Deep Learning for Vision: Tricks of the Trade

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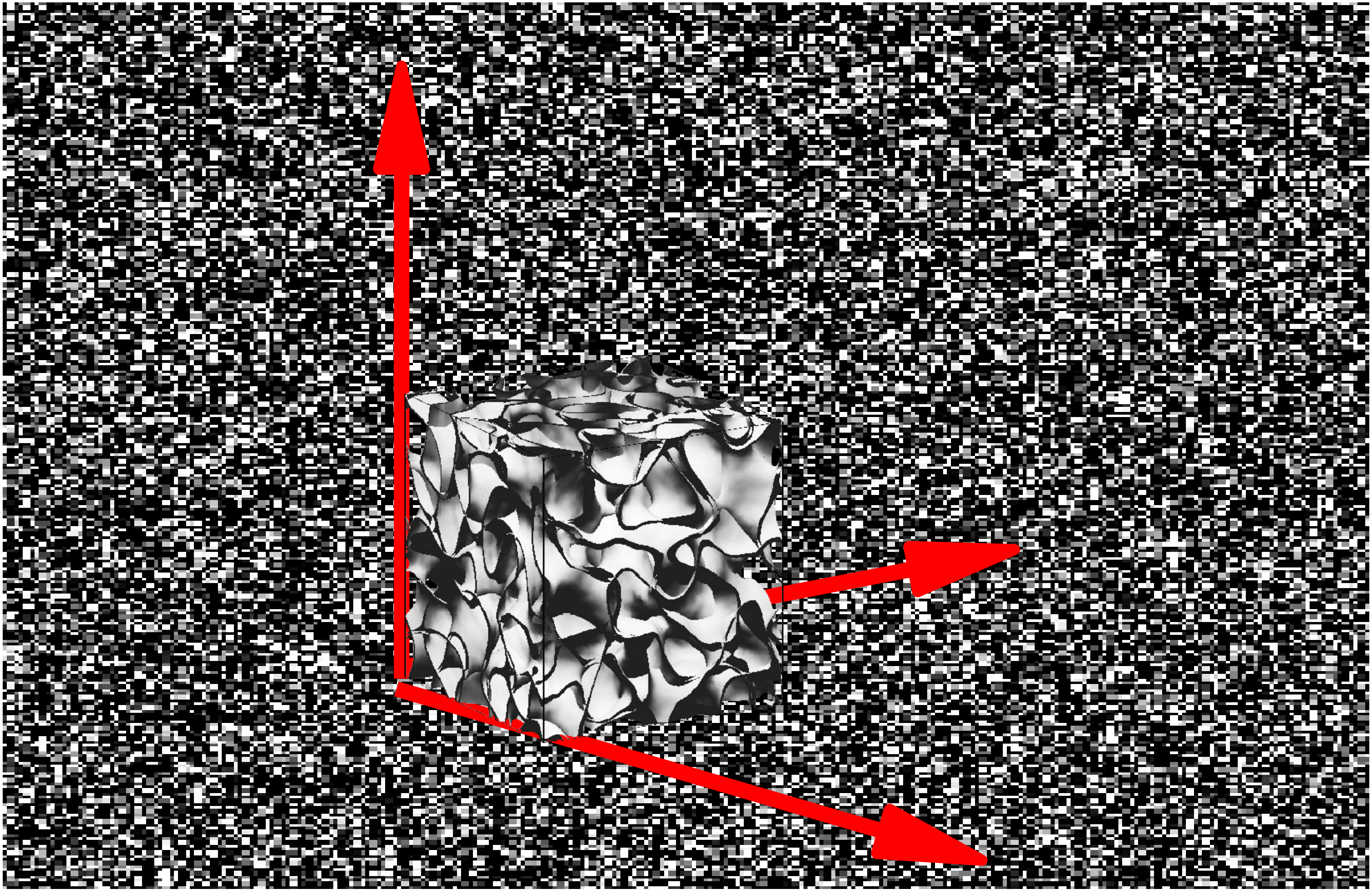
Ideal Features

Ideal Feature Extractor

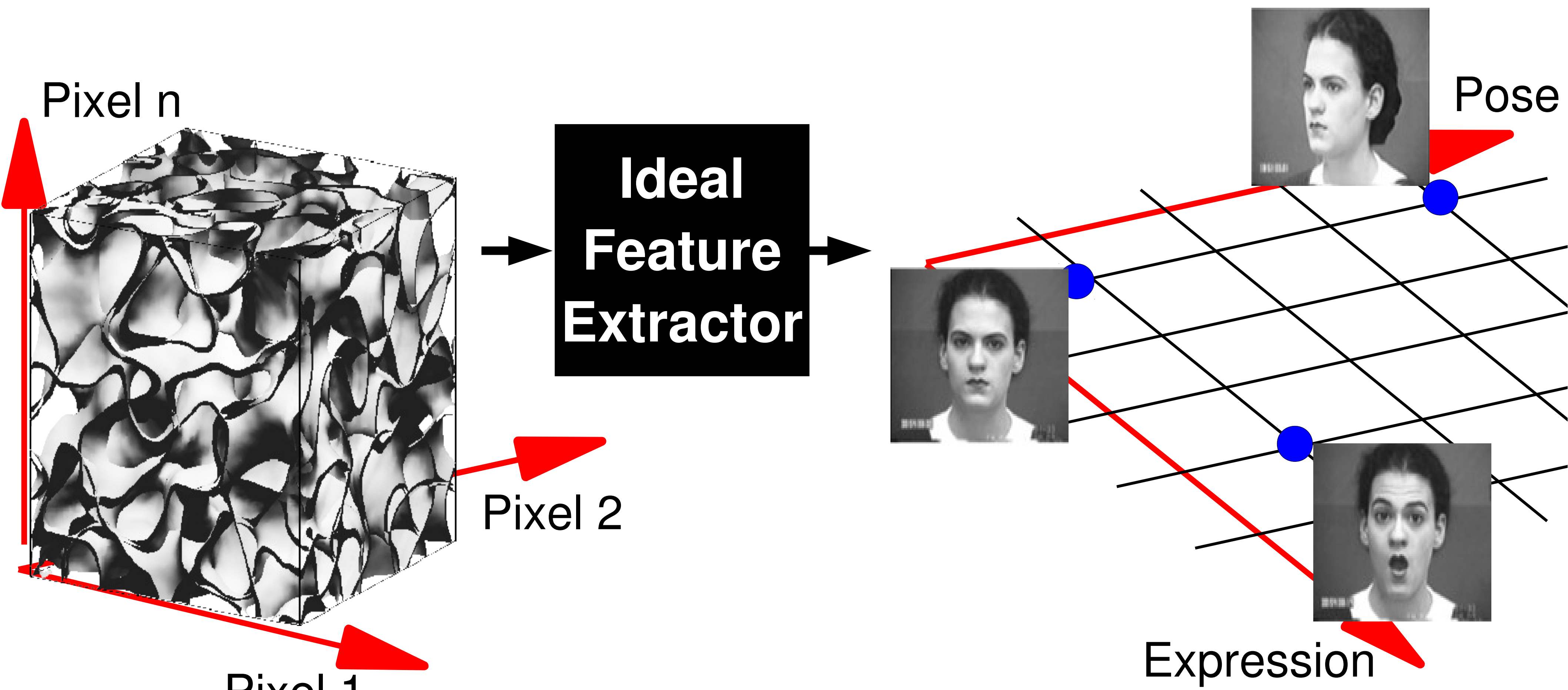
- window, right
- chair, left
- monitor, top of shelf
- carpet, bottom
- drums, corner
- ...
- pillows on couch

Q.: What objects are in the image? Where is the lamp? What is on the couch? ...

The Manifold of Natural Images



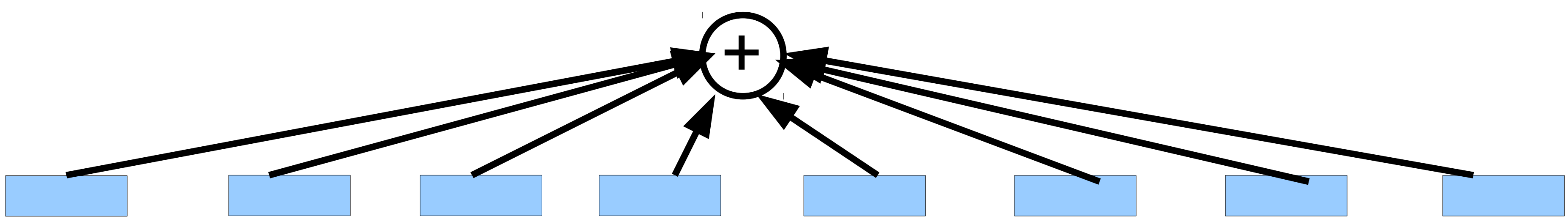
Ideal Feature Extraction



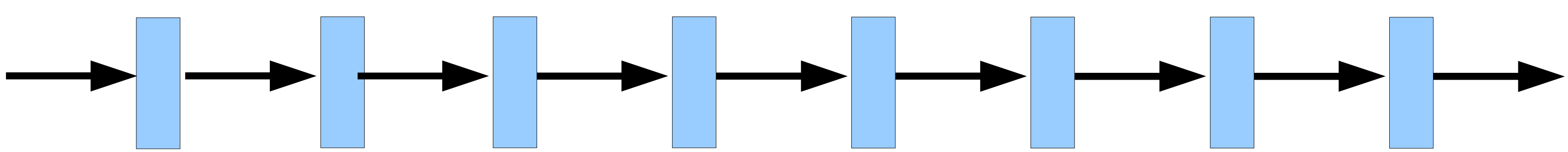
Learning Non-Linear Features

Given a dictionary of simple non-linear functions: $g_1, \dots, g_n$

Proposal #1: linear combination $f(x) \approx \sum_j g_j$



Proposal #2: composition $f(x) \approx g_1(g_2(\dots g_n(x)\dots))$



Learning Non-Linear Features

Given a dictionary of simple non-linear functions: $g_1, \ldots, g_n$

Proposal #1: linear combination $f(x) \approx \sum_j g_j$

- Kernel learning
- Boosting
- ...

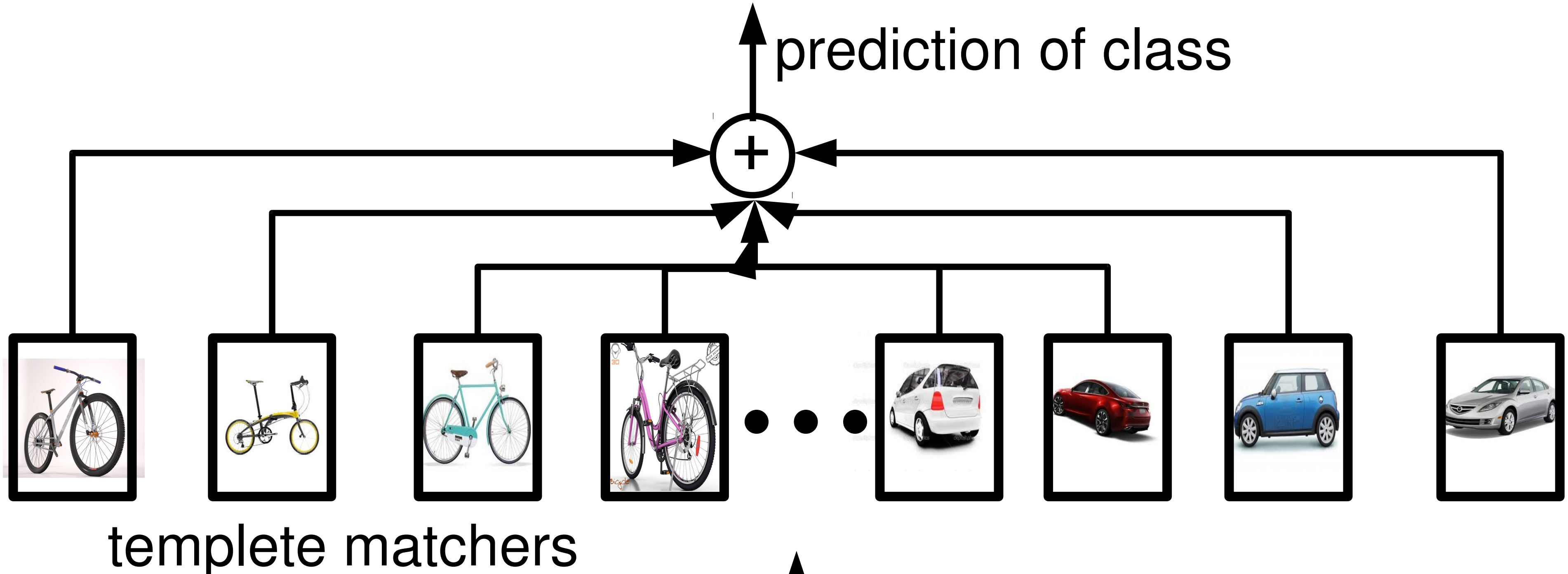
Shallow

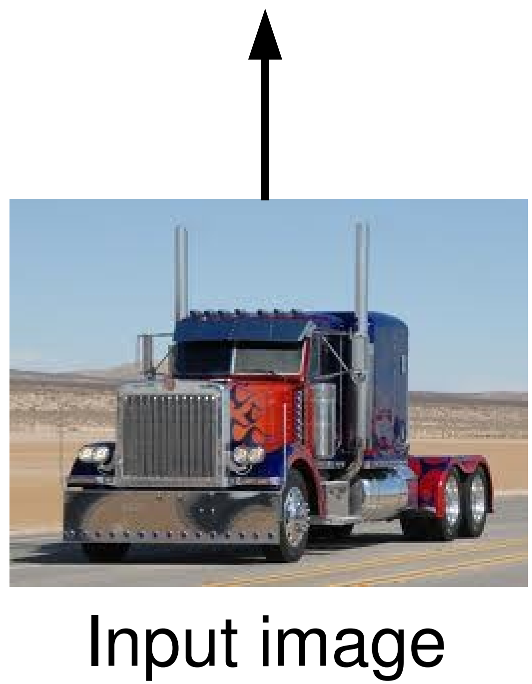
Proposal #2: composition $f(x) \approx g_1(g_2(\ldots g_n(x)\ldots))$

- Deep learning
- Scattering networks (wavelet cascade)
- S.C. Zhou & D. Mumford "grammar"

Deep

Linear Combination





BAD: it may require an exponential nr. of templates!!!

Composition

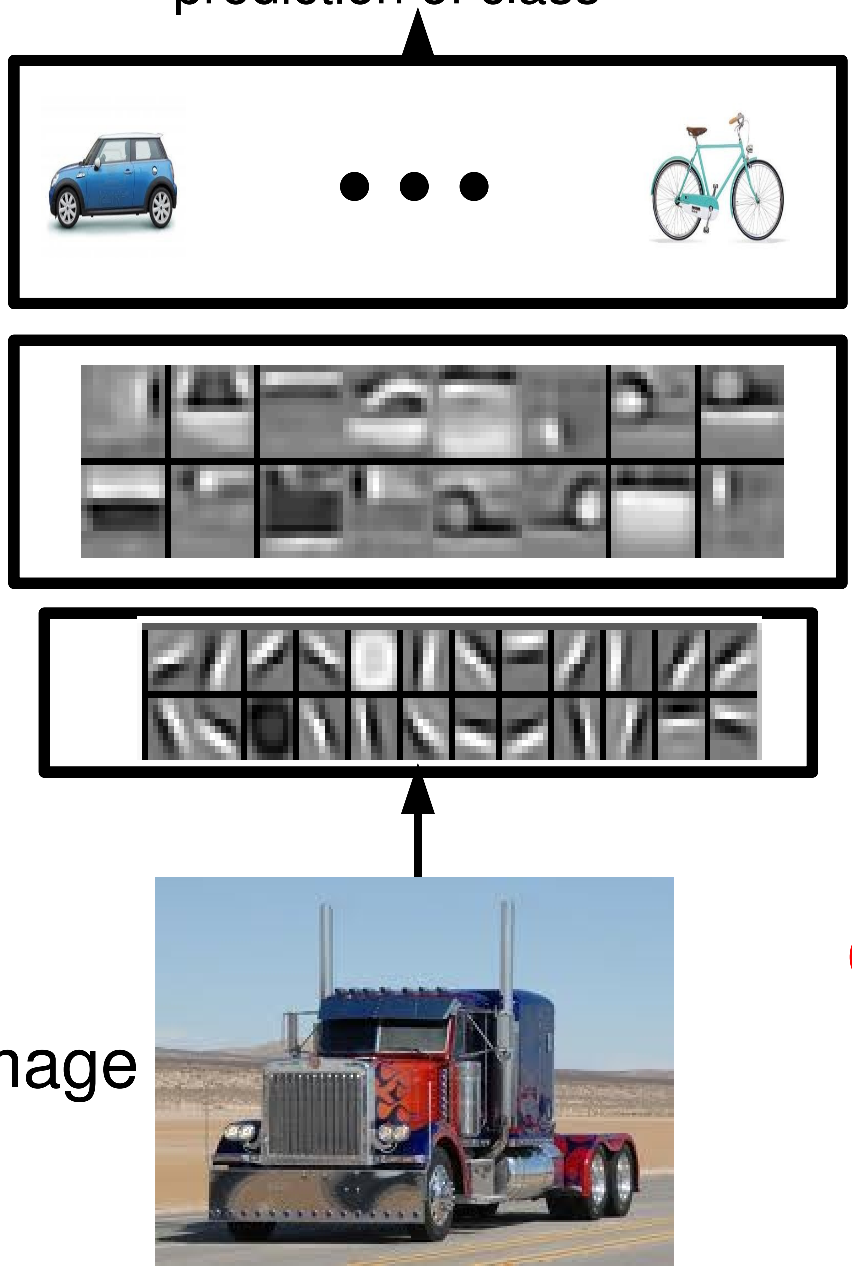
prediction of class

high-level parts

mid-level parts

low level parts

Input image



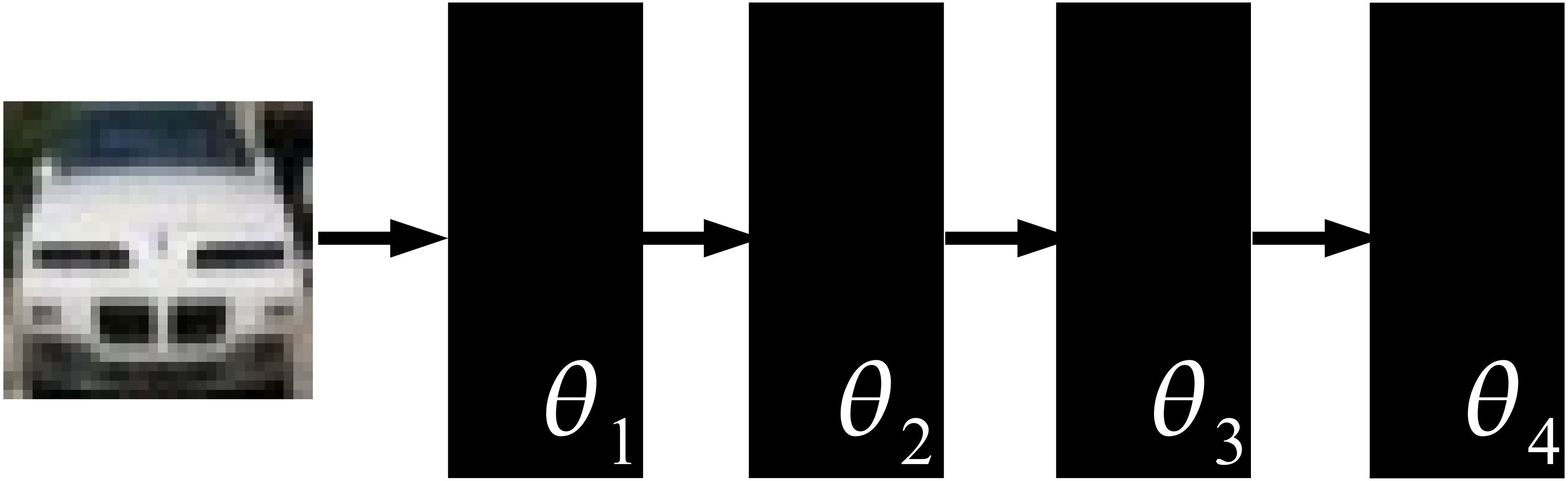
- reuse intermediate parts
- distributed representations

GOOD: (exponentially) more efficient

Lee et al. “Convolutional DBN's ...” ICML 2009, Zeiler & Fergus

A Potential Problem with Deep Learning

Optimization is difficult: non-convex, non-linear system



A Potential Problem with Deep Learning

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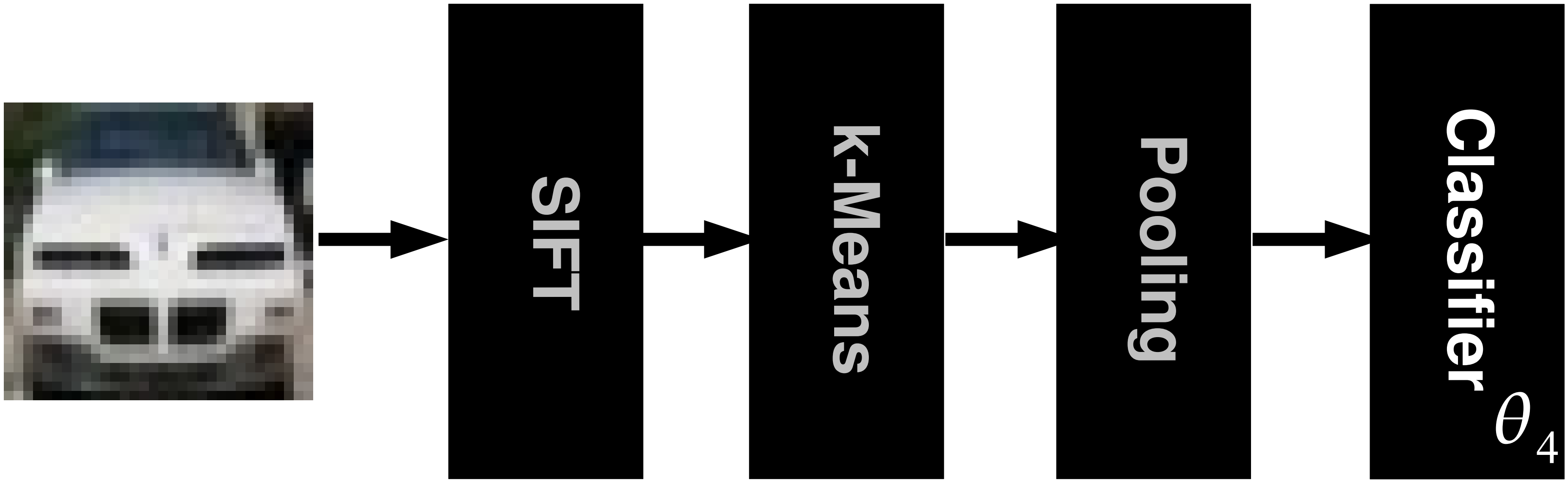


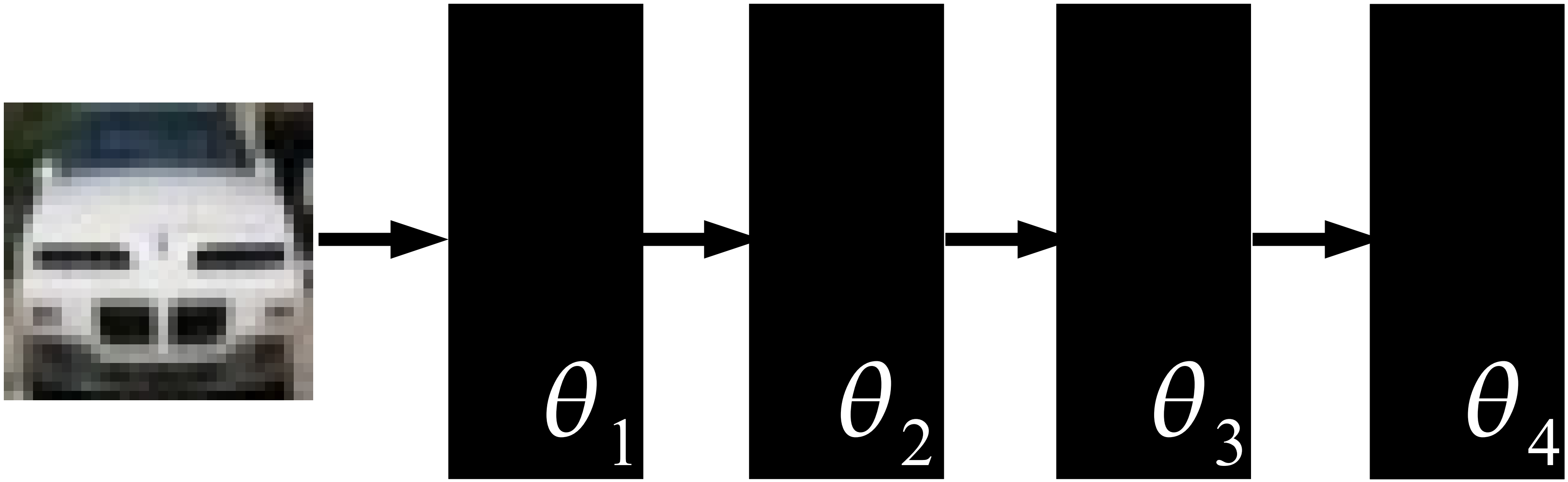
Solution #1: freeze first N-1 layer (engineer the features)

It makes it shallow!

- How to design features of features?
- How to design features for new imagery?

A Potential Problem with Deep Learning

Optimization is difficult: non-convex, non-linear system



Solution #2: live with it!

It will converge to a local minimum.

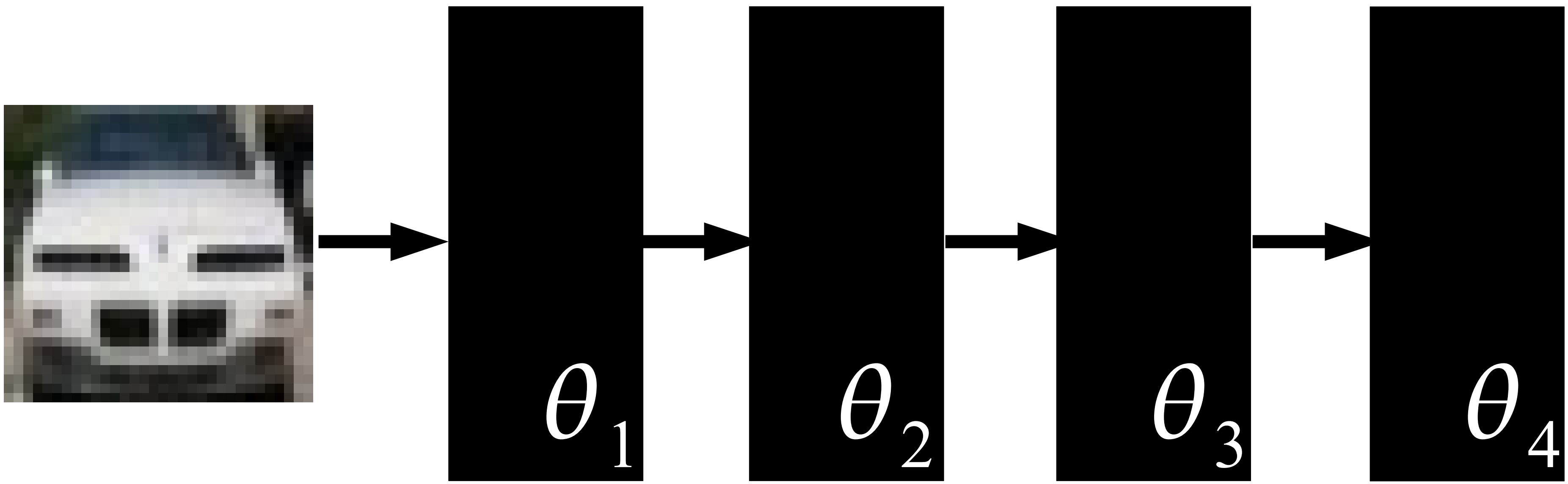
It is much more powerful!!

