Multilingual NLP

10. Sentence Encoders
(+ Contrastive learning & Knowledge distillation)

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Image: Alexander Mikhalchyk

After this lecture, you'll...

- Know how to obtain sentence-level encoders
- Understand how to train multilingual sentence encoders
- Be able to explain what contrastive learning is
- Understand what knowledge distillation is

Content

- **Sentence Embeddings**
- (Multilingual) Sentence Encoders
  + Contrastive Learning
  + Knowledge Distillation
- Self-Supervised Sentence Encoders

Sentence Embeddings

- **Sentence embedding** is a semantic representation of a sentence – a vector that captures the (fine-grained) meaning of the sentence
- Q: What do we need sentence embeddings for?
- Q: Can't we simply aggregate (e.g., average) sentence embeddings from word embeddings?

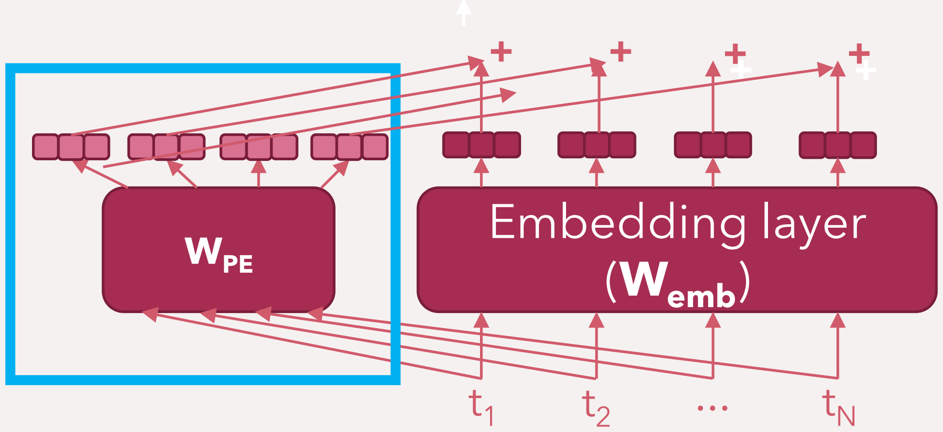
Sentence Embeddings

- **Sentence embedding** is a semantic representation of a sentence – a vector that captures the (fine-grained) meaning of the sentence
- Q: What do we need sentence embeddings for?
  - Information retrieval (find the sentence with the closest meaning)
  - Parallel data (bitext) mining (training data for MT)
  - Computationally efficient supervised training for sentence-level tasks
  - Data efficient supervised training for sentence-level tasks
- Q: Can't we simply aggregate (e.g., average) sentence embeddings from word-embeddings?
  - We can, but we won't get very good sentence representations
  - *the dog bit the man* vs. *the man bit the dog*?

Positional Embeddings

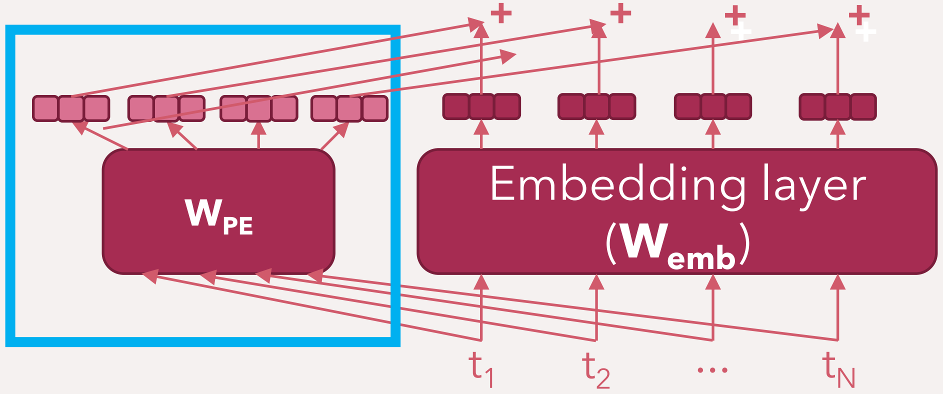
- But with pretrained Transformers, we have contextualized embeddings
- And these embeddings also encode the positions of tokens

- We also have special start tokens (e.g., [CLS] in BERT) that attend over all input tokens
- Q: just average token representations, output of the Transformer?
- Q: just take the output representation of the [CLS] token?



Positional Embeddings

- Q: just average token representations, output of the Transformer?
- Q: just take the output representation of the [CLS] token?
- Neither is <u>good enough</u> out of the box!
- Pretrained LMs are trained for predicting <u>(masked) words</u>, *not* encoding sentences!
  - Additional sentence-level training needed
  - Think of it as fine-tuning of a PLM to produce <u>sentence-level embeddings</u>



Training Sentence Encoders

- Obtaining a **sentence-level encoder** (i.e., a neural model that produces meaningful embeddings for input sentences) requires sentence-level training tasks/objectives
- Q: What could such task be?
  - It needs to require some kind of semantic comparison between two (or more) sentences
  - Ideally, requires fine-grained (precise) modeling of sentence meaning (small changes in wording can change the meaning much)
- Some tasks that fit:
  - Semantic text similarity (STS), Natural Language Inference (NLI), Paraphrase detection (PD)
  - Multilingually: translation detection – predict if sentences are translations of each other; Q: why not MT?
  - Q: where to get the data/annotations from?

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  - Knowledge Distillation
- Self-Supervised Sentence Encoders

Training Sentence Encoders

Conneau, A., Kiela, D., Schwenk, H., Barrault, L., & Bordes, A. (2017, September). Supervised learning of universal sentence representations from natural language inference data. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing (pp. 670-680). Association for Computational Linguistics.

