Loss: 0.4479
Epoch 15/16, Train Loss: 0.4229
Epoch 16/16, Train Loss: 0.4536
    Validation Loss: 0.5485, Precision@K: 0.1111
  Test Loss (Outer Fold 3): 0.6168, Precision@K: 0.2222
Outer Fold 4
  Inner Fold 1
Epoch 1/16, Train Loss: 0.5898
Epoch 2/16, Train Loss: 0.5660
Epoch 3/16, Train Loss: 0.5655
Epoch 4/16, Train Loss: 0.5585
Epoch 5/16, Train Loss: 0.5752
Epoch 6/16, Train Loss: 0.5338
Epoch 7/16, Train Loss: 0.5544
Epoch 8/16, Train Loss: 0.5511
Epoch 9/16, Train Loss: 0.4882
Epoch 10/16, Train Loss: 0.5512
Epoch 11/16, Train Loss: 0.5209
Epoch 12/16, Train Loss: 0.5409
Epoch 13/16, Train Loss: 0.5126
Epoch 14/16, Train Loss: 0.4966
Epoch 15/16, Train Loss: 0.5137
Epoch 16/16, Train Loss: 0.5102
    Validation Loss: 0.5672, Precision@K: 0.2361
  Inner Fold 2
Epoch 1/16, Train Loss: 0.5213
Epoch 2/16, Train Loss: 0.4796
Epoch 3/16, Train Loss: 0.5114
Epoch 4/16, Train Loss: 0.5227
Epoch 5/16, Train Loss: 0.5197
Epoch 6/16, Train Loss: 0.4985
Epoch 7/16, Train Loss: 0.4833
Epoch 8/16, Train Loss: 0.5042
Epoch 9/16, Train Loss: 0.4774
Epoch 10/16, Train Loss: 0.5039
Epoch 11/16, Train Loss: 0.5022
Epoch 12/16, Train Loss: 0.5071
Epoch 13/16, Train Loss: 0.4820
Epoch 14/16, Train Loss: 0.4941
Epoch 15/16, Train Loss: 0.4887
Epoch 16/16, Train Loss: 0.4926
    Validation Loss: 0.5213, Precision@K: 0.4444
  Inner Fold 3
Epoch 1/16, Train Loss: 0.4429
Epoch 2/16, Train Loss: 0.4727
Epoch 3/16, Train Loss: 0.4415
Epoch 4/16, Train Loss: 0.4592
Epoch 5/16, Train Loss: 0.4573
Epoch 6/16, Train Loss: 0.4602
Epoch 7/16, Train Loss: 0.4441
Epoch 8/16, Train Loss: 0.4190
Epoch 9/16, Train Loss: 0.4524
Epoch 10/16, Train Loss: 0.4460
Epoch 11/16, Train Loss: 0.4446
Epoch 12/16, Train Loss: 0.4497
Epoch 13/16, Train Loss: 0.4627
Epoch 14/16, Train Loss: 0.4357
Epoch 15/16, Train Loss: 0.4272
Epoch 16/16, Train Loss: 0.4152
    Validation Loss: 0.6954, Precision@K: 0.3148
  Inner Fold 4
Epoch 1/16, Train Loss: 0.5426
Epoch 2/16, Train Loss: 0.5040
Epoch 3/16, Train Loss: 0.5242
Epoch 4/16, Train Loss: 0.5403
Epoch 5/16, Train Loss: 0.5223
Epoch 6/16, Train Loss: 0.5086
Epoch 7/16, Train Loss: 0.4930
Epoch 8/16, Train Loss: 0.5440
Epoch 9/16, Train Loss: 0.5200
Epoch 10/16, Train Loss: 0.5384
Epoch 11/16, Train Loss: 0.5032
Epoch 12/16, Train Loss: 0.4856
Epoch 13/16, Train Loss: 0.4913
Epoch 14/16, Train Loss: 0.5035
Epoch 15/16, Train Loss: 0.5178
Epoch 16/16, Train Loss: 0.4950
```

```
    Validation Loss: 0.3460, Precision@K: 0.1667
  Inner Fold 5
Epoch 1/16, Train Loss: 0.4364
Epoch 2/16, Train Loss: 0.4608
Epoch 3/16, Train Loss: 0.4749
Epoch 4/16, Train Loss: 0.4496
Epoch 5/16, Train Loss: 0.4338
Epoch 6/16, Train Loss: 0.4581
Epoch 7/16, Train Loss: 0.4284
Epoch 8/16, Train Loss: 0.4134
Epoch 9/16, Train Loss: 0.4449
Epoch 10/16, Train Loss: 0.4522
Epoch 11/16, Train Loss: 0.4509
Epoch 12/16, Train Loss: 0.4369
Epoch 13/16, Train Loss: 0.4174
Epoch 14/16, Train Loss: 0.4145
Epoch 15/16, Train Loss: 0.4248
Epoch 16/16, Train Loss: 0.4078
    Validation Loss: 0.5865, Precision@K: 0.2778
  Test Loss (Outer Fold 4): 0.7586, Precision@K: 0.0694
Outer Fold 5
  Inner Fold 1
Epoch 1/16, Train Loss: 0.6519
Epoch 2/16, Train Loss: 0.6442
Epoch 3/16, Train Loss: 0.6334
Epoch 4/16, Train Loss: 0.6014
Epoch 5/16, Train Loss: 0.6211
Epoch 6/16, Train Loss: 0.5933
Epoch 7/16, Train Loss: 0.6105
Epoch 8/16, Train Loss: 0.6350
Epoch 9/16, Train Loss: 0.5753
Epoch 10/16, Train Loss: 0.5795
Epoch 11/16, Train Loss: 0.5540
Epoch 12/16, Train Loss: 0.5754
Epoch 13/16, Train Loss: 0.6039
Epoch 14/16, Train Loss: 0.5819
Epoch 15/16, Train Loss: 0.5534
Epoch 16/16, Train Loss: 0.5662
    Validation Loss: 0.6046, Precision@K: 0.1250
  Inner Fold 2
Epoch 1/16, Train Loss: 0.6051
Epoch 2/16, Train Loss: 0.5639
Epoch 3/16, Train Loss: 0.5671
Epoch 4/16, Train Loss: 0.5898
Epoch 5/16, Train Loss: 0.5803
Epoch 6/16, Train Loss: 0.5980
Epoch 7/16, Train Loss: 0.5529
Epoch 8/16, Train Loss: 0.5681
Epoch 9/16, Train Loss: 0.5344
Epoch 10/16, Train Loss: 0.5483
Epoch 11/16, Train Loss: 0.5521
Epoch 12/16, Train Loss: 0.5707
Epoch 13/16, Train Loss: 0.5481
Epoch 14/16, Train Loss: 0.5716
Epoch 15/16, Train Loss: 0.5437
Epoch 16/16, Train Loss: 0.5510
    Validation Loss: 0.5040, Precision@K: 0.2593
  Inner Fold 3
Epoch 1/16, Train Loss: 0.5336
Epoch 2/16, Train Loss: 0.5237
Epoch 3/16, Train Loss: 0.5042
Epoch 4/16, Train Loss: 0.5146
Epoch 5/16, Train Loss: 0.5326
Epoch 6/16, Train Loss: 0.5280
Epoch 7/16, Train Loss: 0.5168
Epoch 8/16, Train Loss: 0.5183
Epoch 9/16, Train Loss: 0.5243
Epoch 10/16, Train Loss: 0.5235
Epoch 11/16, Train Loss: 0.5052
Epoch 12/16, Train Loss: 0.5199
Epoch 13/16, Train Loss: 0.4868
Epoch 14/16, Train Loss: 0.4905
Epoch 15/16, Train Loss: 0.5203
Epoch 16/16, Train Loss: 0.5099
    Validation Loss: 0.5884, Precision@K: 0.3333
  Inner Fold 4
Epoch 1/16, Train Loss: 0.5226
Epoch 2/16, Train Loss: 0.5303
Epoch 3/16, Train Loss: 0.5041
Epoch 4/16, Train Loss: 0.4862
Epoch 5/16, Train Loss: 0.5012
Epoch 6/16, Train Loss: 0.4840
Epoch 7/16, Train Loss: 0.4993
Epoch 8/16, Train Loss: 0.5006
Epoch 9/16, Train Loss: 0.5074
Epoch 10/16, Train Loss: 0.4933
Epoch 11/16, Train Loss: 0.4997
```

