(Not very) Recent progresses in machine learning and possible application to particle physics

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About me

- **Yuta Nakashima**
  Institute for Datability Science, Osaka University
  Associate Professor

- Bio
  - -2012: Ph.D Course, Osaka University
  - 2012: Visiting Scholar, UNC Charlotte
  - 2012-2016: Assistant Prof., Nara Institute for Science and Technology
  - 2015-2016: Visiting Scholar, CMU
  - 2017- : Current Position

- Research interests
  - Computer Vision; CV
  - Pattern Recognition; PR
  - (Natural Language Processing; NLP)

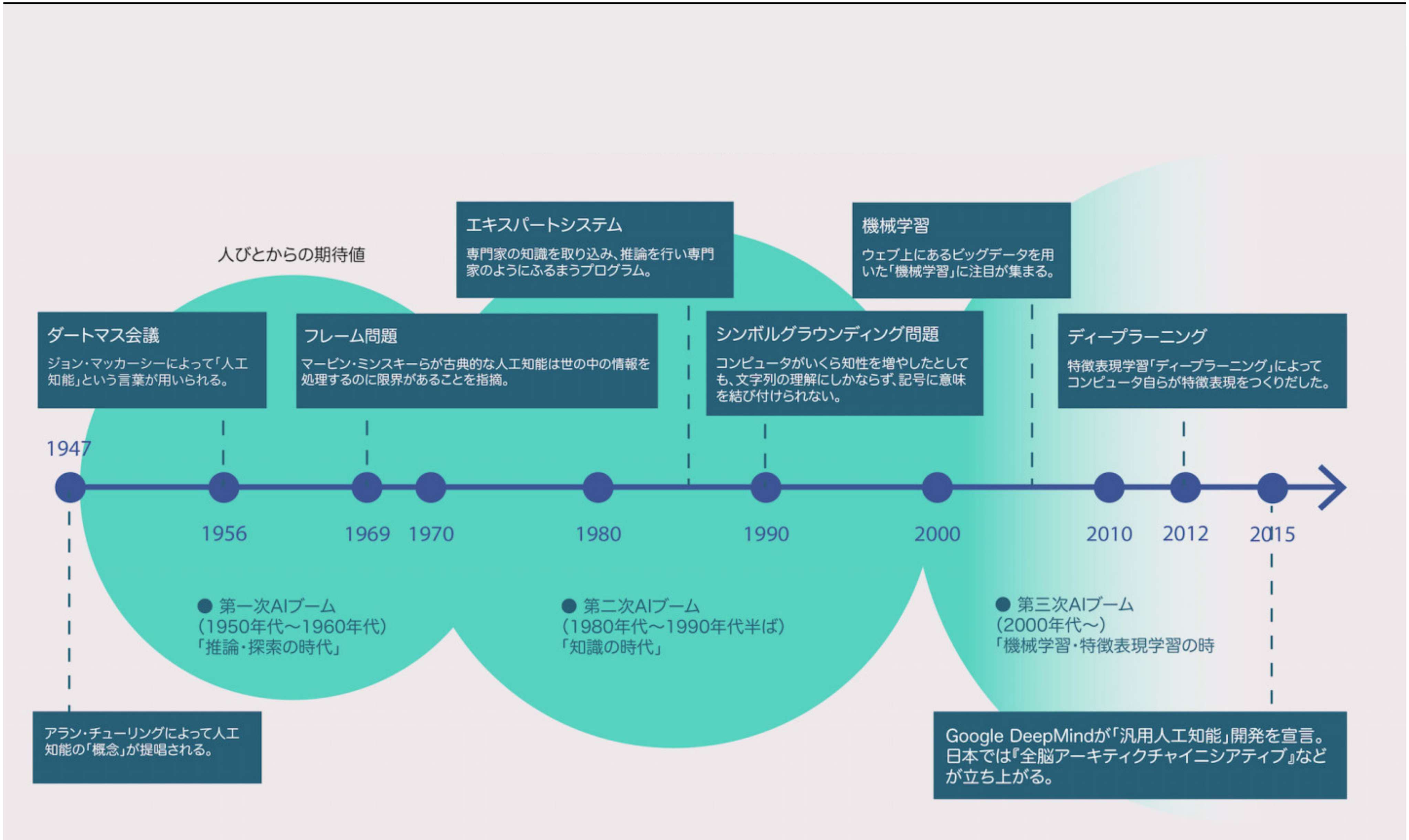
Agenda

- AI? Machine learning? Deep learning?
- Why deep learning?
- Training a neural network
- Problems in neural networks
- An application to Physics
- Shortcut learning?

AI?
Machine learning?
Deep learning?

History of AI

Image taken from: http://ja.catalyst.red/articles/ai-infographic-01/



Relationships among AI-related fields

Artificial Intelligence, AI

- Rule bases
- Expert systems

Machine Learning, ML

- Support vector machine
- Logistic regression
- Ridge regression
- (shallow) neural networks

Representation Learning, RL

- (shallow) autoencoder
- Dictionary learning

Deep Learning, DL

- Restricted Boltzmann machine
- Deep neural networks

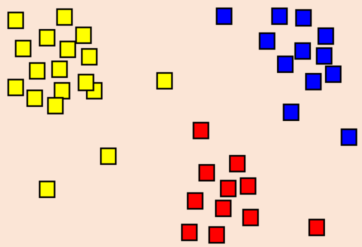
Tasks in Machine Learning

Machine Learning

…

Unsupervised learning

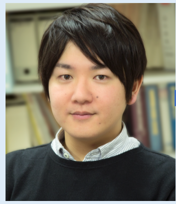
- Dimensionality reduction
- Clustering



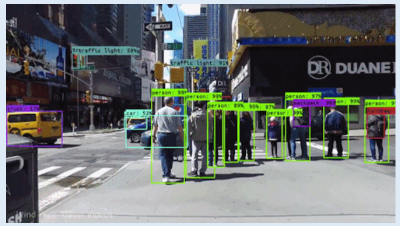
Supervised learning

- Classification
- Regression
- Detection
- Segmentation

From: https://thegradient.pub/semantic-segmentation/



$\rightarrow 35.4 \in \mathbb{R}_+$



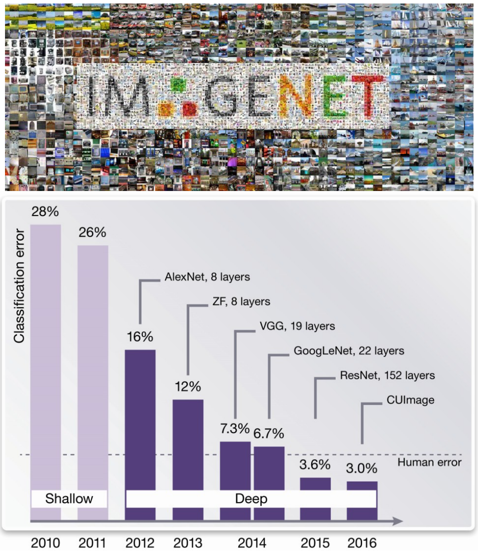
From: https://towardsdatascience.com/google-ais-new-object-detection-competition-6dde25cf099d

Reinforcement learning

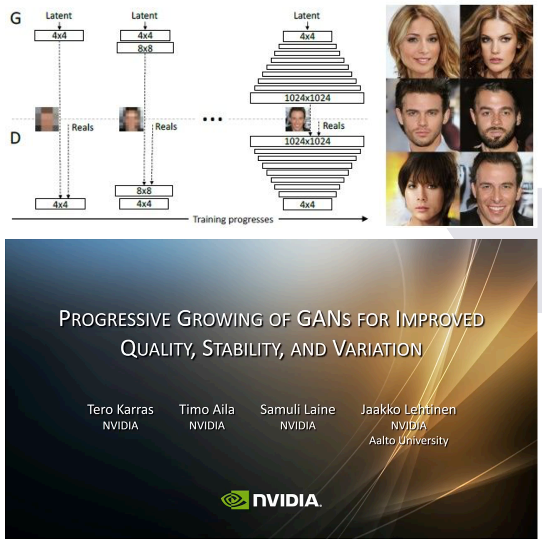
…

Why deep learning?

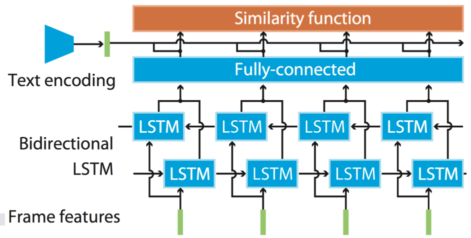
What deep learning can do



[Russakvsky 2015]

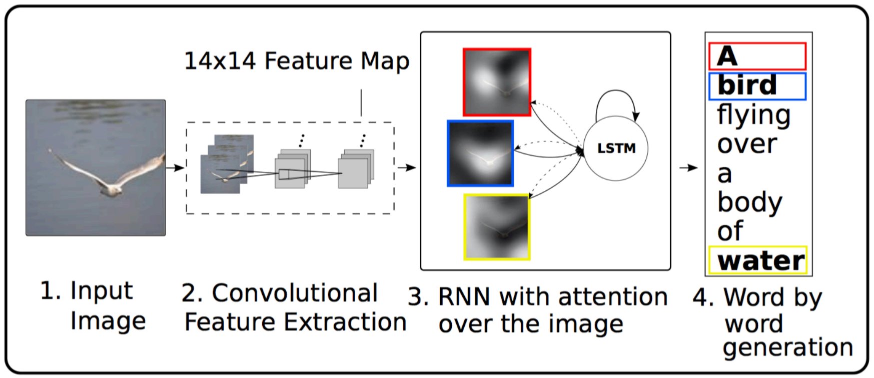


[Karras 2018]



Learning to Retrieve Video Parts with Natural Language

Example videos



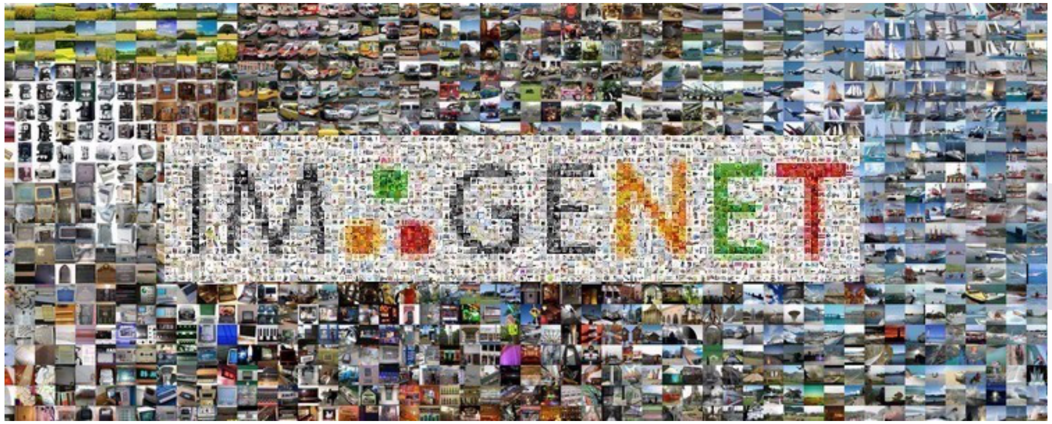
[Xu 2015]

Visual to Sound: Generating Natural Sound for Videos in the Wild

[Zhou 2017]

