# COL 772 <br> Natural Language Processing 

Instructor: Mausam

(Slides adapted from Heng Ji, Dan Klein, Jurafsky \& Martin, Noah Smith, Luke Zettlemoyer)

## Personnel

- Instructor: Mausam, SIT 402, mausam@cs.washington.edu

TAs:

- Vishal Saley
- Pranjal Aggarwal


## Logistics

- Course Website: www.cse.iitd.ac.in/~mausam/courses/col772/spring2024
- Join class discussion group on Piazza (access code col772) https://piazza.com/iit_delhi/winter2024/col772
- Textbook:

Yoav Goldberg. Neural Network Methods in Natural Language Processing. Morgan and Claypool (2017).
Dan Jurafsky and James Martin. Speech and Language Processing, 2nd Edition, Prentice-Hall (2008).
$3^{\text {rd }}$ Edition (under preparation)
Course notes by Michael Collins: www.cs.columbia.edu/~mcollins/

- Grading:
- $45 \%$ assignments
- $20 \%$ midsem
- $25 \%$ major
- 10\% quiz
- Extra credit: constructive participation in class and discussion group


## Assignments and Project

- 3-4 programming assignments
- assignments done individually!
- late policy: penalty of $10 \%$ maximum grade every day for a week
- Project
- No project this time
- Request HPC approval after A1!
- End date: 30 $0^{\text {th }}$ May 2024
- Please don't complain if HPC is busy
- TAs: do an extra class on best practices for HPC


## Academic Integrity

- Cheating $\rightarrow$ negative penalty (and possibly more)
- Exception: if one person/team is identified as cheater
- Non-cheater gets a zero
- Collaboration is good!!! Cheating is bad!!! Who is a cheater?
- No sharing of part-code
- No written/soft copy notes
- Right to information rule
- Kyunki saas bhi kabhi bahu thi Rule

OOOMO HITNOCTID



## Class Requirements \& Prereqs

- Class requirements
- Uses a variety of skills / knowledge:
- Probability and statistics
- Deep learning
- Probabilistic graphical models
- Basic linguistics background
- Excellent coding skills
- Deep Learning
- Most people are probably missing one of the above
- You will often have to work to fill the gaps
- Official Prerequisites
- Data structures
- Unofficial Prerequisites
- Deep Learning -


# Timings 

- Tue/Fri 2-3:30
- Office hours
- By appointment
- Audit criteria
- B-


## Goals of this course

- Learn the issues and techniques of modern NLP
- Build realistic NLP tools
- See the latest trends in field of NLP $\rightarrow$ deep learning
- See where the holes in the field still are!
- Computer Engineer
- very relevant field in the modern age
- Computer Scientist
- an excellent source of research problems


## Theory vs. Modeling vs. Applications

- Lecture balance tilted towards modeling
- Assignment balance tilted towards applications
- ~No theorems or proofs
- Desired work - lots!


## Three Way Crossing in NLP



## MOTIVATION

## The Dream

- It'd be great if machines could
- Process our email (usefully)
- Translate languages accurately
- Help us manage, summarize, and aggregate information
- Use speech as a UI (when needed)
- Talk to us / listen to us
- But they can't:
- Language is complex, ambiguous, flexible, and subtle
- Good solutions need linguistics and machine learning knowledge



## What is NLP?



- Fundamental goal: deep understanding of broad language
- Not just string processing or keyword matching!
- End systems that we want to build:
- Simple: spelling correction, text categorization...
- Complex: speech recognition, machine translation, information extraction, dialog interfaces, question answering...
- Unknown: human-level comprehension


## What is NLP?

## Computer processing of human language



Machine Translation, Summarization, Chatbots

## Some Early NLP History

- 1950s:
- Foundational work: automata, information theory, etc.
- First speech systems
- Machine translation (MT) hugely funded by military (imagine that)
- Toy models: MT using basically word-substitution
- Optimism!
- 1960s and 1970s: NLP Winter
- Bar-Hillel (FAHQT) and ALPAC reports kills MT
- "Little John was looking at his toy box. Finally, he found it. The box was in the pen. John was very happy."
- Work shifts to deeper models, syntax
- ... but toy domains / grammars (SHRDLU, LUNAR)