- InferSENT: „pretrains" a (recurrent) sentence encoder on NLI
  - NLI is the sentence-pair task with largest training data
  - The same parametrized encoder Enc(s|θ) independently encoders both sentences
    - This architecture is often called Bi-Encoder or Siamese Network
  - Embeddings: **u** = Enc(s_1|θ), **v** = Enc(s_2|θ)
  - Concatenation of **u**, **v**, their absolute elementwise difference |**u**-**v**|, and their element-wise product **u***v**
    - Fed into the feed-forward softmax classifier
    - Predicts one of three NLI classes
    - Cross-entropy loss

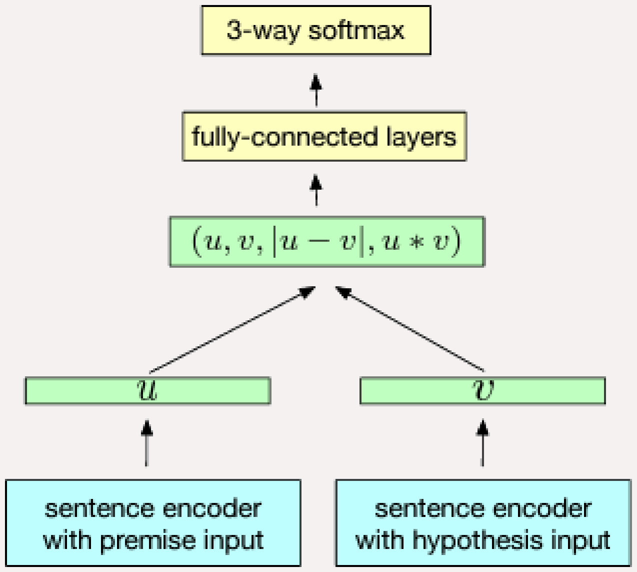
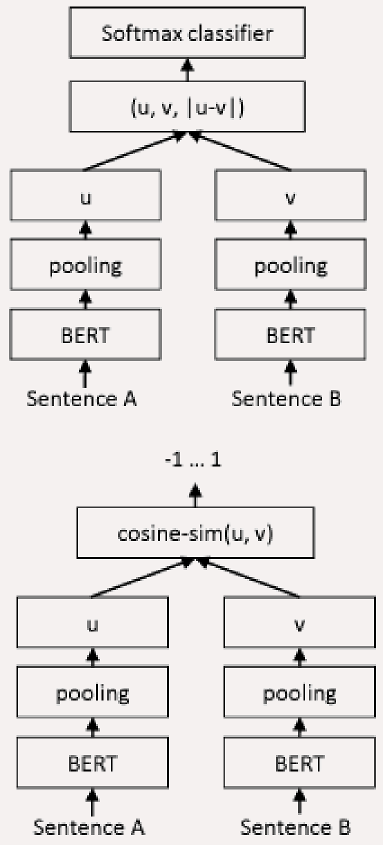


Image from the paper

Sentence-BERT

Reimers, N., & Gurevych, I. (2019, November). Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing (EMNLP) (pp. 3982-3992).

- SentenceBERT: fine-tuning BERT into a sentence-level encoder
- Trained on
  - NLI (classification objective)
    - Effectively the same as InferSent
    - But initialization with pretrained BERT (as opposed to random init of a deep Bi-LSTM in InferSent)
  - STS (regression objective)
    - Cosine between sentence embeddings compared against the human similarity score
      - Loss: mean square error



Sentence-BERT

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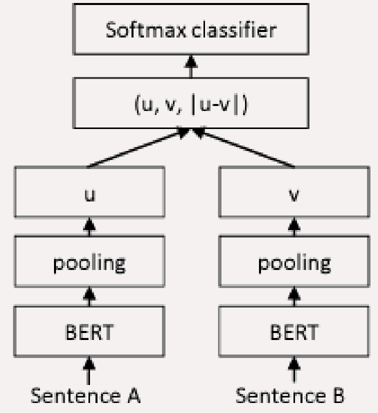
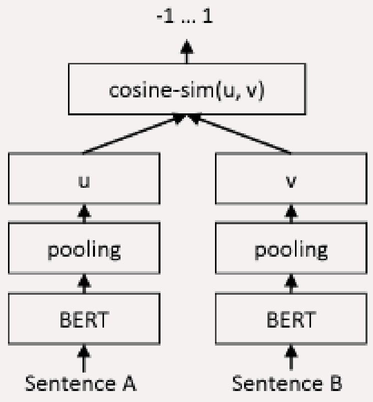
- SentenceBERT: supervised fine-tuning of BERT to obtain a sentence-level SBERT encoder
- But the large-scale data exists only in English
  - Primarily the NLI data
- Q: Can we obtain a multilingual sentence encoder the same way? How?
- Q: Fine-tune mBERT or XLM-R on the English NLI data?
  - Worse sentence embeddings for English compared to fine-tuning monolingual English PLMs
  - Bad performance for other languages due to large English-only fine-tuning





Multilingual Sentence Encoders

- Q: Which type of data do we generally have that aligns sentences across languages by meaning?
  - Parallel data (remember Lecture 9 and MT :)!
- Much of the work on training multilingual sentence encoders relies on (large amounts of) parallel data
- Two main approaches:
  1. Pretraining from scratch (or from general-purpose PLMs)
     - Typically with **contrastive learning** objectives
  2. Transfering sentence-encoding knowledge from a monolingual sentence encoder to a multilingual PLM
     - Typically via **knowledge distillation**

Multilingual Sentence Encoders

Artetxe, M., & Schwenk, H. (2019). Massively multilingual sentence embeddings for zero-shot cross-lingual transfer and beyond. Transactions of the Association for Computational Linguistics, 7, 597-610.

