Lecture 4:
Transfer Learning in NLP

Transfer Learning

Let's say we need to train a text classification model

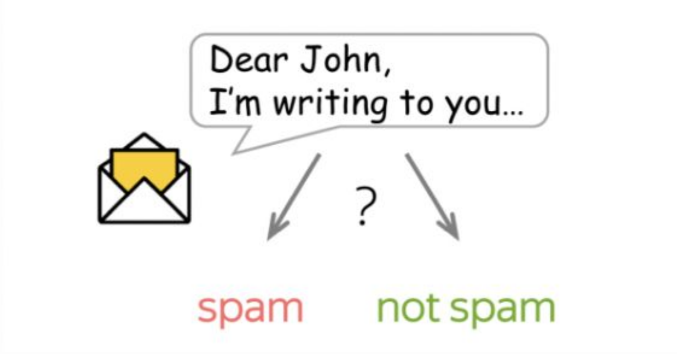

Image source: [NLP Course - For you]()

Transfer Learning

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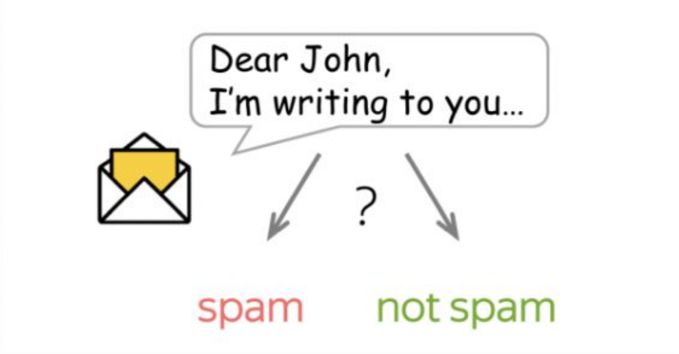

To train from scratch, we need

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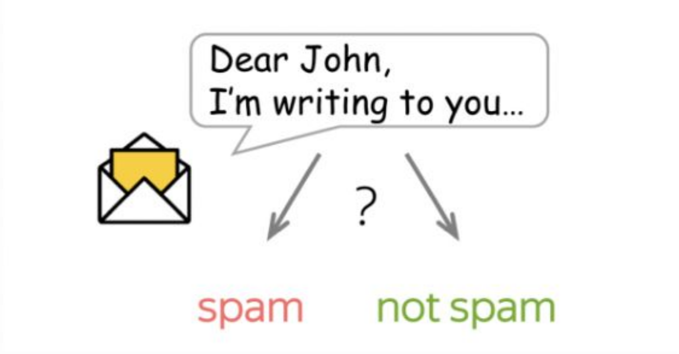

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Image source: [NLP Course - For you]()

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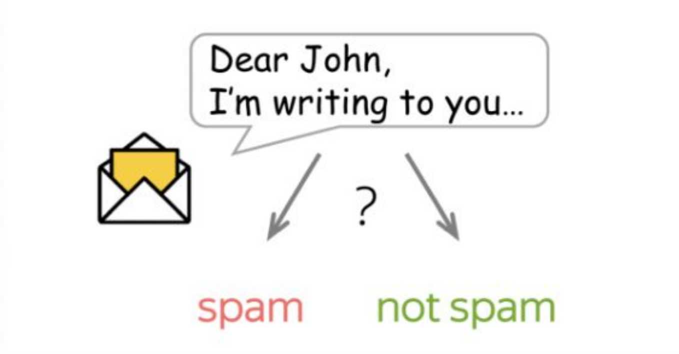

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Expensive to obtain

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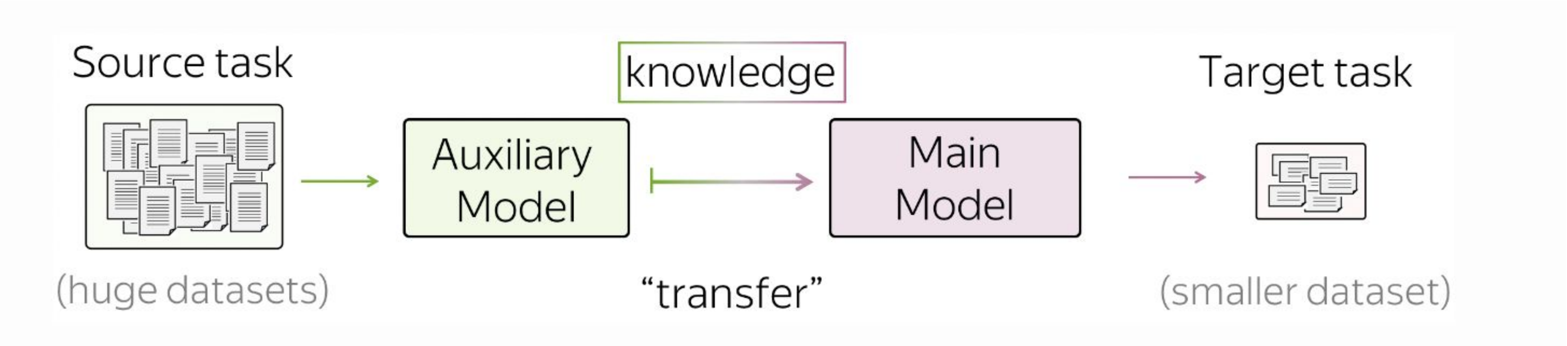
Which features are useful???

Transfer Learning



Transfer Learning is a technique of exploiting the properties and data distribution of a given (task, dataset) pair on different tasks and datasets of interest

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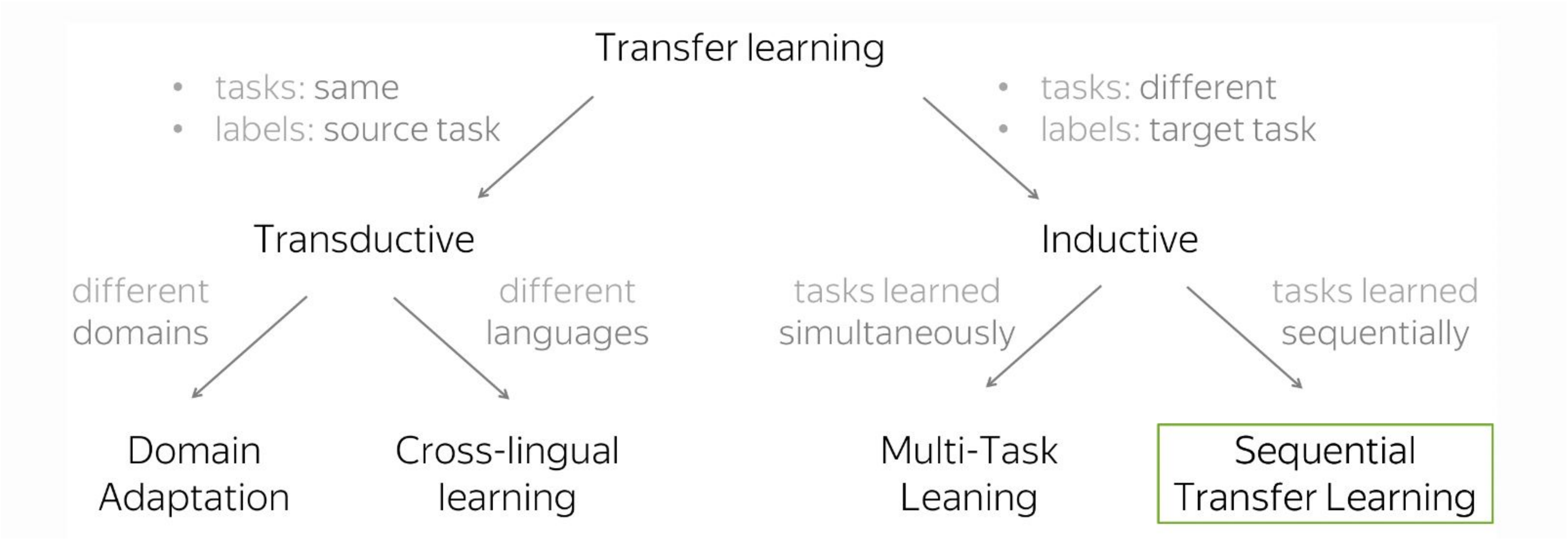
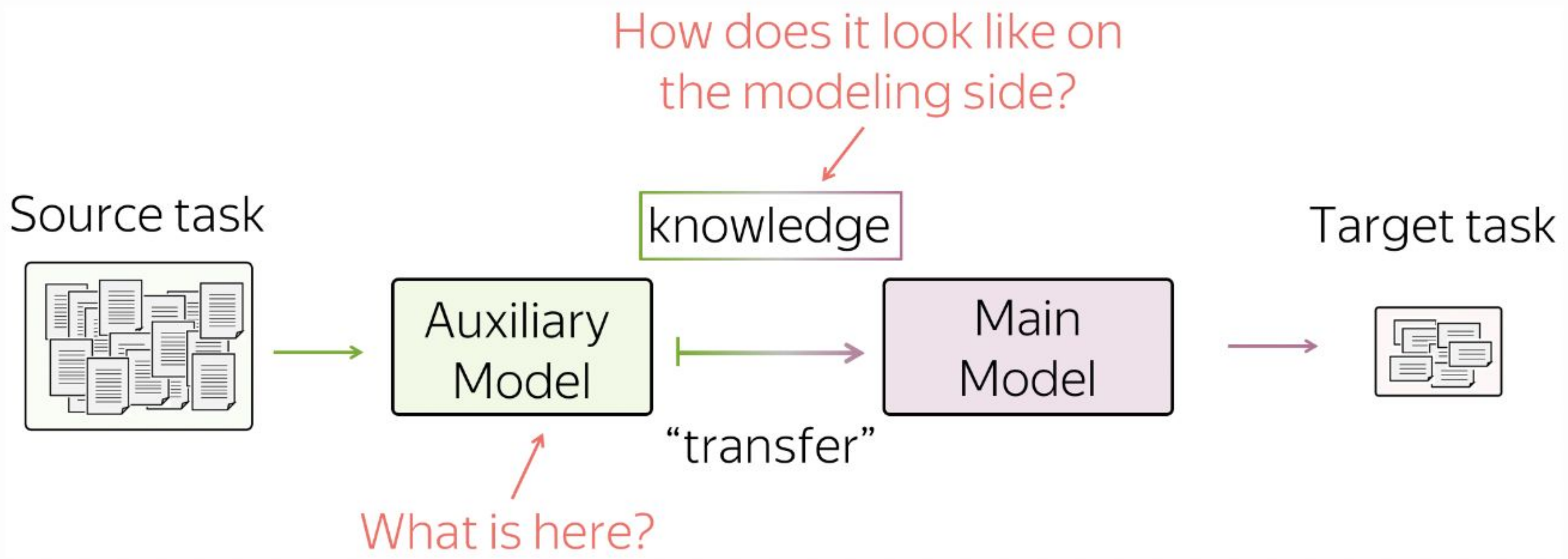
Transfer Learning Taxonomy



