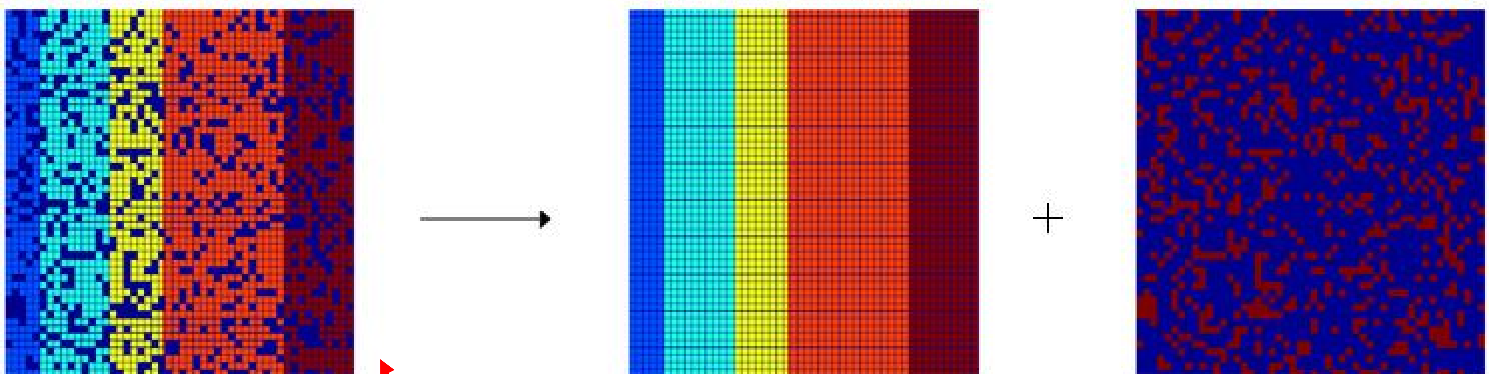
Recap: how to build such a space

- Solution
  - Low rank matrix approximation

*Imagine this is *true* concept-document matrix*



Matrix of corrupted observations *Underlying low-rank matrix* *Sparse error matrix*

Imagine this is our observed term-document matrix

Random noise over the word selection in each document

Recap: Latent Semantic Analysis (LSA)

- Solve LSA by SVD

Map to a lower dimensional space

$$\hat{Z} = \underset{Z|rank(Z)=k}{\operatorname{argmin}} \|C - Z\|_F$$

$$= \underset{Z|rank(Z)=k}{\operatorname{argmin}} \sqrt{\sum_{i=1}^{M} \sum_{j=1}^{N} \left(C_{ij} - Z_{ij}\right)^2}$$

$$= C_{M\times N}^{k}$$

  - Procedure of LSA
    1. Perform SVD on document-term adjacency matrix
    2. Construct $C_{M\times N}^{k}$ by only keeping the largest k singular values in Σ non-zero

