10707
Deep Learning

Russ Salakhutdinov

Machine Learning Department
rsalakhu@cs.cmu.edu

Sequence Models

Sequences

- Words, Letters

> *50 years ago, the fathers of artificial intelligence convinced everybody that logic was the key to intelligence. Somehow we had to get computers to do logical reasoning. The alternative approach, which they thought was crazy, was to forget logic and try and understand how networks of brain cells learn things. Curiously, two people who rejected the logic based approach to AI were Turing and Von Neumann. If either of them had lived I think things would have turned out differently... now neural networks are everywhere and the crazy approach is winning.*

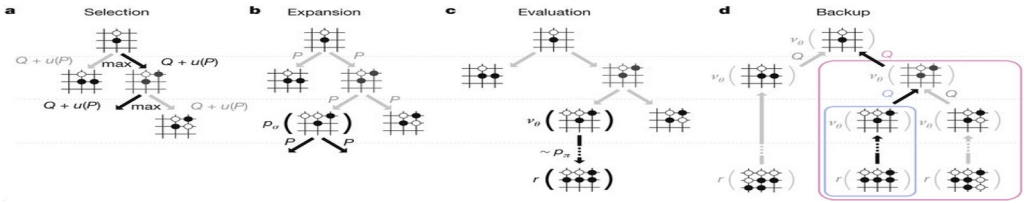
- Speech

- Images, Videos

- Programs

```
while (*d++ = *s++);
```

- Sequential Decision Making (RL)



Classical Models for Sequence Prediction

- Sequence prediction was classically handled as a structured prediction task
    - Most were built on conditional independence assumptions
    - Others such as DAGGER were based on supervisory signals and auxiliary information

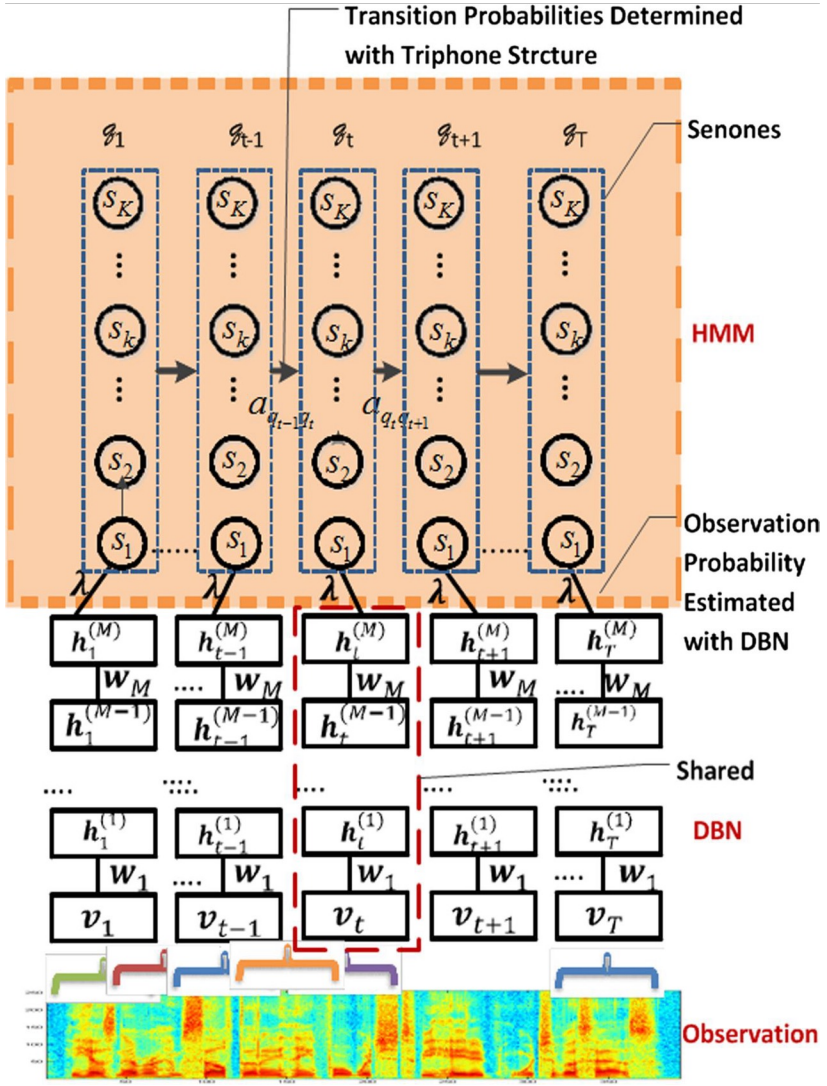
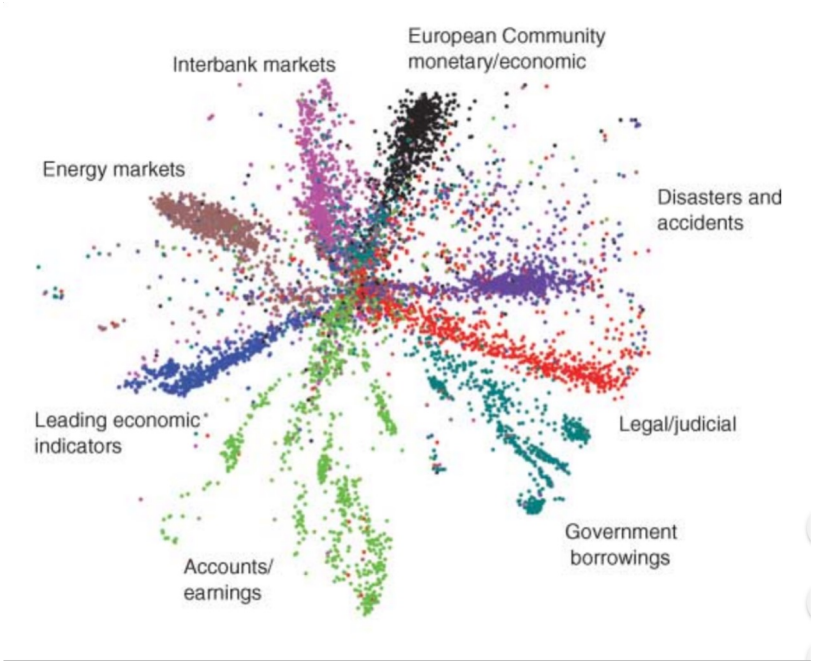


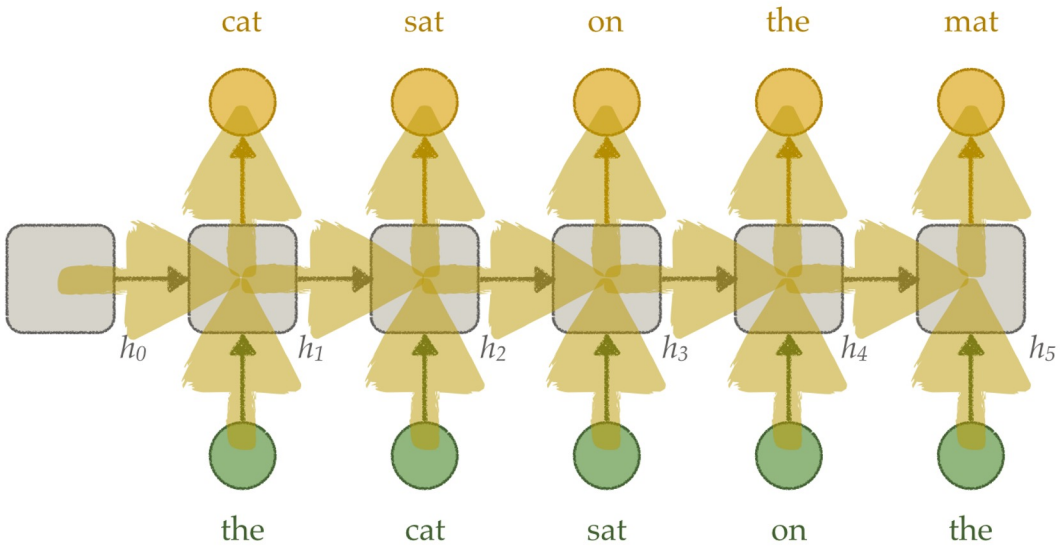
Figure credit: Li Deng

Two Key Ingredients

Neural Embeddings



Recurrent Language Models



Hinton, G., Salakhutdinov, R. "Reducing the Dimensionality of Data with Neural Networks." *Science (2006)*

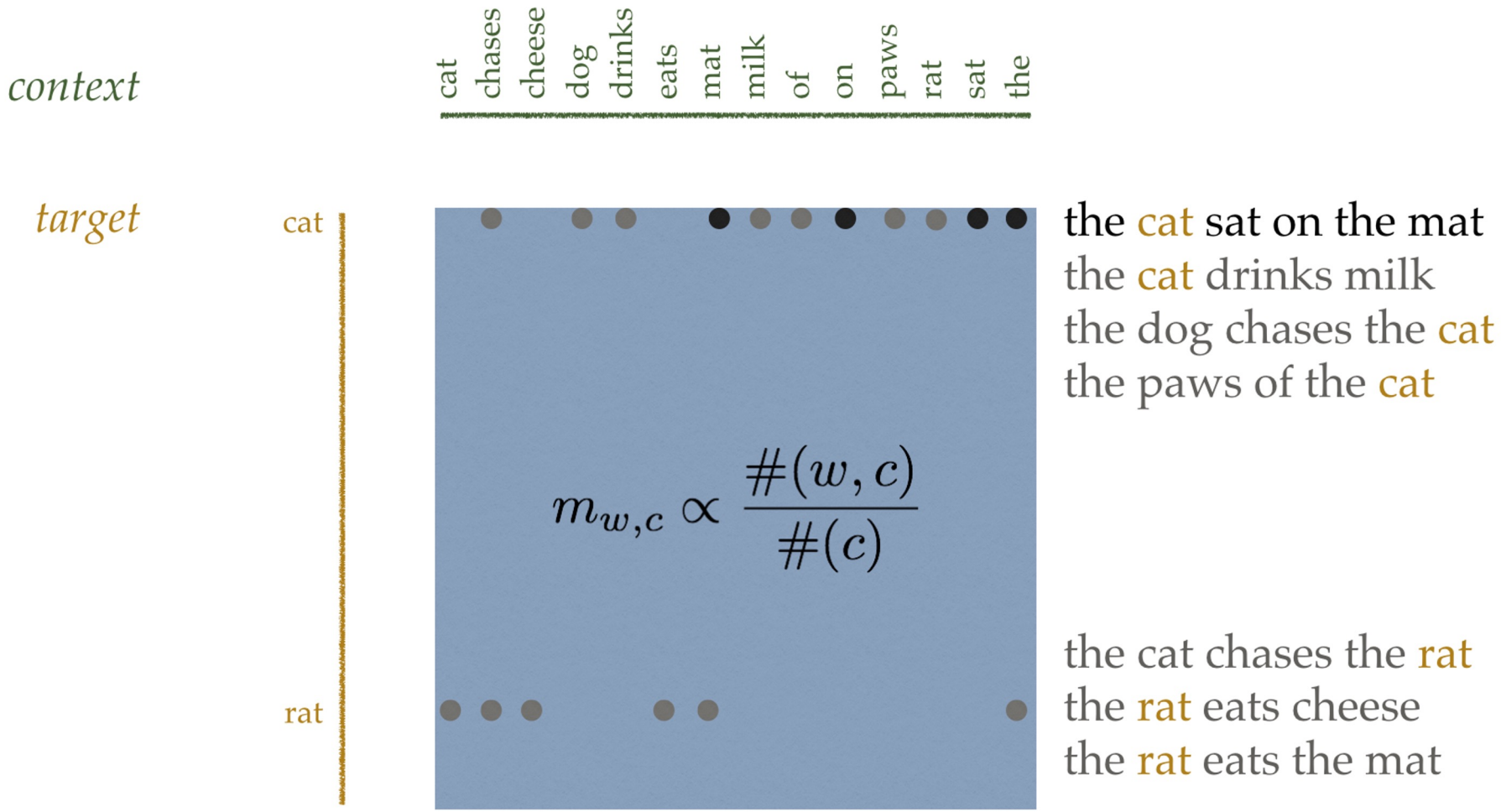
Mikolov, T., et al. "Recurrent neural network based language model." *Interspeech (2010)*

Language Models

context					*target*	$P(w_t \mid w_{t-1}, w_{t-2}, \ldots w_{t-5})$
the	cat	sat	on	the	**mat**	0.15
$w_{t\text{-}5}$	$w_{t\text{-}4}$	$w_{t\text{-}3}$	$w_{t\text{-}2}$	$w_{t\text{-}1}$	w_t	
the	cat	sat	on	the	**rug**	0.12
the	cat	sat	on	the	**hat**	0.09
the	cat	sat	on	the	**dog**	0.01
the	cat	sat	on	the	**the**	0
the	cat	sat	on	the	**sat**	0
the	cat	sat	on	the	**robot**	?
the	cat	sat	on	the	**printer**	?

Slide Credit: Piotr Mirowski

N-grams



Slide Credit: Piotr Mirowski

N-grams

$$P(w_1, w_2, \ldots, w_{T-1}, w_T) \approx \prod_{t=1}^{T} P(w_t | w_{t-1}, \ldots, w_{t-n+1})$$

the	cat	sat	on	the	mat	$P(w_1)$
the	**cat**	sat	on	the	mat	$P(w_2 \mid w_1)$
the	cat	**sat**	on	the	mat	$P(w_3 \mid w_2, w_1)$
the	cat	sat	**on**	the	mat	$P(w_4 \mid w_3, w_2)$
the	cat	sat	on	**the**	mat	$P(w_5 \mid w_4, w_3)$
the	cat	sat	on	the	**mat**	$P(w_6 \mid w_5, w_4)$

