In [1]:
```python
from utils.data import Dataset
from utils.conllu import read_conllu_dataset
import numpy as np
```

In [2]:
```python
dataset = Dataset()

train_sentences = read_conllu_dataset("data/ro_rrt-ud-train.conllu")
test_sentences = read_conllu_dataset("data/ro_rrt-ud-test.conllu")

# Fit on training data
X_train, y_train = dataset.fit(train_sentences, mode="chars")

# Encode test data (fixed shape)
X_test, y_test = dataset.encode(test_sentences)
```

In [3]:
```python
X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

Out[3]:
```
((8043, 163, 55), (8043, 163, 17), (729, 163, 55), (729, 163, 17))
```

In [4]:
```python
import tensorflow as tf
```

In [5]:
```python
_, seq_len, char_feat_len = X_train.shape
output_dim = y_train.shape[-1]
```

In [6]:
```python
sample_weight = np.where(np.argmax(y_train, axis=-1) != 0, 1.0, 0.0)
```

In [7]:
```python
input_layer = tf.keras.layers.Input(shape=(seq_len, char_feat_len))
lstm = tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(128, return_sequences=True))(input_layer)
output_layer = tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(output_dim, activation='softmax'))(lstm)

model = tf.keras.models.Model(inputs=input_layer, outputs=output_layer)
model.compile(optimizer=tf.keras.optimizers.Adam(0.001), loss='categorical_crossentropy', weighted_metrics=['accuracy'])

model.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 163, 55)	0
bidirectional (Bidirectional)	(None, 163, 256)	188,416
time_distributed (TimeDistributed)	(None, 163, 17)	4,369

Total params: 192,785 (753.07 KB)

Trainable params: 192,785 (753.07 KB)

Non-trainable params: 0 (0.00 B)

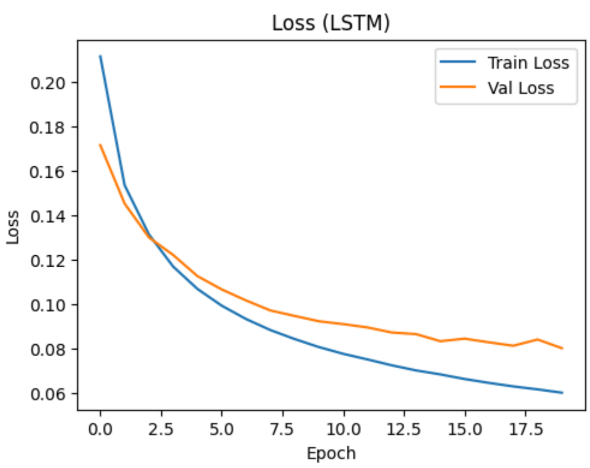
In [8]:
```
history = model.fit(
    X_train, y_train,
    validation_split=0.1,
    epochs=20,
    batch_size=64,
    sample_weight = sample_weight
)
```

