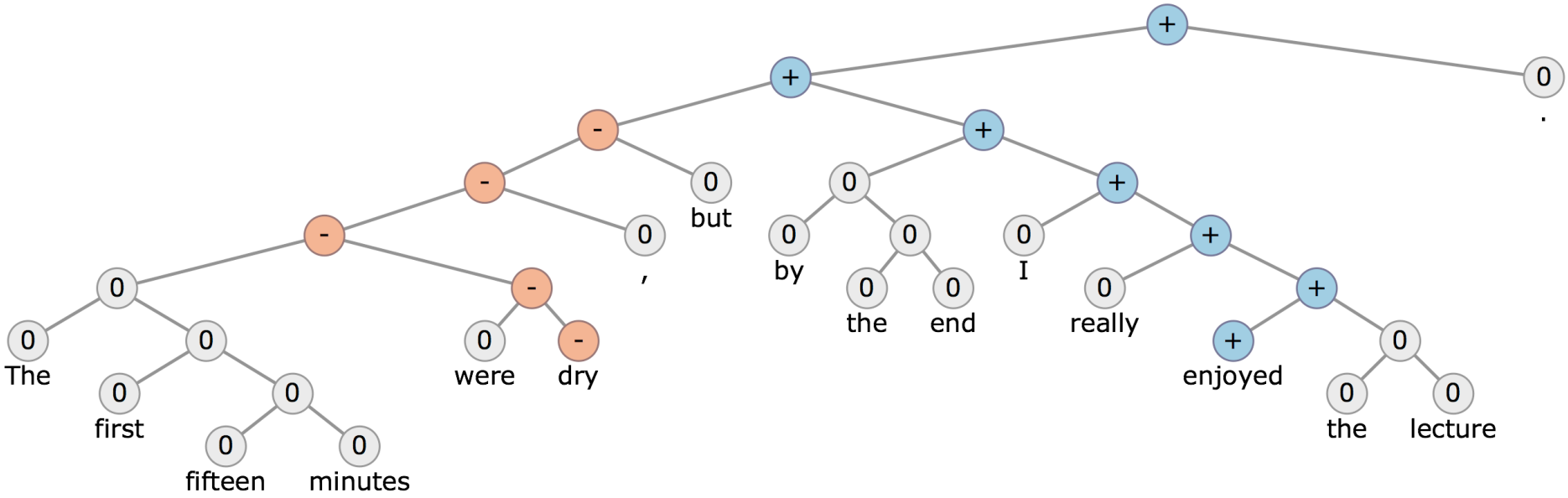
CS224d
Deep Learning
for Natural Language Processing

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/CEO at MetaMind)
- TAs: James Hong, Bharath Ramsundar, Sameep Bagadia, David Dindi, ++

- Time: Tuesday, Thursday 3:00-4:20
- Location: Gates B1

- There will be 3 problem sets (with lots of programming), a midterm and a final project
- For syllabus and office hours, see http://cs224d.stanford.edu/
- Slides uploaded before each lecture, video + lecture notes after

Pre-requisites

- Proficiency in Python
  - All class assignments will be in Python. 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 simple derivatives
  - performing optimization with gradient descent.

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!)
  - Attend at least 1 project advice office hour: 2%
  - Final write-up, project and presentation: 33%
  - 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'

High Level Plan for Problem Sets

- The first half of the course and the first 2 PSets will be hard

- PSet 1 is in pure python code (numpy etc.) to really understand the basics
- Released on April 4th

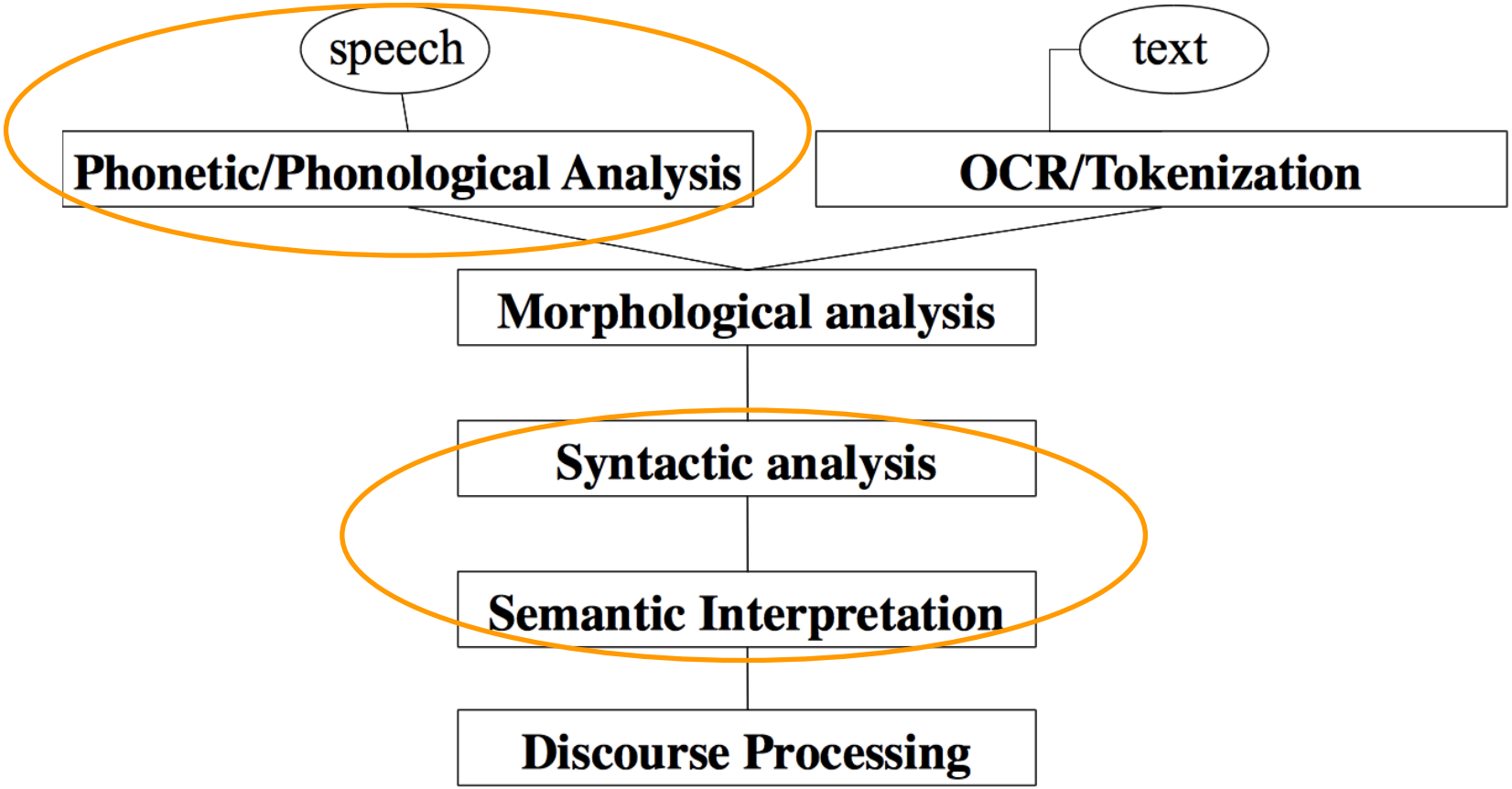
- New: PSets 2 & 3 will be in TensorFlow, a library for putting together new neural network models quickly (→ special lecture)
- PSet 3 will be shorter to increase time for final project