Introduction to Natural Language Processing

Hongning Wang
CS@UVa

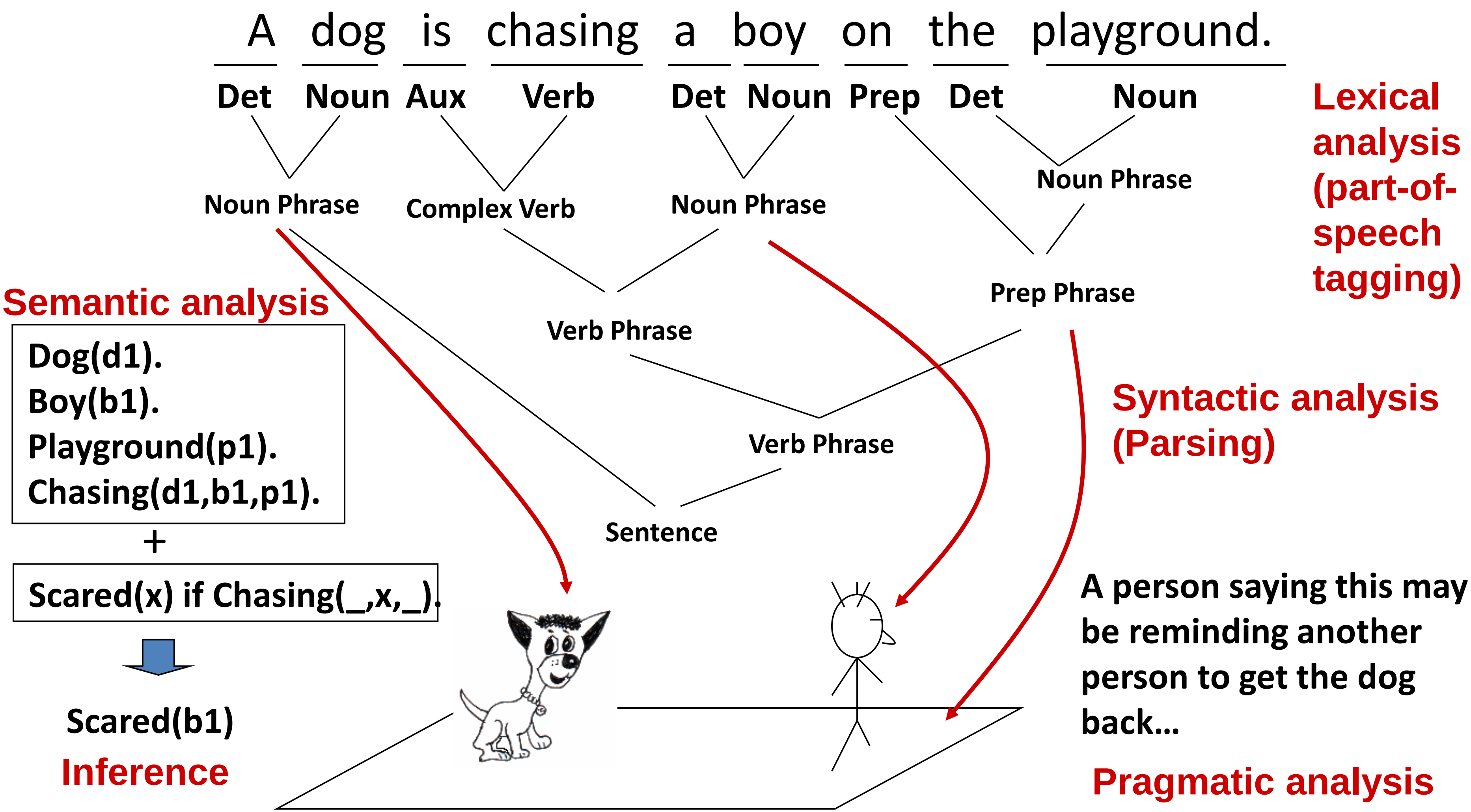
What is NLP?

Arabic text كلب هو مطاردة صبي في الملعب.

How can a computer make **sense** out of this **string?**

Morphology	- What are the basic units of meaning (words)? - What is the meaning of each word?
Syntax	- How are words related with each other?
Semantics	- What is the "combined meaning" of words?
Pragmatics	- What is the "meta-meaning"? (speech act)
Discourse	- Handling a large chunk of text
Inference	- Making sense of everything

An example of NLP

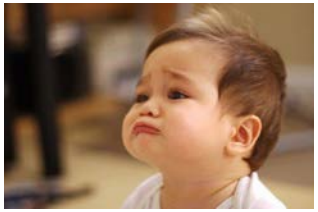


- *Automatically answer our emails*
- *Translate languages accurately*
- *Help us manage, summarize, and aggregate information*
- *Use speech as a UI (when needed)*
- *Talk to us / listen to us*

If we can do this for all the sentences in all languages, then …

BAD N

- **Unf ght now.**
- **Gen ”**



NLP is difficult!!!!!!!

- Natural language is designed to make human communication efficient. Therefore,
  – We omit a lot of “common sense” knowledge, which we assume the hearer/reader possesses
  – We keep a lot of ambiguities, which we assume the hearer/reader knows how to resolve
- This makes EVERY step in NLP hard
  – Ambiguity is a “killer”!
  – Common sense reasoning is pre-required

An example of ambiguity

- Get the cat with the gloves.



Examples of challenges

- Word-level ambiguity
  - "design" can be a noun or a verb (Ambiguous POS)
  - "root" has multiple meanings (Ambiguous sense)
- Syntactic ambiguity
  - "natural language processing" (Modification)
  - "A man saw a boy <u>*with a telescope*</u>." (PP Attachment)
- Anaphora resolution
  - "John persuaded Bill to buy a TV for himself." (himself = John or Bill?)
- Presupposition
  - "He has quit smoking." implies that he smoked before.