## SHRDLU

Person: Pick up a big red block.
Computer: OK.
Person: Grasp the pyramid.
Computer: I DON'T UNDERSTAND WHICH PYRAMID YOU MEAN.
Person (changing their mind): Find a block which is taller than the one you are
holding and put it into the box.
Computer: BY "IT", I ASSUME YOU MEAN THE BLOCK WHICH IS TALLER
THAN THE ONE I AM HOLDING.
Computer: OK.
Person: What does the box contain?
Computer: THE BLUE PYRAMID AND THE BLUE BLOCK.
Person: What is the pyramid supported by?
Computer: THE BOX.
Person: How many blocks are not in the box?
Computer: FOUR OF THEM.
Person: Is at least one of them narrower than the one which i told you to pick up?
Computer: YES, THE RED CUBE.
Person: Is it supported?
Computer: YES, BY THE TABLE.
Person: Can the table pick up blocks?
Computer: NO.

## Not vet solved: CLEVR (2016)

Questions in CLEVR test various aspects of visual reasoning including attribute identification, counting, comparison, spatial relationships, and logical operations.


Q: Are there an equal number of large things and metal spheres?
Q: What size is the cylinder that is left of the brown metal thing that is left of the big sphere?
Q: There is a sphere with the same size as the metal cube; is it made o the same material as the small red sphere?
Q: How many objects are either small cylinders or red things?

## NLP History: pre-statistics

- (1) Colorless green ideas sleep furiously.
- (2) Furiously sleep ideas green colorless
- It is fair to assume that neither sentence (1) nor (2) (nor indeed any part of these sentences) had ever occurred in an English discourse. Hence, in any statistical model for grammaticalness, these sentences will be ruled out on identical grounds as equally "remote" from English. Yet (1), though nonsensical, is grammatical, while (2) is not." (Chomsky 1957)
- 70s and 80s: more linguistic focus
- Emphasis on deeper models, syntax and semantics
- Toy domains / manually engineered systems
- Weak empirical evaluation


## NLP: machine learning and empiricism

"Whenever I fire a linguist our system performance improves." -Jelinek, 1988

- 1990s: Empirical Revolution
- Corpus-based methods produce the first widely used tools
- Deep linguistic analysis often traded for robust approximations
- Empirical evaluation is essential
- 2000s: Richer linguistic representations used in statistical approaches, scale to more data!
- 2010s: Probabilistic NLP gives way to Neural NLP
- 2020s: Pre-trained language models, Foundation models


## Three/Four? Generations of NLP

- Hand-crafted Systems - Knowledge Engineering
[1950s- ]
- Rules written by hand; adjusted by error analysis
- Require experts who understand both the systems and domain
- Iterative guess-test-tweak-repeat cycle

- Automatic, Trainable (Machine Learning) Systems with engineered features [1985s-2012]
- The tasks use statistical models with hand-coded features
- More robust techniques based on rich annotations
- Perform better than rules (Parsing 90\% vs. 75\% accuracy)
- Automatic, Trainable Neural architectures with no/limited engineered features [2012--]
- The tasks use deep learning
- Perform much better than hand-coded features


## What is Nearby NLP?

- Computational Linguistics
- Using computational methods to learn more about how language works
- We end up doing this and using it

- Cognitive Science
- Figuring out how the human brain works
- Includes the bits that do language
- Humans: the only working NLP prototype!
- Speech?
- Mapping audio signals to text
- Traditionally separate from NLP, converging?
- Two components: acoustic models and language models
- Language models in the domain of stat NLP



## Web Search ... n. 0

find all web pages containing the word Liebermann
read the last 3 months of the NY Times and provide a summary of Biden's presidency so far

## Caveat

## NLP has an Al aspect to it.

- We're often dealing with ill-defined problems
- We don't often come up with exact solutions/algorithms
- We can't let either of those facts get in the way of making progress


## NLP is AI Complete

## Turing Test

young woman: Men are all alike.
eliza: In what way?
young woman: They're always bugging us about something specific or other.
eliza: Can you think of a specific example?
young woman: Well, my boyfriend made me come here.
eliza: Your boyfriend made you come here?

ELIZA (Weizenbaum, 1966): first computer dialogue system based on keyword matching

## Levels of Linguistic Knowledge



## Orthography

ลูกศิษย์วัดกระทิงยังยื้อปิดถนนทางขึ้นไปนมัสการพระบาทเขาคิชมกูฏ หวิดปะทะ กับเจ้าถิ่นที่ออกมาเผชิญหน้าเพราะเดือดร้อนสัญจรไม่ได้ ผวจ.เร่งทุกฝ่ายเจรจา ก่อนที่ชื่อเสียงของจังหวัดจะเสียหายไปมากกว่านี้ พร้อมเสนอหยุดจัดงาน 15 วัน $\ldots$.

