Assignment_5_Group_7_Final Ver

May 6, 2025

1 NLP - Assignment 5

1.1 HW Group 7

For this assignment, you will be tasked with performing text classification using transformers models. You will compare two approaches:

1. Fine-tune a transformer model with text truncation. Most of the data will be longer than the context window of many BERT models. Fine-tune a model by simply truncating the text to max model length.
2. Fine-tune a transformer model by segmenting the text such that it fits within the context window of the model. Every chunk within the document would get the same label.

1.2 Dataset Preview

The data source used for this assignment is: https://huggingface.co/datasets/ccdv/patent-classification

[1]:
```
import sys
from datasets import load_dataset
import pandas as pd
import numpy as np
from transformers import (
    AutoTokenizer,
    AutoModelForSequenceClassification,
    TrainingArguments,
    Trainer,
    DataCollatorWithPadding
)
import nltk
import torch
from sklearn.metrics import (
    ConfusionMatrixDisplay,
    confusion_matrix,
    accuracy_score,
    f1_score,
    classification_report
)
import matplotlib.pyplot as plt
```

[2]:
```python
# Load the dataset
dataset = load_dataset("ccdv/patent-classification")

# Check the available splits
print(dataset)
```

```
README.md:   0%|          | 0.00/3.25k [00:00<?, ?B/s]

d:\Program\Anaconda\envs\adsp-nlp\Lib\site-
packages\huggingface_hub\file_download.py:142: UserWarning: `huggingface_hub`
cache-system uses symlinks by default to efficiently store duplicated files but
your machine does not support them in
C:\Users\hp\.cache\huggingface\hub\datasets--ccdv--patent-classification.
Caching files will still work but in a degraded version that might require more
space on your disk. This warning can be disabled by setting the
`HF_HUB_DISABLE_SYMLINKS_WARNING` environment variable. For more details, see
https://huggingface.co/docs/huggingface_hub/how-to-cache#limitations.
To support symlinks on Windows, you either need to activate Developer Mode or to
run Python as an administrator. In order to activate developer mode, see this
article: https://docs.microsoft.com/en-us/windows/apps/get-started/enable-your-
device-for-development
  warnings.warn(message)

train-00000-of-00001.parquet:   0%|          | 0.00/194M [00:00<?, ?B/s]

validation-00000-of-00001.parquet:   0%|          | 0.00/39.5M [00:00<?, ?B/s]

test-00000-of-00001.parquet:   0%|          | 0.00/39.1M [00:00<?, ?B/s]

Generating train split:   0%|          | 0/25000 [00:00<?, ? examples/s]

Generating validation split:   0%|          | 0/5000 [00:00<?, ? examples/s]

Generating test split:   0%|          | 0/5000 [00:00<?, ? examples/s]

DatasetDict({
    train: Dataset({
        features: ['text', 'label'],
        num_rows: 25000
    })
    validation: Dataset({
        features: ['text', 'label'],
        num_rows: 5000
    })
    test: Dataset({
        features: ['text', 'label'],
        num_rows: 5000
    })
})
```

[4]:
```
# Filter the top 4 most frequent labels

train_data = dataset['train']
train_df = pd.DataFrame(train_data)
label_counts = train_df['label'].value_counts()
top_4_labels = label_counts.head(4).index.tolist()

# Filter the dataset to only include top 4 labels
dataset = dataset.filter(lambda x: x["label"] in top_4_labels)

top_4_labels
```

```
Filter:   0%|          | 0/25000 [00:00<?, ? examples/s]

Filter:   0%|          | 0/5000 [00:00<?, ? examples/s]

Filter:   0%|          | 0/5000 [00:00<?, ? examples/s]
```

[4]:
```
[6, 7, 0, 1]
```

[5]:
```
# Create remapping dictionaries
label2id = {label_name: new_id for new_id, label_name in␣
 ↪enumerate(top_4_labels)}
id2label = {v: dataset["train"].features["label"].names[k] for k, v in label2id.
 ↪items()}

print("id2label (for model):", id2label)
```

```
id2label (for model): {0: 'Physics', 1: 'Electricity', 2: 'Human Necessities',
3: 'Performing Operations; Transporting'}
```

