Start coding or generate with AI.

Double-click (or enter) to edit

Task 4: Named Entity Recognition (NER) from News Articles

Description:

- Dataset (Recommended): CoNLL003 (Kaggle)
- Identify named entities (like people, locations, and organizations) from article content
- Use rule-based and model-based NER approaches
- Highlight and categorize extracted entities in the text

BERT-based Named Entity Recognition (NER) model

```
!pip install seqeval==1.2.2
```

```
Collecting seqeval==1.2.2
  Downloading seqeval-1.2.2.tar.gz (43 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 43.6/43.6 kB 2.3 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.12/dist-packages
Requirement already satisfied: scikit-learn>=0.21.3 in /usr/local/lib/python3.12/dist-pa
```

```
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.12/dist-packages (
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.12/dist-packages
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.12/dist-pa
Building wheels for collected packages: seqeval
  Building wheel for seqeval (setup.py) ... done
  Created wheel for seqeval: filename=seqeval-1.2.2-py3-none-any.whl size=16162 sha256=a
  Stored in directory: /root/.cache/pip/wheels/5f/b8/73/0b2c1a76b701a677653dd79ece07cfab
Successfully built seqeval
Installing collected packages: seqeval
Successfully installed seqeval-1.2.2
```

This dataset is divided into train.txt, test.txt and valid.txt The Tokens are labeled under one of the following tags [I-LOC B-ORG O B-PER I-PER I-MISC B-MISC I-ORG B-LOC]

```
import os
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader

from transformers import (
    BertTokenizerFast,
    BertModel,
    get_scheduler
)

from seqeval.metrics import classification_report, f1_score, precision_score, recall_score


class CFG:
    model_name = "bert-base-cased"
    max_len = 128
    train_batch_size = 16
    valid_batch_size = 16
    lr = 5e-5
    epochs = 2
    device = "cuda" if torch.cuda.is_available() else "cpu"

# Label mapping (CoNLL2003)
label_list = ["O", "B-PER", "I-PER", "B-ORG", "I-ORG",
              "B-LOC", "I-LOC", "B-MISC", "I-MISC"]

label2id = {label: idx for idx, label in enumerate(label_list)}
id2label = {idx: label for label, idx in label2id.items()}

tokenizer = BertTokenizerFast.from_pretrained(CFG.model_name)
```

```
/usr/local/lib/python3.12/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https:/
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public model
  warnings.warn(
```

tokenizer_config.json: 100% 49.0/49.0 [00:00<00:00, 5.10kB/s]

vocab.txt: 100% 213k/213k [00:00<00:00, 7.34MB/s]

tokenizer.json: 100% 436k/436k [00:00<00:00, 34.4MB/s]

config.json: 100% 570/570 [00:00<00:00, 55.2kB/s]

```python
# ====================================================
# 📌 Cell 4: Dataset loader
# ====================================================
def read_conll_data(filepath):
    texts, tags = [], []
    words, labels = [], []
    with open(filepath, encoding="utf-8") as f:
        for line in f:
            if line.startswith("-DOCSTART-") or line.strip() == "":
                if words:
                    texts.append(words)
                    tags.append(labels)
                    words, labels = [], []
                continue
            splits = line.strip().split()
            words.append(splits[0])
            labels.append(splits[-1])
        if words:  # last sentence
            texts.append(words)
            tags.append(labels)
    return texts, tags

train_texts, train_tags = read_conll_data("/content/train.txt")
valid_texts, valid_tags = read_conll_data("/content/valid.txt")
test_texts, test_tags   = read_conll_data("/content/valid.txt")

print("✅ Loaded dataset:", len(train_texts), len(valid_texts), len(test_texts))
```

```
✅ Loaded dataset: 14041 3250 3250
```

```python
class NERDataset(Dataset):
    def __init__(self, texts, tags, tokenizer, label2id, max_len):
        self.encodings = encode_examples(texts, tags, tokenizer, label2id, max_len)

    def __len__(self):
```

```
        return len(self.encodings["input_ids"])

    def __getitem__(self, idx):
        item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items()}
        return item

train_dataset = NERDataset(train_texts, train_tags, tokenizer, label2id, CFG.max_len)
valid_dataset = NERDataset(valid_texts, valid_tags, tokenizer, label2id, CFG.max_len)

train_loader = DataLoader(train_dataset, batch_size=CFG.train_batch_size, shuffle=True)
valid_loader = DataLoader(valid_dataset, batch_size=CFG.valid_batch_size)


class NERModel(nn.Module):
    def __init__(self, model_name, num_labels):
        super(NERModel, self).__init__()
        self.bert = BertModel.from_pretrained(model_name)
        self.dropout = nn.Dropout(0.3)
        self.classifier = nn.Linear(self.bert.config.hidden_size, num_labels)

    def forward(self, input_ids, attention_mask, labels=None):
        outputs = self.bert(input_ids=input_ids, attention_mask=attention_mask)
        sequence_output = self.dropout(outputs.last_hidden_state)
        logits = self.classifier(sequence_output)

        loss = None
        if labels is not None:
            loss_fct = nn.CrossEntropyLoss(ignore_index=-100)
            loss = loss_fct(logits.view(-1, logits.shape[-1]), labels.view(-1))
        return loss, logits

model = NERModel(CFG.model_name, len(label2id)).to(CFG.device)
```

