NLP is interdisciplinary

- Artificial intelligence
- Machine learning (ca. 2000—today); statistical models, neural networks
- Linguistics (representation of language)
- Social sciences/humanities (models of language at use in culture/society)
NLP = processing language with computers
processing as “understanding”
Turing test

Distinguishing human vs.
computer only through
written language
Dave Bowman: Open the pod bay doors, HAL
HAL: I’m sorry Dave. I’m afraid I can’t do that

<table>
<thead>
<tr>
<th>Agent</th>
<th>Movie</th>
<th>Complex human emotion mediated through language</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hal</td>
<td>2001</td>
<td>Mission execution</td>
</tr>
<tr>
<td>Samantha</td>
<td>Her</td>
<td>Love</td>
</tr>
<tr>
<td>IG-11</td>
<td>The Mandalorian</td>
<td>“to nurse and protect”</td>
</tr>
</tbody>
</table>
Where we are now
Where we are now
Where we are now
Q: What is your favorite animal?
A: My favorite animal is a dog.

Q: Why?
A: Because dogs are loyal and friendly.

Q: What are two reasons that a dog might be in a bad mood?
A: Two reasons that a dog might be in a bad mood are if it is hungry or if it is hot.

Q: How many bonks are in a quoit?
A: There are three bonks in a quoit.

Q: How many rainbows does it take to jump from Hawaii to seventeen?
A: It takes two rainbows to jump from Hawaii to seventeen.

What makes language hard?

- Language is a complex social process
- Tremendous ambiguity at every level of representation
- Modeling it is AI-complete (requires first solving general AI)
What makes language hard?

• Speech acts (“can you pass the salt?)
  [Austin 1962, Searle 1969]

• Conversational implicature (“The opera singer was amazing; she sang all of the notes”).
  [Grice 1975]

• Shared knowledge (“Warren ran for president”)
Elizabeth Warren
2020

Warren G. Harding
1920
What makes language hard?

• Speech acts (“can you pass the salt?)
  [Austin 1962, Searle 1969]

• Conversational implicature (“The opera singer was amazing; she sang all of the notes”).
  [Grice 1975]

• Shared knowledge (“Warren ran for president”)

• Variation/Indexicality (“This homework is wicked hard”)
  [Labov 1966, Eckert 2008]
Ambiguity

“One morning I shot an elephant in my pajamas”

*Animal Crackers*
Ambiguity

“One morning I shot an elephant in my pajamas”

Animal Crackers
Ambiguity

“One morning I shot an elephant in my pajamas”
Ambiguity

“One morning I shot an elephant in my pajamas”
processing as representation

• NLP generally involves representing language for some end, e.g.:
  • dialogue
  • translation
  • speech recognition
  • text analysis
Information theoretic view

“One morning I shot an elephant in my pajamas”

Shannon 1948
Information theoretic view

When I look at an article in Russian, I say: 'This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode.'

Weaver 1955
Rational speech act view

“One morning I shot an elephant in my pajamas”

Communication involves recursive reasoning: how can X choose words to maximize understanding by Y?

Frank and Goodman 2012
Pragmatic view

“One morning I shot an elephant in my pajamas”

Meaning is co-constructed by the interlocutors and the context of the utterance
Whorfian view

“One morning I shot an elephant in my pajamas”

Weak relativism: structure of language influences thought
Whorfian view

Weak relativism: structure of language influences thought
“One morning I shot an elephant in my pajamas”
discourse

semantics

syntax

morphology

words
Words

- One morning I shot an elephant in my pajamas
- I didn't shoot an elephant
- Imma let you finish but Beyonce had one of the best videos of all time
- 一天早上我穿着睡衣射了一只大象
Parts of speech

One morning I shot an elephant in my pajamas
Named entities

person

Imma let you finish but Beyoncé had one of the best videos of all time
One morning I shot an elephant in my pajamas
"Unfortunately I already had this exact picture tattooed on my chest, but this shirt is very useful in colder weather."

