Lecture 14:

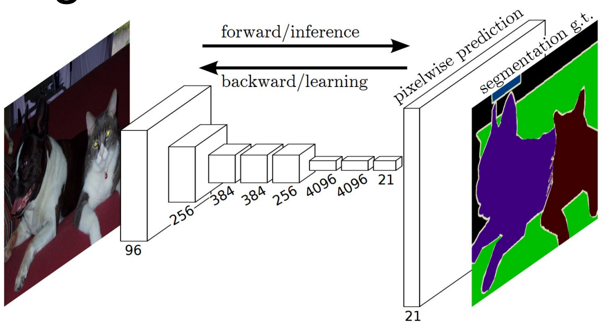
Videos
Unsupervised Learning

Administrative

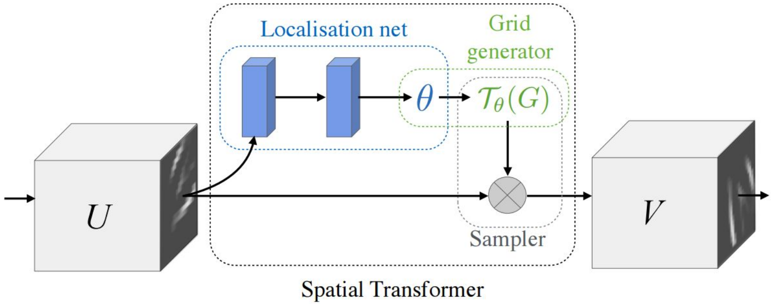
- Everyone should be done with Assignment 3 now
- Milestone grades will go out soon

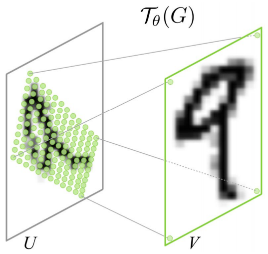
Last class

Segmentation

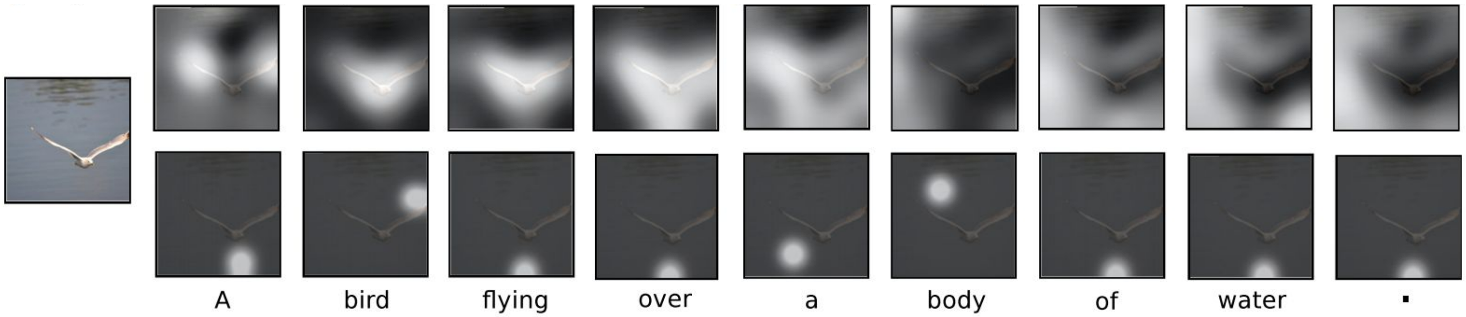


Spatial Transformer



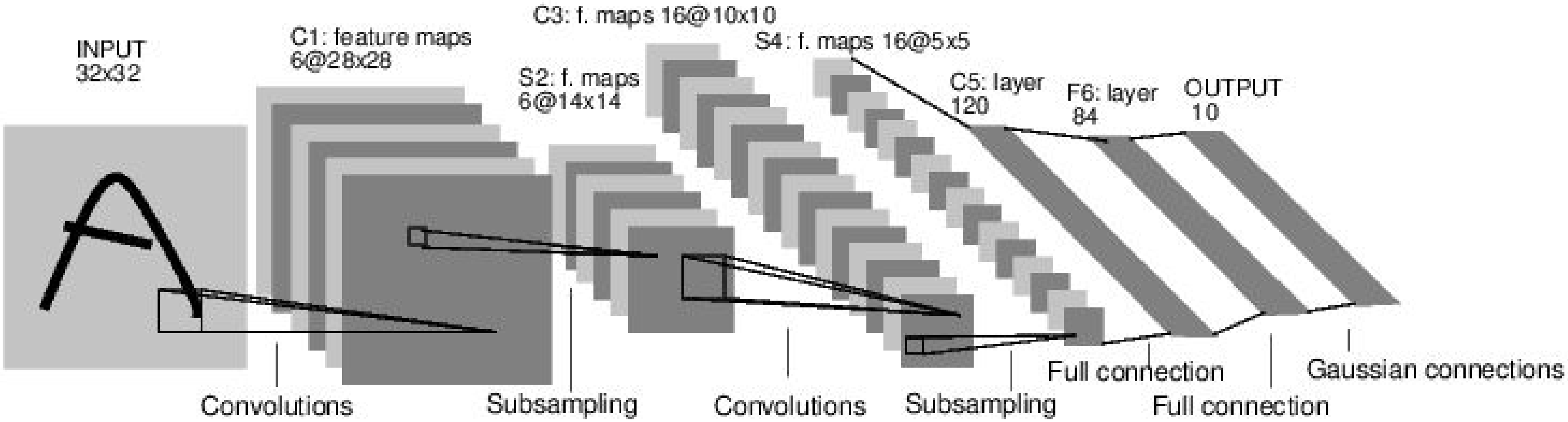


Soft Attention



Videos

ConvNets for images

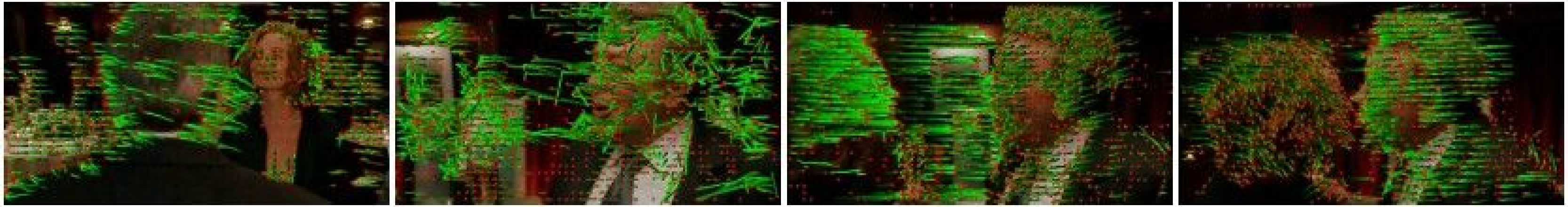


Feature-based approaches to Activity Recognition

Dense trajectories and motion boundary descriptors for action recognition
Wang et al., 2013

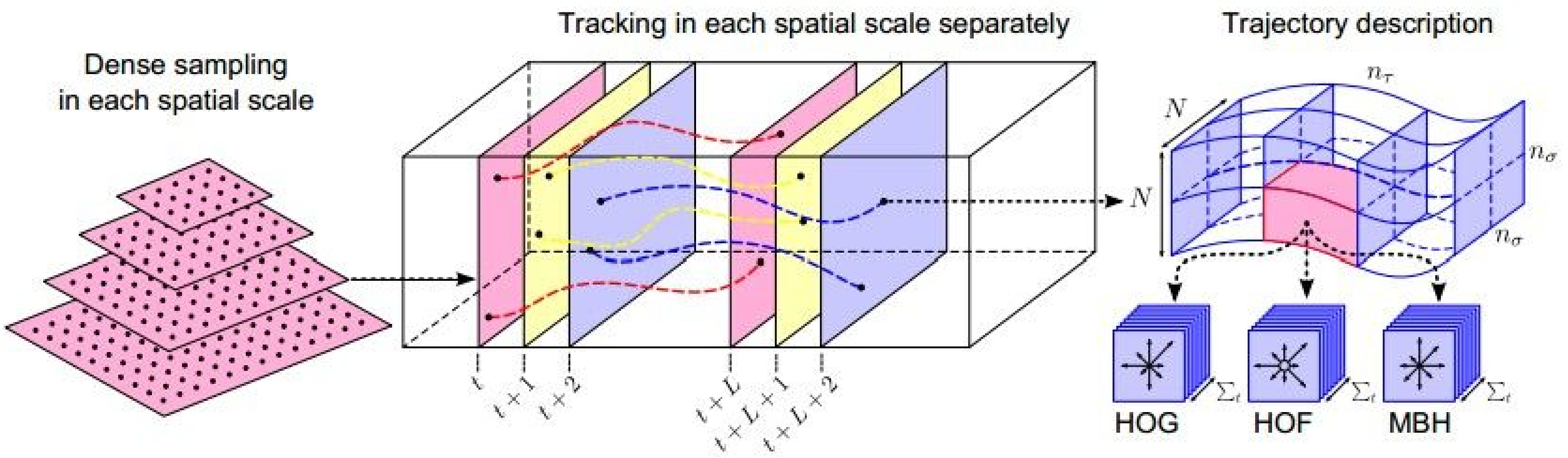
Action Recognition with Improved Trajectories
Wang and Schmid, 2013

(code available!)



Dense trajectories

Dense trajectories and motion boundary descriptors for action recognition
Wang et al., 2013

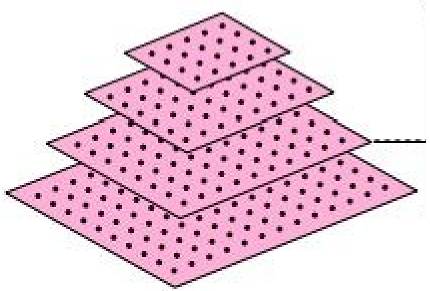


detect feature points

track features with optical flow

extract HOG/HOF/MBH features in the (stabilized) coordinate system of each tracklet

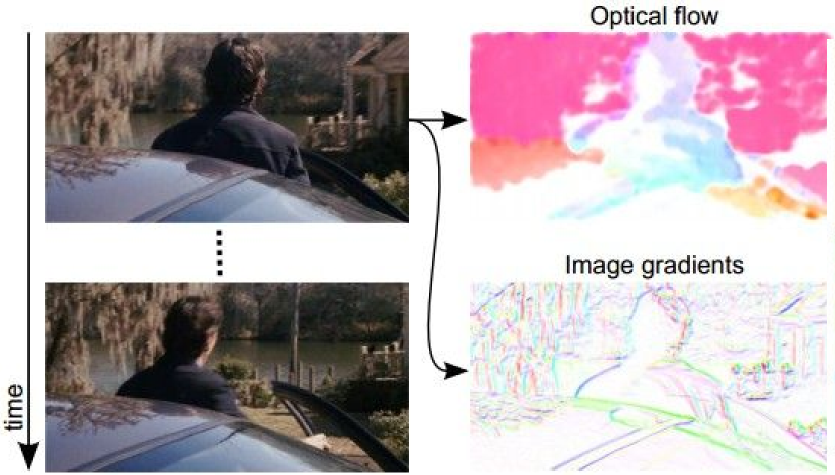
Dense trajectories and motion boundary descriptors for action recognition
Wang et al., 2013



detected feature points

[J. Shi and C. Tomasi, “Good features to track,” CVPR 1994]
[Ivan Laptev 2005]

Dense trajectories and motion boundary descriptors for action recognition
Wang et al., 2013

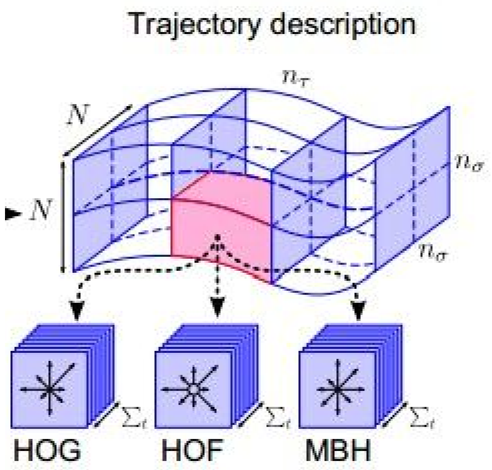


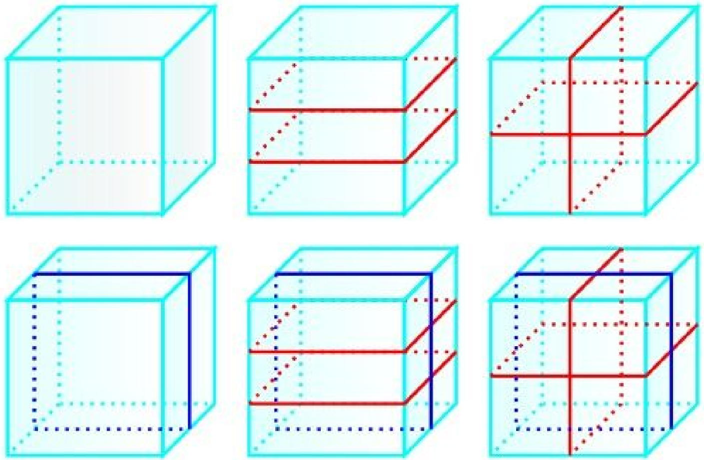
Overlaid image | Farnebäck [39] | Brox and Malik [41]

track each keypoint using **optical flow.**

[G. Farnebäck, “Two-frame motion estimation based on polynomial expansion,” 2003]
[T. Brox and J. Malik, “Large displacement optical flow: Descriptor matching in variational motion estimation,” 2011]

Dense trajectories and motion boundary descriptors for action recognition
Wang et al., 2013



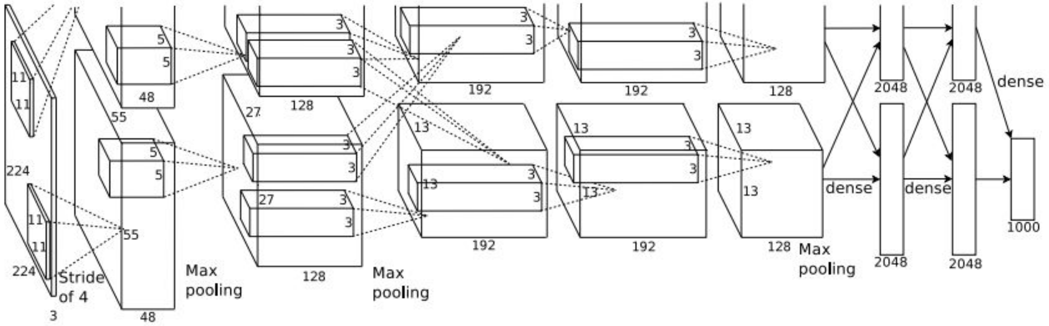


Extract features in the local coordinate system of each tracklet.

Accumulate into histograms, separately according to multiple spatio-temporal layouts.

Case Study: AlexNet

[Krizhevsky et al. 2012]

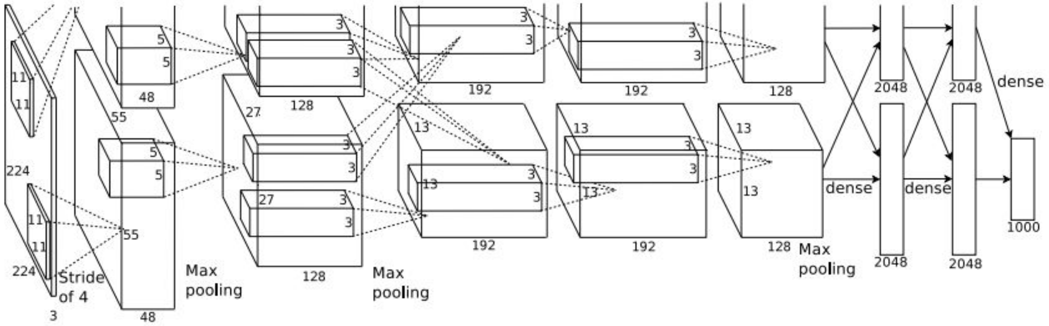


Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**
Q: What if the input is now a small chunk of video? E.g. [227x227x3x15] ?

Case Study: AlexNet

[Krizhevsky et al. 2012]



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**
Q: What if the input is now a small chunk of video? E.g. [227x227x3x15] ?
A: Extend the convolutional filters in time, perform spatio-temporal convolutions!
E.g. can have 11x11xT filters, where T = 2..15.

Spatio-Temporal ConvNets

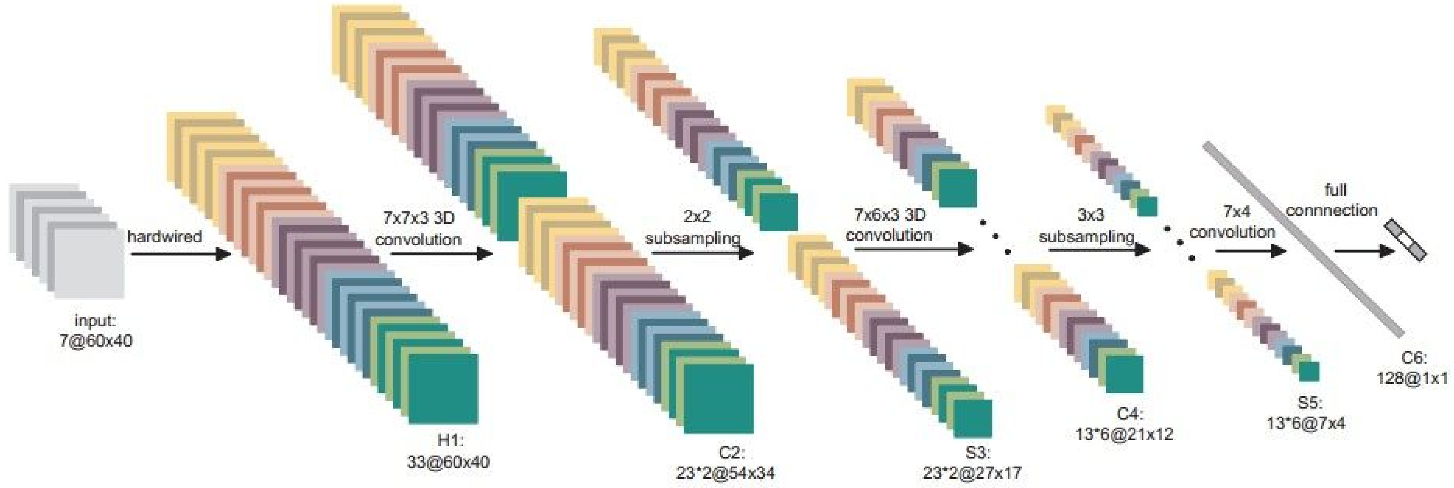
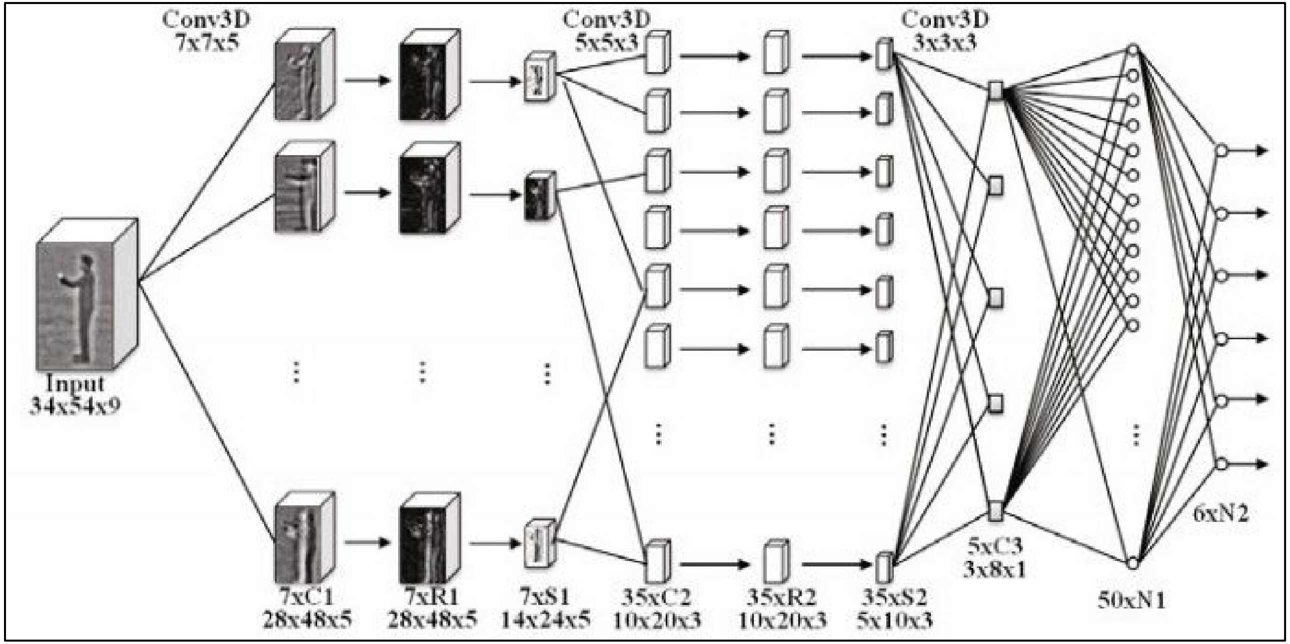


Figure 3. A 3D CNN architecture for human action recognition. This architecture consists of 1 hardwired layer, 3 convolution layers, 2 subsampling layers, and 1 full connection layer. Detailed descriptions are given in the text.