```
Epoch 12/16, Train Loss: 0.4866
Epoch 13/16, Train Loss: 0.4761
Epoch 14/16, Train Loss: 0.4869
Epoch 15/16, Train Loss: 0.4879
Epoch 16/16, Train Loss: 0.4851
    Validation Loss: 0.5720, Precision@K: 0.2222
  Inner Fold 5
Epoch 1/16, Train Loss: 0.5299
Epoch 2/16, Train Loss: 0.5126
Epoch 3/16, Train Loss: 0.5138
Epoch 4/16, Train Loss: 0.4856
Epoch 5/16, Train Loss: 0.4961
Epoch 6/16, Train Loss: 0.4947
Epoch 7/16, Train Loss: 0.4934
Epoch 8/16, Train Loss: 0.4986
Epoch 9/16, Train Loss: 0.4748
Epoch 10/16, Train Loss: 0.4961
Epoch 11/16, Train Loss: 0.4623
Epoch 12/16, Train Loss: 0.4878
Epoch 13/16, Train Loss: 0.4989
Epoch 14/16, Train Loss: 0.4607
Epoch 15/16, Train Loss: 0.4700
Epoch 16/16, Train Loss: 0.4671
    Validation Loss: 0.5693, Precision@K: 0.1667
  Test Loss (Outer Fold 5): 0.5626, Precision@K: 0.1528
Average Test Loss: 0.6089
Average Precision@K: 0.1639
```

In [38]:
```
model_2_trained_all = nested_k_fold_training(
    outer_split=5,
    inner_split=5,
    model_constructor=lambda: model_constructor(
        pretrained_model_name=PRE_TRAINED_MODEL_NAME_ALL,
        config=distil_bert_all.config,
        num_labels=len(classes),
        freeze_encoder=True,
        soft_labels=True
    ),
    dataset=dataset_2_all,
    learning_rate=1e-4,
    weight_decay=0.01,
    num_epochs=16
)
```

```
Outer Fold 1
  Inner Fold 1
Epoch 1/16, Train Loss: 0.5485
Epoch 2/16, Train Loss: 0.5987
Epoch 3/16, Train Loss: 0.5881
Epoch 4/16, Train Loss: 0.5307
Epoch 5/16, Train Loss: 0.5695
Epoch 6/16, Train Loss: 0.5068
Epoch 7/16, Train Loss: 0.5909
Epoch 8/16, Train Loss: 0.5291
Epoch 9/16, Train Loss: 0.5327
Epoch 10/16, Train Loss: 0.4709
Epoch 11/16, Train Loss: 0.5009
Epoch 12/16, Train Loss: 0.4964
Epoch 13/16, Train Loss: 0.5610
Epoch 14/16, Train Loss: 0.4630
Epoch 15/16, Train Loss: 0.5008
Epoch 16/16, Train Loss: 0.4904
    Validation Loss: 0.7448, Precision@K: 0.1825
  Inner Fold 2
Epoch 1/16, Train Loss: 0.4958
Epoch 2/16, Train Loss: 0.6162
Epoch 3/16, Train Loss: 0.5117
Epoch 4/16, Train Loss: 0.5577
Epoch 5/16, Train Loss: 0.4938
Epoch 6/16, Train Loss: 0.5536
Epoch 7/16, Train Loss: 0.5768
Epoch 8/16, Train Loss: 0.4984
Epoch 9/16, Train Loss: 0.4814
Epoch 10/16, Train Loss: 0.4791
Epoch 11/16, Train Loss: 0.4576
Epoch 12/16, Train Loss: 0.5632
Epoch 13/16, Train Loss: 0.6161
Epoch 14/16, Train Loss: 0.5935
Epoch 15/16, Train Loss: 0.5365
Epoch 16/16, Train Loss: 0.6252
    Validation Loss: 0.5778, Precision@K: 0.1349
  Inner Fold 3
Epoch 1/16, Train Loss: 0.5465
Epoch 2/16, Train Loss: 0.5815
Epoch 3/16, Train Loss: 0.5354
Epoch 4/16, Train Loss: 0.5411
Epoch 5/16, Train Loss: 0.5256
Epoch 6/16, Train Loss: 0.5431
Epoch 7/16, Train Loss: 0.5176
Epoch 8/16, Train Loss: 0.5885
Epoch 9/16, Train Loss: 0.5327
Epoch 10/16, Train Loss: 0.5299
Epoch 11/16, Train Loss: 0.6034
Epoch 12/16, Train Loss: 0.5456
Epoch 13/16, Train Loss: 0.5752
Epoch 14/16, Train Loss: 0.5417
Epoch 15/16, Train Loss: 0.5294
Epoch 16/16, Train Loss: 0.5329
    Validation Loss: 0.4212, Precision@K: 0.2222
  Inner Fold 4
Epoch 1/16, Train Loss: 0.5067
Epoch 2/16, Train Loss: 0.5456
Epoch 3/16, Train Loss: 0.5177
Epoch 4/16, Train Loss: 0.5561
Epoch 5/16, Train Loss: 0.5184
Epoch 6/16, Train Loss: 0.5908
Epoch 7/16, Train Loss: 0.5288
Epoch 8/16, Train Loss: 0.5048
Epoch 9/16, Train Loss: 0.5290
Epoch 10/16, Train Loss: 0.5577
Epoch 11/16, Train Loss: 0.5381
Epoch 12/16, Train Loss: 0.5350
Epoch 13/16, Train Loss: 0.4954
Epoch 14/16, Train Loss: 0.5594
Epoch 15/16, Train Loss: 0.4950
Epoch 16/16, Train Loss: 0.5170
    Validation Loss: 0.5134, Precision@K: 0.2315
  Inner Fold 5
Epoch 1/16, Train Loss: 0.5512
Epoch 2/16, Train Loss: 0.4937
Epoch 3/16, Train Loss: 0.5276
Epoch 4/16, Train Loss: 0.5222
Epoch 5/16, Train Loss: 0.4843
Epoch 6/16, Train Loss: 0.5163
Epoch 7/16, Train Loss: 0.5545
Epoch 8/16, Train Loss: 0.5195
Epoch 9/16, Train Loss: 0.4609
Epoch 10/16, Train Loss: 0.5251
Epoch 11/16, Train Loss: 0.5551
Epoch 12/16, Train Loss: 0.4914
Epoch 13/16, Train Loss: 0.5221
```

