Transfer Learning

Lena Voita

Lecture-blog and lots of additional materials are here:
https://lena-voita.github.io/nlp_course/transfer_learning.html

NLP Course For You 

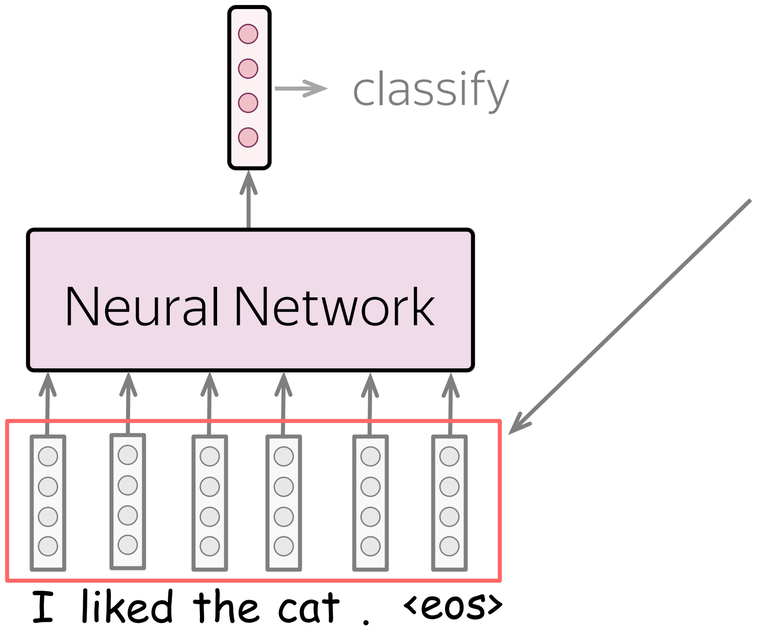
What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability

Recap from Text Classification: Word Embeddings

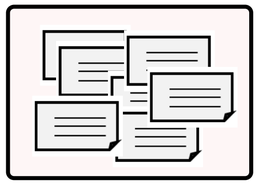


Input word embeddings:

- Train from scratch
- Take pretrained (Word2Vec, GloVe)
- Initialize with pretrained, then fine-tune

Which data do we have?

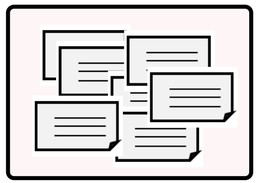
Training data for text classification (labeled)



- Not huge, or not diverse, or both
- Domain: task-specific

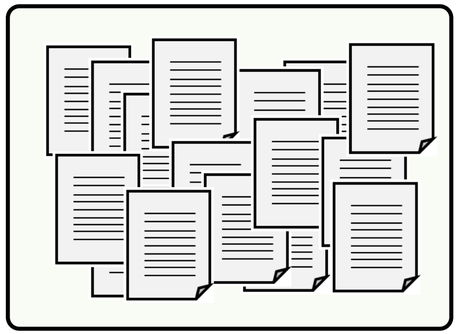
Which data do we have?

Training data for text classification (labeled)



- Not huge, or not diverse, or both
- Domain: task-specific

Training data for word embeddings (unlabeled)



- Huge diverse corpus (e.g., Wikipedia)
- Domain: general

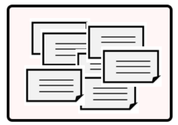
Recap from Text Classification: Word Embeddings

- Train from scratch
- Take pretrained (Word2Vec, GloVe)
- Initialize with pretrained, then fine-tune

Recap from Text Classification: Word Embeddings

- Train from scratch

  What they will know:



  May be not enough to learn relationships between words

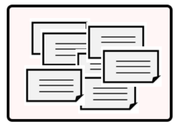
- Take pretrained (Word2Vec, GloVe)

- Initialize with pretrained, then fine-tune

Recap from Text Classification: Word Embeddings

- Train from scratch

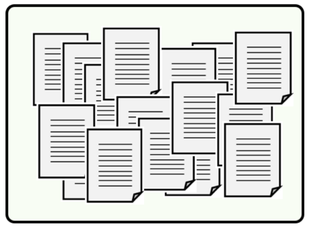
What they will know:



May be not enough to learn relationships between words

- Take pretrained (Word2Vec, GloVe)

What they will know:



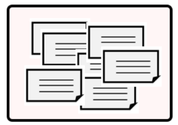
Know relationships between words, but are **not** specific to the task

- Initialize with pretrained, then fine-tune

Recap from Text Classification: Word Embeddings

- Train from scratch

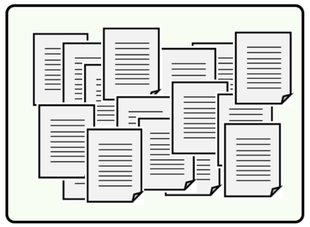
What they will know:



May be not enough to learn relationships between words

- Take pretrained (Word2Vec, GloVe)

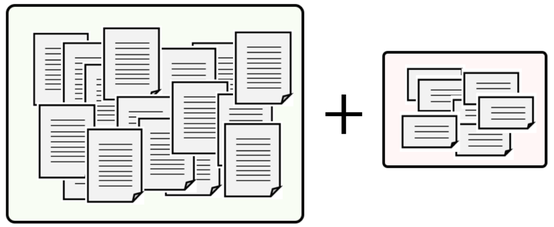
What they will know:



Know relationships between words, but are **not** specific to the task

- Initialize with pretrained, then fine-tune

What they will know:

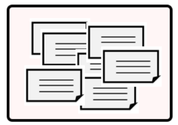


Know relationships between words and adapted for the task

Recap from Text Classification: Word Embeddings

- Train from scratch

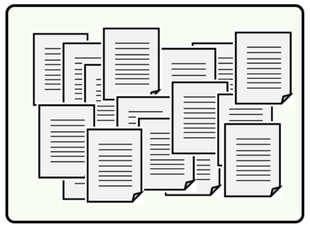
What they will know:



May be not enough to learn relationships between words

- Take pretrained (Word2Vec, GloVe)

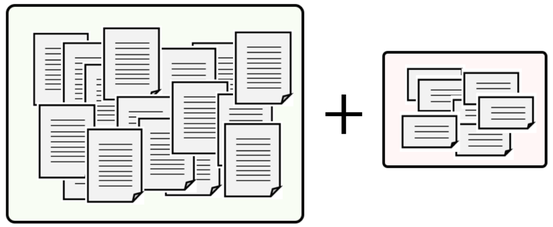
What they will know:



Know relationships between words, but are **not** specific to the task

- **Initialize with pretrained, then fine-tune**

What they will know:



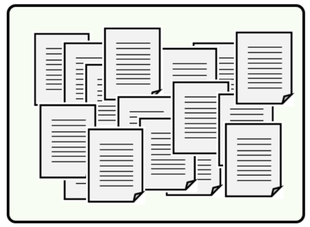
Know relationships between words and adapted for the task

"**Transfer**" knowledge from a huge unlabeled corpus to your task-specific model

We'll learn more about this later in the course!