LASER: „Universal language agnostic sentence embedder"

- Pretraining from scratch:
- Massively multilingual: 93 languages
- Recurrent sentence encoder (Bi-LSTM) trained via encoder-decoder NMT

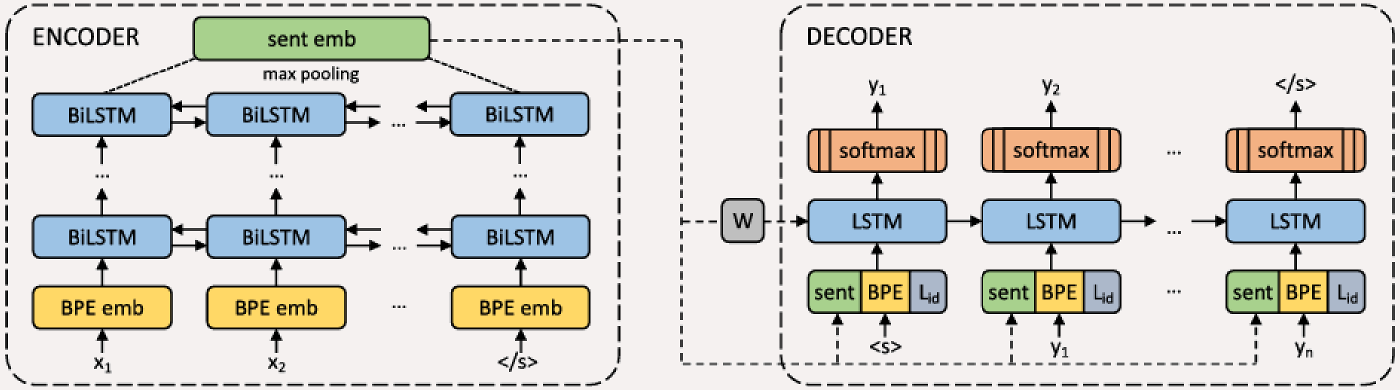


Image from the paper

Multilingual Sentence Encoders

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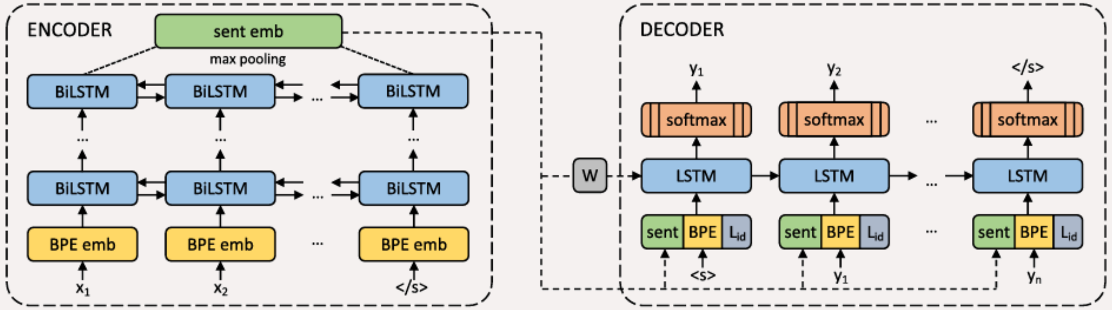
LASER: „Universal language agnostic sentence embedder"

- Sentence embedding (semb): max-pooled token-level representations, output of the last Bi-LSTM layer of the encoder
- Initial state of the decoder = sentence embedding linearly projected (matrix **W**)
- Sentence embeddings also fed as input to decoder at each step
- Trainable language ID vectors (also at input to decoder)
- Shared BPE vocabulary across the 93 languages

Image from the paper



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Multilingual Sentence Encoders

Chidambaram, M., Yang, Y., Cer, D., Yuan, S., Sung, Y., Strope, B., & Kurzweil, R. (2019, August). Learning Cross-Lingual Sentence Representations via a Multi-task Dual-Encoder Model. In Proceedings of the 4th Workshop on Representation Learning for NLP (RepL4NLP-2019) (pp. 250-259).

mUSE: „Multilingual Universal Sentence Embeddings"

- Transformer encoder (trained from scratch, not a PLM)
- Train bilingual rather than multilingual encoders
- Multi-task training: 4 training tasks tasks
  - NLI – same as in InferSent and SBERT
  - Other are ranking tasks with a contrastive objective
  - 3 tasks are actually monolingual English
- Cross-lingual sentence ranking
  - For an input sentence in English, score the target language sentences (translation should be on top of the ranking)

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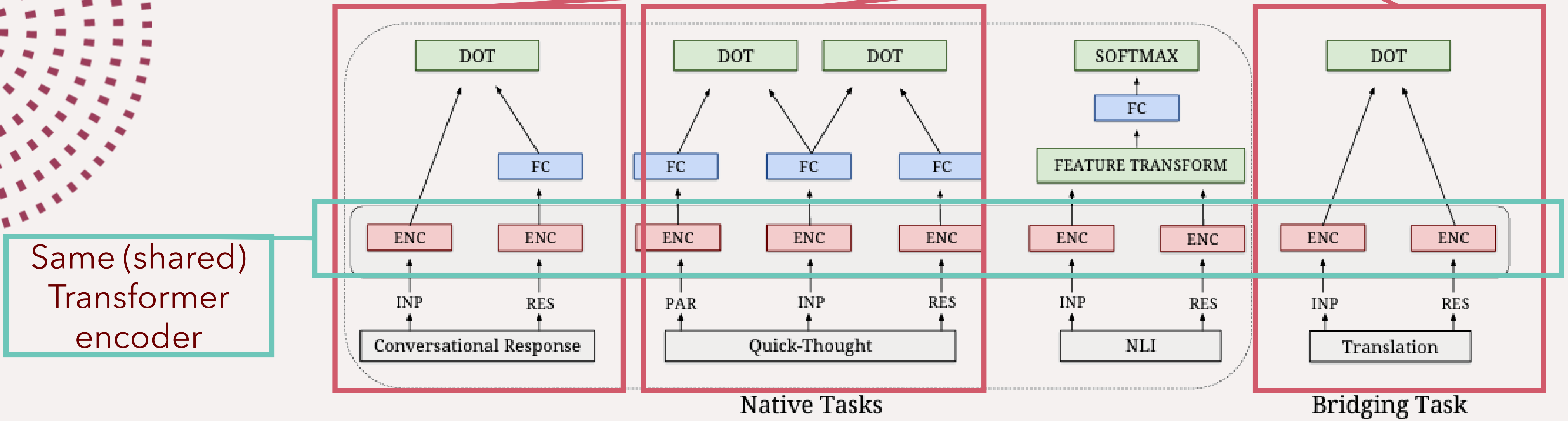


