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SCHOOL OF ENGINEERING

Visualization and Attention Mechanisms

A. Maier, V. Christlein, K. Breininger, S. Vesal, F. Meister, C. Liu, S. Gündel, S. Jaganathan, N. Maul, M. Vornehm, L. Reeb, F. Thamm, M. Hoffmann, C. Bergler, F. Denzinger, W. Fu, B. Geissler, Z. Yang
Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg

June 5, 2020

Outline


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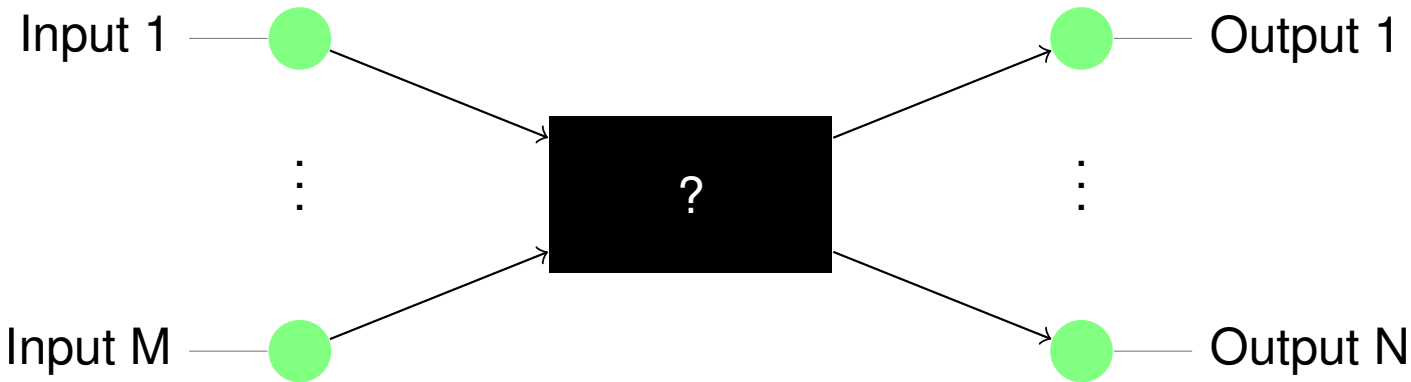
Motivation


SIGILLUM ACADEMIAE FRIDERICO ALEXANDRINAE

Motivation - Why do we need visualization?

- Neural networks often treated as black box:



- Today: How can we understand and communicate the inner-workings of a network?

Motivation

An incomplete list why understanding and visualization matters:

- Communicate architectures between researchers
- Identify issues during training (not converging, dying ReLUs)
- Identify faulty training/test data
- Understanding how, why and what networks learn

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Three (main) types of visualization:

- Architecture
- Training
- Learned parameters/weights

  ➔ Visualize **representation** of data in the network

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Network Architecture Visualization

Network Architecture Visualization

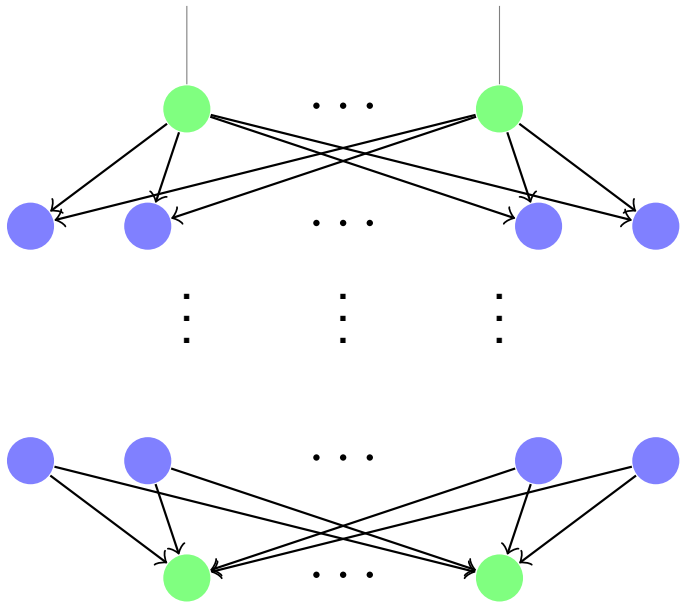
- Important to communicate architectures effectively
- Priors imposed by the architecture may be most important factor for good performance
- Mostly graph-based structures with different granularity
- Compare Lecture 6: Neural Network Architectures

Network Architecture Visualization

Three categories:

- Node-link diagrams: Neurons = nodes, (weighted) connections = edges
- Block diagrams: Layer = solid block, single connection between layers
- “Others”

Network Architecture Visualization - The node-link diagram



- Detailed representation, focus on connectivity
- Only for small (sub-)networks, building blocks
- Variants, e.g., with explicit weights, recurrent connections, ...

Network Architecture Visualization

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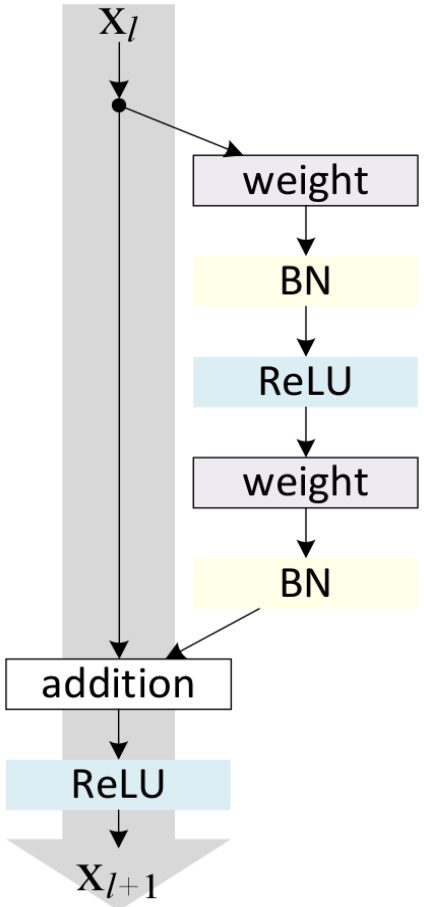
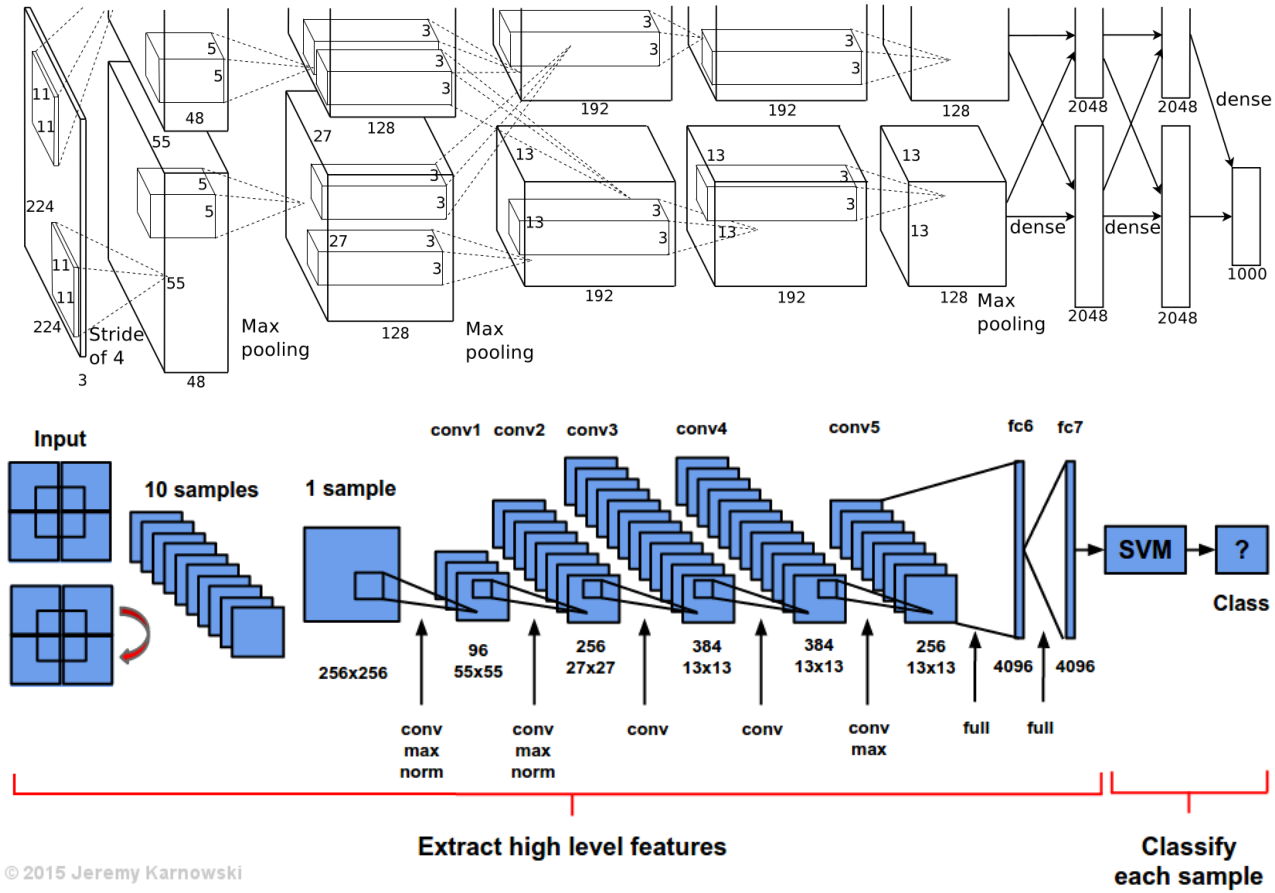
Network Architecture Visualization - Block diagrams



Block diagram of a ResNet-module.

- Blocks: mathematical operations/layers
- Arrows: **direction of flow** of the data
- Blocks can have different granularity – often hierarchical descriptions
- Textual description of hyperparameters (filter size, # of filters, . . .) common

Network Architecture Visualization - Block Diagrams (cont.)

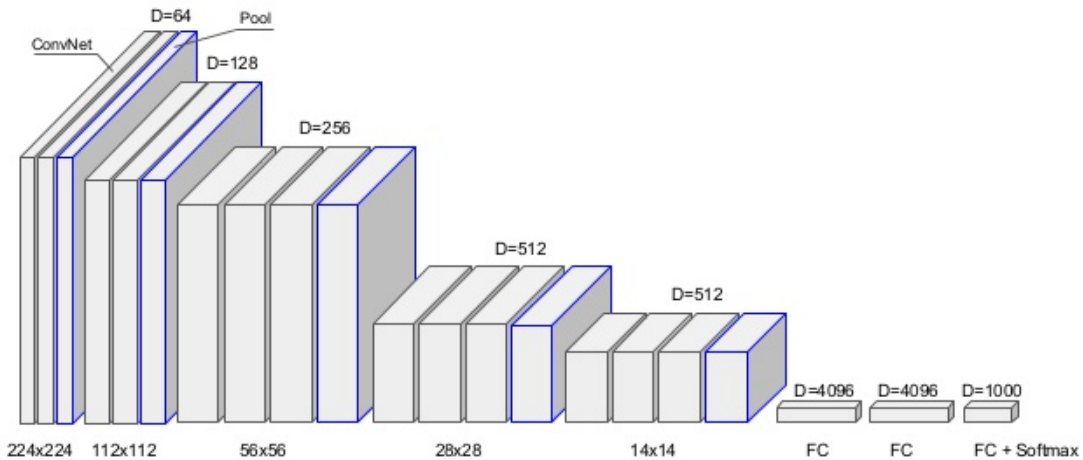


Two different visualizations for AlexNet

Source: https://jeremykarnowski.wordpress.com/2015/07/15/alexnet-visualization/, [12]

Network Architecture Visualization - Block diagrams (cont.)

- Most common representation, but many variants
  ➔ 3D/pseudo-3D layers, receptive fields, colors, . . .
- Recommendation: Pick one that clearly represents what you want to show
  ➔ Good combination of text & figure is key!
- Most DL libraries have tools to display defined computational graphs
  ➔ Good for debugging, usually not good for reports



Block diagram of VGG16

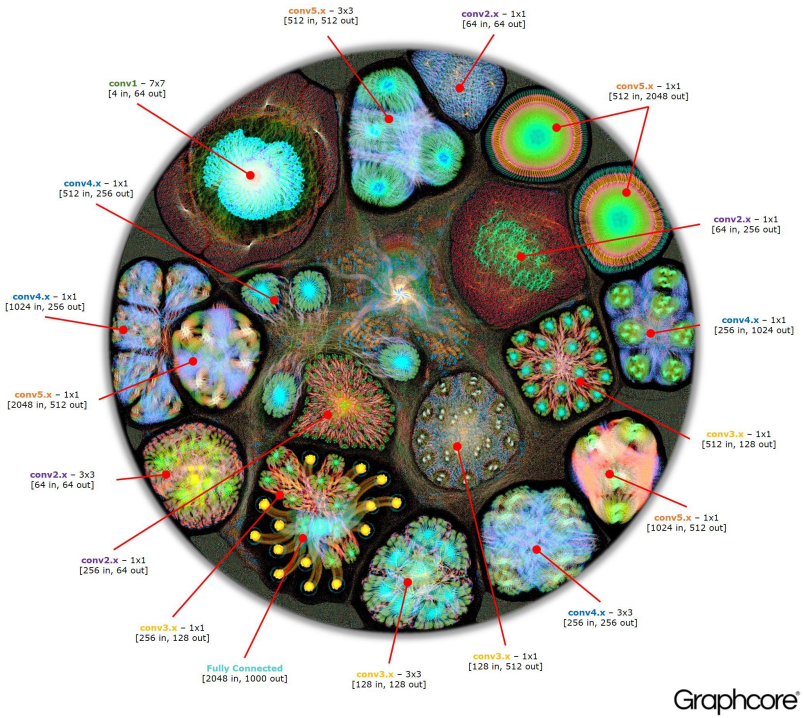
Network Architecture Visualization

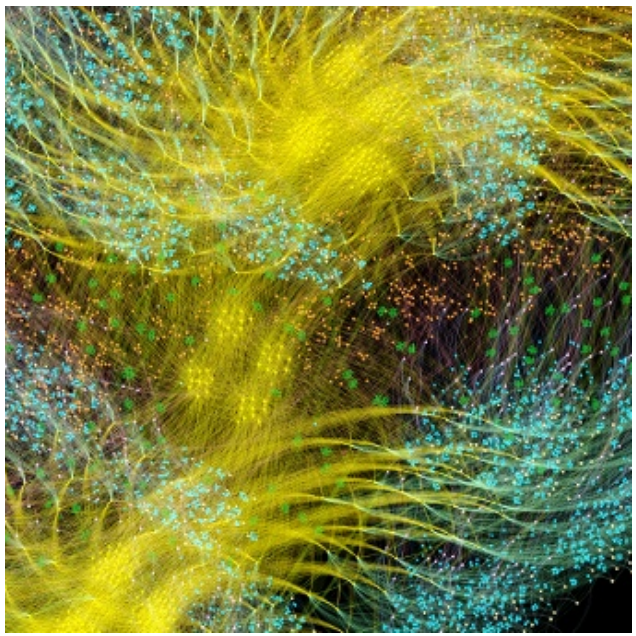
Visualization strategies break down into three categories:

- Node-link diagrams: Neurons = nodes, weighted connections = edges
- Block diagrams: Layer = solid block, single connection between layers
- “Others”

Network Architecture Visualization - Others

- Deep Visualization [25]: Combination of architecture & parameter visualization (see next sections).
- Graphcore Poplar™ – fancy graph visualization:





Resnet 50 visualized with Graphcore Poplar.

Source: https://www.graphcore.ai/posts/what-does-machine-learning-look-like

Visualization of Training

Visualization of Training

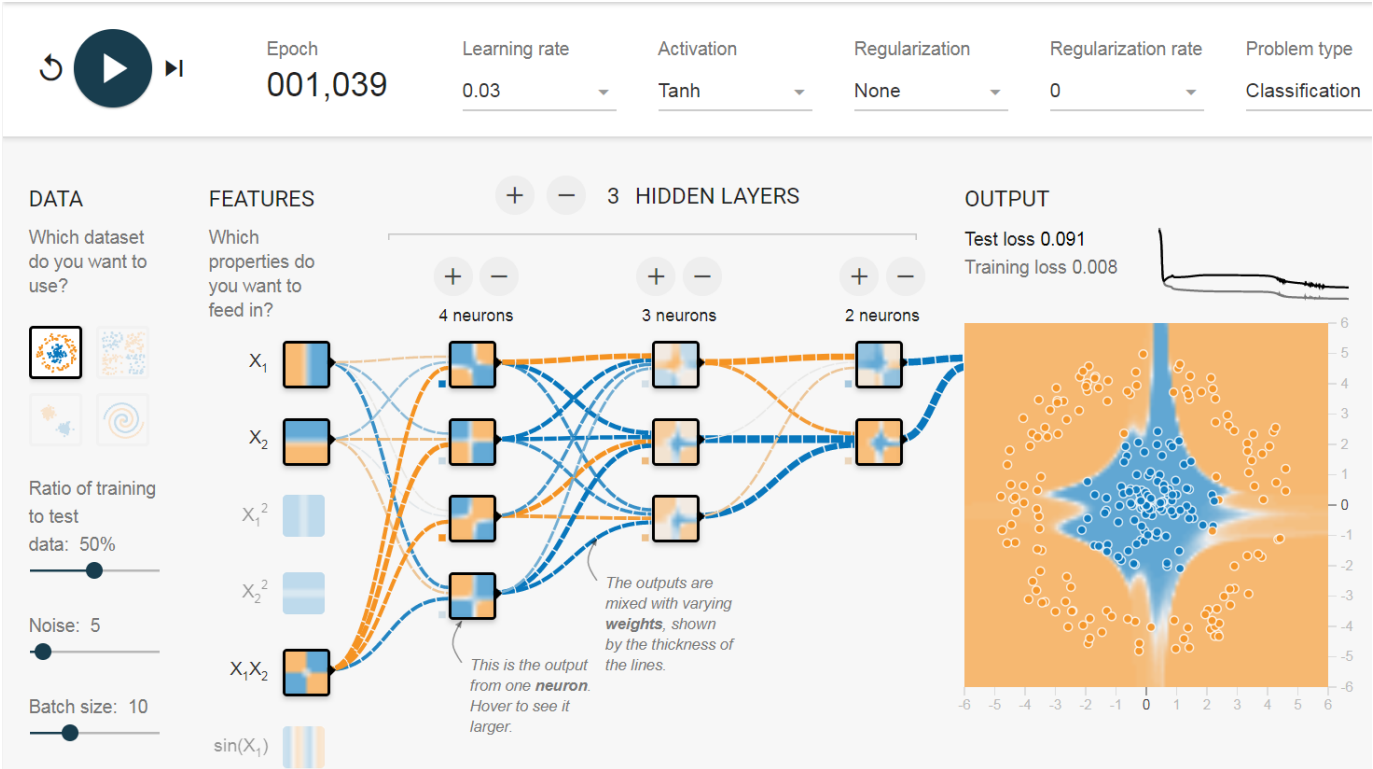
Lots of interesting information available during training:

- Input data (images, text, ...)
- Parameters (weights, biases, ...)
- Hidden layer data (activations, hidden states, ...)
- Output data (classification, loss curves, ...)

Tracking information helps!