- Libraries like TensorFlow (or Torch) are becoming standard tools
- But still some problems

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
- Automating customer support

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”

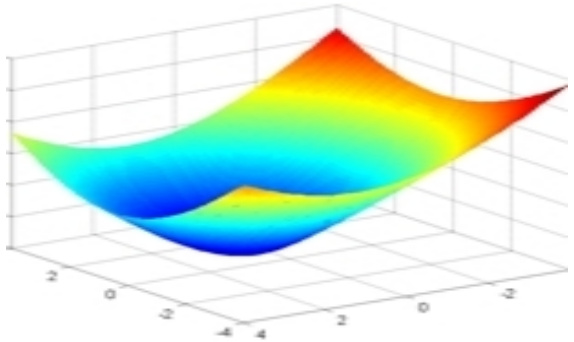
What's Deep Learning (DL)?

- Deep learning is a subfield of machine learning

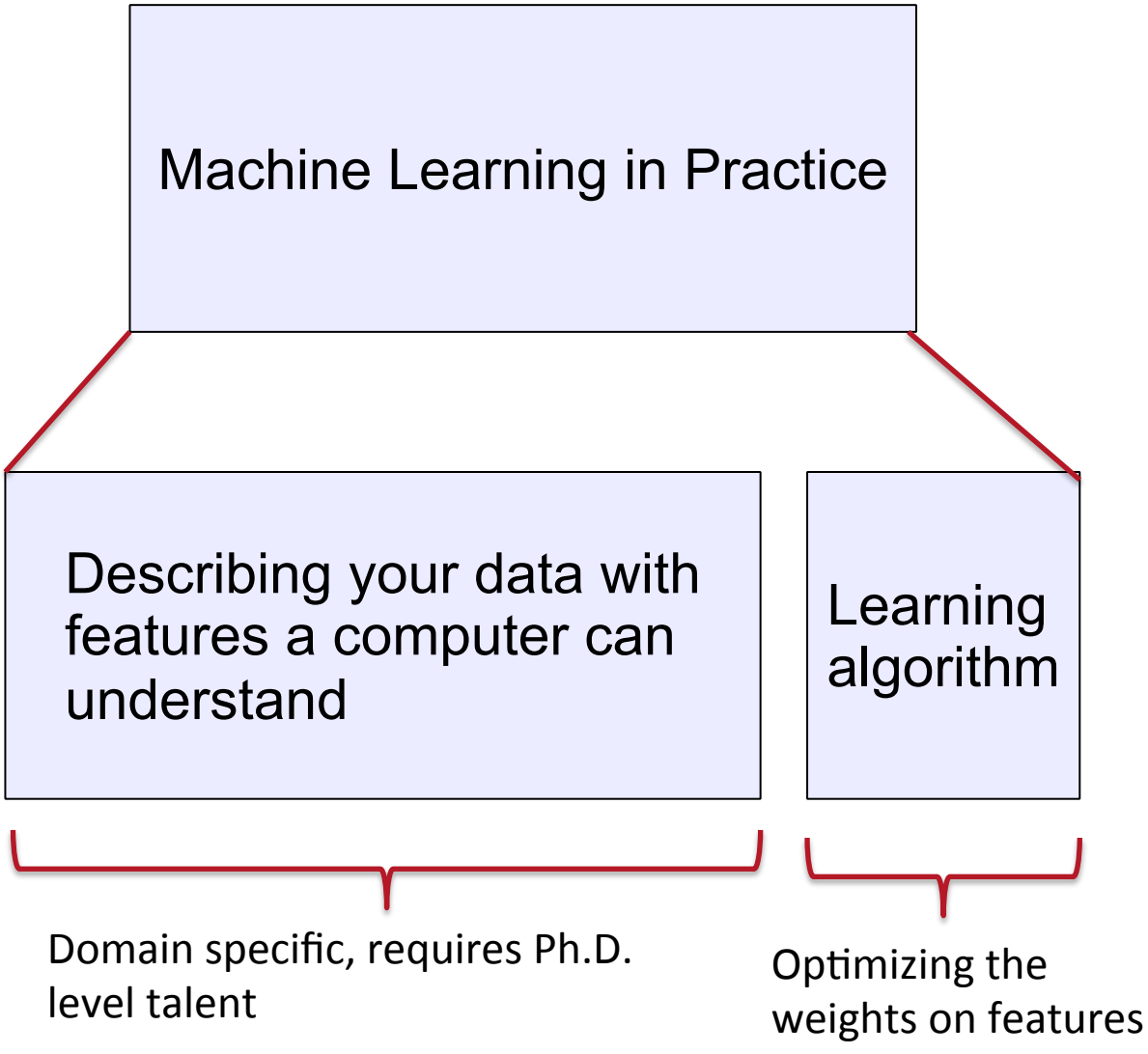
- Most machine learning methods work well because of human-designed representations and input features
  - For example: features for finding named entities like locations or organization names (Finkel, 2010):

