

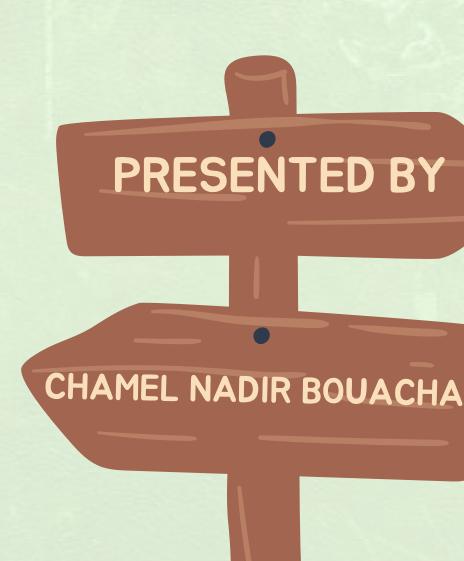


FUNDAMENTALS OF NLP

NLP101











WORKSHOP PLAN

INTRODUCTION

TEXT PREPROCESSING

WORD EMBEDDINGS

- WORD2VEC,
- **Q** GLOVE
- **FASTTEXT CONCEPTS**

APPLICATION:

NLTK

SPACY









INTRODUCTION



ELIZA

1966

REGEX

CHATGPT

2022

TRANSFORMERS











HOW REGEX CAN SIMULATE A CHATBOT ?















ELIZA

PATTERN MATCHING + SUBSTITUTION = CONVERSATION.

User: I am unhappy.

ELIZA: DO YOU THINK COMING HERE WILL HELP YOU NOT TO BE UNHAPPY

User: I need some help, that much seems certain.

ELIZA: WHAT WOULD IT MEAN TO YOU IF YOU GOT SOME HELP

User: Perhaps I could learn to get along with my mother.

ELIZA: TELL ME MORE ABOUT YOUR FAMILY

User: My mother takes care of me.

ELIZA: WHO ELSE IN YOU FAMILY TAKES CARE OF YOU

User: My father. ELIZA: YOUR FATHER

User: You are like my father in some ways.

Weizenbaum (1966)











ELIZA

PATTERN MATCHING + SUBSTITUTION = CONVERSATION.

```
s/.* YOU ARE (depressed|sad) .*/I AM SORRY TO HEAR YOU ARE \1/
s/.* YOU ARE (depressed|sad) .*/WHY DO YOU THINK YOU ARE \1/
s/.* all .*/IN WHAT WAY/
s/.* always .*/CAN YOU THINK OF A SPECIFIC EXAMPLE/
```











SIMPLE WORD PROCESSING TECHNIQUE COULD CREATE A DECENT RESULT

BUT

WHAT COUNTS AS A WORD?













SPEECH RECOGNITION



WE CONSIDER
PUNCTUATION AS A
WORD





DEPENDS ON THE TASK

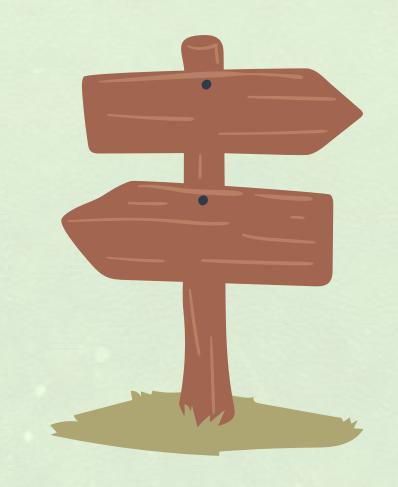












SPEECH











CORPORA











WORD TYPES: 3

WORD INSTANCES: 4









CORPORA



LEMMAS VS. WORDFORMS



FORM OF A WORD

WORDFORMS: FULL
INFLECTED OR DERIVED
FORMS

CAT FOR CATS

CATS FROM CAT









WORD TOKENIZATION

- PREPARES TEXT FOR ANALYSIS
- EASIER TO PROCESS TEXT
- FOUNDATION FOR TEXT REPRESENTATION (E.G WORD EMBEDDINGS)









