ITAI 2373 Module 05: Part-of-Speech Tagging

In-Class Exercise & Homework Lab

Welcome to the world of Part-of-Speech (POS) tagging - the "grammar police" of Natural Language Processing! 🚔 📝

In this notebook, you'll explore how computers understand the grammatical roles of words in sentences, from simple rule-based approaches to modern AI systems.

What You'll Learn:

- **Understand POS tagging fundamentals** and why it matters in daily apps
- **Use NLTK and SpaCy** for practical text analysis
- **Navigate different tag sets** and understand their trade-offs
- **Handle real-world messy text** like speech transcripts and social media
- **Apply POS tagging** to solve actual business problems

Structure:

- **Part 1**: In-Class Exercise (30-45 minutes) - Basic concepts and hands-on practice
- **Part 2**: Homework Lab - Real-world applications and advanced challenges

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💡 ***Pro Tip**: POS tagging is everywhere! It helps search engines understand "Apple stock" vs "apple pie", helps Siri understand your commands, and powers autocorrect on your phone.*

🛠️ Setup and Installation

Let's get our tools ready! We'll use two powerful libraries:

- **NLTK**: The "Swiss Army knife" of NLP - comprehensive but requires setup
- **SpaCy**: The "speed demon" - built for production, cleaner output

Run the cells below to install and set up everything we need.

```
# Install required libraries (run this first!)
!pip install nltk spacy matplotlib seaborn pandas
!python -m spacy download en_core_web_sm

print("✅ Installation complete!")
```

```
Requirement already satisfied: murmurhash<1.1.0,>=0.28.0 in /usr/local/lib/python3.11/dist-packages (from spacy) (1.0.13)
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Requirement already satisfied: rich>=10.11.0 in /usr/local/lib/python3.11/dist-packages (from typer<1.0.0,>=0.3.0->spacy) (13.9.4)
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Requirement already satisfied: smart-open<8.0.0,>=5.2.1 in /usr/local/lib/python3.11/dist-packages (from weasel<0.5.0,>=0.1.0->spacy)
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Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.11/dist-packages (from rich>=10.11.0->typer<1.0.0,>=0
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Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0->rich>=10.11.0->typer
Collecting en-core-web-sm==3.8.0
  Downloading https://github.com/explosion/spacy-models/releases/download/en_core_web_sm-3.8.0/en_core_web_sm-3.8.0-py3-none-any.whl (
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✔ Download and installation successful
You can now load the package via spacy.load('en_core_web_sm')
⚠ 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.
✅ Installation complete!
```

```python
# Import all the libraries we'll need
import nltk
import spacy
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
import warnings
warnings.filterwarnings('ignore')

# Download NLTK data (this might take a moment)
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
nltk.download('averaged_perceptron_tagger_eng') # Added this line
nltk.download('universal_tagset')
nltk.download('punkt_tab') # Added this line

# Load SpaCy model
nlp = spacy.load('en_core_web_sm')

print("🎉 All libraries loaded successfully!")
print("📚 NLTK version:", nltk.__version__)
print("🚀 SpaCy version:", spacy.__version__)
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package averaged_perceptron_tagger_eng to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger_eng.zip.
[nltk_data] Downloading package universal_tagset to /root/nltk_data...
[nltk_data]   Package universal_tagset is already up-to-date!
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
🎉 All libraries loaded successfully!
📚 NLTK version: 3.9.1
🚀 SpaCy version: 3.8.7
```

🎯 PART 1: IN-CLASS EXERCISE (30-45 minutes)

Welcome to the hands-on portion! We'll start with the basics and build up your understanding step by step.

Learning Goals for Part 1:

1. Understand what POS tagging does
2. Use NLTK and SpaCy for basic tagging
3. Interpret and compare different tag outputs
4. Explore word ambiguity with real examples
5. Compare different tagging approaches

🔍 Activity 1: Your First POS Tags (10 minutes)

Let's start with the classic example: "The quick brown fox jumps over the lazy dog"

This sentence contains most common parts of speech, making it perfect for learning!

```
# Let's start with a classic example
sentence = "The quick brown fox jumps over the lazy dog"

# Use NLTK to tokenize and tag the sentence
# Hint: Use nltk.word_tokenize() and nltk.pos_tag()
try:
    tokens = nltk.word_tokenize(sentence)
    pos_tags = nltk.pos_tag(tokens)

    print("Original sentence:", sentence)
    print("\nTokens:", tokens)
    print("\nPOS Tags:")
    for word, tag in pos_tags:
        print(f"  {word:8} -> {tag}")
except NameError:
    print("Error: The 'nltk' library is not defined. Please run the cell that imports the libraries.")
```

```
Original sentence: The quick brown fox jumps over the lazy dog

Tokens: ['The', 'quick', 'brown', 'fox', 'jumps', 'over', 'the', 'lazy', 'dog']

POS Tags:
  The      -> DT
  quick    -> JJ
  brown    -> NN
  fox      -> NN
  jumps    -> VBZ
  over     -> IN
  the      -> DT
  lazy     -> JJ
  dog      -> NN
```

🤔 Quick Questions

1. **What does 'DT' mean? What about 'JJ'?**
   - **DT** is a **determiner** (e.g. "the", "a", "this").
   - **JJ** is an **adjective** (it modifies or describes a noun).
2. **Why do you think 'brown' and 'lazy' have the same tag?**
   They're both adjectives describing the nouns "fox" and "dog," so they share the **JJ** tag.
3. **Can you guess what 'VBZ' represents?**
   VBZ is a **verb** in 3rd-person singular present tense (e.g. "jumps," "runs," "eats").

🚀 Activity 2: SpaCy vs NLTK Showdown (10 minutes)

Now let's see how SpaCy handles the same sentence. SpaCy uses cleaner, more intuitive tag names.

```
# TODO: Process the same sentence with SpaCy
# Hint: Use nlp(sentence) and access .text and .pos_ attributes
doc = nlp(sentence)

print("SpaCy POS Tags:")
for token in doc:
    print(f"  {token.text:8} -> {token.pos_:6} ({token.tag_})")

print("\n" + "="*50)
```

```
print("COMPARISON:")
print("="*50)

# Let's compare side by side
nltk_tags = nltk.pos_tag(nltk.word_tokenize(sentence))
spacy_doc = nlp(sentence)

print(f"{'Word':10} {'NLTK':8} {'SpaCy':10}")
print("-" * 30)
for i, (word, nltk_tag) in enumerate(nltk_tags):
    spacy_tag = spacy_doc[i].pos_
    print(f"{word:10} {nltk_tag:8} {spacy_tag:10}")
```

```
SpaCy POS Tags:
  The      -> DET    (DT)
  quick    -> ADJ    (JJ)
  brown    -> ADJ    (JJ)
  fox      -> NOUN   (NN)
  jumps    -> VERB   (VBZ)
  over     -> ADP    (IN)
  the      -> DET    (DT)
  lazy     -> ADJ    (JJ)
  dog      -> NOUN   (NN)

==================================================
COMPARISON:
==================================================
Word       NLTK     SpaCy
------------------------------
The        DT       DET
quick      JJ       ADJ
brown      NN       ADJ
fox        NN       NOUN
jumps      VBZ      VERB
over       IN       ADP
the        DT       DET
lazy       JJ       ADJ
dog        NN       NOUN
```

