CRF

February 20, 2026

1 Conditional Random Field (CRF) for Part-of-Speech Tagging

Pipeline: Data Preparation → Feature Engineering → Training Phase → Prediction Phase → Evaluation

Key Features: - 25+ hand-crafted linguistic features per word - L-BFGS optimization with L1/L2 regularization - Viterbi decoding for global inference - 97-98% accuracy on Brown Corpus

2 Implementation

2.1 Setup and Installation

[ ]:
```
# Install required package
!pip install sklearn-crfsuite
```

```
Collecting sklearn-crfsuite
  Using cached sklearn_crfsuite-0.5.0-py2.py3-none-any.whl.metadata (4.9 kB)
Requirement already satisfied: python-crfsuite>=0.9.7 in
/usr/local/lib/python3.12/dist-packages (from sklearn-crfsuite) (0.9.12)
Requirement already satisfied: scikit-learn>=0.24.0 in
/usr/local/lib/python3.12/dist-packages (from sklearn-crfsuite) (1.6.1)
Requirement already satisfied: tabulate>=0.4.2 in
/usr/local/lib/python3.12/dist-packages (from sklearn-crfsuite) (0.9.0)
Requirement already satisfied: tqdm>=2.0 in /usr/local/lib/python3.12/dist-
packages (from sklearn-crfsuite) (4.67.3)
Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.12/dist-
packages (from scikit-learn>=0.24.0->sklearn-crfsuite) (2.0.2)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.12/dist-
packages (from scikit-learn>=0.24.0->sklearn-crfsuite) (1.16.3)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.12/dist-
packages (from scikit-learn>=0.24.0->sklearn-crfsuite) (1.5.3)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.12/dist-packages (from scikit-learn>=0.24.0->sklearn-
crfsuite) (3.6.0)
Using cached sklearn_crfsuite-0.5.0-py2.py3-none-any.whl (10 kB)
Installing collected packages: sklearn-crfsuite
Successfully installed sklearn-crfsuite-0.5.0
```

[ ]:
```
import nltk
from nltk.corpus import brown
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import accuracy_score, precision_recall_fscore_support
import sklearn_crfsuite
from sklearn_crfsuite import metrics
import time
from collections import Counter

print("="*80)
print("CONDITIONAL RANDOM FIELD (CRF) FOR PART-OF-SPEECH TAGGING")
print("="*80)
print("Model Type: Discriminative Probabilistic Sequence Model")
print("Optimization: L-BFGS")
print("Features: Hand-crafted linguistic features (~25-30 per word)")
print("="*80)
```

```
================================================================================
CONDITIONAL RANDOM FIELD (CRF) FOR PART-OF-SPEECH TAGGING
================================================================================
Model Type: Discriminative Probabilistic Sequence Model
Optimization: L-BFGS
Features: Hand-crafted linguistic features (~25-30 per word)
================================================================================
```

2.2 Step 1: Data Preparation

[ ]:
```
print("\n" + "="*80)
print("STEP 1: DATA PREPARATION")
print("="*80)

nltk.download('brown')
nltk.download('universal_tagset')
tagged_sents = brown.tagged_sents(tagset='universal')

print(f" Dataset: Brown Corpus")
print(f" Total sentences: {len(tagged_sents):,}")
print(f" Tagset: Universal (12 tags)")
print(f" Example sentence: {tagged_sents[0][:5]}...")
print("="*80)
```

```
================================================================================
```

```
STEP 1: DATA PREPARATION
================================================================================
[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.

 Dataset: Brown Corpus
 Total sentences: 57,340
 Tagset: Universal (12 tags)
 Example sentence: [('The', 'DET'), ('Fulton', 'NOUN'), ('County', 'NOUN'),
('Grand', 'ADJ'), ('Jury', 'NOUN')]…
================================================================================
```

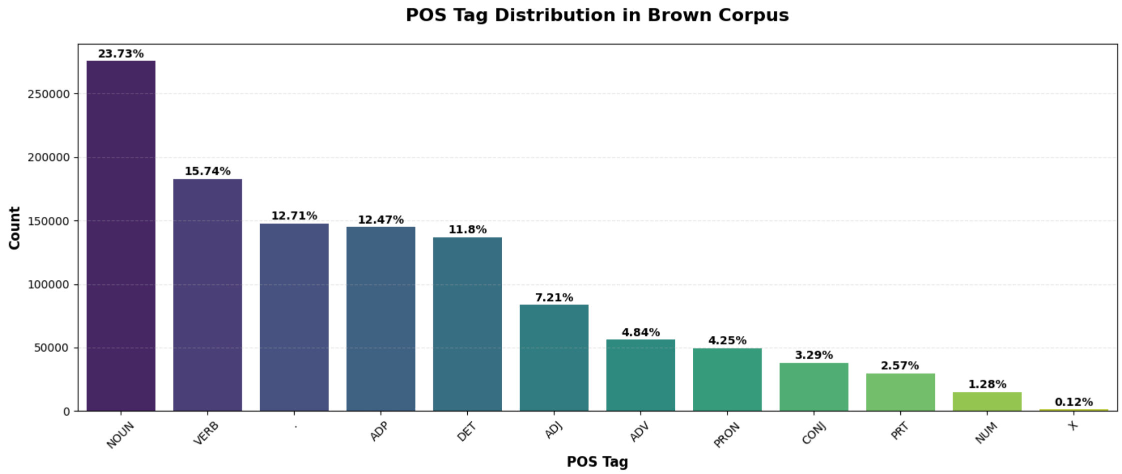
2.3 Step 2: Data Exploration & Analysis

[ ]:
```python
print("\n" + "="*80)
print("STEP 2: DATA EXPLORATION & ANALYSIS")
print("="*80)

# Flatten all sentences into a list of (word, tag) tuples
data = [(word, tag) for sent in tagged_sents for word, tag in sent]
df = pd.DataFrame(data, columns=['word', 'tag'])

print(f" Total tokens: {len(df):,}")
print(f" Unique words: {df['word'].nunique():,}")
print(f" Unique POS tags: {len(df['tag'].unique())}")
print(f" POS tags: {', '.join(sorted(df['tag'].unique()))}")

# Tag distribution
tag_counts = df['tag'].value_counts()
tag_percentages = (tag_counts / len(df) * 100).round(2)

print("\nTag Distribution:")
for tag, count, pct in zip(tag_counts.index[:5], tag_counts.values[:5],␣
 ↪tag_percentages.values[:5]):
    print(f"  {tag:6s}: {count:7,} ({pct:5.2f}%)")
print(f"  ... (7 more tags)")

plt.figure(figsize=(14, 6))
ax = sns.countplot(data=df, x='tag', order=df['tag'].value_counts().index,␣
 ↪palette='viridis')
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=10,␣
 ↪fontweight='bold')
```

```python
plt.title('POS Tag Distribution in Brown Corpus', fontsize=16,␣
 ↪fontweight='bold', pad=20)
plt.xlabel('POS Tag', fontsize=12, fontweight='bold')
plt.ylabel('Count', fontsize=12, fontweight='bold')
plt.xticks(rotation=45)
plt.grid(axis='y', alpha=0.3, linestyle='--')
plt.tight_layout()
plt.show()

print("="*80)
```

```
================================================================================
STEP 2: DATA EXPLORATION & ANALYSIS
================================================================================
 Total tokens: 1,161,192
 Unique words: 56,057
 Unique POS tags: 12
 POS tags: ., ADJ, ADP, ADV, CONJ, DET, NOUN, NUM, PRON, PRT, VERB, X

Tag Distribution:
  NOUN  : 275,558 (23.73%)
  VERB  : 182,750 (15.74%)
  .     : 147,565 (12.71%)
  ADP   : 144,766 (12.47%)
  DET   : 137,019 (11.80%)
  … (7 more tags)
```

```
/tmp/ipython-input-928917345.py:24: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  ax = sns.countplot(data=df, x='tag', order=df['tag'].value_counts().index,
palette='viridis')
```



