THE UNIVERSITY OF BRITISH COLUMBIA

Topics in AI (CPSC 532L):
Multimodal Learning with Vision, Language and Sound

Lecture 9: Unsupervised Learning, Autoencoders

Course **Logistics**

- **Paper choices** (google form) was due Yesterday
- **Projects** (google form) will be available by Monday
- **Projects** pitches & feedback today
- Project proposals (in class on **Feb 15th**)

Remaining lectures before the break …

Jan 30 — RNNs and encoder-decoder architectures (including with attention)

LSTMS and variants, Applications: Language translation, Captioning, VQA, Action Recognition

Feb 1 — Unsupervised learning and Auto-encoders

Feb 6 — Joint multimodal learning and embedding models

Metric learning based models; various losses

Feb 8 — Generative models

Variational Auto Encoders (VAE), Generative Adversarial Networks (GANs), PixelRNN

Feb 13 — Deep Reinforcement Learning

The basics

Feb 15 — Project proposals in class

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Assignment 4

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Final **Project** (50% of grade total) – Reminder

- Group project (groups of 3 are encouraged, but fewer maybe possible)
- Groups are self-formed, you will not be assigned to a group
- You need to come up with a project proposal and then work on the project as a group (each person in the group gets the same grade for the project)
- Project needs to be **research** oriented (not simply implementing an existing paper); you can use code of existing paper as a starting point though

Project proposal + class presentation: 15%
Project + final presentation: 35%

Don’t be shy, come talk to me about your projects (individually or in groups)

scope, datasets, paper references, etc.

(helps if you have an **initial idea** to start from)

Project proposal and class presentation — **15%** of grade

Presentation (~5 minutes irrespective of the group size)

1. Clear explanation of the **overall problem** you want to solve and relationship to the topics covered in class
2. What **model/algorithms** you planning to explore: at this can be somewhat abstract (e.g., CNN+RNN)
3. The **dataset(s)** you will use and how will you **evaluate** performance
4. List of **papers** you plan to read as references
5. How will you **structure the project**, who will do what and a rough timeline

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After presentation you will get the feedback from me

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Proposal

— Same as above but in more refined form, with well defined algorithms and timeline (will be due **after break**)

— Will be in the form of the **Piazza** post or **Web** page

Unsupervised Learning

We have access to $\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \cdots, \mathbf{x}_N\}$ but not $\{\mathbf{y}_1, \mathbf{y}_2, \mathbf{y}_3, \cdots, \mathbf{y}_N\}$

*slide from Louis-Philippe Morency

Unsupervised Learning

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Why would we want to tackle such a task:

1. Extracting interesting information from data
   - Clustering
   - Discovering interesting trend
   - Data compression
2. Learn better representations

*slide from Louis-Philippe Morency

Unsupervised Representation Learning

Force our **representations** to better model input distribution

— Not just extracting features for classification

— Asking the model to be good at representing the data and not overfitting to a particular task (we get this with ImageNet, but maybe we can do better)

— Potentially allowing for better generalization

Use for **initialization of supervised task**, especially when we have a lot of unlabeled data and much less labeled examples

*slide from Louis-Philippe Morency

Restricted Boltzmann Machines (in one slide)

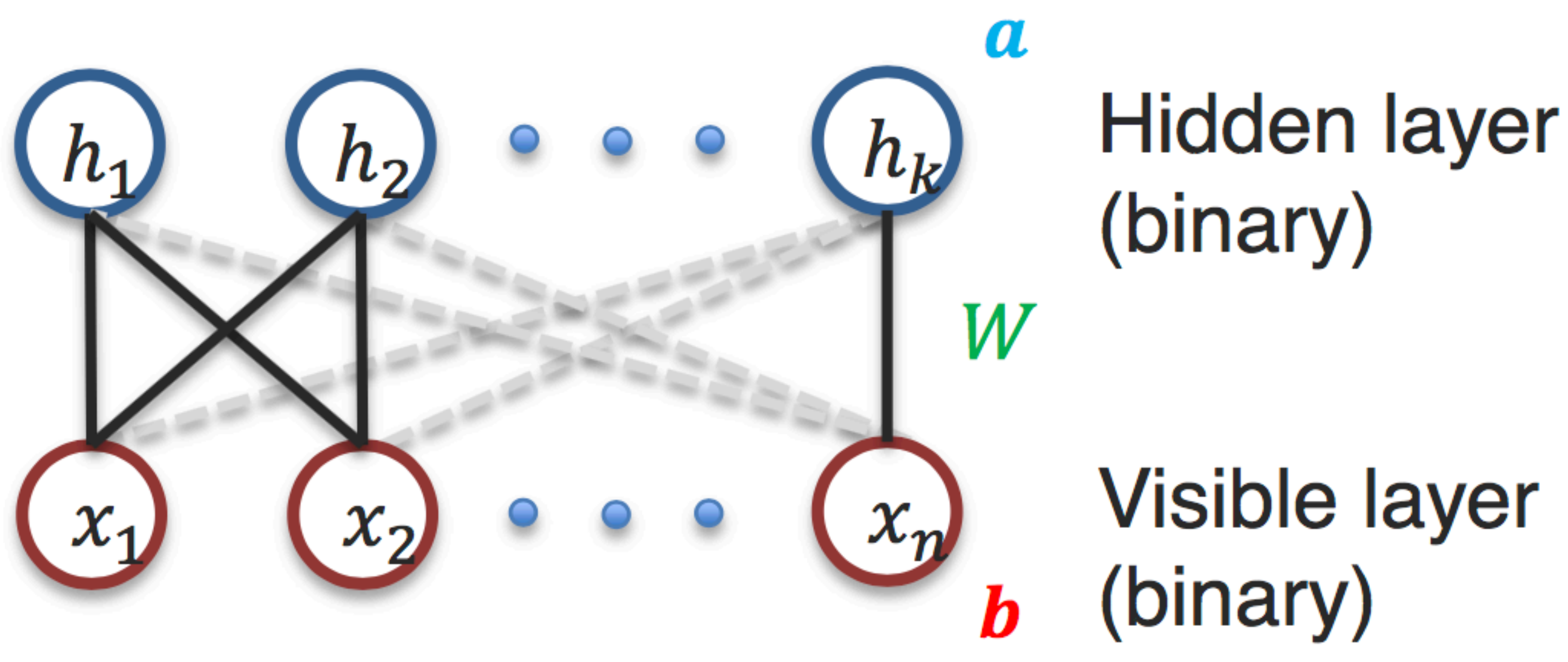
Model the **joint probability** of hidden state and observation

$$p(\boldsymbol{x}, \boldsymbol{h}; \theta) = \frac{\exp(-\mathrm{E}(\boldsymbol{x}, \boldsymbol{h}; \theta))}{Z}$$

$$Z = \sum_{\boldsymbol{x}} \sum_{\boldsymbol{h}} \exp(-\mathrm{E}(\boldsymbol{x}, \boldsymbol{h}; \theta))$$

$$\mathrm{E} = -\boldsymbol{x}W\boldsymbol{h} - \boldsymbol{b}^T\boldsymbol{x} - \boldsymbol{a}^T\boldsymbol{h}$$

$$\mathrm{E} = -\underbrace{\sum_i \sum_j w_{i,j} x_i h_j}_{\text{Interaction term}} - \underbrace{\sum_i b_i x_i - \sum_j a_j h_j}_{\text{Bias terms}}$$



Objective, maximize likelihood of the data

*slide from Louis-Philippe Morency

Autoencoders

*slide from Louis-Philippe Morency

Autoencoders

Self (i.e. self-encoding)

*slide from Louis-Philippe Morency

Autoencoders

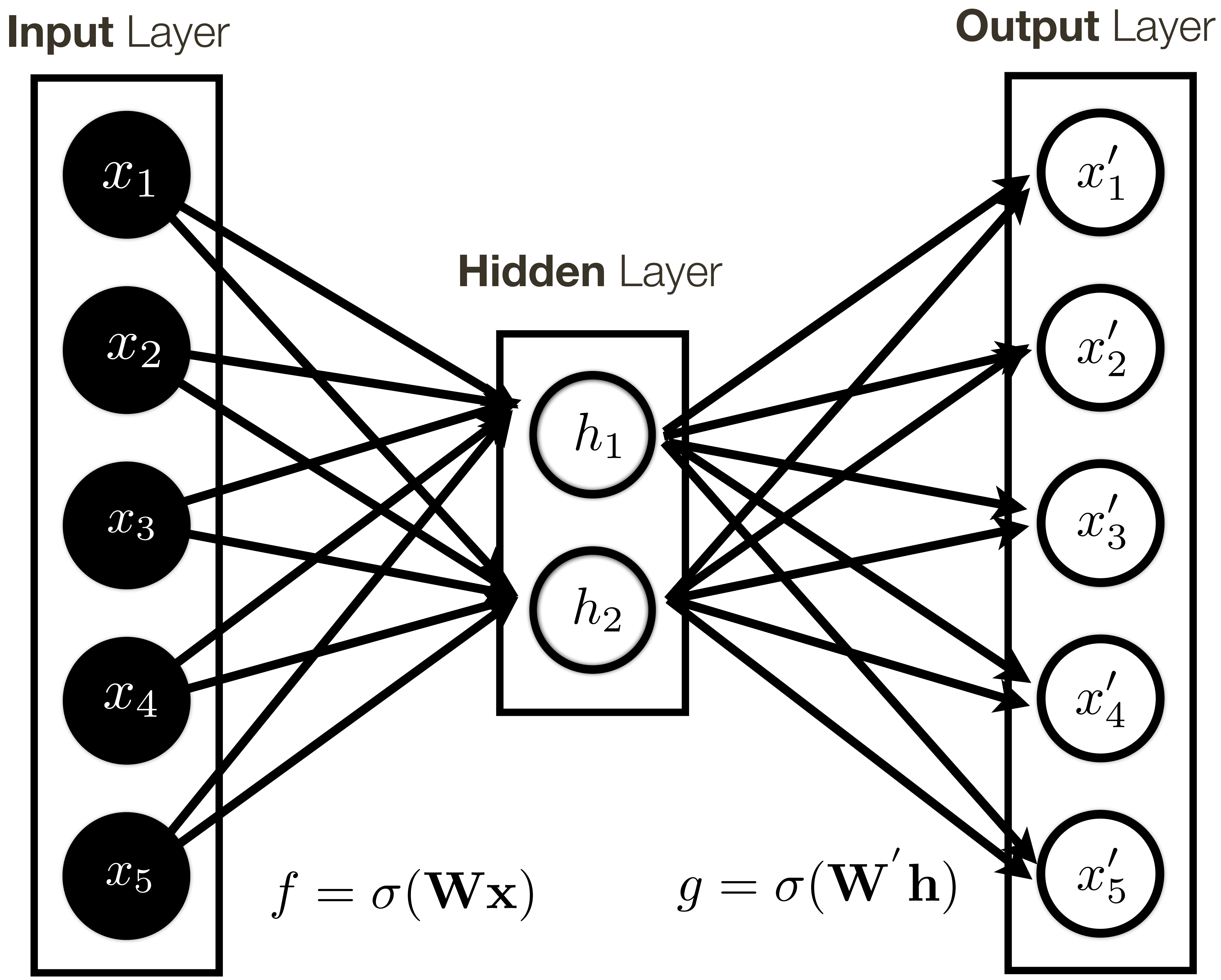
Self (i.e. self-encoding)

