

Synergy of Linguistic Science and Technology: NLP's Linguistic Endeavors

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IIT Guwahati



OUTLINE:

1. **Introduction**
2. **What is NLP ?**
3. **The Linguistic Landscape**
4. **NLP Tasks and Applications**
5. **Importance of NLP in Multidisciplinary Context**
6. **Synergy of Linguistic Science and Technology**
7. **Challenges and Future Directions**
8. **Conclusion and Q&A**

1. Introduction

- Welcome to the presentation
- Overview
 - Explore the intersection of linguistic science and technology
- Agenda
 - Journey through key NLP applications
 - Significance of these applications in addressing everyday linguistic challenges

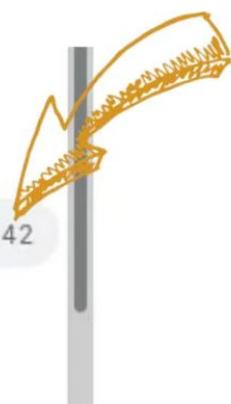
 Scheduled

 All Mail

 **Spam** 42

 Trash

 Categories



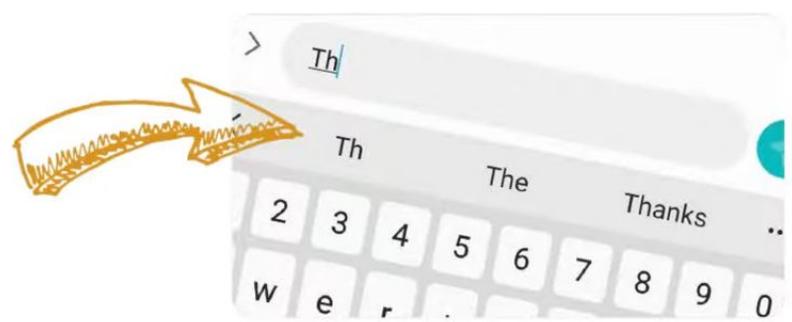
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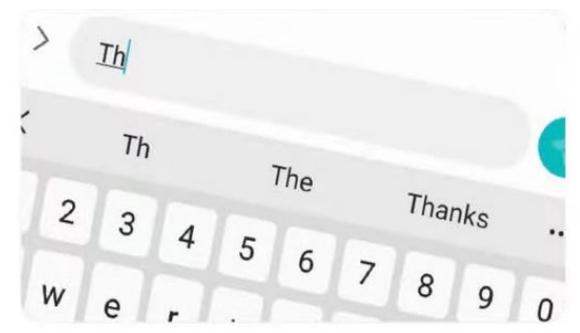
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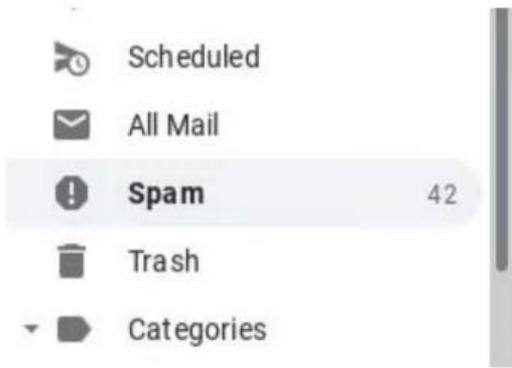
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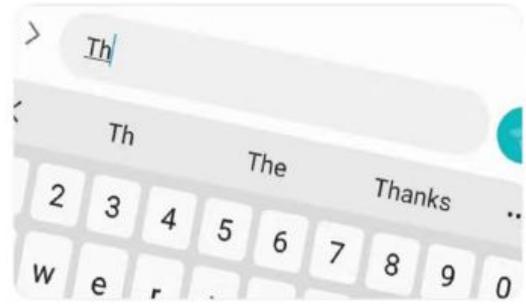


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-  Trash
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Google



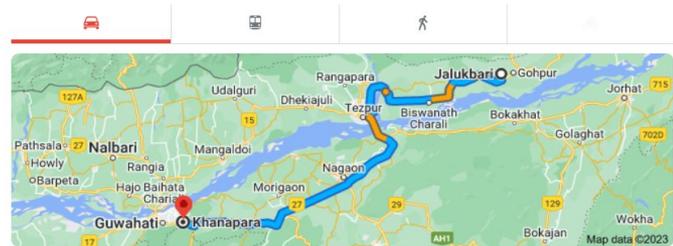
Drive from Jalukbari to Khanapara

Maps By car Bus Images Bus fare Videos Shopping News Books

About 85,600 results (0.43 seconds)

