Course material at:

https://github.com/lyeskhalil/mlbootcamp2022/

Advanced Topics

Friday

FASE ML Bootcamp

Based on material from various sources:
Data augmentation, Hyperparameter tuning, CNN understanding, Attention, GANs:
http://cs231n.stanford.edu/schedule.html
Uncertainty in Deep Learning: https://www.gatsby.ucl.ac.uk/~balaji/balaji-uncertainty-talk-cifar-dlrl.pdf
Graph Neural Networks: http://tkipf.github.io/misc/SlidesCambridge.pdf
Reinforcement Learning: https://www.davidsilver.uk/wp-content/uploads/2020/03/deep_rl_tutorial_small_compressed.pdf

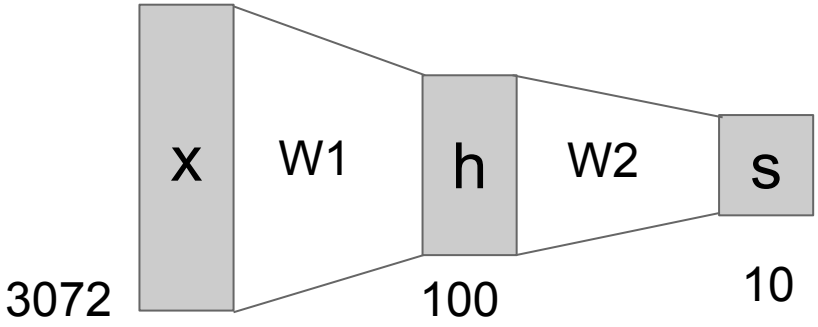
2022 Free PDF book on all of ML by Kevin Murphy (Google): https://probml.github.io/pml-book/book1.html

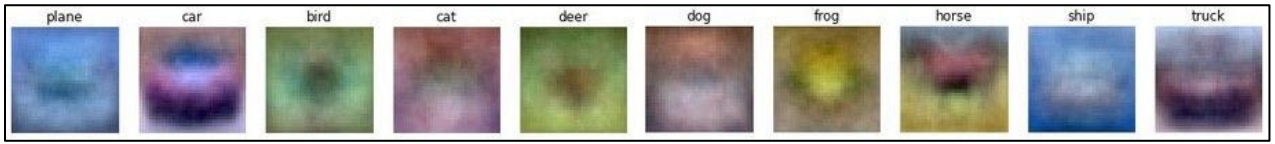
Where we are now...

Neural Networks

Linear score function: $f = Wx$

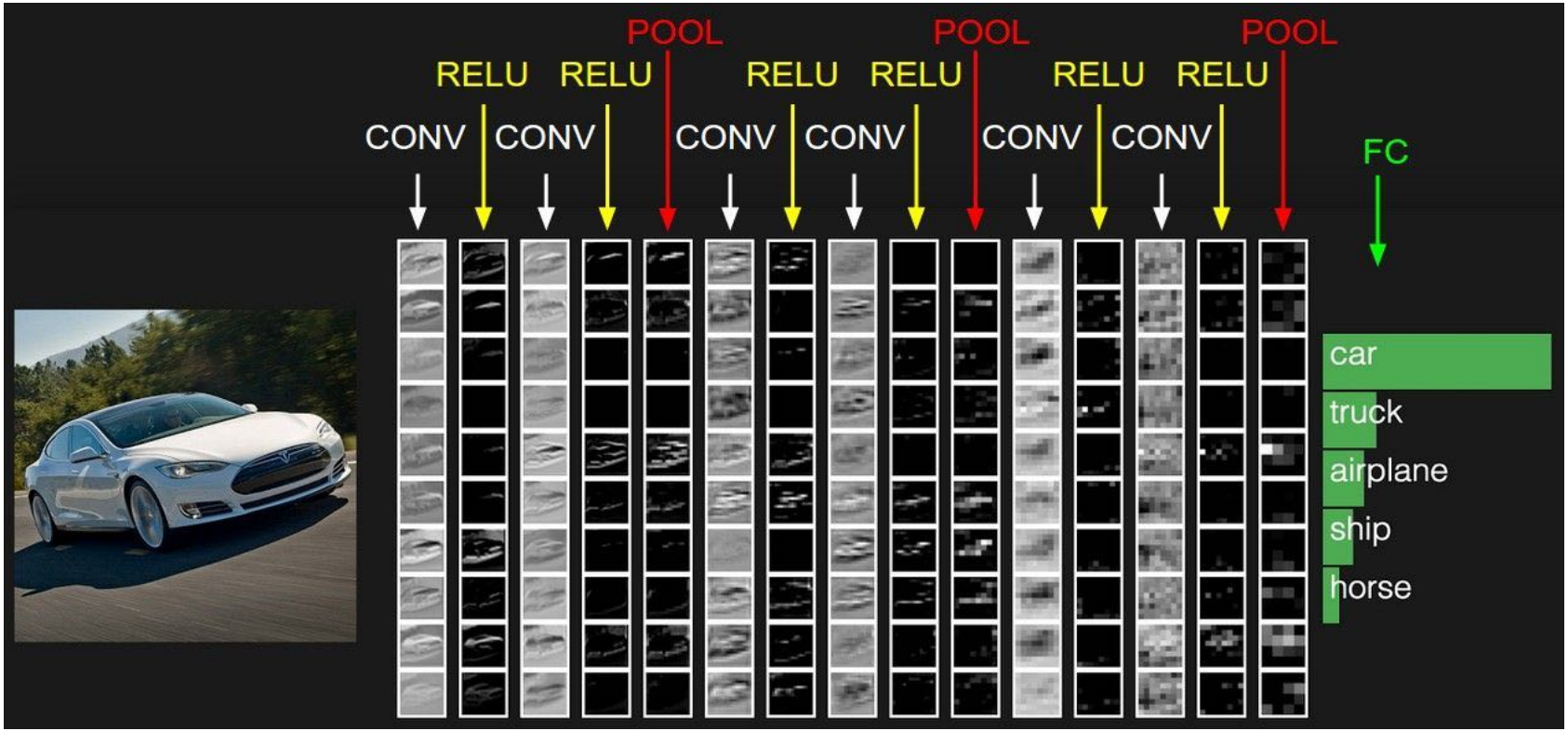
2-layer Neural Network $f = W_2 \max(0, W_1 x)$





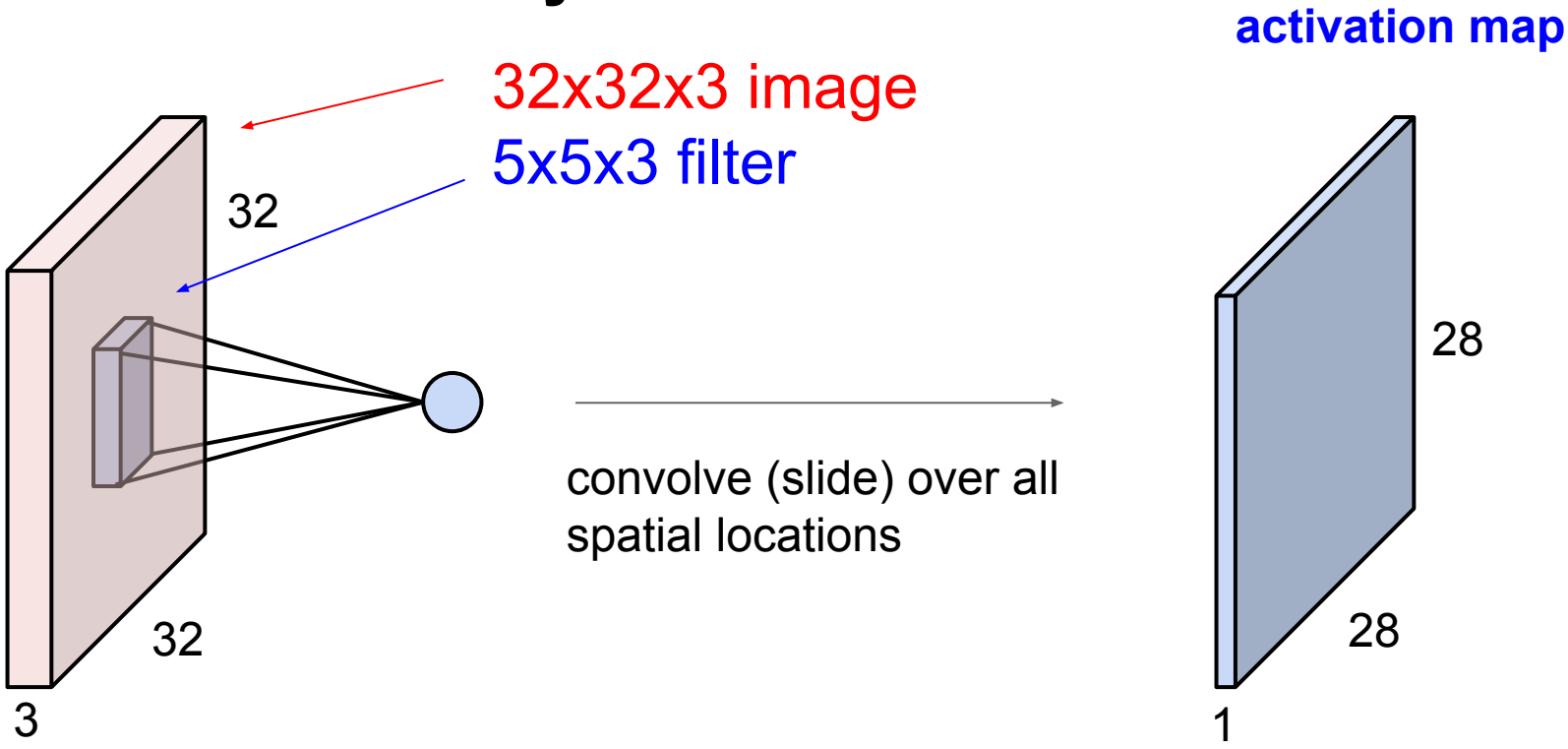
Where we are now...

Convolutional Neural Networks



Where we are now...

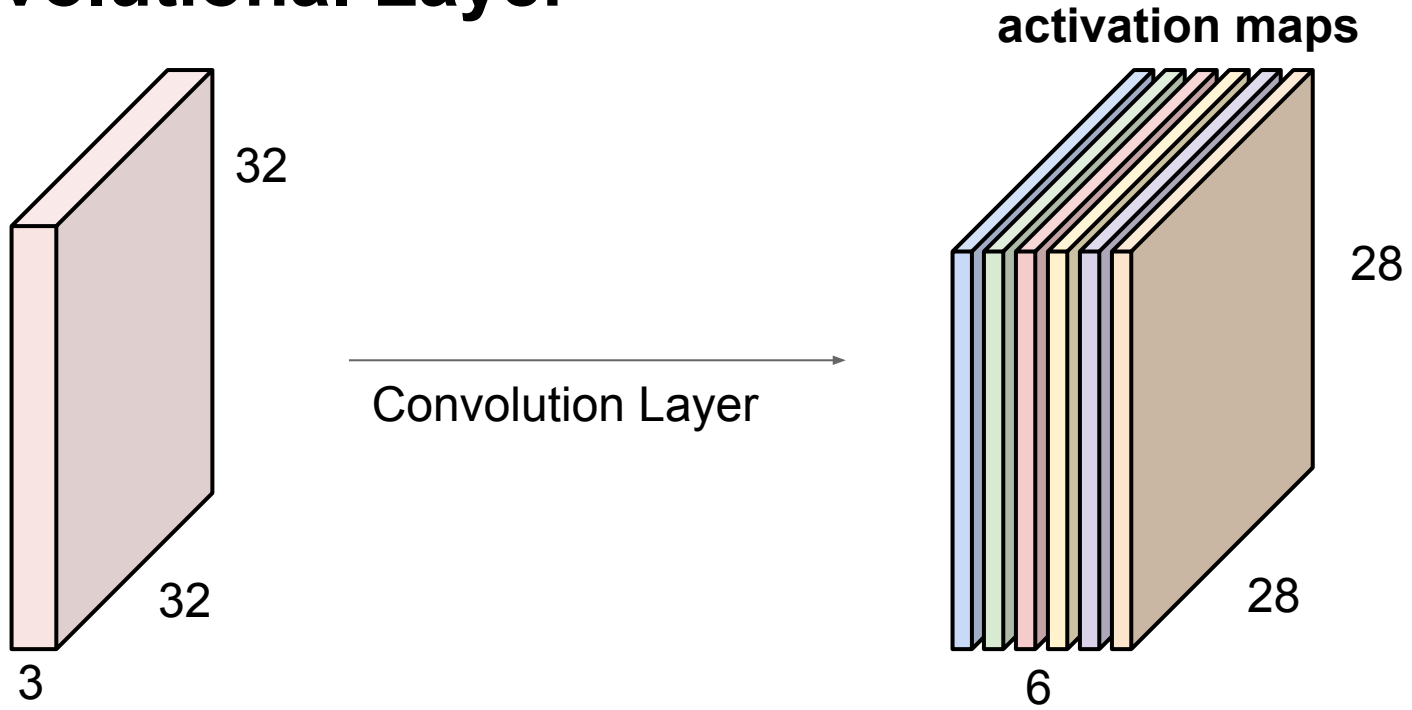
Convolutional Layer



Where we are now...

Convolutional Layer

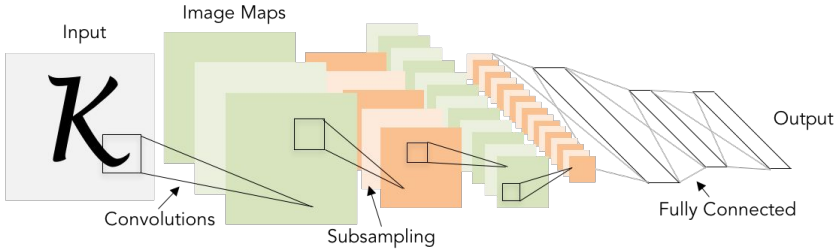
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

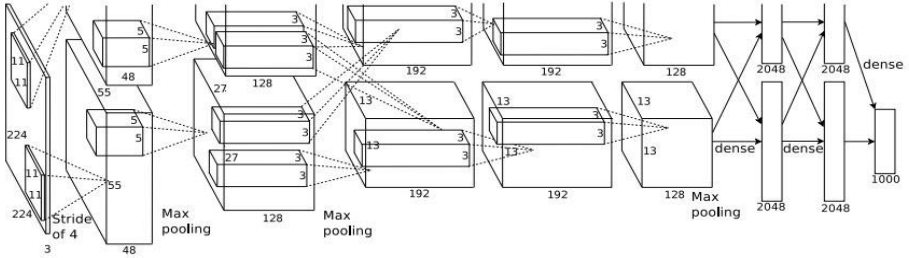


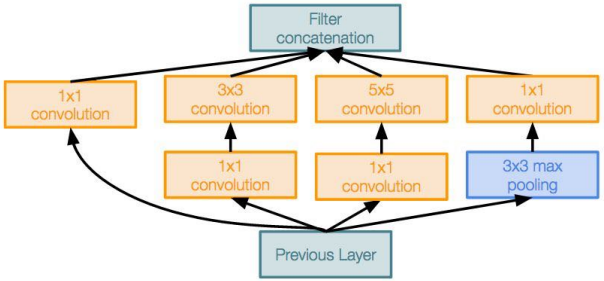
We stack these up to get a "new image" of size 28x28x6!

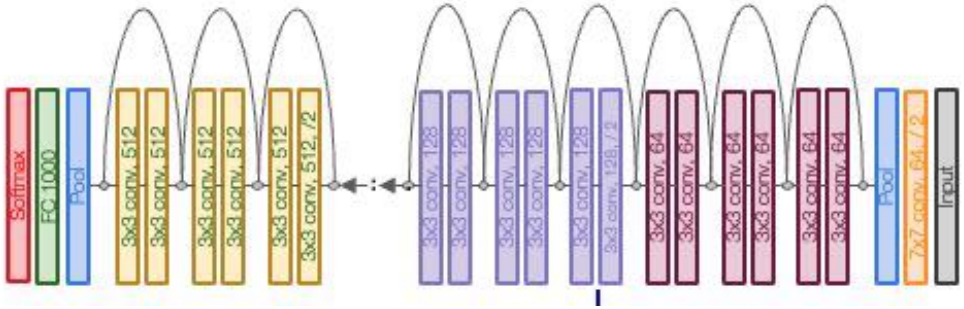
Where we are now...

CNN Architectures



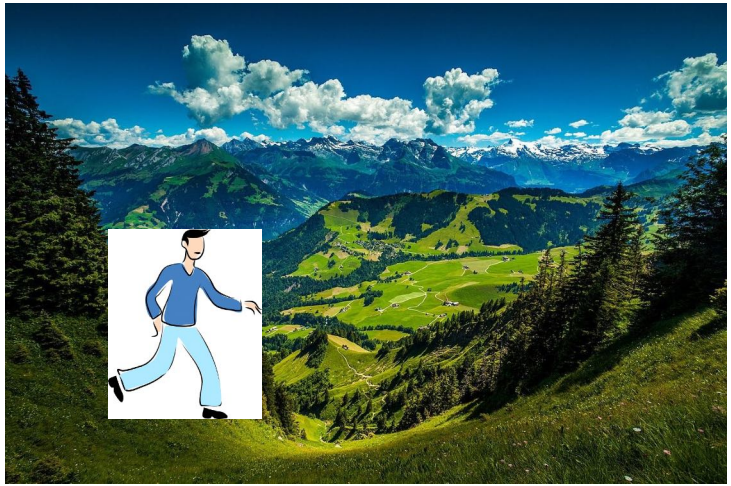


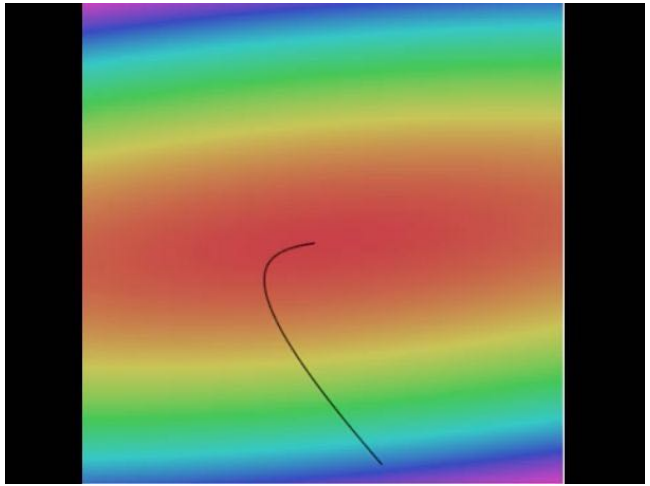




Where we are now...

Learning network parameters through optimization





```
# Vanilla Gradient Descent

while True:
  weights_grad = evaluate_gradient(loss_fun, data, weights)
  weights += - step_size * weights_grad # perform parameter update
```

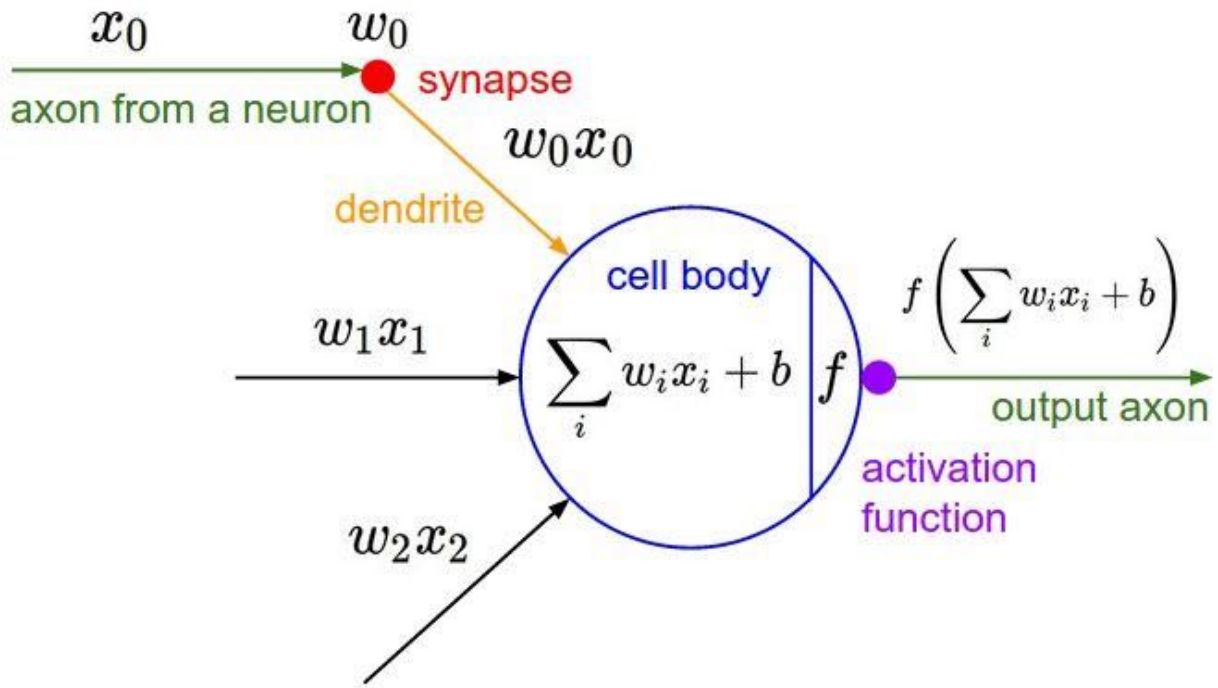
Where we are now...

Mini-batch SGD

Loop:

1. **Sample** a batch of data
2. **Forward** prop it through the graph (network), get loss
3. **Backprop** to calculate the gradients
4. **Update** the parameters using the gradient

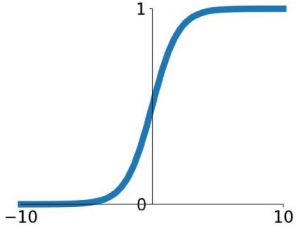
Activation Functions



Activation Functions

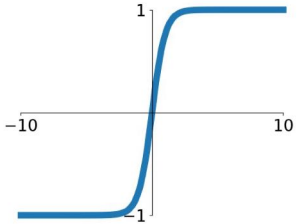
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



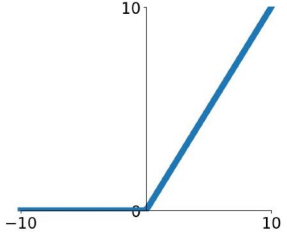
tanh

$$\tanh(x)$$



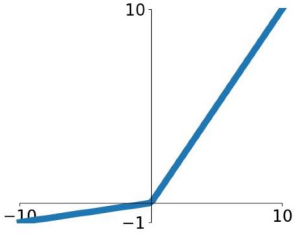
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

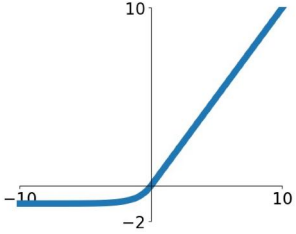


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



TLDR: In practice:

- Use ReLU. Be careful with your learning rates
- Try out Leaky ReLU / Maxout / ELU / SELU
  - To squeeze out some marginal gains
- Don’t use sigmoid or tanh

Data Preprocessing

TLDR: In practice for Images: center only

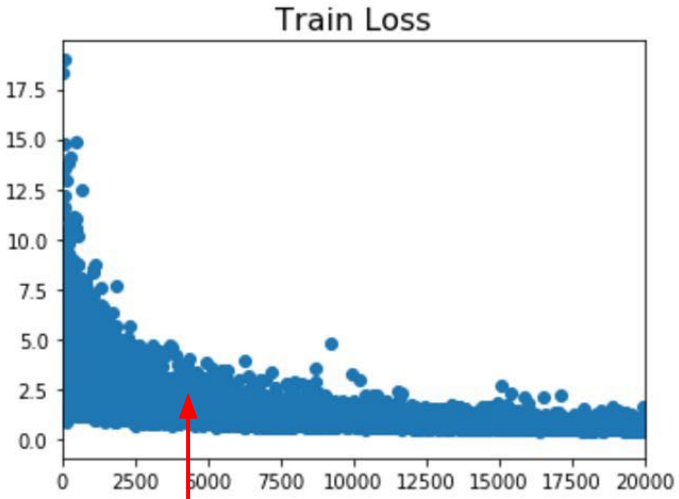
e.g. consider CIFAR-10 example with [32,32,3] images

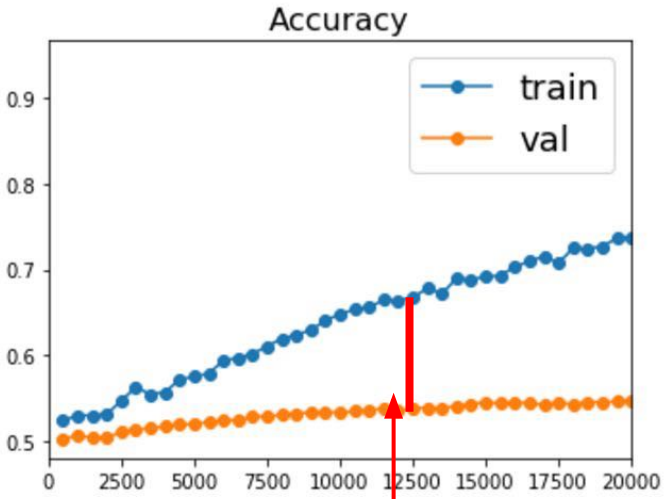
- Subtract the mean image (e.g. AlexNet)
  (mean image = [32,32,3] array)
- Subtract per-channel mean (e.g. VGGNet)
  (mean along each channel = 3 numbers)
- Subtract per-channel mean and
  Divide by per-channel std (e.g. ResNet)
  (mean along each channel = 3 numbers)

Not common to do PCA or whitening

Training vs. Testing Error

Beyond Training Error

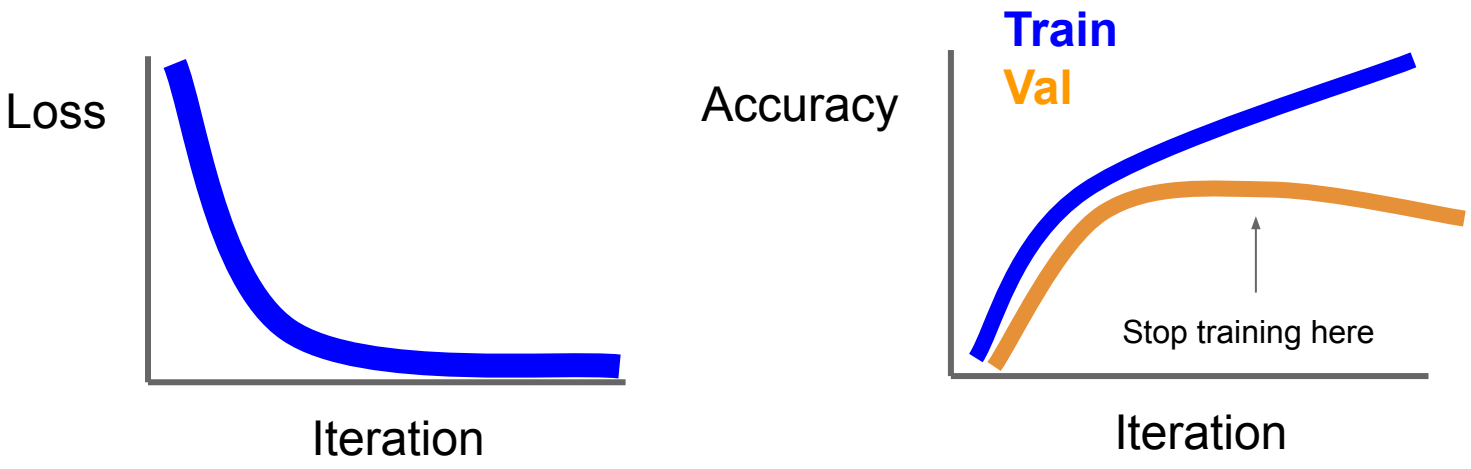




Better optimization algorithms help reduce training loss

But we really care about error on new data - how to reduce the gap?

