# CS 4644-DL / 7643-A: LECTURE 9
# DANFEI XU

Topics:

- Convolutional Neural Networks Architectures (cont.)
- Training Neural Networks (Part 1)

# Administrative

- PS1/HW1 due **today** (grace period till Sep 21st)
- PS2/HW2 out: **Difficult assignment. Start early!**
- Project proposal due **Sep 26th**. **No extension!**

# CNN Architectures

## Case Studies

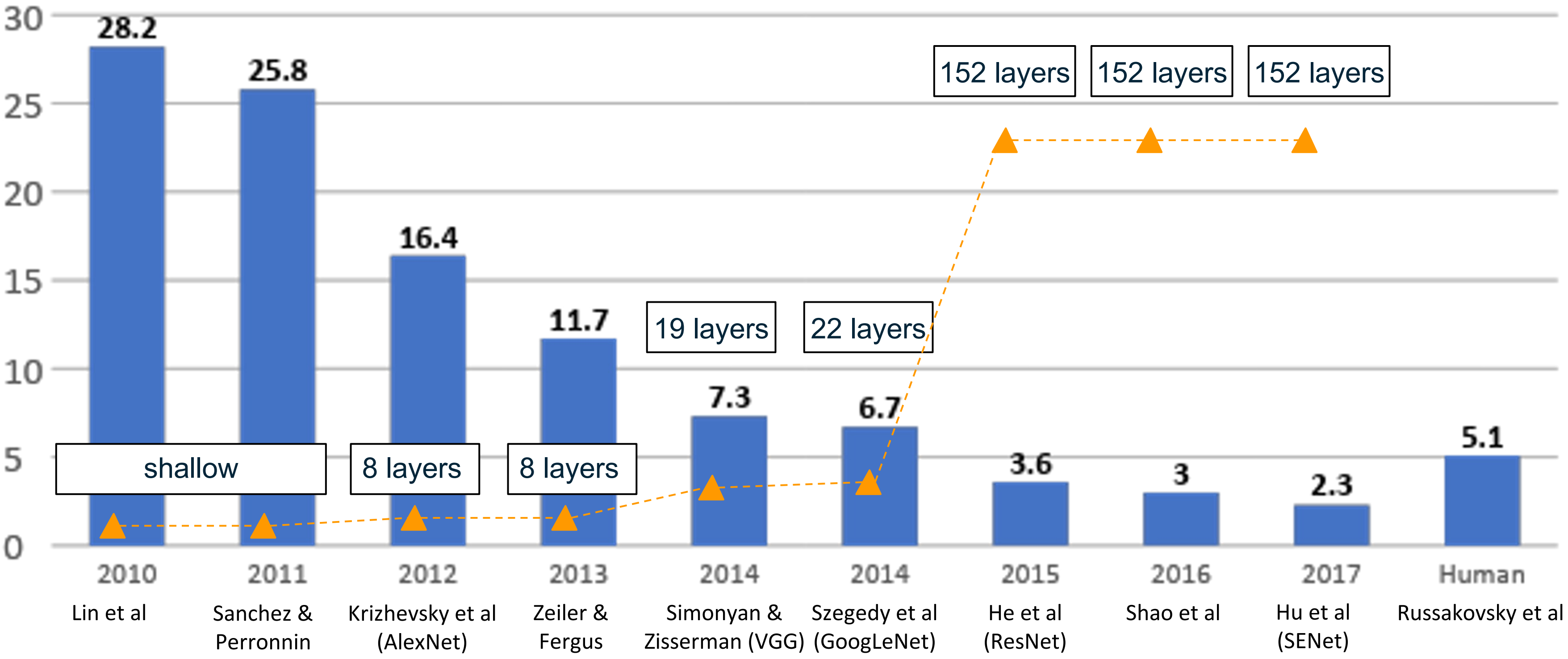
- AlexNet
- VGG
- GoogLeNet
- ResNet

## Also....

- SENet
- Wide ResNet
- ResNeXT

- DenseNet
- MobileNets
- NASNet
- EfficientNet

# ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



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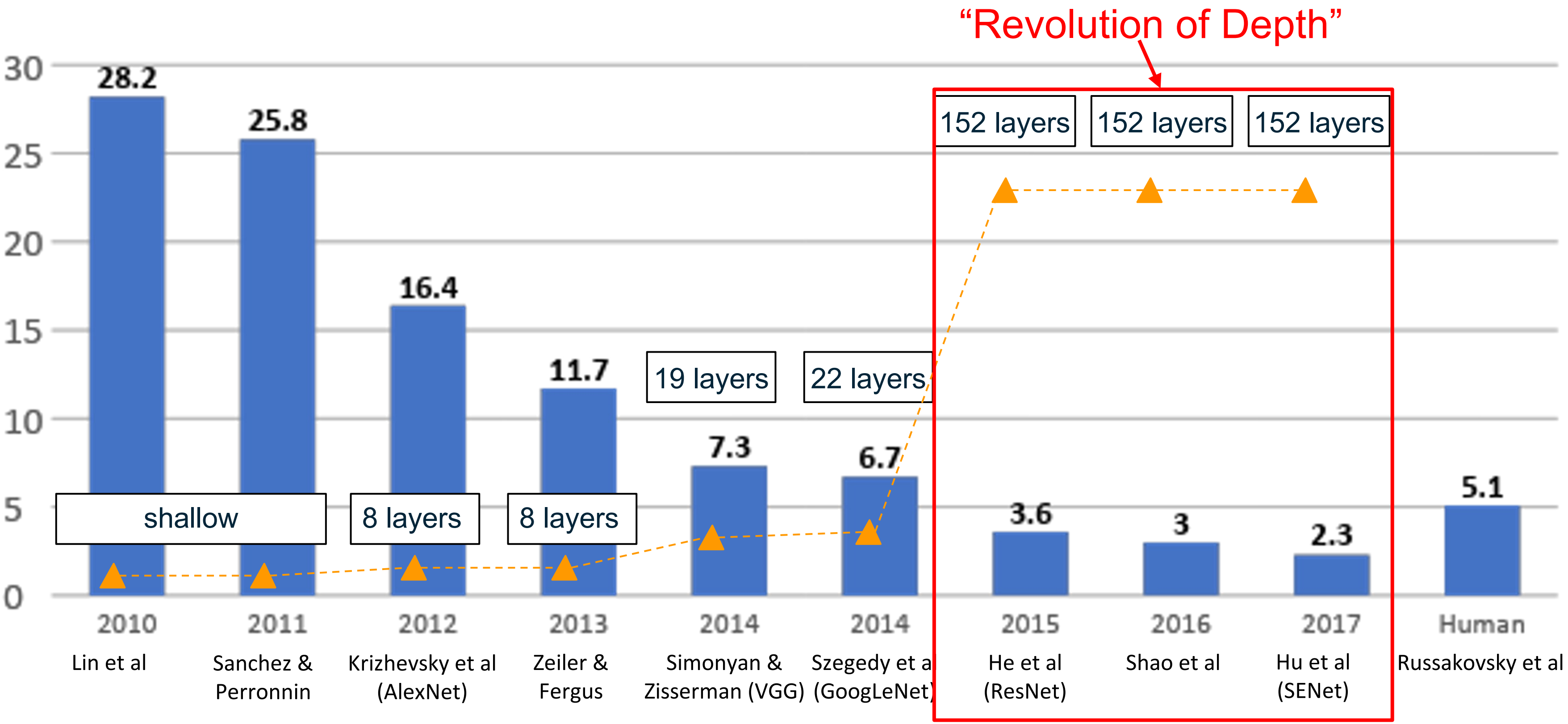
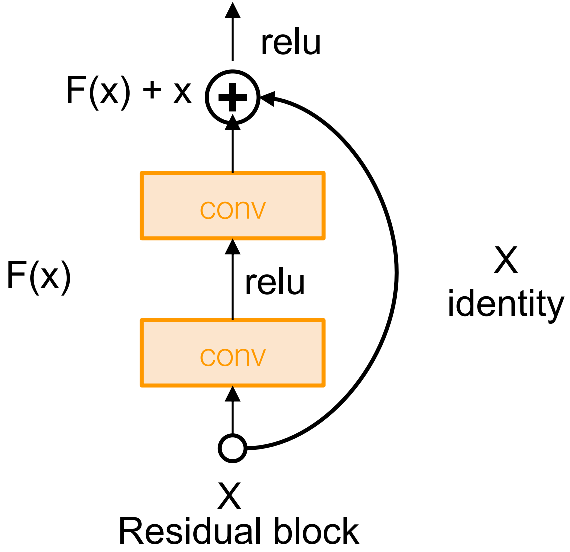


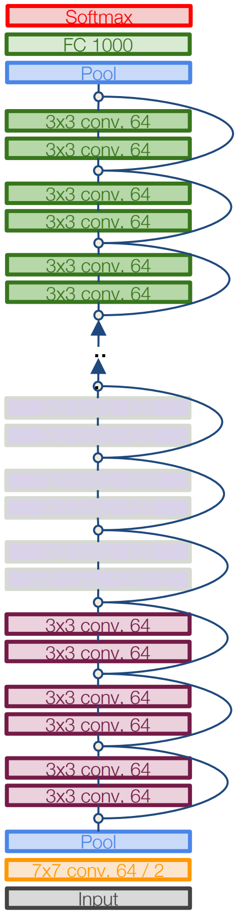
# Case Study: ResNet

*[He et al., 2015]*

Very deep networks using residual connections

- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!



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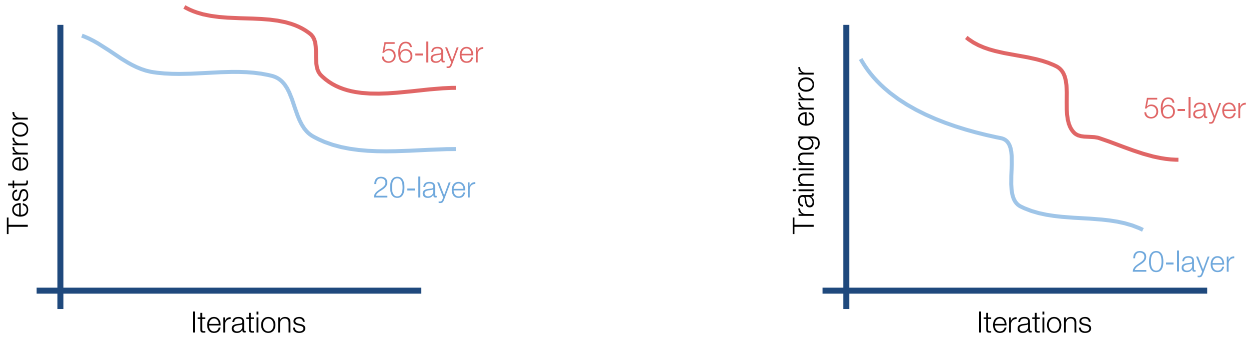

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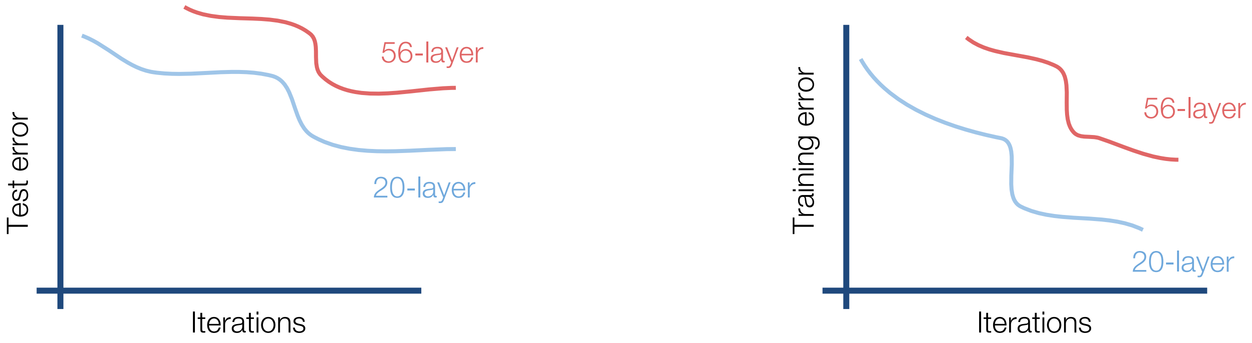



56-layer model performs worse on both test and training error
-> The deeper model performs worse, but it's not caused by overfitting!

# Case Study: ResNet

*[He et al., 2015]*

Fact: Deep models have more representation power (more parameters) than shallower models.

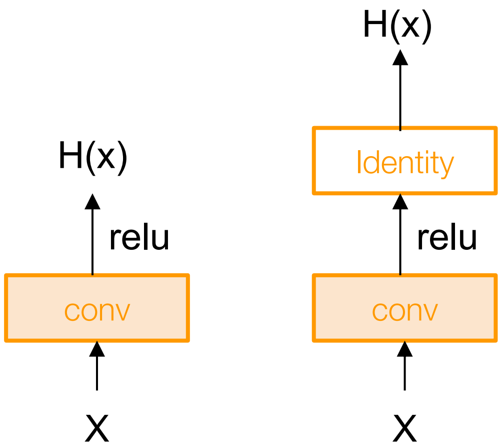
Hypothesis: the problem is an *optimization* problem, **deeper models are harder to optimize**

# Case Study: ResNet

*[He et al., 2015]*

A deeper model can **emulate** a shallower model: copy layers from shallower model, set extra layers to identity

Thus deeper models should do at least as good as shallow models



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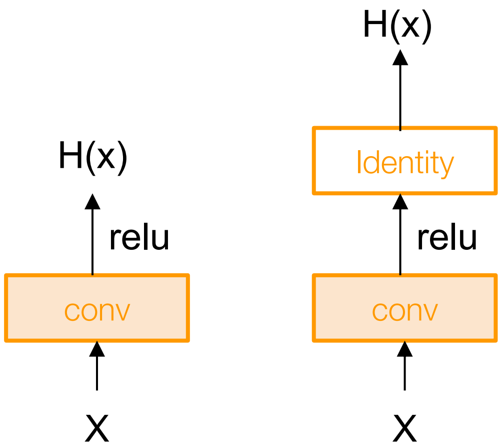

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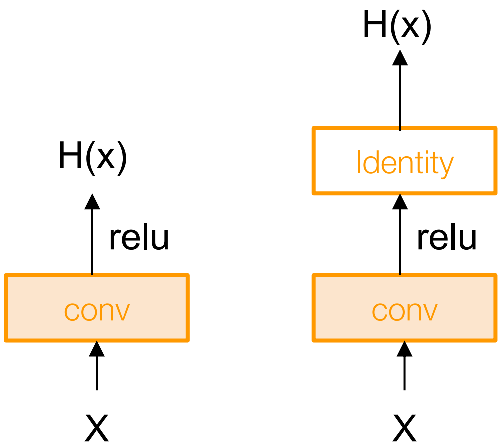
**Solution**: Change the network so learning identity functions (no-op) as extra layers is easy



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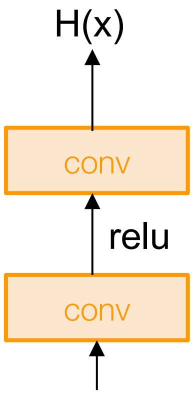


“Plain” layers

# Case Study: ResNet

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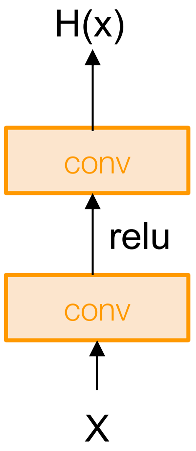
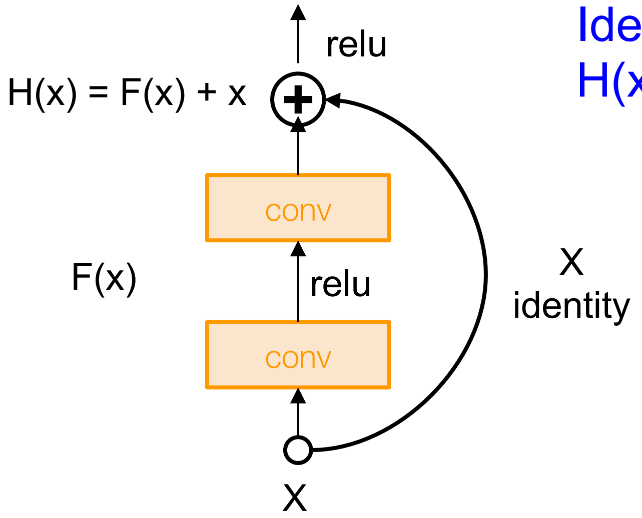



"Plain" layers




Residual block

Identity mapping:
H(x) = x if F(x) = 0

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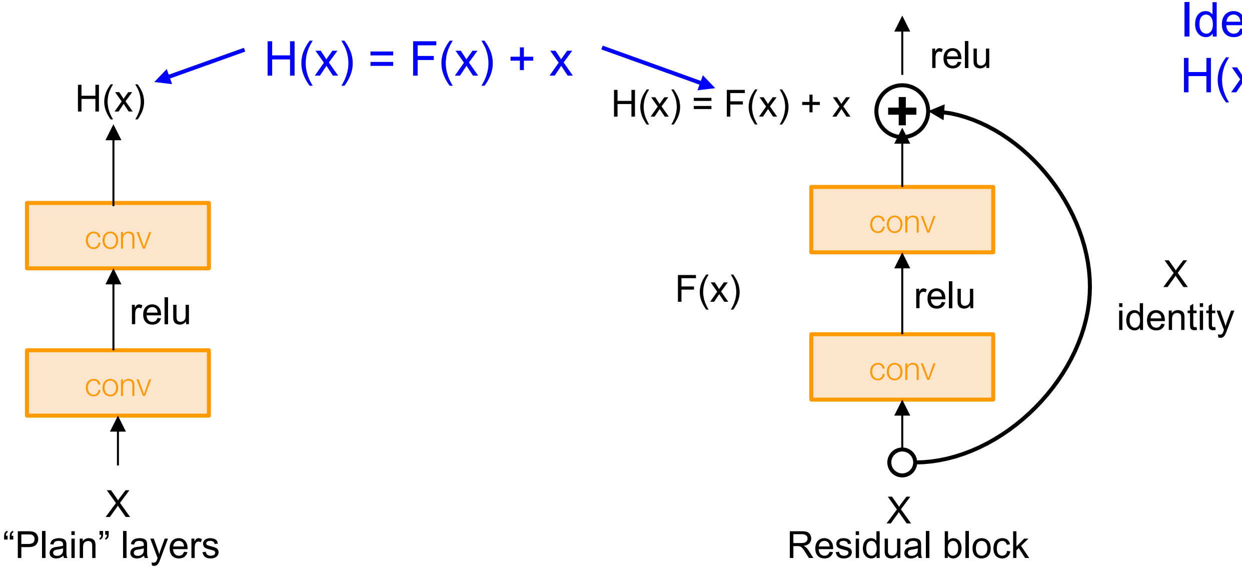


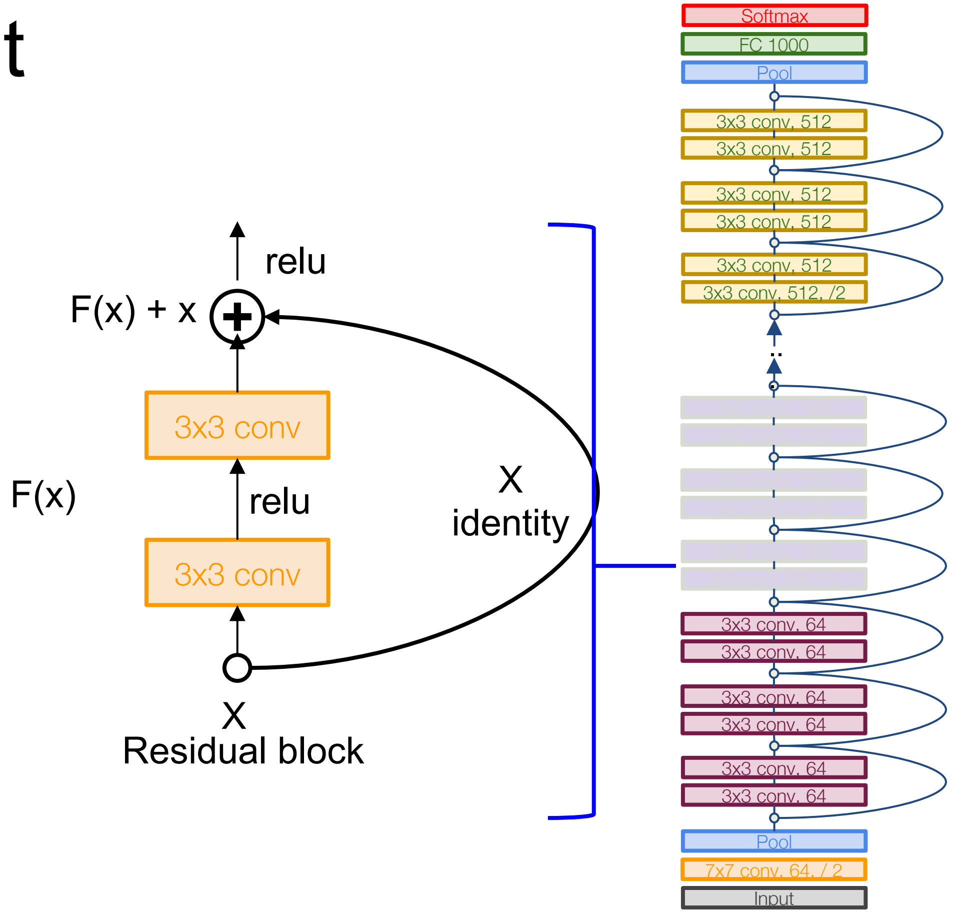

Identity mapping:
H(x) = x if F(x) = 0

Use layers to fit **residual** F(x) = H(x) - x instead of H(x) directly

# Case Study: ResNet

*[He et al., 2015]*

Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers



# Case Study: ResNet

*[He et al., 2015]*

Full ResNet architecture:

- Stack residual blocks
- Every residual block has two 3x3 conv layers
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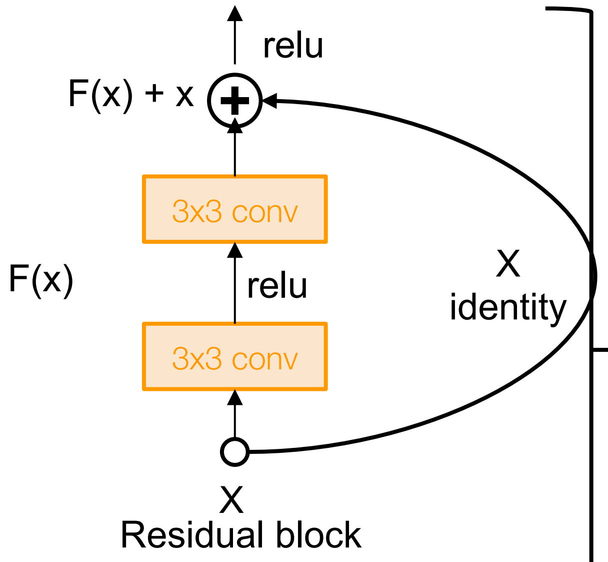


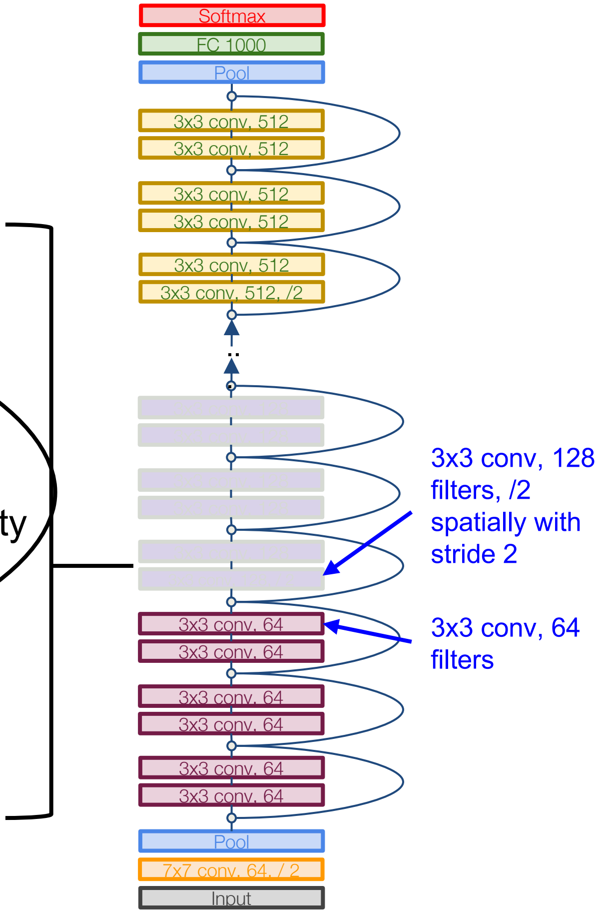

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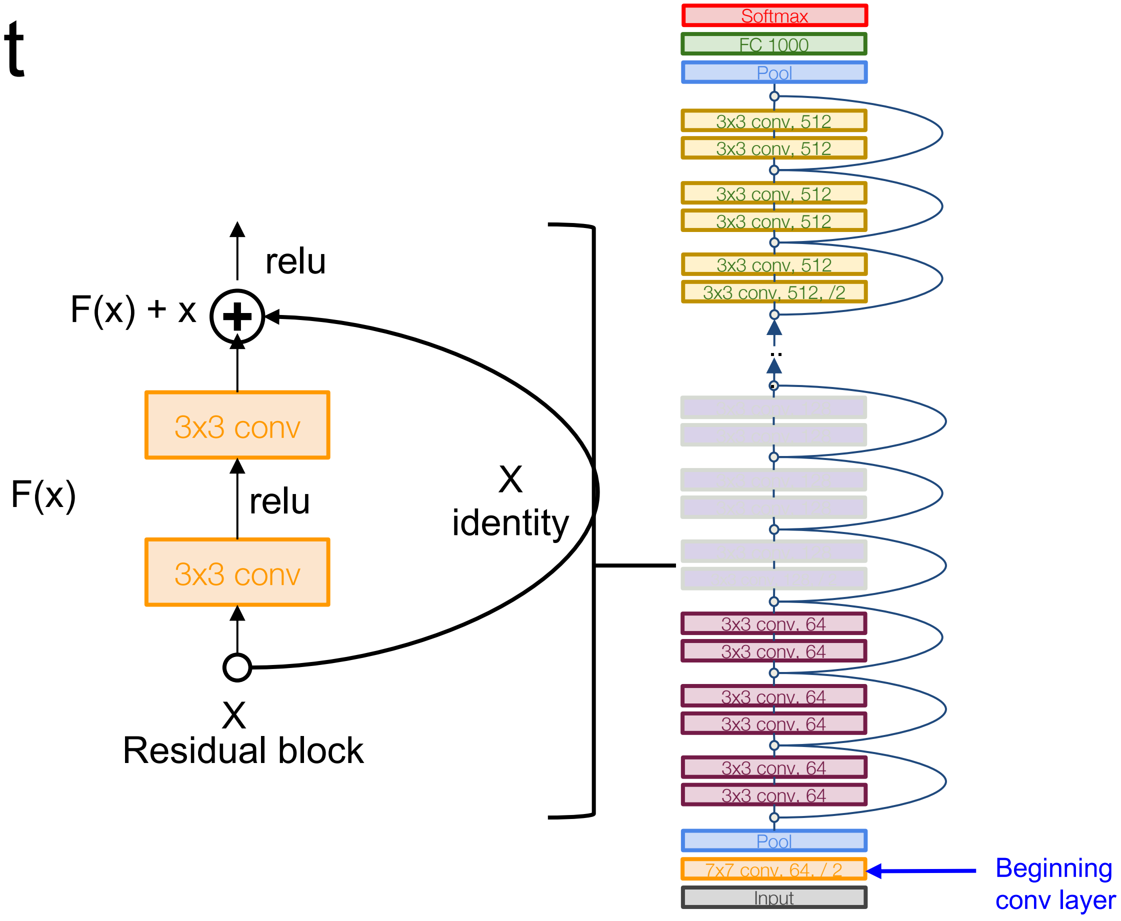
- Additional conv layer at the beginning (stem)



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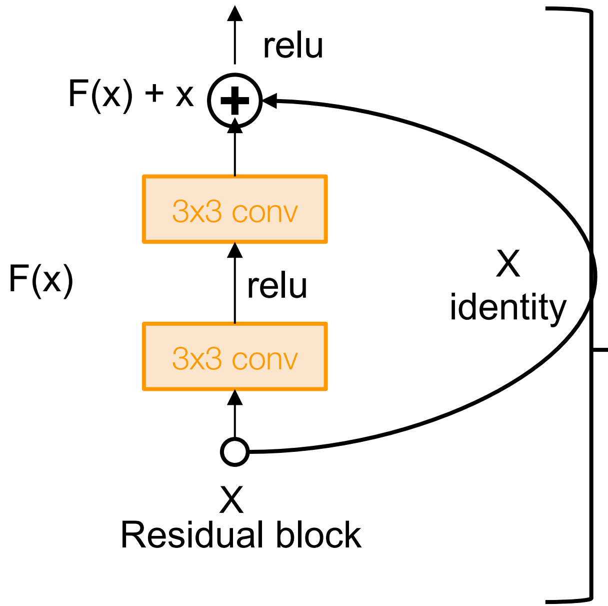
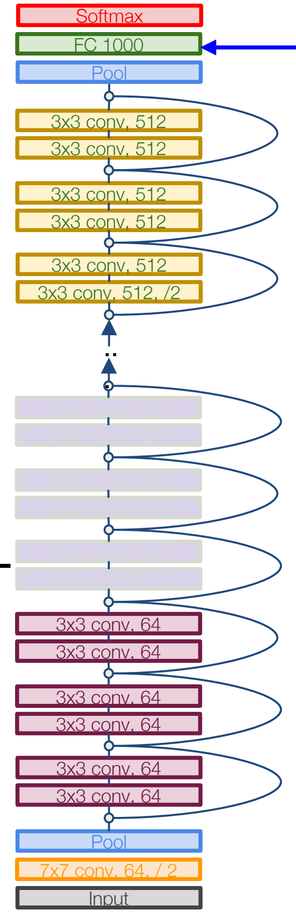
- Additional conv layer at the beginning (stem)
- No FC layers at the end (only FC 1000 to output classes)



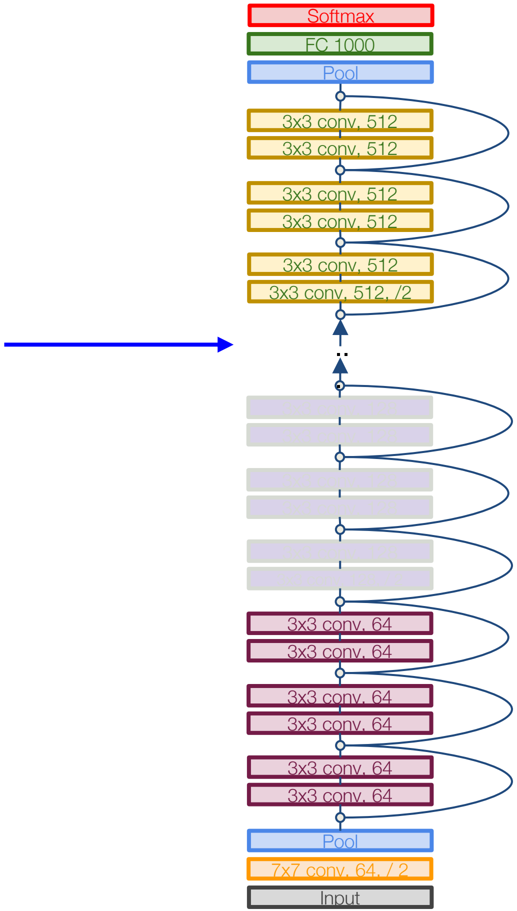

No FC layers besides FC 1000 to output classes

Global average pooling layer after last conv layer

# Case Study: ResNet

*[He et al., 2015]*

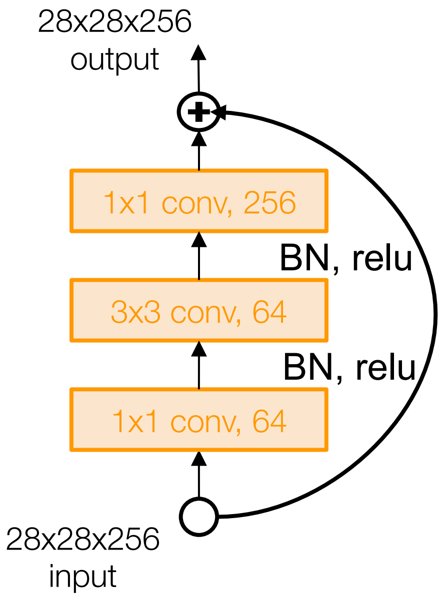
Total depths of 18, 34, 50, 101, or 152 layers for ImageNet



# Case Study: ResNet

*[He et al., 2015]*

For deeper networks (ResNet-50+), use "bottleneck" layer to improve efficiency (similar to GoogLeNet)



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For deeper networks (ResNet-50+), use "bottleneck" layer to improve efficiency (similar to GoogLeNet)

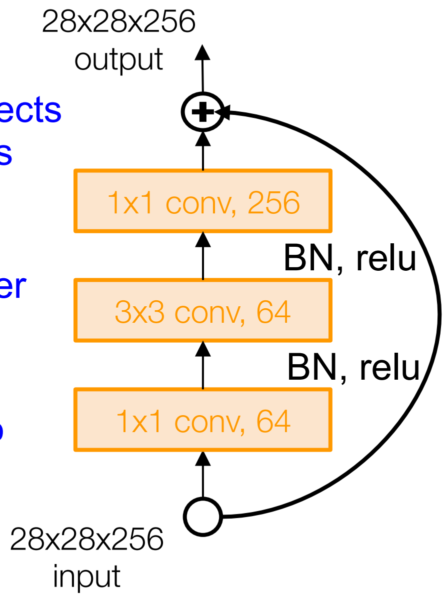
1x1 conv, 256 filters projects back to 256 feature maps (28x28x256)

↑

3x3 conv operates over only 64 feature maps

↑

1x1 conv, 64 filters to project to 28x28x64



# Case Study: ResNet

*[He et al., 2015]*

Training ResNet in practice:

- Batch Normalization after every CONV layer (this lecture)
- Xavier initialization from He et al. (this lecture)
- SGD + Momentum (this lecture)
- Learning rate: 0.1, divided by 10 when validation error plateaus
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout used

# Case Study: ResNet

*[He et al., 2015]*

Experimental Results

- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on Cifar)
- Deeper networks now achieve lower training error as expected
- Swept 1st place in all ILSVRC and COCO 2015 competitions

MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

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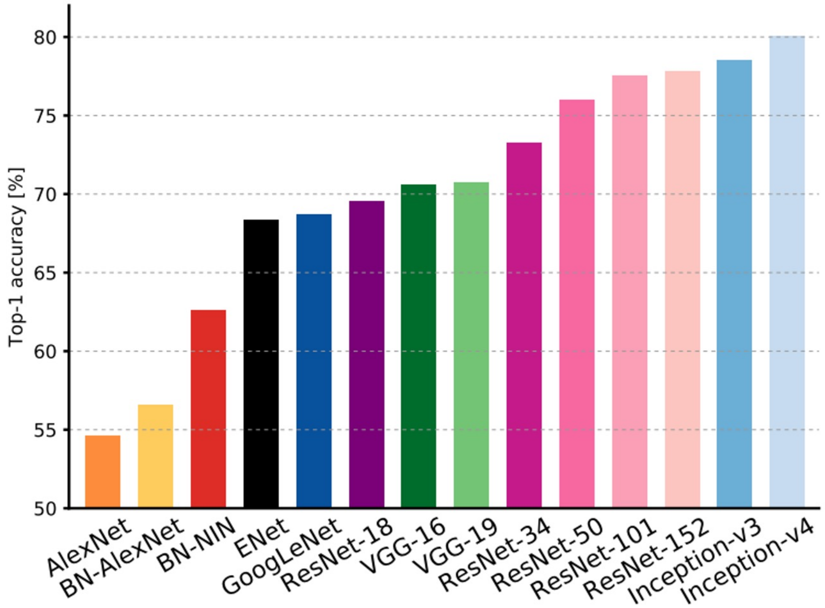
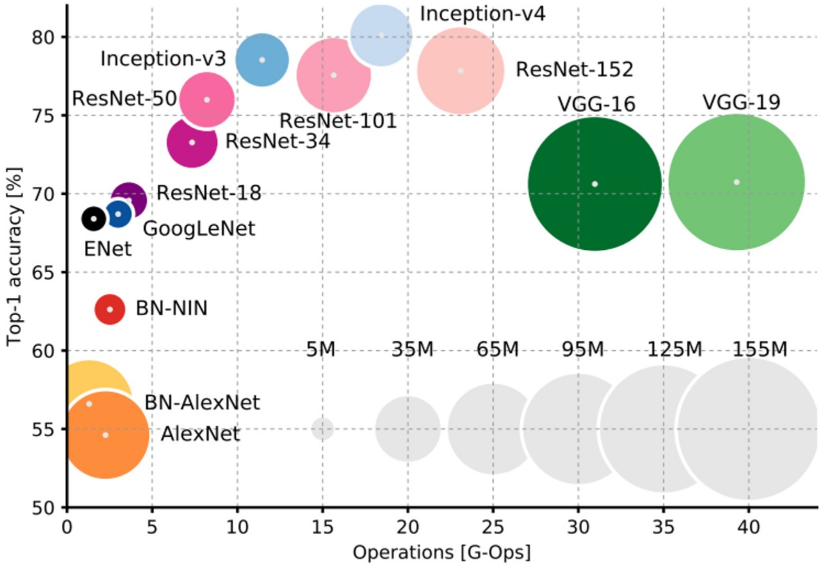
ILSVRC 2015 classification winner (3.6% top 5 error) -- better than "human performance"! (Russakovsky 2014)

# Comparing complexity...

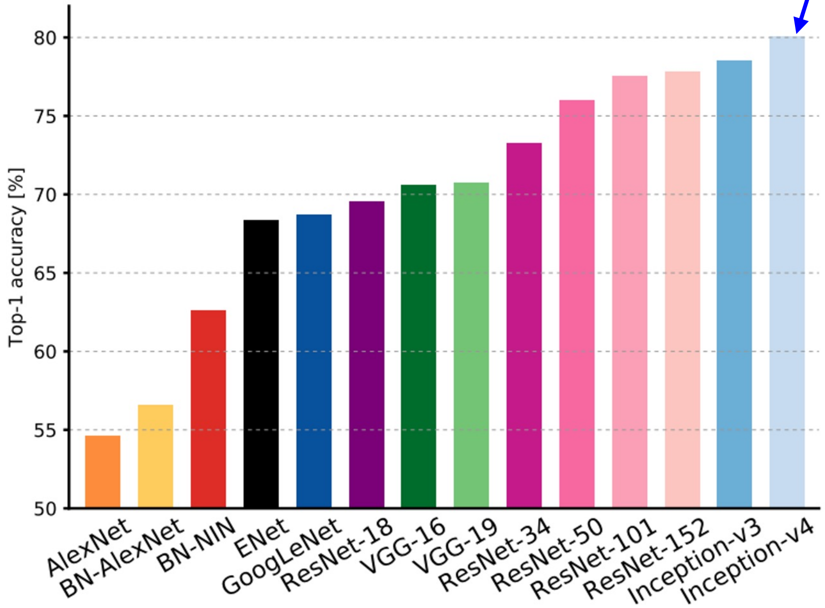


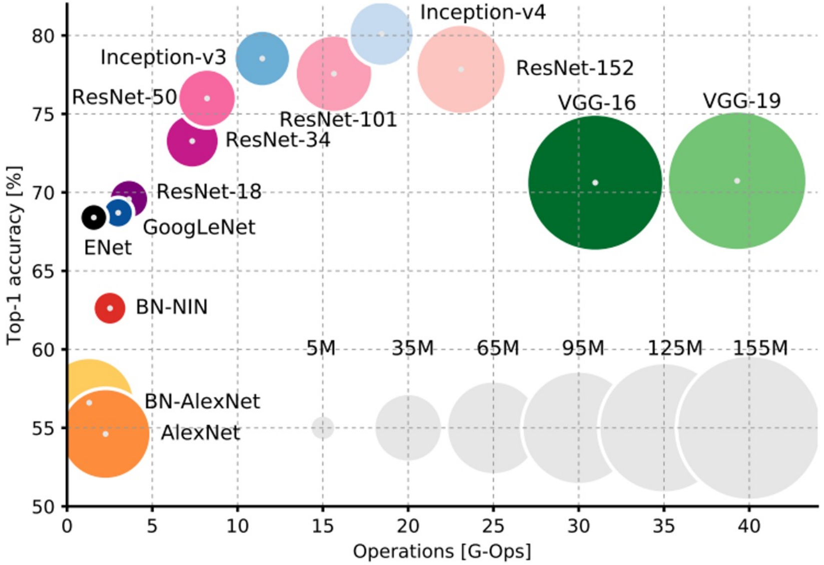




An Analysis of Deep Neural Network Models for Practical Applications, 2017.

# Comparing complexity...

Inception-v4: Resnet + Inception!

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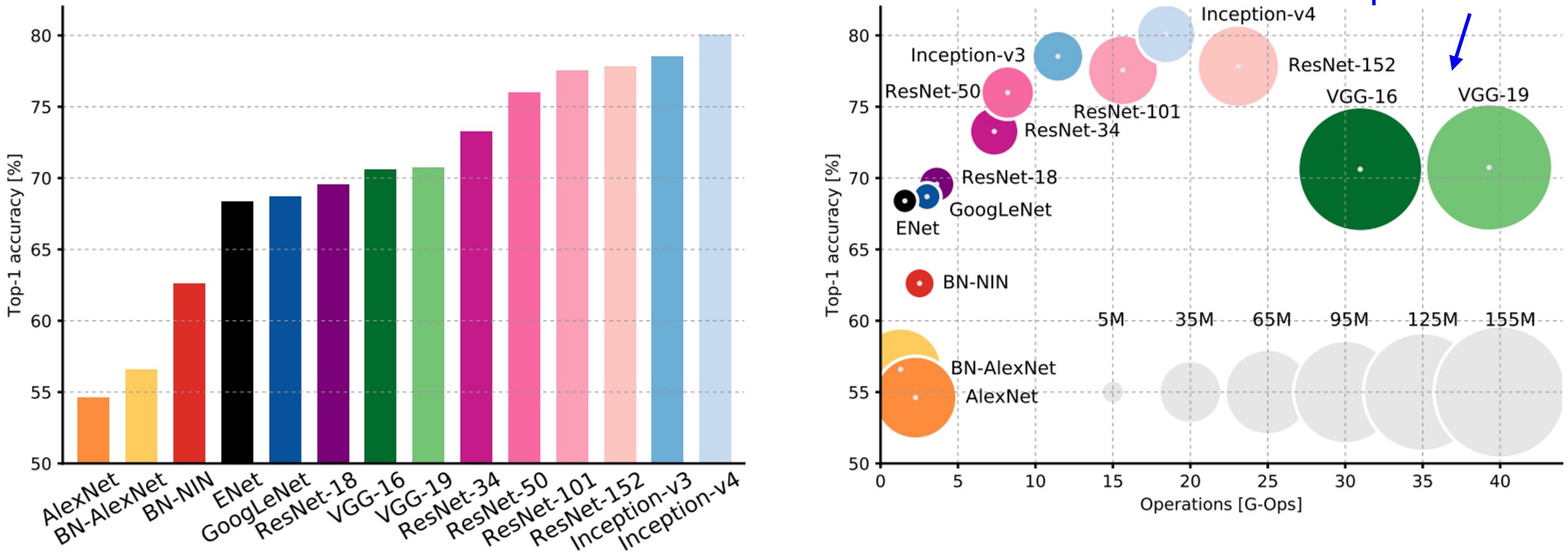
# Comparing complexity...

