CS378: Natural Language Processing
Lecture 1: Introduction

Greg Durrett
(he/him)

Credit: Stephen Roller

Texas
The University of Texas at Austin

Administrivia

- Lecture: Tuesdays and Thursdays 11:00am - 12:15pm in JGB 2.216
  - Recordings available afterwards on LecturesOnline
- Course website (including syllabus):
- Discussion board: link on the course website
- Office hours: see course website, all on Zoom
- TAs: Xi Ye and Lokesh Pugalenthi
- Office hours start today, and I will stay around after this class if you have questions

Course Requirements

- CS 429
- Recommended: CS 331, familiarity with probability and linear algebra, programming experience in Python
- Helpful: Exposure to AI and machine learning (e.g., CS 342/343/363)
- Assignment 0 is out now (optional):
  - If this seems like it'll be challenging for you, come and talk to me (this is smaller-scale than the other assignments, which are smaller-scale than the final project)

Format and Accessibility

- Lectures will build in time for discussion, in-class exercises, and questions. Additional material is available as videos to watch either before or after lectures
- Format: in-person to encourage discussion, but all materials are available asynchronously afterwards
- Equipment: useful to have a device for lecture to do Instapolls. For homework:
  - Lab machines available via SSH
  - A GPU is not required to complete the assignments! Having a GPU, GCP credits, or Google Colab access will be helpful for the final project though
What’s the goal of NLP?

- Be able to solve problems that require deep understanding of text
- Example: dialogue systems

![Image of Siri and a phone]

Siri, what’s your favorite kind of movie?

I like superhero movies!

What’s come out recently?

Dr. Strange in the Multiverse of Madness

Machine Translation

The Political Bureau of the CPC Central Committee held a meeting on July 30 to analyze and study the current economic situation and plan economic work in the second half of the year.

People’s Daily, August 10, 2020

Question Answering

When was Abraham Lincoln born?

<table>
<thead>
<tr>
<th>Name</th>
<th>Birthday</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lincoln, Abraham</td>
<td>2/12/1809</td>
</tr>
<tr>
<td>Washington, George</td>
<td>2/22/1732</td>
</tr>
<tr>
<td>Adams, John</td>
<td>10/30/1735</td>
</tr>
</tbody>
</table>

February 12, 1809

How many visitor centers are there in Rocky Mountain National Park?

The park has a total of five visitor centers

5

NLP Analysis Pipeline

Text

Text Analysis

- Syntactic parses
- Coreference resolution
- Entity disambiguation
- Discourse analysis

Annotations

Applications

- Summarize
- Extract information
- Answer questions
- Identify sentiment
- Translate

- NLP is about building these pieces! (largely using statistical approaches)

- Lots of this is done end-to-end with neural nets. But analysis is still useful...
How do we represent language?

### Labels
- the movie was good
- Beyoncé had one of the best videos of all time
- subjective

### Sequences/tags
- Tom Cruise stars in the new Mission Impossible film

### Trees
- \( \lambda x. \text{flight}(x) \land \text{dest}(x) = \text{Miami} \)
- I eat cake with icing
- flights to Miami

How do we use these representations?

### Text
- The city council refused the demonstrators a permit because they advocated violence
- The city council refused the demonstrators a permit because they feared violence
- The city council refused the demonstrators a permit because they _____ violence

### Applications
- Learn tree-to-tree machine translation models
- ... end-to-end models

Why is language hard? (and how can we handle that?)

- Hector Levesque (2011): “Winograd schema challenge” (named after Terry Winograd, the creator of SHRDLU)
- >5 datasets in the last two years examining this problem and commonsense reasoning
- Referential ambiguity

Language is Ambiguous!
Language is **Really** Ambiguous!

- There aren’t just one or two possibilities which are resolved pragmatically

  - *il fait vraiment beau*
    - It is really nice out
    - It’s really nice
    - The weather is beautiful
    - It is really beautiful outside
    - He makes truly beautiful
    - It fact actually handsome

- Combinatorially many possibilities, many you won’t even register as ambiguities, but systems still have to resolve them

What techniques do we use?
(to combine data, knowledge, linguistics, etc.)

