CS 1699: Deep Learning

Advanced and Recent Topics

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April 2, 2020

Plan for this lecture

- Alternative representations
  - I. Graph networks (pp 3-22)
- Alternative learning mechanisms
  - II. Self supervision (pp 23-63)
  - III. Reinforcement learning (pp 64-101)
- Alternative tasks
  - IV. Generation (pp 102-190)
- V. Bias and ethics (pp 191-256)

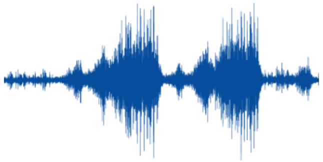
Part I: Graph Networks

- Types of graph networks
  - Graph convolutional networks
  - Graph attention networks
- Applications
  - Semi-supervised learning
  - Visual question answering

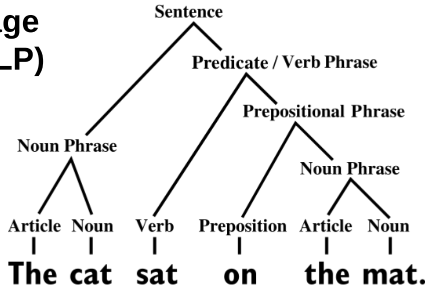
Types of data typically handled with Deep Learning

IMAGENET

Speech data



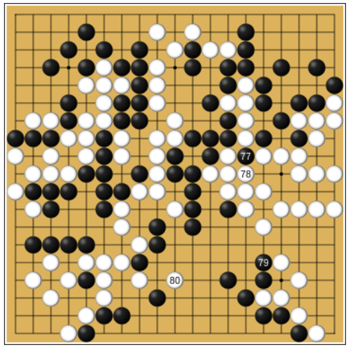
Natural language processing (NLP)



Sentence
Predicate / Verb Phrase
Prepositional Phrase
Noun Phrase
Noun Phrase
Article Noun Verb Preposition Article Noun
The cat sat on the mat.

…

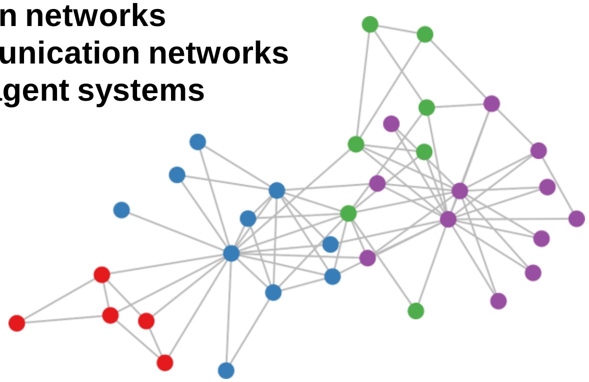
Grid games

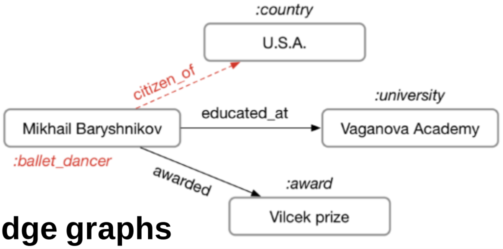


Graph-structured data

A lot of real-world data does not “live” on grids

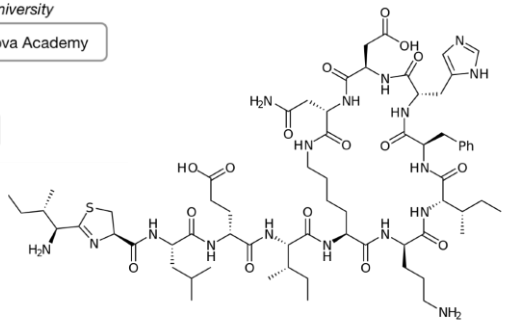
Social networks
Citation networks
Communication networks
Multi-agent systems



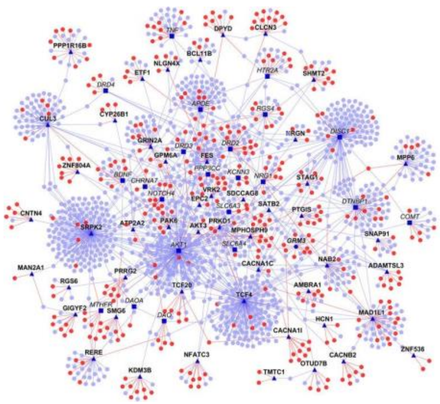


:country
U.S.A.
citizen_of
Mikhail Baryshnikov
:ballet_dancer
educated_at
:university
Vaganova Academy
awarded
:award
Vilcek prize

Knowledge graphs



Molecules



Protein interaction networks

Standard deep learning architectures like CNNs and RNNs don’t work here!

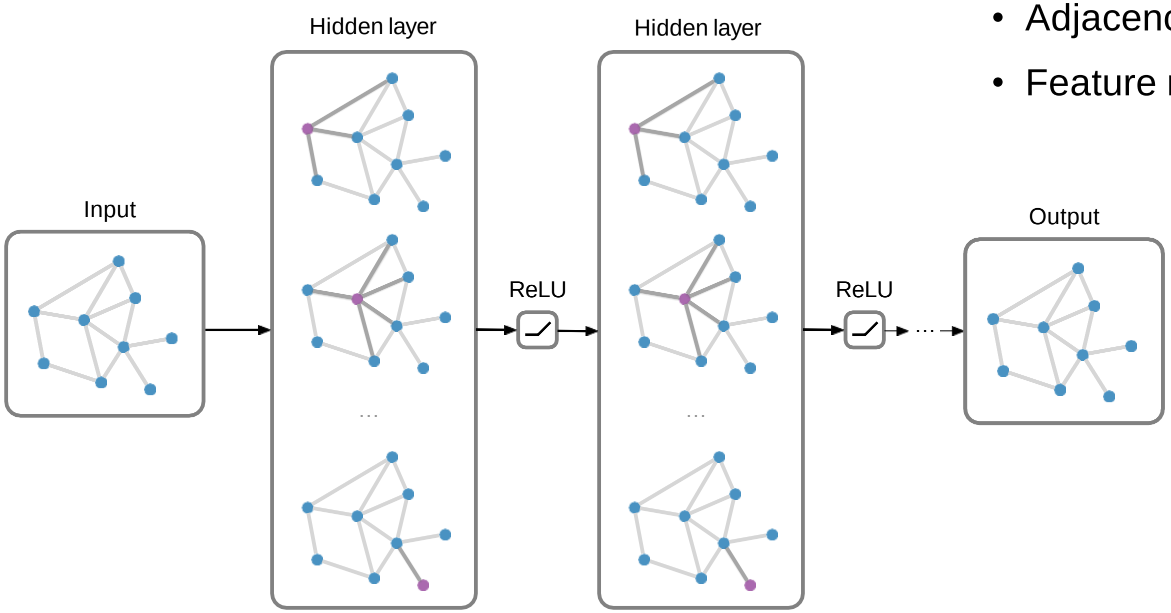
Road maps

Graph Neural Networks (GNNs)

The bigger picture:

Notation: $G = (\mathbf{A}, \mathbf{X})$

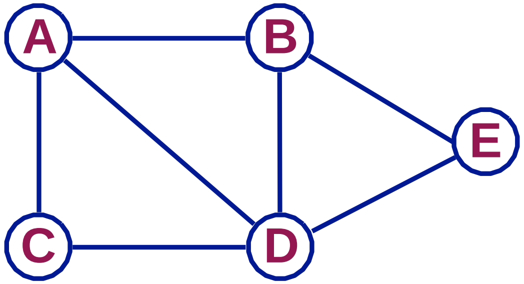
- Adjacency matrix $\mathbf{A}$ $\mathrm{R}^{N \rightarrow N}$
- Feature matrix $\mathbf{X}$ $\mathrm{R}^{N \rightarrow F}$



Main idea: Pass messages between pairs of nodes & agglomerate

Graph convolutional networks

Graph: $G = (\mathcal{V}, \mathcal{E})$



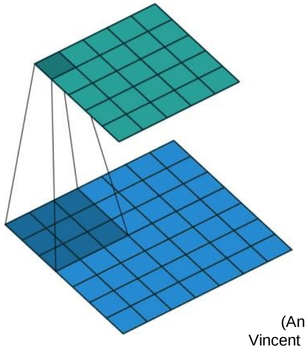
Adjacency matrix: A

$$\begin{array}{cc} & \begin{array}{ccccc} A & B & C & D & E \end{array} \\ \begin{array}{c} A \\ B \\ C \\ D \\ E \end{array} & \begin{pmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \end{pmatrix} \end{array}$$

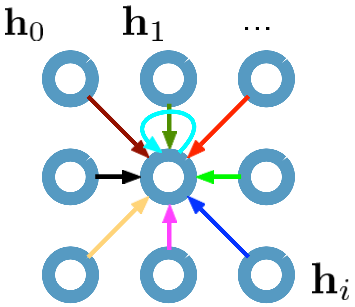
Kipf and Welling, “Semi-supervised learning with deep generative models”, ICLR 2017 (slides by Thomas Kipf)

Recap: Convolutional neural networks (on grids)

Single CNN layer with 3x3 filter:



(Animation by Vincent Dumoulin)



Update for a single pixel:

- Transform messages individually $\mathbf{W}_i\mathbf{h}_i$
- Add everything up $\sum_i \mathbf{W}_i\mathbf{h}_i$

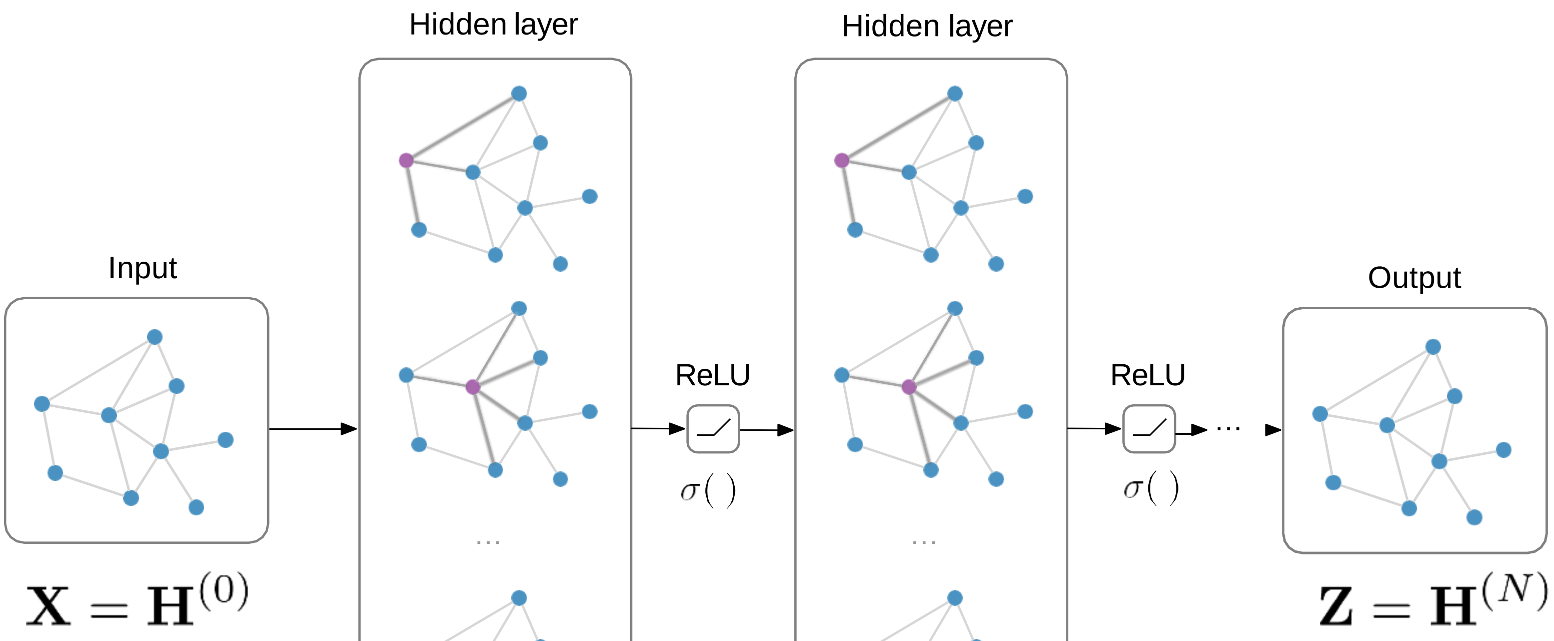
$\mathbf{h}_i$ *in* R^F are (hidden layer) activations of a pixel/node

Full update:

$$\mathbf{h}_4^{(l+1)} = \sigma\left(\mathbf{W}_0^{(l)}\mathbf{h}_0^{(l)} + \mathbf{W}_1^{(l)}\mathbf{h}_1^{(l)} + \cdots + \mathbf{W}_8^{(l)}\mathbf{h}_8^{(l)}\right)$$

Graph convolutional networks

Input: Feature matrix $\mathbf{X} \in \mathbb{R}^{N \times E}$, preprocessed adjacency matrix $\hat{\mathbf{A}}$



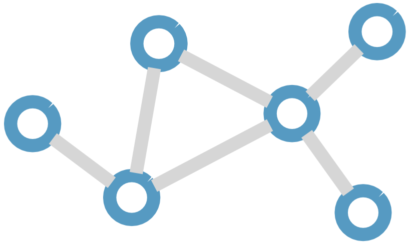
$$\mathbf{H}^{(l+1)} = \sigma\left(\hat{\mathbf{A}}\mathbf{H}^{(l)}\mathbf{W}^{(l)}\right)$$

Kipf and Welling, “Semi-supervised learning with deep generative models”, ICLR 2017 (slides by Thomas Kipf)

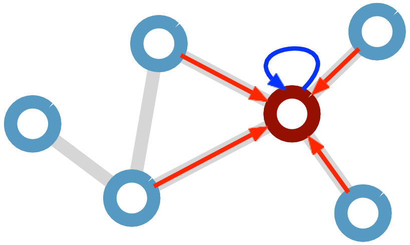
Graph convolutional networks (GCNs)

Kipf & Welling (ICLR 2017), related previous works by Duvenaud et al. (NIPS 2015) and Li et al. (ICLR 2016)

Consider this undirected graph:



Calculate update for node in red:



Update rule:

$$\mathbf{h}_i^{(l+1)} = \sigma\left(\mathbf{h}_i^{(l)}\mathbf{W}_0^{(l)} + \sum_{j\in\mathcal{N}_i}\frac{1}{c_{ij}}\mathbf{h}_j^{(l)}\mathbf{W}_1^{(l)}\right)$$

Scalability: subsample messages [Hamilton et al., NIPS 2017]

$\mathcal{N}_i$: neighbor indices

c_{ij} : norm. constant (fixed/trainable)

Alternatives

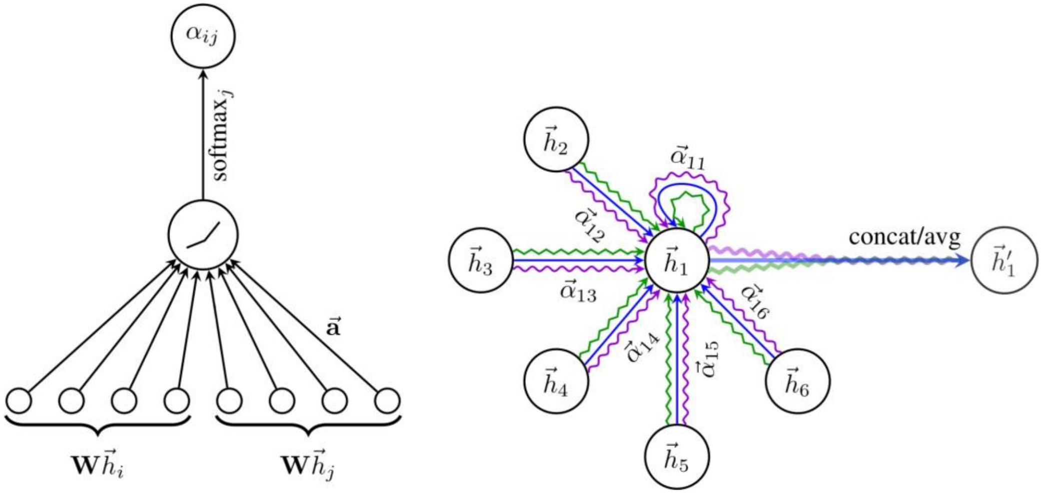
How else can we propagate information over a graph?

How can we improve the propagation using ideas from RNNs?

From CNNs?

Graph neural networks with attention

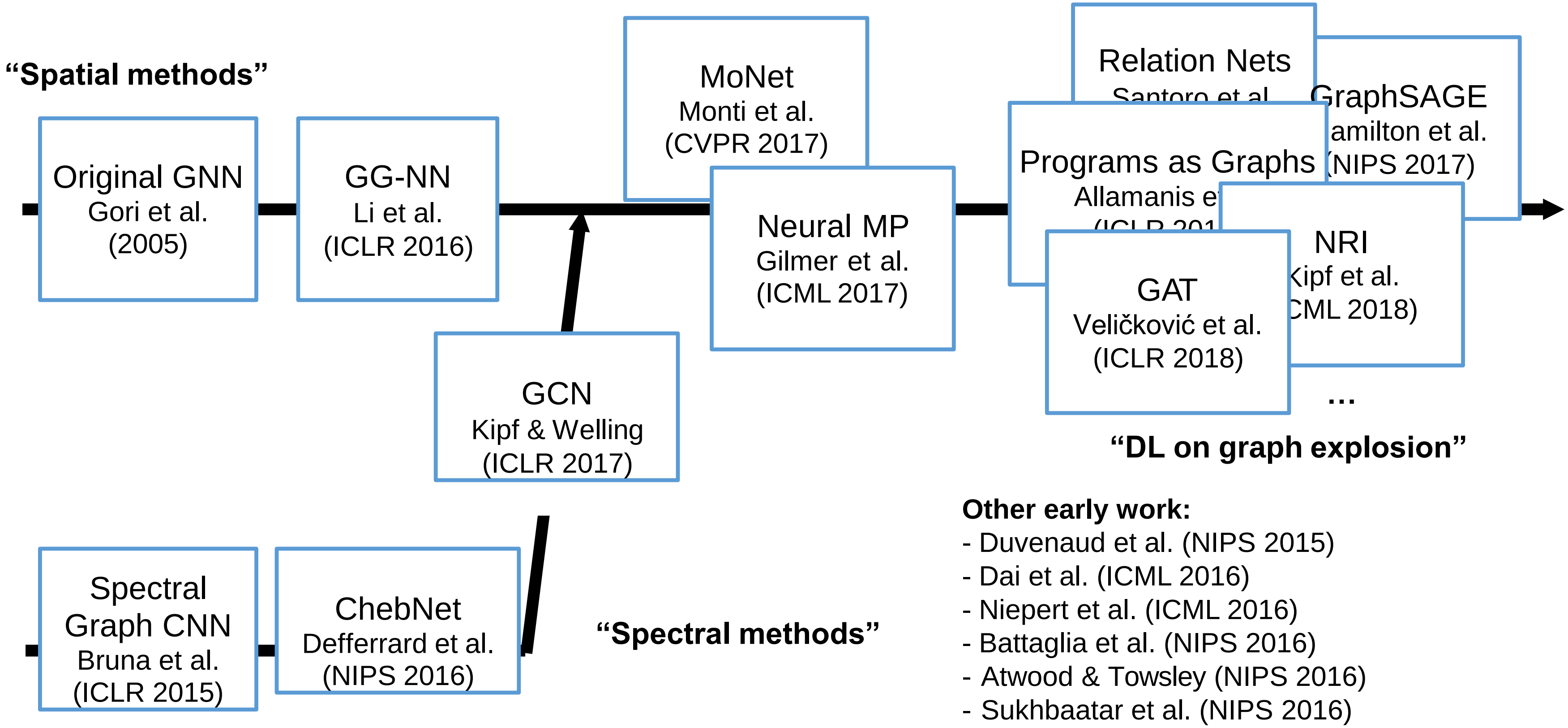
Monti et al. (CVPR 2017), Hoshen (NIPS 2017), Veličković et al. (ICLR 2018)



[Figure from Veličković et al. (ICLR 2018)]

$$\vec{h}'_i = \sigma\left(\frac{1}{K}\sum_{k=1}^{K}\sum_{j\in\mathcal{N}_i}\alpha_{ij}^{k}\mathbf{W}^{k}\vec{h}_j\right) \qquad \alpha_{ij} = \frac{\exp\left(\text{LeakyReLU}\left(\vec{\mathbf{a}}^{T}[\mathbf{W}\vec{h}_i \| \mathbf{W}\vec{h}_j]\right)\right)}{\sum_{k\in\mathcal{N}_i}\exp\left(\text{LeakyReLU}\left(\vec{\mathbf{a}}^{T}[\mathbf{W}\vec{h}_i \| \mathbf{W}\vec{h}_k]\right)\right)}$$

A brief history of graph neural nets



“Spatial methods”

Original GNN
Gori et al.
(2005)

GG-NN
Li et al.
(ICLR 2016)

MoNet
Monti et al.
(CVPR 2017)

Neural MP
Gilmer et al.
(ICML 2017)

GCN
Kipf & Welling
(ICLR 2017)

Relation Nets
Santoro et al.

GraphSAGE
amilton et al.
(NIPS 2017)

Programs as Graphs
Allamanis e
(ICLR 201

NRI
Kipf et al.
CML 2018)

GAT
Veličković et al.
(ICLR 2018)

...

“DL on graph explosion”

Spectral
Graph CNN
Bruna et al.
(ICLR 2015)

ChebNet
Defferrard et al.
(NIPS 2016)

“Spectral methods”

Other early work:

- Duvenaud et al. (NIPS 2015)
- Dai et al. (ICML 2016)
- Niepert et al. (ICML 2016)
- Battaglia et al. (NIPS 2016)
- Atwood & Towsley (NIPS 2016)
- Sukhbaatar et al. (NIPS 2016)

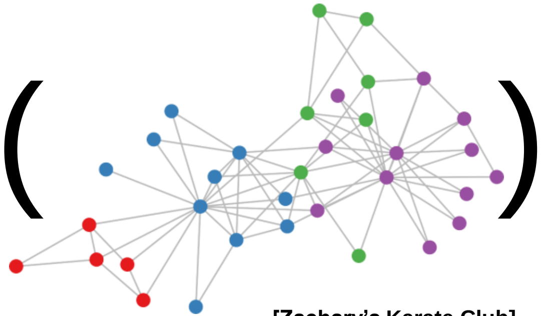
(slide inspired by Alexander Gaunt’s talk on GNNs)

What do learned representations look like?

Forward pass through **untrained** 3-layer GCN model

Parameters initialized randomly

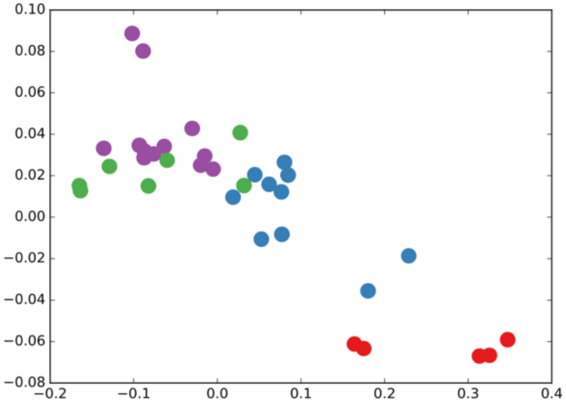
f(



[Zachary's Karate Club]

) =

2-dim output per node



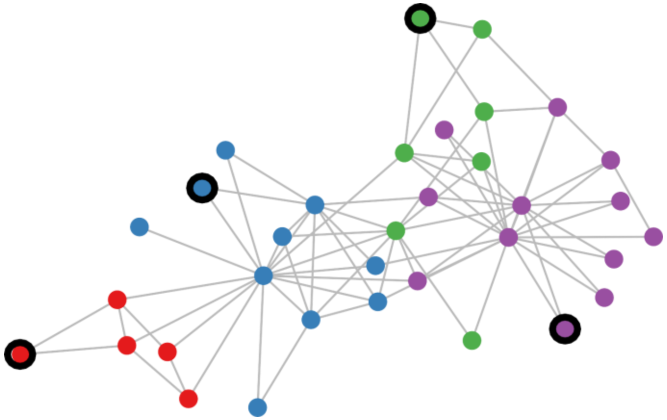
What else are graph representations good for?