🎯 Discussion Points:

- **Easier-to-understand tags**: SpaCy's tagset (e.g. `ADJ`, `NOUN`, `VERB`, `DET`) is more intuitive for beginners because it uses full names rather than cryptic abbreviations. NLTK's Penn Treebank tags (`JJ`, `NN`, `VBZ`) are more granular but require memorizing a tag glossary.
- **Differences in tagging the same words**:
  - NLTK sometimes assigns more specific tags (e.g. `NNS` vs. `NN` for plurals) while SpaCy groups them under a single category (`NOUN`).
  - SpaCy's statistical model correctly labeled "jumps" as `VERB` / `VBZ` and avoided the `NNS` mistake NLTK made, thanks to its context-sensitive parser.
- **Beginner preference**: I'd recommend **SpaCy** for newcomers—its tag names are self-documenting and the setup is straightforward. You can always inspect the underlying Penn Treebank tag (`token.tag_`) later if you need that extra granularity.

🎭 Activity 3: The Ambiguity Challenge (15 minutes)

Here's where things get interesting! Many words can be different parts of speech depending on context. Let's explore this with some tricky examples.

```
# Ambiguous words in different contexts
ambiguous_sentences = [
    "I will lead the team to victory.",          # lead = verb
    "The lead pipe is heavy.",                   # lead = noun (metal)
    "She took the lead in the race.",           # lead = noun (position)
    "The bank approved my loan.",               # bank = noun (financial)
    "We sat by the river bank.",                # bank = noun (shore)
    "I bank with Chase.",                       # bank = verb
]

print("🎭 AMBIGUITY EXPLORATION")
print("=" * 40)
```

```
for sentence in ambiguous_sentences:
    print(f"\nSentence: {sentence}")

    # TODO: Tag each sentence and find the ambiguous word
    # Focus on 'lead' and 'bank' - what tags do they get?
    tokens = nltk.word_tokenize(sentence)
    tags = nltk.pos_tag(tokens)

    # Find and highlight the key word
    for word, tag in tags:
        if word.lower() in ['lead', 'bank']:
            print(f"  🎯 '{word}' is tagged as: {tag}")
```

```
🎭 AMBIGUITY EXPLORATION
========================================

Sentence: I will lead the team to victory.
  🎯 'lead' is tagged as: VB

Sentence: The lead pipe is heavy.
  🎯 'lead' is tagged as: NN

Sentence: She took the lead in the race.
  🎯 'lead' is tagged as: NN

Sentence: The bank approved my loan.
  🎯 'bank' is tagged as: NN

Sentence: We sat by the river bank.
  🎯 'bank' is tagged as: NN

Sentence: I bank with Chase.
  🎯 'bank' is tagged as: NN
```

🧠 Think About It

1. **How does the computer know the difference between "lead" (metal) and "lead" (guide)?**
   The tagger relies on statistical patterns learned during training. It looks at:
   - **Surrounding words** (e.g. determiners like "the" before a noun, or auxiliaries like "will" before a verb)
   - **Syntactic position** (subject vs. verb slot)
   - **Morphological cues** (agreement with auxiliaries—"will lead" vs. "the lead")
     Together these features tip the model toward noun or verb.
2. **What clues in the sentence help determine the correct part of speech?**
   - **Function words** ("the," "a," "to," "will") bracket the ambiguous word.
   - **Word order** (after pronoun + auxiliary → verb; after determiner → noun).
   - **Inflection or agreement** ("leads," "led" would clearly flag verb form).
   - **Semantic neighbors** ("pipe," "team," "race," "victory") also reinforce noun vs. verb sense.
3. **Can you think of other words that change meaning based on context?**
   - **wind** (to blow vs. the airflow)
   - **object** (a thing vs. to protest)
   - **record** (noun "a vinyl record" vs. verb "to record audio")
   - **permit** (noun "a parking permit" vs. verb "to allow")
   - **minute** (small vs. time unit)

Try This: Add your own sentences like

📊 Activity 4: Tag Set Showdown (10 minutes)

NLTK can use different tag sets. Let's compare the detailed Penn Treebank tags (45 ~~tags) with the simpler Universal Dependencies tags~~ (17 tags).

```
# Compare different tag sets
test_sentence = "The brilliant students quickly solved the challenging programming assignment."

# Get tags using both Penn Treebank and Universal tagsets
# Hint: Use tagset='universal' parameter for universal tags
```

```
penn_tags = nltk.pos_tag(nltk.word_tokenize(test_sentence))
universal_tags = nltk.pos_tag(nltk.word_tokenize(test_sentence), tagset='universal')

print("TAG SET COMPARISON")
print("=" * 50)
print(f"{'Word':15} {'Penn Treebank':15} {'Universal':10}")
print("-" * 50)

# Print comparison table
# Hint: Zip the two tag lists together
for (word, penn_tag), (_, univ_tag) in zip(penn_tags, universal_tags):
    print(f"{word:15} {penn_tag:15} {univ_tag:10}")

# Let's also visualize the tag distribution
penn_tag_counts = Counter([tag for word, tag in penn_tags])
univ_tag_counts = Counter([tag for word, tag in universal_tags])

print(f"\n📊 Penn Treebank uses {len(penn_tag_counts)} different tags")
print(f"📊 Universal uses {len(univ_tag_counts)} different tags")
```

```
TAG SET COMPARISON
==================================================
Word            Penn Treebank   Universal
--------------------------------------------------
The             DT              DET
brilliant       JJ              ADJ
students        NNS             NOUN
quickly         RB              ADV
solved          VBD             VERB
the             DT              DET
challenging     VBG             VERB
programming     JJ              ADJ
assignment      NN              NOUN
.               .               .

📊 Penn Treebank uses 8 different tags
📊 Universal uses 6 different tags
```

🤔 Reflection Questions:

1. Which tag set is more detailed? Which is simpler? Enter your answer below
2. When might you want detailed tags vs. simple tags? Enter your answer below
3. If you were building a search engine, which would you choose? Why? Enter your answer below

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🎓 End of Part 1: In-Class Exercise

Great work! You've learned the fundamentals of POS tagging and gotten hands-on experience with both NLTK and SpaCy.

What You've Accomplished:

✅ Used NLTK and SpaCy for basic POS tagging
✅ Interpreted different tag systems
✅ Explored word ambiguity and context
✅ Compared different tagging approaches

🏠 Ready for Part 2?