— Feed forward network intended to reproduce the input

— Encoder/Decoder architecture

Encoder: $f = \sigma(\mathbf{W}\mathbf{x})$

Decoder: $g = \sigma(\mathbf{W}^{'}\mathbf{h})$



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Autoencoders

Self (i.e. self-encoding)

— Feed forward network intended to reproduce the input

— Encoder/Decoder architecture

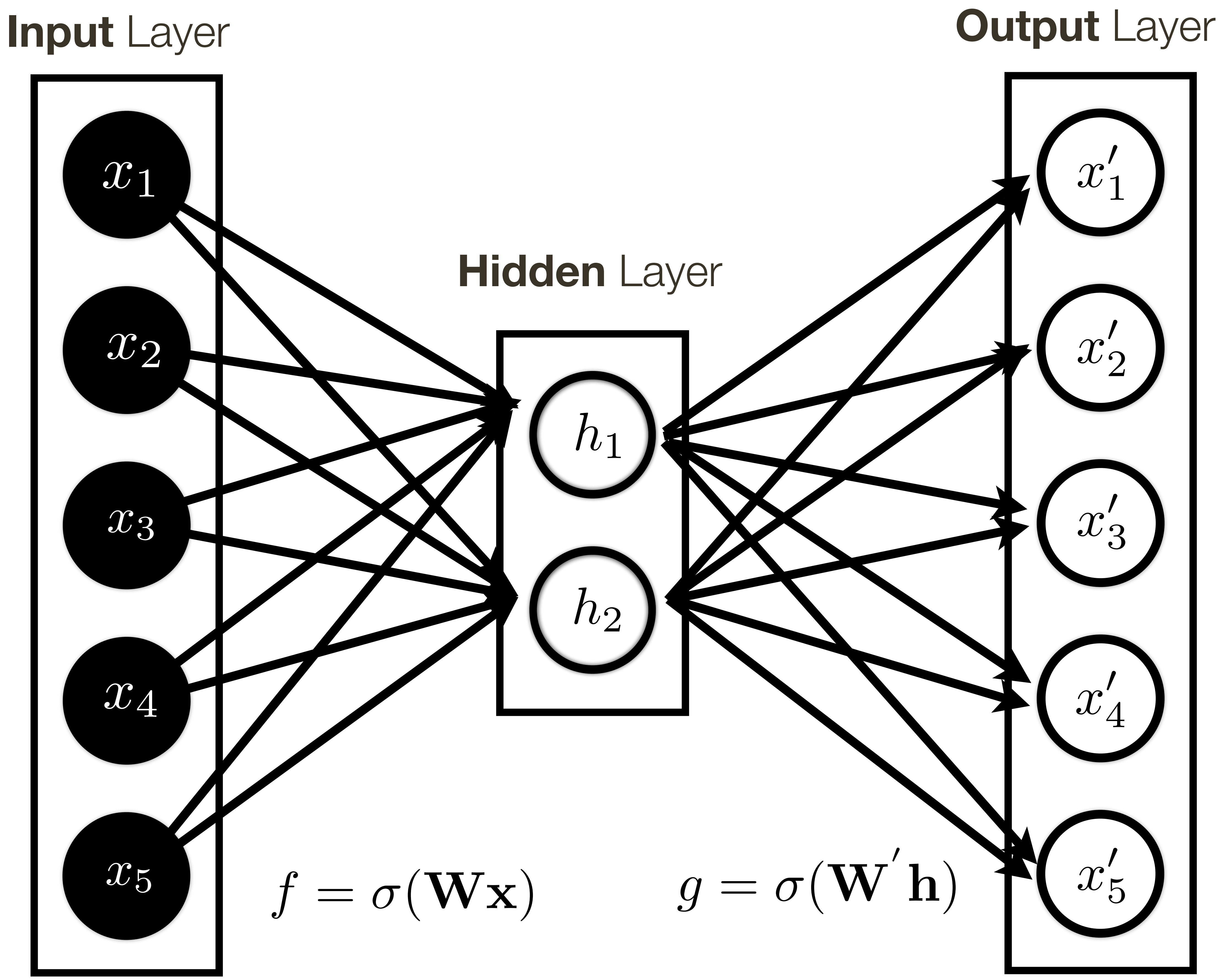
Encoder: $f = \sigma(\mathbf{W}\mathbf{x})$

Decoder: $g = \sigma(\mathbf{W}'\mathbf{h})$

— Score function

$$\mathbf{x}' = f(g(\mathbf{x}))$$

$$\mathcal{L}(\mathbf{x}', \mathbf{x})$$



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Autoencoders

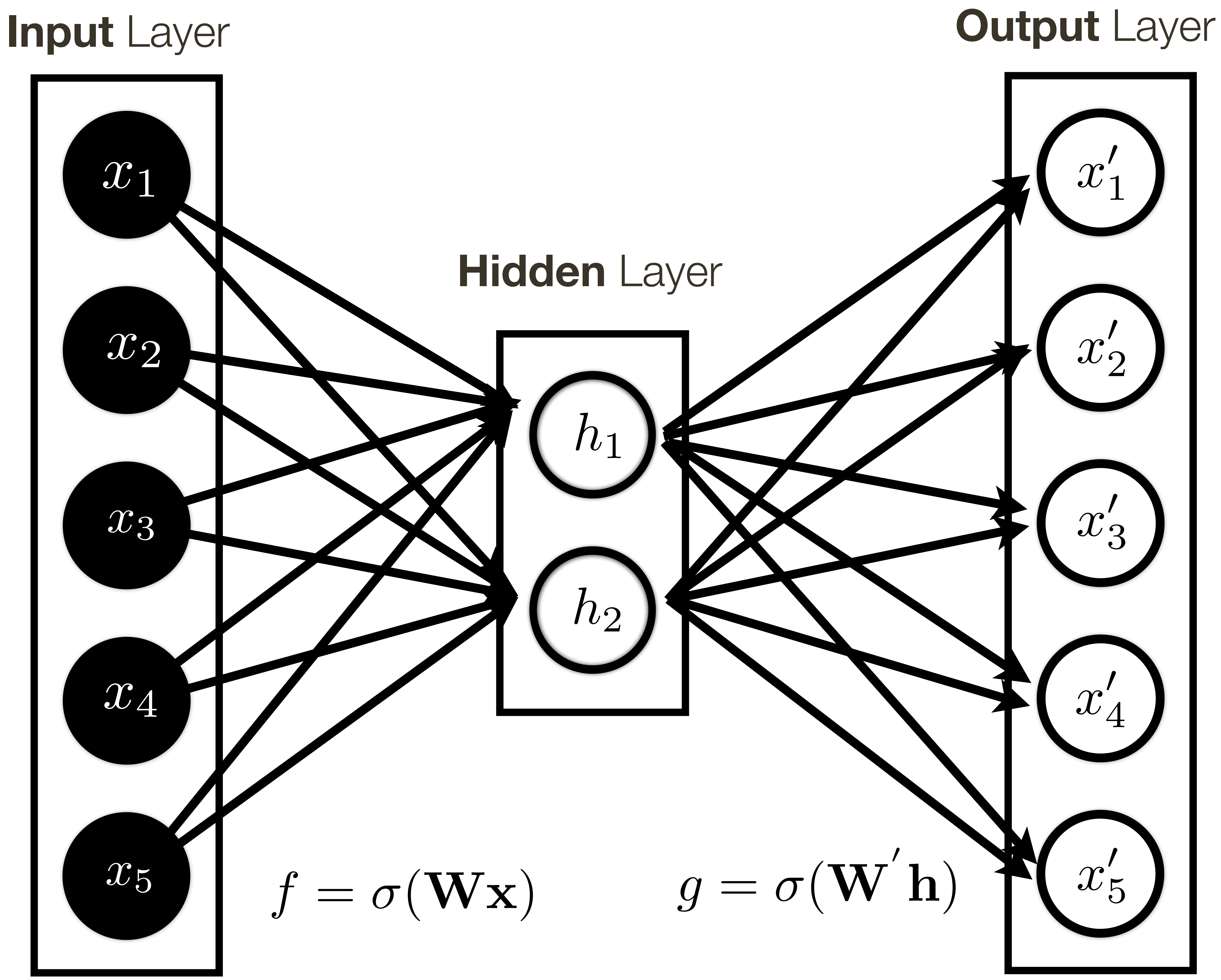
A standard neural network architecture (linear layer followed by non-linearity)

— Activation depends on type of data

(e.g., sigmoid for binary; linear for real valued)

— Often use tied weights

$$\mathbf{W}' = \mathbf{W}$$



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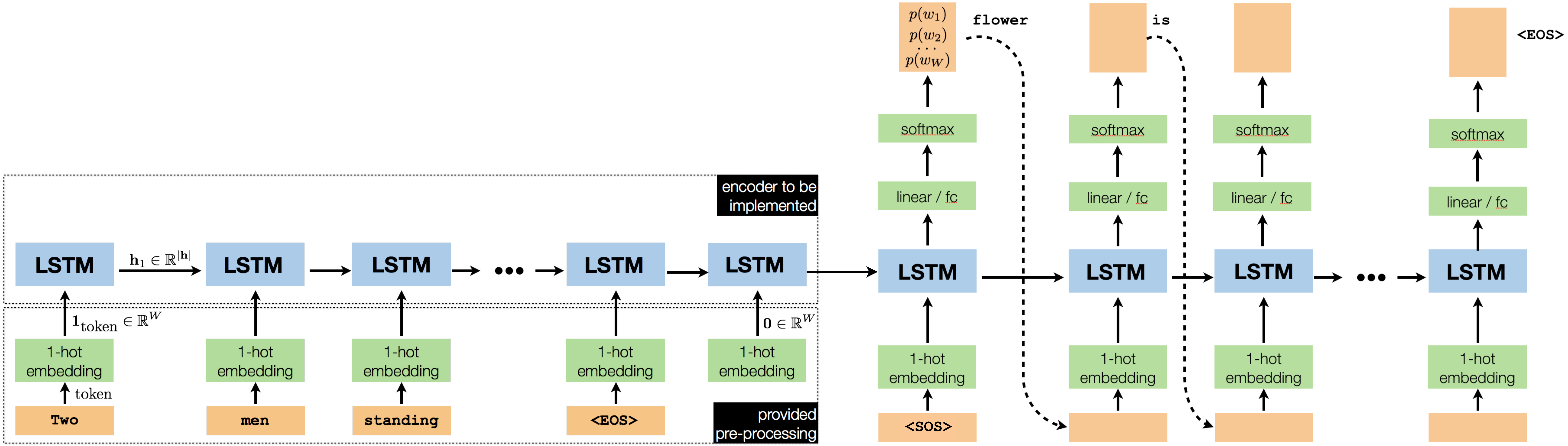
Autoencoders

