Machine Learning for Natural Language Processing

Transfer Learning with Neural Modeling for NLP

Lecture 6

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Lecture 5 summary

- Language Model
  - N-gram
  - Neural Language Model
- The Transformer Architecture
- The Sequence to Sequence paradigm

Lecture Outline

- Transfer Learning
- Word2vec + Task-Specific Architecture
- Language Modelling : Focus on BERT
- Challenges and Limits of NLP
  - The 4 challenges of NLP
  - The 4 questions of any NLP project

Transfer Learning in NLP

Transfer Learning

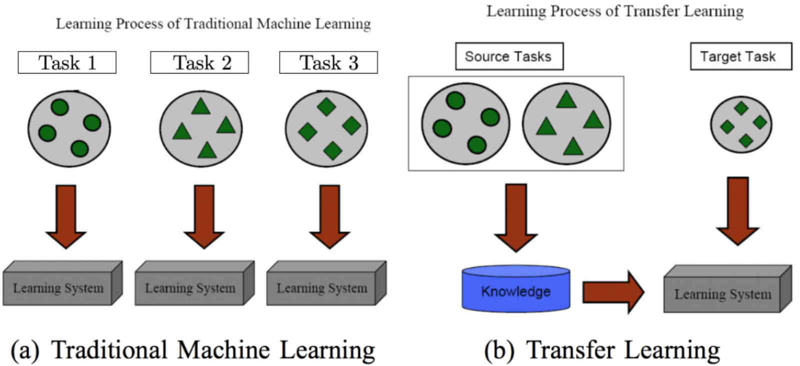

Figure: Pan and Yang (2009)

Transfer Learning

Machine Learning Framework

- Let A a task, on observation $(X_i, Y_i)_i$, learn a predictive model p_A of $X_i \to Y_i$

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Transfer Learning Framework

- Let A and B two tasks. $(X_1, Y_i)_i$, $(W_i, Z_i)_i$ observations.
  - Learn a model p_A learn a predictive model p_A of $X_i \to Y_i$
  - Reuse p_A to learn a predictive model p_B of $W_i \to Z_i$

Machine Learning Framework

- Let A a task, $(X_1, ..X_T)_i, (Y_1, .., Y_T)_i$ variables,
  Goal: Learn a predictive model p_A

$$(X_1, ..X_T)_i \xrightarrow{p_A} (Y_1, .., Y_T)_i$$

Transfer Learning for Natural Language Processing

Machine Learning Framework

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Transfer Learning Framework

- Let A and B two tasks.
  $(X_1, ..X_T)_i, (Y_1, .., Y_T)_i, (W_1, .., W_T)_i, (Z_1, .., Z_T)_i$ variables.
  - Learn a model p_A learn a predictive model p_A of $X \to Y$
  - **Goal**: Reuse p_A to learn a predictive model p_B

$$p_A, (W_1, ..W_T)_i \xrightarrow{p_B} (Z_1, .., Z_T)_i$$

Different types of Transfer Learning for text

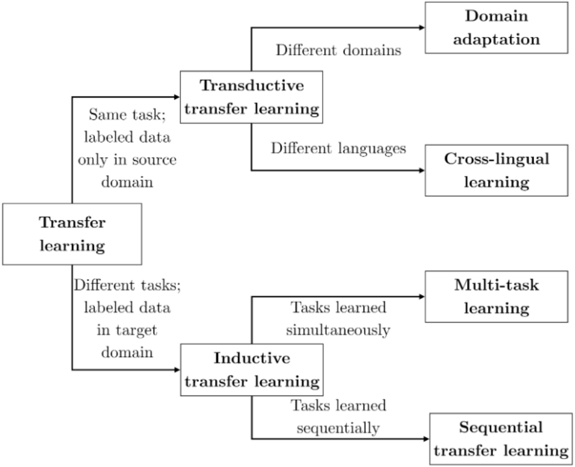


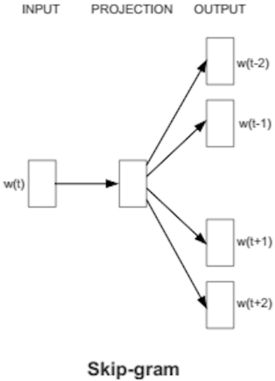
Figure: Ruder (2019)

