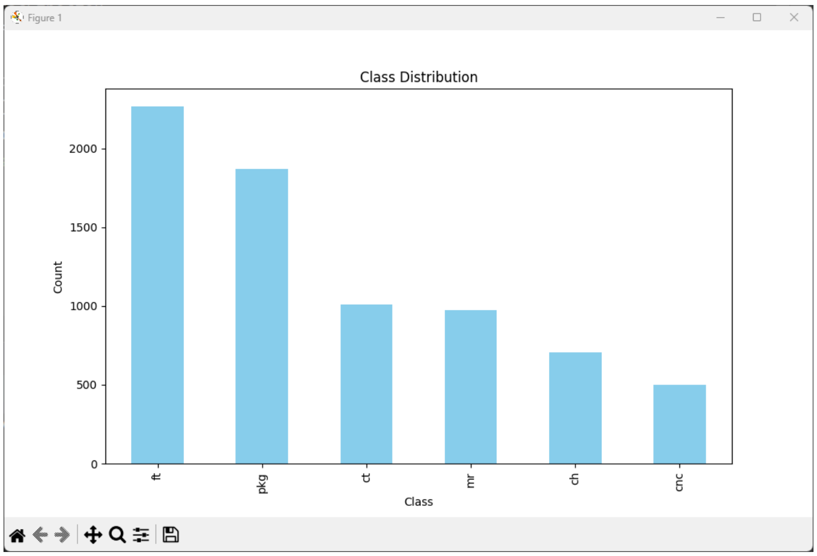
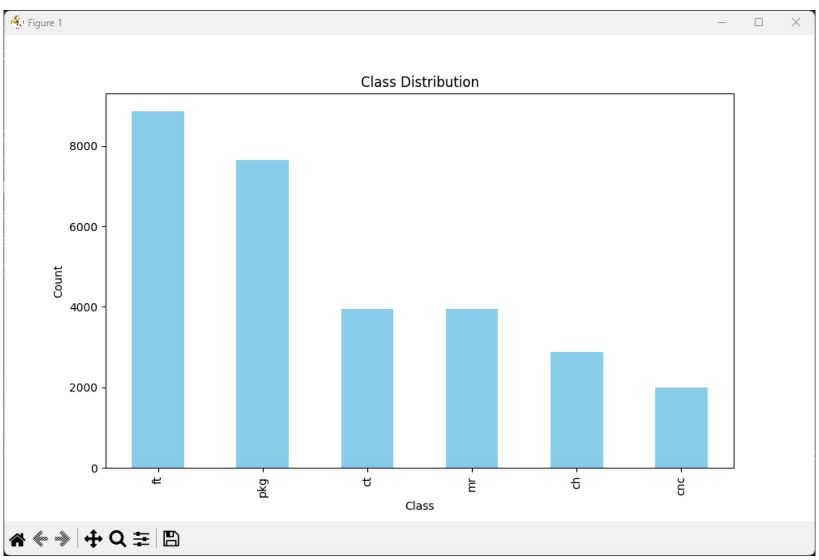
Task:

Develop and deploy a machine learning model to classify German text phrases into predefined categories

Overview of data:

The data has around 37000 lines with 2 column, a text column and a label. There are 6 labels in total. Following is the class distribution in data:





There is not much class imbalance since three is a linear increase in class frequency. The absence of a significant difference in frequency between adjacent classes can contribute to a reduction in class imbalance.

Preprocessing (preprocessing.py):

There are chinese words in the data, since the task is to classify german phrases i chose to remove these fields since they can generate noise and affect the model. Fields that had missing label or test were also removed. Fields with only number were also removed since they did not seem to provide meaningful information but fields with special characters such as emails were kept since they could provide meaningful information.

The accuracy and precision of model seem to decline by 0.004 - 0.007 after removing the chinese words but it is likely because all the chinese words in the dataset were same, so once it was used during training, so everytime it appear in the testing data it will be predicted accurately hence making it seem like the overall performance has increased.

The data is cleaned and put in a csv file named “cleaned_data” as performed in the “preprocessing.py” file.

Model training:

A pretrained language model named “DistilBERT” was finetuned thorough the training data and then saved to be later tested on testing data.

DistilBERT was used for a couple of reasons:
It’s a transformer based model designed for NLP tasks and performs good in understanding and classifying text data and also works on german language which fits our task description. It can also capture semantic relationships and contextual information from text which can help in things like classifying texts based on emotion, But since our data doesn’t show on what basis the phrases are classified it may or may not be needed but it benefits from transfer learning through which i was able to use the given data to fine tune the pretrained model on the given problem dataset. In traditional models, feature engineering is often a crucial step. With DistilBERT, the model automatically learns meaningful representations.

