Unsupervised Deep Learning

Tutorial – Part I

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facebook
Artificial Intelligence Research

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Part 1 – Alex Graves

- Introduction to unsupervised learning
- Autoregressive models
- Representation learning
- Unsupervised reinforcement learning
- 10-15 minute break

Part 2 – Marc'Aurelio Ranzato

- Practical Recipes of Unsupervised Learning
- Learning representations
- Learning to generate samples
- Learning to map between two domains
- Open Research Problems
- 10-15 minutes questions (both presenters)

Introduction to Unsupervised Learning

Types of Learning

	With Teacher	**Without Teacher**
Active	Reinforcement Learning / Active Learning	Intrinsic Motivation / Exploration
Passive	Supervised Learning	Unsupervised Learning

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1. Targets / rewards can be **difficult to obtain** or define
2. Unsupervised learning feels more **human**
3. Want rapid **generalisation** to **new tasks** and situations

Transfer Learning

- Teaching on one task and **transferring** to another (multi-task learning, one-shot learning…) *kind of works*
- E.g. **Retraining** speech recognition systems from a language with lots of data can improve performance on a related language with little data
- But never seems to transfer as **far** or as **fast** as we want it to
- Maybe there just isn't enough **information** in the targets/rewards to learn transferable **skills**?

Stop learning tasks, start learning skills – Satinder Singh

The Cherry on the Cake

- The **targets** for supervised learning contain **far less** information than the input data
- RL **reward signals** contain even less
- Unsupervised learning gives us an essentially **unlimited** supply of information about the world: surely we should exploit that?

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.

– Yann LeCun

Example

- ImageNet training set contains ~1.28M images, each assigned one of 1000 labels
- If labels are equally probable, complete set of randomly shuffled labels contains ~$\log_2(1000)$*1.28M ≈ 12.8 Mbits
- Complete set of images uncompressed at 128 x128 contains ~500 Gbits: > 4 orders of magnitude more
- A large conv net (~30M weights) can memorise randomised ImageNet labellings. Could it memorise randomised pixels?

UNDERSTANDING DEEP LEARNING REQUIRES RETHINKING GENERALIZATION, Zhang et. al. 2016

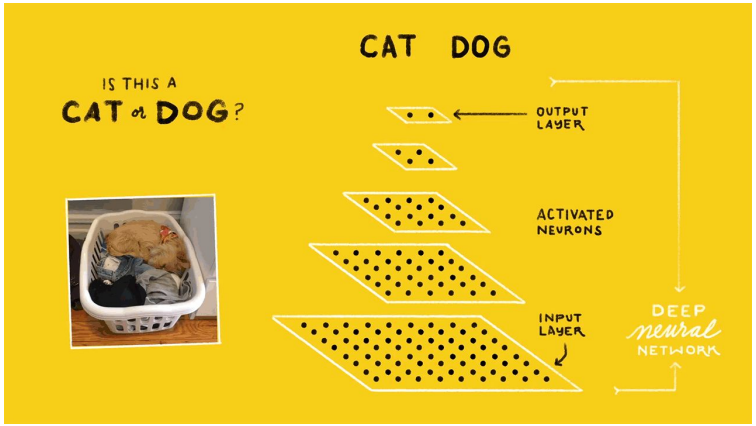
Supervised Learning

- Given a dataset *D* of **inputs *x*** labelled with **targets *y***, learn to predict ***y*** from ***x***, typically with **maximum likelihood**:

$$\mathcal{D} = \{(x, y)\}$$

$$L(\mathcal{D}) = \sum_{(x,y)\in\mathcal{D}} -\log p(y|x)$$

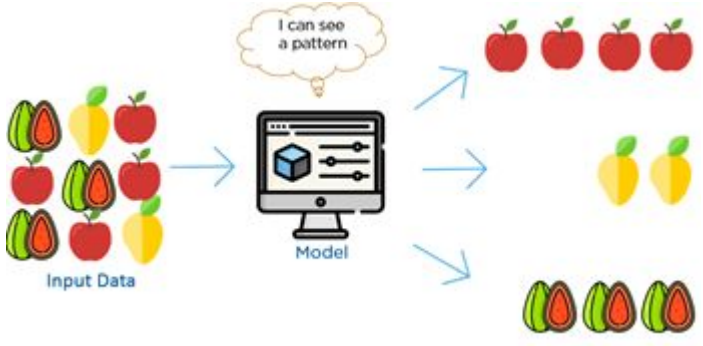
- (Still) the dominant paradigm in deep learning: image classification, speech recognition, translation…



Unsupervised Learning

- Given a dataset *D* of inputs *x*, learn to predict… what?

$$\mathcal{D} = \{x\}$$
$$L(\mathcal{D}) = ???$$



- Basic challenge of unsupervised learning is that the task is **undefined**
- Want a single task that will allow the network generalise to many other tasks (**which ones?**)

Density Modelling

- Simplest approach: do **maximum likelihood** on the data instead of the targets

$$\mathcal{D} = \{x\}$$

$$L(\mathcal{D}) = \sum_{x \in \mathcal{D}} -\log p(x)$$

- Goal is to learn the **'true' distribution** from which the data was drawn
- Means attempting to learn **everything** about the data

Where to Look

Not everyone agrees that trying to understand everything is a good idea. Shouldn't we instead **focus** on things that we believe will one day be **useful** for us?

… we lived our lives under the constantly changing sky without sparing it a glance or a thought. And why indeed should we? If the various formations had had some meaning*, if, for example, there had been concealed signs and messages for us which it was important to decode correctly, unceasing attention to what was happening would have been inescapable…*

– Karl Ove Knausgaard, *A Death in the Family*

Problems with Density Modelling

- **First problem:** density modelling is **hard**! From having too few bits to learn from, we now have too many (e.g. video, audio), and we have to deal with complex interactions between variables (**curse of dimensionality**)
- **Second Problem: not all bits are created equal**. Log-likelihoods depend much more on low-level details (pixel correlations, word N-Grams) than on high-level structure (image contents, semantics)
- **Third problem:** even if we learn the underlying structure, it isn't always clear how to access and exploit that knowledge for future tasks (**representation learning**)

Generative Models

- Modelling densities also gives us a **generative model** of the data (as long as we can draw samples) $\hat{x} \sim p(x)$
- Allows us to **'see'** what the model has and hasn't learned
- Can also use generative models to **imagine** possible scenarios, e.g. for **model-based RL**

What I cannot create, I do not understand
– Richard Feynman

Autoregressive Models

The Chain Rule for Probabilities

$$P(w_1, w_2, \ldots, w_{T-1}, w_T) = \prod_{t=1}^{T} P(w_t | w_{t-1}, w_{t-2}, \ldots, w_1)$$

the	cat	sat	on	the	mat	$P(w_1)$
the	**cat**	sat	on	the	mat	$P(w_2 \mid w_1)$
the	cat	**sat**	on	the	mat	$P(w_3 \mid w_2, w_1)$
the	cat	sat	**on**	the	mat	$P(w_4 \mid w_3, w_2, w_1)$
the	cat	sat	on	**the**	mat	$P(w_5 \mid w_4, w_3, w_2, w_1)$
the	cat	sat	on	the	**mat**	$P(w_6 \mid w_5, w_4, w_3, w_2, w_1)$

Slide Credit: Piotr Mirowski

Autoregressive Networks

- Basic trick: split high dimensional data up into a sequence of small pieces, predict each piece from those before (~~curse of dimensionality~~)
- Conditioning on past is done via network state (LSTM/GRU, masked convolutions, transformers…), output layer parameterises predictions

$$\mathcal{D} = \{\mathbf{x}\}$$

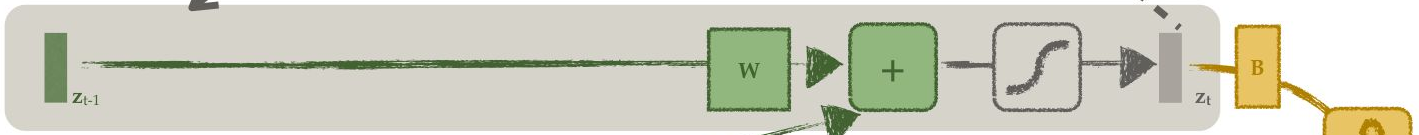
$$\mathbf{x} = (x_1, \ldots, x_T)$$

$$p(\mathbf{x}) = \prod_{t=1}^{T} p(x_t | x_{<t})$$

$$L(\mathcal{D}) = \sum_{\mathbf{x} \in \mathcal{D}} \sum_{t=1}^{T} -\log p(x_t | x_{<t})$$

Recurrent Neural Network Language Models

[Jeffrey L Elman (1991) "Distributed representations, simple recurrent networks and grammatical structure", *Machine Learning*; Tomas Mikolov et al. (2010) "Recurrent neural network based language model", *INTERSPEECH*]



"persistent memory":
state variable
for arbitrarily
long contexts

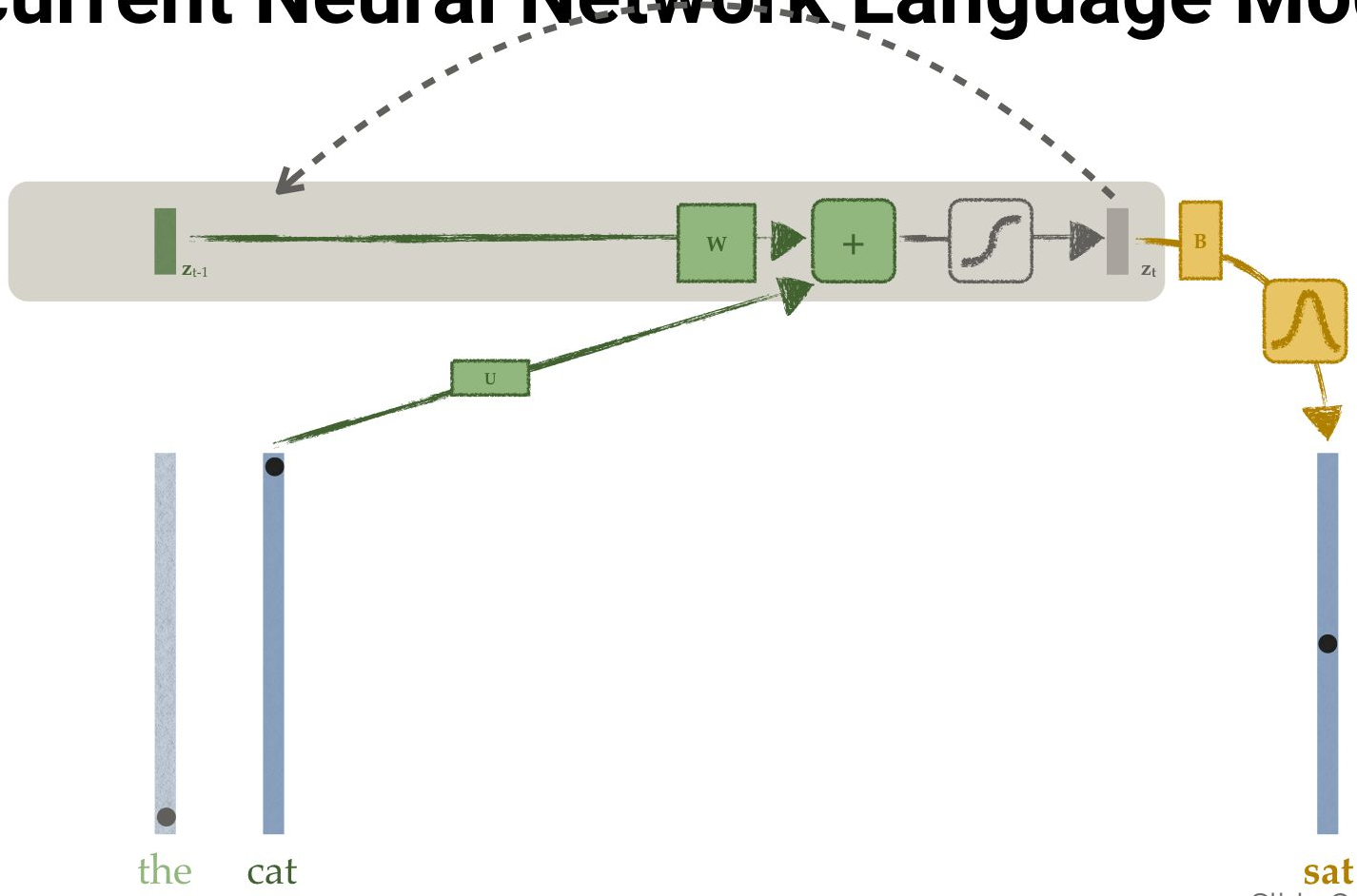
$$z_t = \tanh(W z_{t-1} + U w_t)$$
$$p(w_{t+1}) = softmax(B z_t)$$

the

cat

Slide Credit: Piotr Mirowski

Recurrent Neural Network Language Models



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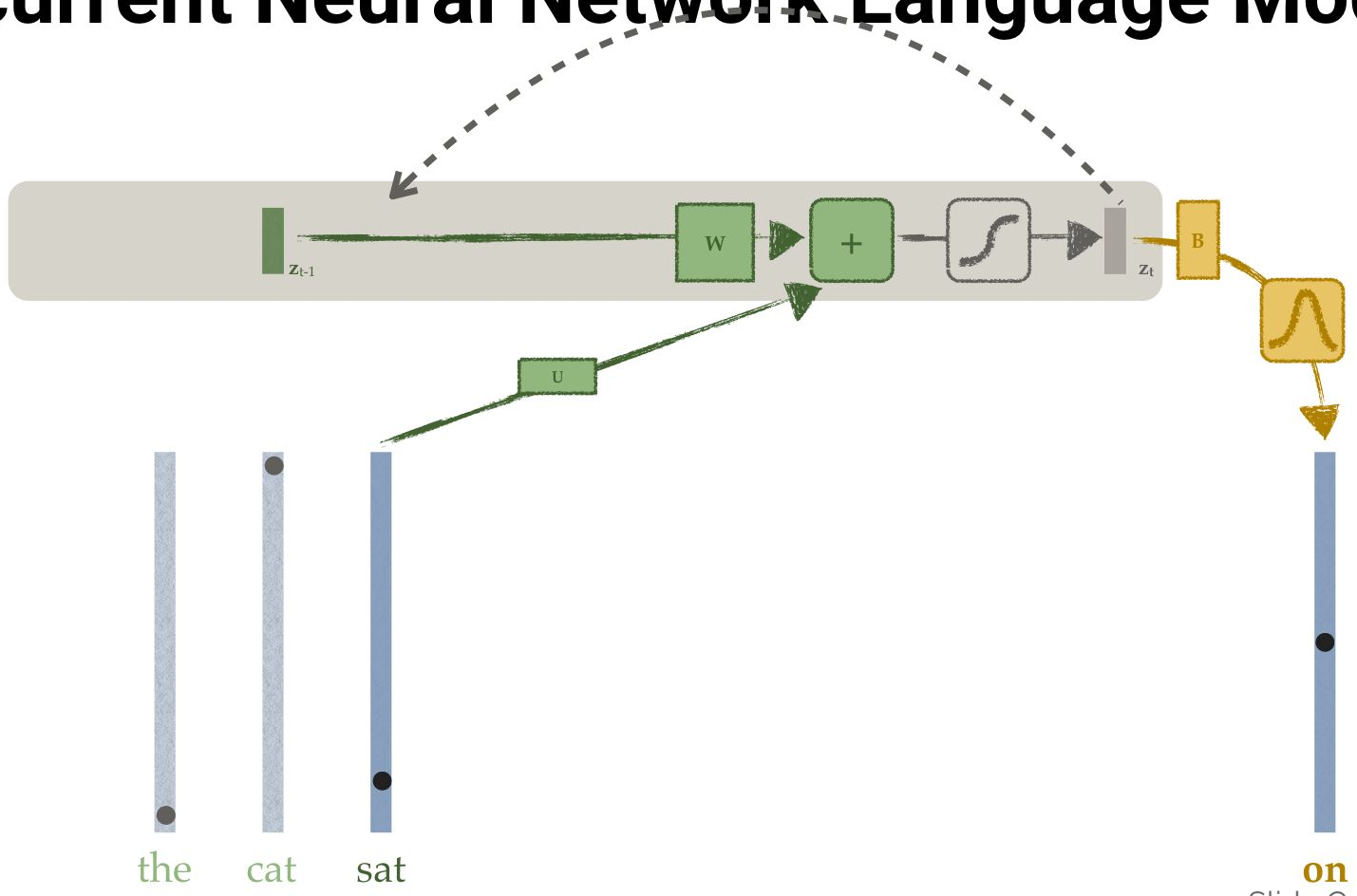
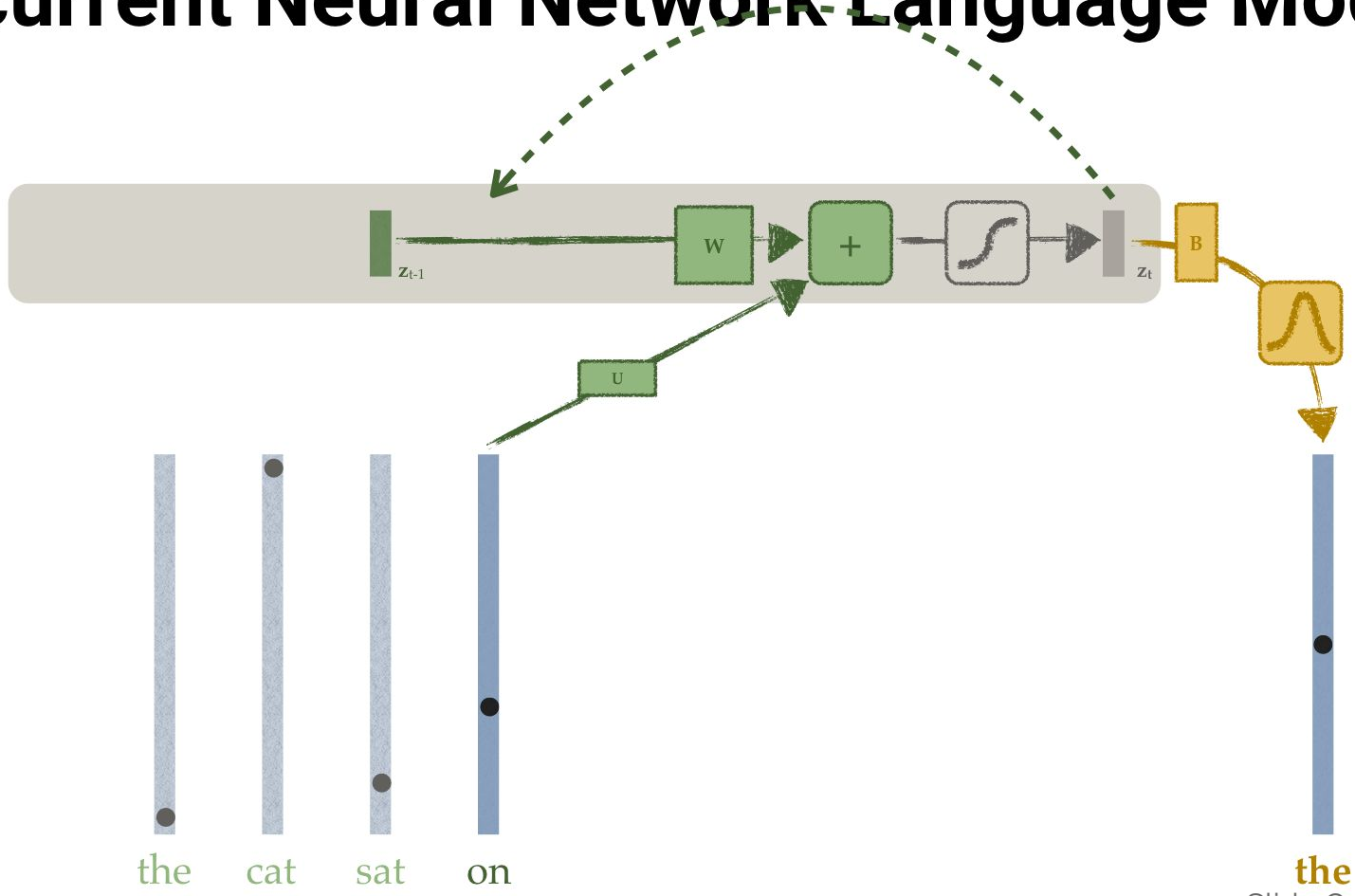
Recurrent Neural Network Language Models



Slide Credit: Piotr Mirowski

Recurrent Neural Network Language Models



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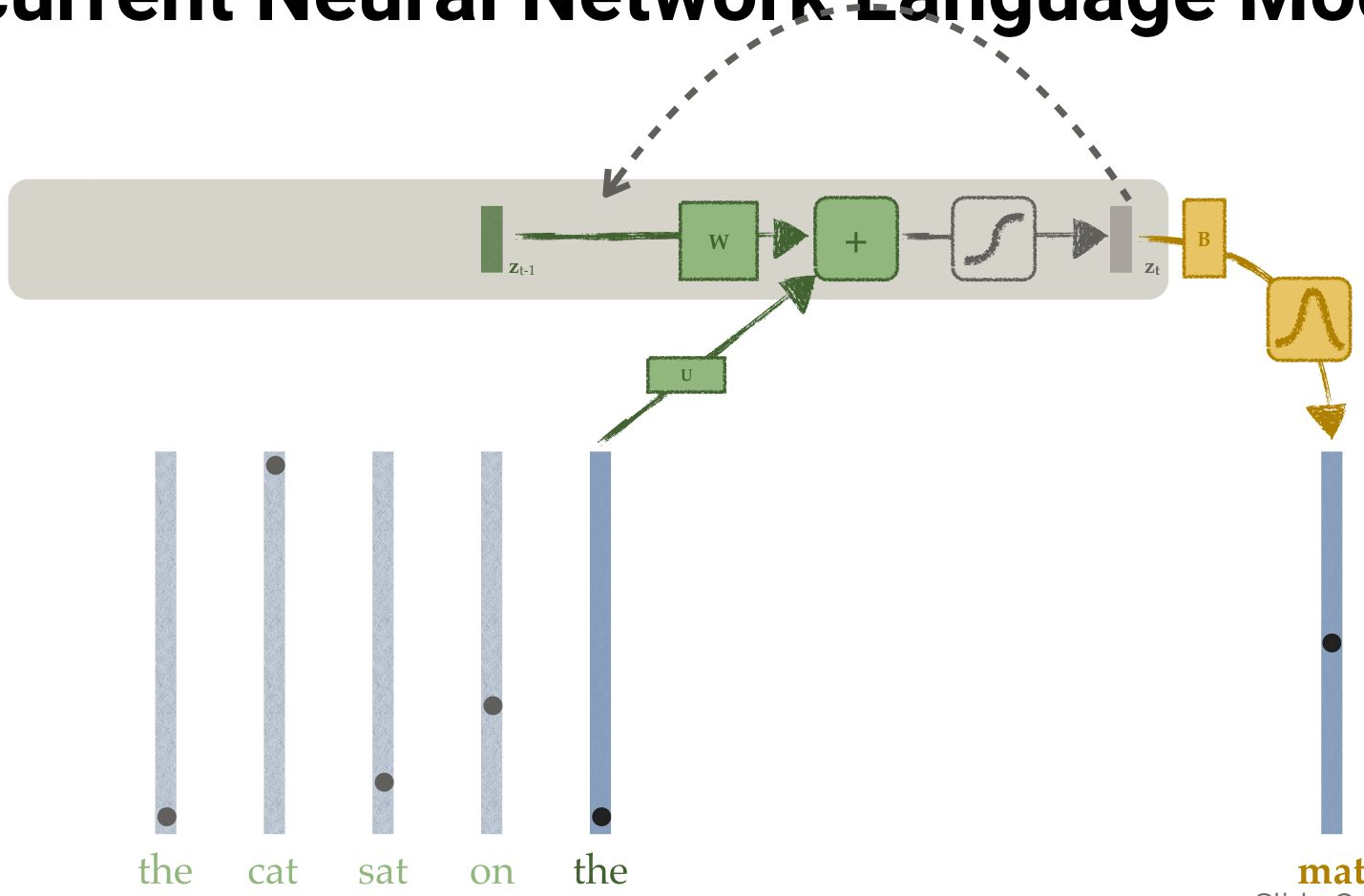


Slide Credit: Piotr Mirowski

Advantages of Autoregressive Models

- **Simple to define:** just have to pick an ordering
- **Easy to generate samples:** just sample from each predictive distribution, then feed in the sample at the next step as if it's real data (dreaming for neural networks?)
- **Best log-likelihoods for many types of data:** images, audio, video, text…

Disadvantages of Autoregressive Models

- **Very expensive** for high-dimensional data (e.g millions of predictions per second for video); can mitigate with **parallelisation** during training, but **generating** still slow
- **Order dependent**: get very different results depending on the order in which predictions are made, and can't easily **impute** out of order
- **Teacher forcing**: only learning to predict one step ahead, not many (potentially brittle generation and myopic representations)

Language Modelling

Some of the obese people lived five to eight years longer than others.

Abu Dhabi is going ahead to build solar city and no pollution city.

Or someone who exposes exactly the truth while lying.

VIERA , FLA . -- Sometimes, Rick Eckstein dreams about baseball swings.

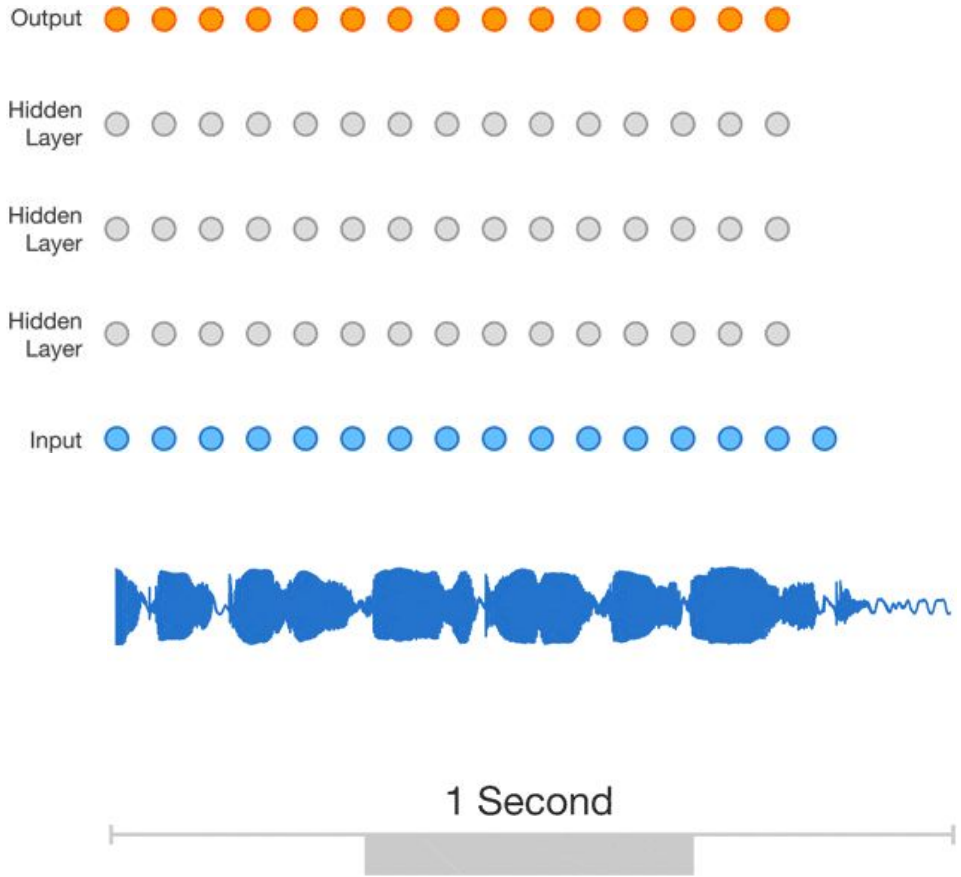
For decades, the quintessentially New York city has elevated its streets to the status of an icon.

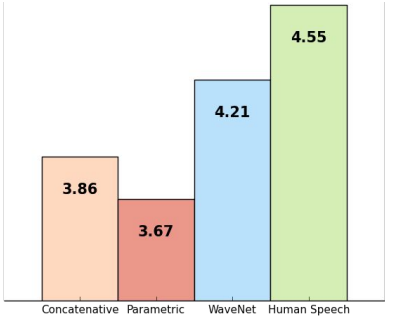
The lawsuit was captioned as United States ex rel.

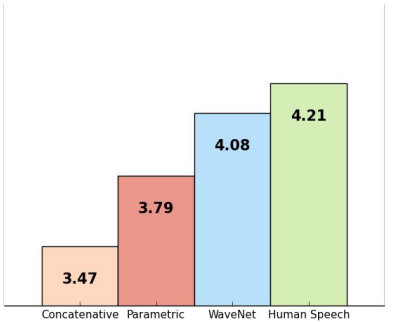
Model	Test Perplexity
Large Ensemble (Chelba et al., 2013)	43.8
RNN+KN-5 (Williams et al., 2015)	42.4
RNN+KN-5 (Ji et al., 2015a)	42.0
RNN+SNM10-skip (Shazeer et al., 2015)	41.3
Large Ensemble (Shazeer et al., 2015)	41.0
Our 10 best LSTM models (equal weights)	26.3
Our 10 best LSTM models (optimal weights)	26.1
10 LSTMs + KN-5 (equal weights)	25.3
10 LSTMs + KN-5 (optimal weights)	25.1
10 LSTMs + SNM10-skip (Shazeer et al., 2015)	**23.7**

R. Jozefowicz et. al. *Exploring the Limits of Language Modeling* (2016)

WaveNets

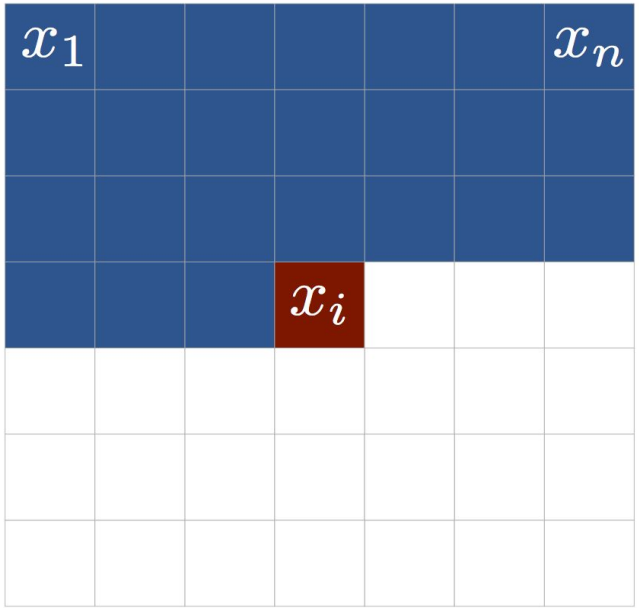






van den Oord, A., et al. “WaveNet: A Generative Model for Raw Audio.” *arxiv (2016).*

PixelRNN - Model



$$p(\mathbf{x}) = \prod_{i=1}^{n^2} p(x_i | x_1, \ldots, x_{i-1})$$

- Fully visible
- Model pixels with **Softmax**
- ‘Language model’ for images

van den Oord, A., et al. “Pixel Recurrent Neural Networks.” *ICML (2016).*

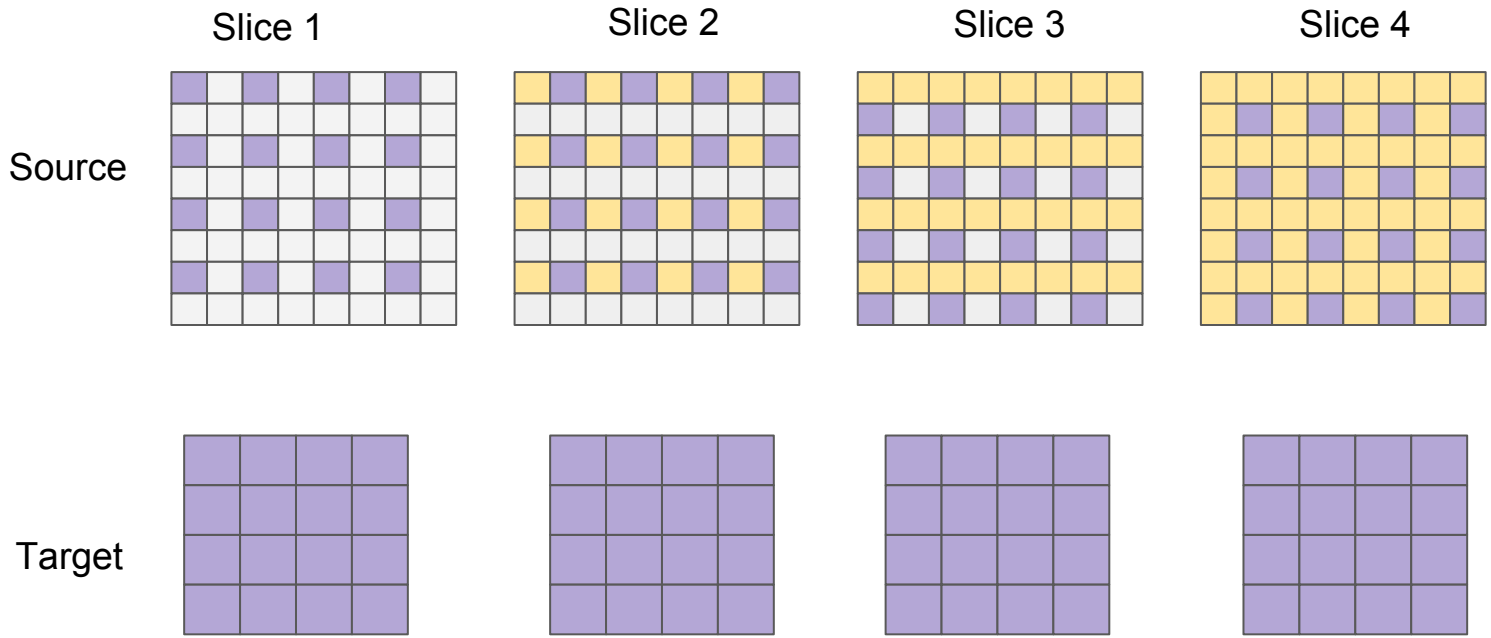
Pixel RNN - Samples

van den Oord, A., et al. “Pixel Recurrent Neural Networks.” *ICML (2016).*

Conditional Pixel CNN

van den Oord, A., et al. “Conditional Pixel CNN.” *NIPS (2016).*

Autoregressive over slices, then pixels within a slice



J. Menick et. al. *Generating High Fidelity Images with subsample pixel networks and multidimensional upscaling* (2018)

256 x 256 CelebA-HQ

J. Menick et. al. *Generating High Fidelity Images with subsample pixel networks and multidimensional upscaling* (2018)

128 x128 ImageNet

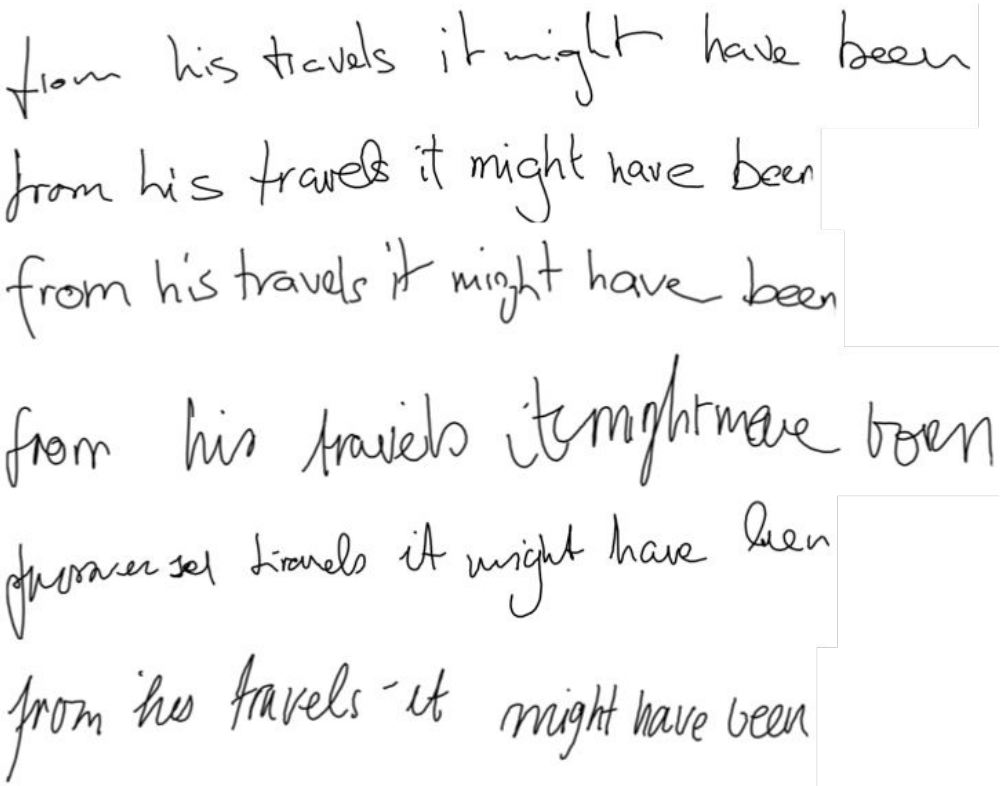
J. Menick et. al. *Generating High Fidelity Images with subsample pixel networks and multidimensional upscaling* (2018)

Video Pixel Network (VPN)

Model	Test
(Shi et al., 2015)	367.2
(Srivastava et al., 2015a)	341.2
(Brabandere et al., 2016)	285.2
(Patraucean et al., 2015)	179.8
Baseline model	110.1
VPN	**87.6**
Lower Bound	86.3

Kalchbrenner, N., et al. “Video Pixel Networks.” ***ICML (2017)***.