Jalukbari, Assam

Khanapara, Guwahati, Assam

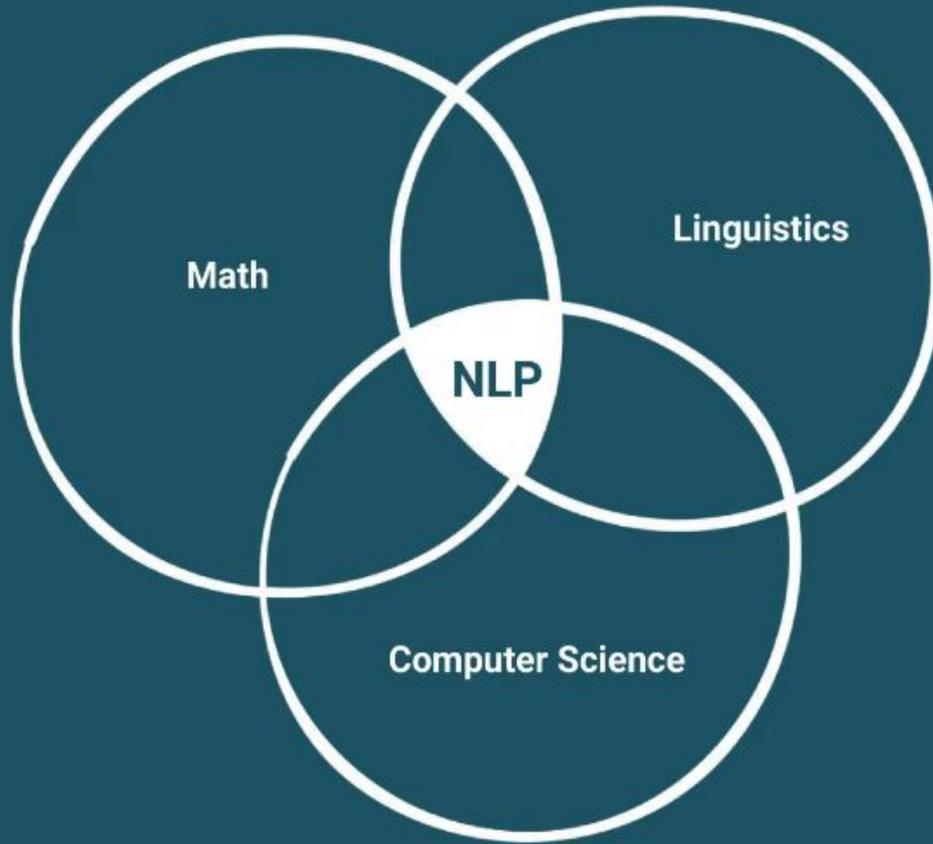


5 hr 58 min (282.0 km) via NH 15 and NH 27

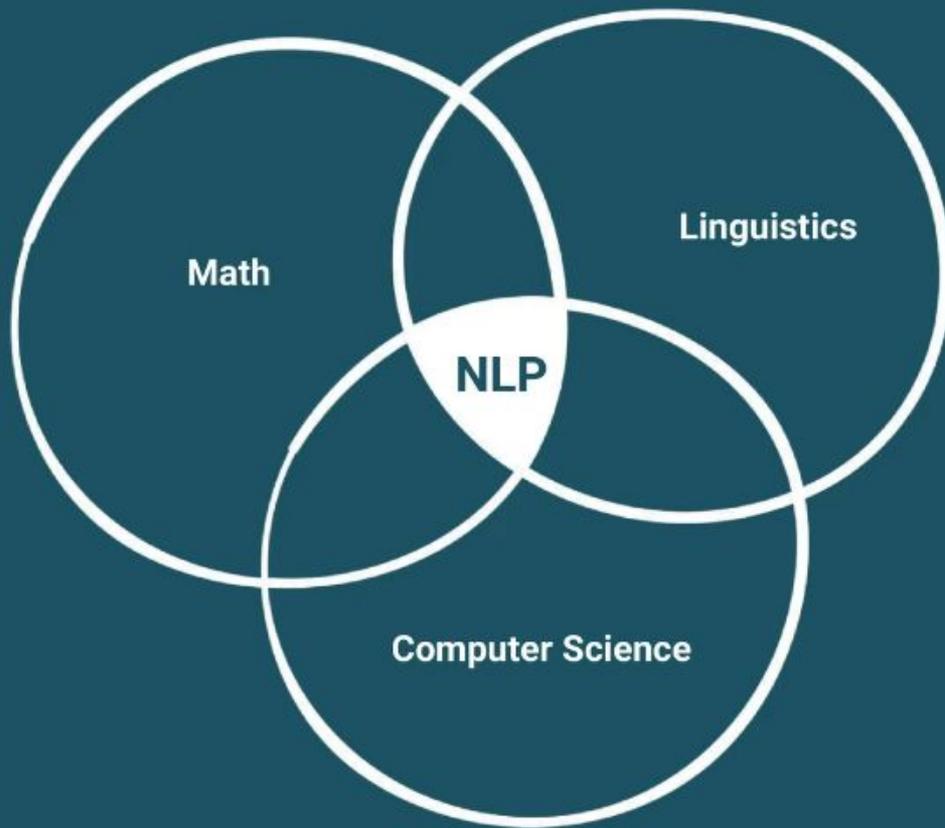
Directions



2. What is NLP ?

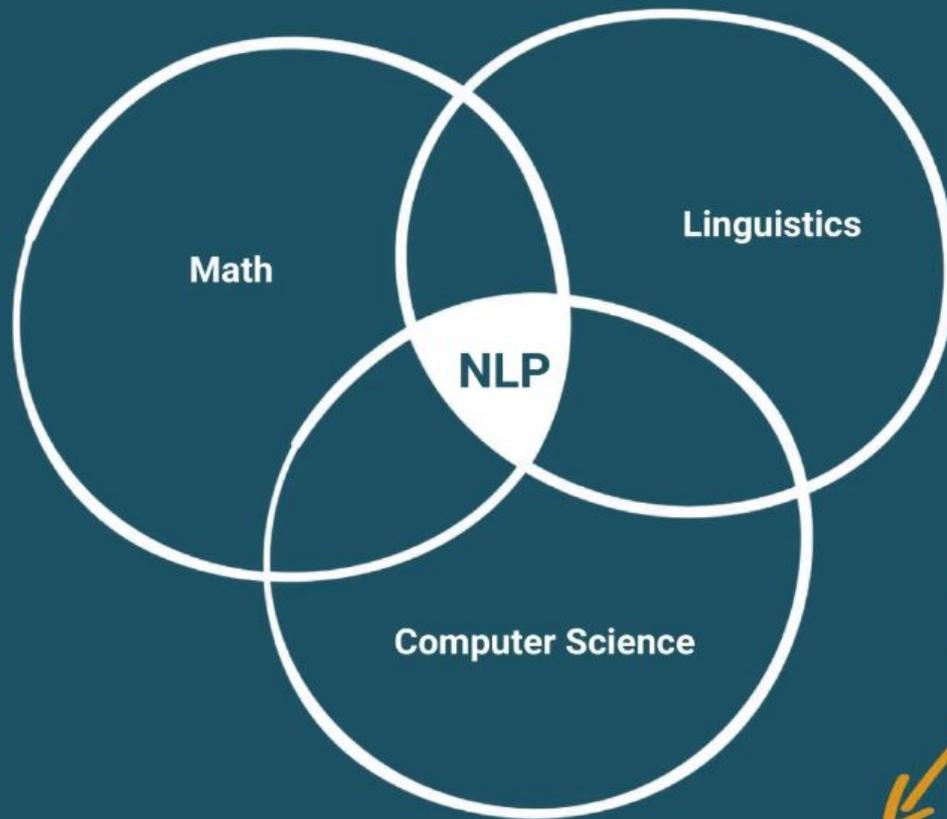


2. What is NLP ?



Goal: Get computers to do useful things with *natural language* data.

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3. The Linguistic Landscape

Why is NLP difficult?

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Why is NLP difficult?

Ambiguity

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“Stolen painting found by tree”

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Why is NLP difficult?

