BiLSTM

February 20, 2026

1 Data Preparation

Pipeline: Raw Text → Data Preprocessing → Model Training → Evaluation → Results

1.1 Setup

[ ]:
```
import nltk
from nltk.corpus import brown
import numpy as np
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
```

1.2 Data Discovery

Load Dataset

[ ]:
```
nltk.download('brown')
nltk.download('universal_tagset')
tagged_sents = brown.tagged_sents(tagset='universal')
```

```
[nltk_data] Downloading package brown to /root/nltk_data…
[nltk_data]   Unzipping corpora/brown.zip.
[nltk_data] Downloading package universal_tagset to /root/nltk_data…
[nltk_data]   Unzipping taggers/universal_tagset.zip.
```

[ ]:
```
print(tagged_sents[0])
```

```
[('The', 'DET'), ('Fulton', 'NOUN'), ('County', 'NOUN'), ('Grand', 'ADJ'),
('Jury', 'NOUN'), ('said', 'VERB'), ('Friday', 'NOUN'), ('an', 'DET'),
('investigation', 'NOUN'), ('of', 'ADP'), ("Atlanta's", 'NOUN'), ('recent',
'ADJ'), ('primary', 'NOUN'), ('election', 'NOUN'), ('produced', 'VERB'), ('``',
'.'), ('no', 'DET'), ('evidence', 'NOUN'), ("''", '.'), ('that', 'ADP'), ('any',
'DET'), ('irregularities', 'NOUN'), ('took', 'VERB'), ('place', 'NOUN'), ('.',
'.')]
```

Flatten all sentences into a list of (word, tag) tuples

[ ]:
```
data = [(word, tag) for sent in tagged_sents for word, tag in sent]
```

Convert data array into pandas dataframe

[ ]:
```
df = pd.DataFrame(data, columns=['word', 'tag'])
```

[ ]:
```
df.head()
```

[ ]:

	word	tag
0	The	DET
1	Fulton	NOUN
2	County	NOUN
3	Grand	ADJ
4	Jury	NOUN

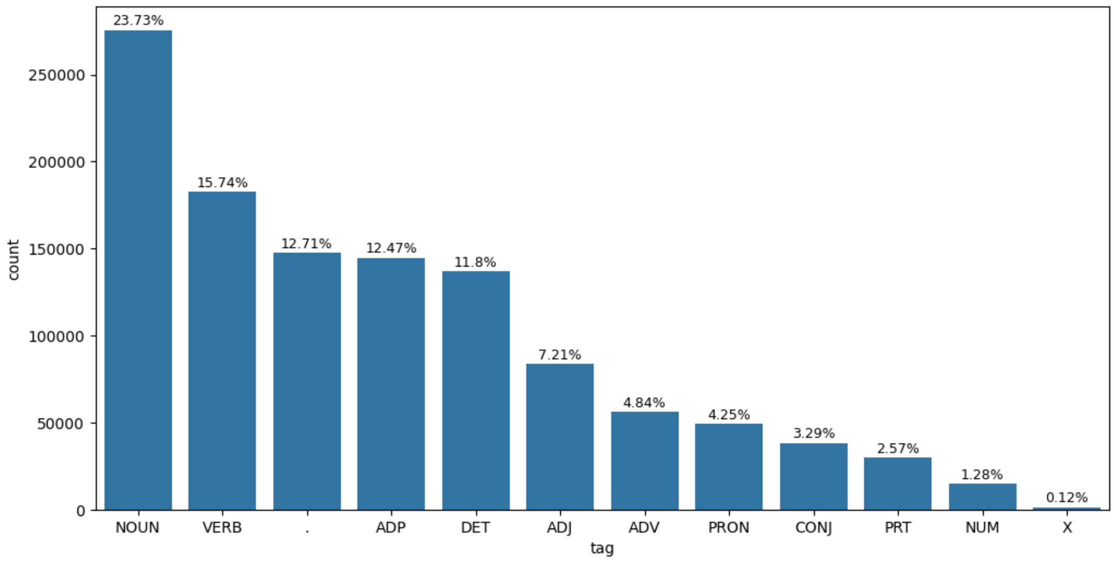
[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1161192 entries, 0 to 1161191
Data columns (total 2 columns):
 #   Column  Non-Null Count    Dtype
---  ------  --------------    -----
 0   word    1161192 non-null  object
 1   tag     1161192 non-null  object
dtypes: object(2)
memory usage: 17.7+ MB
```

[ ]:
```
df['tag'].unique()
```

[ ]:
```
array(['DET', 'NOUN', 'ADJ', 'VERB', 'ADP', '.', 'ADV', 'CONJ', 'PRT',
       'PRON', 'NUM', 'X'], dtype=object)
```

[ ]:
```
tag_counts = df['tag'].value_counts()
tag_percentages = (tag_counts / len(df) * 100).round(2)