[3D Convolutional Neural Networks for Human Action Recognition, Ji et al., 2010]

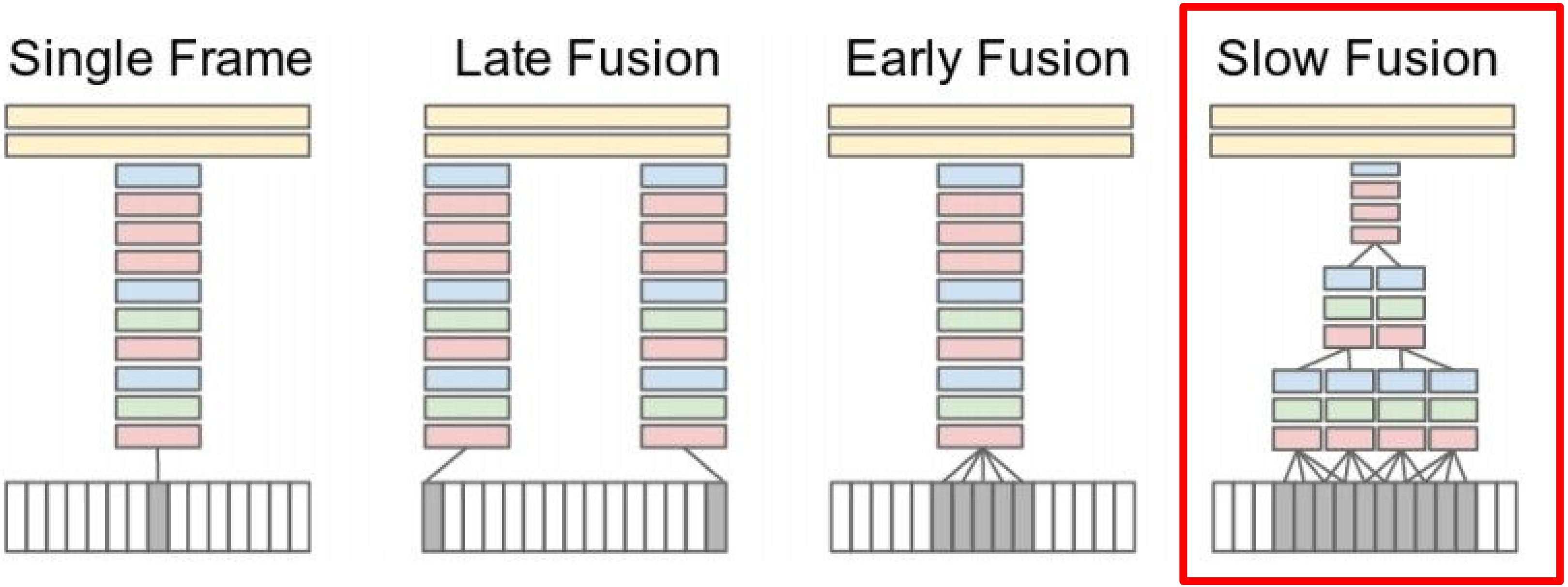
Spatio-Temporal ConvNets



Sequential Deep Learning for Human Action Recognition, Baccouche et al., 2011

Spatio-Temporal ConvNets

spatio-temporal convolutions; worked best.



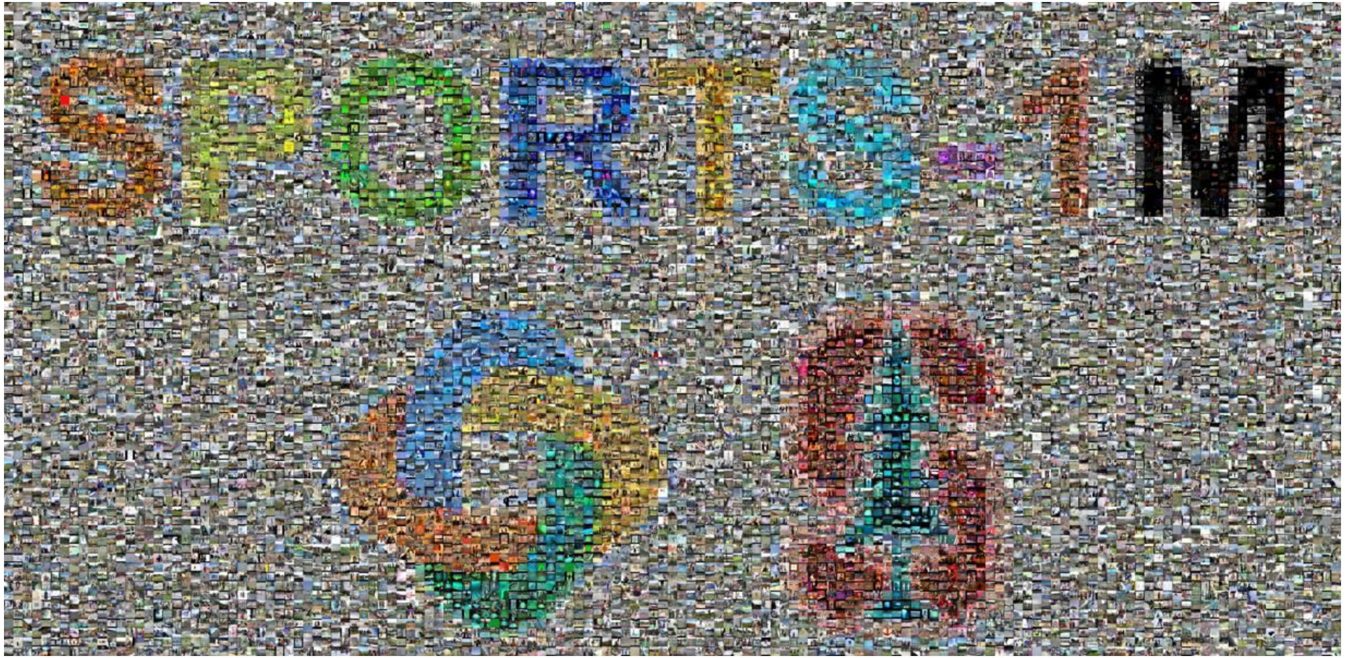
[Large-scale Video Classification with Convolutional Neural Networks, Karpathy et al., 2014]

Spatio-Temporal ConvNets

Learned filters on the first layer

[Large-scale Video Classification with Convolutional Neural Networks, Karpathy et al., 2014]

Spatio-Temporal ConvNets



1 million videos
487 sports classes

[Large-scale Video Classification with Convolutional Neural Networks, Karpathy et al., 2014]

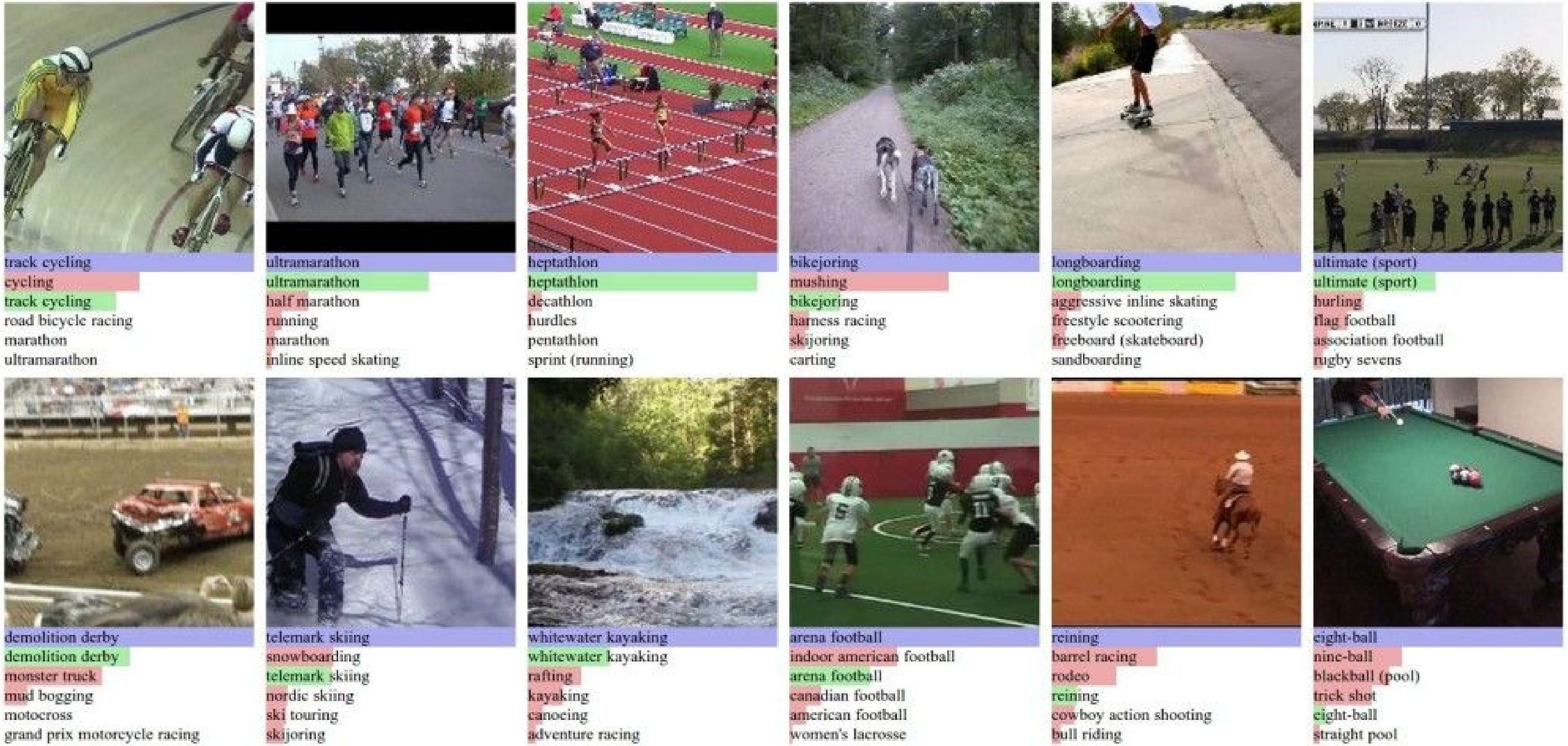
Spatio-Temporal ConvNets

Model	Clip Hit@1	Video Hit@1	Video Hit@5
Feature Histograms + Neural Net	-	55.3	-
Single-Frame	41.1	59.3	77.7
Single-Frame + Multires	**42.4**	**60.0**	**78.5**
Single-Frame Fovea Only	30.0	49.9	72.8
Single-Frame Context Only	38.1	56.0	77.2
Early Fusion	38.9	57.7	76.8
Late Fusion	40.7	59.3	78.7
Slow Fusion	**41.9**	**60.9**	**80.2**
CNN Average (Single+Early+Late+Slow)	41.4	63.9	82.4

The motion information didn't add all that much...

[Large-scale Video Classification with Convolutional Neural Networks, Karpathy et al., 2014]

Spatio-Temporal ConvNets



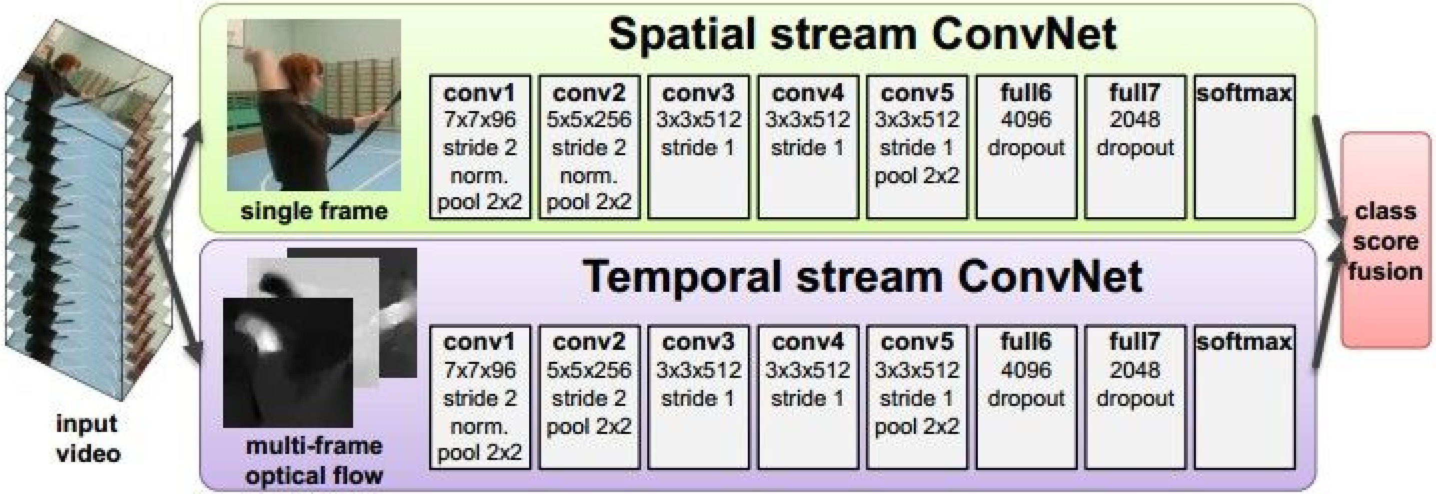
Spatio-Temporal ConvNets

Figure 3. **C3D architecture**. C3D net has 8 convolution, 5 max-pooling, and 2 fully connected layers, followed by a softmax output layer. All 3D convolution kernels are $3 \times 3 \times 3$ with stride 1 in both spatial and temporal dimensions. Number of filters are denoted in each box. The 3D pooling layers are denoted from `pool1` to `pool5`. All pooling kernels are $2 \times 2 \times 2$, except for `pool1` is $1 \times 2 \times 2$. Each fully connected layer has 4096 output units.

3D VGGNet, basically.

[Learning Spatiotemporal Features with 3D Convolutional Networks, Tran et al. 2015]

Spatio-Temporal ConvNets

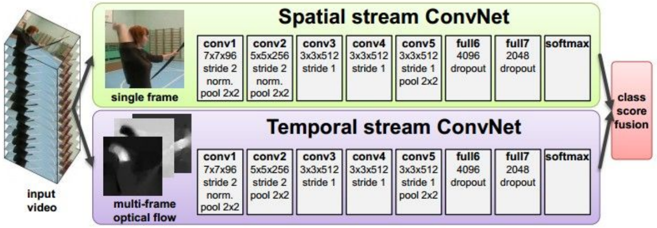


(of VGGNet fame)

[Two-Stream Convolutional Networks for Action Recognition in Videos, **Simonyan** and Zisserman 2014]

[T. Brox and J. Malik, “Large displacement optical flow: Descriptor matching in variational motion estimation,” 2011]

Spatio-Temporal ConvNets



Spatial stream ConvNet	73.0%	40.5%
Temporal stream ConvNet	83.7%	54.6%
Two-stream model (fusion by averaging)	86.9%	58.0%
Two-stream model (fusion by SVM)	**88.0%**	**59.4%**

Two-stream version works much better than either alone.

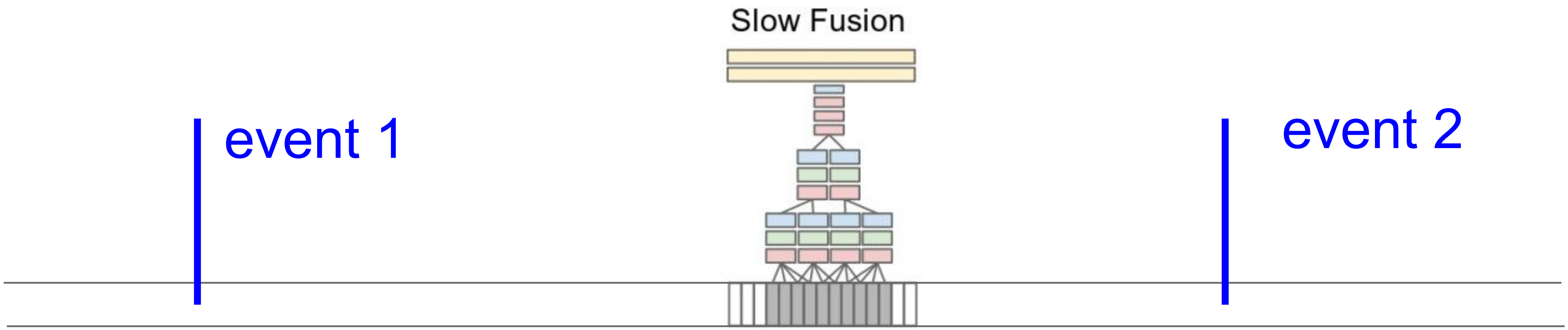
[Two-Stream Convolutional Networks for Action Recognition in Videos, **Simonyan** and Zisserman 2014]

[T. Brox and J. Malik, “Large displacement optical flow: Descriptor matching in variational motion estimation,” 2011]

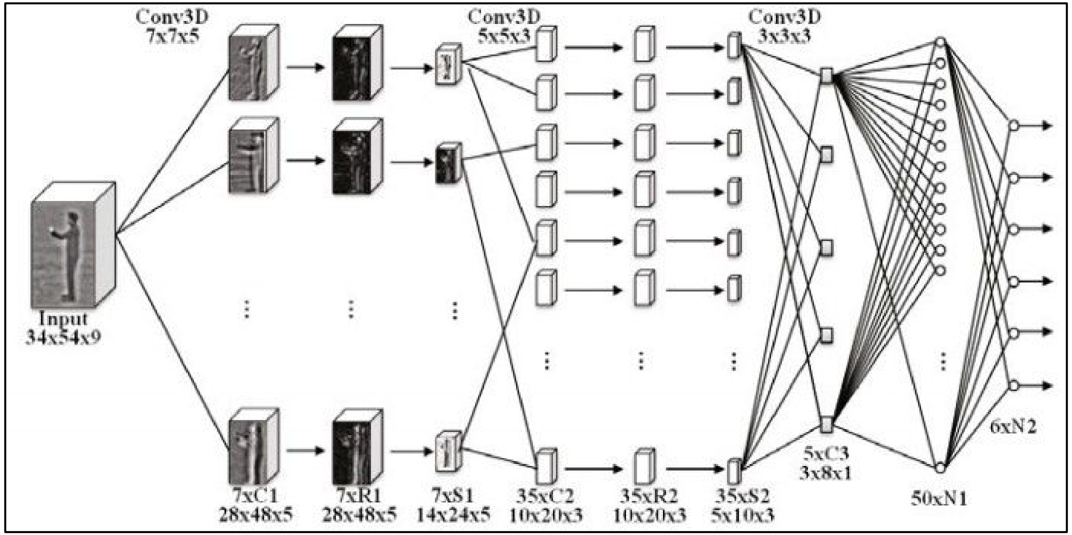
Long-time Spatio-Temporal ConvNets

All 3D ConvNets so far used local motion cues to get extra accuracy (e.g. half a second or so)

Q: what if the temporal dependencies of interest are much much longer? E.g. several seconds?



Long-time Spatio-Temporal ConvNets

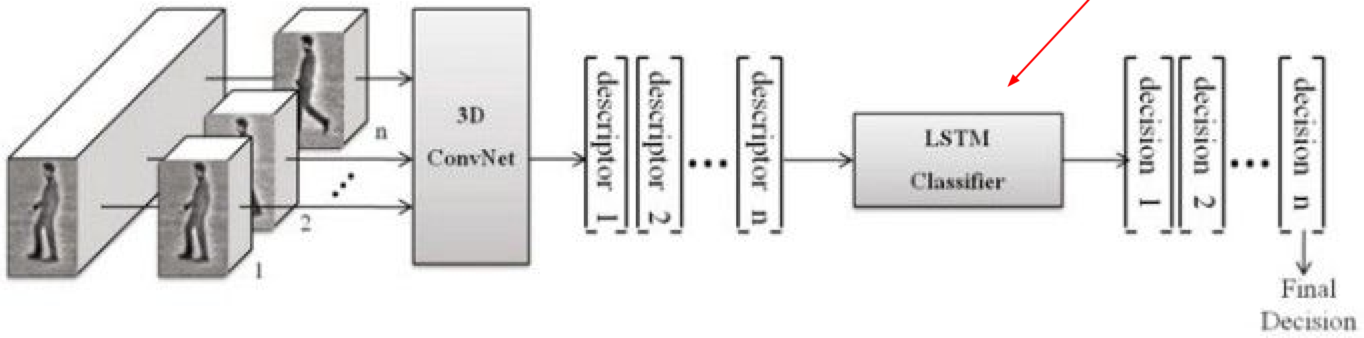


(This paper was way ahead of its time. Cited 65 times.)