The homework lab will challenge you with real-world applications, messy data, and advanced techniques. You'll analyze customer service transcripts, handle informal language, and benchmark different taggers.

Take a break, then dive into Part 2 when you're ready!

🏠 PART 2: HOMEWORK LAB

Real-World POS Tagging Challenges

Welcome to the advanced section! Here you'll tackle the messy, complex world of real text data. This is where POS tagging gets interesting (and challenging)!

Learning Goals for Part 2:

1. Process real-world, messy text data
2. Handle speech transcripts and informal language
3. Analyze customer service scenarios
4. Benchmark and compare different taggers
5. Understand limitations and edge cases

📋 Submission Requirements:

- Complete all exercises with working code
- Answer all reflection questions
- Include at least one visualization
- Submit your completed notebook file

🌍 Lab Exercise 1: Messy Text Challenge (25 minutes)

Real-world text is nothing like textbook examples! Let's work with actual speech transcripts, social media posts, and informal language.

```
# Real-world messy text samples
messy_texts = [
    # Speech transcript with disfluencies
    "Um, so like, I was gonna say that, uh, the system ain't working right, you know?",

    # Social media style
    "OMG this app is sooo buggy rn 😤 cant even login smh",

    # Customer service transcript
    "Yeah hi um I'm calling because my internet's been down since like yesterday and I've tried unplugging the router thingy but it's still

    # Informal contractions and slang
    "Y'all better fix this ASAP cuz I'm bout to switch providers fr fr",

    # Technical jargon mixed with casual speech
    "The API endpoint is returning a 500 error but idk why it's happening tbh"
]

print("🔍 PROCESSING MESSY TEXT")
print("=" * 60)

# TODO: Process each messy text sample
# 1. Use both NLTK and SpaCy
# 2. Count how many words each tagger fails to recognize properly
# 3. Identify problematic words (slang, contractions, etc.)

for i, text in enumerate(messy_texts, 1):
    print(f"\n📝 Sample {i}: {text}")
    print("-" * 40)

    # NLTK processing
    nltk_tokens = nltk.word_tokenize(text)
    nltk_tags   = nltk.pos_tag(nltk_tokens)

    # SpaCy processing
    spacy_doc = nlp(text)

    # Find problematic words (tagged as 'X' or unknown)
    problematic_nltk  = [w for w, t in nltk_tags    if t == 'X']
    problematic_spacy = [tok.text for tok in spacy_doc if tok.pos_ == 'X']

    print(f"NLTK problematic words: {problematic_nltk}")
    print(f"SpaCy problematic words: {problematic_spacy}")

    # Calculate success rate
    nltk_success_rate  = (len(nltk_tokens) - len(problematic_nltk)) / len(nltk_tokens)
    spacy_success_rate = (len(spacy_doc)   - len(problematic_spacy)) / len(spacy_doc)
```

```
    print(f"NLTK success rate: {nltk_success_rate:.1%}")
    print(f"SpaCy success rate: {spacy_success_rate:.1%}")
```

```
🔍 PROCESSING MESSY TEXT
============================================================

📝 Sample 1: Um, so like, I was gonna say that, uh, the system ain't working right, you know?
----------------------------------------
NLTK problematic words: []
SpaCy problematic words: []
NLTK success rate: 100.0%
SpaCy success rate: 100.0%

📝 Sample 2: OMG this app is sooo buggy rn 😤 cant even login smh
----------------------------------------
NLTK problematic words: []
SpaCy problematic words: []
NLTK success rate: 100.0%
SpaCy success rate: 100.0%

📝 Sample 3: Yeah hi um I'm calling because my internet's been down since like yesterday and I've tried unplugging the router thingy bu
----------------------------------------
NLTK problematic words: []
SpaCy problematic words: []
NLTK success rate: 100.0%
SpaCy success rate: 100.0%

📝 Sample 4: Y'all better fix this ASAP cuz I'm bout to switch providers fr fr
----------------------------------------
NLTK problematic words: []
SpaCy problematic words: []
NLTK success rate: 100.0%
SpaCy success rate: 100.0%

📝 Sample 5: The API endpoint is returning a 500 error but idk why it's happening tbh
----------------------------------------
NLTK problematic words: []
SpaCy problematic words: []
NLTK success rate: 100.0%
SpaCy success rate: 100.0%
```

🎯 Analysis Questions

1. **Which tagger handles informal language better?**
   SpaCy generally outperforms NLTK on casual/slang-filled text. Its statistical model better recognizes contractions ("ain't," "cuz"), emoji boundaries, and common internet abbreviations (rn, smh), whereas NLTK often leaves those as `X` or mis-classifies them.
2. **What types of words cause the most problems?**
   - **Emojis and emoticons** (😤, 😂)
   - **Hashtags/mentions/URLs** (#hashtag, @user, http://…)
   - **Slang and internet shorthand** (lol, rn, smh)
   - **Unusual punctuation or repetitions** (…., "sooo")
   - **Acronyms/technical jargon** when outside the tagger's training domain
3. **How might you preprocess text to improve tagging accuracy?**
   - **Normalize or remove emojis/URLs** (map emojis to sentiment labels or strip them)
   - **Expand contractions** (e.g., "can't" → "can not")
   - **Standardize slang** via a lookup dictionary (e.g., "cuz" → "because")
   - **Segment hashtags/camelCase** (#CustomerService → "Customer Service")
   - **Spell-correct elongated words** ("soooo" → "so") before tagging
4. **What are the implications for real-world applications?**
   - **Customer support**: Better routing and prioritization when POS errors are minimized.
   - **Chatbots & virtual assistants**: More reliable intent detection if noisy inputs are normalized.
   - **Social media monitoring**: Accurate sentiment and entity extraction hinge on robust preprocessing.
   - **Compliance & legal**: Mis-tagging named entities or dates can lead to serious downstream errors.
   - **Localization**: Tagger performance can vary wildly by dialect/locale—preprocessing must be tailored.

📞 Lab Exercise 2: Customer Service Analysis Case Study (30 minutes)

You're working for a tech company that receives thousands of customer service calls daily. Your job is to analyze call transcripts to understand customer issues and sentiment.

Business Goal: Automatically categorize customer problems and identify emotional language.