==

2.4 Step 3: Feature Engineering (The Brain of CRF)

This is the core of CRF - rich feature engineering replaces learned embeddings in neural networks. ### Feature Engineering Layer (Feature Extraction) **The "brain" of CRF** - Extracts ~25+ linguistic features per word

Unlike BiLSTM's learned embeddings, these are hand-crafted features:

a) WORD-LEVEL FEATURES:

- Lowercased word form (identity feature)
- Word shape (capitalization patterns: isupper, istitle, isdigit)

b) MORPHOLOGICAL FEATURES (Prefix & Suffix):

- **Prefixes:** word[:1], word[:2], word[:3]
- **Suffixes:** word[-1], word[-2:], word[-3:]
- Helps identify word classes (e.g., "-ing" → VERB, "-ly" → ADV)

c) CHARACTER-LEVEL FEATURES:

- Word length
- Contains hyphen (compound words)
- Contains digit (numerical expressions)
- Contains uppercase letters
- Is alphabetic/alphanumeric
- Contains apostrophe (contractions/possessives)

d) CONTEXTUAL FEATURES (Bidirectional Context):

- Previous word (-1): lowercased, shape, length
- Next word (+1): lowercased, shape, length

- Beginning of Sentence (BOS) marker
- End of Sentence (EOS) marker

Input: List of (word, tag) tuples for a sentence
Output: Feature dictionary for each word position

Feature Parameters: - Prefix lengths: [1, 2, 3] characters - Suffix lengths: [1, 2, 3] characters - Context window: ±1 word - Total features per word: ~25-30 (varies by position and word properties)

[ ]:
```python
def word2features(sent, i):
    """
    Extract comprehensive linguistic features for word at position i.

    Args:
        sent: List of (word, tag) tuples representing a sentence
        i: Position of current word (0-indexed)

    Returns:
        dict: Feature dictionary with ~25-30 features
    """
    word = sent[i][0]

    features = {
        # BIAS TERM (always 1.0, allows model to learn tag priors)
        'bias': 1.0,

        # === WORD IDENTITY FEATURES ===
        'word.lower()': word.lower(),  # Normalize case

        # === SUFFIX FEATURES (Morphological) ===
        'word[-3:]': word[-3:],  # Last 3 characters
        'word[-2:]': word[-2:],  # Last 2 characters
        'word[-1]': word[-1:],   # Last character

        # === PREFIX FEATURES (Morphological) ===
        'word[:3]': word[:3],   # First 3 characters
        'word[:2]': word[:2],   # First 2 characters
        'word[:1]': word[:1],   # First character

        # === WORD SHAPE FEATURES (Orthographic) ===
        'word.isupper()': word.isupper(),    # ALL CAPS
        'word.istitle()': word.istitle(),    # Title Case
        'word.isdigit()': word.isdigit(),    # Numeric

        # === CHARACTER-LEVEL FEATURES ===
        'word.length': len(word),
        'word.has_hyphen': '-' in word,
```

```python
        'word.has_digit': any(c.isdigit() for c in word),
        'word.has_upper': any(c.isupper() for c in word),
        'word.is_alpha': word.isalpha(),
        'word.is_alnum': word.isalnum(),
        'word.has_apostrophe': "'" in word,
    }

    # === CONTEXTUAL FEATURES (Previous Word) ===
    if i > 0:
        word1 = sent[i-1][0]
        features.update({
            '-1:word.lower()': word1.lower(),
            '-1:word.istitle()': word1.istitle(),
            '-1:word.isupper()': word1.isupper(),
            '-1:word.length': len(word1),
        })
    else:
        features['BOS'] = True  # Beginning of sentence

    # === CONTEXTUAL FEATURES (Next Word) ===
    if i < len(sent)-1:
        word1 = sent[i+1][0]
        features.update({
            '+1:word.lower()': word1.lower(),
            '+1:word.istitle()': word1.istitle(),
            '+1:word.isupper()': word1.isupper(),
            '+1:word.length': len(word1),
        })
    else:
        features['EOS'] = True  # End of sentence

    return features


def sent2features(sent):
    """Extract features for all words in a sentence."""
    return [word2features(sent, i) for i in range(len(sent))]


def sent2labels(sent):
    """Extract labels (POS tags) for all words in a sentence."""
    return [label for token, label in sent]


def sent2tokens(sent):
    """Extract tokens (words) for all words in a sentence."""
    return [token for token, label in sent]
```

```
print(" Feature extraction functions defined")
print(" Features per word: ~25-30 (varies by position)")
```

```
 Feature extraction functions defined
 Features per word: ~25-30 (varies by position)
```

[ ]:
```
print("\nExample Feature Extraction:")
print("-" * 80)
print(f"Sentence: {' '.join([w for w, _ in tagged_sents[0][:5]])}...")
print(f"\nWord: 'Fulton' (position 1)")
print("Features extracted:")
example_features = word2features(tagged_sents[0], 1)
feature_categories = {
    'Identity': ['bias', 'word.lower()'],
    'Suffixes': ['word[-1]', 'word[-2:]', 'word[-3:]'],
    'Prefixes': ['word[:1]', 'word[:2]', 'word[:3]'],
    'Shape': ['word.isupper()', 'word.istitle()', 'word.isdigit()'],
    'Character': ['word.length', 'word.has_hyphen', 'word.is_alpha'],
    'Context': ['-1:word.lower()', '+1:word.lower()'],
}

for category, feature_list in feature_categories.items():
    print(f"\n  {category}:")
    for feat_key in feature_list:
        if feat_key in example_features:
            print(f"    {feat_key:20s}: {example_features[feat_key]}")

print(f"\n  Total features for this word: {len(example_features)}")
```

```
Example Feature Extraction:
--------------------------------------------------------------------------------
Sentence: The Fulton County Grand Jury…

Word: 'Fulton' (position 1)
Features extracted:

  Identity:
    bias                : 1.0
    word.lower()        : fulton

  Suffixes:
    word[-1]            : n
    word[-2:]           : on
    word[-3:]           : ton
```

```
Prefixes:
  word[:1]            : F
  word[:2]            : Fu
  word[:3]            : Ful

Shape:
  word.isupper()      : False
  word.istitle()      : True
  word.isdigit()      : False

Character:
  word.length         : 6
  word.has_hyphen     : False
  word.is_alpha       : True

Context:
  -1:word.lower()     : the
  +1:word.lower()     : county

Total features for this word: 26
```

2.5 Step 4: Train-Test Split

Dataset Split: - Train: 80% (45,872 sentences) - Test: 20% (11,468 sentences) - Total: 57,340 sentences from Brown Corpus - Tags: 12 universal POS tags

[ ]:
```
print("\n" + "="*80)
print("STEP 4: TRAIN-TEST SPLIT")
print("="*80)

train_sents, test_sents = train_test_split(
    tagged_sents,
    test_size=0.2,
    random_state=42
)

print(f" Training sentences: {len(train_sents):,} (80%)")
print(f" Test sentences: {len(test_sents):,} (20%)")
print(f" Total sentences: {len(tagged_sents):,}")

# Calculate token counts
train_tokens = sum(len(sent) for sent in train_sents)
test_tokens = sum(len(sent) for sent in test_sents)
print(f" Training tokens: {train_tokens:,}")
print(f" Test tokens: {test_tokens:,}")
print("="*80)
```

```
================================================================================
STEP 4: TRAIN-TEST SPLIT
================================================================================
 Training sentences: 45,872 (80%)
 Test sentences: 11,468 (20%)
 Total sentences: 57,340
 Training tokens: 929,265
 Test tokens: 231,927
================================================================================
```