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“Stolen painting found by tree”

By a tree, a stolen painting
was found.

3. The Linguistic Landscape

Why is NLP difficult?

Ambiguity

“Stolen painting found by tree”

By a tree, a stolen painting
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vs.

A tree found a stolen
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3. The Linguistic Landscape

Why is NLP difficult?

Ambiguity

“Stolen painting found **by tree**”



Prepositional Phrase

By a tree, a stolen painting
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vs.

A tree found a stolen
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3. The Linguistic Landscape

Why is NLP difficult?

Ambiguity

"Stolen painting found by tree"



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Prepositional Phrase

PP-attachment problem
syntactic ambiguity

3. The Linguistic Landscape

Why is NLP difficult?

Ambiguity

“He's at the bank.”

3. The Linguistic Landscape

Why is NLP difficult?

Ambiguity

“He's at the bank.”



vs.



lexical ambiguity

3. The Linguistic Landscape

Why is NLP difficult?

Ambiguity

“She flew in last night.”

3. The Linguistic Landscape

Why is NLP difficult?

Ambiguity

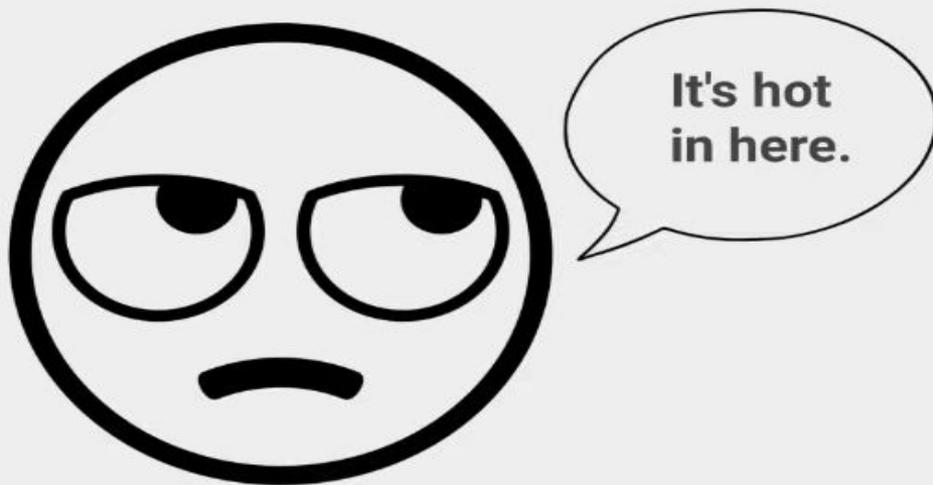
“She flew in last night.”



3. The Linguistic Landscape

Why is NLP difficult?

Beyond text (tones and gestures)



3. The Linguistic Landscape

Why is NLP difficult?

Beyond text (tones and gestures)



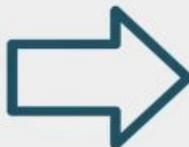
Really: "I'm bored and tired and I hate you for bringing me here."

Pragmatics (how people use language)

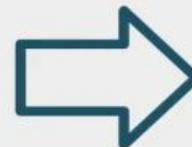
Progress in NLP

NLP Progress

1950s: Rules-based systems.



Late 1980s: “Statistical revolution”; incorporating Machine Learning.



Early 2010s: Neural Networks; Deep Learning.

4. NLP Tasks and Applications

Common NLP Tasks and Applications



Translation



Summarization



Question Answering



Speech Recognition



Classification



Assisted Writing

And so much more...

4.1 Few Classic NLP Problems: POS

Part-of-Speech (POS) Tagging

Classifying how a word is used in a sentence.

{ noun, verb, adjective, ... }

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POS tagging assigns each word in a sentence its corresponding POS.

[John, watched, an, old, movie, at, the, cinema, .]

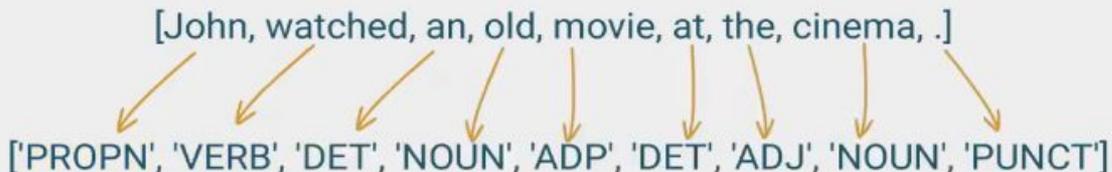
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Part-of-Speech (POS) Tagging

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Parts of speech can help discover intent or action.



