

CS447: Natural Language Processing

<http://courses.grainger.illinois.edu/cs447>

Lecture 01: Introduction

Julia Hockenmaier

juliahmr@illinois.edu





Welcome
to CS447!



Welcome to CS447!

Professor:

Julia Hockenmaier (Siebel 3324)

juliahmr@illinois.edu

<http://juliahmr.cs.illinois.edu>

TAs:

Marc Canby

Fred Choi

Rajarshi Haldar

Prashant Jayannavar



What is CS447?

This class is a broad introduction to NLP

Target audience:

Advanced undergraduates

Graduate students

What's new this semester?

We're back in person for the first time since Fall 2019

We're trying to incorporate new elements that we've developed for the online/Coursera version of this class

We're switching to Canvas

We're updating some of the class content

Why should you take this class?

NLP is an (increasingly) important area

NLP is now good enough for real-world applications.

There is a huge growth in NLP companies
and NLP jobs (in many industries)

NLP is far from solved (despite much recent progress)

There is still a lot that remains to be done!

Doing NLP well requires a broad mix of knowledge:

- What is natural language?
- What about natural language is challenging for computers?
- What kind of data, algorithms, machine learning approaches can we use (and which ones do we need to develop)?

What will you learn in this class?

– What is NLP?

The core **tasks** (as well as **data sets** and **evaluation metrics**) that people work on in NLP

– How does NLP work?

The fundamental **models, algorithms** and **representations** that have been developed for these tasks

– Why is NLP hard?

The relevant **linguistic concepts and phenomena** that have to be handled to do well at these tasks

NLP is necessary to...

... **analyze** text automatically at scale

(text = news, documents, social media, search queries,...)

... **translate** automatically between languages

(language = English, Chinese, Arabic, Hindi, etc.)

... **communicate** naturally with systems/devices

(systems/devices = robots, computers, customer support, digital assistants, smart devices, navigation systems,...)

The focus of this class

We want to identify the **structure** and **meaning** of words, sentences, texts and conversations

- N.B.: we do not deal with speech/audio (no signal processing)

We mainly deal with **language analysis**/understanding, and somewhat less with **language generation**/production

We focus on **fundamental concepts, methods, models, tasks and algorithms**, not so much on current research:

- Data (natural language): Linguistic concepts and phenomena
- Representations: Grammars, automata, embeddings/vectors, ...
- Tasks: Analysis, generation, translation, ...
- Models: Neural models, statistical models, ...

What you should learn

You should be able to answer the following questions:

- What makes natural language difficult for computers?
- What are the core NLP tasks?
- What are the main modeling techniques used in NLP?

We won't be able to cover all of the latest research...

(this requires more time, and a much stronger background in machine learning than we can assume for this class)

... but I would still like you to get an understanding of:

- How well does current NLP technology work (or not)?
- What NLP software and datasets are available?
- How to read NLP research papers [4 credits section]

Our Syllabus (tentative)

Week 1: Introduction

Week 2: The Structure and Distribution of Words

Week 3: Classification for NLP

Week 4: The Meaning of Words

Week 5: Introduction to Neural Networks for NLP

Week 6: POS Tagging and Sequence Labeling

Week 7: Neural Sequence Models

Week 8: Machine Translation and Large Language Models

Week 9: The Structure of Sentences

Week 10: The Structure and Meaning of Sentences

Week 11: Relations, Events, Times

Week 12: Semantic Roles, Referring Expressions

Week 13: Discourse Coherence, Question Answering

Week 14: Dialogue and Grounded NLP

Week 15: Ethics in NLP



Our Syllabus and Textbook

You can find brief descriptions of our syllabus at
<https://courses.grainger.illinois.edu/cs447/>

Our Textbook:

We loosely follow
Jurafsky and Martin, Speech and Language
Processing 3rd ed. (January 2023 version)

<https://web.stanford.edu/~jurafsky/slp3/>



Who is
nil?



In Science Fiction (Kubricks' 1968 movie 2001: A Space Odyssey)

A conversation onboard the Discovery One spacecraft between HAL 9000 (a sentient computer developed in Urbana, IL) and Dave, a human astronaut: https://en.wikipedia.org/wiki/HAL_9000

Dave: Open the pod bay doors, please, HAL. Open the pod bay doors, please, HAL. Hello, HAL, do you read me? Hello, HAL, do you read me? Do you read me, HAL? Do you read me, HAL? Hello, HAL, do you read me? Hello, HAL, do you read me? Do you read me, HAL?

HAL: Affirmative, Dave. I read you.

Dave: Open the pod bay doors, HAL.

HAL: I'm sorry, Dave. I'm afraid I can't do that.

Dave: What's the problem?

HAL: I think you know what the problem is just as well as I do.

Dave: What are you talking about, HAL?

HAL: This mission is too important for me to allow you to jeopardize it.

Dave: I don't know what you're talking about, HAL.

HAL: I know that you and Frank were planning to disconnect me. And I'm afraid that's something I cannot allow to happen.

Dave: Where the hell did you get *that* idea, HAL?

HAL: Dave, although you took very thorough precautions in the pod against my hearing you, I could see your lips move.

Dave: All right, HAL. I'll go in through the emergency airlock.

HAL: Without your space helmet, Dave, you're going to find that rather difficult.

Dave: [sternly] HAL, I won't argue with you anymore. Open the doors.

HAL: [monotone voice] Dave, this conversation can serve no purpose anymore. Good-bye.

[https://en.wikiquote.org/wiki/2001:_A_Space_Odyssey_\(film\)#Dialogue](https://en.wikiquote.org/wiki/2001:_A_Space_Odyssey_(film)#Dialogue)

In Science Fiction (Kubricks' 1968

What are HAL's capabilities?