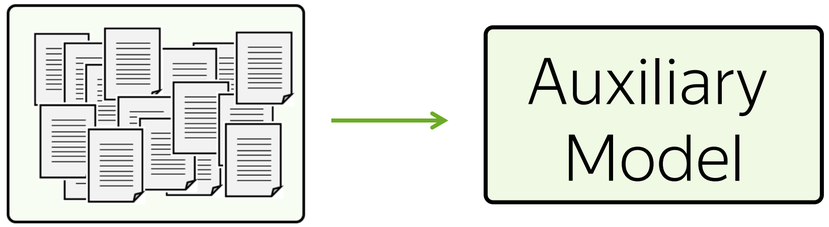
Transfer Learning Idea

Source task

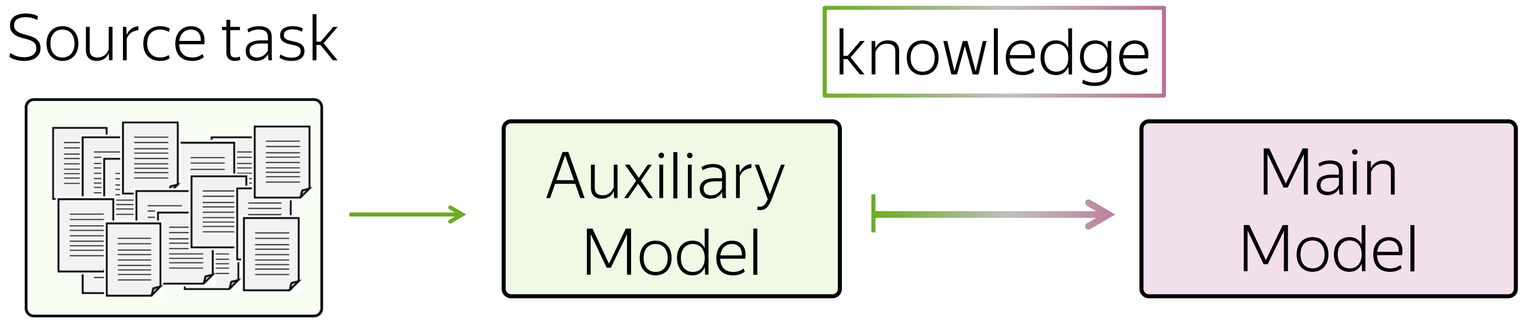


Transfer Learning Idea

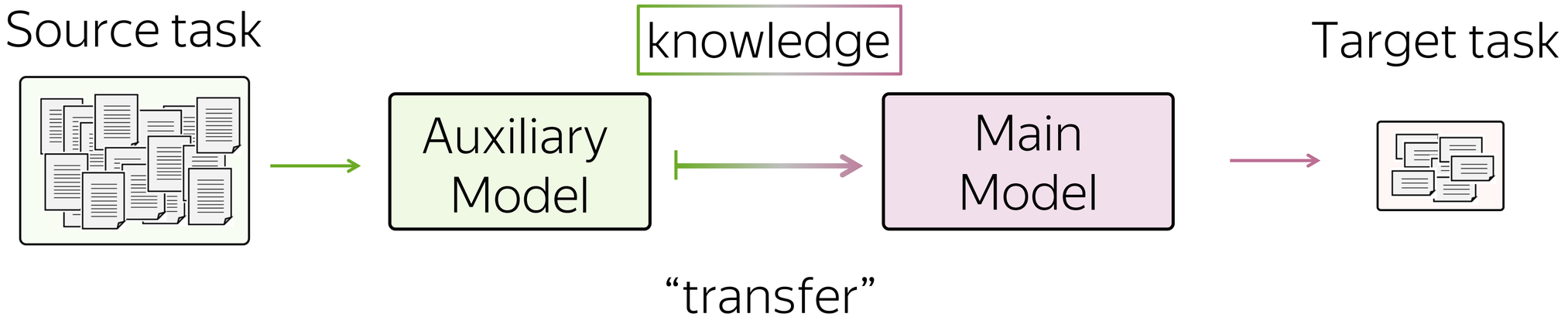
Source task



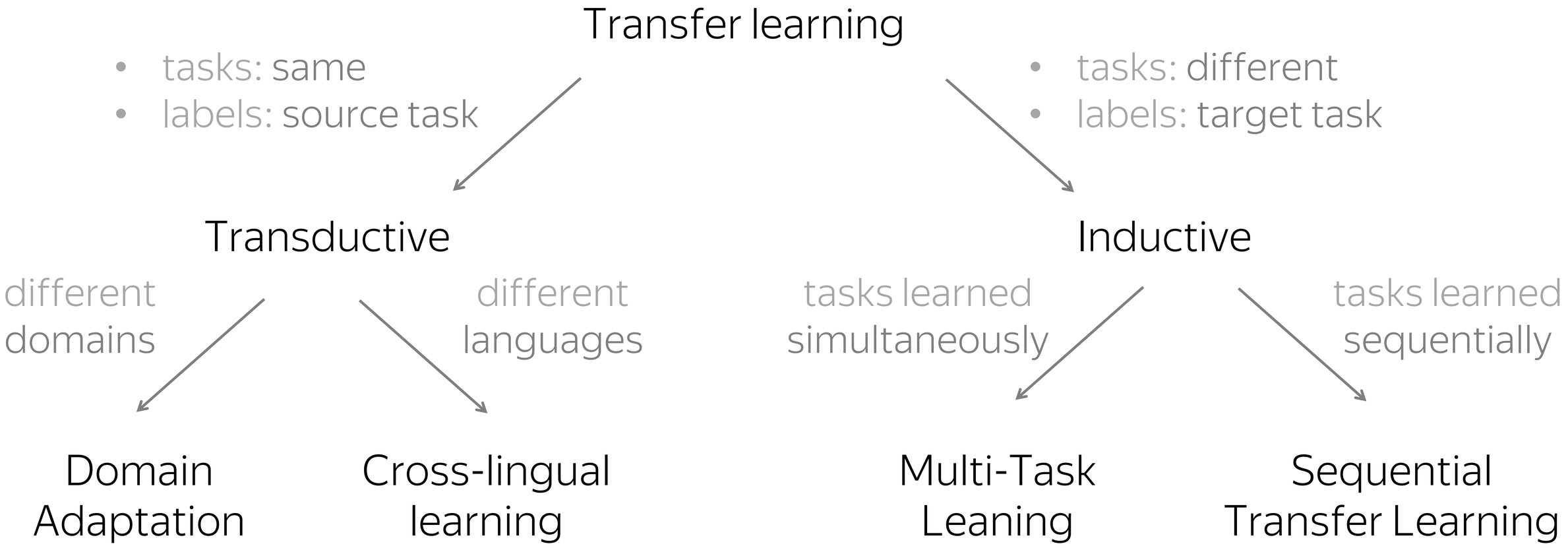
Transfer Learning Idea



Transfer Learning Idea

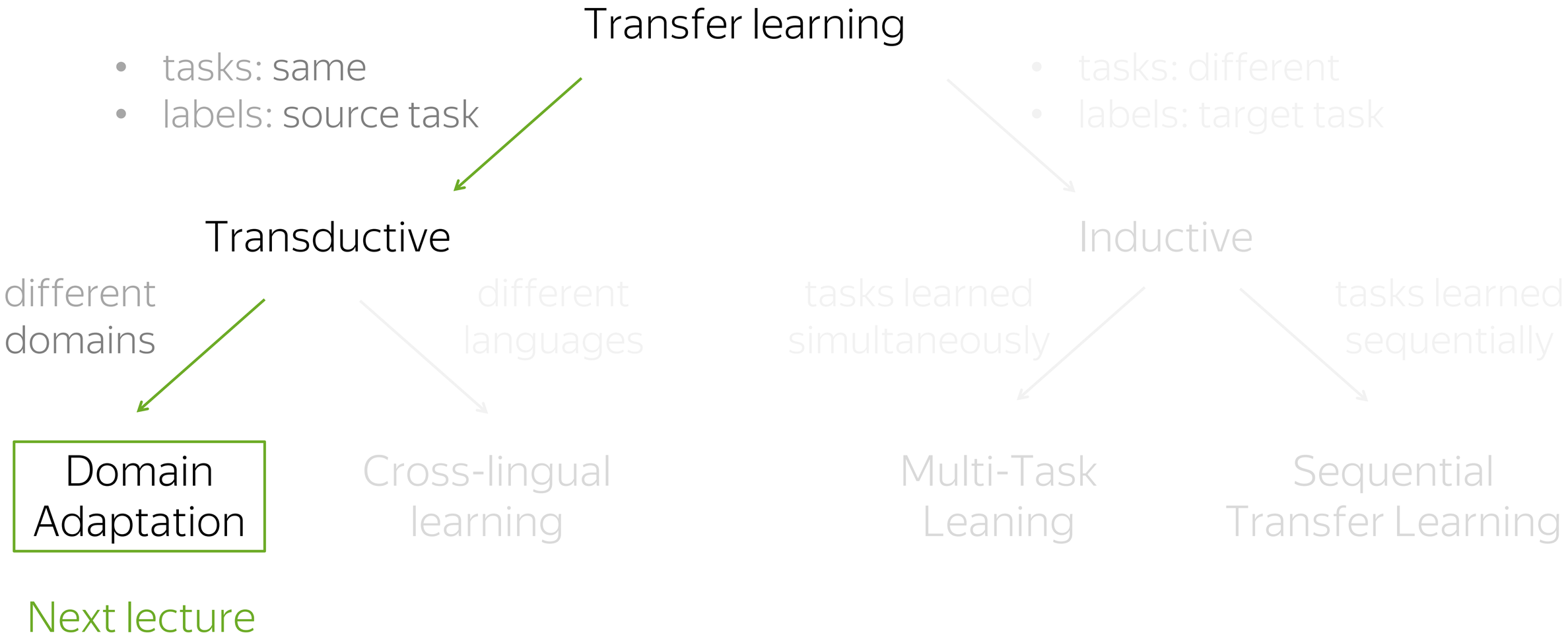


A Taxonomy of Transfer Learning in NLP



This taxonomy is from Ruder, 2019

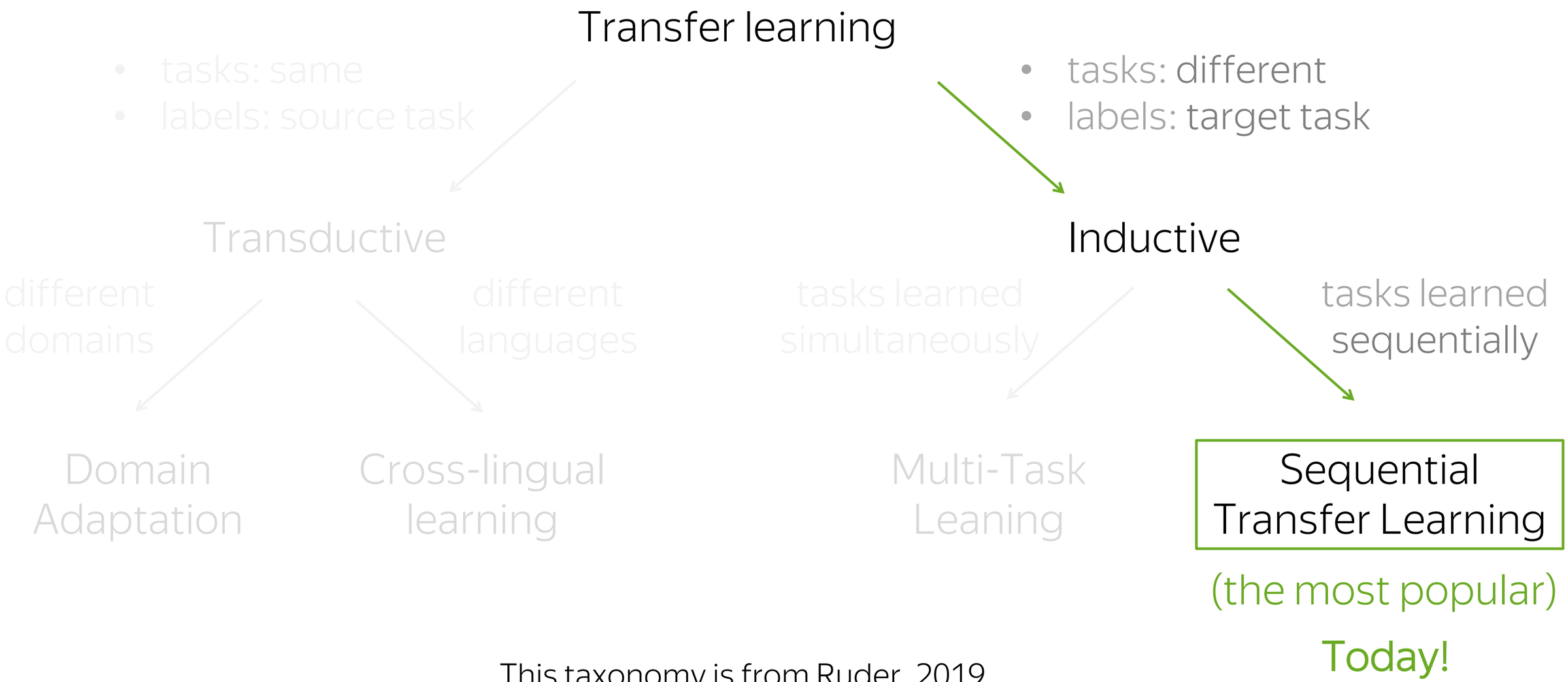
A Taxonomy of Transfer Learning in NLP



Next lecture

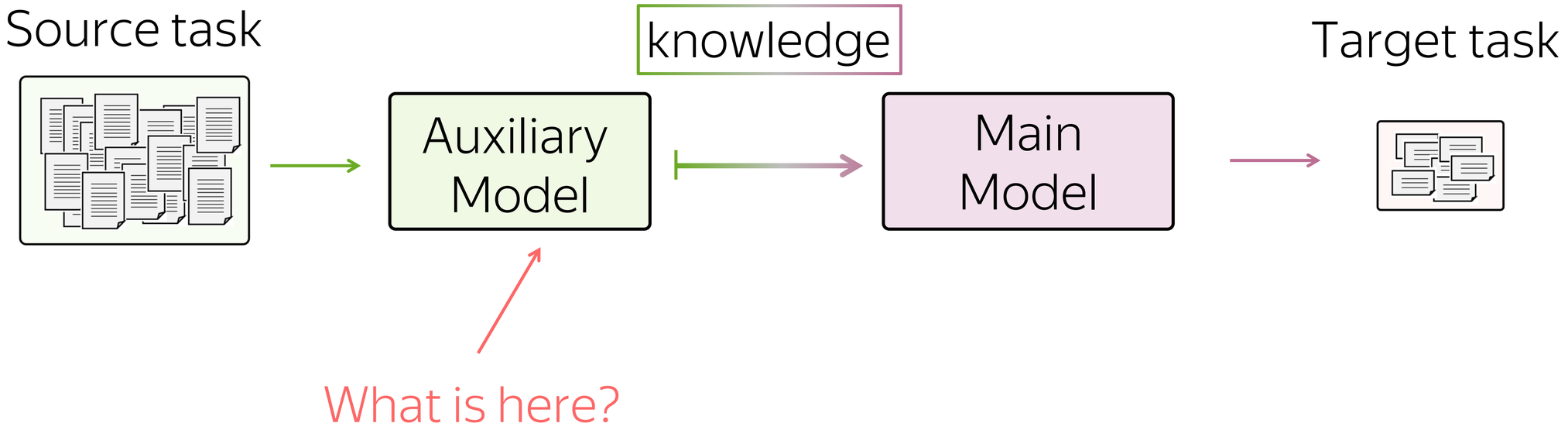
This taxonomy is from Ruder, 2019

A Taxonomy of Transfer Learning in NLP

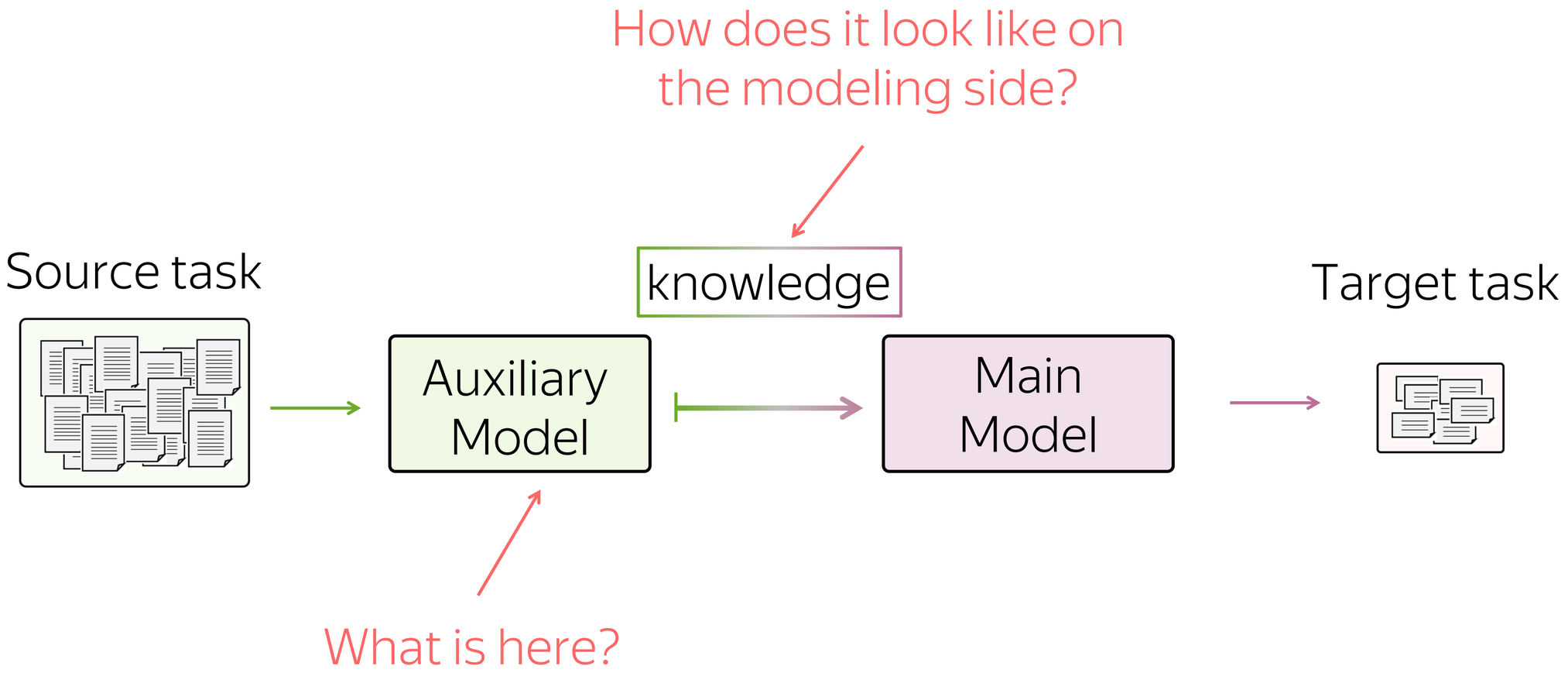


This taxonomy is from Ruder, 2019

Transfer Learning Idea



Transfer Learning Idea



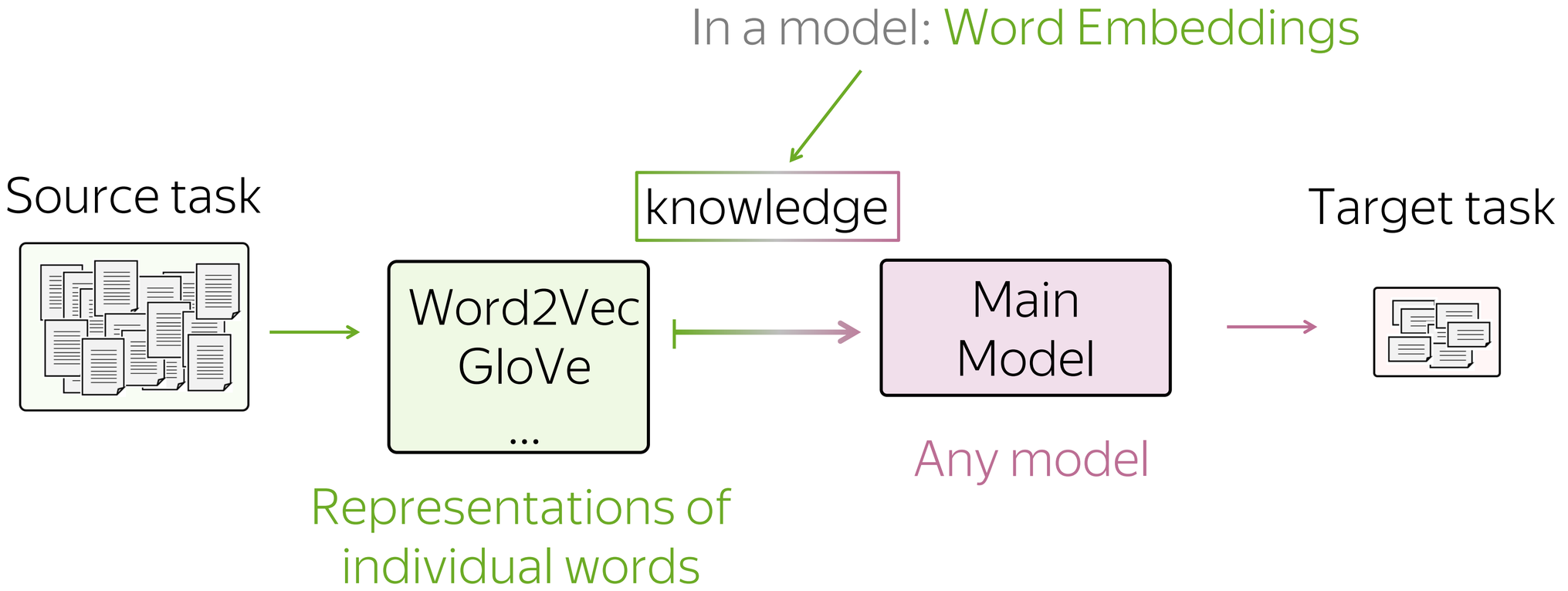
What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability

What is going to happen:

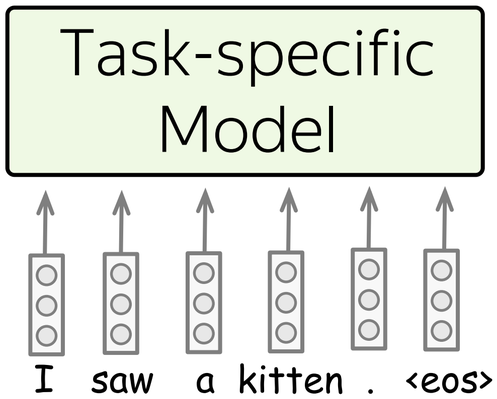
- Transfer Learning Idea
- Pretrained Models
  - (recap) Word Embeddings
  - ELMo
  - BERT
  - (a note on) GPT
  - (a note on) Adaptors
-  Analysis and Interpretability

Simplest (recap once again): Word Embeddings (Word2Vec, GloVe)



Transfer Through Word Embedding

Before

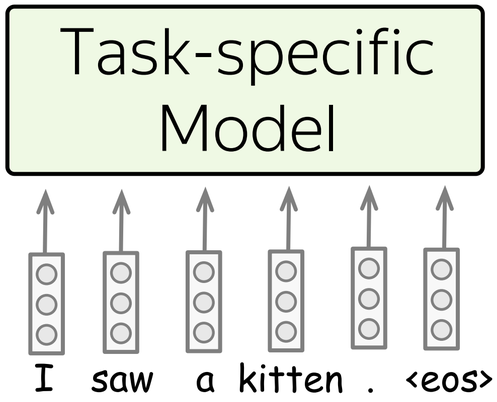


Word Embeddings

Know nothing, trained from scratch with the model

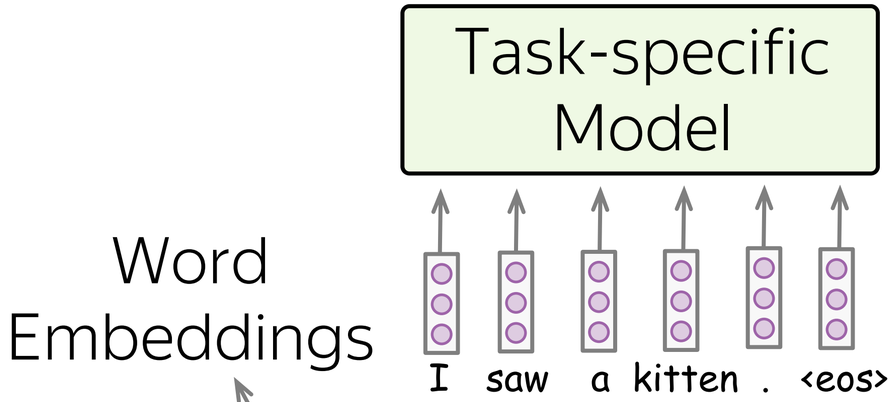
Transfer Through Word Embedding

Before



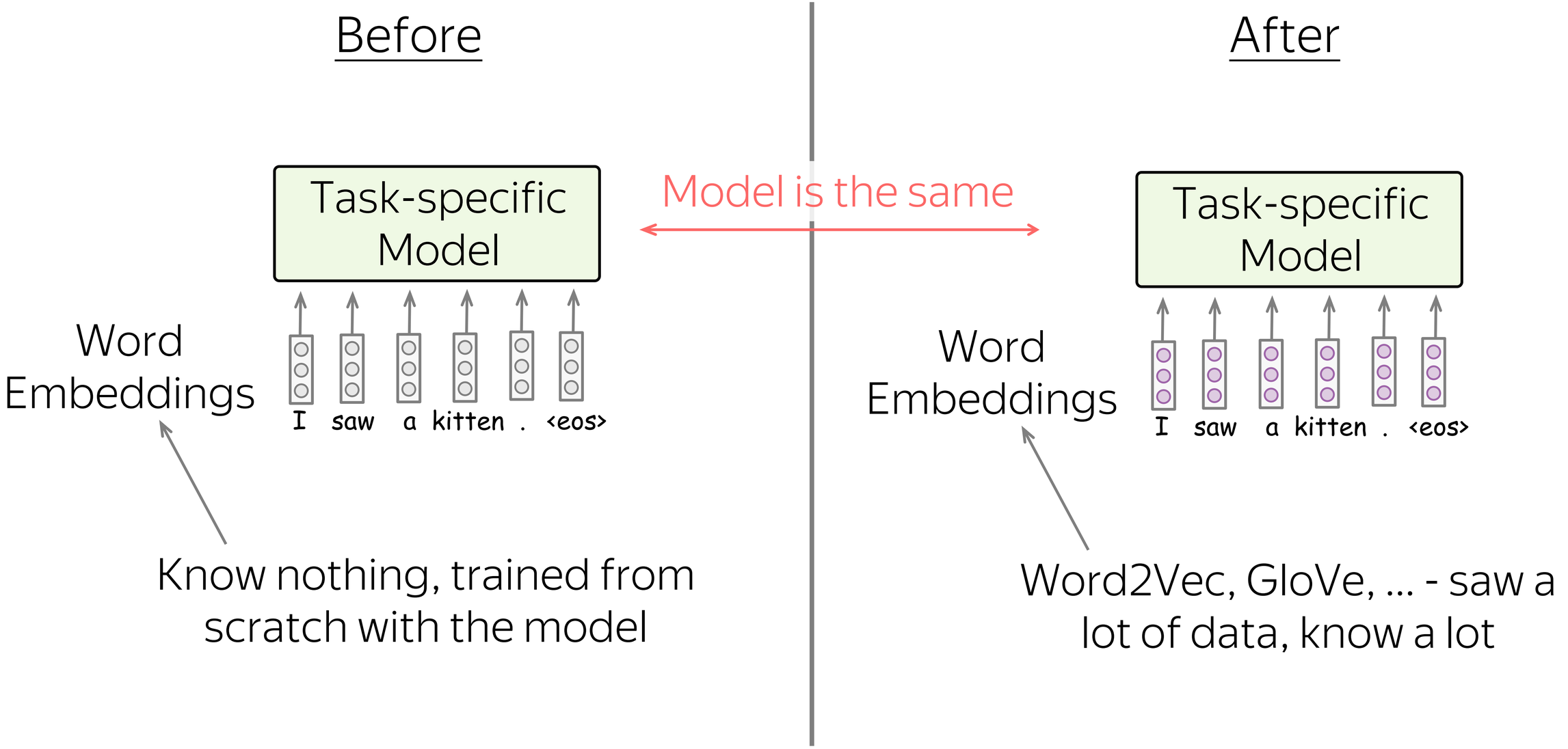
Know nothing, trained from scratch with the model