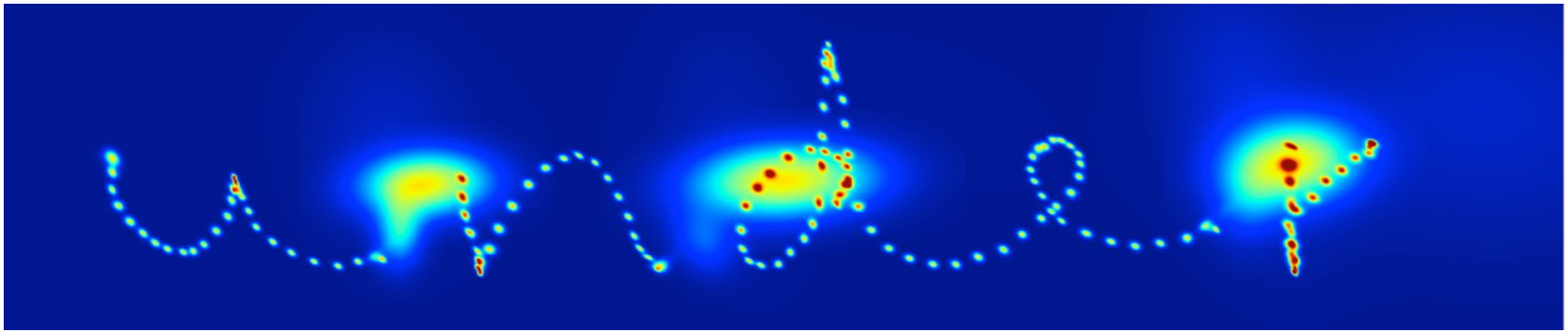
Handwriting Synthesis



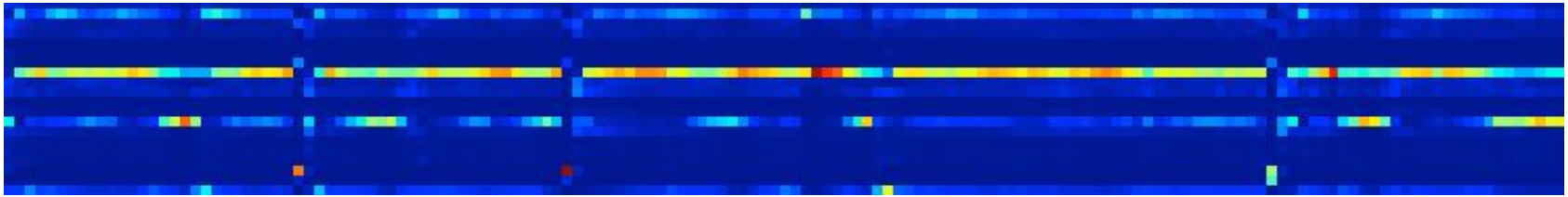
A. Graves, *Generating Sequences with Recurrent Neural Networks* (2013)

Autoregressive Mixture Models

Co-ordinate Density



Component Weights



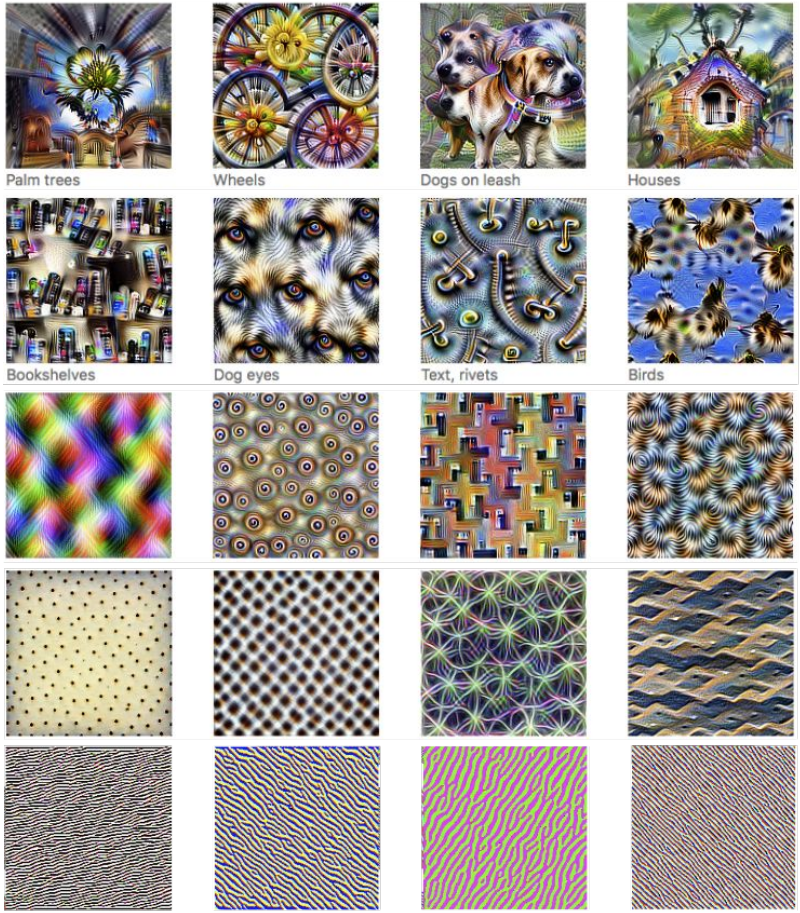
Distribution over Sequences

Carter et. al., *Experiments in Handwriting with a Neural Network* (2016)

Representation Learning

The Language of Neural Networks

- Deep networks work by learning complex, often hierarchical internal **representations** of input data
- These form a kind of **language** the network uses to describe the data
- Language can **emerge** from **tasks** like object recognition: has pointy ears, whiskers, tail => cat (c.f. **Wittgenstein**)



The visual vocabulary of a convolutional neural network. For each layer of the network, images are generated that maximally activate particular neurons. The response of these neurons to other images can then be interpreted as the presence or absence of visual "words": textures, bookshelves, dog snouts, birds

C. Olah et. al. *Feature Visualization,* distill (2018)

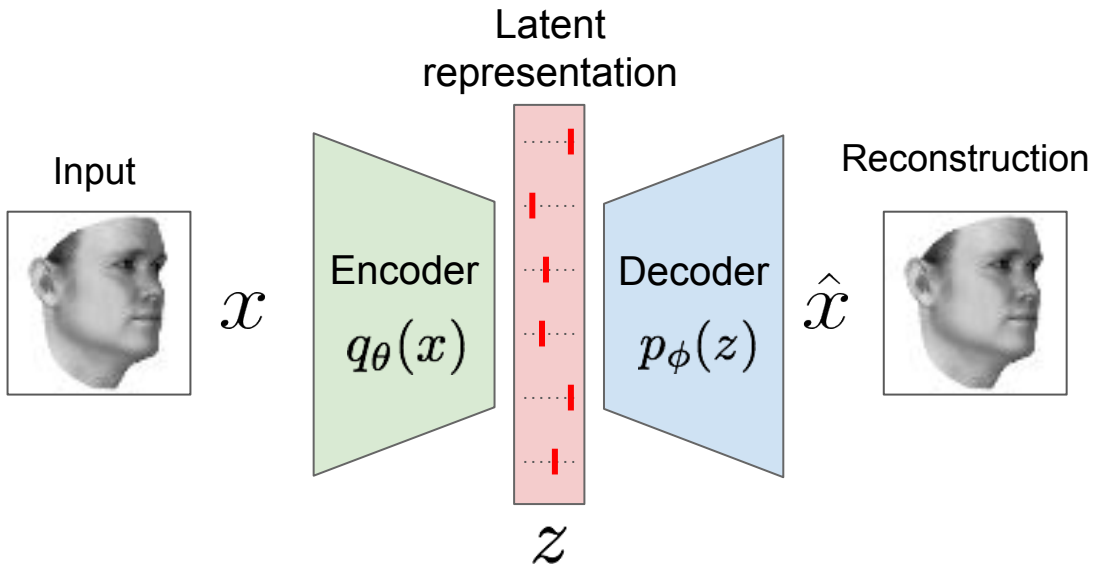
Unsupervised Representations

- Task-driven representations are limited by the **requirements** of the task: e.g. don't need to internalise the laws of physics to recognise objects
- Unsupervised representations ***should*** be more general: as long as the laws of physics help to model observations in the world, they are worth representing

Reading the Latent Language

- We want neural networks to **describe** the data to us (image captioning without the captions?)
- Then we can **re-use** the descriptions to **plan**, **reason**, and **generalise** at a more abstract level
- Good density models ***must*** learn a rich internal language, but we can't read it (distil for WaveNet?): we need to break open the black box
- One way to make representations more **accessible** is to force them through a **bottleneck**

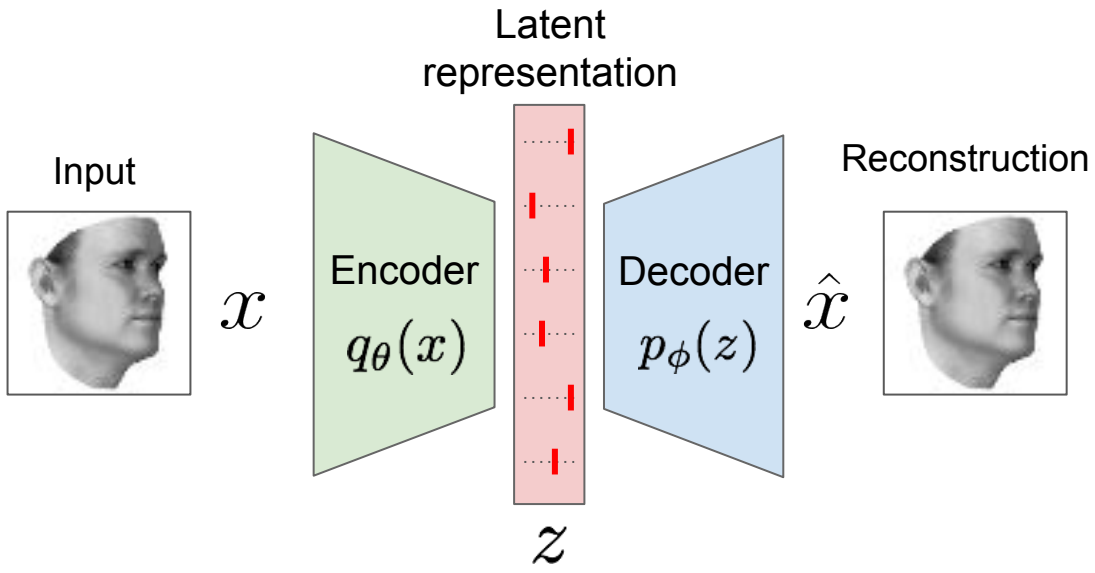
Autoencoder



$$\mathcal{L}^{AE}(\mathbf{x};\theta,\phi) = \underbrace{\left[\mathbf{x} - p_\theta(q_\phi(\mathbf{x})\right]^2}_{\text{Reconstruction cost}}$$

Slide: Irina Higgins, Loïc Matthey

Autoencoder



$$\mathcal{L}^{AE}(\mathbf{x};\theta,\phi) = \cancel{\left[\mathbf{x} - p_\theta(q_\phi(\mathbf{x}))\right]^2} - \log p_\theta(q_\phi(\mathbf{x}))$$

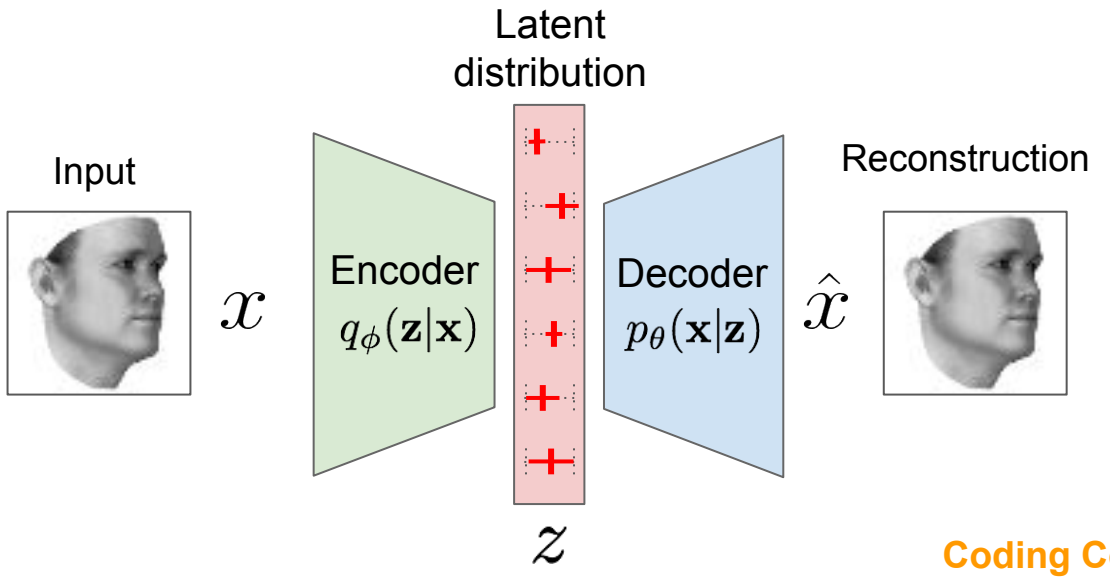
Reconstruction cost

DeepMind

Slide: Irina Higgins, Loïc Matthey

Variational AutoEncoder

Kingma et al, 2014
Rezende et al, 2014



$$\mathcal{L}_{VAE}(\mathbf{x};\theta,\phi) = \underbrace{\mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}\left[-\log p_\theta(\mathbf{x}|\mathbf{z})\right]}_{\text{Reconstruction cost}} + \overbrace{KL\left(q_\phi(\mathbf{z}|\mathbf{x})||p(\mathbf{z})\right)}^{\text{Coding Cost}}$$

DeepMind

Slide: Irina Higgins, Loïc Matthey

Minimum **D**escription **L**ength for **VAE**

- Alice wants to transmit $\boldsymbol{x}$ as compactly as possible to Bob, who knows only the prior $\boldsymbol{p(z)}$ and the decoder weights
- The **coding cost** is the number of bits required for Alice to transmit a sample from $\boldsymbol{q_\theta(z|x)}$ to Bob (e.g. **bits-back** coding)
- The **reconstruction cost** measures the number of additional error bits Alice will need to send to Bob to reconstruct the data given the latent sample (e.g. **arithmetic** coding)
- The sum of the two costs is the total length of the message Alice needs to send to Bob to allow him to recover $\boldsymbol{x}$ (c.f. **variational inference**)

Chen at. al., *Variational Lossy Autoencoder* (2017)

Code Collapse

- Ideally a VAE would put **high-level** information in the codes, leave **low-level** information to the decoder
- ***But*** when the decoder is sufficiently powerful (e.g. autoregressive) the coding distribution tends to **'collapse'** to the prior ***p(z)***
- This means no information is passed through the bottleneck and no latent representation is learned
- **MDL** suggests a reason: **a powerful decoder can implicitly learn *p(z)***, meaning that if each ***x*** is **independently** transmitted, the number of bits saved by the decoder by conditioning on ***z*** ≈ the cost of transmitting ***z***

Thought Experiments

- **Experiment 1:** An MNIST Decoder learns a uniform mixture over 10 disjoint models. Prior is uniform over 10 classes. Conditioning on the image class saves ~ $\log_2(10)$ bits, encoding the class costs ~ $\log_2(10)$ bits

- **Experiment 2:** Pick 100 character strings at random from an encyclopedia. The context from the paragraph, article etc. is missing. Is it worth appending that information to each of the strings?

Learn the **Dataset**, Not the **Datapoints**

- Suggests a fundamental flaw with using log-likelihoods to find representations: never worth encoding high-level information
- Example: conditioning on ImageNet labels makes a huge difference to samples, tiny difference to log-probs ($\approx \log_2(1000)$ bits)
- **But** one label applies to many data, so worth encoding high-level information **if we only encode it once for the whole dataset** ($\approx 1000 \times \log_2(1000)$ bits)
- Want to **amortise** the coding cost over the whole dataset
- Use high level information to **organise** low level data, not **annotate** it

…one must take seriously the idea of working with datasets, rather than datapoints, as the key objects to model.
– Edwards & Storkey, *Towards a Neural Statistician*, (2017)

Associative **C**ompression **N**etworks

- ACNs modify the VAE loss by replacing the **unconditional** prior **p(z)** with a **conditional** prior **p(z|z')**, where **z'** is the latent representation of an **associated** data point (one of the ***K nearest Euclidean neighbours*** to **z**)
- **p(z|z')** – parameterised by an MLP – models only part of the latent space, rather than the whole thing, which **greatly reduces the coding cost**
- **Implicit amortisation**: the more clustered the codes, the cheaper they are
- **Result:** rich, informative codes are learned, even with powerful decoders.

Graves et. al., *Associative Compression Networks for Representation Learning* (2018)

MDL for ACN

- Alice now wants to transmit the entire ***dataset*** to Bob, **in any order** (justified for **IID** data?)
- Bob has the weights of the associative prior, decoder **and encoder**
- Alice chooses an ordering for the data that minimises total coding cost (**travelling salesman**) and sends the data to Bob **one at a time**.
- After receiving each latent code + error bits, he decodes the datapoint, then re-encodes it and uses the result to determine the **associative prior** for the next code

Red bits are different from standard VAE, The rest is the same

Algorithm 1 Associative Compression Network Training

Initialise C: $c(x) \sim \mathcal{N}(0, 1)\ \forall x \in \mathbf{X}$

repeat

Sample x uniformly from $\mathbf{X}$

Run encoder network, get $q(z|x)$

Update **C** with new code: $c(x) \leftarrow \mathbb{E}_{z \sim q(z|x)}[z]$

$KNN(x) \leftarrow K$ nearest Euc. neighbours to $c(x)$ in $\mathbf{C}$

Pick $\hat{c}$ randomly from $KNN(x)$

Run prior network, get $r(z|\hat{c})$

$z \sim q(z|x)$

Run decoder network, compute $-\log p(x|z)$

$L^{ACN}(x) = KL(q(z|x)||r(z|\hat{c})) - \log p(x|z)$

Compute gradients, update network weights

until convergence

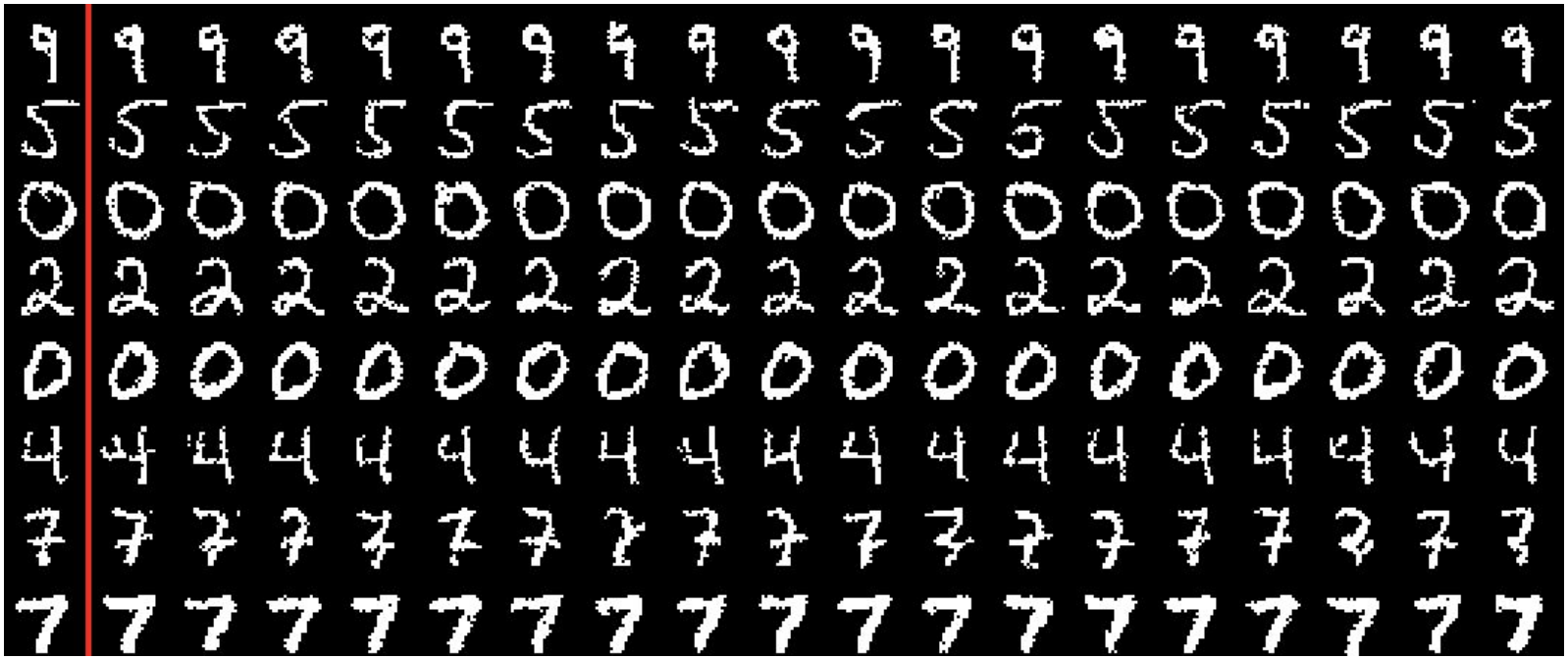
Table 3. Binarized MNIST linear classification results

INPUT	ACCURACY (%)
PCA (16 COMPONENTS)	82.8
PIXELS	89.4
STANDARD VAE CODES	95.4
GATED PIXELVAE CODES	97.9
ACN CODES	**98.5**

Table 1. Binarized MNIST test set compression results

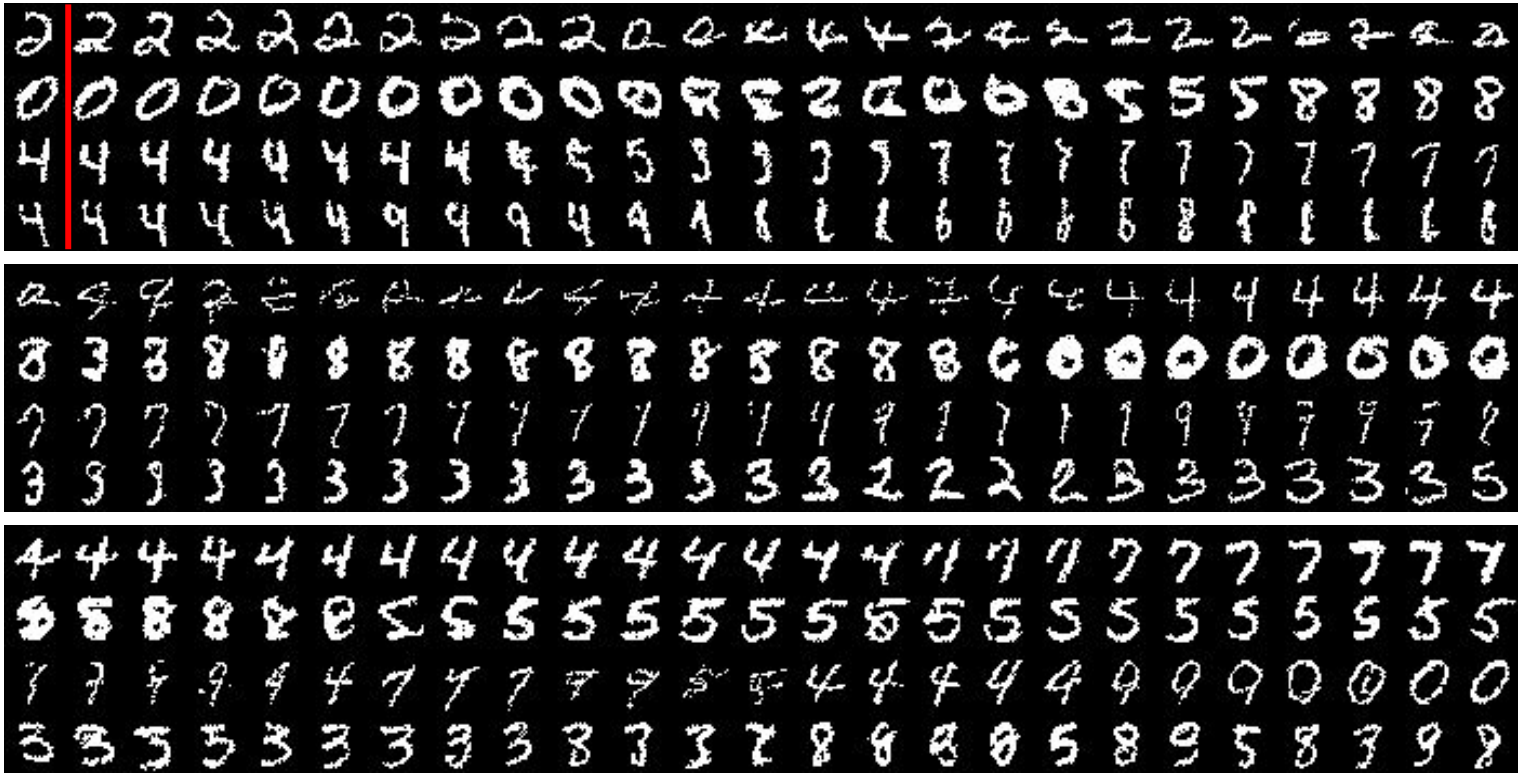
MODEL	NATS / IMAGE
GATED PIXEL CNN (OURS)	81.6
PIXEL CNN (OORD ET AL., 2016A)	81.3
DISCRETE VAE (ROLFE, 2016)	81.0
DRAW (GREGOR ET AL., 2015)	$\leq$ 81.0
PIXEL RNN (OORD ET AL., 2016A)	79.2
VLAE (CHEN ET AL., 2016B)	79.0
GLN (VENESS ET AL., 2017)	79.0
MATNET (BACHMAN, 2016)	$\leq$ 78.5
ACN (UNORDERED)	$\leq$ 80.9
ACN (ORDERED)	$\leq$ **73.9**

Unordered: KL from unconditional prior
Ordered: KL from conditional ACN prior



Binary MNIST reconstructions: leftmost column are test set images

CelebA Reconstructions: leftmost column from test set



‘Daydream’ sampling: encode data, sample latent from conditional prior, generate new data conditioned on latent, repeat

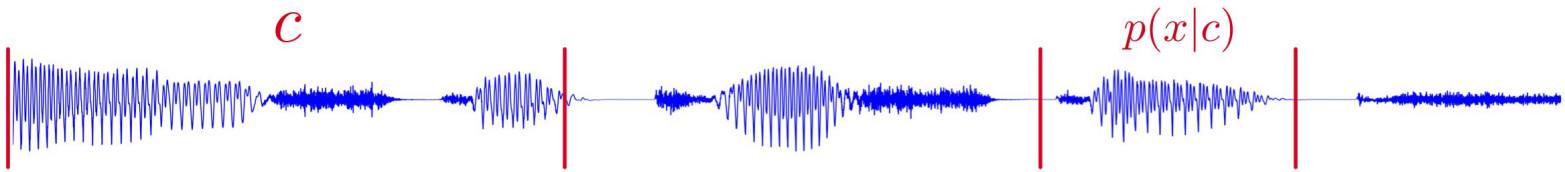
Mutual Information

- Want codes that **'describe'** the data as well as possible
- Mathematically, we want to maximise the **mutual information** between the code ***z*** and the data ***x***

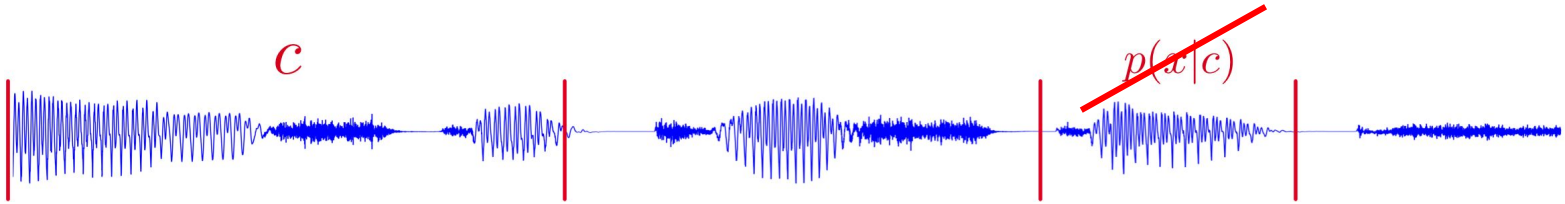
$$MI(z, x) = KL(p(z, x)||p(z)p(x))$$

- For an autoencoder, the difference between decoding ***x*** with ***z*** and (optimally) decoding without ***z*** is a **lower bound** on ***MI(x, z)***, so minimising the **reconstruction** cost maximises **MI**
- But decoding is very **expensive** if we just want codes
- Are there other ways to maximise **MI?**

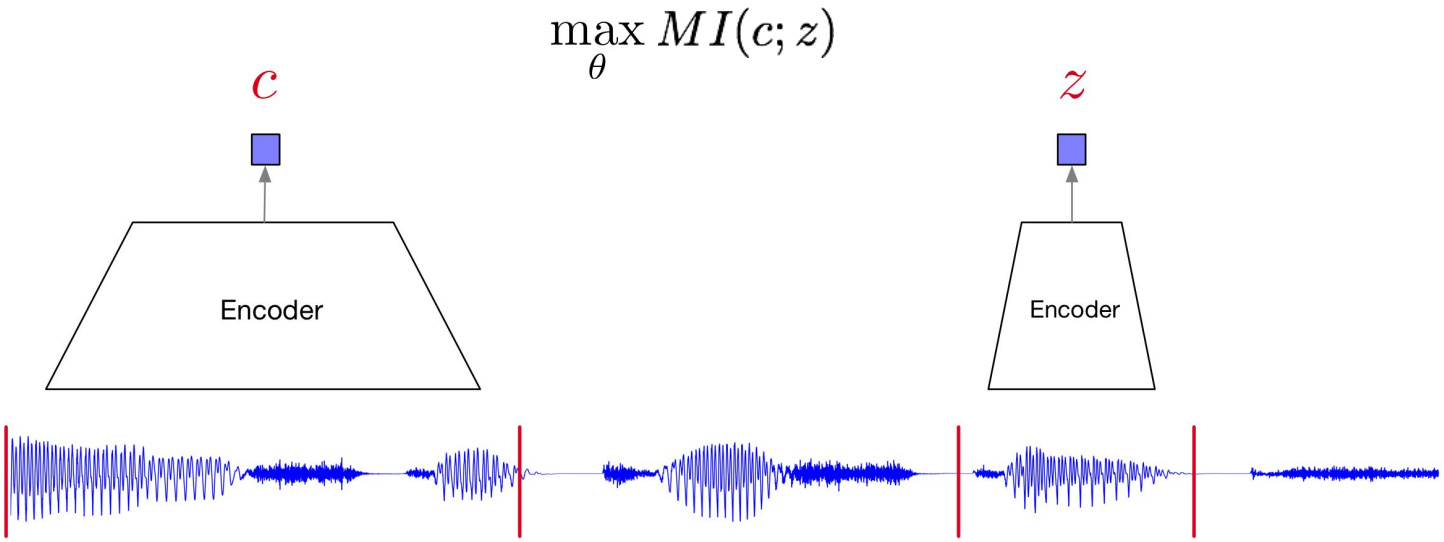
Contrastive Predictive Coding



van den Oord et al., *Representation Learning with Contrastive Predictive Coding* (2018)



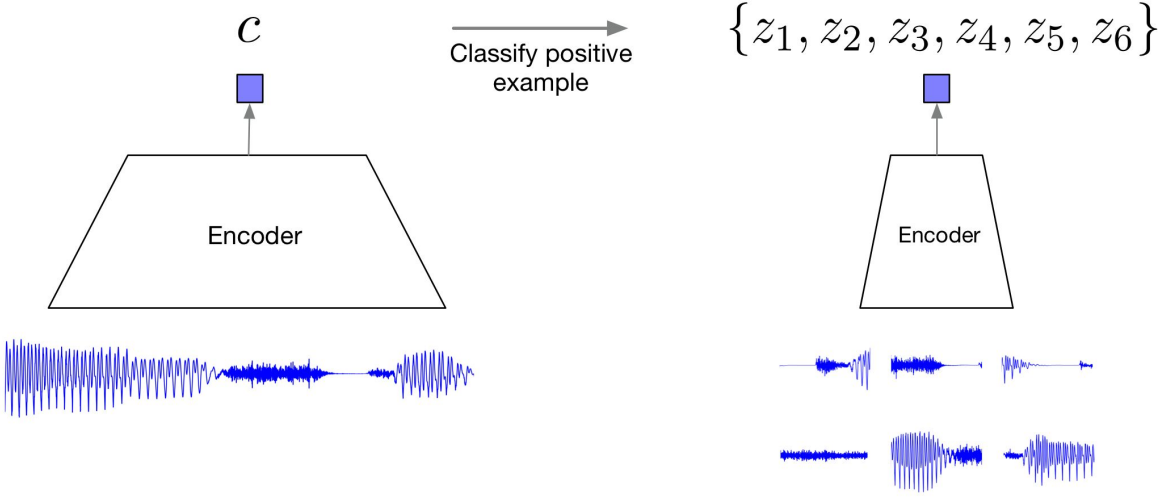
van den Oord et al., *Representation Learning with Contrastive Predictive Coding* (2018)



van den Oord et al., *Representation Learning with Contrastive Predictive Coding* (2018)