Given lots of data, engineer less and learn more!!

Just need to know a few tricks of the trade...

Deep Learning in Practice

Optimization is easy, need to know a few tricks of the trade.

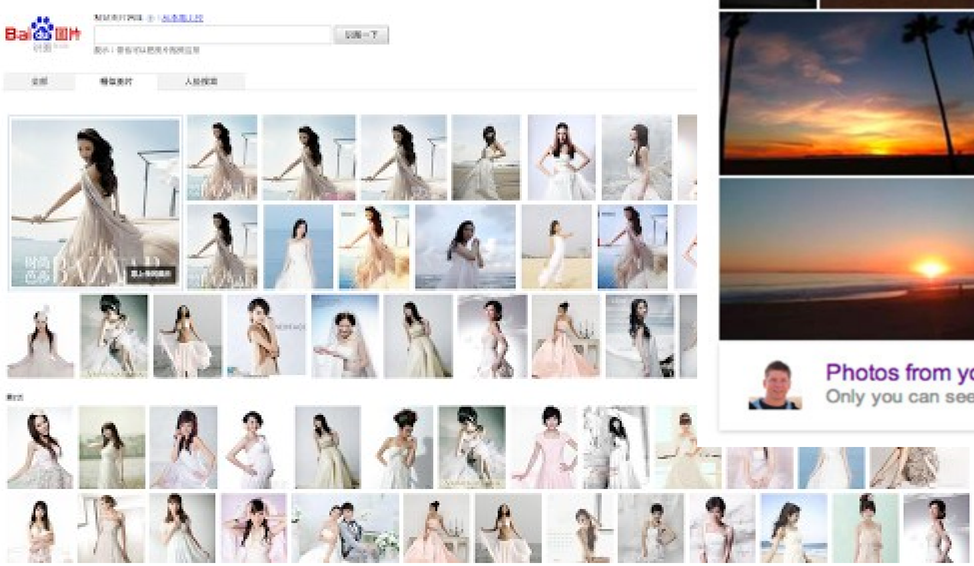


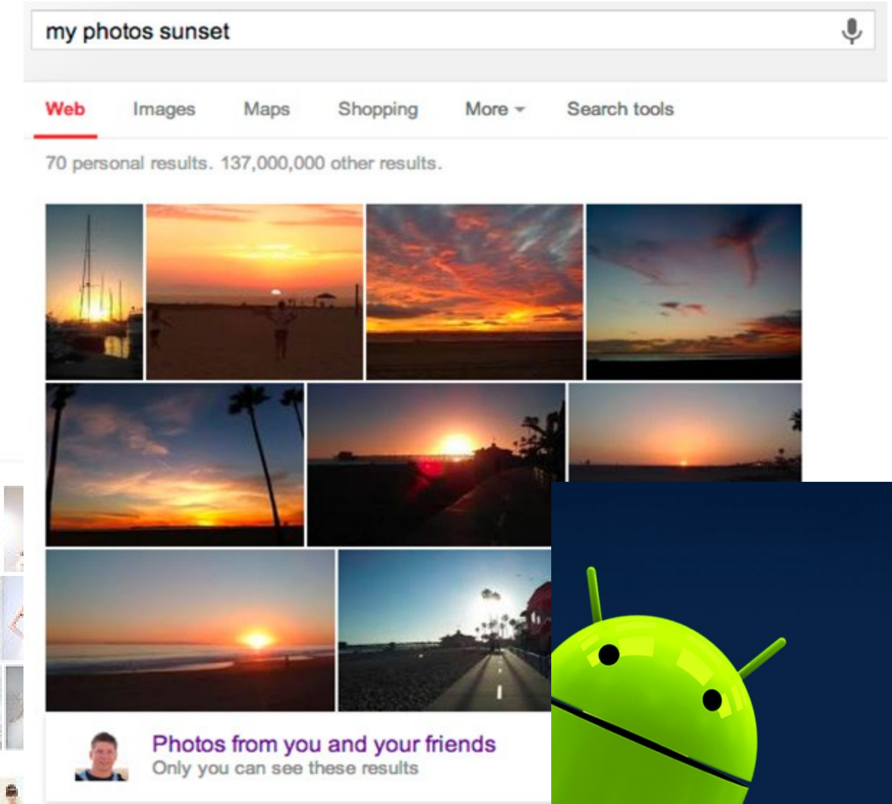
Q: What's the feature extractor? And what's the classifier?

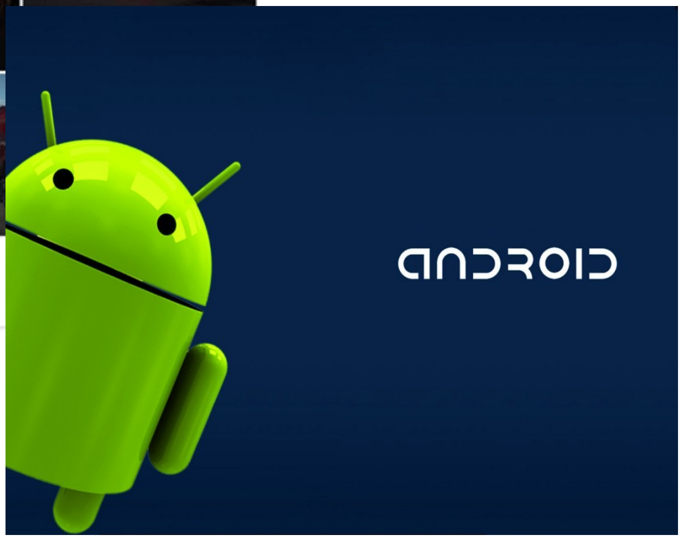
A: No distinction, end-to-end learning!

Deep Learning in Practice

It works very well in practice:







KEY IDEAS: WHY DEEP LEARNING

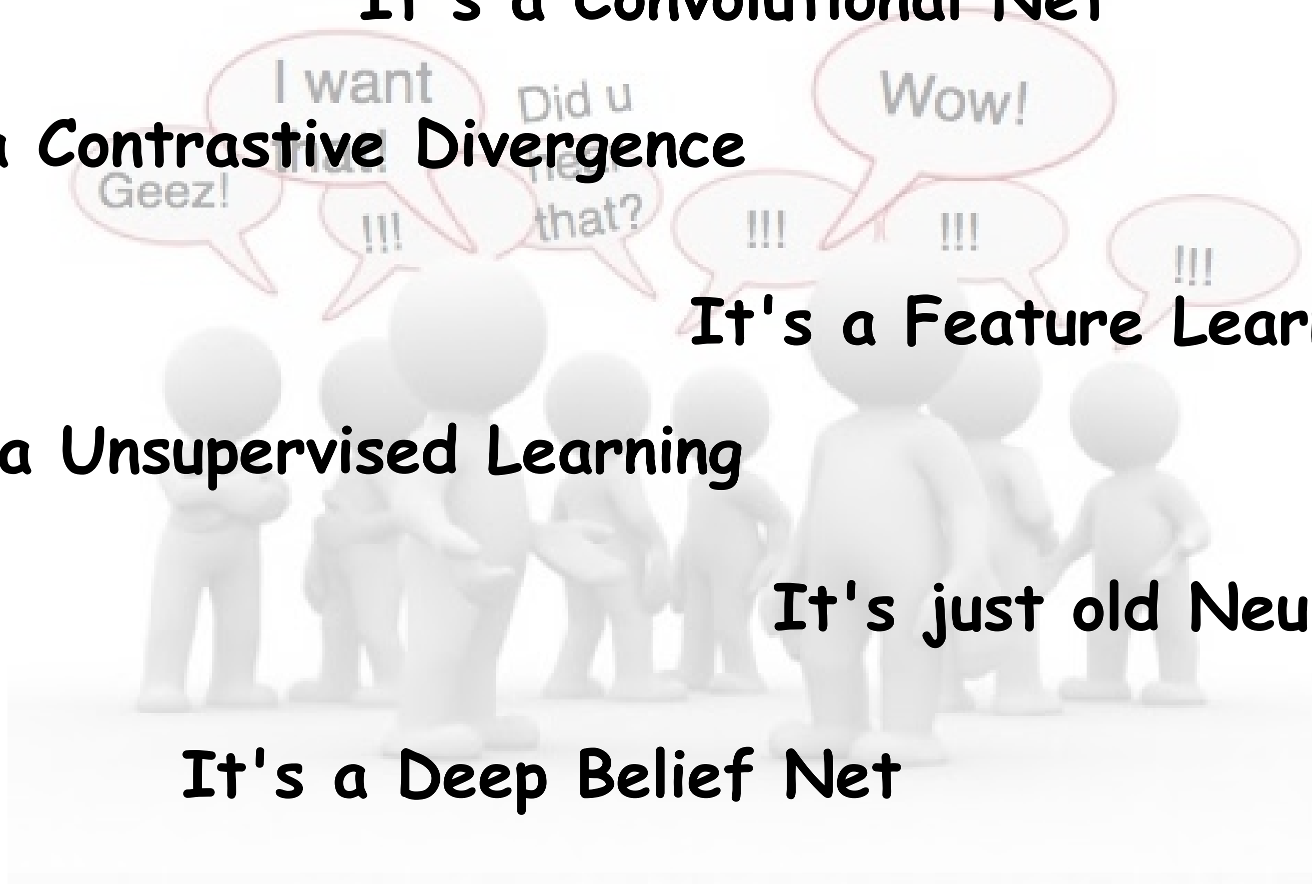
- We need non-linear system
- We need to learn it from data
- Build feature hierarchies
  - Distributed representations
  - Compositionality
- End-to-end learning

What Is Deep Learning?

Buzz Words

It's a Convolutional Net

It's a Contrastive Divergence



It's a Feature Learning

It's a Unsupervised Learning

It's just old Neural Nets

It's a Deep Belief Net

(My) Definition

A Deep Learning method is: a method which makes predictions by using a sequence of non-linear processing stages. The resulting intermediate representations can be interpreted as feature hierarchies and the whole system is jointly learned from data.

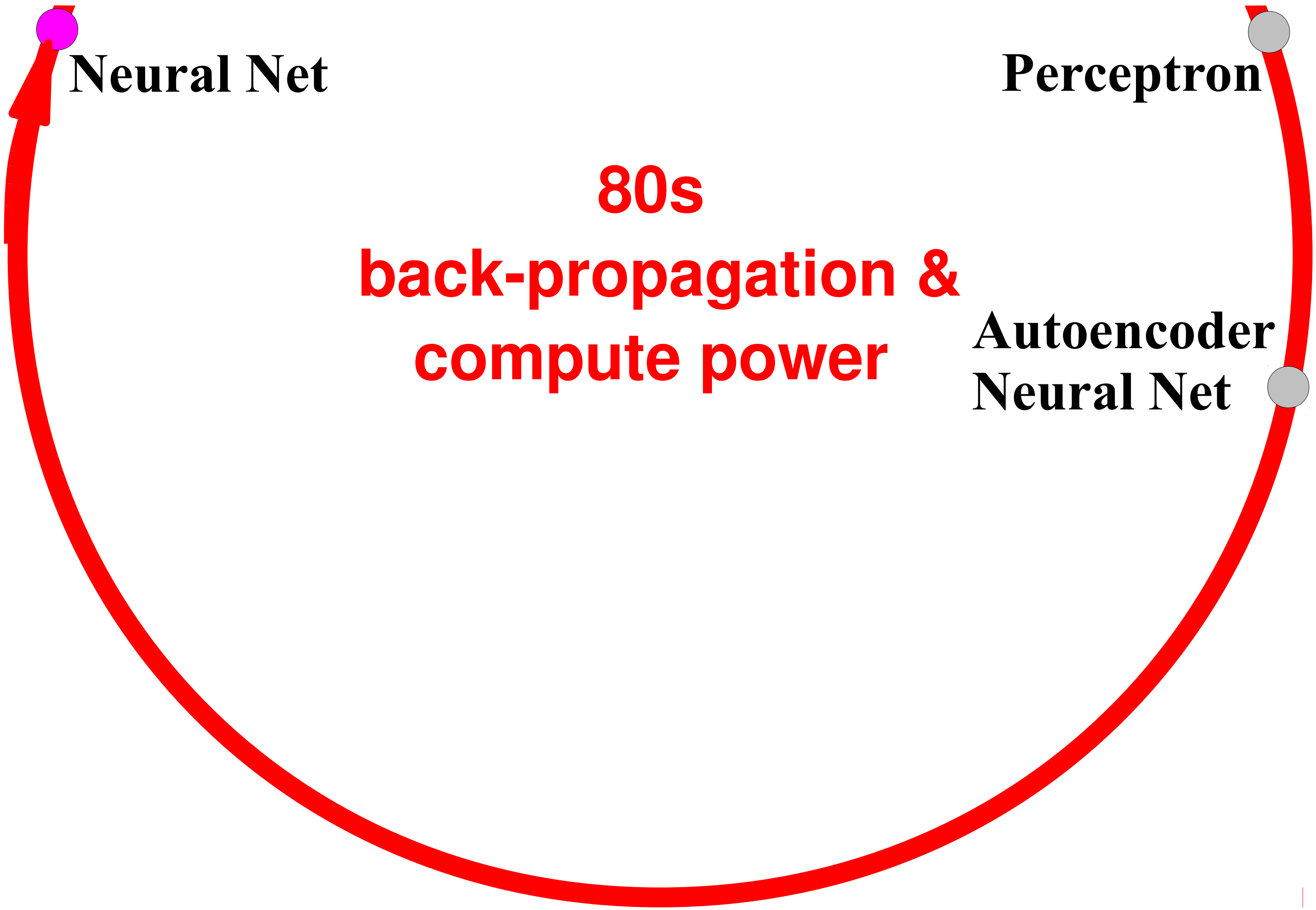
Some deep learning methods are probabilistic, others are loss-based, some are supervised, other unsupervised...

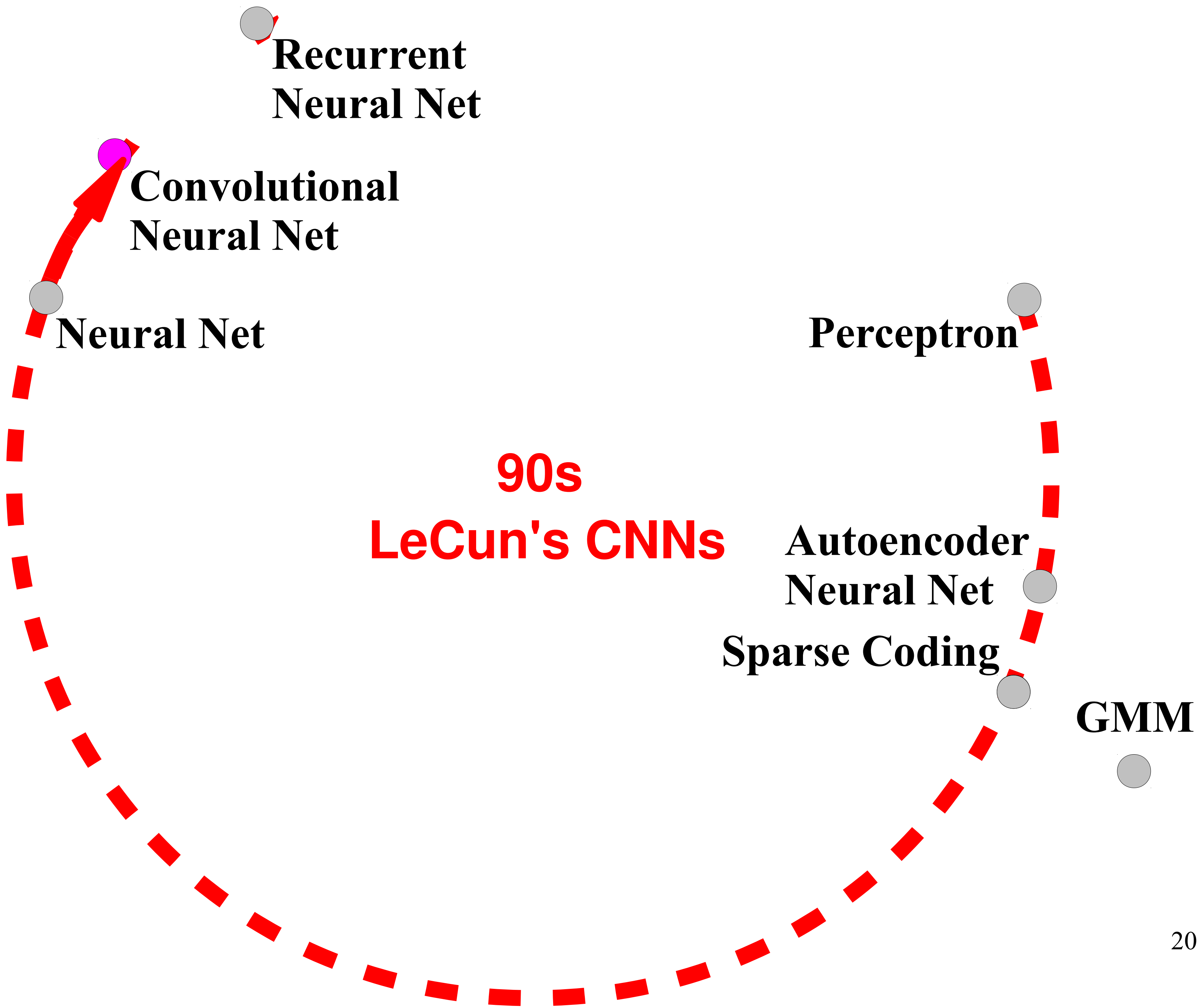
It's a large family!

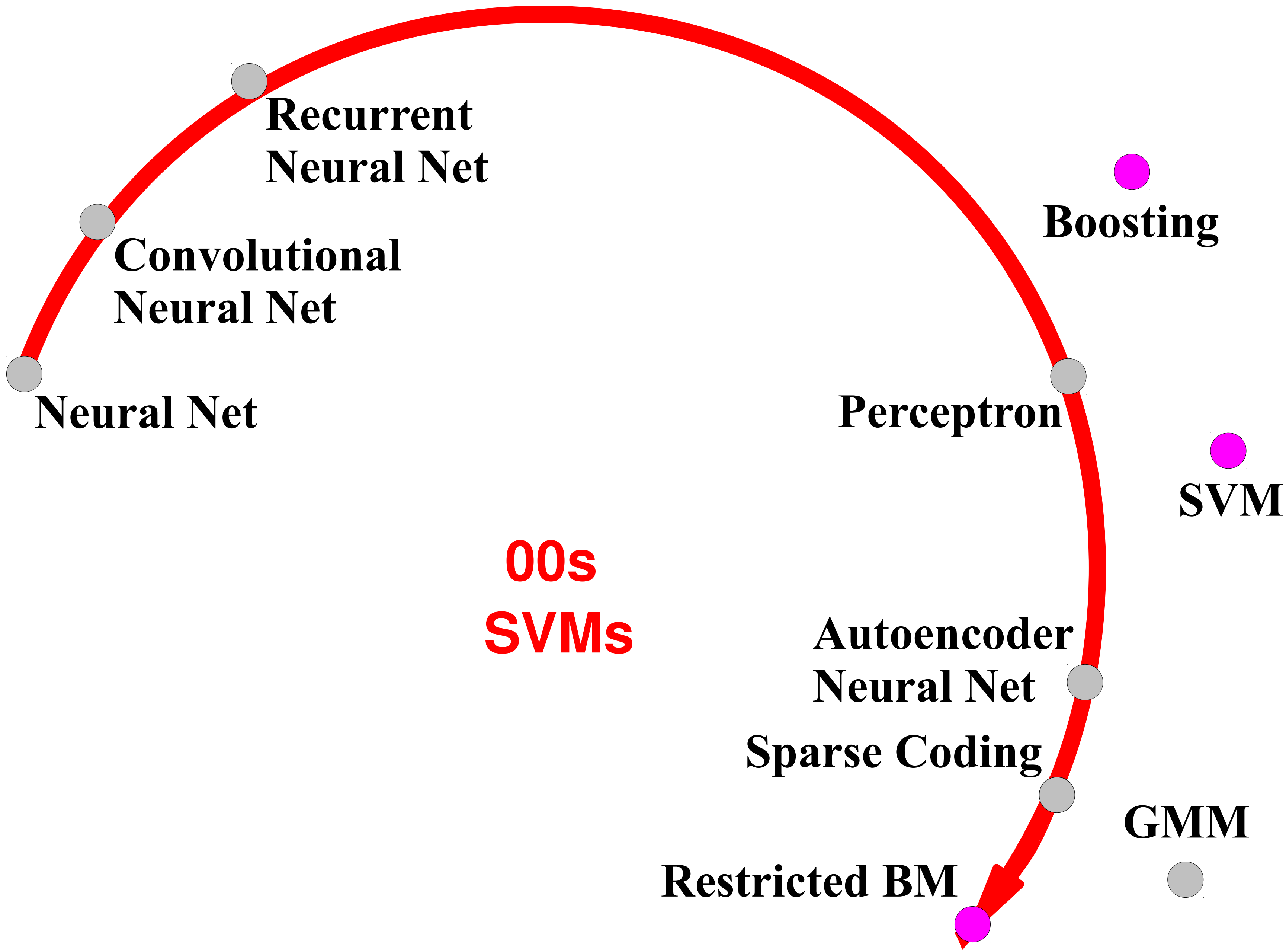
Perceptron

1957
Rosenblatt

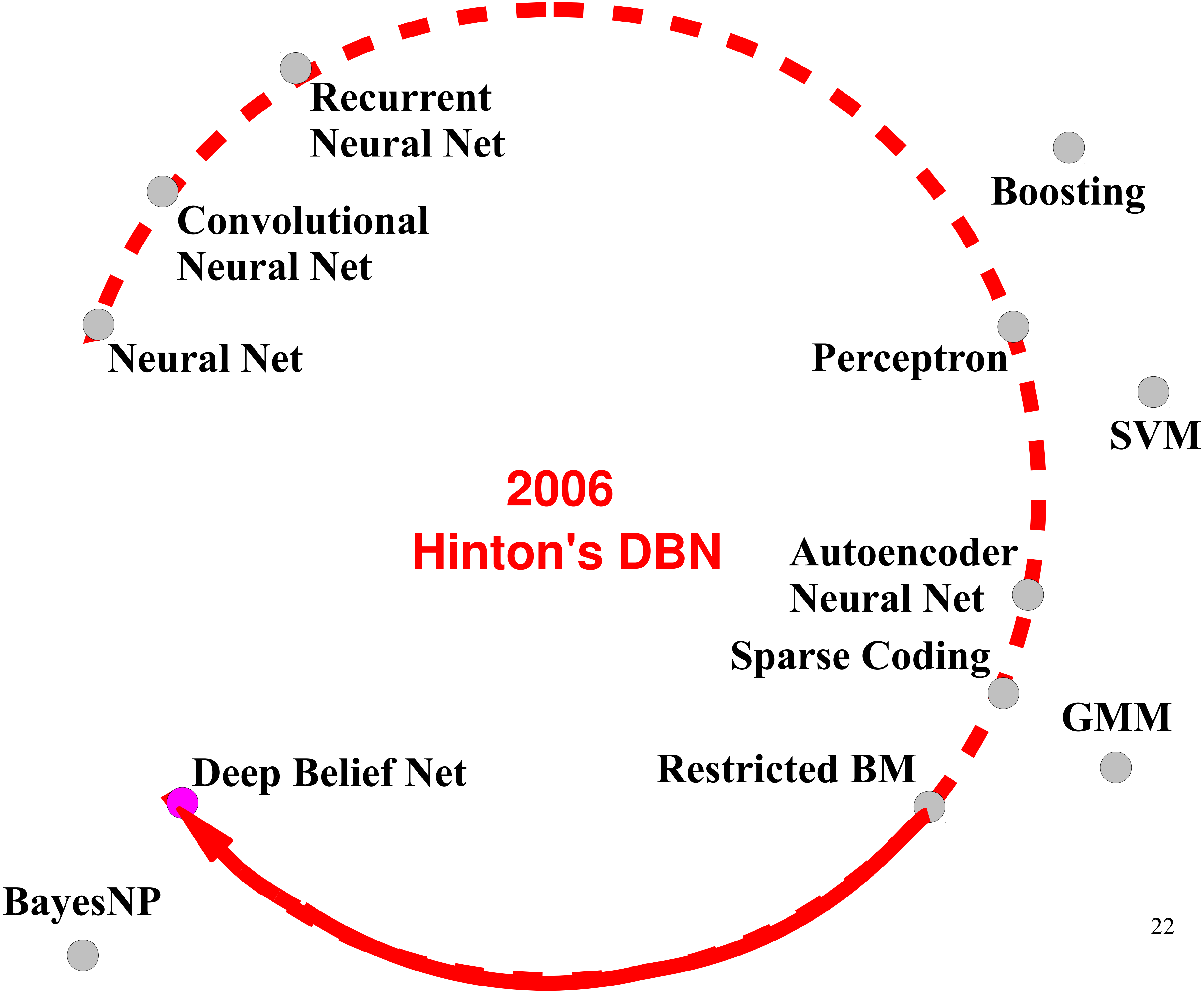
THE SPACE OF MACHINE LEARNING METHODS


Neural Net
Perceptron
80s
back-propagation &
compute power
Autoencoder
Neural Net