VGG: most parameters, most operations

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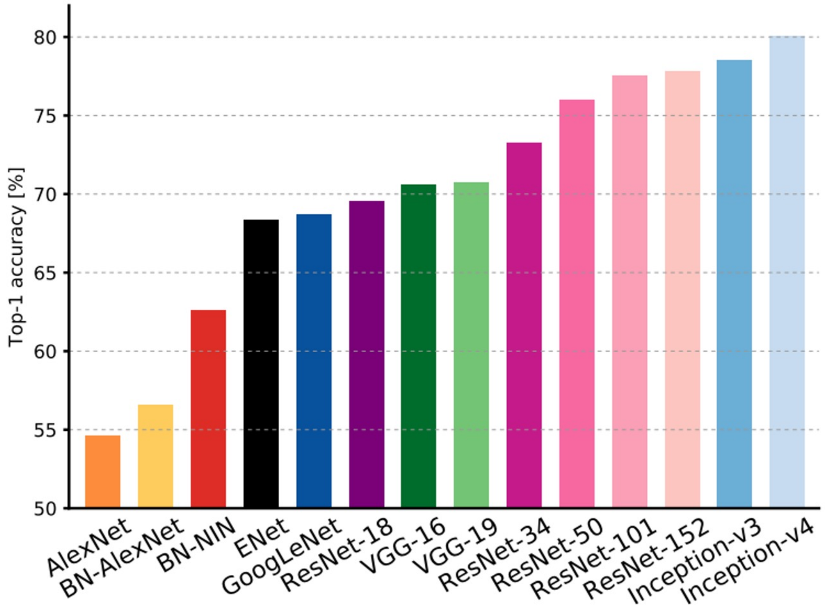
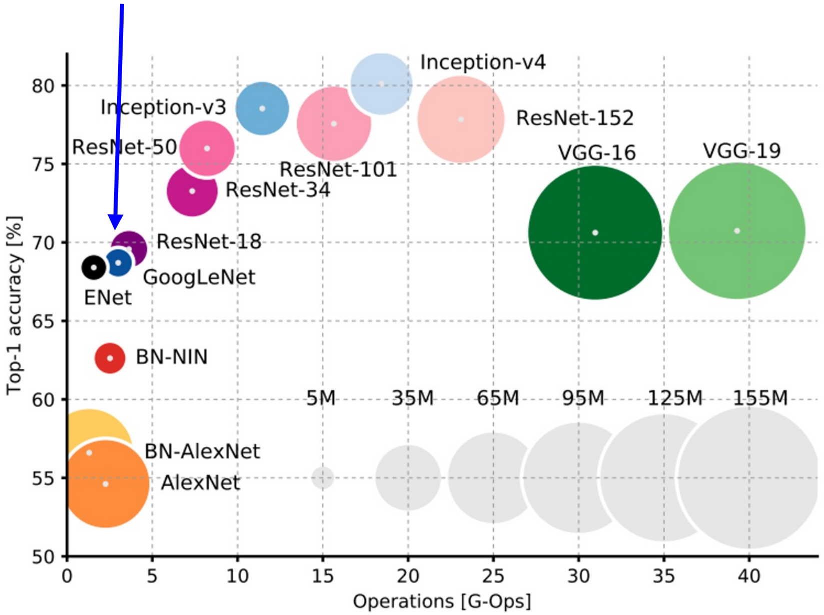
# Comparing complexity...

GoogLeNet:
most efficient

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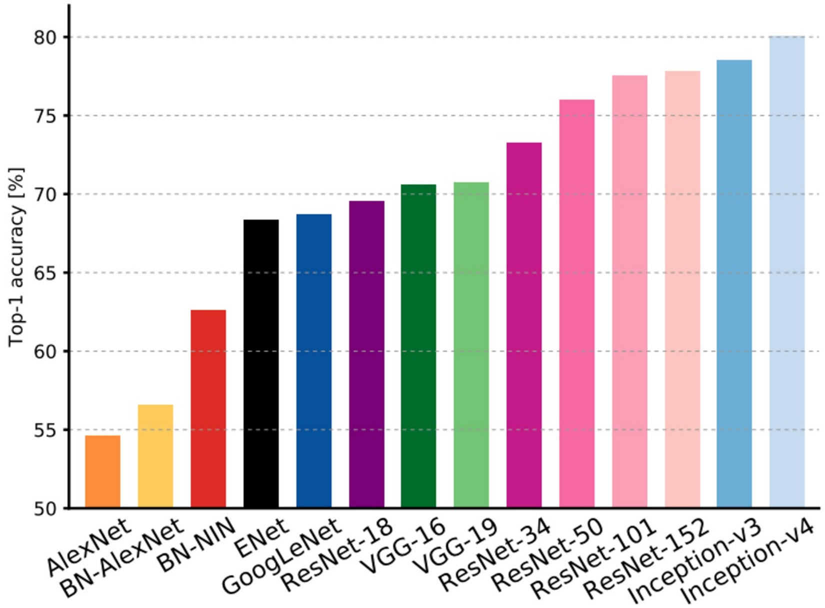
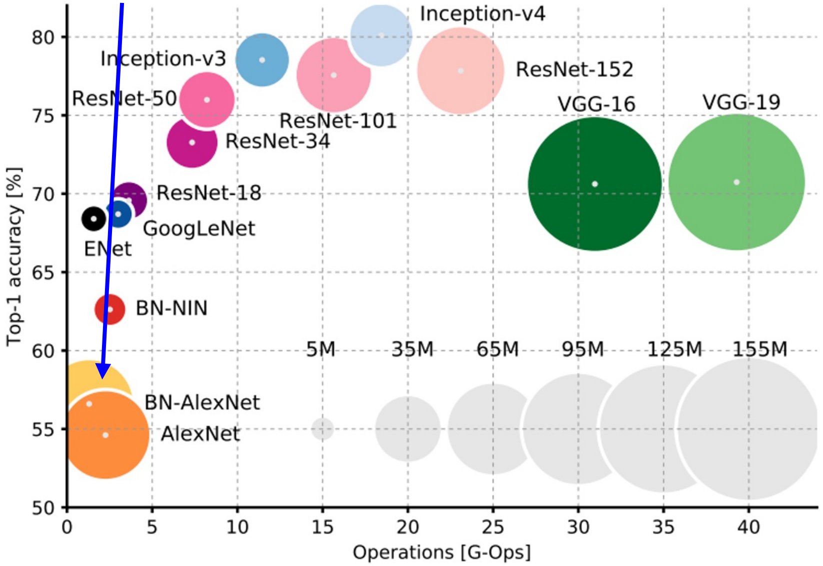
# Comparing complexity...

AlexNet:
Smaller compute, still memory heavy, lower accuracy

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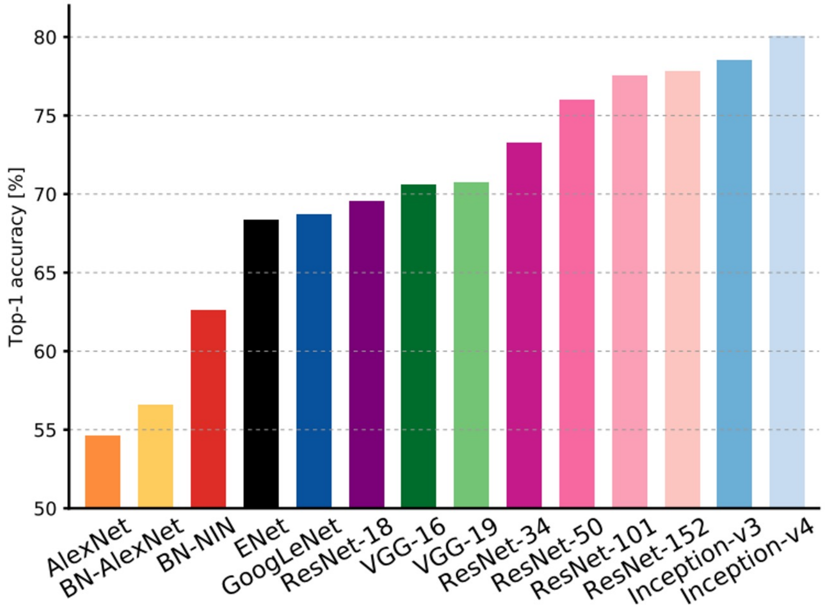
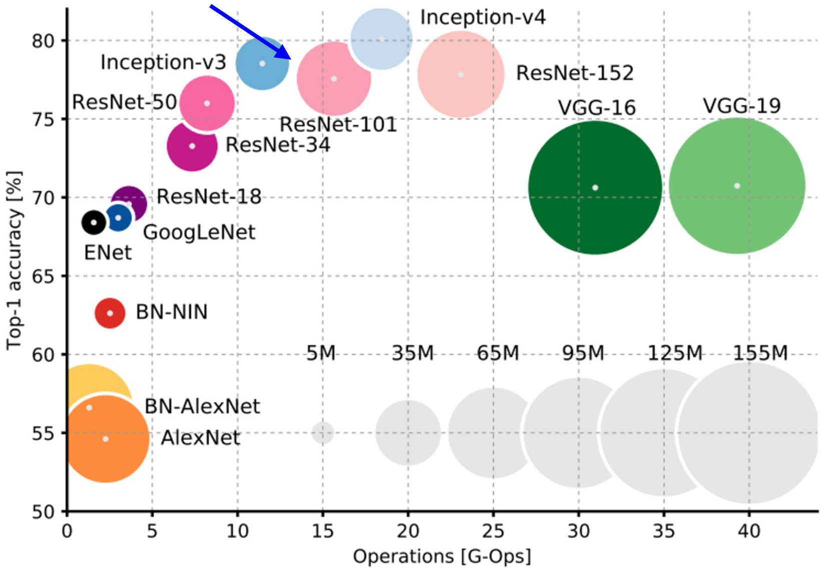
# Comparing complexity...

ResNet:
Moderate efficiency depending on model, highest accuracy

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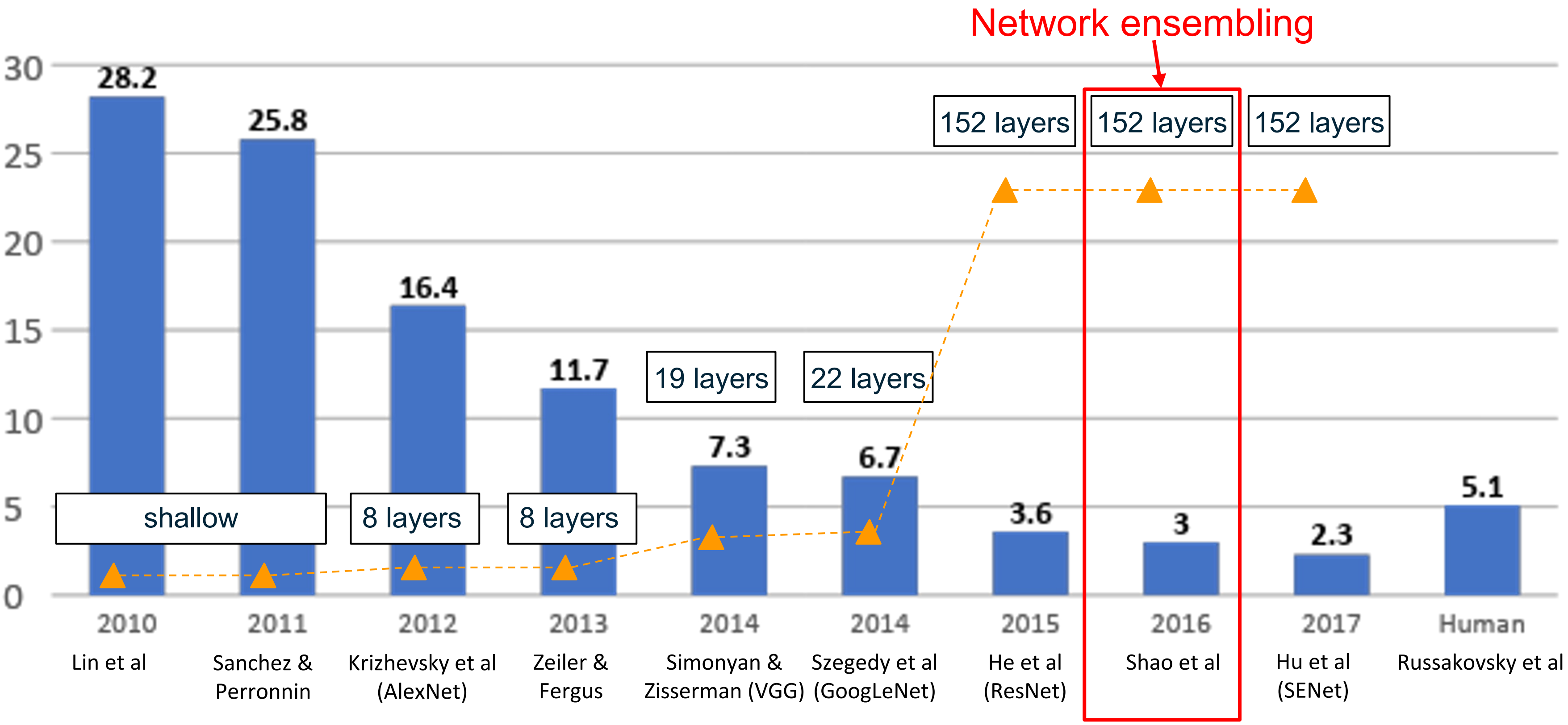

# Improving ResNets...

## "Good Practices for Deep Feature Fusion"

*[Shao et al. 2016]*

- Multi-scale ensembling of Inception, Inception-Resnet, Resnet, Wide Resnet models
- ILSVRC'16 classification winner

| | Inception-v3 | Inception-v4 | Inception-Resnet-v2 | Resnet-200 | Wrn-68-3 | Fusion（Val.） | Fusion（Test） |
|---|---|---|---|---|---|---|---|
| Err. (%) | 4.20 | 4.01 | 3.52 | 4.26 | 4.65 | 2.92 (-0.6) | 2.99 |

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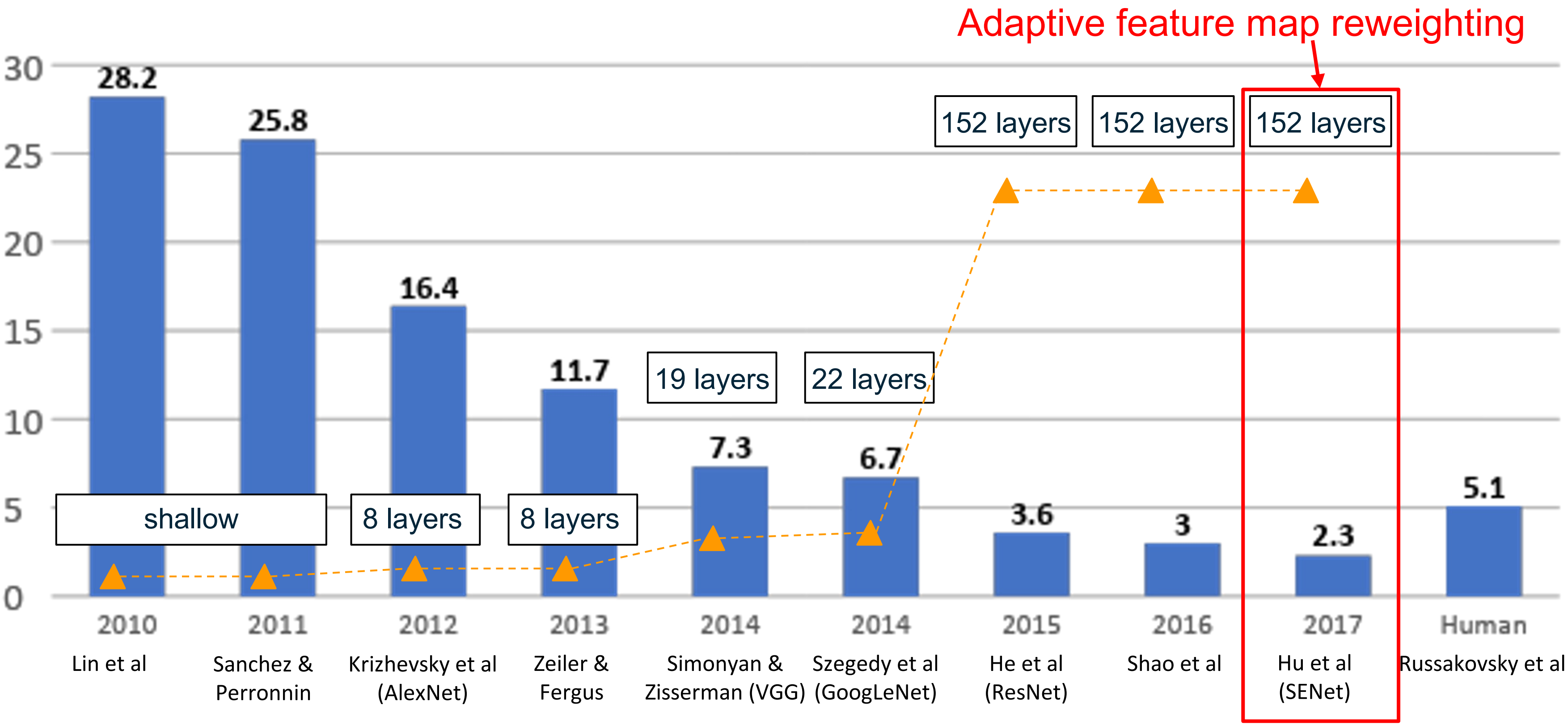

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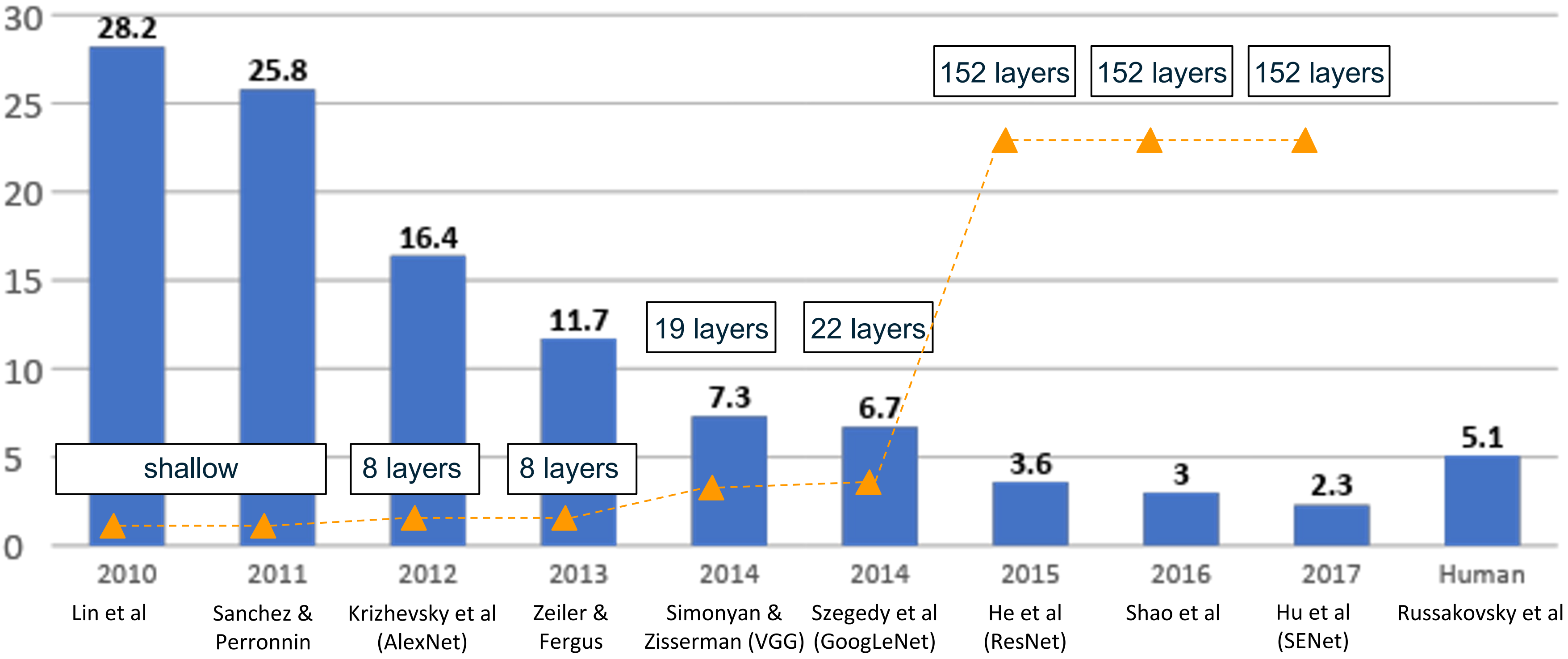

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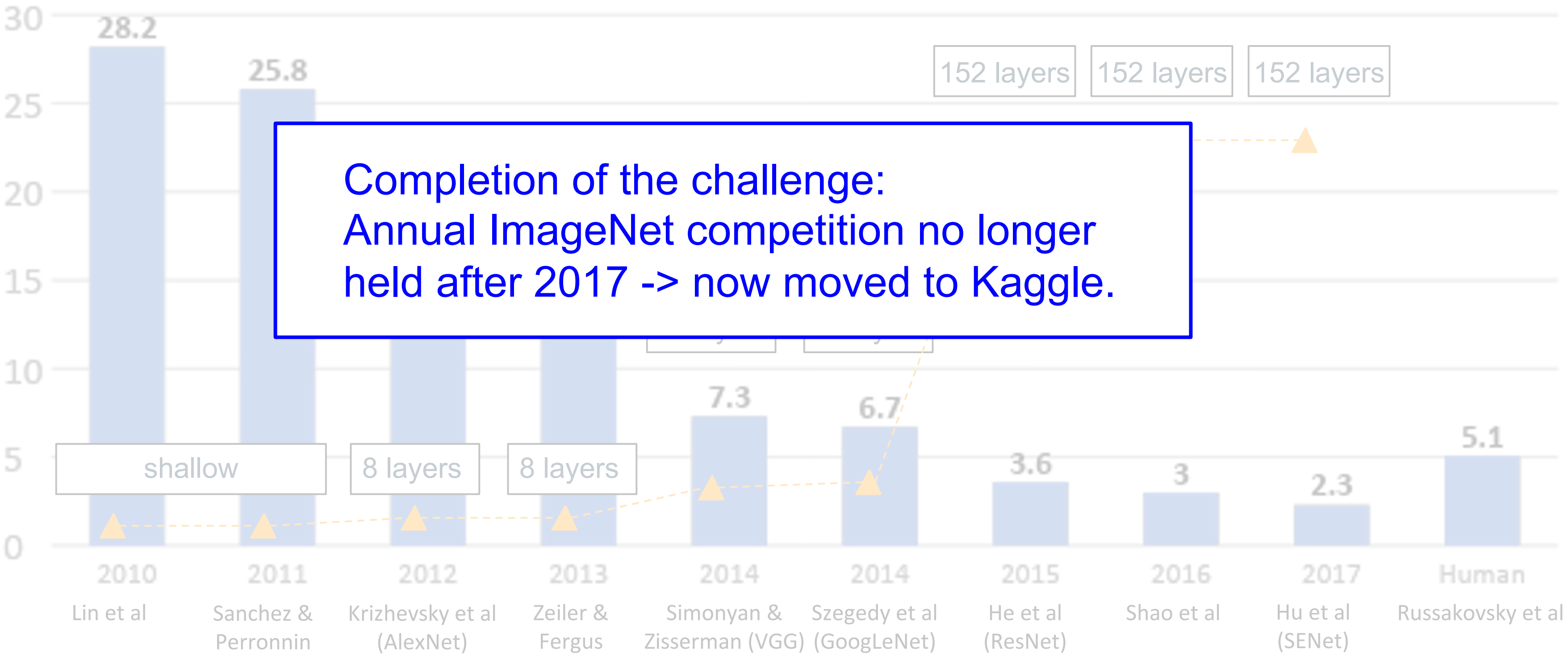



Completion of the challenge:
Annual ImageNet competition no longer held after 2017 -> now moved to Kaggle.