Semi-supervised classification on graphs

Setting:

Some nodes are labeled (black circle)
All other nodes are unlabeled

Task:
Predict node label of unlabeled nodes



Evaluate loss on labeled nodes only:

$$\mathcal{L} = -\sum_{l \in \mathcal{Y}_L} \sum_{f=1}^{F} Y_{lf} \ln Z_{lf}$$

$\mathcal{Y}_L$ set of labeled node

$\mathbf{Y}$ indices label matrix

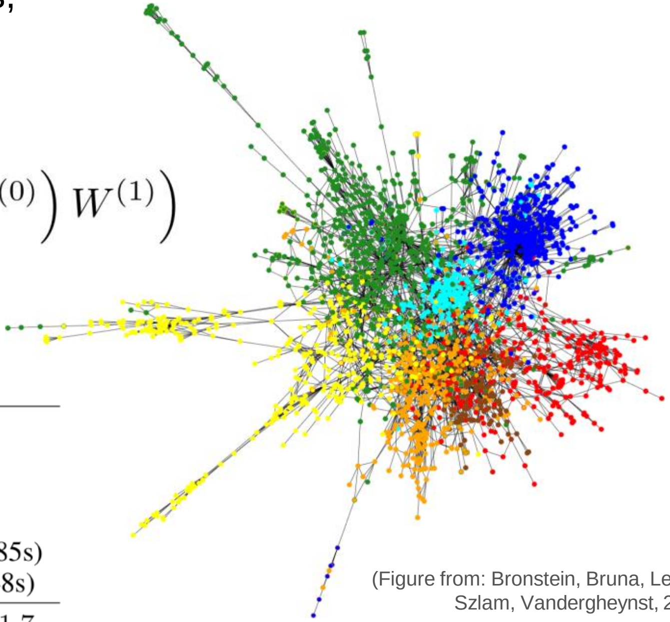
$\mathbf{Z}$ GCN output (after softmax)

Application: Classification on citation networks

Input: Citation networks (nodes are papers, edges are citation links, optionally bag-of-words features on nodes)

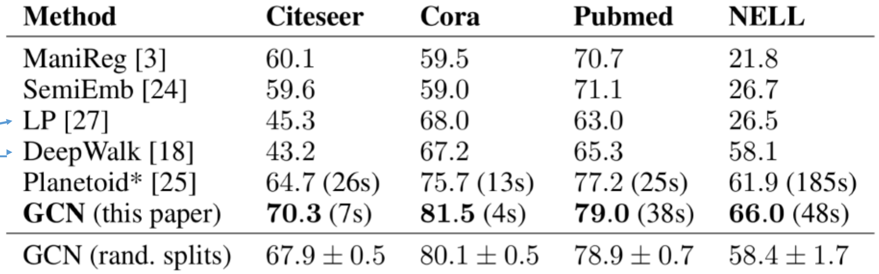
Target: Paper category (e.g. stat.ML, cs.LG, …)

Model: 2-layer GCN $$Z = f(X, A) = \mathrm{softmax}\Big(\hat{A}\ \mathrm{ReLU}\Big(\hat{A}XW^{(0)}\Big)\, W^{(1)}\Big)$$



(Figure from: Bronstein, Bruna, LeCun, Szlam, Vandergheynst, 2016)

Classification results (accuracy)



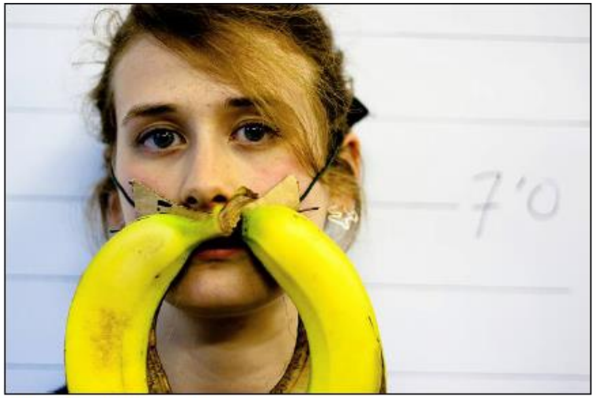
Method	Citeseer	Cora	Pubmed	NELL
ManiReg [3]	60.1	59.5	70.7	21.8
SemiEmb [24]	59.6	59.0	71.1	26.7
LP [27]	45.3	68.0	63.0	26.5
DeepWalk [18]	43.2	67.2	65.3	58.1
Planetoid* [25]	64.7 (26s)	75.7 (13s)	77.2 (25s)	61.9 (185s)
GCN (this paper)	**70.3** (7s)	**81.5** (4s)	**79.0** (38s)	**66.0** (48s)
GCN (rand. splits)	67.9 ± 0.5	80.1 ± 0.5	78.9 ± 0.7	58.4 ± 1.7

no input features

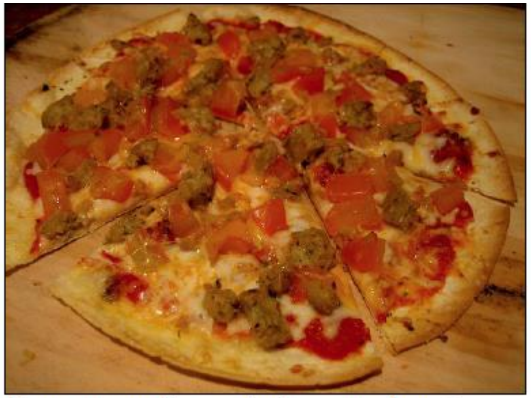
Kipf & Welling, Semi-Supervised Classification with Graph Convolutional Networks, ICLR 2017

Visual Question Answering (VQA)

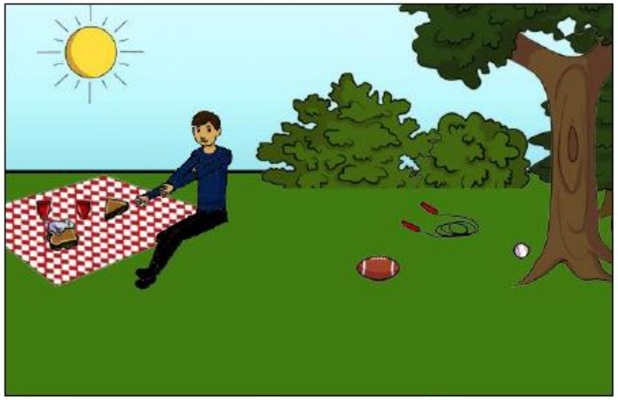
Task: Given an image and a natural language open-ended question, generate a natural language answer.



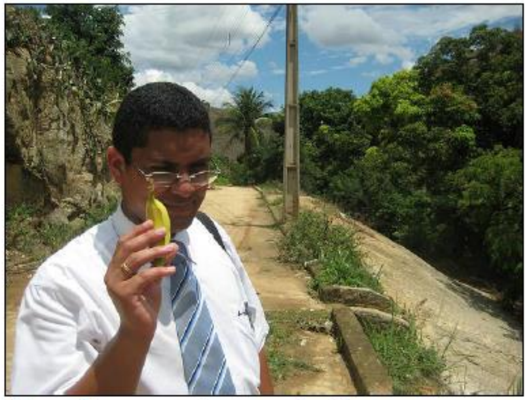
What color are her eyes?
What is the mustache made of?



How many slices of pizza are there?
Is this a vegetarian pizza?



Is this person expecting company?
What is just under the tree?



Does it appear to be rainy?
Does this person have 20/20 vision?

Agrawal et al., "VQA: Visual Question Answering", ICCV 2015

Visual Question Answering (VQA)

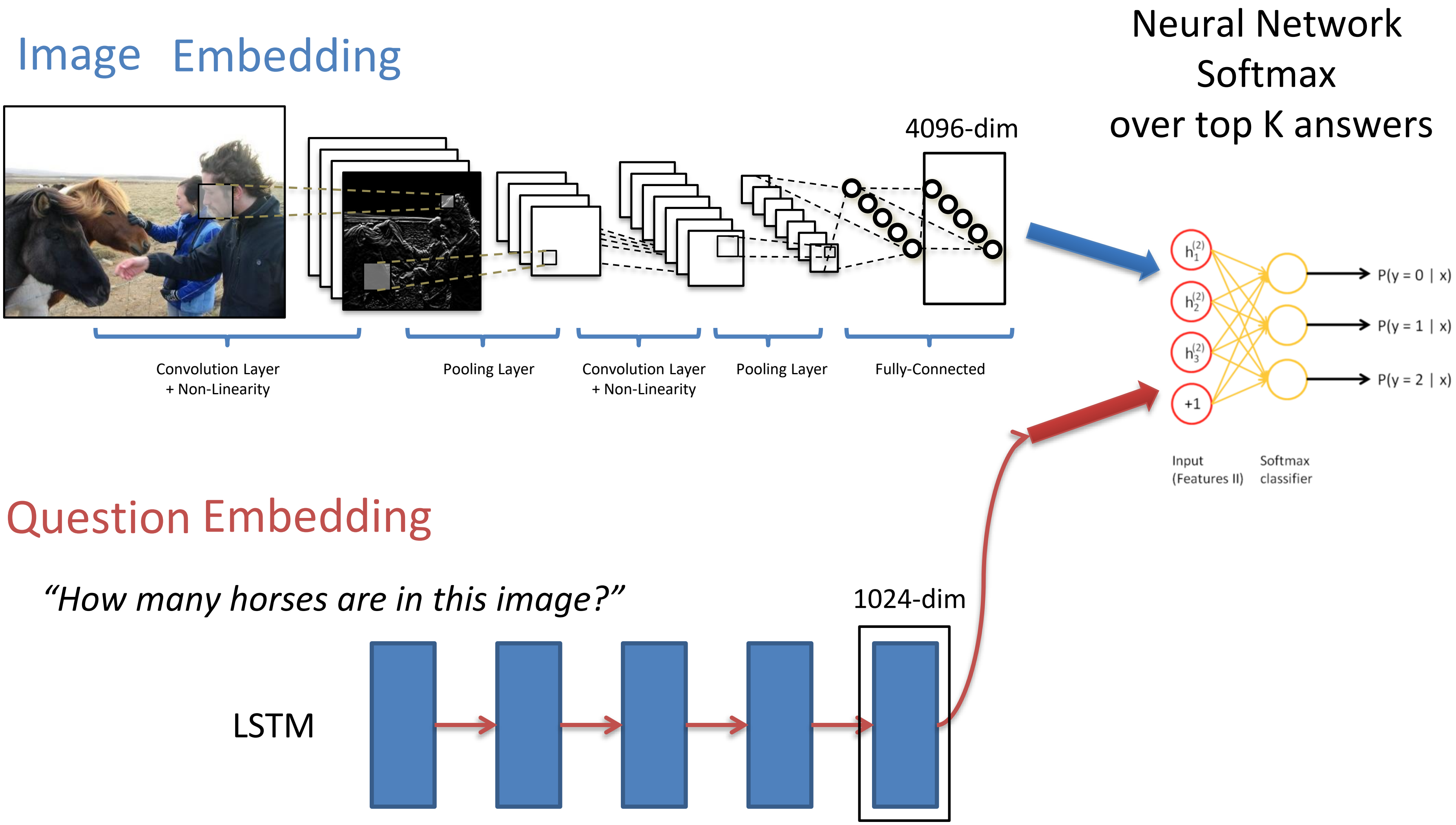


Image Embedding

Neural Network Softmax over top K answers

4096-dim

Question Embedding

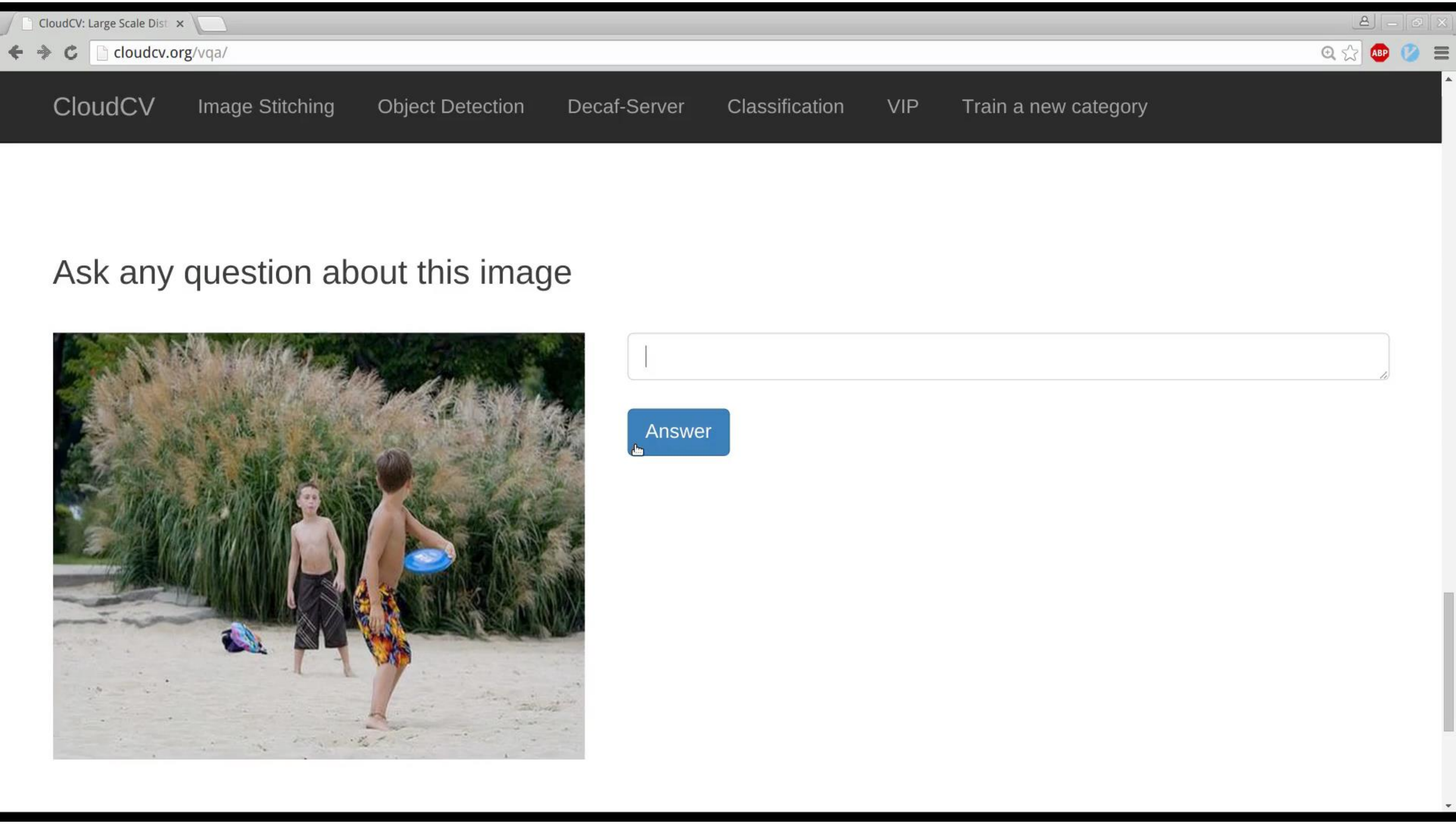
“How many horses are in this image?”

1024-dim

LSTM

Agrawal et al., “VQA: Visual Question Answering”, ICCV 2015

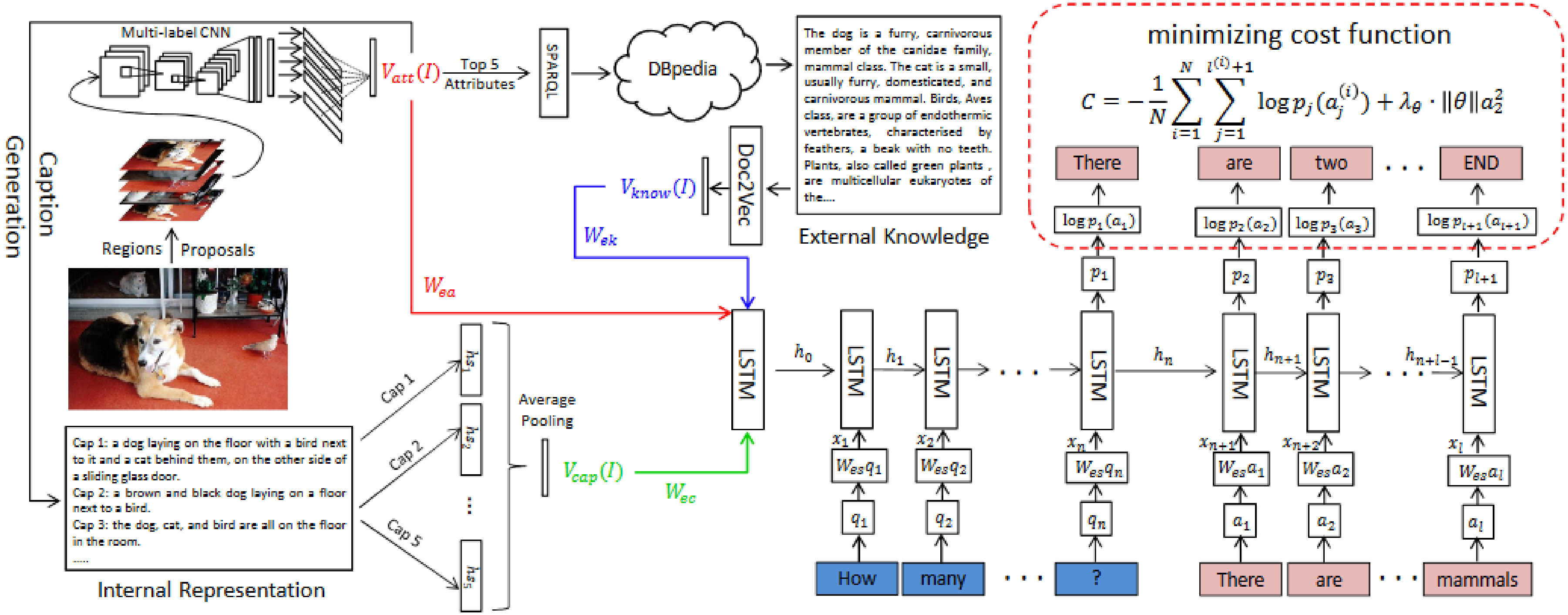
Visual Question Answering (VQA)



Ask any question about this image

Agrawal et al., “VQA: Visual Question Answering”, ICCV 2015

Visual Question Answering (VQA)



$$C = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{l^{(i)}+1} \log p_j(a_j^{(i)}) + \lambda_\theta \cdot \|\theta\|_2^2$$

The dog is a furry, carnivorous member of the canidae family, mammal class. The cat is a small, usually furry, domesticated, and carnivorous mammal. Birds, Aves class, are a group of endothermic vertebrates, characterised by feathers, a beak with no teeth. Plants, also called green plants , are multicellular eukaryotes of the....

Cap 1: a dog laying on the floor with a bird next to it and a cat behind them, on the other side of a sliding glass door.
Cap 2: a brown and black dog laying on a floor next to a bird.
Cap 3: the dog, cat, and bird are all on the floor in the room.
.....

Figure 2. Our proposed framework: given an image, a CNN is first applied to produce the attribute-based representation $V_{att}(I)$. The internal textual representation is made up of image captions generated based on the image-attributes. The hidden state of the caption-LSTM after it has generated the last word in each caption is used as its vector representation. These vectors are then aggregated as $V_{cap}(I)$ with average-pooling. The external knowledge is mined from the KB (in this case DBpedia) and the responses encoded by Doc2Vec, which produces a vector $V_{know}(I)$. The 3 vectors V are combined into a single representation of scene content, which is input to the VQA LSTM model which interprets the question and generates an answer.

Wu et al., "Ask Me Anything: Free-Form Visual Question Answering Based on Knowledge From External Sources", CVPR 2016

Reasoning for VQA

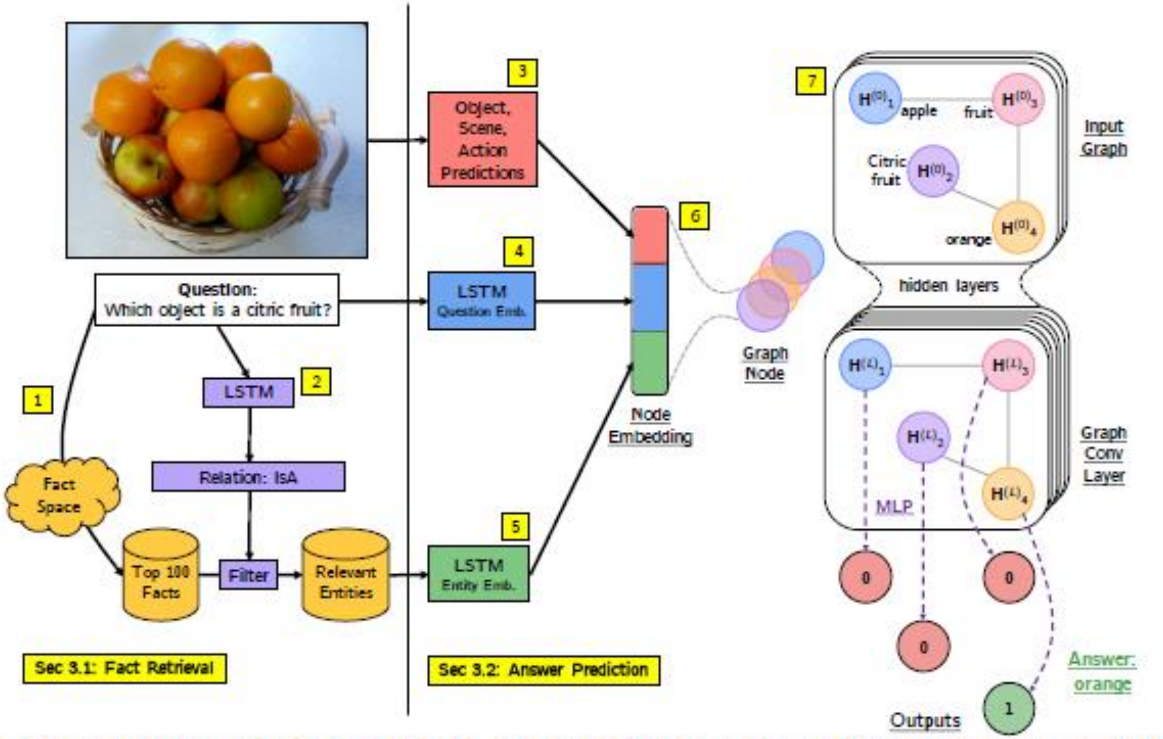


Figure 2: Outline of the proposed approach: Given an image and a question, we use a similarity scoring technique (1) to obtain relevant facts from the fact space. An LSTM (2) predicts the relation from the question to further reduce the set of relevant facts and its entities. An entity embedding is obtained by concatenating the visual concepts embedding of the image (3), the LSTM embedding of the question (4), and the LSTM embedding of the entity (5). Each entity forms a single node in the graph and the relations constitute the edges (6). A GCN followed by an MLP performs joint assessment (7) to predict the answer. Our approach is trained end-to-end.

Narasimhan and Schwing, "Out of the Box: Reasoning with Graph Convolution Nets for Factual Visual Question Answering", NeurIPS 2018

Graphs for advertisements

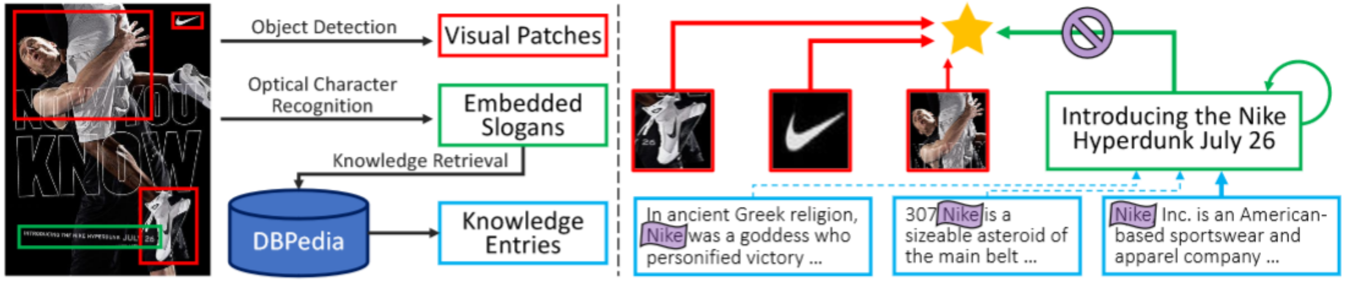
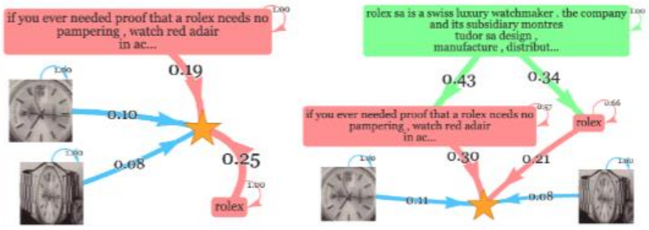
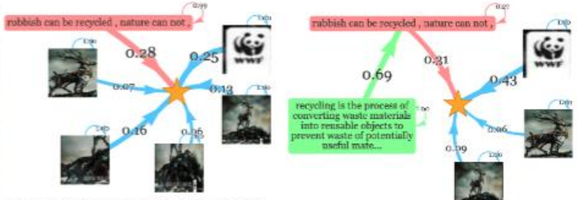

Object Detection
Visual Patches
Optical Character Recognition
Embedded Slogans
Knowledge Retrieval
DBPedia
Knowledge Entries
Introducing the Nike Hyperdunk July 26
In ancient Greek religion, Nike was a goddess who personified victory ...
307 Nike is a sizeable asteroid of the main belt ...
Nike Inc. is an American-based sportswear and apparel company ...

