LT2222 Machine learning for NLP: intro, Winter 2022

Lecture 0: Introduction; formal foundations

Asad Sayeed
with some material from `https://github.com/jonsafari/lt1`

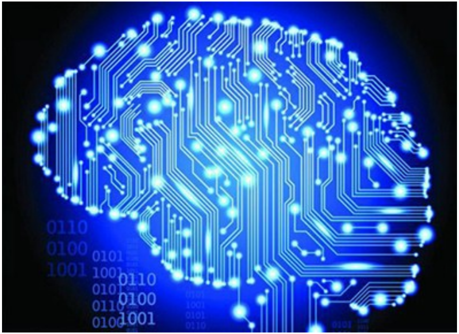
University of Gothenburg

Welcome! Today's agenda:

1. A lot of boring review
2. Format and topics of the course
3. Administrative details

Part 1: Some boring review...

Statistical approaches to Natural Language Processing are ubiquitous.



Something that statistical NLP is not.

It's easy to think of statistical NLP in the consumer market. . . or is it?

The ubiquity of statistical NLP

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- Popular question-answering systems on your smartphones, e.g., Siri, Cortana.
- Basically: any language technology that must deal with highly variable input involves statistical NLP in practice — and that's practically all of them worth talking about.

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Let's illustrate what this really means... (you saw this last semester...)

Q: Does language have anything to do with the weather?

A: Yes. But first...

. . . a tongue-twister in English.

How much wood could a woodchuck chuck if a woodchuck could chuck wood?

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How much wood could a woodchuck chuck if a woodchuck could chuck wood?

One possible answer:

As much wood as a woodchuck could chuck.

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To estimate the likelihood of an answer (in the form of a sentence), you need:

- An evidentiary basis.
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  - Assume sentences are made of words.
  - So the probability of a sentence might have something to do with the probability of the words in the sentence.

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  - Assume sentences are made of words.
  - So the probability of a sentence might have something to do with the probability of the words in the sentence.
- A means to combine the pieces of evidence.
  ⇒ if words matter, then we need a theory of sentence structure from words.

Why do we want a likelihood?

Consider natural language processing systems in real life. E.g., machine translation:

- Translate "How much wood could a woodchuck chuck?" to French.
  - The word "could": possibility in French expressible with two different grammatical forms (*"peut"*/*"pourrait"*).
  - Choose better one *in context*.
  - Hard to do over all words deterministically $\leftarrow$ years of effort to create the "rules", but never succeed.
- Countless other applications: such as answering a question. . . .

So how do we get the evidence?

Count words.

how much wood could a woodchuck chuck if a woodchuck could chuck wood ?

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a	2
chuck	2
could	2
how	1
if	1

word type	token count
much	1
wood	2
woodchuck	2
?	1

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Then calculate probability per type of word as count/14.

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The joint probability of multiple words: how likely they are to occur in the same text.

$$p(w_1, w_2, \ldots) = p(w_1)p(w_2)\ldots$$

Calculate some joint probabilities:

- $p(\text{if,woodchuck}) =$
- $p(\text{wood,woodchuck}) =$
- $p(\text{how,could,a}) =$

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- p(if,woodchuck) = 0.07 x 0.14 = 0.01
- p(wood,woodchuck) = 0.14 x 0.14 = 0.02
- p(how,could,a) = 0.07 x 0.14 x 0.14 = 0.001

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Now we can calculate the joint probability of our answer.

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- $p(\text{as},\text{much},\text{wood},\text{as},\text{a},\text{woodchuck},\text{could},\text{chuck}) =$

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  $0.07 \times 0.14 \times 0.14 \times 0.14 \times 0.14 \times 0.14 = 3.76\text{e-}05$

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- Joint unigram probability: the same, no matter what, as "as much wood as a woodchuck could chuck".
- We definitely don't want that to be true. So our theory must include sequences.

And this is what language has to do with the weather.

What was the weather like two years ago in Holland?

Average temperature at Amsterdam Schiphol:

18.11.2014
8 C

And what was it the day before that?

Average temperature at Amsterdam Schiphol:

17.11.2014	18.11.2014
10 C	8 C

And before that?