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

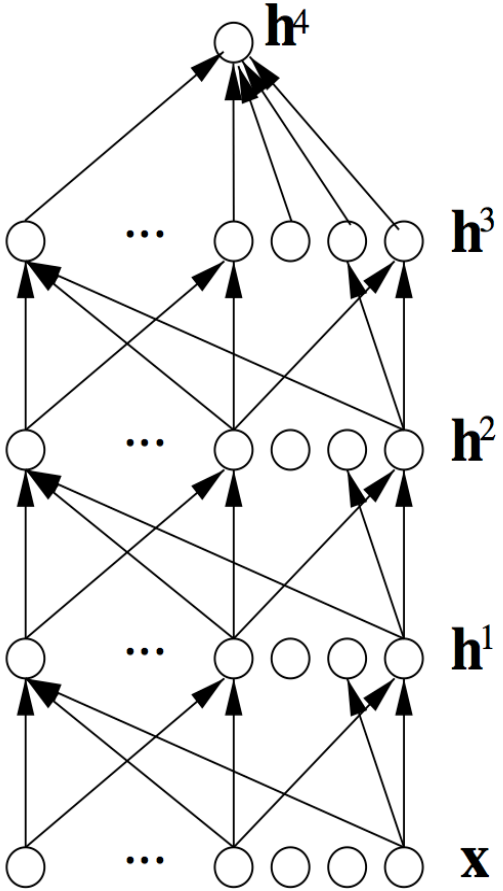


What's Deep Learning (DL)?

- 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 (end-to-end) 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

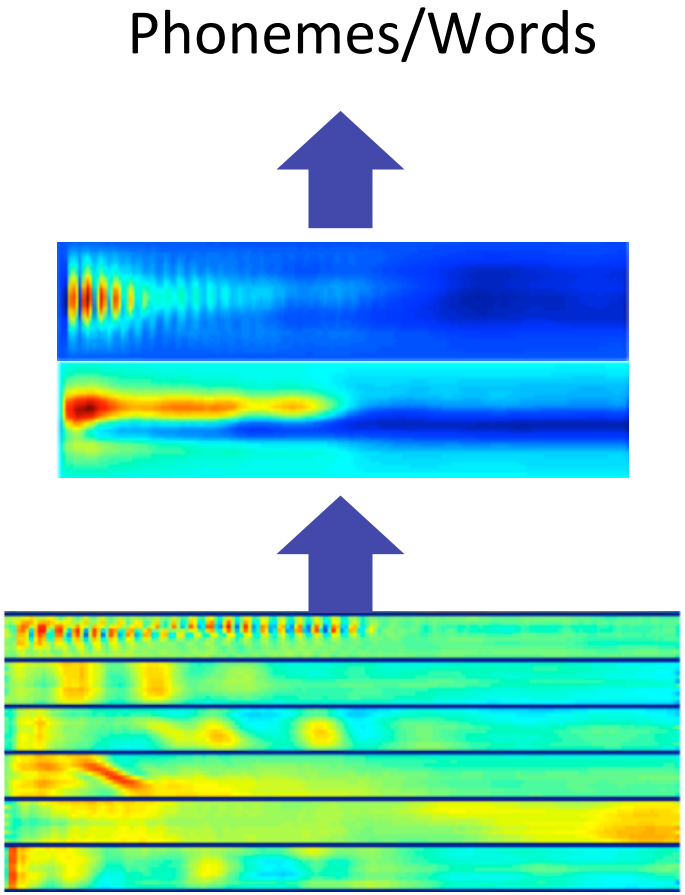
- In 2006 **deep** learning techniques started outperforming other machine learning techniques. Why now?