Despite all the challenges, research in NLP has also made a lot of progress…

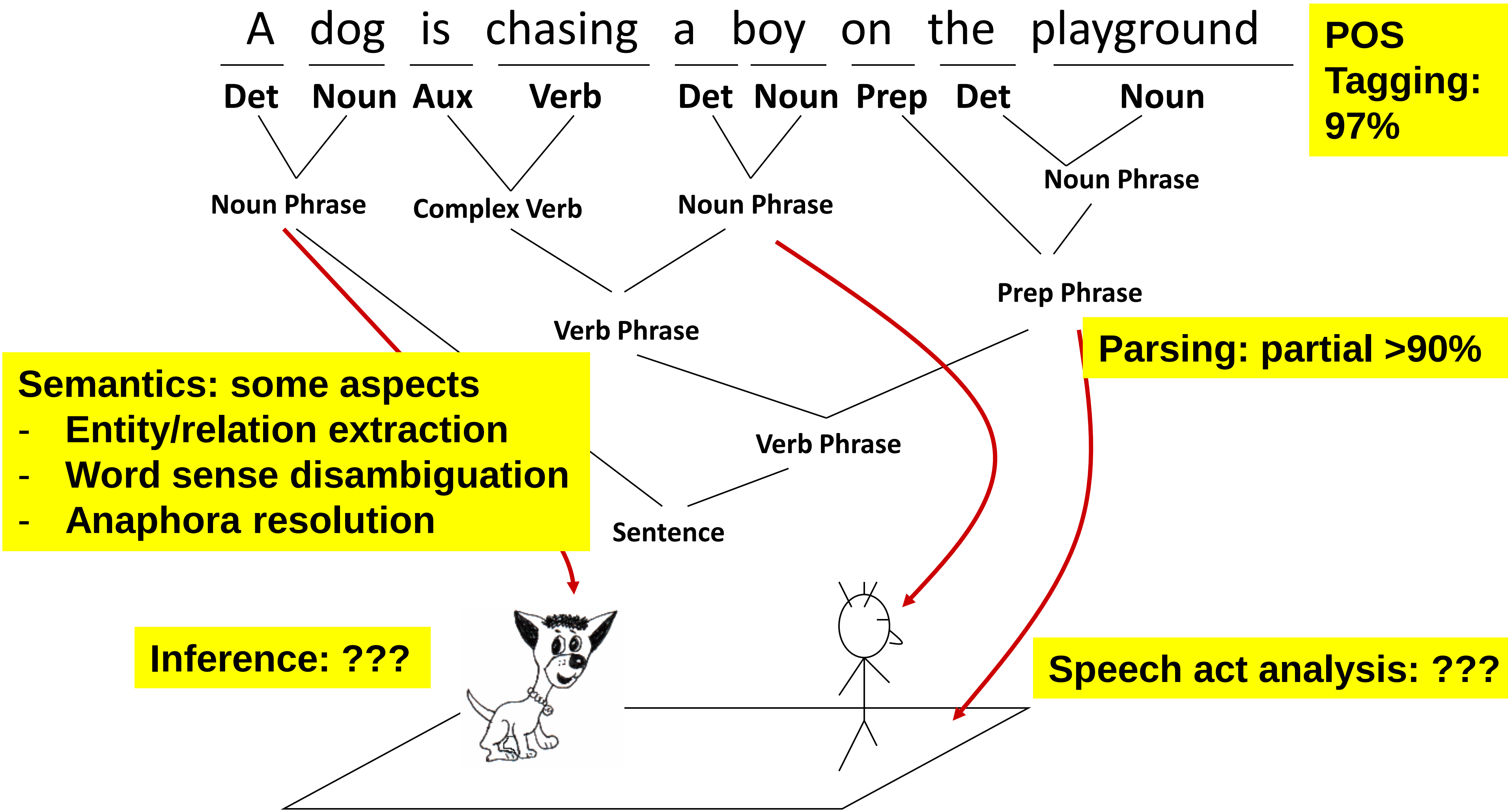
A brief history of NLP

- Early enthusiasm (1950's): Machine Translation
  - Too ambitious
  - Bar-Hillel report (1960) concluded that fully-automatic high-quality translation could not be accomplished without knowledge (Dictionary + Encyclopedia)
- Less ambitious applications (late 1960's & early 1970's): Limited success, failed to scale up
  - Speech recognition
  - Dialogue (Eliza) **Shallow understanding**
  - Inference and domain knowledge (SHRDLU="block world")

Deep understanding in limited domain

- Real world evaluation (late 1970's – now)
  - Story understanding (late 1970's & early 1980's) **Knowledge representation**
  - Large scale evaluation of speech recognition, text retrieval, information extraction (1980 – now) **Robust component techniques**
  - Statistical approaches enjoy more success (first in speech recognition & retrieval, later others) **Statistical language models**
- Current trend:
  - Boundary between statistical and symbolic approaches is disappearing.
  - We need to use all the available knowledge **Applications**
  - Application-driven NLP research (bioinformatics, Web, Question answering…)

The state of the art



Machine translation

English | Spanish | French | English - detected

it's a question, but also an expression of disbelief.
Those who get lost driving can use GPS. If you lose your iPhone, there's an app to track it down. Scientists successfully plotted the course for a spacecraft that landed on a speeding asteroid.
How did weather affect AirAsia flight?
But something goes wrong aboard a 123-foot, 67-ton passenger jet and rescuers must resort to scouring the ocean?
"Why is it easier to find an iPhone (than) to find a plane?" one Twitter user, Catalina Buitano, asked.
There are dozens of similar questions on social media. They hint at the same sentiment: in a world where people's locations are tracked for everything from map apps to what ads appear on a web browser, why does Big Brother's gaze avoid the skies?