Assignment 3 can be interpreted as a language autoencoder



Autoencoders: Hidden Layer Dimensionality

Smaller than the input

— Will compress the data, reconstruction of the data far from the training distribution will be difficult

— Linear-linear encoder-decoder with Euclidian loss is actually equivalent to PCA (under certain data normalization)

*slide from Louis-Philippe Morency

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Side note, this is useful for **anomaly detection**

*slide from Louis-Philippe Morency

Autoencoders: Hidden Layer Dimensionality

Smaller than the input

— Will compress the data, reconstruction of the data far from the training distribution will be difficult

— Linear-linear encoder-decoder with Euclidian loss is actually equivalent to PCA (under certain data normalization)

Larger than the input

— No compression needed

— Can trivially learn to just copy, no structure is learned (unless you regularize)

— Does not encourage learning of meaningful features (unless you regularize)

*slide from Louis-Philippe Morency

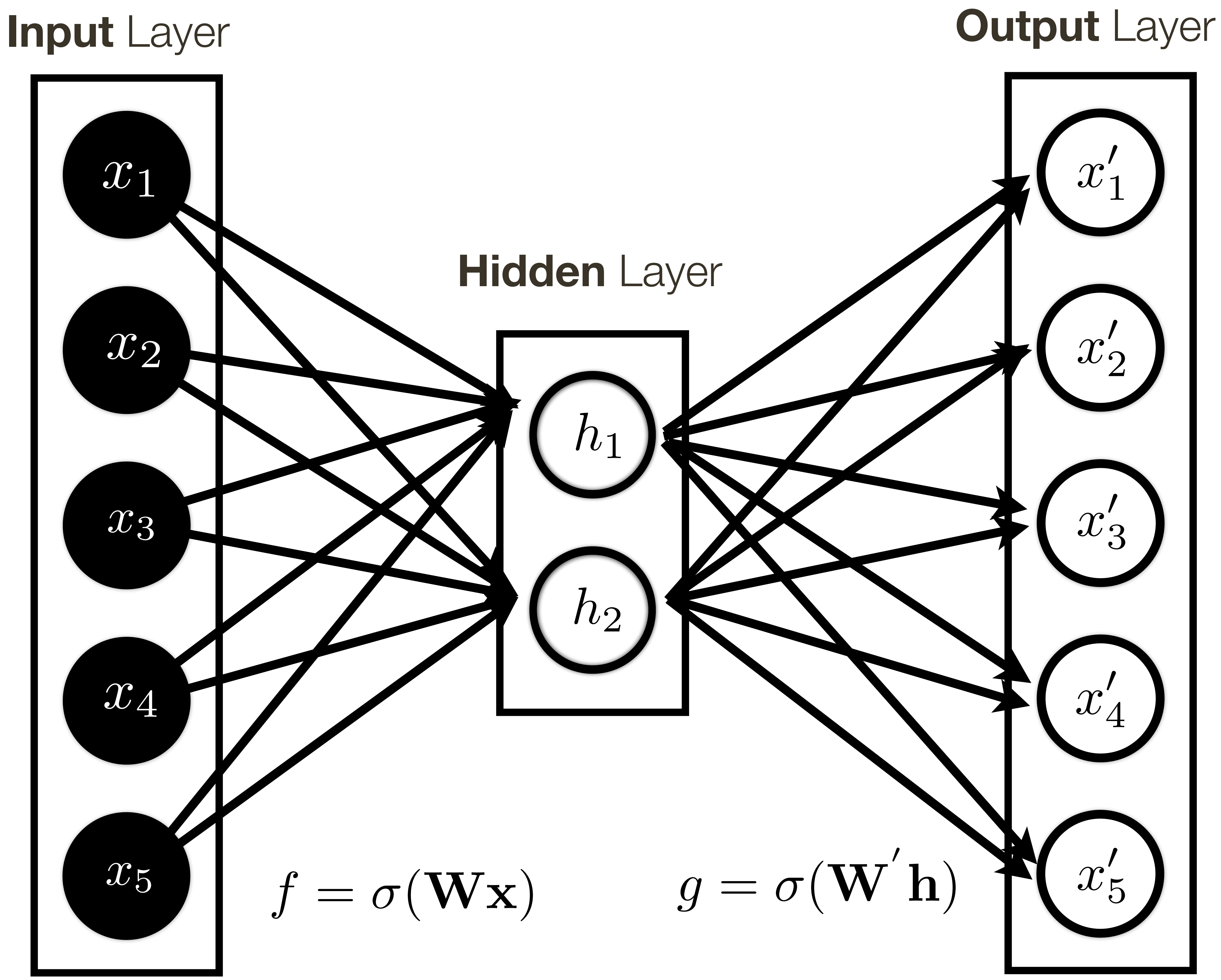
De-noising Autoencoder

Idea: add noise to input but learn to reconstruct the original

— Leads to better representations

— Prevents copying

Note: different noise is added during each epoch



*slide from Louis-Philippe Morency

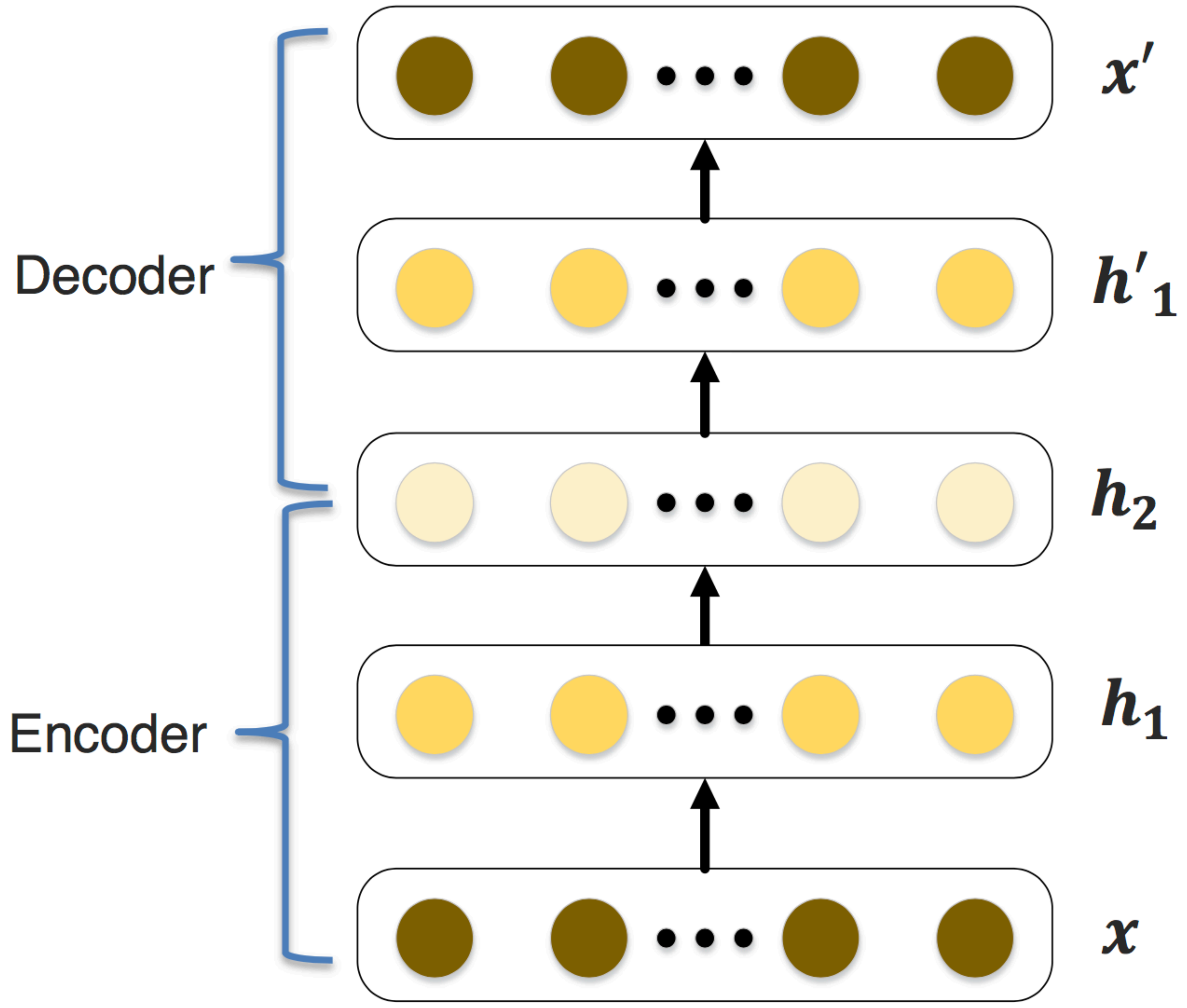
Stacked (deep) Autoencoders and Denoising Autoencoders

What **can we do** with them?