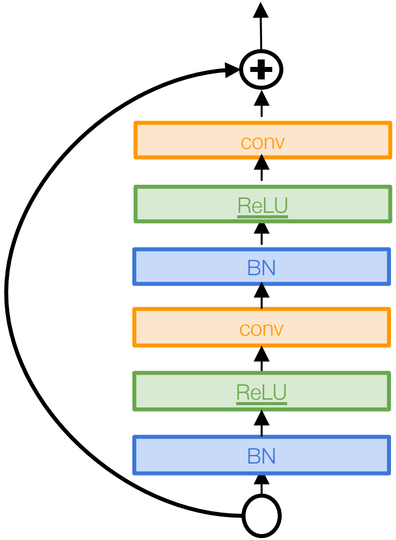
But research into CNN architectures is still flourishing

# Improving ResNets...

## Identity Mappings in Deep Residual Networks

*[He et al. 2016]*

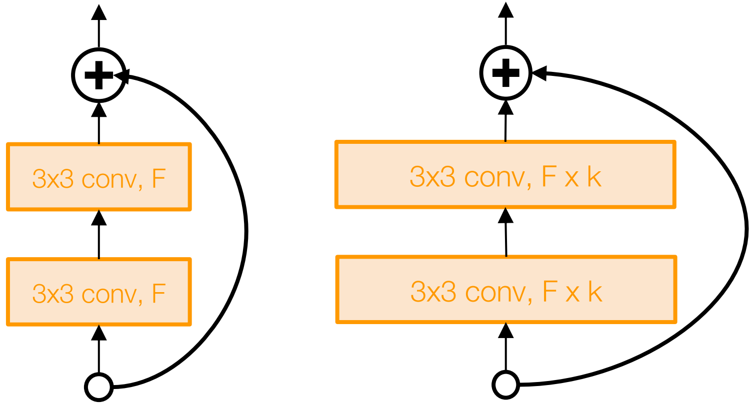
- Improved ResNet block design from creators of ResNet
- Creates a more direct path for propagating information throughout network
- Gives better performance



# Wide Residual Networks

*[Zagoruyko et al. 2016]*

- Argues that residuals are the important factor, not depth
- Use wider residual blocks (F x k filters instead of F filters in each layer)
- 50-layer wide ResNet outperforms 152-layer original ResNet
- Increasing width instead of depth more computationally efficient (parallelizable)




Basic residual block

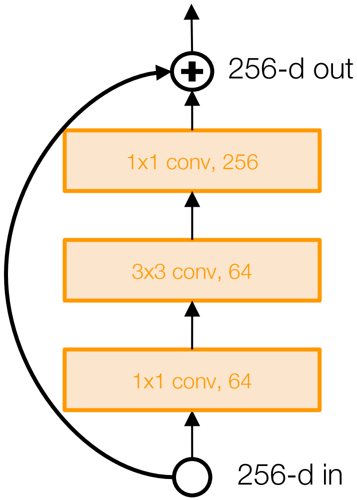
Wide residual block

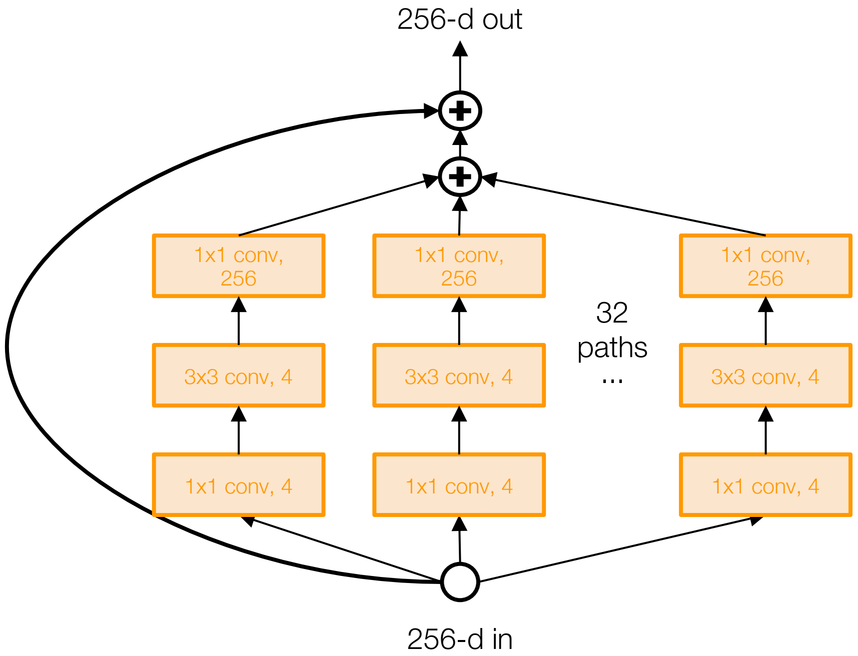
Improving ResNets...

# Aggregated Residual Transformations for Deep Neural Networks (ResNeXt)

*[Xie et al. 2016]*

- Also from creators of ResNet
- Increases width of residual block through multiple parallel pathways ("cardinality")
- Parallel pathways similar in spirit to Inception module



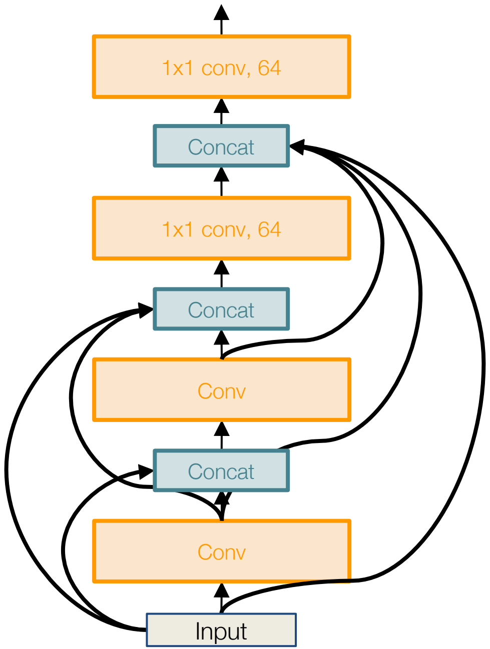



# Other ideas...

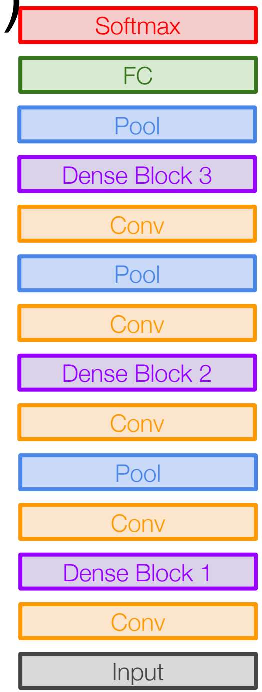
## Densely Connected Convolutional Networks (DenseNet)

*[Huang et al. 2017]*

- Dense blocks where each layer is connected to every other layer in feedforward fashion
- Alleviates vanishing gradient, strengthens feature propagation, encourages feature reuse
- Showed that shallow 50-layer network can outperform deeper 152 layer ResNet




Dense Block

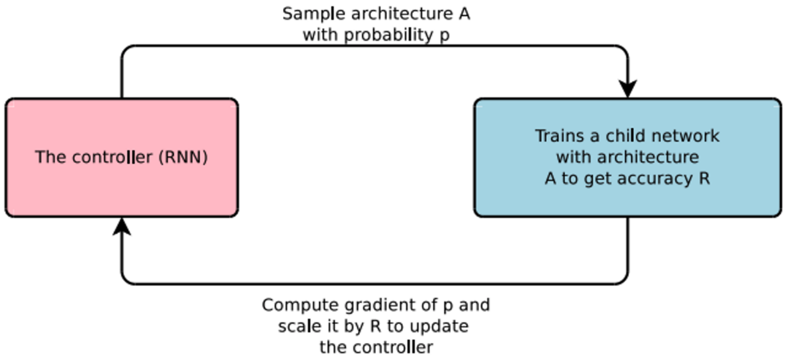


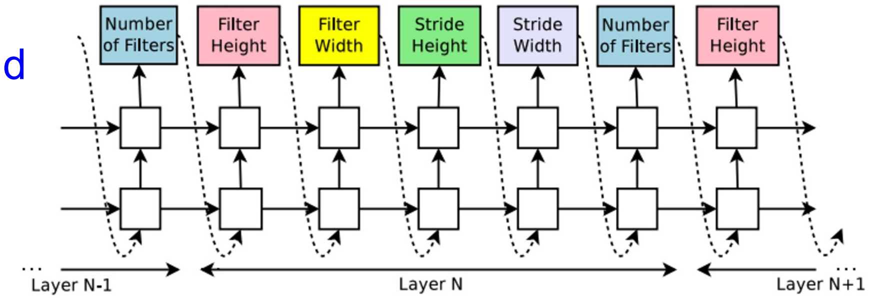
# Learning to search for network architectures...

## Neural Architecture Search with Reinforcement Learning (NAS)

*[Zoph et al. 2016]*

- “Controller” network that learns to design a good network architecture (output a string corresponding to network design)
- Iterate:
  1) Sample an architecture from search space
  2) Train the architecture to get a “reward” R corresponding to accuracy
  3) Compute gradient of sample probability, and scale by R to perform controller parameter update (i.e. increase likelihood of good architecture being sampled, decrease likelihood of bad architecture)



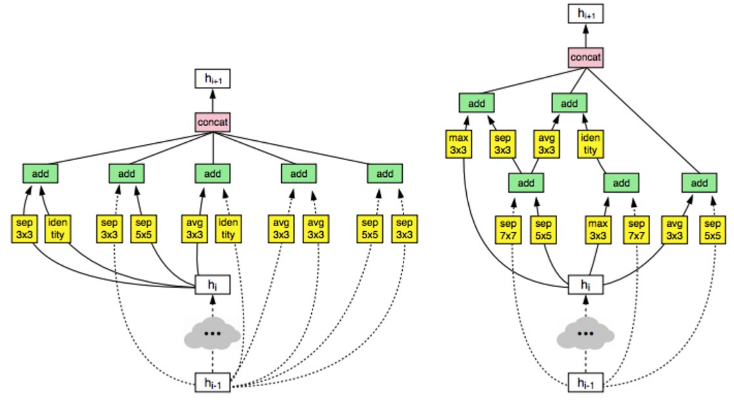



# Learning to search for network architectures...

## Learning Transferable Architectures for Scalable Image Recognition

*[Zoph et al. 2017]*

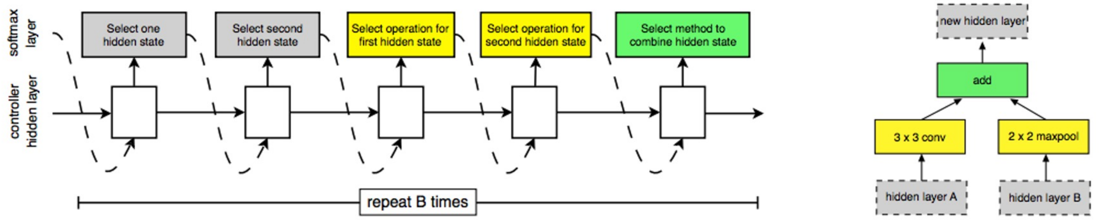
- Applying neural architecture search (NAS) to a large dataset like ImageNet is expensive
- Design a search space of building blocks ("cells") that can be flexibly stacked
- NASNet: Use NAS to find best cell structure on smaller CIFAR-10 dataset, then transfer architecture to ImageNet




Normal Cell

Reduction Cell

- Many follow-up works in this space e.g. AmoebaNet (Real et al. 2019) and ENAS (Pham, Guan et al. 2018)



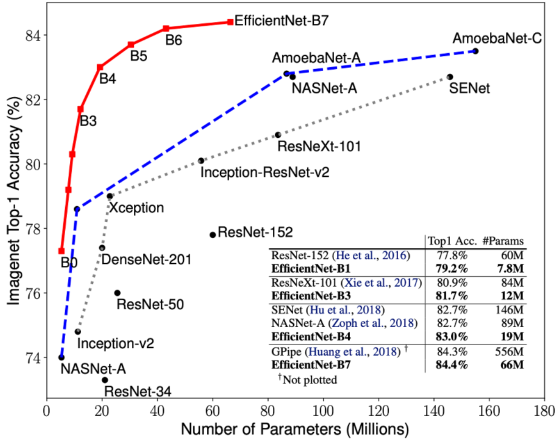
# But sometimes smart heuristic is better than NAS ...

## EfficientNet: Smart Compound Scaling

*[Tan and Le. 2019]*

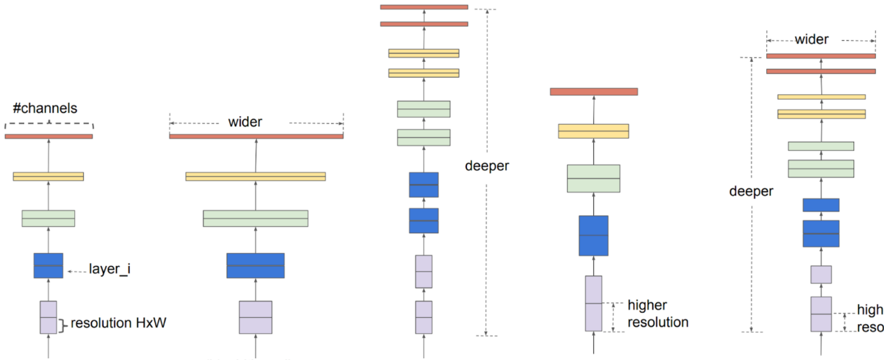
- Increase network capacity by scaling width, depth, and resolution, while balancing accuracy and efficiency.
- Search for optimal set of compound scaling factors given a compute budget (target memory & flops).
- Scale up using smart heuristic rules

$$\text{depth: } d = \alpha^{\phi}$$
$$\text{width: } w = \beta^{\phi}$$
$$\text{resolution: } r = \gamma^{\phi}$$
$$\text{s.t. } \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$$
$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$



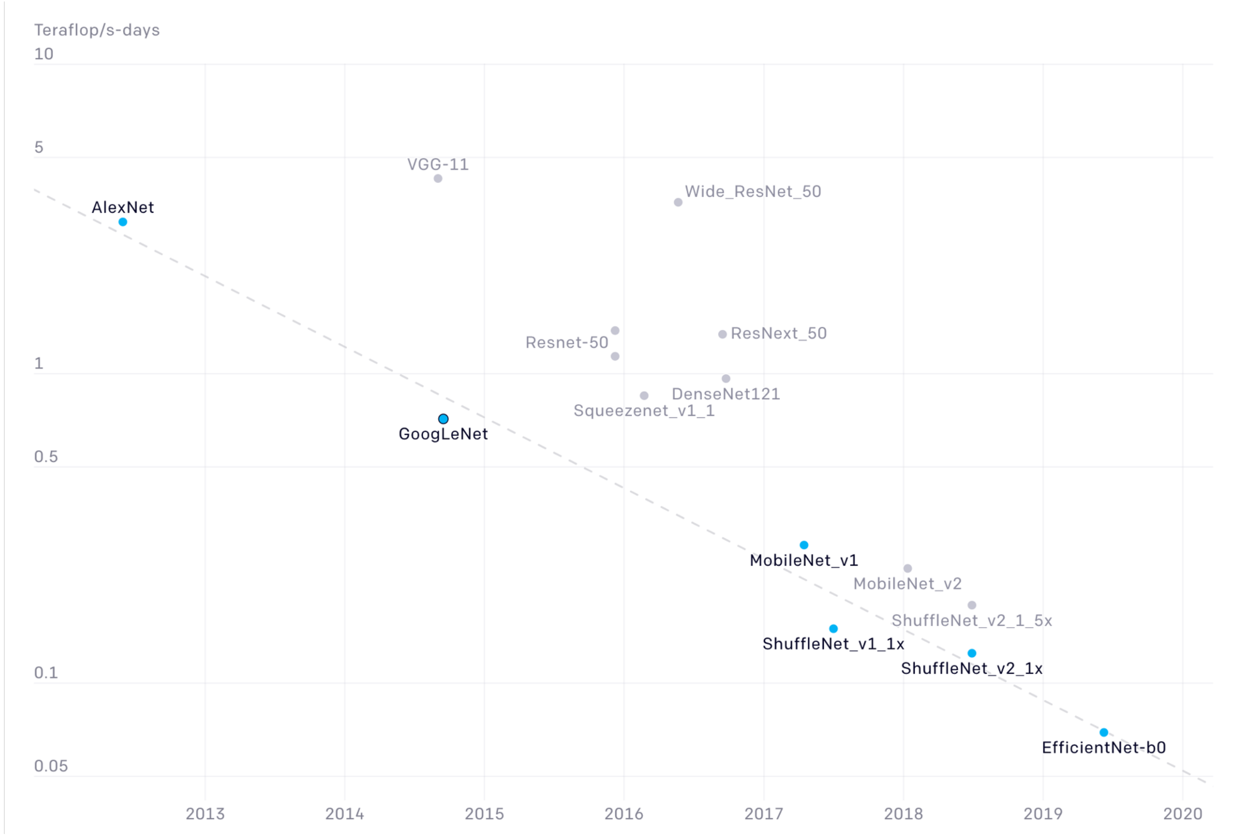

| | Top1 Acc. | #Params |
|---|---|---|
| ResNet-152 (He et al., 2016) | 77.8% | 60M |
| **EfficientNet-B1** | **79.2%** | **7.8M** |
| ResNeXt-101 (Xie et al., 2017) | 80.9% | 84M |
| **EfficientNet-B3** | **81.7%** | **12M** |
| SENet (Hu et al., 2018) | 82.7% | 146M |
| NASNet-A (Zoph et al., 2018) | 82.7% | 89M |
| **EfficientNet-B4** | **83.0%** | **19M** |
| GPipe (Huang et al., 2018) † | 84.3% | 556M |
| **EfficientNet-B7** | **84.4%** | **66M** |

†Not plotted




(a) baseline (b) width scaling (c) depth scaling (d) resolution scaling (e) compound scaling

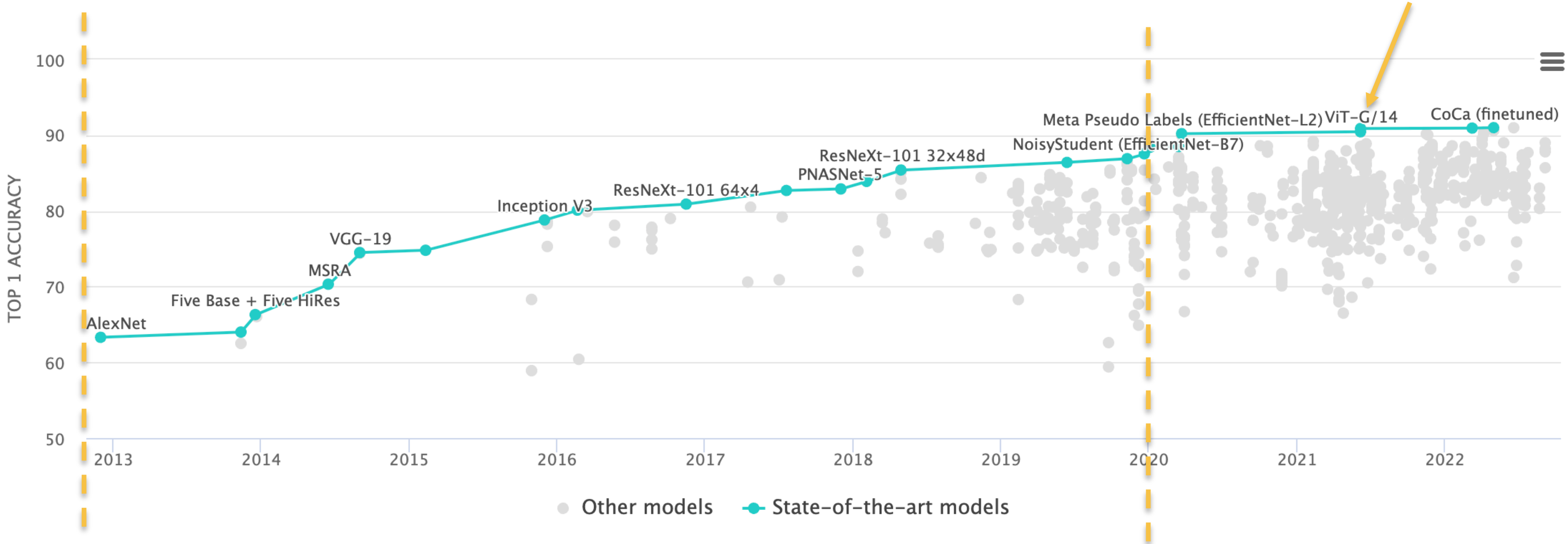
# Amount of compute required to reach “AlexNet performance”




https://openai.com/blog/ai-and-efficiency/

Transformer (later this sem.)