这是一个问题，但也不敢相信的表情。
这些谁迷路驾驶可以使用GPS。如果你失去了你的iPhone，有一个应用程序来追查。科学家成功绘制过程中的飞船降落在小行星飞驰。
没有天气如何影响亚航的班机吗？
但不顺心的事一般123英尺，67吨重的喷气式客机和救援人员必须求助于淘海洋？
"为什么更容易找到一个iPhone（比）找到飞机？"1 Twitter的用户，卡塔利娜Buitano，问道。
有几十个在社交媒体上类似的问题。他们暗示相同的感悟：在这个世界上，人的位置进行跟踪，一切从地图应用程序，以广告出现在网页浏览器，为什么大哥的目光避开天空是什么？

Machine translation

English (detected) ▾

Advances in computation, communication, and data storage techniques in recent decades significantly reduced the cost of data acquisition, leading to an explosion of data generated across different interconnected platforms. Apart from the computational difficulties arise from nonconvex formulations; the sheer volume and spatial disparity of data also pose challenges to traditional learning procedures, which typically require centralized training sets. Reaping the dividend offered by the data deluge, it then urges for the development of collaborative learning methods capable of making inferences from data over the network. Edit

Chinese Simplified ▾

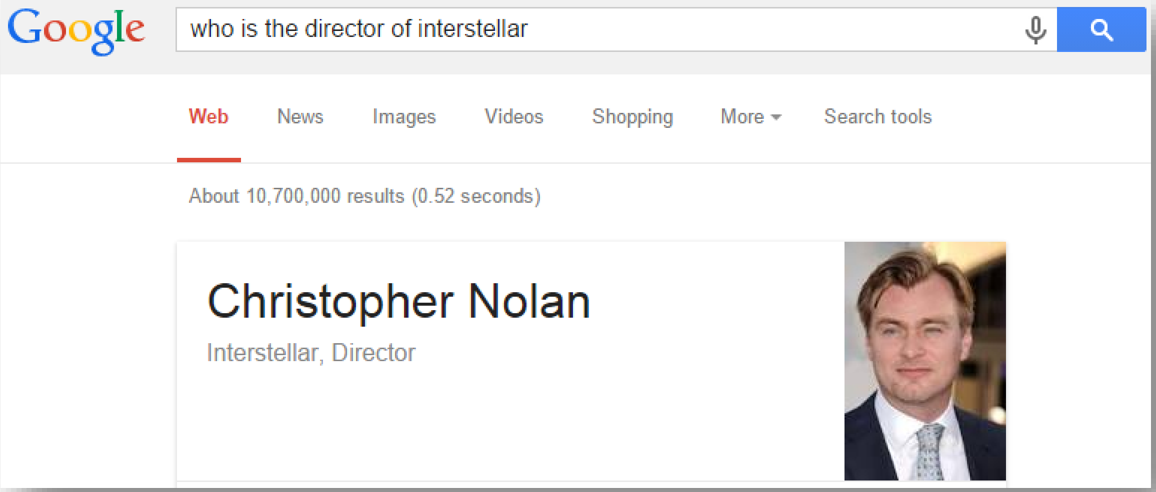
近几十年来，计算、通信和数据存储技术的进步大大降低了数据采集成本，导致跨不同互联平台生成的数据激增。除了计算困难产生于非凸公式;数据的数量和空间差异也对传统的学习程序构成挑战，传统的学习程序通常需要集中的培训。通过获得数据泛滥带来的红利，促使开发能够从网络上的数据进行推断的协作学习方法。

ENGLISH | CHINESE (SIMPLIFIED) | SPANI

Advances in computing, communications, and data storage technologies have dramatically reduced data collection costs in recent decades, resulting in a surge in data generated across different interconnected platforms. In addition to computational difficulties arising from non-convex formulas; the amount of data and spatial differences also pose challenges to traditional learning procedures, which often require centralized training. By gaining the benefits of data flooding, it has led to the development of collaborative learning methods that can infer data from the web.