Slide Credit: Piotr Mirowski

Chain Rule

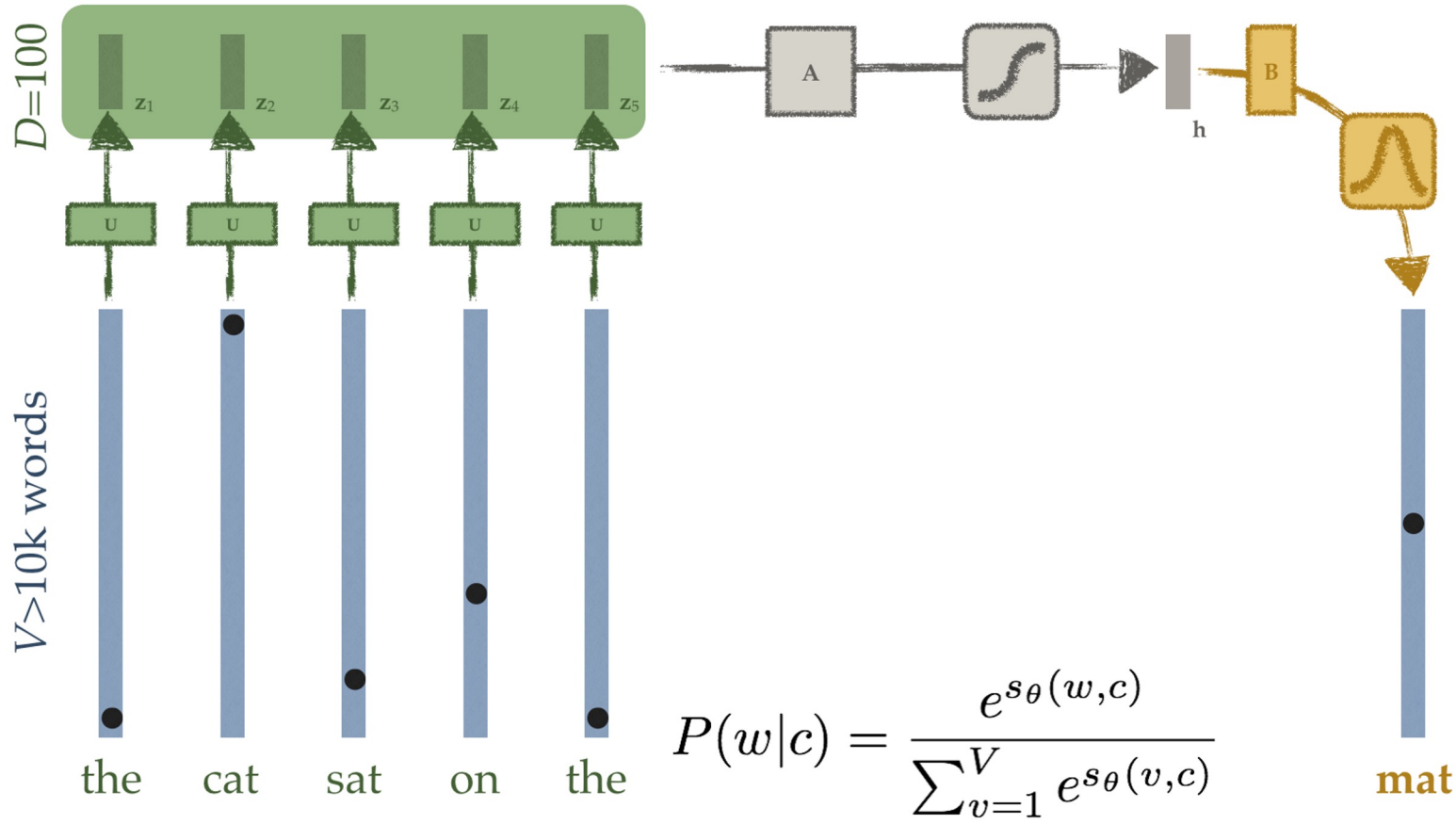
$$P(w_1, w_2, \ldots, w_{T-1}, w_T) = \prod_{t=1}^{T} P(w_t | w_{t-1}, w_{t-2}, \ldots, w_1)$$

the	cat	sat	on	the	mat	$P(w_1)$
the	**cat**	sat	on	the	mat	$P(w_2 \mid w_1)$
the	cat	**sat**	on	the	mat	$P(w_3 \mid w_2, w_1)$
the	cat	sat	**on**	the	mat	$P(w_4 \mid w_3, w_2, w_1)$
the	cat	sat	on	**the**	mat	$P(w_5 \mid w_4, w_3, w_2, w_1)$
the	cat	sat	on	the	**mat**	$P(w_6 \mid w_5, w_4, w_3, w_2, w_1)$

Slide Credit: Piotr Mirowski

Key Insight: Vectorizing Context

$$p(w_t|w_1,\ldots,w_{t-1}) = p_\theta(w_t|f_\theta(w_1,\ldots,w_{t-1}))$$

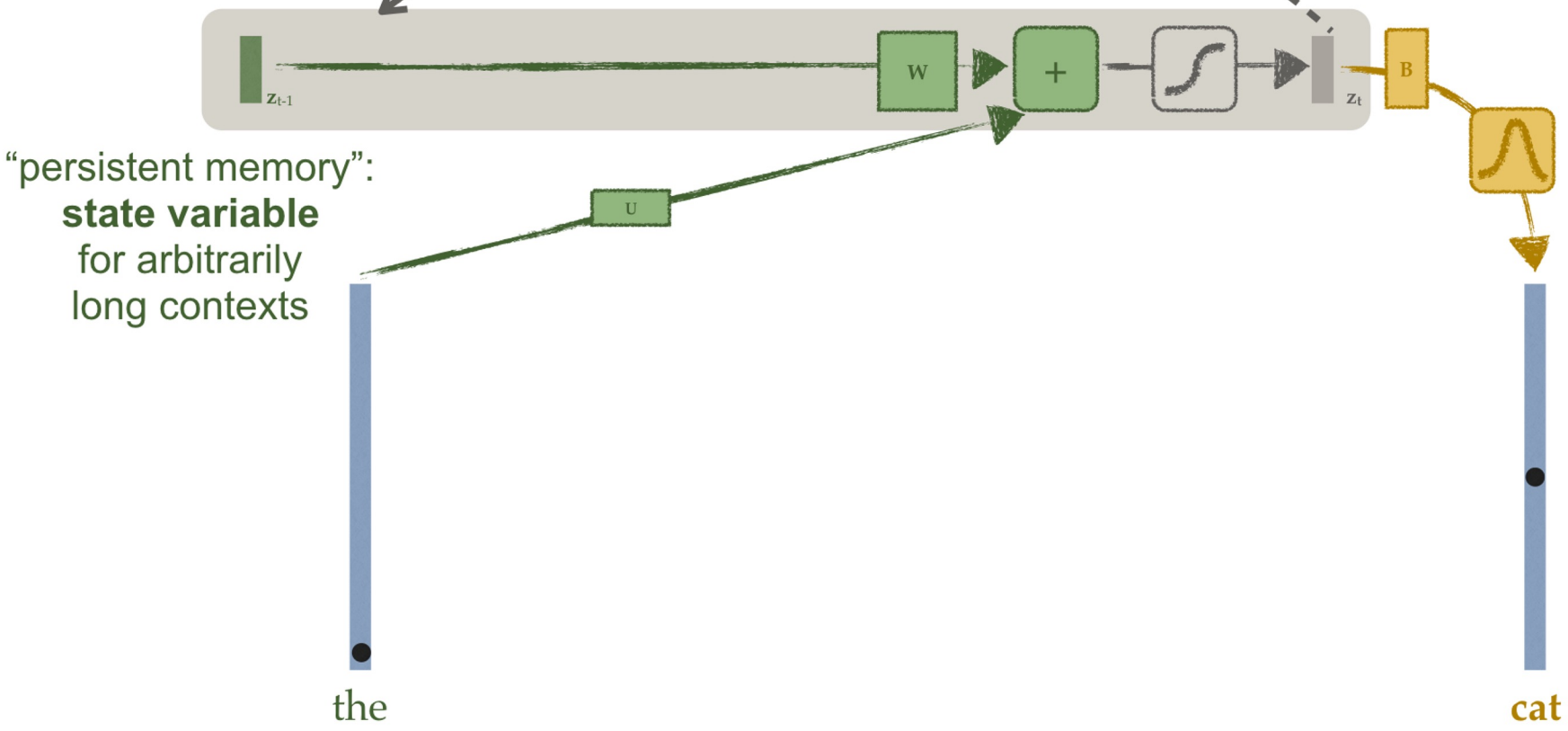


Bengio, Y. et al., "A Neural Probabilistic Language Model", *JMLR (2001, 2003)*
Mnih, A., Hinton, G., "Three new graphical models for statistical language modeling", *ICML 2007*

Slide Credit: Piotr Mirowski

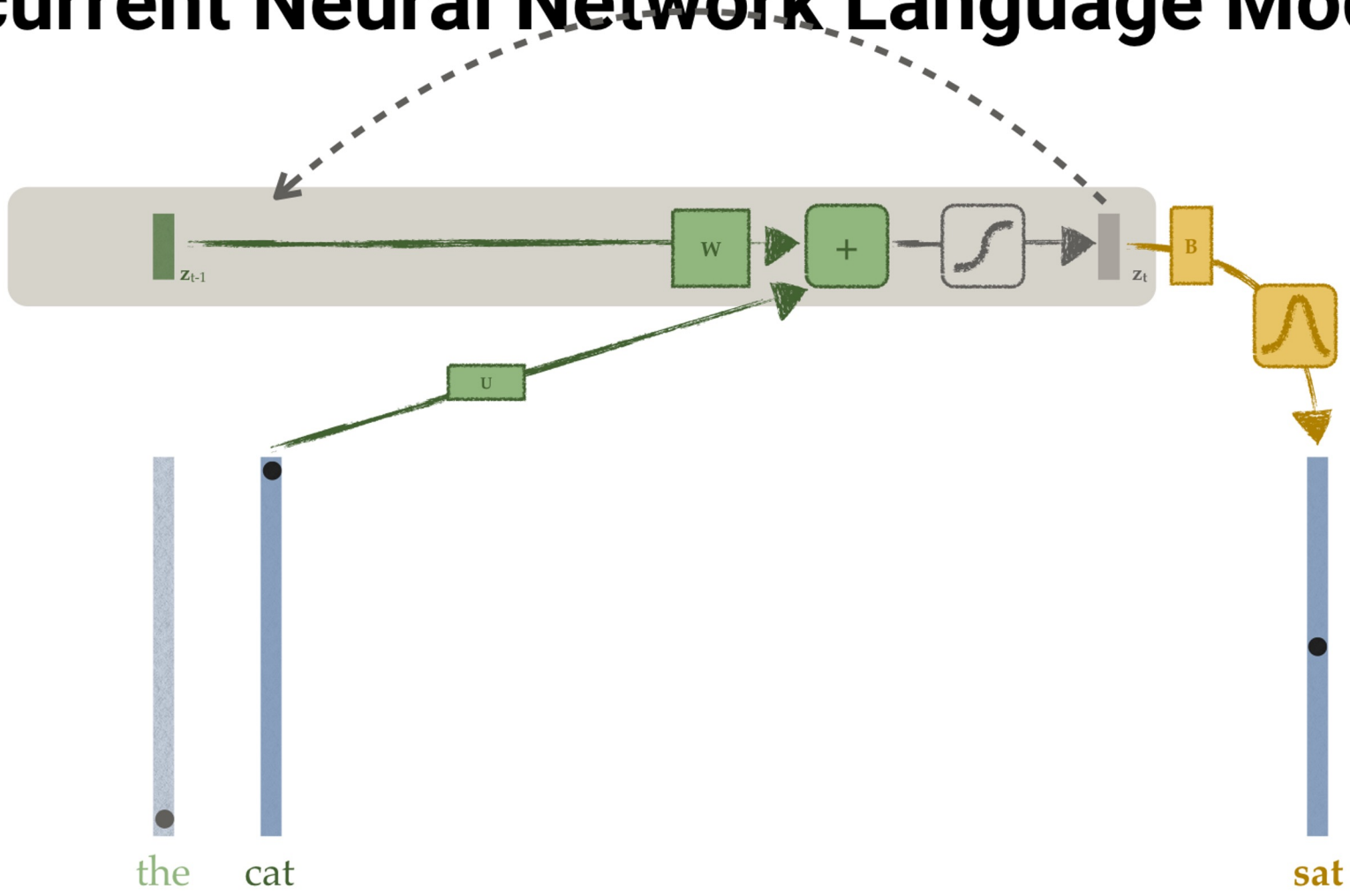
Recurrent Neural Network Language Models

[Jeffrey L Elman (1991) "Distributed representations, simple recurrent networks and grammatical structure", *Machine Learning*; Tomas Mikolov et al. (2010) "Recurrent neural network based language model", *INTERSPEECH*]



