#DLUPC

Day 9 Lecture 1

Unsupervised Learning

[course site]

Xavier Giro-i-Nieto
xavier.giro@upc.edu

Associate Professor
Universitat Politecnica de Catalunya
Technical University of Catalonia

Acknowledgements

Insight

DCU

Kevin McGuinness, “Unsupervised Learning” Deep Learning for Computer Vision. [Slides 2016] [Slides 2017]

Outline

1. Motivation
2. Unsupervised Learning
3. Predictive Learning
4. Self-supervised Learning

Outline

1. **Motivation**
2. Unsupervised Learning
3. Predictive Learning
4. Self-supervised Learning

Motivation

Alpha Go Takes the Match, 3-0 (i-programmer.info)

117

Posted by timothy on Saturday March 12, 2016 @10:24AM from the rhyming-singlet dept.

mikejuk writes:

> Google's AlphaGo has won the Deep Mind Challenge, by winning the third match in a row of five against the 18-time world champion Lee Se-dol. AlphaGo is now the number three Go player in the world and this is an event that will be remembered for a long time. Most AI experts thought that it would take decades to achieve but now we know that we have been on the right track since the 1980s or earlier. AlphaGo makes use of nothing dramatically new — it learned to play Go using a deep neural network and reinforcement learning, both developments on classical AI techniques. We know now that we don't need any big new breakthroughs to get to true AI. The results of the final two games are going to be interesting but as far as AI is concerned the match really is all over.

Motivation

Yann LeCun

Monday at 10:15 · Edited ·

Statement from a Slashdot post about the AlphaGo victory: "We know now that we don't need any big new breakthroughs to get to true AI"

That is completely, utterly, ridiculously wrong.

As I've said in previous statements: most of human and animal learning is unsupervised learning. If intelligence was a cake, unsupervised learning would be the cake, supervised learning would be the icing on the cake, and reinforcement learning would be the cherry on the cake. We know how to make the icing and the cherry, but we don't know how to make the cake.

We need to solve the unsupervised learning problem before we can even think of getting to true AI. And that's just an obstacle we know about. What about all the ones we don't know about?

#deeplearning #AI #AlphaGo

Greff, Klaus, Antti Rasmus, Mathias Berglund, Tele Hao, Harri Valpola, and Juergen Schmidhuber. "Tagger: Deep unsupervised perceptual grouping." NIPS 2016 [video] [code]

Motivation

Yann Lecun's Black Forest cake

- "Pure" Reinforcement Learning (cherry)
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- Supervised Learning (icing)
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- Unsupervised/Predictive Learning (cake)
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

- (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)

Motivation

We can categorize three types of learning procedures:

1. Supervised Learning:

$$\mathbf{y} = f(\mathbf{x})$$

Predict label y corresponding to observation x

2. Unsupervised Learning:

$$f(\mathbf{x})$$

Estimate the distribution of observation x

3. Reinforcement Learning (RL):

$$\mathbf{y} = f(\mathbf{x})$$

$$\mathbf{z}$$

Predict action y based on observation x, to maximize a future reward z

Motivation

We can categorize three types of learning procedures:

1. Supervised Learning:

$$\mathbf{y} = f(\mathbf{x})$$

2. Unsupervised Learning:

$$f(\mathbf{x})$$

3. Reinforcement Learning (RL):

$$\mathbf{y} = f(\mathbf{x})$$

$$\mathbf{z}$$

Unsupervised Learning

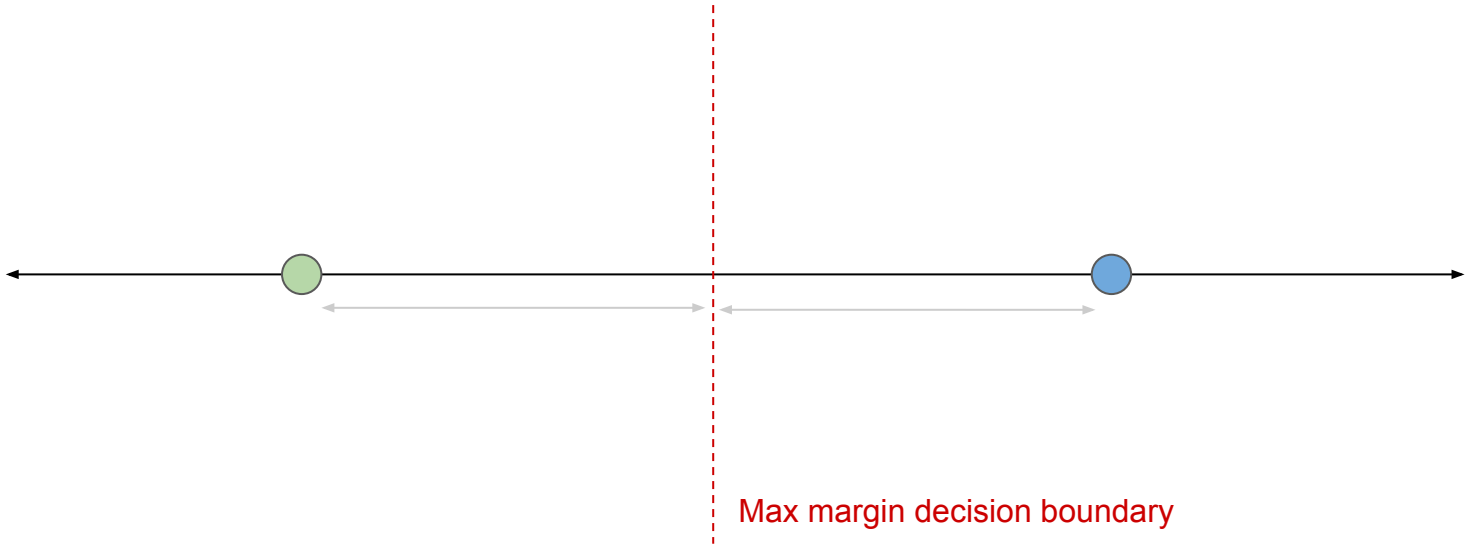
Why Unsupervised Learning?

- It is the nature of how intelligent beings percept the world.
- It can save us tons of efforts to build a human-alike intelligent agent compared to a totally supervised fashion.
- Vast amounts of unlabelled data.

Outline

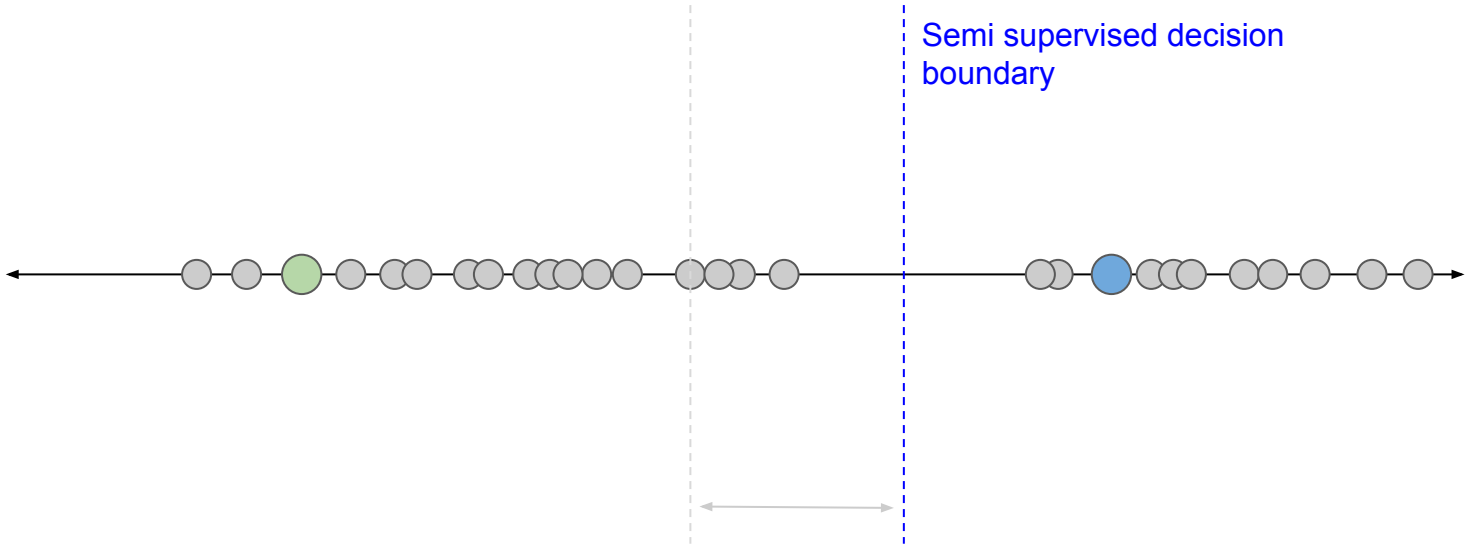
1. Motivation
2. **Unsupervised Learning**
3. Predictive Learning
4. Self-supervised Learning

How data distribution P(x) influences decisions (1D)



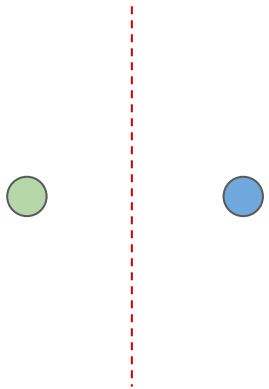
Slide credit: Kevin McGuinness (DLCV UPC 2017)

How data distribution P(x) influences decisions (1D)



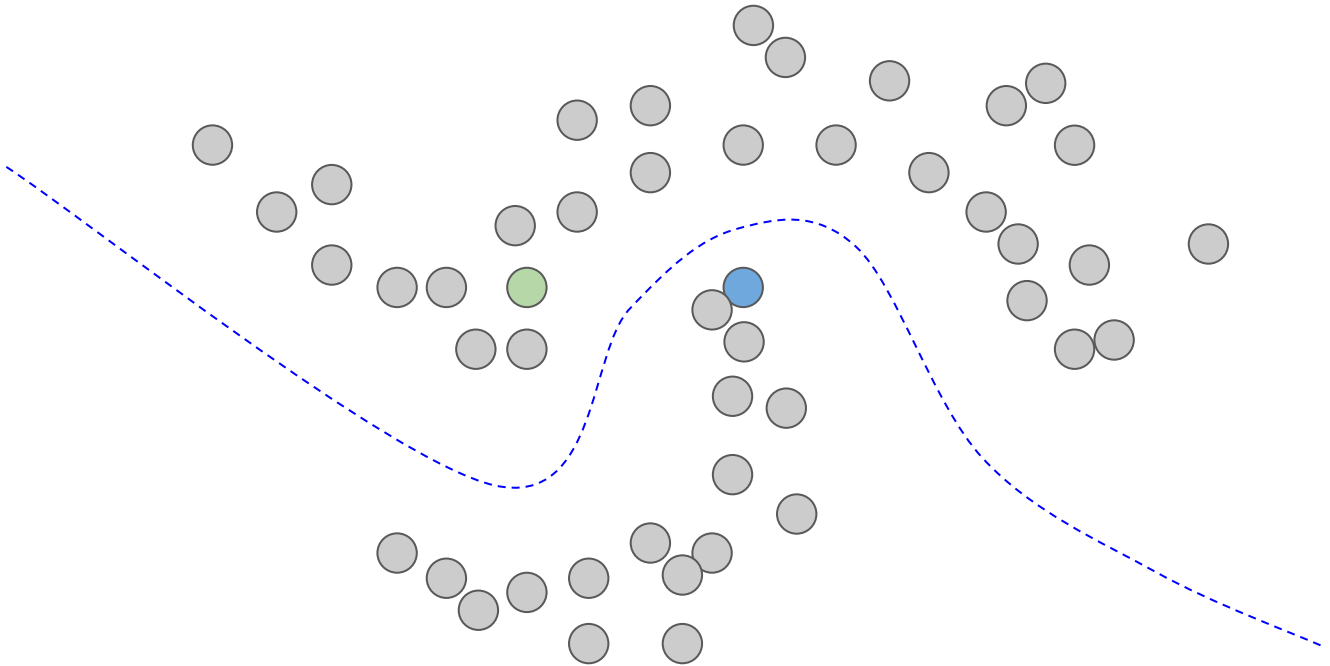
Slide credit: Kevin McGuinness (DLCV UPC 2017)

How data distribution P(x) influences decisions (2D)



Slide credit: Kevin McGuinness (DLCV UPC 2017)

How data distribution P(x) influences decisions (2D)



Slide credit: Kevin McGuinness (DLCV UPC 2017)

How P(x) is valuable for naive Bayesian classifier

Bayes rule

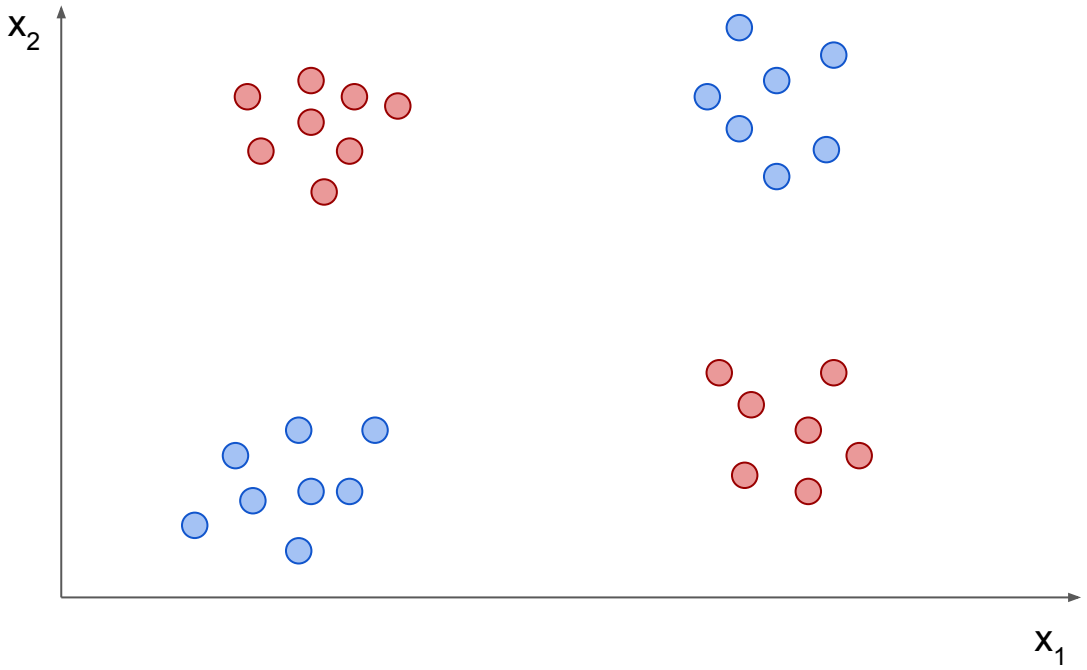
$$P(Y = y|X) = \frac{P(X|Y)P(Y)}{P(X)}$$

X: Data
Y: Labels

- P(Y|X) depends on P(X|Y) and P(X)
- **Knowledge of distribution P(X) can help to predict P(Y|X)**
- Good model of P(X) must have Y as an implicit latent variable

Slide credit: Kevin McGuinness (DLCV UPC 2017)

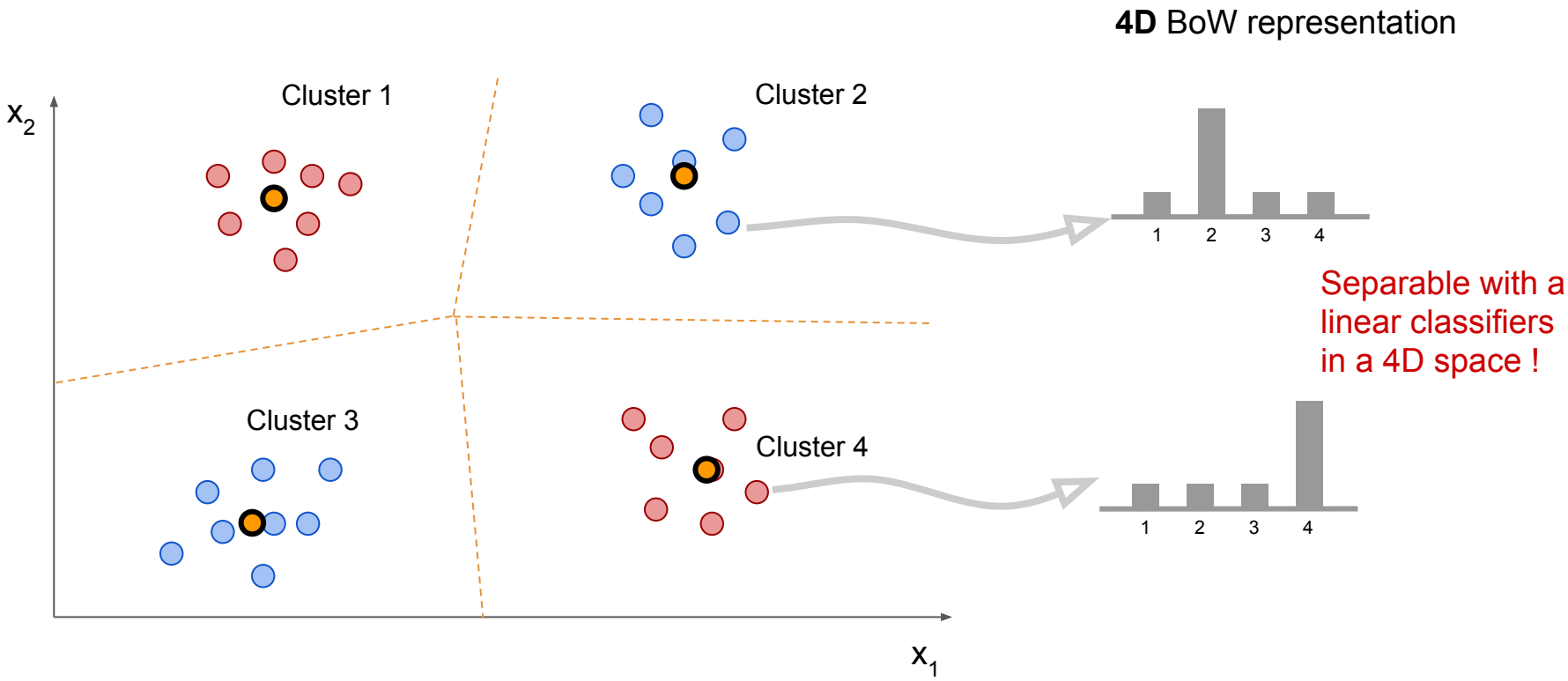
How clustering is valueble for linear classifiers



Not linearly separable in this 2D space :(

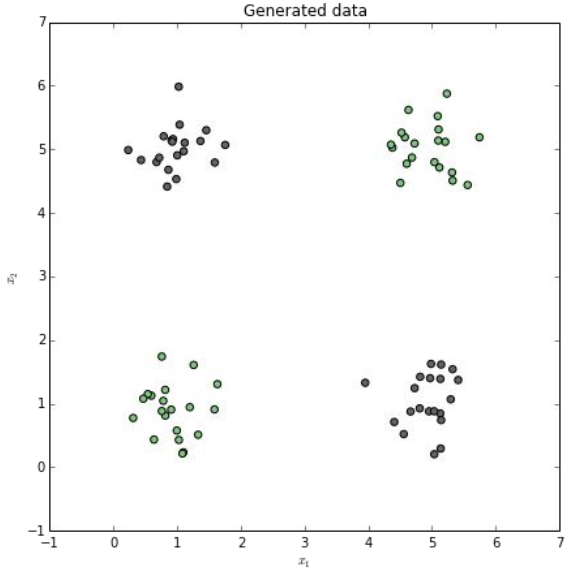
Slide credit: Kevin McGuinness (DLCV UPC 2017)

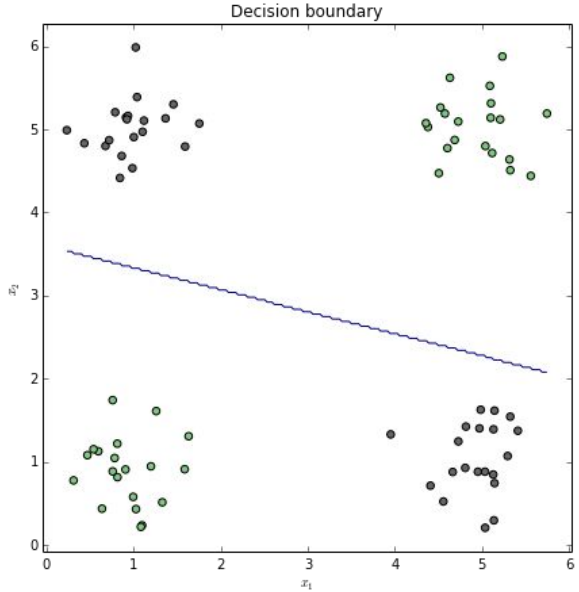
How clustering is valueble for linear classifiers

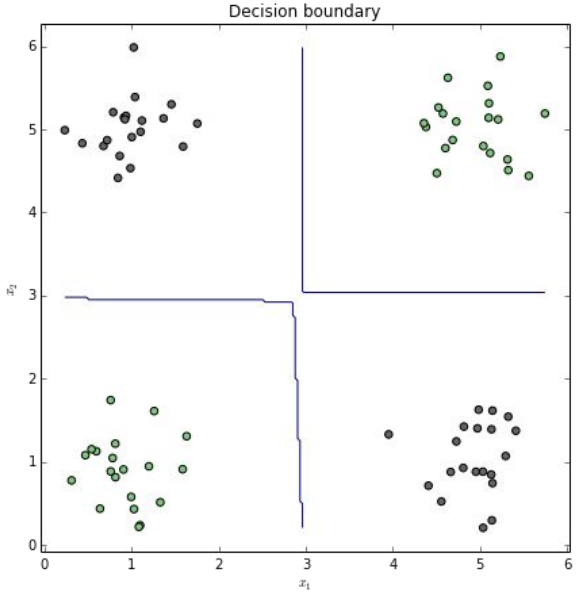


Slide credit: Kevin McGuinness (DLCV UPC 2017)

How clustering is valueble for linear classifiers







Example from [Kevin McGuinness Juyter notebook](#).

Assumptions for unsupervised learning

To model P(X) given data, it is necessary to make some assumptions

“You can’t do inference without making assumptions”

-- David MacKay, Information Theory, Inference, and Learning Algorithms

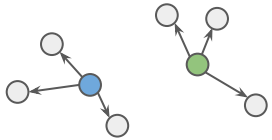
Typical assumptions:

- Smoothness assumption
  - Points which are close to each other are more likely to share a label.
- Cluster assumption
  - The data form discrete clusters; points in the same cluster are likely to share a label
- **Manifold assumption**
  - The data lie approximately on a manifold of much lower dimension than the input space.