Contrastive Learning

- **Contrastive learning** is a learning paradigm that trains some model (parameters) by constrasting (comparing) two or more instances
- In traditional learning objectives, the model sees each instance independently (and makes some prediction for the instance)

$$\boldsymbol{loss_{tr}}(model(\mathbf{x}|\boldsymbol{\theta}), y)$$

- In contrastive learning, the loss is a function based on comparison of model's predictions for two or more instances

$$\boldsymbol{loss_{ctr}}(\boldsymbol{cmp}(model(\mathbf{x}_1|\boldsymbol{\theta}), model(\mathbf{x}_2|\boldsymbol{\theta}), \ldots, model(\mathbf{x}_n|\boldsymbol{\theta})))$$

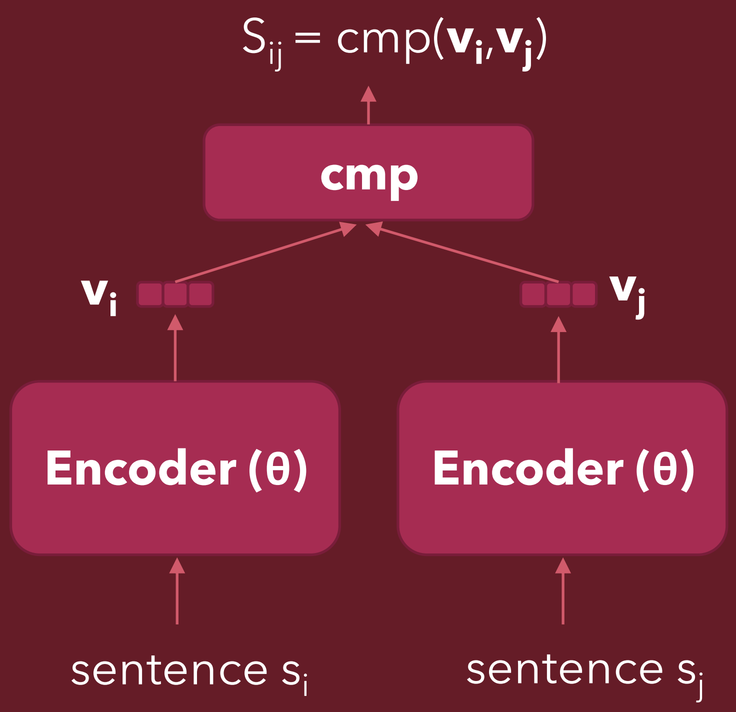
- Cmp is the function that compares the model outputs for instances
- Closely related to the concept of metric learning

Contrastive Learning

- **Bi-Encoder** (or Siamese Network) is common architecture on top of which contrastive learning objectives are applied
- Two instances are fed independently to the encoder

$$\mathbf{v_i} = \text{Encoder}(s_i|\boldsymbol{\theta})$$
$$\mathbf{v_j} = \text{Encoder}(s_j|\boldsymbol{\theta})$$

- **cmp** is then some distance of similarity metric that compares $\mathbf{v_i}$ and $\mathbf{v_j}$
  - Typically non-parameterized!
  - Euclidean dist. or cosine sim.

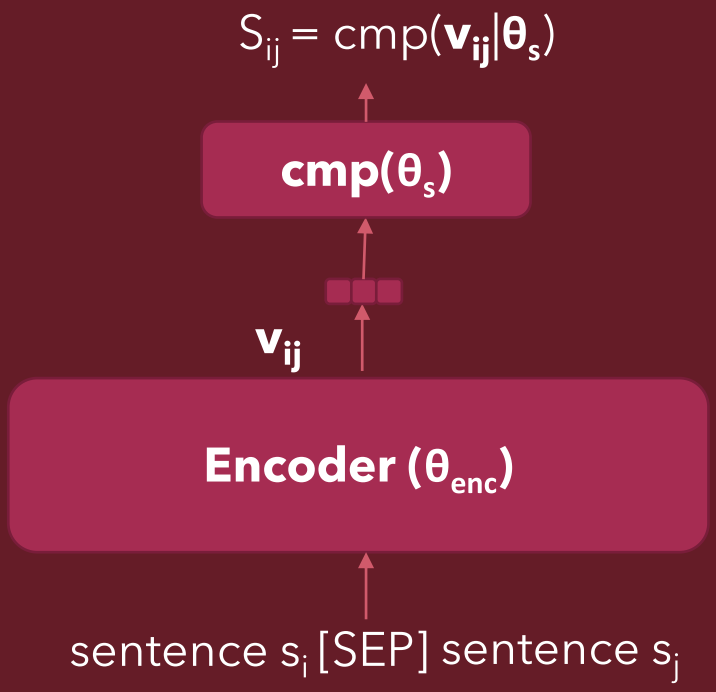


Contrastive Learning

- In the Bi-Encoder architecture, each sentence is encoded <u>independently</u> – encoding of each sentence does not reflect the other
  - Can be quite important in some tasks (e.g., NLI)
- Alternative: **Cross-Encoder** architecture
  - Pair of sentences encoded together
  - Concatenated at input to the encoder

$$\mathbf{v}_{ij} = \text{Encoder}(s_i + s_j | \theta_{enc})$$

- Encoder outputs a joint representation for a sentence pair (s_i, s_j)
- Must have a parameterized (θ_s) scoring function cmp to convert $\mathbf{v}_{ij}$ into a scalar score
  - <u>Cannot obtain embeddings of individual sentences</u>