- 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

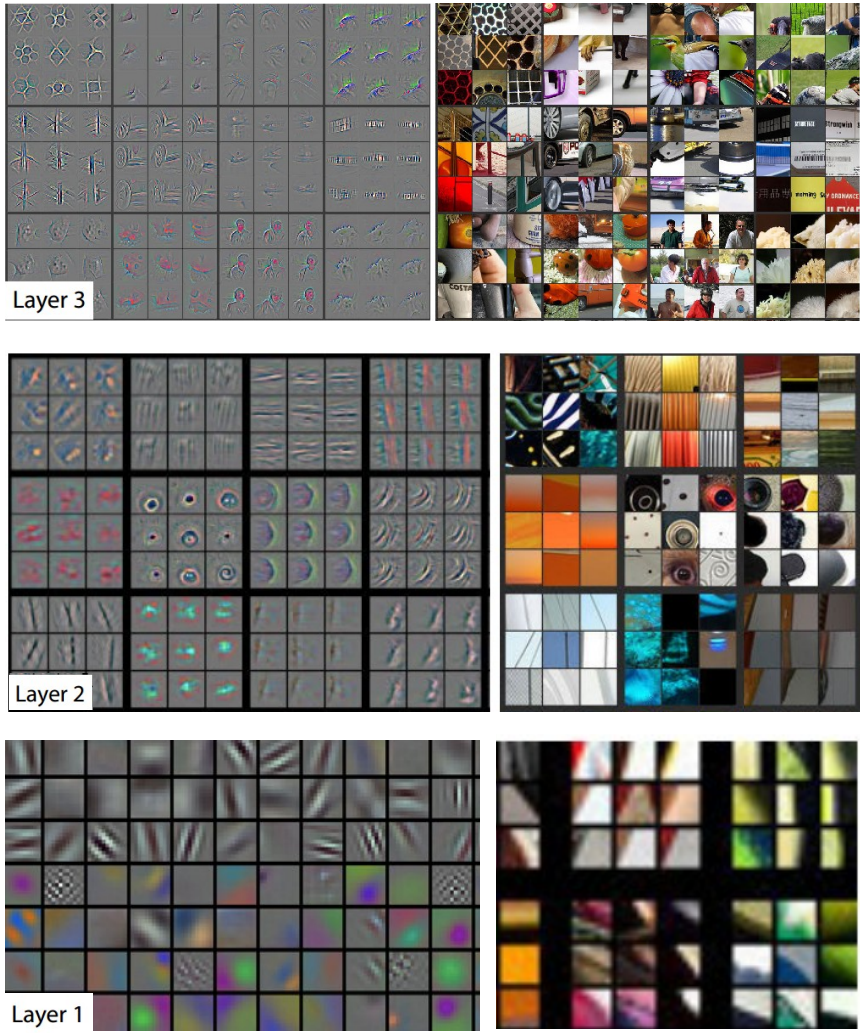
- The first breakthrough results of "deep learning" on large datasets happened in speech recognition
- Context-Dependent Pre-trained Deep Neural Networks for Large Vocabulary Speech Recognition Dahl et al. (2010)



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 2 years ago) 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	Postalveolar	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.

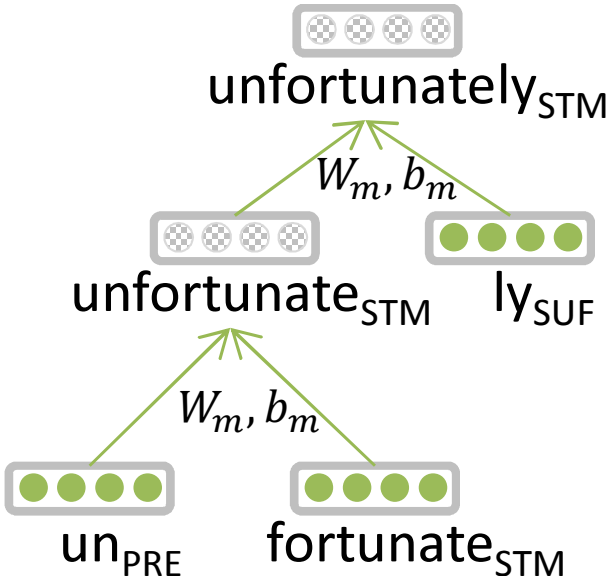
- DL: trains to predict phonemes (or words directly) from sound features and represent them as **vectors**

Representations at NLP Levels: Morphology

- Traditional: Morphemes

prefix	stem	suffix
un	interest	ed

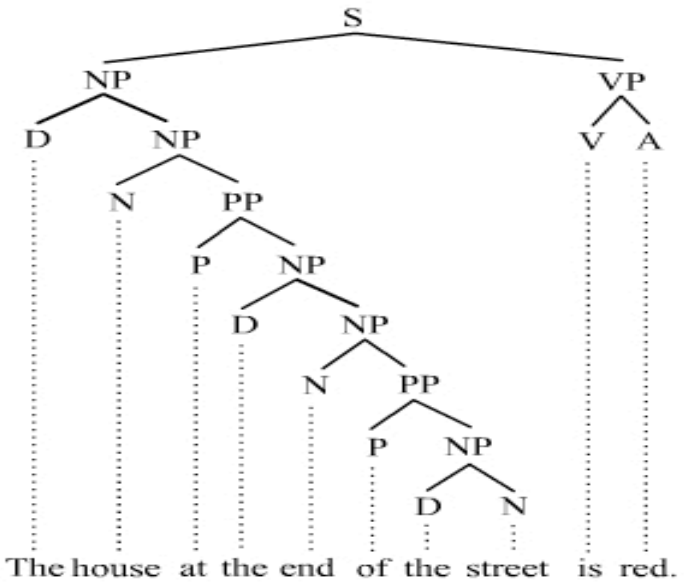
- DL:
  - every morpheme is a vector
  - a neural network combines two vectors into one vector
  - Thang et al. 2013