```
Epoch 14/16, Train Loss: 0.4622
Epoch 15/16, Train Loss: 0.5525
Epoch 16/16, Train Loss: 0.4992
    Validation Loss: 0.5154, Precision@K: 0.4352
  Test Loss (Outer Fold 1): 0.6003, Precision@K: 0.1597
Outer Fold 2
  Inner Fold 1
Epoch 1/16, Train Loss: 0.6679
Epoch 2/16, Train Loss: 0.6201
Epoch 3/16, Train Loss: 0.5836
Epoch 4/16, Train Loss: 0.5658
Epoch 5/16, Train Loss: 0.5003
Epoch 6/16, Train Loss: 0.5263
Epoch 7/16, Train Loss: 0.5398
Epoch 8/16, Train Loss: 0.5686
Epoch 9/16, Train Loss: 0.5425
Epoch 10/16, Train Loss: 0.5401
Epoch 11/16, Train Loss: 0.6431
Epoch 12/16, Train Loss: 0.5688
Epoch 13/16, Train Loss: 0.5171
Epoch 14/16, Train Loss: 0.5149
Epoch 15/16, Train Loss: 0.5520
Epoch 16/16, Train Loss: 0.5626
    Validation Loss: 0.7340, Precision@K: 0.2540
  Inner Fold 2
Epoch 1/16, Train Loss: 0.5732
Epoch 2/16, Train Loss: 0.6122
Epoch 3/16, Train Loss: 0.6225
Epoch 4/16, Train Loss: 0.5728
Epoch 5/16, Train Loss: 0.6111
Epoch 6/16, Train Loss: 0.5567
Epoch 7/16, Train Loss: 0.5847
Epoch 8/16, Train Loss: 0.6656
Epoch 9/16, Train Loss: 0.7075
Epoch 10/16, Train Loss: 0.5468
Epoch 11/16, Train Loss: 0.5376
Epoch 12/16, Train Loss: 0.6725
Epoch 13/16, Train Loss: 0.6399
Epoch 14/16, Train Loss: 0.5955
Epoch 15/16, Train Loss: 0.5876
Epoch 16/16, Train Loss: 0.5898
    Validation Loss: 0.4436, Precision@K: 0.2143
  Inner Fold 3
Epoch 1/16, Train Loss: 0.5294
Epoch 2/16, Train Loss: 0.5635
Epoch 3/16, Train Loss: 0.5967
Epoch 4/16, Train Loss: 0.5886
Epoch 5/16, Train Loss: 0.5886
Epoch 6/16, Train Loss: 0.4985
Epoch 7/16, Train Loss: 0.5782
Epoch 8/16, Train Loss: 0.5589
Epoch 9/16, Train Loss: 0.5364
Epoch 10/16, Train Loss: 0.5474
Epoch 11/16, Train Loss: 0.5540
Epoch 12/16, Train Loss: 0.5740
Epoch 13/16, Train Loss: 0.5590
Epoch 14/16, Train Loss: 0.5506
Epoch 15/16, Train Loss: 0.5720
Epoch 16/16, Train Loss: 0.5580
    Validation Loss: 0.5482, Precision@K: 0.2685
  Inner Fold 4
Epoch 1/16, Train Loss: 0.5078
Epoch 2/16, Train Loss: 0.5028
Epoch 3/16, Train Loss: 0.5470
Epoch 4/16, Train Loss: 0.5311
Epoch 5/16, Train Loss: 0.4763
Epoch 6/16, Train Loss: 0.4915
Epoch 7/16, Train Loss: 0.5049
Epoch 8/16, Train Loss: 0.5285
Epoch 9/16, Train Loss: 0.4832
Epoch 10/16, Train Loss: 0.5208
Epoch 11/16, Train Loss: 0.5164
Epoch 12/16, Train Loss: 0.4892
Epoch 13/16, Train Loss: 0.4670
Epoch 14/16, Train Loss: 0.5525
Epoch 15/16, Train Loss: 0.4756
Epoch 16/16, Train Loss: 0.4864
    Validation Loss: 0.7343, Precision@K: 0.2407
  Inner Fold 5
Epoch 1/16, Train Loss: 0.5453
Epoch 2/16, Train Loss: 0.5693
Epoch 3/16, Train Loss: 0.5621
Epoch 4/16, Train Loss: 0.5625
Epoch 5/16, Train Loss: 0.5777
Epoch 6/16, Train Loss: 0.5619
Epoch 7/16, Train Loss: 0.5417
Epoch 8/16, Train Loss: 0.5486
```

