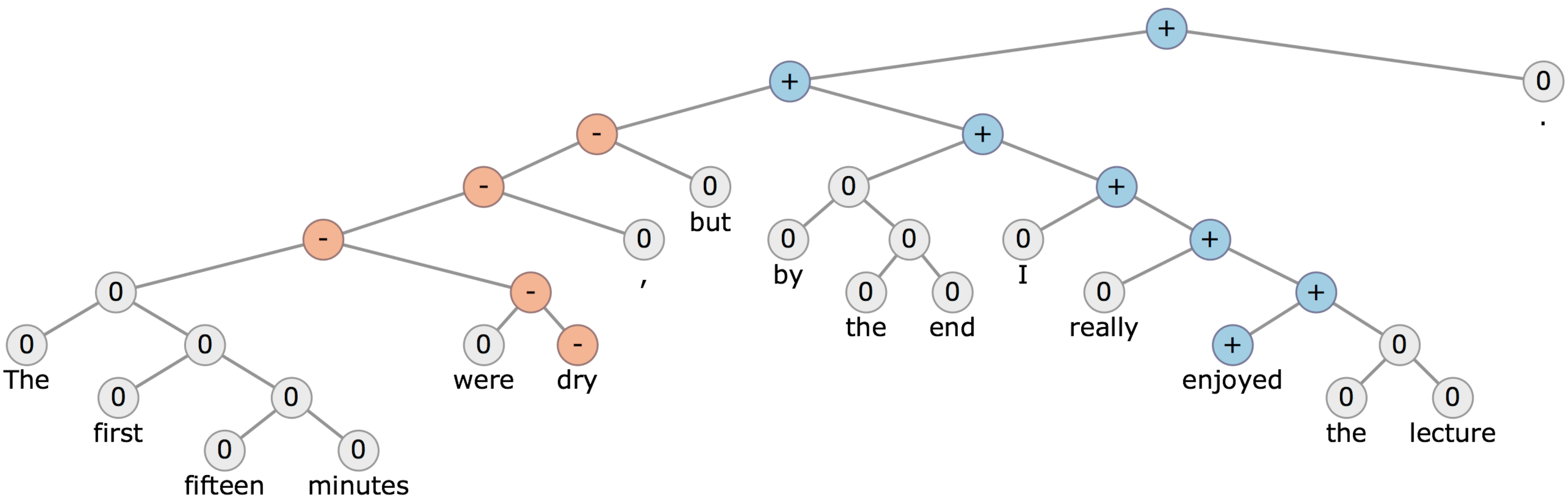
CS224d
Deep Learning
for Natural Language Processing

Richard Socher, PhD

Welcome



1. CS224d logistics

2. Introduction to NLP, deep learning and their intersection

Course Logistics

- Instructor: Richard Socher
  (Stanford PhD, 2014; now Founder, CTO at MetaMind)

- TAs: Ian Tenney, Francois Chaubard, Peng Qi

- Time/Place: **320-105, 1 – 2:15pm MW**

- There will be problem sets (with lots of programming), a midterm and a final project
- For syllabus and office hours, see http://cs224d.stanford.edu/
- No course notes but slides and videos

Grading Policy

- 3 Problem Sets: 15% x 3 = 45%
- Midterm Exam: 15%
- Final Course Project: 40%
  - Milestone: 5% (2% bonus if you have your data and ran an experiment!)
  - Final write-up, project and presentation: 35%
  - Bonus points for exceptional poster presentation
- Late policy
  - 7 free late days – use as you please
  - Afterwards, 25% off per day late
  - PSets Not accepted after 3 late days per PSet
  - Does not apply to Final Course Project
- Collaboration policy: Read the student code book and Honor Code!
- Understand what is 'collaboration' and what is 'academic infraction'

Pre-requisites

- Proficiency in Python
  - All class assignments will be in Python (and use numpy). There is a tutorial here

- College Calculus, Linear Algebra (e.g. MATH 19 or 41, MATH 51)