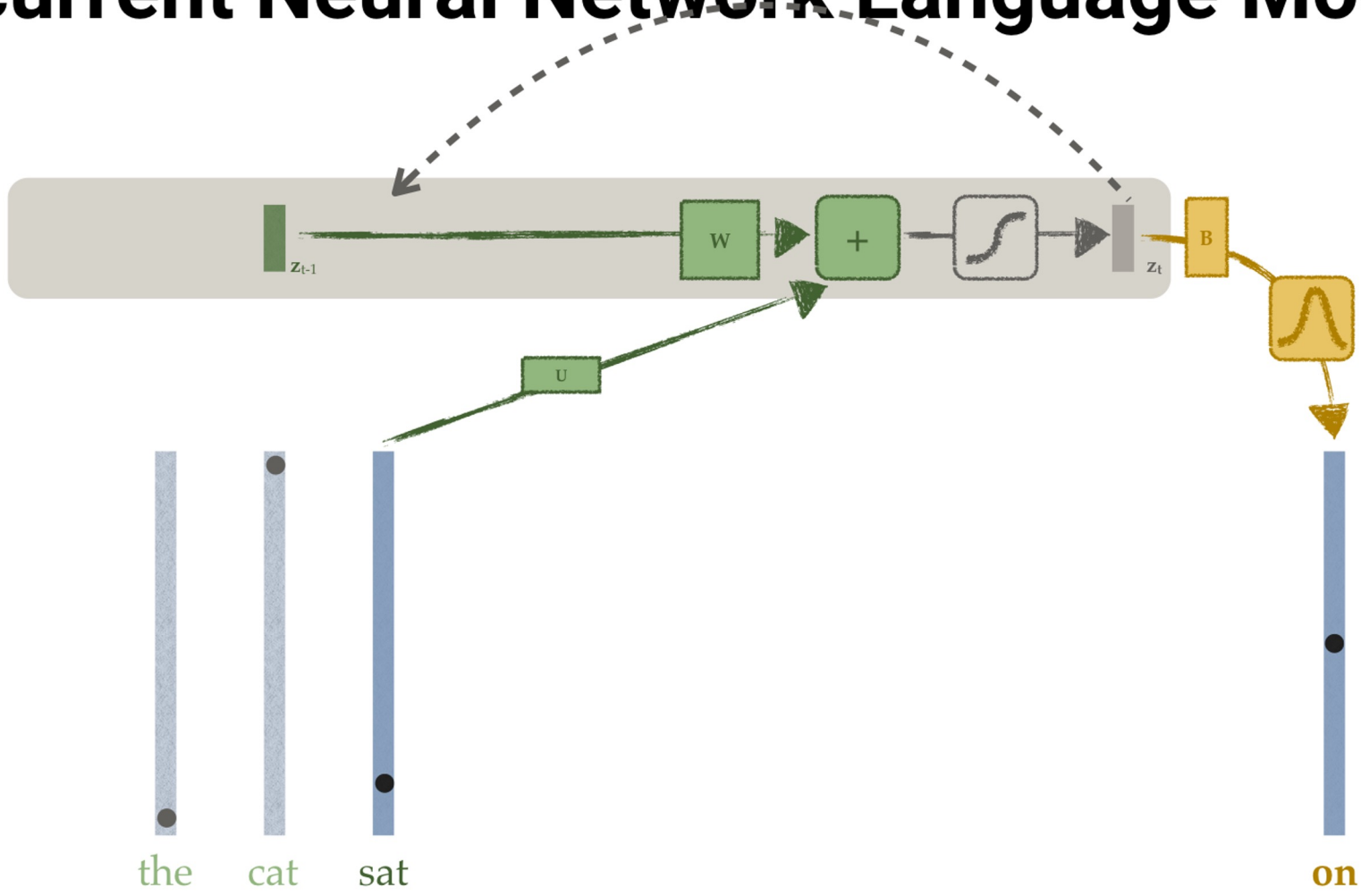
Slide Credit: Piotr Mirowski

Recurrent Neural Network Language Models



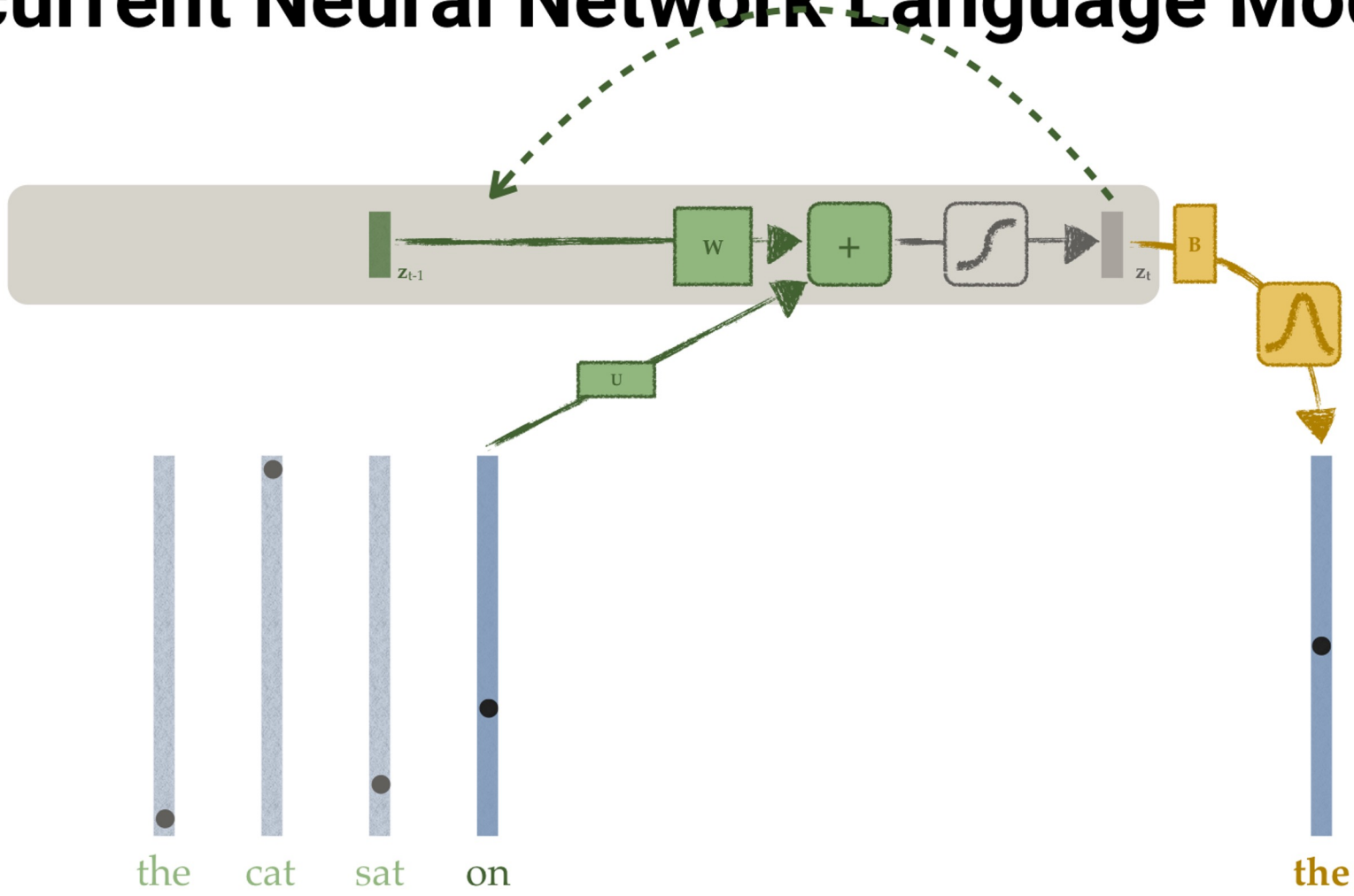
Slide Credit: Piotr Mirowski

Recurrent Neural Network Language Models



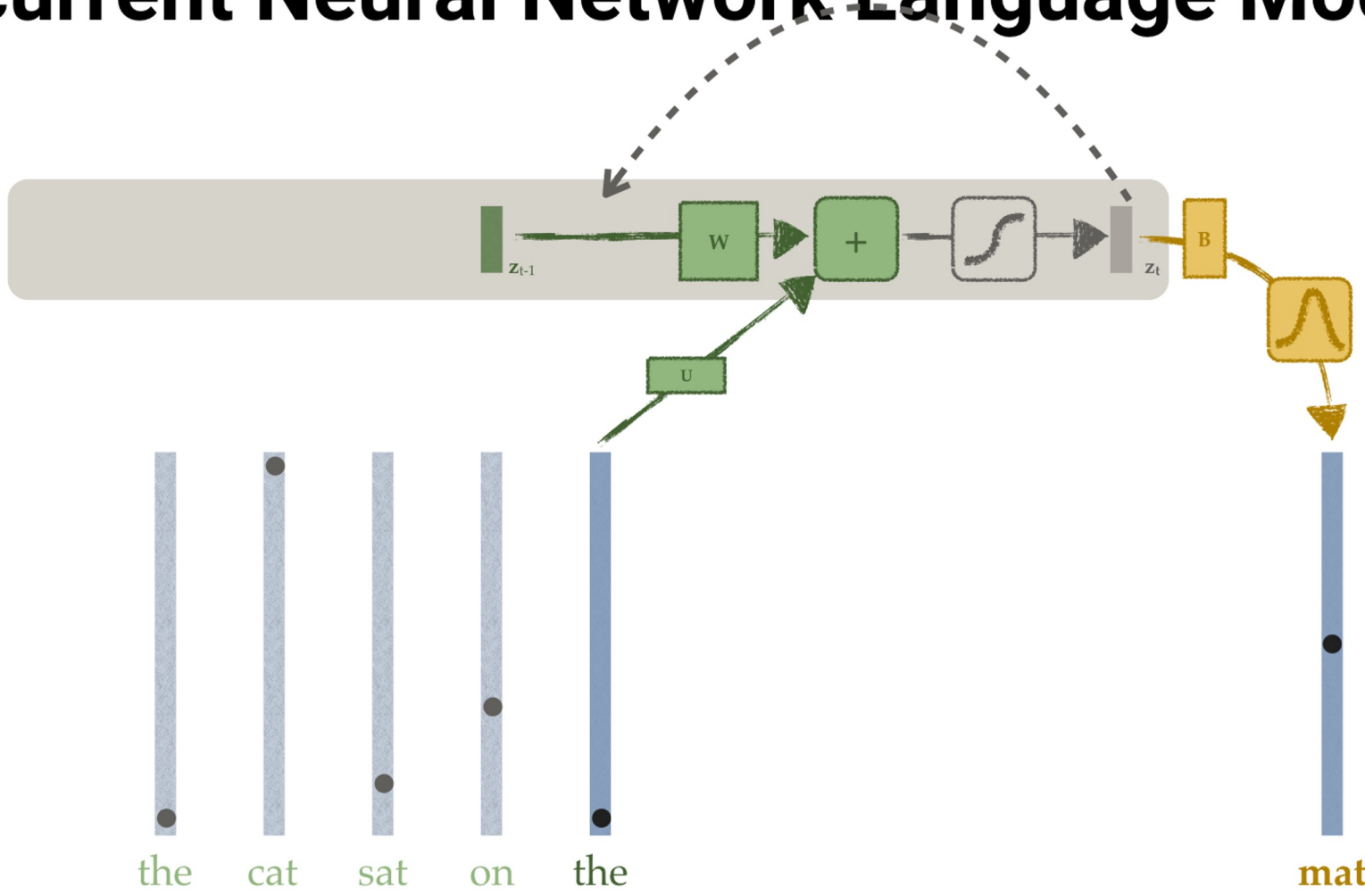
Slide Credit: Piotr Mirowski

Recurrent Neural Network Language Models



Slide Credit: Piotr Mirowski

Recurrent Neural Network Language Models

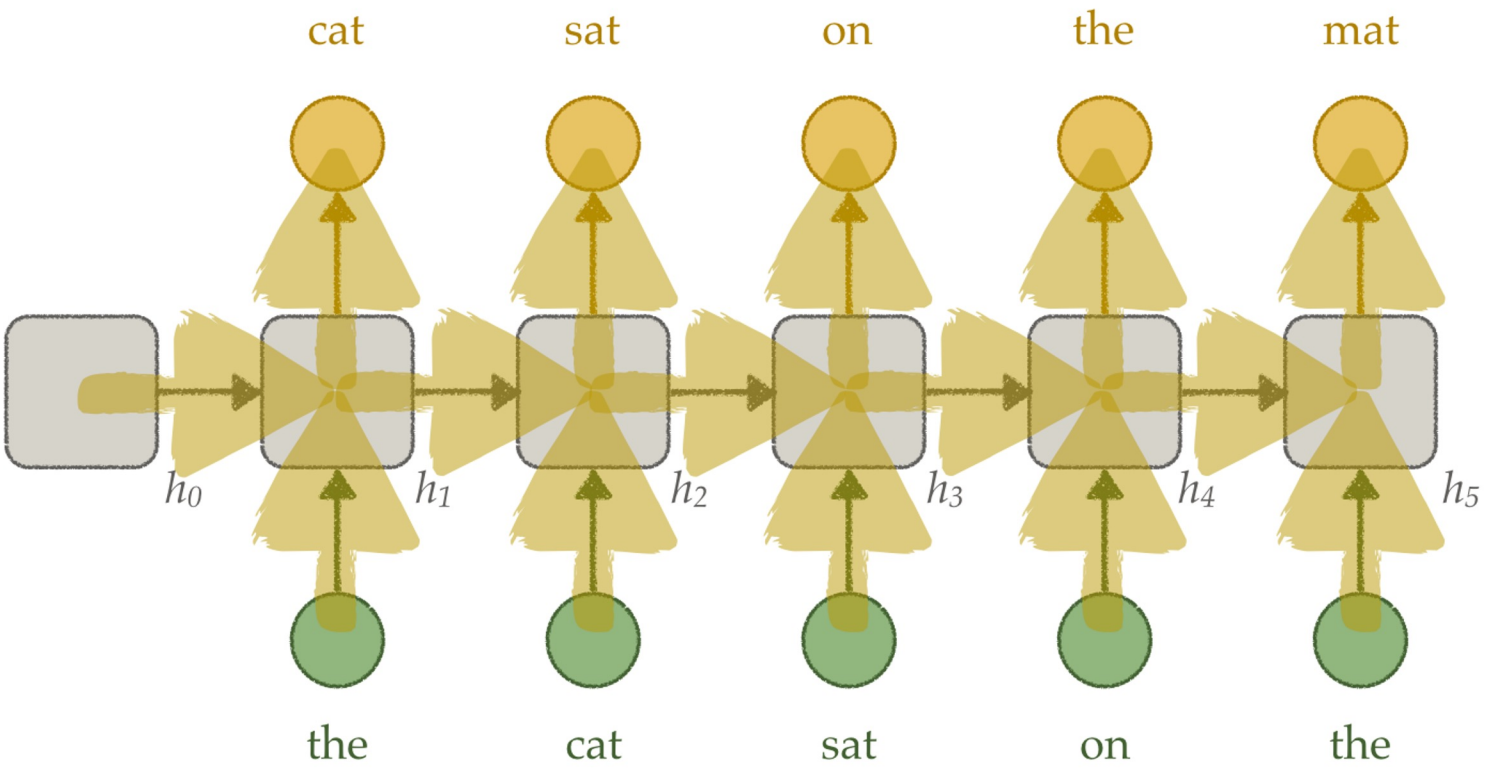


Slide Credit: Piotr Mirowski

What do we Optimize?

$$\theta^* = \arg\max_{\theta} E_{w \sim data} \log P_\theta(w_1, \ldots, w_T)$$

Recurrent Neural Network Language Models

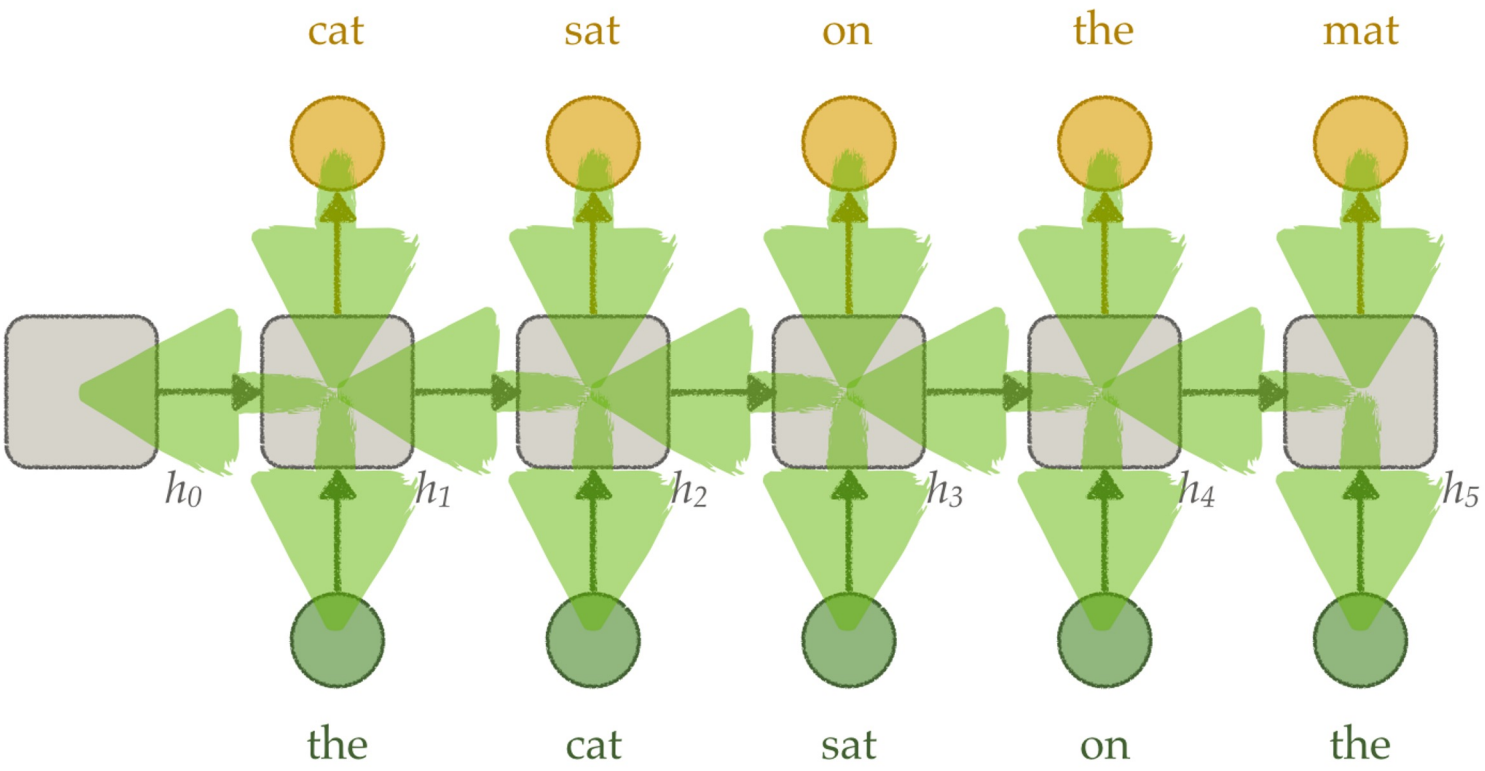


Learning Sequences — **Piotr Mirowski**

- Forward Pass

Slide Credit: Piotr Mirowski

Recurrent Neural Network Language Models



Learning Sequences — **Piotr Mirowski**

- Backward Pass

Slide Credit: Piotr Mirowski

Seq2Seq

Joint Language and Translation Modeling with Recurrent Neural Networks

Michael Auli, Michel Galley, Chris Quirk, Geoffrey Zweig
Microsoft Research
Redmond, WA, USA
{michael.auli,mgalley,chrisq,gzweig}@microsoft.com

Abstract

We present a joint language and translation model based on a recurrent neural network which predicts target words based on an unbounded history of both source and target words. The weaker independence assumptions of this model result in a vastly larger search space compared to related feed-forward-based language or translation models. We tackle this issue with a new lattice rescoring algorithm and demonstrate its effectiveness empirically. Our joint model builds on a well known recurrent neural network language model (Mikolov, 2012) augmented by a layer of additional inputs from the source language. We show competitive accuracy compared to the traditional channel model features. Our best results improve the output of a system trained on WMT 2012 French-English data by up to 1.5 BLEU, and by 1.1 BLEU on average across several test sets.