Sequential Transfer Learning



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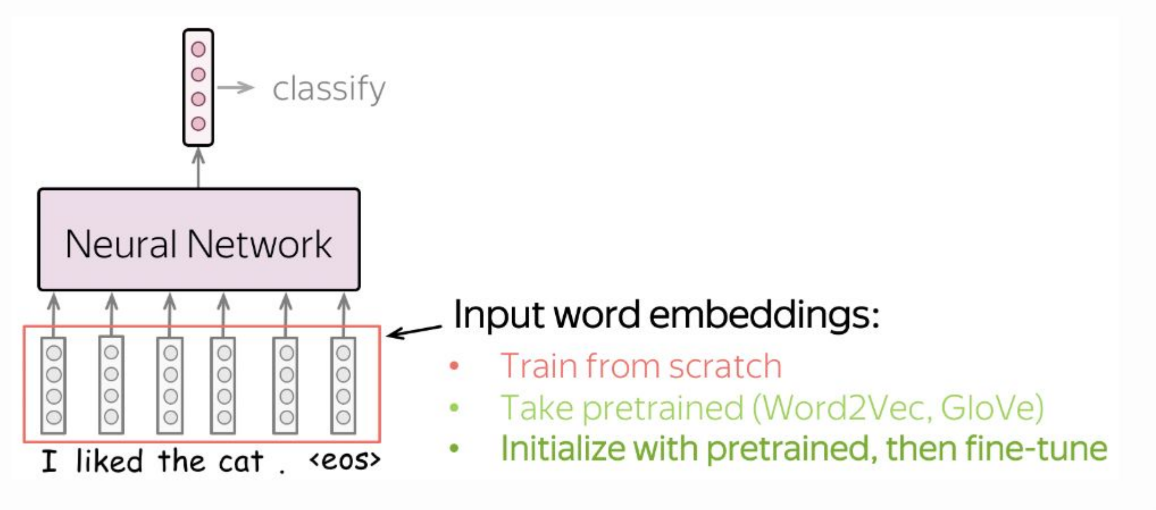
Transfer Learning via Word Embeddings

- Let's look at embedding layer in classification pipeline



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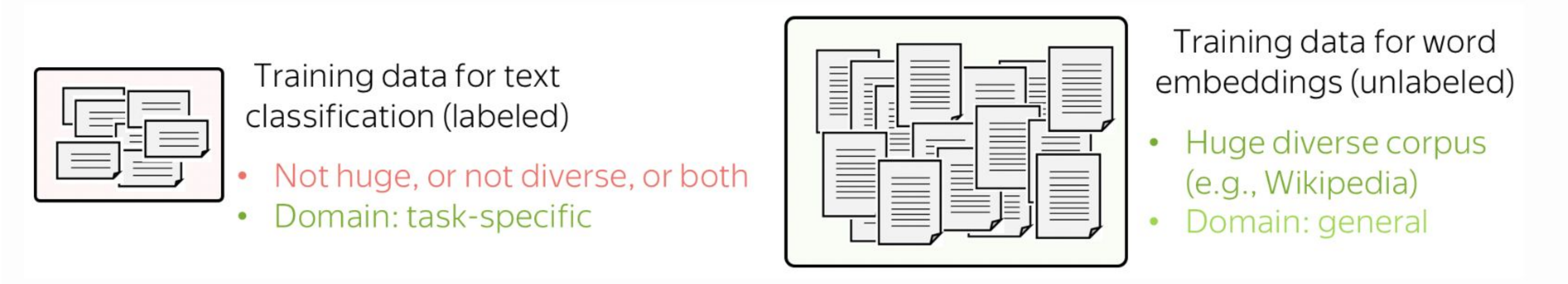
Transfer Learning via Word Embeddings

- Which data distribution was embedding layer attuned to?

<u>Embedding layer from scratch</u>
(trained jointly for cls)

<u>Embedding layer == word2vec</u>



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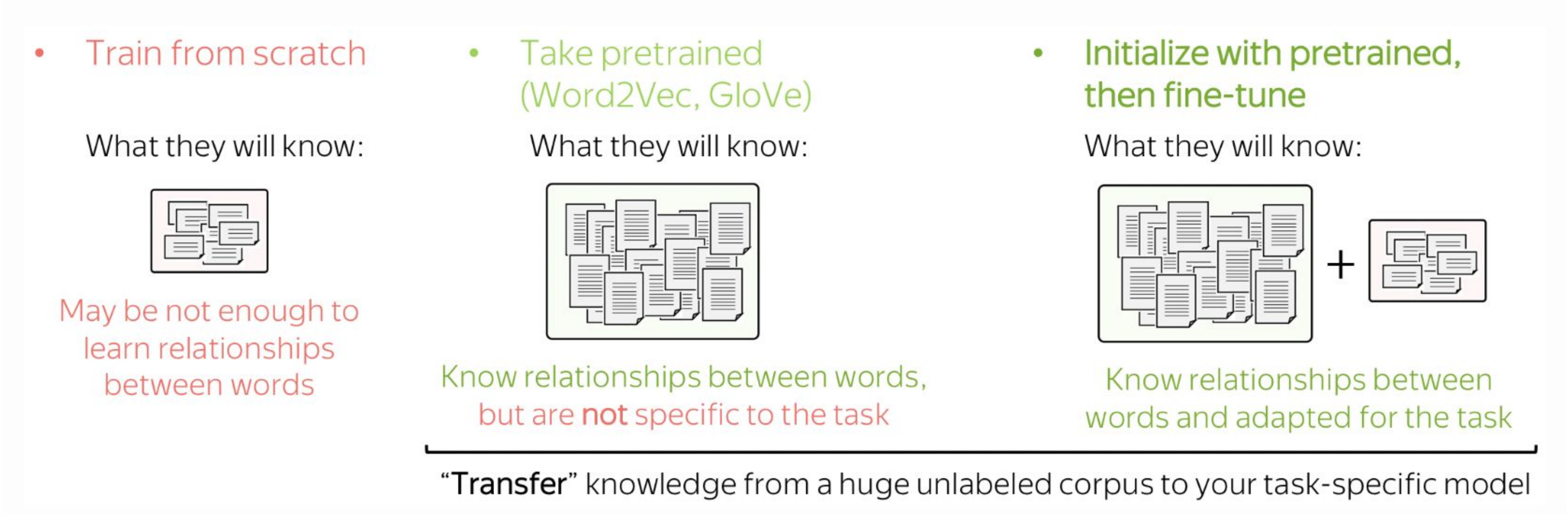
Transfer Learning via Word Embeddings



