# Transfer Learning

# Self-Supervision

**Learning goals**

- Understand the difference to other learning paradigms
- Learn to recognize self-supervision when you see it

# DEFINITION

*Unsupervised Learning:*

- No labels attached to the data
- Learn patterns / clusters from the features only

*Supervised Learning:*

- (Gold) Labels attached to the data
- Learn from the association between features and labels

**Self-Supervised Learning:**

- No *external* labels attached to the data
  $\rightarrow$ Samples with suitable labels can be generated from the known structure of the data itself
- *Technically* supervised learning, but *no labeling effort* $+$ simultaneous ability to generate massive amounts of labeled data points

# PRE-TRAINING OBJECTIVES

**Self-supervised objectives:**

- Skip-gram objective (cf. word2vec ▸ Mikolov et al. (2013a))
- Language modeling objective (cf. ▸ Bengio et al. (2003))
- *Masked language modeling (MLM)* objective (cf. chapter 10)
  → Replace words by a `[MASK]` token and train the model to predict
- *Permutation language modeling (PLM)* objective (cf. chapter 11)
  → Autoregressive objective of XLNet
- *Replaced token detection* objective (cf. chapter 11)
  → Requires two models: One performing MLM & the second model to discriminate between actual and the predicted tokens

# CONTEXTUALITY

**1st Generation of neural embeddings are "context-free":**

- Breakthrough paper by Mikolov et al, 2013 (Word2Vec)
- Followed by Pennington et al, 2014 (GloVe)
- Extension of Word2Vec by Bojanowski et al, 2016 (FastText)

**Why "Context-free"?**

- Models learn *one single* embedding for each word
- Why could this possibly be problematic?
  - "The *default* setting of the function is xyz."
  - "The probability of *default* is rather high."
- Would be nice to have different embeddings for these two occurrences

# CONTEXTUAL EMBEDDINGS


Source: *Jay Alammar*

# ELMO ‣ PETERS ET AL., 2018

- Bidirectional language model (LM)
- Combines a forward LM

$$p\left(t_1, t_2, \ldots, t_N\right) = \prod_{k=1}^{N} p\left(t_k | t_1, t_2, \ldots, t_{k-1}\right)$$

and a backward LM

$$p\left(t_1, t_2, \ldots, t_N\right) = \prod_{k=1}^{N} p\left(t_k | t_{k+1}, t_{k+2}, \ldots, t_N\right)$$

to arrive at the following loglikelihood:

$$\begin{aligned} \textstyle\sum_{k=1}^{N} \Big( \log p \left( t_k | t_1, \ldots, t_{k-1}; \Theta_x, \overrightarrow{\Theta}_{LSTM}, \Theta_s \right) \\ + \log p \left( t_k | t_{k+1}, \ldots, t_N; \Theta_x, \overleftarrow{\Theta}_{LSTM}, \Theta_s \right) \Big) \end{aligned}$$

# ELMO EMBEDDINGS

- Character-based (context-independent) token representations

$$x_k^{LM}$$

- Two-layer biLSTM as main architecture:
  - Two context-dependent token representations *per layer*, i.e.

    $\overrightarrow{\mathbf{h}}_{k,j}^{LM}$ & $\overleftarrow{\mathbf{h}}_{k,j}^{LM}$ for the $k$-th token in the $j$-th layer.

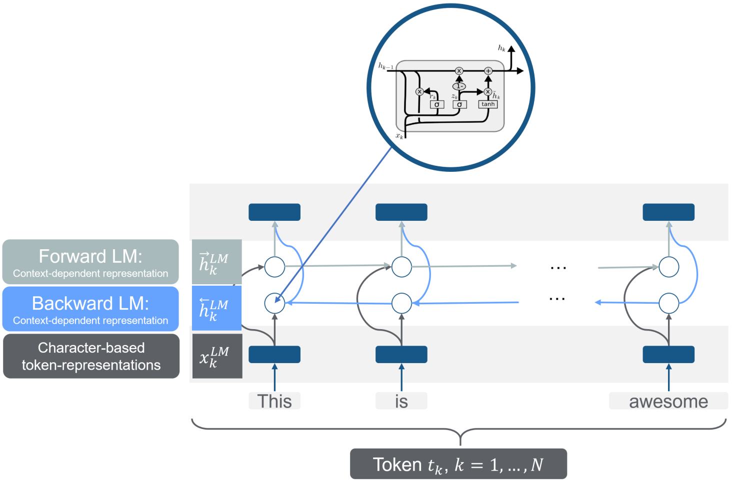
  - Four context-dependent token representations in total:

$$\left\{ \overrightarrow{\mathbf{h}}_{k,j}^{LM}, \overleftarrow{\mathbf{h}}_{k,j}^{LM} | j = 1, 2 \right\}$$

- Five representations per token in total:

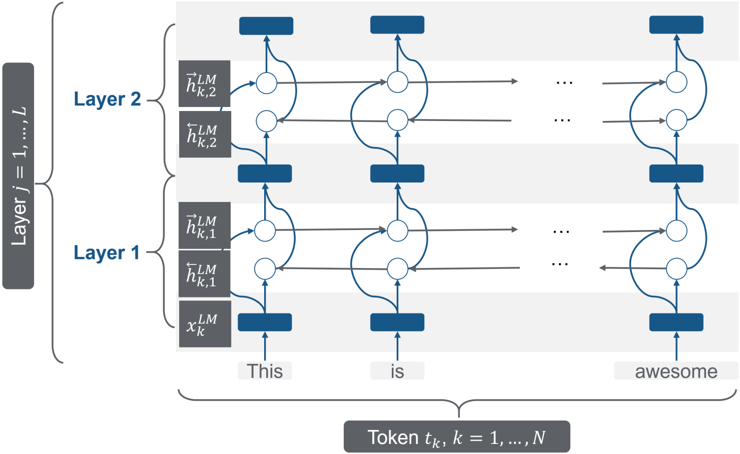
$$\begin{aligned} R_k &= \left\{ \mathbf{x}_k^{LM}, \overrightarrow{\mathbf{h}}_{k,j}^{LM}, \overleftarrow{\mathbf{h}}_{k,j}^{LM} | j = 1, \ldots, L \right\} \\ &= \left\{ \mathbf{h}_{k,j}^{LM} | j = 0, 1, 2 \right\} \end{aligned}$$

# GRAPHICAL REPRESENTATION




Source: *Carolin Becker*

# GRAPHICAL REPRESENTATION




Source: *Carolin Becker*

# TASK ADAPTION

**Including ELMo in downstream tasks:**

- Calculate task-specific weights of all five representations:

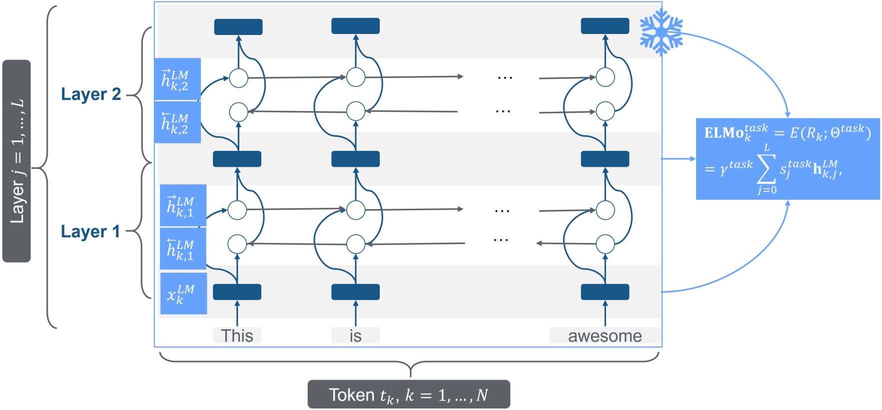
$$\mathbf{ELMo}_k^{task} = E\left(R_k; \Theta^{task}\right) = \gamma^{task} \sum_{j=0}^{L} s_j^{task} \mathbf{h}_{k,j}^{LM},$$

  where the $\mathbf{h}_{k,j}^{LM}$ are **not trainable** anymore.
- Trainable parameters during the adaption:
  - $s_j^{task}$ are trainable (softmax-normalized) weights
  - $\gamma^{task}$ is a trainable scaling parameter

**Advantages over context free-embeddings:**

- Task-specific model has access to *multiple* representations of each token
- Model learns to which degree to use the different representations depending on the task at hand

# TASK ADAPTION




Source: *Carolin Becker*

# PERFORMANCE

| TASK | PREVIOUS SOTA | | OUR BASELINE | ELMO + BASELINE | INCREASE (ABSOLUTE/ RELATIVE) |
|---|---|---|---|---|---|
| SQuAD | Liu et al. (2017) | 84.4 | 81.1 | 85.8 | 4.7 / 24.9% |
| SNLI | Chen et al. (2017) | 88.6 | 88.0 | $88.7 \pm 0.17$ | 0.7 / 5.8% |
| SRL | He et al. (2017) | 81.7 | 81.4 | 84.6 | 3.2 / 17.2% |
| Coref | Lee et al. (2017) | 67.2 | 67.2 | 70.4 | 3.2 / 9.8% |
| NER | Peters et al. (2017) | $91.93 \pm 0.19$ | 90.15 | $92.22 \pm 0.10$ | 2.06 / 21% |
| SST-5 | McCann et al. (2017) | 53.7 | 51.4 | $54.7 \pm 0.5$ | 3.3 / 6.8% |

Table 1: Test set comparison of ELMo enhanced neural models with state-of-the-art single model baselines across six benchmark NLP tasks. The performance metric varies across tasks – accuracy for SNLI and SST-5; $F_1$ for SQuAD, SRL and NER; average $F_1$ for Coref. Due to the small test sizes for NER and SST-5, we report the mean and standard deviation across five runs with different random seeds. The "increase" column lists both the absolute and relative improvements over our baseline.

Source: *Peters et al. (2018)*

# SUMMARY

- Embeddings are (bidirectionally!) contextualized (as opposed to word2vec)
- Embeddings are *not* adapted to target domain/task (similar as for word2vec)
- Additional weights are learned for each downstream task (i.e. besides the embeddings, no shared knowledge across tasks)