Advanced Topics in Computational Semantics

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ILLC
University of Amsterdam

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Taught by...


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Lecture 1: Introduction

- Overview of the course
- Semantics in wider NLP
- Statistical semantics and representation learning
- Word representations
- Sentence representations

Overview of the course

- Focus on language understanding and modelling meaning
  - Methods for **learning meaning representations** from linguistic data
  - Analysis of meaning representations learnt
  - Applications
- This is a research seminar
  - Focus on recent progress in the field
  - Lectures
  - You will present and critique research papers
  - and conduct a research project

Overview of the topics

Focus on deep learning, joint learning and modularity

- Different neural architectures (e.g. LSTMs, attention, transformers)
- Language models: BERT, GPT and recent LLMs
- Modularity: subnetworks, adapters etc.
- Multilingual joint learning
- Learning from multiple modalities (language and vision)
- Instruction-tuning and in-context learning
- LLM alignment

Interdisciplinary topics and applications

- Interpretability of deep learning models

- Cross-cultural NLP

- Social bias and stereotypes in NLP models

Assessment

- Presentation and participation (25%)
  - Present 1 paper in class
  - Read and discuss other papers
- Practical assignment (25%)
  1. Implement a model of sentence meaning
  2. Evaluate it in a set of NLP tasks
  3. **Mini-report submission deadline**: 19 April 2024
- Research project (50%)

No exam!

More information at the first lab session on Wednesday, 3 April.

Research project

- Goal: Investigate a **new research question**
  - Apply the models discussed in the course
  - Perform experiments and analyse results
  - Write a research paper
  - Present the results at the poster session (24 May)
- Organisation
  - Work in groups of 5
  - We will propose projects on several topics – you choose
  - **Deadline**: 27 May 2024

It gets even better...

Best Poster Award

Also note:

Course materials and more info:
`https://cl-illc.github.io/semantics-2024`

Slack for discussions: `see the sign up link on Canvas`

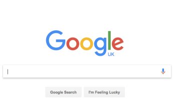
Contact

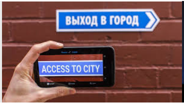
- Assignments: Alina, Vera, Alberto and Sara
- Paper presentations: Katia

Sign up to groups on Canvas by Friday, 5 April.

Natural Language Processing

Many popular applications



...and the emerging ones

Why is NLP difficult?

Similar strings mean different things, different strings mean the same thing.

- Synonymy: different strings can mean the same thing

  The King's speech *gave the much needed reassurance to his people.*
  His majesty's address *reassured the crowds.*

- Ambiguity: same strings can mean different things

  His majesty's address *reassured the crowds.*
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Computational semantics

Computational semantics = Natural language understanding (NLU)

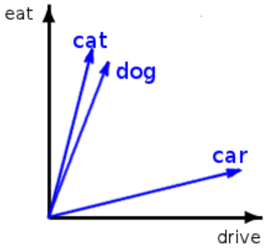
> *an area of NLP concerned with language interpretation and modelling meaning*

1. Lexical semantics: modelling the meaning of words
2. Compositional semantics: modelling the meaning of sentences
3. Discourse processing: modelling larger text passages
4. Pragmatics: modelling meaning in wider situational context (e.g. social meaning)

Statistical semantics

Distributional semantics

- The meaning of a word can be defined by its use
- as a distribution of contexts
- extracted from a text corpus



N: dog
248 bark
197 eat
193 take
110 walk
101 run
...

N: car
493 drive
428 park
317 steal
248 stop
102 break
...

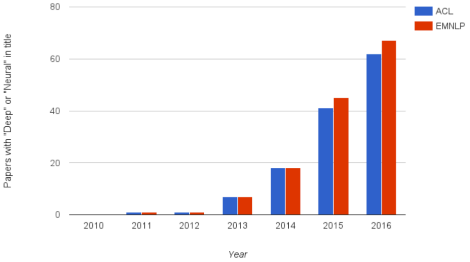
Statistical semantics in pre-deep learning era

- Vector space models (dimensionality reduction, SVD etc.)
- Information theoretic approaches
- Supervised learning with hand-engineered features
  - a range of classifiers (SVM, decision trees etc.)
  - features based on lexico-syntactic patterns
  - or lexical resources (such as WordNet)
- Unsupervised learning
  - Clustering

Paradigm shift: representation learning

Deep learning

- dominates the field since ≈2014
- led to performance improvements in many tasks



Paradigm shift: representation learning

But why?