This Lecture




https://paperswithcode.com/sota/image-classification-on-imagenet

# What we have learned so far …

Deep Neural Networks:

- What they are (composite parametric, non-linear functions)
- Where they come from (biological inspiration, brief history of ANN)
- How they are optimized, in principle (analytical gradient via computational graphs, backpropagation)
- What they look like in practice (Deep ConvNets for vision)

# Next few lectures:

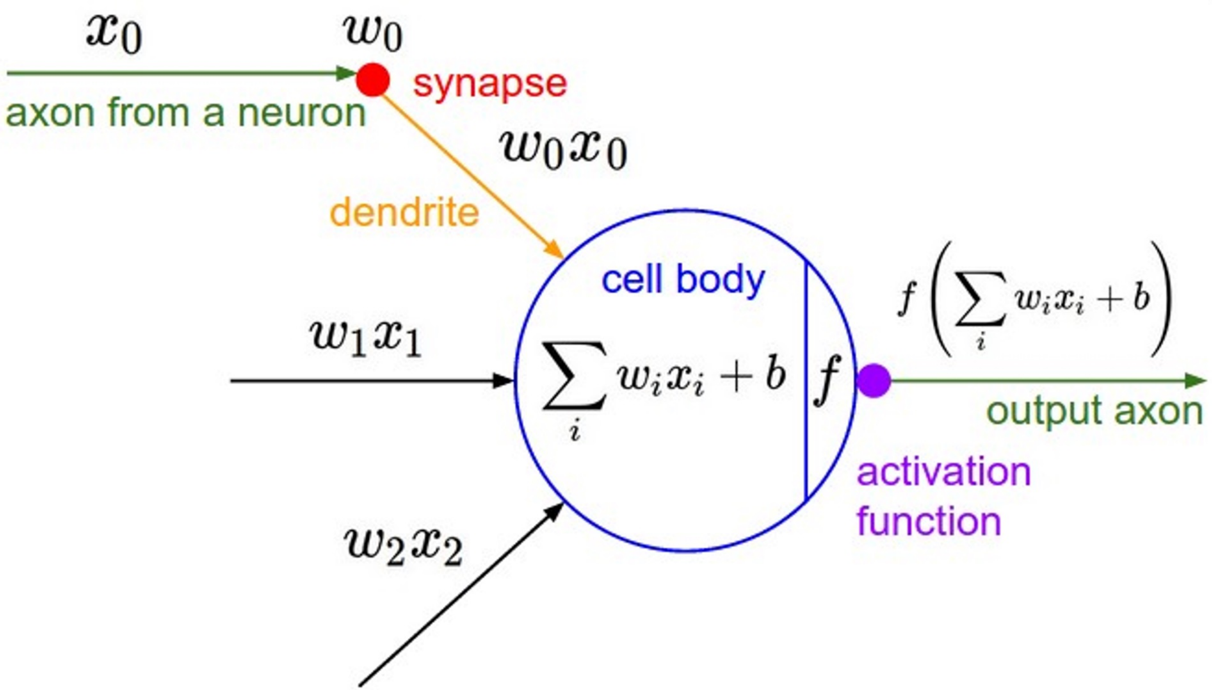
**Training** Deep Neural Networks

- Details of the non-linear activation functions
- Data normalization
- Weight Initialization
- Batch Normalization
- Regularization
- Advanced Optimization
- Data Augmentation
- Transfer learning
- Hyperparameter Tuning
- Model Ensemble

# Today: Training Deep NNs (Part 1)

- Details of the non-linear activation functions
- Data normalization
- Weight Initialization

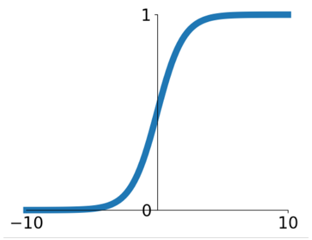
# Activation Functions



# Activation Functions

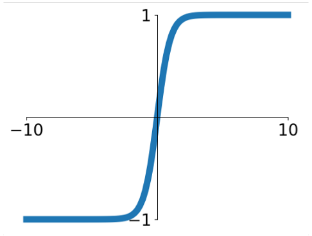
**Sigmoid**

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



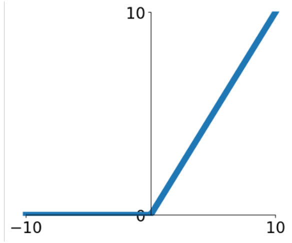

**tanh**

$\tanh(x)$



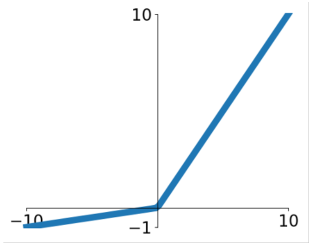

**ReLU**

$\max(0, x)$




**Leaky ReLU**

$\max(0.1x, x)$

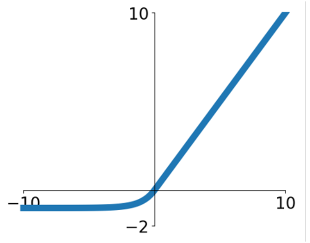



**Maxout**

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

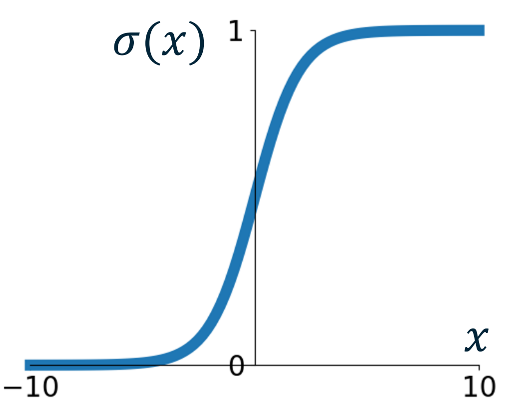
**ELU**

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



# Activation Functions

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




**Sigmoid**

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating "firing rate" of a neuron

# Activation Functions

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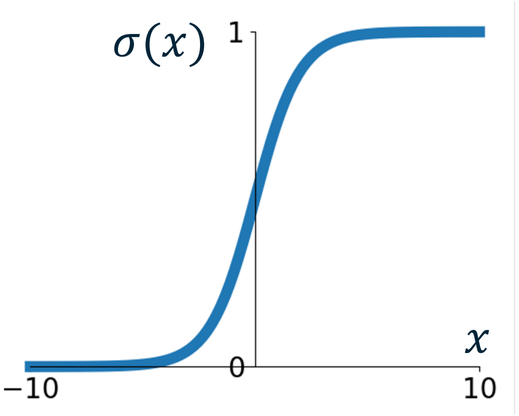


**Sigmoid**

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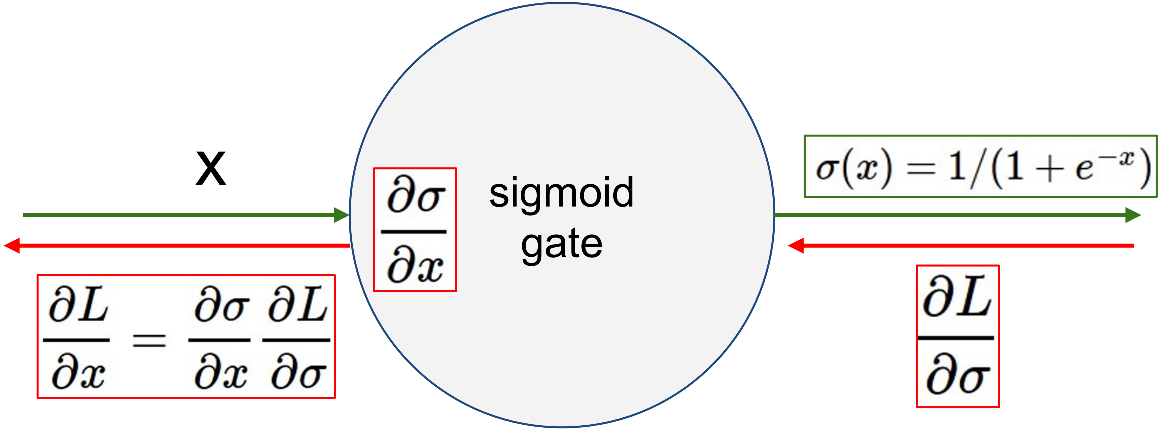
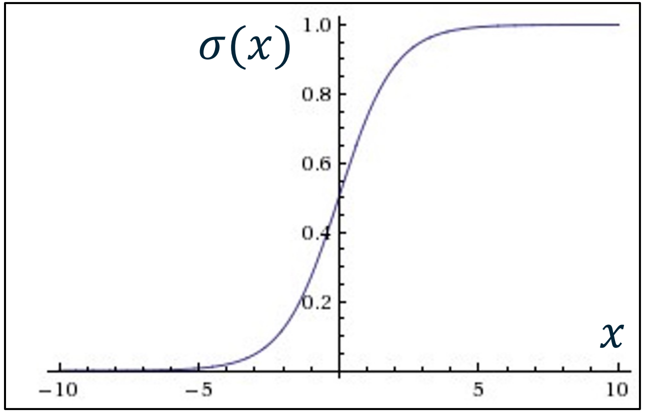
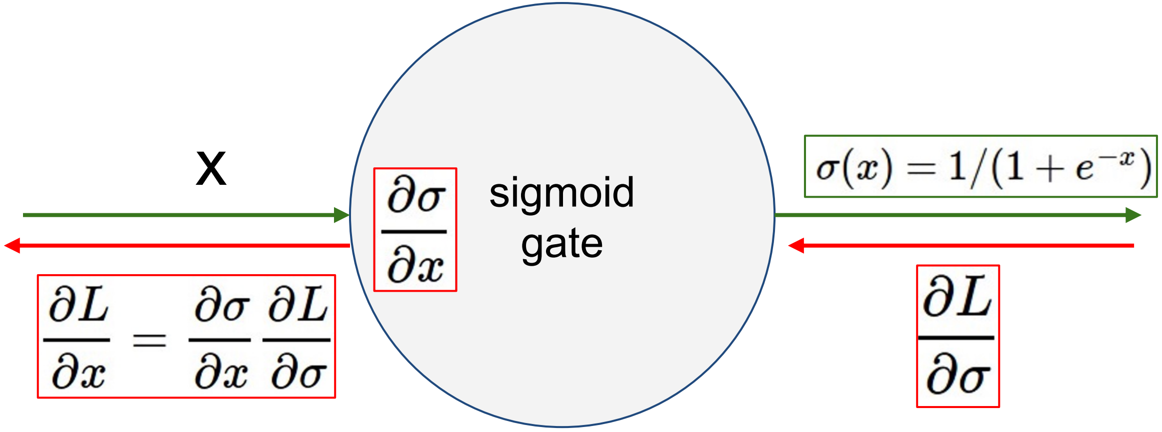
Problems:

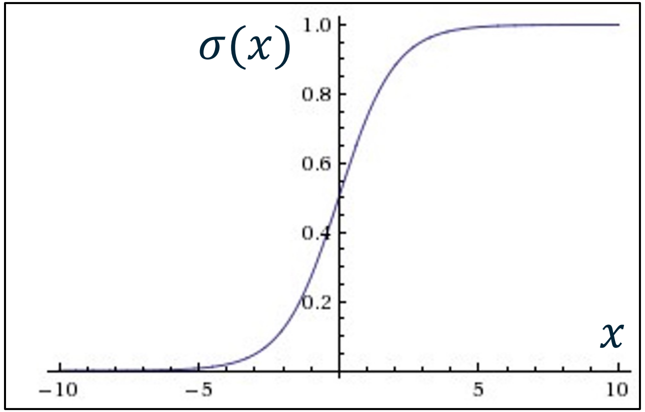
1. Saturated neurons "kill" the gradients



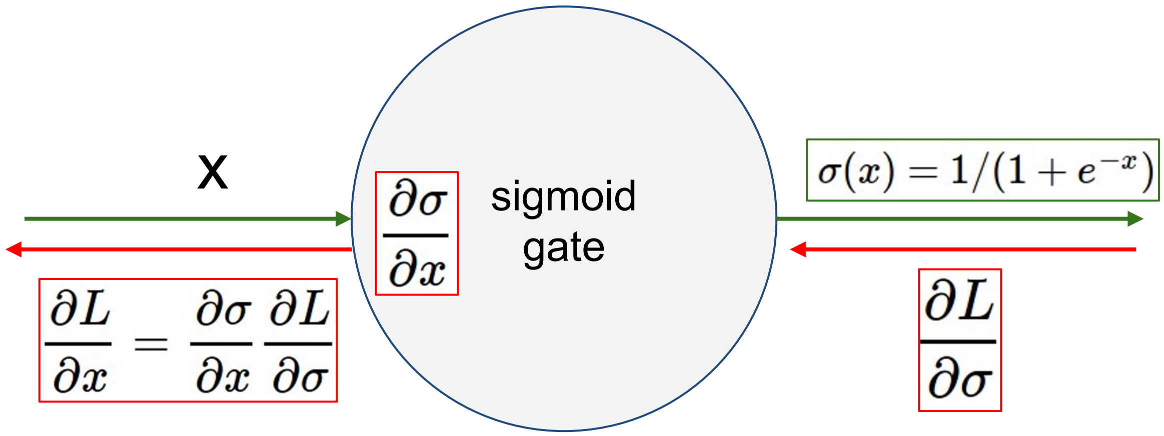

$$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)\,(1 - \sigma(x)\,)$$

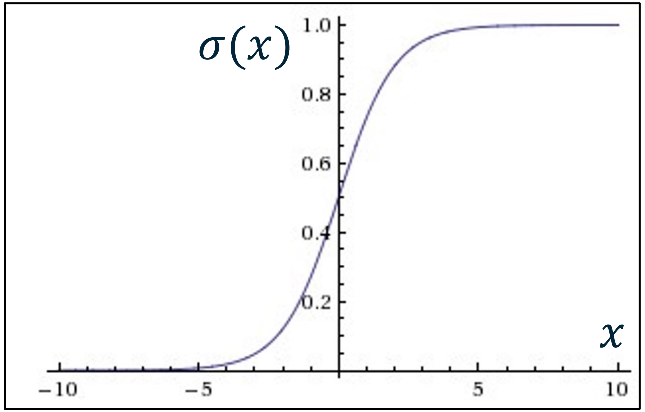



What happens when x = -10?

$$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)\,(1 - \sigma(x))$$



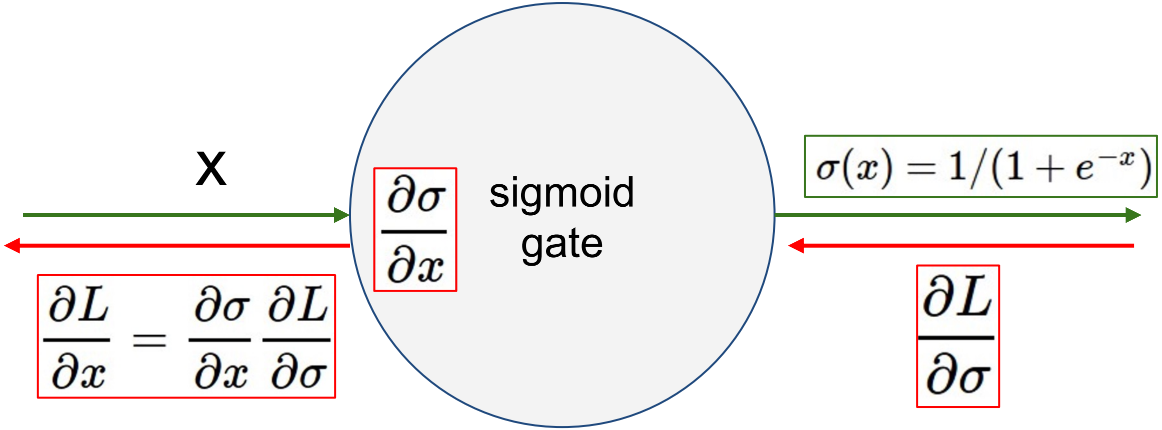



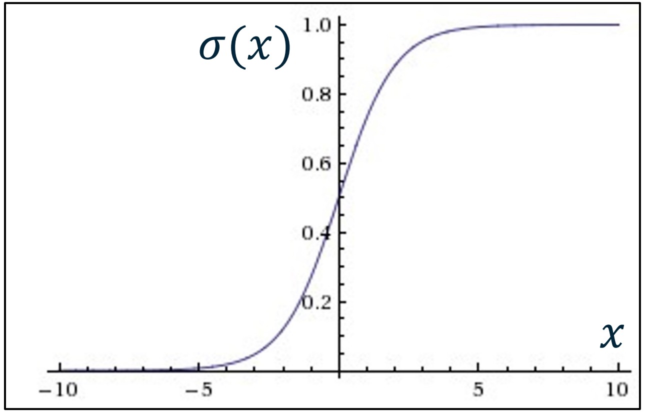

$$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)\,(1 - \sigma(x)\,)$$

## What happens when x = -10?

$$\sigma(x) \;= \sim 0$$

$$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)\,(1 - \sigma(x)\,) = 0(1-0) \;=\; 0$$

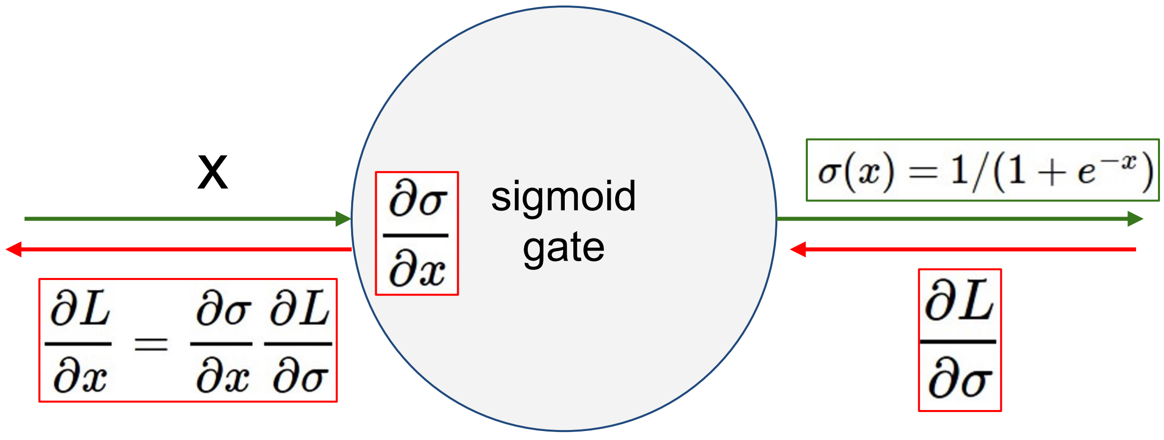


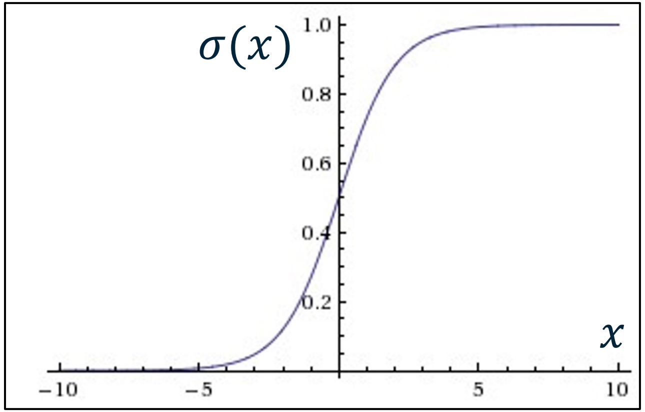




What happens when x = -10?

What happens when x = 10?

$$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)\,(1 - \sigma(x)\,)$$



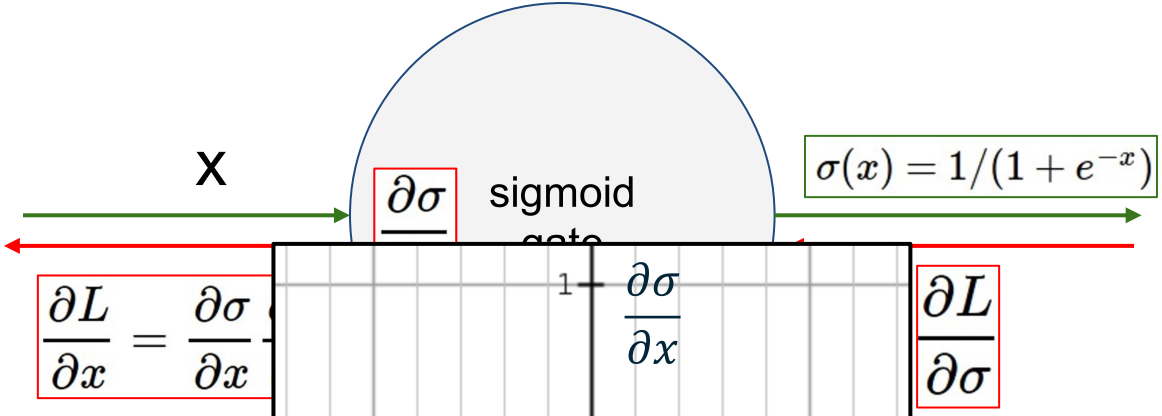



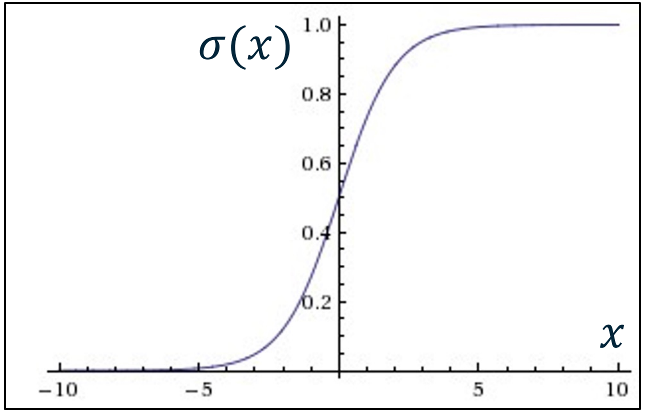

What happens when x = -10?