1 Introduction

Recently, several feed-forward neural network-based language and translation models have achieved impressive accuracy improvements on statistical machine translation tasks (Allauzen et al., 2011; Le et al., 2012b; Schwenk et al., 2012). In this paper we focus on recurrent neural network architectures, which have recently advanced the state of the art in language modeling (Mikolov et al., 2010; Mikolov et al., 2011a; Mikolov, 2012), outperforming multi-layer feed-forward based networks in both perplexity and word error rate in speech recognition (Arisoy et al., 2012; Sundermeyer et al., 2013). The major attraction of recurrent architectures is their potential to capture long-span dependencies since predictions are based on an *unbounded history* of previous words. This is in contrast to feed-forward networks as well as conventional n-gram models, both of which are limited to fixed-length contexts. Building on the success of recurrent architectures, we base our joint language and translation model on an extension of the recurrent neural network language model (Mikolov and Zweig, 2012) that introduces a layer of additional inputs (§2).

Most previous work on neural networks for speech recognition or machine translation used a rescoring setup based on n-best lists (Arisoy et al., 2012; Mikolov, 2012) for evaluation, thereby side stepping the algorithmic and engineering challenges of direct decoder-integration.[1] Instead, we exploit *lattices*, which offer a much richer representation of the decoder output, since they compactly encode an exponential number of translation hypotheses in polynomial space. In contrast, n-best lists are typically very redundant, representing only a few combinations of top scoring arcs in the lattice. A major challenge in lattice rescoring with a recurrent neural network model is the effect of the unbounded history on search since the usual dynamic programming assumptions which are exploited for efficiency do not hold up anymore. We apply a novel algorithm to the task of rescoring with an unbounded language model and empirically demonstrate its effectiveness (§3).

The algorithm proves robust, leading to significant improvements with the recurrent neural network language model over a competitive n-gram baseline across several language pairs. We even observe consistent gains when pairing the model with a large n-gram model trained on up to 575 times more

[1] One notable exception is Le et al. (2012a) who rescore reordering lattices with a feed-forward network-based model.

Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1044–1054, Seattle, Washington, USA, 18-21 October 2013.

Recurrent Continuous Translation Models

Nal Kalchbrenner **Phil Blunsom**
Department of Computer Science
University of Oxford
{nal.kalchbrenner,phil.blunsom}@cs.ox.ac.uk

Abstract

We introduce a class of probabilistic continuous translation models called Recurrent Continuous Translation Models that are purely based on continuous representations for words, phrases and sentences and do not rely on alignments or phrasal translation units. The models have a generation and a conditioning aspect. The generation of the translation is modelled with a target Recurrent Language Model, whereas the conditioning on the source sentence is modelled with a Convolutional Sentence Model. Through various experiments, we show first that our models obtain a perplexity with respect to gold translations that is > 43% lower than that of state-of-the-art alignment-based translation models. Secondly, we show that they are remarkably sensitive to the word order, syntax, and meaning of the source sentence despite lacking alignments. Finally we show that they match a state-of-the-art system when rescoring *n*-best lists of translations.

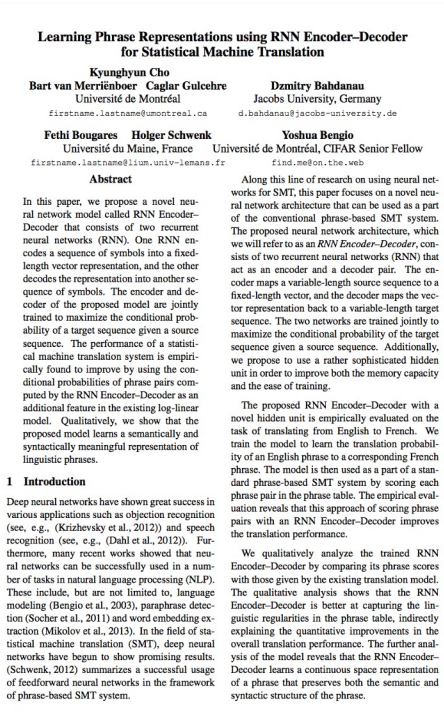
1 Introduction

In most statistical approaches to machine translation the basic units of translation are phrases that are composed of one or more words. A crucial component of translation systems are models that estimate translation probabilities for pairs of phrases, one phrase being from the source language and the other from the target language. Such models count phrase pairs and their occurrences as distinct if the surface forms of the phrases are distinct. Although distinct phrase pairs often share significant similarities, linguistic or otherwise, they do not share statistical weight in the models' estimation of their translation probabilities. Besides ignoring the similarity of phrase pairs, this leads to general sparsity issues. The estimation is sparse or skewed for the large number of rare or unseen phrase pairs, which grows exponentially in the length of the phrases, and the generalisation to other domains is often limited.

Continuous representations have shown promise at tackling these issues. Continuous representations for words are able to capture their morphological, syntactic and semantic similarity (Collobert and Weston, 2008). They have been applied in continuous language models demonstrating the ability to overcome sparsity issues and to achieve state-of-the-art performance (Bengio et al., 2003; Mikolov et al., 2010). Word representations have also shown a marked sensitivity to conditioning information (Mikolov and Zweig, 2012). Continuous representations for characters have been deployed in character-level language models demonstrating notable language generation capabilities (Sutskever et al., 2011). Continuous representations have also been constructed for phrases and sentences. The representations are able to carry similarity and task dependent information, e.g. sentiment, paraphrase or dialogue labels, significantly beyond the word level and to accurately predict labels for a highly diverse range of unseen phrases and sentences (Grefenstette et al., 2011; Socher et al., 2011; Socher et al., 2012; Hermann and Blunsom, 2013; Kalchbrenner and Blunsom, 2013).

Phrase-based continuous translation models were first proposed in (Schwenk et al., 2006) and re-

Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, pages 1700–1709, Seattle, Washington, USA, 18-21 October 2013.



Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation

Kyunghyun Cho
Bart van Merriënboer **Caglar Gulcehre** **Dzmitry Bahdanau**
Université de Montréal Jacobs University, Germany
firstname.lastname@umontreal.ca d.bahdanau@jacobs-university.de
Fethi Bougares **Holger Schwenk** **Yoshua Bengio**
Université du Maine, France Université de Montréal, CIFAR Senior Fellow
firstname.lastname@lium.univ-lemans.fr find.me@on.the.web

Abstract

In this paper, we propose a novel neural network model called RNN Encoder–Decoder that consists of two recurrent neural networks (RNN). One RNN encodes a sequence of symbols into a fixed-length vector representation, and the other decodes the representation into another sequence of symbols. The encoder and decoder of the proposed model are jointly trained to maximize the conditional probability of a target sequence given a source sequence. The performance of a statistical machine translation system is empirically found to improve by using the conditional probabilities of phrase pairs computed by the RNN Encoder–Decoder as an additional feature in the existing log-linear model. Qualitatively, we show that the proposed model learns a semantically and syntactically meaningful representation of linguistic phrases.

1 Introduction

Deep neural networks have shown great success in various applications such as objection recognition (see, e.g., (Krizhevsky et al., 2012)) and speech recognition (see, e.g., (Dahl et al., 2012)). Furthermore, many recent works showed that neural networks can be successfully used in a number of tasks in natural language processing (NLP). These include, but are not limited to, language modeling (Bengio et al., 2003), paraphrase detection (Socher et al., 2011) and word embedding extraction (Mikolov et al., 2013). In the field of statistical machine translation (SMT), deep neural networks have begun to show promising results. (Schwenk, 2012) summarizes a successful usage of feedforward neural networks in the framework of phrase-based SMT system.

Along this line of research on using neural networks for SMT, this paper focuses on a novel neural network architecture that can be used as a part of the conventional phrase-based SMT system. The proposed neural network architecture, which we will refer to as an *RNN Encoder–Decoder*, consists of two recurrent neural networks (RNN) that act as an encoder and a decoder pair. The encoder maps a variable-length source sequence to a fixed-length vector, and the decoder maps the vector representation back to a variable-length target sequence. The two networks are trained jointly to maximize the conditional probability of the target sequence given a source sequence. Additionally, we propose to use a rather sophisticated hidden unit in order to improve both the memory capacity and the ease of training.

The proposed RNN Encoder–Decoder with a novel hidden unit is empirically evaluated on the task of translating from English to French. We train the model to learn the translation probability of an English phrase to a corresponding French phrase. The model is then used as a part of a standard phrase-based SMT system by scoring each phrase pair in the phrase table. The empirical evaluation reveals that this approach of scoring phrase pairs with an RNN Encoder–Decoder improves the translation performance.

We qualitatively analyze the trained RNN Encoder–Decoder by comparing its phrase scores with those given by the existing translation model. The qualitative analysis shows that the RNN Encoder–Decoder is better at capturing the linguistic regularities in the phrase table, indirectly explaining the quantitative improvements in the overall translation performance. The further analysis of the model reveals that the RNN Encoder–Decoder learns a continuous space representation of a phrase that preserves both the semantic and syntactic structure of the phrase.

Sequence to Sequence Learning with Neural Networks

Ilya Sutskever **Oriol Vinyals** **Quoc V. Le**
Google Google Google
ilyasu@google.com vinyals@google.com qvl@google.com

Abstract

Deep Neural Networks (DNNs) are powerful models that have achieved excellent performance on difficult learning tasks. Although DNNs work well whenever large labeled training sets are available, they cannot be used to map sequences to sequences. In this paper, we present a general end-to-end approach to sequence learning that makes minimal assumptions on the sequence structure. Our method uses a multilayered Long Short-Term Memory (LSTM) to map the input sequence to a vector of a fixed dimensionality, and then another deep LSTM to decode the target sequence from the vector. Our main result is that on an English to French translation task from the WMT'14 dataset, the translations produced by the LSTM achieve a BLEU score of 34.8 on the entire test set, where the LSTM's BLEU score was penalized on out-of-vocabulary words. Additionally, the LSTM did not have difficulty on long sentences. For comparison, a phrase-based SMT system achieves a BLEU score of 33.3 on the same dataset. When we used the LSTM to rerank the 1000 hypotheses produced by the aforementioned SMT system, its BLEU score increases to 36.5, which is close to the previous best result on this task. The LSTM also learned sensible phrase and sentence representations that are sensitive to word order and are relatively invariant to the active and the passive voice. Finally, we found that reversing the order of the words in all source sentences (but not target sentences) improved the LSTM's performance markedly, because doing so introduced many short term dependencies between the source and the target sentence which made the optimization problem easier.

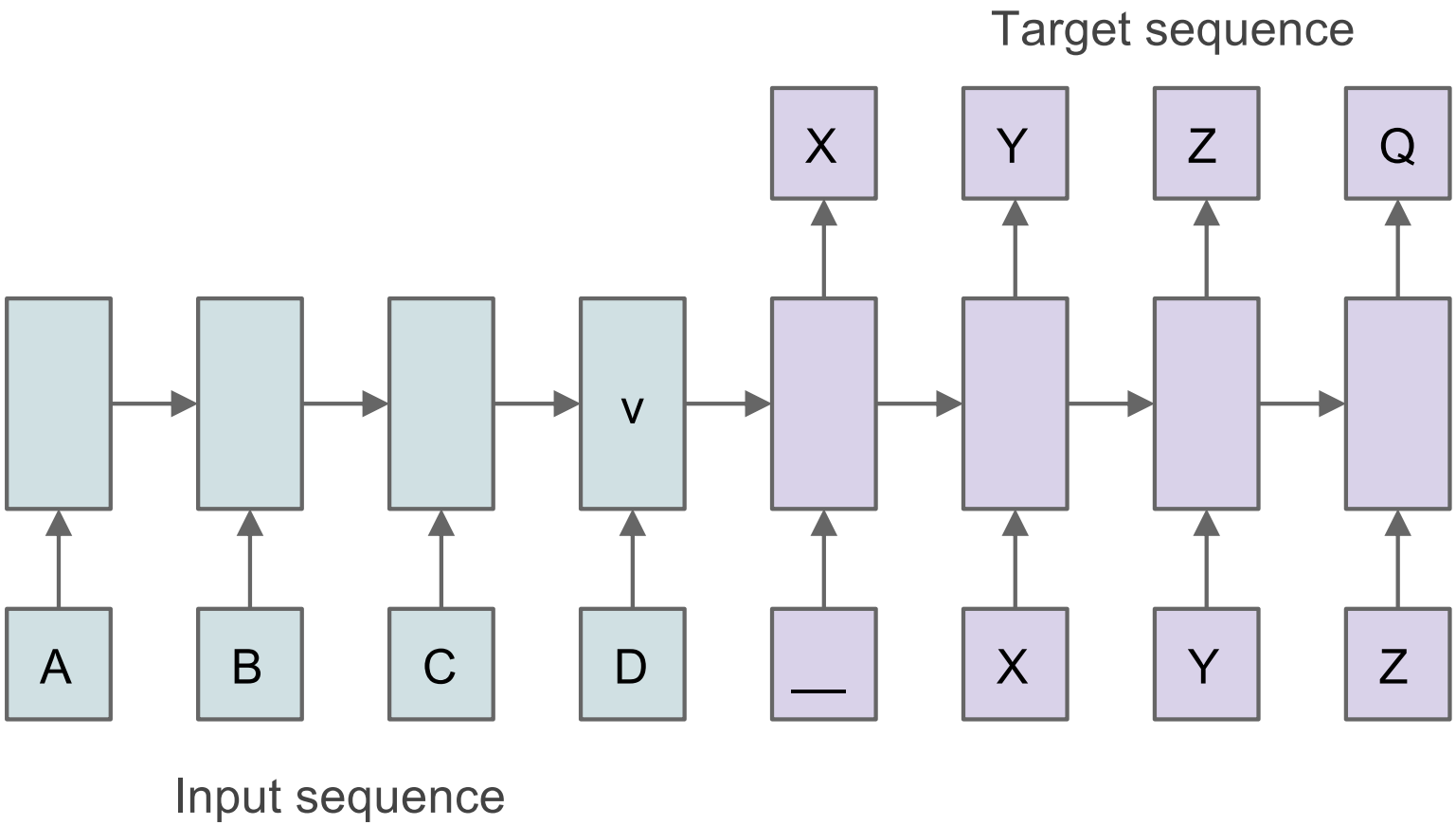
1 Introduction

Deep Neural Networks (DNNs) are extremely powerful machine learning models that achieve excellent performance on difficult problems such as speech recognition [13, 7] and visual object recognition [19, 6, 21, 20]. DNNs are powerful because they can perform arbitrary parallel computation for a modest number of steps. A surprising example of the power of DNNs is their ability to sort N N-bit numbers using only 2 hidden layers of quadratic size [27]. So, while neural networks are related to conventional statistical models, they learn an intricate computation. Furthermore, large DNNs can be trained with supervised backpropagation whenever the labeled training set has enough information to specify the network's parameters. Thus, if there exists a parameter setting of a large DNN that achieves good results (for example, because humans can solve the task very rapidly), supervised backpropagation will find these parameters and solve the problem.