[overlook1977]
NLP

• Machine translation
• Question answering
• Information extraction
• Conversational agents
• Summarization
NLP + X
Computational Social Science

- Inferring ideal points of politicians based on voting behavior, speeches
- Detecting the triggers of censorship in blogs/social media
- Inferring power differentials in language use
Computational Journalism

What do Journalists do with Documents?
Field Notes for Natural Language Processing Researchers

Jonathan Stray
Columbia Journalism School
jms2361@columbia.edu

- Robust import
- Robust analysis
- Search, not exploration
- Quantitative summaries
- Interactive methods
- Clarity and Accuracy
Computational Humanities

Ted Underwood (2018), “Why Literary Time is Measured in Minutes”

Ryan Heuser, Franco Moretti, Erik Steiner (2016), The Emotions of London

Richard Jean So and Hoyt Long (2015), “Literary Pattern Recognition”


Franco Moretti (2005), Graphs, Maps, Trees

Holst Katsma (2014), Loudness in the Novel


Text-driven forecasting

General Market Media Buyer

Job listing for a Marketing role in San Francisco

By Clay Satherfield and Jensen Harris

Our agency needs a killer media buyer. Fast-paced, no kidding here. We tend to work hard and we hope you will too. We’re smart and passionate; you need to be as well. We’re rapidly expanding and need an experienced media buyer and a visionary leader. While we’re focused on television, experience in other mediums is a huge plus. You understand when you need to look at the bigger picture and when to go the general market route.

Do you have a great sense of humor? Do you want to work somewhere your unique voice will be heard? Are you driven by the ability to set and exceed ambitious goals? When you see something that’s a problem, do you make a change or just complain?

A couple of things that you must do in this role:

- Work with vendors to mature exciting partnerships for our clients
- Teach everyone in the company something new in technology
Methods

- Finite state automata/transducers (tokenization, morphological analysis)
- Rule-based systems
Methods

• Probabilistic models

• Naive Bayes, Logistic regression, HMM, MEMM, CRF, language models

\[
P(Y = y | X = x) = \frac{P(Y = y)P(X = x | Y = y)}{\sum_y P(Y = y)P(X = x | Y = y)}
\]
Methods

- Dynamic programming (combining solutions to subproblems)

Viterbi algorithm, CKY
Methods

• Dense representations for features/labels (generally: inputs and outputs)

\[
\text{vec} \left( \begin{array}{c}
\alpha_1 \\
\alpha_2 \\
\phi(x) \\
\end{array} \right) \rightarrow \text{vec} \left( \begin{array}{c}
\mathbb{R}^d \\
\mathbb{R}^d \\
\mathbb{R}^N \\
\end{array} \right) \rightarrow \text{vec} \left( \begin{array}{c}
d \times d \times N \\
\mathbb{R}^{dN} \\
\end{array} \right)
\]

Feature tensor, Feature vector $\in \mathbb{R}^{dN}$

Srikumar and Manning (2014), "Learning Distributed Representations for Structured Output Prediction" (NIPS)

• Neural networks: multiple, highly parameterized layers of (usually non-linear) interactions mediating the input/output

Vaswani et al. (2017), "Attention is All You Need" (NeurIPS)

Figure 1: The Transformer - model architecture.
Methods

- Latent variable models (specifying probabilistic structure between variables and inferring likely latent values)

Info 159/259

• This is a class about models.

  • You’ll learn and implement algorithms to solve NLP tasks efficiently and understand the fundamentals to innovate new methods.

• This is a class about the linguistic representation of text.

  • You’ll annotate texts for a variety of representations so you’ll understand the phenomena you’ll be modeling.
Prerequisites

- Strong programming skills
  - Translate pseudocode into code (Python)
  - Analysis of algorithms (big-O notation)
- Basic probability/statistics
- Calculus
function VITERBI(observations of len $T$, state-graph of len $N$) returns best-path

create a path probability matrix $viterbi[N+2,T]$

for each state $s$ from 1 to $N$ do
    $viterbi[s,1] \leftarrow a_{0,s} \times b_s(o_1)$
    $backpointer[s,1] \leftarrow 0$
end for each state $s$

for each time step $t$ from 2 to $T$ do
    for each state $s$ from 1 to $N$ do
        $viterbi[s,t] \leftarrow \max_{s'}^{N} viterbi[s',t-1] \times a_{s',s} \times b_s(o_t)$
        $backpointer[s,t] \leftarrow \arg\max_{s'}^{N} viterbi[s',t-1] \times a_{s',s}$
    end for each state $s$
end for each time step $t$

