CS11-747 Neural Networks for NLP

# Attention

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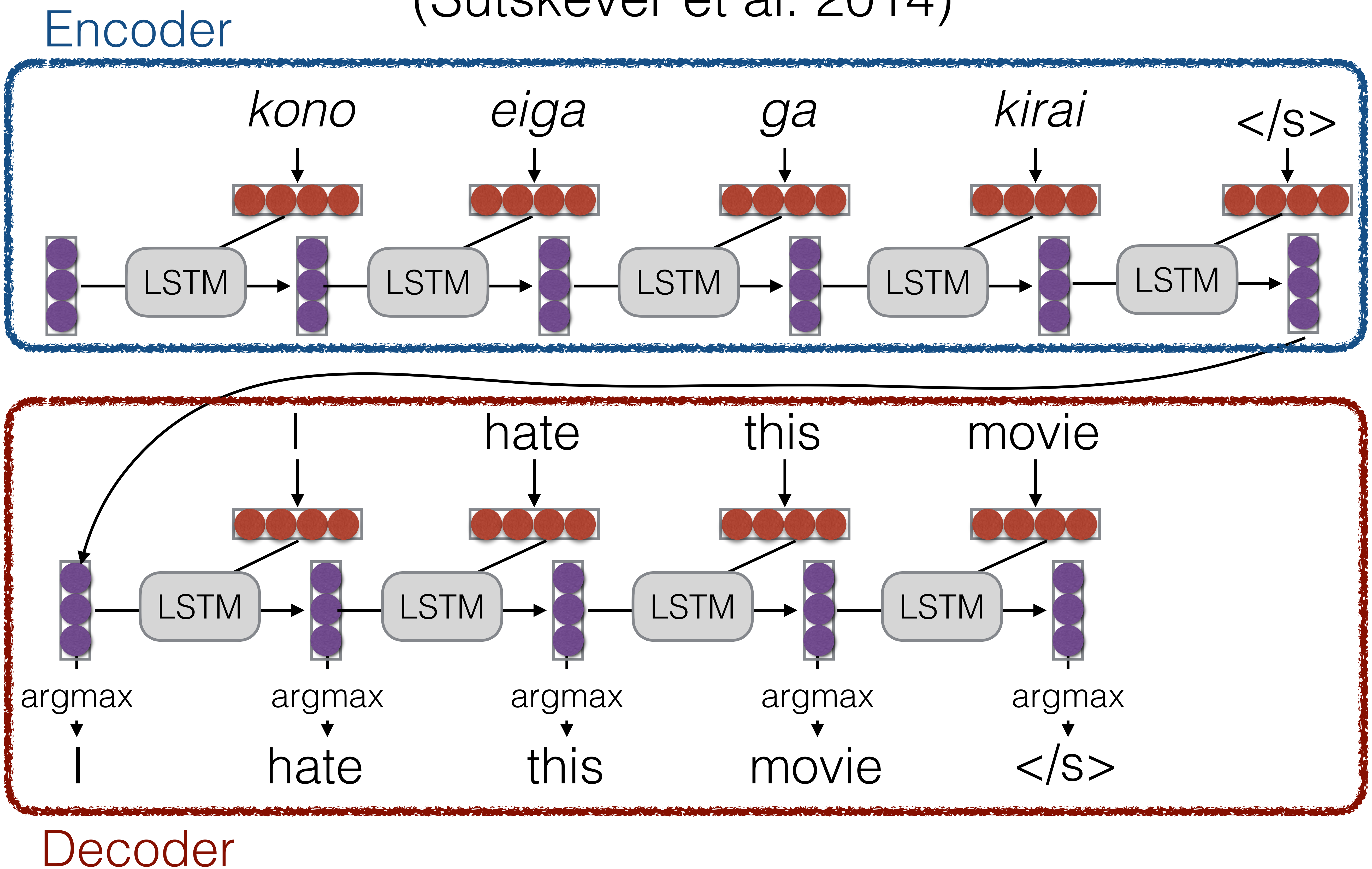
Site

https://phontron.com/class/nn4nlp2021/

# Encoder-decoder Models

(Sutskever et al. 2014)



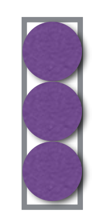
# Sentence Representations

**Problem!**

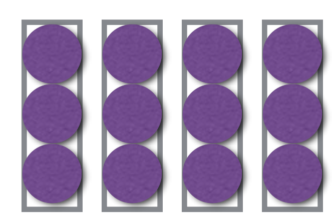
> "You can't cram the meaning of a whole %&!$ing sentence into a single $&!*ing vector!"
> — Ray Mooney

- But what if we could use multiple vectors, based on the length of the sentence.

this is an example →



this is an example →



# Attention

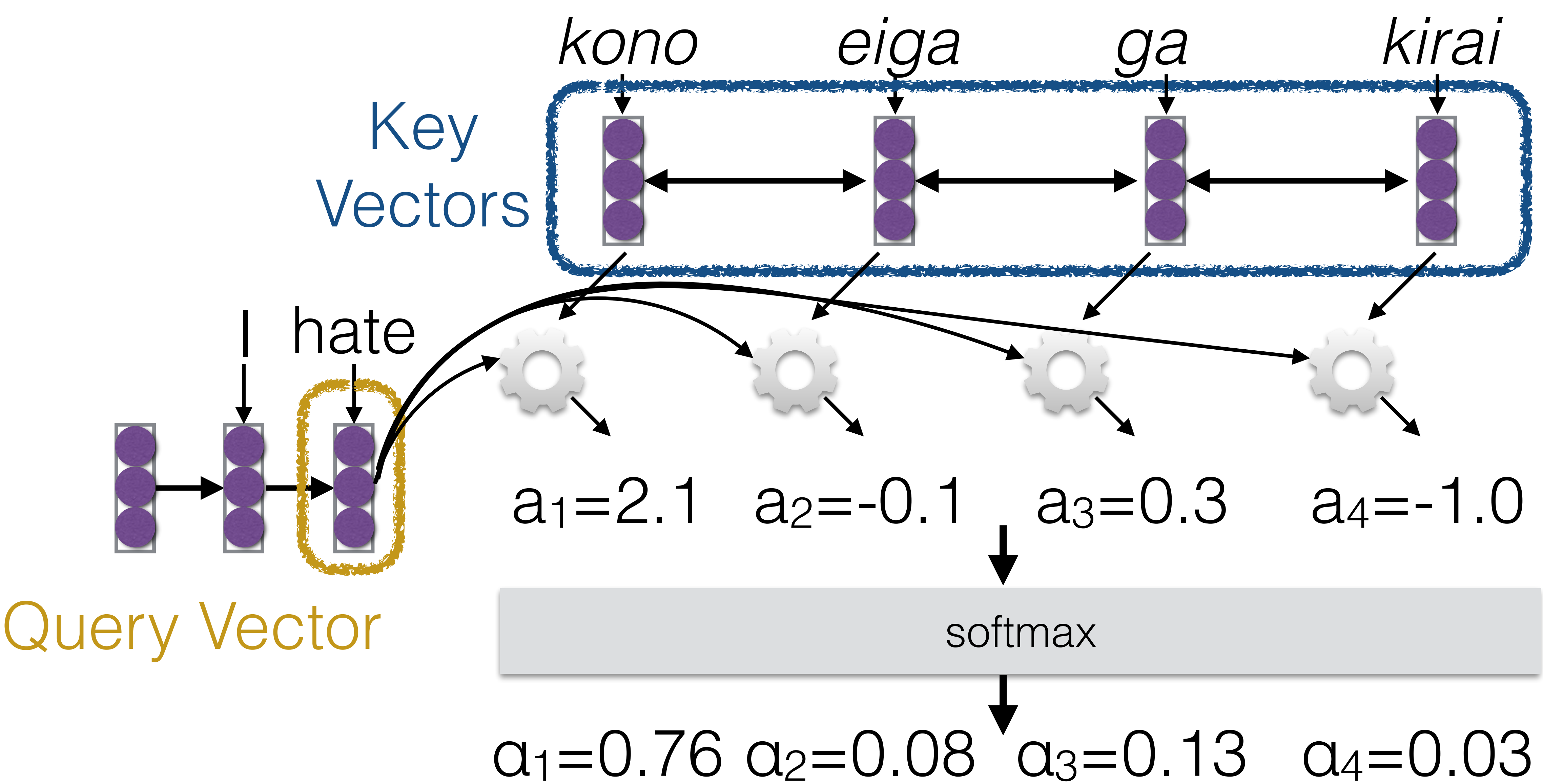
# Basic Idea

## (Bahdanau et al. 2015)

- Encode each word in the sentence into a vector
- When decoding, perform a linear combination of these vectors, weighted by “attention weights”
- Use this combination in picking the next word