Despite their flexibility and power, DNNs can only be applied to problems whose inputs and targets can be sensibly encoded with vectors of fixed dimensionality. It is a significant limitation, since many important problems are best expressed with sequences whose lengths are not known a-priori. For example, speech recognition and machine translation are sequential problems. Likewise, question answering can also be seen as mapping a sequence of words representing the question to a

1. Auli, M., et al. "Joint Language and Translation Modeling with Recurrent Neural Networks." *EMNLP (2013)*
2. Kalchbrenner, N., et al. “Recurrent Continuous Translation Models.” *EMNLP (2013)*
3. Cho, K., et al. “Learning Phrase Representations using RNN Encoder-Decoder for Statistical MT.” *EMNLP (2014)*
4. Sutskever, I., et al. “Sequence to Sequence Learning with Neural Networks.” *NIPS (2014)*

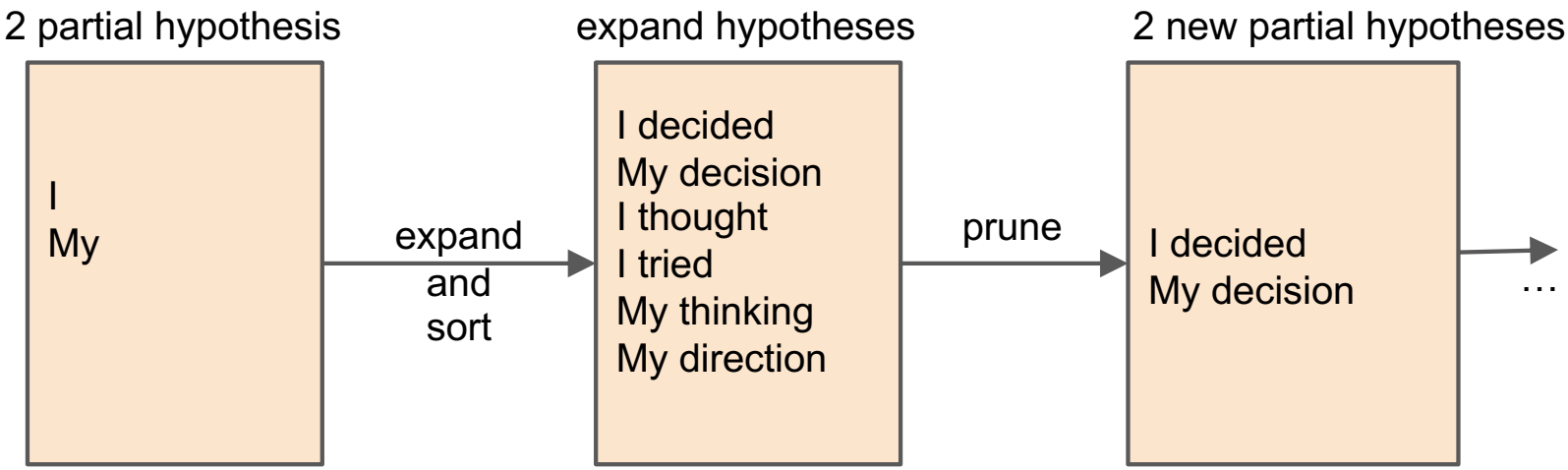
Seq2Seq



$$P(y_1, \ldots, y_{T'} | x_1, \ldots, x_T) = \prod_{t=1}^{T'} p(y_t | v, y_1, \ldots, y_{t-1})$$

Decoding in a Nutshell (Beam Size 2)

$$y^* = \arg \max_{y_1,\ldots,y_{T'}} P(y_1, \ldots, y_{T'} | x_1, \ldots, x_T)$$



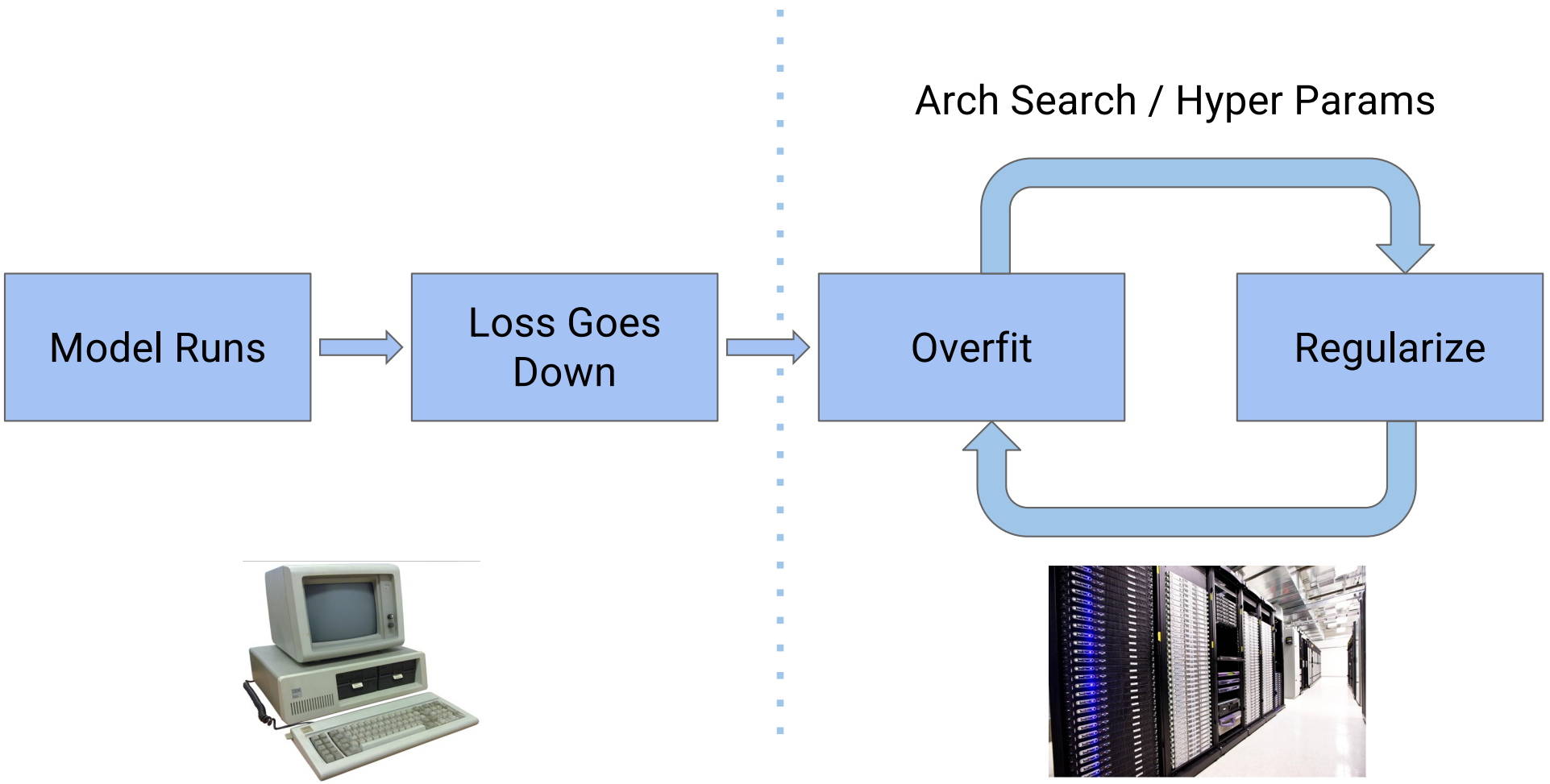
Code

Source:

https://github.com/keveman/tensorflow-tutorial/blob/master/PTB%20Word%20Language%20Modeling.ipynb

```
class LSTMCell(object):
  def __init__(self, state_size):
    self.state_size = state_size
    self.W_f = tf.Variable(self.initializer())
    self.W_i = tf.Variable(self.initializer())
    self.W_o = tf.Variable(self.initializer())
    self.W_C = tf.Variable(self.initializer())
    self.b_f = tf.Variable(tf.zeros([state_size]))
    self.b_i = tf.Variable(tf.zeros([state_size]))
    self.b_o = tf.Variable(tf.zeros([state_size]))
    self.b_C = tf.Variable(tf.zeros([state_size]))
  def __call__(self, x_t, h_t1, C_t1):
    X = tf.concat(1, [h_t1, x_t])
    f_t = tf.sigmoid(tf.matmul(X, self.W_f) + self.b_f)
    i_t = tf.sigmoid(tf.matmul(X, self.W_i) + self.b_i)
    o_t = tf.sigmoid(tf.matmul(X, self.W_o) + self.b_o)
    Ctilde_t = tf.tanh(tf.matmul(X, self.W_C) + self.b_C)
    C_t = f_t * C_t1 + i_t * Ctilde_t
    h_t = o_t * tf.tanh(C_t)
    return h_t, C_t
  def initializer(self):
    return tf.random_uniform([2*self.state_size, self.state_size],
                             -0.1, 0.1)
```

Vicious Cycle



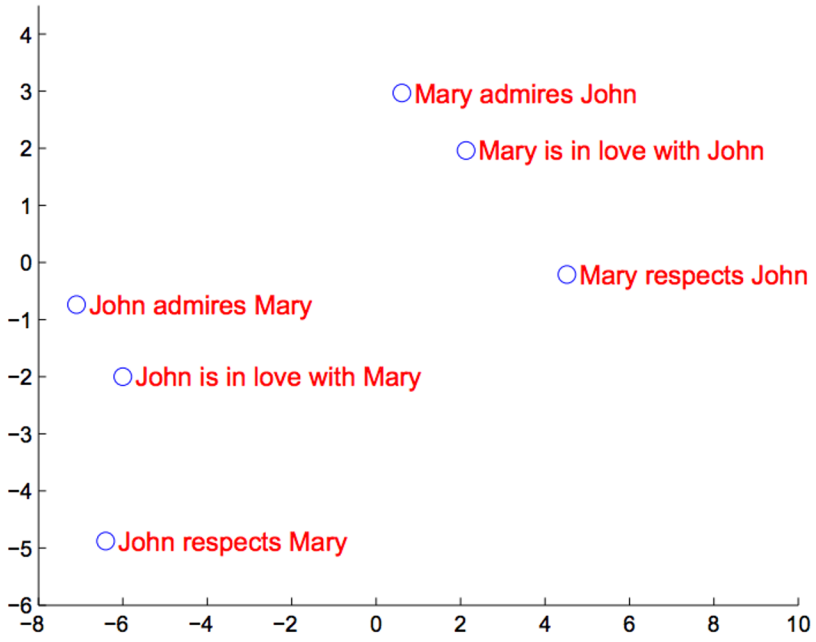
(Some) Tricks of the Trade

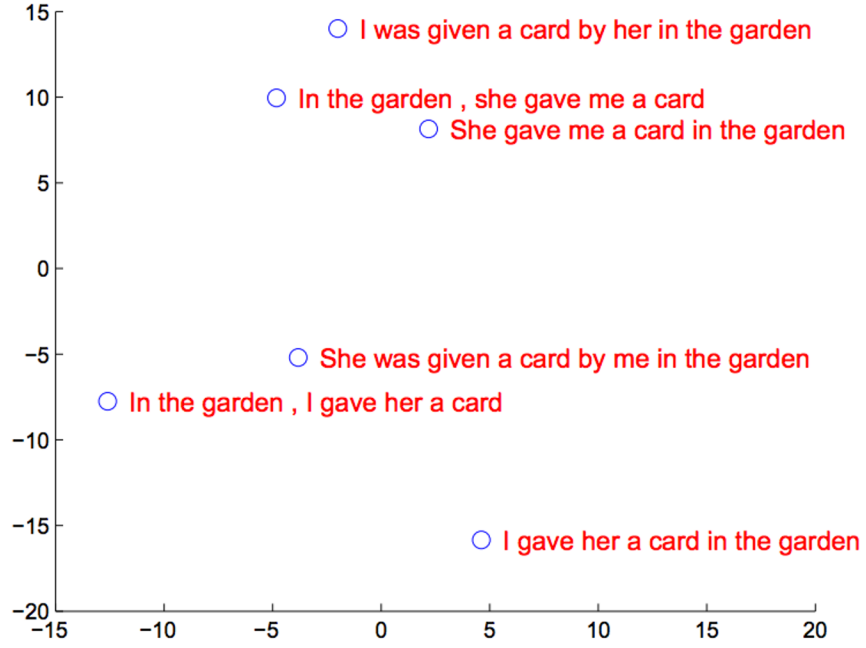
- Long sequences?
  - Attention
  - Bigger state
- Can't overfit?
  - Bigger hidden state
  - Deep LSTM + Skip Connections
- Overfit?
  - Dropout + Ensembles
- Tuning
  - Keep calm and decrease your learning rate
  - Initialization of parameters is critical (in seq2seq we used U(-0.05, 0.05))
  - Clip the gradients!
    - E.g. if ||grad|| > 5: grad = grad/||grad|| * 5

Applications

Machine Translation

Method	test BLEU score (ntst14)
Bahdanau et al. [2]	28.45
Baseline System [29]	33.30
Single forward LSTM, beam size 12	26.17
Single reversed LSTM, beam size 12	30.59
Ensemble of 5 reversed LSTMs, beam size 1	33.00
Ensemble of 2 reversed LSTMs, beam size 12	33.27
Ensemble of 5 reversed LSTMs, beam size 2	34.50
Ensemble of 5 reversed LSTMs, beam size 12	**34.81**

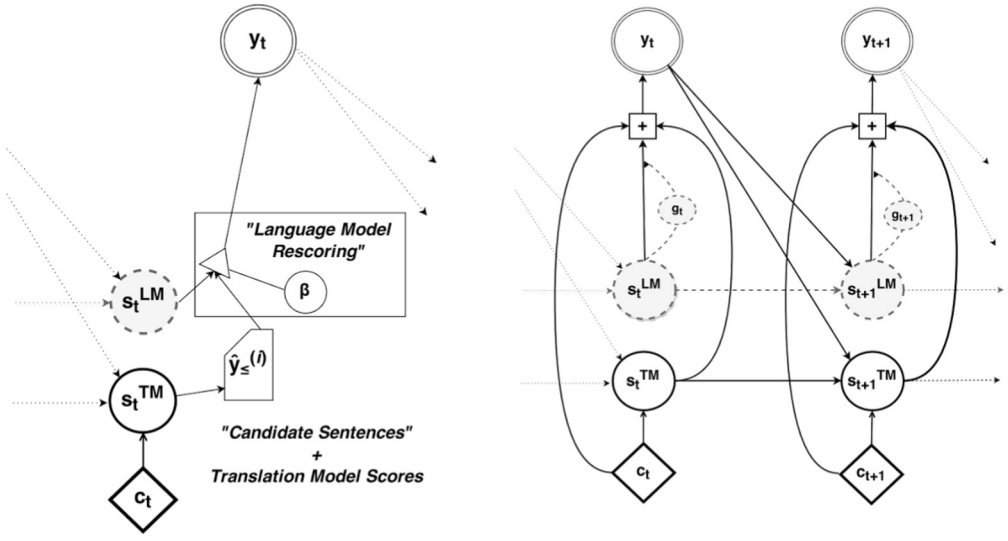




Sutskever, I., et al. “Sequence to Sequence Learning with Neural Networks.” *NIPS (2014)*

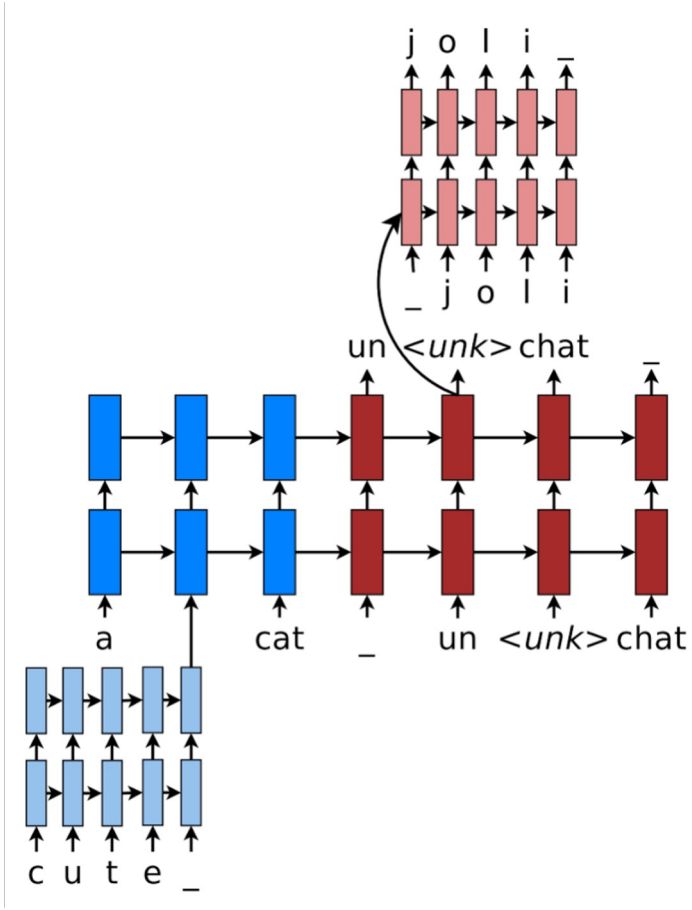
Machine Translation: Concerns

- Using Language Models [1]
- OOV words [2]
- Sequence length



(a) Shallow Fusion (Sec. 4.1)

(b) Deep Fusion (Sec. 4.2)



1. Gulcehre, C., et al. "On using monolingual corpora in neural machine translation." *arXiv* (2015).
2. Luong, T., and Manning, C. "Achieving open vocabulary neural MT with hybrid word-character models." *arXiv* (2016).