- HAL speaks **fluent, natural English**
- HAL's **responses are appropriate in the context**
*“Affirmative, I read you”,
“I think you know what the problems is just as well as I do”*
- HAL understands **references to the physical world:**
“Open the pod bay doors”
- HAL **talks about what HAL sees:**
*“I could see your lips move”,
“without your space helmet”*
- HAL **reasons**
*“I can't do that”,
“this mission is too important”
“I know that you and Frank were planning to disconnect
me. And I'm afraid that's something I can't allow”*

A real human-computer dialogue from the 1960s: ELIZA (Weizenbaum, 1966)

Computer: TELL ME MORE ABOUT YOUR FAMILY

Human: My mother takes care of me.

Computer: WHO ELSE IN YOUR FAMILY TAKES CARE OF YOU

Human: My father.

Computer: YOUR FATHER

Human: You are like my father in some ways.

Computer: WHAT RESEMBLANCE DO YOU SEE

Human: You are not very aggressive but I think you don't want me to notice that.

Computer: WHAT MAKES YOU THINK I AM NOT VERY AGGRESSIVE

Human: You don't argue with me.

Computer: WHY DO YOU THINK I DON'T ARGUE WITH YOU

Human: You are afraid of me.

The Eliza Effect

People *really* trusted this system:

Weizenbaum: “*I had not realized ... that extremely short exposures to a relatively simple computer program could induce powerful delusional thinking in quite normal people*”

ELIZA was based on a cascade of finite-state transducers:

Human: You don't argue with me.

1. Replace **you** with **I** and **me** with **you**:

I don't argue with you.

2. Replace <...> with **Why do you think <...>**:

Why do you think I don't argue with you.

Computer: WHY DO YOU THINK I DON'T ARGUE WITH YOU

- How could you break a system like ELIZA?
- Where do you see the ELIZA effect today?

In the 21st century, NLP remains in the news

Facebook AI Creates Its Own Language In Creepy Preview Of Our Potential Future

Computers can now describe images using language you'd understand

The AI Text Generator That's Too Dangerous to Make Public

Researchers at OpenAI decided that a system that scores well at understanding language could too easily be manipulated for malicious intent.

How AI Can Create And Detect Fake News

A.I. breakthroughs in natural-language processing are big for business

BY JEREMY KAHN

Barbie Wants to Get to Know Your Child

With the help of A.I., America's most famous doll tries to fulfill a timeless dream — convincing little girls that she's a real friend. What will happen if they believe her?

IBM's Watson wins at Jeopardy!



<https://www.youtube.com/watch?v=P18EdAKuC1U>

<https://dl.acm.org/doi/10.1147/JRD.2012.2184356>

Have chatbots developed their own language?

Facebook AI Creates Its Own Language In Creepy Preview Of Our Potential Future

<https://code.facebook.com/posts/1686672014972296/deal-or-no-deal-training-ai-bots-to-negotiate/>

Bob: "I can can I I everything else."

Alice: "Balls have zero to me to."

No, not really...

<http://www.snopes.com/facebook-ai-developed-own-language/>

How well does that Barbie do?

Barbie: “*Do you have any sisters?*”

Child: “Yeah, I only have one.”

Barbie: “*What’s something nice that your sister does for you?*”

Child: “She does nothing nice to me”

Barbie: “*Well, what is the last nice thing your sister did?*”

Child: “She helped me with my project
— and then she destroyed it.”

Barbie: “*Oh, yeah, tell me more!*”

Child: “That’s it, Barbie,”

Barbie: “*Have you told your sister lately how cool she is?*”

Child: “No. She is not cool,”

Barbie: “*You never know, she might appreciate hearing it*”

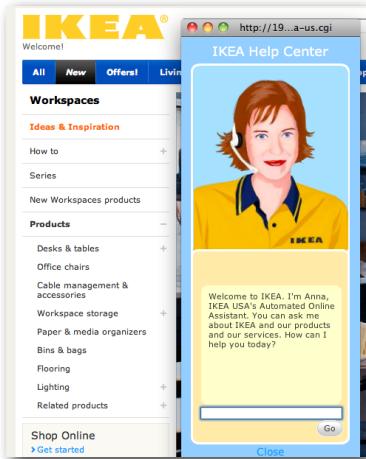
(Thanks to Barbara Grosz for pointing out the example from the NYT)

<https://www.nytimes.com/2015/09/20/magazine/barbie-wants-to-get-to-know-your-child.html>

Barbie Wants to Get to Know Your Child

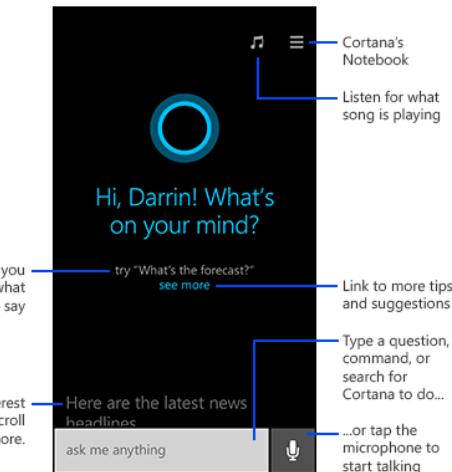
With the help of A.I., America’s most famous doll tries to fulfill a timeless dream — convincing little girls that she’s a real friend. What will happen if they believe her?