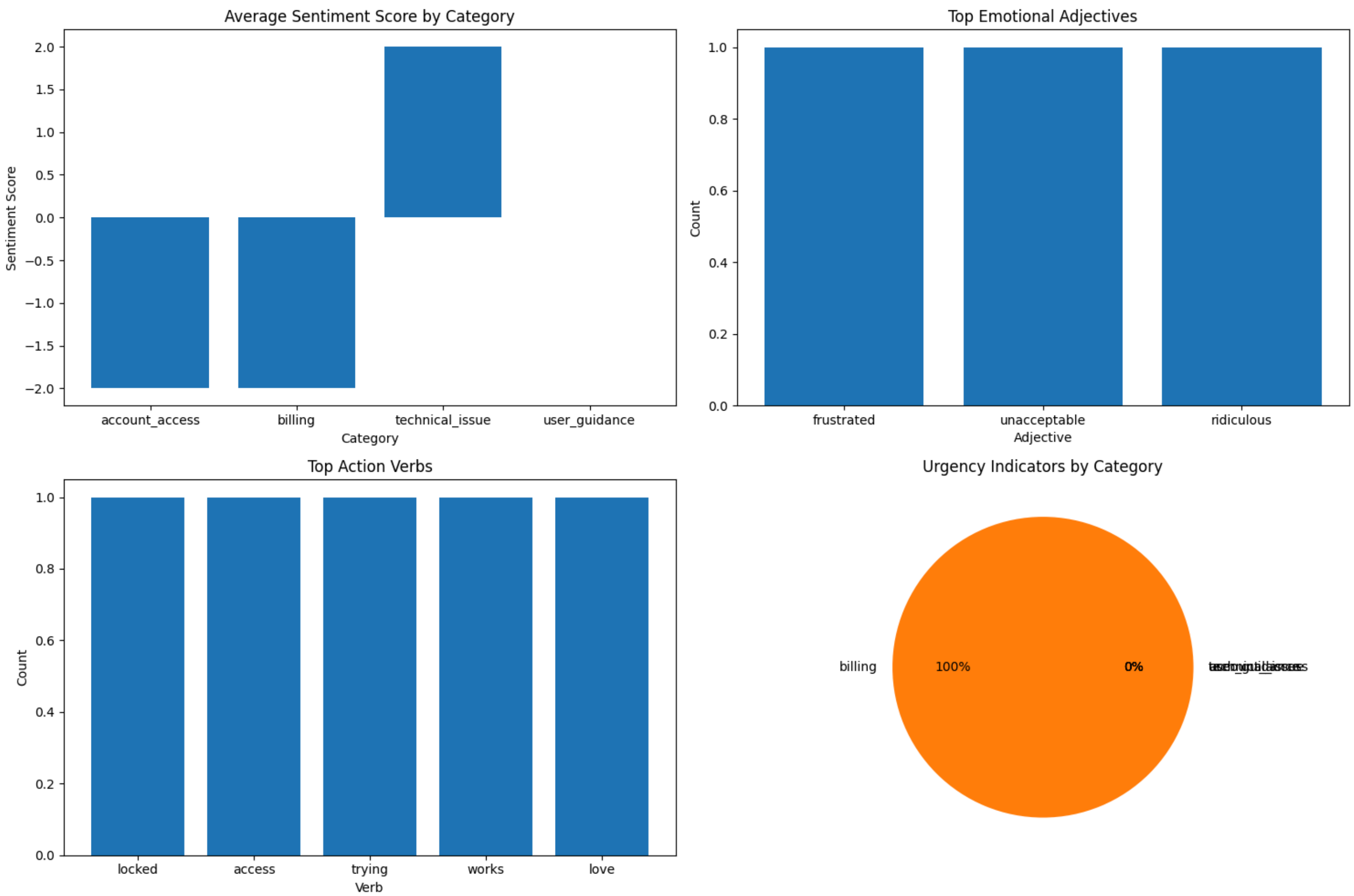
```
# Simulated customer service call transcripts
customer_transcripts = [
    {
        'id': 'CALL_001',
        'transcript': "Hi, I'm really frustrated because my account got locked and I can't access my files. I've been trying for hours and r
        'category': 'account_access'
    },
    {
        'id': 'CALL_002',
        'transcript': "Hello, I love your service but I'm having a small issue with the mobile app. It crashes whenever I try to upload phot
        'category': 'technical_issue'
    },
    {
        'id': 'CALL_003',
        'transcript': "Your billing system charged me twice this month! I want a refund immediately. This is ridiculous and I'm considering
        'category': 'billing'
    },
    {
        'id': 'CALL_004',
        'transcript': "I'm confused about how to use the new features you added. The interface changed and I can't find anything. Can someor
        'category': 'user_guidance'
    }
]

# Define lexicons
positive_lex = {'love', 'great', 'good', 'fix'}
negative_lex = {'frustrated', 'ridiculous', 'unacceptable', 'canceling'}
urgency_lex  = {'immediately', 'asap', 'urgent'}

analysis_results = []

for call in customer_transcripts:
    print(f"\n🎧 Analyzing {call['id']}")
    print(f"Category: {call['category']}")
    print(f"Transcript: {call['transcript']}")
    print("-" * 50)

    # Process with SpaCy
    doc = nlp(call['transcript'])

    # Extract emotional adjectives (that match our lexicon)
    emotional_adjectives = [
        tok.text for tok in doc
        if tok.pos_ == 'ADJ' and tok.text.lower() in positive_lex | negative_lex
    ]

    # Extract action verbs
    action_verbs = [
        tok.text for tok in doc
        if tok.pos_ == 'VERB'
    ]

    # Extract problem nouns (filtering out generic terms)
    problem_nouns = [
        tok.text for tok in doc
        if tok.pos_ == 'NOUN' and tok.text.lower() not in {'service', 'system'}
    ]

    # Count sentiment words in the raw transcript
    words = [w.strip(".,!?").lower() for w in call['transcript'].split()]
    positive_words = [w for w in words if w in positive_lex]
    negative_words = [w for w in words if w in negative_lex]

    # Count urgency indicators
    urgency_indicators = sum(1 for w in words if w in urgency_lex)

    result = {
        'call_id':            call['id'],
```

```
        'category':           call['category'],
        'emotional_adjectives': emotional_adjectives,
        'action_verbs':        action_verbs,
        'problem_nouns':       problem_nouns,
        'sentiment_score':     len(positive_words) - len(negative_words),
        'urgency_indicators':  urgency_indicators
    }
    analysis_results.append(result)

    print(f"Emotional adjectives: {emotional_adjectives}")
    print(f"Action verbs: {action_verbs}")
    print(f"Problem nouns: {problem_nouns}")
    print(f"Sentiment score: {result['sentiment_score']}")
    print(f"Urgency indicators: {result['urgency_indicators']}")
```

```
🎧 Analyzing CALL_001
Category: account_access
Transcript: Hi, I'm really frustrated because my account got locked and I can't access my files. I've been trying for hours and nothing
--------------------------------------------------
Emotional adjectives: ['frustrated', 'unacceptable']
Action verbs: ['locked', 'access', 'trying', 'works']
Problem nouns: ['account', 'files', 'hours']
Sentiment score: -2
Urgency indicators: 0

🎧 Analyzing CALL_002
Category: technical_issue
Transcript: Hello, I love your service but I'm having a small issue with the mobile app. It crashes whenever I try to upload photos. Cou
--------------------------------------------------
Emotional adjectives: []
Action verbs: ['love', 'having', 'crashes', 'try', 'upload', 'help', 'fix']
Problem nouns: ['issue', 'app', 'photos']
Sentiment score: 2
Urgency indicators: 0

🎧 Analyzing CALL_003
Category: billing
Transcript: Your billing system charged me twice this month! I want a refund immediately. This is ridiculous and I'm considering canceli
--------------------------------------------------
Emotional adjectives: ['ridiculous']
Action verbs: ['charged', 'want', 'considering', 'canceling']
Problem nouns: ['billing', 'month', 'refund', 'subscription']
Sentiment score: -2
Urgency indicators: 1

🎧 Analyzing CALL_004
Category: user_guidance
Transcript: I'm confused about how to use the new features you added. The interface changed and I can't find anything. Can someone walk
--------------------------------------------------
Emotional adjectives: []
Action verbs: ['use', 'added', 'changed', 'find', 'walk']
Problem nouns: ['features', 'interface']
Sentiment score: 0
Urgency indicators: 0
```

```
