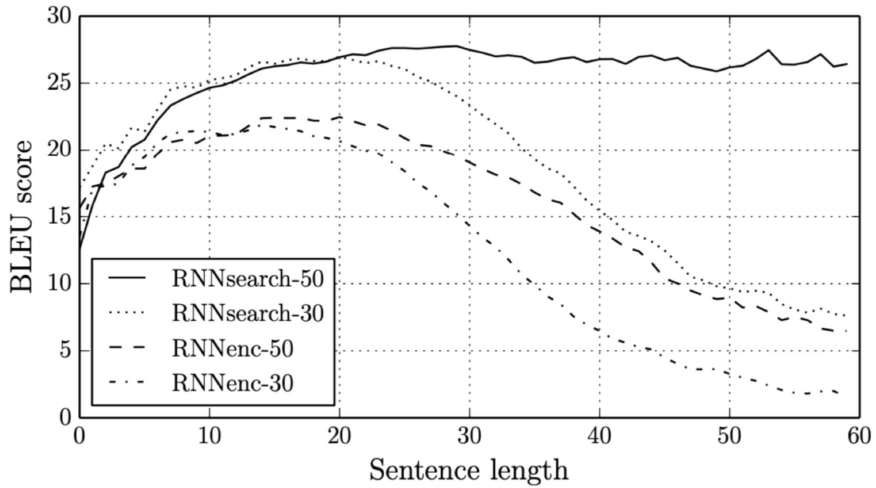
Attention

The problem

- For very long sentences, the score for machine translation really goes down after 30-40 words.



With attention

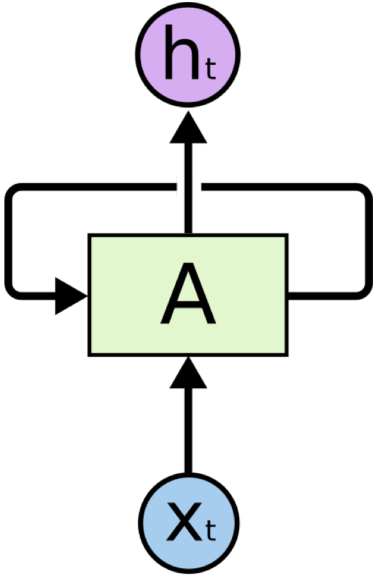
Performance degradation

Bahdanau et al 2014. Neural machine translation by jointly learning to align and translate.

Basic structure of a RNN

- We want to have notion of “time” or “sequence”

Hidden state



$$\mathbf{A}_t = \boldsymbol{\theta}_c \mathbf{A}_{t-1} + \boldsymbol{\theta}_x \mathbf{x}_t$$

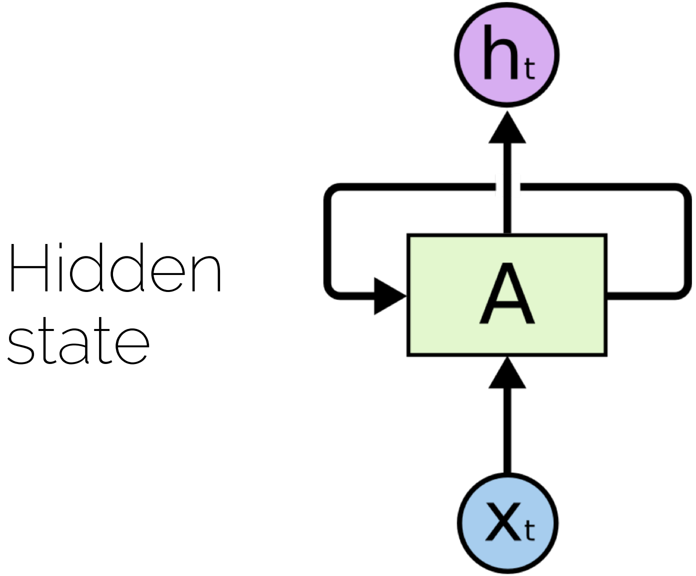
Previous hidden state

input

[Christopher Olah] Understanding LSTMs

Basic structure of a RNN

- We want to have notion of “time” or “sequence”

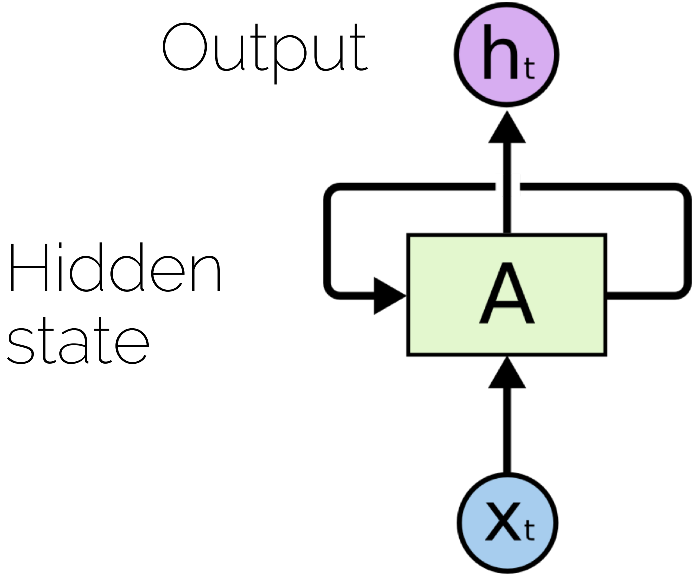


$$\mathbf{A}_t = \boldsymbol{\theta}_c \mathbf{A}_{t-1} + \boldsymbol{\theta}_x \mathbf{x}_t$$

Parameters to be learned

Basic structure of a RNN

- We want to have notion of "time" or "sequence"



$$\mathbf{A}_t = \boldsymbol{\theta}_c \mathbf{A}_{t-1} + \boldsymbol{\theta}_x \mathbf{x}_t$$

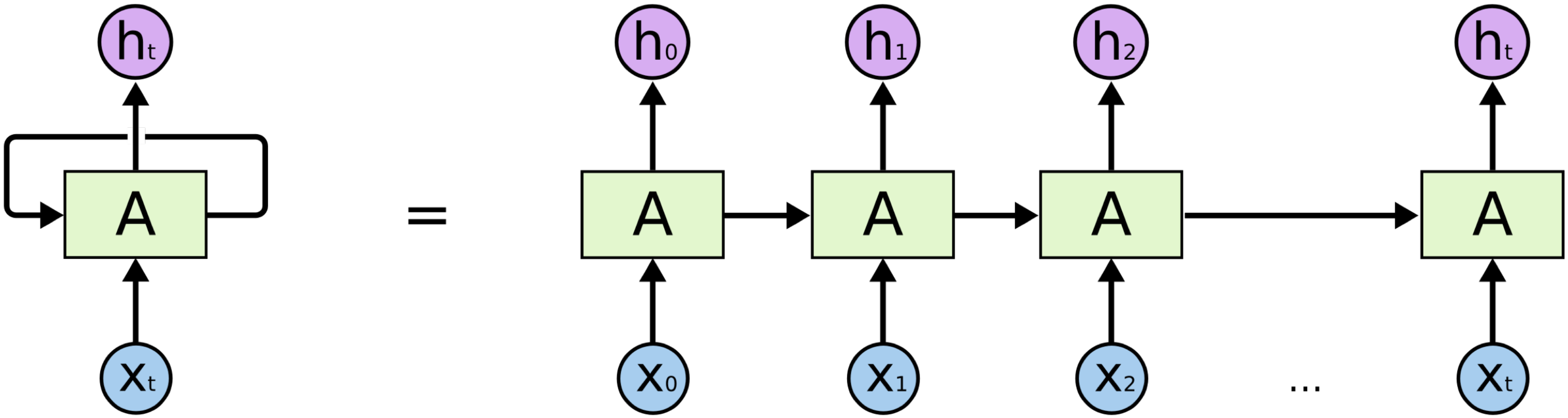
$$\mathbf{h}_t = \boldsymbol{\theta}_h \mathbf{A}_t$$

Same parameters for each time step = generalization!