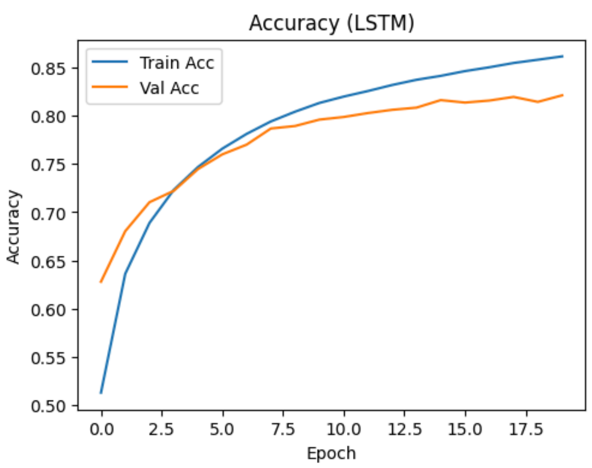
```
Epoch 1/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 153s 1s/step - accuracy: 0.4310 - loss: 0.2563 - val_accuracy: 0.6280 - val_loss: 0.1717
Epoch 2/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 129s 1s/step - accuracy: 0.6226 - loss: 0.1600 - val_accuracy: 0.6803 - val_loss: 0.1453
Epoch 3/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 130s 1s/step - accuracy: 0.6784 - loss: 0.1348 - val_accuracy: 0.7104 - val_loss: 0.1301
Epoch 4/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 131s 1s/step - accuracy: 0.7195 - loss: 0.1189 - val_accuracy: 0.7222 - val_loss: 0.1221
Epoch 5/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 130s 1s/step - accuracy: 0.7417 - loss: 0.1093 - val_accuracy: 0.7447 - val_loss: 0.1126
Epoch 6/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 140s 1s/step - accuracy: 0.7617 - loss: 0.1016 - val_accuracy: 0.7599 - val_loss: 0.1066
Epoch 7/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 131s 1s/step - accuracy: 0.7798 - loss: 0.0950 - val_accuracy: 0.7700 - val_loss: 0.1016
Epoch 8/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.7924 - loss: 0.0881 - val_accuracy: 0.7867 - val_loss: 0.0971
Epoch 9/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 140s 1s/step - accuracy: 0.8025 - loss: 0.0844 - val_accuracy: 0.7893 - val_loss: 0.0946
Epoch 10/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 127s 1s/step - accuracy: 0.8118 - loss: 0.0815 - val_accuracy: 0.7959 - val_loss: 0.0922
Epoch 11/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 125s 1s/step - accuracy: 0.8184 - loss: 0.0779 - val_accuracy: 0.7986 - val_loss: 0.0909
Epoch 12/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 142s 1s/step - accuracy: 0.8249 - loss: 0.0750 - val_accuracy: 0.8027 - val_loss: 0.0895
Epoch 13/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 140s 1s/step - accuracy: 0.8323 - loss: 0.0725 - val_accuracy: 0.8061 - val_loss: 0.0872
Epoch 14/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 127s 1s/step - accuracy: 0.8381 - loss: 0.0697 - val_accuracy: 0.8083 - val_loss: 0.0864
Epoch 15/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 142s 1s/step - accuracy: 0.8410 - loss: 0.0685 - val_accuracy: 0.8161 - val_loss: 0.0833
Epoch 16/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 132s 1s/step - accuracy: 0.8463 - loss: 0.0669 - val_accuracy: 0.8136 - val_loss: 0.0844
Epoch 17/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 130s 1s/step - accuracy: 0.8509 - loss: 0.0642 - val_accuracy: 0.8157 - val_loss: 0.0827
Epoch 18/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 143s 1s/step - accuracy: 0.8547 - loss: 0.0631 - val_accuracy: 0.8194 - val_loss: 0.0812
Epoch 19/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 134s 1s/step - accuracy: 0.8578 - loss: 0.0612 - val_accuracy: 0.8143 - val_loss: 0.0840
Epoch 20/20
114/114 ━━━━━━━━━━━━━━━━━━━━ 132s 1s/step - accuracy: 0.8611 - loss: 0.0599 - val_accuracy: 0.8211 - val_loss: 0.0801
```

In [9]:
```
import matplotlib.pyplot as plt
```

In [10]:
```
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label="Train Loss")
plt.plot(history.history['val_loss'], label="Val Loss")
plt.title("Loss (LSTM)")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label="Train Acc")
plt.plot(history.history['val_accuracy'], label="Val Acc")
plt.title("Accuracy (LSTM)")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```





In [11]:
```
model.save('pos_lstm_model.keras')
```

In [12]:
```
test_loss, test_acc = model.evaluate(X_test, y_test, sample_weight=np.where(np.argmax(y_test, axis=-1) != 0, 1.0, 0.0))
print(f"\nTest Loss: {test_loss:.4f} | Test Accuracy: {test_acc:.4f}")
```

```
23/23 ━━━━━━━━━━━━━━━━━━━━ 2s 98ms/step - accuracy: 0.8251 - loss: 0.0716

Test Loss: 0.0728 | Test Accuracy: 0.8246
```

In [13]:
```
import numpy as np
y_pred = model.predict(X_test)
y_pred_ids = np.argmax(y_pred, axis=-1)
y_true_ids = np.argmax(y_test, axis=-1)

# Reverse label index
idx2label = {i: l for l, i in dataset.label2id.items()}

# Show sample predictions
for i in range(3):
    print(f"\n--- Sentence {i+1} ---")
    for j in range(seq_len):
        word_vec = X_test[i, j]
        if np.all(word_vec == 0): continue  # padding

        pred_label = idx2label.get(y_pred_ids[i, j]-1, "UNK")
        true_label = idx2label.get(y_true_ids[i, j]-1, "UNK")
        print(f"{j:2}: Pred: {pred_label:6} | True: {true_label}")
```

```
23/23 ━━━━━━━━━━━━━━━━━━━━ 7s 203ms/step

--- Sentence 1 ---
 0: Pred: INTJ   | True: INTJ
 1: Pred: PART   | True: PART
 2: Pred: SCONJ  | True: SCONJ
 3: Pred: INTJ   | True: SCONJ
 4: Pred: ADP    | True: ADP
 5: Pred: PART   | True: PART
 6: Pred: ADV    | True: ADV
 7: Pred: SCONJ  | True: SCONJ
 8: Pred: ADJ    | True: ADJ
 9: Pred: INTJ   | True: INTJ
10: Pred: PROPN  | True: PROPN