Figure 2: **Overview of the proposed model.** Given a single image ad, we first expand the representation using object detection and OCR, and also retrieve relevant knowledge based on slogan snippets (left). We build a graph-based model to infer the overall message using all available information (right). For more effective training, we mask query keywords and randomly drop certain knowledge pieces (shown in purple). More details are in Sec. 3.

If you ever needed proof that a Rolex needs no pampering, watch Red Adair in action.
ROLEX


if you ever needed proof that a rolex needs no pampering , watch red adair in ac...
0.19
0.10
0.08
0.25
rolex
rolex sa is a swiss luxury watchmaker . the company and its subsidiary montres tudor sa design , manufacture , distribut...
0.43
0.34
if you ever needed proof that a rolex needs no pampering , watch red adair in ac...
rolex
0.30
0.21
0.11
0.08

I should wear a rolex Because it can stand up to use by tough active guys
I should be wearing Rolex Because I am a Winner
I should wear a Rolex watch Because Red Adair wears one


rubbish can be recycled , nature can not .
0.28
0.25
0.07
0.13
0.16
0.06
WWF
rubbish can be recycled , nature can not .
0.69
0.31
0.43
recycling is the process of converting waste materials into reusable objects to prevent waste of potentially useful mate...
0.06
0.09
WWF

I should recycle because nature cant
I should recycle because garbage can harm animals
I should recycle because it will ultimately affect our environment

Ye, Zhang and Kovashka

Part II: Self-Supervised Learning

- Learn representations from context in raw data
- Language – predict nearby words [*already covered]*
  - Word2Vec
  - Transformers, BERT
- Vision – predict pixels from other pixels
  - Predict nearby patches in an image
  - Predict order of frames in a video
  - Predict what you will see as you move
  - Predict physics

Jitendra Malik: "**Supervision** is the opium of the AI researcher"
Alyosha Efros: "The AI revolution will not be **supervised**"
Yann LeCun: "**Self-supervised** learning is the cake, **supervised** learning is the icing on the cake, **reinforcement learning** is the cherry on the cake"

Motivation

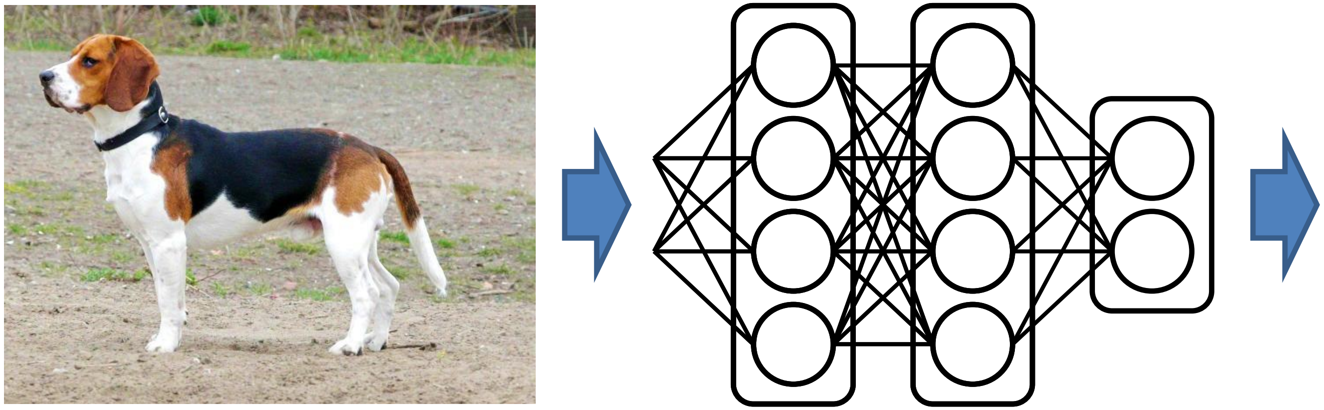
- What’s the data we’ve learned from thus far?
- Labeled static datasets
  - Expensive to obtain
  - Doesn’t match how humans learn
- Alternatives
  - Unsupervised learning (no labels)
  - Self-supervised learning (“fake”/emergent labels)
  - Embodied/active learning (agents in environments)

Unsupervised Visual Representation Learning by Context Prediction

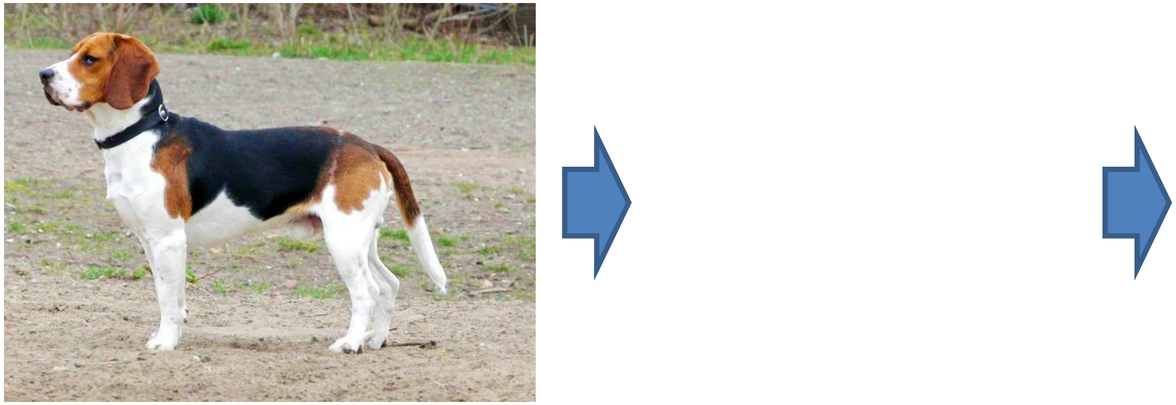
Carl Doersch, Alexei Efros and Abhinav Gupta

ICCV 2015

ImageNet + Deep Learning



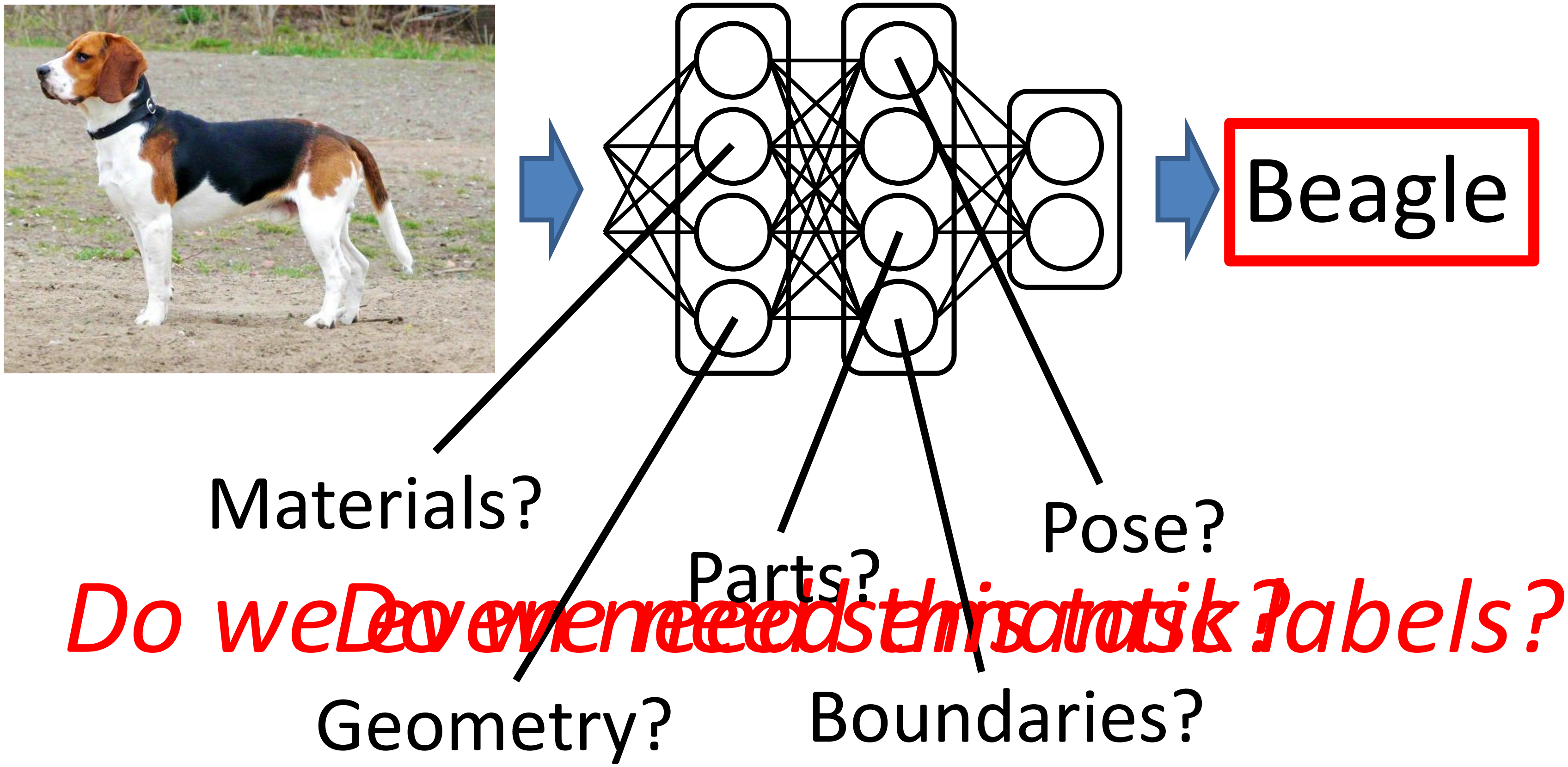
Beagle



- Image Retrieval
- Detection (RCNN)
- Segmentation (FCN)
- Depth Estimation
- …

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

ImageNet + Deep Learning



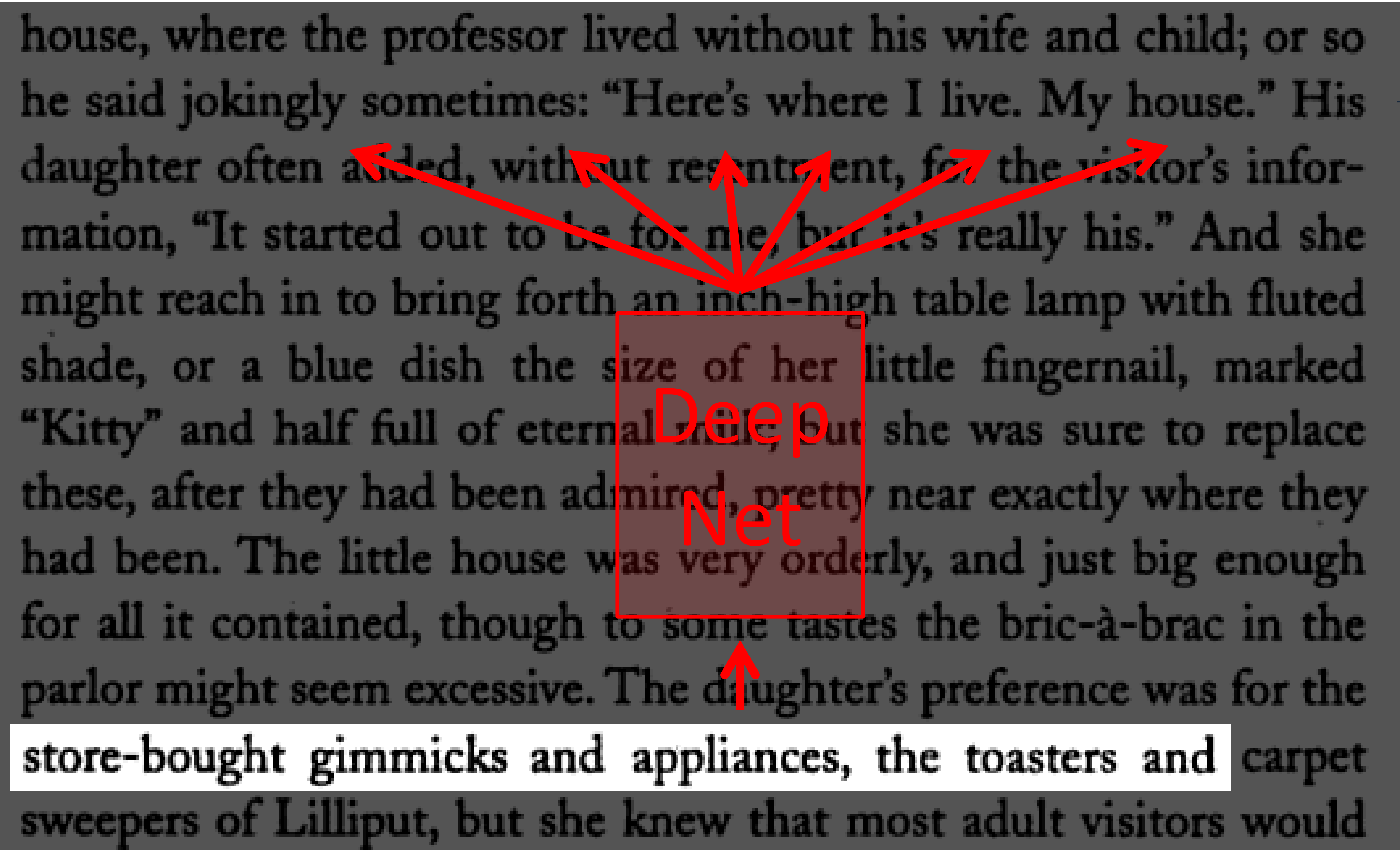
Do we need semantic labels?

Do we even need this task?

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

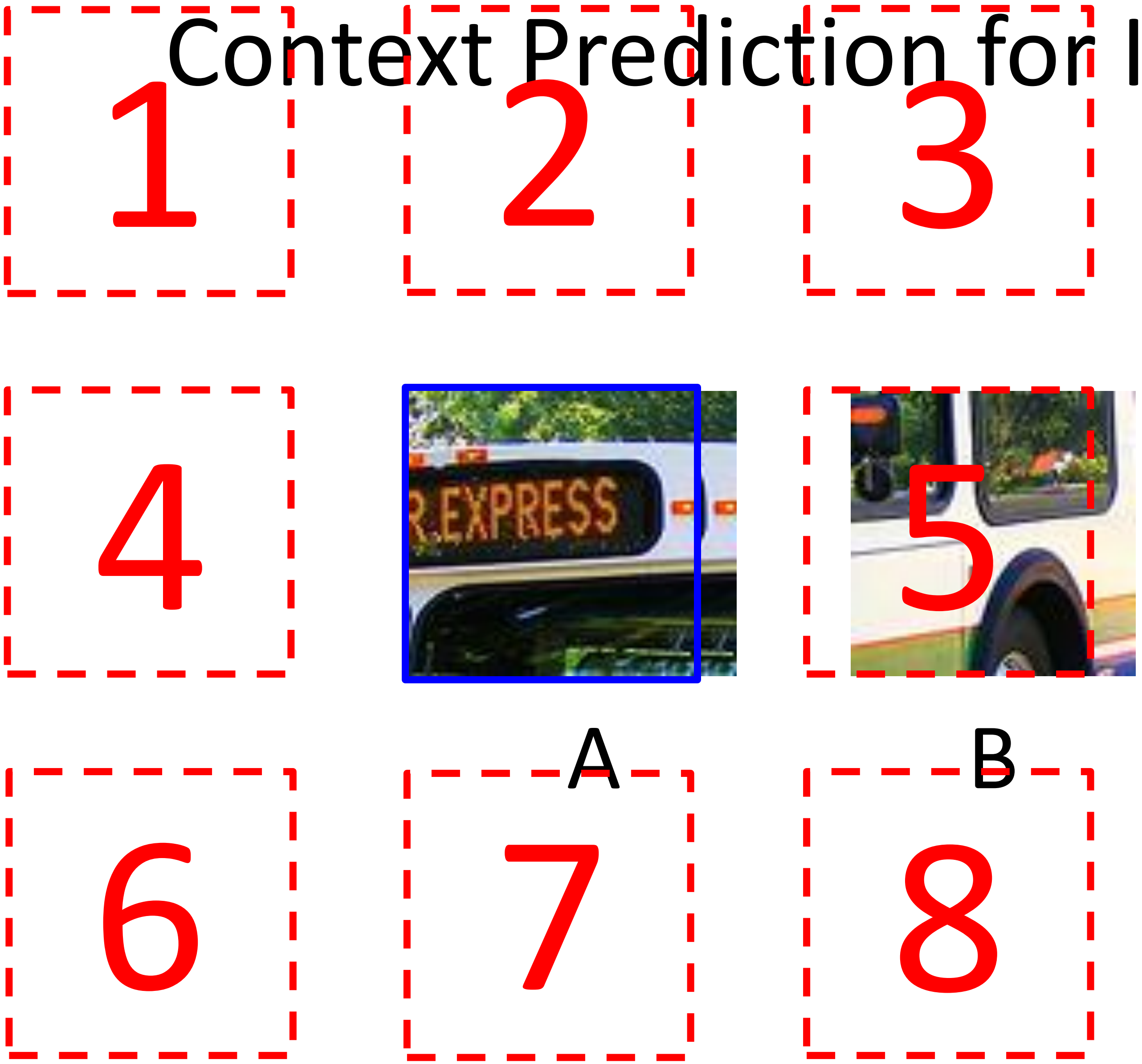
Context as Supervision

[Collobert & Weston 2008; Mikolov et al. 2013]



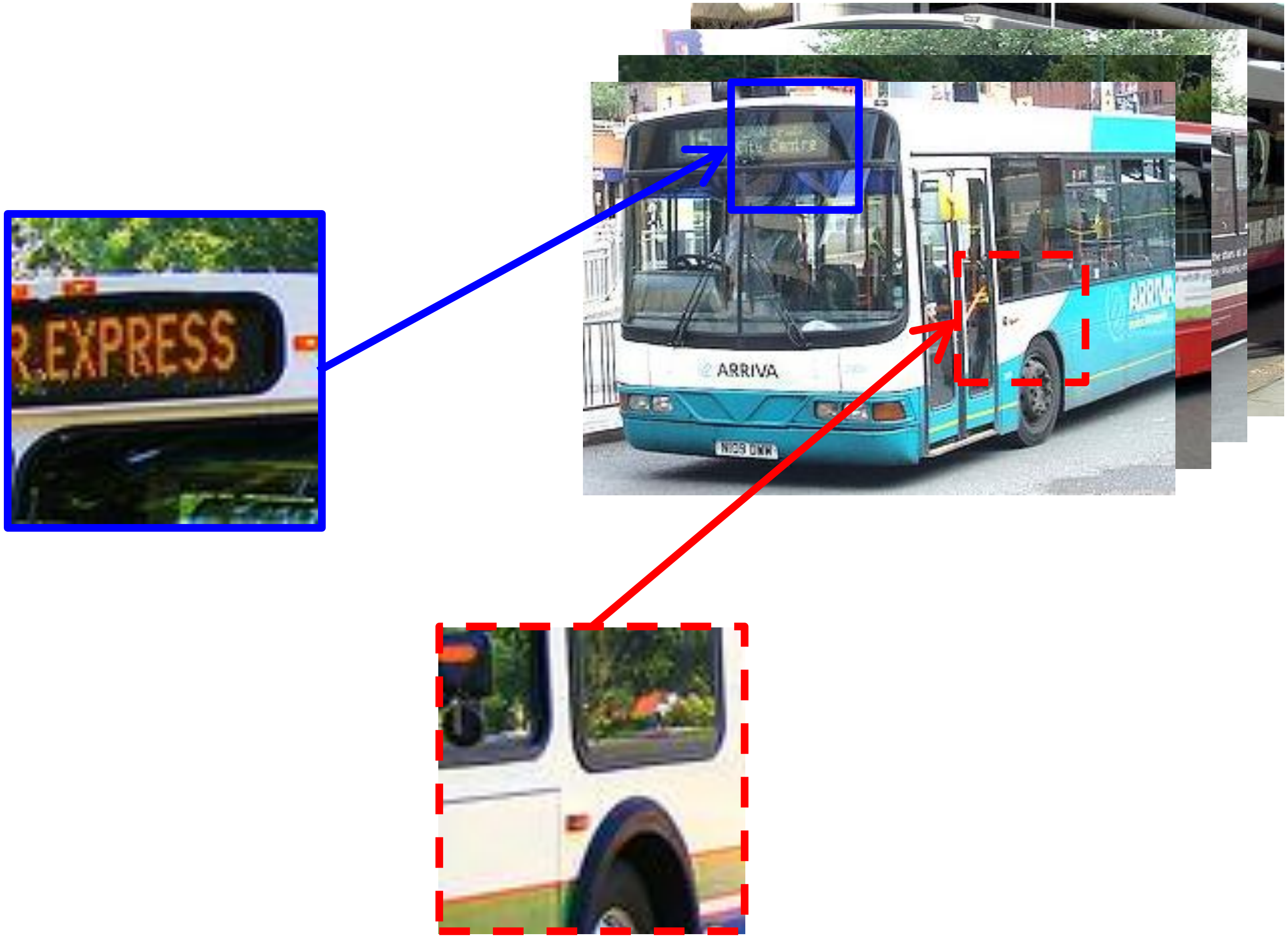
house, where the professor lived without his wife and child; or so he said jokingly sometimes: "Here's where I live. My house." His daughter often added, without resentment, for the visitor's information, "It started out to be for me, but it's really his." And she might reach in to bring forth an inch-high table lamp with fluted shade, or a blue dish the size of her little fingernail, marked "Kitty" and half full of eternal milk, but she was sure to replace these, after they had been admired, pretty near exactly where they had been. The little house was very orderly, and just big enough for all it contained, though to some tastes the bric-à-brac in the parlor might seem excessive. The daughter's preference was for the store-bought gimmicks and appliances, the toasters and carpet sweepers of Lilliput, but she knew that most adult visitors would

Context Prediction for Images



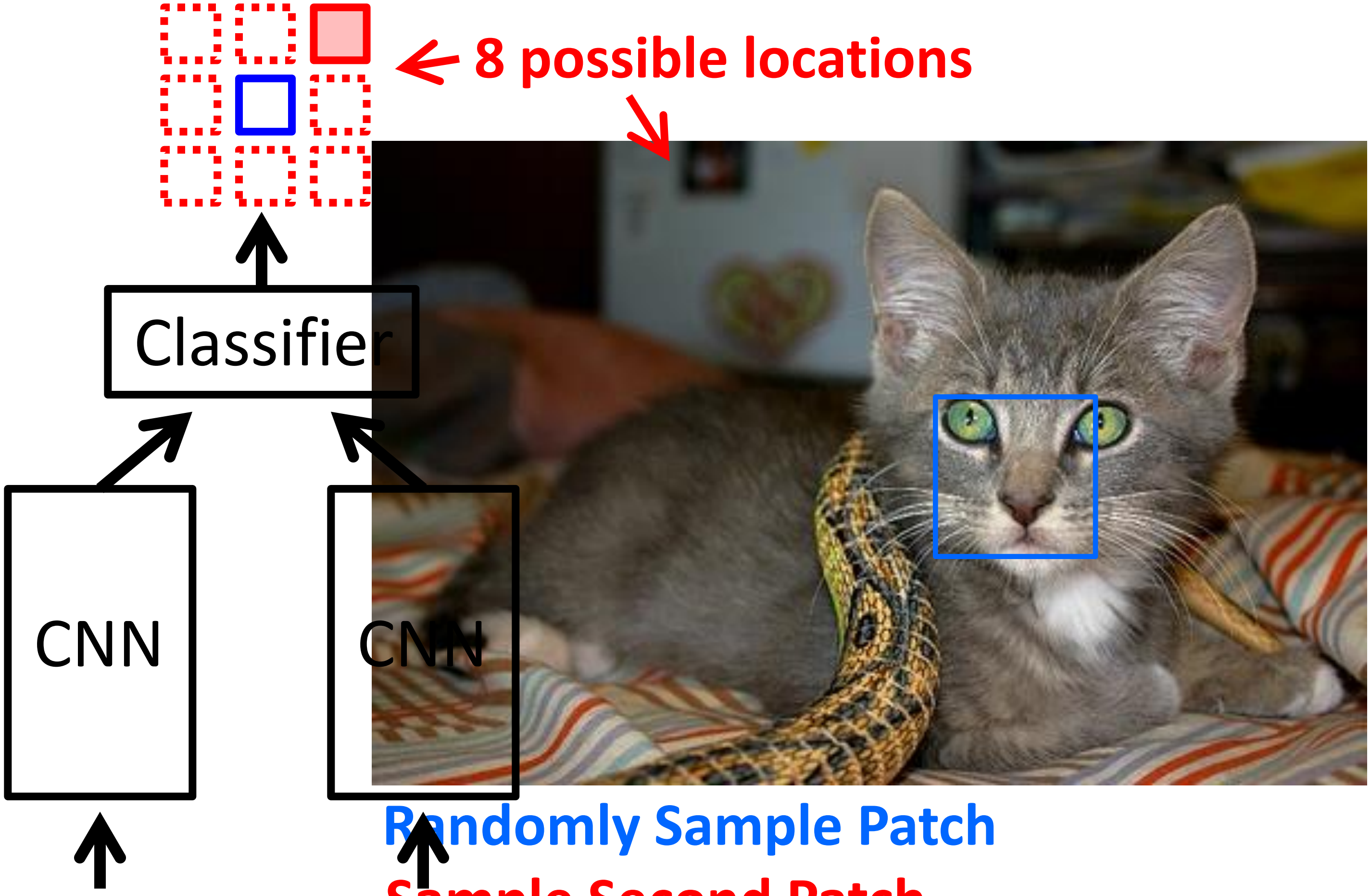
Doersch et al., “Unsupervised Visual Representation Learning by Context Prediction”, ICCV 2015