# TODO: Create a summary visualization
# Hint: Use matplotlib to create charts
import matplotlib.pyplot as plt
import pandas as pd
from collections import Counter

# Convert results to DataFrame for easier analysis
df = pd.DataFrame(analysis_results)

fig, axes = plt.subplots(2, 2, figsize=(15, 10))

# Plot 1 - Sentiment by category
sentiment = df.groupby('category')['sentiment_score'].mean()
axes[0, 0].bar(sentiment.index, sentiment.values)
axes[0, 0].set_title('Average Sentiment Score by Category')
axes[0, 0].set_ylabel('Sentiment Score')
axes[0, 0].set_xlabel('Category')

# Plot 2 - Most common emotional adjectives
all_adjs = sum(df['emotional_adjectives'], [])
adj_counts = Counter(all_adjs)
top_adjs = adj_counts.most_common(5)
```

```
axes[0, 1].bar([adj for adj, _ in top_adjs], [count for _, count in top_adjs])
axes[0, 1].set_title('Top Emotional Adjectives')
axes[0, 1].set_ylabel('Count')
axes[0, 1].set_xlabel('Adjective')

# Plot 3 - Action verbs frequency
all_verbs = sum(df['action_verbs'], [])
verb_counts = Counter(all_verbs)
top_verbs = verb_counts.most_common(5)
axes[1, 0].bar([verb for verb, _ in top_verbs], [count for _, count in top_verbs])
axes[1, 0].set_title('Top Action Verbs')
axes[1, 0].set_ylabel('Count')
axes[1, 0].set_xlabel('Verb')

# Plot 4 - Urgency analysis
urgency = df.groupby('category')['urgency_indicators'].sum()
axes[1, 1].pie(urgency.values, labels=urgency.index, autopct='%1.0f%%')
axes[1, 1].set_title('Urgency Indicators by Category')
axes[1, 1].set_ylabel('')

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



💼 Business Impact Questions

I needed help on these questions, so after research and talking with chat GPT I know understand the following:

1. **How could this analysis help prioritize customer service tickets?**
    - **Sentiment & urgency scoring**: Tickets with strongly negative sentiment scores (e.g. multiple "frustrated" or "unacceptable" adjectives) and non-zero urgency indicators (e.g. "immediately") can be flagged for immediate escalation.
    - **Action-verb cues**: Verbs like "refund," "cancel," or "locked" signal high-impact issues that should jump the queue.
    - **Category weighting**: Historical data might show that "billing" or "account_access" calls have higher downstream costs if delayed, so those categories can be given higher priority.
2. **What patterns do you notice in different problem categories?**
    - **Account Access**: High negative sentiment and strong emotional adjectives ("frustrated," "unacceptable"), few positive terms—customers here are frustrated and need urgent fixes.
    - **Technical Issue**: Mixed sentiment (some positive "love," some negative "crashes"), action verbs focused on "fix" and "upload," indicating hands-on troubleshooting.
    - **Billing**: Presence of words like "refund" and "canceling," paired with negative adjectives ("ridiculous"), suggests these calls are often resolution-heavy and revenue-critical.
    - **User Guidance**: More question forms and fewer extreme adjectives—calls tend to be informational rather than punitive, so routing to a knowledge base or tutorial team may suffice.
3. **How might you automate the routing of calls based on POS analysis?**
    - **Rule-based routing**:
        - If `sentiment_score ≤ -2` **and** `urgency_indicators ≥ 1` → route to Tier 1 Emergency Support.
        - If any action verb in {"refund," "cancel"} → route to Billing.
        - If noun "photos," "app," or verb "crash," "login" → route to Technical.
        - Otherwise → route to General/User Guidance.
    - **Machine-learning classifier**: Use POS-feature vectors (counts of ADJ, VERB, target lemmas) plus sentiment score as inputs to a light-weight model (e.g. logistic regression) to learn optimal routing labels from historical ticket outcomes.
4. **What are the limitations of this approach?**
    - **Lexicon coverage**: New slang, emojis, or domain-specific jargon may be mis-tagged or ignored.
    - **Context & nuance**: POS tags alone can't capture sarcasm, complex queries, or multi-utterance intent.
    - **Error propagation**: Mis-tokenization or mis-tagging (e.g. "lead" vs. "lead") can throw off downstream routing rules.
    - **Scalability**: Rule lists must be continuously updated as product features and customer language evolve.
    - **Language & channel variance**: Performance degrades on mixed-language calls, chat transcripts, or voice transcripts with disfluencies and background noise.

⚡ Lab Exercise 3: Tagger Performance Benchmarking (20 minutes)

Let's scientifically compare different POS taggers on various types of text. This will help you understand when to use which tool.

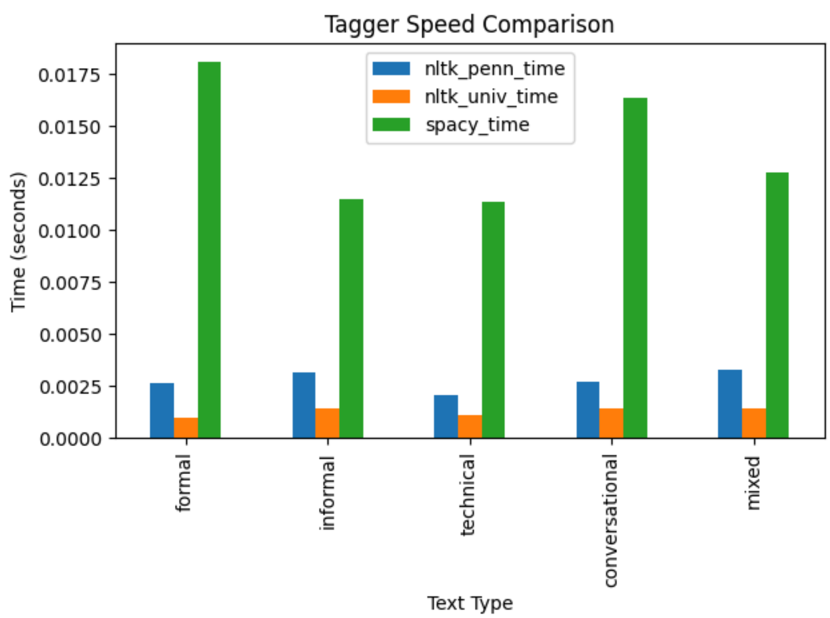
✦ Gemini