— Good for compression (better than PCA)

— Disregard the decoder and use the middle layer as a representation

— Fine-tune the autoencoder for a task



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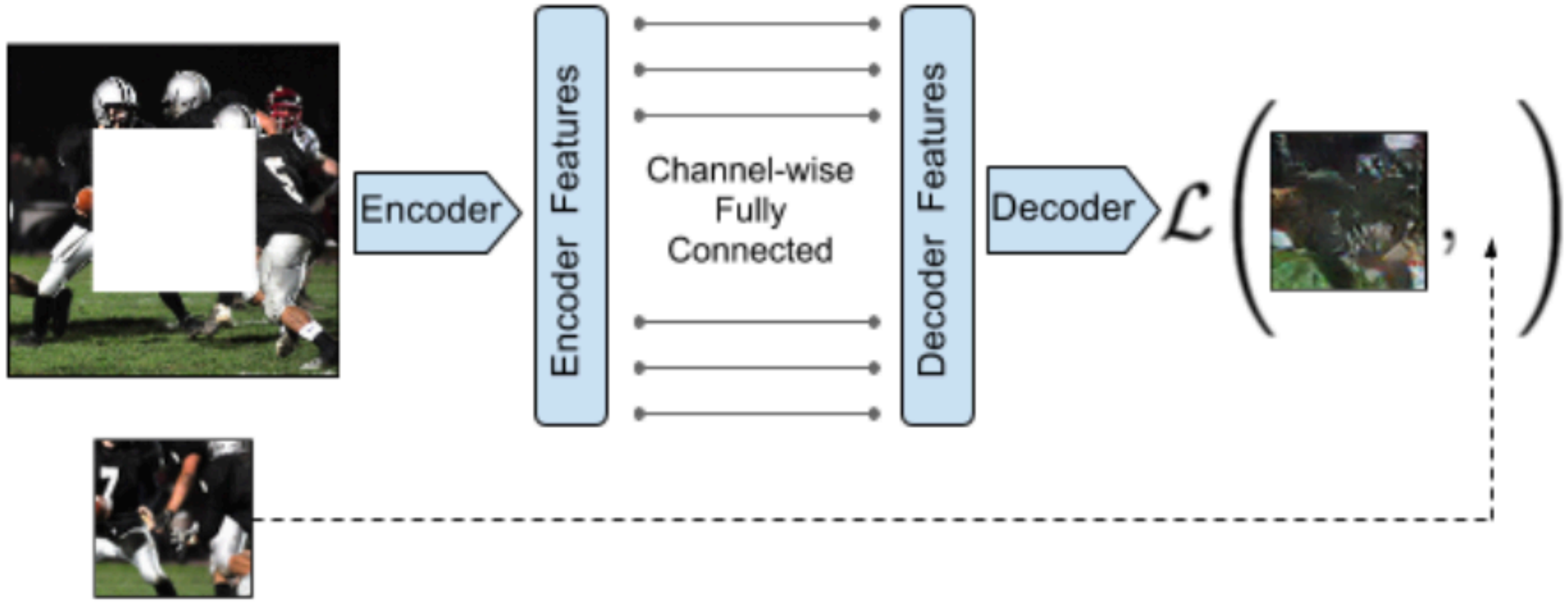
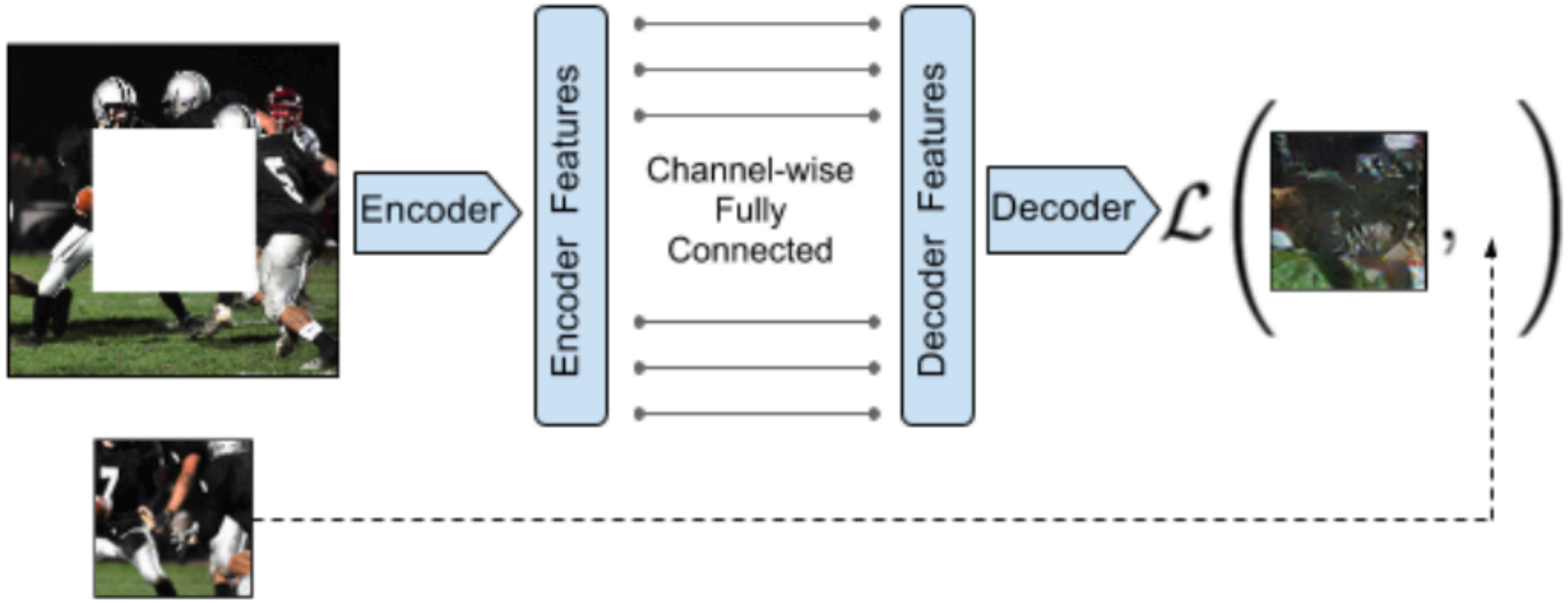
Context Encoders

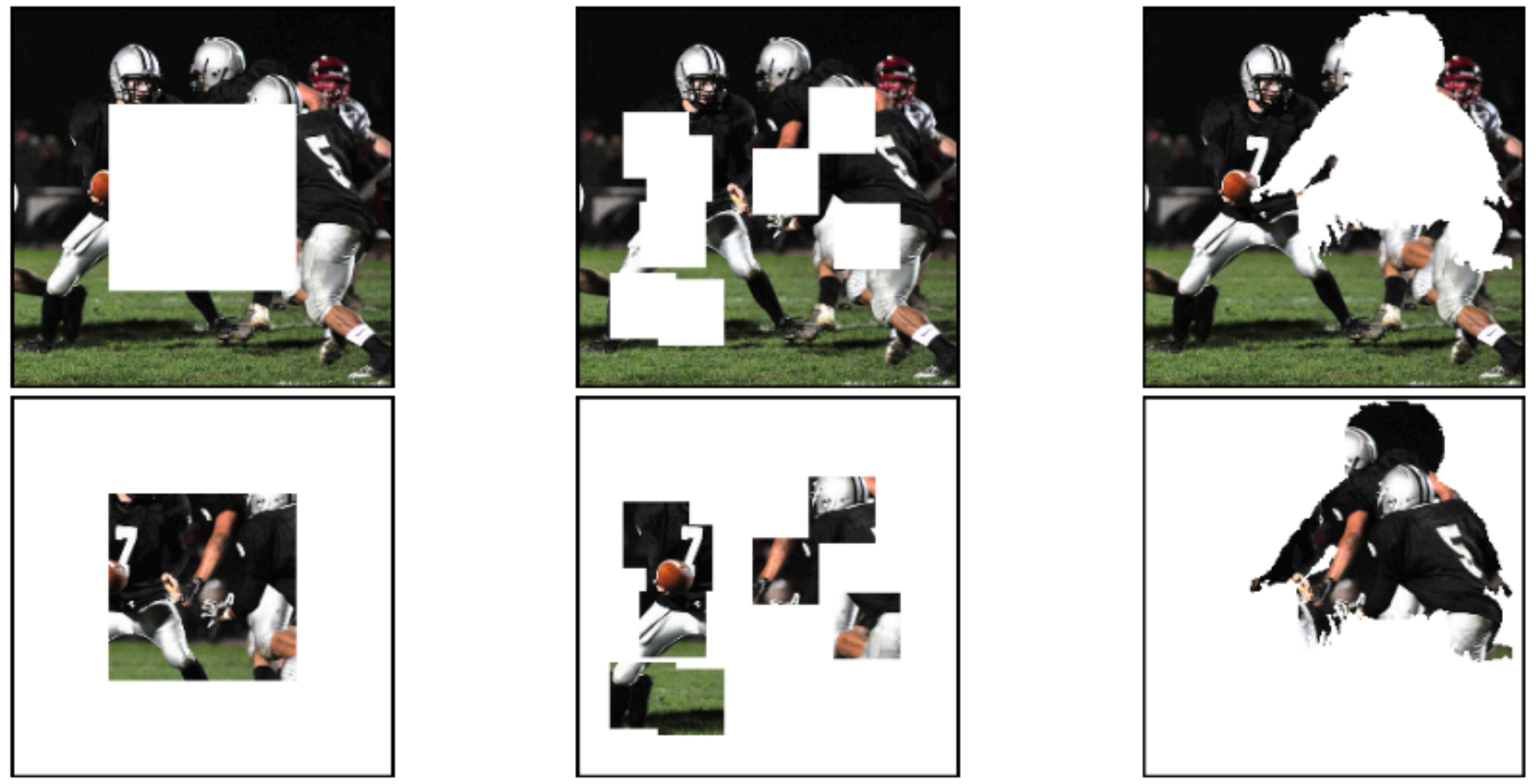
[Pathak et al., 2016]



Context Encoders

[Pathak et al., 2016]

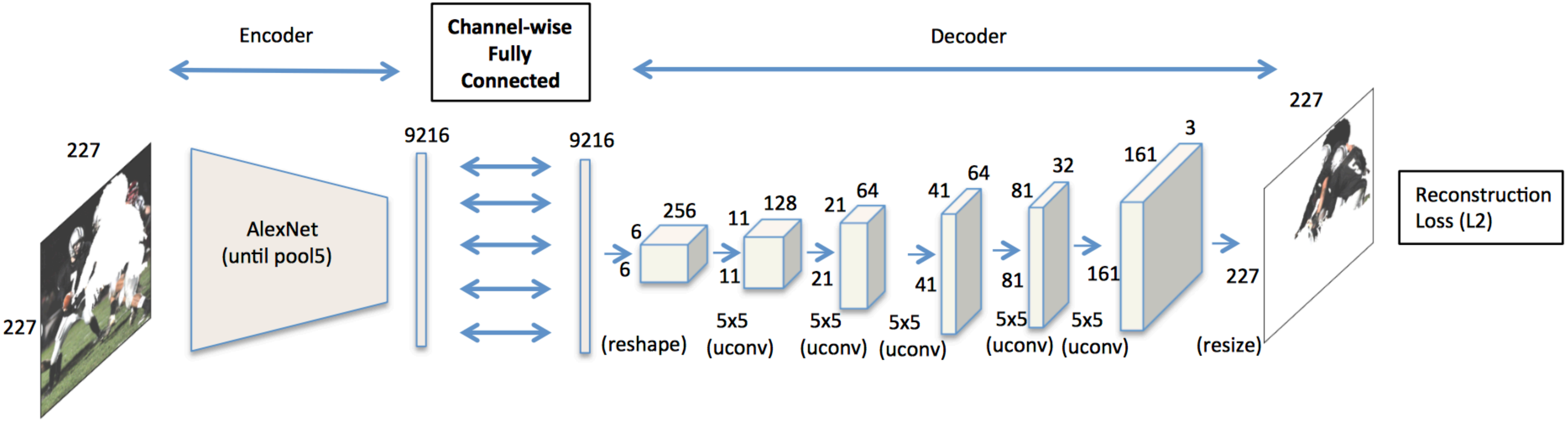




(a) Central region (b) Random block (c) Random region

Context Encoders

[Pathak et al., 2016]