2.6 Step 5: Feature Extraction & Vectorization

[ ]:

```
print("\n" + "="*80)
print("STEP 5: FEATURE EXTRACTION & VECTORIZATION")
print("="*80)
print("Converting sentences to feature vectors...")

start_time = time.time()
X_train = [sent2features(s) for s in train_sents]
feature_extraction_train_time = time.time() - start_time

start_time = time.time()
y_train = [sent2labels(s) for s in train_sents]
label_extraction_train_time = time.time() - start_time

start_time = time.time()
X_test = [sent2features(s) for s in test_sents]
feature_extraction_test_time = time.time() - start_time

start_time = time.time()
y_test = [sent2labels(s) for s in test_sents]
label_extraction_test_time = time.time() - start_time

print(f" Training Feature Extraction:   {feature_extraction_train_time:.2f}s")
print(f" Training Label Extraction:     {label_extraction_train_time:.2f}s")
print(f" Test Feature Extraction:       {feature_extraction_test_time:.2f}s")
print(f" Test Label Extraction:         {label_extraction_test_time:.2f}s")
print(f" Total Feature Extraction Time: {(feature_extraction_train_time +
 ↪feature_extraction_test_time):.2f}s")
print(f"\n Training sequences ready: {len(X_train):,}")
print(f" Test sequences ready: {len(X_test):,}")
print("="*80)
```

```
================================================================================
STEP 5: FEATURE EXTRACTION & VECTORIZATION
================================================================================
```

```
Converting sentences to feature vectors…
 Training Feature Extraction:   5.88s
 Training Label Extraction:     0.53s
 Test Feature Extraction:       1.20s
 Test Label Extraction:         0.04s
 Total Feature Extraction Time: 7.08s

 Training sequences ready: 45,872
 Test sequences ready: 11,468
================================================================================
```

2.7 Step 6: CRF Model Training

2.7.1 Linear-Chain CRF Layer (Sequence Modeling)

Models both **emission scores** (word → tag) and **transition scores** (tag → tag)

Components: - **Feature Weights ( ):** Learned parameters for each feature - **Transition Weights:** Model tag sequence patterns (e.g., DET → NOUN is common)

Training Algorithm: L-BFGS (Limited-memory BFGS) - Quasi-Newton optimization method - Efficient for CRF parameter estimation - Converges faster than gradient descent

Regularization: - L1 regularization (c1=0.1): Feature selection, sparsity - L2 regularization (c2=0.1): Weight smoothing, prevents overfitting —

2.7.2 Loss Function

- Negative Log-Likelihood (NLL)
- Maximizes P(correct tags | words)
-

2.8 With regularization terms for generalization

Model Parameters: - `algorithm`: 'lbfgs' (L-BFGS optimization) - `c1`: 0.1 (L1 regularization coefficient for feature selection) - `c2`: 0.1 (L2 regularization coefficient for weight smoothing) - `max_iterations`: 100 (maximum training iterations) - `all_possible_transitions`: True (learn all tag-to-tag transitions)