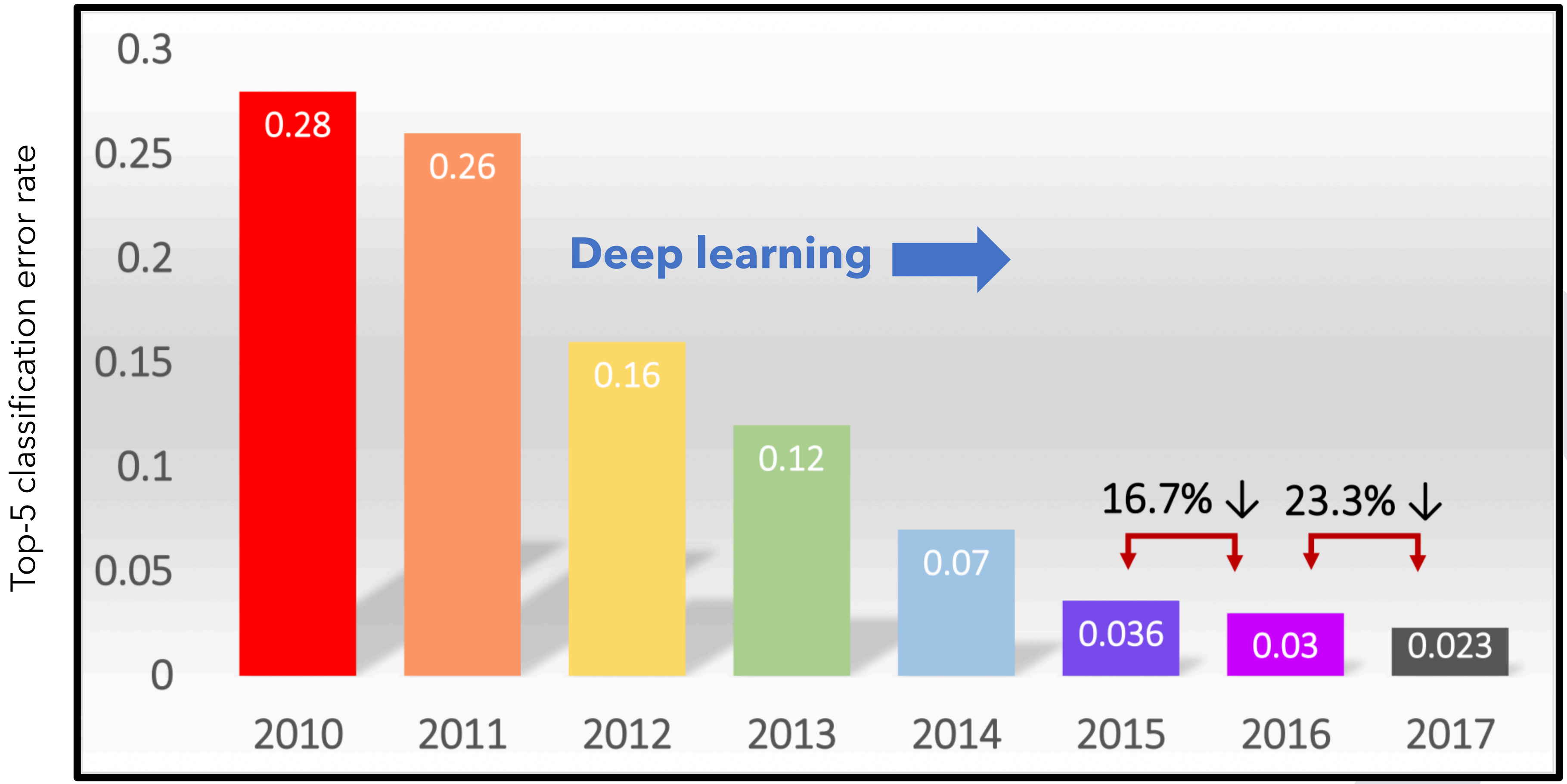
An image recognition task

- ImageNet Large Scale Visual Recognition Competition



- 1,000 classes
- 1,461,406 images

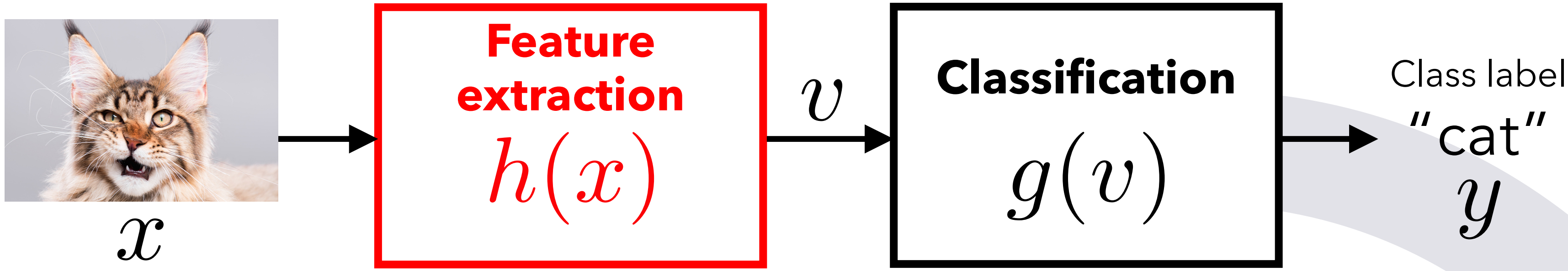
(Not so) recent models



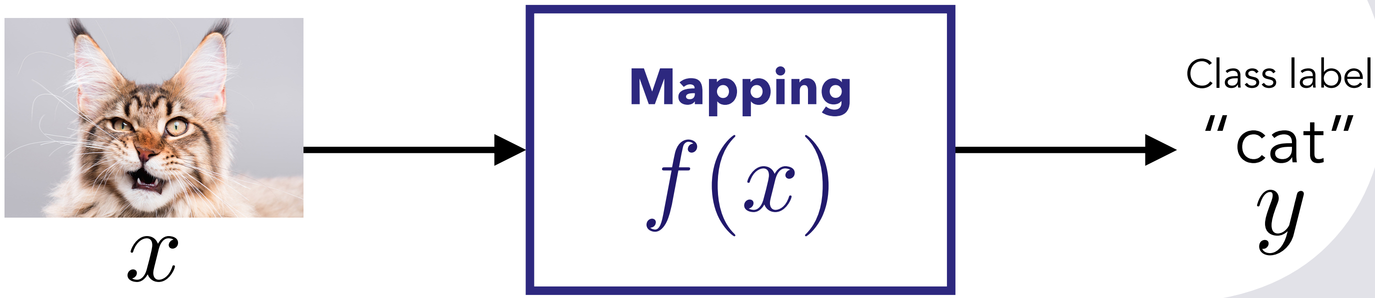
From: http://image-net.org/challenges/talks_2017/ILSVRC2017_overview.pdf

Difference between conventional machine learning and deep learning

- Conventional machine learning

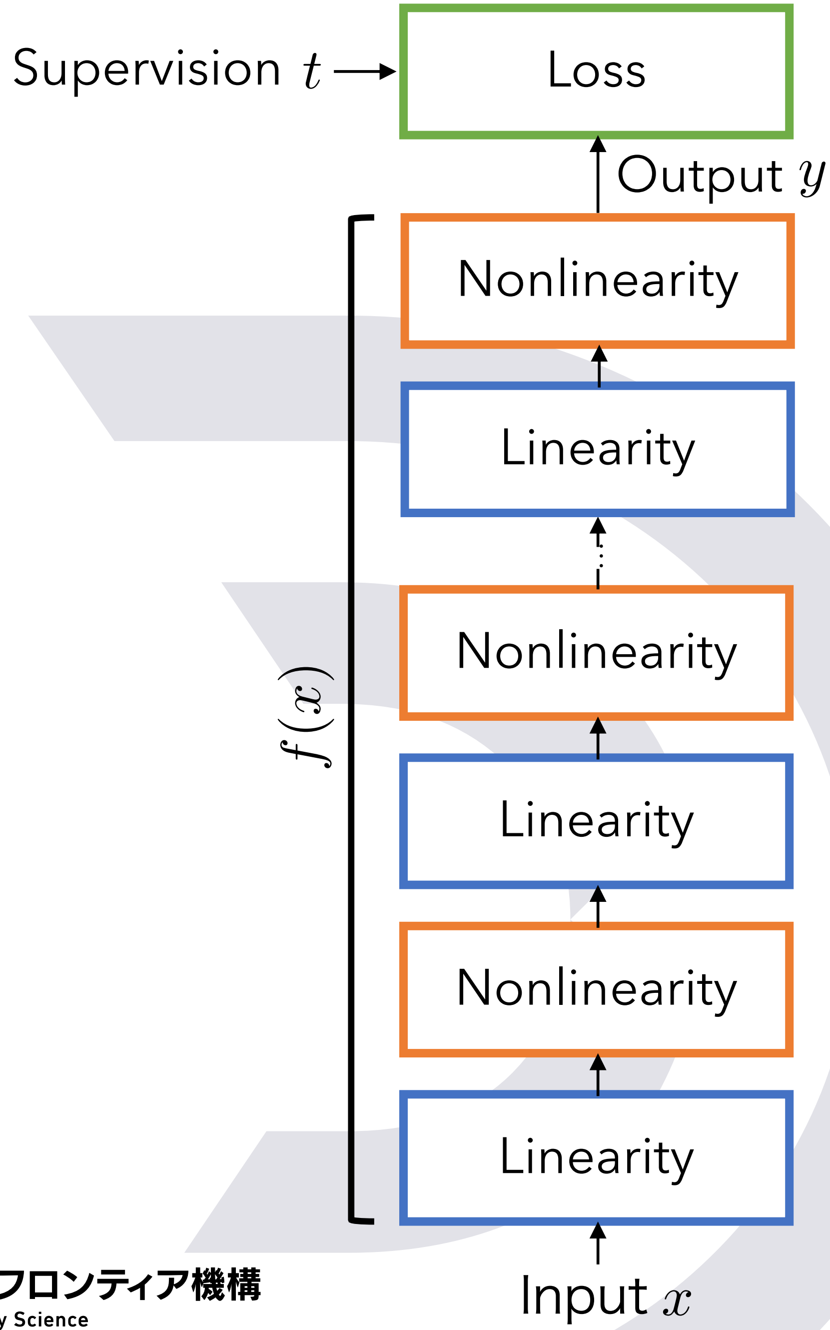


- Deep learning



Building blocks of neural networks

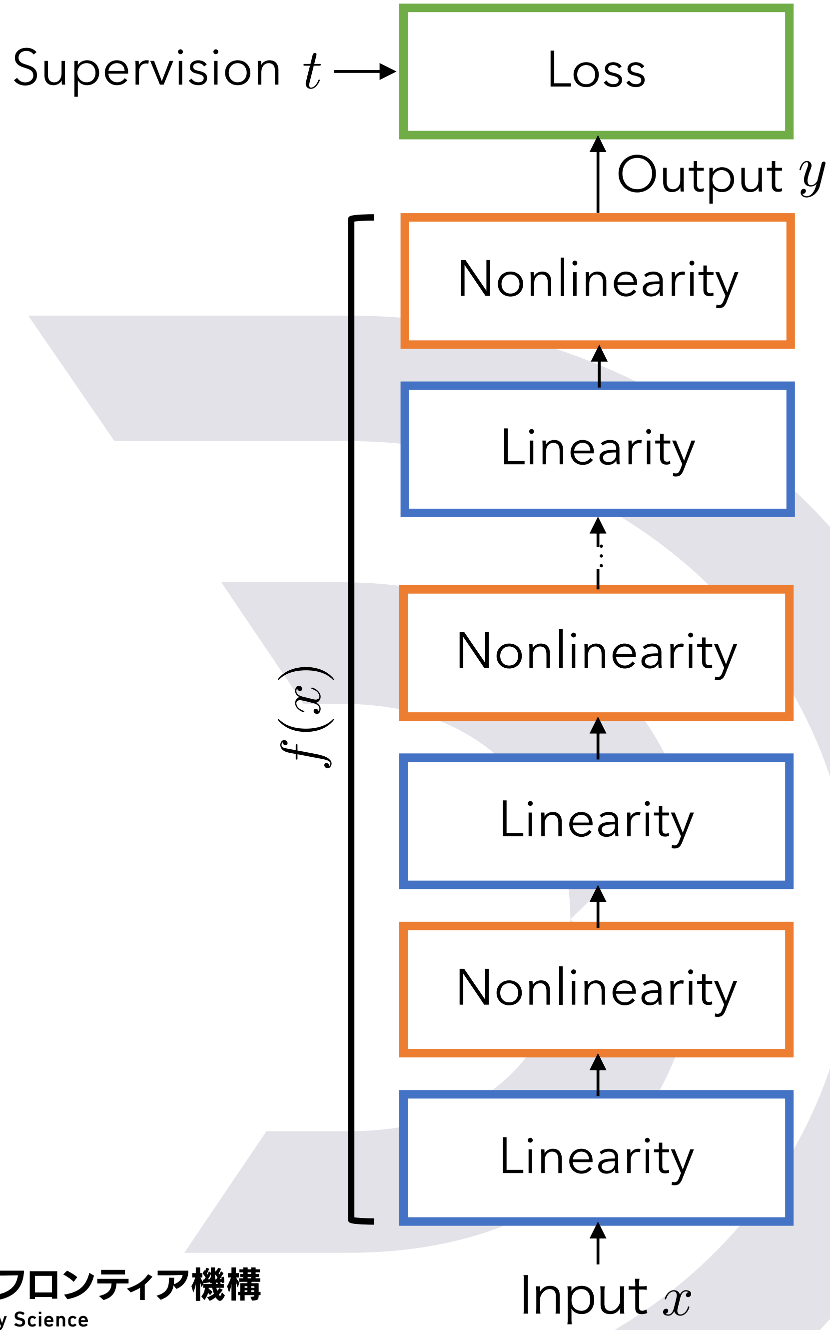
- Linearity: $h = Wx + b$
  - Convolution layer for images
- Nonlinearity: $y = \sigma(h)$
  - Hyperbolic tangent $\sigma(h) = \tanh(h)$
  - ReLU $\sigma(h) = \max(0, h)$
  - etc.
- Loss: $L(x, t)$
- Others:
  - Batch normalization
  - Pooling
  - etc.