While other state-of-the-art algorithms such as decision trees, Naive Bayes, and SVM are viable options, each has its own set of limitations. Decision trees, for instance, can be prone to overfitting. Naive Bayes assumes feature independence, which may not hold true for text classification tasks where contextual relationships matter. Support Vector Machines (SVM) are effective but might not capture complex linguistic nuances. Bag of Words (BoW) relies on fixed features based on word occurrences, potentially limiting its performance in tasks requiring a nuanced understanding of language. In this context, employing the DistilBERT model appeared to be a more robust and promising approach for my text classification problem.

Here's how the model training works (BARTmodel.py):

- It loads a cleaned dataset from a CSV file
- Encodes labels using a LabelEncoder
- Splits the data into training (80%) and testing sets (20%).
- Loads a smaller pre-trained DistilBERT model and tokenizer for the German language.
- Tokenizes and encodes the training data with a specified sequence length using the DistilBERT tokenizer.
- Saves the training and testing data with encoded labels to CSV files.
- Defines the DistilBERT model for sequence classification with a specified number of output labels.
- Sets up data loaders for training using PyTorch's DataLoader.
- Trains the model using the AdamW optimizer with gradient accumulation over a defined number of epochs.
- Saves the trained DistilBERT model and the label encoder to files.

The code allows flexibility in adjusting parameters such as sequence length, batch size, learning rate, and epochs.

Testing of the model (testing.py):

Here's what the testing.py file performs:
- Reads the test data from a CSV file (test_data.csv).
- Loads the pre-trained DistilBERT model and label encoder saved during training.
- Iteratively tokenizes and encodes batches of test text data using the DistilBERT tokenizer.
- Performs inference using the loaded model to obtain predictions for each batch.
- Decodes the model predictions and actual labels using the loaded label encoder.
- Appends the decoded predictions and actual labels to the test data.
- Saves the test data with predictions and actual labels to a new CSV file (predictions.csv).
- Calculates and print various classification metrics, including accuracy, precision, recall, and F1 score..

```
Accuracy: 0.8737
Precision: 0.8781
Recall: 0.8737
F1 Score: 0.8743
Classification Report:
              precision    recall  f1-score   support

          ch       0.91      0.83      0.87       689
         cnc       0.80      0.72      0.76       504
          ct       0.90      0.87      0.89       971
          ft       0.94      0.88      0.91      2238
          mr       0.75      0.89      0.81       934
         pkg       0.86      0.91      0.88      1923

    accuracy                           0.87      7259
   macro avg       0.86      0.85      0.85      7259
weighted avg       0.88      0.87      0.87      7259
```

Development (main.py):

Application Setup:
- The FastAPI application is created.
- CORS middleware is added to allow cross-origin requests, allowing the frontend to interact with the backend.

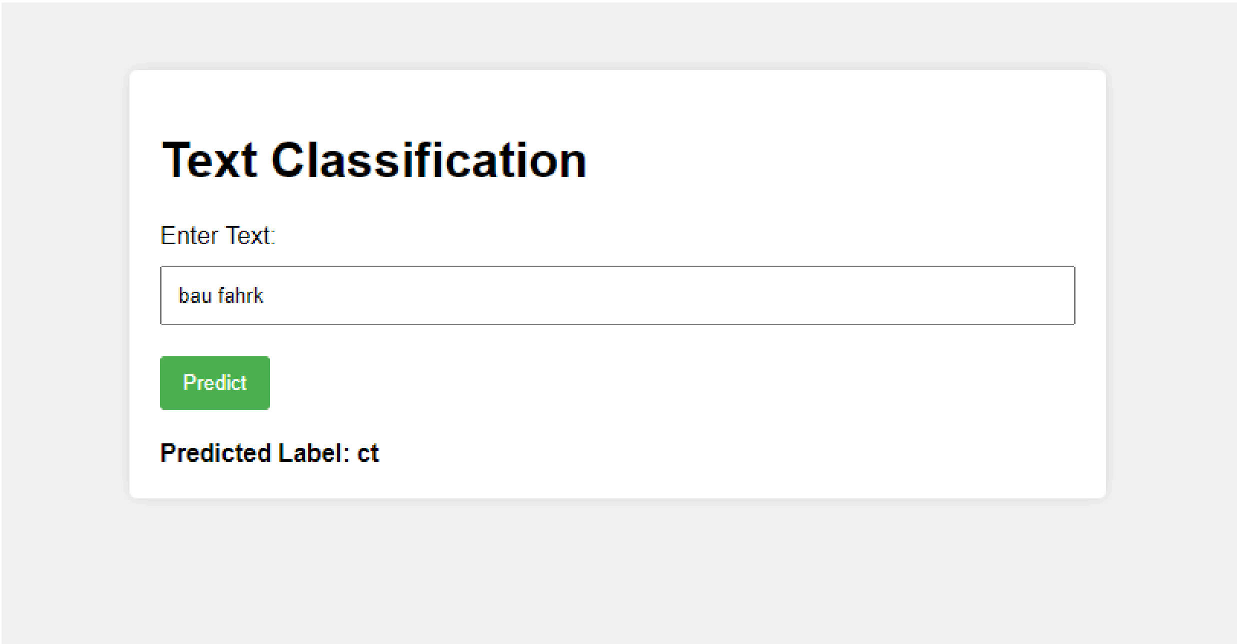
Model Loading:
- A fine-tuned DistilBERT model, tokenizer, and label encoder are loaded into the application.

