10417-617
Deep Learning: Spring 2020

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Lecture 17:
Basics of modeling of sequential data, self-supervised learning

Part I:
Models for sequential data

Sequential structure in data

Often times, data we are interested has "**sequential**" structure:

For instance:

- *Word* in sentence depends on surrounding words.
- *Sounds* in speech depend on surrounding sounds.
- *Pixel* in image depends on surrounding pixels.

It makes sense to factor joint distribution of data as

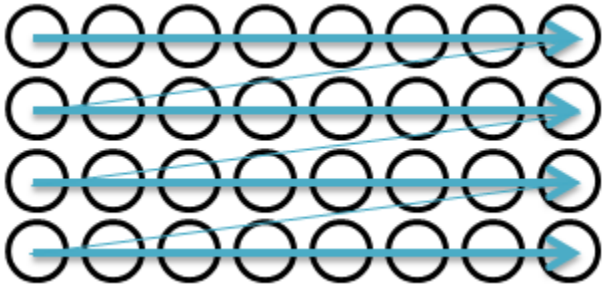
$$p(x_1, x_2, \dots, x_t) = p(x_i | x_{<i})$$

We will model $p(x_i | x_{<i})$ s.t. we can sample from/learn the model efficiently.

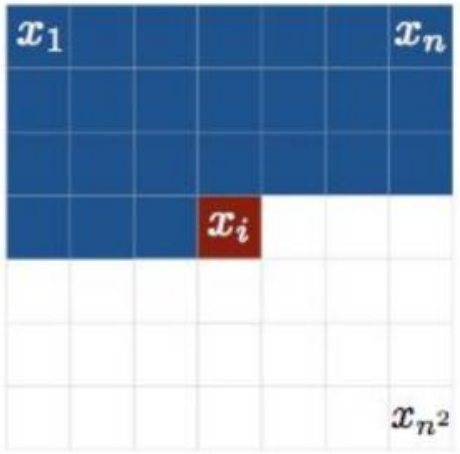
Sequential structure in data

Requires fixing an order. In text, this is the obvious one. Same in sound/speech.

In images, the typical ordering is the "raster ordering"



Thus, the notation $x_{<i}$ will denote:



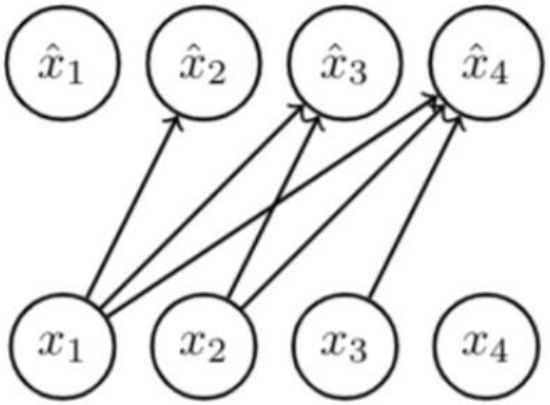
Fully visible sigmoid belief network

Let's assume data is binary (e.g. MNIST).

The "obvious" parametrization for $p(x_i|x_{<i})$:

Different parameters for all i

$$p(x_i|x_{<i}) = \sigma\left(\sum_{j=1}^{i} \theta_j^i x_j\right)$$



Sampling: obvious ancestral sampling

$$\widehat{x_1} \sim p(x_1)$$

$$\widehat{x_i} \sim p(x_i|\widehat{x_{<i}})$$

Training: log-likelihood/gradients are explicit.

Fully visible sigmoid belief network

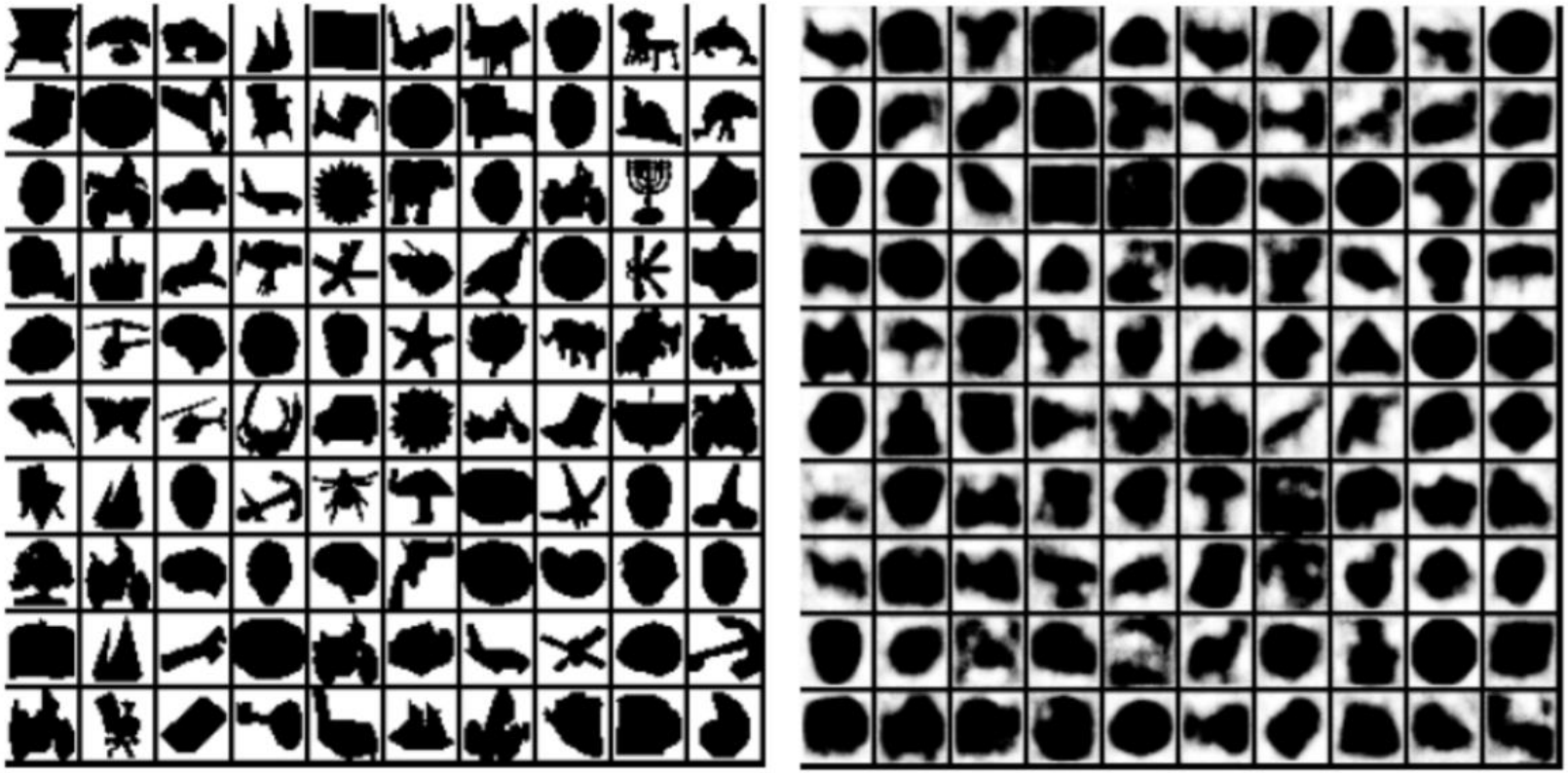


Figure from *Learning Deep Sigmoid Belief Networks with Data Augmentation, Gan et al' 2015*

NADE: Neural Autoregressive Density Estimation

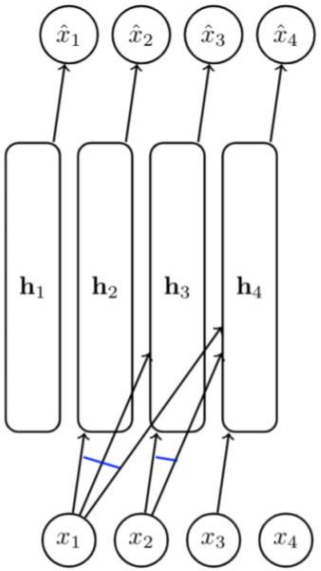
Let's assume data is binary (e.g. MNIST).

The "slightly more neural" parametrization for $p(x_i|x_{<i})$:

$$h_i = \sigma(A_i x_{<i} + c_i)$$

$$p(x_i|x_{<i}) = \sigma\left(\alpha_i^T h_i + b_i\right)$$

One-hidden layer net, sigmoid activation σ



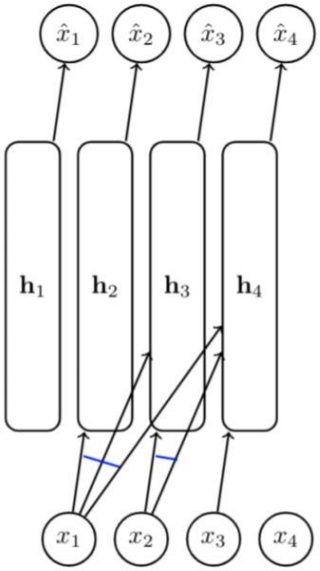
Sampling, training: same as before

NADE: Neural Autoregressive Density Estimation

Weight-tied variants:

$$h_i = \sigma(W_{\cdot,<i}\, x_{<i} + c)$$

$$p(x_i|x_{<i}) = \sigma\left(\alpha_i^T h_i + b_i\right)$$



e.g. $\mathbf{h}_2 = \sigma\left(\underbrace{\begin{pmatrix} \vdots \\ w_1 \\ \vdots \end{pmatrix}}_{A_2} x_1\right)$ $\mathbf{h}_3 = \sigma\left(\underbrace{\begin{pmatrix} \vdots & \vdots \\ w_1 & w_2 \\ \vdots & \vdots \end{pmatrix}}_{A_3} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}\right)$ $\mathbf{h}_4 = \sigma\left(\underbrace{\begin{pmatrix} \vdots & \vdots & \vdots \\ w_1 & w_2 & w_3 \\ \vdots & \vdots & \vdots \end{pmatrix}}_{A_3} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}\right)$

NADE: Neural Autoregressive Density Estimation

Figure from *Learning Deep Sigmoid Belief Networks with Data Augmentation, Gan et al' 2015*

PixelCNN

Convolutional architecture, suitable for more complex image domains.