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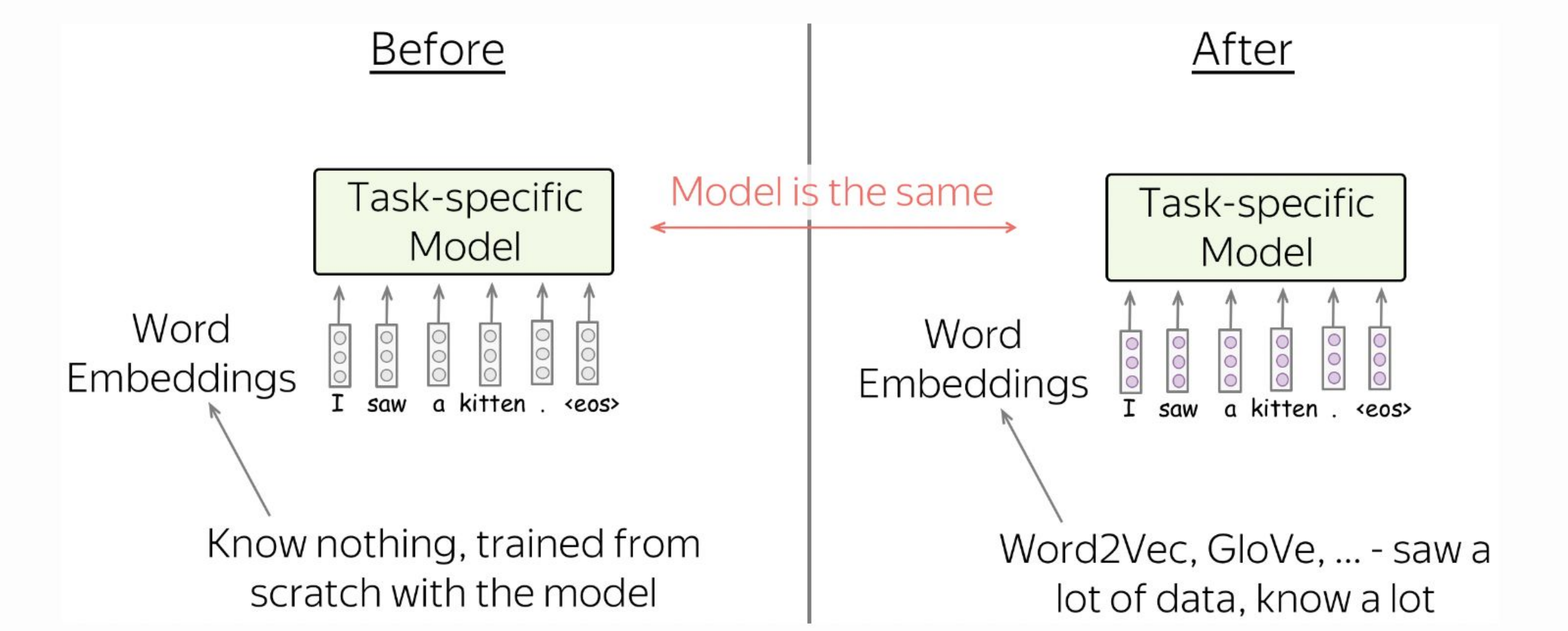
Transfer Learning via Word Embeddings



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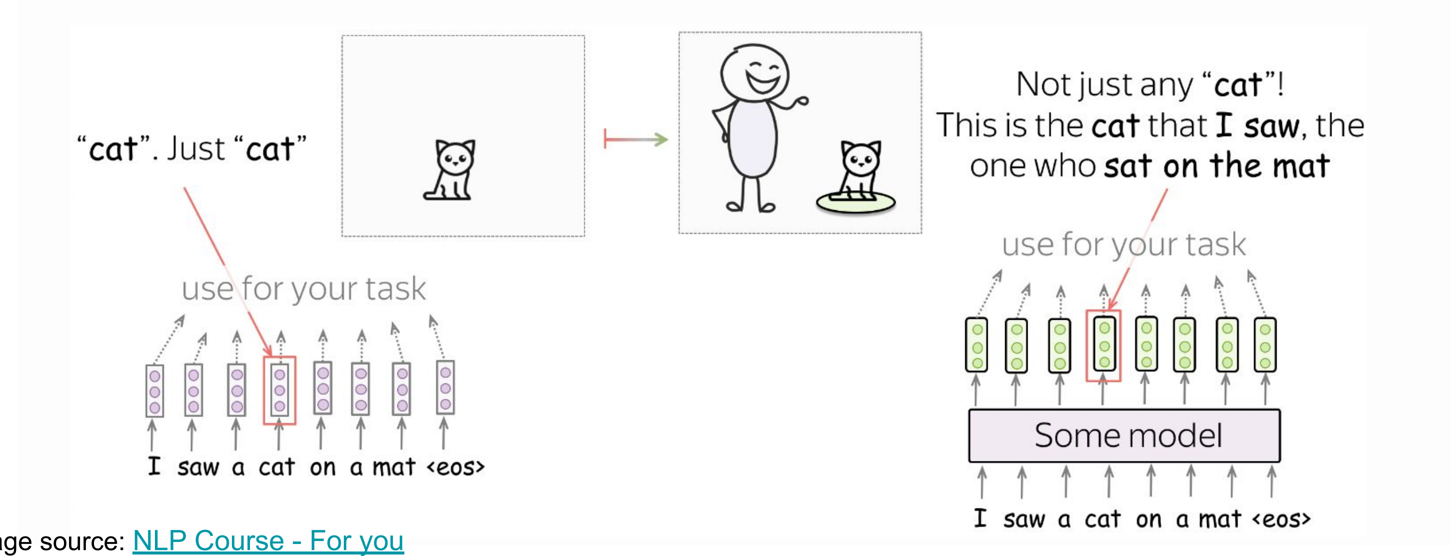
Transfer Learning via Contextualized Representations

- Word vectors do not model any intra-token relationships

Transfer Learning via Contextualized Representations

- Word vectors do not model any intra-token relationships
- **<u>The same way as words, we can learn to encode words along with the context they are used in</u>**



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Transfer Learning via Contextualized Representations

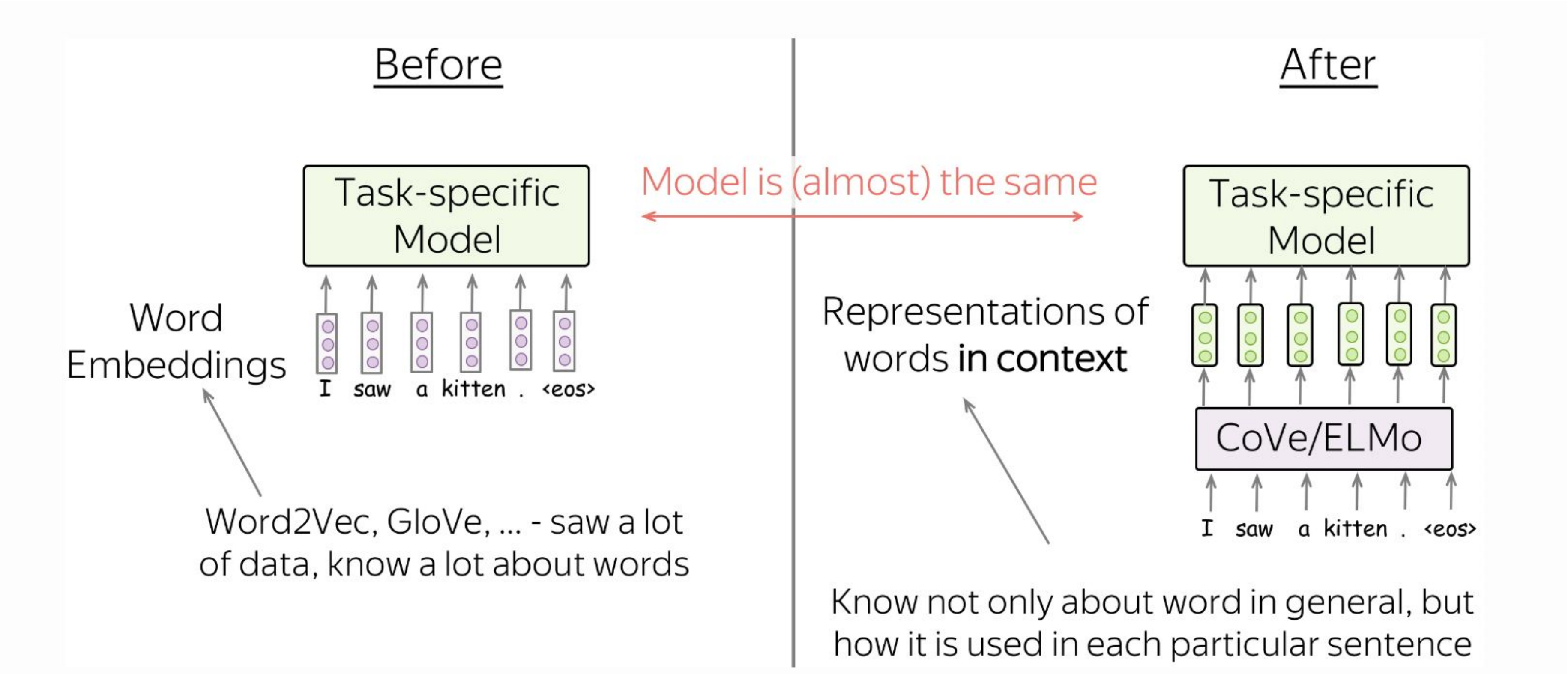


Image source: [NLP Course - For you]