Basic structure of a RNN

- Unrolling RNNs

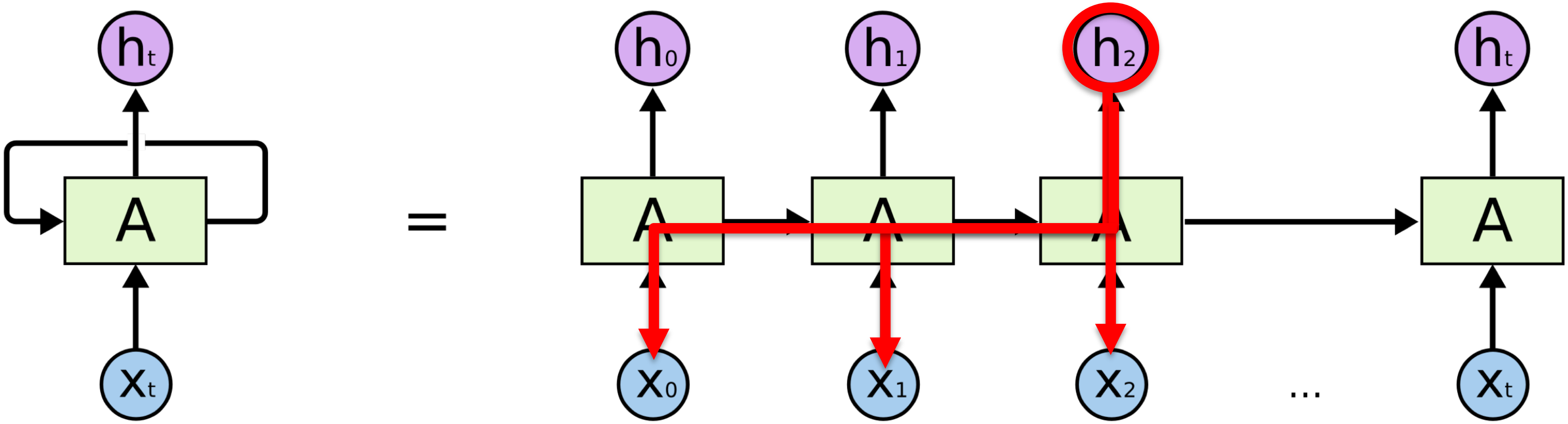
Hidden state is the same



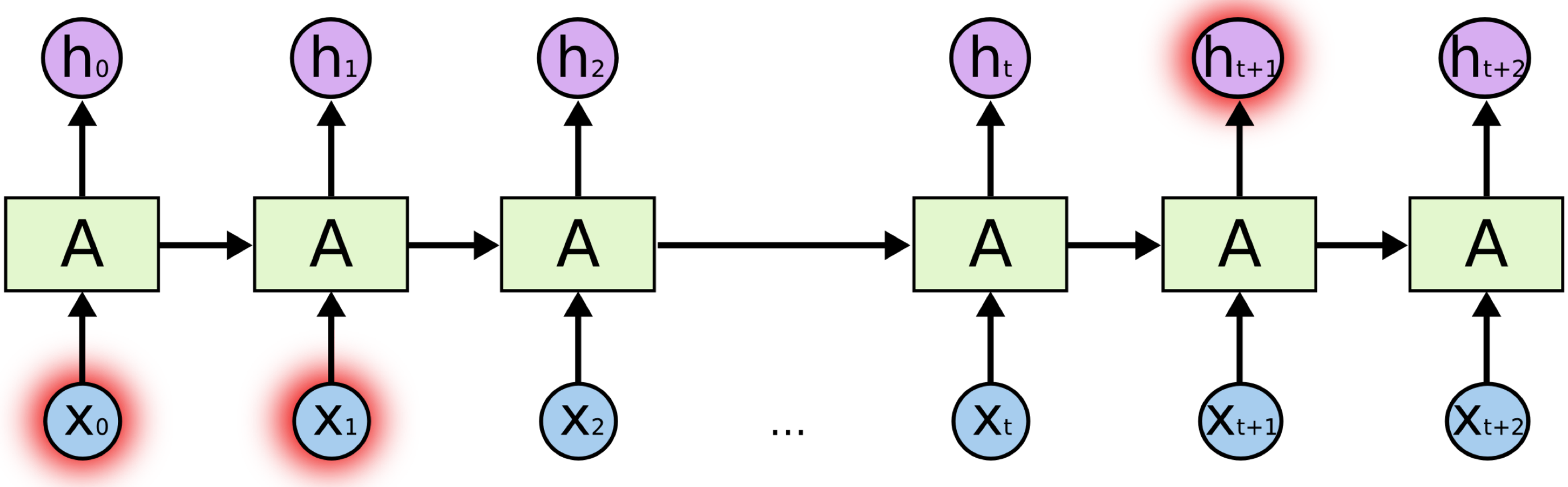
[Christopher Olah] Understanding LSTMs

Basic structure of a RNN

- Unrolling RNNs

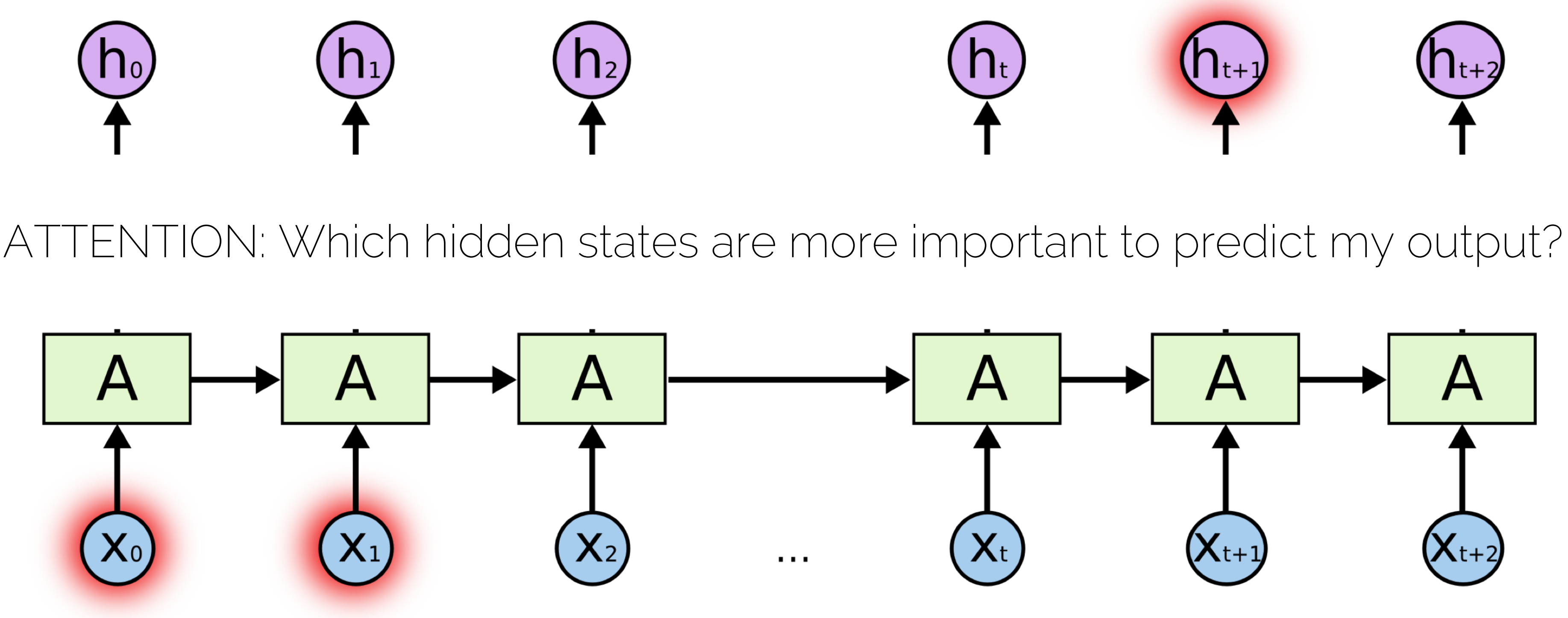


Long-term dependencies



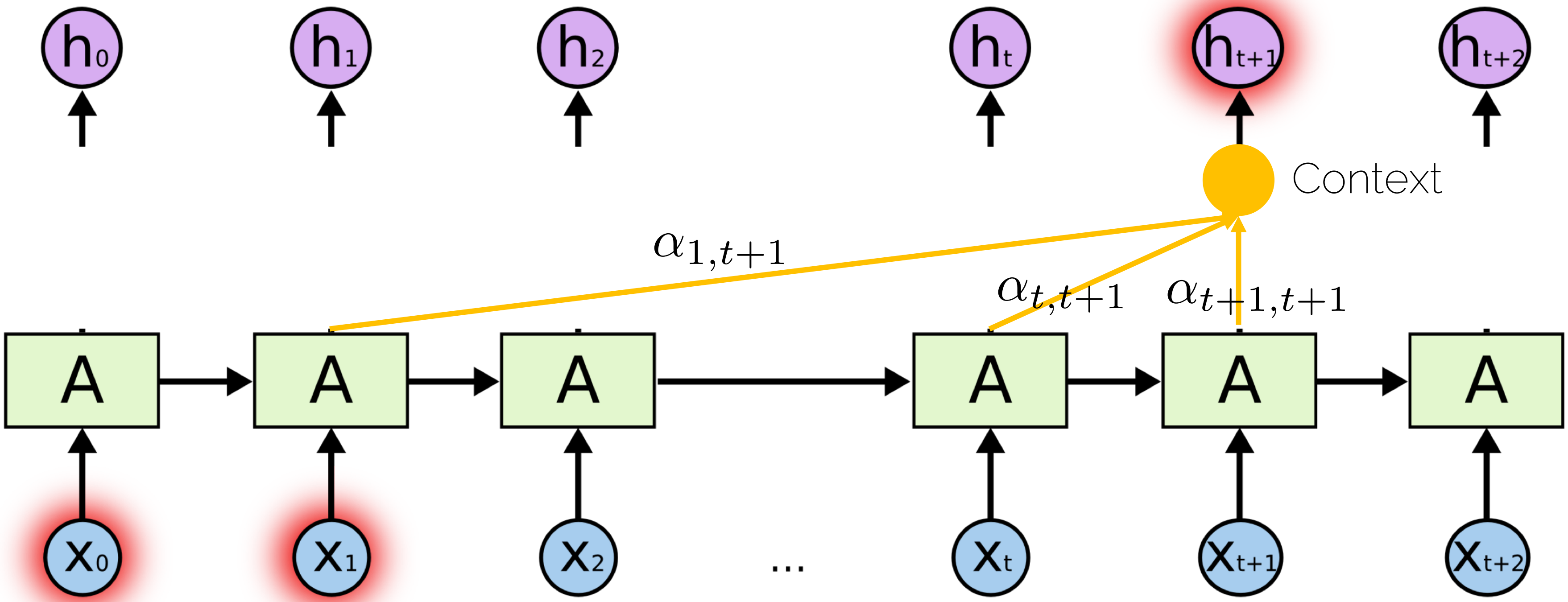
I moved to Germany … so I speak German fluently

Attention: intuition



I moved to Germany … so I speak German fluently

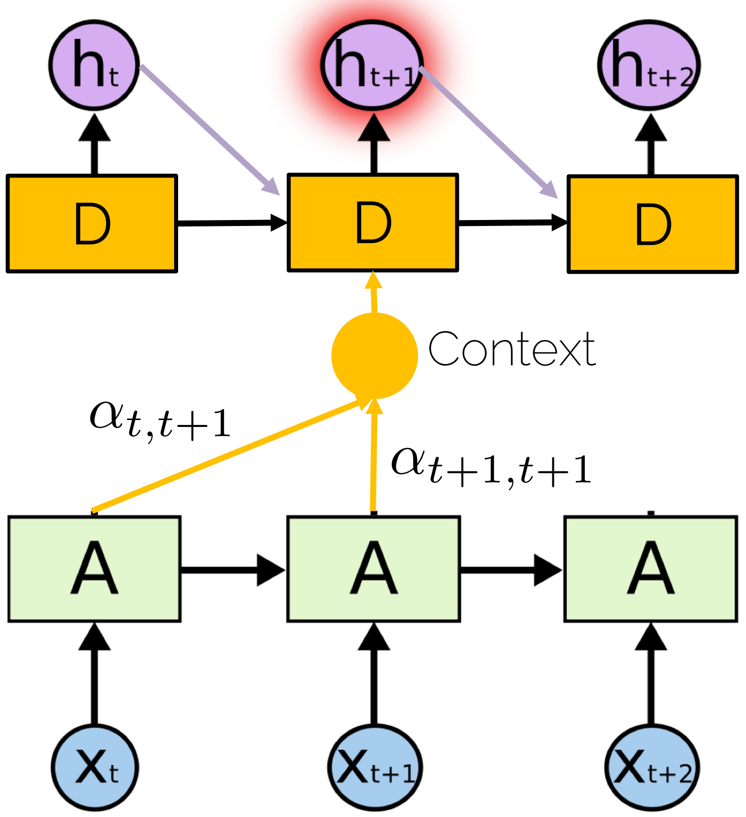
Attention: intuition



I moved to Germany … so I speak German fluently

Attention: architecture

- A decoder processes the information
- Decoders take as input:
  - Previous decoder hidden state
  - Previous output
  - Attention



Attention

- $\alpha_{1,t+1}$ indicates how much the word in the position 1 is important to translate the work in position $t+1$

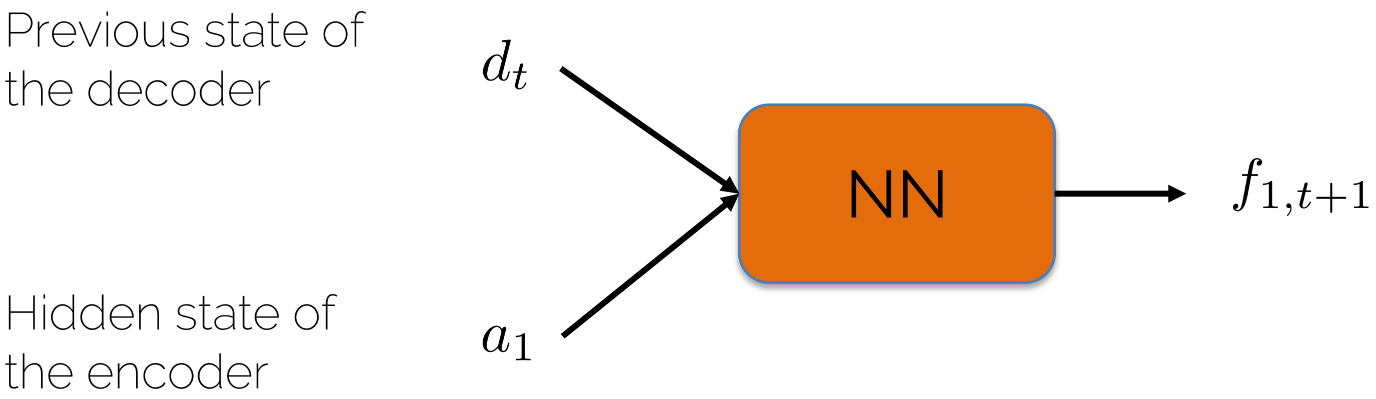
- The context aggregates the attention

$$c_{t+1} = \sum_{k=1}^{t+1} \alpha_{k,t+1} a_k$$

- Soft attention: All attention masks alpha sum up to 1

Computing the attention mask

- We can train a small neural network

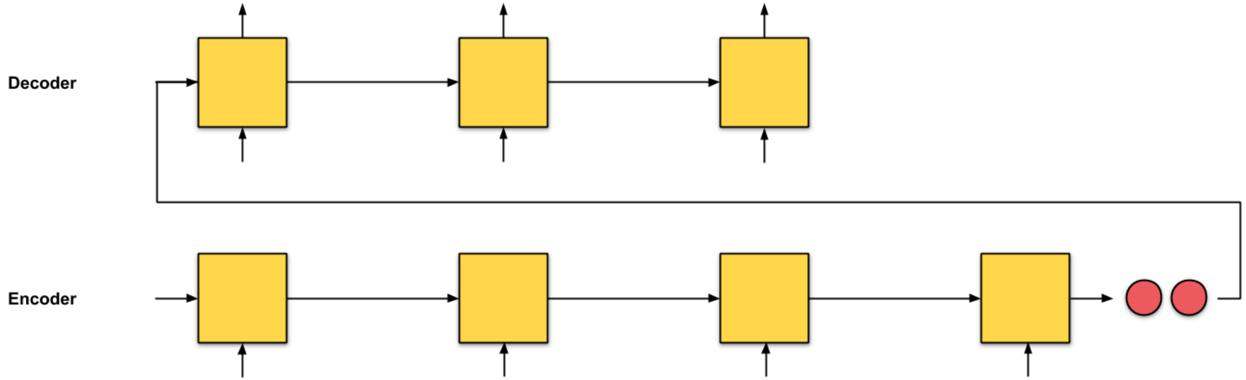


- Normalize $$\alpha_{1,t+1} = \frac{\exp^{f_{1,t+1}}}{\sum_{k=1}^{t+1} \exp^{f_{k,t+1}}}$$

- Animations? As a summary with the se2seq example in here https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Seq2Seq

- How do we translate?
- First read *the whole* sentence in language 1.
- *Afterwards*, translate the whole sentence in language 2.



Sutskever et al. „Sequence to Sequence Learning with Neural Networks". NIPS 2014
Picture from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

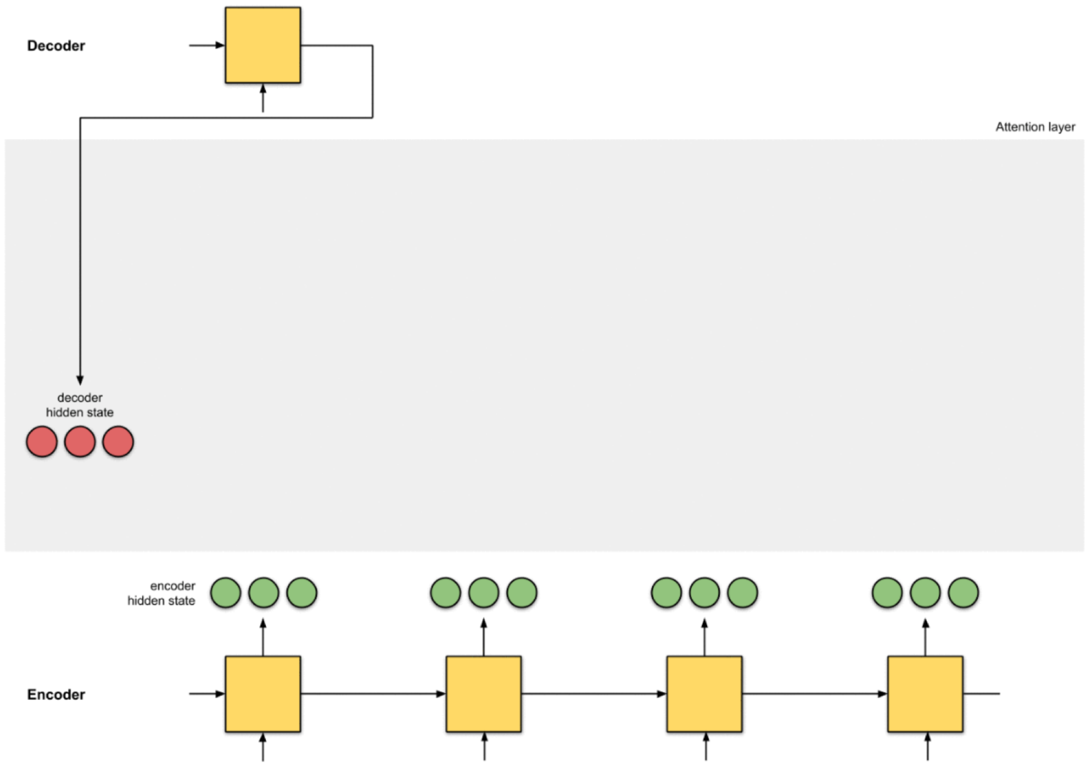
Seq2Seq + Attention?

- If the sentence is very long, we might have forgotten what was said at the beginning.

- Solution: take "notes" of keywords as we read the sentence in language 1.

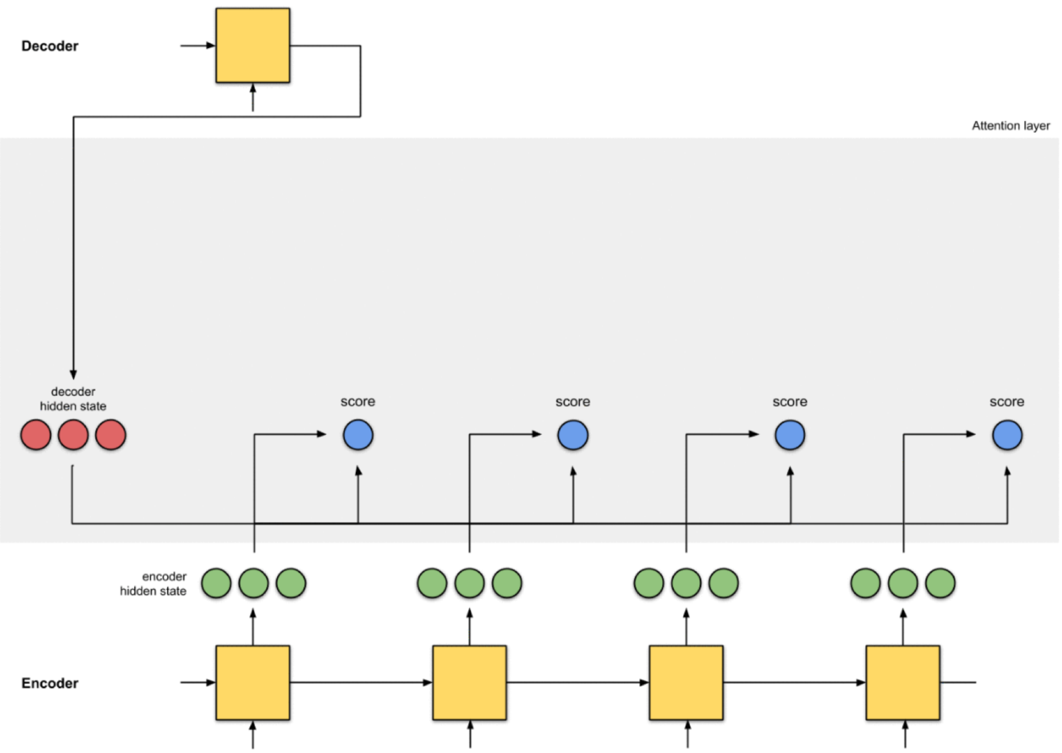
- Use attention!

