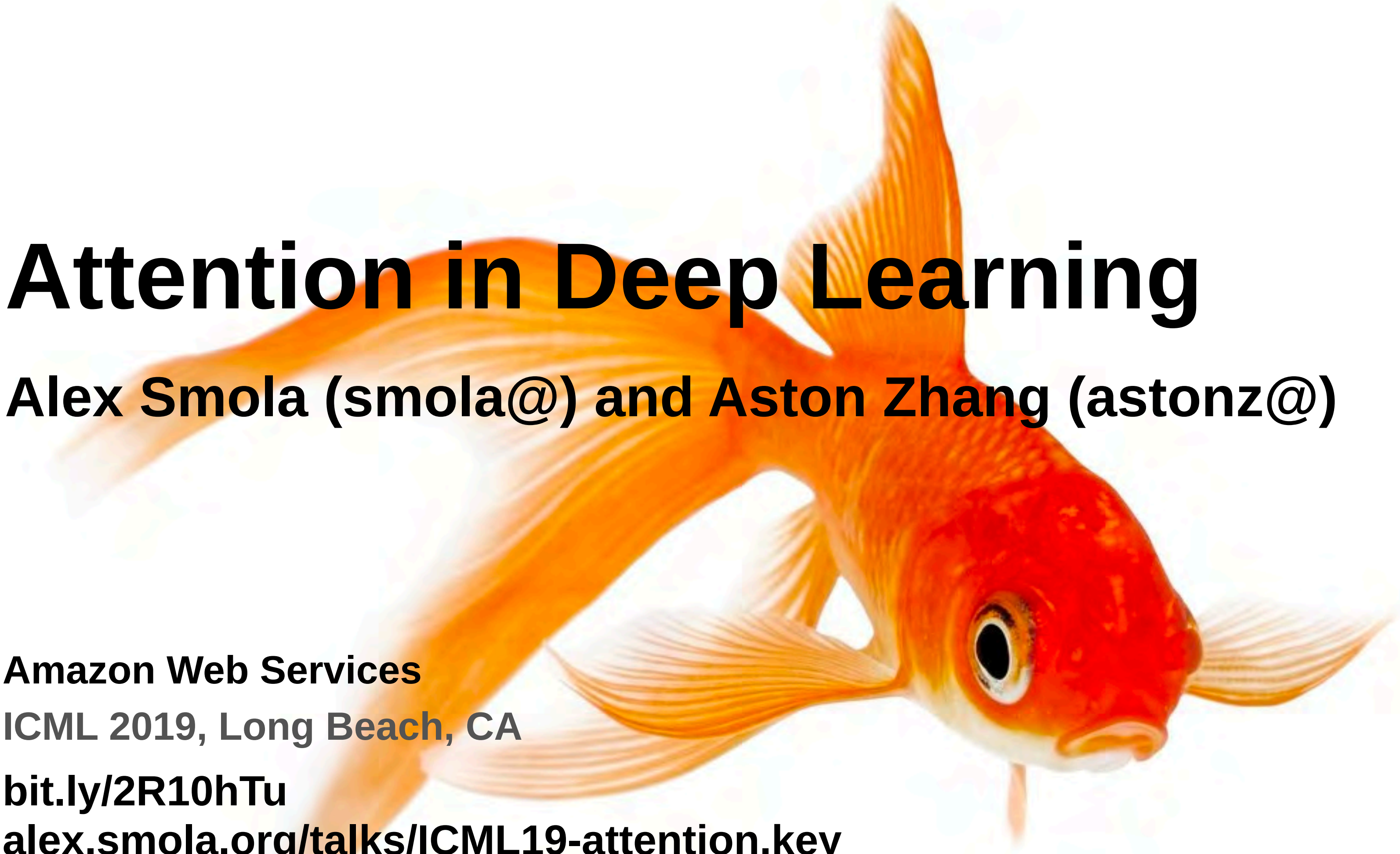
Attention in Deep Learning

Alex Smola (smola@) and Aston Zhang (astonz@)



Amazon Web Services

ICML 2019, Long Beach, CA

bit.ly/2R10hTu
alex.smola.org/talks/ICML19-attention.key
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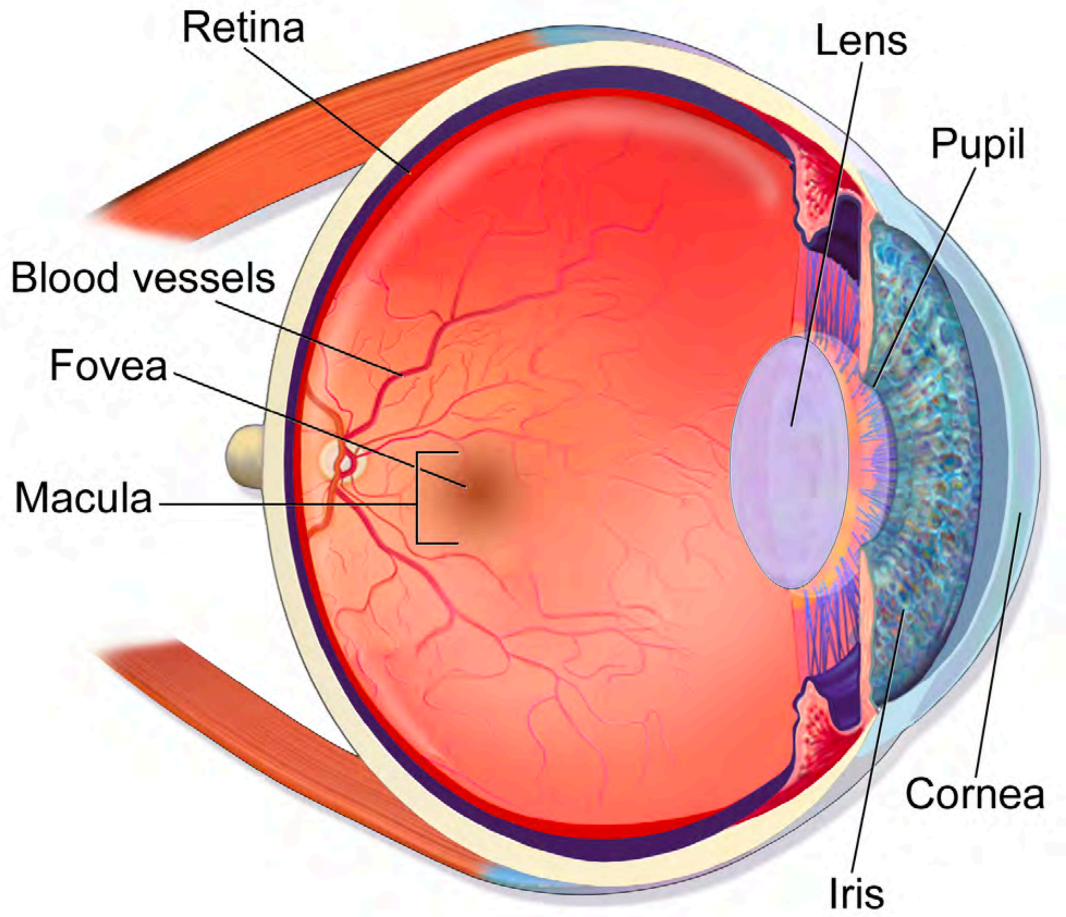
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Pupil
Blood vessels
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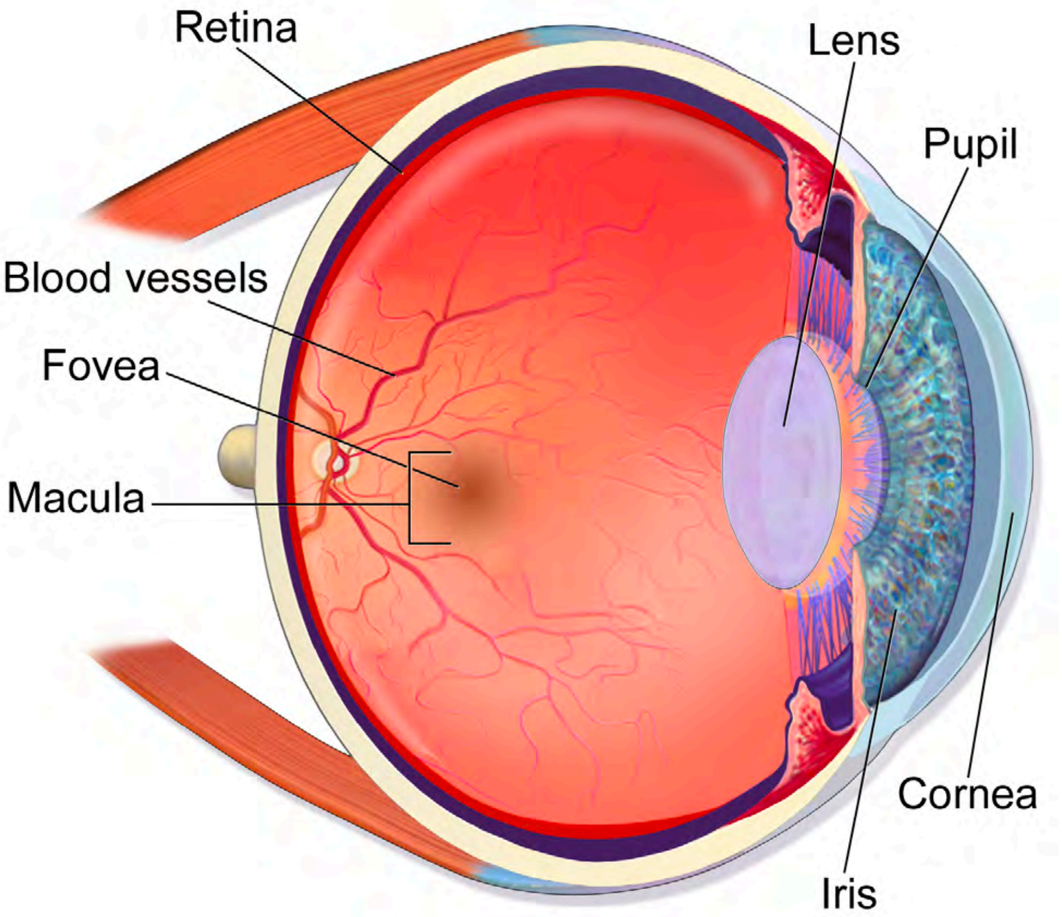
Macula
Cornea
Iris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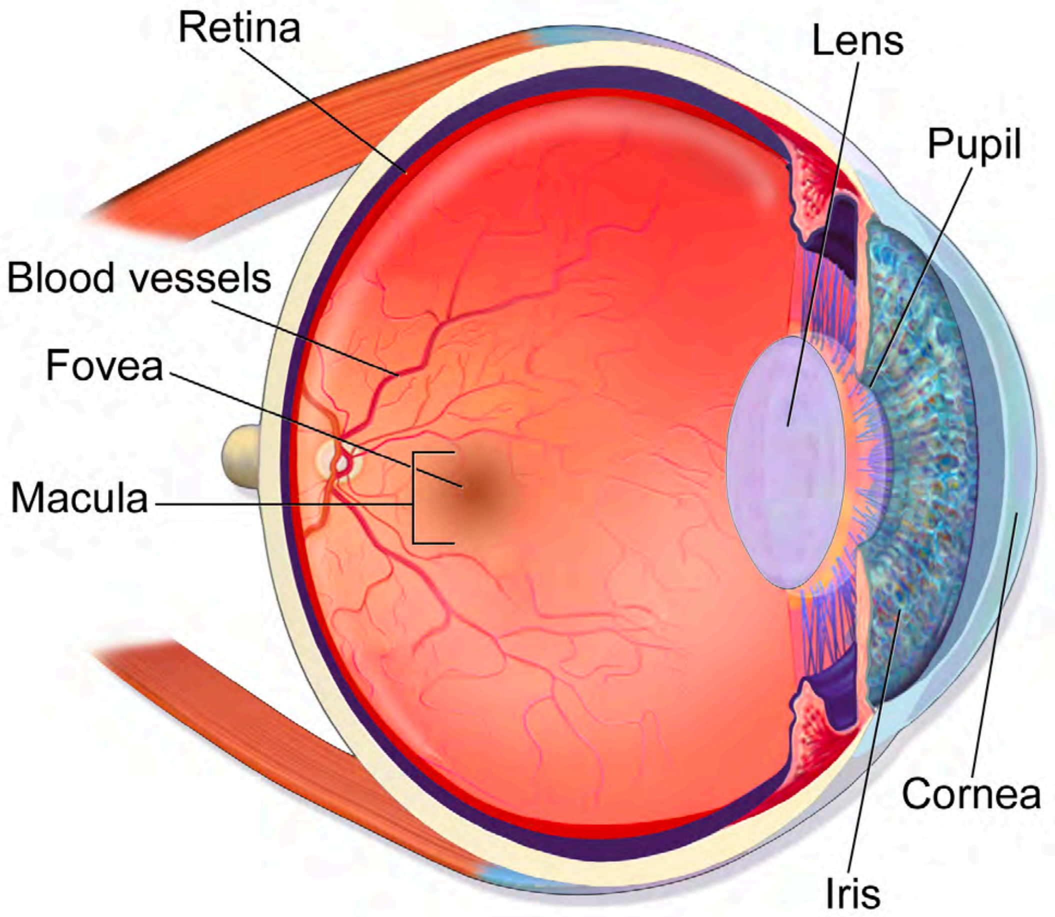
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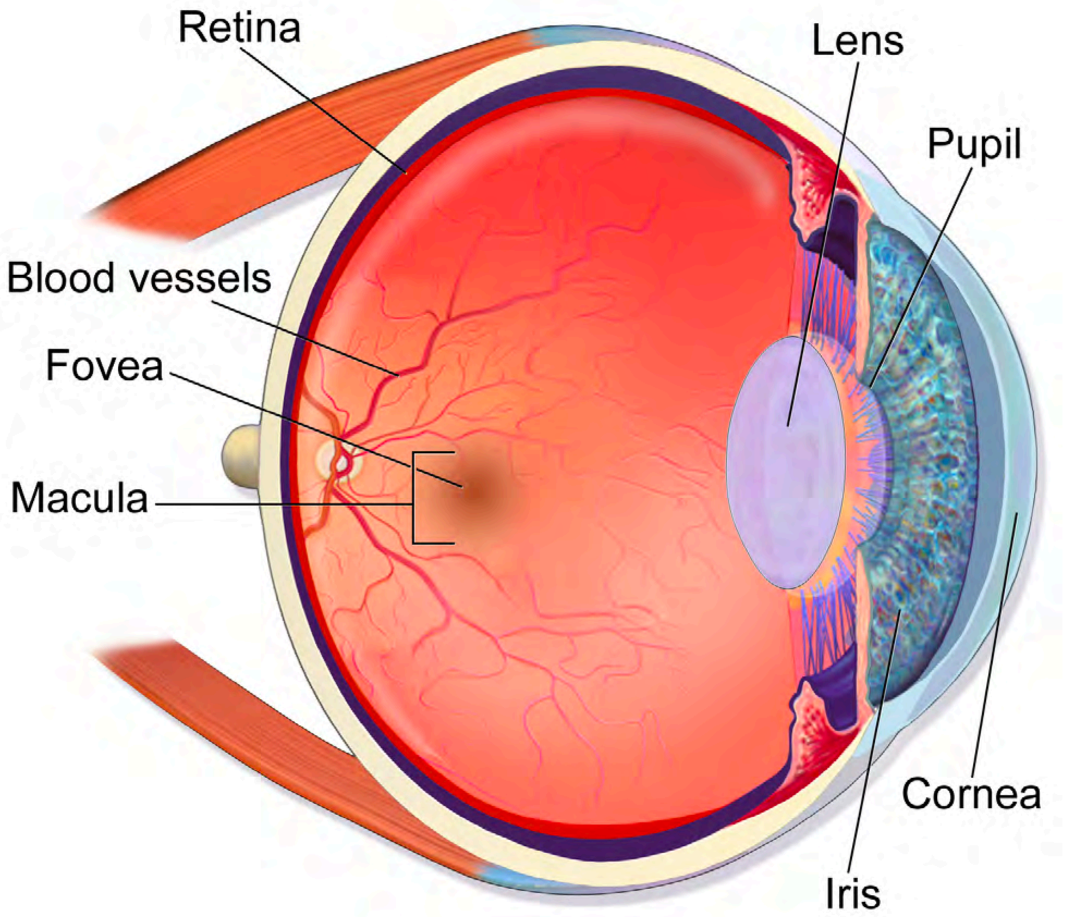
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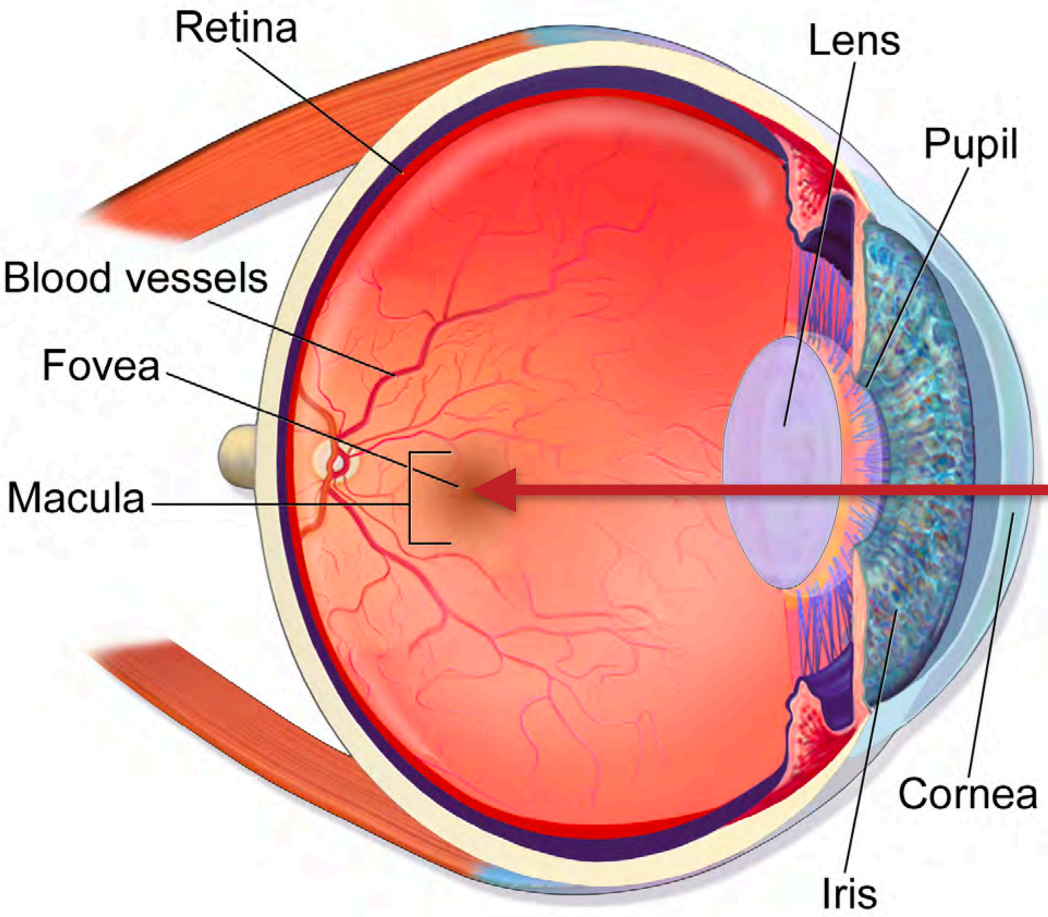
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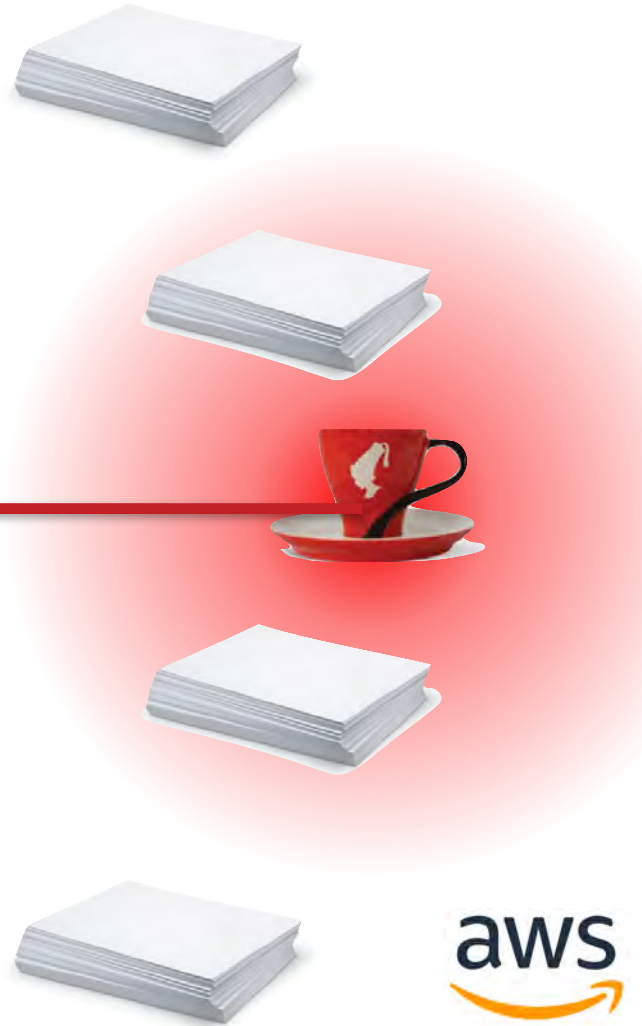