```
Epoch 9/16, Train Loss: 0.5707
Epoch 10/16, Train Loss: 0.5366
Epoch 11/16, Train Loss: 0.5261
Epoch 12/16, Train Loss: 0.5734
Epoch 13/16, Train Loss: 0.5401
Epoch 14/16, Train Loss: 0.5624
Epoch 15/16, Train Loss: 0.5386
Epoch 16/16, Train Loss: 0.5540
    Validation Loss: 0.4756, Precision@K: 0.3241
  Test Loss (Outer Fold 2): 0.5278, Precision@K: 0.1597
Outer Fold 3
  Inner Fold 1
Epoch 1/16, Train Loss: 0.5045
Epoch 2/16, Train Loss: 0.5159
Epoch 3/16, Train Loss: 0.6421
Epoch 4/16, Train Loss: 0.5433
Epoch 5/16, Train Loss: 0.5547
Epoch 6/16, Train Loss: 0.5622
Epoch 7/16, Train Loss: 0.4848
Epoch 8/16, Train Loss: 0.4890
Epoch 9/16, Train Loss: 0.4850
Epoch 10/16, Train Loss: 0.4698
Epoch 11/16, Train Loss: 0.5252
Epoch 12/16, Train Loss: 0.5828
Epoch 13/16, Train Loss: 0.5702
Epoch 14/16, Train Loss: 0.5717
Epoch 15/16, Train Loss: 0.5483
Epoch 16/16, Train Loss: 0.5592
    Validation Loss: 0.6296, Precision@K: 0.1905
  Inner Fold 2
Epoch 1/16, Train Loss: 0.5985
Epoch 2/16, Train Loss: 0.6017
Epoch 3/16, Train Loss: 0.6209
Epoch 4/16, Train Loss: 0.6164
Epoch 5/16, Train Loss: 0.6011
Epoch 6/16, Train Loss: 0.5840
Epoch 7/16, Train Loss: 0.6074
Epoch 8/16, Train Loss: 0.5781
Epoch 9/16, Train Loss: 0.5992
Epoch 10/16, Train Loss: 0.5672
Epoch 11/16, Train Loss: 0.6057
Epoch 12/16, Train Loss: 0.5535
Epoch 13/16, Train Loss: 0.5220
Epoch 14/16, Train Loss: 0.5800
Epoch 15/16, Train Loss: 0.5696
Epoch 16/16, Train Loss: 0.6192
    Validation Loss: 0.3581, Precision@K: 0.3254
  Inner Fold 3
Epoch 1/16, Train Loss: 0.5299
Epoch 2/16, Train Loss: 0.5639
Epoch 3/16, Train Loss: 0.5539
Epoch 4/16, Train Loss: 0.4703
Epoch 5/16, Train Loss: 0.5673
Epoch 6/16, Train Loss: 0.4993
Epoch 7/16, Train Loss: 0.5483
Epoch 8/16, Train Loss: 0.5159
Epoch 9/16, Train Loss: 0.5273
Epoch 10/16, Train Loss: 0.4950
Epoch 11/16, Train Loss: 0.4770
Epoch 12/16, Train Loss: 0.5214
Epoch 13/16, Train Loss: 0.4575
Epoch 14/16, Train Loss: 0.5169
Epoch 15/16, Train Loss: 0.5034
Epoch 16/16, Train Loss: 0.5359
    Validation Loss: 0.5887, Precision@K: 0.2778
  Inner Fold 4
Epoch 1/16, Train Loss: 0.5075
Epoch 2/16, Train Loss: 0.5065
Epoch 3/16, Train Loss: 0.4662
Epoch 4/16, Train Loss: 0.4619
Epoch 5/16, Train Loss: 0.4530
Epoch 6/16, Train Loss: 0.4804
Epoch 7/16, Train Loss: 0.4927
Epoch 8/16, Train Loss: 0.5027
Epoch 9/16, Train Loss: 0.4365
Epoch 10/16, Train Loss: 0.4979
Epoch 11/16, Train Loss: 0.4349
Epoch 12/16, Train Loss: 0.4716
Epoch 13/16, Train Loss: 0.4430
Epoch 14/16, Train Loss: 0.4842
Epoch 15/16, Train Loss: 0.4432
Epoch 16/16, Train Loss: 0.4481
    Validation Loss: 0.7085, Precision@K: 0.2685
  Inner Fold 5
Epoch 1/16, Train Loss: 0.5376
Epoch 2/16, Train Loss: 0.5510
Epoch 3/16, Train Loss: 0.4976
```

```
Epoch 4/16, Train Loss: 0.5259
Epoch 5/16, Train Loss: 0.5775
Epoch 6/16, Train Loss: 0.4542
Epoch 7/16, Train Loss: 0.5452
Epoch 8/16, Train Loss: 0.5700
Epoch 9/16, Train Loss: 0.5133
Epoch 10/16, Train Loss: 0.4481
Epoch 11/16, Train Loss: 0.4460
Epoch 12/16, Train Loss: 0.5071
Epoch 13/16, Train Loss: 0.5373
Epoch 14/16, Train Loss: 0.4749
Epoch 15/16, Train Loss: 0.4644
Epoch 16/16, Train Loss: 0.5484
    Validation Loss: 0.5353, Precision@K: 0.1574
  Test Loss (Outer Fold 3): 0.6154, Precision@K: 0.2014
Outer Fold 4
  Inner Fold 1
Epoch 1/16, Train Loss: 0.5869
Epoch 2/16, Train Loss: 0.5382
Epoch 3/16, Train Loss: 0.4884
Epoch 4/16, Train Loss: 0.5641
Epoch 5/16, Train Loss: 0.5334
Epoch 6/16, Train Loss: 0.5678
Epoch 7/16, Train Loss: 0.6101
Epoch 8/16, Train Loss: 0.5499
Epoch 9/16, Train Loss: 0.5421
Epoch 10/16, Train Loss: 0.4479
Epoch 11/16, Train Loss: 0.5272
Epoch 12/16, Train Loss: 0.5390
Epoch 13/16, Train Loss: 0.4700
Epoch 14/16, Train Loss: 0.5058
Epoch 15/16, Train Loss: 0.5332
Epoch 16/16, Train Loss: 0.5120
    Validation Loss: 0.6284, Precision@K: 0.2619
  Inner Fold 2
Epoch 1/16, Train Loss: 0.5821
Epoch 2/16, Train Loss: 0.4531
Epoch 3/16, Train Loss: 0.4739
Epoch 4/16, Train Loss: 0.4406
Epoch 5/16, Train Loss: 0.4429
Epoch 6/16, Train Loss: 0.4680
Epoch 7/16, Train Loss: 0.4539
Epoch 8/16, Train Loss: 0.4987
Epoch 9/16, Train Loss: 0.5047
Epoch 10/16, Train Loss: 0.5447
Epoch 11/16, Train Loss: 0.5415
Epoch 12/16, Train Loss: 0.5517
Epoch 13/16, Train Loss: 0.4931
Epoch 14/16, Train Loss: 0.4977
Epoch 15/16, Train Loss: 0.4986
Epoch 16/16, Train Loss: 0.5465
    Validation Loss: 0.6376, Precision@K: 0.2698
  Inner Fold 3
Epoch 1/16, Train Loss: 0.5194
Epoch 2/16, Train Loss: 0.4460
Epoch 3/16, Train Loss: 0.5377
Epoch 4/16, Train Loss: 0.4757
Epoch 5/16, Train Loss: 0.4866
Epoch 6/16, Train Loss: 0.4943
Epoch 7/16, Train Loss: 0.5136
Epoch 8/16, Train Loss: 0.5485
Epoch 9/16, Train Loss: 0.5011
Epoch 10/16, Train Loss: 0.4473
Epoch 11/16, Train Loss: 0.5071
Epoch 12/16, Train Loss: 0.4970
Epoch 13/16, Train Loss: 0.4830
Epoch 14/16, Train Loss: 0.4426
Epoch 15/16, Train Loss: 0.4852
Epoch 16/16, Train Loss: 0.4668
    Validation Loss: 0.6137, Precision@K: 0.2870
  Inner Fold 4
Epoch 1/16, Train Loss: 0.5412
Epoch 2/16, Train Loss: 0.5698
Epoch 3/16, Train Loss: 0.5880
Epoch 4/16, Train Loss: 0.5468
Epoch 5/16, Train Loss: 0.4903
Epoch 6/16, Train Loss: 0.5706
Epoch 7/16, Train Loss: 0.5371
Epoch 8/16, Train Loss: 0.5580
Epoch 9/16, Train Loss: 0.5410
Epoch 10/16, Train Loss: 0.5341
Epoch 11/16, Train Loss: 0.5552
Epoch 12/16, Train Loss: 0.4777
Epoch 13/16, Train Loss: 0.5258
Epoch 14/16, Train Loss: 0.4733
Epoch 15/16, Train Loss: 0.5187
Epoch 16/16, Train Loss: 0.4739
```

