Transfer Learning for NLP

COM4513/6513 Natural Language Processing

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The University Of Sheffield.

In lectures 6 and 8...

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- Labelled data is cheap, i.e. large publicly available corpora (aka **self supervision**)
- Can we make use of this knowledge in downstream tasks where data might be scarce?

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- **Transfer learning:** Re-use and adapt already pre-trained supervised machine learning models on a target task
- How we can re-use and neural LMs on target tasks (e.g. text classification, machine translation, question answering, etc.)

Definition of Transfer Learning

A machine learning approach where models trained on a **source** task (or domain) are adapted to a related **target** task[1] (or domain)

[1] Pan, S. J., & Yang, Q. (2009). A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10), 1345-1359

Definition of Transfer Learning (more formally)

$$\begin{aligned} \text{Domain: } & \mathcal{D} = \{\mathcal{X}, P(X)\} \\ \text{Task: } & \mathcal{T} \text{ where } y \in \mathcal{Y} \\ \text{Cond. Prob. Distrib.: } & P(Y|X) \end{aligned}$$

Given a source domain $\mathcal{D}_S$ and a corresponding task $\mathcal{T}_S$, a target domain $\mathcal{D}_T$ and task $\mathcal{T}_T$, learn a new model that computes the target conditional probability distribution $P(Y_T|X_T)$ in $\mathcal{D}_T$ given information from $\mathcal{D}_S$ and $\mathcal{T}_S$

Transfer Learning Variants

- $\mathcal{X}_S \neq \mathcal{X}_T$: Different feature spaces in source and target domains, e.g. documents written in different languages (**cross-lingual adaptation**)

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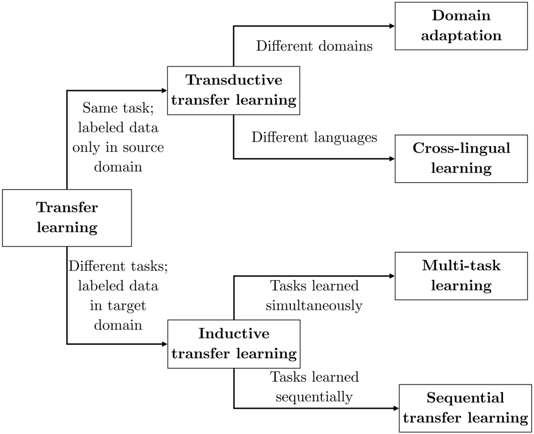
- $P(Y_S|X_S) \neq P(Y_T|X_T)$: Different conditional probability distributions between source and target tasks, e.g. source and target documents are unbalanced regarding to their classes

Transfer Learning Taxonomy[2]



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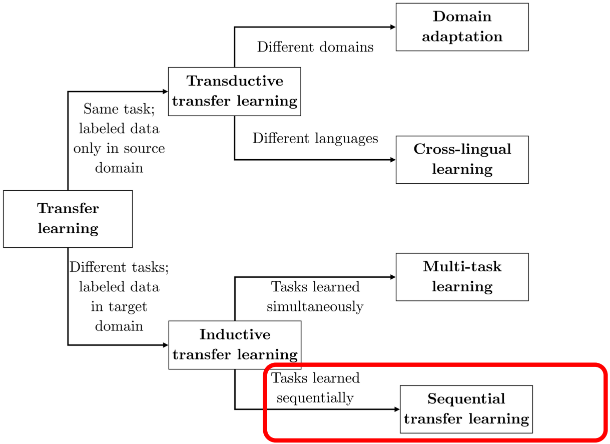

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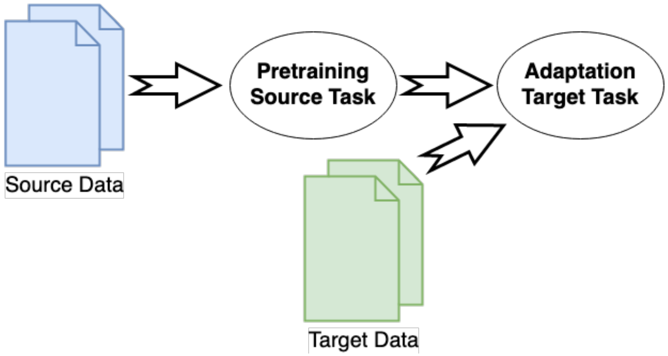
Sequential Transfer Learning



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- Models?

Pretraining: Models

- Feedforward networks, e.g. word2vec[3]

[3] Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems (pp. 3111-3119)

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[5] Vaswani, Ashish, et al. (2017) "Attention is all you need." Advances in neural information processing systems.

[6] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies(pp. 4171-4186).