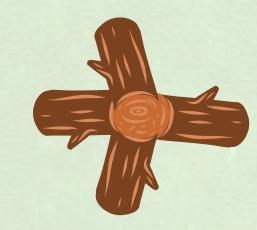


WORD TOKENIZATION

1-TOP-DOWN (RULE-BASED) TOKENIZATION

DEFINING RULES (MAINLY REGEX) THAT WILL SPLIT CORPORA INTO TOKENS













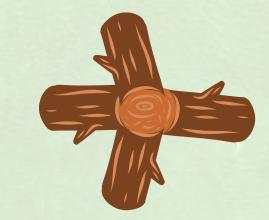




WORD TOKENIZATION

1-TOP-DOWN (RULE-BASED) TOKENIZATION

```
Input: "The San Francisco-based restaurant," they said, "doesn't charge $10".
Output: ['The', 'San', 'Francisco-based', 'restaurant', ',', '"', 'does', "n't",
'charge', '$', '10', '.']
```















WORD TOKENIZATION

2-BOTTOM-UP TOKENIZATION

```
5 1 o w
2 1 o w e s t
6 n e w e r
3 w i d e r
2 n e w
```

l, o, w, e, r, s, t, er, ne, low, newer.







WORD NORMALIZATION





RAW CORPORA

NORMALIZED CORPORA IN STANDARD FORMAT







WORD NORMALIZATION **CASE FOLDING**

CONVERTS ALL CHARACTERS TO LOWERCASE.

EFFECTIVE FOR INFORMATION RETRIEVAL AND SPEECH RECOGNITION













WORD NORMALIZATION CHOOSE A SINGLE STANDARD FORM FOR VARIATIONS

EXAMPLE: USA AND US, UH-HUH AND UHHUH.

USEFUL IN TASKS LIKE INFORMATION RETRIEVAL, WHERE WE WANT TO RETRIEVE DOCUMENTS MENTIONING EITHER FORM.







WORD NORMALIZATION LEMMATIZATION

IDENTIFIES THE ROOT FORM (LEMMA) OF A WORD

```
am , are , and is → be .
dinner and dinners → dinner .
```















WORD NORMALIZATION **LEMMATIZATION**

HELPS IN WEB SEARCH OR INFORMATION RETRIEVAL BY TREATING VARIATIONS OF A WORD AS EQUIVALENT:

Example: A guery for woodchucks should also return results for woodchuck.











WORD NORMALIZATION LEMMATIZATION

COMPLICATED TO DETECTS LEMMA BECAUSE IT USES SOPHISTICATED METHODS USING

MORPHEMES

AFFIXES

Example: Spanish word amaren (if in the future they would love) →

(to love) + morphological features (third person plural, future subjunctive).











WORD NORMALIZATION **STEMMING**

- NAIVE WAY COMPARED TO LEMMATIZATION
- CHOPPING OFF WORD ENDINGS (AFFIXES) WITHOUT UNDERSTANDING THE MORPHOLOGICAL STRUCTURE.













WORD NORMALIZATION STEMMING



This was not the map we found in Billy Bones's chest, but an accurate copy, complete in all things-names and heights and soundings-with the single exception of the red crosses and the written notes.



Stemmed text:

Thi wa not the map we found in Billi Bone s chest but an accur copi complet in all thing name and height and sound with the singl except of the red cross and the written note.