What happens when x = 10?

$$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)\,(1 - \sigma(x)\,)$$

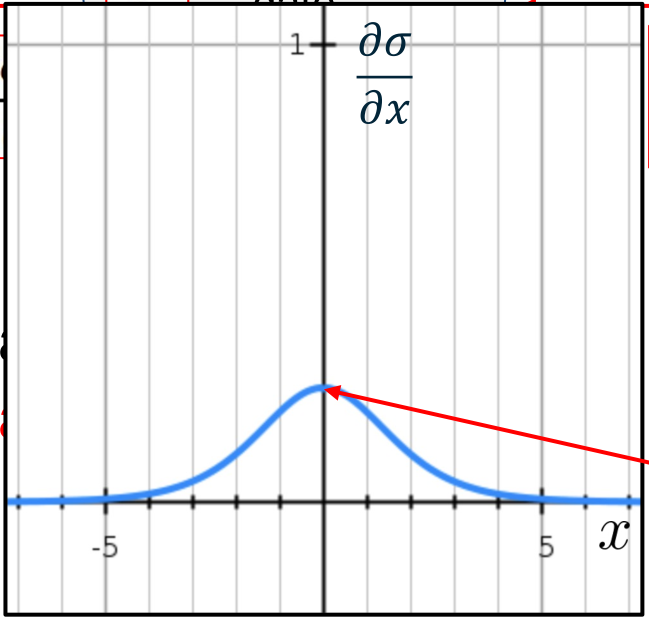
$$\sigma(x) \;=\sim 1 \qquad \frac{\partial \sigma(x)}{\partial x} = \sigma(x)\,(1 - \sigma(x)\,) = 1(1-1) \;=\; 0$$



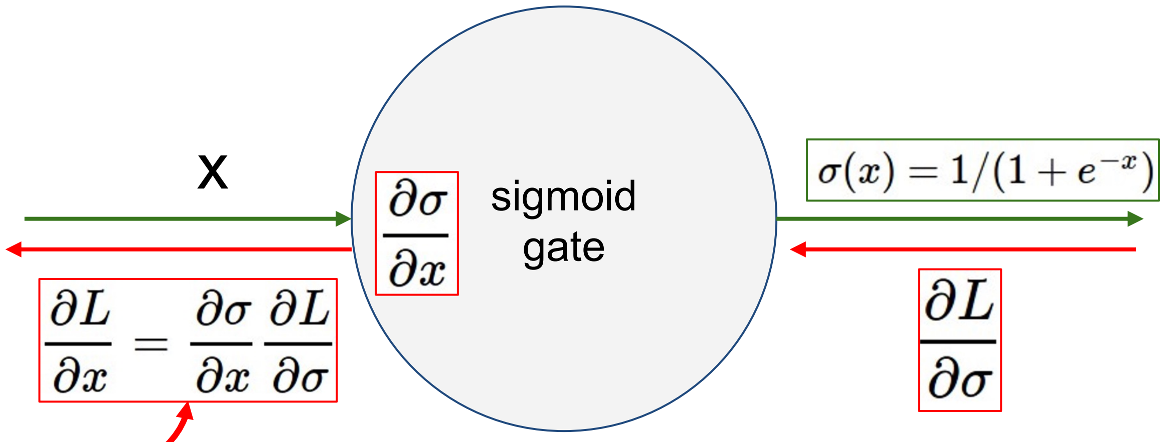

What h

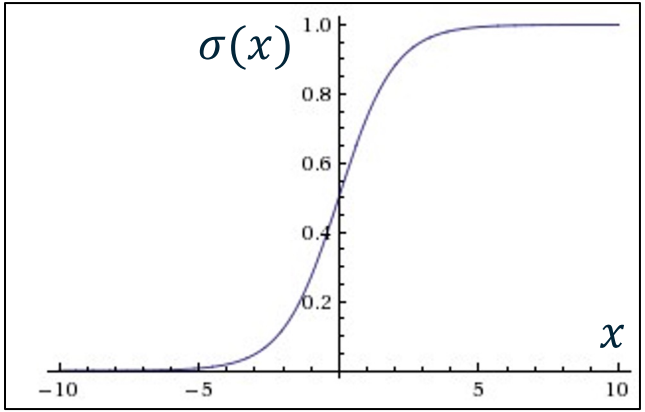
What h




$$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)\,(1 - \sigma(x)\,)$$

Non-zero but small:
still problematic, causes
vanishing gradient



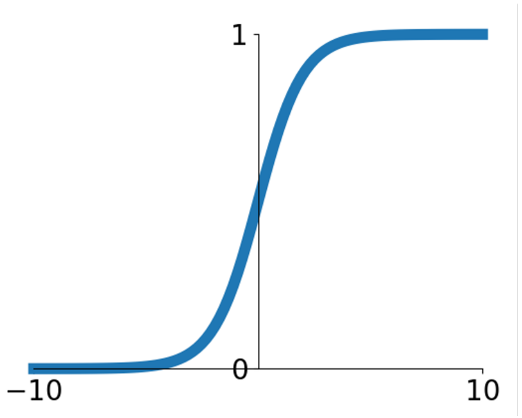

$$\frac{\partial \sigma(x)}{\partial x} = \sigma(x)\,(1 - \sigma(x))$$

Why is this a problem?

If all the gradients flowing back will be zero and weights will never change (aka "Vanishing Gradient")

# Activation Functions

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




**Sigmoid**

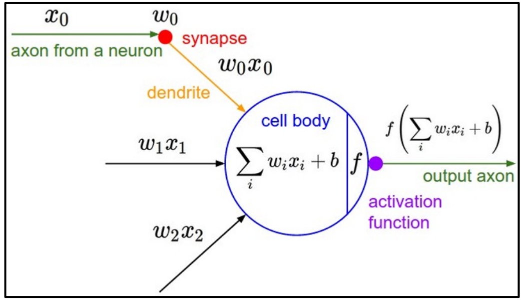
- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating "firing rate" of a neuron

Problems:

1. Saturated neurons "kill" the gradients
2. **Sigmoid outputs are not zero-centered**

Consider what happens when the input to a neuron **is always positive...**

$$f\left(\sum_i w_i x_i + b\right)$$




What can we say about the gradients on **w**?

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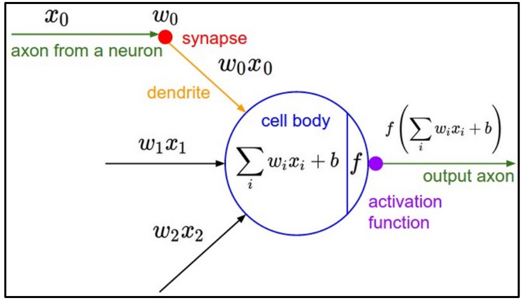
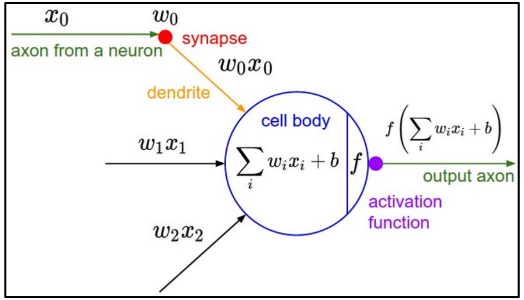



What can we say about the gradients on **w**?

$$\frac{\partial L}{\partial w} = \sigma(\textstyle\sum_i w_i x_i + b)(1 - \sigma(\textstyle\sum_i w_i x_i + b))x \times upstream\_gradient$$

Consider what happens when the input to a neuron **is always positive...**

$$f\left(\sum_i w_i x_i + b\right)$$

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We know that local gradient of sigmoid is always positive

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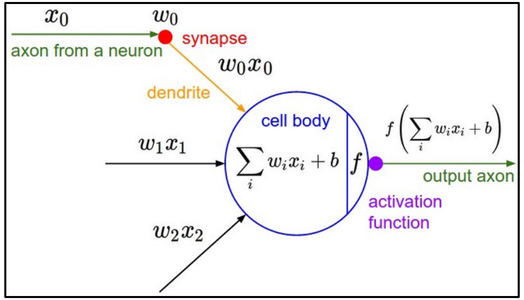


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We know that local gradient of sigmoid is always positive
We are assuming x is positive

$$\frac{\partial L}{\partial w} = \sigma(\textstyle\sum_i w_i x_i + b)(1 - \sigma(\sum_i w_i x_i + b))x \times upstream\_gradient$$

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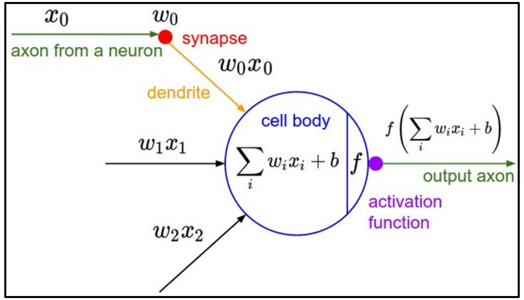
$$f\left(\sum_i w_i x_i + b\right)$$




What can we say about the gradients on **w**?

We know that local gradient of sigmoid is always positive

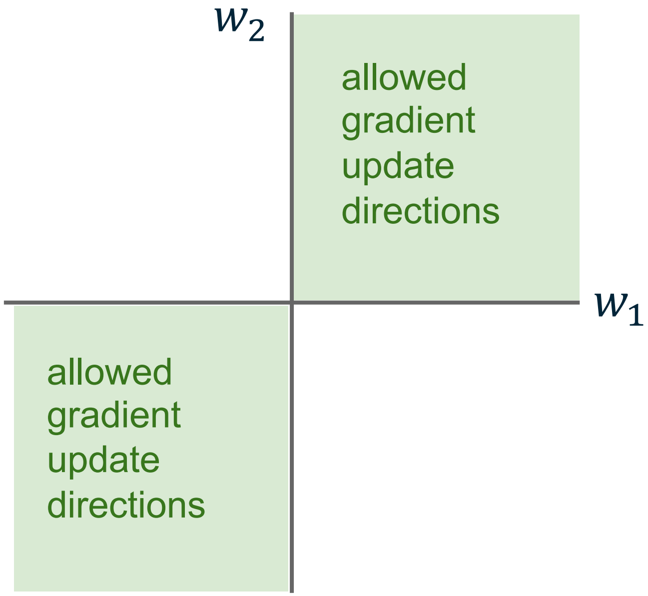
We are assuming x is positive

Sign of gradient **for all** $\mathbf{w_i}$ is the same as the sign of upstream gradient.
That is, local gradient cannot change the sign of global gradient

$$\frac{\partial L}{\partial w} = \sigma\left(\sum_i w_i x_i + b\right)\left(1 - \sigma\left(\sum_i w_i x_i + b\right)\right) x \times upstream\_gradient$$

Consider what happens when the input to a neuron is always positive...

$$f\left(\sum_i w_i x_i + b\right)$$




Local gradient cannot change the sign of global gradient.

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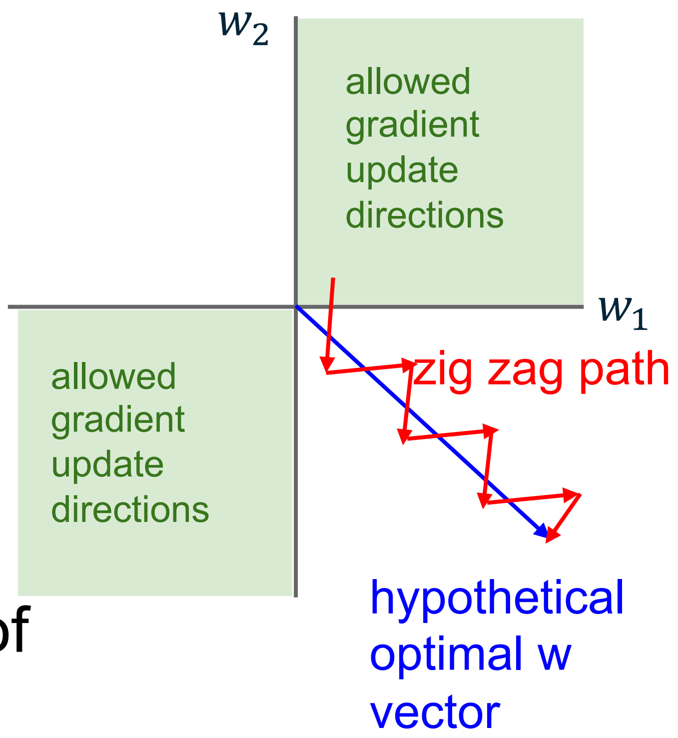
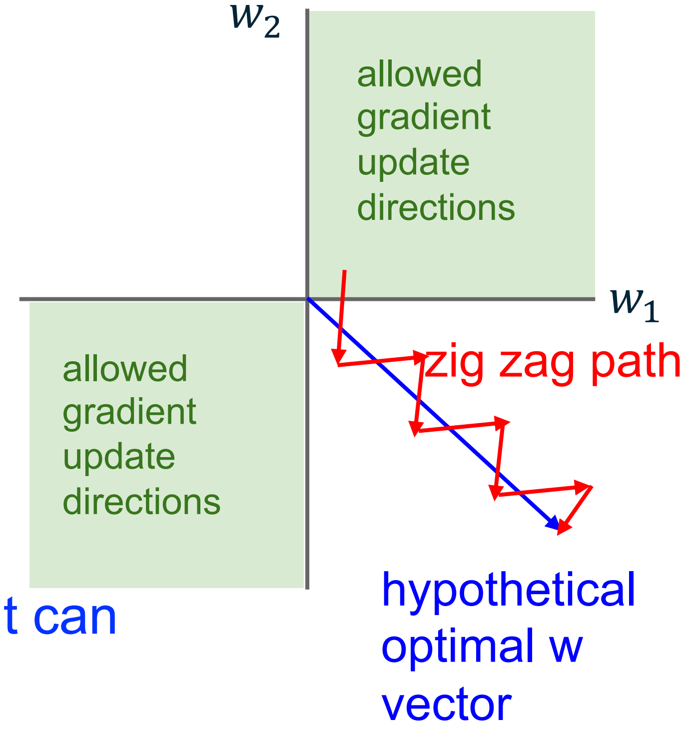



Local gradient cannot change the sign of global gradient.

Can easily lead to all-positive or all-negative gradient update (zig-zag).

# Consider what happens when the input to a neuron is always positive...

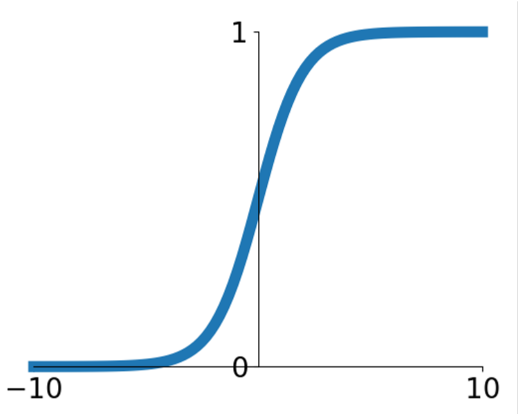
$$f\left(\sum_i w_i x_i + b\right)$$




**Remark**: both upstream gradient and local input can change the sign of gradient irrespective of the activation, but having a zero-centered activation function (output spans both positive and negative) can further minimize the “zig-zag” effect

# Activation Functions

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




**Sigmoid**

- Squashes numbers to range [0,1]
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Problems:

1. Saturated neurons “kill” the gradients
2. Sigmoid outputs are not zero-centered (output does not span both positive and negative)

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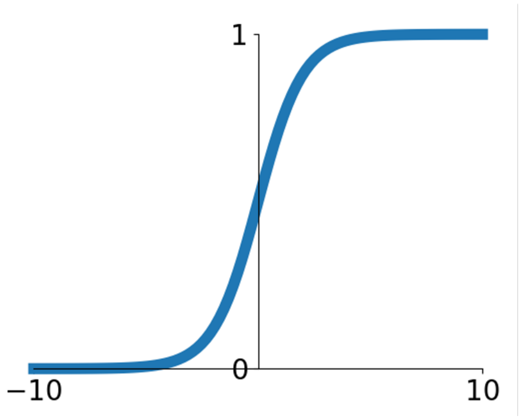


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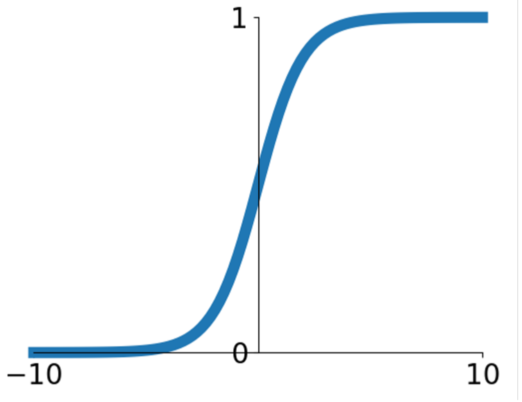
Problems:

1. Saturated neurons "kill" the gradients
2. Sigmoid outputs are not zero-centered (output does not span both positive and negative)
3. exp() is a bit compute expensive

# Activation Functions

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

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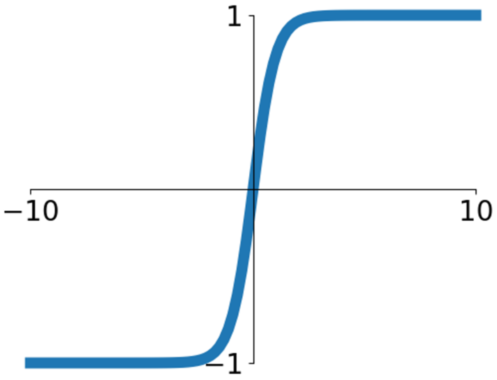
**Worst problem in practice: Saturated neurons "kill" the gradients / vanishing gradient**

# Activation Functions

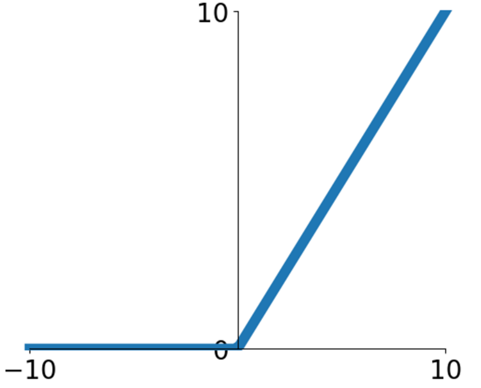



**tanh(x)**

- Squashes numbers to range [-1,1]
- zero centered (nice)
- still kills gradients when saturated :(

[LeCun et al., 1991]

# Activation Functions



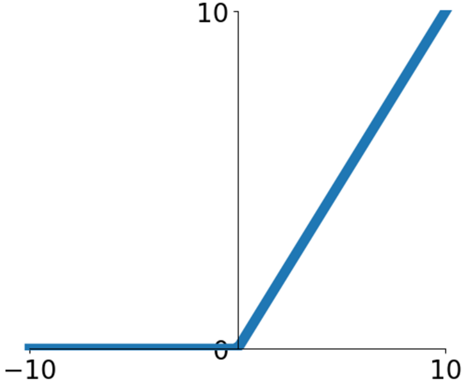

**ReLU**
(Rectified Linear Unit)

- Computes **f(x) = max(0,x)**

- Does not saturate (in +region)
- Very computationally efficient
- Converges much faster than sigmoid/tanh in practice (e.g. 6x)

[Krizhevsky et al., 2012]

# Activation Functions

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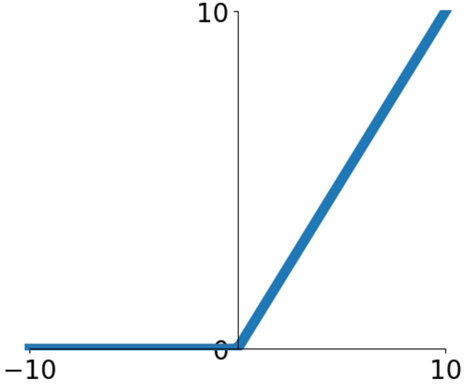
# Activation Functions

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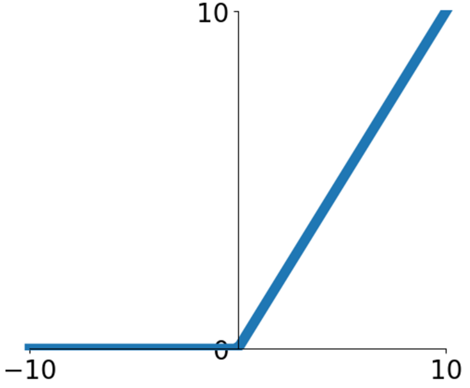
- Not zero-centered output
- An annoyance:

hint: what is the gradient when x < 0?

