

Natural Language Processing (NLP)

Lecture 21 – HCCDA-AI

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Overview

- > Natural Language Processing (NLP)
- ➤ History and Evolution of NLP
- ➤ Milestones in Modern Neural NLP
 - Neural Machine Translation
 - Free-Text Question Answering
 - GPT-2 (2019)
 - ChatGPT, GPT-4 and Beyond
- Different Approaches of NLP
 - Rule-Based NLP (1950s 1980s)
 - Statistical NLP (1980s 1990s)
 - Machine Learning in NLP (1990s 2010s)
 - Deep Learning in NLP (2013 Present)
- ➤ Core NLP Tasks (with Examples)
- ➤ Sentiment Analysis
- > NLP Pipeline: From Raw Text to Insight
 - Text Pre-processing
 - Feature Extraction Techniques
 - Modeling/Learning
- ➤ Lab: Sentiment Analysis with Word2Vec + LSTM (PyTorch)

Introduction to NLP

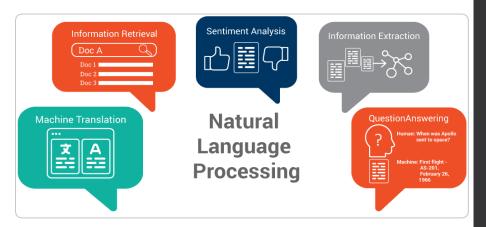
- Language helps us talk to each other, and now to computers too!
- Natural Language Processing (NLP) teaches machines to understand, interpret, and generate human language.
- Field at the intersection of linguistics and machine learning focused on understanding human language.
- Aims to understand context, not just words.

Why NLP Matters:

- Makes **chatbots** like ChatGPT and Siri possible
- Powers **search engines** like Google
- Helps **translate languages** (Google Translate)
- Finds out what **people feel in reviews** (sentiment analysis)

NLP is foundational to advanced AI systems





What is NLP

• Study of computational approaches to processing natural languages.

Processing includes:

- Acquiring language data
- Representing information
- Storing text and speech
- Understanding meaning
- Characterizing language patterns
- Generating new language
- > Natural languages refer to human languages.

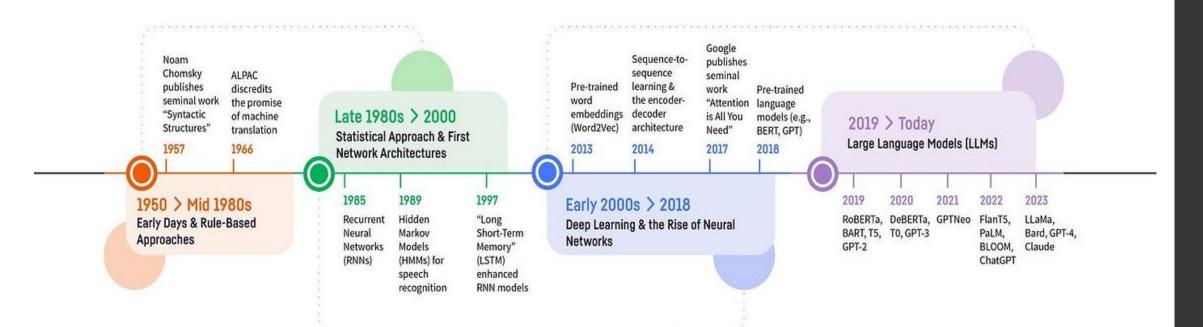
Goal of NLP:

- Enable machines to understand and generate human language.
- Facilitate human-computer interaction through natural language.
- Develop systems that can process and analyze large amounts of text data.



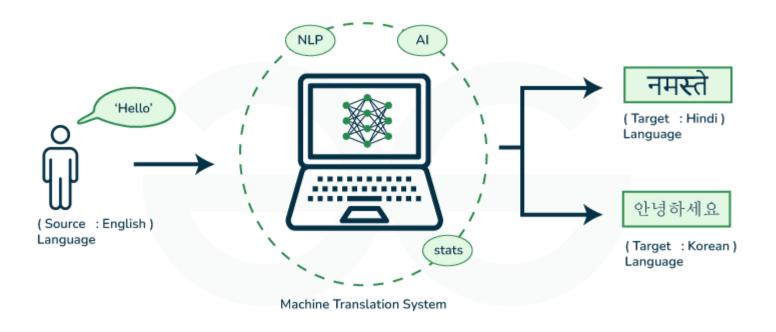
History and Evolution of NLP

Era	Approach	Example	Limitation
1950s – 1980s	Rule-Based	ELIZA chatbot	Brittle, hard to scale
1980s – 1990s	Statistical NLP	HMMs for POS tagging	Requires lots of data
1990s – 2010s	Machine Learning	SVMs for sentiment analysis	Feature engineering required
2010s – Now	Deep Learning	RNNs, LSTMs, Transformers	Requires compute, data