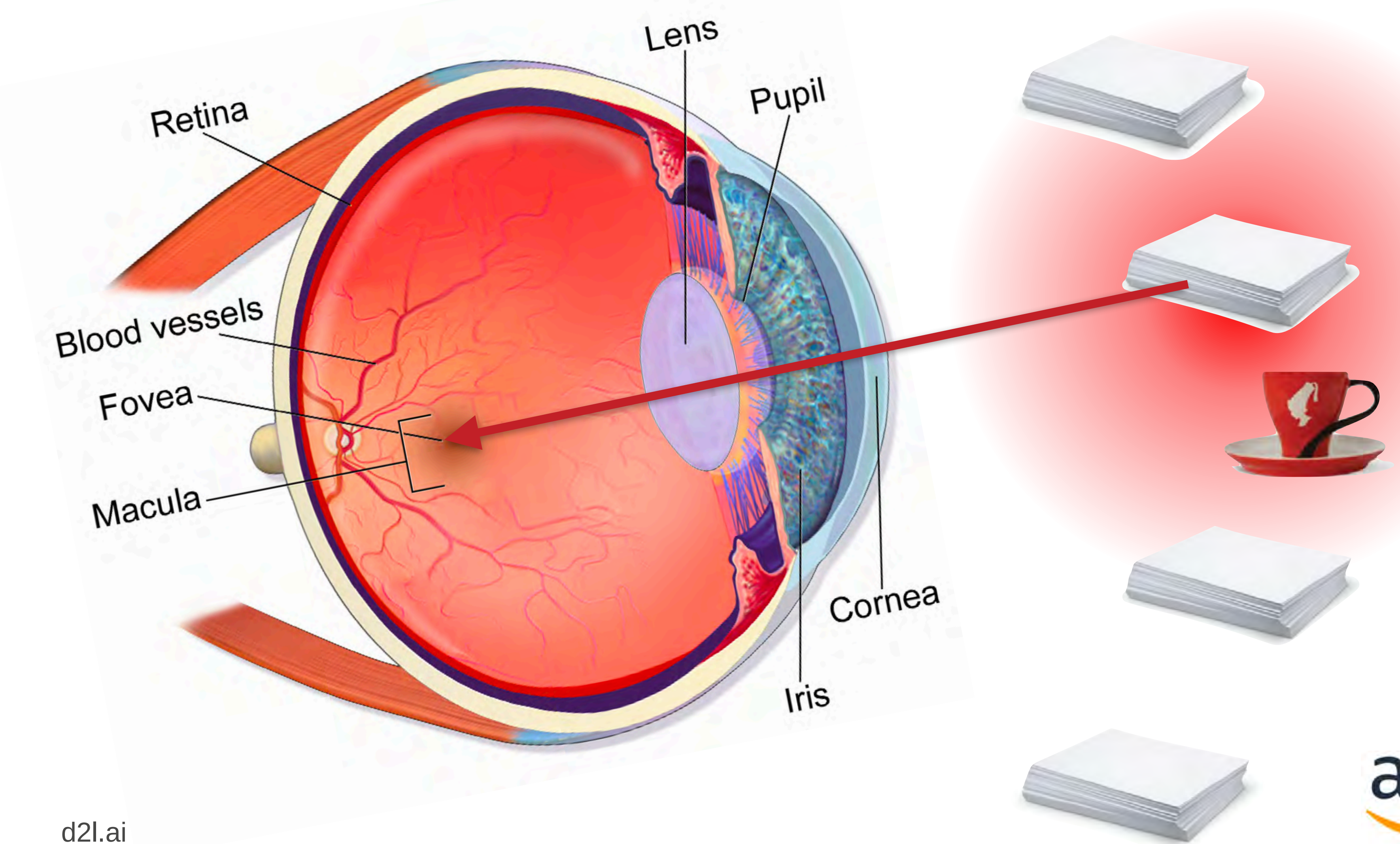
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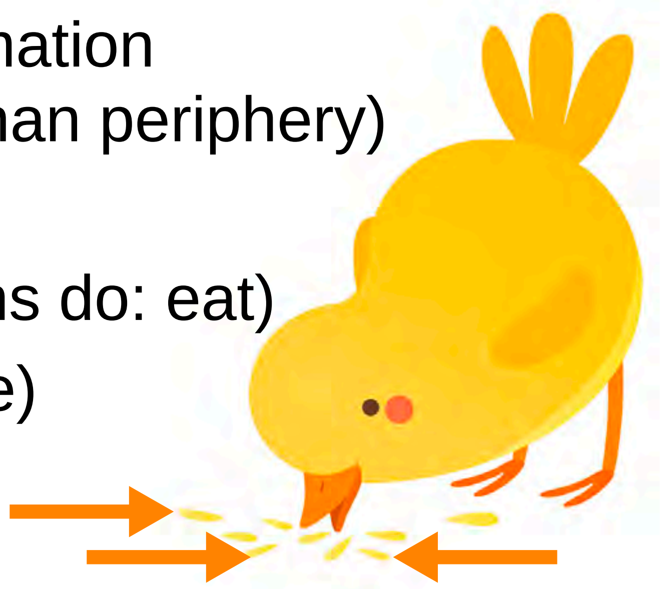
Attention in Animals

- **Resource saving**
  - Only need **sensors** where relevant bits are (e.g. fovea vs. peripheral vision)
  - Only **compute** relevant bits of information (e.g. fovea has many more ‘pixels’ than periphery)
- **Variable state manipulation**
  - Manipulate environment (for all grains do: eat)
  - Learn modular subroutines (not state)
- **In machine learning - nonparametric**



Outline

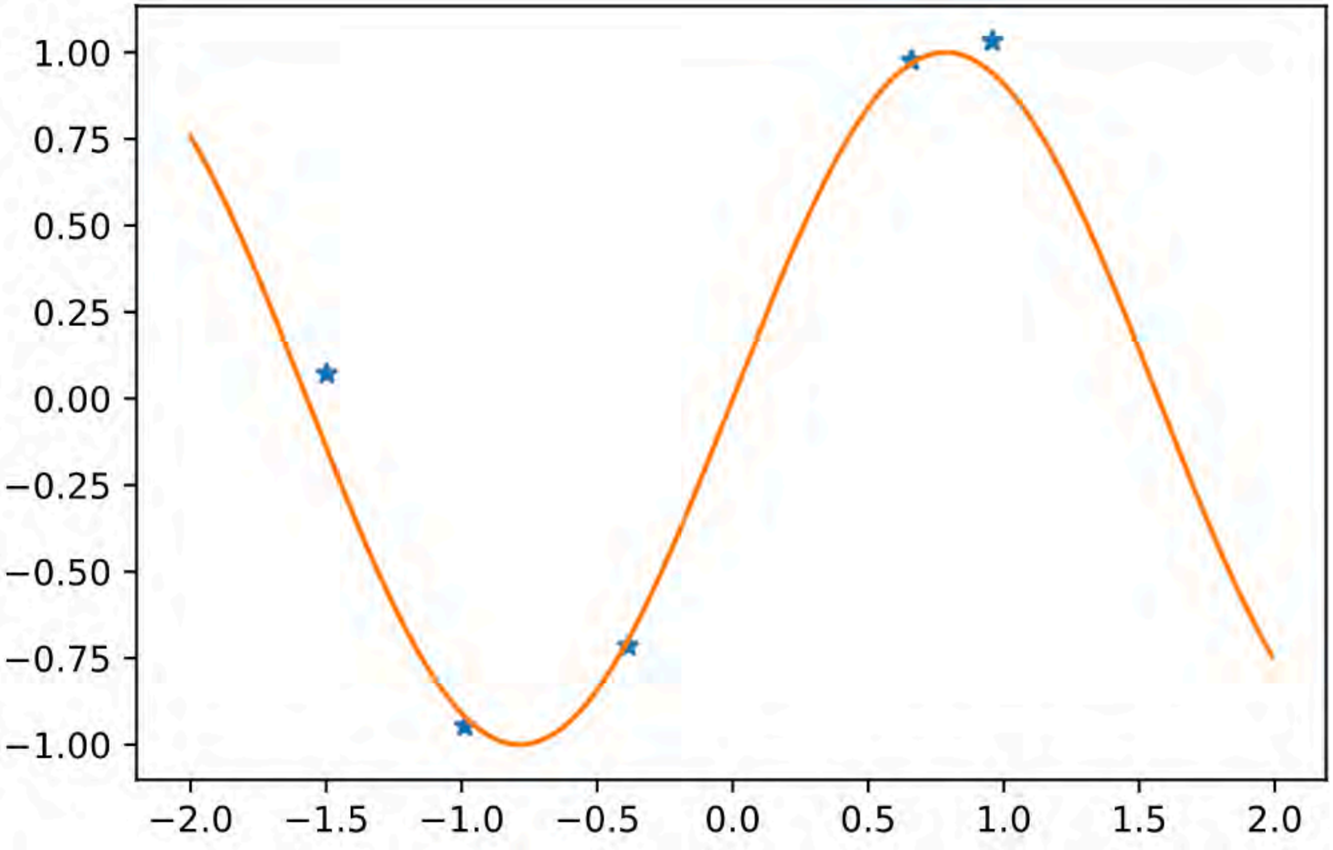
1. **Watson Nadaraya Estimator**
2. **Pooling**
    - Single objects - Pooling to attention pooling
    - Hierarchical structures - Hierarchical attention networks
3. **Iterative Pooling**
   Question answering / memory networks
4. **Iterative Pooling and Generation**
   Neural machine translation
5. **Multiple Attention Heads**
    - Transformers / BERT
    - Lightweight, structured, sparse
6. **Resources**

1. Watson Nadaraya Estimator ‘64

Geoffrey Watson

Elizbar Nadaraya

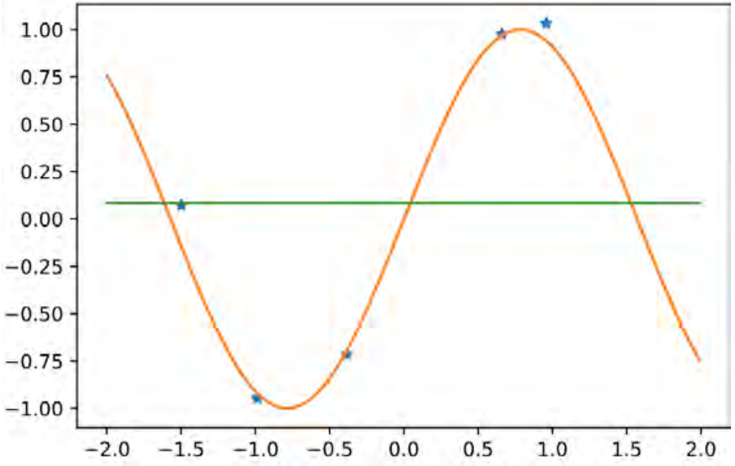
Regression Problem



Solving the regression problem

- Data $\{x_1, \ldots x_m\}$ and labels $\{y_1, \ldots y_m\}$
- Estimate label y at new location x
- **The world's dumbest estimator**
  Average over all labels

$$y = \frac{1}{m}\sum_{i=1}^{m} y_i$$



- **Better idea (Watson, Nadaraya, 1964)**
  Weigh the labels according to location

$$y = \sum_{i=1}^{m} \alpha(x, x_i) y_i$$

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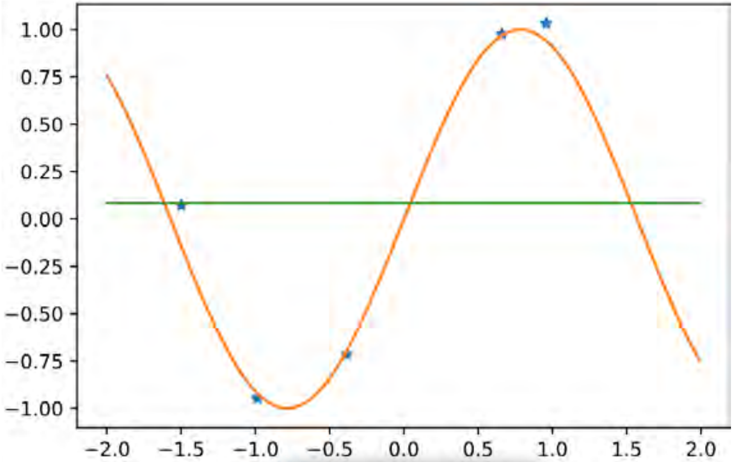


- **Better idea (Watson, Nadaraya, 1964)**
  Weigh the labels according to location

$$y = \sum_{i=1}^{m} \alpha(x, x_i) y_i$$

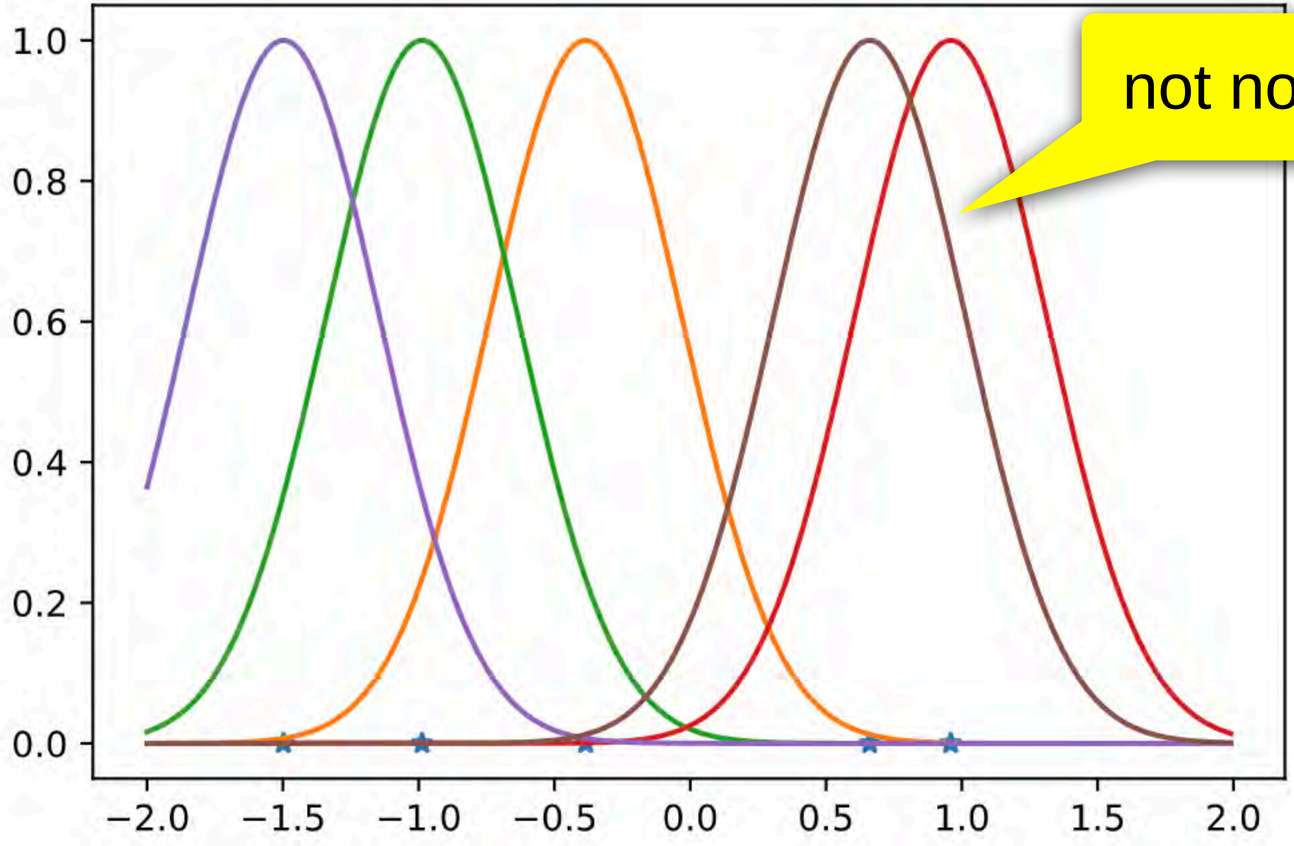
key

$\alpha(x, x_i)y_i$

query

value

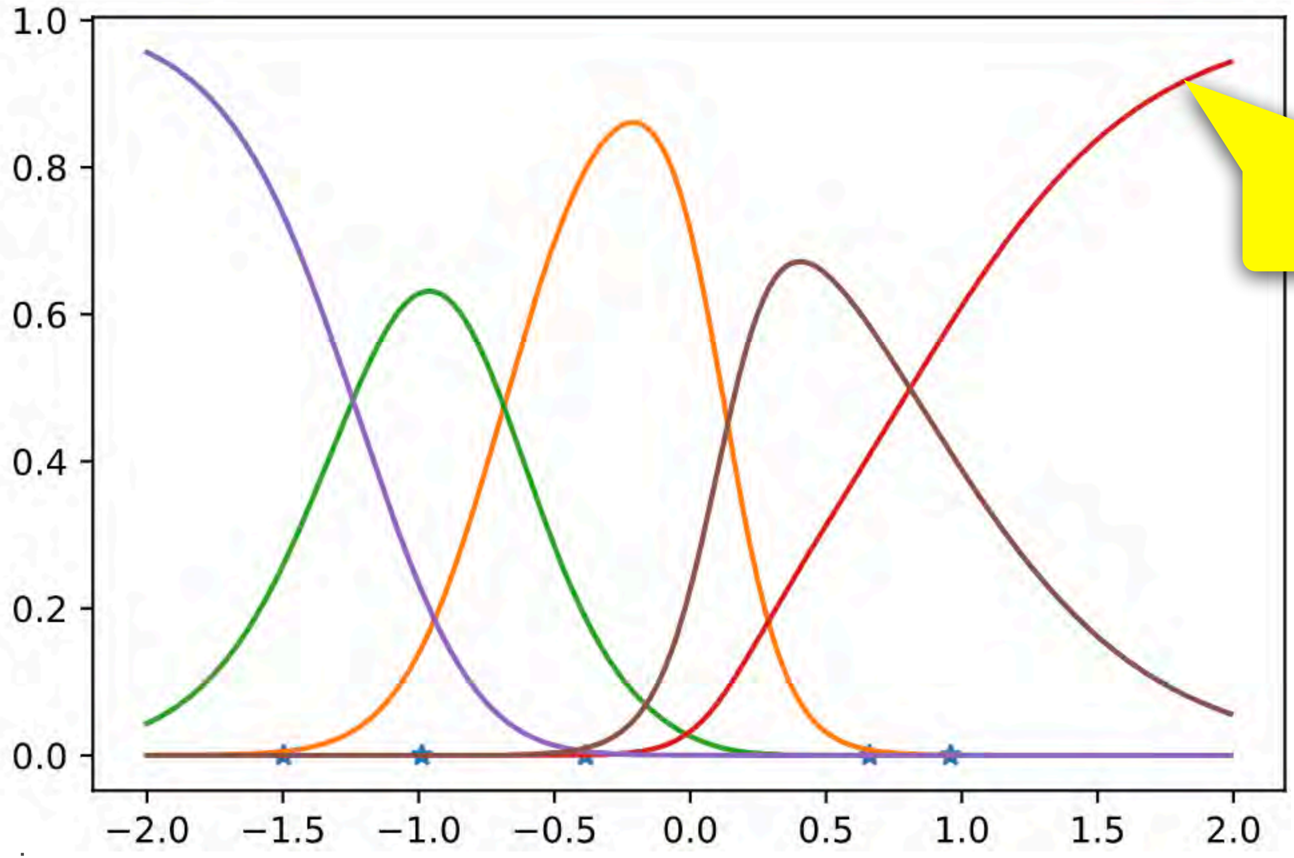
Weighing the locations (e.g. with Gaussians)



not normalized

$$\alpha(x, x_i) \propto k(x_i, x)$$

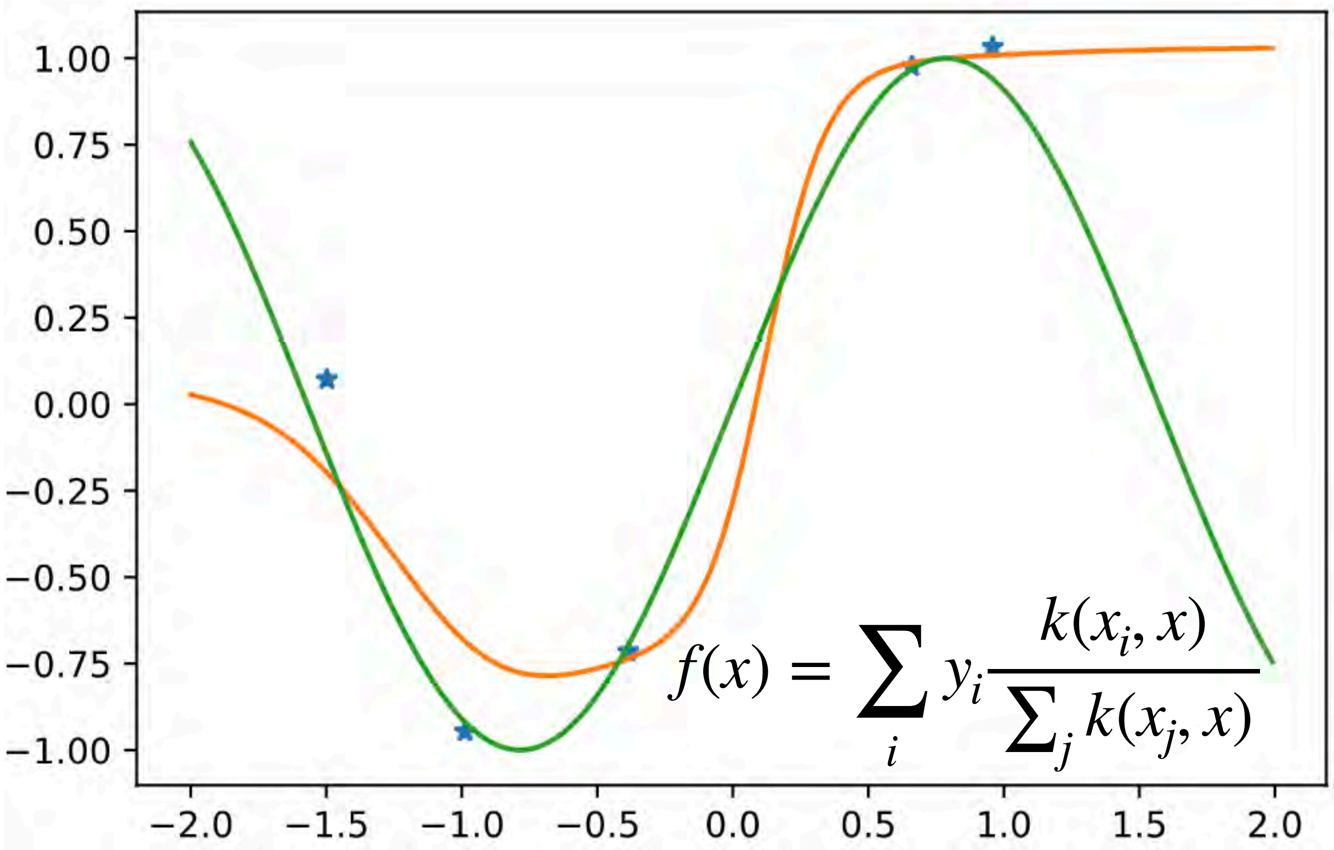
Weighing the locations (e.g. with Gaussians)



normalized

$$\alpha_i(x) = \frac{k(x_i, x)}{\sum_j k(x_j, x)}$$

Weighted regression estimate



$$f(x) = \sum_i y_i \frac{k(x_i, x)}{\sum_j k(x_j, x)}$$

Why bother with a 55 year old algorithm?

- **Consistency**
  Given enough data this algorithm converges to the optimal solution (can your deep net do this?)
- **Simplicity**
  No free parameters - information is in the data not weights (or very few if we try to learn the weighting function)

Why bother with a 55 year old algorithm?

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- **Simplicity**
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- **Deep Learning Variant**
  - Learn weighting function
  - Replace averaging (pooling) by weighted pooling

2. Pooling

Deep Sets (Zaheer et al. 2017)

- Deep (Networks on) Sets $X = \{x_1, \ldots x_n\}$
  - Need permutation invariance for elements in set (e.g. LSTM doesn't work to ingest elements)
  - Theorem - all functions are of the form*

$$f(X) = \rho\left(\sum_{x \in X} \phi(x)\right)$$

  *or some combination thereof

- Applications - point clouds, set extension, red shift for galaxies, text retrieval, tagging, etc.