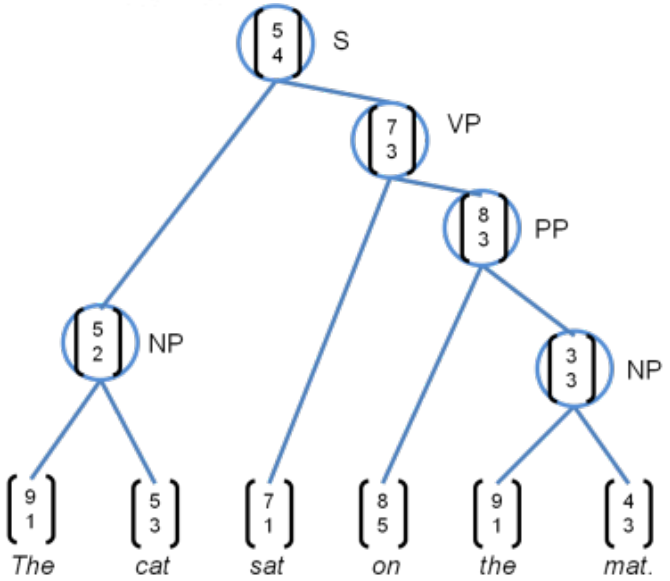
Neural word vectors - visualization

Representations at NLP Levels: Syntax

- Traditional: Phrases
  Discrete categories like NP, VP

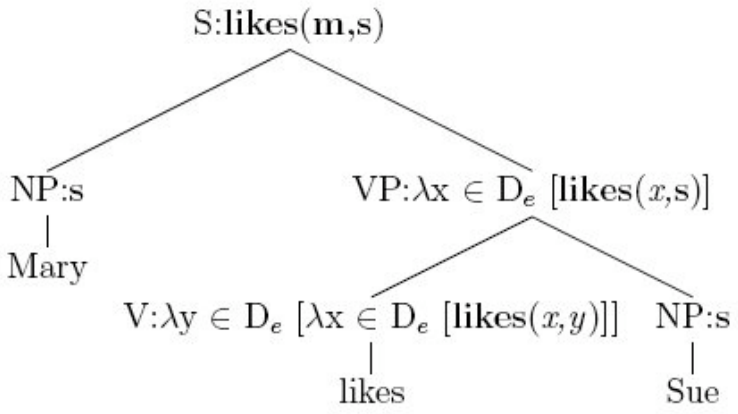


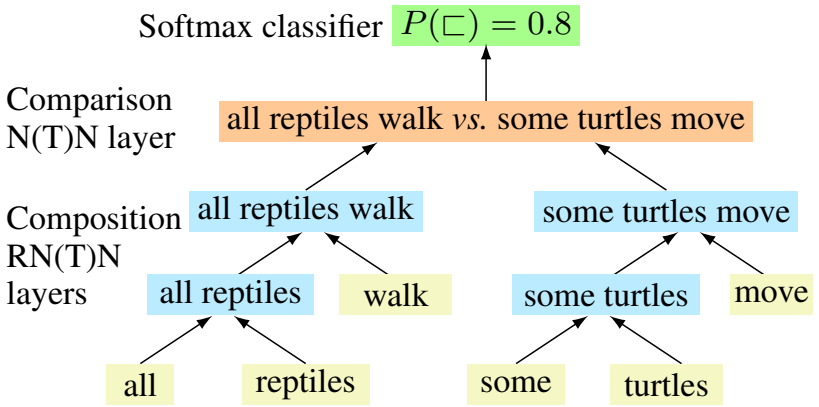
- DL:
  - Every word and every phrase is a vector
  - a neural network combines two vectors into one vector
  - Socher et al. 2011



Representations at NLP Levels: Semantics

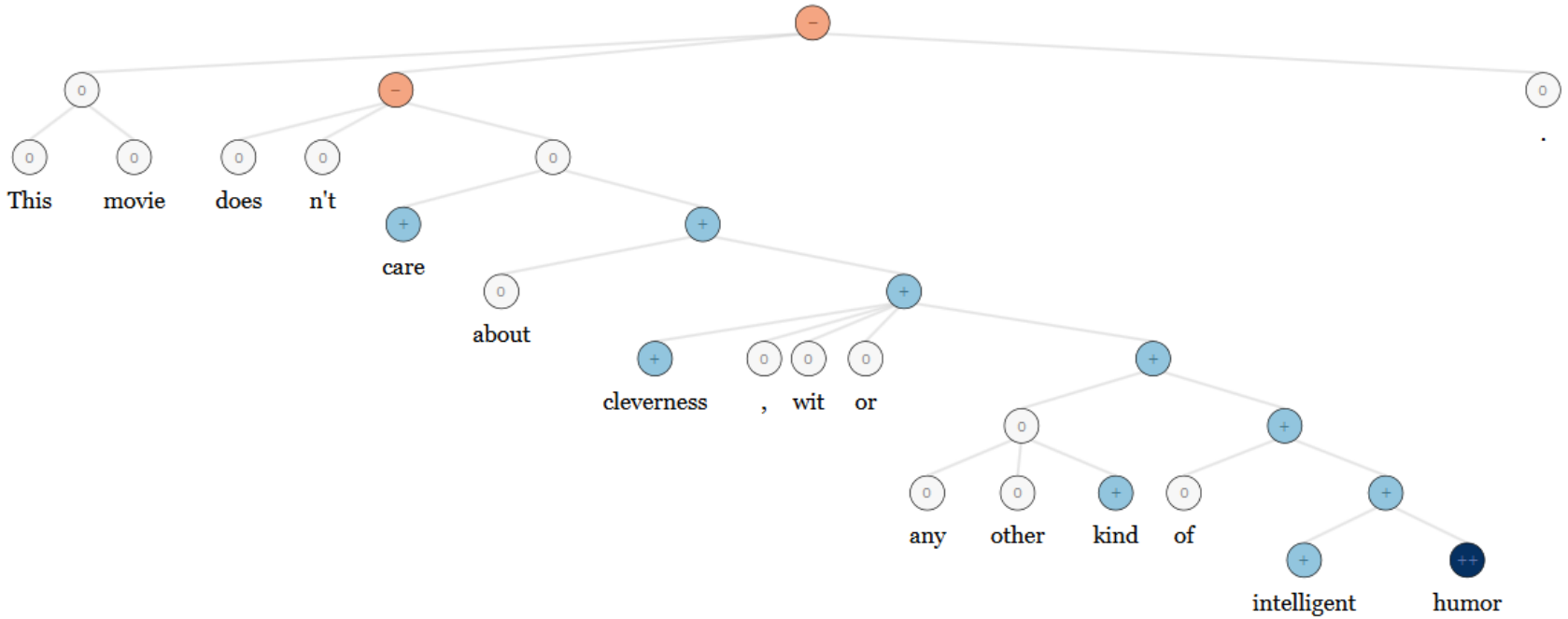
- Traditional: Lambda calculus
  - Carefully engineered functions
  - Take as inputs specific other functions
  - No notion of similarity or fuzziness of language
- DL:
  - Every word and every phrase and every logical expression is a vector
  - a neural network combines two vectors into one vector
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