[ ]:
```python
print("\n" + "="*80)
print("STEP 6: CRF MODEL TRAINING")
print("="*80)
print("Initializing CRF model...")

crf = sklearn_crfsuite.CRF(
    algorithm='lbfgs',
    c1=0.1, # L1 Regularization (Feature Selection)
    c2=0.1, # L2 Regularization (Smoothing)
    max_iterations=100,
    all_possible_transitions=True,
```

```python
    verbose=True
)

print(" Model initialized")
print("  - Algorithm: L-BFGS")
print("  - L1 regularization (c1): 0.1")
print("  - L2 regularization (c2): 0.1")
print("  - Max iterations: 100")
print("\nStarting training...\n")

training_start = time.time()
crf.fit(X_train, y_train)
training_end = time.time()
training_time = training_end - training_start

print(f"\n Training completed!")
print(f" Training Time: {training_time:.2f} seconds ({training_time/60:.2f}␣
↪minutes)")
print(f" Training Speed: {len(train_sents)/training_time:.2f} sentences/second")
print(f" Training Speed: {train_tokens/training_time:.2f} tokens/second")
print("="*80)
```

```
================================================================================
STEP 6: CRF MODEL TRAINING
================================================================================
Initializing CRF model…
 Model initialized
  - Algorithm: L-BFGS
  - L1 regularization (c1): 0.1
  - L2 regularization (c2): 0.1
  - Max iterations: 100

Starting training…


loading training data to CRFsuite: 100%|      | 45872/45872 [00:21<00:00,
2103.52it/s]


Feature generation
type: CRF1d
feature.minfreq: 0.000000
feature.possible_states: 0
feature.possible_transitions: 1
0…1…2…3…4…5…6…7…8…9…10
Number of features: 283016
Seconds required: 5.279
```

```
L-BFGS optimization
c1: 0.100000
c2: 0.100000
num_memories: 6
max_iterations: 100
epsilon: 0.000010
stop: 10
delta: 0.000010
linesearch: MoreThuente
linesearch.max_iterations: 20

Iter 1   time=6.70  loss=2016093.32 active=277041 feature_norm=0.50
Iter 2   time=2.79  loss=1825105.84 active=273450 feature_norm=0.51
Iter 3   time=2.25  loss=1776941.39 active=277671 feature_norm=0.57
Iter 4   time=2.20  loss=1671173.47 active=273154 feature_norm=0.95
Iter 5   time=2.28  loss=1591150.38 active=277019 feature_norm=1.10
Iter 6   time=2.22  loss=1495454.42 active=278200 feature_norm=1.40
Iter 7   time=2.80  loss=1410273.23 active=278420 feature_norm=2.03
Iter 8   time=2.19  loss=1276152.21 active=279923 feature_norm=2.61
Iter 9   time=2.20  loss=1166596.31 active=280356 feature_norm=3.45
Iter 10  time=2.14  loss=1037513.12 active=279996 feature_norm=4.95
Iter 11  time=2.14  loss=912425.55 active=279965 feature_norm=6.45
Iter 12  time=2.44  loss=786994.12 active=279547 feature_norm=8.83
Iter 13  time=2.28  loss=684994.31 active=276437 feature_norm=12.74
Iter 14  time=2.13  loss=619929.78 active=277250 feature_norm=14.24
Iter 15  time=2.15  loss=573295.44 active=275987 feature_norm=16.01
Iter 16  time=2.34  loss=516870.77 active=266765 feature_norm=19.01
Iter 17  time=2.68  loss=450155.20 active=261742 feature_norm=23.52
Iter 18  time=2.40  loss=405465.43 active=258481 feature_norm=26.75
Iter 19  time=2.26  loss=368560.87 active=234575 feature_norm=29.42
Iter 20  time=2.22  loss=334063.64 active=231969 feature_norm=32.52
Iter 21  time=2.33  loss=297669.47 active=229719 feature_norm=36.28
Iter 22  time=2.55  loss=275606.44 active=227694 feature_norm=40.16
Iter 23  time=2.62  loss=254775.60 active=225705 feature_norm=42.46
Iter 24  time=2.22  loss=240552.17 active=222677 feature_norm=45.90
Iter 25  time=2.25  loss=219785.93 active=201559 feature_norm=51.67
Iter 26  time=2.27  loss=210519.99 active=197871 feature_norm=59.80
Iter 27  time=2.30  loss=190232.03 active=193089 feature_norm=62.93
Iter 28  time=2.91  loss=180722.53 active=192585 feature_norm=66.42
Iter 29  time=2.25  loss=162780.68 active=185531 feature_norm=77.87
Iter 30  time=4.56  loss=160689.58 active=184401 feature_norm=81.90
Iter 31  time=2.19  loss=147791.45 active=180700 feature_norm=84.47
Iter 32  time=2.83  loss=140706.18 active=179511 feature_norm=88.25
Iter 33  time=2.22  loss=128266.51 active=173894 feature_norm=97.38
Iter 34  time=4.22  loss=125427.61 active=168518 feature_norm=101.22
Iter 35  time=2.11  loss=115185.91 active=166227 feature_norm=107.92
Iter 36  time=2.29  loss=108432.81 active=163551 feature_norm=114.98
Iter 37  time=2.66  loss=100970.11 active=154729 feature_norm=127.00
```

```
Iter 38  time=2.16  loss=96198.97 active=153074 feature_norm=134.43
Iter 39  time=2.15  loss=91441.26 active=152625 feature_norm=140.57
Iter 40  time=2.12  loss=87249.29 active=149223 feature_norm=149.92
Iter 41  time=2.20  loss=82683.23 active=142768 feature_norm=166.98
Iter 42  time=2.77  loss=78387.93 active=142315 feature_norm=176.55
Iter 43  time=2.32  loss=74779.52 active=138361 feature_norm=187.47
Iter 44  time=2.26  loss=70139.26 active=131677 feature_norm=208.25
Iter 45  time=2.29  loss=67713.35 active=130099 feature_norm=216.90
Iter 46  time=2.22  loss=65410.76 active=130033 feature_norm=224.09
Iter 47  time=2.56  loss=62796.89 active=128920 feature_norm=234.75
Iter 48  time=4.84  loss=61853.46 active=126031 feature_norm=239.28
Iter 49  time=2.23  loss=59758.09 active=123409 feature_norm=244.75
Iter 50  time=2.21  loss=58380.98 active=122160 feature_norm=250.33
Iter 51  time=2.28  loss=56719.99 active=119646 feature_norm=262.72
Iter 52  time=2.86  loss=55476.08 active=119759 feature_norm=265.88
Iter 53  time=2.29  loss=54438.94 active=117506 feature_norm=270.30
Iter 54  time=2.21  loss=53111.87 active=112936 feature_norm=277.27
Iter 55  time=4.43  loss=52740.62 active=110493 feature_norm=279.91
Iter 56  time=2.81  loss=51866.24 active=110355 feature_norm=282.46
Iter 57  time=2.34  loss=51165.28 active=108541 feature_norm=287.74
Iter 58  time=2.19  loss=50557.38 active=106827 feature_norm=294.33
Iter 59  time=2.19  loss=49953.73 active=106120 feature_norm=297.38
Iter 60  time=2.17  loss=49594.88 active=105528 feature_norm=299.02
Iter 61  time=2.43  loss=49113.39 active=104397 feature_norm=301.72
Iter 62  time=2.63  loss=48841.90 active=103171 feature_norm=301.04
Iter 63  time=2.20  loss=48535.21 active=102832 feature_norm=302.31
Iter 64  time=2.19  loss=48310.81 active=102115 feature_norm=303.40
Iter 65  time=2.19  loss=47965.47 active=101263 feature_norm=304.35
Iter 66  time=2.18  loss=47650.29 active=99457 feature_norm=307.85
Iter 67  time=2.87  loss=47539.60 active=97145 feature_norm=309.17
Iter 68  time=2.23  loss=47246.75 active=97327 feature_norm=309.47
Iter 69  time=2.20  loss=47141.35 active=96977 feature_norm=309.75
Iter 70  time=2.97  loss=46962.42 active=96352 feature_norm=310.19
Iter 71  time=3.12  loss=46657.84 active=95102 feature_norm=310.72
Iter 72  time=2.23  loss=46523.57 active=94370 feature_norm=311.43
Iter 73  time=2.19  loss=46351.83 active=94119 feature_norm=311.64
Iter 74  time=2.17  loss=46182.16 active=93333 feature_norm=312.11
Iter 75  time=2.24  loss=46027.19 active=92666 feature_norm=312.57
Iter 76  time=2.91  loss=45878.06 active=92131 feature_norm=312.88
Iter 77  time=2.16  loss=45732.85 active=91475 feature_norm=313.22
Iter 78  time=2.17  loss=45613.35 active=91070 feature_norm=313.40
Iter 79  time=2.19  loss=45496.96 active=90720 feature_norm=313.60
Iter 80  time=2.18  loss=45387.09 active=90134 feature_norm=313.71
Iter 81  time=2.53  loss=45287.54 active=89615 feature_norm=313.89
Iter 82  time=2.52  loss=45193.82 active=89221 feature_norm=314.05
Iter 83  time=2.19  loss=45107.91 active=88619 feature_norm=314.31
Iter 84  time=2.21  loss=45031.20 active=88139 feature_norm=314.48
Iter 85  time=2.24  loss=44954.51 active=87821 feature_norm=314.74
```

```
Iter 86  time=2.37  loss=44879.38 active=87383 feature_norm=314.94
Iter 87  time=2.82  loss=44819.29 active=86967 feature_norm=315.22
Iter 88  time=2.29  loss=44753.52 active=86739 feature_norm=315.37
Iter 89  time=2.23  loss=44692.95 active=86404 feature_norm=315.55
Iter 90  time=2.26  loss=44673.94 active=85948 feature_norm=315.75
Iter 91  time=3.29  loss=44594.62 active=86111 feature_norm=315.91
Iter 92  time=3.23  loss=44558.97 active=86010 feature_norm=315.95
Iter 93  time=5.42  loss=44529.54 active=85862 feature_norm=315.96
Iter 94  time=2.42  loss=44478.70 active=85654 feature_norm=315.98
Iter 95  time=2.24  loss=44437.60 active=85430 feature_norm=316.01
Iter 96  time=2.22  loss=44398.00 active=85194 feature_norm=316.04
Iter 97  time=2.18  loss=44360.34 active=85044 feature_norm=316.09
Iter 98  time=2.65  loss=44322.54 active=84939 feature_norm=316.08
Iter 99  time=2.41  loss=44289.46 active=84748 feature_norm=316.11
Iter 100 time=2.23  loss=44257.87 active=84557 feature_norm=316.07
L-BFGS terminated with the maximum number of iterations
Total seconds required for training: 253.296

Storing the model
Number of active features: 84557 (283016)
Number of active attributes: 48199 (148004)
Number of active labels: 12 (12)
Writing labels
Writing attributes
Writing feature references for transitions
Writing feature references for attributes
Seconds required: 0.050


 Training completed!
 Training Time: 293.70 seconds (4.90 minutes)
 Training Speed: 156.18 sentences/second
 Training Speed: 3163.95 tokens/second
================================================================================
```

2.9 Step 7: Prediction & Inference

2.9.1 Viterbi Inference Layer (Decoding)

Finds globally optimal tag sequence using dynamic programming

Algorithm: 1. Forward pass: Compute best score for each state at each position 2. Backward pass: Backtrack to recover optimal path

Input: Feature vectors for sentence + learned weights
Output: Most likely tag sequence