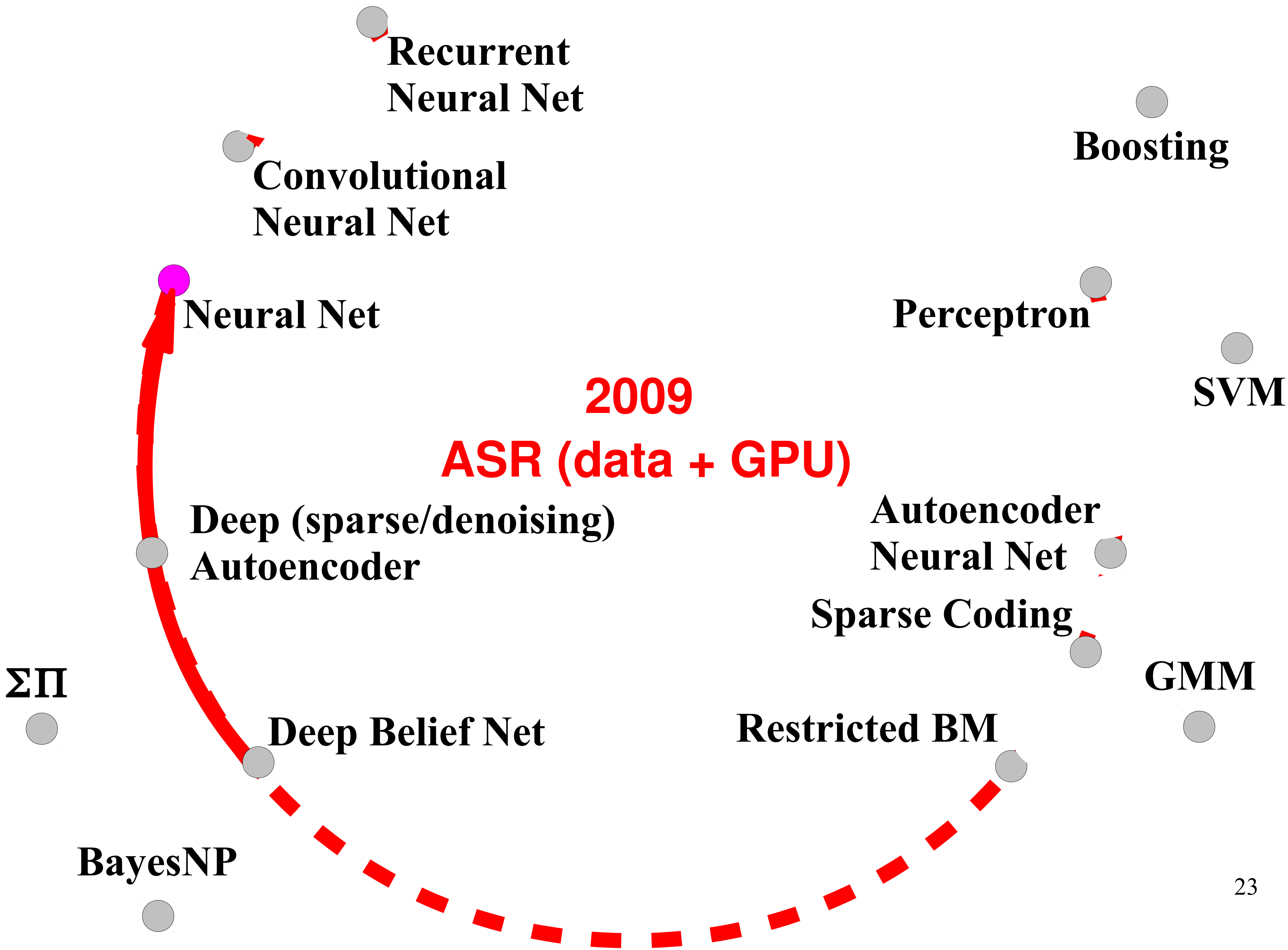

Recurrent
Neural Net
Convolutional
Neural Net
Neural Net
Perceptron
90s
LeCun's CNNs
Autoencoder
Neural Net
Sparse Coding
GMM



Recurrent
Neural Net
Boosting
Convolutional
Neural Net
Neural Net
Perceptron
SVM
00s
SVMs
Autoencoder
Neural Net
Sparse Coding
GMM
Restricted BM


Recurrent
Neural Net
Boosting
Convolutional
Neural Net
Neural Net
Perceptron
SVM
2006
Hinton's DBN
Autoencoder
Neural Net
Sparse Coding
GMM
Deep Belief Net
Restricted BM
BayesNP

2009


Recurrent
Neural Net
Boosting
Convolutional
Neural Net
Neural Net
Perceptron
SVM
2009
ASR (data + GPU)
Deep (sparse/denoising)
Autoencoder
Autoencoder
Neural Net
Sparse Coding
ΣΠ
GMM
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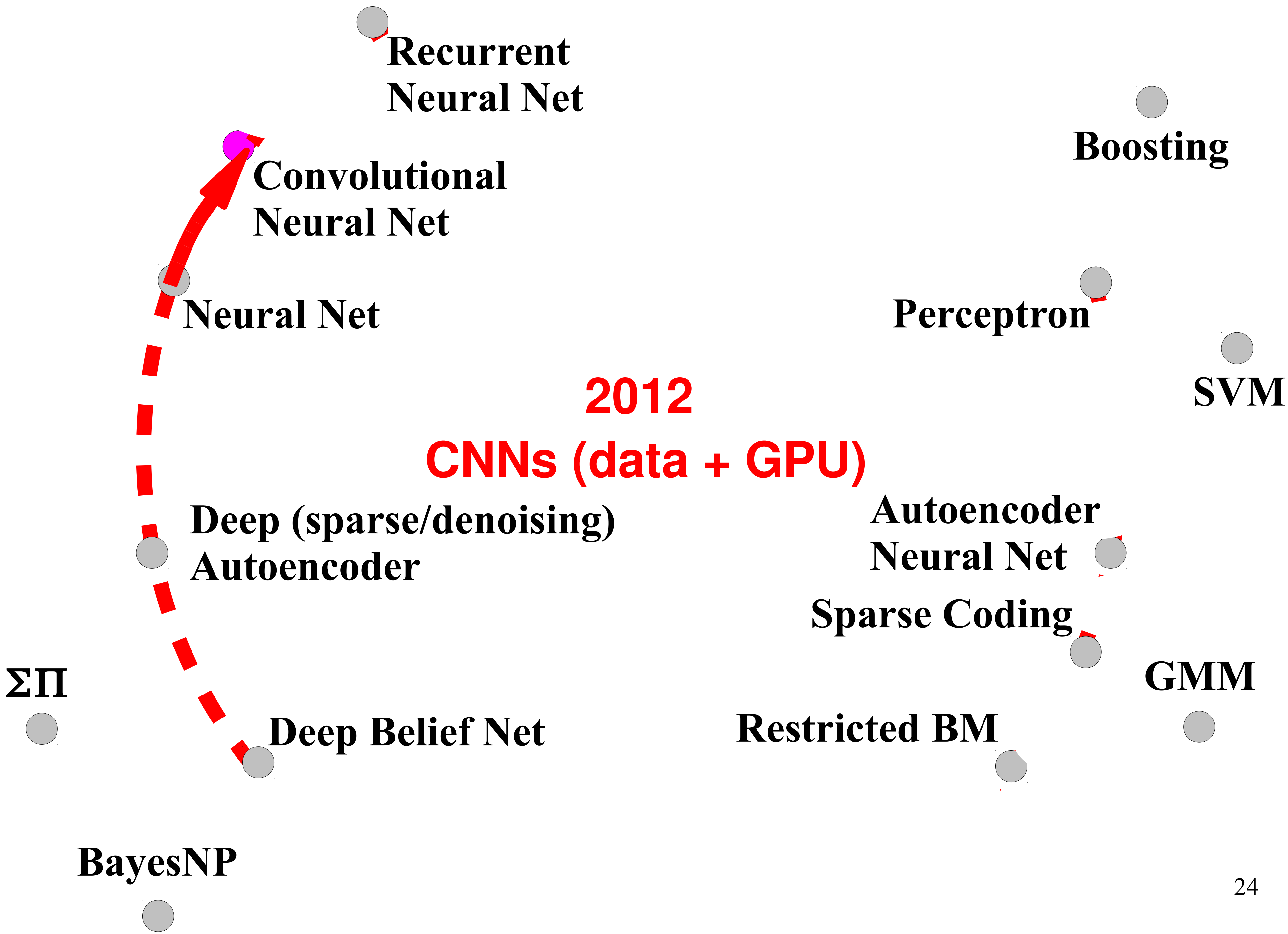
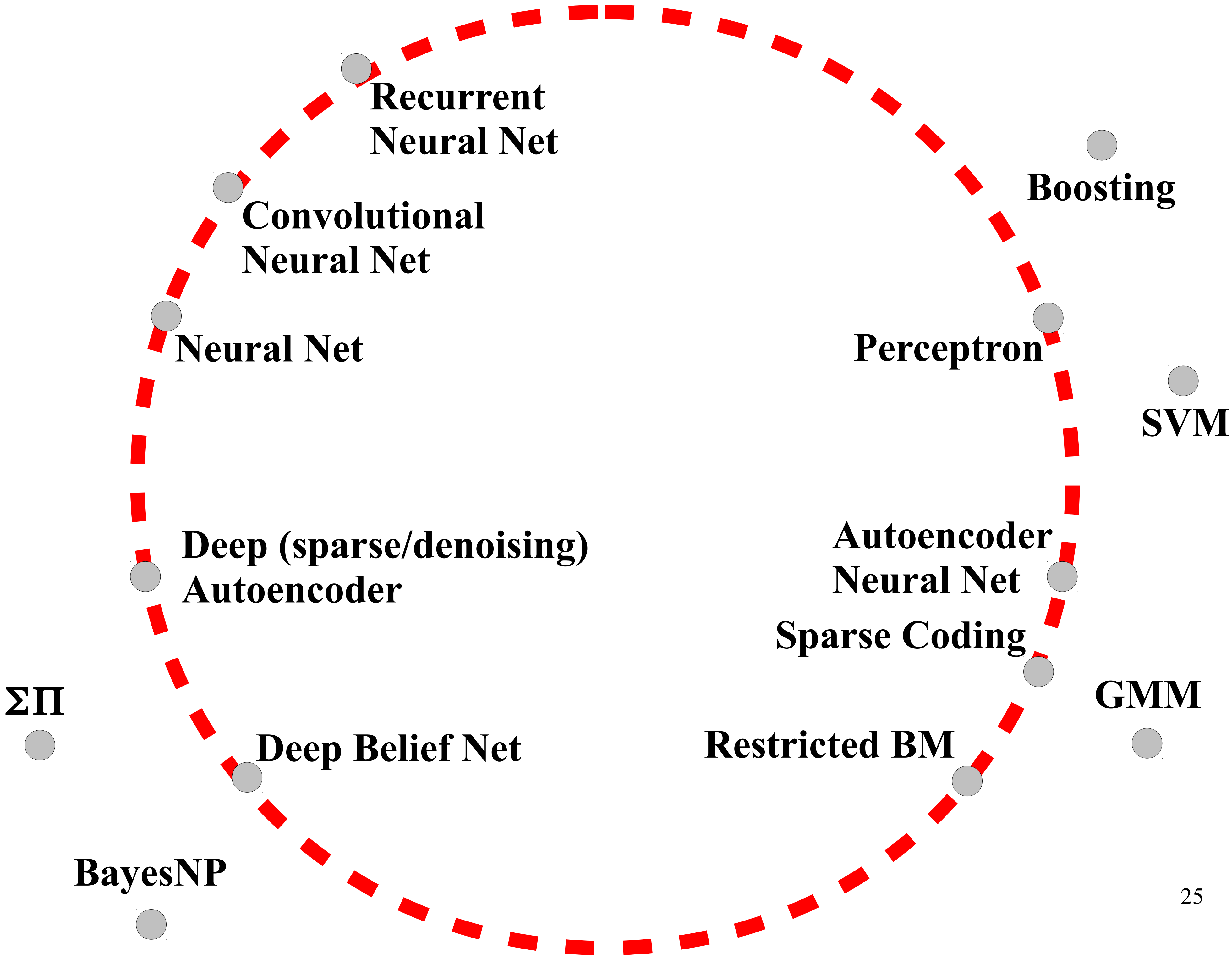
Restricted BM
BayesNP


Recurrent Neural Net
Boosting
Convolutional Neural Net
Neural Net
Perceptron
SVM
2012
CNNs (data + GPU)
Deep (sparse/denoising) Autoencoder
Autoencoder Neural Net
Sparse Coding
ΣΠ
GMM
Deep Belief Net
Restricted BM
BayesNP


Recurrent
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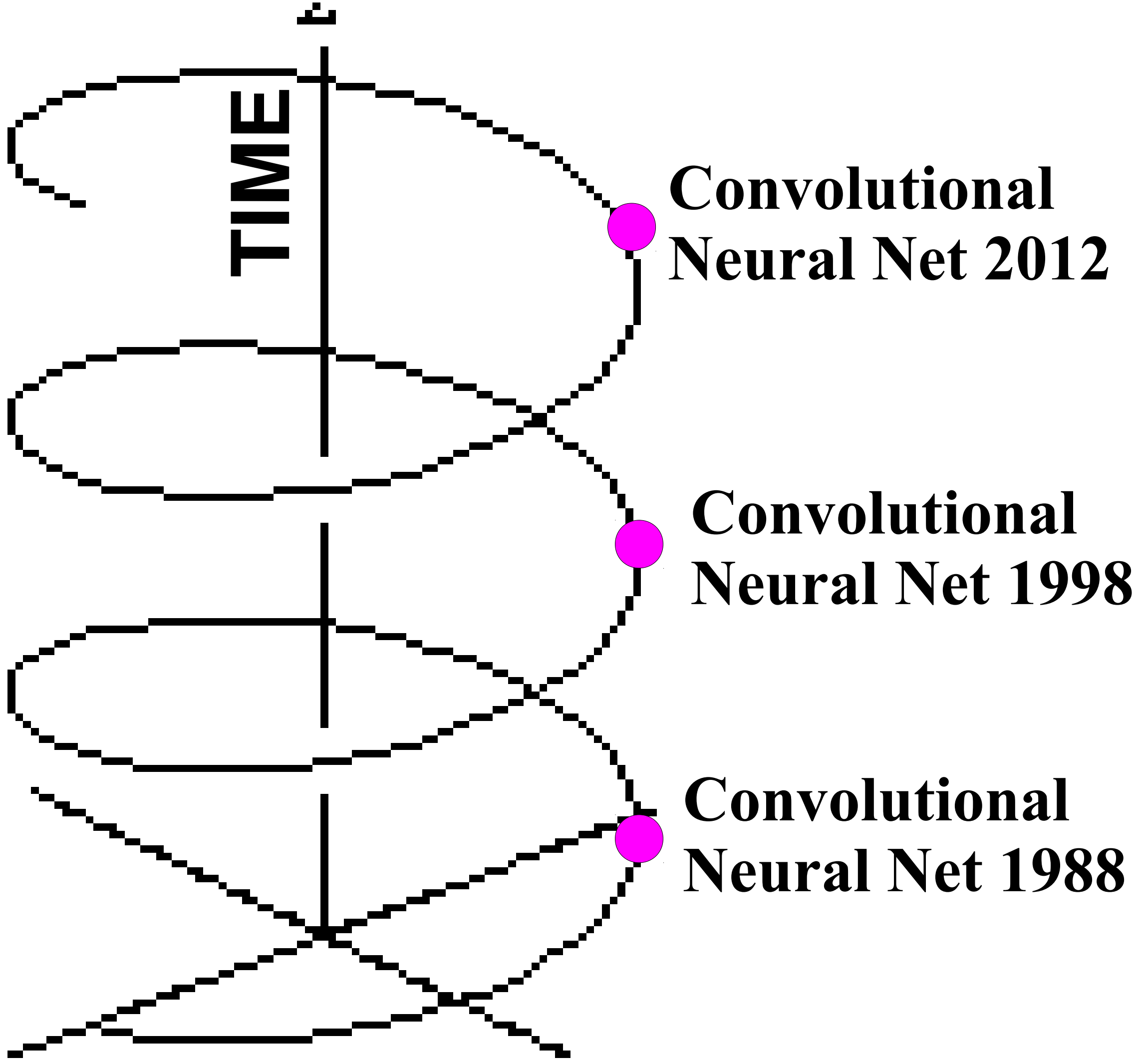


Q.: Did we make any prgress since then?

A.: The main reason for the breakthrough is: **data** and **GPU,** but we have also made networks **deeper** and more **non-linear**.

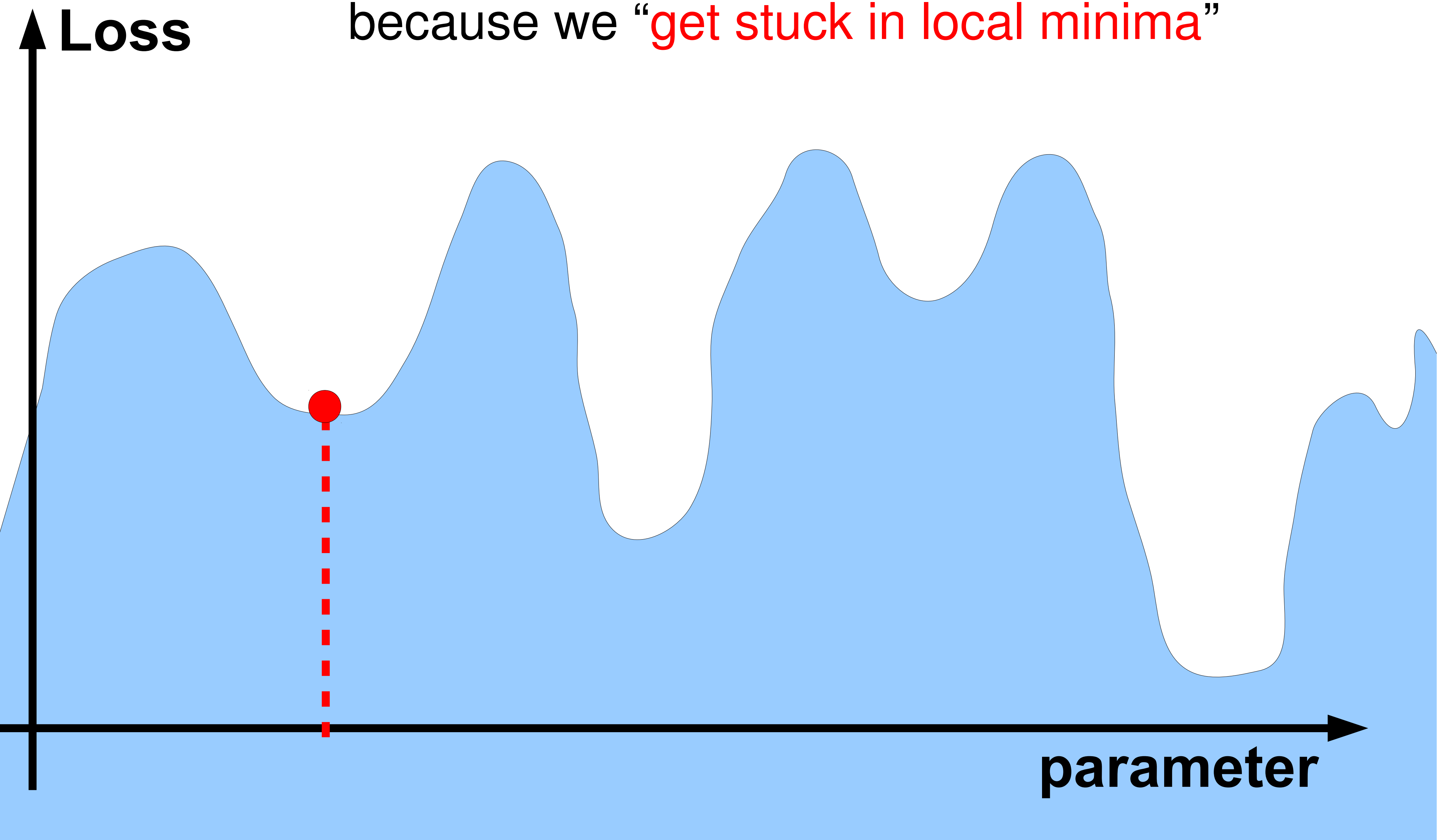
ConvNets: History

- **Fukushima 1980**: designed network with same basic structure but did not train by backpropagation.
- **LeCun from late 80s**: figured out backpropagation for CNN, popularized and deployed CNN for OCR applications and others.
- **Poggio from 1999**: same basic structure but learning is restricted to top layer (k-means at second stage)
- **LeCun from 2006:** unsupervised feature learning
- **DiCarlo from 2008:** large scale experiments, normalization layer
- **LeCun from 2009:** harsher non-linearities, normalization layer, learning unsupervised and supervised.
- **Mallat from 2011:** provides a theory behind the architecture
- **Hinton 2012:** use bigger nets, GPUs, more data

LeCun et al. "Gradient-based learning applied to document recognition" IEEE 1998

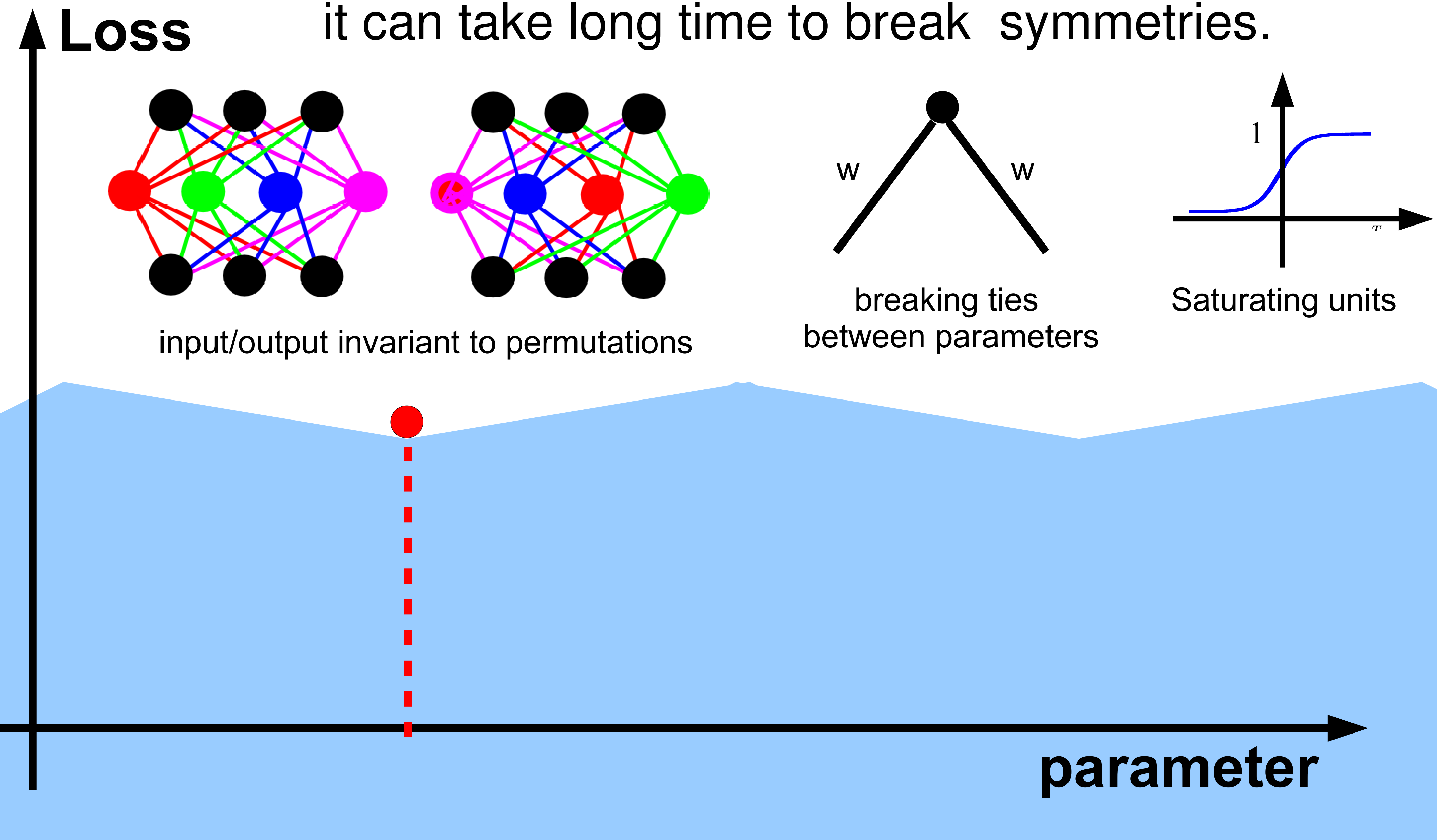
ConvNets: till 2012

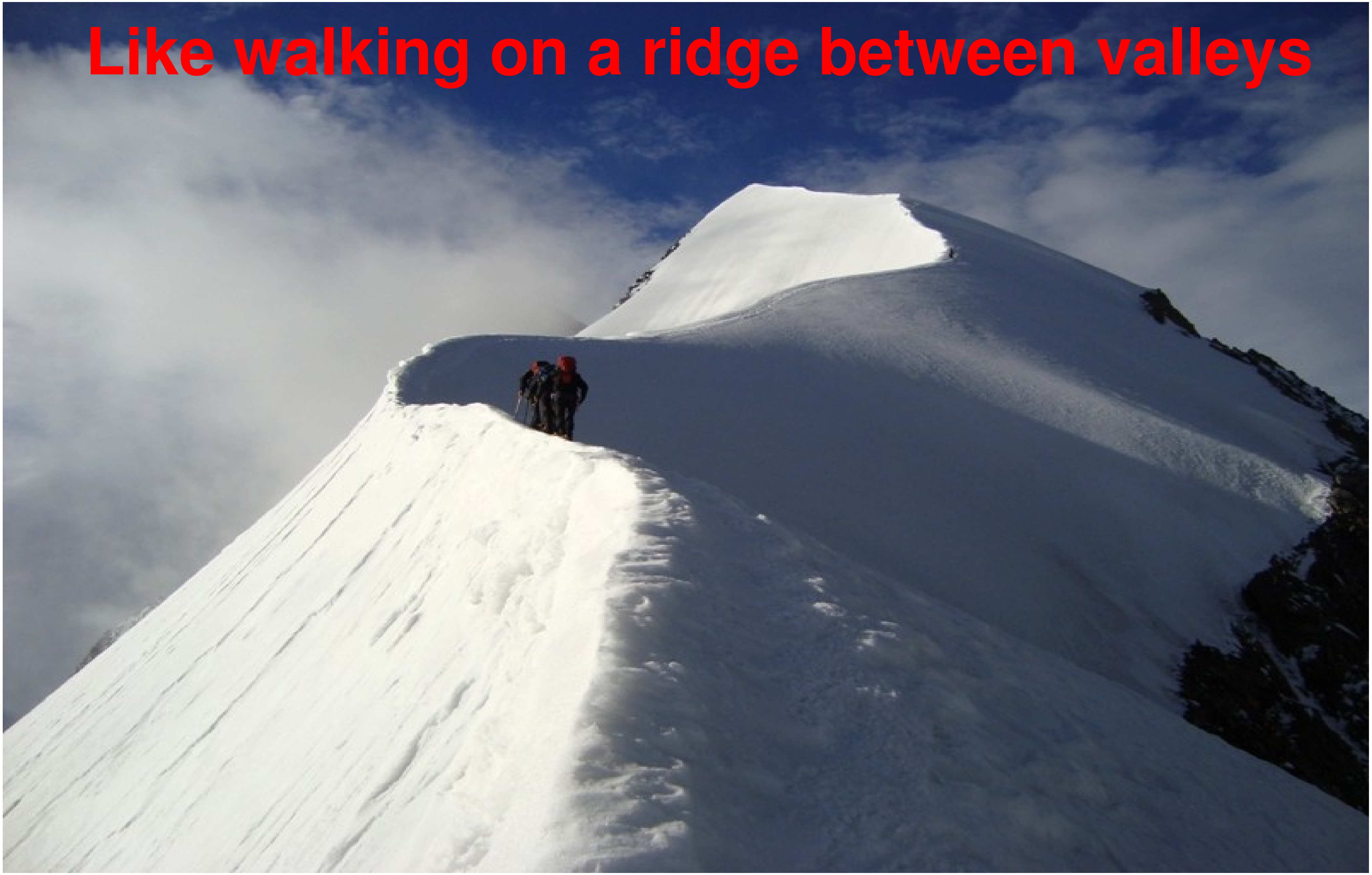
Common wisdom: training does not work because we "get stuck in local minima"



ConvNets: today

Local minima are all similar, there are long plateaus, it can take long time to break symmetries.