Slide credit: Kevin McGuinness (DLCV UPC 2017)

Assumptions for unsupervised learning

Smoothness assumption



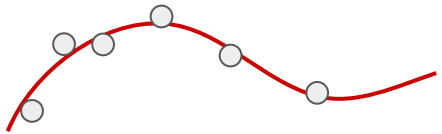
- Label propagation
  - Recursively propagate labels to nearby points
  - Problem: in high-D, your nearest neighbour may be very far away!

Cluster assumption

- Bag of words models
  - K-means, etc.
  - Represent points by cluster centers
  - Soft assignment
  - VLAD
- Gaussian mixture models
  - Fisher vectors

Manifold assumption

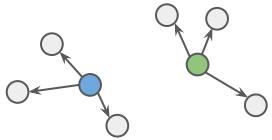
- Linear manifolds
  - PCA
  - Linear autoencoders
  - Random projections
  - ICA
- Non-linear manifolds:
  - Non-linear autoencoders
  - Deep autoencoders
  - Restricted Boltzmann machines
  - Deep belief nets



Slide credit: Kevin McGuinness (DLCV UPC 2017)

Assumptions for unsupervised learning

Smoothness assumption



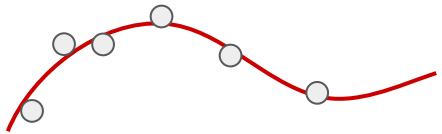
- Label propagation
  - Recursively propagate labels to nearby points
  - Problem: in high-D, your nearest neighbour may be very far away!

Cluster assumption

- Bag of words models
  - K-means, etc.
  - Represent points by cluster centers
  - Soft assignment
  - VLAD
- Gaussian mixture models
  - Fisher vectors

Manifold assumption

- Linear manifolds
  - PCA
  - Linear autoencoders
  - Random projections
  - ICA
- Non-linear manifolds:
  - Non-linear autoencoders
  - Deep autoencoders
  - Restricted Boltzmann machines
  - Deep belief nets



Slide credit: Kevin McGuinness (DLCV UPC 2017)

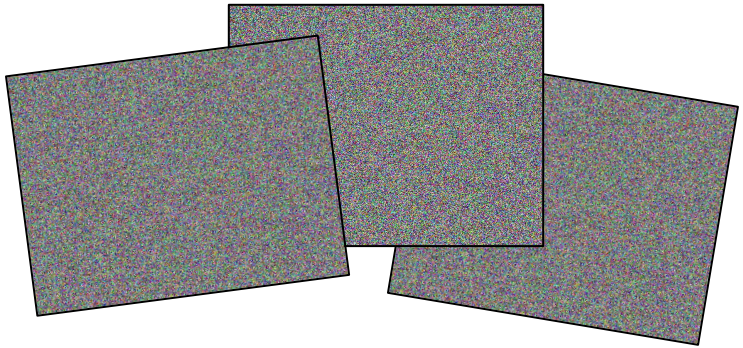
The manifold hypothesis

The data distribution lie close to a low-dimensional manifold

Example: **consider image data**

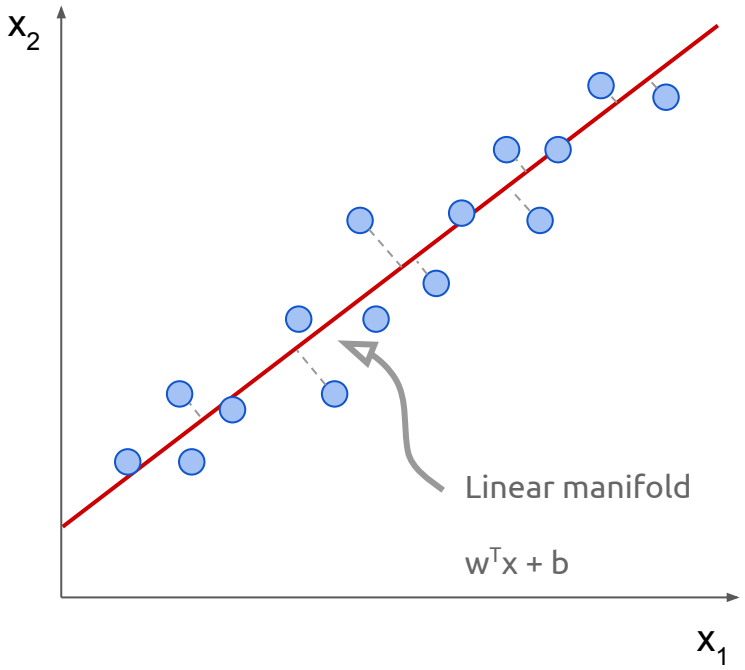
- Very high dimensional (1,000,000D)
- A randomly generated image will almost certainly not look like any real world scene
  - The space of images that occur in nature is almost completely empty
- Hypothesis: real world images lie on a smooth, low-dimensional manifold
  - Manifold distance is a good measure of similarity

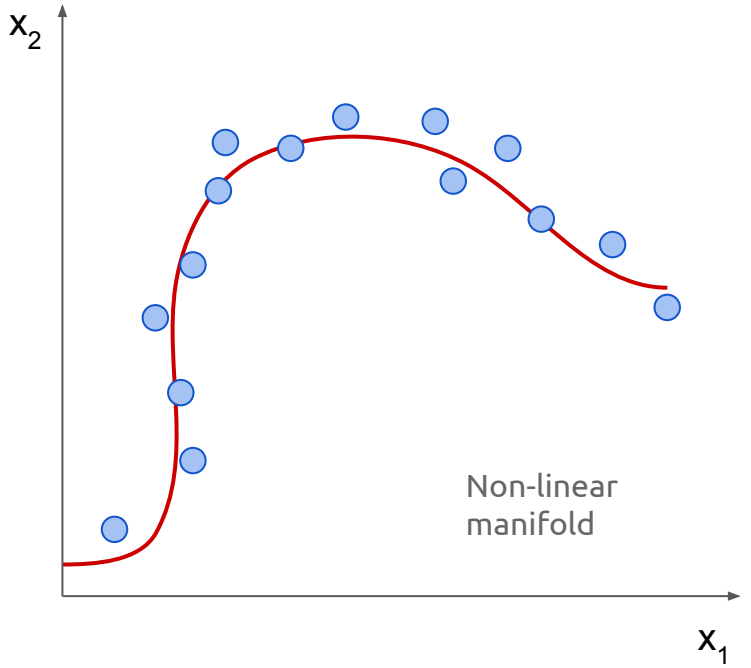
Similar for audio and text



Slide credit: Kevin McGuinness (DLCV UPC 2017)

The manifold hypothesis



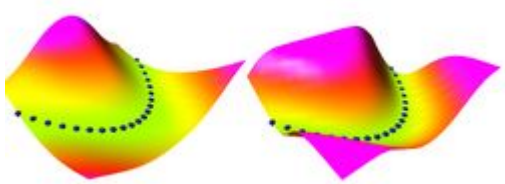


Slide credit: Kevin McGuinness (DLCV UPC 2017)

The manifold hypothesis: Energy-based models

Often intractable to explicitly model probability density

Energy-based model: high energy for data far from manifold, low energy for data near manifold of observed data



Fitting energy-based models

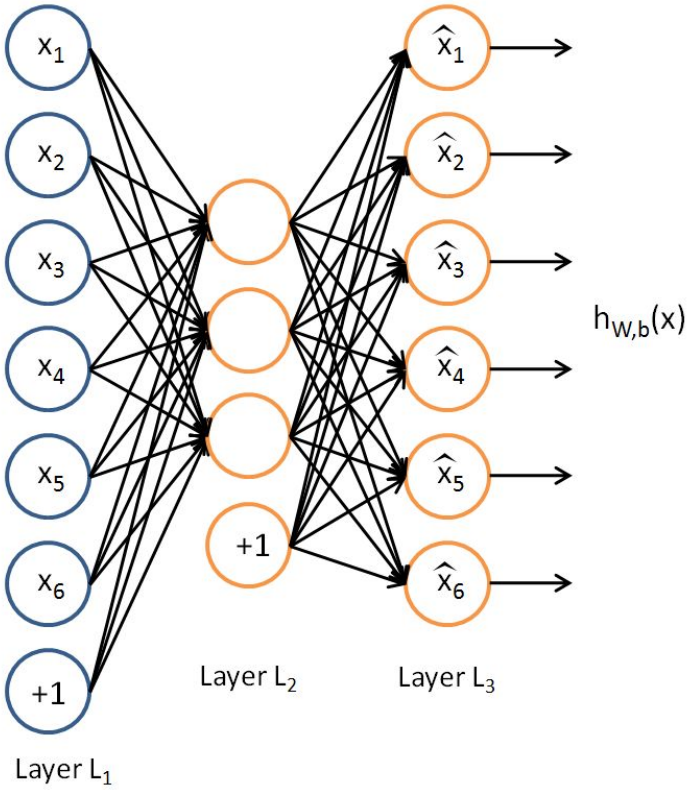
- Push down on area near observations.
- Push up everywhere else.

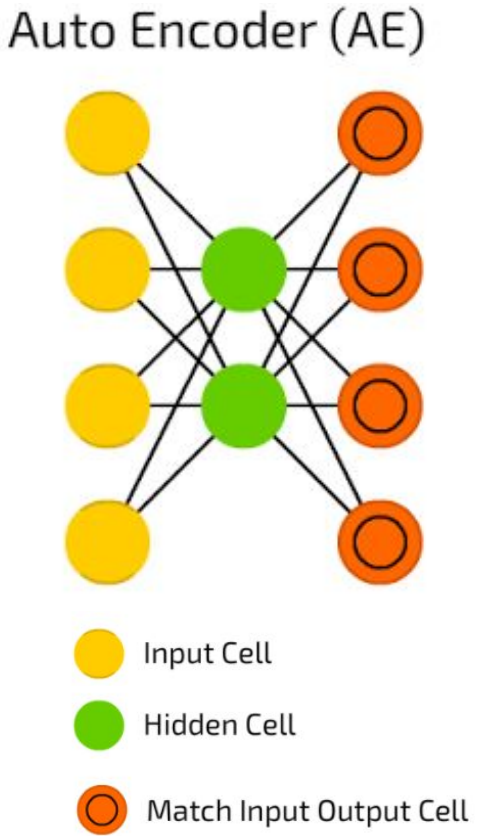
Examples
Encoder-decoder models: measure energy with reconstruction error

- **K-Means**: push down near prototypes. Push up based on distance from prototypes.
- **PCA**: push down near line of maximum variation. Push up based on distance to line.
- **Autoencoders**: non-linear manifolds...

LeCun et al, **A Tutorial on Energy-Based Learning**, Predicting Structured Data, 2006 http://yann.lecun.com/exdb/publis/pdf/lecun-06.pdf

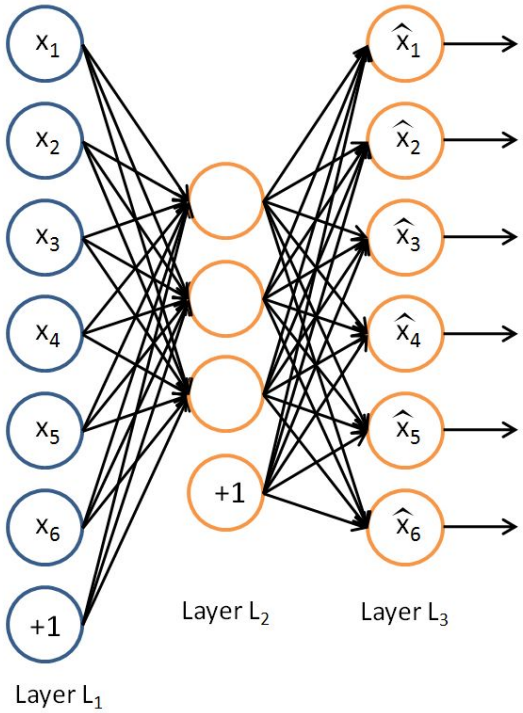
Autoencoder (AE)





F. Van Veen, "The Neural Network Zoo" (2016)

Autoencoder (AE)

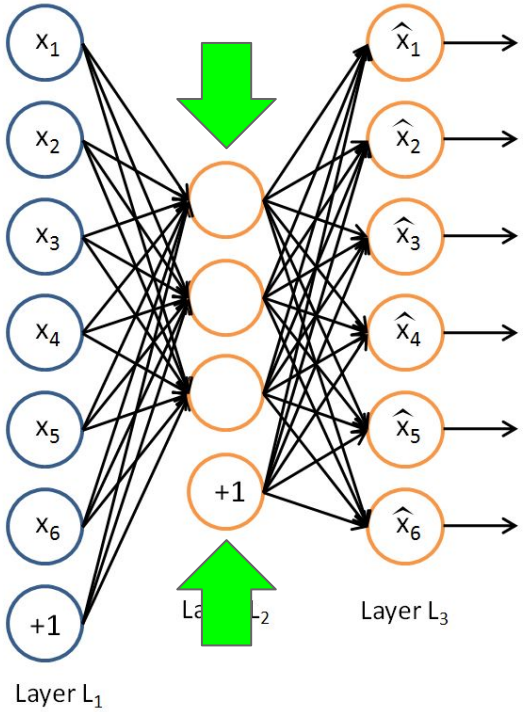


Autoencoders:

- Predict at the output the same input data.
- Do not need labels:

"Deep Learning Tutorial", Dept. Computer Science, Stanford

Autoencoder (AE)



Dimensionality reduction:

- Use hidden layer as a feature extractor of any desired size.

"Deep Learning Tutorial", Dept. Computer Science, Stanford

Autoencoder (AE)

WHY?

Pretraining:

1. Initialize a NN solving an autoencoding problem.

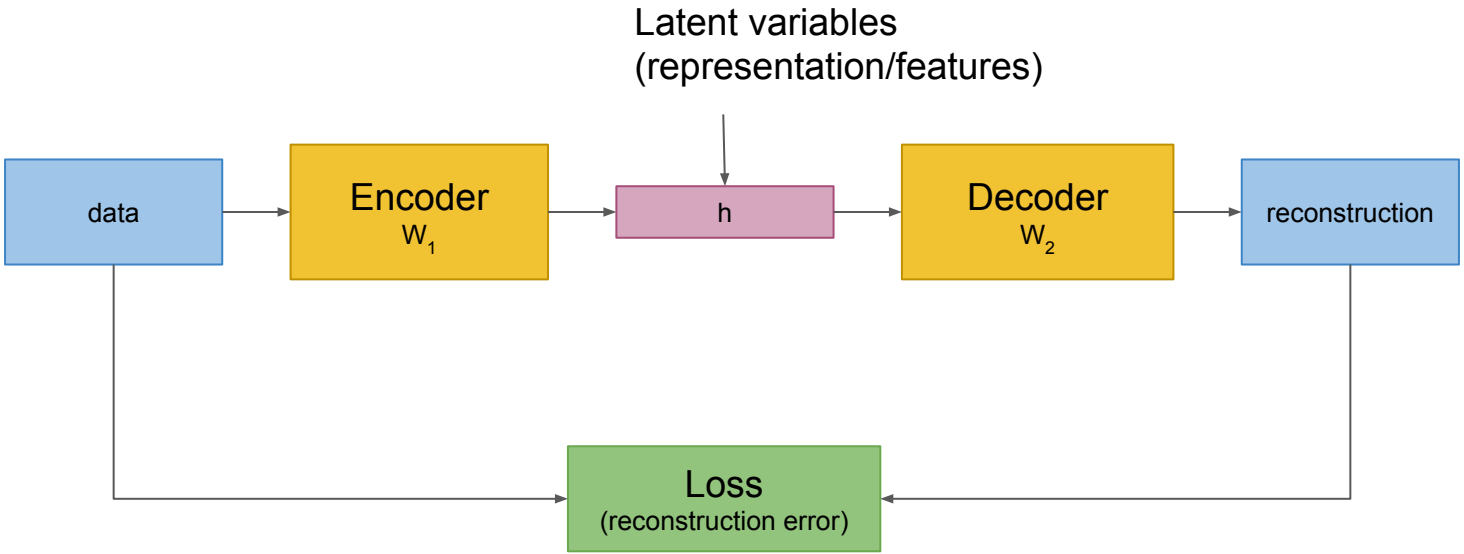


Figure: Kevin McGuinness (DLCV UPC 2017)

Autoencoder (AE)

WHY?

Pretraining:

1. Initialize a NN solving an autoencoding problem.
2. Train for final task with “few” labels.

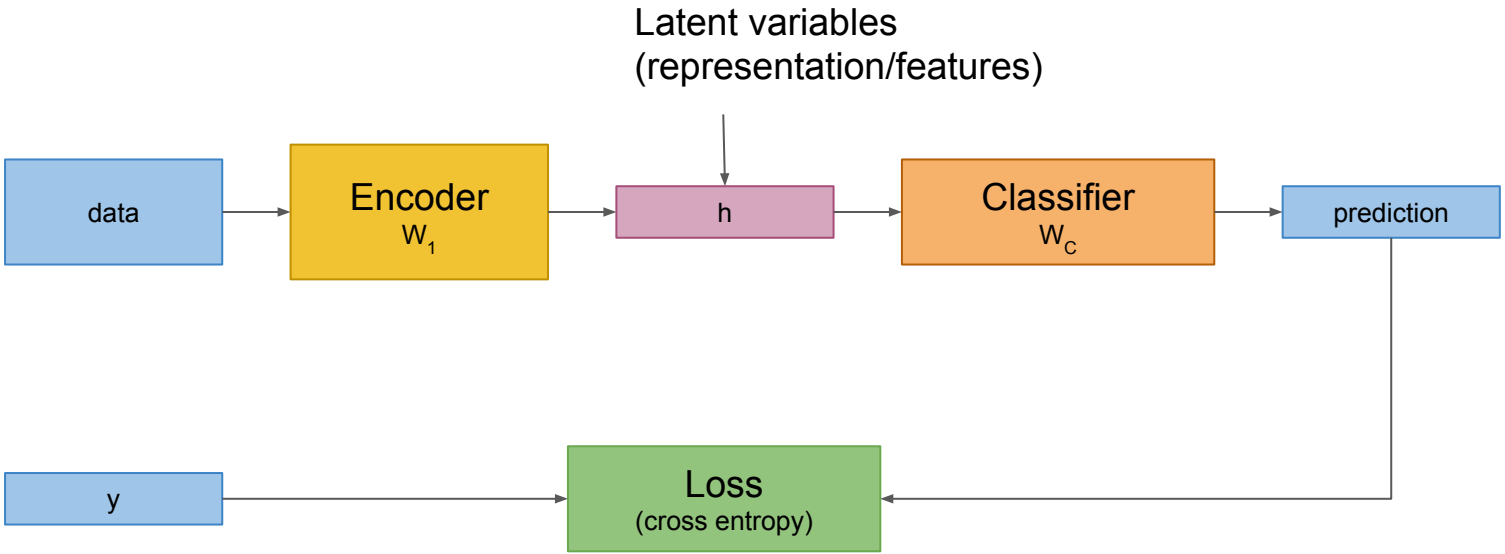
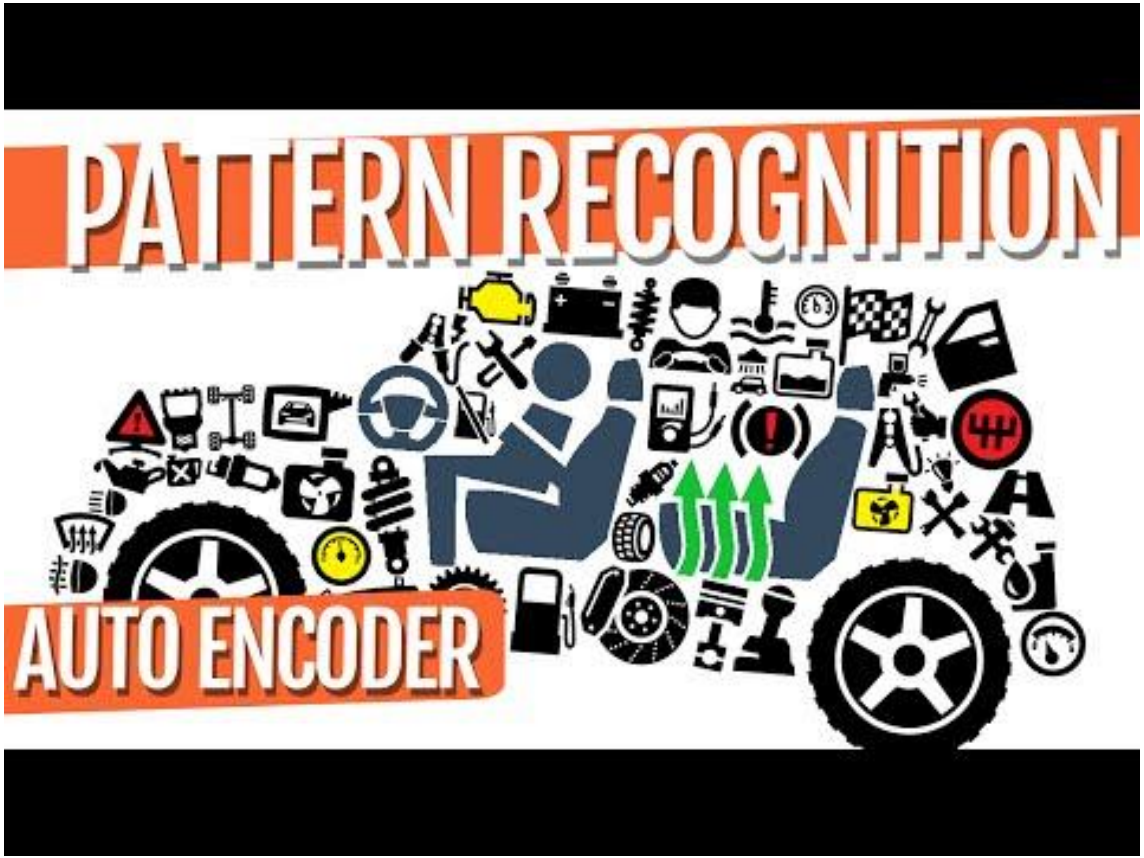


Figure: Kevin McGuinness (DLCV UPC 2017)

Autoencoder (AE)

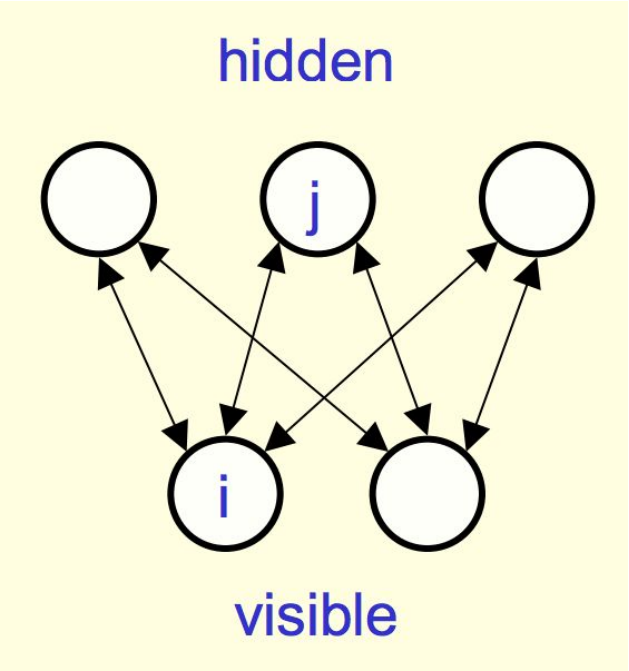


Deep Learning TV, [“Autoencoders - Ep. 10”]

Restricted Boltzmann Machine (RBM)

F. Van Veen, "The Neural Network Zoo" (2016)

Restricted Boltzmann Machine (RBM)

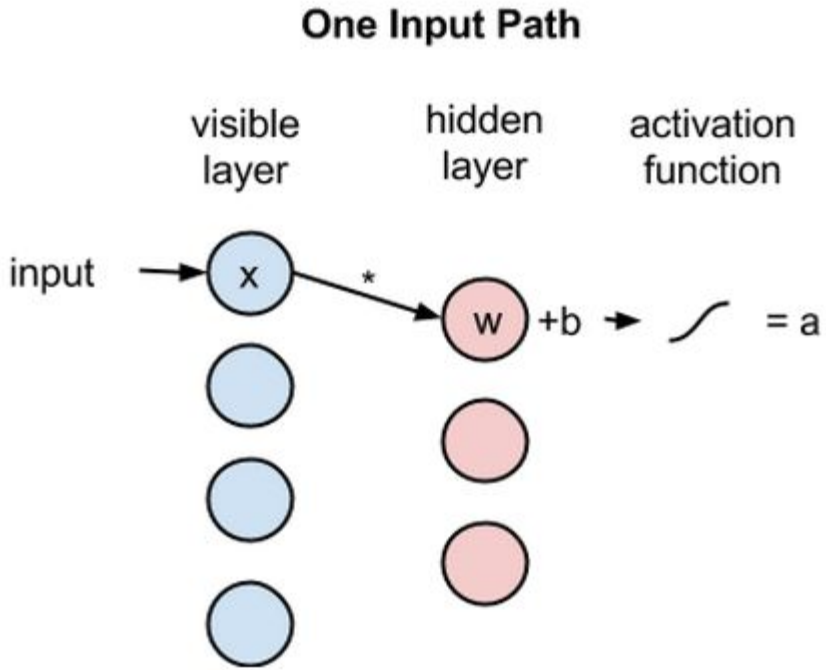


- Shallow two-layer net.
- Restricted = No two nodes in a layer share a connection
-
- Bipartite graph.
- Bidirectional graph
  - Shared weights.
  - Different biases.