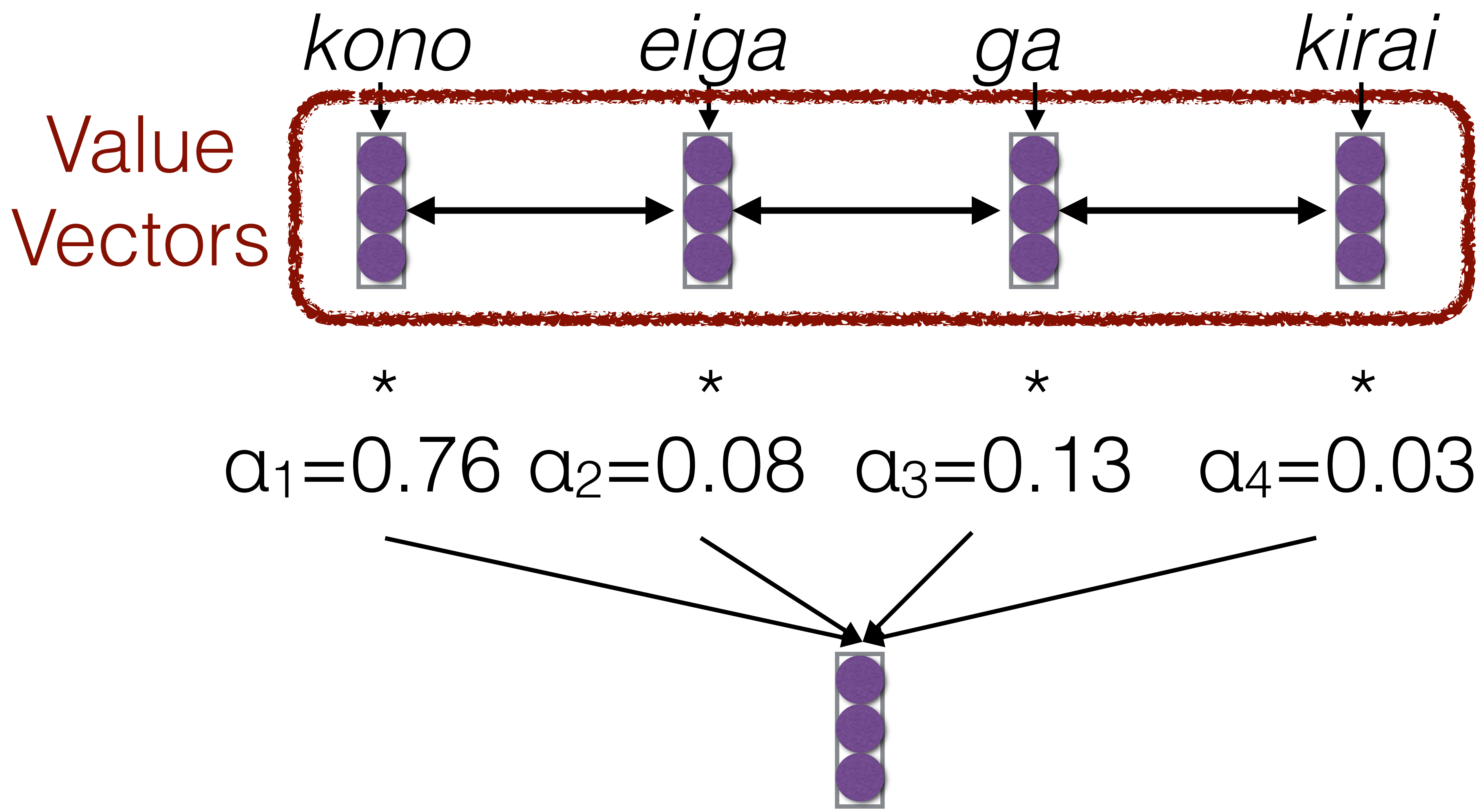
# Calculating Attention (1)

- Use “query” vector (decoder state) and “key” vectors (all encoder states)
- For each query-key pair, calculate weight
- Normalize to add to one using softmax



# Calculating Attention (2)

- Combine together value vectors (usually encoder states, like key vectors) by taking the weighted sum




- Use this in any part of the model you like

# A Graphical Example

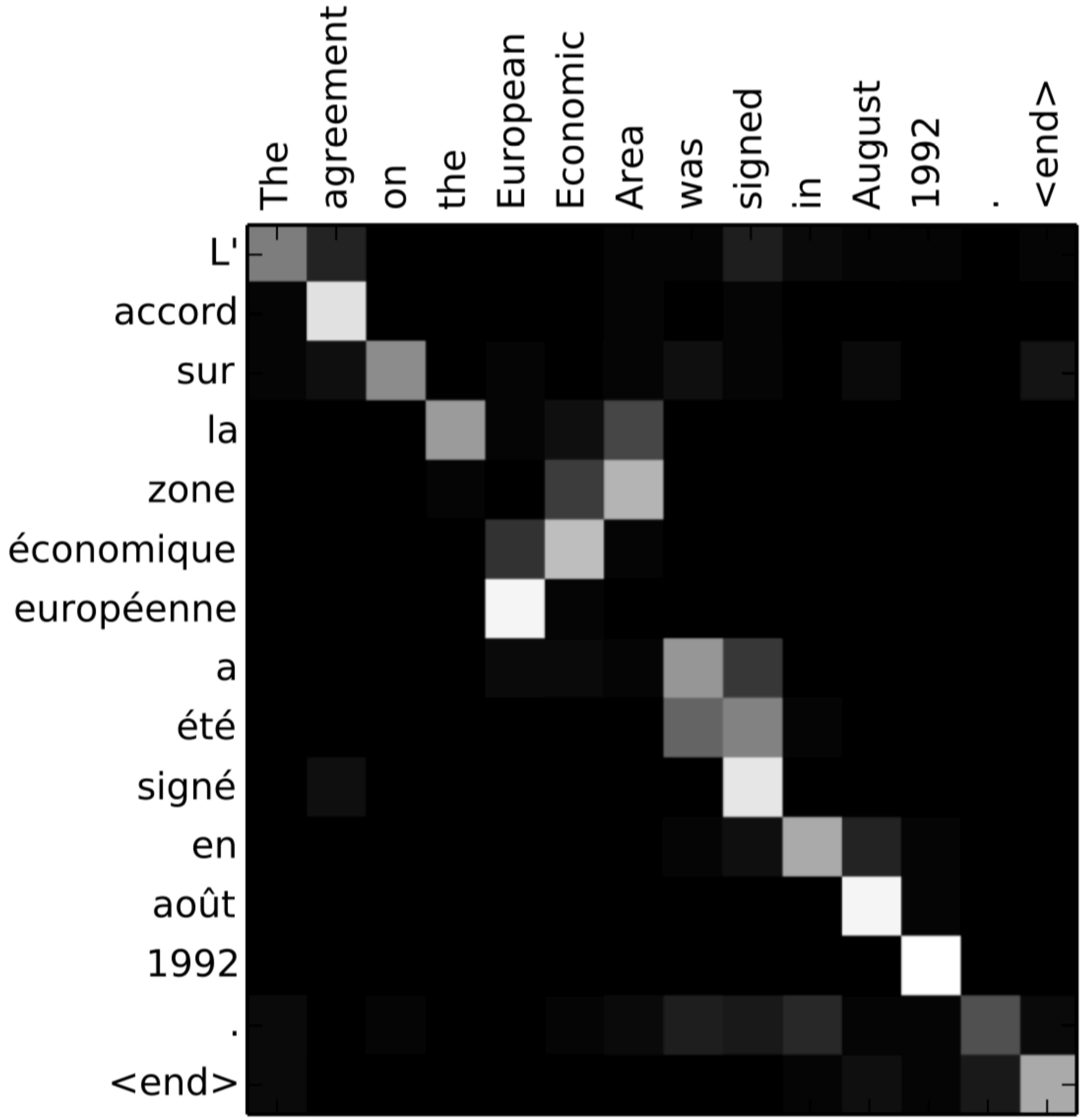
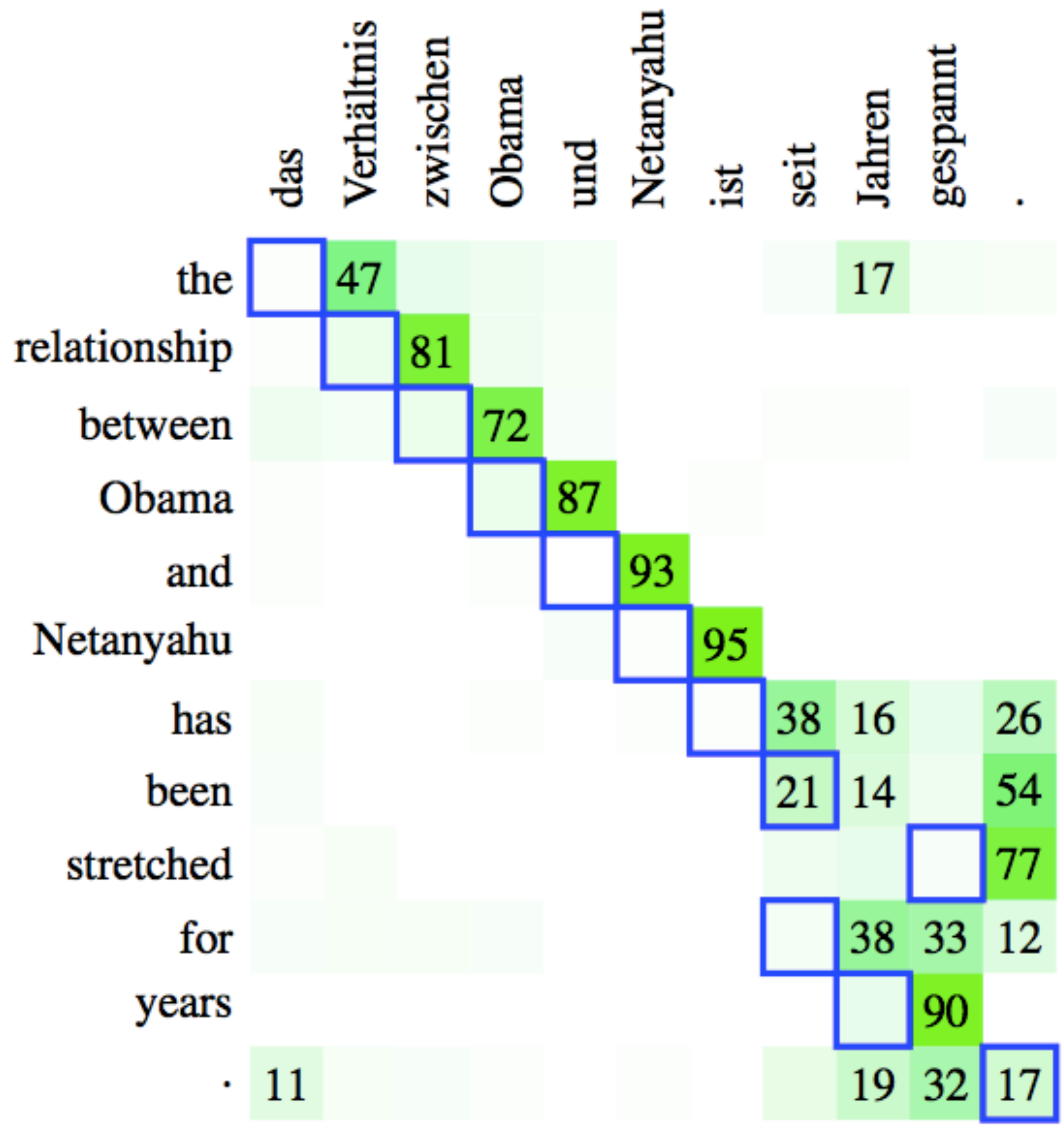