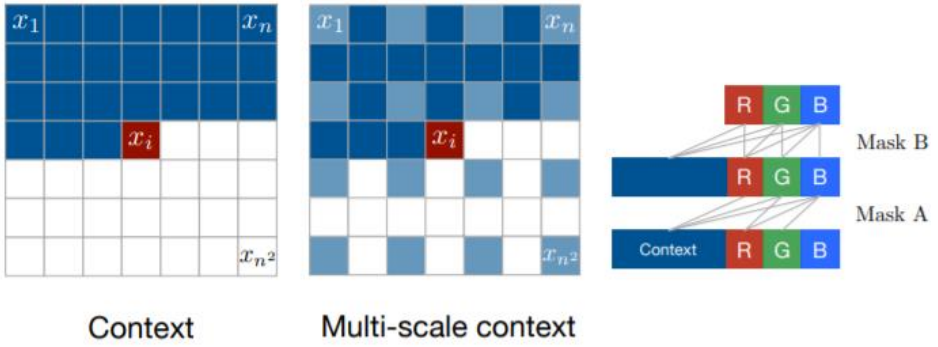


Figure 2. **Left**: To generate pixel x_i one conditions on all the previously generated pixels left and above of x_i. **Center**: To generate a pixel in the multi-scale case we can also condition on the subsampled image pixels (in light blue). **Right**: Diagram of the connectivity inside a masked convolution. In the first layer, each of the RGB channels is connected to previous channels and to the context, but is not connected to itself. In subsequent layers, the channels are also connected to themselves.

Figure from Pixel Recurrent Neural Networks, van den Oord '16

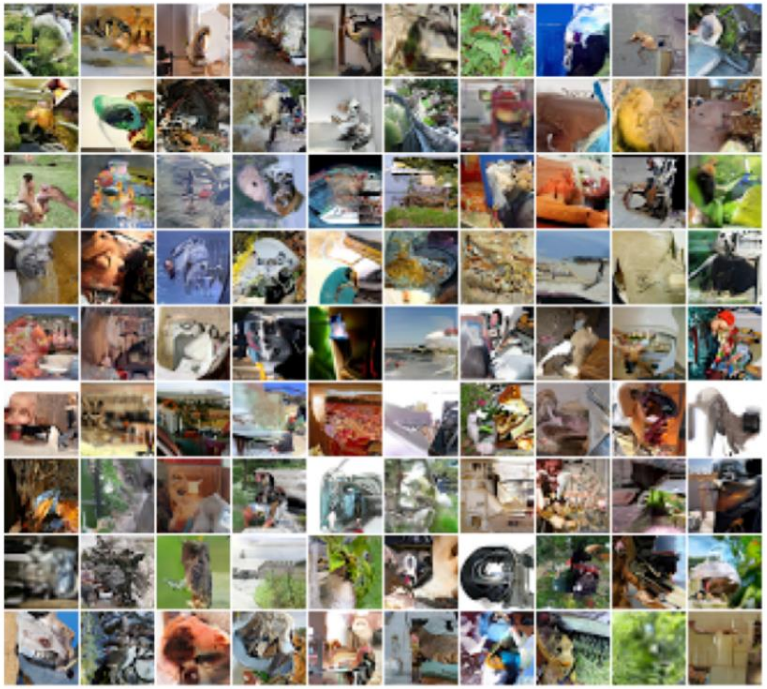
Obvious generalization – only implementation detail: channels are also generated "auto-regressively". $p(x_i|x_{<i})$ is factorized as (Mask A)

$$p(x_{i,R}|\mathbf{x}_{<i})p(x_{i,G}|\mathbf{x}_{<i}, x_{i,R})p(x_{i,B}|\mathbf{x}_{<i}, x_{i,R}, x_{i,G})$$

In upper layers, we use Mask B, in which value of channel can depend on value of same channel below. (This does the correct thing: e.g. G in layer two only depends on R in the input; if we used mask A, G would not depend on current input at all.)

PixelCNN

Figures from Pixel Recurrent Neural Networks, van den Oord ‘16



Recurrent neural networks

The problem with the previous approaches: number of parameters depend on total length.

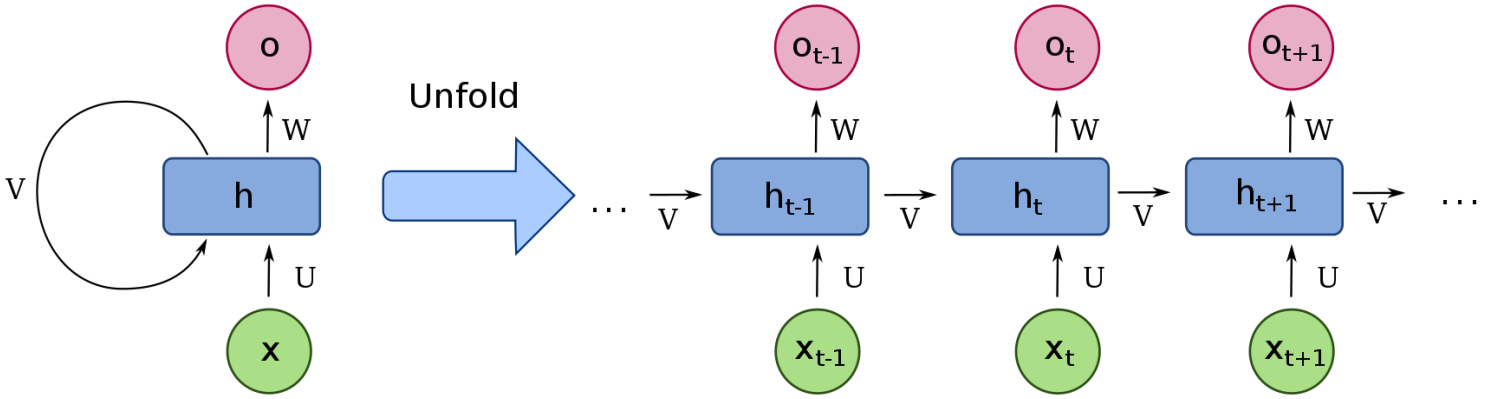
Recurrent neural networks are a way to *weight-tie* the parameters of an autoregressive model, s.t. it can be extended to arbitrary length sequences.

$$h_i = \tanh(W_{hh} h_{i-1} + W_{xh} x_i)$$

$$o_i = W_{ho} h_i$$

o_i specifies parameters for $p(x_i | x_{<i})$, e.g. $\text{softmax}(o_i)$

Recurrent neural networks



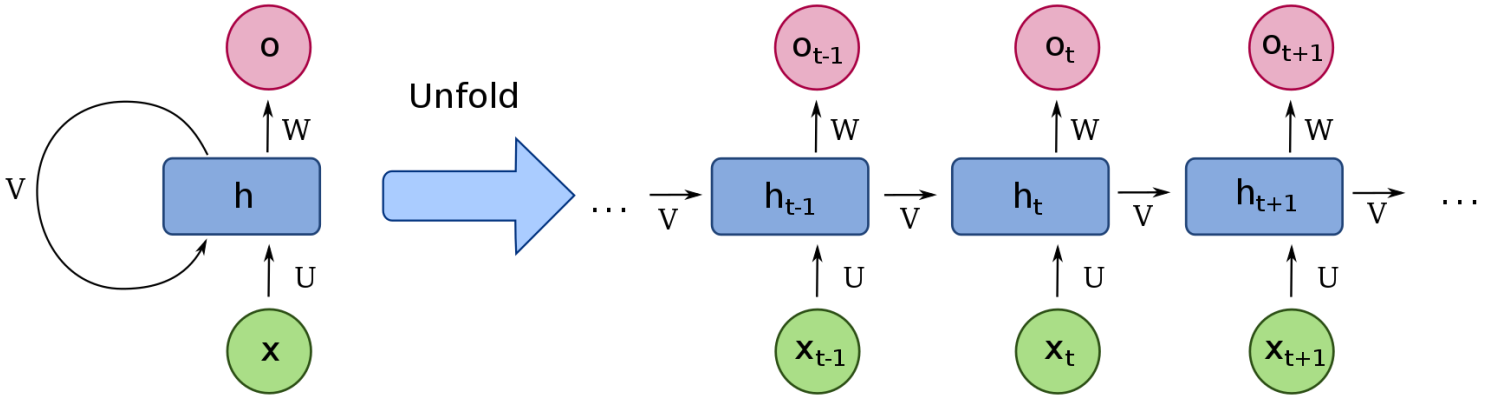
Obvious benefit: copious weight tieing, number of params completely independent of length.

Drawbacks:

Training: backpropagation. Via unfolding equivalence above, same as calculating derivative of a length-t feedforward network.

