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LAB : 6

Title: Challenges of HMM-based POS Tagging on Noisy Text

## Step 1: Import Libraries

```
import nltk
nltk.download('punkt_tab')
import pandas as pd
import spacy
import re
from collections import Counter, defaultdict
import matplotlib.pyplot as plt
import seaborn as sns
```

[nltk\_data] Downloading package punkt\_tab to /root/nltk\_data...

[nltk\_data] Package punkt\_tab is already up-to-date!

## Step 2: Load dataset

```
# Load Tweet text and pre-process /content/Twitter_Data.csv
df = pd.read_csv('/content/Twitter_Data.csv')
df.head()
```

	clean_text	category
0	when modi promised "minimum government maximum...	-1.0
1	talk all the nonsense and continue all the dra...	0.0
2	what did just say vote for modi welcome bjp t...	1.0
3	asking his supporters prefix chowkidar their n...	1.0
4	answer who among these the most powerful world...	1.0

## Step 3: POS tags tweets using NLTK of the tweets

```
# POS tags tweets using NLTK of the tweets
nltk.download('averaged_perceptron_tagger')
nltk.download('averaged_perceptron_tagger_eng')
nltk.download('universal_tagset')
```

[nltk\_data] Downloading package averaged\_perceptron\_tagger to /root/nltk\_data...

[nltk\_data] Package averaged\_perceptron\_tagger is already up-to-date!

[nltk\_data] Downloading package averaged\_perceptron\_tagger\_eng to /root/nltk\_data...

[nltk\_data] Package averaged\_perceptron\_tagger\_eng is already up-to-date!

[nltk\_data] Downloading package universal\_tagset to /root/nltk\_data...

[nltk\_data] Package universal\_tagset is already up-to-date!

True

```
print(df.columns)
```

```
Index(['clean_text', 'category'], dtype='object')
```

## Step 4: Preprocessing the tweets

```
def preprocess_tweets(text):
    if not isinstance(text, str):
        return ""
    text = re.sub(r'http\S+', '', text)
    text = re.sub(r'@[A-Za-z0-9]+', '', text)
    text = re.sub(r'#', '', text)
    text = re.sub(r'^\w\s', '', text)
    # Remove whitespaces as well
    text = re.sub(r'\s+', ' ', text).strip()
    return text
```

```
df['preprocess_text'] = df['clean_text'].apply(preprocess_tweets)
df.head(10)
```

	clean_text	category	preprocess_text
0	when modi promised "minimum government maximum...	-1.0	when modi promised minimum government maximum ...
1	talk all the nonsense and continue all the dra...	0.0	talk all the nonsense and continue all the dra...
2	what did just say vote for modi welcome bjp t...	1.0	what did just say vote for modi welcome bjp to...
3	asking his supporters prefix chowkidar their n...	1.0	asking his supporters prefix chowkidar their n...
4	answer who among these the most powerful world...	1.0	answer who among these the most powerful world...
5	kiya tho refresh maarkefir comment karo	0.0	kiya tho refresh maarkefir comment karo
6	surat women perform yagna seeks divine grace f...	0.0	surat women perform yagna seeks divine grace f...
7	this comes from cabinet which has scholars lik...	0.0	this comes from cabinet which has scholars lik...
8	with upcoming election india saga going import...	1.0	with upcoming election india saga going import...
9	gandhi was gay does modi	1.0	gandhi was gay does modi

#### Step 5: POS tagging using nltk

```
# POS tagging using nltk
def pos_tag_tweet(text):
    tokens = nltk.word_tokenize(text.lower())

    pos_tags = nltk.pos_tag(tokens, tagset='universal')
    return pos_tags

df['pos_tags'] = df['preprocess_text'].apply(pos_tag_tweet)
df.head(10)
```

	clean_text	category	preprocess_text	pos_tags
0	when modi promised "minimum government maximum...	-1.0	when modi promised minimum government maximum ...	[(when, ADV), (modi, NOUN), (promised, VERB), ...
1	talk all the nonsense and continue all the dra...	0.0	talk all the nonsense and continue all the dra...	[(talk, NOUN), (all, DET), (the, DET), (nonsen...
2	what did just say vote for modi welcome bjp t...	1.0	what did just say vote for modi welcome bjp to...	[(what, PRON), (did, VERB), (just, ADV), (say,...
3	asking his supporters prefix chowkidar their n...	1.0	asking his supporters prefix chowkidar their n...	[(asking, VERB), (his, PRON), (supporters, NOU...
4	answer who among these the most powerful world...	1.0	answer who among these the most powerful world...	[(answer, NOUN), (who, PRON), (among, ADP), (t...
5	kiya tho refresh maarkefir comment karo	0.0	kiya tho refresh maarkefir comment karo	[(kiya, NOUN), (tho, NOUN), (refresh, ADJ), (m...
6	surat women perform yagna seeks divine grace f...	0.0	surat women perform yagna seeks divine grace f...	[(surat, ADJ), (women, NOUN), (perform, VERB),...
7	this comes from cabinet which has scholars lik...	0.0	this comes from cabinet which has scholars lik...	[(this, DET), (comes, VERB), (from, ADP), (cab...
8	with upcoming election india saga going import...	1.0	with upcoming election india saga going import...	[(with, ADP), (upcoming, ADJ), (election, NOUN...
9	gandhi was gay does modi	1.0	gandhi was gay does modi	[(gandhi, NOUN), (was, VERB), (gay, NOUN), (do...