# Activation Functions

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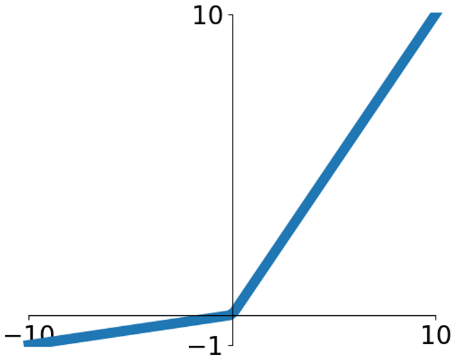
- Not zero-centered output
- An annoyance:

hint: what is the gradient when x < 0?
Always 0 -> no update in weights -> stays 0, A.K.A. “dead ReLU”

# Activation Functions

[Mass et al., 2013]
[He et al., 2015]



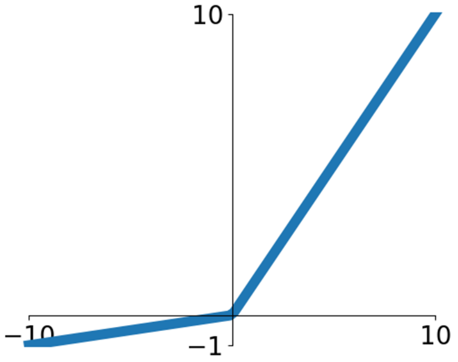

- Does not saturate
- Computationally efficient
- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- **will not "die".**

**Leaky ReLU**

$$f(x) = \max(0.01x, x)$$

# Activation Functions

[Mass et al., 2013]
[He et al., 2015]

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- Converges much faster than sigmoid/tanh in practice! (e.g. 6x)
- **will not “die”.**

**Leaky ReLU**

$$f(x) = \max(0.01x, x)$$

**Parametric Rectifier (PReLU)**

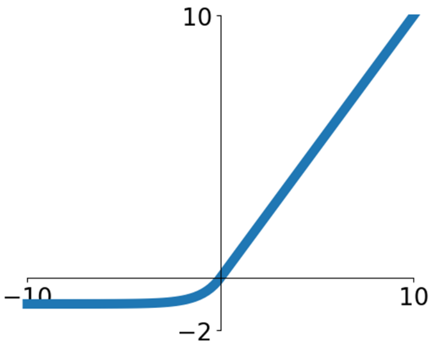
$$f(x) = \max(\alpha x, x)$$

backprop into \alpha (parameter)

# Activation Functions

[Clevert et al., 2015]

## Exponential Linear Units (ELU)




$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \le 0 \end{cases}$$

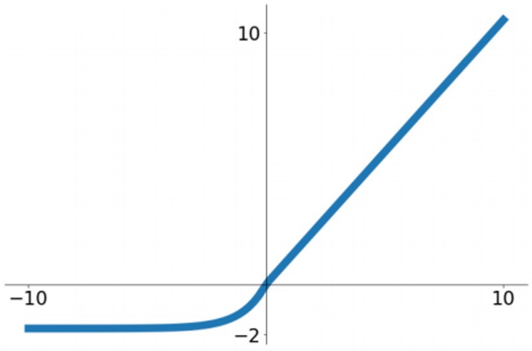
(Alpha default = 1)

- All benefits of ReLU
- Negative saturation encodes presence of features (all goes to $-\alpha$), not magnitude
- Similar in backprop ($\alpha e^{x}$ when $x$ is negative)
- Compared with Leaky ReLU: smooth gradient at 0 (no kink), better optimization landscape

# Activation Functions

[Klambauer et al. ICLR 2017]

## Scaled Exponential Linear Units (SELU)



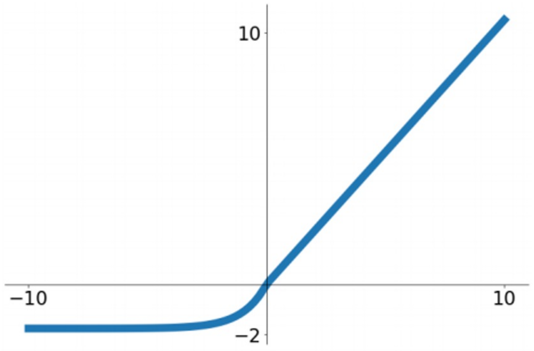

$$f(x) = \begin{cases} \lambda x & \text{if } x > 0 \\ \lambda\alpha(e^x - 1) & \text{otherwise} \end{cases}$$

- Scaled versionof ELU that works better for deep networks
- "Self-normalizing" property: under certain condition, the output of a feedforward network stays around zero-mean and unit variance

# Activation Functions

[Klambauer et al. ICLR 2017]

## Scaled Exponential Linear Units (SELU)




$$f(x) = \begin{cases} \lambda x & \text{if } x > 0 \\ \lambda\alpha(e^x - 1) & \text{otherwise} \end{cases}$$

α = 1.6732632423543772848170429916717
λ = 1.0507009873554804934193349852946

- Scaled versionof ELU that works better for deep networks
- "Self-normalizing" property: under certain condition, the output of a feedforward network stays around zero-mean and unit variance

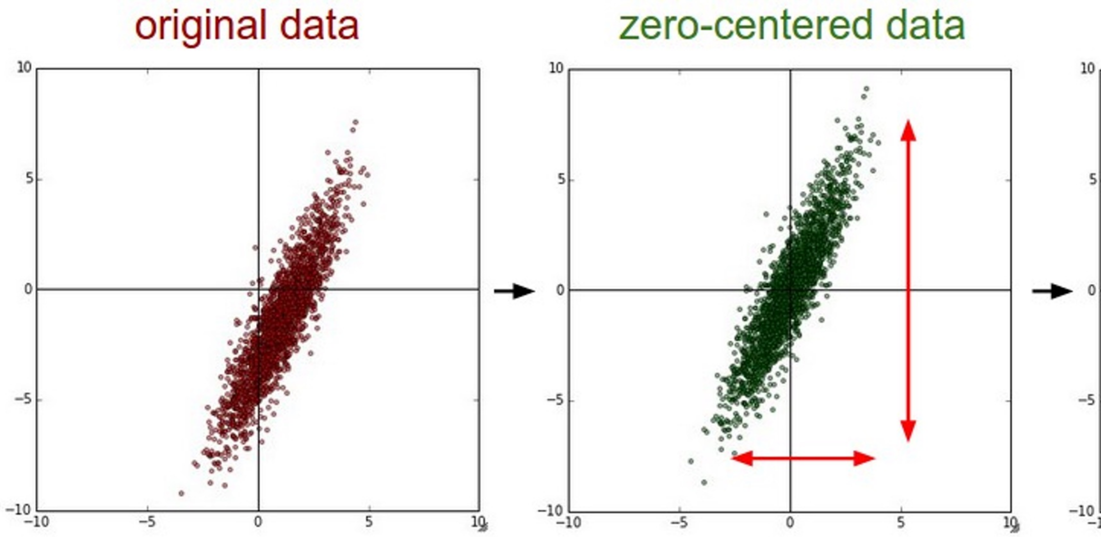
(Klambauer et al, Self-Normalizing Neural Networks, ICLR 2017)

# TLDR: In practice:

- Many possible choices beyond what we've talked here, but …
- Use ReLU. Be careful with your learning rates
- Try out Leaky ReLU / ELU / SELU
  - To squeeze out some marginal gains
- Don't use sigmoid or tanh

# Data Preprocessing

# Data Preprocessing



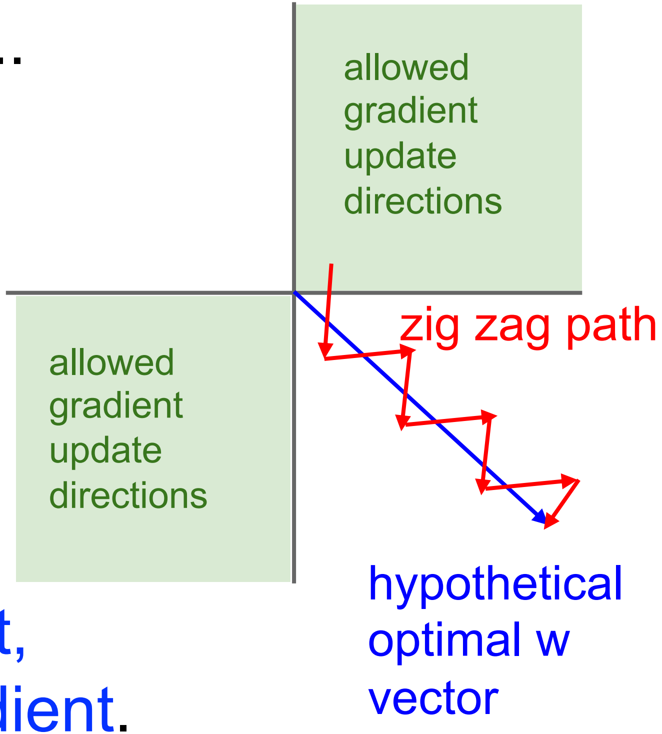

```
X -= np.mean(X, axis = 0)
```

```
X /= np.std(X, axis = 0)
```

(Assume X [NxD] is data matrix, each example in a row)

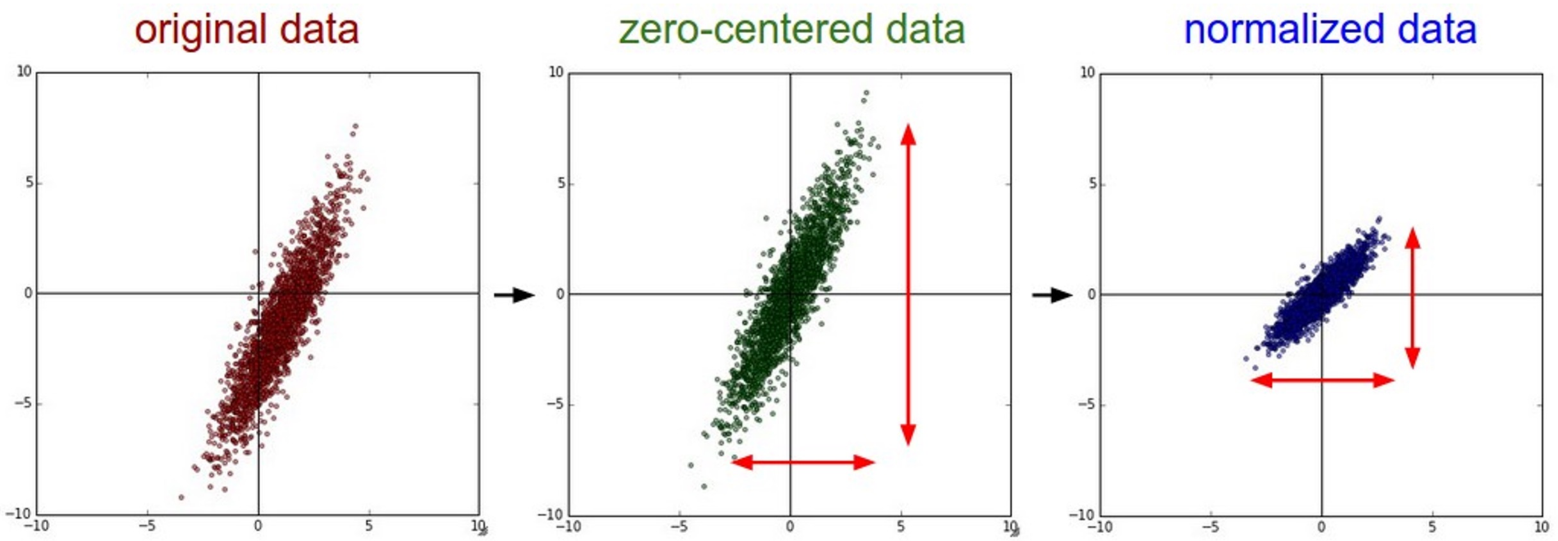
Remember: Consider what happens when the input to a neuron is always positive...

$$f\left(\sum_i w_i x_i + b\right)$$




In addition to upstream and local gradient, input also determines the sign of the gradient. To reduce biases in gradient, we want the input to span both positive and negative value

# Data Preprocessing



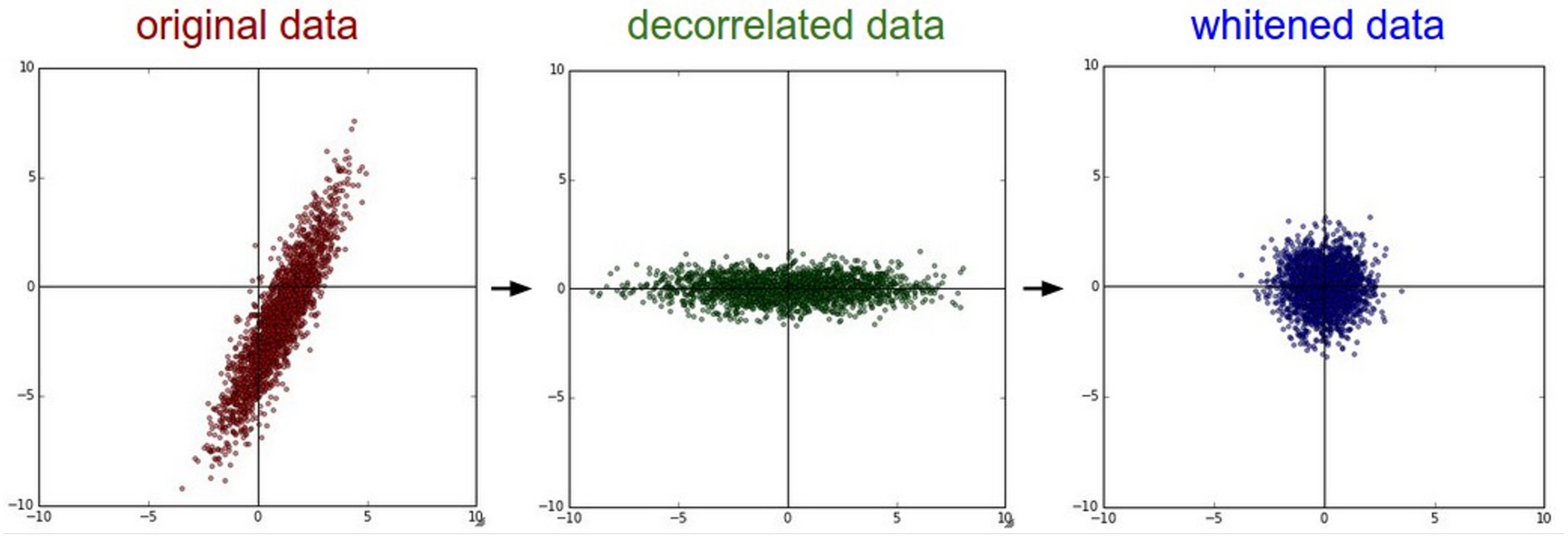

```
X -= np.mean(X, axis = 0)
```

```
X /= np.std(X, axis = 0)
```

(Assume X [NxD] is data matrix, each example in a row)

# Data Preprocessing

In practice, you could also **PCA** and **Whitening** of the data

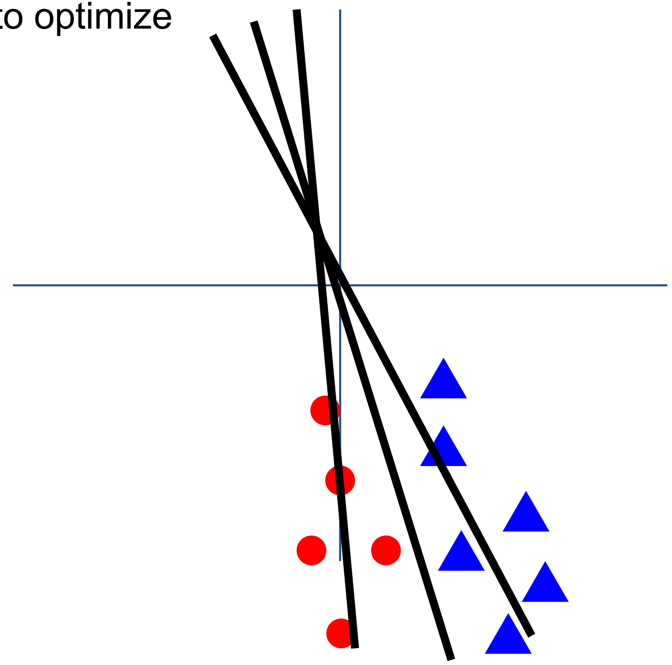



(data has diagonal covariance matrix)

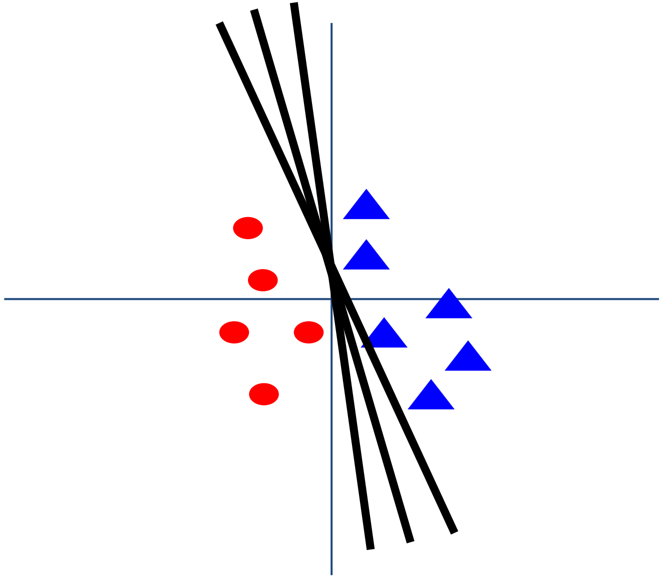
(covariance matrix is the identity matrix)

# Data Preprocessing

**Before normalization**: classification loss very sensitive to changes in weight matrix; hard to optimize



**After normalization**: less sensitive to small changes in weights; easier to optimize



# **Examples:** images

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

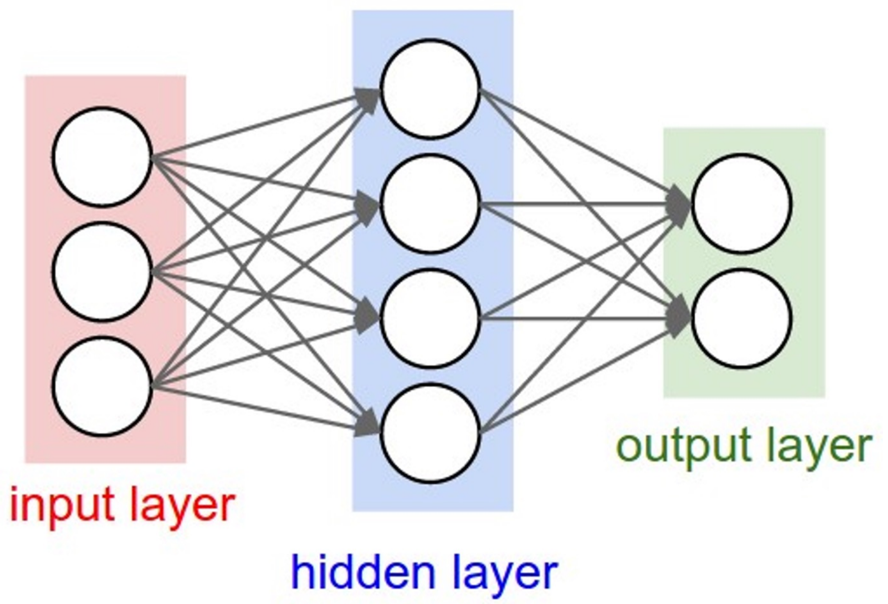
- Subtract the per-pixel mean(e.g. AlexNet)
  (mean image = [32,32,3] array)
- Subtract per-channel mean (e.g. VGGNet)
  (mean along each channel = 3 numbers,)
- Subtract per-channel mean and
  Divide by per-channel std (e.g. ResNet)
  (mean along each channel = 3 numbers)

# **Examples:** other domains

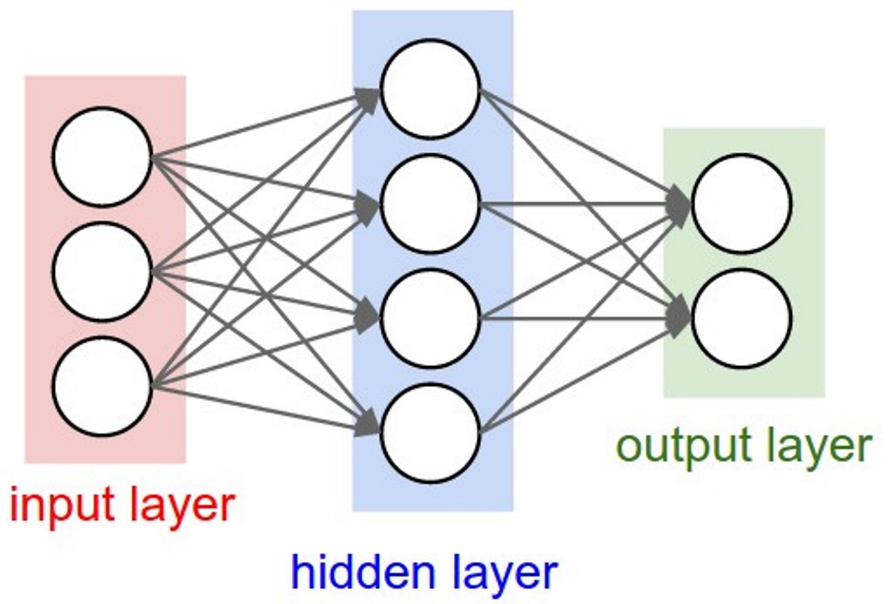
- **Natural language processing:** Normalize word embeddings like Word2Vec or GloVe vectors so that they have a unit norm
- **Graph Neural Networks (GNN):** the feature vector of a node might be scaled by the inverse of its degree or the square root of its degree.
- **Audio data**: Spectral normalize waveforms to ensure that the frequency components are on a similar scale.
- **Reinforcement learning**: reward can be normalized to have zero mean and unit variance to stabilize learning.

# Weight Initialization

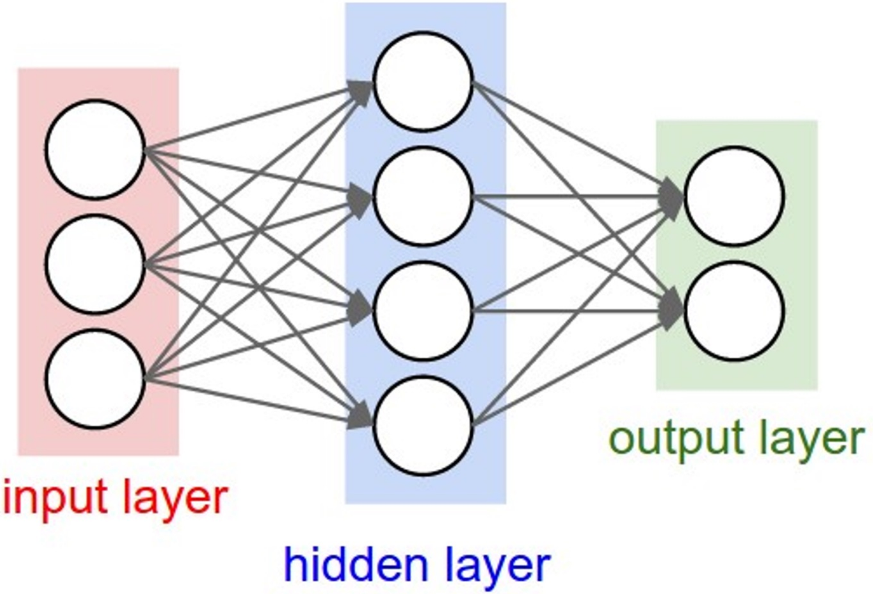
- Q: what happens when W=same initial value is used?



- Q: what happens when W=same initial value is used?
- A: All output will be the same! $w_1^T x = w_2^T x$ if $w_1 = w_2$



- Q: what happens when W=same initial value is used?
- A: All output will be the same! $w_1^T x = w_2^T x$ if $w_1 = w_2$
- Want to **maintain variance** through the layers.



- First idea: **Small random numbers**
(gaussian with zero mean and 1e-2 standard deviation)

```
W = 0.01 * np.random.randn(Din, Dout)
```

- First idea: **Small random numbers**
(gaussian with zero mean and 1e-2 standard deviation)

```
W = 0.01 * np.random.randn(Din, Dout)
```

Works ~okay for small networks, but problems with deeper networks.