Training neural networks

Building blocks of neural networks (again)

- **Linearity**: $h = Wx + b$
  - Convolution layer for images
- **Nonlinearity**: $y = \sigma(h)$
  - Hyperbolic tangent $\sigma(h) = \tanh(h)$
  - ReLU $\sigma(h) = \max(0, h)$
  - etc.
- **Loss**: $L(x, t)$
- **Others:**
  - Batch normalization
  - Pooling
  - etc.



How to train your model (neural network)

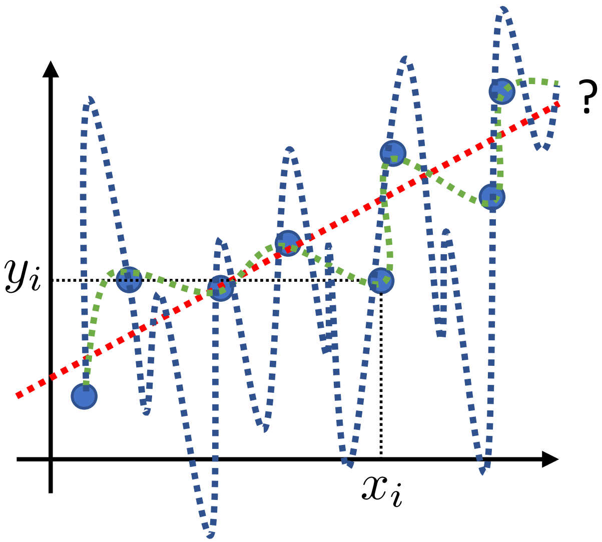
- Stochastic gradient descent
  - A type of gradient descent

- Back-propagation
  - The chain rule of differentiation; differentiation for composite functions

Can you solve? (1)

- Find a line that well explains the given data
  $$D = \{(x_i, y_i) | i = 1, \ldots, N\}$$
  - What type of a line? **Neural network structure**
  - With what criterion? **Selection of the loss**
  - (How accurate fitting should be? **Regularization**)
  - How to find it? **Selection of optimization algorithm**

Common choices:
- A straight line
- Mean squared error



$$y = ax + b$$

$$y = \sum_n a_n x^n$$

$$y = \sum_n a_n x^n$$

Can you solve? (1)

- Suppose $f(x) = ax + b$ and MSE as the loss function

$$L(a, b) = \sum_i \|y_i - f(x_i)\|^2 = \sum_i (y_i - ax_i - b)^2$$

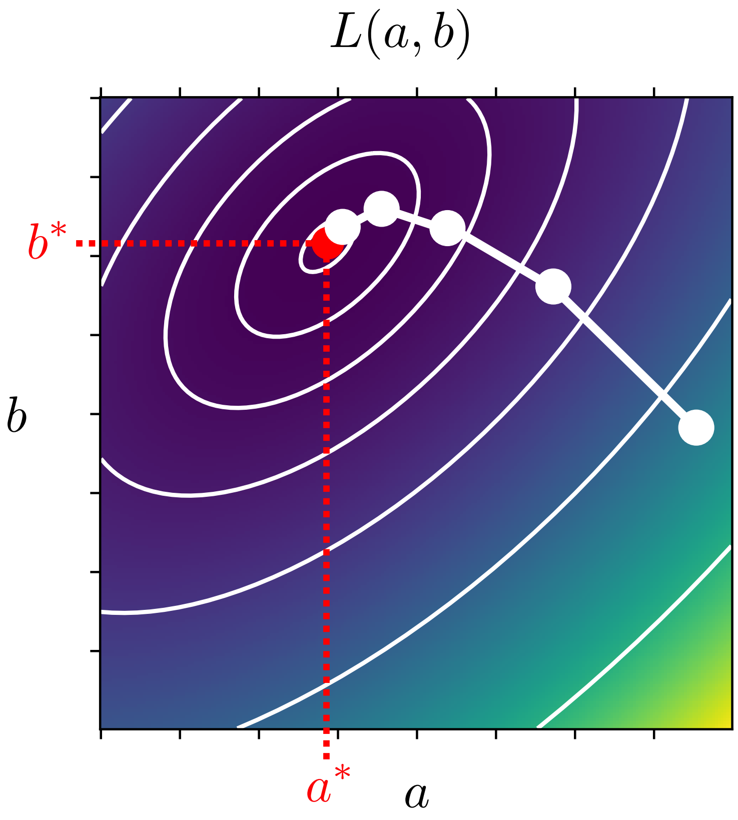
- What we need to find a and b that minimize the loss

$$\frac{\partial L}{\partial a} = 0 \qquad a^* = \frac{\frac{1}{N}\sum_i x_i y_i - (\frac{1}{N}\sum_i x_i)(\frac{1}{N}\sum_i y_i)}{\frac{1}{N}\sum_i x_i^2 - (\frac{1}{N}\sum_i x_i)^2} = \frac{\sigma_{xy}^2}{\sigma_{xx}^2}$$

$$\frac{\partial L}{\partial b} = 0 \qquad b^* = \frac{1}{N}\sum_i y_i - a^* \frac{1}{N}\sum_i x_i = \mu_y - a^* \mu_x$$

There is an analytic solution!

Gradient Descent



- Find parameters with 0 gradients
- That is, shift the param. toward the opposite direction of the gradient from an initial point

$$a \leftarrow a - \alpha \frac{\partial L}{\partial a} \qquad b \leftarrow b - \alpha \frac{\partial L}{\partial b}$$

Gradient descent

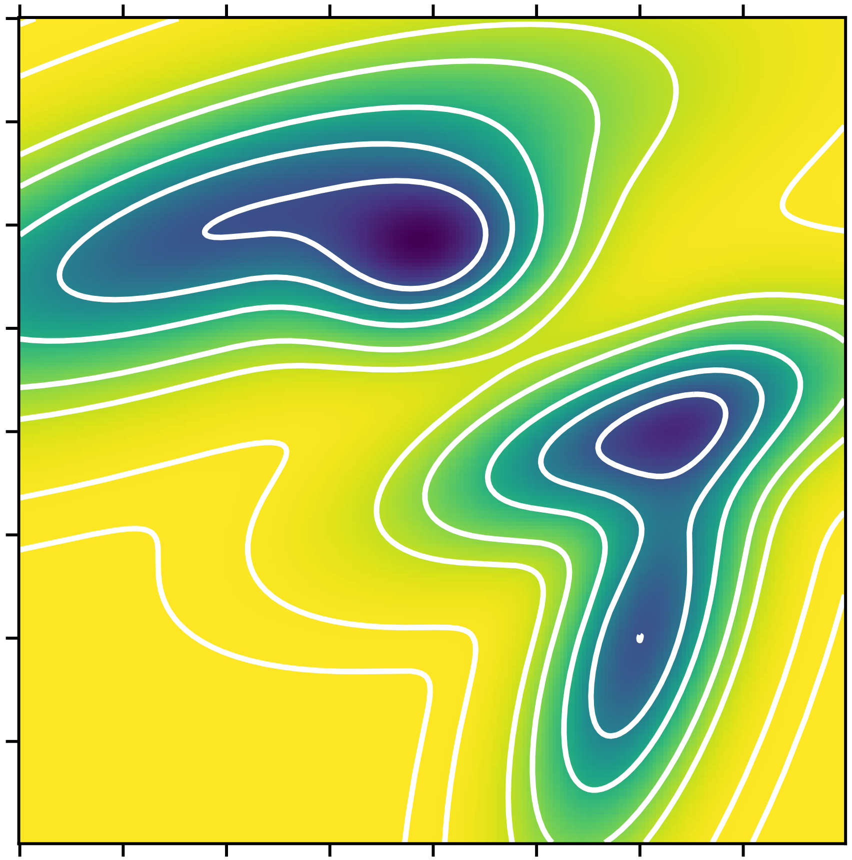
- In general: $\theta \leftarrow \theta - \alpha \frac{\partial L}{\partial \theta}$

θ : parameters to learn

α : learning rate

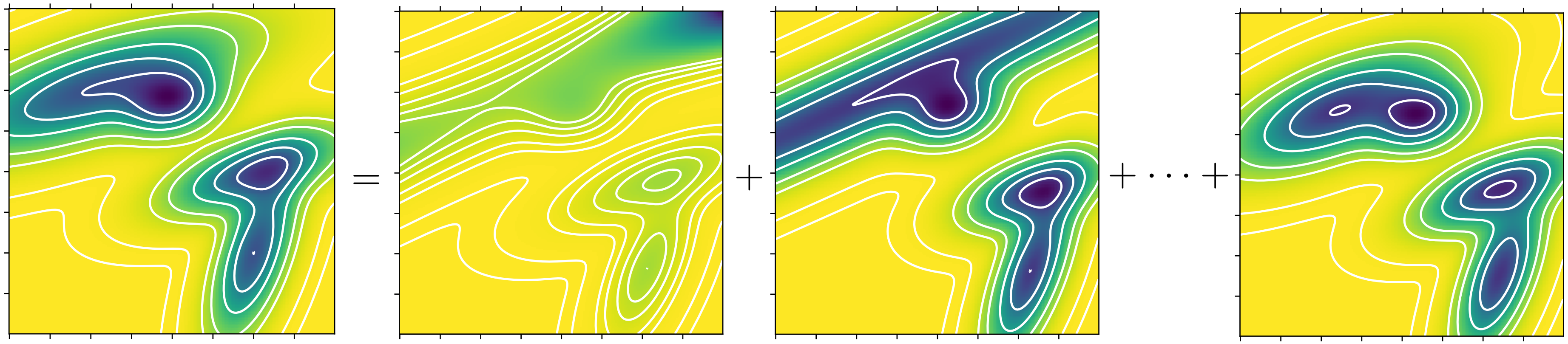
The neural network case

- Neural networks' loss function is multi-modal



Stochastic Gradient Descent

$$L(a,b) = \sum_i \|y_i - f(x_i)\|^2 = \underbrace{\sum_{i\in B_1} \|y_i - f(x_i)\|^2}_{L_1(a,b)} + \underbrace{\sum_{i\in B_2} \|y_i - f(x_i)\|^2}_{L_2(a,b)} + \cdots + \underbrace{\sum_{i\in B_N} \|y_i - f(x_i)\|^2}_{L_N(a,b)}$$



$$\theta \leftarrow \theta - \alpha' \frac{\partial L_n}{\partial \theta}$$

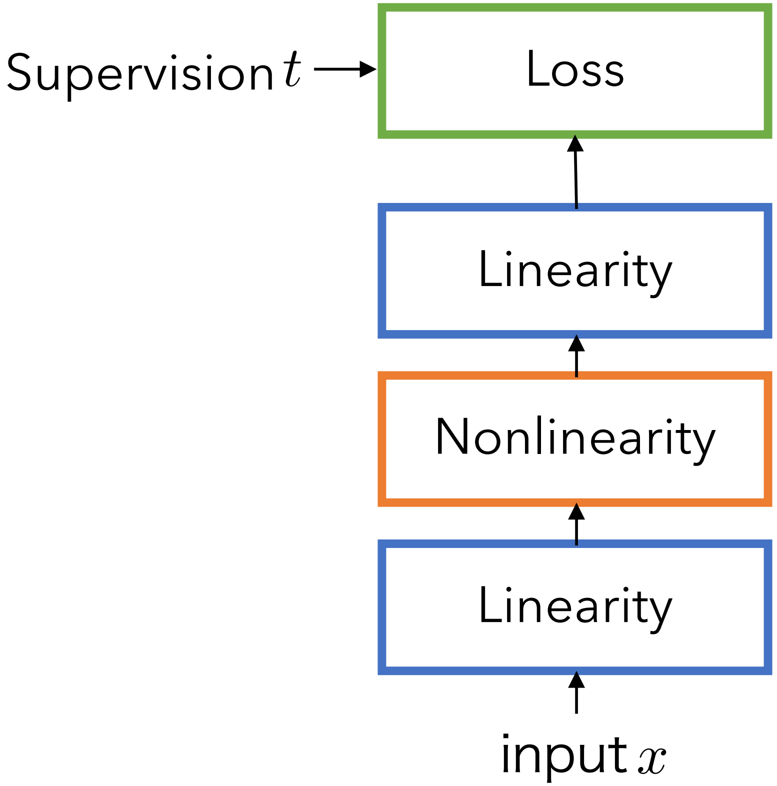
- Faster update
- Possibly go beyond local minima