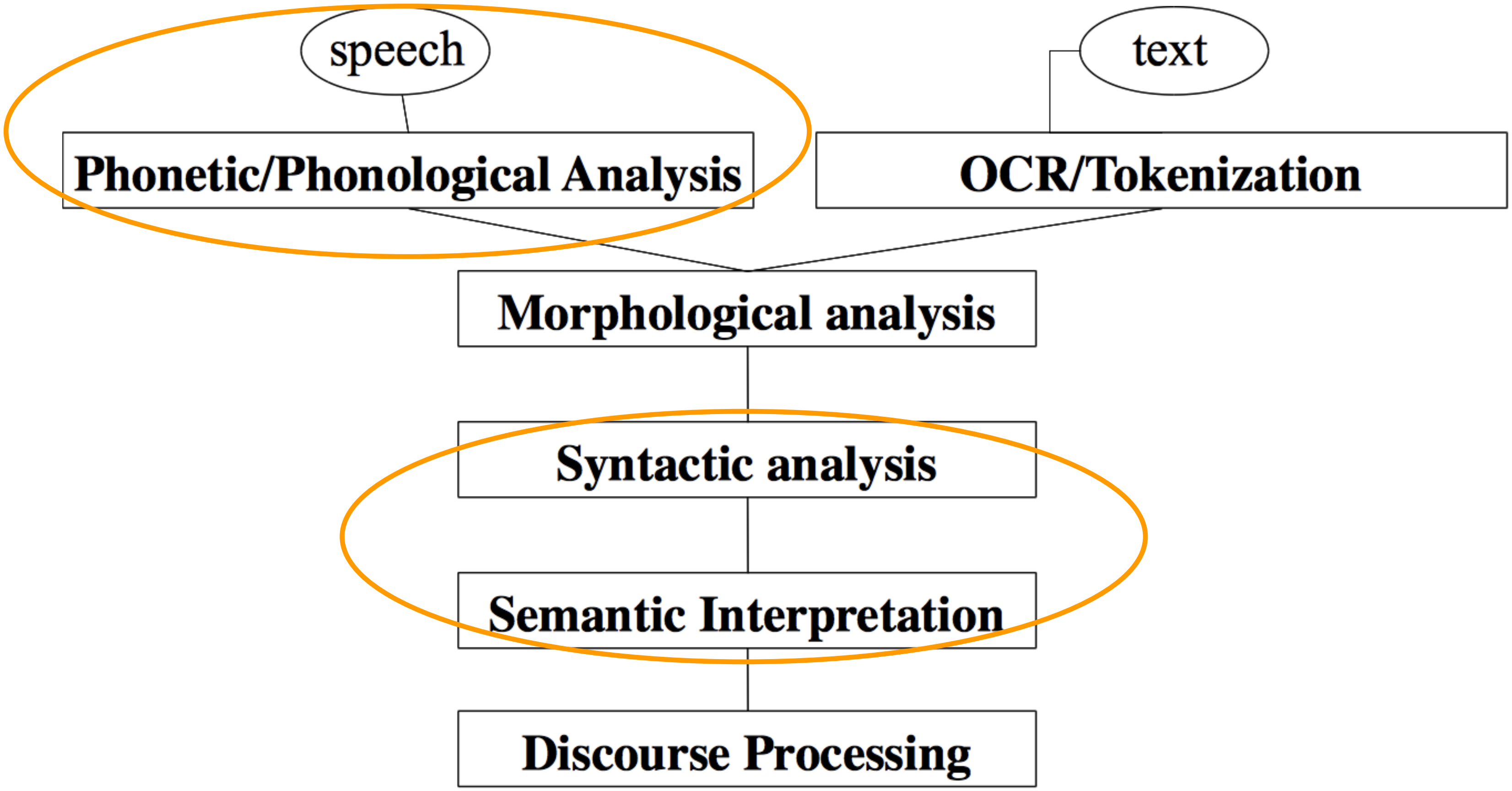
- Basic Probability and Statistics (e.g. CS 109 or other stats course)

- Equivalent knowledge of CS229 (Machine Learning)
  - cost functions,
  - taking derivatives
  - performing optimization with gradient descent.

What is Natural Language Processing (NLP)?

- Natural language processing is a field at the intersection of
  - computer science
  - artificial intelligence
  - and linguistics.
- Goal: for computers to process or “understand” natural language in order to perform tasks that are useful, e.g.
  - Question Answering
- Fully **understanding and representing** the **meaning** of language (or even defining it) is an illusive goal.
- Perfect language understanding is AI-complete

NLP Levels


speech
text
Phonetic/Phonological Analysis
OCR/Tokenization
Morphological analysis
Syntactic analysis
Semantic Interpretation
Discourse Processing

(A tiny sample of) NLP Applications

- Applications range from simple to complex:
- Spell checking, keyword search, finding synonyms
- Extracting information from websites such as
  - product price, dates, location, people or company names
- Classifying, reading level of school texts, positive/negative sentiment of longer documents
- Machine translation
- Spoken dialog systems
- Complex question answering

NLP in Industry

- Search (written and spoken)
- Online advertisement
- Automated/assisted translation
- Sentiment analysis for marketing or finance/trading
- Speech recognition


3/18/11 at 4:00 PM | 17 Comments

Mentions of the Name 'Anne Hathaway' May Drive Berkshire Hathaway Stock

By Patrick Huguenin

The Huffington Post recently pointed

Why is NLP hard?

- Complexity in representing, learning and using linguistic/situational/world/visual knowledge

- Jane hit June and then **she** [fell/ran].

- Ambiguity: “I made her duck”

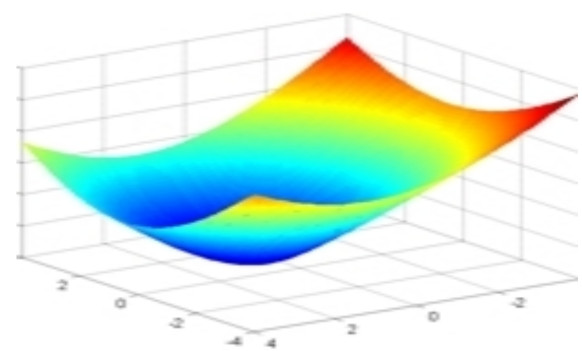
What's Deep Learning (DL)?