Representation Learning (CoVe, ELMO)

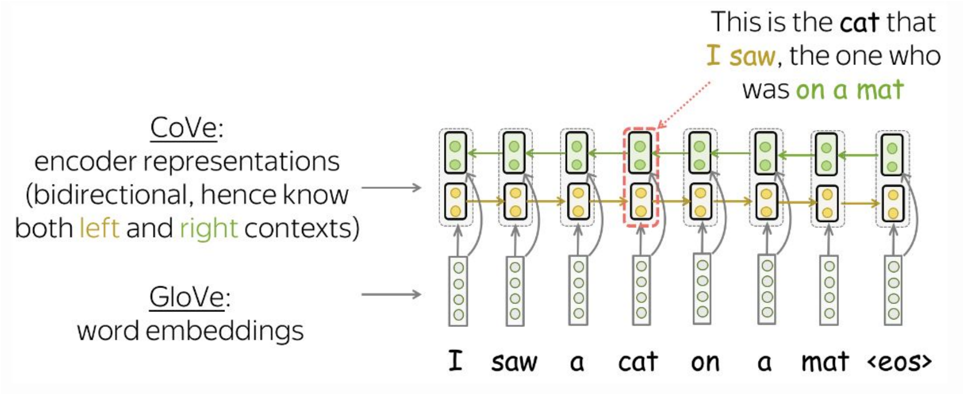
CoVe

CoVe (Contextualized Word Vectors Learned in Translation)

Key Idea: translation of sentence requires modeling complex token dependencies and NMT model learns to “understand” sentence

CoVe

- Train NMT encoder-decoder system
- Take pre-trained encoder as feature extractor
- CoVe = encoder ouputs for a given sequence



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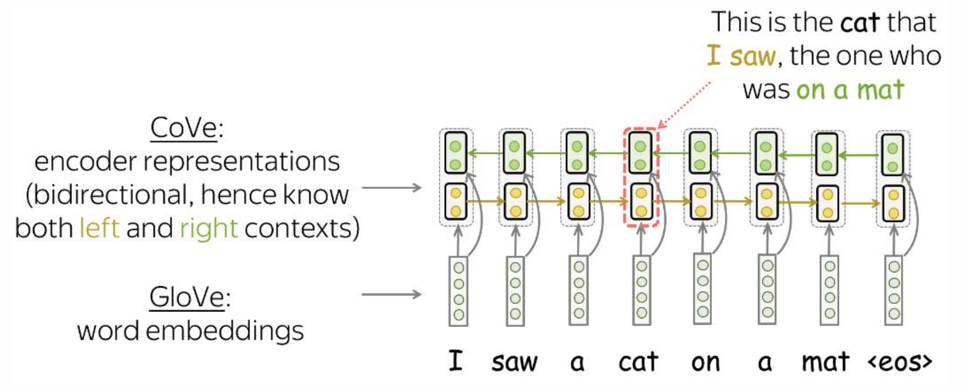
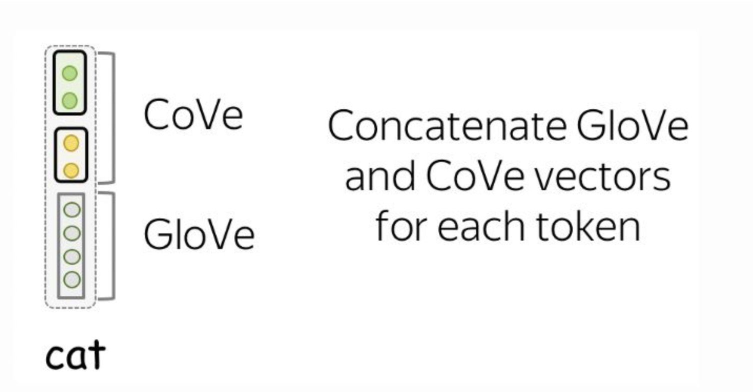
CoVe

- Train NMT encoder-decoder system
- Take pre-trained encoder as feature extractor
- CoVe = encoder ouputs for a given sequence
- For downstream tasks: CoVe + GloVe embeddings





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ELMO

ELMO (Embeddings From Language Models)

Key Idea: similar to CoVe, but instead of NMT use LM pretraining objective

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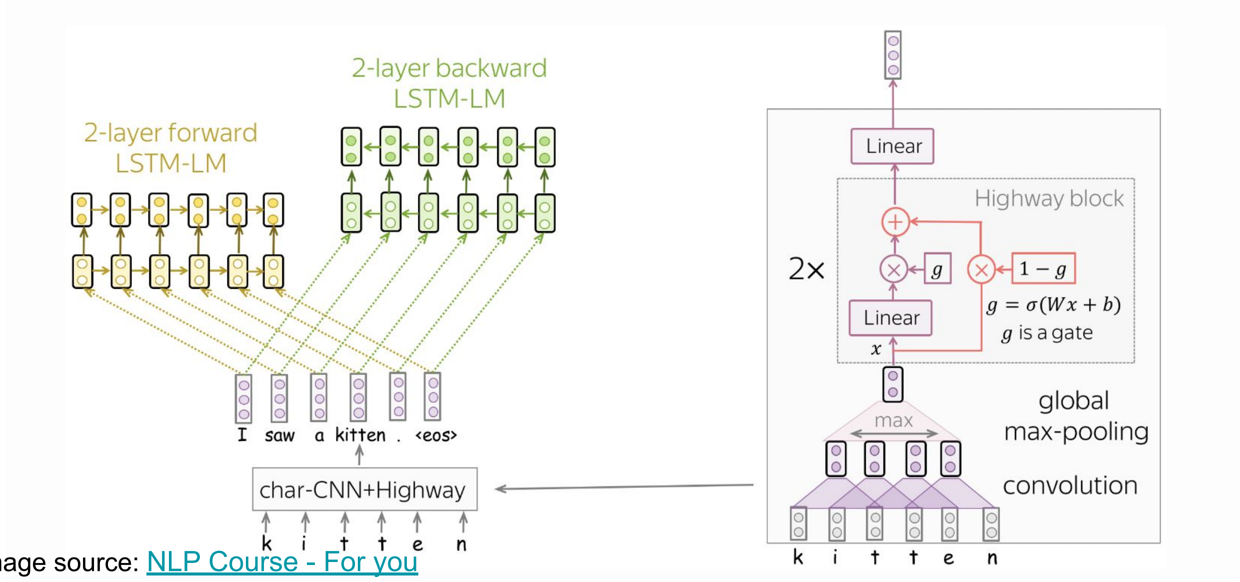