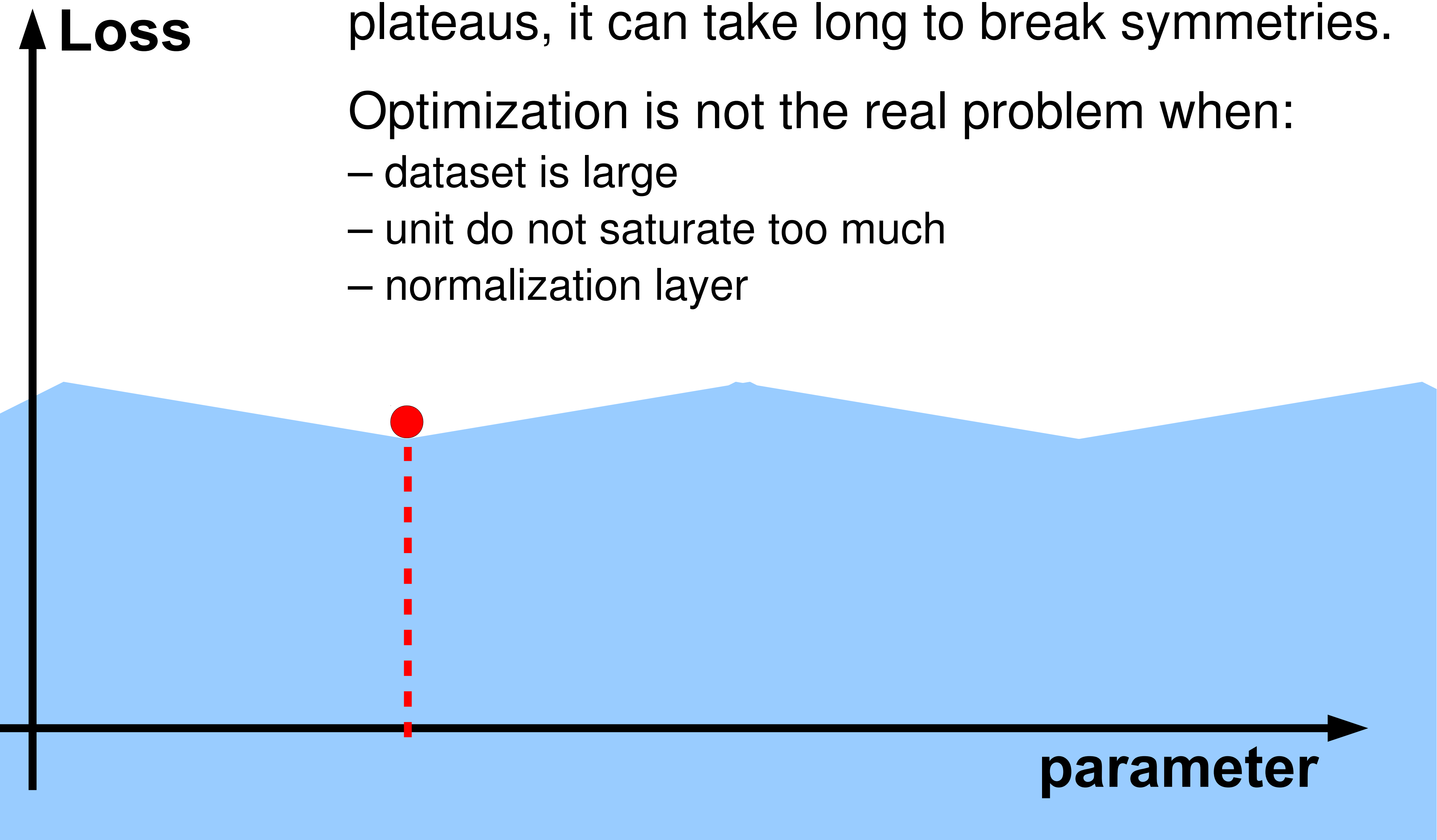



Like walking on a ridge between valleys

ConvNets: today

Local minima are all similar, there are long plateaus, it can take long to break symmetries.

Optimization is not the real problem when:
– dataset is large
– unit do not saturate too much
– normalization layer



ConvNets: today

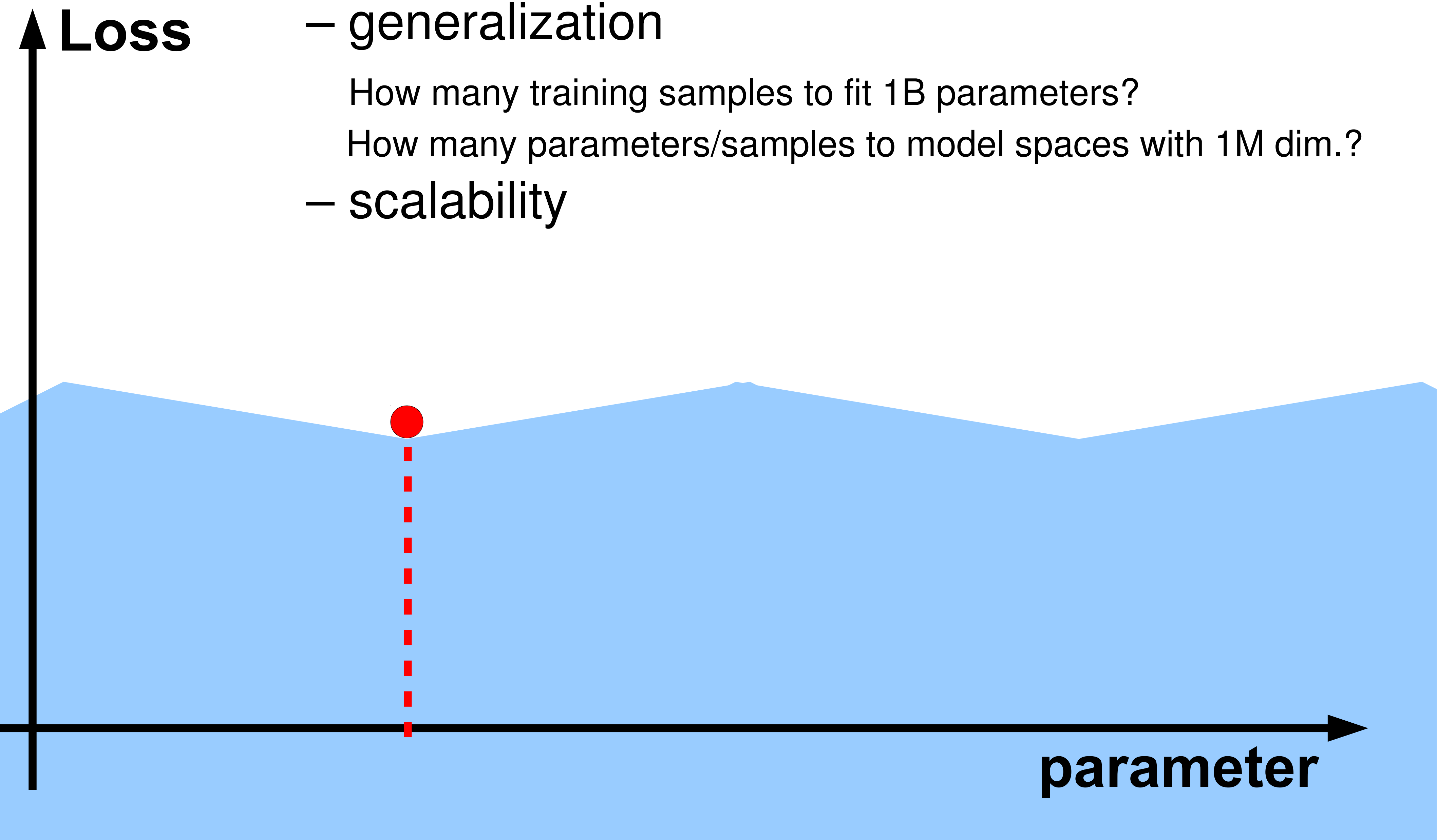
Today's belief is that the challenge is about:

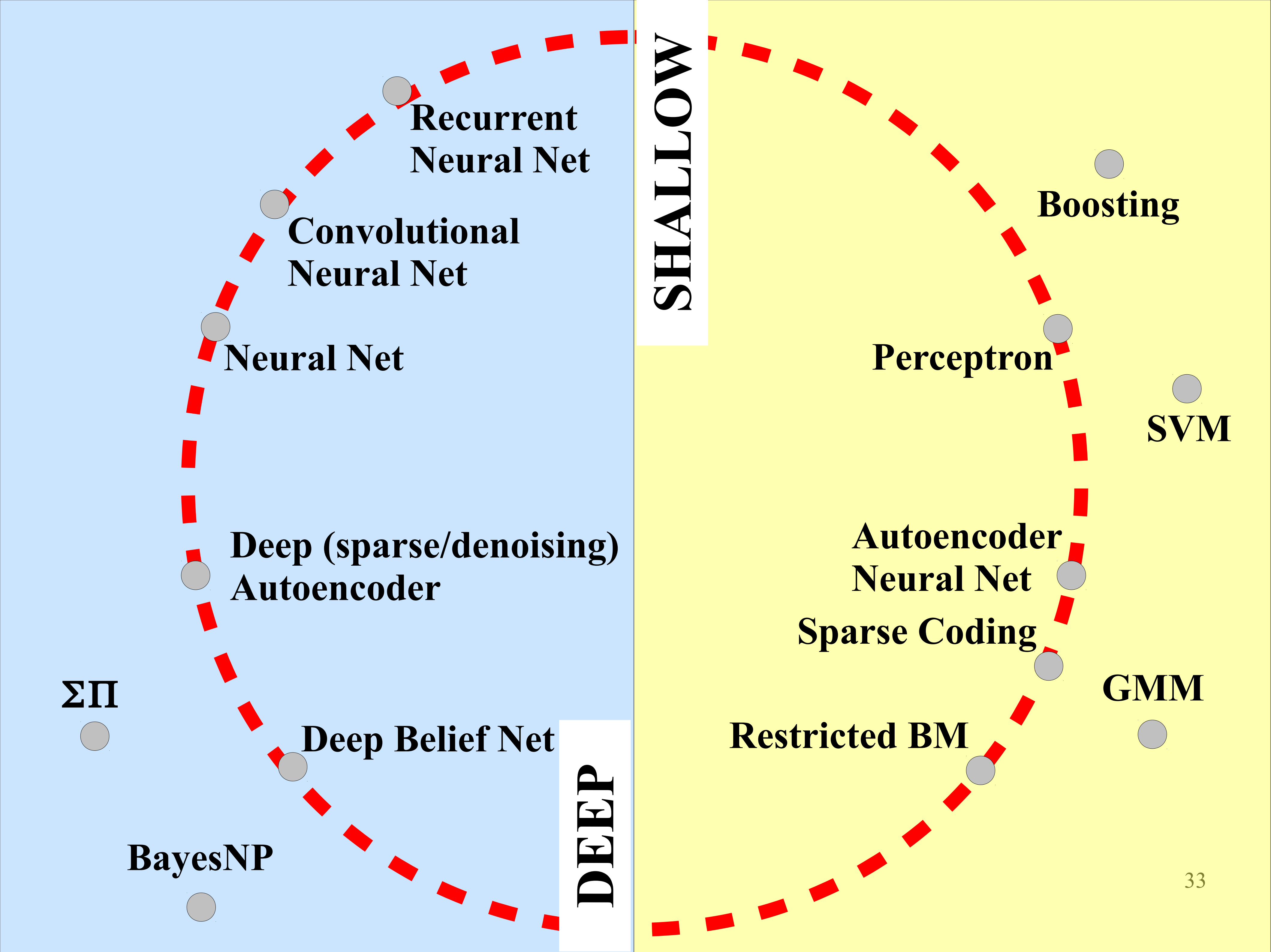
– generalization

How many training samples to fit 1B parameters?

How many parameters/samples to model spaces with 1M dim.?

– scalability




SHALLOW
DEEP
Recurrent Neural Net
Convolutional Neural Net
Neural Net
Deep (sparse/denoising) Autoencoder
ΣΠ
Deep Belief Net
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Perceptron
SVM
Autoencoder Neural Net
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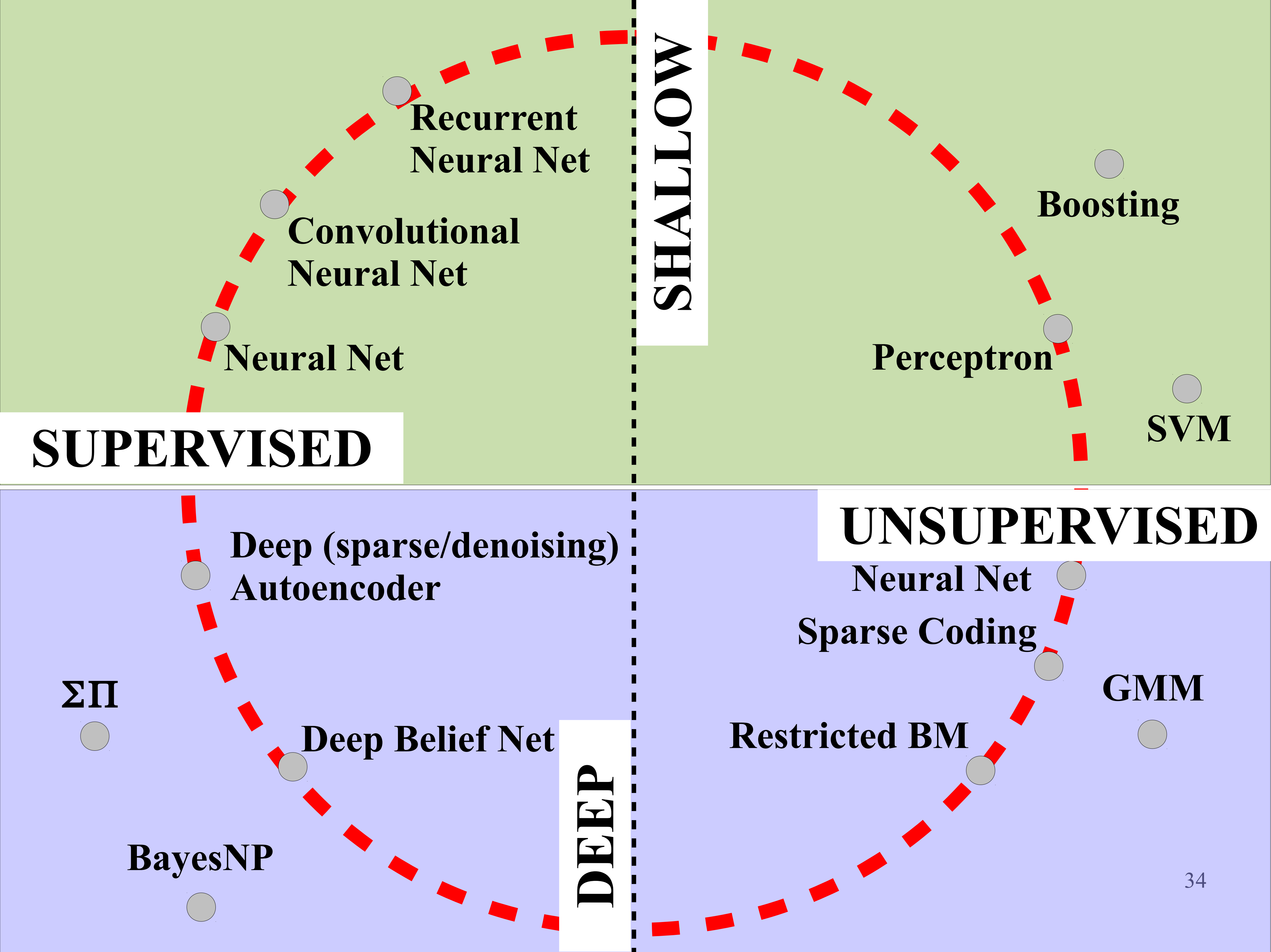
SHALLOW
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SUPERVISED
UNSUPERVISED
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Autoencoder
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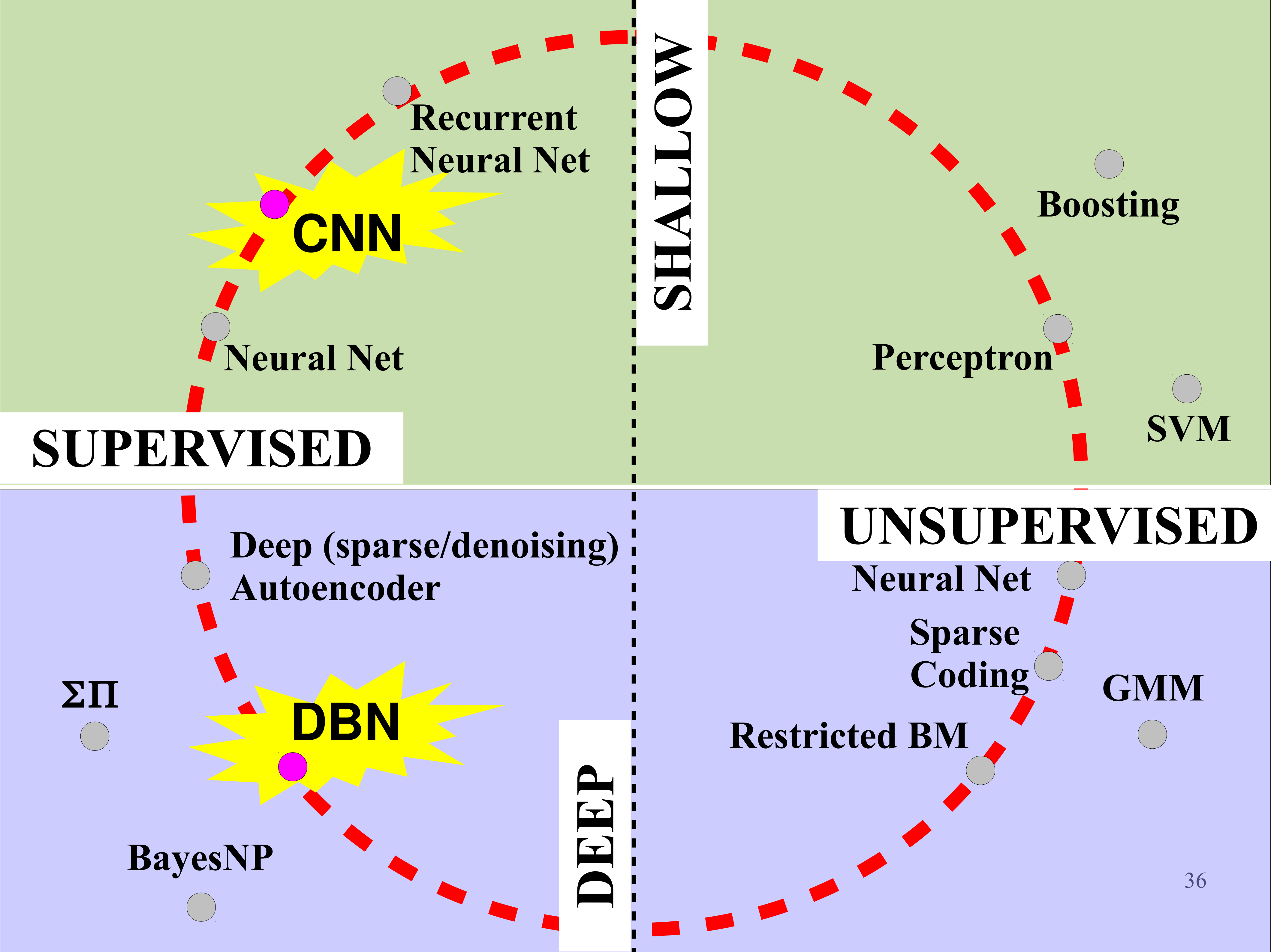
DEEP
Neural Net
Sparse Coding
GMM
Restricted BM

Deep Learning is a very rich family!

I am going to focus on a few methods...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ΣΠ
DBN
BayesNP
Neural Net
Sparse Coding
GMM
Restricted BM

Deep Gated MRF

Layer 1:

$$E(x, h^c, h^m) = \frac{1}{2} x' \Sigma^{-1} x \qquad p(x, h^c, h^m) \propto e^{-E(x, h^c, h^m)}$$

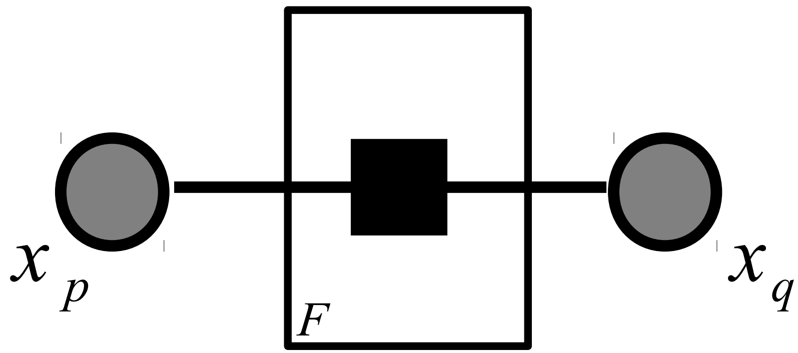
pair-wise MRF

Ranzato et al. "Modeling natural images with gated MRFs" PAMI 2013

Deep Gated MRF

Layer 1:

$$E(x, h^c, h^m) = \frac{1}{2} x' C C' x$$



pair-wise MRF

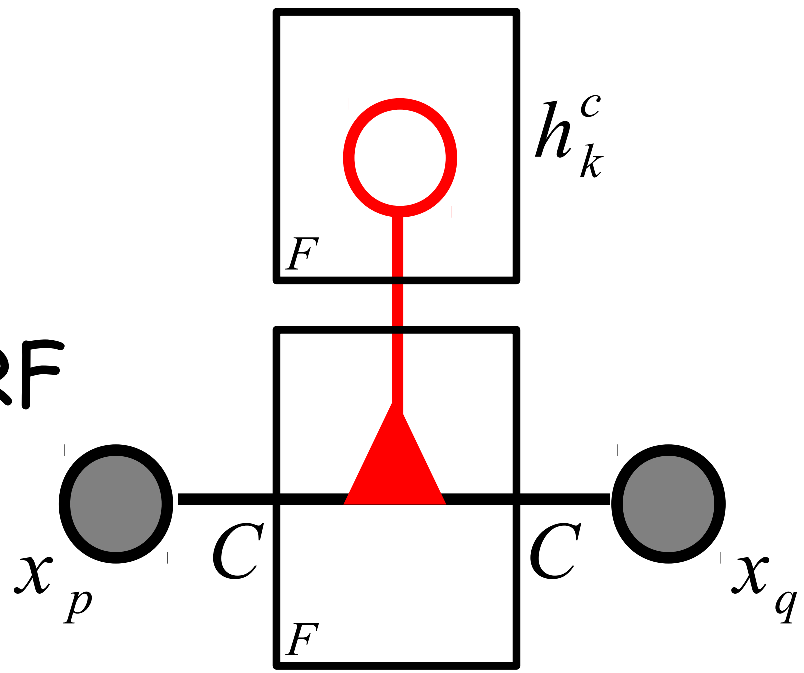
Ranzato et al. “Modeling natural images with gated MRFs” PAMI 2013

Deep Gated MRF

Layer 1:

$$E(x, h^c, h^m) = \frac{1}{2} x' C [diag(h^c)] C' x$$

gated MRF



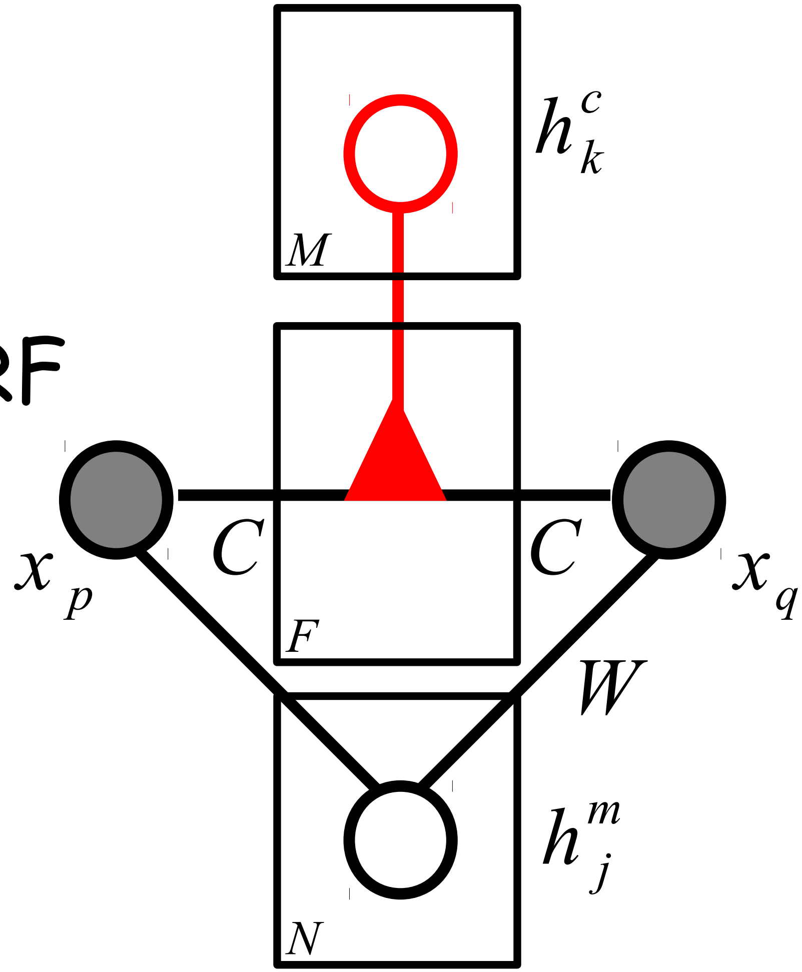
Ranzato et al. "Modeling natural images with gated MRFs" PAMI 2013