model.safetensors: 100% 436M/436M [00:12<00:00, 44.4MB/s]

```
optimizer = torch.optim.AdamW(model.parameters(), lr=CFG.lr)
num_training_steps = len(train_loader) * CFG.epochs
scheduler = get_scheduler("linear", optimizer, num_warmup_steps=0, num_training_steps=num_tr


def train_fn(model, dataloader):
    model.train()
    total_loss = 0
    for batch in dataloader:
        optimizer.zero_grad()
        input_ids = batch["input_ids"].to(CFG.device)
        attention_mask = batch["attention_mask"].to(CFG.device)
        labels = batch["labels"].to(CFG.device)

        loss, _ = model(input_ids, attention_mask, labels)
```

```
        loss.backward()
        optimizer.step()
        scheduler.step()
        total_loss += loss.item()
    return total_loss / len(dataloader)

def eval_fn(model, dataloader):
    model.eval()
    preds, true_labels = [], []
    total_loss = 0
    with torch.no_grad():
        for batch in dataloader:
            input_ids = batch["input_ids"].to(CFG.device)
            attention_mask = batch["attention_mask"].to(CFG.device)
            labels = batch["labels"].to(CFG.device)

            loss, logits = model(input_ids, attention_mask, labels)
            total_loss += loss.item()
            predictions = torch.argmax(logits, dim=-1)

            for i in range(len(labels)):
                pred_labels, true_l = [], []
                for j in range(len(labels[i])):
                    if labels[i][j] != -100:
                        pred_labels.append(id2label[predictions[i][j].item()])
                        true_l.append(id2label[labels[i][j].item()])
                preds.append(pred_labels)
                true_labels.append(true_l)

    f1 = f1_score(true_labels, preds)
    return total_loss / len(dataloader), f1, classification_report(true_labels, preds)

train_losses = []
valid_losses = []
valid_f1_scores = []

for epoch in range(CFG.epochs):
    train_loss = train_fn(model, train_loader)
    valid_loss, f1, report = eval_fn(model, valid_loader)
    train_losses.append(train_loss)
    valid_losses.append(valid_loss)
    valid_f1_scores.append(f1)
    print(f"Epoch {epoch+1}/{CFG.epochs} | Train Loss: {train_loss:.4f} | Valid Loss: {valic
    print(report)
```

```
Epoch 1/2 | Train Loss: 0.0919 | F1: 0.9319
              precision    recall  f1-score   support

         LOC       0.96      0.95      0.96      1837
        MISC       0.84      0.88      0.86       922
         ORG       0.90      0.91      0.91      1341
         PER       0.96      0.97      0.96      1836
```

```
   micro avg       0.93      0.94      0.93      5936
   macro avg       0.91      0.93      0.92      5936
weighted avg       0.93      0.94      0.93      5936

Epoch 2/2 | Train Loss: 0.0219 | F1: 0.9462
              precision    recall  f1-score   support

         LOC       0.97      0.96      0.97      1837
        MISC       0.88      0.91      0.89       922