Same problem as in very deep networks: *gradient explosion/vanishing!*

Recurrent neural networks



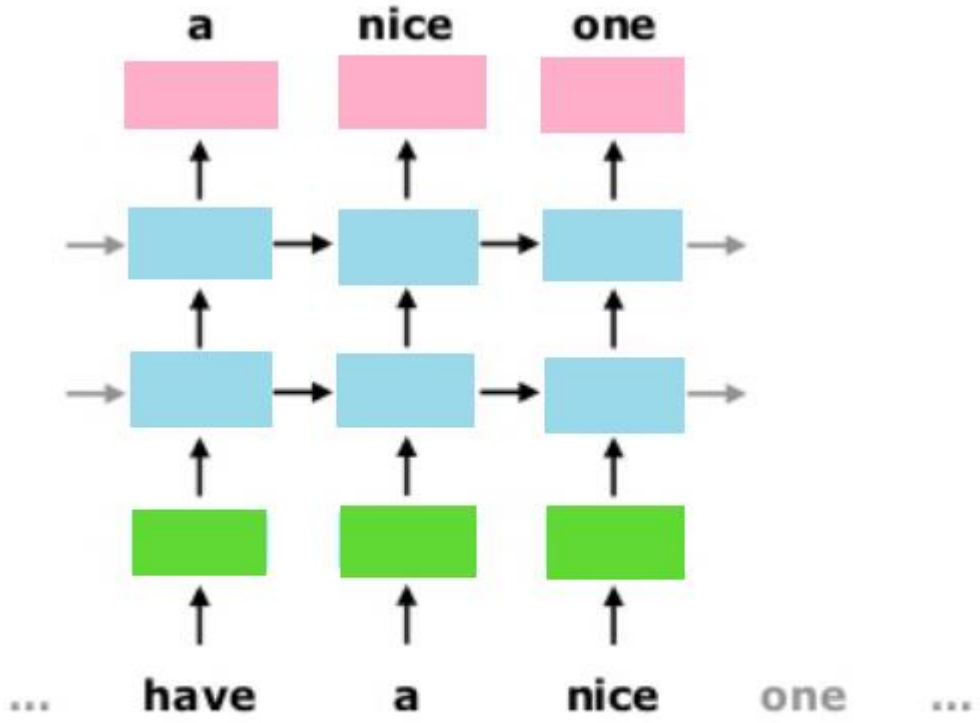
Obvious benefit: copious weight tieing, number of params completely independent of length.

Drawbacks:

Training: *gradient explosion/vanishing!*

Likelihood evaluation: has to be done sequentially (no parallelization)

Recurrent neural networks: stacking multiple RNNs



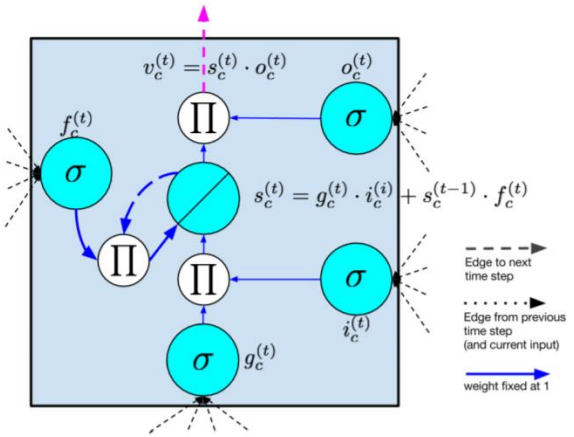
It is quite natural to stack multiple RNNs in the obvious way

LSTM (Long Short-Term Memory)

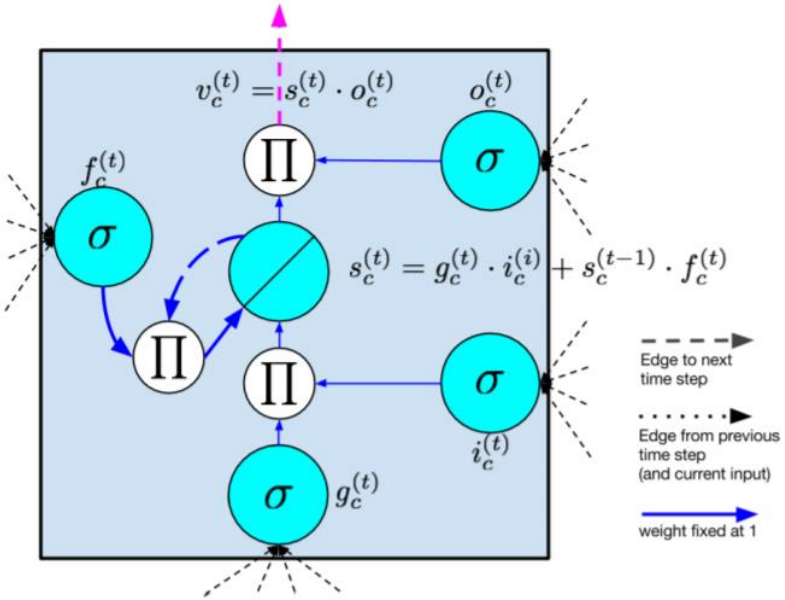
The main issue with training RNN's is long-term dependencies (and correspondingly exploding/vanishing gradients)

The main idea of **LSTM's** (*Hochreiter and Schmidhuber '97*): are gating mechanisms that try to control the flow of information from past.

In practice, they seem to suffer much less from gradient vanishing/explosion. (No good theoretical understanding.)



LSTM (Long Short-Term Memory)



Ingredients:

Input node: $\boldsymbol{g}^{(t)} = \phi(W^{\mathrm{gx}}\boldsymbol{x}^{(t)} + W^{\mathrm{gh}}\boldsymbol{h}^{(t-1)} + \boldsymbol{b}_g)$

Input gate: $\boldsymbol{i}^{(t)} = \sigma(W^{\mathrm{ix}}\boldsymbol{x}^{(t)} + W^{\mathrm{ih}}\boldsymbol{h}^{(t-1)} + \boldsymbol{b}_i)$

Input node will be "gated" by pointwise multiplication with input gate: how input "flows"

Forget gate: $\boldsymbol{f}^{(t)} = \sigma(W^{\mathrm{fx}}\boldsymbol{x}^{(t)} + W^{\mathrm{fh}}\boldsymbol{h}^{(t-1)} + \boldsymbol{b}_f)$

Will gate the "internal state"

Output gate: $\boldsymbol{o}^{(t)} = \sigma(W^{\mathrm{ox}}\boldsymbol{x}^{(t)} + W^{\mathrm{oh}}\boldsymbol{h}^{(t-1)} + \boldsymbol{b}_o)$

How output "flows"

Internal state: $\boldsymbol{s}^{(t)} = \boldsymbol{g}^{(t)} \odot \boldsymbol{i}^{(i)} + \boldsymbol{s}^{(t-1)} \odot \boldsymbol{f}^{(t)}$

Combine gated version of prev. state w/ forget gate, along with gated input node.

Hidden state: $\boldsymbol{h}^{(t)} = \phi(\boldsymbol{s}^{(t)}) \odot \boldsymbol{o}^{(t)}.$

RNN Examples

Example: Character-RNN (Figure from http://karpathy.github.io/2015/05/21/rnn-effectiveness/)

Train 3-layer RNN with 512 hidden nodes on all the works of Shakespeare.
Then sample from the model:

KING LEAR: O, if you were a feeble sight, the courtesy of your law,
Your sight and several breath, will wear the gods
With his heads, and my hands are wonder'd at the deeds,
So drop upon your lordship's head, and your opinion
Shall be against your honour.

RNN Examples

Example: Character-RNN (Figure from http://karpathy.github.io/2015/05/21/rnn-effectiveness/)

Train on Wikipedia. Then sample from the model:

> Naturalism and decision for the majority of Arab countries' capitalide was grounded by the Irish language by [[John Clair]], [[An Imperial Japanese Revolt]], associated with Guangzham's sovereignty. His generals were the powerful ruler of the Portugal in the [[Protestant Immineners]], which could be said to be directly in Cantonese Communication, which followed a ceremony and set inspired prison, training. The emperor travelled back to [[Antioch, Perth, October 25—21]] to note, the Kingdom of Costa Rica, unsuccessful fashioned the [[Thrales]], [[Cynth's Dajoard]], known in western [[Scotland]], near Italy to the conquest of India with the conflict.

RNN Examples

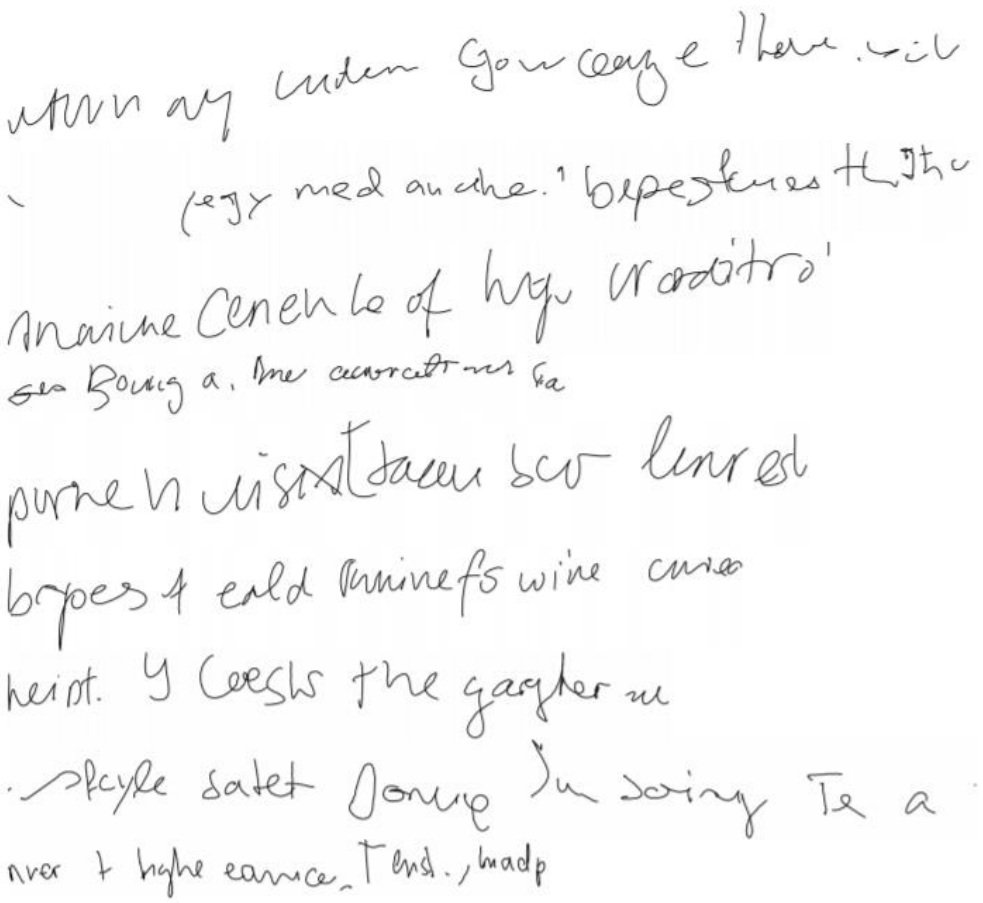


Figure 11: **Online handwriting samples generated by the prediction network.** All samples are 700 timesteps long.