- Neural networks have been around for decades.
- What has changed in the way they are applied in NLP?
- Key conceptual innovation:

  *learning **intermediate meaning representations** in the process of end-to-end training for a particular task.*

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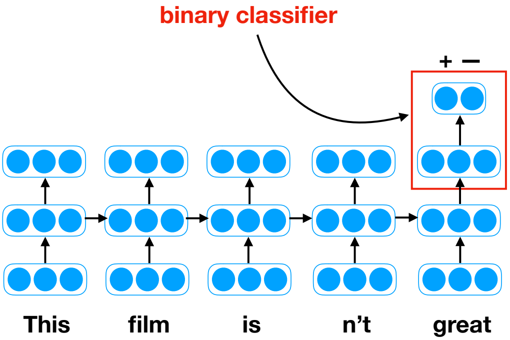
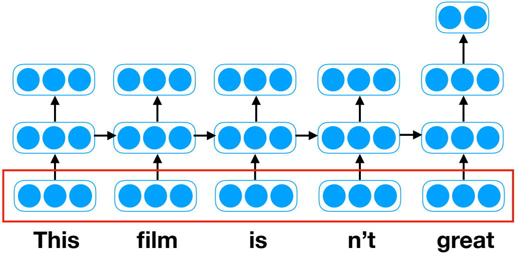
Example: sentiment analysis



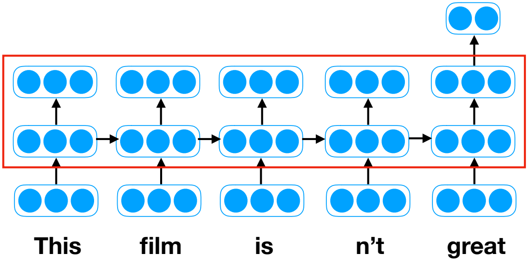
Example: sentiment analysis

Word representations



Example: sentiment analysis

Sentence representations

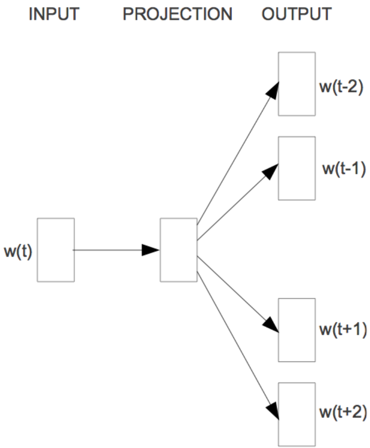


General-purpose word representations

Mikolov et. al. 2013. *Efficient Estimation of Word Representations in Vector Space*.

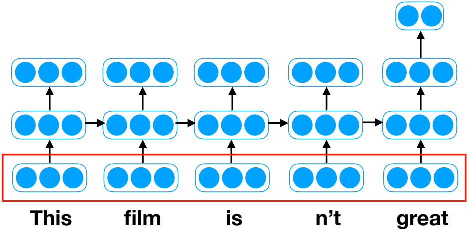
Skip-gram model:

- Given a word
- predict its neighboring words
- learn word representations in the process



Word embeddings in NLP tasks

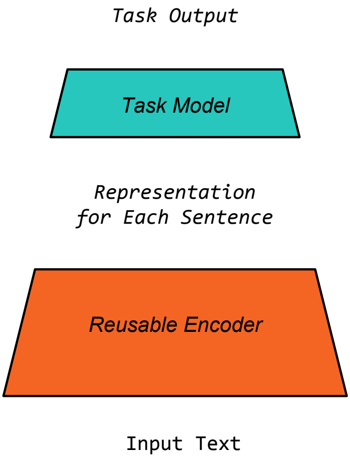
- Random initialization, learn as part of task objective
- External initialization (e.g. skip-gram), update as part of task objective
- External initialization, keep fixed



Learning sentence representations

(Long-term?) goal:

- a **general-purpose** neural network **sentence encoder**
- which can be applied across diverse NLP tasks.



Why is this useful?

1. Improve performance
   - produce **rich semantic representations** for downstream NLP tasks
2. Improve data efficiency
   - provide a model of sentence representation for language understanding tasks which **lack training data**

What can we expect this model to capture?

- Lexical semantics and meaning disambiguation in context
- Word order
- Some syntactic structure
- Semantic composition
- Idiomatic/non-compositional phrase meanings
- Connotation and social meaning.

Sentence representation models

Unsupervised training on **single sentences**:

- Sequence autoencoders (Dai and Le, 2015)
- Paragraph vector (Le and Mikolov, 2015)

Unsupervised training on **running text**:

- SkipThought (Kiros et al., 2015)
- Quick Thoughts (Logeswaran and Lee, 2018)
- BERT (Devlin et al., 2019)
- Generative LMs: GPT$\{2, 3, 4\}$ (Radford et al., 2019)

We will look at these models later in the course.

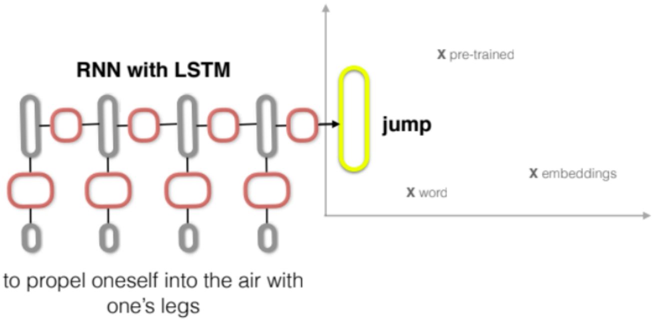
Sentence representation models

Supervised training on **large corpora**:

- Dictionaries (Hill et al. 2015)
- Natural language inference data (Conneau et al. 2017)
- DisSent – discourse connectives (Nie et al. 2019)

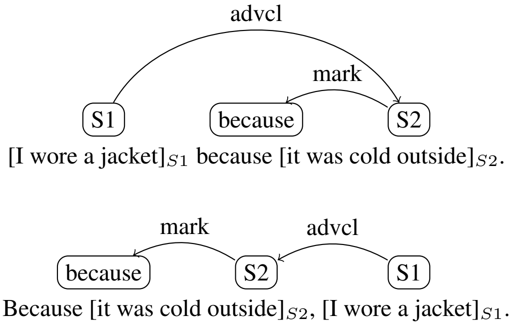
Learning from dictionary definitions

Hill et al., 2016. *Learning to Understand Phrases by Embedding the Dictionary*



DisSent: Predicting discourse connectives

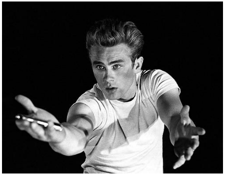
Nie et al., 2019. *DisSent: Sentence Representation Learning from Explicit Discourse Relations*



Natural language inference task

Bowman et al, 2015. *A large annotated corpus for learning natural language inference*

- Stanford Natural Language Inference (SNLI) corpus
- 570k sentence pairs
- labeled for entailment, contradiction, and semantic independence



James Byron Dean refused to move without blue jeans

{**entails**, contradicts, neither}

James Dean didn't dance without pants

More NLI examples

A black race car starts up in front of a crowd of people.

A man is driving down a lonely road.

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CONTRADICTION

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CONTRADICTION

A soccer game with multiple males playing.

Some men are playing a sport.

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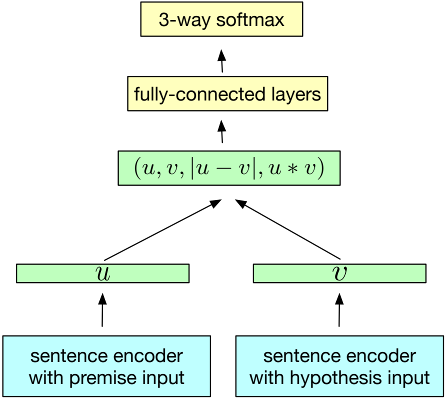
ENTAILMENT

General architecture for NLI

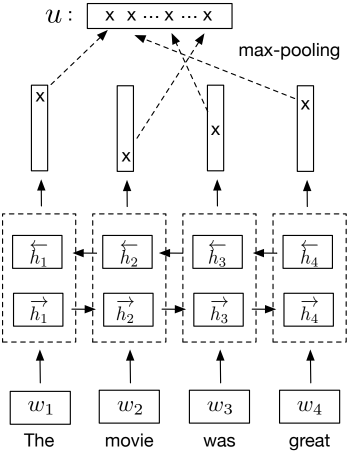
Conneau et al, 2017. *Supervised Learning of Universal Sentence Representations from Natural Language Inference Data*

InferSent model

- Siamese architecture (same encoder to represent premise and hypothesis)
- 3-way classification (*entails, contradicts, neither*)



InferSent encoder: BiLSTM with max pooling



NLI and language understanding

To perform well at NLI, your representations of meaning must handle with the full complexity of compositional semantics...

- Lexical entailment (*cat* vs. *animal*, *cat* vs. *dog*)
- Lexical ambiguity (e.g. *bank, run*)
- Quantification (*all, most, fewer than eight* etc.)
- Modality (*might, should*, etc.)
- Common sense background knowledge

Evaluation framework: SentEval

Conneau and Kiela, 2018. *SentEval: An Evaluation Toolkit for Universal Sentence Representations*

- Formalised an evaluation standard for sentence representations
- Suite of ten tasks
- Software package automatically trains and evaluates per-task classifiers using supplied representations.

SentEval tasks

- Classification tasks:
  - sentiment analysis / opinion polarity
  - subjectivity vs. objectivity
  - question type (e.g. for question answering)
- Natural language inference:
  - several datasets
- Semantic similarity tasks:
  - sentence similarity
  - paraphrasing
  - image caption retrieval

Practical 1

Learning general-purpose sentence representations

- supervised training
- SNLI task
- Implement three variants of the **InferSent** model:
  1. Unidirectional LSTM encoder
  2. Bidirectional (Bi-) LSTM encoder
  3. BiLSTM encoder with max pooling
- Compare to a **baseline** averaging word embeddings
- Evaluate using **SentEval**

Submit a mini-report containing your results and your code
Deadline: 19 April

Research project topics

- Multilingual representation learning
- Model pruning and subnetworks
- Prompting, instruction-tuning and in-context learning
- Bias and stereotypes in NLP models

Detailed project descriptions soon available on Canvas

Coming next...

Tomorrow:

- Lab: Start SNLI practical

Friday:

- Lecture: Attention and Transformers

Next Tuesday:

- Seminar: The BERT model

Acknowledgement

Some images were adapted from Sam Bowman and Steve Clark