         ORG       0.91      0.93      0.92      1341
         PER       0.97      0.97      0.97      1836

   micro avg       0.94      0.95      0.95      5936
   macro avg       0.93      0.94      0.94      5936
weighted avg       0.94      0.95      0.95      5936
```

```python
def predict_sentence(sentence, tokenizer, model, id2label, max_len=128):
    model.eval()
    tokens = sentence.split()

    encoding = tokenizer(
        tokens,
        is_split_into_words=True,
        return_tensors="pt",
        truncation=True,
        padding="max_length",
        max_length=max_len
    )
    word_ids = encoding.word_ids()  # lấy trước khi move to device
    device = next(model.parameters()).device
    input_ids = encoding["input_ids"].to(device)
    attention_mask = encoding["attention_mask"].to(device)

    with torch.no_grad():
        _, logits = model(input_ids=input_ids, attention_mask=attention_mask)

    preds = logits.argmax(-1).squeeze(0).tolist()

    results = []
    seen_word = set()
    for wid, pred in zip(word_ids, preds):
        if wid is None:
            continue
        if wid in seen_word:           # chỉ lấy subword đầu tiên
            continue
        seen_word.add(wid)
        results.append((tokens[wid], id2label[pred]))
    return results
```

```
sentences = [
    "Elon Musk founded SpaceX in the United States",
    "Cristiano Ronaldo joined Al Nassr in Saudi Arabia",
    "Apple Inc. is headquartered in Cupertino",
    "The Olympics will be held in Paris in 2024",
    "Barack Obama met Angela Merkel in Berlin",
    "Vietnam won the gold medal in the SEA Games",
    "Google and Microsoft are competing in artificial intelligence"
]

for s in sentences:
    print(s)
    print(predict_sentence(s, tokenizer, model, id2label))
    print("------")
```

```
Elon Musk founded SpaceX in the United States
[('Elon', 'B-PER'), ('Musk', 'I-PER'), ('founded', 'O'), ('SpaceX', 'B-ORG'), ('in', 'O'
------
Cristiano Ronaldo joined Al Nassr in Saudi Arabia
[('Cristiano', 'B-PER'), ('Ronaldo', 'I-PER'), ('joined', 'O'), ('Al', 'B-ORG'), ('Nassr
------
Apple Inc. is headquartered in Cupertino
[('Apple', 'B-ORG'), ('Inc.', 'I-ORG'), ('is', 'O'), ('headquartered', 'O'), ('in', 'O')
------
The Olympics will be held in Paris in 2024
[('The', 'O'), ('Olympics', 'B-MISC'), ('will', 'O'), ('be', 'O'), ('held', 'O'), ('in',
------
Barack Obama met Angela Merkel in Berlin
[('Barack', 'B-PER'), ('Obama', 'I-PER'), ('met', 'O'), ('Angela', 'B-PER'), ('Merkel',
------
Vietnam won the gold medal in the SEA Games
[('Vietnam', 'B-LOC'), ('won', 'O'), ('the', 'O'), ('gold', 'O'), ('medal', 'O'), ('in',
------
Google and Microsoft are competing in artificial intelligence
[('Google', 'B-ORG'), ('and', 'O'), ('Microsoft', 'B-ORG'), ('are', 'O'), ('competing',
------
```

```
# Save the model
torch.save(model.state_dict(), "ner_model.pth")
print("Model saved successfully!")
```

```
Model saved successfully!
```

