

#### What is natural language computing?

Getting computers to understand everything we say and write.

In this class (and in the field generally), we are interested in the *statistics of language*.

(Occasionally, computer models give insight into how humans process language.)





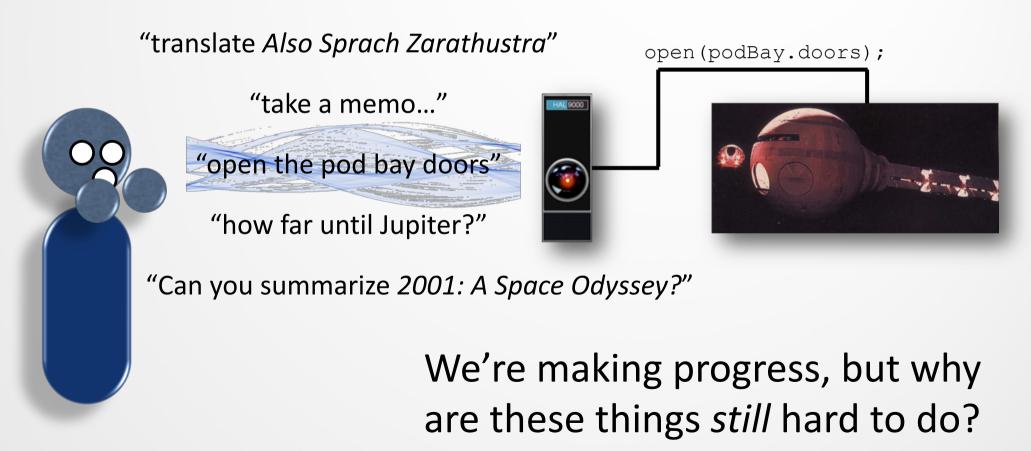
- Common challenges with natural language processing (NLP).
- Applications
  - Translating between languages
  - Speech recognition
  - Answering questions
  - Engaging in dialogue
- Course logistics.





# What can natural language do?

#### The ultimate in **human-computer interaction**.





# A little deeper

- Language has *hidden structures*, e.g.,
  - How are sounds and text related?
    - e.g., why is this:



- not a 'ghoti' (enou**gh**, w<u>o</u>men, na<u>ti</u>on)?
- How are words combined to make sentences?
  - e.g., what makes 'colourless green ideas sleep furiously' correct in a way unlike 'furiously sleep ideas green colourless'?
- How are words and phrases used to produce meaning?
  - e.g., if someone asks 'do you know what time it is?', why is it inappropriate to answer 'yes'?
- We need to organize the way we think about language...



# **Categories of linguistic knowledge**

- Phonology:
- Morphology:

• Syntax:

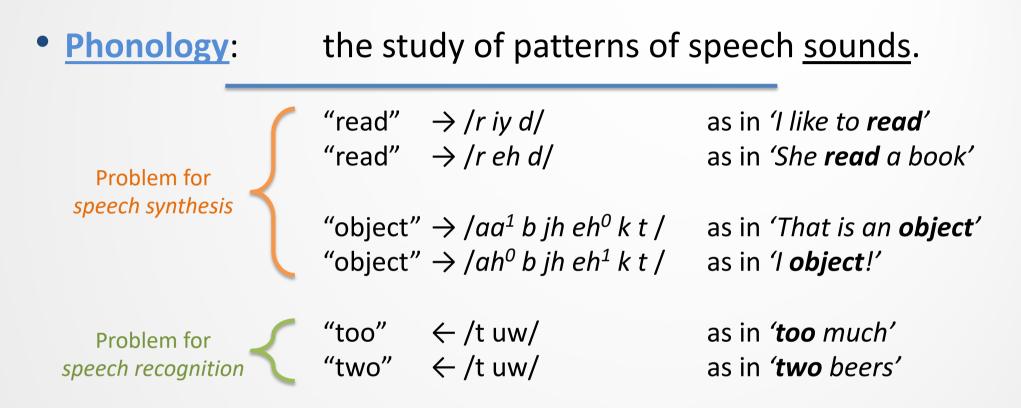
• Semantics:

**Pragmatics:** 

the study of patterns of speech sounds. e.g., "read"  $\rightarrow$  /r iy d/ how words can be changed by inflection or derivation. "read", "reads", "reader", "reading", ... e.g., the ordering and structure between words and phrases (i.e., grammar). NounPhrase  $\rightarrow$  article adjective noun e.g.. the study of how meaning is created by words and phrases. e.g., "book"  $\rightarrow$ the study of meaning in contexts.