Semantics from a non-semantic task



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

Relative Position Task



8 possible locations

Classifier

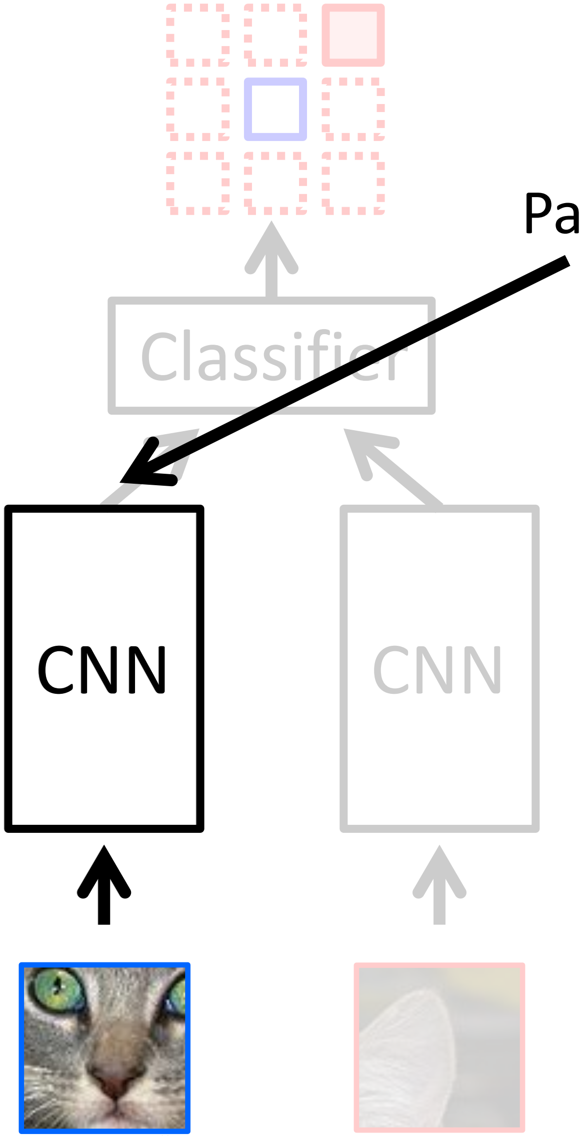
CNN

CNN

Randomly Sample Patch

Sample Second Patch

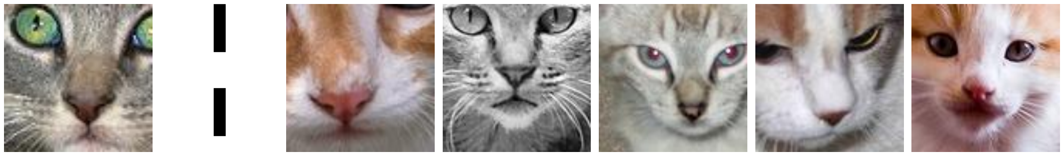
Doersch et al., “Unsupervised Visual Representation Learning by Context Prediction”, ICCV 2015



Patch Embedding

Input

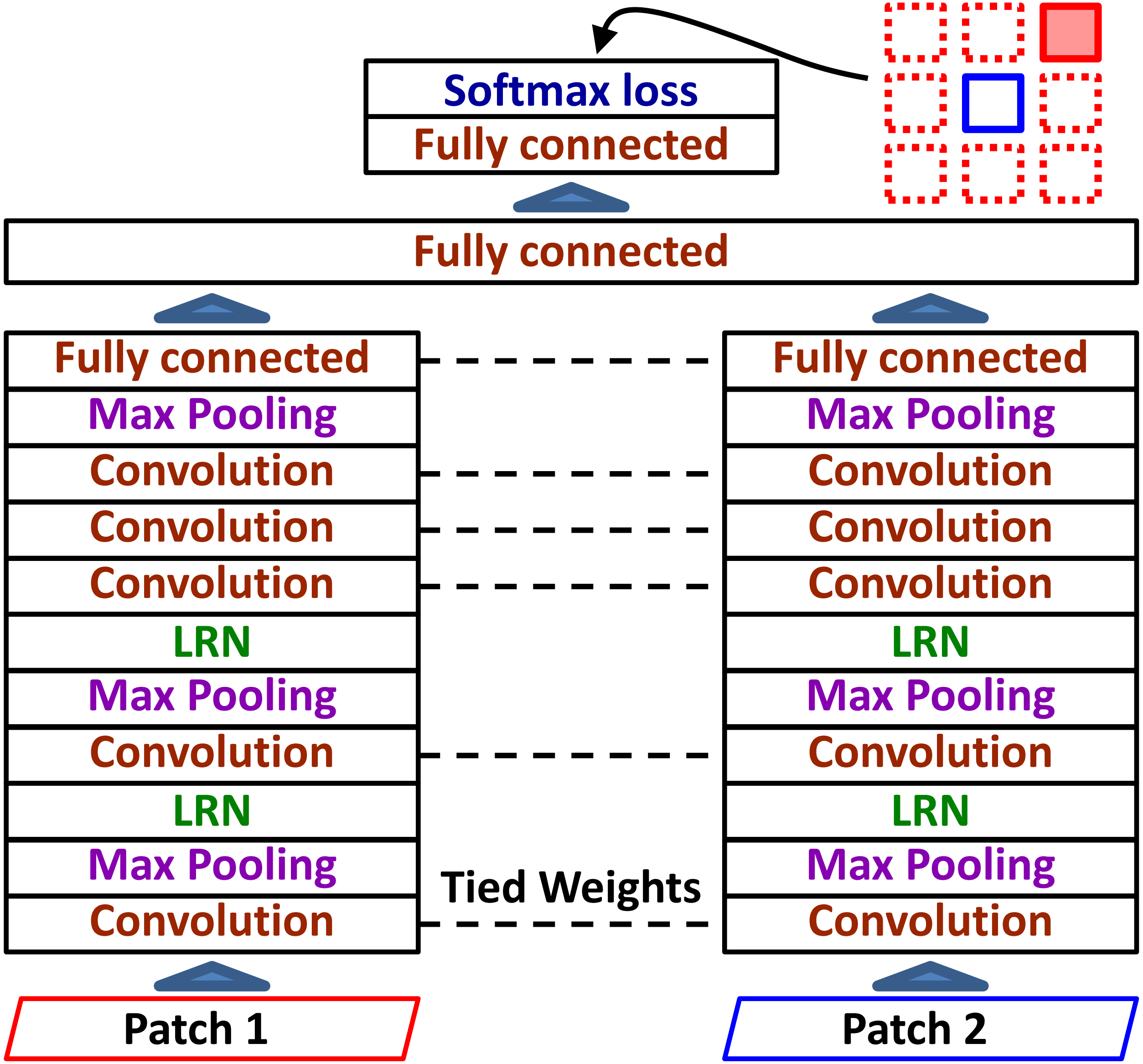
Nearest Neighbors



Note: connects ***across*** instances!

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

Architecture



Softmax loss

Fully connected

Fully connected

Fully connected
Max Pooling
Convolution
Convolution
Convolution
LRN
Max Pooling
Convolution
LRN
Max Pooling
Convolution

Fully connected
Max Pooling
Convolution
Convolution
Convolution
LRN
Max Pooling
Convolution
LRN
Max Pooling
Convolution

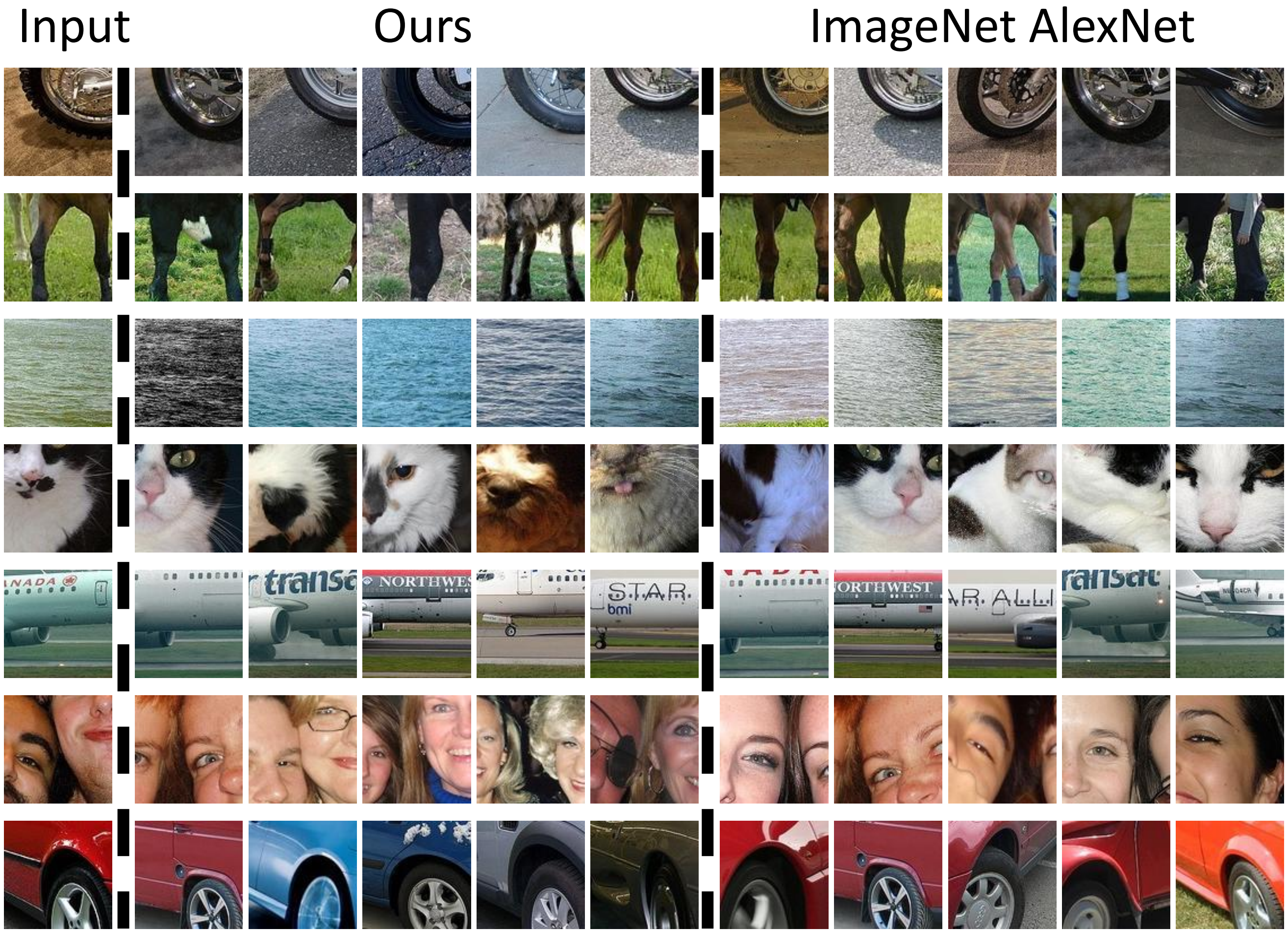
Tied Weights

Patch 1

Patch 2

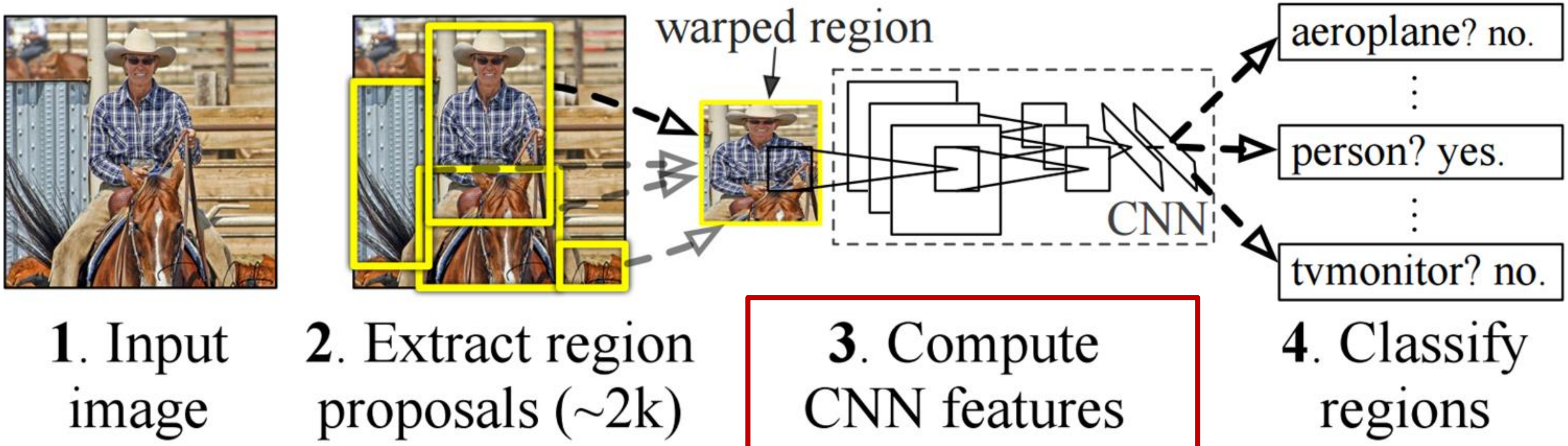
Doersch et al., “Unsupervised Visual Representation Learning by Context Prediction”, ICCV 2015

What is learned?



Doersch et al., "Unsupervised Visual Representation Learning by Context Prediction", ICCV 2015

Pre-Training for R-CNN



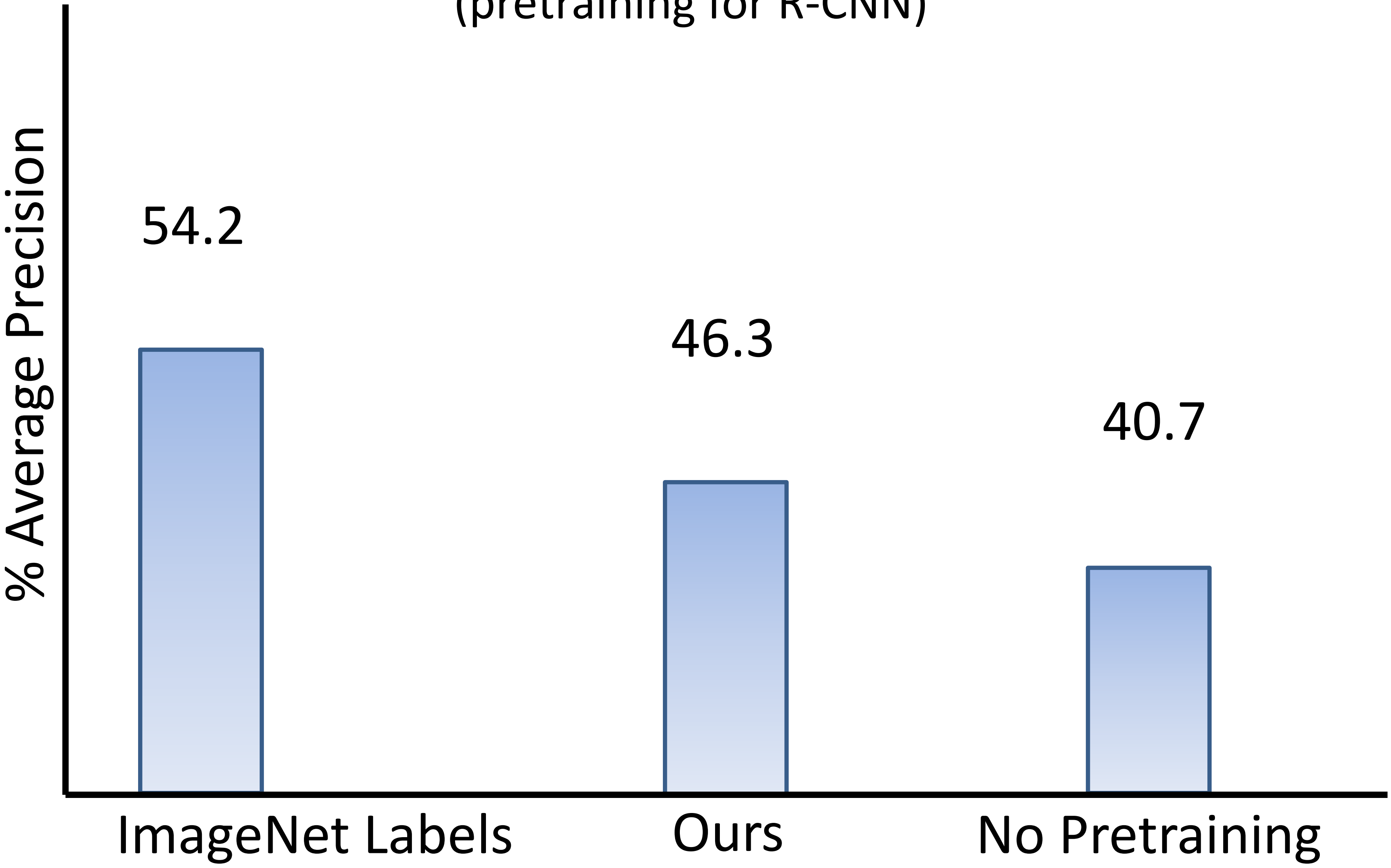
Pre-train on relative-position task, w/o labels

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

[Girshick et al. 2014]

VOC 2007 Performance

(pretraining for R-CNN)



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

- Test on dataset B
- Option 1: pretrain (unsup) on dataset B
- Option 2: pretrain (sup) on dataset A

Shuffle and Learn: Unsupervised Learning using Temporal Order Verification

Ishan Misra, C. Lawrence Zitnick, and Martial Hebert

ECCV 2016

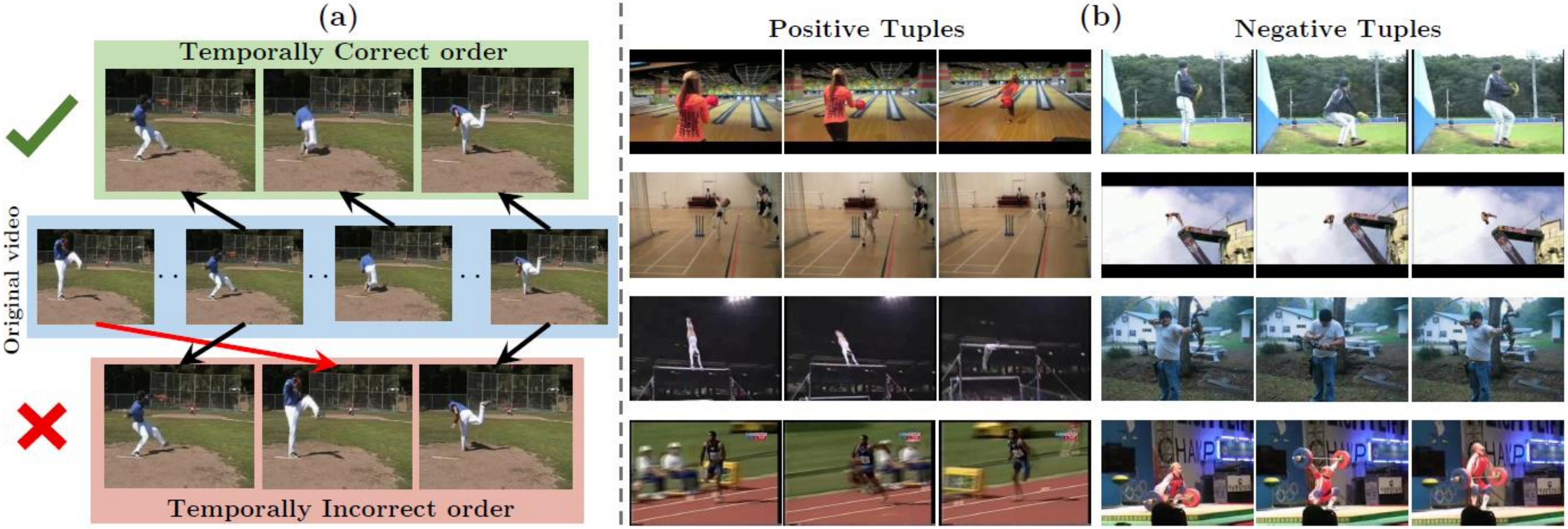


Fig. 1: **(a)** A video imposes a natural temporal structure for visual data. In many cases, one can easily verify whether frames are in the correct temporal order (shuffled or not). Such a simple sequential verification task captures important spatiotemporal signals in videos. We use this task for unsupervised pre-training of a Convolutional Neural Network (CNN). **(b)** Some examples of the automatically extracted positive and negative tuples used to formulate a classification task for a CNN.

Misra et al., "Shuffle and Learn: Unsupervised Learning using Temporal Order Verification", ECCV 2016

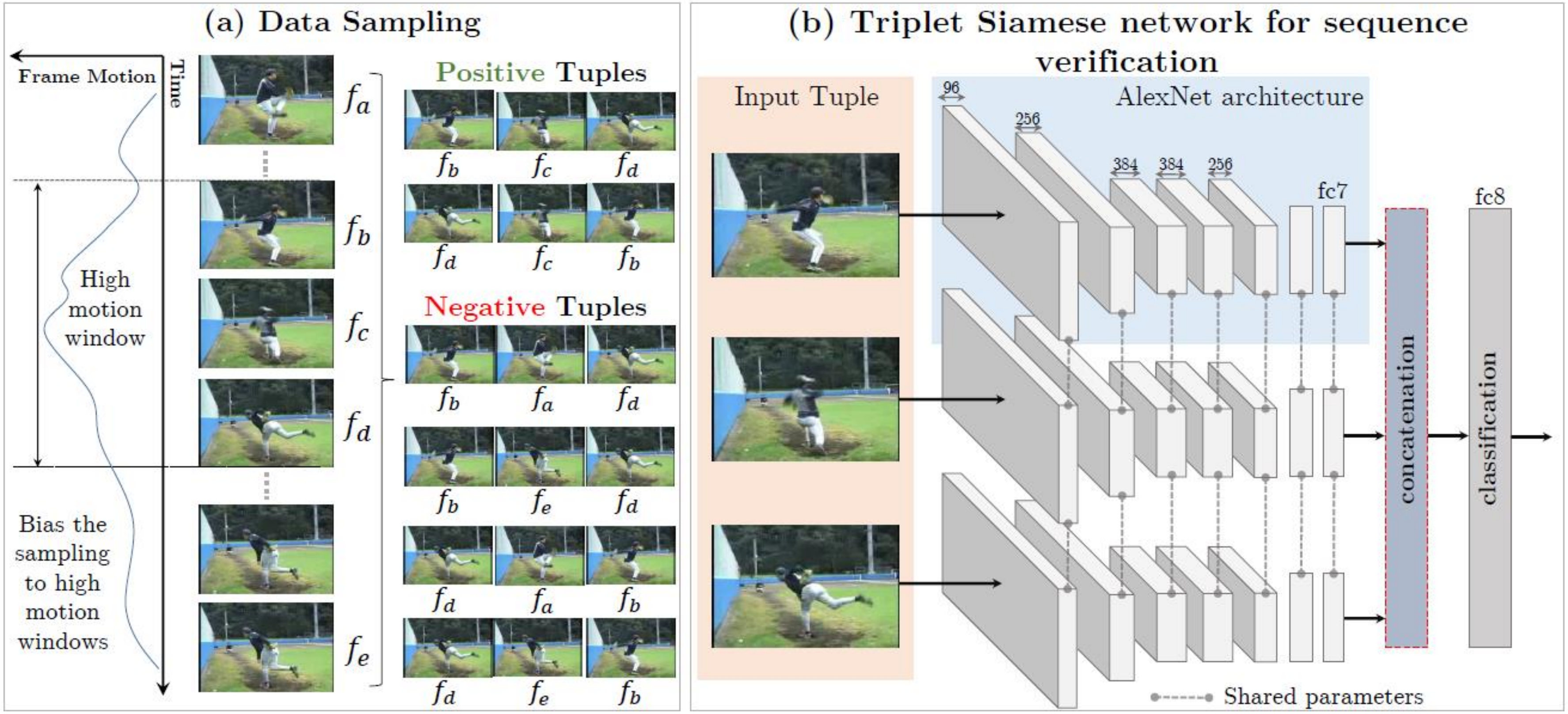


Fig. 2: **(a)** We sample tuples of frames from high motion windows in a video. We form positive and negative tuples based on whether the three input frames are in the correct temporal order. **(b)** Our triplet Siamese network architecture has three parallel network stacks with shared weights upto the `fc7` layer. Each stack takes a frame as input, and produces a representation at the `fc7` layer. The concatenated `fc7` representations are used to predict whether the input tuple is in the correct temporal order.