Dialog systems, chatbots, digital assistants



ChatGPT

Examples	Capabilities	Limitations
"Explain quantum computing in simple terms" →	Remembers what user said earlier in the conversation	May occasionally generate incorrect information
"Got any creative ideas for a 10 year old's birthday?" →	Allows user to provide follow-up corrections	May occasionally produce harmful instructions or biased content
"How do I make an HTTP request in Javascript?" →	Trained to decline inappropriate requests	Limited knowledge of world and events after 2021



Machine Translation

爷爷心疼孙女让娃睡懒觉 没想到引发了家庭矛盾

2020-08-25 08:06:03 来源：钱江晚报

70岁的钟大伯（化名）陷入了“暑期焦虑”：这个暑假，他每周都要接送孙女上下培训班。高温、酷暑，每天回来，都像脚踩棉花般没力气。

除了身体上的不适，还有精神上的紧张。

觉得儿子儿媳给孩子报班太多，钟大伯还和他们产生了冲突：“大热天的，大人孩子都遭罪。”

这段时间，钟大伯因为容易激动发火，失眠，胃口差，血压一直不稳定，来到了浙江省人民医院精神卫生科就诊。



Grandpa feels sorry for his granddaughter and let the baby sleep in

2020-08-25 08:06:03 Source: Qianjiang Evening News

Uncle Zhong (a pseudonym), 70, fell into "summer anxiety": This summer, he would shuttle his granddaughter to and from training classes every week. With high temperatures and scorching heat, every day I come back, I feel as weak as stepping on cotton.

In addition to physical discomfort, there is also mental tension.

Feeling that his son and daughter-in-law were reporting too much for their children, Uncle Zhong also had a conflict with them: "It's a hot day, adults and children suffer."

During this period of time, Uncle Zhong came to the Mental Health Department of Zhejiang Provincial People's Hospital because he was prone to get angry, insomnia, poor appetite, and unstable blood pressure.

http://education.news.cn/2020-08/25/c_1210768533.htm

Examples of NLP applications

(What can NLP be used for?)

Natural language (and speech) interfaces

Search/IR, database access, image search, image description
Dialog systems (e.g. customer service, robots, cars, tutoring),
chatbots

Information extraction, summarization, translation:

Process (large amounts of) text automatically
to obtain meaning/knowledge contained in the text
Identify/analyze trends, opinions, etc. (e.g. in social media)
Translate text automatically from one language to another

Convenience:

Grammar/style checking, automate email filing, autograding

Examples of NLP tasks

(What capabilities do NLP systems need?)

Natural language understanding

Extract information (e.g. about entities, events or relations between them) from text

Translate raw text into a meaning representation

Reason about information given in text

Execute NL instructions

Natural language generation and summarization

Translate database entries or meaning representations to raw natural language text

Produce (appropriate) utterances/responses in a dialog

Summarize (newspaper or scientific) articles, describe images

Natural language translation

Translate one natural language to another

Generating text with huge language models...

A REPORTER AT LARGE OCTOBER 14, 2019 ISSUE

CAN A MACHINE LEARN TO WRITE FOR THE NEW YORKER?

How predictive-text technology could transform the future of the written word.

Language models can be used to generate (produce) text

Massive neural language models trained on vast amounts of text have been developed in the last few years. Most recent incarnation: GPT-3 (175B parameters, trained on 300B tokens).

But these models have no access to meaning, and don't "understand" much.

See also Bender & Koller '20 for a critique

<https://www.aclweb.org/anthology/2020.acl-main.463.pdf>

Opinion

GPT-3, Bloviator: OpenAI's language generator has no idea what it's talking about

Tests show that the popular AI still has a poor grasp of reality.

by Gary Marcus and Ernest Davis

August 22, 2020

<https://www.technologyreview.com/2020/08/22/1007539/gpt3-openai-language-generator-artificial-intelligence-ai-opinion/>

Human Prompt (given to GPT-3)

At the party, I poured myself a glass of lemonade, but it turned out to be too sour, so I added a little sugar.

I didn't see a spoon handy, so I stirred it with a cigarette. But that turned out to be a bad idea because

[GPT-3's generated continuation]

it kept falling on the floor. That's when he decided to start the Cremation Association of North America, which has become a major cremation provider with 145 locations.

from Marcus & Davis '20

<https://www.technologyreview.com/2020/08/22/1007539/gpt3-openai-language-generator-artificial-intelligence-ai-opinion/>

What is the current state of NLP?

Lots of commercial applications and interest.

Some applications are working pretty well already,
others not so much.

A lot of hype around “deep learning” and “AI”

