

# Natural Language Understanding, Generation, and Machine Translation

## Lecture 1: Introduction

---

Alexandra Birch and Shay Cohen

13 January 2025 (week 1)

School of Informatics

University of Edinburgh

[a.birch@ed.ac.uk](mailto:a.birch@ed.ac.uk), [scohen@inf.ed.ac.uk](mailto:scohen@inf.ed.ac.uk)

# 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

# Introduction

---

## Introduction

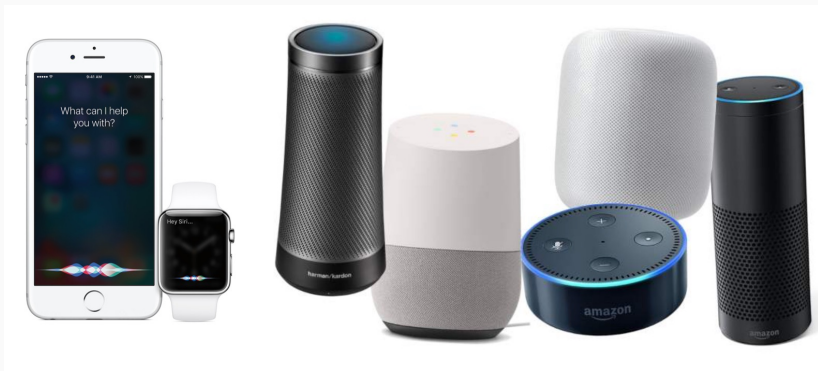
Natural Language Understanding

Natural Language Generation

Machine Translation

# What is Natural Language Understanding?

# What is Natural Language Understanding?

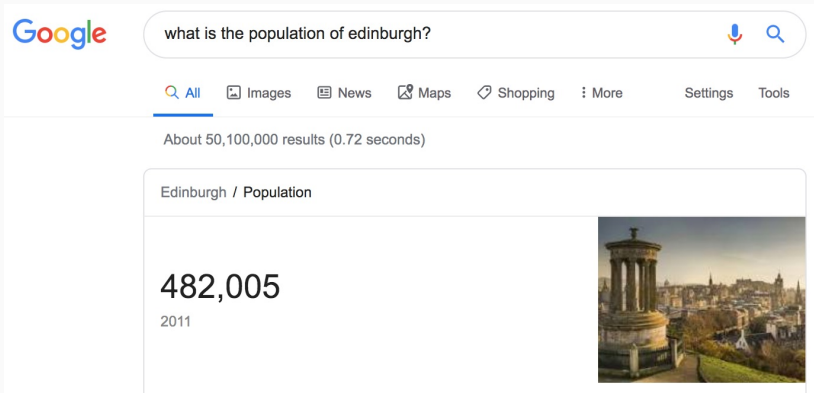


Application: Digital assistants

**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?

## Restaurant Review

User Rating: 2/5

I had a very mixed experience at The Stand. The burger and fries were good. The chocolate shake was divine: rich and creamy. The drive-thru was horrible. It took us at least 30 minutes to order when there were only four cars in front of us. We complained about the wait and got a half-hearted apology. I would go back because the food is good, but my only hesitation is the wait.

### Summary

- ▲ The burger and fries were good
- ▲ The chocolate shake was divine
- ▲ I would go back because the food is good
- ▼ The drive-thru was horrible
- ▼ It took us at least 30 minutes to order

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

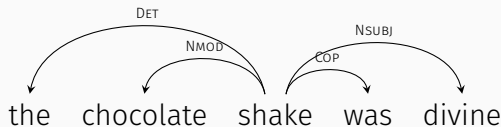
Application: Sentiment analysis

**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?

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

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).

# 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).

NLU often requires a system to resolve (either implicitly or explicitly) many of the same question that human readers efficiently resolve when they read a text.