Seq2Seq + Attention



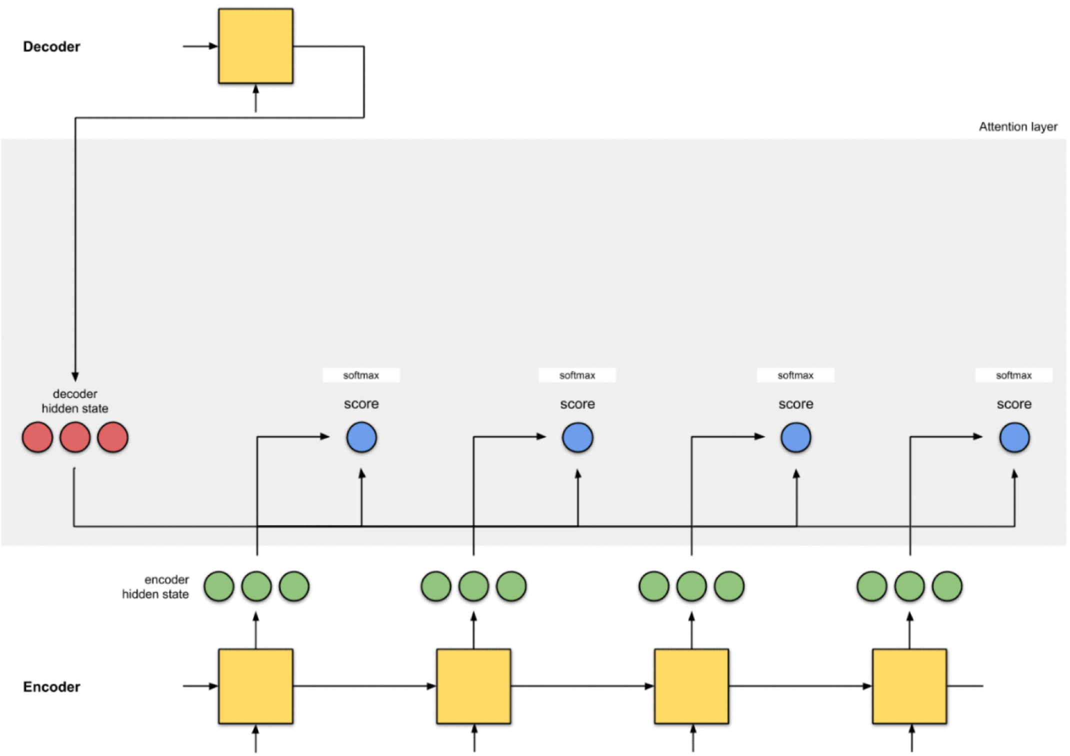
Animation from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Seq2Seq + Attention



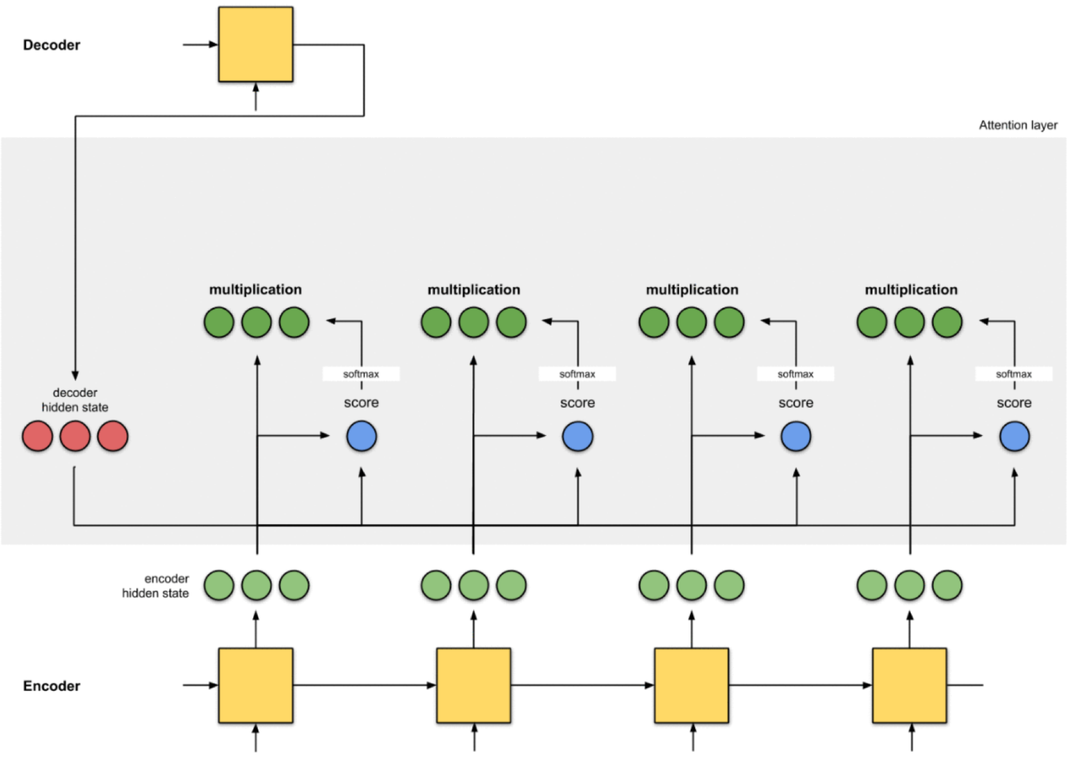
Animation from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Seq2Seq + Attention



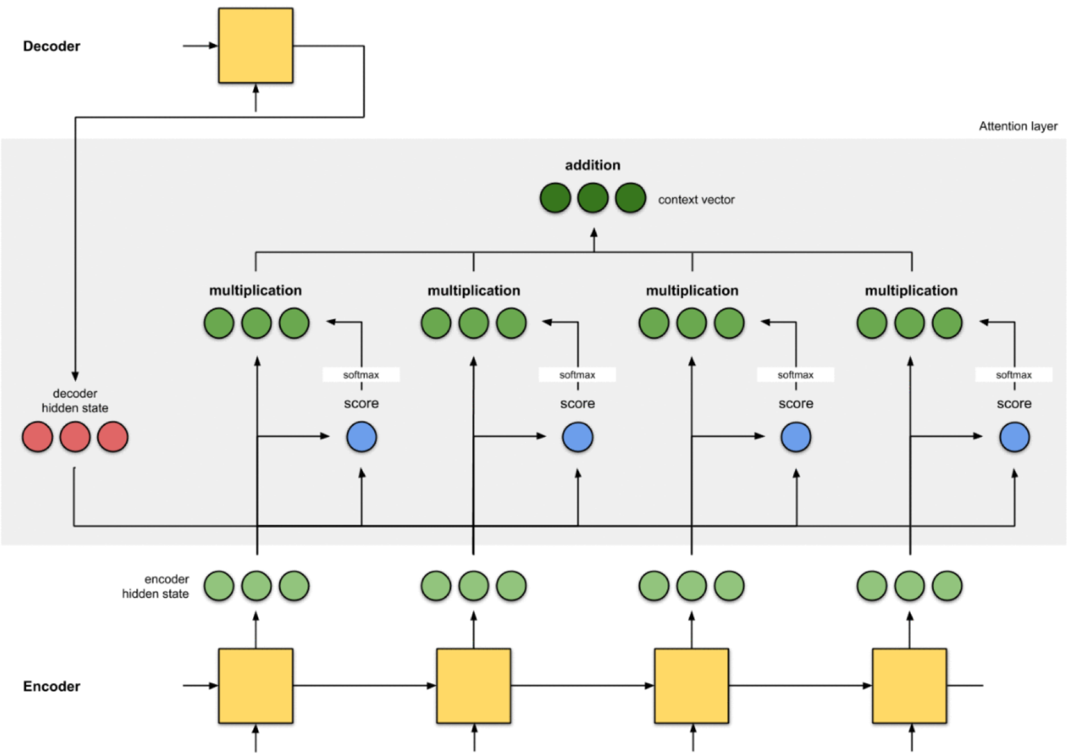
Animation from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Seq2Seq + Attention



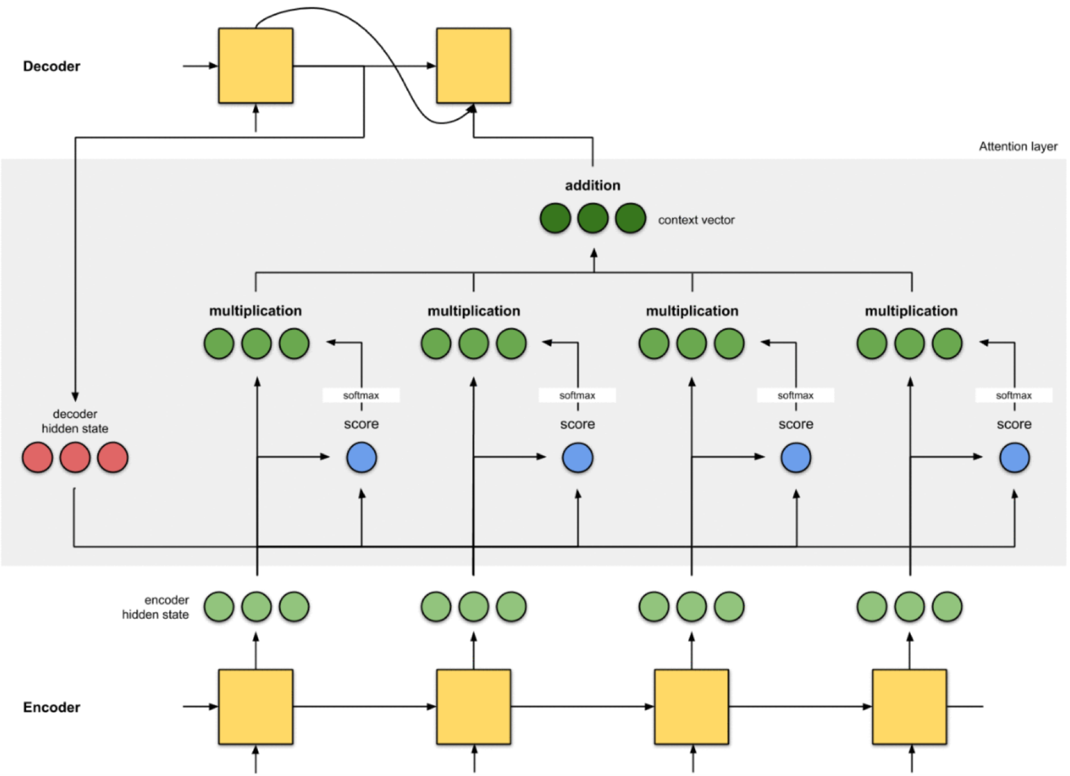
Animation from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Seq2Seq + Attention



Animation from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Seq2Seq + Attention

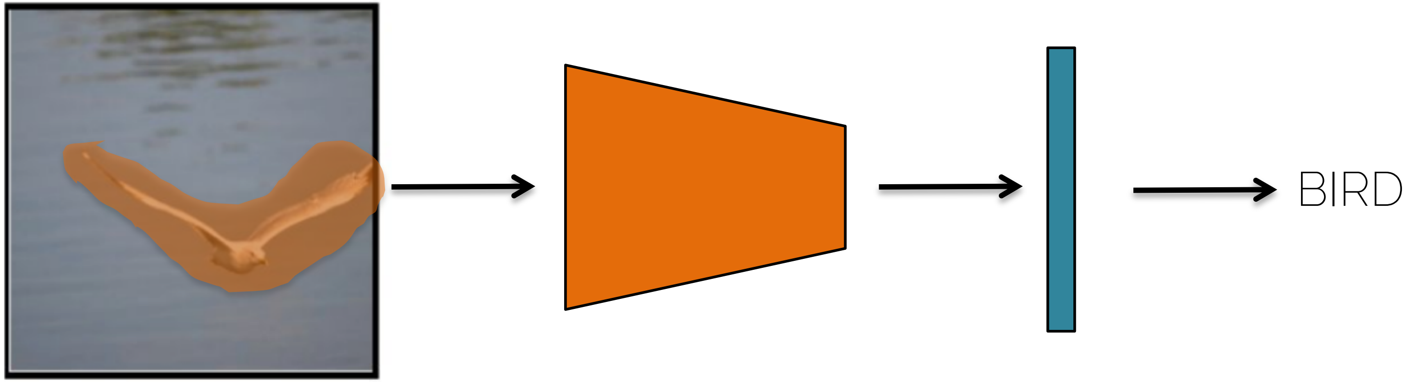


Animation from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Attention for vision

Why do we need attention?