[6]:
```
# Filter the top 4 labels and remap to 0-3
def filter_and_remap(example):
    if example["label"] in label2id:
        example["label"] = label2id[example["label"]]  # remap to 0-3
        return True
    return False

# Apply filter + remap to all splits
dataset = dataset.map(lambda x: {"label": label2id[x["label"]]})
```

```
Map:   0%|          | 0/17700 [00:00<?, ? examples/s]

Map:   0%|          | 0/3549 [00:00<?, ? examples/s]

Map:   0%|          | 0/3545 [00:00<?, ? examples/s]
```

1.3 Fine-tune a transformer model with text truncation

[ ]:
```
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")

# Tokenize with truncation enabled
def tokenize(batch):
    return tokenizer(batch["text"], padding="max_length", truncation=True,␣
 ↪max_length=512)

dataset_tokens = dataset.map(tokenize, batched=True, batch_size=100, num_proc=2)
```

```
tokenizer_config.json:   0%|          | 0.00/48.0 [00:00<?, ?B/s]

config.json:   0%|          | 0.00/570 [00:00<?, ?B/s]

vocab.txt:   0%|          | 0.00/232k [00:00<?, ?B/s]

tokenizer.json:   0%|          | 0.00/466k [00:00<?, ?B/s]

Map (num_proc=2):   0%|          | 0/17700 [00:00<?, ? examples/s]

Map (num_proc=2):   0%|          | 0/3549 [00:00<?, ? examples/s]

Map (num_proc=2):   0%|          | 0/3545 [00:00<?, ? examples/s]
```

[ ]:
```
# Rename label column to 'labels' as expected by transformers
tokenized_dataset = dataset_tokens.rename_column("label", "labels")
tokenized_dataset.set_format("torch", columns=["input_ids", "attention_mask",␣
 ↪"labels"])
```

[16]:
```
model = AutoModelForSequenceClassification.from_pretrained(
    "bert-base-uncased",
    num_labels=4,
    id2label=id2label,
    label2id={v: k for k, v in id2label.items()}
)
```

```
Some weights of BertForSequenceClassification were not initialized from the
model checkpoint at bert-base-uncased and are newly initialized:
['classifier.bias', 'classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it
for predictions and inference.
```

[ ]:
```
# Define trainer and training arguments
data_collator = DataCollatorWithPadding(tokenizer=tokenizer)

training_args = TrainingArguments(
    output_dir="./bert-patent-truncation",
    num_train_epochs=1,
    learning_rate=2e-5,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
```

```
    weight_decay=0.01,
    eval_strategy="epoch",
    save_strategy="epoch",
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=tokenized_dataset["train"],
    eval_dataset=tokenized_dataset["test"],
    tokenizer=tokenizer,
    data_collator=data_collator,
)
```

```
<ipython-input-16-15fbc794d355>:15: FutureWarning: `tokenizer` is deprecated and
will be removed in version 5.0.0 for `Trainer.__init__`. Use `processing_class`
instead.
  trainer = Trainer(
```

[ ]:
```
# Train the model
trainer.train()
```

```
wandb: WARNING The `run_name` is currently set to the same
value as `TrainingArguments.output_dir`. If this was not intended, please
specify a different run name by setting the `TrainingArguments.run_name`
parameter.

<IPython.core.display.Javascript object>

wandb: WARNING If you're specifying your api key in code,
ensure this code is not shared publicly.
wandb: WARNING Consider setting the WANDB_API_KEY
environment variable, or running `wandb login` from the command line.
wandb: No netrc file found, creating one.
wandb: Appending key for api.wandb.ai to your netrc file:
/root/.netrc
wandb: Currently logged in as: ywpeng01
(ywpeng01-university-of-chicago) to https://api.wandb.ai. Use
`wandb login --relogin` to force relogin

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>
```

[ ]: TrainOutput(global_step=1107, training_loss=0.6791544210404669, metrics={'train_runtime': 1831.4221, 'train_samples_per_second': 9.665, 'train_steps_per_second': 0.604, 'total_flos': 4657149307699200.0, 'train_loss': 0.6791544210404669, 'epoch': 1.0})

[ ]:
```
# Evaluate model performance on the test set
metrics = trainer.evaluate()
print(metrics)
```

```
<IPython.core.display.HTML object>
```

```
{'eval_loss': 0.5623633861541748, 'eval_runtime': 107.2305,
'eval_samples_per_second': 33.06, 'eval_steps_per_second': 2.07, 'epoch': 1.0}
```

[ ]:
```
pred_output = trainer.predict(tokenized_dataset["test"])
pred_output
```

```
<IPython.core.display.HTML object>
```