Figure: Geoffrey Hinton (2013)

Salakhutdinov, Ruslan, Andriy Mnih, and Geoffrey Hinton. "Restricted Boltzmann machines for collaborative filtering." Proceedings of the 24th international conference on Machine learning. ACM, 2007.

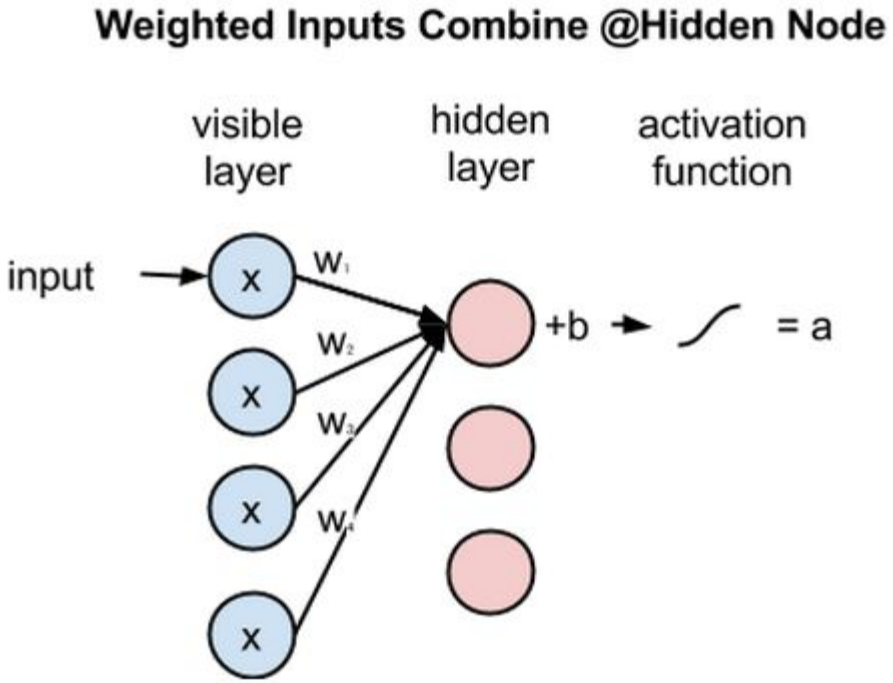
Restricted Boltzmann Machine (RBM)



Forward pass

DeepLearning4j, [“A Beginner’s Tutorial for Restricted Boltzmann Machines”.]

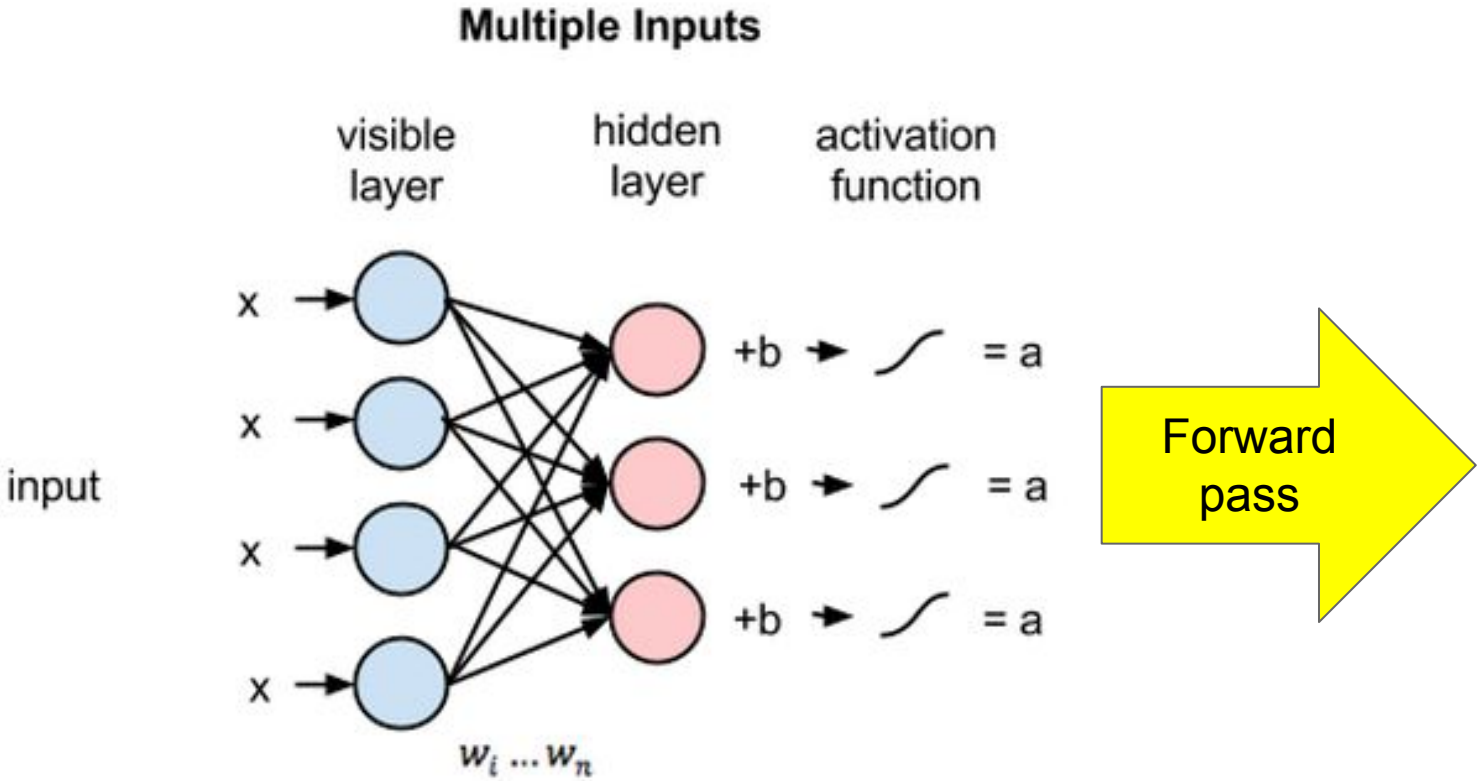
Restricted Boltzmann Machine (RBM)



Forward pass

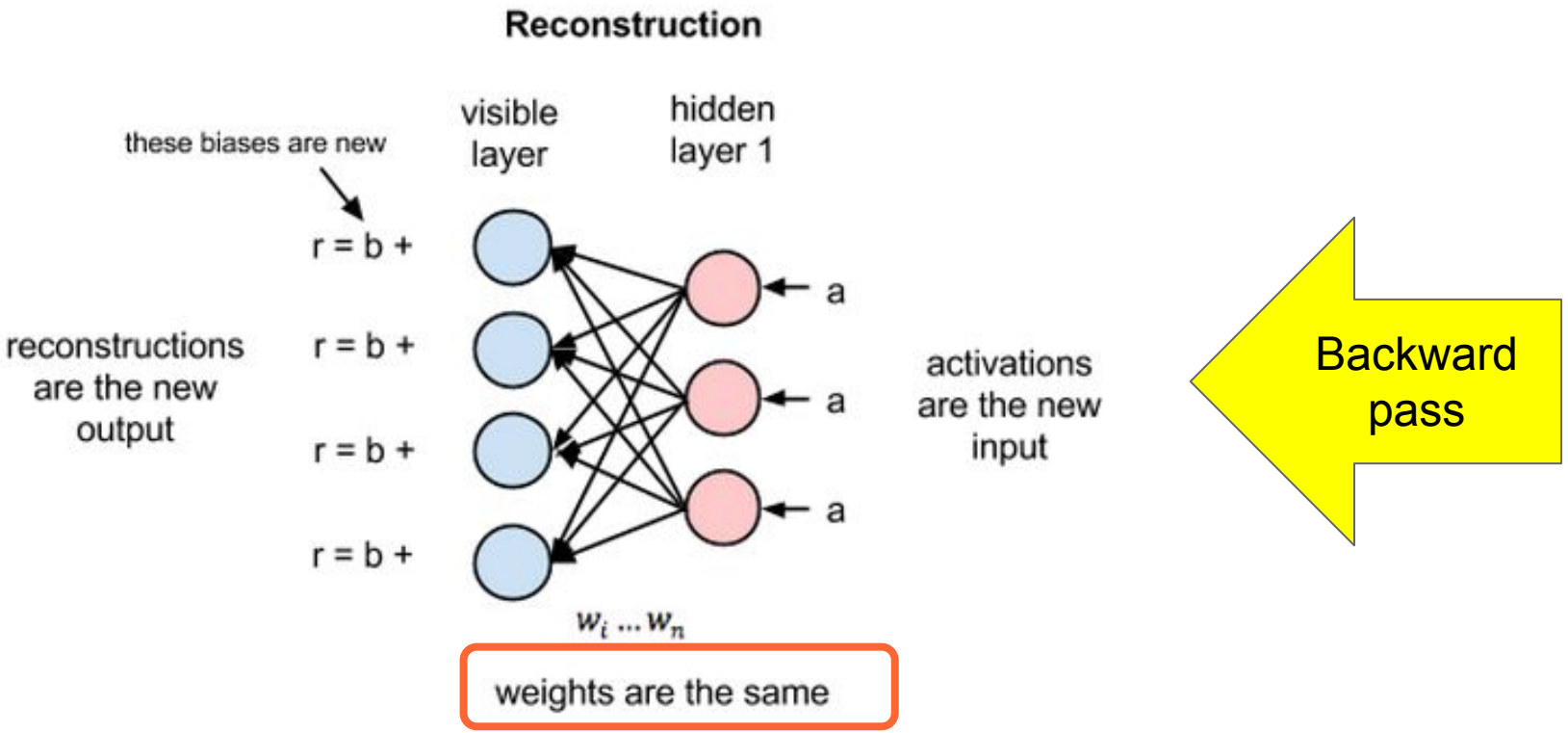
DeepLearning4j, [“A Beginner’s Tutorial for Restricted Boltzmann Machines”.]

Restricted Boltzmann Machine (RBM)



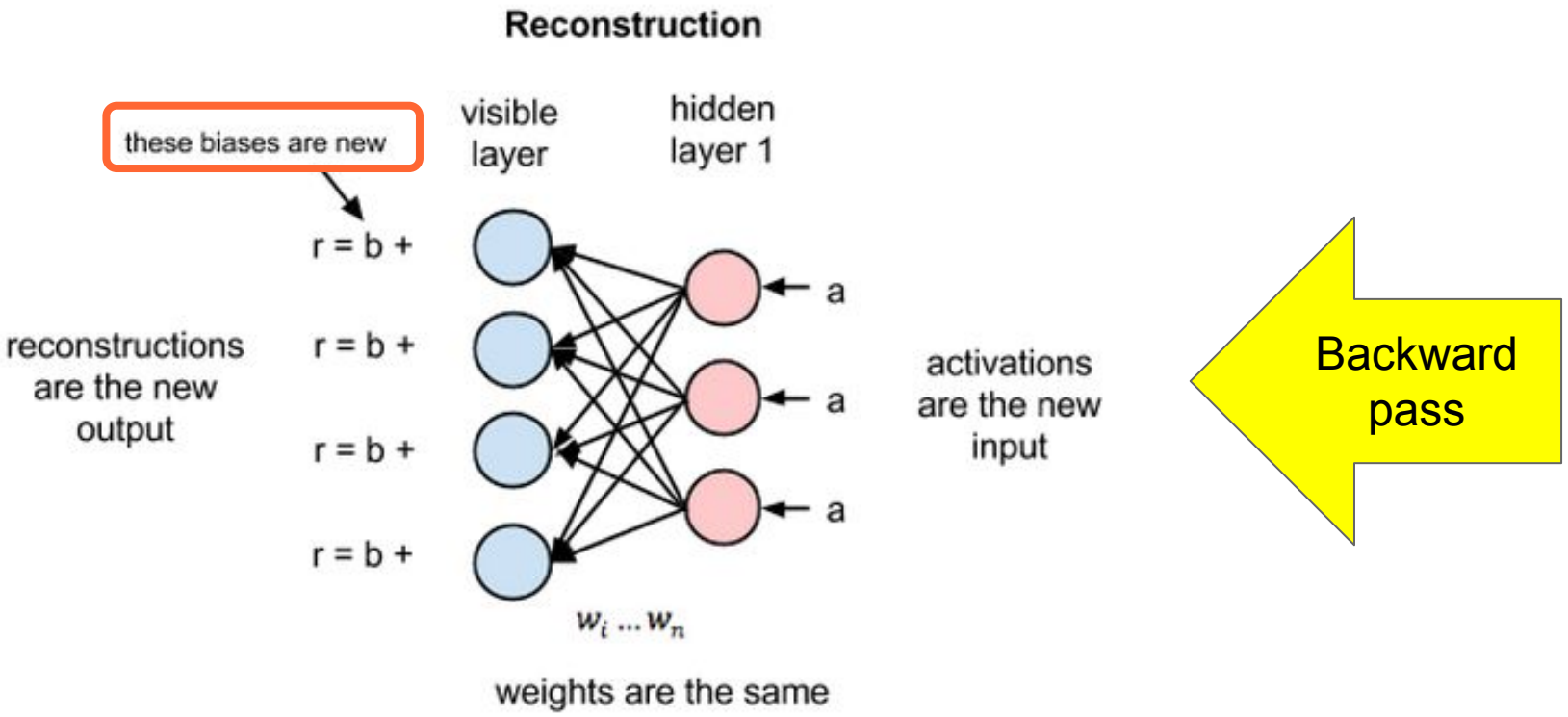
DeepLearning4j, [“A Beginner’s Tutorial for Restricted Boltzmann Machines”.]

Restricted Boltzmann Machine (RBM)



DeepLearning4j, "A Beginner's Tutorial for Restricted Boltzmann Machines".

Restricted Boltzmann Machine (RBM)

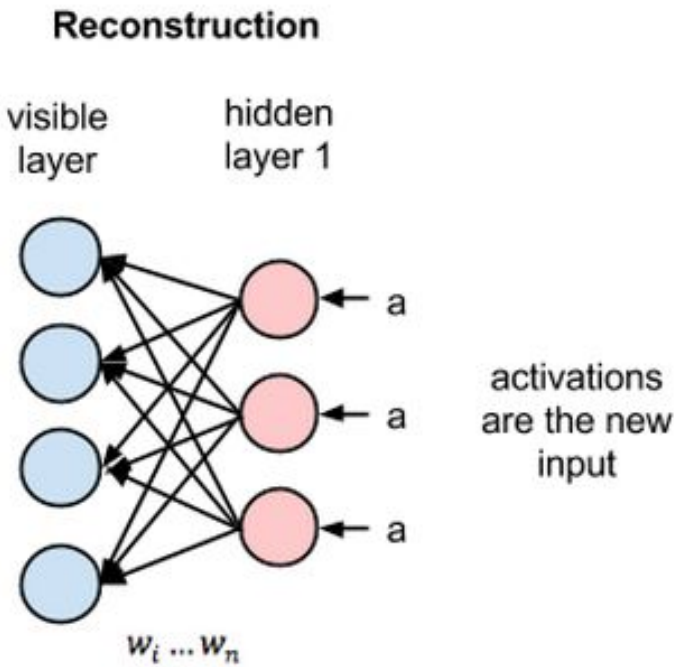


DeepLearning4j, [“A Beginner’s Tutorial for Restricted Boltzmann Machines”.]

Restricted Boltzmann Machine (RBM)

The reconstructed values at the visible layer are compared with the actual ones with the KL Divergence.

$$D_{\mathrm{KL}}(P\|Q) = -\sum_i P(i)\,\log\frac{Q(i)}{P(i)},$$



activations are the new input

Backward pass

DeepLearning4j, "A Beginner's Tutorial for Restricted Boltzmann Machines".

Restricted Boltzmann Machine (RBM)

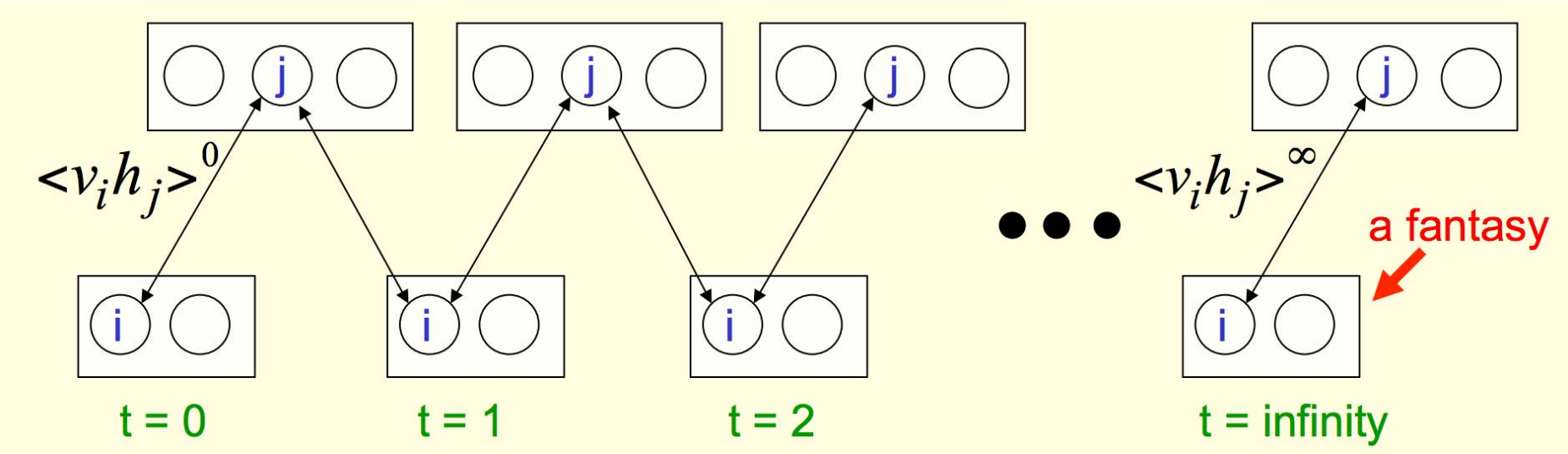
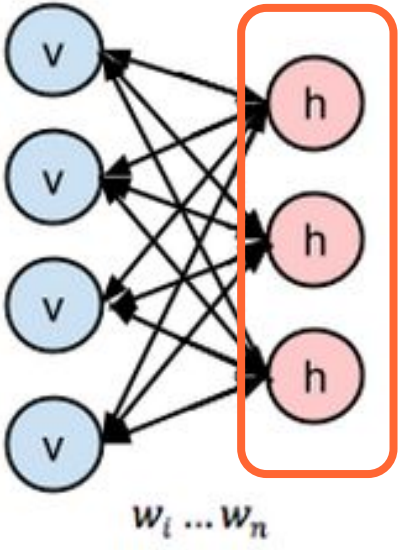


Figure: Geoffrey Hinton (2013)

Salakhutdinov, Ruslan, Andriy Mnih, and Geoffrey Hinton. "Restricted Boltzmann machines for collaborative filtering." Proceedings of the 24th international conference on Machine learning. ACM, 2007.

Restricted Boltzmann Machine (RBM)



RBMs are a specific type of **autoencoder**.

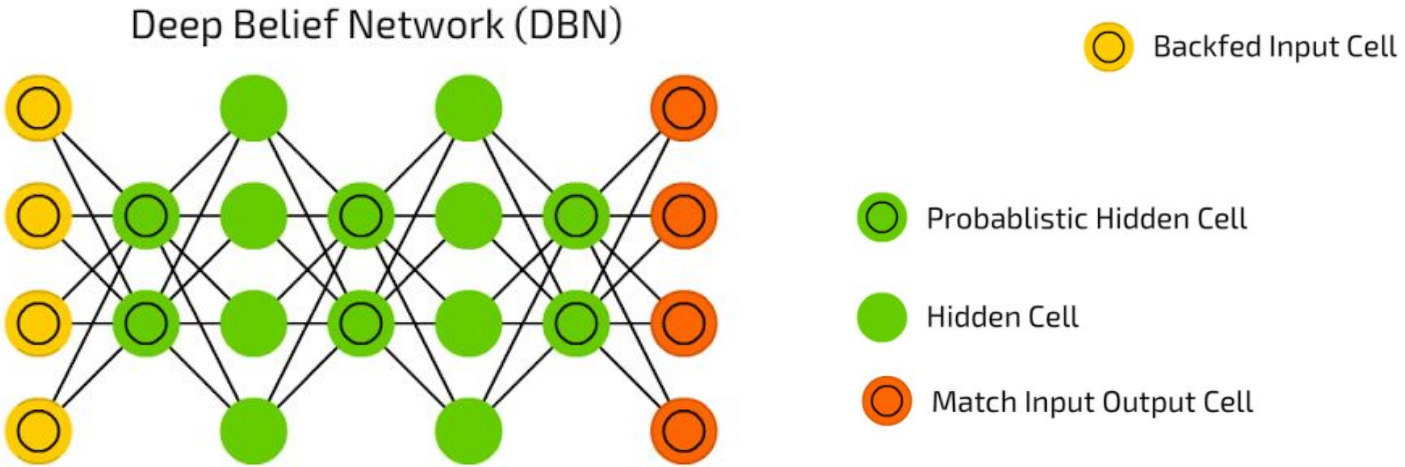
Unsupervised learning

DeepLearning4j, "A Beginner's Tutorial for Restricted Boltzmann Machines".