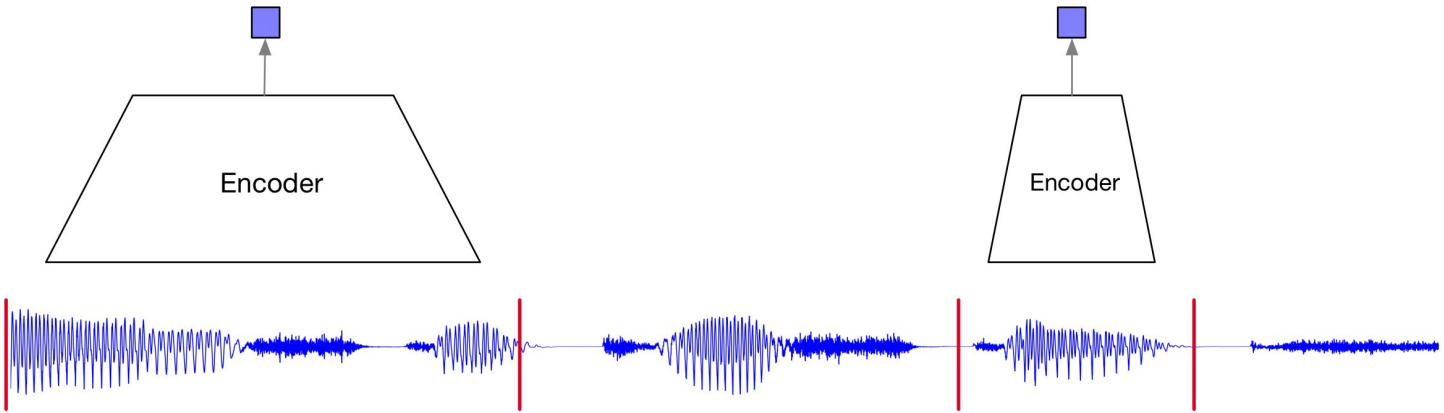
$$\frac{\exp f(c, z_i)}{\sum_j \exp f(c, z_j)}$$

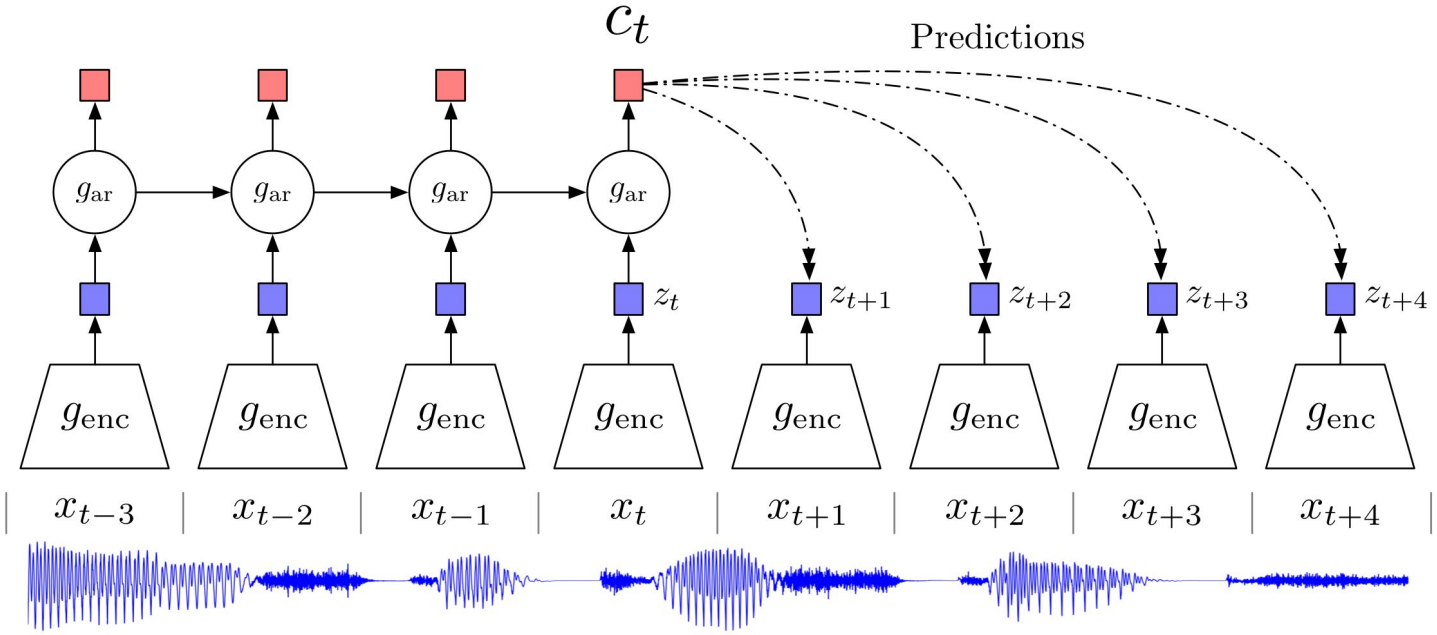
$$f_k(x_{t+k}, c_t) = \exp\left(z_{t+k}^T W_k c_t\right)$$

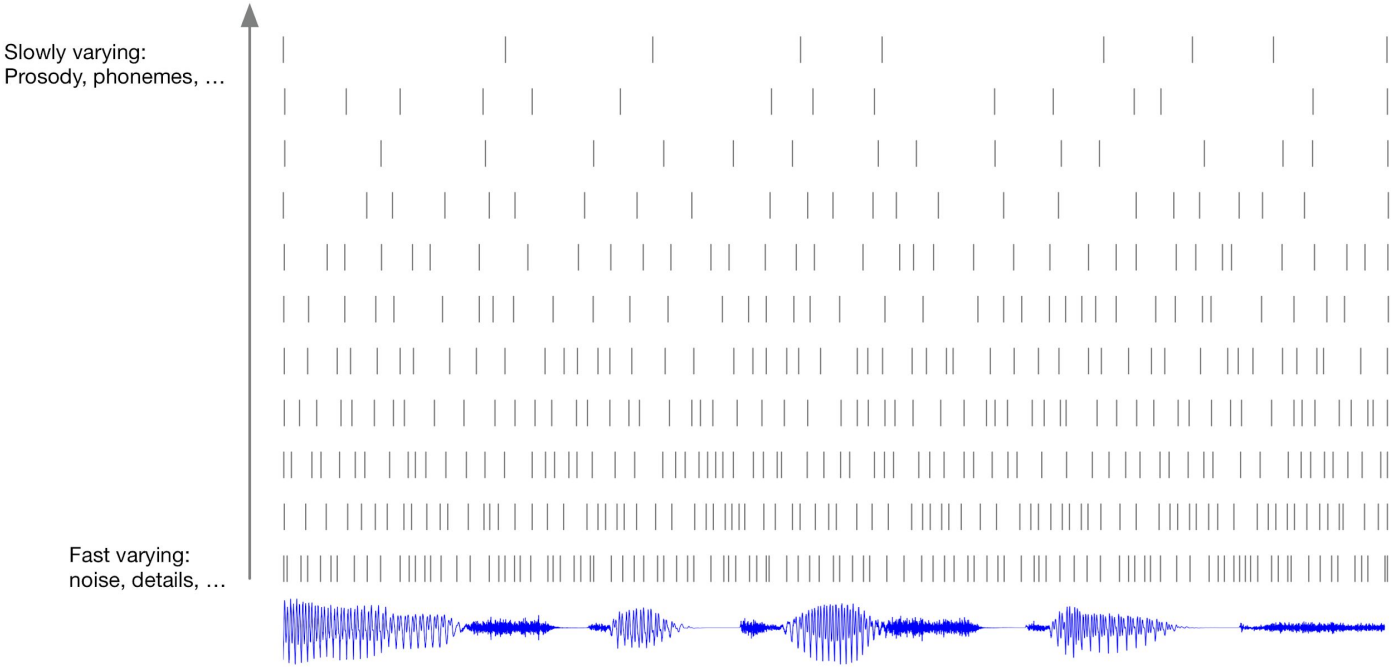


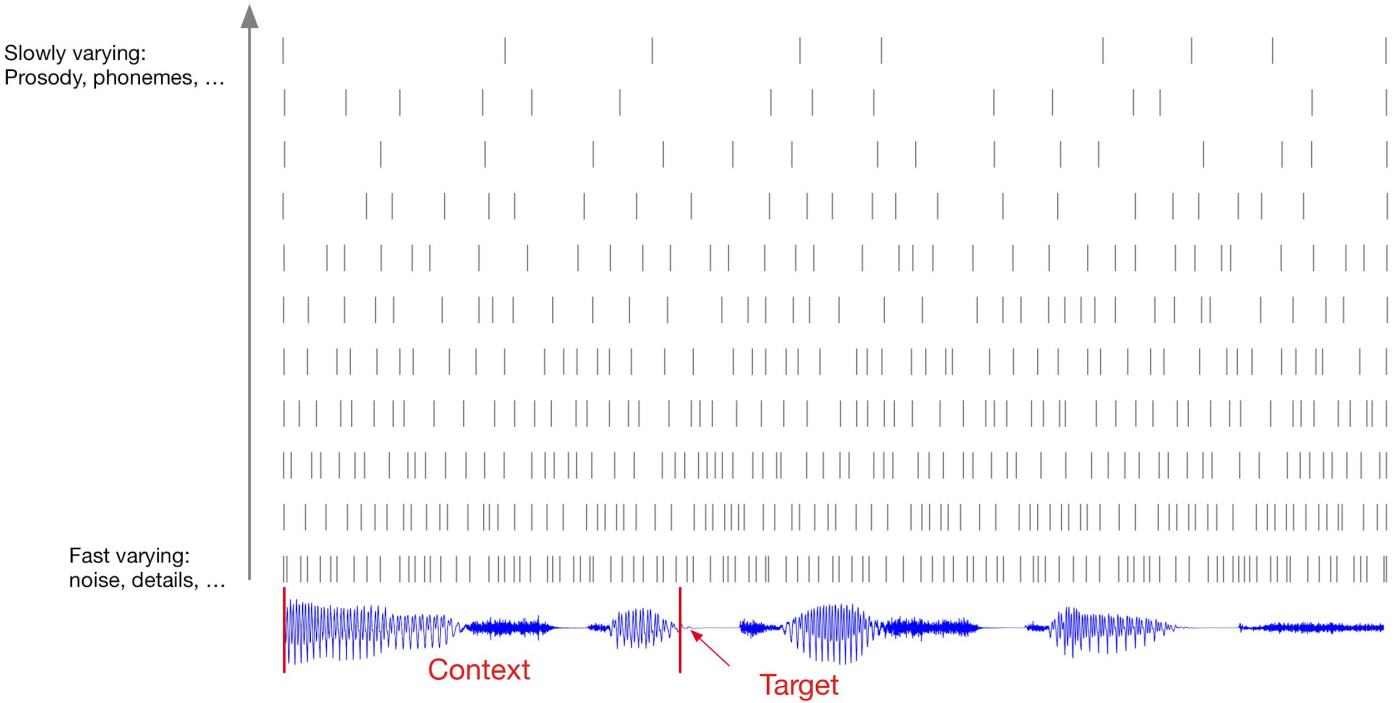
Gutmann et al., *Noise-Contrastive Estimation* (2009)

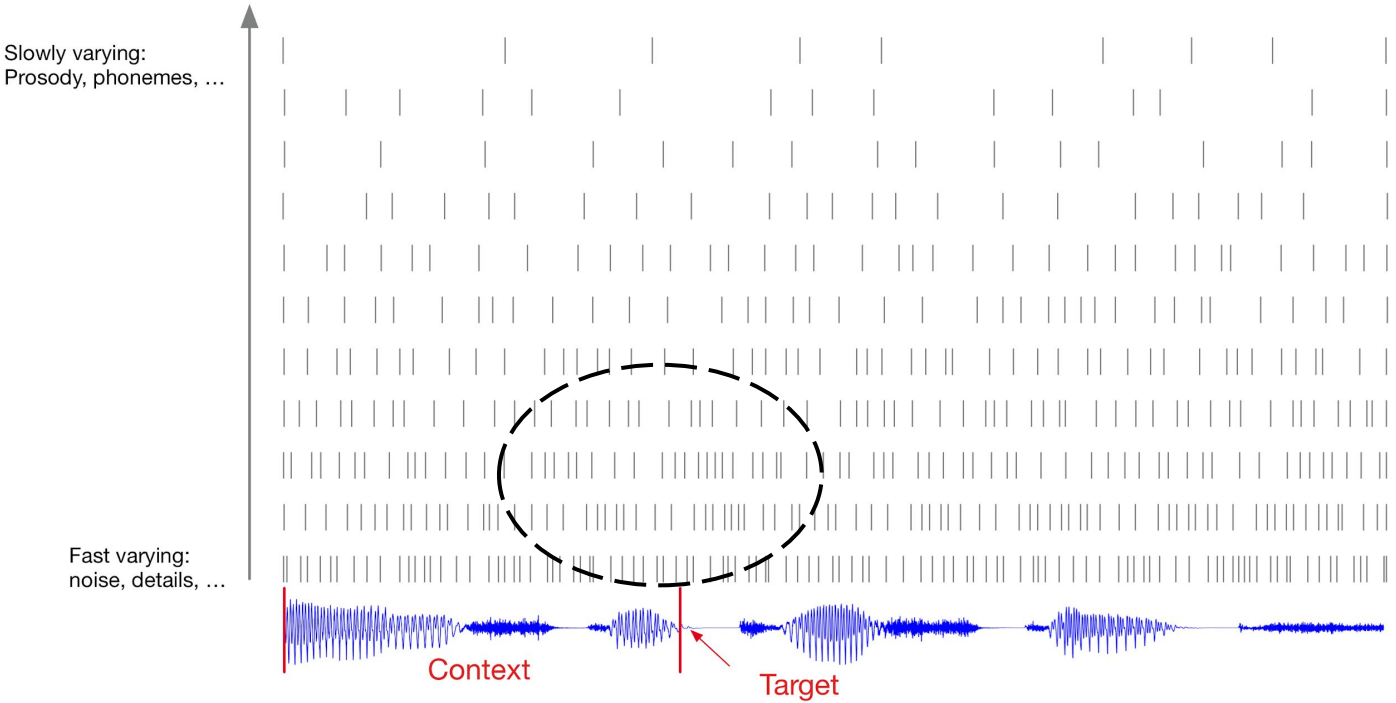
$$MI(x_t, c_t) \geq \log N - \mathcal{L}_N$$

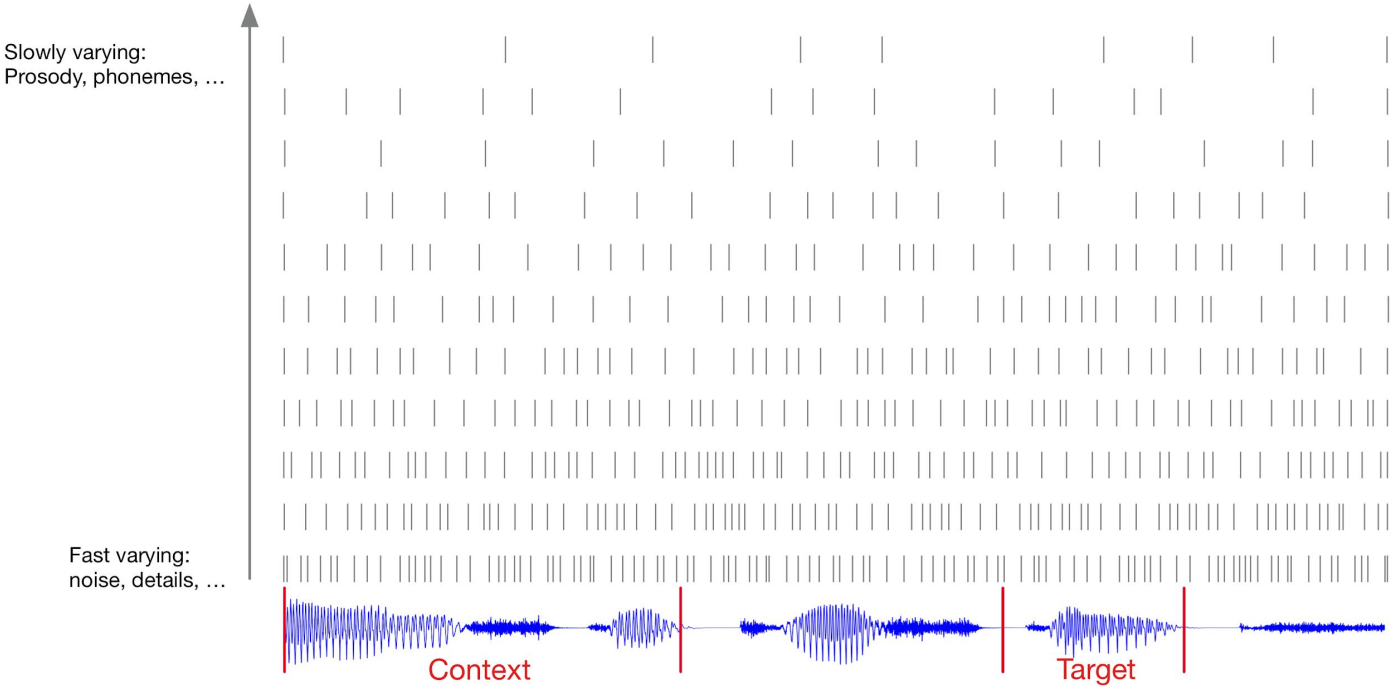


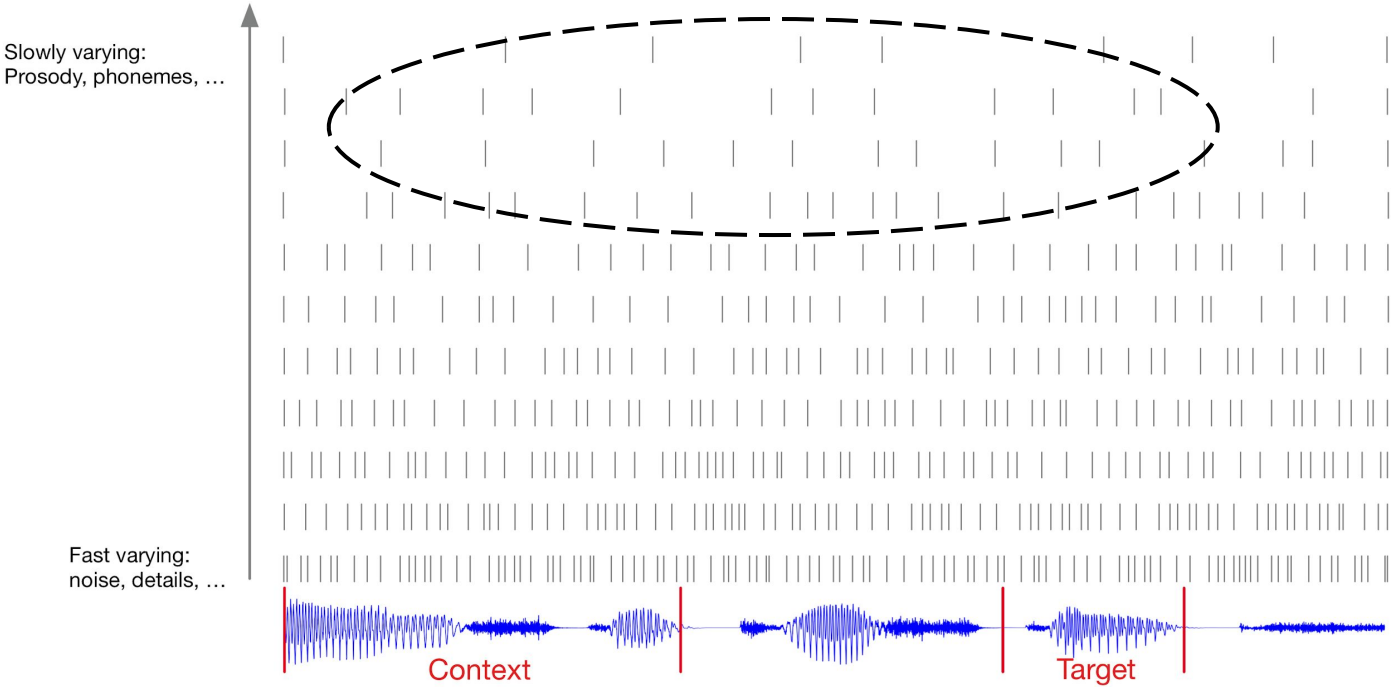

c_t
Predictions
g_{ar}
g_{ar}
g_{ar}
g_{ar}
z_t
z_{t+1}
z_{t+2}
z_{t+3}
z_{t+4}
g_{enc}
g_{enc}
g_{enc}
g_{enc}
g_{enc}
g_{enc}
g_{enc}
g_{enc}
x_{t-3}
x_{t-2}
x_{t-1}
x_t
x_{t+1}
x_{t+2}
x_{t+3}
x_{t+4}


Slowly varying:
Prosody, phonemes, …
Fast varying:
noise, details, …


Slowly varying:
Prosody, phonemes, …
Fast varying:
noise, details, …
Context
Target

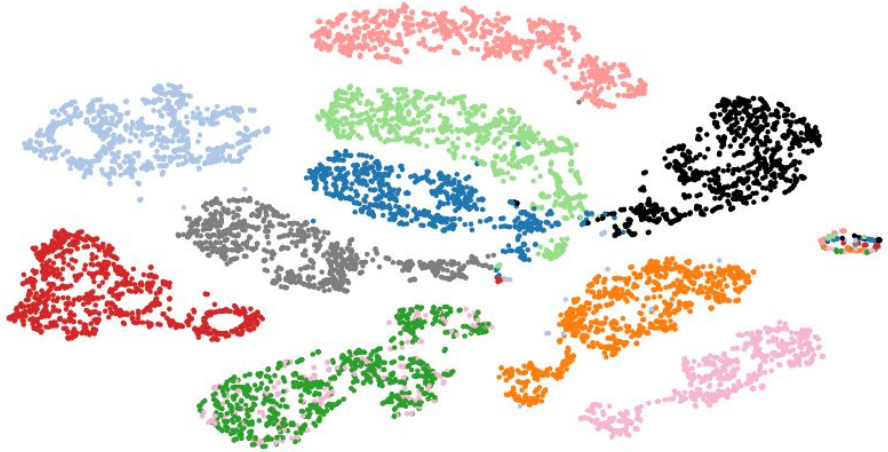

Slowly varying:
Prosody, phonemes, …
Fast varying:
noise, details, …
Context
Target


Slowly varying:
Prosody, phonemes, …
Fast varying:
noise, details, …
Context
Target


Slowly varying:
Prosody, phonemes, …
Fast varying:
noise, details, …
Context
Target

Speech - LibriSpeech

Method	ACC
Phone classification	
Random initialization	27.6
MFCC features	39.7
CPC	64.2
Supervised	74.6
Speaker classification	
Random initialization	1.87
MFCC features	17.6
CPC	97.4
Supervised	98.5



t-SNE on codes coloured by speaker identity

van den Oord et al., *Representation Learning with Contrastive Predictive Coding* (2018)

Images - ImageNet

Method	Top-1 ACC
Using AlexNet conv5	
Video [24]	29.8
Relative Position [10]	30.4
BiGan [25]	34.8
Colorization [9]	35.2
Jigsaw [26] *	38.1
Using ResNet-V2	
Motion Segmentation [27]	27.6
Exemplar [27]	31.5
Relative Position [27]	36.2
Colorization [27]	39.6
CPC	**48.7**

Method	Top-5 ACC
Motion Segmentation (MS)	48.3
Exemplar (Ex)	53.1
Relative Position (RP)	59.2
Colorization (Col)	62.5
Combination of MS + Ex + RP + Col	69.3
CPC	**73.6**

NLP - BookCorpus

Method	MR	CR	Subj	MPQA	TREC
Paragraph-vector [31]	74.8	78.1	90.5	74.2	91.8
Skip-thought vector [32]	75.5	79.3	92.1	86.9	91.4
Skip-thought + LN [33]	79.5	82.6	93.4	89.0	-
CPC	76.9	80.1	91.2	87.7	96.8

Unsupervised Reinforcement Learning

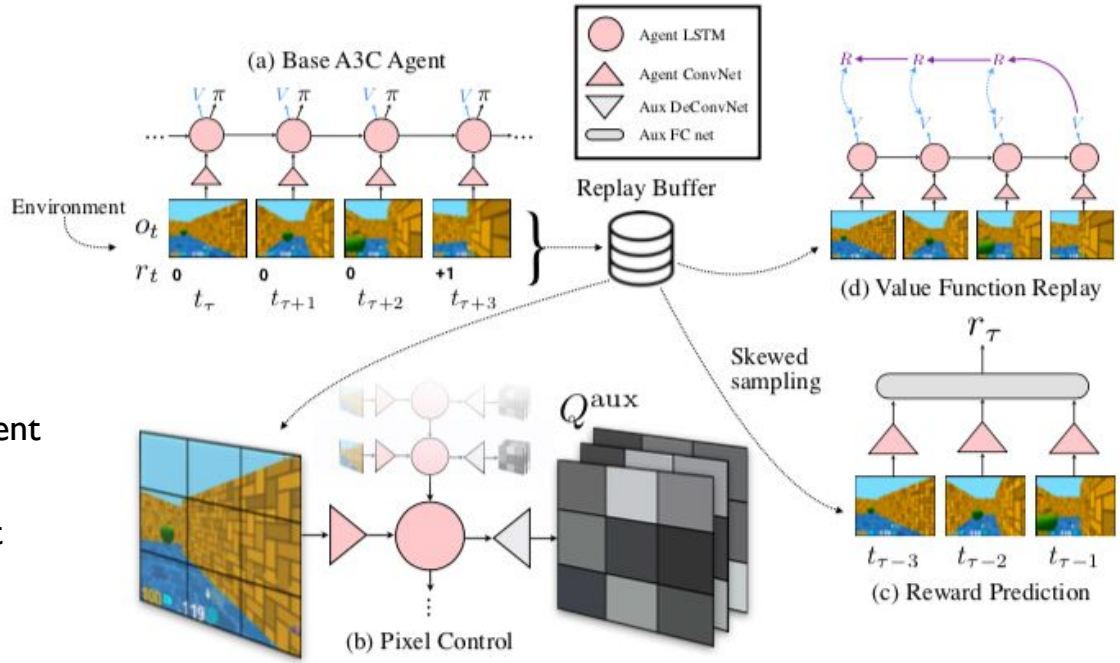
Auxiliary Tasks

- How can unsupervised learning help reinforcement learning?
- Simplest way is as an **auxiliary task**: maximise reward and minimise unsupervised loss with the **same network**
- Hope is that the **representations** learned for the unsupervised task will help with the RL task
- Also applies to supervised learning (e.g. **semi-supervised** learning, unsupervised **pre-training**)

UNREAL Agent

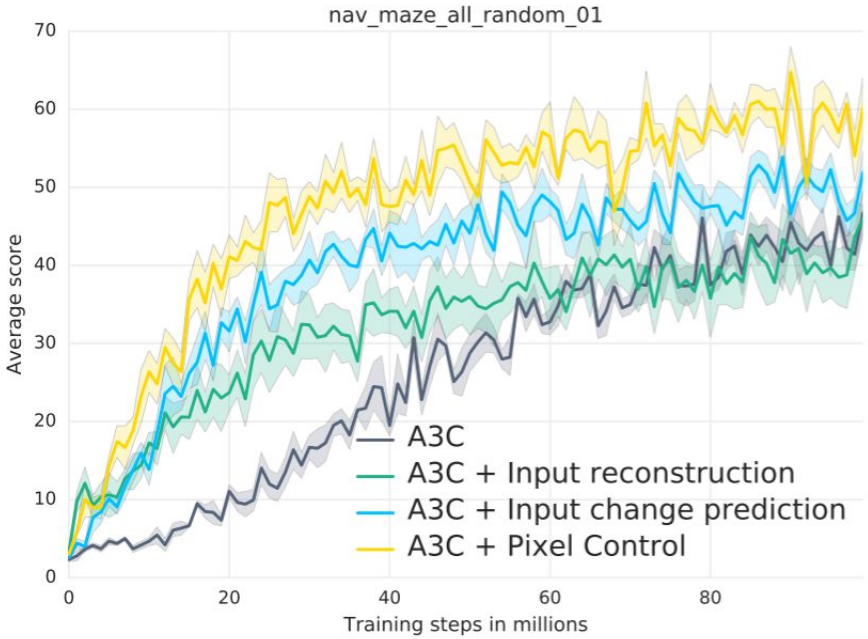
Pixel Control – auxiliary policies are trained to maximise change in pixel intensity of different regions of the input

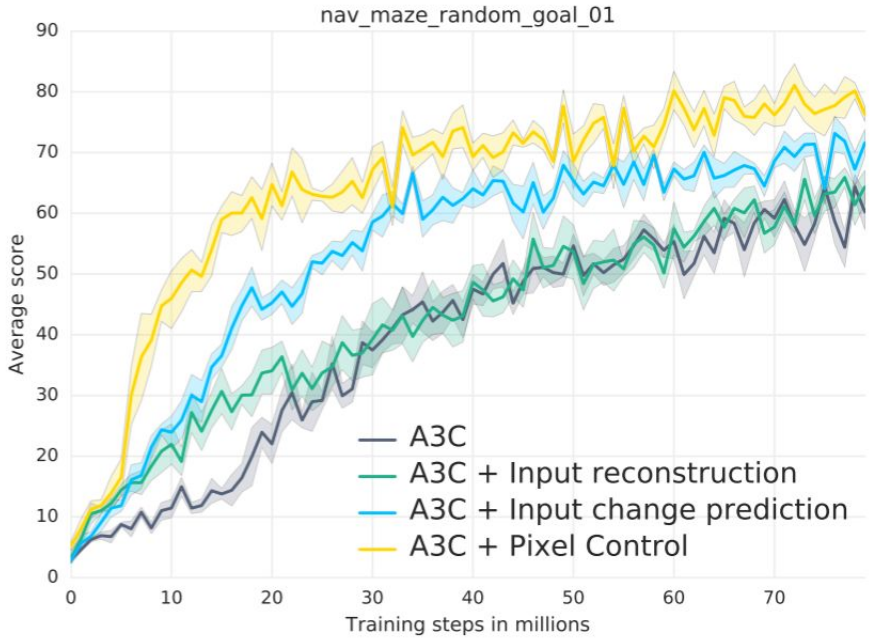
Reward Prediction – given three recent frames, the network must predict the reward that will be obtained in the next unobserved timestep.



M. Jaderberg et. al., *Reinforcement Learning with Unsupervised Auxiliary Tasks.* (2016)

Unsupervised RL Baselines





DeepMind

M. Jaderberg et. al., *Reinforcement Learning with Unsupervised Auxiliary Tasks.* (2016)

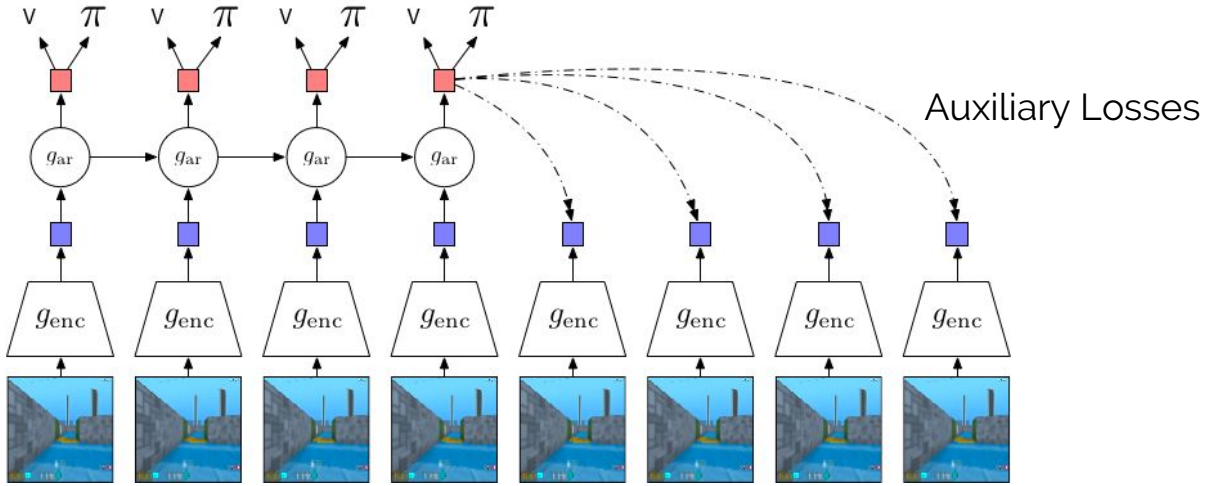
Sparse Rewards? More Cherries!

Single scalar reward signal

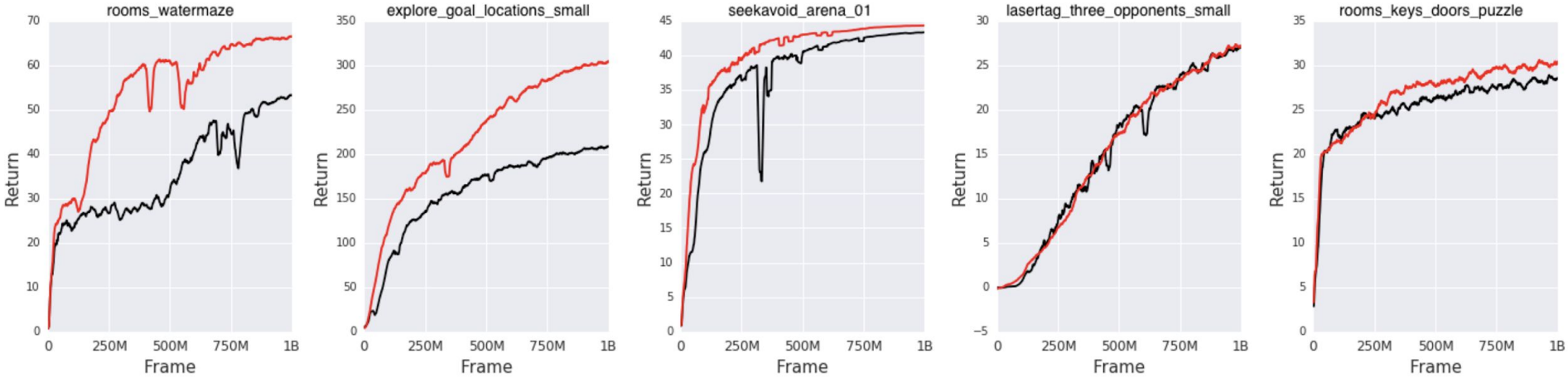
Many reward signals

Reinforcement Learning on DM-Lab

Auxiliary loss is on policy
Predict 30 steps in the future



Reinforcement Learning on DM-Lab



-- Batched A2C

-- Aux loss

Intrinsic Motivation

- Unsupervised learning can guide the policy of an RL agent as well as shaping the representations
- Agent becomes **intrinsically motivated** to **discover** or **control** aspects of the environment, with or without an **extrinsic reward**
- Many variants, no consensus…

Curious Agents

Can reward the agent's **curiosity** by guiding it towards 'novel' observations from which it can rapidly learn. Many curiosity signals can be used:

(a) learn to explore on Level-1

(b) explore faster on Level-2

- Prediction Error: choose actions to maximise prediction error in observations. Problem is **noise addiction**: inherently unpredictable environments become unreasonably interesting. One solution is to make predictions in **latent space** instead: network doesn't import noise into latent representations, only useful structure

Pathak et. al. *Curiosity-driven Exploration by Self-supervised Prediction* (2017)

Curious Agents (cotd.)