Image from Bahdanau et al. (2015)

# Attention is not Alignment!
## (Koehn and Knowles 2017)

- Attention is often blurred
- Attention is often off by one
- It can even be manipulated to be non-intuitive! (Jain and Wallace 2019, Pruthi et al. 2020)



# Attention Score Functions (1)

- $\boldsymbol{q}$ is the query and $\boldsymbol{k}$ is the key
- **Multi-layer Perceptron** (Bahdanau et al. 2015)

$$a(\boldsymbol{q}, \boldsymbol{k}) = \boldsymbol{w}_2^{\intercal} \tanh(W_1[\boldsymbol{q}; \boldsymbol{k}])$$

  - Flexible, often very good with large data
- **Bilinear** (Luong et al. 2015)

$$a(\boldsymbol{q}, \boldsymbol{k}) = \boldsymbol{q}^{\intercal} W \boldsymbol{k}$$

# Attention Score Functions (2)

- **Dot Product** (Luong et al. 2015)

$$a(\boldsymbol{q}, \boldsymbol{k}) = \boldsymbol{q}^\intercal \boldsymbol{k}$$

  - No parameters! But requires sizes to be the same.

- **Scaled Dot Product** (Vaswani et al. 2017)

  - *Problem:* scale of dot product increases as dimensions get larger

  - *Fix:* scale by size of the vector

$$a(\boldsymbol{q}, \boldsymbol{k}) = \frac{\boldsymbol{q}^\intercal \boldsymbol{k}}{\sqrt{|\boldsymbol{k}|}}$$

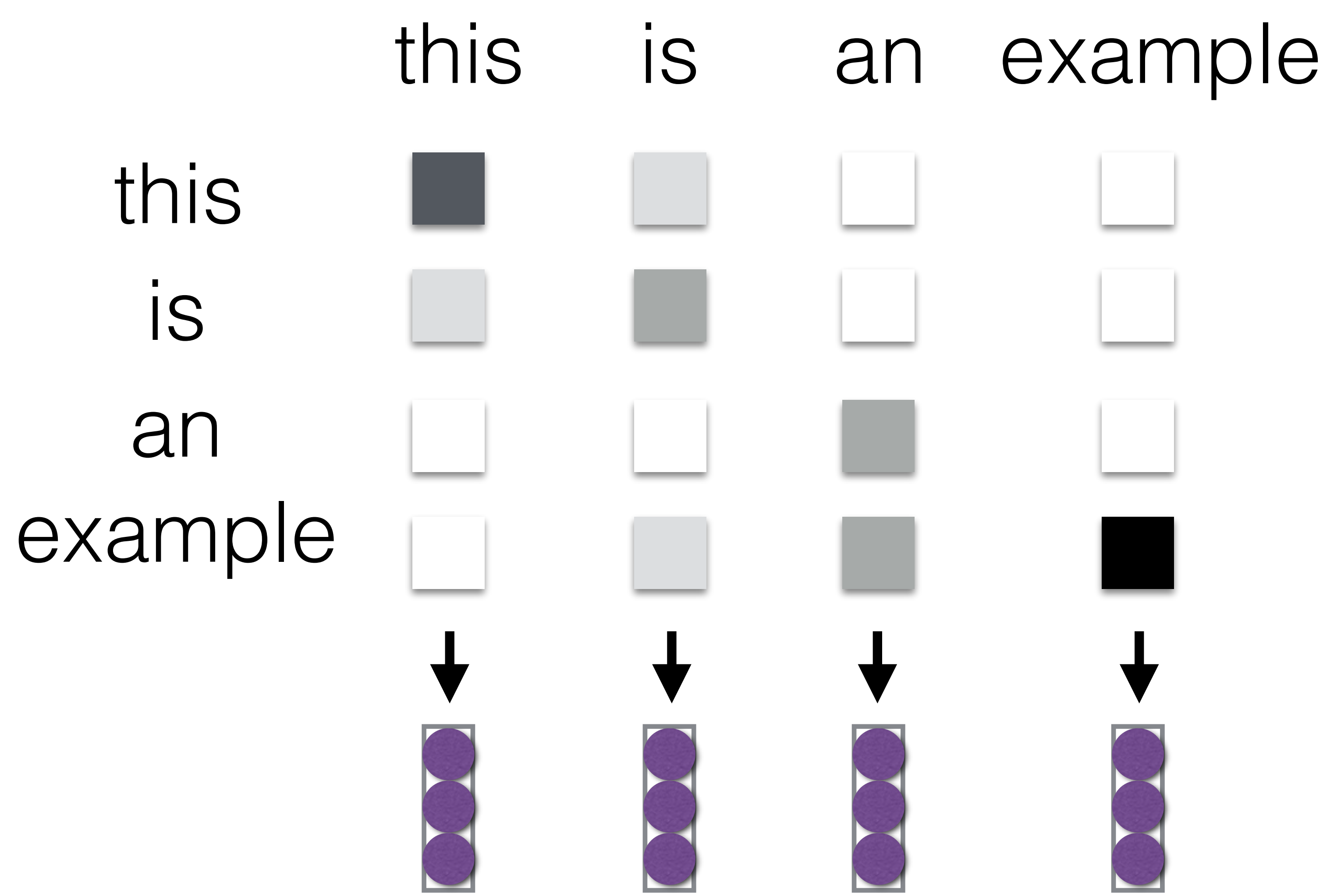
# Let's Try it Out!

`batched_attention.py`

**Try it Yourself:** This code uses MLP attention. What would you do to implement a different variety of attention?

# Self Attention
## (Cheng et al. 2016, Vaswani et al. 2017)

- Each element in the sentence attends to other elements → context sensitive encodings!



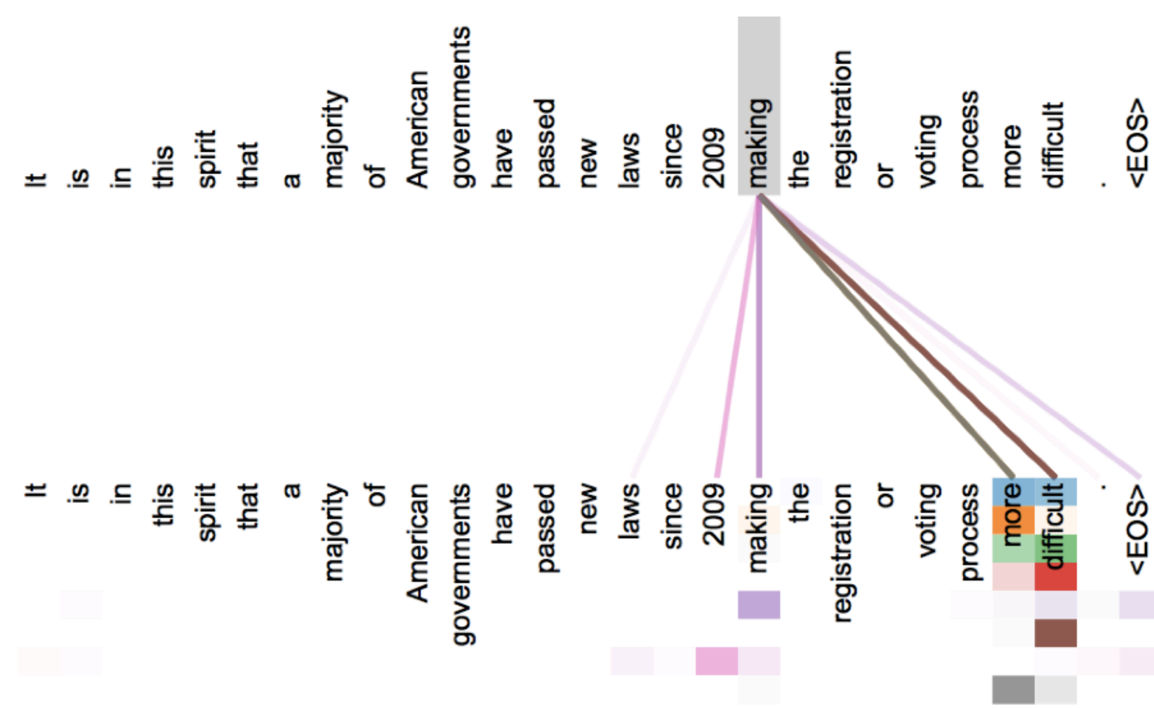
# Multi-headed Attention

- **Idea:** multiple attention "heads" focus on different parts of the sentence

- e.g. Different heads for "copy" vs regular (Allamanis et al. 2016)