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?

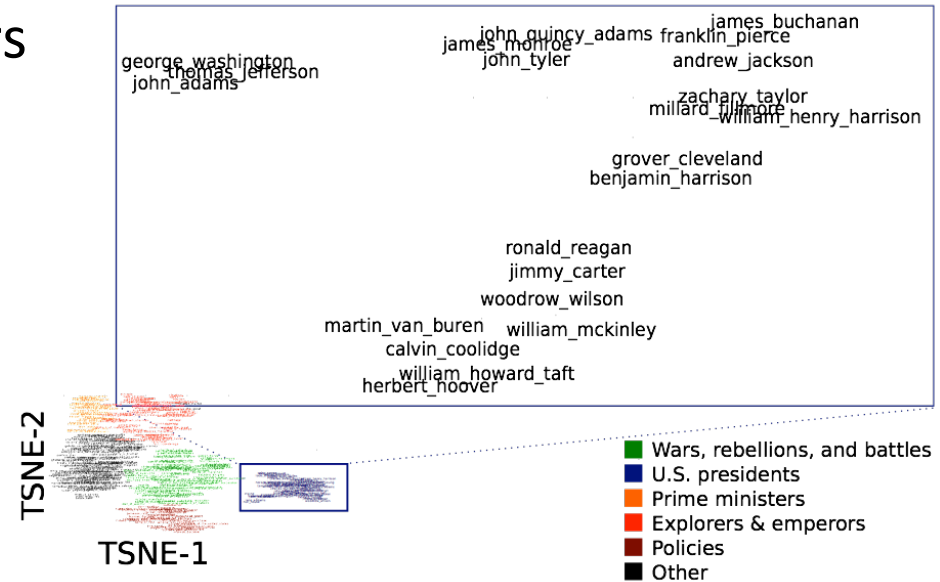
Yes

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

No

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