Sequential Deep Learning for Human Action Recognition, Baccouche et al., **2011**

Long-time Spatio-Temporal ConvNets

LSTM way before it was cool



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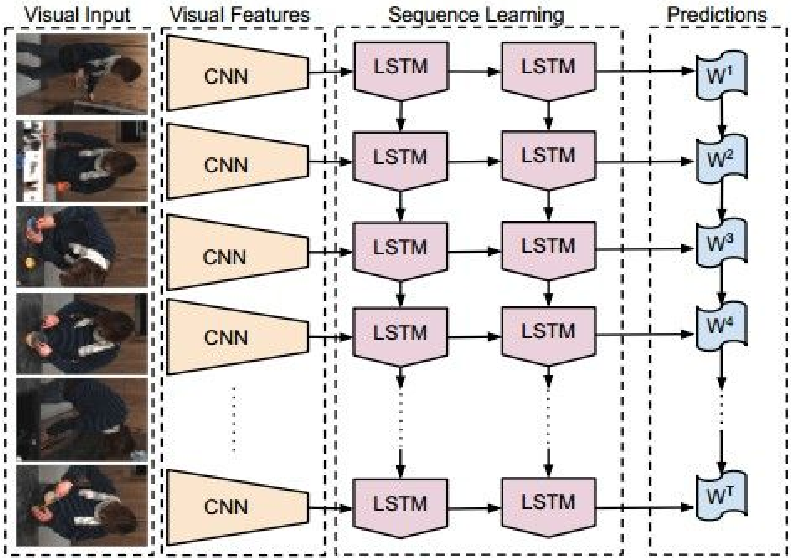
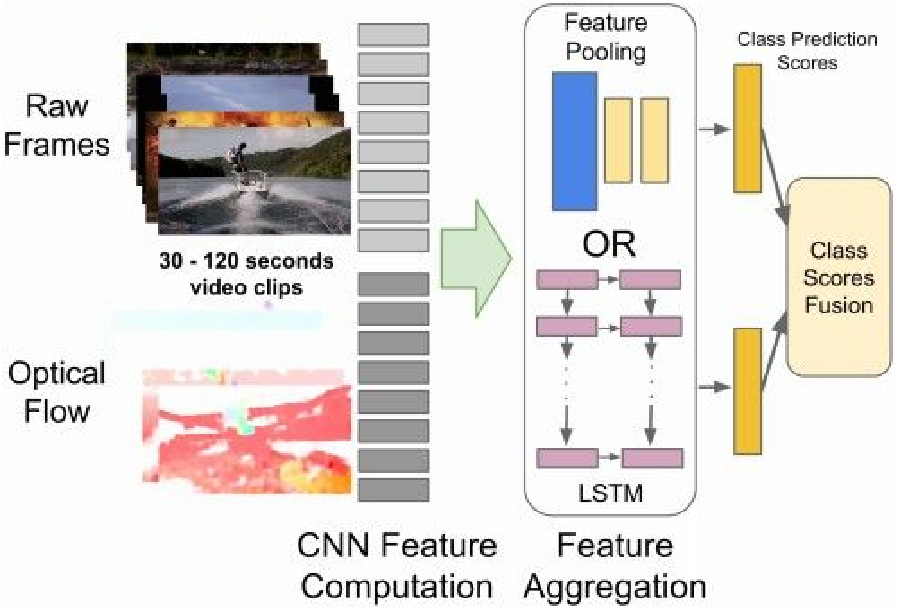
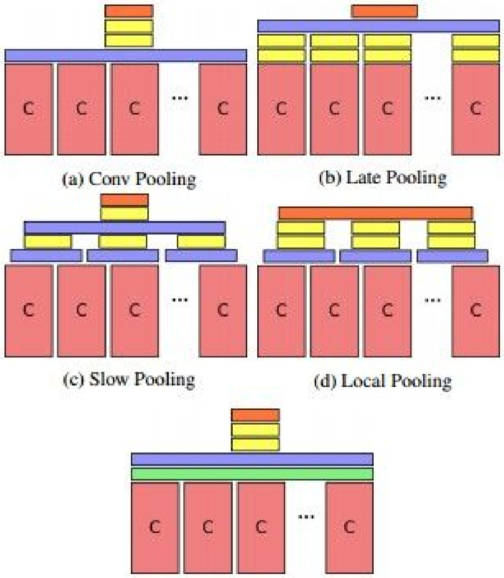
Long-time Spatio-Temporal ConvNets



[Long-term Recurrent Convolutional Networks for Visual Recognition and Description, Donahue et al., 2015]

Long-time Spatio-Temporal ConvNets





[Beyond Short Snippets: Deep Networks for Video Classification, Ng et al., 2015]

Summary so far

We looked at two types of architectural patterns:

1. Model temporal motion locally (3D CONV)

2. Model temporal motion globally (LSTM / RNN)

\+ Fusions of both approaches at the same time.

Summary so far

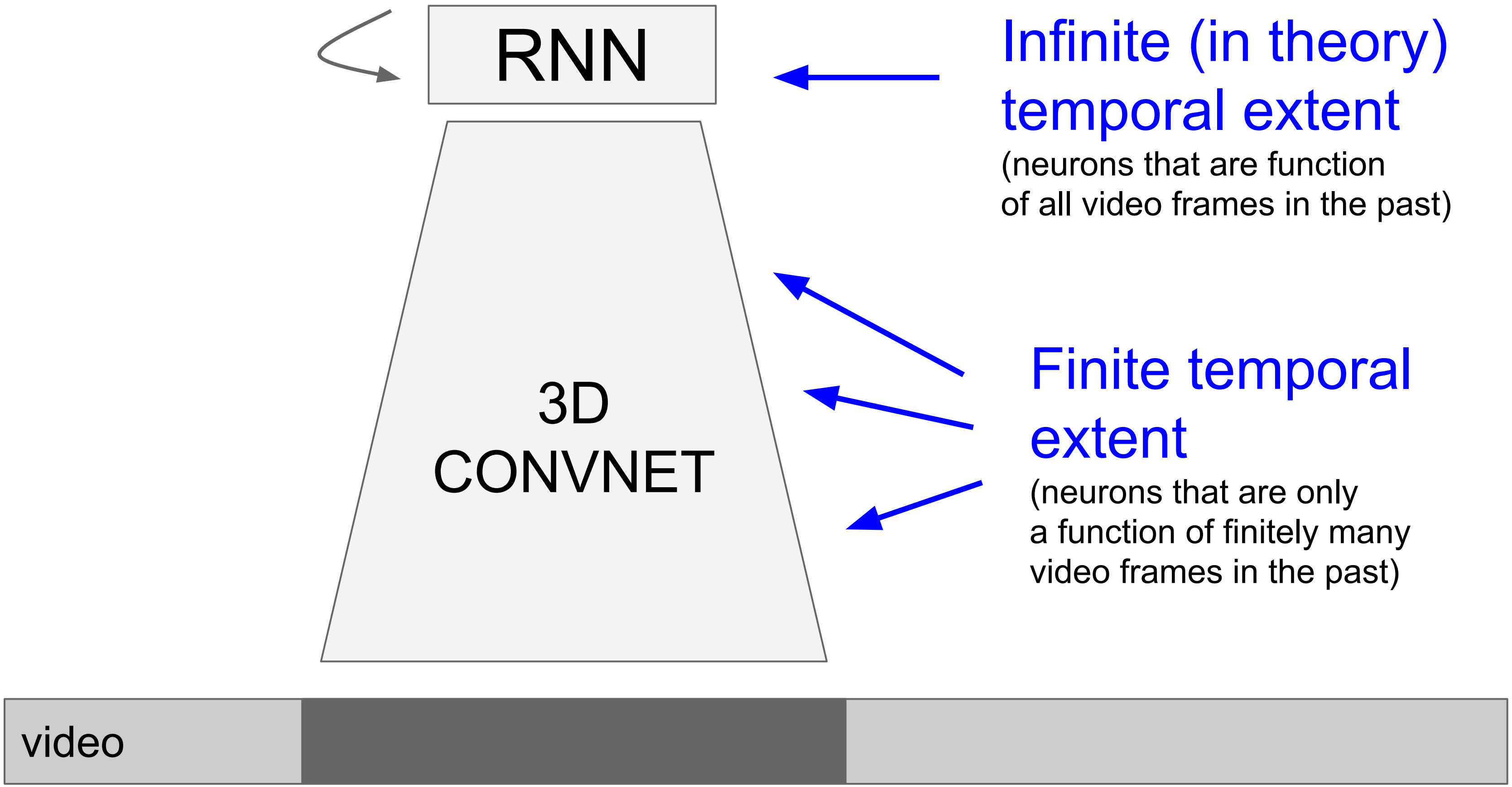
We looked at two types of architectural patterns:

1. Model temporal motion locally (3D CONV)

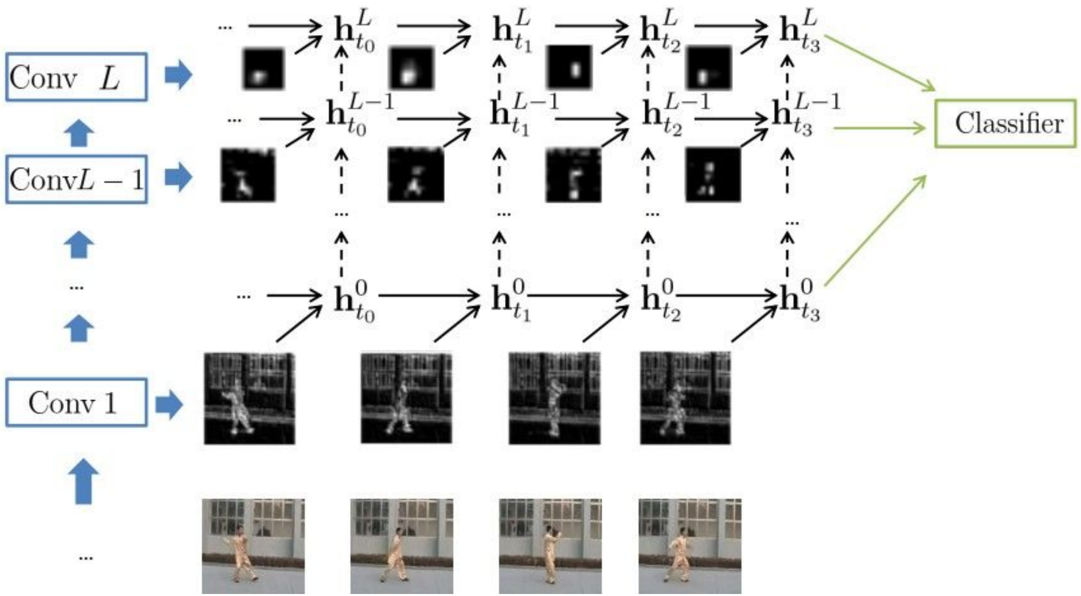
2. Model temporal motion globally (LSTM / RNN)

\+ Fusions of both approaches at the same time.

There is another (cleaner) way!


RNN
3D
CONVNET
video
Infinite (in theory) temporal extent
(neurons that are function of all video frames in the past)
Finite temporal extent
(neurons that are only a function of finitely many video frames in the past)

Long-time Spatio-Temporal ConvNets



Beautiful:
All neurons in the ConvNet are recurrent.

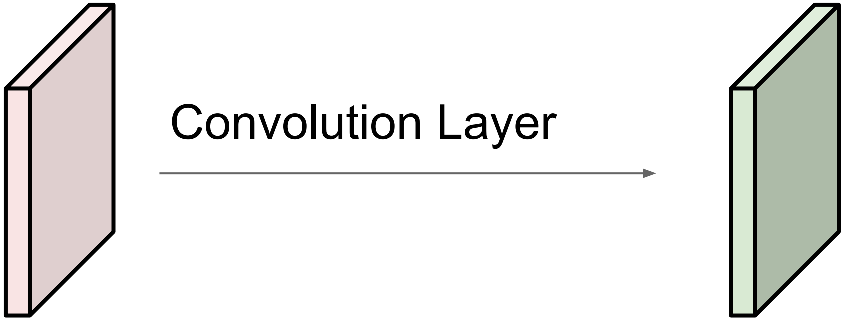
$$
\begin{aligned}
\mathbf{z}_t^l &= \sigma(\mathbf{W}_z^l * \mathbf{x}_t^l + \mathbf{U}_z^l * \mathbf{h}_{t-1}^l), \\
\mathbf{r}_t^l &= \sigma(\mathbf{W}_r^l * \mathbf{x}_t^l + \mathbf{U}_r^l * \mathbf{h}_{t-1}^l), \\
\tilde{\mathbf{h}}_t^l &= \tanh(\mathbf{W}^l * \mathbf{x}_t^l + \mathbf{U} * (\mathbf{r}_t^l \odot \mathbf{h}_{t-1}^l), \\
\mathbf{h}_t^l &= (1 - \mathbf{z}_t^l)\mathbf{h}_{t-1}^l + \mathbf{z}_t^l \tilde{\mathbf{h}}_t^l,
\end{aligned}
$$

Only requires (existing) 2D CONV routines. No need for 3D spatio-temporal CONV.

[Delving Deeper into Convolutional Networks for Learning Video Representations, Ballas et al., 2016]

Long-time Spatio-Temporal ConvNets

Normal ConvNet:



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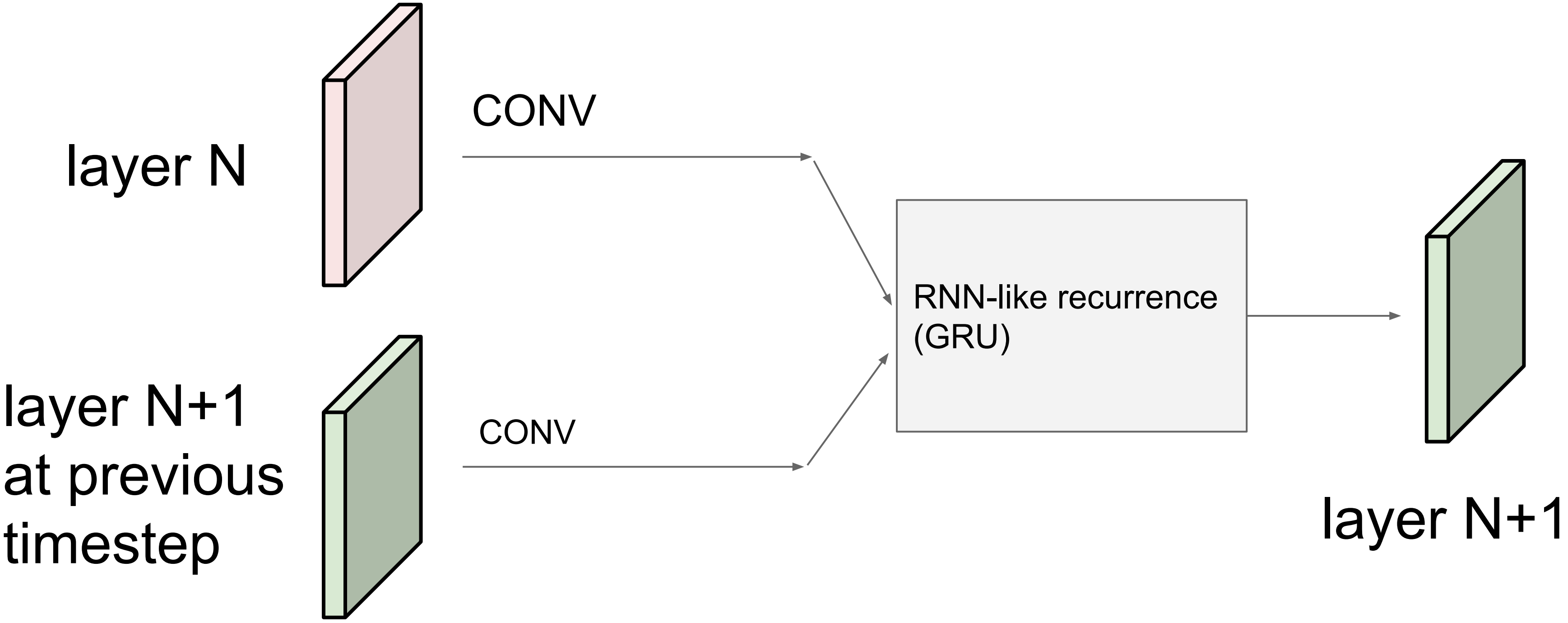
Long-time Spatio-Temporal ConvNets



[Delving Deeper into Convolutional Networks for Learning Video Representations, Ballas et al., 2016]

Long-time Spatio-Temporal ConvNets

Recall: RNNs

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

Vanilla RNN

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

GRU

$$
\begin{aligned}
\mathbf{z}_t &= \sigma(\mathbf{W}_z\mathbf{x}_t + \mathbf{U}_z\mathbf{h}_{t-1}),\\
\mathbf{r}_t &= \sigma(\mathbf{W}_r\mathbf{x}_t + \mathbf{U}_r\mathbf{h}_{t-1}),\\
\tilde{\mathbf{h}}_t &= \tanh(\mathbf{W}\mathbf{x}_t + \mathbf{U}(\mathbf{r}_t \odot \mathbf{h}_{t-1})\\
\mathbf{h}_t &= (1-\mathbf{z}_t)\mathbf{h}_{t-1} + \mathbf{z}_t\tilde{\mathbf{h}}_t,
\end{aligned}
$$

LSTM

$$
\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \mathrm{sigm} \\ \mathrm{sigm} \\ \mathrm{sigm} \\ \tanh \end{pmatrix} W^l \begin{pmatrix} h_t^{l-1} \\ h_{t-1}^l \end{pmatrix}
$$

$$
\begin{aligned}
c_t^l &= f \odot c_{t-1}^l + i \odot g\\
h_t^l &= o \odot \tanh(c_t^l)
\end{aligned}
$$

[Delving Deeper into Convolutional Networks for Learning Video Representations, Ballas et al., 2016]

Long-time Spatio-Temporal ConvNets

Recall: RNNs

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

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$$\begin{aligned}
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\mathbf{h}_t &= (1 - \mathbf{z}_t)\mathbf{h}_{t-1} + \mathbf{z}_t \tilde{\mathbf{h}}_t,
\end{aligned}$$

Matrix multiply
=>
CONV

$$\begin{aligned}
\mathbf{z}_t^l &= \sigma(\mathbf{W}_z^l * \mathbf{x}_t^l + \mathbf{U}_z^l * \mathbf{h}_{t-1}^l),\\
\mathbf{r}_t^l &= \sigma(\mathbf{W}_r^l * \mathbf{x}_t^l + \mathbf{U}_r^l * \mathbf{h}_{t-1}^l),\\
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\end{aligned}$$

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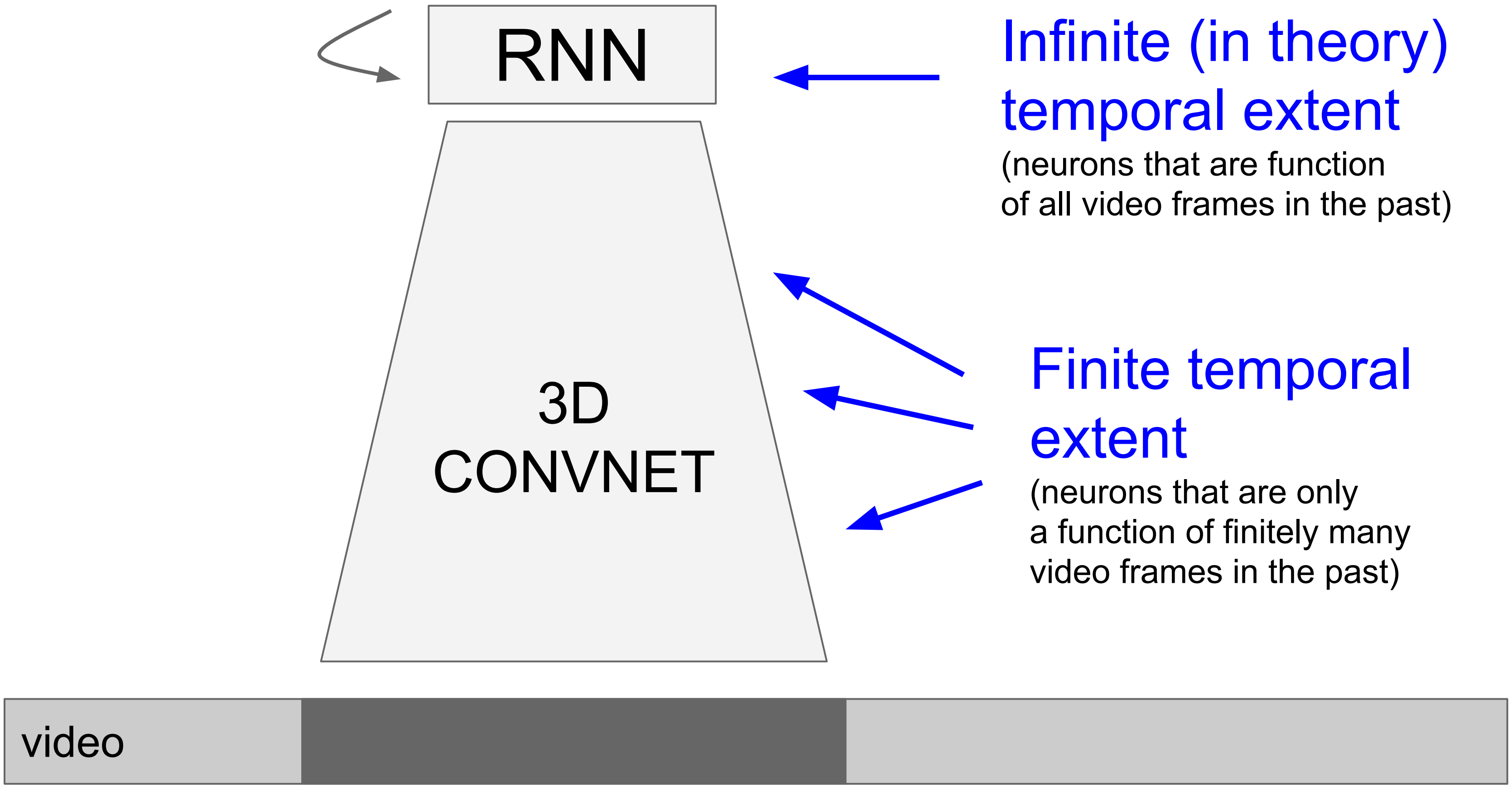
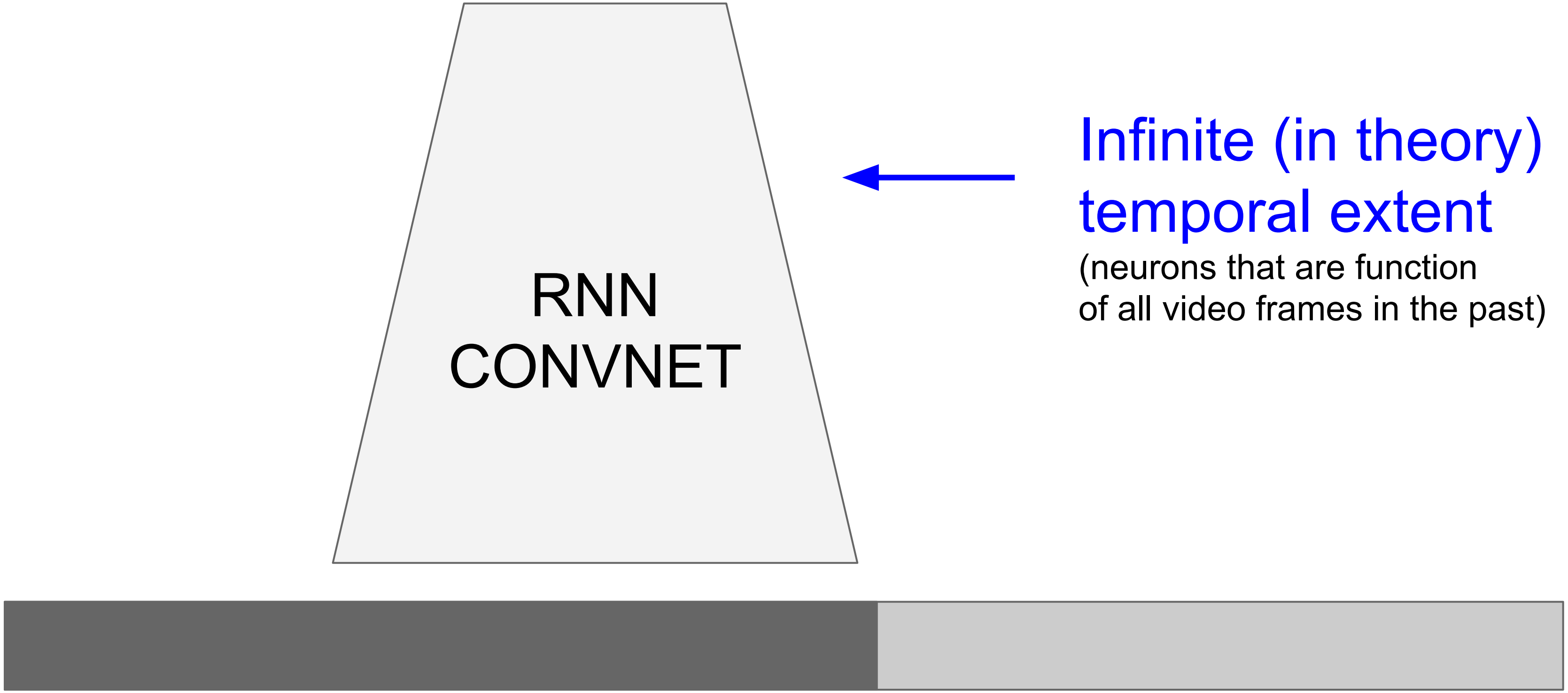


Infinite (in theory) temporal extent

(neurons that are function of all video frames in the past)

Finite temporal extent

(neurons that are only a function of finitely many video frames in the past) i.e. we obtain:


RNN
CONVNET
Infinite (in theory)
temporal extent
(neurons that are function
of all video frames in the past)

Summary

- You think you need a Spatio-Temporal Fancy Video ConvNet
- STOP. Do you really?
- Okay fine: do you want to model:
  - local motion? (use 3D CONV), or
  - global motion? (use LSTM).
- Try out using Optical Flow in a second stream (can work better sometimes)
- Try out GRU-RCN! (imo best model)

Unsupervised Learning

Unsupervised Learning Overview

- Definitions
- Autoencoders
  - Vanilla
  - Variational
- Adversarial Networks

Supervised vs Unsupervised

Supervised Learning

Data: (x, y)
x is data, y is label

Goal: Learn a *function* to map x -> y

Examples: Classification, regression, object detection, semantic segmentation, image captioning, etc

Supervised vs Unsupervised

Supervised Learning

Data: (x, y)
x is data, y is label

Goal: Learn a *function* to map x -> y

Examples: Classification, regression, object detection, semantic segmentation, image captioning, etc

Unsupervised Learning

Data: x
Just data, no labels!