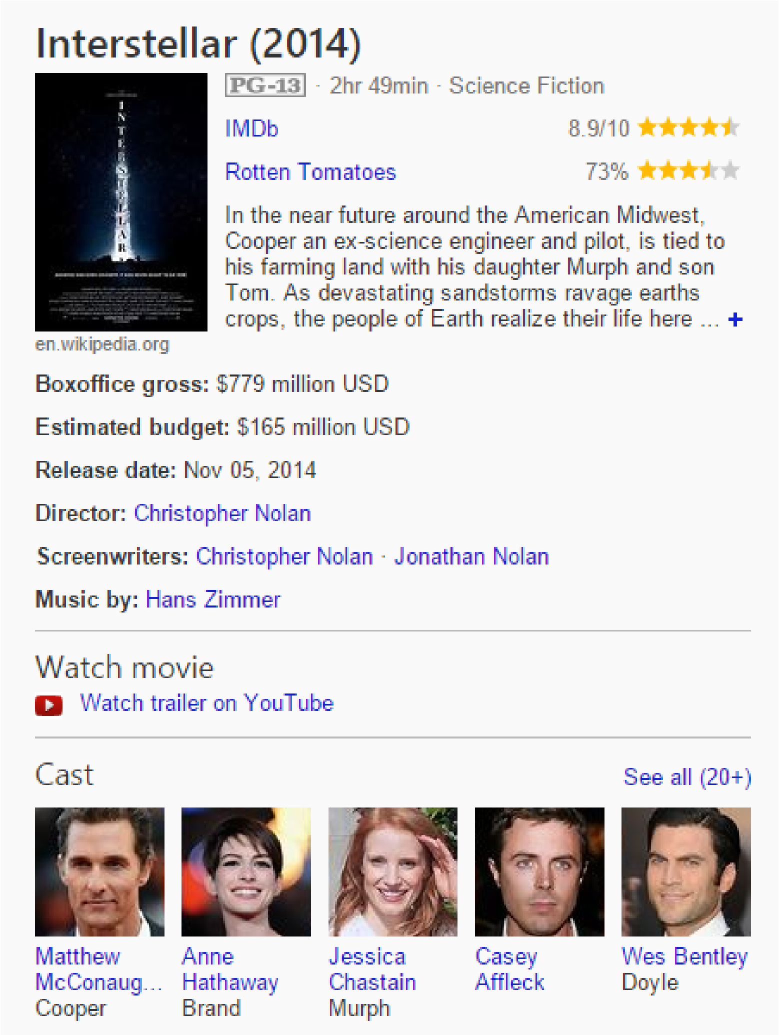
Dialog systems

Apple's siri system

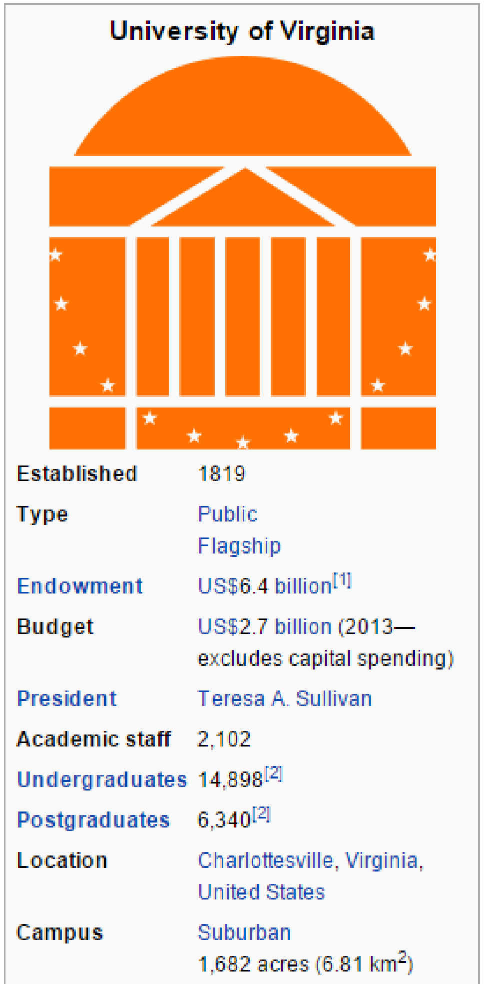


Google search

Information extraction

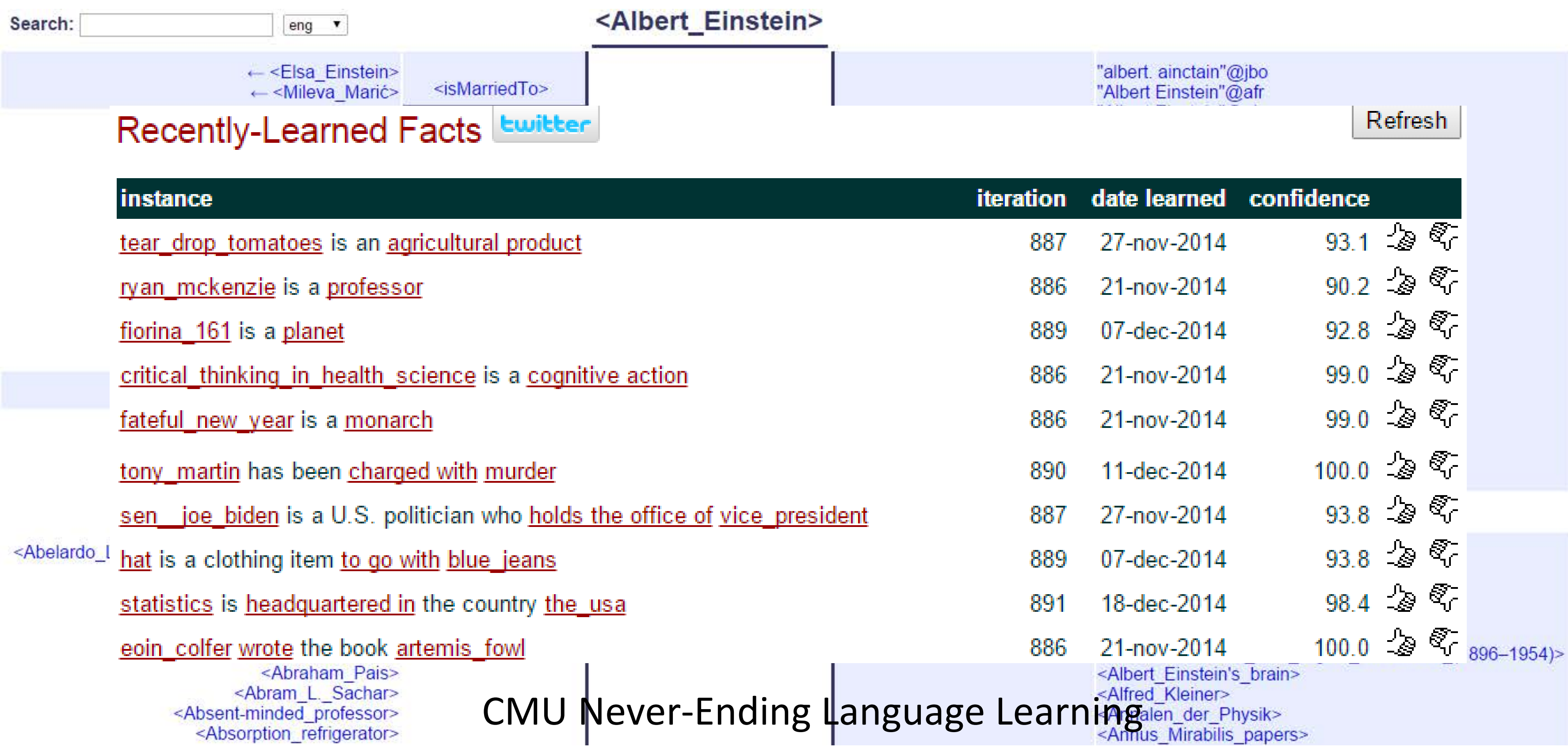


Google Knowledge Graph



Wiki Info Box

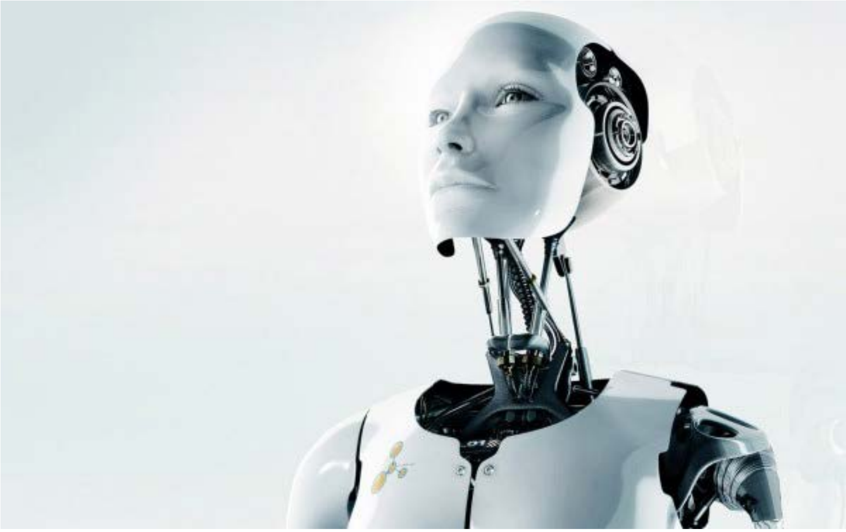
Information extraction



instance	iteration	date learned	confidence
tear_drop_tomatoes is an agricultural product	887	27-nov-2014	93.1
ryan_mckenzie is a professor	886	21-nov-2014	90.2
fiorina_161 is a planet	889	07-dec-2014	92.8
critical_thinking_in_health_science is a cognitive action	886	21-nov-2014	99.0
fateful_new_year is a monarch	886	21-nov-2014	99.0
tony_martin has been charged with murder	890	11-dec-2014	100.0
sen__joe_biden is a U.S. politician who holds the office of vice_president	887	27-nov-2014	93.8
hat is a clothing item to go with blue_jeans	889	07-dec-2014	93.8
statistics is headquartered in the country the_usa	891	18-dec-2014	98.4
eoin_colfer wrote the book artemis_fowl	886	21-nov-2014	100.0

CMU Never-Ending Language Learning

YAGO Knowledge Base



Building a computer that 'understands' text: The NLP pipeline

Tokenization/Segmentation

- Split text into words and sentences
  - Task: what is the most likely segmentation /tokenization?

There was an earthquake near D.C. I've even felt it in Philadelphia, New York, etc.

There + was + an + earthquake + near + D.C.