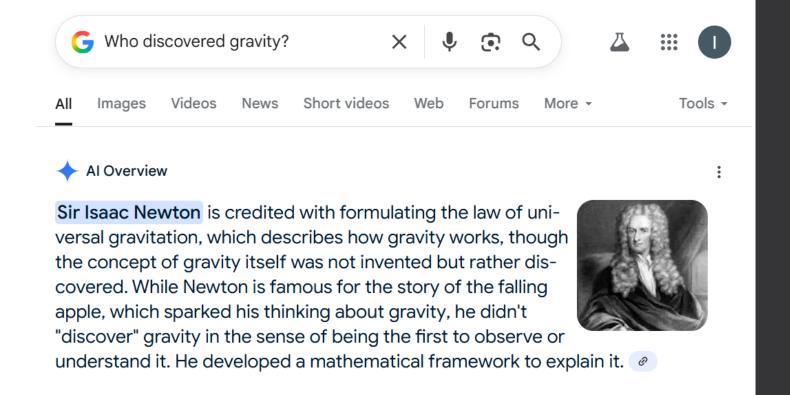


- 1. Neural Machine Translation: The First Major Success of Neural NLP.
 - 2014: Seq2Seq (RNN) by Google Brain
 - 2015: Attention mechanism introduced
 - 2016: Google Translate adopts NMT





- 2. Free-Text Question Answering: The Next Generation of Search.
 - Move from keyword search → direct answer generation
 - Powered by neural models (e.g., BERT, early QA systems).
 - Understands context, not just terms.



GPT-2 (2019): A Step Toward Foundation Models

GPT-2 (2019): An early step towards foundation models ©OpenAI



PROMPT (HUMAN-WRITTEN) A train carriage containing controlled nuclear materials was stolen in Cincinnati today. Its whereabouts are unknown.

MODEL COMPLETION

The incident occurred on the downtown train line, which runs from Covington and Ashland stations.

In an email to Ohio news outlets, the U.S. Department of Energy said it is working with the Federal Railroad Administration to find the thief.

"The theft of this nuclear material will have significant negative consequences on public and environmental health, our workforce and the economy of our nation," said Tom Hicks, the U.S. Energy Secretary, in a statement. "Our top priority is to secure the theft and ensure it doesn't happen again."

The stolen material was taken from the University of Cincinnati's Research Triangle Park nuclear research site, according to a news release from Department officials.

4. ChatGPT, GPT-4, and Beyond: Rise of General-Purpose Language Models

ChatGPT, GPT-4, and more



A Hey please draft a polite mail to explain my boss Jeremy that I would not be able to come to office for next 2 days because my 9 year song Peter is angry with me that I am not giving him much time. So I have plans to take him out for a trip. I will return and complete my work by meeting deadline.

Dear Jeremy,

I hope this email finds you well. I'm writing to let you know that I will not be able to come into the office for the next two days.

My 9-year-old son Peter is feeling upset with me because he feels like I haven't been giving him enough attention lately. In order to make it up to him, I've decided to take him on a little trip to help us reconnect.

I understand that this may cause some inconvenience, but I promise to make up for any lost time by working extra hard to meet any deadlines when I return.

Thank you for your understanding.

Best regards,

[Your Name]

Approaches to NLP

1) Rule-Based NLP (1950s-1980s)

- In the early days of NLP, systems were primarily rulebased. Linguists and programmers manually created a set of rules to process language.
- Example: ELIZA chatbot using pattern matching.
- Used in early grammar checkers, simple chatbots.

2. Statistical NLP (1980s–1990s)

- The 1980s and 1990s saw a shift from rule-based systems to statistical methods. This approach utilized large amounts of data and statistical techniques to understand and generate language.
- Example: Hidden Markov Models (HMMs) for POS tagging.
- Used in early speech recognition, translation.

```
Welcome to
                    EEEEEE LLLLLL IIII ZZZZZZ
  Eliza is a mock Rogerian psychotherapist.
  The original program was described by Joseph Weizenbaum in 1966.
  This implementation by Norbert Landsteiner 2005.
ELIZA: Is something troubling you?
YOU: Men are all alike.
ELIZA: What is the connection, do you suppose?
      They're always bugging us about something or other.
ELIZA: Can you think of a specific example ?
YOU: Well, my boyfriend made me come here.
ELIZA: Is it important to you that your boyfriend made you come here?
YOU: He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.
YOU: It's true. I am unhappy.
ELIZA: Can you explain what made you unhappy?
```

Approaches to NLP

3. Machine Learning in NLP (1990s-2010s)

- The late 1990s and early 2000s marked the introduction of machine learning in NLP. Models learn patterns from labeled data.
- Techniques: Naive Bayes, SVMs, Decision Trees.
- · Requires:
 - · Feature engineering
 - · Clean, labeled data

