NVIDIA | DEEP LEARNING INSTITUTE

MACHINE LEARNING IN NLP

Building Transformer-Based Natural Language Processing Applications (Part 1)

FULL COURSE AGENDA

Part 1: Machine Learning in NLP

Lecture: NLP background and the role of DNNs leading to the Transformer architecture

Lab: Tutorial-style exploration of a ***translation task*** using the Transformer architecture

Part 2: Self-Supervision, BERT, and Beyond

Lecture: Discussion of how language models with self-supervision have moved beyond the basic Transformer to BERT and ever larger models

Lab: Practical hands-on guide to the NVIDIA NeMo API and exercises to build a ***text classification task*** and a ***named entity recognition task*** using BERT-based language models

Part 3: Production Deployment

Lecture: Discussion of production deployment considerations and NVIDIA Triton Inference Server

Lab: Hands-on deployment of an example ***question answering task*** to NVIDIA Triton

Part 1: Machine Learning in NLP

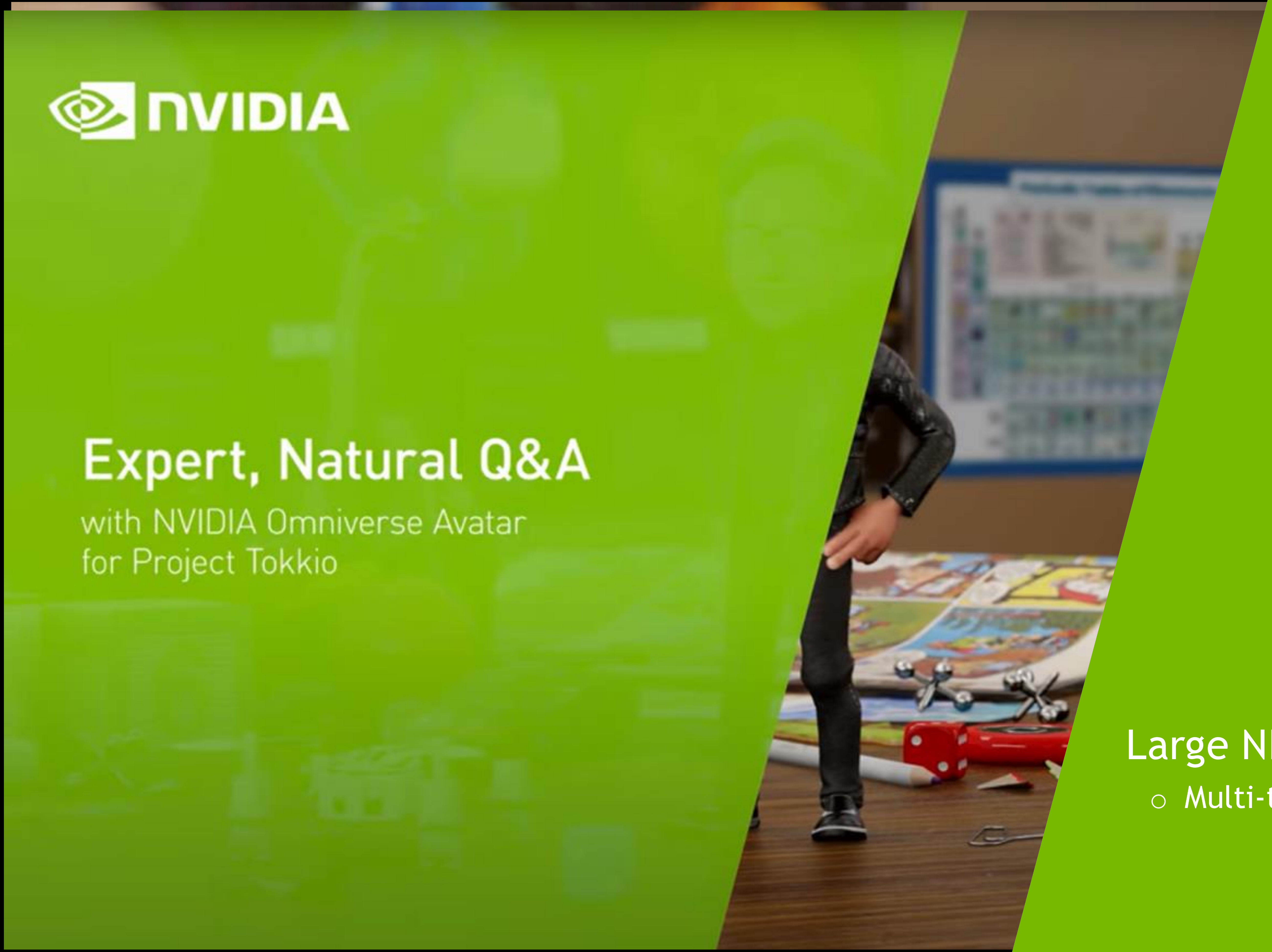
- Lecture
  - What is NLP?
  - Problem Formulation
  - Text Representations
  - Dimensionality Reduction
  - Embeddings
  - RNNs
  - "Attention is All You Need"
- Lab
  - Transformer Architecture
  - BERT Model
  - Pretraining BERT

FOUNDATION OF COUNTLESS APPLICATIONS

NLP TASKS

And many more....

GLIMPSE OF WHAT IS POSSIBLE, TODAY…



Large NLP models powers:

- Multi-turn Information Retrieval for Q&A

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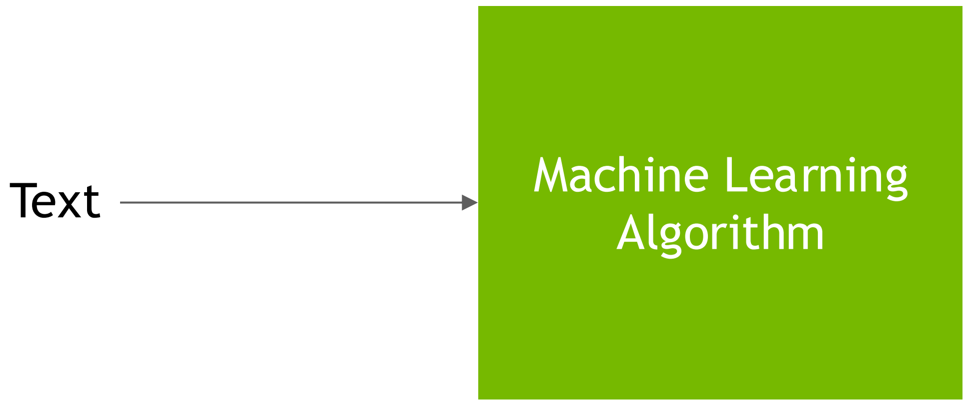
PROBLEM FORMULATION

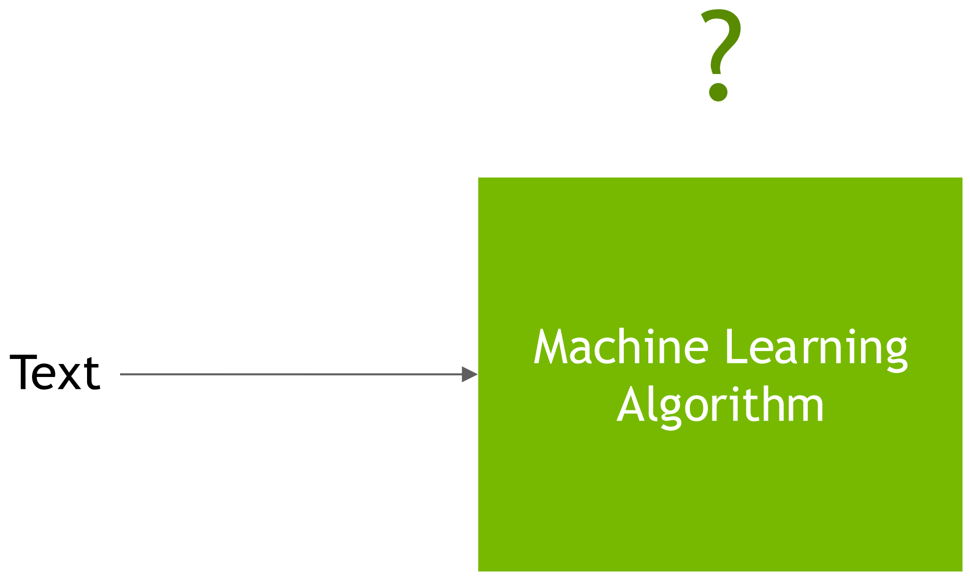
MACHINE LEARNING

Discovering the discussed structures in text



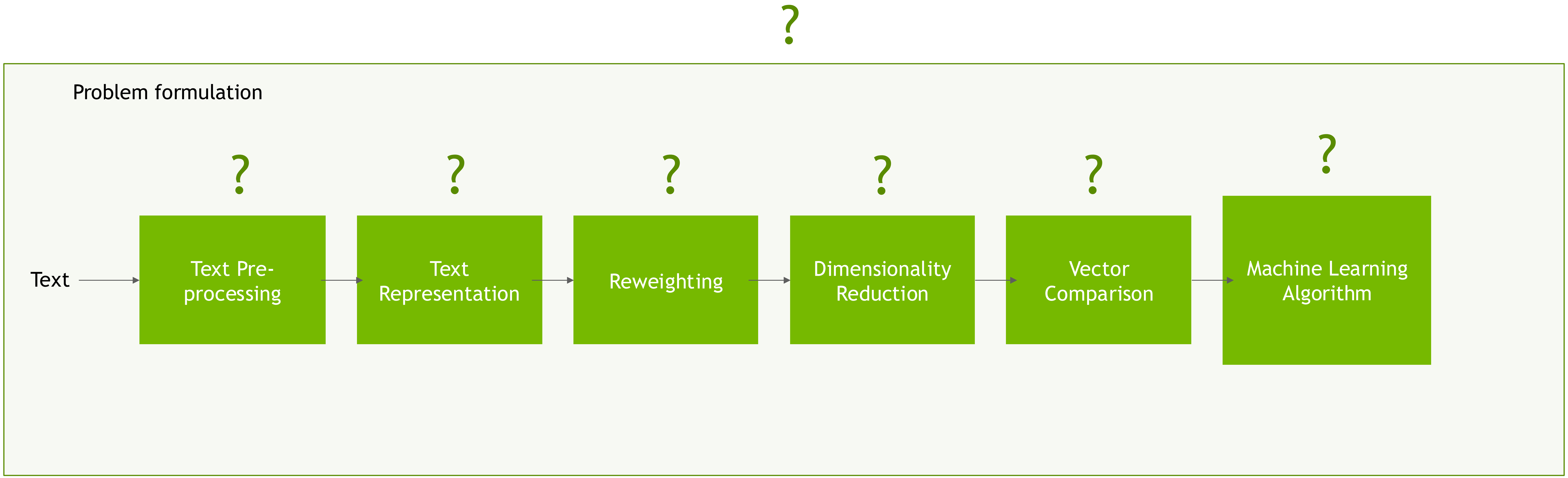
MACHINE LEARNING

Discovering the discussed structures in text



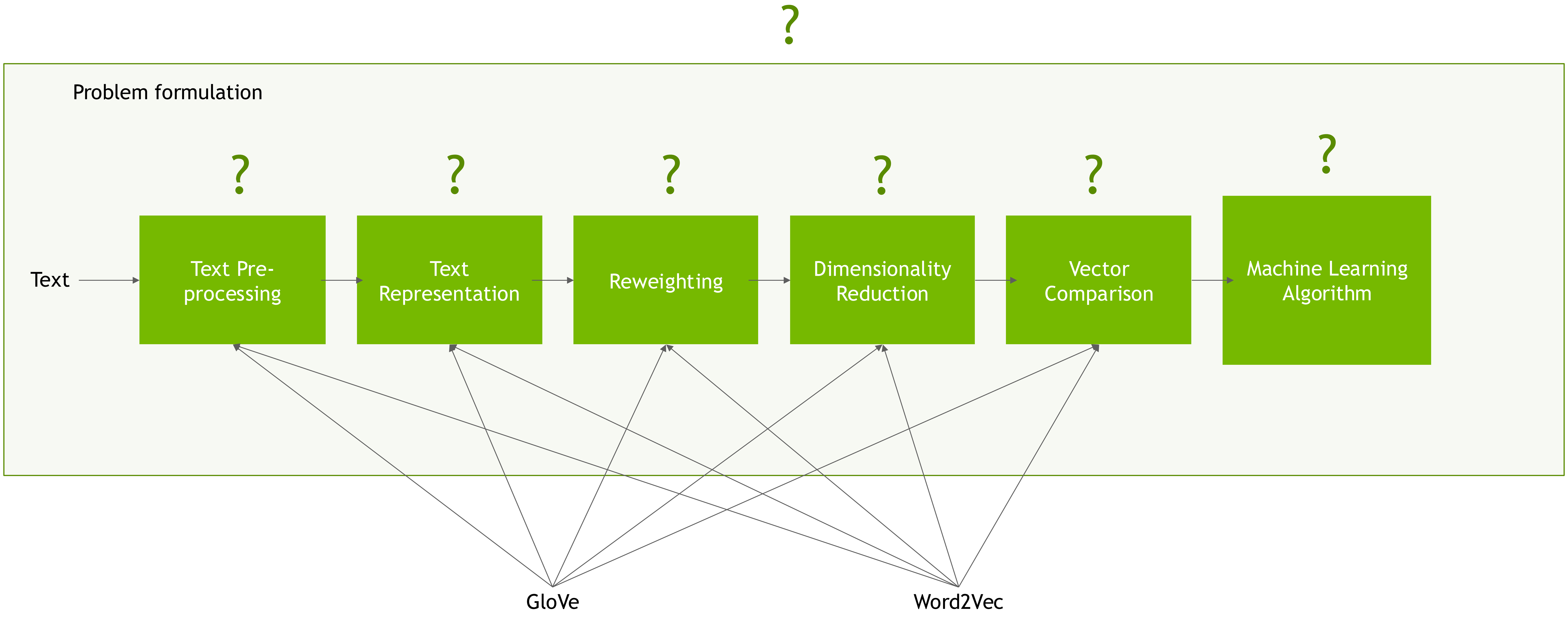
MACHINE LEARNING

Design decisions



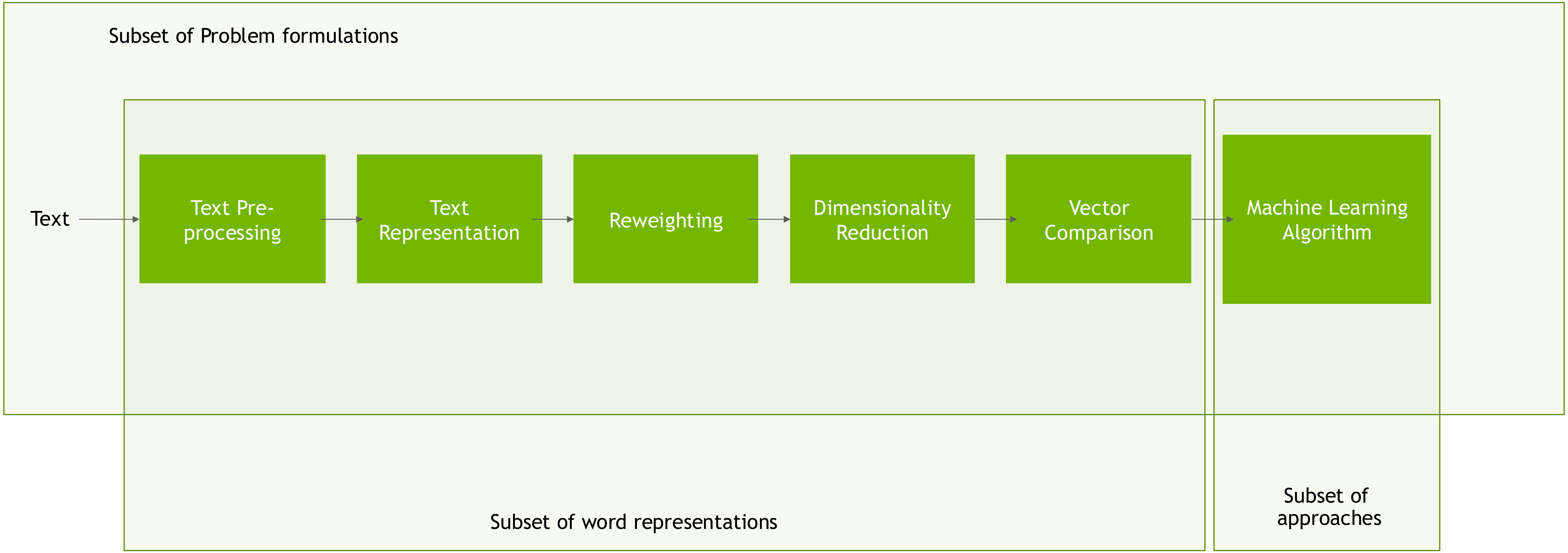
MACHINE LEARNING

All linear combinations feasible



MACHINE LEARNING

In this class



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TEXT REPRESENTATIONS

The bag of words

- Bag of words/ngrams – feature per word/ngram

the cat sat on the mat

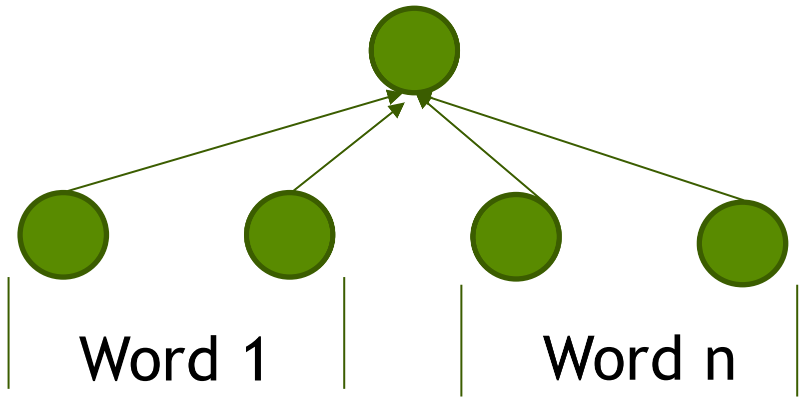
cat	sat	on	the	mat	quic kly
1	1	1	2	1	0

… |Vocabulary|

THE BAG OF WORDS

Key challenges

- Sparse Input (1-hot)



p >> n (overfitting!)

lots of data required,
low accuracy

- No semantic generalization
- *dog:* 1 0 0 0 0 … 0
- *cat:* 0 0 1 0 0 … 0

DISTRIBUTED WORD REPRESENTATIONS

DISTRIBUTIONAL HYPOTHESIS

The intuition

‘You can tell a word by the company it keeps’

Firth 1957

‘Distributional statements can cover all of the material of a language without requiring support from other types of information’

Harris 1954

‘The meaning of a word is its use in the language’

Wittgenstein 1953

‘The complete meaning of a word is always contextual, and no study of meaning apart from context can be taken seriously.’