Early Stopping: Always do this



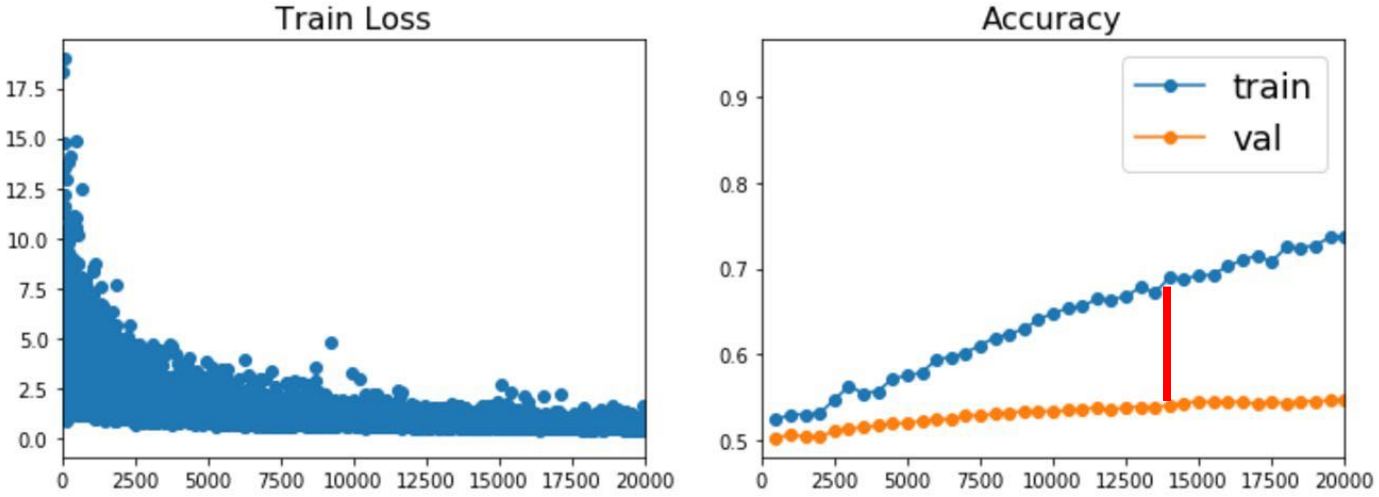
Stop training the model when accuracy on the validation set decreases
Or train for a long time, but always keep track of the model snapshot that worked best on val

Model Ensembles

1. Train multiple independent models
2. At test time average their results
   (Take average of predicted probability distributions, then choose argmax)

Enjoy 2% extra performance

How to improve single-model performance?



Regularization

Regularization: Add term to loss

$$L = \frac{1}{N}\sum_{i=1}^{N}\sum_{j\neq y_i}\max(0, f(x_i; W)_j - f(x_i; W)_{y_i} + 1) + \boxed{\lambda R(W)}$$

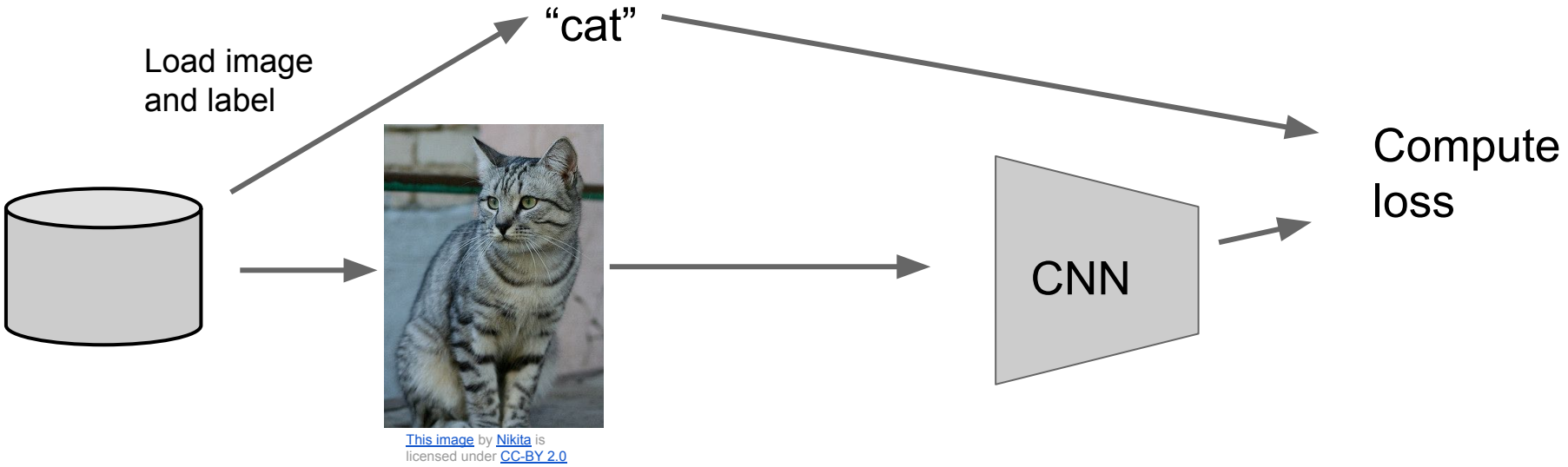
In common use:

L2 regularization $R(W) = \sum_k \sum_l W_{k,l}^2$ (Weight decay)

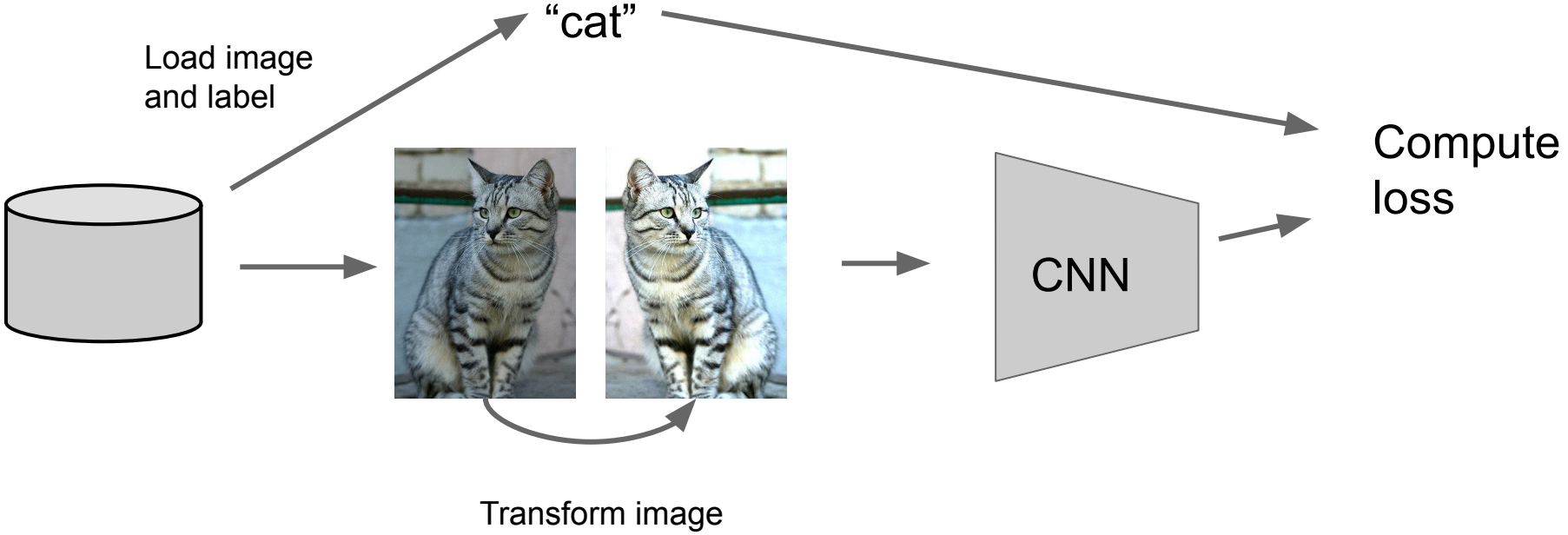
L1 regularization $R(W) = \sum_k \sum_l |W_{k,l}|$

Elastic net (L1 + L2) $R(W) = \sum_k \sum_l \beta W_{k,l}^2 + |W_{k,l}|$

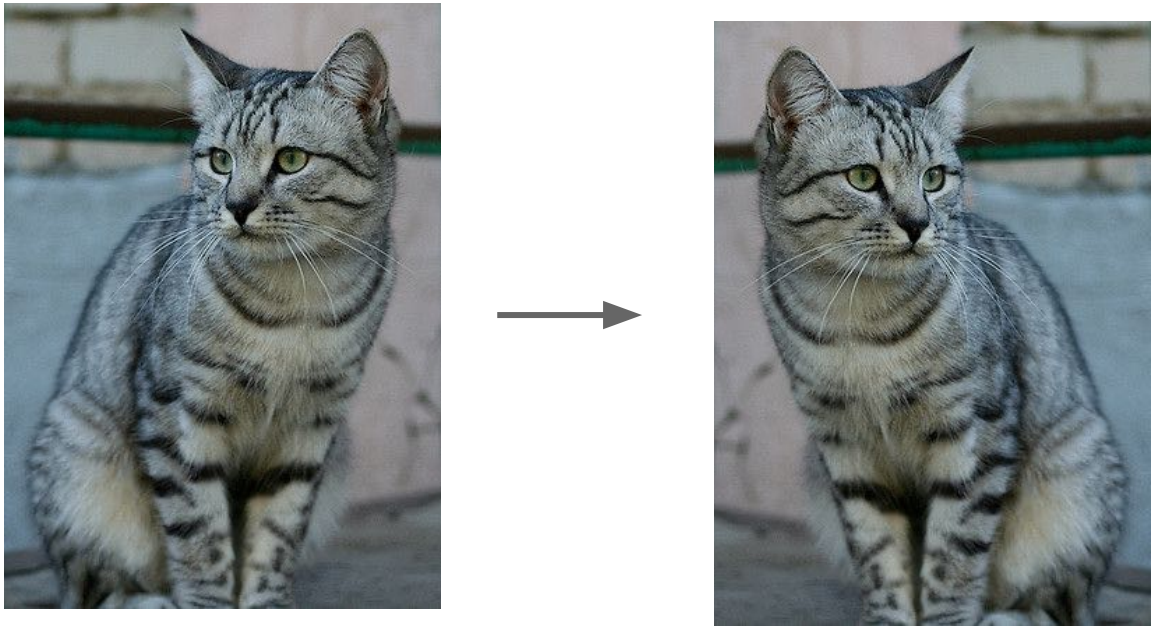
Regularization: Data Augmentation



Regularization: Data Augmentation



Data Augmentation
Horizontal Flips



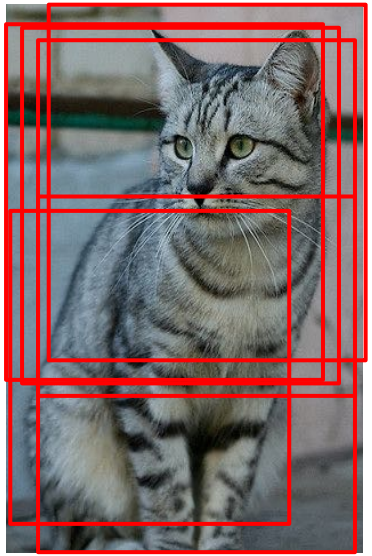
Data Augmentation

Random crops and scales

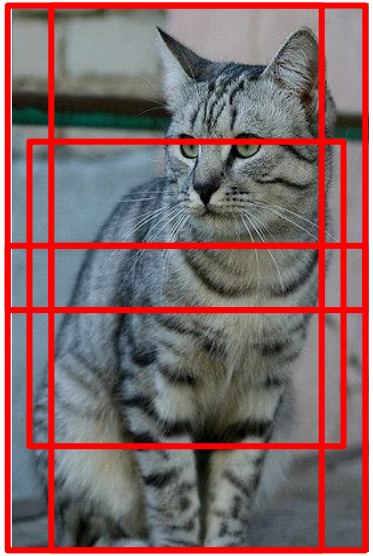
Training: sample random crops / scales

ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224 x 224 patch



Data Augmentation
Random crops and scales



Training: sample random crops / scales

ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224 x 224 patch

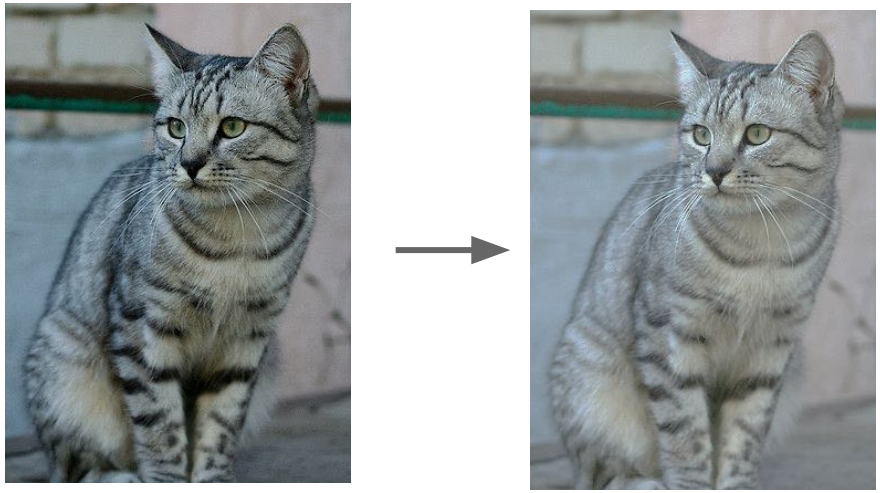
Testing: average a fixed set of crops

ResNet:

1. Resize image at 5 scales: {224, 256, 384, 480, 640}
2. For each size, use 10 224 x 224 crops: 4 corners + center, + flips

Data Augmentation
Color Jitter

Simple: Randomize
contrast and brightness



Data Augmentation

Get creative for your problem!

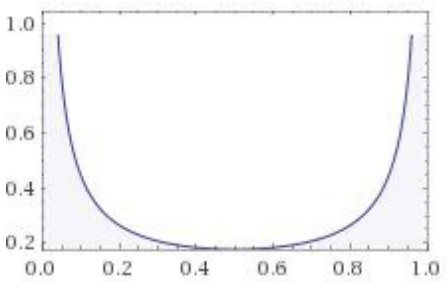
Examples of data augmentations:

- translation
- rotation
- stretching
- shearing,
- lens distortions, … (go crazy)

Regularization: Mixup

Training: Train on random blends of images

Testing: Use original images



Examples:

Dropout
Batch Normalization
Data Augmentation
DropConnect
Fractional Max Pooling
Stochastic Depth
Cutout / Random Crop
Mixup

CNN

Target label:
cat: 0.4
dog: 0.6

Randomly blend the pixels of pairs of training images, e.g. 40% cat, 60% dog

Zhang et al, "*mixup*: Beyond Empirical Risk Minimization", ICLR 2018

Choosing Hyperparameters

(without tons of GPUs)

Choosing Hyperparameters

Step 1: Check initial loss

Turn off weight decay, sanity check loss at initialization
e.g. log(C) for softmax with C classes

Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample

Try to train to 100% training accuracy on a small sample of training data (~5-10 minibatches); fiddle with architecture, learning rate, weight initialization

Loss not going down? LR too low, bad initialization
Loss explodes to Inf or NaN? LR too high, bad initialization

Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down

Use the architecture from the previous step, use all training data, turn on small weight decay, find a learning rate that makes the loss drop significantly within ~100 iterations

Good learning rates to try: 1e-1, 1e-2, 1e-3, 1e-4

Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs

Choose a few values of learning rate and weight decay around what worked from Step 3, train a few models for ~1-5 epochs.

Good weight decay to try: 1e-4, 1e-5, 0

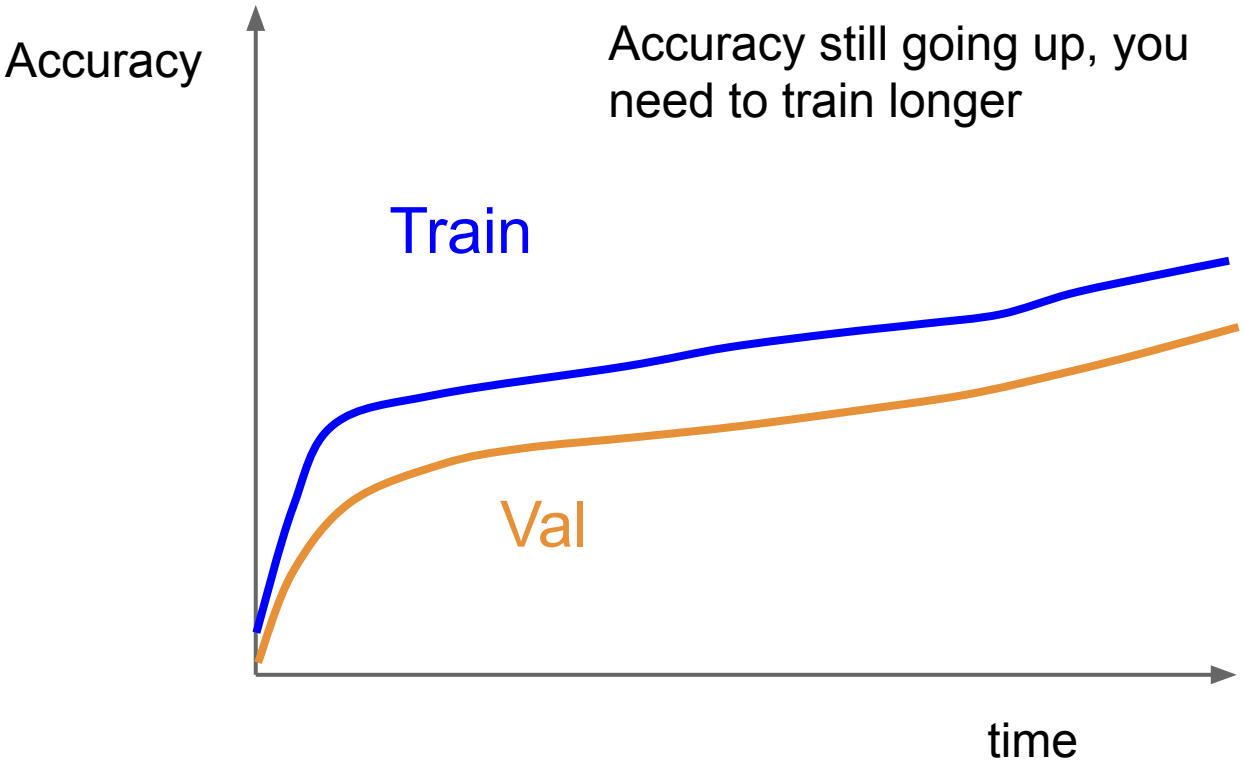
Choosing Hyperparameters

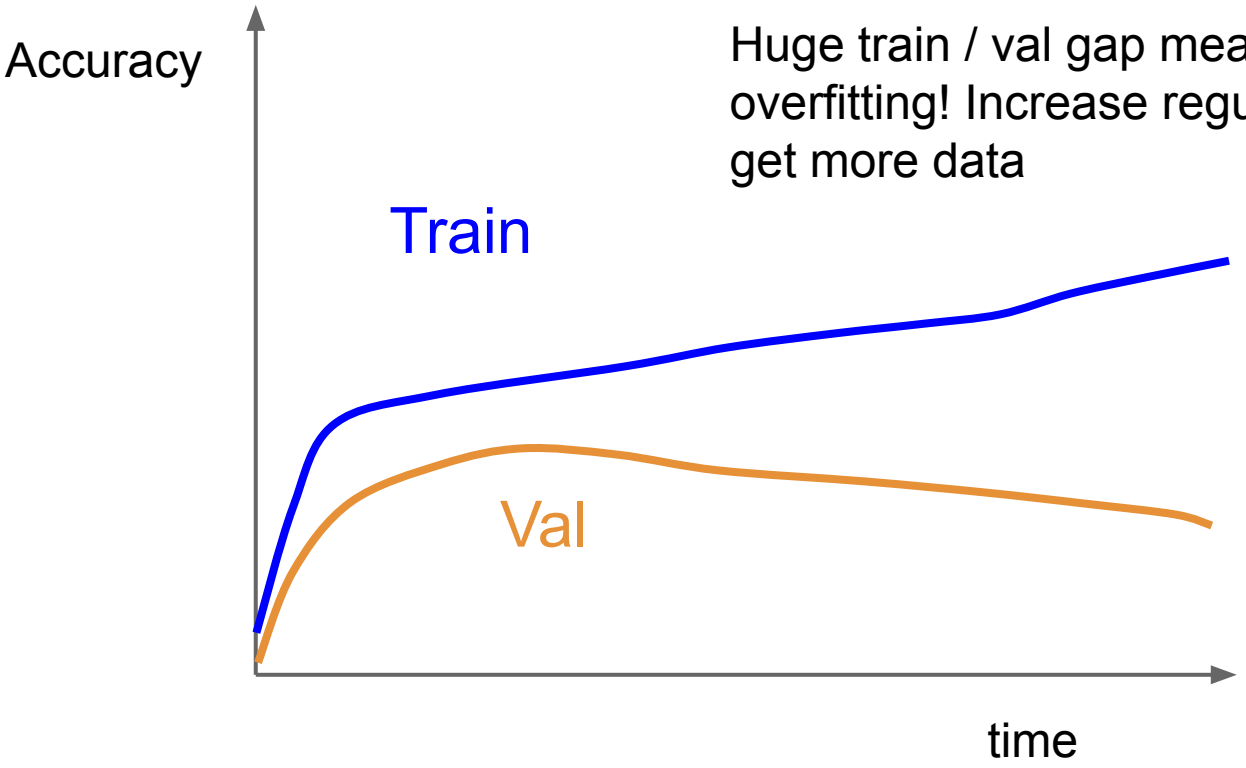
Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer

Pick best models from Step 4, train them for longer (~10-20 epochs) without learning rate decay

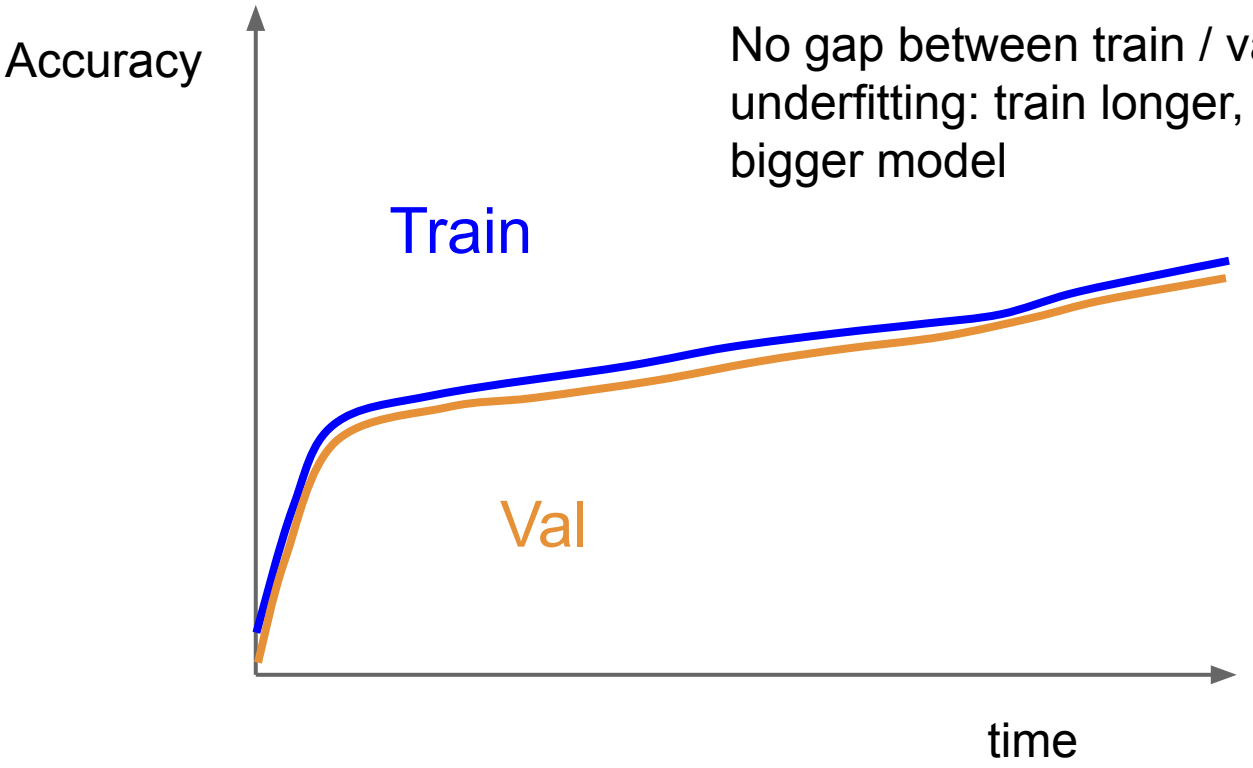
Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer
Step 6: Look at loss and accuracy curves


Accuracy
Accuracy still going up, you need to train longer
Train
Val
time



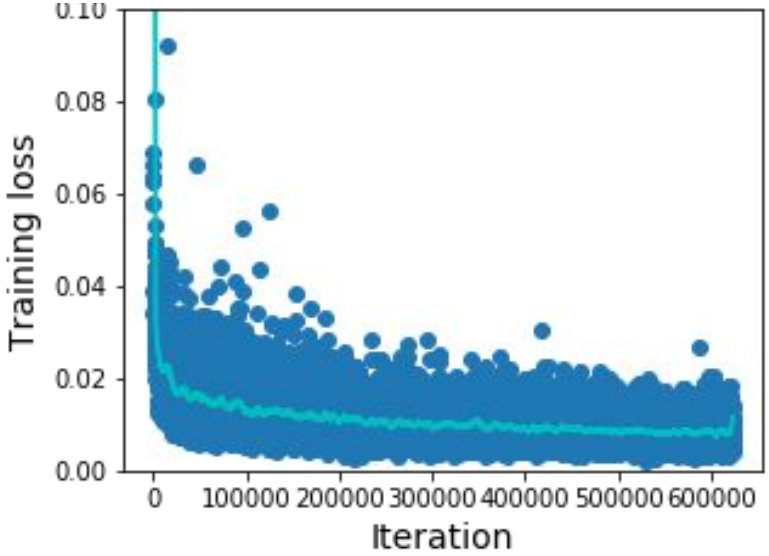
Huge train / val gap means overfitting! Increase regularization, get more data



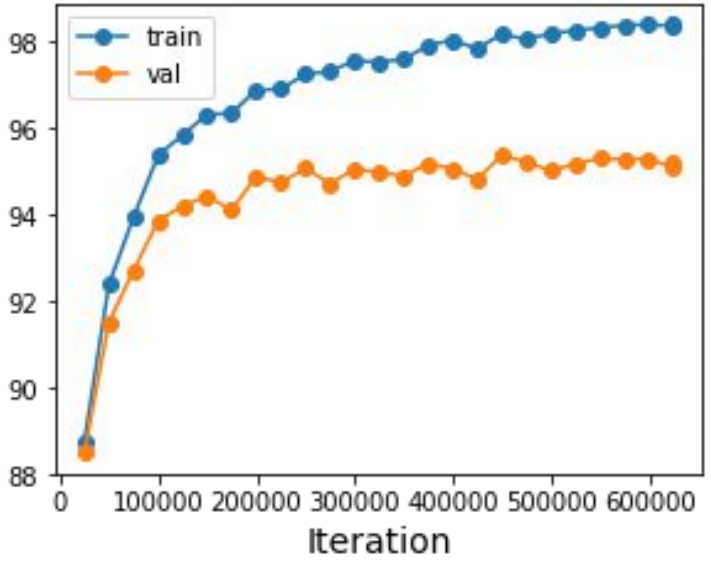
No gap between train / val means underfitting: train longer, use a bigger model

Look at learning curves!

Training Loss



Train / Val Accuracy

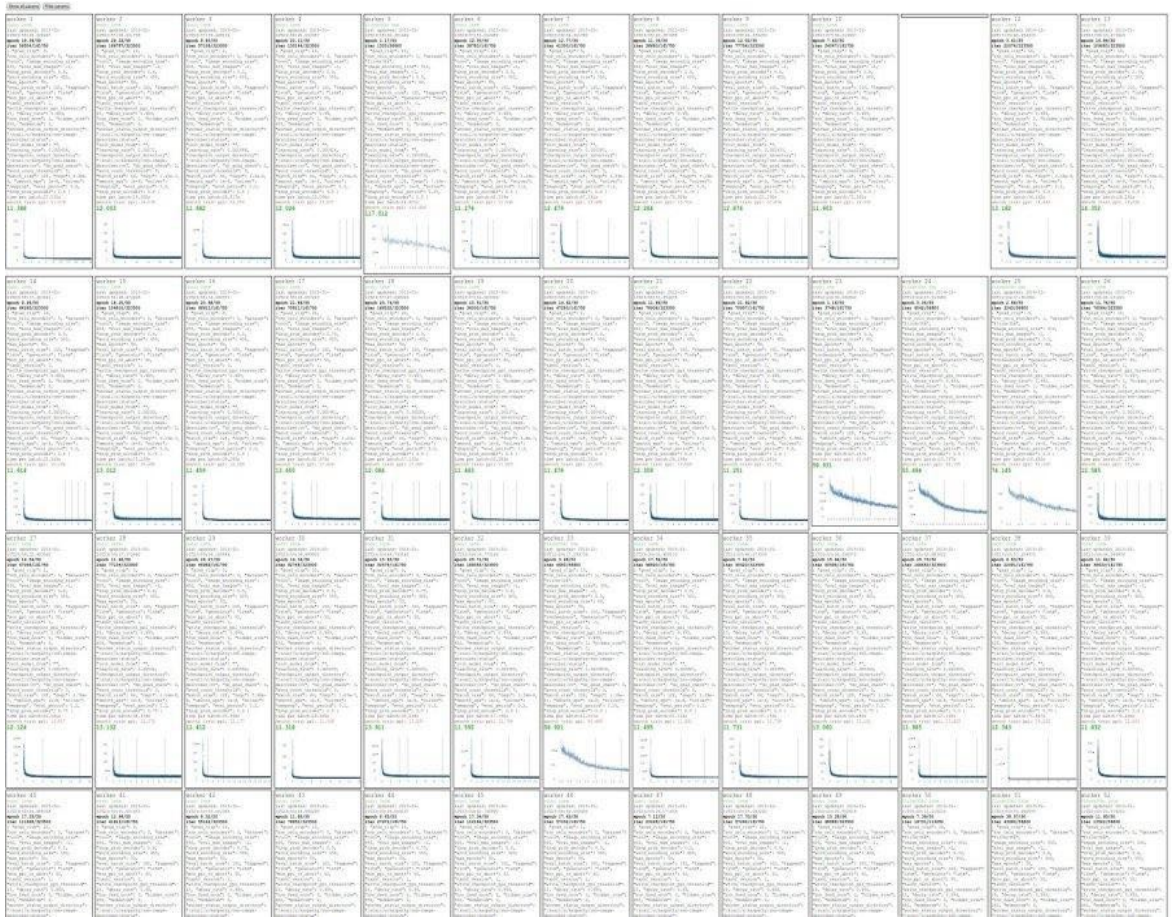


Losses may be noisy, use a scatter plot and also plot moving average to see trends better

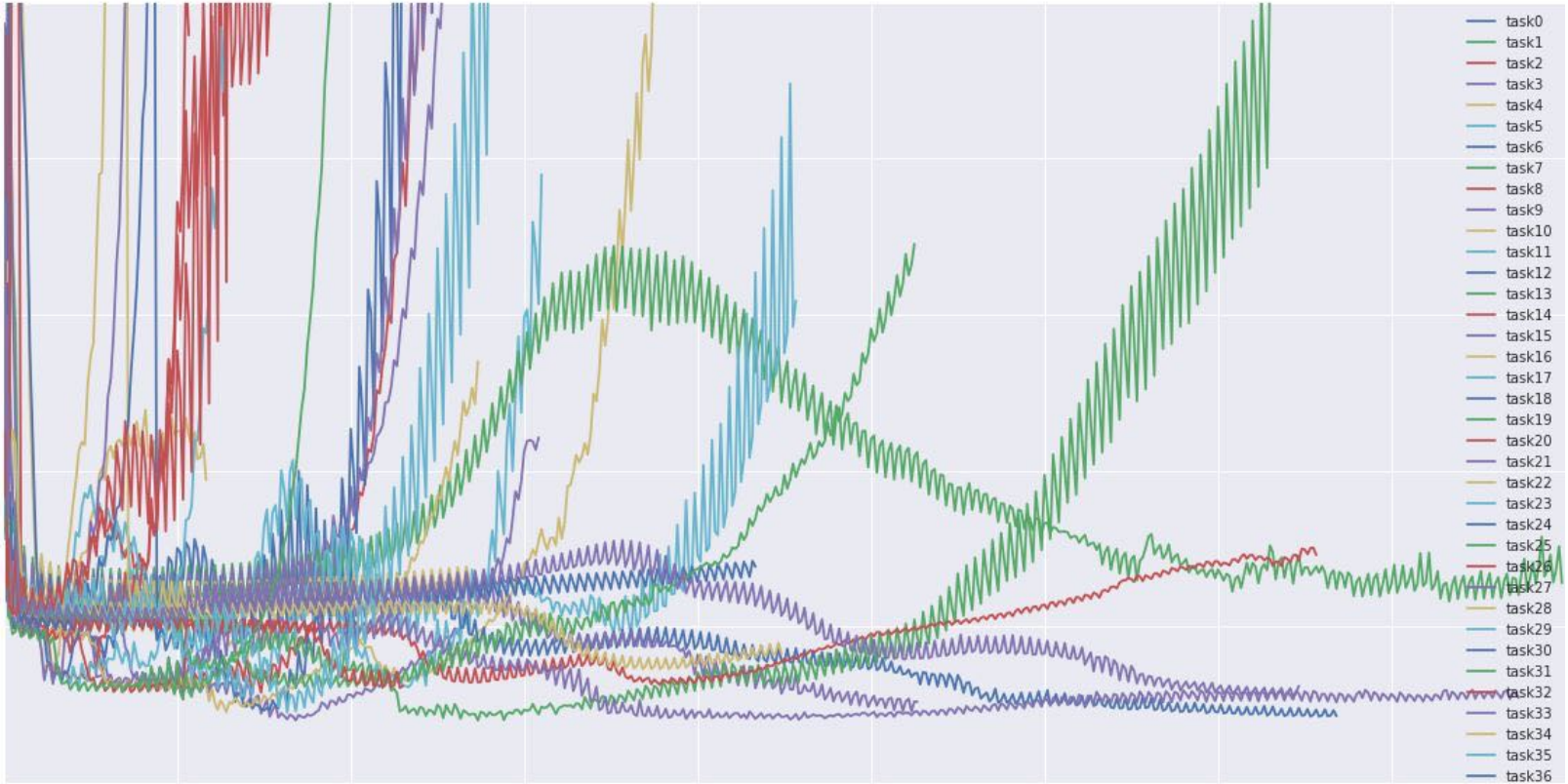
Cross-validation

We develop "command centers" to visualize all our models training with different hyperparameters

check out [weights and biases]



You can plot all your loss curves for different hyperparameters on a single plot



Choosing Hyperparameters

Step 1: Check initial loss
Step 2: Overfit a small sample
Step 3: Find LR that makes loss go down
Step 4: Coarse grid, train for ~1-5 epochs
Step 5: Refine grid, train longer
Step 6: Look at loss and accuracy curves
Step 7: GOTO step 5

Random Search vs. Grid Search

Random Search for Hyper-Parameter Optimization
Bergstra and Bengio, 2012

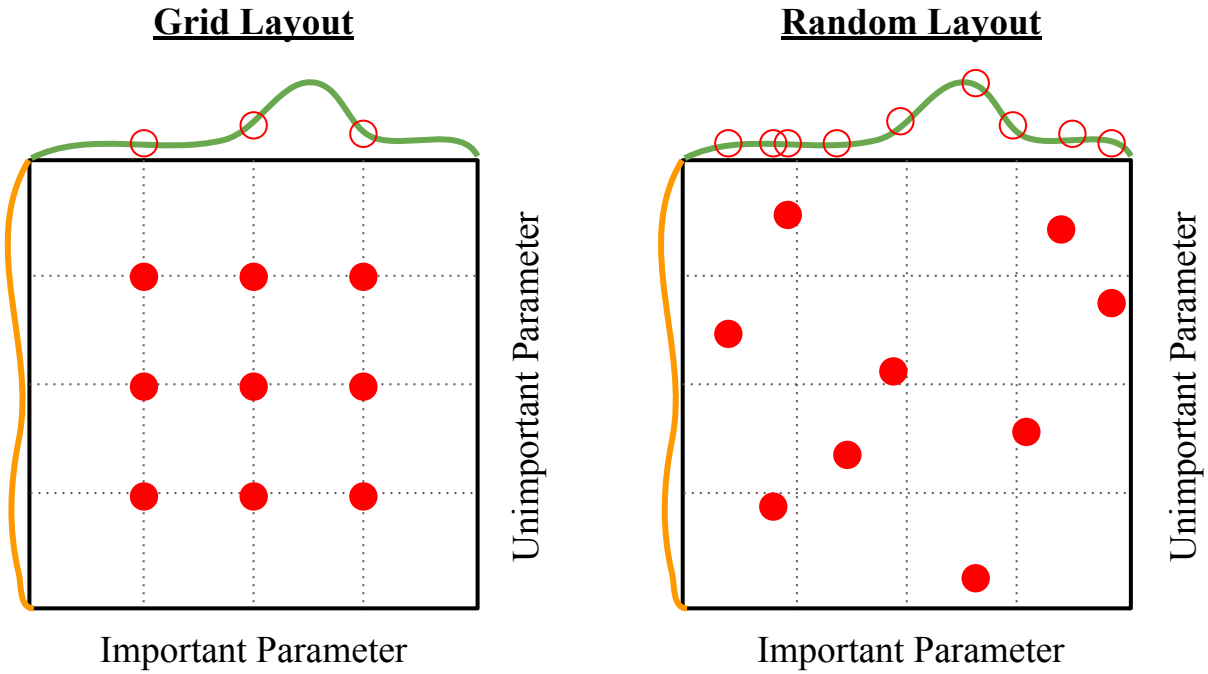
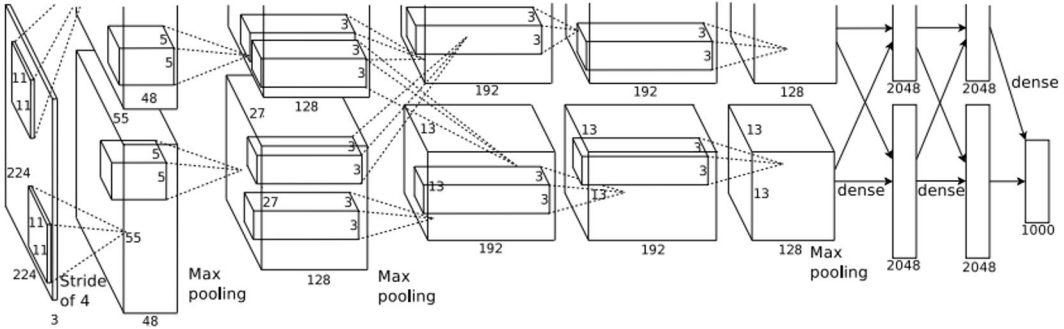


Illustration of Bergstra et al., 2012 by Shayne Longpre, copyright CS231n 2017

Lecture 8: Visualizing and Understanding

Today: What's going on inside ConvNets?



Class Scores:
1000 numbers

Input Image:
3 x 224 x 224

What are the intermediate features looking for?

Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 2012.
Figure reproduced with permission.

Today's agenda

Visualizing what models have learned:

- Visualizing filters
- Visualizing final layer features
- Visualizing activations

Understanding input pixels

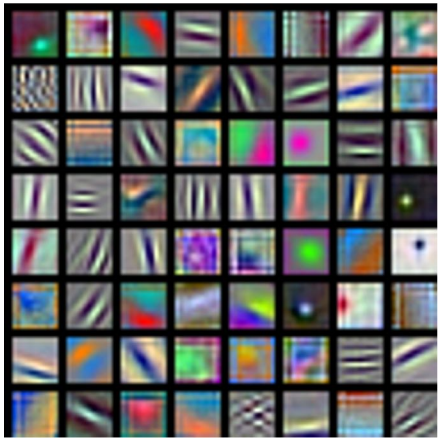
- Identifying important pixels
- Saliency via backprop
- Guided backprop to generate images
- Gradient ascent to visualize features

Adversarial perturbations

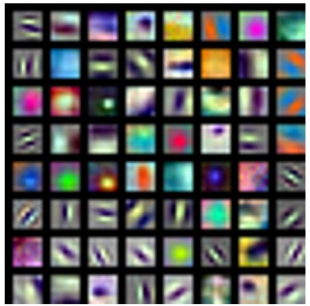
Style transfer

- Features inversion
- Deep dream
- Texture synthesis
- Neural style transfer

First Layer: Visualize Filters

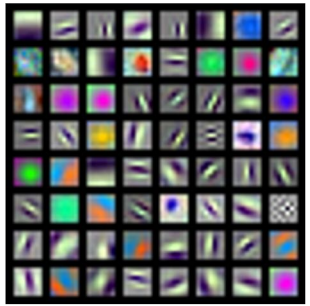


AlexNet:
64 x 3 x 11 x 11

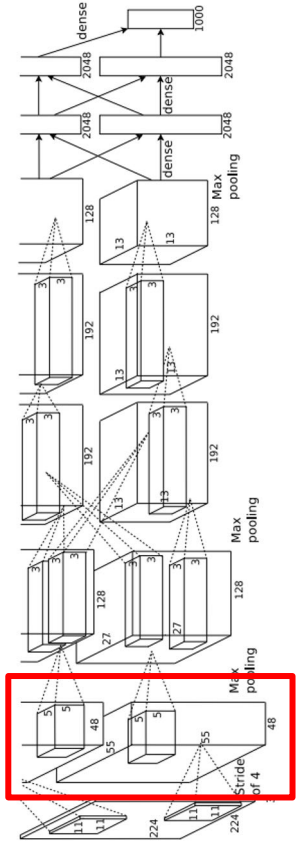


ResNet-18:
64 x 3 x 7 x 7

ResNet-101:
64 x 3 x 7 x 7



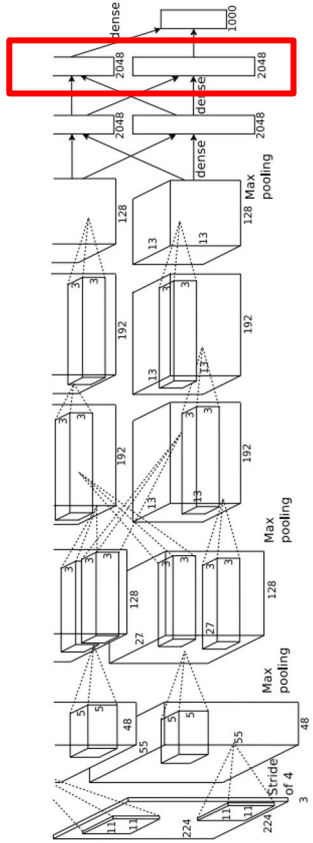
DenseNet-121:
64 x 3 x 7 x 7



Krizhevsky, “One weird trick for parallelizing convolutional neural networks”, arXiv 2014
He et al, “Deep Residual Learning for Image Recognition”, CVPR 2016
Huang et al, “Densely Connected Convolutional Networks”, CVPR 2017

Last Layer

FC7 layer

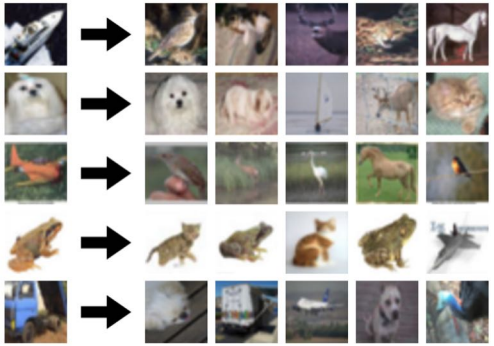


4096-dimensional feature vector for an image (layer immediately before the classifier)

Run the network on many images, collect the feature vectors

Last Layer: Nearest Neighbors

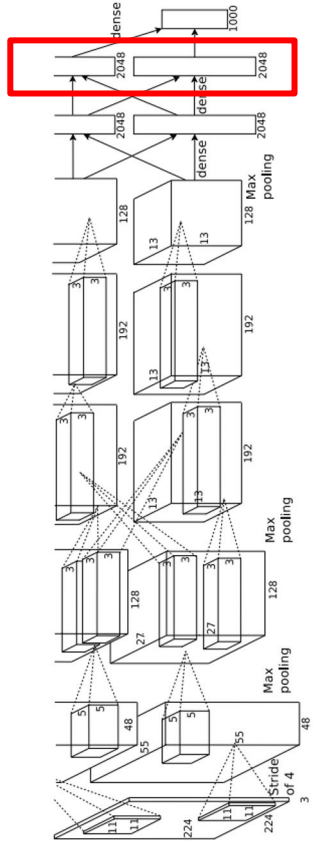
Recall: Nearest neighbors in pixel space



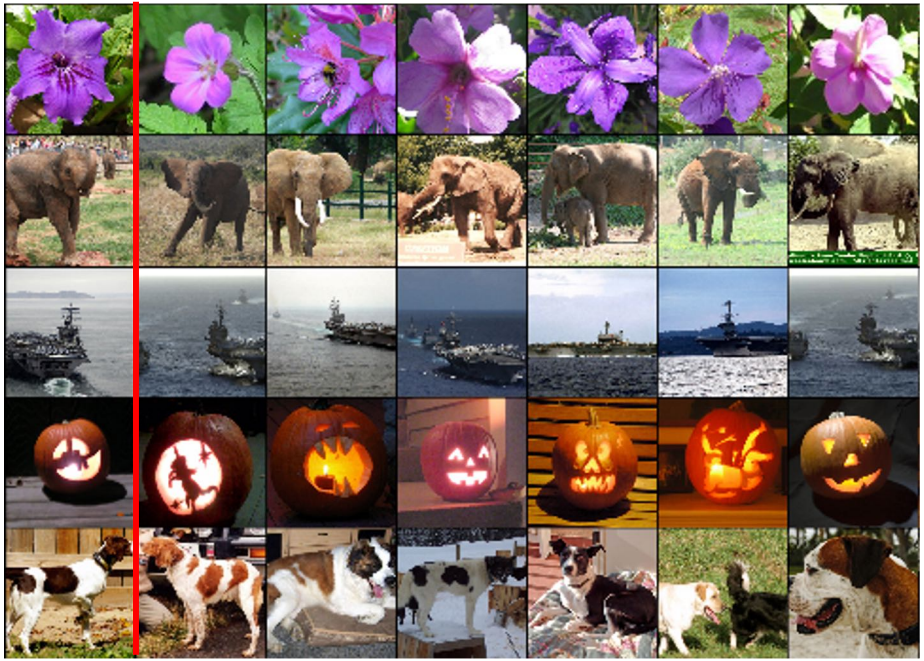
Krizhevsky et al, “ImageNet Classification with Deep Convolutional Neural Networks”, NIPS 2012.
Figures reproduced with permission.

