Natural Language Understanding, Generation, and Machine Translation

Lecture 1: Introduction

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Overview

Reading: Church and Liberman (2021).

Introduction

What is Natural Language Understanding?

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Application: Digital assistants

Input: A command in natural language

Output: Code to carry out that command

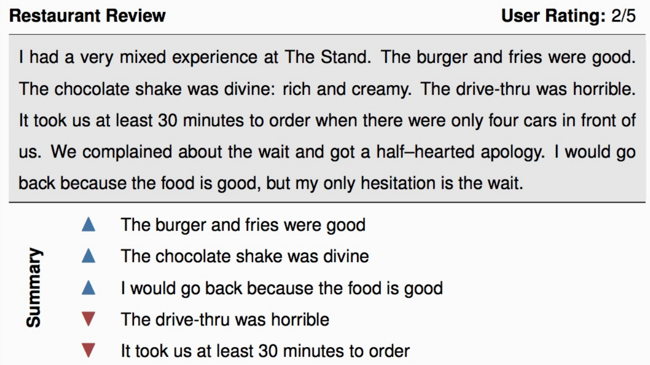
What is Natural Language Understanding?

Application: Question answering

Input: A question in natural language

Output: A natural language answer to that question

What is Natural Language Understanding?



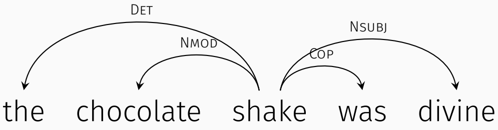
Source: Stefanos Angelidis, *Weakly Supervised Sentiment Analysis and Opinion Extraction*, 2019 PhD thesis

Application: Sentiment analysis

Input: Natural language sentence

Output: Classification of sentence as positive, negative, or neutral towards its subject

What is Natural Language Understanding?



Core NLP task: syntactic parsing

Input: A natural language sentence

Output: A dependency analysis of the sentence

What is Natural Language Understanding?

What countries border France?

$$\lambda x.\mathrm{country}(x) \cap \mathrm{borders}(x, \mathrm{France})$$

Core NLP task: semantic parsing

Input: A natural language sentence

Output: A logical form expressing the meaning of that sentence

Summary of Natural Language Understanding

Broadly: any computational problem where the *input* is natural language, and the *output* is structured information that a computer can store (e.g. in a database) or execute (e.g. a command to a digital assistant).

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Text $\Longrightarrow$ Analyses (syntactic relationships, logical forms, named entities, coreference, user intents, sentiment, etc.)

What is Natural Language Generation?

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Pollen Concentration Data for Scotland

AreaID	Value
1 (North)	6
2 (North West)	5
3 (Central)	5
4 (North East)	6
5 (South West)	8
6 (South East)	8

Monday looks set to bring another day of relatively high pollen counts, with values up to a very high eight in the Central Belt. Further North, levels will be a little better at a moderate to high five to six. However, even at these lower levels it will probably be uncomfortable for Hay fever sufferers.

Application: Data-to-text generation

Input: Structured data (e.g. database tables)

Output: A natural language description of that data

Two small dogs run through the grass.

Application: Image captioning

Input: Image

Output: A natural language description of that image

Summary of Natural Language Generation

Broadly: any computational problem where the *input* is non-linguistic data (e.g. data, images, sound) and the *output* is a natural language description of the input.

Non-linguistic input (logical forms, database entries, images, etc.) $\Longrightarrow$ Text

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What about tasks where *both the input and output are text?*

What is Machine Translation?

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Så varför minskar inte vi våra utsläpp?
So, why are we not reducing our emissions?

Example: Swedish-English machine translation

Input: A sentence in Swedish

Output: A sentence in English expressing the same meaning

What is Machine Translation?

Owls are the order Strigiformes, comprising 200 bird of prey species.

An owl is a bird. There are about 200 kinds of owls.

Application: English text simplification

Input: A sentence in English

Output: Sentences in basic English expressing the same meaning

What is Machine Translation?