# **Ambiguity – Phonological**



- Ambiguities can often be **resolved** in context, but not always.
  - e.g., /h aw t uw r eh<sup>1</sup> k ah ?? n ay<sup>2</sup> z s (b|p) iy ch/
    - $\rightarrow$  'how to recognize speech'
    - ightarrow 'how to wreck a nice beach'



#### **Resolution with syntax**

If you hear the sequence of speech sounds

/b ah f ae l ow b ah f ae l ow b ah f ae l ow b ah f ae l ow ... bahfaelow bahfaelow bahfaelow bahfaelow/

#### which word sequence is being spoken?

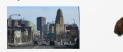
- $\rightarrow$  "Buff a low buff a lobe a fellow Buff a low buff a lobe a fellow..."
- $\rightarrow$  "Buffalo buff aloe buff aloe buff aloe buff aloe buff aloe ..."
- $\rightarrow$  "Buff aloe buff all owe Buffalo buffalo buff a lobe ..."
- $\rightarrow$  "Buff aloe buff all owe Buffalo buff aloe buff a lobe ..."
- $\rightarrow$  "Buffalo buffalo Buffalo buffalo buffalo buffalo Buffalo buffalo"





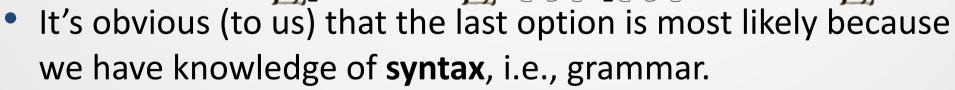












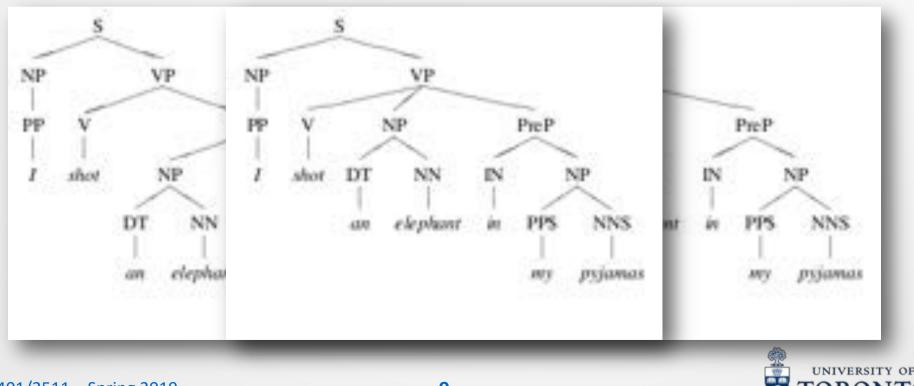


noun

# **Ambiguity – Syntactic**

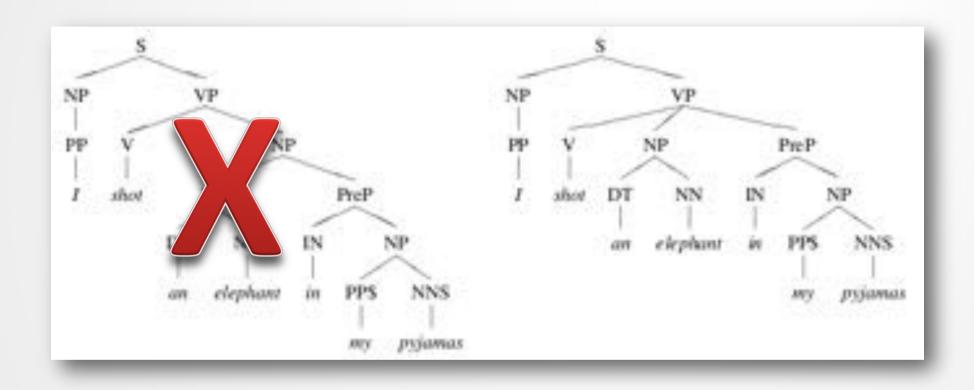
 Syntax: the <u>ordering and structure</u> between words. Words can be grouped into 'parse tree' structures given grammatical 'rules'.

e.g., "I shot an elephant in my pyjamas"



CSC401/2511 – Spring 2019

#### **Resolution with semantics**



 It's obvious (to us) that the elephants don't wear pyjamas, and we can discount one option because of our knowledge of semantics, i.e., meaning.



# **Ambiguity – Semantic**

- <u>Semantics</u>: the study of how <u>meaning</u> is created by the use of words and phrases.
  - "Every man loves a woman"
    - $\rightarrow \forall x man(x) \exists y: (woman(y) \land loves(x, y))$
    - $\rightarrow \exists y: woman(y) \land \forall x (man(x) \rightarrow loves(x, y))$
  - "I made her duck"
    - $\rightarrow$  I cooked waterfowl meat for her to eat.
    - $\rightarrow$  I cooked waterfowl that belonged to her.
    - $\rightarrow$  I carved the wooden duck that she owns.
    - $\rightarrow$  I caused her to quickly lower her head.
  - "Give me the pot"
    - $\rightarrow$  It's time to bake.
    - $\rightarrow$  It's time to get baked.