Contrastive Learning

- Contrastive loss functions contrast the scores s_{ij} of positive pairs (i, j) against the scores s_{ik} (or s_{jk}) of negative pairs (i, k)
- **Positive pair**: pairs of instances (sentences) for which the relation of interest holds, e.g., s_i and s_j are mutual translations
- **Negative pairs**: pairs made of one instance from the positive pair (e.g., s_i) and instances s_k such that the relation that holds for (s_i, s_j) does not hold for (s_i, s_k) (e.g., s_k is not a translation of s_i)
  - We typically contrast (sometimes simultaneously) the same positive pair against multiple negatives

Contrastive Learning

- **Triplet loss** – arguably the simplest contrastive loss:
  - Positive (s_i, s_j) with the score s_{ij} contrasted against a single negative (s_i, s_k) with the score s_{ik}

$$loss_{triplet}(s_i, s_j, s_k) = \max(0, s_{ik} - s_{ij} + \varepsilon)$$

    - This formulation assumes that s is a similarity score
    - If s is supposed to be a distance score, then $\max(0, s_{ij} - s_{ik} + \varepsilon)$

  - Pushes the model to score positive pairs higher than corresponding negative pairs by (at least) a margin ε
  - By minimizing this loss, the encoder must „figure out" what sentences of positive pairs share that those of negative pairs don't

Contrastive Learning

Oord, A. V. D., Li, Y., & Vinyals, O. (2018). Representation learning with contrastive predictive coding. arXiv preprint arXiv:1807.03748.

- Noise Contrastive Estimation (**InfoNCE**): contrast simultaneously the positive pair (s_i, s_j) against N negatives (s_i, s_{k1}), (s_i, s_{k1}), ..., (s_i, s_{kN})

$$\text{loss}(s_i, s_j, s_{k1}, \ldots, s_{kN}) = -\ln \frac{\exp\left(\frac{s_{ij}}{T}\right)}{\exp\left(\frac{s_{ij}}{T}\right) + \sum_{k_1}^{k_N} \exp\left(\frac{s_{ik}}{T}\right)}$$

- Effectively negative log-likelihood of a positive pair, according to a softmax over all scores: for the positive and all negatives
- **T** = temperature hyperparam. of the loss – controls the „strength" of the contrast, i.e., how much we smoothen the raw scores s_{ij}
  - Q: What if $T = 0$? What if $T = \infty$?

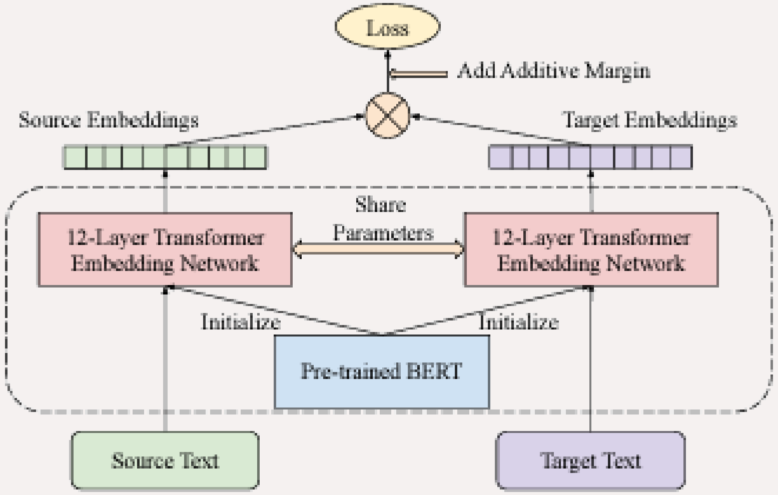
Contrastive Learning

- Positives are typically given in the data we train on
  - E.g., in parallel data – sentences that are translations of each other
- Q: But how do we create negatives?
  - Fixed, predetermined negatives for each positive? Or
  - Dynamically selected within the training batch of the positive?
- Both strategies are used
  - In-batch negatives (aka <u>random</u> (but not fixed) negatives)
  - Fixed, precomputed negatives are selected based on some criteria when we need hard negatives
    - Hard negatives: in some aspect somewhat similar to positives
    - E.g., s_k not a translaton of s_i, but shares some meaning (i.e., not completely semantically unrelated)

Multilingual Sentence Encoders

Feng, F., Yang, Y., Cer, D., Arivazhagan, N., & Wang, W. (2022, May). Language-agnostic BERT Sentence Embedding. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) (pp. 878-891).

- LABSE: „Language-Agnostic BERT Sentence Embedding"
  - Basically mUSE, but the Encoder is initialized with mBERT
  - Cross-lingual sentence ranking using parallel data (100M pairs for each lang!)
    - Modified InfoNCE loss – what they call „additive margin"
    - $\exp(s_{ij} - m)$ instead of $\exp(s_{ij}/T)$ for the pos and only $\exp(s_{ij})$ for the negs
      - „Improves separation between translations and near non-translations"



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Multilingual Sentence Encoders

Reimers, N., & Gurevych, I. (2020, November). Making Monolingual Sentence Embeddings Multilingual using Knowledge Distillation. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP) (pp. 4512-4525).

- Parallel data allows for pretraining multilingual sentence encoders
  - Especially if we start from multilingual MMTs like mBERT
- Monolingual English SBERT:
  - Supervised fine-tuning: NLI, STS, …
  - Stronger (for EN) than multilingual SEs trained from scratch with parallel data
- Idea: „copy" the sentence specialization knowledge of English SBERT into a multilingual MMT like mBERT
  - Supervision for „copying": parallel data!