$viterbi[q_F,T] \leftarrow \max_{s=1}^{N} viterbi[s,T] \times a_s,q_F$; termination step

$backpointer[q_F,T] \leftarrow \arg\max_{s=1}^{N} viterbi[s,T] \times a_s,q_F$; termination step

return the backtrace path by following backpointers to states back in time from $backpointer[q_F,T]$
\[ \frac{dx^2}{dx} = 2x \]
Grading

• Info 159:
  • Homeworks (25%)
  • Annotation project (25%)
  • Weekly quizzes (10%)
  • Midterm (20%)
  • NLP subfield survey (20%)
Annotation project

- This course covers many of the methods and existing tasks in NLP.
- But the most exciting applications of NLP have yet to be invented.
- Design a new NLP task and annotate data to support it, working in groups of exactly 3 students.

Existing tasks

- Question answering
- Named entity recognition
- Sentiment analysis
- Machine translation
- Syntactic parsing
- Coreference resolution
- Text generation
- Word sense disambiguation

...
Respect

• Present one dialogue turn (police/driver) to be rated by people for respect (4-point Likert scale). High IAA.

• Build a predictive model mapping text to respect.

Voigt et al. 2017, “Language from police body camera footage shows racial disparities in officer respect”
I fear then, Emma, Sewell is a knave, and joined in mean collusion with his brother, to distress your husband, who looks upon him as his friend. You are deceived, Charles, I am sure he is Sir James's friend, and mine, by his perpetually dissuading him from play. It may be so; but tell me, Emma, all you know, and all you think of Lady Juliana's sudden departure, what can it mean? …

At length we reached the gates of this noble edifice, and had the pleasure to find the family not retired to rest, by perceiving lights in the hall. … In a few minutes all was hushed, and a man, whom I believed to be an upper servant, was sent to reconnoitre my person, and enquire my name and business. I told him I should not reveal either, but to his master. …
Dogmatism

“T’m supposed to trust the opinion of a MS min- ion? The people that produced Windows ME, Vista and 8? They don’t even understand people, yet they think they can predict the behavior of new, self- guiding AI?” –anonymous

“I think an AI would make it easier for Patients to confide their information because by nature, a robot cannot judge them. Win-win? :D” –anonymous

Given a comment, imagine you hold a well-informed, different opinion from the commenter in question. We’d like you to tell us how likely that commenter would be to engage you in a constructive conversation about your disagreement, where you each are able to explore the other’s beliefs. The options are:

(5): It’s unlikely you’ll be able to engage in any substantive conversation. When you respectfully express your disagreement, they are likely to ignore you or insult you or otherwise lower the level of discourse.

(4): They are deeply rooted in their opinion, but you are able to exchange your views without the conversation degenerating too much.

(3): It’s not likely you’ll be able to change their mind, but you’re easily able to talk and understand each other’s point of view.

(2): They may have a clear opinion about the subject, but would likely be open to discussing alternative viewpoints.

(1): They are not set in their opinion, and it’s possible you might change their mind. If the comment does not convey an opinion of any kind, you may also select this option.

AP deliverables

• AP1. Design a new task (either document classification or sequence labeling) and gather data to support it (must be shareable with the public — nothing private or in copyright).

• AP2. Annotate the data, creating at least 1000 labeled examples + robust set of annotation guidelines, reporting inter-annotator agreement rates.

• AP3. In a separate assignment, a different group will annotate your data only using your annotation guidelines (are your guidelines comprehensive enough that an independent third party could reproduce your judgments?).

• AP4. Build a classifier to automatically predict the labels using the data you've annotated.
NLP subfield survey

• 4-page survey for a specific NLP subfield of your choice (e.g., coreference resolution, question answering, interpretability, narrative generation, etc.), synthesizing at least 25 papers published at ACL, EMNLP, NAACL, EACL, AACL, Transactions of the ACL or Computational Linguistics.