--- Sentence 2 ---
 0: Pred: ADJ    | True: ADJ
 1: Pred: SCONJ  | True: INTJ
 2: Pred: PART   | True: PART
 3: Pred: INTJ   | True: SCONJ
 4: Pred: CCONJ  | True: CCONJ
 5: Pred: INTJ   | True: INTJ
 6: Pred: ADJ    | True: ADJ
 7: Pred: INTJ   | True: INTJ
 8: Pred: ADJ    | True: <PAD>
 9: Pred: ADJ    | True: ADJ
10: Pred: SCONJ  | True: INTJ
11: Pred: AUX    | True: AUX
12: Pred: CCONJ  | True: CCONJ
13: Pred: INTJ   | True: INTJ
14: Pred: PART   | True: PART
15: Pred: PART   | True: PART
16: Pred: SCONJ  | True: SCONJ
17: Pred: INTJ   | True: ADJ
18: Pred: CCONJ  | True: PART
19: Pred: PROPN  | True: PROPN

--- Sentence 3 ---
 0: Pred: AUX    | True: ADV
 1: Pred: CCONJ  | True: CCONJ
 2: Pred: INTJ   | True: INTJ
 3: Pred: ADJ    | True: ADJ
 4: Pred: NOUN   | True: NOUN
 5: Pred: INTJ   | True: INTJ
 6: Pred: PROPN  | True: PROPN
 7: Pred: INTJ   | True: ADP
 8: Pred: SCONJ  | True: INTJ
 9: Pred: AUX    | True: AUX
10: Pred: SCONJ  | True: SCONJ
11: Pred: ADJ    | True: ADJ
12: Pred: INTJ   | True: INTJ
13: Pred: ADJ    | True: ADJ
14: Pred: CCONJ  | True: CCONJ
15: Pred: INTJ   | True: INTJ
16: Pred: ADJ    | True: ADJ
17: Pred: CCONJ  | True: CCONJ
18: Pred: NOUN   | True: NOUN
19: Pred: INTJ   | True: INTJ
20: Pred: ADJ    | True: ADJ
21: Pred: INTJ   | True: INTJ
22: Pred: PROPN  | True: PROPN
```

In [14]:
```
np.argmax(y_test, axis=-1)[0]
```

Out[14]:
```
array([ 8, 11, 15, 15,  3, 11,  4, 15,  2,  8, 13,  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,  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,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0])
```

In [15]:
```
y_true_flat = y_true_ids.reshape((-1,))
y_pred_flat = y_pred_ids.reshape((-1,))
mask = (y_true_flat != 0)
y_true_flat = y_true_flat[mask]
y_pred_flat = y_pred_flat[mask]

np.max(y_true_flat), np.min(y_true_flat), np.max(y_pred_flat), np.min(y_pred_flat)

np.sum(y_true_flat==7), np.sum(y_pred_flat==7)
```

Out[15]:
```
(np.int64(6), np.int64(0))
```

In [16]:

```
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
from matplotlib.colors import LogNorm

# Compute confusion matrix
labels = dataset.labels
label_ids = list(range(len(labels)))

print("Classification Report:")
print(classification_report(y_true_flat, y_pred_flat, labels=label_ids, target_names=labels))

cm = confusion_matrix(y_true_flat, y_pred_flat, labels=label_ids)