Average temperature at Amsterdam Schiphol:

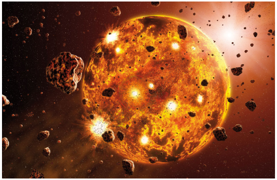
16.11.2014	17.11.2014	18.11.2014
9 C	10 C	8 C

It's as though we know something about the next day from the previous days!

But how many days do we need?

Surely not to the beginning of the Earth!

Average temperature at Amsterdam Schiphol:



. . .

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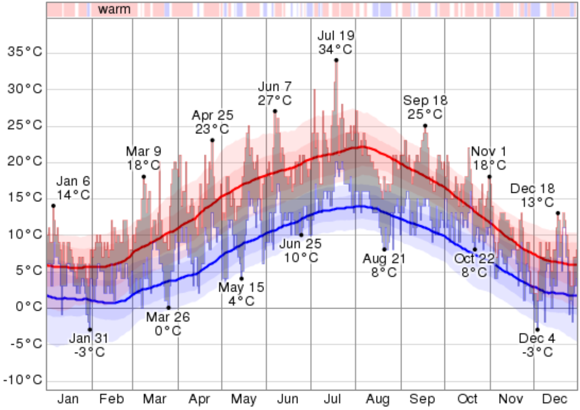
We have expectations about changes.

We know that yesterday is a good clue about today.
Temperatures in Amsterdam in 2014:



The daily temperature is a Markov process.

Let T_d = temperature T on day d.
We can represent the probability conditionally.

Probability of today's temperature given universe

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Then we can calculate the joint probability of a sequence of days:

Markov chain

$p(T_d, T_{d-1}, T_{d-2}) =$
$p(T_d | T_{d-1}, T_{d-2}) p(T_{d-1} | T_{d-2}, T_{d-3}) p(T_{d-2} | T_{d-3}, T_{d-4})$

Getting Markovian with language.

Let's make a Markov assumption over sentences. So how many words previous to "chuck" do we need?

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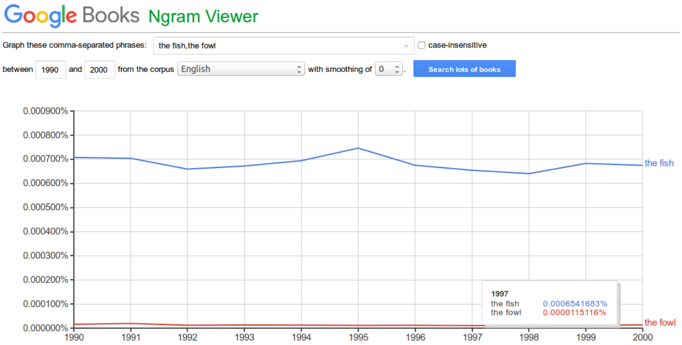
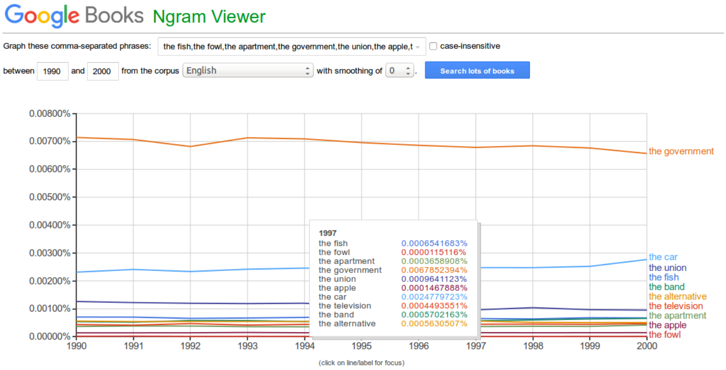
Two words back seems to be a common choice.

We can check a bigger corpus.

Leave aside the woodchucks for a moment. Let's try a couple of 2-word expressions. "The fish" vs "the fowl.".
The Google Books Ngram viewer:



But lots of things follow “the”.



It's not hugely informative...

...because the whole category of nouns can follow "the".