## Morphology

uygarlaștıramadıklarımızdanmıșsınızcasına
"(behaving) as if you are among those whom we could not civilize"

## TIFGOSH ET HA-LELED BA-GAN "you will meet the boy in the park"

unfriend, Obamacare, Manfuckinghattan

Suffix, prefix, infix (tmesis), circumfix
arundhati "leftist" roy, fan-frickin'-tastic,
छुड़ाया chuRAyA $\rightarrow$ छुड़वाया chhurwAyA

## The Challenge of Words

- Segmenting text into words
- Thai example
- Morphological variation
- Turkish and Hebrew examples
- Words with multiple meanings:
- bank, mean
- Domain-specific meanings:
- latex, sport, etc.
- Multiword expressions:
- make a decision, take out, make up


## POS Tagging

ikr smh he asked fir yo last name
so he can add $u$ on $f b$ lololol

## Morphology+Syntax

A ship-shipping ship, shipping shipping-ships.


## Constituency Parsing



## Dependency Parsing



They hid the letter on the shelf

## Dependency Relations

| Argument Dependencies | Description |
| :--- | :--- |
| nsubj | nominal subject |
| csubj |  |
| dobj |  |
| iobj | clausal subject |
| pobj | direct object |
| Modifier Dependencies | indirect object |
| tmod | object of preposition |
| appos | Description |
| det | temporal modifier |
| prep | appositional modifier |

## Semantics

- Lexical Semantics
- Meanings of words
- Frame semantics
- (shallow semantics)
- Sentential semantics
- (full semantics)


## Lexical Semantics

- Synonym
- start-begin, bodoh-dungu, next to-near
- Antonym
- clever x stupid, high x low, big x small, etc.
- Homonym
- identical in spelling and pronounciation
- bear, bank, ...
- Homophones
- sounds identical but are written differently
- site-sight, piece-peace.
- Homograph
- written identically but sound differently
- lead, wind, minute
- Polysemy
- a word which has two (or more) related meaninas


## Semantic Role Labeling: Adding

 semantics into Irees

## Core Arguments

- Arg0 = agent
- Arg1 = direct object / theme / patient
- Arg2 = indirect object / benefactive / instrument / attribute / end state
- Arg3 = start point / benefactive / instrument / attribute
- Arg4 = end point


## Full Sentential Semantics

- Formal/Logical Semantics
- All man are mortal
- India borders a country that borders Afghanistan.


## Information Extraction

- Unstructured text to database entries

New York Times Co. named Russell T. Lewis, 45, president and general manager of its flagship New York Times newspaper, responsible for all business-side activities. He was executive vice president and deputy general manager. He succeeds Lance R. Primis, who in September was named president and chief operating officer of the parent.

| Person | Company | Post | State |
| :--- | :--- | :--- | :--- |
| Russell T. Lewis | New York Times <br> newspaper | president and general <br> manager | start |
| Russell T. Lewis | New York Times <br> newspaper | executive vice <br> president | end |
| Lance R. Primis | New York Times Co. | president and CEO | start |

- SOTA: perhaps $80 \%$ accuracy for pre-defined tables, $90 \%+$ for single easy fields
- But remember: information is redundant!


## KB Slots

| Person |  | Organization |
| :--- | :--- | :--- |
| per:alternate_names | per:title | org:alternate_names |
| per:date_of_birth | per:member_of | org:political/religious_affiliation |
| per:age | per:employee_of | org:top_members/employees |
| per:country_of_birth | per:religion | org:number_of_employees/members |
| per:stateorprovince_of_birth | per:spouse | org:members |
| per:city_of_birth | per:children | org:member_of |
| per:origin | per:parents | org:subsidiaries |
| per:date_of_death | per:siblings | org:parents |
| per:country_of_death | per:other_family | org:founded_by |
| per:stateorprovince_of_death | per:charges | org:founded |
| per:city_of_death |  | org:dissolved |
| per:cause_of_death |  | org:country_of_headquarters |
| per:countries_of_residence |  | org:stateorprovince_of_headquarters |
| per:stateorprovinces_of_residence |  | org:city_of_headquarters |
| per:cities_of_residence |  | org:shareholders |
| per:schools_attended |  | org:website |