Doing some traveling this year and I am looking to build the ultimate travel kit … So far I have a Bonavita 0.5L travel kettle and AeroPress. Looking for a grinder that would maybe fit into the AeroPress. This way I can stack them in each other and have a compact travel kit.

TL;DR: What grinder would you recommend that fits in AeroPress?

Application: summarization

Input: A paragraph or document

Output: A sentence that summarizes the key content of the input

Summary of Machine Translation

Both *input* and *output* are text that convey the same meaning, but written in a different language or style.

Philosophically and technically, machine translation requires both NLU and NLG.

State of NLP

NLP is no longer just about language... and language is about people, anyway

Many domains of research have sprung in recent years with the advent of large language models and other methodology

Issues in ethics, security and safety of large language models, scaling of such models...

We will touch upon these too

Absolutely no clue - word counts

Going on piazza feels like screaming into a void where no questions are actually answered , which is great because at least we have answer keys... oh wait hold on. I was thinking Zipf's law for this but idk how to apply it.

Any help would be appreciated

might be appropriate.

(d) Suppose I have a large corpus, and I make a list of all the words that occur **exactly once in the first half** of the corpus. I then count how many times each of those words occurs in the **second half** of the corpus. Which of the following should I expect to find? (Write the correct letter in your exam book, an explanation is not needed.)

A. On average, these words occur *less than once* in the second half.

B. On average, these words occur *more than once* in the second half.

C. On average, these words occur *exactly once* in the second half.

D. There is no way to predict; any of the above are equally likely. [*2 marks*]

A question on Piazza

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[redacted] (Anon. Gear to classmates) 1 month ago

https://chat.openai.com/share/b94622fb-9351-499d-afcb-b63f733a7a00

helpful! | 2

ChatGPT's Answer

Anonymous

answer the following question from an NLP practice paper: suppose i have a large corpus, and i make a list of all the words that occur exactly once in the first half of the corpus. i then count how many times each of those words occurs in the second half of the corpus. what would i expect about the count of these words in the second half? write a brief answer with short justification.

ChatGPT

In the second half of the corpus, you would generally expect the counts of words that occurred exactly once in the first half to be lower compared to more frequently occurring words. This phenomenon is often described by Zipf's Law, which states that the frequency distribution of words in a language follows a power-law distribution. In a large corpus, a small number of words occur very frequently (high-frequency words), while a large number of words occur infrequently (low-frequency words). Words that occur exactly once in the first half are likely to be among the low-frequency words. Due to the power-law distribution, these low-frequency words are less likely to occur frequently in the second half of the corpus, resulting in lower counts. This observation aligns with the principle that rare words are less likely to be consistently used across different sections of a corpus.

ChatGPT's Answer

Anonymous

explain the irony in using chatGPT to revise for my NLP exam. write a super brief answer.

ChatGPT

The irony lies in using a language model designed for natural language understanding to study for an exam in natural language processing (NLP), as NLP involves creating models and algorithms for machines to understand and process human language, which is the very capability of ChatGPT itself.

NLU + NLG

Text-to-text models are becoming ubiquitous eg. chatGPT

T write a biblical verse in the style of the king james bible explaining how to remove a peanut butter sandwich from a VCR

And it came to pass that a man was troubled by a peanut butter sandwich, for it had been placed within his VCR, and he knew not how to remove it.

And he cried out to the Lord, saying, "Oh, Lord, how can I remove this sandwich from my VCR, for it is stuck fast and will not budge?"

And the Lord spoke unto him, saying, "Fear not, my child, for I shall guide thy hand and show thee the way. Take thy butter knife, and carefully insert it between the sandwich and the VCR, and gently pry them apart. And with patience and perseverance, the sandwich shall be removed, and thy VCR shall be saved."

And the man did as the Lord commanded, and lo and behold, the sandwich was removed from the VCR, and the man was saved.

And the Lord said, "Verily I say unto thee, seek not to put thy peanut butter sandwiches in thy VCR, for it is not a suitable place for such things. Rather, keep thy sandwiches in thy refrigerator or on thy plate, where they belong."