Deep Sets (Zaheer et al. 2017)

Outliers in sets - learn function $f(X)$ on set such that

$$f(\{x\} \cup X) \geq f\left(\{x'\} \cup X\right) + \Delta(x, x')$$

Deep Sets with Attention aka Multi-Instance Learning (Ilse, Tomczak, Welling, ’18)

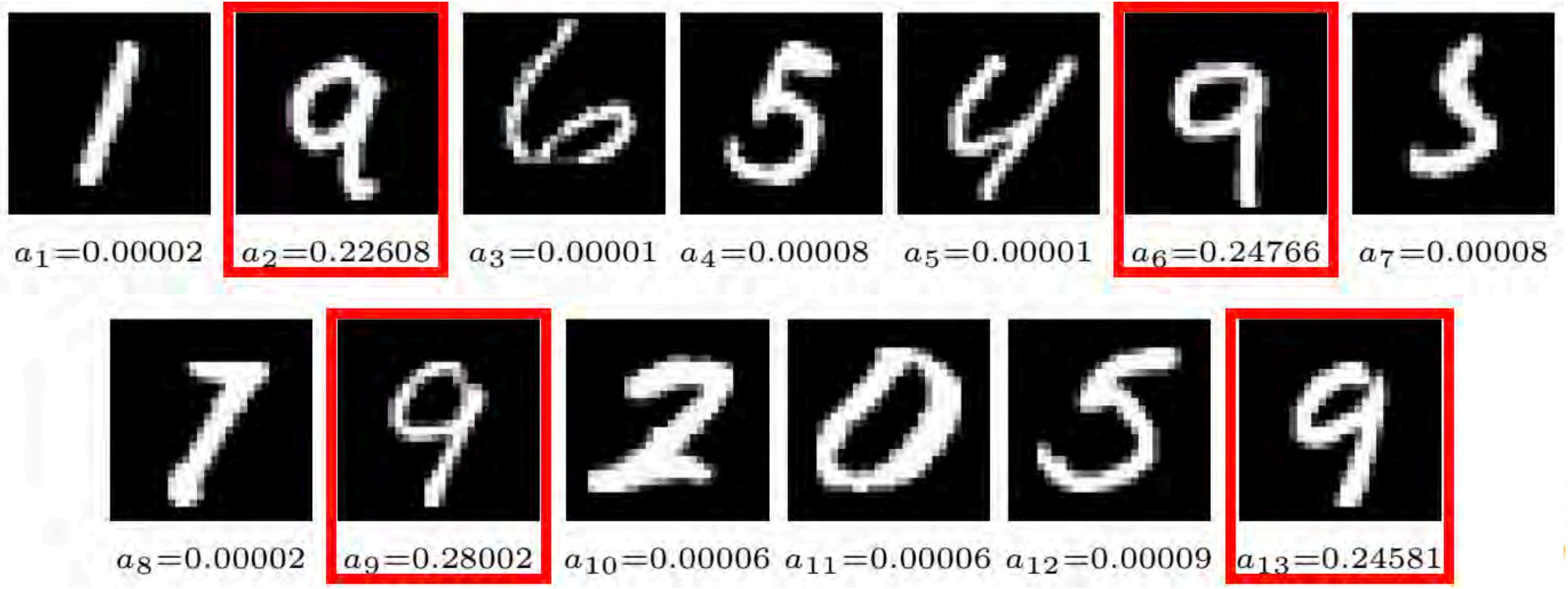
- Multiple Instance Problem
  Set contains one (or more) elements with desirable property (drug discovery, keychain). Identify those sets.
- Deep Sets have trouble focusing, hence weigh it

$$f(X) = \rho\left(\sum_{x \in X} \phi(x)\right) \longrightarrow f(X) = \rho\left(\sum_{x \in X} \alpha(w, x)\phi(x)\right)$$

- Attention function e.g. $\alpha(w, x) \propto \exp\left(w^\top \tanh Vx\right)$

Deep Sets with Attention aka Multi-Instance Learning (Ilse, Tomczak, Welling, ’18)

Identifying sets that contain the digit ‘9’



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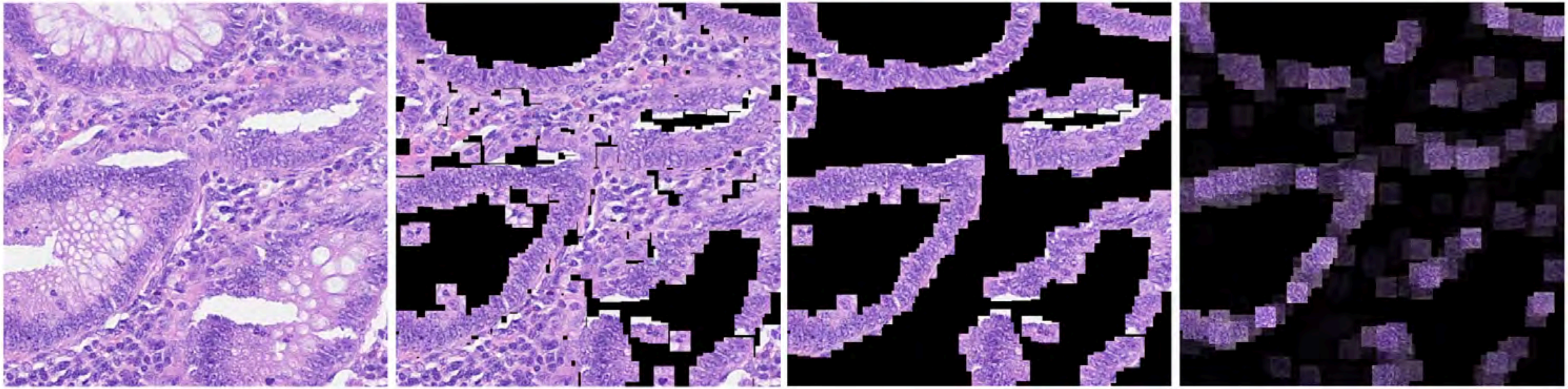


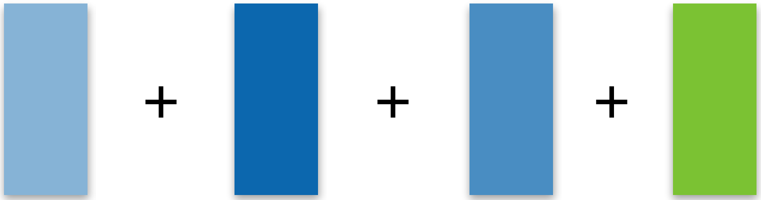
tissue sample | windowed cell nuclei | cancerous cells | attention weights

Bag of words (Salton & McGill, 1986)
Word2Vec (Mikolov et al., 2013)

- Embed each word in sentence (word2vec, binary, GRU …)
- Add them all up
- Classify

$$f(X) = \rho\left(\sum_{i=1}^{n} \phi(x_i)\right)$$

`The tutorial is awesome.`



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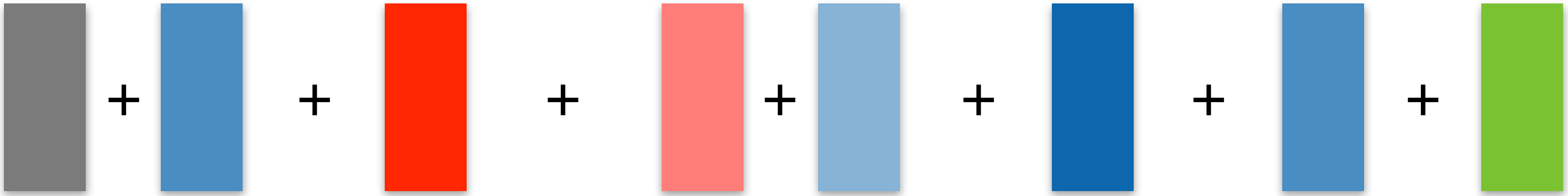

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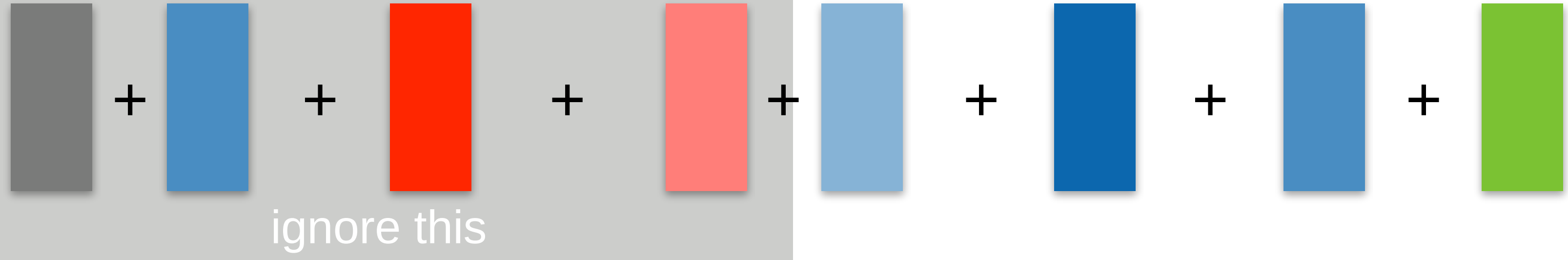
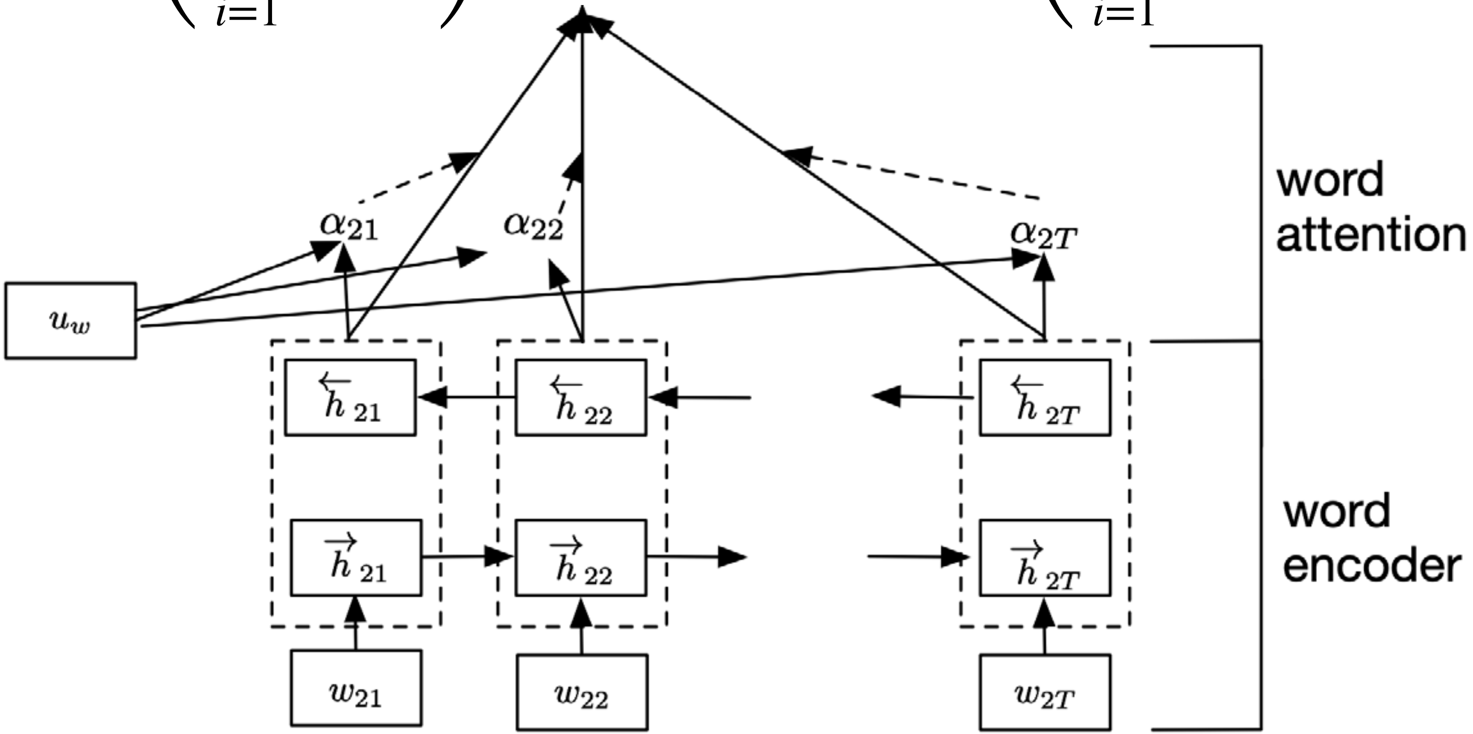


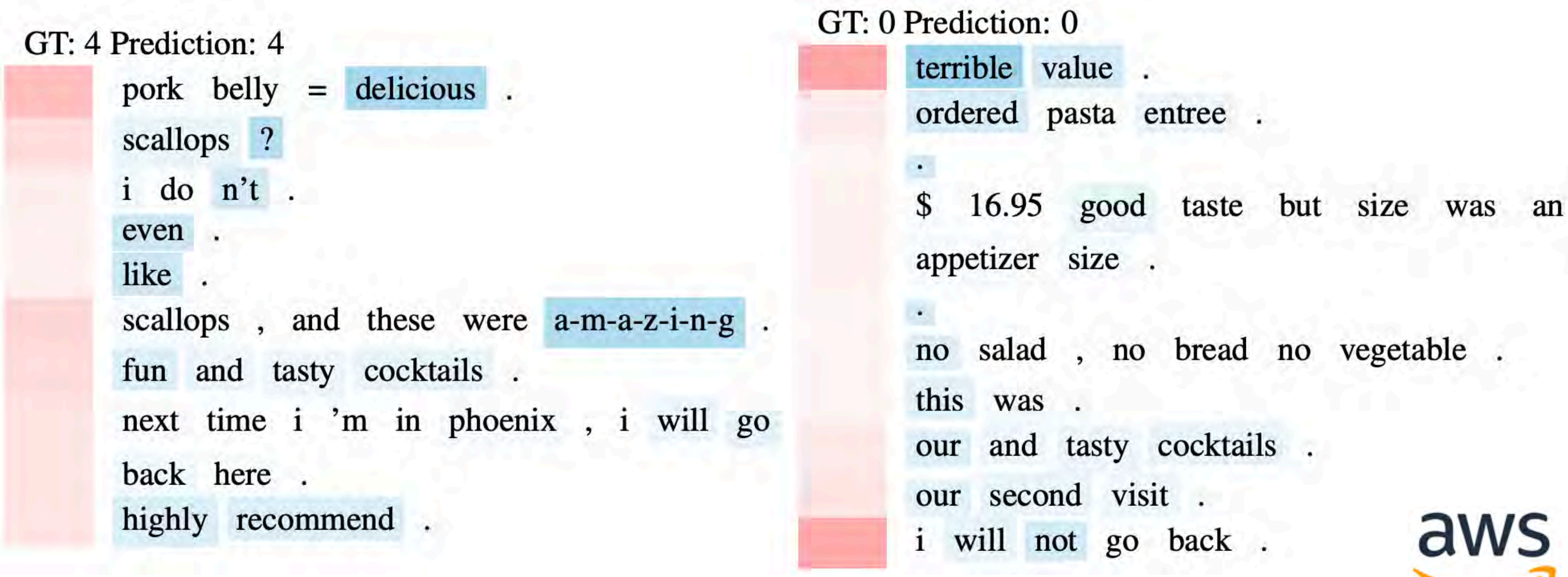
Attention weighting for documents (Wang et al, '16)

$$f(X) = \rho\left(\sum_{i=1}^{n} \phi(w_i)\right) \longrightarrow f(X) = \rho\left(\sum_{i=1}^{n} \alpha(w_i, X)\phi(w_i)\right)$$



Hierarchical attention weighting (Yang et al. ’17)

Some sentences are more important than others …



Hierarchical attention

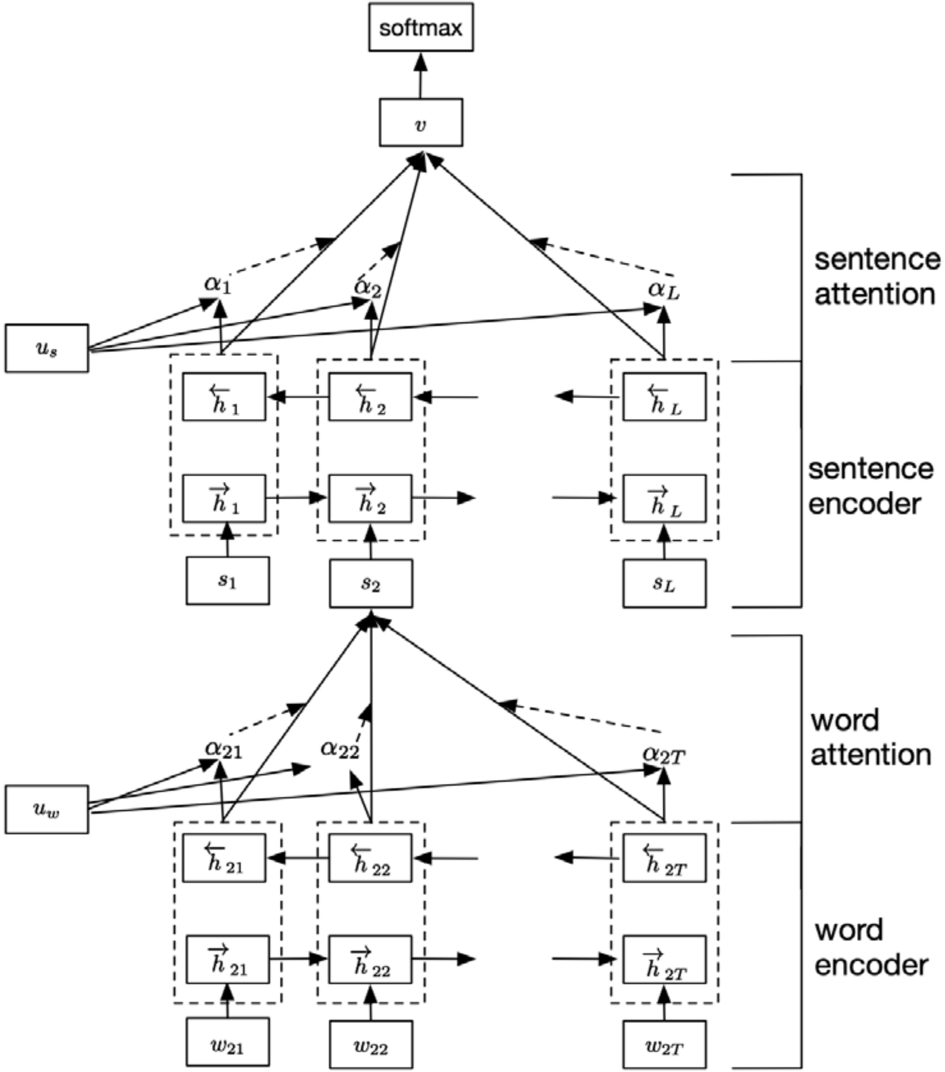
- Word level

$$f(s_i) = \rho\left(\sum_{j=1}^{n_i} \alpha(w_{ij}, s_i)\phi(w_{ij})\right)$$

- Sentence level

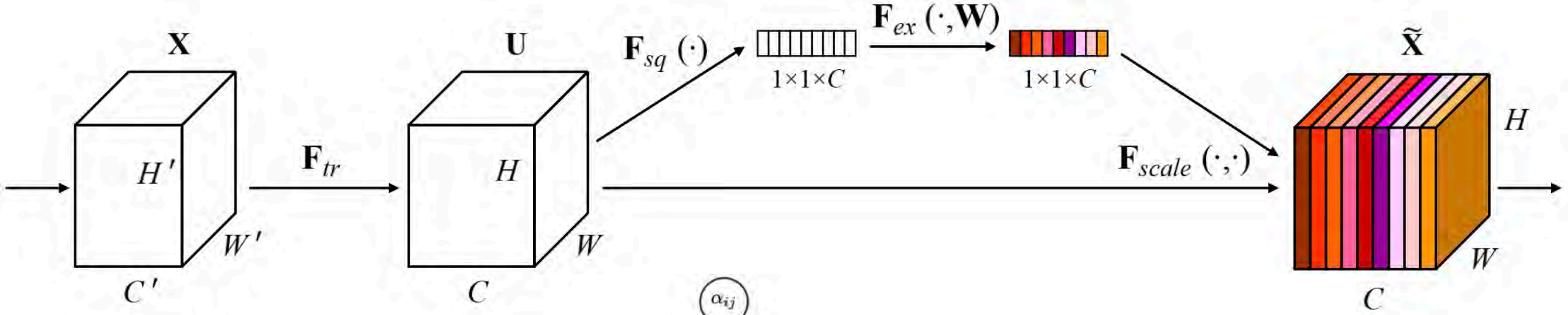
$$g(d) = \rho\left(\sum_{i=1}^{n} \alpha(s_i, d)\phi(f(s_i))\right)$$

- Embeddings e.g. via GRU



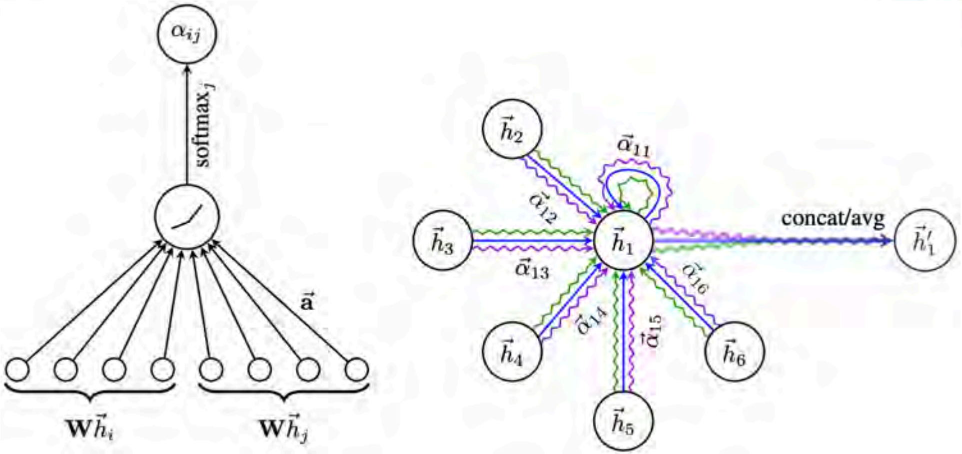
More Applications

Squeeze Excitation Networks (Hu et al., ’18)



Graph Attention Networks

(Velickovic et al., ’18)



Attention Summary

- Pooling

$$f(X) = \rho\left(\sum_{x \in X} \phi(x)\right)$$

- Attention pooling

$$f(X) = \rho\left(\sum_{x \in X} \alpha(x, w)\phi(x)\right)$$

Query w can depend on context

- Attention function (normalized to unit weight) such as

$$\alpha(x, X) \propto \exp\left(w^\top \tanh Ux\right)$$

3. Iterative Pooling

original image

first attention layer

second attention layer

Question Answering

Joe went to the kitchen.
Fred went to the kitchen.
Joe picked up the milk.
Joe travelled to the office.
Joe left the milk.
Joe went to the bathroom.

Where is the milk?

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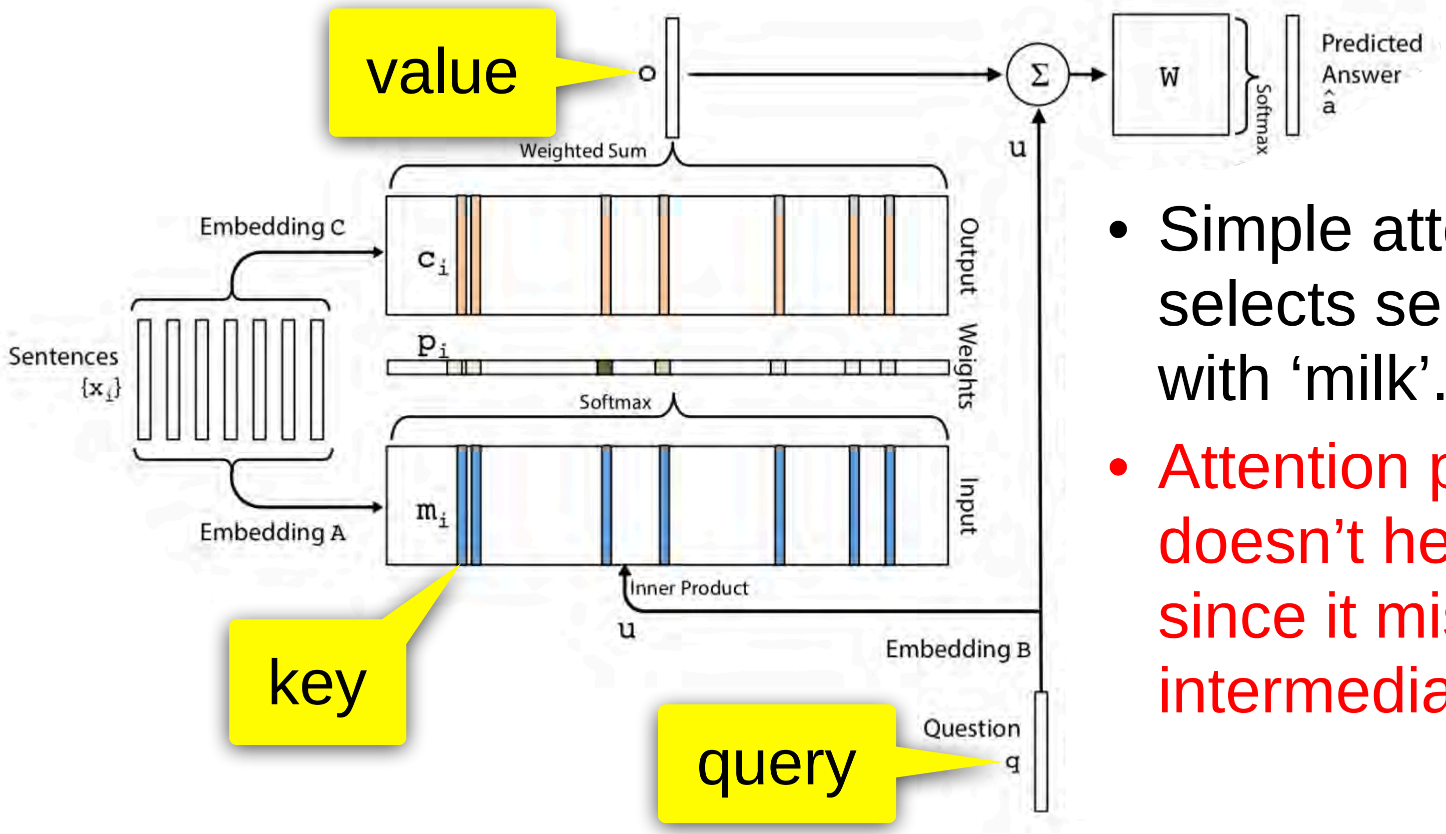
- Simple attention selects sentences with ‘milk’.
- Attention pooling doesn’t help much since it misses intermediate steps.