"How can I help you today?"



"I want to book a hotel room."

VERB

NOUN

e.g. you could scan for VERB-NOUN patterns. Scanning for POS patterns can also help with other tasks such as information extraction.

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Part-of-Speech (POS) Tagging

Classifying how a word is used in a sentence.

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Simply scanning for keywords like “book” isn't enough.

“I want to **book** a hotel room.” vs. “I left the **book** in the hotel room.”

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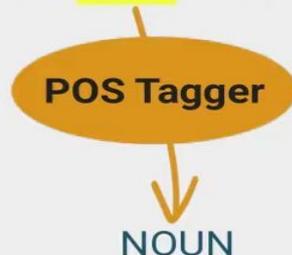
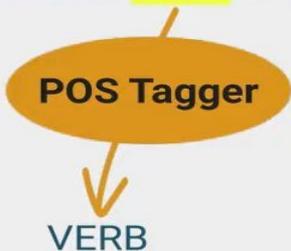
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POS tagging will help with *word sense disambiguation*, determining which meaning of a word is intended based on its context or grammatical relationship with neighbouring words.

4.2 Few Classic NLP Problems: NER

Named Entity Recognition (NER)

Tagging named (“real-world”) entities.

{ a person, a location, an organization, ... }

Named Entity: (roughly) anything that can be referred by a proper name.
They often have a *Proper Noun (PROPN)* POS tag.

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Most Common



Person (PER)

“Alice”, “Isaac Newton”



Location (LOC)

“Bay Area”, “Rocky Mountains”



Geopolitical Entity (GPE)

“Canada”, “Chicago”



Organization (ORG)

“Microsoft”, “Porsche”

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Named Entity Recognition (NER)

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{ a person, a location, an organization, ... }

Named Entity: (roughly) anything that can be referred by a proper name.
They often have a *Proper Noun (PROPN)* POS tag.

But also often extended to other types

 Money

 Time

 Date

.

.

.

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{ a person, a location, an organization, ... }

“Volkswagen is developing an electric sedan which could potentially come to America next fall.”

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Named Entity Recognition (NER)

Tagging named (“real-world”) entities.

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“Volkswagen is developing an electric sedan which could potentially come to America next fall.”



“**Volkswagen [ORG]** is developing an electric sedan which could potentially come to **America [GPE]** **next fall [DATE]**.”

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Useful in a variety of tasks and applications...



Organizing/Categorizing corpus

e.g. identify medical procedures or diseases in research, or categorize support tickets based on entities mentioned.

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Question answering

e.g. extract entities from a question and use NER to narrow down possible candidate answers. A question about a country's capital is going to result in an answer that's either LOC or GPE.

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Critical in information extraction

e.g. extracting events and relationships between entities.

4.2 Few Classic NLP Problems: NER

Named Entity Recognition (NER)

Tagging named (“real-world”) entities.

{ a person, a location, an organization, ... }

Challenges...

An entity can span multiple tokens

“Alexander Hamilton”



Entity *spans* two tokens and the system must identify the boundaries correctly.

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“Alexander Hamilton”

Entity *spans* two tokens and the system must identify the boundaries correctly.

Type ambiguity

“Hamilton”

U.S. President?

F1 driver?

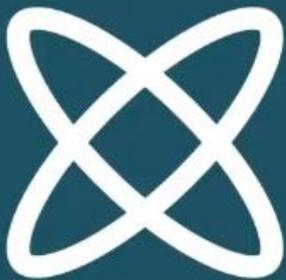
Musical?

City?

Watch company?