Last Layer: Nearest Neighbors

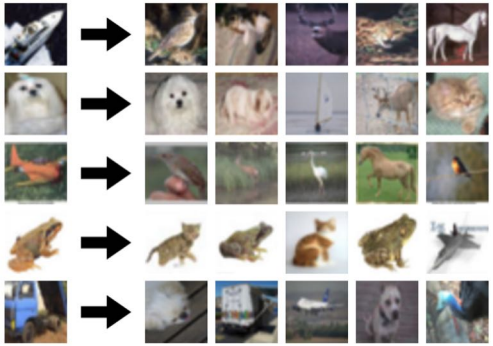
4096-dim vector



Test image L2 Nearest neighbors in feature space



Recall: Nearest neighbors in pixel space



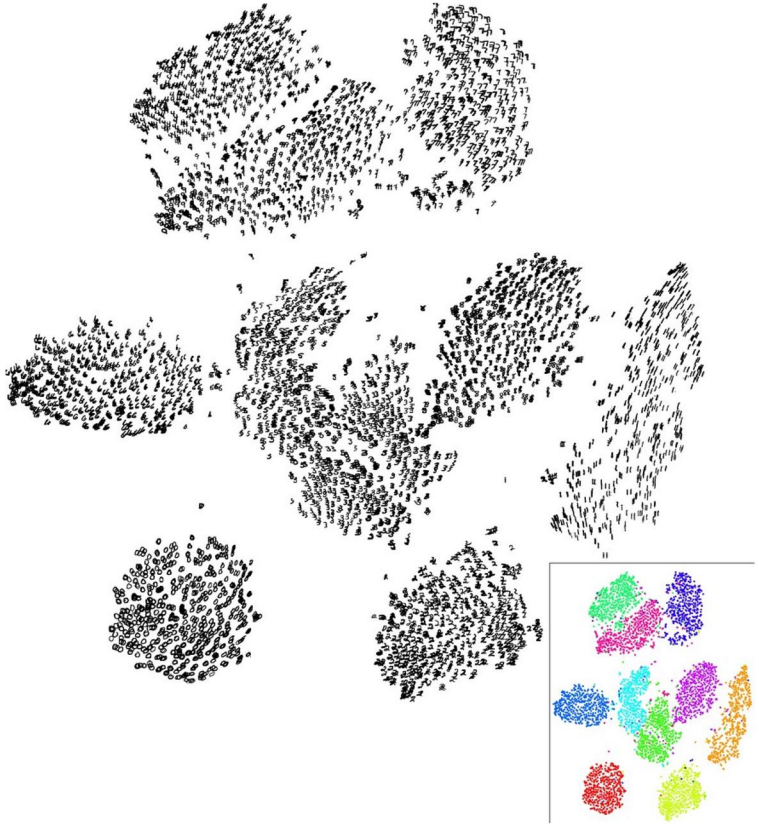
Krizhevsky et al, “ImageNet Classification with Deep Convolutional Neural Networks”, NIPS 2012.
Figures reproduced with permission.

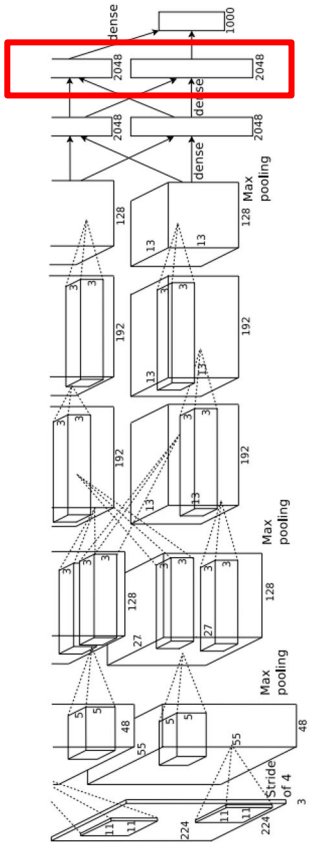
Last Layer: Dimensionality Reduction

Visualize the “space” of FC7 feature vectors by reducing dimensionality of vectors from 4096 to 2 dimensions

Simple algorithm: Principal Component Analysis (PCA)

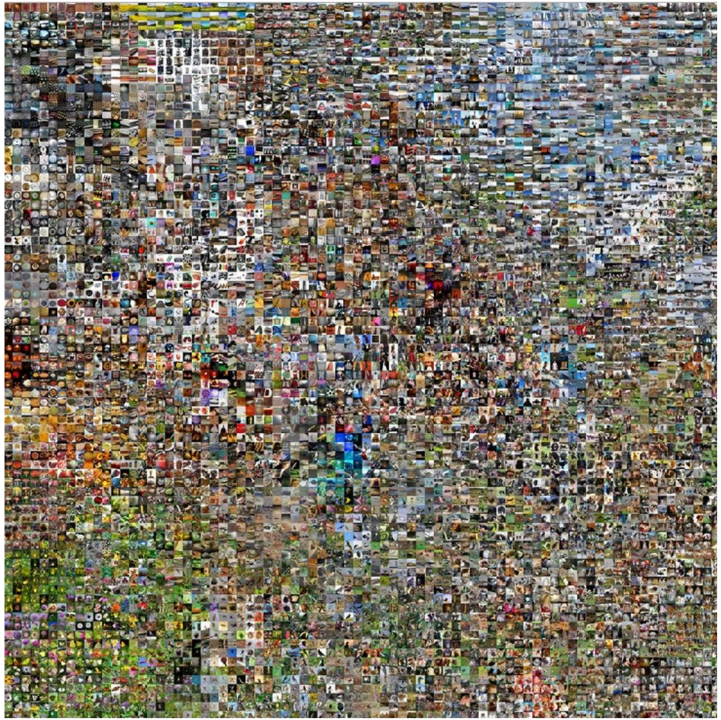
More complex: **t-SNE**

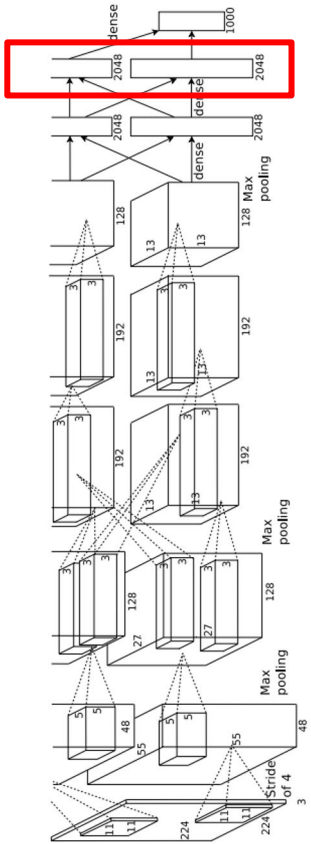




Van der Maaten and Hinton, “Visualizing Data using t-SNE”, JMLR 2008

Last Layer: Dimensionality Reduction



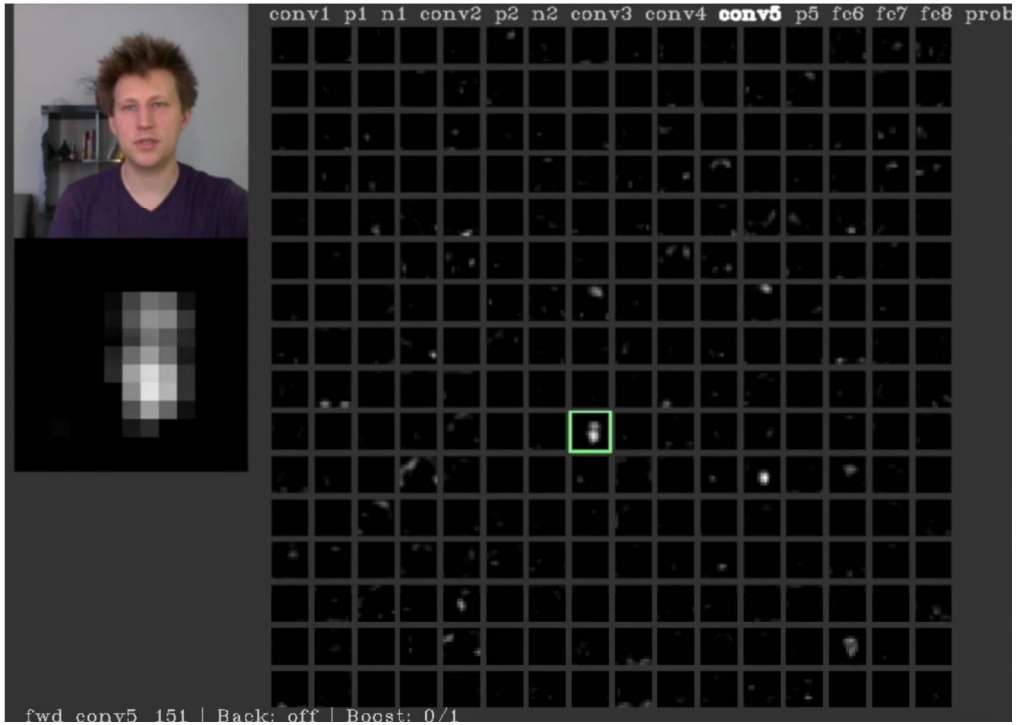


Van der Maaten and Hinton, "Visualizing Data using t-SNE", JMLR 2008
Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 2012.
Figure reproduced with permission.

See high-resolution versions at
http://cs.stanford.edu/people/karpathy/cnnembed/

Visualizing Activations

conv5 feature map is 128x13x13; visualize as 128 13x13 grayscale images



Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.
Figure copyright Jason Yosinski, 2014. Reproduced with permission.

Today's agenda

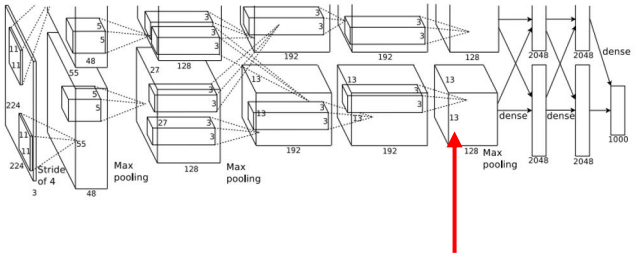
Visualizing what models have learned:
- Visualizing filters
- Visualizing final layer features
- Visualizing activations

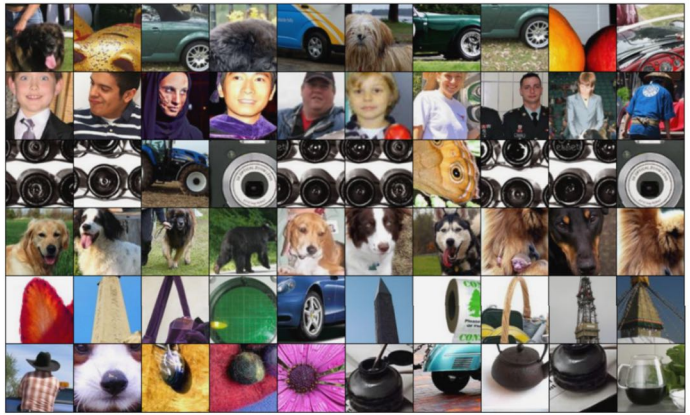
Understanding input pixels
- Identifying important pixels
- Saliency via backprop
- Guided backprop to generate images
- Gradient ascent to visualize features

Adversarial perturbations

Style transfer
- Deep dream
- Features inversion
- Texture synthesis
- Neural style transfer

Maximally Activating Patches





Pick a layer and a channel; e.g. conv5 is 128 x 13 x 13, pick channel 17/128

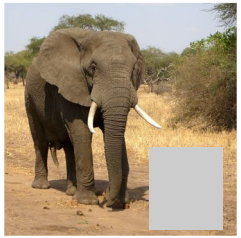
Run many images through the network, record values of chosen channel

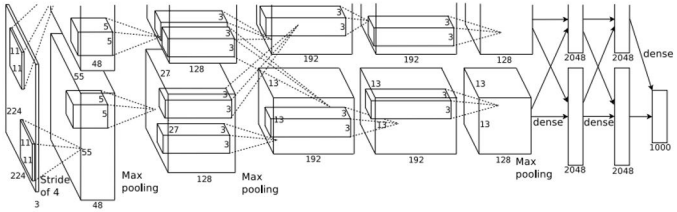
Visualize image patches that correspond to maximal activations

Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015
Figure copyright Jost Tobias Springenberg, Alexey Dosovitskiy, Thomas Brox, Martin Riedmiller, 2015; reproduced with permission.

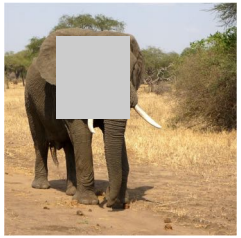
Which pixels matter: Saliency via Occlusion

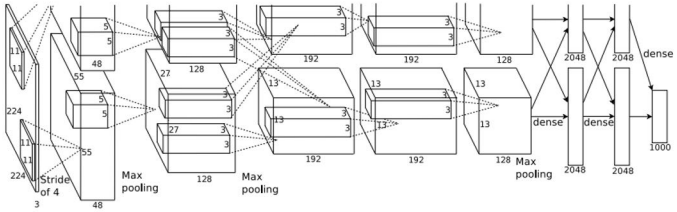
Mask part of the image before feeding to CNN, check how much predicted probabilities change





P(elephant) = 0.95



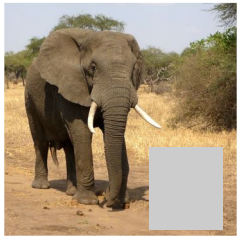


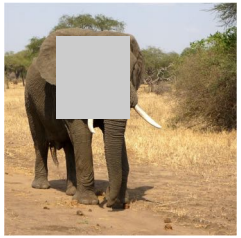
P(elephant) = 0.75

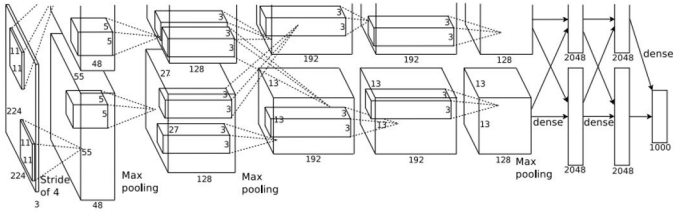
Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014

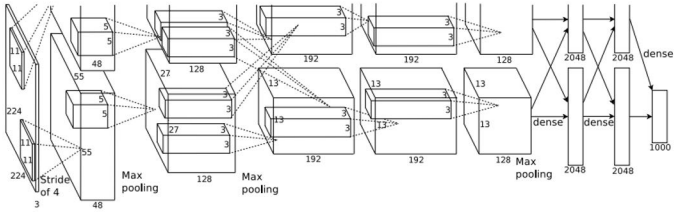
Which pixels matter: Saliency via Occlusion

Mask part of the image before feeding to CNN, check how much predicted probabilities change

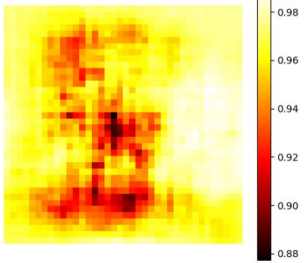




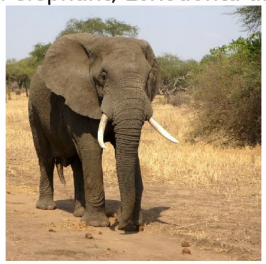


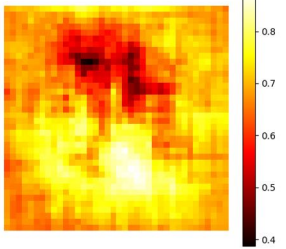


schooner

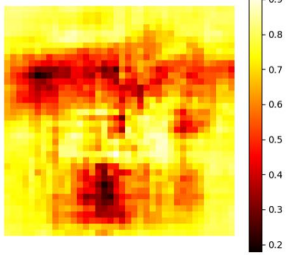


African elephant, Loxodonta africana





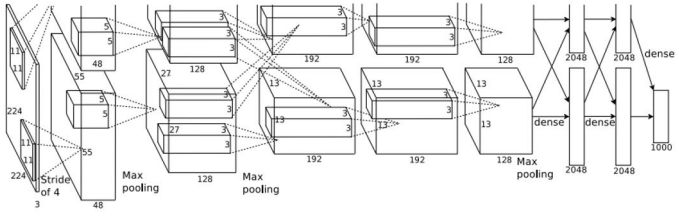
go-kart



Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014

Which pixels matter: Saliency via Backprop

Forward pass: Compute probabilities

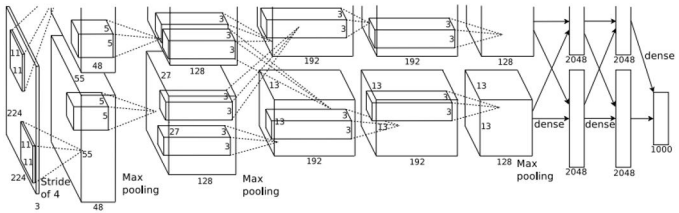


Dog

Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.
Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.

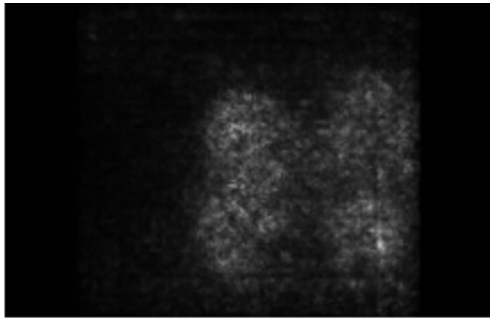
Which pixels matter: Saliency via Backprop

Forward pass: Compute probabilities



Dog

Compute gradient of **(unnormalized) class score** with respect to image pixels, take absolute value and max over RGB channels



Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.
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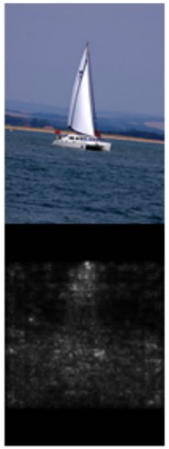
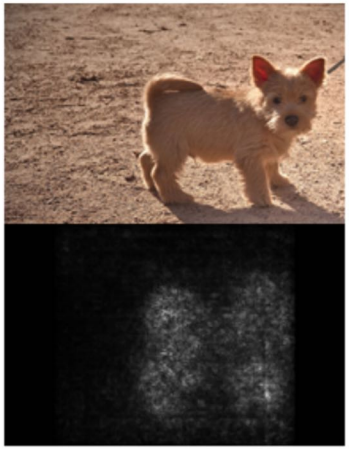
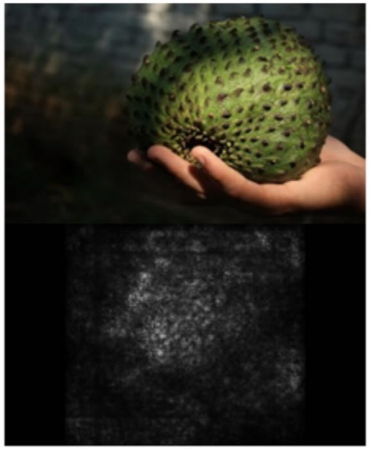
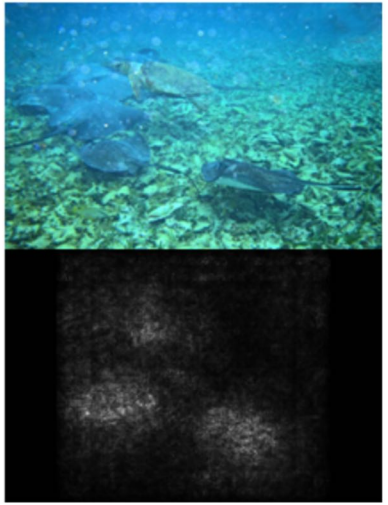
Saliency Maps

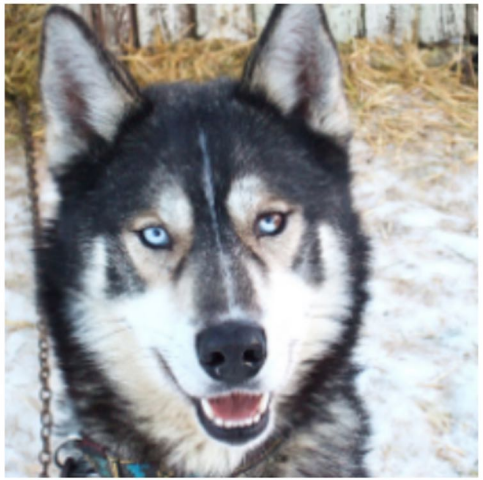


Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.