```
    Validation Loss: 0.3909, Precision@K: 0.2685
  Inner Fold 5
Epoch 1/16, Train Loss: 0.4937
Epoch 2/16, Train Loss: 0.5318
Epoch 3/16, Train Loss: 0.5246
Epoch 4/16, Train Loss: 0.5460
Epoch 5/16, Train Loss: 0.5424
Epoch 6/16, Train Loss: 0.5200
Epoch 7/16, Train Loss: 0.5137
Epoch 8/16, Train Loss: 0.5196
Epoch 9/16, Train Loss: 0.4937
Epoch 10/16, Train Loss: 0.5231
Epoch 11/16, Train Loss: 0.4828
Epoch 12/16, Train Loss: 0.5280
Epoch 13/16, Train Loss: 0.4666
Epoch 14/16, Train Loss: 0.5155
Epoch 15/16, Train Loss: 0.4840
Epoch 16/16, Train Loss: 0.5158
    Validation Loss: 0.4239, Precision@K: 0.2222
  Test Loss (Outer Fold 4): 0.6881, Precision@K: 0.1319
Outer Fold 5
  Inner Fold 1
Epoch 1/16, Train Loss: 0.7463
Epoch 2/16, Train Loss: 0.6111
Epoch 3/16, Train Loss: 0.5322
Epoch 4/16, Train Loss: 0.6011
Epoch 5/16, Train Loss: 0.5557
Epoch 6/16, Train Loss: 0.5708
Epoch 7/16, Train Loss: 0.6042
Epoch 8/16, Train Loss: 0.6442
Epoch 9/16, Train Loss: 0.5580
Epoch 10/16, Train Loss: 0.5873
Epoch 11/16, Train Loss: 0.5406
Epoch 12/16, Train Loss: 0.4990
Epoch 13/16, Train Loss: 0.5466
Epoch 14/16, Train Loss: 0.5487
Epoch 15/16, Train Loss: 0.4867
Epoch 16/16, Train Loss: 0.5710
    Validation Loss: 0.6382, Precision@K: 0.1270
  Inner Fold 2
Epoch 1/16, Train Loss: 0.5239
Epoch 2/16, Train Loss: 0.4946
Epoch 3/16, Train Loss: 0.5490
Epoch 4/16, Train Loss: 0.5835
Epoch 5/16, Train Loss: 0.5441
Epoch 6/16, Train Loss: 0.4895
Epoch 7/16, Train Loss: 0.4720
Epoch 8/16, Train Loss: 0.5779
Epoch 9/16, Train Loss: 0.5831
Epoch 10/16, Train Loss: 0.5976
Epoch 11/16, Train Loss: 0.5815
Epoch 12/16, Train Loss: 0.5364
Epoch 13/16, Train Loss: 0.4788
Epoch 14/16, Train Loss: 0.4623
Epoch 15/16, Train Loss: 0.5705
Epoch 16/16, Train Loss: 0.5338
    Validation Loss: 0.5844, Precision@K: 0.1825
  Inner Fold 3
Epoch 1/16, Train Loss: 0.5681
Epoch 2/16, Train Loss: 0.5340
Epoch 3/16, Train Loss: 0.5413
Epoch 4/16, Train Loss: 0.5680
Epoch 5/16, Train Loss: 0.5897
Epoch 6/16, Train Loss: 0.5480
Epoch 7/16, Train Loss: 0.5326
Epoch 8/16, Train Loss: 0.5669
Epoch 9/16, Train Loss: 0.5455
Epoch 10/16, Train Loss: 0.5379
Epoch 11/16, Train Loss: 0.5264
Epoch 12/16, Train Loss: 0.5371
Epoch 13/16, Train Loss: 0.5129
Epoch 14/16, Train Loss: 0.5616
Epoch 15/16, Train Loss: 0.5615
Epoch 16/16, Train Loss: 0.4956
    Validation Loss: 0.5152, Precision@K: 0.1667
  Inner Fold 4
Epoch 1/16, Train Loss: 0.4984
Epoch 2/16, Train Loss: 0.5787
Epoch 3/16, Train Loss: 0.5493
Epoch 4/16, Train Loss: 0.5653
Epoch 5/16, Train Loss: 0.4868
Epoch 6/16, Train Loss: 0.5701
Epoch 7/16, Train Loss: 0.5052
Epoch 8/16, Train Loss: 0.5698
Epoch 9/16, Train Loss: 0.5278
Epoch 10/16, Train Loss: 0.5607
Epoch 11/16, Train Loss: 0.5302
```

```
Epoch 12/16, Train Loss: 0.5087
Epoch 13/16, Train Loss: 0.5379
Epoch 14/16, Train Loss: 0.5247
Epoch 15/16, Train Loss: 0.5446
Epoch 16/16, Train Loss: 0.5237
    Validation Loss: 0.4326, Precision@K: 0.3241
  Inner Fold 5
Epoch 1/16, Train Loss: 0.5260
Epoch 2/16, Train Loss: 0.5136
Epoch 3/16, Train Loss: 0.4887
Epoch 4/16, Train Loss: 0.4683
Epoch 5/16, Train Loss: 0.5102
Epoch 6/16, Train Loss: 0.5156
Epoch 7/16, Train Loss: 0.4814
Epoch 8/16, Train Loss: 0.4696
Epoch 9/16, Train Loss: 0.4576
Epoch 10/16, Train Loss: 0.4873
Epoch 11/16, Train Loss: 0.4538
Epoch 12/16, Train Loss: 0.4952
Epoch 13/16, Train Loss: 0.4663
Epoch 14/16, Train Loss: 0.4707
Epoch 15/16, Train Loss: 0.5200
Epoch 16/16, Train Loss: 0.5187
    Validation Loss: 0.5886, Precision@K: 0.2778
  Test Loss (Outer Fold 5): 0.6192, Precision@K: 0.1319
Average Test Loss: 0.6101
Average Precision@K: 0.1569
```

The results of the english only and both language models are once again very similar. The final averages show that these model have similar losses as well as precisions with their rankings. These train and valid losses are significatnly smaller than those of the first approach, but are calculated in a different way so this is not meaningful. Overall, the results are poor which could be a consenquence of the already mentioned dataset limitations as well as the initial non fine tuned hyper parameters

Inference

Since the goal of this task is to output top three experts for a ticket description, we will use already trained models and return their top 3 predicted probabilities for expert classes

In [39]:
```
def inference_bert(model, input_sentance, tokenizer, device, k):
    # tokenizing the sentance
    input_tokens = tokenizer(input_sentance, return_tensors='pt').to(device)
    model = model.to(device)
    model.eval()
    with torch.no_grad():
         # passing the sentance and returning the logits