Named_Entity_Recognition_rule_based

```
import spacy
from spacy.tokens import Span
from spacy.language import Language
from spacy import displacy
```

```
import pandas as pd
import re
from collections import defaultdict
from tqdm import tqdm


@Language.component("custom_rule_based_ner")
def custom_rule_based_ner(doc):
    entities = []
    for token in doc:
        if token.is_title and token.text not in spacy.lang.en.stop_words.STOP_WORDS and not
            if token.i + 1 < len(doc) and doc[token.i + 1].is_title:
                span = Span(doc, token.i, token.i + 2, label="ORG")
            else:
                span = Span(doc, token.i, token.i + 1, label="PER")
            entities.append(span)


    org_pattern = r'\b[A-Z][a-z]+ (Inc\.|Corp\.|[A-Z]{2,})\b'
    for match in re.finditer(org_pattern, doc.text):
        start_char, end_char = match.span()
        start_token = min([t.i for t in doc if t.idx >= start_char], default=None)
        end_token = min([t.i for t in doc if t.idx + len(t.text) > end_char], default=None)
        if start_token is not None and end_token is not None and start_token < end_token:
            span = Span(doc, start_token, end_token, label="ORG")
            entities.append(span)

    for token in doc:
        if token.is_title and token.text not in [ent.text for ent in entities] and not toker
            span = Span(doc, token.i, token.i + 1, label="MISC")
            entities.append(span)

    for token in doc:
        if token.like_num and not token.is_stop or token.text in spacy.lang.en.stop_words.ST
            span = Span(doc, token.i, token.i + 1, label="O")
            entities.append(span)

    # filter overlapping entities
    filtered_entities = []
    sorted_entities = sorted(entities, key=lambda ent: (ent.start , -ent.end))
    last_end = -1
    for ent in sorted_entities:
        if ent.start >= last_end:
            filtered_entities.append(ent)
            last_end = ent.end
    doc.ents = filtered_entities
    return doc


def process_text(nlp,token,modename):
    text = ' '.join(token)
    doc = nlp(text)
```

```
    entities = [(ent.text, ent.label_) for ent in doc.ents]
    df = pd.DataFrame(entities, columns=['Entity', 'Label'])
    print(f"\nResults for {modename}:\n")
    print(df)
    return doc ,df


def visualize_entities(doc, model_name, sentence_text):
    print(f"\nVisualization for {model_name} on sentence: {sentence_text}")
    displacy.render(doc, style="ent", jupyter=False)
    print("\n" + "="*50 + "\n")


def evaluate_ner(predicted_df, true_labels, tokens):
    predicted_entities = set((row['Entity'], row['Label']) for _, row in predicted_df.iterro
    true_entities = set()
    i = 0
    while i < len(tokens):
        if true_labels[i].startswith('B-'):
            label = true_labels[i][2:]
            entity_tokens = [tokens[i]]
            j = i + 1
            while j < len(tokens) and true_labels[j].startswith('I-') and true_labels[j][2:]
                entity_tokens.append(tokens[j])
                j += 1
            entity_text = ' '.join(entity_tokens)
            true_entities.add((entity_text, label))
            i = j
        else:
            i += 1

    true_positive = len(predicted_entities & true_entities)
    false_positive = len(predicted_entities - true_entities)
    false_negative = len(true_entities - predicted_entities)

    precision = true_positive / (true_positive + false_positive) if (true_positive + false_p
    recall = true_positive / (true_positive + false_negative) if (true_positive + false_nega
    f1_score = 2 * (precision * recall) / (precision + recall) if (precision + recall) > 0 e