Variants of stochastic gradient descent

- (Vanilla) stochastic gradient descent algorithm
- Stochastic gradient descent with momentum
- AdaGrad
- RMSProp
- Adam

Example: A simple neural network

$$\Theta = \{W_1, b_1, W_2, b_2\}$$



$$L(x, t|\Theta) = \mathrm{XE}(y, t|\Theta)$$

$$y = g_2(h|W_2, b_2) = W_2 h + b_2$$

$$h = \sigma(h') = \tanh(h')$$

$$h' = g_1(x|W_1, b_1) = W_1 x + b_1$$

Gradient required for SGD

$$\frac{\partial L}{\partial W_1} \quad \frac{\partial L}{\partial b_1} \quad \frac{\partial L}{\partial W_2} \quad \frac{\partial L}{\partial b_2}$$

Back-propagation, back-prop

- The chain rule: $\dfrac{\partial f(g(x))}{\partial x} = \dfrac{\partial f}{\partial g}\dfrac{\partial g}{\partial x}$

$$L(x, t|\Theta) = \mathrm{XE}(y, t|\Theta) \implies \frac{\partial L}{\partial y}$$

$$y = g_2(h|W_2, b_2) = W_2 h + b_2 \implies \frac{\partial L}{\partial W_2} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial W_2} \quad \frac{\partial L}{\partial b_2} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial b_2} \quad \frac{\partial L}{\partial h} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial h}$$

$$h = \sigma(h') = \tanh(h') \implies \frac{\partial L}{\partial h'} = \frac{\partial L}{\partial h}\frac{\partial h}{\partial h'}$$

$$h' = g_1(x|W_1, b_1) = W_1 x + b_1 \implies \frac{\partial L}{\partial W_1} = \frac{\partial L}{\partial h'}\frac{\partial h'}{\partial W_1} \quad \frac{\partial L}{\partial b_1} = \frac{\partial L}{\partial h'}\frac{\partial h'}{\partial b_1} \quad \left(\frac{\partial L}{\partial x} = \frac{\partial L}{\partial h'}\frac{\partial h'}{\partial x}\right)$$

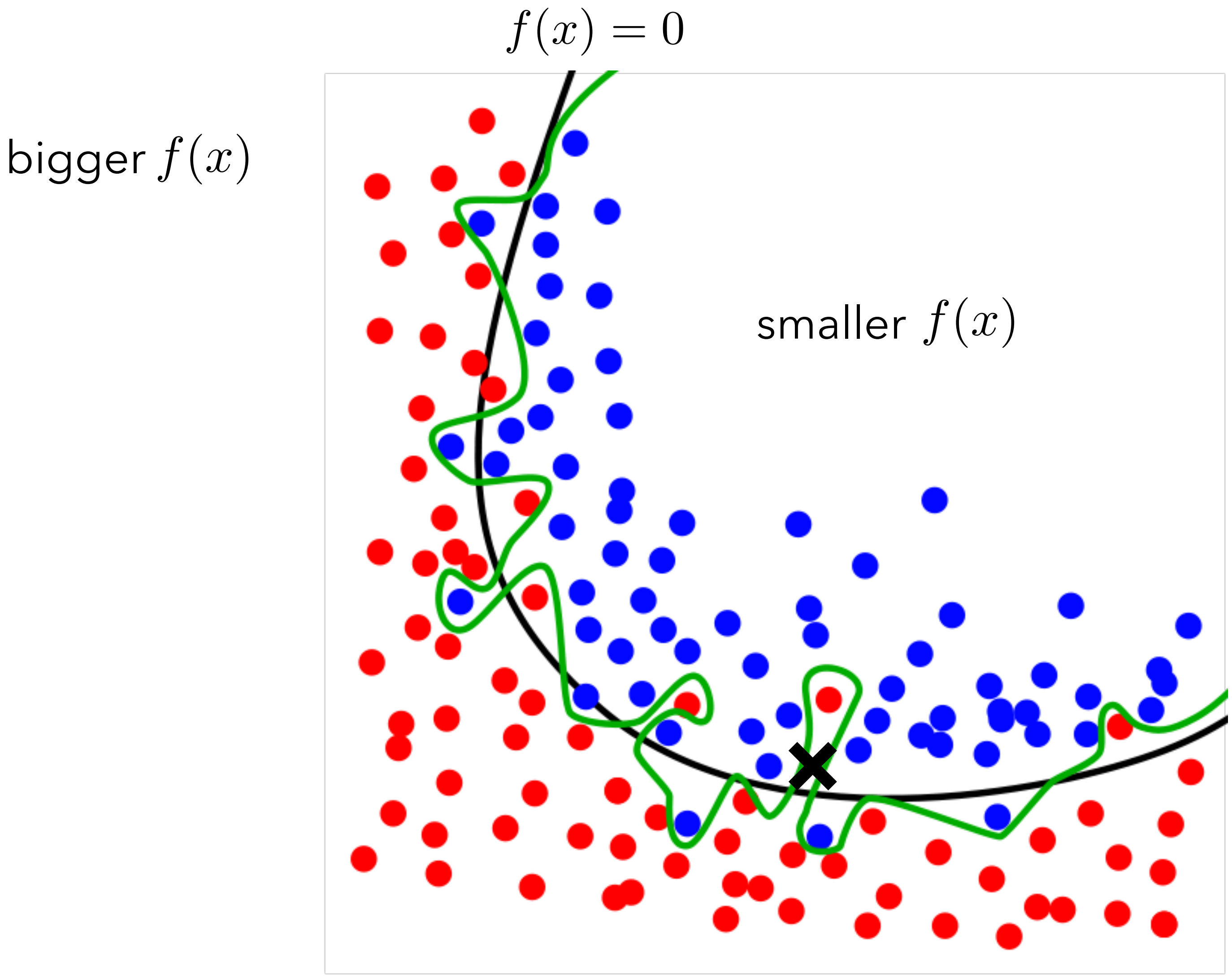
Recent progress in deep neural nets

Especially for image classification

Various problems in deep neural nets

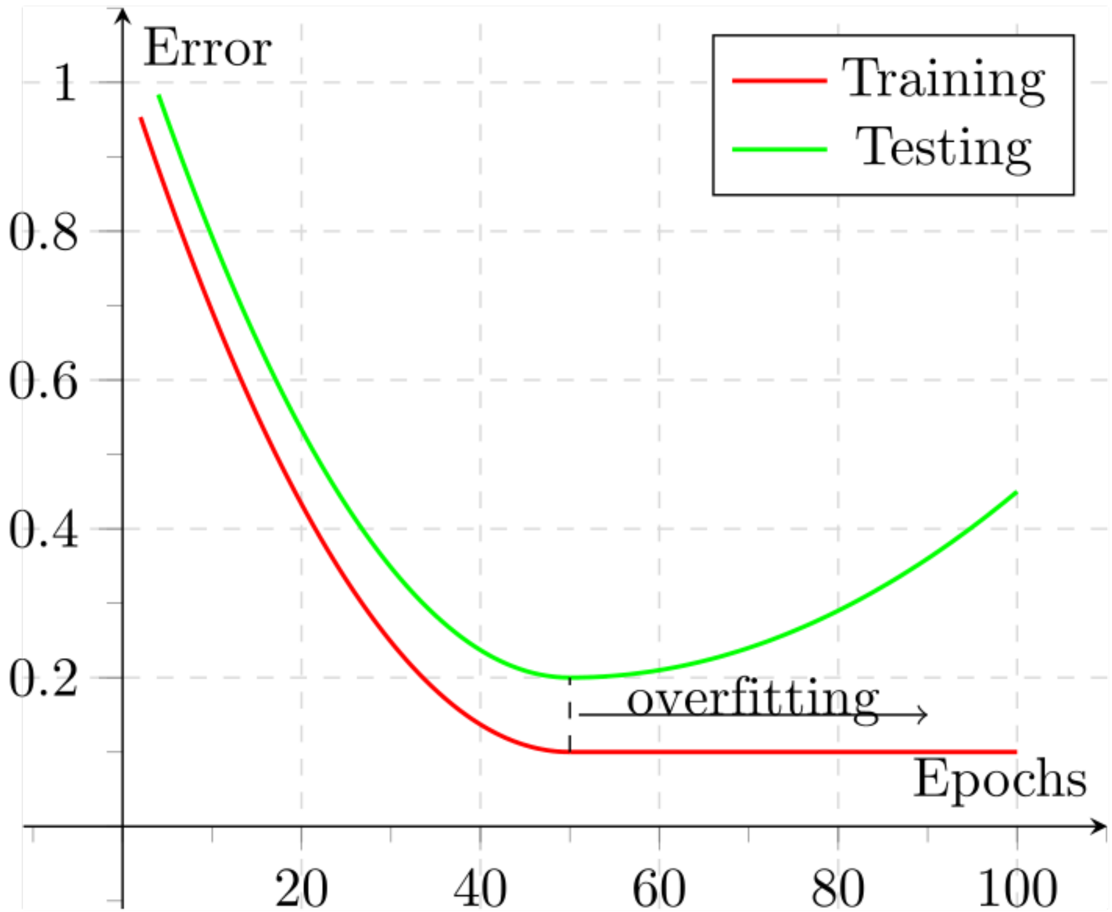
- Overfitting
- Gradient vanishing
- Hyperparameter tuning (# layers, learning rate, etc.)

Which line is better?



Overfitting

- A model is too optimized to the training data and does not work well for unseen (test) data



Back-propagation, again

- The chain rule: $\dfrac{\partial f(g(x))}{\partial x} = \dfrac{\partial f}{\partial g}\dfrac{\partial g}{\partial x}$

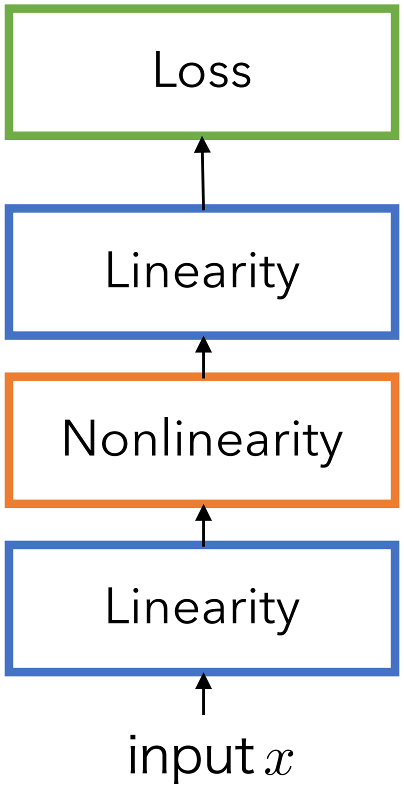
$$L(x, t|\Theta) = \mathrm{XE}(y, t|\Theta) \Longrightarrow \frac{\partial L}{\partial y}$$

$$y = g_2(h|W_2, b_2) = W_2 h + b_2 \Longrightarrow \frac{\partial L}{\partial W_2} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial W_2} \quad \frac{\partial L}{\partial b_2} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial b_2} \quad \frac{\partial L}{\partial h} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial h}$$

$$h = \sigma(h') = \tanh(h') \Longrightarrow \frac{\partial L}{\partial h'} = \frac{\partial L}{\partial h}\frac{\partial h}{\partial h'}$$

$$h' = g_1(x|W_1, b_1) = W_1 x + b_1 \Longrightarrow \frac{\partial L}{\partial W_1} = \frac{\partial L}{\partial h'}\frac{\partial h'}{\partial W_1} \quad \frac{\partial L}{\partial b_1} = \frac{\partial L}{\partial h'}\frac{\partial h'}{\partial b_1} \quad \left(\frac{\partial L}{\partial x} = \frac{\partial L}{\partial h'}\frac{\partial h'}{\partial x}\right)$$