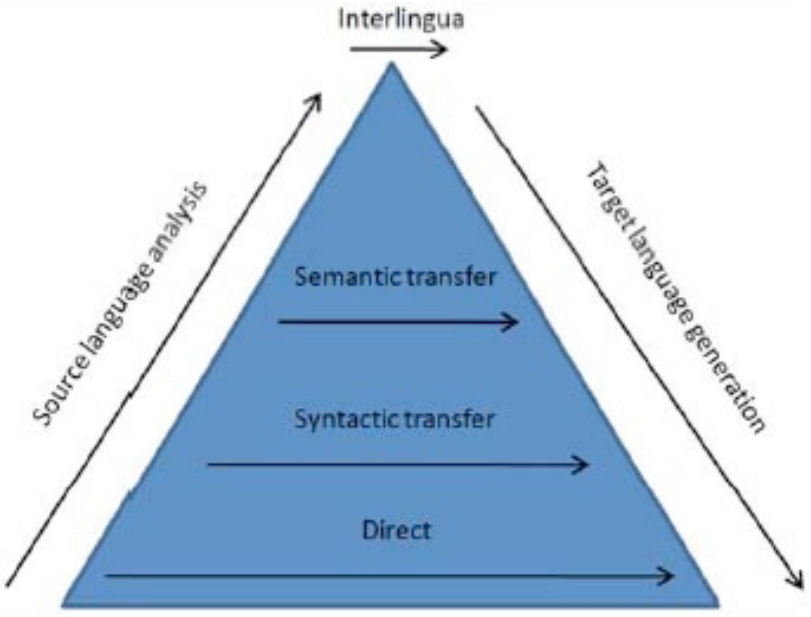


Figure 1: The Vauquois triangle

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

Machine Translation

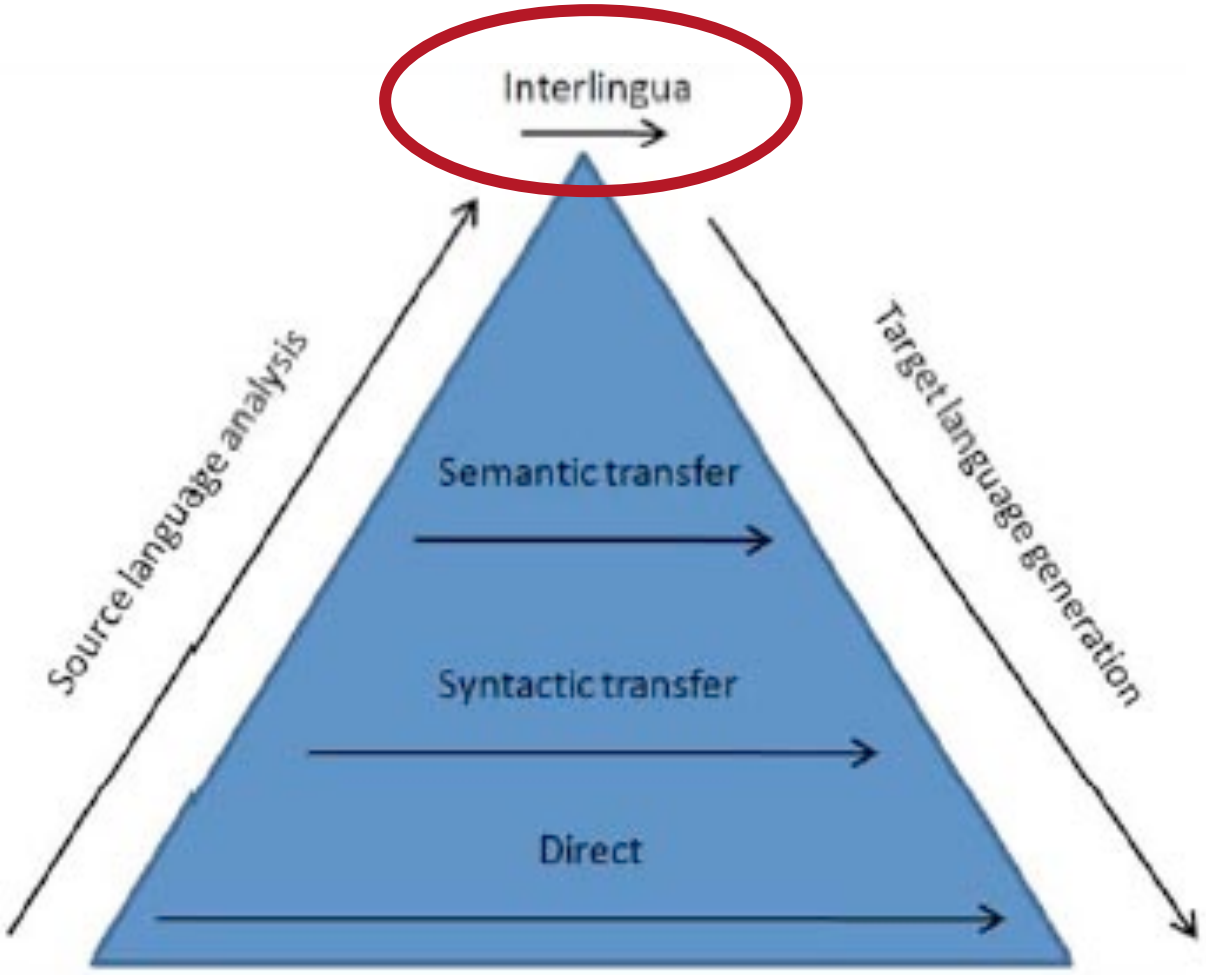
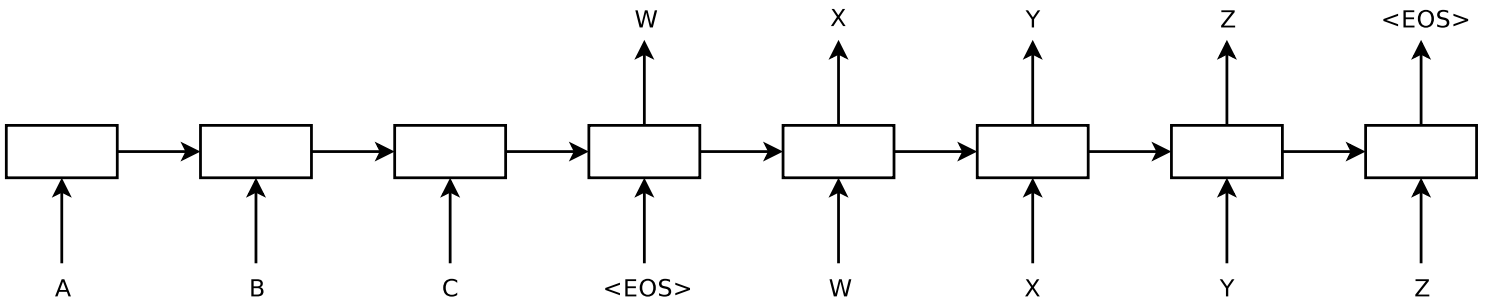