And the man heeded the Lord's words, and from that day forth, he kept his sandwiches in their proper place, and was saved from trouble and woe. Amen.

Tweet from John Koetsier

Introduction to the NLU+ Course

Central Question of the Course

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Suppose I give you many examples of Swedish-English translation:

Q: How can we *learn* a function to translate Swedish to English?

Overall Objective of the Course

NLU+ covers advanced machine learning methods for functions whose input and/or output is natural language.

In slightly more formal terms:

Task	Input type	Output type
Question answering	string	string
Sentiment analysis	string	label
Syntactic parsing	string	tree
Semantic parsing	string	graph (logical form)
Generation	table	string
Image captioning	image	string
Machine translation	string	string

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Courseworks will focus on the fundamentals of these models.

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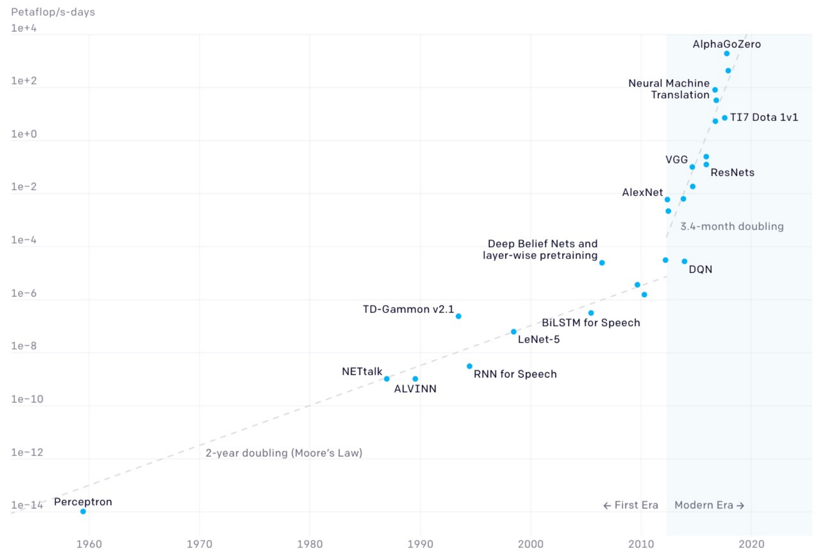
In short: deep learning solves the difficulties of *applying* machine learning to NLP... *But it does not solve NLP!*

Problem: Deep learning technology is energy intensive



What is the carbon cost of a state-of-the-art ML model?

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There are many wider *ethical concerns* about ML/data science, e.g., privacy. We'll focus on NLP in the course, but specific problems in NLP often reflect more general problems.

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And applications:

- paraphrasing
- question answering
- summarization
- data-to-text generation

How the Course will be Run

Relationship to other Courses

This is not an introductory course. You must have previous experience with NLP, ML, and programming.

You must have background in natural language processing:

- *Requires* Accelerated Natural Language Processing OR Foundations of Natural Language Processing (pre-req, *not* a co-req!);

Machine learning and programming:

- AML, ML, MLPR, or MLP (can be taken concurrently);
- CPSLP or equivalent programming experience.

Check above syllabi if you have taken NLP elsewhere. We *cannot* advise you on whether your outside syllabus suffices. Compare it to ANLP, and realistically assess what you know.

Required Preparation for Students on this Course

Background required for the course:

- You should be familiar with Jurafsky and Martin (2023) or the earlier print version of the book Jurafsky and Martin (2008)
- But this textbook serves as background only. Each lecture will rely on one or two book chapters or papers as the main reading. Read them and discuss or ask questions.
- You will need solid maths: probability theory, linear algebra, some calculus. But this is not a maths course: we're not going to examine you on your ability to take derivatives.