    print(f"Precision: {precision:.2f}, Recall: {recall:.2f}, F1-Score: {f1_score:.2f}")

    return precision, recall, f1_score


def process_dataset(nlp_rule, nlp_sm, nlp_lg, dataset, dataset_name, sample_sentence=None):
    metrics = defaultdict(list)
    sample_processed = False

    if not dataset:
        print(f"Warning: {dataset_name} dataset is empty")
        return metrics
```

```
    for i, (tokens, true_labels) in tqdm(enumerate(dataset[:10]), total=min(10, len(dataset)
        if not tokens or not true_labels:
            print(f"Skipping empty or invalid sentence {i} in {dataset_name}")
            continue

        text = " ".join(tokens)
        if sample_sentence and text.startswith(sample_sentence) and not sample_processed:
            print(f"\nProcessing sample sentence from {dataset_name}: {text}")
            print(f"Ground truth labels: {true_labels}")
            sample_processed = True

        # Rule-based NER
        try:
            doc_rule, df_rule = process_text(nlp_rule, tokens, "Rule-Based Model")
            precision_rule, recall_rule, f1_rule = evaluate_ner(df_rule, true_labels, tokens
            metrics['rule_precision'].append(precision_rule)
            metrics['rule_recall'].append(recall_rule)
            metrics['rule_f1'].append(f1_rule)
        except Exception as e:
            print(f"Error processing Rule-Based Model for sentence {i} in {dataset_name}: {e
            continue

        # Small model NER
        try:
            doc_sm, df_sm = process_text(nlp_sm, tokens, "Small Model")
            precision_sm, recall_sm, f1_sm = evaluate_ner(df_sm, true_labels, tokens)
            metrics['sm_precision'].append(precision_sm)
            metrics['sm_recall'].append(recall_sm)
            metrics['sm_f1'].append(f1_sm)
        except Exception as e:
            print(f"Error processing Small Model for sentence {i} in {dataset_name}: {e}")
            continue

        # Large model NER
        try:
            doc_lg, df_lg = process_text(nlp_lg, tokens, "Large Model")
            precision_lg, recall_lg, f1_lg = evaluate_ner(df_lg, true_labels, tokens)
            metrics['lg_precision'].append(precision_lg)
            metrics['lg_recall'].append(recall_lg)
            metrics['lg_f1'].append(f1_lg)
        except Exception as e:
            print(f"Error processing Large Model for sentence {i} in {dataset_name}: {e}")
            continue

        if sample_sentence and text.startswith(sample_sentence):
            visualize_entities(doc_rule, "Rule-Based Model", text)
            visualize_entities(doc_sm, "Small Model", text)
            visualize_entities(doc_lg, "Large Model", text)
            print("\nComparison for Sample Sentence:")
            print("\nRule-Based Entities:")
            print(df_rule[['Entity', 'Label']])
```

```
            print("\nSmall Model Entities:")
            print(df_sm[['Entity', 'Label']])
            print("\nLarge Model Entities:")
            print(df_lg[['Entity', 'Label']])

    if not metrics['rule_precision']:
        print(f"Warning: No metrics collected for {dataset_name}")

    summary = pd.DataFrame({
        'Model': ['Rule-Based', 'Small Model', 'Large Model'],
        'Precision': [sum(metrics['rule_precision']) / len(metrics['rule_precision']) if met
                      sum(metrics['sm_precision']) / len(metrics['sm_precision']) if metrics
                      sum(metrics['lg_precision']) / len(metrics['lg_precision']) if metrics
        'Recall': [sum(metrics['rule_recall']) / len(metrics['rule_recall']) if metrics['ru]
                   sum(metrics['sm_recall']) / len(metrics['sm_recall']) if metrics['sm_reca
                   sum(metrics['lg_recall']) / len(metrics['lg_recall']) if metrics['lg_reca