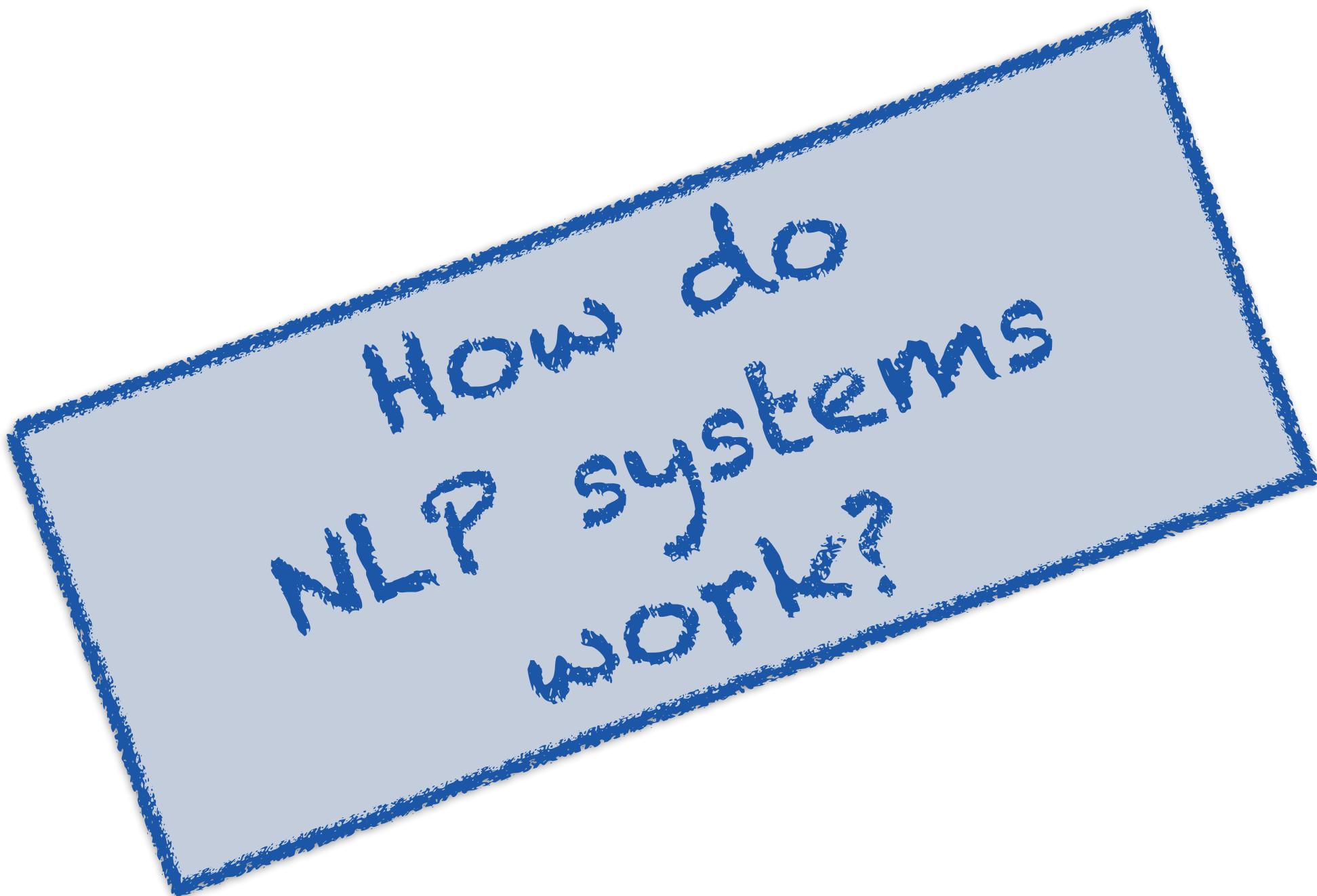
Neural nets are powerful classifiers and sequence models

Public libraries and datasets make it easy for anybody to get a model up and running

“End-to-end” models put into question whether we still need the traditional NLP pipeline.

This paradigm shift is well underway.

But many of the fundamental problems haven’t been solved.



How do
NLP systems
work?

The traditional NLP pipeline

A (traditional) NLP system may use some or all of the following steps:

Tokenizer/Segmenter

to identify words and sentences

Morphological analyzer/POS-tagger

to identify the part of speech and structure of words

Word sense disambiguation

to identify the meaning of words

Syntactic/semantic Parser

to obtain the structure and meaning of sentences

Coreference resolution

to keep track of the various entities mentioned

What does it take to understand text?

死亡谷测得54.4摄氏度高温
美国加州名胜或破世界纪录

รอยัลลิสต์มาร์เก็ตเพลส: เพชบุํก
เตรียมดำเนินทางการกฎหมายกับ
รัฐบาลไทย หลังบังคับบล็อกการเข้า
ถึงกลุ่มปิดที่พุดดุยเกี่ยวกับราชวงศ์

Qabiyyeen xalayaan
dhimma Obbo Lidatu
Ayyaaloorratti MM Abiyyiif
barraa'e maali?

Çavuşoğlu'ndan Atina'ya uyarı:
Bazı ülkelerin dolduruşuna gelip,
kendinizi riske atmayın

አን አዋ እთዔን መስል 12
ክፍለ ተምህርት ክሸረሽ ገበጻስ
ደካናዚ አለ

'Dim angen cau tafarndai a
bwytai i ailagor ysgolion'

Task: Tokenization/segmentation

死亡谷测得54.4摄氏度高温
美国加州名胜或破世界纪录

รอยัลลิสต์มาร์เก็ตเพลส: เพชบุ๊กเตรียม
ดำเนินทางการกฎหมายกับรัฐบาลไทย หลัง
บังคับบังคับลือการเข้าถึงกลุ่มปิดที่พูดคุยเกี่ยว
กับราชวงศ์

We need to split text into words and sentences.

- Languages like Chinese or Thai
don't have spaces between words.
- Even in English, this cannot be done deterministically:
There was an earthquake near D.C. You could even feel it in Philadelphia, New York, etc.

NLP task:

What is the *most likely* segmentation/tokenization?

Task: Part-of-speech-tagging

Open the pod door, Hal.



Verb Det Noun Noun , Name .
Open the pod door , Hal .

open:

Verb, adjective, or noun?

Verb: **open** the door

Adjective: the **open** door

Noun: in the **open**

How do we decide?

We want to know the most likely tags T for the sentence S

$$\operatorname*{argmax}_T P(T|S)$$

We need to define a statistical model of $P(T | S)$, e.g.:

$$\begin{aligned} \underset{T}{\operatorname{argmax}} P(T|S) &= \underset{T}{\operatorname{argmax}} P(T)P(S|T) \\ P(T) &\stackrel{\text{def}}{=} \prod_i P(t_i | \cdot) \\ P(S|T) &\stackrel{\text{def}}{=} \prod_i P(w_i | t_i) \end{aligned}$$

We need to estimate the parameters of $P(T | S)$, e.g.:

$$P(t_i = V \mid t_{i-1} = N) = 0.312$$

Disambiguation requires statistical models

Ambiguity is a core problem for any NLP task

Statistical models* are one of the main tools to deal with ambiguity.