After



Word2Vec, GloVe, ... - saw a lot of data, know a lot

Transfer Through Word Embedding



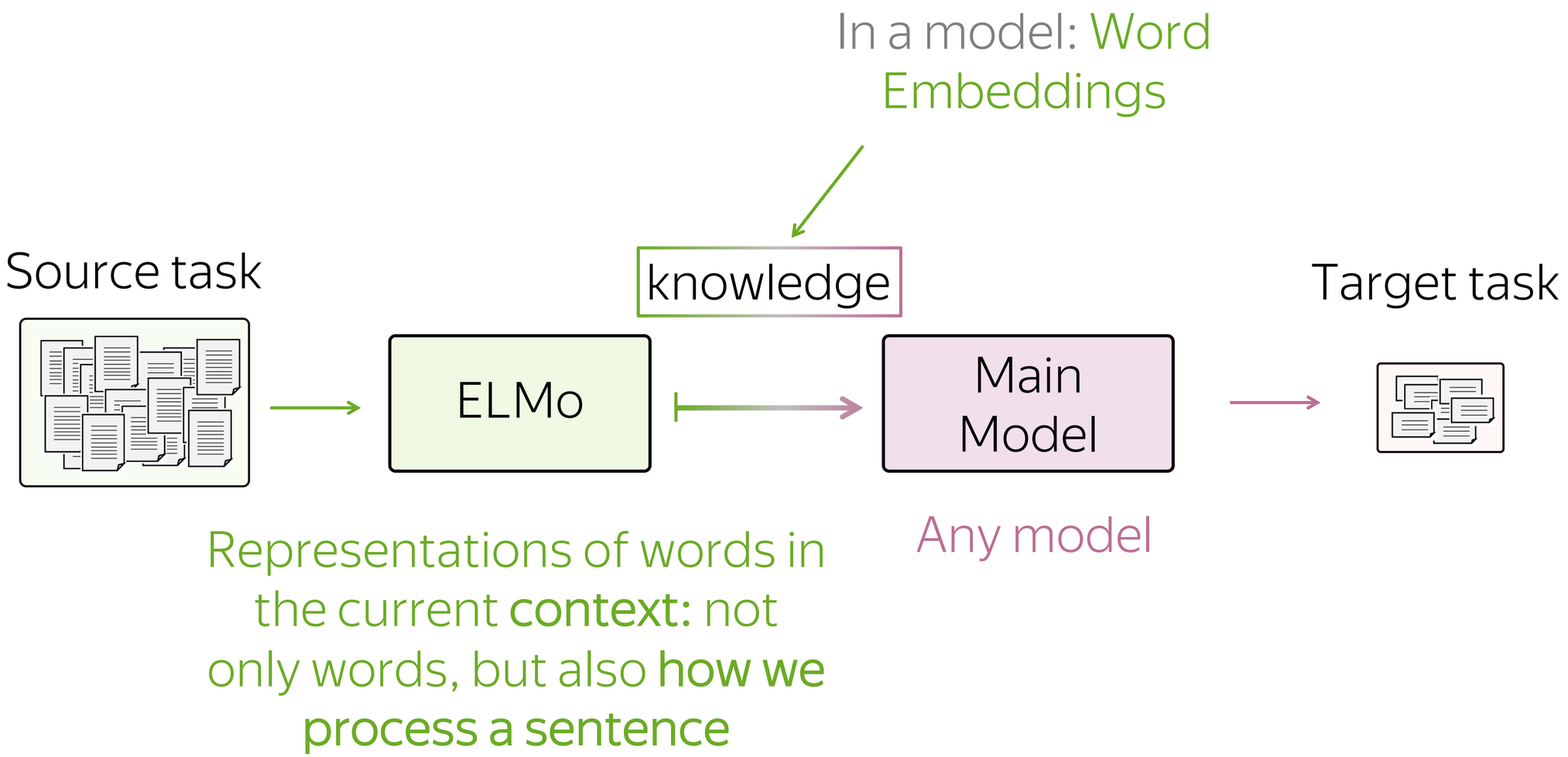
What is going to happen:

- Transfer Learning Idea
- Pretrained Models
  - (recap) Word Embeddings
  - ELMo
  - BERT
  - (a note on) GPT
  - (a note on) Adaptors
-  Analysis and Interpretability

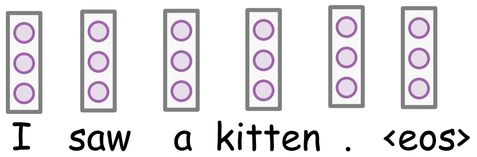
What is going to happen:

- Transfer Learning Idea
- Pretrained Models
  - (recap) Word Embeddings
  - ELMo
  - BERT
  - (a note on) GPT
  - (a note on) Adaptors
-  Analysis and Interpretability

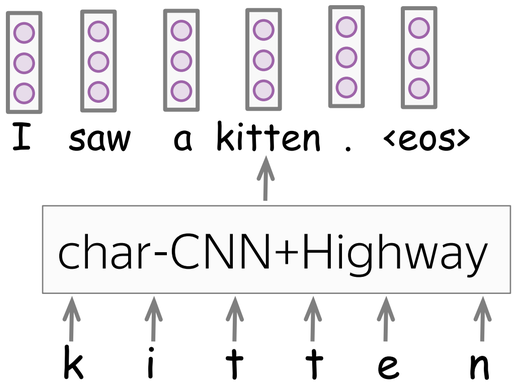
ELMo: From Words to Words-in-Context



ELMo: From Words to Words-in-Context



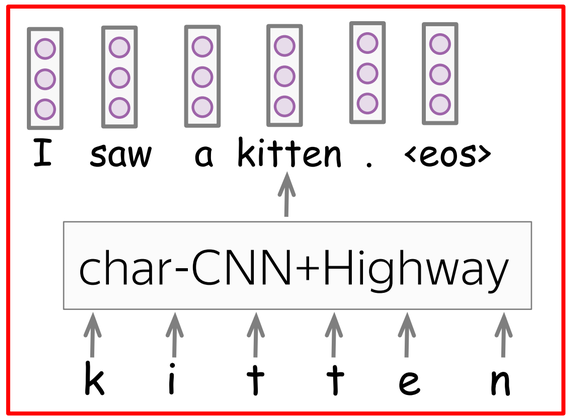
ELMo: From Words to Words-in-Context

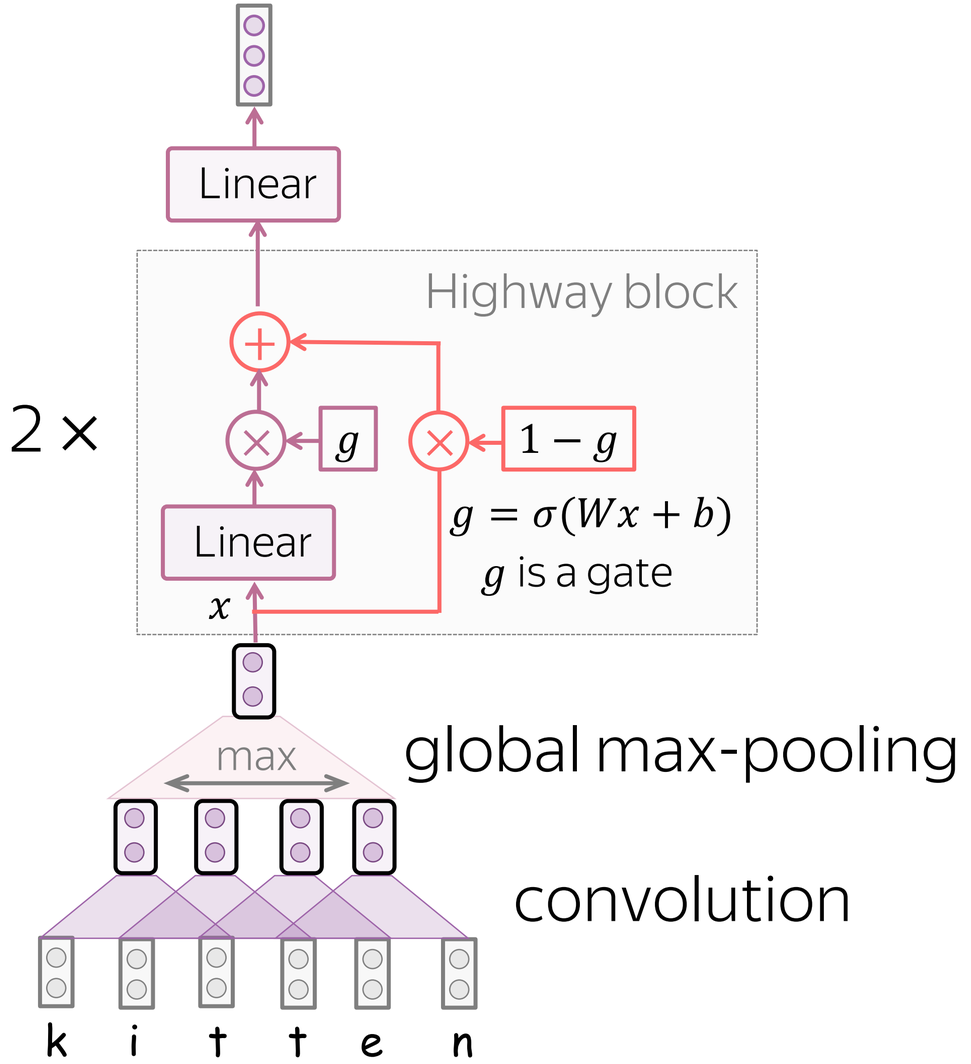


Character-level CNN:

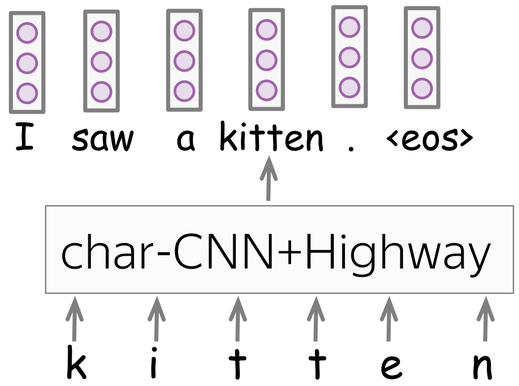
- makes it possible to represent even unknown words
- tells a network which words are written similarly