# **Resolution with pragmatics**

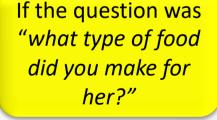
- It's obvious (to us) which meaning is intended given knowledge of the context of the conversation or the world in which it takes place.
  - "Every man loves a woman"  $\rightarrow \forall x man(x) \exists y: (woman(y) \land loves(x, y))$  If you know that no one woman is so popular  $\rightarrow \exists y: woman(y) \land \forall x (man(x) \rightarrow loves(x, y))$
  - "I made her duck"
    - → I cooked waterfowl meat for her to eat.
      → I cooked waterfowl that belonged to her.
      → I carved the wooden duck that she owns.

→ I caused her to quickly lower her head.

"Give me the pot"

 $\rightarrow$  It's time to bake.

 $\rightarrow$  It's time to get baked.







# **Ambiguity – miscellaneous**

Newspaper headlines (spurious or otherwise)



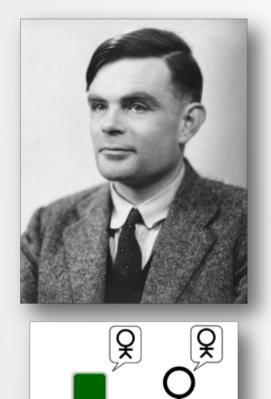


# **NLC as Artificial Intelligence**

- NLC involves **resolving ambiguity** at all levels.
  - Reasoning with world knowledge.
    - In the early days knowledge was explicitly encoded in artificial symbolic systems (e.g., context-free grammars) by experts.
  - Now, algorithms learn using probabilities to distinguish subtly different competing hypotheses.
    - E.g., is *Google* a noun or a verb?
    - An example where Google ∈ Nouns ("Google makes Android"), does not mean that Google is never a verb ("Go Google yourself").
    - $P(Google \in Nouns) > P(Google \in Verbs) > 0$



# **The Turing Test**



- First and most fundamental test of machine intelligence.
- A machine (A) imitates a human using nothing but a text-based instant messenger.
  - If a human interrogator (C) cannot reliably differentiate a real human (B) from the machine, that machine is said to be 'intelligent'.
  - Turing, Alan M. (1950) Computing machinery and intelligence. *Mind*, **59**, pp. 433-460.



CSC401/2511 – Spring 2019

# Aside – Chatterbots

- ELIZA (Weizenbaum, 1966): simple pattern matching to imitate a psychiatrist.
- Surprisingly effective despite no linguistic knowledge.

#### • e.g.,

User: Men are all alike. ELIZA: In what way? User: They're always bugging us about something or other. ELIZA: Can you think of a specific example? User: My boyfriend made me come here. ELIZA: Your boyfriend made you

come here. (Jurafsky and Martin, 2009)





# **Course outline (approximate)**

- Introduction, linguistic data, language models (3 lectures)
- Entropy and information theory (2 lectures) \*
- Features and classification (2 lectures) \*
- Hidden Markov models (3 lectures) \*
- Statistical machine translation (4 lectures) \*\*
- Neural language models (2 lectures) \*
- Articulatory and acoustic phonetics (2 lectures) \*
- Automatic speech recognition (2 lectures) \*\*
- Speech synthesis (1 lecture) \*\*
- Information retrieval (1 or 2 lectures) \*\*
- Dialogue and chatbots (1 lecture) \*\*
- Review (1 lecture)
  - \* techniques

\*\* applications



美国关岛国际机场及其办公室均接获一 名自称沙地阿拉伯富商拉登等发出的电 子邮件,威胁将会向机场等公众地方发 动生化袭击後,关岛经保持高度戒备。



The U.S. island of Guam is maintaining a high state of alert after the Guam airport and its offices both received an e-mail from someone calling himself the Saudi Arabian Osama bin Laden and threatening a biological/chemical attack against public places such as the airport.

- One of the most prized applications in NLC.
- Requires both interpretation and generation.
- Over \$100B spent annually on human translation.