plt.figure(figsize=(12, 6))
ax = sns.countplot(df, x='tag', order=df['tag'].value_counts().index)

for i, (count, pct) in enumerate(zip(tag_counts.values, tag_percentages.
 ↪values)):
    ax.text(i, count + 1000, f'{pct}%', ha='center', va='bottom', fontsize=9)
```



2 Data Preprocessing

There will be no feature engineering for BiLSTM, but we still have to ensure sentences are whole:

- `word`: the current word
- `tag`: the label

2.1 Train test split (Split by sentence)

[ ]:
```
np.random.seed(42)
n = len(tagged_sents)
indices = np.random.permutation(n)

train_size = int(0.8 * n)
val_size = int(0.1 * n)

train_idx = indices[:train_size]
val_idx = indices[train_size:train_size+val_size]
test_idx = indices[val_size+train_size:]

train_sents = [tagged_sents[i] for i in train_idx]
val_sents = [tagged_sents[i] for i in val_idx]
test_sents = [tagged_sents[i] for i in test_idx]

print(f"\nDataset split:")
print(f"  Train: {len(train_sents):,} sentences")
print(f"  Val:   {len(val_sents):,} sentences")
```

```
print(f"  Test:  {len(test_sents):,} sentences")
```

```
Dataset split:
  Train: 45,872 sentences
  Val:   5,734 sentences
  Test:  5,734 sentences
```

[ ]:
```
print(f"Sample training sentence: {train_sents[0]}")
print(f"Sample test sentence: {test_sents[0]}")
print(f"Sample test tags: {val_sents[0]}")
```

```
Sample training sentence: [('Open', 'ADJ'), ('market', 'NOUN'), ('policy',
'NOUN')]
Sample test sentence: [('Even', 'ADV'), ('the', 'DET'), ('officer', 'NOUN'),
('in', 'ADP'), ('charge', 'NOUN'), (',', '.'), ('be', 'VERB'), ('it', 'PRON'),
('a', 'DET'), ('captain', 'NOUN'), ('(', '.'), ('for', 'ADP'), ('small', 'ADJ'),
('display', 'NOUN'), (')', '.'), ('or', 'CONJ'), ('a', 'DET'), ('general',
'NOUN'), (',', '.'), ('is', 'VERB'), ('restrained', 'VERB'), ('by', 'ADP'),
('monitoring', 'VERB'), ('.', '.')]
Sample test tags: [('Boys', 'NOUN'), ('will', 'VERB'), ('be', 'VERB'), ('boys',
'NOUN'), (',', '.'), ('and', 'CONJ'), ('Texans', 'NOUN'), ('will', 'VERB'),
('be', 'VERB'), ('Texans', 'NOUN'), ('.', '.')]
```

3 Feature Encoding

Index word and tag vocabularies from sentences. This is to map each word into a number. The vocab is built using the train data.

Args: - `sentences` (list): List of tagged sentences - `min_freq` (int): Minimum frequency for a word to be included

Returns: - tuple: (word2idx, tag2idx, idx2word, idx2tag)

[ ]:
```
from collections import Counter
```

[ ]:
```
def build_vocabularies(sentences, min_freq=2):

    # Count word frequencies
    word_counter = Counter()
    tag_counter = Counter()

    for sent in sentences:
        for word, tag in sent:
            word_counter[word.lower()] += 1
            tag_counter[tag] += 1

    # Build word vocabulary (only words with freq >= min_freq)
```

```python
    words = ['<PAD>', '<UNK>'] + [w for w, c in word_counter.items() if c >=␣
↪min_freq]
    word2idx = {w: i for i, w in enumerate(words)}
    idx2word = {i: w for w, i in word2idx.items()}