I + ve + even + felt + it + in + Philadelphia, + New + York, + etc.

Part-of-Speech tagging

- Marking up a word in a text (corpus) as corresponding to a particular part of speech
  - Task: what is the most likely tag sequence

A + dog + is + chasing + a + boy + on + the + playground

A	dog	is	chasing	a	boy	on	the	playground
Det	**Noun**	**Aux**	**Verb**	**Det**	**Noun**	**Prep**	**Det**	**Noun**

Named entity recognition

- Determine text mapping to proper names
  - Task: what is the most likely mapping

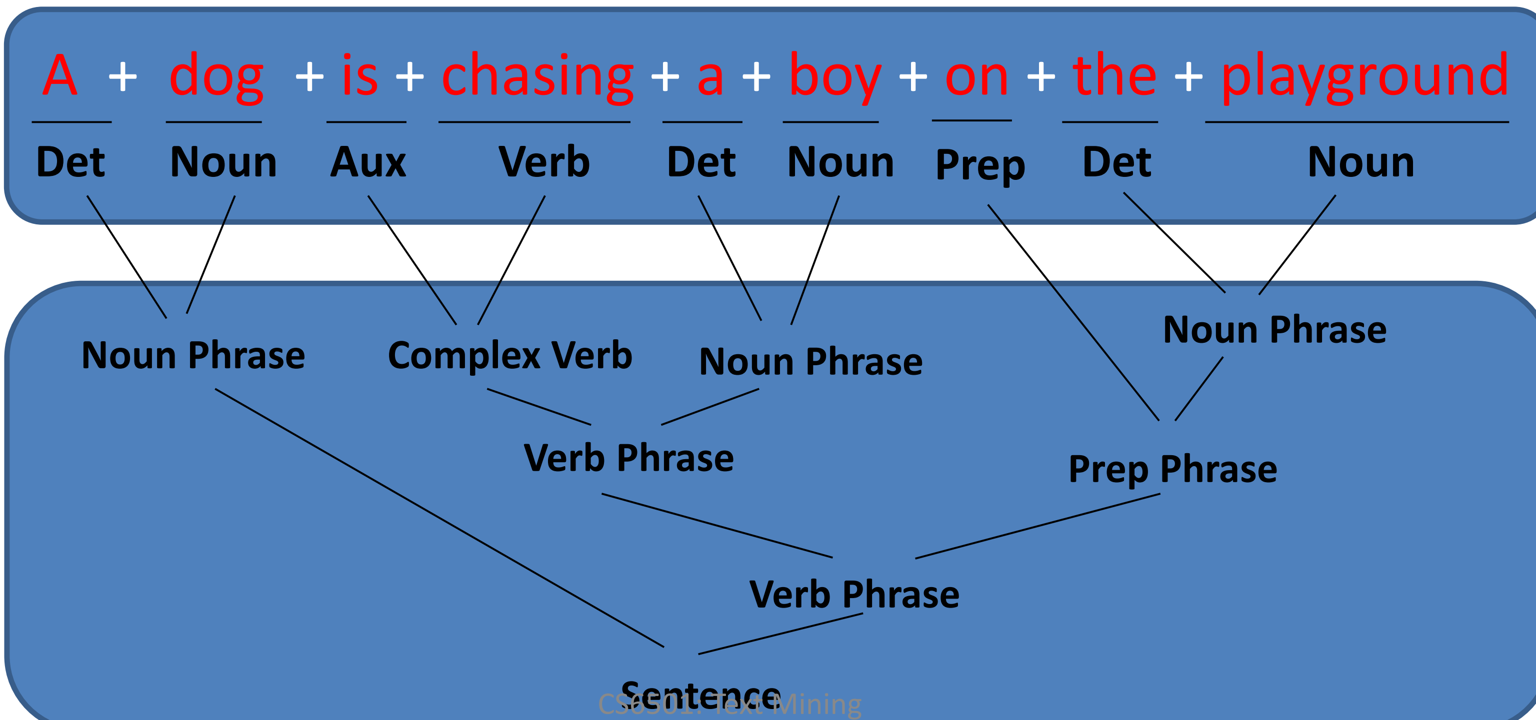
Its initial Board of Visitors included U.S. Presidents Thomas Jefferson, James Madison, and James Monroe.

Its initial Board of Visitors included U.S. Presidents Thomas Jefferson, James Madison, and James Monroe.

Organization, Location, Person

Syntactic parsing

- Grammatical analysis of a given sentence, conforming to the rules of a formal grammar
  - Task: what is the most likely grammatical structure



Relation extraction

- Identify the relationships among named entities
  - Shallow semantic analysis

> Its initial Board of Visitors included U.S. Presidents Thomas Jefferson, James Madison, and James Monroe.

> 1. Thomas Jefferson Is_Member_Of Board of Visitors
> 2. Thomas Jefferson Is_President_Of U.S.