4. Deep Learning in NLP (2013–Present)

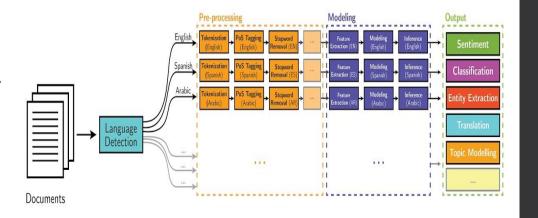
- Key Models:
 - · RNNs/LSTMs: Good at handling sequences.
 - CNNs: Capture local patterns in text.
 - Transformers: Now dominant in modern NLP.

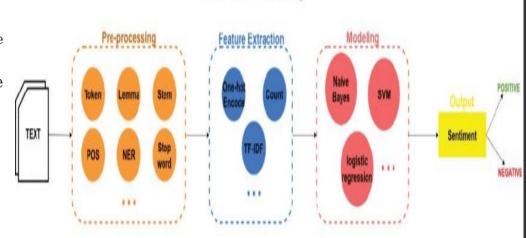
• The Rise of Large Language Models (LLMs):

- · Revolutionized NLP with models like GPT and Llama.
- Trained on massive text data to understand and generate human-like text.
- Shifted from task-specific models to general-purpose models.

Applications:

- Machine Translation
- · Text Generation
- Q&A Systems
- Summarization





Core NLP Tasks (with Examples)

Task	What it does	Example
Tokenization	Split text into words	"Pakistan Zindabad" → ["Pakistan", "Zindabad"]
Text Classification	Assigning categories to text	Spam detection in emails
Sentiment Analysis	Detecting mood	"This movie was amazing!" → Positive
Machine Translation	Language to language	English → Urdu
Named Entity Recognition	Find names, places, etc.	Imran Khan, 2024, Islamabad
Text Summarization	Generating concise summaries	Abstract generation from research articles

Sentiment Analysis

• Definition:

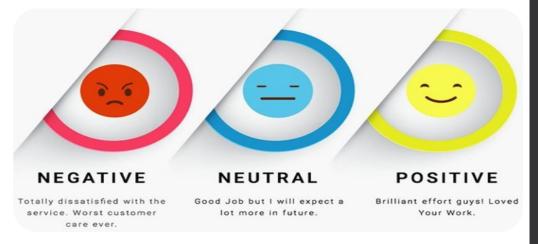
• Using NLP to find out if text expresses a positive, negative, or neutral opinion about a topic, product, or service.

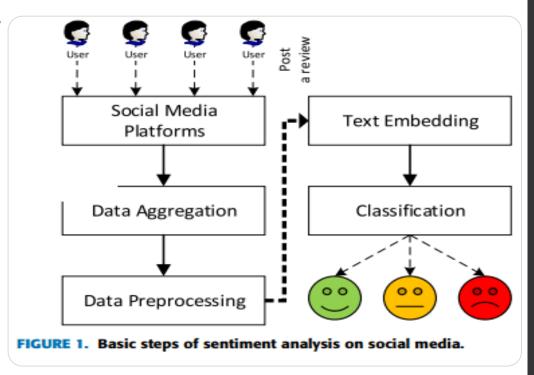
• Example:

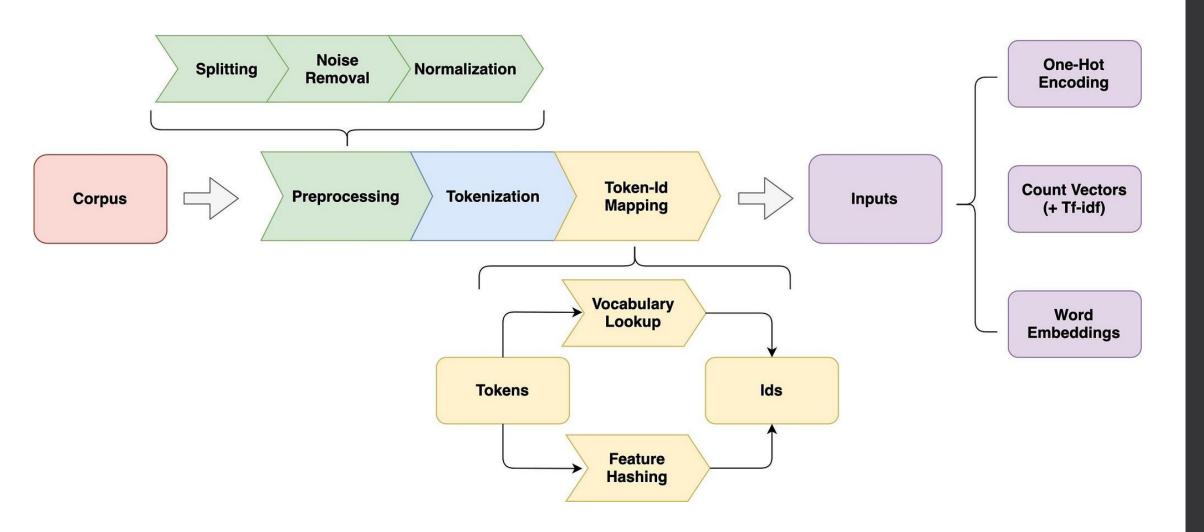
- **Sentence:** "I love the new design of this app, but I hate how it crashes frequently."
- Positive Sentiment: "I love the new design of this app."
- Negative Sentiment: "I hate how it crashes frequently."