# Weight Initialization: Activation statistics

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = 0.01 * np.random.randn(Din, Dout)
    x = np.tanh(x.dot(W))
    hs.append(x)
```

Forward pass for a 6-layer net with hidden size 4096

What will happen to the activations for the last layer?

# Weight Initialization: Activation statistics

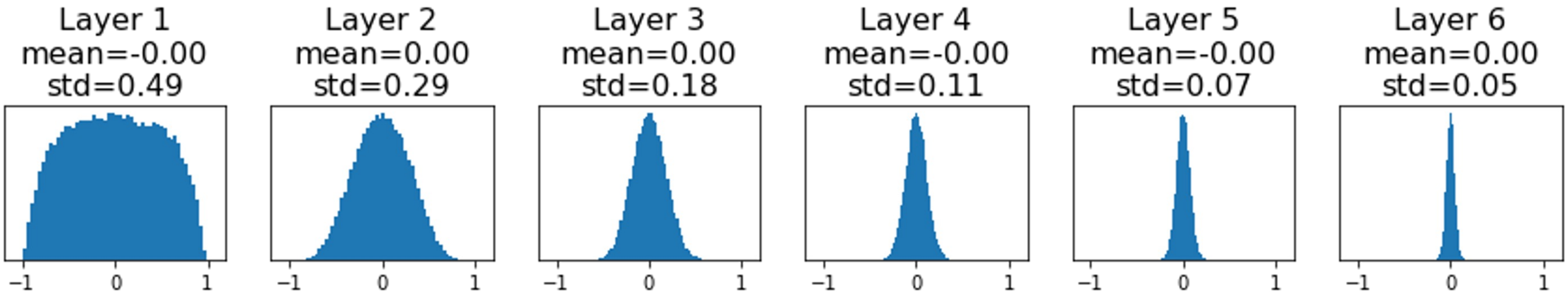
```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = 0.01 * np.random.randn(Din, Dout)
    x = np.tanh(x.dot(W))
    hs.append(x)
```

Forward pass for a 6-layer net with hidden size 4096

All activations tend to zero for deeper network layers

**Q**: What do the gradients dL/dW look like?

Hint: $\frac{\partial L}{\partial w} = x^T \left( \frac{\partial L}{\partial y} \right)$




Visualize distribution of activations

# Weight Initialization: Activation statistics

```
dims = [4096] * 7
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x = np.random.randn(16, dims[0])
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    hs.append(x)
```
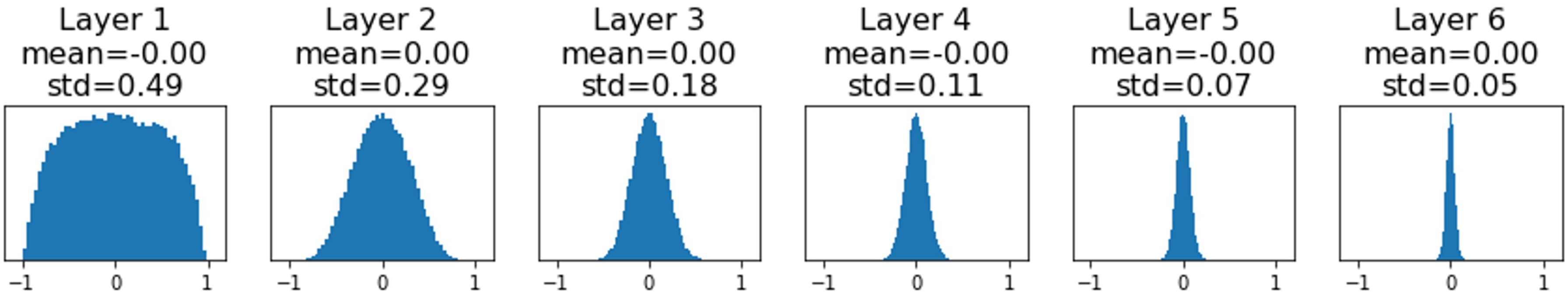

Forward pass for a 6-layer net with hidden size 4096

All activations tend to zero for deeper network layers

**Q**: What do the gradients dL/dW look like?

**A**: All zero, no learning =(




Visualize distribution of activations

# Weight Initialization: Activation statistics

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = 0.05 * np.random.randn(Din, Dout)
    x = np.tanh(x.dot(W))
    hs.append(x)
```

Increase std of initial weights from 0.01 to 0.05

Initialize with higher values

What will happen to the activations for the last layer?

# Weight Initialization: Activation statistics

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = 0.05 * np.random.randn(Din, Dout)
    x = np.tanh(x.dot(W))
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```
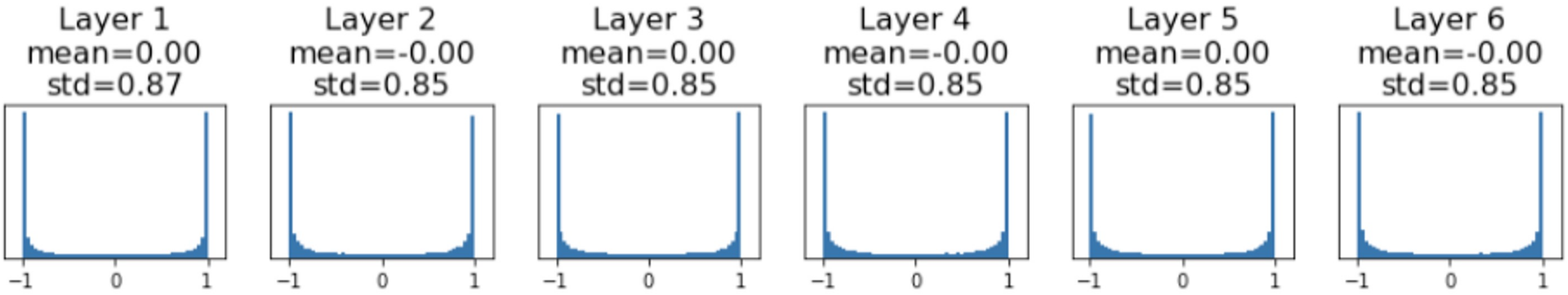

Increase std of initial weights from 0.01 to 0.05

All activations saturate

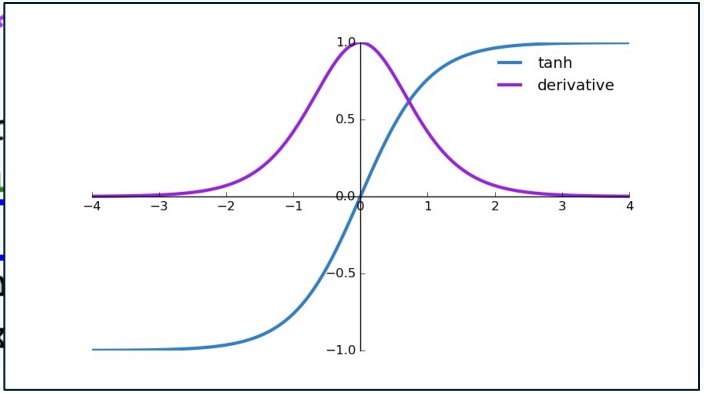
**Q**: What do the gradients look like?




Visualize distribution of activations

# Weight Initialization: Activation statistics

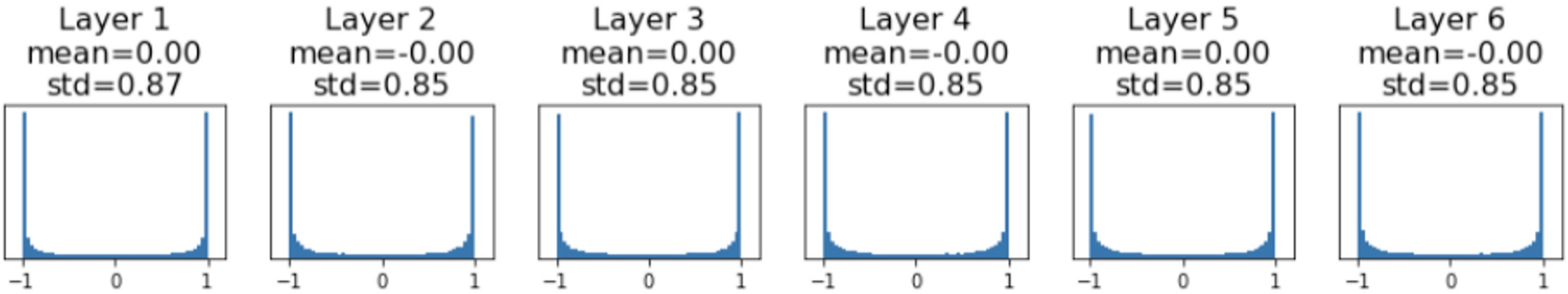
```
dims = [4096] *
hs = []
x = np.random.r
for Din, Dout i
    W = 0.05 *
    x = np.tanh
    hs.append(x
```




All activations saturate

**Q**: What do the gradients look like?

**A**: Local gradients all zero, no learning =(




Visualize distribution of activations

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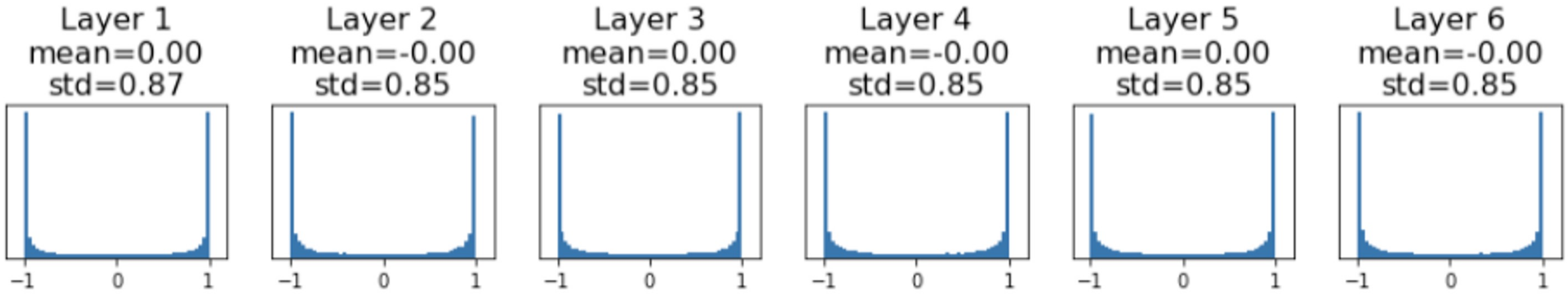
```

Increase std of initial weights from 0.01 to 0.05

All activations saturate

**Q**: What do the gradients look like?

More generally, *gradient explosion* (high w-> high output -> high gradient).




Visualize distribution of activations

# Weight Initialization: "Xavier" Initialization

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) / np.sqrt(Din)
    x = np.tanh(x.dot(W))
    hs.append(x)
```

"Xavier" initialization:
std = 1/sqrt(Din)

Glorot and Bengio, "Understanding the difficulty of training deep feedforward neural networks", AISTAT 2010

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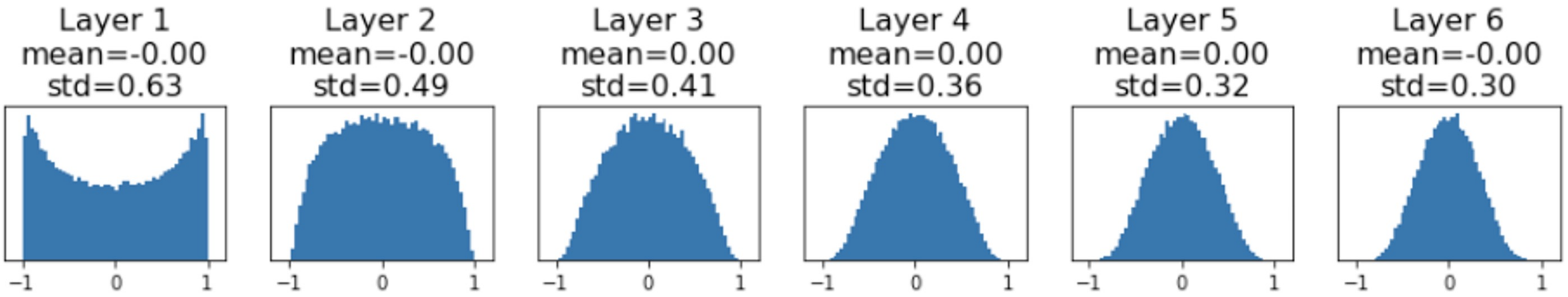
"Xavier" initialization:
std = 1/sqrt(Din)

"Just right": Activations are nicely scaled for all layers!

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Visualize distribution of activations

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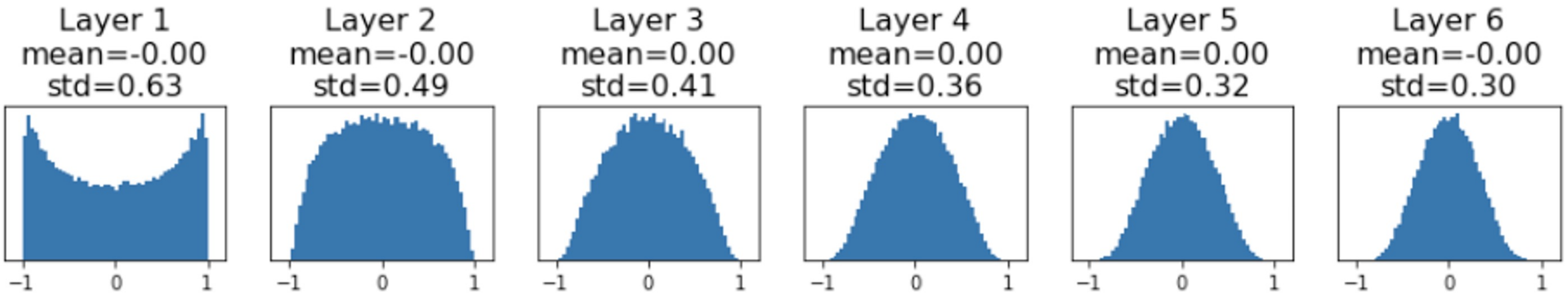
For conv layers, Din is filter_size$^2$ * input_channels

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"Just right": Activations are nicely scaled for all layers!

For conv layers, Din is $\text{filter\_size}^2 * \text{input\_channels}$

**Let:** $y = x_1w_1+x_2w_2+\ldots+x_{Din}w_{Din}$

Glorot and Bengio, "Understanding the difficulty of training deep feedforward neural networks", AISTAT 2010

# Weight Initialization: "Xavier" Initialization

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For conv layers, Din is $filter\_size^2$ * input_channels

**Let:** $y = x_1w_1+x_2w_2+\ldots+x_{Din}w_{Din}$

**Assume:** $Var(x_1) = Var(x_2)= \ldots=Var(x_{Din})$

Glorot and Bengio, "Understanding the difficulty of training deep feedforward neural networks", AISTAT 2010

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**We want:** $Var(y) = Var(x_i)$

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    hs.append(x)
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"Xavier" initialization:
std = 1/sqrt(Din)

"Just right": Activations are nicely scaled for all layers!

For conv layers, Din is $filter\_size^2$ * input_channels

**Let:** $y = x_1w_1+x_2w_2+...+x_{Din}w_{Din}$

**Assume:** $Var(x_1) = Var(x_2)= ...=Var(x_{Din})$

**We want:** $Var(y) = Var(x_i)$

$Var(y) = Var(x_1w_1+x_2w_2+...+x_{Din}w_{Din})$
[substituting value of y]

Glorot and Bengio, "Understanding the difficulty of training deep feedforward neural networks", AISTAT 2010

# Weight Initialization: “Xavier” Initialization

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hs = []
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```

“Xavier” initialization: std = 1/sqrt(Din)

“Just right”: Activations are nicely scaled for all layers!

For conv layers, Din is $filter\_size^2$ * input_channels

**Let:** $y = x_1w_1+x_2w_2+\ldots+x_{Din}w_{Din}$

**Assume:** $Var(x_1) = Var(x_2)= \ldots=Var(x_{Din})$

**We want:** $Var(y) = Var(x_i)$

$Var(y) = Var(x_1w_1+x_2w_2+\ldots+x_{Din}w_{Din})$

$= \Sigma\ Var(x_iw_i) = Din\ Var(x_iw_i)$

[Assume all $x_i$, $w_i$ are iid] $\sigma^2_{X+Y} = \sigma^2_X + \sigma^2_Y$

Glorot and Bengio, “Understanding the difficulty of training deep feedforward neural networks”, AISTAT 2010

# Weight Initialization: "Xavier" Initialization

```
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hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) / np.sqrt(Din)
    x = np.tanh(x.dot(W))
    hs.append(x)
```

"Xavier" initialization:
std = 1/sqrt(Din)

"Just right": Activations are nicely scaled for all layers!

For conv layers, Din is $\text{filter\_size}^2$ * input_channels

**Let:** $y = x_1w_1+x_2w_2+\ldots+x_{Din}w_{Din}$

**Assume:** $Var(x_1) = Var(x_2)= \ldots=Var(x_{Din})$

**We want:** $Var(y) = Var(x_i)$

$Var(y) = Var(x_1w_1+x_2w_2+\ldots+x_{Din}w_{Din})$

$= Din\ Var(x_iw_i)$

$= Din\ Var(x_i)\ Var(w_i)$

[Assume all $x_i$, $w_i$ are zero mean]

$$\mathrm{Var}(XY) = E(X^2Y^2) - (E(XY))^2 = \mathrm{Var}(X)\mathrm{Var}(Y) + \mathrm{Var}(X)(E(Y))^2 + \mathrm{Var}(Y)(E(X))^2$$

Glorot and Bengio, "Understanding the difficulty of training deep feedforward neural networks", AISTAT 2010

# Weight Initialization: “Xavier” Initialization

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) / np.sqrt(Din)
    x = np.tanh(x.dot(W))
    hs.append(x)
```

“Xavier” initialization: std = 1/sqrt(Din)

“Just right”: Activations are nicely scaled for all layers!

For conv layers, Din is $filter\_size^2 * input\_channels$

**Let:** $y = x_1w_1+x_2w_2+...+x_{Din}w_{Din}$

**Assume:** $Var(x_1) = Var(x_2)= ...=Var(x_{Din})$

**We want:** $Var(y) = Var(x_i)$

$Var(y) = Var(x_1w_1+x_2w_2+...+x_{Din}w_{Din})$

$= Din\ Var(x_iw_i)$

$= Din\ Var(x_i)\ Var(w_i)$

[Assume all $x_i$, $w_i$ are iid]

So, $Var(y) = Var(x_i)$ only when $Var(w_i) = 1/Din$

Glorot and Bengio, “Understanding the difficulty of training deep feedforward neural networks”, AISTAT 2010

# Weight Initialization: What about ReLU?

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) / np.sqrt(Din)
    x = np.maximum(0, x.dot(W))
    hs.append(x)
```

Change from tanh to ReLU

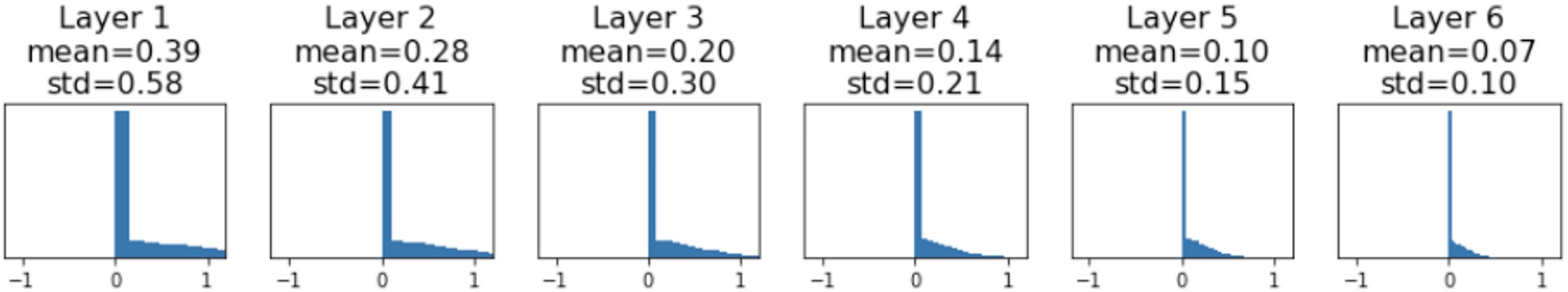
# Weight Initialization: What about ReLU?

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) / np.sqrt(Din)
    x = np.maximum(0, x.dot(W))
    hs.append(x)
```

Change from tanh to ReLU

Xavier assumes zero centered activation function

Activations collapse to zero again, no learning =(




Visualize distribution of activations

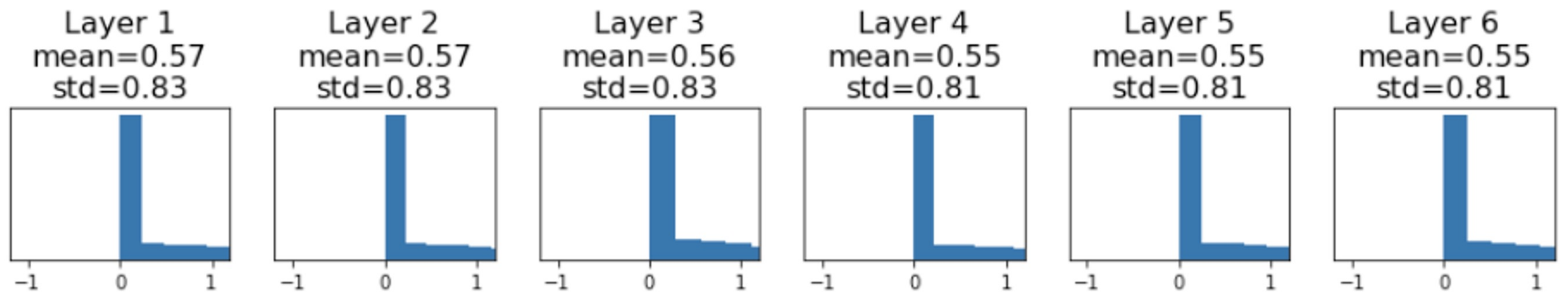
# Weight Initialization: Kaiming / MSRA Initialization

```
dims = [4096] * 7
hs = []
x = np.random.randn(16, dims[0])
for Din, Dout in zip(dims[:-1], dims[1:]):
    W = np.random.randn(Din, Dout) * np.sqrt(2/Din)
    x = np.maximum(0, x.dot(W))
    hs.append(x)
```

ReLU correction: std = sqrt(2 / Din)

Issue: Half of the activation get killed.

Solution: make the non-zero output variance twice as large as input




He et al, “Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification”, ICCV 2015

Visualize distribution of activations

# Proper initialization is an active area of research…

***Understanding the difficulty of training deep feedforward neural networks***
by Glorot and Bengio, 2010

***Exact solutions to the nonlinear dynamics of learning in deep linear neural networks*** by Saxe et al, 2013

***Random walk initialization for training very deep feedforward networks*** by Sussillo and Abbott, 2014

***Delving deep into rectifiers: Surpassing human-level performance on ImageNet classification*** by He et al., 2015

***Data-dependent Initializations of Convolutional Neural Networks*** by Krähenbühl et al., 2015

***All you need is a good init***, Mishkin and Matas, 2015

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# Summary

**Training** Deep Neural Networks

- Details of the non-linear activation functions
    - Sigmoid, Tanh, ReLU, LeakyRELU, ELU, SELU
- Data normalization
    - Zero-centering, decorrelation, image normalization
- Weight Initialization
    - Constant init, random init, Xavier Init, Kaiming Init

# Next time:

**Training** Deep Neural Networks

- Details of the non-linear activation functions
- Data normalization
- Weight Initialization
- Batch Normalization
- Advanced Optimization
- Regularization
- Data Augmentation
- Transfer learning
- Hyperparameter Tuning
- Model Ensemble