Firth 1957

CO-OCCURRENCE PATTERNS

The latent information

	a	big	bug	the	little	but	beetle	bit	back
a	0	5	4	2	1	0	0	3	0
big	5	0	10	8	4	0	4	8	4
bug	4	10	0	8	4	0	4	8	5
the	2	8	8	0	8	3	8	10	3
little	1	4	4	13	1	3	10	8	0
but	0	0	0	7	7	0	7	3	0
beetle	0	4	4	11	11	4	1	8	1
bit	3	8	7	12	9	3	8	0	1
back	0	4	5	3	0	0	1	2	0

CO-OCCURRENCE PATTERNS

Where to find them?

Possible relationships:

- Word to documents (very sparse and very wide)
- Word to word (very dense and compact)
- Word to user / person
- Word to user behaviour
- Word to product
- Word to custom feature (e.g. movie raking)

Not only metrices:

- Word to user to product

CHI '88

Technical Memo Example

(A) Database of Titles

c1: *Human* machine *interface* for *computer* applications
c2: *Survey* of *user* opinion of *computer system response time*
c3: The *EPS user interface* management *system*
c4: *System* and *human system* engineering testing of *EPS*
c5: *User*-perceived *response time* and error measurement

m1: The generation of random, binary, unordered *trees*
m2: The intersection *graph* of paths in *trees*
m3: *Graph minors*: Widths of *trees* and well-quasi-ordering
m4: *Graph minors*: A *survey*

(B) Term by Title Matrix

Terms	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

Figure 1. (A) A sample dataset consisting of the titles of nine technical memoranda. Terms occurring in more than one title are italicized. There are two classes of objects - five titles about human-computer interaction (c1-c5) and four about graphs (m1-m4). (B) This dataset can be described by means of a term by title matrix where each cell entry indicates the frequency with which a term occurs in a title. This matrix was used as the data, X, on which SVD was performed.

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DIMENSIONALITY REDUCTION

Rationale

The need for compact and computationally efficient representations

More robust notions of distance exposing the information captured by our distributional representation

LSA/LSI

LSA/LSI

Latent Semantic Analysis / Latent Semantic Indexing

?

LLSA/LSI

Truncated SVD

Terms x Documents

$$X = T * S * P^T$$

Dumais, Susan T., et al. "Using latent semantic analysis to improve access to textual information." *Proceedings of the SIGCHI conference on Human factors in computing systems*. 1988.

LSA/LSI

Truncated SVD

Terms x Documents

$$X = T * S * P^T$$

K largest singular values

$$X = T_k * S_k * P_k^T$$

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LSA/LSI

Truncated SVD

Terms x Documents

$$X = T * S * P^T$$

K largest singular values

$$X = T_k * S_k * P_k^T$$

Latent Semantic Space

Dumais, Susan T., et al. "Using latent semantic analysis to improve access to textual information." *Proceedings of the SIGCHI conference on Human factors in computing systems*. 1988.

LSA/LSI

Documents that are similar are closer

	Titles								
	c1	c2	c3	c4	c5	m1	m2	m3	m4
Terms	--	--	--	--	--	--	--	--	--
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
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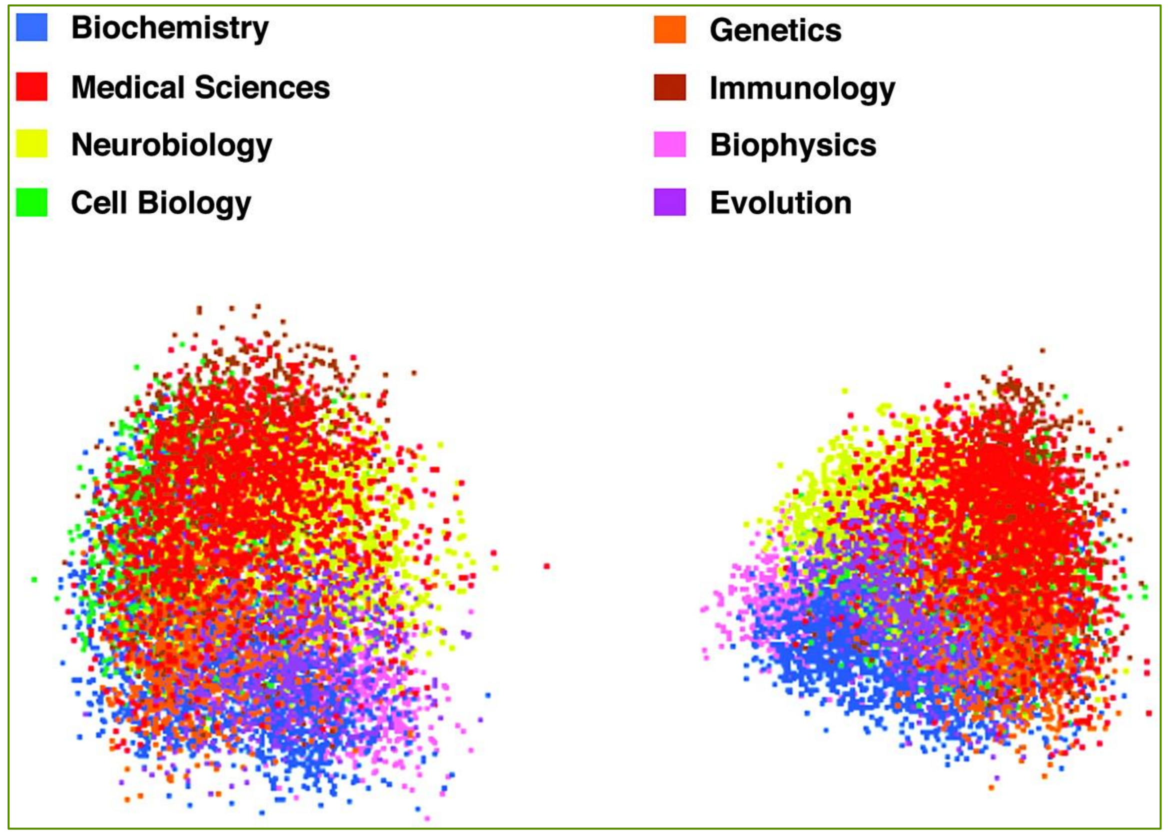
$$X = T_k * S_k * P_k^T$$



Landauer, Thomas K., Darrell Laham, and Marcia Derr. "From paragraph to graph: Latent semantic analysis for information visualization." *Proceedings of the National Academy of Sciences* 101.suppl 1 (2004): 5214-5219.

LSA/LSI

Its so 1988

Dumais, Susan T., et al. "Using latent semantic analysis to improve access to textual information." *Proceedings of the SIGCHI conference on Human factors in computing systems*. 1988.

DID WE MAKE FURTHER PROGRESS?

STATUS AS OF 2010

Yes and No

Clustering Based Representations

- Brown Clustering
- HMM-LDA
- CRF Chunker with HMM
- …

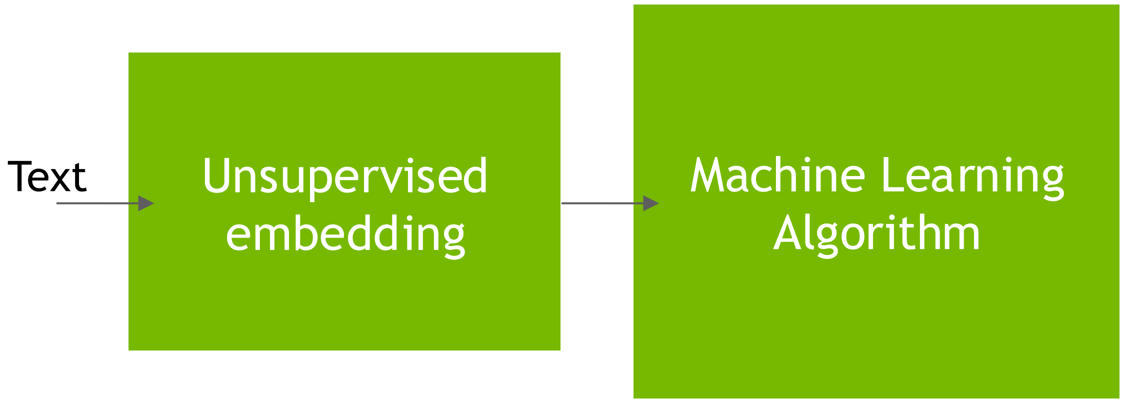
Distributional Representations

- LSA / LSI
- pLSA
- LDA
- HAL
- ICA
- Random Indexing
- …

Distributed Representations

- Collobert and Weston embeddings
- HLBL embeddings
- …

It was not clear that you can combine unsupervised approaches (i.e. embeddings) with supervised models



Turian, Joseph, Lev Ratinov, and Yoshua Bengio. "Word representations: a simple and general method for semi-supervised learning." *Proceedings of the 48th annual meeting of the association for computational linguistics*. 2010.

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WHY NOT DO THE SAME WITH NEURAL NETWORKS?

STATUS AS OF 2010

Not enough computational power

Word embeddings are typically induced using *neural language models*, which use neural networks as the underlying predictive model (Bengio, 2008). Historically, training and testing of neural language models has been slow, scaling as the size of the vocabulary for each model computation (Bengio et al., 2001; Bengio et al., 2003). However, many approaches have been proposed in recent years to eliminate that linear dependency on vocabulary size (Morin & Bengio, 2005; Collobert & Weston, 2008; Mnih & Hinton, 2009) and allow scaling to very large training corpora.

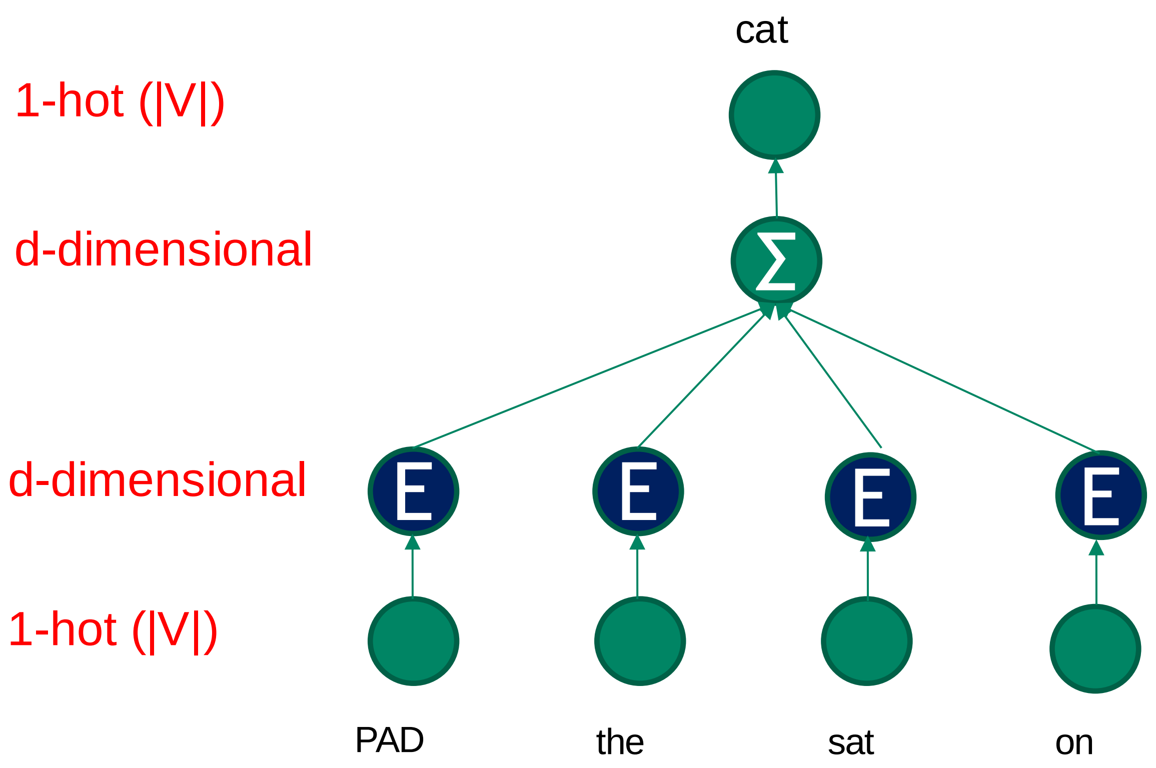
Turian, Joseph, Lev Ratinov, and Yoshua Bengio. "Word representations: a simple and general method for semi-supervised learning." *Proceedings of the 48th annual meeting of the association for computational linguistics*. 2010.

WORD2VEC

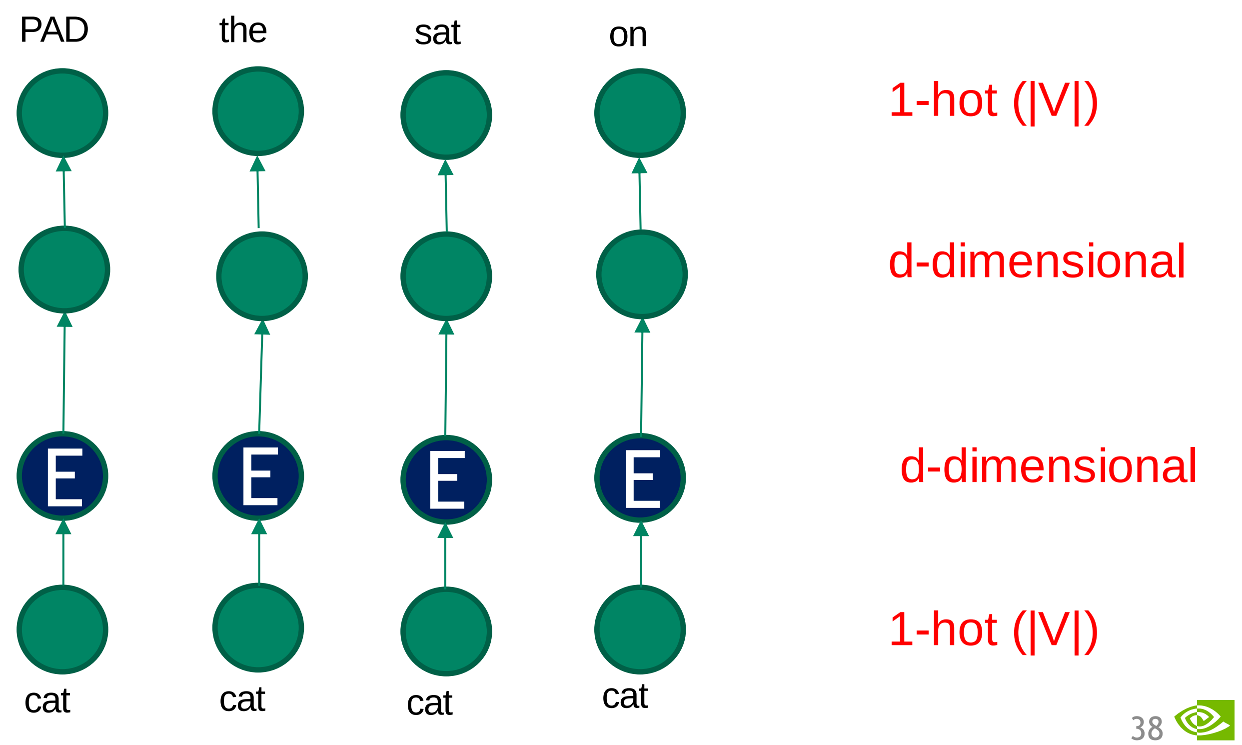
WORD2VEC

- Mikolov et al., 2013 (while at Google)
- Linear model (trains quickly)
- Two models for training embeddings in an *unsupervised* manner:

Continuous Bag-of-Words (CBOW)



Skip-Gram



GLOVE

GLOVE

The objective

To learn vectors for words such that their dot product is proportional to their probability of co-occurence

Probability and Ratio	$k = solid$	$k = gas$	$k = water$	$k = fashion$
$P(k\|ice)$	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(k\|steam)$	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
$P(k\|ice)/P(k\|steam)$	8.9	8.5×10^{-2}	1.36	0.96

Pennington, J., Socher, R., & Manning, C. D. (2014, October). Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)* (pp. 1532-1543).