Restricted Boltzmann Machine (RBM)

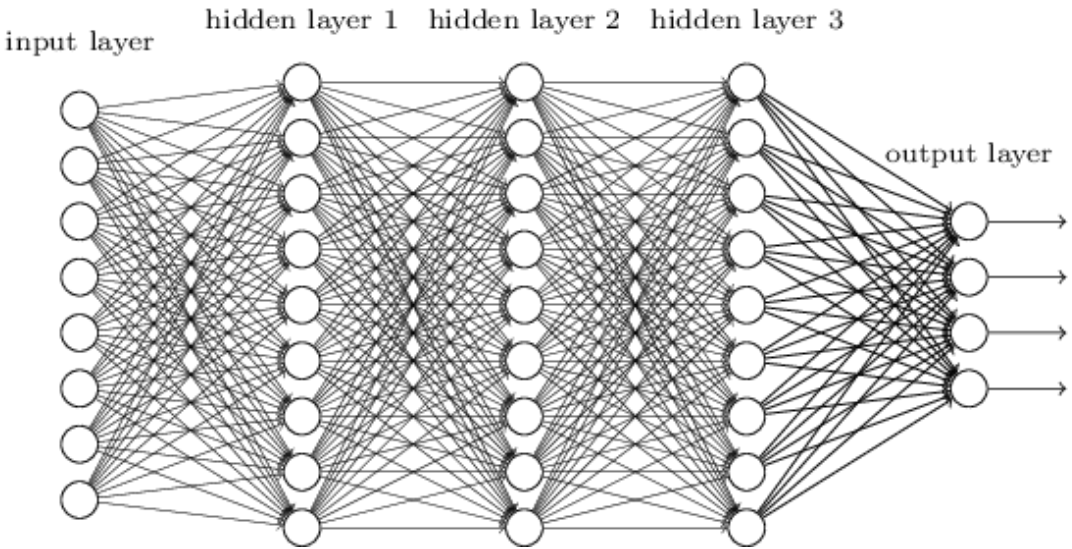
Deep Learning TV, “Restricted Boltzmann Machines”.

Deep Belief Networks (DBN)



F. Van Veen, "The Neural Network Zoo" (2016)

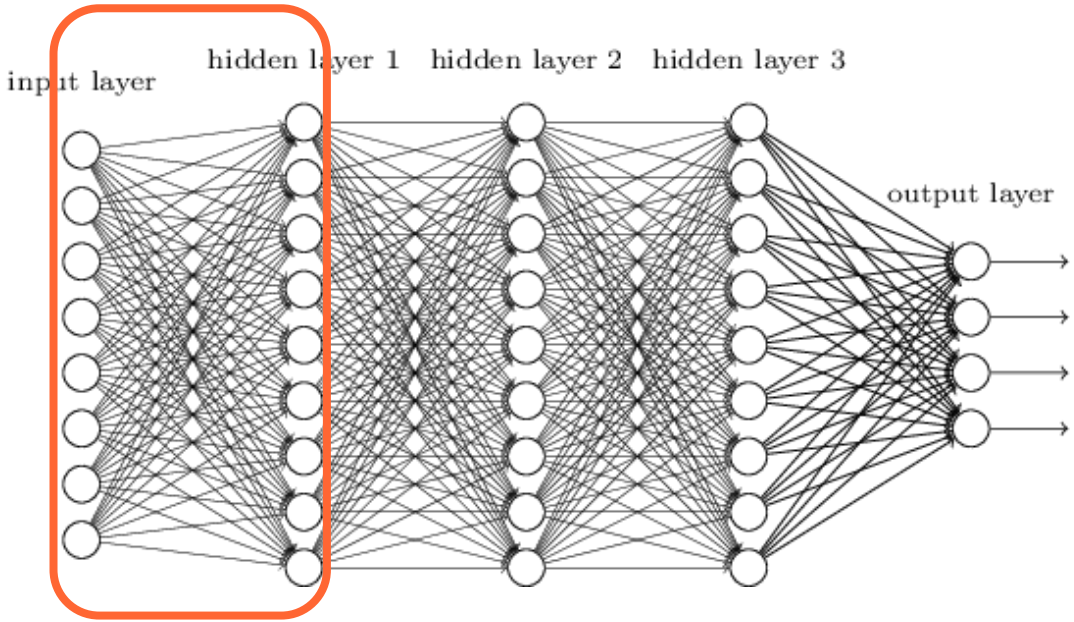
Deep Belief Networks (DBN)



- Architecture like an MLP.
- Training as a stack of RBMs.

Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. "A fast learning algorithm for deep belief nets." Neural computation 18, no. 7 (2006): 1527-1554.

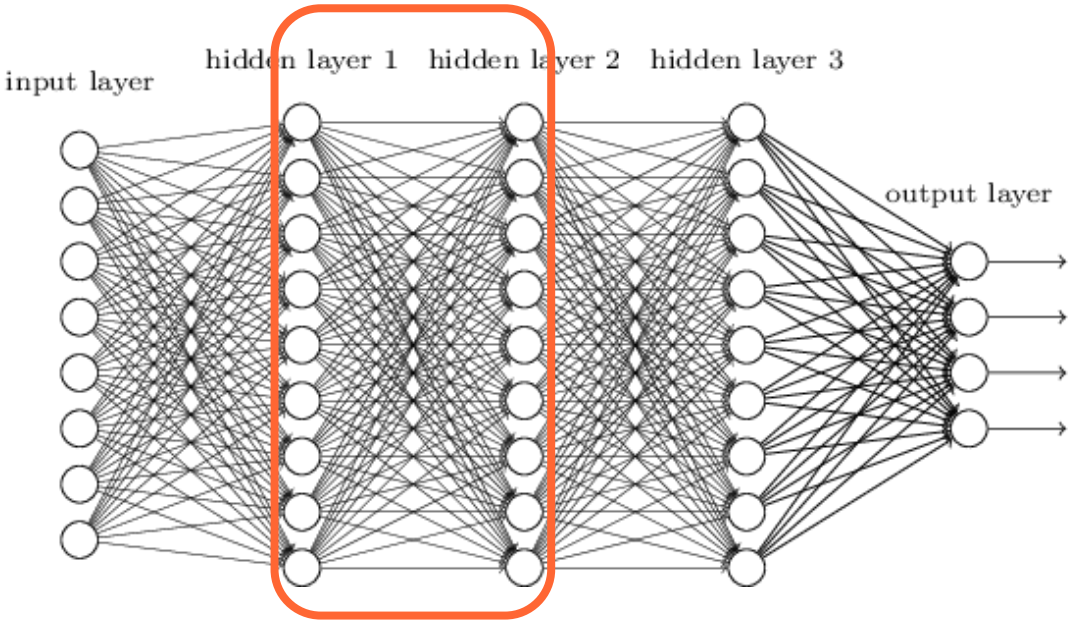
Deep Belief Networks (DBN)



- Architecture like an MLP.
- Training as a stack of RBMs.

Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. "A fast learning algorithm for deep belief nets." Neural computation 18, no. 7 (2006): 1527-1554.

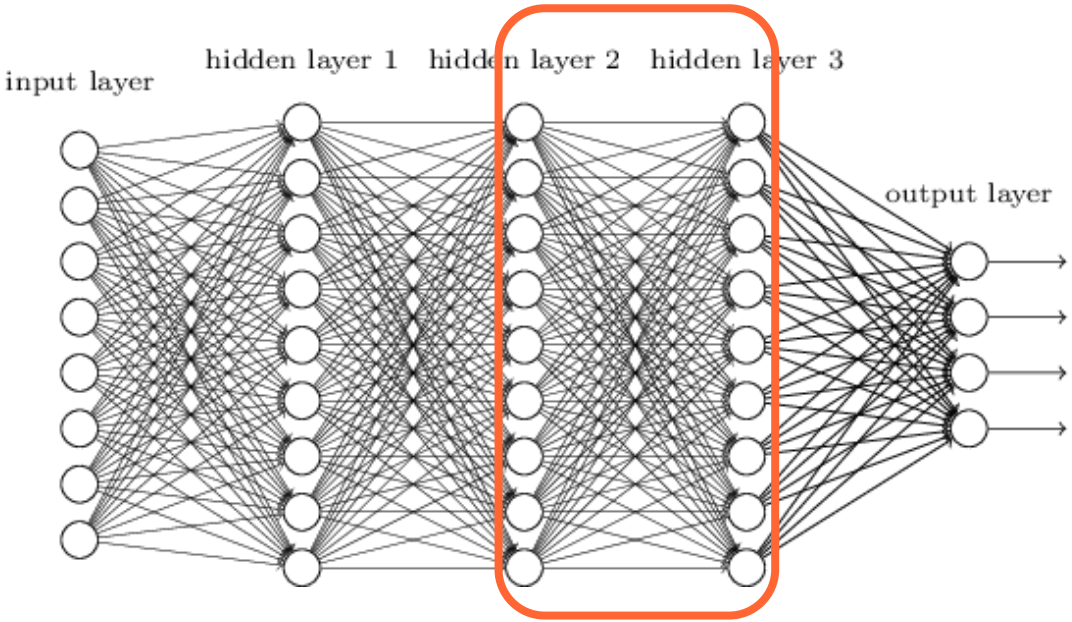
Deep Belief Networks (DBN)



- Architecture like an MLP.
- Training as a stack of RBMs.

Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. "A fast learning algorithm for deep belief nets." Neural computation 18, no. 7 (2006): 1527-1554.

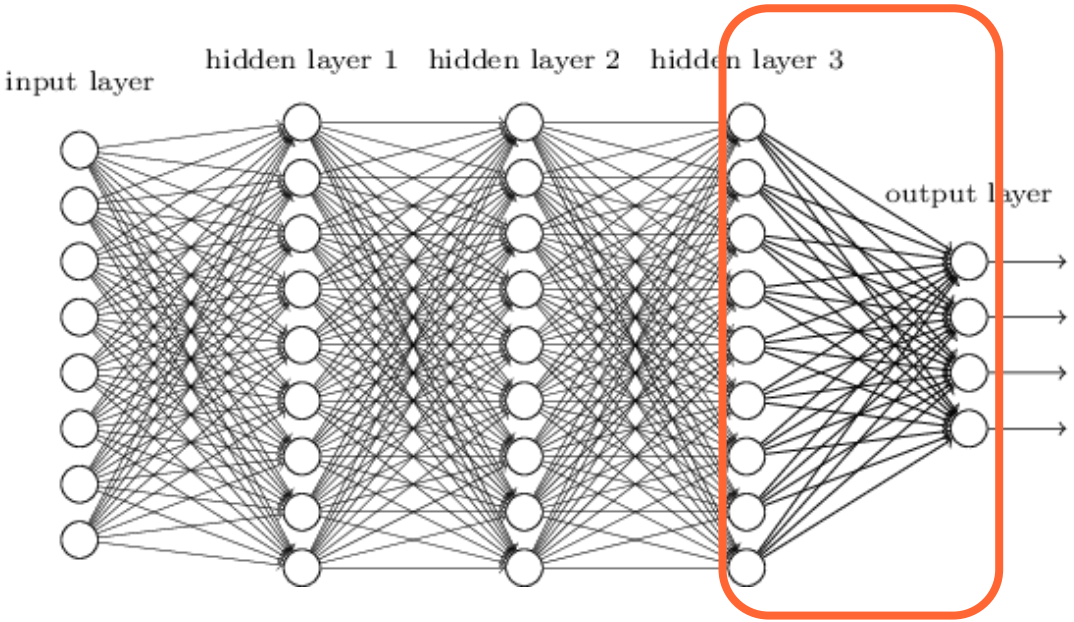
Deep Belief Networks (DBN)



- Architecture like an MLP.
- Training as a stack of RBMs.

Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. "A fast learning algorithm for deep belief nets." Neural computation 18, no. 7 (2006): 1527-1554.

Deep Belief Networks (DBN)

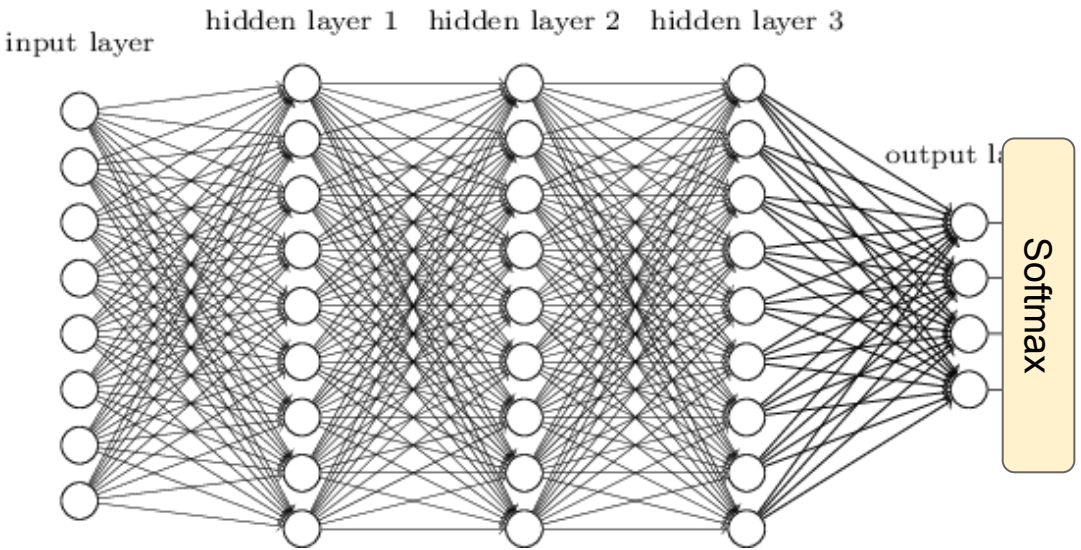


- Architecture like an MLP.
- Training as a stack of RBMs…
- ...so they do not need labels:

Unsupervised learning

Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. "A fast learning algorithm for deep belief nets." Neural computation 18, no. 7 (2006): 1527-1554.

Deep Belief Networks (DBN)

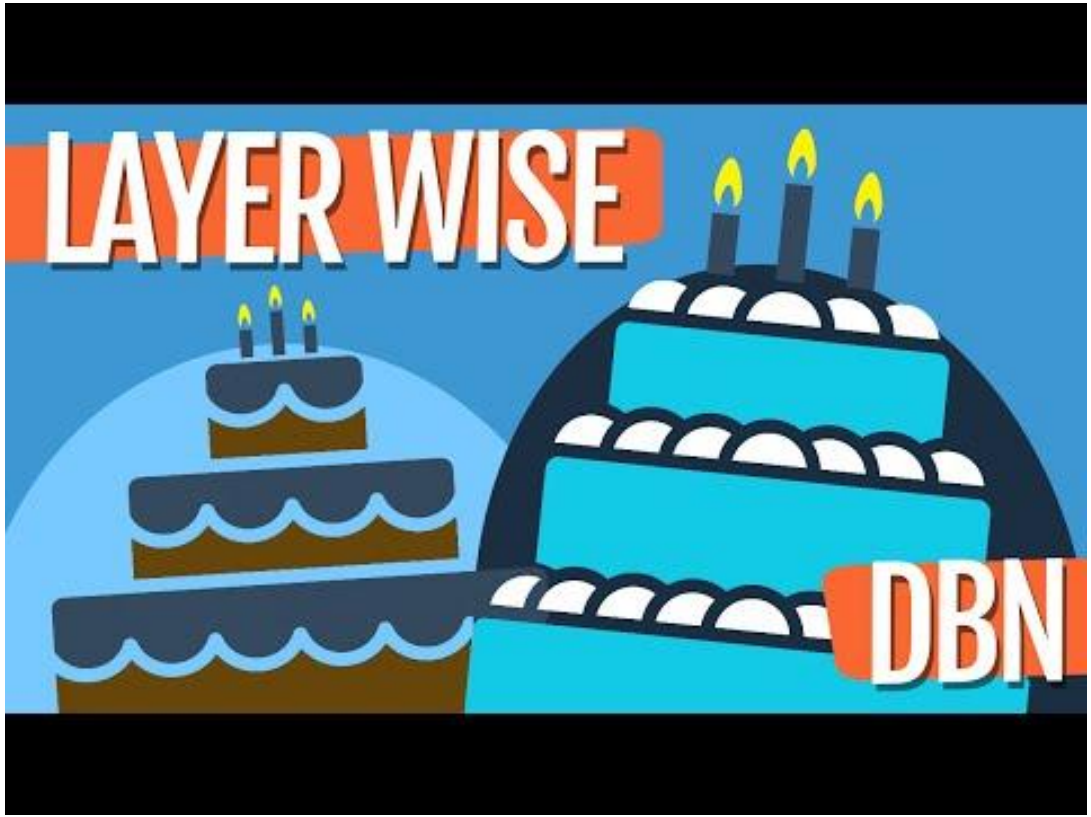


After the DBN is trained, it can be fine-tuned with a **reduced amount of labels** to solve a supervised task with superior performance.

Supervised learning

Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. "A fast learning algorithm for deep belief nets." Neural computation 18, no. 7 (2006): 1527-1554.

Deep Belief Networks (DBN)



Deep Learning TV, “Deep Belief Nets”

Deep Belief Networks (DBN)

Geoffrey Hinton, "Introduction to Deep Learning & Deep Belief Nets" (2012)
Geoorey Hinton, "Tutorial on Deep Belief Networks". NIPS 2007.

Deep Belief Networks (DBN)

Geoffrey Hinton

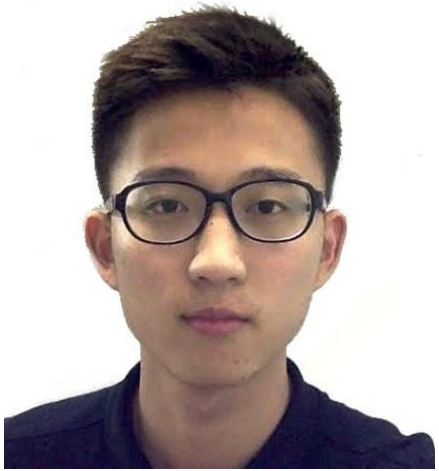
UNIVERSITY OF TORONTO

Research at Google

Outline

1. Motivation
2. Unsupervised Learning
3. **Predictive Learning**
4. Self-supervised Learning

Acknowledgments



Junting Pan

UNIVERSITAT POLITÈCNICA DE CATALUNYA

Barcelona Supercomputing Center
Centro Nacional de Supercomputación

Xunyu Lin

COLUMBIA UNIVERSITY IN THE CITY OF NEW YORK

北京航空航天大学 BEIHANG UNIVERSITY 1952

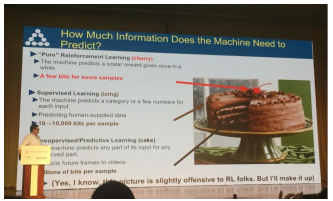
UNIVERSITY OF MICHIGAN

Carnegie Mellon University

Unsupervised Feature Learning

- "Pure" Reinforcement Learning (cherry)
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- Supervised Learning (icing)
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- Unsupervised/Predictive Learning (cake)
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

- (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)

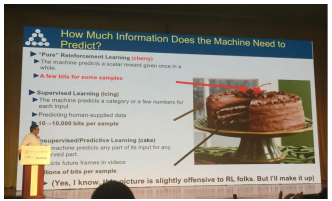


Slide credit:
Yann LeCun

Unsupervised Feature Learning

- "Pure" Reinforcement Learning (cherry)
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- Supervised Learning (icing)
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- Unsupervised/Predictive Learning (cake)
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

- (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)

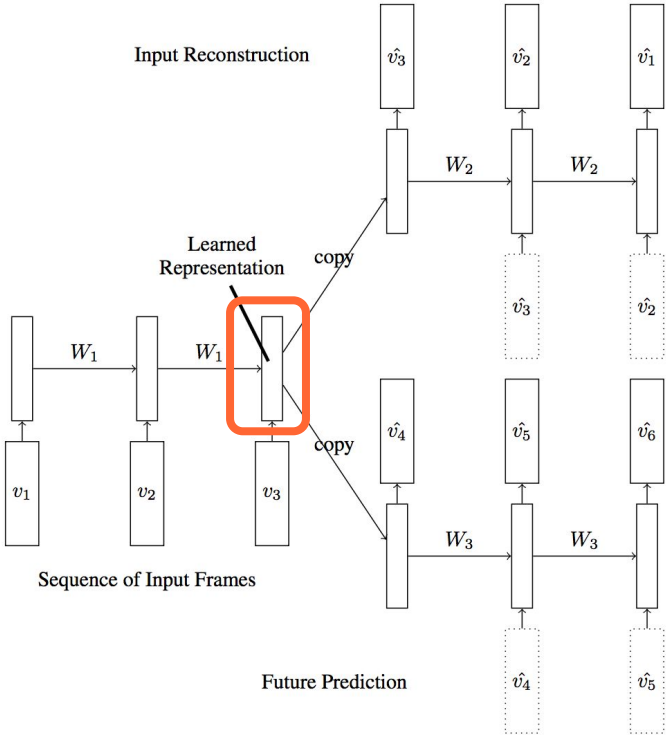


Slide credit:
Yann LeCun

Slide credit: Junting Pan

Frame Reconstruction & Prediction

Unsupervised feature learning (no labels) for...