What does the gradient actually look like



$$L(x, t|\Theta) = \mathrm{XE}(y, t|\Theta)$$

$$y = g_2(h|W_2, b_2) = W_2 h + b_2$$

$$h = \sigma(h') = \tanh(h')$$

$$h' = g_1(x|W_1, b_1) = W_1 x + b_1$$

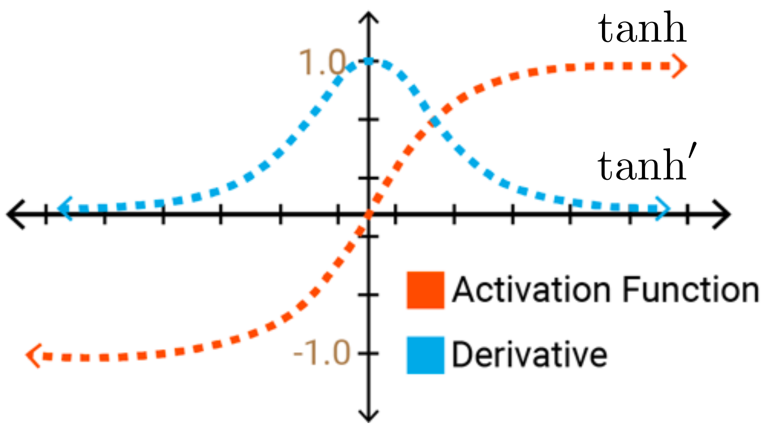
$$\frac{\partial L}{\partial y} = \mathrm{XE}'$$

$$\frac{\partial L}{\partial h} = \frac{\partial L}{\partial y}\frac{\partial y}{\partial h} = \mathrm{XE}'(y,t)W_2$$

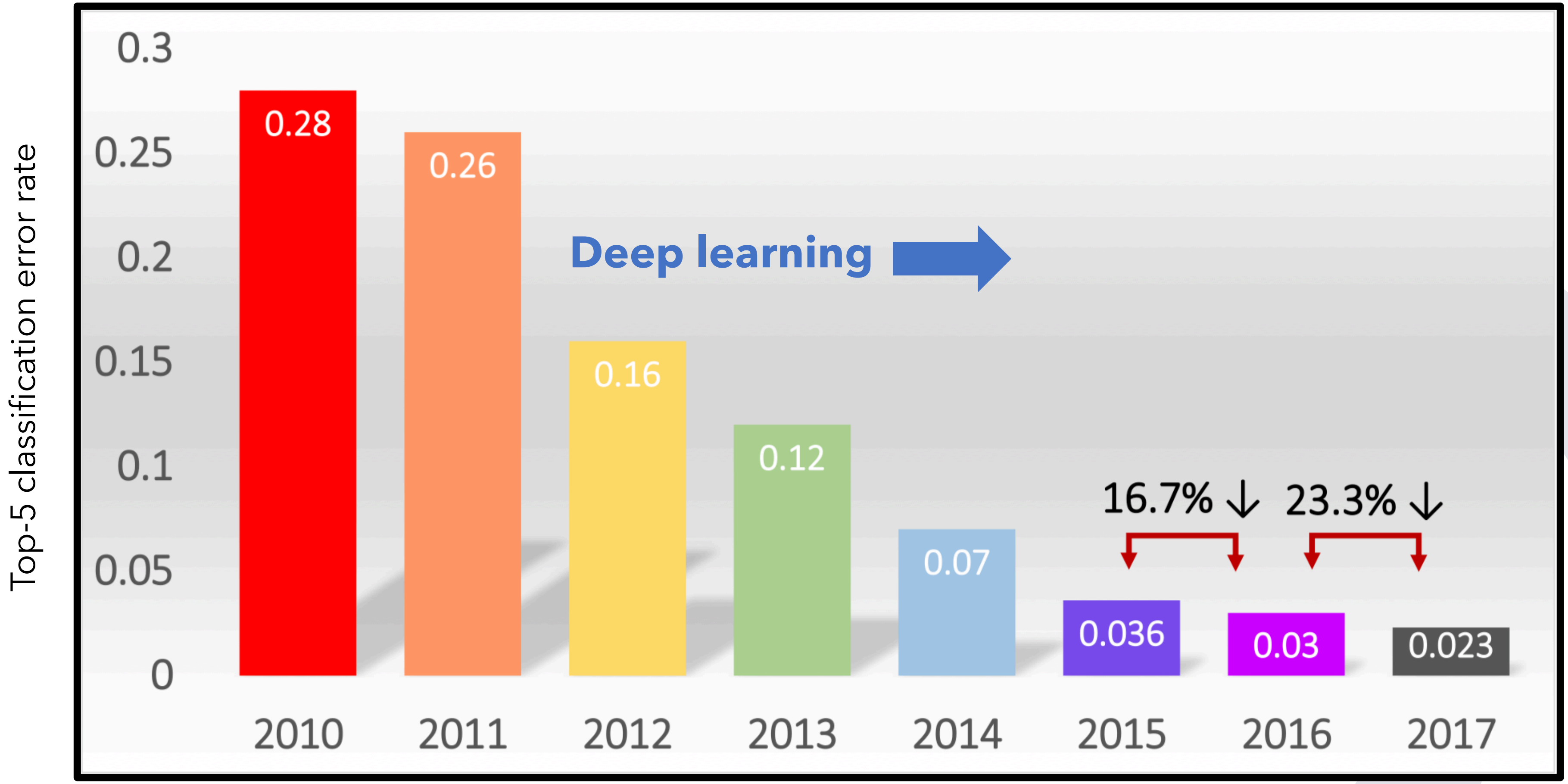
$$\frac{\partial L}{\partial h'} = \frac{\partial L}{\partial h}\frac{\partial h}{\partial h'} = \mathrm{XE}'(y,t)W_2 \tanh'(h')$$

$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial h'}\frac{\partial h'}{\partial x} = \mathrm{XE}'(y,t)W_2 \tanh'(h') W_1$$

Gradient vanishing



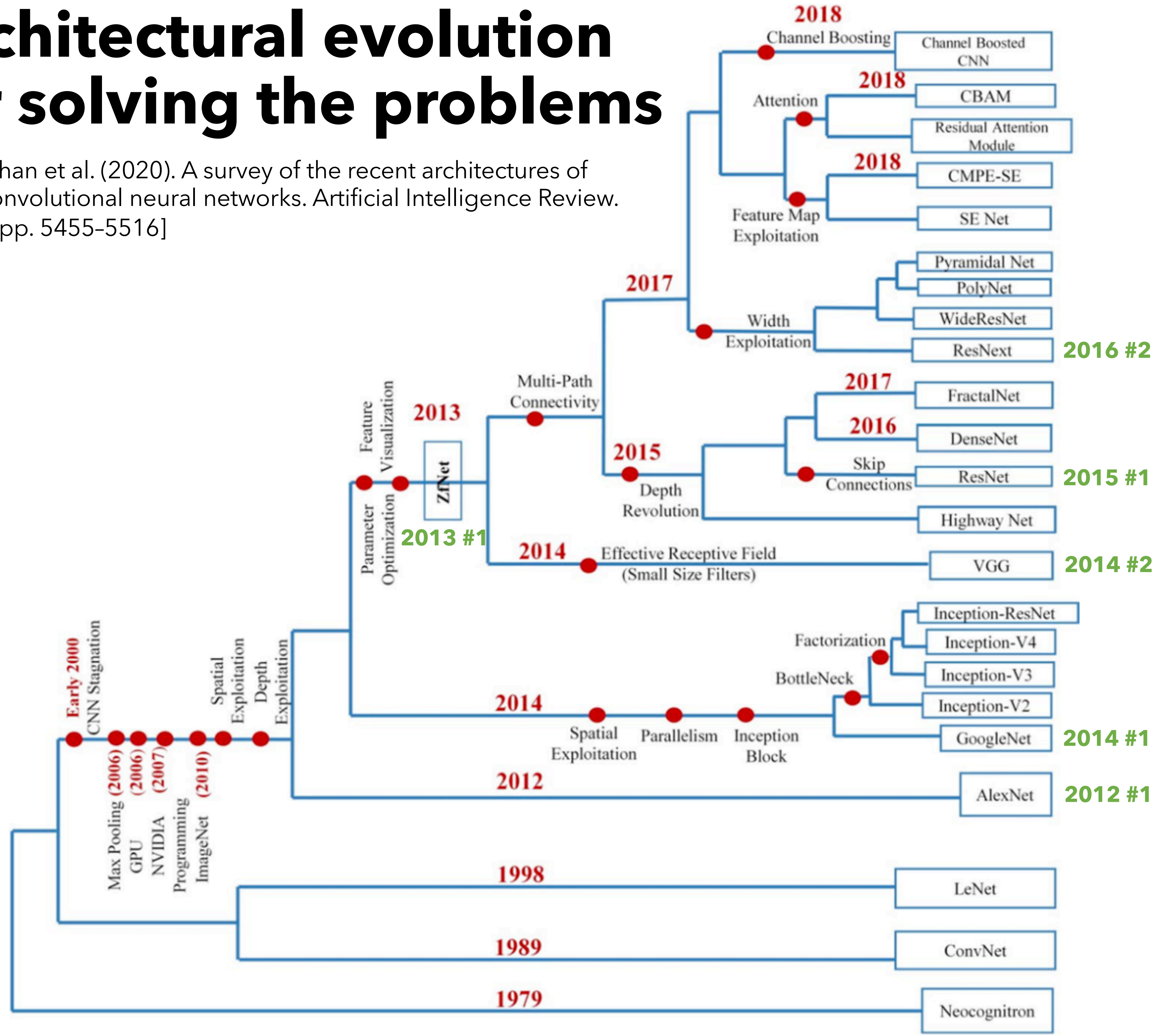
(Not so) recent models (again)



From: http://image-net.org/challenges/talks_2017/ILSVRC2017_overview.pdf

Architectural evolution for solving the problems

From [Khan et al. (2020). A survey of the recent architectures of deep convolutional neural networks. Artificial Intelligence Review. Vol. 53, pp. 5455–5516]