Deep Gated MRF

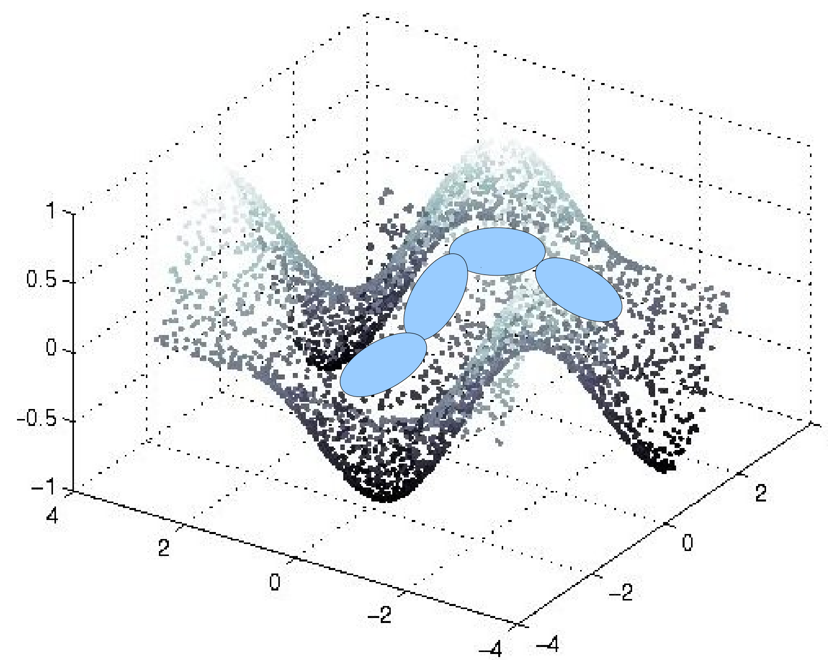
Layer 1:

$$E(x, h^c, h^m) = \frac{1}{2} x' C [diag(h^c)] C' x + \frac{1}{2} x' x - x' W h^m$$

gated MRF



$$p(x) \alpha \int_{h^c} \int_{h^m} e^{-E(x, h^c, h^m)}$$



Ranzato et al. "Modeling natural images with gated MRFs" PAMI 2013

Deep Gated MRF

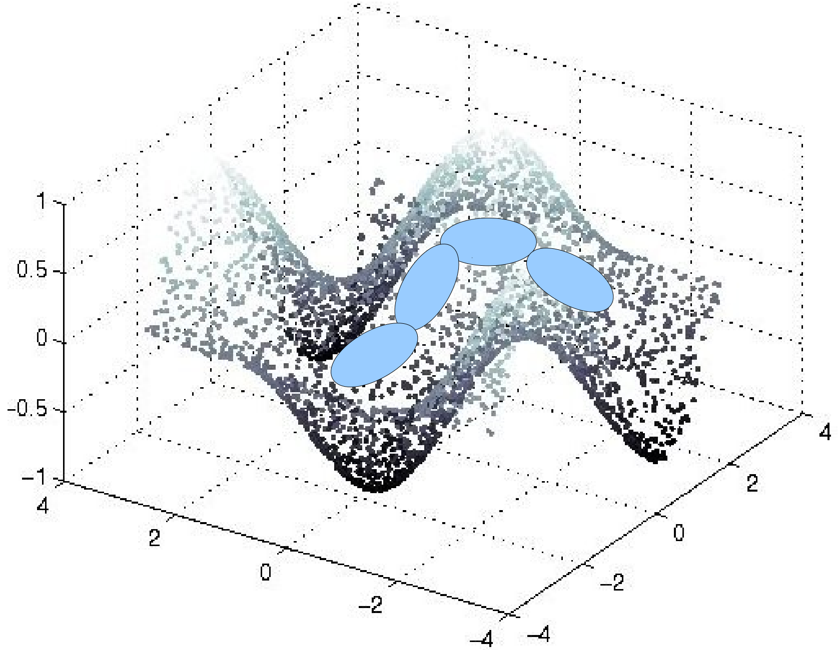
Layer 1:

$$E(x, h^c, h^m) = \frac{1}{2} x' C [diag(h^c)] C' x + \frac{1}{2} x' x - x' W h^m$$

Inference of latent variables:
just a forward pass

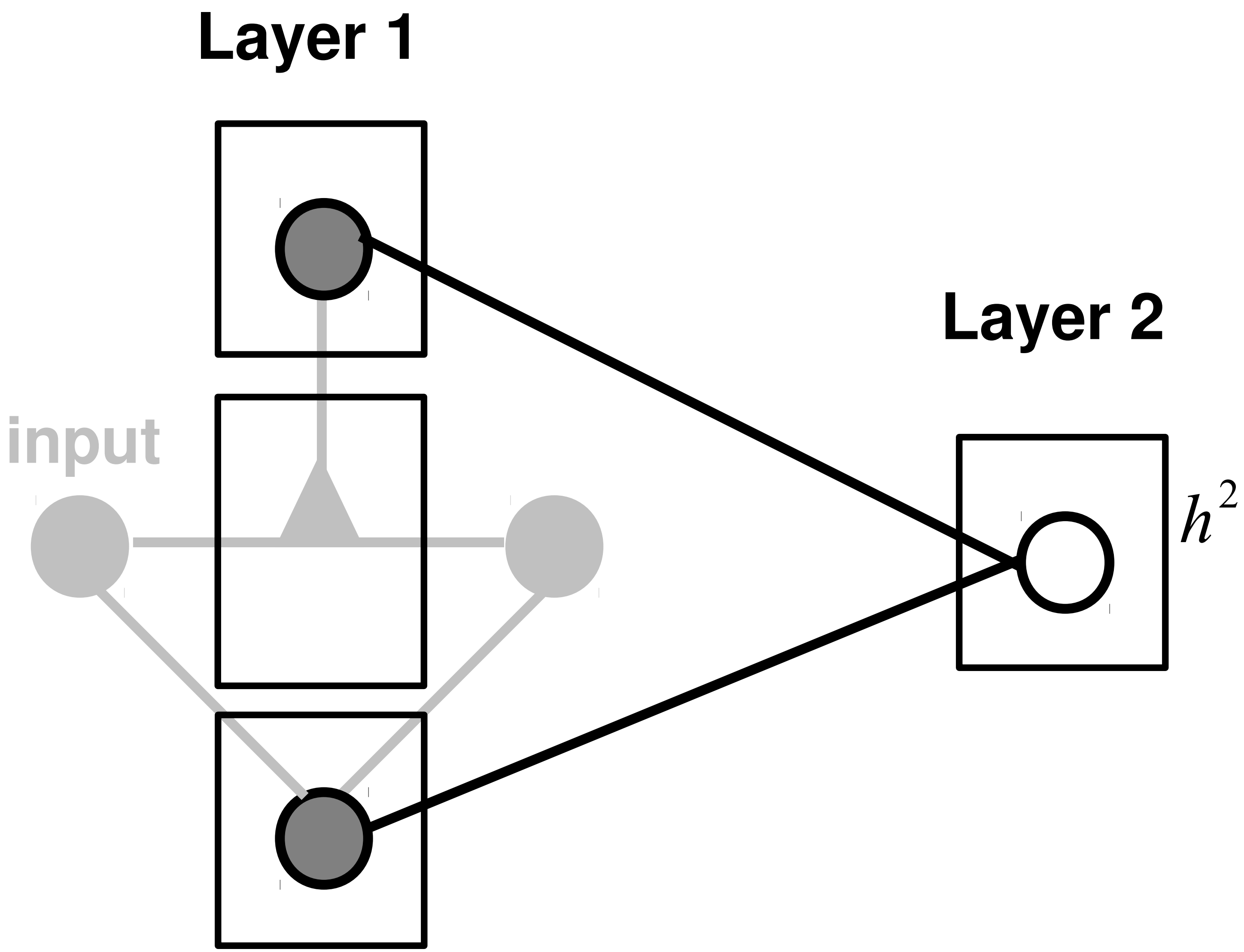
Training:
requires approximations
(here we used MCMC methods)

$$p(x) \alpha \int_{h^c} \int_{h^m} e^{-E(x, h^c, h^m)}$$



Ranzato et al. “Modeling natural images with gated MRFs” PAMI 2013

Deep Gated MRF



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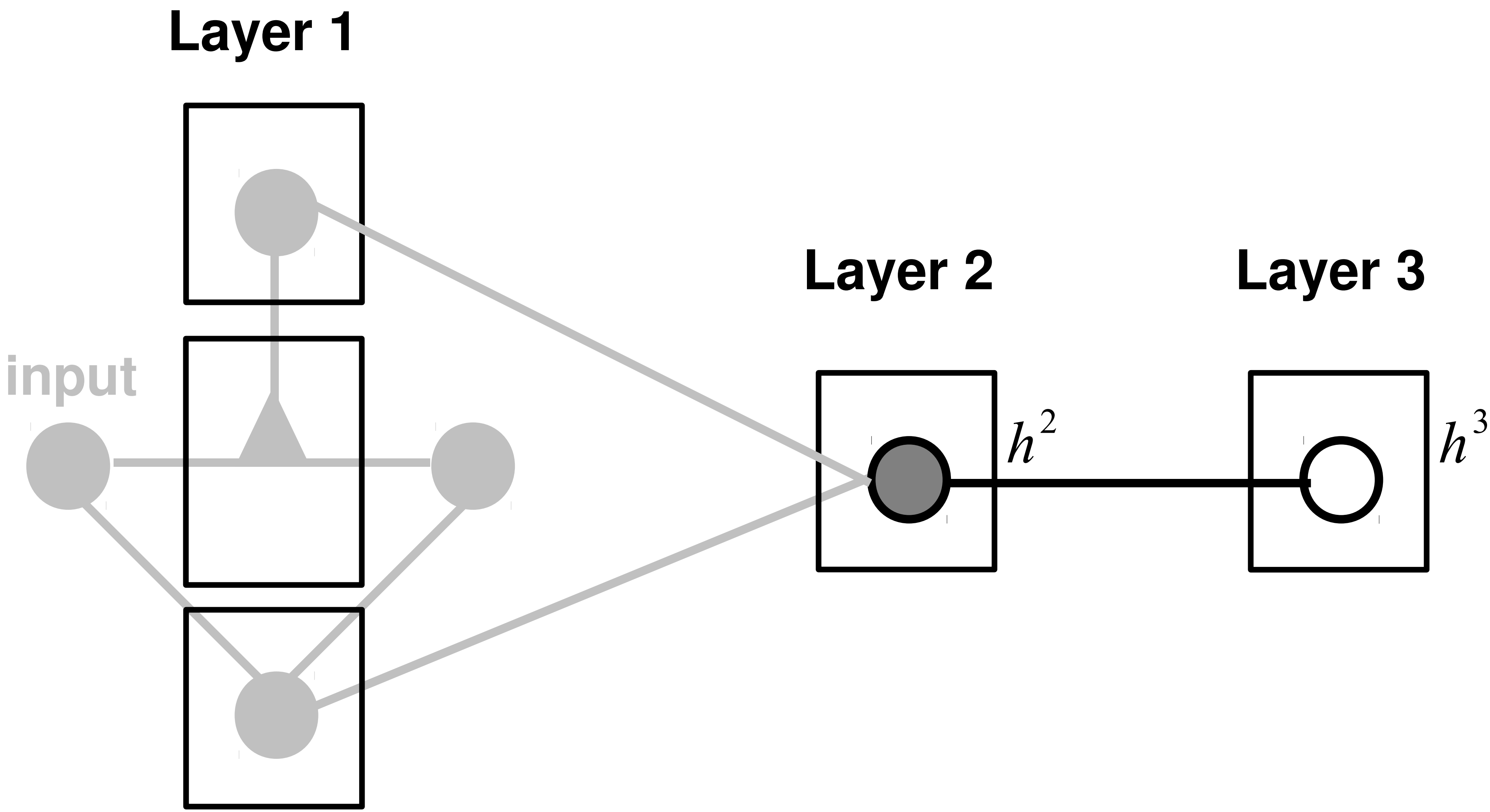
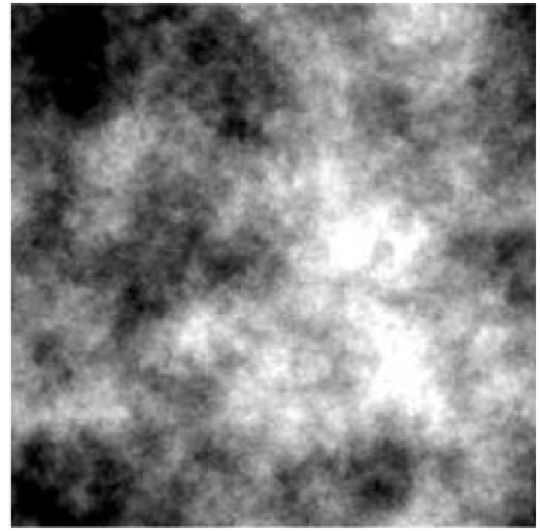
Deep Gated MRF



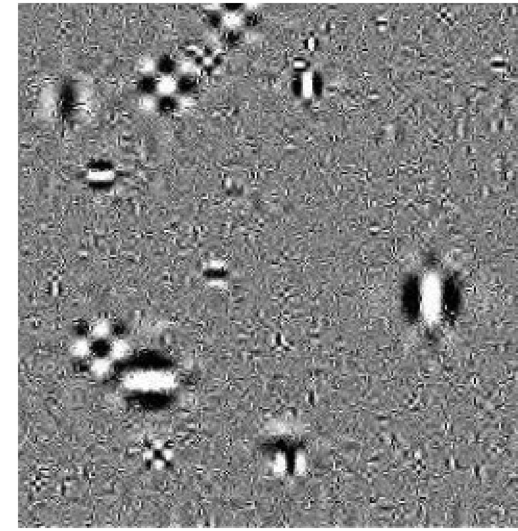
Ranzato et al. “Modeling natural images with gated MRFs” PAMI 2013