Question Answering with Pooling (Sukhbaatar et al., ’15)



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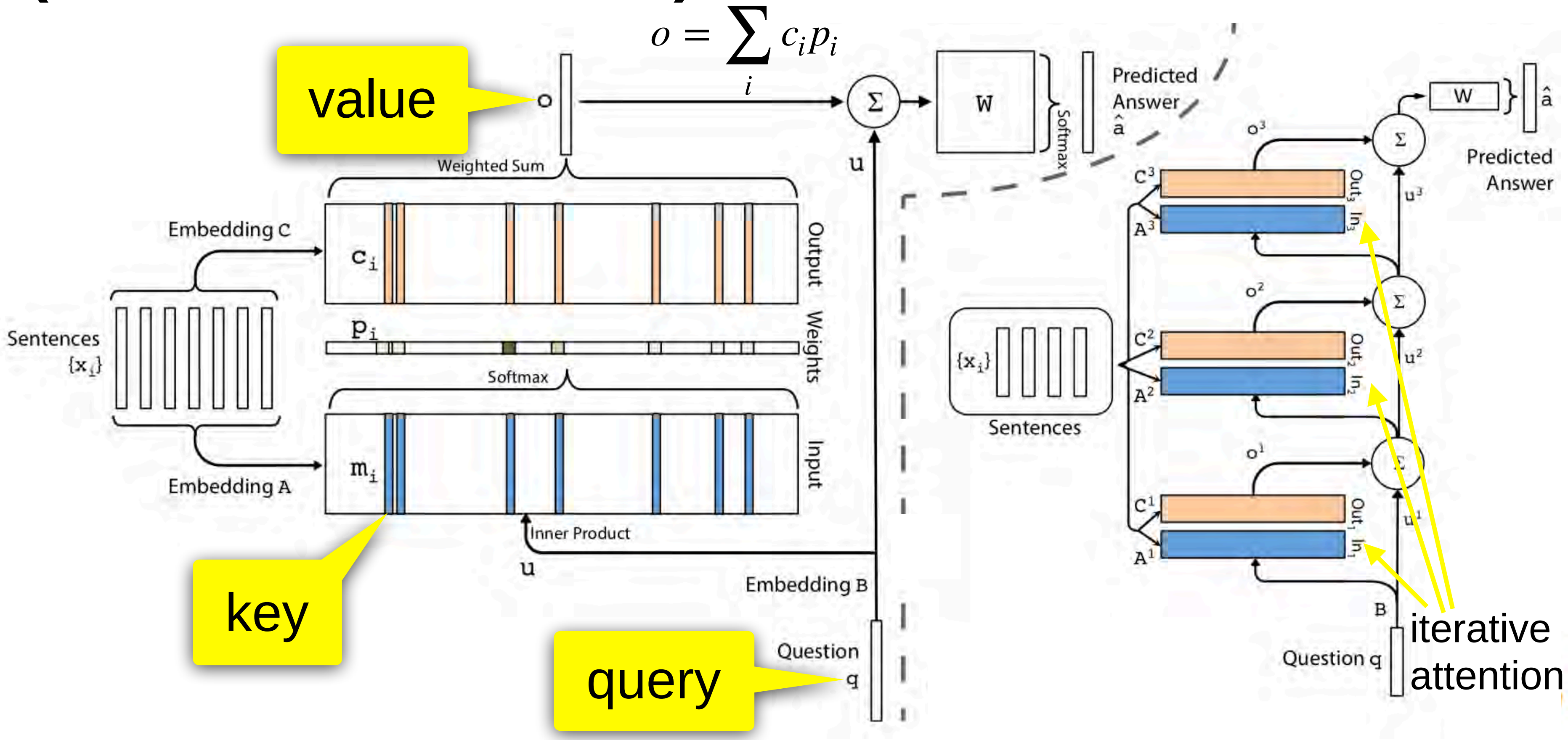
Question Answering with Pooling and Iteration (Sukhbaatar et al., '15)



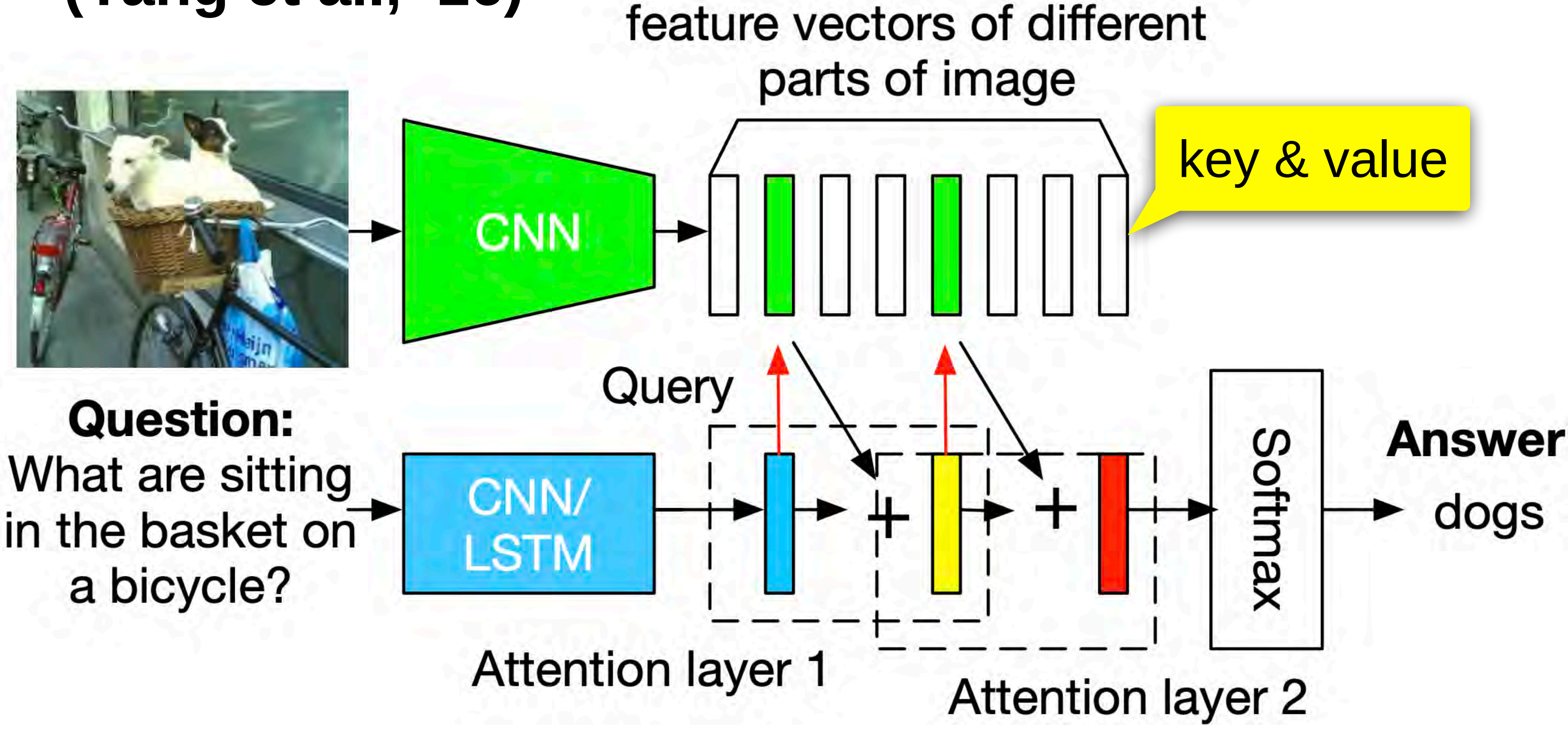
Question Answering with Pooling and Iteration (Sukhbaatar et al., ’15)

Sam walks into the kitchen.
Sam picks up an apple.
Sam walks into the bedroom.
Sam drops the apple.
Q: Where is the apple?
A. Bedroom

Brian is a lion.
Julius is a lion.
Julius is white.
Bernhard is green.
Q: What color is Brian?
A. White

Mary journeyed to the den.
Mary went back to the kitchen.
John journeyed to the bedroom.
Mary discarded the milk.
Q: Where was the milk before the den?
A. Hallway

Question Answering with Pooling and Iteration (Yang et al., ’16)

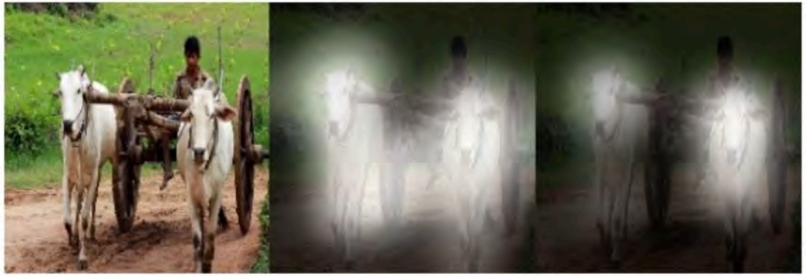


Question Answering with Pooling and Iteration (Yang et al., ’16)

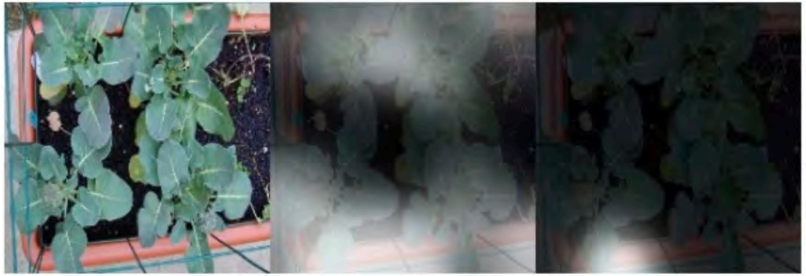
- Encode image via CNN
- Encode text query via LSTM
- Weigh patches according to attention and iterate

- Improving it (2019 tools)
  - Convolutionalize CNN (e.g. ResNet)
  - BERT for query encoding
  - Convolutional weighting (a la SE-Net)

(a) What are pulling a man on a wagon down on dirt road?
Answer: horses Prediction: horses



(b) What is the color of the box ?
Answer: red Prediction: red



(c) What next to the large umbrella attached to a table?
Answer: trees Prediction: tree

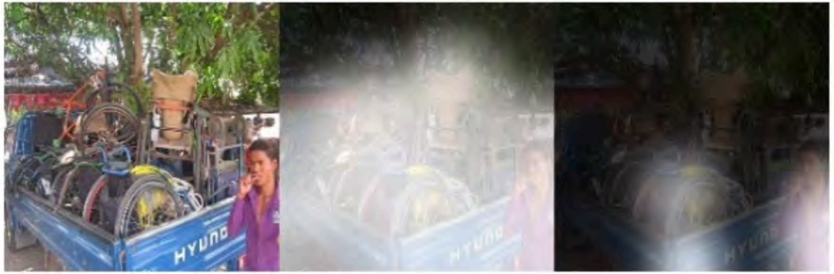
(d) How many people are going up the mountain with walking sticks?
Answer: four Prediction: four

(e) What is sitting on the handle bar of a bicycle?
Answer: bird Prediction: bird

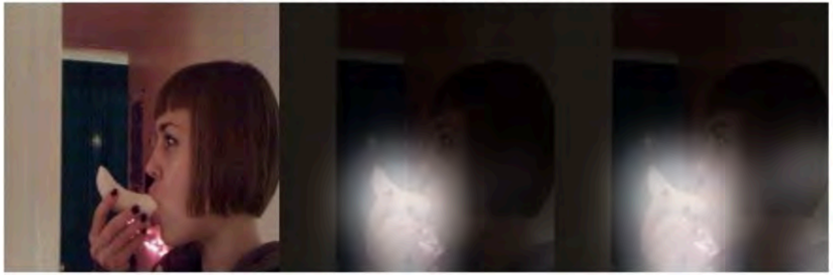
(f) What is the color of the horns?
Answer: red Prediction: red

(a) What swim in the ocean near two large ferries?
Answer: ducks Prediction: boats

(b) What is the color of the shirt?
Answer: purple Prediction: green



(c) What is the young woman eating?
Answer: banana Prediction: donut



(d) How many umbrellas with various patterns?
Answer: three Prediction: two

(e) The very old looking what is on display?
Answer: pot Prediction: vase

(f) What are passing underneath the walkway bridge?
Answer: cars Prediction: trains

Iterative Attention Summary

- Pooling

$$f(X) = \rho\left(\sum_{x \in X} \phi(x)\right)$$

- Attention pooling

$$f(X) = \rho\left(\sum_{x \in X} \alpha(x, w)\phi(x)\right)$$

- Iterative Attention pooling

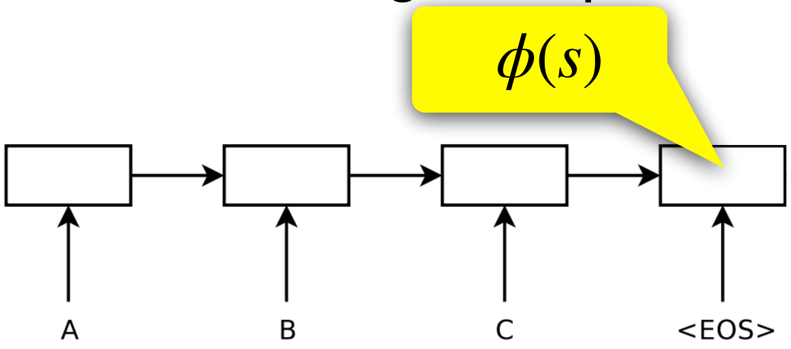
Repeatedly update internal state

$$q_{t+1} = \rho\left(\sum_{x \in X} \alpha(x, q_t)\phi(x)\right)$$


4. Iterative
Output

Seq2Seq for Machine Translation, Sutskever, Vinyals, Le ‘14

- Encode source sequence s via LSTM to representation $\phi(s)$
- Decode to target sequence one character at a time



- ‘The table is round.’ - ‘Der Tisch ist rund.’
- ‘The table is very beautiful with many inlaid patterns, blah blah blah blah’ - ‘Error …’

Seq2Seq for Machine Translation, Sutskever, Vinyals, Le ‘14

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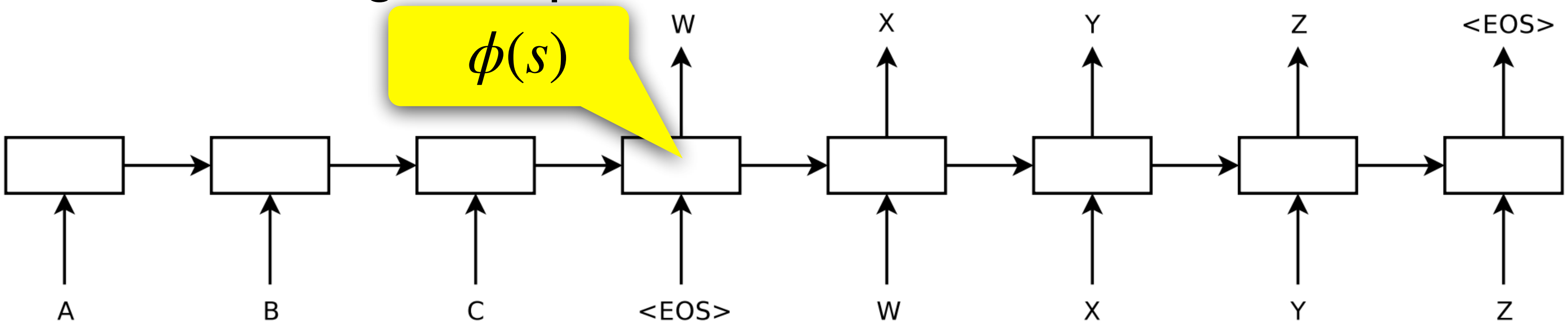

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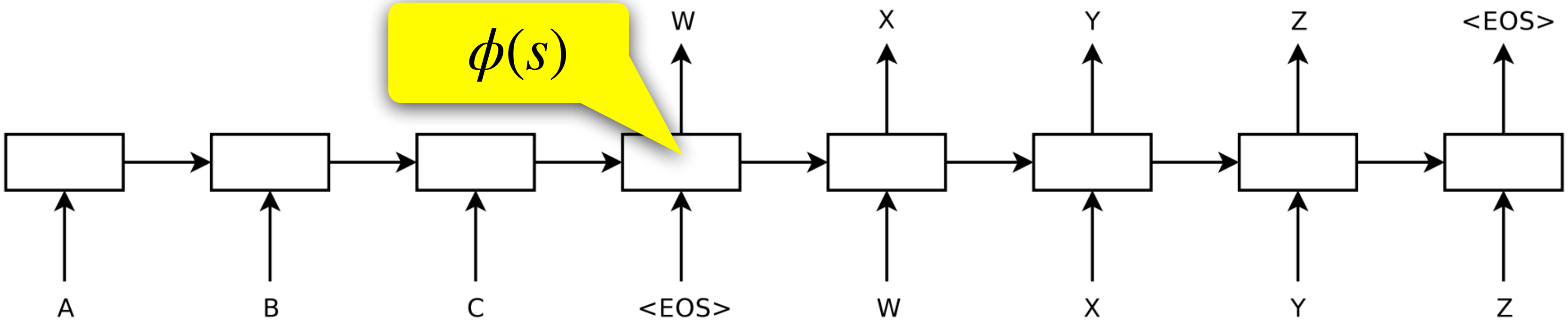
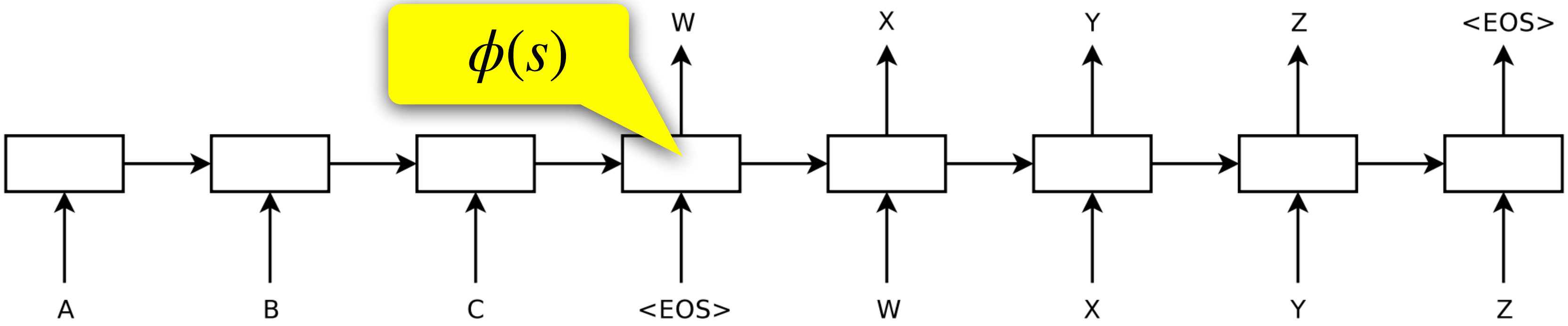


- ‘The table is round.’ - ‘Der Tisch ist rund.’
- ‘The table is very beautiful with r ’ blah blah blah blah’ - ‘Error … ’

Representation not rich enough

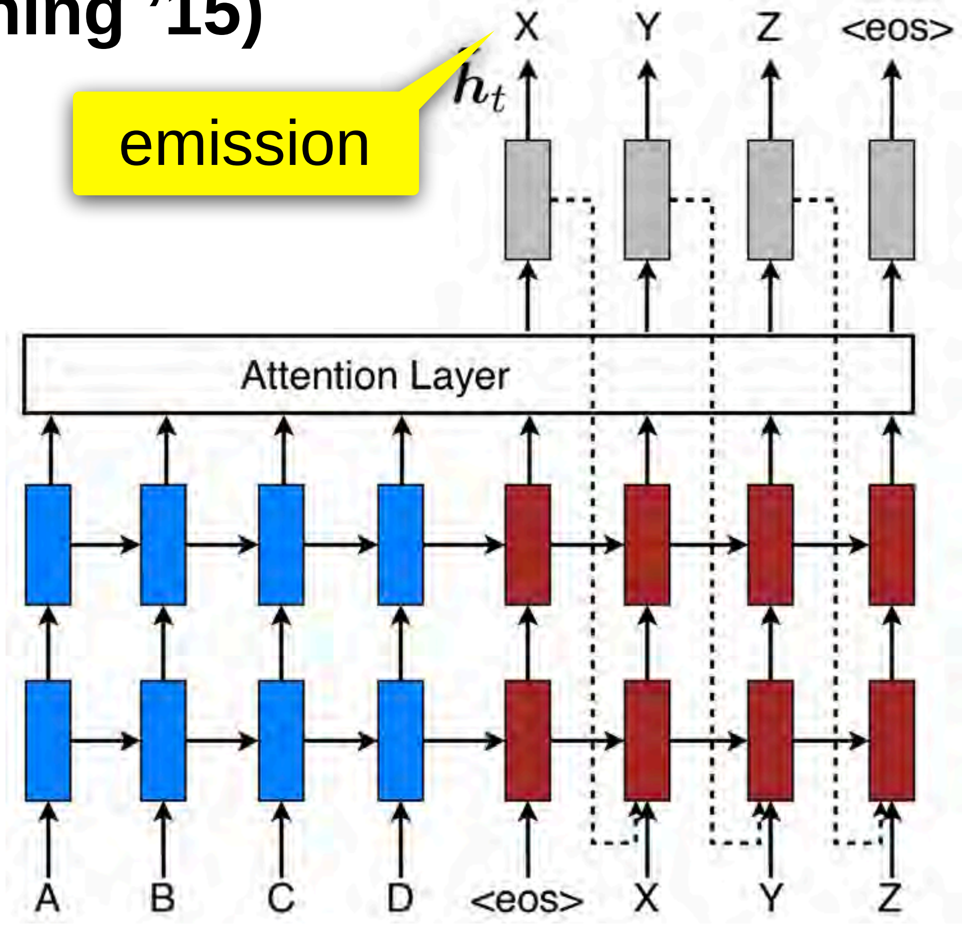
Seq2Seq for Machine Translation, Sutskever, Vinyals, Le '14

- Encode source sequence s via LSTM to latent representation $\phi(s)$
- Decode to target sequence one character at a time



- Need memory for long sequences
- Attention to iterate over source
  (we can look up source at any time after all)

Seq2Seq with attention (Bahdanau, Cho, Bengio ’14) (Pham, Luong, Manning ’15)