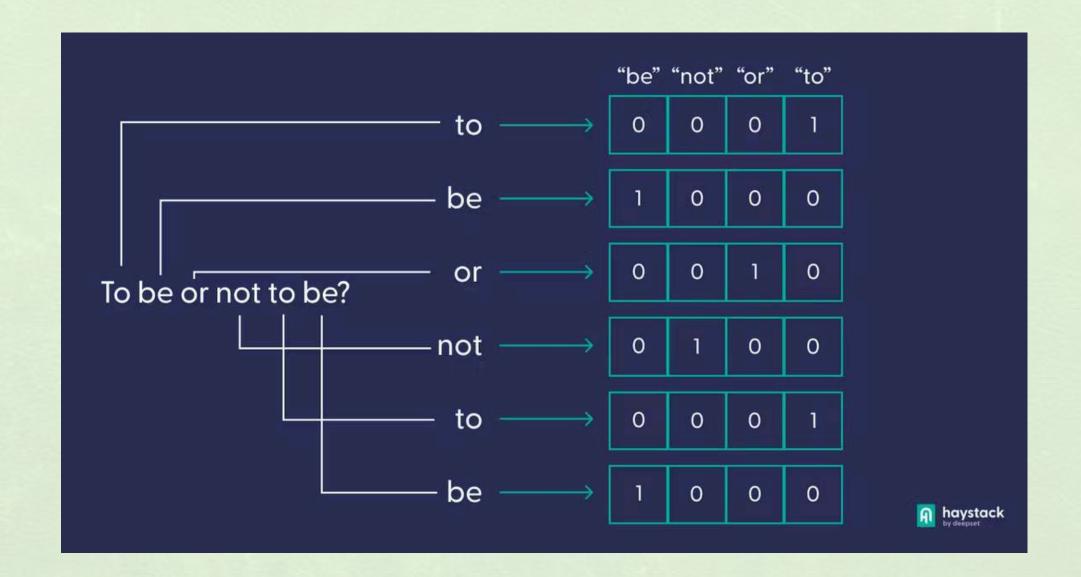








TEXT EMBEDDINGS ARE NUMERICAL REPRESENTATIONS OF WORDS,























CONTEXTUAL UNDERSTANDING

GENERALIZATION

ENHANCED MACHINE LEARNING TASKS

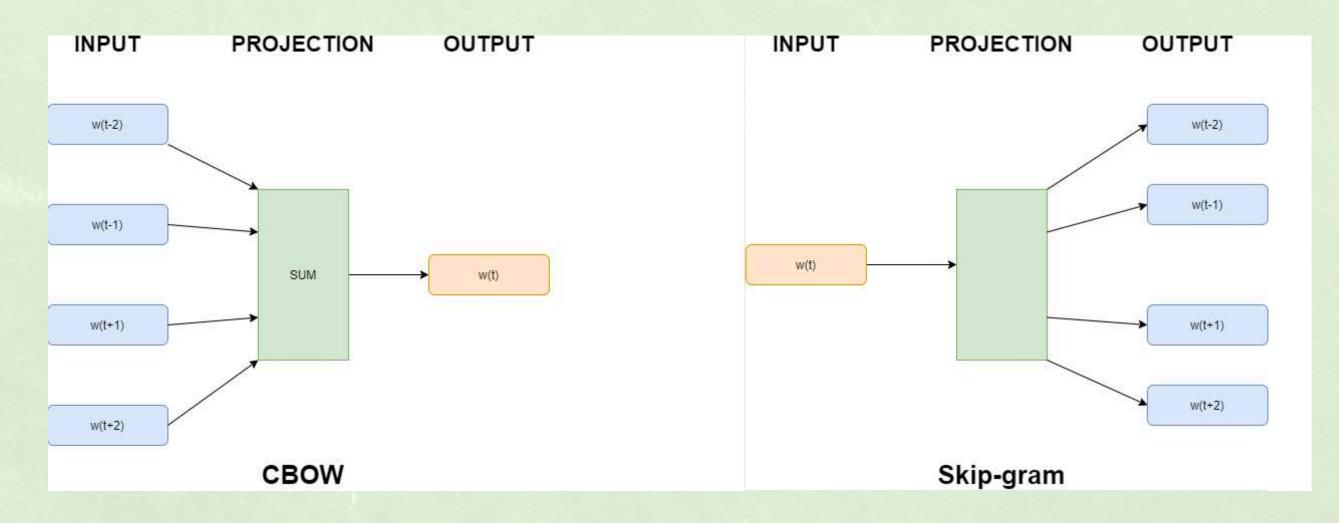






WORD2VEC

LOCAL CONTEXT ONLY













GLOVE

LOCAL CONTEXT + WORD CO-OCCURRENCE











FASTTEXT

- CHARACTER N-GRAMS (E.G., "PLAYING" → "PLAY", "ING", "LAY").
- THESE SUBWORDS ARE TRAINED TO GENERATE EMBEDDINGS











WORD2VEC GLOVE



Feature	Word2Vec	GloVe	FastText
Developer	Google	Stanford	Facebook AI
Core Idea	Context-based	Co-occurrence	Subword-based
Context	Local	Local + Global	Local
Handles OOV?	No	No	Yes
Efficiency	High	Moderate	Moderate
Polysemy	No	No	Partially
Applications	General NLP	Large Corpora	Morphologically rich languages, OOV handling









APPLICATION TIME