Misra et al., “Shuffle and Learn: Unsupervised Learning using Temporal Order Verification”, ECCV 2016

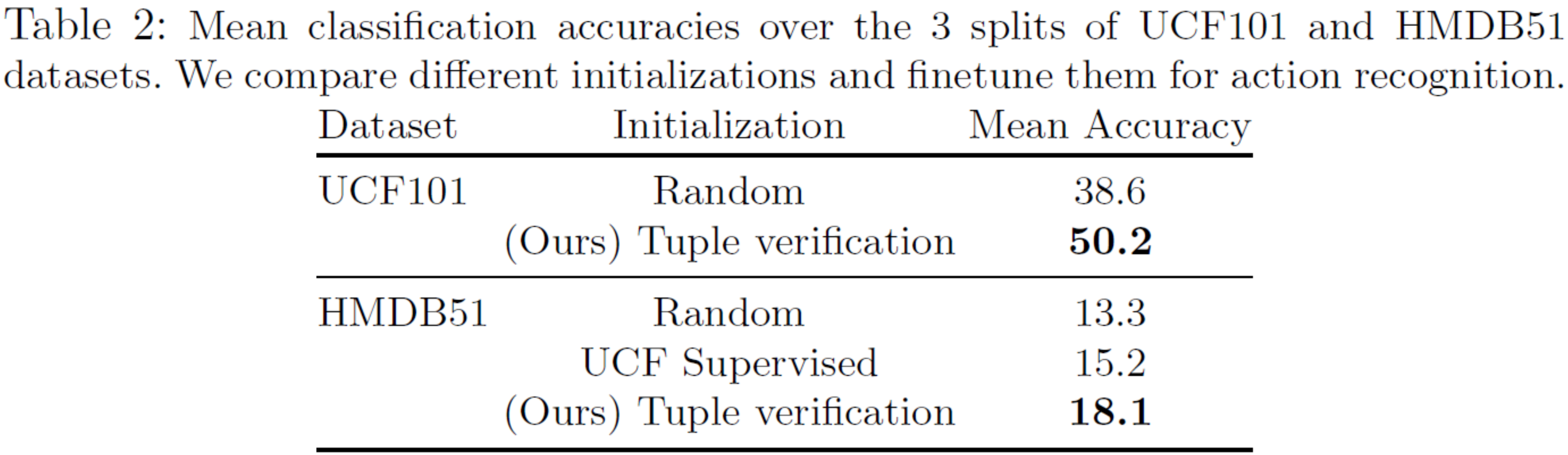


Table 2: Mean classification accuracies over the 3 splits of UCF101 and HMDB51 datasets. We compare different initializations and finetune them for action recognition.

Dataset	Initialization	Mean Accuracy
UCF101	Random	38.6
	(Ours) Tuple verification	**50.2**
HMDB51	Random	13.3
	UCF Supervised	15.2
	(Ours) Tuple verification	**18.1**

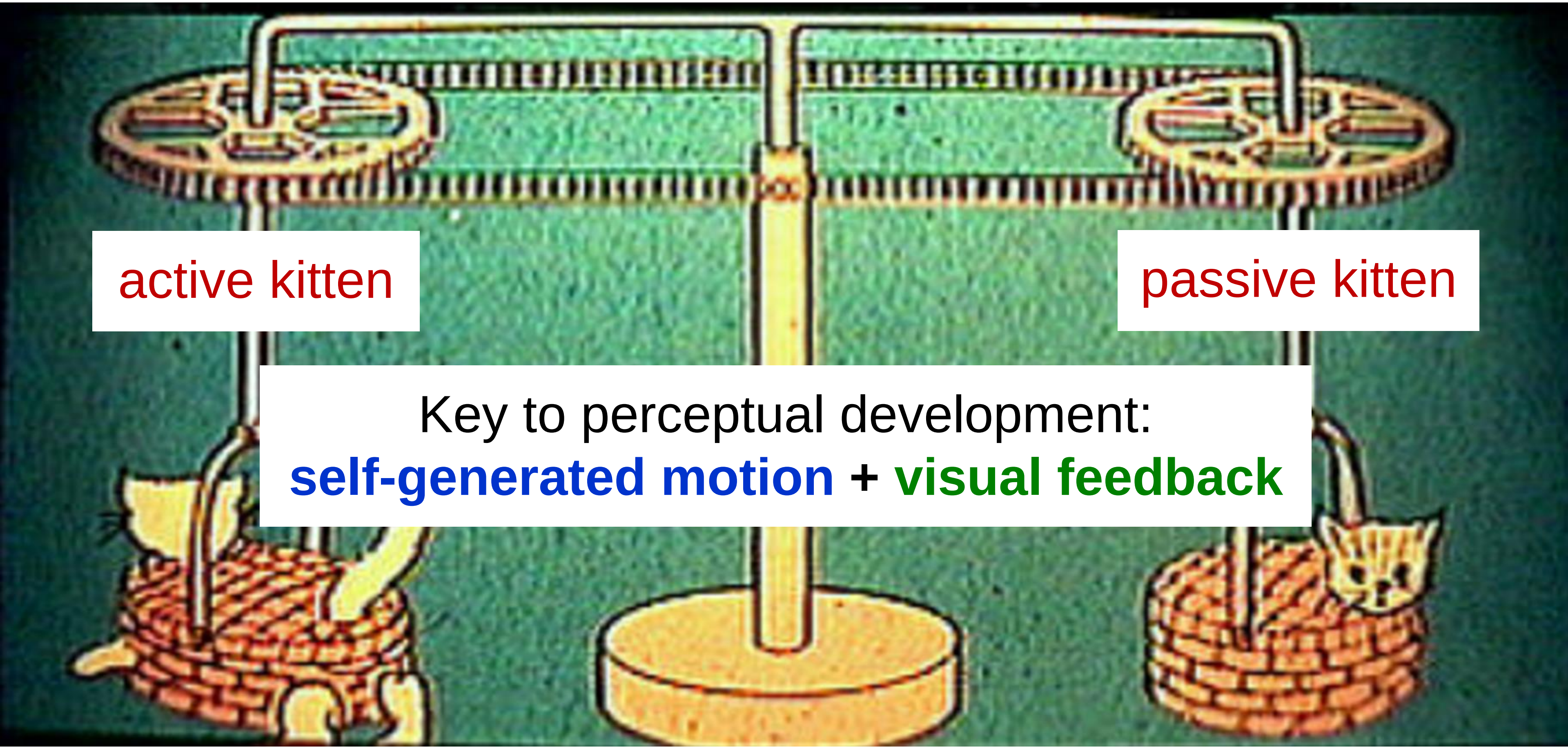
Misra et al., “Shuffle and Learn: Unsupervised Learning using Temporal Order Verification”, ECCV 2016

Learning image representations tied to ego-motion

Dinesh Jayaraman and Kristen Grauman

ICCV 2015

The kitten carousel experiment
[Held & Hein, 1963]



Key to perceptual development:
self-generated motion + visual feedback

Jayaraman and Grauman, “Learning image representations tied to ego-motion”, ICCV 2015

Problem with today's visual learning

Status quo: Learn from "disembodied" bag of labeled snapshots.

Our goal: Learn in the context of acting and moving in the world.

Jayaraman and Grauman, "Learning image representations tied to ego-motion", ICCV 2015

Our idea: Ego-motion ↔ vision

Goal: Teach computer vision system the connection:
"how I move" ↔ "how my visual surroundings change"

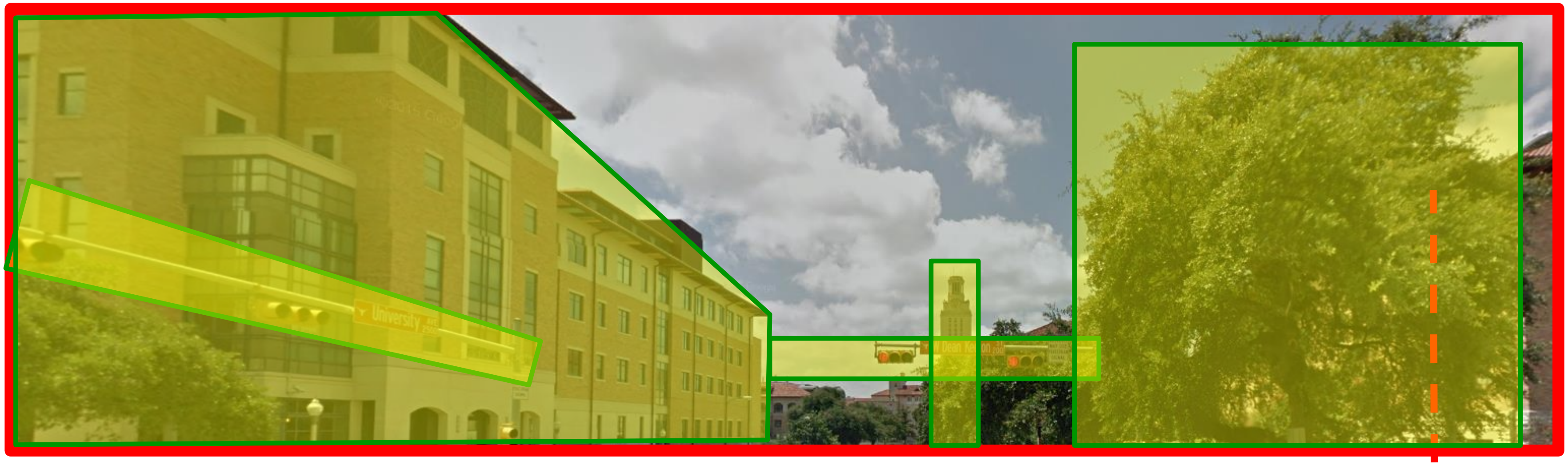
Ego-motion motor signals

+

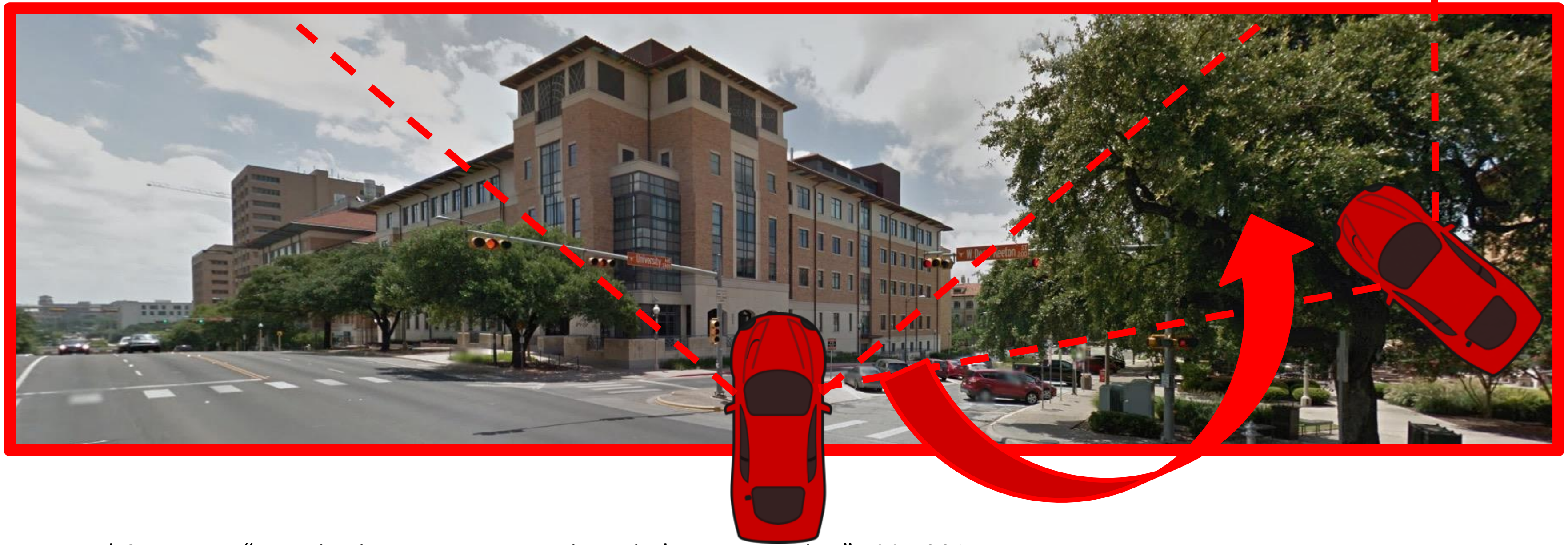
Unlabeled video

Jayaraman and Grauman, "Learning image representations tied to ego-motion", ICCV 2015

Ego-motion ↔ vision: view prediction



After moving:



Jayaraman and Grauman, “Learning image representations tied to ego-motion”, ICCV 2015

Ego-motion ↔ vision for recognition

Learning this connection requires:

- Depth, 3D geometry
- Semantics
- Context

Also key to recognition!

Can be learned without manual labels!

Our approach: unsupervised feature learning using egocentric video + motor signals

Jayaraman and Grauman, "Learning image representations tied to ego-motion", ICCV 2015

Approach idea: Ego-motion equivariance

Invariant features: unresponsive to some classes of transformations

$$\mathbf{z}(g\mathbf{x}) \approx \mathbf{z}(\mathbf{x})$$

Equivariant features : *predictably* responsive to some classes of transformations, through simple mappings (e.g., linear)

"equivariance map"

$$\mathbf{z}(g\mathbf{x}) \approx M_g \mathbf{z}(\mathbf{x})$$

Invariance *discards* information; equivariance *organizes* it.

Jayaraman and Grauman, "Learning image representations tied to ego-motion", ICCV 2015

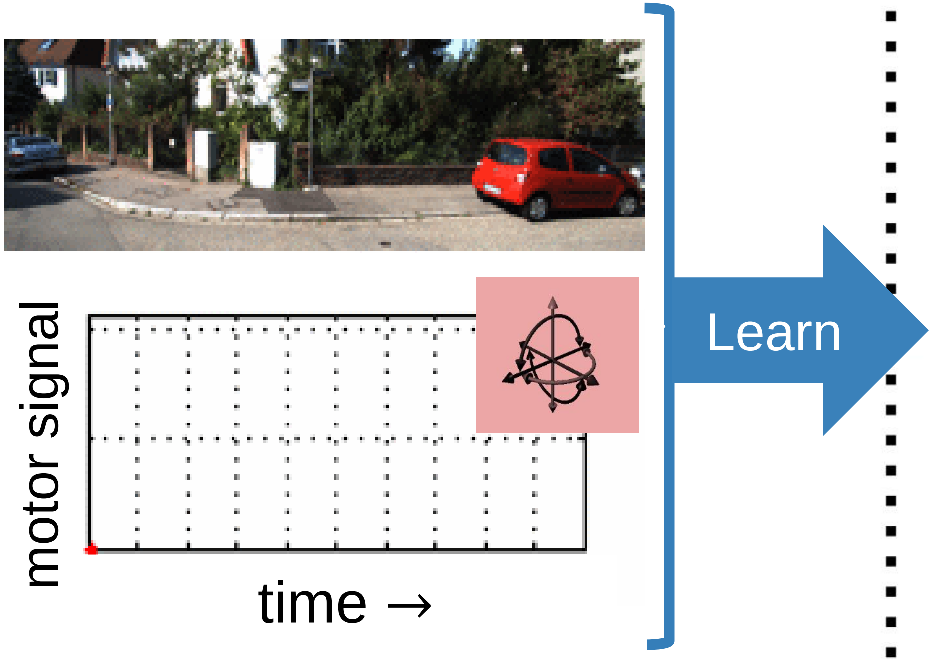
Approach idea: Ego-motion equivariance

Training data

Unlabeled video + motor signals

Equivariant embedding

organized by ego-motions



Pairs of frames related by similar ego-motion should be related by same feature transformation

Jayaraman and Grauman, “Learning image representations tied to ego-motion”, ICCV 2015

Approach overview

Our approach: unsupervised feature learning using egocentric video + motor signals

1. Extract training frame pairs from video

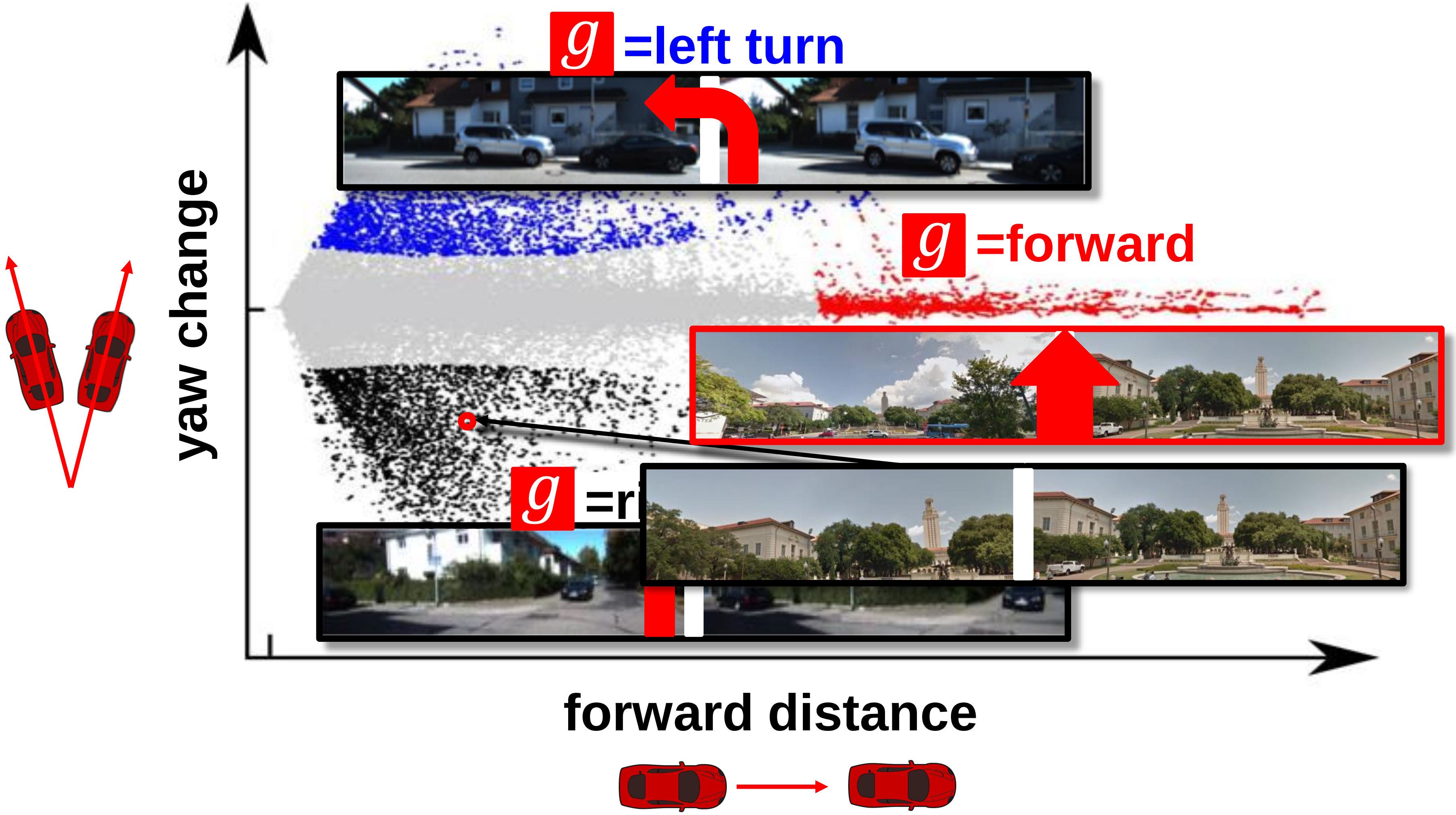
2. Learn ego-motion-equivariant image features

3. Train on target recognition task in parallel

Jayaraman and Grauman, “Learning image representations tied to ego-motion”, ICCV 2015

Training frame pair mining

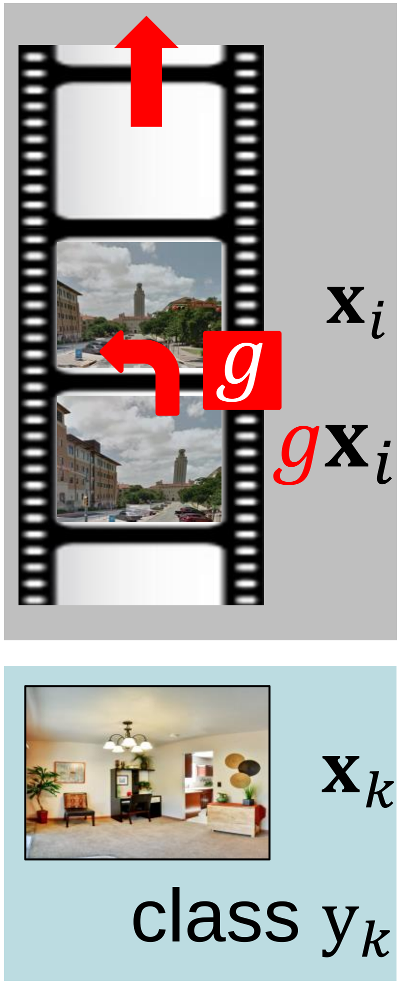
Discovery of ego-motion clusters



Jayaraman and Grauman, “Learning image representations tied to ego-motion”, ICCV 2015

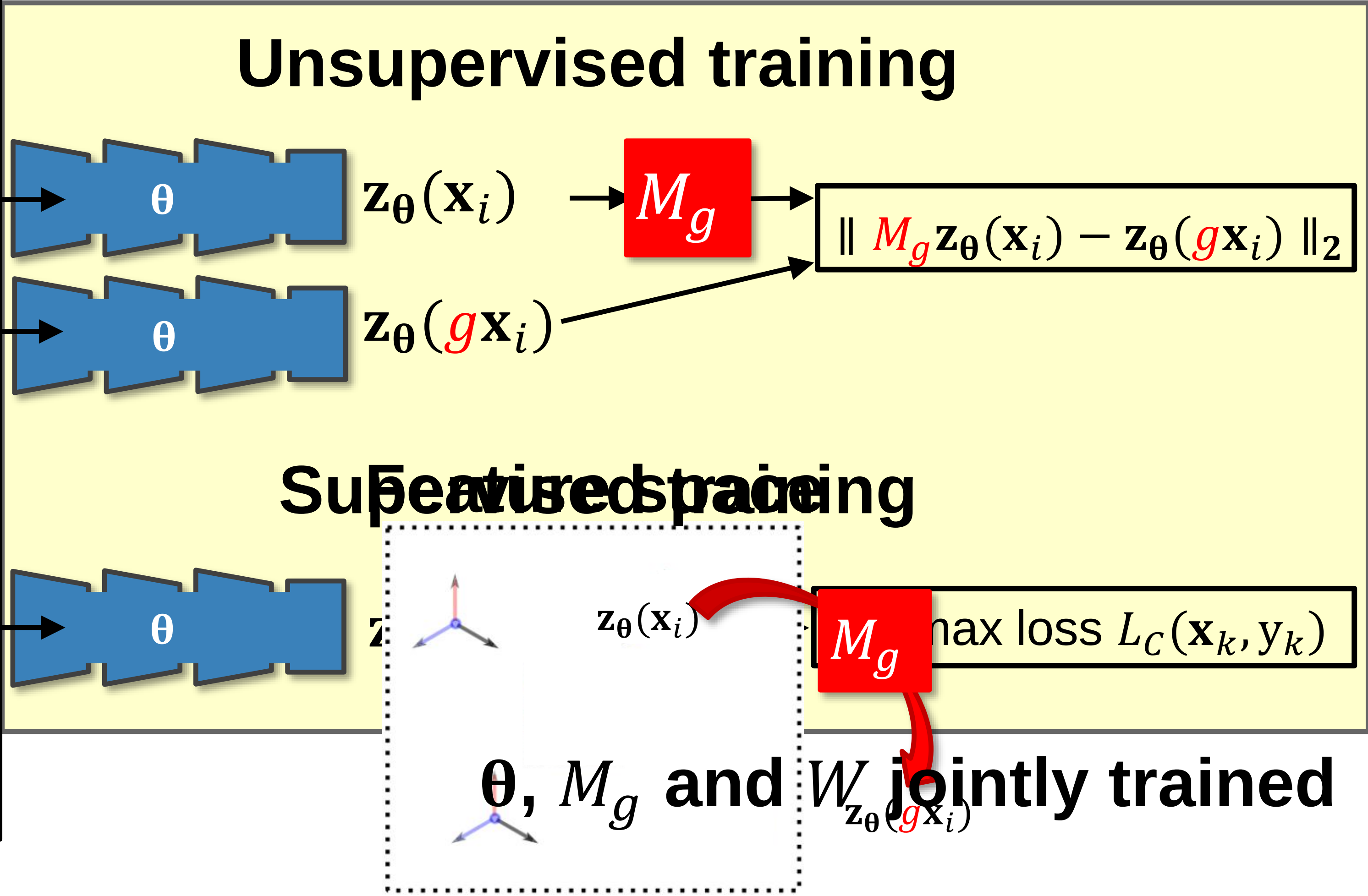
Ego-motion equivariant feature learning

Given:



Desired: for all motions g and all images $\mathbf{x}$,

$$\mathbf{z}_\theta(g\mathbf{x}) \approx M_g \mathbf{z}_\theta(\mathbf{x})$$



Unsupervised training

$\| M_g \mathbf{z}_\theta(\mathbf{x}_i) - \mathbf{z}_\theta(g\mathbf{x}_i) \|_2$

Supervised training

Feature space

max loss $L_C(\mathbf{x}_k, y_k)$

θ, M_g and W jointly trained

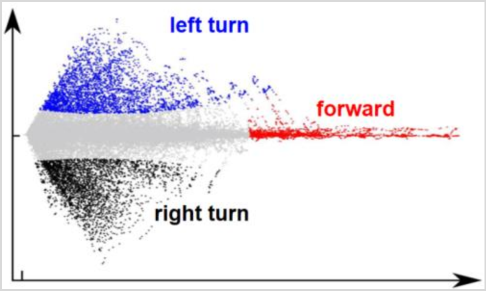
θ
θ
θ
$\mathbf{z}_\theta(\mathbf{x}_i)$
$\mathbf{z}_\theta(g\mathbf{x}_i)$
M_g
$\mathbf{z}_\theta(\mathbf{x}_i)$
M_g
$\mathbf{z}_\theta(g\mathbf{x}_i)$

Jayaraman and Grauman, “Learning image representations tied to ego-motion”, ICCV 2015

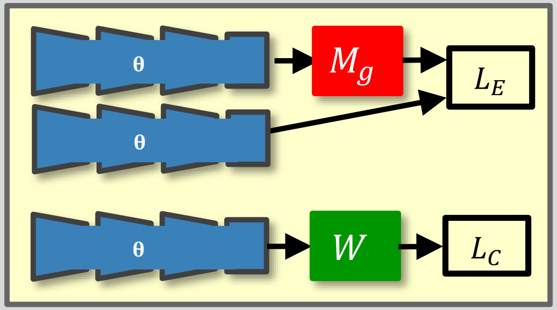
Summary

APPROACH

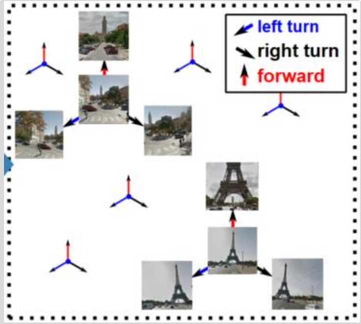
Ego-motion training pairs



Neural network training



Equivariant embedding



RESULTS

Scene and object recognition

Football field?
Pagoda?
Airport?
Cathedral?
Army base?