        'F1-Score': [sum(metrics['rule_f1']) / len(metrics['rule_f1']) if metrics['rule_f1']
                     sum(metrics['sm_f1']) / len(metrics['sm_f1']) if metrics['sm_f1'] else
                     sum(metrics['lg_f1']) / len(metrics['lg_f1']) if metrics['lg_f1'] else
    })
    print(f"\nSummary for {dataset_name}:\n")
    print(summary)

    return metrics
```

```
! python -m spacy download en_core_web_lg
```

```
Collecting en-core-web-lg==3.8.0
  Downloading https://github.com/explosion/spacy-models/releases/download/en_core_web_lg
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 400.7/400.7 MB 3.9 MB/s eta 0:00:00
Installing collected packages: en-core-web-lg
Successfully installed en-core-web-lg-3.8.0
✔ Download and installation successful
You can now load the package via spacy.load('en_core_web_lg')
⚠ Restart to reload dependencies
If you are in a Jupyter or Colab notebook, you may need to restart Python in
order to load all the package's dependencies. You can do this by selecting the
'Restart kernel' or 'Restart runtime' option.
```

```
file_paths = {
    "train": "/content/train.txt",
    "test": "/content/test.txt",
    "valid": "/content/valid.txt"
}

data_sets = {name : read_conll_data(path) for name, path in file_paths.items()}

nlp_small = spacy.load("en_core_web_sm", disable=['lemmatizer','textcat'])
nlp_large = spacy.load("en_core_web_lg", disable=['lemmatizer','textcat'])
```

```
nlp_rule = spacy.blank("en")
ner = nlp_rule.add_pipe("ner")

for label in ["PER", "ORG", "MISC", "O","LOC"]:
    ner.add_label(label)

nlp_rule.add_pipe("custom_rule_based_ner")
nlp_rule.initialize()

nlp_rule.max_length = 2000000
nlp_small.max_length = 2000000
nlp_large.max_length = 2000000

sample_sentence = "The European Commission said on Thursday"

all_metrics = {}
for name, dataset in data_sets.items():
    print(f"\nProcessing {name} dataset...")
    texts, tags = dataset # Unpack the dataset tuple into texts and tags
    # Iterate over zipped texts and tags
    metrics = process_dataset(nlp_rule, nlp_small, nlp_large, list(zip(texts, tags)), name,
    all_metrics[name] = metrics

print("\nCross-Dataset Comparison:")
metric_mapping = {
    'Precision': 'precision',
    'Recall': 'recall',
    'F1-Score': 'f1'
}
for metric in ['Precision', 'Recall', 'F1-Score']:
    print(f"\nAverage {metric}:")
    comparison = pd.DataFrame({
        "Model": ["Rule-Based", "en_core_web_sm", "en_core_web_lg"],
        "Train": [
            sum(all_metrics['train'][f'rule_{metric_mapping[metric]}']) / len(all_metrics['t
            sum(all_metrics['train'][f'sm_{metric_mapping[metric]}']) / len(all_metrics['tra
            sum(all_metrics['train'][f'lg_{metric_mapping[metric]}']) / len(all_metrics['tra
        ],
        "Valid": [
            sum(all_metrics['valid'][f'rule_{metric_mapping[metric]}']) / len(all_metrics['v
            sum(all_metrics['valid'][f'sm_{metric_mapping[metric]}']) / len(all_metrics['val
            sum(all_metrics['valid'][f'lg_{metric_mapping[metric]}']) / len(all_metrics['val
        ],
        "Test": [
            sum(all_metrics['test'][f'rule_{metric_mapping[metric]}']) / len(all_metrics['te
            sum(all_metrics['test'][f'sm_{metric_mapping[metric]}']) / len(all_metrics['test
            sum(all_metrics['test'][f'lg_{metric_mapping[metric]}']) / len(all_metrics['test
        ]
    })
    print(comparison)
```

```
Precision: 0.00, Recall: 0.00, F1-Score: 0.00
```

```
# Save the spaCy models
nlp_small.to_disk("en_core_web_sm_saved")
nlp_large.to_disk("en_core_web_lg_saved")
print("spaCy models saved successfully!")
```

```
spaCy models saved successfully!
```