- Deep learning is a subfield of machine learning

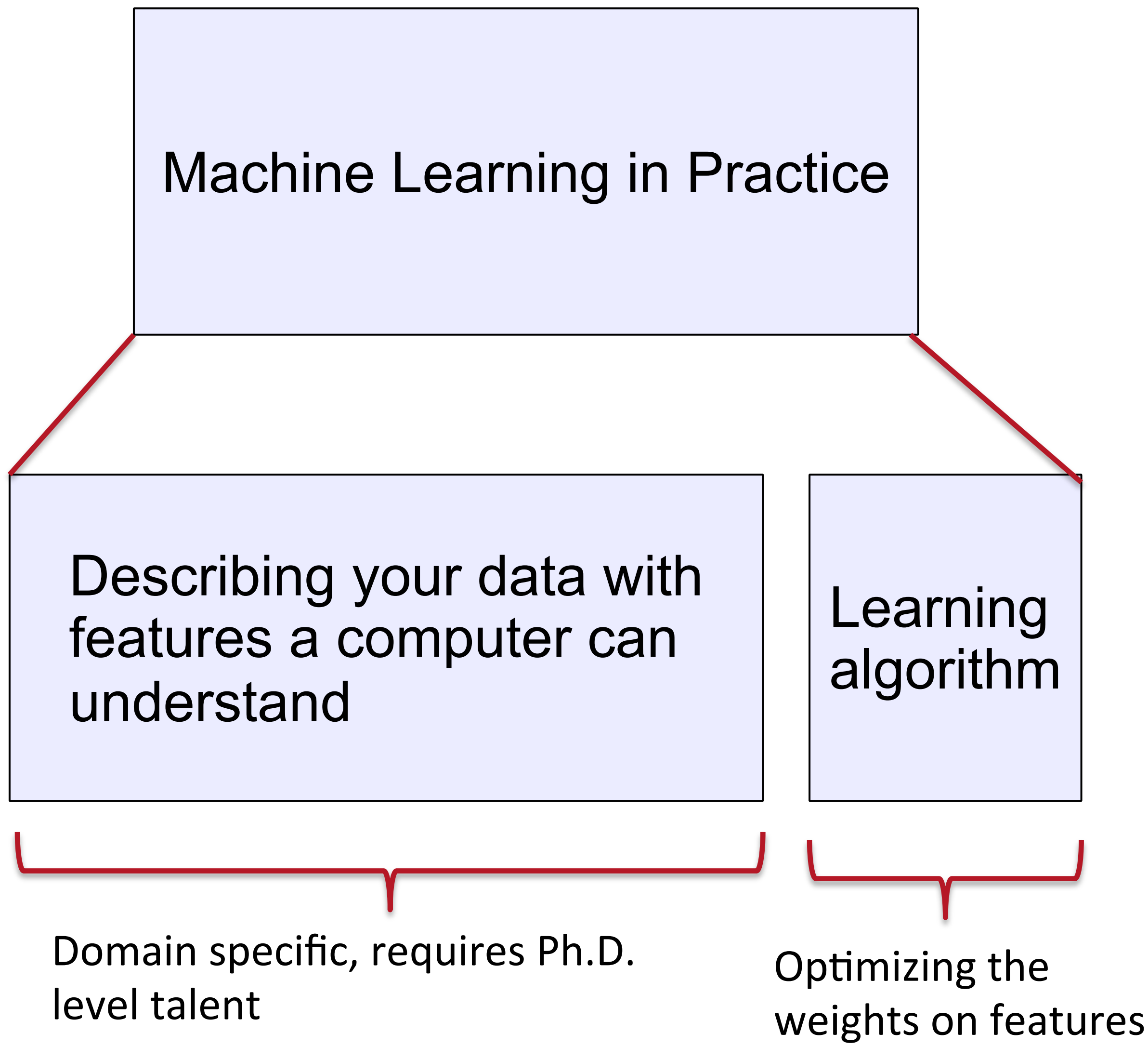
- Most machine learning methods work well because of human-designed representations and input features
  - For example: features for finding named entities like locations or organization names (Finkel, 2010):

Feature	NER
Current Word	✓
Previous Word	✓
Next Word	✓
Current Word Character n-gram	all
Current POS Tag	✓
Surrounding POS Tag Sequence	✓
Current Word Shape	✓
Surrounding Word Shape Sequence	✓
Presence of Word in Left Window	size 4
Presence of Word in Right Window	size 4

- Machine learning becomes just optimizing weights to best make a final prediction

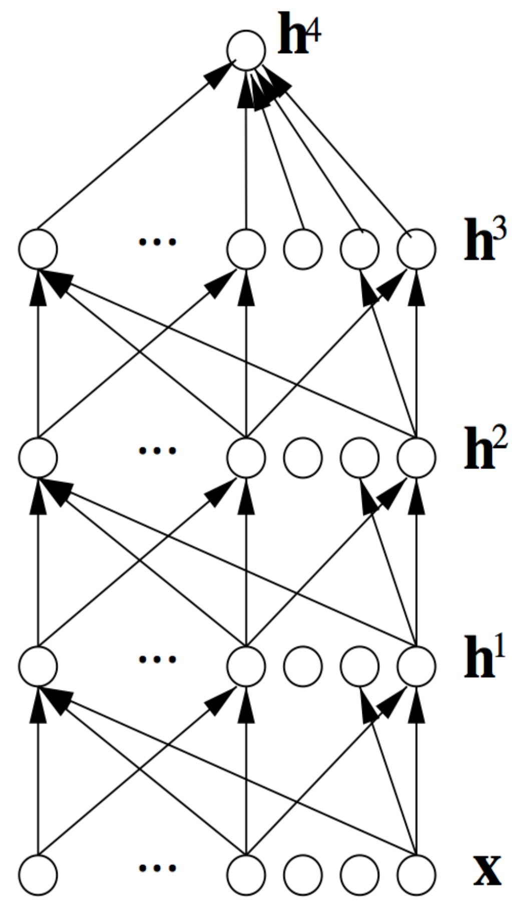


Machine Learning vs Deep Learning



What's Deep Learning (DL)?