| | Target | | Attention Vectors | $\lambda$ |
|---|---|---|---|---|
| $m_1$ | set | $\boldsymbol{\alpha} =$ | <s> { this . use Browser Cache = use Browser Cache ; } </s> | 0.012 |
| | | $\boldsymbol{\kappa} =$ | <s> { this . use Browser Cache = use Browser Cache ; } </s> | |
| $m_2$ | use | $\boldsymbol{\alpha} =$ | <s> { this . use Browser Cache = use Browser Cache ; } </s> | 0.974 |
| | | $\boldsymbol{\kappa} =$ | <s> { this . use Browser Cache = use Browser Cache ; } </s> | |
| $m_3$ | browser | $\boldsymbol{\alpha} =$ | <s> { this . use Browser Cache = use Browser Cache ; } </s> | 0.969 |
| | | $\boldsymbol{\kappa} =$ | <s> { this . use Browser Cache = use Browser Cache ; } </s> | |
| $m_4$ | cache | $\boldsymbol{\alpha} =$ | <s> { this . use Browser Cache = use Browser Cache ; } </s> | 0.583 |
| | | $\boldsymbol{\kappa} =$ | <s> { this . use Browser Cache = use Browser Cache ; } </s> | |
| $m_5$ | END | $\boldsymbol{\alpha} =$ | <s> { this . use Browser Cache = use Browser Cache ; } </s> | 0.066 |
| | | $\boldsymbol{\kappa} =$ | <s> { this . use Browser Cache = use Browser Cache ; } </s> | |

- Or multiple independently learned heads (Vaswani et al. 2017)



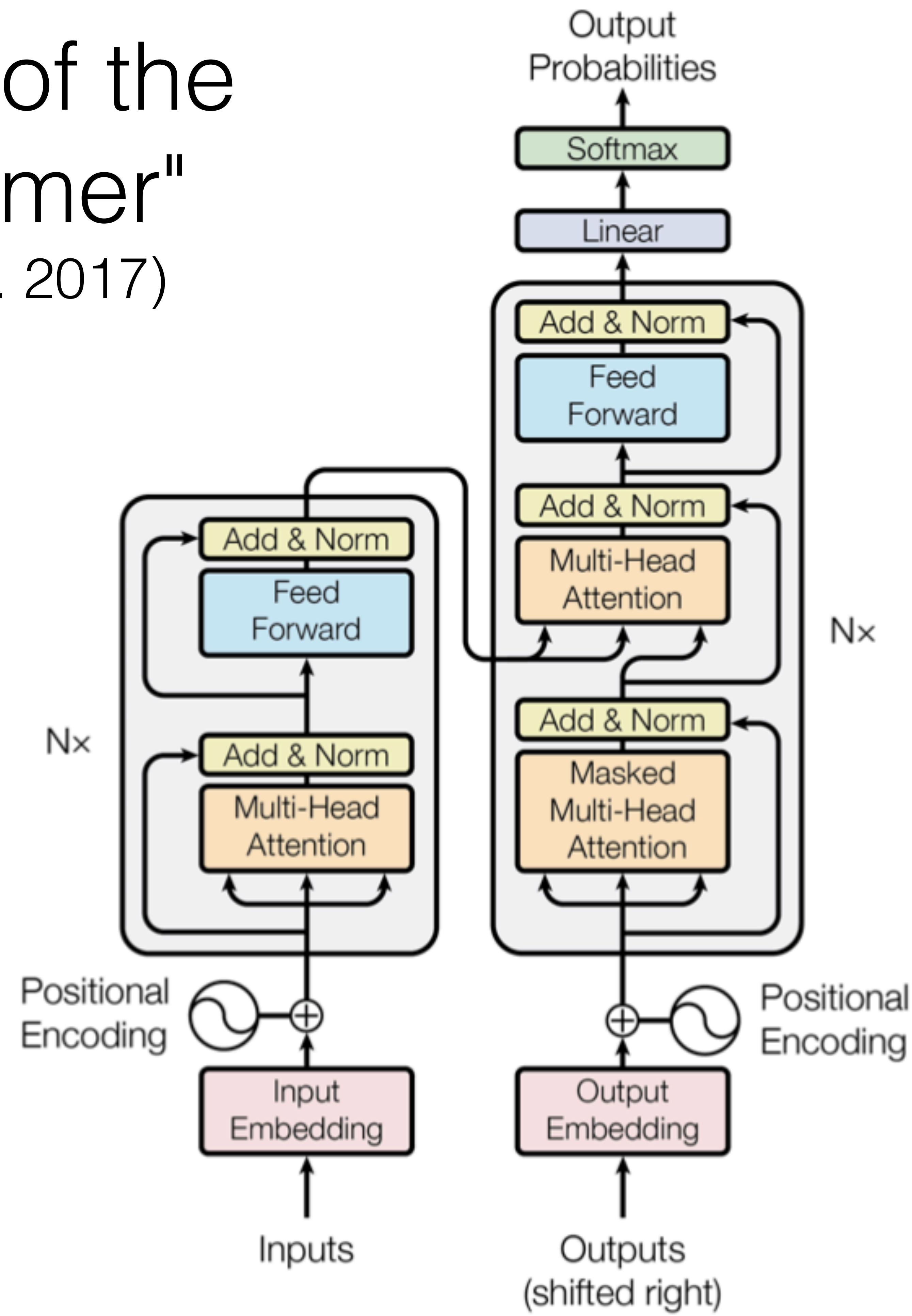

- Or one head for every hidden node! (Choi et al. 2018)

# An Interesting Case Study: “Attention is All You Need”

(Vaswani et al. 2017)

# Summary of the "Transformer" (Vaswani et al. 2017)

- A sequence-to-sequence model based entirely on attention
- Strong results on translation, a wide variety of other tasks
- Fast: only matrix multiplications



# Attention Tricks

- **Self Attention:** Each layer combines words with others
- **Multi-headed Attention:** 8 attention heads learned independently
- **Normalized Dot-product Attention:** Remove bias in dot product when using large networks
- **Positional Encodings:** Make sure that even if we don’t have RNN, can still distinguish positions

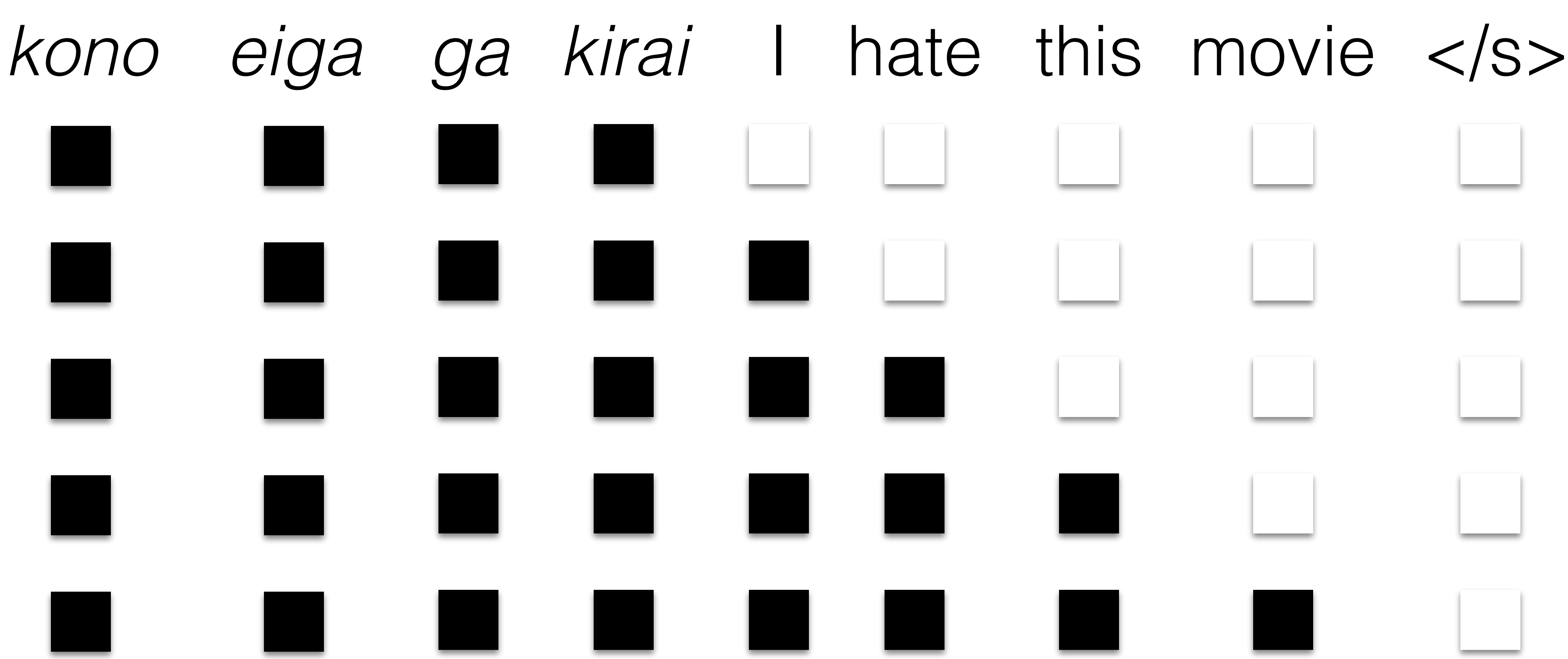
# Training Tricks

- **Layer Normalization:** Help ensure that layers remain in reasonable range
- **Specialized Training Schedule:** Adjust default learning rate of the Adam optimizer
- **Label Smoothing:** Insert some uncertainty in the training process
- **Masking for Efficient Training**