# 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).

NLU often requires a system to resolve (either implicitly or explicitly) many of the same question that human readers efficiently resolve when they read a text. *Who is doing what to whom, and when?*

# 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).

NLU often requires a system to resolve (either implicitly or explicitly) many of the same question that human readers efficiently resolve when they read a text. *Who is doing what to whom, and when?* The answers depend on a variety of cues from morphology, syntax, semantics, discourse, and inferences based on common sense.

# 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).

NLU often requires a system to resolve (either implicitly or explicitly) many of the same question that human readers efficiently resolve when they read a text. *Who is doing what to whom, and when?* The answers depend on a variety of cues from morphology, syntax, semantics, discourse, and inferences based on common sense.

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

## Introduction

Natural Language Understanding

Natural Language Generation

Machine Translation



# What is Natural Language Generation?

# What is Natural Language Generation?

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

# 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

# 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.)  $\implies$  Text

# 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.)  $\implies$  Text

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

## Introduction

Natural Language Understanding

Natural Language Generation

Machine Translation

# What is Machine Translation?

# 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



# 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.

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

# A question on Piazza

## 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

argue or appropriate.

[2 marks]

- (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

## 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

argue or appropriate.

[ 2 marks ]

- (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 ]

(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.



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



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

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

Suppose your goal is to implement an NLG, NLU, or MT system.  
For concreteness, suppose it is Swedish-English translation.

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

# Central Question of the Course

Suppose your goal is to implement an NLG, NLU, or MT system.  
For concreteness, suppose it is Swedish-English translation.

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

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

# Central Question of the Course

Suppose your goal is to implement an NLG, NLU, or MT system.  
For concreteness, suppose it is Swedish-English translation.

**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?

# Central Question of the Course

Suppose your goal is to implement an NLG, NLU, or MT system.  
For concreteness, suppose it is Swedish-English translation.

**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?

**Q3:** How should we deal with ...

# Central Question of the Course

Suppose your goal is to implement an NLG, NLU, or MT system.  
For concreteness, suppose it is Swedish-English translation.

**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?

**Q3:** How should we deal with ...

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

## Introduction to the NLU+ Course

### Part I: Fundamental Tools

### Part II: Big Problems

### Part III: Applications

# Fundamental Methods of the Course

Our primary tool will be *probabilistic models*

# Fundamental Methods of the Course

Our primary tool will be *probabilistic models* parameterized by *deep learning architectures* such as:

# Fundamental Methods of the Course

Our primary tool will be *probabilistic models* parameterized by *deep learning architectures* such as:

- feed-forward neural networks

# Fundamental Methods of the Course

Our primary tool will be *probabilistic models* parameterized by *deep learning architectures* such as:

- feed-forward neural networks
- recurrent neural networks

# Fundamental Methods of the Course

Our primary tool will be *probabilistic models* parameterized by *deep learning architectures* such as:

- feed-forward neural networks
- recurrent neural networks
- transformers

# Fundamental Methods of the Course

Our primary tool will be *probabilistic models* parameterized by *deep learning architectures* such as:

- feed-forward neural networks
- recurrent neural networks
- transformers

... applied primarily to *structured prediction* tasks in NLP.



# Fundamental Methods of the Course

Our primary tool will be *probabilistic models* parameterized by *deep learning architectures* such as:

- feed-forward neural networks
- recurrent neural networks
- transformers

... applied primarily to *structured prediction* tasks in NLP.

The first few weeks will focus on the mathematical foundations of these models, motivated by the problem of machine translation, and setting the stage for other applications.

# Fundamental Methods of the Course

Our primary tool will be *probabilistic models* parameterized by *deep learning architectures* such as:

- feed-forward neural networks
- recurrent neural networks
- transformers

... applied primarily to *structured prediction* tasks in NLP.

The first few weeks will focus on the mathematical foundations of these models, motivated by the problem of machine translation, and setting the stage for other applications.

Courseworks will focus on the fundamentals of these models.