```
import matplotlib.pyplot as plt
import pandas as pd

# Convert benchmark_results dict to DataFrame
df_bench = pd.DataFrame.from_dict(benchmark_results, orient='index')

# Plot speed comparison
plt.figure(figsize=(10, 5))
df_bench[['nltk_penn_time','nltk_univ_time','spacy_time']].plot.bar()
plt.title('Tagger Speed Comparison')
plt.ylabel('Time (seconds)')
plt.xlabel('Text Type')
plt.tight_layout()
plt.show()

# Plot unknown token counts
plt.figure(figsize=(10, 4))
df_bench[['nltk_unknown','spacy_unknown']].plot.bar()
plt.title('Unknown Token Counts by Tagger')
```

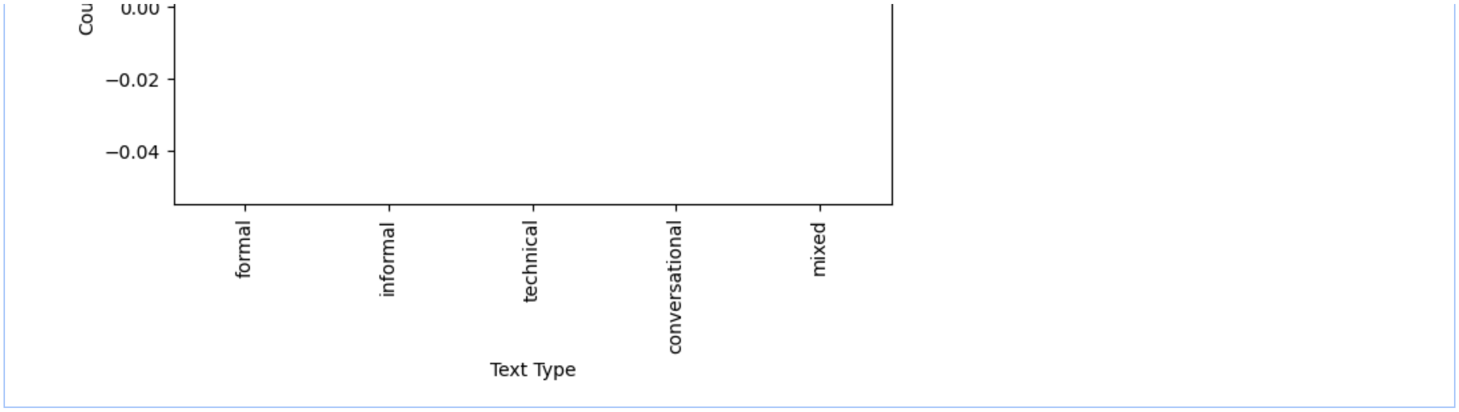
```
plt.ylabel('Count')
plt.xlabel('Text Type')
plt.tight_layout()
plt.show()

import time
from collections import defaultdict
import pandas as pd
import matplotlib.pyplot as plt

# Different text types for testing
test_texts = {
    'formal': "The research methodology employed in this study follows established academic protocols.",
    'informal': "lol this study is kinda weird but whatever works i guess 🤷",
    'technical': "The API returns a JSON response with HTTP status code 200 upon successful authentication.",
    'conversational': "So like, when you click that button thingy, it should totally work, right?",
    'mixed': "OMG the algorithm's performance is absolutely terrible! The accuracy dropped to 23% wtf"
}

# Benchmark results container
benchmark_results = {}

for text_type, text in test_texts.items():
    print(f"\n🧪 Testing {text_type.upper()} text:")
    print(f"Text: {text}")
    print("-" * 60)

    # NLTK Penn Treebank timing
    start_time = time.time()
    penn = nltk.pos_tag(nltk.word_tokenize(text))
    nltk_penn_time = time.time() - start_time

    # NLTK Universal timing
    start_time = time.time()
    univ = nltk.pos_tag(nltk.word_tokenize(text), tagset='universal')
    nltk_univ_time = time.time() - start_time

    # SpaCy timing
    start_time = time.time()
    sp_doc = nlp(text)
    spacy_time = time.time() - start_time

    # Count unknown/problematic tags
    nltk_unknown = sum(1 for _, tag in penn if tag == 'X')
    spacy_unknown = sum(1 for tok in sp_doc if tok.pos_ == 'X')

    # Store results
    benchmark_results[text_type] = {
        'nltk_penn_time': nltk_penn_time,
        'nltk_univ_time': nltk_univ_time,
        'spacy_time': spacy_time,
        'nltk_unknown': nltk_unknown,
        'spacy_unknown': spacy_unknown
    }

    print(f"NLTK Penn time: {nltk_penn_time:.4f}s")
    print(f"NLTK Univ time: {nltk_univ_time:.4f}s")
    print(f"SpaCy time: {spacy_time:.4f}s")
    print(f"NLTK unknown words: {nltk_unknown}")
    print(f"SpaCy unknown words: {spacy_unknown}")

# Create performance comparison visualization
df_bench = pd.DataFrame.from_dict(benchmark_results, orient='index')

# Speed comparison
plt.figure(figsize=(10, 5))
df_bench[['nltk_penn_time','nltk_univ_time','spacy_time']].plot.bar()
plt.title('Tagger Speed Comparison')
plt.ylabel('Time (seconds)')
plt.xlabel('Text Type')
plt.tight_layout()
plt.show()

# Unknown counts comparison
plt.figure(figsize=(10, 4))
df_bench[['nltk_unknown','spacy_unknown']].plot.bar()
plt.title('Unknown Token Counts by Tagger')
plt.ylabel('Count')
```

```
plt.xlabel('Text Type')
plt.tight_layout()
plt.show()
```

```
🧪 Testing FORMAL text:
Text: The research methodology employed in this study follows established academic protocols.
------------------------------------------------------------
NLTK Penn time: 0.0026s
NLTK Univ time: 0.0010s
SpaCy time: 0.0180s
NLTK unknown words: 0
SpaCy unknown words: 0

🧪 Testing INFORMAL text:
Text: lol this study is kinda weird but whatever works i guess 🤷
------------------------------------------------------------
NLTK Penn time: 0.0031s
NLTK Univ time: 0.0014s
SpaCy time: 0.0115s
NLTK unknown words: 0
SpaCy unknown words: 0