    # Build tag vocabulary
    tags = ['<PAD>'] + sorted(tag_counter.keys())
    tag2idx = {t: i for i, t in enumerate(tags)}
    idx2tag = {i: t for t, i in tag2idx.items()}

    return word2idx, tag2idx, idx2word, idx2tag
```

[ ]:
```python
word2idx, tag2idx, idx2word, idx2tag = build_vocabularies(train_sents)
print(f"Vocabulary size: {len(word2idx)}")
print(f"Number of POS tags: {len(tag2idx)}")
print(f"POS tags: {list(tag2idx.keys())}")
```

```
Vocabulary size: 24716
Number of POS tags: 13
POS tags: ['<PAD>', '.', 'ADJ', 'ADP', 'ADV', 'CONJ', 'DET', 'NOUN', 'NUM',
'PRON', 'PRT', 'VERB', 'X']
```

3.1 Encoding Sentences

Convert sentences to numerical indices and pad them. This function uses the vocab dictionary we built earlier to encode the tagged sentences. Words that do not exist in the vocab dictionary appear as 'UNK', while padding is to ensure all sequences in a batch have the same shape. (The NN will not be able to process batches with irregular shape)

Args: - `sentences` (list): List of tagged sentences - `word2idx` (dict): Word to index mapping - `tag2idx` (dict): Tag to index mapping - `max_len` (int): Maximum sequence length (computed if None)

Returns: - tuple: (word_indices, tag_indices, sequence_lengths, max_len)

[ ]:
```python
def encode_sentences(sentences, word2idx, tag2idx, max_len=None):

    # Find max length if not provided
    if max_len is None:
        max_len = max(len(sent) for sent in sentences)

    word_indices = []
    tag_indices = []
    seq_lengths = []

    for sent in sentences:
        # Get original length
        seq_len = len(sent)
        seq_lengths.append(seq_len)
```

```
        # Convert words and tags to indices
        words = [word2idx.get(word.lower(), word2idx['<UNK>']) for word, _ in␣
 ↪sent]
        tags = [tag2idx[tag] for _, tag in sent]

        # Pad sequences
        if len(words) < max_len:
            words += [word2idx['<PAD>']] * (max_len - len(words))
            tags += [tag2idx['<PAD>']] * (max_len - len(tags))
        else:
            # Truncate if needed
            words = words[:max_len]
            tags = tags[:max_len]
            seq_lengths[-1] = max_len

        word_indices.append(words)
        tag_indices.append(tags)

    return np.array(word_indices), np.array(tag_indices), np.
 ↪array(seq_lengths), max_len
```

Encode all datasets

[ ]:
```
train_X, train_y, train_lengths, max_len = encode_sentences(train_sents,␣
 ↪word2idx, tag2idx)
val_X, val_y, val_lengths, _ = encode_sentences(val_sents, word2idx, tag2idx,␣
 ↪max_len)
test_X, test_y, test_lengths, _ = encode_sentences(test_sents, word2idx,␣
 ↪tag2idx, max_len)
```

[ ]:
```
print(f"Max sequence length: {max_len}")
print()
print(f"Training data shape: {train_X.shape}")
print(f"Training labels shape: {train_y.shape}")
print()
print(f"Validation data shape: {val_X.shape}")
print(f"Validation labels shape: {val_y.shape}")
print()
print(f"Test data shape: {test_X.shape}")
print(f"Test labels shape: {test_y.shape}")
```

```
Max sequence length: 172

Training data shape: (45872, 172)
Training labels shape: (45872, 172)

Validation data shape: (5734, 172)
```

```
Validation labels shape: (5734, 172)

Test data shape: (5734, 172)
Test labels shape: (5734, 172)
```

3.2 Create dataloaders

Create a PyTorch DataLoader from numpy arrays.

Args: - `X` (np.array): Input sequences - `y` (np.array): Target sequences - `lengths` (np.array): Actual sequence lengths - `batch_size` (int): Batch size = 64 (common default) - `shuffle` (bool): Whether to shuffle data

Returns: - `DataLoader`: PyTorch DataLoader object

[ ]:
```python
import torch
from torch.utils.data import DataLoader, TensorDataset
```

[ ]:
```python
def create_dataloader(X, y, lengths, batch_size=64, shuffle=True):

    # Convert to PyTorch tensors
    X_tensor = torch.LongTensor(X)
    y_tensor = torch.LongTensor(y)
    lengths_tensor = torch.LongTensor(lengths)