- Bayesian Surprise: maximise **KL** between posterior (after seeing observation) and prior (before seeing it)

  Baldi et. al., *Bayesian Surprise Attracts Human Attention.* (2005)

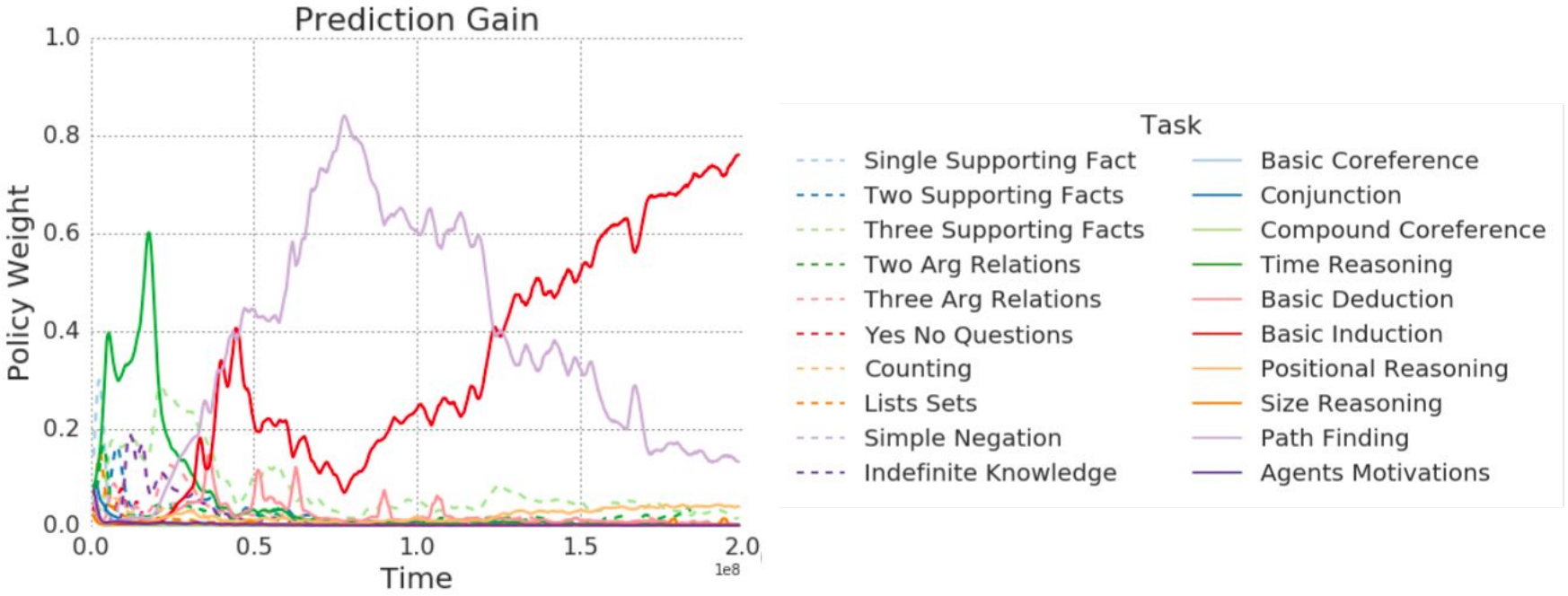
- Prediction Gain: maximise **change** in prediction error before and after seeing an observation. Approximates Bayesian surprise.

  Bellemare et. al. (*Unifying Count-Based Exploration and Intrinsic Motivation.* 2016)

- Complexity Gain: maximise increase in complexity of (regularised) predictive **model**. Assumes a parsimonious model will only increase complexity if it discovers a meaningful regularity. Needs a way of measuring complexity (e.g. VI).

  Graves et. al. *Automated Curriculum learning For Neural Networks.* (2017)

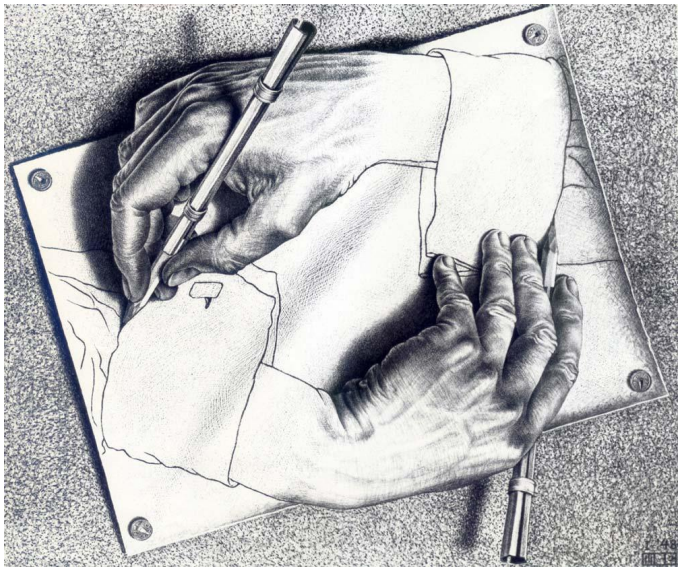
Prediction Gain Syllabus



Automated Curriculum learning For Neural Networks. Graves et. al. (2017)

Curiouser and Curiouser…

- Complexity Gain: Seek out data that maximise the decrease in bits of **everything** the agent has **ever observed** (!). In other words find (or create) the thing that **makes the most sense of the agent's life so far**: science, art, music, jokes…



Driven by Compression Progress: A Simple Principle Explains Essential Aspects of Subjective Beauty, Novelty, Surprise, Interestingness, Attention, Curiosity, Creativity, Art, Science, Music, Jokes, Schmidhuber, 2008

Empowered Agents

Instead of curiosity, agent can be motivated by **empowerment**: attempt to maximise the **Mutual Information** between the agent's actions and the consequences of its actions (e.g. the **state** the actions will lead to). Agent wants to have as much **control** as possible over its future.

Klyubin et. al. *Empowerment: A Universal Agent-Centric Measure of Control* (2005)

One way to maximise mutual information is to **classify** the high level **'option'** that determined the actions from the final state (while keeping the option **entropy** high): contrastive estimation again?

Gregor et. al. *Variational Intrinsic Control* (2016)

Conclusions

- Unsupervised learning gives us much more signal to learn from
- But it isn't clear what the learning objective should be
- Density modelling is one option
- Autoregressive neural networks are a powerful family of density model
- Methods such as autoencoding and predictive coding can yield useful latent representations
- RL can benefit from unsupervised learning as an auxiliary loss, and from intrinsic motivation signals such as curiosity

Unsupervised Deep Learning

Tutorial - Part 2

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facebook
Artificial Intelligence Research

NeurIPS, 3 December 2018

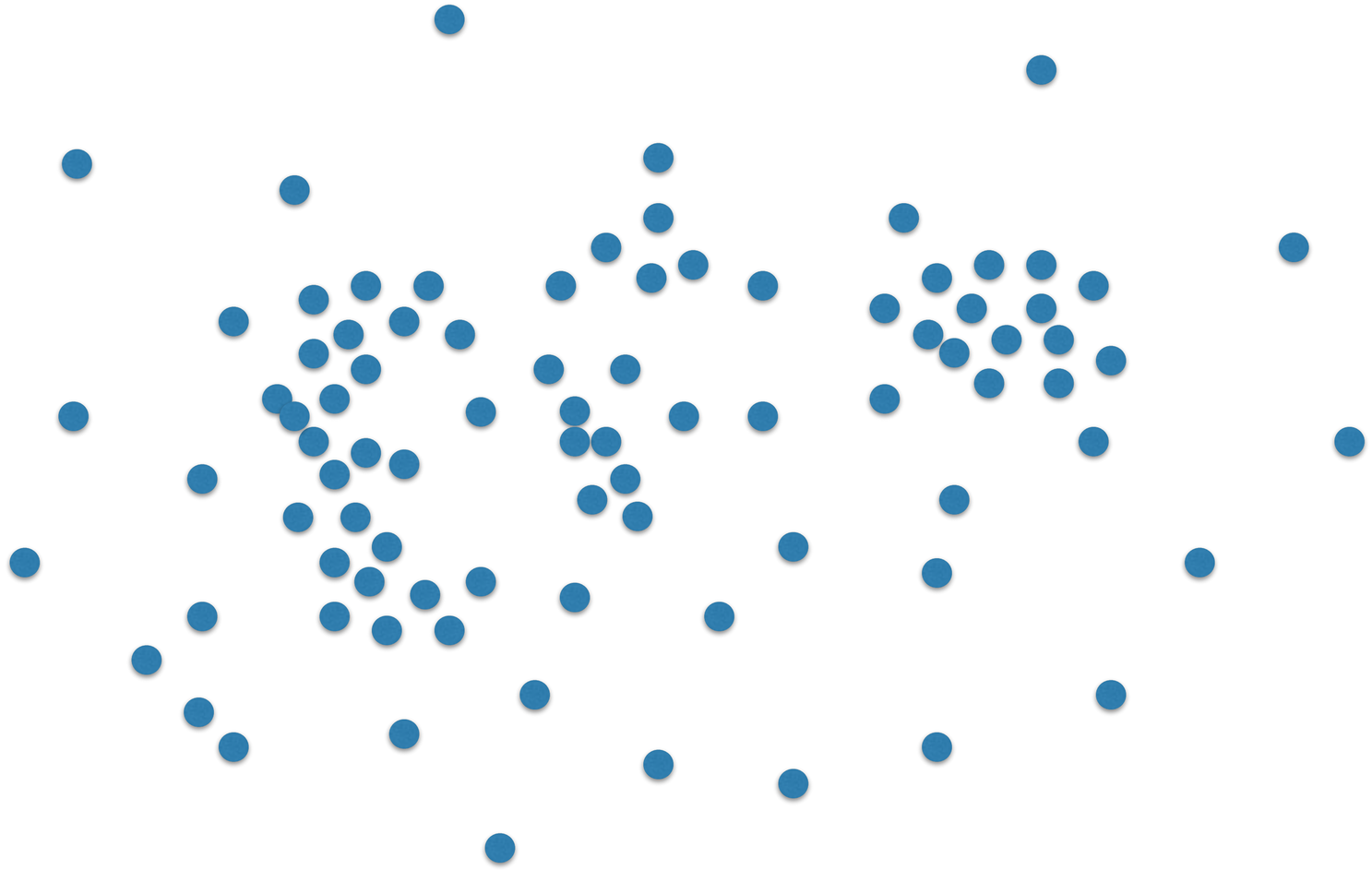
Overview

- Practical Recipes of Unsupervised Learning
  - Learning representations
  - Learning to generate samples
  - Learning to map between two domains
- Open Research Problems

DISCLAIMER

This tutorial is not an exhaustive list of all relevant works!
Goal: overview major research directions in the field and provide pointers for further reading.

Learning Representations: Continuous Case



Toy illustration of the data

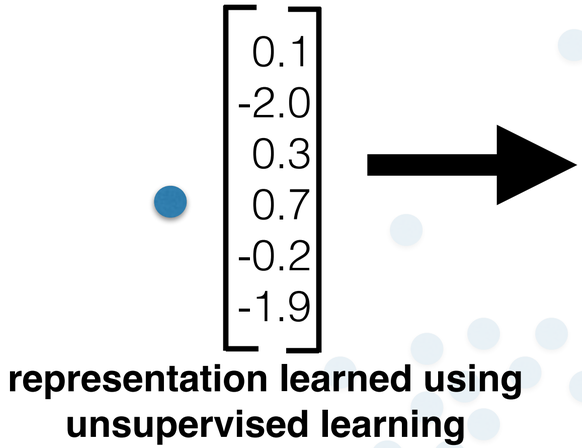
Learning Representations

TIP #1: Always “look” at your data before designing your model!

- **mean & covariance analysis**
- **PCA (check eigenvalue decay)**
- **t-sne visualization**

Toy illustration of the data

Learning Representations

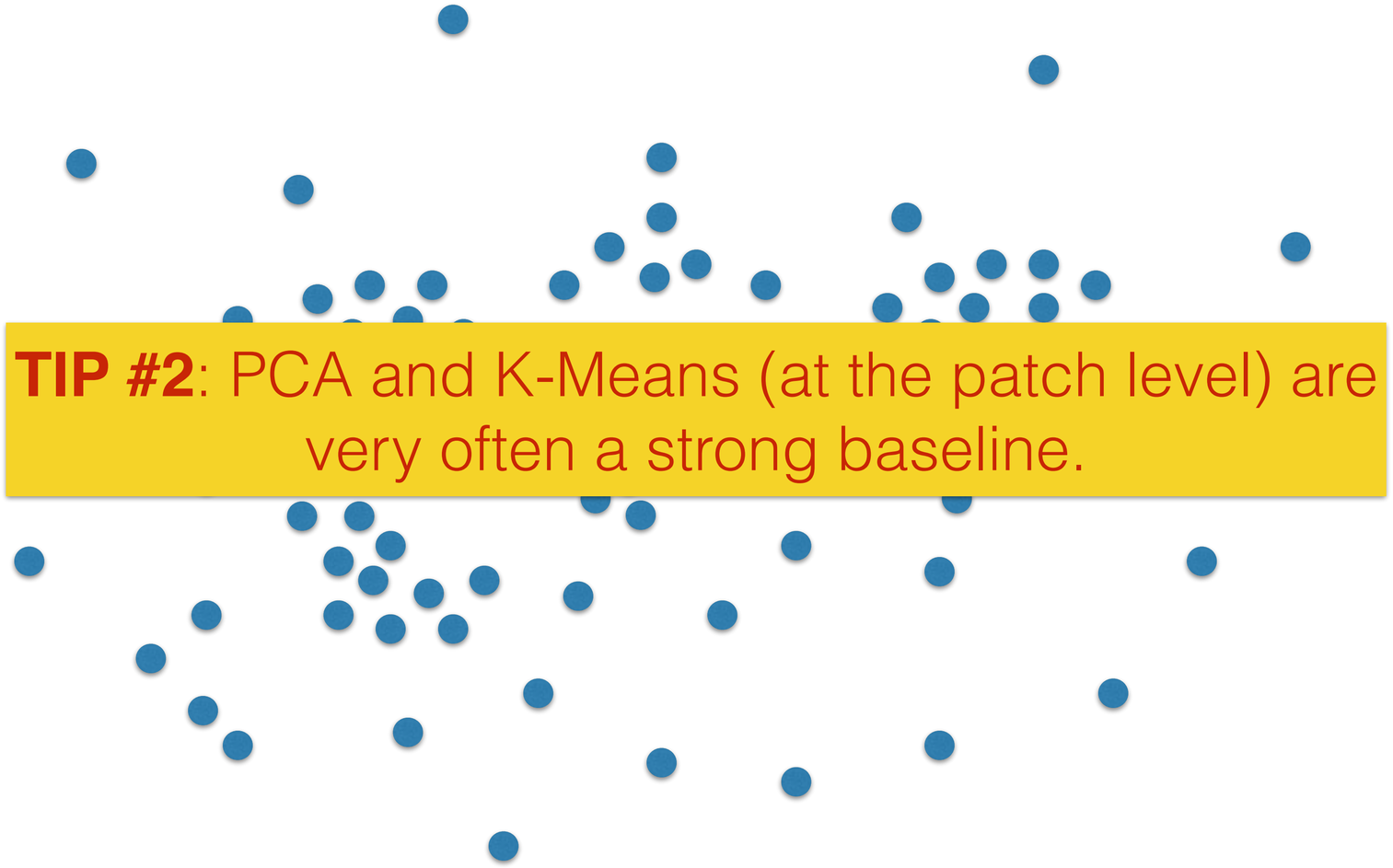


Task 1: is this person smoking?

Task 2: how likely is this person to have diabetes?

Features are (hopefully) useful in down-stream tasks

Learning Representations

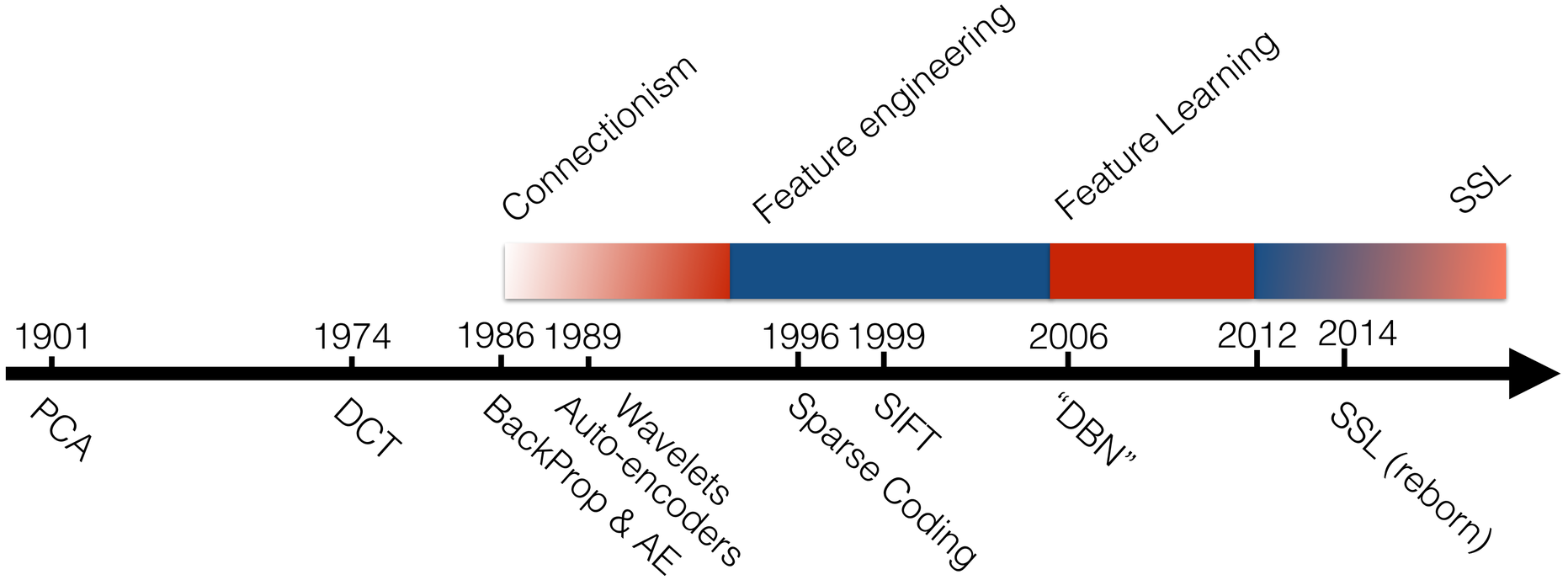


TIP #2: PCA and K-Means (at the patch level) are very often a strong baseline.

Learning **Visual** Representations

- Brief History
- Self-Supervised Learning
- Other Approaches

Unsup. Feature Learning in Vision

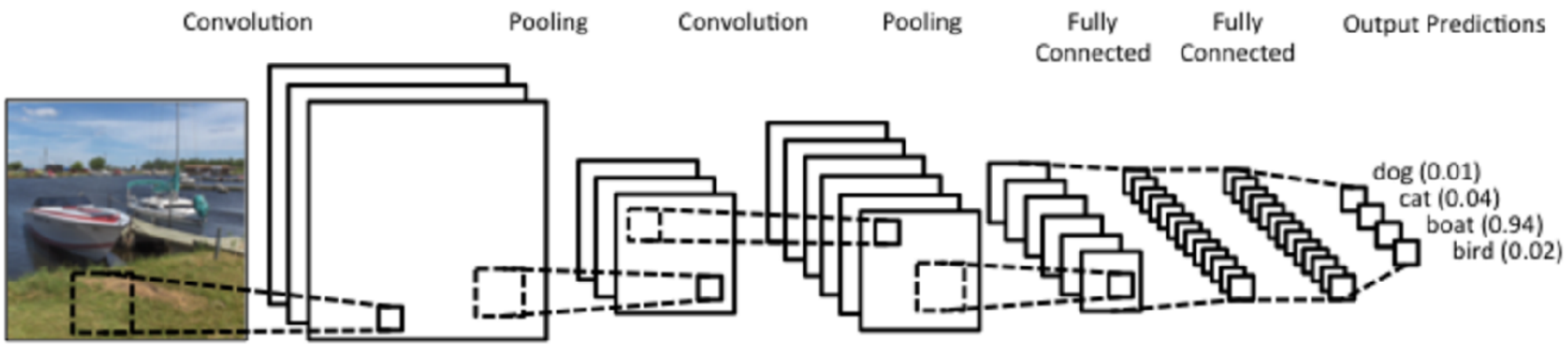


hot

how ML community feels about unsup. feature learning

cold

The Vision Architecture



Convolutional Neural Network

Y. LeCun et al. “Gradient-Based Learning Applied to Document Recognition”, IEEE 1998

A. Krizhevsky et al. “Imagenet classification with CNNs”, NIPS 2012

K. He et al. “Deep Residual Learning for Image Recognition”, CVPR 2016

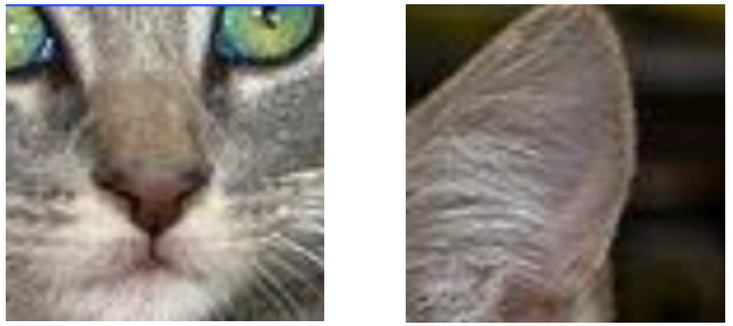
https://ranzato.github.io/publications/ranzato_deeplearn17_lec1_vision.pdf

Credit for figure:: **https://towardsdatascience.com/build-your-own-convolution-neural-network-in-5-mins-4217c2cf964f**

Self-Supervised Learning

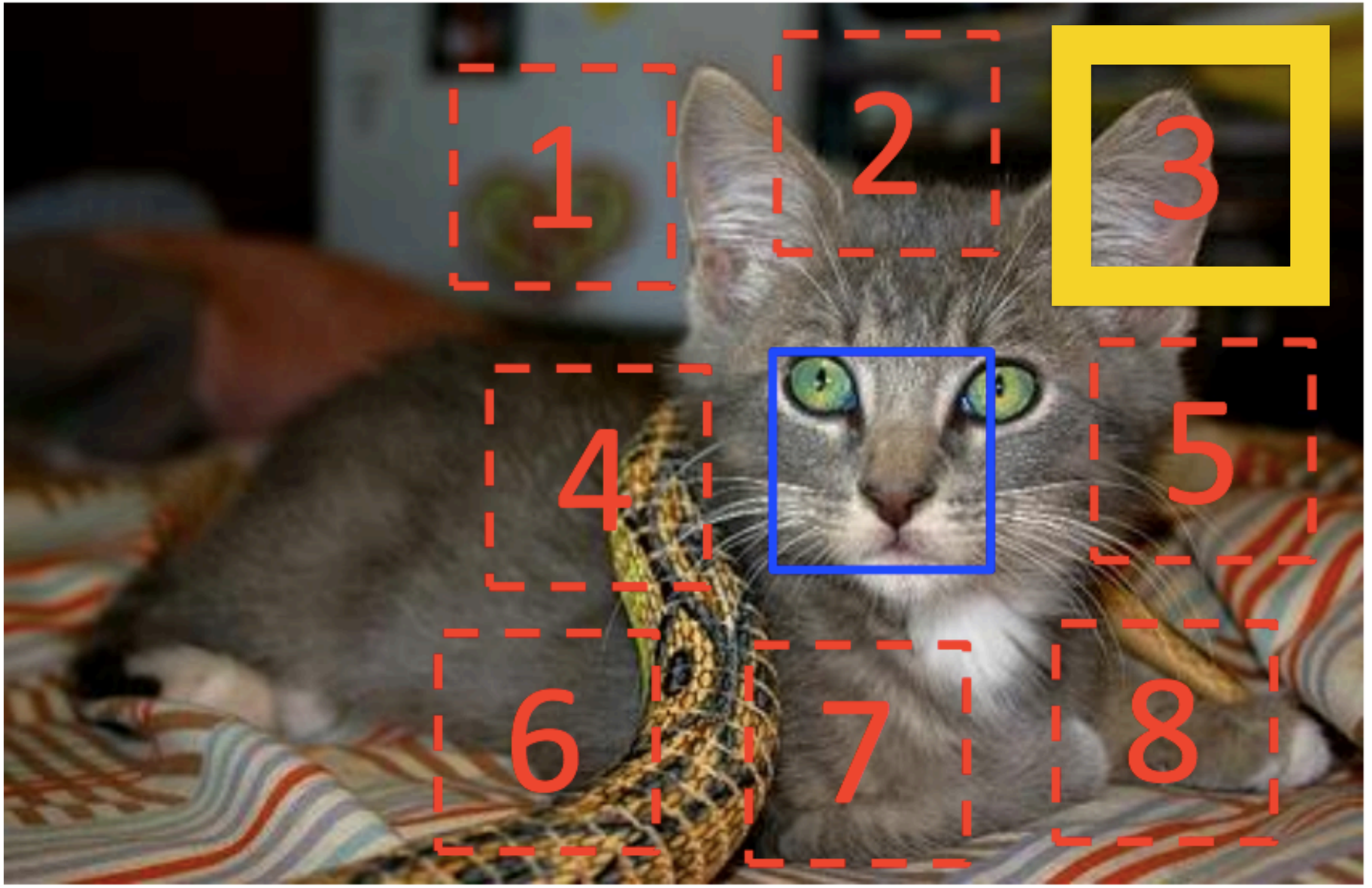
- Unsupervised learning is hard: model has to reconstruct high-dimensional input.
- With domain expertise define a prediction task which requires some semantic understanding.
  - conditional prediction (less uncertainty, less high-dimensional)
  - often times, original regression is turned into a classification task

SSL on Static Images: Example



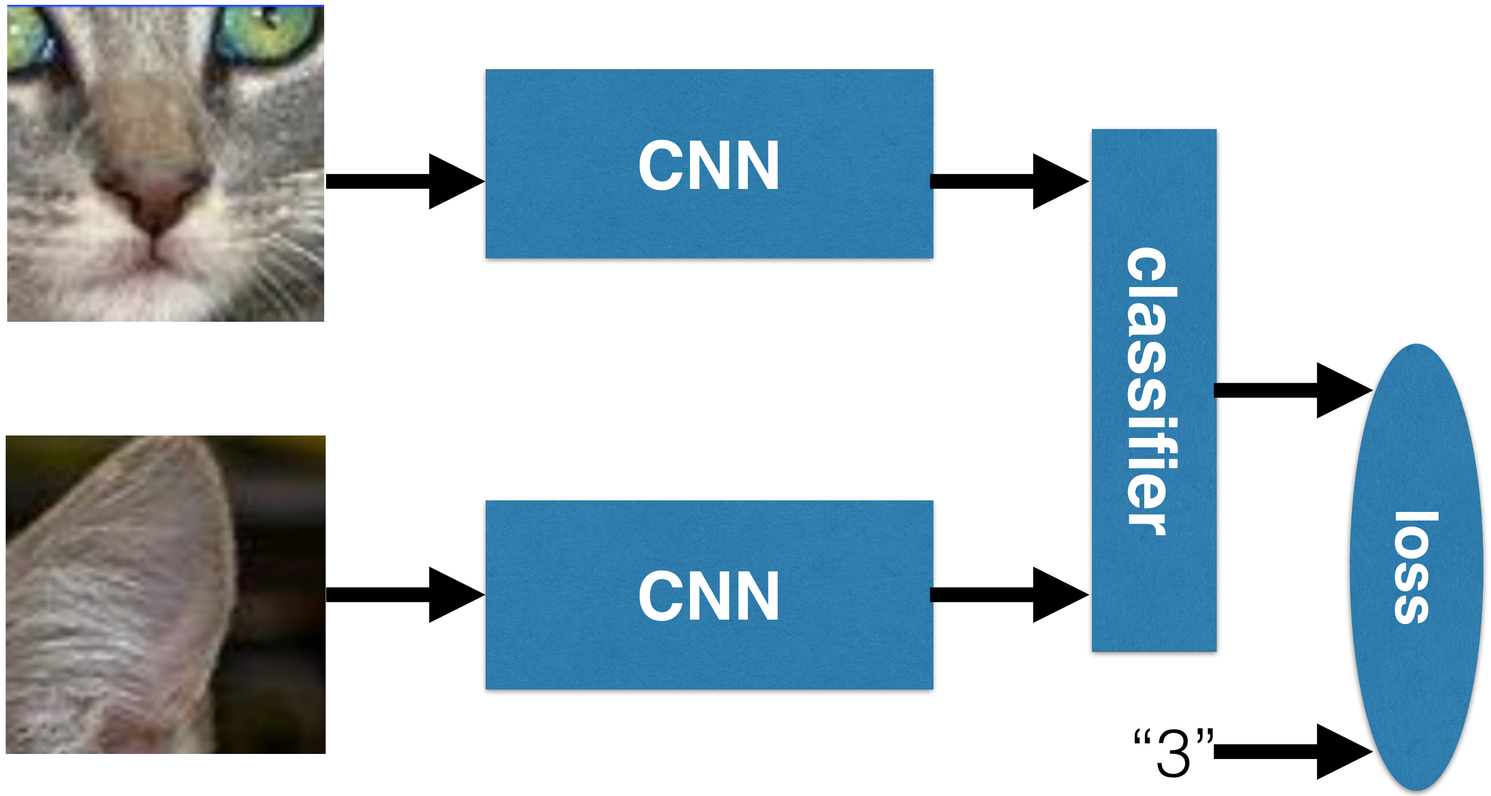
Input: two image patches from the same image.
Task: predict their spatial relationship.

C. Doersch et al. “Unsupervised Visual Representation Learning by Context Prediction”, ICCV 2015



C. Doersch et al. “Unsupervised Visual Representation Learning by Context Prediction”, ICCV 2015

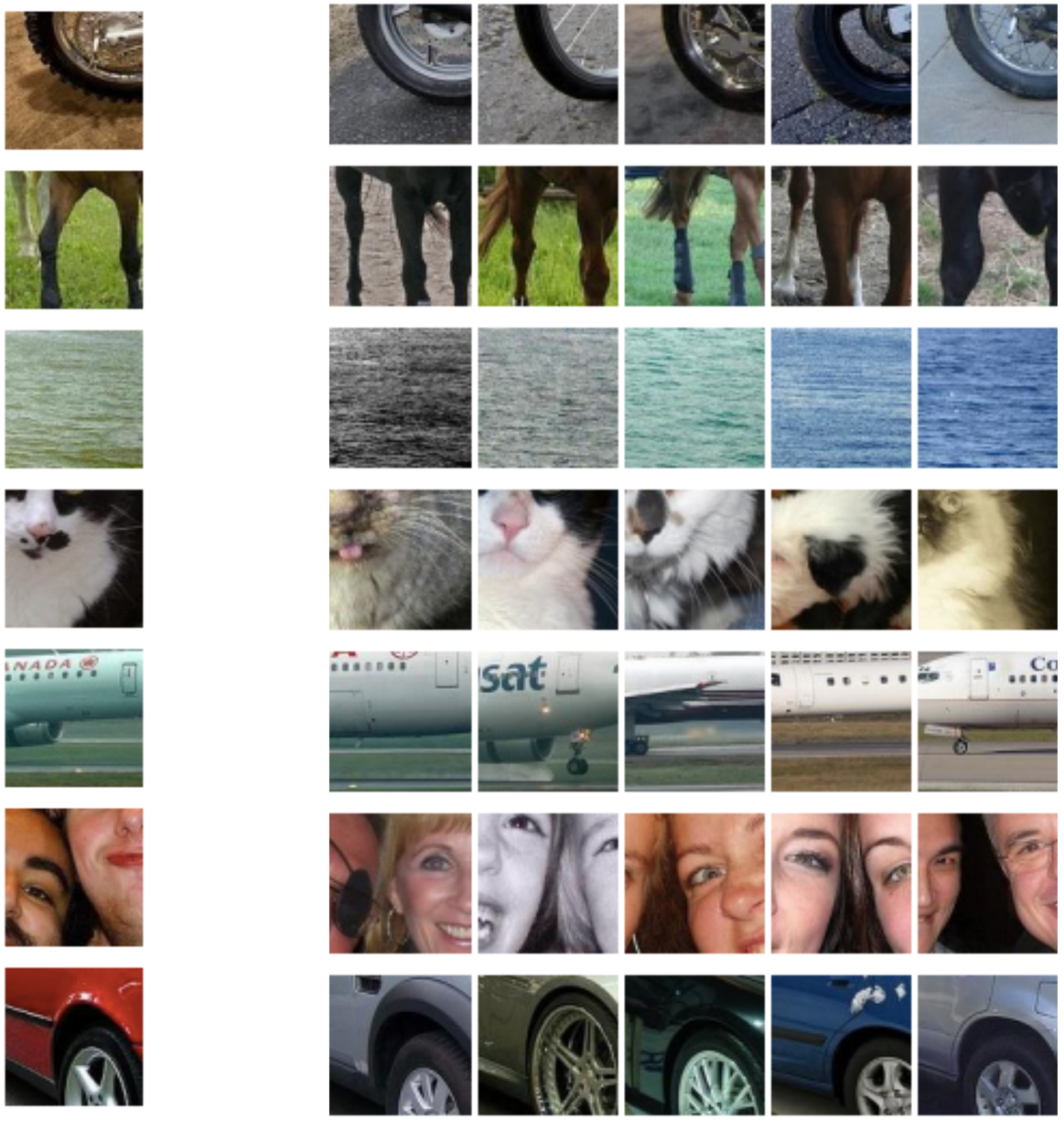
SSL on Static Images: Example



C. Doersch et al. “Unsupervised Visual Representation Learning by Context Prediction”, ICCV 2015

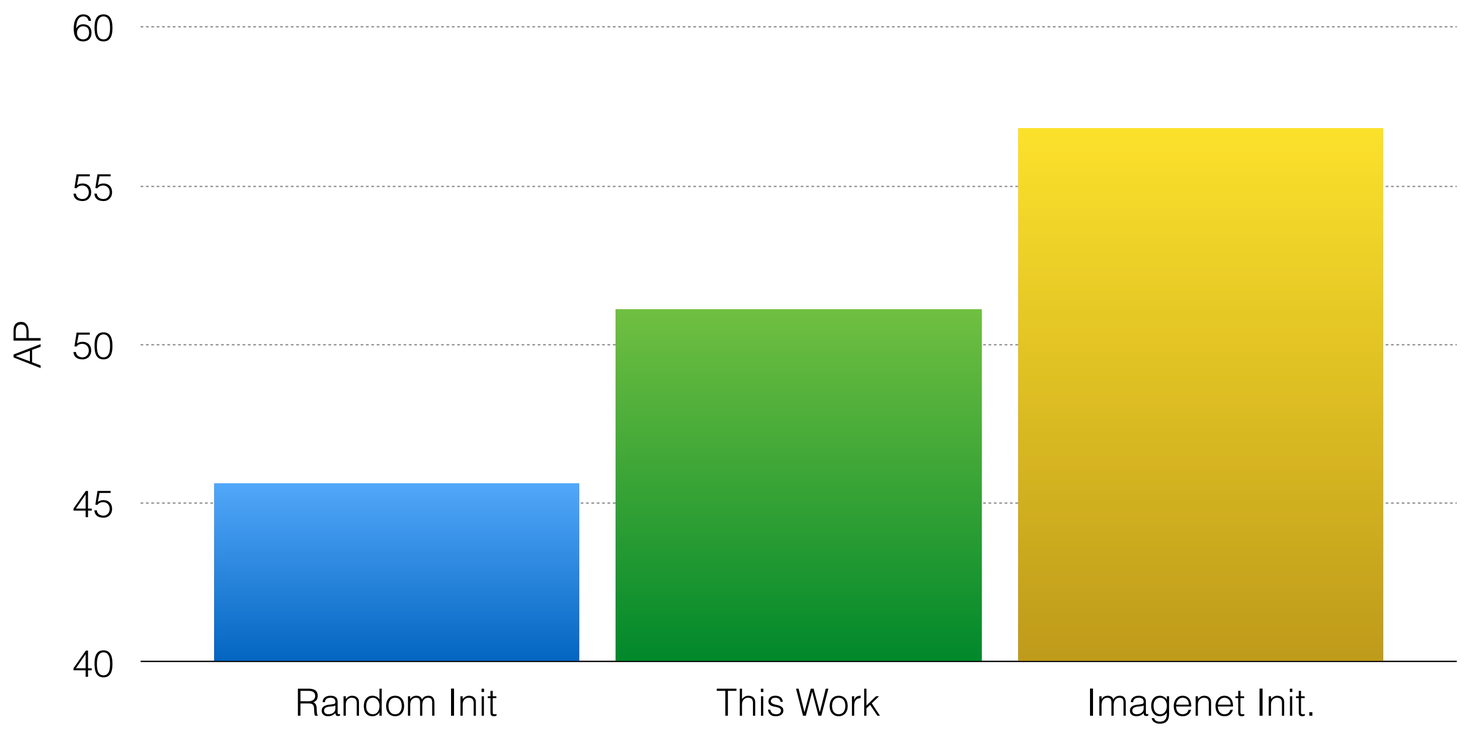
Input

Nearest Neighbors in Feature Space



C. Doersch et al. “Unsupervised Visual Representation Learning by Context Prediction”, ICCV 2015

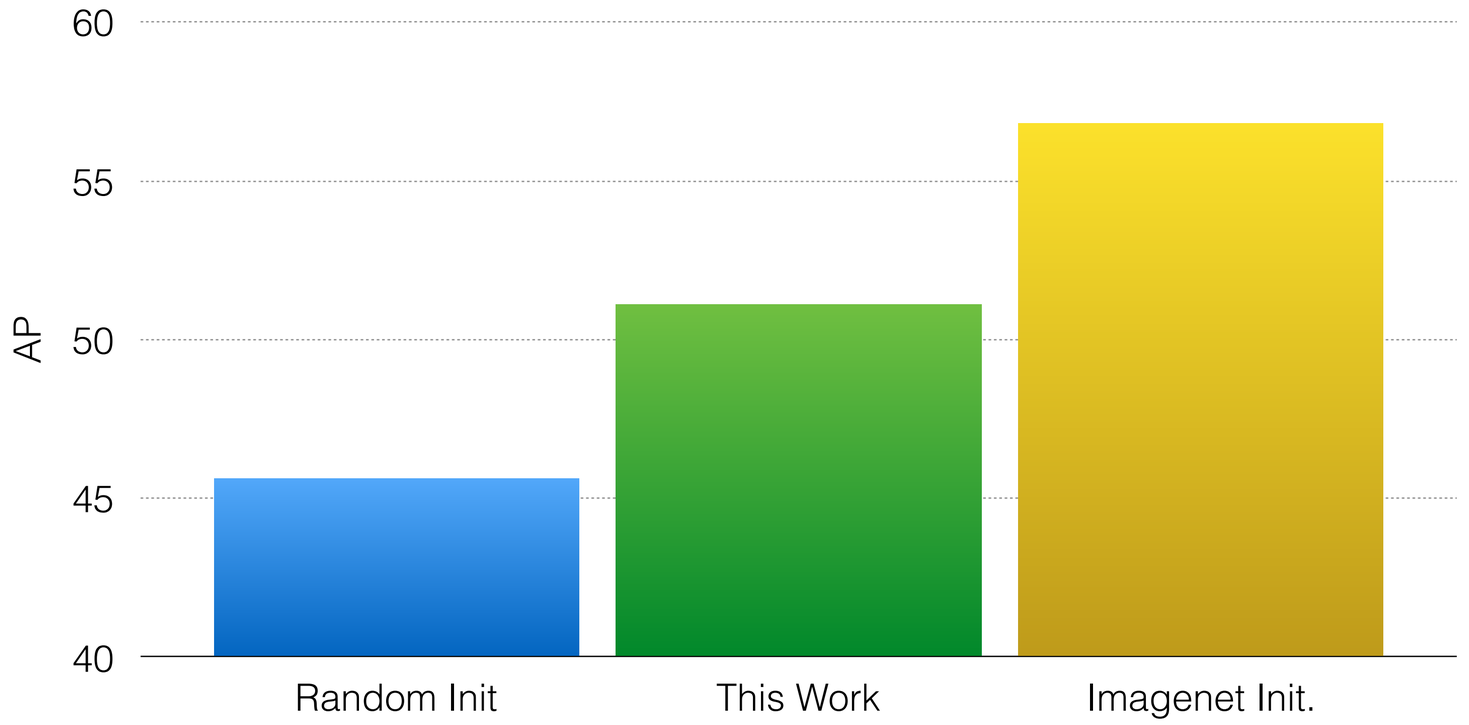
Pascal VOC Detection



C. Doersch et al. “Unsupervised Visual Representation Learning by Context Prediction”, ICCV 2015

Pascal VOC Detection

K. He et al. “Rethinking ImageNet pretraining”, arXiv 2018 shows that with better normalization and with longer training, random initialization works as well as ImageNet pretraining!