- Representation learning attempts to automatically learn good features or representations
- Deep learning algorithms attempt to learn (multiple levels of) representation and an output
- From "raw" inputs **x** (e.g. words)



On the history and term of "Deep Learning"

- We will focus on different kinds of **neural networks**
- The dominant model family inside deep learning

- Only clever terminology for stacked logistic regression units?
  - Somewhat, but interesting modeling principles and actual connections to neuroscience in some cases

- We will not take a historical approach but instead focus on methods which work well on NLP problems now
- For history of deep learning models (starting ~1960s), see: Deep Learning in Neural Networks: An Overview by Schmidhuber

Reasons for Exploring Deep Learning

- Manually designed features are often over-specified, incomplete and take a long time to design and validate
- **Learned Features** are easy to adapt, fast to learn

- Deep learning provides a very flexible, (almost?) universal, learnable framework for **representing** world, visual and linguistic information.

- Deep learning can learn **unsupervised** (from raw text) and **supervised** (with specific labels like positive/negative)

Reasons for Exploring Deep Learning

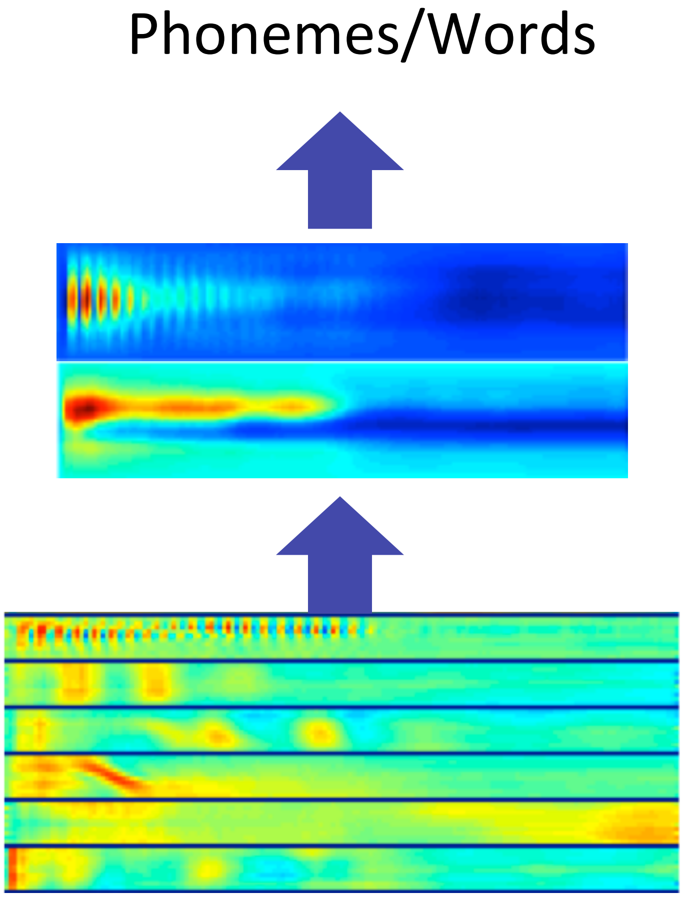
- In 2006 **deep** learning techniques started outperforming other machine learning techniques. Why now?

- DL techniques benefit more from a lot of data
- Faster machines and multicore CPU/GPU help DL
- New models, algorithms, ideas

→ **Improved performance** (first in speech and vision, then NLP)

Deep Learning for Speech

- The first breakthrough results of "deep learning" on large datasets happened in speech recognition
- Context-Dependent Pre-trained Deep Neural Networks for Large Vocabulary Speech Recognition Dahl et al. (2010)



Acoustic model	**Recog \ WER**	**RT03S FSH**	**Hub5 SWB**
Traditional features	1-pass −adapt	**27.4**	**23.6**
Deep Learning	1-pass −adapt	**18.5** (−33%)	**16.1** (−32%)

Deep Learning for Computer Vision

- Most deep learning groups have (until recently) largely focused on computer vision
- Break through paper: ImageNet Classification with Deep Convolutional Neural Networks by Krizhevsky et al. 2012

Zeiler and Fergus (2013)

Deep Learning + NLP = Deep NLP

- Combine ideas and goals of NLP and use representation learning and deep learning methods to solve them

- Several big improvements in recent years across different NLP
  - **levels**: speech, morphology, syntax, semantics
  - **applications**: machine translation, sentiment analysis and question answering

Representations at NLP Levels: Phonology

- Traditional: Phonemes

CONSONANTS (PULMONIC) © 2005 IPA

	Bilabial	Labiodental	Dental	Alveolar	Post alveolar	Retroflex	Palatal	Velar	Uvular	Pharyngeal	Glottal
Plosive	p b			t d		ʈ ɖ	c ɟ	k g	q ɢ		ʔ
Nasal	m	ɱ		n		ɳ	ɲ	ŋ	ɴ		
Trill	ʙ			r					ʀ		
Tap or Flap		ⱱ		ɾ		ɽ					
Fricative	ɸ β	f v	θ ð	s z	ʃ ʒ	ʂ ʐ	ç ʝ	x ɣ	χ ʁ	ħ ʕ	h ɦ
Lateral fricative				ɬ ɮ							
Approximant		ʋ		ɹ		ɻ	j	ɰ			
Lateral approximant				l		ɭ	ʎ	ʟ			

Where symbols appear in pairs, the one to the right represents a voiced consonant. Shaded areas denote articulations judged impossible.