Multilingual Sentence Encoders

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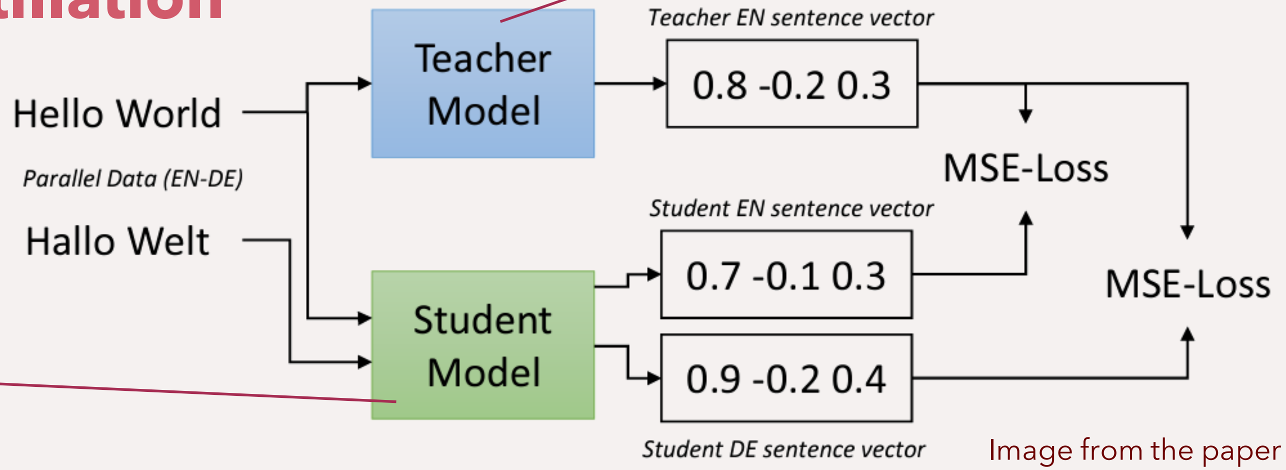
- Idea: „copy" the sentence specialization knowledge of English SBERT into a multilingual MMT like mBERT
  - Supervision for „copying": parallel data!
- „Copying" = **knowledge distillation**

English Sentence-BERT



Initialized with an MMT (mBERT or XLM-R)English SBERT

Image from the paper

Knowledge Distillation

Hinton, G., Vinyals, O., & Dean, J. (2015). Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531.

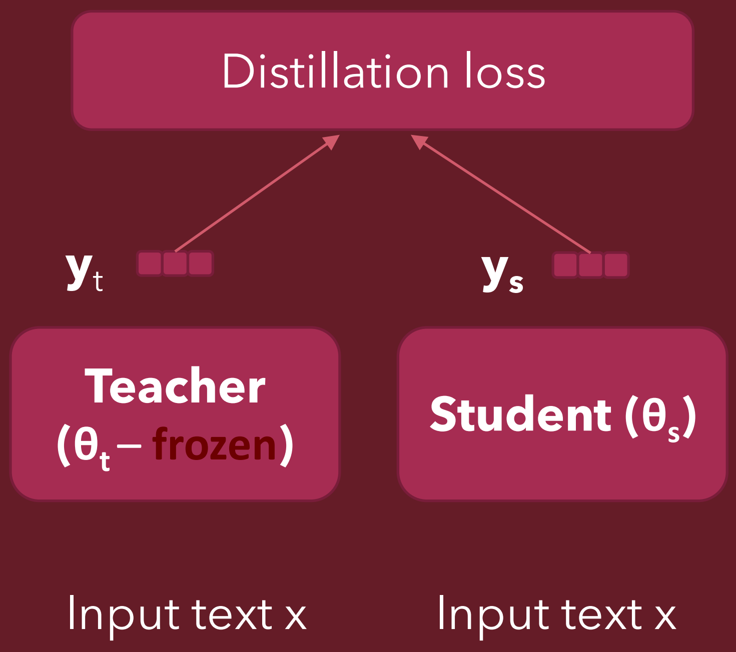
- **Knowledge distillation** is a process of replicating the „knowledge" stored in the parameters of one model – the **teacher** – into the parameters of a new model – the **student**

- Q: Why would we do knowledge distillation?
  - Original work used it to distill multiple models for the same task (an ensemble of models) into a single model
  - Compression – distilling a larger model into a smaller model
    - Pretrained LMs have been shown to be overparametrized!

Knowledge Distillation

Hinton, G., Vinyals, O., & Dean, J. (2015). Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531.

- **Knowledge distillation**: we need some training data for distillation too
  - We feed the same input x to both the teacher and student
- $\mathbf{y}_t$ and $\mathbf{y}_s$ outputs of teacher and student, resp.
  - E.g., an encoding of the sentence
  - E.g., a probability distribution over classes
- Training loss: minimize the difference between the student output and teacher output
  - E.g., minimize Euclidean distance or maximize cosine similarity between $\mathbf{y}_t$ and $\mathbf{y}_s$



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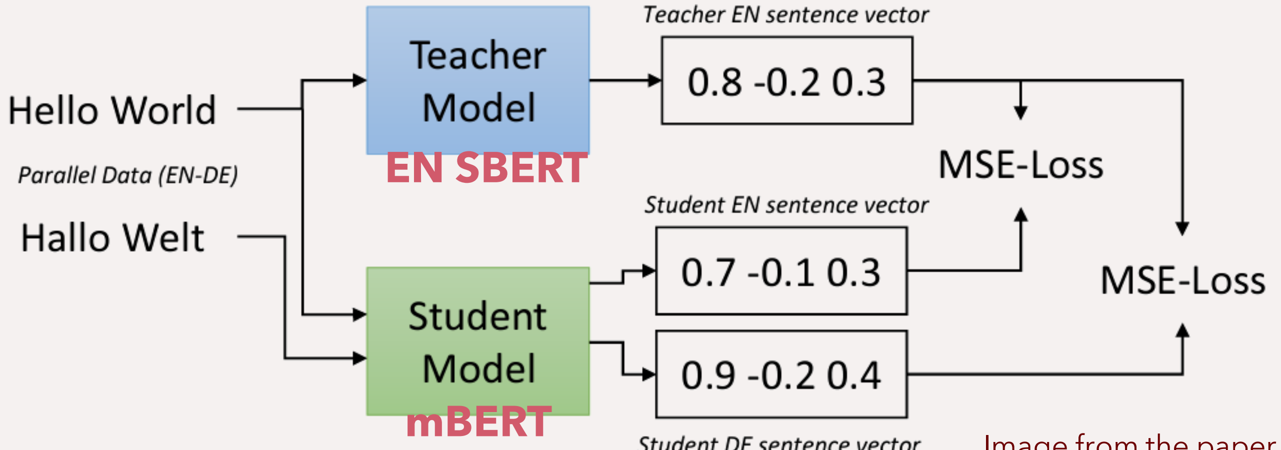
- Sentence-BERT: specialized for encoding sentences in English
  Supervision for „copying“: parallel data!
- mBERT: „understands“ input text in 104 languages
- Distill the knowledge of EN SBERT into mBERT
  - We get a multilingual Sentence-BERT!