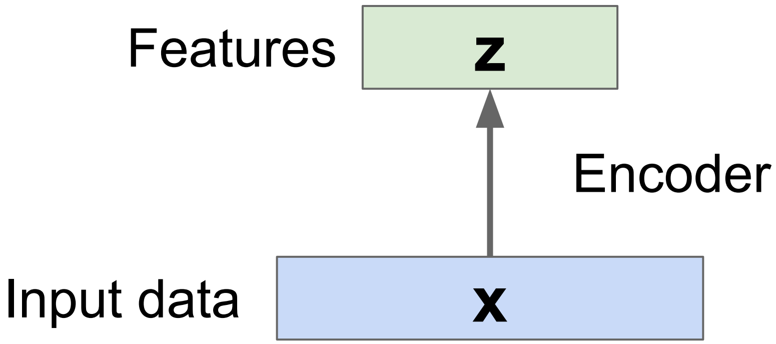
Goal: Learn some *structure* of the data

Examples: Clustering, dimensionality reduction, feature learning, generative models, etc.

Unsupervised Learning

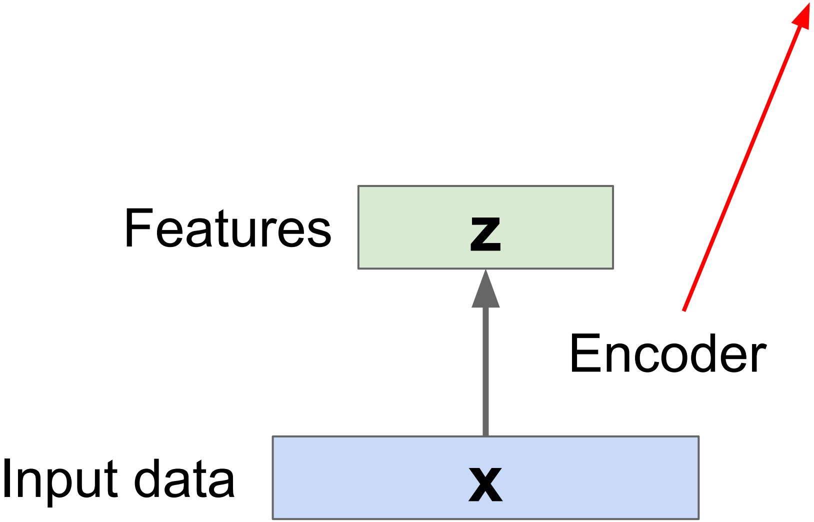
- Autoencoders
  - Traditional: feature learning
  - Variational: generate samples
- Generative Adversarial Networks: Generate samples

Autoencoders



Autoencoders

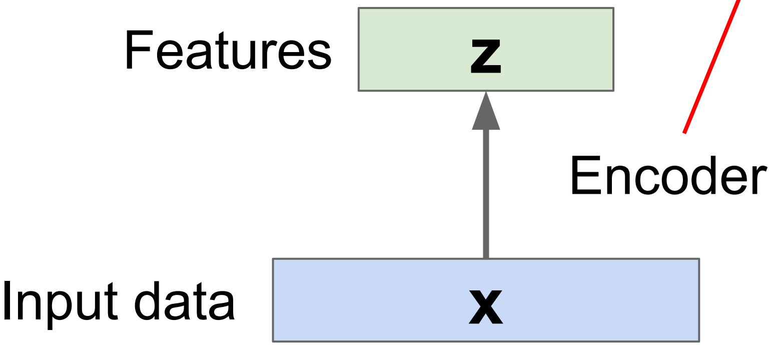
Originally: Linear + nonlinearity (sigmoid)
Later: Deep, fully-connected
Later: ReLU CNN



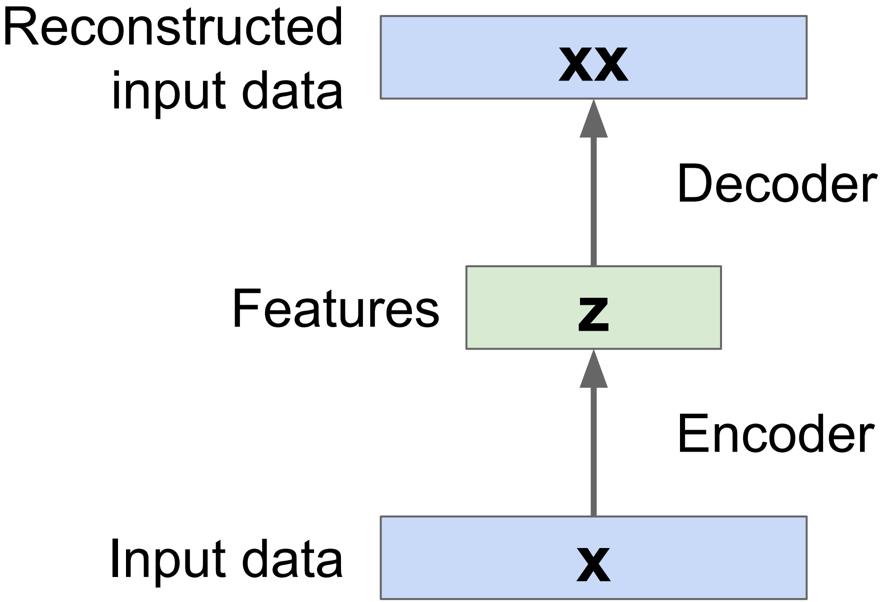
Autoencoders

z usually smaller than **x**
(dimensionality reduction)

Originally: Linear + nonlinearity (sigmoid)
Later: Deep, fully-connected
Later: ReLU CNN



Autoencoders



Autoencoders

Originally: Linear + nonlinearity (sigmoid)
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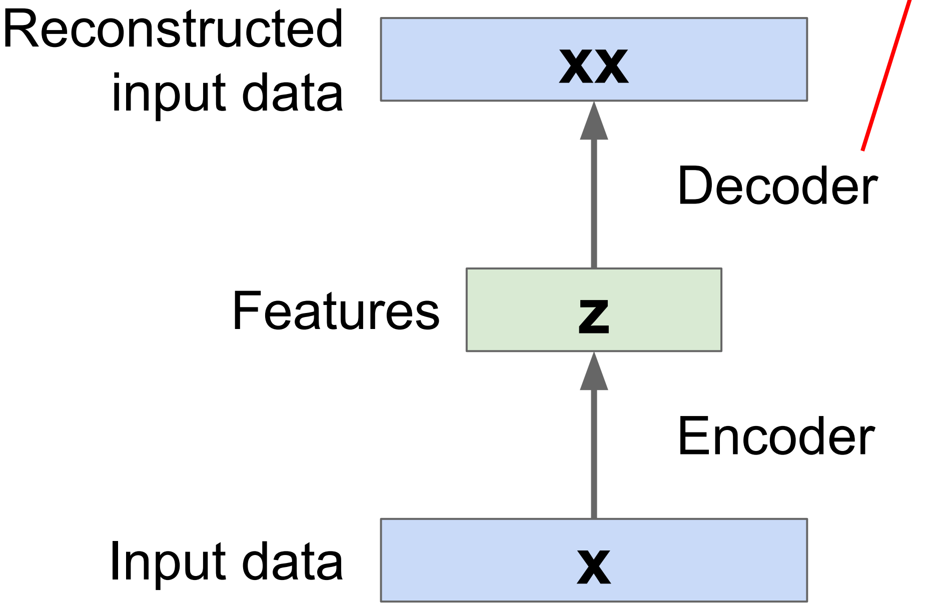
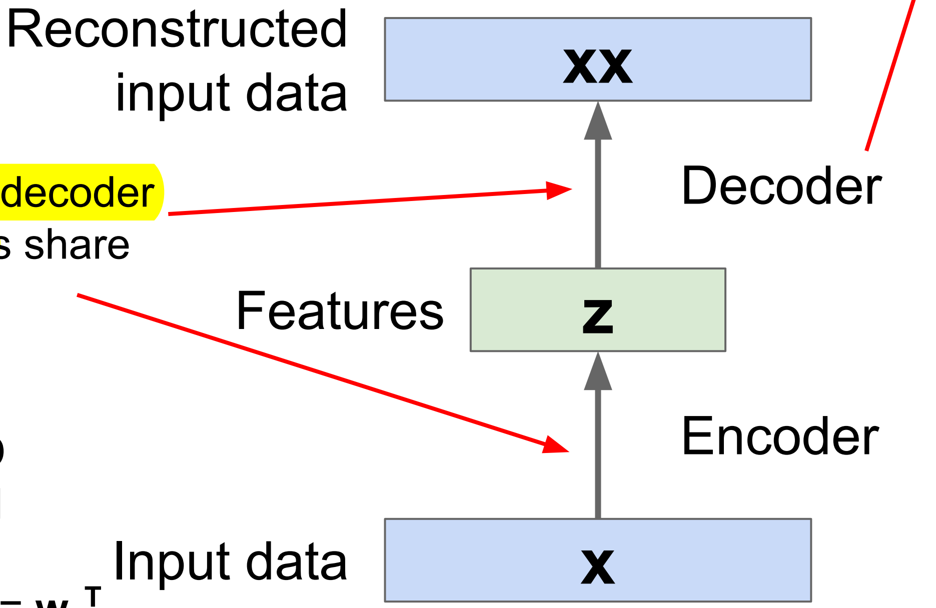


Encoder: 4-layer conv
Decoder: 4-layer upconv

Autoencoders

Originally: Linear + nonlinearity (sigmoid)
Later: Deep, fully-connected
Later: ReLU CNN (upconv)

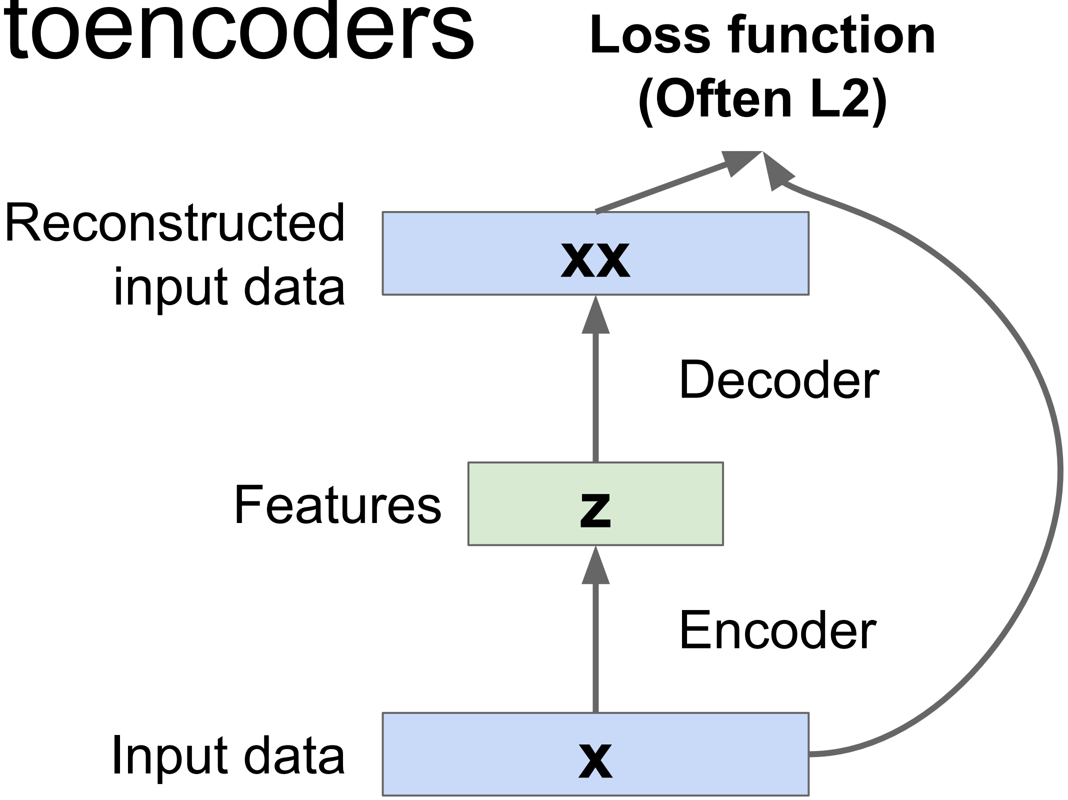
Encoder / decoder sometimes share weights



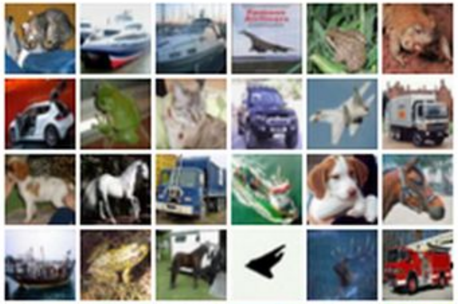
Example:
dim($\mathbf{x}$) = D
dim($\mathbf{z}$) = H
$\mathbf{w}_e$: H x D
$\mathbf{w}_d$: D x H = $\mathbf{w}_e^T$

Train for reconstruction with no labels!

Autoencoders

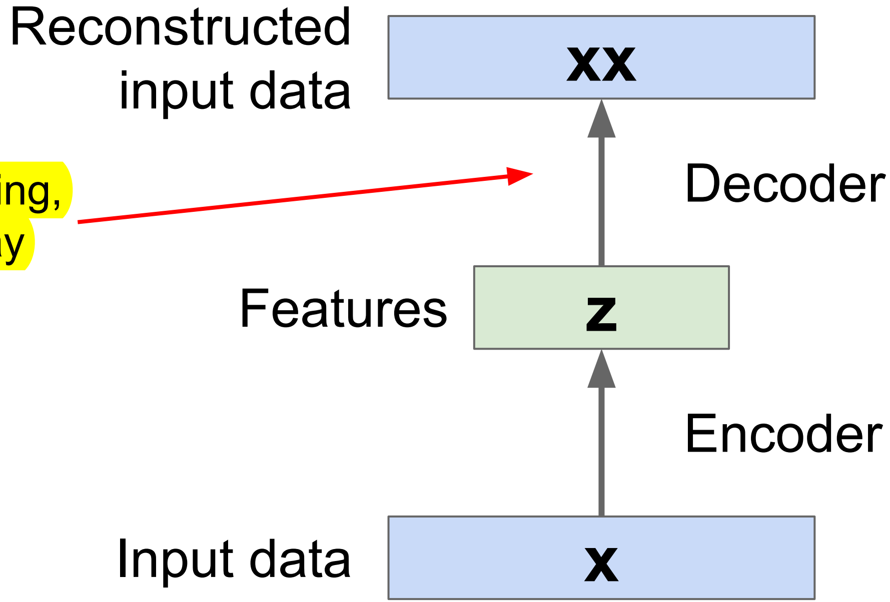


Train for
reconstruction
with no labels!



Autoencoders

After training, throw away decoder!



Autoencoders

Loss function (Softmax, etc)

Predicted Label **yy** **y**

Classifier

Features **z**

Encoder

Input data **x**

Use encoder to initialize a **supervised** model

Fine-tune encoder jointly with classifier

bird plane
dog deer truck

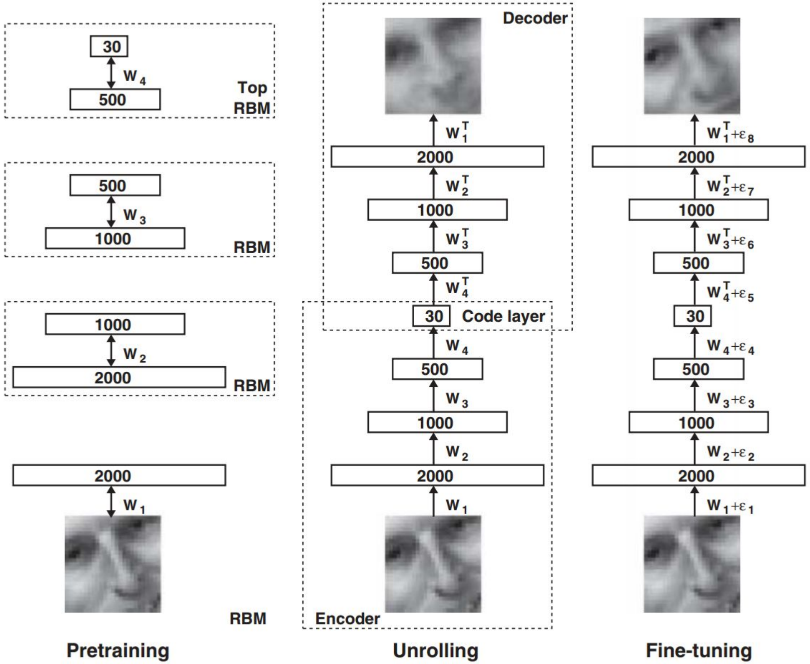
Train for final task (sometimes with small data)

Autoencoders: Greedy Training

In mid 2000s layer-wise pretraining with Restricted Boltzmann Machines (RBM) was common

Training deep nets was hard in 2006!

It is difficult to optimize the weights in nonlinear autoencoders that have multiple hidden layers (*2–4*). With large initial weights, autoencoders typically find poor local minima; with small initial weights, the gradients in the early layers are tiny, making it infeasible to train autoencoders with many hidden layers. If



Hinton and Salakhutdinov, “Reducing the Dimensionality of Data with Neural Networks”, Science 2006

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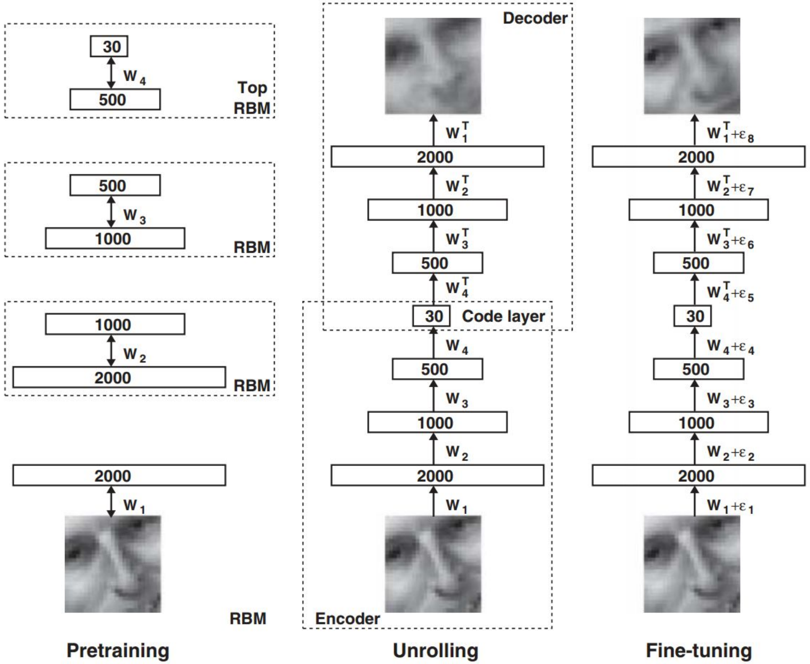
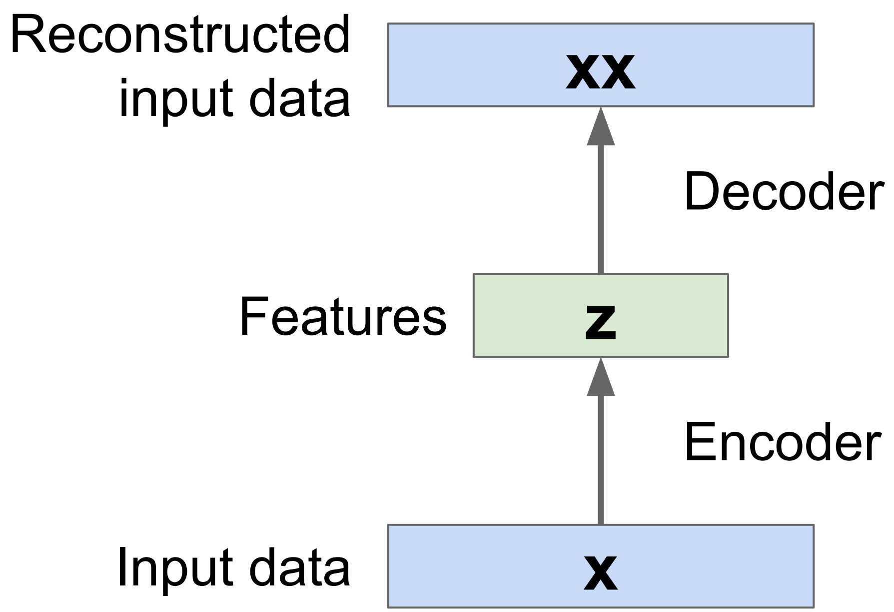


Not common anymore

With ReLU, proper initialization, batchnorm, Adam, etc easily train from scratch

Hinton and Salakhutdinov, “Reducing the Dimensionality of Data with Neural Networks”, Science 2006

Autoencoders



Autoencoders can reconstruct data, and can learn features to initialize a supervised model

Can we generate images from an autoencoder?