- We use the whole image to make the classification



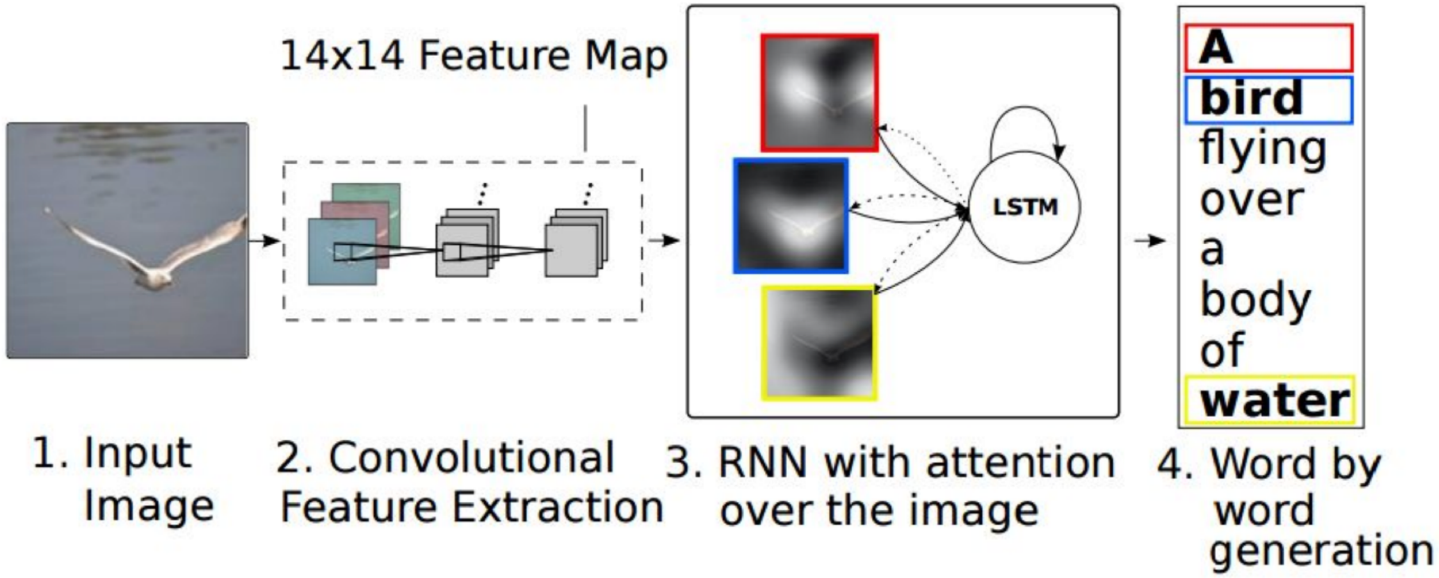
- Are all pixels equally important?

Why do we need attention?

- Wouldn't it be easier and computationally more efficient to just run our classification network on the patch?

Soft attention for captioning

Image captioning

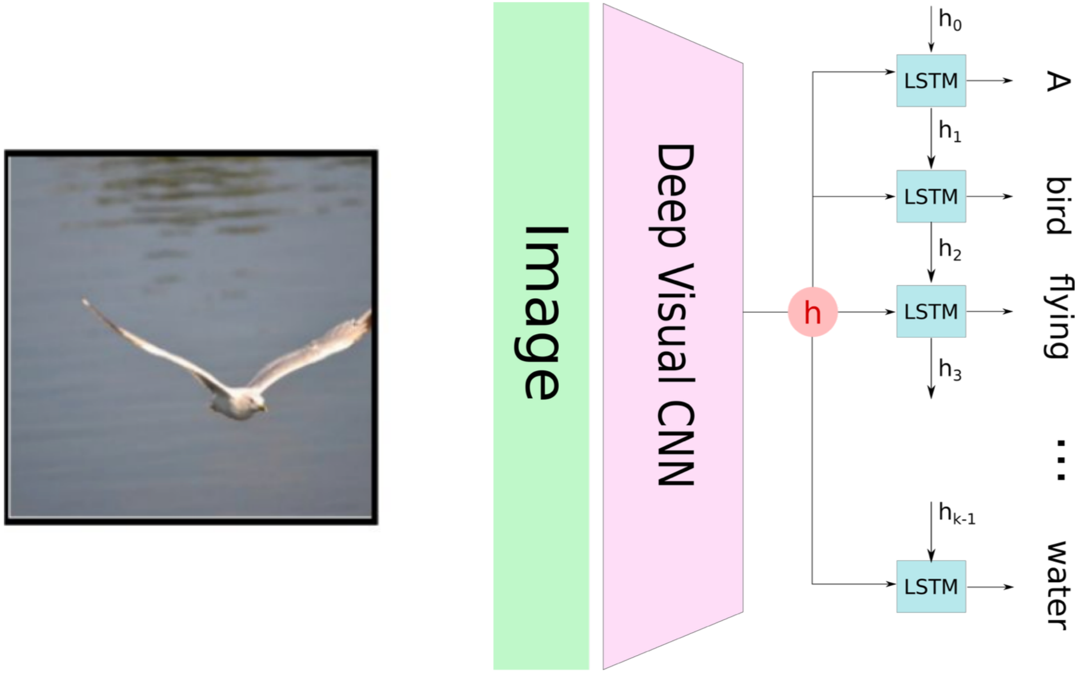


Xu et al 2015. Show attention and tell: neural image caption generation with visual attention.

Image captioning

- Input: image
- Output: a sentence describing the image.
- Encoder: a classification CNN (VGGNet, AlexNet). This computes a feature maps over the image.
- Decoder: an attention-based RNN
  - In each time step, the decoder computes an attention map over the entire image, effectively deciding which regions to focus on.
  - It receives a context vector, which is the weighted average of the conv net features.

Conventional captioning



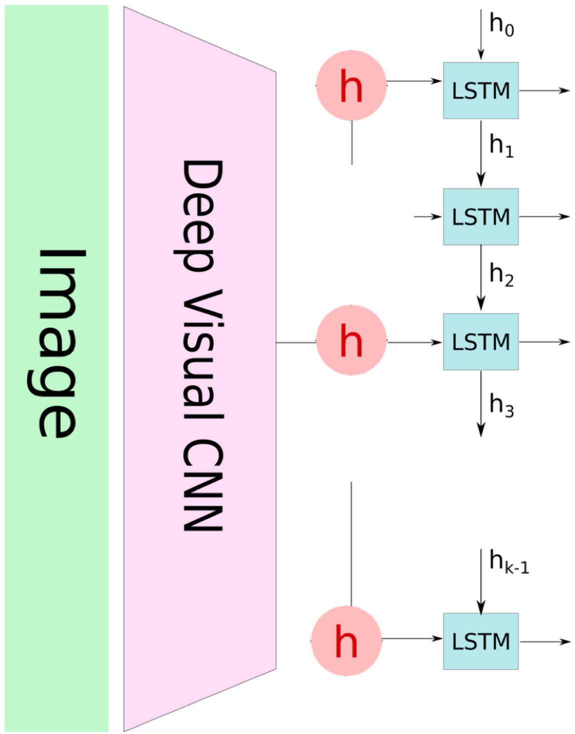
Encoder

Decoder

LSTM only sees the image once!

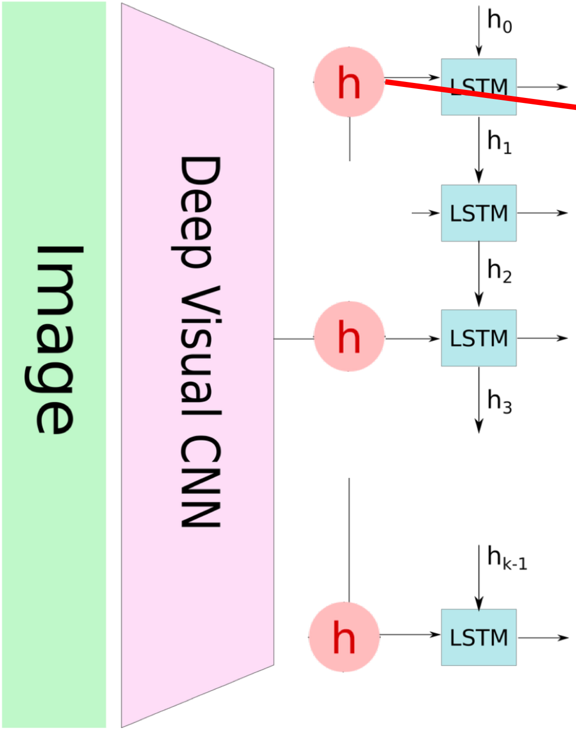
Image from: https://blog.heuritech.com/2016/01/20/attention-mechanism/

Attention mechanism



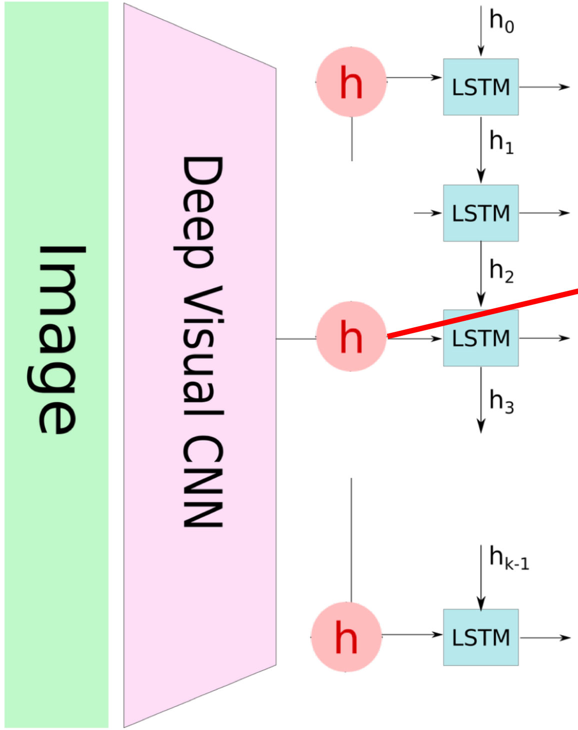
A girl is throwing a frisbee in the park

Attention mechanism



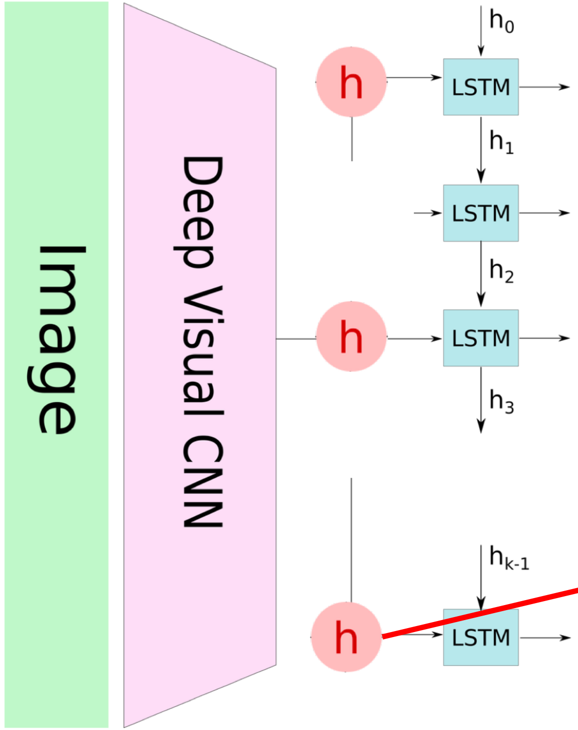
A girl is throwing a frisbee in the park

Attention mechanism



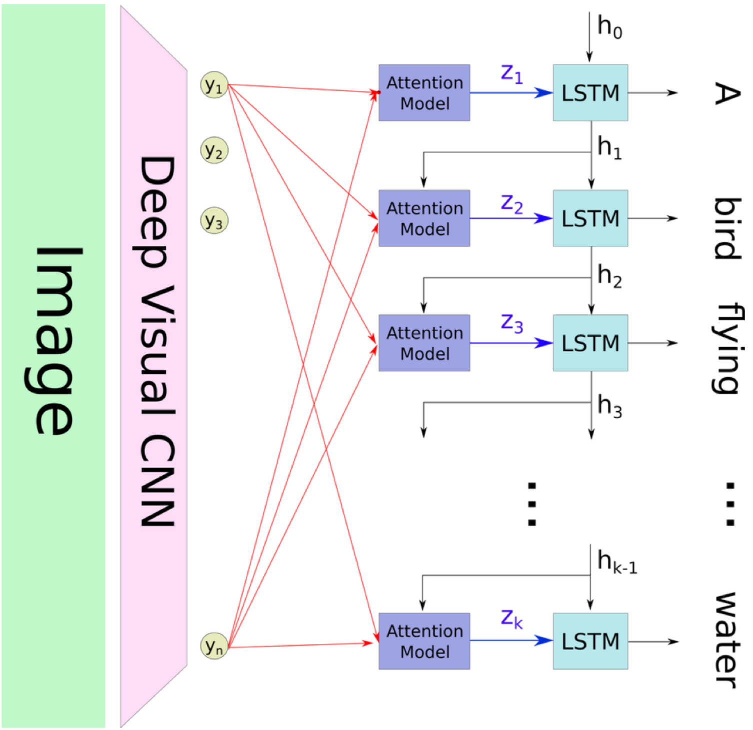
A girl is throwing a frisbee in the park

Attention mechanism



A girl is throwing a frisbee in the park

Attention mechanism

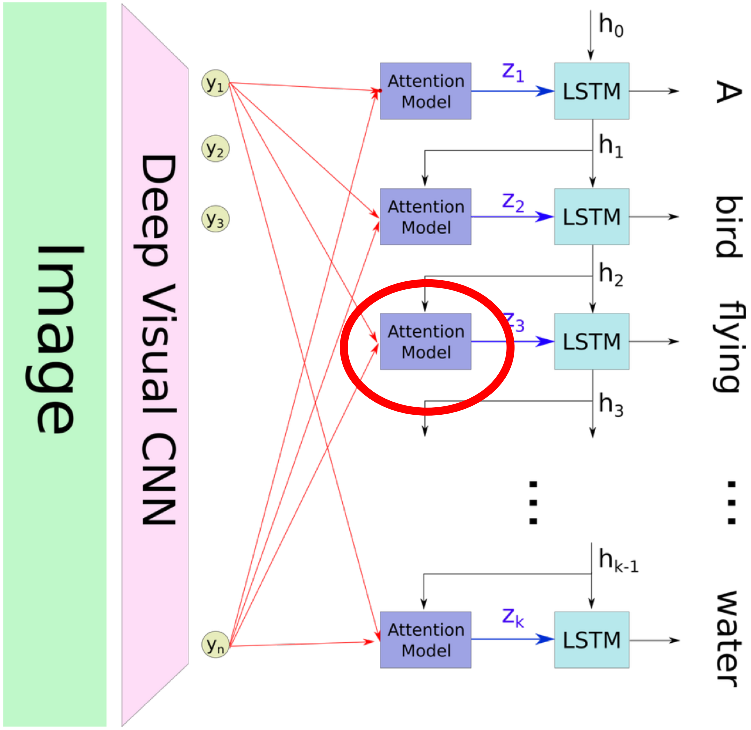


$\mathbf{y_i}$: Output of encoder are the image features which still retain spatial information (no FC layer!)