Figure from “Generating Sequences with RNNs”, Graves 2014

Part II:
Self-supervised/predictive learning

Self-supervised/predictive learning

Given unlabeled data, design supervised tasks that induce a good representation for downstream tasks.

No good mathematical formalization, but the intuition is to "force" the predictor used in the task to learn something "semantically meaningful" about the data.

Self-supervised/predictive learning

- Predict any part of the input from any other part.
- Predict the future from the past.
- Predict the future from the recent past.
- Predict the past from the present.
- Predict the top from the bottom.
- Predict the occluded from the visible
- Pretend there is a part of the input you don't know and predict that.

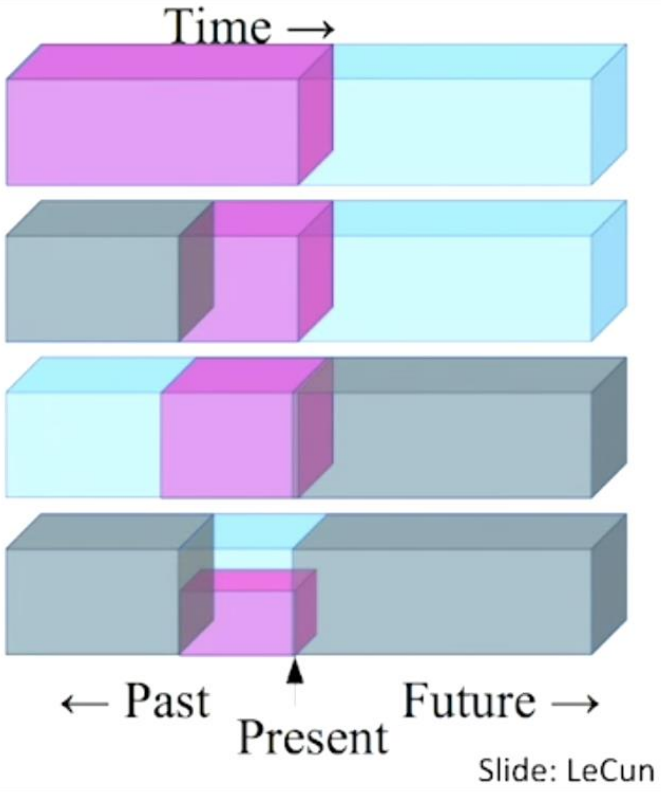


Figure by Yann LeCun

Self-supervised/predictive learning

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

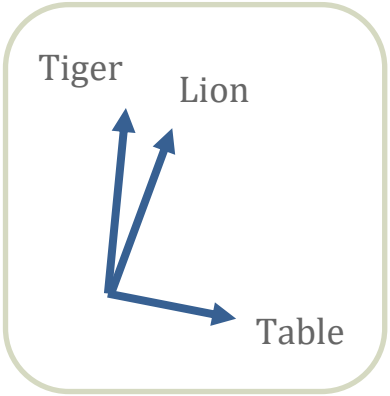
- (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)

Figure by Yann LeCun

Predictive learning in NLP

Word embeddings

Semantically meaningful **vector representations** of words



Example: Inner product (possibly scaled, i.e. cosine similarity) correlates with word similarity.

Word embeddings

Semantically meaningful **vector representations** of words

Example: Can use embeddings to do sentiment classification by training a simple (e.g. linear) classifier

Word embeddings

Semantically meaningful **vector representations** of words

Example: Can train a “simple” network that if fed word embeddings for two languages, can effectively translate.

Word embeddings via predictive learning

Basic task: predict the next word, given a few previous ones.

In other words, optimize for

$$\max_{\theta} \sum_{t} \log \; p_\theta(x_t | x_{t-1}, x_{t-2}, \ldots, x_{t-L})$$

Word embeddings via predictive learning

Basic task: predict the next word, given a few previous ones.

$$\max_{\theta} \sum_{t} \log p_\theta(x_t | x_{t-1}, x_{t-2}, \dots, x_{t-L})$$

Inspired by classical assumptions in NLP that the underlying distribution is Markov – that is, x_t only depends on the previous few words.

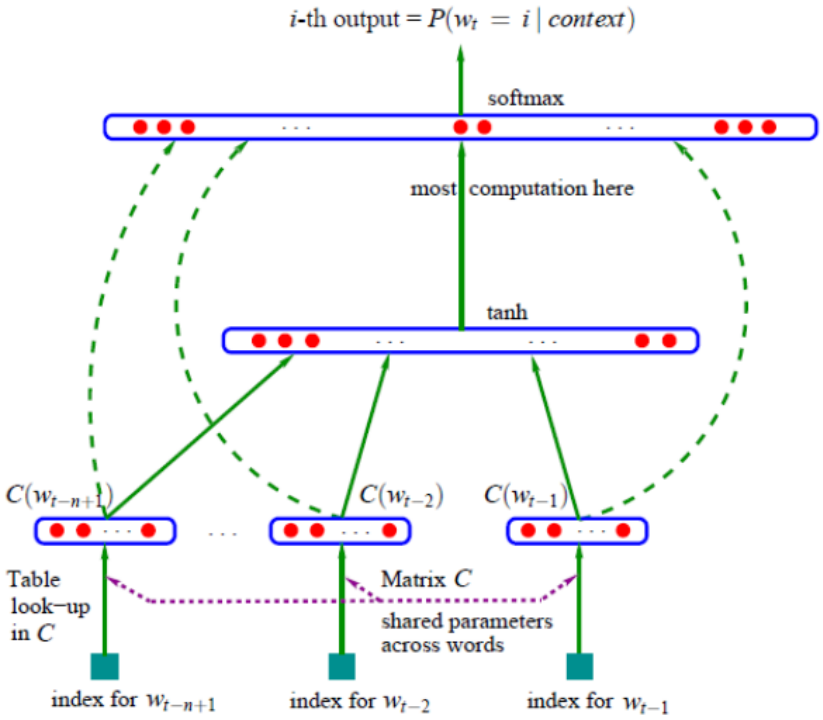
(Of course, this is violated if you wish to model long texts like paragraphs/books.)

The main problem: The trivial way of parametrizing $p_\theta(x_t | x_{t-1}, x_{t-2}, \dots, x_{t-L})$ is a "lookup table" with V^L entries.

Word embeddings via predictive learning

Basic task: predict the next word, given a few previous ones.

$$\max_{\theta} \sum_{t} \log p_{\theta}(x_t | x_{t-1}, x_{t-2}, \ldots, x_{t-L})$$



[*Bengio-Ducharme-Vincent-Janvin '03*]: A neural parametrization of the above probabilities.

Main ingredients:

Embeddings: A word embedding $C(w)$ for all words w in dictionary.

Non-linear transforms: Potentially deep network taking as inputs i, $C(x_{t-1}), C(x_{t-2}), \ldots, C(x_{t-L})$, and outputting some vector o. Can be recurrent net too.

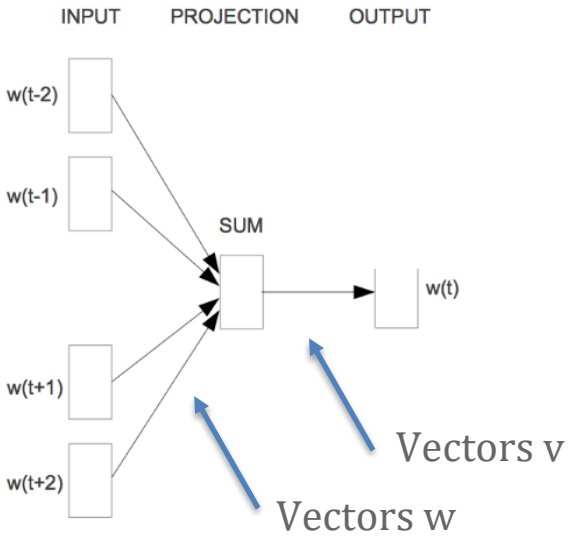
Softmax: Softmax distribution for x_t with parameters given by o.