➔ Debugging, improve model design, ... (see also Lecture 5 - Common Practices)

Visualization of Training

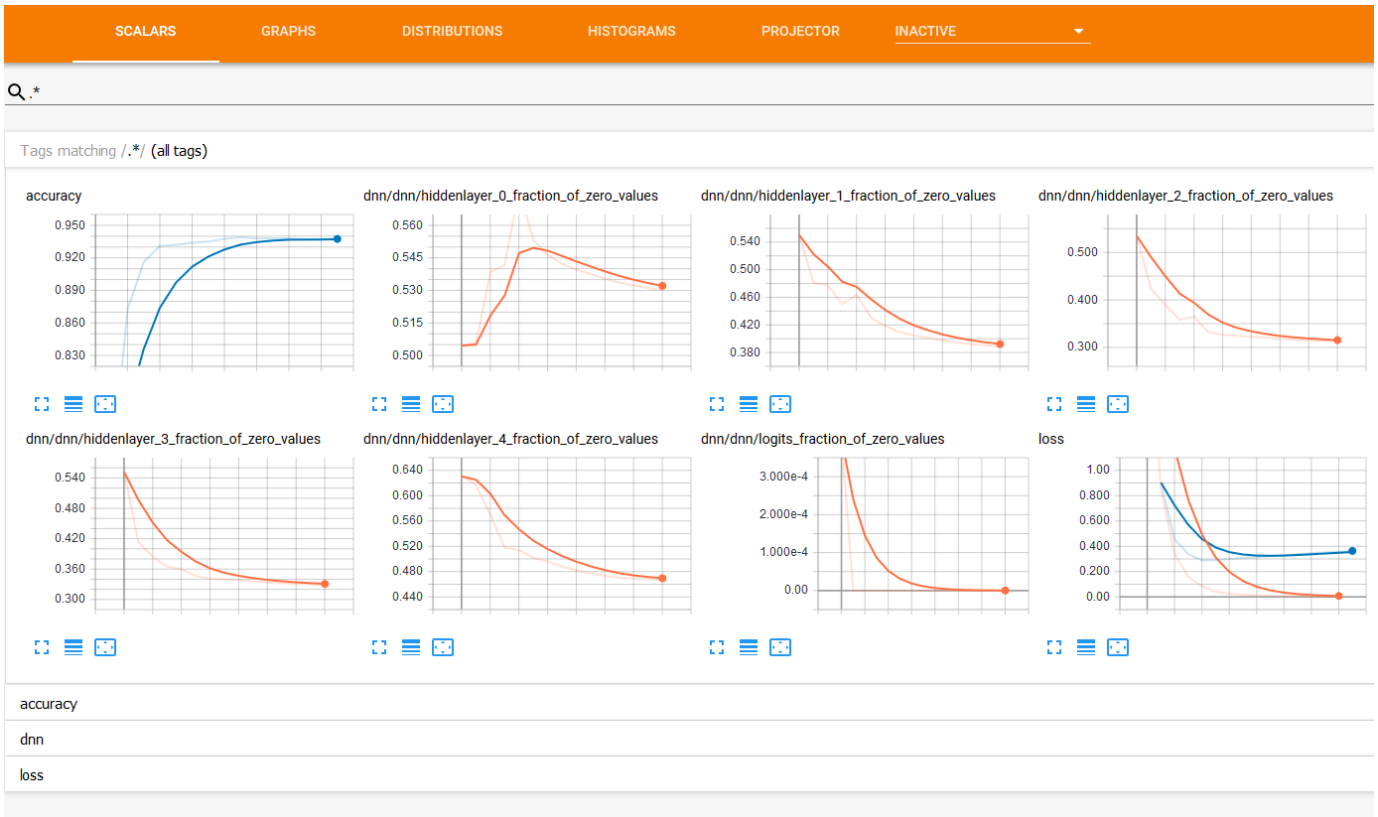


Tensorflow playground

Only 2D-toy examples, but nice concepts, e.g., interactive loss curve, visualization of decision boundary, importance of weights

Source: http://playground.tensorflow.org

Visualization of Training



Tensorboard example (TensorFlow)

Most DL libraries provide tools to record and monitor training - **use them!**

NEXT TIME

ON DEEP LEARNING

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Visualization and Attention Mechanisms - Part 2

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Visualization of Parameters

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- Networks learn **representation** of the training data ➔ Question: What happens with the data in our network?

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- Additional question: Why should we care?

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➔ Answer: To investigate unexpected/unintuitive behavior:

  - Adversarial examples

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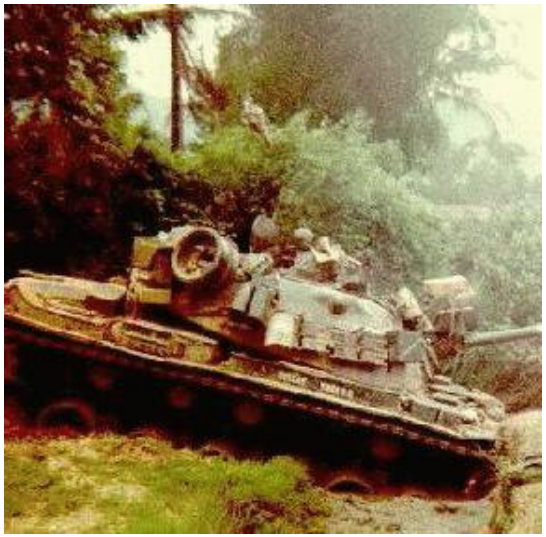
  ➔ (Anecdotal) example: Identification of tanks in photos [5], [10]

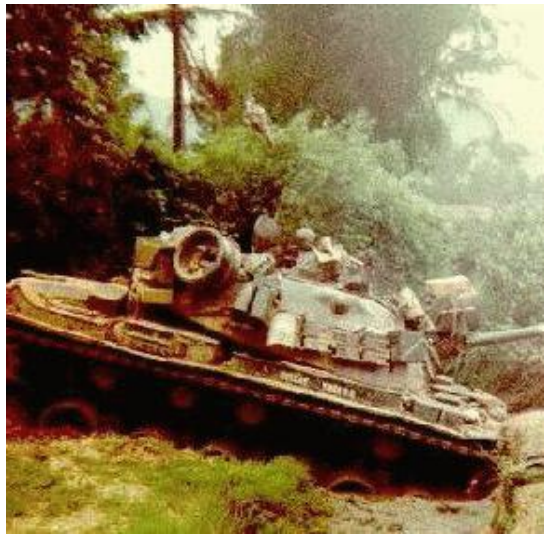
Motivation - Confounds



- Task: Identify whether image shows a tank
- Problem: All tank images recorded on cloudy days, all non-tank images on sunny days

Source: [5]

Motivation - Confounds

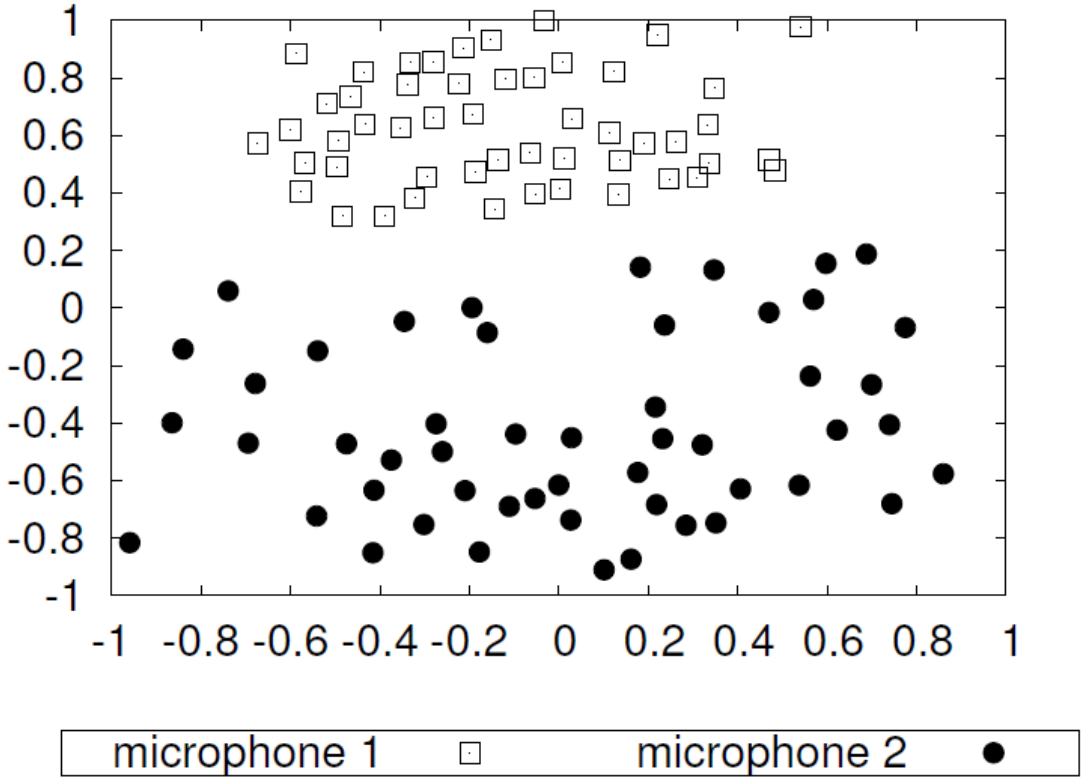


- Task: Identify whether image shows a tank
- Problem: All tank images recorded on cloudy days, all non-tank images on sunny days
- Network learned the **correlated feature** weather, **not** to identify the tank!
- **Important**: Not a fault in the learning algorithm, but in the data!

Source: [5]

Motivation - Confounds (cont.)

Example: Speech recordings with two microphones [15]



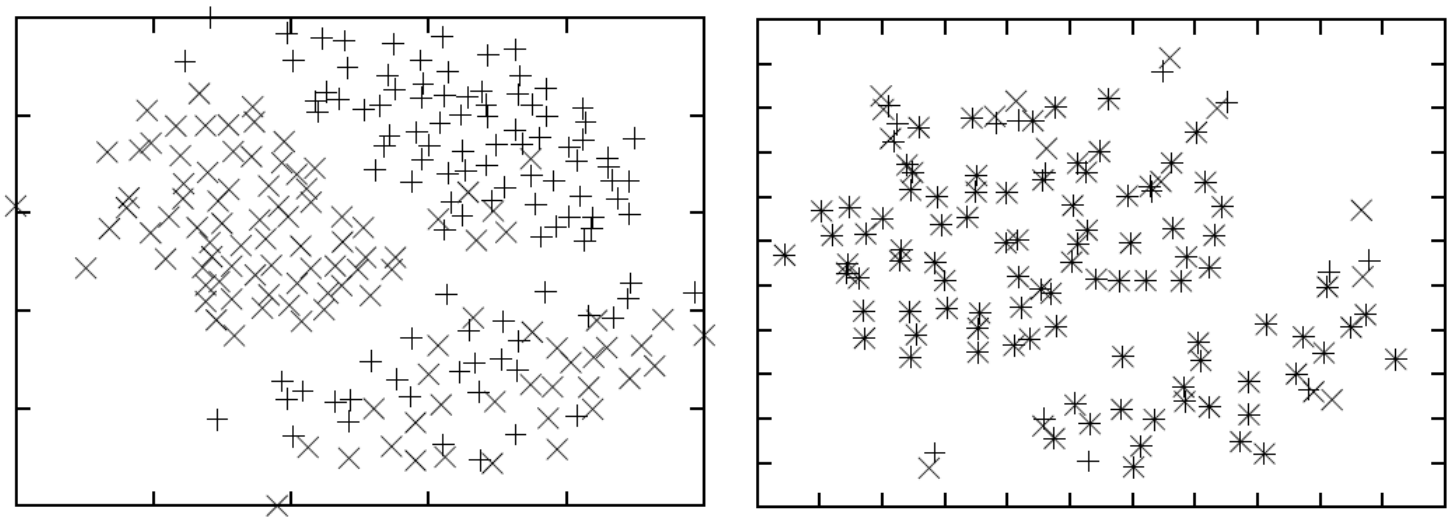
Recordings of the same speaker group with two different microphones

➔ ML will focus on the most discriminative features!

Source: Maier et al. [15]

Motivation - Confounds

- If confounder is **known**, we may be able to correct for it:
- Maier et al. [15]: QMOS – Use knowledge of same participants



Speaker visualization before (left) and after (right) correction for different microphones ($\times$ and $+$).

Source: Maier et al. [15]

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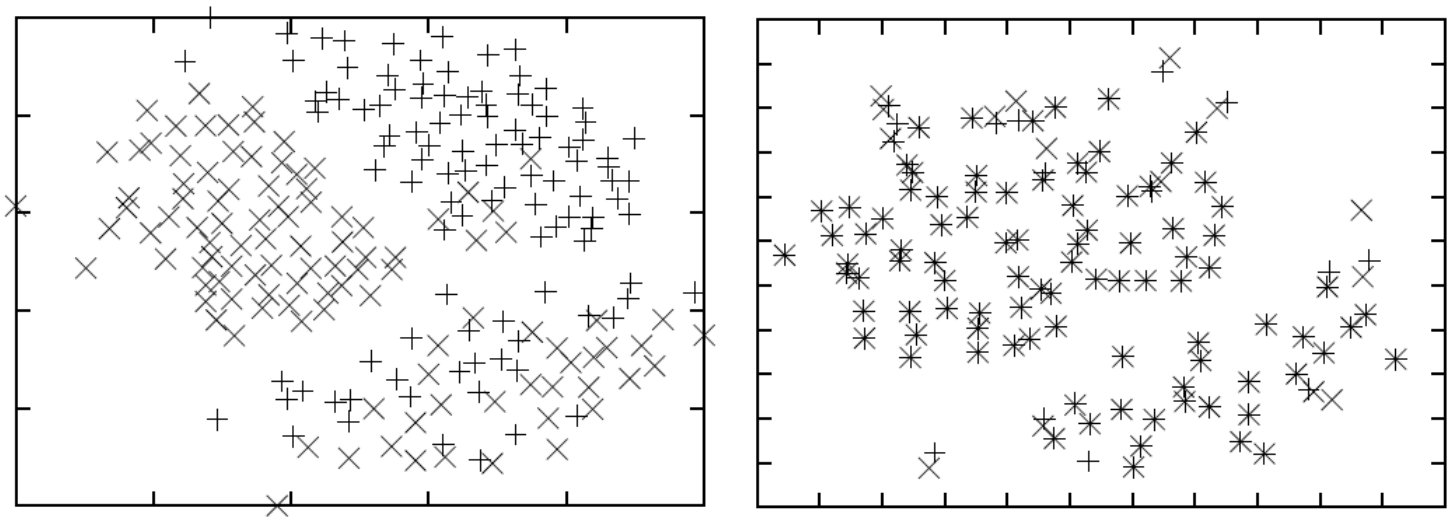


Speaker visualization before (left) and after (right) correction for different microphones ($\times$ and $+$).

- Other confounds: **Sensor**, lighting, age/sex of participants, temperature, . . .
- Best strategy: Be aware and avoid!

Source: Maier et al. [15]

Motivation - Unintuitive Behaviour of Neural Networks

This is a panda, 57.7% certainty

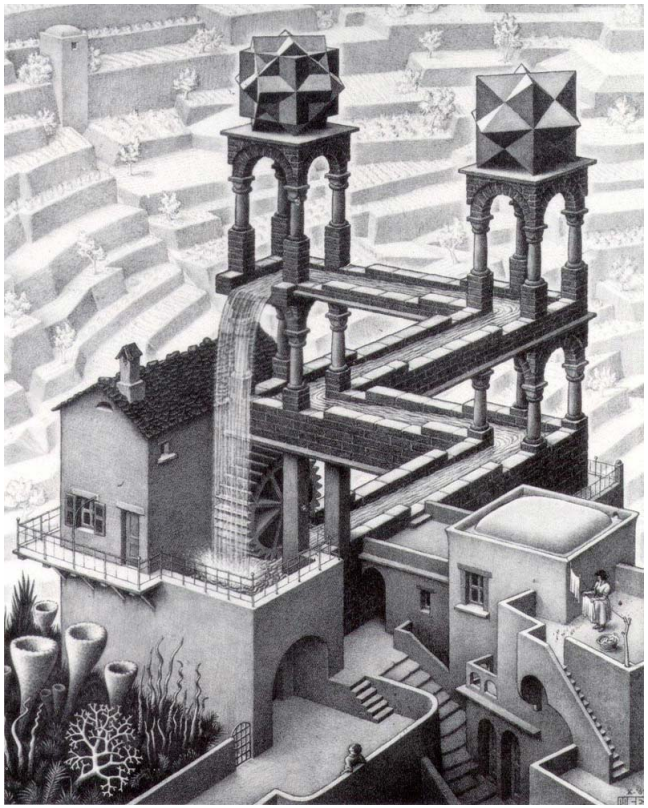
This is a gibbon, 99.3% certainty

- Output of the same network
- No “visible” difference
- **Adversarial Example**: differ only by **specifically optimized**, added “noise”

Source: https://blog.openai.com/adversarial-example-research/

Motivation - Adversarial Examples and Optical Illusions

Human perception is not flawless:



Waterfall, 1961, M.C. Escher

Source: http://totallyhistory.com, Wikicommons

Motivation - Adversarial Examples and Optical Illusions

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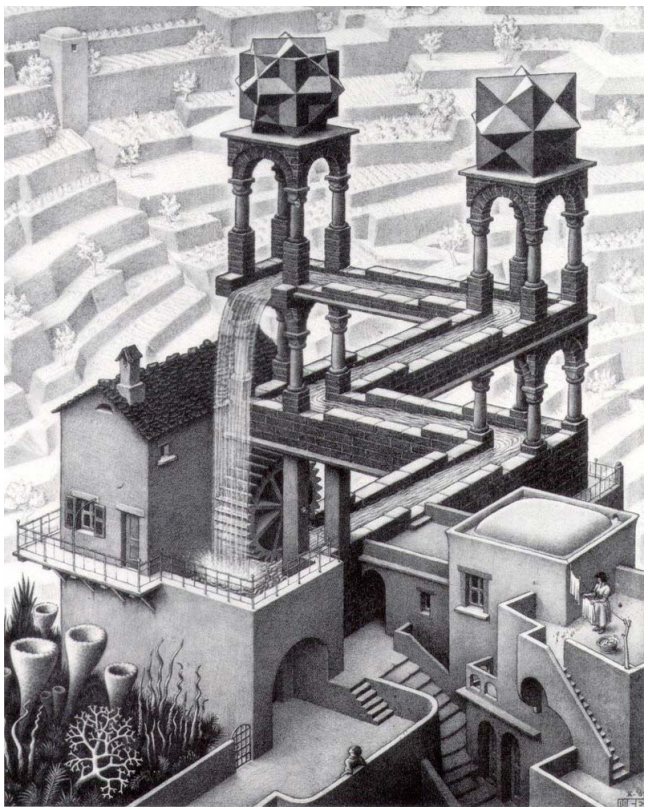


Waterfall, 1961, M.C. Escher

Pareidolia in Neptune's Grotto, Italy

Source: http://totallyhistory.com, Wikicommons

Motivation - Adversarial Examples

- Can be generated to cause a specific mistake
- Example #1: Accessorize to a Crime: Real and Stealthy Attacks on State-of-the-Art Face Recognition (Sharif et al. [19])