Next-best view selection

cup

frying pan

Jayaraman and Grauman, “Learning image representations tied to ego-motion”, ICCV 2015

Results: Recognition

Learn from **unlabeled car video** (KITTI)

Geiger et al, IJRR ’13

Exploit features for **static scene classification** (SUN, 397 classes)

Apse

Window seat

Art school

Library

Auditorium

Bus interior

Cathedral

Freeway

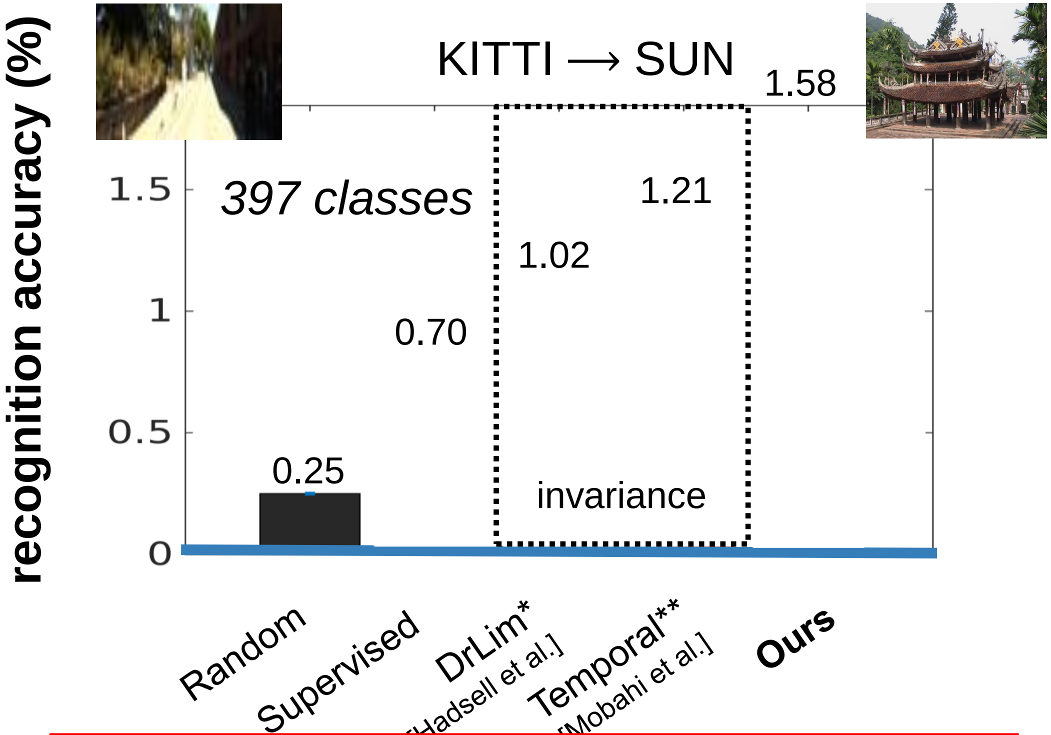
Guardhouse

Xiao et al, CVPR ’10

Jayaraman and Grauman, “Learning image representations tied to ego-motion”, ICCV 2015

Results: Recognition

Do ego-motion equivariant features improve recognition?



6 labeled training examples per class

Up to 30% accuracy increase over state of the art!

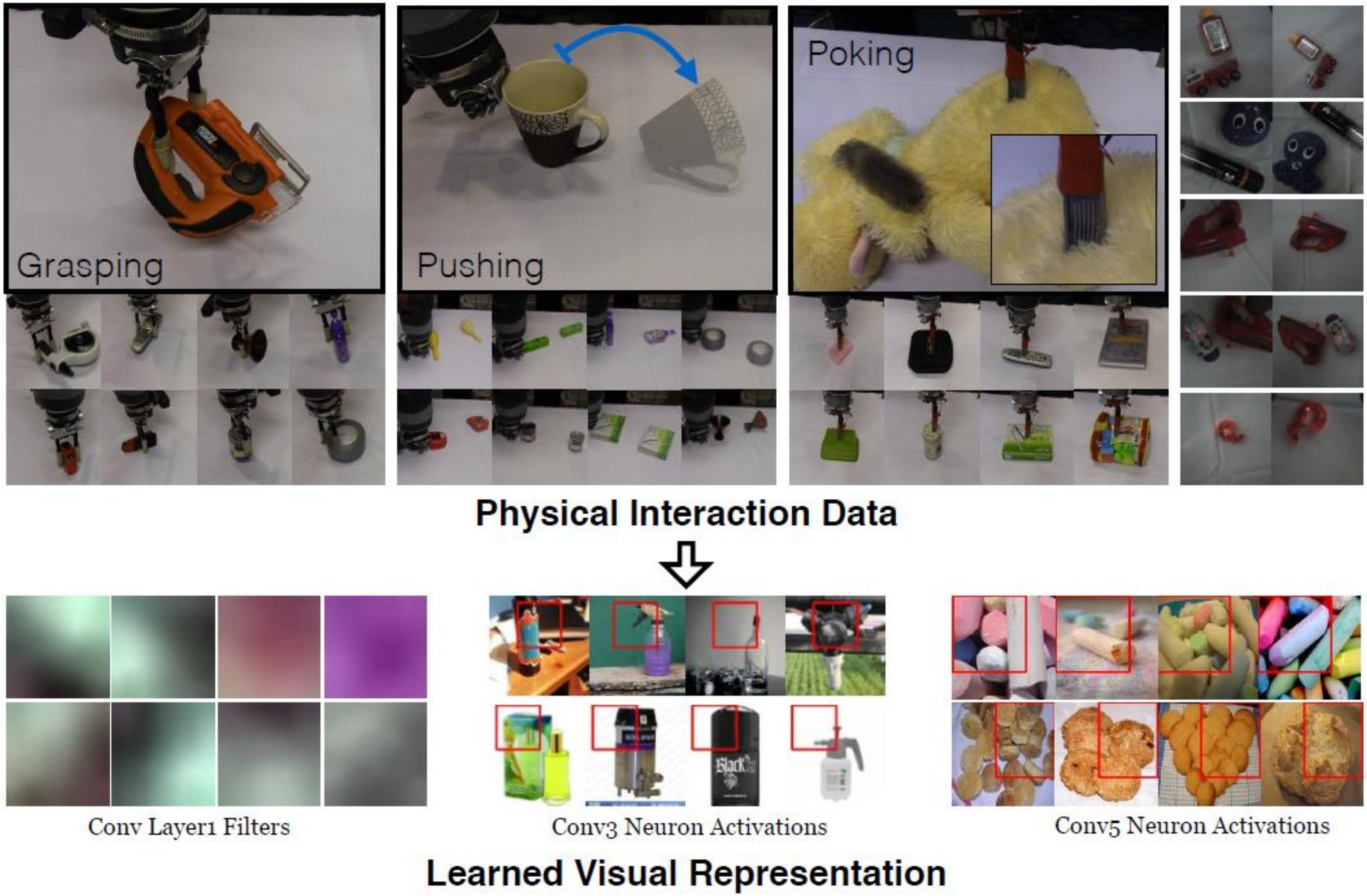
Jayaraman and Grauman, “Learning image representations tied to ego-motion”, ICCV 2015

The Curious Robot: Learning Visual Representations via Physical Interactions

Lerrel Pinto, Dhiraj Gandhi, Yuanfeng Han,
Yong-Lae Park, and Abhinav Gupta

ECCV 2016

Embodied representations



Pinto et al., “The Curious Robot: Learning Visual Representations via Physical Interactions”, ECCV 2016

Grasping

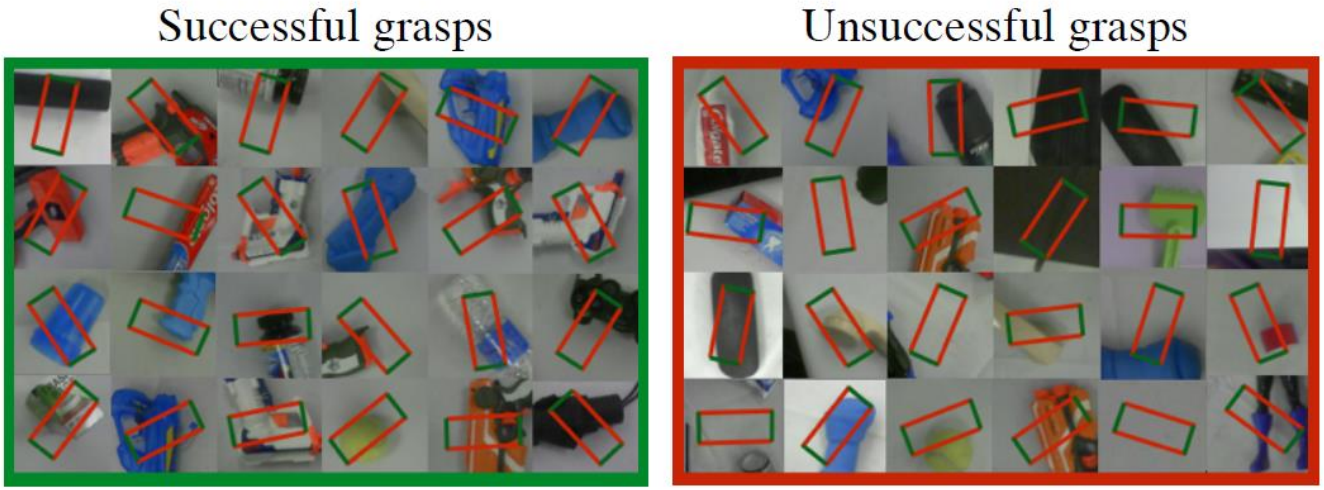


Fig. 2. Examples of successful (left) and unsuccesful grasps (right). We use a patch based representation: given an input patch we predict 18-dim vector which represents whether the center location of the patch is graspable at 0°, 10°, . . . 170°.

Pinto et al., "The Curious Robot: Learning Visual Representations via Physical Interactions", ECCV 2016

Pushing

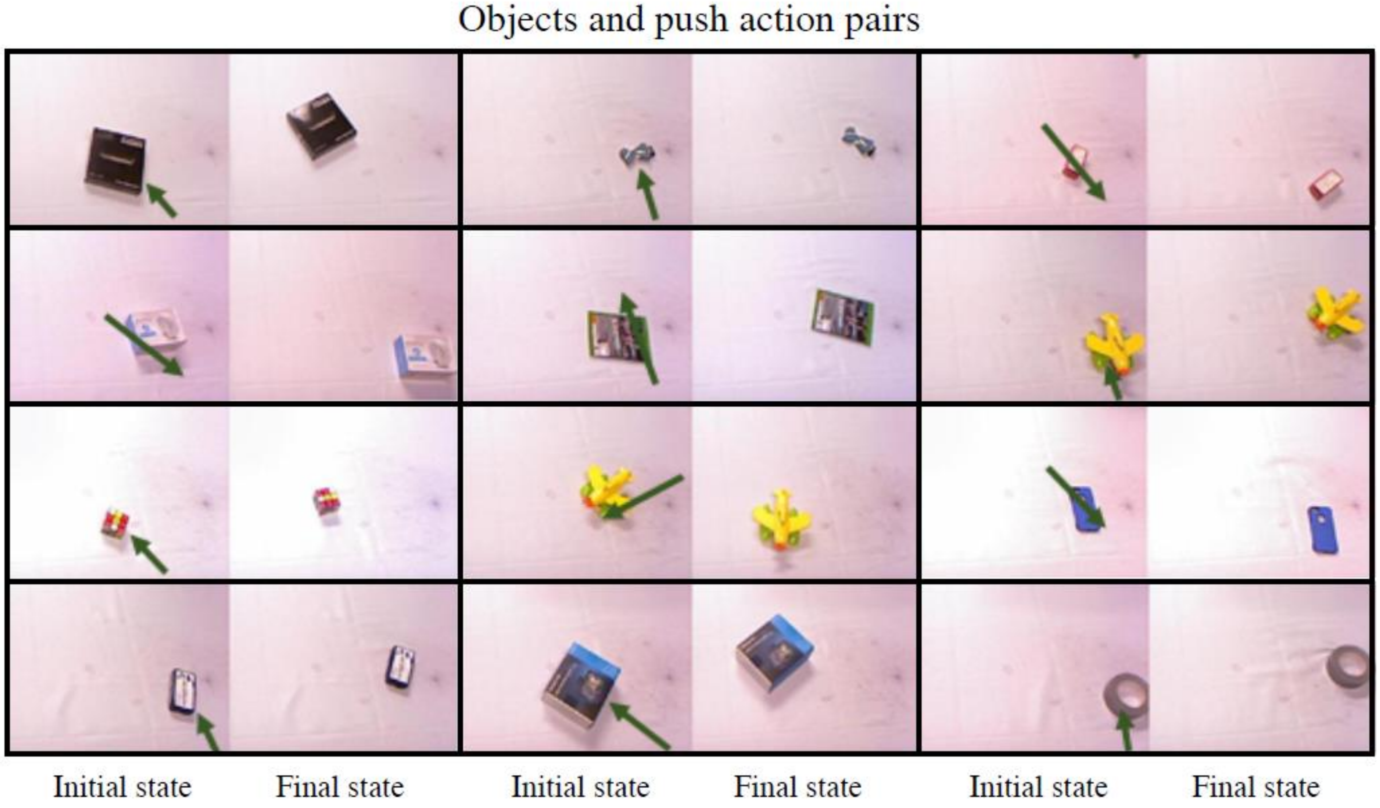
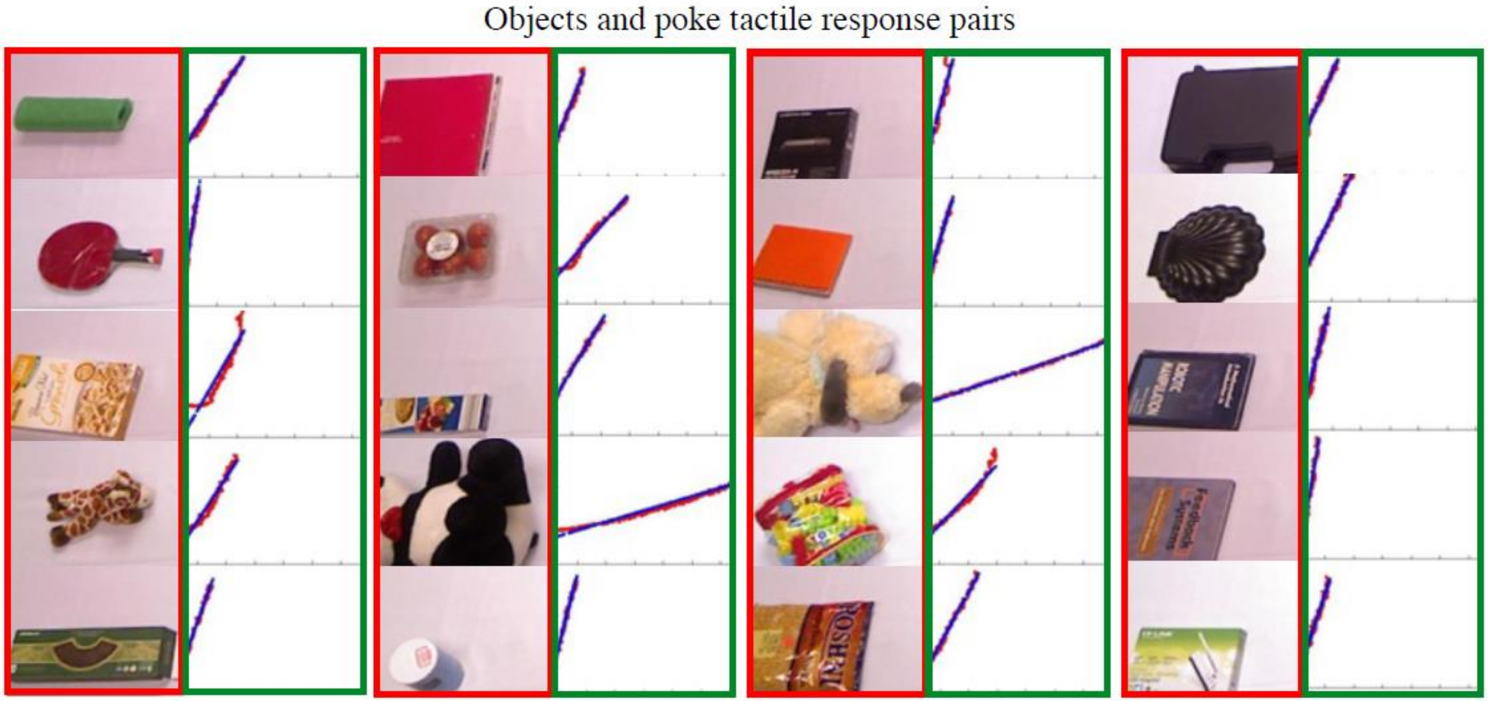


Fig. 4. Examples of initial state and final state images taken for the push action. The arrows demonstrate the direction and magnitude of the push action.

Pinto et al., “The Curious Robot: Learning Visual Representations via Physical Interactions”, ECCV 2016

Poking



Objects and poke tactile response pairs

Fig. 6. Examples of the data collected by the poking action. On the left we show the object poked, and on the right we show force profiles as observed by the tactile sensor.

Pinto et al., “The Curious Robot: Learning Visual Representations via Physical Interactions”, ECCV 2016

Pose/viewpoint invariance

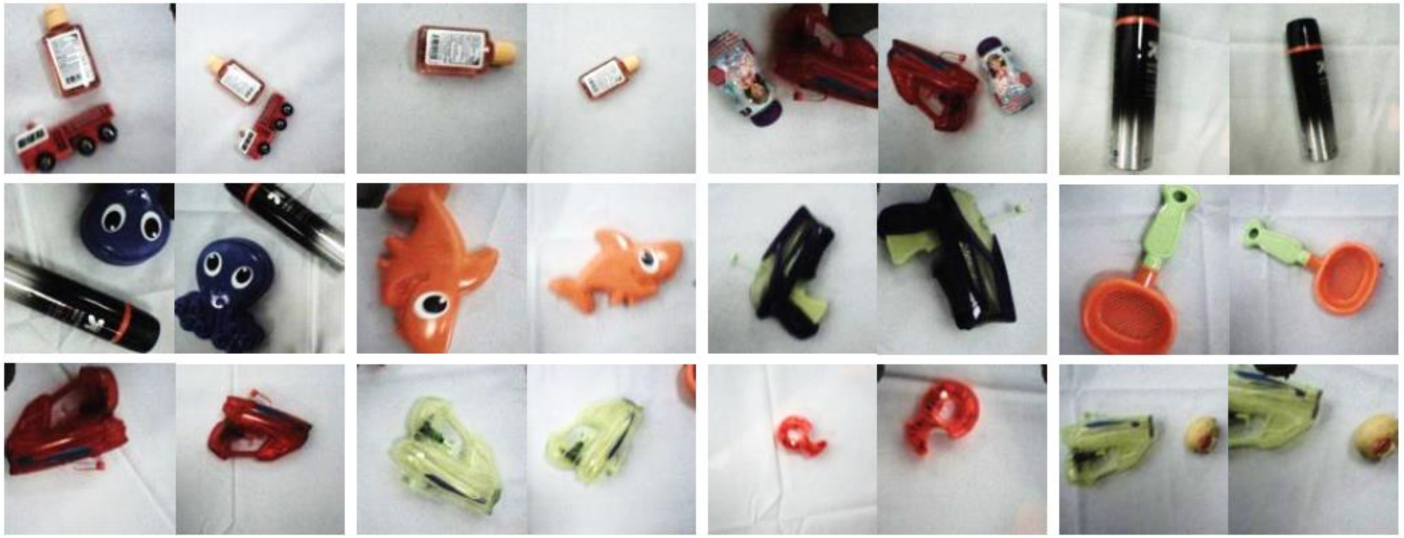


Fig. 7. Examples of objects in different poses provided to the embedding network.

Pinto et al., "The Curious Robot: Learning Visual Representations via Physical Interactions", ECCV 2016

Representations from interactions

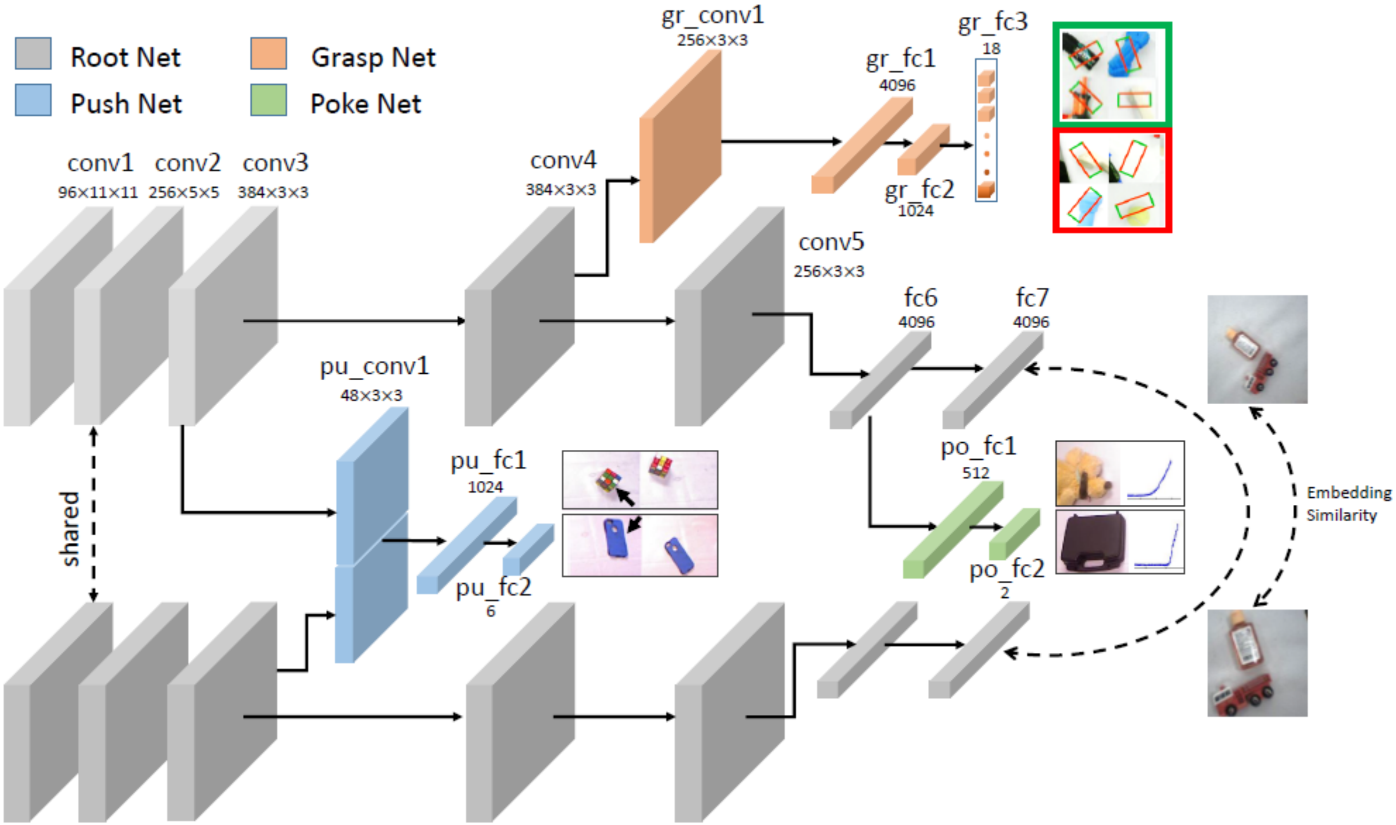


Fig. 8. Our shared convolutional architecture for four different tasks.