# Plot with log scale
plt.figure(figsize=(12, 10))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', norm=LogNorm(vmin=1, vmax=cm.max()),
            xticklabels=labels, yticklabels=labels, cbar_kws={'label': 'Log-scaled count'})
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("Confusion Matrix (LSTM)")
plt.tight_layout()
plt.show()
```

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

       <PAD>       0.00      0.00      0.00         0
         ADJ       0.65      0.50      0.57      1172
         ADP       0.95      0.98      0.96      2333
         ADV       0.67      0.64      0.65       650
         AUX       0.89      0.90      0.89       618
       CCONJ       0.95      0.96      0.95       471
         DET       0.84      0.81      0.82       898
        INTJ       0.00      0.00      0.00         6
        NOUN       0.74      0.85      0.79      4042
         NUM       0.86      0.75      0.80       456
        PART       0.94      0.90      0.92       358
        PRON       0.81      0.74      0.77       862
       PROPN       0.72      0.65      0.68       455
       PUNCT       0.97      1.00      0.98      2083
       SCONJ       0.73      0.77      0.75       154
        VERB       0.79      0.70      0.74      1749
           X       1.00      0.18      0.30        17

    accuracy                           0.82     16324
   macro avg       0.74      0.67      0.68     16324
weighted avg       0.82      0.82      0.82     16324
```

```
d:\anu1m\sem2\NLP\soft\PoSTagging\.venv\lib\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: Precision is i
ll-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
d:\anu1m\sem2\NLP\soft\PoSTagging\.venv\lib\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: Recall is ill-
defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
d:\anu1m\sem2\NLP\soft\PoSTagging\.venv\lib\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: F-score is ill
-defined and being set to 0.0 in labels with no true nor predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
d:\anu1m\sem2\NLP\soft\PoSTagging\.venv\lib\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: Precision is i
ll-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
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d:\anu1m\sem2\NLP\soft\PoSTagging\.venv\lib\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: Precision is i
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  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
d:\anu1m\sem2\NLP\soft\PoSTagging\.venv\lib\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: Recall is ill-
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  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
d:\anu1m\sem2\NLP\soft\PoSTagging\.venv\lib\site-packages\sklearn\metrics\_classification.py:1565: UndefinedMetricWarning: F-score is ill
-defined and being set to 0.0 in labels with no true nor predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

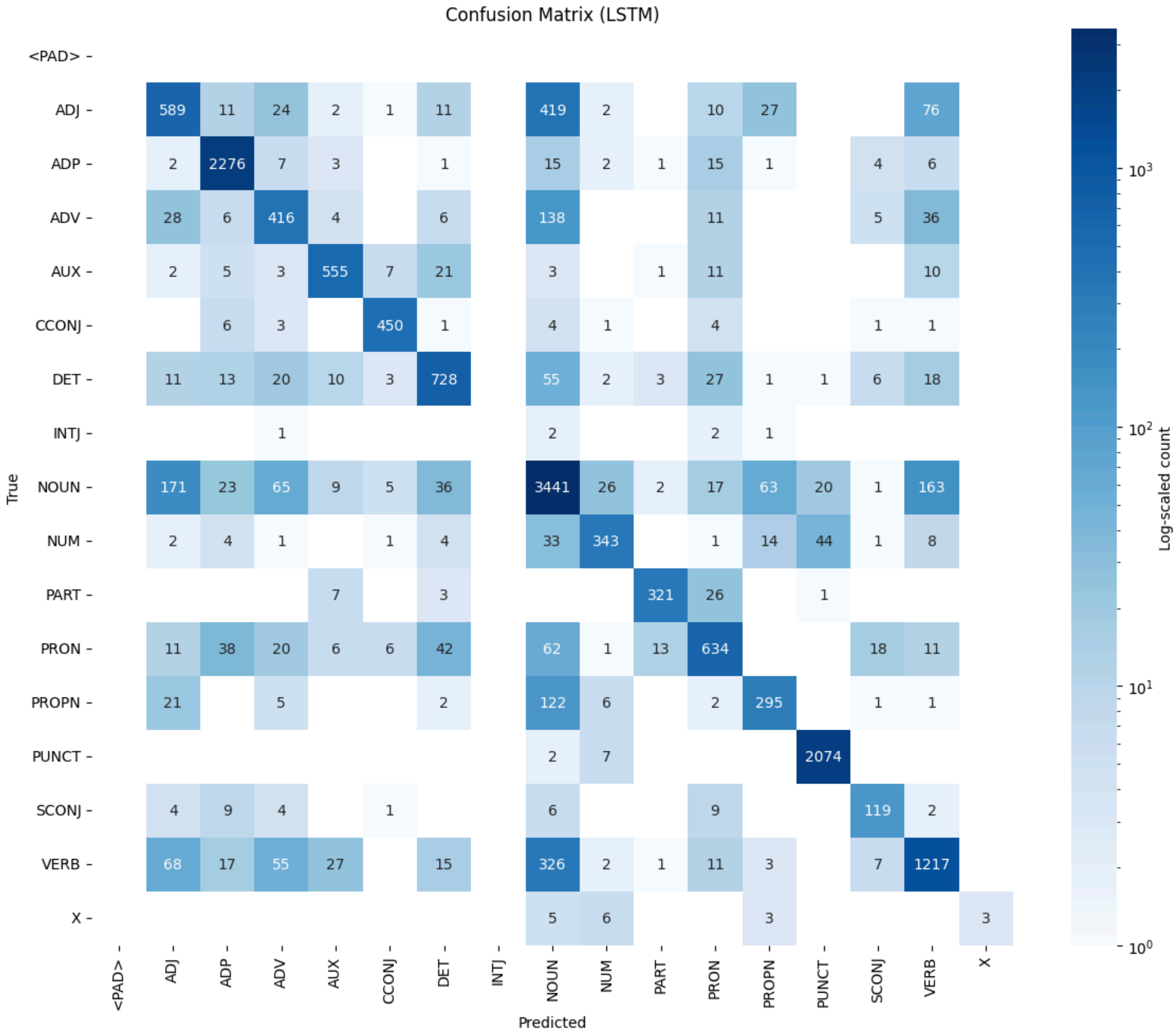

Confusion Matrix (LSTM)
True
Predicted
Log-scaled count
<PAD>
ADJ
ADP
ADV
AUX
CCONJ
DET
INTJ
NOUN
NUM
PART
PRON
PROPN
PUNCT
SCONJ
VERB
X