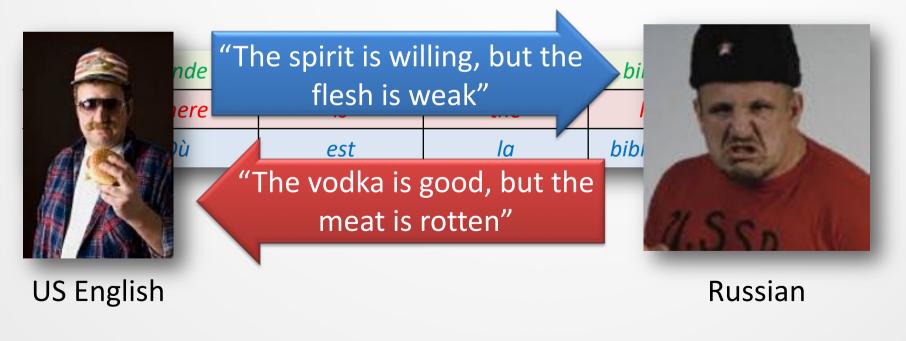


对外经济贸易合作部今天提供的数据表明,今年至十一月中国实际利用外资 四百六十九点五九亿美元,其中包括外商直接投资四百点零七亿美元。

| Human         | According to the data provided today by the Ministry of Foreign Trade<br>and Economic Cooperation, as of November this year, China has<br>actually utilized 46.959B US dollars of foreign capital, including<br>40.007B US dollars of direct investment from foreign businessmen. |
|---------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| IBM4          | The Ministry of Foreign Trade and Economic Cooperation, including foreign direct investment 40.007B US dollars today provide data include that year to November China actually using foreign 46.959B US dollars and                                                               |
| Yamada/Knight | Today's available data of the Ministry of Foreign Trade and Economic<br>Cooperation shows that China's actual utilization of November this<br>year will include 40.007B US dollars for the foreign direct investment<br>among 46.959B US dollars in foreign capital.              |



- In the 1950s and 1960s direct word-for-word replacement was popular.
  - Due to semantic and syntactic ambiguities and differences in source languages, results were mixed.





#### One problem is disparity of meanings in languages.



Stephen Harper nation n. a large body of people, associated with a particular territory, that is sufficiently conscious of its unity to seek or to possess a government of its own

**nation** *n*. an aggregation of persons of the same **ethnic family**, often speaking the same **language** or cognate **languages** 



Pauline Marois



• <u>Solution</u>: automatically learn statistics on parallel texts

... citizen of Canada has the right to vote in an election of members of the House of Commons or of a legislative assembly and to be qualified for membership ...



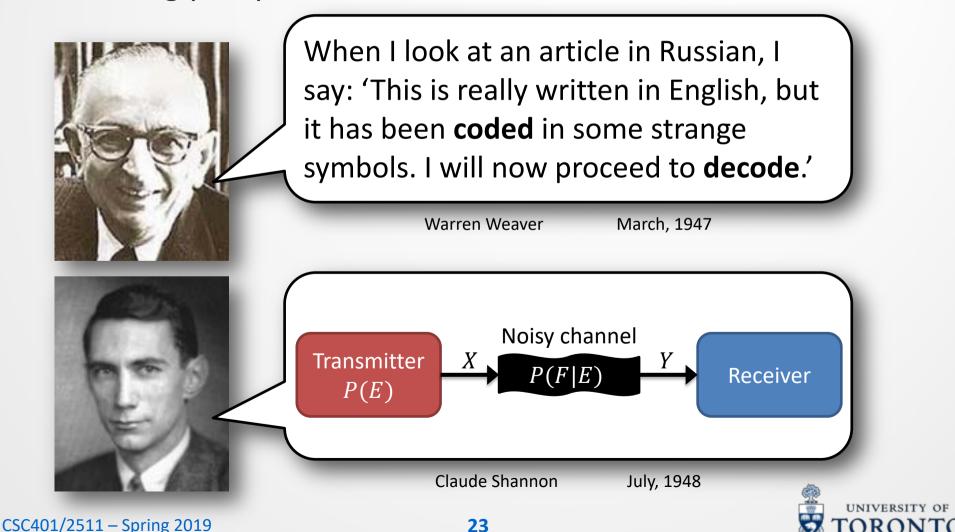
... citoyen canadien a le droit de vote et est éligible aux élections législatives fédérales ou provinciales ...

e.g., the *Canadian Hansards*: bilingual Parliamentary proceedings



# **Statistical machine translation**

Modern statistical machine translation is based on the following perspective...



#### **Aside – Machine translation**

 <u>http://www.translationparty.com</u> uses Google Translate to go back and forth between English and Japanese until we get two consecutive identical English phrases.