Saliency maps: Uncovers biases

Such methods also find biases

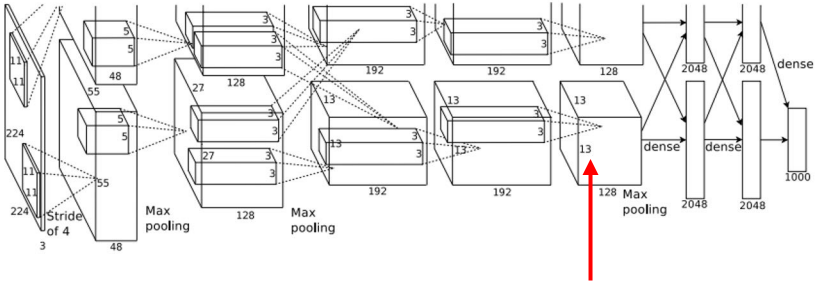
wolf vs dog classifier looks is actually a snow vs no-snow classifier



(a) Husky classified as wolf

(b) Explanation

Intermediate Features via (guided) backprop

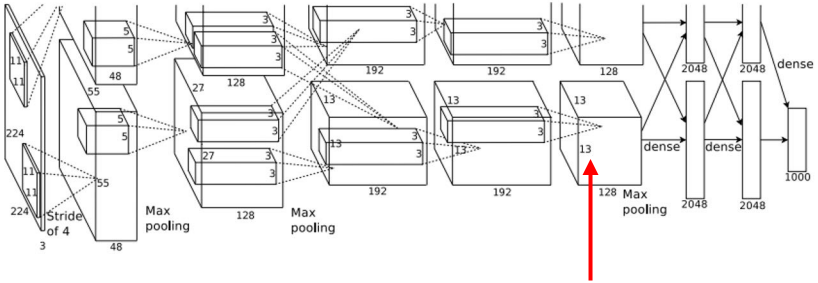


Pick a single intermediate channel, e.g. one value in 128 x 13 x 13 conv5 feature map

Compute gradient of activation value with respect to image pixels

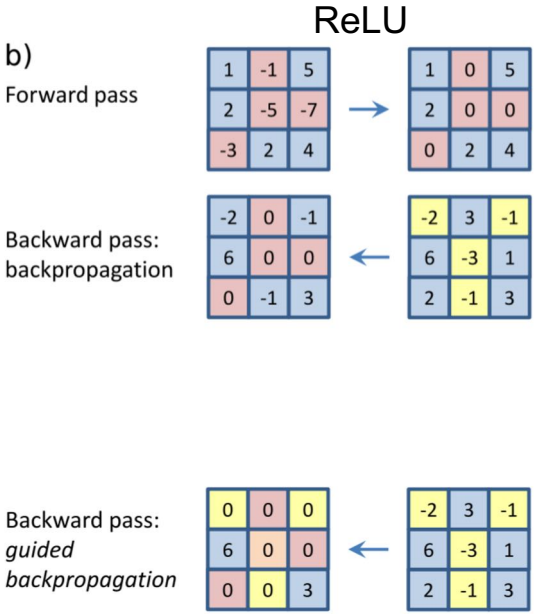
Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

Intermediate Features via (guided) backprop



Pick a single intermediate neuron, e.g. one value in 128 x 13 x 13 conv5 feature map

Compute gradient of neuron value with respect to image pixels



Images come out nicer if you only backprop positive gradients through each ReLU (guided backprop)

Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014
Springenberg et al, "Striving for Simplicity: The All Convolutional Net", ICLR Workshop 2015

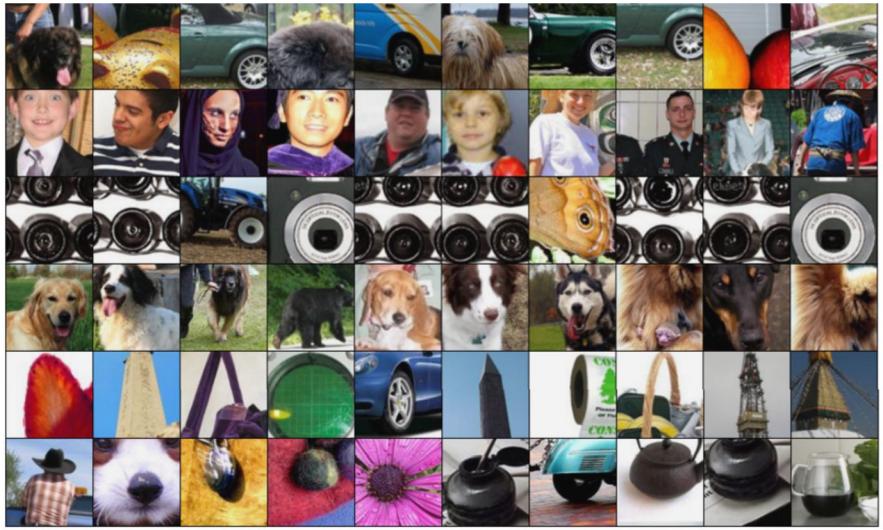
Intermediate features via (guided) backprop

Maximally activating patches
(Each row is a different neuron)

Guided Backprop

Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

Intermediate features via (guided) backprop



Maximally activating patches
(Each row is a different neuron)

Guided Backprop

Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015
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Visualizing CNN features: Gradient Ascent

(Guided) backprop:
Find the part of an image that a neuron responds to

Gradient ascent:
Generate a synthetic image that maximally activates a neuron

$$I^* = \arg\max_I f(I) + R(I)$$

Neuron value

Natural image regularizer

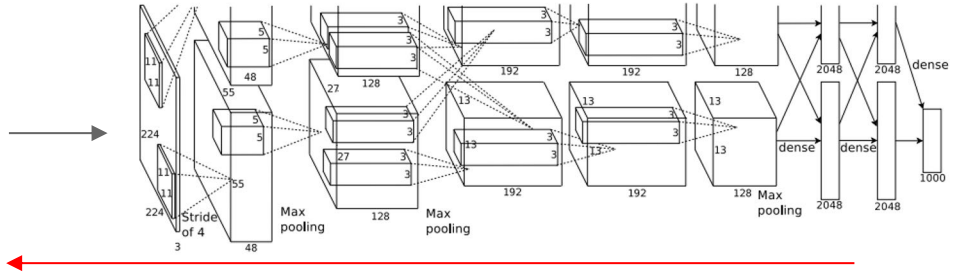
Visualizing CNN features: Gradient Ascent

$$\arg\max_I \boxed{S_c(I)} - \lambda \|I\|_2^2$$

score for class c (before Softmax)

1. Initialize image to zeros

zero image



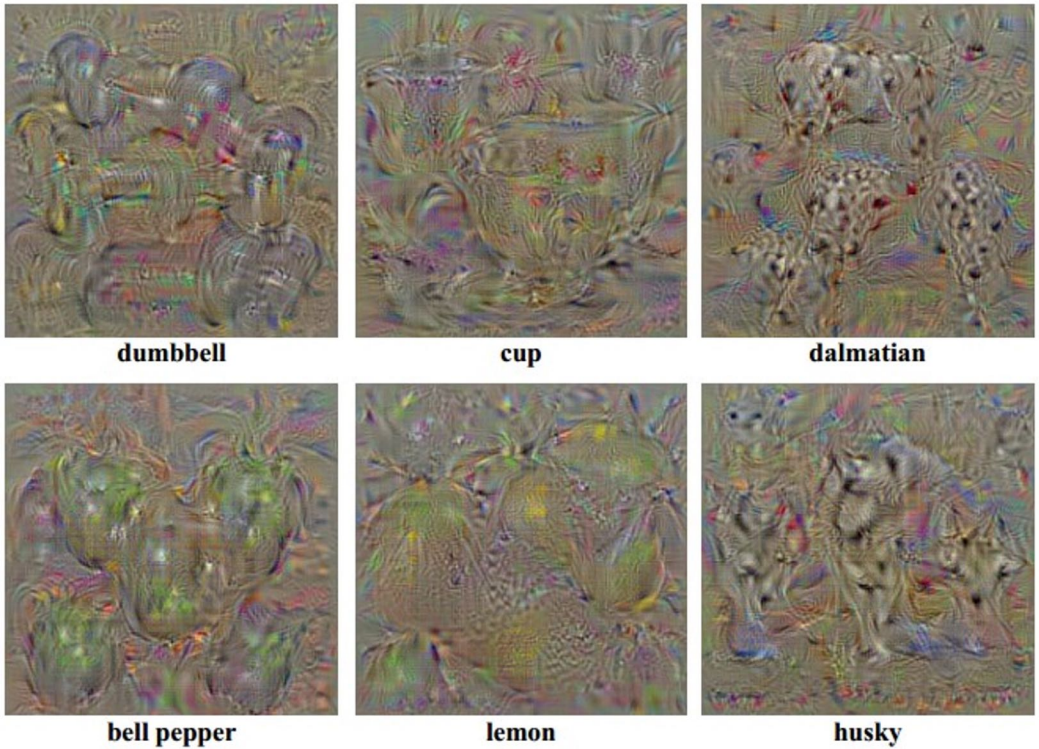
Repeat:

2. Forward image to compute current scores
3. Backprop to get gradient of neuron value with respect to image pixels
4. Make a small update to the image

Visualizing CNN features: Gradient Ascent

$$\arg\max_I S_c(I) - \lambda \|I\|_2^2$$

Simple regularizer: Penalize L2 norm of generated image

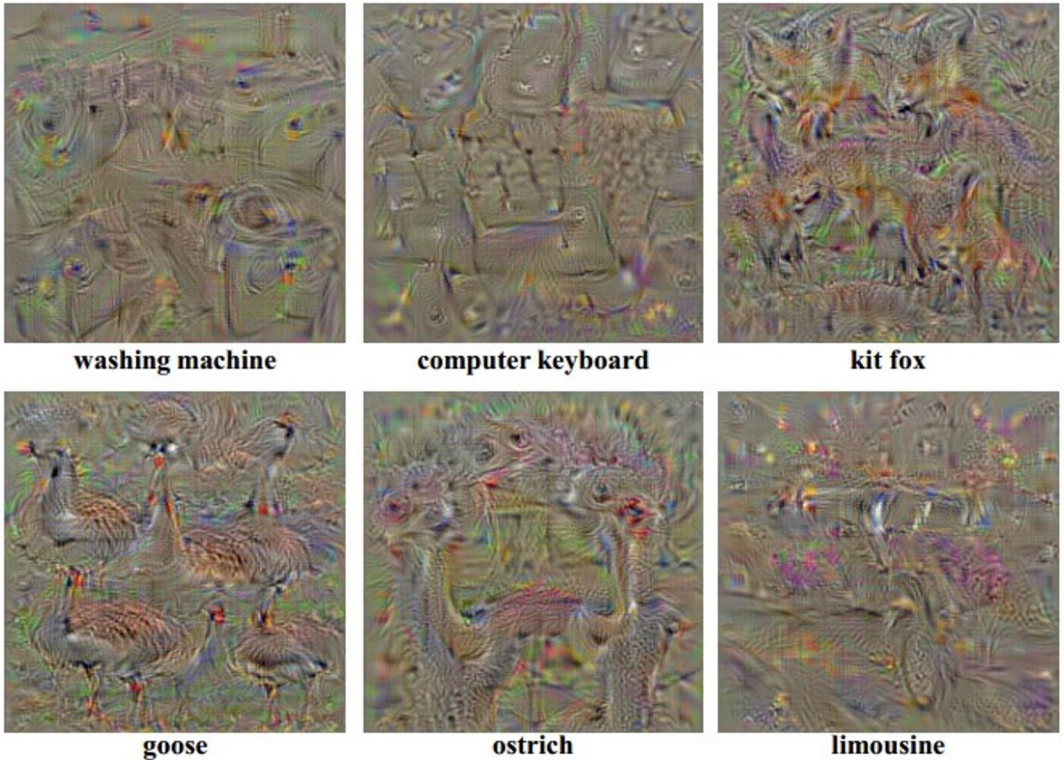


Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.
Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.

Visualizing CNN features: Gradient Ascent

$$\arg\max_I S_c(I) - \lambda \|I\|_2^2$$

Simple regularizer: Penalize L2 norm of generated image



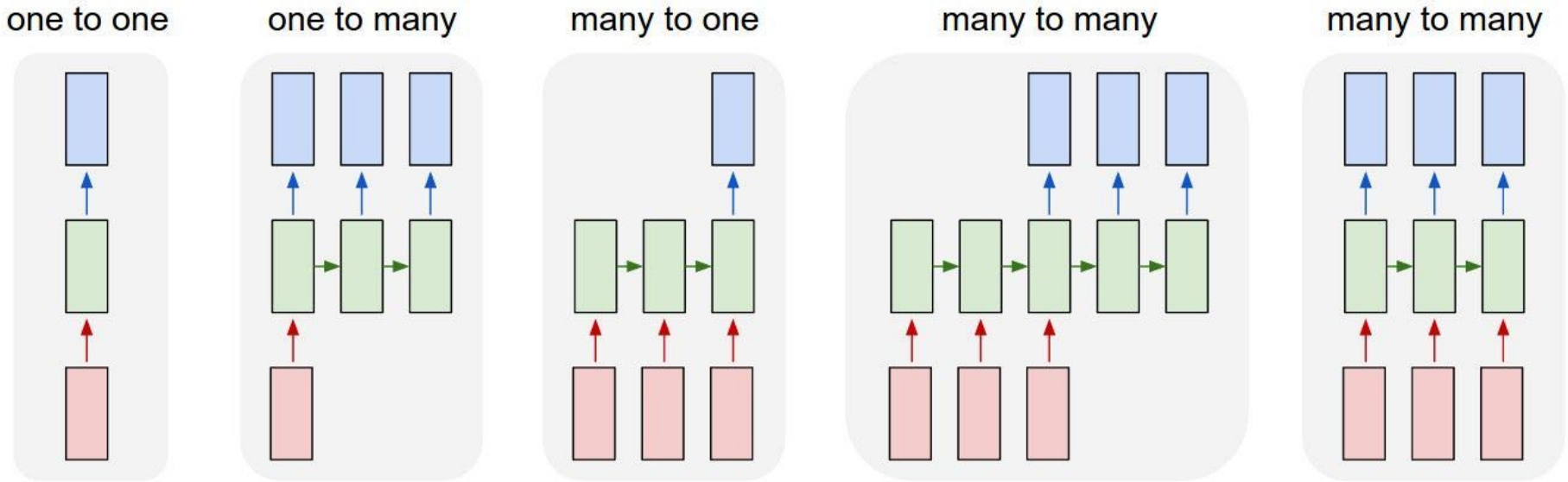
Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014. Figure copyright Jason Yosinski, Jeff Clune, Anh Nguyen, Thomas Fuchs, and Hod Lipson, 2014. Reproduced with permission.

Visualizing CNN features: Gradient Ascent

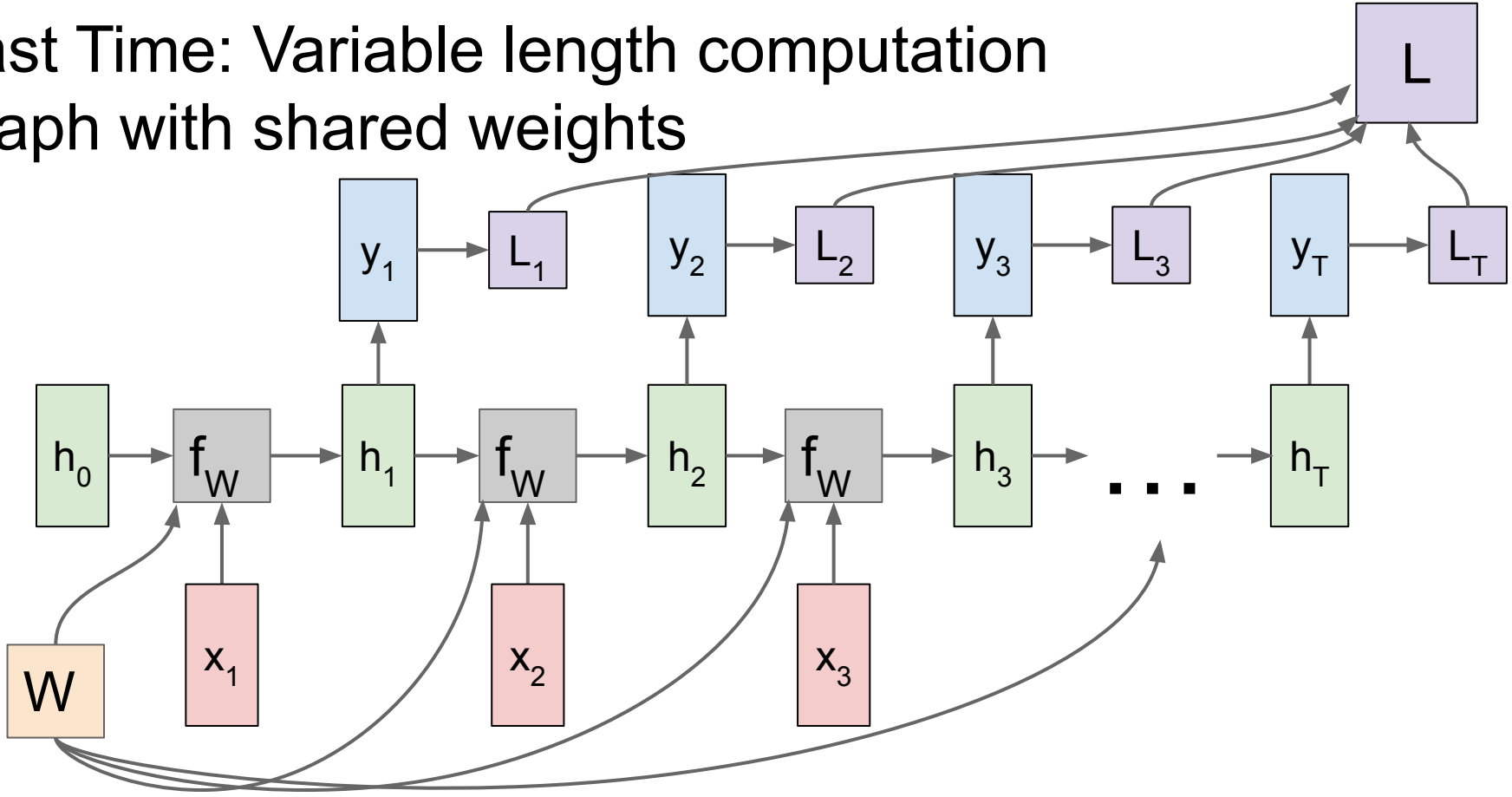
Nguyen et al, "Multifaceted Feature Visualization: Uncovering the Different Types of Features Learned By Each Neuron in Deep Neural Networks", ICML Visualization for Deep Learning Workshop 2016.
Figures copyright Anh Nguyen, Jason Yosinski, and Jeff Clune, 2016; reproduced with permission.

Lecture 11:
Attention and Transformers

Last Time: Recurrent Neural Networks



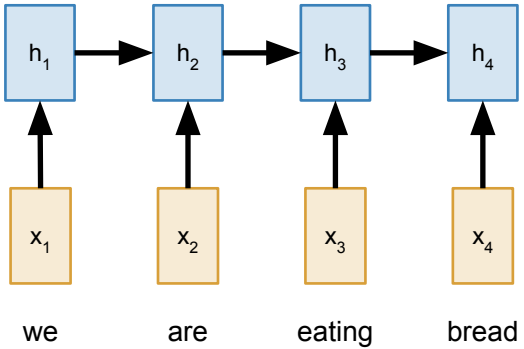
Last Time: Variable length computation graph with shared weights



Sequence to Sequence with RNNs

Input: Sequence $x_1, \ldots x_T$
Output: Sequence $y_1, \ldots, y_{T'}$

Encoder: $h_t = f_W(x_t, h_{t-1})$



Sutskever et al, “Sequence to sequence learning with neural networks”, NeurIPS 2014

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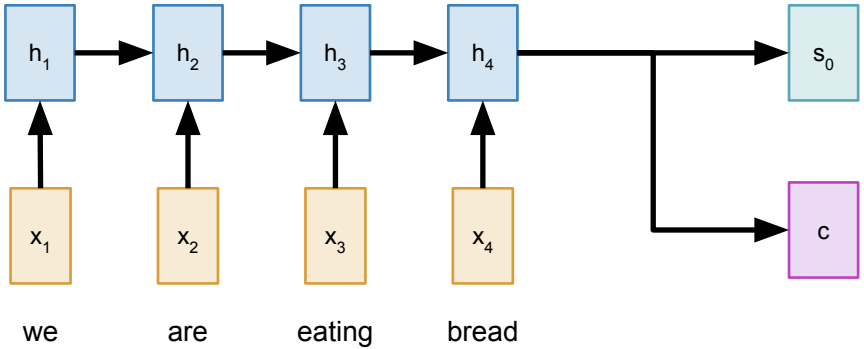
Output: Sequence $y_1, \ldots, y_{T'}$

Encoder: $h_t = f_W(x_t, h_{t-1})$

From final hidden state predict:
Initial decoder state s_0
Context vector c (often $c=h_T$)



Sutskever et al, “Sequence to sequence learning with neural networks”, NeurIPS 2014

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Input: Sequence $x_1, \ldots x_T$
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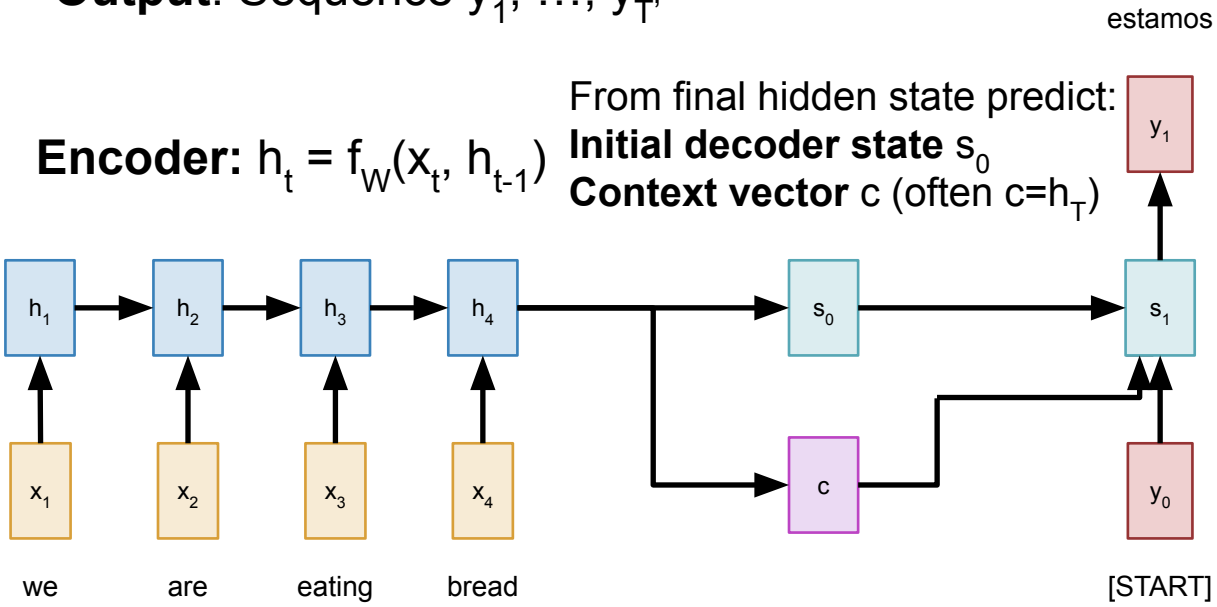
Decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c)$

From final hidden state predict:
Initial decoder state s_0
Context vector c (often $c=h_T$)



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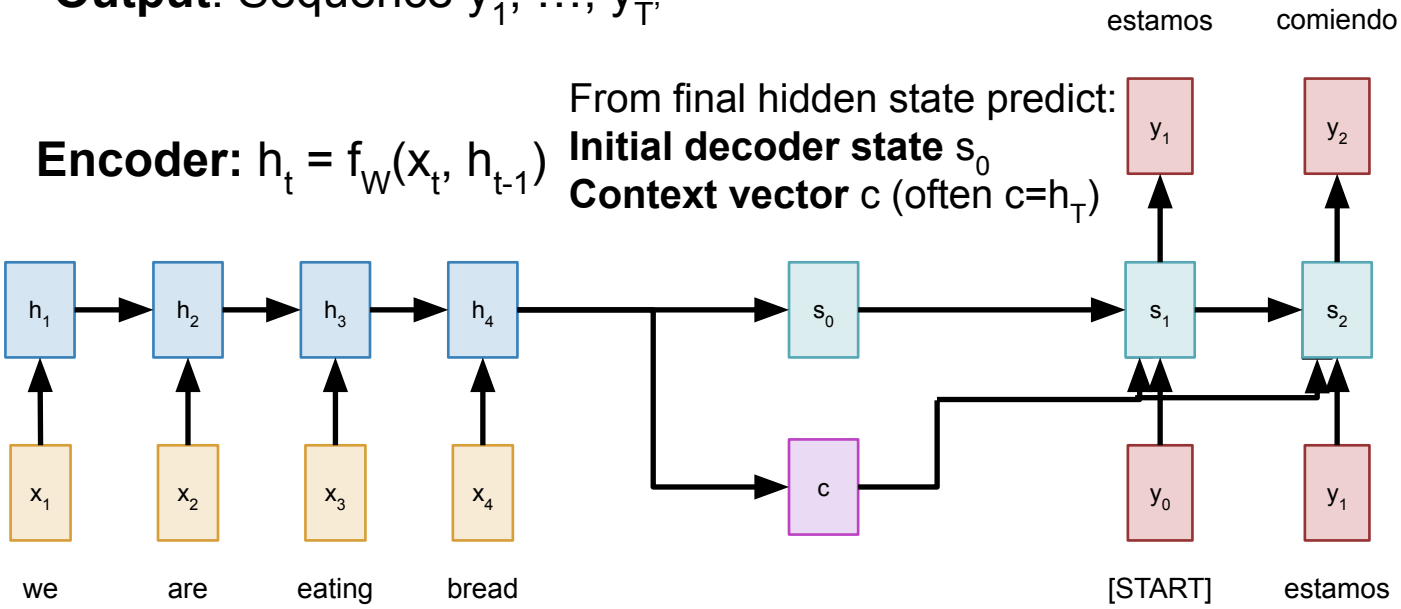

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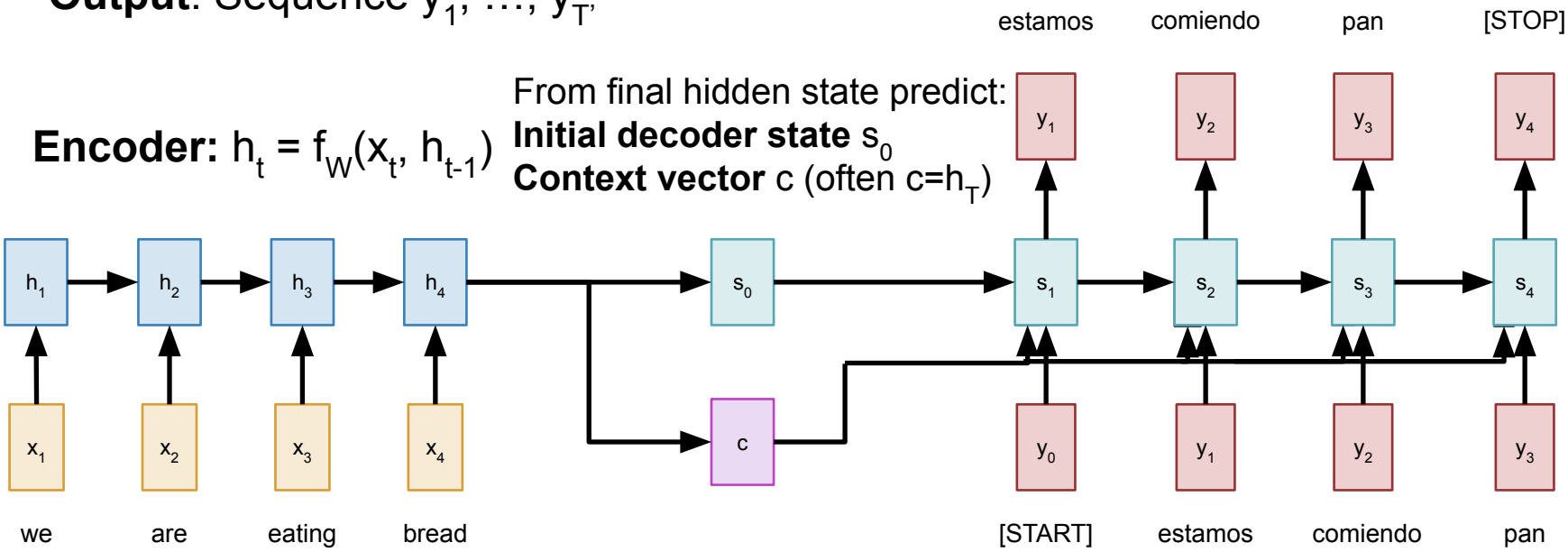