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- LSTM, e.g. Universal Language Model Fine-tuning (ULMFiT[4])
- Transformer[5] Network, e.g. Bidirectional Encoder Representations from Transformers (BERT[6])

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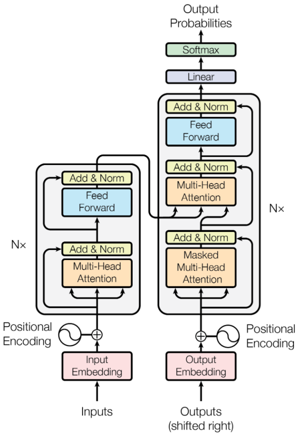

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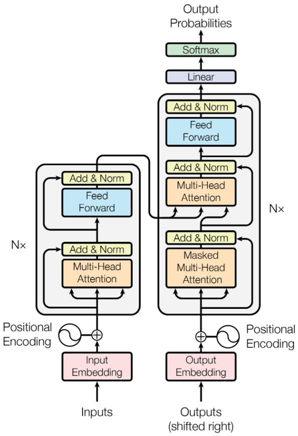

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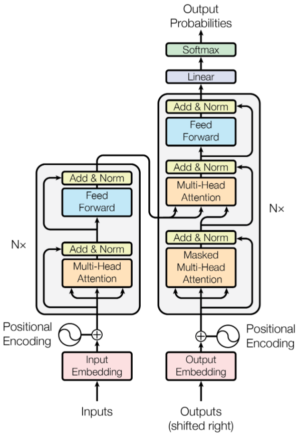

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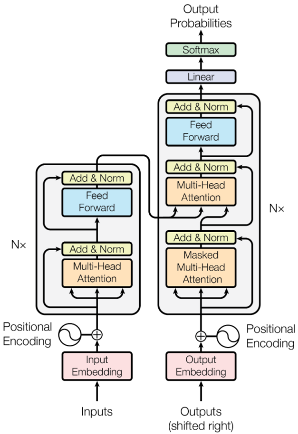

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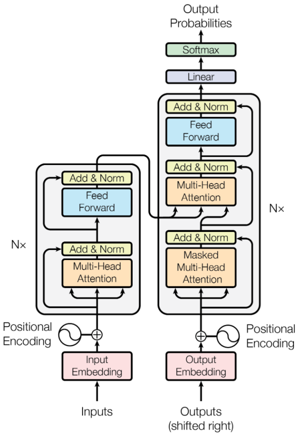

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- Input is combined with a positional embedding (containing information for particular position in the sequence)

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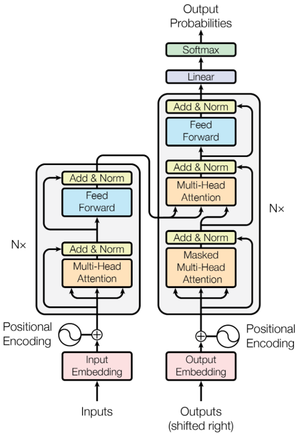

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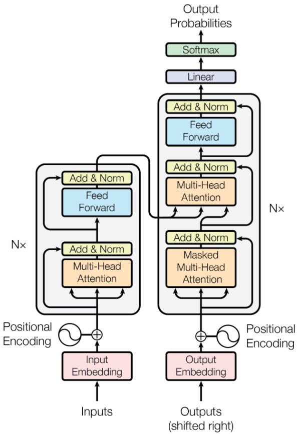

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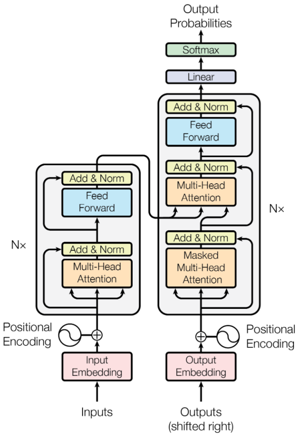

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- BERT variants: XLNet, RoBERTa, ALBERT

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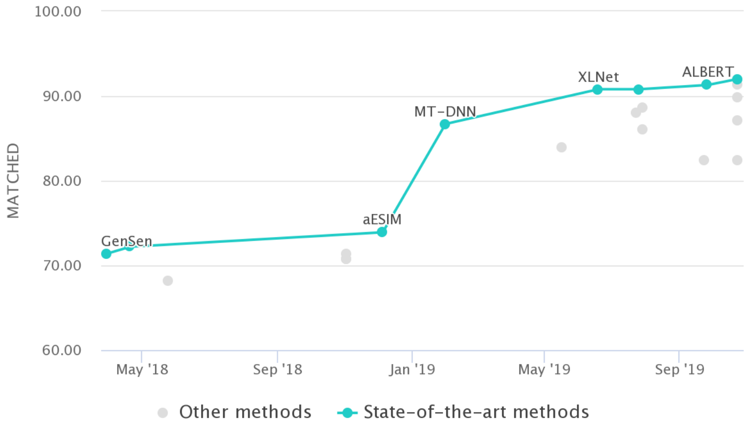
- In ULMFiT, the LM encoder (LSTM) is fine-tuned on the test data before adaptation

Does it work?



Performance on Natural Language Inference on MultiNLI[7]

[7] https://paperswithcode.com/sota/natural-language-inference-on-multinli

Bibliography

- Blog post on Transfer Learning by S. Ruder
- Blog post on Transfer Learning in NLP by S. Ruder
- Blog post on BERT by Samia

Thanks!