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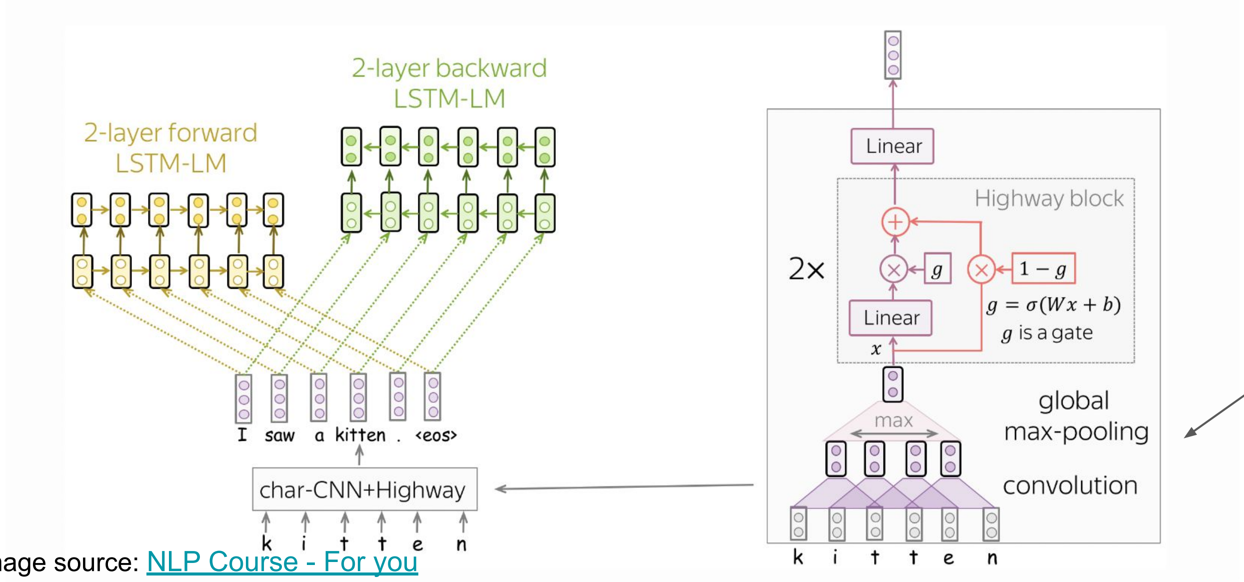
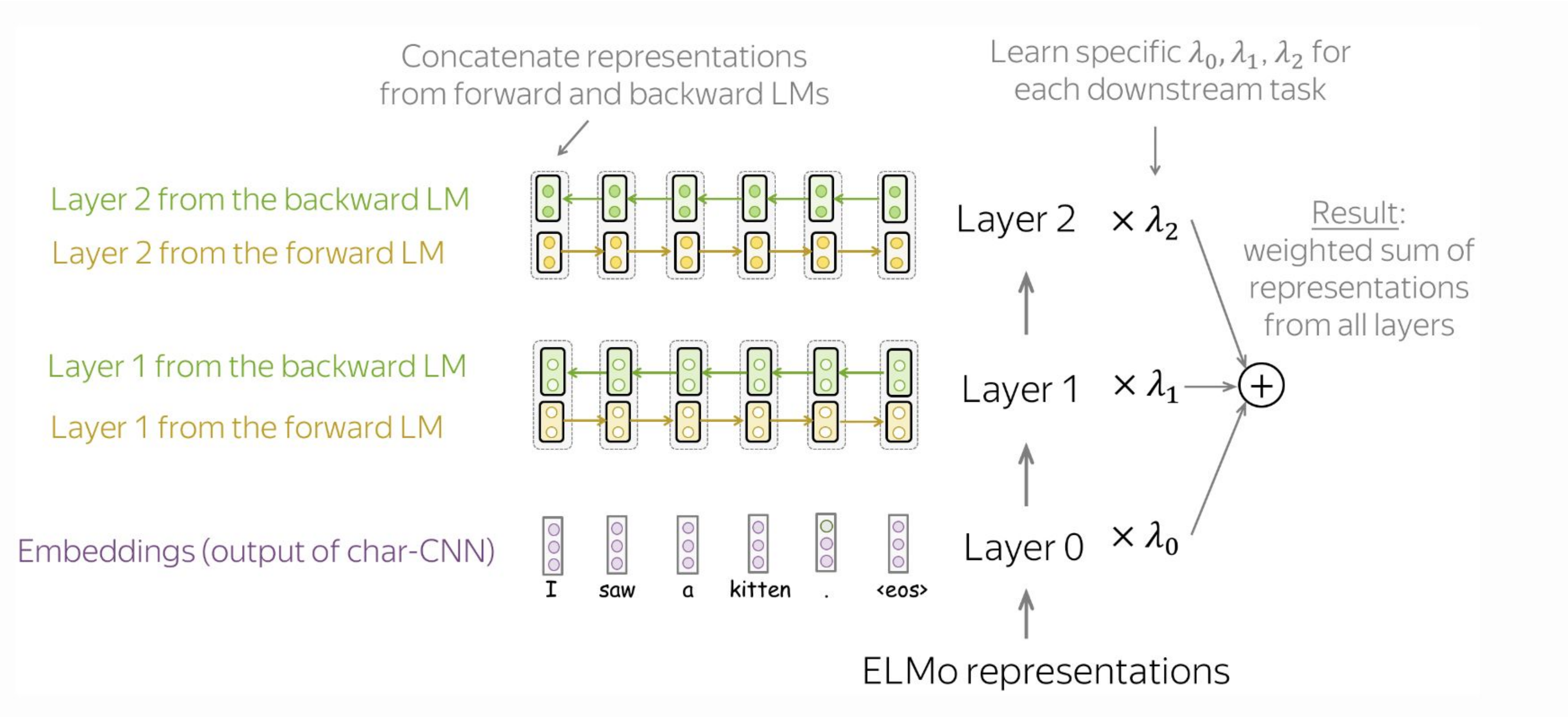


Image source: [NLP Course - For you]()

Initialization

Character-level CNN (robust handling of OOV words)

ELMO: Feature Extraction



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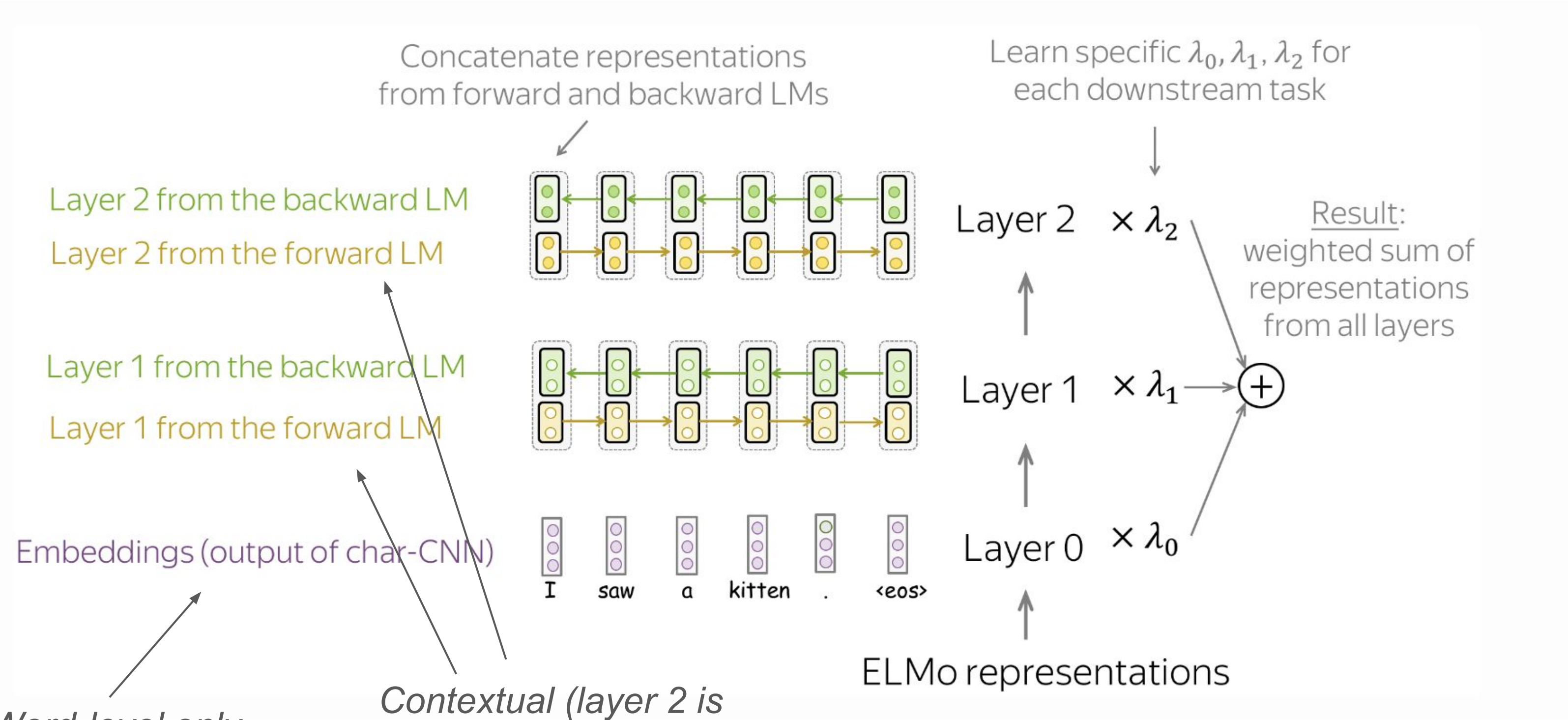
ELMO: Feature Extraction



Word-level only

Contextual (layer 2 is more high-level info)

Image source: [NLP Course - For you]

Transfer Learning via Pretrained Models

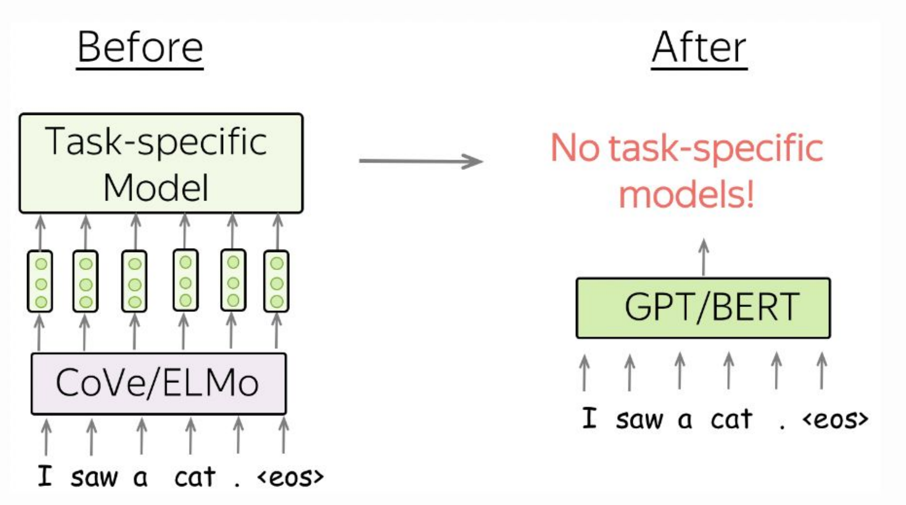
Transfer Learning

Contextualized Representations

- Replace word embedding layer
- Rest of the pipeline should be trained independently for each task