C. Doersch et al. “Unsupervised Visual Representation Learning by Context Prediction”, ICCV 2015

SSL on Static Images: Other Examples

- Predict color from gray scale values.
  R. Zhang et al. “Colorful Image Colorization”, ECCV 2016
- Predict image rotation
  S. Gidaris et al. “Unsupervised Representation Learning by Predicting Image Rotations”, ICLR 2018

TIP #3: Often times, you can learn features without explicitly predicting pixel values.

TIP #4: If you are OK using domain knowledge, you can learn using a variety of auxiliary tasks.

SSL on **Videos**: Example

- Predict whether the video snippet is playing **forward** or **backward**.
- Requires to understand gravity, causality, friction, …

FWD

D. Wei et al. “Self-supervision using the arrow of time”, CVPR 2018

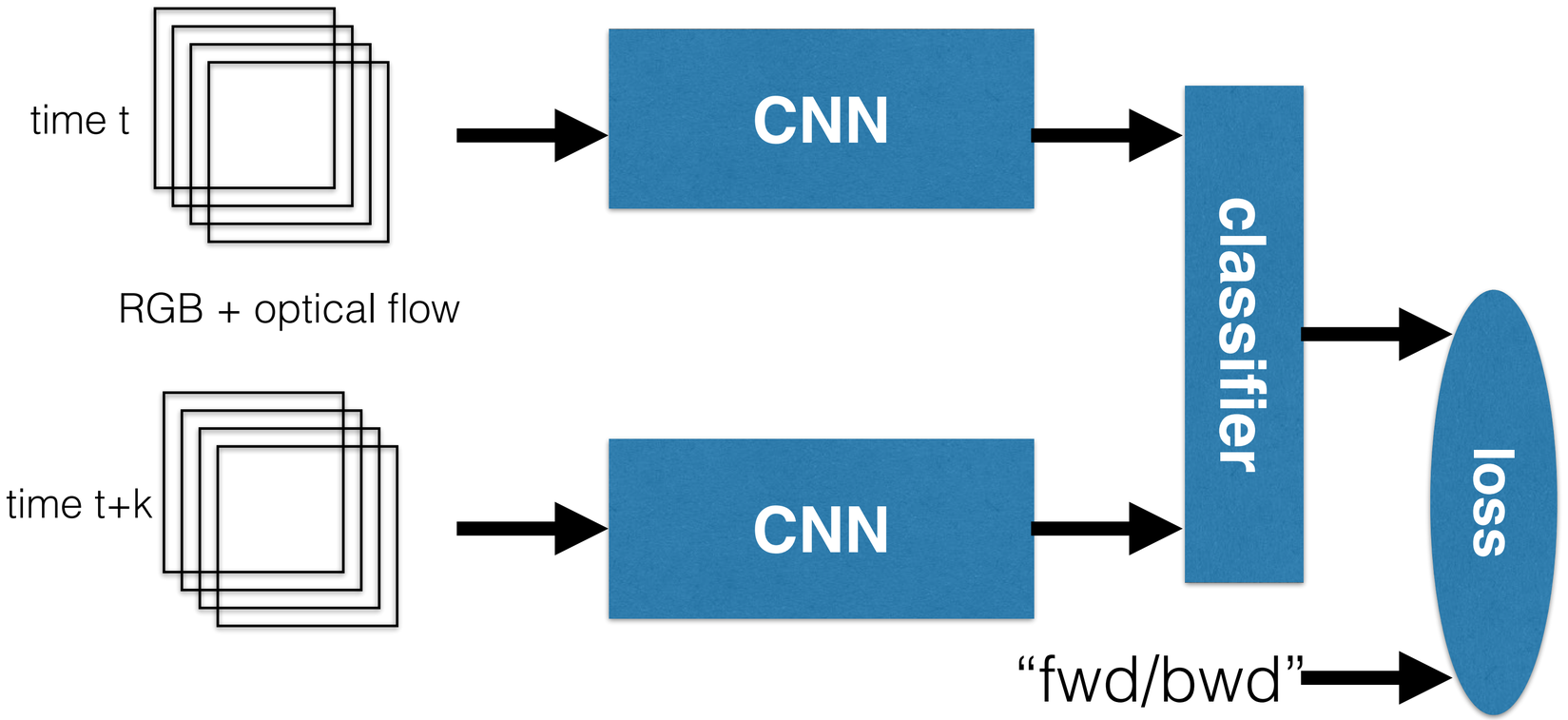
SSL on **Videos**: Example

- Predict whether the video snippet is playing **forward** or **backward**.
- Requires to understand gravity, causality, friction, …

BWD

D. Wei et al. “Self-supervision using the arrow of time”, CVPR 2018

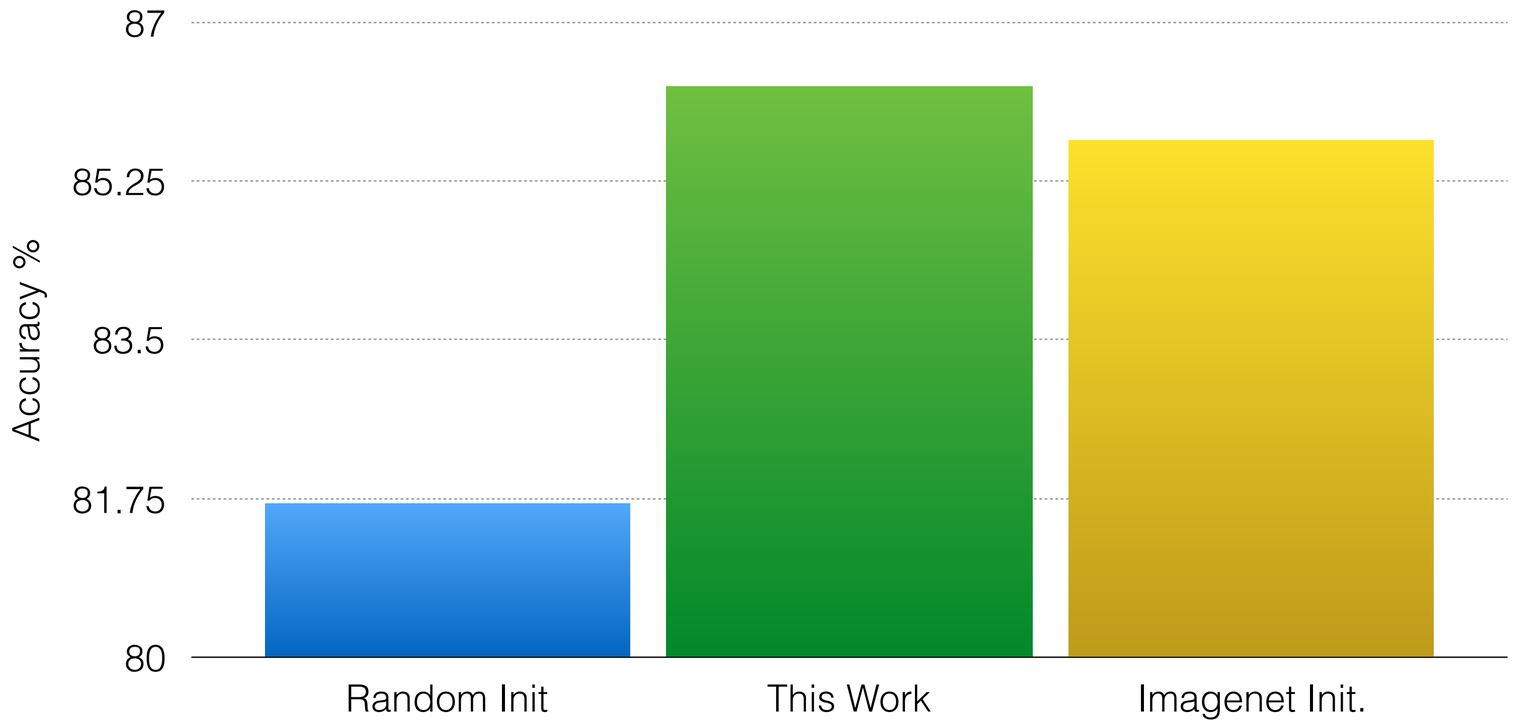
SSL on **Videos**: Example



D. Wei et al. “Self-supervision using the arrow of time”, CVPR 2018

UCF101 Action Recognition

First train using SSL, and then finetune on the task.



D. Wei et al. “Self-supervision using the arrow of time”, CVPR 2018

SSL: Other Examples

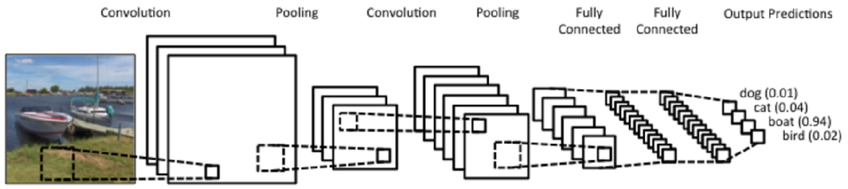
- Learn features by colorizing video sequences.
  C. Vondrik et al. “Tracking emerges from colorizing videos”, ECCV 2018
- Predict whether and how frames are shuffled
  I. Misra et al. “Shuffle and laern: unsupervised learning using temporal order verification”, ECCV 2016
- Future frame prediction
  E. Denton et al. “Unsupervised learning of disentangled representations from video”, NIPS 2017
- Predict one modality from the other
  V. de Sa “Learning classification from unlabeled data”, NIPS 1994
  …
  R. Arandjelovic et al. “Object that sound”, ECCV 2018

Learning **Visual** Representations

- Brief History
- Self-Supervised Learning
- **Other Approaches**

Learning by Clustering

- CNN architecture has many good inductive biases, such as:
  - spatio-temporal stationarity,
  - scale invariance,
  - compositionality, etc.



- (Small) random filters have orientation-frequency selectivity.

- As a result, even randomly initialized CNNs extract non-trivial features.

Learning by Clustering

Randomly initialize the CNN.

Repeat:

1. Extract features from each image and run K-Means in feature space.

2. Train the CNN in supervised mode to predict the cluster id associated to each image (1 epoch).

M. Caron et al. “Deep clustering for unsupervised learning of visual features”, ECCV 2018

Learning by Clustering

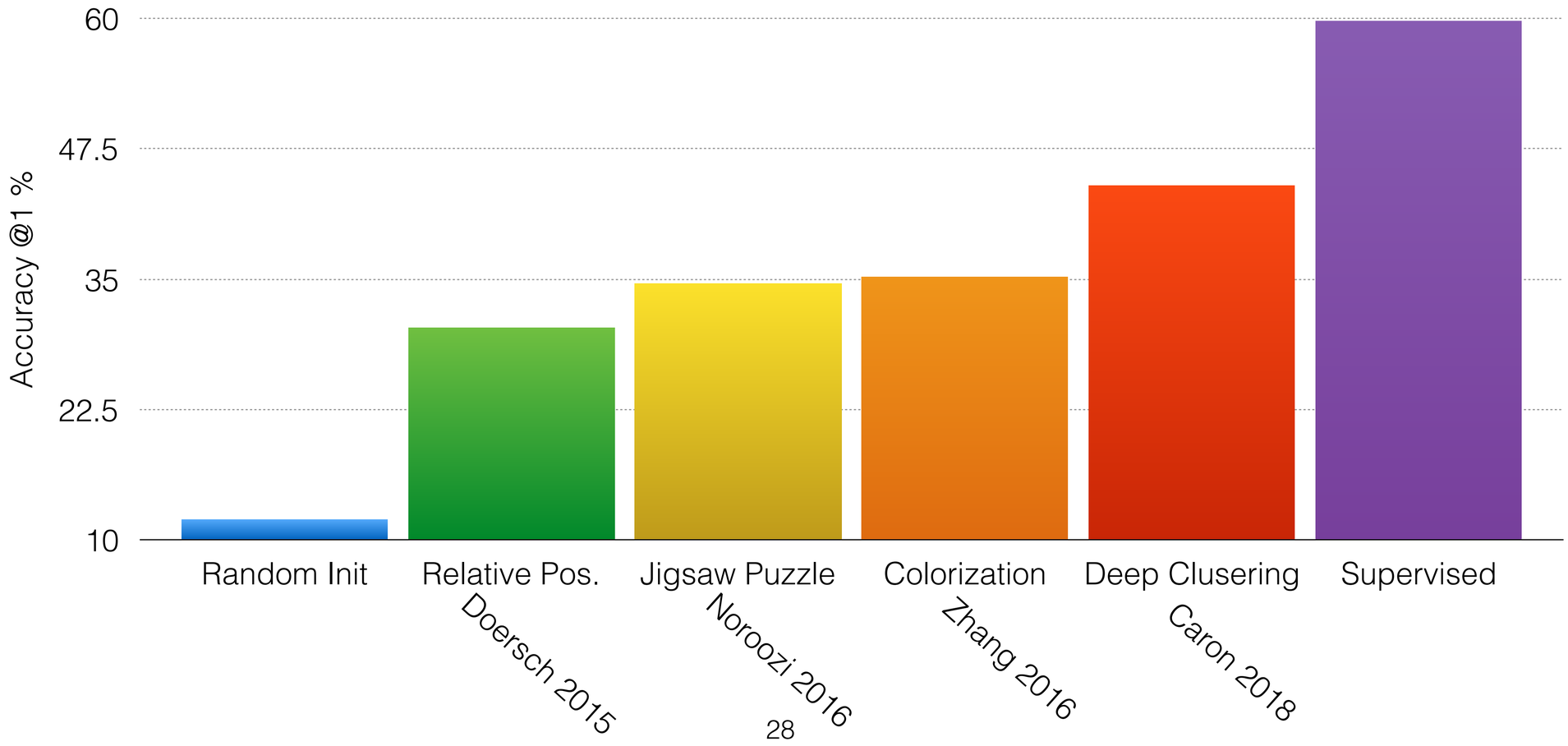
Caveat: watch out for cheating…

- cluster collapsing (re-assign images to empty clusters)
- equalize clusters at training time

M. Caron et al. “Deep clustering for unsupervised learning of visual features”, ECCV 2018

ImageNet Classification

First train unsupervised, then train MLP with supervision using unsupervised features.



Conclusions on Unsupervised Learning of Visual Features

- In general, still a seizable gap between unsupervised feature learning and supervised learning in vision.
- Pixel prediction is hard, many recent approaches define auxiliary classification tasks.
- Domain knowledge can inform the design of tasks that require some level of semantic understanding.
- Network will “cheat” if you are not careful:
  - check for trivial solutions
  - check for biases and artifacts in the data

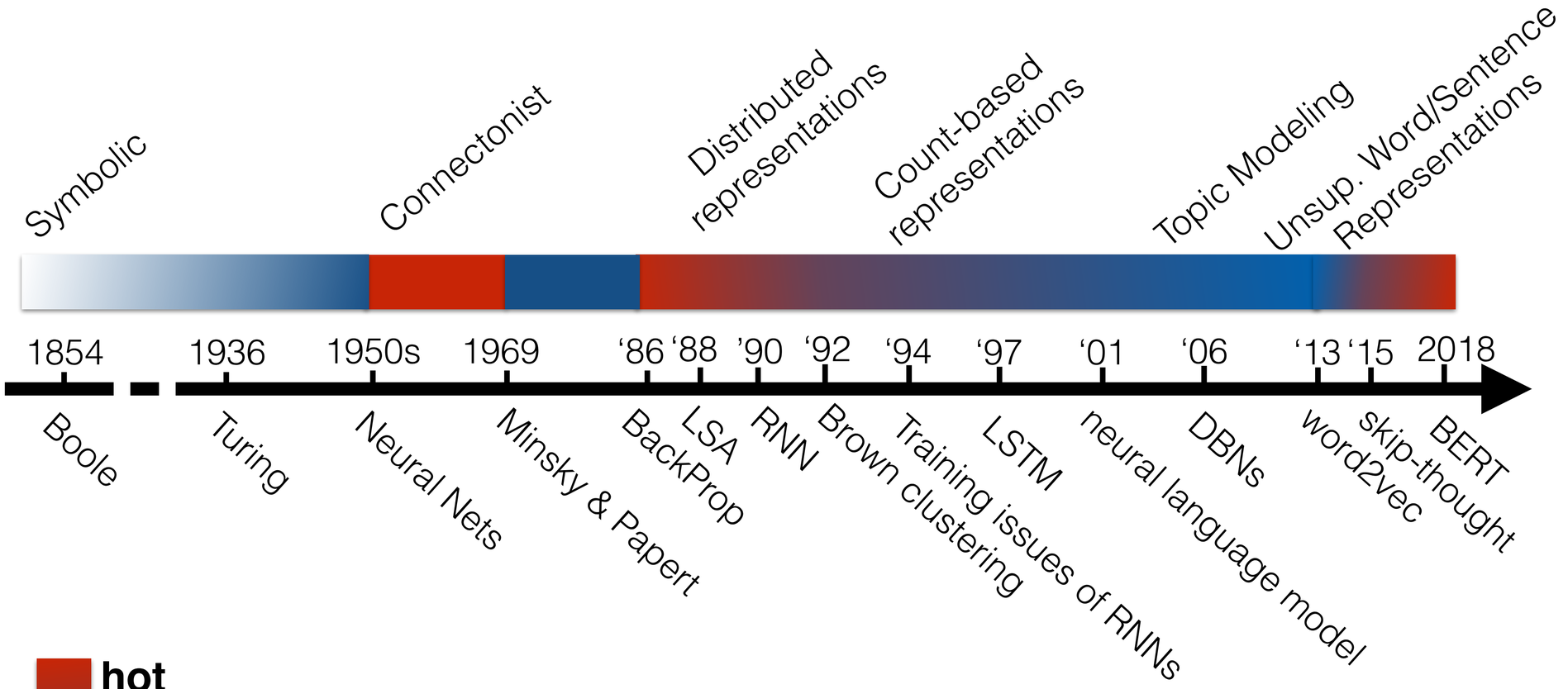
Overview

- Practical Recipes of Unsupervised Learning
  - **Learning representations:** continuous / **discrete**
  - Learning to generate samples: continuous / discrete
  - Learning to map between two domains: continuous / discrete
- Open Research Problems

Vision <—> NLP

- Atomic unit:
  - a word in NLP carries a lot of information.
  - a pixel value in Vision carries negligible information
- Nature of the signal:
  - discrete in NLP: search is hard but modeling of uncertainty is easy.
  - continuous in Vision: search is easy but modeling of uncertainty is hard.

Unsup. Feature Learning in NLP



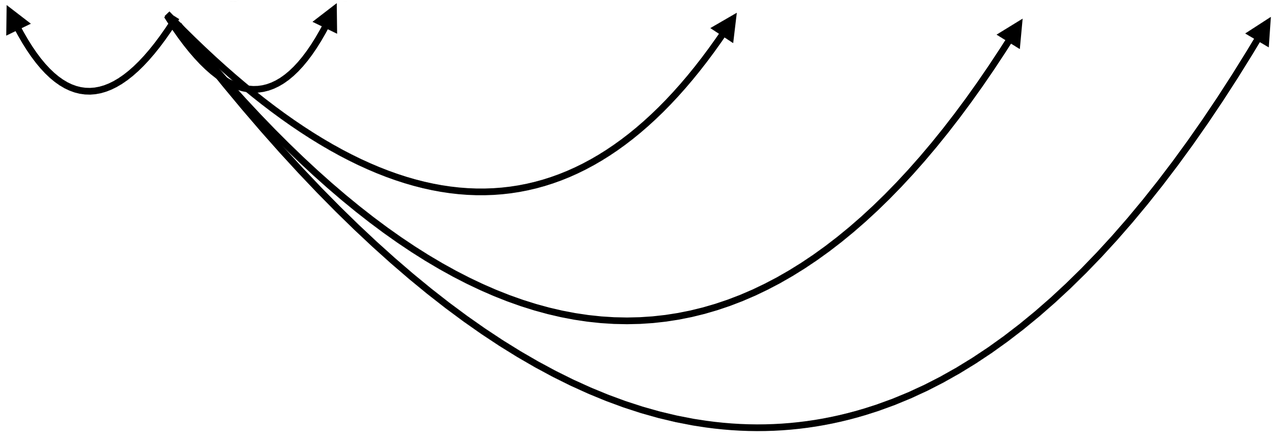
hot

how ML/NLP community feels about unsup. learning of word/sentence representations

cold

word2vec

“All of the sudden a **cat** jumped from a tree to chase a mouse.”

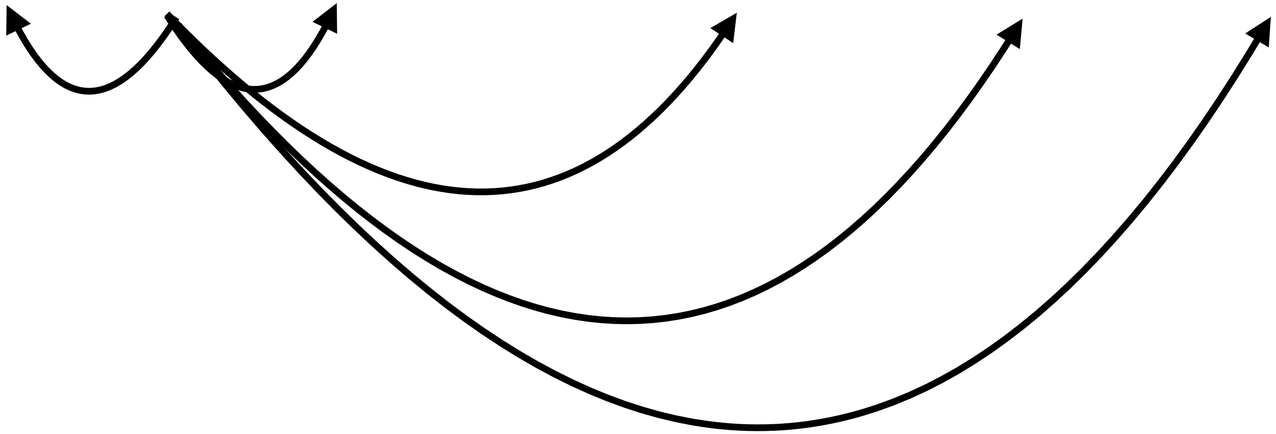


The meaning of a word is determined by its context.

T. Mikolov et al. “Efficient estimation of word representations in vector space” arXiv 2013

word2vec

“All of the sudden a ____ jumped from a tree to chase a mouse.”

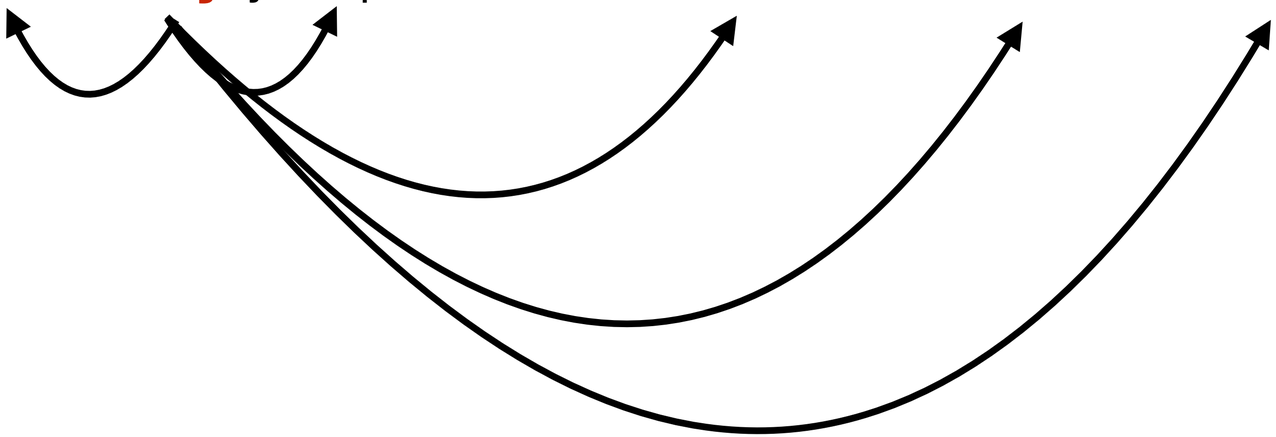


The meaning of a word is determined by its context.

T. Mikolov et al. “Efficient estimation of word representations in vector space” arXiv 2013

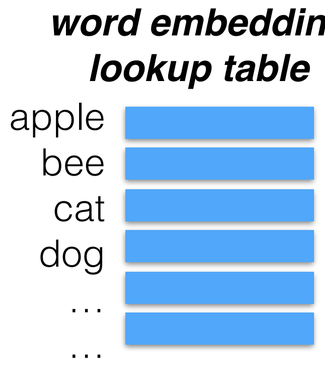
word2vec

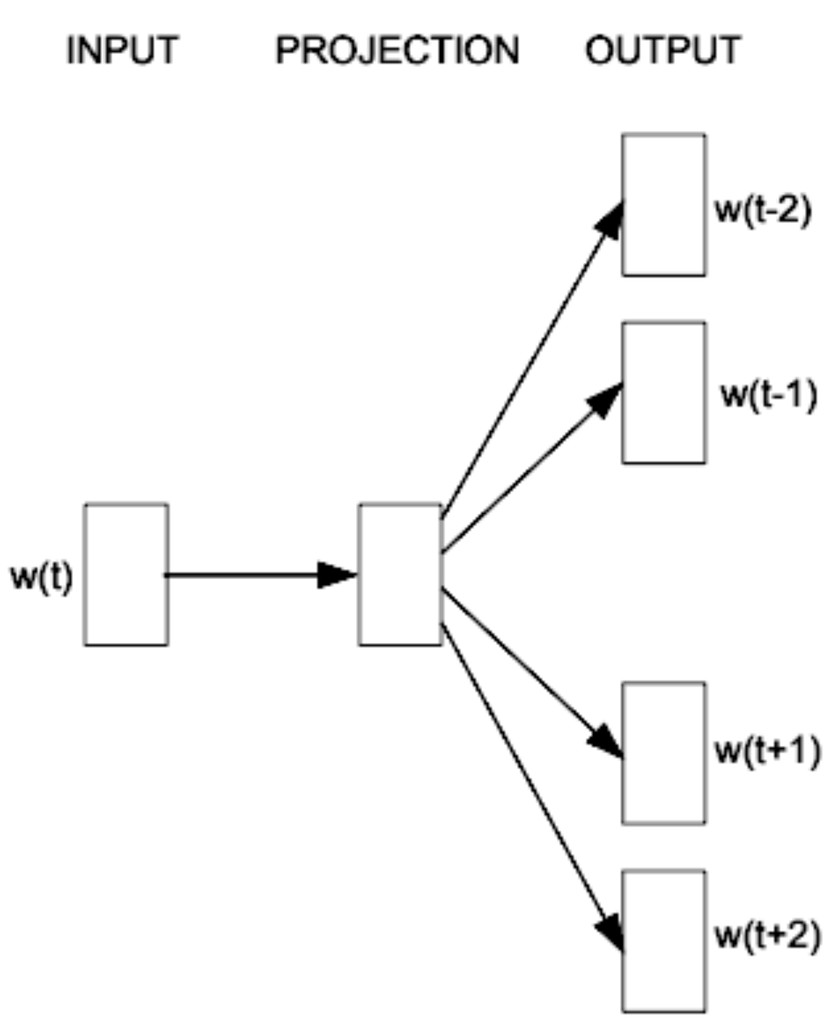
“All of the sudden a **kitty** jumped from a tree to chase a mouse.”



The meaning of a word is determined by its context.
Two words mean similar things if they have similar context.

T. Mikolov et al. “Efficient estimation of word representations in vector space” arXiv 2013





The meaning of a word is determined by its context.
Two words mean similar things if they have similar context.

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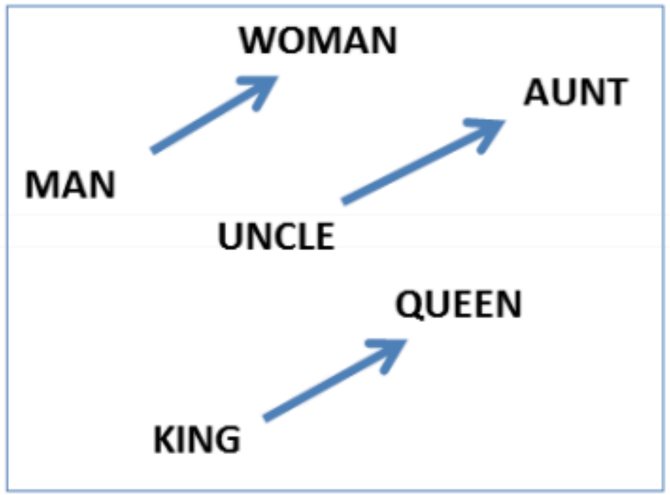
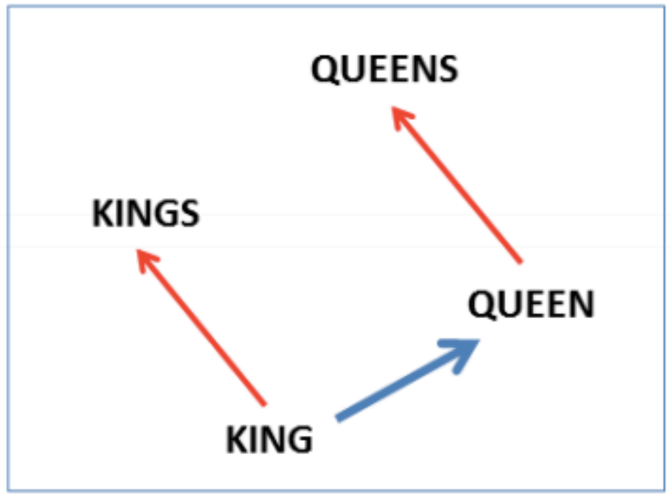
Linguistic Regularities in Word Vector Space





- The word vector space implicitly encodes many regularities among words

credit T. Mikolov from https://drive.google.com/file/d/0B7XkCwpI5KDYRWRnd1RzWXQ2TWc/edit

Recap word2vec

- Word embeddings are useful to:
  - understand similarity between words
  - convert *any discrete input* into continuous -> ML
- Learning leverages large amounts of unlabeled data.
- It's a very simple factorization model (shallow).
- There are very efficient tools publicly available.