• This survey should be able to provide a newcomer (such as yourself at the start of the semester) a sense of the current state of the art in that subfield in 2022, the major historical papers that have defined that area, and the different schools of thought within it.
Grading

• Info 259:
  • Homeworks (20%)
  • Annotation project (20%)
  • Weekly quizzes (10%)
  • Midterm (20%)
  • Project (30%)
259 Project

• Semester-long project (involving 1-3 students) involving natural language processing -- either focusing on core NLP methods or using NLP in support of an empirical research question

  • Project proposal/literature review
  • Midterm report
  • 6-page final report, *workshop quality*
  • Poster presentation
ACL 2021 workshops

• *SEM 2021: The 10th Joint Conference on Lexical and Computational Semantics
• 2nd International Workshop on Computational Approaches to Historical Language Change (LChange’21)
• Workshop on Natural Language Processing for Programming
• Third Workshop on Gender Bias for Natural Language Processing
• Workshop on Online Abuse and Harms
• 17th Workshop on Multiword Expressions (MWE 2021)
• 6th Workshop on Representation Learning for NLP (RepL4NLP-2021)
• Challenges and Applications of Automated Extraction of Socio-political Events from Text (CASE)
Exams

• We’ll have one exam:
  
  • Midterm (3/10, 2-3:30pm, remote).

• We will not be offering alternative exam dates, so if you anticipate a conflict, don’t take this class!
Late submissions

• All homeworks and quizzes are due on the date/time specified.

• You have 3 late days total over the semester to use when turning in homeworks/quizzes (not group annotation project deliverables or 259 project deliverables); each day extends the deadline by 24 hours. If all late days have been used up, homeworks/quizzes can be turned in up to 48 hours late for 50% credit; anything submitted after 48 hours late = 0 credit.

• Late days are assessed immediately once homeworks or quizzes are submitted late and can't be retroactively changed (if you submit 2 homeworks and 2 quizzes late, for example, you can't decide after the fact which ones to apply your 3 slip days to -- they apply to whichever homeworks or quizzes use them up first).
Academic integrity

- We’ll follow the UC Berkeley code of conduct [http://sa.berkeley.edu/code-of-conduct](http://sa.berkeley.edu/code-of-conduct)

- You may discuss homeworks at a high level with your classmates (if you do, include their names on the submission), but each homework deliverable must be completed independently -- all writing and code must be your own; and all quizzes and exams must be completed independently.
Academic integrity

• If you mention the work of others, you must be clear in citing the appropriate source: http://gsi.berkeley.edu/gsi-guide-contents/academic-misconduct-intro/plagiarism/

• This holds for source code as well: if you use others' code (e.g., from StackOverflow), you must cite its source.

• We have zero tolerance policy for cheating and plagiarism; violations will be referred to the Center for Student Conduct and will likely result in failing the class.
Curve

Grades in this class will not be curved.
Lectures

• Recordings of lectures will be available on bCourses.

• Attendance is not required for lectures.
We'll use Piazza as a platform for asking and answering questions about the course material, including homeworks.

Students are encouraged to actively participate on this forum and help others by answering questions that arise (helpful students can see a grade bump across a threshold (e.g., B+ to A-) for this participation.

When helping with homework questions, keep the discussion to the high-level concepts; don't post answers to homeworks or quiz/exam questions.
TAs

- Gautham Koorma (Mon 2-3:30pm)
- Manav Rathod (Tues 3:30-5pm)
- Jerry Shan (Wed 10:30-12pm)
- Shefali Bhatia (Wed 1:30-3pm)
- Tim Schott (Thurs 9-10:30am)
- Aayushi Sanghi (Fri 10-11:30am)

- Visit TA office hours for help with homeworks/quizzes/exams or just to chat about NLP.
- TA OH will be held through Zoom.
TAs

• Keep academic integrity in mind during TA office hours: you may discuss homework questions at a high level with others present, but don't discuss specific answers or share screens with code solutions. Neither the TA office hours or Piazza should be used for pre-grading (asking if a specific answer to a homework or quiz question is correct before the assignment is due).
DB office hours

• DB office hours Wed + Thurs 10am-11am (Zoom link on bCourses)

• Come talk to me to discuss concepts from class and NLP more generally — I’m happy to chat!
Next time:

Lexical semantics/static word embeddings