Pretrained Models

- Replace full task-specific model
- Minimal adaptation or usage “as is”



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Pretrained Models From Language Modeling

Language Modeling is a fertile task for representation learning

- Semi-supervised (labels are implicitly given in data)
- Ubiquitous datasets (web crawl, literature, etc.)
- Complicated and very generic

GPT

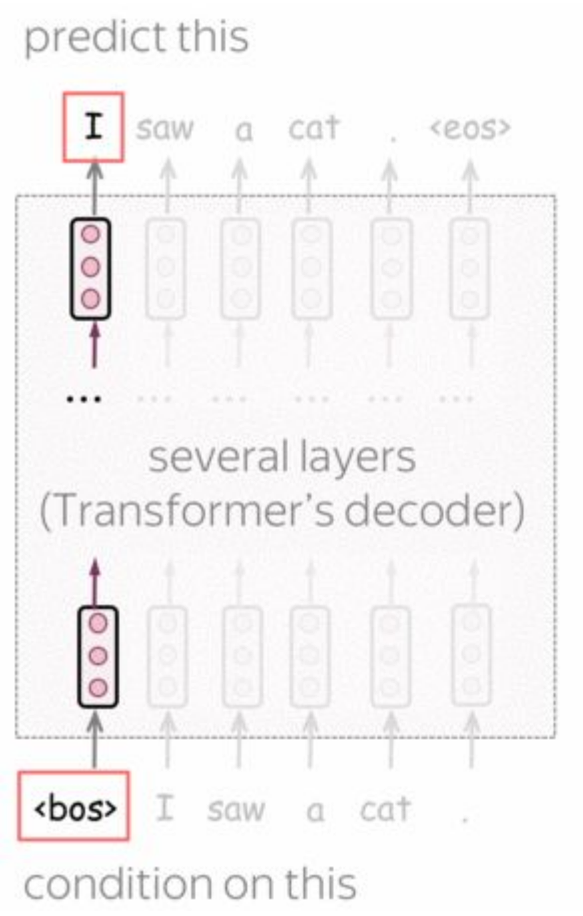
GPT (Generative Pre-Training for Language Understanding)

Key Idea: autoregressive LM with transformer decoder

$$L_{xent} = -\sum_{t=1}^{n} \log(p(y_t | y_{<t})).$$

GPT

- Decoder-only (triangle attention mask)
- Autoregressively predict next token conditioned on left context
- Train on unsupervised corpora with supervised xent loss (*self-supervised learning*)



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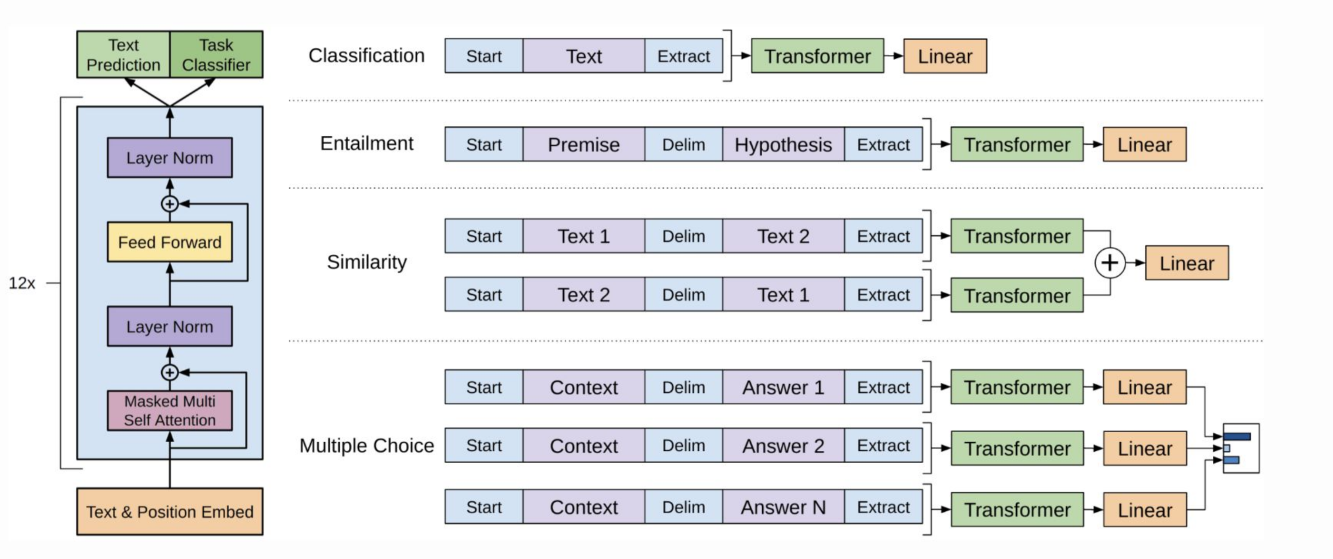
GPT Finetuning (GPT-1)

- Finetune LM parameters using a combination of two losses

$$L = L_{xent} + \lambda \cdot L_{task}.$$



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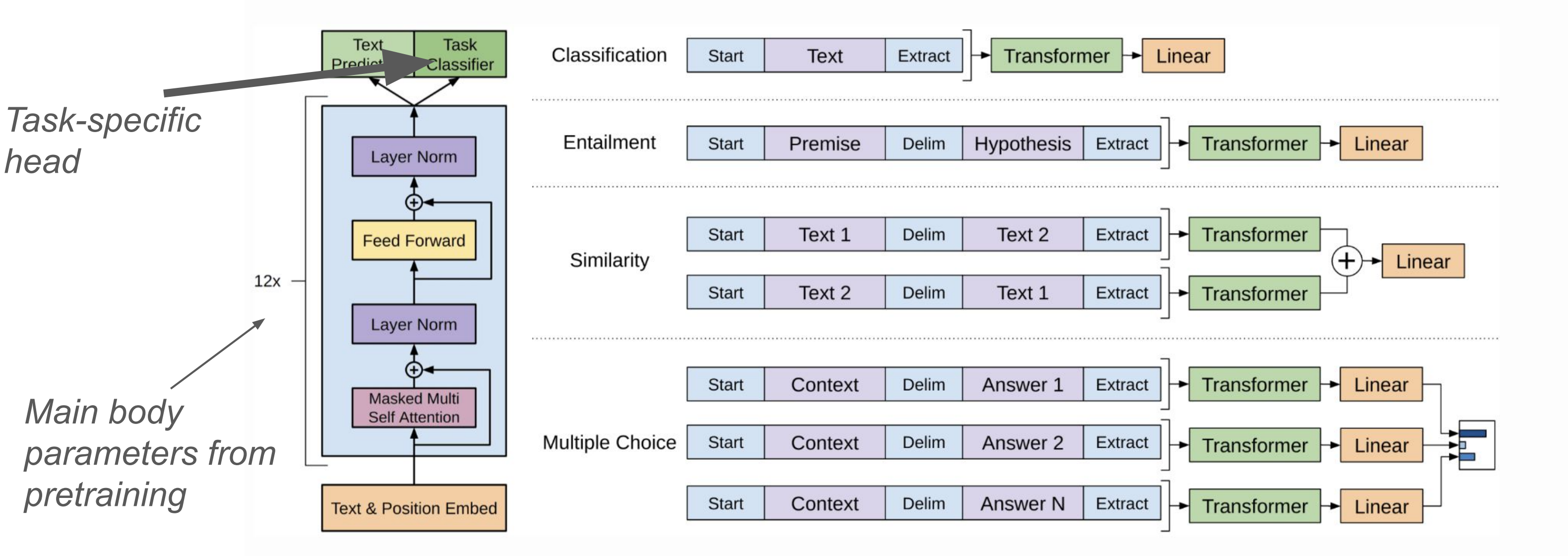


BERT

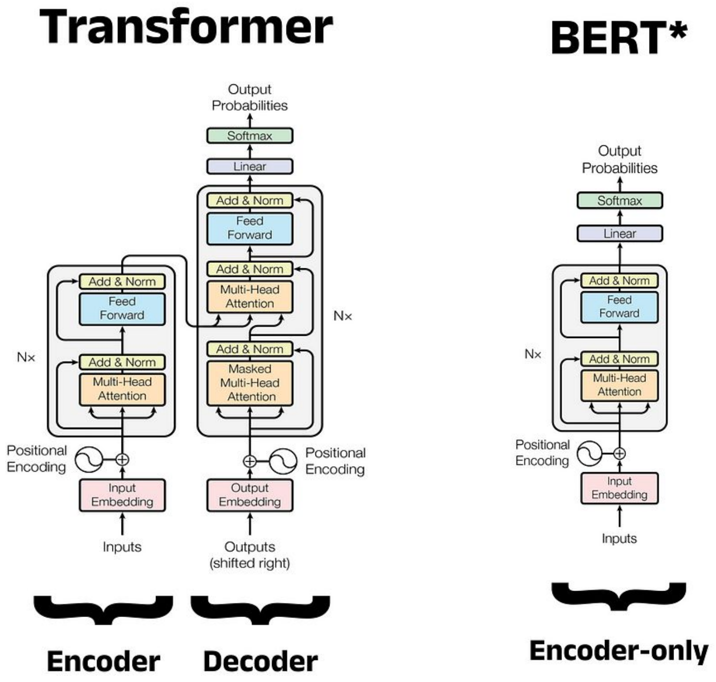
BERT

BERT (Bidirectional Encoder Pre-training for Transformers)