Variational Autoencoder

A Bayesian spin on an autoencoder - lets us generate data!

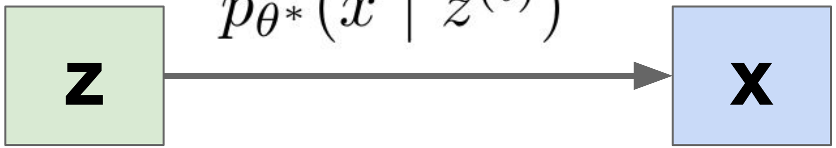
Assume our data $\{x^{(i)}\}_{i=1}^{N}$ is generated like this:

Sample from *true conditional*

$$p_{\theta^*}(x \mid z^{(i)})$$

Sample from *true prior*

$$p_{\theta^*}(z)$$



Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Variational Autoencoder

Intuition: **x** is an image, **z** gives class, orientation, attributes, etc

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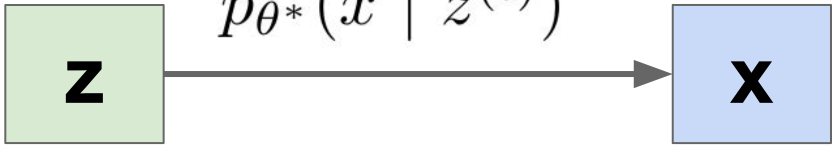

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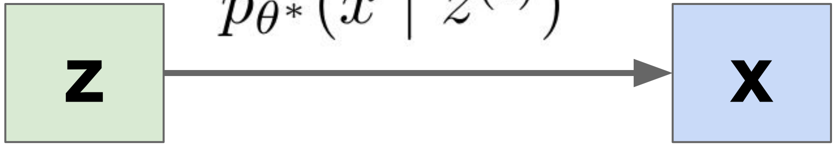

Problem: Estimate θ without access to latent states $z^{(i)}$!

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Variational Autoencoder

Prior: Assume $p_\theta(z)$ is a unit Gaussian

Kingma and Welling, ICLR 2014

Variational Autoencoder

Prior: Assume $p_\theta(z)$ is a unit Gaussian

Conditional: Assume $p_\theta(x \mid z)$ is a diagonal Gaussian, predict mean and variance with neural net

Kingma and Welling, ICLR 2014

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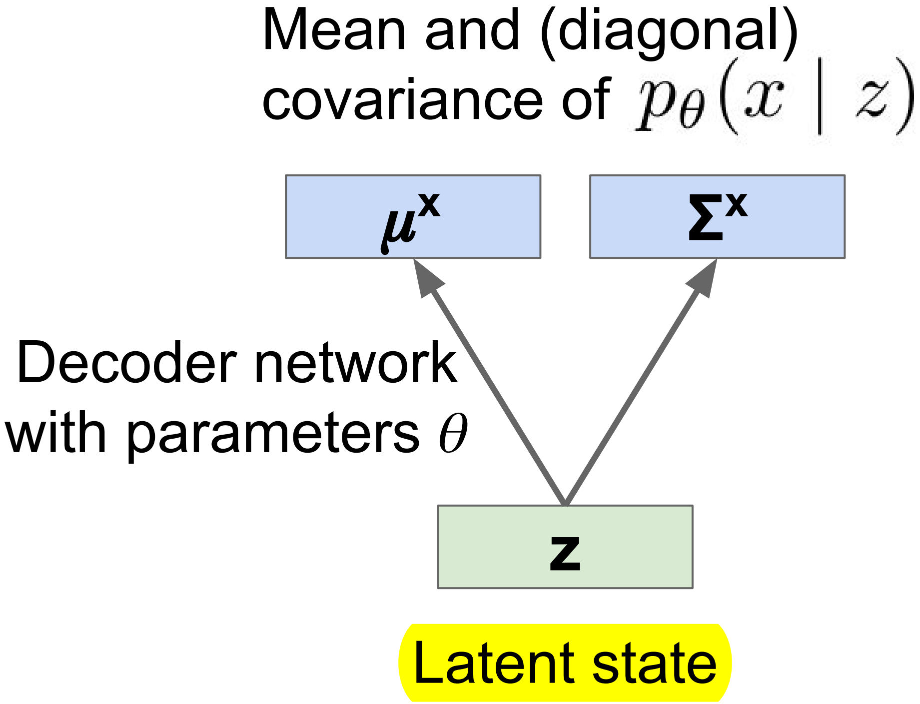

Kingma and Welling, ICLR 2014

Variational Autoencoder

Prior: Assume $p_\theta(z)$ is a unit Gaussian

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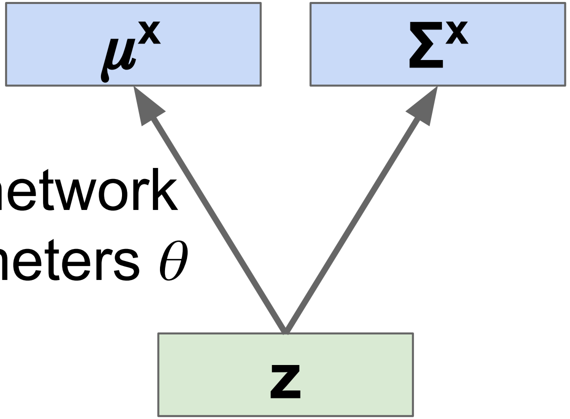
Mean and (diagonal) covariance of $p_\theta(x \mid z)$



Decoder network with parameters θ

Fully-connected or upconvolutional

Latent state

Kingma and Welling, ICLR 2014

Variational Autoencoder: Encoder

By Bayes Rule the posterior is:

$$p_\theta(z \mid x) = \frac{p_\theta(x \mid z)p_\theta(z)}{p_\theta(x)}$$

Kingma and Welling,
ICLR 2014

Variational Autoencoder: Encoder

By Bayes Rule the posterior is:

$$p_\theta(z \mid x) = \frac{\boxed{p_\theta(x \mid z)}\,\boxed{p_\theta(z)}}{\boxed{p_\theta(x)}}$$

Use decoder network =)
Gaussian =)
Intractible integral =(

Kingma and Welling,
ICLR 2014

Variational Autoencoder: Encoder

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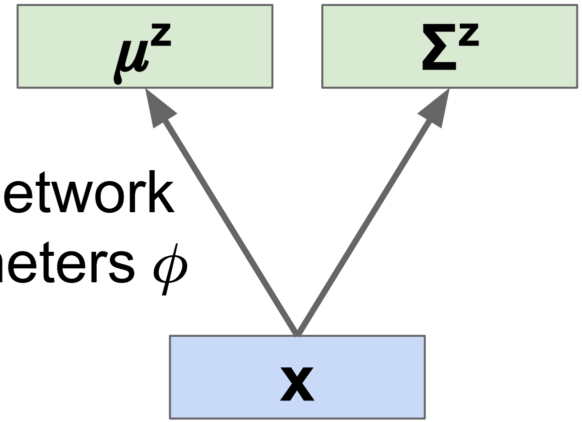
Mean and (diagonal) covariance of $q_\phi(z \mid x)$



Encoder network with parameters ϕ

Data point

Kingma and Welling, ICLR 2014

Variational Autoencoder: Encoder

By Bayes Rule the posterior is:

$$p_\theta(z \mid x) = \frac{\boxed{p_\theta(x \mid z)}\,\boxed{p_\theta(z)}}{\boxed{p_\theta(x)}}$$

Use decoder network =)
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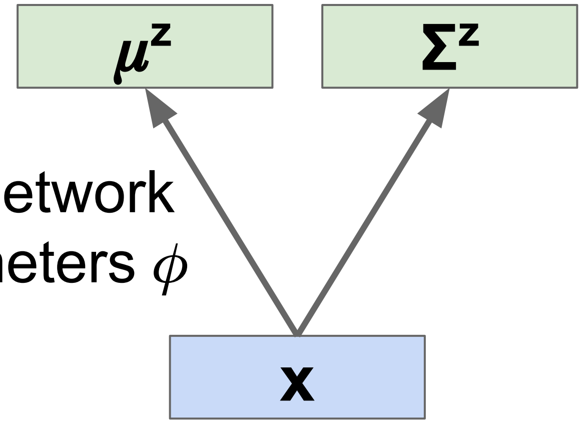
Mean and (diagonal) covariance of

$q_\phi(z \mid x)$



Encoder network with parameters ϕ

Data point

Approximate posterior with **encoder network** $q_\phi(z \mid x)$

Kingma and Welling, ICLR 2014

Variational Autoencoder: Encoder

By Bayes Rule the posterior is:

$$p_\theta(z \mid x) = \frac{\boxed{p_\theta(x \mid z)}\boxed{p_\theta(z)}}{\boxed{p_\theta(x)}}$$

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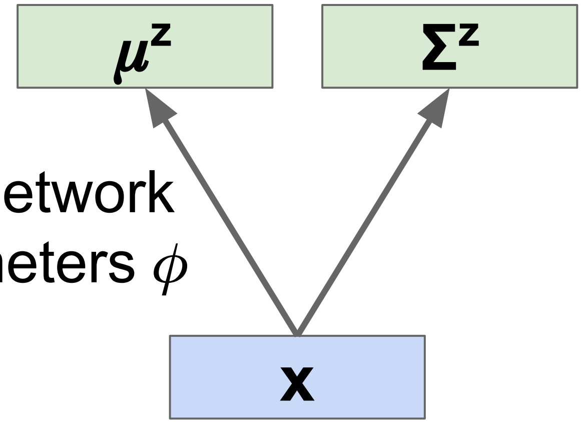
Fully-connected or convolutional

Mean and (diagonal) covariance of $q_\phi(z \mid x)$



Encoder network with parameters ϕ

Data point

Approximate posterior with **encoder network** $q_\phi(z \mid x)$

Kingma and Welling, ICLR 2014

Variational Autoencoder

Data point **x**

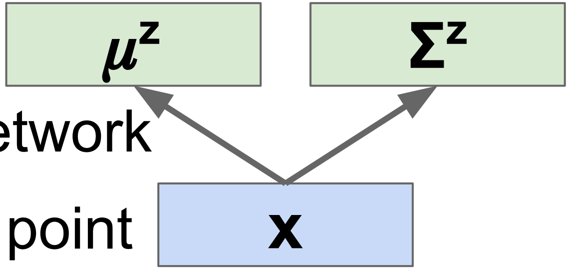
Kingma and Welling, ICLR 2014

Variational Autoencoder

Mean and (diagonal) covariance of $q_\phi(z \mid x)$

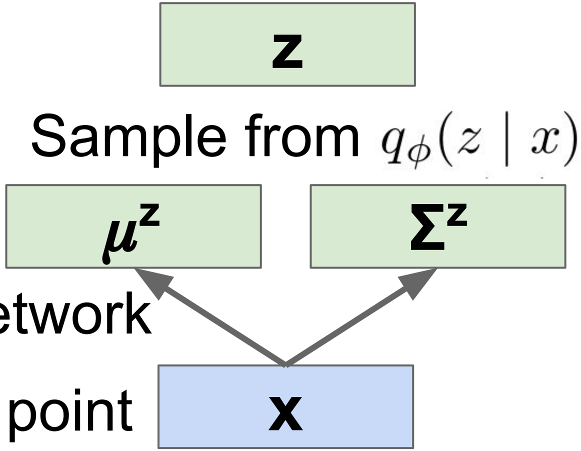
Encoder network

Data point



Kingma and Welling, ICLR 2014

Variational Autoencoder



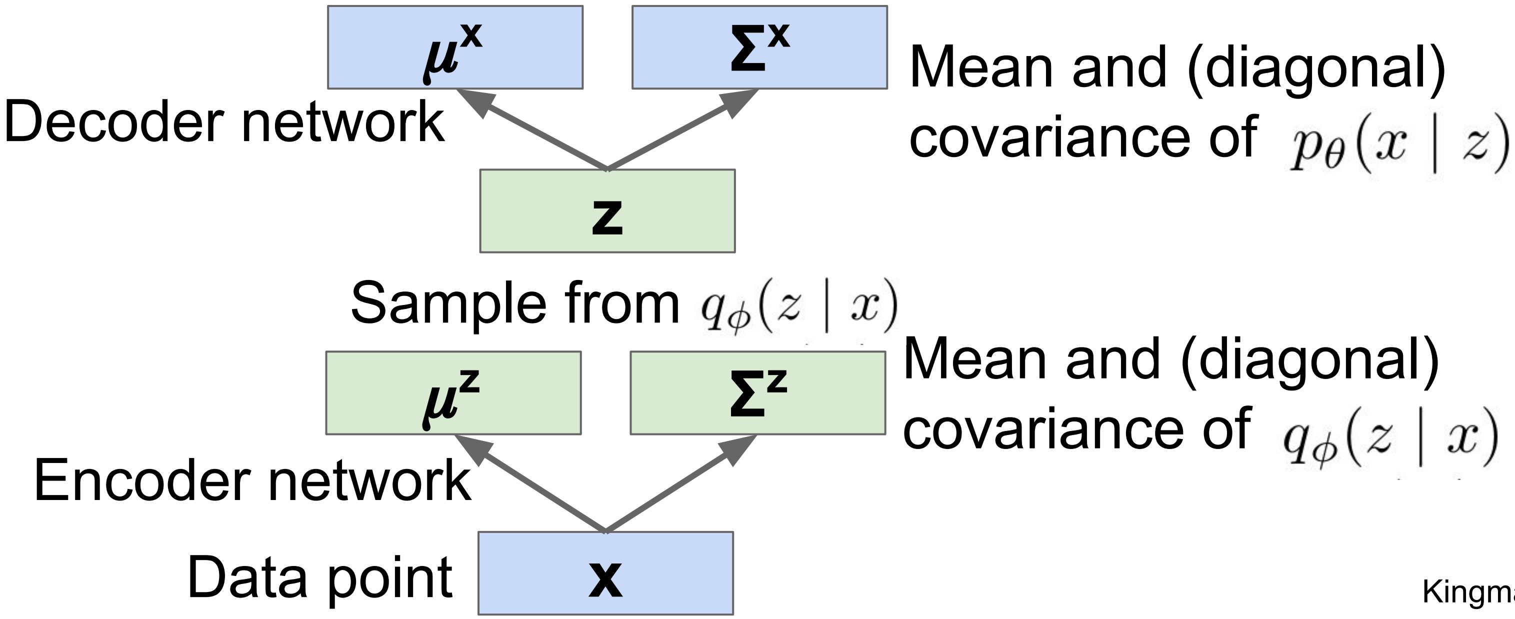
Mean and (diagonal) covariance of $q_\phi(z \mid x)$

Encoder network

Data point

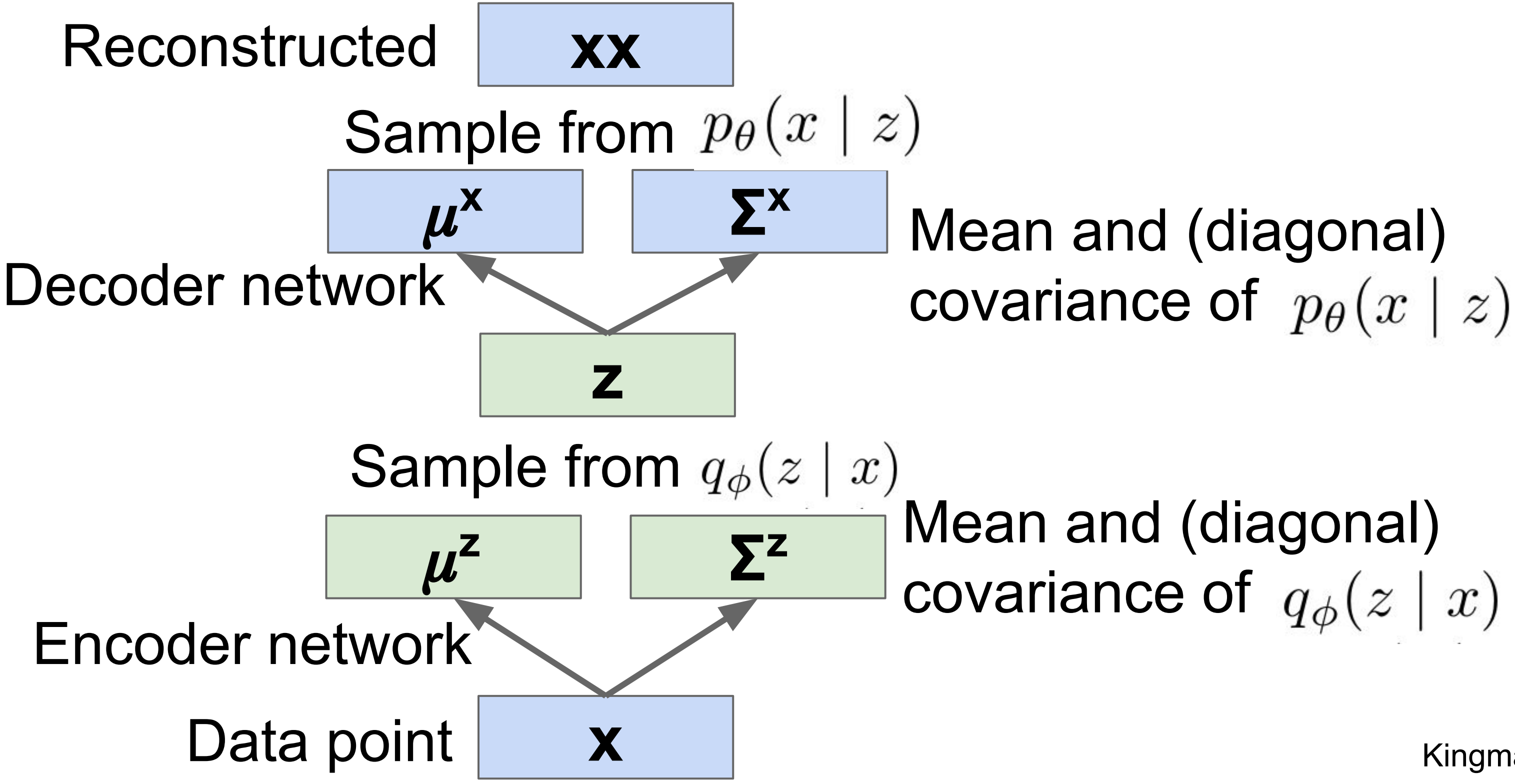
Kingma and Welling, ICLR 2014

Variational Autoencoder



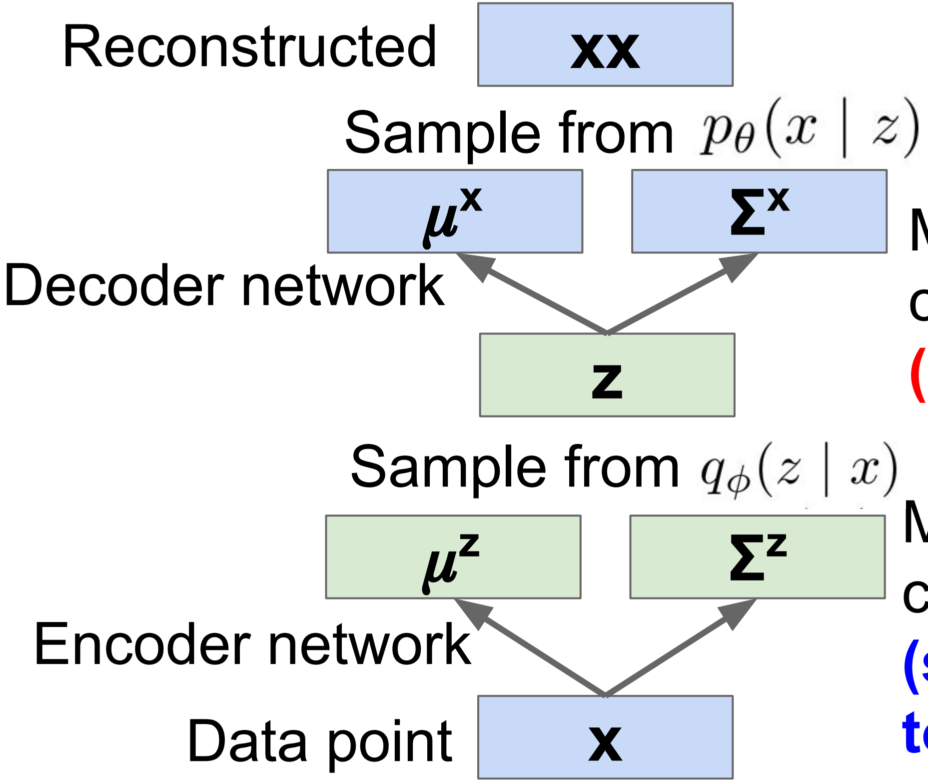
Kingma and Welling, ICLR 2014

Variational Autoencoder



Kingma and Welling, ICLR 2014

Variational Autoencoder



Training like a normal autoencoder: **reconstruction loss** at the end, **regularization toward prior** in middle

Mean and (diagonal) covariance of $p_\theta(x \mid z)$ **(should be close to data x)**

Mean and (diagonal) covariance of $q_\phi(z \mid x)$ **(should be close to prior $p_\theta(z)$)**

Kingma and Welling, ICLR 2014

Variational Autoencoder: Generate Data!