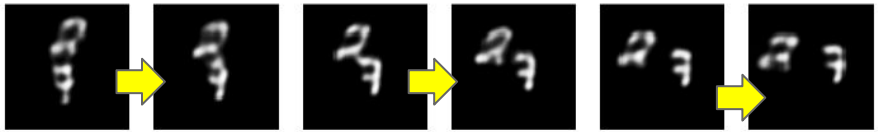


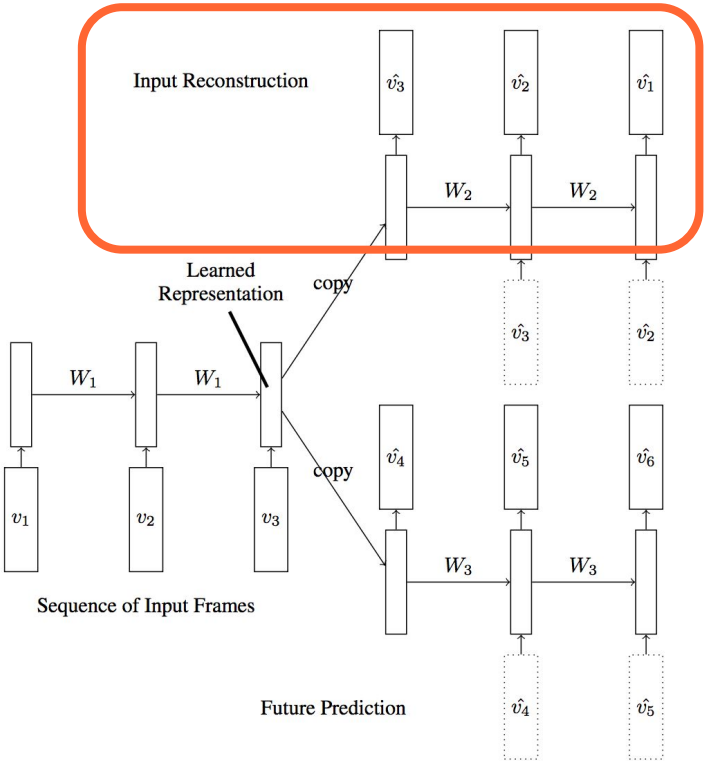
Srivastava, Nitish, Elman Mansimov, and Ruslan Salakhutdinov. "Unsupervised Learning of Video Representations using LSTMs." In ICML 2015. [Github]

Frame Reconstruction & Prediction

Unsupervised feature learning (no labels) for...

...frame prediction.



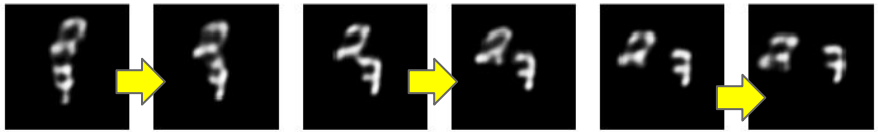


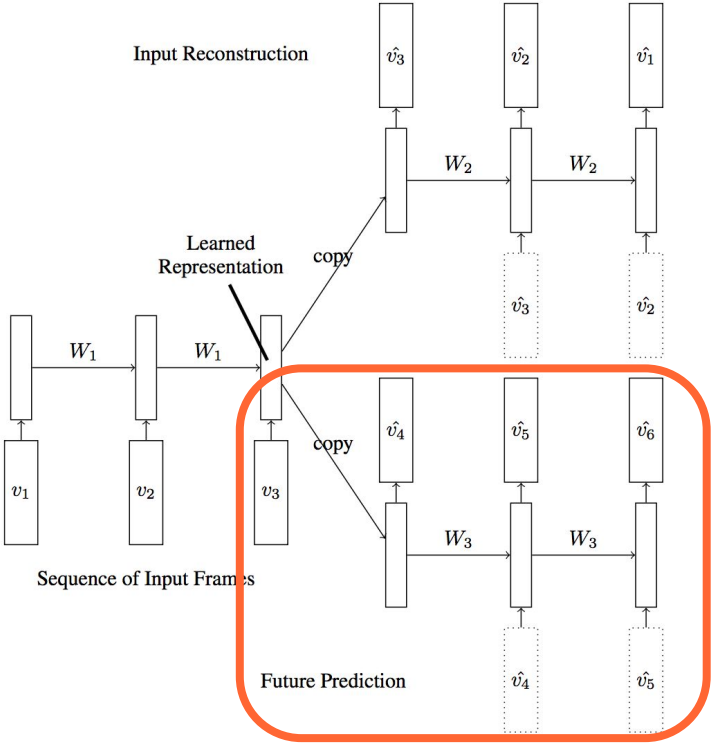
Srivastava, Nitish, Elman Mansimov, and Ruslan Salakhutdinov. "Unsupervised Learning of Video Representations using LSTMs." In ICML 2015. [Github]

Frame Reconstruction & Prediction

Unsupervised feature learning (no labels) for...

...frame prediction.





Srivastava, Nitish, Elman Mansimov, and Ruslan Salakhutdinov. "Unsupervised Learning of Video Representations using LSTMs." In ICML 2015. [Github]

Frame Reconstruction & Prediction

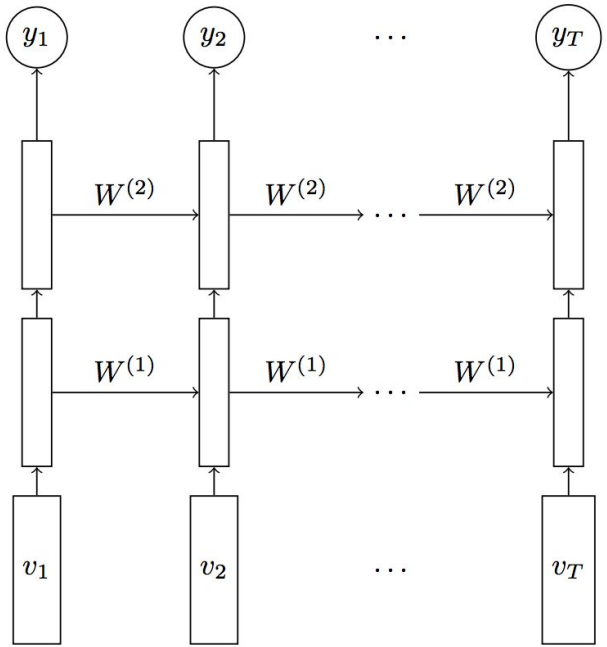


Figure 6. LSTM Classifier.

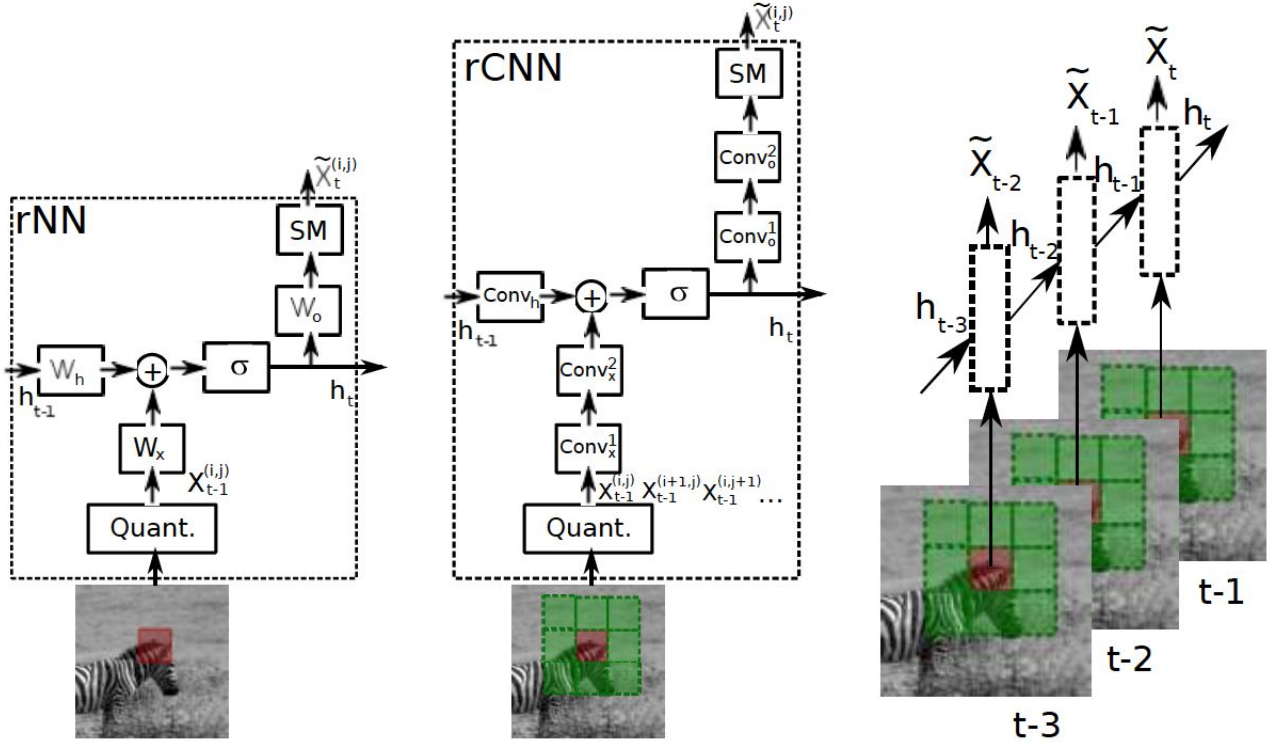
Unsupervised learned features (lots of data) are fine-tuned for activity recognition (little data).

Model	UCF-101 RGB	UCF-101 1- frame flow	HMDB-51 RGB
Single Frame	72.2	72.2	40.1
LSTM classifier	74.5	74.3	42.8
Composite LSTM Model + Finetuning	**75.8**	**74.9**	**44.1**

Table 1. Summary of Results on Action Recognition.

Srivastava, Nitish, Elman Mansimov, and Ruslan Salakhutdinov. "Unsupervised Learning of Video Representations using LSTMs." In ICML 2015. [Github]

Frame Prediction

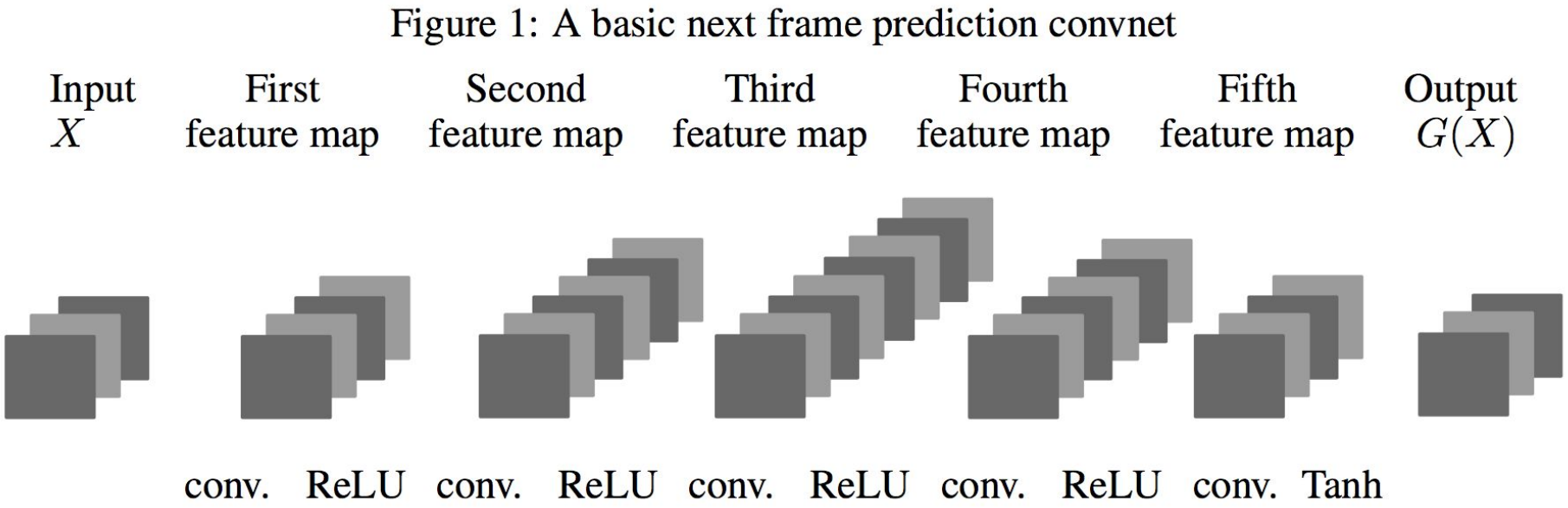


Ranzato, MarcAurelio, Arthur Szlam, Joan Bruna, Michael Mathieu, Ronan Collobert, and Sumit Chopra. "Video (language) modeling: a baseline for generative models of natural videos." arXiv preprint arXiv:1412.6604 (2014).

Frame Prediction

Video frame prediction with a ConvNet.

Figure 1: A basic next frame prediction convnet

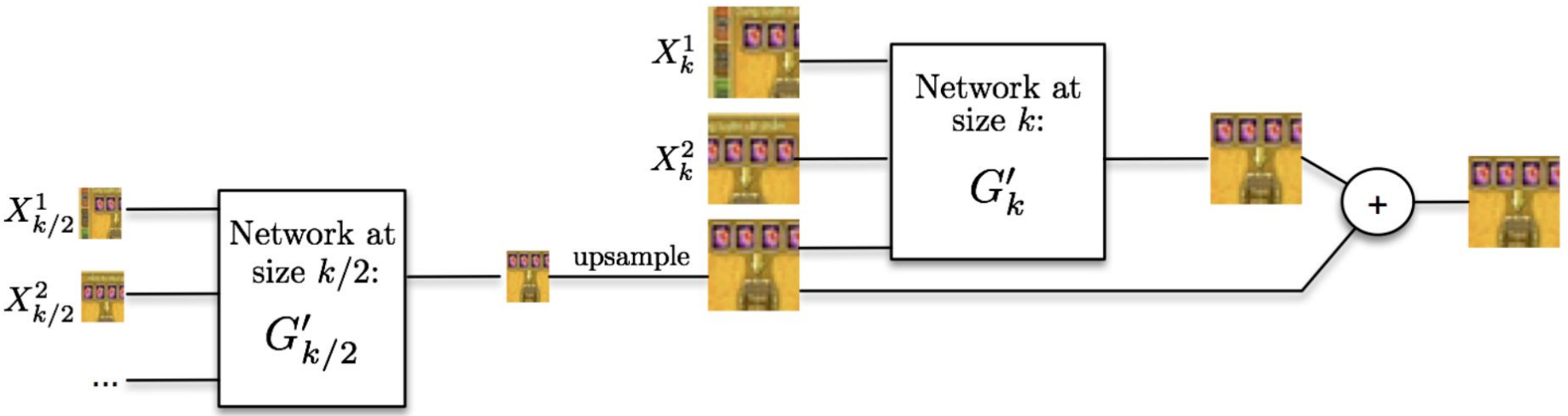


Mathieu, Michael, Camille Couprie, and Yann LeCun. "Deep multi-scale video prediction beyond mean square error." ICLR 2016 [project] [code]

Frame Prediction

The blurry predictions from MSE are improved with **multi-scale architecture**, adversarial learning and an image gradient difference loss function.

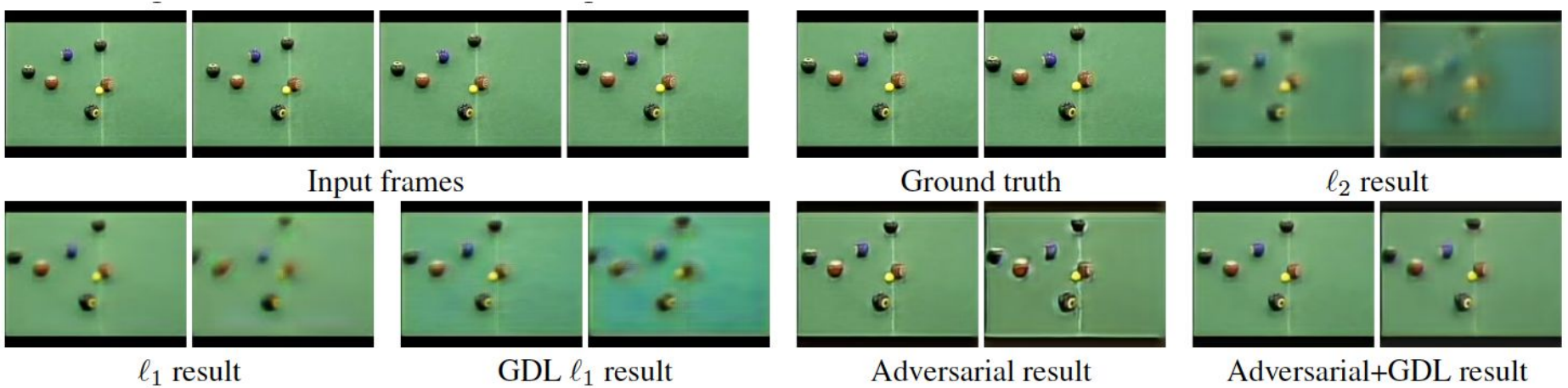
Figure 2: Multi-scale architecture



Mathieu, Michael, Camille Couprie, and Yann LeCun. "Deep multi-scale video prediction beyond mean square error." ICLR 2016 [project] [code]

Frame Prediction

The blurry predictions from MSE (l1) are improved with multi-scale architecture, **adversarial training** and an **image gradient difference loss (GDL)** function.

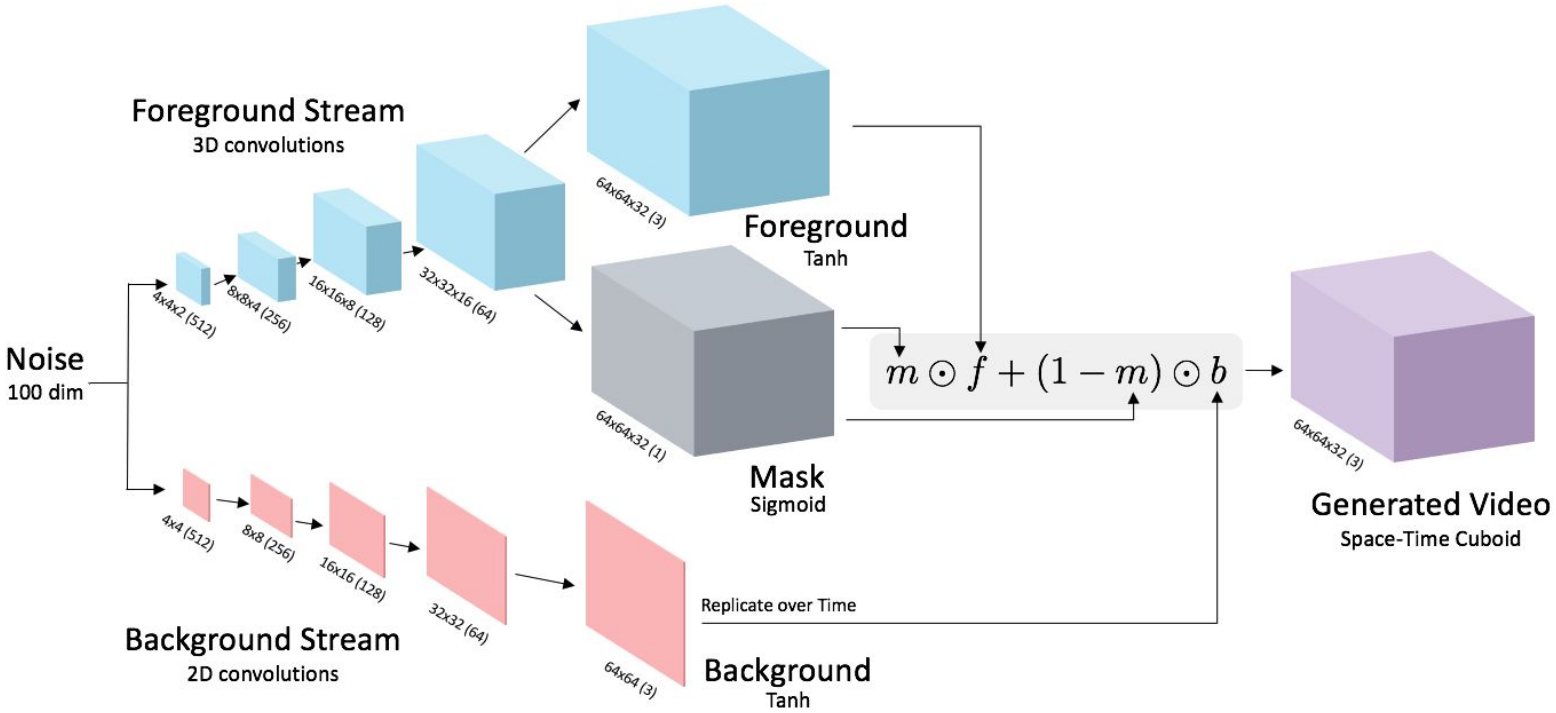


Mathieu, Michael, Camille Couprie, and Yann LeCun. "Deep multi-scale video prediction beyond mean square error." ICLR 2016 [project] [code]

Frame Prediction

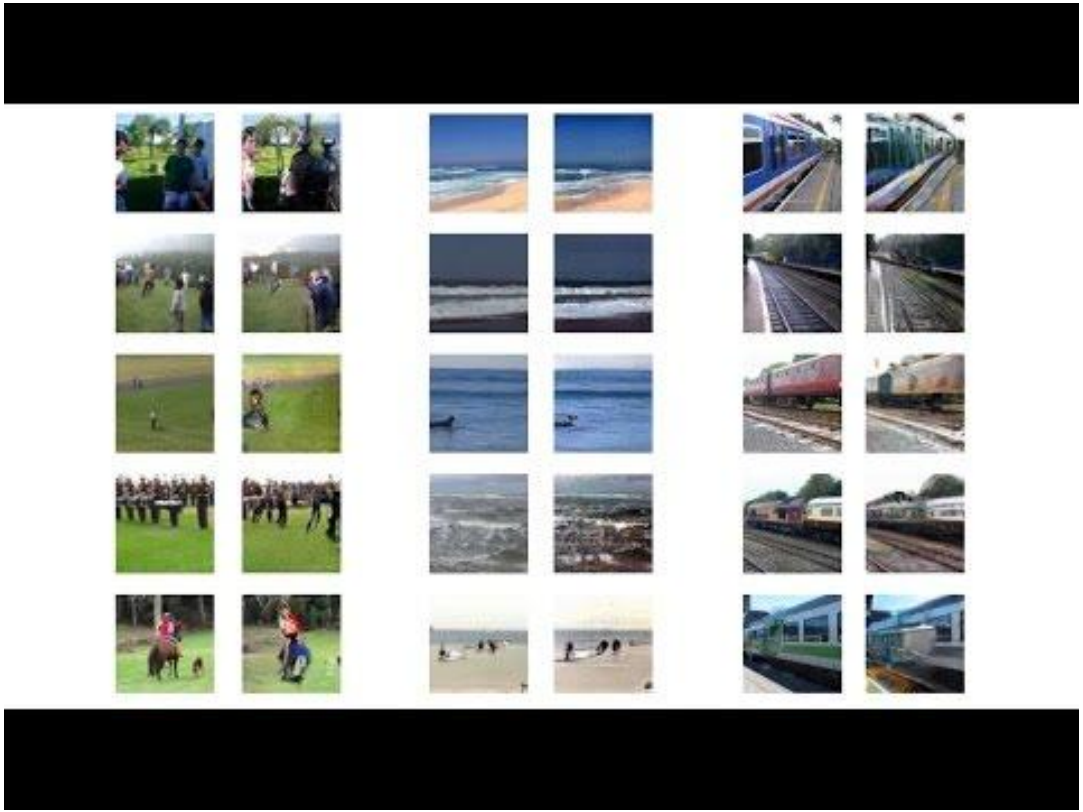
Mathieu, Michael, Camille Couprie, and Yann LeCun. "Deep multi-scale video prediction beyond mean square error." ICLR 2016 [project] [code]