        #logits = model(**input_tokens).output[1]
        logits = model(
            input_ids=input_tokens['input_ids'],
            attention_mask=input_tokens['attention_mask']
        )[0]

        # transforming into probabilities
        log_probs = torch.nn.functional.log_softmax(logits, dim=-1)
        probs = log_probs.exp()
        # getting the top k
        top_k_probs, top_k_indeces = torch.topk(logits, k=k, dim=1)
        top_k_experts = [f'expert_{i}' for i in top_k_indeces.squeeze().tolist()]

    return top_k_experts, top_k_probs.squeeze().tolist()
```

Manual check of classes

In [40]:
```
sentence_class_dict = (
    pd.read_csv('data_all.csv', sep=';')
    .groupby('ticket_description')['expert_id']
    .value_counts()
    .groupby(level=0)
    .apply(lambda x: list(zip(x.index.get_level_values(1), x.values)))
    .to_dict()
)
```

We will use the true labels form our dataset for these two sentances and visually compare them to what our models are outputting. Also, we will provide them with new sentances, with similar key words to "Data not syncing with the cloud." and "Error 404 when accessing the application.", so see if they will return similar experts as these

In [41]:
```
print(sentence_class_dict["Data not syncing with the cloud."])
print(sentence_class_dict["Error 404 when accessing the application."])
```

```
[('expert_2', 2), ('expert_8', 2), ('expert_0', 1), ('expert_5', 1), ('expert_6', 1), ('expert_7', 1)]
[('expert_7', 3), ('expert_9', 3), ('expert_2', 2), ('expert_5', 2), ('expert_6', 2), ('expert_0', 1), ('expert_4', 1)]
```

Vectorization models

In [42]:
```
_, _, vectorizer_bayes, classifier_bayes = do_tfidf_prediction(data_all, max_features = 256, model='Naive Bayes')
_, _, vectorizer_logistic, classifier_logistic = do_tfidf_prediction(data_all, max_features = 256, model='Logistic')
```

In [43]:
```
# new sentences
print("new")
print(inference_vect(classifier_bayes, 'Cloud error regarding data sync.', vectorizer_bayes, k=3))
print(inference_vect(classifier_bayes, 'Application access returns 404.', vectorizer_bayes, k=3))

# old sentences
print("old")
print(inference_vect(classifier_bayes, 'Data not syncing with the cloud.', vectorizer_bayes, k=3))
print(inference_vect(classifier_bayes, 'Error 404 when accessing the application.', vectorizer_bayes, k=3))

print()

# new sentences
print("new")
print(inference_vect(classifier_logistic, 'Cloud error regarding data sync.', vectorizer_logistic, k=3))
print(inference_vect(classifier_logistic, 'Application access returns 404.', vectorizer_logistic, k=3))

# old sentences
print("old")
print(inference_vect(classifier_logistic, 'Data not syncing with the cloud.', vectorizer_logistic, k=3))
print(inference_vect(classifier_logistic, 'Error 404 when accessing the application.', vectorizer_logistic, k=3))
```

```
new
(['class_2', 'class_8', 'class_0'], array([0.18271958, 0.15574134, 0.12895185]))
(['class_4', 'class_8', 'class_2'], array([0.16748103, 0.15953274, 0.13364847]))
old
(['class_2', 'class_8', 'class_5'], array([0.23656008, 0.18355121, 0.119714  ]))
(['class_5', 'class_2', 'class_4'], array([0.1669718 , 0.14997842, 0.14265775]))

new
(['class_8', 'class_2', 'class_0'], array([0.15215256, 0.15149754, 0.13095092]))
(['class_4', 'class_8', 'class_2'], array([0.1647941 , 0.14333503, 0.13329366]))
old
(['class_2', 'class_8', 'class_5'], array([0.19787854, 0.17948809, 0.11627695]))
(['class_5', 'class_2', 'class_4'], array([0.14906846, 0.13900373, 0.13532382]))
```

BERT First approach

In [44]:
```
# new sentences
print("new")
print(inference_bert(model_all, "Cloud error regarding data sync.", tokenizer_all, device, k=3))
print(inference_bert(model_all, "Application access returns 404.", tokenizer_all, device, k=3))

# old sentences
print("old")
print(inference_bert(model_all, "Data not syncing with the cloud.", tokenizer_all, device, k=3))
print(inference_bert(model_all, "Error 404 when accessing the application.", tokenizer_all, device, k=3))

print()

# new sentences
print("new")
print(inference_bert(model_eng_only, "Cloud error regarding data sync.", tokenizer_eng, device, k=3))
print(inference_bert(model_eng_only, "Application access returns 404.", tokenizer_eng, device, k=3))

# old sentences
print("old")
print(inference_bert(model_eng_only, "Data not syncing with the cloud.", tokenizer_eng, device, k=3))
print(inference_bert(model_eng_only, "Error 404 when accessing the application.", tokenizer_eng, device, k=3))
```

```
new
(['expert_2', 'expert_4', 'expert_8'], [0.21784040331840515, 0.17881357669830322, 0.11214935779571533])
(['expert_4', 'expert_2', 'expert_8'], [0.2733030617237091, 0.2089579999446869, 0.201898381114400604])
old
(['expert_2', 'expert_8', 'expert_4'], [0.1767909675836563, 0.12201175093650818, 0.108925960958004])
(['expert_2', 'expert_8', 'expert_0'], [0.1987890899181366, 0.16601543128490448, 0.06459085643291473])

new
(['expert_2', 'expert_4', 'expert_0'], [0.3447420001029968, 0.2634940445423126, 0.177247554063797])
(['expert_4', 'expert_2', 'expert_5'], [0.2954951822757721, 0.21484707295894623, 0.1436472237110138])
old
(['expert_0', 'expert_2', 'expert_4'], [0.21205021440982819, 0.19652873277664185, 0.1549534648656845])
(['expert_2', 'expert_4', 'expert_8'], [0.32616883516311646, 0.31080198287963867, 0.13888615369796753])
```

BERT Second approach

In [45]:
```
# new sentences
print("new")
print(inference_bert(model_2_trained_all, "Cloud error regarding data sync.", tokenizer_all, device, k=3))
print(inference_bert(model_2_trained_all, "Application access returns 404.", tokenizer_all, device, k=3))