## Idea: Deep learning simplifies machine learning

Why has deep learning taken over NLP?

# Idea: Deep learning simplifies machine learning

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*.

# Idea: Deep learning simplifies machine learning

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.

# Idea: Deep learning simplifies machine learning

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*.

# Idea: Deep learning simplifies machine learning

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.

# Idea: Deep learning simplifies machine learning

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...



# Idea: Deep learning simplifies machine learning

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!*

## Introduction to the NLU+ Course

Part I: Fundamental Tools

Part II: Big Problems

Part III: Applications

## Problem: Ethical practice lags technical practice

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

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:

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

## Problem: Ethical practice lags technical practice

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:

- 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.

## Problem: Ethical practice lags technical practice

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:

- 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 ...

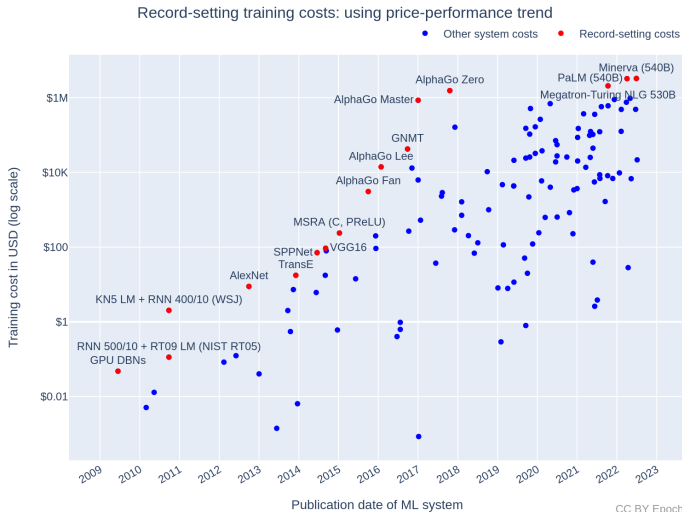
## Problem: Ethical practice lags technical practice

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:

- 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, job losses. We'll focus on NLP in the course, but specific problems in NLP often reflect more general problems.

# Problem: Extremely Heavy use of Resources



<https://epoch.ai/blog/trends-in-the-dollar-training-cost-of-machine-learning-systems>



## Introduction to the NLU+ Course

Part I: Fundamental Tools

Part II: Big Problems

Part III: Applications

## 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:

# 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:

- word embeddings
- pretrained language models
- syntactic parsing
- evaluation

# 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:

- word embeddings
- pretrained language models
- syntactic parsing
- evaluation

And applications:

- machine translation
- question answering
- summarization

## 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);
- 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 \(2024\)](#) 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



## Course Team: Teaching Assistants



Gustavo Cilleruelo



Leonardo Ranaldi

# 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
- *EdStem*: Forum for posting questions about the course material; monitored by TAs and lecturers.
- *Gradescope*: 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.

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 and 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 20 January, due 14 February.
- Coursework 2 issued 28 Feb, due 21 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.

## How to get help

Ask questions. Asking questions is how you learn.

Answer questions. Answering questions is how you demonstrate that you've learned it!

## How to get help

Ask questions. Asking questions is how you learn.

Answer questions. Answering questions is how you demonstrate that you've learned it!

- TA drop-in office hours, starting week 2.

# How to get help

Ask questions. Asking questions is how you learn.

Answer questions. Answering questions is how you demonstrate that you've learned it!

- TA drop-in office hours, starting week 2.
- EdStem 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*).

# How to get help

Ask questions. Asking questions is how you learn.

Answer questions. Answering questions is how you demonstrate that you've learned it!

- TA drop-in office hours, starting week 2.
- EdStem 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.

The rest of this week:

- Lecture 2: Introduction to Machine Translation
- Lecture 3: Conditional Language Models

## References

---

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. (2024). *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition with Language Models*. 3rd edition. Online manuscript released August 20, 2024.