GLOVE

The objective

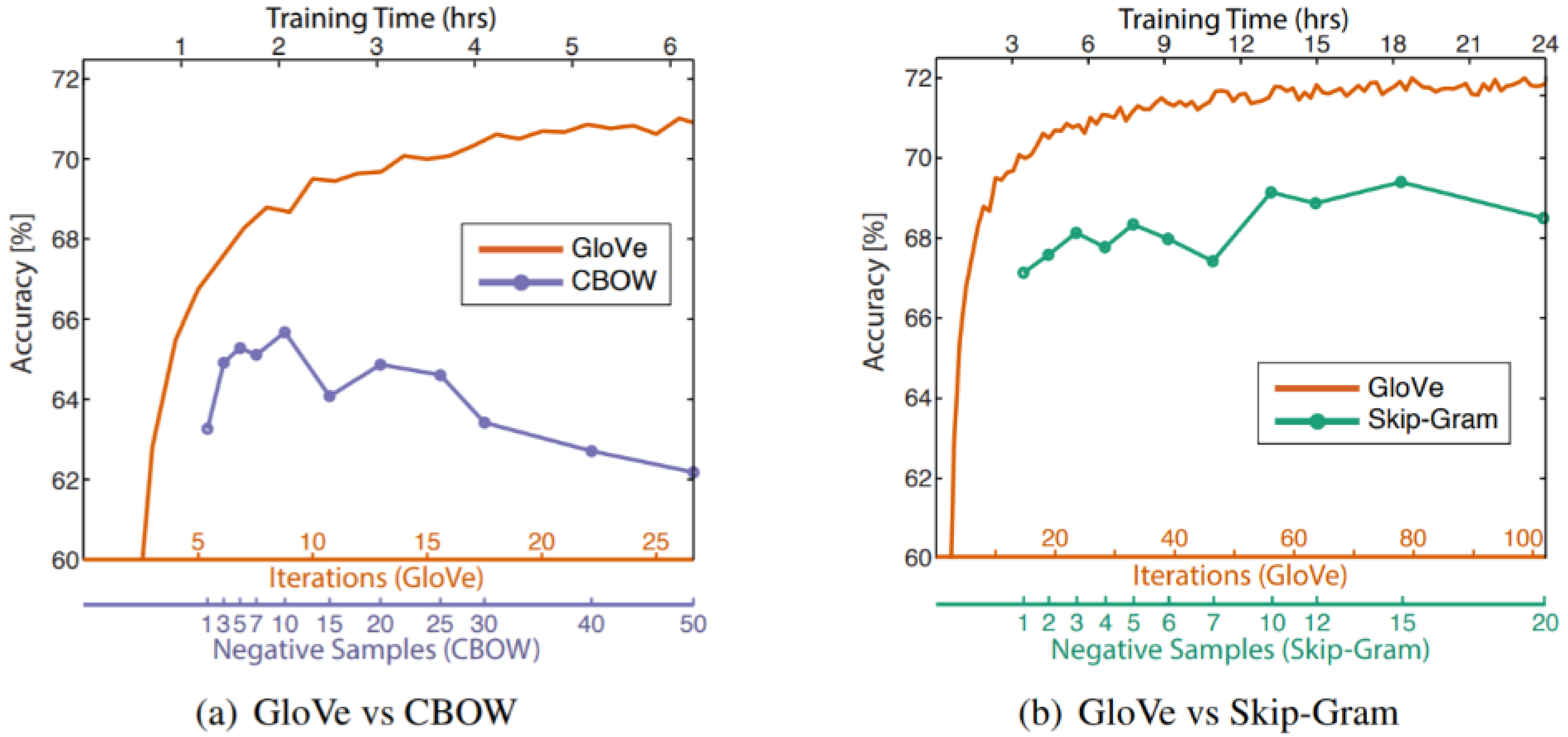
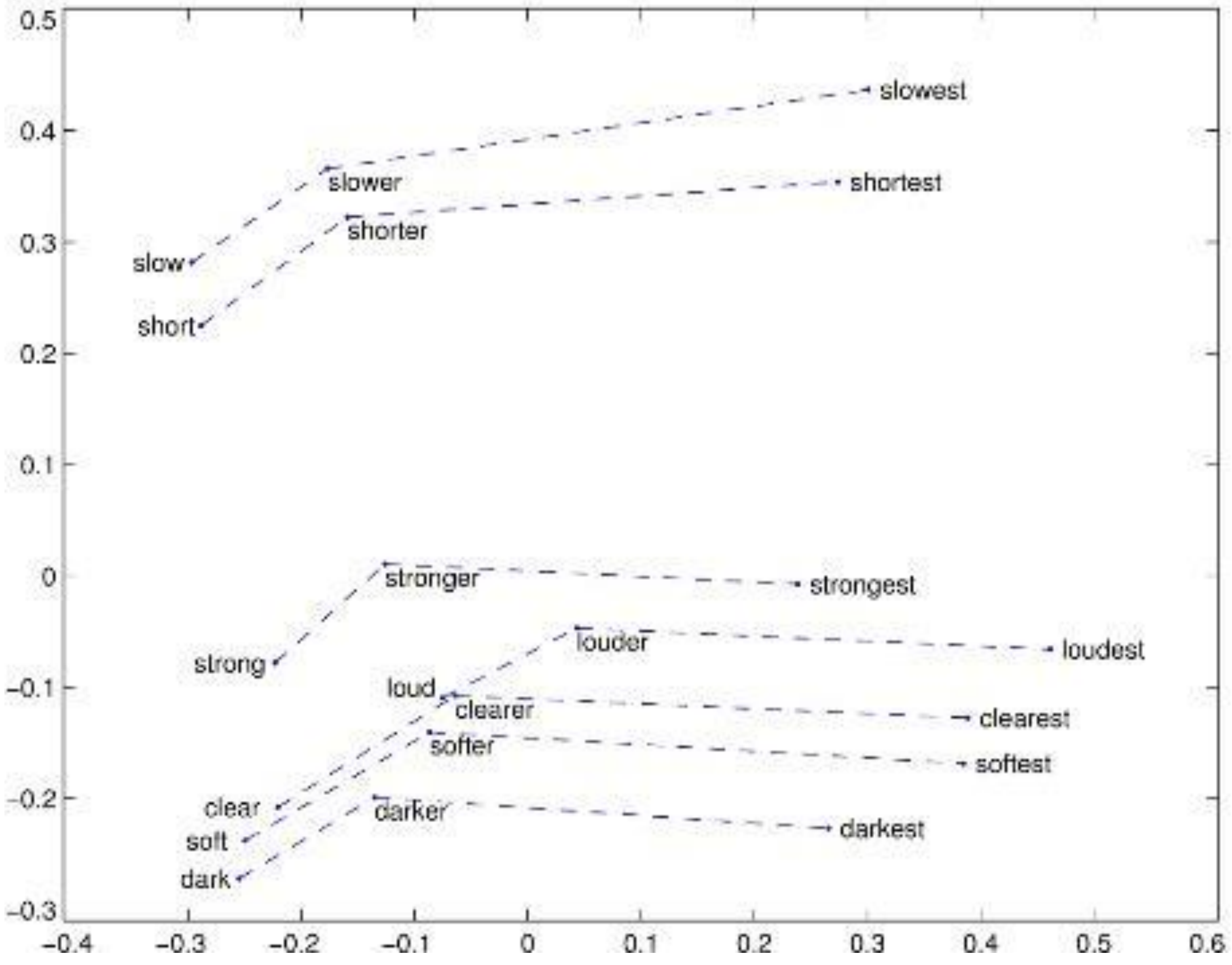


Figure 4: Overall accuracy on the word analogy task as a function of training time, which is governed by the number of iterations for GloVe and by the number of negative samples for CBOW (a) and skip-gram (b). In all cases, we train 300-dimensional vectors on the same 6B token corpus (Wikipedia 2014 + Gigaword 5) with the same 400,000 word vocabulary, and use a symmetric context window of size 10.

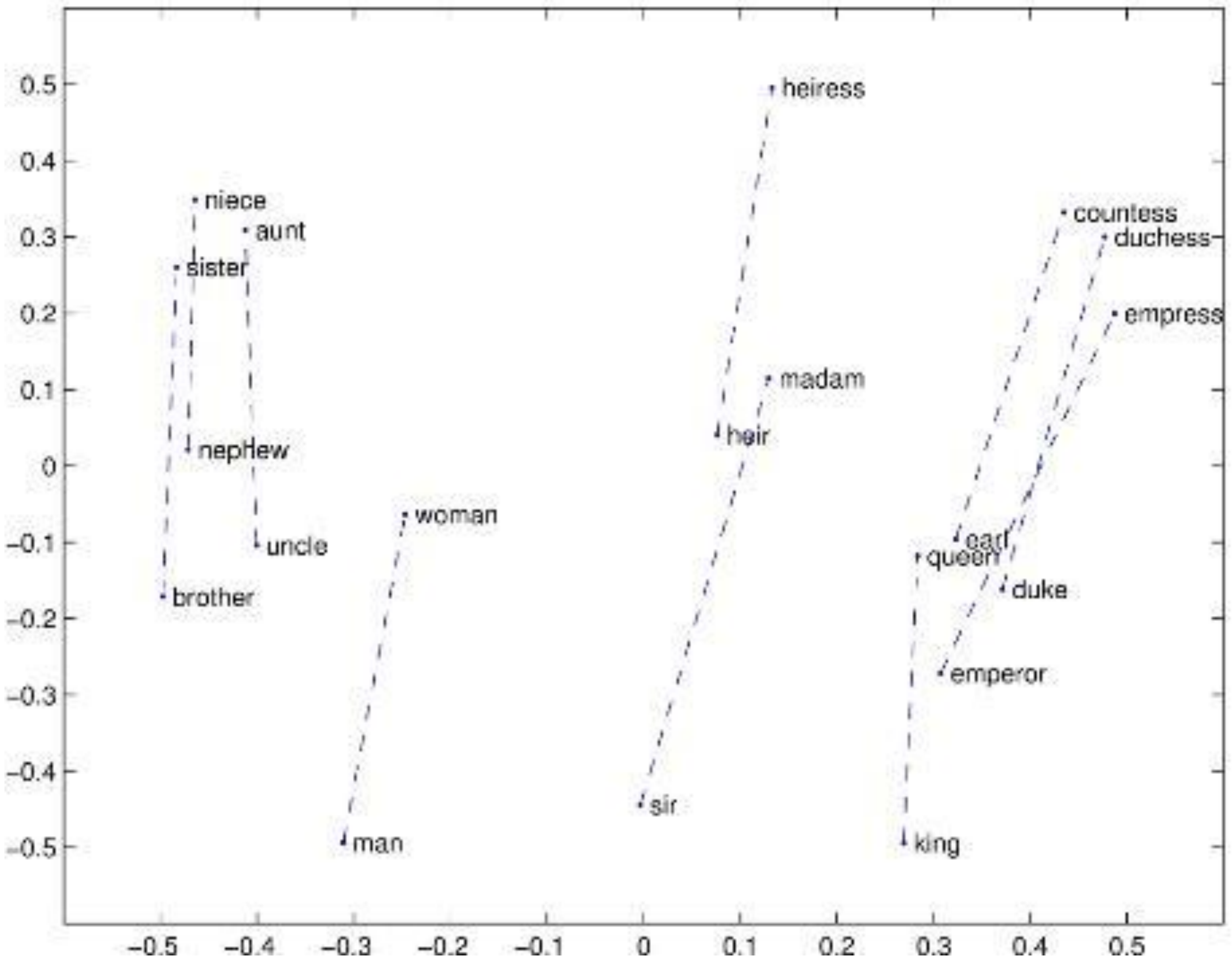
Pennington, J., Socher, R., & Manning, C. D. (2014, October). Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)* (pp. 1532-1543).

GLOVE

Properties



Comparative - Superlative



Man - Woman

Pennington, J., Socher, R., & Manning, C. D. (2014, October). Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)* (pp. 1532-1543).

GLOVE

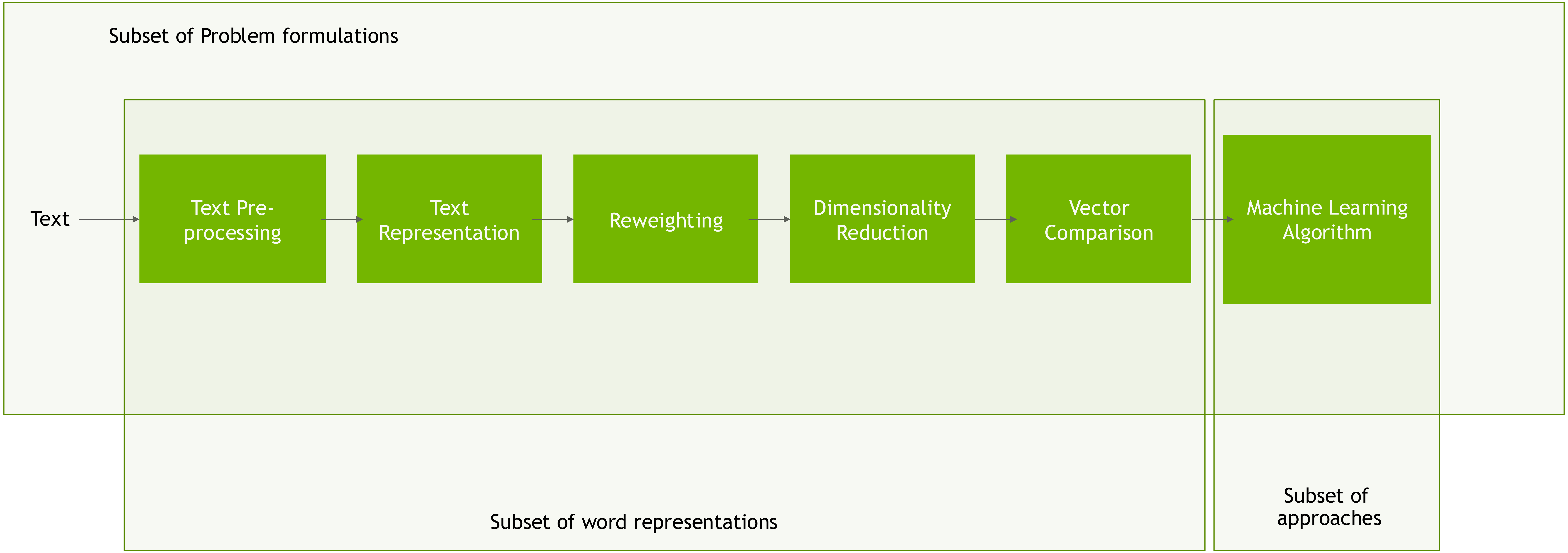
Not a distant past

Pennington, J., Socher, R., & Manning, C. D. (2014, October). Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)* (pp. 1532-1543).