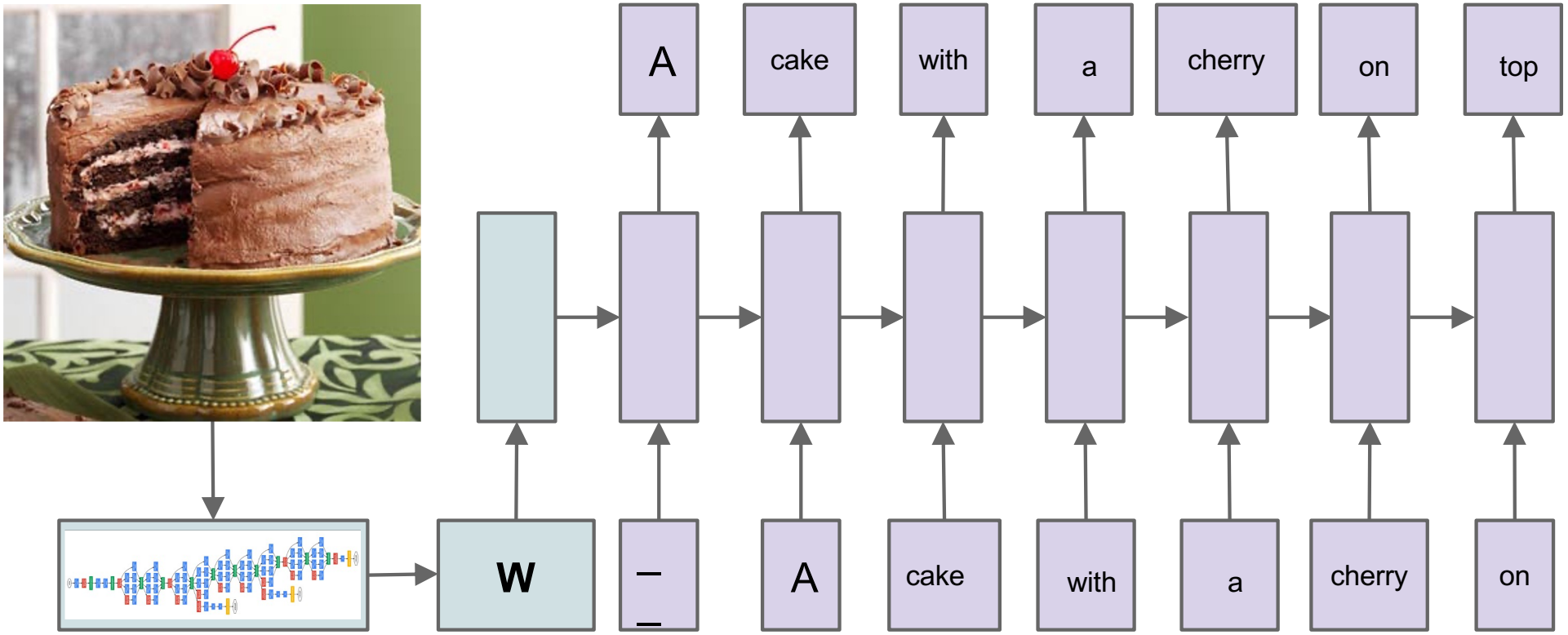
Image Captioning

p(English | French)

p(English | Image)

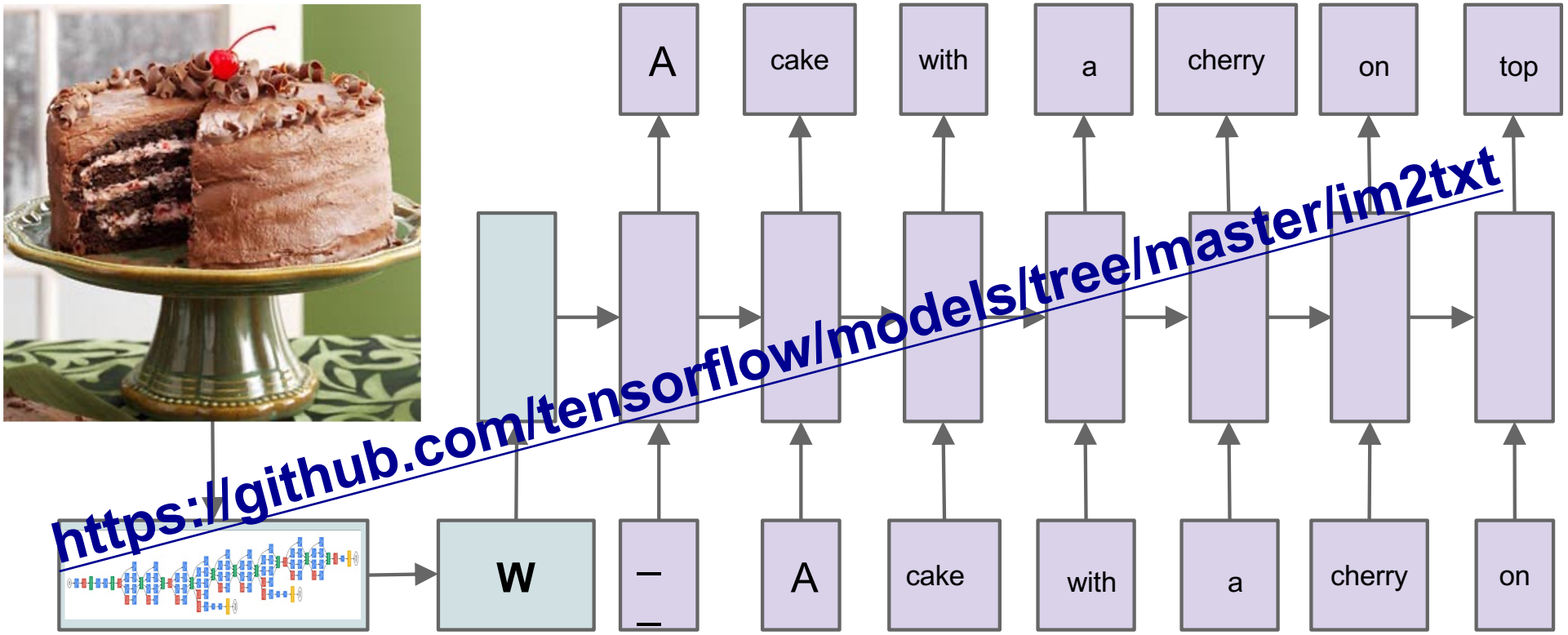
1. Vinyals, O., et al. "Show and Tell: A Neural Image Caption Generator." *CVPR* (2015).
2. Mao, J., et al. "Deep captioning with multimodal recurrent neural networks (m-rnn)." *ICLR (2015).*
3. Karpathy, A., Li, F., "Deep visual-semantic alignments for generating image descriptions." *CVPR (2015)*
4. *Kiros, Zemel, Salakhutdinov, "Unifying Visual-Semantic Embeddings with Multimodal Neural Language Models", TACL 2015*

Image Captioning



$$\theta^{\star} = \arg\max_{\theta} p(S|I)$$

Image Captioning



$$\theta^\star = \arg\max_\theta p(S|I)$$

Image Captioning

a car is parked in
the middle of nowhere .

a wooden table and chairs
arranged in a room .

there is a cat sitting on a shelf .

a ferry boat on a marina
with a group of people .

a little boy with a bunch
of friends on the street .

Image Captioning

Human: A close up of two bananas with bottles in the background.

BestModel: A bunch of bananas and a bottle of wine.

Image Captioning

Human: A woman holding up a yellow banana to her face.

BestModel: A woman holding a banana up to her face.

Image Captioning

Human: A man outside cooking with a sub in his hand.

BestModel: A man is holding a sandwich in his hand.

Image Captioning

Human: Someone is using a small grill to melt his sandwich.

BestModel: A person is cooking some food on a grill.

Image Captioning

Human: A blue , yellow and red train travels across the tracks near a depot.

BestModel: A blue and yellow train traveling down train tracks.

Learning to Execute

- One of the first (modern) examples of learning algorithms
- 2014--??? “era of discovery” → Apply seq2seq to *everything*

Input:

```
j=8584
for x in range(8):
  j+=920
b=(1500+j)
print((b+7567))
```

Target: 25011.

Input:

```
i=8827
c=(i-5347)
print((c+8704) if 2641<8500 else 5308)
```

Target: 12184.

Input:

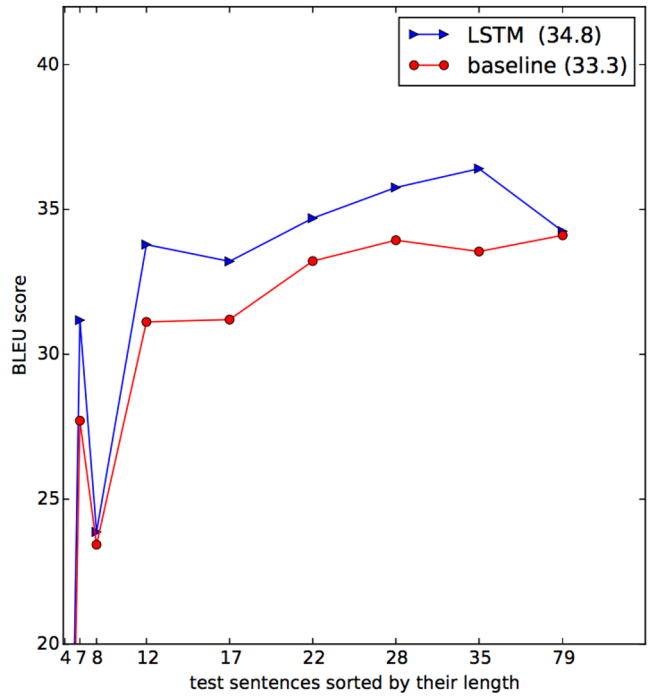
```
vqppkn
sqdvfljmnc
y2vxdddsepnimcbvubkomhrpliibtwztbljipcc
```

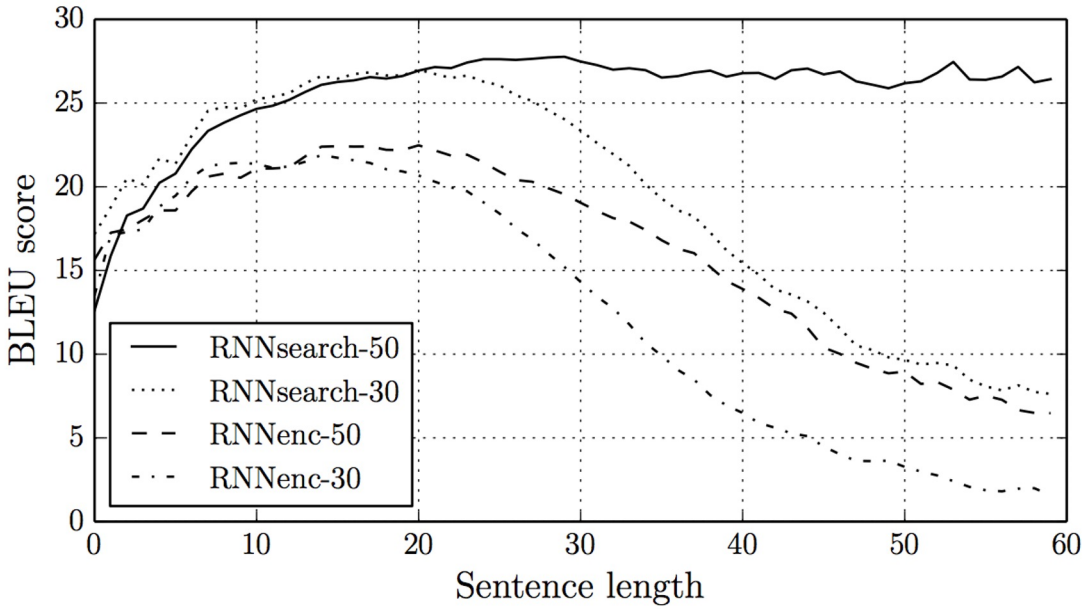
Target: hkhpg

Zaremba, W., Sutskever, I. “Learning To Execute.” *arxiv (2014)*.

Seq2Seq - Limitations

- Fixed Size Embeddings are easily overwhelmed by long inputs or long outputs





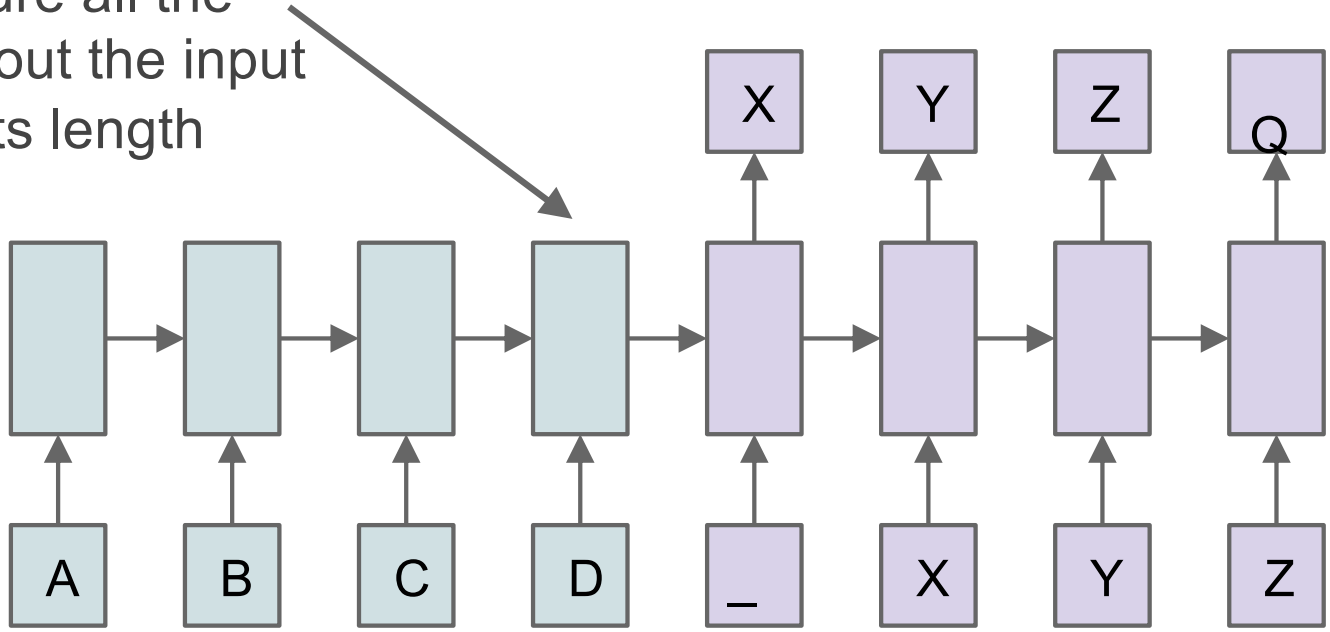
Sutskever, I., et al. “Sequence to Sequence Learning with Neural Networks.” *NIPS (2014)*