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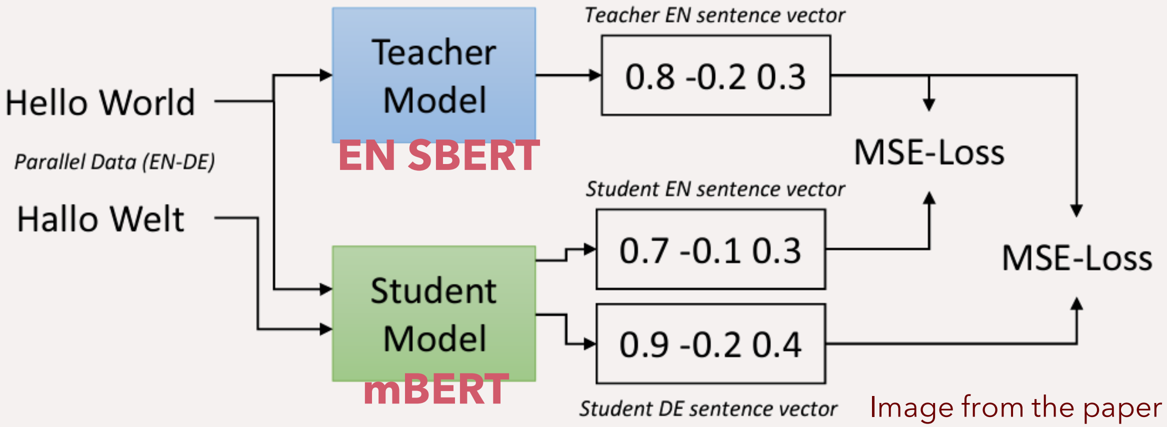
- Distill the knowledge of EN SBERT into mBERT
- Parallel data needed:
  - (s_{EN}, s_{L2}) – one translation pair
  - s_{EN} encoded by both the teacher ($\mathbf{s}^t_{EN}$) and student ($\mathbf{s}^s_{EN}$)
  - s_{L2} encoded by the student ($\mathbf{s}_{L2}$)
  - Distillation loss:

$$MSE(\mathbf{s}^t_{EN}, \mathbf{s}^s_{EN}) + MSE(\mathbf{s}^t_{L2}, \mathbf{s}^s_{EN})$$



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Multilingual Sentence Encoders

Heffernan, K., Çelebi, O., & Schwenk, H. (2022, December). Bitext Mining Using Distilled Sentence Representations for Low-Resource Languages. In Findings of the Association for Computational Linguistics: EMNLP 2022 (pp. 2101-2112).

- All previous multilingual approaches train the same encoder (all parameters shared) for all languages
    - Positive transfer across languages vs. the curse of multilinguality?
- „LASER3": distills a massively multilingual LASER teacher into many student models, one for each language or lang. group
    - Each student with its own language-specific SentPiece tokenizer
    - Since all students are distilled from the same teacher, their output embeddings are comparable (in the same representation space)

Multilingual Sentence Encoders

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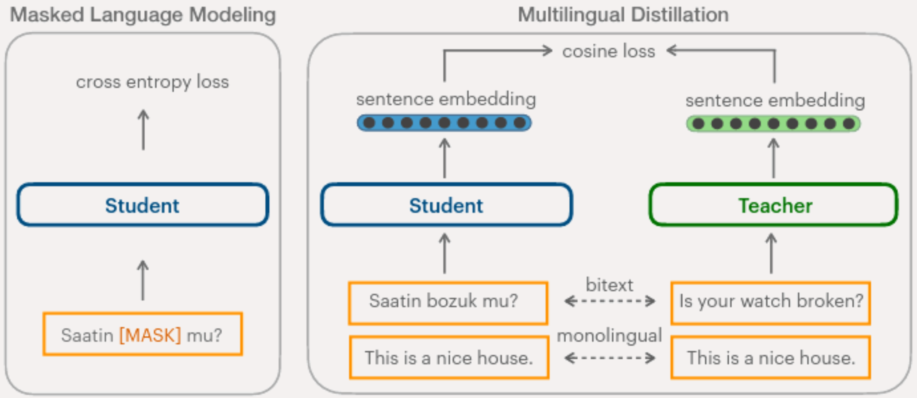
- „LASER3": distills a massively multilingual LASER teacher into many student models, one for each language or language group
  - Teacher: a recurrent model (LASER)
  - Students: 12-layer Transformers
  - Distillation: similar to Reimers & Gurevych
    - Only maximizing cosine similarity instead of minimizing MSE
  - Student additionally trained monolingually on L2 data, via MLM-ing



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- **Self-Supervised Sentence Encoders**

Multilingual Sentence Encoders

- All sentence encoders we introduced so far needed some kind of annotated data for supervision
  - Monolingual EN SBERT: NLI and STS
  - Multilingual SBERT: both NLI/STS (for the teacher) + parallel data (for the distillation)
  - LASER, LaBSE, LASER3: parallel data
- Q: could we train sentence encoders in a self-supervised manner?
  - Like regular PLMs (BERT & co.) are trained via MLM-ing
  - Yes, via data augmentation!
    - For any sentence, we need to automatically create positive pairs
    - Create „paraphrases" (same meaning, different words)
      - In the symbolic or representation space

Multilingual Sentence Encoders

Gao, T., Yao, X., & Chen, D. (2021). SimCSE: Simple Contrastive Learning of Sentence Embeddings. In 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021 (pp. 6894-6910). Association for Computational Linguistics (ACL).