USING THE EMBEDDINGS

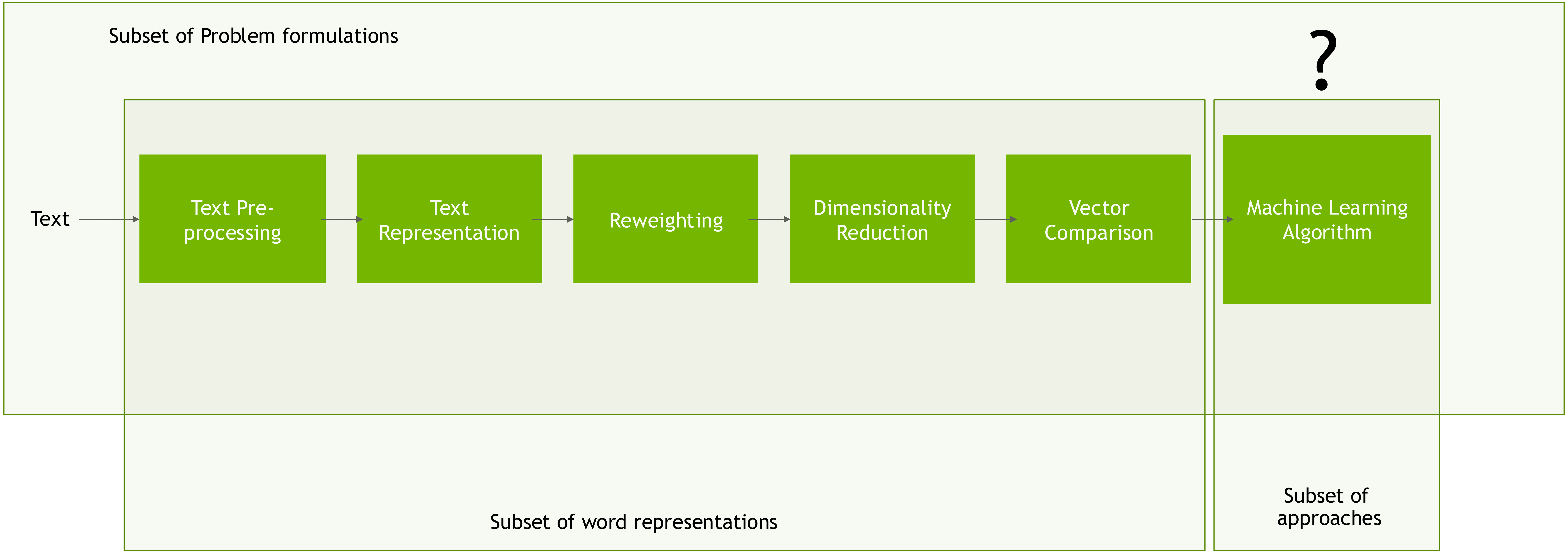
THE APPROACH TO NLP

Unsupervised feature representation + Machine Learning models



THE APPROACH TO NLP

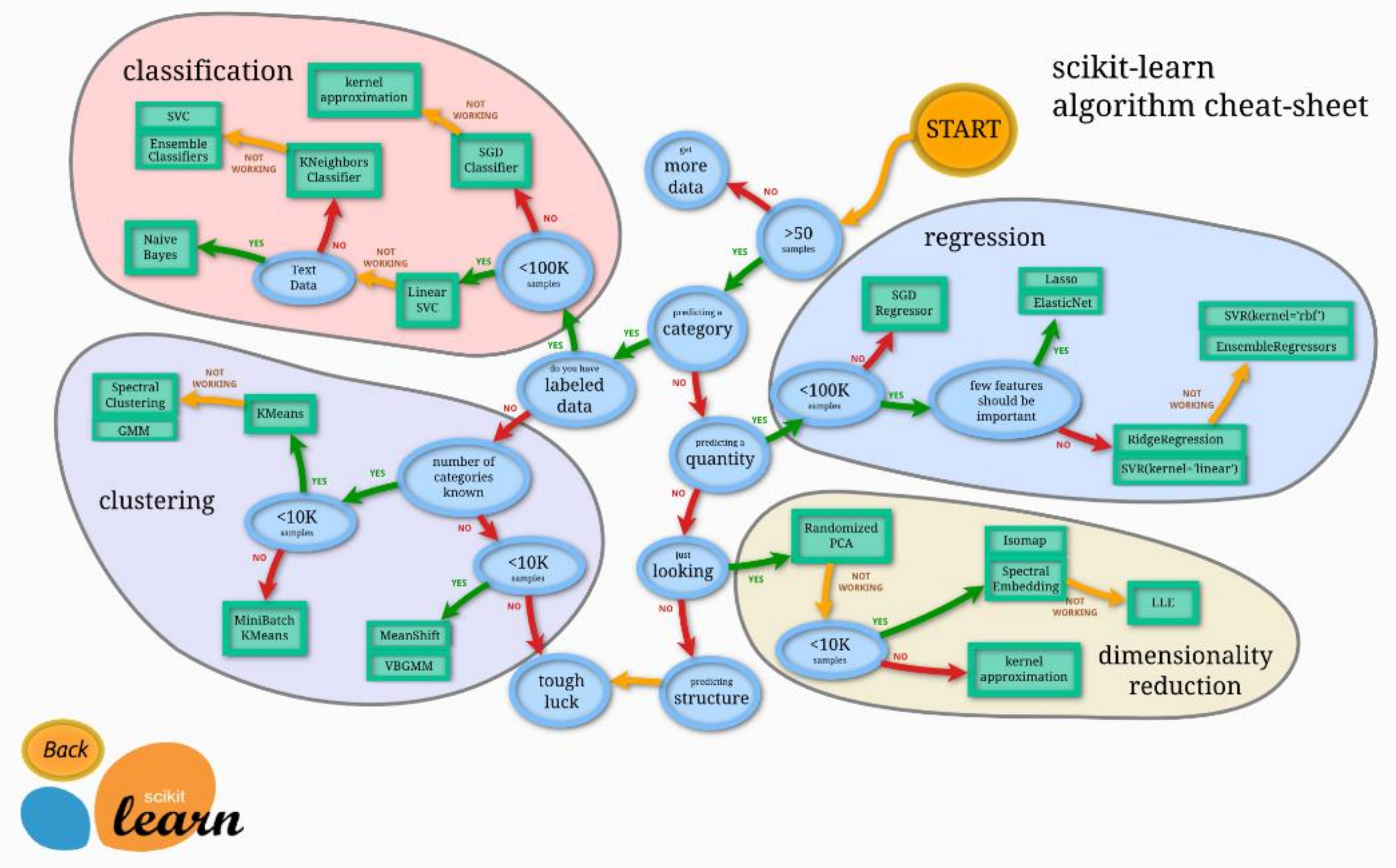
What ML model to choose



CLASSICAL APPROACHES

CLASSICAL APPROACHES

Very broad selection of tools

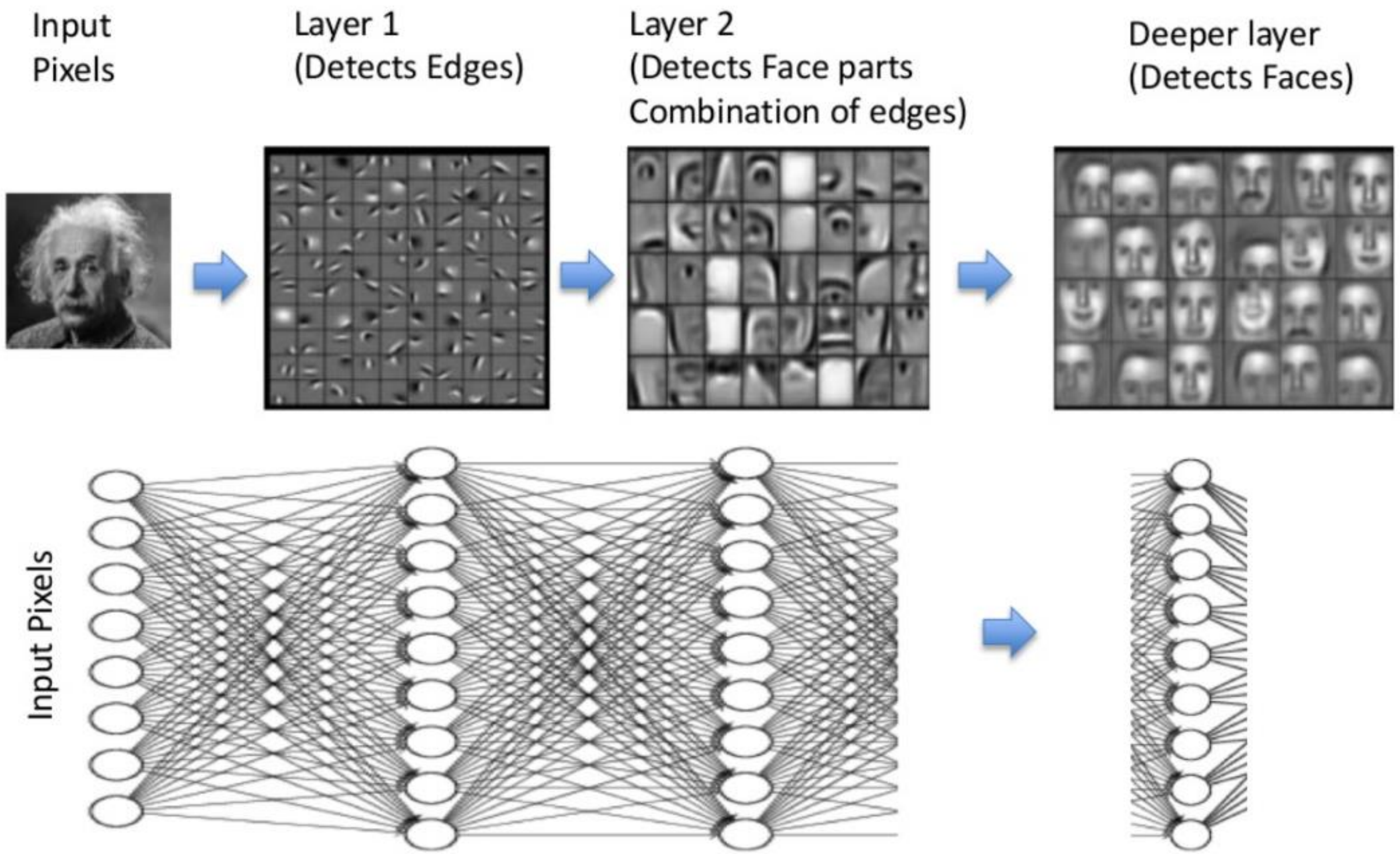


WHAT ABOUT FEATURE ENGINEERING?

DEEP REPRESENTATION LEARNING

DEEP REPRESENTATION LEARNING

Beyond distributional hypothesis



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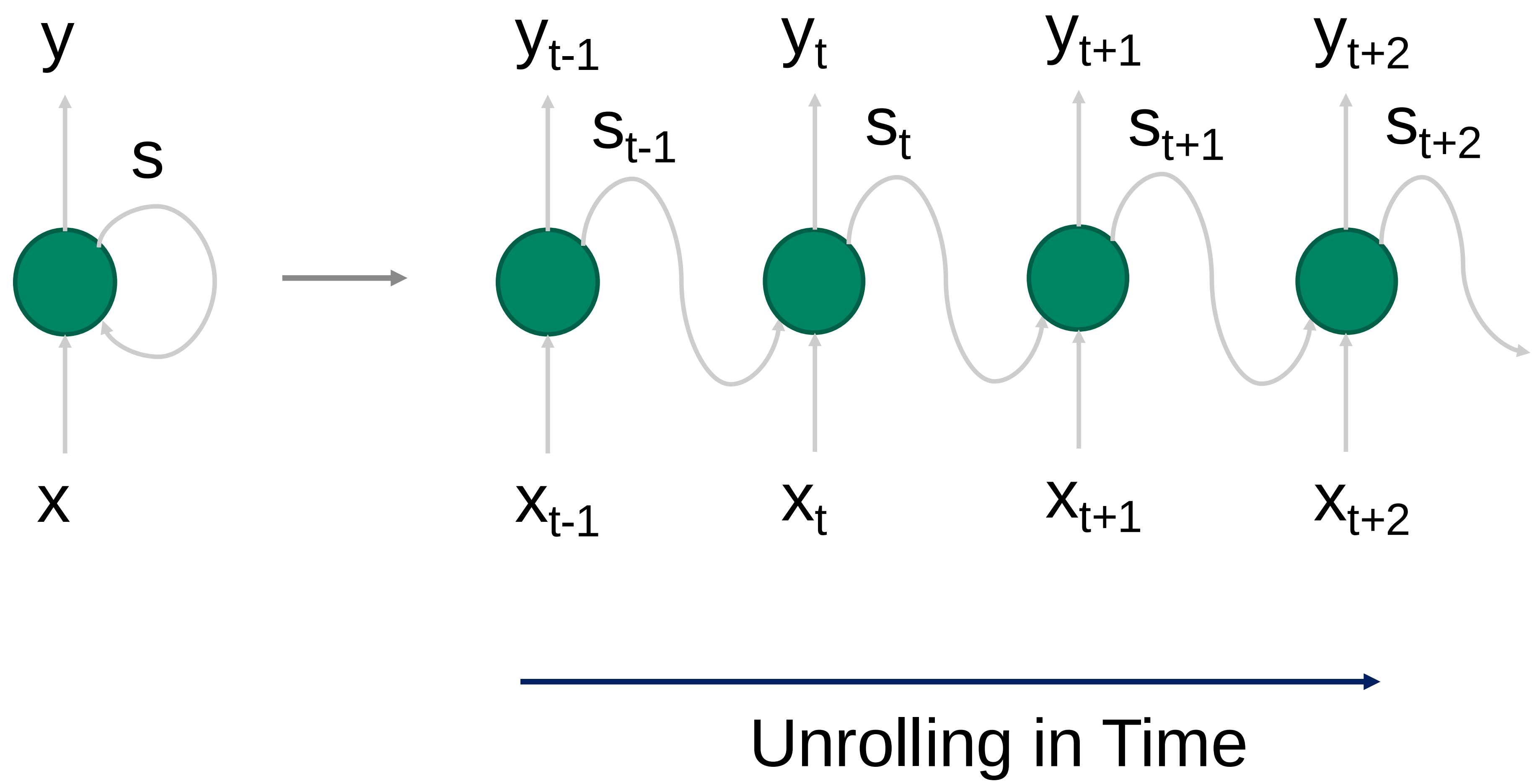
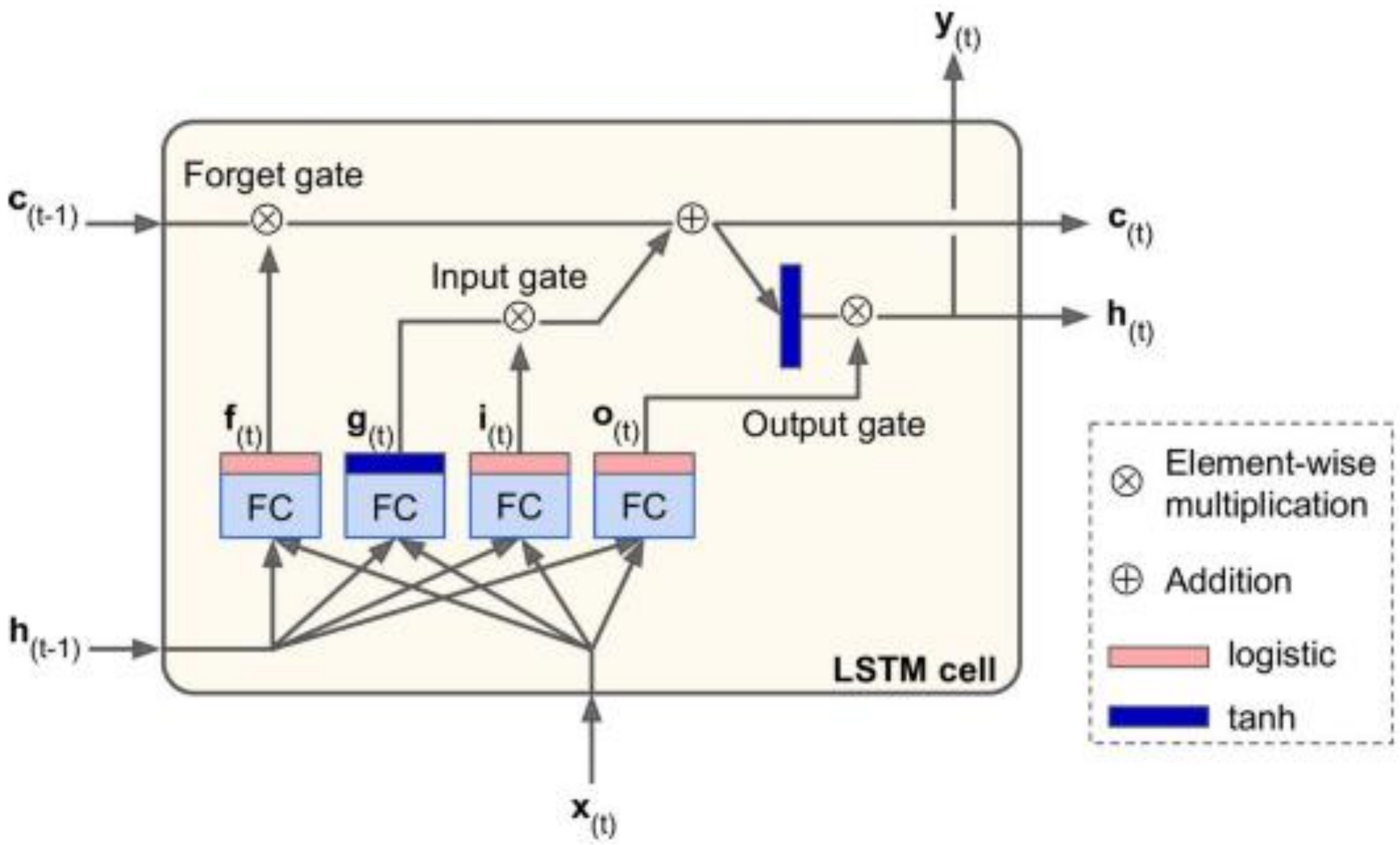
RECURRENT NEURAL NETWORKS