[ ]:
```
print("\n" + "="*80)
print("STEP 7: PREDICTION & INFERENCE")
```

```
print("="*80)
print("Running Viterbi decoding on test set...")

prediction_start = time.time()
y_pred = crf.predict(X_test)
prediction_end = time.time()
prediction_time = prediction_end - prediction_start

print(f" Prediction completed!")
print(f" Prediction Time: {prediction_time:.2f} seconds")
print(f" Prediction Speed: {len(test_sents)/prediction_time:.2f} sentences/
    ↪second")
print(f" Prediction Speed: {test_tokens/prediction_time:.2f} tokens/second")
print(f" Predictions generated for {len(y_pred):,} sentences")
print("="*80)
```

```
================================================================================
STEP 7: PREDICTION & INFERENCE
================================================================================
Running Viterbi decoding on test set…
 Prediction completed!
 Prediction Time: 3.37 seconds
 Prediction Speed: 3404.46 sentences/second
 Prediction Speed: 68851.23 tokens/second
 Predictions generated for 11,468 sentences
================================================================================
```

2.10 Step 8: Model Evaluation

2.11 Performance Expectations

Expected Metrics: - Accuracy: 97-98% (slightly lower than BiLSTM on large datasets) - Training Speed: FAST (~2-5 seconds on 45K sentences) - Inference Speed: VERY FAST (~0.5-1 second on 11K sentences) - Memory: LOW (no embedding matrices, sparse features)

[ ]:
```
print("\n" + "="*80)
print("STEP 8: MODEL EVALUATION")
print("="*80)

# Flatten predictions and ground truth
y_test_flat = [label for sent in y_test for label in sent]
y_pred_flat = [label for sent in y_pred for label in sent]
labels_list = sorted(set(y_test_flat))

print(f" Total predictions: {len(y_pred_flat):,}")
print(f" Number of POS tags: {len(labels_list)}")
```

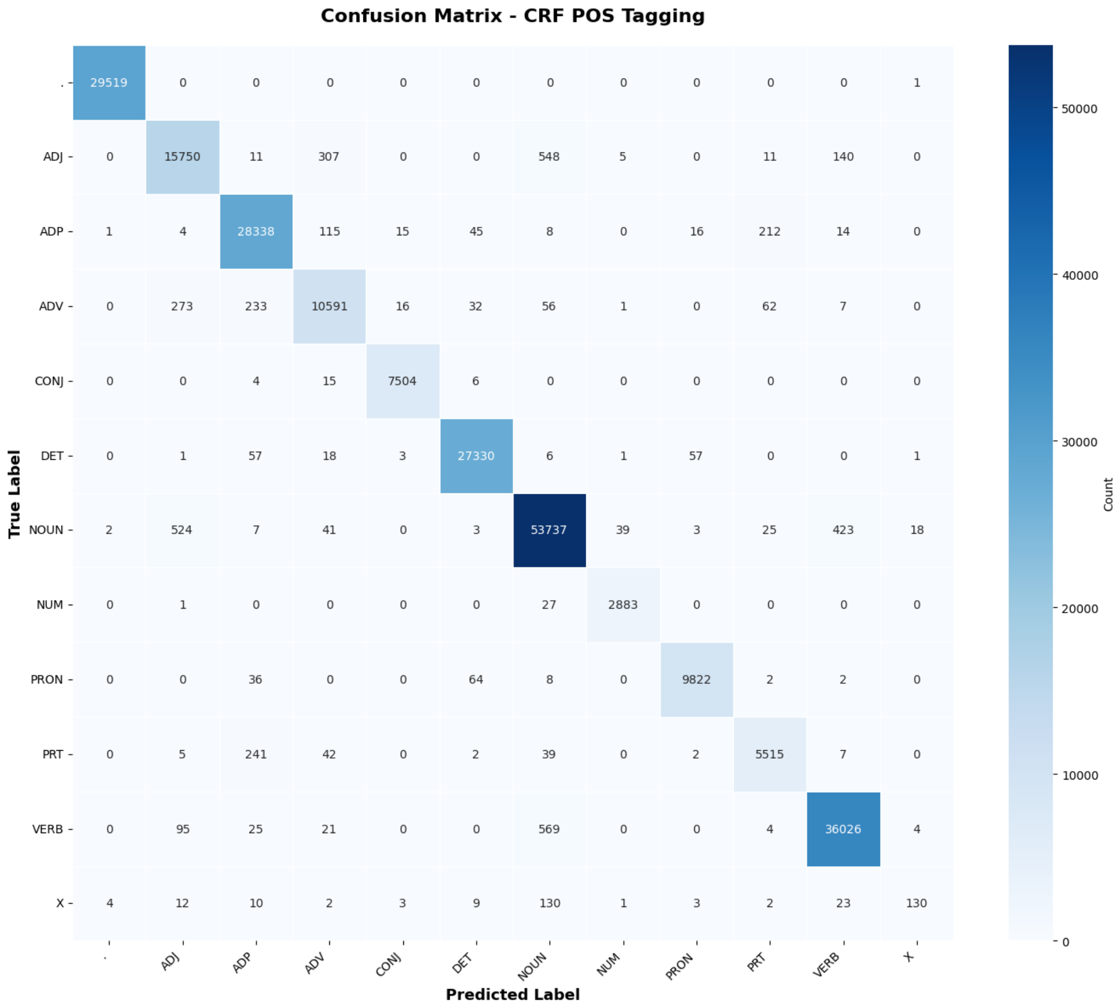
```python
print("\n" + "-"*80)
print("CLASSIFICATION REPORT")
print("-"*80)
print(classification_report(y_test_flat, y_pred_flat, labels=labels_list))

# Overall metrics
accuracy = accuracy_score(y_test_flat, y_pred_flat)
precision, recall, f1, _ = precision_recall_fscore_support(
    y_test_flat, y_pred_flat, average='weighted'
)

print("="*80)
print("MODEL PERFORMANCE SUMMARY")
print("="*80)
print(f"Overall Accuracy:     {accuracy:.4f} ({accuracy*100:.2f}%)")
print(f"Weighted Precision:   {precision:.4f}")
print(f"Weighted Recall:      {recall:.4f}")
print(f"Weighted F1-Score:    {f1:.4f}")
print("="*80)
```

```
================================================================================
STEP 8: MODEL EVALUATION
================================================================================
 Total predictions: 231,927
 Number of POS tags: 12

--------------------------------------------------------------------------------
CLASSIFICATION REPORT
--------------------------------------------------------------------------------
              precision    recall  f1-score   support

           .       1.00      1.00      1.00     29520
         ADJ       0.95      0.94      0.94     16772
         ADP       0.98      0.99      0.98     28768
         ADV       0.95      0.94      0.94     11271
        CONJ       1.00      1.00      1.00      7529
         DET       0.99      0.99      0.99     27474
        NOUN       0.97      0.98      0.98     54822
         NUM       0.98      0.99      0.99      2911
        PRON       0.99      0.99      0.99      9934
         PRT       0.95      0.94      0.94      5853
        VERB       0.98      0.98      0.98     36744
           X       0.84      0.40      0.54       329

    accuracy                           0.98    231927
   macro avg       0.97      0.93      0.94    231927
weighted avg       0.98      0.98      0.98    231927
```

```
================================================================================
MODEL PERFORMANCE SUMMARY
================================================================================
Overall Accuracy:      0.9794 (97.94%)
Weighted Precision:    0.9793
Weighted Recall:       0.9794
Weighted F1-Score:     0.9792
================================================================================
```