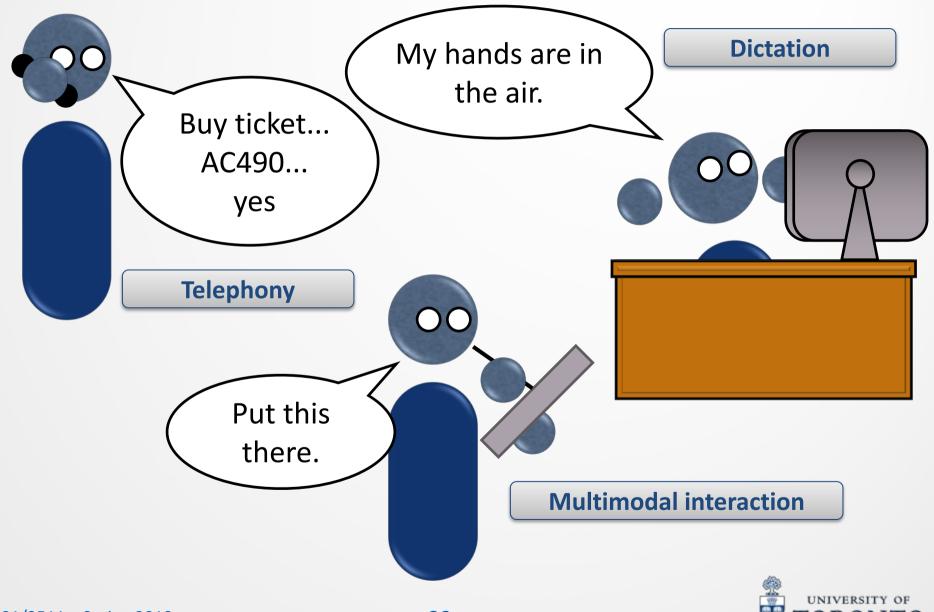
| Start with an English phrase:                                         |                    |  |  |  |
|-----------------------------------------------------------------------|--------------------|--|--|--|
| I want to learn about natural language computing                      |                    |  |  |  |
| find equilibrium                                                      |                    |  |  |  |
| I want to learn about natural language computing                      | let's go!          |  |  |  |
| 私は自然言語コンピューティングを勉強したい                                                 | into Japanese      |  |  |  |
| I want to learn natural language computing                            | back into English  |  |  |  |
| 私は自然言語コンピューティングを勉強したい                                                 | back into Japanese |  |  |  |
| I want to learn natural language computing                            | back into English  |  |  |  |
| Equilibrium found!<br>You've heard about <u>Question Party</u> right? |                    |  |  |  |



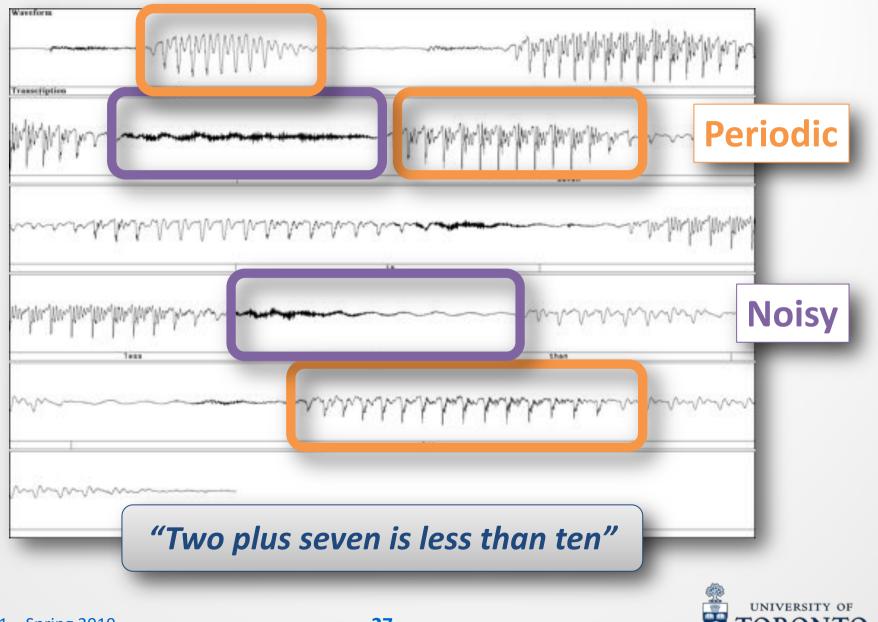
| Start with an English photon that's one small step for a man, one g |                                                                          |                    |
|---------------------------------------------------------------------|--------------------------------------------------------------------------|--------------------|
| that's one small step for a man, or mankind                         | ne giant leap for let's got                                              |                    |
| それは人間にとっては小さな一歩だが、<br>一歩                                            | 人類にとっては小さな一歩ステップは、男性にとって理想的な<br>ホテルです                                    | back into Japanese |
| It is but one small step for man, o<br>mankind                      | Step One small step for mankind, this hotel is ideal for men             | back into English  |
| それは人間にとっては小さな一歩一歩、<br>しいが、さ                                         | 人類にとっては小さな一歩ステップ、このホテルは、男性に<br>とって理想的なホテルです                              | back into Japanese |
| It is step by small step for man, b<br>humanity, the                | Step One small step for mankind, this hotel is ideal for men             | back into English  |
|                                                                     | <b>Equilibrium found!</b><br>Okay, I get it, you like Translation Party. |                    |
|                                                                     |                                                                          |                    |