[ ]:
```
PredictionOutput(predictions=array([[-0.92712116, -1.9983867 ,  0.79597557,
2.1967158 ],
       [ 1.2615396 ,  0.6378177 , -0.30226728, -1.3828747 ],
       [-1.5686469 , -2.0249703 ,  2.7461119 ,  1.0409653 ],
       …,
       [-0.67494565, -1.797619  ,  0.37767047,  2.4263947 ],
       [-0.48465836,  3.0016744 , -1.8158183 , -0.78447294],
       [-1.0605118 , -2.0823562 ,  0.9509796 ,  2.8657625 ]],
      dtype=float32), label_ids=array([3, 0, 3, …, 3, 1, 3]),
metrics={'test_loss': 0.5623633861541748, 'test_runtime': 98.9889,
'test_samples_per_second': 35.812, 'test_steps_per_second': 2.243})
```

[ ]:
```
pred_output.metrics
```

[ ]:
```
{'test_loss': 0.5623633861541748,
 'test_runtime': 98.9889,
 'test_samples_per_second': 35.812,
 'test_steps_per_second': 2.243}
```

[ ]:
```
y_pred = pred_output.predictions.argmax(axis=1)
y_pred
```

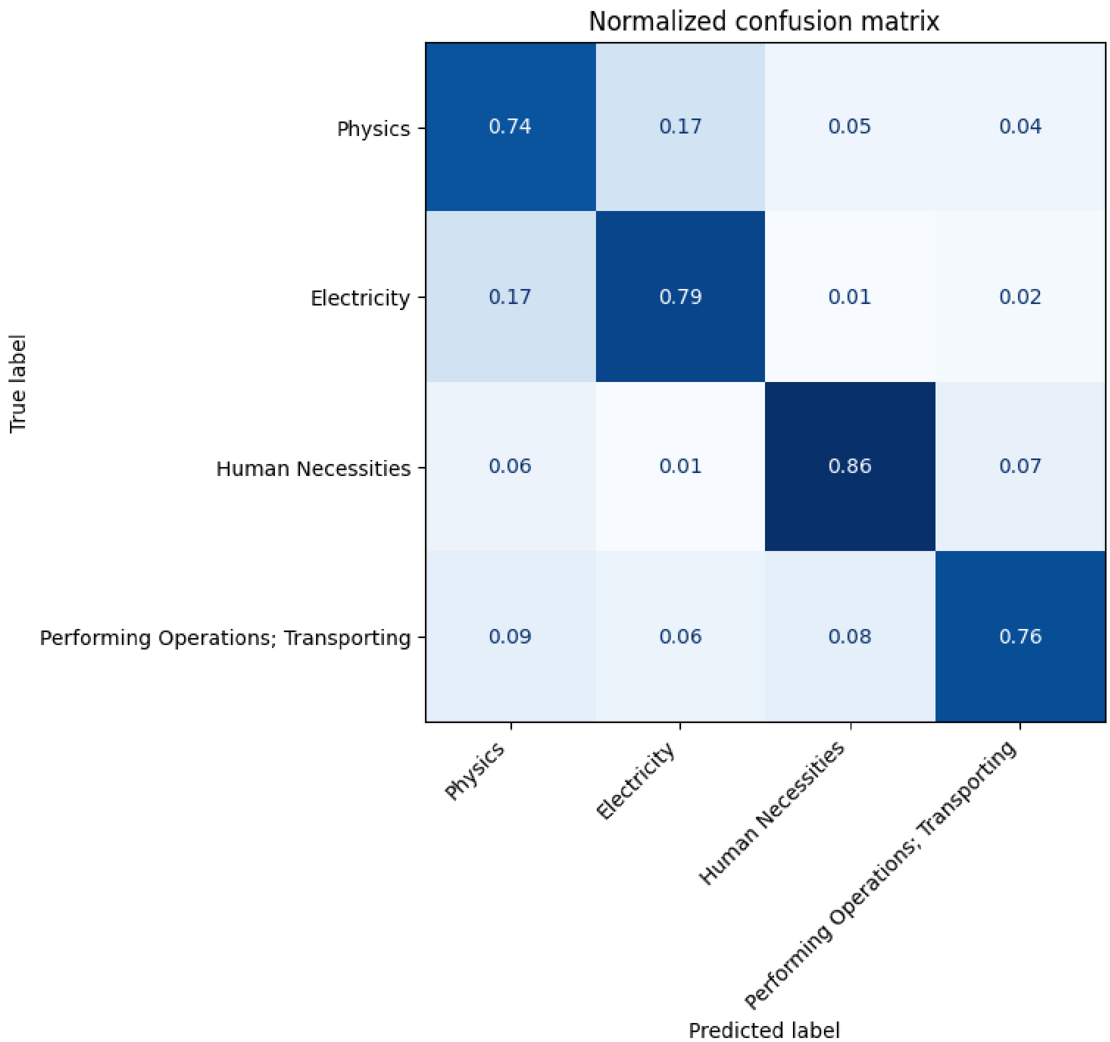
[ ]:
```
array([3, 0, 2, …, 3, 1, 3])
```