# Masking for Training

- We want to perform training in as few operations as possible using big matrix multiplies

- We can do so by "masking" the results for the output



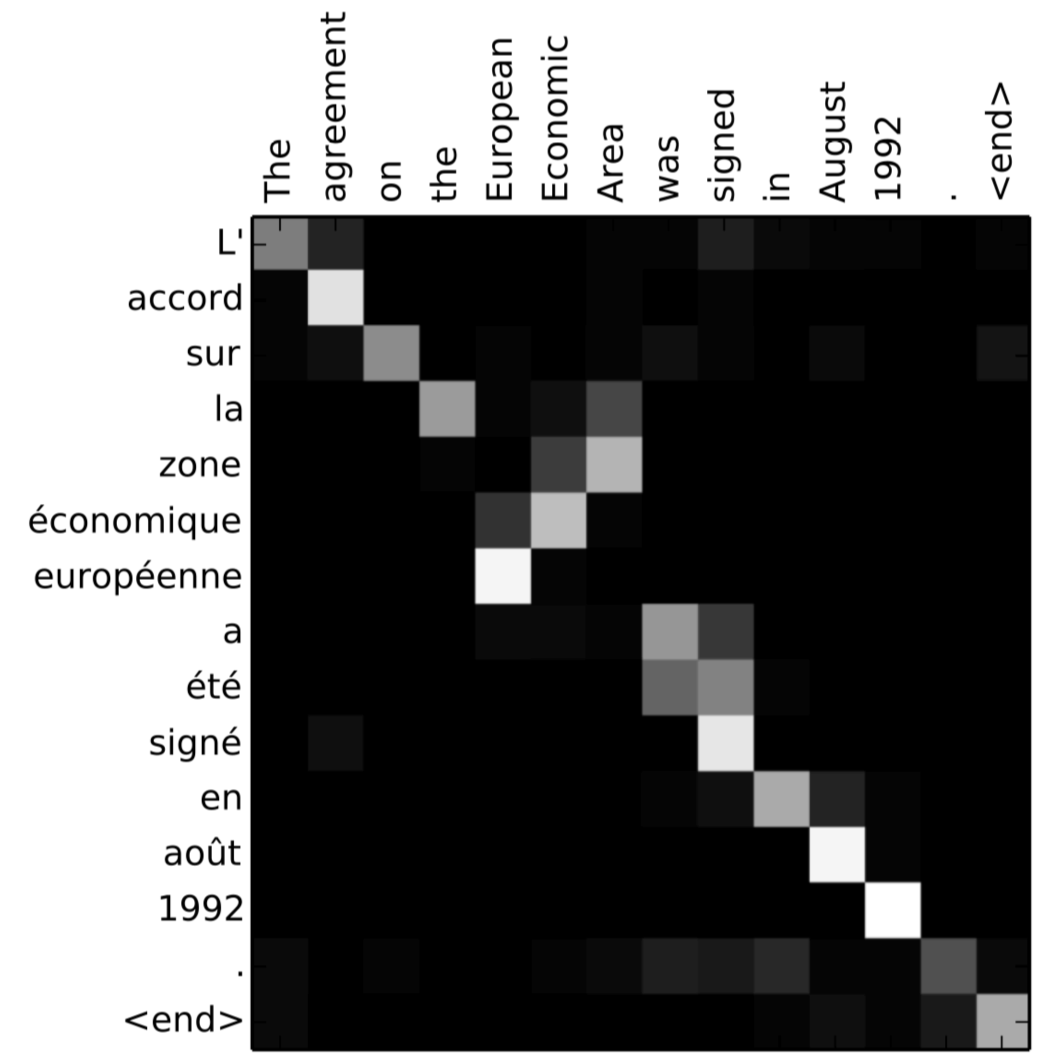
# A Caveat: Attention Is Not All You Need?

- Transformers are very popular, for good reason, but
- They can be **slow to decode** at test time (Zhang et al. 2018)
- They **don't necessarily outperform RNNs** on the decoder side of seq2seq tasks (Chen et al. 2018)
- They can be **hard to train on small data** (Nguyen and Salazar 2019)
- Use them, but also be aware of limitations!

# Better Modeling for Attention

# Incorporating Markov Properties
(Cohn et al. 2015)

- **Intuition:** attention from last time tends to be correlated with attention this time




- Add information about the last attention when making the next decision

# Hard Attention

- Instead of a soft interpolation, make a **zero-one decision** about where to attend (Xu et al. 2015)
  - Harder to train, requires methods such as reinforcement learning (see later classes)
- Perhaps this helps interpretability? (Lei et al. 2016)

***Review***

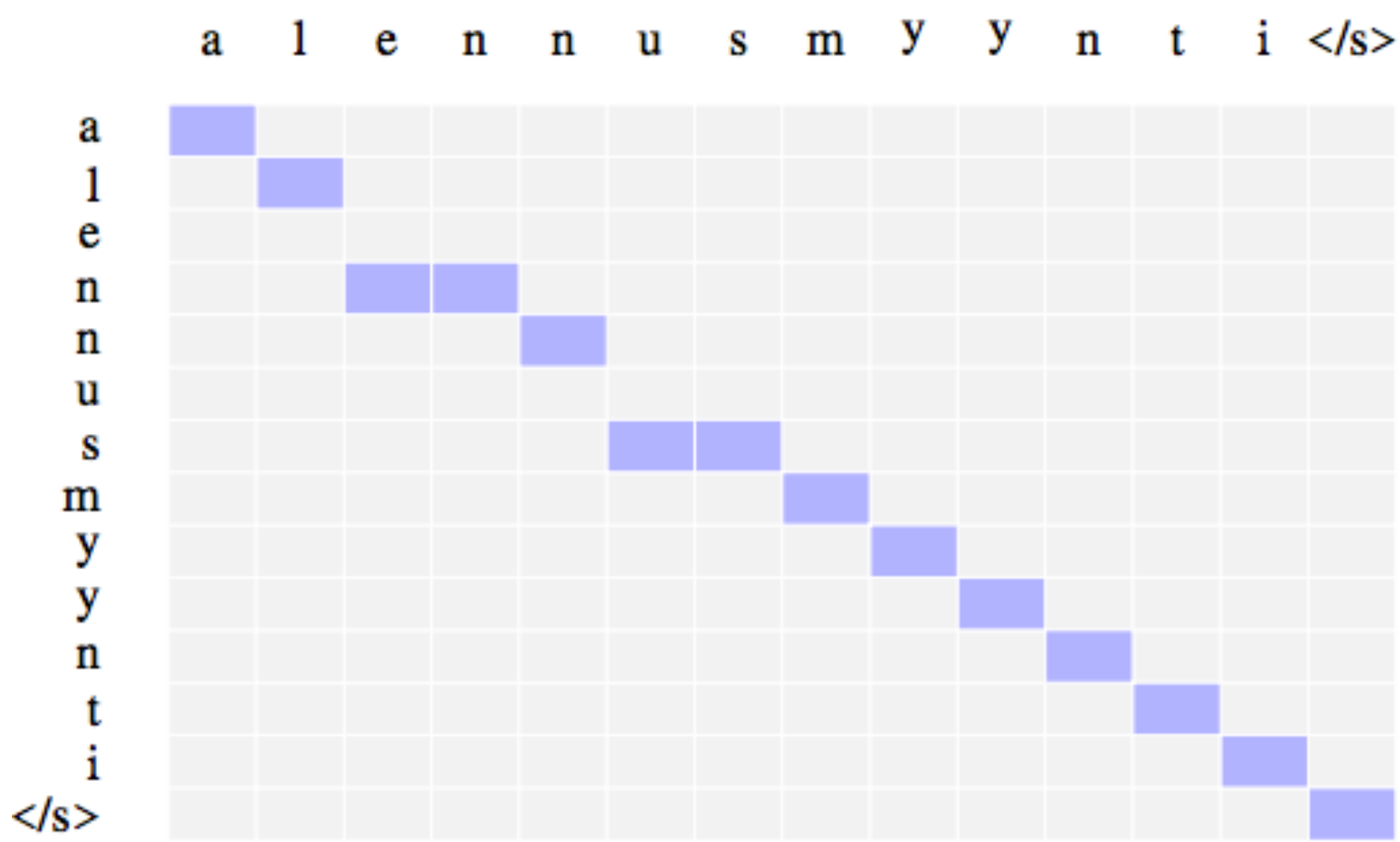
the beer was n't what i expected, and i'm not sure it's "true to style", but i thought it was delicious. **a very pleasant ruby red-amber color** with a relatively brilliant finish, but a limited amount of carbonation, from the look of it. aroma is what i think an amber ale should be - a nice blend of caramel and happiness bound together.