    # Create dataset
    dataset = TensorDataset(X_tensor, y_tensor, lengths_tensor)

    # Create dataloader
    dataloader = DataLoader(dataset, batch_size=batch_size, shuffle=shuffle)

    return dataloader
```

[ ]:
```python
train_loader = create_dataloader(train_X, train_y, train_lengths, shuffle=True)
val_loader = create_dataloader(val_X, val_y, val_lengths, shuffle=False)
test_loader = create_dataloader(test_X, test_y, test_lengths, shuffle=False)
```

[ ]:
```python
print(f"Number of training batches: {len(train_loader)}")
print(f"Number of validation batches: {len(val_loader)}")
print(f"Number of test batches: {len(test_loader)}")
```

```
Number of training batches: 717
Number of validation batches: 90
Number of test batches: 90
```

4 Build BiLSTM Model

The model has bidirectional context (looks both forward and backward in the sentence). It is also designed to have long-range dependencies (captures relationships across distant words).

4.1 Model Architecture:

1. Embedding Layer
    - Transforms encoded words into dense vectors
    - Creates a lookup table where each word gets a unique vector, which are trained during backpropagation
    - Input: one-hot encoded words (word indices)
    - Output: 100-dimensional vectors for each word
2. BiLSTM Layers (2 layers)
    - Captures sequential patterns and bidirectional context (the brain layer)
    - Addresses lexical ambiguity in the English language
    - Input: Word embeddings
    - Output: 256-dimensional hidden states for each word (128 x 2 bidirectional = 256)
3. Dropout Layer (Only Active for training)
    - Prevents overfitting by randomly dropping neurons during training
    - Helps the model generalize better by learning patterns and not noise
4. Fully Connected Layer
    - Transforms BiLSTM hidden states into tag scores
    - Maps LSTM features to tags
    - Input: Hidden states
    - Output: Tag scores (for each word -> 13 scores)
5. Output Layer (Softmax)
    - Converts scores into probabilities
    - Input: Tag scores
    - Output: All tag probabilities for each word

Args: - `vocab_size` (int): Size of vocabulary - `embedding_dim` (int): Dimension of word embeddings - `hidden_dim` (int): Dimension of LSTM hidden state - `output_size` (int): Number of output tags - `num_layers` (int): Number of LSTM layers - `dropout` (float): Dropout probability

Returns: - `nn.Module`: PyTorch model

[ ]:
```
import torch.nn as nn
```

[ ]:
```
def create_bilstm_model(vocab_size, embedding_dim, hidden_dim, output_size,
                        num_layers=2, dropout=0.3):

    model = nn.Sequential()

    class BiLSTM(nn.Module):
        def __init__(self):
            super(BiLSTM, self).__init__()

            # Embedding layer
            self.embedding = nn.Embedding(vocab_size, embedding_dim,␣
↪padding_idx=0)

            # BiLSTM layer
            self.lstm = nn.LSTM(
```

```python
                embedding_dim,
                hidden_dim,
                num_layers=num_layers,
                bidirectional=True,
                dropout=dropout if num_layers > 1 else 0,
                batch_first=True
            )

            # Dropout layer
            self.dropout = nn.Dropout(dropout)

            # Output layer (hidden_dim * 2 because bidirectional)
            self.fc = nn.Linear(hidden_dim * 2, output_size)

        def forward(self, x, lengths):
            # x shape: (batch_size, seq_len)
            # lengths shape: (batch_size)
            batch_size, seq_len = x.size()
            # Embedding: (batch_size, seq_len, embedding_dim)
            embedded = self.embedding(x)

            # Pack padded sequence for efficient processing
            packed = nn.utils.rnn.pack_padded_sequence(
                embedded, lengths.cpu(), batch_first=True, enforce_sorted=False
            )

            # BiLSTM: (batch_size, seq_len, hidden_dim * 2)
            lstm_out, _ = self.lstm(packed)

            # Unpack sequence
            lstm_out, _ = nn.utils.rnn.pad_packed_sequence(
                lstm_out,
                batch_first=True,
                total_length=seq_len)

            # Apply dropout
            lstm_out = self.dropout(lstm_out)

            # Output projection: (batch_size, seq_len, output_size)
            output = self.fc(lstm_out)

            return output

    return BiLSTM()