Seq2Seq with attention (Bahdanau, Cho, Bengio ’14) (Pham, Luong, Manning ’15)

$$\alpha_{ij} \propto \exp(a(\tilde{h}_{i-1}, h_j))$$

query

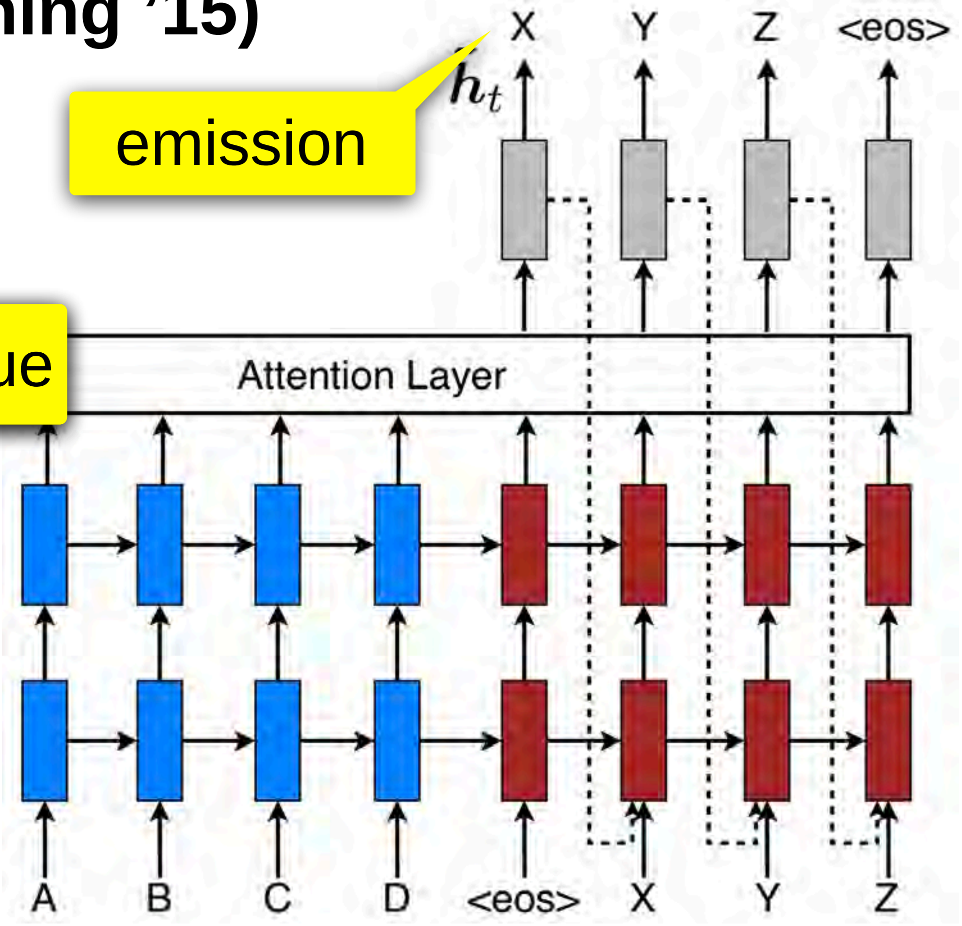
key & value

$$c_i = \sum_{j=1}^{n} \alpha_{ij} h_j$$

$$\tilde{h}_i = f(s_{i-1}, y_{i-1}, c_i)$$

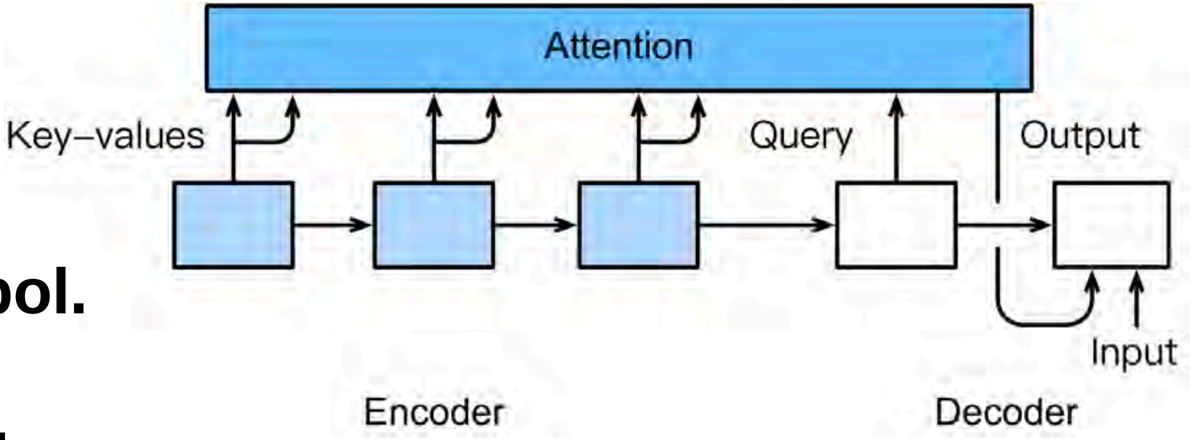
y_i

emission



Seq2Seq with attention (Bahdanau, Cho, Bengio ’14) (Pham, Luong, Manning ’15)

- Iterative attention model
  - Compute (next) attention weights
  - Aggregate next state
  - Emit next symbol
- Repeat
- **Memory networks emit only one symbol.**
- **NMT with attention emits many symbols.**



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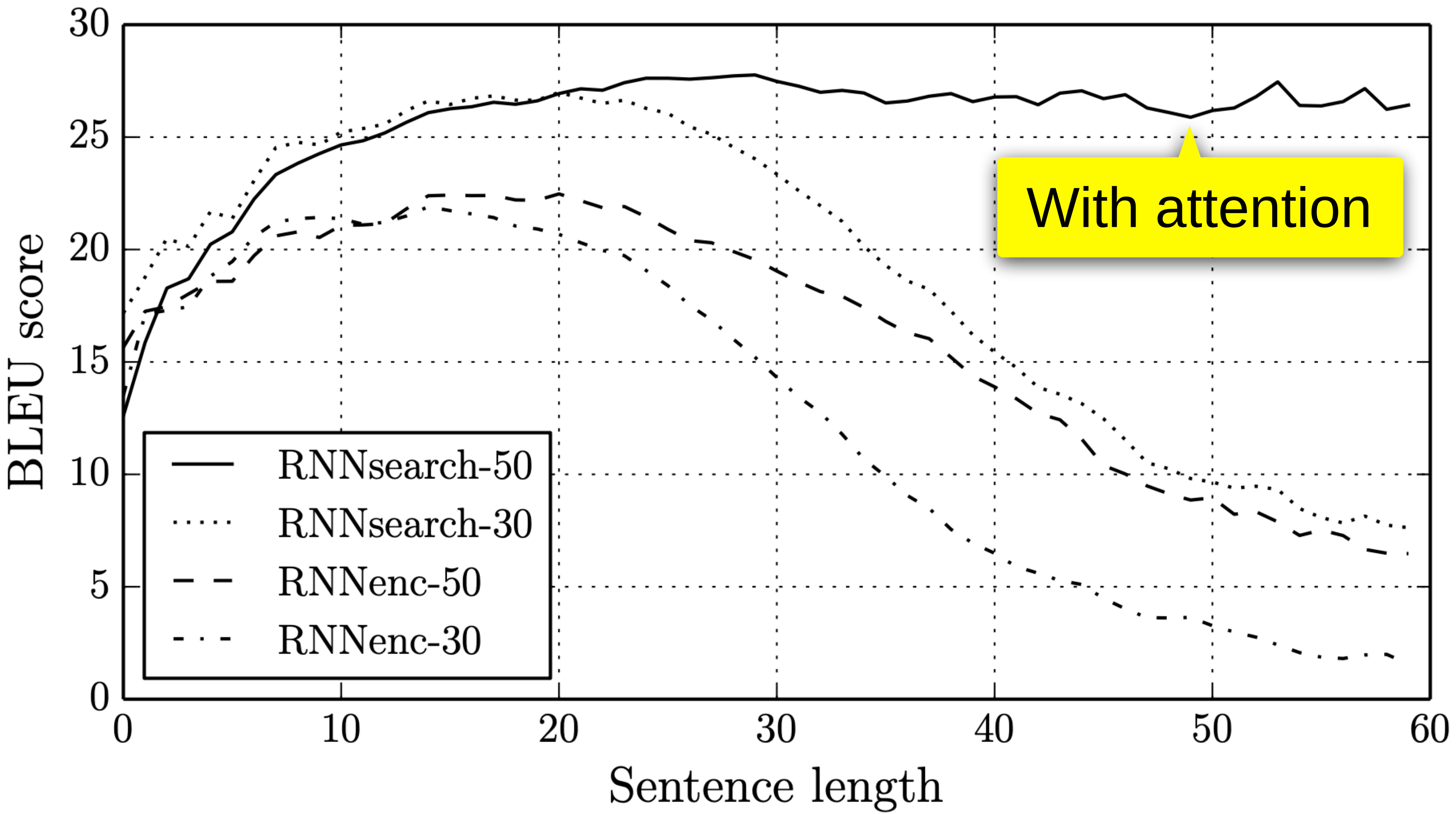


Variations on a Theme

BWV 988

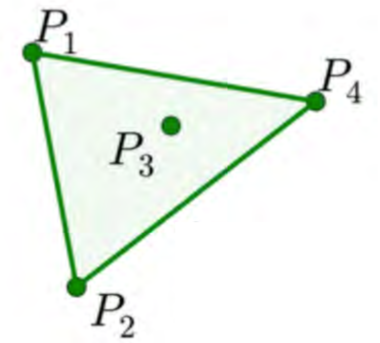
(PART I)

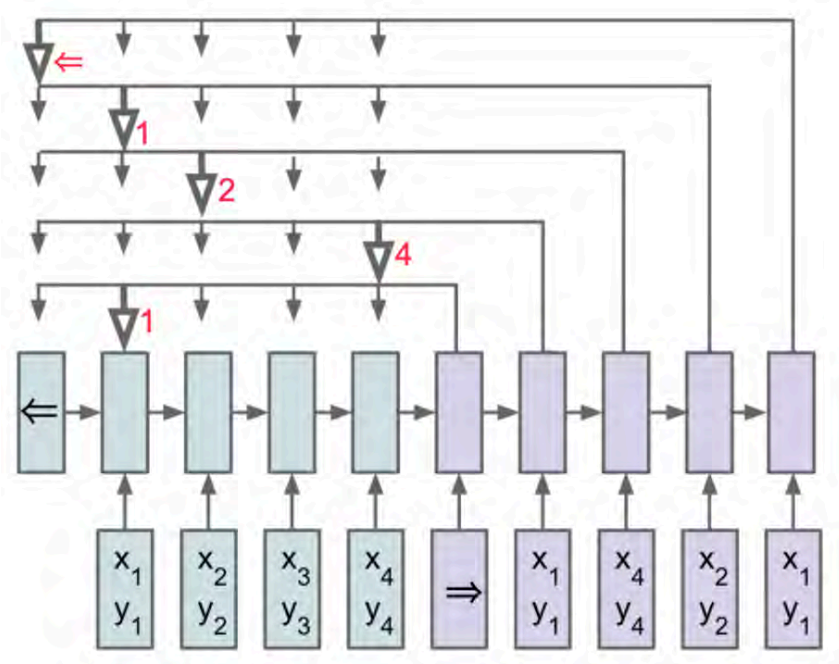
J.S.Bach (1685-1750)

Pointer networks for finding convex hull (Vinyals et al., '15)

$$\text{Input } P = \{P_1, \ldots P_4\}$$

$$\text{Output } O = \{1,4,2,1\}$$





Pointer networks for finding convex hull (Vinyals et al., ‘15)

$$\text{Input } P = \{P_1, \ldots P_4\}$$

$$\text{Output } O = \{1,4,2,1\}$$

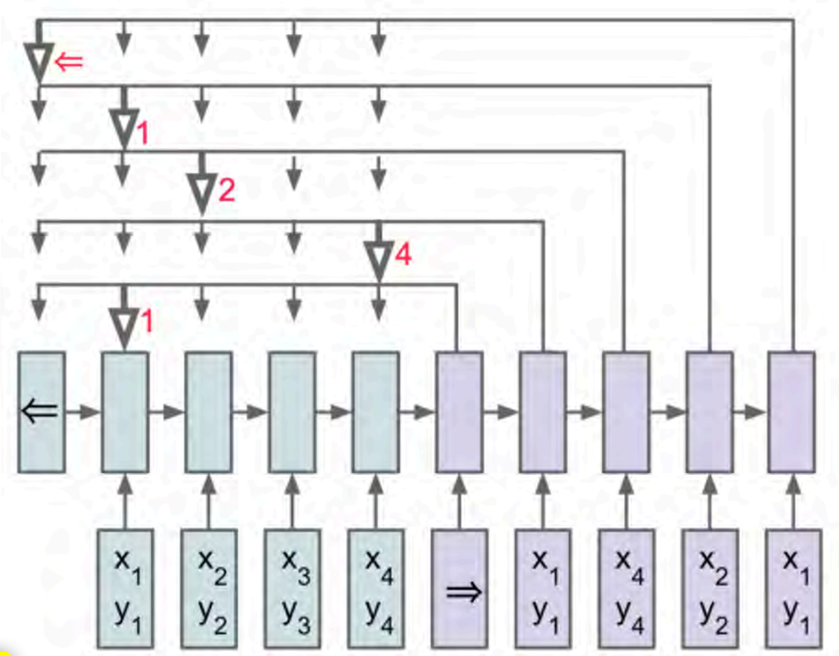
key

query

$$u_{ij} = v^\top \tanh(W[e_j, d_i])$$

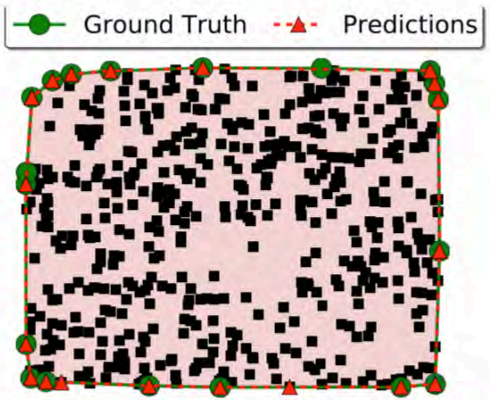
$$p(C_i \mid C_{[1:i-1]}, P) = \text{softmax}(u_i)$$

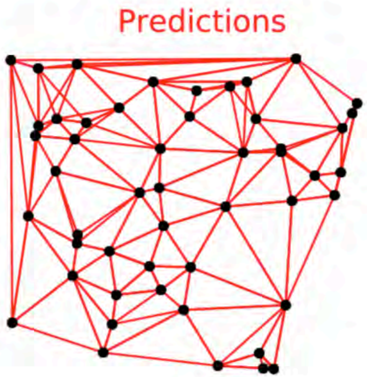
attention weight as prediction distribution

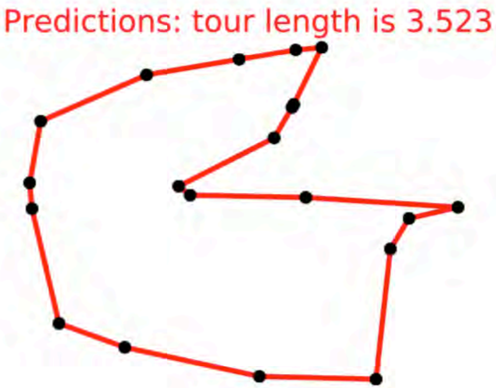


encoder state: e_j decoder state: d_i

Convex hulls, Delaunay triangulation, and TSP







2019 style improvements

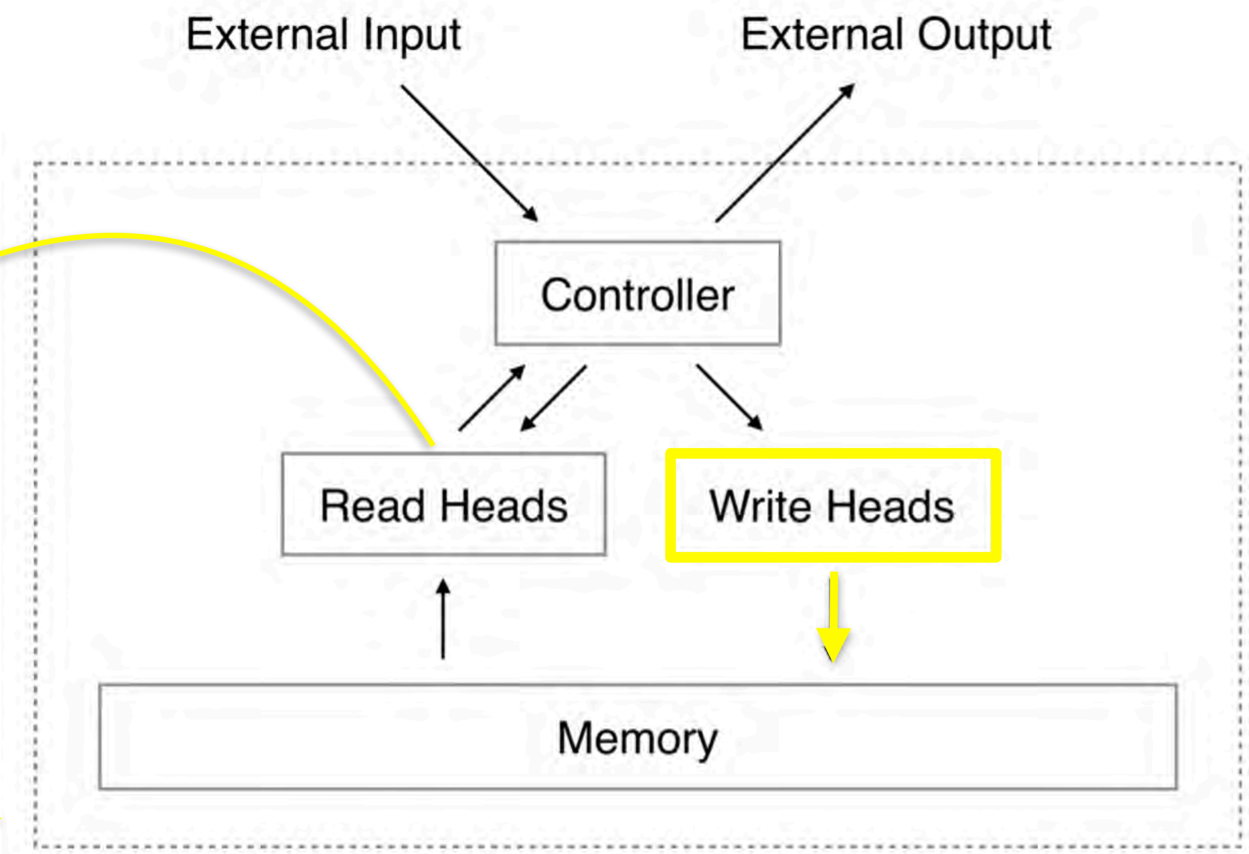
- Transformer to encode inputs (and outputs)
- Graph neural networks for local interactions

Neural Turing Machines (Graves et al., '14)