***Ratings***

*Look:* 5 stars    *Smell:* 4 stars

# Monotonic Attention
## (e.g. Yu et al. 2016)

- In some cases, we might know the output will be the same order as the input
  - Speech recognition, incremental translation, morphological inflection (?), summarization (?)




- **Basic idea:** hard decisions about whether to read more

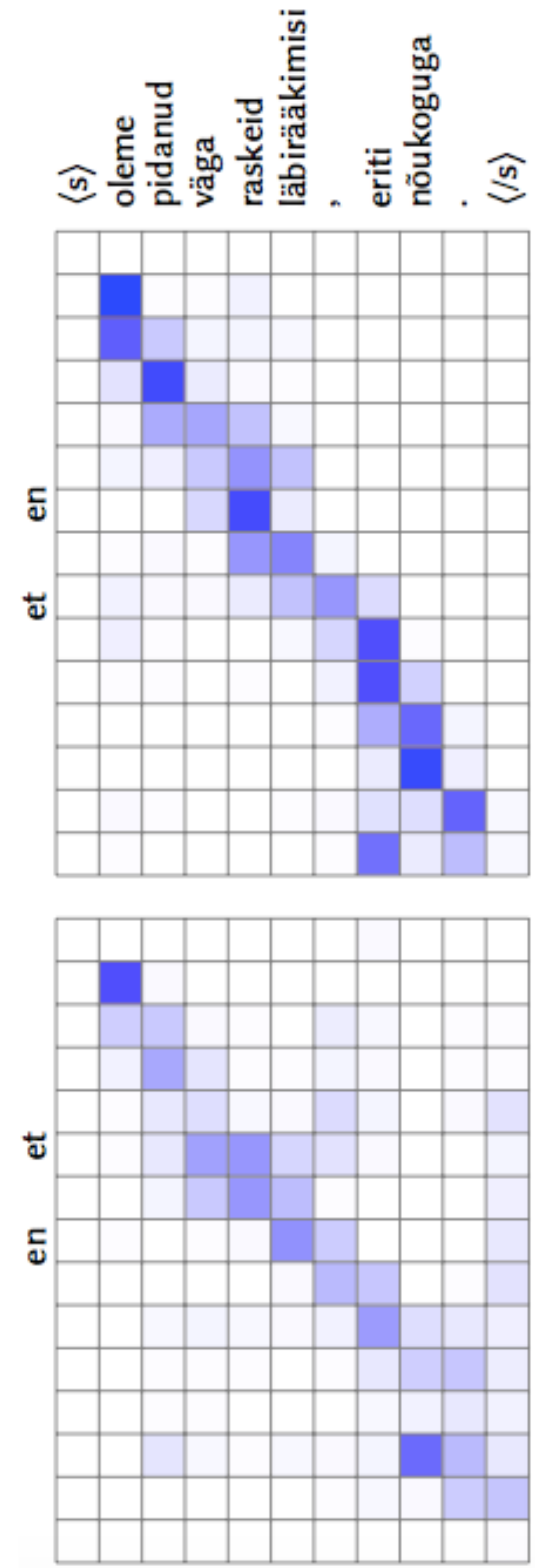
# Better Training for Attention

# Coverage

- **Problem:** Neural models tends to drop or repeat content
- **Solution:** Model how many times words have been covered
  - Impose a penalty if attention not approx.1 over each word (Cohn et al. 2015)
  - Add embeddings indicating coverage (Mi et al. 2016)

# Bidirectional Training

(Cohn et al. 2015)




- **Intuition:** Our attention should be roughly similar in forward and backward directions

- **Method:** Train so that we get a bonus based on the trace of the matrix product for training in both directions

$$\mathrm{tr}(A_{X\rightarrow Y} A^{\intercal}_{Y\rightarrow X})$$

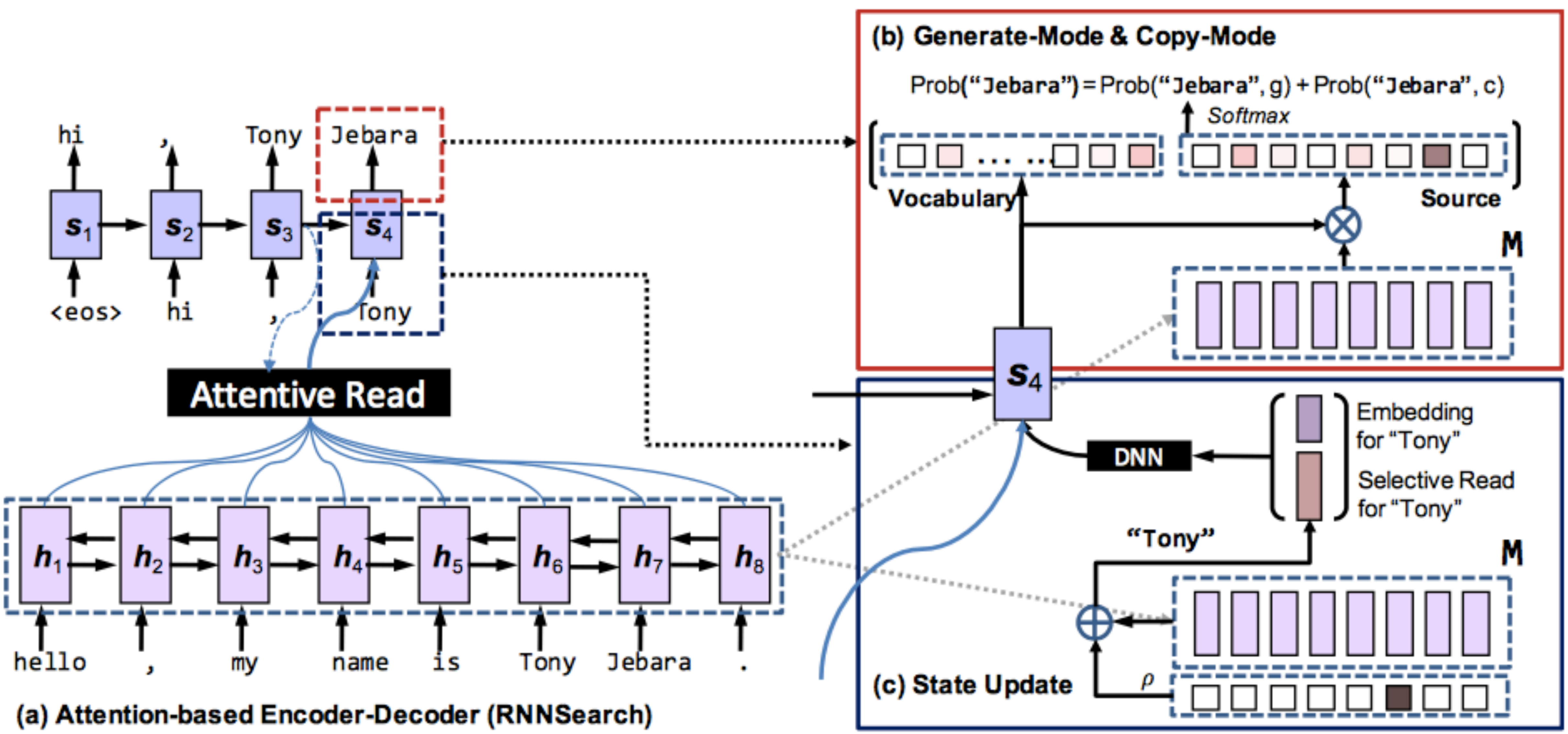
# Supervised Training
## (Mi et al. 2016)

- Sometimes we can get “gold standard” alignments *a-priori*
  - Manual alignments
  - Pre-trained with strong alignment model
- **Train the model to match** these strong alignments

# What Else Can We Attend To?

# Input Sentence: Copy

- Like the previous explanation
- But also, more directly through a *copy mechanism* (Gu et al. 2016)



# Input Sentence: Dictionary Probabilities

- If you have a translation dictionary, use it to bias outputs (Arthur et al. 2016)