#### **Preview: Speech recognition**



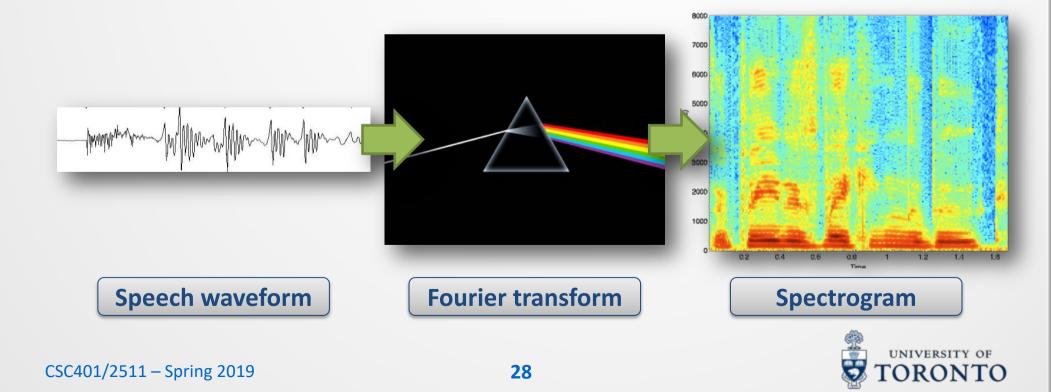
# **Speech waveforms**



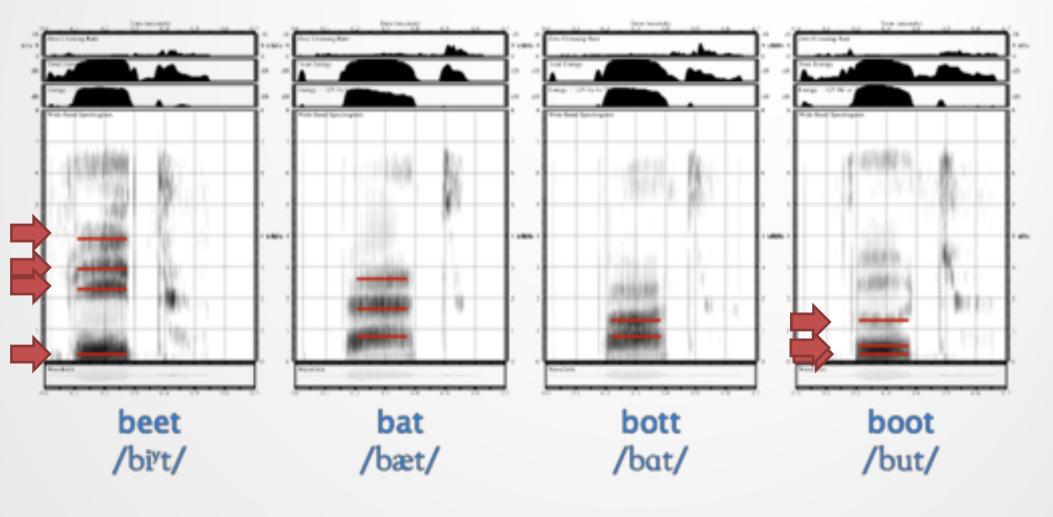
#### **Spectrograms**

• Speech sounds can be thought of as overlapping sine waves.

- Speech is split apart into a 3D graph called a 'spectrogram'.
- Spectrograms allow machines to extract statistical features that differentiate between different kinds of sounds.

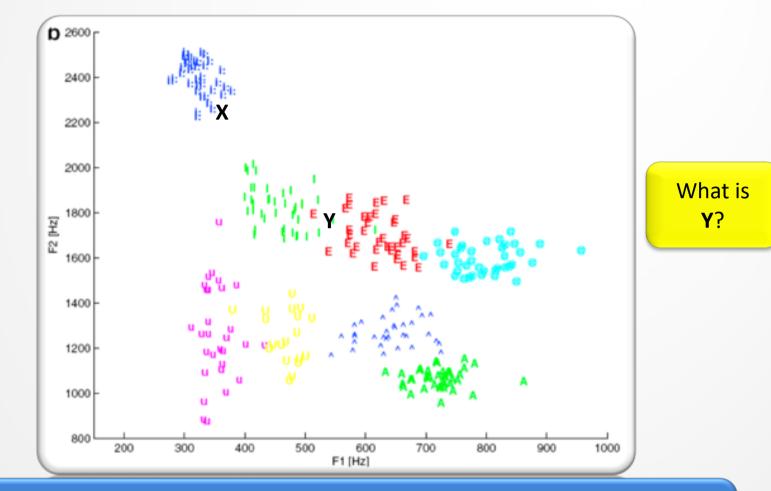


# **Speech recognition**





#### **Preview: Speech recognition**



 In order to classify an unknown observation (e.g., X), we need a statistical model of the distribution of sounds



#### **Preview: Questions and answers**

Which woman has won more than 1 Nobel prize?



(Marie Curie)

• Question Answering (QA) and Information Retrieval (IR) involve many of the same principles.