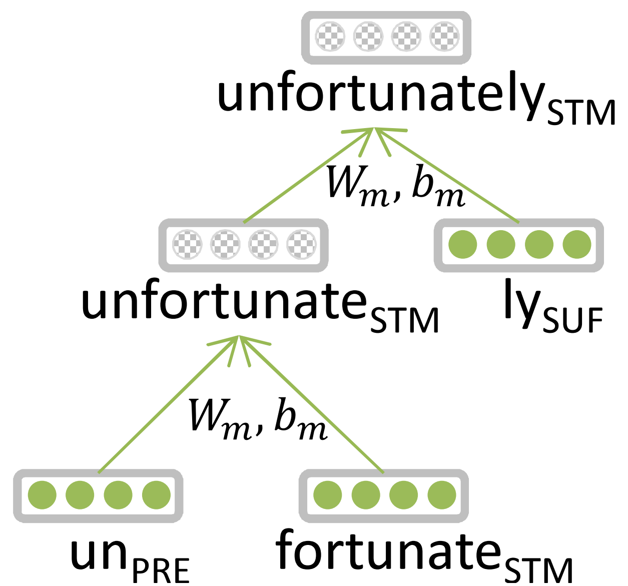
- DL: trains to predict phonemes (or words directly) from sound features and represent them as **vectors**

Representations at NLP Levels: Morphology

- Traditional: Morphemes

prefix	stem	suffix
un	interest	ed

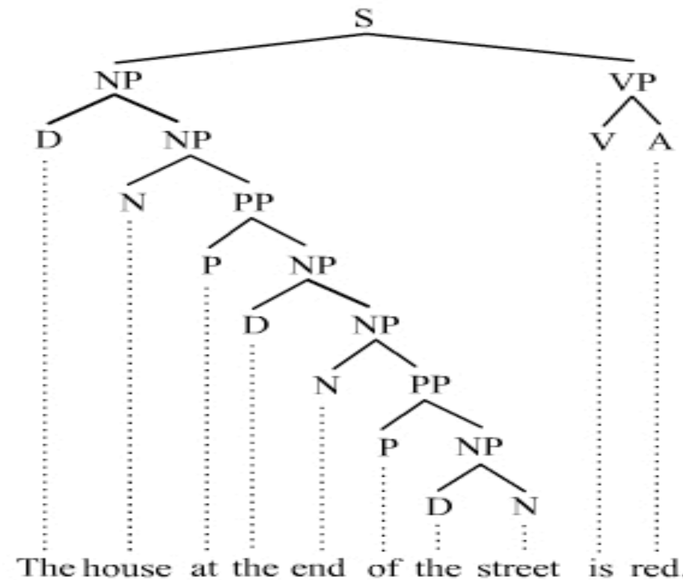
- DL:
  - every morpheme is a vector
  - a neural network combines two vectors into one vector
  - Thang et al. 2013