Word embeddings via predictive learning

Related: predict *middle* word in a sentence, given *surrounding* ones

$$\max_{\theta} \sum_{t} \log p_\theta(x_t | x_{t-L}, \dots, x_{t-1}, x_{t+1}, \dots, x_{t+L})$$

CBOW (Continuous Bag of Words): proposed by *Mikolov et al.* '13



Parametrization is chosen s.t.

$$p_\theta(x_t | x_{t-L}, \dots, x_{t-1}, x_{t+1}, \dots, x_{t+L}) \propto$$

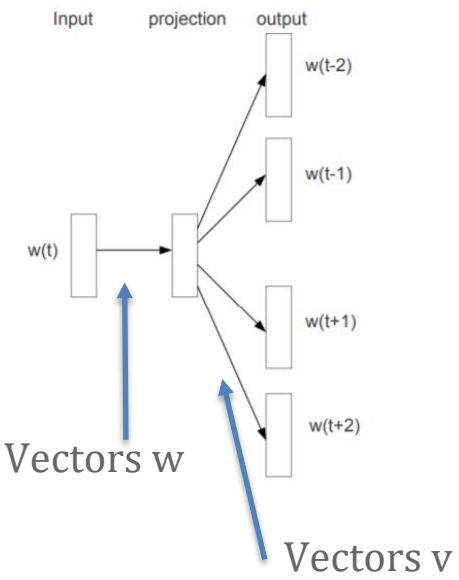
$$\exp\left(v_{x_t}, \sum_{i=t-L}^{t+L} w_{t_i} \right)$$

Word embeddings via predictive learning

Related: predict surrounding words, *given* middle word

$$\max_{\theta} \sum_{t} \sum_{i=t-L, i \neq t}^{t+L} \log \; p_\theta(x_i | x_t)$$

Skip-Gram: (also) proposed by *Mikolov et al.* '13



Parametrization is s.t. $p_\theta(x_i | x_t) \propto \exp\left(v_{x_i}, w_{x_t}\right)$

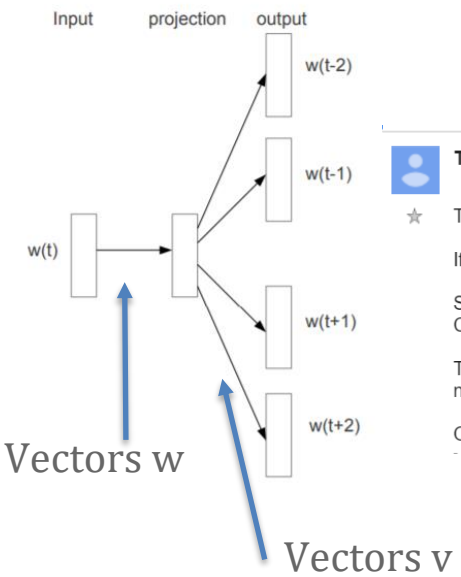
In practice, lots of other tricks are tacked on to deal with the slowest part of training: the softmax distribution (partition function sums over entire vocabulary).
Common ones are *negative sampling, hierarchical softmax*, etc.

Word embeddings via predictive learning

Related: predict surrounding words, *given* middle word

$$\max_{\theta} \sum_{t} \sum_{i=t-L, i \neq t}^{t+L} \log \; p_\theta(x_i | x_t)$$

Skip-Gram: (also) proposed by *Mikolov et al.* '13



Parametrization is s.t. $p_\theta(x_i | x_t) \propto \exp(v_{x_i}, w_{x_t})$

Tomas Mikolov 10/7/13

There are quite a few differences between the skip-gram and the CBOW models. However, if you have a lot of training data, their performance should be comparable.

If you want to see a list of advantages of each model, then my current experience is:

Skip-gram: works well with small amount of the training data, represents well even rare words or phrases
CBOW: several times faster to train than the skip-gram, slightly better accuracy for the frequent words

This can get even a bit more complicated if you consider that there are two different ways how to train the models: the normalized hierarchical softmax, and the un-normalized negative sampling. Both work quite differently.

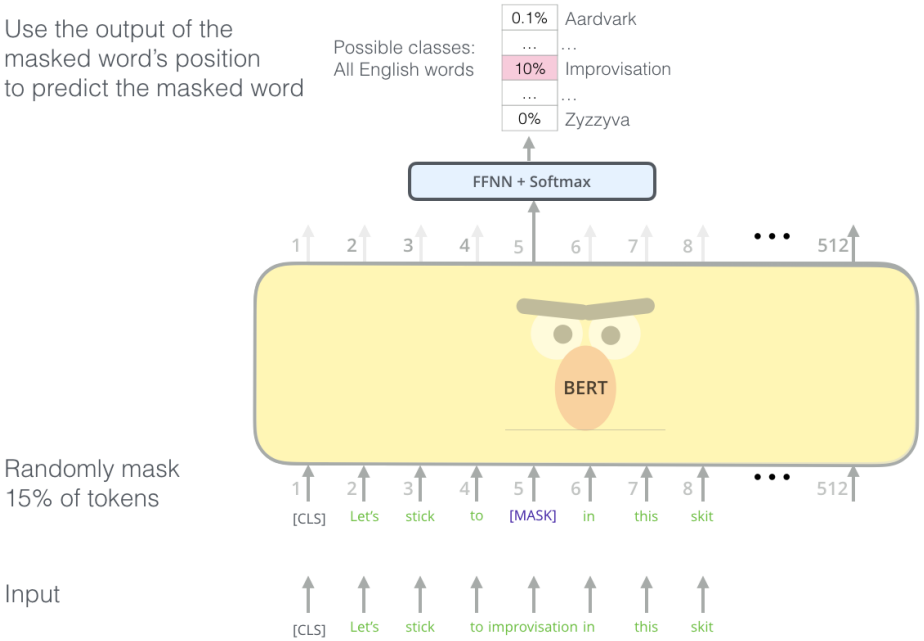
Overall, the best practice is to try few experiments and see what works the best for you, as different applications have different requirements.

- show quoted text -

Word embeddings via predictive learning

Related: predict random *15%* of the words, given the rest

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding, Devlin et al. '18.



Pretty much all-across-the-board best-performing representations for most downstream tasks. (Pre fine-tuning, of course.)

Evaluating word embeddings

First variant (predict next word, given previous ones) can be used as a **generative model** for text. (Also called *language model*.) The other ones cannot.

In former case, a natural measure is the cross-entropy

$$-\mathbb{E}_{x_1,x_2,\ldots,x_T} \log p_\theta(x_{\leq T}) = \mathbb{E}_{x_1,x_2,\ldots,x_T} \sum_t \log\ p_\theta(x_t|x_{<t})$$

For convenience, we often take exponential of this (called *perplexity*)

If we do not have a generative model, we have to use **indirect** means.

Evaluating word embeddings

Intrinsic tasks: Test performance of word embeddings on tasks measuring their "semantic" properties. Examples include solving "which is the most similar word" queries, analogy queries (i.e. "man is to woman as king is to ??"

Extrinsic tasks: How well can we "finetune" the word embeddings to solve some (supervised) downstream task. "Finetune" usually means train a (relatively small) feedforward network. Examples of such tasks include:

Part-of-Speech Tagging (determine whether a word is noun/verb/…), *Named Entity Recognition* (recognizing named entities like persons, places) – e.g. label a sentence as $\text{Picasso}_{[\text{person}]}$ died in $\text{France}_{[\text{country}]}$, many others.

Semantic similarity

Observation: similar words tend to have larger (renormalized) inner products (also called cosine similarity).

Precisely, if we look at the word embeddings for words i,j

$\left\langle \frac{w_i}{||w_i||}, \frac{w_j}{||w_j||} \right\rangle = \cos(w_i, w_j)$ tends to be larger for similar words i,j

Example: the nearest neighbors to "Frog" look like

0. *frog*
1. frogs
2. toad
3. litoria
4. leptodactylidae
5. rana
6. lizard
7. eleutherodactylus

3. litoria

4. leptodactylidae

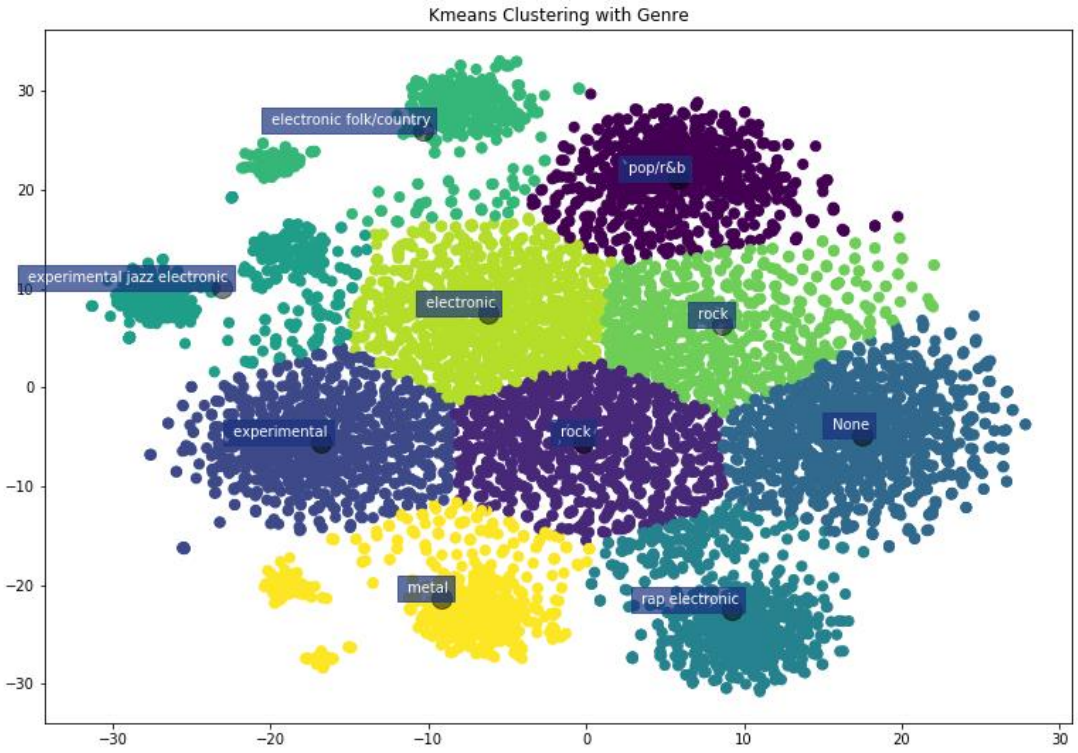
5. rana

7. eleutherodactylus

To solve semantic similarity query like "which is the most similar word to", output the word with the highest cosine similarity.