# **Preview: Information retrieval**

| what | woman | won more | than one n | obel prize |      |          | ٩     |
|------|-------|----------|------------|------------|------|----------|-------|
| All  | News  | Videos   | Images     | Shopping   | More | Settings | Tools |

Marie Curie won the Nobel prize in 1903 for Physics and 1911 in Chemistry; Linus Pauling in 1954 (for Chemistry) and 1962 (for Peace); John Bardeen in 1956 (for Physics) and 1972; Frederick Sanger in Chemistry in 1958 and 1980. Who has won more than one Nobel prize? Apr 1, 2007

Who has won more than one Nobel prize? - Times of India timesofindia.indiatimes.com/home/...won-more-than-one-Nobel-prize/.../1839923.cms

People also ask Who has won Nobel Prize twice?  $\sim$ What women won the Nobel Prize?  $\sim$ How many women have won the Nobel Prize?  $\sim$ How many women have been awarded the Nobel Peace Prize?  $\sim$ Feedback

WolframAlpha<sup>\*</sup> computational. Knowledge engine which woman has won more than 1 nobel prize? (?) Solution: white the second sec WolframAlpha<sup>\*</sup> computational knowledge engine ☆ 日 what woman won more than one nobel prize? 🔤 🖸 🖽 🐙 Using closest WolframIAlpha interpretation: won more than one ื่อ More interpretations: nobel prize woman Assuming Korean won for "won" | Use North Korean won instead

| 1 | 2010 | Richard<br>F. Heck           | chemistry  | United States     | United States |
|---|------|------------------------------|------------|-------------------|---------------|
|   | 2010 | Christopher<br>A. Pissarides | economics  | United<br>Kingdom | Cyprus        |
|   | 2010 | Dale T.<br>Mortensen         | economics  | United States     | United States |
|   | 2010 | Peter A.<br>Diamond          | economics  | United States     | United States |
|   | 2010 | Mario<br>Vargas Llosa        | literature | Peru              | Peru          |



CSC401/2511 - Spring 2019

E Feedback

About this result

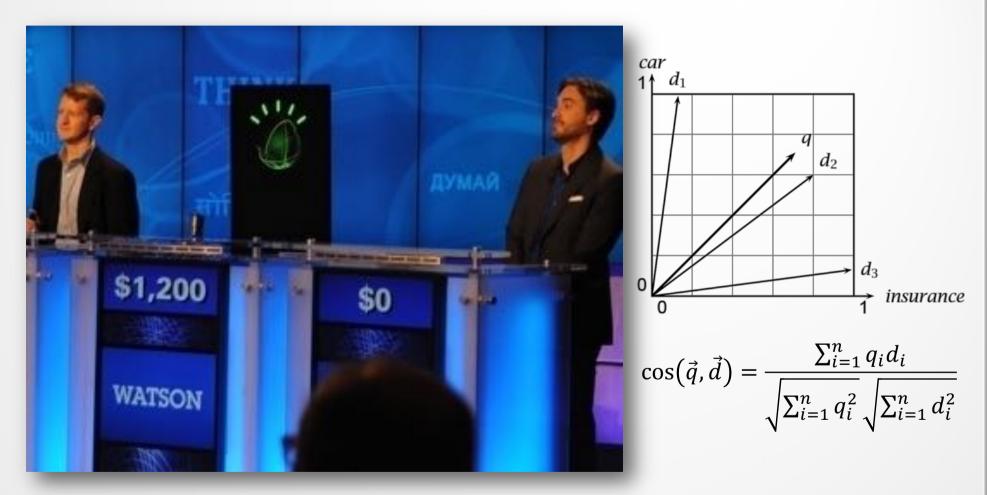
# **Aside – Question answering**

|                | 🐳 Wo            | olframAlpha <sup>®</sup> computation       | onal<br>engine |
|----------------|-----------------|--------------------------------------------|----------------|
| ow much pota   | assium is in 45 | 0,000 cubic kilometers of bananas?         | 8              |
|                |                 |                                            |                |
|                |                 |                                            |                |
| put interpreta | tion:           | 2                                          |                |
| banana         | amount          | 450 000 km <sup>3</sup> (cubic kilometers) | potassium      |





#### **Answer questioning?**



 Retrieving information can be a clever combination of many very simple concepts and algorithms.



# **Overview: NLC**

• Is natural language computing (the discipline) hard?

- Yes, because natural language
  - is highly ambiguous at all levels,
  - is complex and subtle,
  - is fuzzy and probabilistic,
  - involves real-world reasoning.
- No, because computer science
  - gives us many powerful statistical techniques,
  - allows us to break the challenges down into more manageable features.
- Is Natural Language Computing (the course) hard?
  - More on this soon...





# Natural language computing

- Instructor: Frank Rudzicz and Chloé Pou-Prom (csc401.2019@gmail)
- **TAS**: Zhewei Sun, Maryam Fallah, Mohamed Abdalla, TBD, Amanjit Kainth, Jianan Chen
- Meetings: MF (lecture, PB250), W (tutorial, MB128) at 10h-11h
- Languages: English, Python.
- <u>Website</u>: <u>http://www.cs.toronto.edu/~frank/csc401/</u>
- <u>You</u>: Understand basic **probability**, can **program**, or can pick these up as we go.
- Syllabus: Key theory and methods in statistical natural language computing.
   Focus will be on Markov and neural models, machine translation, and speech recognition.