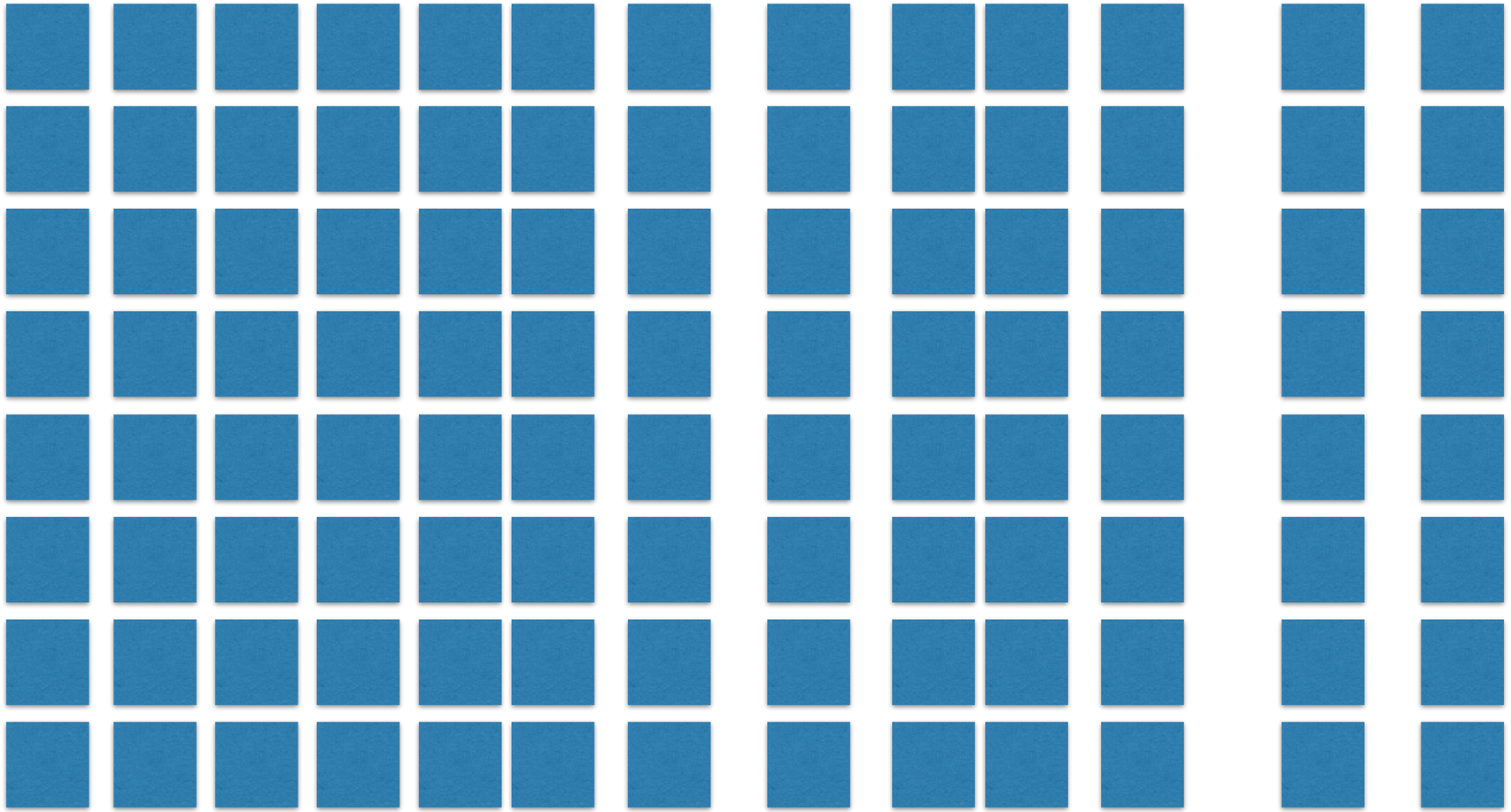
https://fasttext.cc/

Joulin et al. "Bag of tricks for efficient text classification" ACL 2016

Representing Sentences

- word2vec can be extended to small phrases, but not much beyond that.
- Sentence representation needs to leverage compositionality.
- A lot of work on learning unsupervised sentence representations (auto-encoding / prediction of nearby sentences).

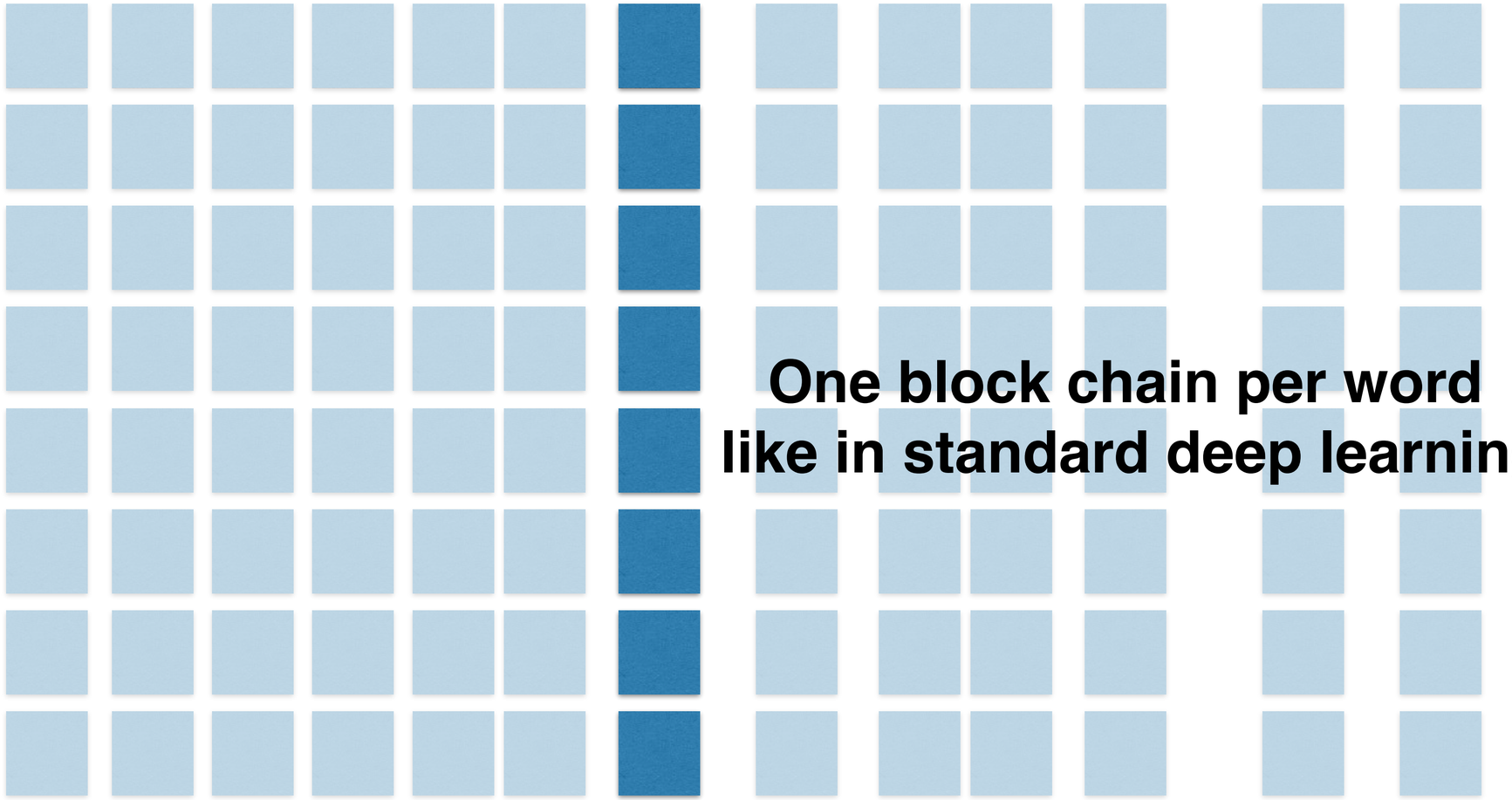
BERT



<s> The cat sat on the mat <sep> It fell asleep soon after

J. Devlin et al. “BERT: Pre-training of deep bidirectional transformers for language understanding”, arXiv:1810.04805, 2018

BERT



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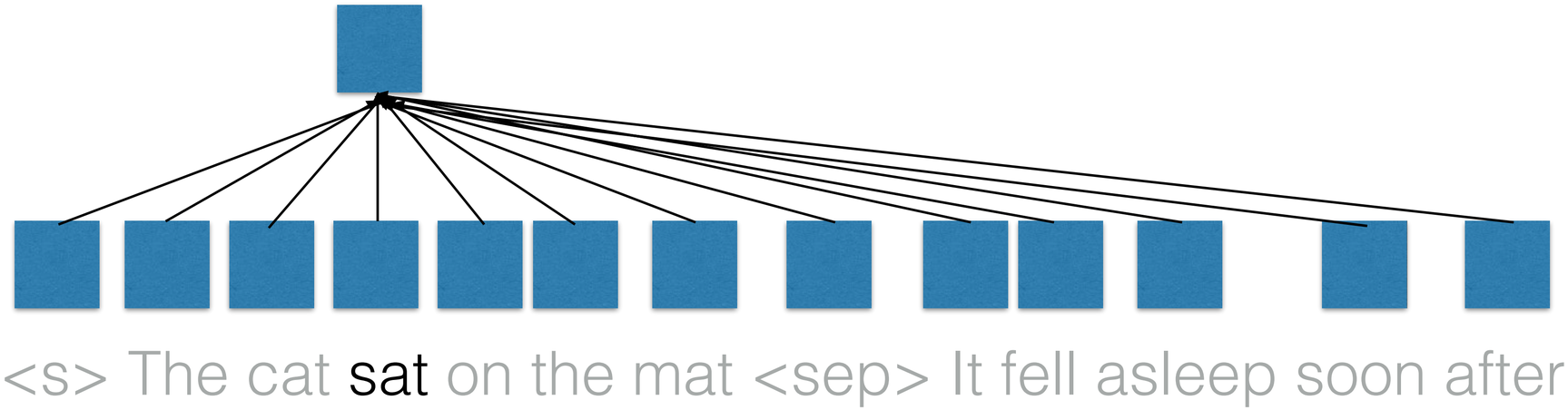
J. Devlin et al. “BERT: Pre-training of deep bidirectional transformers for language understanding”, arXiv:1810.04805, 2018

BERT

Each block receives input from all the blocks below. Mapping must handle variable length sequences…



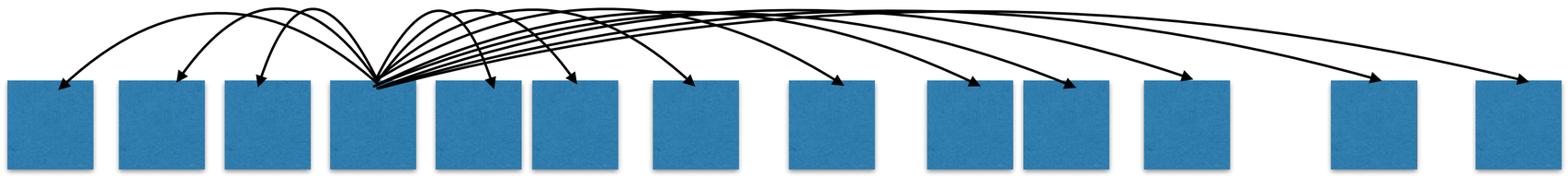
J. Devlin et al. “BERT: Pre-training of deep bidirectional transformers for language understanding”, arXiv:1810.04805, 2018

BERT

This accomplished by using attention (each block is a Transformer)

For each layer and for each block in a layer do (simplified version):

1) let each current block representation at this layer be: h_j
2) compute dot products: $h_i \cdot h_j$
3) normalize scores: $\alpha_i = \frac{\exp(h_i \cdot h_j)}{\sum_k \exp(h_k \cdot h_j)}$
4) compute new block representation as in: $h_j \leftarrow \sum_k \alpha_k h_k$



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A. Vaswani et al. “Attention is all you need”, NIPS 2017

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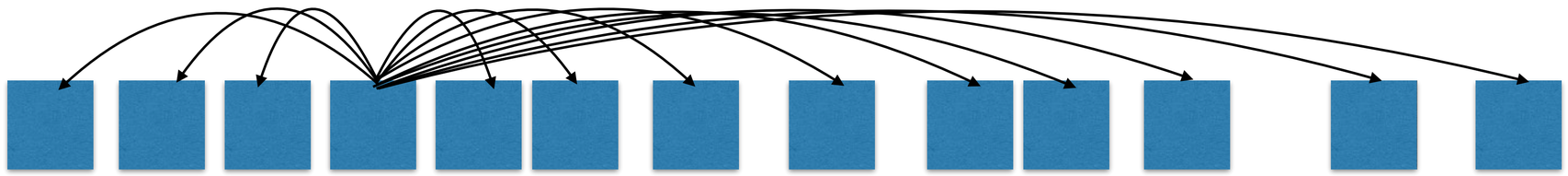
in practice different features are used at each of these steps…

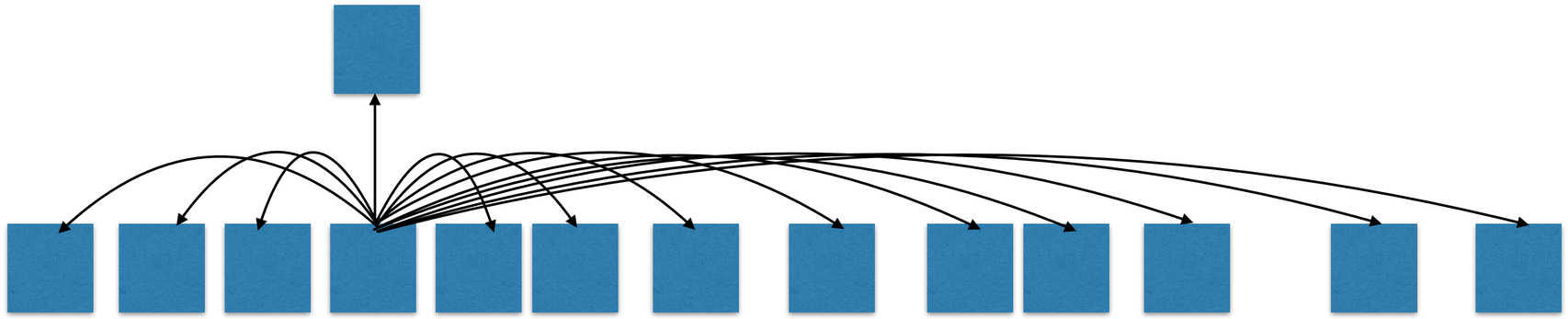


<s> The cat sat on the mat <sep> It fell asleep soon after

A. Vaswani et al. “Attention is all you need”, NIPS 2017

BERT

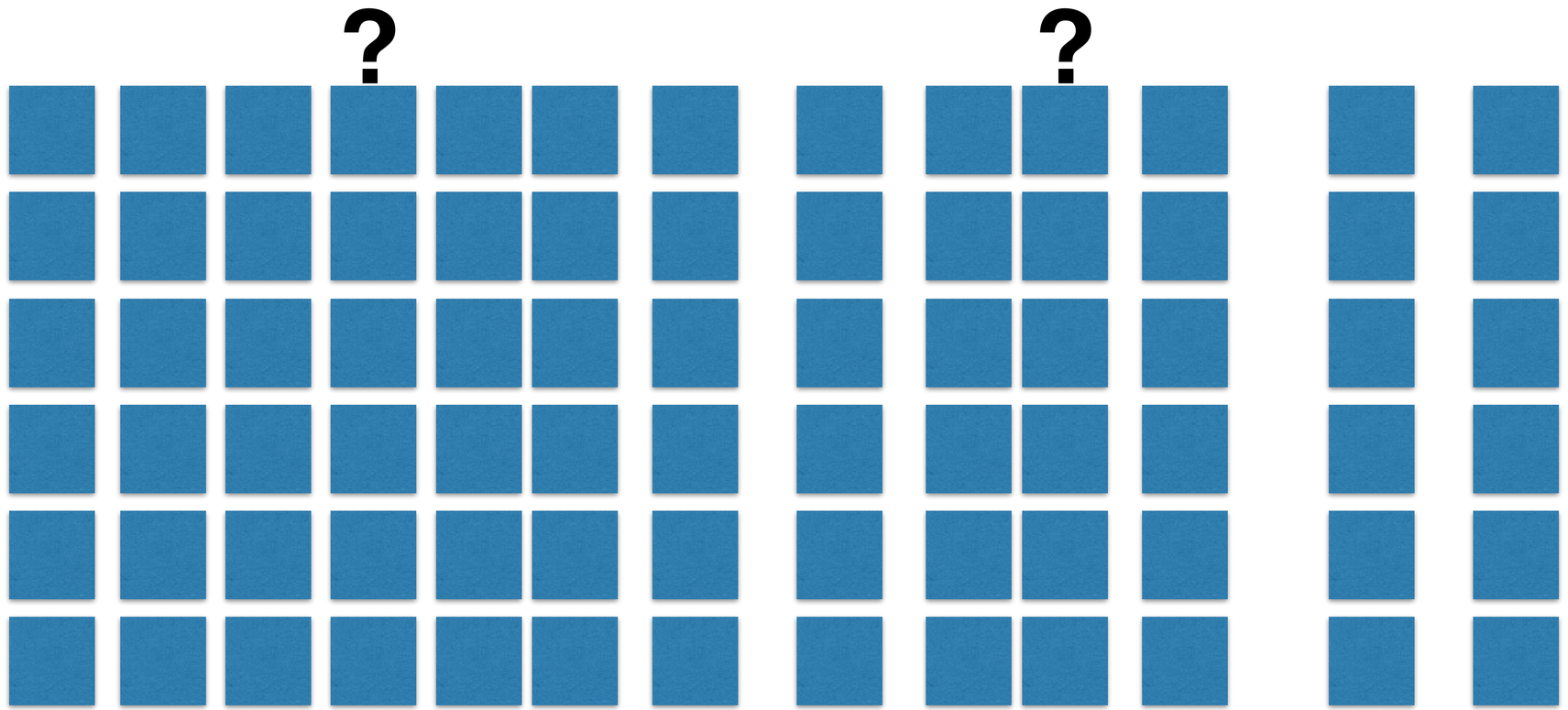
The representation of each word at each layer depends on all the words in the context.
And there are lots of such layers…



J. Devlin et al. “BERT: Pre-training of deep bidirectional transformers for language understanding”, arXiv:1810.04805, 2018

BERT: Training

Predict blanked out words.



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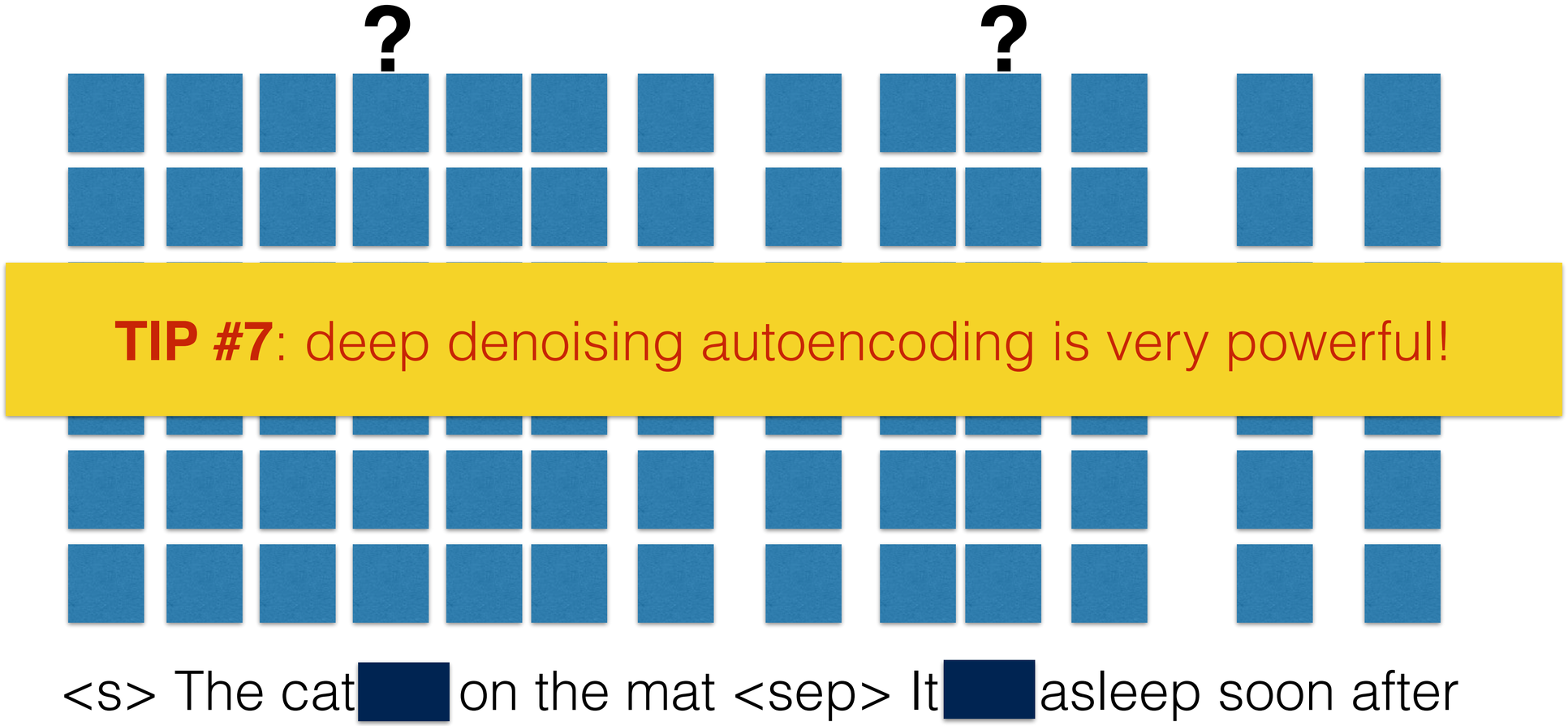
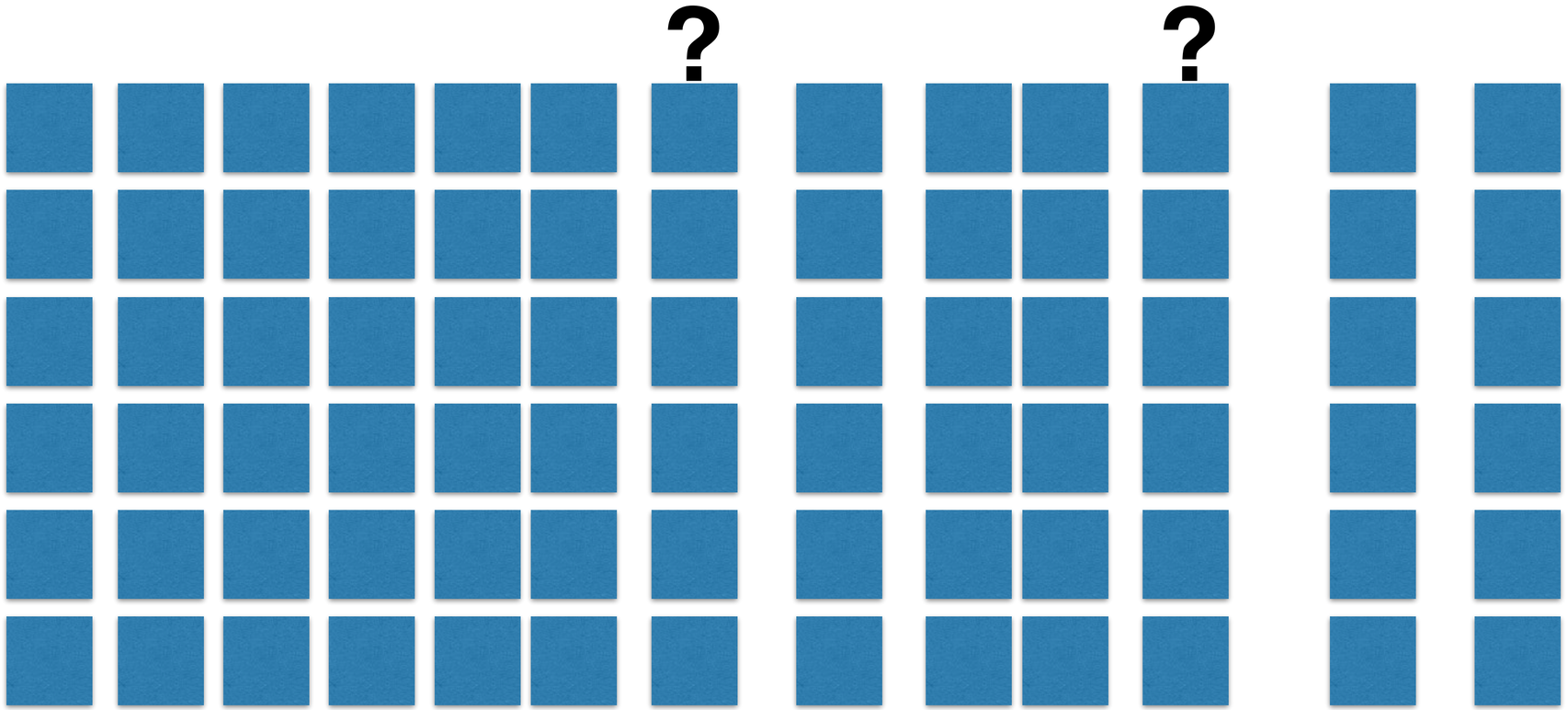


J. Devlin et al. “BERT: Pre-training of deep bidirectional transformers for language understanding”, arXiv:1810.04805, 2018

BERT: Training

Predict words which were replaced with random words.

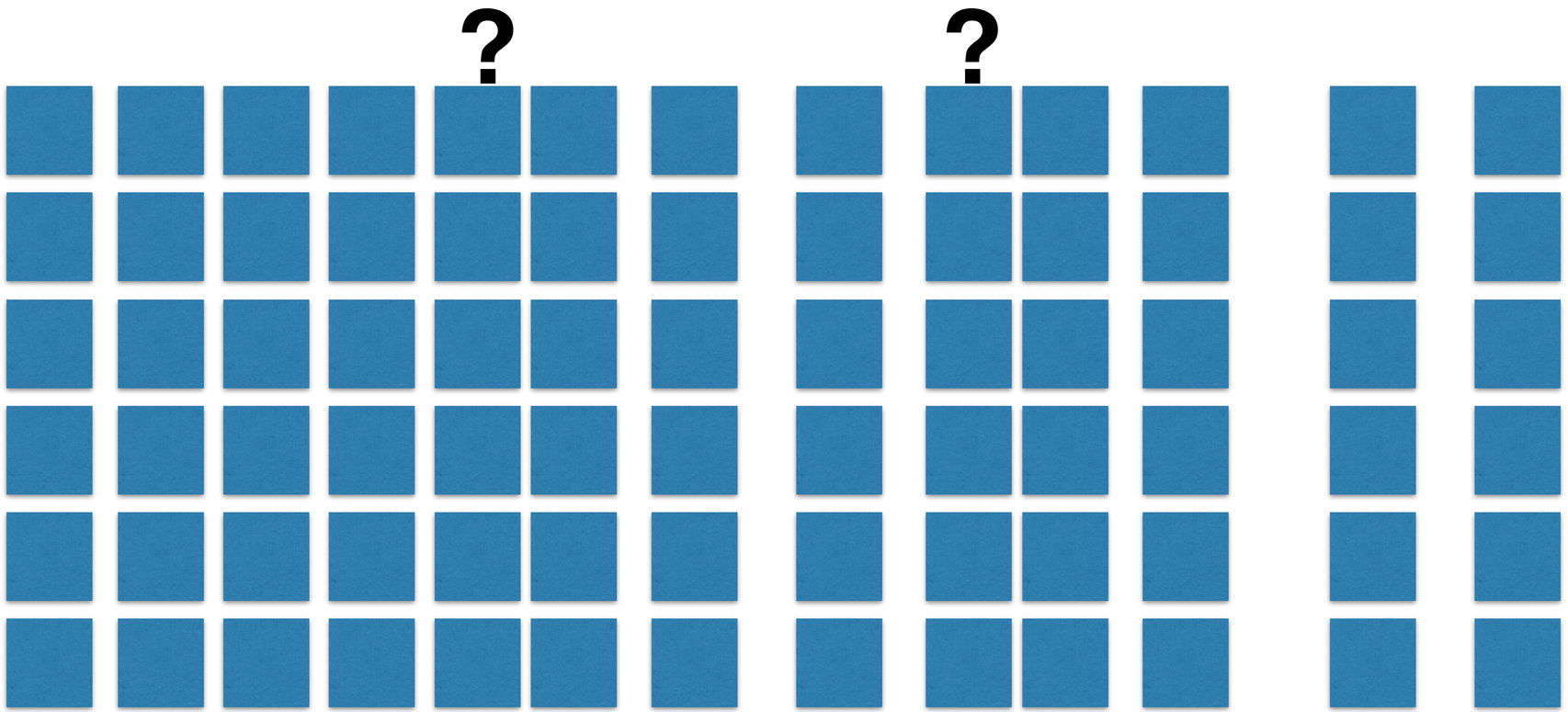


<s> The cat sat on the wine <sep> It fell scooter soon after

J. Devlin et al. “BERT: Pre-training of deep bidirectional transformers for language understanding”, arXiv:1810.04805, 2018

BERT: Training

Predict words from the input.

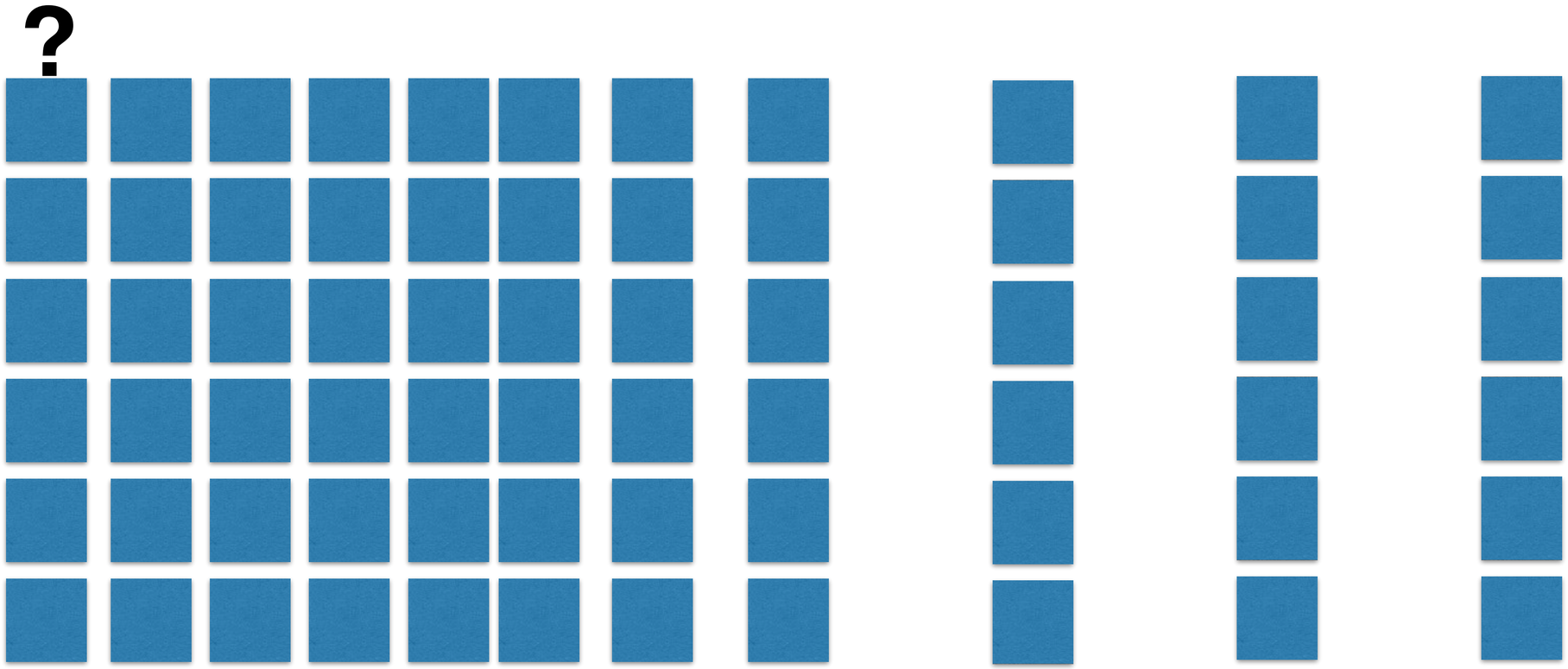


<s> The cat sat on the mat <sep> It fell asleep soon after

J. Devlin et al. “BERT: Pre-training of deep bidirectional transformers for language understanding”, arXiv:1810.04805, 2018

BERT: Training

Predict whether the next sentence is taken at random.

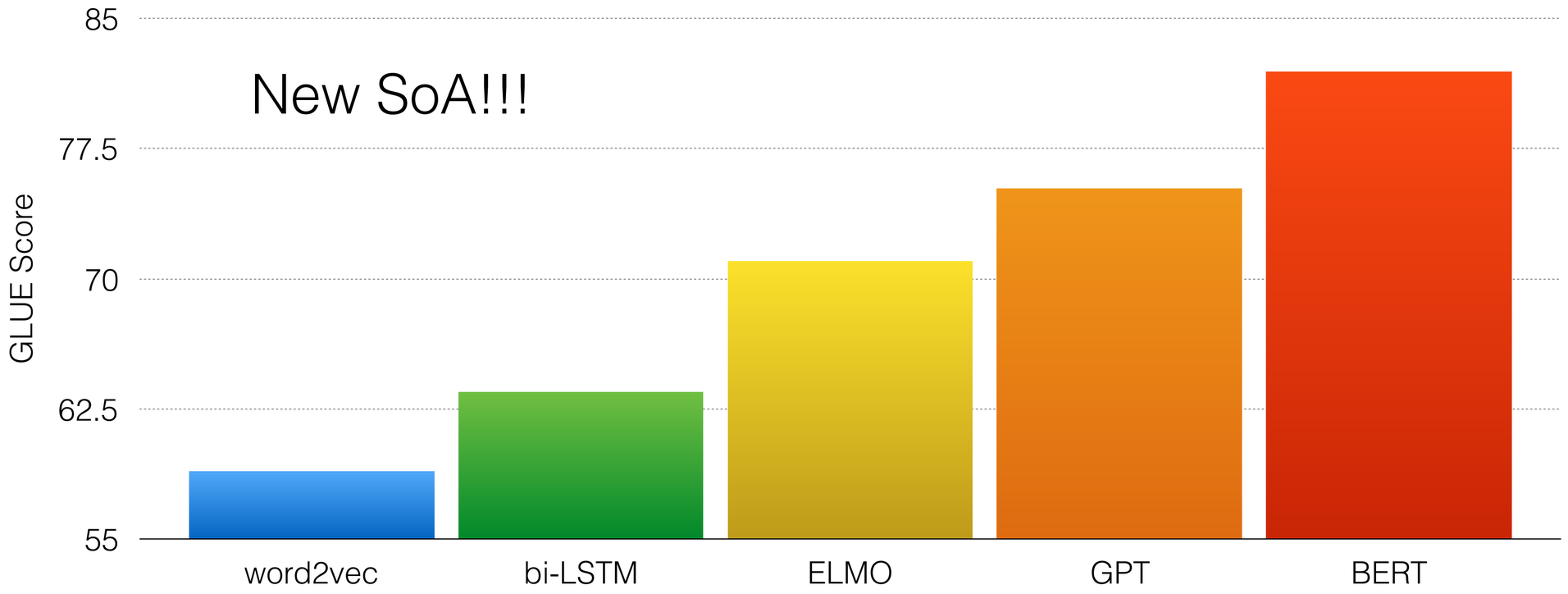


<s> The cat sat on the mat <sep> Unsupervised learning rocks

J. Devlin et al. “BERT: Pre-training of deep bidirectional transformers for language understanding”, arXiv:1810.04805, 2018

GLUE Benchmark (11 tasks)

Unsupervised pretraining followed by supervised finetuning



J. Devlin et al. “BERT: Pre-training of deep bidirectional transformers for language understanding”, arXiv:1810.04805, 2018

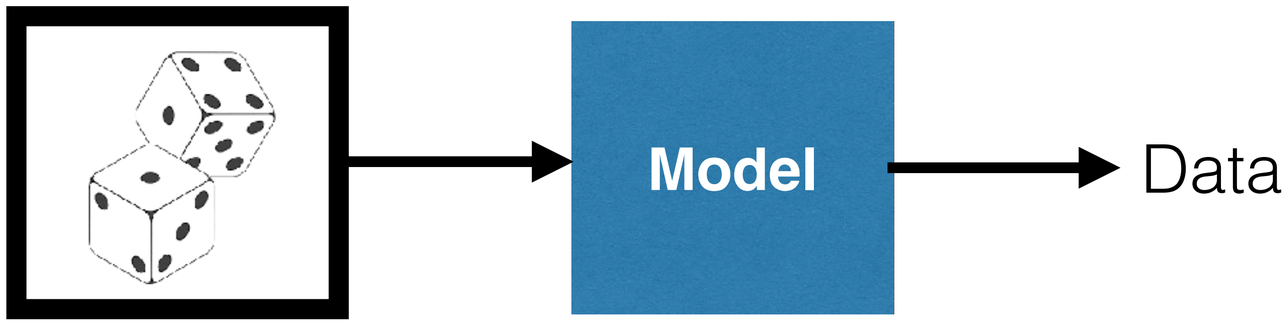
Conclusions on Learning Representation from Text

- Unsupervised learning has been very successful in NLP.
- Key idea: learn (deep) representations by predicting a word from the context (or vice versa).
- Current SoA performance across a large array of tasks.