# Model hyperparameters
EMBEDDING_DIM = 100
```

```
HIDDEN_DIM = 128
NUM_LAYERS = 2
DROPOUT = 0.3
```

[ ]:
```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model = create_bilstm_model(
    vocab_size=len(word2idx),
    embedding_dim=EMBEDDING_DIM,
    hidden_dim=HIDDEN_DIM,
    output_size=len(tag2idx),
    num_layers=NUM_LAYERS,
    dropout=DROPOUT
).to(device)
```

[ ]:
```
print(f"Device: {device}")
print(f"Model Architecture:\n{model}")
print(f"\nTotal Parameters: {sum(p.numel() for p in model.parameters())}")
```

```
Device: cpu
Model Architecture:
BiLSTM(
  (embedding): Embedding(24716, 100, padding_idx=0)
  (lstm): LSTM(100, 128, num_layers=2, batch_first=True, dropout=0.3,
bidirectional=True)
  (dropout): Dropout(p=0.3, inplace=False)
  (fc): Linear(in_features=256, out_features=13, bias=True)
)

Total Parameters: 3105725
```

5 Training and Evaluation

5.1 Loss function and optimizer setup

- `criterion`: Cross Entropy Loss function with ignore_index for padding (ignore 'PAD' tokens)
- `optimizer`: Adam optimizer with 0.001 learning rate

[ ]:
```
import torch.optim as optim
```

[ ]:
```
criterion = nn.CrossEntropyLoss(ignore_index=tag2idx['<PAD>'])
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

Train the model for one epoch

[ ]:
```
def train_epoch(model, dataloader, criterion, optimizer, device):

    model.train()
    total_loss = 0
```

```
    total_correct = 0
    total_tokens = 0

    for batch_idx, (inputs, targets, lengths) in enumerate(dataloader):
        # Move to device
        inputs = inputs.to(device)
        targets = targets.to(device)
        lengths = lengths.to(device)

        # Zero gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(inputs, lengths)  # (batch_size, seq_len, num_tags)

        # Reshape for loss calculation
        outputs_flat = outputs.view(-1, outputs.shape[-1])  # (batch_size *␣
↪seq_len, num_tags)
        targets_flat = targets.view(-1)  # (batch_size * seq_len)

        # Calculate loss
        loss = criterion(outputs_flat, targets_flat)

        # Backward pass
        loss.backward()

        # Clip gradients to prevent exploding gradients
        torch.nn.utils.clip_grad_norm_(model.parameters(), max_norm=5.0)

        # Update weights
        optimizer.step()

        # Calculate accuracy (excluding padding)
        predictions = outputs.argmax(dim=-1)  # (batch_size, seq_len)
        mask = targets != tag2idx['<PAD>']  # Create mask for non-padding tokens

        correct = (predictions == targets) & mask
        total_correct += correct.sum().item()
        total_tokens += mask.sum().item()
        total_loss += loss.item()

        # Print progress every 100 batches
        if (batch_idx + 1) % 100 == 0:
            print(f"  Batch {batch_idx + 1}/{len(dataloader)}, Loss: {loss.
↪item():.4f}")

    avg_loss = total_loss / len(dataloader)
```

```
    accuracy = total_correct / total_tokens

    return avg_loss, accuracy
```

[ ]:
```
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix
```

Evaluate the model on a dataset

[ ]:
```
def evaluate(model, dataloader, criterion, device):

    model.eval()
    total_loss = 0
    all_predictions = []
    all_targets = []

    with torch.no_grad():
        for inputs, targets, lengths in dataloader:
            # Move to device
            inputs = inputs.to(device)
            targets = targets.to(device)
            lengths = lengths.to(device)

            # Forward pass
            outputs = model(inputs, lengths)

            # Calculate loss
            outputs_flat = outputs.view(-1, outputs.shape[-1])
            targets_flat = targets.view(-1)
            loss = criterion(outputs_flat, targets_flat)
            total_loss += loss.item()

            # Get predictions
            predictions = outputs.argmax(dim=-1)

            # Store predictions and targets (excluding padding)
            for i in range(len(inputs)):
                seq_len = lengths[i].item()
                pred_seq = predictions[i, :seq_len].cpu().numpy()
                target_seq = targets[i, :seq_len].cpu().numpy()

                all_predictions.extend(pred_seq)
                all_targets.extend(target_seq)

    avg_loss = total_loss / len(dataloader)
    accuracy = accuracy_score(all_targets, all_predictions)

    return avg_loss, accuracy, all_predictions, all_targets
```