## Knowledge Base Linking (Wikification)



## Google Knowledge Graph (2012)



## QA / NL Interaction

- Question Answering:
- More than search
- Can be really easy: "What's the capital of Wyoming?"
- Can be harder: "How many US states' capitals are also their largest cities?"
- Can be open ended: "What are the main issues in the global warming debate?"
- Natural Language Interaction:
- Understand requests and act on them
- "Make me a reservation for two at Quinn's tonight"


Web

Your search - How many US states' capitals are also their largest cities? - did not match any documents.

Suggestions:

- Make sure all words are spelled correctly.
- Try different keywords.
- Try more general keywords.
- Try fewer keywords.


## Google Home - - Business Solutions - About Google

## capital of Wyoming: Information From Answers.com

Note: click on a word meaning below to see its connections and related words
The noun capital of Wyoming has one meaning: Meaning \#1 : the capital.
wow answers.com/topic/capital-of-wyoming - 21 k - Cached - Similar pages
Cheyenne: Weather and Much More From Answers.com
Chey enne (shī-ăn ', -ĕn ' ) The capital of Wyoming, in the southeast part of the state near the Nebraska and Colorado borders.
whw answers com/topic/cheyenne-wyoming - 74k - Cached - Similar pages

## Jeopardy! World Champion



US Cities: Its largest airport is named for a World War II hero; its second largest, for a World War II battle. http://www.youtube.com/ watch?v=qpKolfTukrA


## Coreference

" But the little prince could not restrain aimirafiom "Oh! How beautiful you are!" at the same moment as the sun..."

- The little prince could guess easily enough that she was not any too modest--but how moving--and exciting--she was!
- "I think it is time for breakfast," she added an instant later. "If you would have the kindness to think of my needs--"
- And the little prince, completely abashed, went to look for a sprinkling-can of fresh water. So, he tended the flower.


## Summarization

- Condensing documents
- Single or multiple docs
- Extractive or synthetic
- Aggregative or representative

STORY HIGHLIGHTS

- Obama's address less stirring than others but more candid, analyst says
- Schneider: At a time of crisis, president must be reassuring
- Country has chosen "hope over fear, unity of purpose over ... discord," Obama said
- Obama's speech was a cool speech, not a hot one, Schneider says
- Very contextdependent!
- An example of analysis with generation


## Machine Translation



- Translate text from one language to another
- Recombines fragments of example translations
- Challenges:
- What fragments? [learning to translate]
- How to make efficient? [fast translation search]
- Fluency vs fidelity


## 2013 Google Translate: French

## EN GE MOMENT Impôts Kenya Syrie Pakistan Emploi Scandale Prism

## Impôt sur le revenu : vous en 2014 ?



Sélectionnez votre revenu et votre situe bénéficiez de la pause fiscale.

Comment le budget pour 2014 est-il réparti ? ..ll visuel interactif

Un budget 2014 soumis aux critiques


Le chômage baisse pour la première fois depuis avril 2011 post de blog

AT THIS MOMENT Taxes Kenya Syria Pakistan Use Prismscandal

## Income tax: how much do you pay in 2014?



Select your income and family situation to see if you get the tax break.

How is the budget for 2014 is allocated? .ll INTERACTIVE VISUAL

A 2014 budget submitted to criticism


Unemployment fell for the first time since April 2011 post blog

Budget: these expenses no government can reduce

Budget 2014: the retail savings .It interactive visual
découvrez tous les services abonnés
S'abonner au Monde à partir de $1 €$ E

## CALL FOR EYIDENCE

## Member (s) of Europe

 Ecology-Greens, do you share the finding of severe Christmas Mamère EELV?Share your experience

## Continuous

7:53 Budget: the fixed expenses
7:36 Heard the "Fashion Week" in Paris
7:19 control giant Airbus
7:04 Complaint against "Actual Values"
7:01 Venezuela: 17 people arrested
6:59 Vidberg: the new budget came
6:50 The "noble mission" of the NSA
6:38 Roma: jousting between Brussels a

## D E <br> F U R S A C

automne-hiver 13/14

## 2013 Google Translate: Russian



## English -- Russian

- The spirit is willing but the flesh is weak. (English)
- The vodka is good but the meat is rotten. (Russian)