Logic inference

- Convert chunks of text into more formal representations
  - Deep semantic analysis: e.g., first-order logic structures

Its initial Board of Visitors included U.S. Presidents Thomas Jefferson, James Madison, and James Monroe.

$\exists x$ (Is_Person(x) & Is_President_Of(x,'U.S.') & Is_Member_Of(x,'Board of Visitors'))

Towards understanding of text

More than a decade ago, Carl Lewis stood on the threshold of what was to become the greatest athletics career in history. He had just broken two of the legendary Jesse Owens' college records, but never believed he would become a corporate icon, the focus of hundreds of millions of dollars in advertising. His sport was still nominally amateur. Eighteen Olympic and World Championship gold medals and 21 world records later, Lewis has become the richest man in the history of track and field -- a multi-millionaire.

- Who is Carl Lewis?
- Did Carl Lewis break any records?

Major NLP applications

- Speech recognition: e.g., auto telephone call routing
- Text mining
  - Text clustering
  - Text classification
  - Text summarization
  - Topic modeling
  - Question answering

Our focus

- Language tutoring
  - Spelling/grammar correction
- Machine translation
  - Cross-language retrieval
  - Restricted natural language
- Natural language user interface

NLP & text mining

- Better NLP => Better text mining
- Bad NLP => ~~Bad text mining?~~

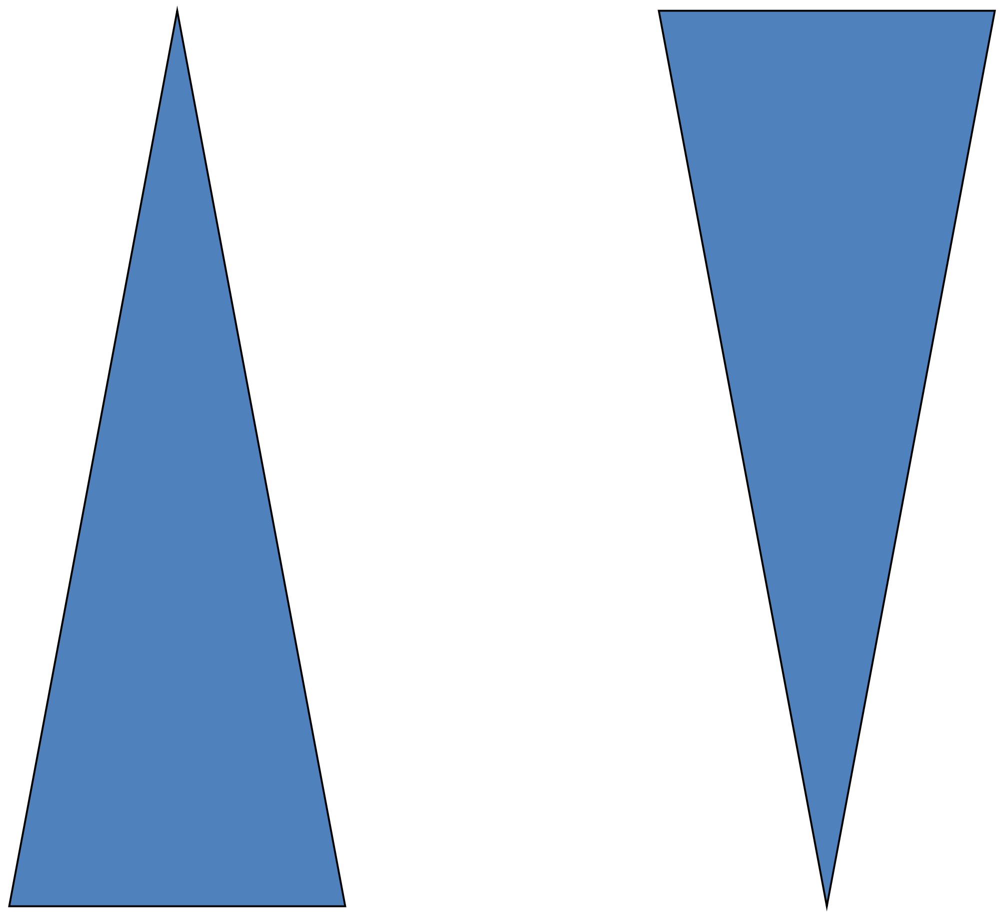
Robust, shallow NLP tends to be more useful than deep, but fragile NLP.

Errors in NLP can hurt text mining performance…

How much NLP is really needed?

Tasks | **Dependency on NLP** | **Scalability**

- Classification
- Clustering
- Summarization
- Extraction
- Topic modeling
- Translation
- Dialogue
- Question Answering
- Inference
- Speech Act



So, what NLP techniques are the most useful for text mining?

- Statistical NLP in general.
- The need for high robustness and efficiency implies the dominant use of simple models

What you should know

- Different levels of NLP
- Challenges in NLP
- NLP pipeline