Data Models:
- Two Pydantic models (Item and PredictionResult) are defined to handle input data and prediction results.

Root Endpoint:
- A root endpoint ("/") is set up to return a simple greeting message and instruct users to open the HTML code to start predictions.

Prediction Endpoint:
- A POST endpoint ("/predict") is implemented to receive text input, tokenize it using DistilBERT, and make predictions using a pre-trained model.
- The predicted label is decoded using a label encoder, and the result is returned in the response.

Additionally, there is a basic HTML, CSS, and JavaScript code for the frontend. This code receives the input of a string through a designated field, posts it to the API for prediction, and then displays the response.



Test cases:

Test Case 1 (test_read_root):
Checks if the root endpoint ("/") is accessible and returns a valid response.

Test Case 2 (test_invalid_endpoint):
Verifies the behavior when trying to access an invalid endpoint.

Test Case 3 (test_complete_request_cycle):
Tests the complete cycle of making a prediction request with a sample input ("bau fahrk").

Test Case 4 (test_large_input):
Assesses the server's handling of a large input string (10,000 characters).

Note:
The test case for null input is not explicitly performed, as the server-side check for empty input is implemented on the client side, preventing null input from reaching the server.

```
============================= test session starts =============================
collecting ... collected 4 items

test_cases.py::test_read_root PASSED                                     [ 25%]
test_cases.py::test_invalid_endpoint PASSED                              [ 50%]
test_cases.py::test_complete_request_cycle PASSED                        [ 75%]
test_cases.py::test_large_input PASSED                                   [100%]

============================== 4 passed in 7.51s ==============================
```

Suggestions for future work and improvements if I had more time:

If I had more time, I'd explore using word embeddings, which are like super-smart word representations, to make the model even better at understanding the context of our text. Also, I'd compare our current model with some older models like decision trees or Support Vector Machines to see if there's a better fit for our problem. This would help me choose the right tool for the job and improve the text classification even more.

I did obtain word embeddings and tried to use it with BERT model but it was computationally expensive for me and i couldn’t find a way around to get it done in the given time. Another problem i encountered with word embeddings was to find a model with decent german vocabulary that could cater the words in given dataset so i don't have to deal with many OOV (out of vocabulary words). The OOV words can be dealt with multiple approaches like taking mean or giving null vector but excess of OOV can cause significant information loss.

Below is a snippet of the word embeddings i got:

	text	label	word_vectors	encoded_label
1	zulieferer für leben...	pkg	[0.01706123, 0.034633584, 0.104049675, 0.45882326, 0...	5
2	prawn craker	ft	[-0.25382102, 0.107287884, 0.4206393, -0.49894556, 0....	3
3	Silikon vakuumguss	ch	[-0.14916055, -0.4290634, -0.10622405, -0.08992568, 0....	0
4	erdbohrgeräte geb...	ct	[-0.54014397, 0.17828512, -0.28843042, 0.363127, 0.14...	2
5	pharmazeutische c...	ch	[0.7725972, 0.14039369, 0.5581987, -0.08985862, -0.25...	0
6	dynamische berech...	ct	[-0.7791578, -0.30780917, -0.2659576, -0.5631037, 0.17...	2
7	fruchtgummis nahr...	ft	[-0.15474533, -0.33027124, 0.028239017, 0.78858316, -...	3
8	kisten aus PUR-Kalt...	pkg	[-0.41981384, -0.122550935, -0.26658395, 0.2515771, 0...	5
9	Montagen von Alu...	ct	[-0.5087983, -0.0077935075, 0.0003078218, 0.7983208,...	2
10	bioaktive peptide	ch	[-0.37216717, -0.50164956, 0.24973151, 0.54452133, 0....	0
11	rako kisten 40x30...	pkg	[-0.6962658, -0.6359233, 0.29939133, 0.04211502, 0.42...	5
12	Parkbank fässer au...	pkg	[-0.41428667, 0.02696119, 0.037465952, 0.17521632, 0....	5
13	u-profil kunststoff	pkg	[-0.6968918, -0.16078167, -0.102691926, -0.23310177,...	5
14	herstellen papierta...	pkg	[-0.5092007, -0.40659863, 0.43535772, 0.04161539, 0.6...	5
15	folien beutel karton	pkg	[-0.7380489, -0.9186477, -0.0793767, 0.6428528, -0.138...	5
16	italienische weine...	ft	[-0.549814, -0.5781118, 0.18003201, 0.8175701, -0.104...	3
17	enzyme fleischwaren	ft	[-0.2569416, -0.28991273, -0.38639402, 0.52388304, -0....	3
18	Edelstahl schwingg...	mr	[-0.45647553, -0.027015833, -0.21721809, -0.01291308...	4