After network is trained:

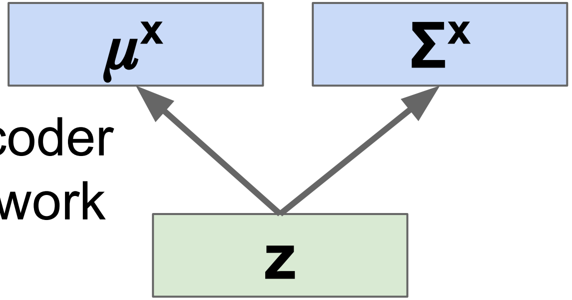
z

Sample from prior $p_\theta(z)$

Variational Autoencoder: Generate Data!

After network is trained:

Decoder network



Sample from prior $p_\theta(z)$

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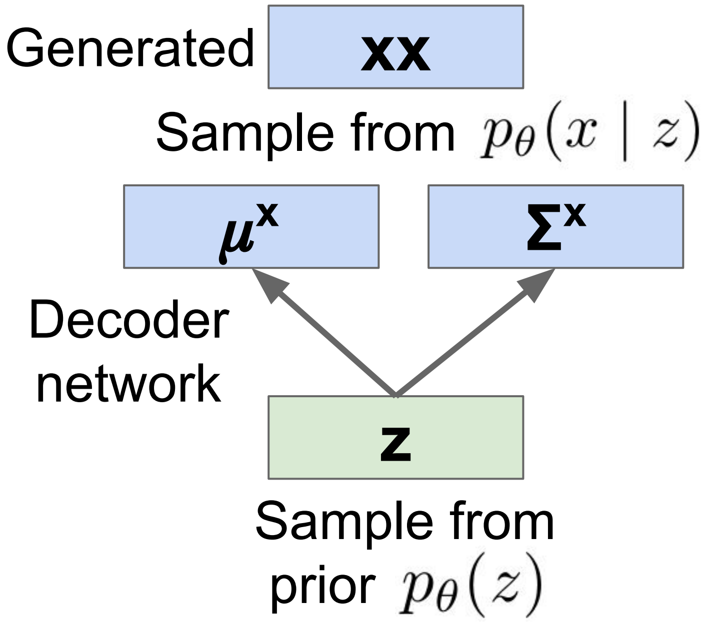

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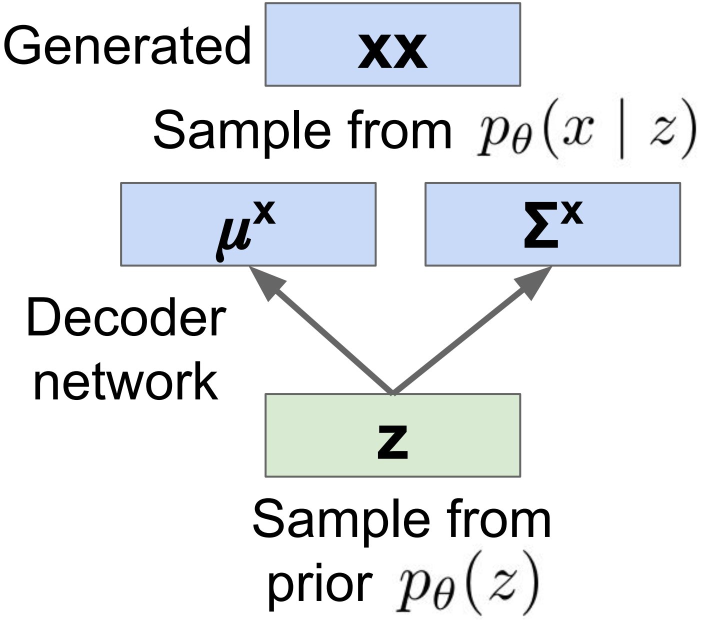

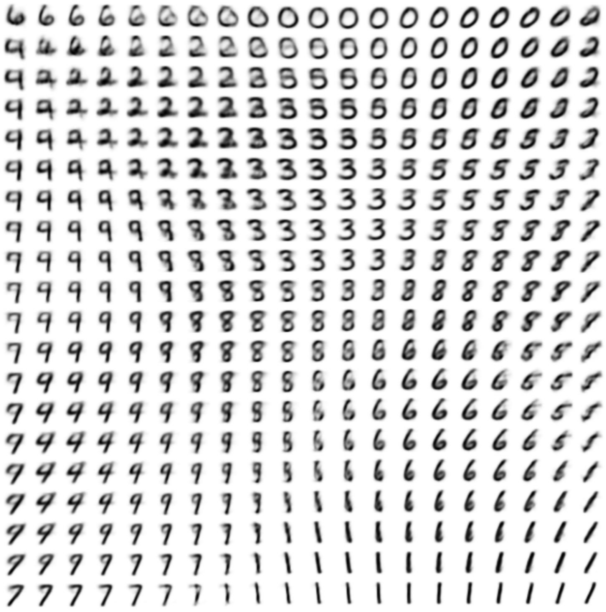

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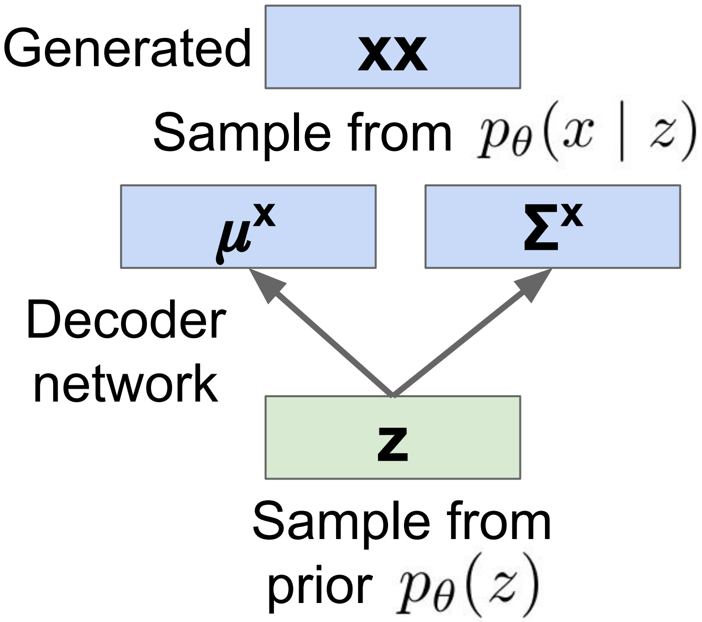

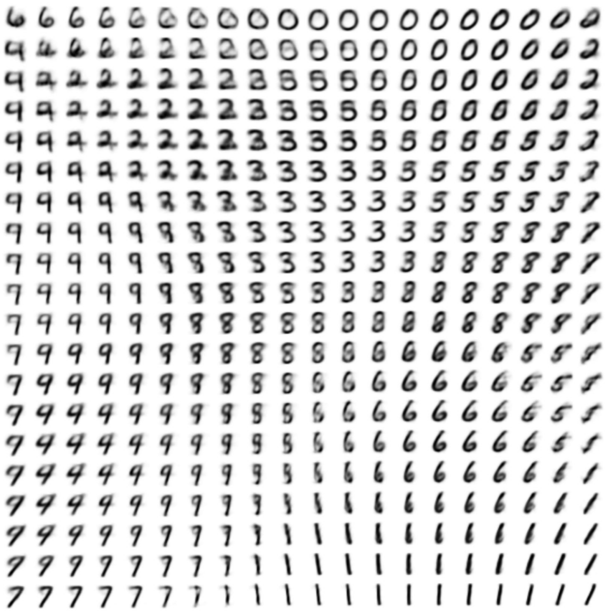

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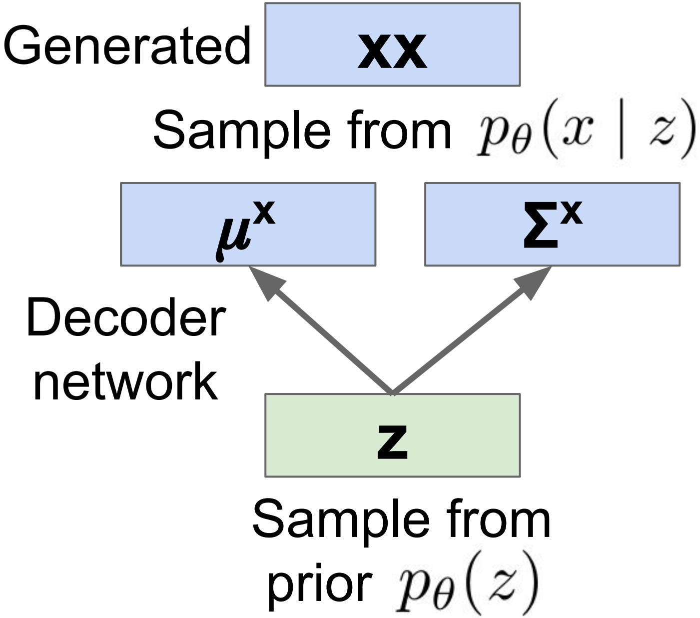
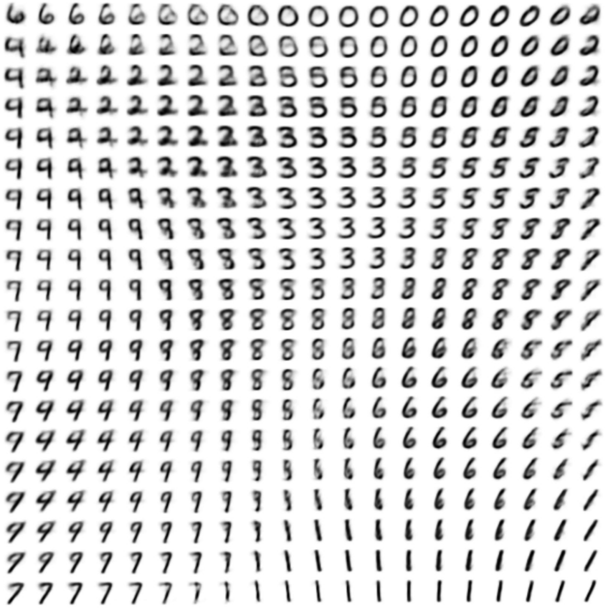


Diagonal prior on **z** => independent latent variables



Variational Autoencoder: Math
Maximum Likelihood?

$$\theta^* = \arg\max_\theta \prod_{i=1}^{N} p_\theta(x^{(i)})$$

Maximize likelihood of dataset $\{x^{(i)}\}_{i=1}^N$

Kingma and Welling, ICLR 2014

Variational Autoencoder: Math
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$$= \arg\max_\theta \sum_{i=1}^{N} \log p_\theta(x^{(i)})$$

Maximize log-likelihood instead because sums are nicer

Kingma and Welling, ICLR 2014

Variational Autoencoder: Math Maximum Likelihood?

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Maximize log-likelihood instead because sums are nicer

$$p_\theta(x^{(i)}) = \int p_\theta(x^{(i)}, z)dz$$

Marginalize joint distribution

Kingma and Welling, ICLR 2014

Variational Autoencoder: Math
Maximum Likelihood?

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Maximize likelihood of dataset $\{x^{(i)}\}_{i=1}^N$

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Maximize log-likelihood instead because sums are nicer

$$p_\theta(x^{(i)}) = \int p_\theta(x^{(i)}, z)dz = \int p_\theta(x^{(i)} \mid z)p_\theta(z)dz$$

Intractible integral =(

Variational Autoencoder: Math

$$\log p_\theta(x^{(i)})$$

Variational Autoencoder: Math

$$\log p_\theta(x^{(i)}) = \mathbf{E}_{z\sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \quad (p_\theta(x^{(i)}) \text{ Does not depend on } z)$$

Variational Autoencoder: Math

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Variational Autoencoder: Math

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$$= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z)}\right] + \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z \mid x^{(i)})}\right] \qquad \text{(Logarithms)}$$

Variational Autoencoder: Math

$$\log p_\theta(x^{(i)}) = \mathbf{E}_{z \sim q_\phi(z|x^{(i)})} \left[\log p_\theta(x^{(i)}) \right] \qquad (p_\theta(x^{(i)}) \text{ Does not depend on } z)$$

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$$= \mathbf{E}_z \left[\log p_\theta(x^{(i)} \mid z) \right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z)) + D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z \mid x^{(i)}))$$

Variational Autoencoder: Math

$$
\begin{aligned}
\log p_\theta(x^{(i)}) &= \mathbf{E}_{z\sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \qquad (p_\theta(x^{(i)}) \text{ Does not depend on } z) \\
&= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})}\right] \qquad (\text{Bayes' Rule}) \\
&= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})} \frac{q_\phi(z \mid x^{(i)})}{q_\phi(z \mid x^{(i)})}\right] \qquad (\text{Multiply by constant}) \\
&= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z)}\right] + \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z \mid x^{(i)})}\right] \qquad (\text{Logarithms}) \\
&= \underbrace{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}_{\mathcal{L}(x^{(i)},\theta,\phi)} + D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z \mid x^{(i)}))
\end{aligned}
$$

“Elbow”

Variational Autoencoder: Math

$$
\begin{aligned}
\log p_\theta(x^{(i)}) &= \mathbf{E}_{z \sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \quad (p_\theta(x^{(i)}) \text{ Does not depend on } z) \\
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&= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z) p_\theta(z)}{p_\theta(z \mid x^{(i)})} \frac{q_\phi(z \mid x^{(i)})}{q_\phi(z \mid x^{(i)})}\right] \quad (\text{Multiply by constant}) \\
&= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z)}\right] + \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z \mid x^{(i)})}\right] \quad (\text{Logarithms}) \\
&= \underbrace{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}_{\mathcal{L}(x^{(i)}, \theta, \phi)} + \underbrace{D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z \mid x^{(i)}))}_{\geq 0}
\end{aligned}
$$

"Elbow"

Variational Autoencoder: Math

$$\log p_\theta(x^{(i)}) = \mathbf{E}_{z\sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \qquad (p_\theta(x^{(i)}) \text{ Does not depend on } z)$$

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$$= \underbrace{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}_{\mathcal{L}(x^{(i)},\theta,\phi)\ \text{“Elbow”}} + \underbrace{D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z \mid x^{(i)}))}_{\geq 0}$$

$$\log p_\theta(x^{(i)}) \geq \mathcal{L}(x^{(i)},\theta,\phi)$$

Variational lower bound (elbow)

Variational Autoencoder: Math

$$\log p_\theta(x^{(i)}) = \mathbf{E}_{z\sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \qquad (p_\theta(x^{(i)}) \text{ Does not depend on } z)$$

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$$= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})}\frac{q_\phi(z \mid x^{(i)})}{q_\phi(z \mid x^{(i)})}\right] \qquad \text{(Multiply by constant)}$$

$$= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z)}\right] + \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z \mid x^{(i)})}\right] \qquad \text{(Logarithms)}$$

$$= \underbrace{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}_{\mathcal{L}(x^{(i)},\theta,\phi)} + \underbrace{D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z \mid x^{(i)}))}_{\geq 0}$$

"Elbow"

$$\log p_\theta(x^{(i)}) \geq \mathcal{L}(x^{(i)},\theta,\phi)$$

Variational lower bound (elbow)

$$\theta^*, \phi^* = \arg\max_{\theta,\phi} \sum_{i=1}^{N} \mathcal{L}(x^{(i)},\theta,\phi)$$

Training: Maximize lower bound

Variational Autoencoder: Math

$$\log p_\theta(x^{(i)}) = \mathbf{E}_{z\sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \quad (p_\theta(x^{(i)}) \text{ Does not depend on } z)$$

Reconstruct the input data

$$= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})}\right] \quad \text{(Bayes' Rule)}$$

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Training: Maximize lower bound

Variational Autoencoder: Math

Latent states should follow the prior

Reconstruct the input data

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Variational Autoencoder: Math

Latent states should follow the prior

Reconstruct the input data

Sampling with reparam. trick (see paper)

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Reconstruct the input data

Sampling with reparam. trick (see paper)

Latent states should follow the prior

Everything is Gaussian, closed form solution!

"Elbow"

$$\log p_\theta(x^{(i)}) \geq \mathcal{L}(x^{(i)},\theta,\phi)$$

Variational lower bound (elbow)

$$\theta^*, \phi^* = \arg\max_{\theta,\phi} \sum_{i=1}^{N} \mathcal{L}(x^{(i)},\theta,\phi)$$

Training: Maximize lower bound

Autoencoder Overview

- Traditional Autoencoders
  - Try to reconstruct input
  - Used to learn features, initialize supervised model
  - Not used much anymore
- Variational Autoencoders
  - Bayesian meets deep learning
  - Sample from model to generate images

Generative Adversarial Nets

Goodfellow et al, “Generative Adversarial Nets”, NIPS 2014

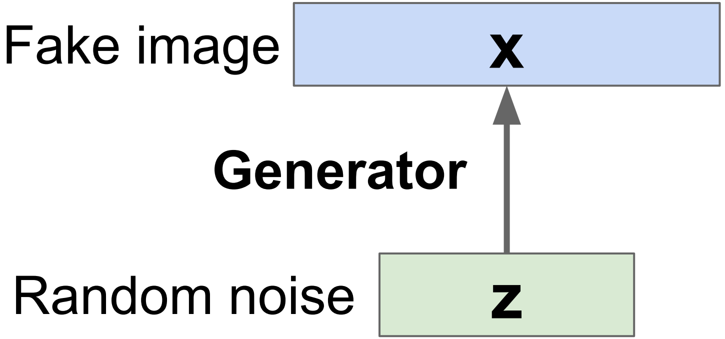
Can we generate images with less math?

Random noise $\boxed{\mathbf{z}}$

Generative Adversarial Nets

Goodfellow et al, "Generative Adversarial Nets", NIPS 2014

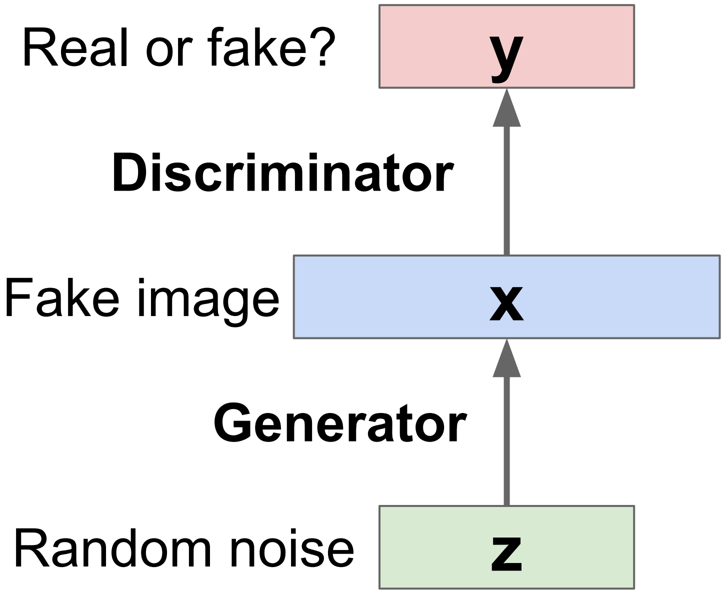
Can we generate images with less math?



Goodfellow et al, “Generative Adversarial Nets”, NIPS 2014

Generative Adversarial Nets

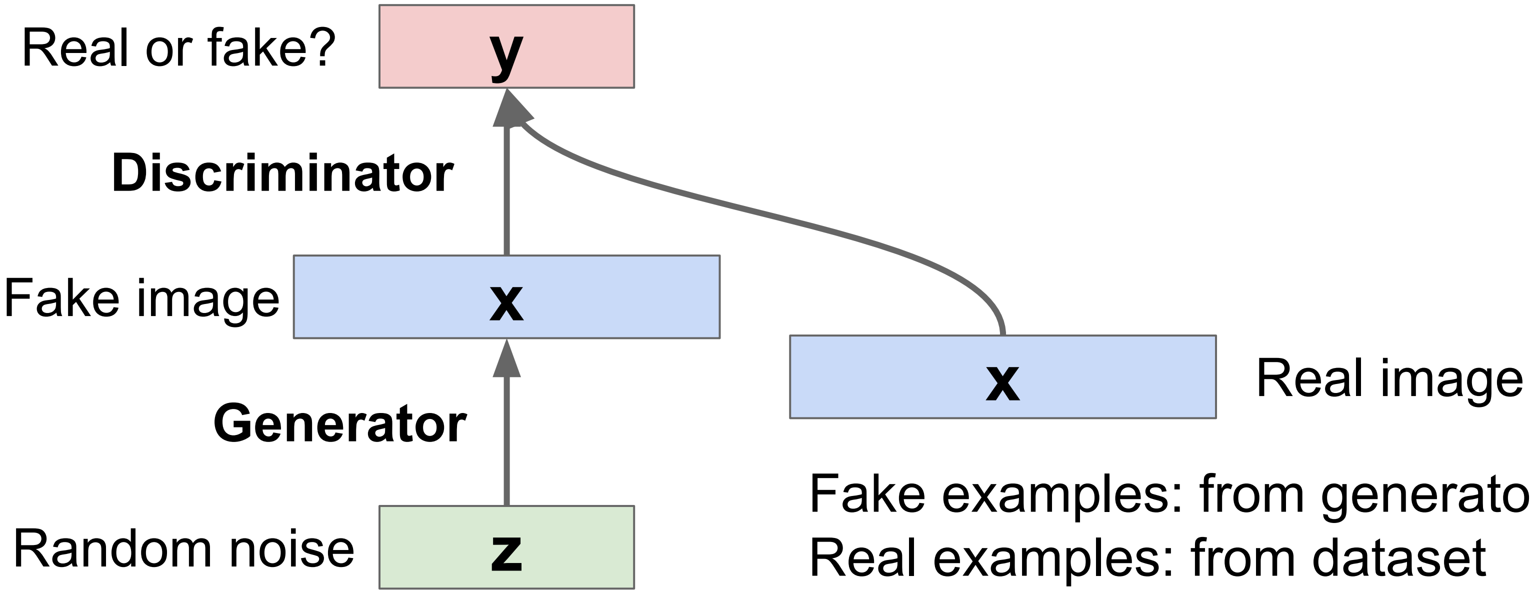
Can we generate images with less math?