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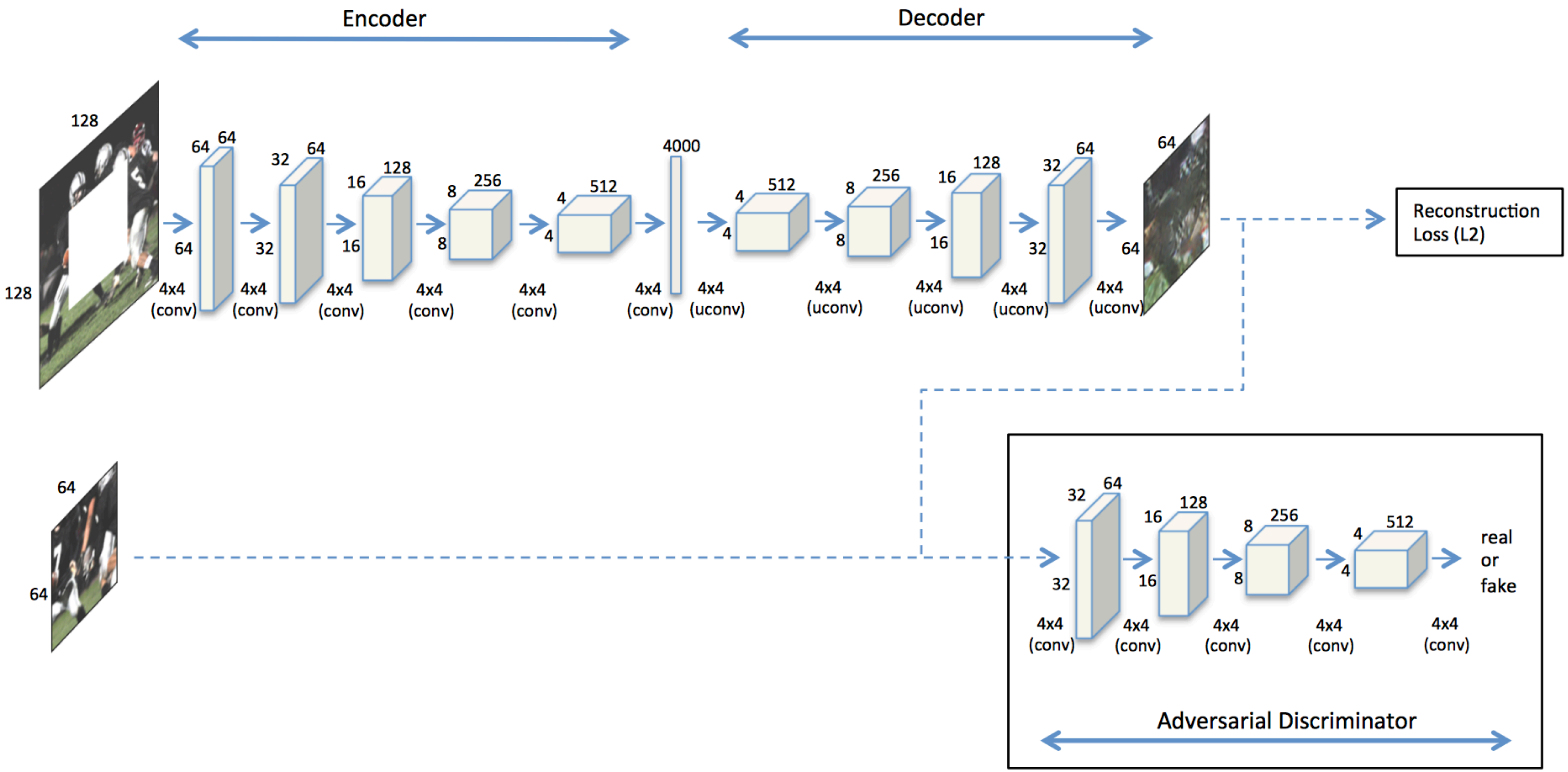

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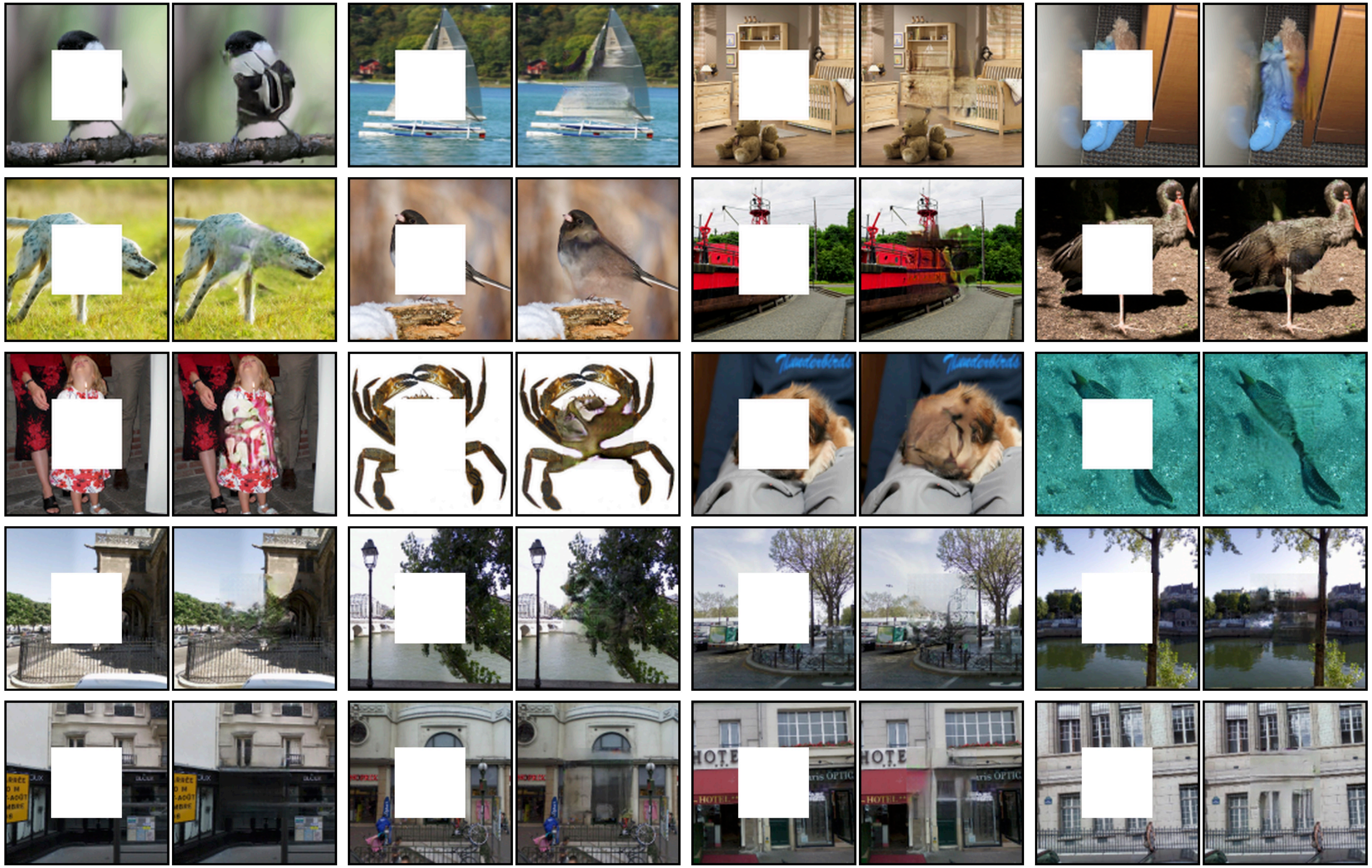


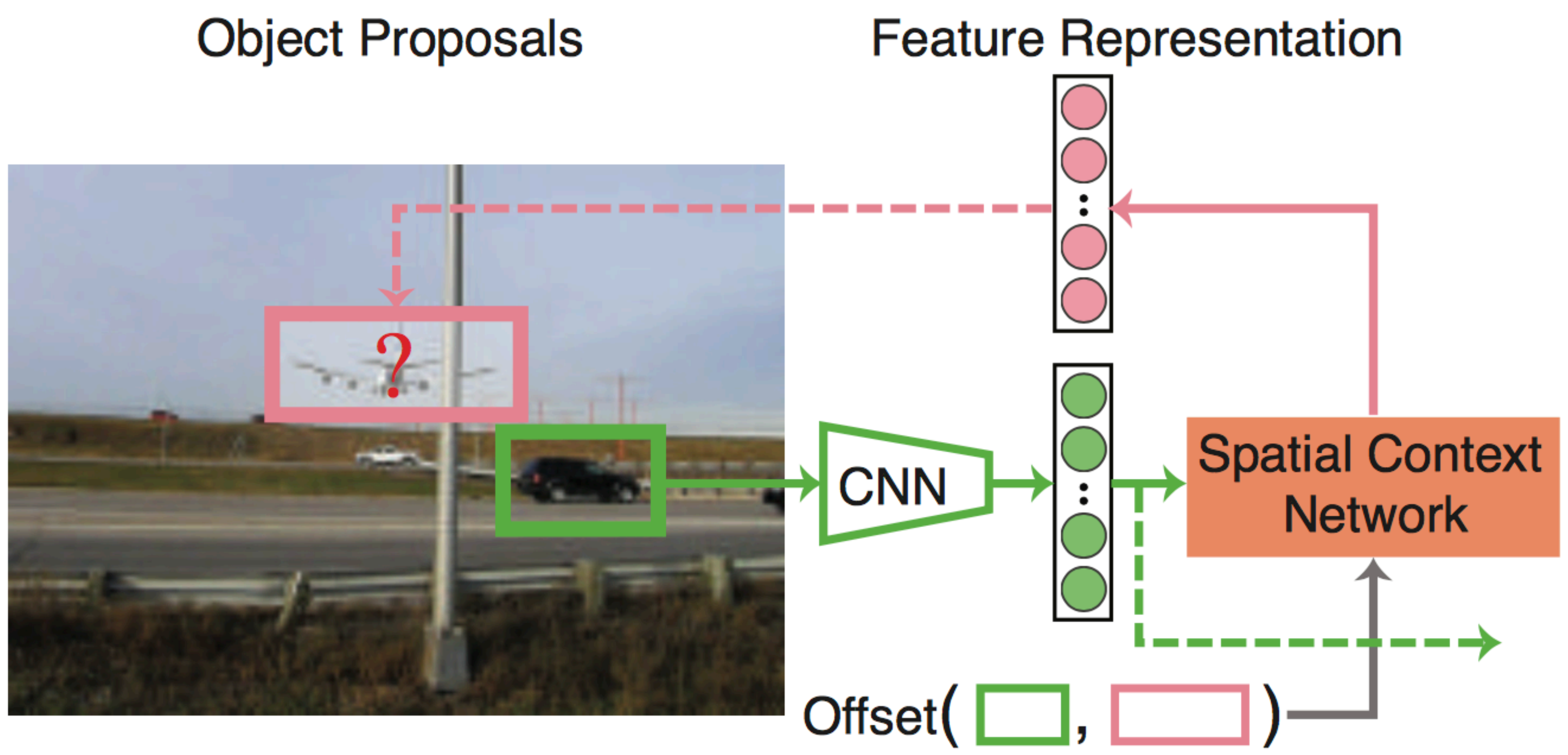
Context Encoders

[Pathak et al., 2016]