ELMo: From Words to Words-in-Context

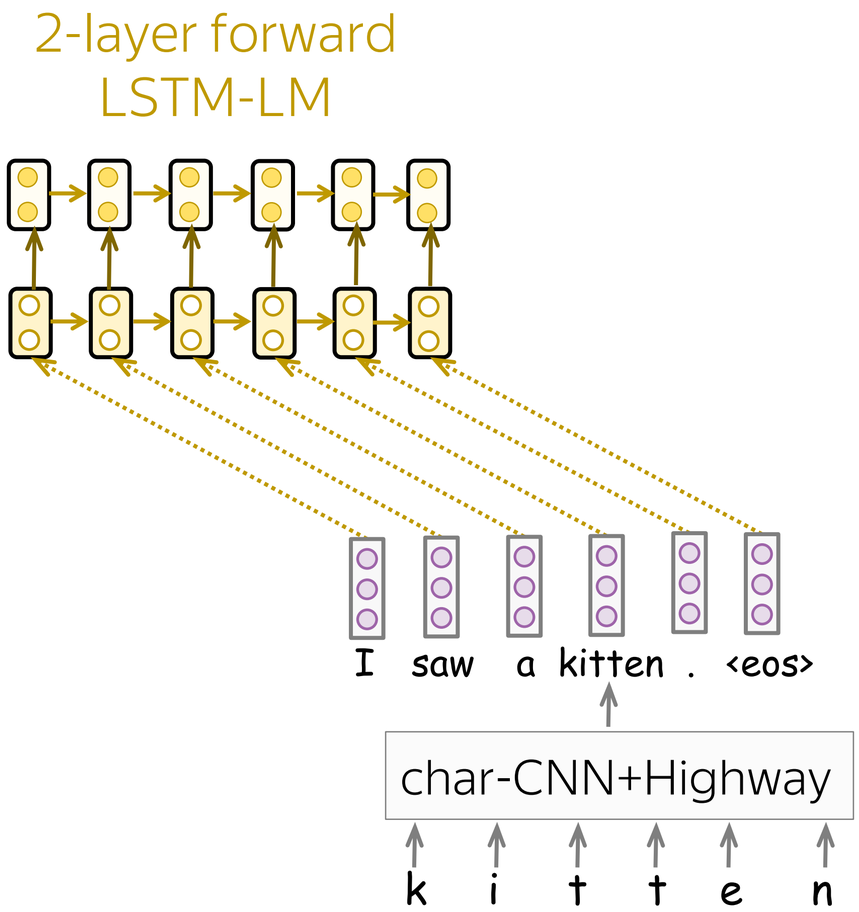




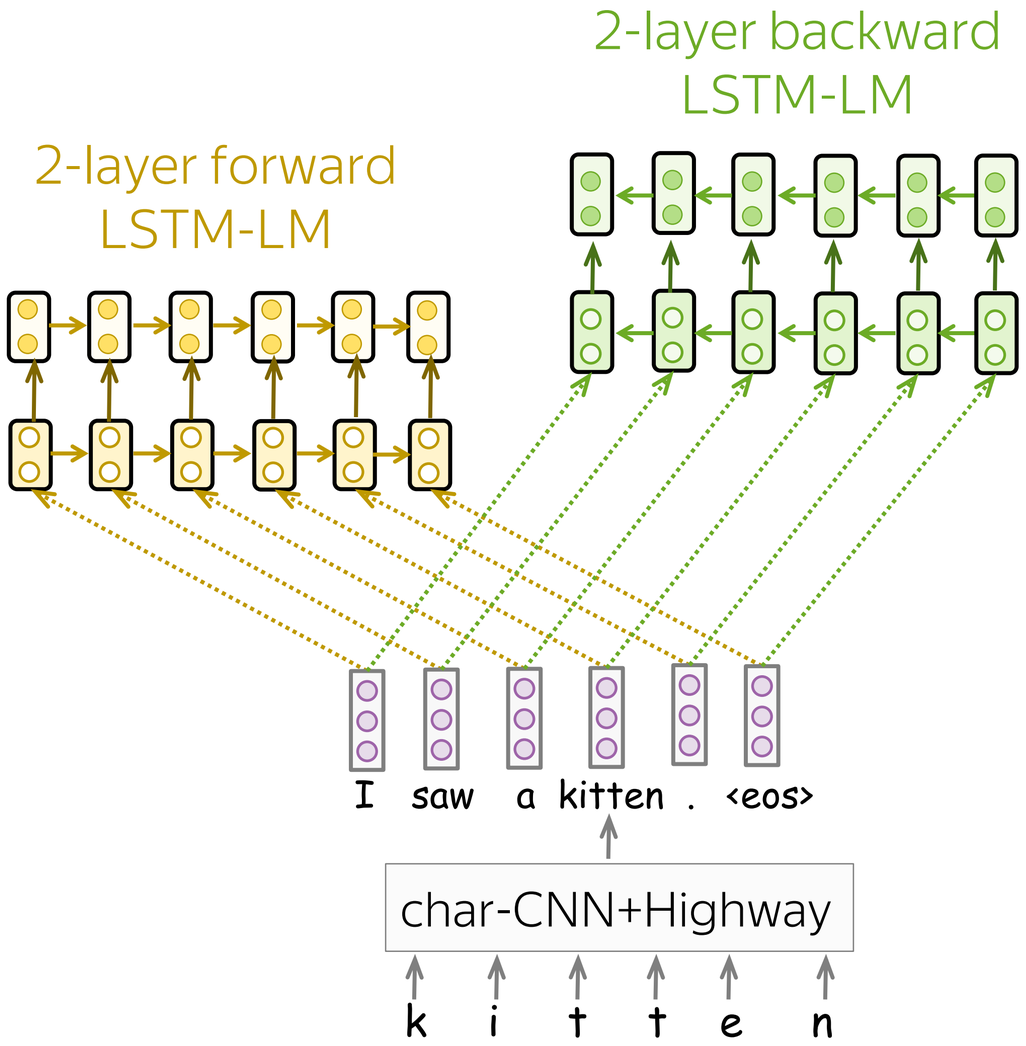
ELMo: From Words to Words-in-Context



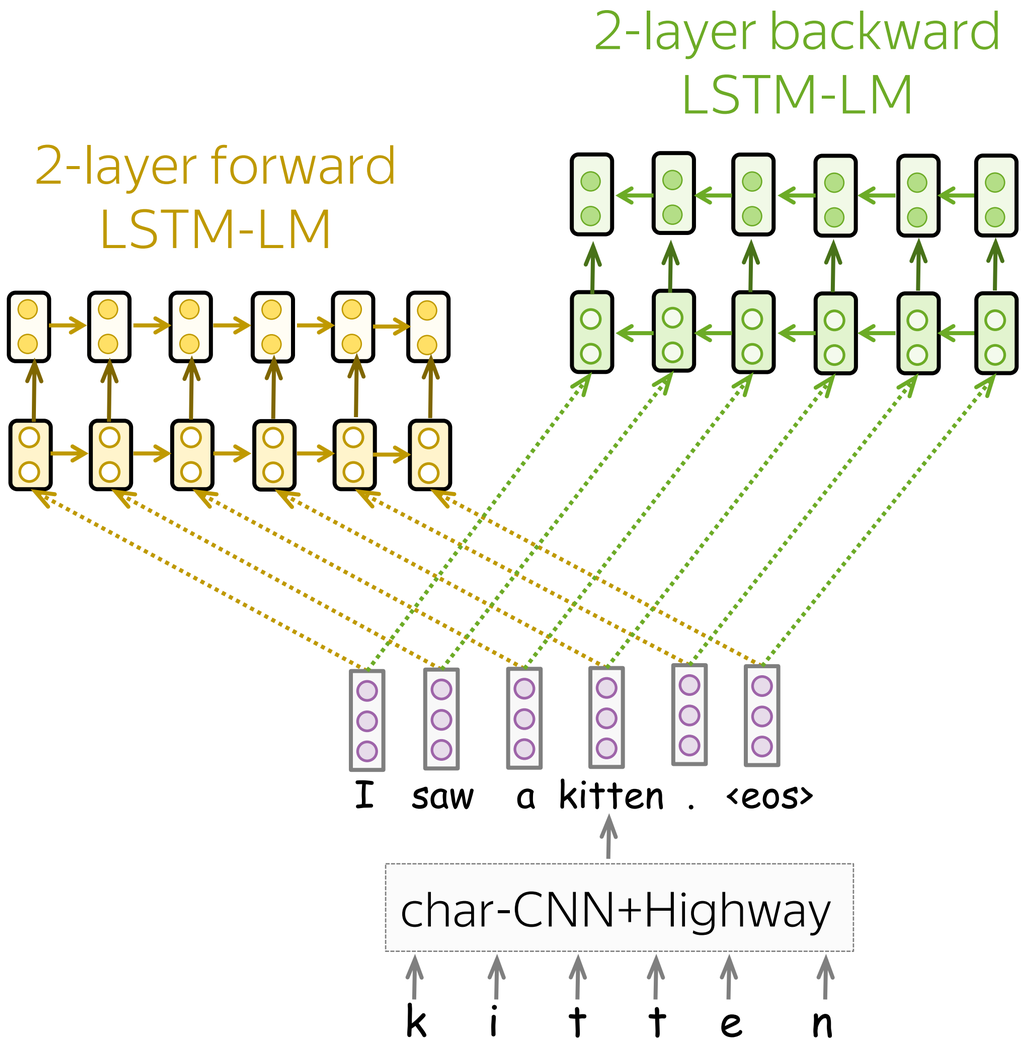
ELMo: From Words to Words-in-Context

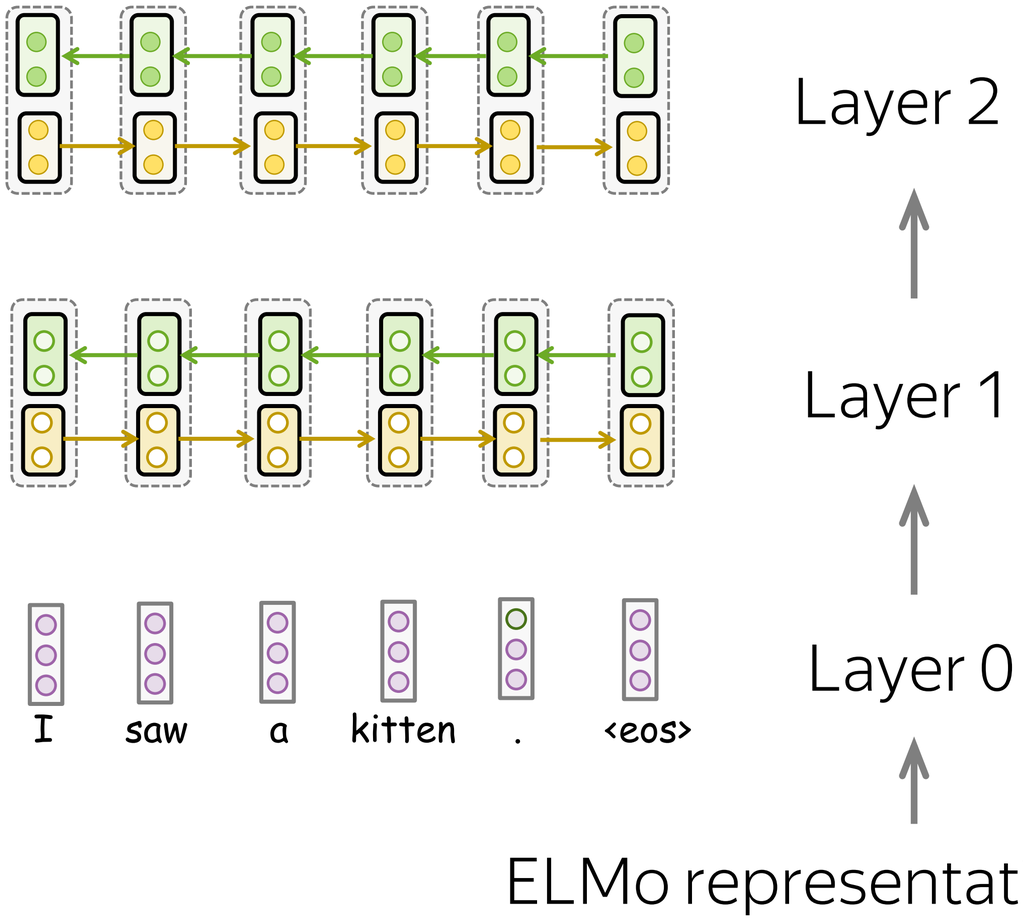


ELMo: From Words to Words-in-Context

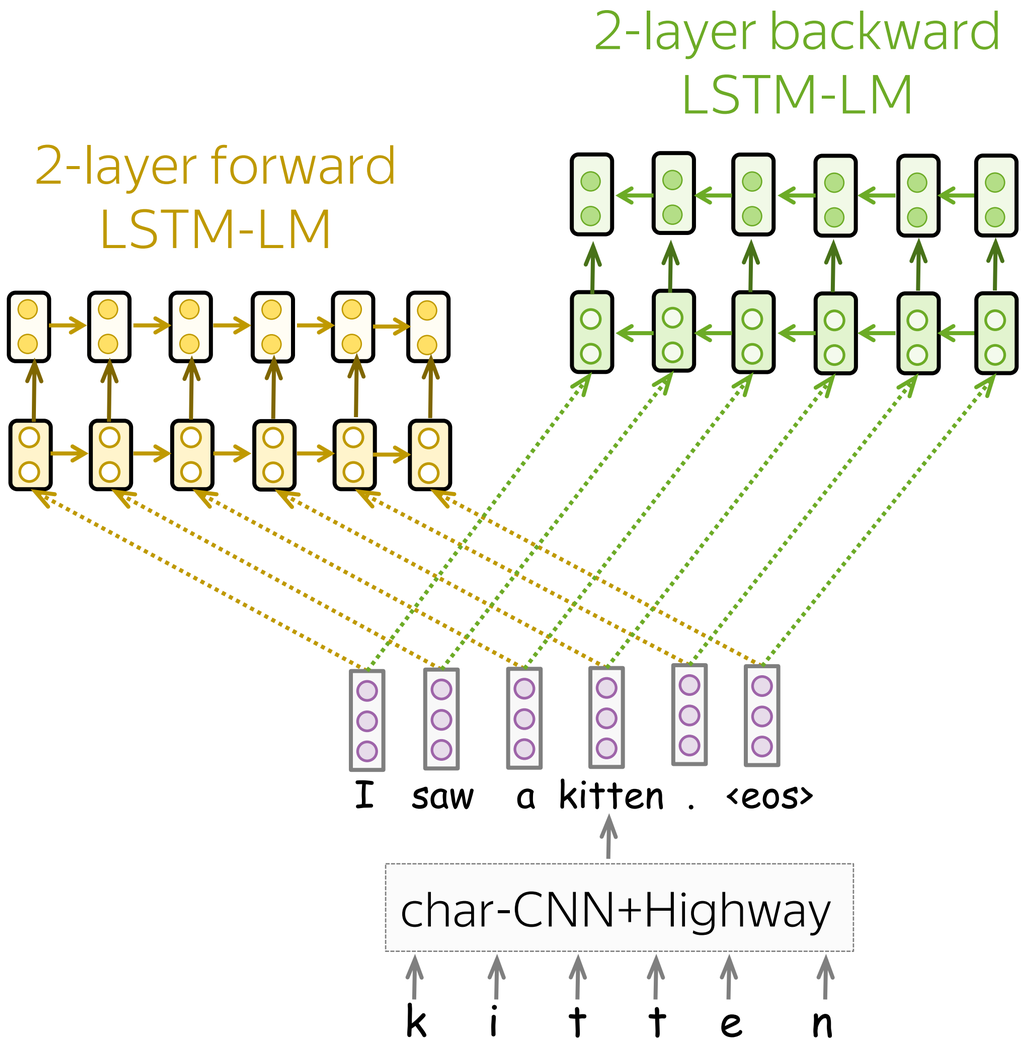


ELMo: From Words to Words-in-Context

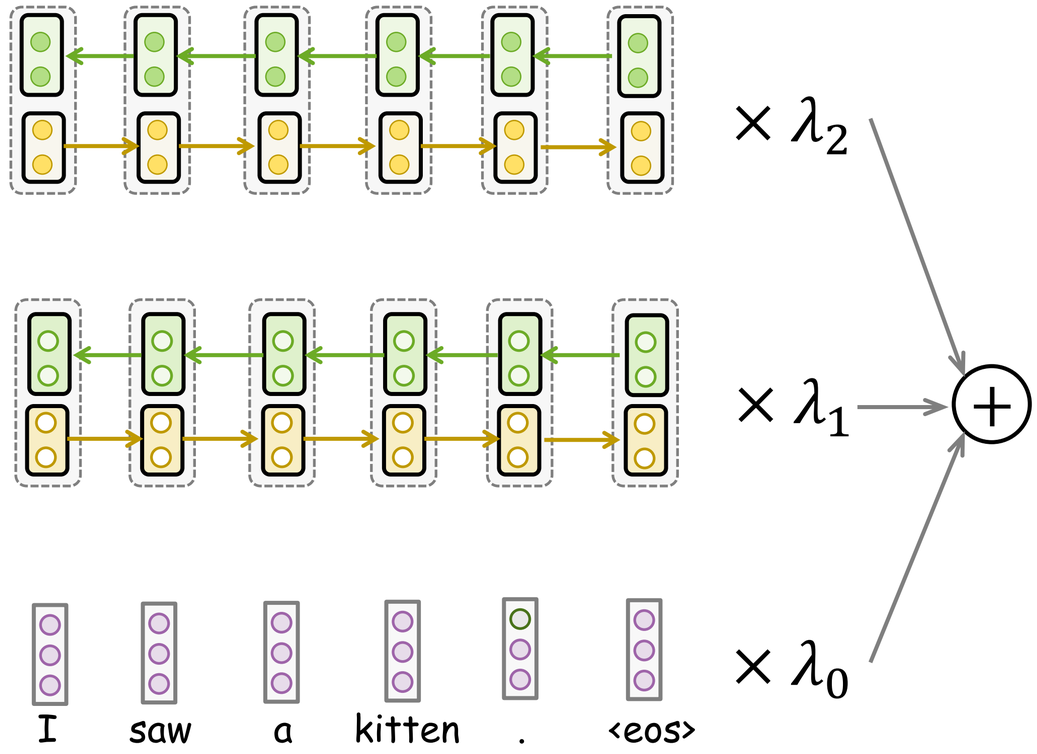




ELMo: From Words to Words-in-Context

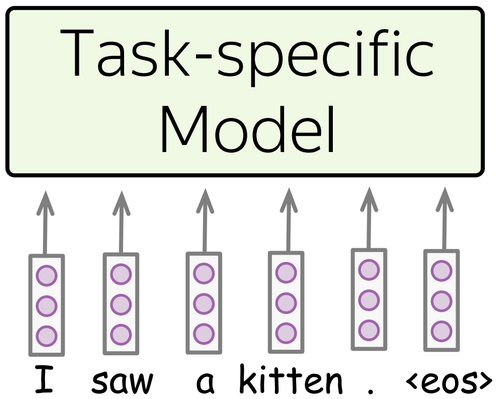


Learn specific $\lambda_0, \lambda_1, \lambda_2$ for each task



ELMo: How to Use?

Before

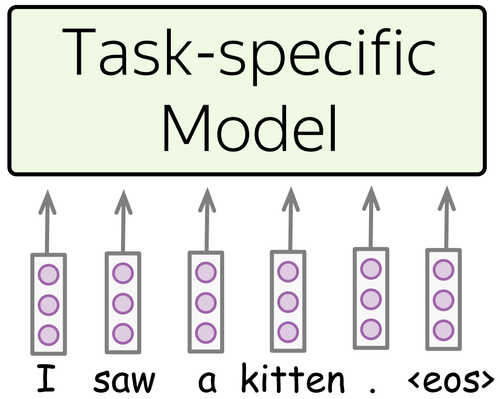


Word Embeddings

Word2Vec, GloVe, ... - saw a lot of data, know a lot

ELMo: How to Use?

Before

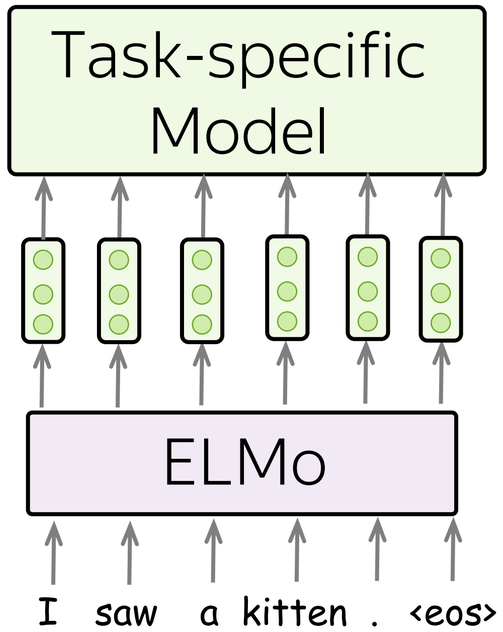


Word Embeddings

Word2Vec, GloVe, ... - saw a lot of data, know a lot

After

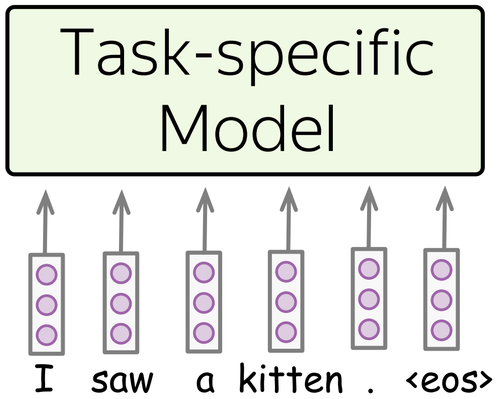
Representations of words **in context**



We used huge unlabeled dataset to learn not only words, but **how to process entire texts**

ELMo: How to Use?

Before



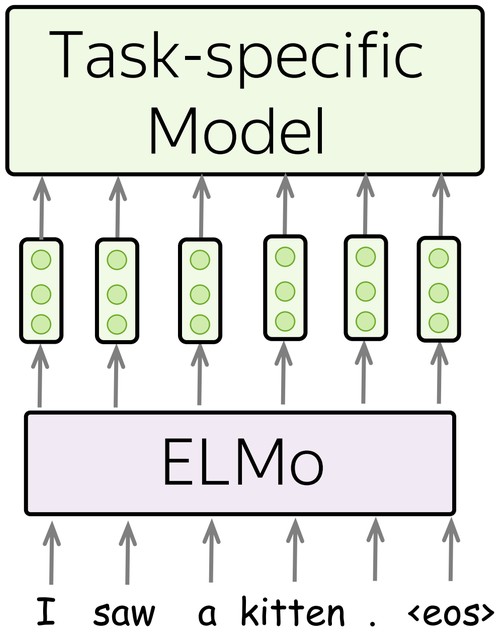
Word Embeddings

Word2Vec, GloVe, ... - saw a lot of data, know a lot

Model is (almost) the same

After

Representations of words **in context**



We used huge unlabeled dataset to learn not only words, but **how to process entire texts**

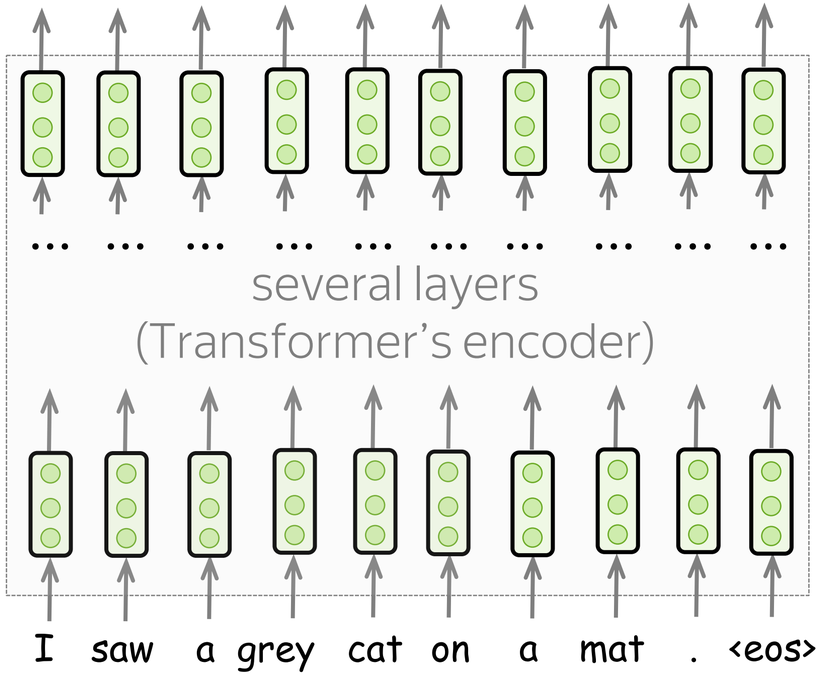
What is going to happen:

- Transfer Learning Idea
- Pretrained Models
  - (recap) Word Embeddings
  - ELMo
  - BERT
  - (a note on) GPT
  - (a note on) Adaptors
-  Analysis and Interpretability

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
  - (recap) Word Embeddings
  - ELMo
  - BERT
  - (a note on) GPT
  - (a note on) Adaptors
-  Analysis and Interpretability

BERT: Transformer Encoder with Fancy Training



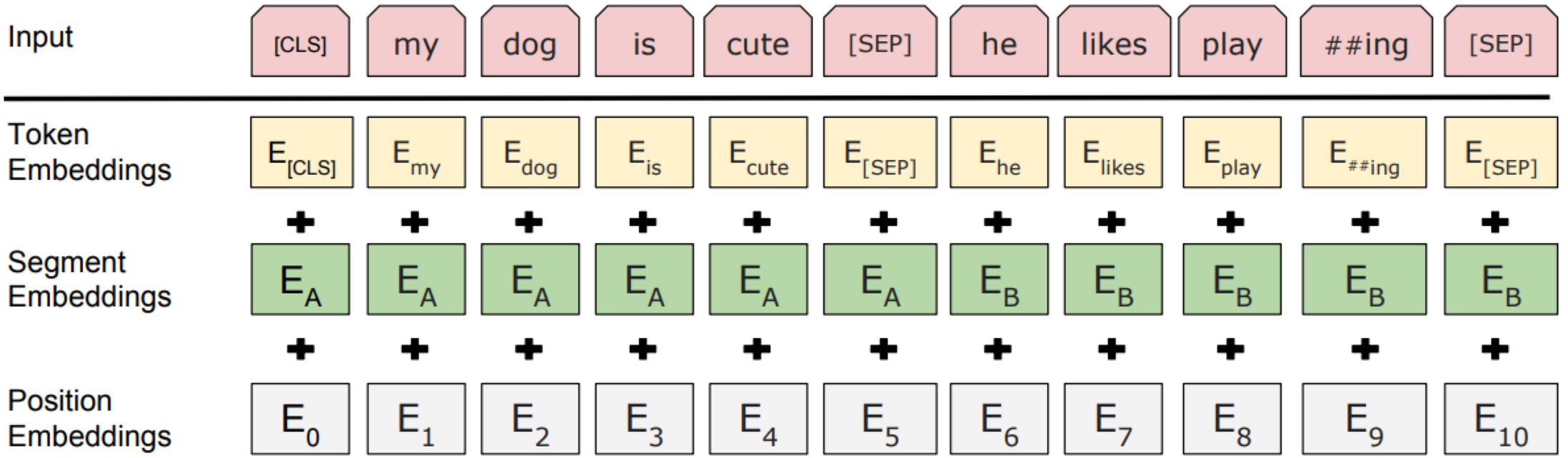
Model architecture:

- Transformer encoder

What is special about it:

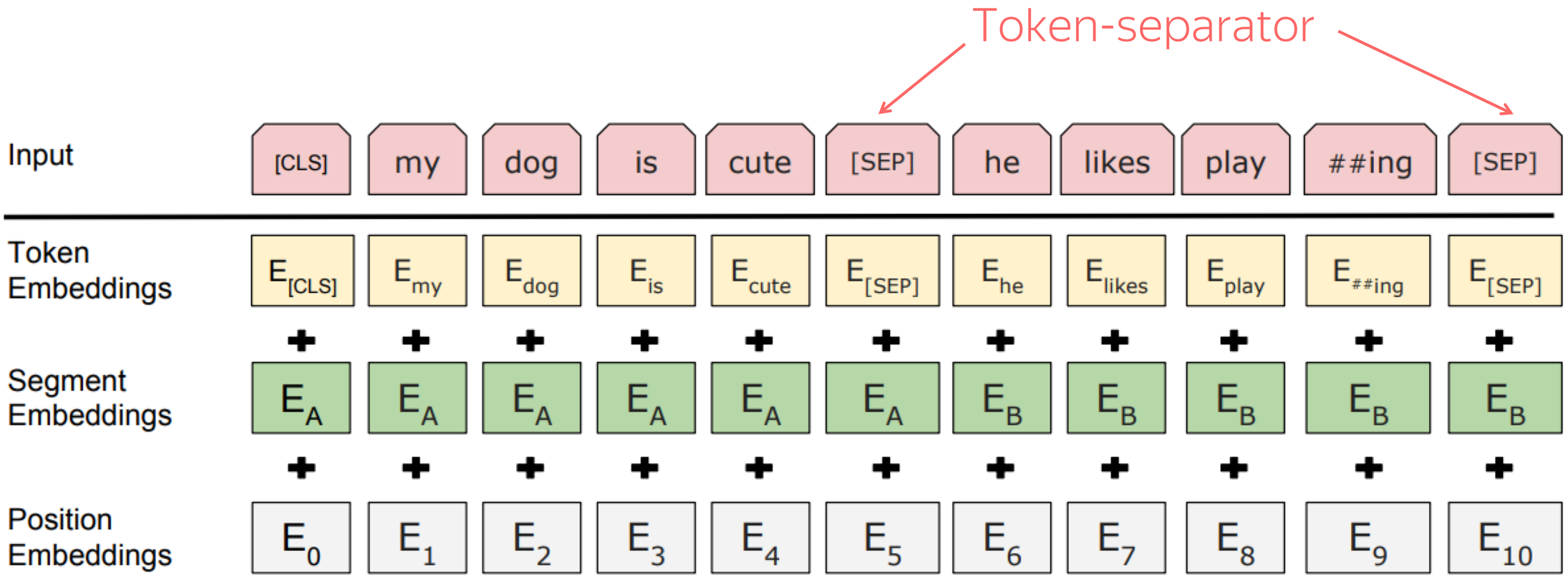
- Training objectives
  - MLM: Masked language modeling
  - NSP: Next sentence prediction
- Lots of data

BERT: Input



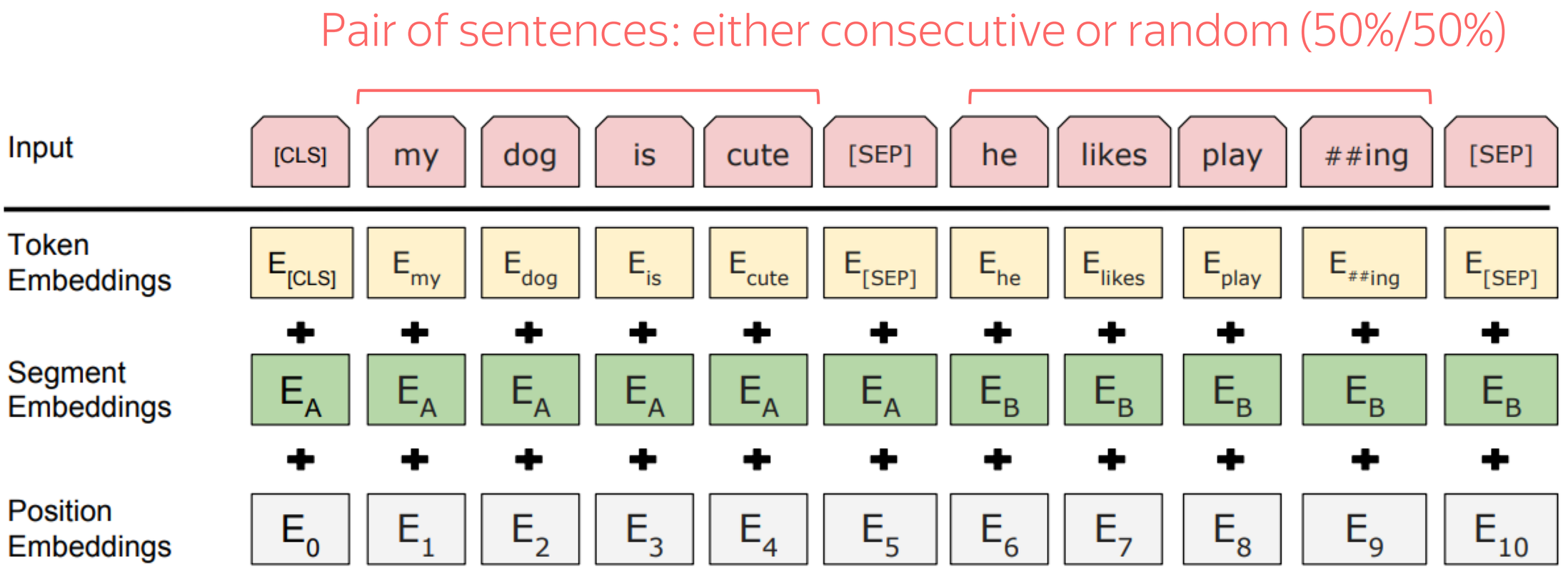
The figure is from the original BERT paper

BERT: Input



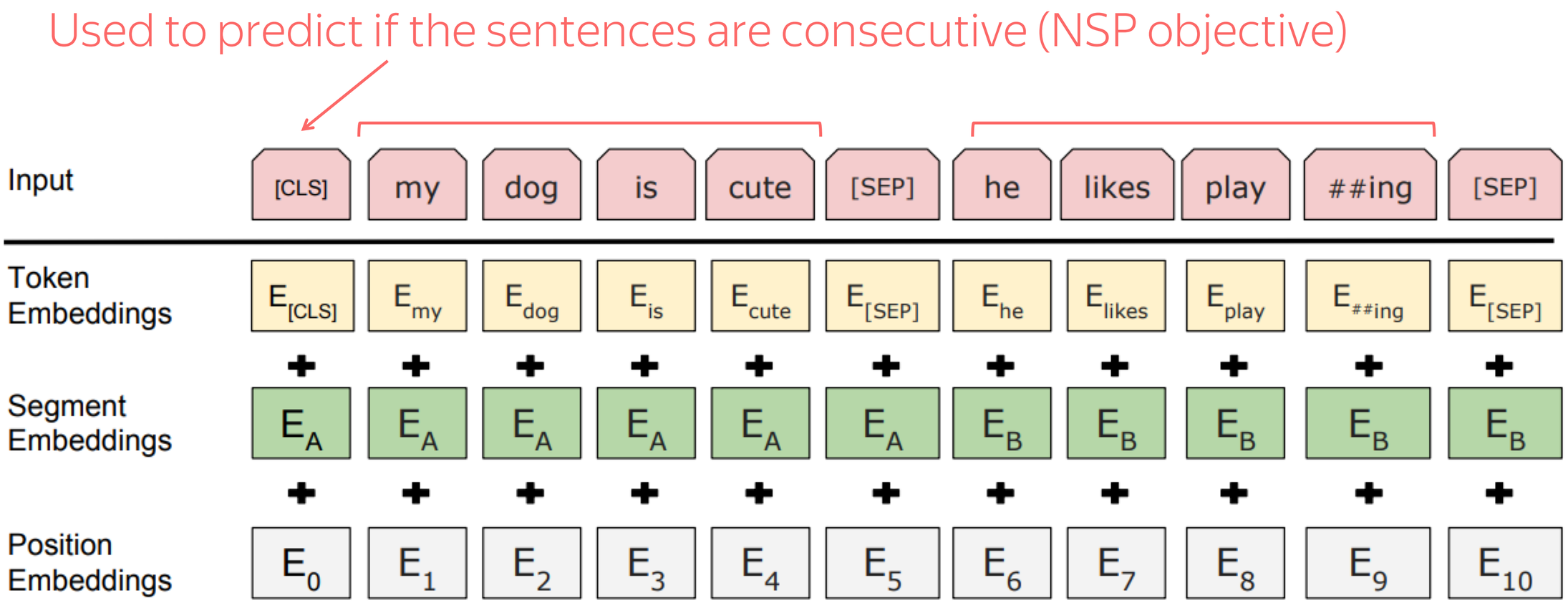
The figure is from the original BERT paper

BERT: Input



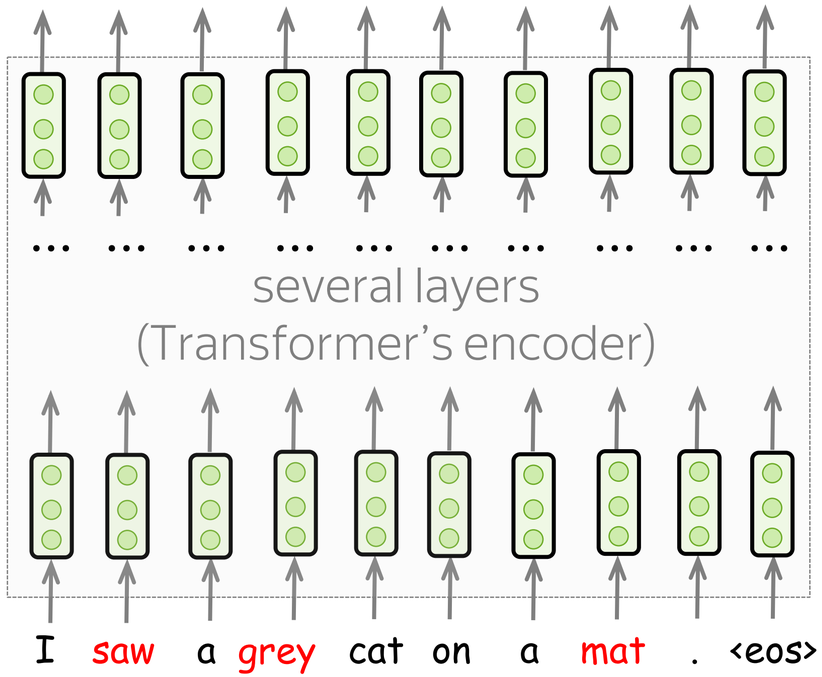
The figure is from the original BERT paper

BERT: Input



The figure is from the original BERT paper

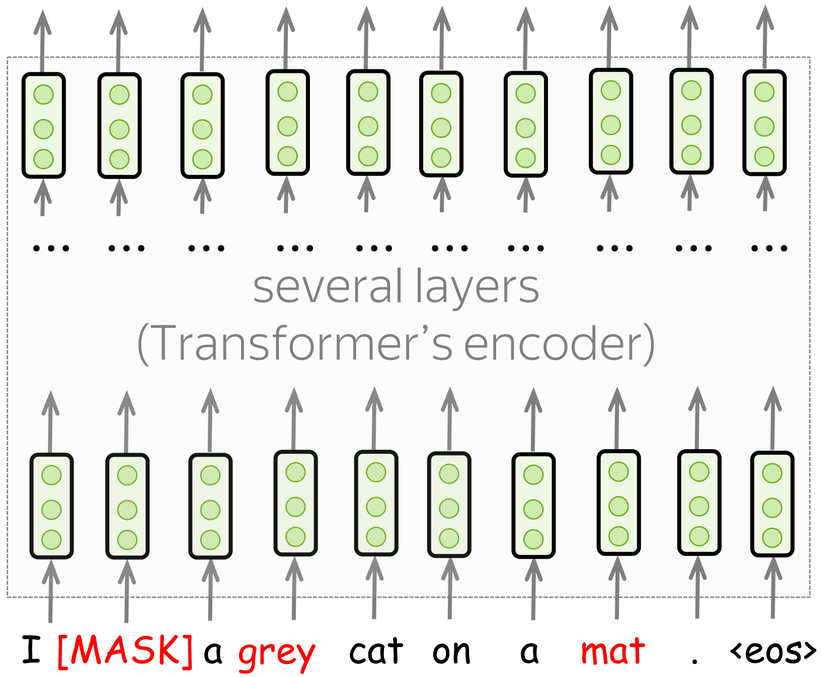
BERT: Masked Language Modeling Objective



At each training step:

- pick randomly 15% of tokens

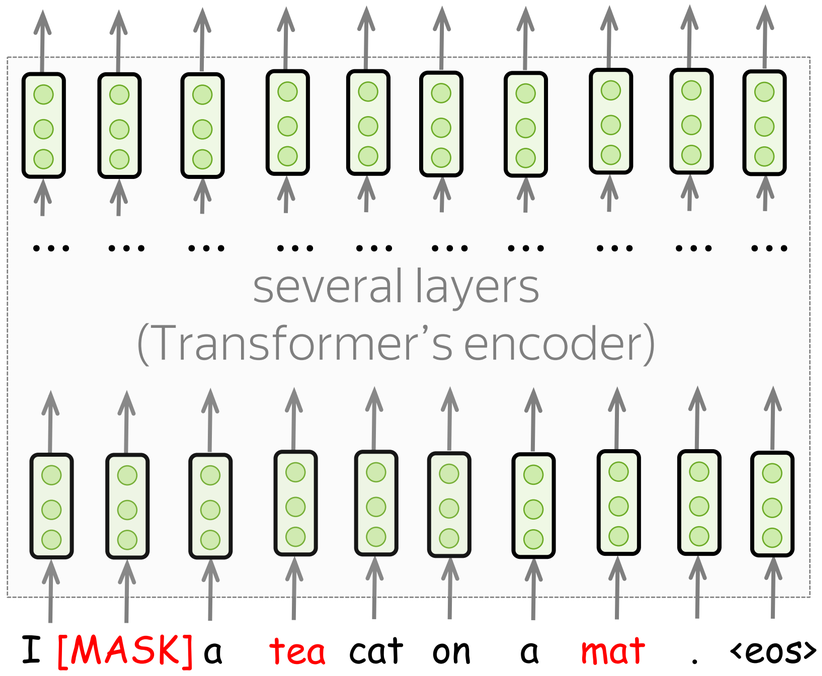
BERT: Masked Language Modeling Objective



At each training step:

- pick randomly 15% of tokens
- replace each of the chosen tokens with
  - **[MASK]** with prob. 80%

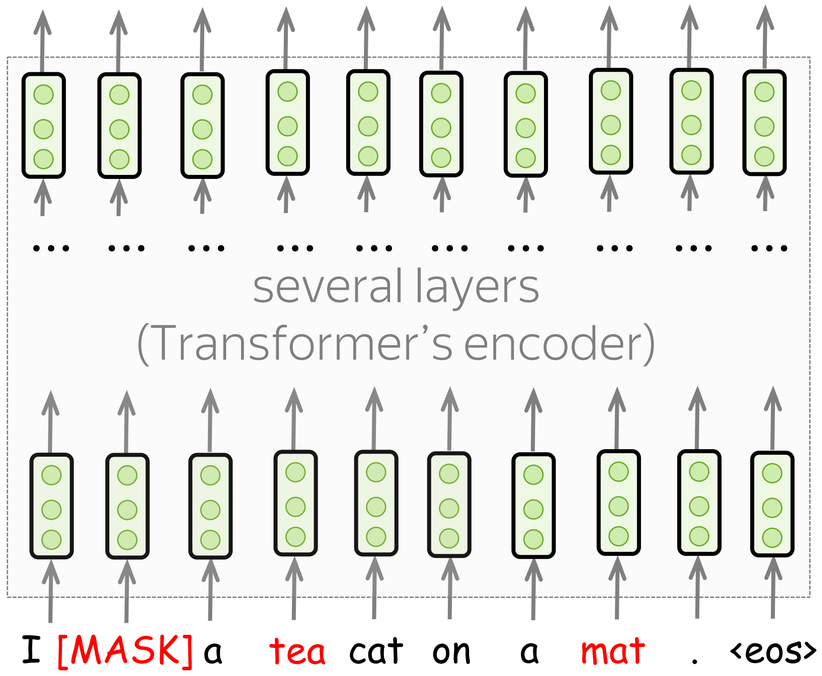
BERT: Masked Language Modeling Objective



At each training step:

- pick randomly 15% of tokens
- replace each of the chosen tokens with
  - **[MASK]** with prob. 80%
  - **random token** with prob. 10%

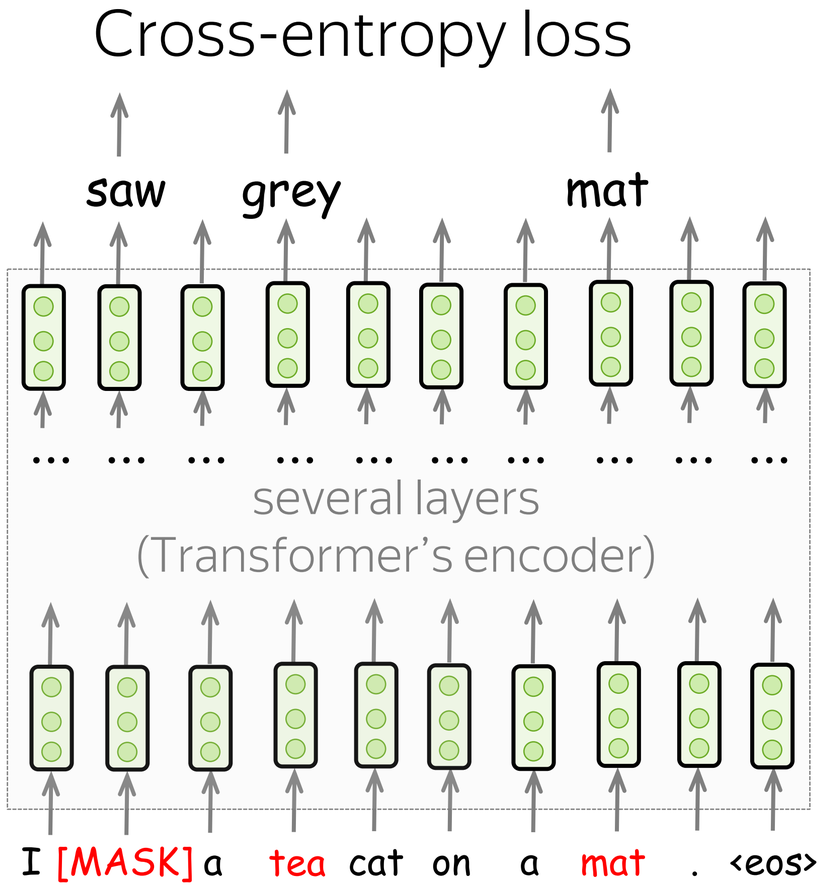
BERT: Masked Language Modeling Objective