Basic principles



LONG SHORT TERM (LSTM) CELL

Addressing problems of stability

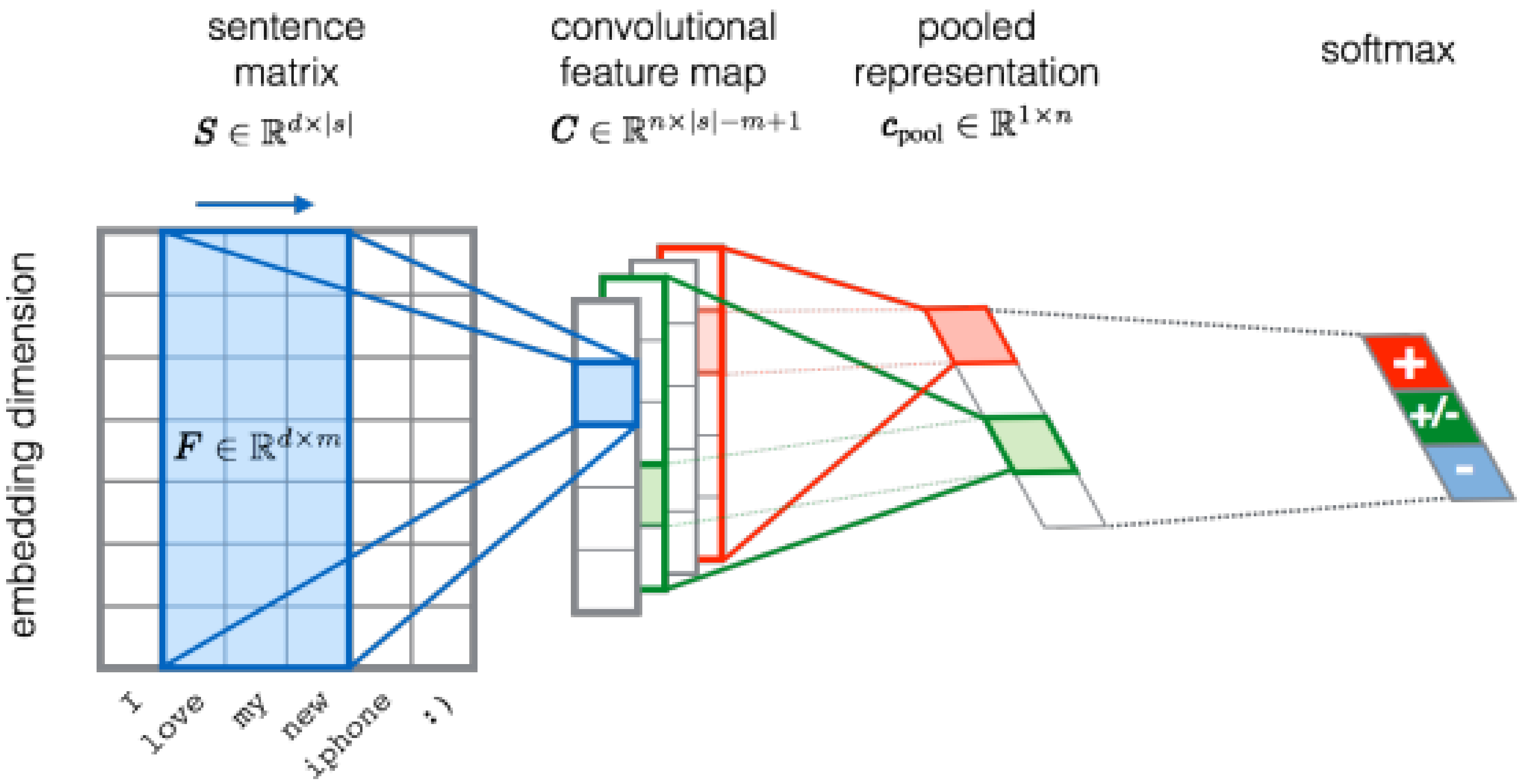


$$
\begin{aligned}
\mathbf{i}_{(t)} &= \sigma(\mathbf{W}_{xi}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hi}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_i) \\
\mathbf{f}_{(t)} &= \sigma(\mathbf{W}_{xf}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hf}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_f) \\
\mathbf{o}_{(t)} &= \sigma(\mathbf{W}_{xo}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{ho}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_o) \\
\mathbf{g}_{(t)} &= \tanh\,(\mathbf{W}_{xg}{}^{T} \cdot \mathbf{x}_{(t)} + \mathbf{W}_{hg}{}^{T} \cdot \mathbf{h}_{(t-1)} + \mathbf{b}_g) \\
\mathbf{c}_{(t)} &= \mathbf{f}_{(t)} \otimes \mathbf{c}_{(t-1)} + \mathbf{i}_{(t)} \otimes \mathbf{g}_{(t)} \\
\mathbf{y}_{(t)} &= \mathbf{h}_{(t)} = \mathbf{o}_{(t)} \otimes \tanh\,(\mathbf{c}_{(t)})
\end{aligned}
$$

CNNS

CONVOLUTIONAL NEURAL NETWORKS

Basic principles



Severyn, Aliaksei, and Alessandro Moschitti. "Unitn: Training deep convolutional neural network for twitter sentiment classification." *Proceedings of the 9th international workshop on semantic evaluation (SemEval 2015)*. 2015.

ATTENTION

WHAT ABOUT LONG SEQUENCES?

The challenge illustrated with SQuAD

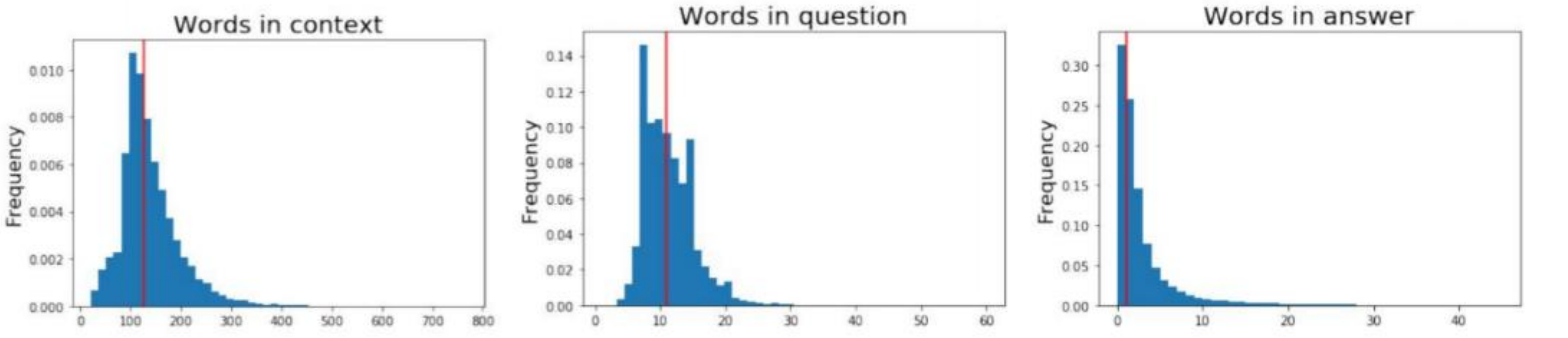


Figure 1: Number of words in contexts, questions, and answers in SQuAD training set.

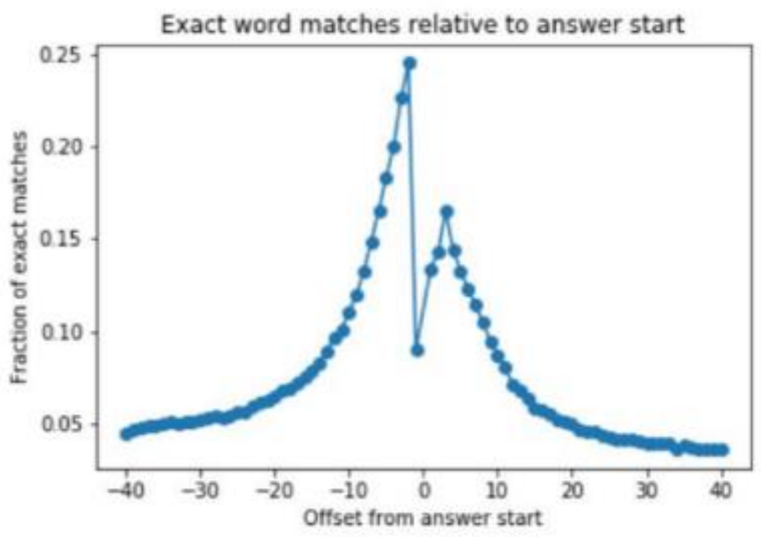
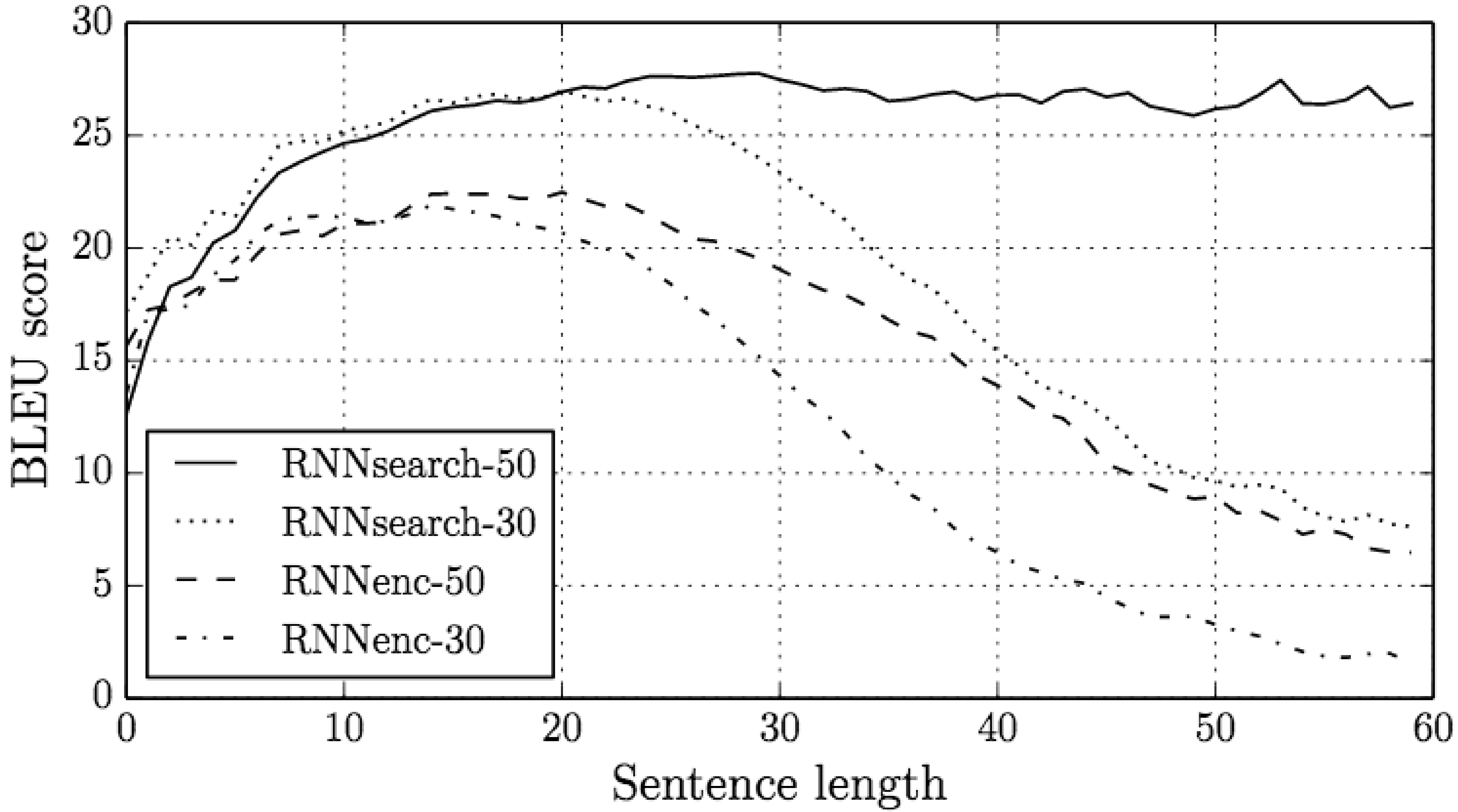


Figure 2: Frequency of exact word matches relative to answer start position

The impact of attention mechanism on Question Answering performance

WHAT ABOUT LONG SEQUENCES?

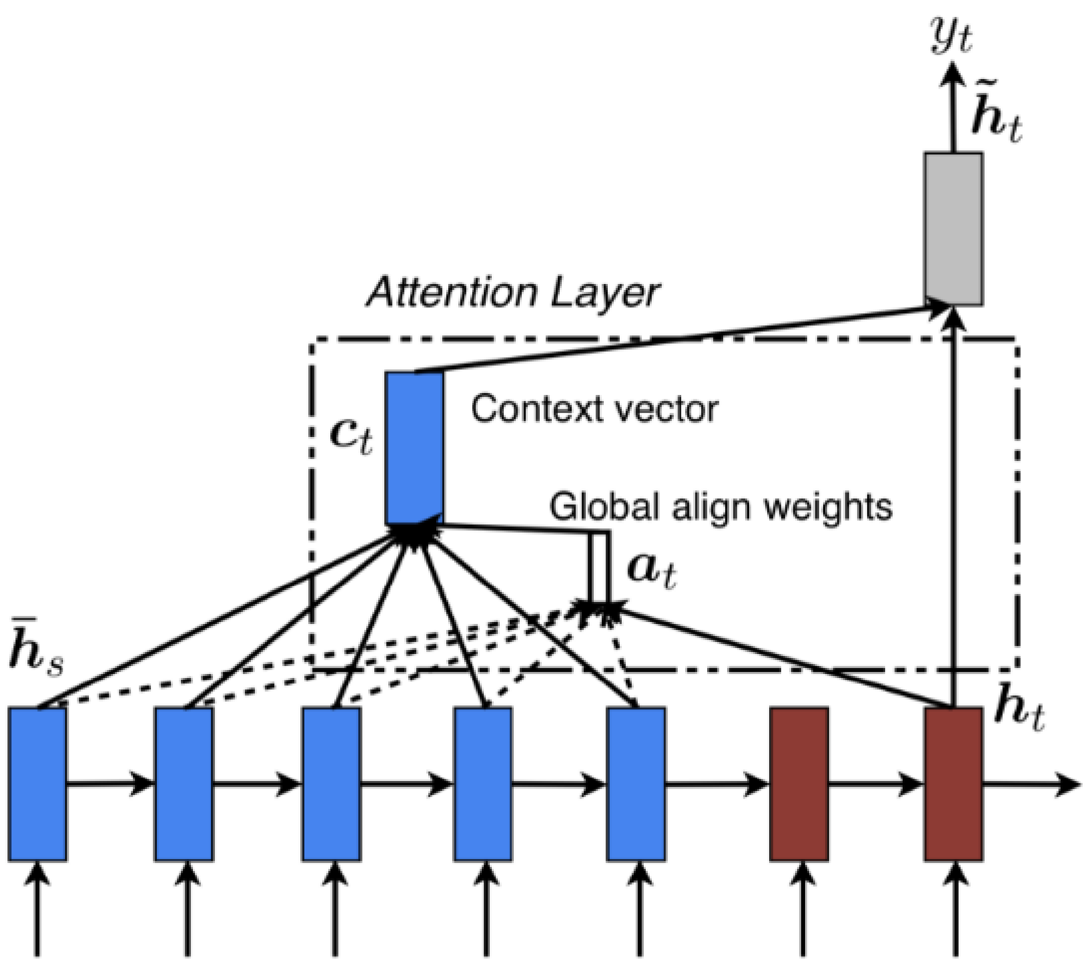
The challenge



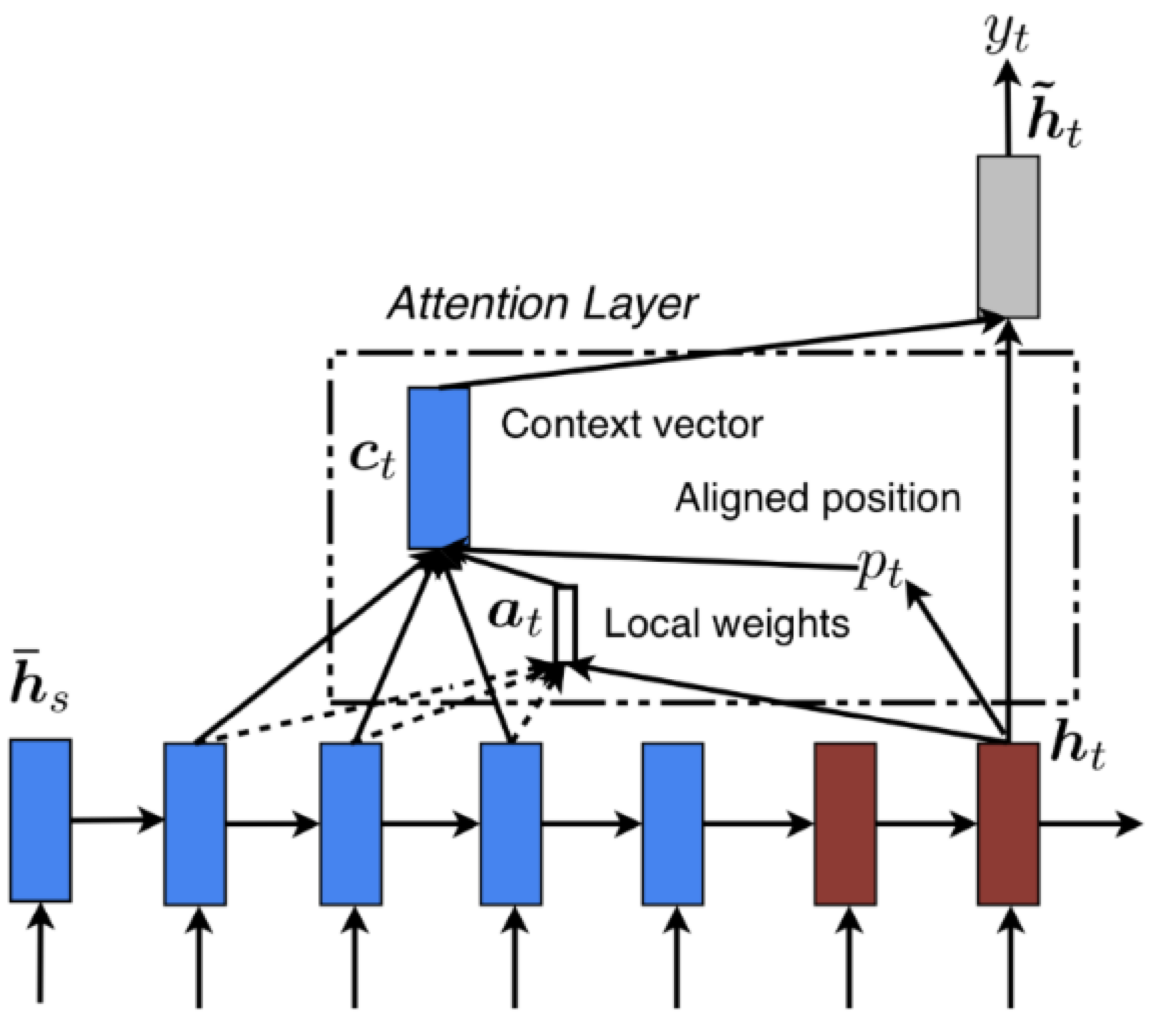
Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*.