Train model on specified epochs

```
[ ]: def train_model(model, train_loader, val_loader, criterion, optimizer, device,␣
      ↪num_epochs=10):

         history = {
             'train_loss': [],
             'train_acc': [],
             'val_loss': [],
             'val_acc': []
         }

         best_val_acc = 0.0

         for epoch in range(num_epochs):
             print(f"\nEpoch {epoch + 1}/{num_epochs}")
             print("-" * 50)

             # Train
             train_loss, train_acc = train_epoch(model, train_loader, criterion,␣
      ↪optimizer, device)
             print(f"Train Loss: {train_loss:.4f}, Train Acc: {train_acc:.4f}")

             # Validate
             val_loss, val_acc, _, _ = evaluate(model, val_loader, criterion, device)
             print(f"Val Loss: {val_loss:.4f}, Val Acc: {val_acc:.4f}")

             # Save history
             history['train_loss'].append(train_loss)
             history['train_acc'].append(train_acc)
             history['val_loss'].append(val_loss)
             history['val_acc'].append(val_acc)

             # Save best model
             if val_acc > best_val_acc:
                 best_val_acc = val_acc
                 print(f"  → New best validation accuracy: {best_val_acc:.4f}")

         return history
```

Train the model

```
[ ]: import time
```

```
[ ]: training_start = time.perf_counter()
     history = train_model(model, train_loader, val_loader, criterion, optimizer,␣
      ↪device)
     training_end = time.perf_counter()
```

```
Epoch 1/10
--------------------------------------------------
  Batch 100/717, Loss: 0.6550
  Batch 200/717, Loss: 0.4209
  Batch 300/717, Loss: 0.3611
  Batch 400/717, Loss: 0.2586
  Batch 500/717, Loss: 0.2778
  Batch 600/717, Loss: 0.2416
  Batch 700/717, Loss: 0.2398
Train Loss: 0.4641, Train Acc: 0.8471
Val Loss: 0.1891, Val Acc: 0.9371
  → New best validation accuracy: 0.9371

Epoch 2/10
--------------------------------------------------
  Batch 100/717, Loss: 0.1581
  Batch 200/717, Loss: 0.1802
  Batch 300/717, Loss: 0.1430
  Batch 400/717, Loss: 0.1625
  Batch 500/717, Loss: 0.1554
  Batch 600/717, Loss: 0.1468
  Batch 700/717, Loss: 0.1299
Train Loss: 0.1690, Train Acc: 0.9447
Val Loss: 0.1229, Val Acc: 0.9595
  → New best validation accuracy: 0.9595

Epoch 3/10
--------------------------------------------------
  Batch 100/717, Loss: 0.1065
  Batch 200/717, Loss: 0.1078
  Batch 300/717, Loss: 0.1089
  Batch 400/717, Loss: 0.0992
  Batch 500/717, Loss: 0.1244
  Batch 600/717, Loss: 0.1036
  Batch 700/717, Loss: 0.0859
Train Loss: 0.1141, Train Acc: 0.9629
Val Loss: 0.0987, Val Acc: 0.9674