Pinto et al., "The Curious Robot: Learning Visual Representations via Physical Interactions", ECCV 2016

Classification/retrieval performance

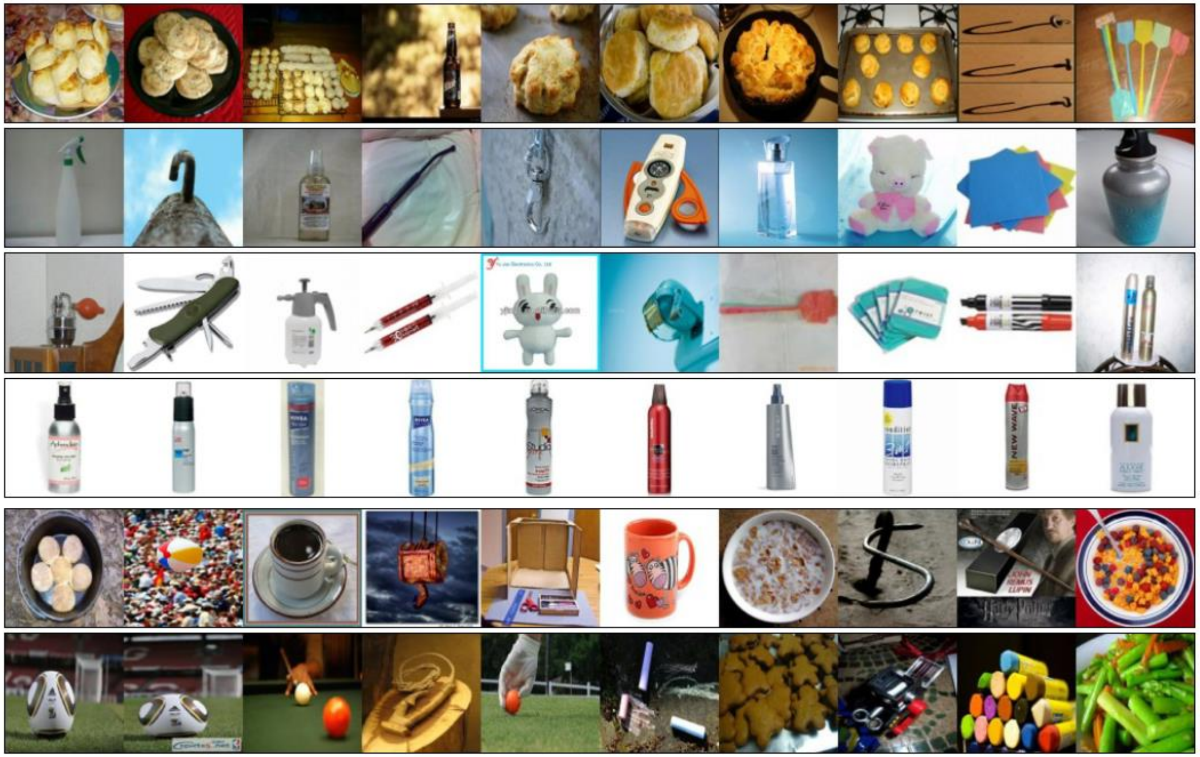


Fig. 10. The first column corresponds to query image and rest show the retrieval. Note how the network learns that cups and bowls are similar (row 5).

Pinto et al., “The Curious Robot: Learning Visual Representations via Physical Interactions”, ECCV 2016

Classification/retrieval performance

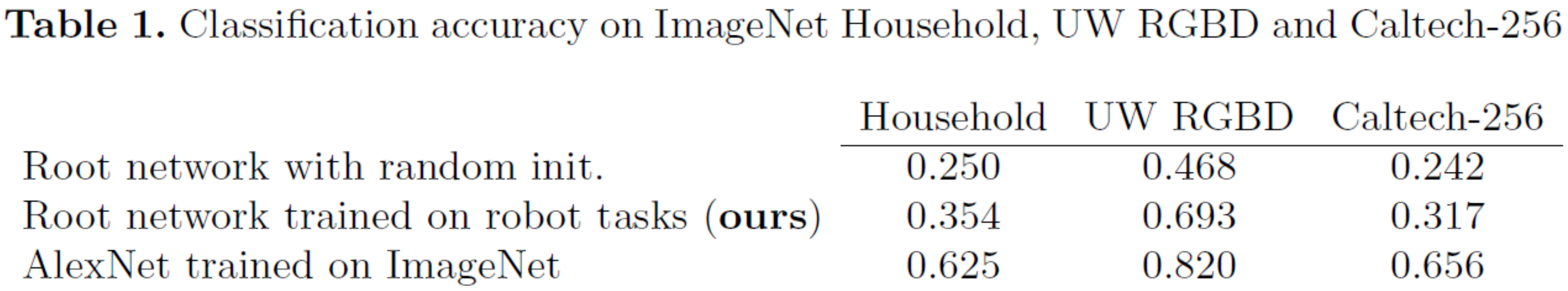


Table 1. Classification accuracy on ImageNet Household, UW RGBD and Caltech-256

	Household	UW RGBD	Caltech-256
Root network with random init.	0.250	0.468	0.242
Root network trained on robot tasks (**ours**)	0.354	0.693	0.317
AlexNet trained on ImageNet	0.625	0.820	0.656

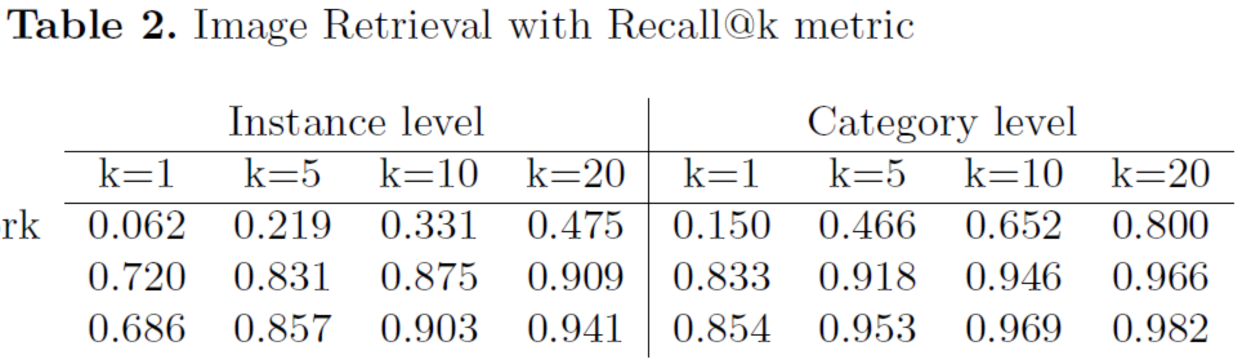


Table 2. Image Retrieval with Recall@k metric

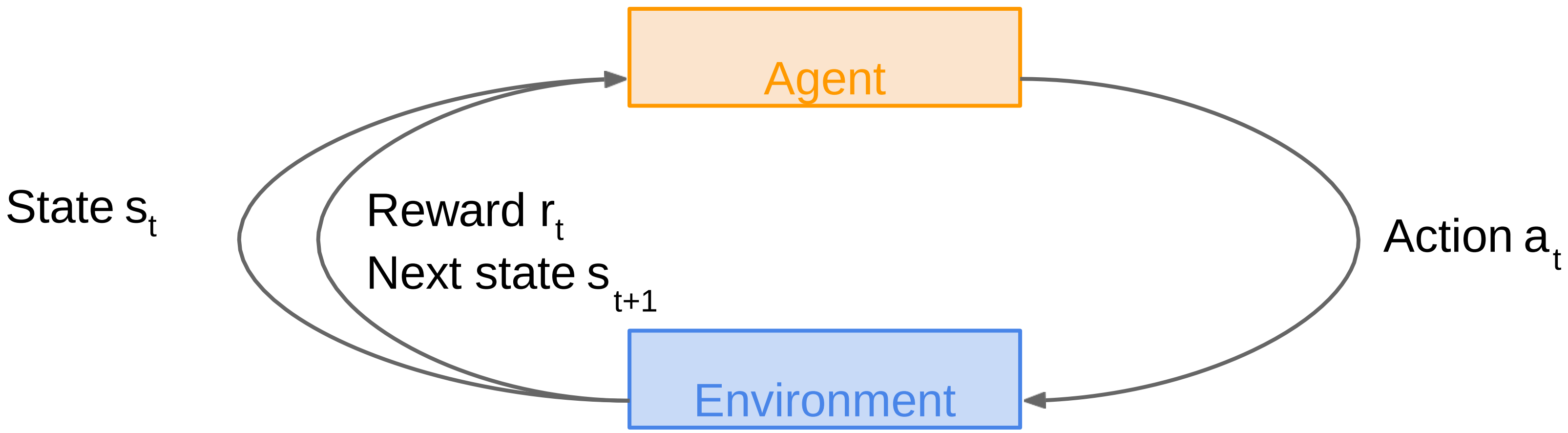
	Instance level				Category level			
	k=1	k=5	k=10	k=20	k=1	k=5	k=10	k=20
Random Network	0.062	0.219	0.331	0.475	0.150	0.466	0.652	0.800
Our Network	0.720	0.831	0.875	0.909	0.833	0.918	0.946	0.966
AlexNet	0.686	0.857	0.903	0.941	0.854	0.953	0.969	0.982

Pinto et al., “The Curious Robot: Learning Visual Representations via Physical Interactions”, ECCV 2016

Part III: Reinforcement Learning

- Basics: actions, states, rewards, MDP
- Different techniques (Q learning, policy gradients, actor-critic, etc.)
- Example applications

Reinforcement Learning



Agent

State s_t

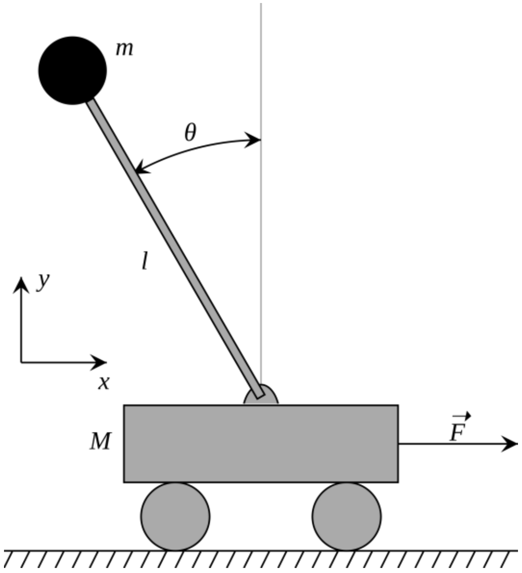
Reward r_t

Next state s_{t+1}

Action a_t

Environment

Cart-Pole Problem



Objective: Balance a pole on top of a movable cart

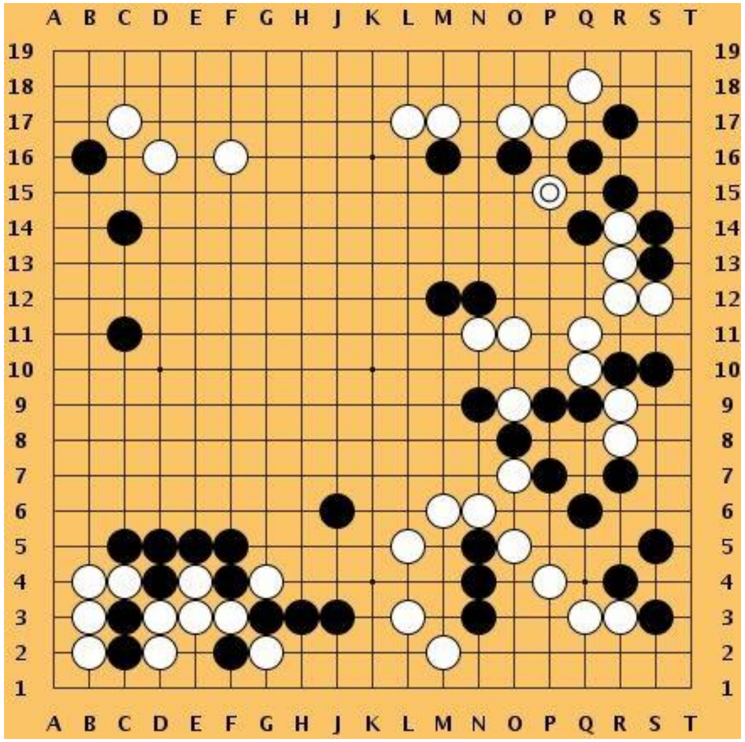
State: angle, angular speed, position, horizontal velocity
Action: horizontal force applied on the cart
Reward: 1 at each time step if the pole is upright

Atari Games

Objective: Complete the game with the highest score

State: Raw pixel inputs of the game state
Action: Game controls e.g. Left, Right, Up, Down
Reward: Score increase/decrease at each time step

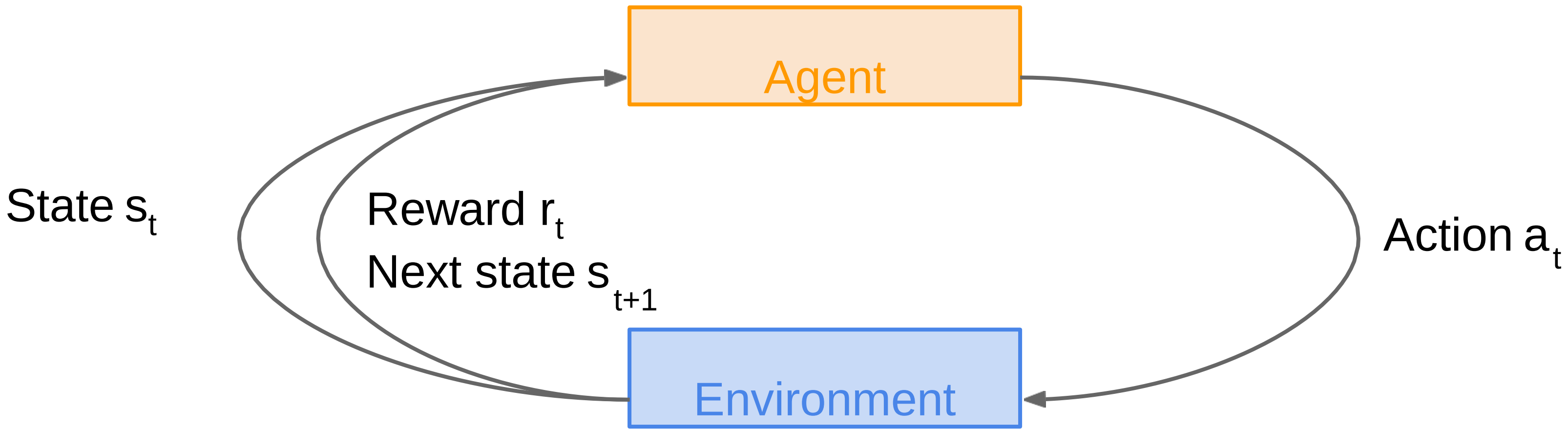
Go



Objective: Win the game!

State: Position of all pieces
Action: Where to put the next piece down
Reward: 1 if win at the end of the game, 0 otherwise

How can we mathematically formalize the RL problem?



Markov Decision Process

- Mathematical formulation of the RL problem
- **Markov property**: Current state completely characterises the state of the world

Defined by: $(\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathbb{P}, \gamma)$

$\mathcal{S}$: set of possible states
$\mathcal{A}$: set of possible actions
$\mathcal{R}$: distribution of reward given (state, action) pair
$\mathbb{P}$: transition probability i.e. distribution over next state given (state, action) pair
γ : discount factor

Markov Decision Process

- At time step t=0, environment samples initial state $s_0 \sim p(s_0)$
- Then, for t=0 until done:
  - Agent selects action a_t
  - Environment samples reward $r_t \sim R(. | s_t, a_t)$
  - Environment samples next state $s_{t+1} \sim P(. | s_t, a_t)$
  - Agent receives reward r_t and next state s_{t+1}

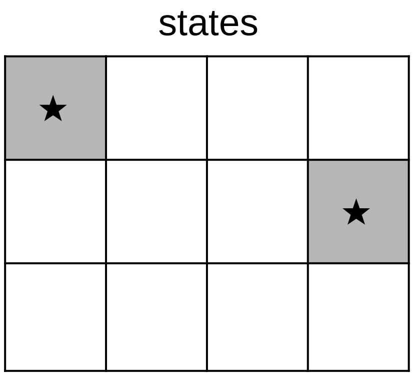
- A policy u is a function from S to A that specifies what action to take in each state
- **Objective**: find policy u* that maximizes cumulative discounted reward: $\sum_{t \geq 0} \gamma^t r_t$

A simple MDP: Grid World

actions = {

1. right →
2. left ←
3. up ↑
4. down ↓

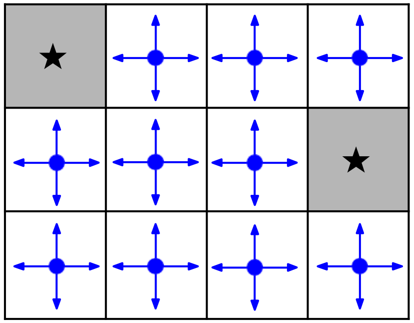
}



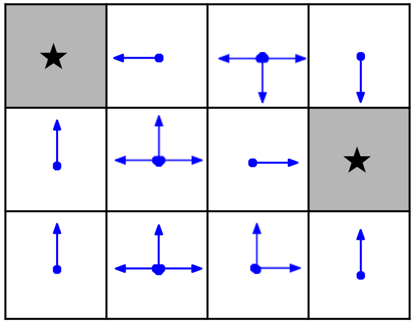
Set a negative “reward”
for each transition
(e.g. $r = -1$)

Objective: reach one of terminal states (greyed out) in least number of actions

A simple MDP: Grid World



Random Policy



Optimal Policy

The optimal policy u*

We want to find optimal policy u* that maximizes the sum of rewards.

How do we handle the randomness (initial state, transition probability…)?

The optimal policy u*

We want to find optimal policy u* that maximizes the sum of rewards.

How do we handle the randomness (initial state, transition probability…)?
Maximize the **expected sum of rewards!**

Formally: $\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t\geq 0} \gamma^t r_t | \pi\right]$ with $s_0 \sim p(s_0), a_t \sim \pi(\cdot|s_t), s_{t+1} \sim p(\cdot|s_t, a_t)$

Definitions: Value function and Q-value function

Following a policy produces sample trajectories (or paths) s_0, a_0, r_0, s_1, a_1, r_1, …

How good is a state?

The **value function** at state s, is the expected cumulative reward from following the policy from state s:

$$V^{\pi}(s) = \mathbb{E}\left[\sum_{t\geq 0} \gamma^t r_t | s_0 = s, \pi\right]$$

How good is a state-action pair?

The **Q-value function** at state s and action a, is the expected cumulative reward from taking action a in state s and then following the policy:

$$Q^{\pi}(s,a) = \mathbb{E}\left[\sum_{t\geq 0} \gamma^t r_t | s_0 = s, a_0 = a, \pi\right]$$

Bellman equation

The optimal Q-value function Q* is the maximum expected cumulative reward achievable from a given (state, action) pair:

$$Q^*(s,a) = \max_{\pi} \mathbb{E}\left[\sum_{t\geq 0} \gamma^t r_t | s_0 = s, a_0 = a, \pi\right]$$

Q* satisfies the following **Bellman equation**:

$$Q^*(s,a) = \mathbb{E}_{s' \sim \mathcal{E}}\left[r + \gamma \max_{a'} Q^*(s',a') | s, a\right]$$

Intuition: if the optimal state-action values for the next time-step Q*(s’,a’) are known, then the optimal strategy is to take the action that maximizes the expected value of

$r + \gamma Q^*(s',a')$

The optimal policy u* corresponds to taking the best action in any state as specified by Q*

Solving for the optimal policy: Q-learning

Q-learning: Use a function approximator to estimate the action-value function

$$Q(s, a; \theta) \approx Q^*(s, a)$$

function parameters (weights)

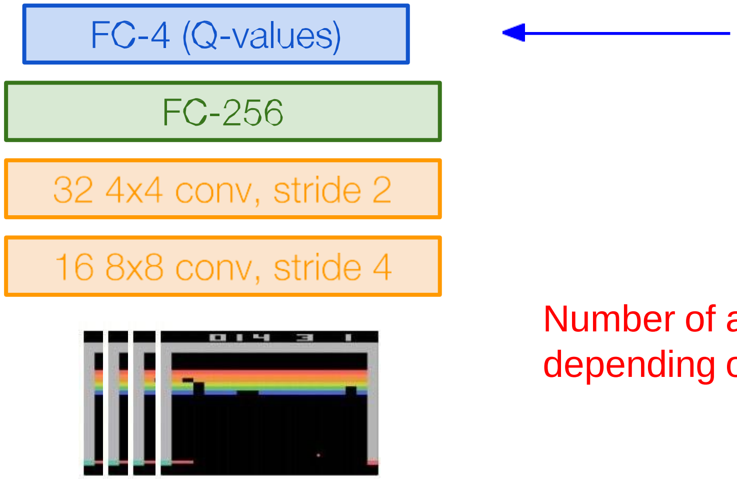
If the function approximator is a deep neural network => **deep q-learning**!

[Mnih et al. NIPS Workshop 2013; Nature 2015]

Q-network Architecture

$Q(s,a;\theta)$: neural network with weights θ

A single feedforward pass to compute Q-values for all actions from the current state => efficient!