ATTENTION

The mechanism



Global Attention Model



Local Attention Model

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DEEP LEARNING INSTITUTE

ATTENTION

The mechanism

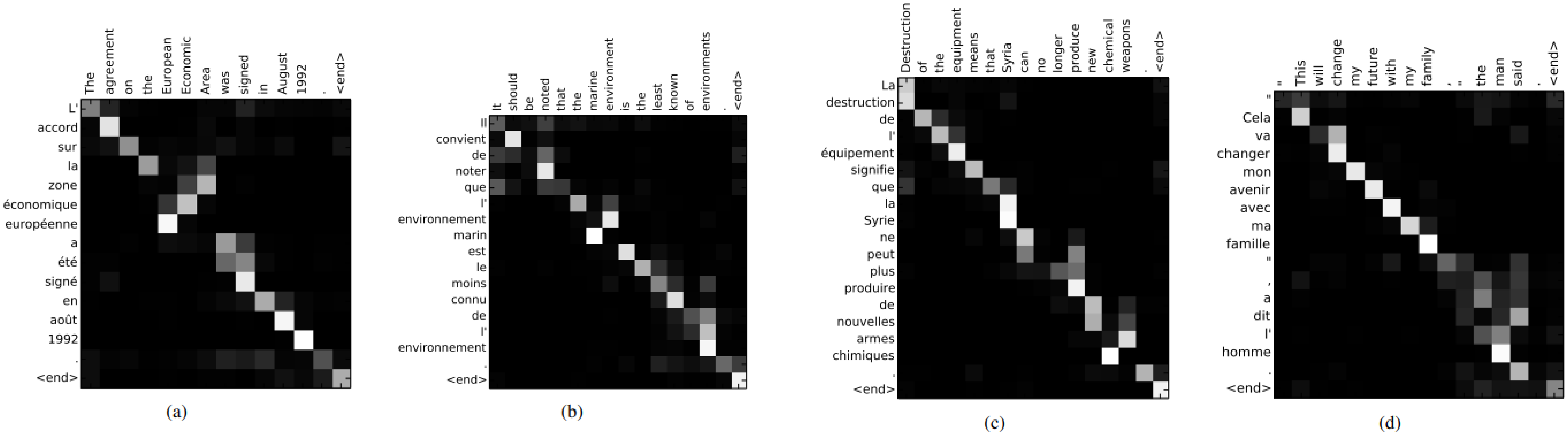
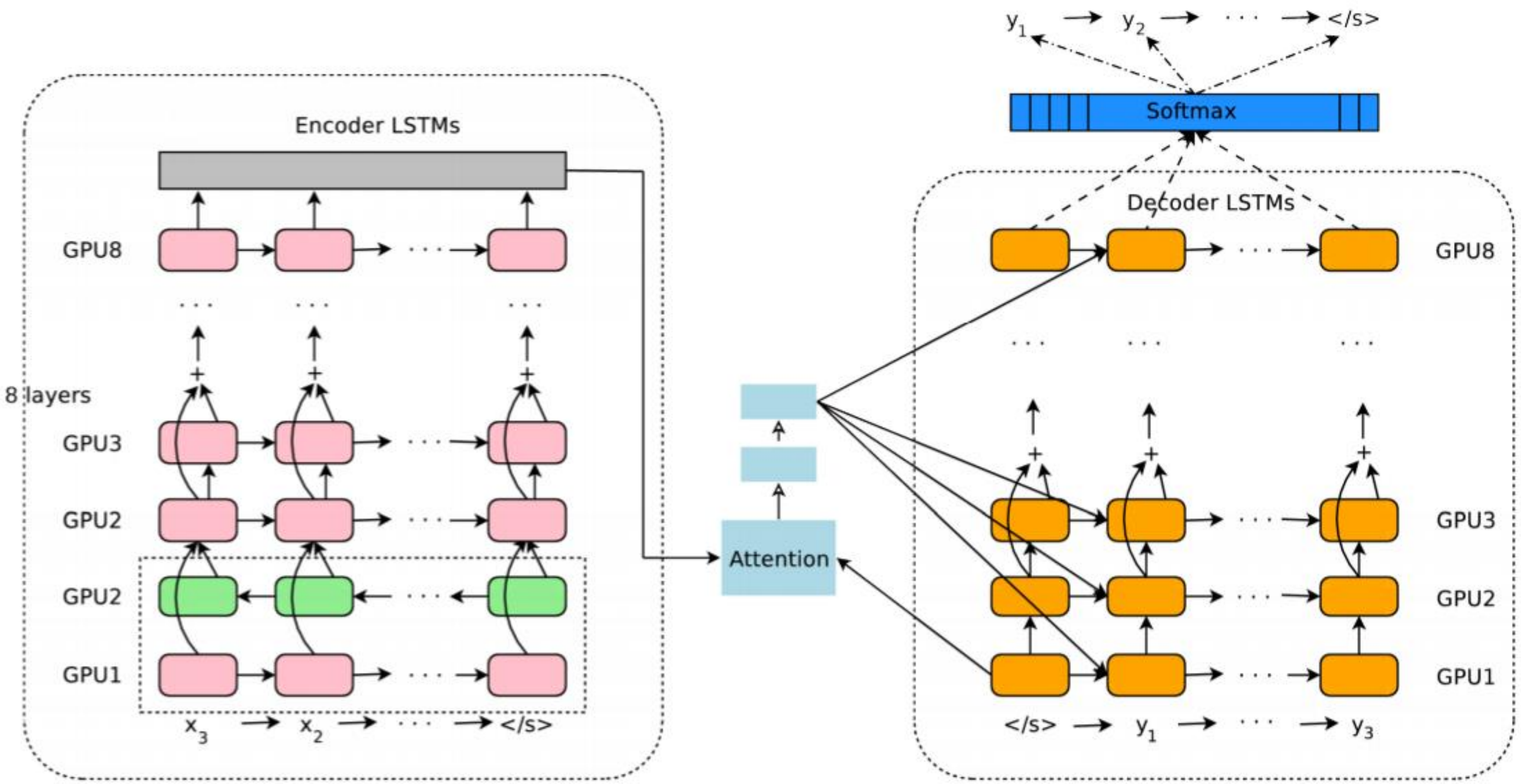


Figure 3: Four sample alignments found by RNNsearch-50. The x-axis and y-axis of each plot correspond to the words in the source sentence (English) and the generated translation (French), respectively. Each pixel shows the weight α_{ij} of the annotation of the j-th source word for the i-th target word (see Eq. (6)), in grayscale (0: black, 1: white). (a) an arbitrary sentence. (b–d) three randomly selected samples among the sentences without any unknown words and of length between 10 and 20 words from the test set.

Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*.

ATTENTION

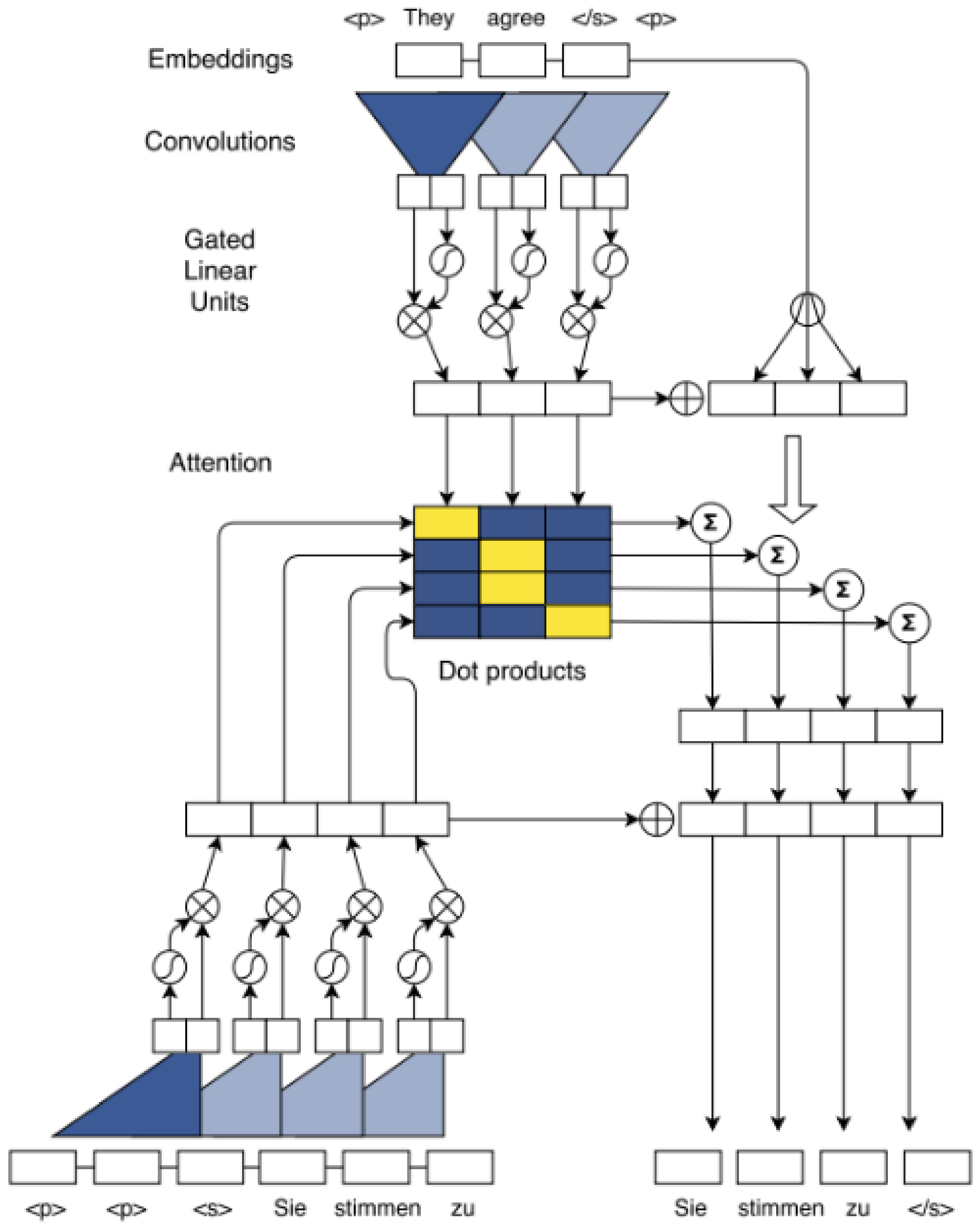
Examples



Wu, Y., Schuster, M., Chen, Z., Le, Q. V., Norouzi, M., Macherey, W., ... & Klingner, J. (2016). Google's neural machine translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*.

ATTENTION

Examples



Gehring, J., Auli, M., Grangier, D., Yarats, D., & Dauphin, Y. N. (2017, July). Convolutional sequence to sequence learning. In *International conference on machine learning* (pp. 1243-1252). PMLR.

Part 1: Machine Learning in NLP

- Lecture
  - What is NLP?
  - Problem Formulation
  - Text Representations
  - Dimensionality Reduction
  - Embeddings
  - RNNs
  - "Attention is All You Need"
- Lab
  - Transformer Architecture
  - BERT Model
  - Pretraining BERT

ATTENTION IS ALL YOU NEED

Design

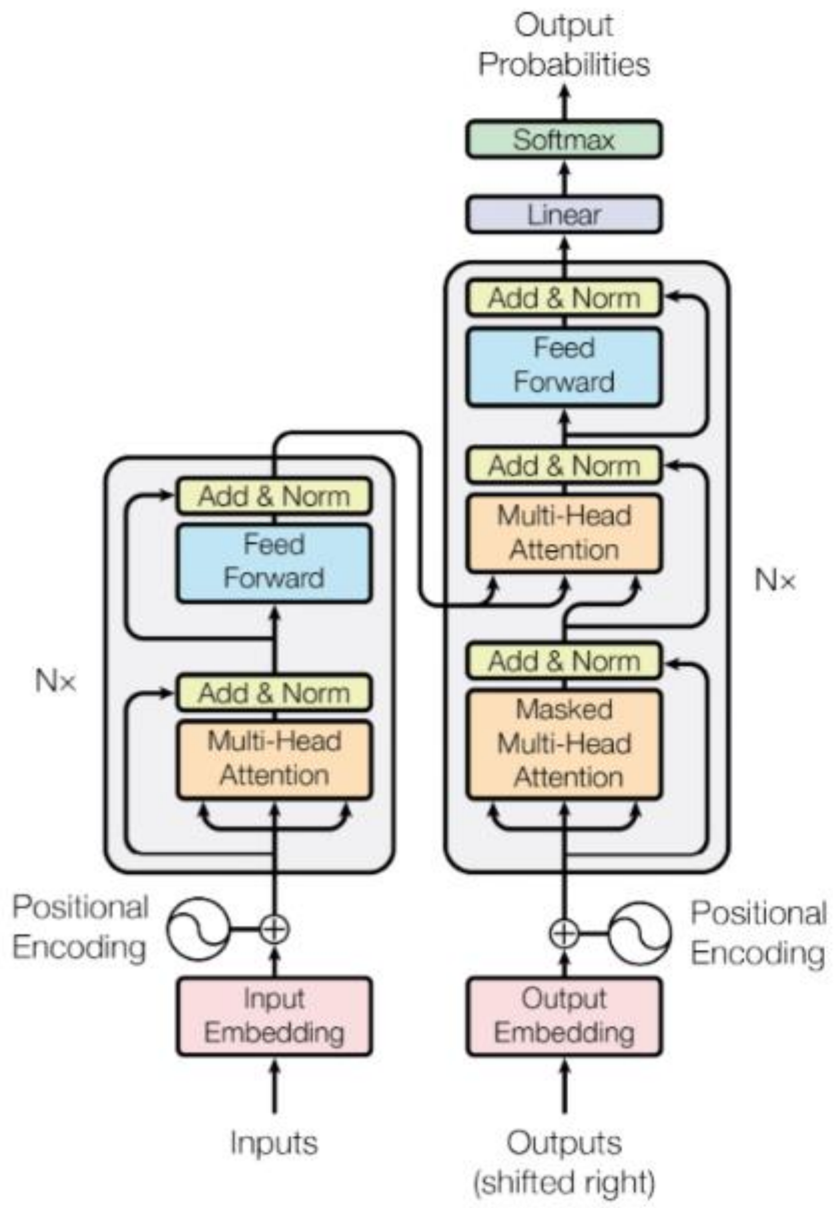
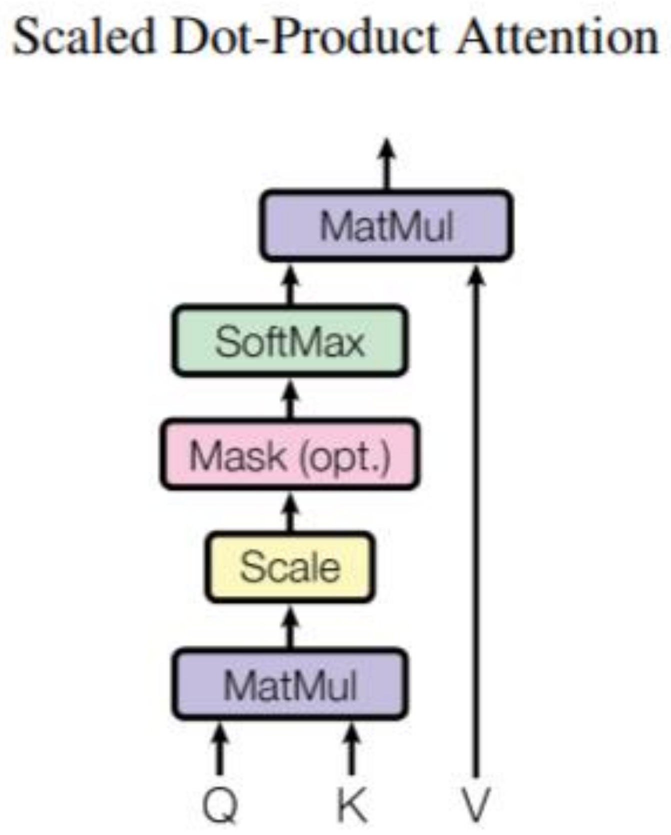