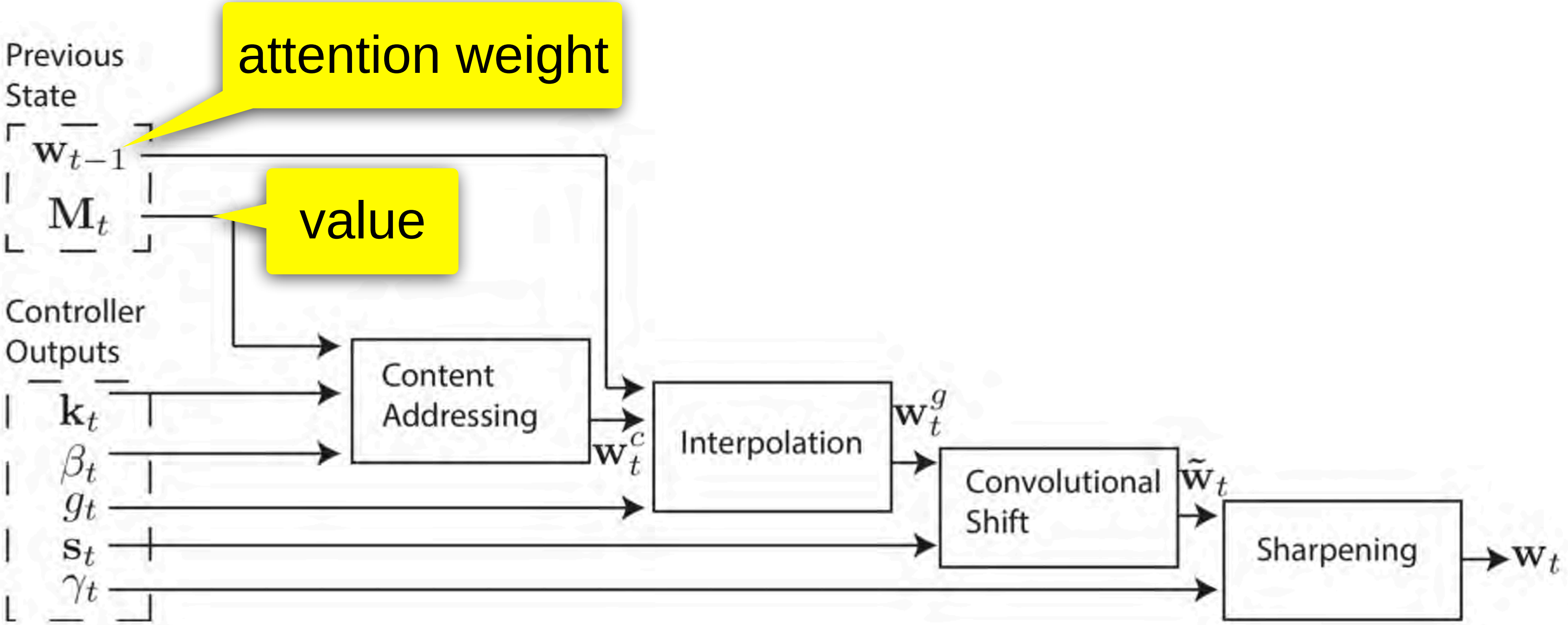
attention weight

$$r_t \leftarrow \sum_i w_t(i) M_t(i)$$

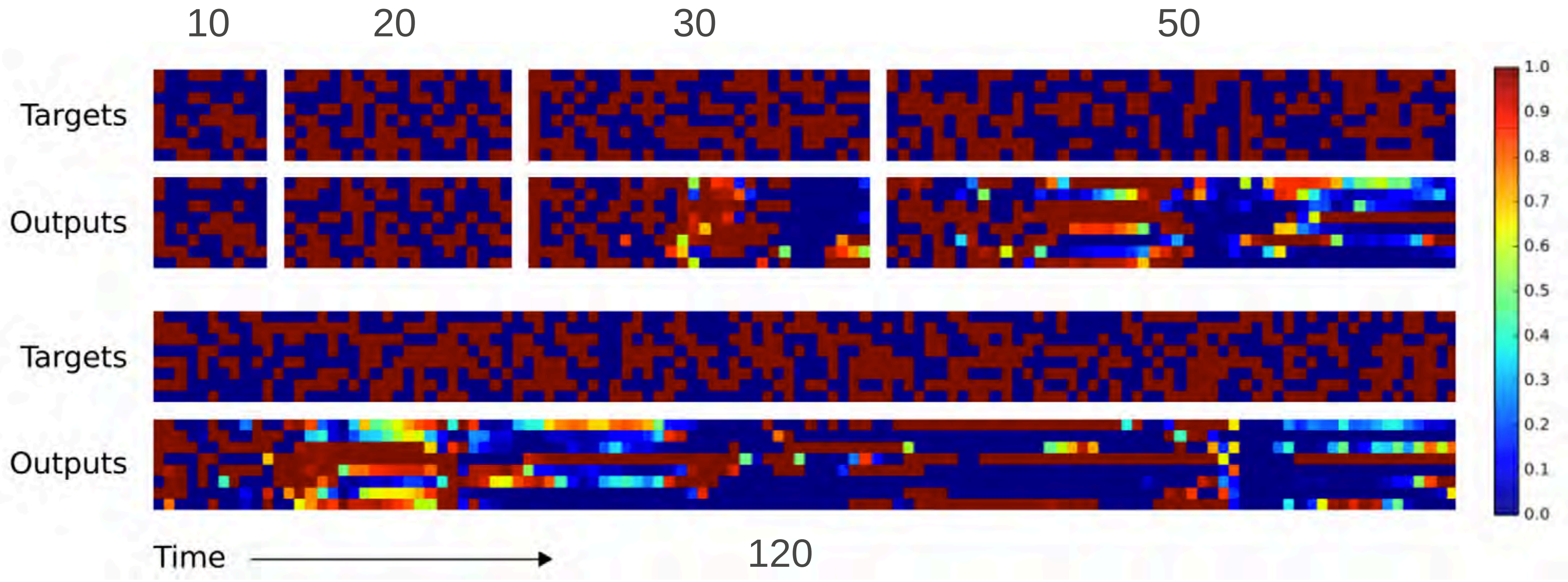
value



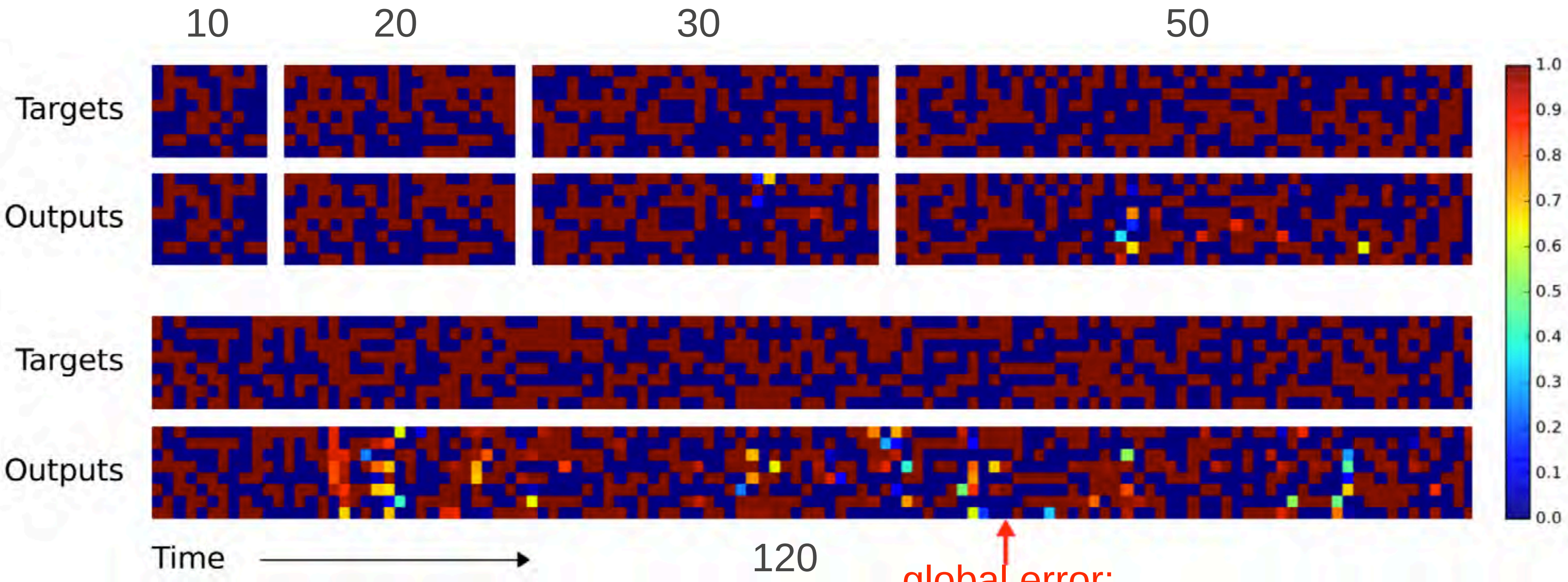
Attention weights can be stateful (values, too)



Copying a sequence (with LSTM)



Copying a sequence (with NTM)

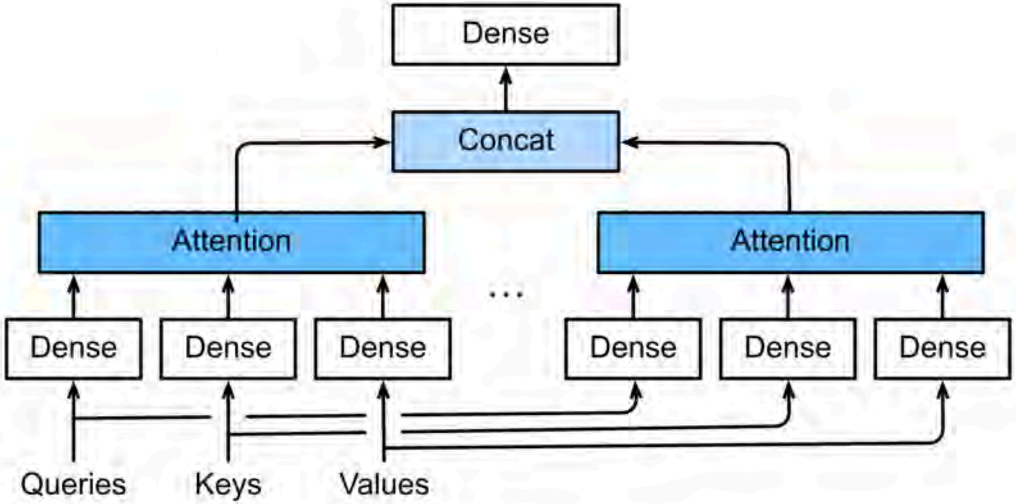


global error:
push all subsequent
vectors one step back


5. Multiple Heads

Multi-head attention (Vaswani et al., '17)

Q: query
K: key
V: value



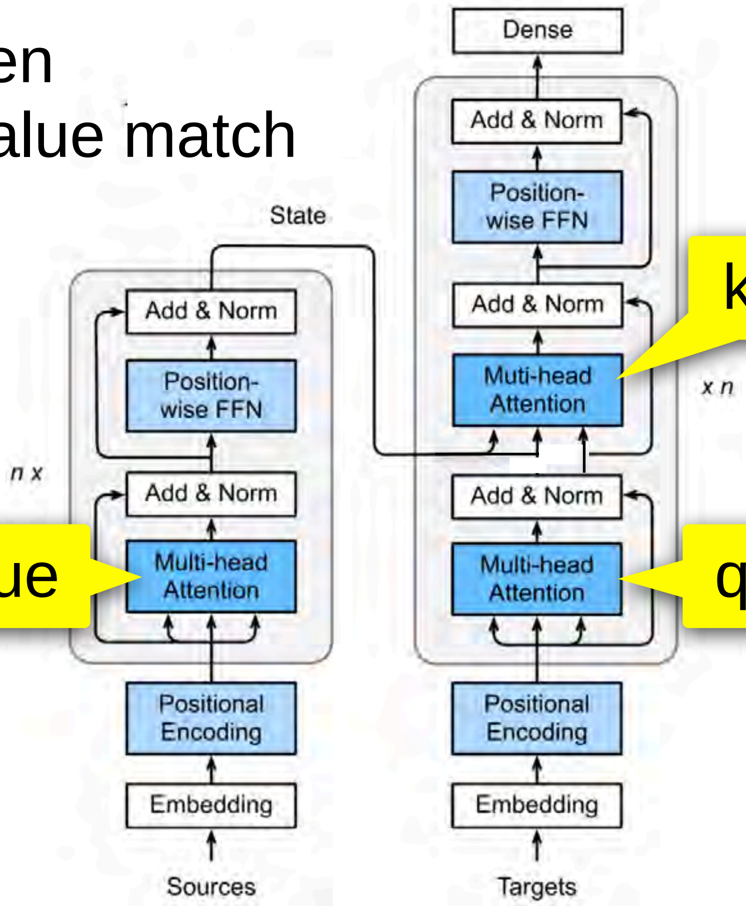
$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots \text{head}_h)W^O$$

$$\text{where head}_i = \text{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right)$$

Transformer with multi-head attention (Vaswani et al., ‘17)

Self-attention when
query, key, and value match



key = value

query = key = value

query = key = value

Semantic Segmentation

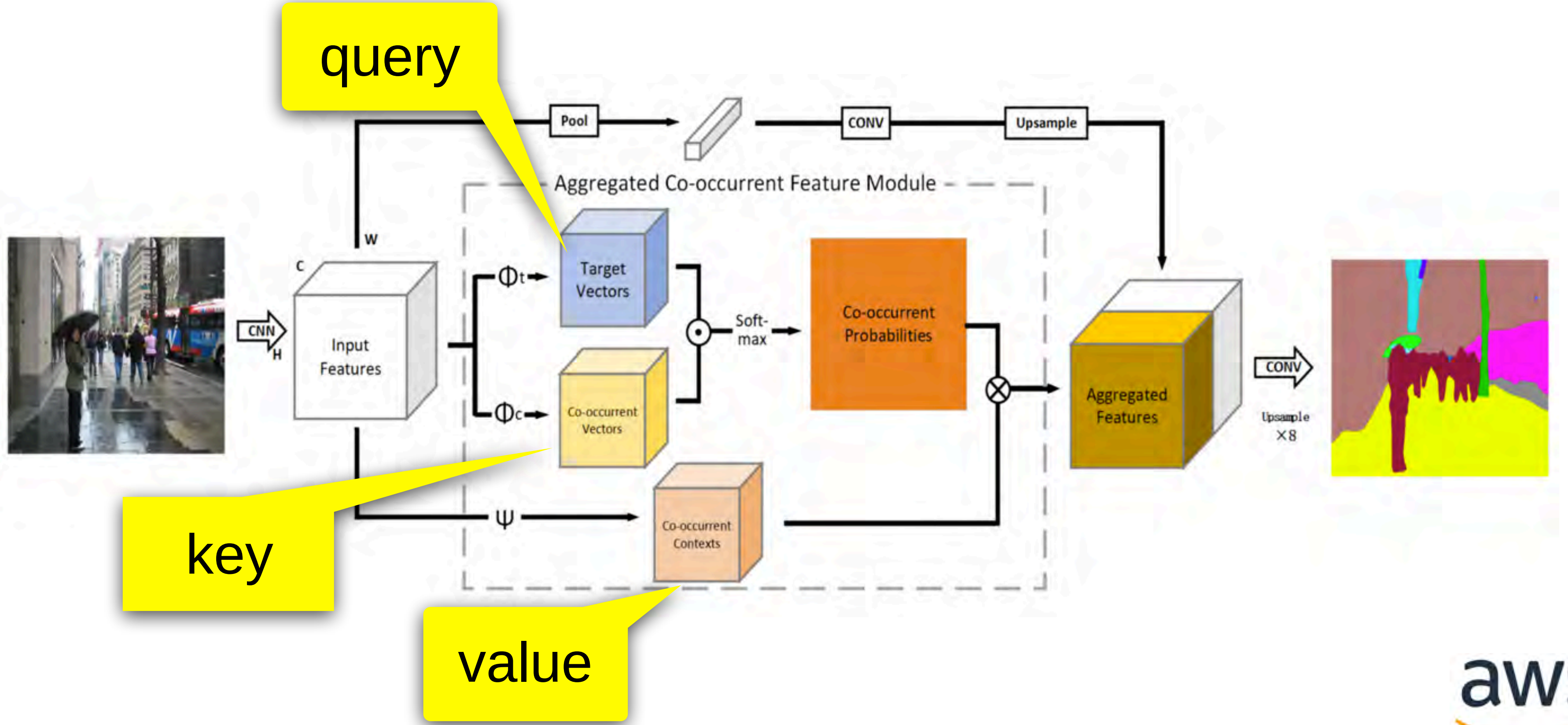
'sea' or 'water'?

Semantic Segmentation

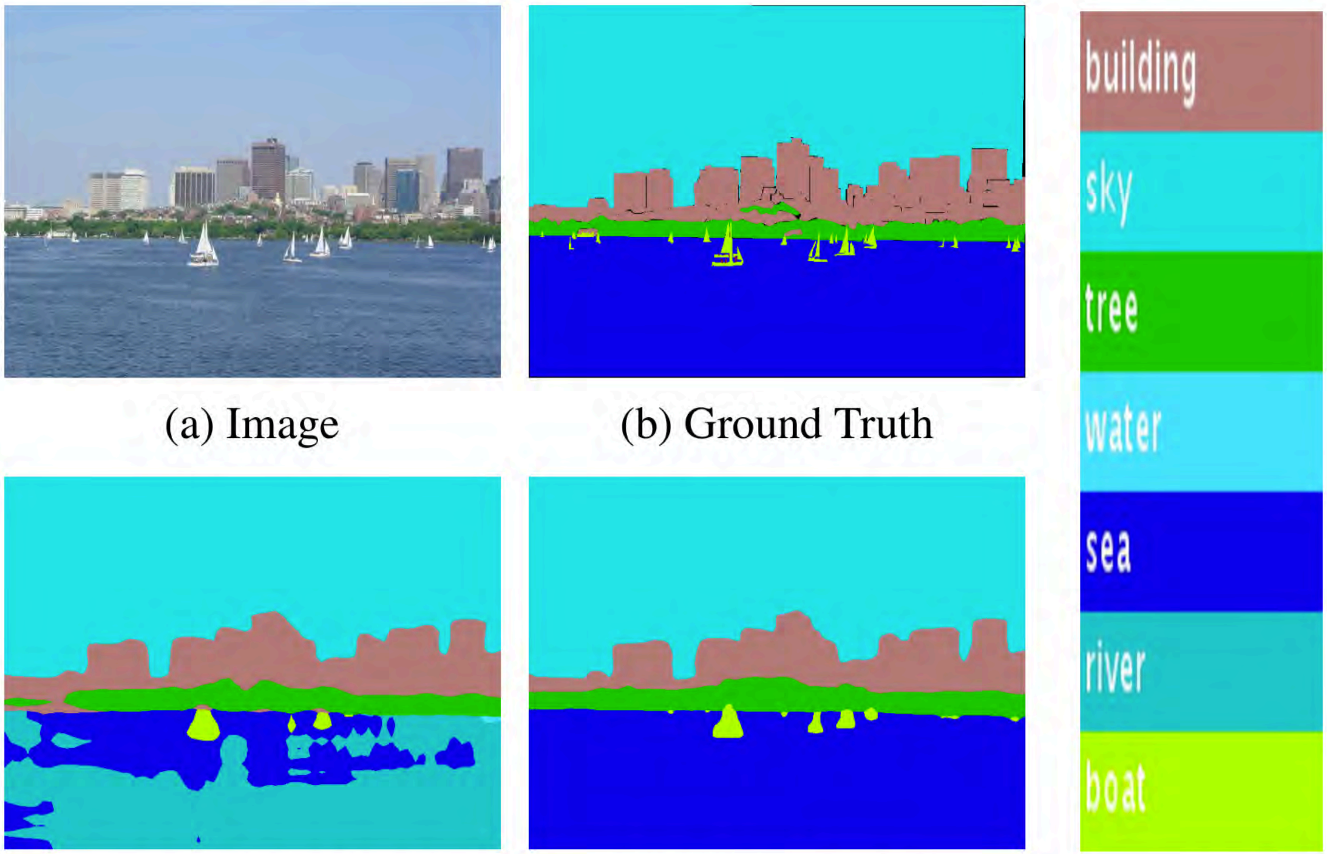
'sea' or 'water'?

Semantic Segmentation

Multi-head attention for semantic segmentation (Zhang et al., ‘19)



Classify pixels co-occurring with boat as sea rather than water



(a) Image (b) Ground Truth

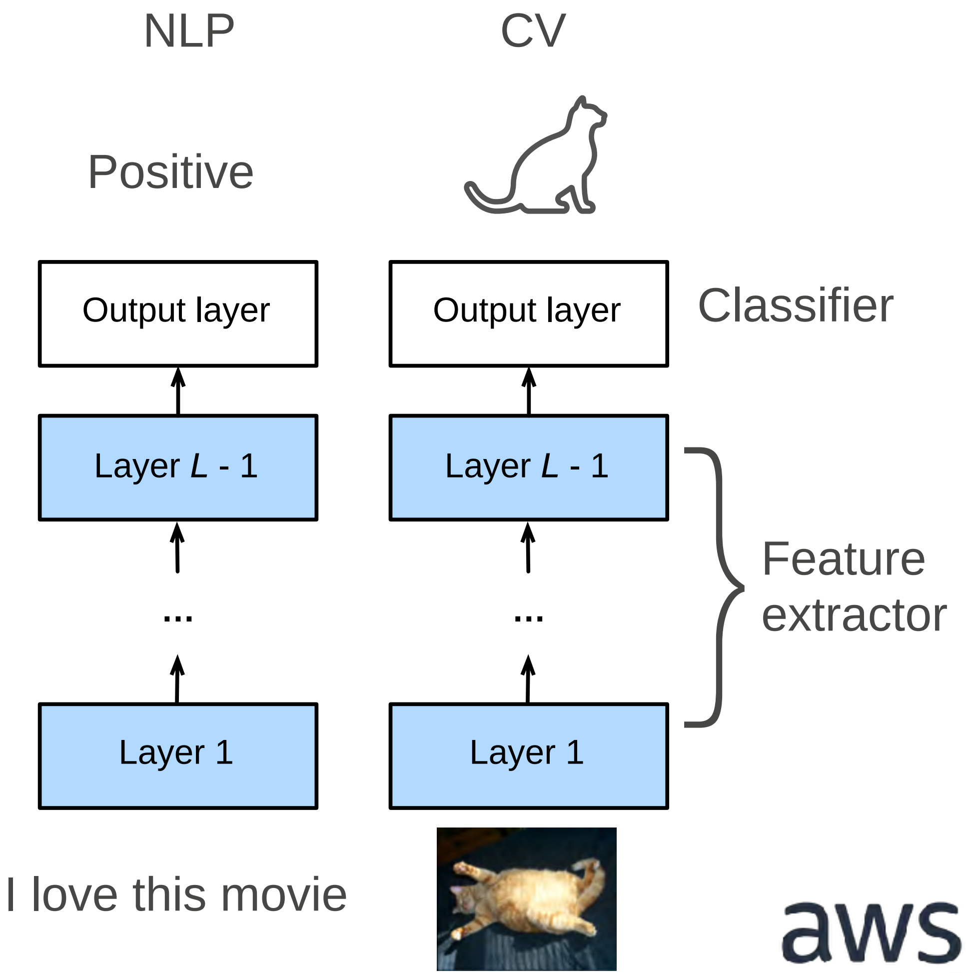
(c) FCN (baseline) (d) CFNet (ours) (e) legend

BERT
Bidirectional Encoder Representations from Transformers (Devlin et al, 2018)

SOTA on 11 NLP tasks

Motivation

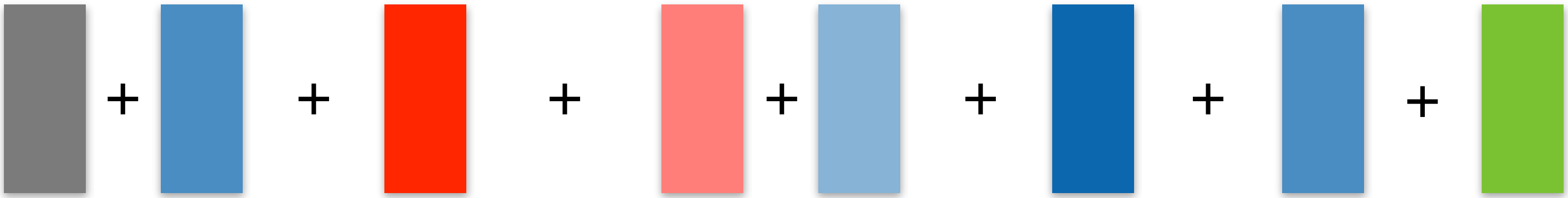
- Fine-tuning for NLP (learning a prior for NLP)
- Pre-trained model captures prior
- Only add one (or more) output layers for new task



Transfer Learning with Embeddings

- Pre-trained embeddings for new models (e.g. word2vec)

```
Alex is obnoxious but the tutorial is awesome.
```



- Word2vec ignores sequential information entirely

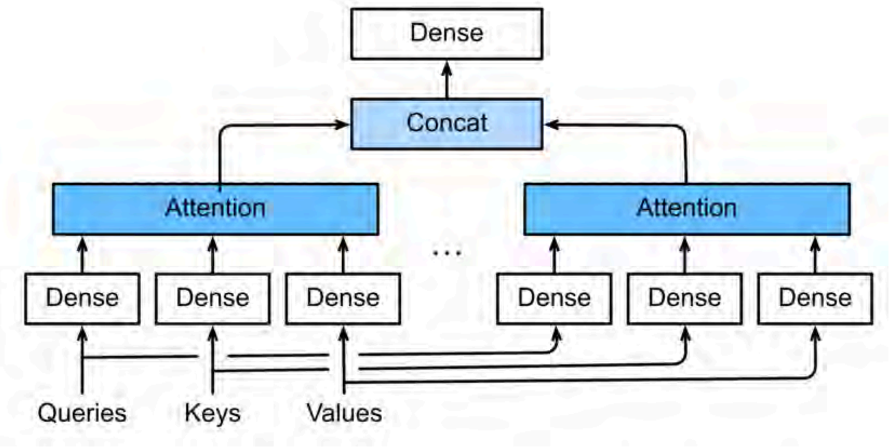
GPT uses Transformer Decoder (Radford et al., ‘18)

- Pre-train language model, then fine-tune on each task
- **Trained on full length documents**
- 12 blocks, 768 hidden units, 12 heads
- SOTA for 9 NLP tasks

- Language model only looks **forward**
  - `I went to the bank to deposit some money.`
  - `I went to the bank to sit down.`

Architecture

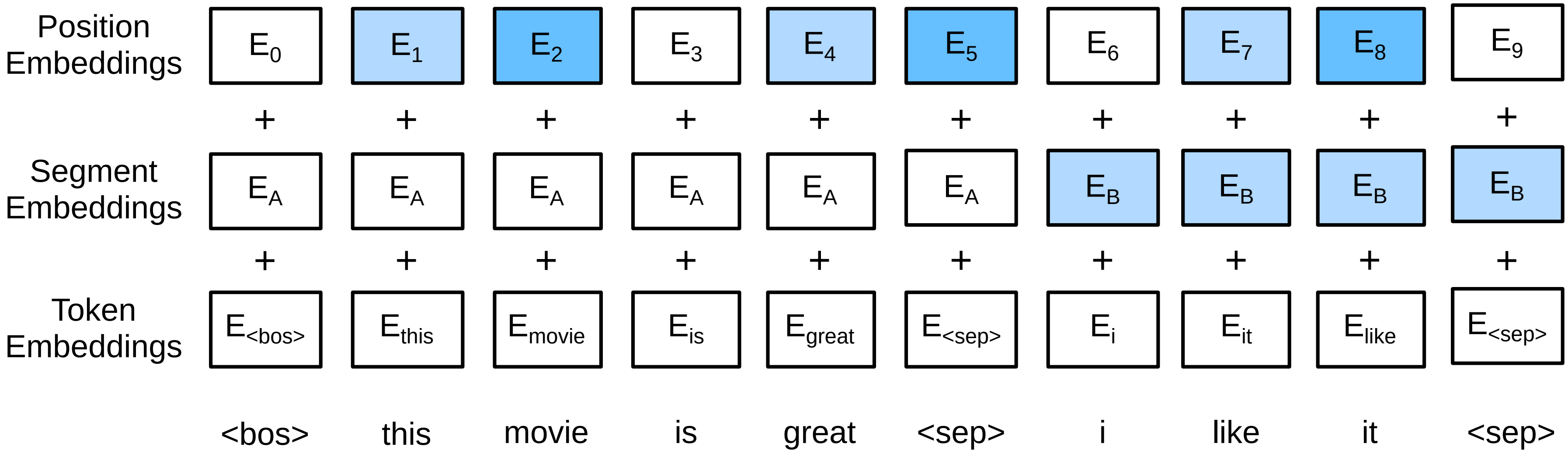
- (Big) transformer encoder
- Train on large corpus (books, wikipedia) with > 3B words



	blocks	hidden units	heads	parameters
small	12	768	12	110M
large	24	1024	16	340M

Input Encoding

- Each example is a pair of sentences
- Add segment embedding and position embedding