$\mathbf{Z_i}$: Output of attention model

$\mathbf{h_i}$: Hidden state of LSTM

Attention mechanism

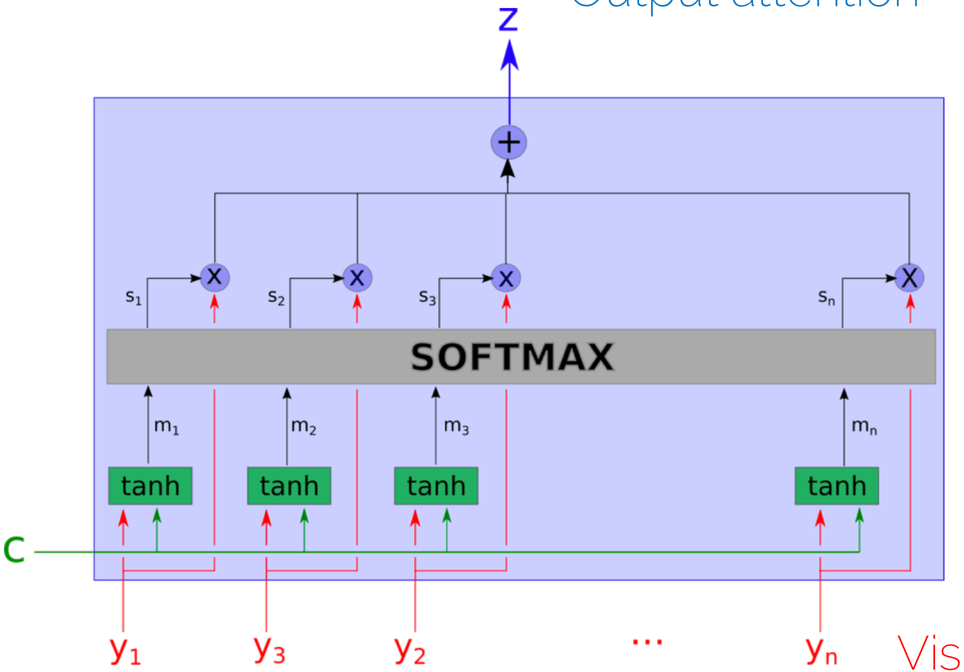


How does the attention model look like?

Attention model

- Attention architecture

Output attention



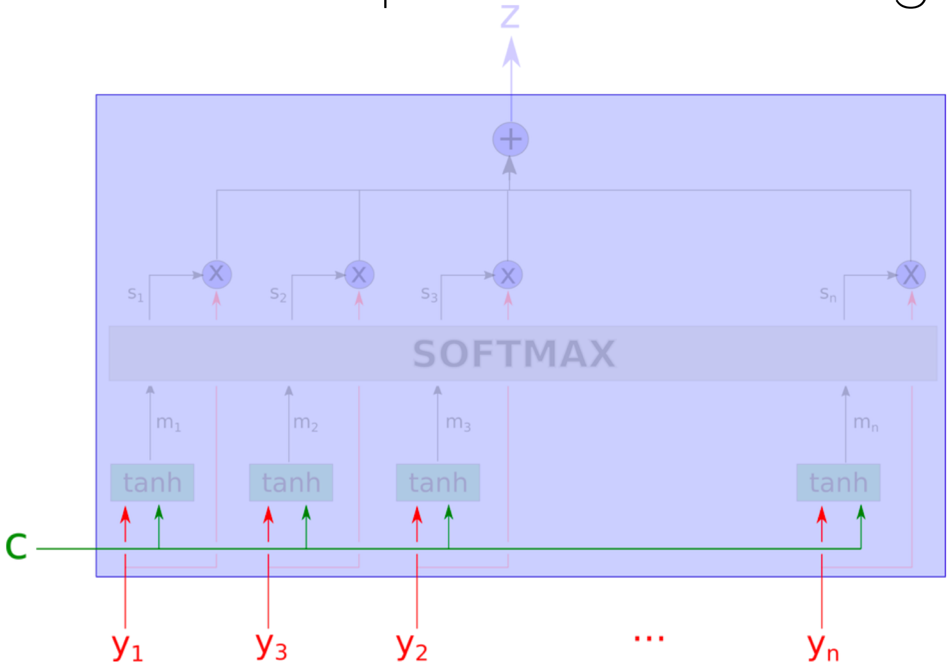
Any past hidden state

Visual features

Image: https://blog.heuritech.com/2016/01/20/attention-mechanism/

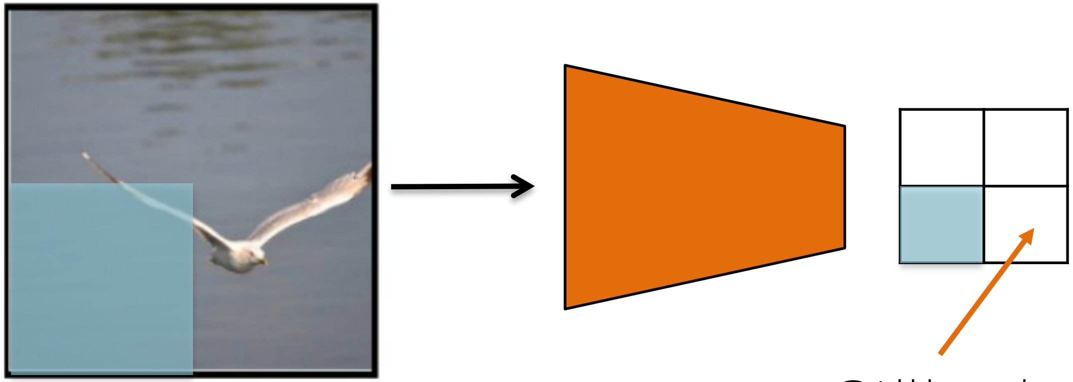
Attention model

- Inputs = feature descriptor for each image patch



Attention model

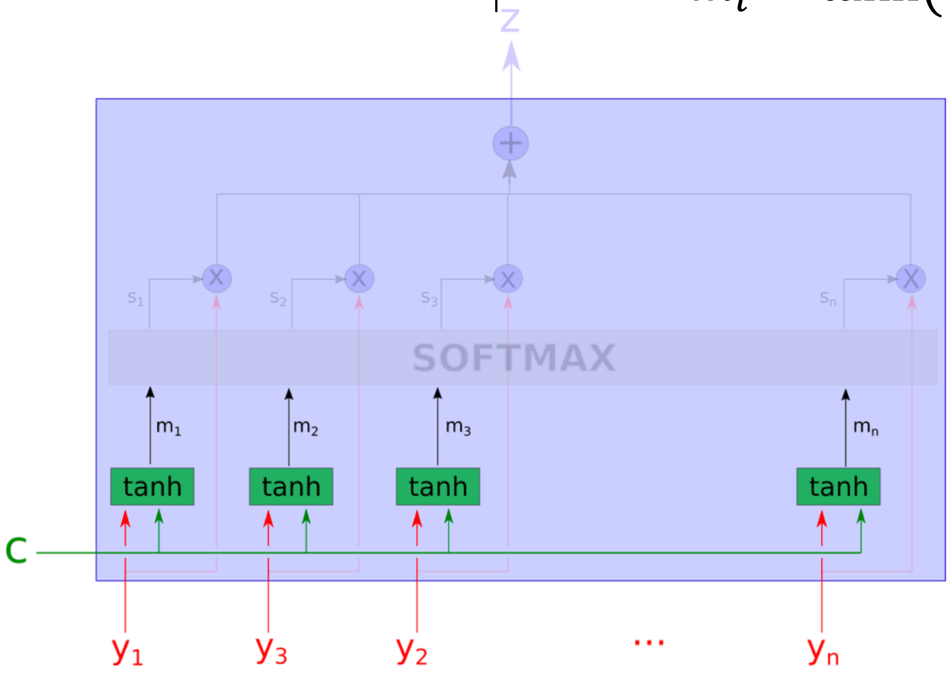
- Inputs = feature descriptor for each image patch



Still related to the spatial location of the image

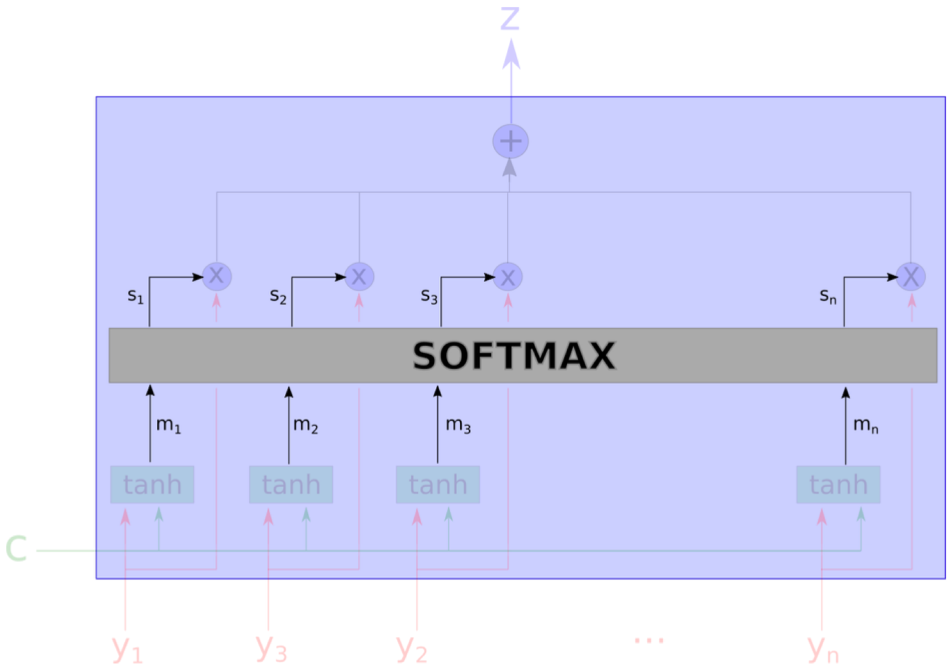
Attention model

- We want an bounded output $m_i = \tanh(W_{cm}c + W_{ym}\, y_i)$



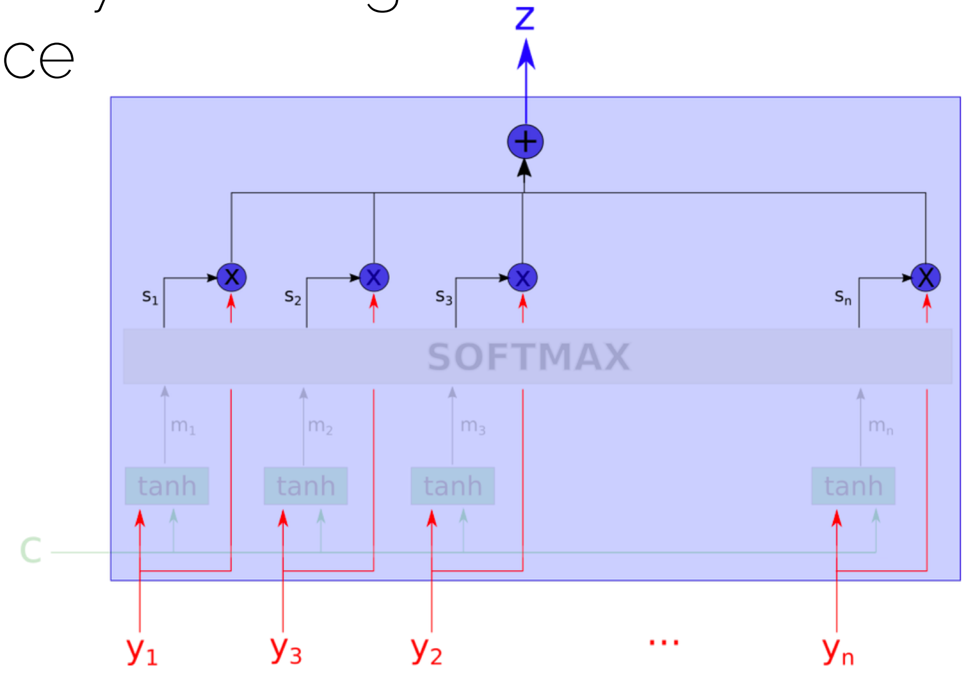
Attention model

- Softmax to create the attention values between 0 and 1



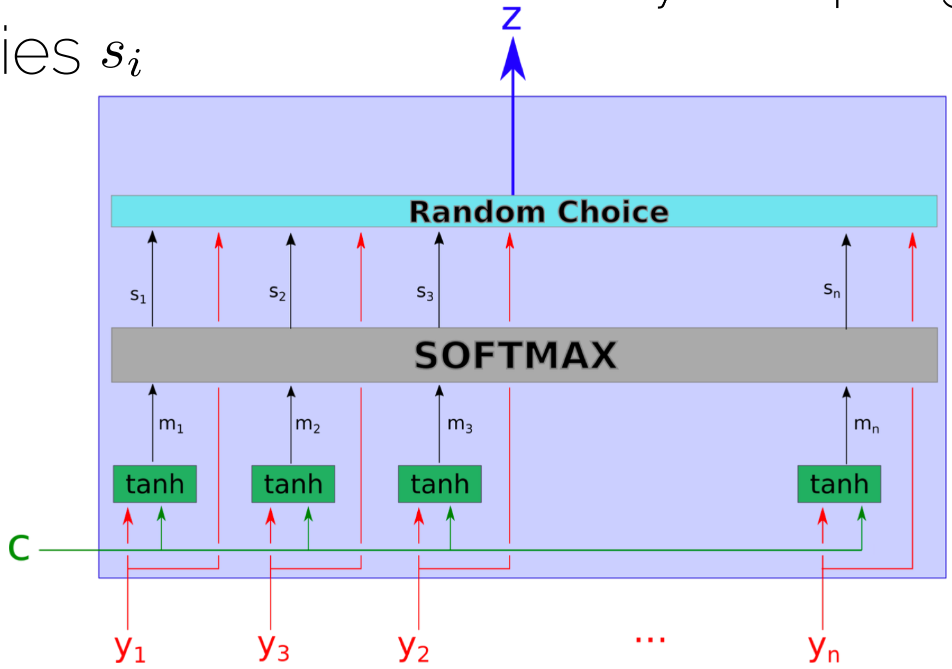
Attention model

- Multiplied by the image features → ranking by importance



Hard attention model

- Choosing one of the features by sampling with probabilities s_i



Types of attention

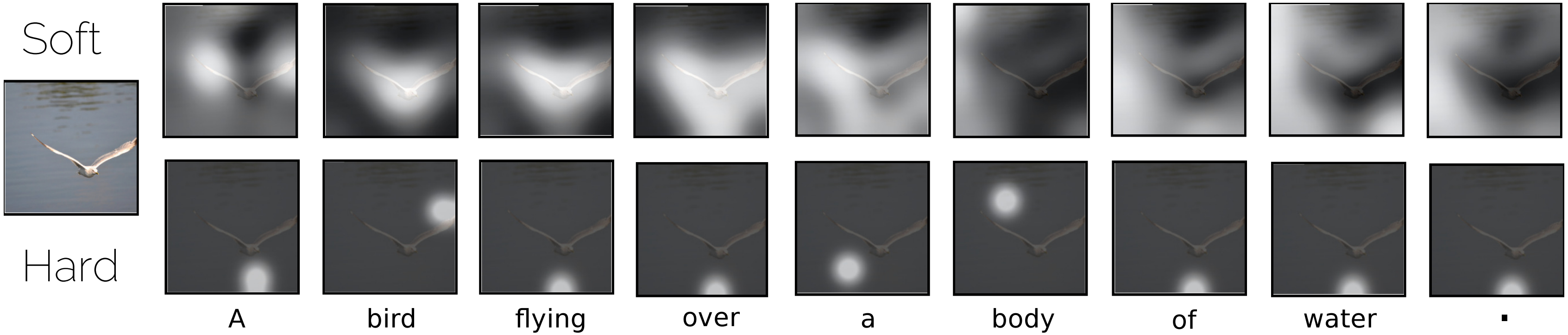
- **Soft attention**: deterministic process that can be backproped

- **Hard attention**: stochastic process, gradient is estimated through Monte Carlo sampling.