# old sentences
print("old")
print(inference_bert(model_2_trained_all, "Data not syncing with the cloud.", tokenizer_all, device, k=3))
```

```
print(inference_bert(model_2_trained_all, "Error 404 when accessing the application.", tokenizer_all, device, k=3))

print()

# new sentance
print("new")
print(inference_bert(model_2_trained_eng, "Cloud error regarding data sync.", tokenizer_eng, device, k=3))
print(inference_bert(model_2_trained_eng, "Application access returns 404.", tokenizer_eng, device, k=3))

# old sentances
print("old")
print(inference_bert(model_2_trained_eng, "Data not syncing with the cloud.", tokenizer_eng, device, k=3))
print(inference_bert(model_2_trained_eng, "Error 404 when accessing the application.", tokenizer_eng, device, k=3))
```

```
new
(['expert_4', 'expert_0', 'expert_8'], [0.6433902978897095, 0.22902728617191315, 0.17955441772937775])
(['expert_4', 'expert_0', 'expert_8'], [0.6231966614723206, 0.29855334758758545, 0.2281108945608139])
old
(['expert_4', 'expert_0', 'expert_8'], [0.39226704835891724, 0.29382625222206116, 0.2352864146232605])
(['expert_4', 'expert_8', 'expert_3'], [0.4368797242641449, 0.21978406608104706, 0.16806474328041077])

new
(['expert_2', 'expert_0', 'expert_4'], [0.5909643769264221, 0.44338110089302063, 0.39951393008232117])
(['expert_2', 'expert_4', 'expert_3'], [0.751166045665741, 0.5333460569381714, 0.4010883569717407])
old
(['expert_2', 'expert_8', 'expert_0'], [0.7733923196792603, 0.5409674048423767, 0.5092843174934387])
(['expert_2', 'expert_0', 'expert_4'], [0.7070170640945435, 0.4895773231983185, 0.4284771978855133])
```

It appears that all of the models are mostly outputting these classes: 4,8,2,0. This might be becasue their distributions are the amongst the higest in the dataset. The sentance: "Data not syncing with the cloud." is assigned exactly these classes in the dataset, and by just observing the new setance similar to it, it seems like the models are making a good prediction for the experts. However, that is why we added another new sentance similar to: "Error 404 when accessing the application." and we get the experts from the same subset as the first sentance, even though the correct experts from the dataset are totaly different for this sentance.

In [46]:
```
print(inference_bert(model_2_trained_eng, "Why are you outputting the same classes?", tokenizer_eng, device, k=3))
```

```
(['expert_4', 'expert_2', 'expert_3'], [0.575684130191803, 0.5419238209724426, 0.29540565609931946])
```

All of the sentaces and their classes

In [47]:
```
sentence_class_dict
```

```
Out[47]: {'Application fails to save settings.': [('expert_0', 3),
           ('expert_2', 1),
           ('expert_3', 1),
           ('expert_4', 1),
           ('expert_5', 1),
           ('expert_7', 1),
           ('expert_8', 1),
           ('expert_9', 1)],
          'Backup process fails intermittently.': [('expert_1', 3),
           ('expert_3', 2),
           ('expert_8', 2),
           ('expert_0', 1),
           ('expert_2', 1),
           ('expert_4', 1)],
          'Data not syncing with the cloud.': [('expert_2', 2),
           ('expert_8', 2),
           ('expert_0', 1),
           ('expert_5', 1),
           ('expert_6', 1),
           ('expert_7', 1)],
          "Des fuites de mémoire sont observées lors de l'exécution d'opérations intensives ou prolongées.": [('expert_3',
            4),
           ('expert_5', 2),
           ('expert_8', 2),
           ('expert_4', 1),
           ('expert_6', 1),
           ('expert_9', 1)],
          "Déconnexion inattendue du système après une longue période d'inactivité sur l'application.": [('expert_5',
            5),
           ('expert_2', 2),
           ('expert_1', 1),
           ('expert_6', 1),
           ('expert_7', 1)],
          'Email notifications not being sent.': [('expert_2', 2),
           ('expert_0', 1),
           ('expert_3', 1),
           ('expert_4', 1),
           ('expert_5', 1),
           ('expert_8', 1),
           ('expert_9', 1)],
          "Erreur 404 rencontrée systématiquement lors de l'accès à certaines sections de l'application.": [('expert_4',
            2),
           ('expert_6', 2),
           ('expert_8', 2),
           ('expert_2', 1),
           ('expert_3', 1),
           ('expert_9', 1)],
          "Erreur de délai d'attente avec la passerelle de paiement lors de transactions importantes.": [('expert_2',
            4),
           ('expert_9', 3),
           ('expert_3', 2),
           ('expert_8', 2),
           ('expert_0', 1),
           ('expert_5', 1),
           ('expert_6', 1)],
          'Error 404 when accessing the application.': [('expert_7', 3),
           ('expert_9', 3),
           ('expert_2', 2),
           ('expert_5', 2),
           ('expert_6', 2),
           ('expert_0', 1),
           ('expert_4', 1)],
          'Error in processing bulk uploads.': [('expert_4', 2),
           ('expert_7', 2),
           ('expert_0', 1),
           ('expert_8', 1),
           ('expert_9', 1)],
          'Firewall blocks application traffic.': [('expert_9', 3),
           ('expert_0', 2),
           ('expert_2', 2),
           ('expert_8', 2),
           ('expert_1', 1),
           ('expert_3', 1),
           ('expert_4', 1),
           ('expert_5', 1)],
          "Impossible de se connecter à la base de données à cause d'une erreur d'authentification utilisateur.": [('expert_1',
            2),
           ('expert_8', 2),
           ('expert_0', 1),
           ('expert_2', 1),
           ('expert_9', 1)],
          'Incorrect timezone in reports.': [('expert_0', 3),
           ('expert_1', 2),
           ('expert_4', 2),
           ('expert_8', 2),
           ('expert_2', 1),
           ('expert_5', 1),
```