Task 1 - Masked Language Model

- Estimate $p(x_i \mid x_{[1:i-1]}, x_{[i+1:n]})$ rather than $p(x_i \mid x_{[1:i-1]})$
  - Randomly mask 15% of all tokens and predict token
  - 80% of them - replace token with <mask>
  - 10% of them - replace with <random token>
  - 10% of them - replace with <token>

```
Alex is obnoxious but the tutorial    is awesome.
Alex is obnoxious but the <mask>      is awesome.
Alex is obnoxious but the <banana>    is awesome.
Alex is obnoxious but the <tutorial>  is awesome.
```

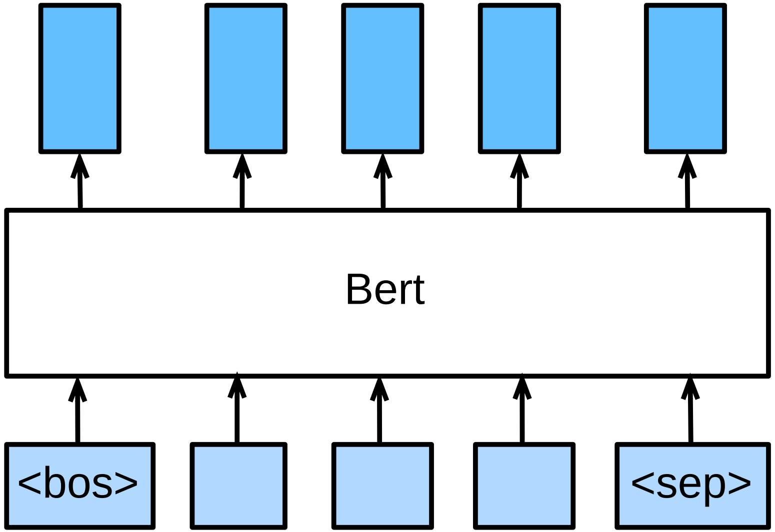
Task 2 - Next Sentence Prediction

- Predict next sentence
  - 50% of the time, replace it by random sentence
  - Feed the Transformer output into a dense layer to predict if it is a sequential pair.
- **Learn logical coherence**

```
<BOS> Alex is obnoxious <SEP> I don’t like his shirt
<BOS> Alex is obnoxious <SEP> Look a Martian
```

Using BERT

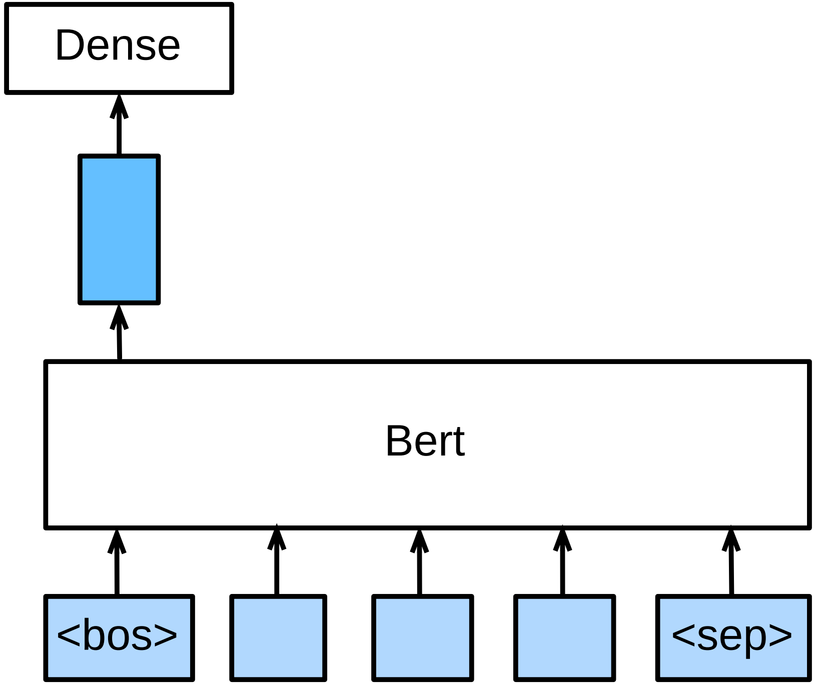
- BERT returns a feature vector for each token.
- Embedding captures context



Using BERT - Sentence Classification

- BERT returns a feature vector for each token.
- Embedding captures context

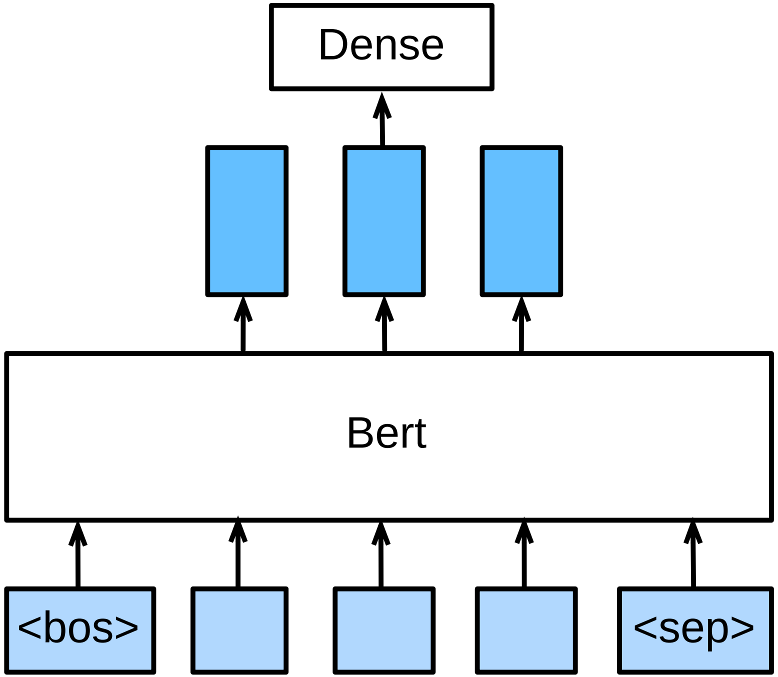
- Feed <bos> embedding into dense layer
- Works for pairs, too



Using BERT - Named Entity Recognition

- BERT returns a feature vector for each token.
- Embedding captures context

- Identify if token is an entity
- Use embedding for each non-special token and classify via dense layer.

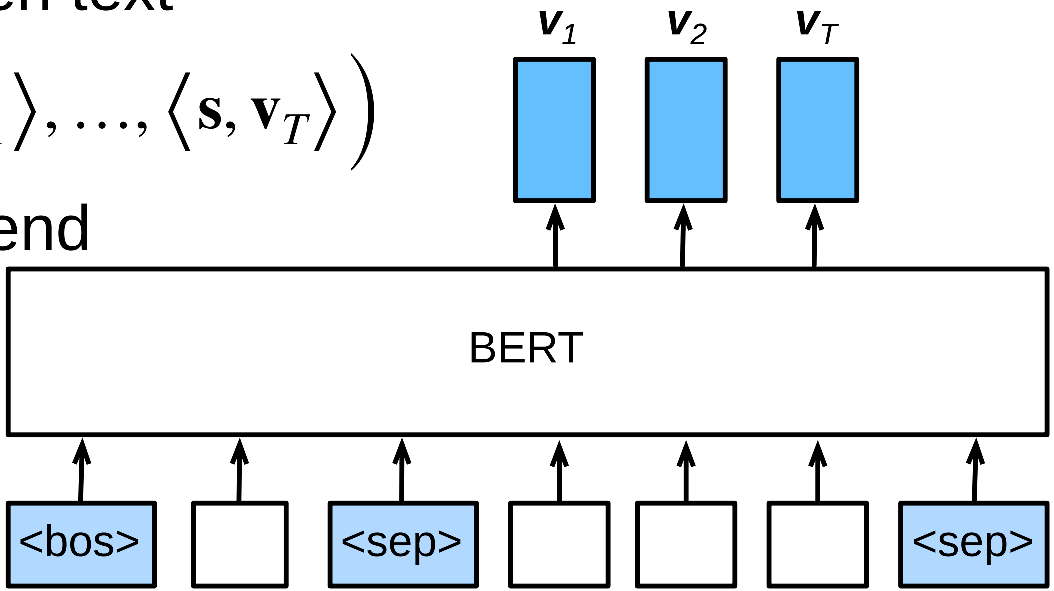


Using BERT - Question Answering

- Given question, find answer as segment of text
- Encode question first, then text

$$p_1, \ldots, p_T = \mathrm{softmax}\left(\langle \mathbf{s}, \mathbf{v}_1 \rangle, \ldots, \langle \mathbf{s}, \mathbf{v}_T \rangle\right)$$

- Model sequence start & end probability for answer.



GPT2 (it gets even bigger, Radford et al., ‘19)

- Pretrained on 8M webpages (WebText, 40GB)
- Without fine-tuning SOTA on 7 language models

	blocks	hidden units	parameters
small	12	768	110M
large	24	1024	340M
GPT2	48	1600	1.5B

GPT2 Demo (gluon-nlp.mxnet.io)

```
$python sampling_demo.py --model 117M
Please type in the start of the sentence
>>> average human attention span is even shorter than that of a
goldfish
-----  Begin Sample 0 -----
average human attention span is even shorter than that of a
goldfish strutting its way down the jaws. An estimate by the USA
TODAY Science team of 80 human-sized models reveals that a complex
jaw becomes a grandiose mitesaur in 100 million years, less than an
exothermic Holocene huge sea lion, and towering 500 meters tall.

Similar mitesaur-sized jaws would burden as trillions

Scientists would expect a lost at least four million times as much
time in the same distances ocean as other mammals
```


Sparse
Structured
Lightweight

Heavy parameterization in multi-head attention

9. Attention Mechanism > 9.3. Transformer

In practice, we often use $p_q = p_k = p_v = d_o/h$. The hyper-parameters for a multi-head attention, feature size d_o.

```
class MultiHeadAttention(nn.Block):
    def __init__(self, units, num_heads, dropout, **kwargs):  # units = d_o
        super(MultiHeadAttention, self).__init__(**kwargs)
        assert units % num_heads == 0
        self.num_heads = num_heads
        self.attention = d2l.DotProductAttention(dropout)
        self.W_q = nn.Dense(units, use_bias=False, flatten=False)
        self.W_k = nn.Dense(units, use_bias=False, flatten=False)
        self.W_v = nn.Dense(units, use_bias=False, flatten=False)

    # query, key, and value shape: (batch_size, num_items, dim)
    # valid_length shape is either (bathc_size, ) or (batch_size, num_items)
    def forward(self, query, key, value, valid_length):
        # Project and transpose from (batch_size, num_items, units) to
        # (batch_size * num_heads, num_items, p), where units = p * num_heads.
        query, key, value = [transpose_qkv(X, self.num_heads) for X in (
            self.W_q(query), self.W_k(key), self.W_v(value))]
```

parameterization of fully connected (dense) layers

Quaternion Transformer - 75% fewer parameters (Tay et al., ’19)

Quaternion is 4D hypercomplex number

fully connected

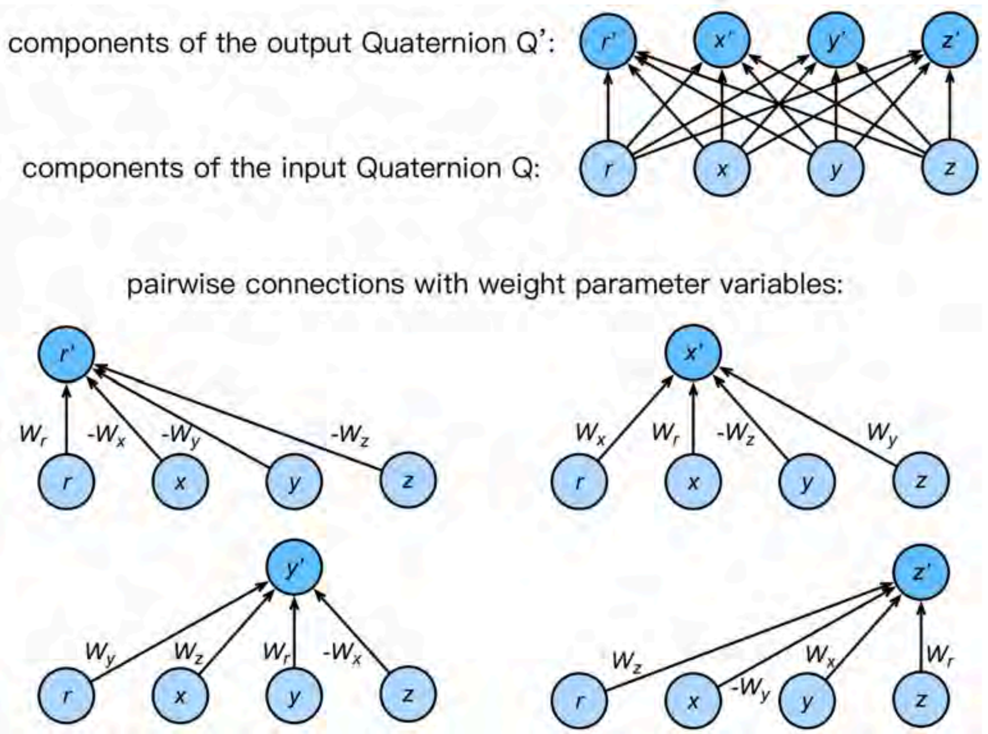
$$W = W_r + W_x\mathbf{i} + W_y\mathbf{j} + W_z\mathbf{k}$$

$$Q = r + x\mathbf{i} + y\mathbf{j} + z\mathbf{k}$$

Hamilton product

$$\begin{bmatrix} W_r & -W_x & -W_y & -W_z \\ W_x & W_r & -W_z & W_y \\ W_y & W_z & W_r & -W_x \\ W_z & -W_y & W_x & W_r \end{bmatrix} \begin{bmatrix} r \\ x \\ y \\ z \end{bmatrix}$$

only 4 degrees of freedom
(16 for real-valued matrix)



High computational cost for a long sequence

9. Attention Mechanism > 9.1. Attention Mechanism

Assume $\mathbf{Q} \in \mathbb{R}^{m\times d}$ contains m queries and $\mathbf{K} \in \mathbb{R}^{n\times d}$ has all n keys. We can compute all mn sco

$$\alpha(\mathbf{Q}, \mathbf{K}) = \mathbf{Q}\mathbf{K}^T/\sqrt{d}.$$

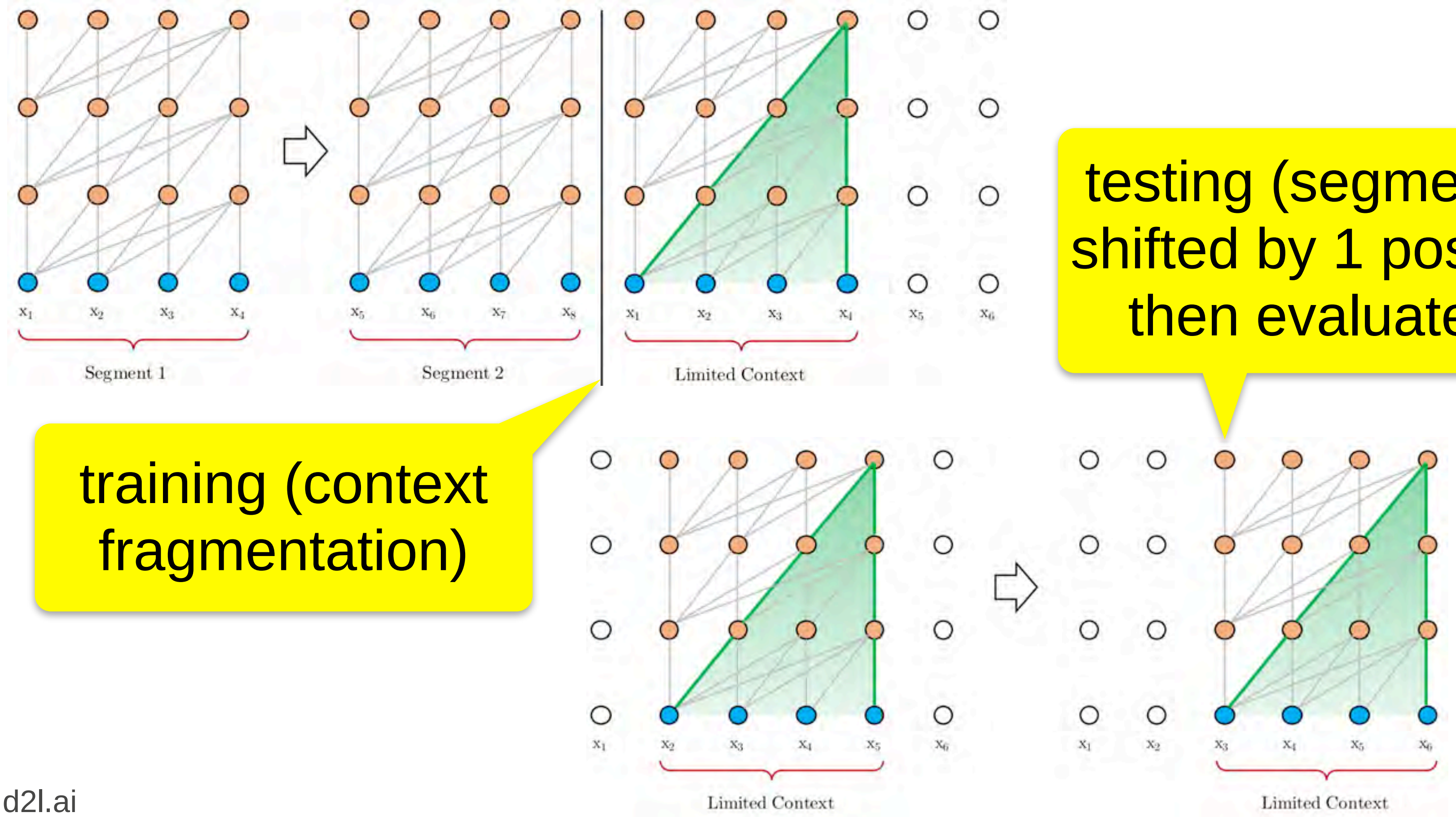
Now let's implement this layer that supports a batch of queries and key-value pairs. In addition, it su
attention weights as a regularization.

```
class DotProductAttention(nn.Block):  # This class is saved in d2l.
    def __init__(self, dropout, **kwargs):
        super(DotProductAttention, self).__init__(**kwargs)
        self.dropout = nn.Dropout(dropout)

    # query: (batch_size, #queries, d)
    # key: (batch_size, #kv_pairs, d)
    # value: (batch_size, #kv_pairs, dim_v)
    # valid_length: either (batch_size, ) or (batch_size, xx)
    def forward(self, query, key, value, valid_length=None):
        d = query.shape[-1]
        # set transpose_b=True to swap the last two dimensions of key
        scores = nd.batch_dot(query, key, transpose_b=True) / math.sqrt(d)
        attention_weights = self.dropout(masked_softmax(scores, valid_length))
        return nd.batch_dot(attention_weights, value)
```

O(n^2d) in self attention
(sequence length n)
(hidden size d)

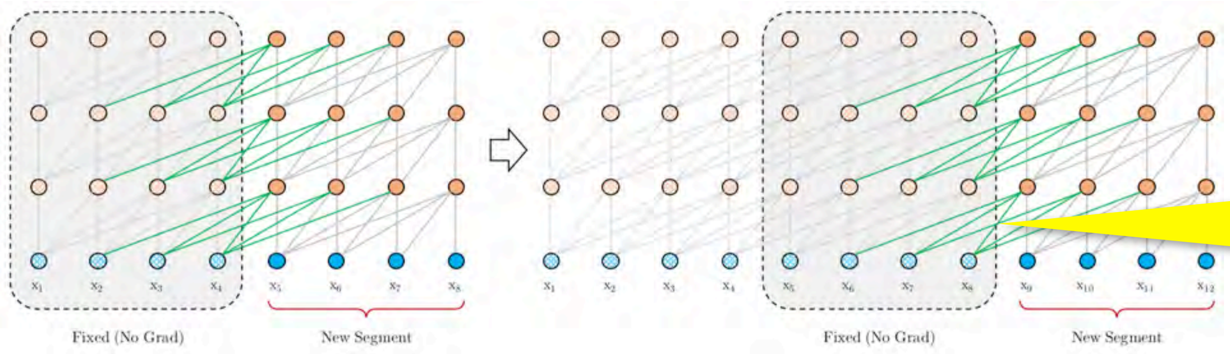
Structured attention on long sequences (Al-Rfou et al., '18)



testing (segment is shifted by 1 position then evaluated)

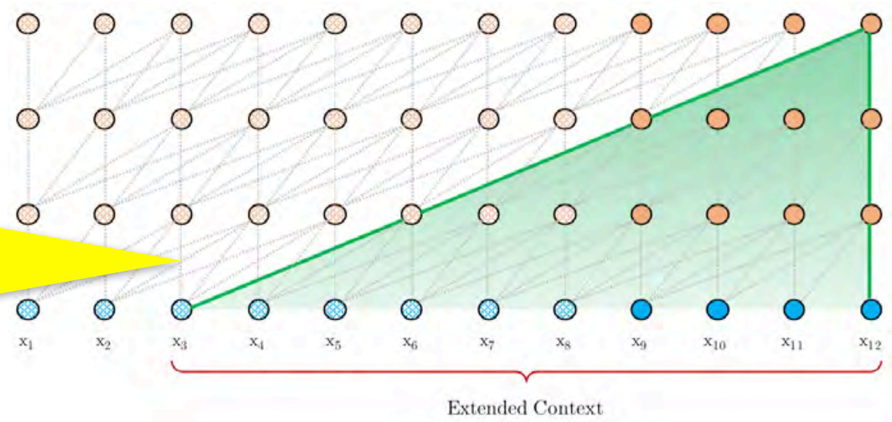
training (context fragmentation)

Transformer-XL with recurrence (Dai et al., ‘19)

