# Assignment - 1

#### **Tokenization:**

#### 1. Sentence Tokenizer:

Handles sentence boundaries, and avoids splitting on common abbreviations (e.g., "Mr.", "Ms.", "Dr.") by utilizing negative look behinds.

#### 2. Word Tokenizer:

Extracts individual words, allowing alphanumeric characters and hyphens in words. Maintains word boundaries in the tokenized output.

#### 3. Placeholder Usage:

Introduces placeholders ("<NUM>", "<MAILID>", "<URL>", "<HASHTAG>", "<MENTION>") to mask specific types of information (e.g., numbers, email addresses, URLs, hashtags, mentions) in the tokenized text.

#### 4. Punctuation Tokenizer:

Extracts punctuation marks from words and preserves punctuation information in the tokenized output.

## 5. Output:

The final output is a list of lists, where each inner list represents a sentence. The inner lists contain tokens (words and punctuation marks) with placeholders replacing identified patterns.

#### **N-Grams:**

## • Preprocessing of corpus:

- Replaces the newline ('\n') with space (' ') and removes contractions using Python's contraction module.
- Tokenizes the preprocessed corpus and adds n-1 start tokens (<s>) at the beginning of a sentence and 1 end token (<\s>) at the end of the sentence.
- Replaces the punctuation mark with a space (' '). All the tokens with frequency 1 are replaced by <UNK>.

## • Good Turing Smoothing:

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 $S(N_0)=1$ 

$$P(w_3|w_1w_2) = rac{\operatorname{Count}^*(w_1w_2w_3)}{\sum_{w_i \in V} \operatorname{Count}^*(w_1w_2w_i)}$$

Nr for unknown values is estimated from

$$log(N_r) = a + b log(r)$$

a, b are intercept and slope of log(Zr) - log(r) regression line.

#### • Interpolation:

$$P(t_3|t_1,t_2) = \lambda_1 \hat{P}(t_3) + \lambda_2 \hat{P}(t_3|t_2) + \lambda_3 \hat{P}(t_3|t_1,t_2)$$
(6)

 $\hat{P}$  are maximum likelihood estimates of the probabilities, and  $\lambda_1 + \lambda_2 + \lambda_3 = 1$ , so P again represent probability distributions.

Unigrams: 
$$\hat{P}(t_3) = \frac{f(t_3)}{N}$$
  
Bigrams:  $\hat{P}(t_3|t_2) = \frac{f(t_2,t_3)}{f(t_2)}$   
Trigrams:  $\hat{P}(t_3|t_1,t_2) = \frac{f(t_1,t_2,t_3)}{f(t_1,t_2)}$ 

lambda values are estimated as follows:

```
set \lambda_1=\lambda_2=\lambda_3=0 foreach trigram t_1,t_2,t_3 with f(t_1,t_2,t_3)>0 depending on the maximum of the following three values: \operatorname{case} \ \frac{f(t_1,t_2,t_3)-1}{f(t_1,t_2)-1}: \ \operatorname{increment} \ \lambda_3 \ \operatorname{by} \ f(t_1,t_2,t_3) \operatorname{case} \ \frac{f(t_2,t_3)-1}{f(t_2)-1}: \ \operatorname{increment} \ \lambda_2 \ \operatorname{by} \ f(t_1,t_2,t_3) \operatorname{case} \ \frac{f(t_3)-1}{N-1}: \ \operatorname{increment} \ \lambda_1 \ \operatorname{by} \ f(t_1,t_2,t_3) end end \operatorname{end} \ \operatorname{normalize} \ \lambda_1,\lambda_2,\lambda_3
```

## **Average Perplexity Scores:**

LM_TYPE	TRAIN SET	TEST SET
LM-1: pride and prejudice - gt	622721364.1088043	8809439.417691033

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LM_TYPE	TRAIN SET	TEST SET
LM-2: pride and prejudice - i	15.381154391717658	314.95857002977056
LM-3: ulysses - gt	5092318718.764593	136758968.79318216
LM-4: ulysses - i	33.89745816908959	486.1538076733941

#### Generation:

• For the N-gram model (without smoothing), as the value of N increases it generates the correct word because of long history. (No.of guesses decreases).

## **Example:**

**Sentence:** I must throw in a good word for my little Lizzy.

```
**Shravya@shravya-inspiron-11:-/Desktop/sem 6/INLP/ass1s* python3 generator.py p pride.txt 10
//usr/lib/python3/dist-packages/scipy/__init__.py:146: UserWarning: A NumPy version >=1.17.3 and <1.25.0 is required for this version of SciPy (detected version 1.26.3
warnings.warn(f"A NumPy version >=(np_minversion)* and <{np_maxversion}*
input sentence: I must throw in a good
input n: 2
[('humour', 8.760402978537013e-05), ('cunk>', 7.008322382829611e-05), ('opinion', 7.008322382829611e-05), ('erough', 3.5041611914148054e-05), ('spirits', 4.38
02014892063065e-05), ('humoured', 3.5041611914148054e-05), ('news', 3.5041611914148054e-05), ('breeding', 3.504161191414148054e-05), ('breeding', 3.5041611914148054e-05), ('breeding', 3.5041611914148054e-05), (
```

#### • OOD scenario:

- N-gram models struggle in out-of-data contexts as they rely heavily on the training data leading to poor generations.
- N-gram models may face challenges in capturing long-term dependencies between words, especially when the context spans a considerable distance.

#### **Example:**

**Sentence:** Solemnly he came forward and mounted the round gunrest.

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## • Using Smoothing Techniques:

Applying these smoothing techniques enhances the adaptability of N-gram models to out-of-data contexts by mitigating issues related to zero probabilities and promoting more robust language modeling.

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