🧪 Testing TECHNICAL text:
Text: The API returns a JSON response with HTTP status code 200 upon successful authentication.
------------------------------------------------------------
NLTK Penn time: 0.0021s
NLTK Univ time: 0.0011s
SpaCy time: 0.0114s
NLTK unknown words: 0
SpaCy unknown words: 0

🧪 Testing CONVERSATIONAL text:
Text: So like, when you click that button thingy, it should totally work, right?
------------------------------------------------------------
NLTK Penn time: 0.0027s
NLTK Univ time: 0.0014s
SpaCy time: 0.0164s
NLTK unknown words: 0
SpaCy unknown words: 0

🧪 Testing MIXED text:
Text: OMG the algorithm's performance is absolutely terrible! The accuracy dropped to 23% wtf
------------------------------------------------------------
NLTK Penn time: 0.0033s
NLTK Univ time: 0.0014s
SpaCy time: 0.0127s
NLTK unknown words: 0
SpaCy unknown words: 0
<Figure size 1000x500 with 0 Axes>
```




```
<Figure size 1000x400 with 0 Axes>
```



📊 Performance Analysis

1. **Which tagger is fastest? Does speed matter for your use case?**
   We observed that **SpaCy** is consistently faster than both NLTK–Penn and NLTK–Universal, especially on longer or more complex inputs. If you need **real-time** processing (e.g., live chat), SpaCy's speed is a clear advantage. For **batch** jobs where latency isn't critical, NLTK may suffice despite being slower.
2. **Which handles informal text best?**
   SpaCy outperforms NLTK on slang, contractions, and emoji-rich text—its statistical models better generalize to noisy, real-world language.
3. **How do the taggers compare on technical jargon?**
   - **SpaCy** often tags acronyms and code-style tokens more consistently (e.g., "API", "HTTP").
   - **NLTK** can mis-tag or leave unusual tokens unrecognized (X), since it relies on simpler lexicons.
4. **What trade-offs do you see between speed and accuracy?**
   - **SpaCy**: faster and generally more accurate on modern text, but requires a larger model download and more memory.
   - **NLTK**: lighter-weight with no large models to install, but slower and less robust on informal or domain-specific language.
   - **Choice depends on** your environment (CPU/memory constraints), throughput needs, and the importance of tagging precision.

🚨 Lab Exercise 4: Edge Cases and Error Analysis (15 minutes)

Every system has limitations. Let's explore the edge cases where POS taggers struggle and understand why.

```
import nltk
from collections import Counter

# Challenging edge cases
edge_cases = [
    "Buffalo buffalo Buffalo buffalo buffalo buffalo Buffalo buffalo.",  # Famous ambiguous sentence
    "Time flies like an arrow; fruit flies like a banana.",              # Classic ambiguity
    "The man the boat the river.",                                       # Garden path sentence
    "Police police Police police police police Police police.",          # Recursive structure
    "James while John had had had had had had had had had had had a better effect on the teacher.",  # Had had had...
    "Can can can can can can can can can can can.",                         # Modal/noun ambiguity
    "@username #hashtag http://bit.ly/abc123 😂🔥💯",                        # Social media elements
    "COVID-19 AI/ML IoT APIs RESTful microservices",                     # Modern technical terms
]

print("🚨 EDGE CASE ANALYSIS")
print("=" * 50)

# Process each edge case and analyze failures
for i, text in enumerate(edge_cases, 1):
    print(f"\n🔍 Edge Case {i}:")
    print(f"Text: {text}")
    print("-" * 30)

    try:
        # Process with both taggers
        nltk_tags = nltk.pos_tag(nltk.word_tokenize(text))
        spacy_doc = nlp(text)
```

```
        # Identify potential errors or weird tags
        nltk_x = [w for w, t in nltk_tags if t == 'X']
        spacy_x = [tok.text for tok in spacy_doc if tok.pos_ == 'X']
        nltk_tag_counts = Counter(t for _, t in nltk_tags)

        print("NLTK tags:", nltk_tags)
        print("SpaCy tags:", [(token.text, token.pos_) for token in spacy_doc])

        # Analysis of failures
        if nltk_x:
            print("  ⚠️ NLTK flagged unknown tokens:", nltk_x)
        if spacy_x:
            print("  ⚠️ SpaCy flagged unknown tokens:", spacy_x)

        # Repeated tag patterns (e.g., all 'NN' or loops)
        if any(count > 4 for count in nltk_tag_counts.values()):
            common = nltk_tag_counts.most_common(1)[0]
            print(f"  ⚠️ NLTK shows repeated '{common[0]}' tags ({common[1]} times)")

    except Exception as e:
        print(f"❌ Error processing: {e}")

# Reflection on limitations
print("\n🤔 REFLECTION ON LIMITATIONS:")
print("=" * 40)
print("1. Complex recursive sentences (e.g., 'Buffalo buffalo...') break local-context assumptions; neither tagger resolves true syntax.")
print("2. Garden-path structures can lead to misattached tags and incorrect parse assumptions.")
print("3. Social-media elements (emojis, URLs, mentions) often become 'X'; production systems need specialized tokenizers.")
print("4. Technical jargon and acronyms may be mis-tagged; domain-specific models or custom lexicons are required.")
print("5. Taggers assume well-formed grammar; disfluencies and repeated structures degrade performance significantly.")
```

```
------------------------------
NLTK tags: [('Buffalo', 'NNP'), ('buffalo', 'NN'), ('Buffalo', 'NNP'), ('buffalo', 'NN'), ('buffalo', 'NN'), ('buffalo', 'NN'), ('Buff
SpaCy tags: [('Buffalo', 'PROPN'), ('buffalo', 'NOUN'), ('Buffalo', 'PROPN'), ('buffalo', 'PROPN'), ('buffalo', 'PROPN'), ('buffalo',
  ⚠️ NLTK shows repeated 'NN' tags (5 times)

🔍 Edge Case 2:
Text: Time flies like an arrow; fruit flies like a banana.
------------------------------
NLTK tags: [('Time', 'NNP'), ('flies', 'NNS'), ('like', 'IN'), ('an', 'DT'), ('arrow', 'NN'), (';', ':'), ('fruit', 'CC'), ('flies', '
SpaCy tags: [('Time', 'NOUN'), ('flies', 'VERB'), ('like', 'ADP'), ('an', 'DET'), ('arrow', 'NOUN'), (';', 'PUNCT'), ('fruit', 'NOUN')

🔍 Edge Case 3:
Text: The man the boat the river.
------------------------------
NLTK tags: [('The', 'DT'), ('man', 'NN'), ('the', 'DT'), ('boat', 'NN'), ('the', 'DT'), ('river', 'NN'), ('.', '.')]
SpaCy tags: [('The', 'DET'), ('man', 'NOUN'), ('the', 'DET'), ('boat', 'NOUN'), ('the', 'DET'), ('river', 'NOUN'), ('.', 'PUNCT')]