A brief history of (modern) NLP

- Largely rule-based, expert systems
- Penn treebank
- Collins vs. Charniak parsers
- Unsup: topic models, grammar induction
- Semi-sup, structured prediction
- Neural

- Ratnaparkhi tagger
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- earliest stat MT work at IBM
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**Pretraining**

- Language modeling: predict the next word in a text $P(w_i|w_1, \ldots, w_{i-1})$
  
  $P(w | I \text{ want to go to}) = 0.01$ Hawai’i  
  $0.005$ LA  
  $0.0001$ class

/ GPT-3: use this model for other purposes

$P(w | \text{ the acting was horrible, I think the movie was}) = 0.1$ bad  
$0.001$ good

- Model understands some sentiment?

- Train a neural network to do language modeling on massive unlabeled text, fine-tune it to do {tagging, sentiment, question answering, …}

  Peters et al. (2018), Devlin et al. (2019)

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**Interpretability**

- When we have complex models, how do we understand their decisions?

  The movie is mediocre, maybe even bad. **Negative 99.8%**
  
  The movie is **mediocre**, maybe even bad. **Negative 98.0%**
  The movie is **mediocre**, maybe even bad. **Negative 98.7%**
  The movie is **mediocre**, maybe even bad. **Positive 63.4%**
  The movie is **mediocre**, maybe even bad. **Positive 74.5%**
  The movie is **mediocre**, maybe even bad. **Negative 97.9%**

  The movie is **mediocre**, maybe even bad.

  Wallace, Gardner, Singh  
  Interpretability Tutorial at EMNLP 2020

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**Where are we?**

- We have very powerful neural models that can fit lots of datasets

- Data: we need data that is not just correctly labeled, but reflects what we actually want to be able to do

- Users: systems are not useful unless they do something we want

- Language/outreach: who are we building this for? What languages/dialects do they speak?

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**Social Impact**

- NLP systems are increasingly used in the world

  ![OpenAI](logo.png)  
  ![Google](logo.png)

  …and increasingly we have to reckon with their impact

- This lecture: let’s warm up by thinking about these issues a bit
Social Impact

‣ Rate your awareness of the social impact of NLP, AI, and machine learning from 1 to 5, where 1 is little awareness and 5 is strong awareness (5 = you feel like you could write a blog post about a current issue).

‣ Describe one scenario where you think deployment of an NLP system might pose ethical challenges due to the application itself (i.e., using NLP to do “bad stuff”)

‣ Describe one scenario where you think deployment of an NLP system might pose ethical challenges due to unintended consequences (e.g., unfairness, indirectly causing bad things to happen, etc.).

Outline of the Course

‣ Classification: linear and neural, word representations (3.5 weeks)
‣ Text analysis: tagging and parsing (3 weeks) <= takes us to the midterm
‣ Generation, applications: language modeling, machine translation (3 weeks)
‣ Question answering, pre-training (2 weeks)
‣ Applications and miscellaneous (2.5 weeks)

‣ Goals:
  • Cover fundamental techniques used in NLP
  • Understand how to look at language data and approach linguistic phenomena
  • Cover modern NLP problems encountered in the literature: what are the active research topics in 2020?

Coursework

‣ Five assignments, worth 40% of grade
‣ Mix of writing and implementation;
‣ Assignment 0 is out now, optional diagnostic
‣ ~2 weeks per assignment except for A5
‣ 5 “slip days” throughout the semester to turn in assignments 24 hours late
‣ Submission on Gradescope

These assignments require understanding the concepts, writing performant code, and thinking about how to debug complex systems. **They are challenging; start early!**

Office hours: please come! However, the course staff are not here to debug your code! We will help you understand the concepts and come up with debugging strategies!

Coursework

‣ Midterm (25% of grade), take-home
‣ Similar to written homework problems

‣ Final project (25% of grade)
‣ Groups of 1 or 2
‣ Standard project: understanding dataset biases
‣ Independent projects are possible: these must be proposed earlier (to get you thinking early) and will be held to a high standard!

‣ Social Impact Responses, UT Instapoll (10% of the grade)
‣ These will be done online and can be done during or after class
Academic Honesty

‣ You may work in groups, but your final writeup and code must be your own

‣ Don’t share code with others!

Conduct

A climate conducive to learning and creating knowledge is the right of every person in our community. Bias, harassment and discrimination of any sort have no place here.

Survey

‣ See Instapoll (you can answer later as well)