Key Idea: language modeling task + transformer encoder

BERT

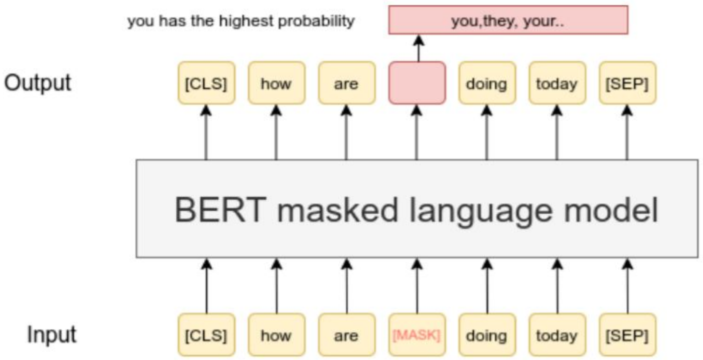
- Encoder-only
- Bidirectional Encoder Representations from Transformers (MLM task)
- Based on Transformer architecture
- Bidirectional context encoding
- Pretrained on Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) tasks

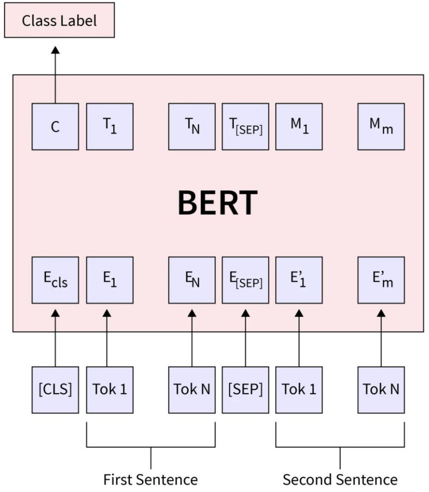


2018

BERT. Pretrain Tasks.

- Masked Language Model (MLM)
  - 15% of tokens are randomly masked
  - 80% replaced with [MASK]
  - 10% replaced with a random word
  - 10% remain unchanged
- Next Sentence Prediction (NSP)
  - Model learns to predict if sentence B logically follows sentence A

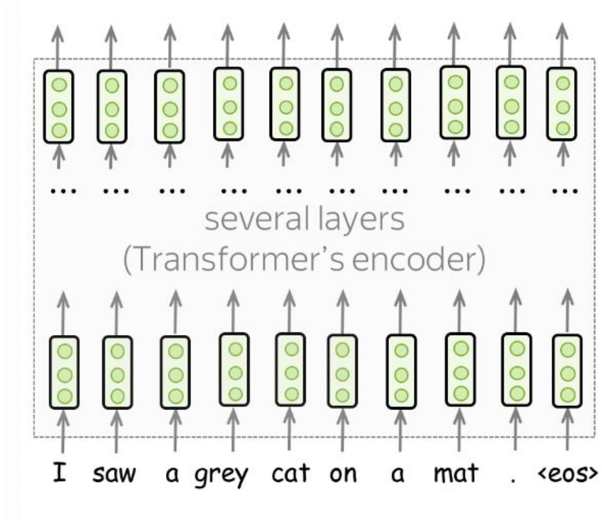




source1, source2

BERT

<u>Q.</u>: how to do LM using transformer encoder (no triangle mask) ?



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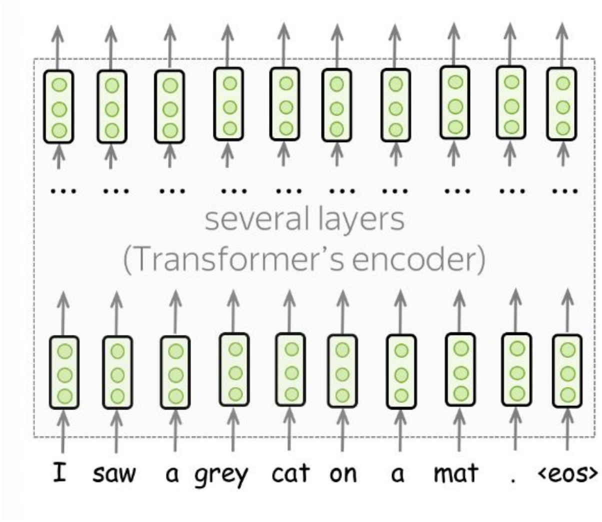

- Standard l2r objective can not be used due to “lookahead”
- Let’s hide some tokens and train the model to predict masked positions

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BERT

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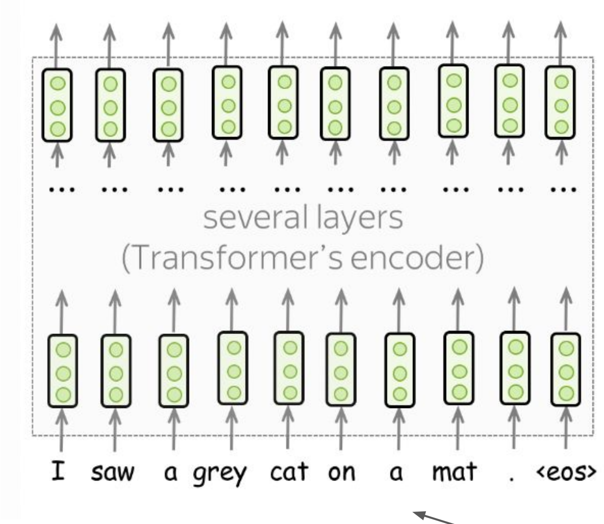

- Standard l2r objective can not be used due to “lookahead”
- Let’s hide some tokens and train the model to predict masked positions

- Replace with special [MASK token]
- Classification head over final layer embeddings

Image source: [NLP Course - For you]

BERT pretraining objective

First part: Masked Language Modeling (MLM)

Second part: model pairwise sentence dependencies

- NSP (Next Sentence Prediction)
- Whether or not two sentences directly follow each other
- [CLS] token to encode “full sentence meaning”

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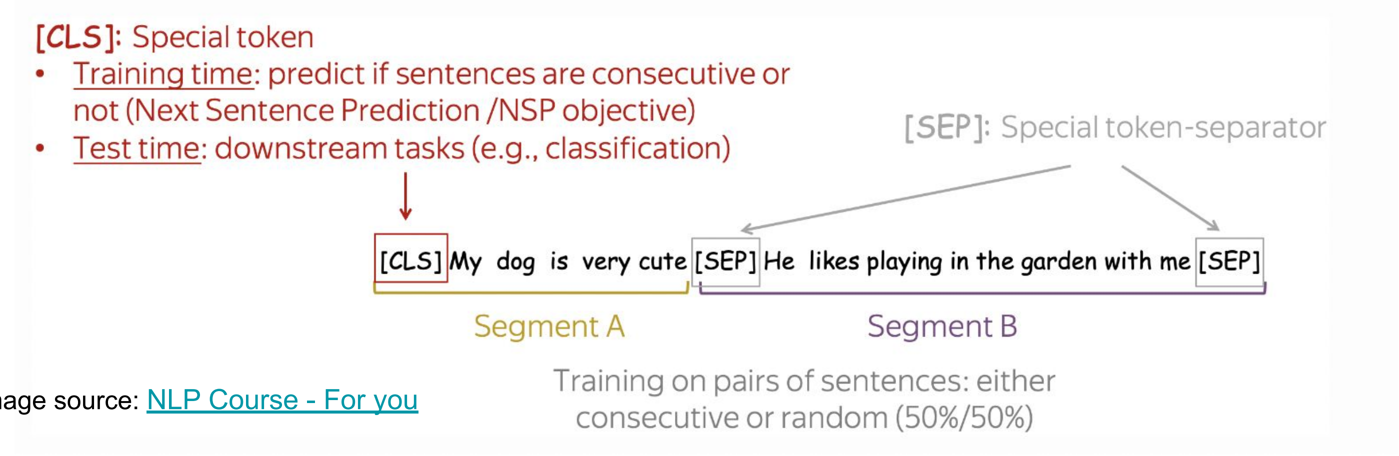


Image source: NLP Course - For you

BERT Pretraining (NSP)