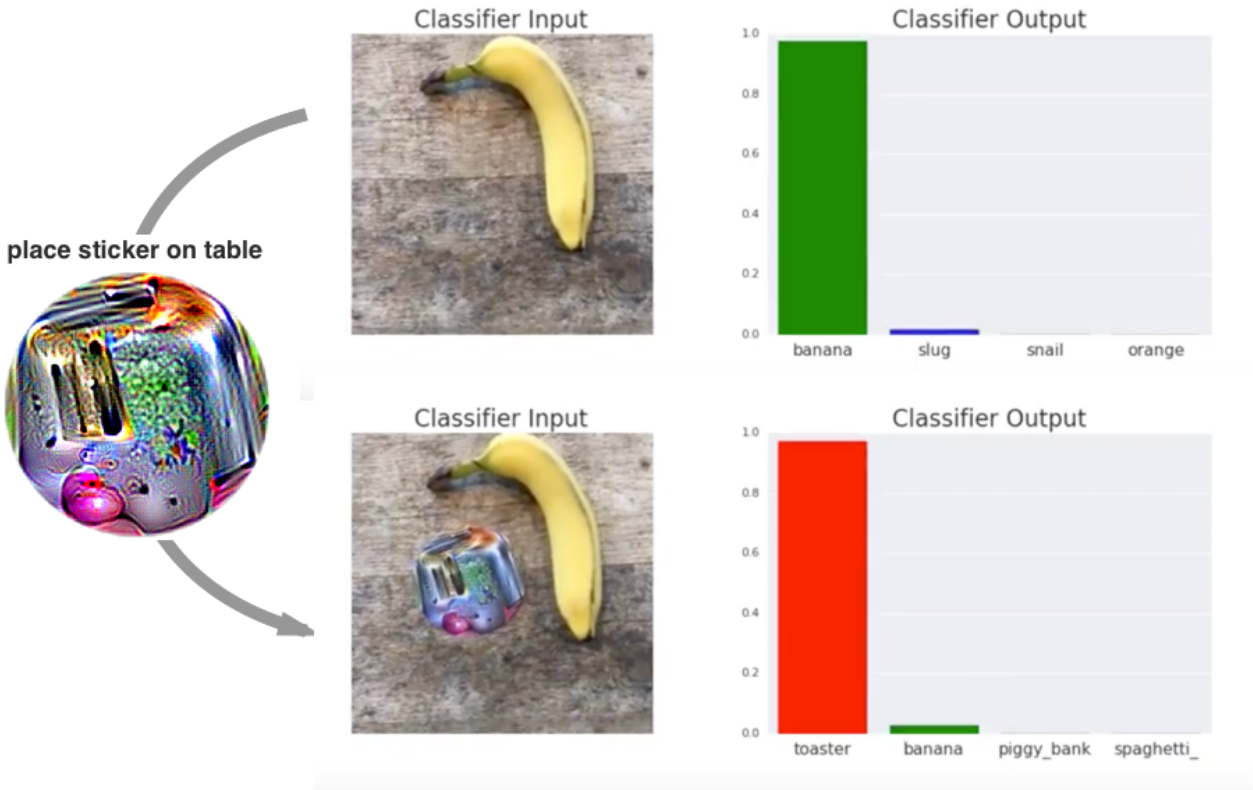


Reese Witherspoon impersonating Russel Crowe with a set of glasses

Source: Sharif et al. [19]

Motivation - Adversarial Examples

- Example #2: Adversarial Stickers [2]



Small printed sticker is added to a scence. Link to video

Source: Brown et al. [2]

Motivation - Summary

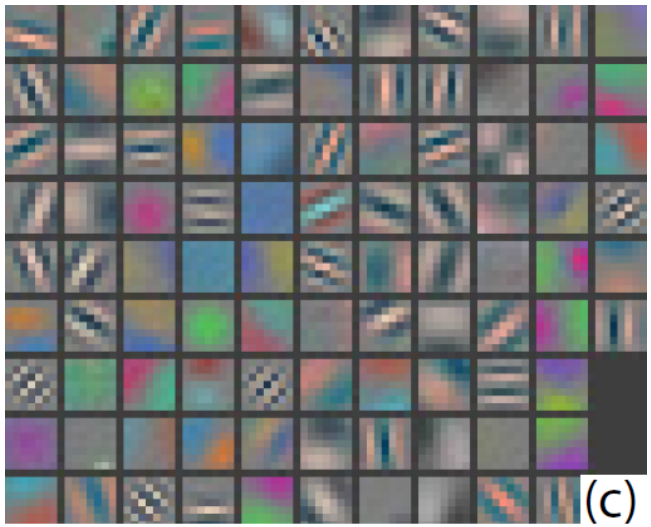
Main goal: Understand how the network represents data

- Identify confounds
- Explain why a network works (or why not)
- Increase confidence in predictions
- Understand (or at least investigate) limitations (➔ adversarial examples)

Simple Parameter Visualization

Direct Visualization of Learned Kernels

- Idea: Plot learned filter weights directly
- Easy to implement, easy to interpret for the first layer(s)
  - Mostly edge and Gabor filters
  - Example MNIST: stroke detection
  - Very noisy first layer filters: something wrong with the setup



First layer filters in AlexNet (11 $\times$ 11 conv)

Source: Image from [26]

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- Easy to implement, easy to interpret for the first layer(s)
  - Mostly edge and Gabor filters
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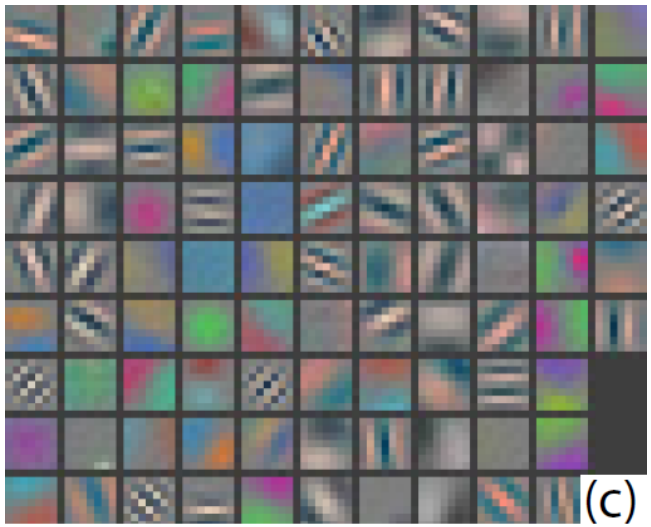
  - Very noisy first layer filters: something wrong with the setup
- Apart from that, mostly uninteresting
- No easy interpretation for higher layers, esp. with small kernel sizes, e.g., 3×3



First layer filters in AlexNet (11×11 conv)

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Visualization of Activations

- Problem: Kernels difficult to interpret

  ➔ Idea: Instead visualize activations generated by kernels
- Strong response: feature is present, weak response: feature is absent
- Possible for any layer/neuron in the network, with different resolutions

Source: https://medium.com/@awjuliani/visualizing-neural-network-layer-activation-tensorflow-tutorial-d45f8bf7bbc4

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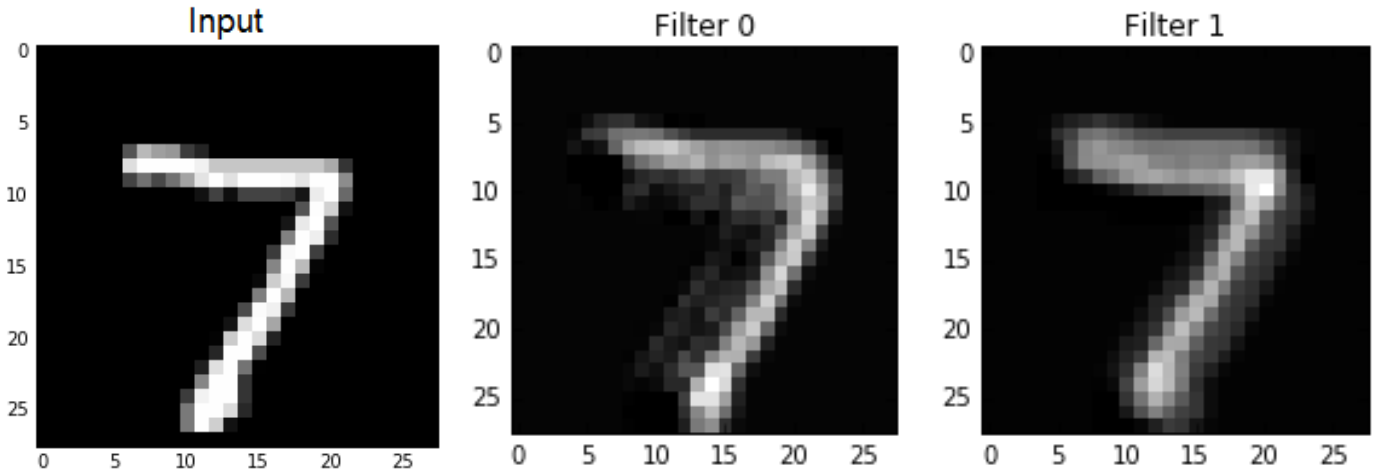
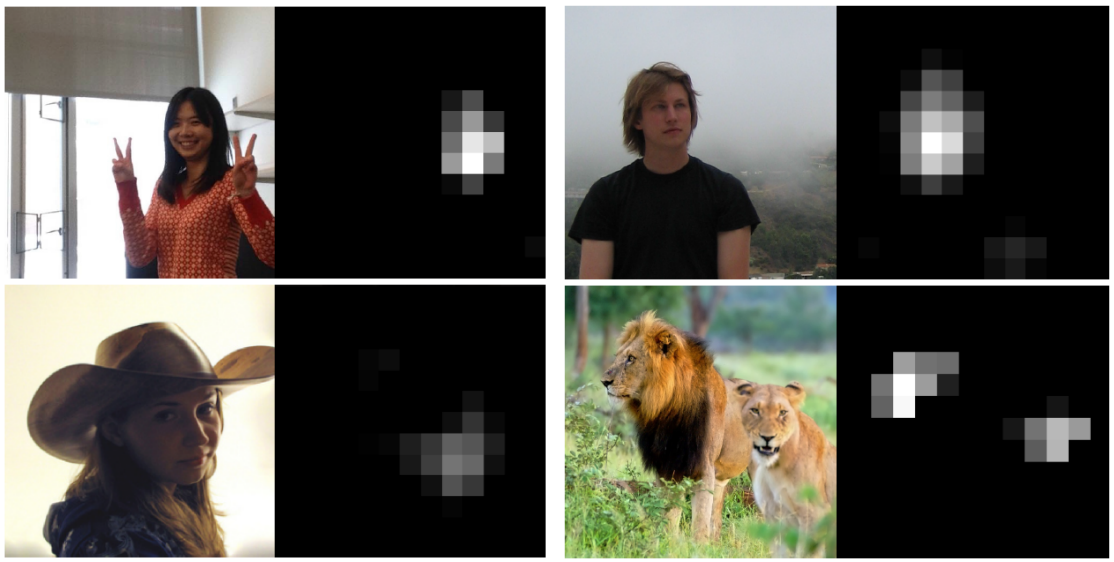
  ➔ Idea: Instead visualize activations generated by kernels
- Strong response: feature is present, weak response: feature is absent
- Possible for any layer/neuron in the network, with different resolutions
- For first-layer neurons, activations look like normal filter responses:



Source: https://medium.com/@awjuliani/visualizing-neural-network-layer-activation-tensorflow-tutorial-d45f8bf7bbc4

Visualization of Activations (cont.)

- For higher-level neurons, the activation maps are usually more coarse (remember: pooling layers)
- Channels may correspond to specific features, e.g., faces:



- Deep Visualization Toolbox [25]: Code online available
- Drawback: No insight into what exactly caused the response, coarse representation

Source: Yosinski et al. [25]

Investigating Features via Occlusion

- Idea: Move a masking patch around the input image
- If occlusions cause a significant drop in prediction confidence ➔ area important for classification (Zeiler et al. [26]).

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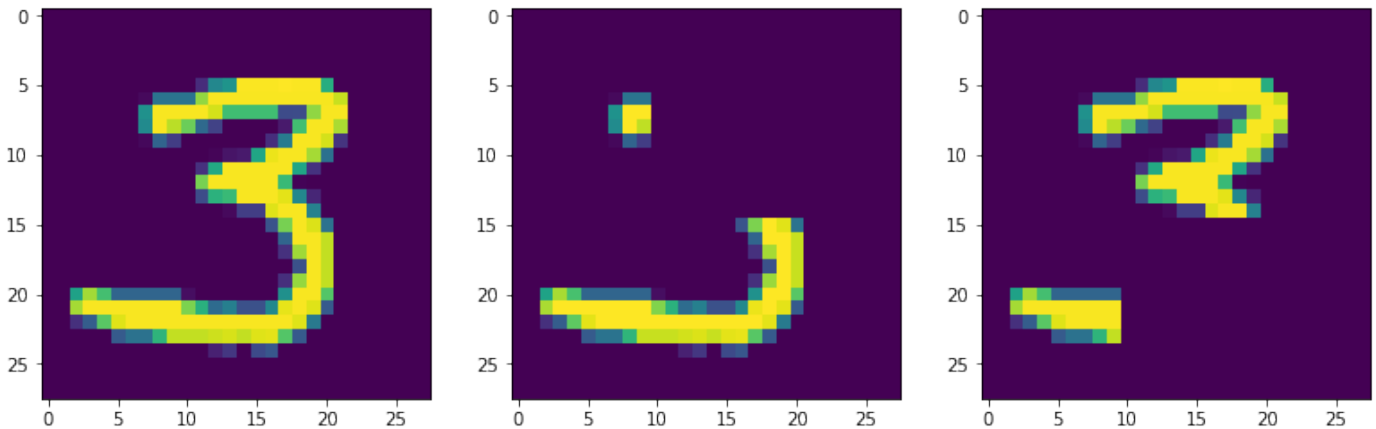
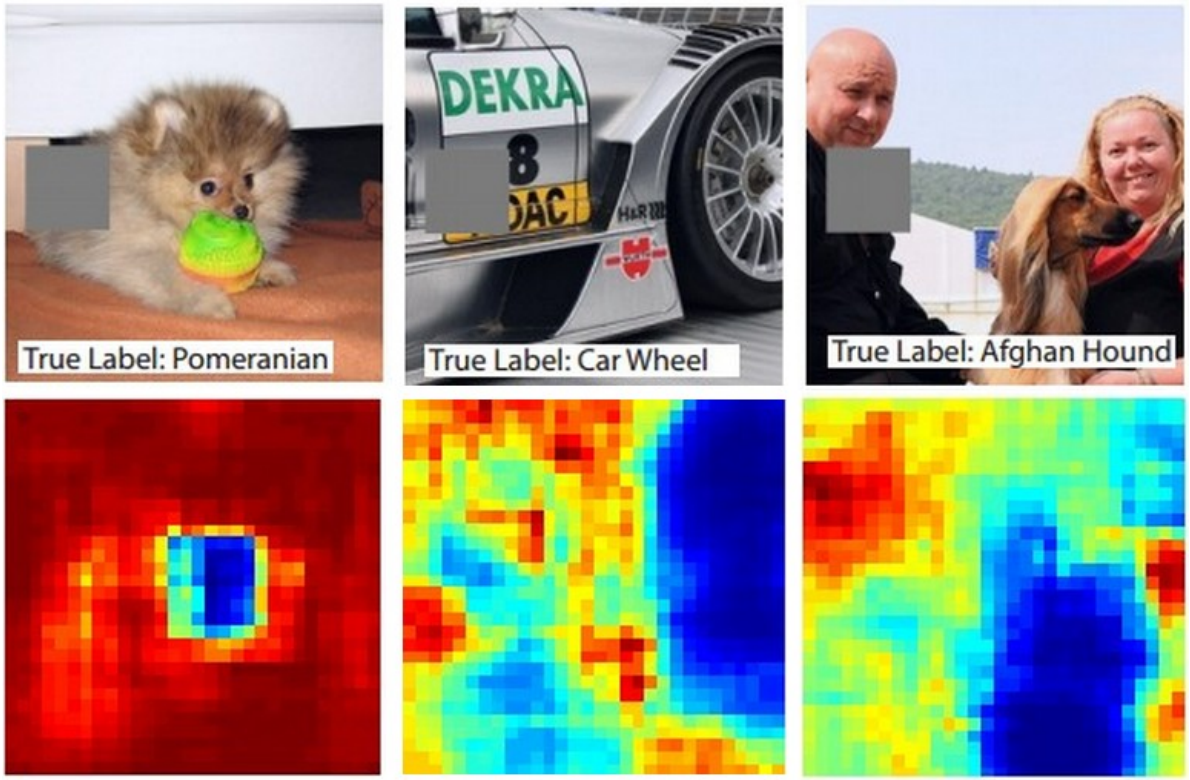


3 with 97.4% confidence 3 with 83% confidence 3 with 94% confidence

➔ Can identify confounds, e.g., wrong focus

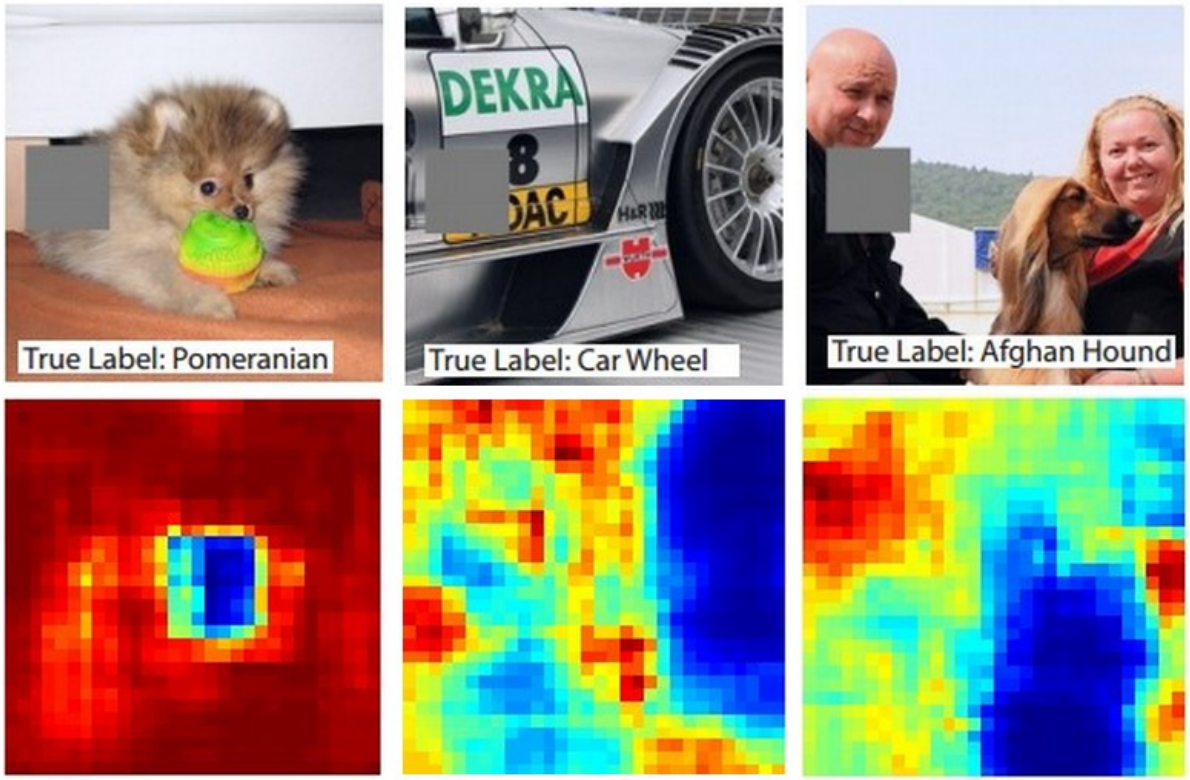
Investigating Features via Occlusion (cont.)



- Shift mask over input generates **probability heatmap** for a class

Source: Zeiler et al. [26]

Investigating Features via Occlusion (cont.)



