# **CS395T: Structured Models for NLP** Lecture 1: Introduction



## Greg Durrett



## Administrivia

- Lecture: Tuesdays and Thursdays 9:30am 10:50am
- Course website: http://www.cs.utexas.edu/~gdurrett/courses/fa2017-cs395t.shtml
- Piazza: https://piazza.com/utexas/fall2017/cs395t/home
- My office hours: Wednesday 10am-noon, GDC 3.420
- TA: Ye Zhang; Office hours:
  - Tuesday 2pm-3pm GDC 1.302 Desk 2

Thursday 2pm-3pm, GDC 1.302 Desk 1 (until 2:30), Desk 4 (2:30 onwards)



- 391L Machine Learning (or equivalent)
- 311 or 311H Discrete Math for Computer Science (or equivalent)
- Python experience
- Additional prior exposure to probability, linear algebra, optimization, linguistics, and NLP useful but not required

## Course Requirements



- I want everyone to be able to take this class!
- Priority ordering:
  - CS grad students
  - Other grad students
  - CS undergrads who have satisfied the prerequisites
  - Other undergrads who have satisfied the prerequisites
  - Other undergrads

## Enrollment



# What's the goal of NLP?

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





## Automatic Summarization

POLITICS

## Google Critic Ousted From Think Tank Funded by the Tech Giant

WASHINGTON — In the hours after European antitrust regulators levied a record <u>\$2.7 billion fine</u> against Google in late June, an influential Washington think tank learned what can happen when a tech giant that shapes public policy debates with its enormous wealth is criticized.

But not long after one of New America's scholars posted a statement on the think tank's website praising the European Union's penalty against Google, Mr. Schmidt, who had been chairman of New America until 2016, communicated his displeasure with the statement to the group's president, Anne-Marie Slaughter, according to the scholar.

Ms. Slaughter told Mr. Lynn that "the time has come for Open Markets and New America to part ways," according to an email from Ms. Slaughter to Mr. Lynn. The email suggested that the entire Open Markets team — nearly 10 full-time employees and unpaid fellows — would be exiled from New America.

compress text

provide missing context

One of New America's writers posted a statement critical of Google. Eric Schmidt, Google's CEO, was displeased.

The writer and his team were dismissed.

> paraphrase to provide clarity







## Machine Translation



Judgments	Hypothesis
contradiction CCCCCC	The man is sleeping
neutral N N E N N	Two men are smiling and laughing at the cats playing on the flo
contradiction CCCCC	A man is driving down a lonely road.
	Judgments contradiction CCCCCC neutral NNENN contradiction CCCCC

## Text is connected to intelligence and knowledge in a fundamental way!

- What makes this analysis hard?

## Textual Entailment

SNLI (Bowman et al., 2015)

Goal of NLP (solving problems with text) requires analyzing and understanding text









Hector Levesque (2011): "Winograd schema challenge" (named after Terry Winograd, the creator of SHRDLU)

The city council refused the demonstrators a permit because they

This is so complicated that it's an AI challenge problem! (AI-complete)

Can try to use the web to learn pragmatics, but that's not giving us a deep understanding of text

# Language is Ambiguous!





# Language is Ambiguous!

- Headlines
  - Teacher Strikes Idle Kids
  - Hospitals Sued by 7 Foot Doctors
  - Ban on Nude Dancing on Governor's Desk
  - Iraqi Head Seeks Arms
  - Stolen Painting Found by Tree
  - Kids Make Nutritious Snacks
  - Local HS Dropouts Cut in Half
- Why are these funny?
- Pragmatics can resolve this...right?

slide credit: Dan Klein





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



- but systems still have to resolve them!
- So our goal (analyze text) is harder than we thought...how do we do it?

# Language is **Really** Ambiguous!



exponential number

 $\bullet \bullet \bullet$ 

gh as in tough o as in women ti as in motion

Combinatorially many possibilities, many you won't even register as ambiguities,







# A brief history of (modern) NLP

## 



- need to label
- Supervised techniques work well on very little data



annotation (two hours!)

unsupervised learning

- Even neural nets can do pretty well!
- Balance tradeoff of data/algorithms/compute

## Structured Prediction

All of these techniques are data-driven! Some data is naturally occurring, but may



Garrette and Baldridge (2013)









Klein and Manning (2003)

Petrov et al. (2006)

VBZ		
es	sells	takes
ies	goes	works
des	owns	is
ts	provides	takes
/S	adds	Says
ves	means	thinks
ects	makes	calls
ns	expects	wants
	's	gets
	is	remains
S	's	is
es	Is	Does



Hall, Durrett, Klein (2014)



## The yield on the benchmark issue rose to 10% from 5%



(S(NP(NP(DT The)(NN yield ...