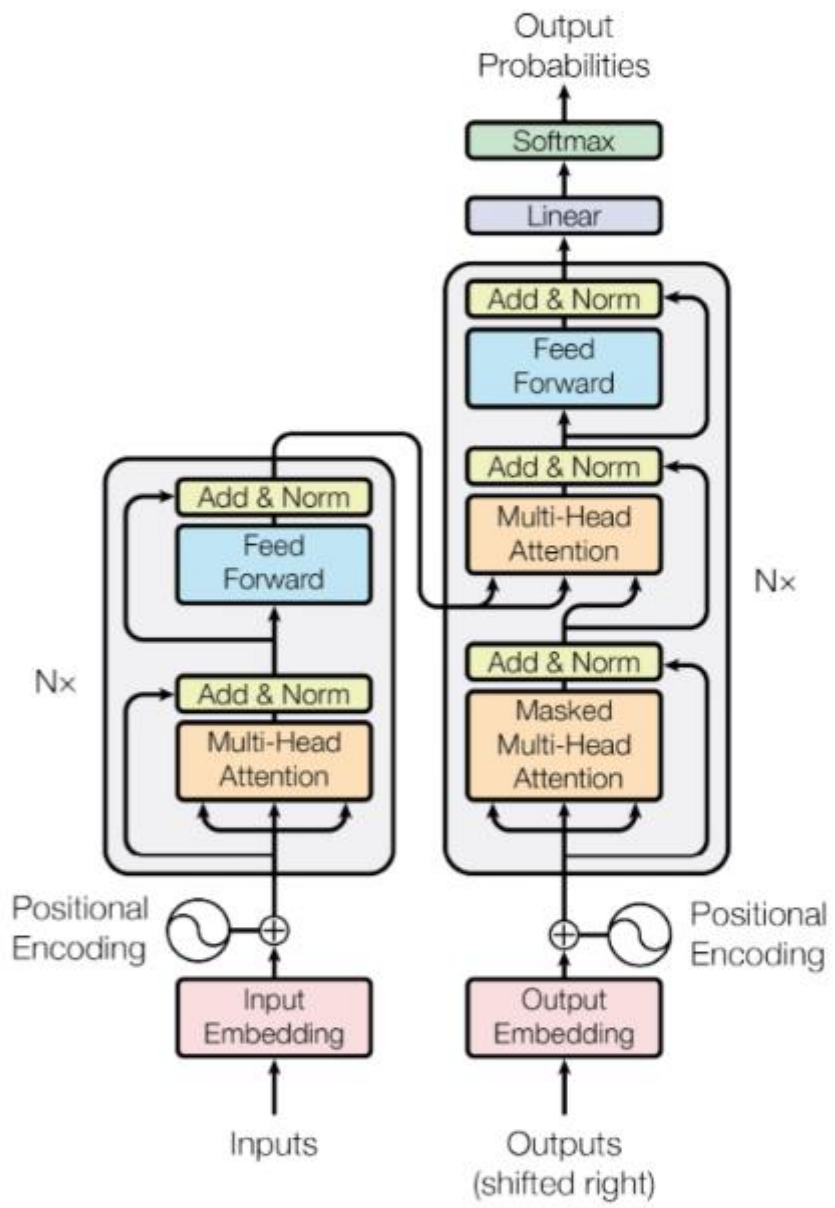
Figure 1: The Transformer - model architecture.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. In *Advances in neural information processing systems* (pp. 5998-6008).

ATTENTION IS ALL YOU NEED

Design





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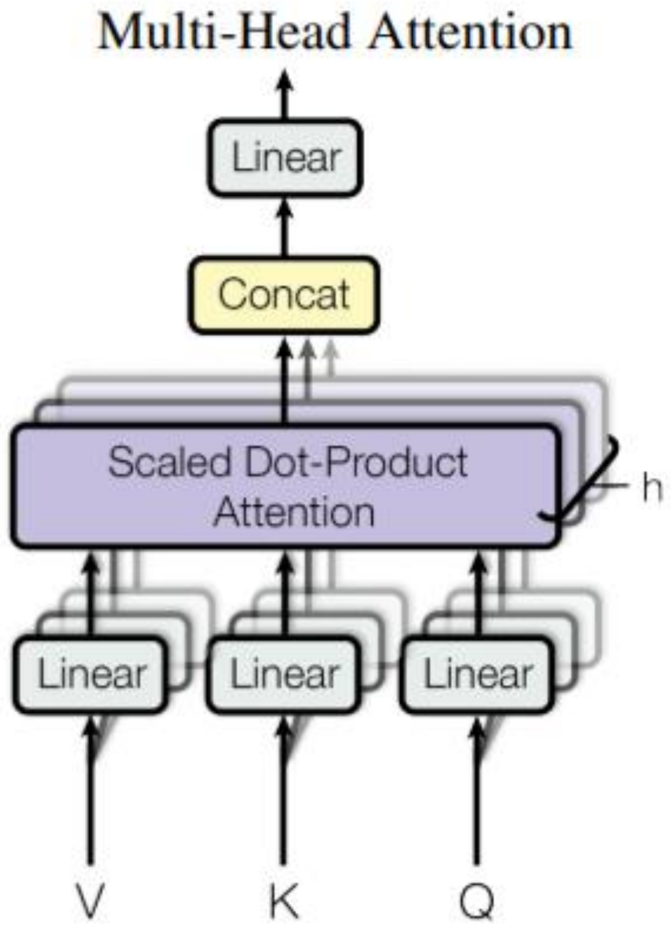


Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. In *Advances in neural information processing systems* (pp. 5998-6008).

WAS IT A BREAKTHROUGH IN ITSELF?

ATTENTION IS ALL YOU NEED

Not a breakthrough in itself

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [32]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [31]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [8]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. In *Advances in neural information processing systems* (pp. 5998-6008).

ATTENTION IS ALL YOU NEED

But …

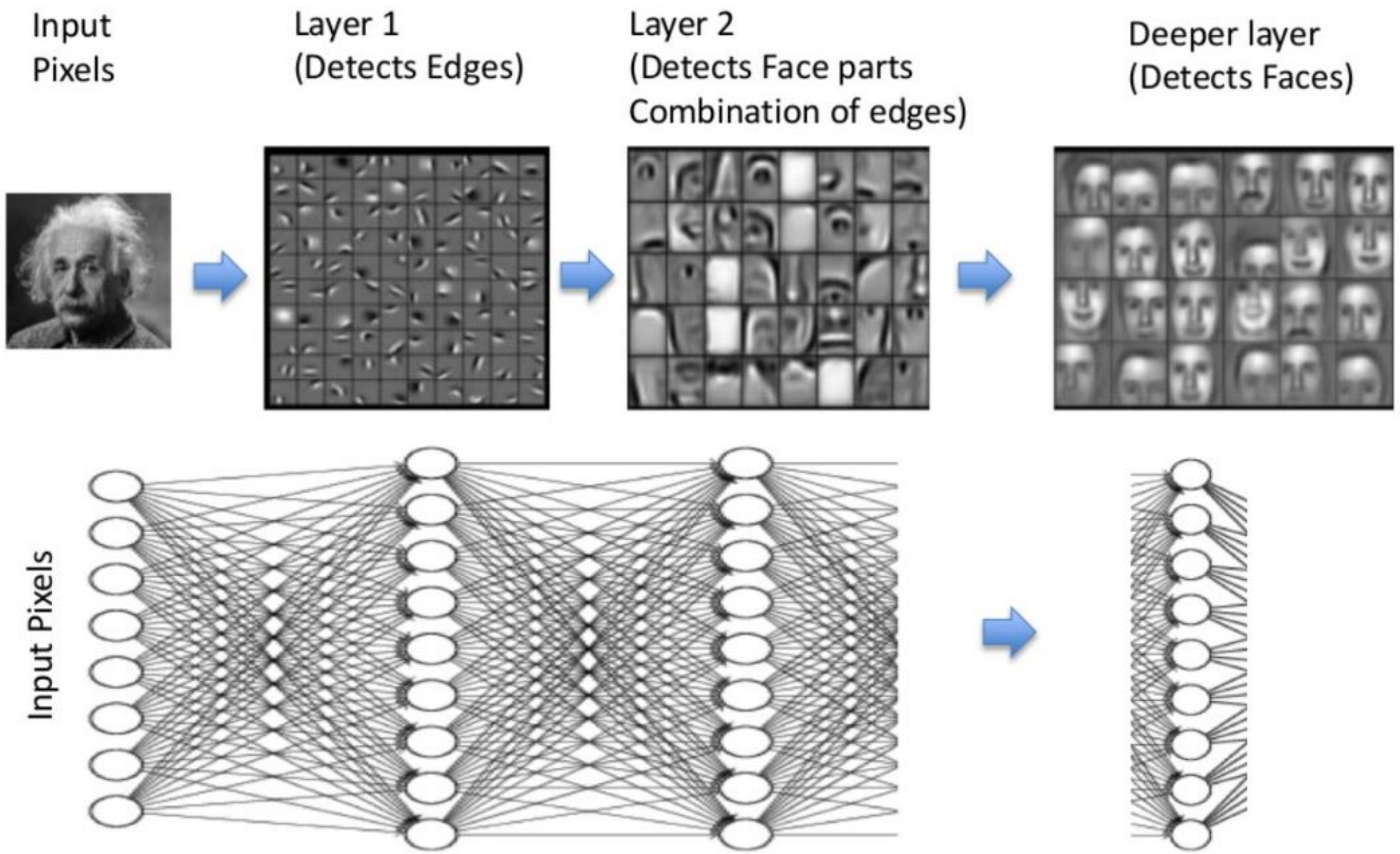
“ … the Transformer can be trained significantly faster than architectures based on recurrent or convolutional layers.”

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. In *Advances in neural information processing systems* (pp. 5998-6008).

NEURAL EMBEDDINGS

FEATURE REUSE

The opportunity



IT WAS DIFFICULT TO REUSE NLP EMBEDDINGS

SEMI-SUPERVISED SEQUENCE LEARNING

More complex representations

We present two approaches that use unlabeled data to improve sequence learning with recurrent networks. The first approach is to predict what comes next in a sequence, which is a conventional language model in natural language processing. The second approach is to use a sequence autoencoder, which reads the input sequence into a vector and predicts the input sequence again. These two algorithms can be used as a "pretraining" step for a later supervised sequence learning algorithm. In other words, the parameters obtained from the unsupervised step can be used as a starting point for other supervised training models. In our experiments, we find that long short term memory recurrent networks after being pretrained with the two approaches are more stable and generalize better. With pretraining, we are able to train long short term memory recurrent networks up to a few hundred timesteps, thereby achieving strong performance in many text classification tasks, such as IMDB, DBpedia and 20 Newsgroups.

Dai, A. M., & Le, Q. V. (2015). Semi-supervised sequence learning. In *Advances in neural information processing systems* (pp. 3079-3087).

SEMI-SUPERVISED SEQUENCE LEARNING

More complex representations

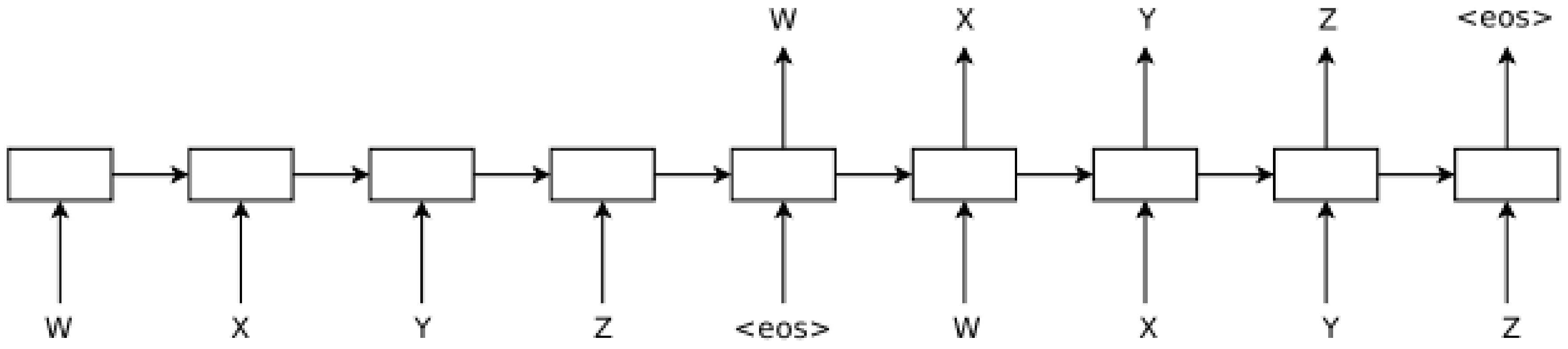


Figure 1: The sequence autoencoder for the sequence "WXYZ". The sequence autoencoder uses a recurrent network to read the input sequence in to the hidden state, which can then be used to reconstruct the original sequence.

Dai, A. M., & Le, Q. V. (2015). Semi-supervised sequence learning. In *Advances in neural information processing systems* (pp. 3079-3087).

SEMI-SUPERVISED SEQUENCE LEARNING

More complex representations

After training the recurrent language model or the sequence autoencoder for roughly 500K steps with a batch size of 128, we use both the word embedding parameters and the LSTM weights to initialize the LSTM for the supervised task. We then train on that task while fine tuning both the embedding parameters and the weights and use early stopping when the validation error starts to increase. We choose the dropout parameters based on a validation set.

Using SA-LSTMs, we are able to match or surpass reported results for all datasets. It is important to emphasize that previous best results come from various different methods. So it is significant that one method achieves strong results for all datasets, presumably because such a method can be used as a general model for any similar task. A summary of results in the experiments are shown in Table 1. More details of the experiments are as follows.

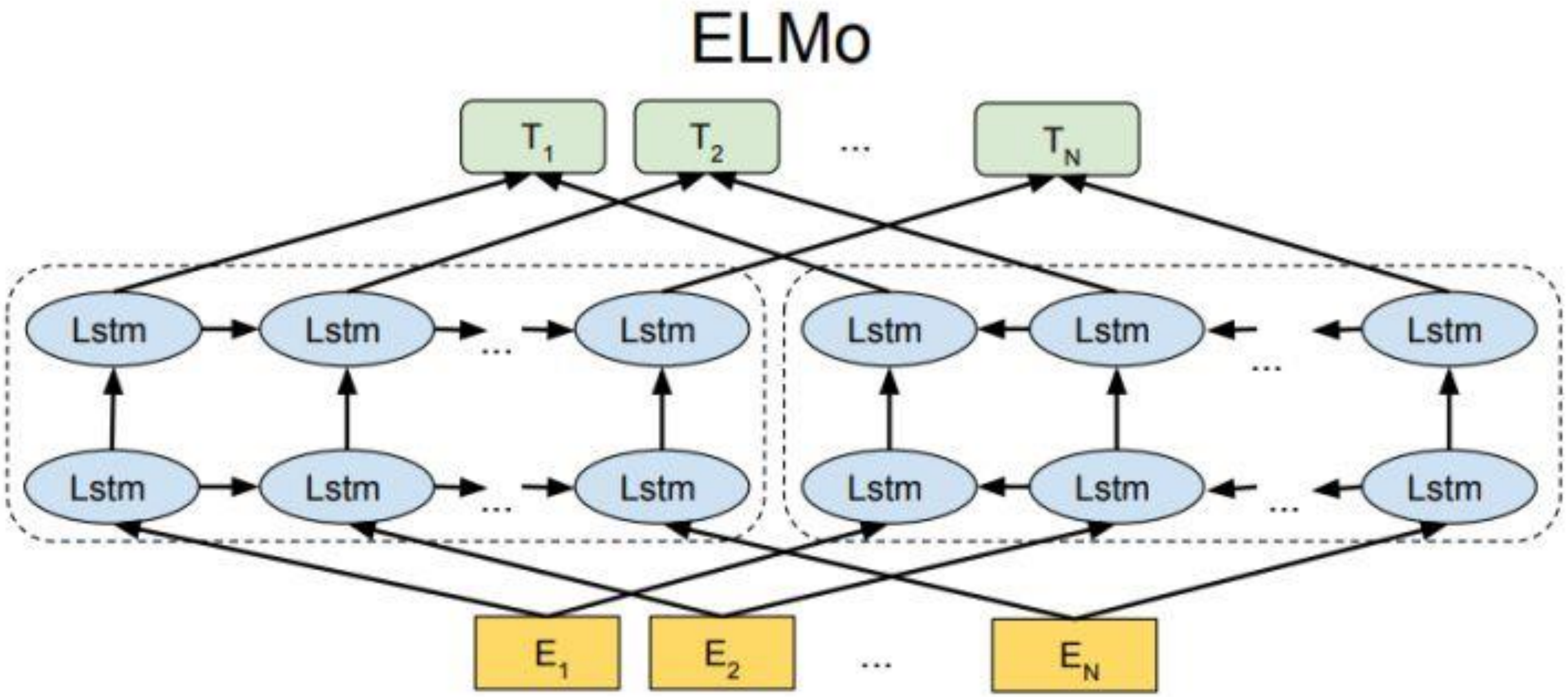
Table 1: A summary of the error rates of SA-LSTMs and previous best reported results.

Dataset	**SA-LSTM**	**Previous best result**
IMDB	7.24%	7.42%
Rotten Tomatoes	16.7%	18.5%
20 Newsgroups	15.6%	17.1%
DBpedia	1.19%	1.74%

Dai, A. M., & Le, Q. V. (2015). Semi-supervised sequence learning. In *Advances in neural information processing systems* (pp. 3079-3087).