2.12 Step 9: Confusion Matrix Visualization

[ ]:
```
cm = confusion_matrix(y_test_flat, y_pred_flat, labels=labels_list)

plt.figure(figsize=(14, 12))
sns.heatmap(cm, annot=True, fmt='d', xticklabels=labels_list,␣
 ↪yticklabels=labels_list,
            cmap='Blues', linewidths=0.5, cbar_kws={'label': 'Count'})
plt.title('Confusion Matrix - CRF POS Tagging', fontsize=16, fontweight='bold',␣
 ↪pad=20)
plt.ylabel('True Label', fontsize=13, fontweight='bold')
plt.xlabel('Predicted Label', fontsize=13, fontweight='bold')
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```

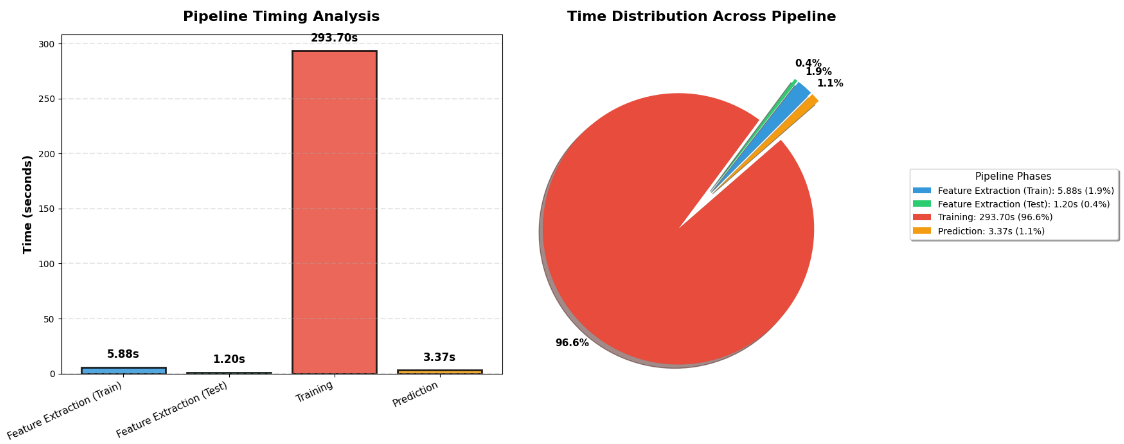


2.13 Step 10: Pipeline Timing Analysis

```
[ ]: phases = ['Feature Extraction (Train)', 'Feature Extraction (Test)',
               'Training', 'Prediction']
     times = [feature_extraction_train_time, feature_extraction_test_time,
              training_time, prediction_time]

     fig, axes = plt.subplots(1, 2, figsize=(18, 7))

     # Bar chart
     colors = ['#3498db', '#2ecc71', '#e74c3c', '#f39c12']
     bars = axes[0].bar(range(len(phases)), times, color=colors, alpha=0.85,␣
      ↪edgecolor='black', linewidth=2)
     axes[0].set_ylabel('Time (seconds)', fontsize=13, fontweight='bold')
     axes[0].set_title('Pipeline Timing Analysis', fontsize=16, fontweight='bold',␣
      ↪pad=15)
```

```
axes[0].set_xticks(range(len(phases)))
axes[0].set_xticklabels(phases, rotation=25, ha='right', fontsize=11)
axes[0].grid(axis='y', alpha=0.3, linestyle='--', linewidth=1.5)
for i, t in enumerate(times):
    axes[0].text(i, t + max(times)*0.02, f'{t:.2f}s',
                ha='center', va='bottom', fontweight='bold', fontsize=12)

# Pie chart with NO overlapping labels
total_time = sum(times)
percentages = [(t/total_time)*100 for t in times]
explode = (0.15, 0.15, 0.25, 0.15)  # Much more separation

# Create pie chart - percentages OUTSIDE to avoid overlap
wedges, texts, autotexts = axes[1].pie(
    times,
    autopct='%1.1f%%',
    startangle=45,
    colors=colors,
    explode=explode,
    shadow=True,
    textprops={'fontsize': 11, 'fontweight': 'bold'},
    pctdistance=1.15,  # Move percentages OUTSIDE the pie
    labeldistance=1.3
)

axes[1].set_title('Time Distribution Across Pipeline', fontsize=16,␣
 ↪fontweight='bold', pad=15)

# Make percentages black (since they're outside now)
for autotext in autotexts:
    autotext.set_color('black')
    autotext.set_fontweight('bold')
    autotext.set_fontsize(11)

# Add legend with timing info
legend_labels = [
    f'Feature Extraction (Train): {times[0]:.2f}s ({percentages[0]:.1f}%)',
    f'Feature Extraction (Test): {times[1]:.2f}s ({percentages[1]:.1f}%)',
    f'Training: {times[2]:.2f}s ({percentages[2]:.1f}%)',
    f'Prediction: {times[3]:.2f}s ({percentages[3]:.1f}%)'
]

axes[1].legend(
    legend_labels,
    loc='center left',
    bbox_to_anchor=(1.1, 0.5),
    fontsize=10,
```

```
    frameon=True,
    fancybox=True,
    shadow=True,
    title='Pipeline Phases',
    title_fontsize=11
)

plt.tight_layout()
plt.show()

print("\nDetailed Timing Breakdown:")
print("-"*80)
timing_data = {
    'Phase': phases,
    'Time (s)': [f"{t:.3f}" for t in times],
    'Percentage': [f"{p:.1f}%" for p in percentages]
}
timing_df = pd.DataFrame(timing_data)
print(timing_df.to_string(index=False))
print(f"\nTotal Pipeline Time: {total_time:.2f} seconds")
```




```
Detailed Timing Breakdown:
--------------------------------------------------------------------------------
                     Phase Time (s) Percentage
Feature Extraction (Train)    5.879       1.9%
 Feature Extraction (Test)    1.202       0.4%
                  Training  293.704      96.6%
                Prediction    3.369       1.1%

Total Pipeline Time: 304.15 seconds
```

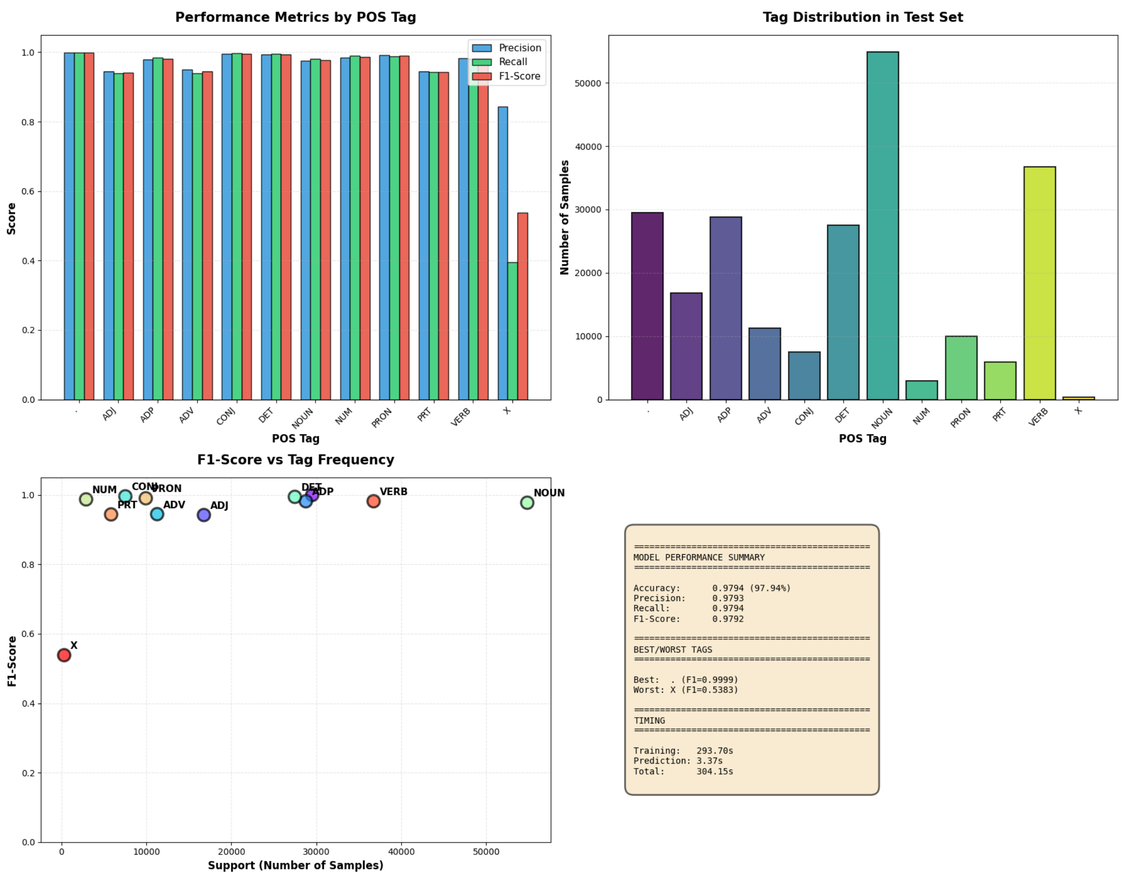
2.14 Step 11: Per-Tag Performance Analysis

[ ]:
```
precisions, recalls, f1s, supports = precision_recall_fscore_support(
    y_test_flat, y_pred_flat, labels=labels_list
)