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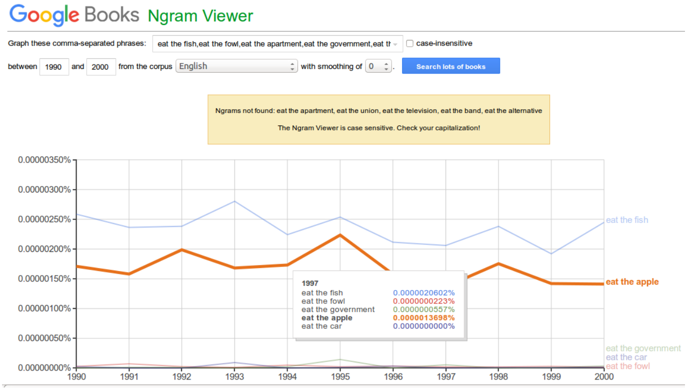
So what if we add another word, "eat":



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So this is a way language is **not** like the weather.

- Sure, tomorrow will resemble today, in terms of temperature.
    - But knowing what happened yesterday doesn't drastically change the estimate.
- But make your **bi**gram into a **tri**gram:
    - The distribution radically changes.
    - "eat" is very informative.

We can even look for 4-grams.

Thus we just call these *n*-grams, for any *n*.
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It's not always the case that trigrams work, but they're often practical because of sparsity.

And that involved a lot of things we're going to talk about during the rest of the course.

Part 2: the course

Who are we?

You already know me, but:

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- Asad Sayeed ("course organizer")
  - Senior Lecturer with FLoV (CLASP, GRIPES projects)
  - Ph.D., Computer Science, University of Maryland (2011).
  - Research areas: machine learning for NLP, computational psycholinguistics, and more

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- Warrick Macmillan
  - Teaching assistant.
  - Student from previous edition of course (LT2212 V19).

Format of the course

The “rhythm” of the course will look approximately like this, with occasional exceptions:

- Mondays: Q&A (on any previous video lecture)
- Wednesdays: help sessions for assignments (starting when assignments first given.
- Thursdays (starting Feb 3): sometimes in-person live demo

All content will be posted as video lectures, slides, etc on the Canvas page.

Evaluation of the course

- Deliverables (by you :)):
  - 3 assignments, including programming and problem-solving, each expected to take 2-3 weeks (can break this up based on student preference)
  - There is **no** final written exam.
- Tentative course grade: 33% per assignment plus 1 free percent.
- Tentative standard:
  - Pass (G): Complete 3 assignments, obtain min 50% on each assignment.
  - Pass-with-distinction (VG): Complete 3 assignments, get min 90% average overall.

Assignments

- Individual submission, can help each other in small groups.
- coding projects, mostly Python, possibly some mathematics
- submission via Canvas.
- We will aim for 15 business days of turnaround from submission, if submitted on time. Otherwise, latest by the summer.
- First assignment will be out very soon.

Please review the university's academic integrity policies.

Emphasis of the course

- Practical skills in statistical NLP.
  - Emphasis on the data pipeline.
  - Goal: getting from data to analysis/model/application.
  - Gain familiarity with some statistical NLP tools.
- Foundational theoretical skills.
  - Getting an intuitive grasp of the mathematical underpinnings of statistical NLP techniques.
  - Just enough for application.
  - (Preliminary knowledge required for machine learning course in Fall!)

Tentative topic list

Based on how we progress (I sometimes change direction based on student request/preferences/progress).

- Math review.
- More programming topics and computing skills for statistical NLP.
- Working with text data.
- Introduction to modern machine learning techniques (incl. deep learning)
- Applications in various areas of NLP (e.g., document classification, machine translation) based on an *ad hoc* basis.

Technical details

I'm assuming you have a background in basic Python programming from previous courses.

- Programming: mostly Python 3.x, using nltk, scikit-learn, pandas, and other relevant Python packages.
- We will introduce neural networks via PyTorch.
- Recommended to have your own laptop with a Linux installation, but we will also use mltgpu or eduserv.
- We will introduce git and make use of command-line techniques.

This course is contiguous with the Machine Learning for NLP advanced course in the fall.