## And more recently (FB: Bangla $\rightarrow$ English)

- The conversation went like this:
- End of the day conversation:
- Me: What did you do today?
- Ma: I watched Kedarnath.
- Me: What did you learn from watching Kedarnath?
- Ma: That Sushant Singh Rajput is very strong.
- Me: How did you know this?
- Ma: He was lugging people around on his back.
- Me: What else did you learn?
- Ma (thinks for a bit): That Saif Ali Khan is very "paaka" (Paaka refers to someone who does things before it is appropriate for them to do so age-wise).
- Me: How do you know?
- Ma: Such a grown up daughter at such a young age!

Our words at the end of the day:
Me: what did you do today?
Mother: Kedarnath saw.
Me : what did you learn to see?
Mother: there is a lot of force on the good lion rajput.

Me: what do you know?
Many many happy returns of the day.
Me : and what do you know?
Mother (for a while thought): Saif Ali Khan was very ripe.

Me: what do you know?
Mother: such a big girl at such a young age.

## Language Comprehension/Common-Sense

"The rock was still wet. The animal was glistening, like it was still swimming," recalls Hou Xianguang. Hou discovered the unusual fossil while surveying rocks as a paleontology graduate student in 1984, near the Chinese town of Chengjiang. "My teachers always talked about the Burgess Shale animals. It looked like one of them. My hands began to shake." Hou had indeed found a Naraoia like those from Canada. However, Hou's animal was 15 million years older than its Canadian relatives.

It can be inferred that Hou Xianguang's "hands began to shake", because he was:
(A) afraid that he might lose the fossil
(B) worried about the implications of his finding
(C) concerned that he might not get credit for his work
(D) uncertain about the authenticity of the fossil
(E) excited about the magnitude of his discovery

## ConvAI/ChatBots/Dialog Systems

Write a tweet about the importance of learning Al and ML learning skills and embracing the new possibilities of this sector.
"Embracing \#Al and \#MachineLearning is more than a trend; it's a pathway to the future. Acquiring these skills opens doors to innovation, creativity, and endless possibilities in tech. Don't miss out on shaping tomorrow. Invest in learning today! [. \#FutureTech \#LearnAl"

Write a tweet about the importance of learning Al and ML learning skills and embracing the new possibilities of this sector.

My goal is to entice readers to subscriber to my newsletter and download my guides for using automation to become more productive.
"Unlock the power of \#Al and \#MachineLearning! \& Enhance productivity and discover O 円 new horizons with our expert guides. Subscribe to our newsletter and download FREE tools to automate your life. Don't just keep up with the future - lead it! $\theta$ [Your Link Here]

## Levels of Linguistic Knowledge



## Why is NLP hard?

- Ambiguity
- Ambiguity
- Ambiguity
- Sparsity


## Ambiguities

- Headlines: Why are these funny?
- Ban on Nude Dancing on Governor's Desk
- Iraqi Head Seeks Arms
- Juvenile Court to Try Shooting Defendant
- Teacher Strikes Idle Kids
- Stolen Painting Found by Tree
- Local High School Dropouts Cut in Half
- Red Tape Holds Up New Bridges
- Clinton Wins on Budget, but More Lies Ahead
- Hospitals Are Sued by 7 Foot Doctors
- Kids Make Nutritious Snacks


## PP Attachment Ambiguity



## Coordination Ambiguity

| Modifier | \% of Total | Example from Surveys (modifiers underlined) |
| :--- | :---: | :--- |
| Noun | 46.4 | ( It ) targeted the project and election managers |
| Adjective | 23.2 | ... define $\underline{\text { architectural components and connectors }}$ |
| Prep | 15.9 | Facilitate the scheduling and performing of works |
| Verb | 5.8 | capacity and network resources required |
| Adverb | 4.4 | ( It ) might be automatically rejected or flagged |
| Rel. Clause | 2.2 | Assumptions and dependencies that are of importance |
| Number | 0.7 | zero mean values and standard deviation |
| Other | 1.4 | increased by the lack of funding and local resources |

## Semantic Ambiguity

At last, a computer that understands you like your mother.