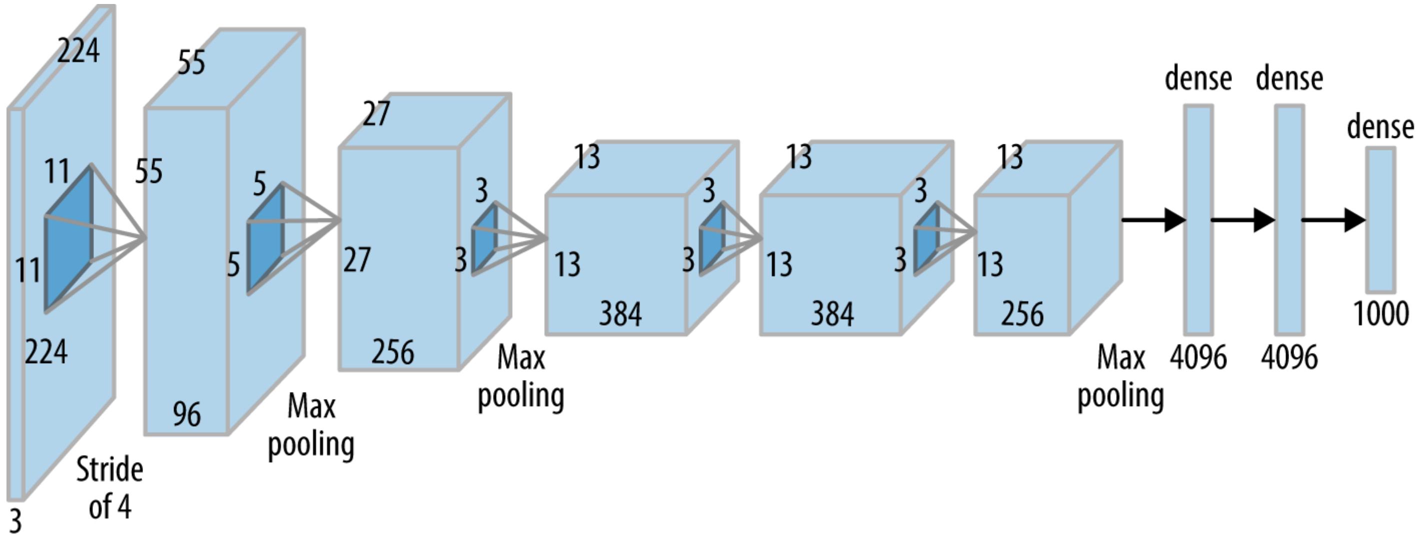


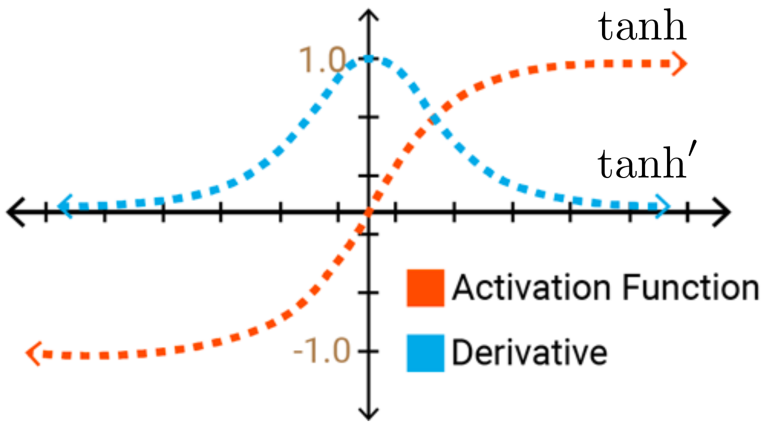
Comparison among models

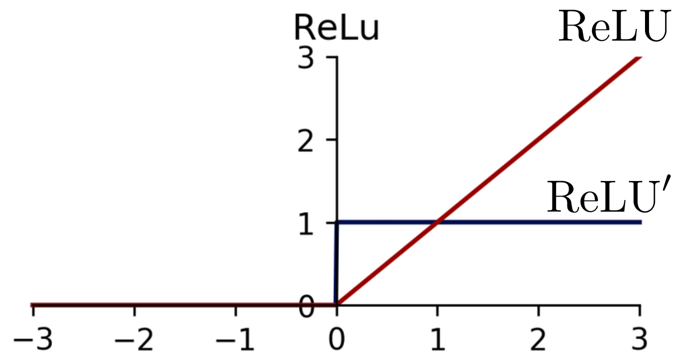
	Performance	# layers	# Parameters
• AlexNet ('12)	0.16	8	61M
• VGG ('14)	0.088?	19	138M
• GoogLeNet ('14)	0.07	22	11M
• ResNet ('16)	0.036	152	25M

AlexNet

- The first neural net that won the ImageNet competition
  - Krizhevsky et al. (2012). ImageNet classification with deep convolutional neural networks. Communications of the ACM 60(6).

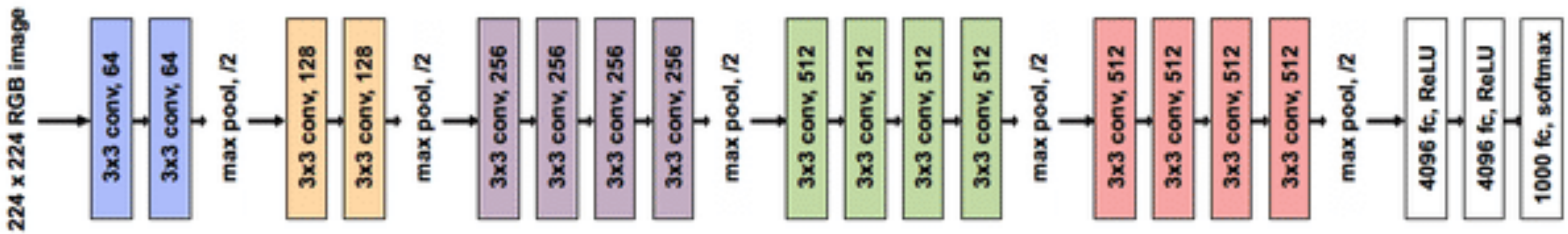




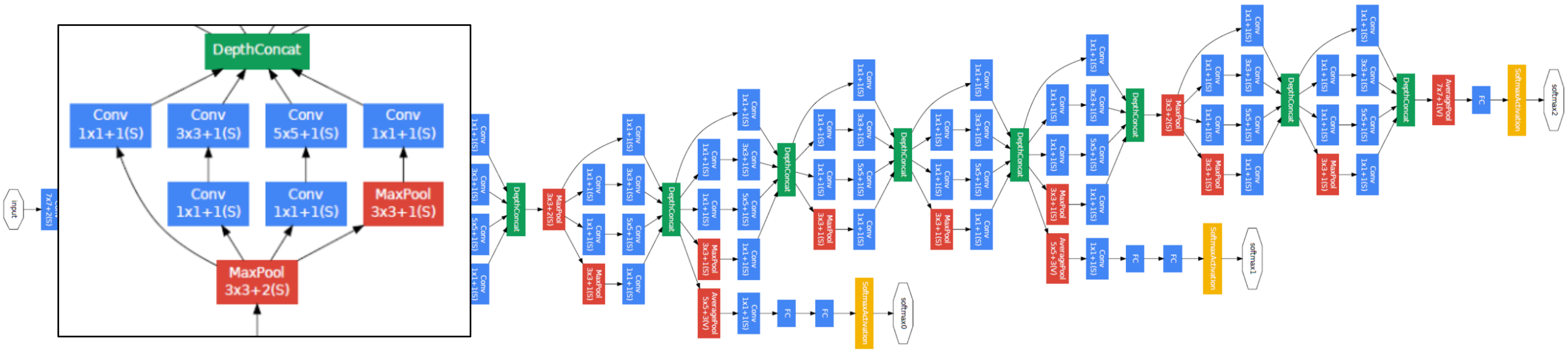


VGG vs. GoogLeNet

- 2014 ImageNet competition runner-up (19 layers)
  - Simonyan and Zisserman (2015). Very Deep Convolutional Networks for Large-Scale Image Recognition. ICLR.

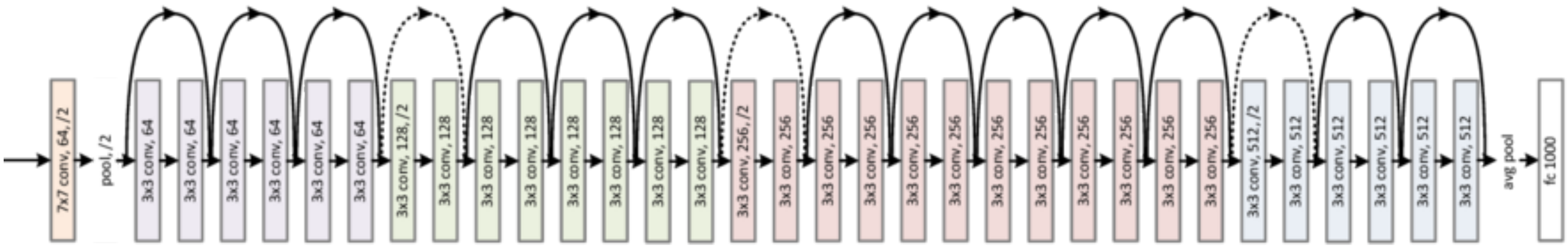


- 2014 ImageNet competition winner (22 layers)
  - Szegedy et al. (2015). Going deeper with convolutions. CVPR.



ResNet

- 2015 ImageNet Competition winner (152 layers!)
  - He et al. (2016). Deep residual learning image recognition. CVPR.



(A smaller variant, as 152 layers do not fit to the page)

Some component-level techniques

- Overfitting
  - Regularization (Dropout, weight decay)
  - Data augmentation
  - (Larger amount of data)
- Gradient vanishing
  - ReLU and its variants
  - Batch normalization
- Hyperparameter tuning (# layers, learning rate, etc.)
  - Bayesian optimization
  - Researcher's experience

An application to Physics

Our collaboration with physics researchers

- Flavor classification
  日本物理学会全国大会
  Kishida, Iwasaki, et al.

- 3-class classification with variable-length data
  - Classification into cc / bb / uds events

- A classic approach hand-crafted features and use a shallow NN for classification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1.173989e+00 9.484937e-01 4.421300e-01 5.134615e-01 4.317461e-04 -9.262173e-04 -8.300396e-05
1.497720e+01 -2.482940e-01 -2.815872e+00 -1.470736e+01 6.750966e-04 -5.952772e-05 2.457871e-01
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3.627837e+00 -4.301256e-01 -6.421792e-01 -3.541795e+00 -1.627690e-03 1.090212e-03 2.115826e-02
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8.765116e+00 -2.147219e+00 3.149943e+00 -7.891456e+00 2.122391e-05 1.446769e-05 1.484219e-03
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1.291064e+00 -2.293424e-01 2.425964e-01 -1.239318e+00 -1.155399e-02 -1.092275e-02 1.093272e-02
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2.505493e+00 2.134482e+00 1.072338e-02 1.304561e+00 -2.055256e-06 4.090974e-04 -7.864043e-04
1.150009e+00 1.100459e+00 3.559504e-02 3.012568e-01 3.065370e-05 -9.476924e-04 -1.204631e-03

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1.271398e+00 -9.386227e-01 -7.905339e-01 -3.016746e-01 -4.916799e-05 5.837850e-05 -1.463579e-04
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8.365110e+00 4.553502e+00 6.939693e+00 -1.030462e+00 -2.500419e-04 1.640658e-04 -2.612930e-05
4.788787e+00 2.600081e+00 3.960575e+00 -6.829442e-01 -2.342055e-04 1.537537e-04 -5.630392e-04
3.193298e+01 -1.736678e+01 -2.564500e+01 7.773324e+00 -2.151546e-04 1.457026e-04 1.544318e-04
9.597038e+00 -4.968049e+00 -7.827353e+00 2.476827e+00 -7.555278e-05 4.795361e-05 -4.799157e-04
5.994937e-01 -2.606283e-01 -4.785615e-01 2.072592e-01 -4.846878e-04 2.639648e-04 2.408668e-04
1.509809e+01 -8.182952e+00 -1.203910e+01 4.004019e+00 -2.050355e-04 1.393622e-04 -1.444807e-03
5.880010e-01 -2.661611e-01 -3.555807e-01 3.591345e-01 6.112219e-04 -4.575149e-04 1.796477e-03
5.184984e-01 -3.343684e-01 -4.406086e-02 -3.682511e-01 -5.408319e-05 4.104257e-04 6.405641e-04
1.031485e+00 -8.673196e-02 -5.570330e-01 8.524468e-01 -3.491654e-03 5.436626e-04 1.576995e-03
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7.069286e-01 1.592936e-01 6.699767e-01 7.756654e-02 -6.074407e-04 1.444250e-04 6.109483e-04
5.652046e-01 5.003294e-01 2.010196e-01 -9.607132e-02 7.025477e-04 -1.748612e-03 1.183726e-03
8.943885e+00 5.767168e+00 6.642895e+00 -1.607893e+00 -1.287538e-04 1.117803e-04 8.316932e-04
1.661793e+01 9.009043e+00 1.325890e+01 -4.378908e+00 -2.109819e-04 1.433561e-04 1.535002e-04
2.896062e+01 1.570820e+01 2.304081e+01 -7.814831e+00 9.634620e-06 -6.568455e-06 -2.311663e-04
8.448735e-01 -3.011931e-01 -7.731972e-01 7.597274e-02 -1.156947e+00 4.506800e-01 7.684941e-01
2.957734e+00 -1.846016e+00 -2.197302e+00 7.019877e-01 2.776428e-01 -2.332557e-01 -2.085605e-01