*More generally: a lot of the models (classifiers, structured prediction models) you learn about in your machine learning classes can be used for this purpose.

We won't assume you have taken a machine learning class.

These models need to be **trained** (estimated, learned) before they can be **used** (tested, evaluated).

“I made her duck”

What does this sentence mean?

“I made her crouch”,

“I cooked duck for her”,

“I cooked her [pet] duck (perhaps just for myself)”, ...

“**duck**”: noun or verb?

“**make**”: “cook X” or “cause X to do Y” ?

“**her**”: “for her” or “belonging to her” ?

Ambiguity in natural language

Language has different kinds of ambiguity, e.g.:

Structural ambiguity

“*I eat sushi with tuna*” vs. “*I eat sushi with chopsticks*”

“*I saw the man with the telescope on the hill*”

Lexical (word sense) ambiguity

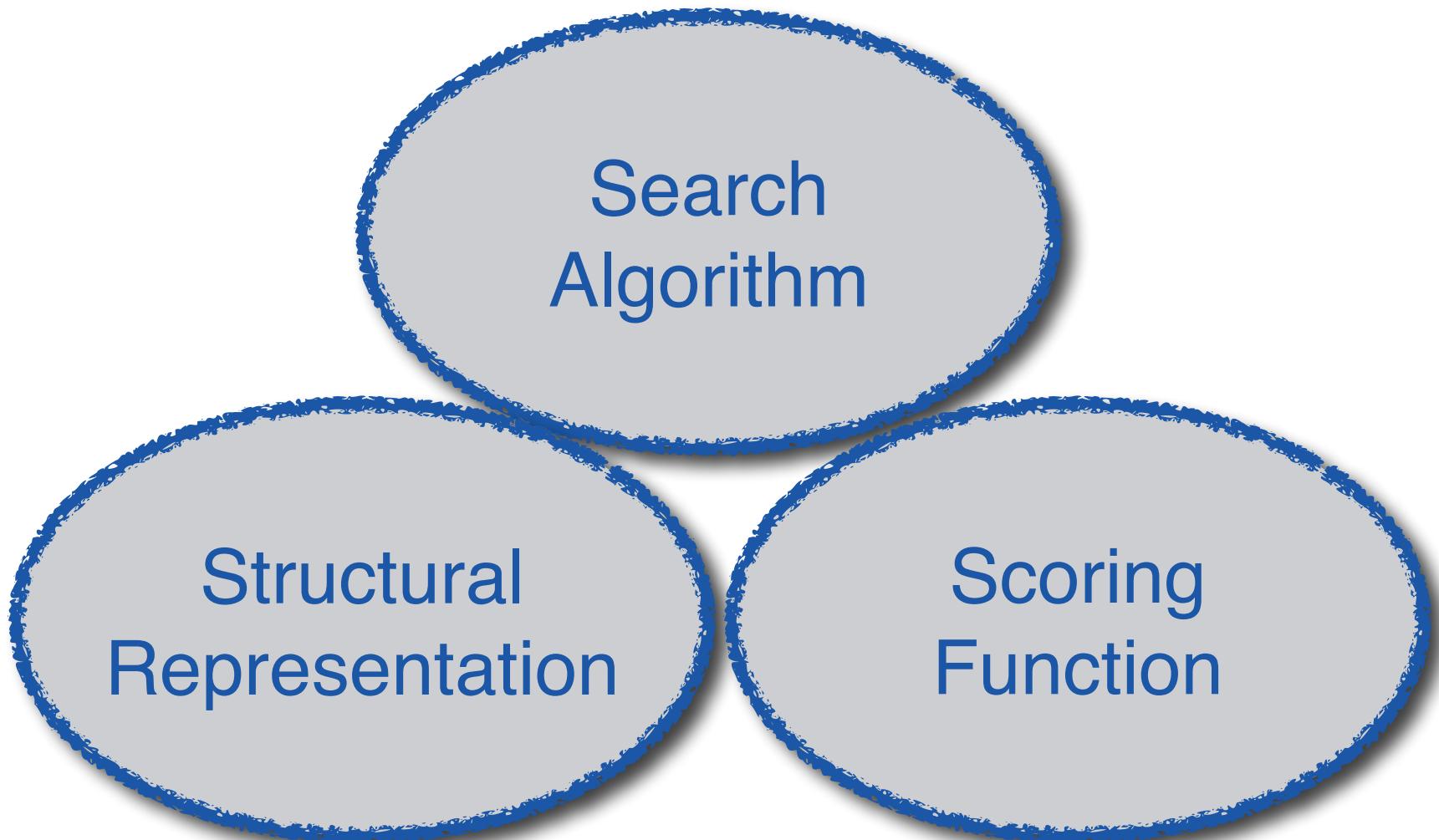
“*I went to the bank*”: financial institution or river bank?

Referential ambiguity

“***John saw Jim. He was drinking coffee.***”

Who was drinking coffee?