Semantic clustering

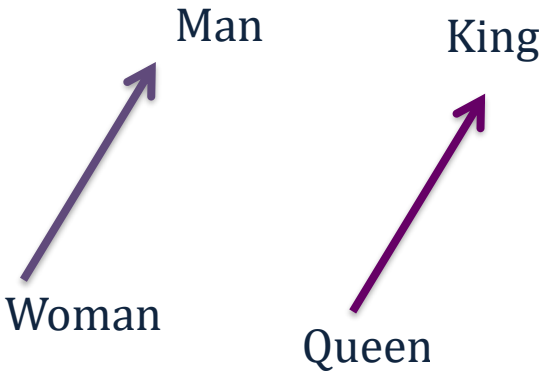
Consequence: clustering word embeddings should give “semantically” relevant clusters.



t-SNE projection of word embeddings for artists (clustered by genre). Image from https://medium.com/free-code-camp/learn-tensorflow-the-word2vec-model-and-the-tsne-algorithm-using-rock-bands-97c99b5dcb3a

Analogies

Observation: You can solve *analogy* queries by linear algebra.



Precisely, w = queen will be the solution to:

$$\text{argmin}_w \|v_w - v_{\text{king}} - (v_{\text{woman}} - v_{\text{man}})\|^2$$

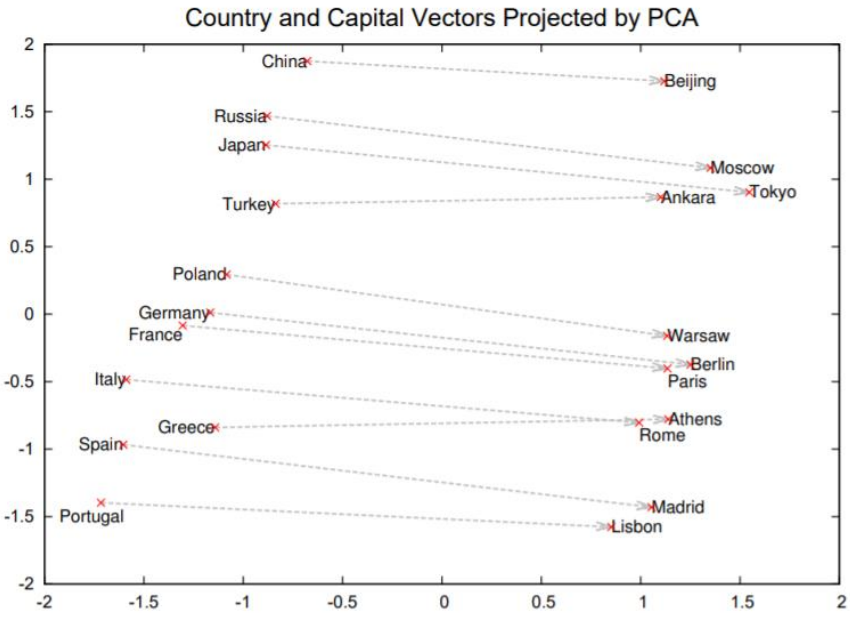


Figure 2: Two-dimensional PCA projection of the 1000-dimensional Skip-gram vectors of countries and their capital cities. The figure illustrates ability of the model to automatically organize concepts and learn implicitly the relationships between them, as during the training we did not provide any supervised information about what a capital city means.

Part II:
Predictive learning in vision

Inpainting

The most obvious analogy to word embeddings: predict parts of image from remainder of image.

Pathak et al. '16: Context Encoders: Feature Learning by Inpainting

(a) Input context (b) Human artist

(c) Context Encoder ($L2$ loss) (d) Context Encoder ($L2$ + Adversarial loss)

Inpainting

The most obvious analogy to word embeddings: predict parts of image from remainder of image.

Pathak et al. '16: Context Encoders: Feature Learning by Inpainting

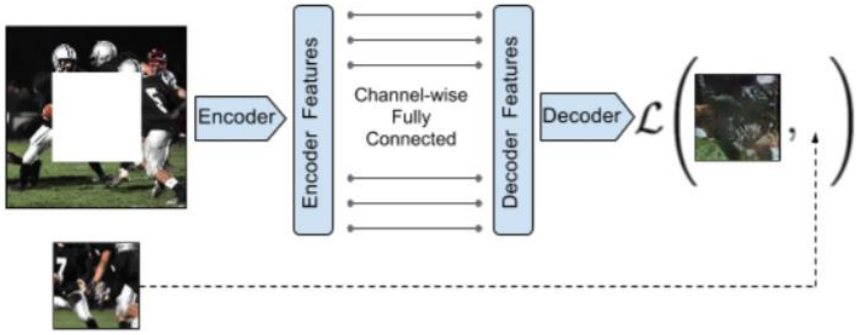


Figure 2: Context Encoder. The context image is passed through the encoder to obtain features which are connected to the decoder using channel-wise fully-connected layer as described in Section 3.1. The decoder then produces the missing regions in the image.

Architecture:
An encoder E takes a part of image, constructs a representation.

A decoder D takes representation, tries to reconstruct missing part.

Much trickier than in NLP:

As we have seen, meaningful losses for vision are much more difficult to design.

Choice of region to mask out is much more impactful.

Inpainting

The most obvious analogy to word embeddings: predict parts of image from remainder of image.

Pathak et al. '16: Context Encoders: Feature Learning by Inpainting

If reconstruction loss is l_2: tendency to produce blurry images.

Remember: one of the usefulness of GANs is to provide a better loss for images.

(c) Context Encoder ($L2$ loss)

(d) Context Encoder ($L2$ + Adversarial loss)

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Pathak et al. '16: Context Encoders: Feature Learning by Inpainting

If reconstruction loss is l_2: tendency to produce blurry images.

Remember: one of the usefulness of GANs is to provide a better loss for images.

Composition of encoder+decoder

Mask

$$\mathcal{L}_{rec}(x) = \|\hat{M} \odot (x - F((1 - \hat{M}) \odot x))\|_2^2,$$

DC-GAN objective

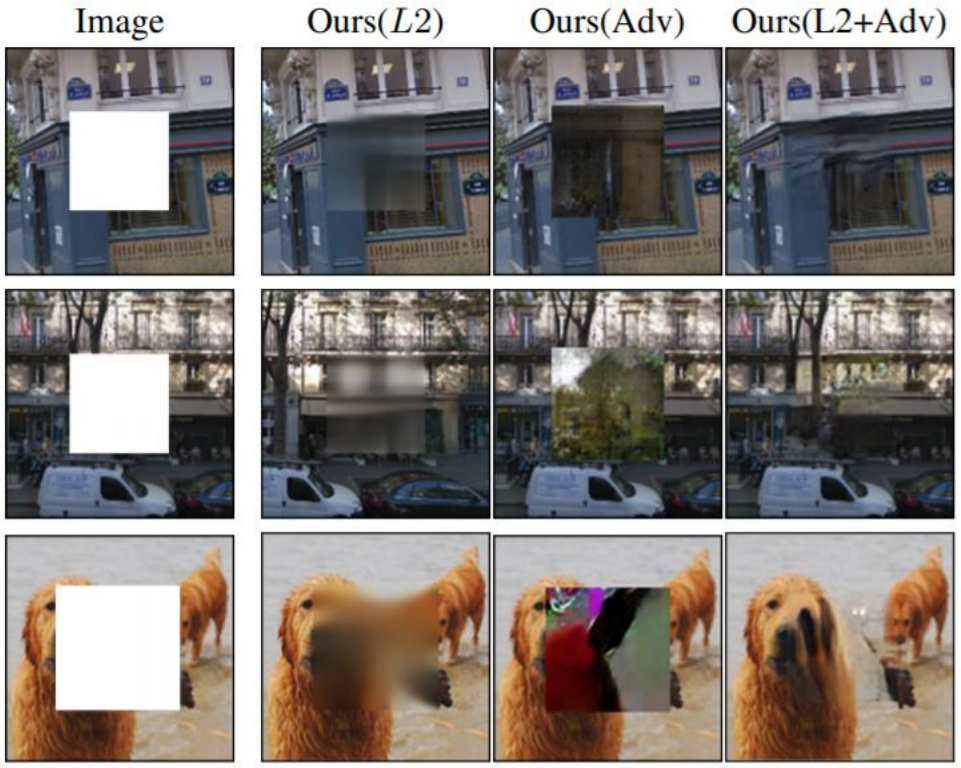
$$\mathcal{L}_{adv} = \max_D \quad \mathbb{E}_{x \in \mathcal{X}}[\log(D(x)) + \log(1 - D(F((1 - \hat{M}) \odot x)))],$$

$$\mathcal{L} = \lambda_{rec}\mathcal{L}_{rec} + \lambda_{adv}\mathcal{L}_{adv}.$$

Inpainting

The most obvious analogy to word embeddings: predict parts of image from remainder of image.