- Direct Meanings:
- It understands you like your mother (does) [presumably well]
- It understands (that) you like your mother
- It understands you like (it understands) your mother
- But there are other possibilities, e.g. mother could mean:
- a woman who has given birth to a child
- a stringy slimy substance consisting of yeast cells and bacteria; is added to cider or wine to produce vinegar
- Context matters, e.g. what if previous sentence was:
- Wow, Amazon predicted that you would need to order a big batch of new vinegar brewing ingredients. :)
[Example from L. Lee]


## Dark Ambiguities

- Dark ambiguities: most structurally permitted analyses are so bad that you can't get your mind to produce them

This analysis corresponds to the correct parse of
"This will panic buyers!"

- Unknown words and new usages

- Solution: We need mechanisms to focus attention on the best ones, probabilistic techniques do this


## Ambiguities (contd)

- Get the cat with the gloves.



## Ambiguity

- Find at least 5 meanings of this sentence: - I made her duck


## Ambiguity

- Find at least 5 meanings of this sentence:
- I made her duck
- I cooked waterfowl for her benefit (to eat)
- I cooked waterfowl belonging to her
- I created the (plaster?) duck she owns
- I caused her to quickly lower her head or body
- I waved my magic wand and turned her into undifferentiated waterfowl


## Ambiguity is Pervasive

- I caused her to quickly lower her head or body
- Lexical category: "duck" can be a N or V
- I cooked waterfowl belonging to her.
- Lexical category: "her" can be a possessive ("of her") or dative ("for her") pronoun
- I made the (plaster) duck statue she owns
- Lexical Semantics: "make" can mean "create" or "cook"


## Ambiguity is Pervasive

- Grammar: Make can be:
- Transitive: (verb has a noun direct object)
- I cooked [waterfowl belonging to her]
- Ditransitive: (verb has 2 noun objects)
-1 made [her] (into) [undifferentiated waterfowl]
- Action-transitive (verb has a direct object and another verb)
- I caused [her] [to move her body]


## Ambiguity is Pervasive

- Phonetics!
- I mate or duck
- I'm eight or duck
- Eye maid; her duck
- Aye mate, her duck
- I maid her duck
- I'm aid her duck
- I mate her duck
- I'm ate her duck
- I'm ate or duck
- I mate or duck


## Abbrevations out of context

- Medical Domain: 33\% of abbreviations are ambiguous (Liu et al., 2001), major source of errors in medical NLP (Friedman et al., 2001)

| RA | "rheumatoid arthritis", "renal artery", "right atrium", "right atrial", <br> "refractory anemia", "radioactive", "right arm", "rheumatic <br> arthritis", ... |
| :--- | :--- |
| PN | "Penicillin"; "Pneumonia"; "Polyarteritis"; "Nodosa"; "Peripheral <br> neuropathy"; "Peripheral nerve"; "Polyneuropathy"; <br> "Pyelonephritis"; "Polyneuritis"; "Parenteral nutrition"; "Positional <br> Nystagmus"; "Periarteritis nodosa", ... |

- Military Domain
- "GA ADT 1, USDA, USAID, Turkish PRT, and the DAIL staff met to create the Wardak Agricultural Steering Committee. "
- "DST" = "District Stability Team" or "District Sanitation Technician"?


## Uncertainty: Ambiguity Example



## Problem: Sparsity

- However: sparsity is always a problem
- New unigram (word), bigram (word pair)



## NLP Topics in the Course

- tokenization,
- language models,
- part of speech tagging,
- noun phrase chunking,
- named entity recognition,
- coreference resolution,
- parsing,
- information extraction,
- sentiment analysis,
- question answering,
- text classification,
- document clustering,
: document summarization,


## We will make NLP Models

- Model: an abstract, theoretical, predictive construct. Includes:
- a (partial) representation of the world
- a method for creating or recognizing worlds
- a system for reasoning about worlds
- NLP uses many tools for modeling.
- Surprisingly shallow models work fine for some applications.


## ML Models in the Course

- Naive Bayes, MaxEnt Classifiers
- Expectation Maximization,
- Conditional Random Fields,
- Probabilistic Context Free Grammars,
- CNNs, Recurrent NNs, Transformers
- Sequence to Sequence models
- Neural Language Models
- Pre-trained Language Models
- Advanced Ideas


## Disclaimer

- This course will be highly biased
- won't focus much on linguistics
- won't focus much on historical perspectives
- won't be all deep learning
- This course will be highly biased
- I will teach you what I like
- I will teach what I can easily learn ... ©