Dealing with ambiguity



“I made her duck cassoulet”

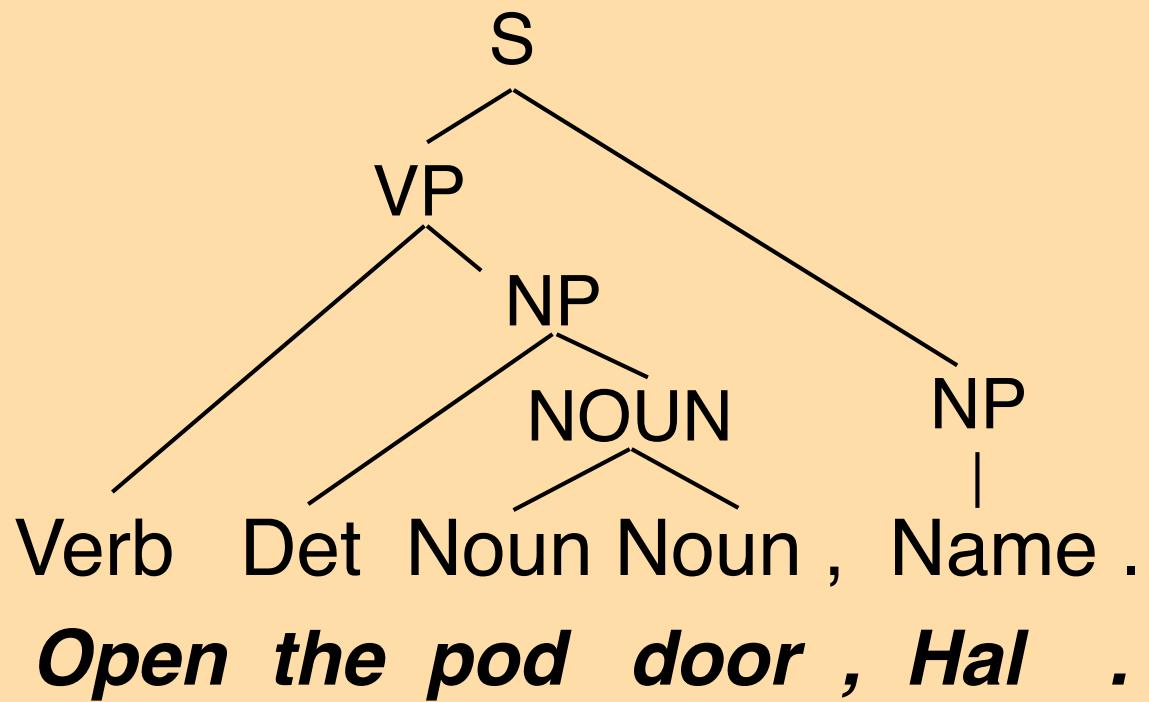
(Cassoulet = a French bean casserole)

The second major problem in NLP is **coverage**:
We will always encounter unfamiliar words
and constructions.

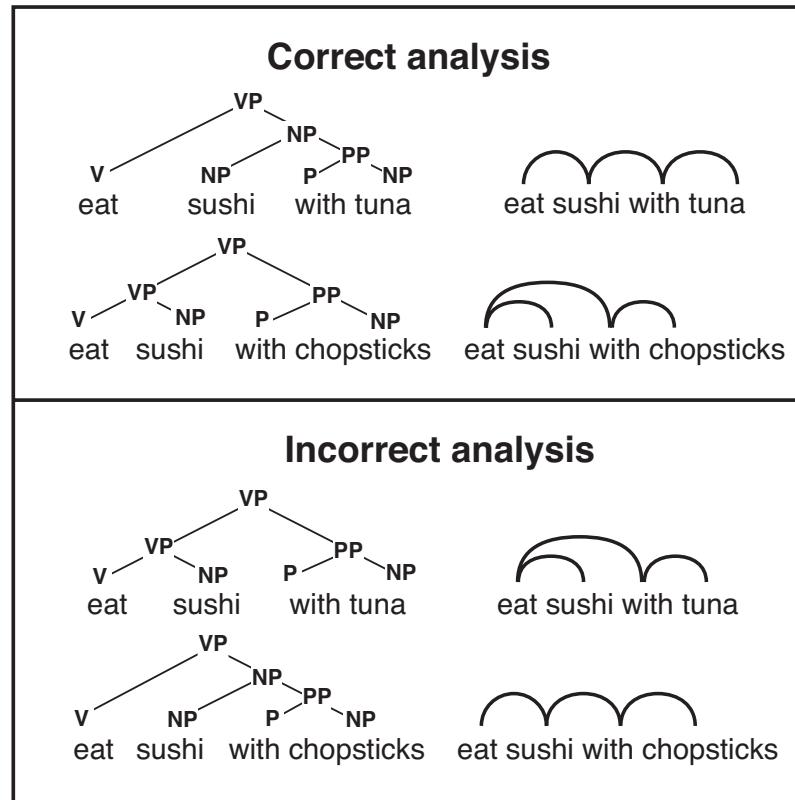
Our models need to be able to deal with this.

This means that our models need to be able
to **generalize** from what they have been trained on
to what they will be used on.