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Source: Zeiler et al. [26]

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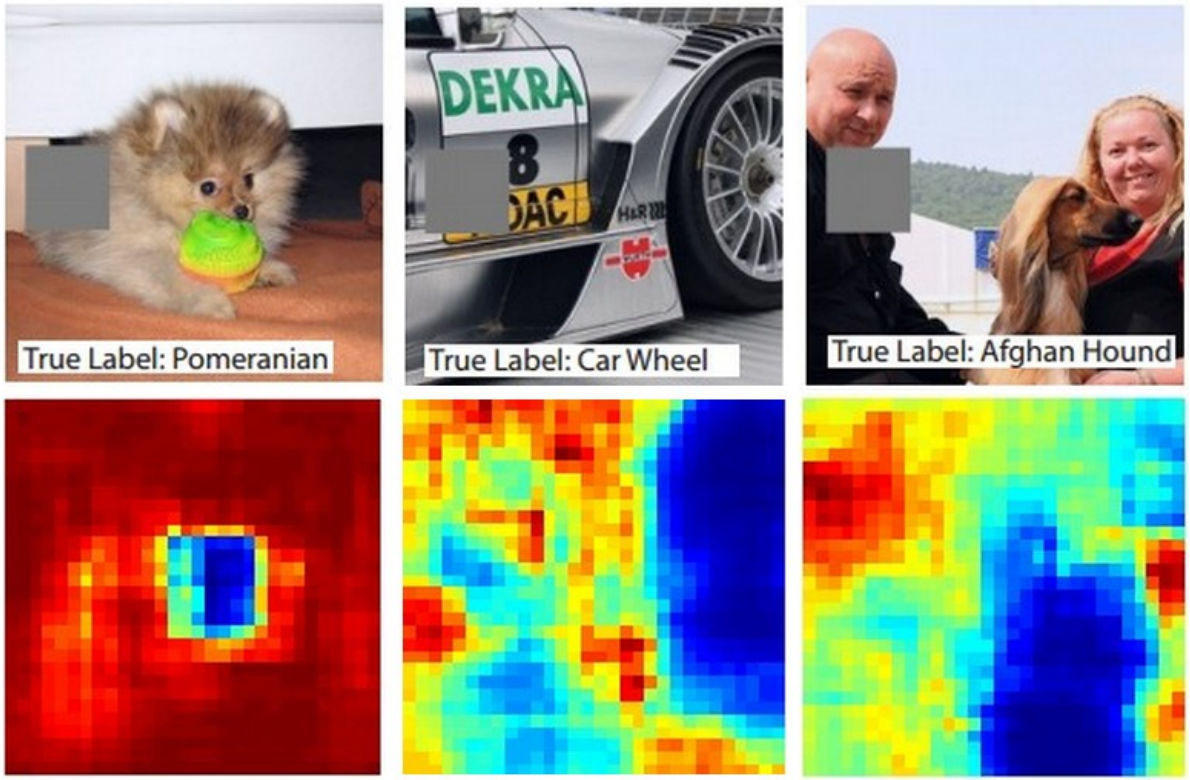

- Shift mask over input generates **probability heatmap** for a class
- Pomeranian: Only occlusion of dog's face causes a drop in performance
- Car wheel: Occlusion of advertisements - correlated feature learned?

Source: Zeiler et al. [26]

Investigating Features via Maximally Activating Images

- So far: Looking at activations for single images ➔ cumbersome
- More general question: Which inputs cause high activations?

Source: Girshick et al. [6]

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- More general question: Which inputs cause high activations?
- Idea: Find input that activates a specific neuron the most ➔"maximally activating image" [6]
- Example: Dog face? Dark spots?

Source: Girshick et al. [6]

Investigating Features via Maximally Activating Images (cont.)

- Benefits: Easy to implement, “false friends” are comparatively easy to find
- Drawbacks: Neurons don’t necessarily have semantic meaning by themselves, rather “basis vectors” of a representation

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Red flowers (and tomato sauce?)

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Specular highlights

Source: Girshick et al. [6]

t-SNE visualization of CNN codes

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- Question: How to define and show similarity?

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➔ t-SNE: t-Distributed Stochastic Neighbor Embedding

- Performs dimensionality reduction for high-dimensional datasets
- Result: 2-D embedding that respects high-dimensional distances of activations

➔ 2-D map of images

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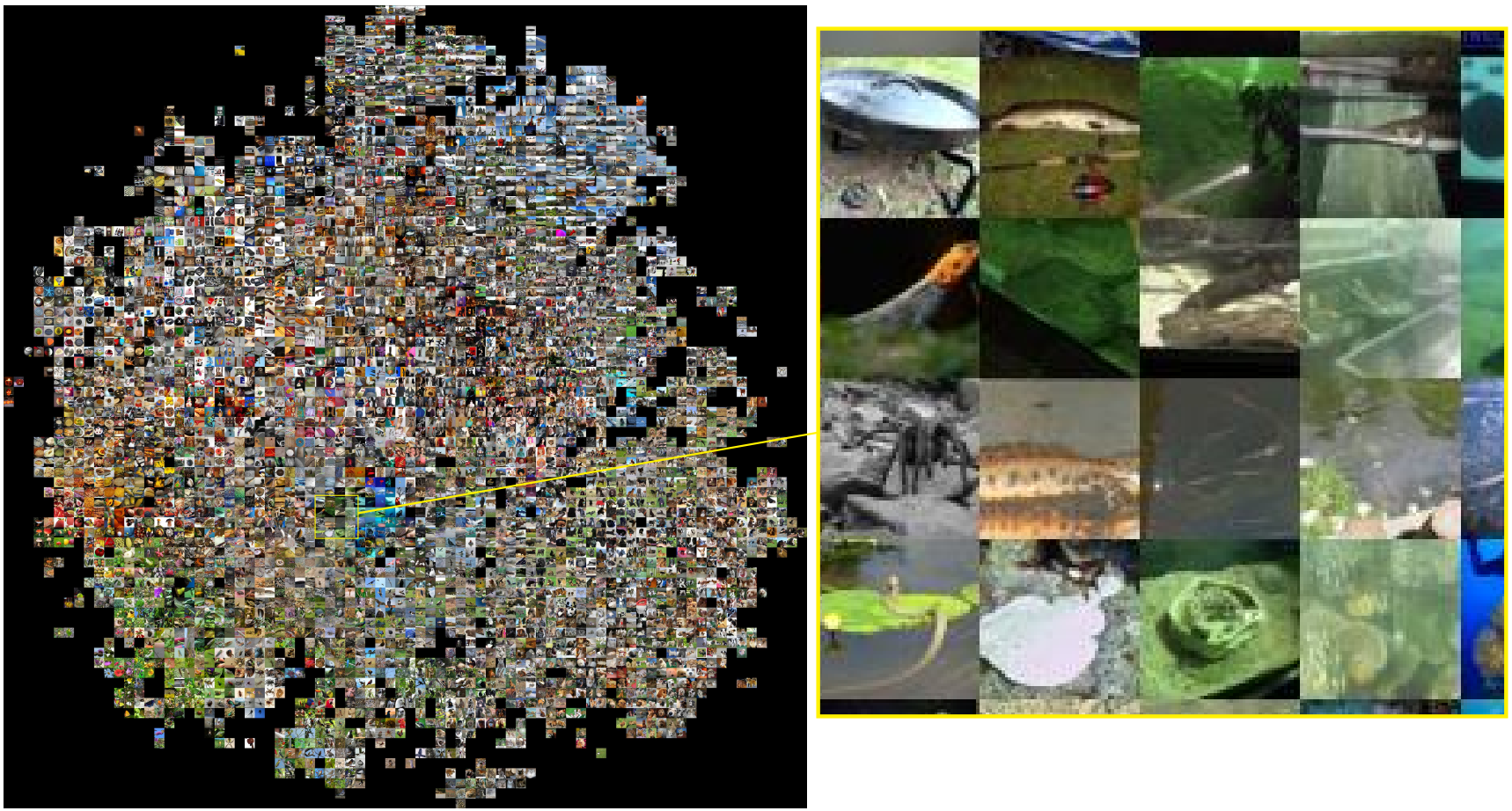
  ➔ 2-D map of images

- Can help to assess whether the network grasps the correct concept of “similarity”
- Drawback: 2-D embedding of **very** high dimensional space, difficult to interpret

t-SNE visualization of CNN codes (cont.)



Macroscopic patterns (colored regions/backgrounds - confounds?), local similarity

Source: http://cs.stanford.edu/people/karpathy/cnnembed/

NEXT TIME

ON DEEP LEARNING

Visualization and Attention Mechanisms - Part 3

A. Maier, V. Christlein, K. Breininger, S. Vesal, F. Meister, C. Liu, S. Gündel, S. Jaganathan, N. Maul, M. Vornehm, L. Reeb, F. Thamm, M. Hoffmann, C. Bergler, F. Denzinger, W. Fu, B. Geissler, Z. Yang
Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg
June 5, 2020

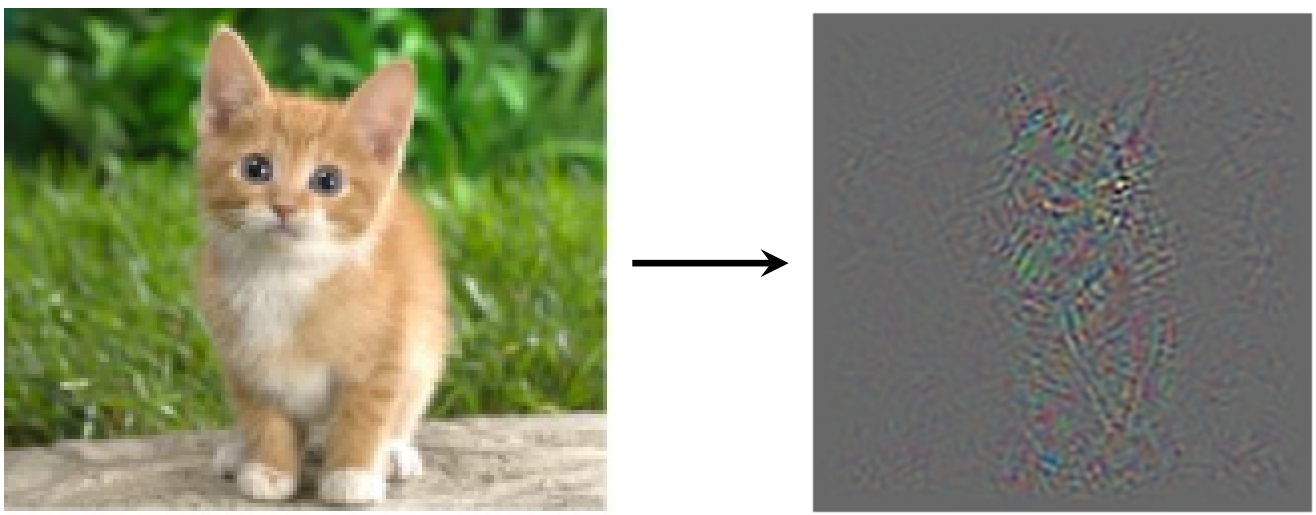
Gradient-Based Visualization

Backpropagation for Visualization

- Question: Which pixels are most significant to a neuron? Which would have most affected neuron output, had they been different?

➔ For which pixels x_i will $\frac{\partial \text{neuron}}{\partial x_i}$ be large?

- Use backpropagation to compute this gradient for a specific neuron



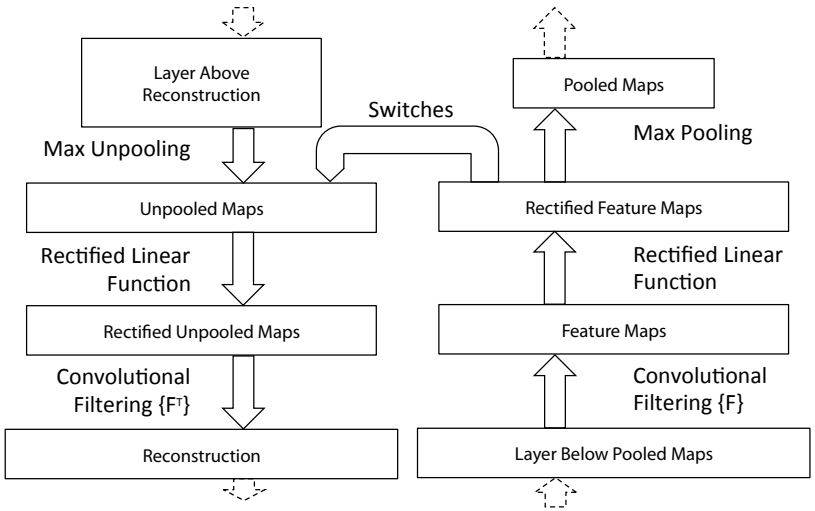
Source: [21]

Backpropagation for Visualization [20]

- Backpropagation ➔ we need a loss that we can backpropagate
- Pseudo loss: $f_n(\boldsymbol{x})$
- f_n: activation of an arbitrary neuron of any layer
- Nearly equivalent alternative (next slide): Use “reverse” network

Feature Visualization – Deconvnet [26]

- Input: trained network, image
- Choose one activation and set all others to zero
- Use reverse network (deconvnet)



Source: [26]

Feature Visualization – Deconvnet [26]

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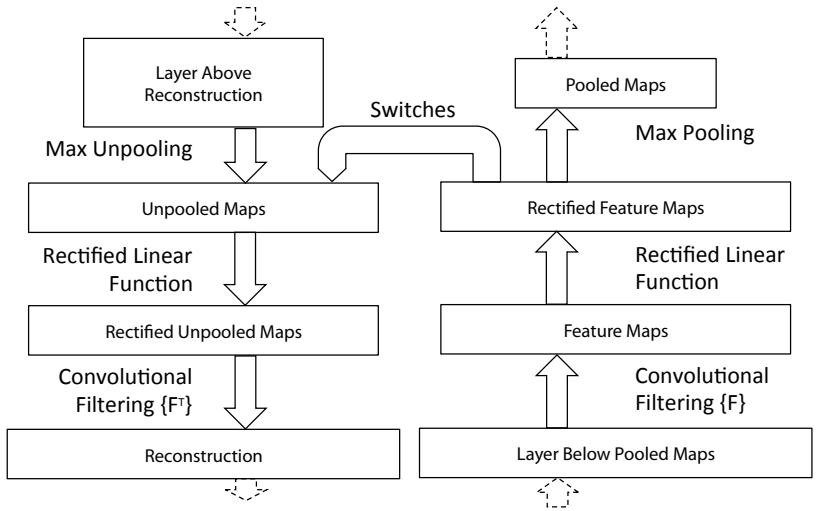
- Choose one activation and set all others to zero
- Use reverse network (deconvnet)

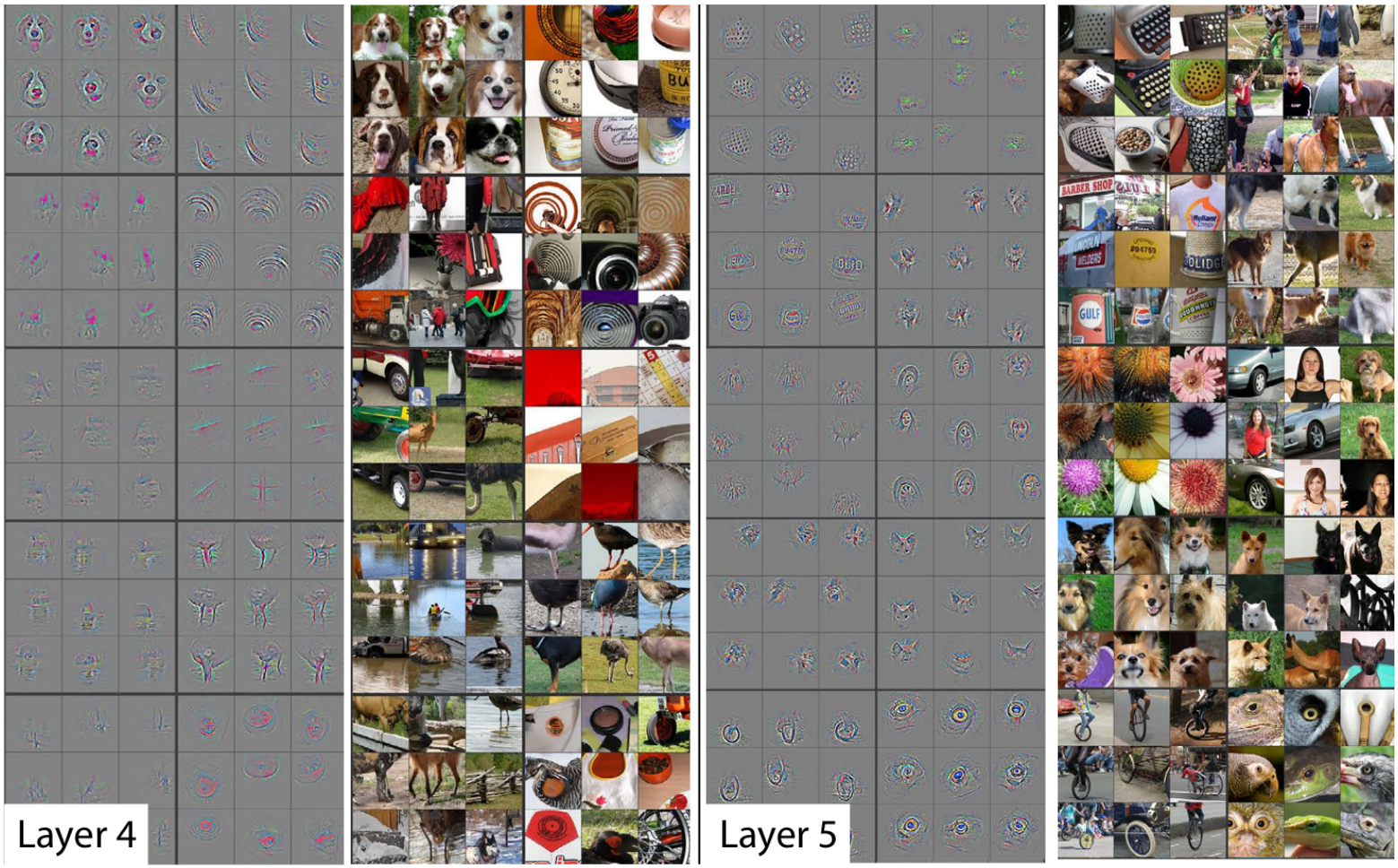


- No training involved (just record pooling locations: “switches”)
- Forward pass of reverse network effectively the same as backward pass of the network (apart from ReLU)!