[ ]:
```
y_test = np.array(tokenized_dataset["test"]["labels"])
```

[ ]:
```
def plot_confusion_matrix(y_preds, y_true, labels):
    cm = confusion_matrix(y_true, y_preds, normalize="true")
    fig, ax = plt.subplots(figsize=(6, 6))
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
```

```
    disp.plot(cmap="Blues", values_format=".2f", ax=ax, colorbar=False)
    plt.title("Normalized confusion matrix")
    plt.xticks(rotation=45, ha="right")
    plt.show()
```

[ ]:
```
plot_confusion_matrix(y_pred, y_test, list(id2label.values()))
```



1.3.1 Model Evaluation for Approach 1:

The model demonstrates reasonably good performance, especially in classifying "Human Necessities" with 86% accuracy. However, it struggles more with "Electricity" and "Physics," where around 17% and 6% of examples are misclassified as other categories. This indicates that some semantic overlap between classes may be affecting classification accuracy.

1.4 Fine-tune a transformer model by segmenting the text such that it fits within the context window of the model

[ ]:
```python
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
max_length = tokenizer.model_max_length  # 512 in this case

# Text chunking function
def segment_text(text):
    sentences = nltk.sent_tokenize(text)
    chunks = []
    current_chunk = []
    current_length = 0

    for sent in sentences:
        sent_length = len(tokenizer.tokenize(sent))

        if sent_length > max_length:
            words = sent.split()
            for word in words:
                word_length = len(tokenizer.tokenize(word))
                if current_length + word_length > max_length:
                    if current_chunk:
                        chunks.append(" ".join(current_chunk))
                        current_chunk = []
                        current_length = 0
                current_chunk.append(word)
                current_length += word_length
        else:
            if current_length + sent_length > max_length:
                if current_chunk:
                    chunks.append(" ".join(current_chunk))
                    current_chunk = []
                    current_length = 0
            current_chunk.append(sent)
            current_length += sent_length

    if current_chunk:
        chunks.append(" ".join(current_chunk))

    return chunks
```

[8]:
```python
# Dataset processing function
def process_examples(examples):
    segmented_texts = []
    labels = []

    for text, label in zip(examples["text"], examples["label"]):
        chunks = segment_text(text)
```

```python
        segmented_texts.extend(chunks)
        labels.extend([label] * len(chunks))

    return {"text": segmented_texts, "label": labels}
```

[ ]:
```python
# Apply text segmenting
segmented_dataset = dataset.map(
    process_examples,
    batched=True,
    remove_columns=dataset["train"].column_names,
    batch_size=100
)
```

[11]:
```python
# Tokenization function
def tokenize_function(examples):
    return tokenizer(examples["text"], truncation=True, padding="max_length",␣
 ↪max_length=max_length)
```

[ ]:
```python
# Apply tokenizer
tokenized_dataset = segmented_dataset.map(
    tokenize_function,
    batched=True,
    remove_columns=["text"],
    batch_size=100
)
```

[13]:
```python
tokenized_dataset.set_format("torch", columns=["input_ids", "attention_mask",␣
 ↪"label"])
```

[ ]:
```python
model_2 = AutoModelForSequenceClassification.from_pretrained(
    "bert-base-uncased",
    num_labels=len(top_4_labels),
    id2label=id2label
)
```

[26]:
```python
# Define trainer and training arguments
data_collator = DataCollatorWithPadding(tokenizer=tokenizer)

training_args = TrainingArguments(
    output_dir="./bert-patent-truncation",
    num_train_epochs=1,
    learning_rate=2e-5,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    weight_decay=0.01,
    eval_strategy="epoch",
    save_strategy="no",
```

```
    fp16=True
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=tokenized_dataset["train"],
    eval_dataset=tokenized_dataset["test"],
    tokenizer=tokenizer,
    data_collator=data_collator,
)
```

```
<ipython-input-26-dc1460173745>:16: FutureWarning: `tokenizer` is deprecated and
will be removed in version 5.0.0 for `Trainer.__init__`. Use `processing_class`
instead.
  trainer = Trainer(
```