Pretraining Method	Supervision	Pretraining time	Classification	Detection	Segmentation
ImageNet [26]	1000 class labels	3 days	**78.2%**	**56.8%**	**48.0%**
Random Gaussian	initialization	$<$ 1 minute	53.3%	43.4%	19.8%
Autoencoder	-	14 hours	53.8%	41.9%	25.2%
Agrawal *et al.* [1]	egomotion	10 hours	52.9%	41.8%	-
Doersch *et al.* [7]	context	4 weeks	55.3%	**46.6%**	-
Wang *et al.* [39]	motion	1 week	**58.4%**	44.0%	-
Ours	context	14 hours	56.5%	44.5%	**29.7%**

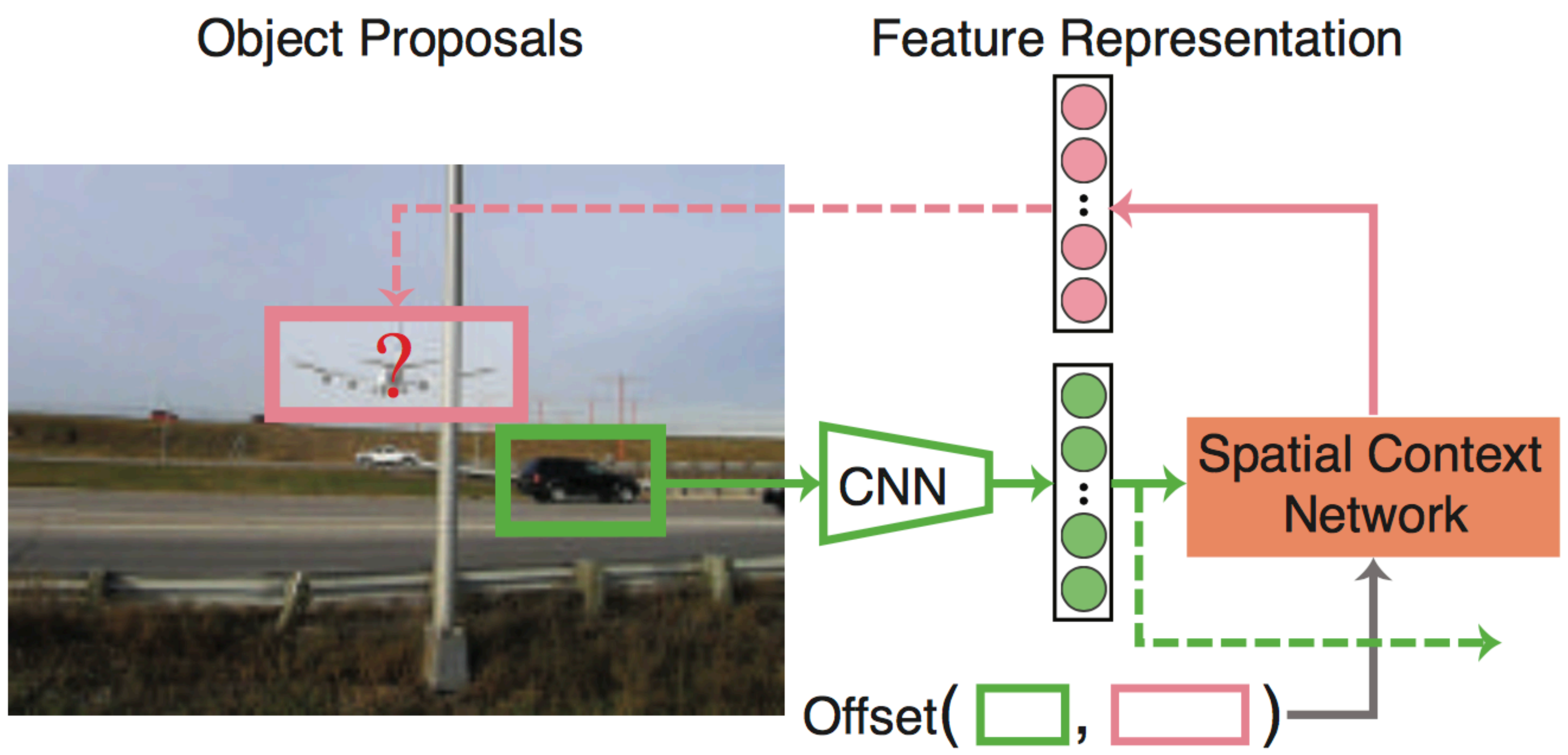
Spatial Context Networks

[Wu, Sigal, Davis, 2017]



Spatial Context Networks

[Wu, Sigal, Davis, 2017]



	Initialization	Supervision	Pretraining time	Classification	Detection
Random Gaussian	random	N/A	< 1 minute	53.3	43.4
Wang *et al.* [32]	random	motion	1 week	58.4	44.0
Doersch *et al.* [3]	random	context	4 weeks	55.3	46.6
*Doersch *et al.* [3]	1000 class labels	context	–	65.4	50.4
Pathak *et al.* [21]	random	context inpainting	14 hours	56.5	44.5
Zhang *et al.* [36]	random	color	–	65.6	46.9
ImageNet [21]	random	1000 class labels	3 days	78.2	56.8
*ImageNet	random	1000 class labels	3 days	76.9	58.7
SCN-EdgeBox	1000 class labels	context	10 hours	79.0	**59.4**

Multimodal Representations

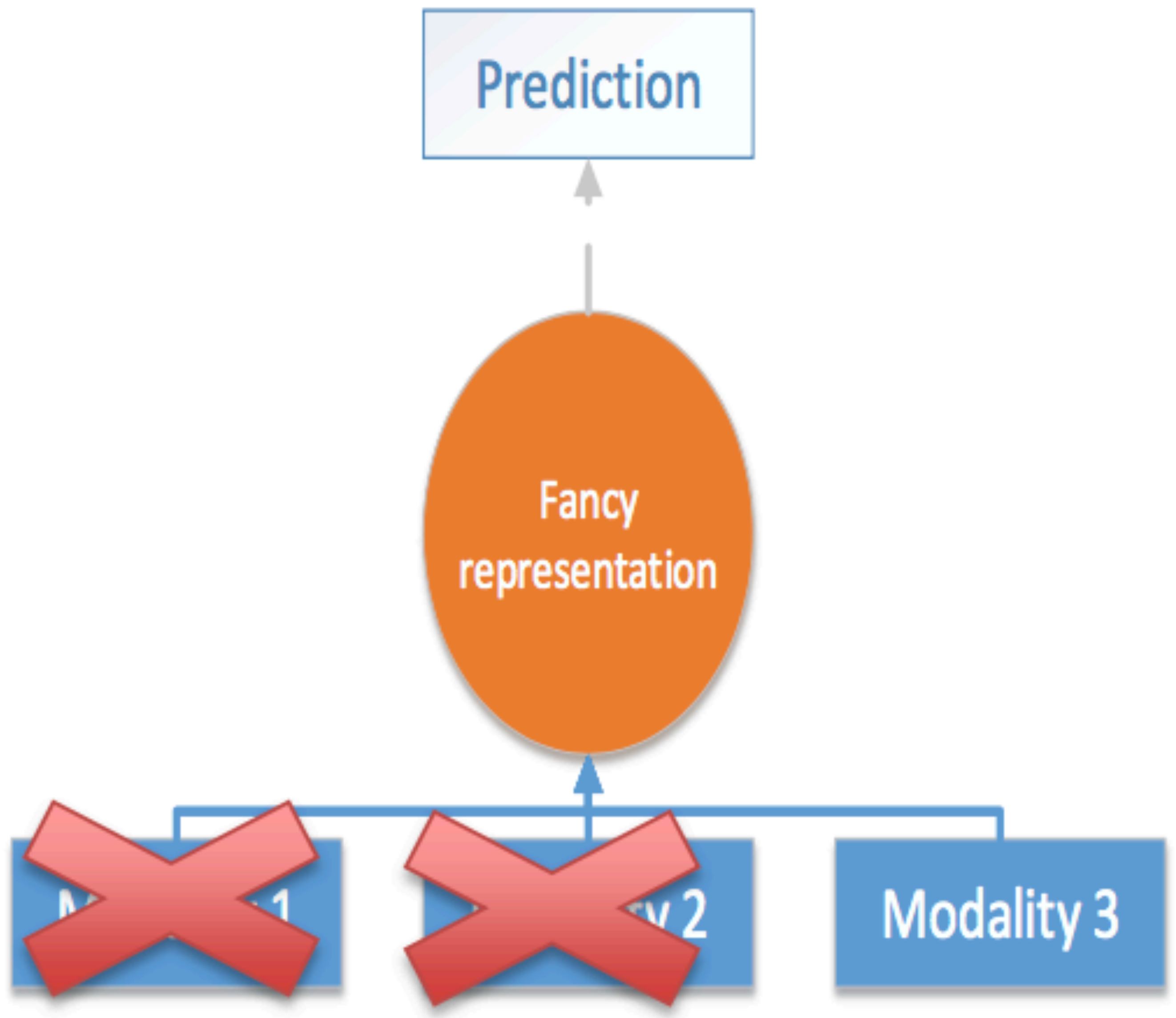
What is a **good** multimodal representation?