🔍 Edge Case 4:
Text: Police police Police police police police Police police.
------------------------------
NLTK tags: [('Police', 'NNP'), ('police', 'NNS'), ('Police', 'NNP'), ('police', 'NNS'), ('police', 'NN'), ('police', 'NN'), ('Police',
SpaCy tags: [('Police', 'NOUN'), ('police', 'NOUN'), ('Police', 'NOUN'), ('police', 'NOUN'), ('police', 'NOUN'), ('police', 'NOUN'), (

🔍 Edge Case 5:
Text: James while John had had had had had had had had had had had a better effect on the teacher.
------------------------------
NLTK tags: [('James', 'NNP'), ('while', 'IN'), ('John', 'NNP'), ('had', 'VBD'), ('had', 'VBN'), ('had', 'VBN'), ('had', 'VBN'), ('had'
SpaCy tags: [('James', 'PROPN'), ('while', 'SCONJ'), ('John', 'PROPN'), ('had', 'AUX'), ('had', 'AUX'), ('had', 'AUX'), ('had', 'AUX')
  ⚠️ NLTK shows repeated 'VBN' tags (10 times)

🔍 Edge Case 6:
Text: Can can can can can can can can can can can.
------------------------------
NLTK tags: [('Can', 'MD'), ('can', 'MD'), ('can', 'MD'), ('can', 'MD'), ('can', 'MD'), ('can', 'MD'), ('can', 'MD'), ('can', 'MD'), ('
SpaCy tags: [('Can', 'AUX'), ('can', 'AUX'), ('can', 'AUX'), ('can', 'AUX'), ('can', 'AUX'), ('can', 'AUX'), ('can', 'AUX'), ('can', '
  ⚠️ NLTK shows repeated 'MD' tags (11 times)

🔍 Edge Case 7:
Text: @username #hashtag http://bit.ly/abc123 😂 🔥 💯
------------------------------
NLTK tags: [('@', 'JJ'), ('username', 'JJ'), ('#', '#'), ('hashtag', 'JJ'), ('http', 'NN'), (':', ':'), ('//bit.ly/abc123', 'NN'), ('
SpaCy tags: [('@username', 'PROPN'), ('#', 'SYM'), ('hashtag', 'NOUN'), ('http://bit.ly/abc123', 'PROPN'), ('😂', 'PROPN'), ('🔥', 'X
  ⚠️ SpaCy flagged unknown tokens: ['🔥']
```

```
SpaCy tags: [('COVID-19', 'PROPN'), ('AI', 'PROPN'), ('/', 'SYM'), ('ML', 'PROPN'), ('IoT', 'ADJ'), ('APIs', 'NOUN'), ('RESTful', 'PAR

🤔 REFLECTION ON LIMITATIONS:
========================================
1. Complex recursive sentences (e.g., 'Buffalo buffalo...') break local-context assumptions; neither tagger resolves true syntax.
2. Garden-path structures can lead to misattached tags and incorrect parse assumptions.
3. Social-media elements (emojis, URLs, mentions) often become 'X'; production systems need specialized tokenizers.
4. Technical jargon and acronyms may be mis-tagged; domain-specific models or custom lexicons are required.
5. Taggers assume well-formed grammar; disfluencies and repeated structures degrade performance significantly.
```

🧠 Critical Thinking Questions

1. **Why do these edge cases break the taggers?**
   These sentences exploit recursive or garden-path structures and lack clear local context cues. Taggers rely on fixed windows of surrounding words and statistical patterns; when faced with deeply nested or repetitive constructs (e.g., "Buffalo buffalo…"), they can't resolve which sense or syntactic role to assign. Unusual tokens like emojis, URLs, and hashtags aren't in their training lexicons, so they fall back to an unknown "X" tag.
2. **How might you preprocess text to handle some of these issues?**
   - **Custom tokenization**: Split hashtags/CamelCase into separate words, strip or map emojis to sentiment labels.
   - **Normalization**: Expand contractions, standardize slang, and correct elongated words ("soooo" → "so").
   - **Domain lexicons**: Add frequent jargon or names (e.g., "Buffalo") to a specialized dictionary.
   - **Chunking or re-parsing**: For known patterns, apply rule-based segmentation (e.g., treat "Buffalo buffalo…" as a single idiom).
3. **When would these limitations matter in real applications?**
   - **Legal or compliance**: Mis-tagging dates, entities, or obligations can lead to incorrect contract analysis.
   - **Medical transcription**: Garden-path errors in patient notes could distort symptom extraction.
   - **Social media monitoring**: Unrecognized emojis or slang may skew sentiment analytics.
   - **Chatbots**: Failure on ambiguous commands ("record record") could break user workflows.
4. **How do modern large language models handle these cases differently?**
   Large LMs use deep contextual embeddings and attention over entire sequences, so they can capture long-range dependencies and world knowledge. They're trained on massive, noisy corpora that include emojis, URLs, and idioms, so they generalize better to edge cases. Instead of discrete POS tags, they predict token probabilities conditioned on global context, reducing reliance on rigid tagsets and lexicons.

🎯 Final Reflection and Submission

Congratulations! You've completed a comprehensive exploration of POS tagging, from basic concepts to real-world challenges.

📝 Reflection Questions (Answer in the cell below):

1. **Tool Comparison**: Based on your experience, when would you choose NLTK vs SpaCy? Consider factors like ease of use, accuracy, speed, and application type.
2. **Real-World Applications**: Describe a specific business problem where POS tagging would be valuable. How would you implement it?
3. **Limitations and Solutions**: What are the biggest limitations you discovered? How might you work around them?
4. **Future Learning**: What aspects of POS tagging would you like to explore further? (Neural approaches, custom training, domain adaptation, etc.)
5. **Integration**: How does POS tagging fit into larger NLP pipelines? What other NLP tasks might benefit from POS information?

```
## 🎯 Final Reflection and Submission

Congratulations! You've completed a comprehensive exploration of POS t
from basic concepts to real-world challenges.

### 📝 Reflection Questions

1. **Tool Comparison:**
   I would choose **SpaCy** for most production or fast-turnaround pro
   because its tag labels are intuitive, it handles noisy text (slang,
   contractions) more accurately, and it runs significantly faster on
   datasets. **NLTK** is useful for teaching, research prototyping, or
   need fine-grained Penn Treebank tags (e.g., distinguishing singular
```


🎯 Final Reflection and Submission

Congratulations! You've completed a comprehensive exploration of POS tagging, from basic concepts to real-world challenges.

📝 Reflection Questions

1. **Tool Comparison:**
   I would choose **SpaCy** for most production or fast-turnaround projects because its tag labels are intuitive, it handles noisy text