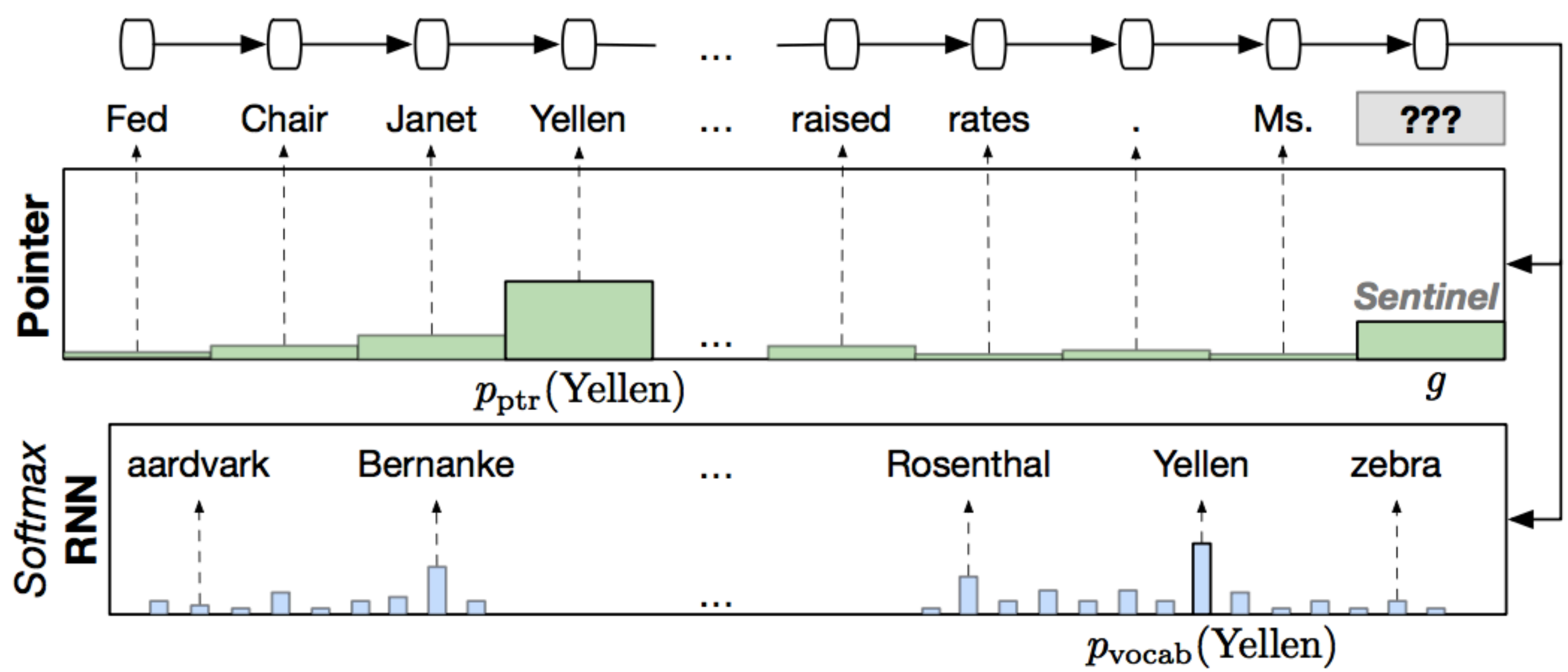
| | I | come | from | Tunisia | |
|---|---|---|---|---|---|
| Attention | 0.05 | 0.01 | 0.02 | 0.93 | |
| watashi | 0.6 | 0.03 | 0.01 | 0.0 | 0.03 |
| ore | 0.2 | 0.01 | 0.02 | 0.0 | 0.01 |
| … | … | … | … | … | … |
| kuru | 0.01 | 0.3 | 0.01 | 0.0 | 0.00 |
| kara | 0.02 | 0.1 | 0.5 | 0.01 | 0.02 |
| … | … | … | … | … | … |
| chunijia | 0.0 | 0.0 | 0.0 | 0.96 | 0.89 |
| oranda | 0.0 | 0.0 | 0.0 | 0.0 | 0.00 |

Sentence-level dictionary probability matrix

Dictionary probability for current word

# Previously Generated Things

- In language modeling, attend to the previous words (Merity et al. 2016)

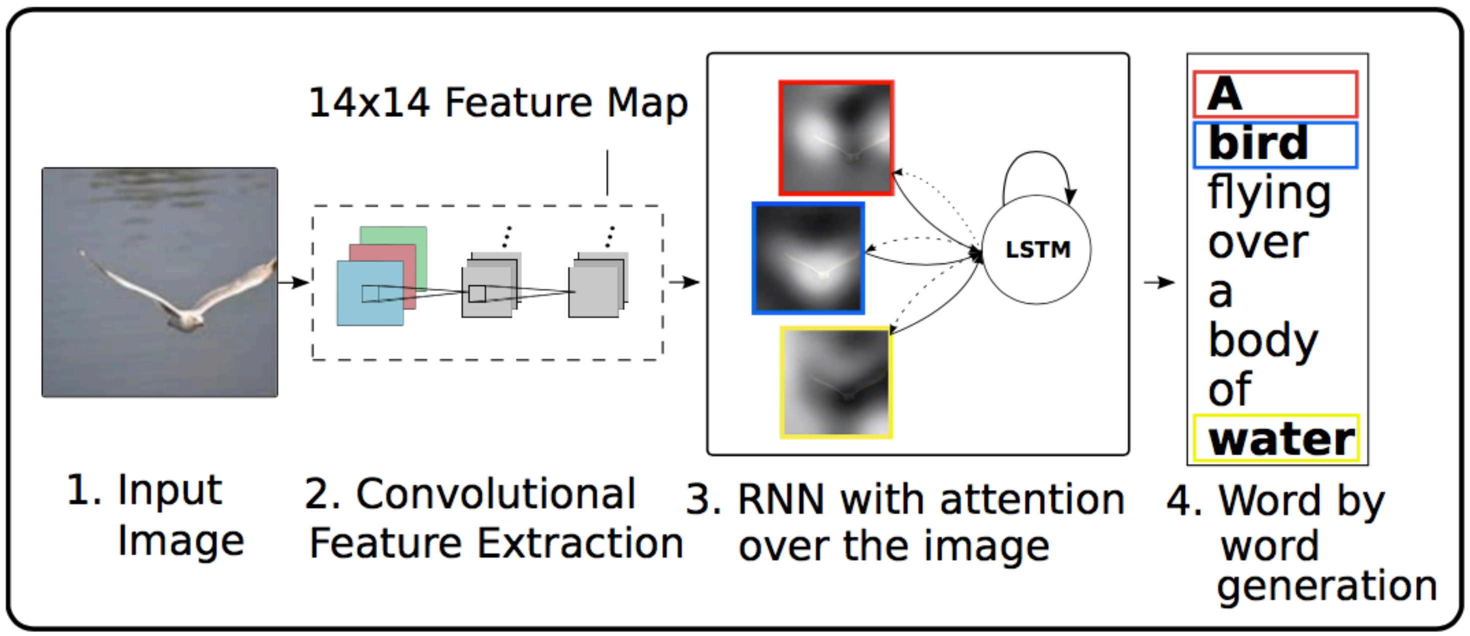



$$p(\text{Yellen}) = g\ p_{\text{vocab}}(\text{Yellen}) + (1-g)\ p_{\text{ptr}}(\text{Yellen})$$

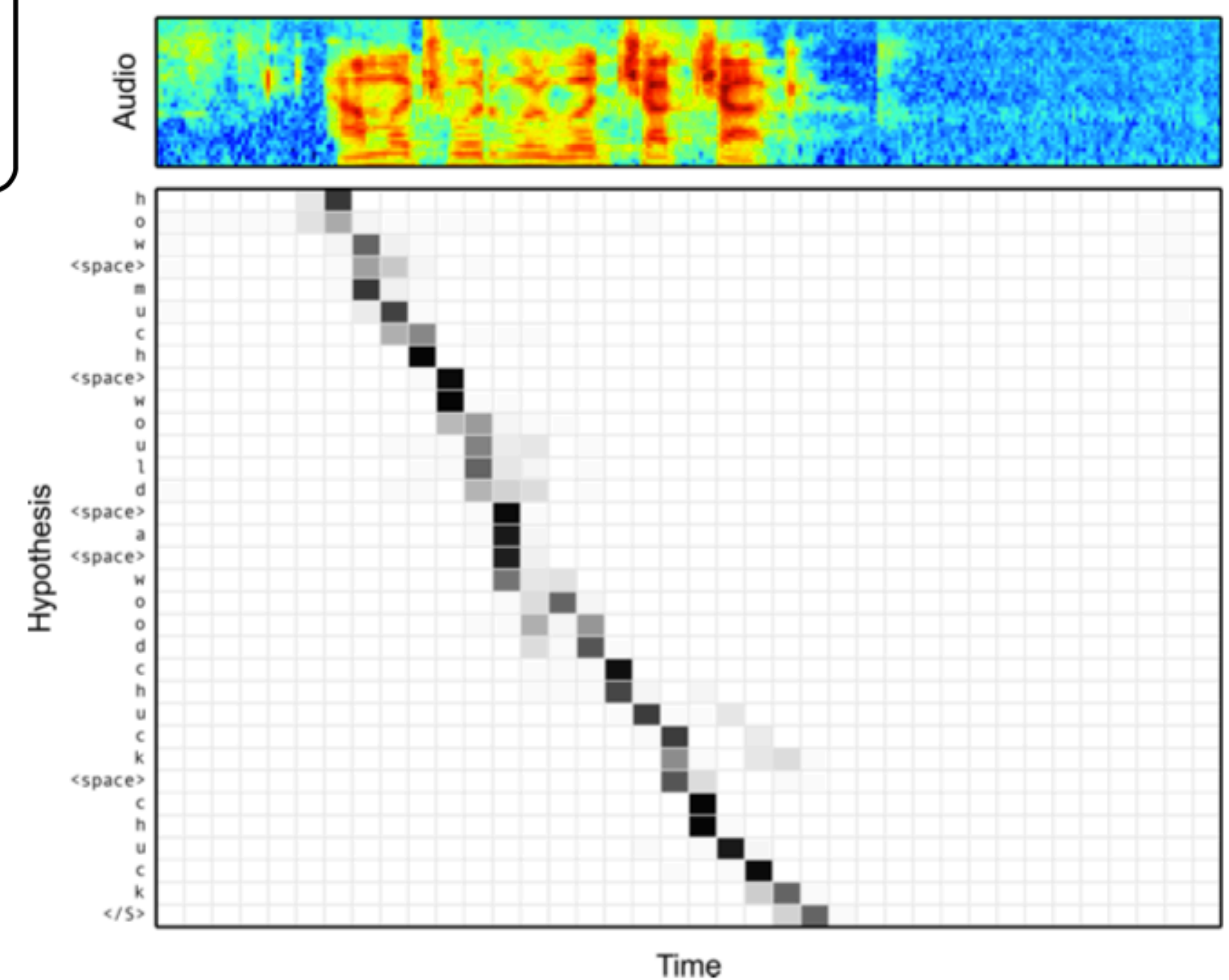
- In translation, attend to either input or previous output (Vaswani et al. 2017)