Goodfellow et al, "Generative Adversarial Nets", NIPS 2014

Generative Adversarial Nets

Can we generate images with less math?

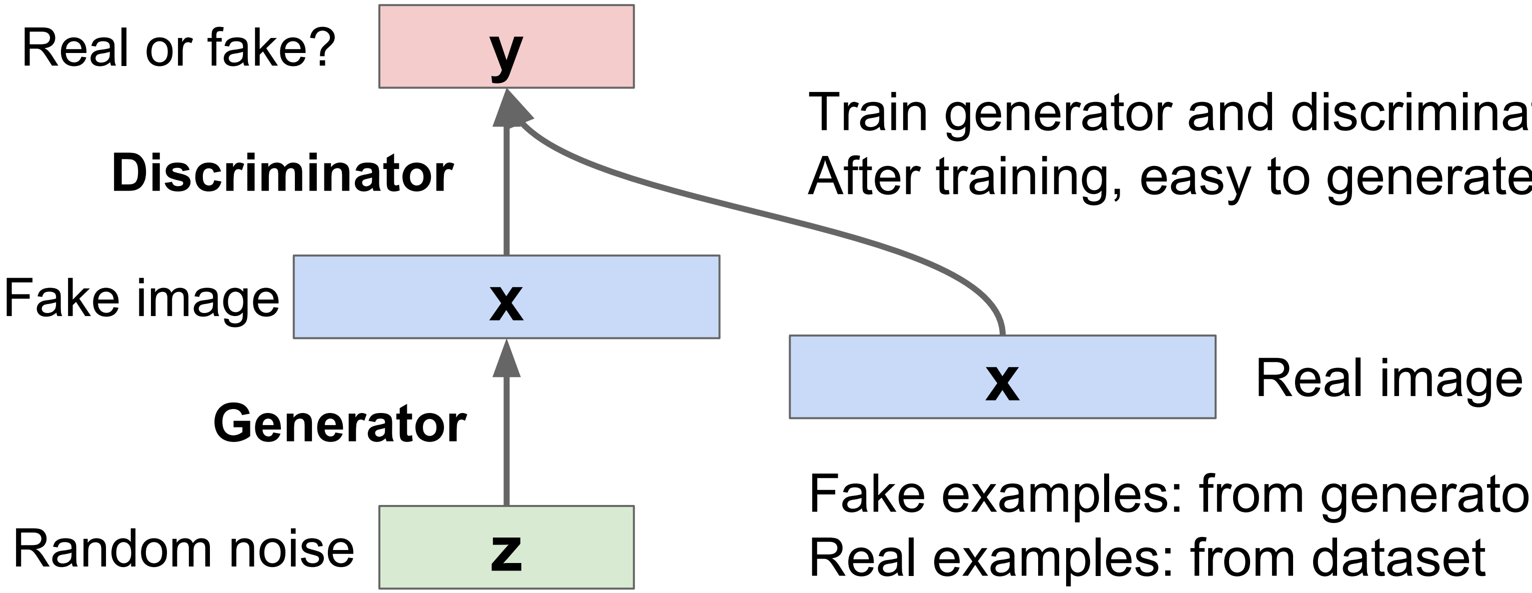


Fake examples: from generator
Real examples: from dataset

Goodfellow et al, “Generative Adversarial Nets”, NIPS 2014

Generative Adversarial Nets

Can we generate images with less math?

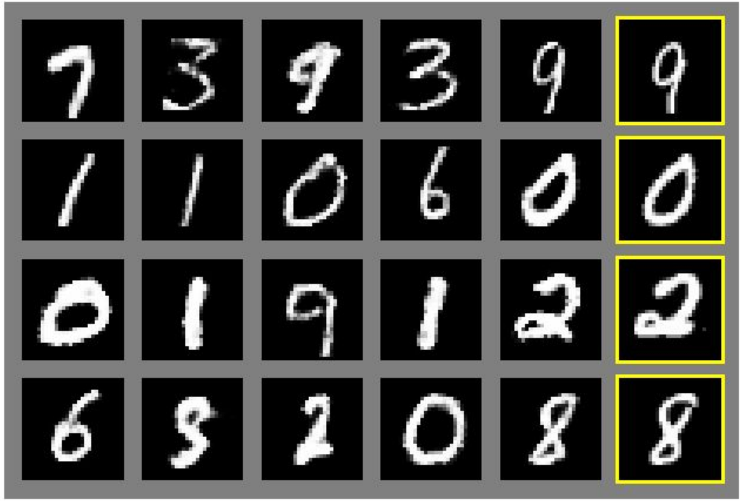


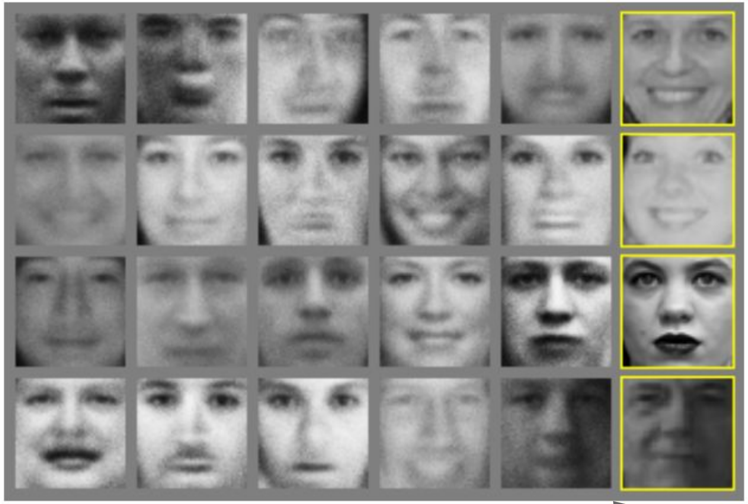
Train generator and discriminator jointly
After training, easy to generate images

Fake examples: from generator
Real examples: from dataset

Generative Adversarial Nets

Generated samples





Nearest neighbor from training set

Goodfellow et al, “Generative Adversarial Nets”, NIPS 2014

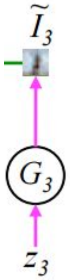
Generative Adversarial Nets

Generated samples (CIFAR-10)

Nearest neighbor from training set

Goodfellow et al, “Generative Adversarial Nets”, NIPS 2014

Generative Adversarial Nets: Multiscale

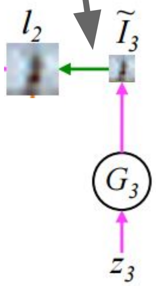


Generate
low-res

Denton et al, "Deep generative image models using a Laplacian pyramid of adversarial networks", NIPS 2015

Generative Adversarial Nets: Multiscale

Upsample



Generate
low-res

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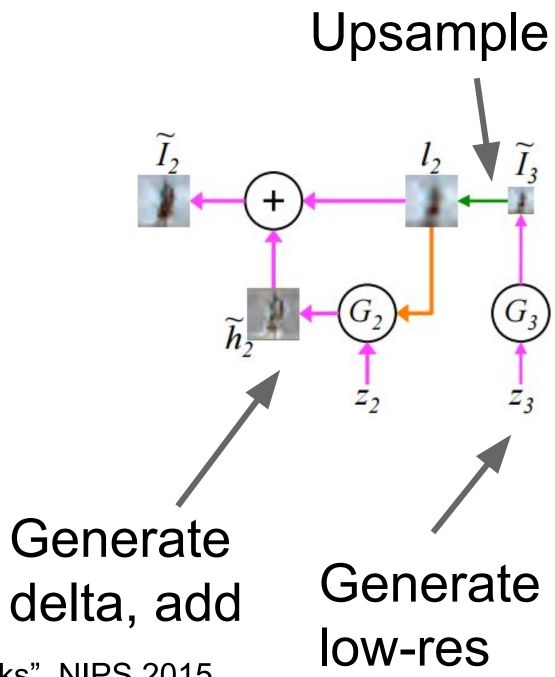
Generative Adversarial Nets: Multiscale

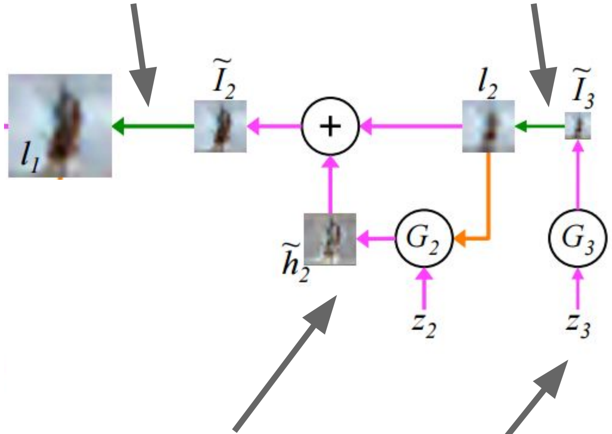


Denton et al, “Deep generative image models using a Laplacian pyramid of adversarial networks”, NIPS 2015

Generative Adversarial Nets: Multiscale

Upsample

Upsample

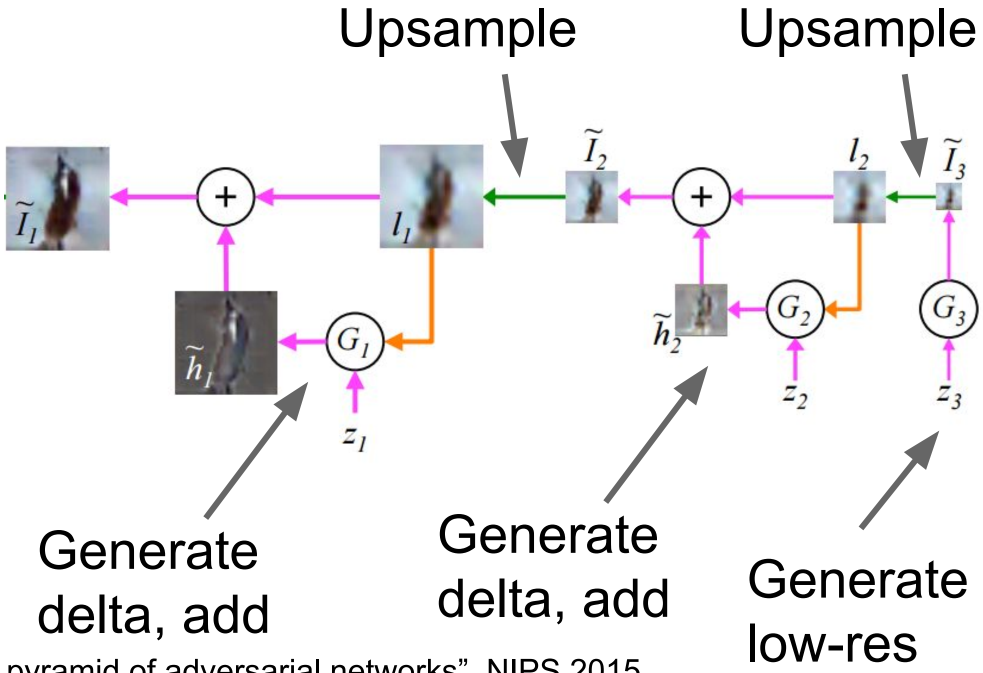


Generate delta, add

Generate low-res

Denton et al, "Deep generative image models using a Laplacian pyramid of adversarial networks", NIPS 2015

Generative Adversarial Nets: Multiscale



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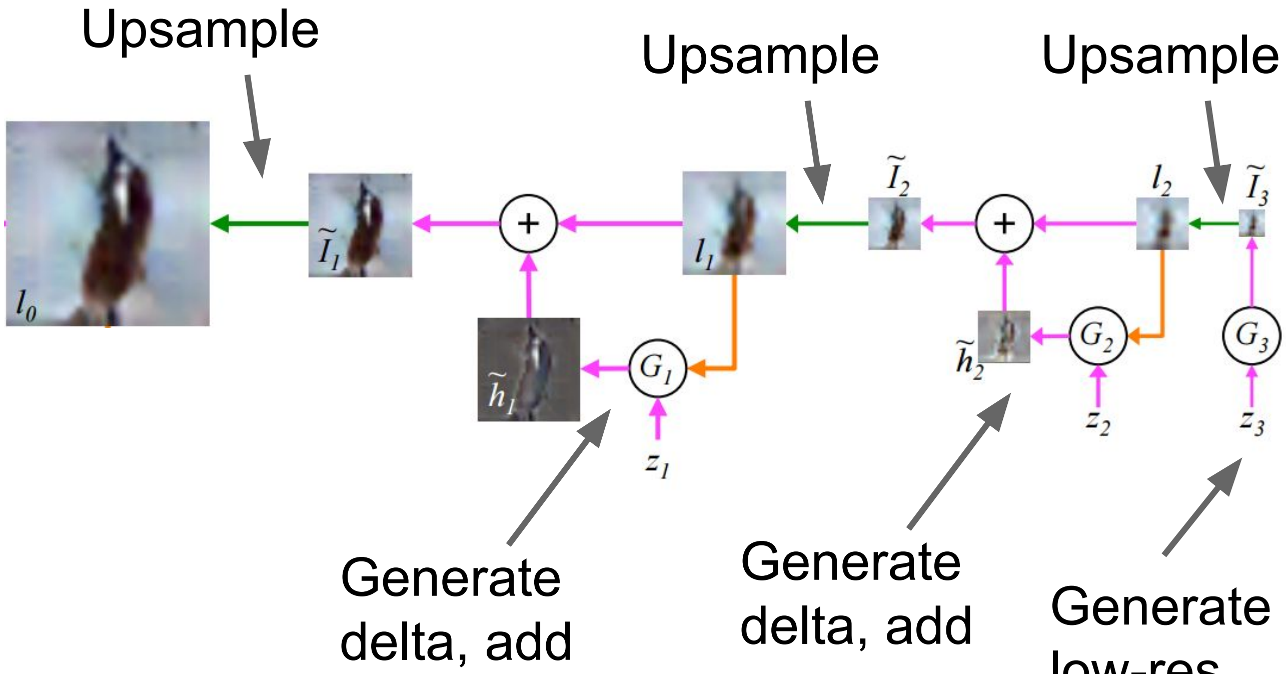

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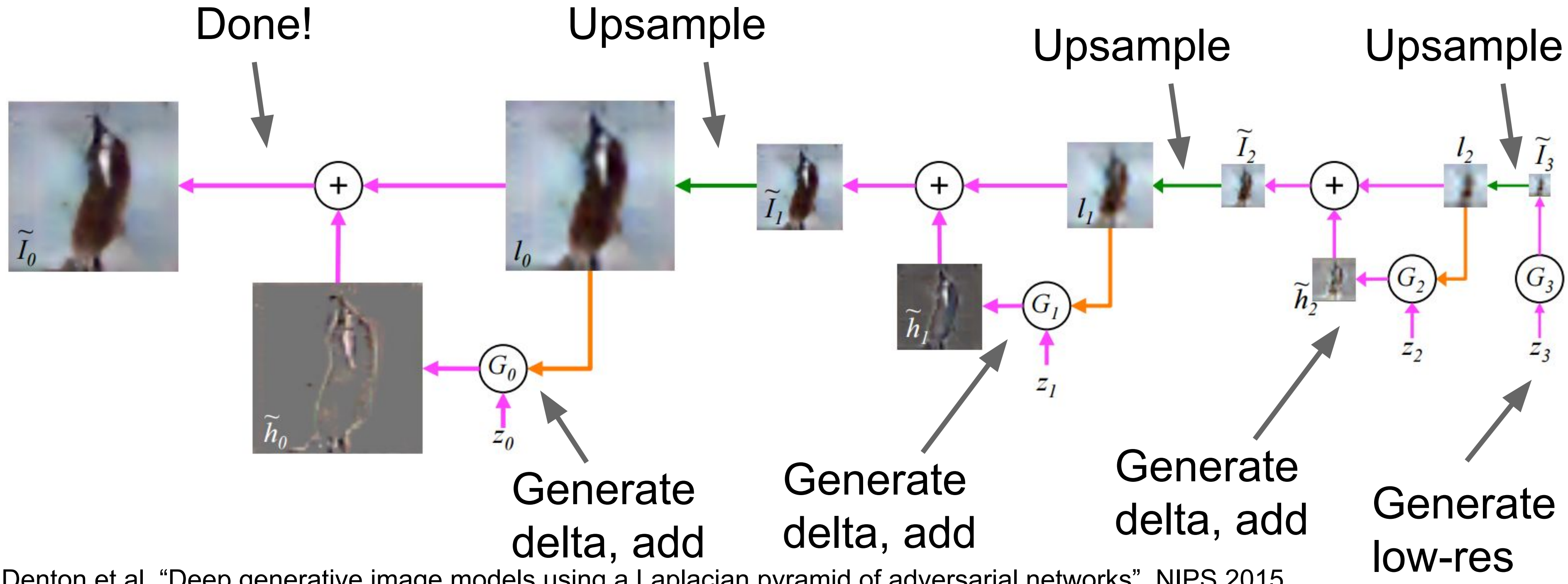

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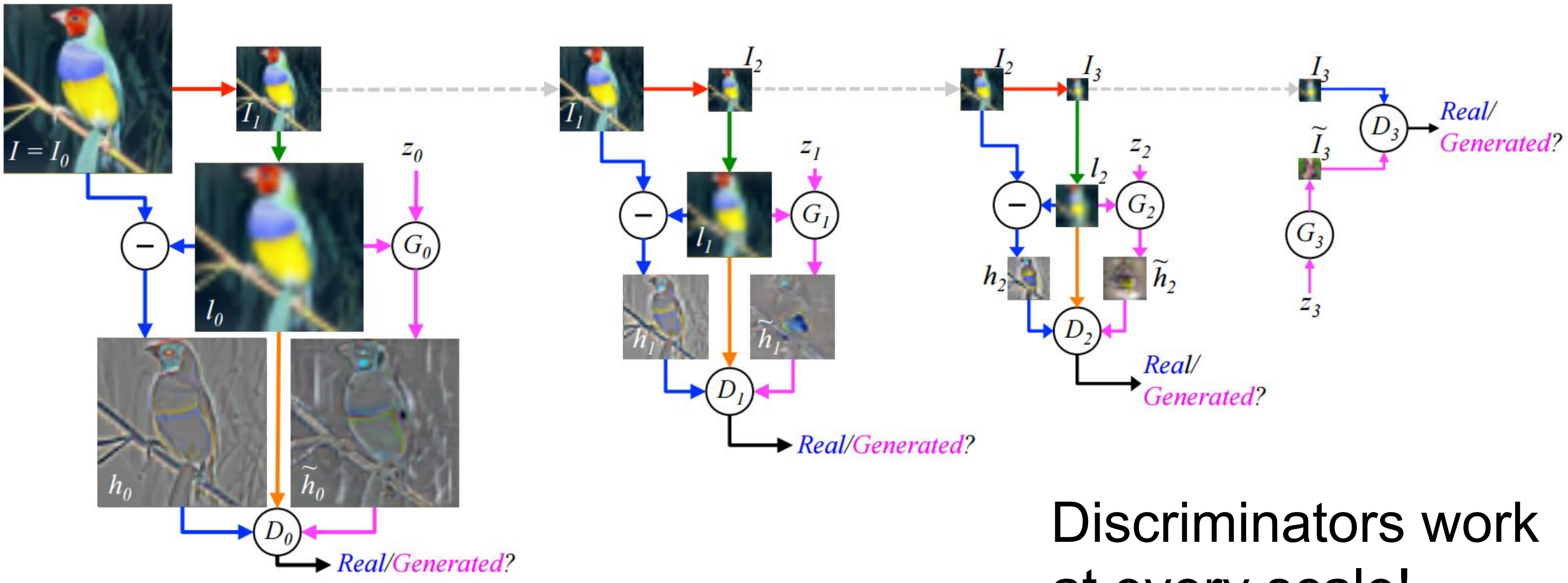
Generative Adversarial Nets: Multiscale



Discriminators work at every scale!