Axis = 5.974050e-01 1.278940e-01 -7.916757e-01
3.049313e-01 -1.623508e-01 -6.926404e-02 -2.057660e-01 -1.983575e-04 4.649383e-04 -2.028446e-03
7.209612e+00 1.938623e+00 -2.098141e+00 -6.618049e+00 -1.331579e-03 -1.230342e-03 6.710476e-04
5.150765e-01 1.658504e-01 -1.082958e-01 -4.545121e-01 -2.174730e-03 -3.330504e-03 7.520762e-03
1.678753e+00 -1.290594e+00 -2.777172e-01 1.027601e+00 -2.396811e-05 1.113834e-04 -2.948495e-03
6.548814e-01 2.440873e-01 -6.591185e-02 5.877572e-01 -1.311447e-03 -4.856600e-03 -2.521130e-02
3.653267e+00 -2.359638e+00 -1.324441e+00 2.450477e+00 -4.433464e-04 7.898703e-04 -2.487400e-04
1.567742e+00 -1.162674e+00 -2.325280e-01 1.016094e+00 -2.251710e-04 1.125888e-03 -6.892465e-04
3.339994e+00 -2.530942e+00 5.964277e-02 2.174131e+00 2.972407e-05 1.261342e-03 4.765579e-04
5.687092e+00 2.224050e+00 1.222246e+00 -5.087558e+00 2.174687e-04 -3.957153e-04 1.547311e-03
3.241751e-01 1.498072e-02 3.884113e-02 -2.896002e-01 2.677136e-01 -1.032551e-01 -1.827803e+00
2.469065e+00 5.190706e-01 -4.482230e-01 -2.367795e+00 -2.130605e-03 -2.467376e-03 5.546636e-03
7.371763e-01 -5.912202e-01 -4.382983e-02 -4.153052e-01 -2.480594e-05 3.346072e-04 -6.643218e-04
1.397669e+00 -7.329600e-01 2.139268e-01 1.162323e+00 -1.915298e-05 -6.562228e-05 2.637747e-03
1.323121e+00 -1.076112e+00 -4.241892e-01 6.270614e-01 -2.701272e-04 6.852772e-04 -6.450472e-04
1.405716e+00 -7.930601e-01 -5.207458e-01 1.027827e+00 4.824278e-04 -7.347045e-04 -7.288544e-04
1.346273e+01 -9.457000e+00 -3.075803e+00 9.073605e+00 -1.748960e-04 5.377430e-04 3.593510e-04
8.412551e+00 -5.518426e+00 -2.187031e+00 5.959479e+00 -5.581507e-05 1.408354e-04 1.103661e-03

Axis = 3.412007e-01 1.835908e-01 -9.218875e-01
6.053452e-01 3.034199e-01 3.451085e-01 -3.684984e-01 3.315940e-04 -2.915379e-04 9.809227e-05
2.242314e+01 4.252006e+00 2.555588e+00 -2.186704e+01 -6.775484e-04 1.127310e-03 1.631619e-03
4.615541e+01 8.030405e+00 4.904001e+00 -4.518591e+01 1.053577e-04 -1.725254e-04 -2.396392e-03
4.786486e+00 1.006292e+00 3.551062e-01 -4.663929e+00 5.546928e-04 -1.571877e-03 -2.141325e-02
2.076962e+00 -1.814143e+00 -9.196438e-01 3.967639e-01 -6.725764e-04 1.326763e-03 -9.279762e-04
2.990477e+00 -2.494993e+00 -1.465914e+00 7.413309e-01 1.613478e-04 -2.746147e-04 -5.321354e-04
5.352460e-01 3.369886e-01 -1.539671e-01 -3.601845e-01 8.891475e-04 1.946081e-03 -1.093706e-04
4.906971e-01 4.581366e-01 1.067404e-01 3.572935e-03 -1.206956e-04 5.180335e-04 6.616275e-04
1.510841e+00 4.635163e-01 1.346416e-01 -1.424843e+00 1.232350e-03 -4.242479e-03 -2.825476e-02
1.730957e+00 5.970972e-01 1.082349e-01 -1.615080e+00 6.187534e-04 -3.413463e-03 1.363038e-02
5.387886e+00 -2.463795e+00 -4.764452e+00 4.894180e-01 -6.337707e+01 3.277357e+01 -7.450118e-01
6.558535e+00 -6.543017e+00 -6.038268e-02 4.244774e-01 5.559014e-01 -6.023701e+01 3.993892e+00
6.793306e-01 1.701942e-01 2.753585e-03 -6.426727e-01 -7.009438e-03 4.332408e-01 -1.019863e+01
```

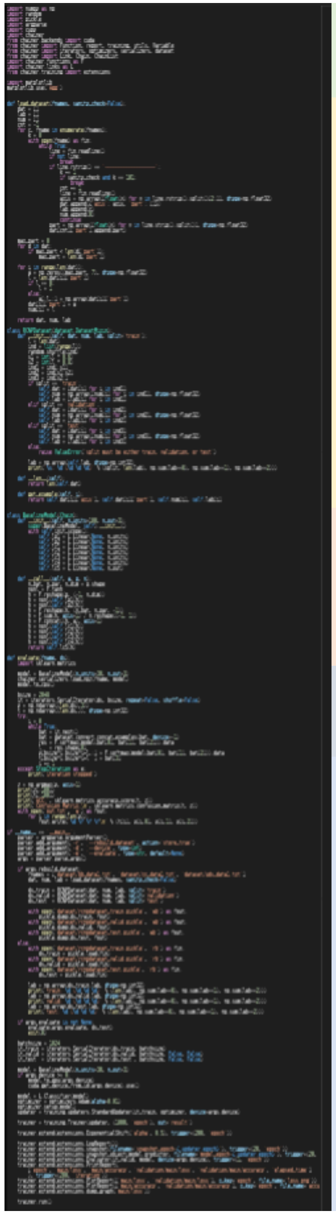
Power of deep learning?

- Look into the data…