Source: [26]

Deconvnet Examples

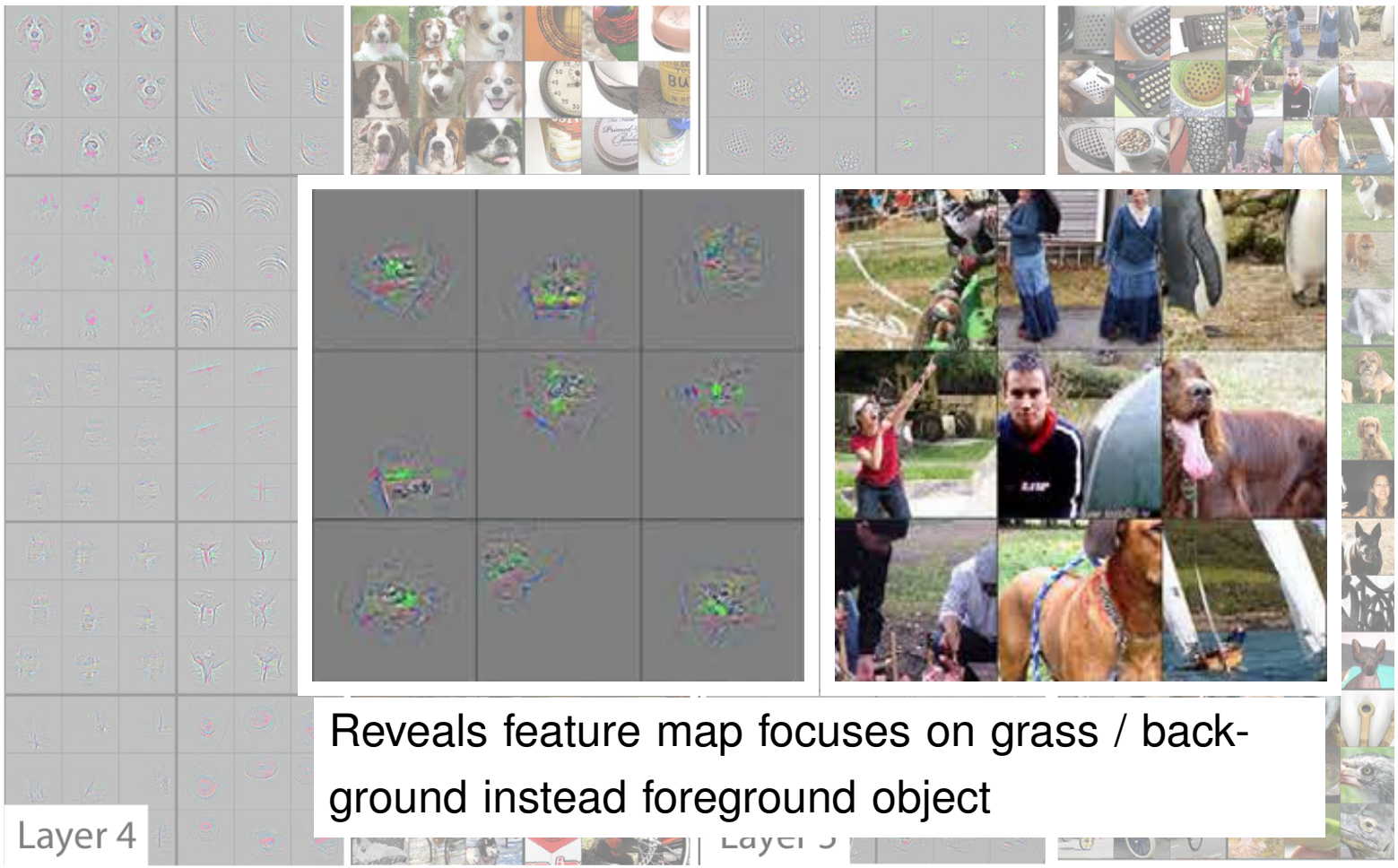
Visualization of the top 9 activations + corresponding patch



Source: [26]

Deconvnet Examples

Visualization of the top 9 activations + corresponding patch



Reveals feature map focuses on grass / background instead foreground object

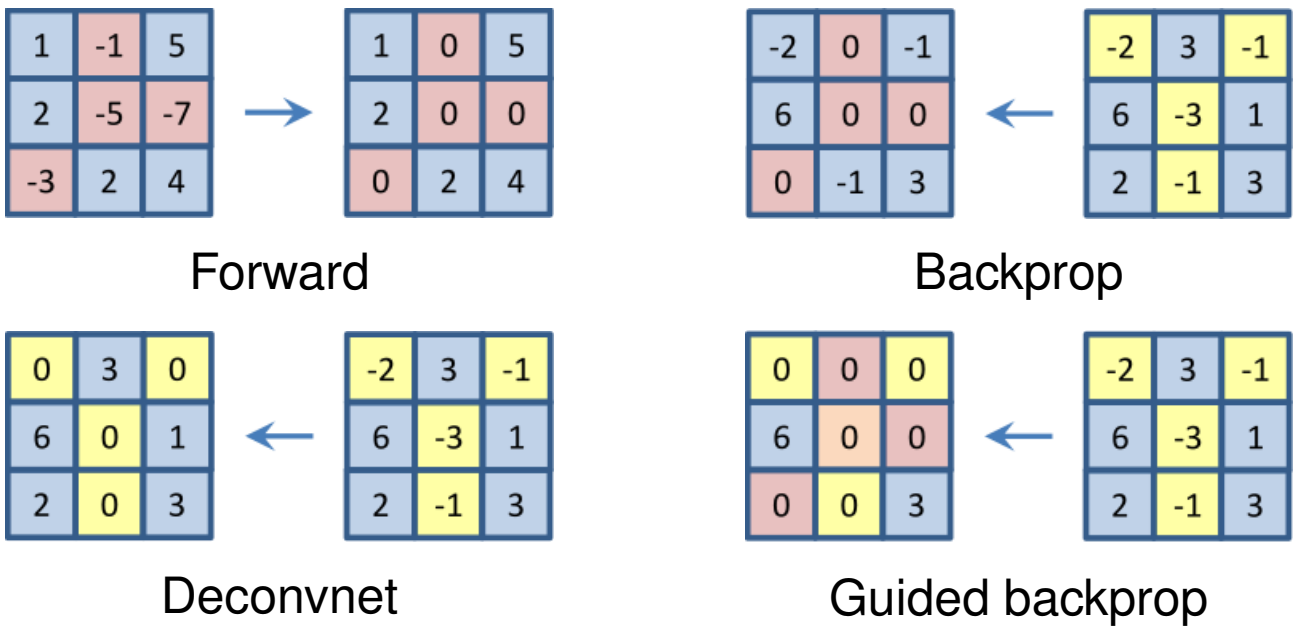
Source: [26]

Guided Backpropagation

- Improve result by "guiding" the backpropagation process
- Idea behind guided backpropagation:
  - Positive gradients = features the neuron is interested in
  - Negative gradients = features the neuron is not interested in

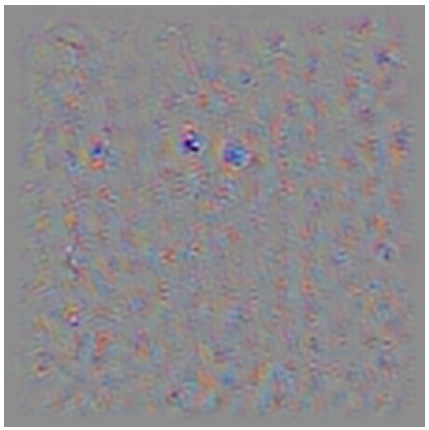
➔ Set all negative gradients in the backpropagation process to zero

- Propagating through ReLU:

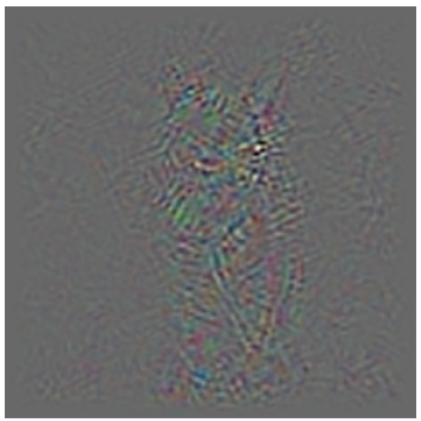


Guided backpropagation

Often interesting for higher-layer neurons ➔might reveal neurons that focus on very abstract features



Deconvnet



Backprop

Guided backprop

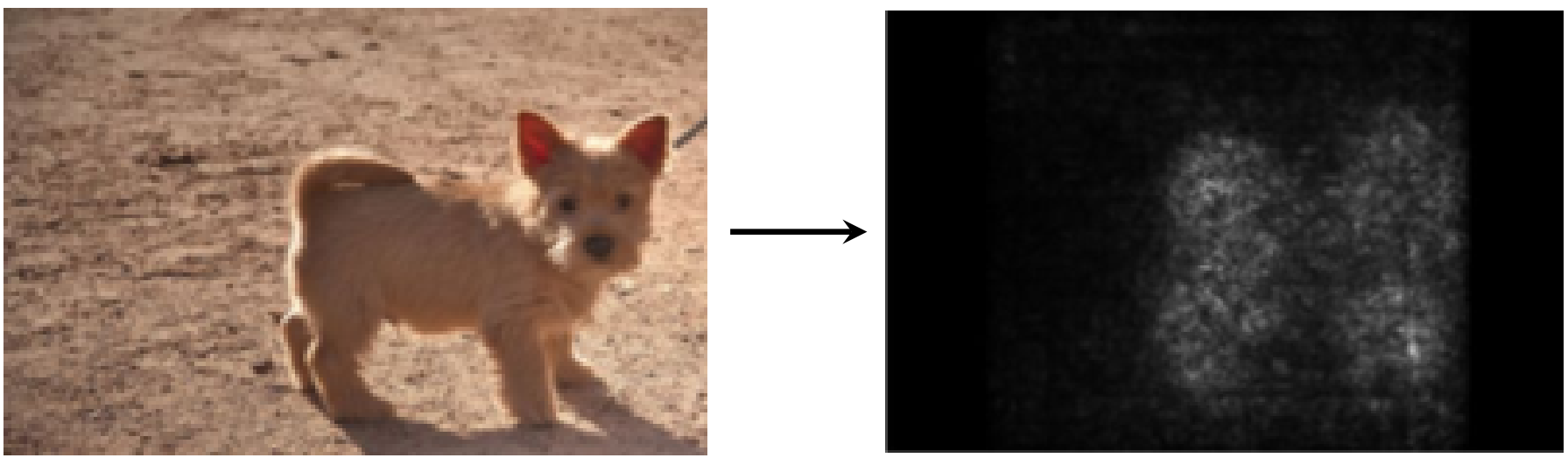
Source: [21]

Saliency maps

- Instead of investigating what influences neurons, investigate impact of pixels on **class score**
- Pseudo loss is now unnormalized class score f_c

➔ Compute gradient w.r.t. image pixels and use the absolute values

- Interesting observation: Saliency map "localizes" dog in the image, even though the network was never trained on localization!



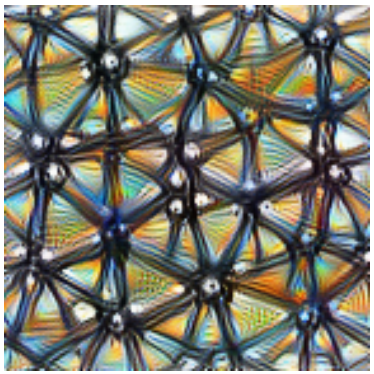
Saliency map w.r.t. class score 'dog'

Source: [20]

Parameter Visualization via Optimization

Optimization Objectives

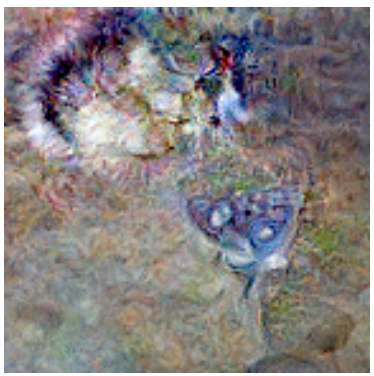
Neuron



Activation map

Layer

Logits

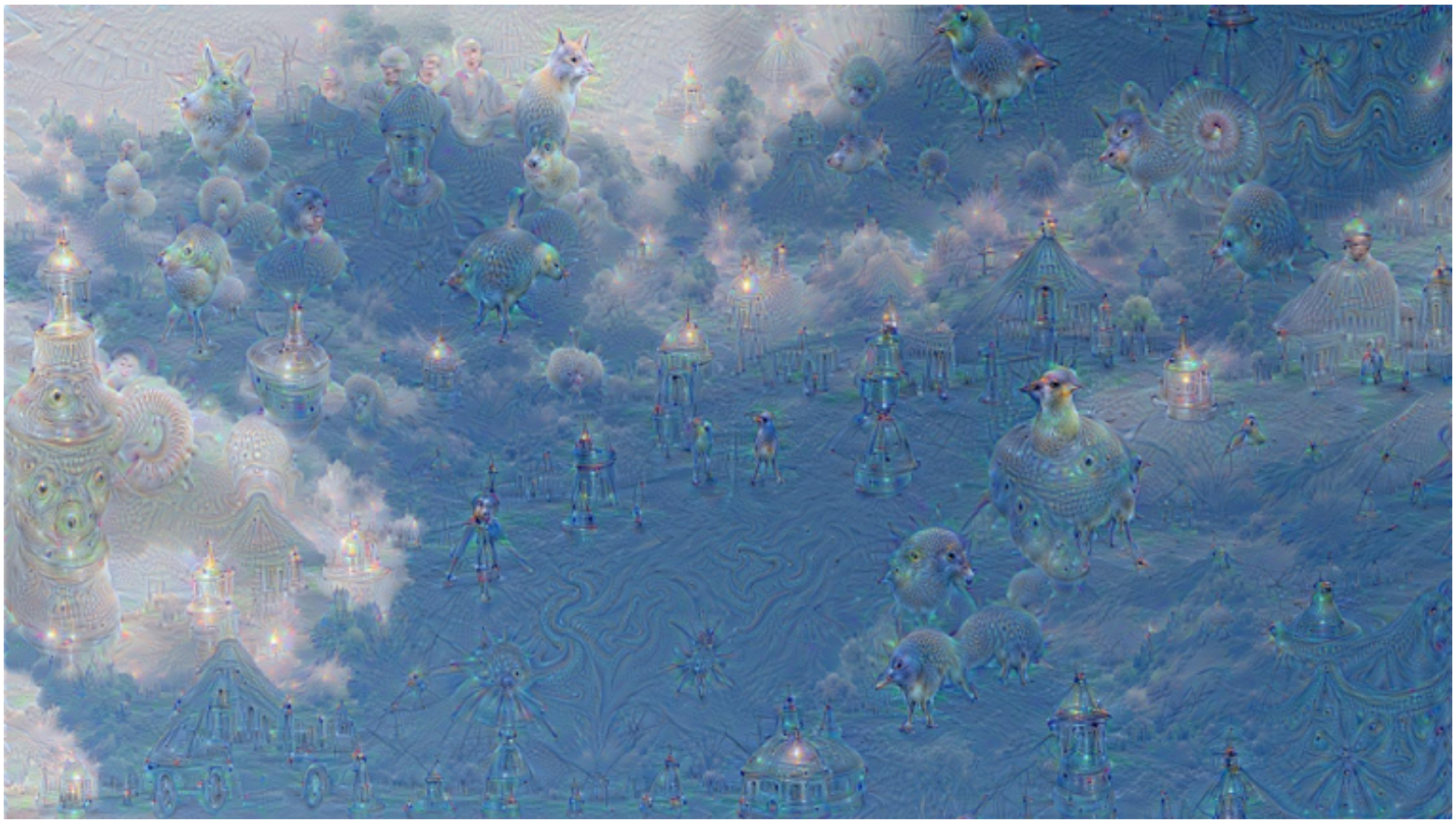


Class probability
(softmax)

Source: [174]

Google DeepDream / Inceptionism

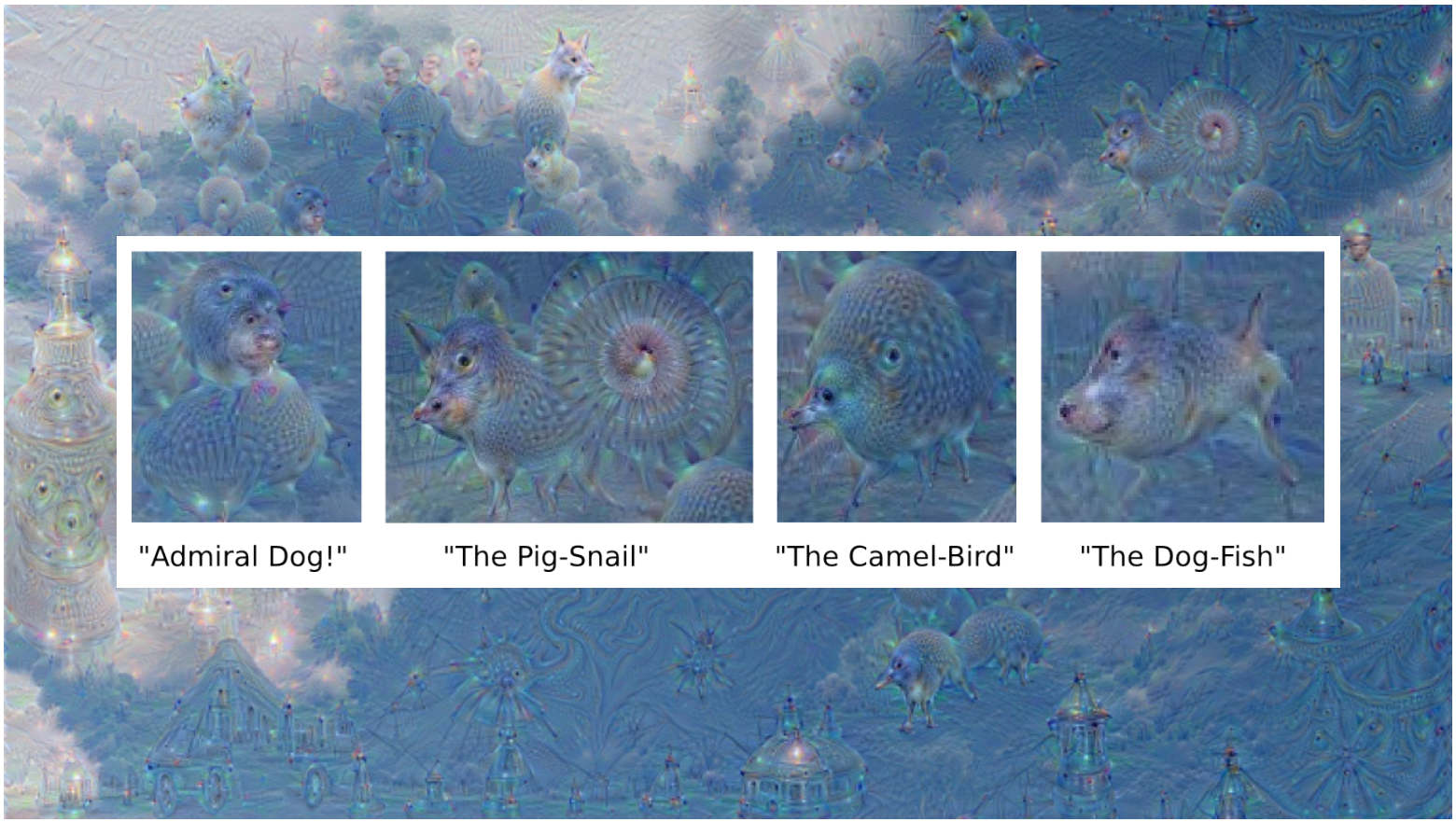
Recall from first lecture:



Source: https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

Google DeepDream / Inceptionism

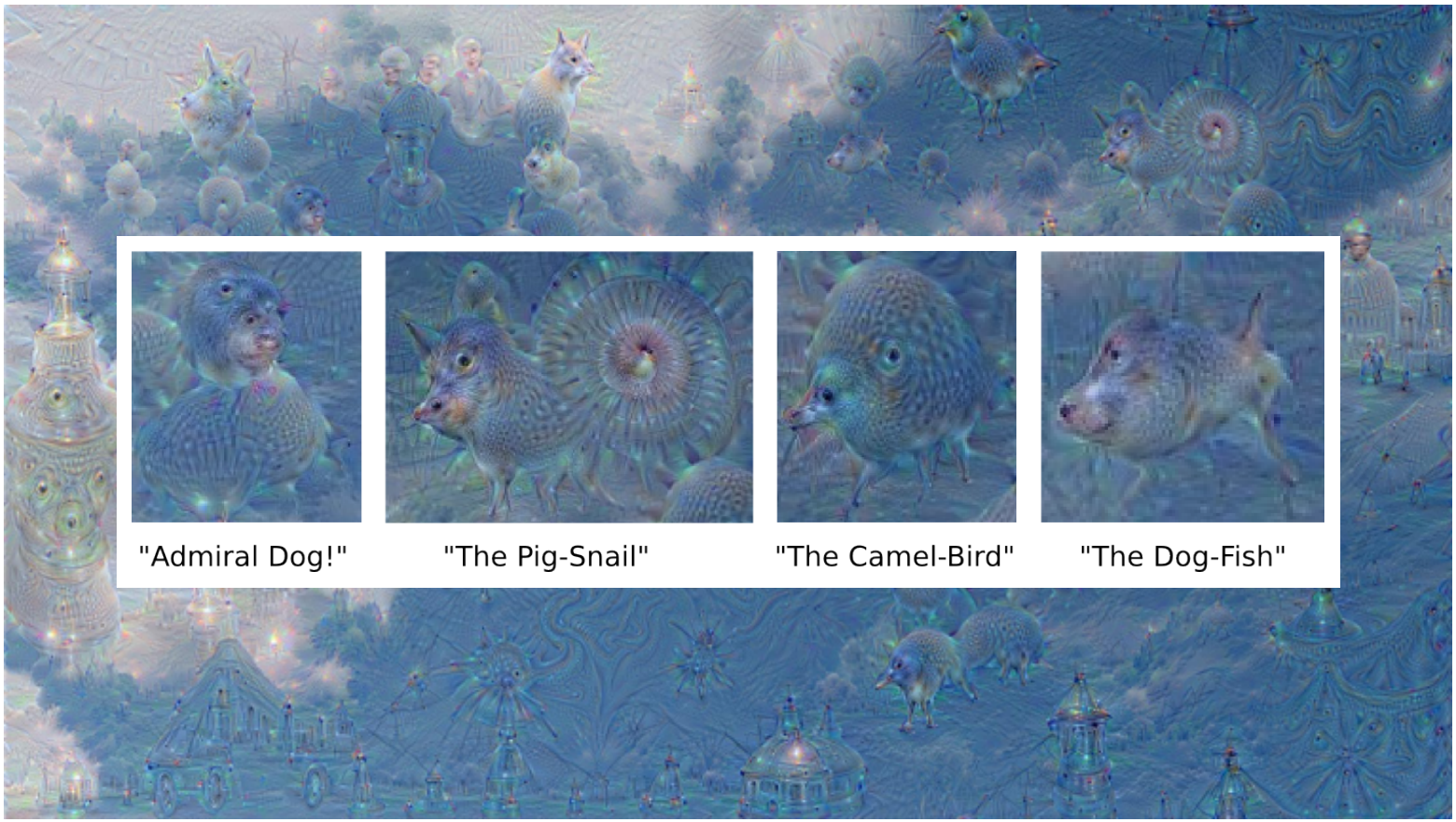
Recall from first lecture:



Source: https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

Google DeepDream / Inceptionism

Recall from first lecture:



Original idea: layer visualization

Source: https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

Google DeepDream / Inceptionism

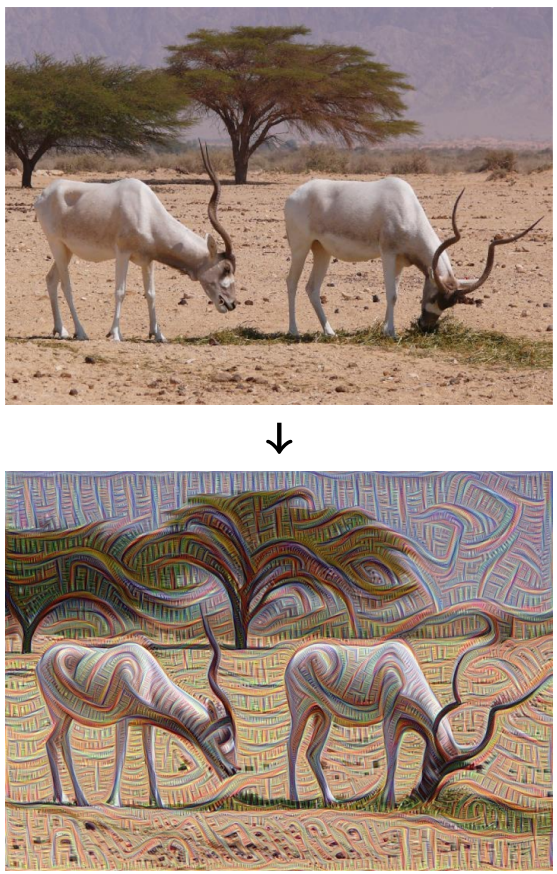
Attempt to understand the inner workings of the network: What it "dreams" about when presented with images.

Idea:

- Arbitrary image or noise as input.
- Instead of adjusting network parameters, tweak image towards high activations of a complete layer.

➔ Search for images, the layer finds interesting

- Different layers enhance different features (low or high level).



Source: https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

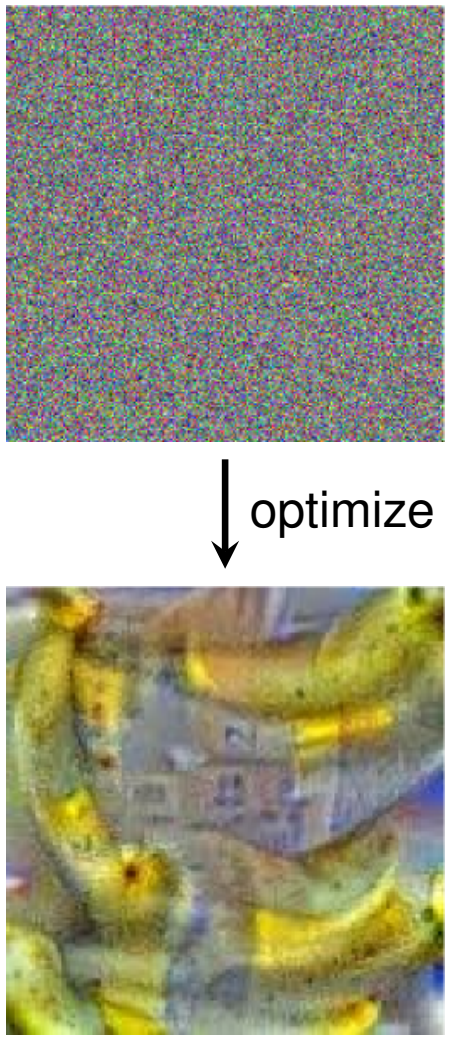
Google DeepDream / Inceptionism

Find an ℓ_2-regularised image $\boldsymbol{x}$, such that the activation $f_n(\boldsymbol{x})$ is high:

$$\max_{\boldsymbol{x}} f_n(\boldsymbol{x}) - \lambda \|\boldsymbol{x}\|_2^2$$

Algorithm

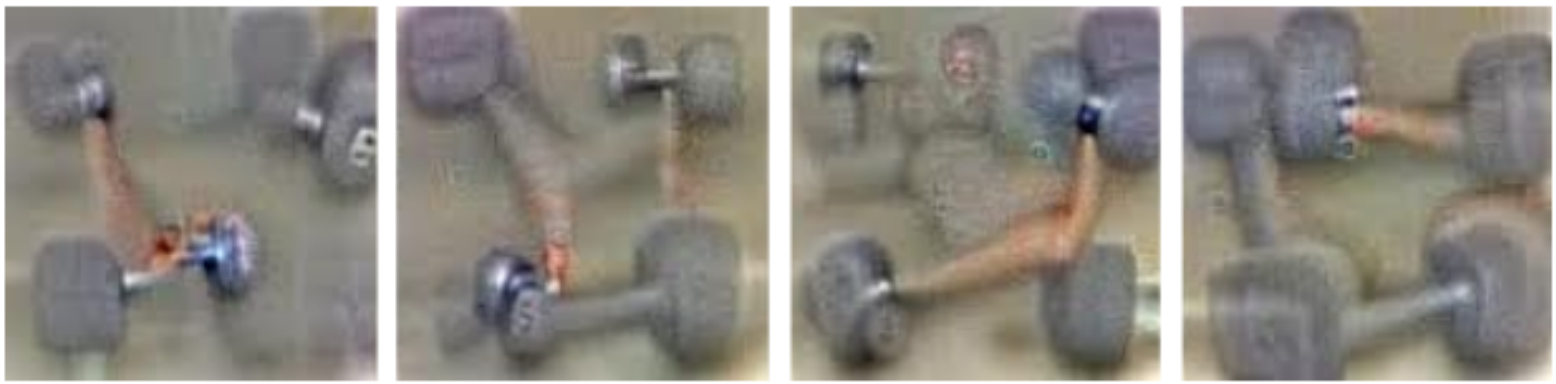
- For some fixed #iterations (10-20) do
  - Forward propagate until this layer
  - No cost minimization. Instead: maximize the L2 norm of activations of particular NN layer (gradients = layer's activations)
  - Backpropagate **all** the way to the input layer
  - ➔ Input image gets modified!
- ➔ Abstract features emerge
- Use image cascade (from small to large scales) ➔"Inceptionism"



Source: https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

Google DeepDream / Inceptionism

- This can reveal hidden weaknesses in the NN classification process



Dumbbell

- Problem: NN learned arm as part of the dumbbell

➔ Once more: good data is important!

Source: https://research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

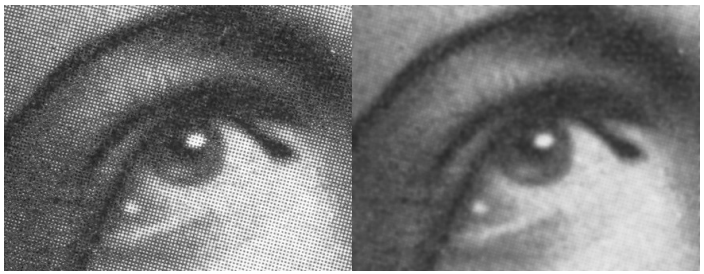
Inversion

- Inversion attempts to construct an image from a given layer activation $\hat{\boldsymbol{y}}$
- This problem corresponds to the following optimization problem [14]:

$$\boldsymbol{x}^* = \min_{\boldsymbol{x}} \left(\left\| f(\boldsymbol{x}) - \hat{\boldsymbol{y}} \right\|_2^2 + \lambda r(\boldsymbol{x}) \right)$$

  - $\boldsymbol{x}^*$ is the reconstructed RGB-image
  - $f(\boldsymbol{x})$ is the network output for input image $\boldsymbol{x}$
  - $\hat{\boldsymbol{y}}$ is the measured network output
  - $r(.)$ is a regularization function (e.g.: ℓ_2, TV)
- Clearly visible features in the reconstructed image correspond to features which matter most to the CNN

Three families of Regularizers



High frequency penalization

- **High frequency noise** degrades the reconstructions
- **TV** can be used as $r(\mathbf{x})$ to encourage sparse gradients
- **Low-pass** filters can be applied in every iteration to $\mathbf{x}$
- **Edge preserving** filters have also been proposed

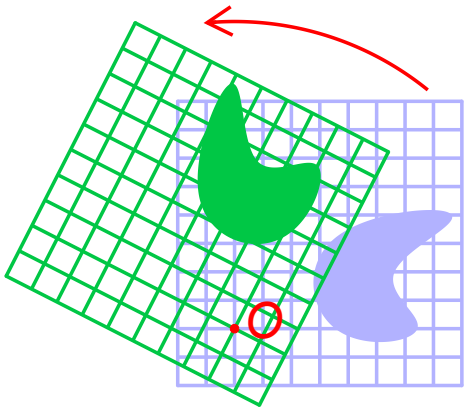
Properties

\+ Simple

\+ **Effective** in producing recognizable features

– **Suppresses legitimate** high frequency features

Three families of Regularizers



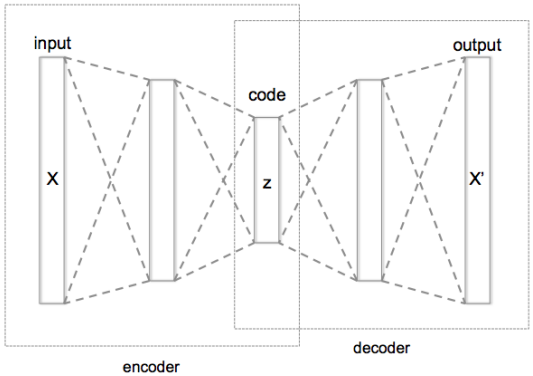
Transform robustness

- Input should be **invariant** to spatial **transformations**
- Same as **data augmentations**
- Randomly **rotate, scale or jitter x**

Properties

+ Simple
+ **Effective** in producing recognizable features
− **Orientation is suppressed** even if it was informative

Three families of Regularizers



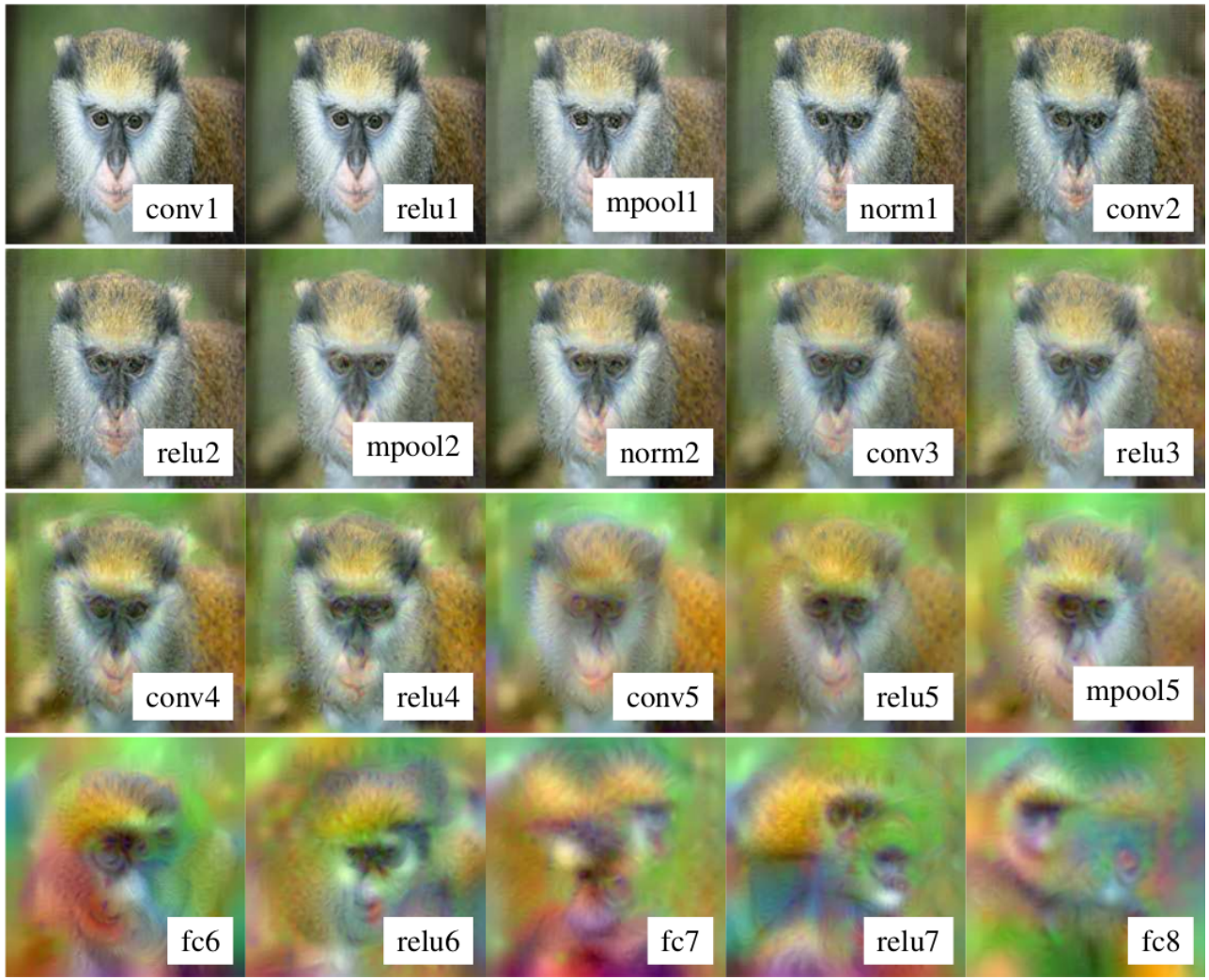
Learned priors

- Enforce a **prior** on **x** to look like a natural image
- Needs a **generative model**
- Use a **GAN** or **VAE**
- Instead of optimizing **x** optimize in **latent space**

Properties

- Needs a **trained** generative model
+ Very **nice images**
- **Ambiguous** whether to attribute features in result to the prior or the network

Inversion – Examples



Source: [14]

NEXT TIME

ON DEEP LEARNING

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG

SCHOOL OF ENGINEERING

Visualization and Attention Mechanisms - Part 4

A. Maier, V. Christlein, K. Breininger, S. Vesal, F. Meister, C. Liu, S. Gündel, S. Jaganathan, N. Maul, M. Vornehm, L. Reeb, F. Thamm, M. Hoffmann, C. Bergler, F. Denzinger, W. Fu, B. Geissler, Z. Yang
Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg

June 5, 2020

Attention Mechanisms

What is Attention?

Humans process data by actively shifting their focus:

- Different parts of an image carry different information
- Words derive their specific meaning from **context**
- Remember specific, **related** events in the past
- Allows to follow one thought at a time while suppressing information **irrelevant** to the task
- Example: Cocktail party problem

Source: https://www.nidcd.nih.gov/newsletter/2012/summer/cocktail-party-problem-how-brain-decides-what-not-hear

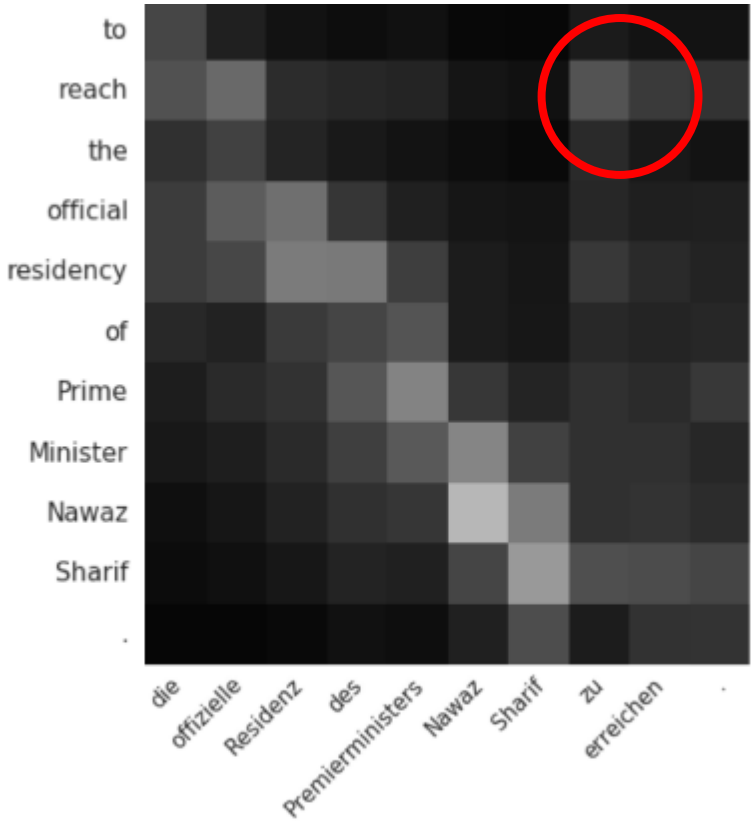
Implicit attention

Reminder: Saliency maps (impact of pixels on class score)

Source: Adapted from [9], [20]

Implicit attention

Reminder: Saliency maps (impact of pixels on class score)



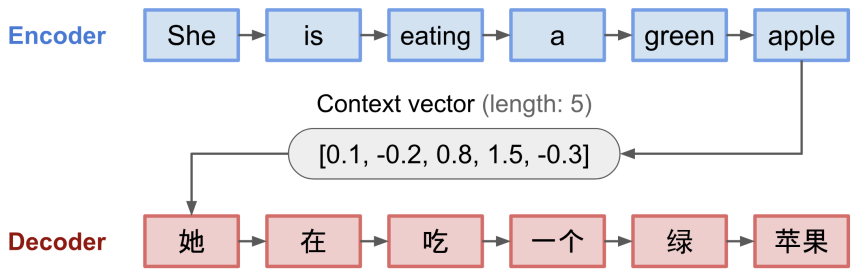
Plotting gradients from CNN in English to German translation

- ➔ Networks learn attention implicitly
- ➔ Can **explicit attention mechanisms** boost performance?