Figure 1: The Vauquois triangle

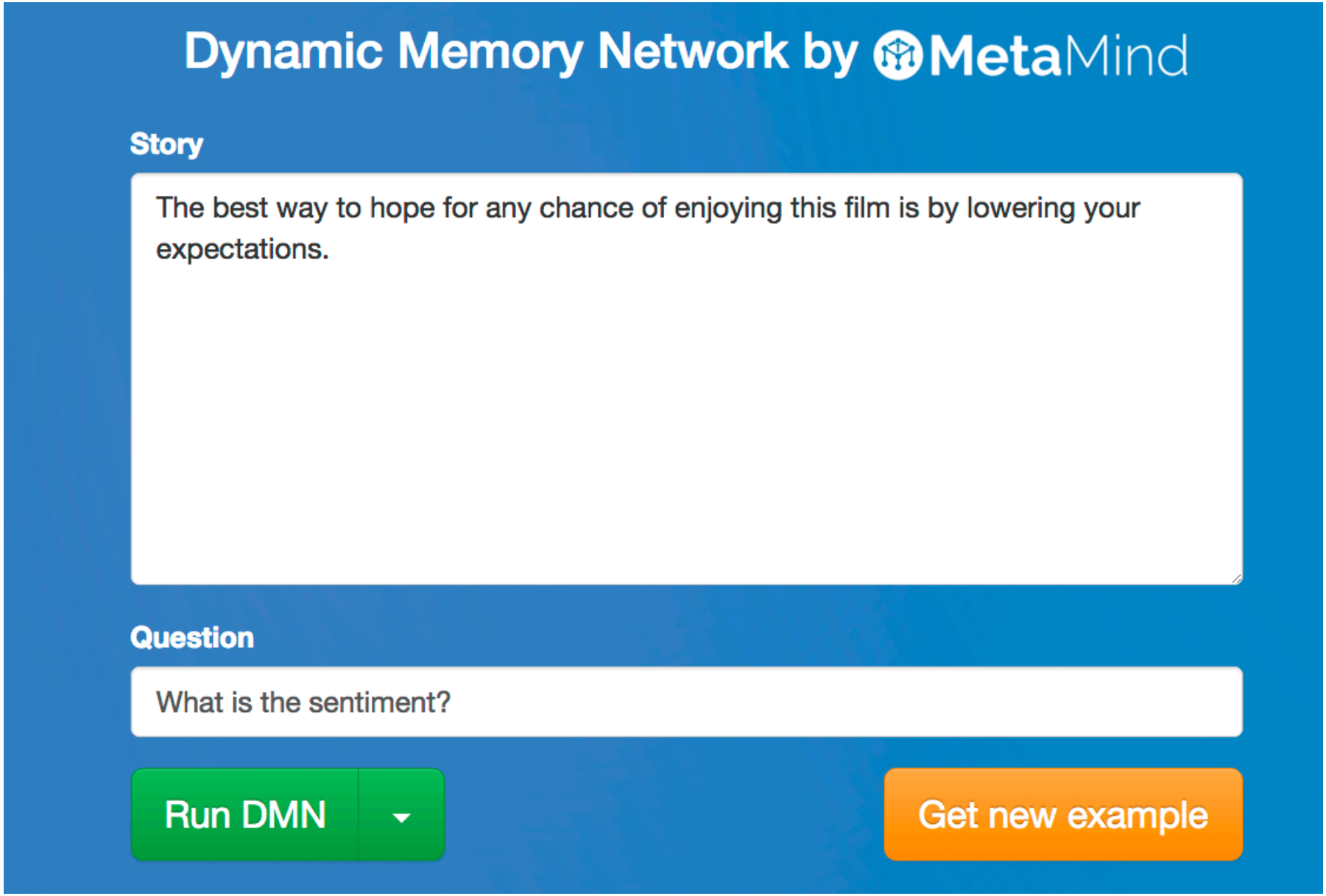
Machine Translation

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



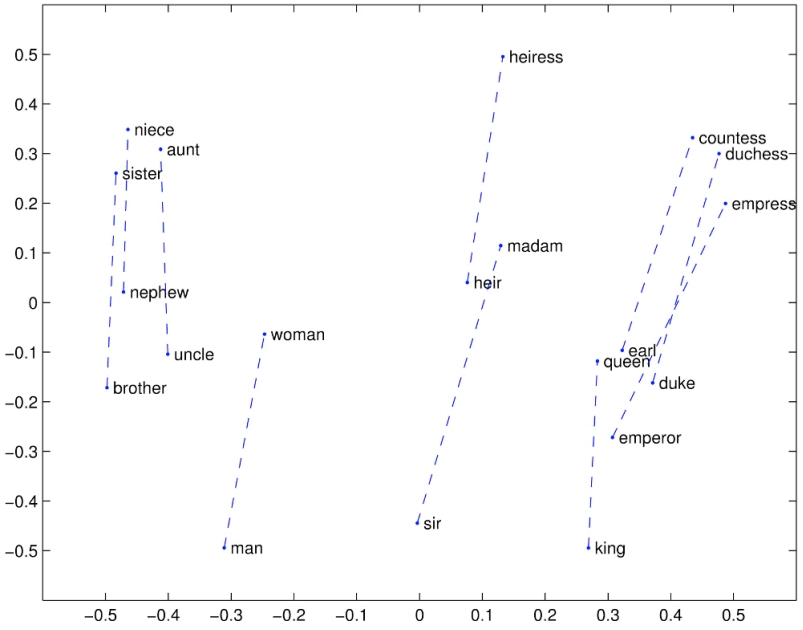
- Sequence to Sequence Learning with Neural Networks by Sutskever et al. 2014; Luong et al. 2016

- About to replace very complex hand engineered architectures


Dynamic Memory Network by MetaMind
Story
The best way to hope for any chance of enjoying this film is by lowering your expectations.
Question
What is the sentiment?
Run DMN
Get new example

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