  → New best validation accuracy: 0.9674

Epoch 4/10
--------------------------------------------------
  Batch 100/717, Loss: 0.0786
  Batch 200/717, Loss: 0.0973
  Batch 300/717, Loss: 0.0612
  Batch 400/717, Loss: 0.0715
  Batch 500/717, Loss: 0.0616
  Batch 600/717, Loss: 0.1010
```

```
  Batch 700/717, Loss: 0.0799
Train Loss: 0.0869, Train Acc: 0.9715
Val Loss: 0.0877, Val Acc: 0.9705
  → New best validation accuracy: 0.9705

Epoch 5/10
--------------------------------------------------
  Batch 100/717, Loss: 0.0808
  Batch 200/717, Loss: 0.0659
  Batch 300/717, Loss: 0.0576
  Batch 400/717, Loss: 0.0644
  Batch 500/717, Loss: 0.0584
  Batch 600/717, Loss: 0.0848
  Batch 700/717, Loss: 0.1022
Train Loss: 0.0700, Train Acc: 0.9771
Val Loss: 0.0813, Val Acc: 0.9731
  → New best validation accuracy: 0.9731

Epoch 6/10
--------------------------------------------------
  Batch 100/717, Loss: 0.0641
  Batch 200/717, Loss: 0.0344
  Batch 300/717, Loss: 0.0387
  Batch 400/717, Loss: 0.0520
  Batch 500/717, Loss: 0.0528
  Batch 600/717, Loss: 0.0436
  Batch 700/717, Loss: 0.0530
Train Loss: 0.0588, Train Acc: 0.9805
Val Loss: 0.0784, Val Acc: 0.9743
  → New best validation accuracy: 0.9743

Epoch 7/10
--------------------------------------------------
  Batch 100/717, Loss: 0.0396
  Batch 200/717, Loss: 0.0444
  Batch 300/717, Loss: 0.0368
  Batch 400/717, Loss: 0.0346
  Batch 500/717, Loss: 0.0538
  Batch 600/717, Loss: 0.0695
  Batch 700/717, Loss: 0.0512
Train Loss: 0.0496, Train Acc: 0.9834
Val Loss: 0.0794, Val Acc: 0.9743

Epoch 8/10
--------------------------------------------------
  Batch 100/717, Loss: 0.0352
  Batch 200/717, Loss: 0.0271
  Batch 300/717, Loss: 0.0485
```

```
  Batch 400/717, Loss: 0.0377
  Batch 500/717, Loss: 0.0408
  Batch 600/717, Loss: 0.0396
  Batch 700/717, Loss: 0.0374
Train Loss: 0.0428, Train Acc: 0.9856
Val Loss: 0.0793, Val Acc: 0.9753
  → New best validation accuracy: 0.9753

Epoch 9/10
--------------------------------------------------
  Batch 100/717, Loss: 0.0385
  Batch 200/717, Loss: 0.0288
  Batch 300/717, Loss: 0.0288
  Batch 400/717, Loss: 0.0345
  Batch 500/717, Loss: 0.0406
  Batch 600/717, Loss: 0.0325
  Batch 700/717, Loss: 0.0333
Train Loss: 0.0368, Train Acc: 0.9875
Val Loss: 0.0814, Val Acc: 0.9752

Epoch 10/10
--------------------------------------------------
  Batch 100/717, Loss: 0.0295
  Batch 200/717, Loss: 0.0303
  Batch 300/717, Loss: 0.0242
  Batch 400/717, Loss: 0.0347
  Batch 500/717, Loss: 0.0366
  Batch 600/717, Loss: 0.0422
  Batch 700/717, Loss: 0.0388
Train Loss: 0.0320, Train Acc: 0.9891
Val Loss: 0.0852, Val Acc: 0.9748
```