Course Team: Lecturers

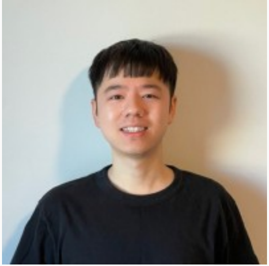
Alexandra Birch

Shay Cohen

Pasquale Minervini

Course Team: Teaching Assistants

Jonas Waldendorf



Yifu Qiu

Course Infrastructure

- *Blackboard Learn:* Official Course information: links to everything (timetable/live lectures), assignments, contact information, announcements
- *OpenCourse:* Hosts all course materials (lecture slides, readings, tutorials, labs) and weekly schedule
- *Piazza:* Forum for posting questions about the course material; monitored by TAs and lecturers.
- *TurnItIn:* Coursework submission system, linked with Learn. Used for courseworks, includes plagiarism checking.
- *Dice:* Informatics computing environment, used for courseworks. If you don't have a Dice account yet, apply for one through the ITO.

Course Mechanics

The course will have a weekly rhythm:

- *Friday* of every week: *readings* for the next week released; expectations for this week clarified. Lecture slides will often be available then too.
- *Three in-person lectures each week;* these are also live streamed and recorded for later viewing
- You can ask questions in person during the lectures
- In each week, there is either a *tutorial* or a *lab session.* More on the next slide.

Tutorials and Lab Sessions

- These run weeks 3 to 10 and *alternate weekly.* So each week has *either* a tutorial *or* a lab session.
- *Tutorials* are run in small groups led by a tutor. You should try to solve the tutorial exercises ahead of time, and then discuss your solutions in the tutorial session.
- *Lab sessions* are practical sessions in which you solve programming exercises (often in preparation for an coursework).
- Labs are run in larger groups. Two lab demonstrators are on hand to help if you get stuck.
- Both tutorial and lab exercises are issued a week before.

Tutorials will or labs will run *in person.*

Tutorials and Lab Sessions

- If you're enrolled for this course, you will be automatically assigned a tutorial group and a lab group.
- If you are unhappy with your assigned groups, please use the group change request form to request a change.
- If you have not yet been assigned a tutorial and a lab group, please contact the ITO.
- Tutorials start in week 4, labs in week 3.

Assessment

Assessment will consist of:

- Two courseworks, each worth 20%.
- A final exam, worth 60%.

When you will be assessed:

- Coursework 1 issued 22 January, due 16 February.
- Coursework 2 issued 1 March, due 22 March.
- Final exam in the April/May exam period (date tba).

Assessment

- *Courseworks* require you to implement and run code; the experiments can be time consuming, so start early!
- Courseworks will include intermediate milestones and recommended timelines.
- Courseworks are accompanied by *lab sessions* in which you can ask questions about the coursework.
- The *final exam* is timed and will consist of problem-solving questions.
- It will emphasize *understanding* and *synthesis* of ideas, rather than rote memorization of technical details.

More on Courseworks

- Courseworks can be done in pairs.
- This means you will work together with a classmate and submit a single solution.
- Both members of the pair will receive the same mark.
- You don't *have* to work in pairs, but it's strongly encouraged.
- You can work with the *same* partner for both courseworks.
- Details on how pairs are formed will be released ahead of Coursework 1.

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- *Don't ask us questions over email.* We might not see your question for days. And when we do, we will just repost it to Piazza, so that everyone can see the answer.

Preview

The rest of this week:

- Read Church and Liberman (2021), a historical perspective on NLP/CL and deep learning.
- Lecture 2: Introduction to Machine Translation
- Lecture 3: Conditional Language Models

References

Church, K. and Liberman, M. (2021). The future of computational linguistics: On beyond alchemy. *Frontiers in Artificial Intelligence*, 4:625341.

Jurafsky, D. and Martin, J. H. (2008). *Speech and Language Processing: An introduction to speech recognition, computational linguistics and natural language processing*. Upper Saddle River, NJ: Prentice Hall.

Jurafsky, D. and Martin, J. H. (2023). *Speech and Language Processing 3rd Edition (draft)*. Upper Saddle River, NJ: Prentice Hall.