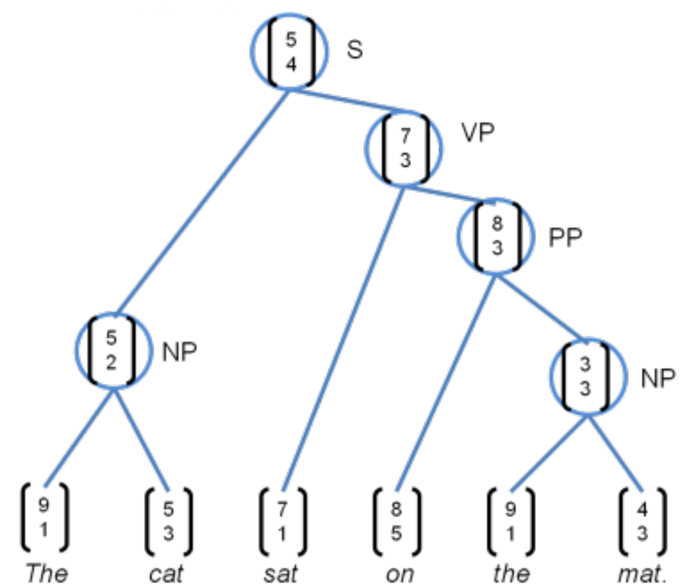
Neural word vectors - visualization

Representations at NLP Levels: Syntax

- Traditional: Phrases
  Discrete categories like NP, VP

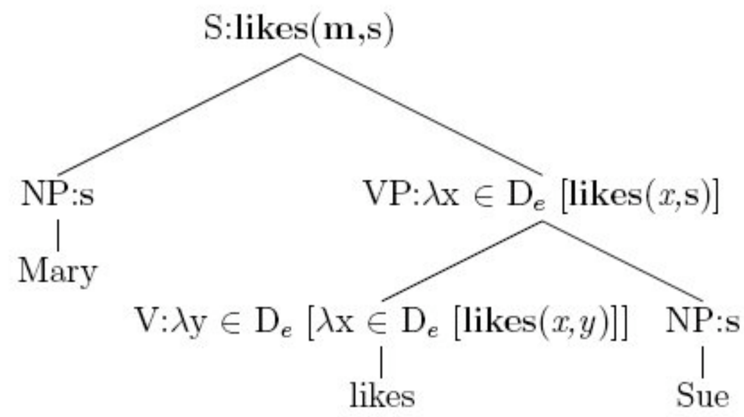


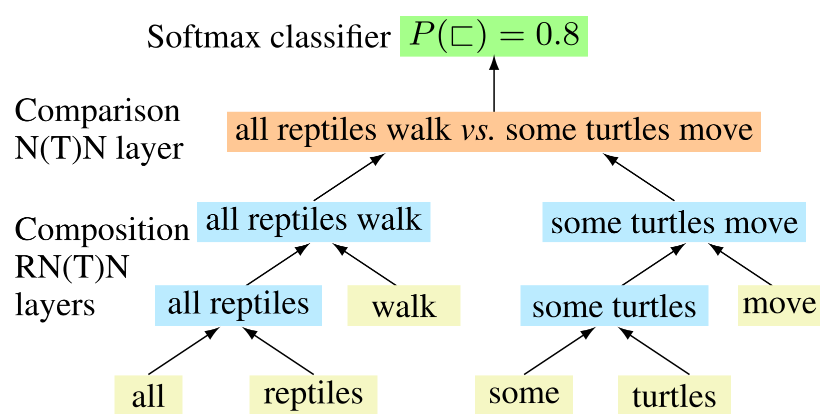
- DL:
  - Every word and every phrase is a vector
  - a neural network combines two vectors into one vector
  - Socher et al. 2011



Representations at NLP Levels: Semantics

- Traditional: Lambda calculus
  - Carefully engineered functions
  - Take as inputs specific other functions
  - No notion of similarity or fuzziness of language
- DL:
  - Every word and every phrase and every logical expression is a vector
  - a neural network combines two vectors into one vector
  - Bowman et al. 2014

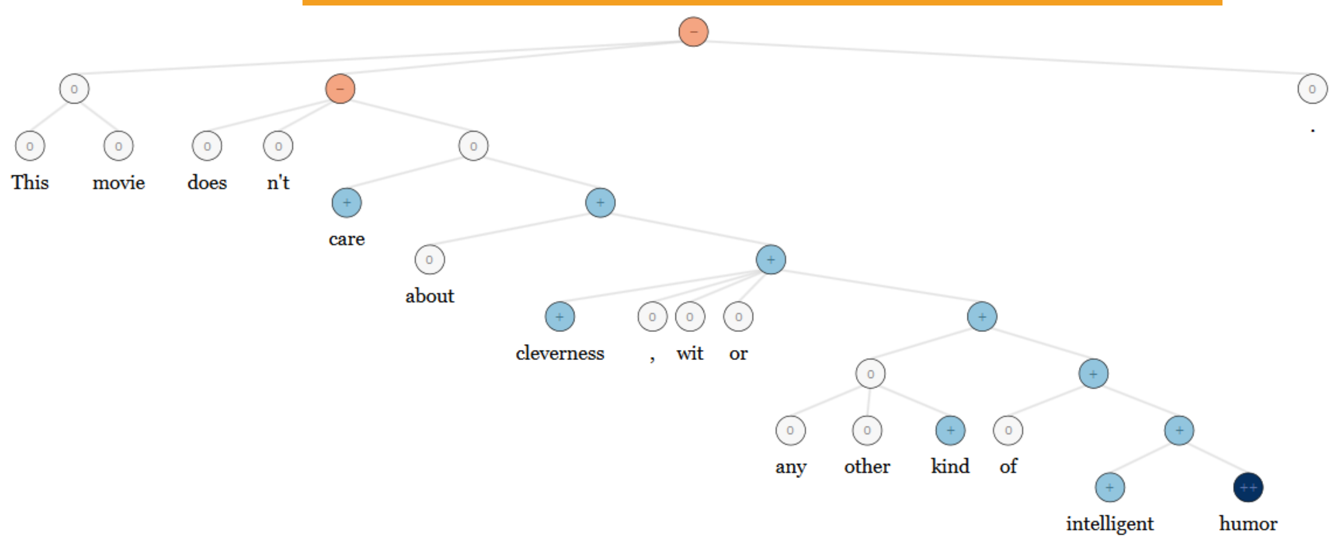




NLP Applications: Sentiment Analysis

- Traditional: Curated sentiment dictionaries combined with either bag-of-words representations (ignoring word order) or hand-designed negation features (ain't gonna capture everything)
- Same deep learning model that was used for morphology, syntax and logical semantics can be used! → RNN

- Demo time: http://nlp.stanford.edu/sentiment/



Question Answering

- Common: A lot of feature engineering to capture world and other knowledge, e.g. regular expressions, Berant et al. (2014)

Is main verb trigger?