Readings/textbook

- No regular readings in the beginning, this is principally a practical course.
- Students are encouraged to do their own research on the Internet to find clarificatory material on topics (there is a wealth of it, and it is an important skill in this business).
- Main textbook: "Natural Language Processing with PyTorch", readings will start in the middle of the course. (also used in first half of Machine Learning course) – a bit outdated now.

Student discussion of course desiderata

We will return with video lecture.

Part 3: More boring review

Formal Languages

- Once Upon a Time...

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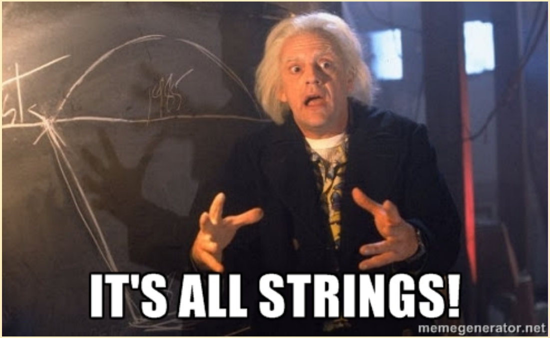

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  is a perfectly valid vocabulary for a formal language. But we usually use boring symbols like {a, b, c}
- (Similar to musical/poetic form analysis)

Formal Grammar

- A formal grammar is a way of telling what a valid string is in a formal language
- Formal grammars can also **generate** valid strings

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- If two different grammars can generate/accept the same structures as well, then they have the same **strong generative capacity**

Formal Language Hierarchy

	Formal Language
	Non-Turing-acceptable
0:	**Recursively enumerable**
	Recursive/ Decidable
1:	Context-sensitive
	Indexed
	Mildly context-sensitive
2:	**Context-free**
	Deterministic context-free
3:	**Regular**
	Finite

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This is extended from the older *Chomsky hierarchy*. We'll discuss the ones in boldface, as they're relevant to natural languages.

Why is this Stuff Relevant??

- Knowing what types of formal languages a grammar/automaton can generate & accept will give you an idea of what phenomena in natural languages that they can handle

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- Knowing what types of formal languages a grammar/automaton can generate & accept will give you an idea of what phenomena in natural languages that they can handle
- For example: long-distance dependencies, complex reordering in machine translation, reduplication, etc.
- You can also get an idea of how fast or slow it will take for a computer (or human) to process sequential stuff (like natural language!)

Finite Languages

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- For natural language, this would correspond to having a finite number of possible sentences

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- (There's more discussion on the interwebs if you're interested)

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- We can characterize what this means in terms of the length of the input string, which we'll call n.
- Then we have something called big-$\mathcal{O}$ notation from computer science. To make a long story short:

$\mathcal{O}(1)$	"constant time"	# units unrelated to input
$\mathcal{O}(n)$	"linear time"	# units lin. proportional to input string
$\mathcal{O}(n^2)$	"quadratic time"	# unites quadrat. prop. to input string
...		

Regular Languages

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- Let's assume that the vocabulary (Σ) is still fixed (or finite), but we can generate an infinite number of sentences from this fixed vocab
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- Processing regular languages can be done in linear time ($\mathcal{O}(n)$), with a constant size of memory ($\mathcal{O}(1)$)

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- Processing MCS languages can be done in about $\mathcal{O}(n^6)$ time, with quadratic memory usage ($\mathcal{O}(n^2)$)
- Mildly context-sensitive is very different from context-sensitive, which is much more powerful
- Some grammar formalisms that can handle MCS langs:
  - Tree Adjoining Grammar (TAG)
  - Combinatory Categorial Grammar (CCG)
  - Linear Indexed Grammars (LIG) (easy to understand)

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- Because different structures enable different computations!
- For example: context-free languages harder to machine-learn than regular languages.

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  - Machine learning: perhaps just map structures in one language to structures in another? No meaning required.
  - Computer vision – maybe we really want explicit descriptions of objects in human language.

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- Dictionary problem: what is the meaning of a feature? Define words in terms of other words?

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  - Does this really represent the meaning relationships well?
- The main question of formal semantics: what do we need to reason about language?

To put a long story short. . .

- We want to model complex formal objects robustly.
- The rest of this course is about exploiting continuous distributions of values to do so.