Sampling High-Resolution Images

Gaussian model

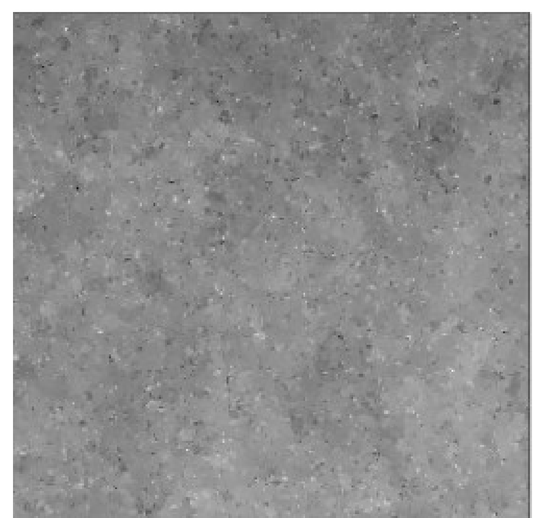


marginal wavelet

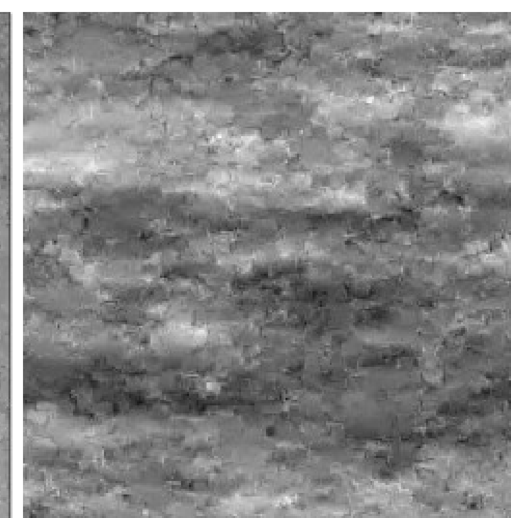


from Simoncelli 2005

Pair-wise MRF



FoE



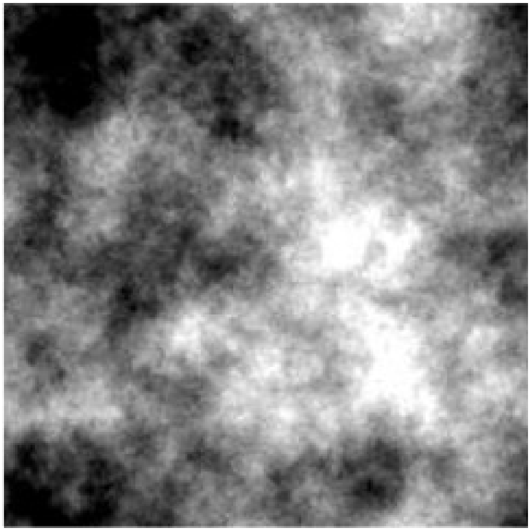
from Schmidt, Gao, Roth CVPR 2010

Sampling High-Resolution Images

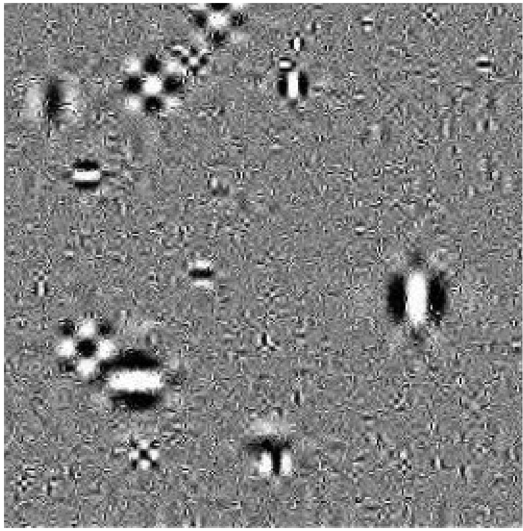
gMRF: **1 layer**

Ranzato et al. PAMI 2013

Gaussian model

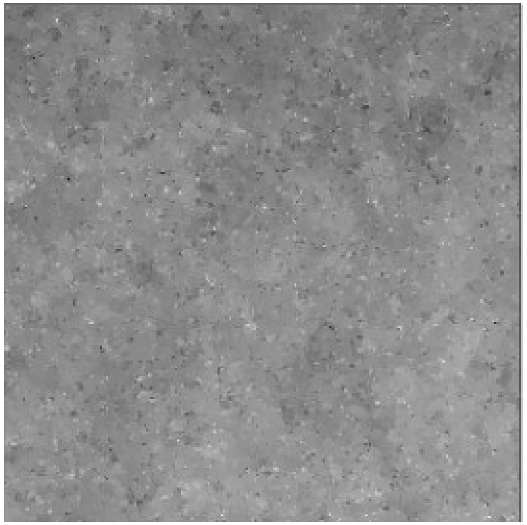


marginal wavelet



from Simoncelli 2005

Pair-wise MRF

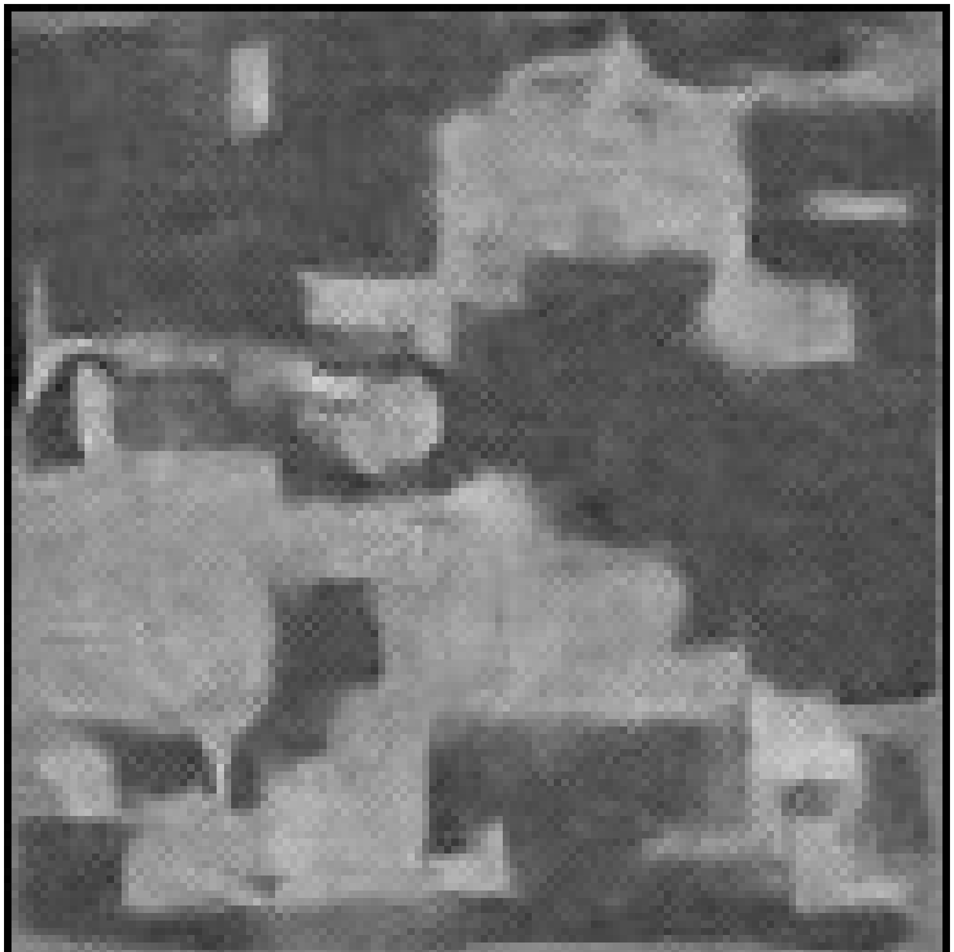


FoE

from Schmidt, Gao, Roth CVPR 2010

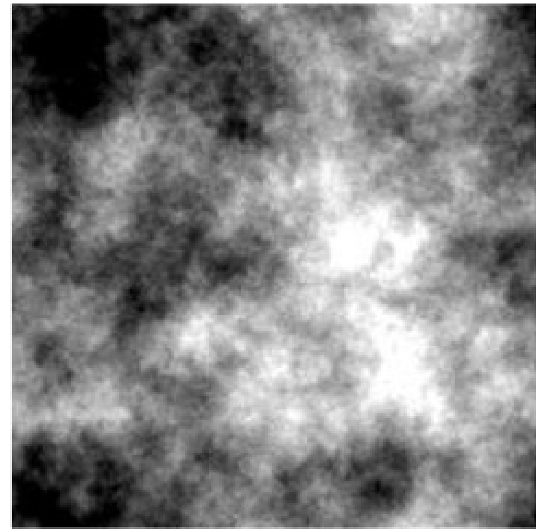
Sampling High-Resolution Images

gMRF: **1 layer**

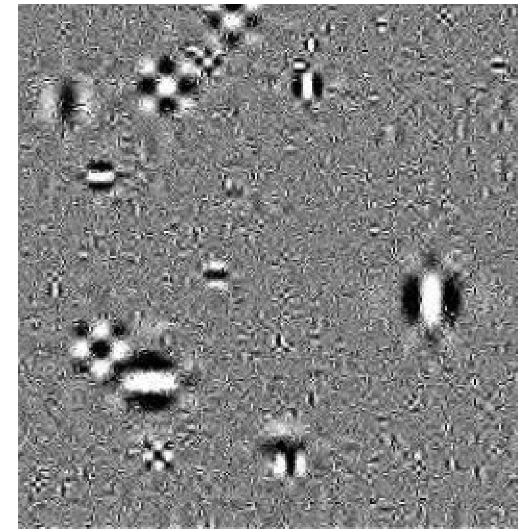


Ranzato et al. PAMI 2013

Gaussian model

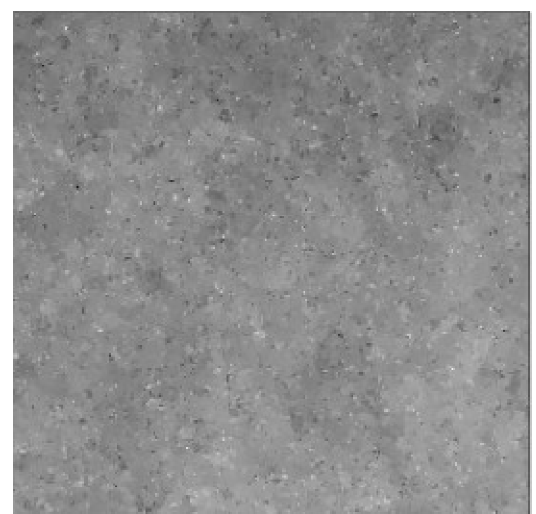


marginal wavelet

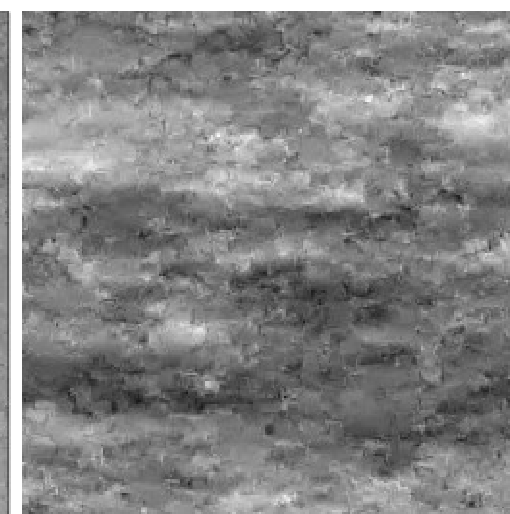


from Simoncelli 2005

Pair-wise MRF



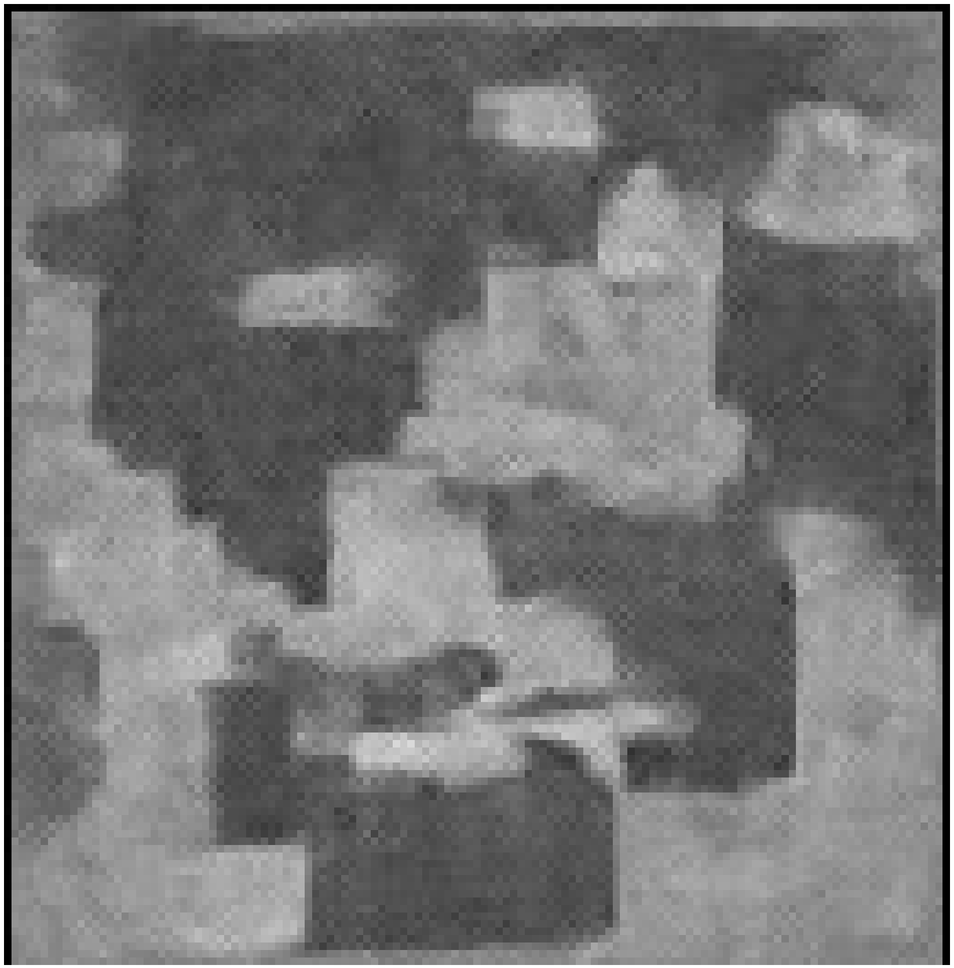
FoE



from Schmidt, Gao, Roth CVPR 2010

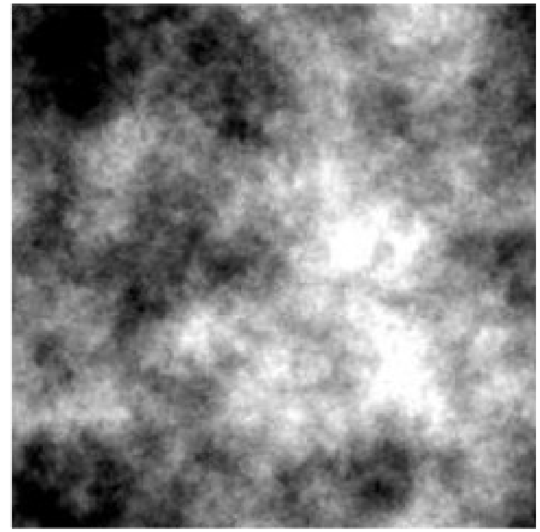
Sampling High-Resolution Images

gMRF: **1 layer**

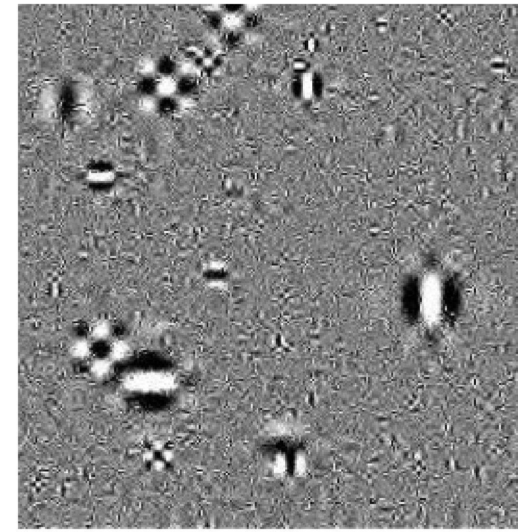


Ranzato et al. PAMI 2013

Gaussian model

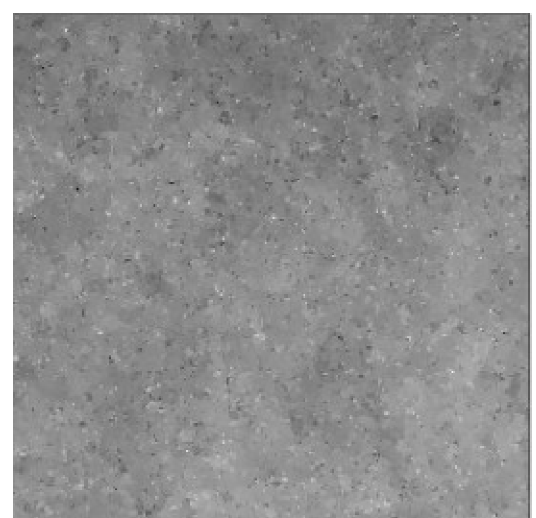


marginal wavelet

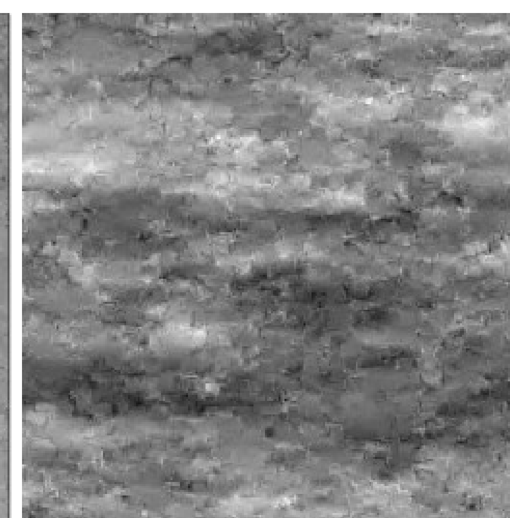


from Simoncelli 2005

Pair-wise MRF



FoE



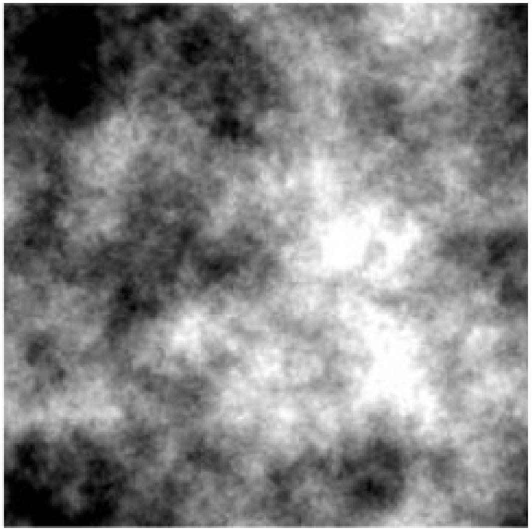
from Schmidt, Gao, Roth CVPR 2010

Sampling High-Resolution Images

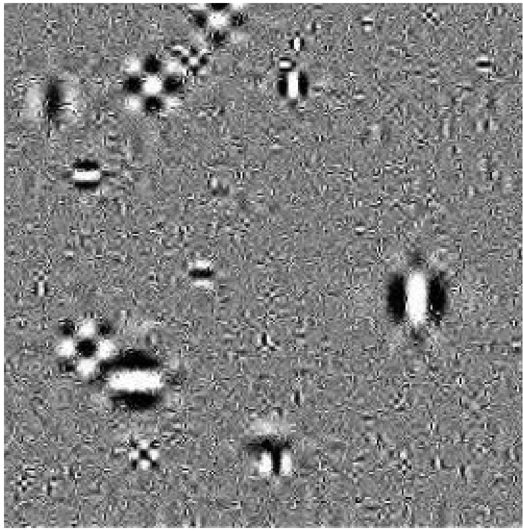
gMRF: **3 layers**

Ranzato et al. PAMI 2013

Gaussian model



marginal wavelet



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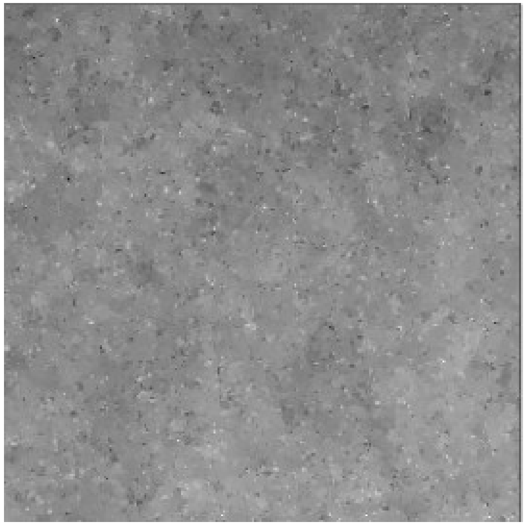
Pair-wise MRF

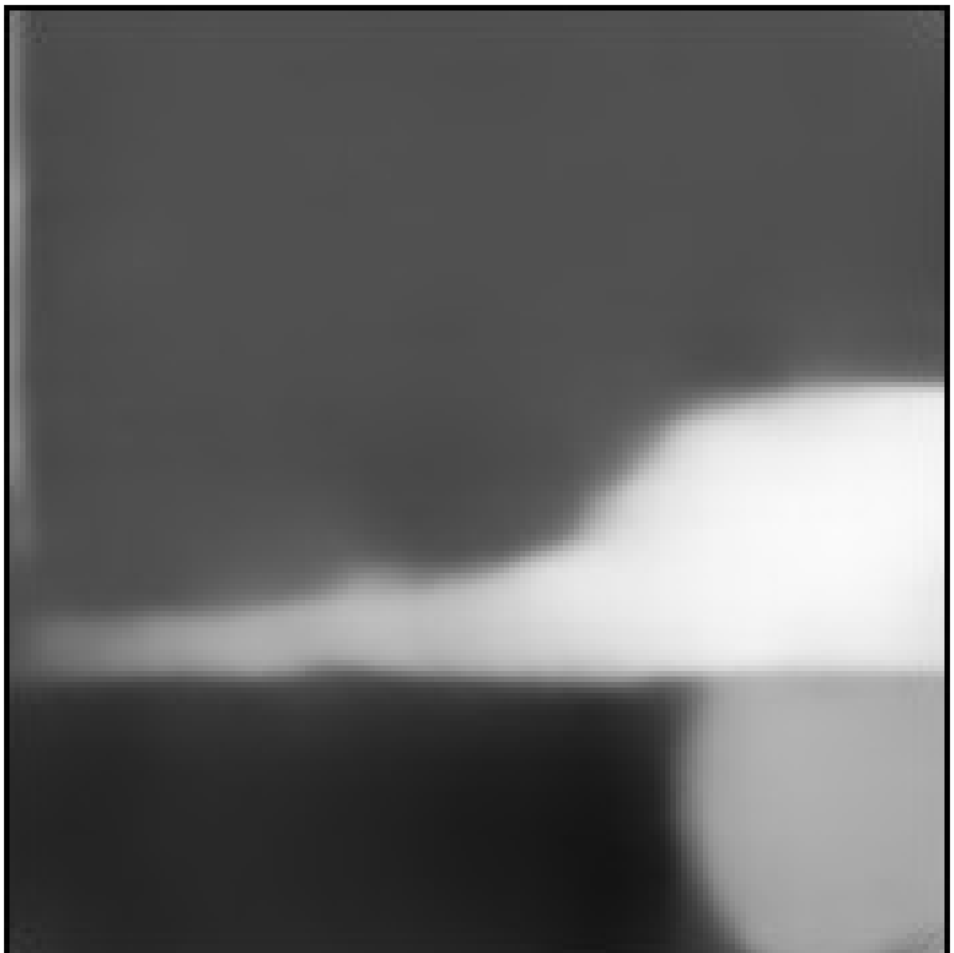


FoE

from Schmidt, Gao, Roth CVPR 2010

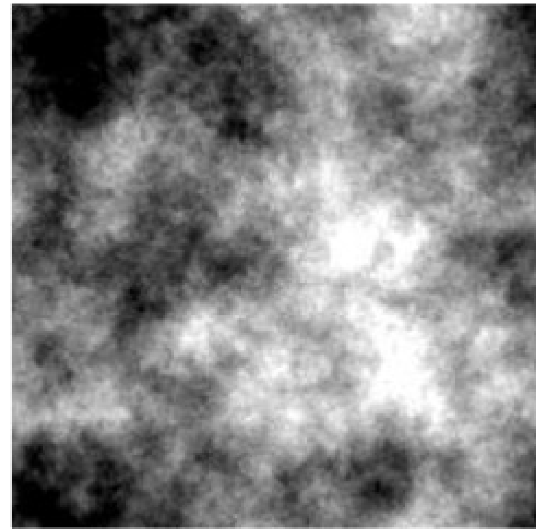
Sampling High-Resolution Images

gMRF: **3 layers**

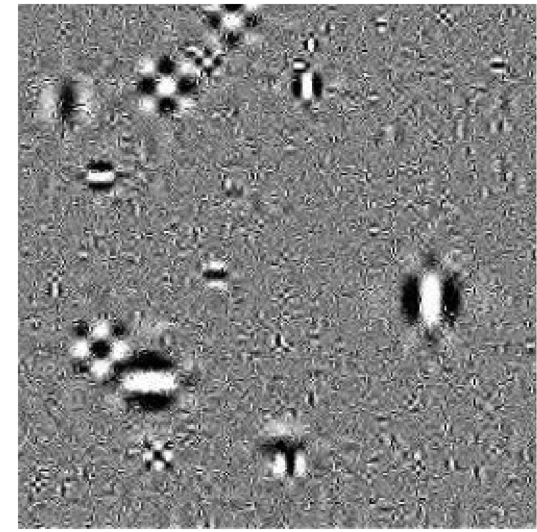


Ranzato et al. PAMI 2013

Gaussian model



marginal wavelet



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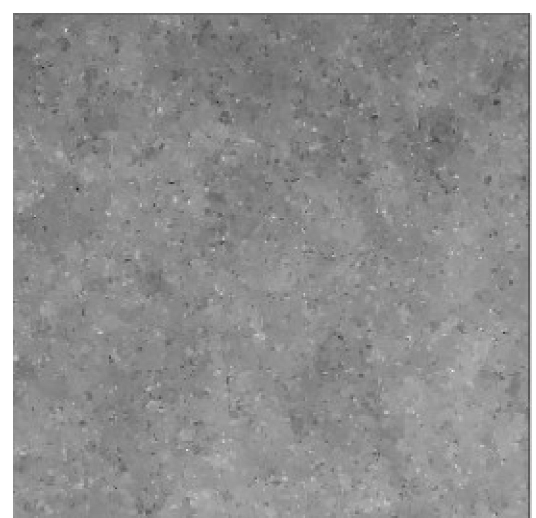
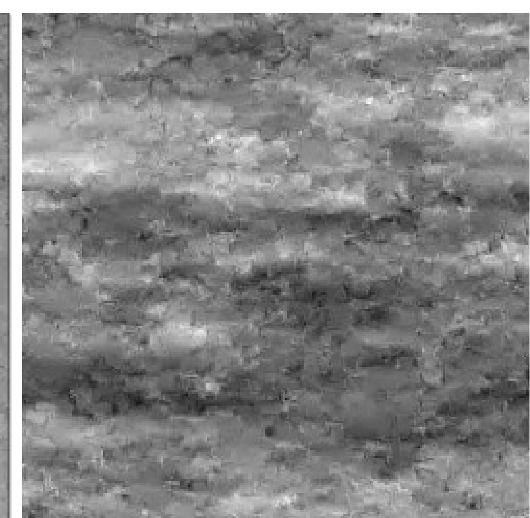


FoE



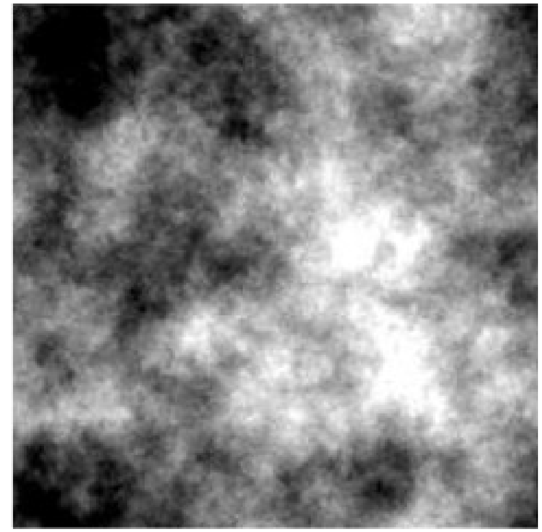
from Schmidt, Gao, Roth CVPR 2010

Sampling High-Resolution Images

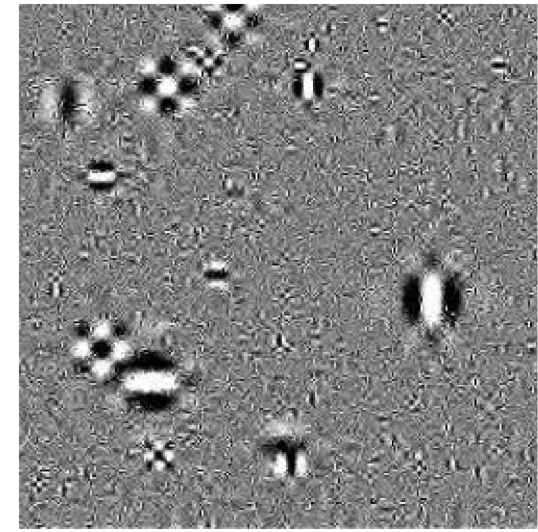
gMRF: **3 layers**

Ranzato et al. PAMI 2013

Gaussian model

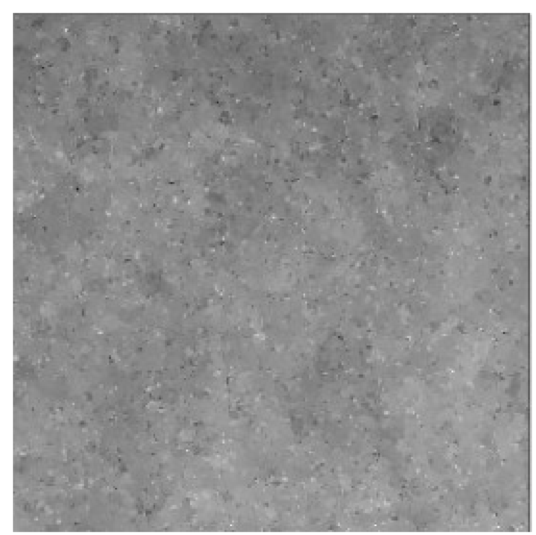


marginal wavelet

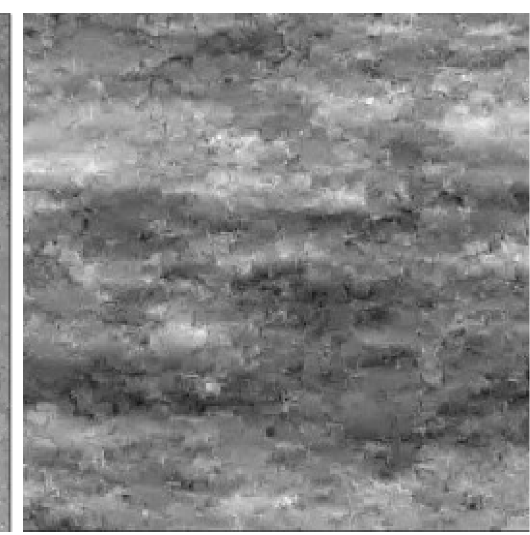


from Simoncelli 2005

Pair-wise MRF



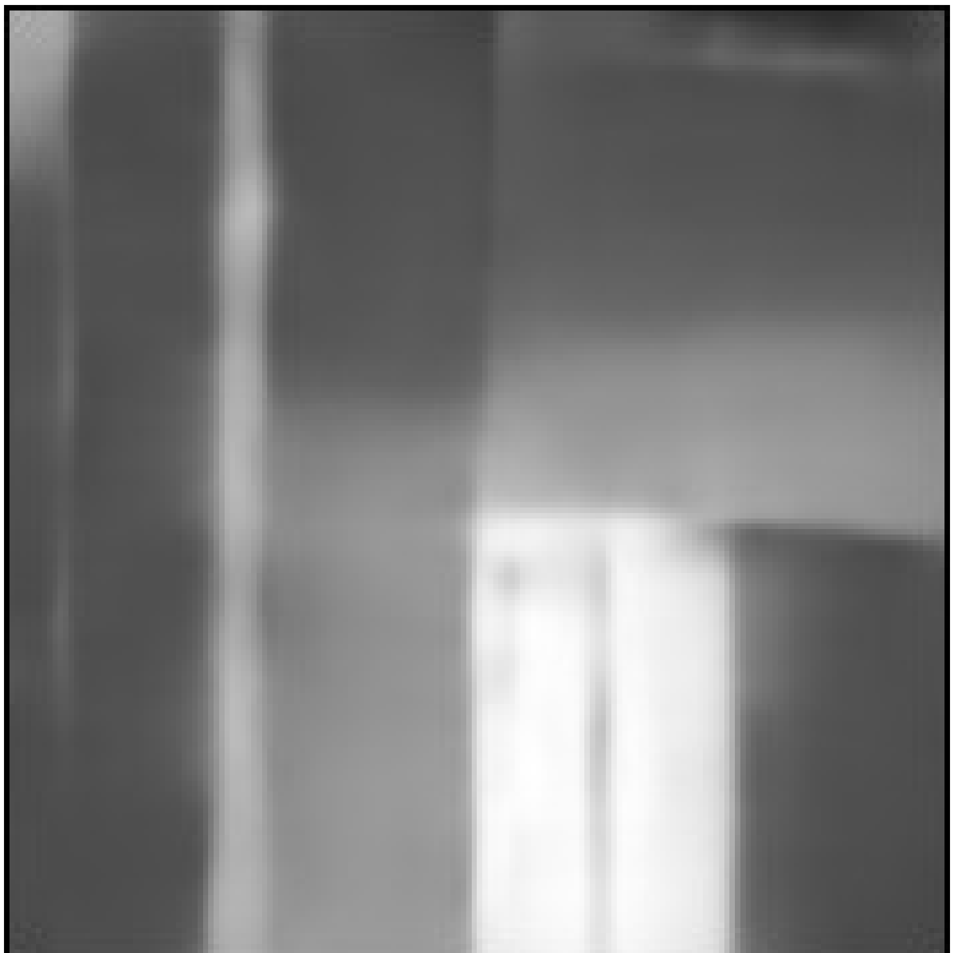
FoE



from Schmidt, Gao, Roth CVPR 2010

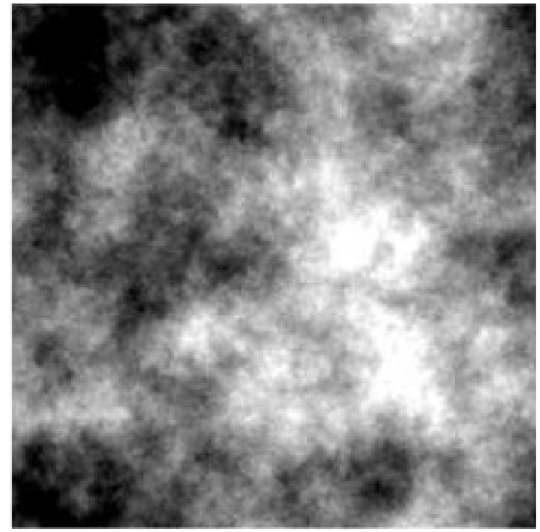
Sampling High-Resolution Images

gMRF: **3 layers**

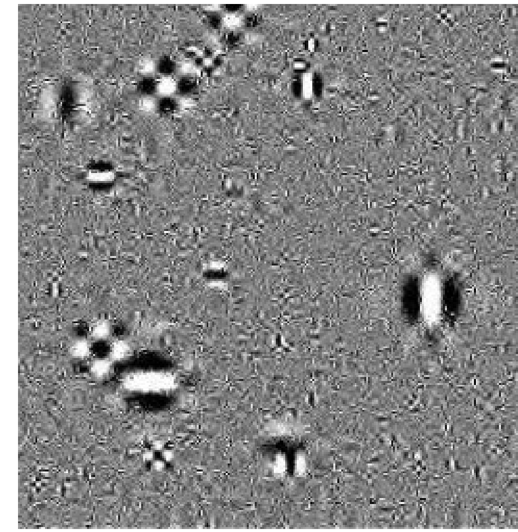


Ranzato et al. PAMI 2013

Gaussian model



marginal wavelet



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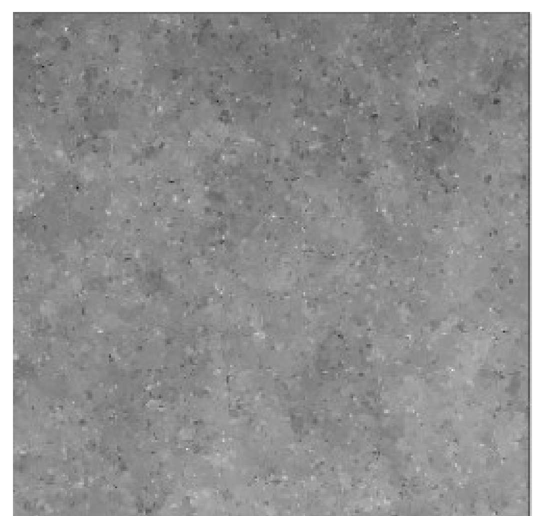
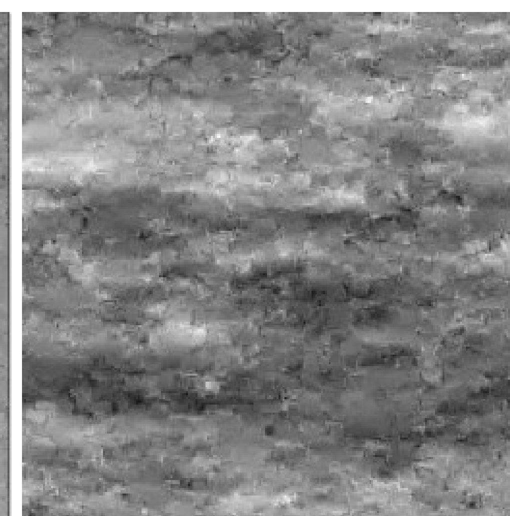
Pair-wise MRF