Source: Adapted from [9], [20]

Sequence to sequence models

- Encoder/decoder architecture, typically RNNs

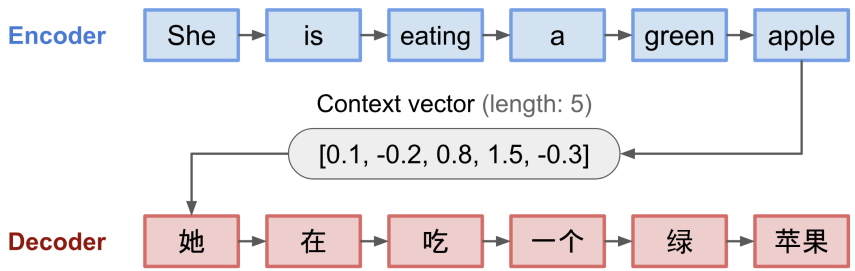


Encoder-decoder for translation

Source: https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html#neural-turing-machines

Sequence to sequence models

- Encoder/decoder architecture, typically RNNs
- Encoder network
  - Receives input sequence $\{\mathbf{x}_1, \ldots, \mathbf{x}_T\}$
  - ➔ Computes hidden states $\{\mathbf{h}_1, \ldots, \mathbf{h}_T\}$



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Sequence to sequence models

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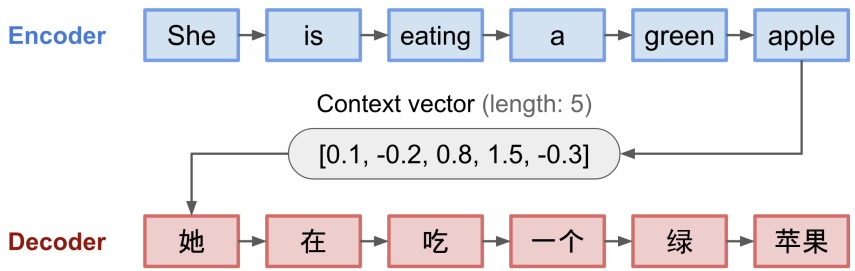
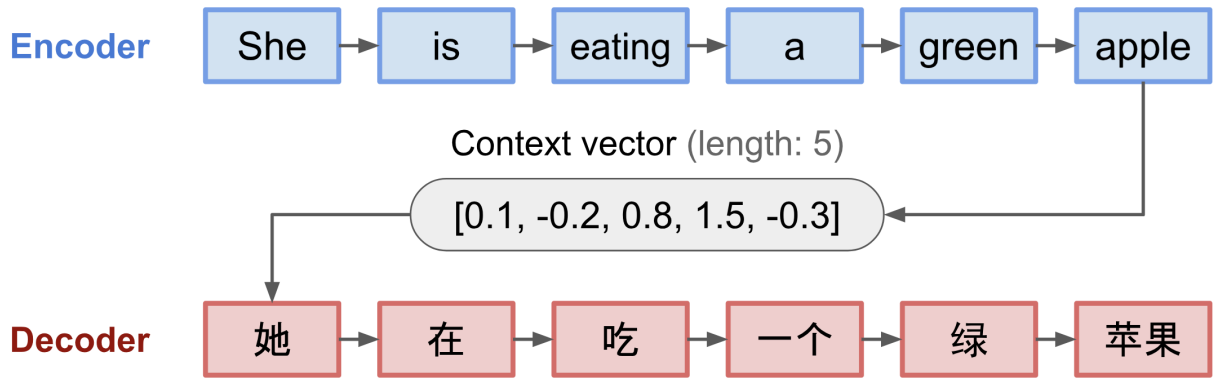
  - Receives input sequence $\{\mathbf{x}_1, \ldots, \mathbf{x}_T\}$
  - ➔ Computes hidden states $\{\mathbf{h}_1, \ldots, \mathbf{h}_T\}$
- Decoder network:
  - Receives **"context vector" $\mathbf{h}_T$**
  - Computes own hidden states $\{\mathbf{s}_1, \ldots, \mathbf{s}_{T'}\}$
  - ➔ Generates output sequence $\{\mathbf{y}_1, \ldots, \mathbf{y}_{T'}\}$
- Split allows different length in input/output



Encoder-decoder for translation

Source: https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html#neural-turing-machines

Sequence to sequence models (cont.)



Encoder-decoder for translation

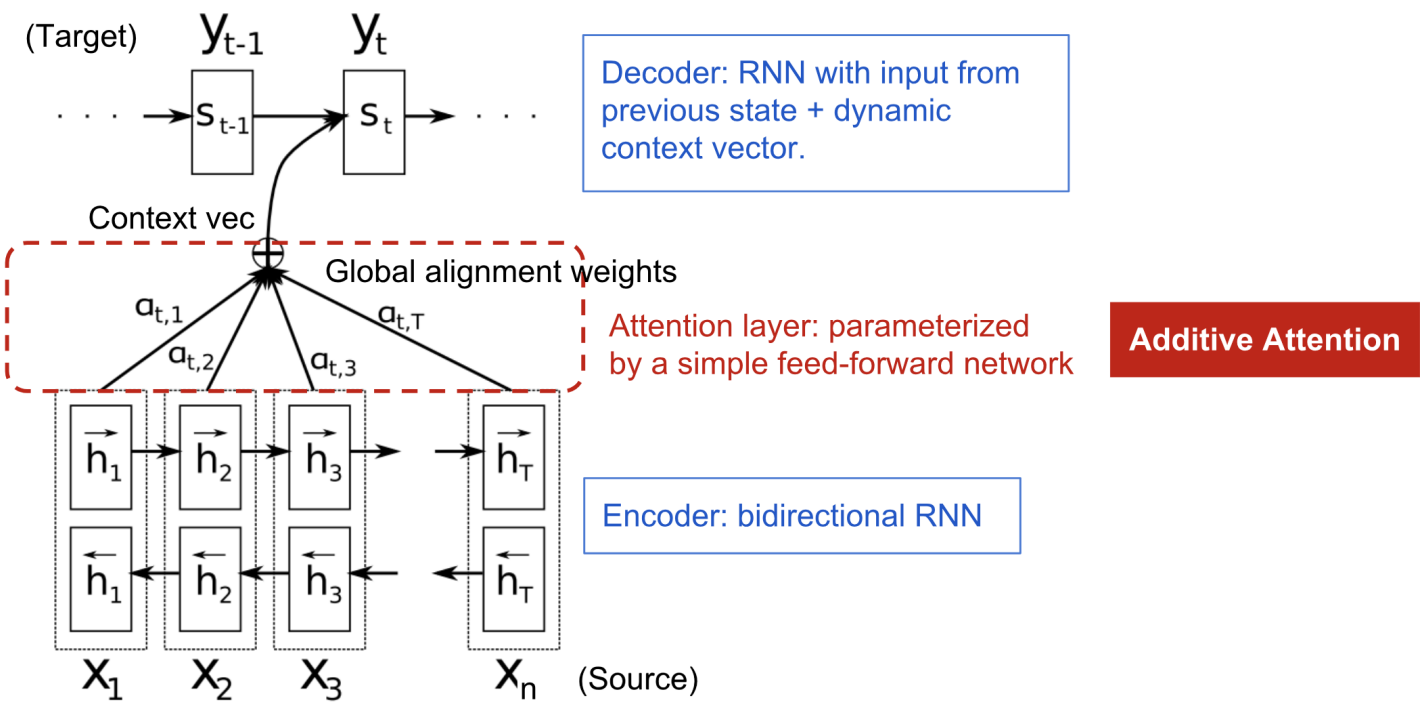
- Different parts of input relate to different parts of output
- Encoding complete content difficult (even for **LSTMs**)

Source: https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html#neural-turing-machines

Attention for Seq2Seq: Context vector

- Issue: Context vector $\mathbf{h}_T$ provides no access to earlier inputs

➔ Provide access with shortcuts: **dynamic** context vector as **combination** of all previous hidden states



Source: https://lilianweng.github.io/lil-log/2018/06/24/attention-attention.html#neural-turing-machines, adapted from [1]

Attention for Seq2Seq: Context vector

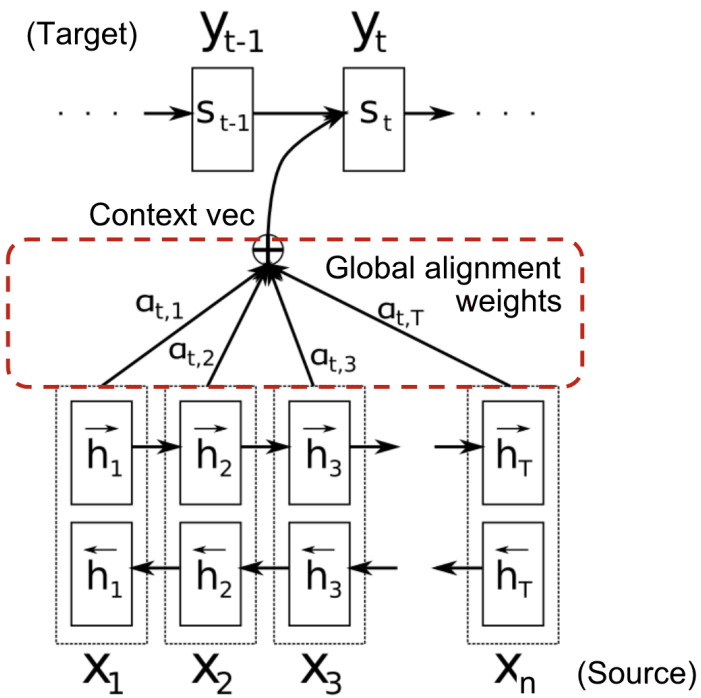
Bahdanau et al. [1]:

"Neural machine translation by jointly learning to align and translate"

- Encoder: **Bidirectional** LSTM with
  $\mathbf{h}_i = [\overrightarrow{\mathbf{h}_i}, \overleftarrow{\mathbf{h}_i}]$
- Dynamic context vector
  $\mathbf{c}_t = \sum_i \alpha_{t,i} \mathbf{h}_i$
  with alignment weights

$$\alpha_{t,i} = \text{align}(y_t, x_i)$$
$$= \frac{\exp(\text{score}(\mathbf{s}_{t-1}, \mathbf{h}_i))}{\sum_i \exp(\text{score}(\mathbf{s}_{t-1}, \mathbf{h}_i))}$$

according to a **score** function



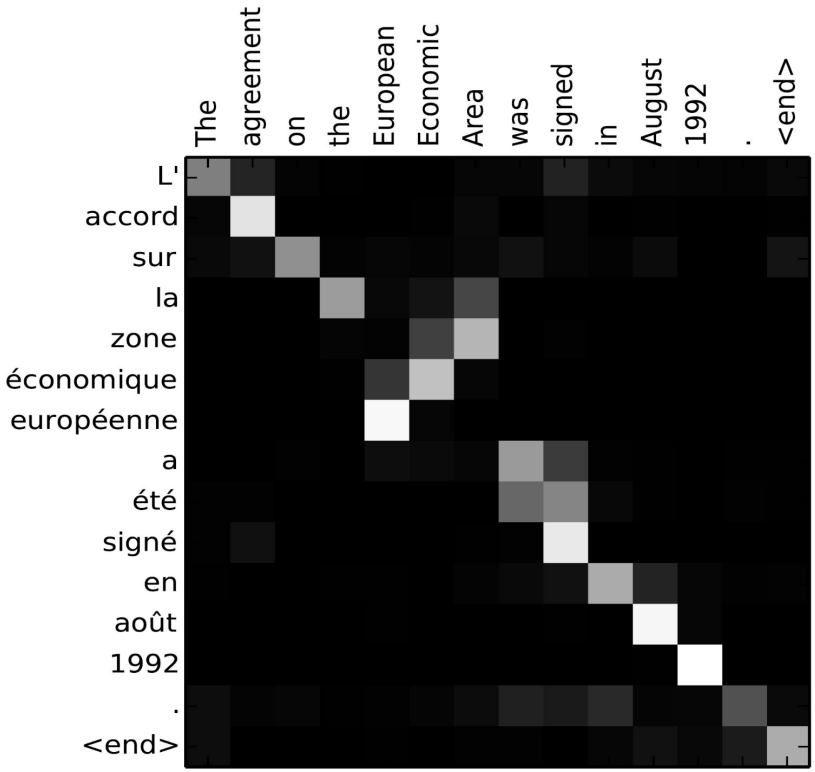
Source: Adapted from [1]

Attention for Seq2Seq: Score Function (cont.)

- Bahdanau et al.: **score** function represented by single layer FCN

$$\text{score}(\mathbf{s}_t, \mathbf{h}_i) = \mathbf{v}_\alpha^T \mathbf{W}_\alpha [\mathbf{s}_t, \mathbf{h}_t]$$

  with **trainable** weights $\mathbf{v}_\alpha$ and $\mathbf{W}_\alpha$
- Determines **alignment**: Which inputs are important for which outputs
- Alignment scores allow for **interpretation**



Source: Adapted from [1]

Attention for Seq2Seq: Alternative Score Functions

- Content-based (cosine similarity) [7]:

$$\text{score}(\mathbf{s}_t, \mathbf{h}_i) = \textbf{cosine}(\mathbf{s}_t, \mathbf{h}_i)$$

- General [13]:

$$\text{score}(\mathbf{s}_t, \mathbf{h}_i) = \mathbf{s}_t^T \mathbf{W}_\alpha \mathbf{h}_i$$

- Dot-product [13]:

$$\text{score}(\mathbf{s}_t, \mathbf{h}_i) = \mathbf{s}_t^T \mathbf{h}_i$$

- Scaled Dot-product [23]:

$$\text{score}(\mathbf{s}_t, \mathbf{h}_i) = \frac{\mathbf{s}_t^T \mathbf{h}_i}{\sqrt{n}}$$

where n is the size of the hidden state

Soft Attention vs. Hard Attention

- So far: Attention is computed over all patches/inputs: **Soft/global attention**

+ Model is fully differentiable

− Not effective/efficient for large inputs

Soft Attention vs. Hard Attention

- So far: Attention is computed over all patches/inputs: **Soft/global attention**

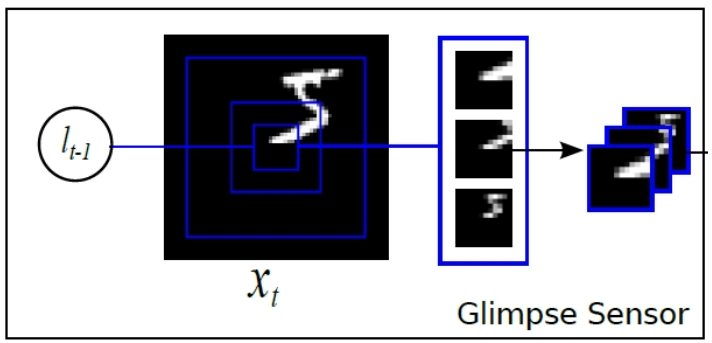
\+ Model is fully differentiable

– Not effective/efficient for large inputs

- Alternative: **Hard attention**
  Fixed size glimpses on the input, e.g., by sampling from a distribution

\+ Lower computation times

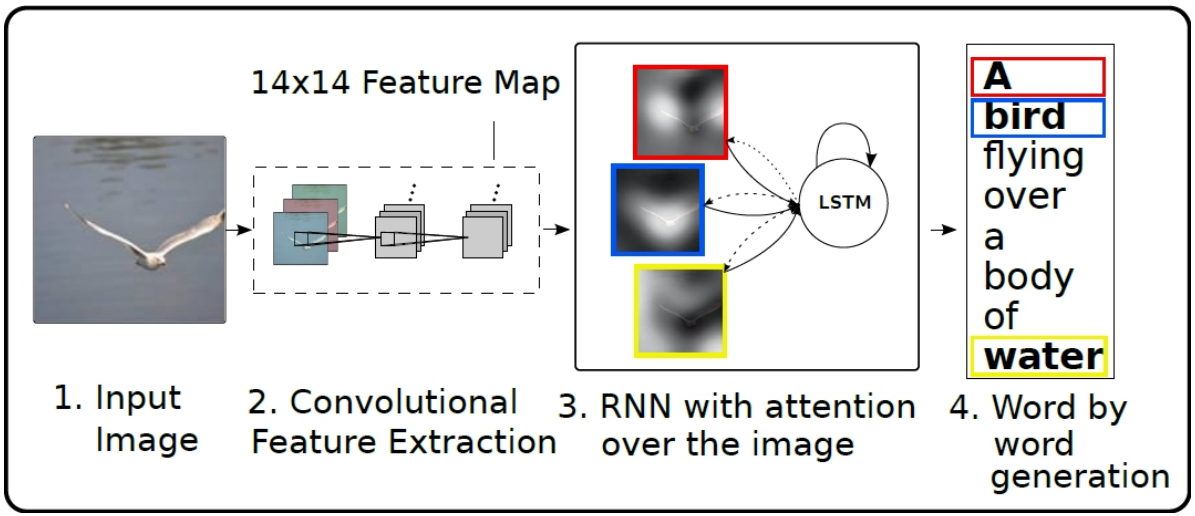
– Not differentiable, requires e.g. reinforcement learning techniques to train (➔ Lecture 9)



Number parsing using glimpses [16]

- "Local attention" [8], [13] as blend: predict center position for focus window/kernel

Show-Attend-Tell [24]



Show-Attend-Tell

- Task: Automatic generation of image captions
- Different elements and their relationship in the image trigger different words

➔ Attention mechanism to improve caption quality

Source: Adapted from [24]

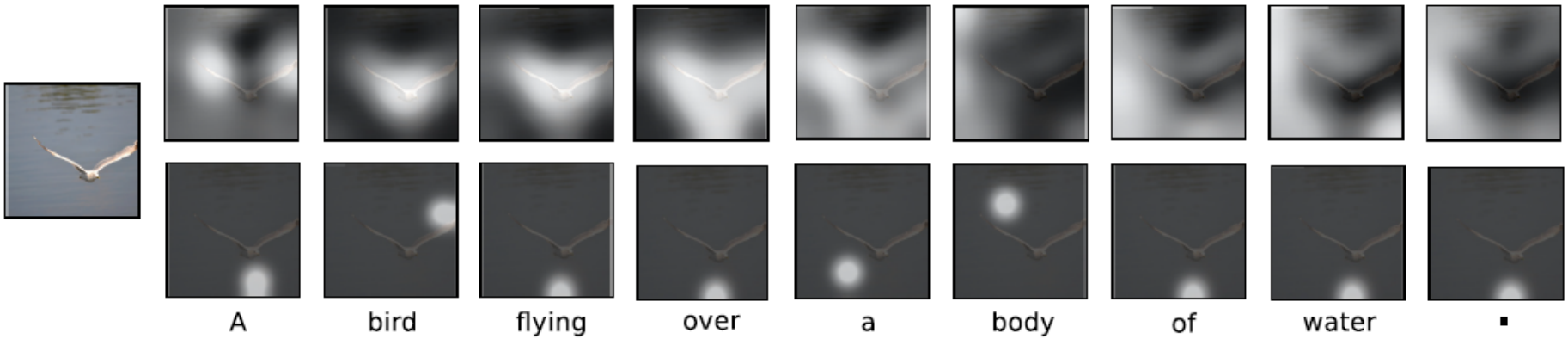
Show-Attend-Tell [24] (cont.)

A woman is throwing a frisbee in a park.

Attention weighs CNN feature maps according to caption produced **so far** ➔ allows for interpretation

Source: Adapted from [24]

Show-Attend-Tell [24] - Soft vs. Hard Attention



Soft (top row) vs. hard attention (bottom row). Both models produced the same sequence.

- Deterministic soft attention: Trained end-to-end
- Stochastic hard attention: Trained with reinforcement learning
- Sharp vs. fuzzy attention
- Slight performance benefit of hard attention in [24], but RL usually connected to much longer training times

Self-Attention

- Computes attention of sequence to "itself"
- Example: "*The animal didn't cross the street because it was too tired.*"
  Does "*it*" refer to "*animal*" or "*street*"?