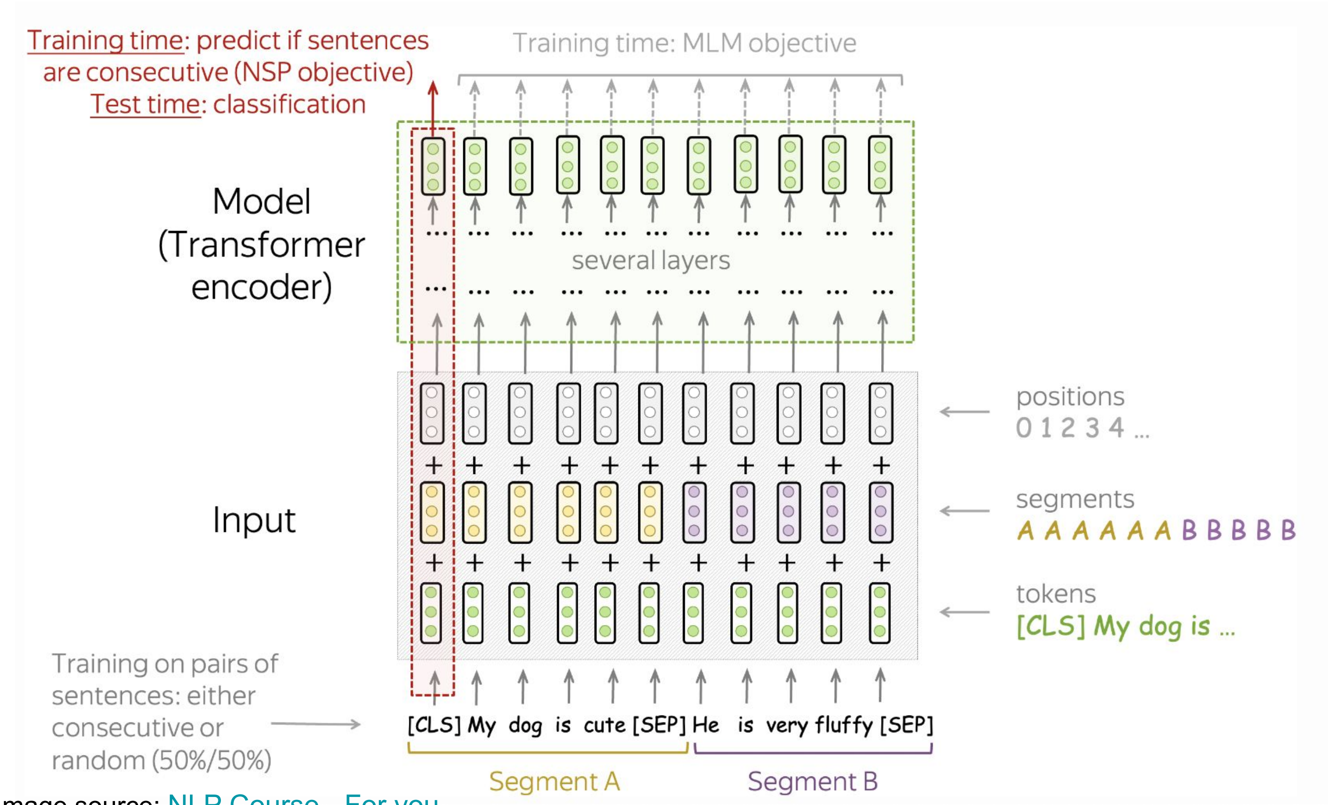
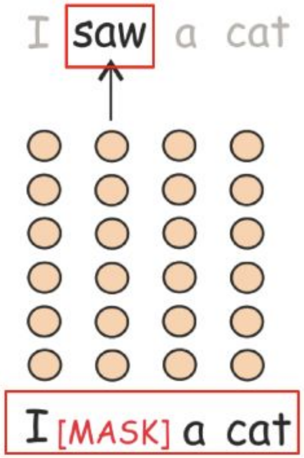


Image source: [NLP Course - For you]

BERT Pretraining (MLM)

- Target: current token (the true one)
- Prediction: $P(* \mid \text{I [MASK] a cat})$



sees the whole text, but
something is corrupted

Image source: [NLP Course - For you]

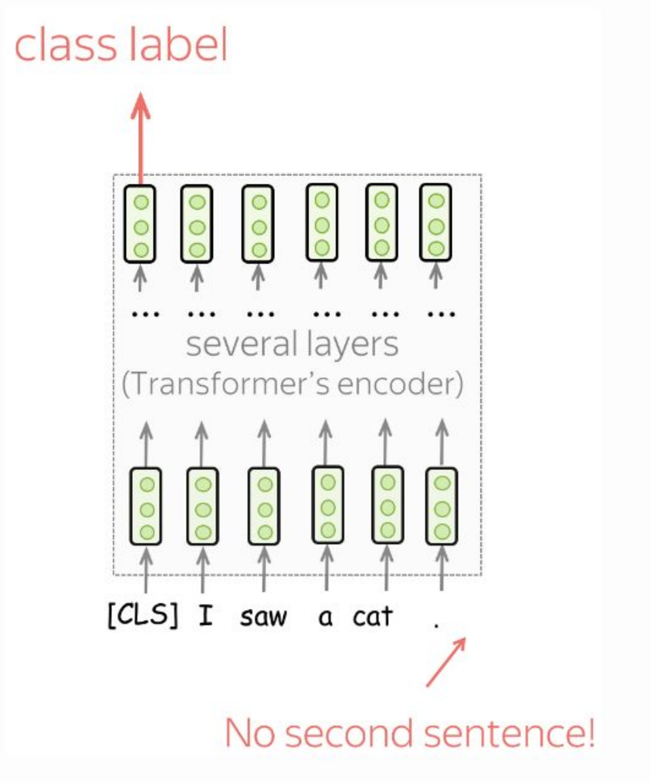
BERT Finetuning

<u>Sentence Classification</u>

BERT Finetuning

Sentence Classification

- Input: [CLS] + Sent
- [CLS] embedding as a feature



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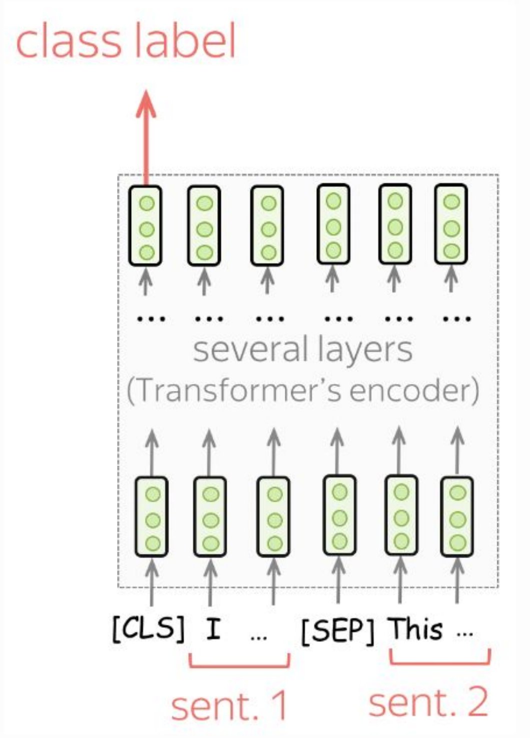
BERT Finetuning

Sentence Pair Classification

BERT Finetuning

Sentence Pair Classification

- Input: [CLS] + Sent1 + [SEP] + Sent2
- [CLS] embedding as feature



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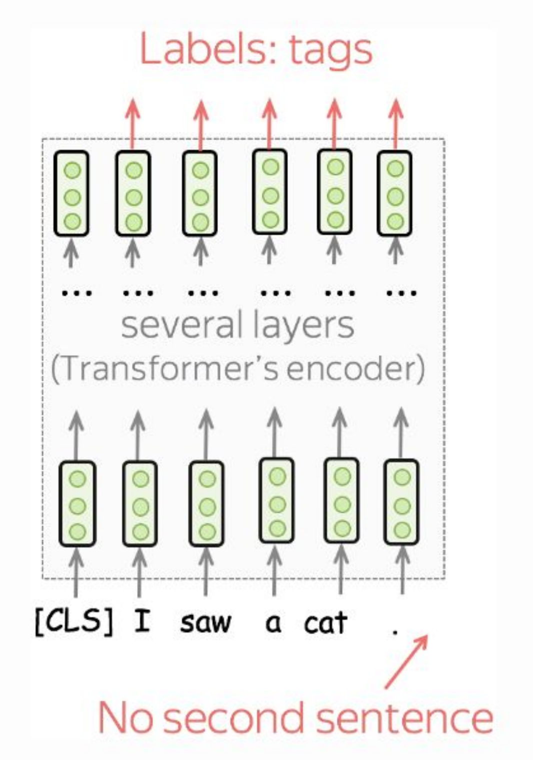
BERT Finetuning

Sentence Tagging (token classification)

BERT Finetuning

Sentence Tagging (token classification)

- Input: [CLS] + sent
- Each token's feature is its embedding



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Thanks for attention!

This lecture heavily uses plots and images from amazing NLP Course - For you by Lena Voita. Check it out if you wish to dig deeper!