ELMO

Embeddings for Language Models



Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., & Zettlemoyer, L. (2018). Deep contextualized word representations. arXiv preprint arXiv:1802.05365.

ELMO

Embeddings for Language Models

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.

Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., & Zettlemoyer, L. (2018). Deep contextualized word representations. arXiv preprint arXiv:1802.05365.

ULM-FIT

Universal Language Model Fine-Tuning for Text Classification

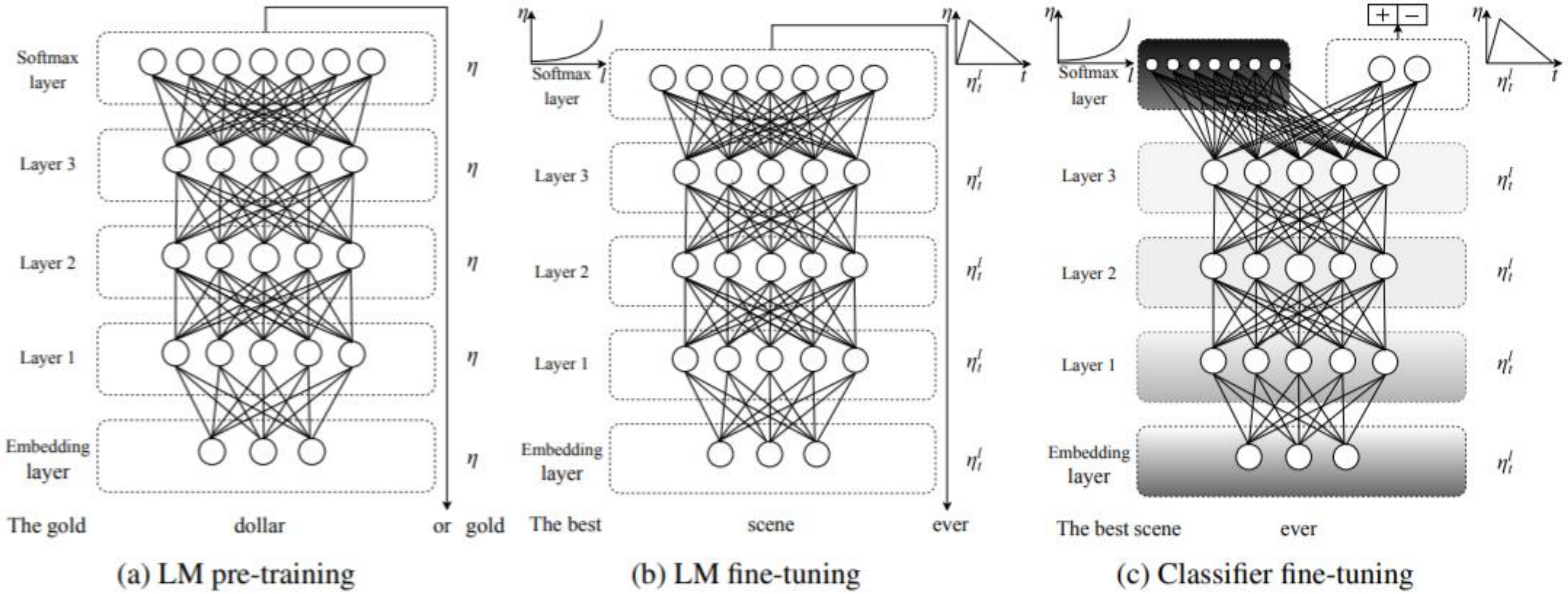


Figure 1: ULMFiT consists of three stages: a) The LM is trained on a general-domain corpus to capture general features of the language in different layers. b) The full LM is fine-tuned on target task data using discriminative fine-tuning (‘*Discr*’) and slanted triangular learning rates (STLR) to learn task-specific features. c) The classifier is fine-tuned on the target task using gradual unfreezing, ‘*Discr*’, and STLR to preserve low-level representations and adapt high-level ones (shaded: unfreezing stages; black: frozen).

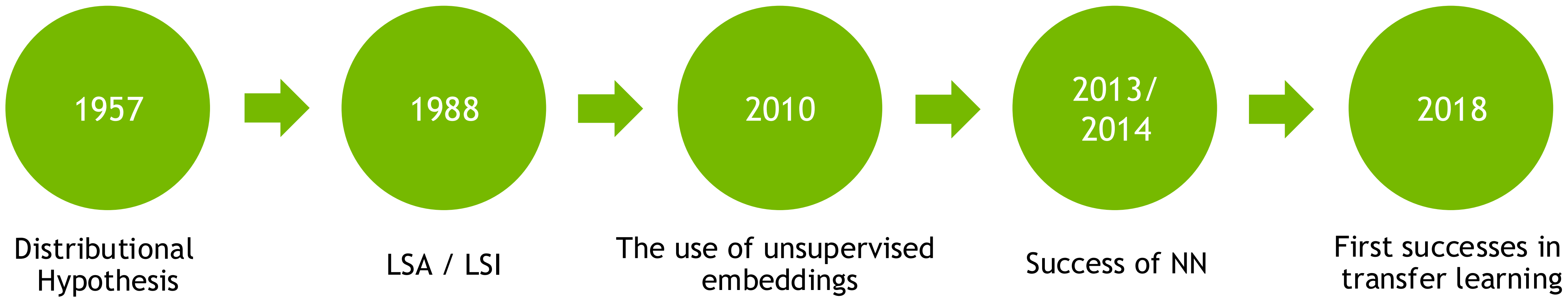
Howard, J., & Ruder, S. (2018). Universal language model fine-tuning for text classification. arXiv preprint arXiv:1801.06146.

TRANSFER LEARNING IN NLP

Not trivial to use and not universally applicable

Howard, J., & Ruder, S. (2018). Universal language model fine-tuning for text classification. arXiv preprint arXiv:1801.06146.

Peters, M. E., Neumann, M., Iyyer, M., Gardner, M., Clark, C., Lee, K., & Zettlemoyer, L. (2018). Deep contextualized word representations. arXiv preprint arXiv:1802.05365.

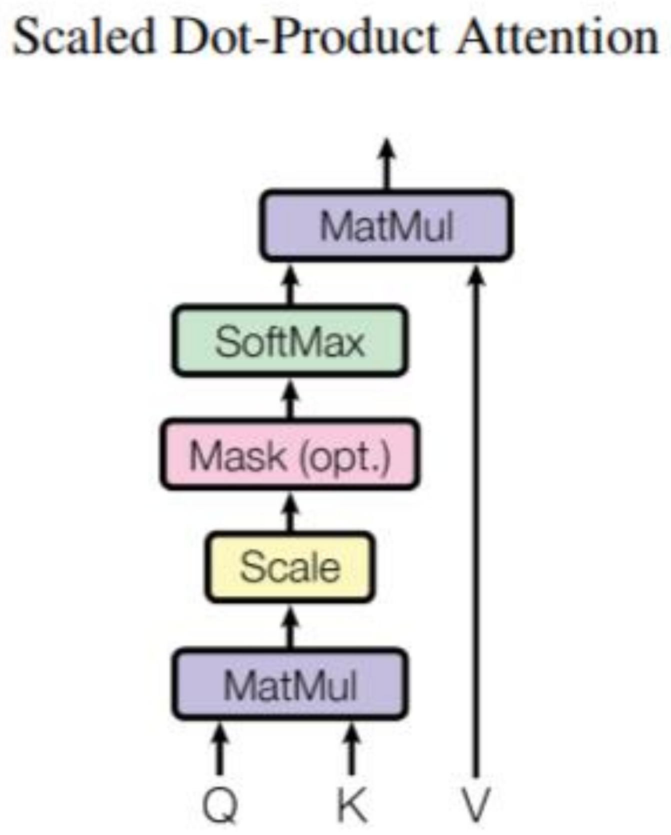


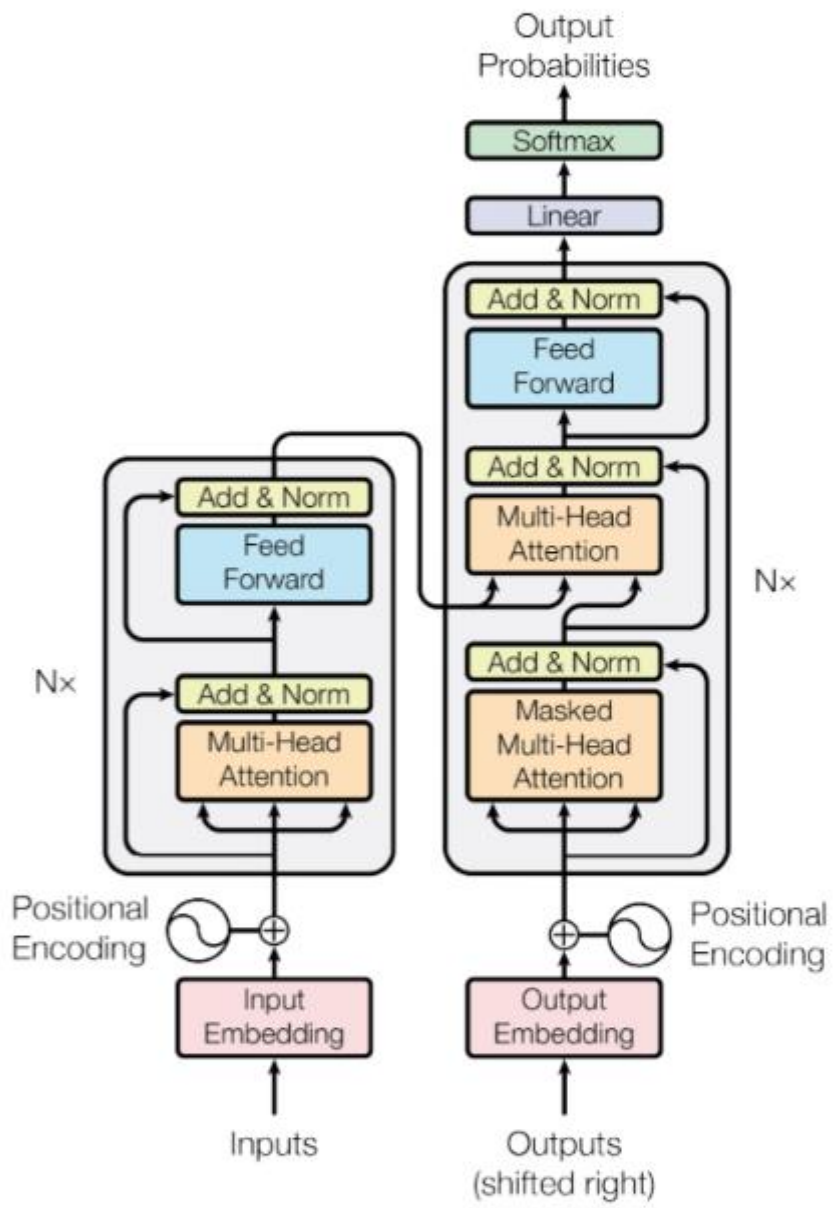
THIS CREATED A FOUNDATION FOR THE NEW NLP MODELS
(DISCUSSED IN THE NEXT CLASS)

THE LAB

ATTENTION IS ALL YOU NEED

Deep dive into the transformer design





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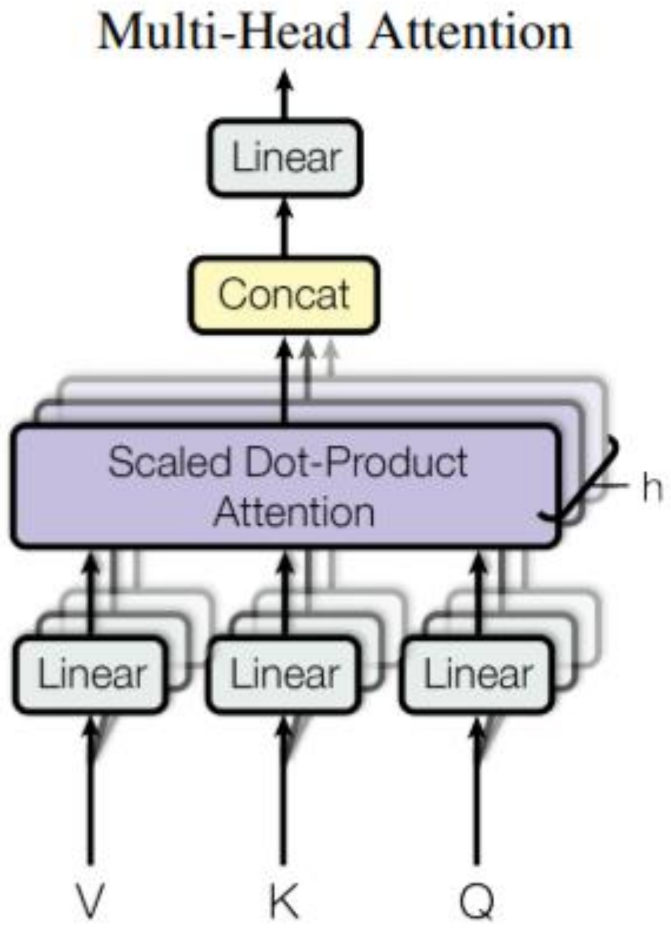

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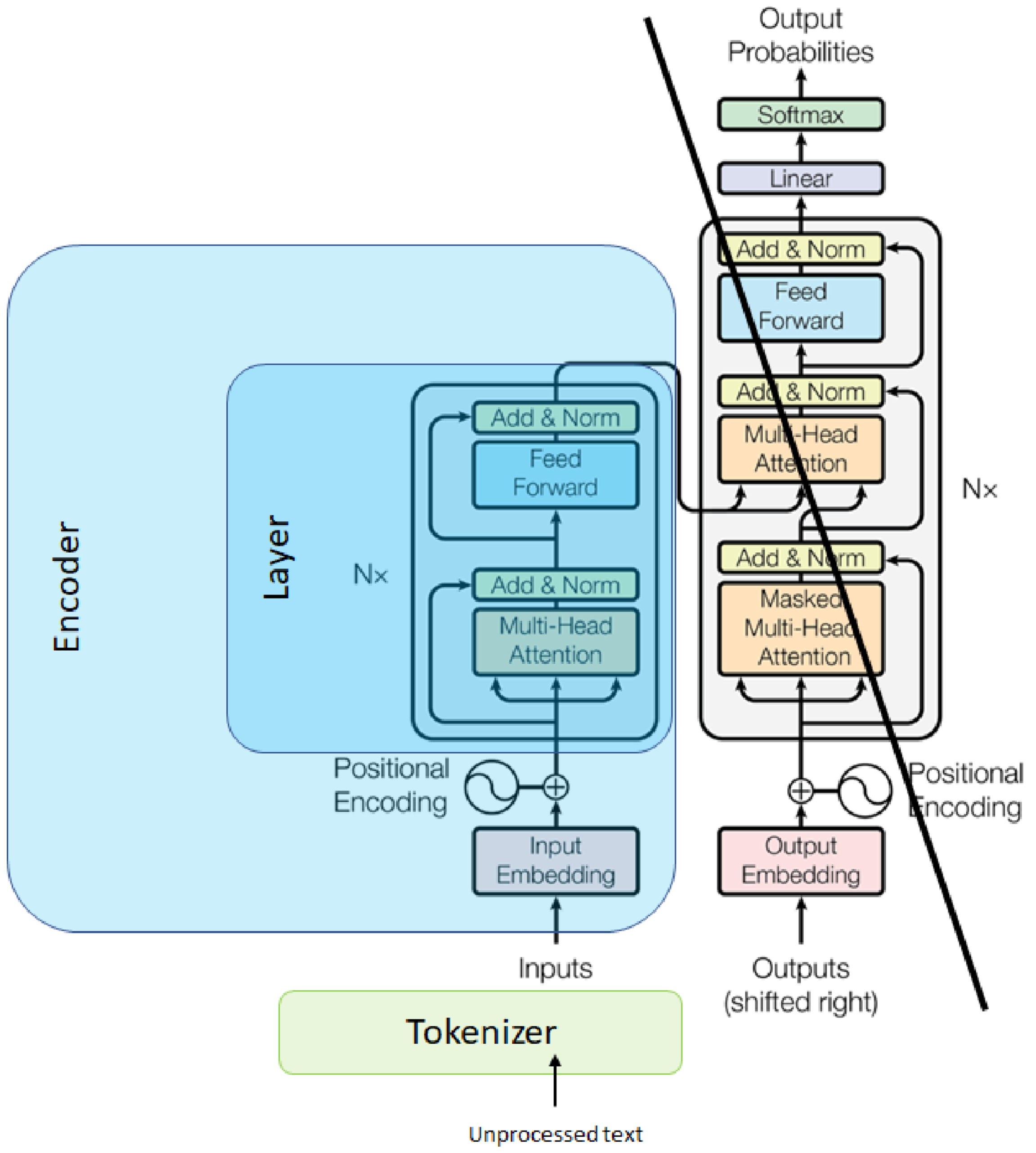
BERT

How it relates to transformer and pretraining



IN THE NEXT CLASS…

SELF-SUPERVISION, BERT, AND BEYOND

Why did models start to work well? What does the future hold?

?

Part 1: Machine Learning in NLP

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  - Transformer Architecture
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NVIDIA

DEEP
LEARNING
INSTITUTE