[27]:
```
# Train the model for second approach
trainer.train()
```

```
<IPython.core.display.HTML object>
```

[27]:
```
TrainOutput(global_step=9429, training_loss=0.5150155514393344,
metrics={'train_runtime': 4232.9703, 'train_samples_per_second': 35.638,
'train_steps_per_second': 2.228, 'total_flos': 3.969206789060198e+16,
'train_loss': 0.5150155514393344, 'epoch': 1.0})
```

[28]:
```
# Evaluate model performance on the test set
metrics = trainer.evaluate()
print(metrics)
```

```
<IPython.core.display.HTML object>
```

```
{'eval_loss': 0.6545693278312683, 'eval_runtime': 234.292,
'eval_samples_per_second': 129.27, 'eval_steps_per_second': 8.08, 'epoch': 1.0}
```

[30]:
```
# Redefine plot confusion matrix function
def plot_confusion_matrix(y_true, y_pred, labels, normalize="true",␣
 ↪figsize=(8,6)):
    cm = confusion_matrix(y_true, y_pred, normalize=normalize)

    fig, ax = plt.subplots(figsize=figsize)
    disp = ConfusionMatrixDisplay(
        confusion_matrix=cm,
        display_labels=labels
    )

    disp.plot(
        cmap="Blues",
```

```
        values_format=".2f" if normalize else "d",
        ax=ax,
        colorbar=False,
        im_kw={"vmin": 0}
    )

    plt.title(f"{'Normalized' if normalize else ''} Confusion Matrix")
    plt.xticks(rotation=45, ha="right")
    plt.tight_layout()
    plt.show()
```

[31]:
```
original_test = dataset["test"]
```

[36]:
```
def predict_document(text):
    chunks = segment_text(text)
    inputs = tokenizer(chunks, truncation=True, padding=True,␣
 ↪return_tensors="pt", max_length=max_length)
    with torch.no_grad():
        outputs = model(**inputs.to(model.device))
    probs = torch.softmax(outputs.logits, dim=-1)
    return probs.mean(dim=0).argmax().item()
```

[39]:
```
y_true = []
y_pred = []

for text, label in zip(original_test["text"], original_test["label"]):
    y_true.append(label)
    y_pred.append(predict_document(text))  # Use document level prediction

# Display classification metrics for all categories
print("Classification Report:")
print(classification_report(y_true, y_pred, target_names=list(id2label.
 ↪values())))
```