Sutskever et al. (2015), Bahdanau et al. (2014)







DeNero et al. (2008)

## Bahdanau et al. (2014)







Maybe manual structure would help...

## Trump Pope family watch a hundred years a year in the White House balcony





- Neural nets don't always work out of do
- Coreference: rule-based systems are still about as good as deep learning out-of-domain
- LORELEI: transition point below which p based systems are better
- Why is this? Inductive bias!
- Can multi-task learning help?

## Does manual structure have a place?

		CoNLL		
omain!		Avg. F <sub>1</sub>		
_	Newswire			
	rule-based	55.60		
	berkeley	61.24		
	cort	63.37		
	deep-coref [conll]	65.39		
	deep-coref [lea]	65.60		
hrase-	Wikipedia			
	rule-based	51.77		
	berkeley	51.01		
	cort	49.94		
	deep-coref [conll]	52.65		
	deep-coref [lea]	53.14		
	deep-coref	51.01		

Moosavi and Strube (2017)



- Solving problems with text requires analyzing text
- Many possibilities: rule-based systems, CRFs, neural networks, ...
- Knowing which of these to use requires understanding dataset size, problem complexity, and a lot of tricks!
- What do all of these models have in common? What do they need to capture in order to be successful?

## Where are we?

## Break!



## High-capacity models + data!

SOURCE	Cela constituerait un conduire à terme à u
HUMAN	That would be an intervention work towards a bindi
1x DATA	[this] [constituerait] [a [licences] [to] [terme]
10x DATA	[it] [would] [a solutio [to] [term] [to a] [chai
100x DATA	[this] [would be] [a tra charter] [legally bindi
1000x DATA	[that would be] [a tra lead to] [a binding ch

- ne solution transitoire qui permettrait de ine charte à valeur contraignante.
- erim solution which would make it possible to ing charter in the long term .
- assistance] [transitoire] [who] [permettrait] [.] [to] [a] [charter] [to] [value] [contraignante]
- n] [transitional] [which] [would] [of] [lead] rter] [to] [value] [binding] [.]
- ansitional solution] [which would] [lead to] [a ing] [.]
- insitional solution] [which would] [eventually narter] [.]

slide credit: Dan Klein



World knowledge: have access to information beyond the training data



On Sept. 1, 1715 Louis XIV died in this city, site of a fabulous palace he built.

Answer: What is **Versailles**?

## What's important?

Died





1 September 1715 (aged 76) Palace of Versailles, Versailles, France





## Grounding: learn what fundamental concepts actually mean in a data-driven way



Golland et al. (2010)

## What's important?

## McMahan and Stone (2015)

![](_page_22_Picture_0.jpeg)

(and humanlike!) in our reasoning

![](_page_22_Picture_3.jpeg)

**Dell** is headquartered just outside **Austin**. The company ...

## What's important?

## Multitask interactions: recognize constraints to be more statistically efficient

## coreference resolution

![](_page_22_Picture_8.jpeg)

## entity disambiguation

Durrett and Klein (2014)

![](_page_22_Picture_11.jpeg)

![](_page_23_Picture_0.jpeg)

- Linguistic structure
- In the second second
- However, linguistics tells us what phenomena we need to be able to deal with and gives us hints about how language works
  - a. John has been having a lot of trouble arranging his vacation.
  - b. He cannot find anyone to take over his responsibilities. (he = John)  $C_b = John; C_f = {John}$
  - c. He called up Mike yesterday to work out a plan. (he = John)  $C_b$  = John;  $C_f$  = {John, Mike} (CONTINUE)
  - d. Mike has annoyed him a lot recently.  $C_b$  = John;  $C_f$  = {Mike, John} (RETAIN)
  - e. He called John at 5 AM on Friday last week. (he = Mike)  $C_b = Mike; C_f = \{Mike, John\} (SHIFT)$

Centering Theory Grosz et al. (1995)

![](_page_23_Picture_12.jpeg)

![](_page_24_Picture_0.jpeg)

# How do we build systems to do all this?

- Structured statistical models
- Structured: lets us incorporate cross-task constraints, inductive biases from linguistics, knowledge, etc.
- Statistical: harness the power of data to do really large-scale pattern recognition and learn from labeled + unlabeled data + interaction with the world