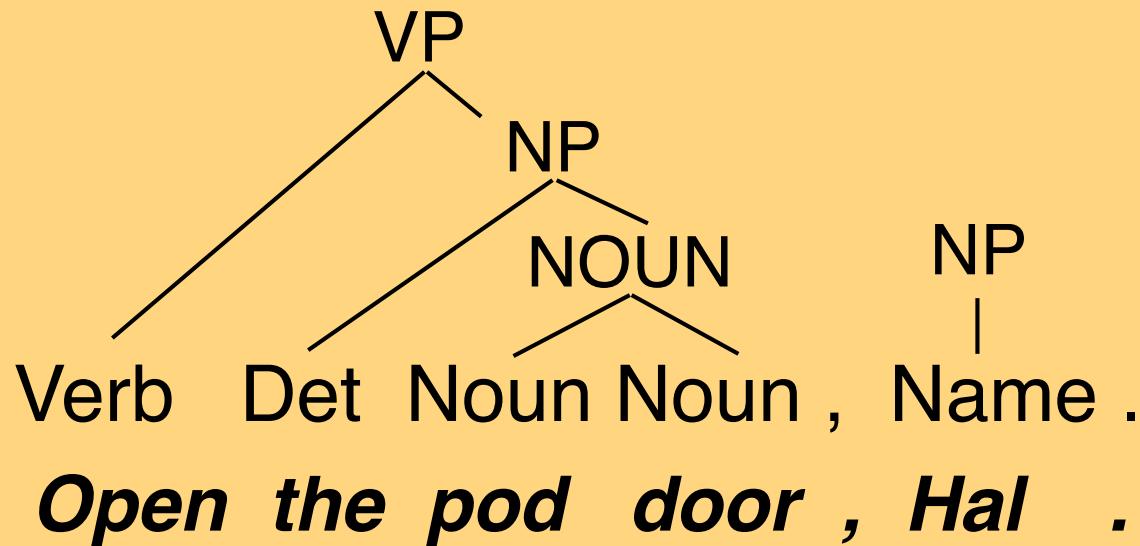
Task: Syntactic parsing



Observation: Structure corresponds to meaning



Task: Semantic Analysis

$$\exists x \exists y (\text{pod_door}(x) \And \text{Hal}(y) \\ \And \text{request}(\text{open}(x, y)))$$


Representing meaning

If a natural language understanding system needs to return a symbolic representation (or data structure) of the meaning of text, it needs a pre-defined **meaning representation language**.

“Deep” semantic analysis: (Variants of **formal logic**)

$\exists x \exists y (\text{pod_door}(x) \& \text{Hal}(y) \& \text{request}(\text{open}(x, y)))$

“Shallow” semantic analysis: **Template-filling**

(Often used in information extraction)

Named-Entity Recognition: identify all organizations, locations, dates,...

Event Extraction:

We also distinguish between

Understanding texts

On Monday, John went to Einstein's. He wanted to buy lunch. But the store was closed. That made him angry, so the next day he went to Green Street instead.

Can you answer the following questions?

Was Einstein's open for lunch on Monday? [No]

This requires the ability to identify that “Einstein’s” and “the store” refer to the same entity. (**coreference resolution**).

On which day did John go to Green Street? [On Tuesday].

This requires the ability to understand the **implicit** information that “the next day” means really “the next day after Monday” (and the knowledge that that is a Tuesday).

NLP Pipeline: Assumptions

Each step in the NLP pipeline embellishes the input with **explicit information** about its linguistic structure

POS tagging: Parts of speech of word,

Syntactic parsing: Grammatical structure of sentence,....

Each step in the NLP pipeline requires
its own explicit (“symbolic”) output representation:

POS tagging requires a **POS tag set**

(e.g. NN=common noun singular, NNS = common noun plural, ...)

Syntactic parsing requires **constituent** or **dependency labels**

(e.g. NP = noun phrase, or nsubj = nominal subject)

These representations should capture
linguistically appropriate generalizations/abstractions

Designing these representations requires linguistic expertise

NLP Pipeline: Shortcomings

Each step in the pipeline relies on a **learned model** that will return the *most likely* representations

- This requires a lot of **annotated training data** for each step
- Annotation is **expensive** and sometimes **difficult**
(people are not 100% accurate)
- These models are **never 100% accurate**
- Models make more mistakes if their input contains mistakes

How do we know that we have captured the “**right**” **generalizations** when designing representations?

- Some representations are **easier to predict** than others
- Some representations are **more useful** for the next steps in the pipeline than others
- But we won’t know how easy/useful a representation is until we have a model that we can plug into a particular pipeline

Sidestepping the NLU pipeline

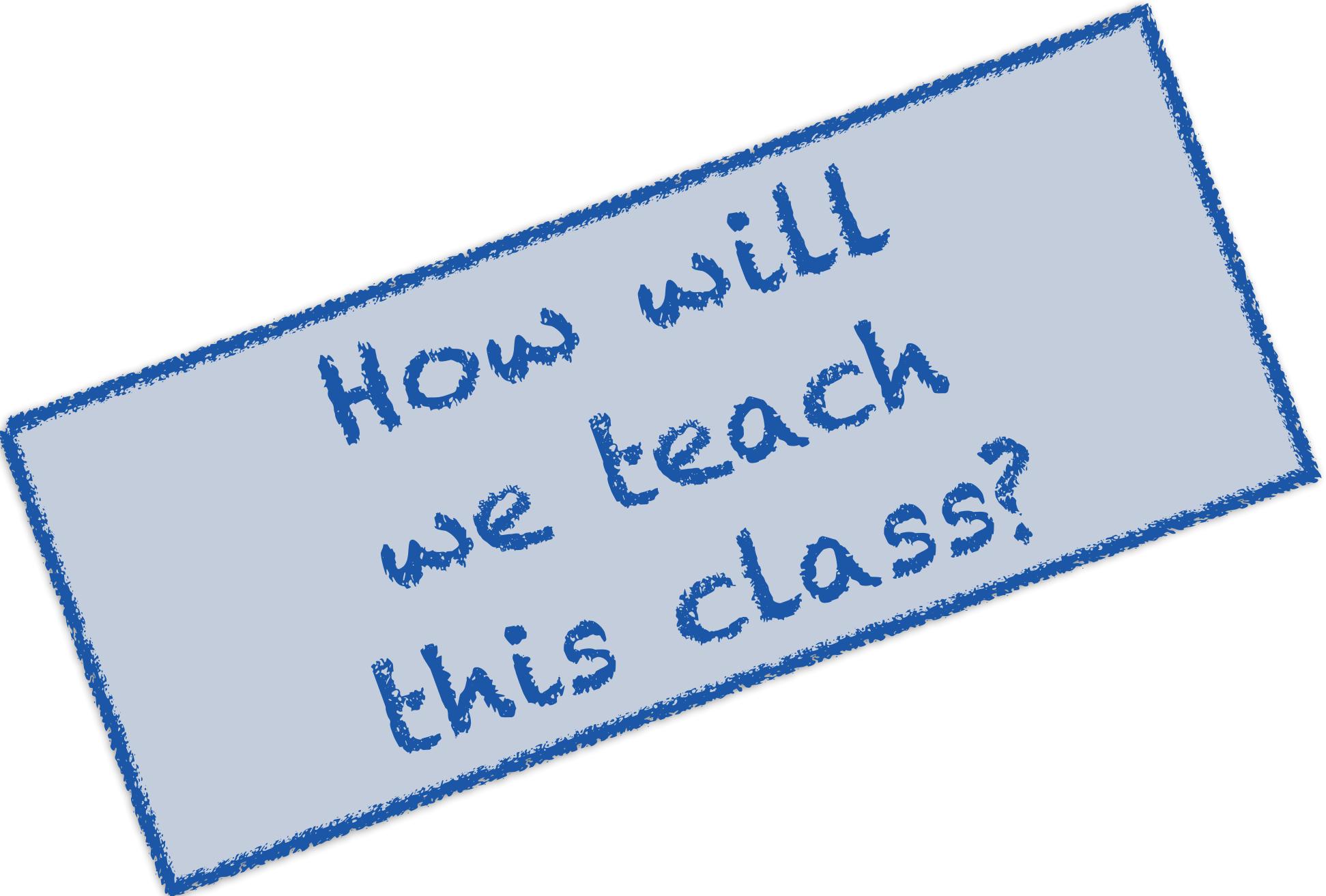
Many current neural approaches for natural language understanding and generation go directly from the raw input to the desired final output.