Source: [3]

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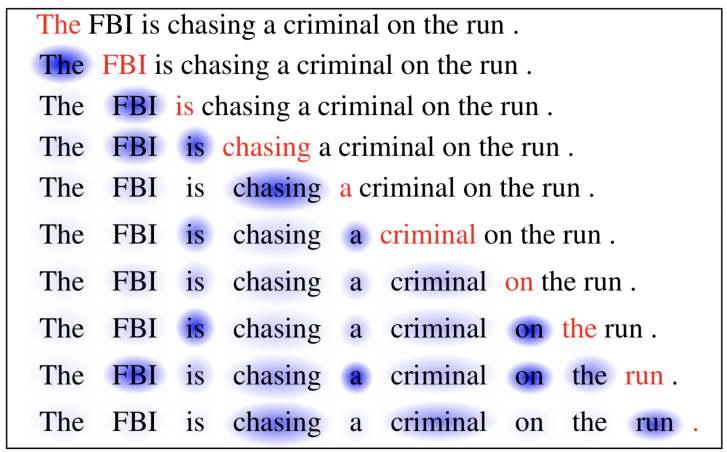


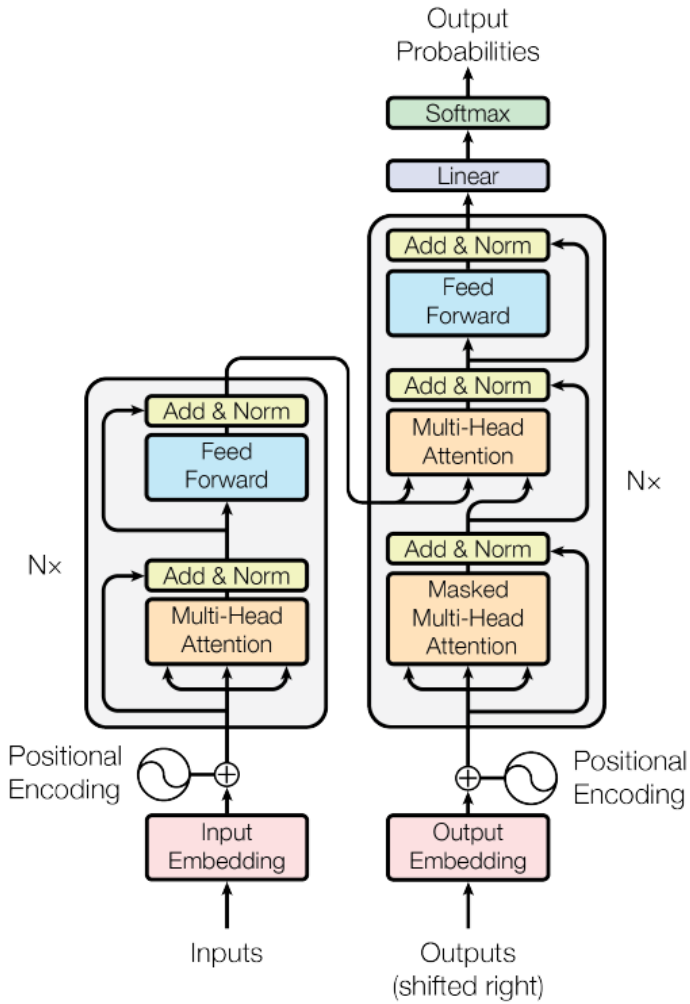
Self-attention w. r. t. word in red.

Source: [3]

Attention is all you need (AIAYN) [23]

- Vaswani et al. [23]: Machine translation based **only on attention**, no convolution or recurrence
- Core idea: Iteratively improve representation by self-attention

➔ “Transformer” architecture



Attention is all you need (AIAYN) [23]

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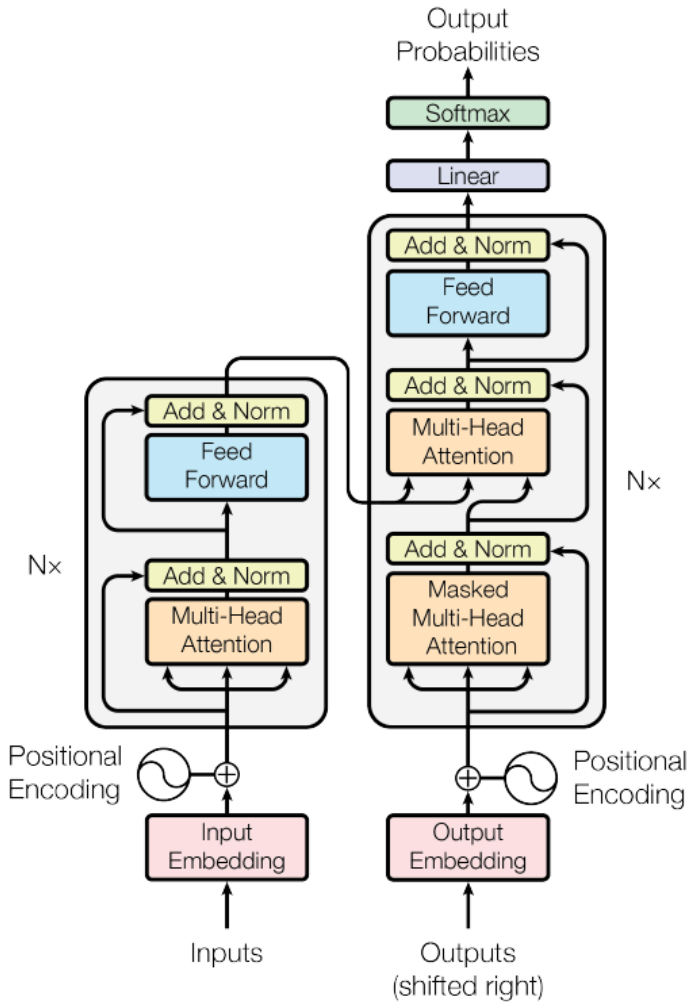
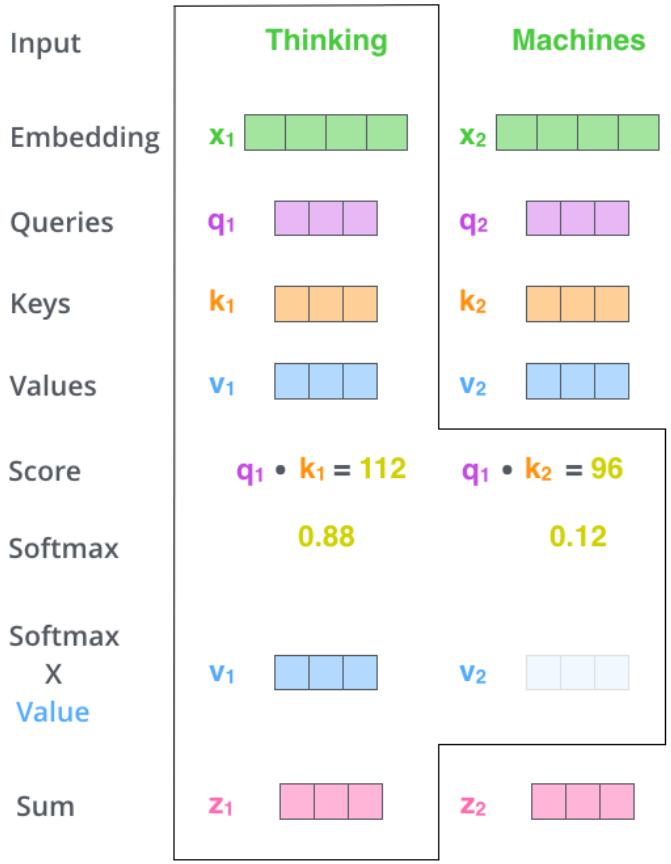
➔ "Transformer" architecture

- Core blocks encoder:
  - Self-attention step
  - Local fully connected layer



AIAYN: Encoder

- Each input token is translated into vector of same length using an **embedding** algorithm

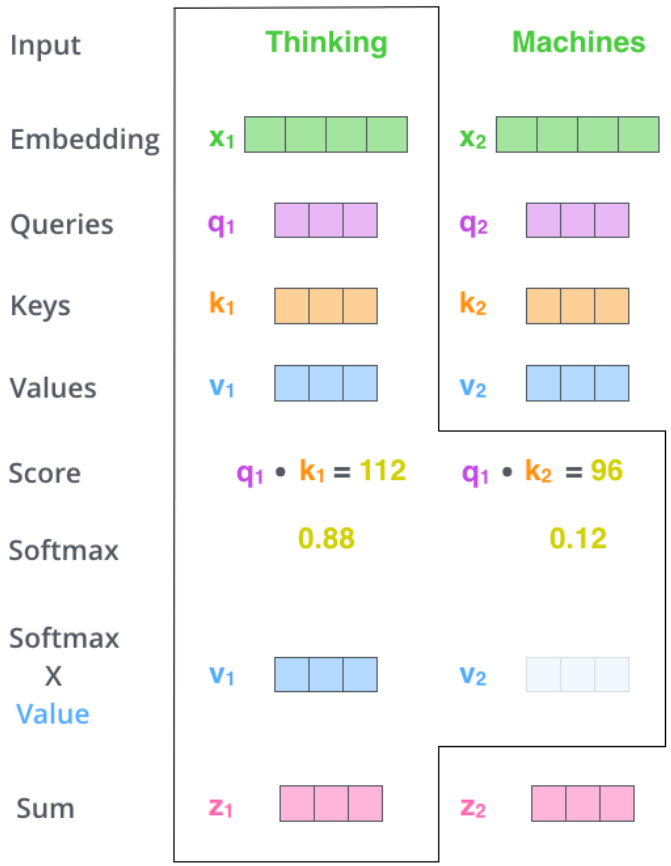


Source: http://jalammar.github.io/illustrated-transformer/

AIAYN: Encoder

- Each input token is translated into vector of same length using an **embedding** algorithm
- Self attention: For each token, compute
  - query **q**: what a token is "looking for"
  - key **k**: "description" for query
  - value **v**: potential "information"

  using trainable weights $\mathbf{W}_q, \mathbf{W}_k, \mathbf{W}_v$



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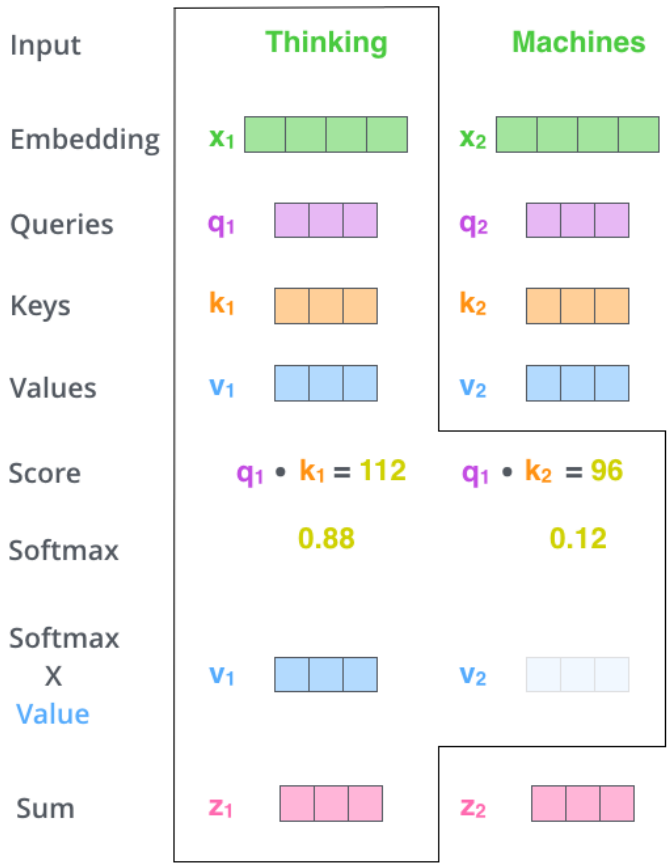
  using trainable weights $\mathbf{W}_q, \mathbf{W}_k, \mathbf{W}_v$
- Alignment between query and key (scaled dot product) determines influence of elements in **v**:

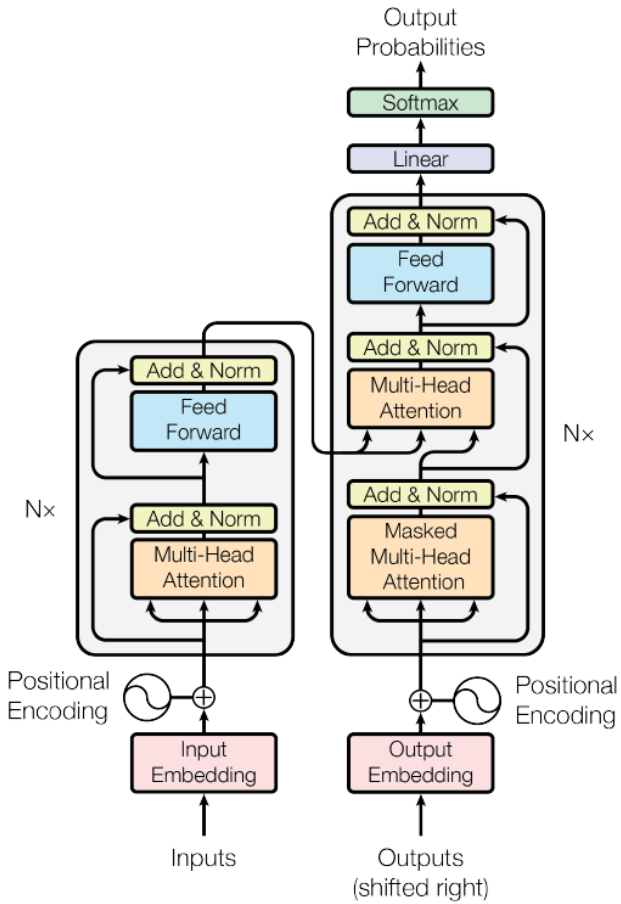
$$\text{attention}(\mathbf{q}, \mathbf{k}, \mathbf{v}) = \text{softmax}(\frac{\mathbf{q}\mathbf{k}^T}{\sqrt{d_k}})\mathbf{v}$$



Source: http://jalammar.github.io/illustrated-transformer/

AIAYN: Encoder (cont.)

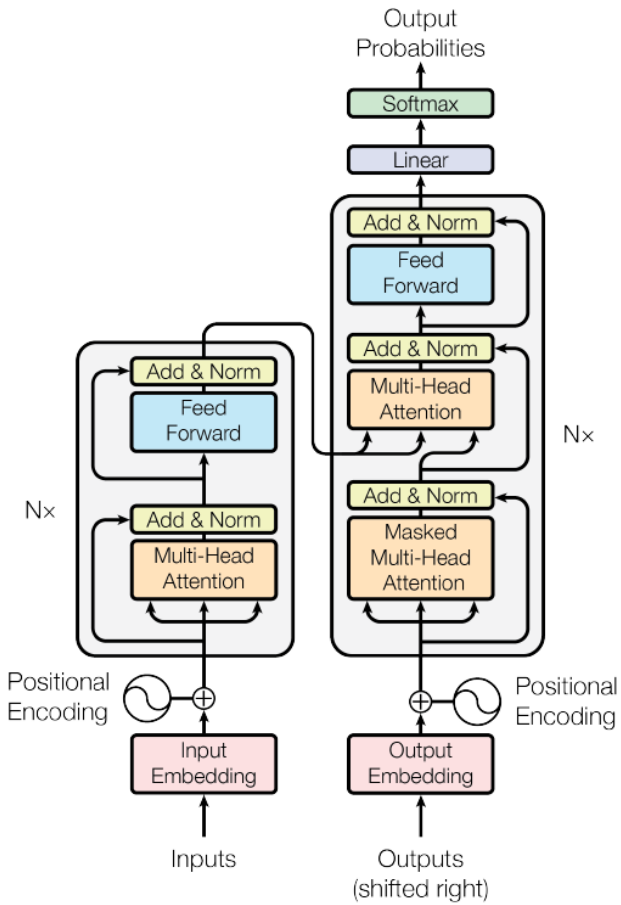
- Multi-Head attention: Multiple attention vectors per token
  → **Representation subspaces**
- Local (per token) recombination using a fully connected layer



Source: [23]

AIAYN: Encoder (cont.)

- Multi-Head attention: Multiple attention vectors per token
  ➔ **Representation subspaces**
- Local (per token) recombination using a fully connected layer
- Stacked attention blocks (6× in [23])
  ➔ step-by-step context integration
- Additional positional encoding to represent word order

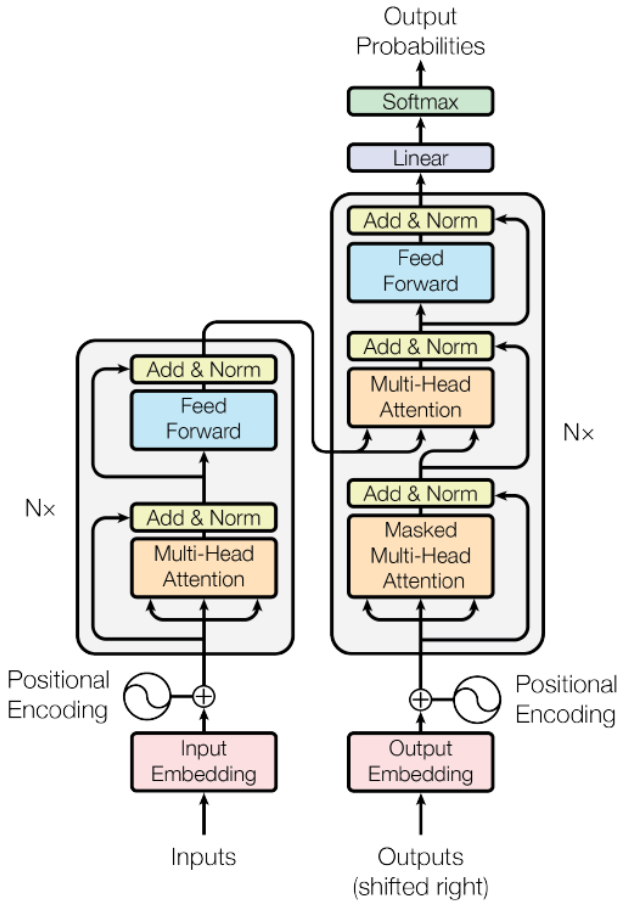


Source: [23]

AIAYN: Decoder

Decoder follows same concept as encoder:

- Additional input/output attention step
- Self-attention only computed on **previous** outputs



Source: [23]

AIAYN: But why?

- Allows for integration of knowledge independent of distance
- Positional encoding still allows to learn convolution-like steps
- Extremely versatile
- Extensions allow pretraining on unlabeled text (e.g., [4])
- **State-of-the-art** performance and **faster** training

Attention: Summary

- Alignment and/or relevance of input elements w. r. t. output elements
- Attention scores allow interpretation
- Allows to reformulate non-sequential tasks as sequential ones
- Attention alone very powerful (Transformer)
- State-of-the-art technique for many NLP tasks, e. g., machine translation, question answering, sentiment analysis, etc.
- ... but also in vision (e. g. SAGAN [27])
- Attention often used in combination with convolutions ➔ Attention layers as replacements for convolutions? [18]


NEXT TIME
ON DEEP LEARNING

Coming Up: Deep Reinforcement Learning

- A training paradigm capable of producing **superhuman** performance
- An algorithm to determine a game **strategy** from playing
- Neural networks moving beyond perception to making **decisions**
- Instructions to finally **beat all your friends** in Atari **games**
- A recipe to **beat every human in Go**

Comprehensive Questions

- Why is visualization important?
- What can visualization help with? What can't it help with?
- Why are confounds a problem?
- Why could adversarial examples pose a security problem?
- How does occlusion work?
- What is the difference between deconvolution, backpropagation and guided backpropagation regarding feature visualization?
- How is Google DeepDream related to visualization?
- What is a Saliency map?
- What is the idea behind attention?
- What is the difference between "normal" and self-attention
- How does the transformer architecture avoid recurrence and convolutions?

Further Reading

- Yosinski et al.: Deep Visualization Toolbox
  `http://yosinski.com/deepvis`
- Olah et al.: Feature Visualization
  `https://distill.pub/2017/feature-visualization/`
- Adam Harley: MNIST Demo
  `http://scs.ryerson.ca/~aharley/vis/conv/`

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