Bahdanau, D., et al. “Neural Machine Translation by Jointly Learning to Align and Translate.” *ICLR (2015)*

Attention

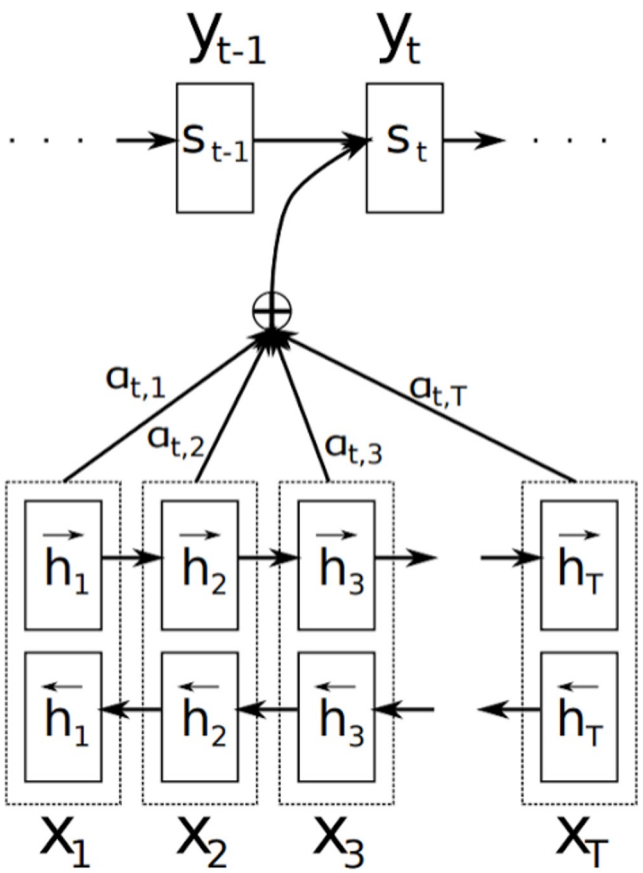
Seq2Seq - The issue with long inputs

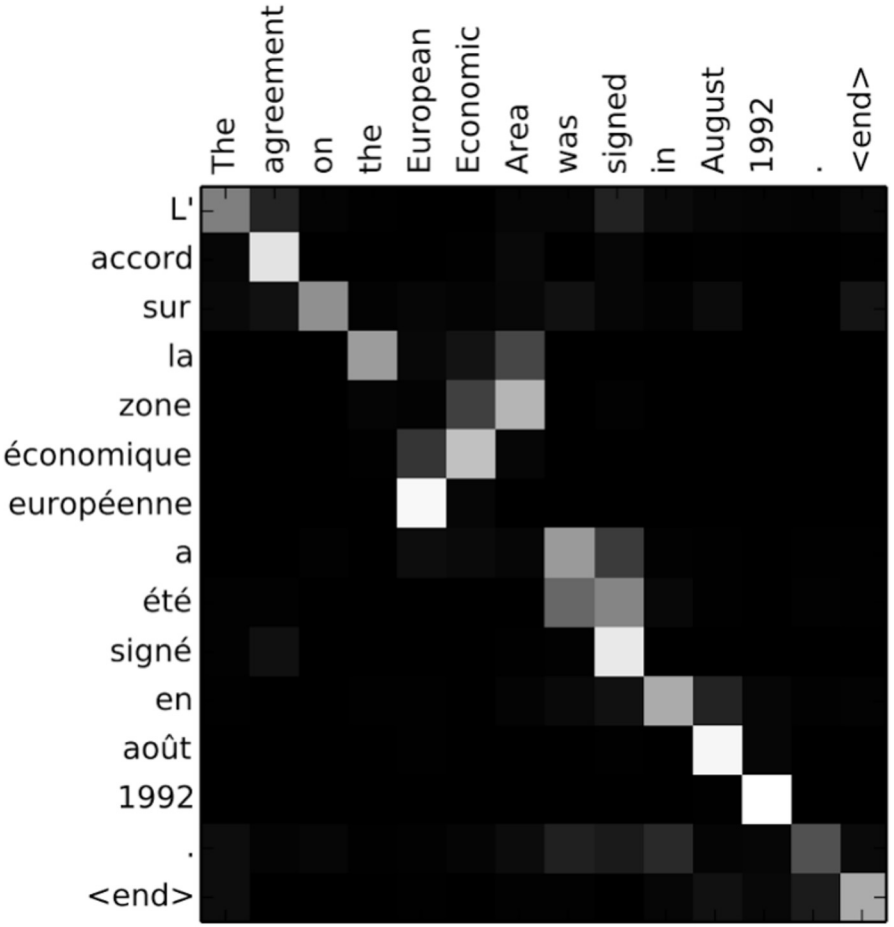
- Same embedding informs the entire output
- Needs to capture all the information about the input regardless of its length



Is there a better way to pass the information from encoder to the decoder ?

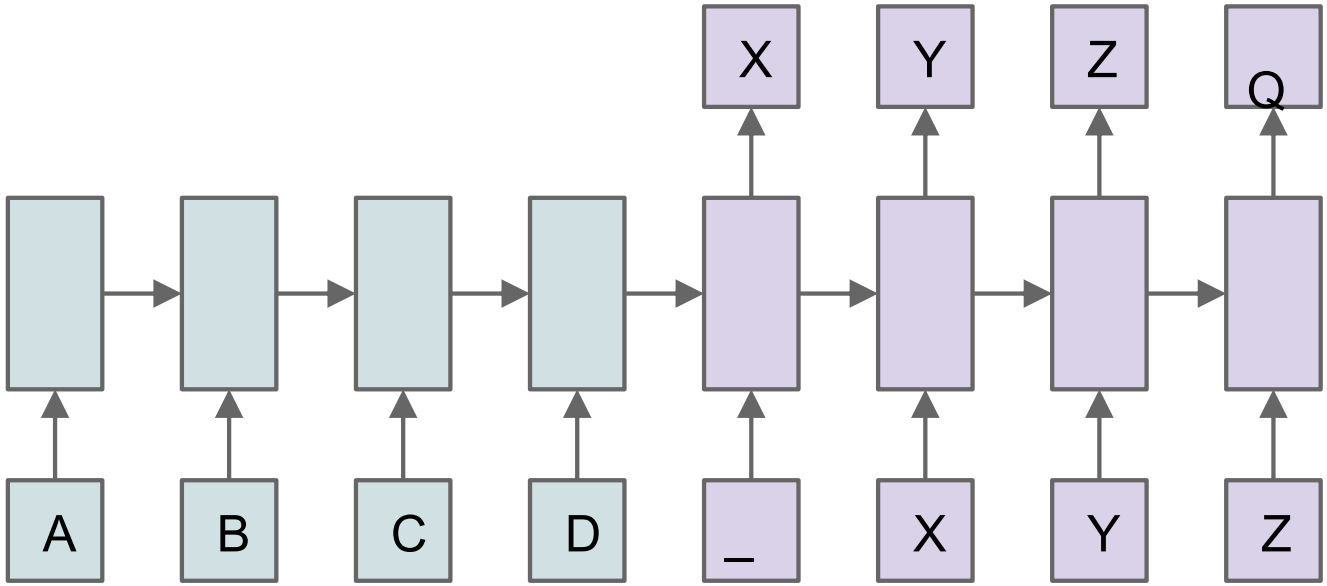
Seq2Seq with Attention





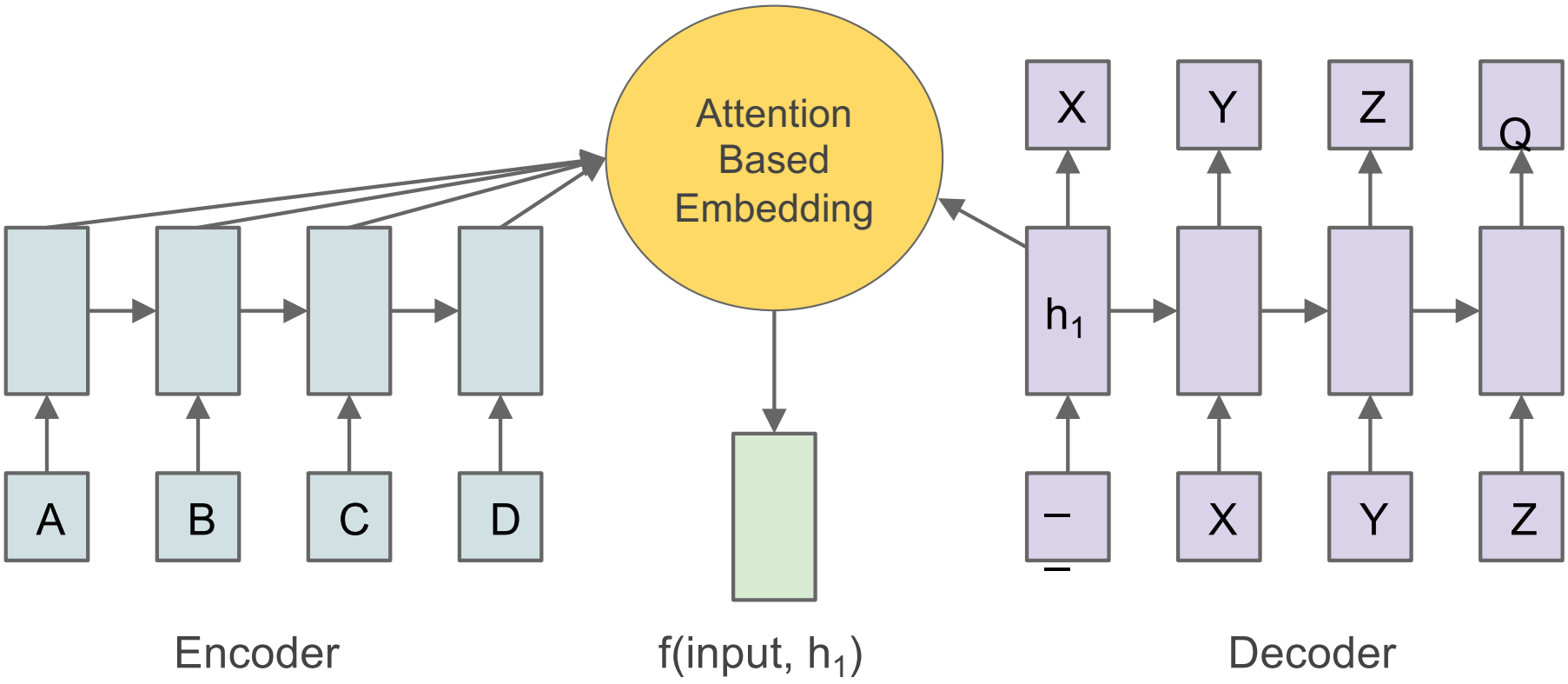
Bahdanau, D., et al. “Neural Machine Translation by Jointly Learning to Align and Translate.” *ICLR (2015)*