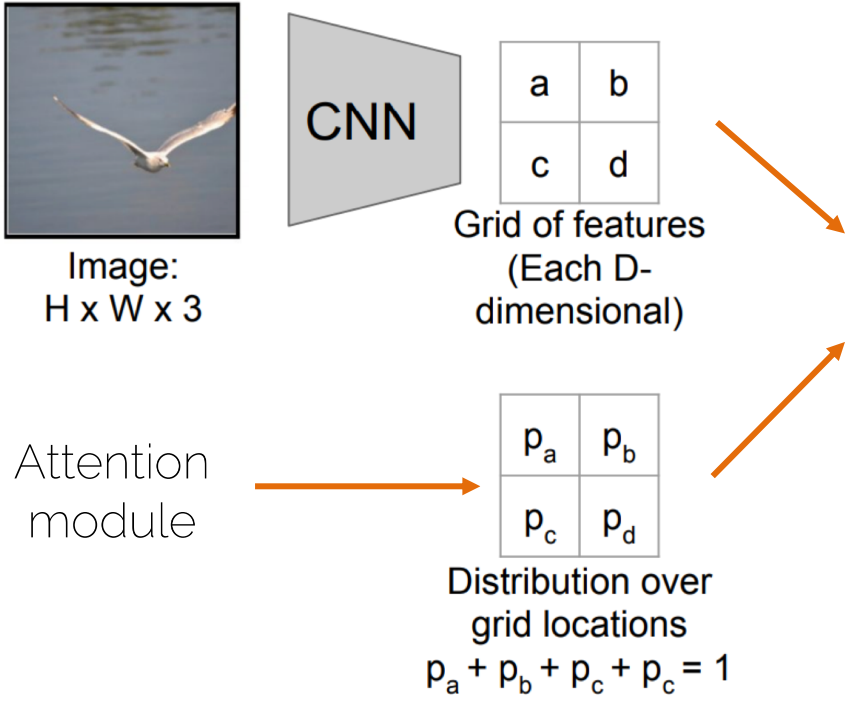
- Soft attention is the most commonly used since it can be incorporated into the optimization more easily

Types of attention

- Soft vs hard attention



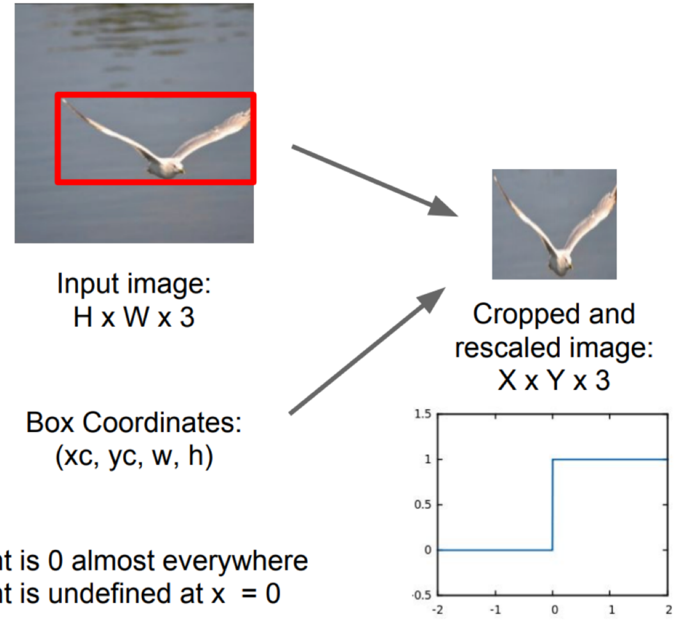
Types of attention: soft



- Can be backproped
- Uses all the image

Image: Stanford CS231n lecture

Types of attention: hard



Gradient is 0 almost everywhere
Gradient is undefined at x = 0

- You can view it as an image cropping!
- If we cannot use gradient descent, what alternative could we use to train this function?

Reinforcement Learning

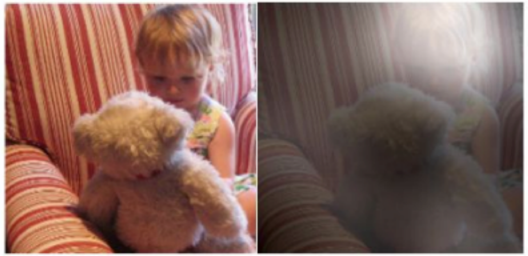
Image: Stanford CS231n lecture

Image captioning with attention

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.



A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

Xu et al 2015. Show attention and tell: neural image caption generation with visual attention.

Interesting works on attention

- Luong et al, "Effective Approaches to Attentionbased Neural Machine Translation," EMNLP 2015
- Chan et al, "Listen, Attend, and Spell", arXiv 2015
- Chorowski et al, "Attention-based models for Speech Recognition", NIPS 2015
- Yao et al, "Describing Videos by Exploiting Temporal Structure", ICCV 2015
- Xu and Saenko, "Ask, Attend and Answer: Exploring Question-Guided Spatial Attention for Visual Question Answering", arXiv 2015
- Zhu et al, "Visual7W: Grounded Question Answering in Images", arXiv 2015
- Chu et al. „Online Multi-Object Tracking Using CNN-based Single Object Tracker with Spatial-Temporal Attention Mechanism". ICCV 2017

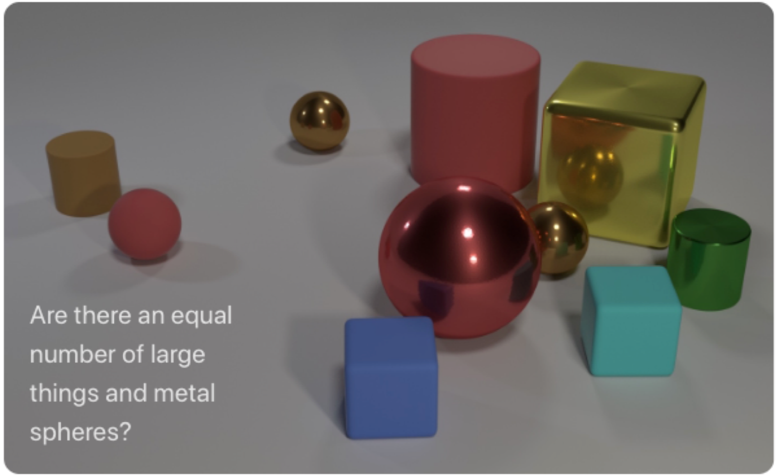
Conditioning

When do we need conditioning?

- Scene understanding from an image and an audio source. Both need to be processed!

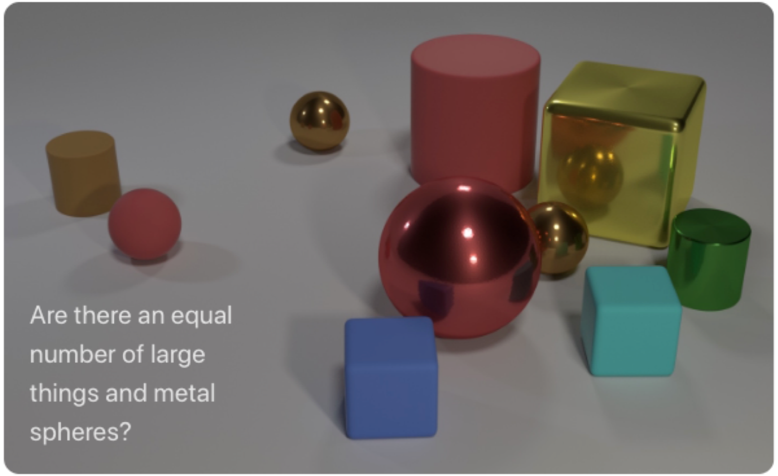
When do we need conditioning?

- Visual Question and Answering: the sentence (question) needs to be understood, the image is needed to create the answer.



When do we need conditioning?

- Visual Question and Answering: the sentence (question) needs to be understood, the image is needed to create the answer.



When do we need conditioning?

- We have two sources, can we process one **in the context** of the other?

- **Conditioning**: the computation carried out by a model is conditioned or *modulated* by information extracted from an auxiliary input.

- Note: a similar thing can be obtained with attention (see p. 39)

When do we need conditioning?

- Generate images based on a word
- Do we need to retrain a model for each word?

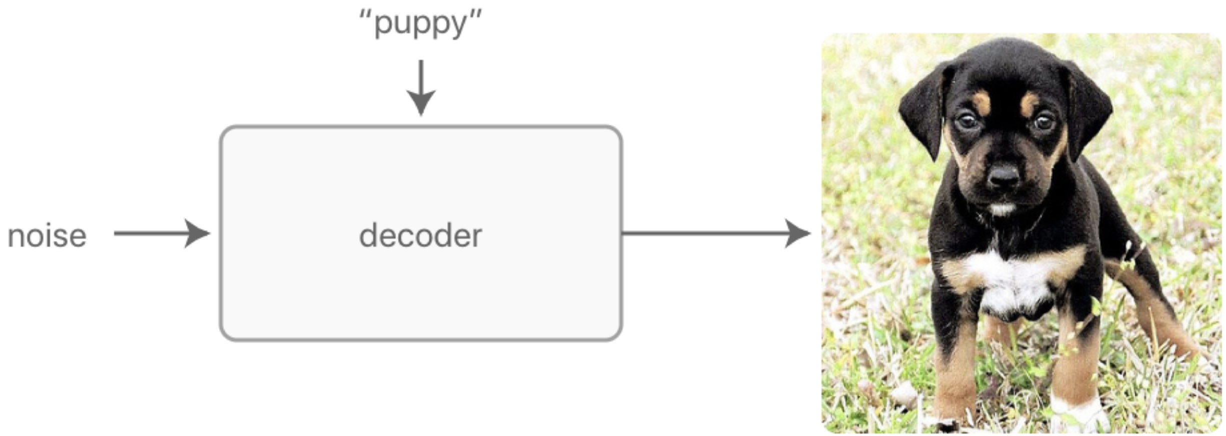
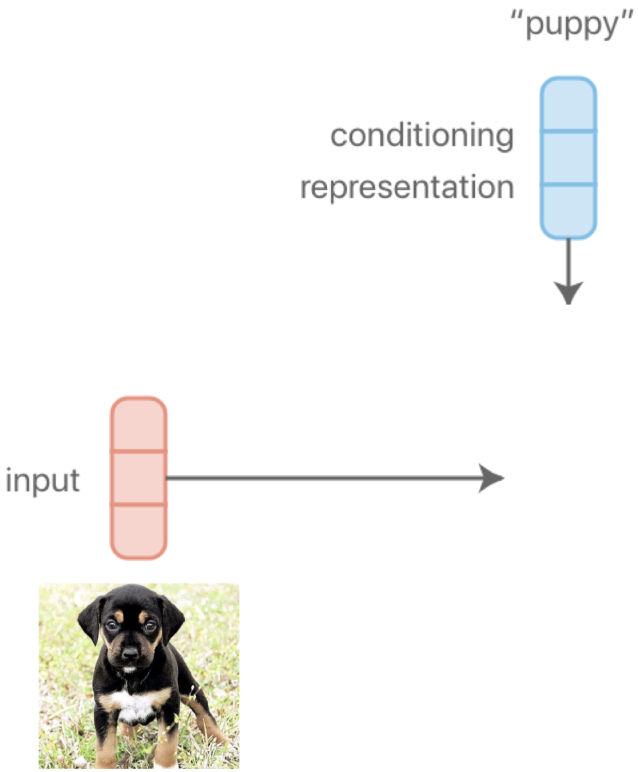


Image: https://distill.pub/2018/feature-wise-transformations/

Concatenation-based conditioning



Concatenation-based conditioning simply concatenates the conditioning representation to the input.