Frame Prediction

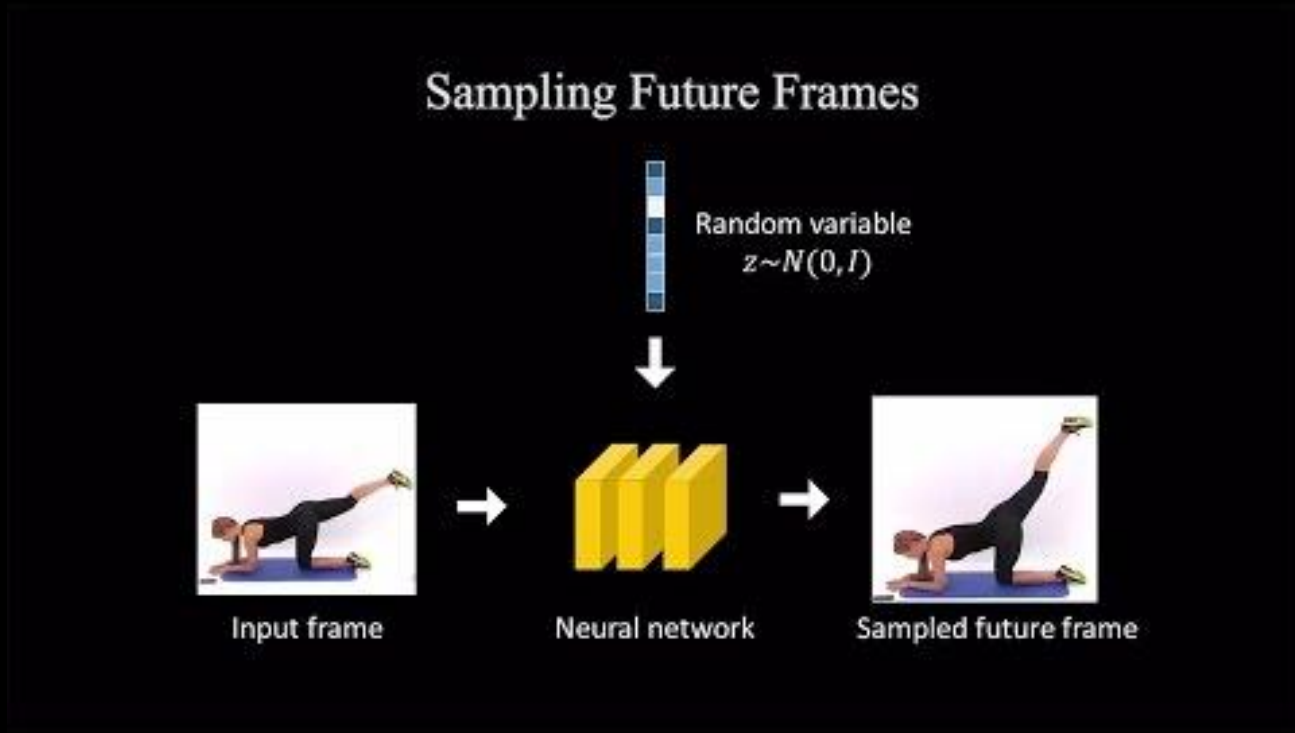


Vondrick, Carl, Hamed Pirsiavash, and Antonio Torralba. "Generating videos with scene dynamics." NIPS 2016.

Frame Prediction



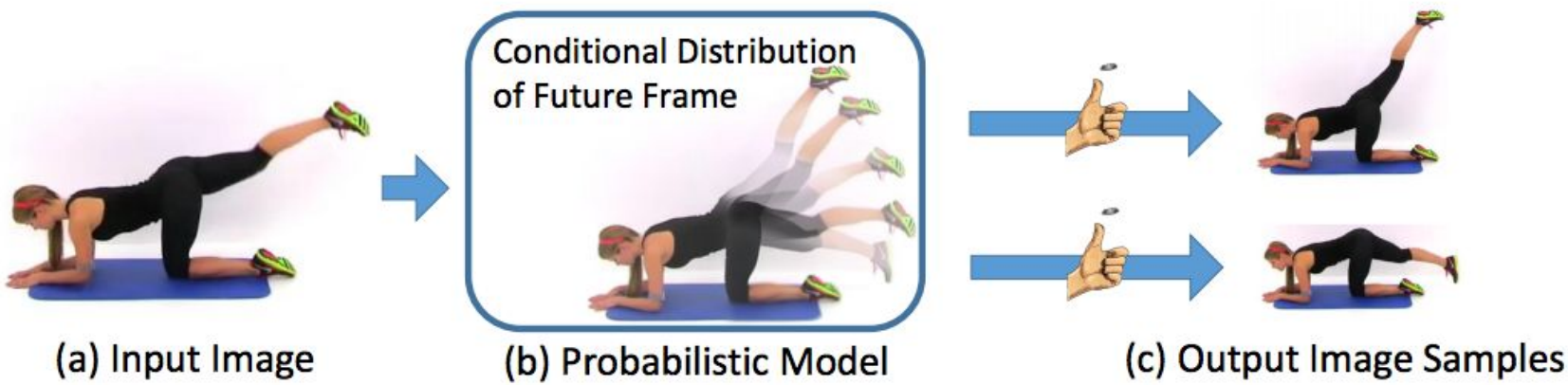
Vondrick, Carl, Hamed Pirsiavash, and Antonio Torralba. "Generating videos with scene dynamics." NIPS 2016.



Xue, Tianfan, Jiajun Wu, Katherine Bouman, and Bill Freeman. "Visual dynamics: Probabilistic future frame synthesis via cross convolutional networks." NIPS 2016 [video]

Frame Prediction

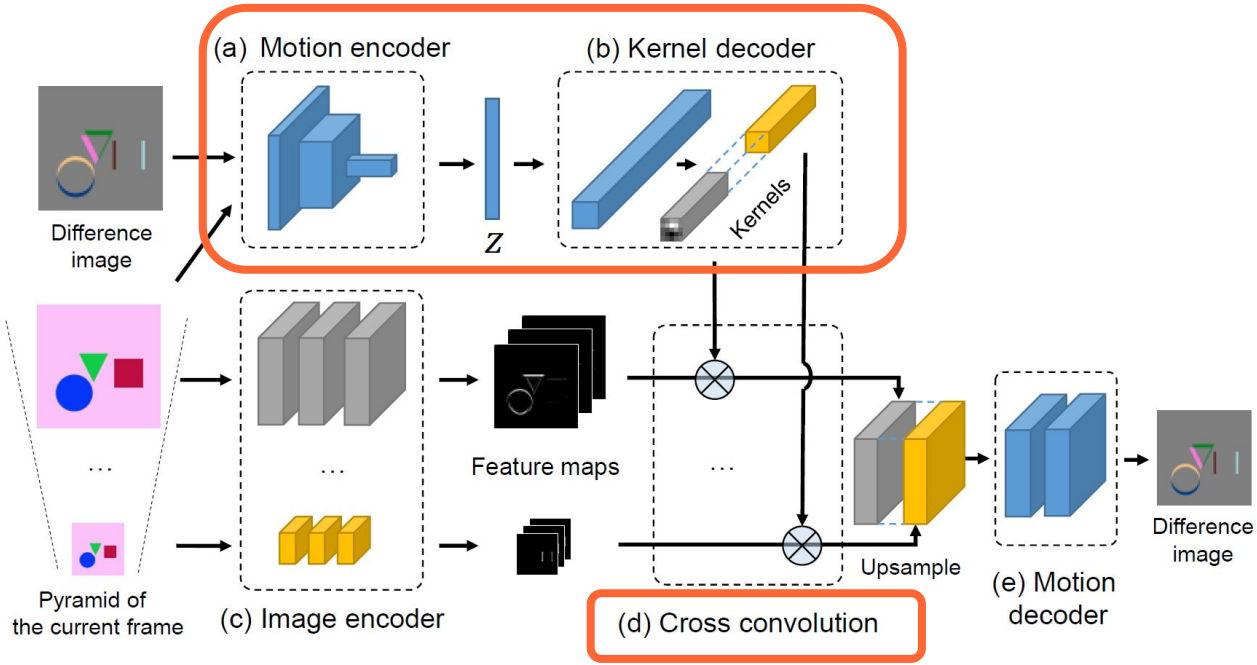
Given an input image, probabilistic generation of future frames with a **Variational AutoEncoder (VAE)**.



Xue, Tianfan, Jiajun Wu, Katherine Bouman, and Bill Freeman. "Visual dynamics: Probabilistic future frame synthesis via cross convolutional networks." NIPS 2016 [video]

Frame Prediction

Encodes image as feature maps, and motion as and **cross-convolutional kernels**.

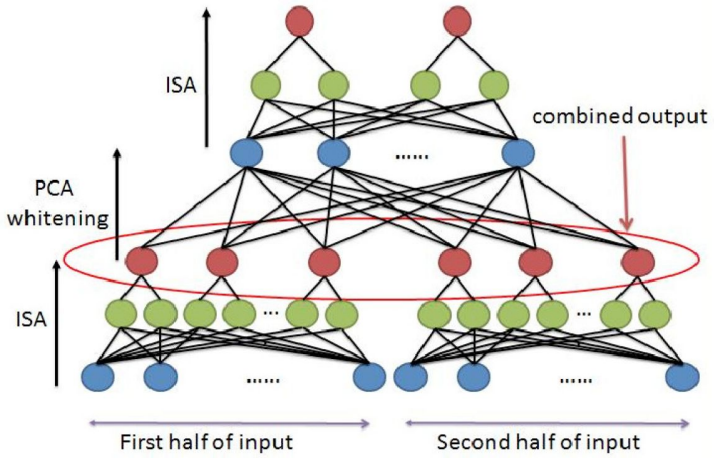


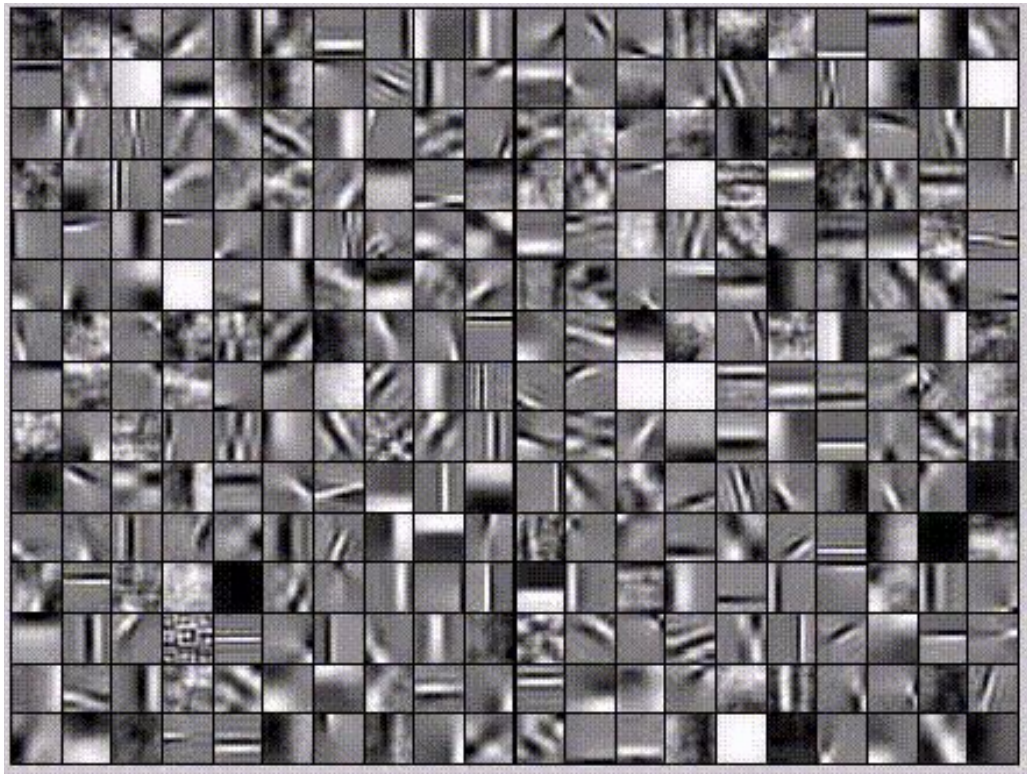
Xue, Tianfan, Jiajun Wu, Katherine Bouman, and Bill Freeman. "Visual dynamics: Probabilistic future frame synthesis via cross convolutional networks." NIPS 2016 [video]

Outline

1. Motivation
2. Unsupervised Learning
3. Predictive Learning
4. **Self-supervised Learning**

First steps in video feature learning

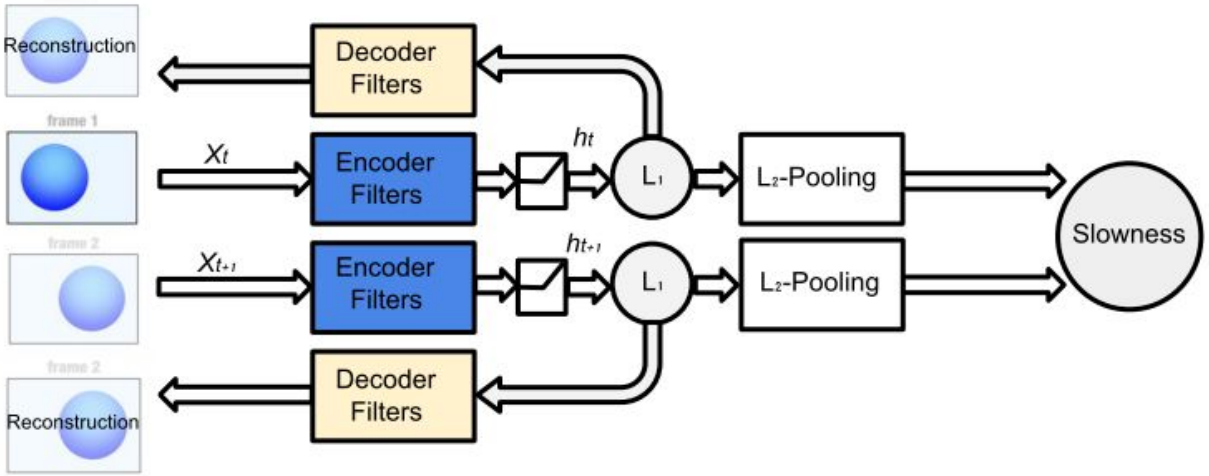




Le, Quoc V., Will Y. Zou, Serena Y. Yeung, and Andrew Y. Ng. "Learning hierarchical invariant spatio-temporal features for action recognition with independent subspace analysis." CVPR 2011

Temporal Weak Labels

Assumption: adjacent video frames contain semantically similar information.
Autoencoder trained with regularizations by slowliness and sparisty.



Goroshin, Ross, Joan Bruna, Jonathan Tompson, David Eigen, and Yann LeCun. "Unsupervised learning of spatiotemporally coherent metrics." ICCV 2015.

Temporal Weak Labels

Slow feature analysis

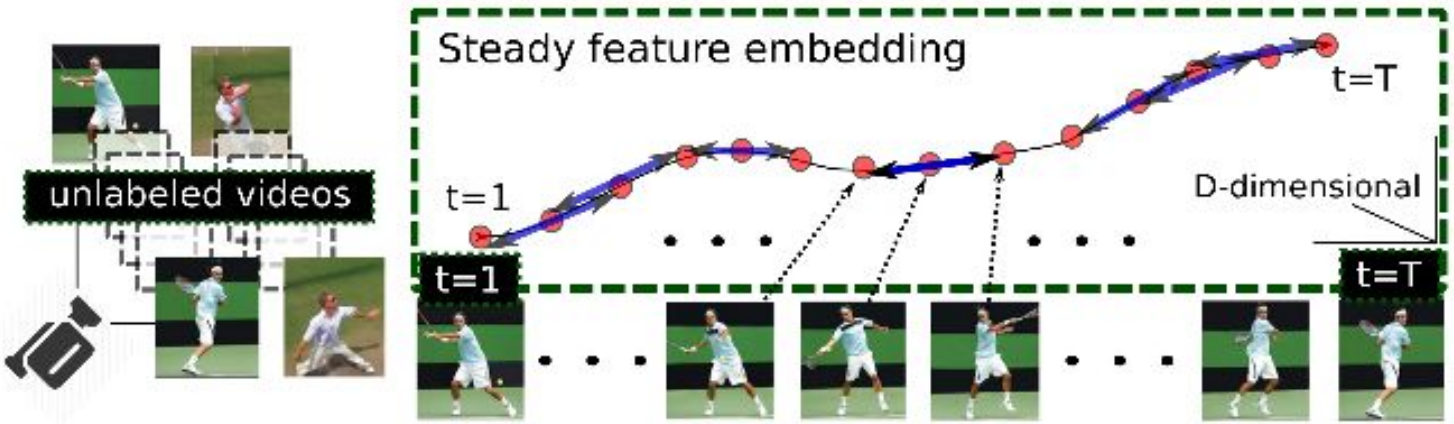
- Temporal coherence assumption: features should change slowly over time in video

Steady feature analysis

- Second order changes also small: changes in the past should resemble changes in the future

Train on triplets of frames from video

Loss encourages nearby frames to have slow and steady features, and far frames to have different features



Jayaraman, Dinesh, and Kristen Grauman. "Slow and steady feature analysis: higher order temporal coherence in video." CVPR 2016. [video]

Temporal Weak Labels

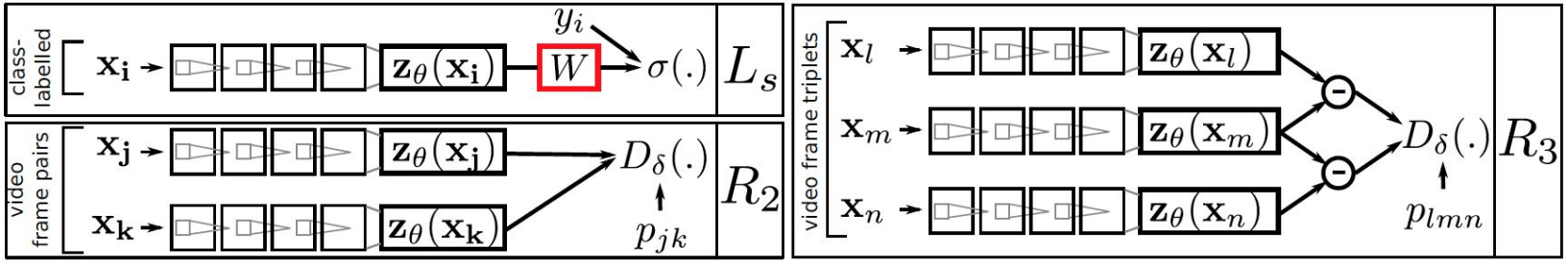


Figure 2: "Siamese" network configuration (shared weights for the $\mathbf{z}_\theta$ layer stacks) with portions corresponding to the 3 terms L_s, R_2 and R_3 in our objective. R_2 and R_3 compose the unsupervised loss L_u in Eq (1). L_s is the supervised loss for recognition in static images.

Task	Img/frame dims	#Classes	Recog. Task	#Train	#Test	Unsup. Input Type	#Pairs (1:3)	#Triplets (1:1)
NORB→NORB	96×96×1	25	object	150	8100	pose-reg. images	50,000	75,000
KITTI→SUN	32×32×1	397	scene	2382	7940	car-mounted video	100,000	100,000
HMDB→PASCAL-10	32×32×3	10	action	50	2000	web video	100,000	100,000

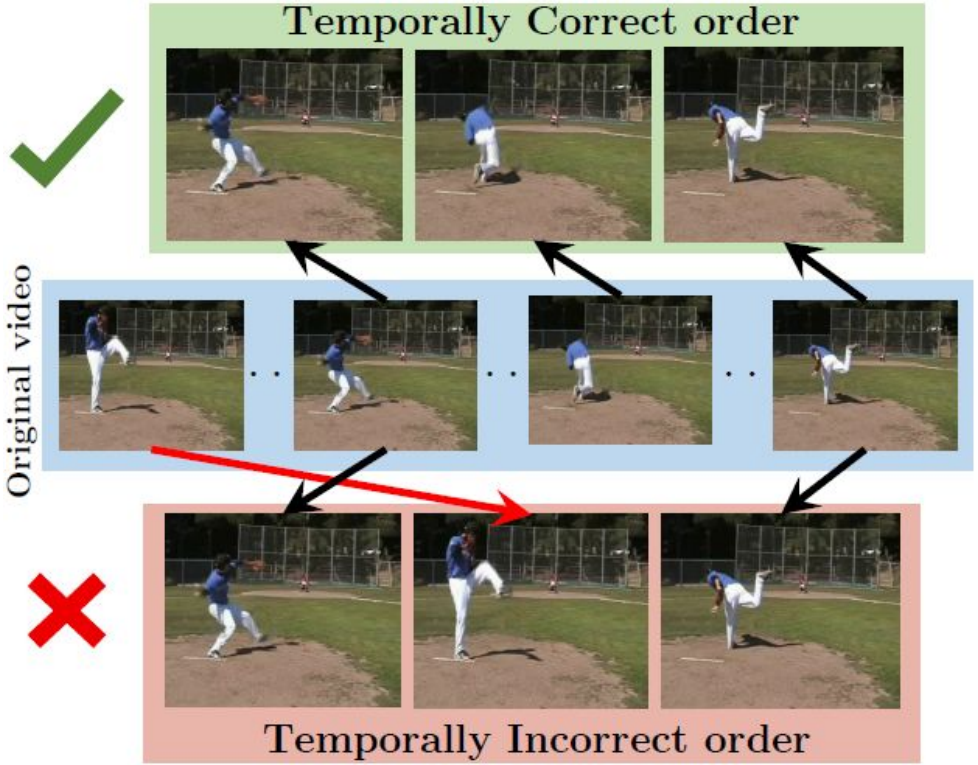
Datasets→	NORB	KITTI	HMDB
SFA-1 [30]	0.95	31.04	2.70
SFA-2 [14]	0.91	8.39	2.27
SSFA (ours)	**0.53**	**7.79**	**1.78**

Table 1: Left: Statistics for the unsupervised and supervised datasets ($\mathcal{U} \rightarrow \mathcal{S}$) used in the recognition tasks (positive to negative ratios for pairs and triplets indicated in headers). **Right:** Sequence completion normalized correct candidate rank η. Lower is better. (See Sec 4.2.)