Classification Report

[ ]:
```
inference_start = time.perf_counter()
test_loss, test_acc, test_predictions, test_targets = evaluate(model,␣
↪test_loader, criterion, device)
inference_end = time.perf_counter()

print(f"Training time: {training_end - training_start:.4f}s")
print(f"Inference time: {inference_end - inference_start:.4f}s")
```

```
Training time: 4215.5727s
Inference time: 6.7825s
```

[ ]:
```
print(f"Test Loss: {test_loss:.4f}")
print(f"Test Accuracy: {test_acc:.4f}")
```

```
Test Loss: 0.0908
```

```
Test Accuracy: 0.9737
```

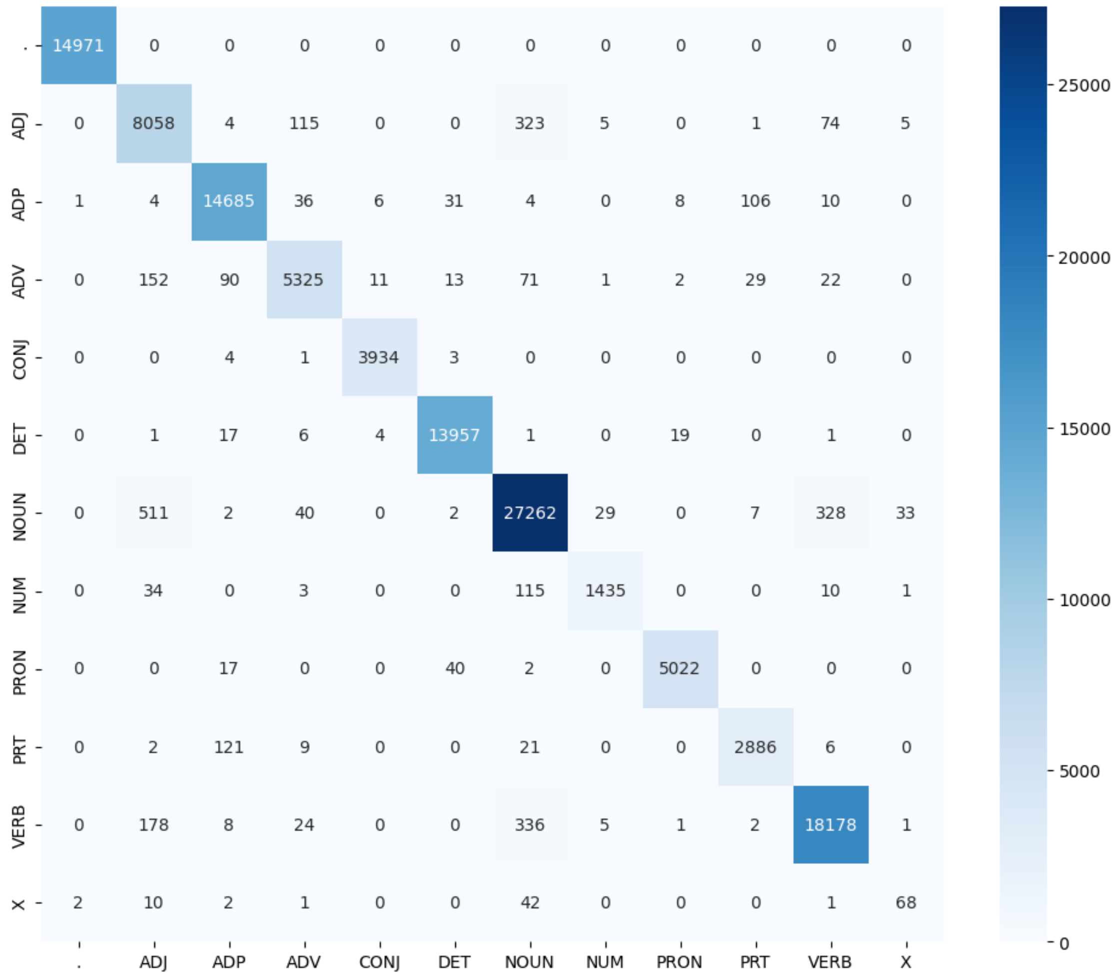
[ ]:
```
tag_names = [tag for tag in sorted(tag2idx.keys()) if tag != '<PAD>'] # exclude␣
↪padding
print(classification_report(test_targets, test_predictions,
                            target_names=tag_names,
                            labels=[tag2idx[tag] for tag in tag_names],
                            zero_division=0))
```

```
              precision    recall  f1-score   support

           .       1.00      1.00      1.00     14971
         ADJ       0.90      0.94      0.92      8585
         ADP       0.98      0.99      0.98     14891
         ADV       0.96      0.93      0.94      5716
        CONJ       0.99      1.00      1.00      3942
         DET       0.99      1.00      1.00     14006
        NOUN       0.97      0.97      0.97     28214
         NUM       0.97      0.90      0.93      1598
        PRON       0.99      0.99      0.99      5081
         PRT       0.95      0.95      0.95      3045
        VERB       0.98      0.97      0.97     18733
           X       0.63      0.54      0.58       126

    accuracy                           0.97    118908
   macro avg       0.94      0.93      0.94    118908
weighted avg       0.97      0.97      0.97    118908
```

Confusion Matrix

[ ]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

[ ]:
```
cm = confusion_matrix(test_targets, test_predictions, labels=[tag2idx[tag] for␣
↪tag in tag_names])
plt.figure(figsize=(12, 10))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=tag_names,␣
↪yticklabels=tag_names)
plt.show()
```



Training and validation metrics

```
[ ]: fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Plot loss
axes[0].plot(history['train_loss'], label='Train Loss', marker='o')
axes[0].plot(history['val_loss'], label='Val Loss', marker='s')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Loss')
axes[0].set_title('Training and Validation Loss')
axes[0].legend()
axes[0].grid(True, alpha=0.3)

# Plot accuracy
axes[1].plot(history['train_acc'], label='Train Accuracy', marker='o')
axes[1].plot(history['val_acc'], label='Val Accuracy', marker='s')
axes[1].set_xlabel('Epoch')
```

```
axes[1].set_ylabel('Accuracy')
axes[1].set_title('Training and Validation Accuracy')
axes[1].legend()
axes[1].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()
```