# **Office hours**

- Time:
  - Mondays, 11h30-12h30
- Location:
  - The Vector Institute (MaRS West, Suite 710)
  - The streets





# **Theme – NLC in a post-truth society**

• The **truth** is the most important thing in the Universe.

- At the very least, the truth allows us to rationally optimize legal, political, and personal decisions.
- The truth can sometimes be obscured deliberately via deception, or inadvertently through bias, fallacy, or intellectual laziness.
  - Nowhere is this perhaps more obvious than on social media or in pseudo-journalism.
- Natural language processing gives us tools to combat this scourge.



### **Evaluation policies**

- General: Three assignments: 15%, 20%, 25% (ranked by your mark) Final exam : 40%
- Lateness: 10% deduction applied to electronic submissions that are 1 minute late. Additional 10% applied every 24 hours up to 72 hours total, at which point grade is zero.
- <u>Final</u>: If you fail the final exam, then you fail the course.
- <u>Ethics</u>: Plagiarism and unauthorized collaboration can result in a grade of zero on the homework, failure of the course, or suspension from the University. See the course website.



# Assignments

- Assignment 1: Corpus statistics, sentiment analysis
   task: bias analysis on Reddit
  - learn: statistical techniques, features, and classification.
- Assignment 2: Statistical machine translation
  - task \*: translate between political extremes learn: statistical *n*-grams, smoothing, and multilingual word alignment.
- Assignment 3: Automatic speech recognition
  - task: detect lies in speechlearn: signal processing, phonetics, andhidden Markov models.



\* Hopefully

41

# Assignment 1 – Bias in social media

- Involves:
  - Working with social media data
    - (i.e., gathering statistics on some data from Reddit),
  - Part-of-speech tagging (more on this later),
  - Classification.
- Announcements: Piazza forum, email.
- You should get an early start.





# Projects – graduate students only

- Graduate students can optionally undertake a full-term project worth 60% of their grade instead of the assignments.
  - Good for those, e.g., who prefer to work in teams.
     You might even get a publication!
- Teams must consist of 1 or 2 humans (no more, no fewer).
- Projects must contain a significant programming and scientific component.
- Projects must be **relevant** to the course.



## **Projects – graduate students only**

- Some possible ideas for projects include:
  - A deception filter for news media online.
  - A novel method of using data in language A to train a classification system in language B for A ≠ B.
- If you decide to take this option, you have to notify us by email about your team by 18 January!
- You will need to periodically submit checkpoints that build on their antecedents.
  - See course webpage for detailed requirements!



#### Reading

CSC401/2011 - Spring 2010

#### FOUNDATIONS OF STATISTICAL NATURAL LANGUAGE PROCESSING

Mandatory

(and FREE

online!)

CHRISTOPHER D. MANNING AND HINRICH SCHÜTZE

https://search.library.utoronto.ca/de tails?10552907

#### **Optional**

#### SPEECH AND Language processing

An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition



DANIEL JURAFSKY & JAMES H. MARTIN

45



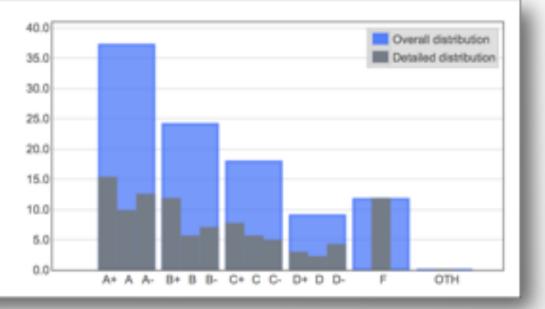
## Stats from 2017

The average overall grade among **undergraduates** was 63.0% ( $\sigma=26.7$ ). The average overall grade among **graduates** was 74.4% ( $\sigma=31.7$ ).

The grade *range* breakdown among undergraduates was:

| А  | 37.2% | B 24.1%  | C 17.9% | D 9%    |
|----|-------|----------|---------|---------|
| A+ | 15.2% | B+ 11.7% | C+ 7.6% | D+ 2.8% |
| А  | 9.7%  | B 5.5%   | C 5.5%  | D 2.1%  |
| A- | 12.4% | B- 6.9%  | C- 4.8% | D- 4.1% |
| F  | 11.7% | OTH 0%   | Average | Median  |
| F  | 11.7% | OTH 0%   | 70.01 % | 76 %    |

Class average excluding exam no shows: 75.20% Fails excluding exam no shows: 3.79%





# **Assignment 1 and reading**

• Assignment 1 available (on course webpage)!

- Due 11 February
- TAS: Zhewei Sun (zheweisun@cs); Maryam Fallah (mary.fallah@mail.utoronto).

#### • Reading:

Manning & Schütze: Sections 1.3—1.4.2,

Sections 6.0—6.2.1.