Overview

- Practical Recipes of Unsupervised Learning
  - Learning representations
  - **Learning to generate samples (just a brief mention)**
  - Learning to map between two domains
- Open Research Problems

Generative Models



Useful for:

- learning representations (rarely the case nowadays),
- useful for planning (only in limited settings), or
- just for *fun* (most common use-case today)…

Generative Models: Vision

- GAN variants currently dominate the field.

T. Kerras et al. “Progressive growing of GANs for improved quality, stability, and variation”, ICLR 2018

Generative Models: Vision

- GAN variants currently dominate the field.

A. Brock et al. “Large scale GAN training for high fidelity natural image synthesis” arXiv 1809:11096 2018

Generative Models: Vision

- GAN variants currently dominate the field.
  A. Brock et al. “Large scale GAN training for high fidelity natural image synthesis” arXiv 1809:11096 2018

- Other approaches:

  - Auto-regressive
    A. Oord et al. “Conditional image generation with PixelCNN”, NIPS 2016
  - GLO
    P. Bojanowski et al. “Optimizing the latent state of generative networks”, ICML 2018
  - Flow-based algorithms.
    G. Papamakarios et al. “Masked auto-regressive flow for density estimation”, NIPS 2017

- Choice of architecture (CNN) seems more crucial than actual learning algorithm.

Generative Models: Vision

Open challenges:

- how to model high dimensional distributions,
- how to model uncertainty,
- meaningful metrics & evaluation tasks!

Anonymous “GenEval: A benchmark suite for evaluating generative models”, in submission to ICLR 2019

Generative Models: Text

- Auto-regressive models (RNN/CNN/Transformers) are good at generating short sentences. See Alex's examples.
  I. Serban et al. "Building end-to-end dialogue systems using generative hierarchical neural network models" AAAI 2016
- Retrieval-based approaches are often used in practice.
  A. Bordes et al. "Question answering with subgraph embeddings" EMNLP 2014
  R. Yan et al. "Learning to Respond with Deep Neural Networks for Retrieval-Based Human-Computer Conversation System", SIGIR 2016
  M. Henderson et al. "Efficient natural language suggestion for smart reply", arXiv 2017
  …
- The two can be combined
  J. Gu et al. "Search Engine Guided Non-Parametric Neural Machine Translation", arXiv 2017
  K. Guu et al. "Generating Sentences by Editing Prototypes", ACL 2018
  …

Generative Models: Text

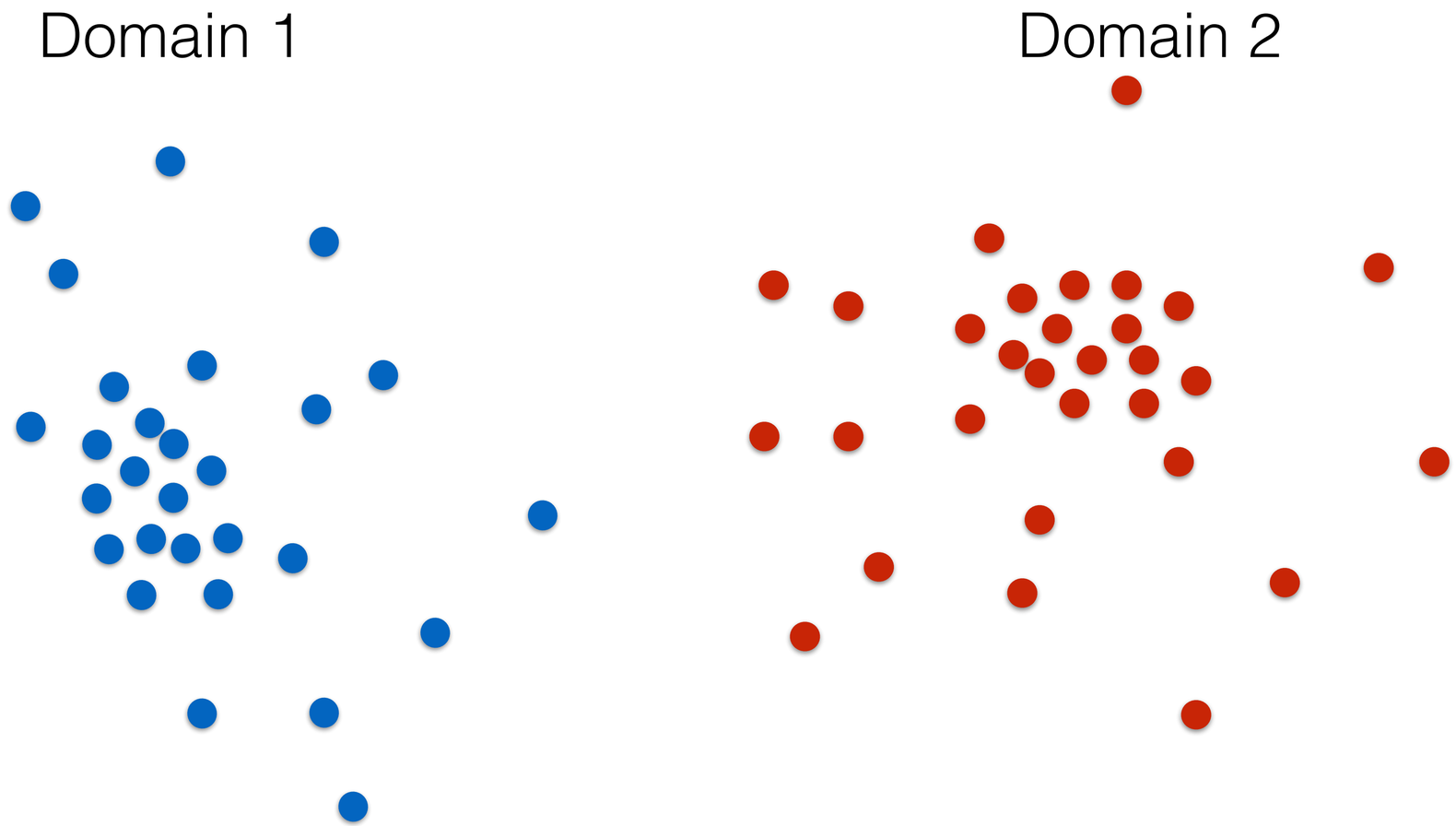
Open challenges:

- how to generate documents (long pieces of text) that are coherent,
- how to keep track of state,
- how to model uncertainty,
  M. Ott et al. “Analyzing uncertainty in NMT” ICML 2018
- how to ground,
  starting with D. Roy / J. Siskind’s work from early 2000’s
- meaningful metrics & standardized tasks!

Overview

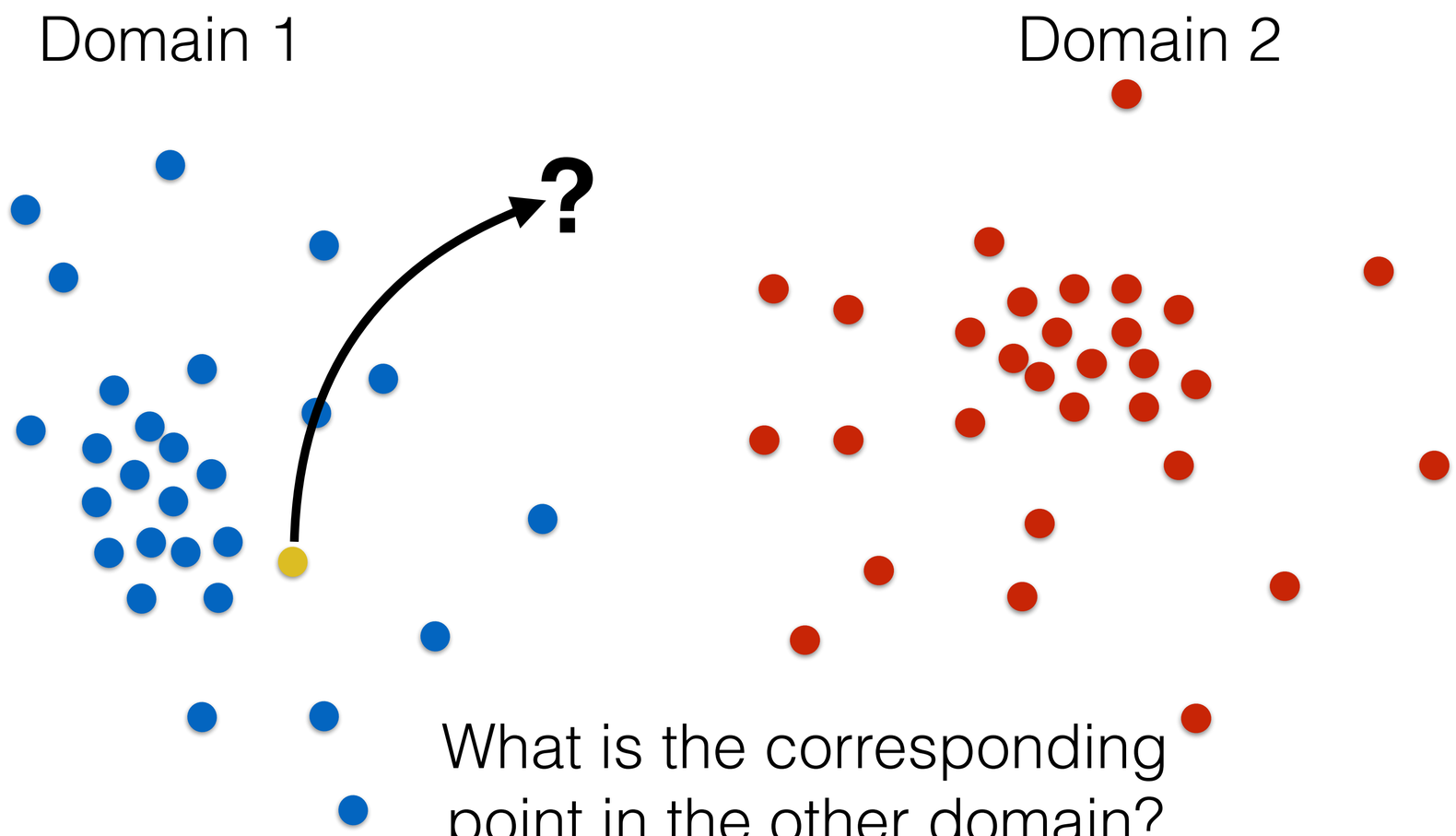
- Practical Recipes of Unsupervised Learning
  - Learning representations
  - Learning to generate samples
  - **Learning to map between two domains**
- Open Research Problems

Learning to Map



Toy illustration of the data

Learning to Map



Toy illustration of the data

Why Learning to Map

- There are fun applications: making analogies in vision.
- It is useful; e.g., enables to leverage lots of (unlabeled) monolingual data in machine translation.
- Arguably, an AI agent has to be able to perform analogies to quickly adapt to a new environment.

Vision: Cycle-GAN

Domain 1

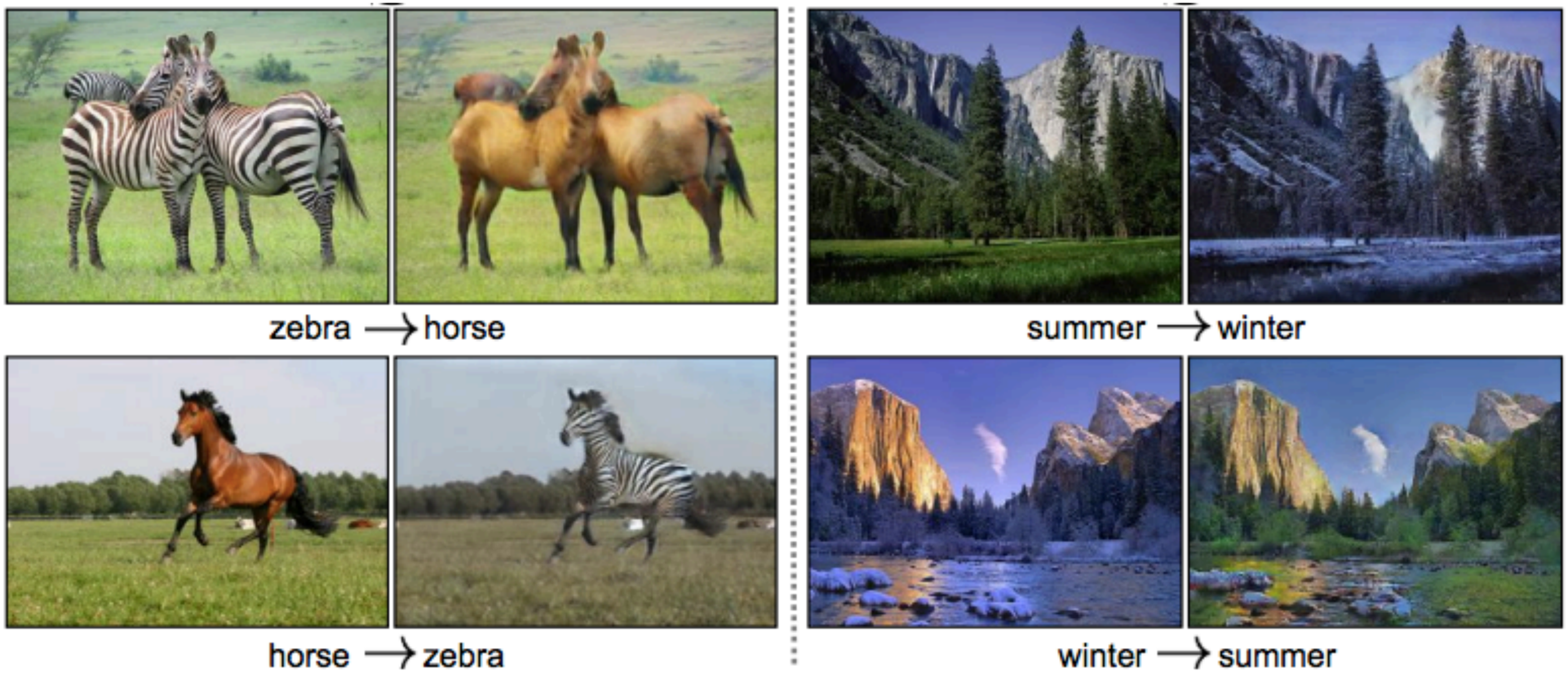
Domain 2

J. Zhu et al. “Unpaired image-to-image translation using cycle consistent adversarial networks”, ICCV 2017

Vision: Cycle-GAN

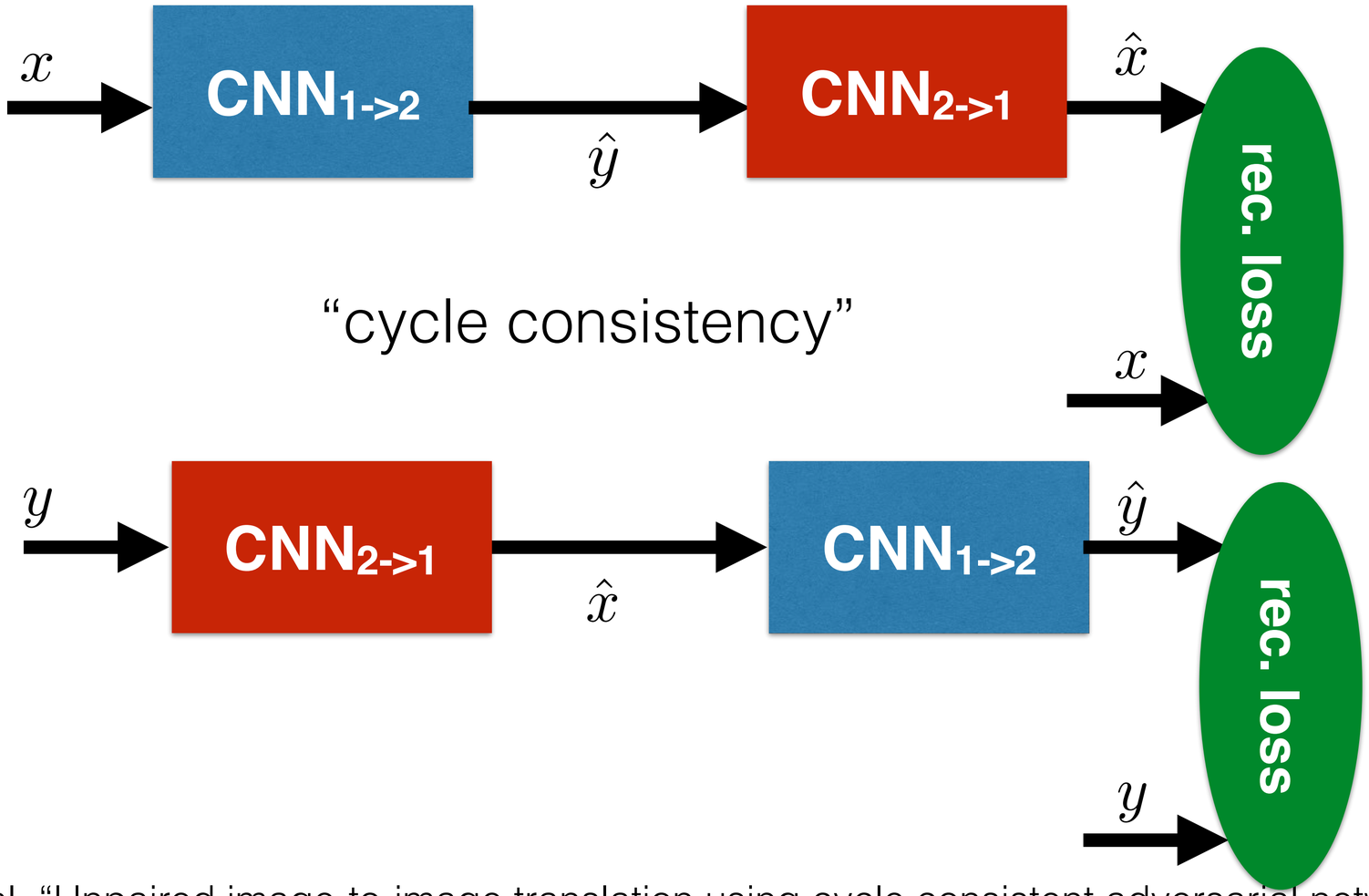
J. Zhu et al. “Unpaired image-to-image translation using cycle consistent adversarial networks”, ICCV 2017

Vision: Cycle-GAN



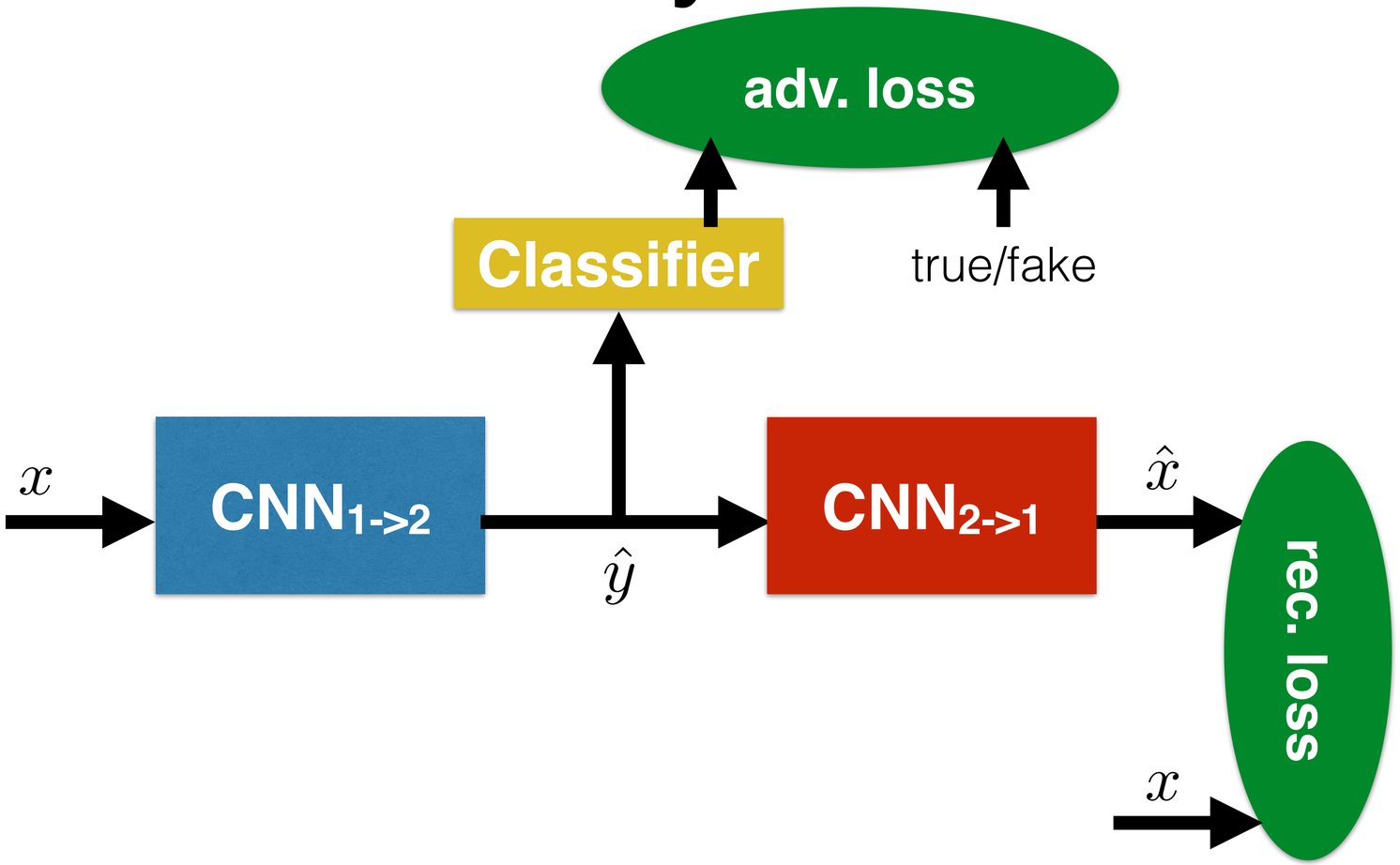
J. Zhu et al. “Unpaired image-to-image translation using cycle consistent adversarial networks”, ICCV 2017

Vision: Cycle-GAN



J. Zhu et al. "Unpaired image-to-image translation using cycle consistent adversarial networks", ICCV 2017

Vision: Cycle-GAN



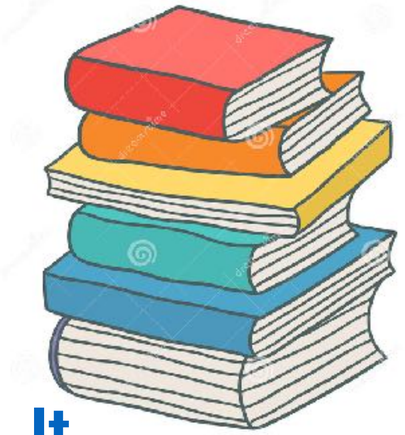
constrain generation to belong to desired domain

J. Zhu et al. “Unpaired image-to-image translation using cycle consistent adversarial networks”, ICCV 2017

Unsupervised Machine Translation

- Similar principles may apply also to NLP, e.g. for machine translation (MT).

En



It

Learning to translate without access to any single translation, just lots of (monolingual) data in each language.

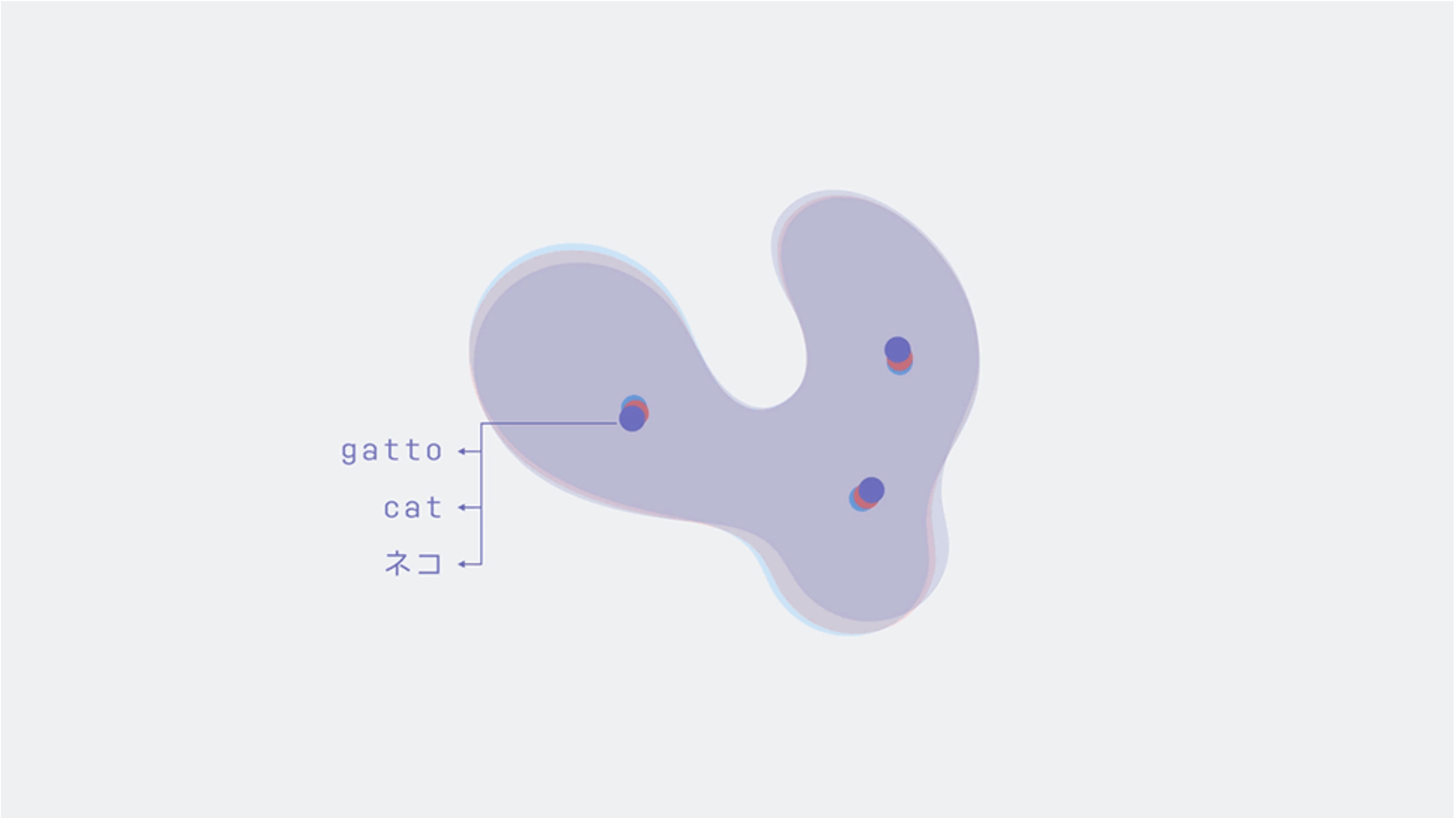
Unsupervised Machine Translation

- Similar principles may apply also to NLP for machine translation (MT).
- Can we do unsupervised MT?
  - There is little if any parallel data in most language pairs.
- Challenges:
  - discrete nature of text
  - domain mismatch
  - languages may have very different morphology, grammar, ..

Unsupervised **Word** Translation

- Motivation: A pre-requisite for unsupervised sentence translation.
- Problem: given two monolingual corpora in two different languages, estimate bilingual lexicon.
- Hint: the context of a word, is often similar across languages since each language refers to the same underlying physical world.

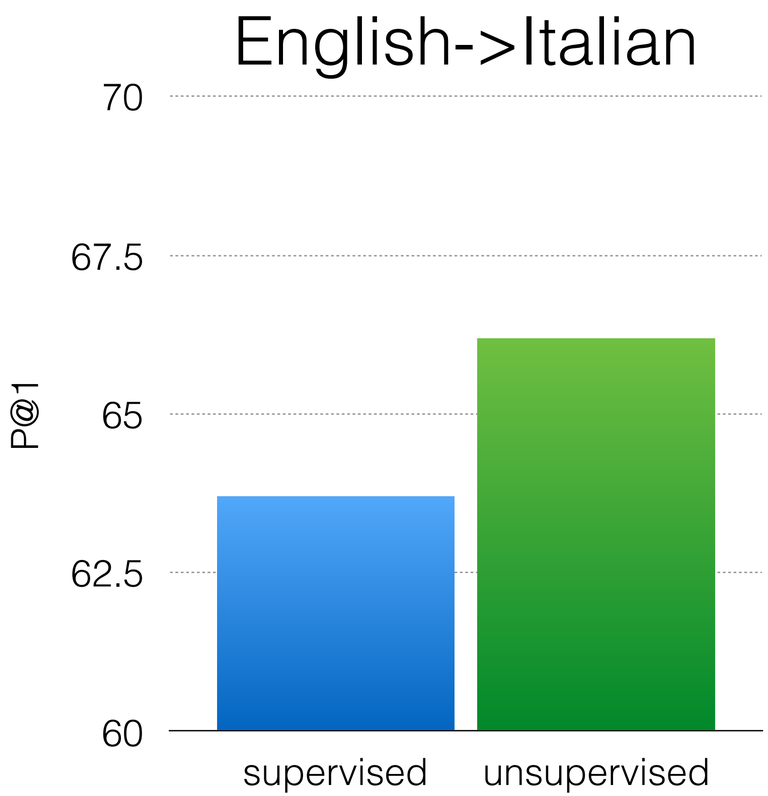
Unsupervised **Word** Translation

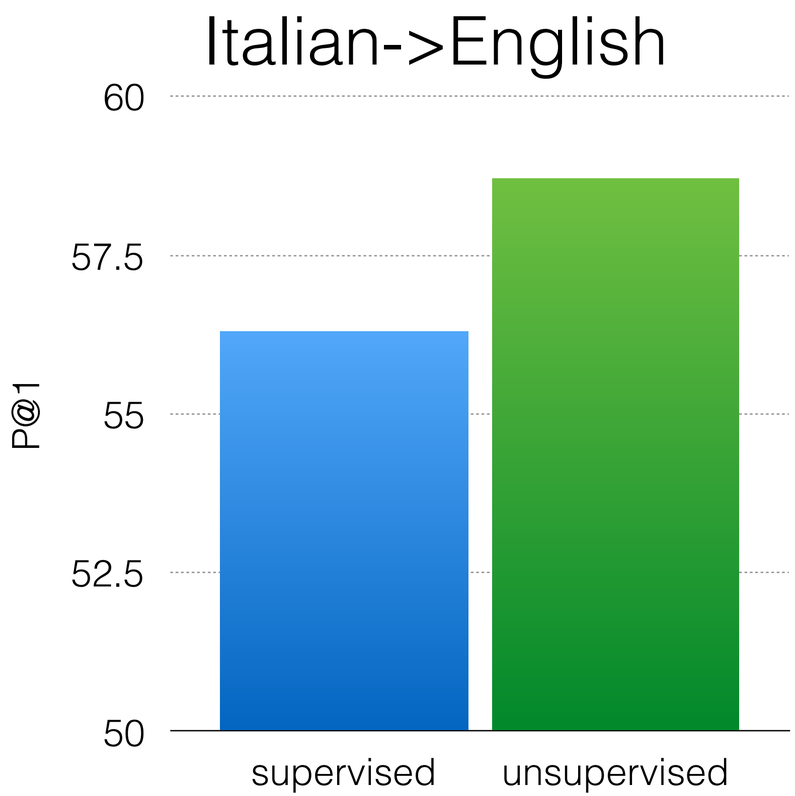


1) Learn embeddings separately.
2) Learn joint space via adversarial training + refinement.

A. Conneau et al. “Word translation without parallel data” ICLR 2018

Results on Word Translation





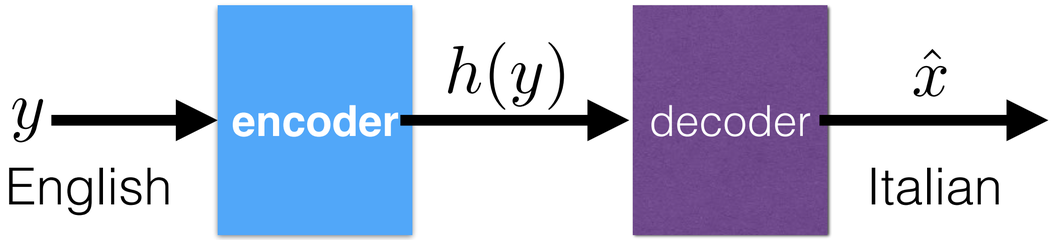
By using more anchor points and lots of unlabeled data, MUSE outperforms supervised approaches!

https://github.com/facebookresearch/MUSE

Naïve Application of MUSE

- In general, this may not work on sentences because:
  - Without leveraging compositional structure, space is exponentially large.
  - Need good sentence representations.
  - Unlikely that a linear mapping is sufficient to align sentence representations of two languages.