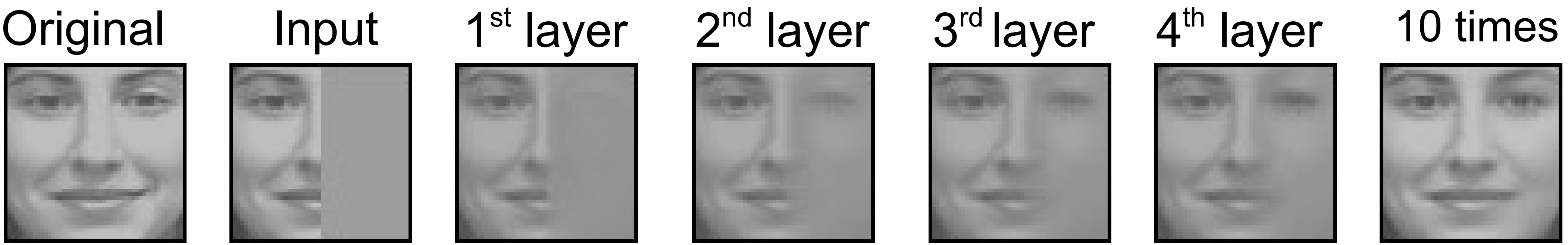
FoE



from Schmidt, Gao, Roth CVPR 2010

Sampling After Training on Face Images

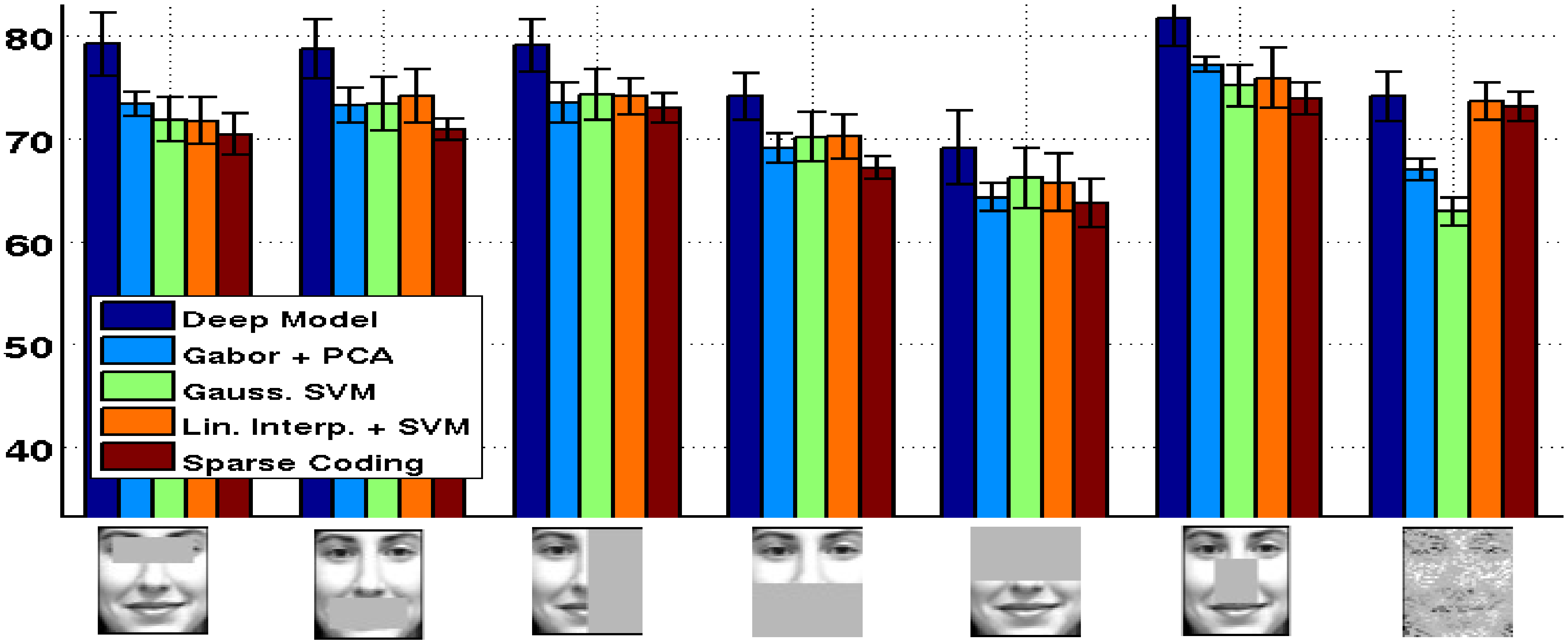
unconstrained samples



conditional (on the left part of the face) samples

Ranzato et al. PAMI 2013

Expression Recognition Under Occlusion



Ranzato et al. PAMI 2013

Pros

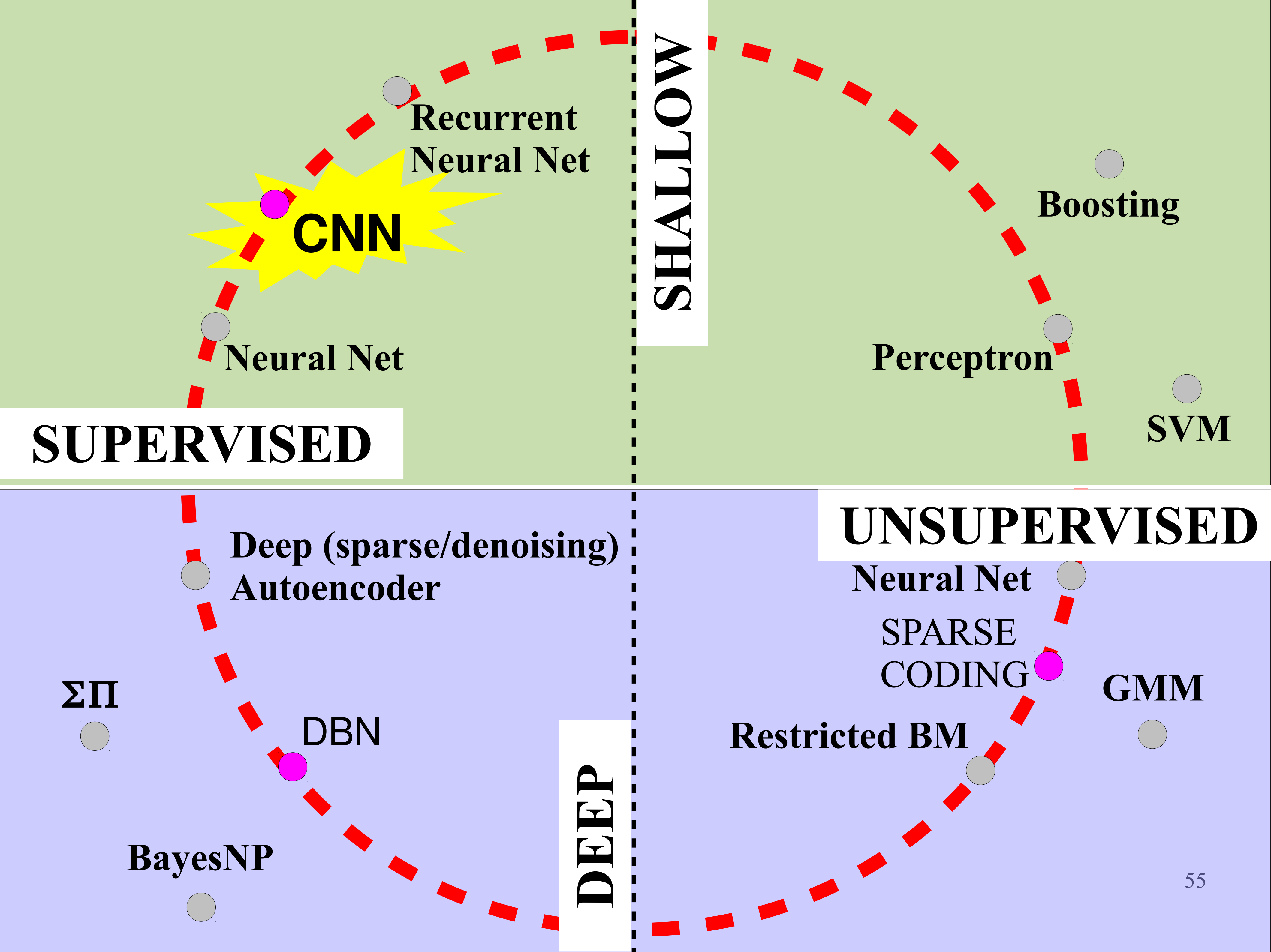
- Feature extraction is fast
- Unprecedented generation quality
- Advances models of natural images
- Trains without labeled data

Cons

- Training is inefficient
  - Slow
  - Tricky
- Sampling scales badly with dimensionality
- What's the use case of generative models?

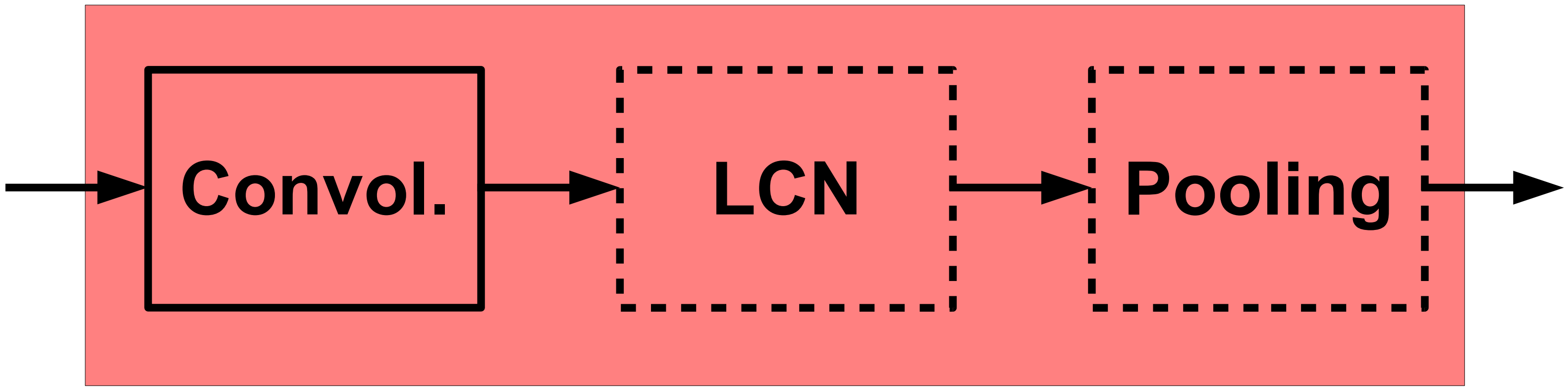
Conclusion

- If generation is not required, other feature learning methods are more efficient (e.g., sparse auto-encoders).
- What's the use case of generative models?

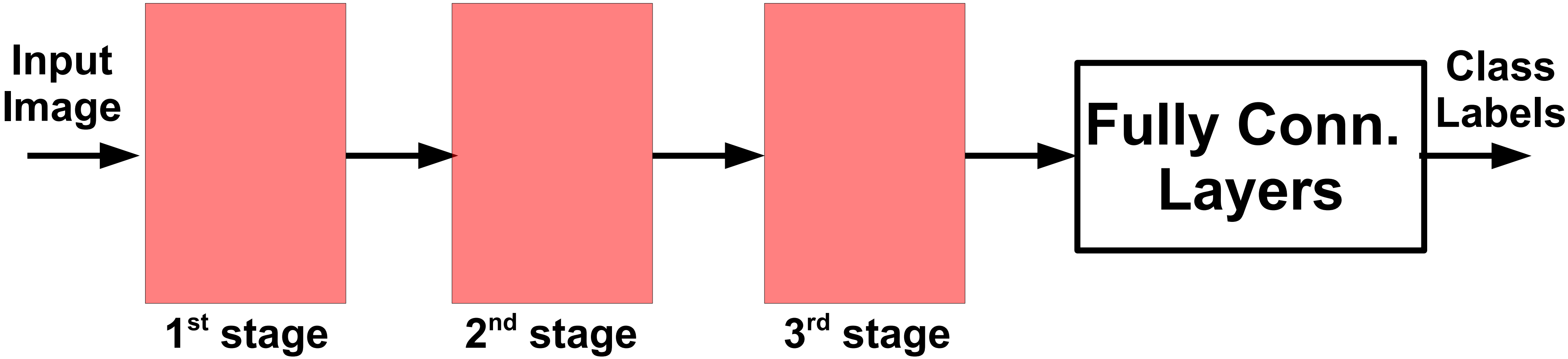

SHALLOW
Recurrent
Neural Net
CNN
Neural Net
SUPERVISED
Boosting
Perceptron
SVM
UNSUPERVISED
Deep (sparse/denoising)
Autoencoder
ΣΠ
DBN
BayesNP
DEEP
Neural Net
SPARSE
CODING
GMM
Restricted BM

CONV NETS: TYPICAL ARCHITECTURE

One stage (zoom)

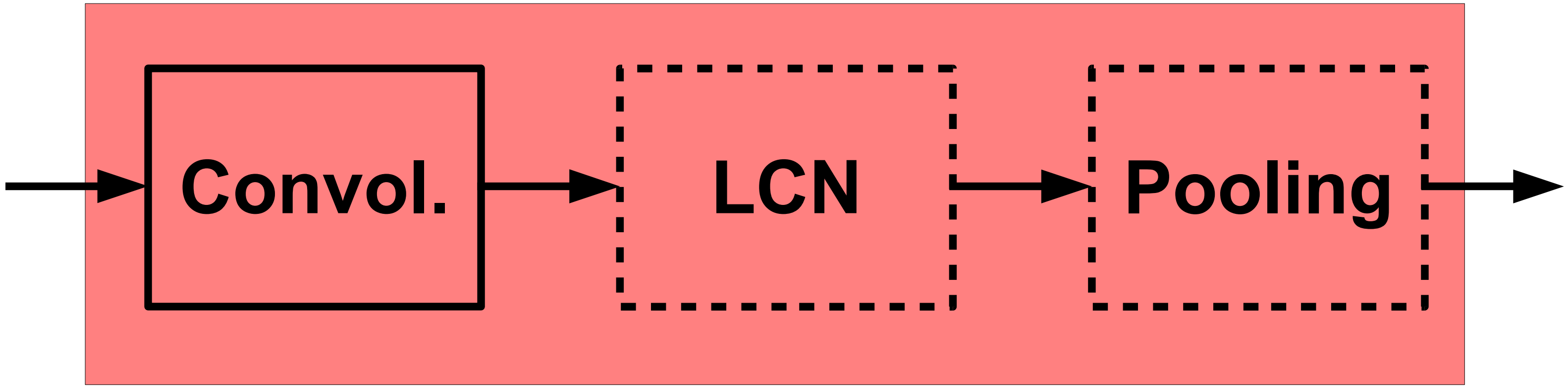


Whole system



CONV NETS: TYPICAL ARCHITECTURE

One stage (zoom)



Conceptually similar to:

SIFT → K-Means → Pyramid Pooling → SVM

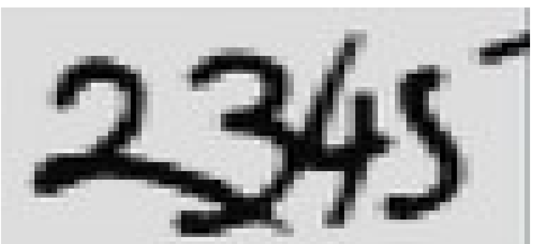
Lazebnik et al. “...Spatial Pyramid Matching...” CVPR 2006

SIFT → Fisher Vect. → Pooling → SVM

Sanchez et al. “Image classifcation with F.V.: Theory and practice” IJCV 2012

CONV NETS: EXAMPLES

- **OCR / House number & Traffic sign classification**

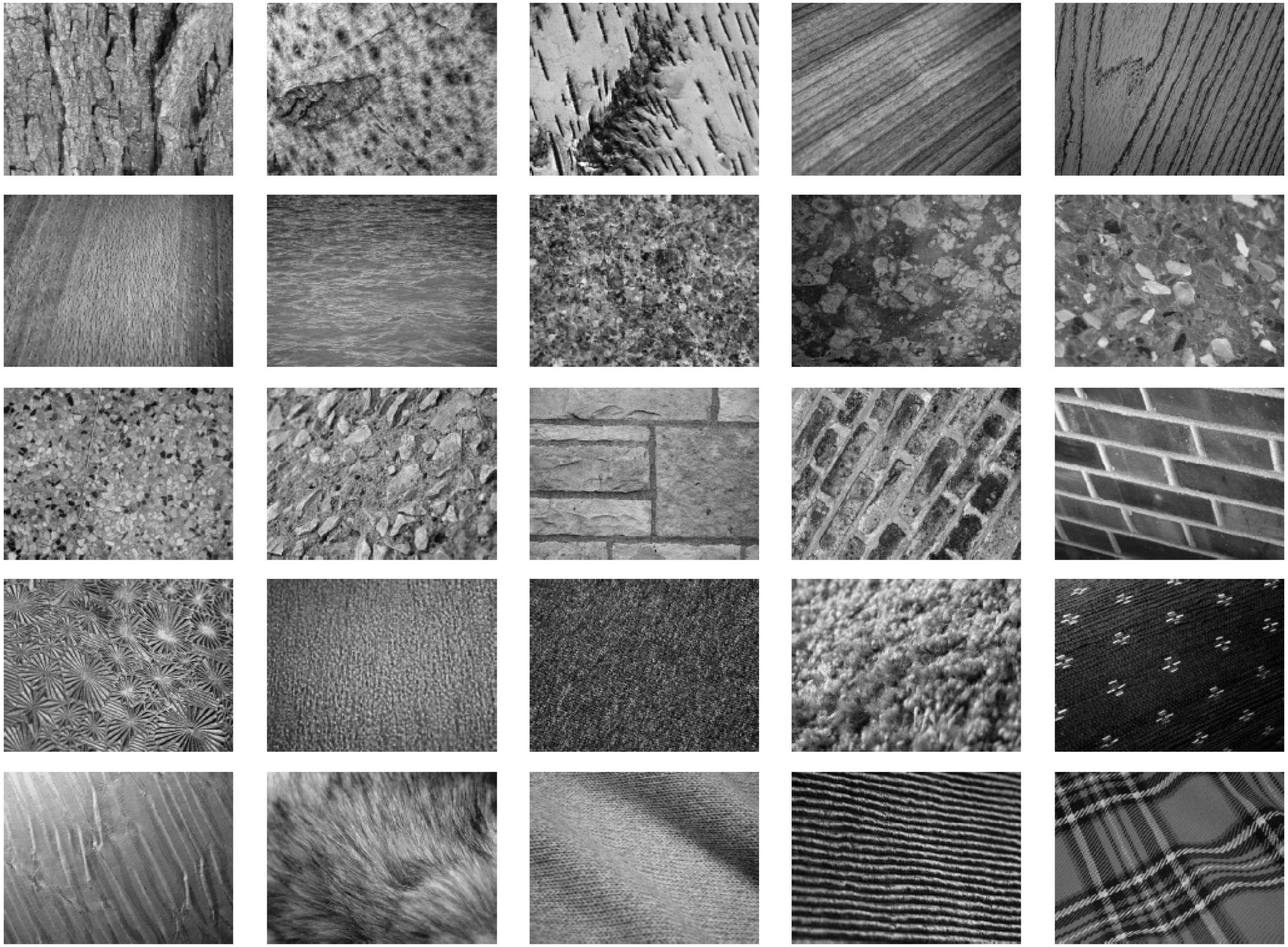


Ciresan et al. “MCDNN for image classification” CVPR 2012

Wan et al. “Regularization of neural networks using dropconnect” ICML 2013

CONV NETS: EXAMPLES

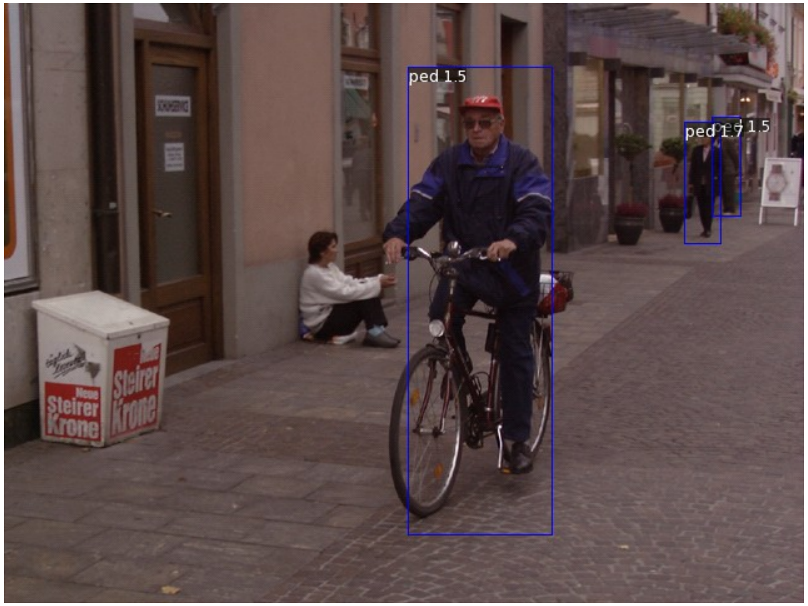
- **Texture classification**

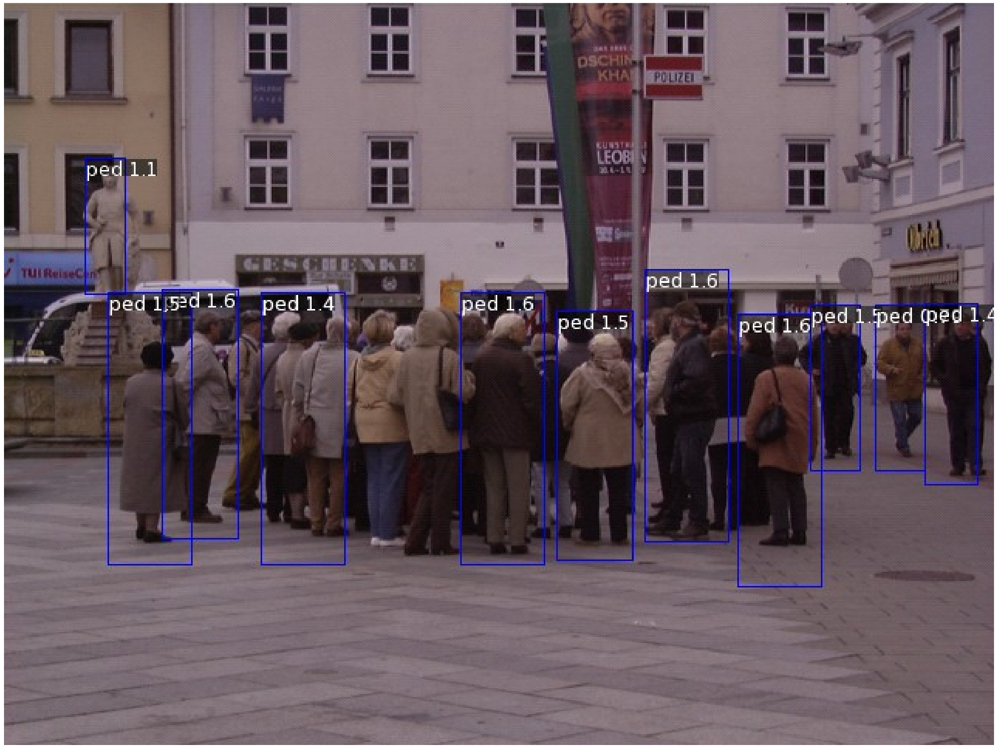


Sifre et al. “Rotation, scaling and deformation invariant scattering...” CVPR 2013

CONV NETS: EXAMPLES

- **Pedestrian detection**

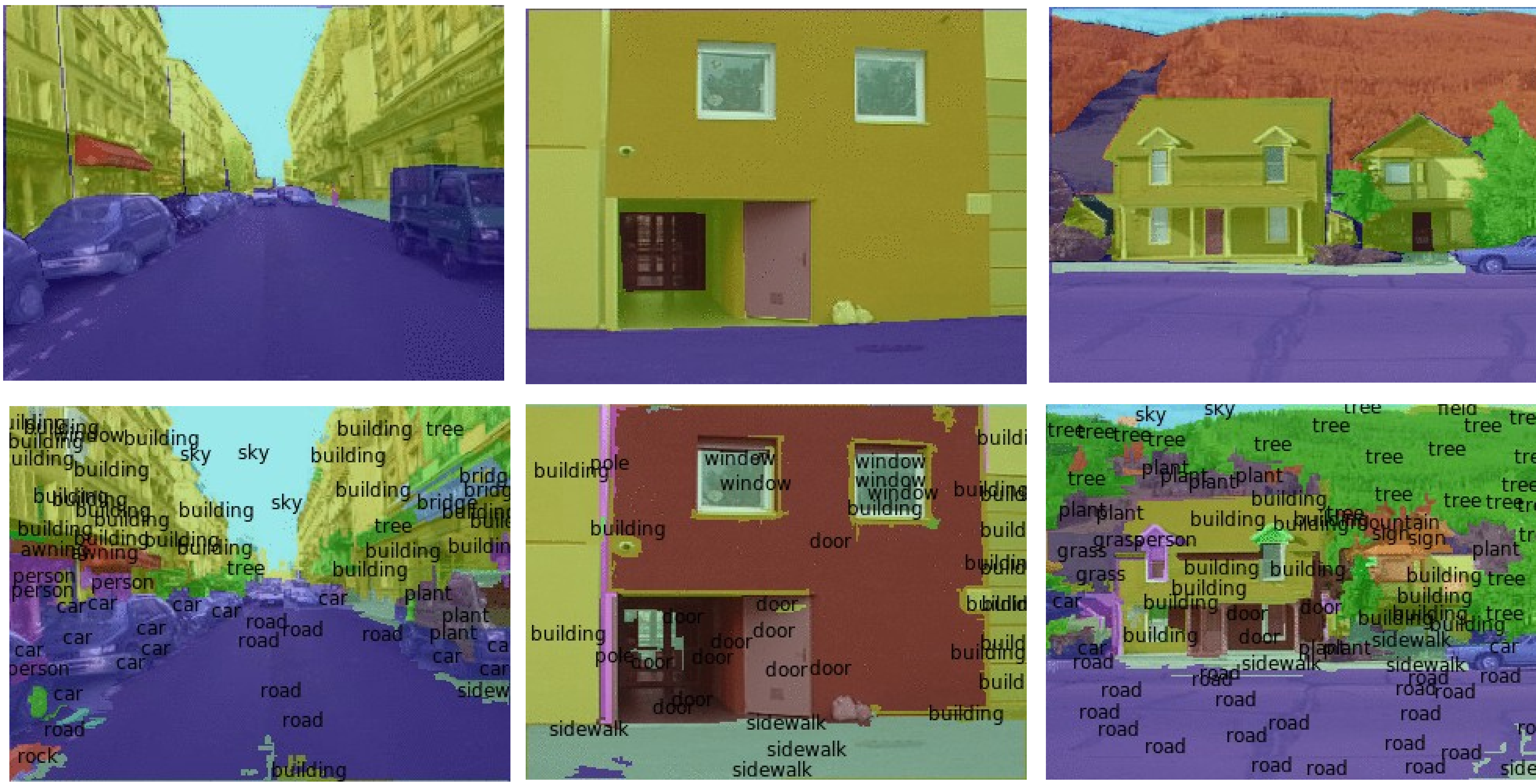




Sermanet et al. “Pedestrian detection with unsupervised multi-stage..” CVPR 2013

CONV NETS: EXAMPLES

- **Scene Parsing**



Farabet et al. “Learning hierarchical features for scene labeling” PAMI 2013

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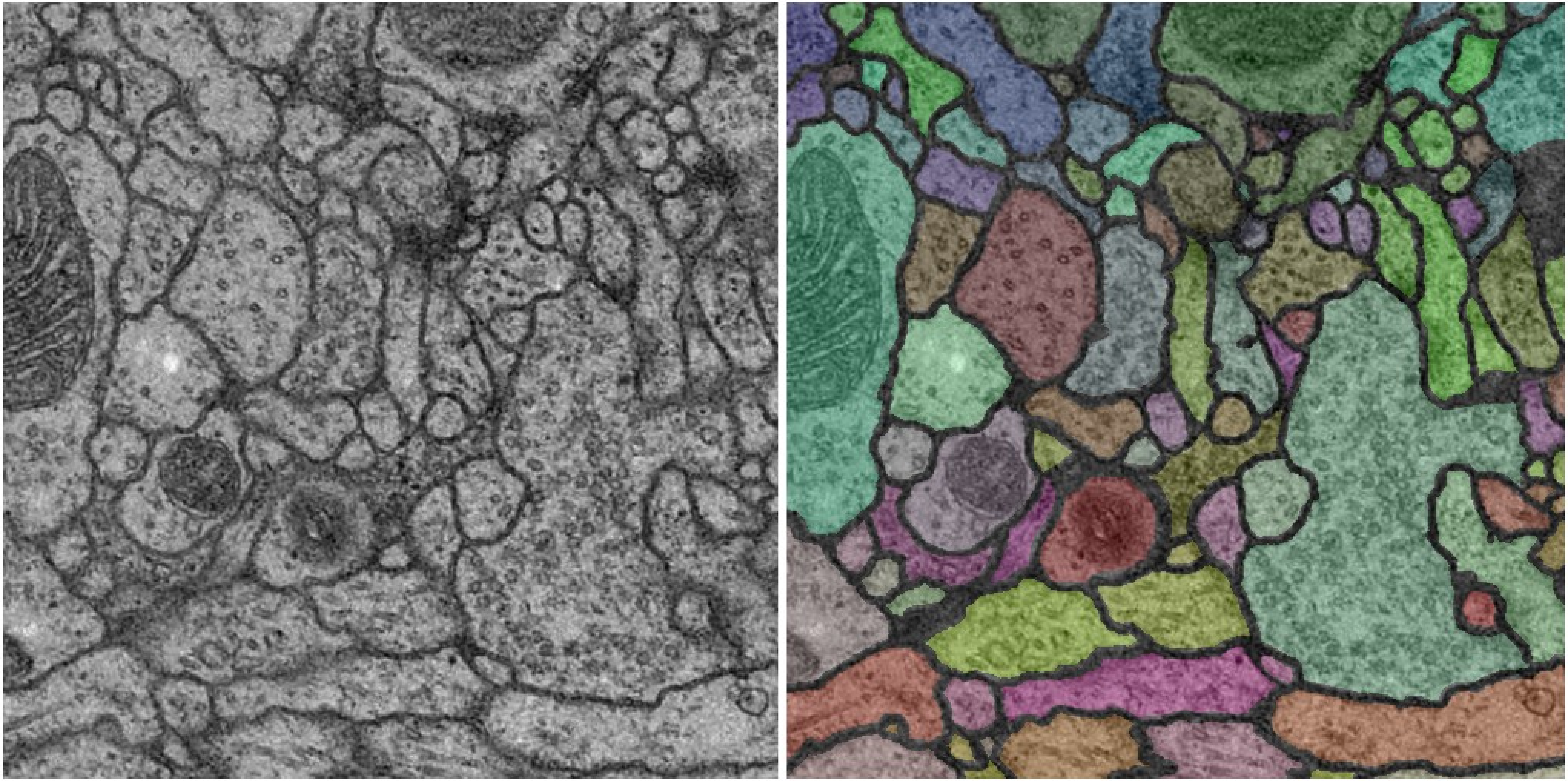
CONV NETS: EXAMPLES