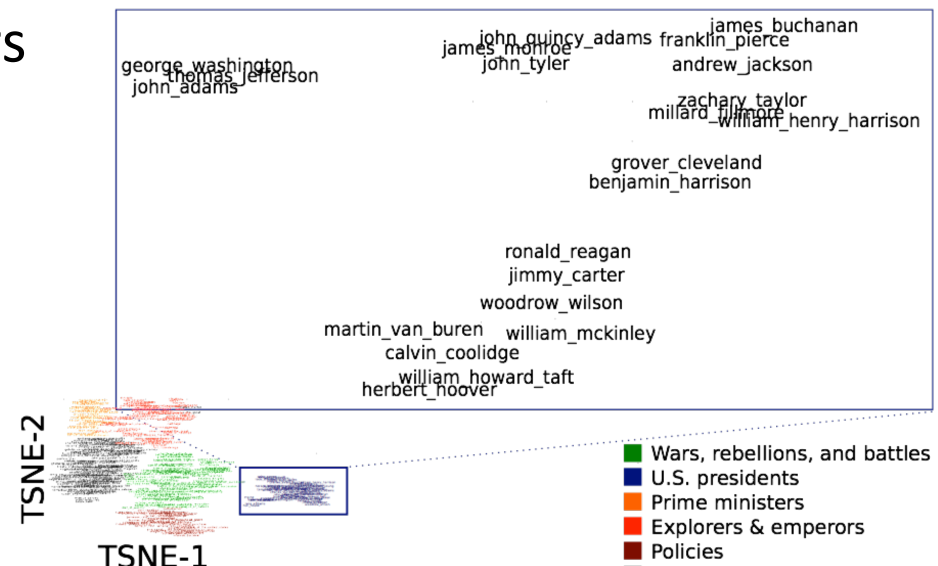
Yes

Condition	Regular Exp.
Wh- word subjective?	AGENT
Wh- word object?	THEME

No

Condition	Regular Exp.
default	$(\text{ENABLE}\|\text{SUPER})^{+}$
DIRECT	(ENABLE|SUPER)
PREVENT	$(\text{ENABLE}\|\text{SUPER})^{*}\text{PREVENT}(\text{ENABLE}\|\text{SUPER})^{*}$

- DL: Same deep learning model that was used for morphology, syntax, logical semantics and sentiment can be used!
- Facts are stored in vectors



Machine Translation

- Many levels of translation have been tried in the past:

- Traditional MT systems are very large complex systems

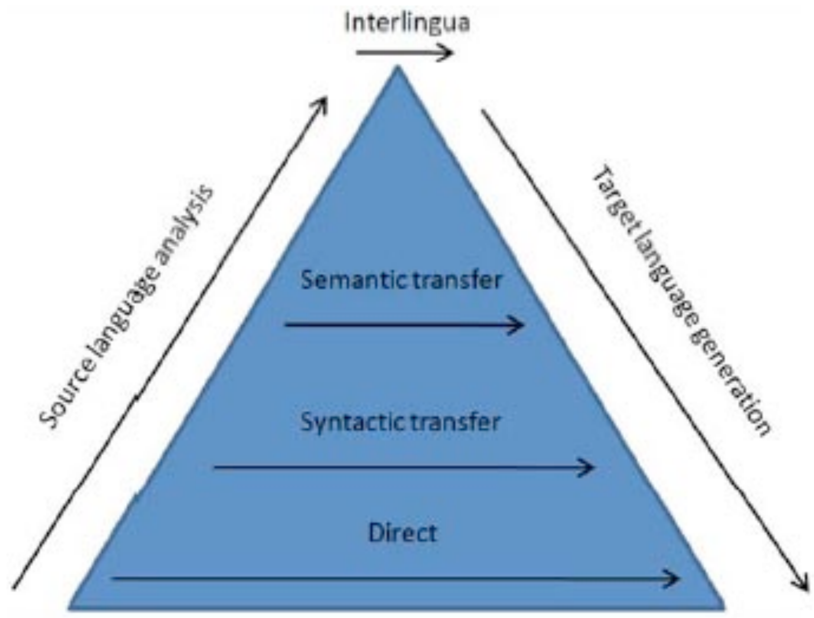


Figure 1: The Vauquois triangle

- What do you think is the interlingua for the DL approach to translation?