Image: https://distill.pub/2018/feature-wise-transformations/

Concatenation-based conditioning

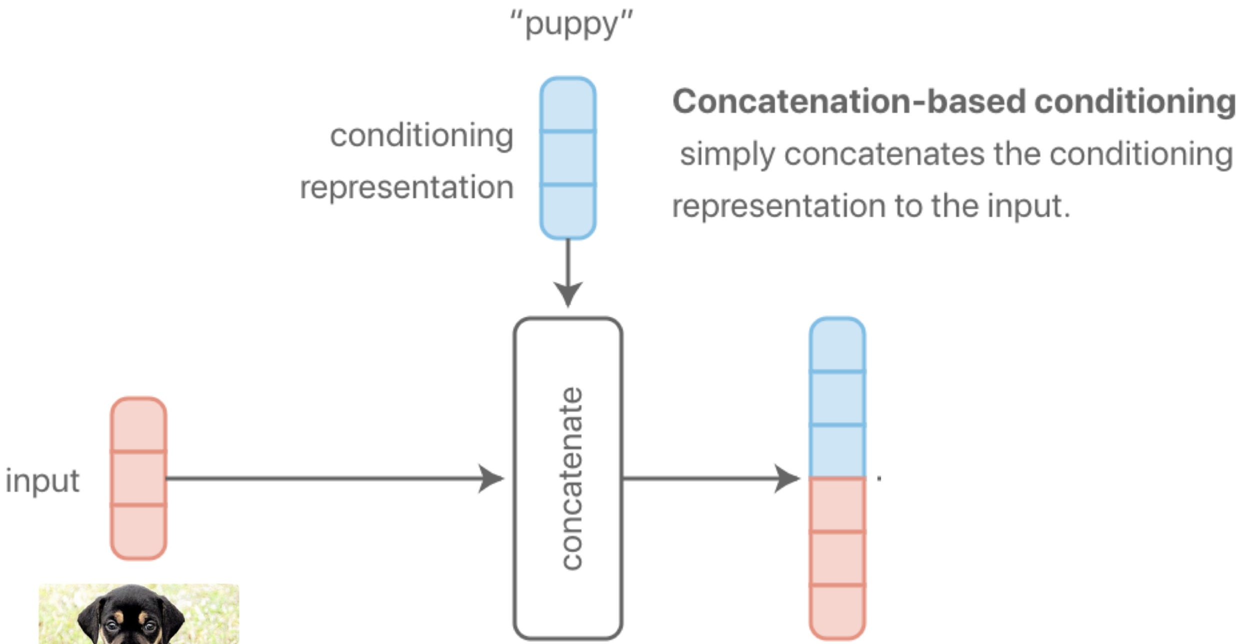


Image: https://distill.pub/2018/feature-wise-transformations/

Concatenation-based conditioning

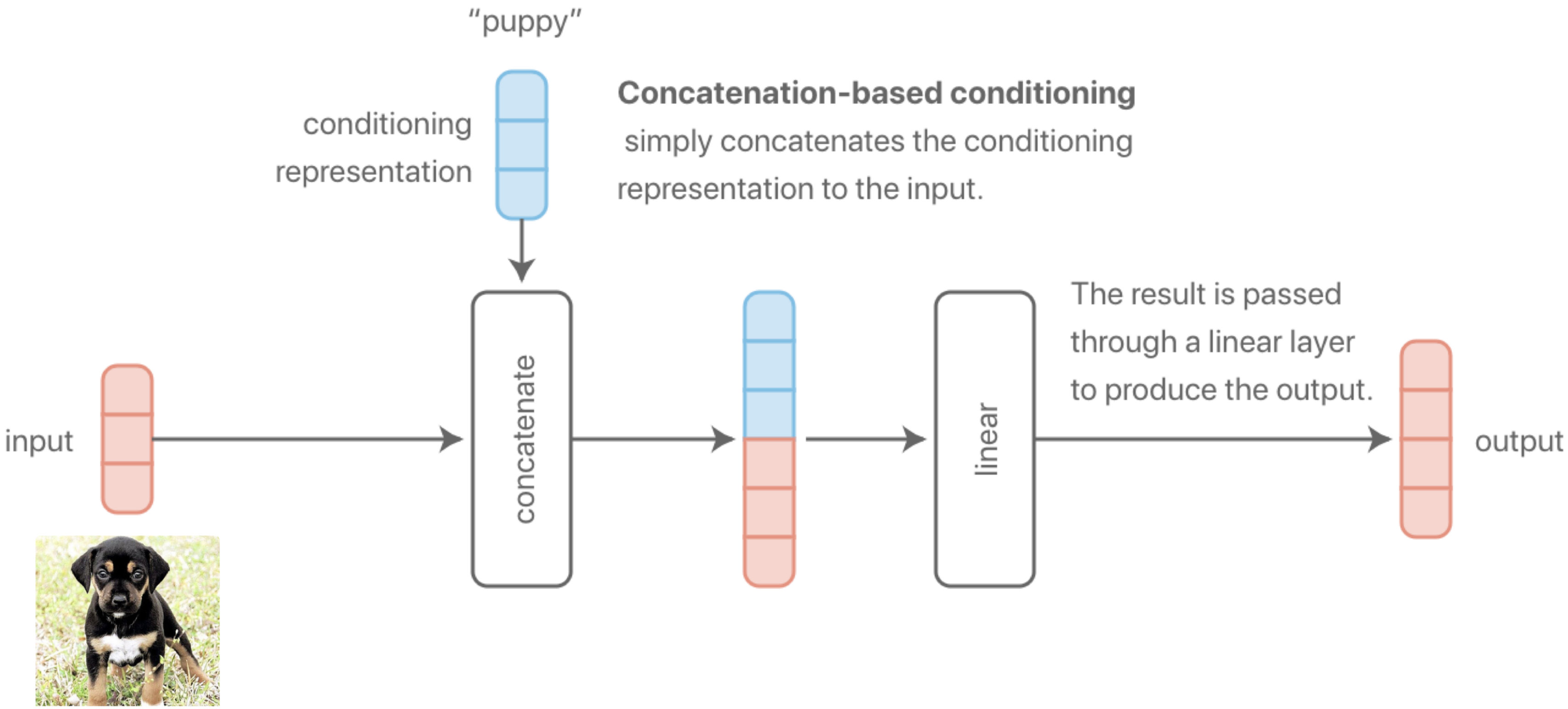
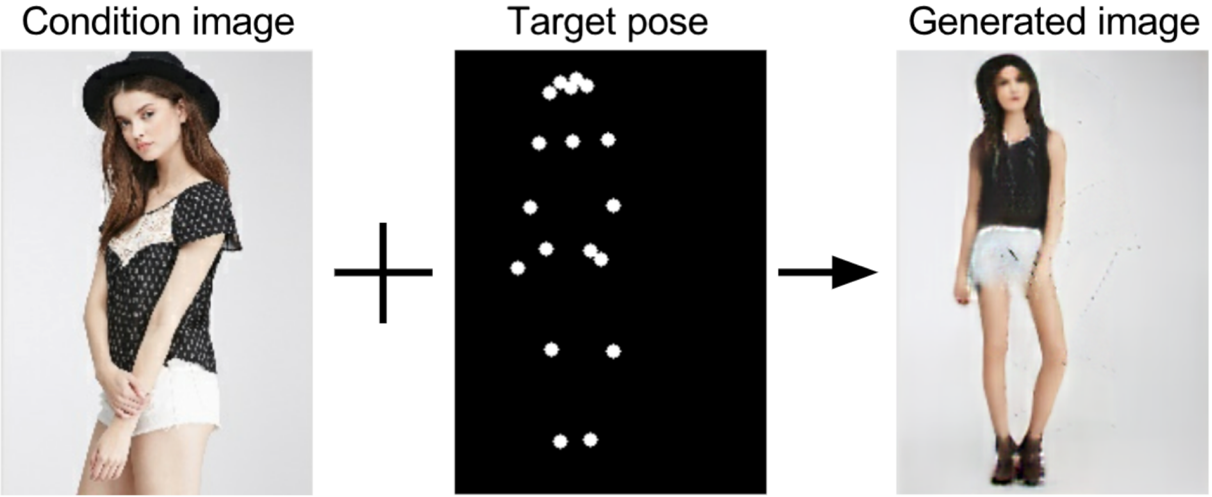


Image: https://distill.pub/2018/feature-wise-transformations/

Concatenation-based conditioning

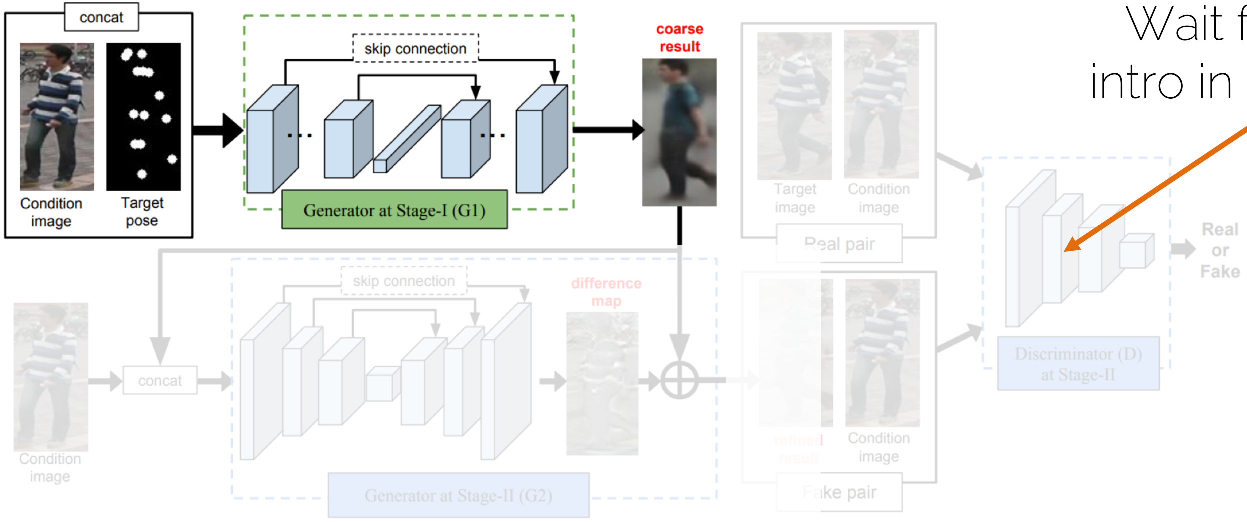
- Source: image (high-dimensional) and pose (low-dimensional)
  → expressed as an image (same dimensionality)



L. Ma et al. „Pose guided person image generation". NIPS 2017

Concatenation-based conditioning

- Source: image (high-dimensional) and pose (low-dimensional)
  → expressed as an image (same dimensionality)

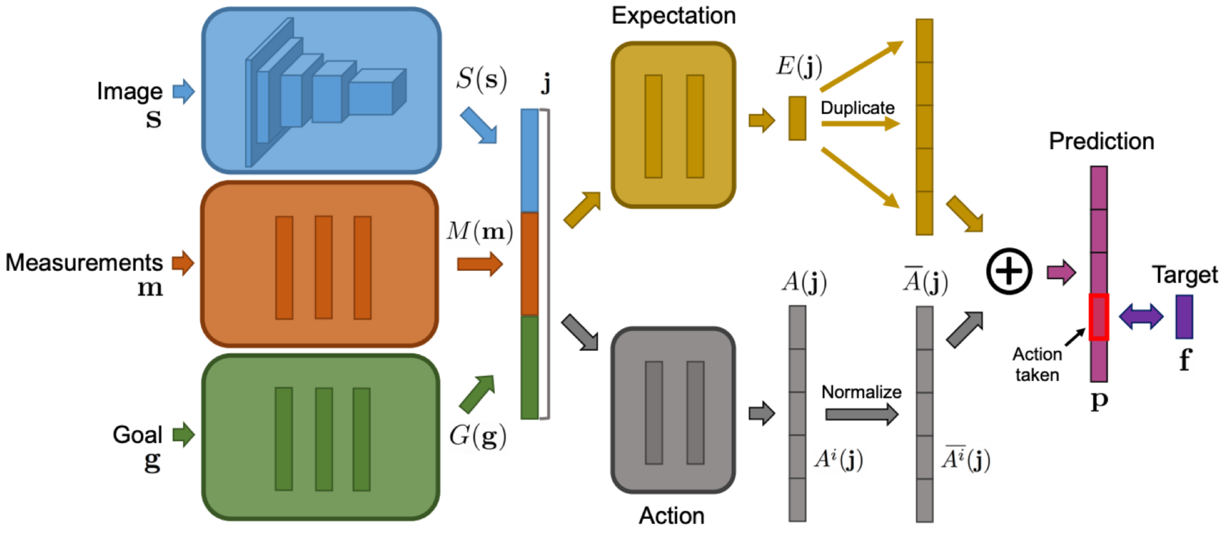


Wait for the GAN intro in a few weeks!

L. Ma et al. „Pose guided person image generation". NIPS 2017

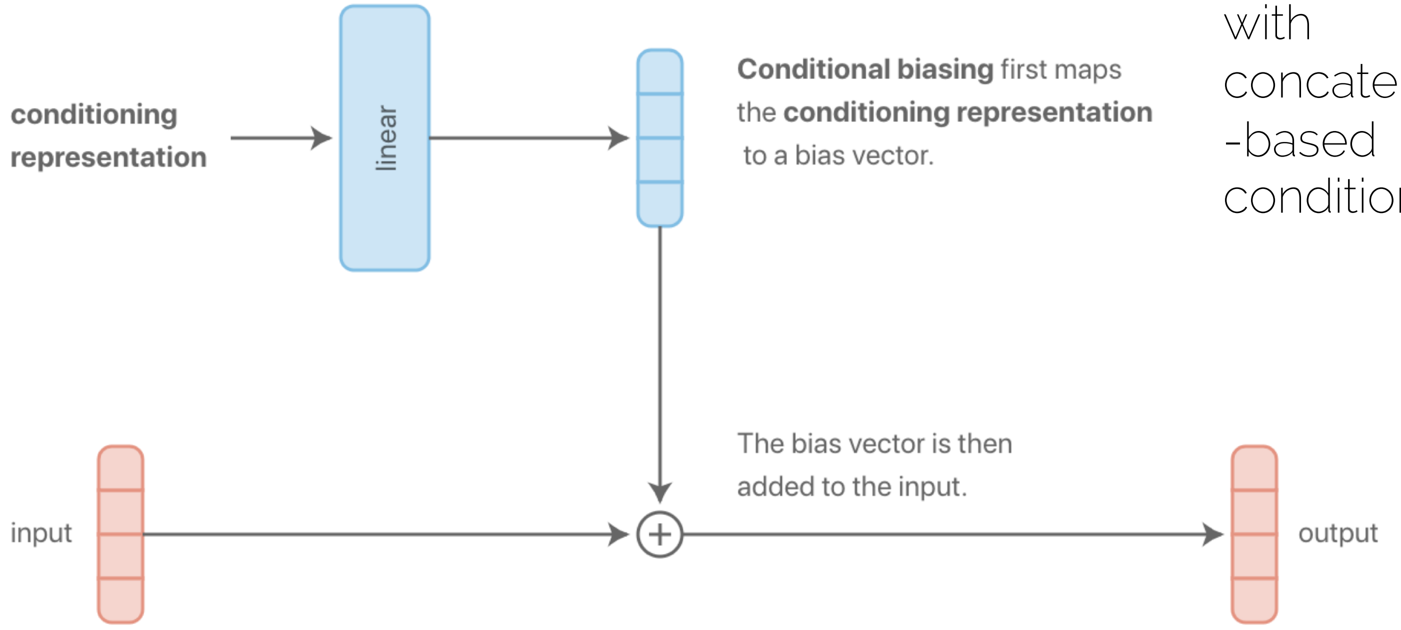
Concatenation-based conditioning

- Sources: image (high-dimensional) and measurements (low-dimensional)



A. Dosovitskiy and V. Koltun. Learning to act by predicting the future. ICLR 2017

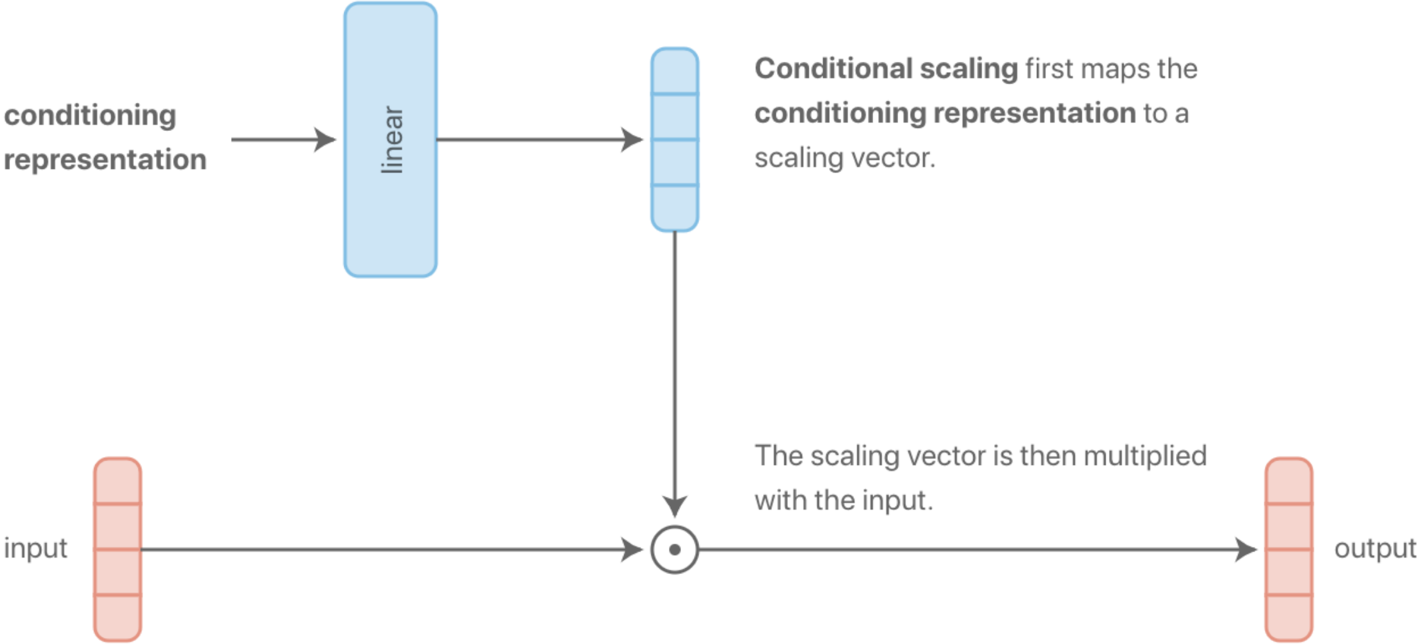
Conditional biasing



Think about the similarities with concatenation-based conditioning

Image: https://distill.pub/2018/feature-wise-transformations/

Conditional scaling



Conditional scaling first maps the **conditioning representation** to a scaling vector.