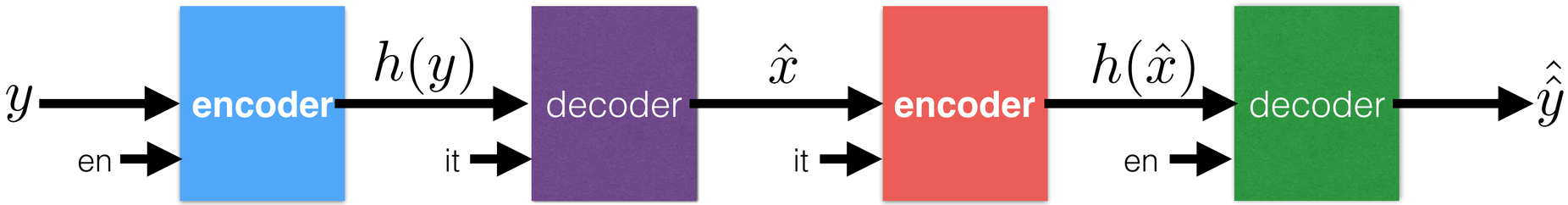
Method



We want to learn to translate, but we do not have targets…

G. Lample et al. “Phrase-based and neural unsupervised machine translation” EMNLP 2018

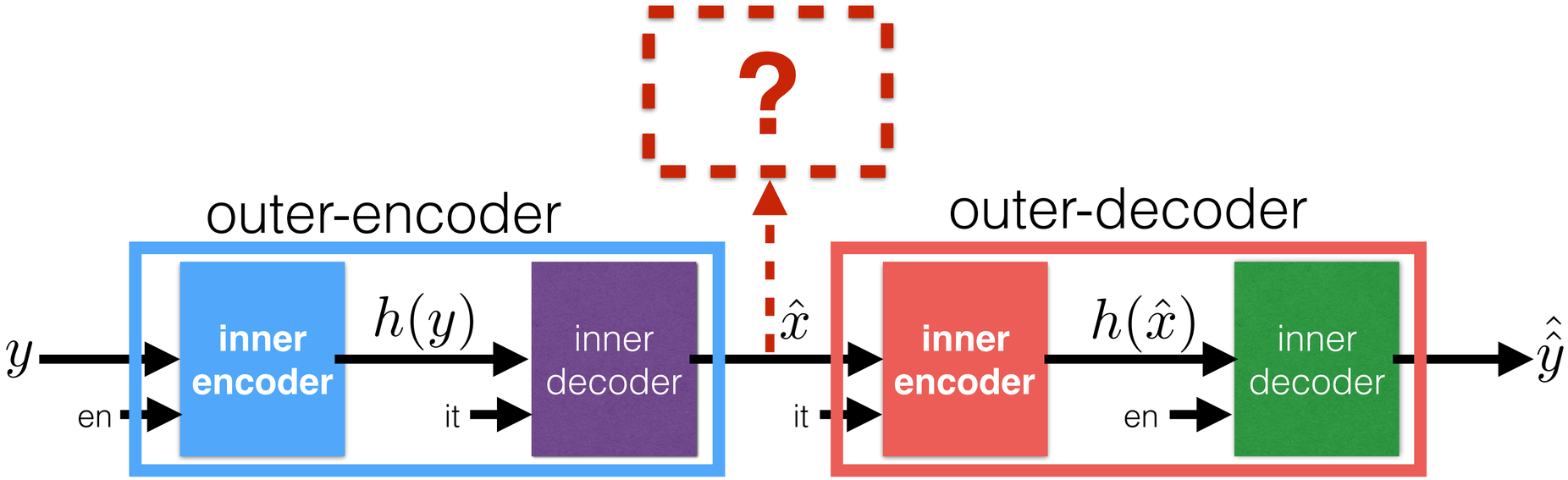
Method



use the same cycle-consistency principle (back-translation)

G. Lample et al. “Phrase-based and neural unsupervised machine translation” EMNLP 2018

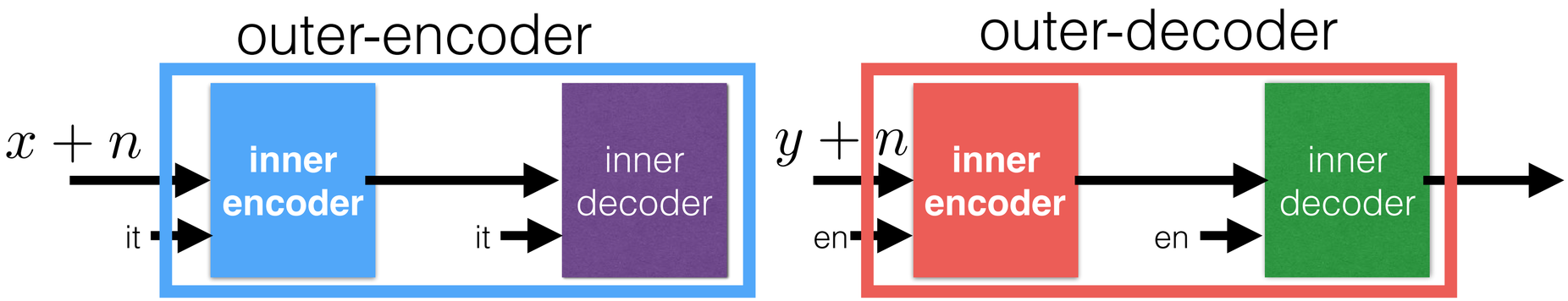
Method



How to ensure the intermediate output is a valid sentence?
Can we avoid back-propping through a discrete sequence?

G. Lample et al. “Phrase-based and neural unsupervised machine translation” EMNLP 2018

Adding Language Modeling

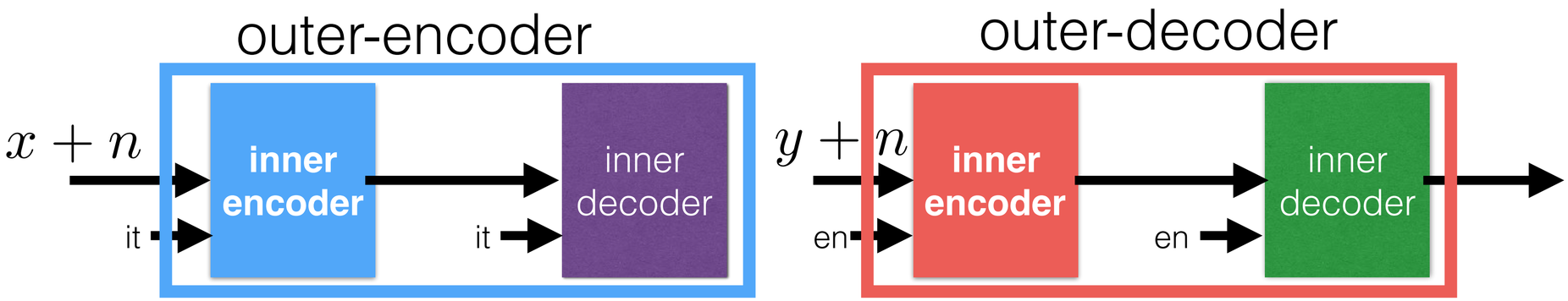


Since inner decoders are shared between the LM and MT task, it should constrain the intermediate sentence to be fluent.

Noise: word drop & swap.

G. Lample et al. “Phrase-based and neural unsupervised machine translation” EMNLP 2018

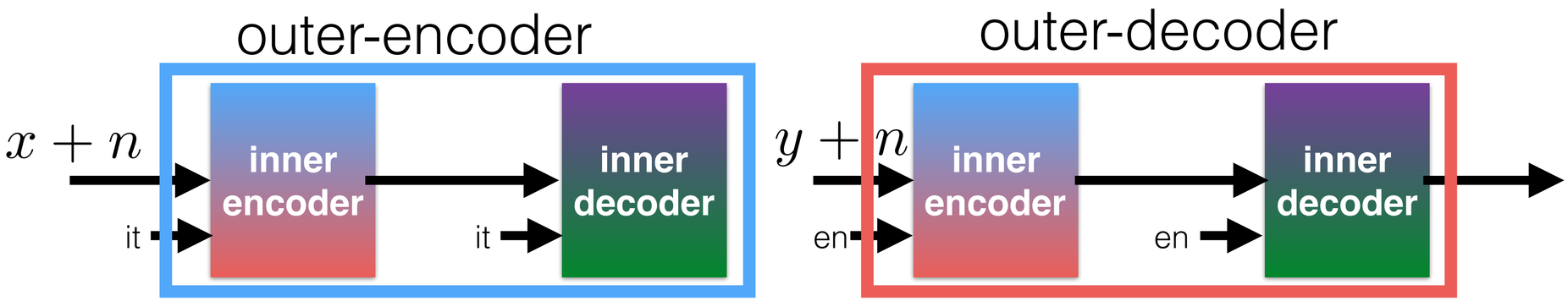
Adding Language Modeling



Potential issue: Model can learn to denoise well, reconstruct well from back-translated data and yet not translate well, if it splits the latent representation space.

G. Lample et al. “Phrase-based and neural unsupervised machine translation” EMNLP 2018

NMT: Sharing Latent Space

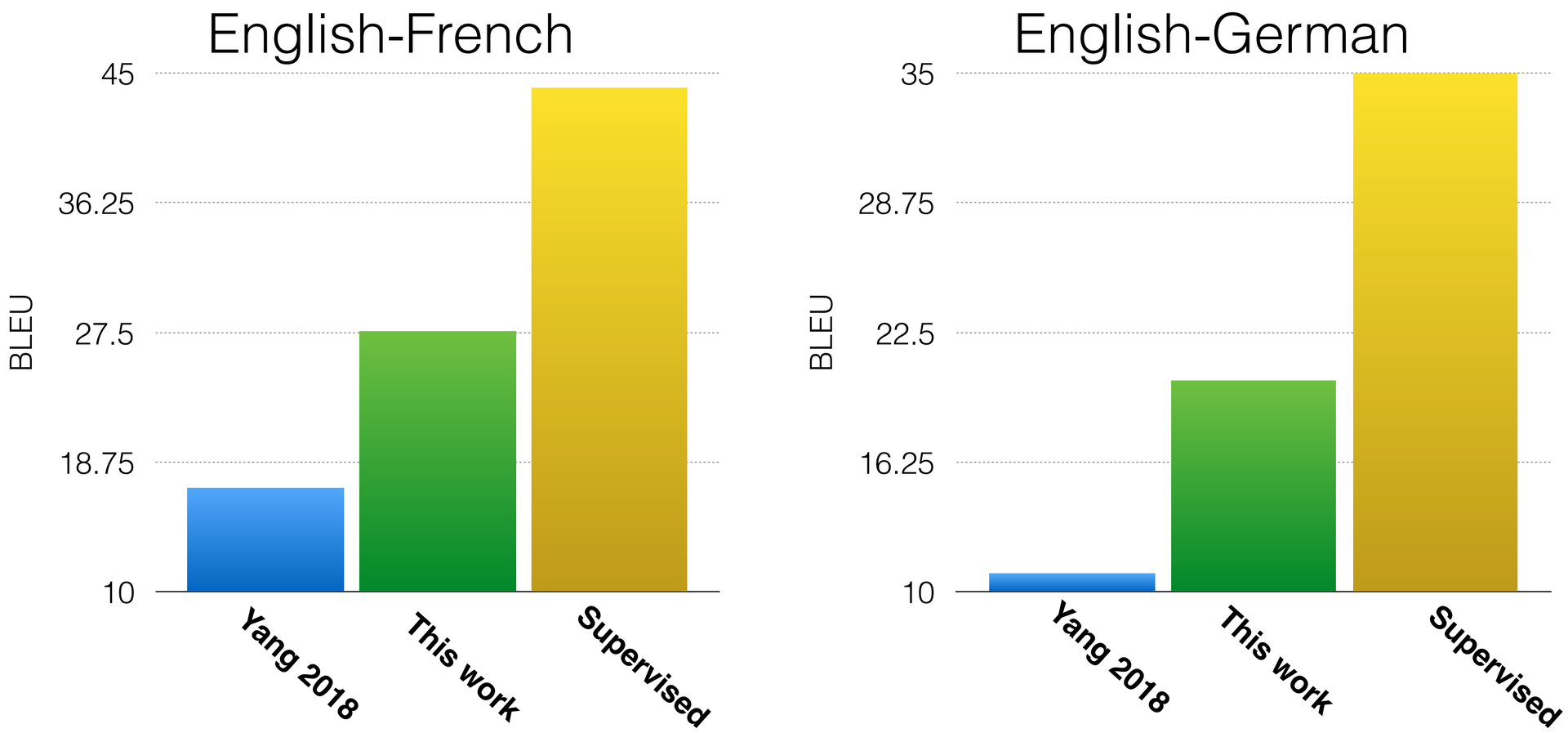


Sharing achieved via:

1) shared encoder (and also decoder).
2) joint BPE embedding learning / initialize embeddings with MUSE.

Note: first decoder token specifies the language on the target-side.

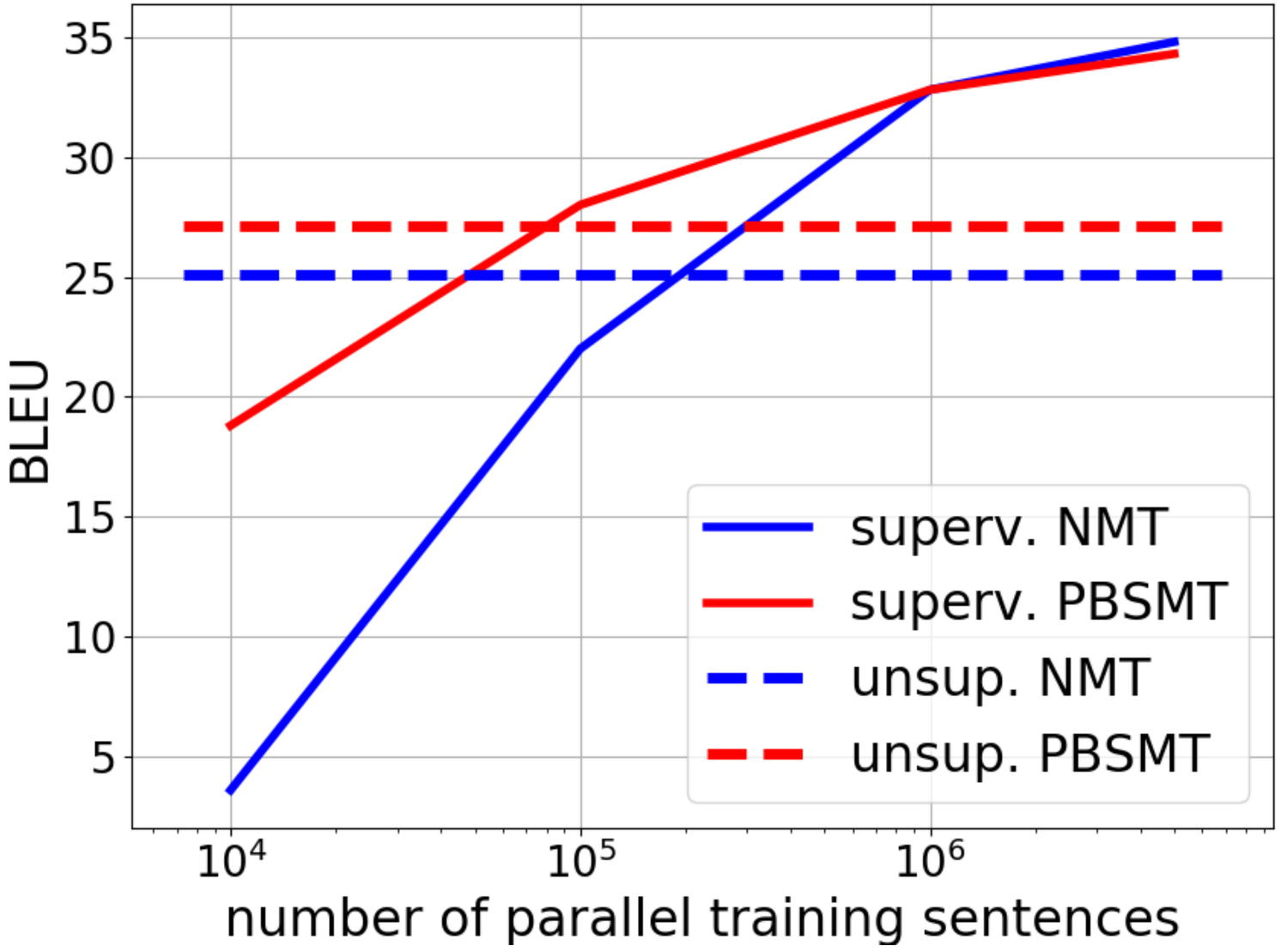
Experiments on WMT



Before 2018, performance of fully unsupervised methods was essentially 0 on these large scale benchmarks!

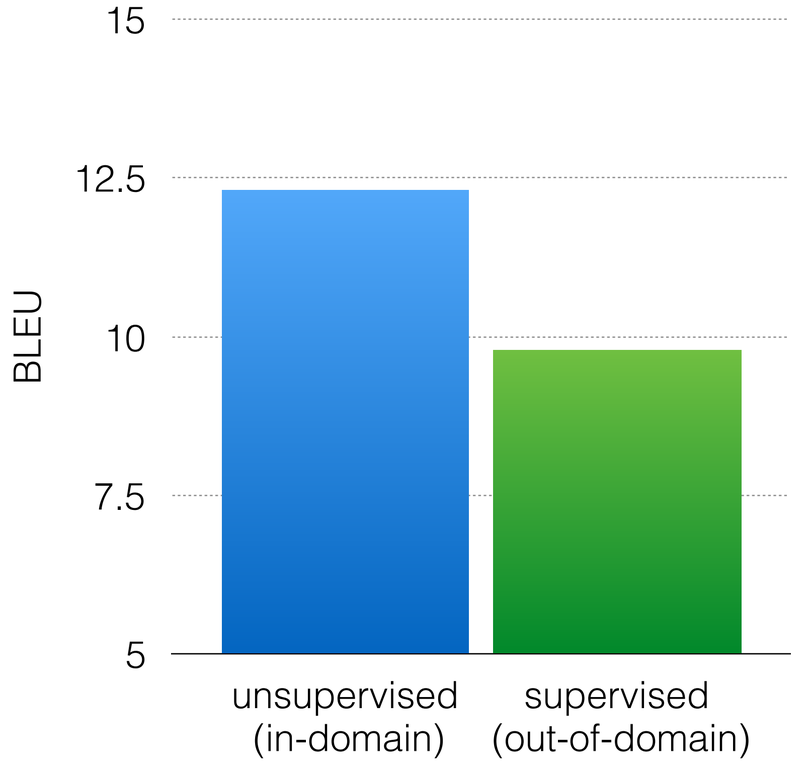
G. Lample et al. “Phrase-based and neural unsupervised machine translation” EMNLP 2018

Experiments on WMT



Distant & Low-Resource Language Pair: En-Ur

https://www.bbc.com/urdu/pakistan-44867259



G. Lample et al. “Phrase-based and neural unsupervised machine translation” EMNLP 2018

Conclusion on Unsupervised Learning to Translate

- General principles: initialization, matching target domain and cycle-consistency.
- Extensions: semi-supervised, more than two domains, more than a single attribute, …
- Challenges:
  - domain mismatch / ambiguous mappings
  - domains with very different properties

Overview

- Practical Recipes of Unsupervised Learning
  - Learning representations
  - Learning to generate samples (just a brief mention)
  - Learning to map between two domains
- **Open Research Problems**

Challenge #1: Metrics & Tasks

Unsupervised Feature Learning:

Q: What are good down-stream tasks?

What are good metrics for such tasks?

In NLP there is some consensus for this: **https://github.com/facebookresearch/SentEval**
https://gluebenchmark.com/

Generation:

Q: What is a good metric?

In NLP there has been some effort towards this: **http://www.statmt.org/**
http://www.parl.ai/

Challenge #1: Metrics & Tasks

Unsupervised Feature Learning:

Q: What are good down-stream tasks?

What are good metrics for such tasks?

Only in NLP there is some consensus for this: **https://gluebenchmark.com/**

What about in Vision?

Good metrics and representative tasks are key to drive the field forward.

In NLP there has been some effort towards this: **http://www.statmt.org/**
http://www.parl.ai/

A. Wang et al. “GLUE: A multi-task benchmark and analysis platform for NLU” arXiv 1804:07461

Challenge #2: General Principle

Is there a **general** principle of unsupervised feature learning?

The current SoA in NLP: word2vec, BERT, etc. are **not entirely satisfactory** - very local predictions of a single missing token..

E.g.: This tutorial is … … because I learned … …!
Impute: This tutorial is **really awesome** because I learned **a lot**!
Feature extraction: topic={education, learning}, style={personal}, …

Ideally, we would like to be able to impute any missing information given some context, we would like to extract features describing any subset of input variables.

Challenge #2: General Principle

Is there a **general** principle of unsupervised feature learning?

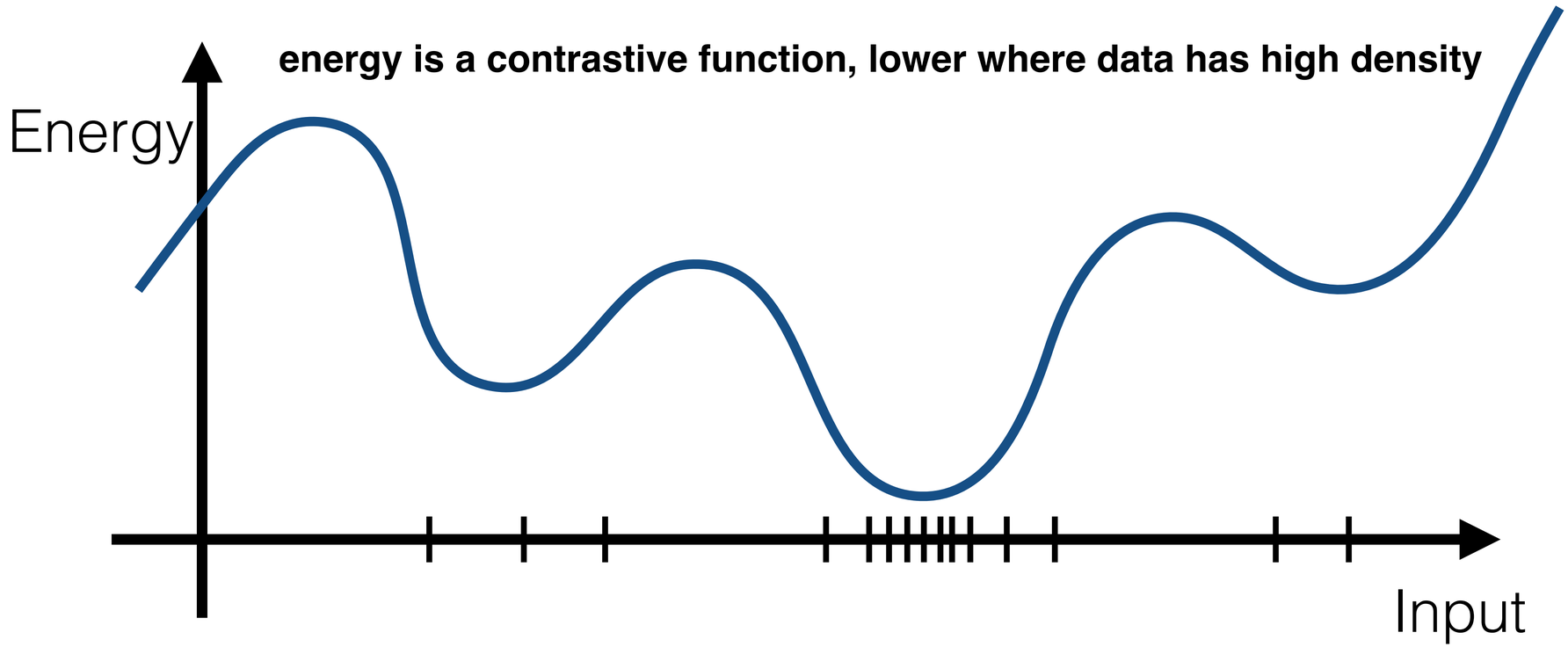
The current SoA in NLP: word2vec, BERT, etc. are **not entirely satisfactory** - very local predictions of a single missing token..

The current SoA in Vision: SSL is **not entirely satisfactory** - which auxiliary task and how many more tasks do we need to design?

Limitations of auto-regressive models: need to specify order among variables making some prediction tasks easier than others, slow at generation time.

Challenge #2: General Principle

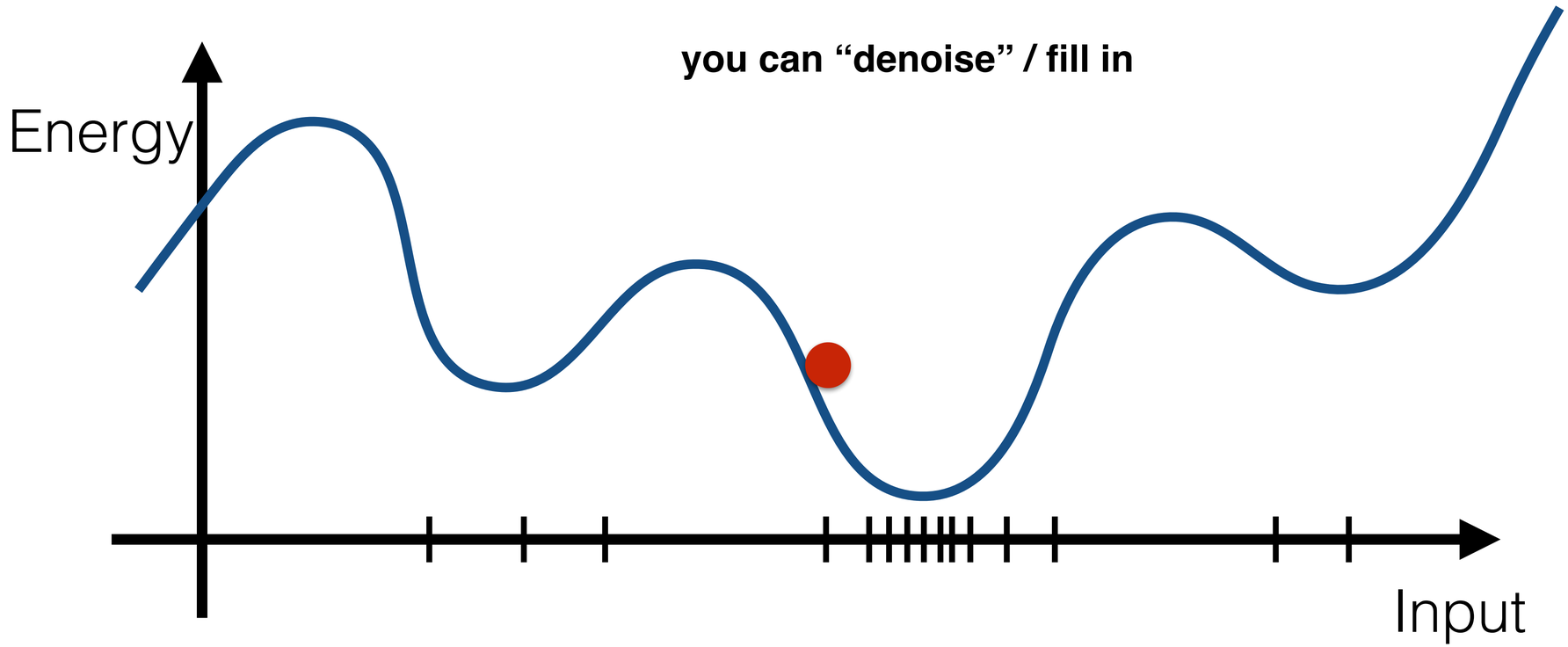
A brief case study of a more general framework: EBMs



Y. LeCun et al. “A tutorial on energy-based learning” MIT Press 2006

Challenge #2: General Principle

A brief case study of a more general framework: EBMs

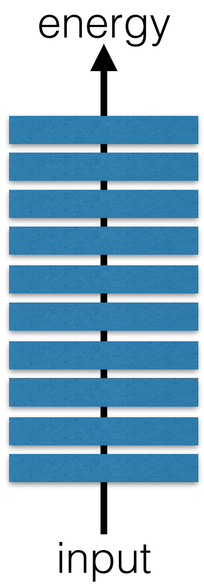


Y. LeCun et al. “A tutorial on energy-based learning” MIT Press 2006

Challenge #2: General Principle

One possibility: energy-based modeling

you can do feature extraction using any intermediate representation from E(x)



Y. LeCun et al. “A tutorial on energy-based learning” MIT Press 2006

Challenge #2: General Principle

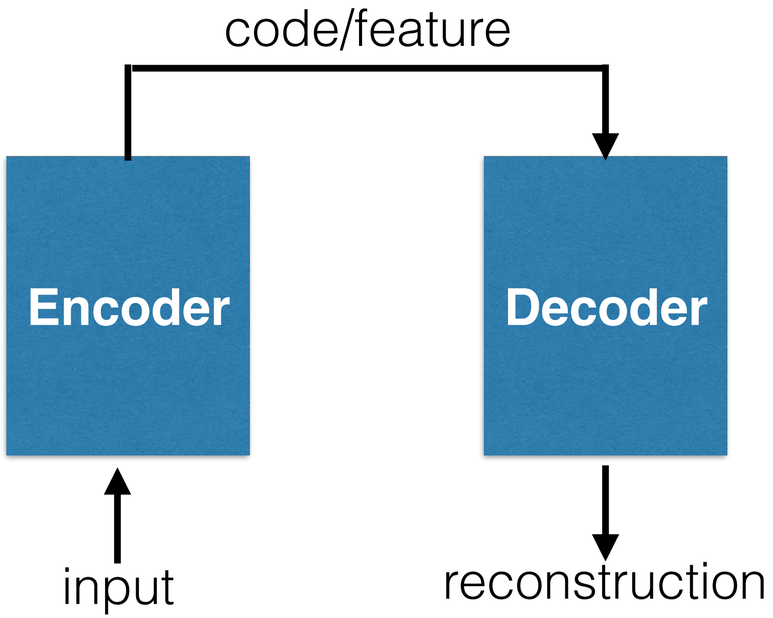
One possibility: energy-based modeling

The generality of the framework comes at a price…

Learning such contrastive function is in general very hard.

Y. LeCun et al. “A tutorial on energy-based learning” MIT Press 2006

Challenge #2: General Principle

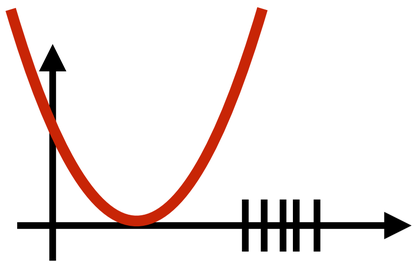


Learning contrastive energy function by pulling up on fantasized "negative data":

- via search
- via sampling (*CD)

and/or by **limiting amount of information** going through the "code":

- sparsity
- low-dimensionality
- noise



M. Ranzato et al. "A unified energy-based framework for unsupervised learning" AISTATS 2007
A. Hyvärinen "Estimation of non-normalized statistical models by score matching" JMNR 2005
K. Kavukcuoglu et al. "Fast inference in sparse coding algorithms…" arXiv 1406:5266 2008

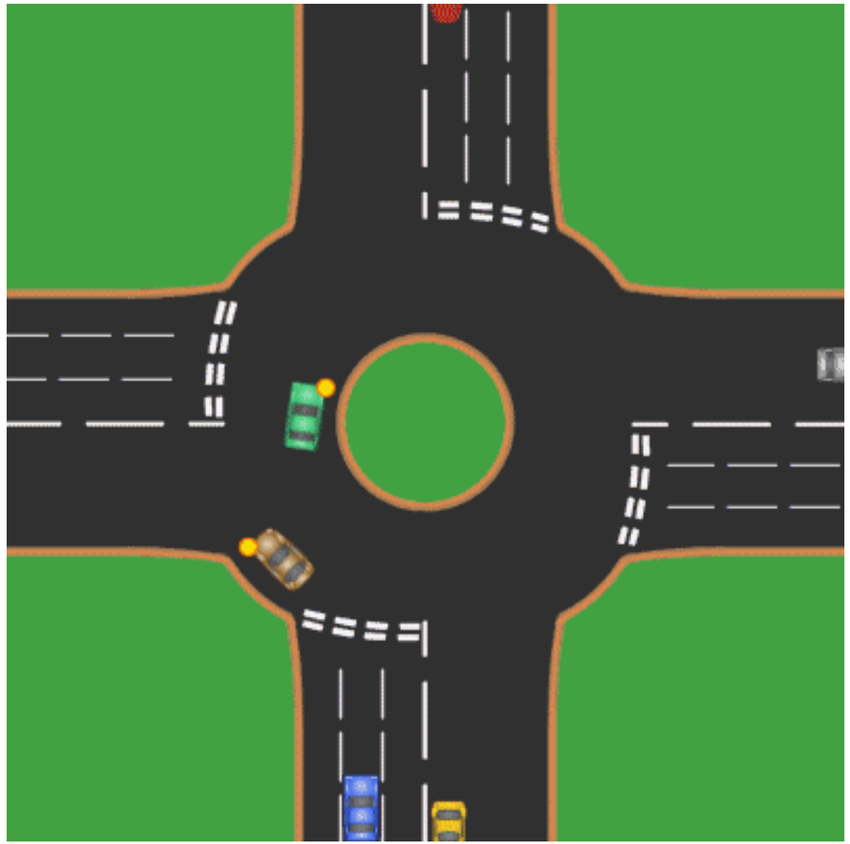
Challenge #2: General Principle

Challenge: If the space is very high-dimensional, it is difficult to figure out the right “pull-up” constraint that can properly shape the energy function.

- Are there better ways to pull up?
- Is there a better framework?
- To which extent should these principles be agnostic of the architecture and domain of interest?

Challenge #3: Modeling Uncertainty

- Most predictions tasks have uncertainty.



where is the red car going?

Challenge #3: Modeling Uncertainty

- Most predictions tasks have uncertainty.

E.g.: This tutorial is … … because I learned … …!
Impute: This tutorial is **really awesome** because I learned **a lot**!
This tutorial is **so bad** because I learned **really nothing**!

Challenge #3: Modeling Uncertainty

- Most predictions tasks have uncertainty.
- Several ways to model uncertainty:
  - latent variables
  - GANs
  - shaping energies to have lots of minima
  - quantizing continuous signals…

What are efficient ways to learn and do inference?

How to model uncertainty in continuous distributions?

The Big Picture

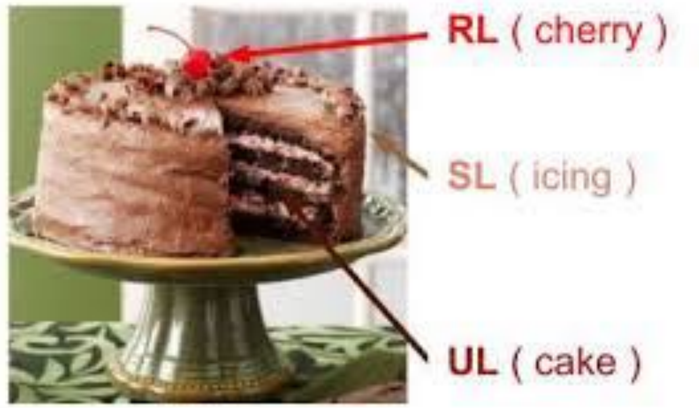
- A big challenge in AI: learning with less labeled data.
- Lots of sub-fields in ML tackling this problem from other angles:
  - few-shot learning
  - meta-learning
  - life-long learning
  - transfer learning
  - semisupervised
  - …
- Unsupervised learning is part of a broader effort.

The Big Picture

Unsupervised Learning should eventually be considered as a component within a bigger system.

- RL models can work more efficiently by leveraging information present in the input observations (unsupervised learning).
- Unsupervised learning is an important tool, but sparse rewards (RL) can inform about what unsupervised tasks are meaningful. Environment can provide further constraints.

you can't eat just the cherry, nor just the filling….
you gotta eat a whole slice!



picture/metaphor credit: Y. LeCun

Conclusions

- Unsupervised Learning is a key ingredient for any agent that learns from few interactions / few labeled examples.
- Lots of sub-areas: feature learning, learning to align domains, learning to generate samples, …
- Unsupervised learning currently works very well in restricted settings and in few applications.
- Biggest challenges:
  - metrics & tasks,
  - generality and efficiency of current algorithms,
  - integration of unsupervised learning with other learning components.


תודה
Dankie
Gracias
Спасибо
شكراً
Merci
Takk
Köszönjük
Terima kasih
Grazie
Dziękujemy
Dėkojame
Ďakujeme
Vielen Dank
Paldies
Kiitos
Täname teid
谢谢
Thank You
Tak
感謝您
Obrigado
Teşekkür Ederiz
감사합니다
Σας Ευχαριστούμ
ขอบคุณ
Bedankt
Děkujeme vám
ありがとうございます
Tack