Seq2Seq



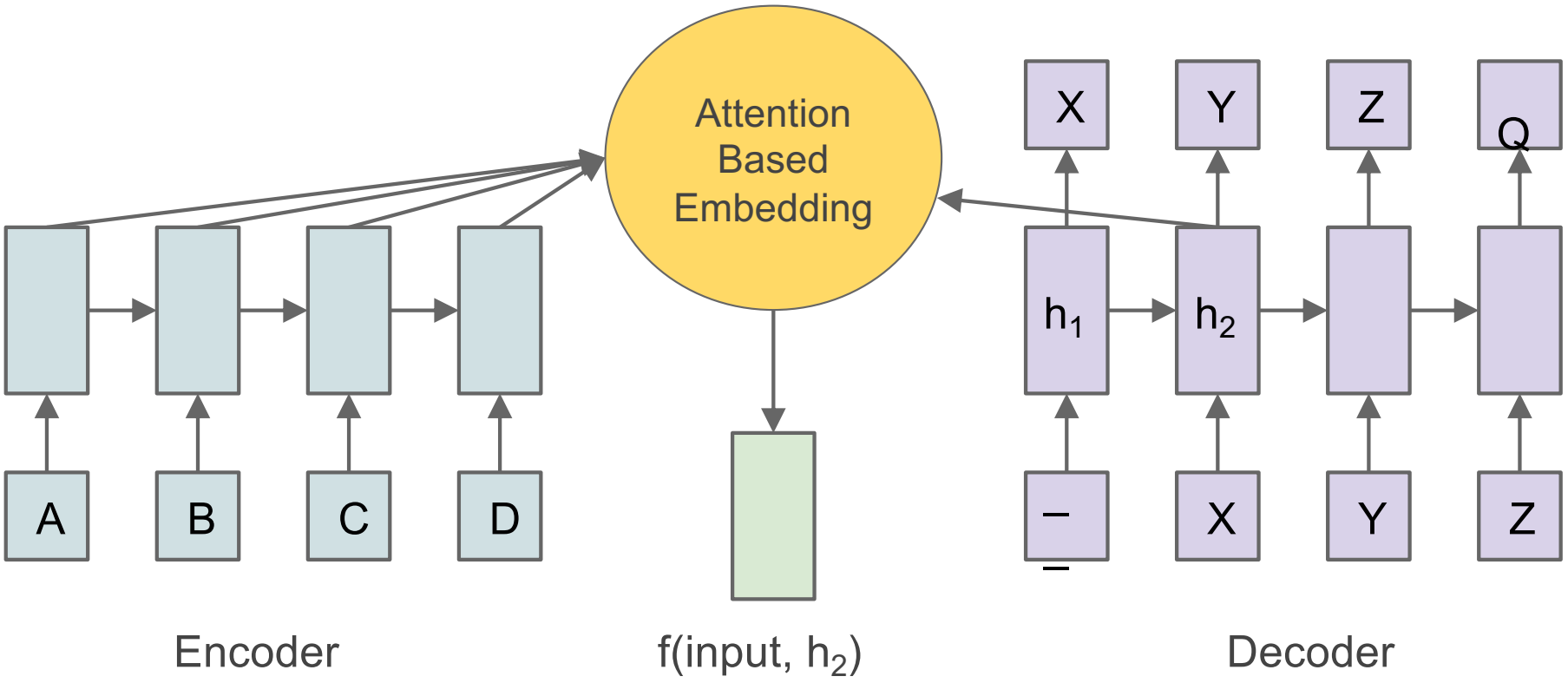
Seq2Seq with Attention

- A different embedding computed for every output step



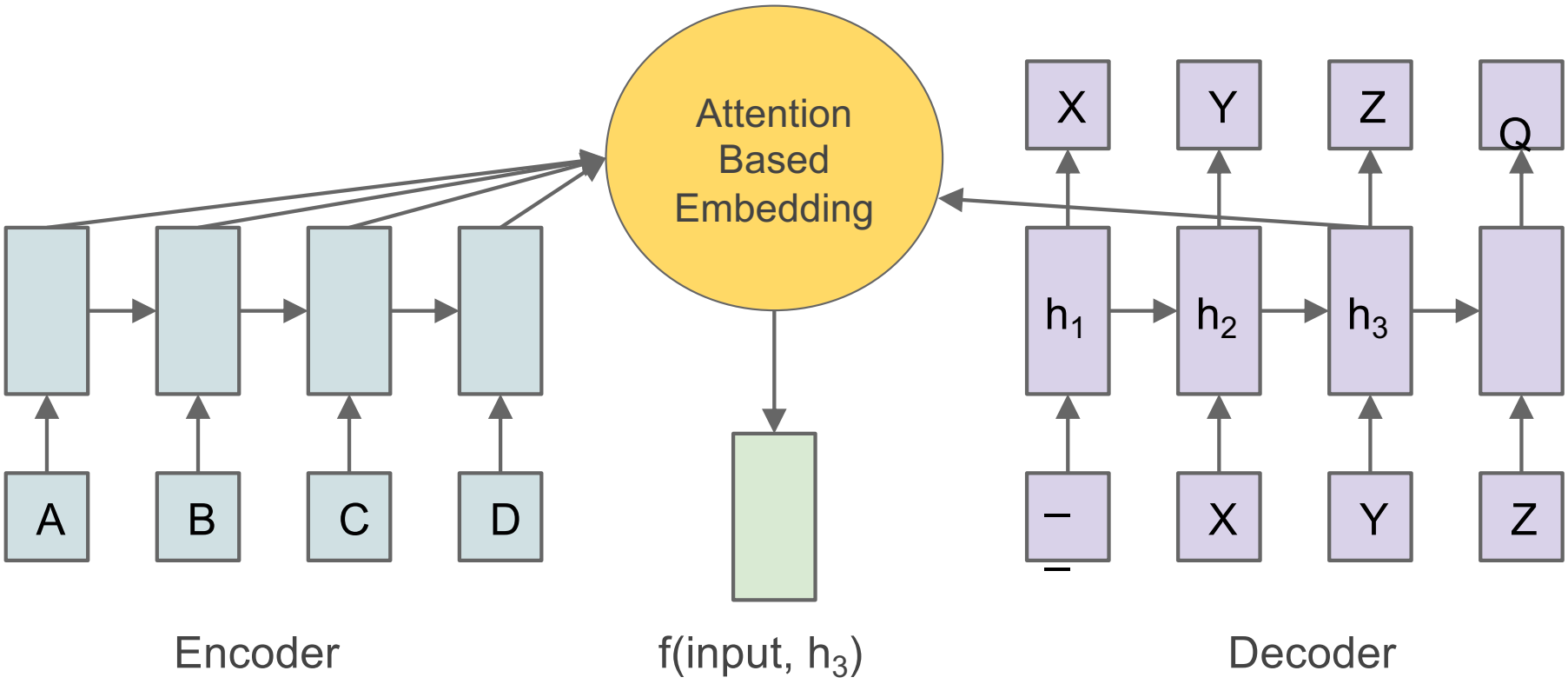
Seq2Seq with Attention

- A different embedding computed for every output step



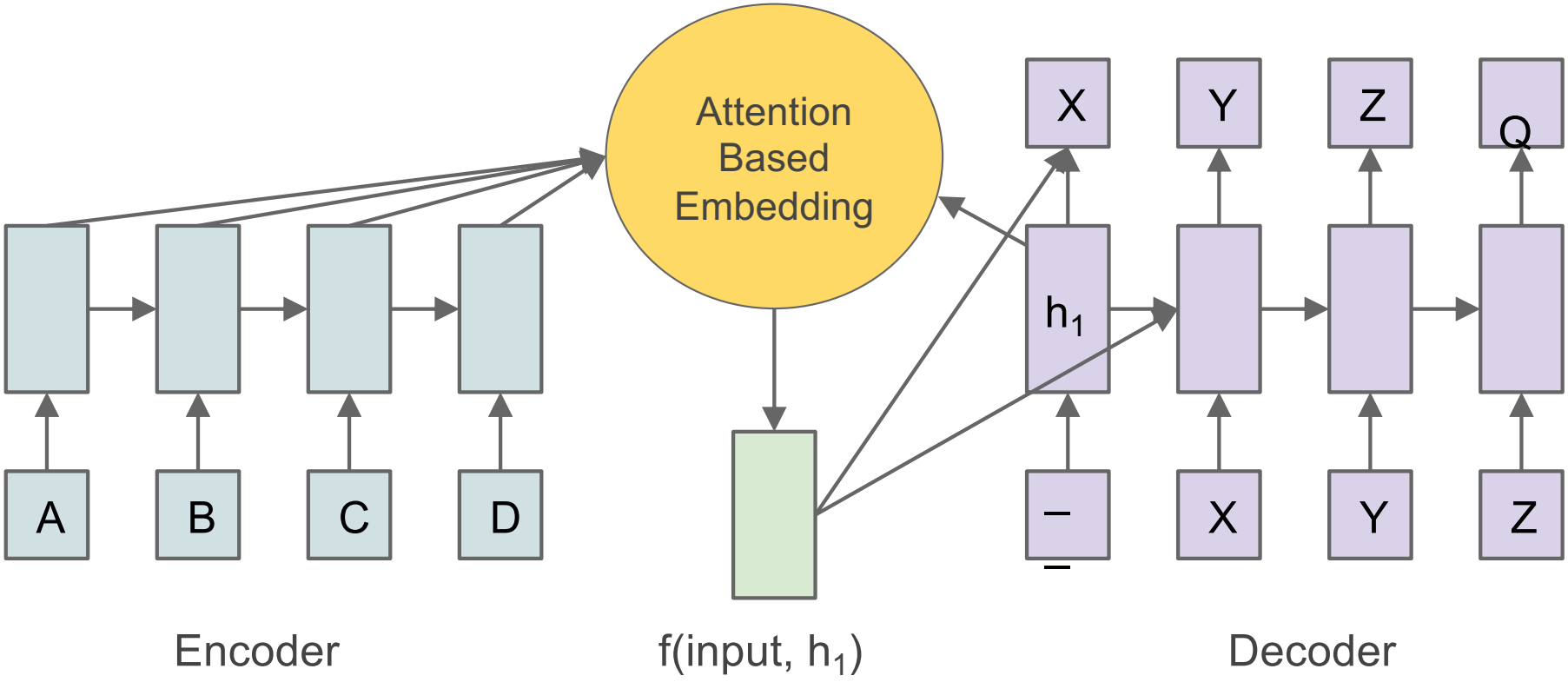
Seq2Seq with Attention

- A different embedding computed for every output step



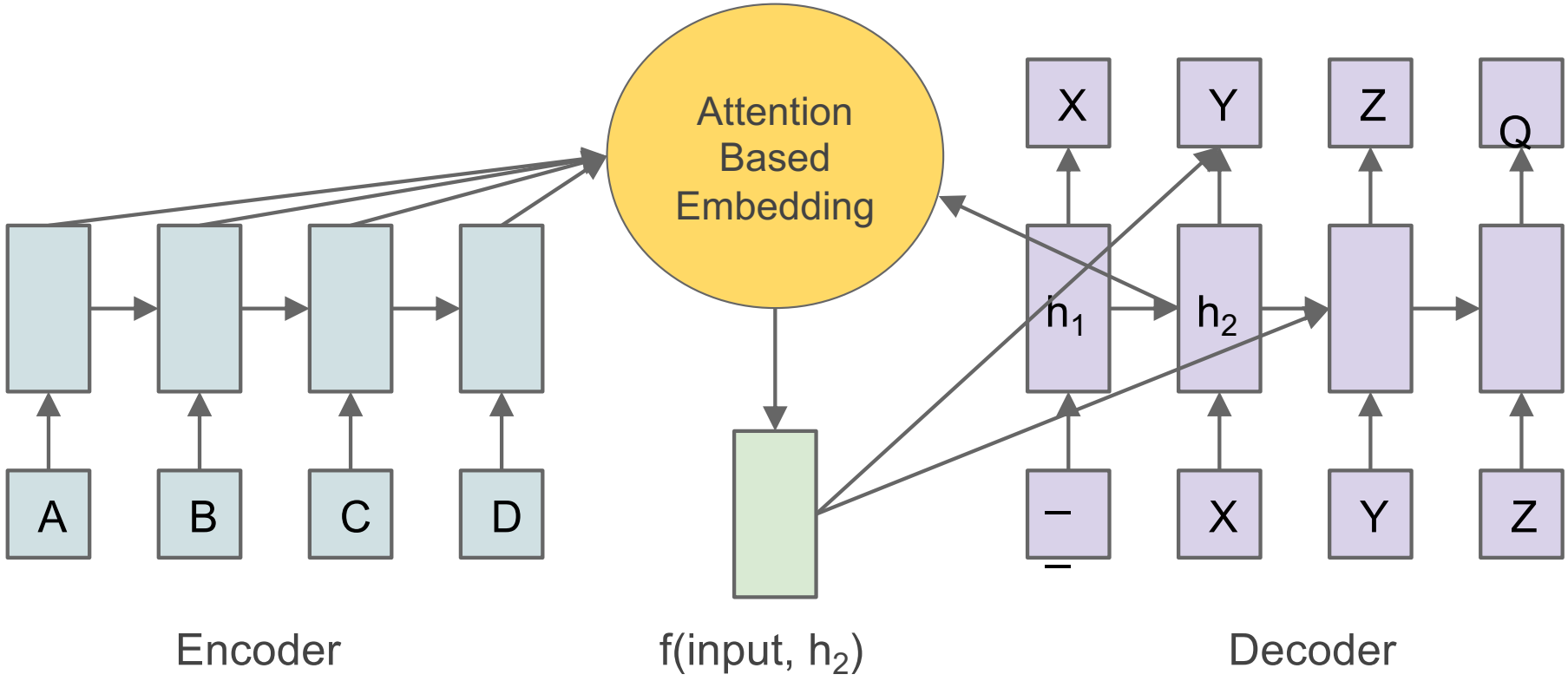
Seq2Seq with Attention

- Embedding used to predict output, and compute next hidden state



Seq2Seq with Attention

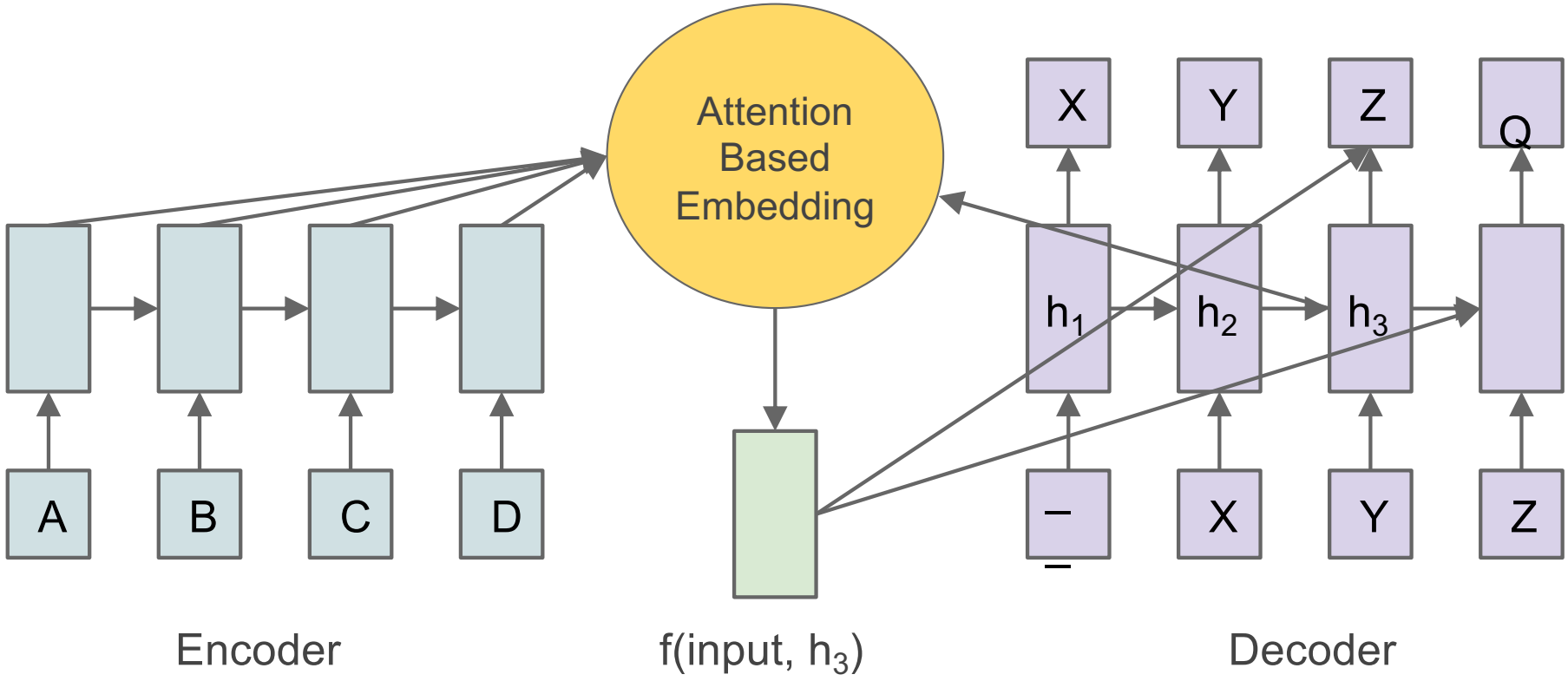
- Embedding used to predict output, and compute next hidden state



- Attention arrows for step 1 omitted

Seq2Seq with Attention

- Embedding used to predict output, and compute next hidden state



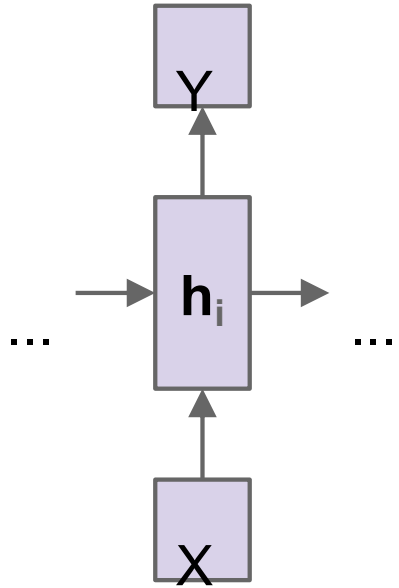
- Attention arrows for steps 1 and 2 omitted

Attention Based Embedding

- Linear blending of embedding RNN states $\mathbf{e}_1$ $\mathbf{e}_2$ $\mathbf{e}_3$ $\mathbf{e}_4$ is a natural choice
- How to produce the coefficients (attention vector) for blending ?
  - Content based coefficients based on query state $\mathbf{h}_i$ and embedding RNN states $\mathbf{e}_1$ $\mathbf{e}_2$ $\mathbf{e}_3$ $\mathbf{e}_4$

Dot product Attention

- Inputs: “I am a cat.”
- Input RNN states: $\mathbf{e_1}$ $\mathbf{e_2}$ $\mathbf{e_3}$ $\mathbf{e_4}$
- Decoder RNN state at step i (query): $\mathbf{h_i}$
- Compute scalars $\mathbf{h_i^T e_1}$, $\mathbf{h_i^T e_2}$, $\mathbf{h_i^T e_3}$, $\mathbf{h_i^T e_4}$ representing similarity / relevance between encoder steps and query.
- Normalize $\mathbf{[h_i^T e_1, h_i^T e_2, h_i^T e_3, h_i^T e_4]}$ with softmax to produce attention weights, e.g. [0.0 0.05 0.9 0.05]



Content Based Attention

Attention [Bahdanau, Cho and Bengio, 2014]

$$u_j = v^T \tanh(W_1 e_j + W_2 d) \quad j \in (1, \ldots, n)$$

$$a_j = \text{softmax}(u_j) \quad j \in (1, \ldots, n)$$

$$d' = \sum_{j=1}^{n} a_j e_j$$

Graves, A., et al. “Neural Turing Machines.” *arxiv (2014)*

Weston, J., et al. “Memory Networks.” *arxiv (2014)*

Other strategies for attention models

- Tensored attention
  - Minh-Thang Luong, Hieu Pham, and Christopher D. Manning. “Effective Approaches to Attention-based Neural Machine Translation.” EMNLP’15.
- Multiple heads
- Pyramidal encoders
  - William Chan, Navdeep Jaitly, Quoc Le, Oriol Vinyals. “Listen Attend and Spell”. ICASSP 2015.
- Hierarchical Attention
  - Andrychowicz, Marcin, and Karol Kurach. "Learning efficient algorithms with hierarchical attentive memory." *arXiv preprint arXiv:1602.03218* (2016).
- Hard Attention
  - Xu, Kelvin, et al. “Show, attend and tell: Neural image caption generation with visual attention.” ICML 2015