Sequential Transfer Learning

Sequential Transfer Learning: 2 study cases

- Continuous distributional word vectors used within a task-specific Architecture
- Language Model: Focus on BERT

Task A: Skip-gram model [1]



By training a model to predict ***context*** words, we learn an ***Embedding*** matrix of word vectors

[1] cf. Lecture 2

Task B: POS tagging [2]

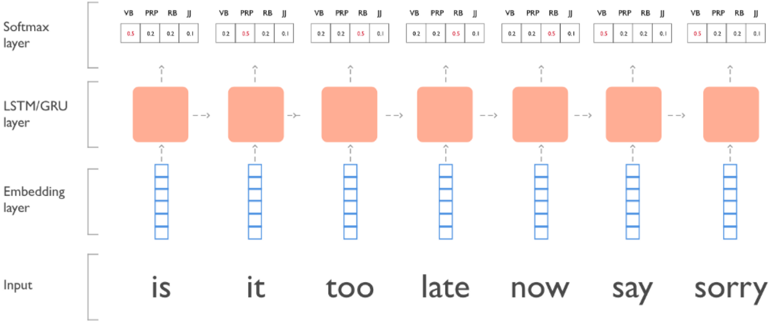


Figure: POS tagging LSTM recurrent network

By default we learn the Embedding layer as any other layers (random initialization)

[2] cf. Lecture 4

Transferring word vectors to POS tagging

1. (Pre-)Train a skip-gram model with Embedding Matrix E
2. Initialize the POS tagger Word Embedding Layer with Embedding Matrix E
3. Train the POS tagger with backprop (as seen in Lecture 4)

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Intuition:

- By doing so, the distributional representation learnt during pre-training are adapted, fine-tuned with regard to the downstream POS tagging task.
- The tagger makes use of the word embedding structure to predict POS labels.

Impact of transfer

- For most NLP tasks, using pre-trained word embedding layer and tuning it gives a significant improvement compared to random intialization

For instance for Name-Entity-Recognition

LSTM NER model	
init	F1
random	80.88
skip-gram	90.33

Table: NER S-LSTM performance CoNLL-03 test set [3]

[3] Lample et al. (2016)

Sequential Transfer Learning:

- Distributional word vectors used within a task-specific Architecture
- Language Models as contextual word vectors: Focus on BERT

BERT

BERT

- BERT is a Transformer Architecture
- Trained as a Masked-Language Model
- published and released by Google in October 2018 (Devlin et al., 2018)

BERT lead to several breakthroughs in NLP

BERT objective

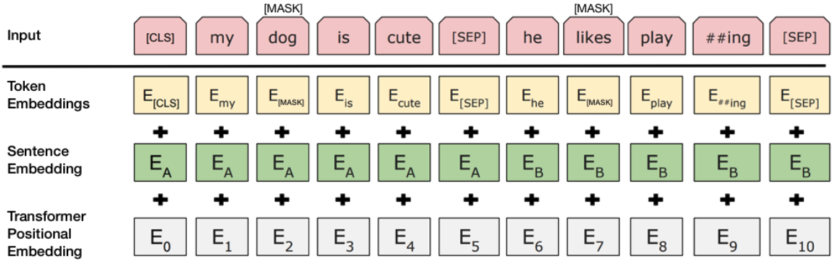

Figure: Bert input and output

BERT input

- BERT works at the sub-word units

  $\rightarrow$ No Out-Of-Vocabulary problem

  $\rightarrow$ Can have on shared vocabulary for multiple languages

Subword

- Out-of-Vocabulary problem
- A solution is to work at another level than words
- character level is a solution since there is no UNK at this level
- character level models are extremelly slow
- How to build bigger units than character with no UNK?
- This units should be at a subword level to cover new words