4.3 Few Common NLP Problems: Classification

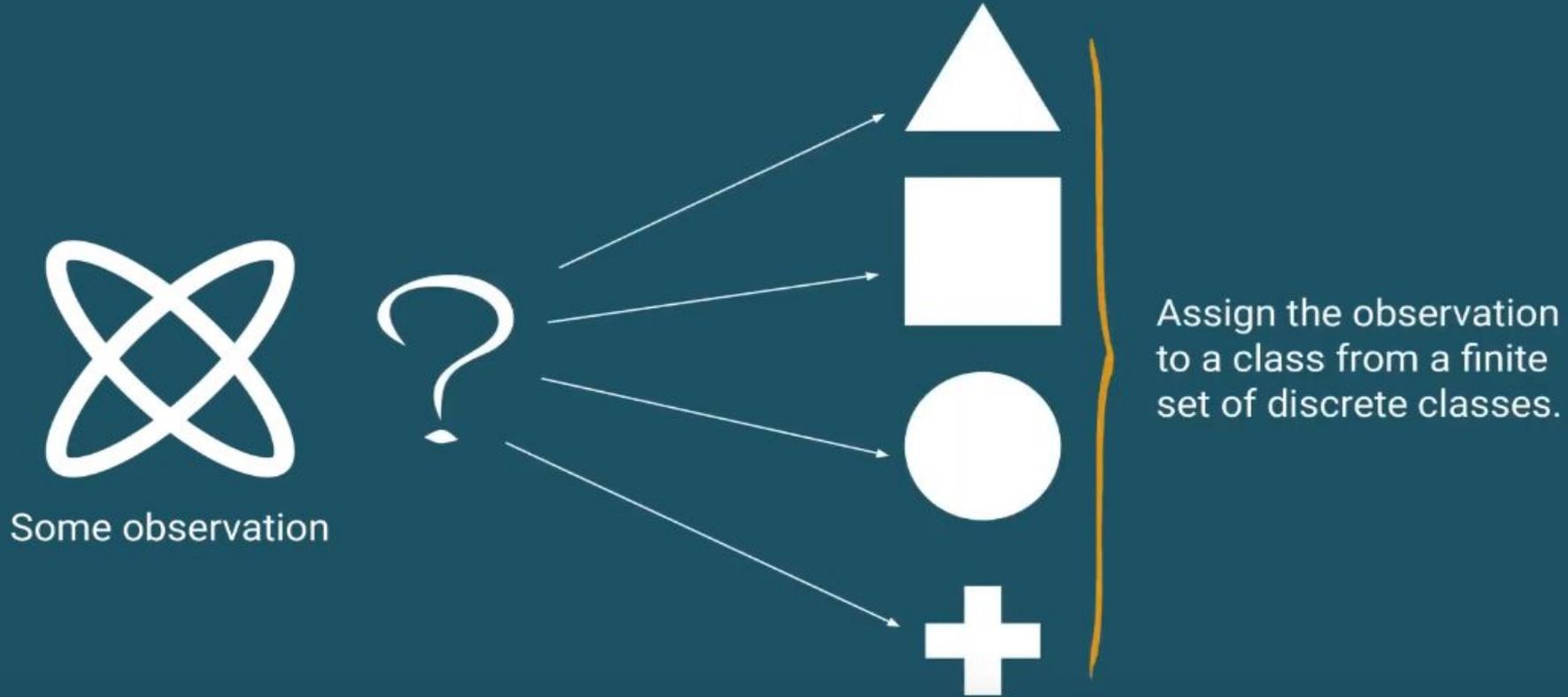
Classification



Some observation

4.3 Few Common NLP Problems: Classification

Classification



4.3 Few Common NLP Problems: Classification

Classification



Product review
sentiment

4.3 Few Common NLP Problems: Classification

Classification



Product review
sentiment



Support ticket
categorization

4.3 Few Common NLP Problems: Classification

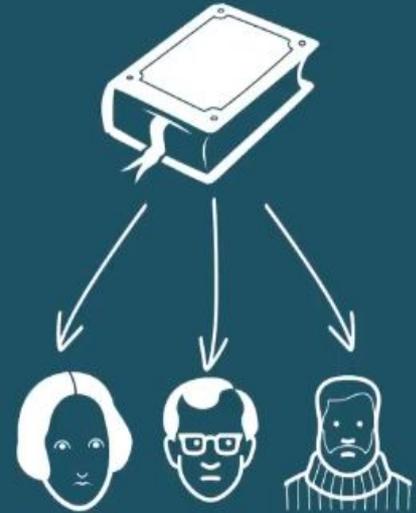
Classification



Product review
sentiment



Support ticket
categorization



Author identification

4.4 Few Advanced NLP Problems: Sequence2Sequence



Translation



Summarization

4.4 Few Advanced NLP Problems: Sequence2Sequence



Translation



Dialogue



Summarization



Question Answering

4.4 Few Advanced NLP Problems: Sequence2Sequence



Translation



Dialogue



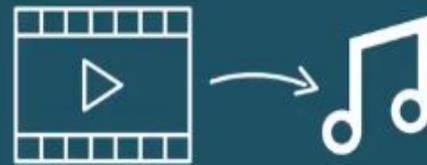
Spec-To-Code



Summarization



Question Answering

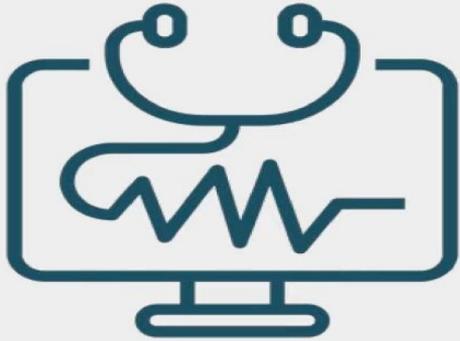


Video-To-Music

5. Importance of NLP in Multidisciplinary Context

- **Cross-Industry Applications:** Similar NLP approaches can be applied in various industries:
 - **Healthcare:** Accurate translation in medical contexts for better patient care.

NLP in Industry

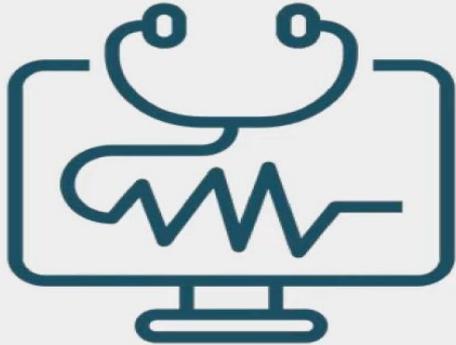


Clinical decision support in medicine.

5. Importance of NLP in Multidisciplinary Context

- **Cross-Industry Applications:** Similar NLP approaches can be applied in various industries:
 - **Law:** Help with the precedence search in Law.

NLP in Industry

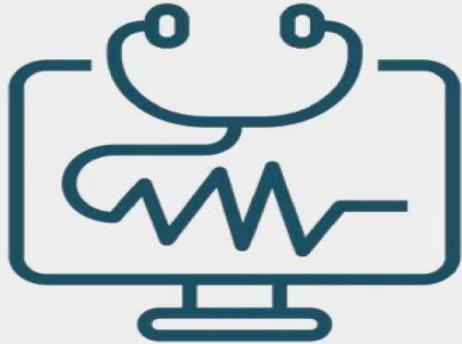


Information extraction to help with precedence search in law.

5. Importance of NLP in Multidisciplinary Context

- **Cross-Industry Applications:** Similar NLP approaches can be applied in various industries:
 - **Finance:** Report and News analysis in Finance.

NLP in Industry



Report and news analysis in finance.



5. Importance of NLP in Multidisciplinary Context

- **Cross-Industry Applications:** Similar NLP approaches can be applied in various industries:
 - **Education:** Language learning apps that adapt to individual needs.



duolingo ai

6. Synergy of Linguistic Science and Technology

- **Linguistic Expertise Enhances NLP**
 - **Rule Formulation:**
 - Linguistic experts formulate rules and guidelines. For example, understanding that names can have different forms, titles, or nicknames helps improve the precision of NER models.
 - **Training Data Creation:**
 - Expertise crucial for creating training data in tasks like Machine Translation, POS Tagging, Dependency Parsing etc. for state-of-the-art models.
 - **Outcome Validation:**
 - Only linguistic experts can effectively validate outcomes of certain linguistic experiments.
 - **Key to Research:**
 - Well-versed linguistic experts are essential for multidisciplinary computational linguistic research.