#### Step 6: Simple HMM for POS tagging with parameter extraction.

```
class SimpleHMM:
    """
    Simple HMM for POS tagging with parameter extraction.
    """
    def __init__(self):
        self.transition_counts = defaultdict(lambda: defaultdict(int))
        self.emission_counts = defaultdict(lambda: defaultdict(int))
        self.tag_counts = defaultdict(int)
        self.vocabulary = set()
        self.tagset = set()

    def train(self, tagged_sentences):
        """
        Train HMM from tagged sentences.
        """
```

```

"""
for sentence in tagged_sentences:
    if len(sentence) == 0:
        continue

    # Add start state
    prev_tag = '<START>'
    self.tag_counts[prev_tag] += 1

    for word, tag in sentence:
        # Emission counts: P(word|tag)
        self.emission_counts[tag][word] += 1
        self.tag_counts[tag] += 1
        self.vocabulary.add(word)
        self.tagset.add(tag)

        # Transition counts: P(tag|prev_tag)
        self.transition_counts[prev_tag][tag] += 1
        prev_tag = tag

    # Add end state
    self.transition_counts[prev_tag]['<END>'] += 1

def get_transition_prob(self, prev_tag, tag, smoothing=1e-6):
    """
    Calculate transition probability with Laplace smoothing.
    """
    count = self.transition_counts[prev_tag][tag]
    total = sum(self.transition_counts[prev_tag].values())
    vocab_size = len(self.tagset) + 1 # +1 for <END>
    return (count + smoothing) / (total + smoothing * vocab_size)

def get_emission_prob(self, tag, word, smoothing=1e-6):
    """
    Calculate emission probability with Laplace smoothing.
    """
    count = self.emission_counts[tag][word]
    total = self.tag_counts[tag]
    vocab_size = len(self.vocabulary)
    return (count + smoothing) / (total + smoothing * vocab_size)

# Train HMM
hmm = SimpleHMM()
hmm.train(df['pos_tags'].tolist())

print(f"HMM Training Complete!")
print(f"\nVocabulary size: {len(hmm.vocabulary)}")
print(f"Tagset size: {len(hmm.tagset)}")
print(f"Tags: {sorted(hmm.tagset)}")

```

HMM Training Complete!

Vocabulary size: 107055

Tagset size: 12

Tags: ['.', 'ADJ', 'ADP', 'ADV', 'CONJ', 'DET', 'NOUN', 'NUM', 'PRON', 'PRT', 'VERB', 'X']

## Step 7: Emission Probability Snapshots

```

# Emission Probability Snapshots
print("\n Emission Probability Examples")
print("="*60)

sample_tags = list(hmm.tagset)[:5] # First 5 tags

for tag in sample_tags:
    # Get top 10 most likely words for this tag
    words_probs = [(word, hmm.get_emission_prob(tag, word))
                    for word in list(hmm.emission_counts[tag].keys())[:20]]
    words_probs.sort(key=lambda x: x[1], reverse=True)

    print(f"\n{tag}:")
    for word, prob in words_probs[:10]:
        print(f" {word:20s} → {prob:.6f}")

```

Emission Probability Examples

=====

```

.:
modi          → 0.398743
modis         → 0.041428
india         → 0.036249

```

ndtv	→ 0.025892
till	→ 0.020714
yes	→ 0.015535
baar	→ 0.010357
modiin	→ 0.010357
kiya	→ 0.005178
vikas	→ 0.005178

VERB:

will	→ 0.041686
should	→ 0.010409
did	→ 0.010109
get	→ 0.007220
say	→ 0.006028
take	→ 0.005720
think	→ 0.005308
vote	→ 0.004674
does	→ 0.004115
rahul	→ 0.002000

ADP:

for	→ 0.250188
with	→ 0.100317
that	→ 0.084863
from	→ 0.078367
like	→ 0.057043
about	→ 0.045517
against	→ 0.032225
after	→ 0.031409
than	→ 0.025333
because	→ 0.024379

ADV:

not	→ 0.130469
now	→ 0.049626
why	→ 0.046662
just	→ 0.035301
when	→ 0.034690
how	→ 0.033257
again	→ 0.024714
modi	→ 0.015198
more	→ 0.014695
well	→ 0.013435

ADJ:

modi	→ 0.045280
narendra	→ 0.013841
great	→ 0.008997
important	→ 0.002990