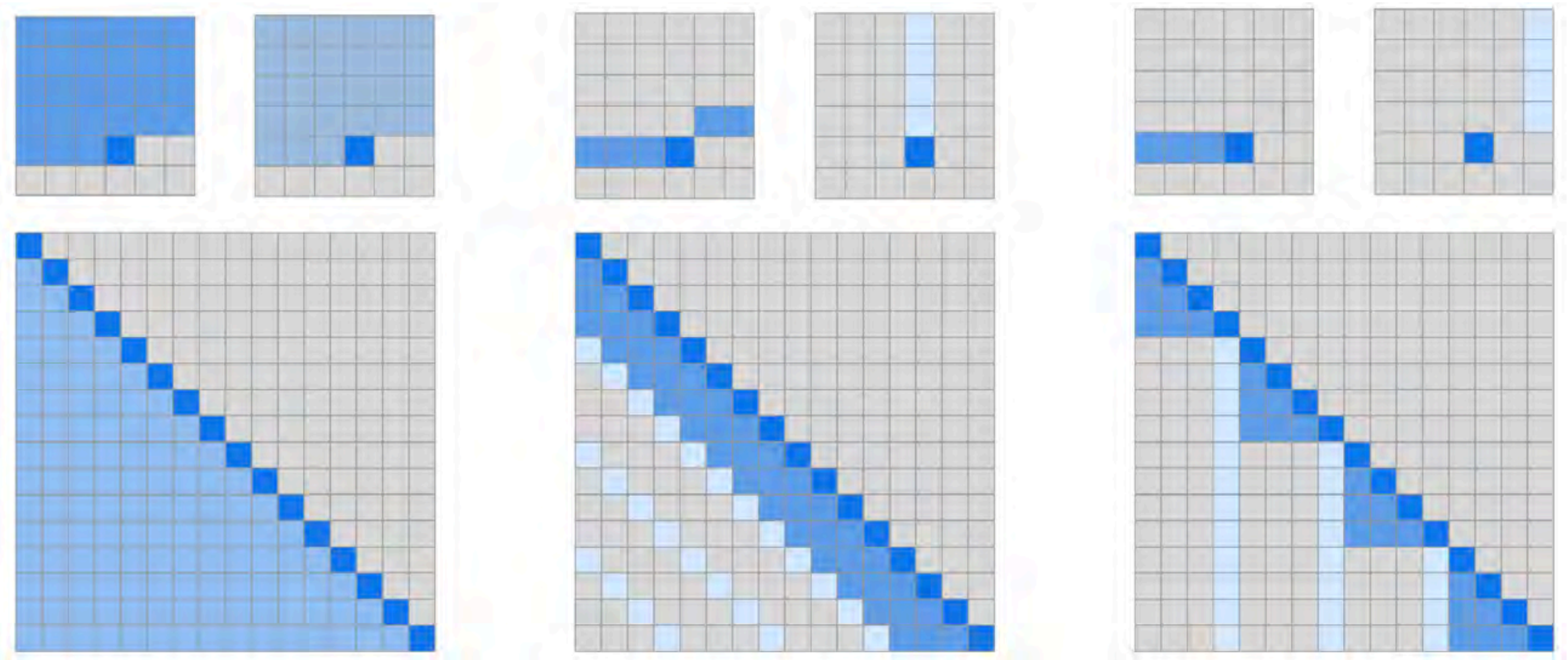


training - cache previous segments ‘truncated BPTT’

testing - reuse previous segments (like in RNN)



Sparse Transformer (Child et al., ‘19)



Transformer

strided
(for images)

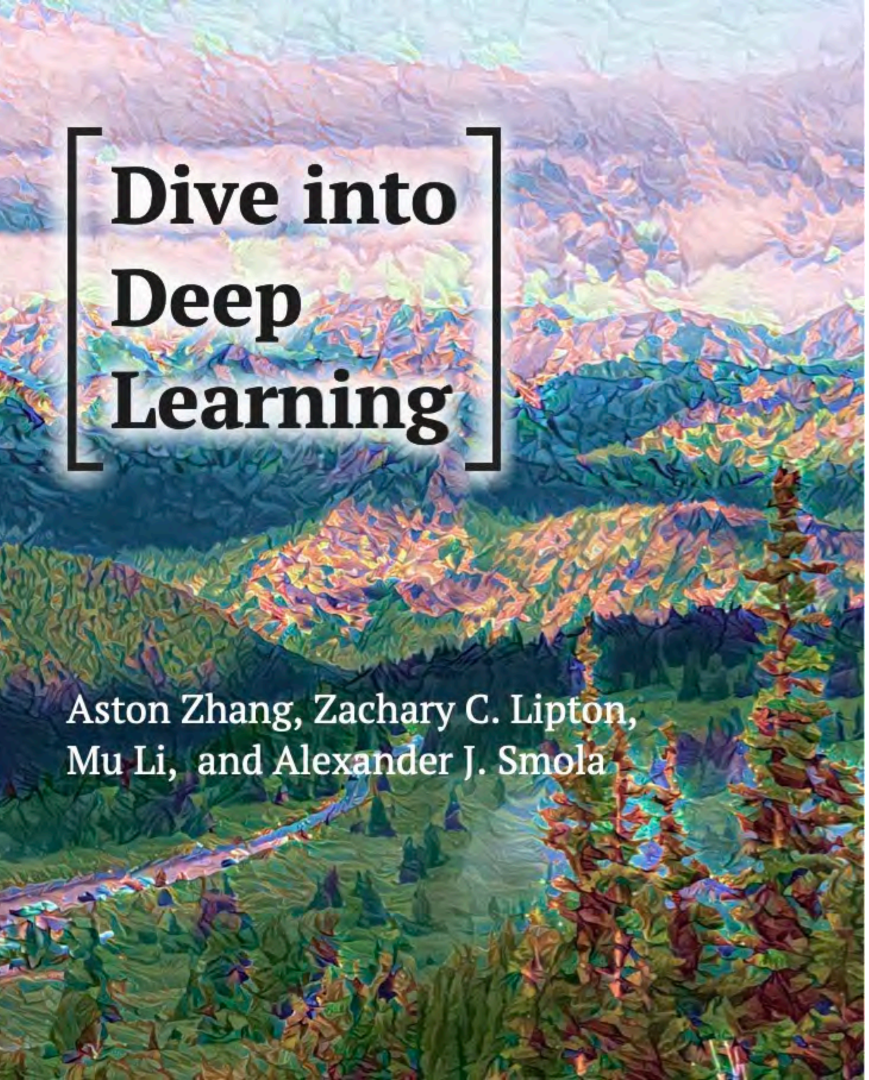
fixed
(for text)

Open Questions

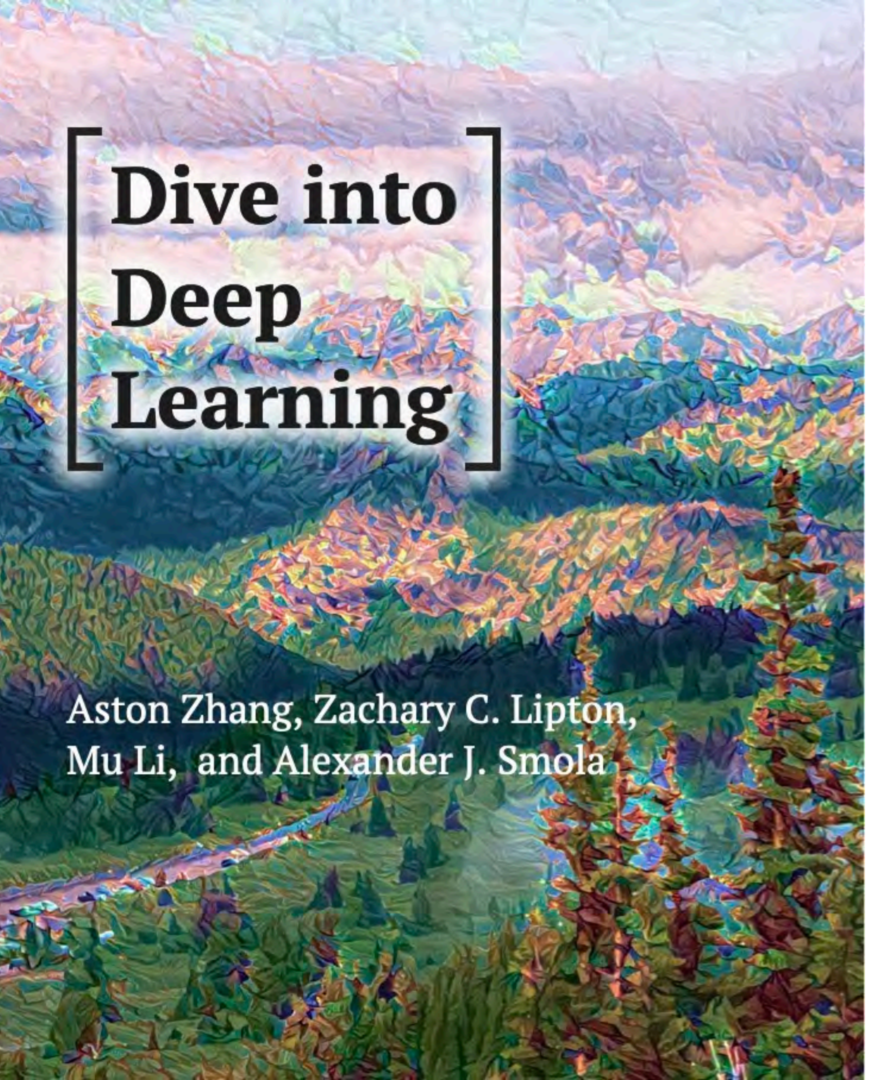
- **Theory**
  - Function complexity
    (design complex function via simple attention mechanism)
  - Convergence analysis for mechanism vs. parameters
    (similar to Watson-Nadaraya estimator)
  - Regularization
- **Interpretation**
  - Attention vs. meaning
    (e.g. Hewitt & Manning, ’19; Coenen et al., ’19 for BERT)
  - Multiple steps of reasoning
    Can we guide it? Structure it? Can we learn from it?

Open Questions

- **Large State Spaces**
  - Factorizing space
    (design automatically rather than manually per head)
  - Pseudorandom dense (beyond quaternions)
  - Learn sparse structure (transfer for attention?)
- **Computation**
  - Avoid computation when no attention
  - Memory footprint
- **Low Hanging Fruit**
  Rewrite papers with attention / Transformers / BERT


Dive into
Deep
Learning
Aston Zhang, Zachary C. Lipton,
Mu Li, and Alexander J. Smola

6. Resources

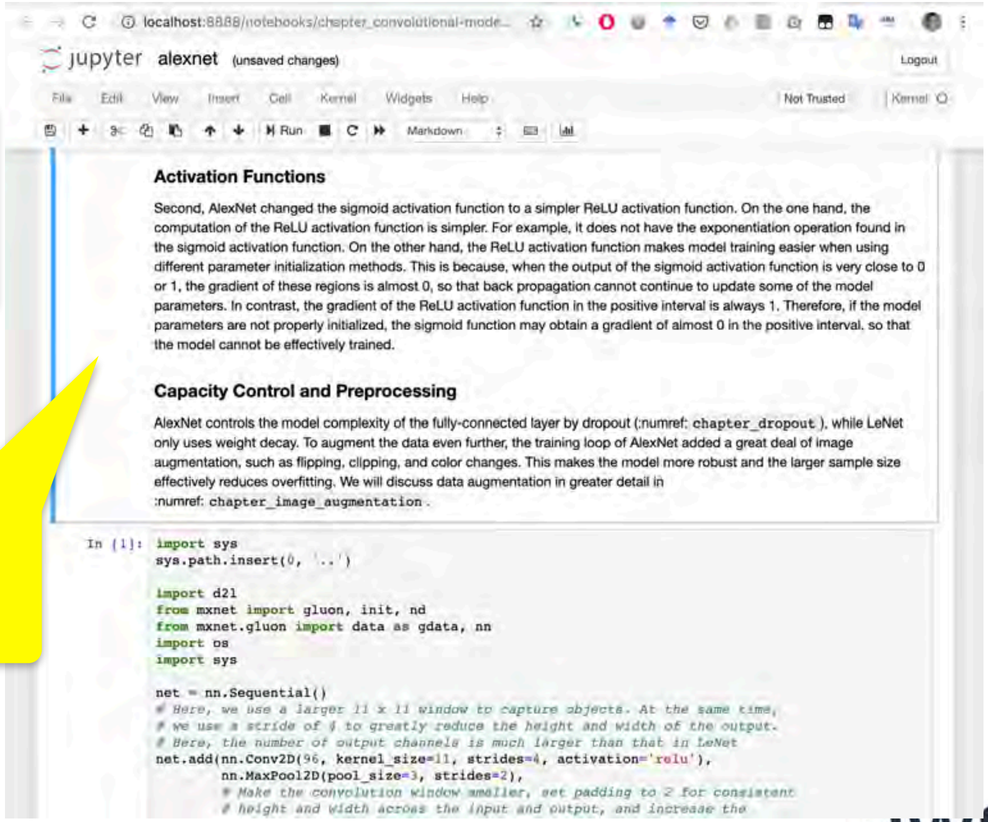


- Self-contained tutorials
- Statistics, linear algebra, optimization
- Machine learning basics
- 150+ Jupyter Notebooks, fully executed
- GPU and parallel examples
- Ready to use for applications
- Teachable content
- Adopted as a textbook or reference book at Berkeley, CMU, UCLA, UIUC, Gatech, Shanghai Jiao Tong, Zhejiang U, USTC
- Slides, videos from Berkeley class courses.d2l.ai
- Multilingual content EN, ZH (in progress: KO, JA, FR, TR)

One Code - Multiple Formats & Devices

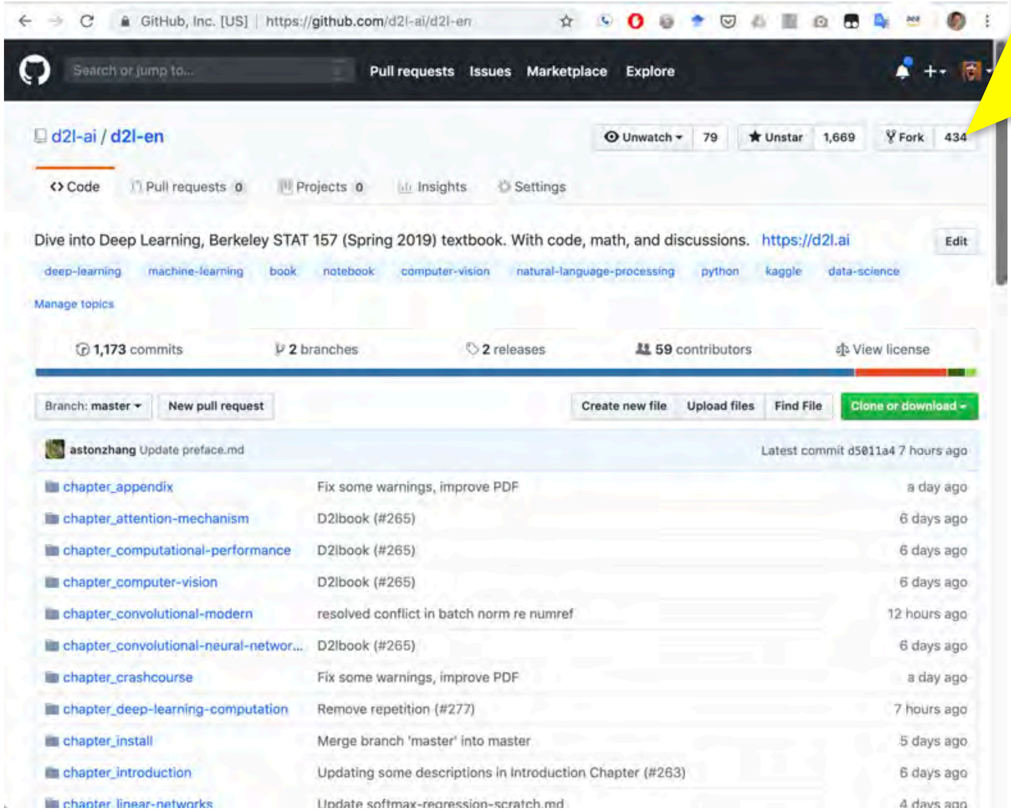
Mobile friendly

Jupyter Notebook

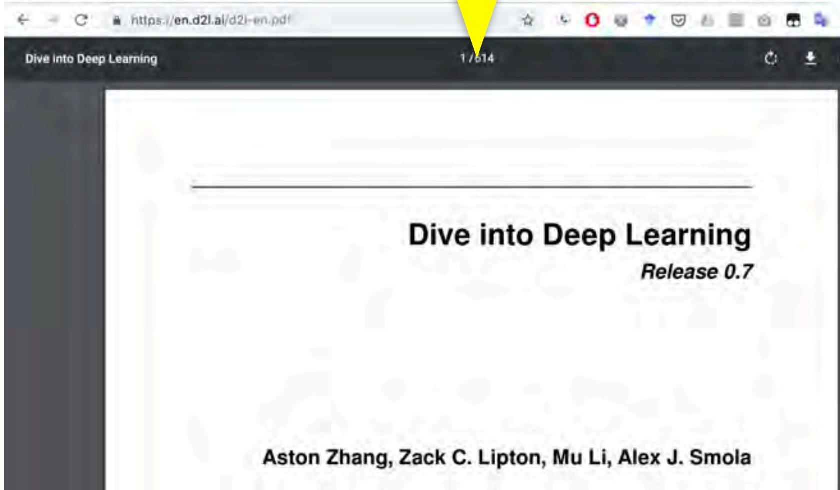


Open Source

Active Development



PDF



https://d2l.ai

STAT 157, Spring 19

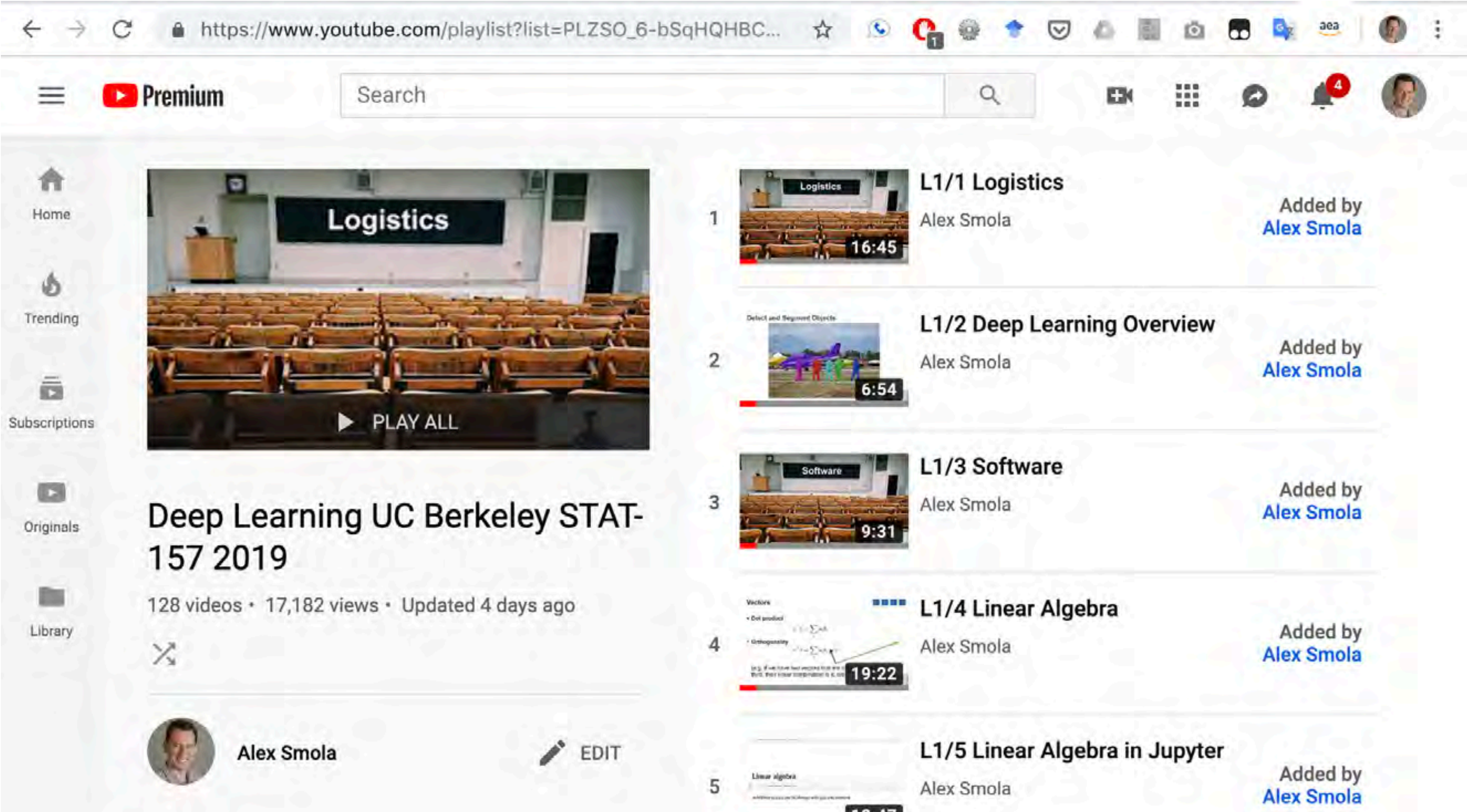
Syllabus

- Syllabus
- Assignments
- Projects
- Units
- FAQ

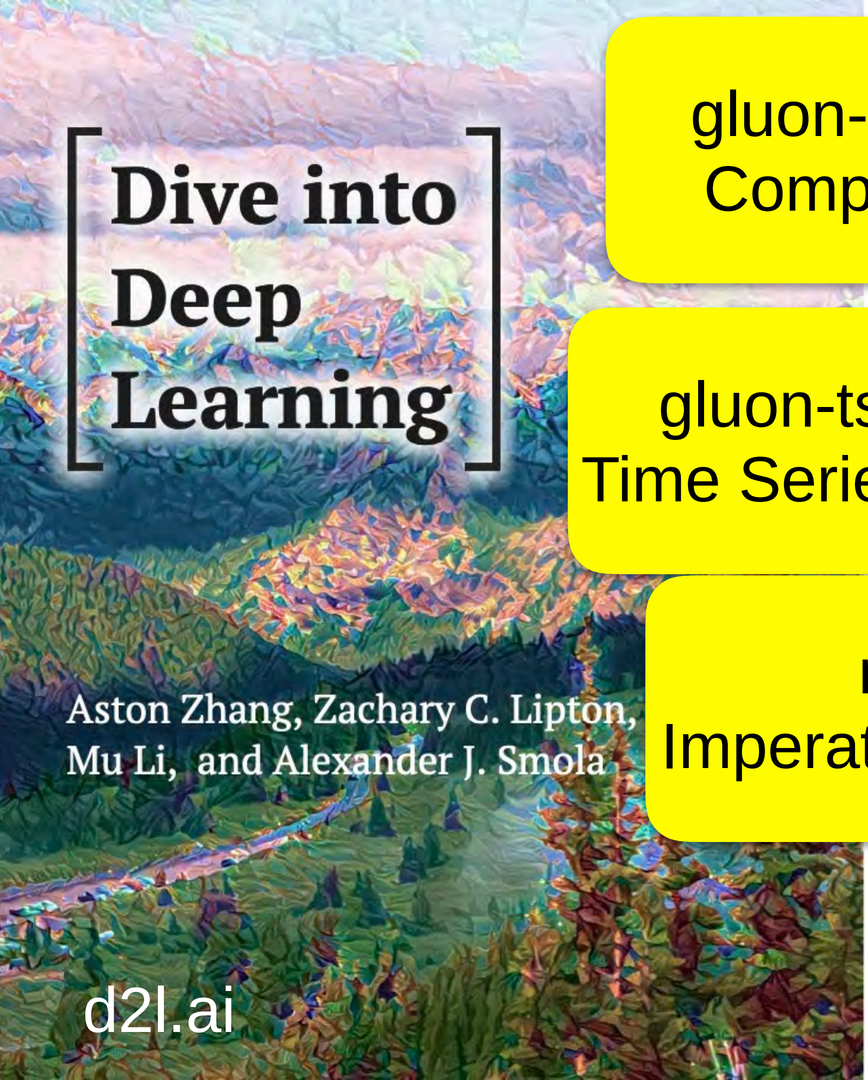
Date	Topics
1/22	Logistics, Software, Linear Algebra
1/24	Probability and Statistics (Bayes Rule, Sampling Naive Bayes, Sampling)
1/29	Gradients, Chain Rule, Automatic differentiation
1/31	Linear Regression, Basic Optimization
2/5	Likelihood, Loss Functions, Logisitic Regression, Information Theory
2/7	Multilayer Perceptron
2/12	Model Selection, Weight Decay, Dropout
2/14	Numerical Stability, Hardware
2/19	Environment
2/21	Layers, Parameters, GPUs
2/26	Convolutional Layers

UC Berkeley
Spring ‘19

120+ Videos on YouTube (+20 slide decks)



aws



gluon-cv.mxnet.io
Computer Vision

gluon-nlp.mxnet.io
Natural Language

gluon-ts.mxnet.io
Time Series Prediction

tvm.ai
Deep Learning
Compiler

mxnet.io
Imperative & Symbolic

dgl.ai
Deep Learning on
Graphs

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