Jayaraman, Dinesh, and Kristen Grauman. "Slow and steady feature analysis: higher order temporal coherence in video." CVPR 2016. [video]

Temporal Weak Labels

Temporal order of frames is exploited as the supervisory signal for learning.

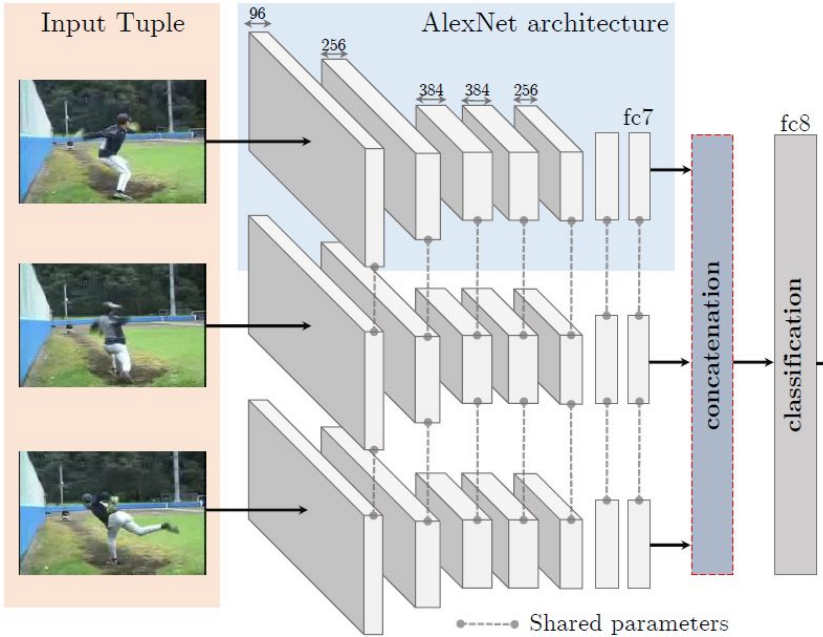


(Slides by Xunyu Lin): Misra, Ishan, C. Lawrence Zitnick, and Martial Hebert. "Shuffle and learn: unsupervised learning using temporal order verification." ECCV 2016. [code]

Temporal Weak Labels

Take temporal order as the supervisory signals for learning

Shuffled sequences



Binary classification

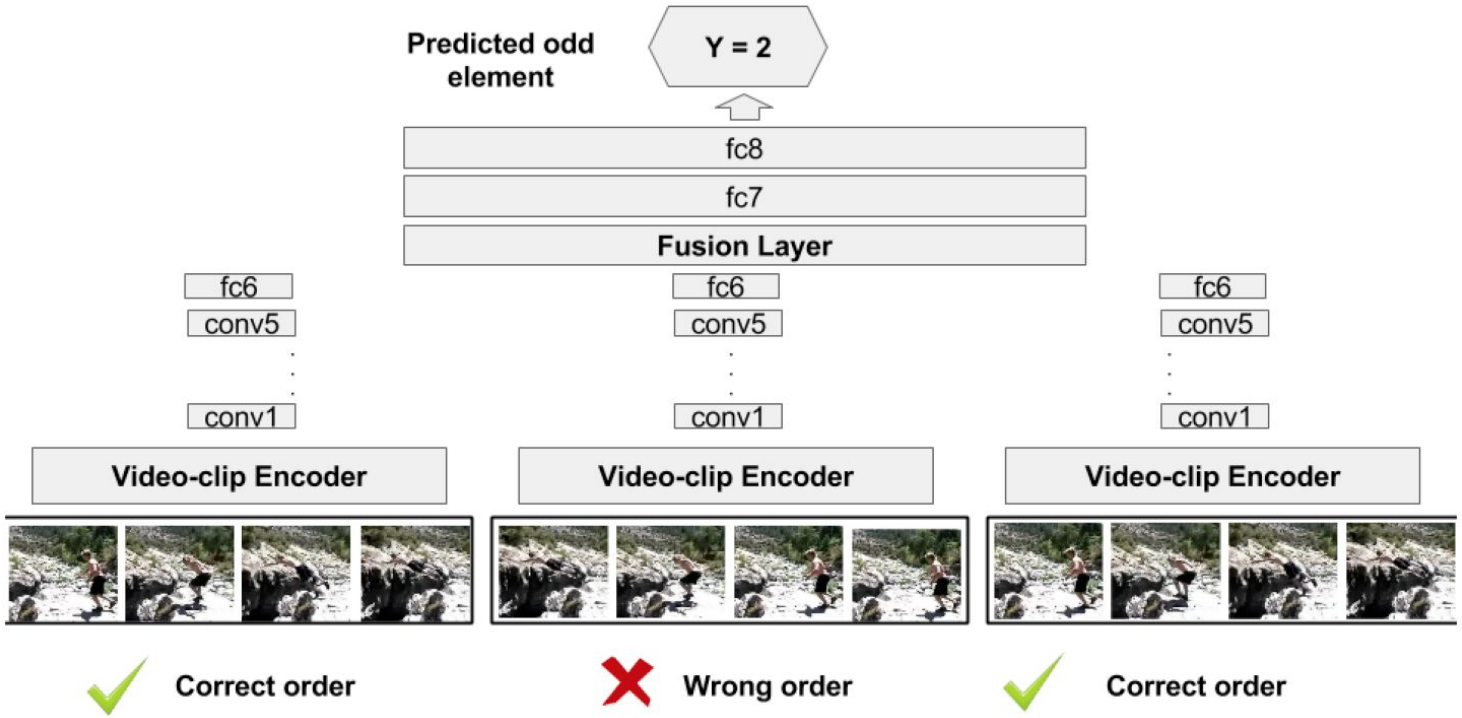
In order

Not in order

(Slides by Xunyu Lin): Misra, Ishan, C. Lawrence Zitnick, and Martial Hebert. "Shuffle and learn: unsupervised learning using temporal order verification." ECCV 2016. [code]

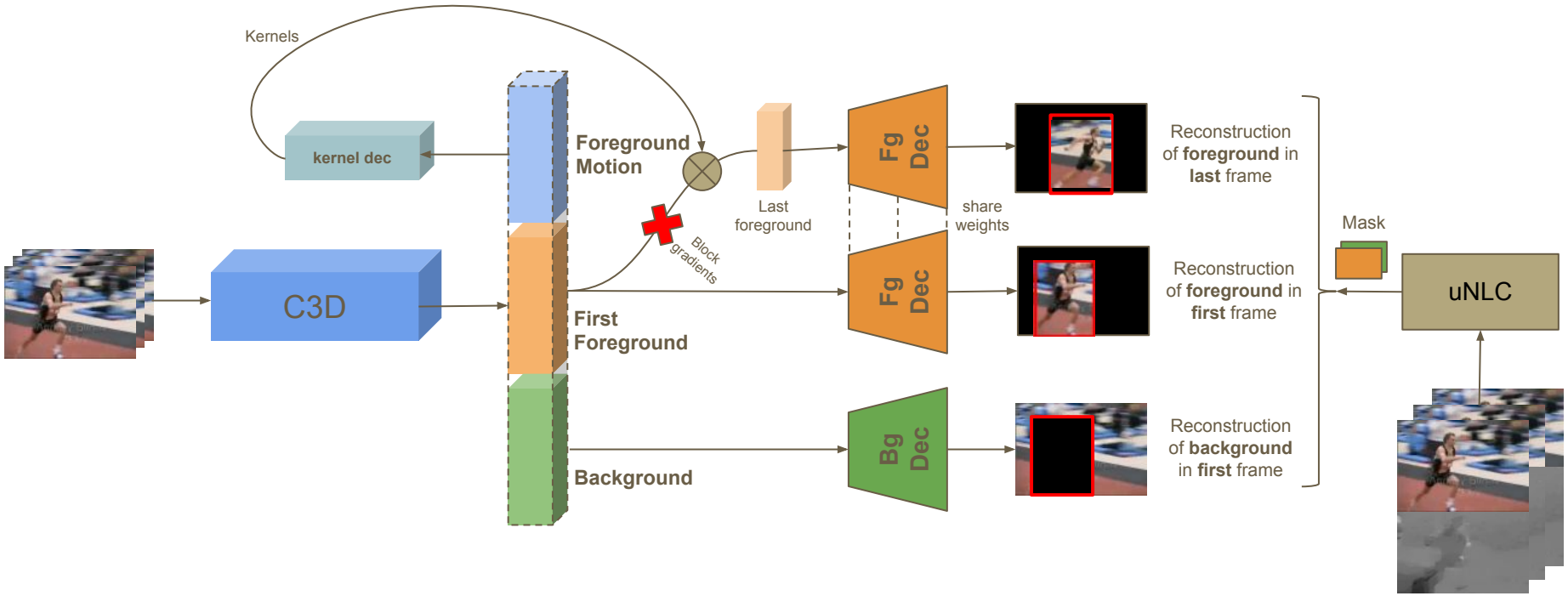
Temporal Weak Labels

Train a network to detect which of the video sequences contains frames wrong order.



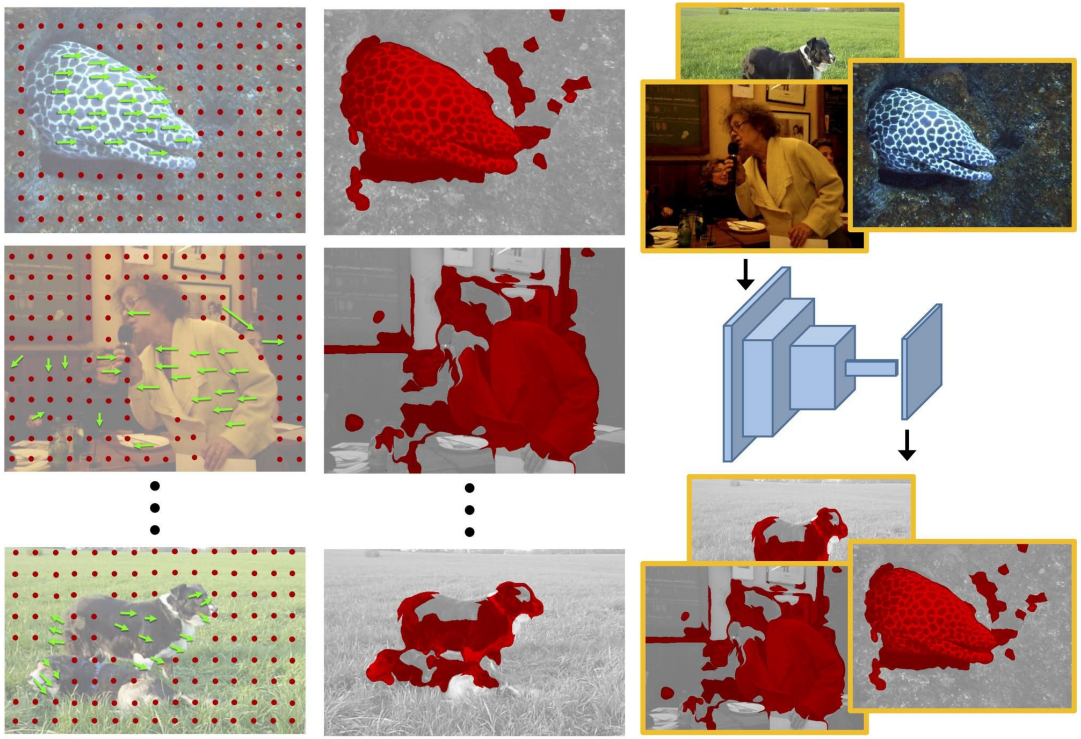
Fernando, Basura, Hakan Bilen, Efstratios Gavves, and Stephen Gould. "Self-supervised video representation learning with odd-one-out networks." CVPR 2017

Spatio-Temporal Weak Labels



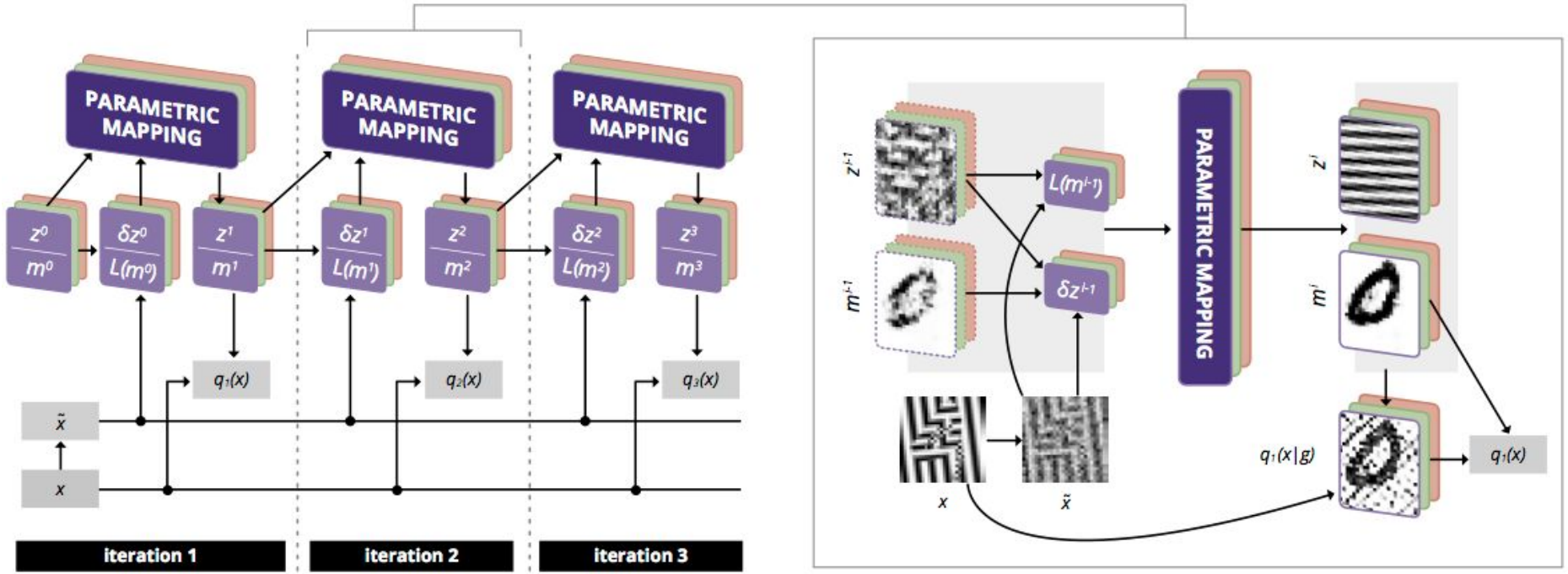
X. Lin, Campos, V., Giró-i-Nieto, X., Torres, J., and Canton-Ferrer, C., "**Disentangling Motion, Foreground and Background Features in Videos**", in *CVPR 2017 Workshop Brave New Motion Representations*

Spatio-Temporal Weak Labels



Pathak, Deepak, Ross Girshick, Piotr Dollár, Trevor Darrell, and Bharath Hariharan. "Learning features by watching objects move." CVPR 2017

Spatio-Temporal Weak Labels



Greff, Klaus, Antti Rasmus, Mathias Berglund, Tele Hao, Harri Valpola, and Juergen Schmidhuber. "Tagger: Deep unsupervised perceptual grouping." NIPS 2016 [video] [code]

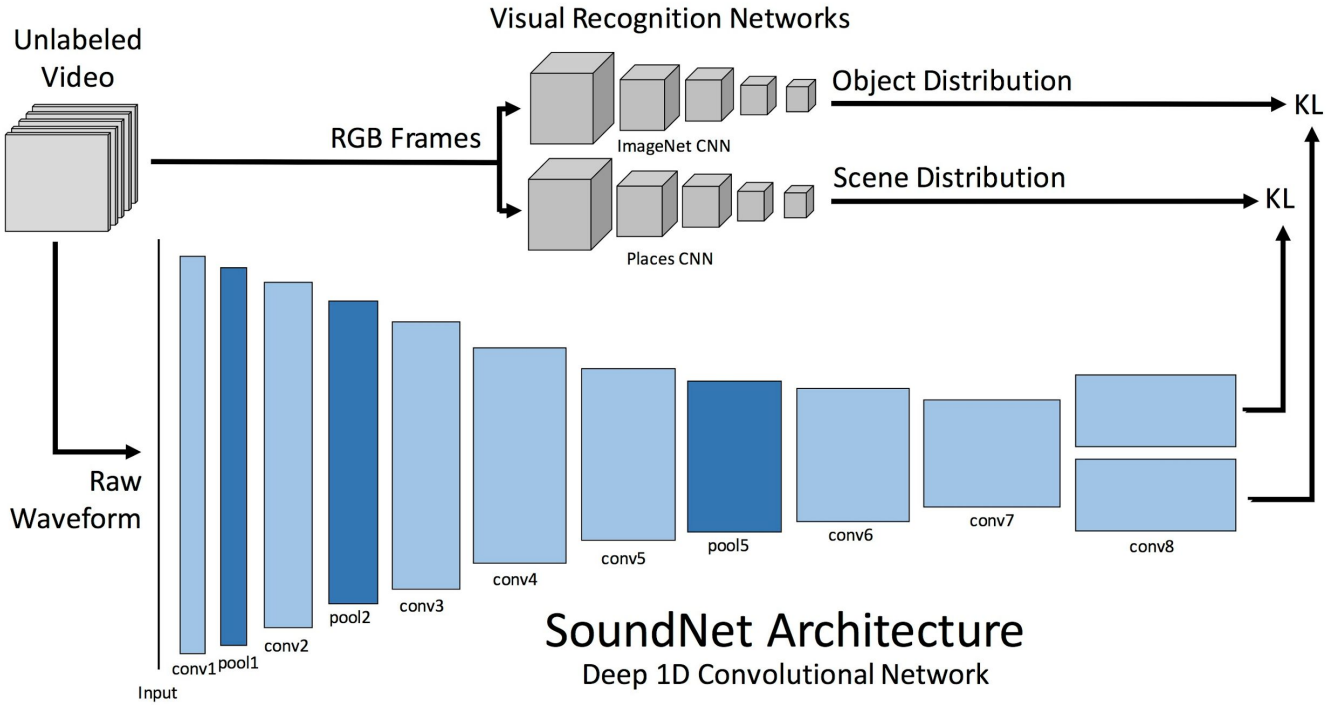
Predicted Objects and Scenes from Sound Only

(Videos are blurred so you can try to recognize yourself!)

Aytar, Yusuf, Carl Vondrick, and Antonio Torralba. "Soundnet: Learning sound representations from unlabeled video." NIPS 2016.

Audio Features from Visual weak labels

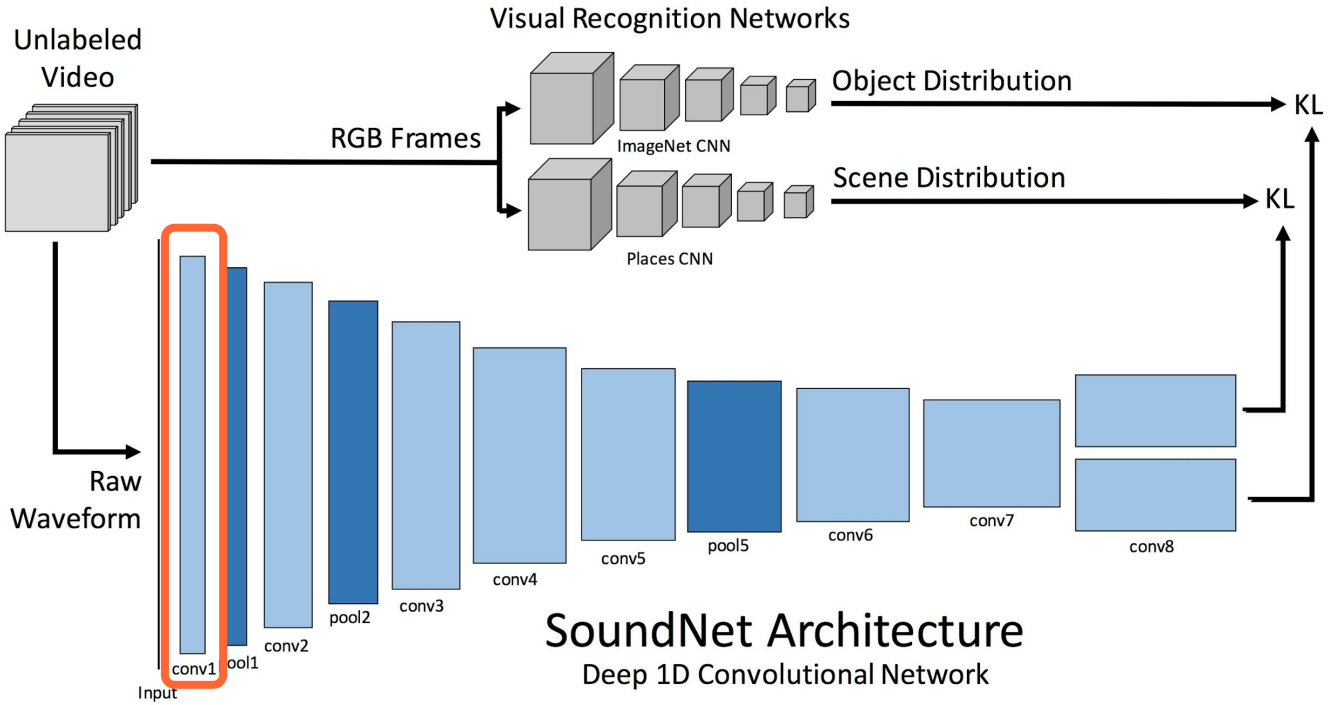
Object & Scenes recognition in videos by analysing the audio track (only).



Aytar, Yusuf, Carl Vondrick, and Antonio Torralba. "Soundnet: Learning sound representations from unlabeled video." NIPS 2016.

Audio Features from Visual weak labels

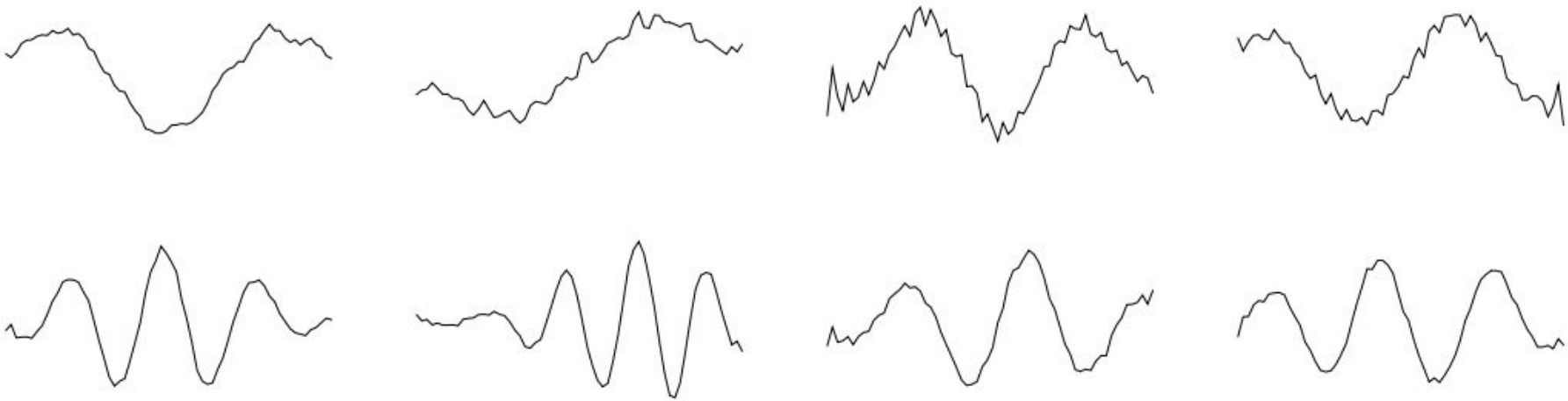
Visualization of the 1D filters over raw audio in conv1.