Machine Translation

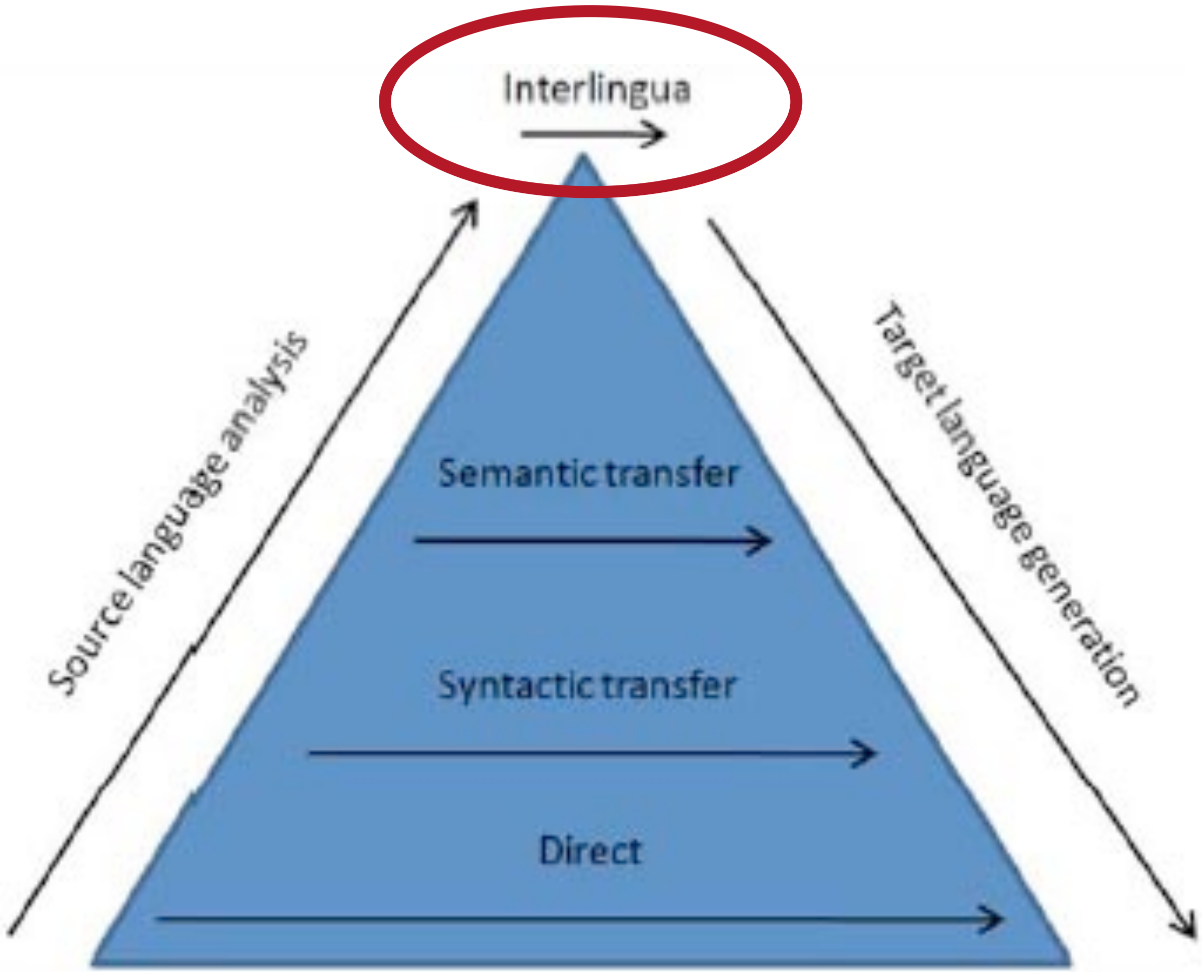
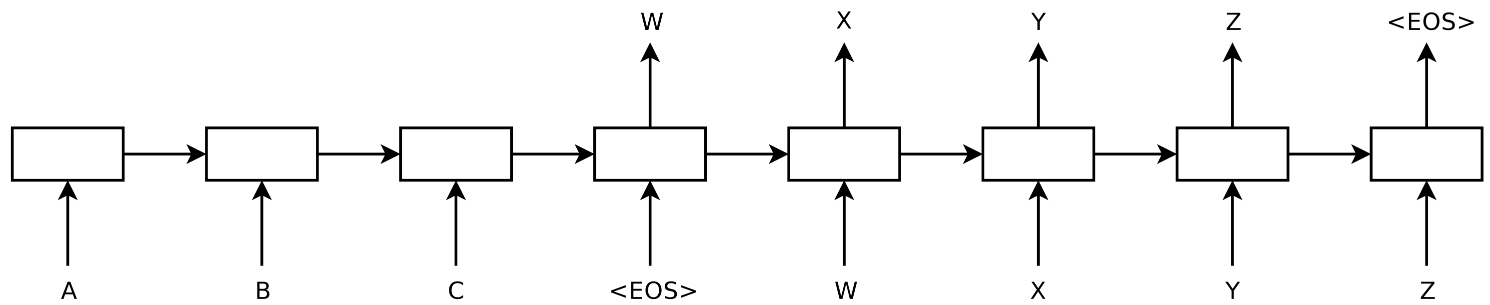


Figure 1: The Vauquois triangle

Machine Translation

- Source sentence mapped to vector, then output sentence generated.

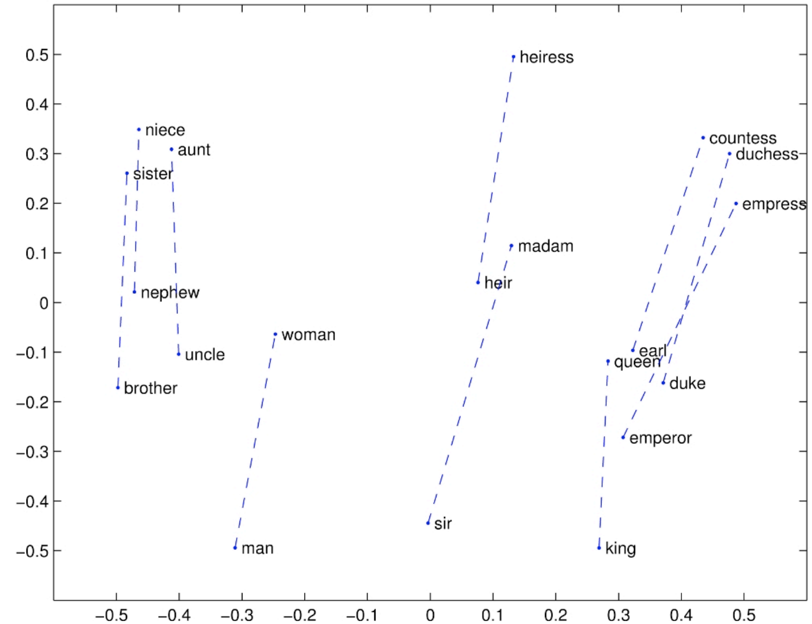


- Sequence to Sequence Learning with Neural Networks by Sutskever et al. 2014

- Very new but could replace very complex architectures!

Representation for all levels: Vectors

- We will learn in the next lecture how we can learn vector representations for words and what they actually **represent.**



- Next week: neural networks and how they can use these vectors for all NLP levels and many different applications