# Various Modalities

- Images (Xu et al. 2015)

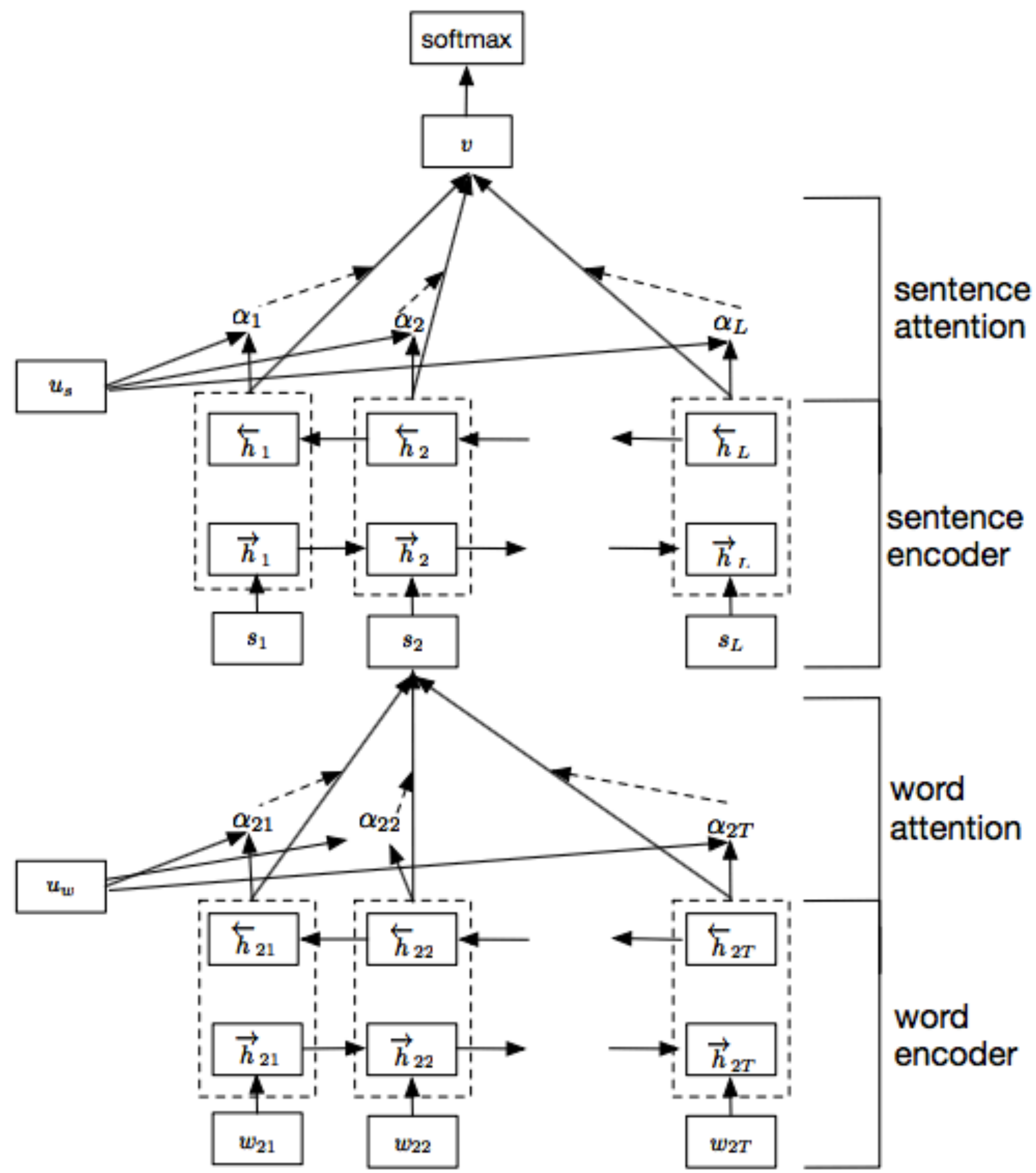



- Speech (Chan et al. 2015)



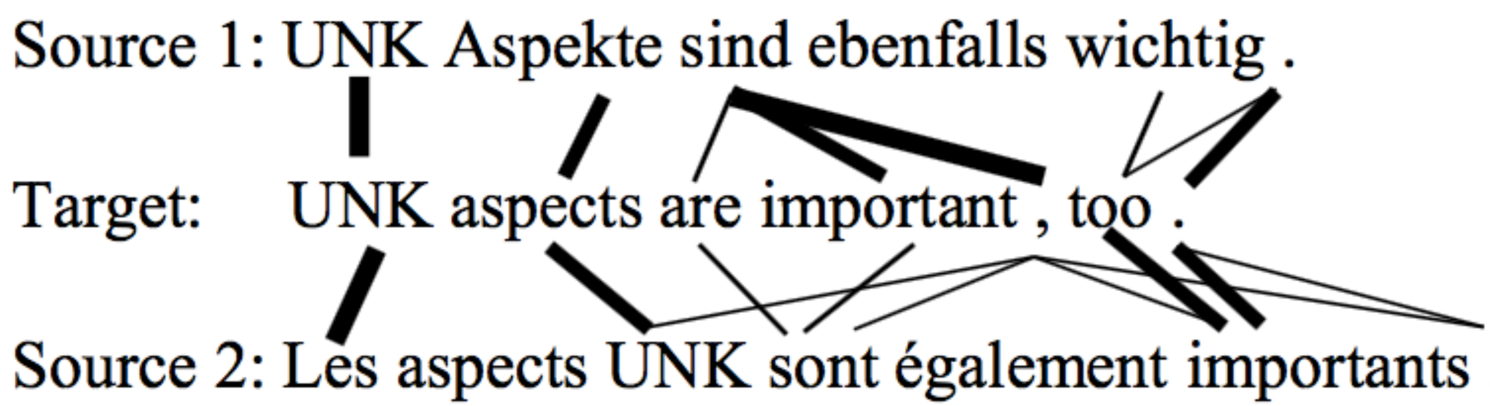
# Hierarchical Structures
(Yang et al. 2016)

- Encode with attention over each sentence, then attention over each sentence in the document



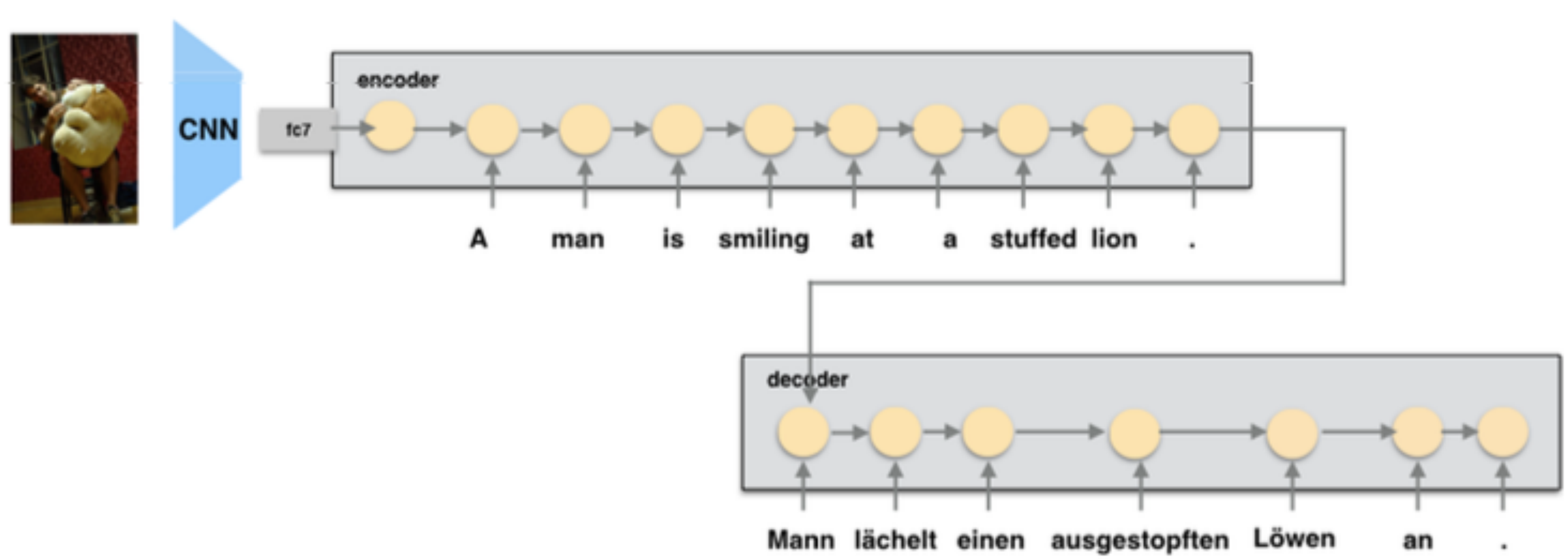
# Multiple Sources

- Attend to multiple sentences (Zoph et al. 2015)




  - Libovicky and Helcl (2017) compare multiple strategies

- Attend to a sentence and an image (Huang et al. 2016)



# Questions?