6. Synergy of Linguistic Science and Technology

- **Technology Facilitates Linguistic Research**
 - **Automatic POS and NER Tagger:**
 - **Build an automatic system for part-of-speech (POS) tagging and Named Entity Recognition (NER) to enhance linguistic analysis**
 - **Automatic Translator and Transliterator:**
 - **Create an automated system for translation and transliteration tasks.**
 - **Automatic Sentiment Analyzer, Language Identifier:**
 - **Build an automated system for sentiment analysis and language identification.**
 - **Chatbots, Conversational AI models:**
 - **Develop intelligent Chatbots and state-of-the-art Conversational AI model like ChatGPT, GPT4 for interactive linguistic interactions.**

7. Challenges and Future Directions:

- Sentiment Analysis & Sarcasm Detection
On user generated Social Media Content

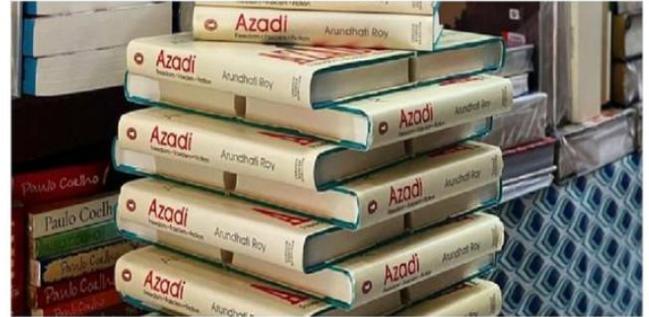


Good time to launch amidst acute shortage of Toilet papers



20h

And #ArundhatiRoy has her latest book out now in stores



7. Challenges and Future Directions:

- Language Identification, Machine Translation & Transliteration in code-mixed Social Media Data



7. Challenges and Future Directions:

Text Documents Websites

GUJARATI - DETECTED ENGLISH GUJARATI ASSAMESE

ENGLISH ASSAMESE GUJARATI

 @himantabiswa apunr bule students blkr krne bht mrom etya kot gol mrm 🙄?? Amk kio mitrur mukhr loi thli ase mama?? Youth mttrs #CancelAssamBoardExams #BoycottRanojPegu #WeWantJusticeNotInjustice

@Himantabiswa apunr bule students blkr krne bht mrom etya kot gol mrm 🙄?? Amk kio mitrur mukhr loi thli ase mama?? Youth mttrs #CancelAssamBoardExams #BoycottRanojPegu #WeWantJusticeNotInjustice

Did you mean: @himantabiswa apunr bule students blkr krne bht mrom etya kot gol mrm 🙄?? Amk kio mitrur **muke** loi **thali** ase mama?? Youth **matters** #CancelAssamBoardExams #BoycottRanojPegu #WeWantJusticeNotInjustice

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@himantabiswa apunr bule ছাত্র-ছাত্রী সকল blkr krne bht mrom এত্যা কোট গোল mrm 🙄?? আমক কিও মিত্ৰৰ মুখৰ লয়ই থলি আসে মামা ?? যুৱক-যুৱতী mttrs #অসমবৰ্ড পৰীক্ষা বাতিল কৰক #বয়কট ৰাণোজপেগু #আমি ন্যায় বিচাৰো অন্যায় নহয়



8. Conclusion

- **Linguistic-Technology Fusion**
- **Diverse NLP Applications**
- **Significance in Multidisciplinary Context**
- **Ongoing Challenges and Future Directions**
- **Call to Collaborate**

Q&A

**THANK YOU
FOR
LISTENING**

References

<https://krishnaik.in/>

<http://jalammar.github.io/>

<https://colah.github.io/>

<https://www.nlpdemystified.org>

8. Conclusion and Q&A

1. Linguistic-Technology Fusion:

- The presentation showcased the powerful fusion of linguistic insights with technological advancements in the realm of Natural Language Processing (NLP).

2. Diverse NLP Applications:

- From automatic POS and NER tagging to translation, sentiment analysis, and chatbots, NLP applications demonstrated the versatility of linguistic science and technology collaboration.

3. Significance in Multidisciplinary Context:

- Highlighted the relevance of NLP in diverse fields, emphasizing its importance in healthcare, business, education, and beyond.

4. Ongoing Challenges and Future Directions:

- Acknowledged current challenges in tasks like sentiment analysis, processing user-generated data and looked ahead to future directions, indicating the continuous evolution of NLP.

5. Call to Collaborate:

- Encouraged ongoing collaboration between linguists and technologists, underlining the collective impact in advancing natural language understanding and technology integration.