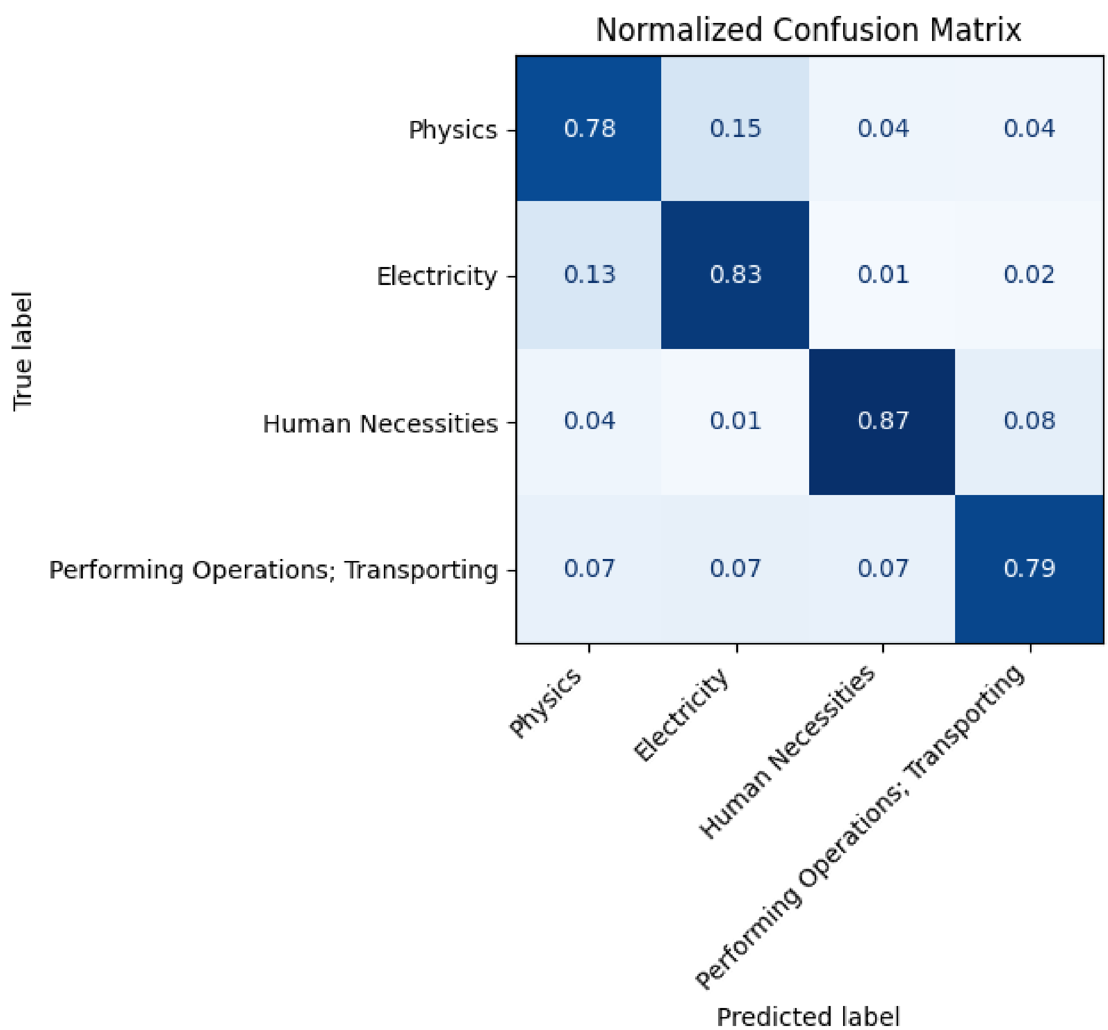
```
Classification Report:
                                     precision    recall  f1-score   support

                           Physics       0.80      0.78      0.79      1107
                       Electricity       0.80      0.83      0.81      1035
                 Human Necessities       0.87      0.87      0.87       754
Performing Operations; Transporting       0.81      0.79      0.80       649

                          accuracy                           0.82      3545
                         macro avg       0.82      0.82      0.82      3545
                      weighted avg       0.82      0.82      0.82      3545
```

[40]:
```
print("\nConfusion Matrix:")
plot_confusion_matrix(y_true, y_pred, list(id2label.values()))
```

```
Confusion Matrix:
```



[41]:
```
# Display chunk statistics
print(f"\nChunk Statistics: Avg chunks per doc =␣
↪{len(tokenized_dataset['test']) / len(original_test):.1f}")
```

```
Chunk Statistics: Avg chunks per doc = 8.5
```

1.4.1 Model Evaluation for Approach 2

The second approach slightly improves overall classification accuracy, particularly for "Physics" (78%) and "Electricity" (83%). Misclassification rates across all categories are lower compared to Approach 1, suggesting that the model benefits from improved input formatting by segmenting instead of text truncation in this approach.

1.4.2 Segmentation Approach

For the segmentation-based fine-tuning approach, *we* implemented a dynamic sentence-aware chunking strategy to split long patent texts into manageable segments that fit within the transformer model's maximum context window (e.g., 512 tokens for BERT). Below is the detailed procedure of the approach: 1. Segmentation - Sentence-first splitting: We used nltk.sent_tokenize() to split documents into sentences, which helps preserve linguistic boundaries. For sentences longer than max_length, fell back to word-level splitting to avoid truncation. - Dynamic chunking: We ieratively merged sentences into chunks until adding the next sentence would exceed max_length. 2. Label Assignment - All chunks from the same document shared the original label. To sum it up, the segmentation apporach ensures no hard truncation and semantic coherence.

1.4.3 What kind of post-processing would you need to use to assign a new document to a class?

For the segmentation approach where a document is split into multiple chunks while each receiving its own prediction, the key post-processing step is **aggregating chunk-level predictions** into a final document-level label. Some common ways of aggregation include majority voting, which is to assign the label that appears most frequently across chunks, and probability mean, which is to average the softmax probabilities of all chunks and then argmax the result. To balance performance and simplicity, we choose and implement the **probability mean** as the aggregation approach in the above code to test the model performance. For the assignment of a new document in the future, we also need to use the aggregation approach to firstly aggregate the chunk-level predictions, and make the final document level label assignment.