Sutskever et al, “Sequence to sequence learning with neural networks”, NeurIPS 2014

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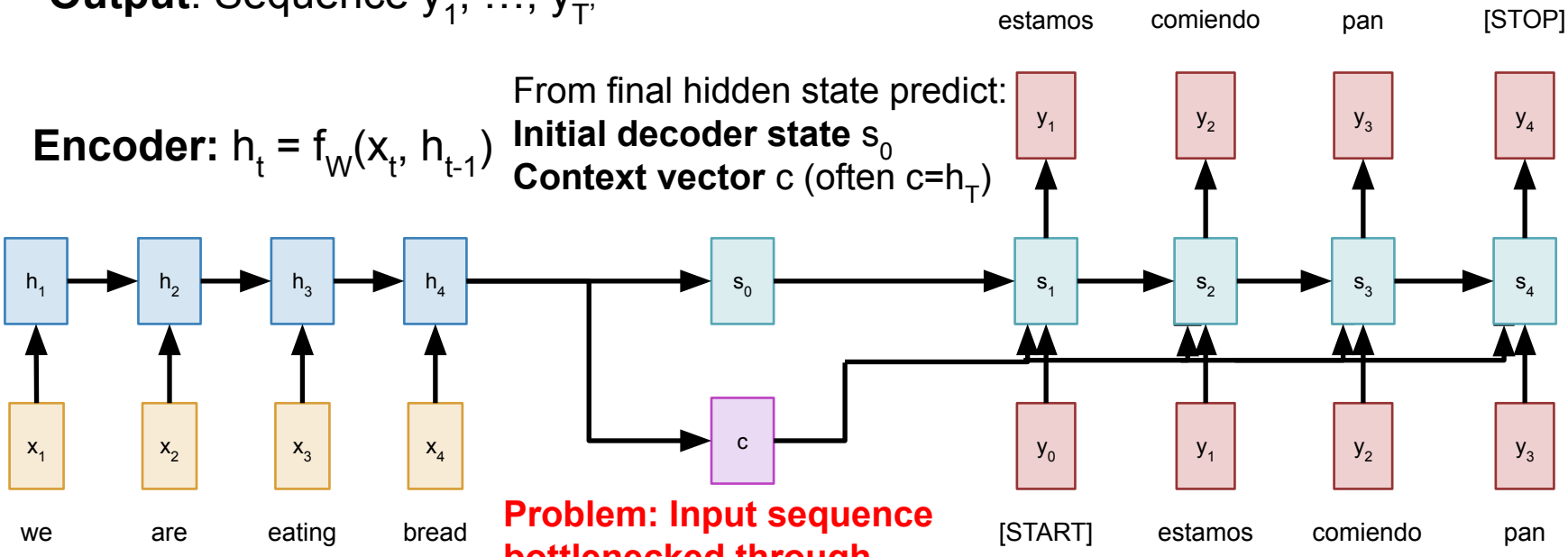

Problem: Input sequence bottlenecked through fixed-sized vector. What if T=1000?

Sutskever et al, "Sequence to sequence learning with neural networks", NeurIPS 2014

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Input: Sequence $x_1, \ldots x_T$
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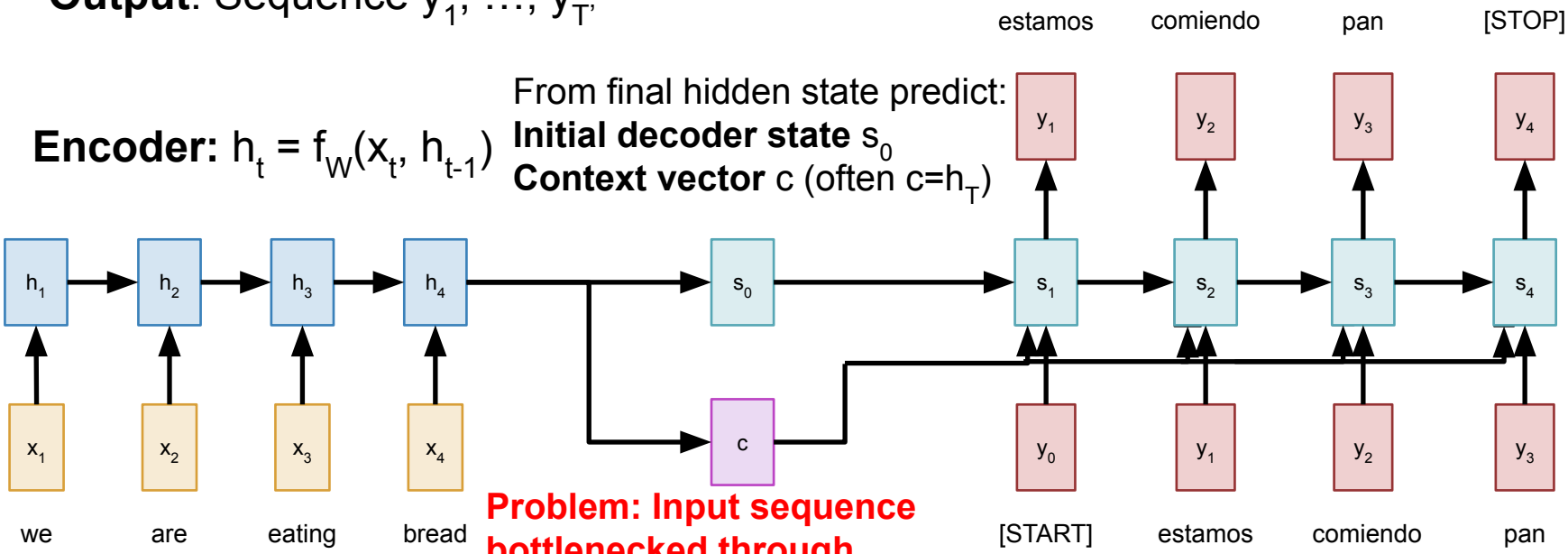


Problem: Input sequence bottlenecked through fixed-sized vector. What if T=1000?

Idea: use new context vector at each step of decoder!

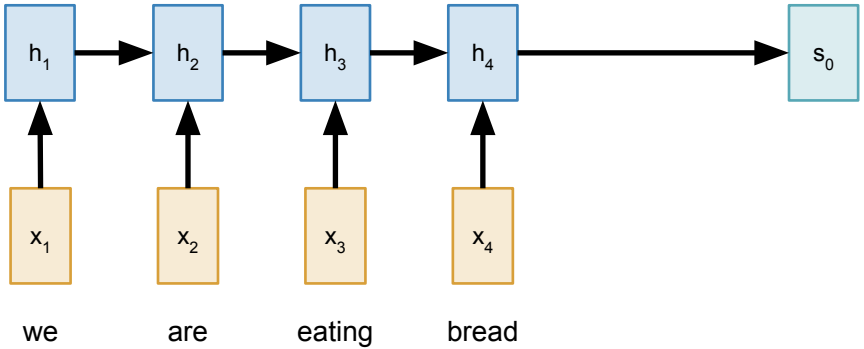
Sutskever et al, "Sequence to sequence learning with neural networks", NeurIPS 2014

Sequence to Sequence with RNNs and Attention

Input: Sequence $x_1, \ldots x_T$
Output: Sequence $y_1, \ldots, y_{T'}$

Encoder: $h_t = f_W(x_t, h_{t-1})$

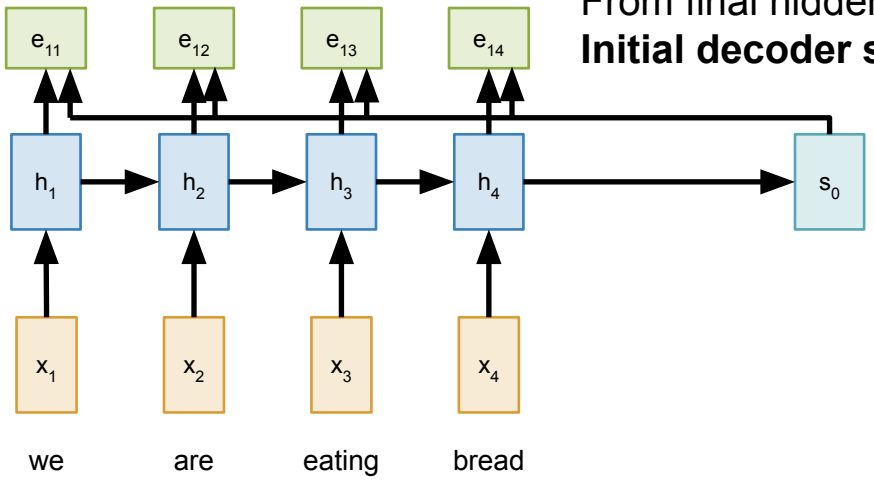
From final hidden state:
Initial decoder state s_0



Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention

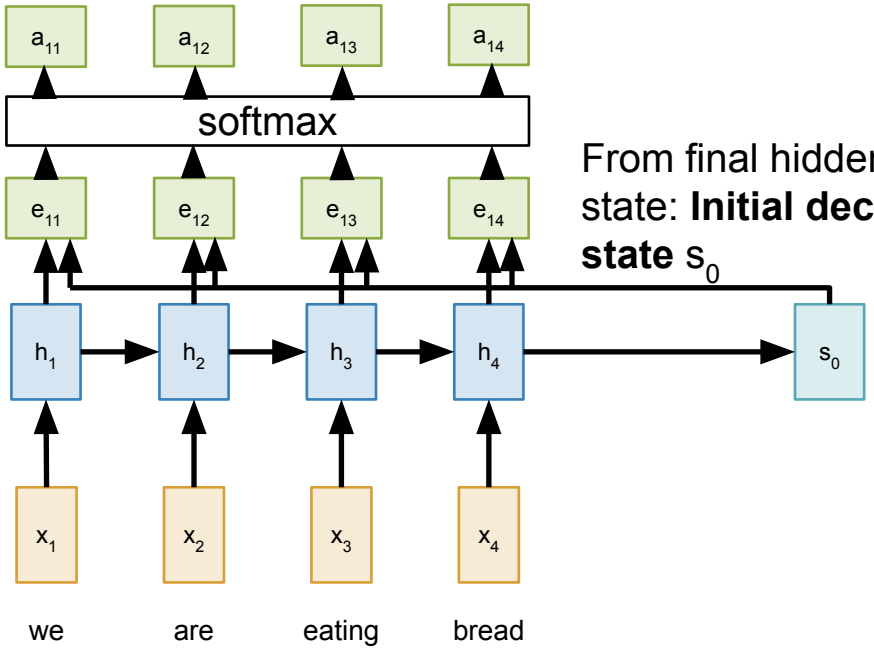
Compute (scalar) **alignment scores**
$e_{t,i} = f_{att}(s_{t-1}, h_i)$ (f_{att} is an MLP)



From final hidden state:
Initial decoder state s_0

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention



From final hidden state: **Initial decoder state** s_0

Compute (scalar) **alignment scores**

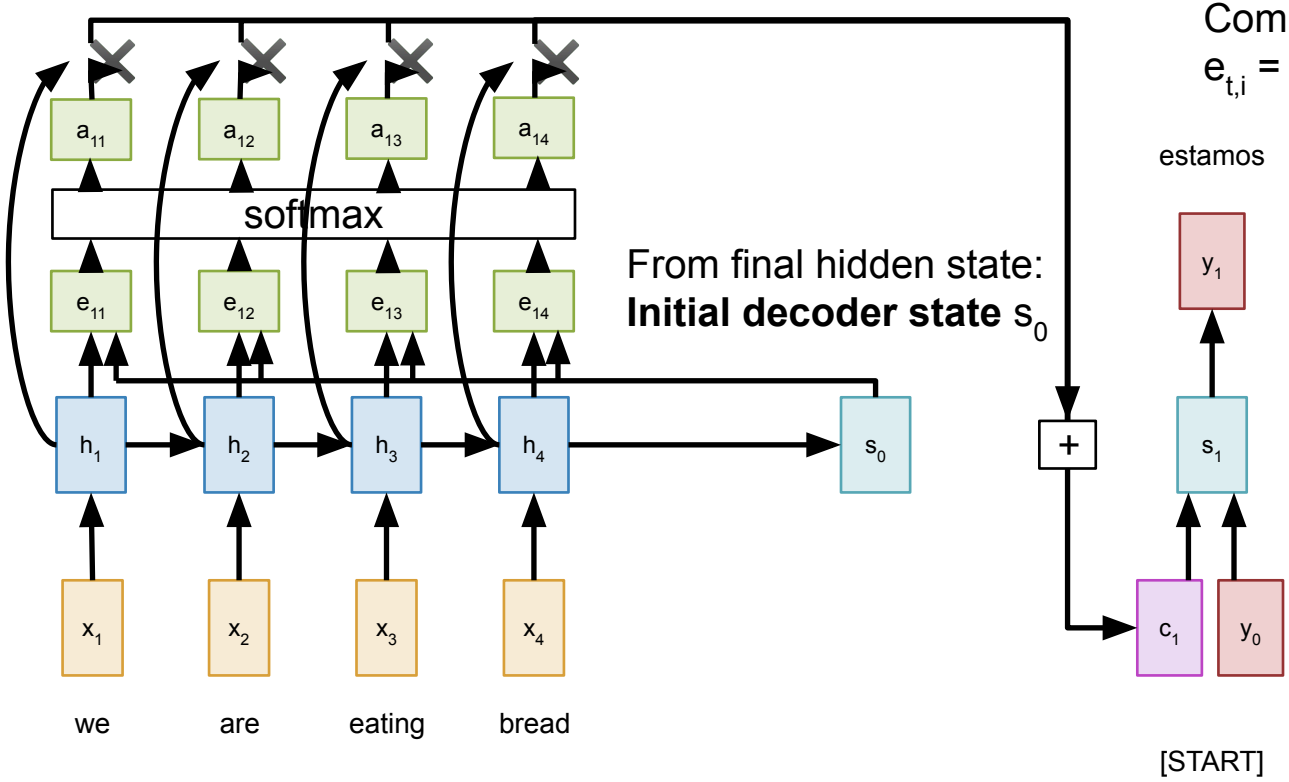
$e_{t,i} = f_{att}(s_{t-1}, h_i)$ (f_{att} is an MLP)

Normalize alignment scores to get **attention weights**

$0 < a_{t,i} < 1 \quad \sum_i a_{t,i} = 1$

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention



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Normalize alignment scores to get **attention weights**

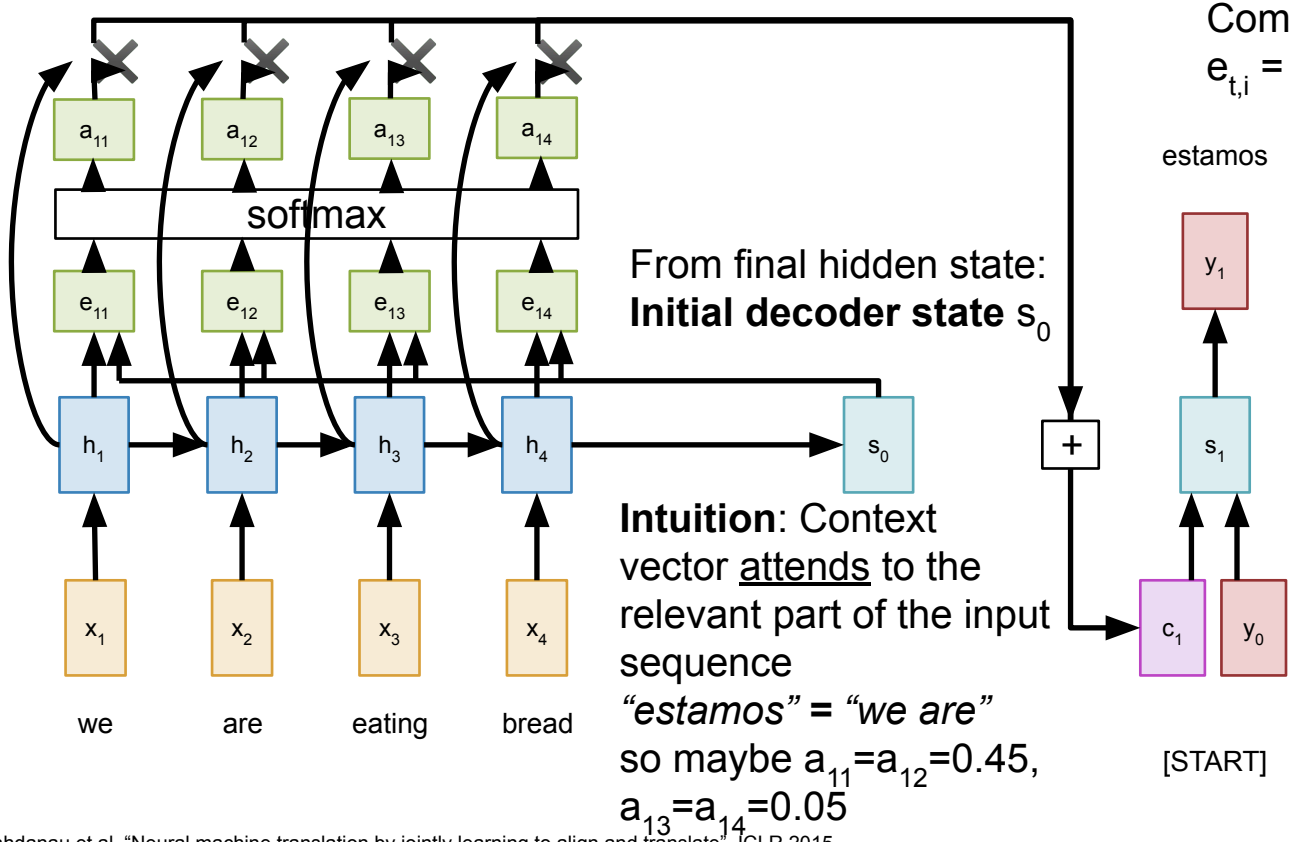
$0 < a_{t,i} < 1 \quad \sum_i a_{t,i} = 1$

Compute context vector as linear combination of hidden states

$c_t = \sum_i a_{t,i} h_i$

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention



From final hidden state:
Initial decoder state s_0

Intuition: Context vector attends to the relevant part of the input sequence
"estamos" = "we are"
so maybe a_{11}=a_{12}=0.45, a_{13}=a_{14}=0.05

Compute (scalar) **alignment scores**
$e_{t,i} = f_{att}(s_{t-1}, h_i)$ (f_{att} is an MLP)

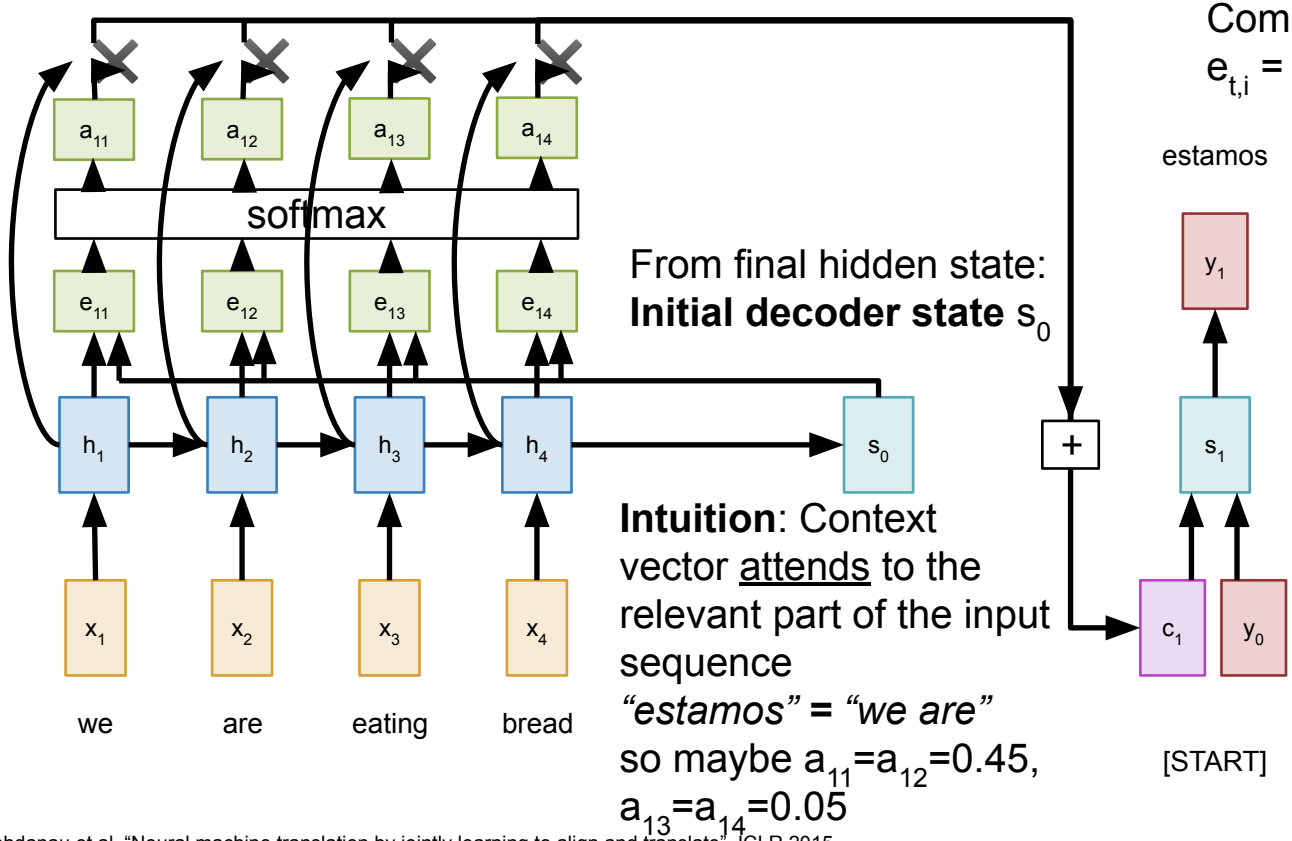
Normalize alignment scores to get **attention weights**
$0 < a_{t,i} < 1$ $\sum_i a_{t,i} = 1$

Compute context vector as linear combination of hidden states
$c_t = \sum_i a_{t,i} h_i$

Use context vector in decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c_t)$

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention



From final hidden state:
Initial decoder state s_0

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Normalize alignment scores to get **attention weights**
$0 < a_{t,i} < 1$ $\sum_i a_{t,i} = 1$

Compute context vector as linear combination of hidden states
$c_t = \sum_i a_{t,i} h_i$