Start coding or generate with AI.

Task

Create a Gradio interface to compare the NER predictions of a BERT model and two spaCy models (`en_core_web_sm` and `en_core_web_lg`).

Install gradio

Subtask:

Add a code cell to install the Gradio library.

Reasoning: The subtask is to install the Gradio library. This requires adding a new code cell with the pip install command for gradio.

```
!pip install gradio
```

```
Requirement already satisfied: gradio in /usr/local/lib/python3.12/dist-packages (5.43.1
Requirement already satisfied: aiofiles<25.0,>=22.0 in /usr/local/lib/python3.12/dist-pa
Requirement already satisfied: anyio<5.0,>=3.0 in /usr/local/lib/python3.12/dist-package
Requirement already satisfied: brotli>=1.1.0 in /usr/local/lib/python3.12/dist-packages
Requirement already satisfied: fastapi<1.0,>=0.115.2 in /usr/local/lib/python3.12/dist-p
Requirement already satisfied: ffmpy in /usr/local/lib/python3.12/dist-packages (from gr
Requirement already satisfied: gradio-client==1.12.1 in /usr/local/lib/python3.12/dist-p
Requirement already satisfied: groovy~=0.1 in /usr/local/lib/python3.12/dist-packages (f
Requirement already satisfied: httpx<1.0,>=0.24.1 in /usr/local/lib/python3.12/dist-pack
Requirement already satisfied: huggingface-hub<1.0,>=0.33.5 in /usr/local/lib/python3.12
Requirement already satisfied: jinja2<4.0 in /usr/local/lib/python3.12/dist-packages (fr
Requirement already satisfied: markupsafe<4.0,>=2.0 in /usr/local/lib/python3.12/dist-pa
Requirement already satisfied: numpy<3.0,>=1.0 in /usr/local/lib/python3.12/dist-package
Requirement already satisfied: orjson~=3.0 in /usr/local/lib/python3.12/dist-packages (f
Requirement already satisfied: packaging in /usr/local/lib/python3.12/dist-packages (fro
Requirement already satisfied: pandas<3.0,>=1.0 in /usr/local/lib/python3.12/dist-packag
Requirement already satisfied: pillow<12.0,>=8.0 in /usr/local/lib/python3.12/dist-packa
```

```
Requirement already satisfied: pydantic<2.12,>=2.0 in /usr/local/lib/python3.12/dist-pac
Requirement already satisfied: pydub in /usr/local/lib/python3.12/dist-packages (from gr
Requirement already satisfied: python-multipart>=0.0.18 in /usr/local/lib/python3.12/dis
Requirement already satisfied: pyyaml<7.0,>=5.0 in /usr/local/lib/python3.12/dist-packag
Requirement already satisfied: ruff>=0.9.3 in /usr/local/lib/python3.12/dist-packages (f
Requirement already satisfied: safehttpx<0.2.0,>=0.1.6 in /usr/local/lib/python3.12/dist
Requirement already satisfied: semantic-version~=2.0 in /usr/local/lib/python3.12/dist-p
Requirement already satisfied: starlette<1.0,>=0.40.0 in /usr/local/lib/python3.12/dist-
Requirement already satisfied: tomlkit<0.14.0,>=0.12.0 in /usr/local/lib/python3.12/dist
Requirement already satisfied: typer<1.0,>=0.12 in /usr/local/lib/python3.12/dist-packag
Requirement already satisfied: typing-extensions~=4.0 in /usr/local/lib/python3.12/dist-
Requirement already satisfied: uvicorn>=0.14.0 in /usr/local/lib/python3.12/dist-package
Requirement already satisfied: fsspec in /usr/local/lib/python3.12/dist-packages (from g
Requirement already satisfied: websockets<16.0,>=10.0 in /usr/local/lib/python3.12/dist-
Requirement already satisfied: idna>=2.8 in /usr/local/lib/python3.12/dist-packages (fro
Requirement already satisfied: sniffio>=1.1 in /usr/local/lib/python3.12/dist-packages (
Requirement already satisfied: certifi in /usr/local/lib/python3.12/dist-packages (from 
Requirement already satisfied: httpcore==1.* in /usr/local/lib/python3.12/dist-packages 
Requirement already satisfied: h11>=0.16 in /usr/local/lib/python3.12/dist-packages (fro
Requirement already satisfied: filelock in /usr/local/lib/python3.12/dist-packages (from
Requirement already satisfied: requests in /usr/local/lib/python3.12/dist-packages (from
Requirement already satisfied: tqdm>=4.42.1 in /usr/local/lib/python3.12/dist-packages (
Requirement already satisfied: hf-xet<2.0.0,>=1.1.3 in /usr/local/lib/python3.12/dist-pa
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.12/dist-
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-packages (
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-packages
Requirement already satisfied: annotated-types>=0.6.0 in /usr/local/lib/python3.12/dist-
Requirement already satisfied: pydantic-core==2.33.2 in /usr/local/lib/python3.12/dist-p
Requirement already satisfied: typing-inspection>=0.4.0 in /usr/local/lib/python3.12/dis
Requirement already satisfied: click>=8.0.0 in /usr/local/lib/python3.12/dist-packages (
Requirement already satisfied: shellingham>=1.3.0 in /usr/local/lib/python3.12/dist-pack
Requirement already satisfied: rich>=10.11.0 in /usr/local/lib/python3.12/dist-packages 
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.12/dist-packages (from
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.12/dist-p
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.12/dist
Requirement already satisfied: charset_normalizer<4,>=2 in /usr/local/lib/python3.12/dis
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.12/dist-pack
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.12/dist-packages (fr
```

Load models

Subtask:

Load the saved BERT model and the saved spaCy models (`en_core_web_sm_saved` and `en_core_web_lg_saved`).

Reasoning: Load the saved BERT and spaCy models for use in the Gradio interface.

```
model.load_state_dict(torch.load("ner_model.pth", map_location=CFG.device))
nlp_small_loaded = spacy.load("en_core_web_sm_saved")
```

```
nlp_large_loaded = spacy.load("en_core_web_lg_saved")

print("Models loaded successfully!")
```

```
Models loaded successfully!
```

Define prediction functions

Subtask:

Create Python functions that take a sentence as input and return NER predictions in a user-friendly format for the BERT model and both spaCy models.

