Overview

Introduction

Natural Language Understanding

Natural Language Generation

Machine Translation

Introduction to the NLU+ Course

Part I: Fundamental Tools

Part II: Big Problems

Part III: Applications

How the Course will be Run

Reading: *Church and Liberman (2021).*
Introduction
What is Natural Language Understanding?

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?

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?

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

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 $\implies$ Analyses (syntactic relationships, logical forms, named entities, coreference, user intents, sentiment, etc.)
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.
What is Natural Language Generation?

Pollin Concentration Data for Scotland

<table>
<thead>
<tr>
<th>AreaID</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (North)</td>
<td>6</td>
</tr>
<tr>
<td>2 (North West)</td>
<td>5</td>
</tr>
<tr>
<td>3 (Central)</td>
<td>5</td>
</tr>
<tr>
<td>4 (North East)</td>
<td>6</td>
</tr>
<tr>
<td>5 (South West)</td>
<td>8</td>
</tr>
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Application: Data-to-text generation

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

**Output:** A natural language description of that data
What is Natural Language Generation?

Two small dogs run through the grass.

Application: Image captioning

Input: Image

Output: A natural language description of that image
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.) $\implies$ Text
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Non-linguistic input (logical forms, database entries, images, etc.) $\implies$ Text

What about tasks where \textit{both the input and output are text}?
What is Machine Translation?

Example: Swedish-English machine translation
Input:
A sentence in Swedish
Output:
A sentence in English expressing the same meaning
What is Machine Translation?

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
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
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.
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 ick how to apply it.

Any help would be appreciated.

(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.
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(Anon. Gear to classmates) 1 month ago
https://chat.openai.com/share/b94622fb-9351-499d-afeb-b63f733a7a00
helpful! 2
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.
**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.
Text-to-text models are becoming ubiquitous eg. chatGPT

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.
Introduction to the NLU+ Course
Suppose your goal is to implement an NLG, NLU, or MT system. For concreteness, suppose it is Swedish-English translation.
Central Question of the Course

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**Q1:** How would you write a function to translate Swedish to English?
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**Q1:** How would you write a function to translate Swedish to English?

**Q1:** How should we deal with ambiguity?

**Q2:** How should we deal with morphosyntactic differences?

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

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

<table>
<thead>
<tr>
<th>Task</th>
<th>Input type</th>
<th>Output type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Question answering</td>
<td>string</td>
<td>string</td>
</tr>
<tr>
<td>Sentiment analysis</td>
<td>string</td>
<td>label</td>
</tr>
<tr>
<td>Syntactic parsing</td>
<td>string</td>
<td>tree</td>
</tr>
<tr>
<td>Semantic parsing</td>
<td>string</td>
<td>graph (logical form)</td>
</tr>
<tr>
<td>Generation</td>
<td>table</td>
<td>string</td>
</tr>
<tr>
<td>Image captioning</td>
<td>image</td>
<td>string</td>
</tr>
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<td>Machine translation</td>
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• feed-forward neural networks
• recurrent neural networks
• transformers

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Fundamental Methods of the Course

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Courseworks will focus on the fundamentals of these models.
Why has deep learning taken over NLP?

• Deep learning simplifies the design of probabilistic models, by replacing complex dependencies and independence assumptions with universal function approximators.
• Deep learning gives us representation learning: data representations are learned rather than engineered.
• Learned representations are easy to obtain and reusable, enabling multi-task learning.
• Deep learning provides a uniform, flexible, trainable framework that can easily mix and match different data types: strings, labels, trees, graphs, data, and images.

In short: deep learning solves the difficulties of applying machine learning to NLP… But it does not solve NLP!
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Problem: Deep learning technology is energy intensive

What is the carbon cost of a state-of-the-art ML model?
Modern NLP originated in laboratory experiments with machine learning methods on linguistically annotated text. But NLP has escaped the lab, and can have a direct effect on people’s lives:
Problem: Ethical practice lags technical practice

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- An Alexa chatbot responded to “Should I sell my house?” with “Sell sell sell!”

- Facebook’s emotional contagion experiment manipulated people on a large scale, without their consent.

- NLP is now used to recommend products, services, jobs, loans, medical treatments, prison sentences … 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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Applications of Fundamental Ideas

The second half of the course will focus on the application of deep models to a variety of core NLP tasks:
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- machine translation
- word embeddings
- pretrained language models
- syntactic parsing
- semantic parsing

And applications:

- paraphrasing
- question answering
- summarization
- data-to-text generation
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How the Course will be Run
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 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).
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.
How to get help

Ask questions. Asking questions is how you learn.

• TA drop-in office hours, starting week 2.
• Piazza forum: course staff will answer questions once a day, Monday through Friday. You can answer questions any time! Your questions can be anonymous to classmates. They can be private (use this if the question pertains only to you).
• 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.
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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