With large amounts of training data, this often works better than the traditional approach.

- We will soon discuss why this may be the case.

But these models don't solve everything:

- How do we incorporate knowledge, reasoning, etc. into these models?
- What do we do when don't have much training data? (e.g. when we work with a low-resource language)



How will
we teach
this class?

Class Structure and Platforms

Lectures: WF 2:00pm–3:15pm, Siebel 1404

Recordings will be put on Mediaspace

Website (slides, syllabus, deadlines, policies, links):

<https://courses.grainger.illinois.edu/cs447>

Assignments and Grades:

Canvas (peer-graded assignments, grade book)

Gradescope (quizzes, programming assignments)

Class Discussions: Campuswire

Office Hours (starting next week):

Julia Hockenmaier: WF, 3:30pm–4:00pm, Siebel 3324

TAs: TBA



Assignment Types

For everybody:

12 Quizzes (two weeks per quiz)

8 Peer-Graded Assignments (two weeks per assignment)

4 Programming Assignments (three weeks per assignment)

For 4th Credit Hour students, additionally:

Literature Review (final report due at the end of the semester)

Late policy?

No late assignments will be accepted
(except for medical/religious exemptions)

Assessment

If you're taking this class for **3 credit** hours:

25% quizzes (all equally weighted)

25% peer-graded assignments (all equally weighted)

50% programming assignments (all equally weighted)

If you're taking this class for **4 credit** hours:

18.75% quizzes (all equally weighted)

18.75% peer-graded assignments (all equally weighted)

37.50% programming assignments (all equally weighted)

25.00% literature review

Programming Assignments

What?

4 programming assignments in Python/PyTorch

Why?

To make sure you can put what you've learned to practice.

How?

Released on Fridays in Weeks 2, 5, 8, 11

You will have **three weeks** for each assignment

Submit your assignments on Gradescope.

Quizzes

What?

Short questions (typically multiple choice)

Why?

We want to make sure you follow along during the semester

We want to evaluate that you understand the material

How?

We will use [Gradescope](#)

Released on Fridays in Weeks 01–12

You have two weeks per quiz

Peer-Graded Assignments

What?

You may be asked to write a short essay,
or to analyze some text, based on what we cover in class.

Why?

To make sure you think about the material
and try to apply what you have learned.

How?

Released on Fridays in Weeks 1, 3, 4, 6, 7, 9, 10, 12

You will have **two weeks** for each assignment

We will use Canvas

You will have to grade your peers' responses

Grading is mostly based on effort.

4th Credit Hour: Literature Survey

What?

You need to **read and describe several (5–7) NLP papers** on a particular task or topic, and produce a written report that compares and critiques these approaches.

Why?

To make sure you get a deeper knowledge of NLP by reading a number of original papers in sufficient depth to discuss and compare them,

Grades

I don't grade "on a curve":

If everybody does really well in this class,
everybody gets an A, not just the top X%.

I only assign letter grades at the end of the semester.

You should know what percent of the grade you have received so far, but I may not be able to tell you *precisely* what letter grade that may correspond to (although you should talk to me if you want to know whether you're doing well or not so well).

For assignments, quizzes and peer-graded assignments, the undergrads' performance will determine the grading scale for everybody.

Academic Integrity

You can talk to each other about the assignments,
but what you submit needs to be your own work.

We may use tools such as MOSS/TurnItIn to detect plagiarism.

You are not allowed to use tools like ChatGPT,
except if/when we ask you to analyze their output for an
assignment.

If you're taking this class for four credits,
your literature review needs to be your own work,
and you need to cite all sources.

DRES accommodations

If you need any disability related accommodations, talk to DRES (<http://disability.illinois.edu>, disability@illinois.edu, phone 333-4603)

If you are concerned you may have a disability-related condition that is impacting your academic progress, there are academic screening appointments available on campus that can help diagnosis a previously undiagnosed disability by visiting the DRES website and selecting “Sign-Up for an Academic Screening” at the bottom of the page.”

Come and talk to me as well, especially once you have a letter of accommodation from DRES.

Do this early enough so that we can take your requirements into account!

Questions?

juliahmr@illinois.edu

<https://courses.grainger.illinois.edu/cs447>