Subword

- Building subword units by segmenting words into subparts
- wishlist for word segmentation algorithm:
- open-vocabulary: encode all words through small vocabulary
- encoding generalizes to unseen words
- small sequence size (e.g., unlike character level)
- Current best solution: segmentation via byte pair encoding (BPE)

Byte pair encoding for word segmentation

- BPE is a bottom-up character merging algorithm
- compress representation based on information theory

from Sennrich's class

http://www.inf.ed.ac.uk/teaching/courses/mt/syllabus.html

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- BPE algorithm:
  0. Split the vocabulary of a dataset at the character level
     - '[hey, hello, et]' → 'h','e','y',' ','h','e','l','l','o',' ','e','t'

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  1. Compute frequencies of consecutive symbol pairs
     - {'h','e'}= 2; {'l','l'} = 1;...

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  2. replace most frequent consecutive symbol pair ('A','B') with 'AB'
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- Works as a preprocessing of the train set

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Applying BPE preprocessing

- Once the BPE codes are computed, we have a list of merges

$$M = [\text{'e s'} \mapsto \text{'es'}, \text{'es t'} \mapsto \text{'est'}, \ldots]$$

- Steps to preprocess a dataset with BPE codes:
    1. split dataset in sequence of characters
    2. apply the sequence of merges to the dataset to form BPE codes

- It is a deterministic process with a unique segmentation

from Sennrich's class
`http://www.inf.ed.ac.uk/teaching/courses/mt/syllabus.html`

BPE: pros and cons

- Pros:
  - Very simple
  - Models trained on BPE segmentations share information between words (e.g., prefix, suffix...)
  - BPE vocabulary is a best trade-off between vocabulary size and average sequence length
- Cons:
  - Characters are not necessarily in the final vocabulary $\rightarrow$ no guarantees open vocabulary (still covers 99.9%)
  - Heuristic, does not work well for all train sets

Other sub-word tokenization algorithm

- WordPiece tokenization
- SentencePiece tokenization

BERT training

- BERT has been trained on around 60GB of textual data (English Wikipedia, the BookCorpus)

BERT fine-tuning

- BERT is a sequence labelling model that use both left and right context for Mask-Language Modelling
- Why not using the full model for a specific task ?
- Constraints:
  - The downstream tasks should be formulated as a sequence labelling/classification task.

BERT-base

- 110M parameters
- 12 self-attention layers (778 dim)
- 12 heads per layers
- 512 tokens sequence

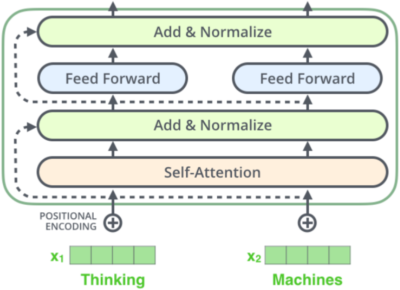

Figure:

Fine-tuning BERT for NER

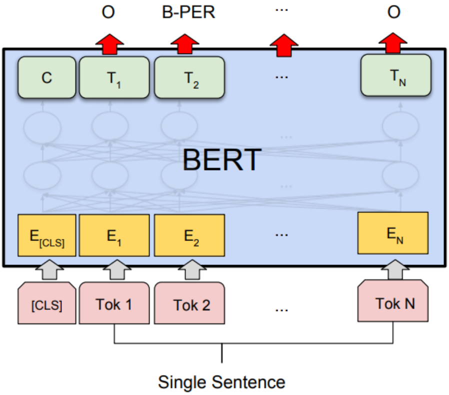

Figure: BERT for NER

Fine-tuning process

1. Take BERT model
2. Add an extra task-specific layer (e.g. Dense layer)
3. Fine-Tune everything with backpropagation on the new input-output data
4. Optimization done with a much smaller learning rate to avoid *catastrophic forgetting*