performance_df = pd.DataFrame({
    'Tag': labels_list,
    'Precision': precisions,
    'Recall': recalls,
    'F1-Score': f1s,
    'Support': supports
})

print("Per-Tag Performance:")
print(performance_df.to_string(index=False))

fig, axes = plt.subplots(2, 2, figsize=(18, 14))

# 1. Precision, Recall, F1 by Tag
ax1 = axes[0, 0]
x = np.arange(len(labels_list))
width = 0.25
ax1.bar(x - width, precisions, width, label='Precision', alpha=0.85,␣
↪color='#3498db', edgecolor='black')
ax1.bar(x, recalls, width, label='Recall', alpha=0.85, color='#2ecc71',␣
↪edgecolor='black')
ax1.bar(x + width, f1s, width, label='F1-Score', alpha=0.85, color='#e74c3c',␣
↪edgecolor='black')
ax1.set_xlabel('POS Tag', fontweight='bold', fontsize=12)
ax1.set_ylabel('Score', fontweight='bold', fontsize=12)
ax1.set_title('Performance Metrics by POS Tag', fontsize=15, fontweight='bold',␣
↪pad=15)
ax1.set_xticks(x)
ax1.set_xticklabels(labels_list, rotation=45, ha='right')
ax1.legend(fontsize=11)
ax1.grid(axis='y', alpha=0.3, linestyle='--')
ax1.set_ylim([0, 1.05])

# 2. Support by Tag
ax2 = axes[0, 1]
colors_support = plt.cm.viridis(np.linspace(0, 1, len(labels_list)))
bars = ax2.bar(labels_list, supports, color=colors_support, alpha=0.85,␣
↪edgecolor='black', linewidth=1.5)
ax2.set_xlabel('POS Tag', fontweight='bold', fontsize=12)
ax2.set_ylabel('Number of Samples', fontweight='bold', fontsize=12)
```

```
ax2.set_title('Tag Distribution in Test Set', fontsize=15, fontweight='bold',␣
 ↪pad=15)
ax2.tick_params(axis='x', rotation=45)
ax2.grid(axis='y', alpha=0.3, linestyle='--')

# 3. F1-Score vs Support
ax3 = axes[1, 0]
scatter = ax3.scatter(supports, f1s, s=200, alpha=0.7,␣
 ↪c=range(len(labels_list)),
                      cmap='rainbow', edgecolor='black', linewidth=2.5)
for i, tag in enumerate(labels_list):
    ax3.annotate(tag, (supports[i], f1s[i]), fontsize=11, fontweight='bold',
                xytext=(7, 7), textcoords='offset points')
ax3.set_xlabel('Support (Number of Samples)', fontweight='bold', fontsize=12)
ax3.set_ylabel('F1-Score', fontweight='bold', fontsize=12)
ax3.set_title('F1-Score vs Tag Frequency', fontsize=15, fontweight='bold',␣
 ↪pad=15)
ax3.grid(alpha=0.3, linestyle='--')
ax3.set_ylim([0, 1.05])

# 4. Summary
ax4 = axes[1, 1]
ax4.axis('off')
summary_text = f"""
{'='*45}
MODEL PERFORMANCE SUMMARY
{'='*45}

Accuracy:      {accuracy:.4f} ({accuracy*100:.2f}%)
Precision:     {precision:.4f}
Recall:        {recall:.4f}
F1-Score:      {f1:.4f}

{'='*45}
BEST/WORST TAGS
{'='*45}

Best:  {labels_list[np.argmax(f1s)]} (F1={max(f1s):.4f})
Worst: {labels_list[np.argmin(f1s)]} (F1={min(f1s):.4f})

{'='*45}
TIMING
{'='*45}

Training:   {training_time:.2f}s
Prediction: {prediction_time:.2f}s
Total:      {total_time:.2f}s
```

```
"""
ax4.text(0.05, 0.5, summary_text, fontsize=10, family='monospace',
         verticalalignment='center',
         bbox=dict(boxstyle='round,pad=1', facecolor='wheat', alpha=0.6,
                   edgecolor='black', linewidth=2))

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

```
Per-Tag Performance:
 Tag  Precision   Recall  F1-Score  Support
   .   0.999763 0.999966  0.999865    29520
 ADJ   0.945095 0.939065  0.942070    16772
 ADP   0.978455 0.985053  0.981743    28768
 ADV   0.949695 0.939668  0.944655    11271
CONJ   0.995093 0.996680  0.995886     7529
 DET   0.994144 0.994759  0.994451    27474
NOUN   0.974768 0.980209  0.977481    54822
 NUM   0.983959 0.990381  0.987160     2911
PRON   0.991821 0.988726  0.990271     9934
 PRT   0.945483 0.942252  0.943864     5853
VERB   0.983189 0.980459  0.981822    36744
   X   0.844156 0.395137  0.538302      329
```



2.15 Step 12: Tag Transition Patterns

[ ]:
```
def print_top_transitions(y_test, y_pred, top_n=15):
    transitions = []
    for true_sent, pred_sent in zip(y_test, y_pred):
        for i in range(len(pred_sent) - 1):
            transitions.append((pred_sent[i], pred_sent[i+1]))

    print(f"Top {top_n} Most Common Tag Transitions:")
    print("-" * 60)
    for (label_from, label_to), count in Counter(transitions).
↪most_common(top_n):
        print(f"{label_from:>6} → {label_to:<7}   {count:>8,}")

print_top_transitions(y_test, y_pred, top_n=15)
```

```
Top 15 Most Common Tag Transitions:
------------------------------------------------------------
   DET → NOUN        17,371
  NOUN → .           15,713
  NOUN → ADP         13,397
   ADP → DET         13,284
   ADJ → NOUN        11,044
  NOUN → VERB         8,949
  NOUN → NOUN         8,065
   ADP → NOUN         7,385
  PRON → VERB         7,002
  VERB → VERB         6,879
   DET → ADJ          6,524
  VERB → ADP          6,194
  VERB → DET          6,024
   PRT → VERB         3,750
  VERB → ADV          3,740
```