- SimCSE: for an input sentence s_i, obtain two different embeddings $\mathbf{s}_i^1$ and $\mathbf{s}_i^2$
  - Q: But how to obtain two different embeddings with the very same encoder?
    - We could add random noise to some intermediate representations in the Transformer, or
    - Dropout!

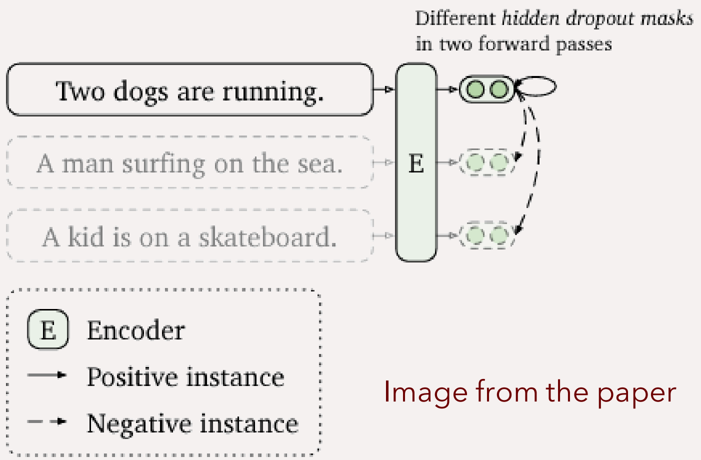


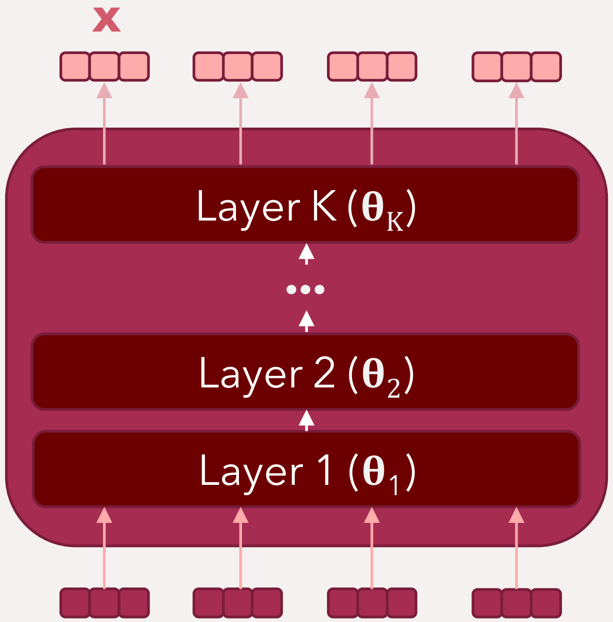
Image from the paper

Dropout

Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. The journal of Machine Learning Research, 15(1), 1929-1958..

- Let **x** be any hidden representation, output of any layer (e.g., in our neural LM)
  - E.g., output of layer K
- Applying dropout on a layer means
  - To modify its output(s) **x** so that each element x_i becomes replaced with x'_i:

$x'_i = 0$ with dropout probability p or
$x'_i = x_i / (1-p)$ with the probability $(1-p)$



Multilingual Sentence Encoders

Gao, T., Yao, X., & Chen, D. (2021). SimCSE: Simple Contrastive Learning of Sentence Embeddings. In 2021 Conference on Empirical Methods in Natural Language Processing, EMNLP 2021 (pp. 6894-6910). Association for Computational Linguistics (ACL).

- SimCSE: for an input sentence s_i, obtain two different embeddings $\mathbf{s}_i^1$ and $\mathbf{s}_i^2$
  - Same sentence passed through encoder twice, with two different dropout masks
  - The obtained embeddings $(\mathbf{s}_i^1, \mathbf{s}_i^2)$ then make a positive pair for contrastive training
  - Negative pairs: $(\mathbf{s}_i^1, \mathbf{s}_j)$ or $(\mathbf{s}_i^2, \mathbf{s}_j)$ where $\mathbf{s}_j$ is the embedding of some other sentence s_j

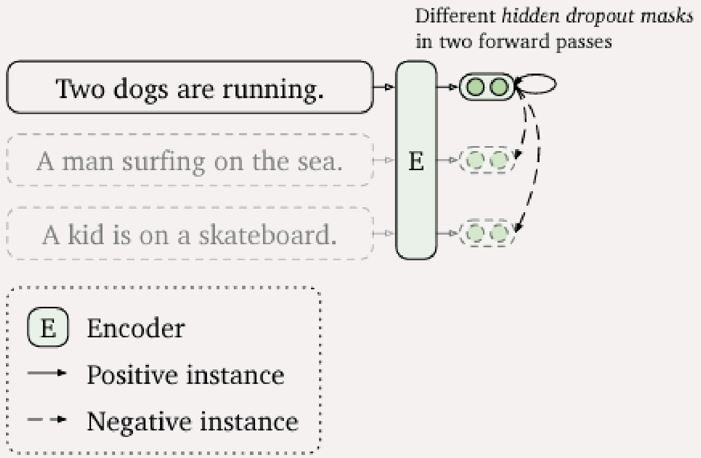


Image from the paper

Image: Alexander Mikhalchyk