Denton et al, NIPS 2015

Generative Adversarial Nets: Multiscale

Train separate model per-class on CIFAR-10

Denton et al, NIPS 2015

Generative Adversarial Nets: Simplifying

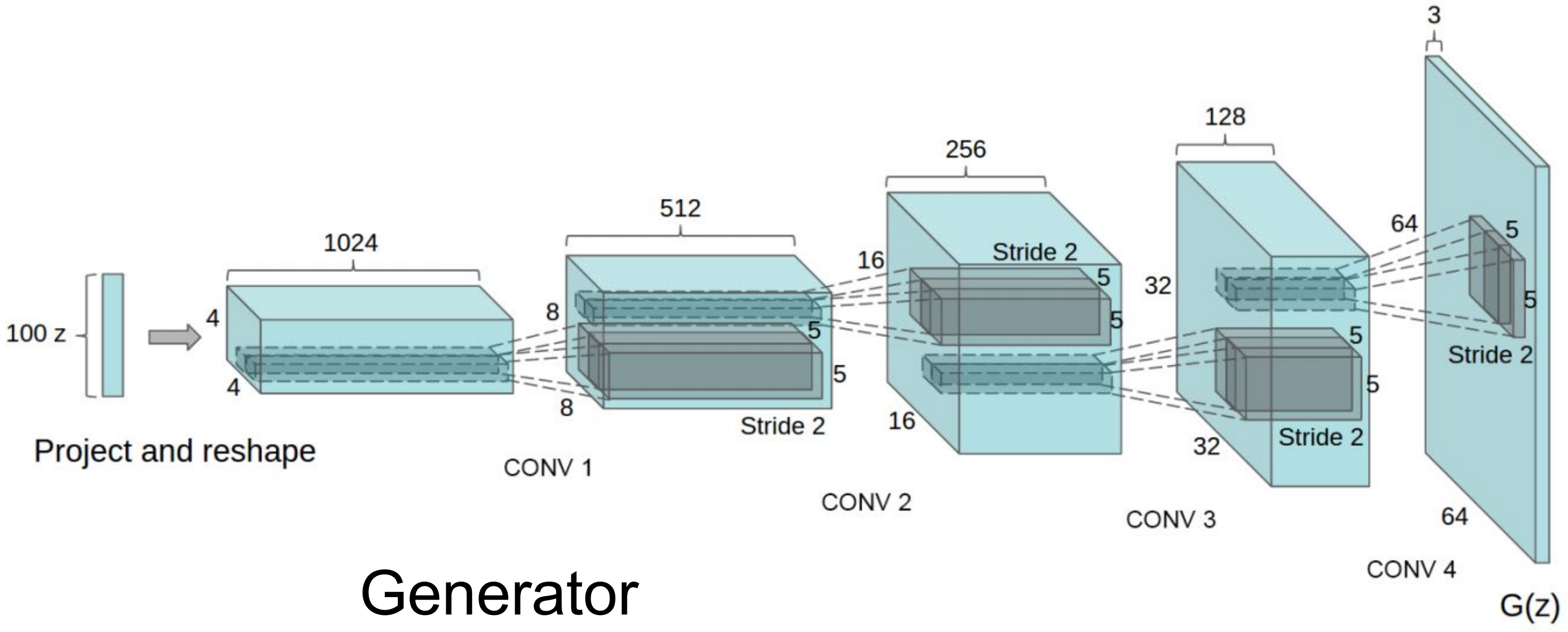
Generator is an upsampling network with fractionally-strided convolutions
Discriminator is a convolutional network

Architecture guidelines for stable Deep Convolutional GANs

- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

Radford et al, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", ICLR 2016

Generative Adversarial Nets: Simplifying



Generator

Radford et al, “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks”, ICLR 2016

Generative Adversarial Nets: Simplifying

Samples from the model look amazing!

Radford et al, ICLR 2016

Generative Adversarial Nets: Simplifying

Interpolating between random points in laten space

Radford et al, ICLR 2016

Generative Adversarial Nets: Vector Math

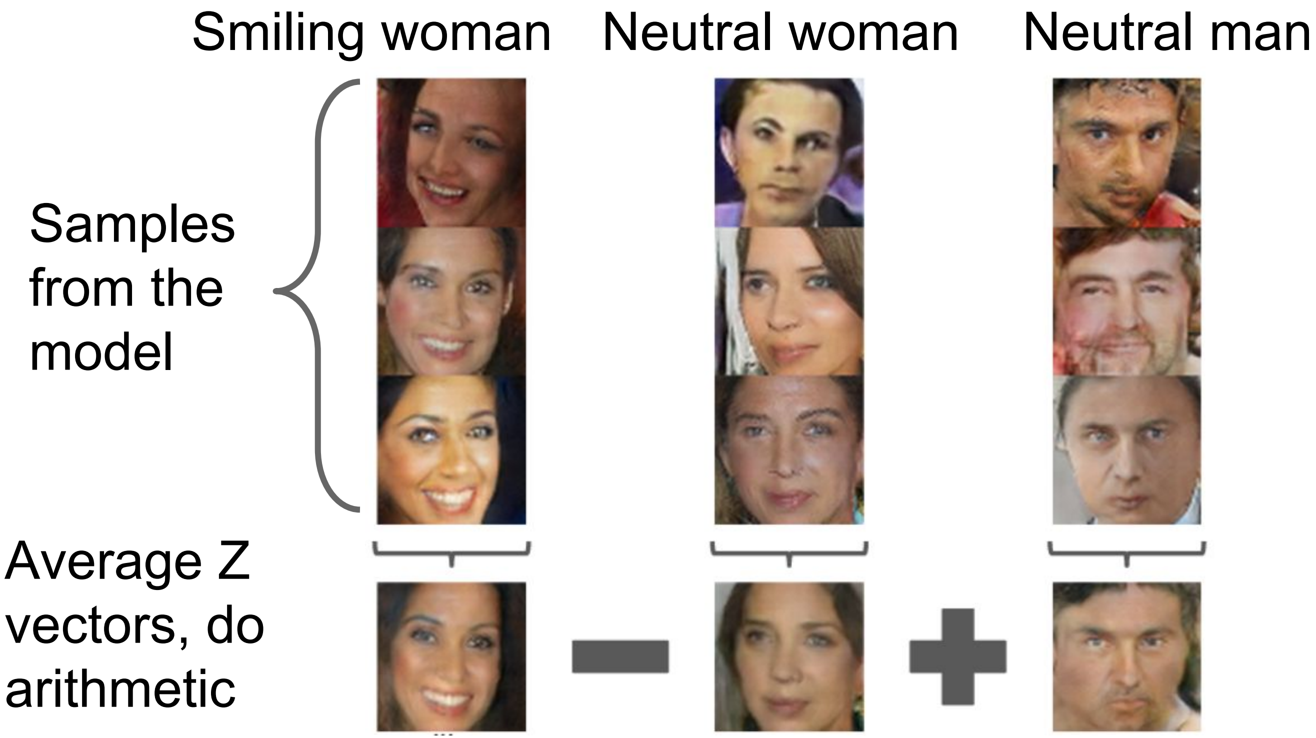
Radford et al, ICLR 2016

Smiling woman Neutral woman Neutral man

Samples from the model

Generative Adversarial Nets: Vector Math

Radford et al, ICLR 2016



Generative Adversarial Nets: Vector Math

Radford et al, ICLR 2016

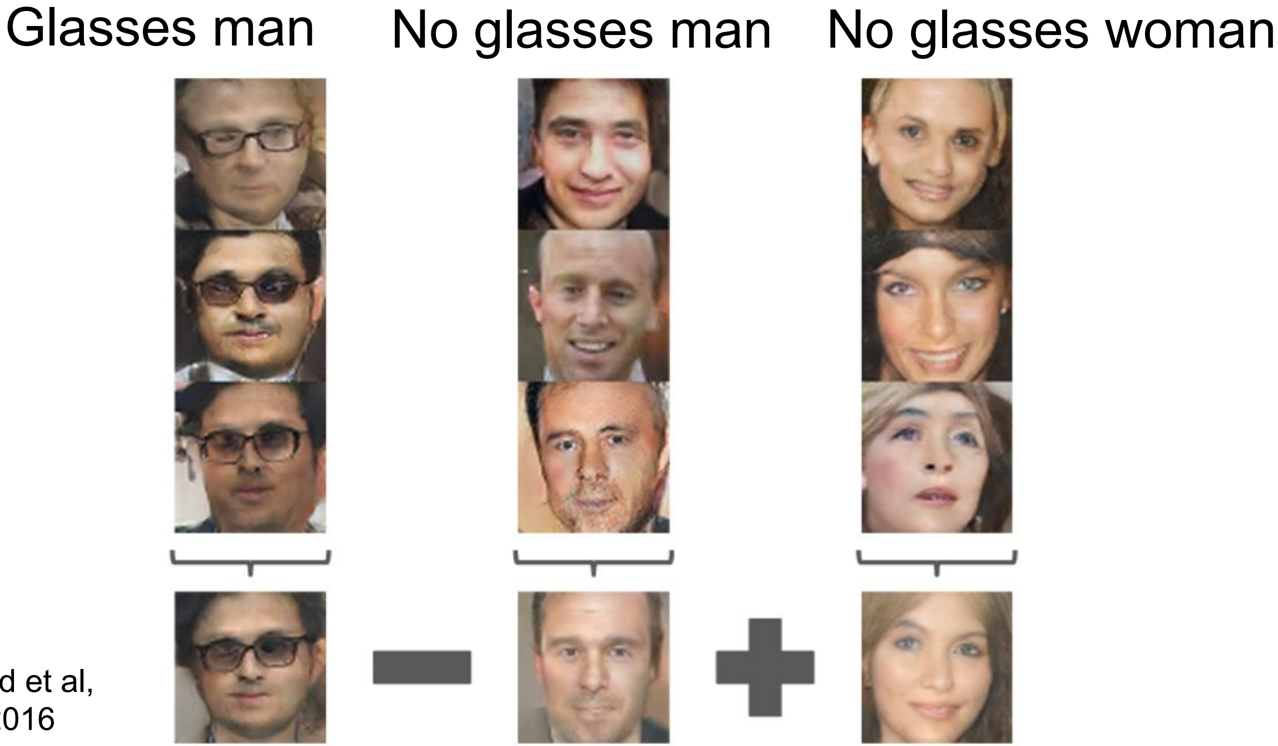
Smiling woman | Neutral woman | Neutral man

Samples from the model

Smiling Man

Average Z vectors, do arithmetic

Generative Adversarial Nets: Vector Math



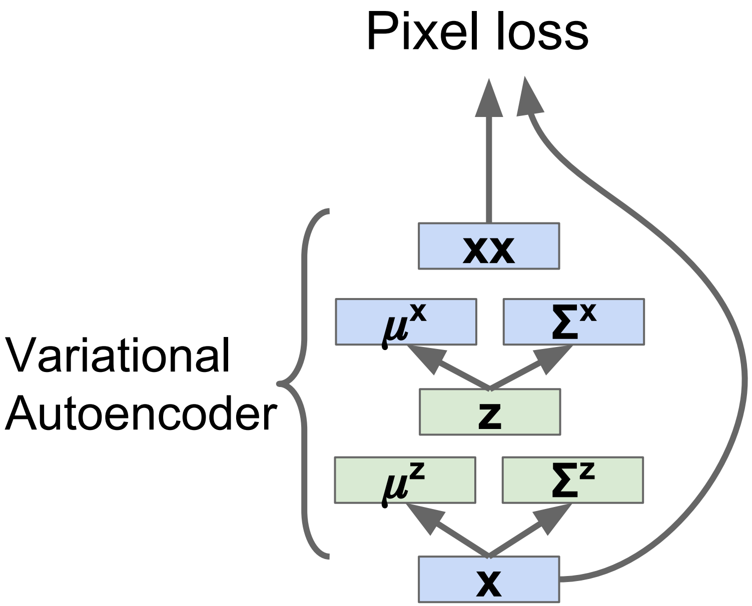
Radford et al, ICLR 2016

Generative Adversarial Nets: Vector Math

Radford et al, ICLR 2016

Putting everything together

Dosovitskiy and Brox, “Generating Images with Perceptual Similarity Metrics based on Deep Networks”, arXiv 2016



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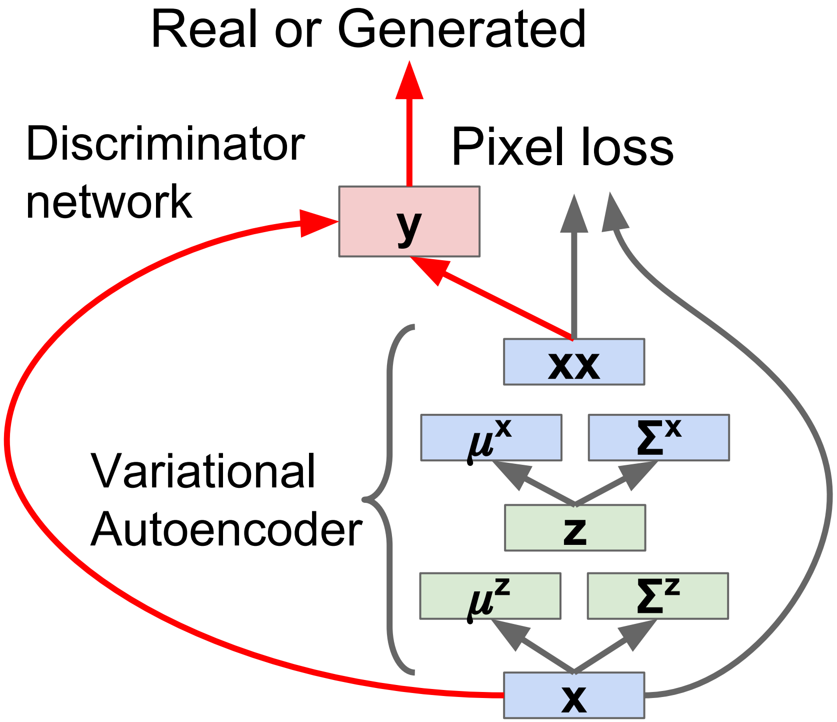

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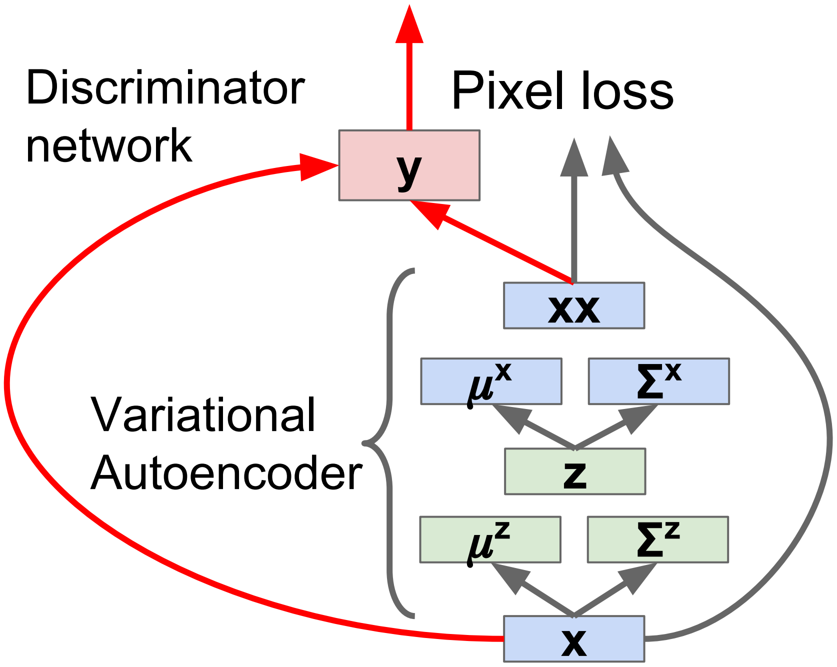
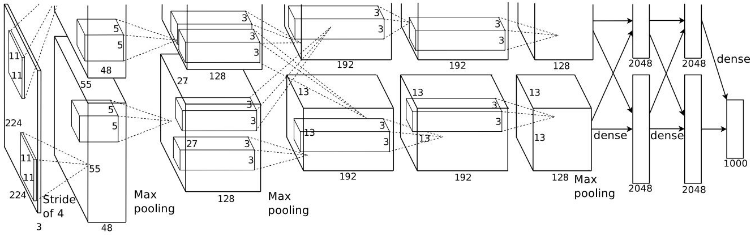


Pretrained AlexNet



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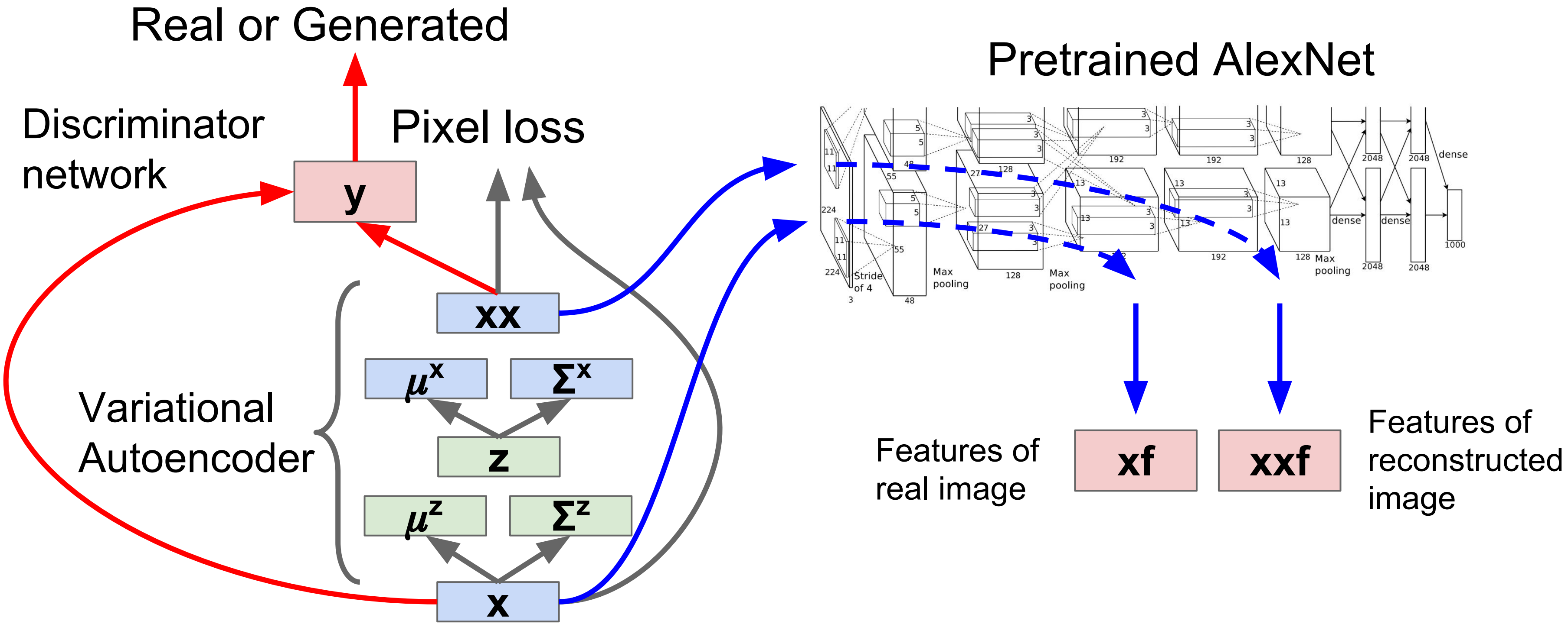

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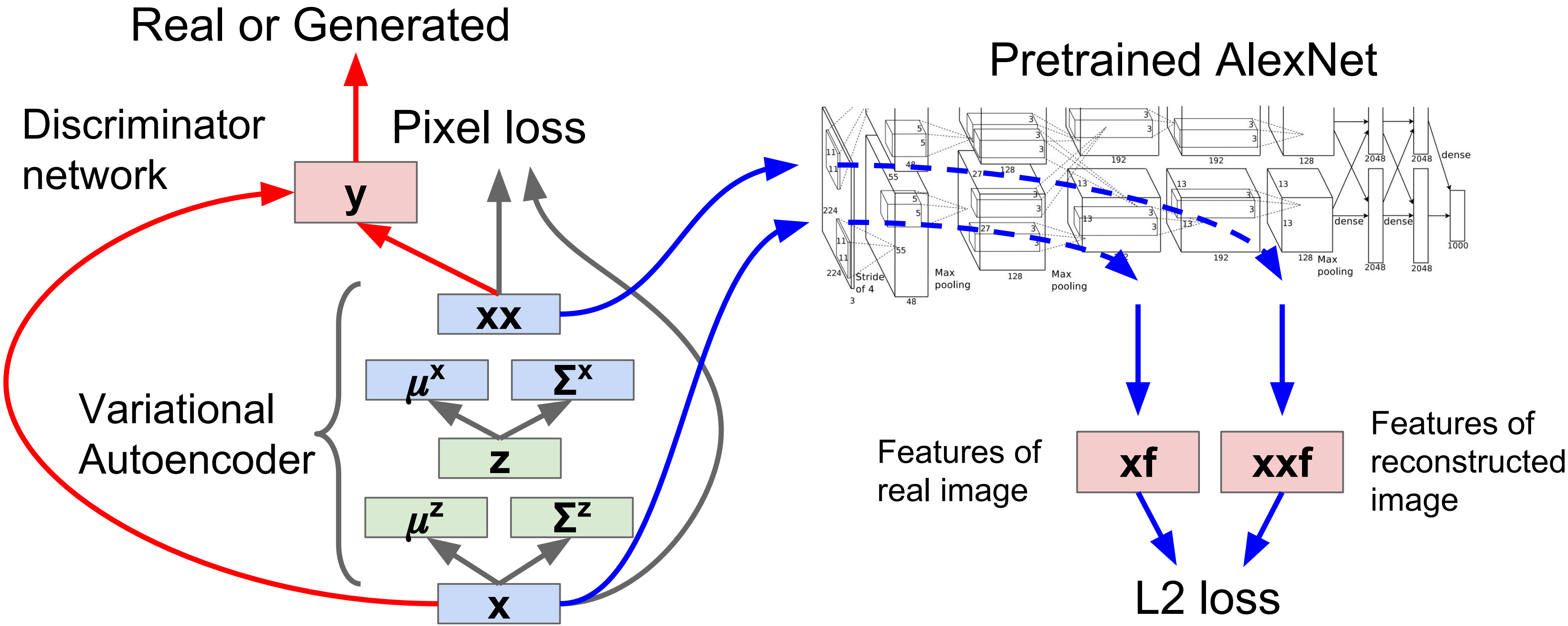

Putting everything together

Dosovitskiy and Brox, “Generating Images with Perceptual Similarity Metrics based on Deep Networks”, arXiv 2016

Samples from the model, trained on ImageNet

Recap

- Videos
- Unsupervised learning
  - Autoencoders: Traditional / variational
  - Generative Adversarial Networks
- Next time: Guest lecture from Jeff Dean