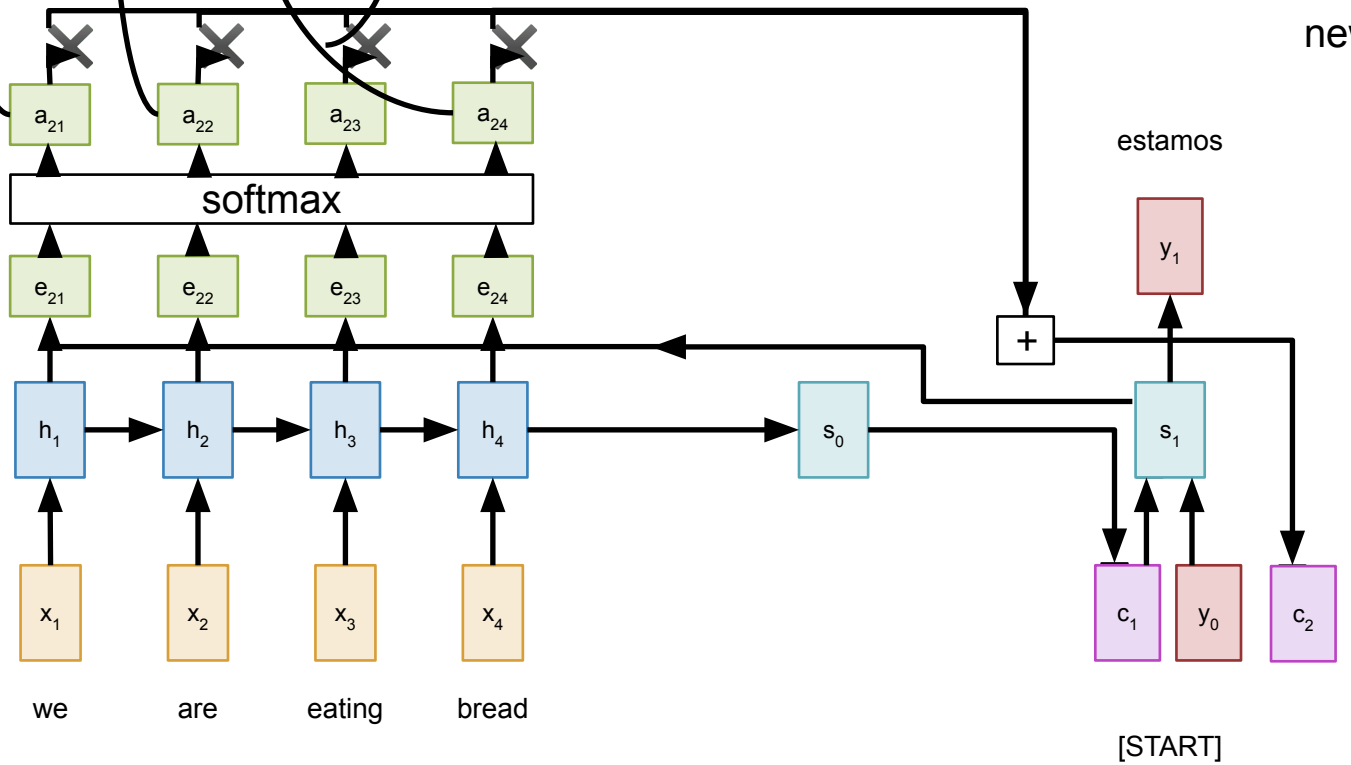
Use context vector in decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c_t)$

This is all differentiable! No supervision on attention weights – backprop through everything

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

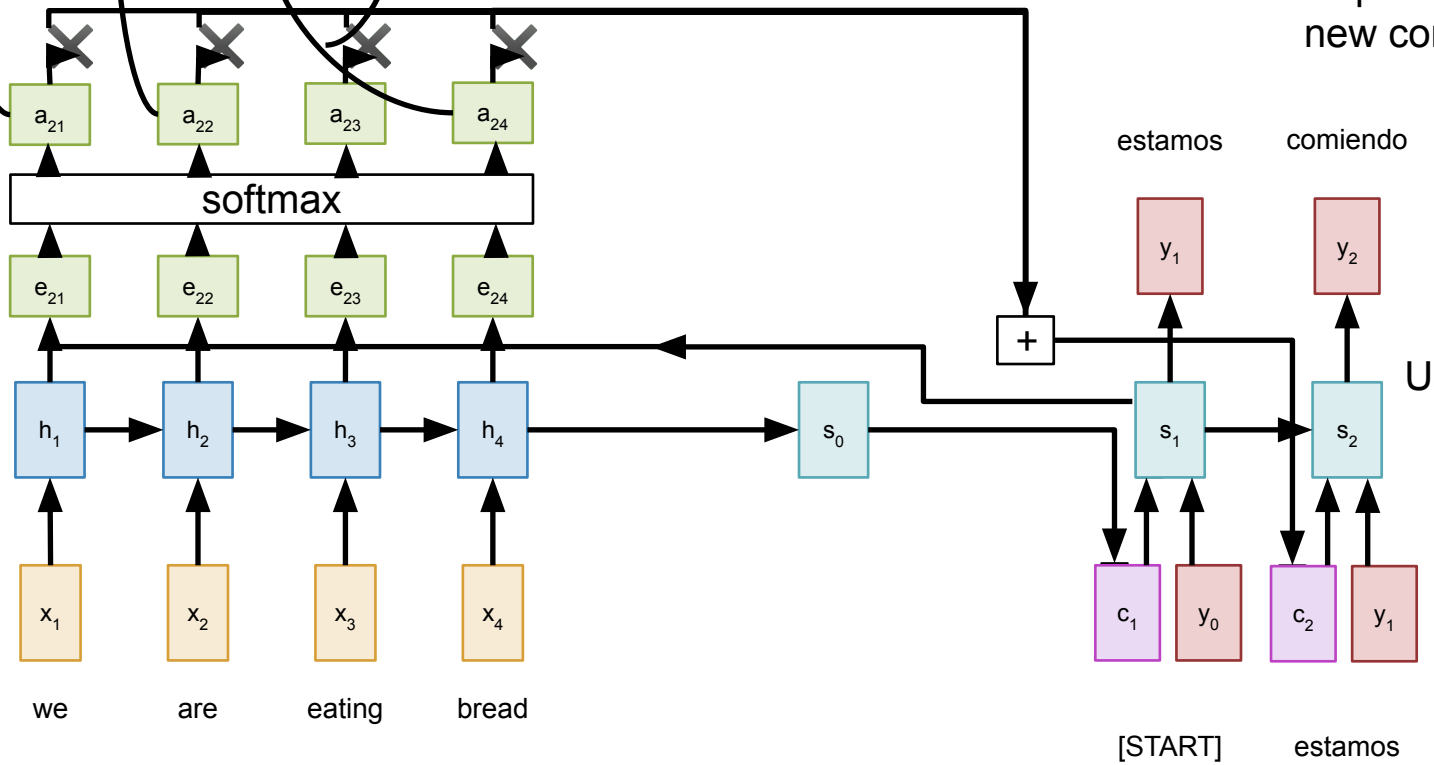
Sequence to Sequence with RNNs and Attention

Repeat: Use s_1 to compute new context vector c_2



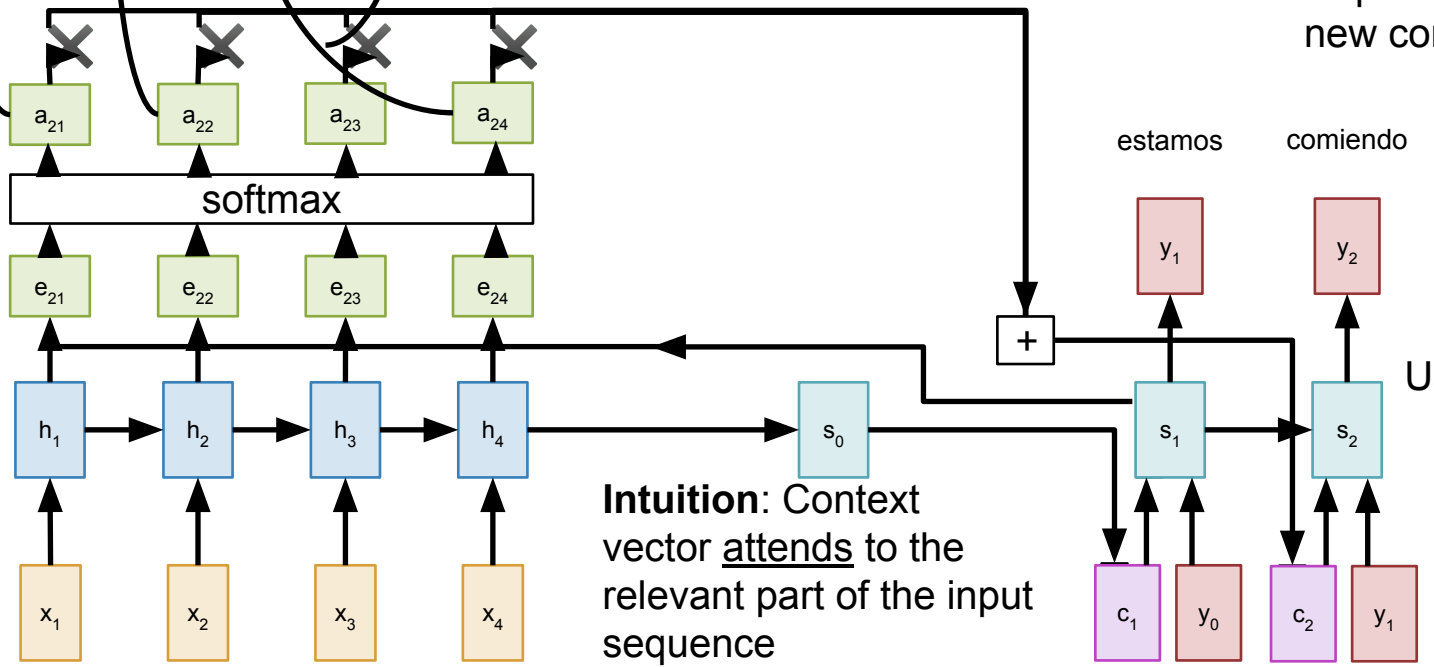
Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention



Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention



Intuition: Context vector attends to the relevant part of the input sequence

"comiendo" = "eating"

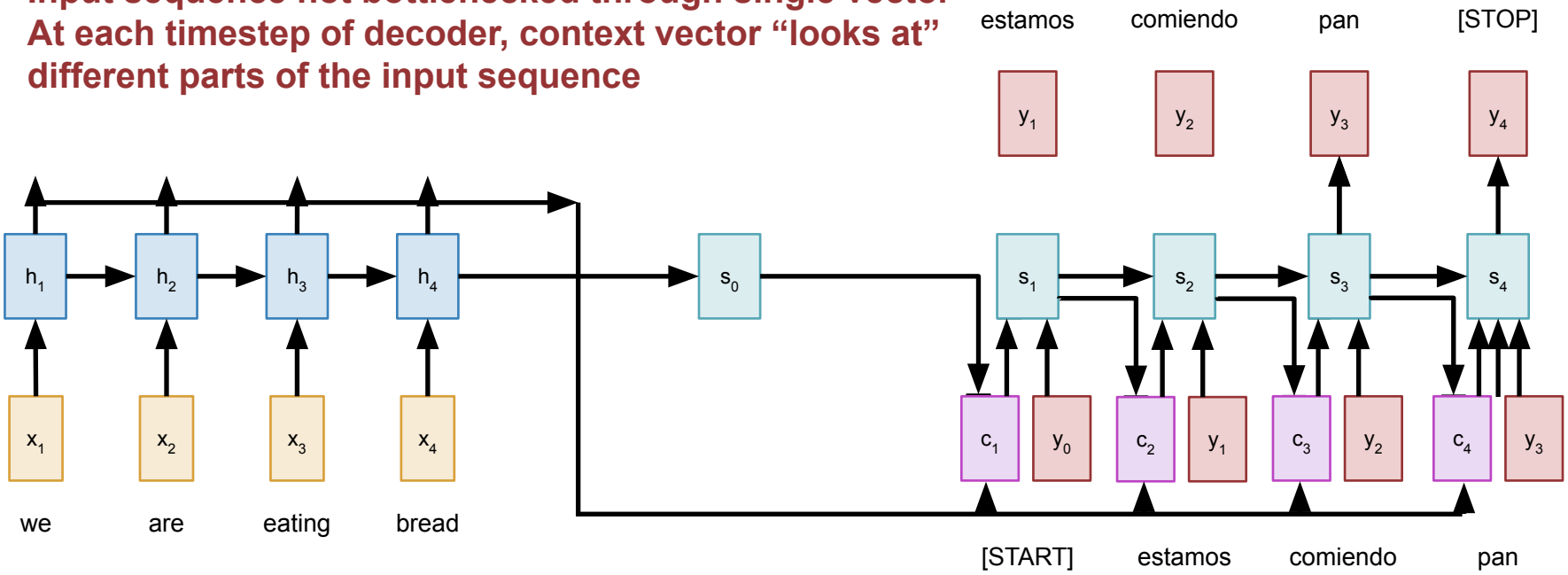
so maybe $a_{21}=a_{24}=0.05$, $a_{22}=0.1$, $a_{23}=0.8$

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention

Use a different context vector in each timestep of decoder

- **Input sequence not bottlenecked through single vector**
- **At each timestep of decoder, context vector "looks at" different parts of the input sequence**



Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

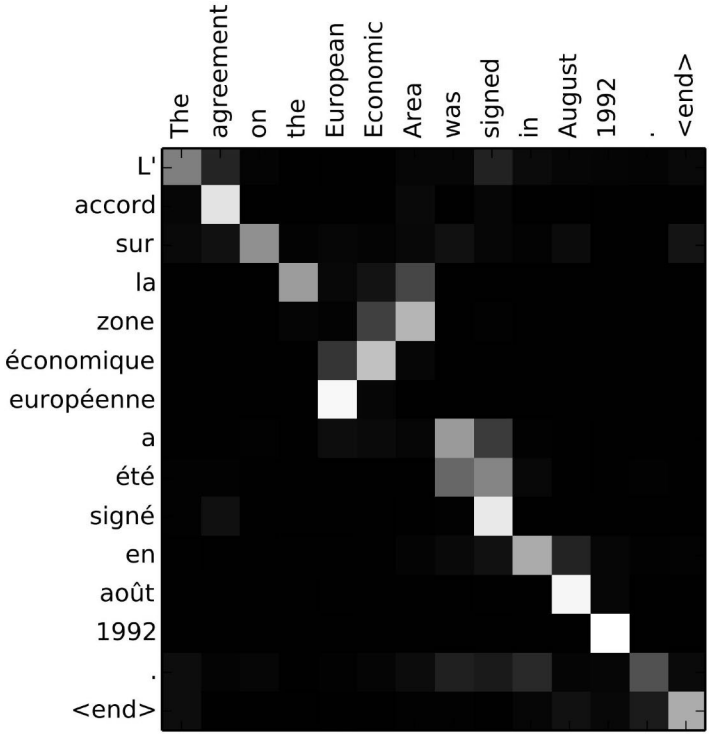
Sequence to Sequence with RNNs and Attention

Example: English to French translation

Input: “The agreement on the European Economic Area was signed in August 1992.”

Output: “L’accord sur la zone économique européenne a été signé en août 1992.”

Visualize attention weights $a_{t,i}$



Bahdanau et al, “Neural machine translation by jointly learning to align and translate”, ICLR 2015

Sequence to Sequence with RNNs and Attention

Example: English to French translation

Input: "**The agreement on the** European Economic Area was signed **in August 1992**."

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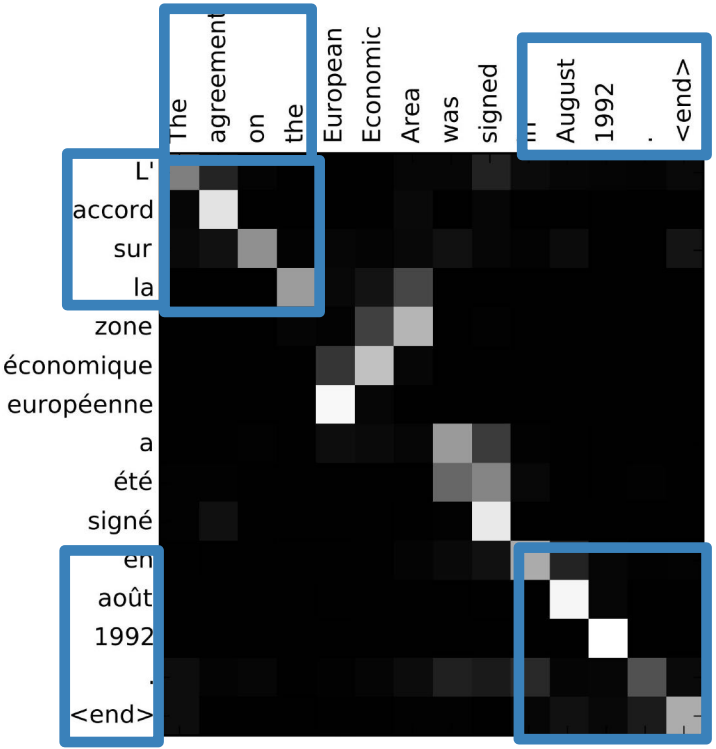

Diagonal attention means words correspond in order

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Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention

Example: English to French translation

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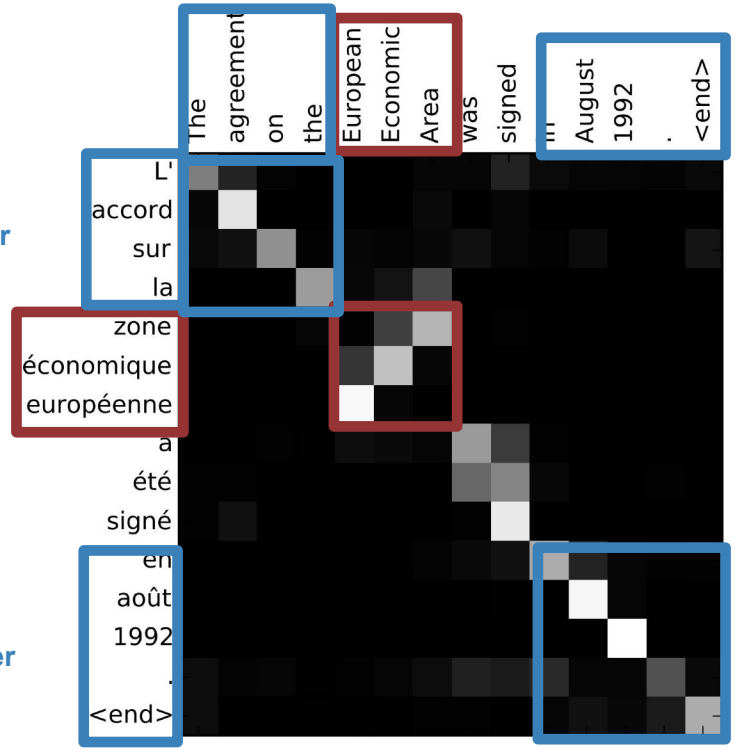


Diagonal attention means words correspond in order

Attention figures out different word orders

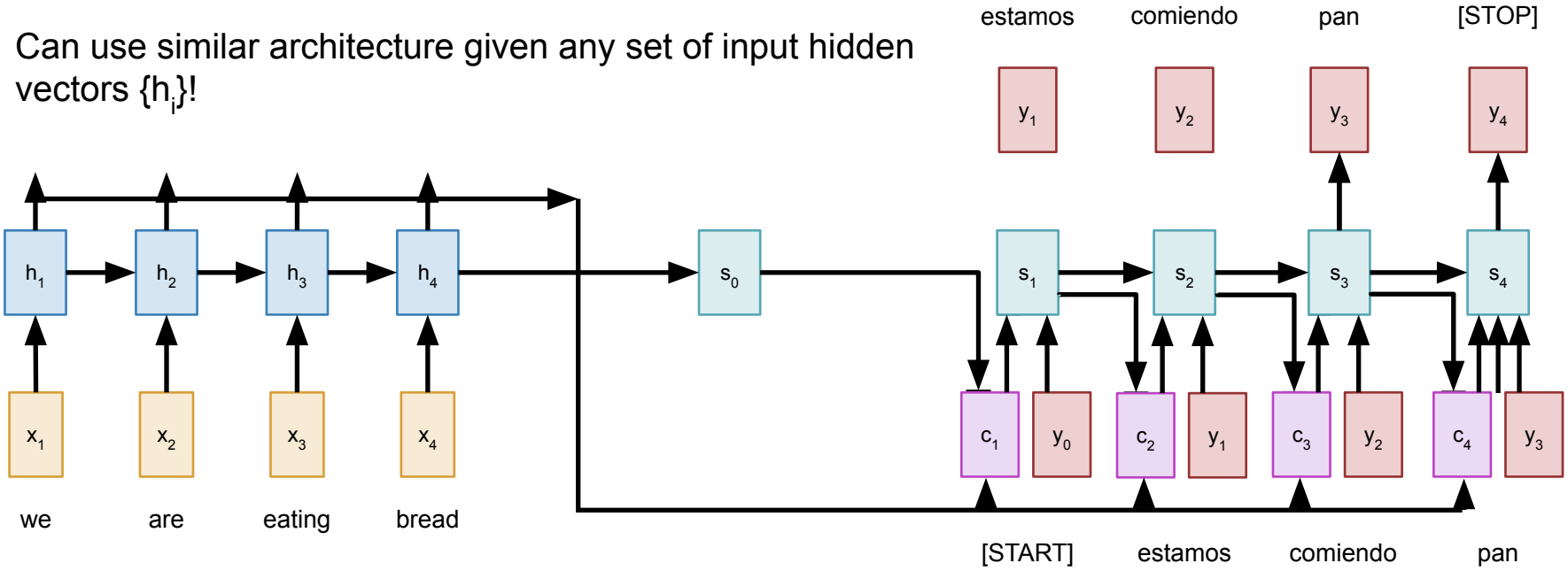
Diagonal attention means words correspond in order

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention

The decoder doesn't use the fact that h_i form an ordered sequence – it just treats them as an unordered set $\{h_i\}$

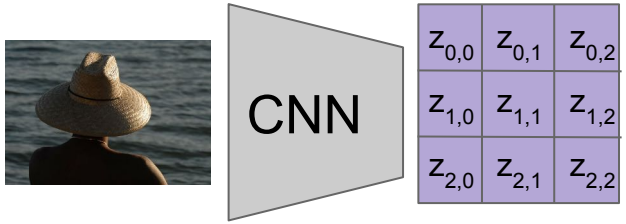
Can use similar architecture given any set of input hidden vectors $\{h_i\}$!



Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Image Captioning using spatial features

Input: Image **I**
Output: Sequence **y** = $y_1, y_2, ..., y_T$



Extract spatial features from a pretrained CNN

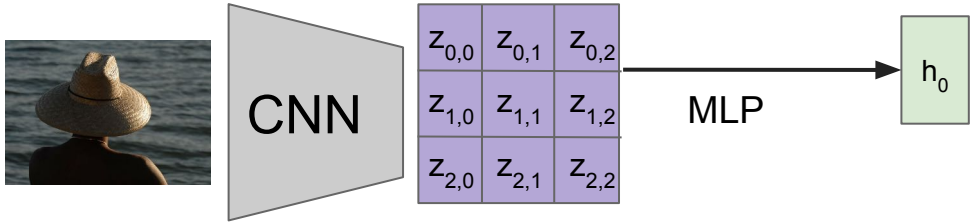
Features: H x W x D

Xu et al, “Show, Attend and Tell: Neural Image Caption Generation with Visual Attention”, ICML 2015

Image Captioning using spatial features

Input: Image **I**
Output: Sequence **y** = $y_1, y_2, ..., y_T$

Encoder: $h_0 = f_{\mathbf{W}}(\mathbf{z})$
where **z** is spatial CNN features
$f_{\mathbf{W}}(.)$ is an MLP



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Features: H x W x D

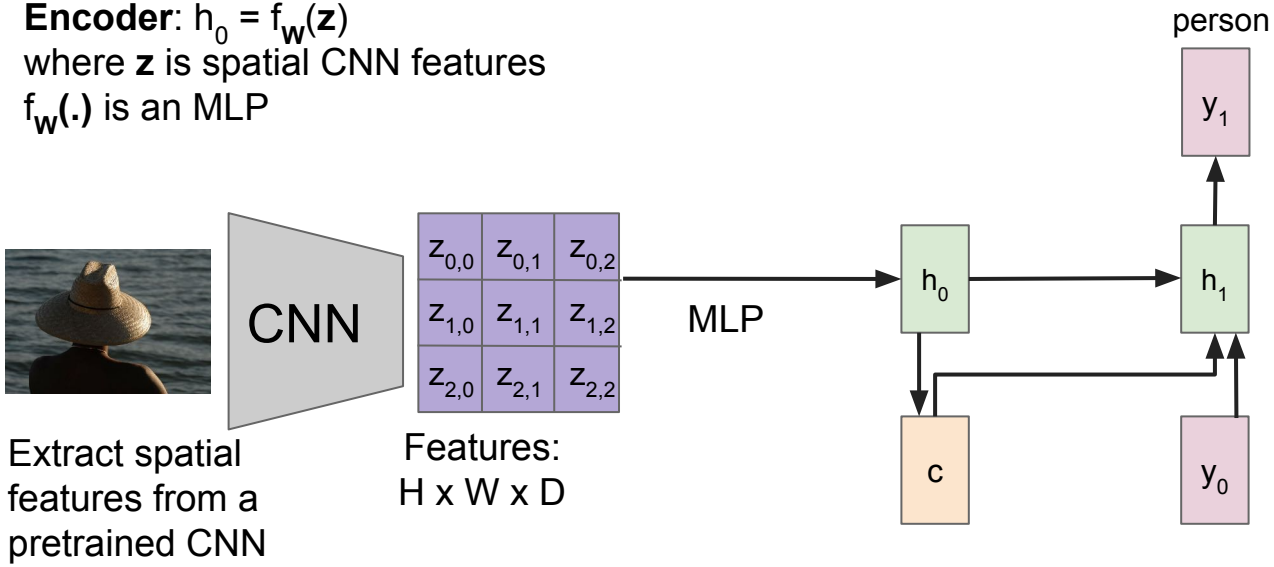
Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning using spatial features

Input: Image **I**
Output: Sequence **y** = $y_1, y_2, ..., y_T$

Decoder: $y_t = g_{\mathbf{V}}(y_{t-1}, h_{t-1}, c)$
where context vector c is often $c = h_0$

Encoder: $h_0 = f_{\mathbf{W}}(\mathbf{z})$
where **z** is spatial CNN features
$f_{\mathbf{W}}(.)$ is an MLP



Extract spatial features from a pretrained CNN

Features: H x W x D

Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning using spatial features

Input: Image **I**
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Decoder: $y_t = g_V(y_{t-1}, h_{t-1}, c)$
where context vector c is often $c = h_0$

Encoder: $h_0 = f_W(\mathbf{z})$
where **z** is spatial CNN features
$f_W(.)$ is an MLP

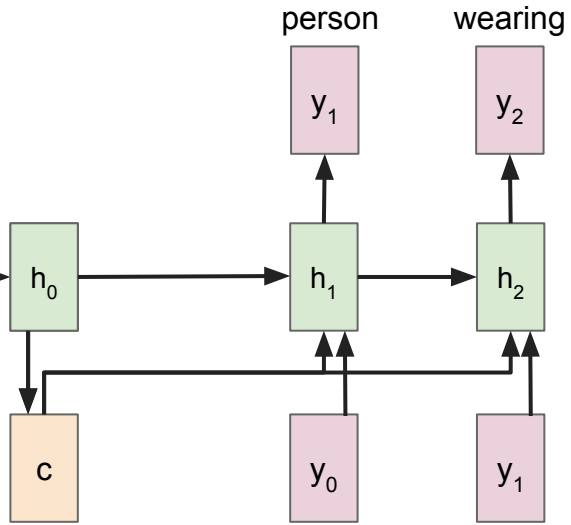
CNN

Extract spatial features from a pretrained CNN

$z_{0,0}$ $z_{0,1}$ $z_{0,2}$
$z_{1,0}$ $z_{1,1}$ $z_{1,2}$
$z_{2,0}$ $z_{2,1}$ $z_{2,2}$

Features: H x W x D

MLP



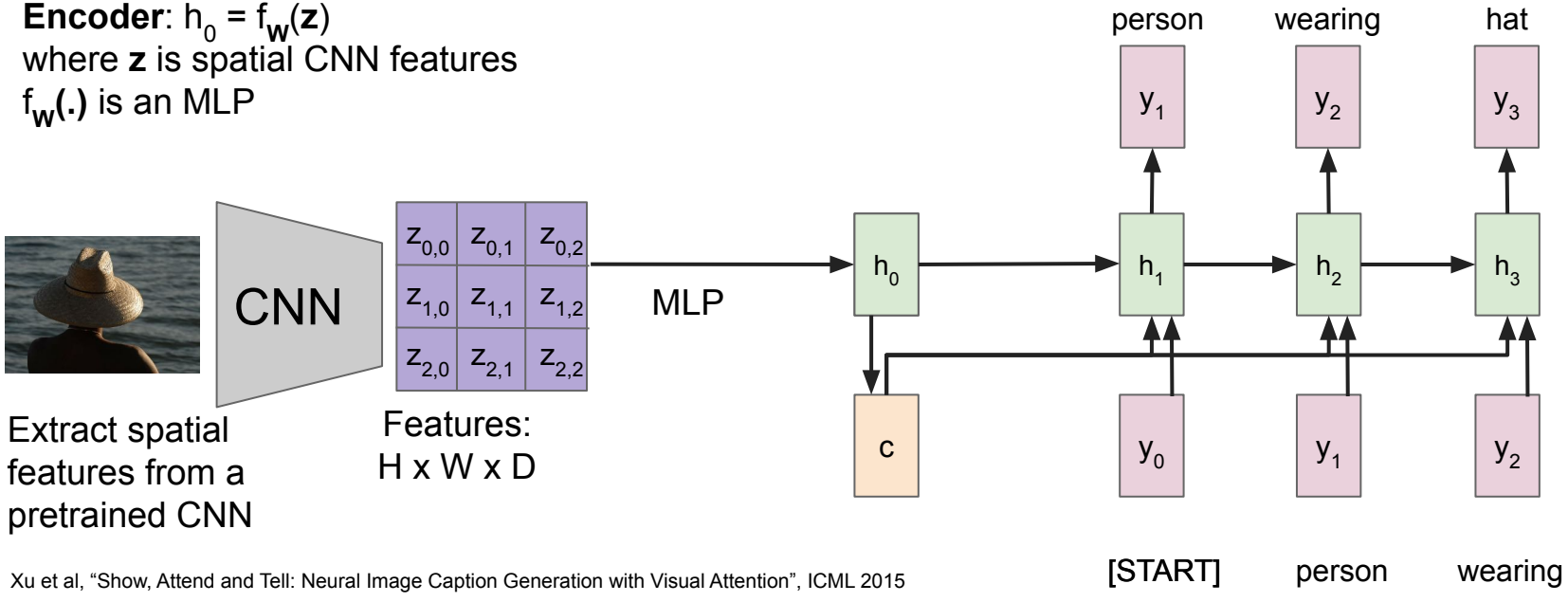
Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning using spatial features

Input: Image **I**
Output: Sequence **y** = $y_1, y_2, ..., y_T$

Decoder: $y_t = g_V(y_{t-1}, h_{t-1}, c)$
where context vector c is often $c = h_0$

Encoder: $h_0 = f_W(\mathbf{z})$
where **z** is spatial CNN features
$f_W(.)$ is an MLP



Extract spatial features from a pretrained CNN

Features: H x W x D

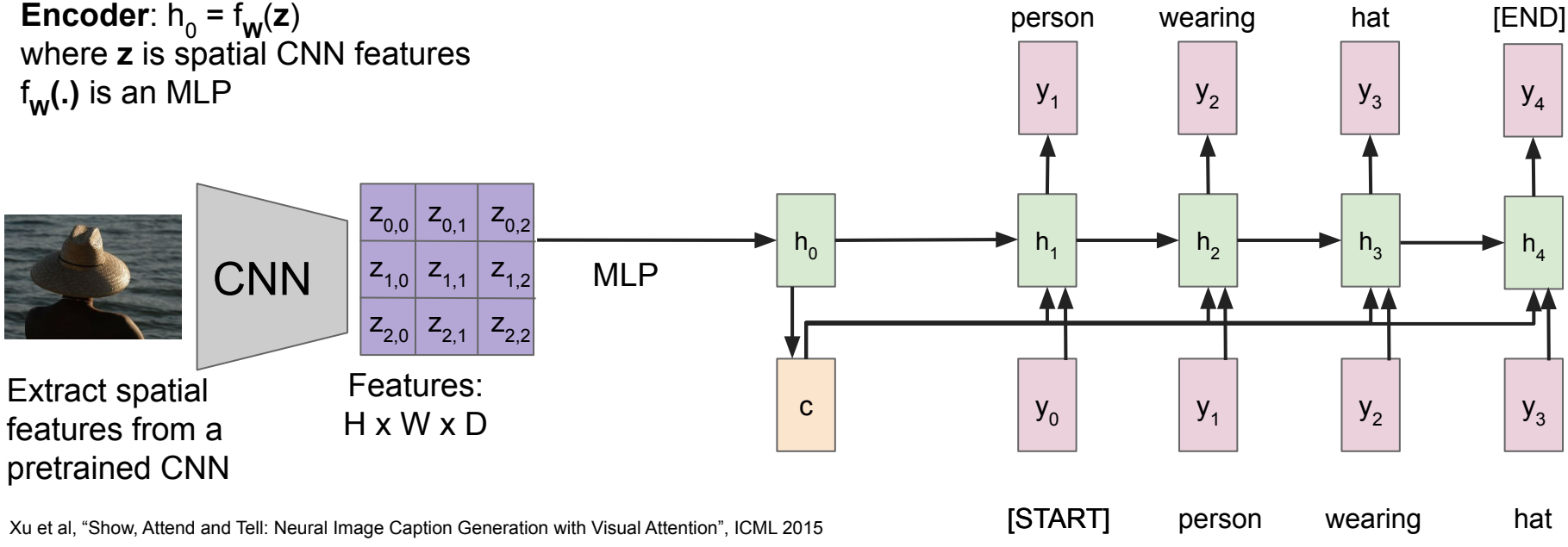
Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning using spatial features

Input: Image **I**
Output: Sequence **y** = $y_1, y_2, ..., y_T$

Decoder: $y_t = g_V(y_{t-1}, h_{t-1}, c)$
where context vector c is often $c = h_0$

Encoder: $h_0 = f_W(\mathbf{z})$
where **z** is spatial CNN features
$f_W(.)$ is an MLP



Extract spatial features from a pretrained CNN

Features: H x W x D

Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning using spatial features

Problem: Input is "bottlenecked" through c

- Model needs to encode everything it wants to say within c

This is a problem if we want to generate really long descriptions? 100s of words long

CNN

$z_{0,0}$ $z_{0,1}$ $z_{0,2}$
$z_{1,0}$ $z_{1,1}$ $z_{1,2}$
$z_{2,0}$ $z_{2,1}$ $z_{2,2}$

Extract spatial features from a pretrained CNN

Features: H x W x D

MLP

h_0 h_1 h_2 h_3 h_4

c

y_0 y_1 y_2 y_3

[START] person wearing hat

y_1 y_2 y_3 y_4

person wearing hat [END]

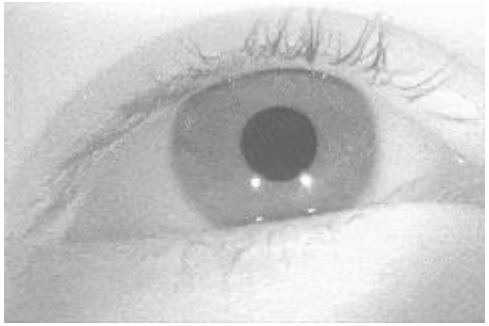
Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with RNNs and Attention

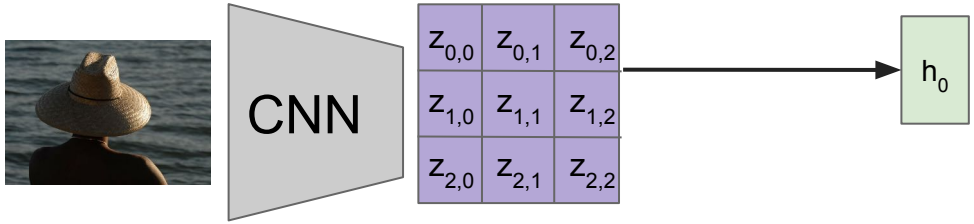
gif source

Attention idea: New context vector at every time step.

Each context vector will attend to different image regions



Attention Saccades in humans



Extract spatial features from a pretrained CNN

Features: H x W x D

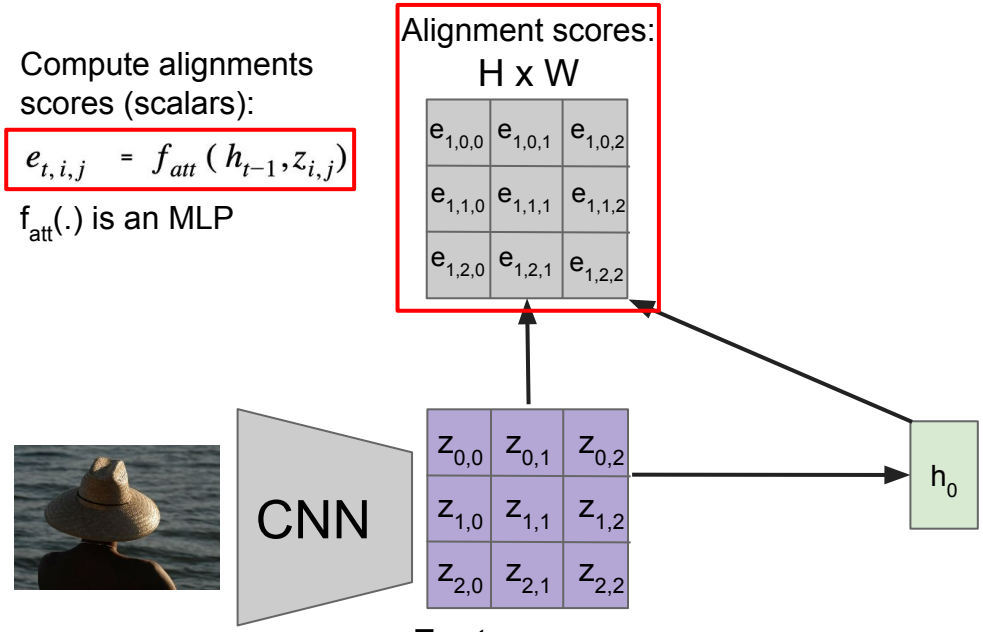
Xu et al, “Show, Attend and Tell: Neural Image Caption Generation with Visual Attention”, ICML 2015

Image Captioning with RNNs and Attention

Compute alignments scores (scalars):

$$e_{t,i,j} = f_{att}(h_{t-1}, z_{i,j})$$

$f_{att}(.)$ is an MLP



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with RNNs and Attention

Compute alignments scores (scalars):

$e_{t,i,j} = f_{att}(h_{t-1}, z_{i,j})$

$f_{att}(.)$ is an MLP

Alignment scores: H x W

$e_{1,0,0}$	$e_{1,0,1}$	$e_{1,0,2}$
$e_{1,1,0}$	$e_{1,1,1}$	$e_{1,1,2}$
$e_{1,2,0}$	$e_{1,2,1}$	$e_{1,2,2}$

Attention: H x W

$a_{1,0,0}$	$a_{1,0,1}$	$a_{1,0,2}$
$a_{1,1,0}$	$a_{1,1,1}$	$a_{1,1,2}$
$a_{1,2,0}$	$a_{1,2,1}$	$a_{1,2,2}$

Normalize to get attention weights:

$a_{t,:,:} = softmax(e_{t,:,:})$

$0 < a_{t,i,j} < 1$,
attention values sum to 1

CNN

$z_{0,0}$	$z_{0,1}$	$z_{0,2}$
$z_{1,0}$	$z_{1,1}$	$z_{1,2}$
$z_{2,0}$	$z_{2,1}$	$z_{2,2}$

h_0

Extract spatial features from a pretrained CNN

Features: H x W x D

Xu et al, “Show, Attend and Tell: Neural Image Caption Generation with Visual Attention”, ICML 2015

Image Captioning with RNNs and Attention

Compute alignments scores (scalars):

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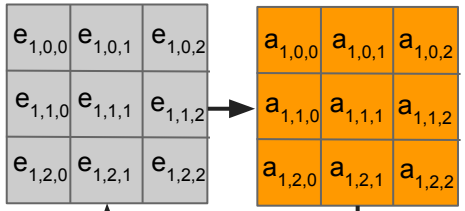
$f_{att}(.)$ is an MLP

Alignment scores: H x W

Attention: H x W



Normalize to get attention weights:

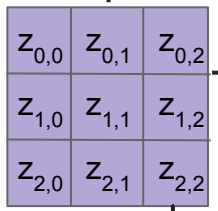
$a_{t,:,:} = softmax(e_{t,:,:})$

$0 < a_{t,i,j} < 1$,
attention values sum to 1

Compute context vector:

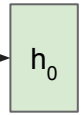
$c_t = \sum_{i,j} a_{t,i,j} z_{t,i,j}$

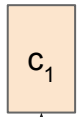
CNN



Extract spatial features from a pretrained CNN

Features: H x W x D





Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with RNNs and Attention

Each timestep of decoder uses a different context vector that looks at different parts of the input image

Decoder: $y_t = g_V(y_{t-1}, h_{t-1}, c_t)$
New context vector at every time step

$$e_{t,i,j} = f_{att}(h_{t-1}, z_{i,j})$$
$$a_{t,:,:} = softmax(e_{t,:,:})$$
$$c_t = \sum_{i,j} a_{t,i,j} z_{t,i,j}$$

CNN

$z_{0,0}$ $z_{0,1}$ $z_{0,2}$
$z_{1,0}$ $z_{1,1}$ $z_{1,2}$
$z_{2,0}$ $z_{2,1}$ $z_{2,2}$

Features:
H x W x D

Extract spatial features from a pretrained CNN

h_0

person

y_1

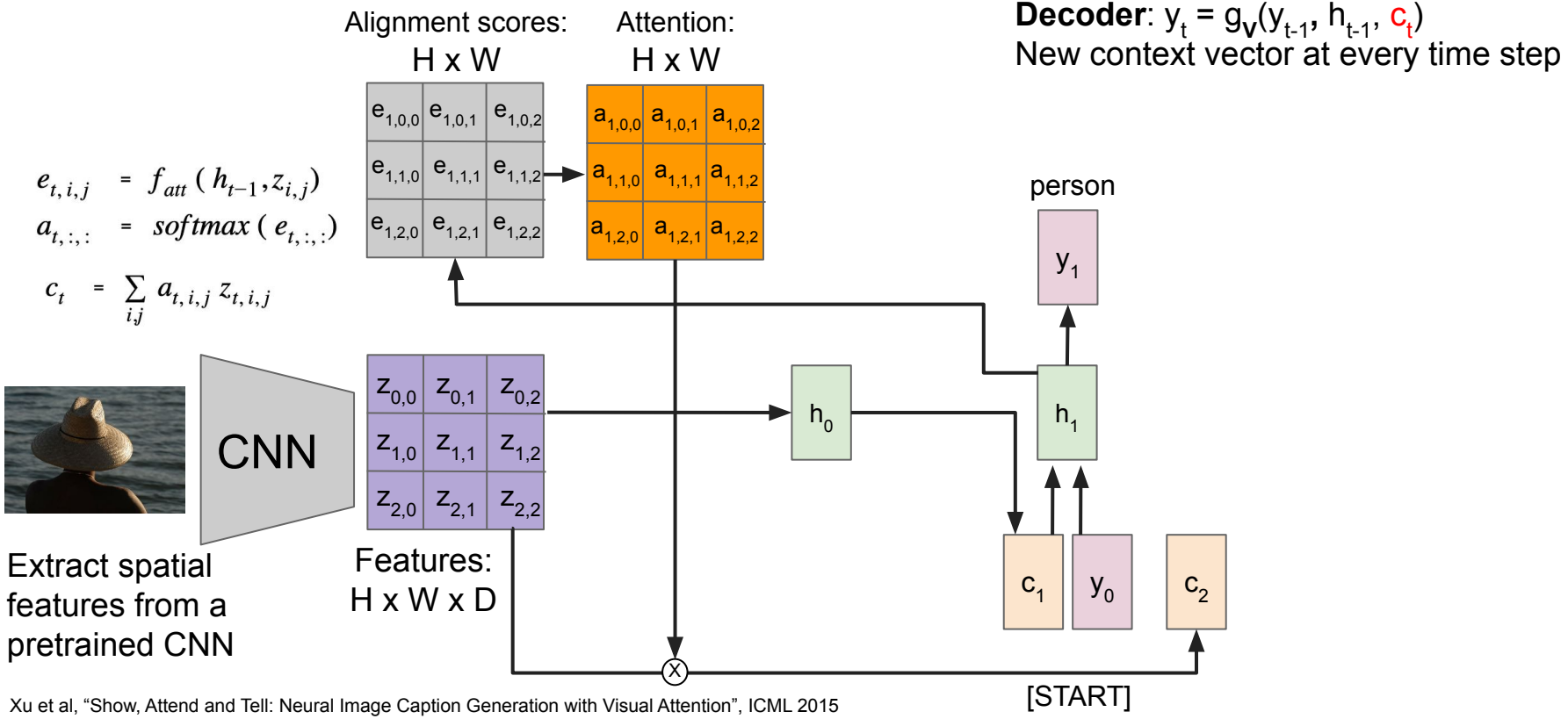
h_1

c_1 y_0

[START]

Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

Image Captioning with RNNs and Attention



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CNN

Extract spatial features from a pretrained CNN

$z_{0,0}$ $z_{0,1}$ $z_{0,2}$
$z_{1,0}$ $z_{1,1}$ $z_{1,2}$
$z_{2,0}$ $z_{2,1}$ $z_{2,2}$

Features: H x W x D

h_0 h_1 h_2

y_1 y_2

person wearing

c_1 y_0 c_2 y_1

[START] person

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Image Captioning with RNNs and Attention

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CNN

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$z_{0,0}$ $z_{0,1}$ $z_{0,2}$
$z_{1,0}$ $z_{1,1}$ $z_{1,2}$
$z_{2,0}$ $z_{2,1}$ $z_{2,2}$

Features: H x W x D

h_0 h_1 h_2 h_3

y_1 y_2 y_3

person wearing hat

c_1 y_0 c_2 y_1 c_3 y_2

[START] person wearing

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Image Captioning with RNNs and Attention

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CNN

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$z_{0,0}$ $z_{0,1}$ $z_{0,2}$
$z_{1,0}$ $z_{1,1}$ $z_{1,2}$
$z_{2,0}$ $z_{2,1}$ $z_{2,2}$

Features: H x W x D

h_0 h_1 h_2 h_3 h_4

y_1 y_2 y_3 y_4

c_1 y_0 c_2 y_1 c_3 y_2 c_4 y_3

person wearing hat [END]

[START] person wearing hat

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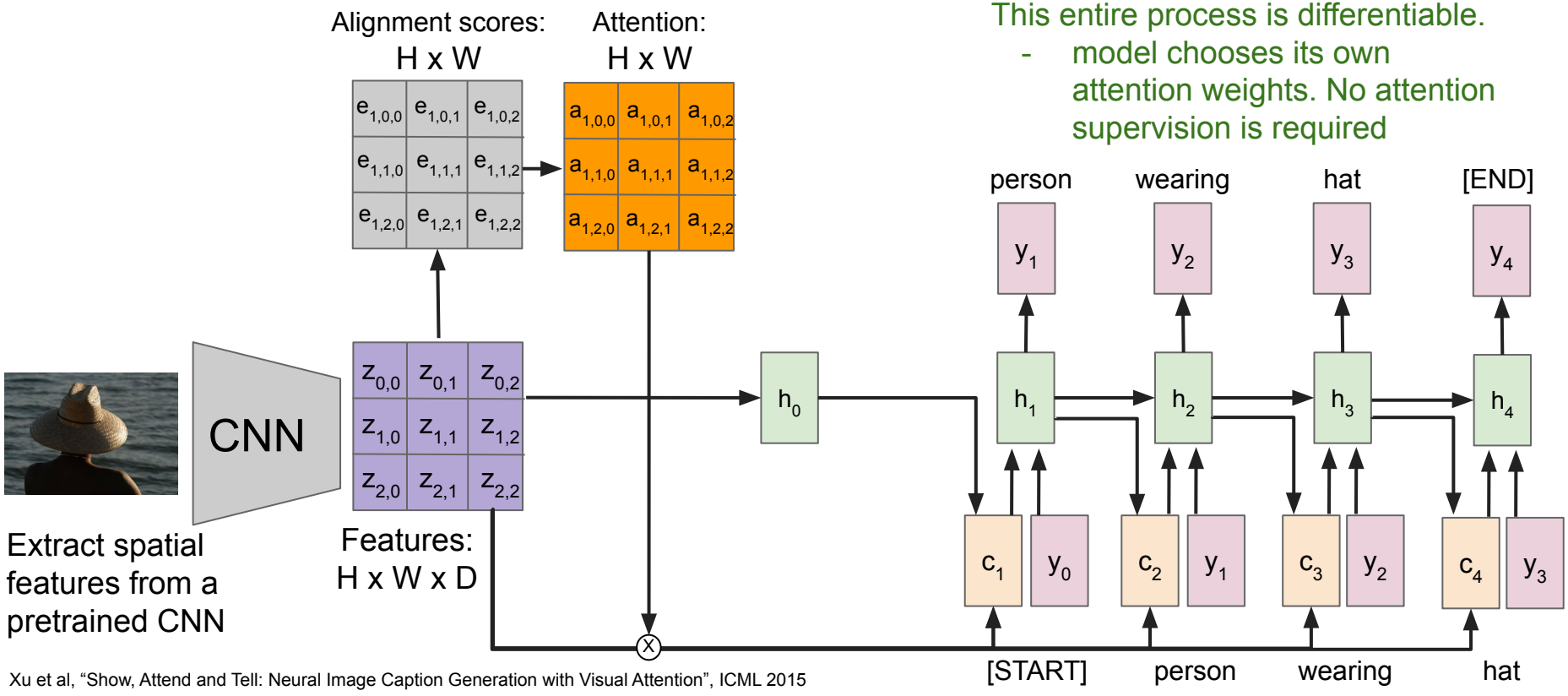
Image Captioning with RNNs and Attention



Xu et al, "Show, Attend and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015

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, "Show, Attend, and Tell: Neural Image Caption Generation with Visual Attention", ICML 2015