Reasoning: Define the functions to get NER predictions from the BERT and spaCy models.

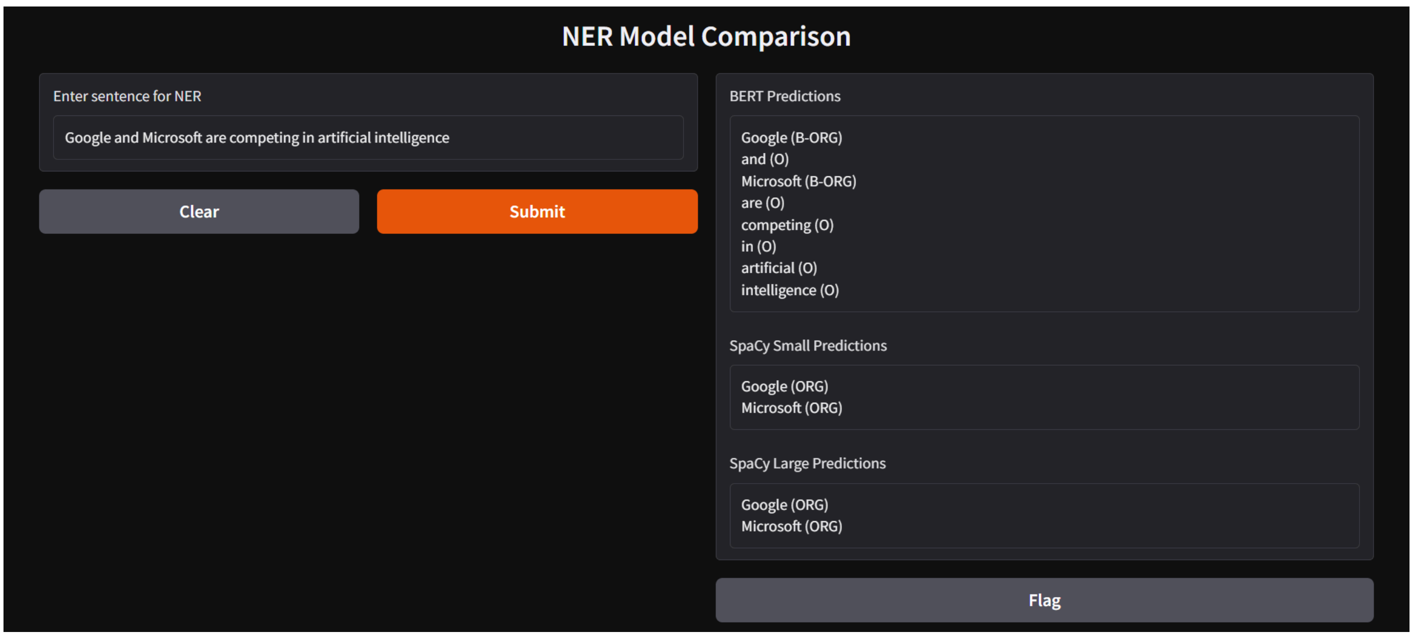
```
def get_bert_predictions(sentence, tokenizer, model, id2label, max_len=128):
    """
    Gets NER predictions from the BERT model for a given sentence.

    Args:
        sentence (str): The input sentence.
        tokenizer: The BERT tokenizer.
        model: The trained BERT model.
        id2label (dict): Dictionary mapping label IDs to labels.
        max_len (int): Maximum sequence length.

    Returns:
        list: A list of (word, label) tuples.
    """
    results = predict_sentence(sentence, tokenizer, model, id2label, max_len)
    return results

def get_spacy_predictions(nlp_model, sentence):
    """
    Gets NER predictions from a spaCy model for a given sentence.

    Args:
        nlp_model: The loaded spaCy language model.
        sentence (str): The input sentence.

    Returns:
        list: A list of (entity_text, label) tuples.
    """
    doc = nlp_model(sentence)
    entities = [(ent.text, ent.label_) for ent in doc.ents]
    return entities
```

Build gradio interface

Subtask:

Design and implement a Gradio interface with input text boxes for the sentence and output displays for the predictions from each model.

Reasoning: Implement the `ner_comparison` function to call the prediction functions and format the output, then create the Gradio interface.



The End!