At each training step:

- pick randomly 15% of tokens
- replace each of the chosen tokens with
  - **[MASK]** with prob. 80%
  - **random token** with prob. 10%
  - **self** with prob. 10%

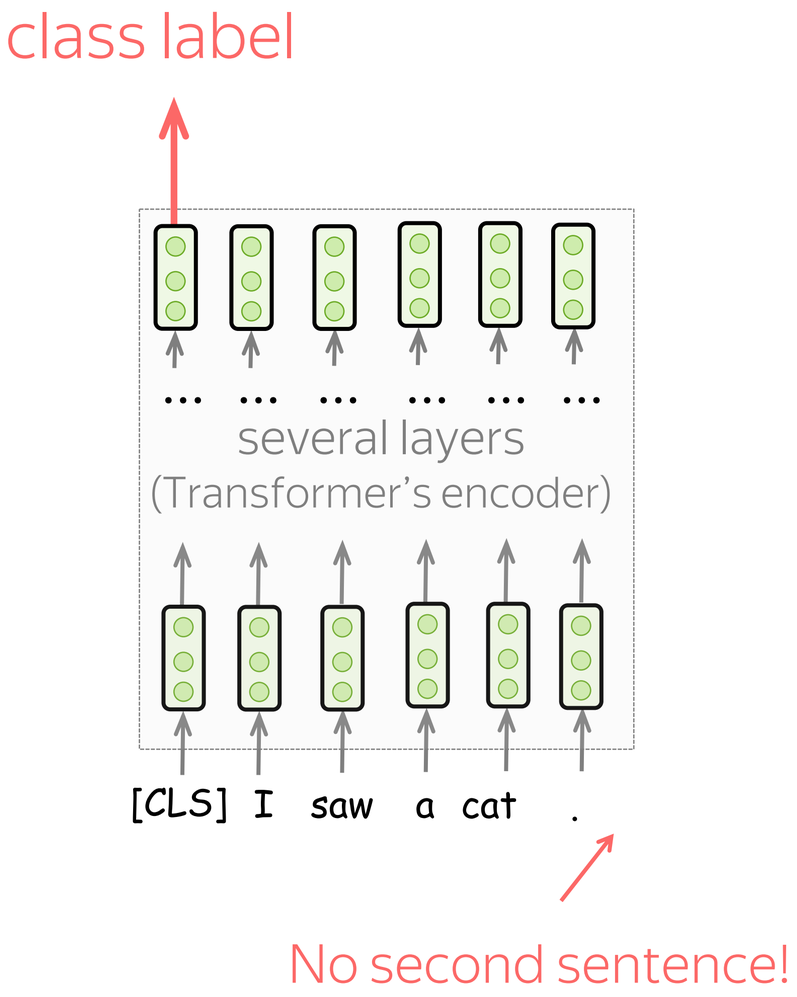
BERT: Masked Language Modeling Objective



At each training step:

- pick randomly 15% of tokens
- replace each of the chosen tokens with
  - **[MASK]** with prob. 80%
  - **random token** with prob. 10%
  - **self** with prob. 10%
- predict original tokens
  (only chosen ones!)

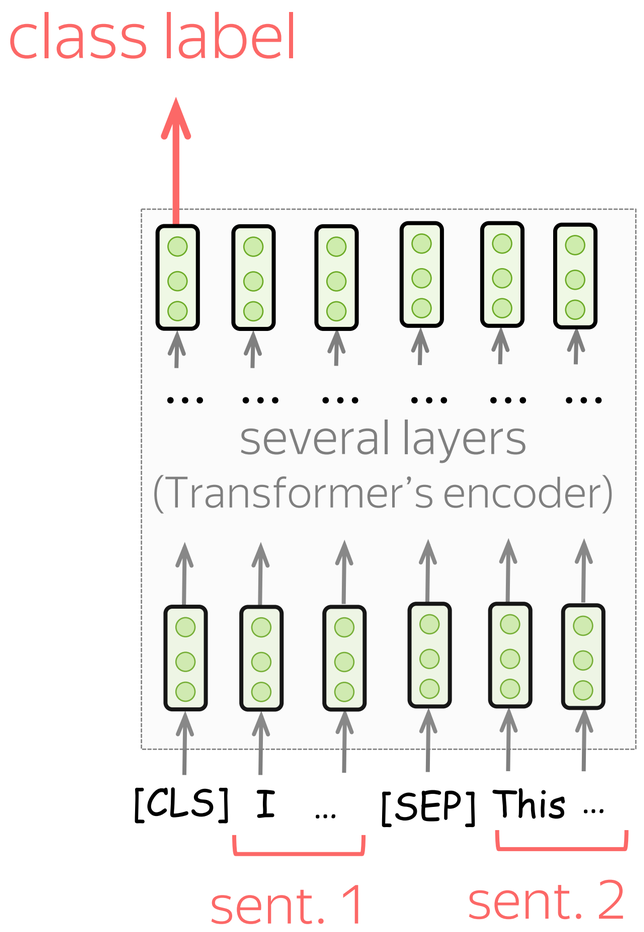
Finetuning BERT: Single-Sentence Classification



Examples of tasks:

- SST-2 – binary sentiment classification (we saw it in the text classification lecture)
- CoLA (Corpus of Linguistic Acceptability) – say whether a sentence is linguistically acceptable

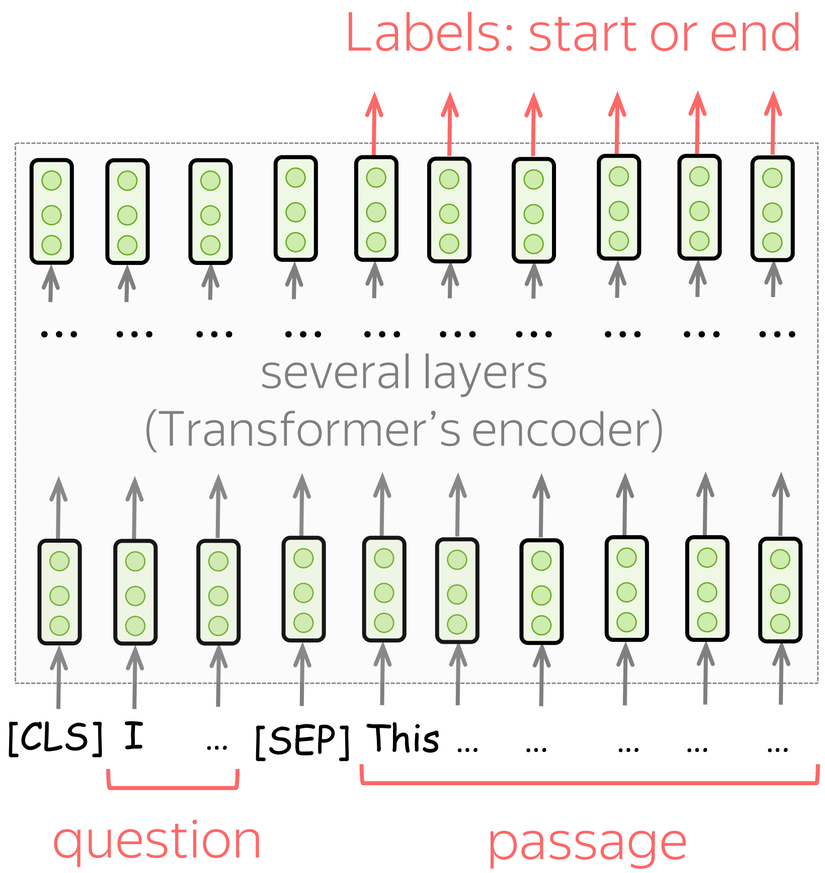
Finetuning BERT: Sentence Pair Classification



Examples of tasks:

- MLNI – entailment classification. Given a pair of sentences, say of the second is an **entailment**, **contradiction** or **neutral**
- QQP (Quora Question Pairs) – given two questions say if they are semantically equivalent
- STS-B – given two sentences return a similarity score from 1 to 5

Finetuning BERT: Question Answering



Examples of tasks:

- **SQUAD** – dataset with pairs of question-passage; the passage contains the answer – need to indicate where

ELMo: What's changed?

Before

Task-specific Model

Word Embeddings

I saw a kitten . <eos>

Word2Vec, GloVe, ... - saw a lot of data, know a lot

Model is the same

After

Task-specific Model

Representations of words **in context**

ELMo

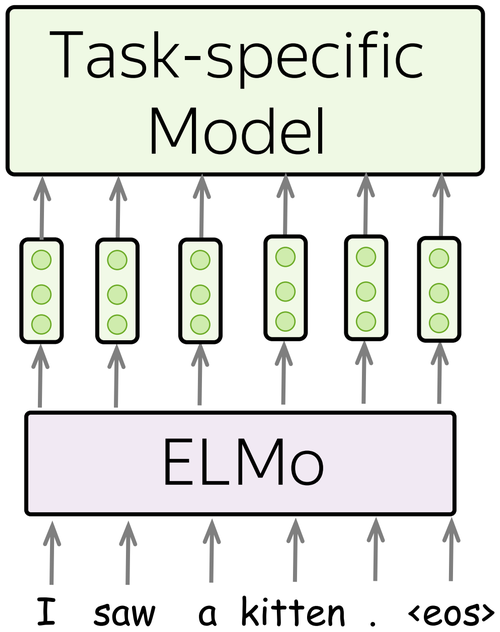
I saw a kitten . <eos>

We used huge unlabeled dataset to learn not only words, but **how to process entire texts**

BERT: What's changed?

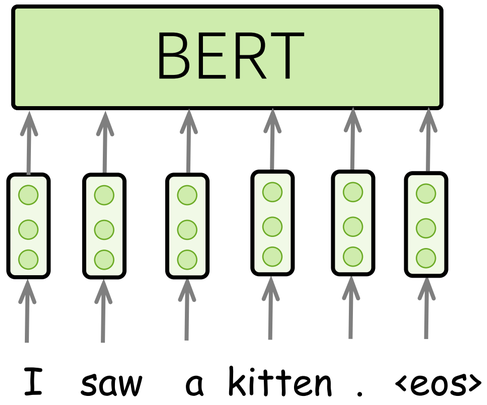
Before

Representations of words **in context**



After

No task-specific model at all!



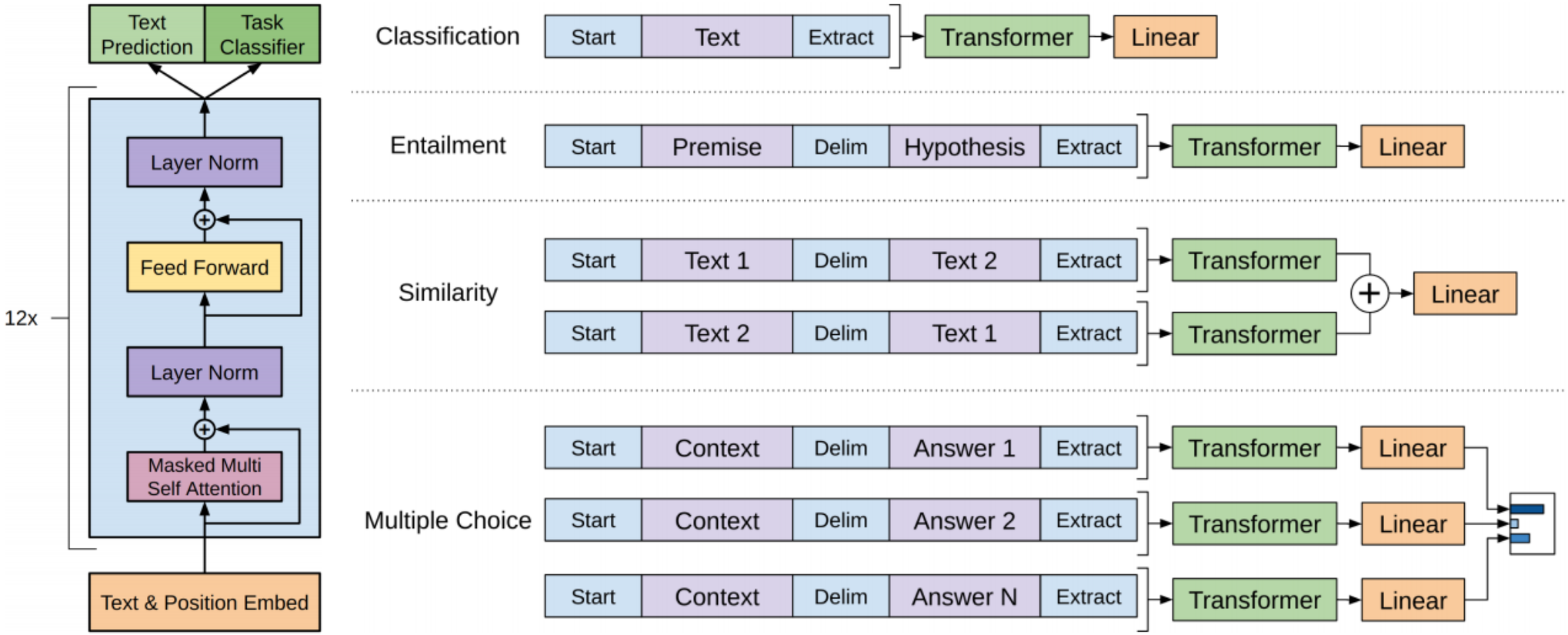
What is going to happen:

- Transfer Learning Idea
- Pretrained Models
  - (recap) Word Embeddings
  - ELMo
  - BERT
  - (a note on) GPT
  - (a note on) Adaptors
-  Analysis and Interpretability

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
  - (recap) Word Embeddings
  - ELMo
  - BERT
  - (a note on) GPT
  - (a note on) Adaptors
-  Analysis and Interpretability

GPT(1-2-3): Transformer Decoder



The figure is from the paper Improving Language Understanding by Generative Pretraining

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
  - (recap) Word Embeddings
  - ELMo
  - BERT
  - (a note on) GPT
  - (a note on) Adaptors
-  Analysis and Interpretability

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
  - (recap) Word Embeddings
  - ELMo
  - BERT
  - (a note on) GPT
  - (a note on) Adaptors
-  Analysis and Interpretability

Adaptors: Parameter-Efficient Adaptation

Finetuning:

- need a new (huge!) model for each task

Parameters updated: 100%

Adaptors: Parameter-Efficient Adaptation

Finetuning:

- need a new (huge!) model for each task

Parameters updated: 100%

Adaptors:

- model is fixed, train only small adaptors

Adaptors: Parameter-Efficient Adaptation

Finetuning:

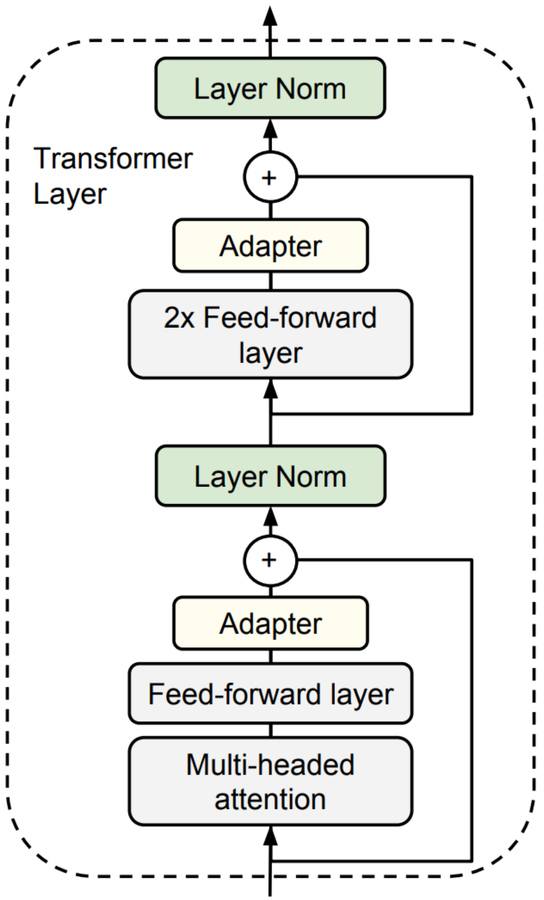
- need a new (huge!) model for each task

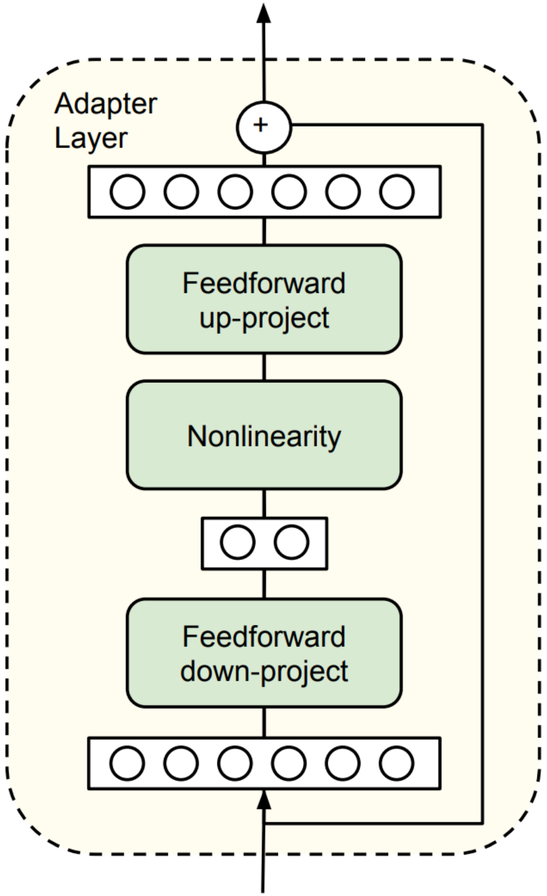
Parameters updated: 100%

Adaptors:

- model is fixed, train only small adaptors

Parameters updated: ≈1%





The figure is from the paper Parameter-Efficient Transfer Learning for NLP

Adaptors: Parameter-Efficient Adaptation

Finetuning:

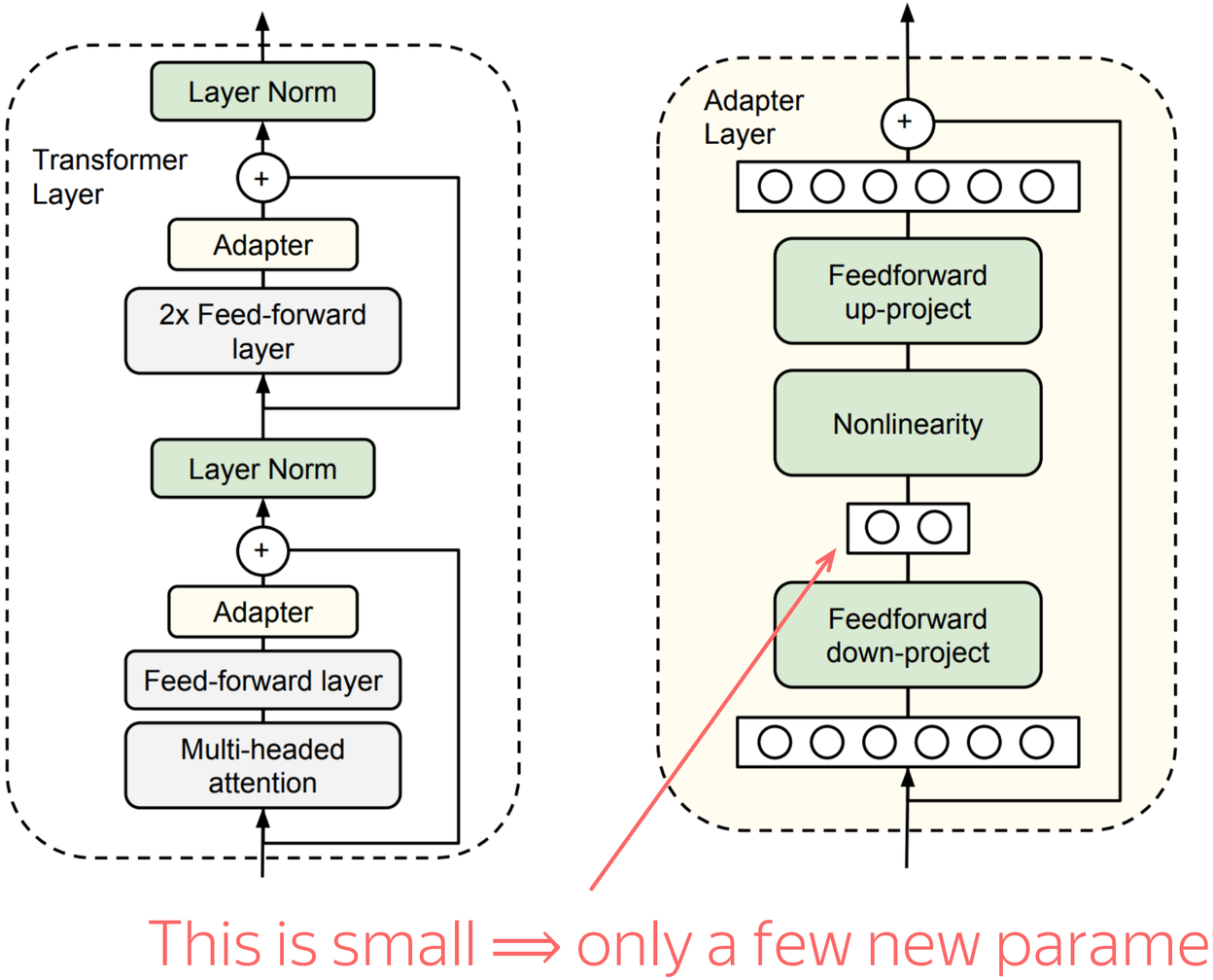
- need a new (huge!) model for each task

Parameters updated: 100%

Adaptors:

- model is fixed, train only small adaptors

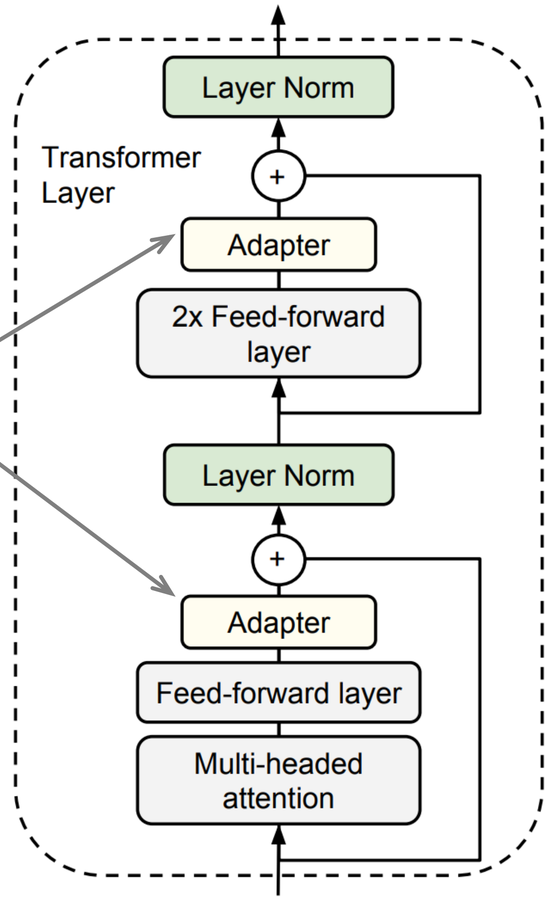
Parameters updated: ≈1%

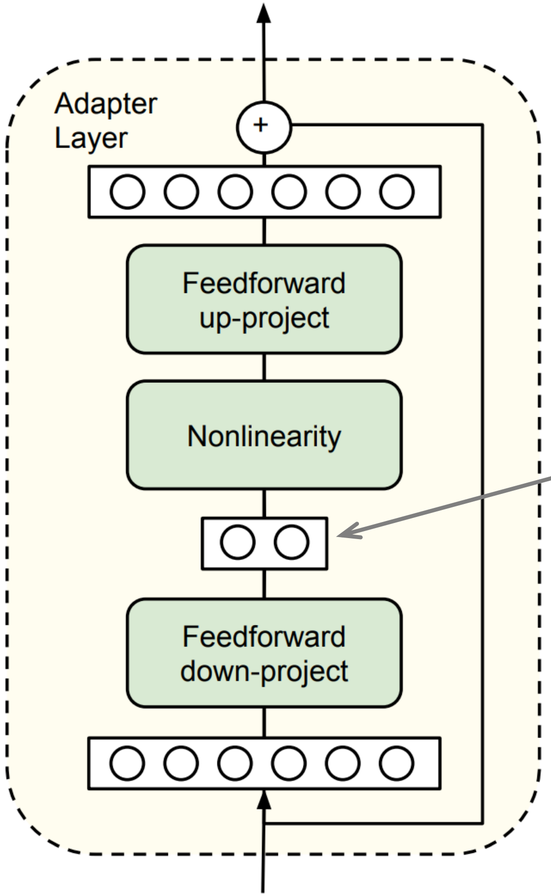


This is small ⟹ only a few new parameters

The figure is from the paper Parameter-Efficient Transfer Learning for NLP

Only these are trained, everything else is fixed and is the same for all tasks





Small hidden size, i.e. an adaptor has only a few parameters (which is good!)

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability

Other Research Directions

- Pretraining Objectives
- How to fine-tune
- How to Adapt
- How to modify for a new task (e.g. image-to-text, multilingual)

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability

Analysis Methods

The methods we used previously:

- (model-specific) looking at model components

Analysis Methods

The methods we used previously:

- (model-specific) looking at model components → Heads in Multi-Head Attention (BERT)

Analysis Methods

The methods we used previously:

- (model-specific) looking at model components → Heads in Multi-Head Attention (BERT)
- (model-agnostic) probing for linguistic structure

Analysis Methods

The methods we used previously:

- (model-specific) looking at model components → Heads in Multi-Head Attention (BERT)
- (model-agnostic) probing for linguistic structure → BERT and the classical NLP pipeline

Analysis Methods

The methods we used previously:

- (model-specific) looking at model components → Heads in Multi-Head Attention (BERT)
- (model-agnostic) probing for linguistic structure → BERT and the classical NLP pipeline
- (model-agnostic) looking at predictions and evaluating specific phenomena

Analysis Methods

The methods we used previously:

- (model-specific) looking at model components → Heads in Multi-Head Attention (BERT)
- (model-agnostic) probing for linguistic structure → BERT and the classical NLP pipeline
- (model-agnostic) looking at predictions and evaluating specific phenomena

Analysis Methods

The methods we used previously:

- (model-specific) looking at model components
- (model-agnostic) probing for linguistic structure
- (model-agnostic) looking at predictions and evaluating specific phenomena

What we will see in this lecture:

- → Heads in Multi-Head Attention (BERT)
- → BERT and the classical NLP pipeline
- → BERT as knowledge base

Analysis Methods

The methods we used previously:

- (model-specific) looking at model components → Heads in Multi-Head Attention (BERT)
- (model-agnostic) probing for linguistic structure → BERT and the classical NLP pipeline
- (model-agnostic) looking at predictions and evaluating specific phenomena → BERT as knowledge base

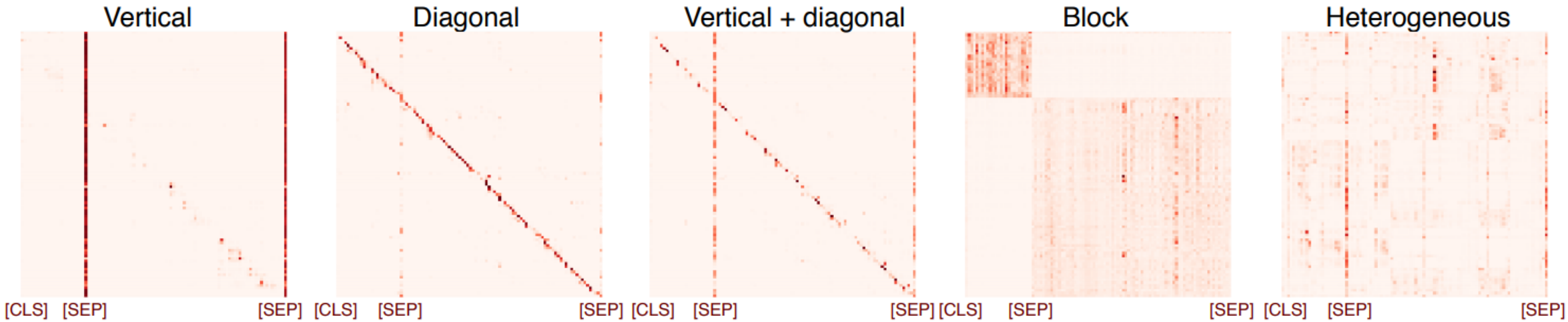
What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability →
  - Model Components
  - Probing
  - Looking at Predictions

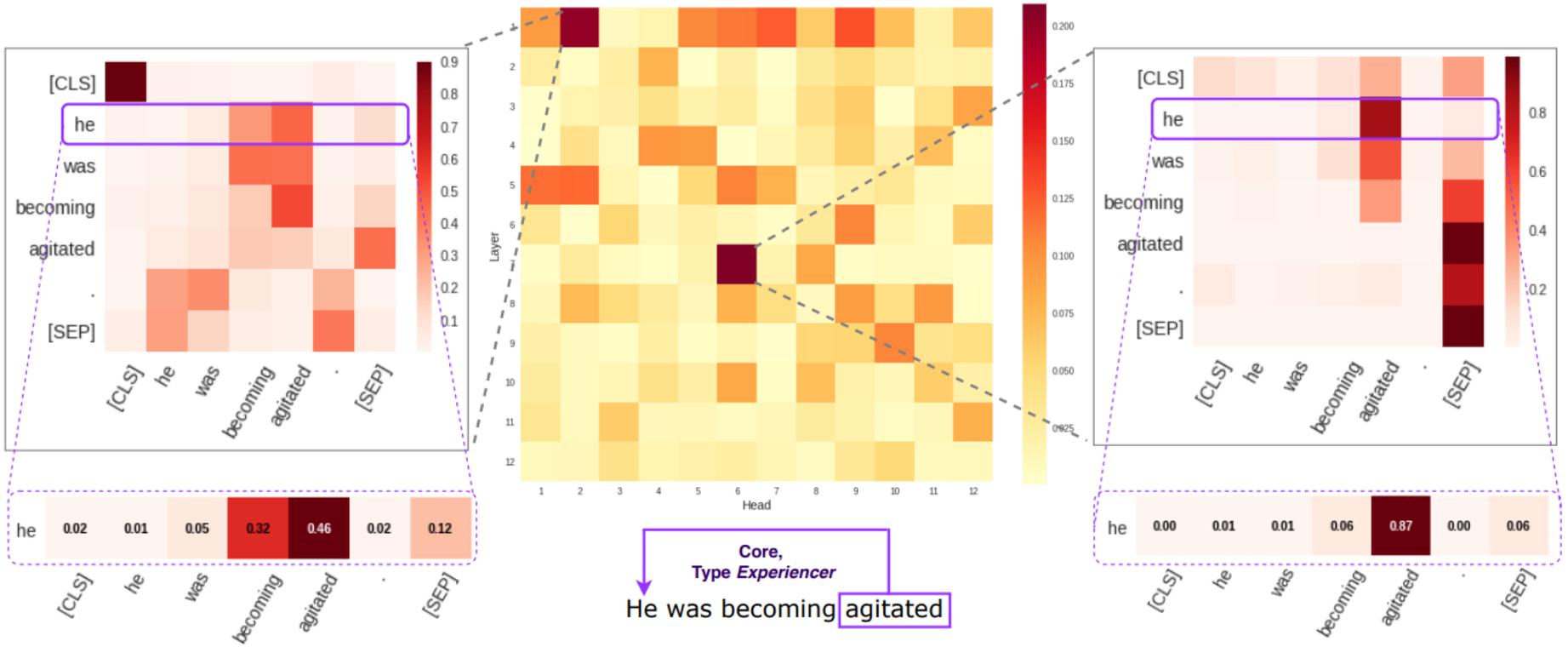
BERT Self-Attention Heads



Typical self-attention patterns

The figure is from the paper Revealing the Dark Secrets of BERT

BERT Self-Attention Heads



Heads that encode information correlated to semantic links in the input text

The figure is from the paper Revealing the Dark Secrets of BERT

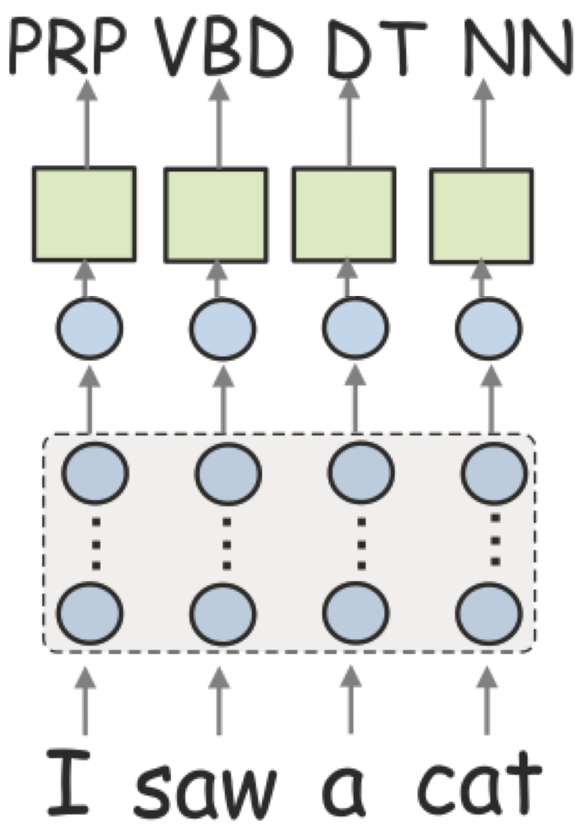
What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability →
  - Model Components
  - Probing
  - Looking at Predictions

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability →
  - Model Components
  - Probing
  - Looking at Predictions

RECAP: Probing for linguistic structure



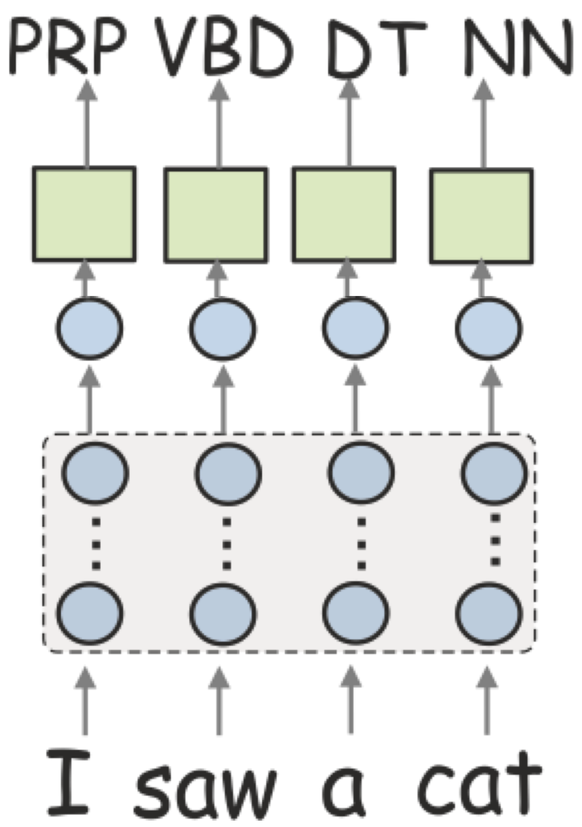
Labels: $y_{1:n}$

Probing classifier

Representations: $x_{1:n}$

Pretrained model

RECAP: Probing for linguistic structure



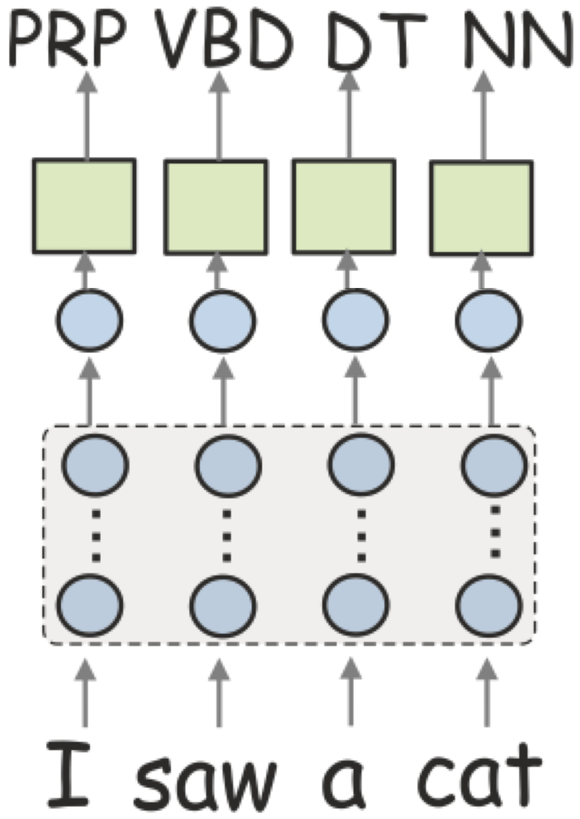
Labels: $y_{1:n}$

Probing classifier

Representations: $x_{1:n}$

Pretrained model

RECAP: Probing for linguistic structure



Labels: $y_{1:n}$

Probing classifier

Representations: use weights for layers (like in ELMo)