The scaling vector is then multiplied with the input.

Image: https://distill.pub/2018/feature-wise-transformations/

Conditional scaling

- Reminds you of…. Gating
  - Long-Short Term Memory units

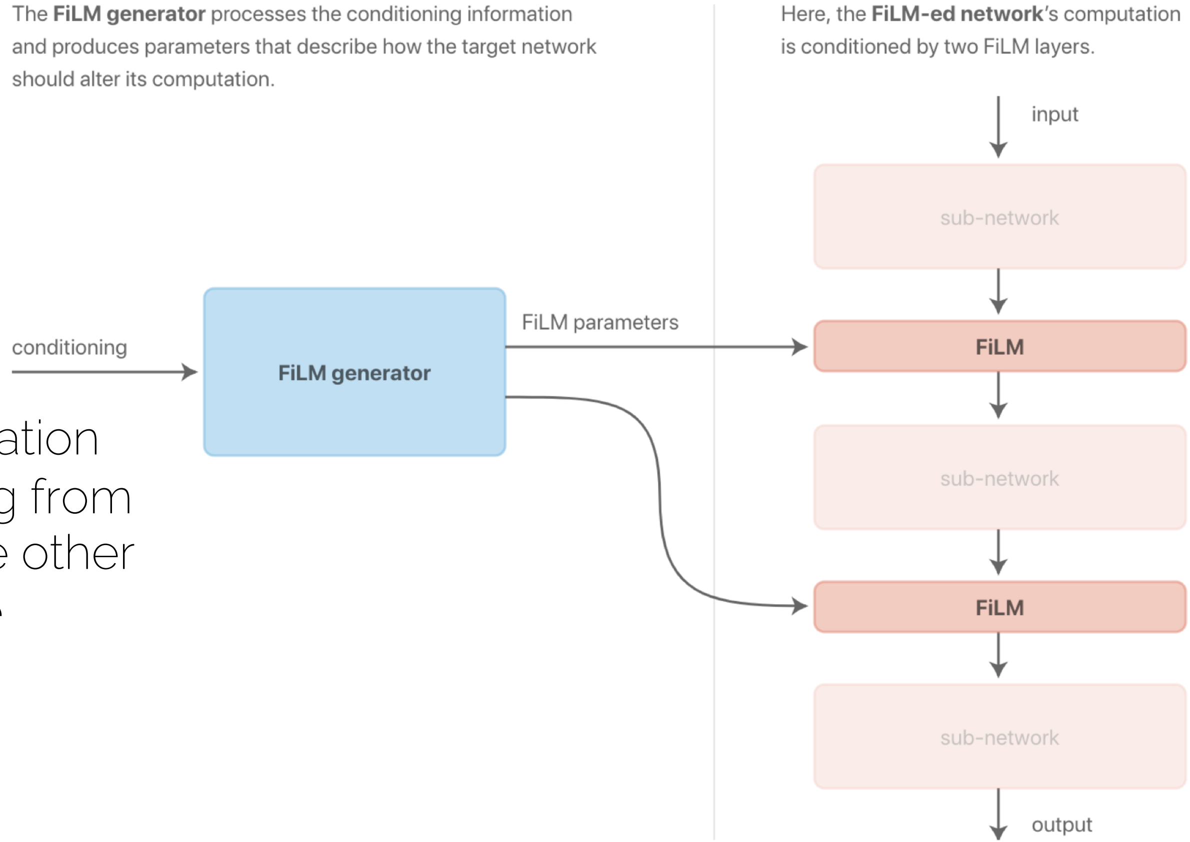
- Gating allows you to learn which inputs are more related between e.g. the two sources

- All conditioning so far is on a feature level → efficient and effective → number of parameters to be learned scales linearly with the number of features of the NN

Conditional scaling

- Can one do both conditional scaling and biasing?

Conditional Affine Transformation



Information coming from e.g. the other source

Image: https://distill.pub/2018/feature-wise-transformations/

E. Perez et al. „FiLM: Visual Reasoning with a General Conditioning Layer". AAAI 2018.

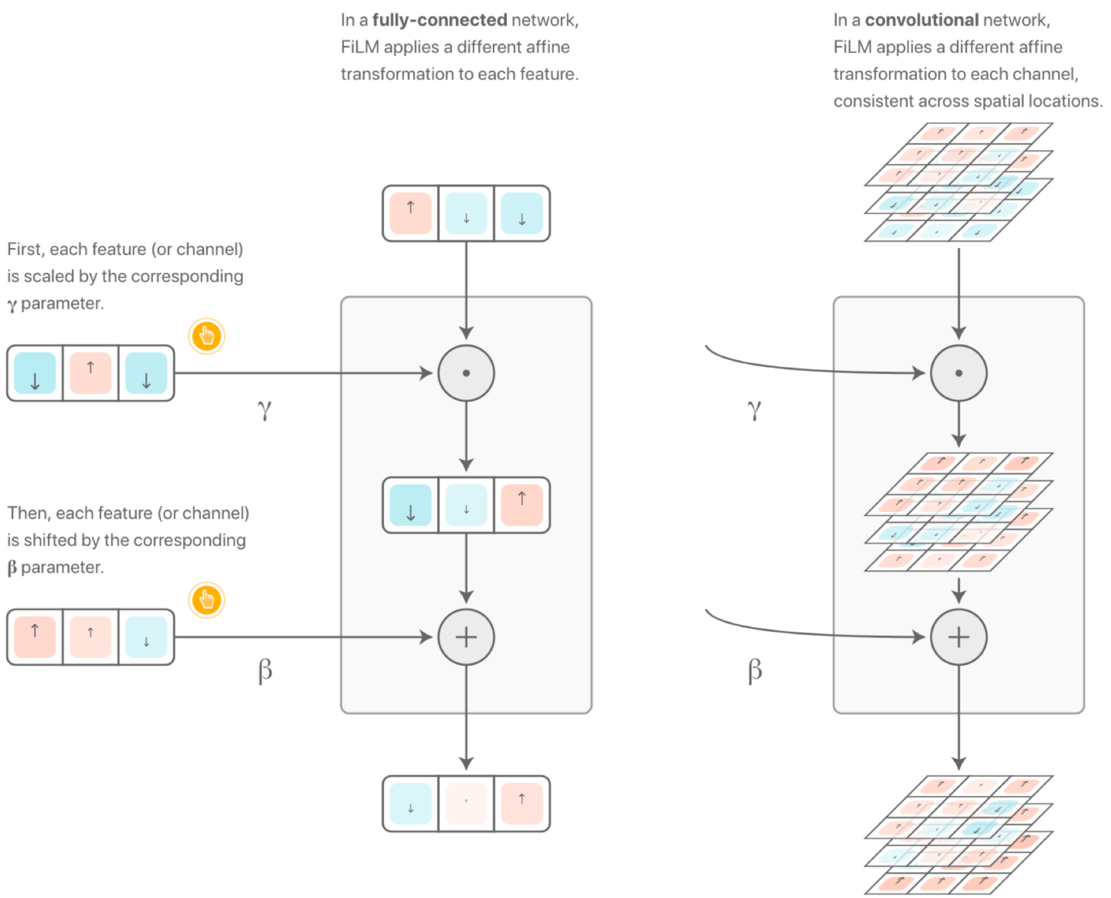


Image: https://distill.pub/2018/feature-wise-transformations/

E. Perez et al. „FiLM: Visual Reasoning with a General Conditioning Layer“. AAAI 2018.

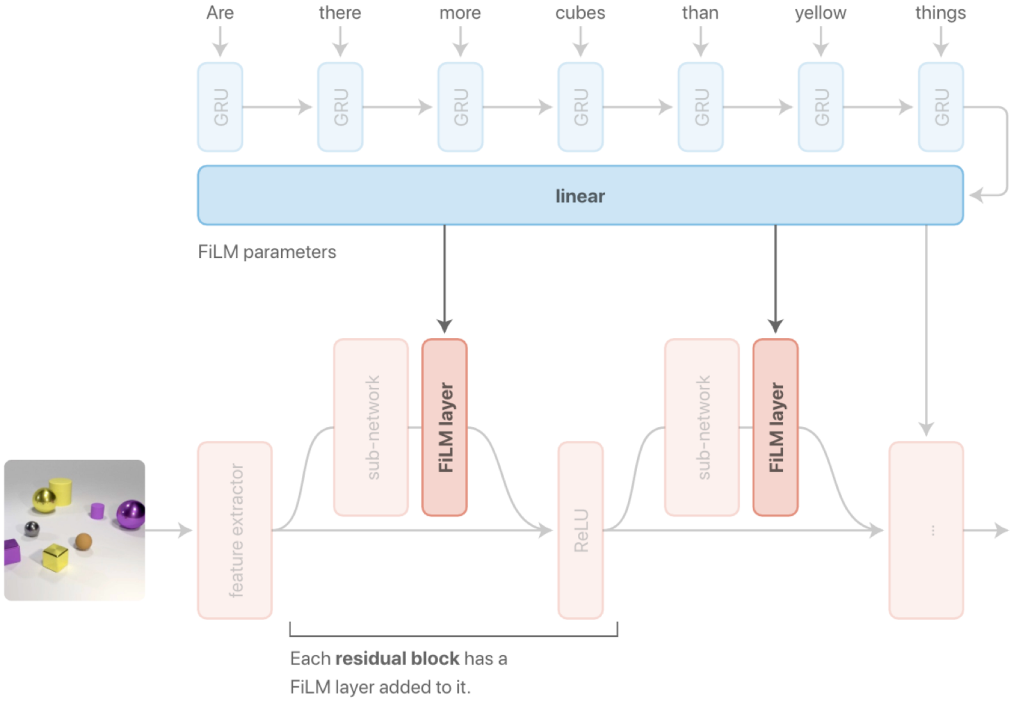
What can we do with conditioning?

- Visual Reasoning with Multi-hop Feature Modulation
Strub et al. ECCV 2018.
- GuessWhat?! Visual object discovery through multi-modal dialogue. de Vries et al CVPR 2017
- A learned representation for artistic style.
Dumoulin et al ICLR 2017
- Conditional image generation with PixelCNN decoders.
van den Oord et al. NIPS 2016

Visual Question and Answering

The **linguistic pipeline** acts as the FiLM generator.

FiLM layers in each residual block modulate the **visual pipeline**.



Attention vs Conditioning

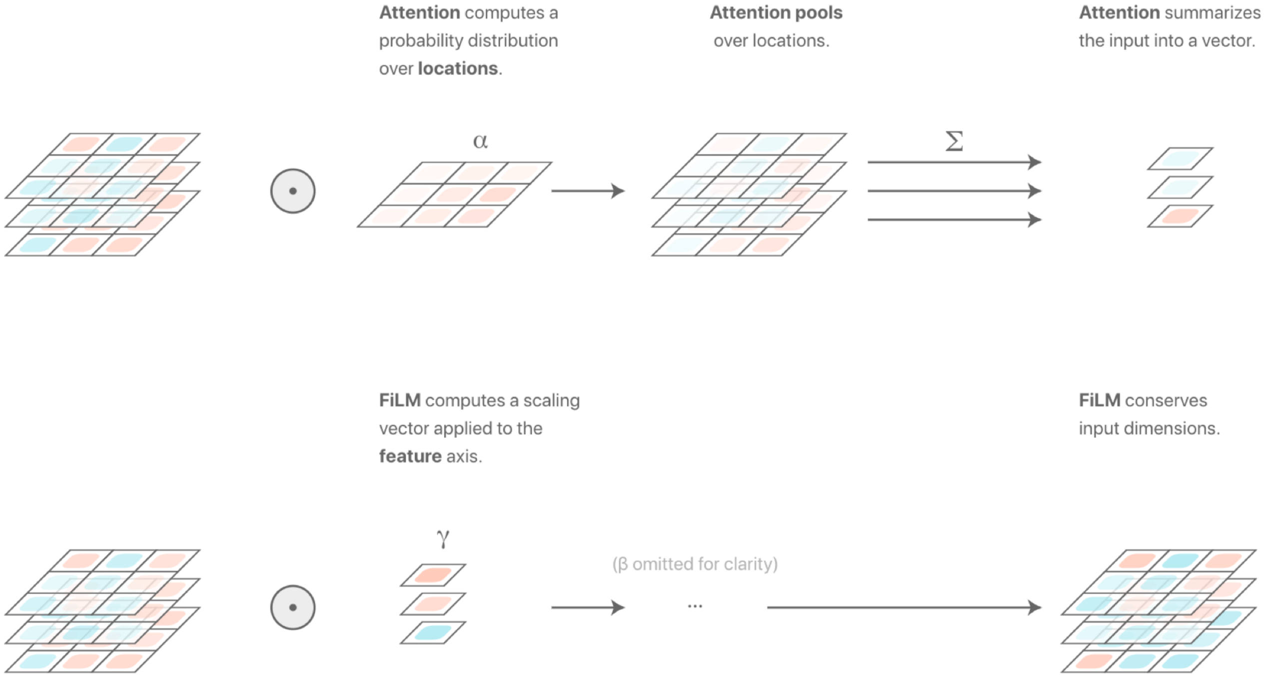


Image: https://distill.pub/2018/feature-wise-transformations/

Attention vs Conditioning

- Attention: assumes that specific **locations** contain the most useful information

- Conditioning: assumes that specific **feature maps** contain the most useful information

Image: https://distill.pub/2018/feature-wise-transformations/

Next lecture

- Next Monday: lecture on visualization