- **Segmentation 3D volumetric images**



Ciresan et al. “DNN segment neuronal membranes...” NIPS 2012
Turaga et al. “Maximin learning of image segmentation” NIPS 2009

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CONV NETS: EXAMPLES

- **Action recognition from videos**

Taylor et al. “Convolutional learning of spatio-temporal features” ECCV 2010

CONV NETS: EXAMPLES

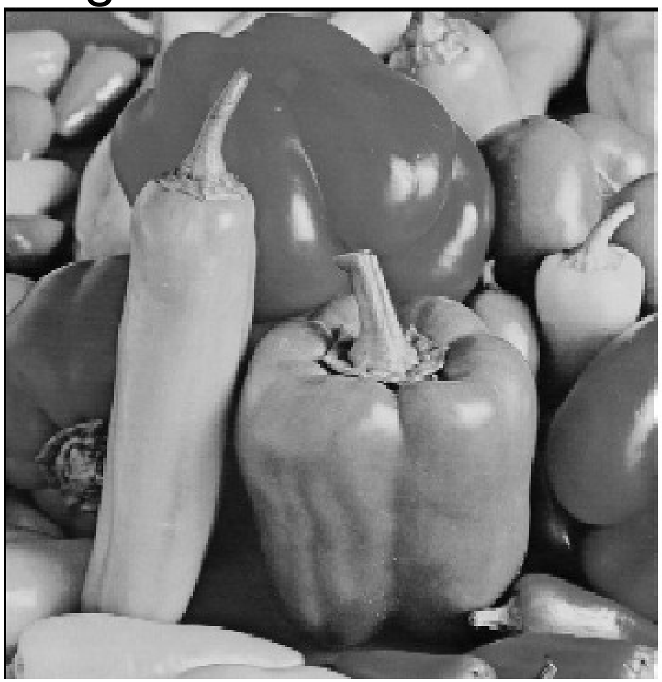
- **Robotics**

Sermanet et al. “Mapping and planning ...with long range perception” IROS 2008

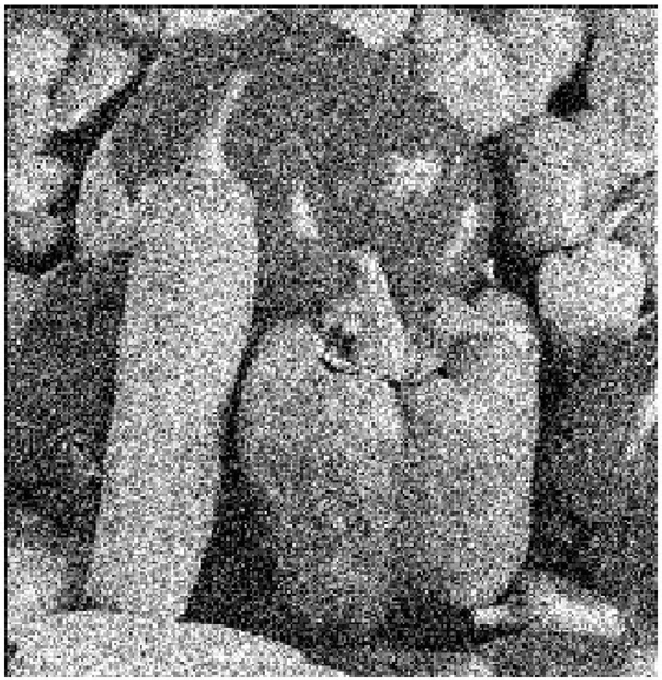
CONV NETS: EXAMPLES

- **Denoising**

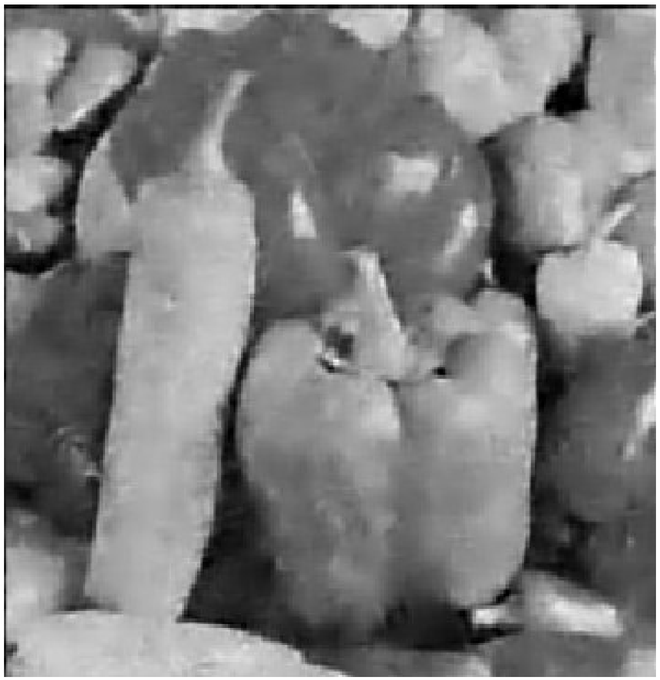
original



noised



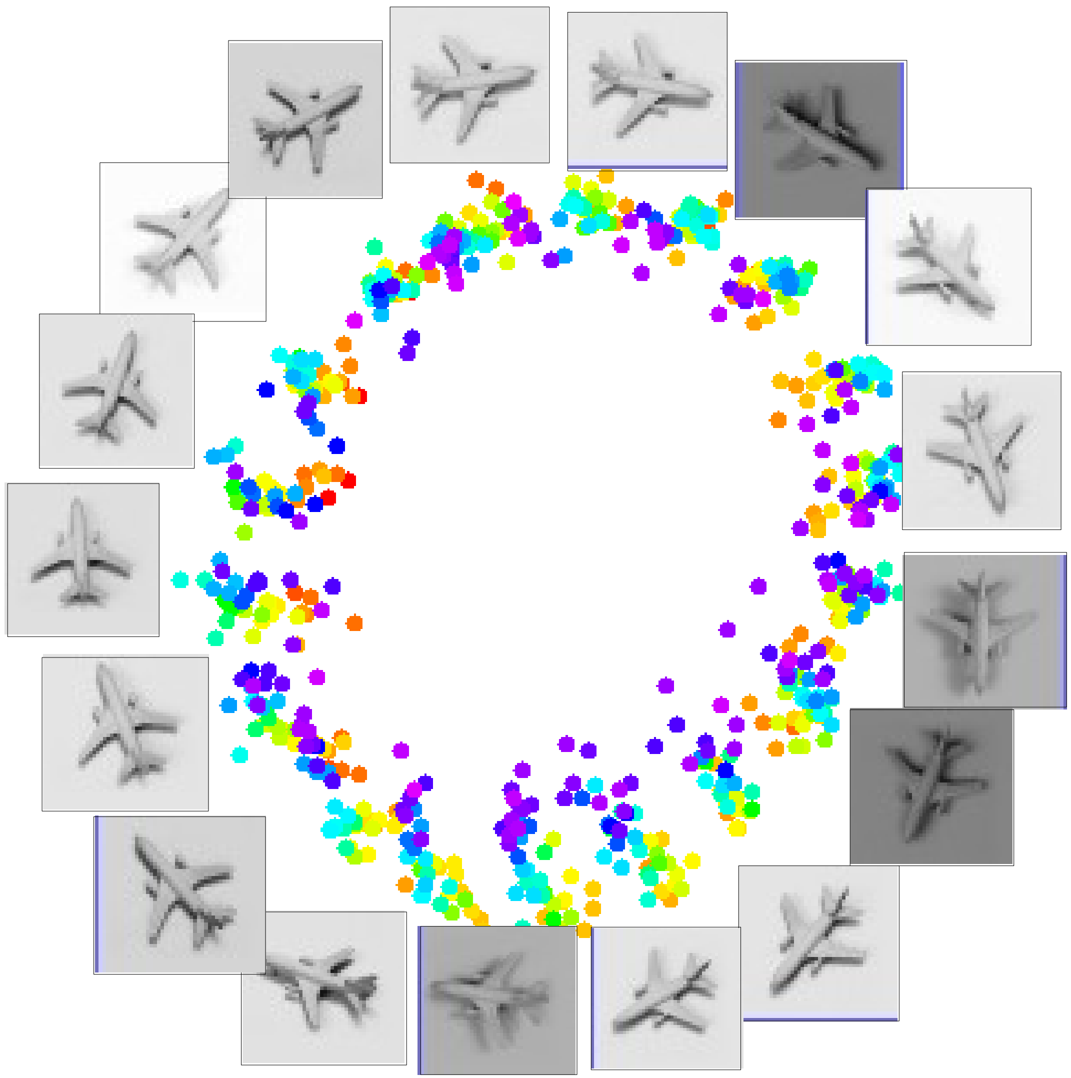
denoised



Burger et al. “Can plain NNs compete with BM3D?” CVPR 2012

CONV NETS: EXAMPLES

- **Dimensionality reduction / learning embeddings**

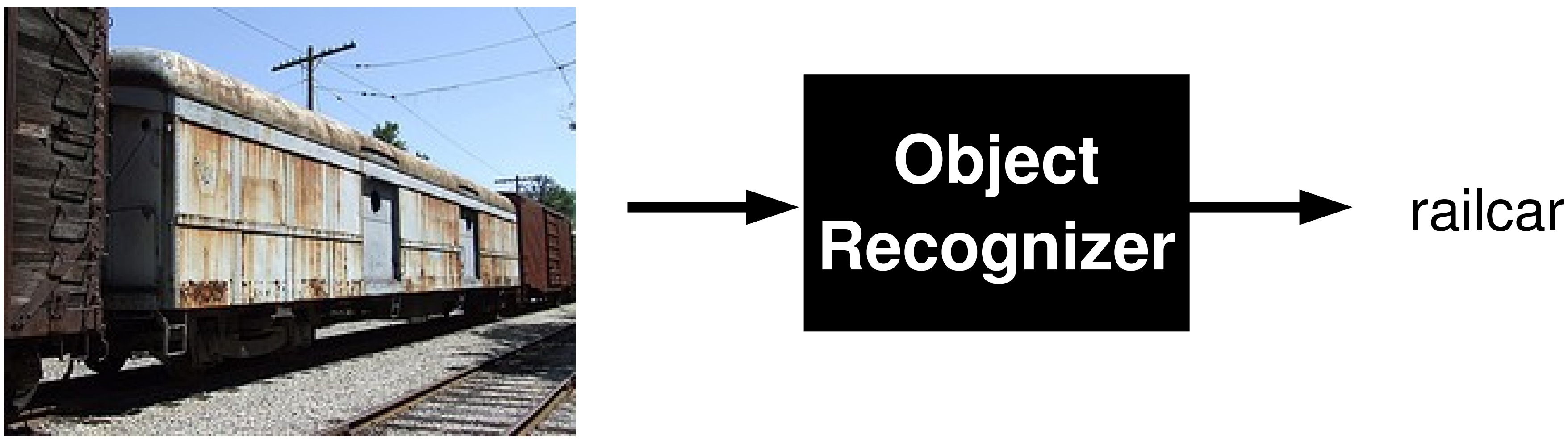


Hadsell et al. “Dimensionality reduction by learning an invariant mapping” CVPR 2006

CONV NETS: EXAMPLES

- **Image classification**

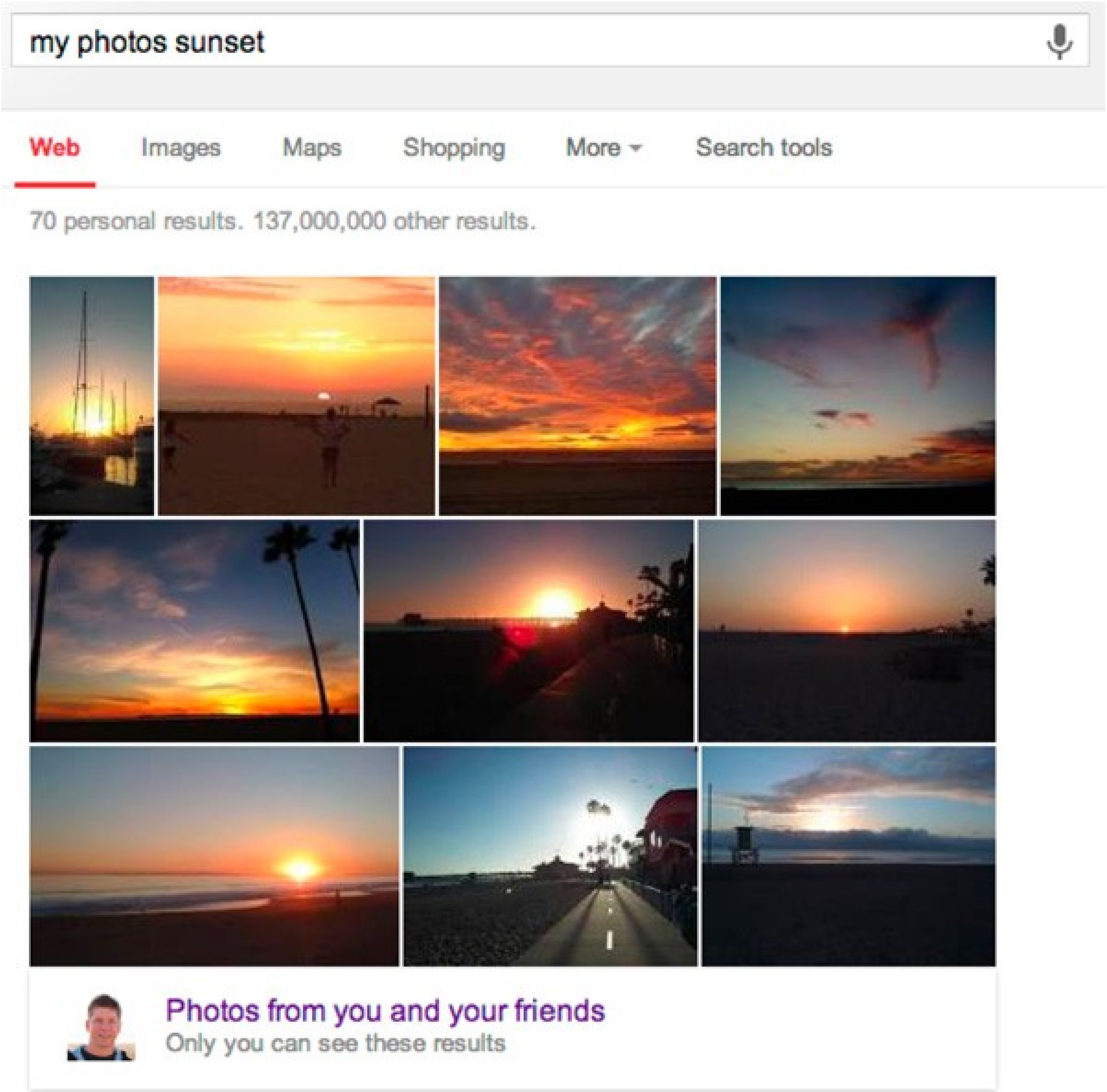
IMAGENET



Krizhevsky et al. "ImageNet Classification with deep CNNs" NIPS 2012

CONV NETS: EXAMPLES

- **Deployed in commercial systems (Google & Baidu, spring 2013)**



How To Use ConvNets...(properly)

CHOOSING THE ARCHITECTURE

- Task dependent

- Cross-validation

- [Convolution $\rightarrow$ LCN $\rightarrow$ pooling]* + fully connected layer

- The more data: the more layers and the more kernels
  - Look at the number of parameters at each layer
  - Look at the number of flops at each layer

- Computational cost

- Be creative :)

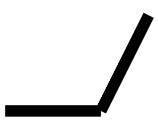
HOW TO OPTIMIZE

- SGD (with momentum) usually works very well

- Pick learning rate by running on a subset of the data

  Bottou “Stochastic Gradient Tricks” Neural Networks 2012

  - Start with large learning rate and divide by 2 until loss does not diverge
  - Decay learning rate by a factor of ~100 or more by the end of training

- Use  non-linearity

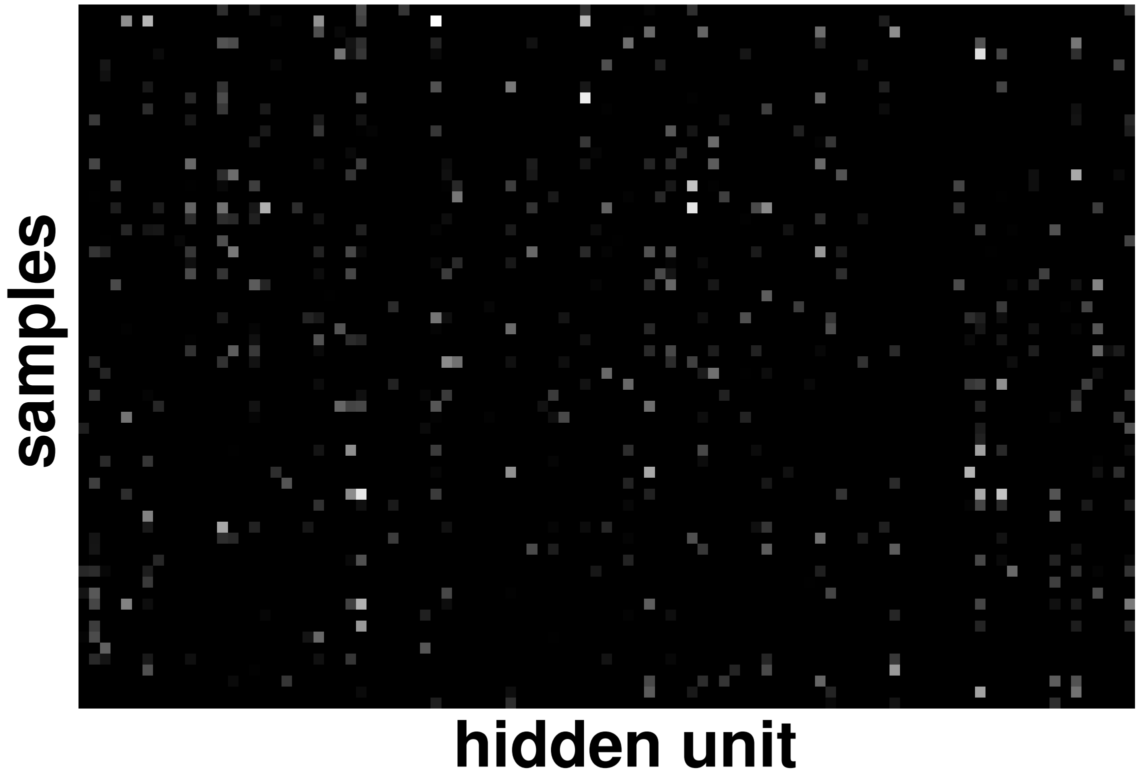
- Initialize parameters so that each feature across layers has similar variance. Avoid units in saturation.

HOW TO IMPROVE GENERALIZATION

- Weight sharing (greatly reduce the number of parameters)
- Data augmentation (e.g., jittering, noise injection, etc.)
- Dropout
  Hinton et al. "Improving Nns by preventing co-adaptation of feature detectors" arxiv 2012
- Weight decay (L2, L1)
- Sparsity in the hidden units
- Multi-task (unsupervised learning)

OTHER THINGS GOOD TO KNOW

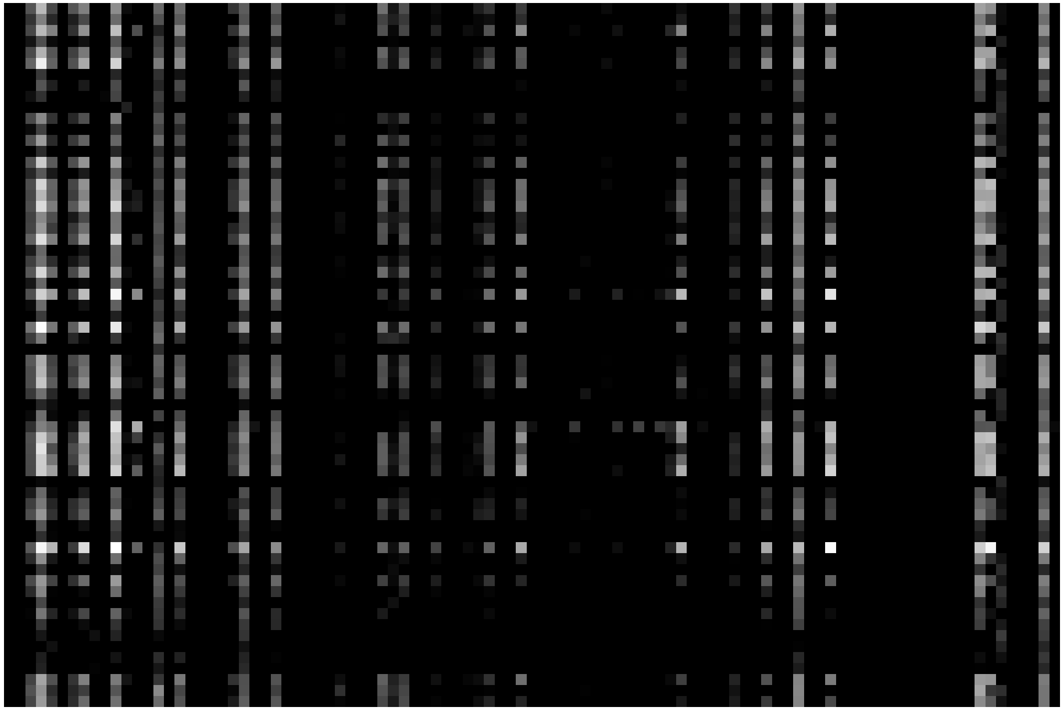
- Check gradients numerically by finite differences
- Visualize features (feature maps need to be uncorrelated) and have high variance.



Good training: hidden units are sparse across samples and across features.

OTHER THINGS GOOD TO KNOW

- Check gradients numerically by finite differences
- Visualize features (feature maps need to be uncorrelated) and have high variance.

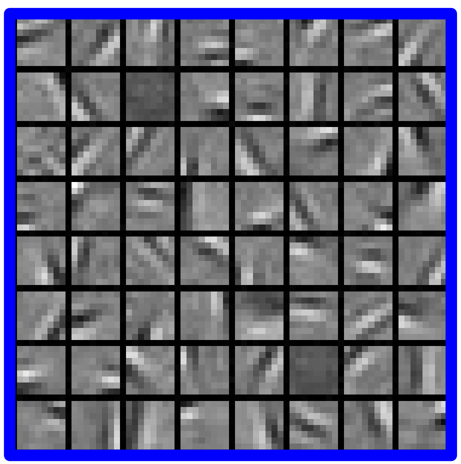


Bad training: many hidden units ignore the input and/or exhibit strong correlations.

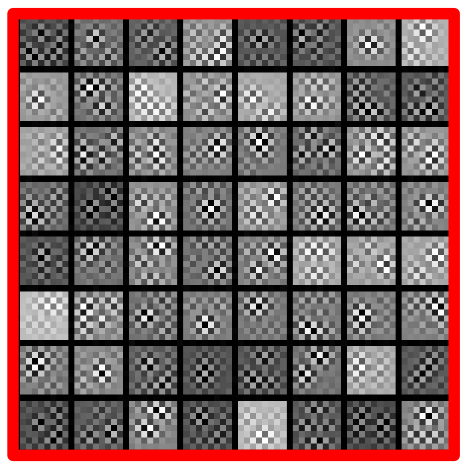
OTHER THINGS GOOD TO KNOW

- Check gradients numerically by finite differences
- Visualize features (feature maps need to be uncorrelated) and have high variance.
- Visualize parameters

GOOD

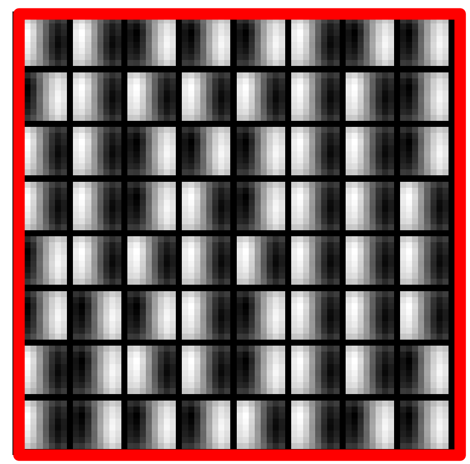


BAD



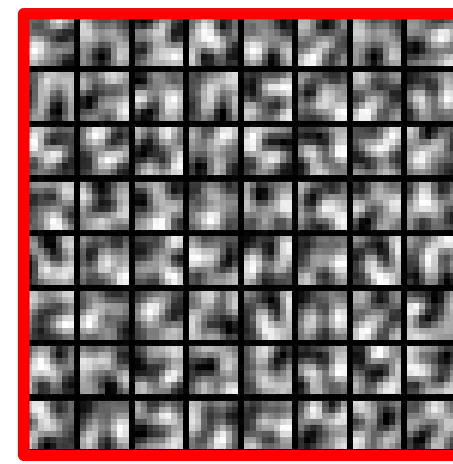
too noisy

BAD



too correlated

BAD



lack structure

Good training: learned filters exhibit structure and are uncorrelated.

OTHER THINGS GOOD TO KNOW

- Check gradients numerically by finite differences
- Visualize features (feature maps need to be uncorrelated) and have high variance.
- Visualize parameters
- Measure error on both training and validation set.
- Test on a small subset of the data and check the error $\rightarrow 0$.

WHAT IF IT DOES NOT WORK?

- Training diverges:
  - Learning rate may be too large $\rightarrow$ decrease learning rate
  - BPROP is buggy $\rightarrow$ numerical gradient checking
- Parameters collapse / loss is minimized but accuracy is low
  - Check loss function:
    - Is it appropriate for the task you want to solve?
    - Does it have degenerate solutions?
- Network is underperforming
  - Compute flops and nr. params. $\rightarrow$ if too small, make net larger
  - Visualize hidden units/params $\rightarrow$ fix optmization
- Network is too slow
  - Compute flops and nr. params. $\rightarrow$ GPU,distrib. framework, make net smaller

SUMMARY

- Deep Learning = Learning Hierarchical representations. Leverage compositionality to gain efficiency.
- Unsupervised learning: active research topic.
- Supervised learning: most successful set up today.
- Optimization
  - Don't we get stuck in local minima? No, they are all the same!
  - In large scale applications, local minima are even less of an issue.
- Scaling
  - GPUs
  - Distributed framework (Google)
  - Better optimization techniques
- Generalization on small datasets (curse of dimensionality):
  - Input distortions
  - weight decay
  - dropout

THANK YOU!

NOTE: IJCV Special Issue on Deep Learning.
Deadline: 9 Feb. 2014.

SOFTWARE

Torch7: learning library that supports neural net training

http://www.torch.ch

http://code.cogbits.com/wiki/doku.php (tutorial with demos by C. Farabet)

Python-based learning library (U. Montreal)

- http://deeplearning.net/software/theano/ (does automatic differentiation)

C++ code for ConvNets (Sermanet)

– http://eblearn.sourceforge.net/

Efficient CUDA kernels for ConvNets (Krizhevsky)

– code.google.com/p/cuda-convnet

More references at the CVPR 2013 tutorial on deep learning:

http://www.cs.toronto.edu/~ranzato/publications/ranzato_cvpr13.pdf