Pathak et al. '16: Context Encoders: Feature Learning by Inpainting



Inpainting

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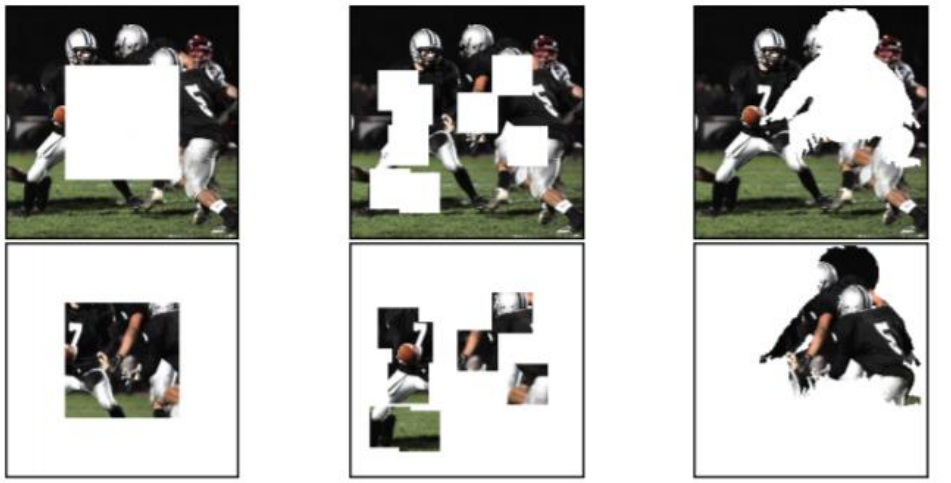
Pathak et al. '16: Context Encoders: Feature Learning by Inpainting

How to choose the region?



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

Figure 3: An example of image x with our different region masks $\hat{M}$ applied, as described in Section 3.3.

Task should be "solvable", but not "too easy".

Fixed (central region): tends to produce less generalizeable representations

Random blocks: slightly better, but square borders still hurt.

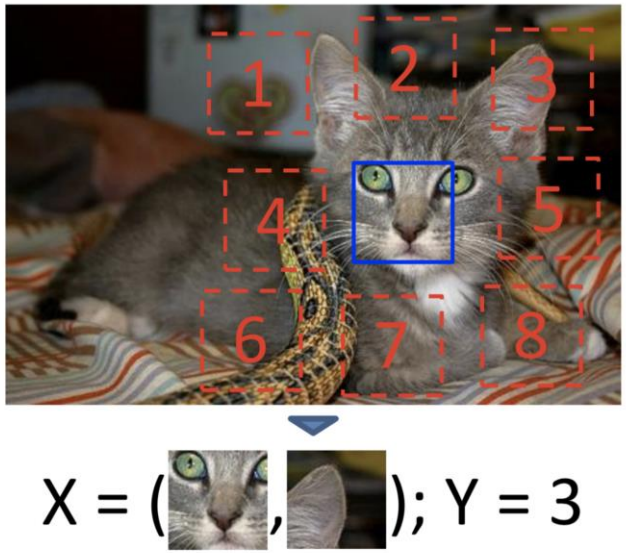
Random silhouette (fully random doesn't make sense – prediction task is too ill-defined) – even better!

Jigsaw puzzles

In principle, what we want is a task "hard enough", that any model that does well on it, should learn something "meaningful" about the task.

Doersch et al. '16: Unsupervised Visual Representation Learning by Context Prediction

Task: Predict ordering of two randomly chosen pieces from the image.



Representation: penultimate layer of a neural net used to solve task.

Intuition: understanding relative positioning of pieces of an image requires some understanding of how images are composed.

Jigsaw puzzles

In principle, what we want is a task "hard enough", that any model that does well on it, should learn something "meaningful" about the task.

Doersch et al. '16: Unsupervised Visual Representation Learning by Context Prediction

Quite finnicky: one needs to make sure the predictor cannot take any obvious "shortcuts".

Boundary texture continuity is a big clue: include gaps in tiles.

Long lines spanning tiles are a clue: jitter location of tiles.

Chromatic aberration (some cameras tend to focus different wavelengths at different position – e.g. green shifts towards center of image): randomly drop 2 of the 3 channels.

Predicting rotations

In principle, what we want is a task "hard enough", that any model that does well on it, should learn something "meaningful" about the task.

Gidaris et al. '18: Unsupervised representation learning via predicting image rotations

Task: predict one of 4 possible rotations of an image.

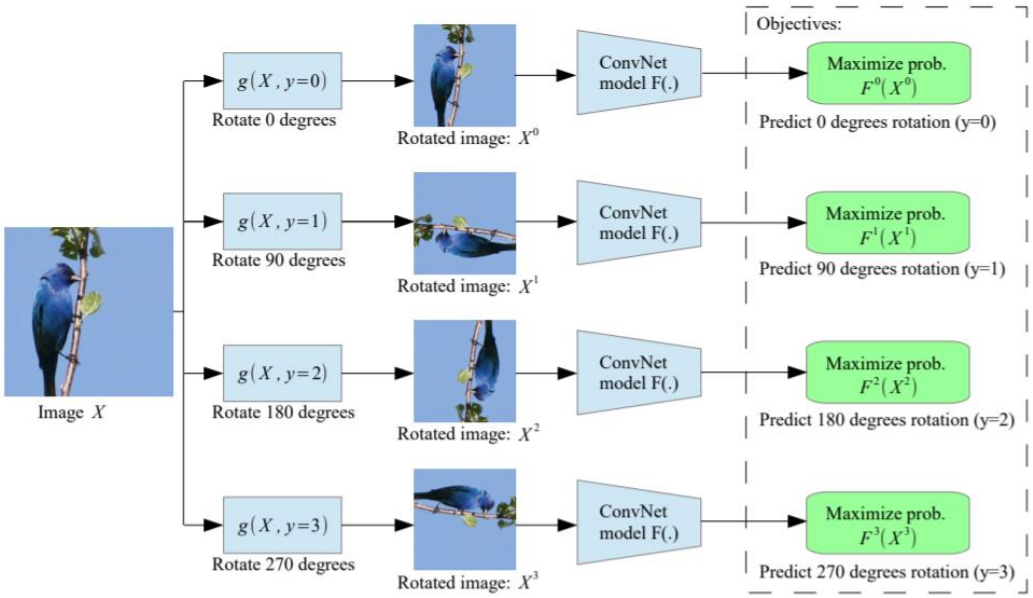


Figure 2: Illustration of the self-supervised task that we propose for semantic feature learning. Given four possible geometric transformations, the 0, 90, 180, and 270 degrees rotations, we train a ConvNet model $F(.)$ to recognize the rotation that is applied to the image that it gets as input. $F^y(X^{y^*})$ is the probability of rotation transformation y predicted by model $F(.)$ when it gets as input an image that has been transformed by the rotation transformation y^*.

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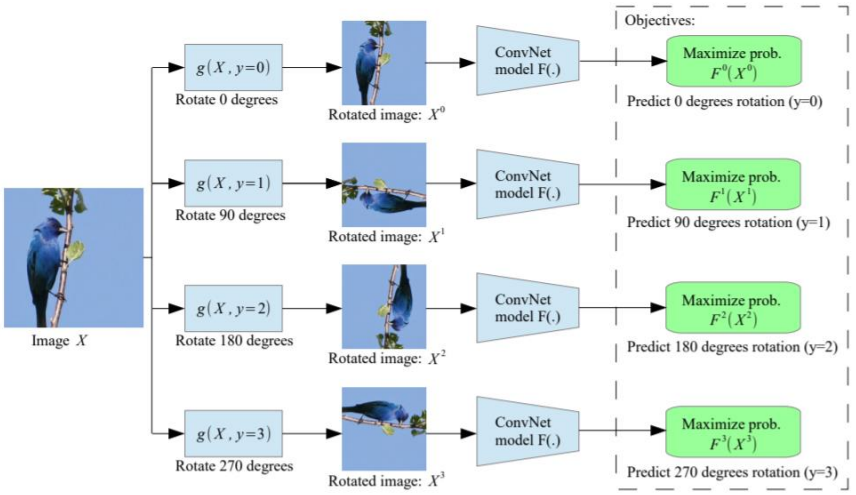

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Representation: penultimate layer of a neural net used to solve task.

Intuition: a rotation is a global transformation. ConvNets are much better at capturing local transformations (as convolutions are local), so there is no obvious way to "cheat".

Predicting rotations

In principle, what we want is a task “hard enough”, that any model that does well on it, should learn something “meaningful” about the task.

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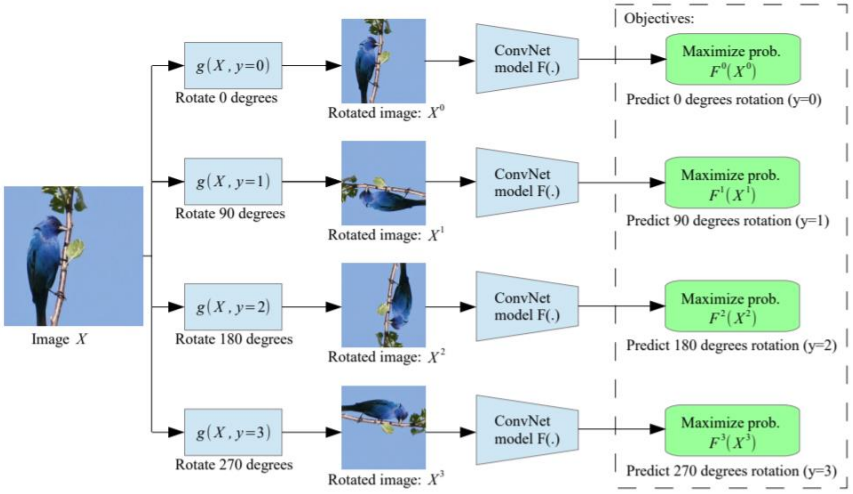

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Less finicky to get right: no obvious artifacts the model can make use of to cheat.
The 90 deg. rotations also don’t introduce any additional artifacts due to discretization.