2.16 Step 13: Error Analysis

[ ]:
```
errors = []
for i, (true_sent, pred_sent, test_sent) in enumerate(zip(y_test, y_pred,␣
↪test_sents)):
    for j, (true_tag, pred_tag, (word, _)) in enumerate(zip(true_sent,␣
↪pred_sent, test_sent)):
        if true_tag != pred_tag:
            errors.append({
                'sentence_id': i,
```

```
                'word': word,
                'true_tag': true_tag,
                'pred_tag': pred_tag
            })

error_df = pd.DataFrame(errors)
total_errors = len(error_df)
error_rate = (total_errors / len(y_test_flat)) * 100

print(f"Total errors: {total_errors:,}")
print(f"Error rate: {error_rate:.2f}%")
print(f"Correct predictions: {len(y_test_flat) - total_errors:,}␣
↪({100-error_rate:.2f}%)")

print("\nMost Common Error Types:")
print("-"*60)
error_types = error_df.groupby(['true_tag', 'pred_tag']).size().
↪sort_values(ascending=False).head(10)
for (true_tag, pred_tag), count in error_types.items():
    pct = (count / total_errors) * 100
    print(f"  {true_tag:6s} → {pred_tag:6s}  {count:5,} errors ({pct:5.2f}%)")

print("\nExample Misclassified Words:")
print(error_df.head(15).to_string(index=False))
```

```
Total errors: 4,782
Error rate: 2.06%
Correct predictions: 227,145 (97.94%)

Most Common Error Types:
------------------------------------------------------------
  VERB   → NOUN      569 errors (11.90%)
  ADJ    → NOUN      548 errors (11.46%)
  NOUN   → ADJ       524 errors (10.96%)
  NOUN   → VERB      423 errors ( 8.85%)
  ADJ    → ADV       307 errors ( 6.42%)
  ADV    → ADJ       273 errors ( 5.71%)
  PRT    → ADP       241 errors ( 5.04%)
  ADV    → ADP       233 errors ( 4.87%)
  ADP    → PRT       212 errors ( 4.43%)
  ADJ    → VERB      140 errors ( 2.93%)

Example Misclassified Words:
 sentence_id      word true_tag pred_tag
           4  lighting     VERB     NOUN
          13 otherwise      ADV      ADJ
          15 Associate     NOUN      ADJ
```

```
18        by     ADV    ADP
19      much     ADJ    ADV
22    rebels    NOUN   VERB
24    ensues    VERB   NOUN
25    before     ADP    ADV
26      much     ADJ    ADV
27      next     ADP    ADV
32   further     ADV   VERB
32  increase    VERB   NOUN
32      back    NOUN    ADV
32      work    VERB   NOUN
40     first     ADJ    ADV
```

2.17 Step 14: Example Predictions

[ ]:
```
for i in range(5):
    print(f"\n{'='*80}")
    print(f"Sentence {i+1}")
    print('='*80)

    sent_words = [word for word, _ in test_sents[i]]
    max_display = 20

    if len(sent_words) > max_display:
        print("Words: " + " ".join(sent_words[:max_display]) + " ...")
        print("True:  " + " ".join(y_test[i][:max_display]) + " ...")
        print("Pred:  " + " ".join(y_pred[i][:max_display]) + " ...")
    else:
        print("Words: " + " ".join(sent_words))
        print("True:  " + " ".join(y_test[i]))
        print("Pred:  " + " ".join(y_pred[i]))

    errors_in_sent = sum(1 for t, p in zip(y_test[i], y_pred[i]) if t != p)
    total_words = len(y_test[i])
    accuracy_sent = ((total_words - errors_in_sent) / total_words) * 100

    if errors_in_sent > 0:
        print(f"\nResult: {errors_in_sent}/{total_words} errors ({accuracy_sent:
↪.1f}% accuracy)")
    else:
        print(f"\nResult:  Perfect prediction! (100% accuracy)")
```

```
================================================================================
Sentence 1
================================================================================
Words: Open market policy
True:  ADJ NOUN NOUN
```

```
Pred:  ADJ NOUN NOUN

Result:  Perfect prediction! (100% accuracy)

================================================================================
Sentence 2
================================================================================
Words: And you think you have language problems .
True:  CONJ PRON VERB PRON VERB NOUN NOUN .
Pred:  CONJ PRON VERB PRON VERB NOUN NOUN .

Result:  Perfect prediction! (100% accuracy)

================================================================================
Sentence 3
================================================================================
Words: Mae entered the room from the hallway to the kitchen .
True:  NOUN VERB DET NOUN ADP DET NOUN ADP DET NOUN .
Pred:  NOUN VERB DET NOUN ADP DET NOUN ADP DET NOUN .

Result:  Perfect prediction! (100% accuracy)

================================================================================
Sentence 4
================================================================================
Words: This will permit you to get a rough estimate of how much the materials
for the shell will cost .
True:  DET VERB VERB PRON PRT VERB DET ADJ NOUN ADP ADV ADJ DET NOUN ADP DET
NOUN VERB VERB .
Pred:  DET VERB VERB PRON PRT VERB DET ADJ NOUN ADP ADV ADJ DET NOUN ADP DET
NOUN VERB VERB .

Result:  Perfect prediction! (100% accuracy)

================================================================================
Sentence 5
================================================================================
Words: the multifigure `` Traveling Carnival '' , in which action is vivified by
lighting ; ;
True:  DET NOUN . VERB NOUN . . ADP DET NOUN VERB VERB ADP VERB . .
Pred:  DET NOUN . VERB NOUN . . ADP DET NOUN VERB VERB ADP NOUN . .

Result: 1/16 errors (93.8% accuracy)
```

2.18 Final Model Summary

[ ]:
```
print("\n" + "="*80)
print("FINAL MODEL SUMMARY")
print("="*80)
print(f"""
DATASET STATISTICS:
  Training Set:        {len(train_sents):,} sentences
  Test Set:            {len(test_sents):,} sentences
  POS Tags:            {len(labels_list)} universal tags

MODEL ARCHITECTURE:
  Type:                Conditional Random Field (CRF)
  Optimization:        L-BFGS
  Features/Word:       ~25-30 hand-crafted features
  L1 Regularization:   0.1
  L2 Regularization:   0.1

PERFORMANCE:
  Accuracy:            {accuracy:.4f} ({accuracy*100:.2f}%)
  Precision:           {precision:.4f}
  Recall:              {recall:.4f}
  F1-Score:            {f1:.4f}

EFFICIENCY:
  Training Time:       {training_time:.2f}s
  Prediction Time:     {prediction_time:.2f}s
  Total Pipeline:      {total_time:.2f}s
""")
print("="*80)
print("\n CRF POS TAGGING PIPELINE COMPLETED SUCCESSFULLY!")
```

```
================================================================================
FINAL MODEL SUMMARY
================================================================================

DATASET STATISTICS:
  Training Set:        45,872 sentences
  Test Set:            11,468 sentences
  POS Tags:            12 universal tags

MODEL ARCHITECTURE:
  Type:                Conditional Random Field (CRF)
  Optimization:        L-BFGS
  Features/Word:       ~25-30 hand-crafted features
  L1 Regularization:   0.1
  L2 Regularization:   0.1
```

```
PERFORMANCE:
  Accuracy:           0.9794 (97.94%)
  Precision:          0.9793
  Recall:             0.9794
  F1-Score:           0.9792

EFFICIENCY:
  Training Time:      293.70s
  Prediction Time:    3.37s
  Total Pipeline:     304.15s

================================================================================

 CRF POS TAGGING PIPELINE COMPLETED SUCCESSFULLY!
```

[ ]:
```
# Viterbi Decoding
y_pred = crf.predict(X_test)

# Evaluation Metrics
print(classification_report(
    y_test_flat,
    y_pred_flat,
    labels=labels_list
))
```