Hugging Face Transformer library (cf. lab 5)

Transformers provides general-purpose architectures (BERT, GPT-2, RoBERTa, XLM, DistilBert, XLNet...) for Natural Language Understanding (NLU) and Natural Language Generation (NLG) with over 32+ pretrained models in 100+ languages and deep interoperability between TensorFlow 2.0 and PyTorch

NB: The Transformer library is **the** NLP library to work with SOTA models

GLUE: a benchmark for sentence representations

GLUE (Wang et al., 2018) contains 11 tasks covering:

- Single-Sentence Tasks (e.g., text classification)
- Similarity and Paraphrase Tasks
- Inference tasks, i.e., predicting relations between sentences (e.g., coreference, NLI,...)

Caveat of GLUE finetuning of models on each task is allowed.
Leaderboard available at `https://gluebenchmark.com/`

Natural language inference (NLI)

- Goal predict relation between a premise (P) and an hypothesis (H)
- 3 types of relations:
  - neutral the two sentences have no relation
    P: A smiling costumed woman is holding an umbrella.
    H: A happy woman in a fairy costume holds an umbrella.
  - contradict the two statements contradict each other
    P: A man inspects the uniform of a figure in some East Asian country.
    H: The man is sleeping.
  - entailment one of the statement can be inferred from the other
    P: A soccer game with multiple males playing.
    H: Some men are playing a sport.
- SNLI: `https://nlp.stanford.edu/projects/snli/`

Natural language inference (NLI) with BERT

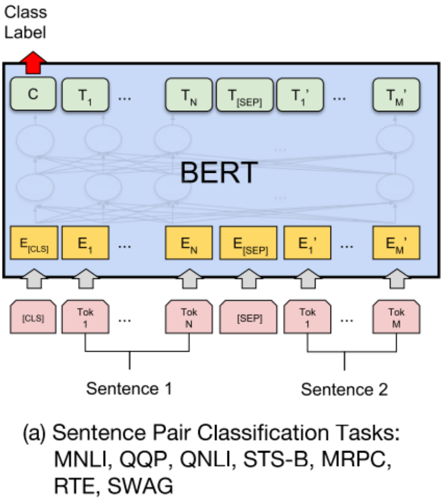

Figure: Devlin et al. (2018)

BERT on GLUE

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Table 1: GLUE Test results, scored by the evaluation server (https://gluebenchmark.com/leaderboard). The number below each task denotes the number of training examples. The "Average" column is slightly different than the official GLUE score, since we exclude the problematic WNLI set.[8] BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.

Figure: Devlin et al. (2018)

Other Languages

- Multilingual BERT-like models (multilingual BERT trained on 104 languages, XLM-R)
- Now monolingual models for many languages (Finish, Dutch, German, Italian, Russian, Chinese,...)
- For French: CamemBERT model [4]

[4] https://camembert-model.fr/

NLP current limits and challenges

NLP current limits and challenges

Modern NLP models are very efficient to perform on specific tasks on a given distribution (language, domain) Several core challenges remain

- Generalization challenge
  Still very hard to generalize across distribution and across tasks
- The *Data Efficiency* challenge (e.g. low ressource, cost...)
- The Cost challenge
  large model expensive to train and to predict with
- The Interpretability challenge
  Best models are black boxes, some use cases require interpretability

The 4 question of any NLP project

The 4 questions of any NLP projects

1. The Data question
2. The Modeling question
3. The Performance question (speed vs accuracy tradeoff)
4. The Ethical question (privacy, biases..)

Course Outline

1. The Why and What of Natural Language Processing
2. Representing text with vectors
3. Task specific Modeling of Text
4. Neural Natural Language Processing
5. Language Modeling
6. Transfer Learning with Neural Modeling for NLP

Final project

- Project: Design, implement and describe an entire NLP project
- Outcome : Self-contained **notebook** uploaded to **github** and **google colab** + 2 pages latek report

References I

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