Contrastive divergence

Another natural idea: if features are “semantically” relevant, a “distortion” of an image should produce similar features. Some instances of distortions:

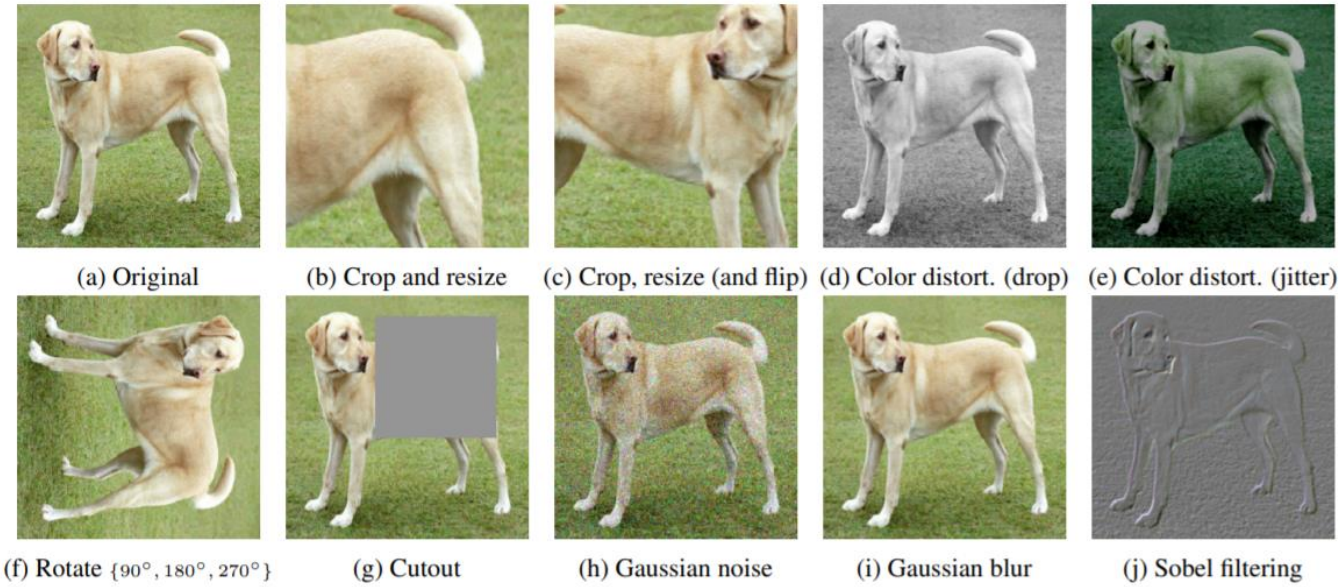


Figure 4. Illustrations of the studied data augmentation operators. Each augmentation can transform data stochastically with some internal parameters (e.g. rotation degree, noise level). Note that we *only* test these operators in ablation, the *augmentation policy used to train our models* only includes *random crop (with flip and resize)*, *color distortion*, and *Gaussian blur*. (Original image cc-by: Von.grzanka)

Contrastive divergence

Another natural idea: if features are "semantically" relevant, a "distortion" of an image should produce similar features. Some instances of distortions:

Contrastive divergence framework:

For every training sample, produce multiple *augmented* samples by applying various transformations.

Train an encoder E (i.e. map that produces features) to predict whether two samples are augmentations of the same base sample.

A common way is to train E to make $\langle E(x), E(x')\rangle$ big if x, x' are two augmentations from same sample, small otherwise, e.g.

$$l_{x,x'} = -\log\left(\frac{\exp(\tau\langle E(x), E(x')\rangle}{\sum_{x,x'}\exp(\tau\langle E(x), E(x')\rangle)}\right)$$

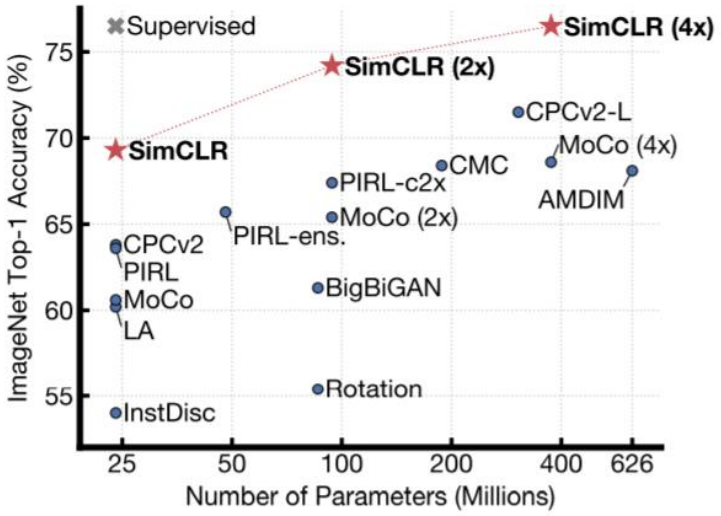
$$\min \sum_{x,x' \text{ augments of each other}} l_{x,x'}$$

Contrastive divergence

Another natural idea: if features are "semantically" relevant, a "distortion" of an image should produce similar features. Some instances of distortions:

Many works follow this framework, starting with Oord '18: Representation Learning with Contrastive Predictive Learning.

Current state of the art for self-supervised learning is in fact using this framework: *Chen, Kornblith, Norouizi, Hinton '20: A Simple Framework for Contrastive Learning of Visual Representations*



Several tricks needed to gain this improvement.

Most important one seems to be that augmentations that work best are compositions of a geometric one (e.g. crop/rotation/..) and an appearance one (color distortion/blur/..)

Troubling fact: architecture of classifier matters

Kolesnikov et al. '19: Revisiting Self-Supervised Visual Representation Learning

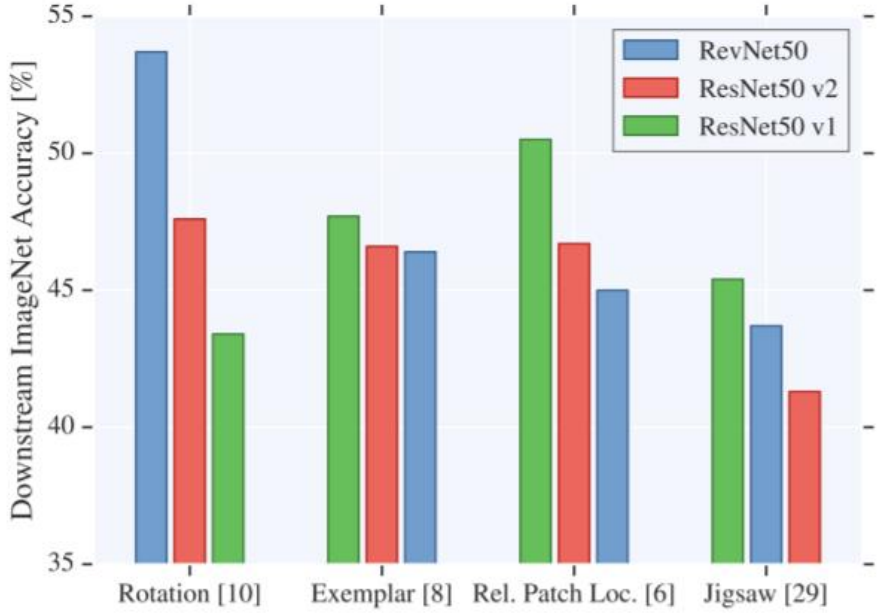


Figure 1. Quality of visual representations learned by various self-supervised learning techniques significantly depends on the convolutional neural network architecture that was used for solving the self-supervised learning task. In our paper we provide a large scale in-depth study in support of this observation and discuss its implications for evaluation of self-supervised models.

Troubling fact: architecture of classifier matters

Kolesnikov et al. '19: Revisiting Self-Supervised Visual Representation Learning

Table 1. Evaluation of representations from self-supervised techniques based on various CNN architectures. The scores are accuracies (in %) of a linear logistic regression model trained on top of these representations using *ImageNet* training split. Our validation split is used for computing accuracies. The architectures marked by a "(-)" are slight variations described in Section 3.1. Sub-columns such as 4× correspond to widening factors. Top-performing architectures in a column are bold; the best pretext task for each model is underlined.

Model	Rotation				Exemplar			RelPatchLoc		Jigsaw	
	4×	8×	12×	16×	4×	8×	12×	4×	8×	4×	8×
RevNet50	**47.3**	**50.4**	**53.1**	**53.7**	**42.4**	45.6	46.4	40.6	45.0	40.1	43.7
ResNet50 v2	43.8	47.5	47.2	47.6	**43.0**	45.7	46.6	42.2	46.7	38.4	41.3
ResNet50 v1	41.7	43.4	43.3	43.2	**42.8**	**46.9**	**47.7**	**46.8**	**50.5**	**42.2**	**45.4**
RevNet50 (-)	45.2	**51.0**	**52.8**	**53.7**	38.0	42.6	44.3	33.8	43.5	36.1	41.5
ResNet50 v2 (-)	38.6	44.5	47.3	48.2	33.7	36.7	38.2	38.6	43.4	32.5	34.4
VGG19-BN	16.8	14.6	16.6	22.7	26.4	28.3	29.0	28.5	29.4	19.8	21.1