![](_page_25_Picture_0.jpeg)

# Outline of the Course

- First half: structured prediction
  - Machine learning basics
  - Sequences, trees
  - Inference, learning

- Second half: deep learning
  - RNNs/LSTMs, convolutional networks
  - Word representations
  - Inference, learning

Date	Topics	Readings	Assignm
Aug 31	Introduction		
Sept 5	Machine learning / Classification review	JM 6.1-6.3	
Sept 7	Multiclass classification	JM 7	
Sept 12	Sequence models I: HMMs	JM 9, JM 10.4	P1 out
Sept 14	Sequence models II: CRFs	Sutton CRFs 2.3, Illinois NER	
Sept 19	Sequence models III: Unsupervised	Painless	
Sept 21	Tree-structured models I: Constituency	JM 13.1-13.7, Unlexicalized, Lexicalized, State-split	
Sept 26	Tree-structured models II: Dependency I	JM 14.1-14.4	
Sept 28	Tree-structured models III: Dependency II		P1 due out
Oct 3	General graphical models I: "loopy" models, etc.	Skip-chain NER, Joint entity	
Oct 5	General graphical models II: ILP models		
Oct 10	Machine Translation		
Oct 12	Neural net basics, word representations	Goldberg 1-6	P2 due
Oct 17	RNNs I: LSTMs, encoder-decoder	Goldberg 10	P3 out
Oct 19	RNNs II: Attention	MT	
Oct 24	RNNs III		
Oct 26	CNNs I	Goldberg 9	
Oct 31	CNNs II / Advanced NNs		
Nov 2	Advanced NNs: Memory networks / pointer networks		P3 due out
Nov 7	Advanced NNs II		
Nov 9	Deep Generative Models: GANs, VAE		Proposa due
Nov 14	Special Topics I		
Nov 16	Special guest lecture: Katrin Erk		
Nov 21	Special Topics II		
Nov 23	NO CLASS (Thanksgiving)		
Nov 28	Special Topics III		
Nov 30	Special Topics IV		
Dec 5	Wrapup		
Dec 7	Project presentations (TBD)		
Dec 15			FP due

![](_page_25_Figure_12.jpeg)

![](_page_26_Picture_0.jpeg)

## NLP: build systems that deal with language data

CL: use computational tools to study language

![](_page_26_Figure_4.jpeg)

# NLP vs. Computational Linguistics

Hamilton et al. (2016)

![](_page_26_Picture_9.jpeg)

![](_page_27_Picture_0.jpeg)

![](_page_27_Figure_3.jpeg)

Bamman, O'Connor, Smith (2013)

![](_page_28_Picture_0.jpeg)

- Cover structured machine learning approaches to NLP
  - Show connections between structured algorithms: generative and discriminative, margin and likelihood, neural and linear, etc.: these are all closely related!
  - Dissect the pieces of these structured models: modeling, inference, learning
- Make you a "producer" rather than a "consumer" of NLP tools
- Expose you to classic problems in NLP

## Course Goals

![](_page_29_Picture_0.jpeg)

- Three projects (16.6% each = 50%)
  - Implementation-oriented, open-ended component to each
  - First will be out on 9/12
  - 2-page writeup with statement of what you did
  - ~2 weeks per project, 7 "slip days" for automatic extensions
- Grading: 10-point scale
  - 6 points for minimal code completion
  - I point for minimal extension
  - I point for minimal 2-page writeup
  - 2 points for better extension, better writeup

8 pc

![](_page_30_Picture_0.jpeg)

- Final project (50%)
  - Groups of 1-2
  - (Brief!) proposal to be approved by me
  - Written in the style and tone of an ACL paper
  - Same 10-point grading scheme, 8 points for minimal completion of proposed work

![](_page_31_Picture_0.jpeg)

- 1. Fill in: I am a [CS / linguistics / other] [grad / undergrad] in year [1 2 3 4 5+]
- 2. Which of the following have you learned in a class?
  - 1. Bayes' Rule
  - 2. SVMs
  - 3. HMMs
  - 4. EM
  - 5. Part-of-speech tagging
- 3. Which of the following have you used?
  - Python 1.
  - 2. numpy/scipy/scikit-learn
  - 3. Tensorflow/(Py)Torch/Theano
- 4. Fill in: Assuming I can enroll, my probability of taking this class is X%

## Survey