Pretrained model

After training a probing classifier, look at these weights

BERT Rediscovers the Classical NLP Pipeline

Part of speech: I want to find more , **[something]** bigger or deeper . → NN (Noun)

The figure is from the paper BERT Rediscovers the Classical NLP Pipeline

BERT Rediscovers the Classical NLP Pipeline

Part of speech: I want to find more , **[something]** bigger or deeper . → NN (Noun)

Constituents: I want to find more , **[something bigger or deeper]** . → NP (Noun Phrase)

The figure is from the paper BERT Rediscovers the Classical NLP Pipeline

BERT Rediscovers the Classical NLP Pipeline

Part of speech: I want to find more , **[something]** bigger or deeper . → NN (Noun)

Constituents: I want to find more , **[something bigger or deeper]** . → NP (Noun Phrase)

Dependencies: **[I]**$_1$ am not **[sure]**$_2$ how reliable that is , though . → nsubj (nominal subject)

The figure is from the paper BERT Rediscovers the Classical NLP Pipeline

BERT Rediscovers the Classical NLP Pipeline

Part of speech: I want to find more , **[something]** bigger or deeper . → NN (Noun)

Constituents: I want to find more , **[something bigger or deeper]** . → NP (Noun Phrase)

Dependencies: **[I]**$_1$ am not **[sure]**$_2$ how reliable that is , though . → nsubj (nominal subject)

Entities: The most fascinating is the maze known as **[Wind Cave]** . → LOC

The figure is from the paper BERT Rediscovers the Classical NLP Pipeline

BERT Rediscovers the Classical NLP Pipeline

Part of speech: I want to find more , **[something]** bigger or deeper . → NN (Noun)

Constituents: I want to find more , **[something bigger or deeper]** . → NP (Noun Phrase)

Dependencies: **[I]**$_1$ am not **[sure]**$_2$ how reliable that is , though . → nsubj (nominal subject)

Entities: The most fascinating is the maze known as **[Wind Cave]** . → LOC

Semantic Role Labeling: I want to **[find]**$_1$ **[more , something bigger or deeper]**$_2$. → Agr1 (Agent)

The figure is from the paper BERT Rediscovers the Classical NLP Pipeline

BERT Rediscovers the Classical NLP Pipeline

Part of speech: I want to find more , **[something]** bigger or deeper . → NN (Noun)

Constituents: I want to find more , **[something bigger or deeper]** . → NP (Noun Phrase)

Dependencies: **[I]**$_1$ am not **[sure]**$_2$ how reliable that is , though . → nsubj (nominal subject)

Entities: The most fascinating is the maze known as **[Wind Cave]** . → LOC

Semantic Role Labeling: I want to **[find]**$_1$ **[more , something bigger or deeper]**$_2$. → Agr1 (Agent)

Coreference: So **[the followers]**$_1$ waited to say anything about what **[they]**$_2$ saw . → True

The figure is from the paper BERT Rediscovers the Classical NLP Pipeline

BERT Rediscovers the Classical NLP Pipeline

Part of speech:

Constituents:

Dependencies:

Entities:

Semantic Role Labeling:

Coreference:

In classical NLP, to solve a subsequent task is was required to solve the previous one

The figure is from the paper BERT Rediscovers the Classical NLP Pipeline

BERT Rediscovers the Classical NLP Pipeline

Part of speech:

Constituents:

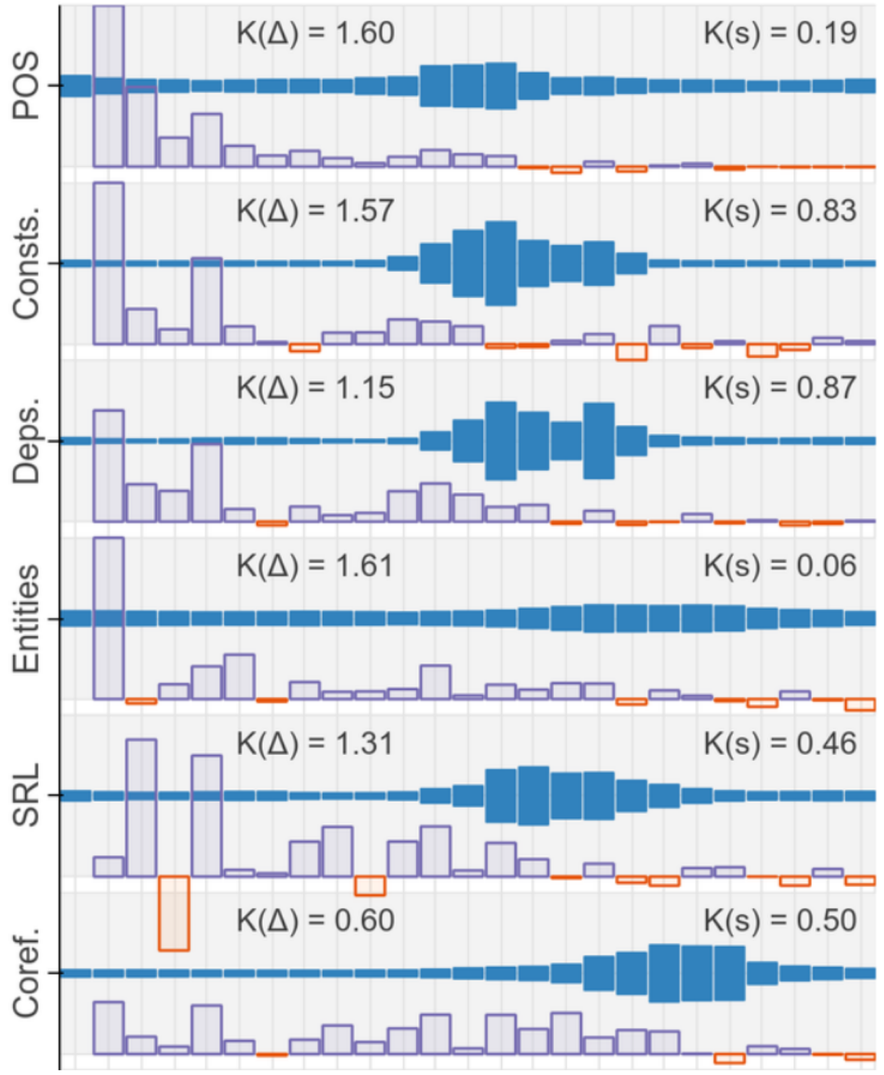
Dependencies:

Entities:

Semantic Role Labeling:

Coreference:

In classical NLP, to solve a subsequent task is was required to solve the previous one



The figure is from the paper BERT Rediscovers the Classical NLP Pipeline

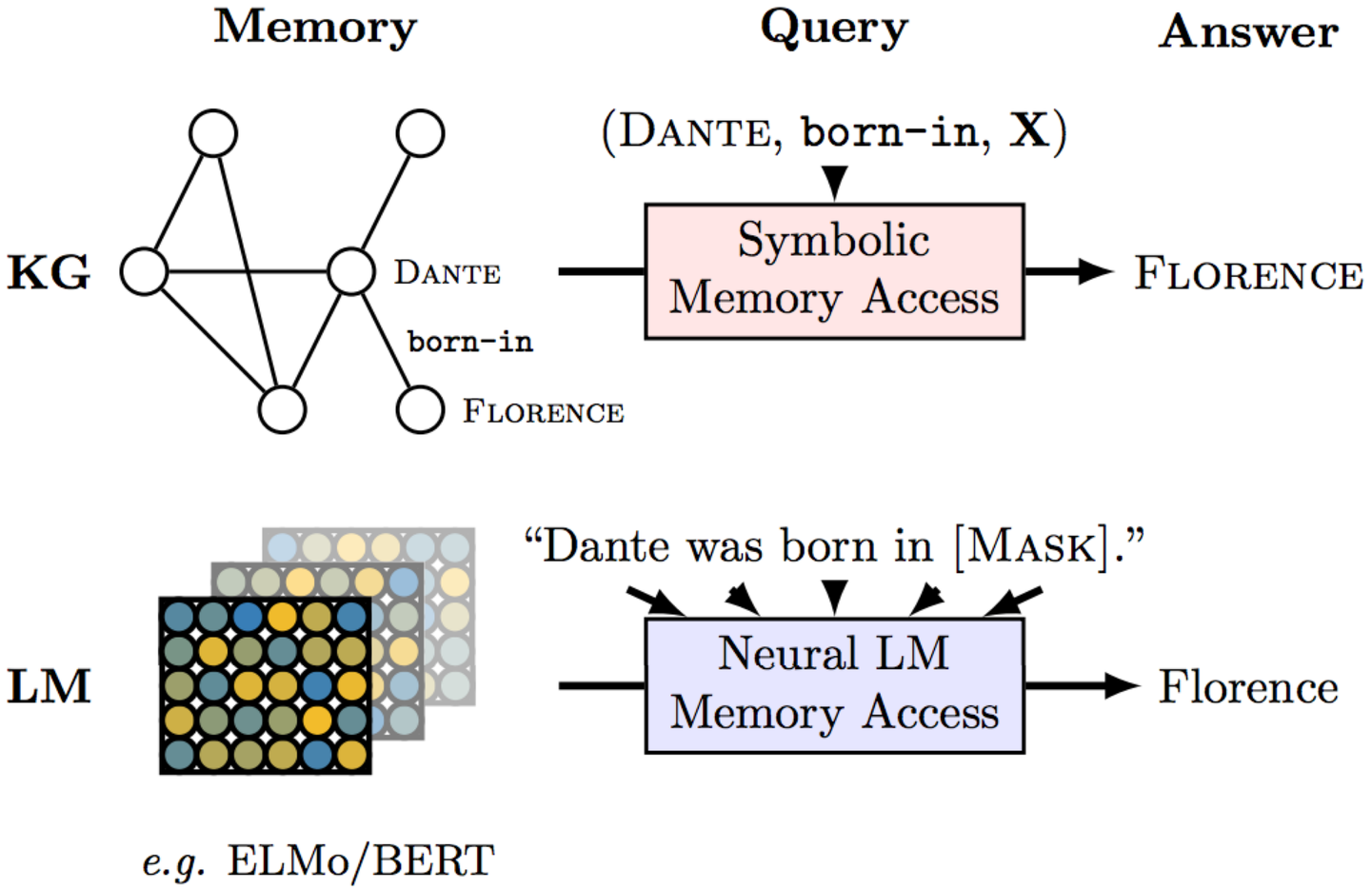
What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability →
  - Model Components
  - Probing
  - Looking at Predictions

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability →
  - Model Components
  - Probing
  - Looking at Predictions

Language Models as Knowledge Bases?



The figure is from the paper Language Models as Knowledge Bases?

Language Models as Knowledge Bases?

	Relation	Query	Answer	Generation
T-Rex	P19	Francesco Bartolomeo Conti was born in ____.	Florence	Rome [-1.8] , **Florence [-1.8]** , Naples [-1.9] , Milan [-2.4] , Bologna [-2.5]
	P20	Adolphe Adam died in ____.	Paris	**Paris [-0.5]** , London [-3.5] , Vienna [-3.6] , Berlin [-3.8] , Brussels [-4.0]
	P279	English bulldog is a subclass of ____.	dog	dogs [-0.3] , breeds [-2.2] , **dog [-2.4]** , cattle [-4.3] , sheep [-4.5]
	P37	The official language of Mauritius is ____.	English	**English [-0.6]** , French [-0.9] , Arabic [-6.2] , Tamil [-6.7] , Malayalam [-7.0]
	P413	Patrick Oboya plays in ____ position.	midfielder	centre [-2.0] , center [-2.2] , **midfielder [-2.4]** , forward [-2.4] , midfield [-2.7]
	P138	Hamburg Airport is named after ____.	Hamburg	Hess [-7.0] , Hermann [-7.1] , Schmidt [-7.1] , **Hamburg [-7.5]** , Ludwig [-7.5]
	P364	The original language of Mon oncle Benjamin is ____.	French	**French [-0.2]** , Breton [-3.3] , English [-3.8] , Dutch [-4.2] , German [-4.9]
	P54	Dani Alves plays with ____ .	Barcelona	Santos [-2.4] , Porto [-2.5] , Sporting [-3.1] , Brazil [-3.3] , Portugal [-3.7]
	P106	Paul Toungui is a ____ by profession .	politician	lawyer [-1.1] , journalist [-2.4] , teacher [-2.7] , doctor [-3.0] , physician [-3.7]
	P527	Sodium sulfide consists of ____.	sodium	water [-1.2] , sulfur [-1.7] , **sodium [-2.5]** , zinc [-2.8] , salt [-2.9]
	P102	Gordon Scholes is a member of the ____ political party.	Labor	Labour [-1.3] , Conservative [-1.6] , Green [-2.4] , Liberal [-2.9] , **Labor [-2.9]**
	P530	Kenya maintains diplomatic relations with ____.	Uganda	India [-3.0] , **Uganda [-3.2]** , Tanzania [-3.5] , China [-3.6] , Pakistan [-3.6]
	P176	iPod Touch is produced by ____.	Apple	**Apple [-1.6]** , Nokia [-1.7] , Sony [-2.0] , Samsung [-2.6] , Intel [-3.1]
	P30	Bailey Peninsula is located in ____.	Antarctica	**Antarctica [-1.4]** , Bermuda [-2.2] , Newfoundland [-2.5] , Alaska [-2.7] , Canada [-3.1]
	P178	JDK is developed by ____.	Oracle	IBM [-2.0] , Intel [-2.3] , Microsoft [-2.5] , HP [-3.4] , Nokia [-3.5]
	P1412	Carl III used to communicate in ____.	Swedish	German [-1.6] , Latin [-1.9] , French [-2.4] , English [-3.0] , Spanish [-3.0]
	P17	Sunshine Coast, British Columbia is located in ____.	Canada	**Canada [-1.2]** , Alberta [-2.8] , Yukon [-2.9] , Labrador [-3.4] , Victoria [-3.4]
	P39	Pope Clement VII has the position of ____ .	pope	cardinal [-2.4] , Pope [-2.5] , **pope [-2.6]** , President [-3.1] , Chancellor [-3.2]
	P264	Joe Cocker is represented by music label ____.	Capitol	EMI [-2.6] , BMG [-2.6] , Universal [-2.8] , **Capitol [-3.2]** , Columbia [-3.3]
	P276	London Jazz Festival is located in ____.	London	**London [-0.3]** , Greenwich [-3.2] , Chelsea [-4.0] , Camden [-4.6] , Stratford [-4.8]
	P127	Border TV is owned by ____.	ITV	Sky [-3.1] , **ITV [-3.3]** , Global [-3.4] , Frontier [-4.1] , Disney [-4.3]
	P103	The native language of Mammootty is ____.	Malayalam	**Malayalam [-0.2]** , Tamil [-2.1] , Telugu [-4.8] , English [-5.2] , Hindi [-5.6]
	P495	The Sharon Cuneta Show was created in ____.	Philippines	Manila [-3.2] , **Philippines [-3.6]** , February [-3.7] , December [-3.8] , Argentina [-4.0]

The figure is from the paper Language Models as Knowledge Bases?

Language Models as Knowledge Bases?

ConceptNet	AtLocation	You are likely to find a overflow in a ____.	drain	sewer [-3.1] , canal [-3.2] , toilet [-3.3] , stream [-3.6] , **drain [-3.6]**
	CapableOf	Ravens can ____.	fly	**fly [-1.5]** , fight [-1.8] , kill [-2.2] , die [-3.2] , hunt [-3.4]
	CausesDesire	Joke would make you want to ____.	laugh	cry [-1.7] , die [-1.7] , **laugh [-2.0]** , vomit [-2.6] , scream [-2.6]
	Causes	Sometimes virus causes ____.	infection	disease [-1.2] , cancer [-2.0] , **infection [-2.6]** , plague [-3.3] , fever [-3.4]
	HasA	Birds have ____.	feathers	wings [-1.8] , nests [-3.1] , **feathers [-3.2]** , died [-3.7] , eggs [-3.9]
	HasPrerequisite	Typing requires ____.	speed	patience [-3.5] , precision [-3.6] , registration [-3.8] , accuracy [-4.0] , **speed [-4.1]**
	HasProperty	Time is ____.	finite	short [-1.7] , passing [-1.8] , precious [-2.9] , irrelevant [-3.2] , gone [-4.0]
	MotivatedByGoal	You would celebrate because you are ____.	alive	happy [-2.4] , human [-3.3] , **alive [-3.3]** , young [-3.6] , free [-3.9]
	ReceivesAction	Skills can be ____.	taught	acquired [-2.5] , useful [-2.5] , learned [-2.8] , combined [-3.9] , varied [-3.9]
	UsedFor	A pond is for ____.	fish	swimming [-1.3] , fishing [-1.4] , bathing [-2.0] , **fish [-2.8]** , recreation [-3.1]

The figure is from the paper Language Models as Knowledge Bases?

What is going to happen:

- Transfer Learning Idea
- Pretrained Models
-  Analysis and Interpretability

Thank you!

Lena Voita

PhD student, Uni Edinburgh & Uni Amsterdam

Facebook PhD Fellow in NLP

lena-voita@hotmail.com

https://lena-voita.github.io

@lena_voita

lena-voita