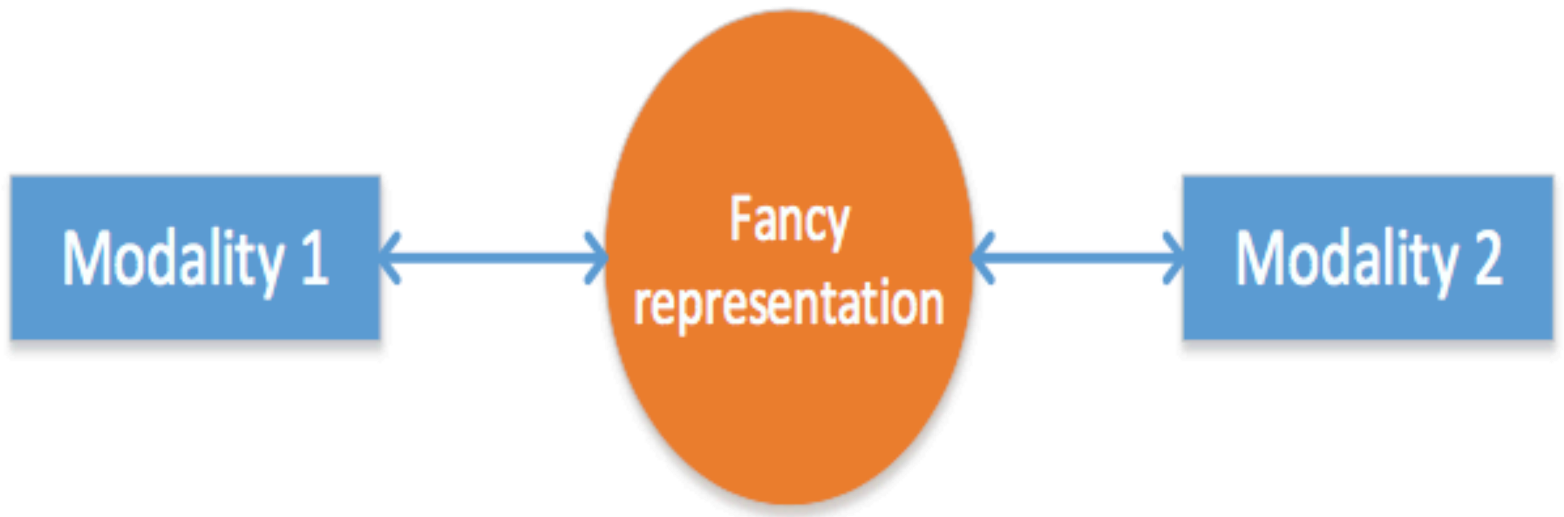
— Similarity in the representation (somehow) implies similarity in corresponding concepts
(we saw this in word2vec)

— Useful for various discriminative tasks (retrieval, mapping, fusion, etc.)

— Possible to obtain in absence of one or mere modalities

— Fill in missing modalities given others (map or translate between modalities)

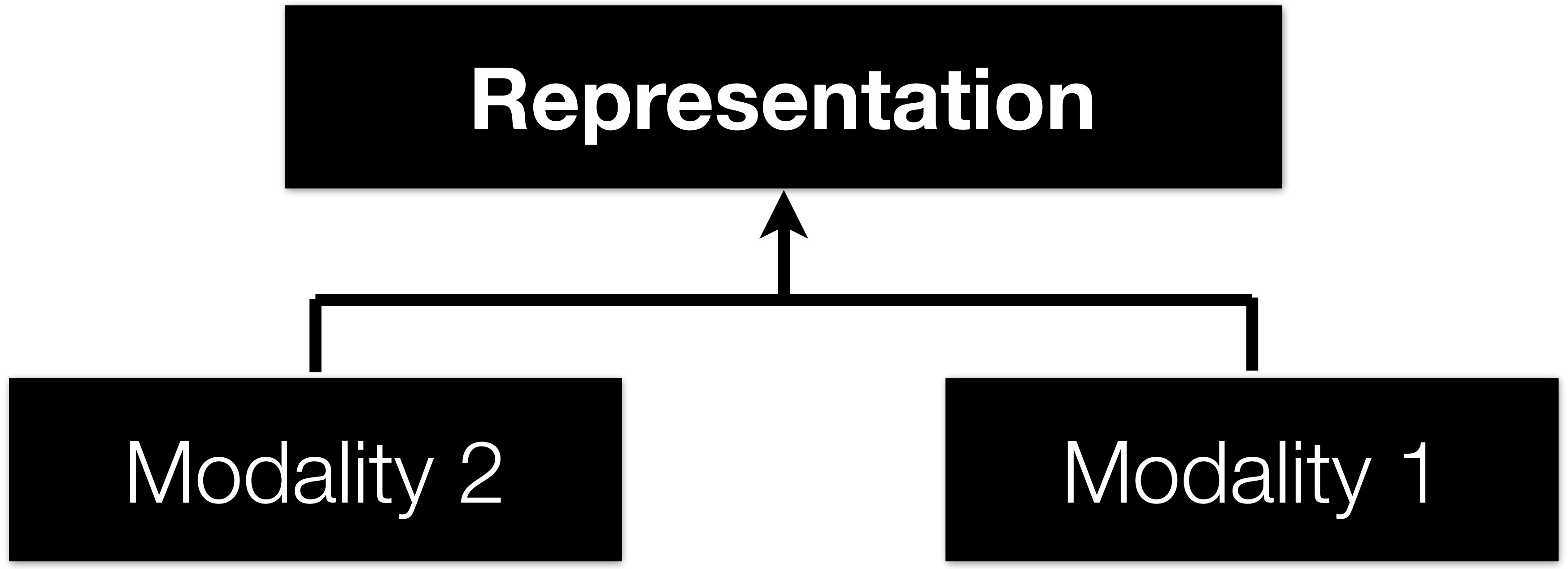




*slide from Louis-Philippe Morency

Multimodal Representation Types

Joint representations:



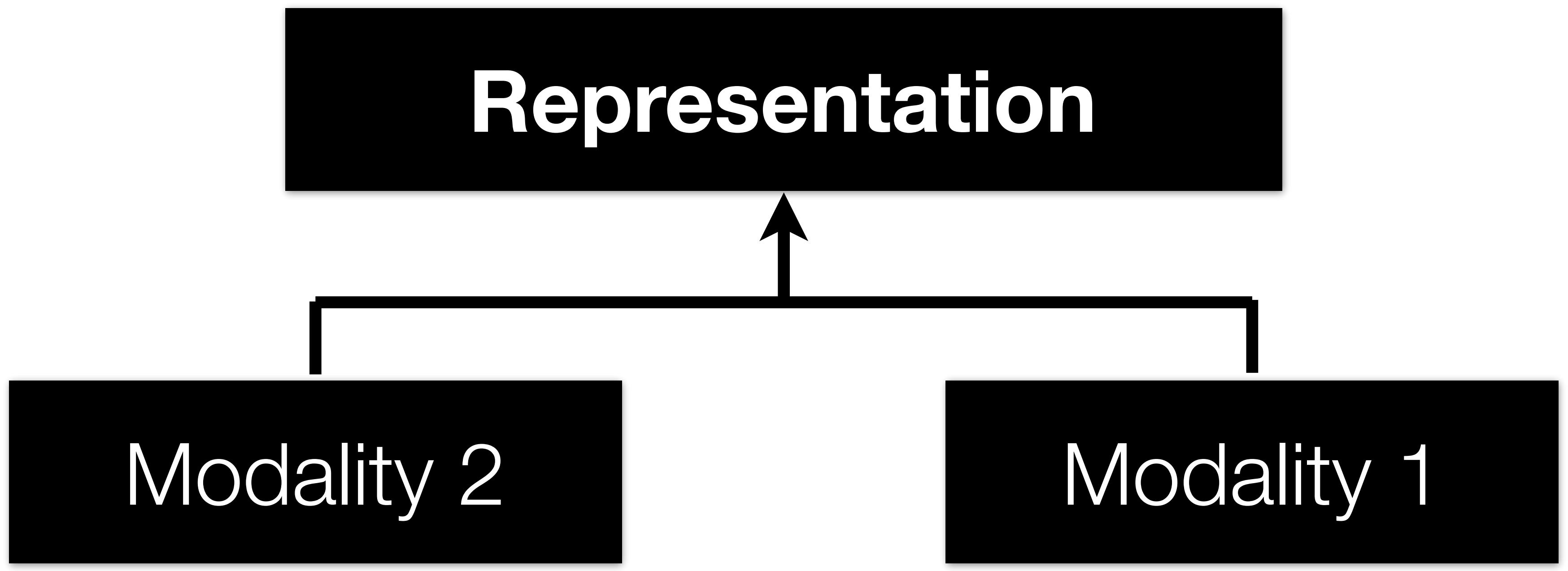
— Simplest version: modality concatenation (early fusion)

— Can be learned supervised or unsupervised

*slide from Louis-Philippe Morency

Multimodal Representation Types

Joint representations:



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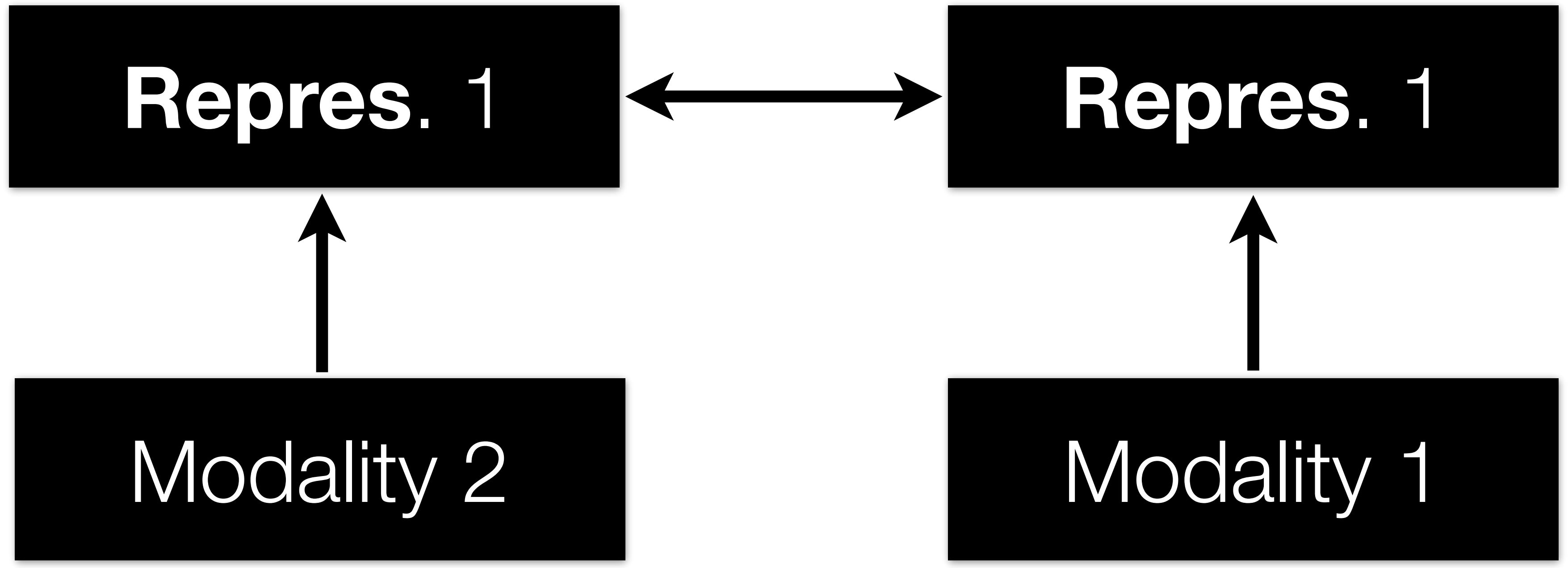
Coordinated representations:



— Similarity-based methods (e.g., cosine distance)

— Structure constraints (e.g., orthogonality, sparseness)

— We will talk about these next week (CCA, joint embeddings)

*slide from Louis-Philippe Morency

Joint Representation: Deep Multimodal Autoencoders

[Ngiam et al., 2011]

Each modality can be pre-trained

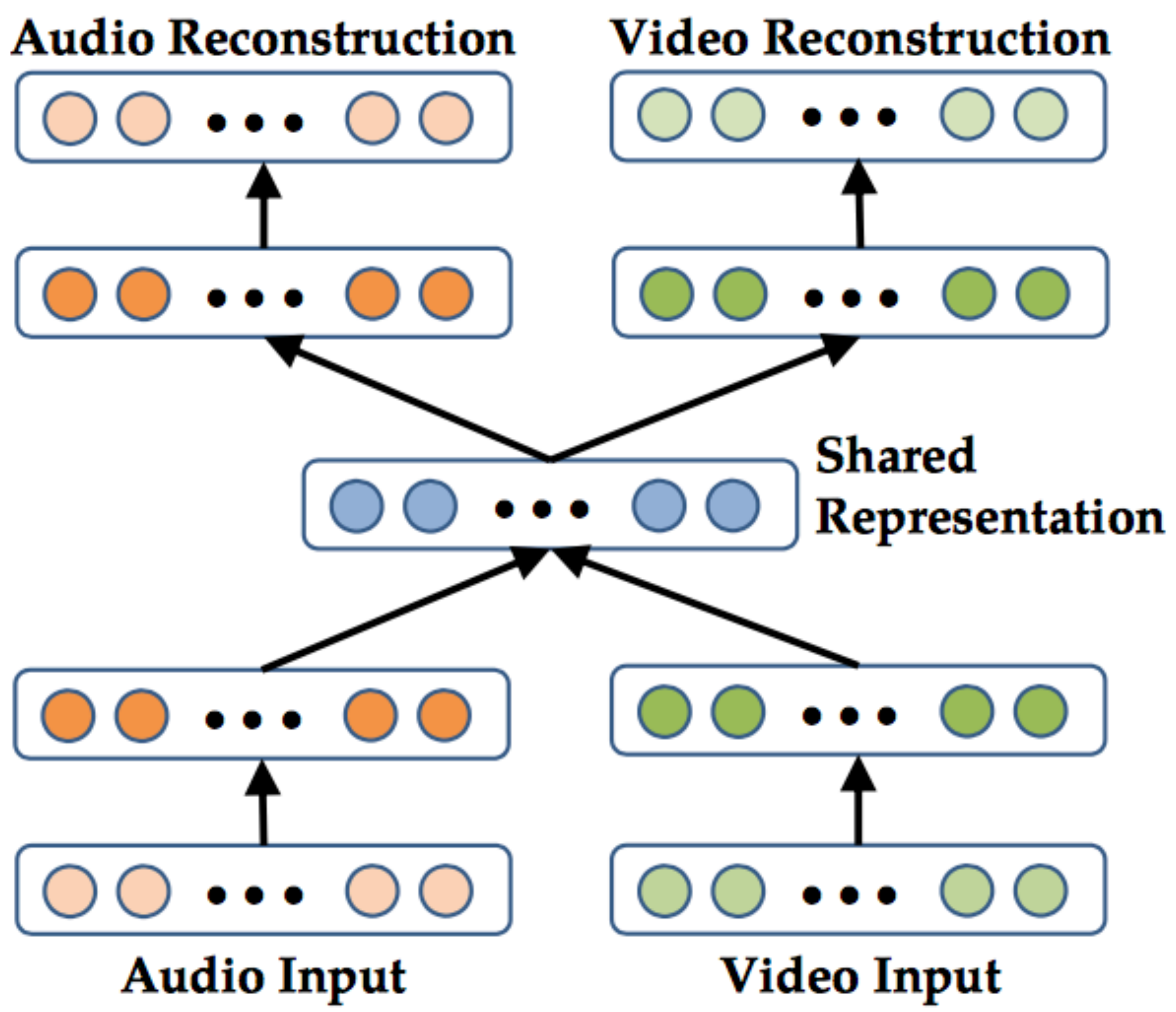
— using denoising autoencoder

To train the model, reconstruct both modalities using

— both Audio & Video

— just Audio

— just Video



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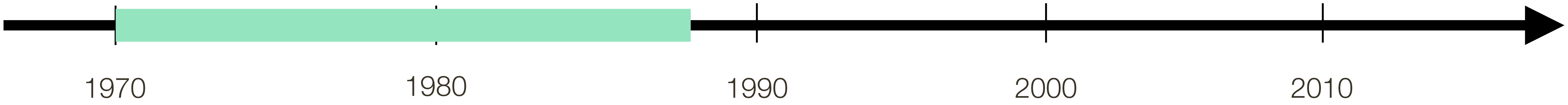
Multimodal Research: Historical Perspective

McGurk Effect (1976)



* video credit: **OK Science**

* Adopted from slides by Louis-Philippe Morency

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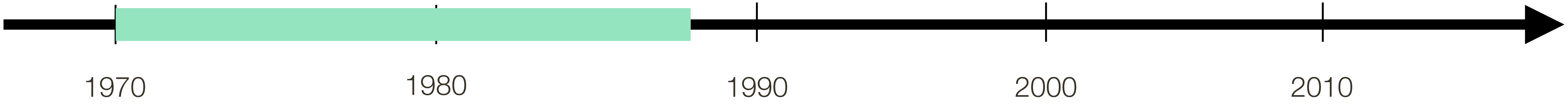


* video credit: **OK Science**

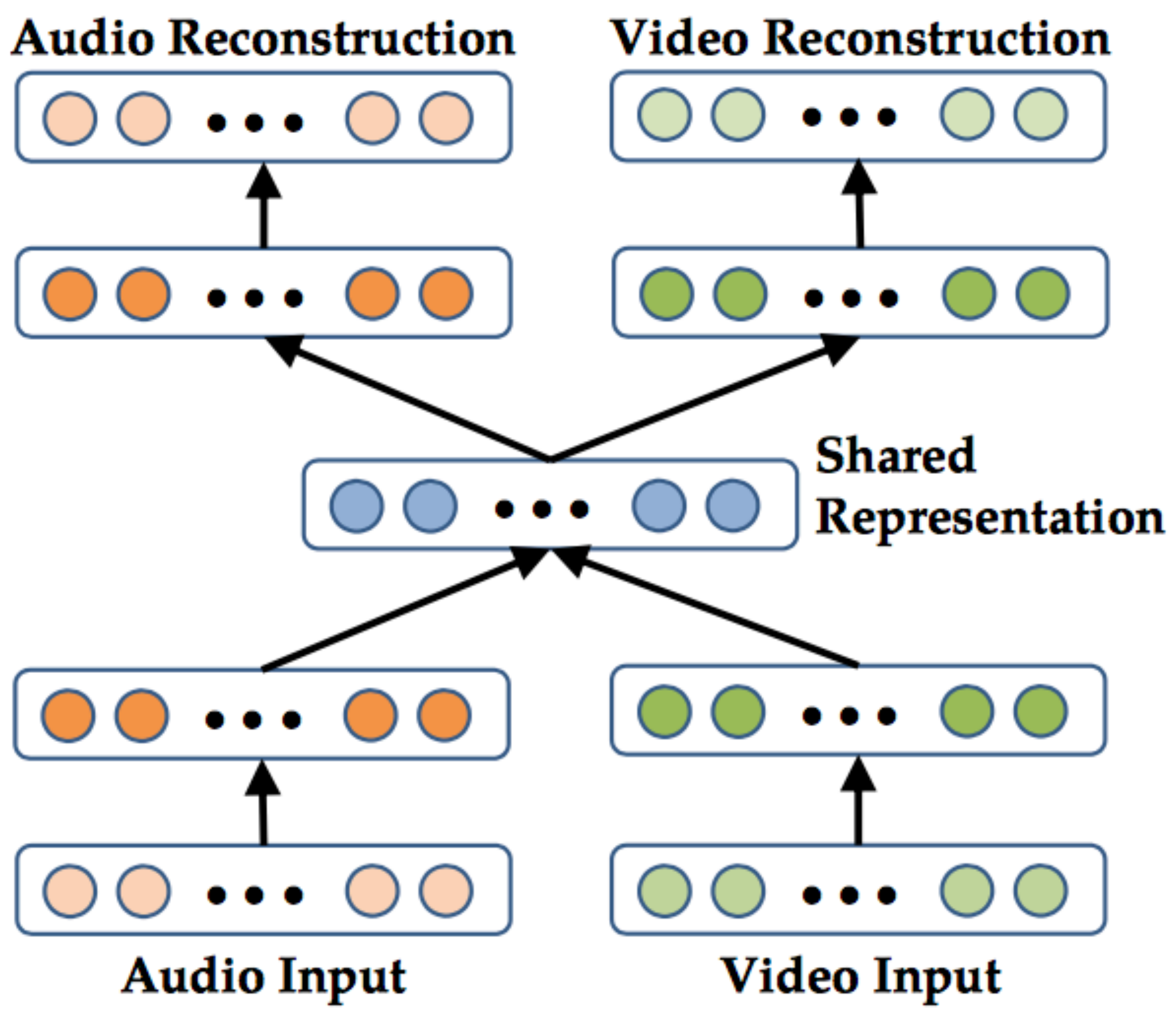
* Adopted from slides by Louis-Philippe Morency

Joint Representation: Deep Multimodal Autoencoders

[Ngiam et al., 2011]

Table 3: McGurk Effect

Audio / Visual Setting	**Model prediction**		
	/ga/	*/ba/*	*/da/*
Visual */ga/*, Audio */ga/*	82.6%	2.2%	15.2%
Visual */ba/*, Audio */ba/*	4.4%	89.1%	6.5%
Visual */ga/*, Audio */ba/*	28.3%	13.0%	58.7%



*slide from Louis-Philippe Morency

Joint Representation: Deep Multimodal Autoencoders

[Ngiam et al., 2011]

Useful when you know you may only be conditioning on one modality at test time

Can be regarded as a form of **regularization**