```
 ('expert_6', 1),
 ('expert_9', 1)],
'Integration with third-party API fails.': [('expert_2', 3),
 ('expert_4', 3),
 ('expert_5', 3),
 ('expert_3', 2),
 ('expert_8', 2),
 ('expert_7', 1)],
"L'application échoue à enregistrer les paramètres après avoir modifié certaines configurations critiques.": [('expert_8',
  3),
 ('expert_0', 2),
 ('expert_1', 1),
 ('expert_2', 1),
 ('expert_4', 1),
 ('expert_5', 1),
 ('expert_7', 1)],
"L'intégration avec l'API tierce échoue à cause d'erreurs de compatibilité des versions.": [('expert_3',
  2),
 ('expert_4', 1),
 ('expert_5', 1),
 ('expert_8', 1),
 ('expert_9', 1)],
'La fonction de recherche retourne souvent des résultats incorrects pour des requêtes spécifiques.': [('expert_0',
  3),
 ('expert_3', 2),
 ('expert_1', 1),
 ('expert_2', 1),
 ('expert_4', 1),
 ('expert_5', 1),
 ('expert_6', 1),
 ('expert_7', 1),
 ('expert_8', 1)],
'La performance devient extrêmement lente pendant les heures de pointe et affecte les utilisateurs.': [('expert_1',
  3),
 ('expert_0', 1),
 ('expert_3', 1),
 ('expert_7', 1),
 ('expert_8', 1)],
"Le pare-feu bloque parfois le trafic légitime de l'application en fonction des paramètres réseau.": [('expert_5',
  2),
 ('expert_8', 2),
 ('expert_9', 2),
 ('expert_0', 1),
 ('expert_1', 1),
 ('expert_2', 1),
 ('expert_3', 1),
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"Le planificateur n'exécute pas les tâches programmées comme attendu pour certains scénarios.": [('expert_1',
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 ('expert_8', 2),
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"Le processus de sauvegarde échoue fréquemment sans message d'erreur explicite ou descriptif.": [('expert_9',
  2),
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 ('expert_7', 1),
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'Le système génère des métriques inexactes dans les rapports hebdomadaires ou mensuels partagés.': [('expert_4',
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 ('expert_1', 2),
 ('expert_0', 1),
 ('expert_2', 1),
 ('expert_3', 1),
 ('expert_7', 1),
 ('expert_8', 1),
 ('expert_9', 1)],
'Le système se bloque complètement lors du chargement des fichiers volumineux ou complexes.': [('expert_0',
  3),
 ('expert_5', 3),
 ('expert_6', 2),
 ('expert_8', 2),
 ('expert_4', 1)],
'Les données ne se synchronisent pas avec le cloud, même après plusieurs tentatives manuelles.': [('expert_3',
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 ('expert_4', 2),
 ('expert_0', 1),
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 ('expert_6', 1)],
'Les notifications par email ne sont pas envoyées malgré la configuration correcte du système.': [('expert_9',
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  3),
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 ('expert_1', 1),
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"Les permissions des rôles d'utilisateur ne fonctionnent pas comme prévu dans certains cas spécifiques.": [('expert_2',
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 ('expert_7', 2),
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 ('expert_0', 1),
 ('expert_5', 1)],
"Les rapports affichent un fuseau horaire incorrect, ce qui cause des problèmes pour l'analyse.": [('expert_1',
  2),
 ('expert_2', 2),
 ('expert_5', 2),
 ('expert_3', 1),
 ('expert_9', 1)],
"Les éléments de l'interface utilisateur ne sont pas réactifs sur certains modèles de téléphones mobiles.": [('expert_3',
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 ('expert_0', 1),
 ('expert_2', 1),
 ('expert_4', 1)],
'Memory leak when running intensive operations.': [('expert_6', 2),
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 ('expert_5', 1),
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'Payment gateway timeout error.': [('expert_2', 3),
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 ('expert_5', 2),
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'Permissions issue for user roles.': [('expert_0', 2),
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 ('expert_4', 1),
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"Scheduler doesn't execute tasks as expected.": [('expert_4', 3),
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'Search functionality returns incorrect results.': [('expert_4', 3),
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 ('expert_2', 1),
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 ('expert_9', 1)],
'Slow performance during peak hours.': [('expert_8', 5),
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 ('expert_9', 1)],
'System crashes when loading files.': [('expert_5', 3),
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 ('expert_1', 1),
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 ('expert_7', 1)],
'System reports inaccurate metrics.': [('expert_4', 3),
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 ('expert_0', 1),
 ('expert_1', 1),
 ('expert_3', 1),
 ('expert_7', 1)],
'UI elements are not responsive on mobile.': [('expert_0', 2),
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 ('expert_4', 2),
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 ('expert_3', 1),
 ('expert_8', 1),
 ('expert_9', 1)],
'Unable to connect to the database.': [('expert_5', 3),
 ('expert_3', 2),
 ('expert_0', 1),
 ('expert_1', 1),
 ('expert_4', 1),
 ('expert_6', 1)],
'Une erreur survient lors du traitement de téléchargements en masse de fichiers très lourds.': [('expert_1',
  3),
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  ('expert_0', 1),
  ('expert_3', 1),
  ('expert_4', 1),
  ('expert_5', 1)],
 'Unexpected logout from the system.': [('expert_5', 2),
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  ('expert_0', 1),
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Final conclusion

The performance of the models in this task is clearly affected by the limitations of the dataset and the complexity of the classification problem. The two approaches: multi-class classification and multi-label classification with soft labels—approach the task differently, each with its own challenges and benefits.

In the first approach, removing duplicate sentences to avoid overfitting reduces the size of the dataset, and the multi-class classification framework struggles with the high number of classes and reassignment of different classes to same sentances. This leads to sparse performance across classes, with many not being predicted correctly even once. The small dataset and hyperparameters further add to the low performance, and even using combined multilingual data doesn't lead to much improvement over the English-only subset.

The second approach takes advantage of nested k-fold cross-validation to make the most out of the grouped unique data, ensuring every sentence is used for training and evaluation. Using soft labels allows the model to make more meaningful predictions based on expert frequencies, but while the validation and test losses in this approach are lower compared to the first, they aren't directly comparable due to the different loss functions. Precision metrics remain low, showing that even with these changes, the models still have trouble generalizing well.

A clear bias toward a few dominant classes, like 4, 8, 2, and 0, was observed in the model outputs. This bias sometimes aligns with correct predictions, as with "Data not syncing with the cloud," but it fails when the expected experts belong to less frequent classes, as seen with "Error 404 when accessing the application." This highlights the need to better handle class imbalances and consider alternative training strategies.

The vectorization-based models, Naive Bayes and Logistic Regression, also demonstrated a tendency to favor the same dominant classes (4, 8, 2, and 0). Both models, relying on TF-IDF vectorization to represent sentences as numerical features, showed limited ability to generalize to less frequent classes.

Overall, the results show how the small dataset, imbalanced distributions, and the challenges of both multi-class and multi-label setups make this task tough for the models. To improve, future efforts could look at fine-tuning hyperparameters more thoroughly, working with larger datasets, or using additional pretraining and fine-tuning strategies.