Aytar, Yusuf, Carl Vondrick, and Antonio Torralba. "Soundnet: Learning sound representations from unlabeled video." NIPS 2016.

Audio Features from Visual weak labels

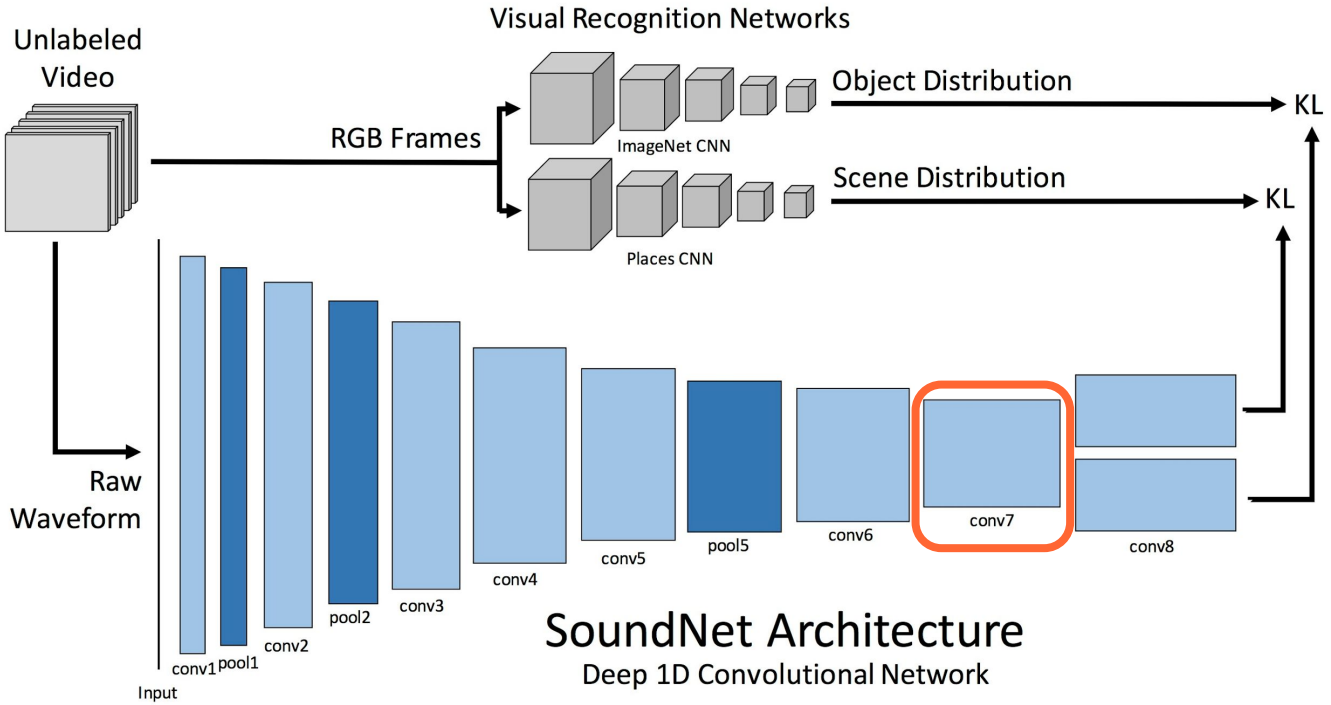
Visualization of the 1D filters over raw audio in conv1.



Aytar, Yusuf, Carl Vondrick, and Antonio Torralba. "Soundnet: Learning sound representations from unlabeled video." NIPS 2016.

Audio Features from Visual weak labels

Visualization of the 1D filters over raw audio in conv1.



Aytar, Yusuf, Carl Vondrick, and Antonio Torralba. "Soundnet: Learning sound representations from unlabeled video." NIPS 2016.

Audio Features from Visual weak labels

Visualization of the video frames associated to the sounds that activate some of the last hidden units of Soundnet (conv7):

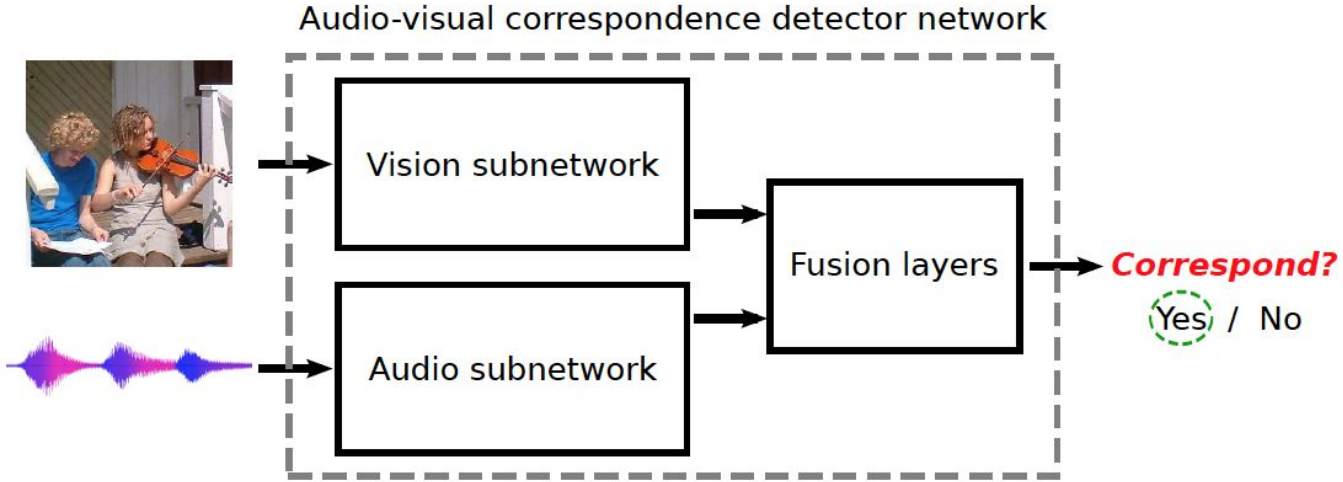
Baby Talk

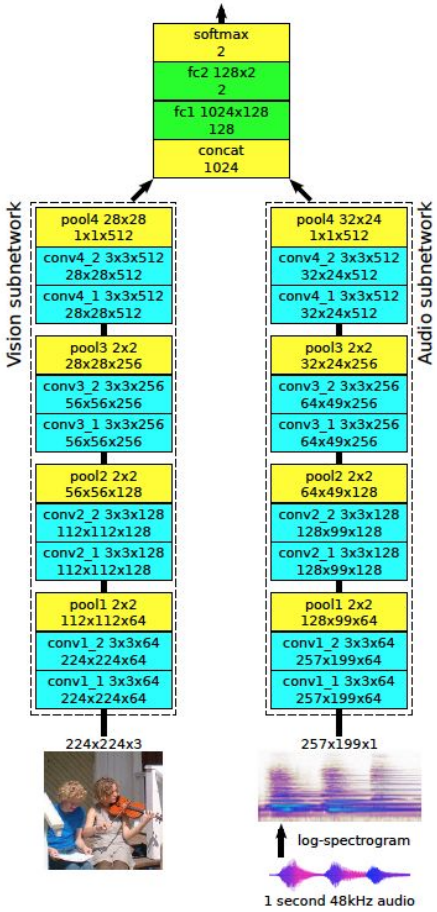
Bubbles

Aytar, Yusuf, Carl Vondrick, and Antonio Torralba. "Soundnet: Learning sound representations from unlabeled video." NIPS 2016.

Audio & Visual features from alignement

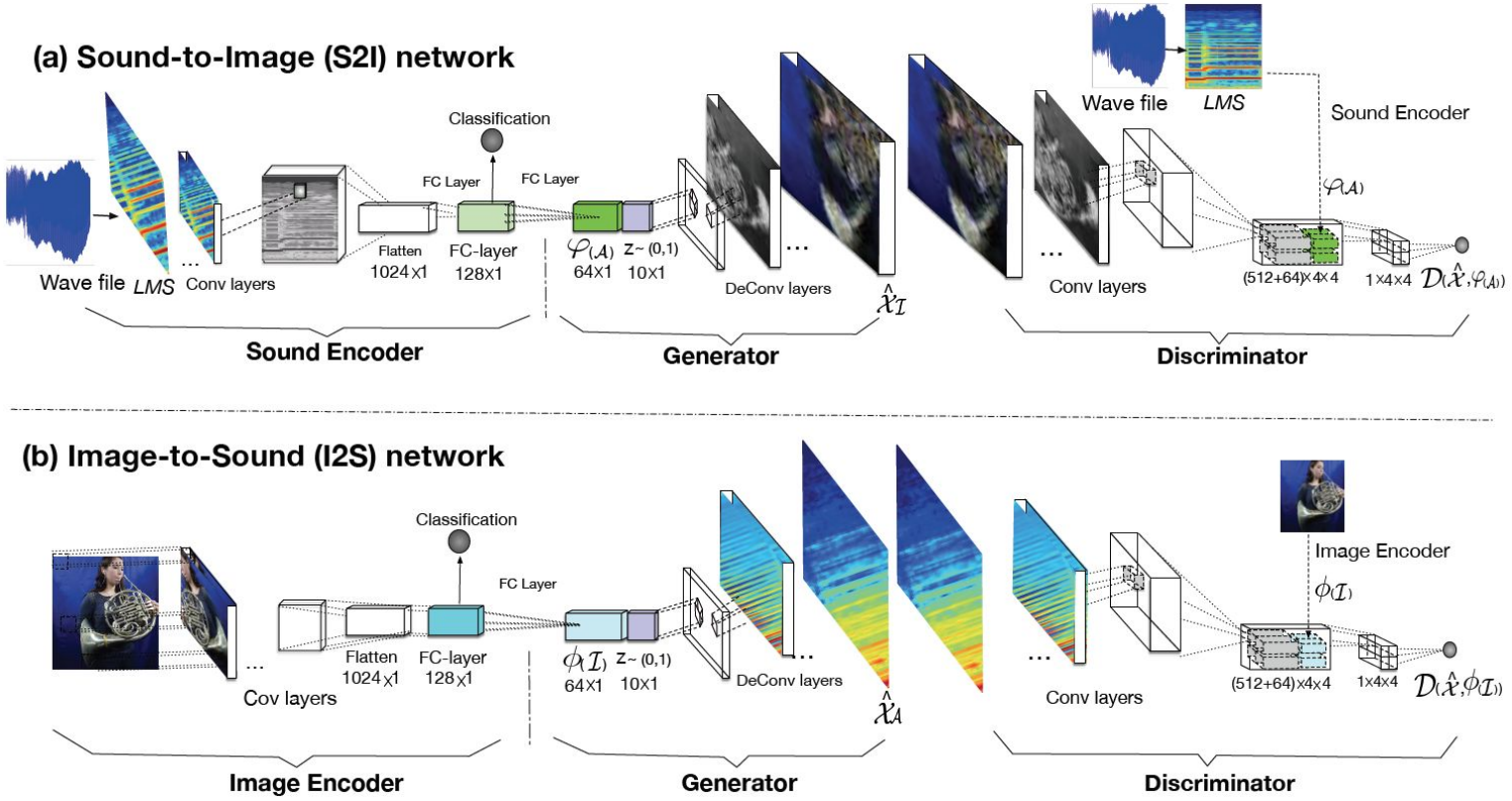
Audio and visual features learned by assessing alignement.





Arandjelović, Relja, and Andrew Zisserman. "Look, Listen and Learn." *ICCV 2017*

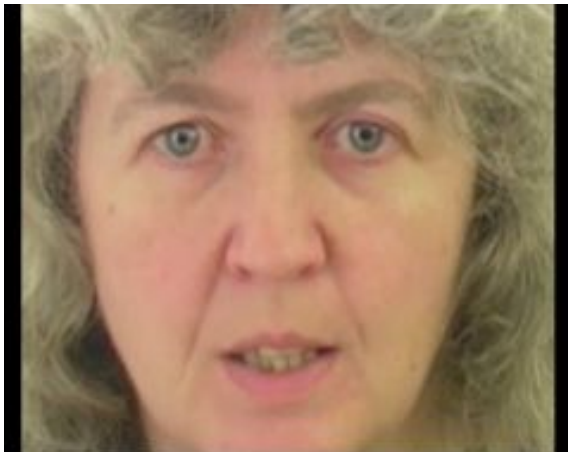
Audio & Visual features from alignement



L. Chen, S. Srivastava, Z. Duan and C. Xu. Deep Cross-Modal Audio-Visual Generation. ACM International Conference on Multimedia Thematic Workshops, 2017.

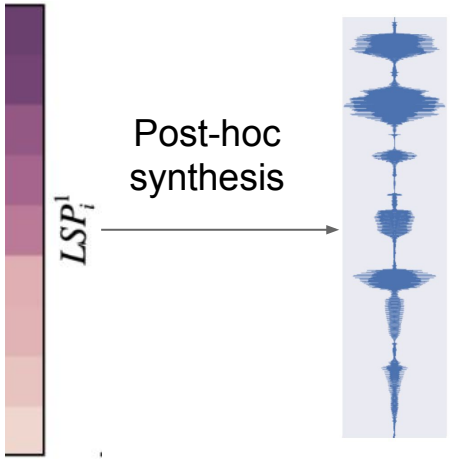
Ephrat, Ariel, and Shmuel Peleg. "Vid2speech: Speech Reconstruction from Silent Video." *ICASSP 2017*

Video to Speech Representations



Frame from a silent video

CNN (VGG)

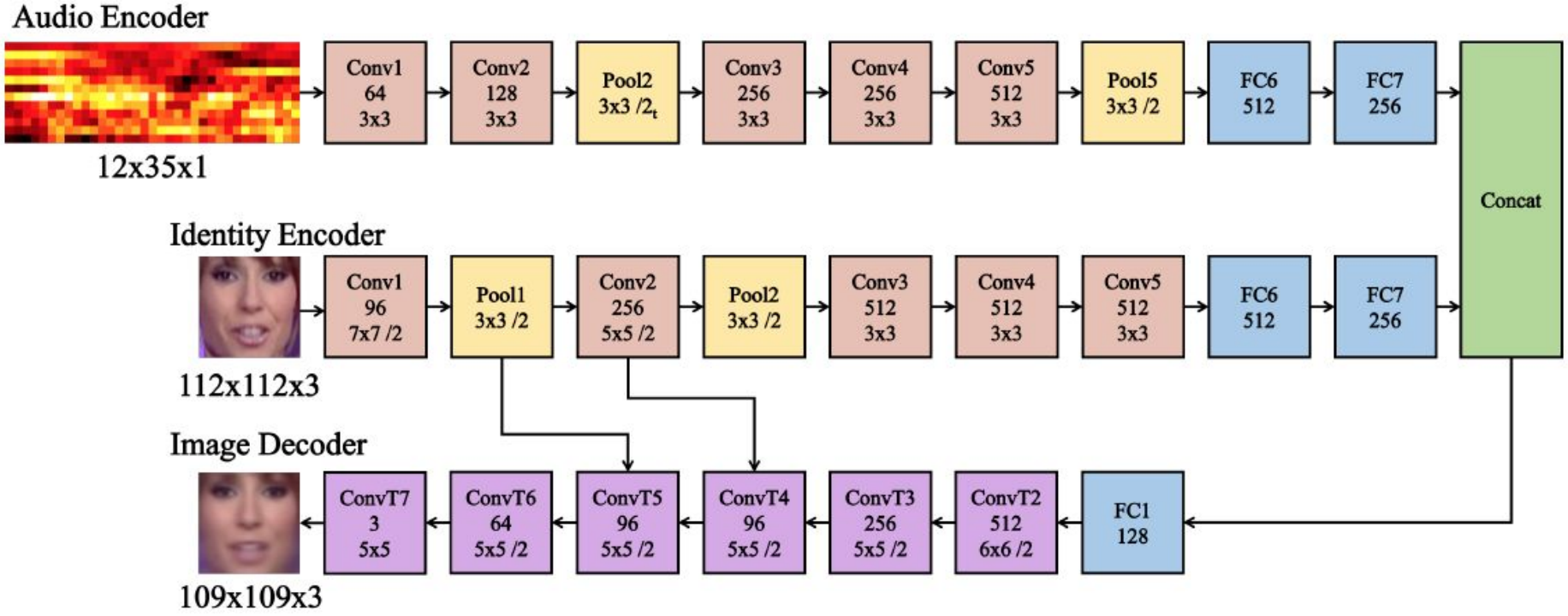


Audio feature

Ephrat, Ariel, and Shmuel Peleg. "Vid2speech: Speech Reconstruction from Silent Video." *ICASSP 2017*

Chung, Joon Son, Amir Jamaludin, and Andrew Zisserman. "You said that?." BMVC 2017.

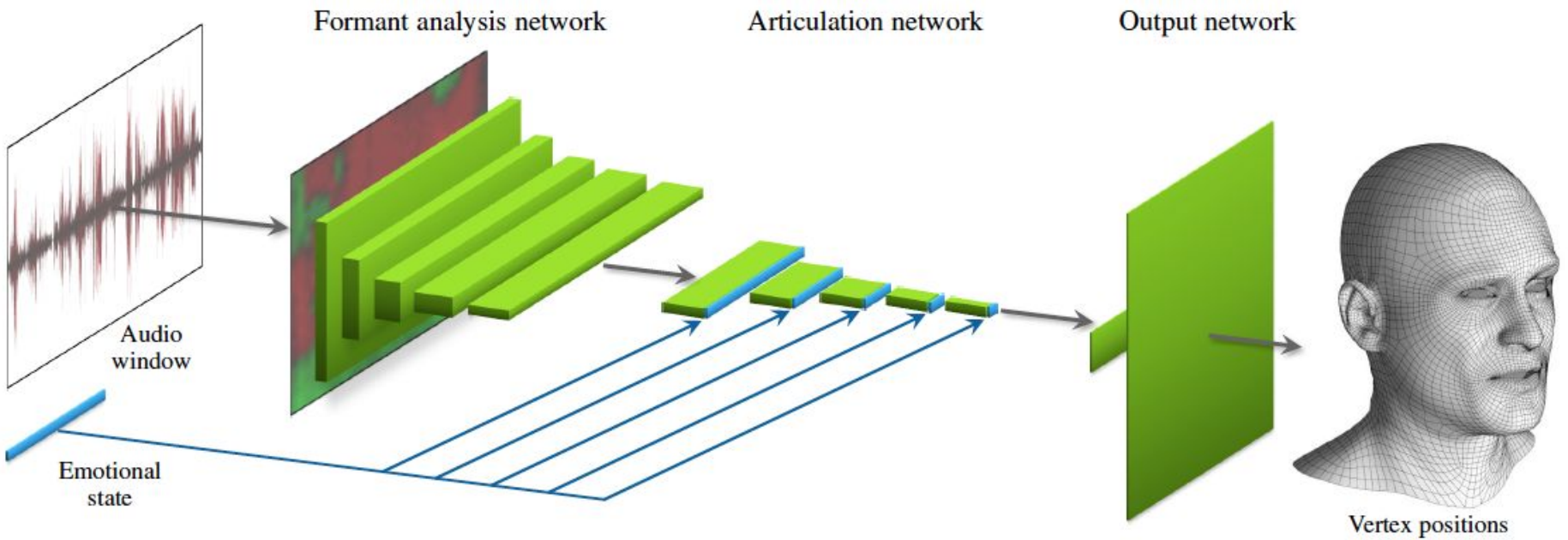
Speech to Video Synthesis (mouth)



Chung, Joon Son, Amir Jamaludin, and Andrew Zisserman. "You said that?." BMVC 2017.

Karras, Tero, Timo Aila, Samuli Laine, Antti Herva, and Jaakko Lehtinen. "Audio-driven facial animation by joint end-to-end learning of pose and emotion." SIGGRAPH 2017

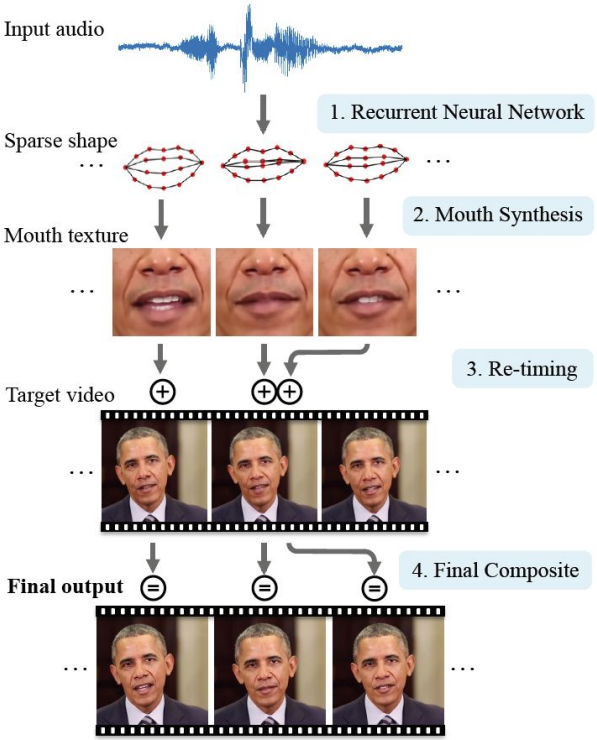
Speech to Video Synthesis (pose & emotion)



Karras, Tero, Timo Aila, Samuli Laine, Antti Herva, and Jaakko Lehtinen. "Audio-driven facial animation by joint end-to-end learning of pose and emotion." SIGGRAPH 2017

Karras, Tero, Timo Aila, Samuli Laine, Antti Herva, and Jaakko Lehtinen. "Audio-driven facial animation by joint end-to-end learning of pose and emotion." SIGGRAPH 2017

Speech to Video Synthesis (mouth)



Suwajanakorn, Supasorn, Steven M. Seitz, and Ira Kemelmacher-Shlizerman. "Synthesizing Obama: learning lip sync from audio." SIGGRAPH 2017.

Outline

1. Motivation
2. Unsupervised Learning
3. Predictive Learning
4. Self-supervised Learning