```
-------------------
Axis = 1.336348e-01 1.270638e-01 9.828512e-01
3.600150e-01 2.364259e-02 2.897407e-01 1.600439e-01 1.355132e-04 -1.105776e-05 7.225226e-04
1.173989e+00 9.484937e-01 4.421300e-01 5.134615e-01 4.317461e-04 -9.262173e-04 -8.300396e-05
1.497720e+01 -2.482940e-01 -2.815872e+00 -1.470736e+01 6.750966e-04 -5.952772e-05 2.457871e-01
2.153059e+01 2.830333e-02 -5.172081e+00 -2.089966e+01 -1.711855e-04 -9.367832e-07 -8.197037e-03
1.474923e+00 -1.793663e-01 -2.634940e-01 -1.433286e+00 1.098547e-03 -7.478053e-04 -2.073109e-02
3.627837e+00 -4.301256e-01 -6.421792e-01 -3.541795e+00 -1.627690e-03 1.090212e-03 2.115826e-02
4.596739e+00 -2.664469e-01 -8.127258e-01 -4.514311e+00 7.059407e-02 -2.314381e-02 7.063290e-01
8.765116e+00 -2.147219e+00 3.149943e+00 -7.891456e+00 2.122391e-05 1.446769e-05 1.484219e-03
5.122196e-01 -1.974702e-01 7.846177e-02 -4.446685e-01 9.285856e-04 2.337036e-03 7.004034e-03
1.291064e+00 -2.293424e-01 2.425964e-01 -1.239318e+00 -1.155399e-02 -1.092275e-02 1.093272e-02
5.983341e-01 -1.612783e-01 -5.590074e-01 -3.947298e-03 5.869276e-05 -1.693335e-05 -9.371412e-04
4.532778e-01 2.528231e-01 1.698745e-01 -3.052798e-01 3.536852e-04 -5.263873e-04 1.886640e-04
2.505493e+00 2.134482e+00 1.072338e-02 1.304561e+00 -2.055256e-06 4.090974e-04 -7.864043e-04
1.150009e+00 1.100459e+00 3.559504e-02 3.012568e-01 3.065370e-05 -9.476924e-04 -1.204631e-03
-------------------
Axis = 5.468222e-01 8.021681e-01 -2.398164e-01
4.201890e+01 -2.260286e+01 -3.380862e+01 1.056676e+01 4.285707e-04 -2.865222e-04 -5.206644e-04
```

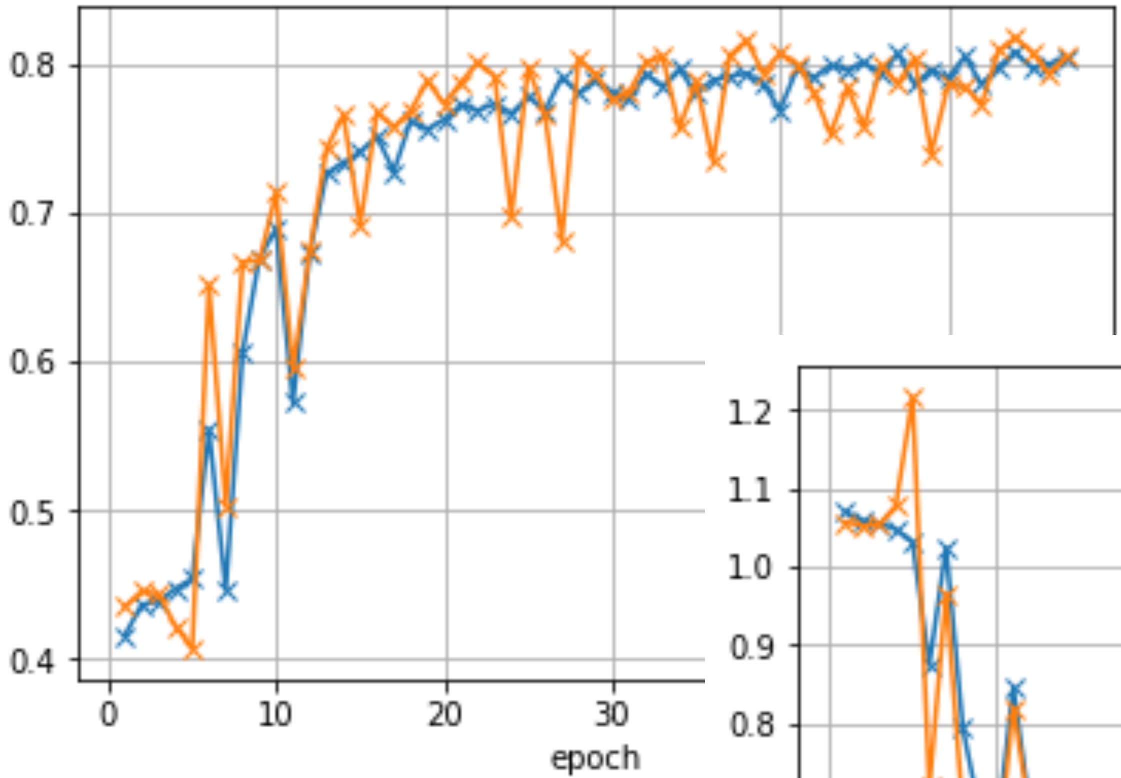
Okay, don't think, just do

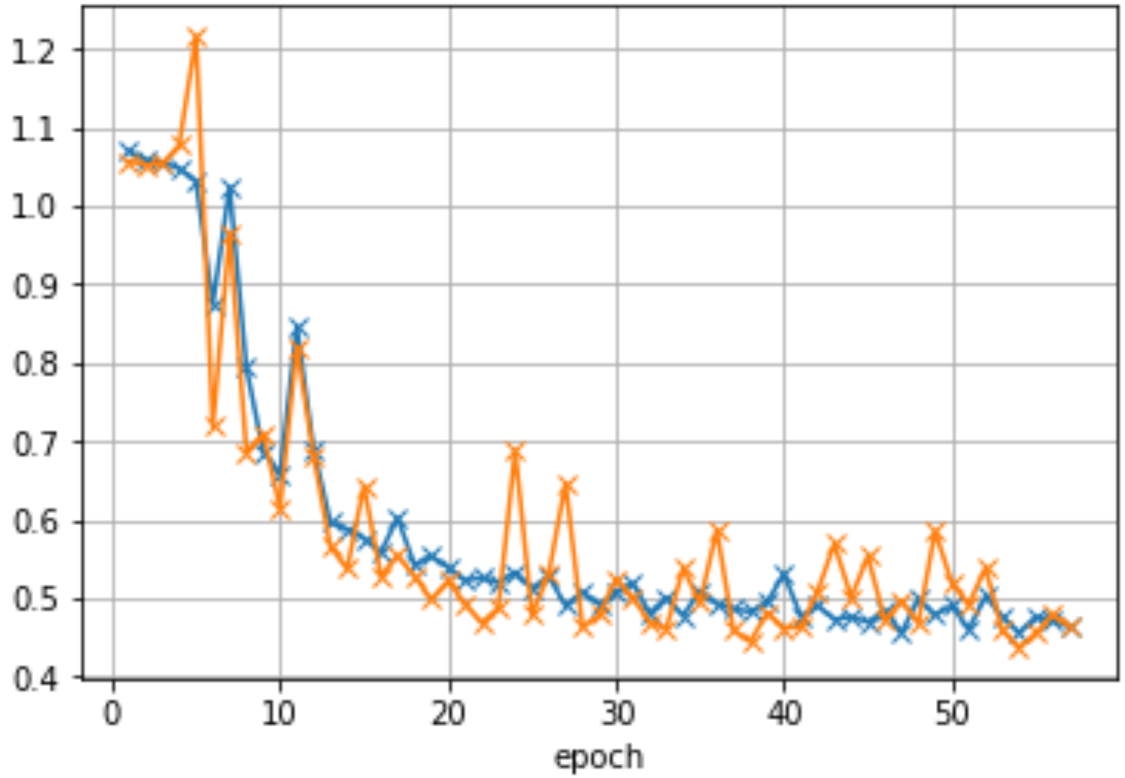
The code (200+ lines)



- Loading required modules
- Reading data
- Defining the neural network structure
- Evaluation
- Configuration and training

What we got


0.8
0.7
0.6
0.5
0.4
0
10
20
30
epoch
main/loss
validation/main/loss


1.2
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0
10
20
30
40
50
epoch

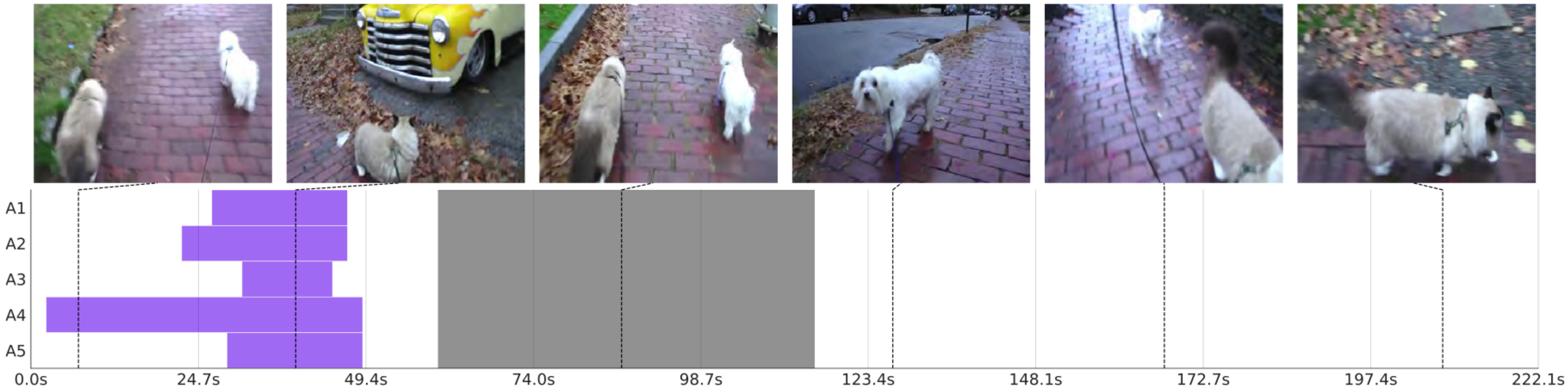
But it might be the time to...

- Think about what's next:
  - Is it possible to extract shared tasks for certain communities?
  - Is it possible to build an open dataset for each of the shared tasks?
  - What is the common input for various downstream tasks?

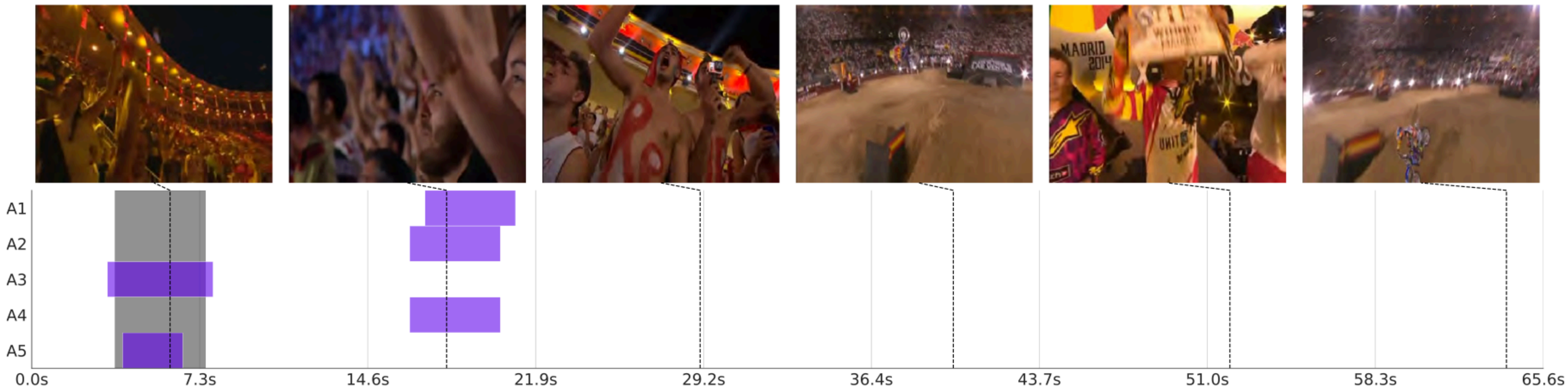
Recent tales of neural networks

Lazy deep neural networks?

Video Moment Retrieval

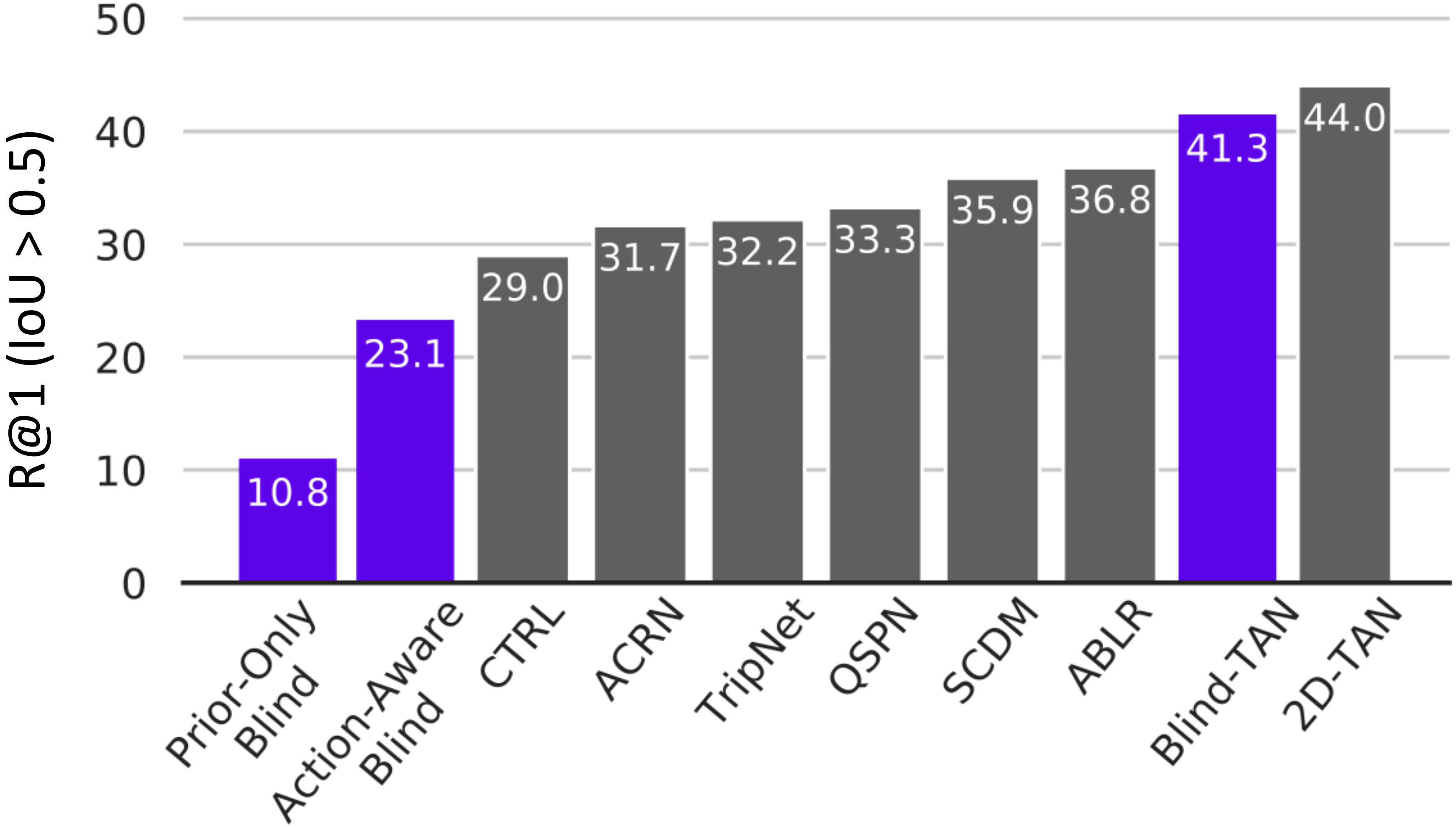


As the walk continues,the cat stops and begins staring at a parked car with large red flames painted on the side.



A crowd of people are cheering.

On a certain dataset



Visual Question Answering

Comparison

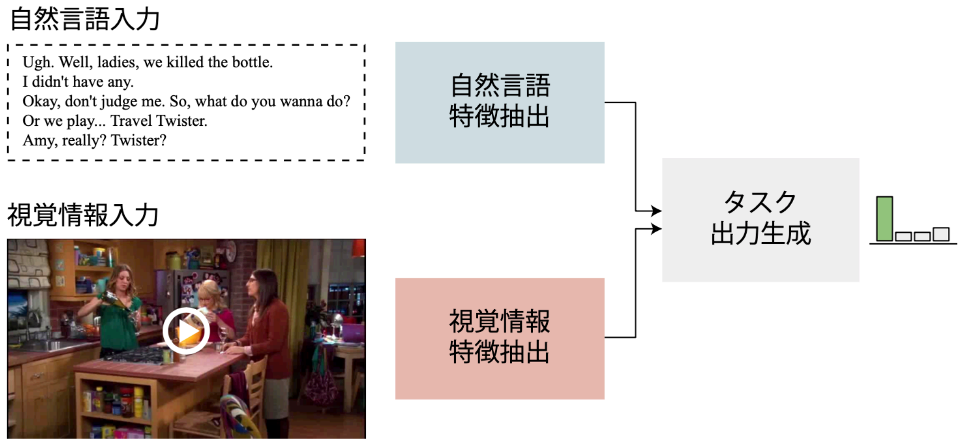
Model	Dataset	Overall	Yes/No	Number	Other	Dataset	Overall	Yes/No	Number	Other
per Q-type prior [5]	VQA v1	35.13	71.31	31.93	08.86	VQA v2	32.06	64.42	26.95	08.76
	VQA-CP v1	08.39	14.70	08.34	02.14	VQA-CP v2	08.76	19.36	11.70	02.39
d-LSTM Q [5]	VQA v1	48.23	79.05	33.70	28.81	VQA v2	43.01	67.95	30.97	27.20
	VQA-CP v1	20.16	35.72	11.07	08.34	VQA-CP v2	15.95	35.09	11.63	07.11
d-LSTM Q + norm I [24]	VQA v1	54.40	79.82	33.87	40.54	VQA v2	51.61	73.06	34.41	39.85
	VQA-CP v1	23.51	34.53	11.40	17.42	VQA-CP v2	19.73	34.25	11.39	14.41
NMN [3]	VQA v1	54.83	80.39	33.45	41.07	VQA v2	51.62	73.38	33.23	39.93
	VQA-CP v1	29.64	38.85	11.23	27.88	VQA-CP v2	27.47	38.94	11.92	25.72
SAN [39]	VQA v1	55.86	78.54	33.46	44.51	VQA v2	52.02	68.89	34.55	43.80
	VQA-CP v1	26.88	35.34	11.34	24.70	VQA-CP v2	24.96	38.35	11.14	21.74
MCB [11]	VQA v1	60.97	81.62	34.56	52.16	VQA v2	59.71	77.91	37.47	51.76
	VQA-CP v1	34.39	37.96	11.80	39.90	VQA-CP v2	36.33	41.01	11.96	40.57

- Datasets with "-CP" reduce dataset bias
- VQA v1/v2 can be answered with 50% accuracy based only on questions
- Even SoTA models performed < 40% accuracy over "-CP" datasets

So...?

Vision hardly helps for vision + language (=multimodal) tasks

- Deep neural networks are lazy?
  - Shortcut learning [Geirhos et al., arXiv:2004:077803]
- They are trapped in superficial correlations
  - “There could be better ways…”
  - “But it’s working…” (though it’s a local minimum)
- **Note this when you use multiple different inputs**



Takeaways

- Deep learning is easy; but don't forget the puzzling problems
  - Overfitting
  - Vanishing gradients
  - Hyperparameter tuning
  - Shortcut learning?

- For better modeling the data, it would be nice to have some shared tasks
  - Common input data (perhaps, closer to detectors?)
  - Shared tasks

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Osaka University Institute for Datability Science