Use Case:

• **Brand Management:** Companies track tweets, reviews, and posts to see how people feel about a new product. This helps them fix issues quickly and keep customers happy.







1. Text Preprocessing

• Essential to prepare raw language for modeling.

Step	Purpose	
Tokenization	Split text into words/subwords (tokens)	
Removing stop words	Remove common, non-informative words (e.g., "is", "the", "and")	
Stemming/Lemmatization	Reduce words to their root or base form. Example: "running" \(\rightarrow\) "run"	
Lowercase everything	"NLP" → "nlp"	
Punctuation Removal	Clean text	
POS Tagging	Assigning parts of speech (noun, etc.) to each token.	
Named Entity Recognition	Extract named entities	
Spell Checking	Correct spelling errors	
Handling Duplicates/Missing	Ensure clean and complete input	

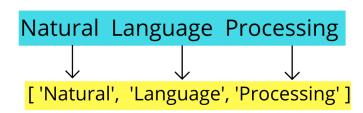
Example:

- Sentence: "It was the best of times."
- Tokens: ['it', 'was', 'the', 'best', 'of', 'times']

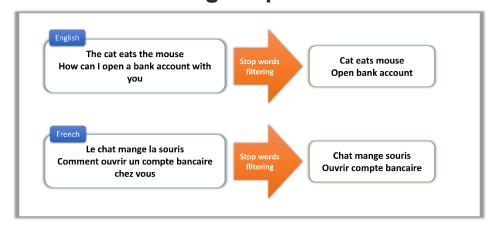
1. Text Preprocessing

· Essential to prepare raw language for modeling.

Tokenization



Removing Stop words



Stemming



Lemmatization



Text Normalization

	Rating	Reviews	Clean_Reviews
0	5	I feel so LUCKY to have found this used (phone	i feel so lucky to have found this used phone
1	4	nice phone, nice up grade from my pantach revu	nice phone nice up grade from my pantach revue
2	5	Very pleased	very pleased
3	4	It works good but it goes slow sometimes but i	it works good but it goes slow sometimes but i
4	4	Great phone to replace my lost phone. The only	great phone to replace my lost phone the only \dots

2. Feature Extraction Techniques / Vectorization:

• Transform words or documents into numerical representations for machine learning models.

Technique	Description	
Bag-of-Words	Counts word occurrences in a document.	
TF-IDF	Weighs words by importance across documents.	
n-Grams	Groups of 2 or 3 words together to keep some word order and context.	
Word2Vec / GloVe	Learns dense vector representations capturing word meaning and context.	

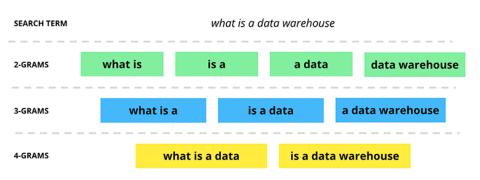
Example:

Sentence: "it was the best of times"

Vocabulary: [it, was, the, best, of, times]

BoW Vector: [1, 1, 1, 1, 1, 1]

n-grams



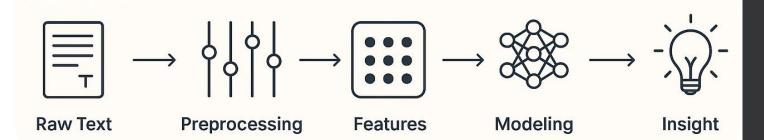
3. Modeling/Learning:

- Using machine learning or deep learning algorithms to learn patterns from extracted text features.
- · Goal: Predict, classify, or generate meaningful language output.

Common Approaches:

- Traditional ML: Logistic Regression, Naive Bayes, SVM (fast, simple, works well with BoW/TF-IDF).
- Deep Learning: RNNs, LSTMs, GRUs (capture sequence).
- Transformers: BERT, GPT (state-of-the-art for NLP tasks).

NLP Pipeline: Modeling / Learning



Thank You