FC-4 (Q-values)

FC-256

32 4x4 conv, stride 2

16 8x8 conv, stride 4

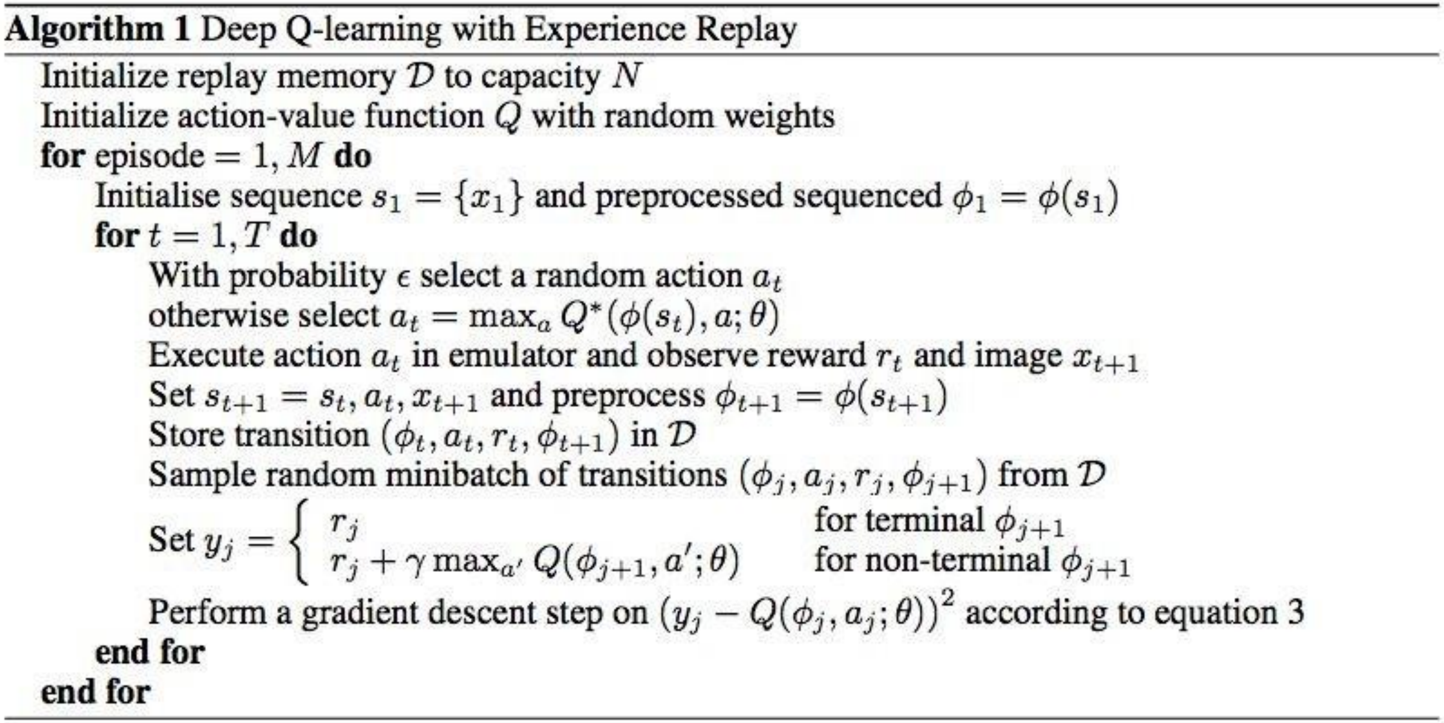
Last FC layer has 4-d output (if 4 actions), corresponding to $Q(s_t, a_1)$, $Q(s_t, a_2)$, $Q(s_t, a_3)$, $Q(s_t,a_4)$

Number of actions between 4-18 depending on Atari game

Current state s_t: 84x84x4 stack of last 4 frames
(after RGB->grayscale conversion, downsampling, and cropping)

[Mnih et al. NIPS Workshop 2013; Nature 2015]

Putting it together: Deep Q-Learning with Experience Replay



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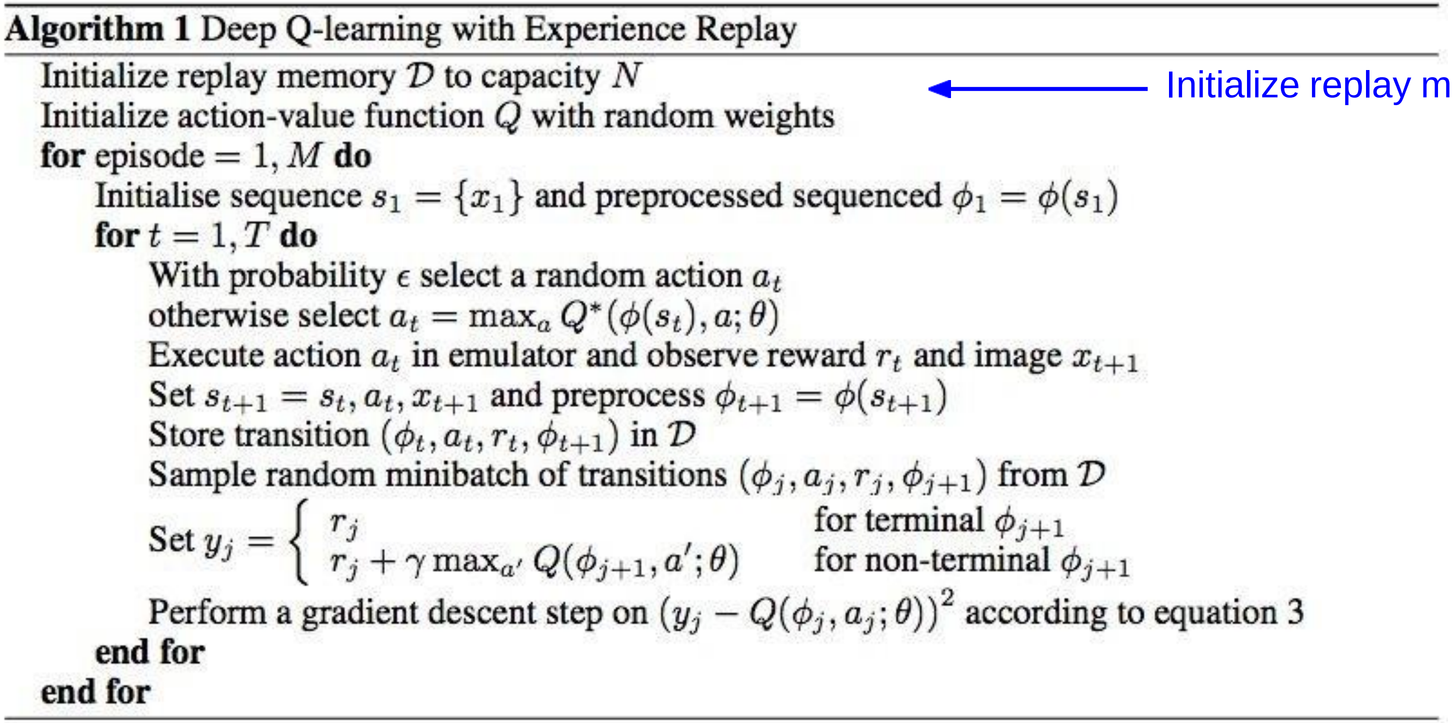
```

[Mnih et al. NIPS Workshop 2013; Nature 2015]

Putting it together: Deep Q-Learning with Experience Replay



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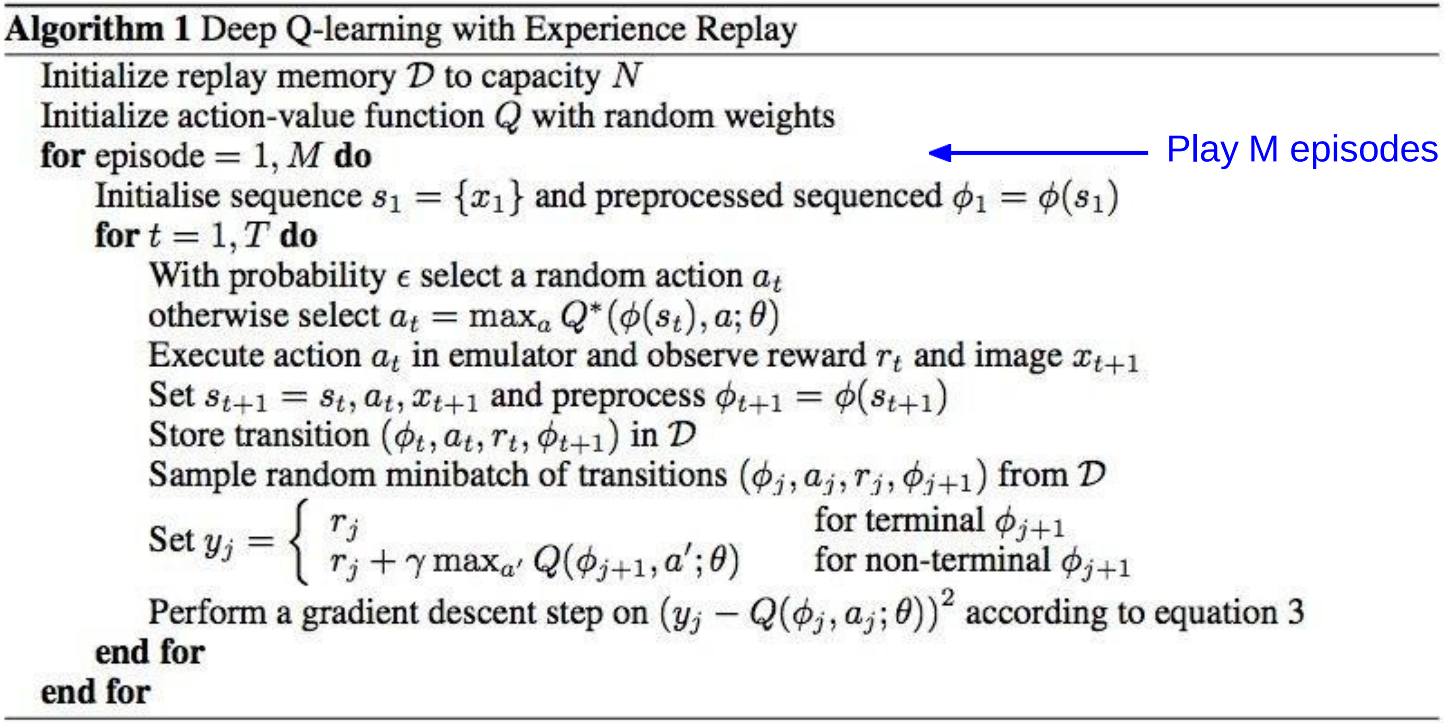
      end for
  end for
```

Initialize replay memory, Q-network

[Mnih et al. NIPS Workshop 2013; Nature 2015]

Putting it together: Deep Q-Learning with Experience Replay



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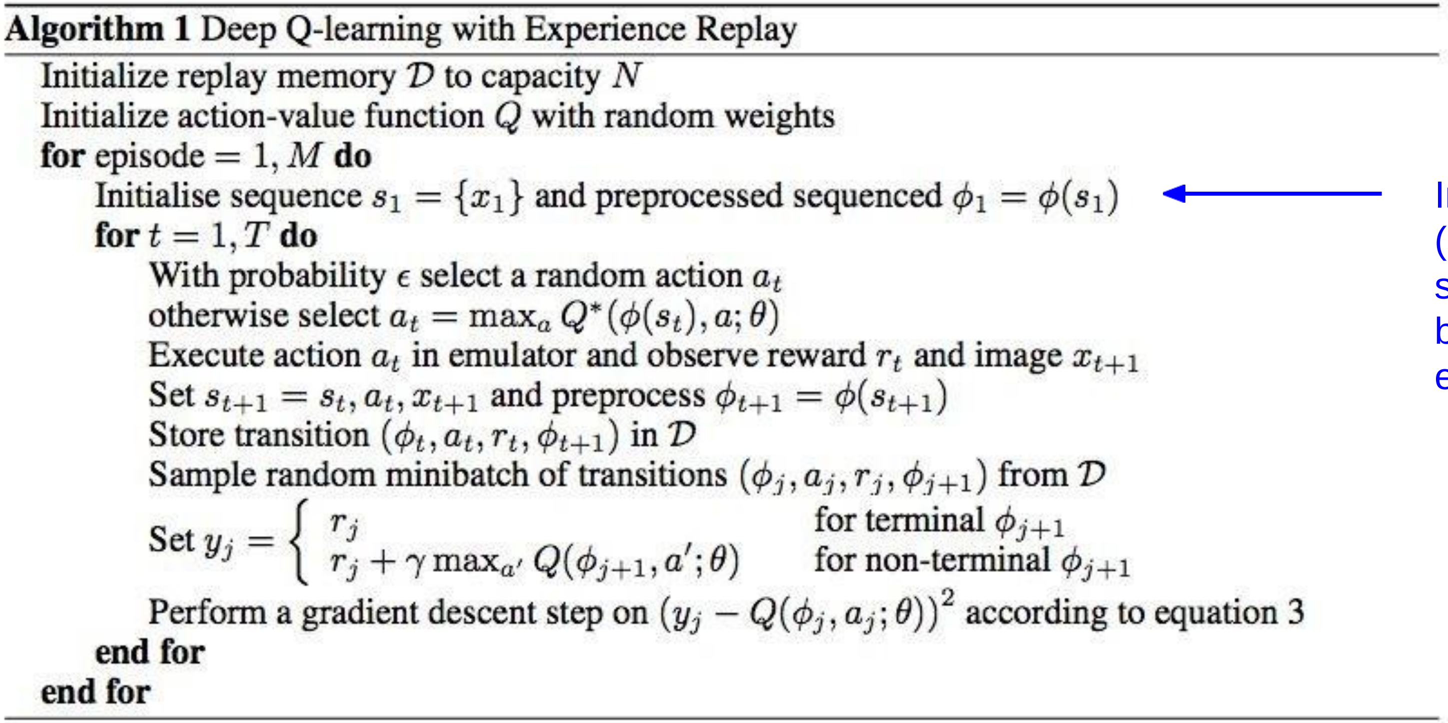
    end for
end for
```

← Play M episodes (full games)

[Mnih et al. NIPS Workshop 2013; Nature 2015]

Putting it together: Deep Q-Learning with Experience Replay



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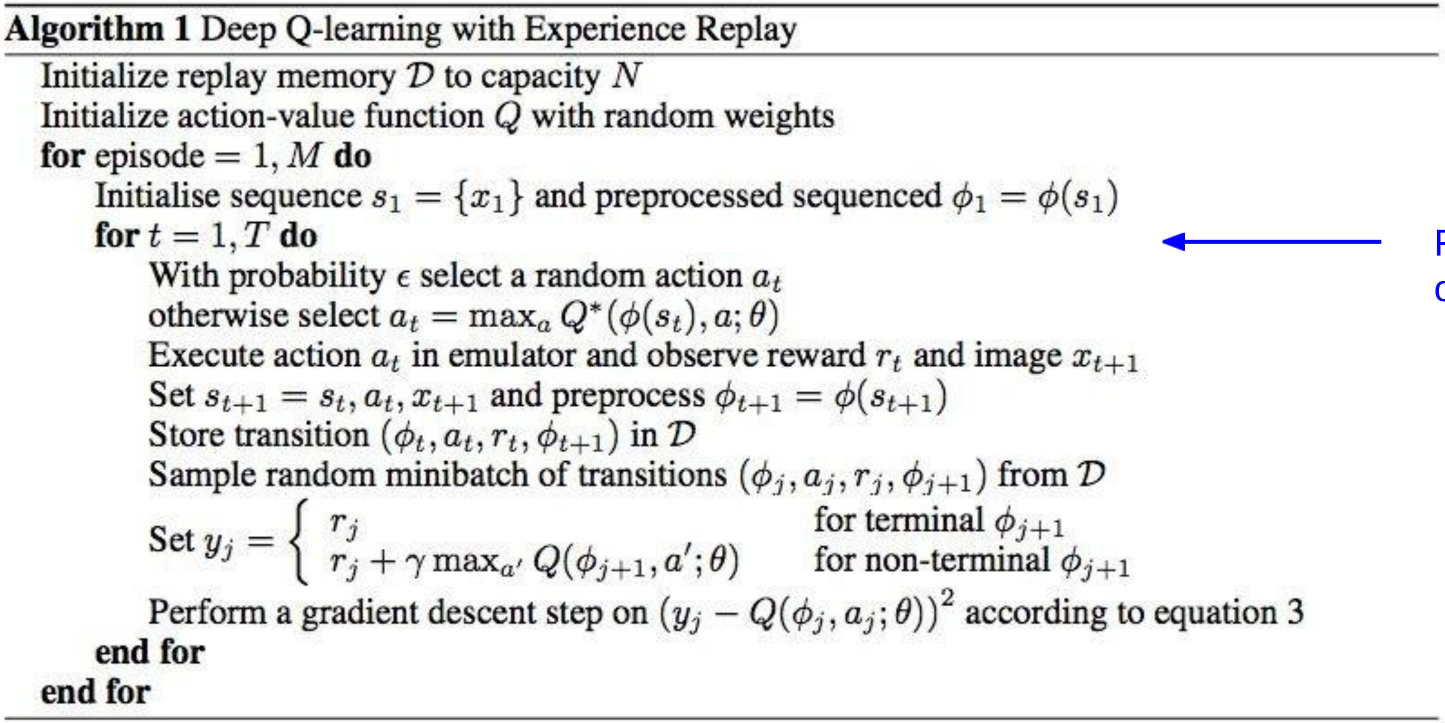
        Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
    end for
end for
```

Initialize state (starting game screen pixels) at the beginning of each episode

[Mnih et al. NIPS Workshop 2013; Nature 2015]

Putting it together: Deep Q-Learning with Experience Replay



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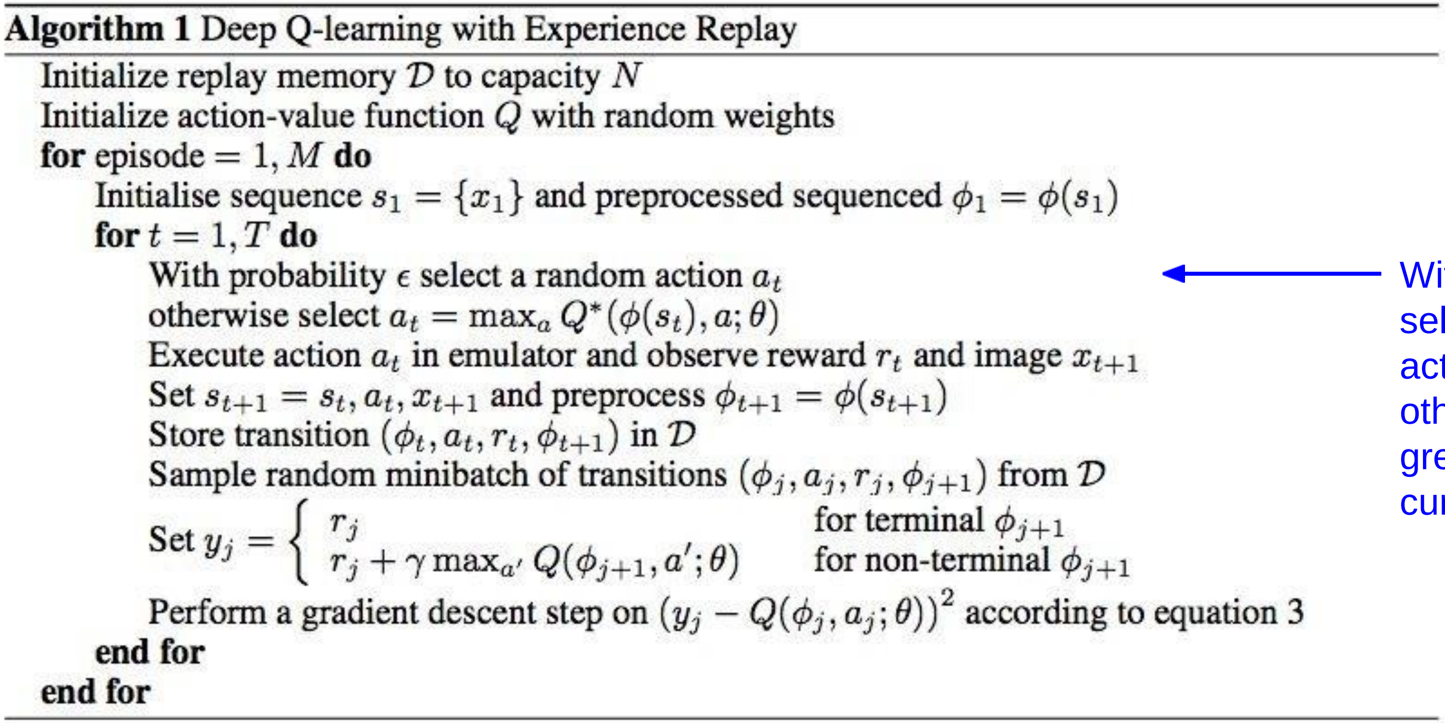
    end for
end for
```

For each timestep t of the game

[Mnih et al. NIPS Workshop 2013; Nature 2015]

Putting it together: Deep Q-Learning with Experience Replay



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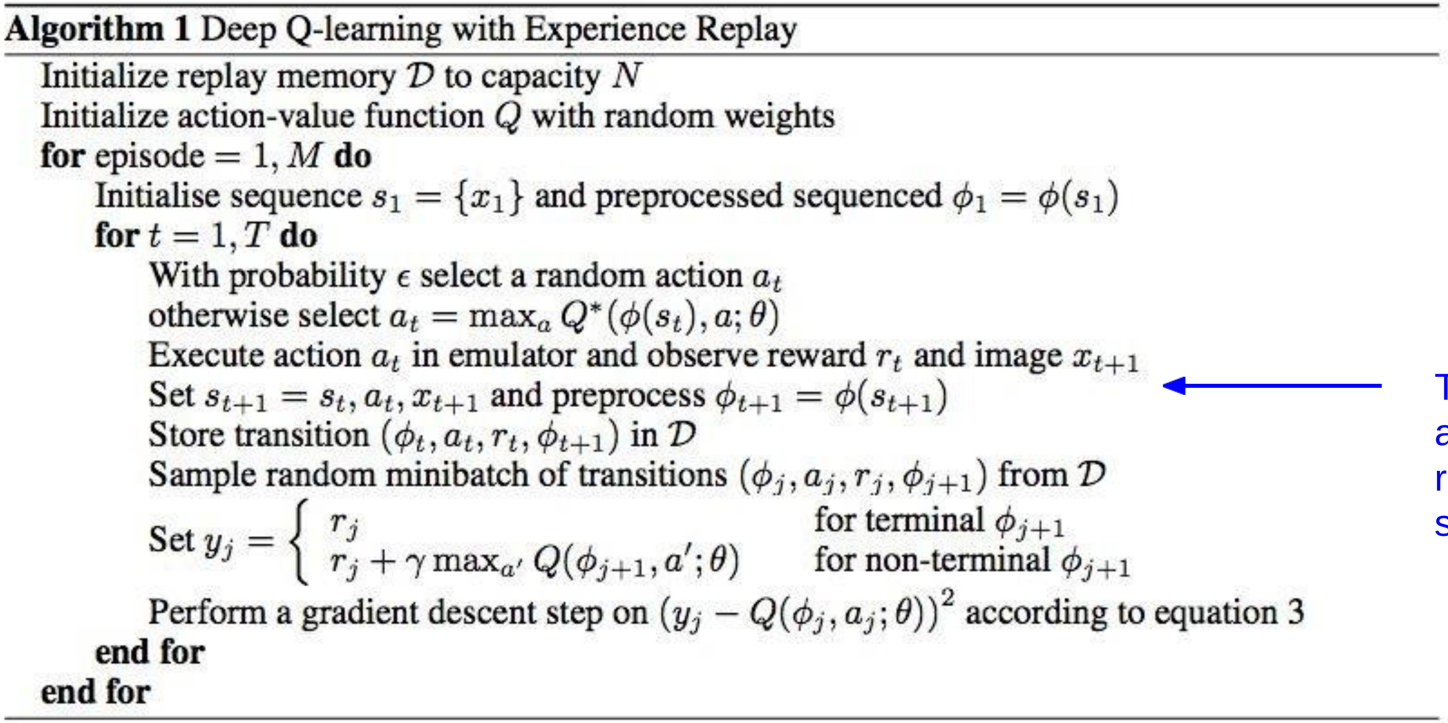
    end for
end for
```

With small probability, select a random action (explore), otherwise select greedy action from current policy

[Mnih et al. NIPS Workshop 2013; Nature 2015]

Putting it together: Deep Q-Learning with Experience Replay



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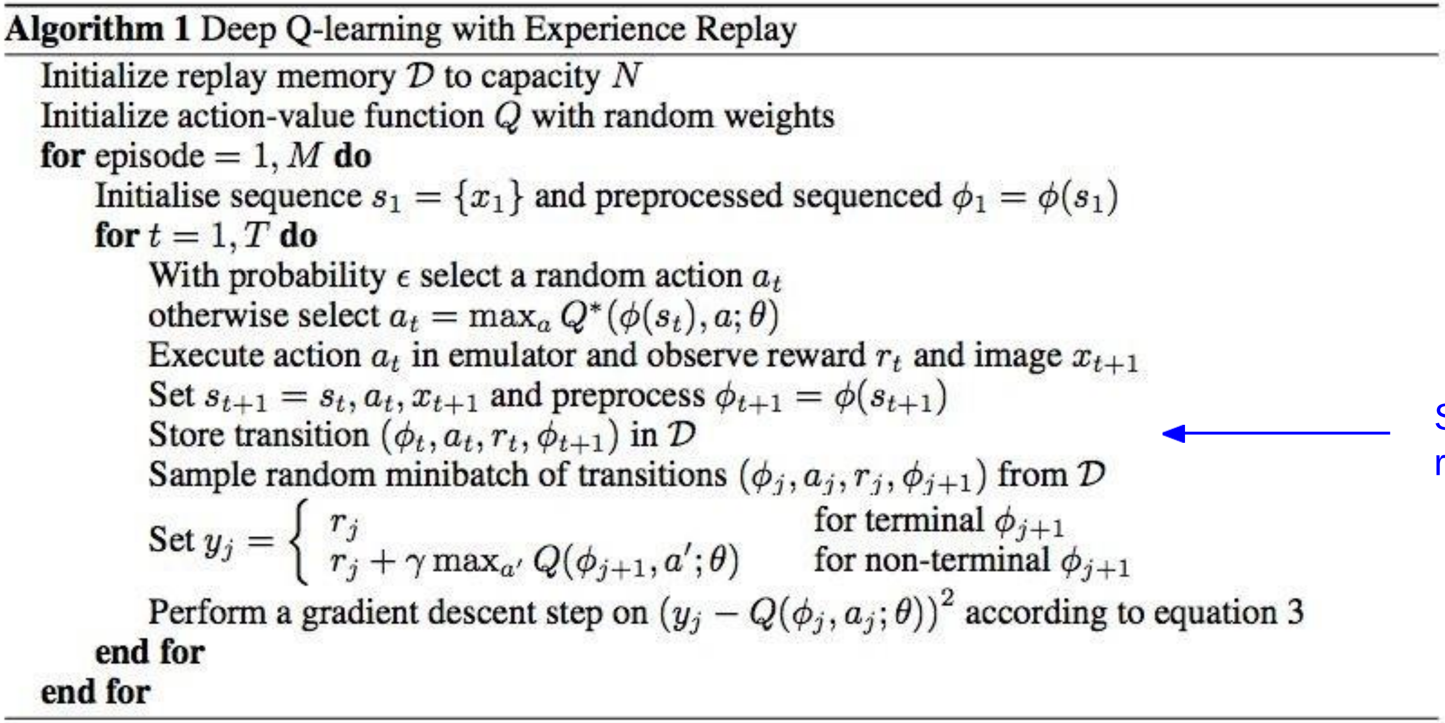
        Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
    end for
end for
```

Take the action (a_t), and observe the reward r_t and next state s_{t+1}

[Mnih et al. NIPS Workshop 2013; Nature 2015]

Putting it together: Deep Q-Learning with Experience Replay



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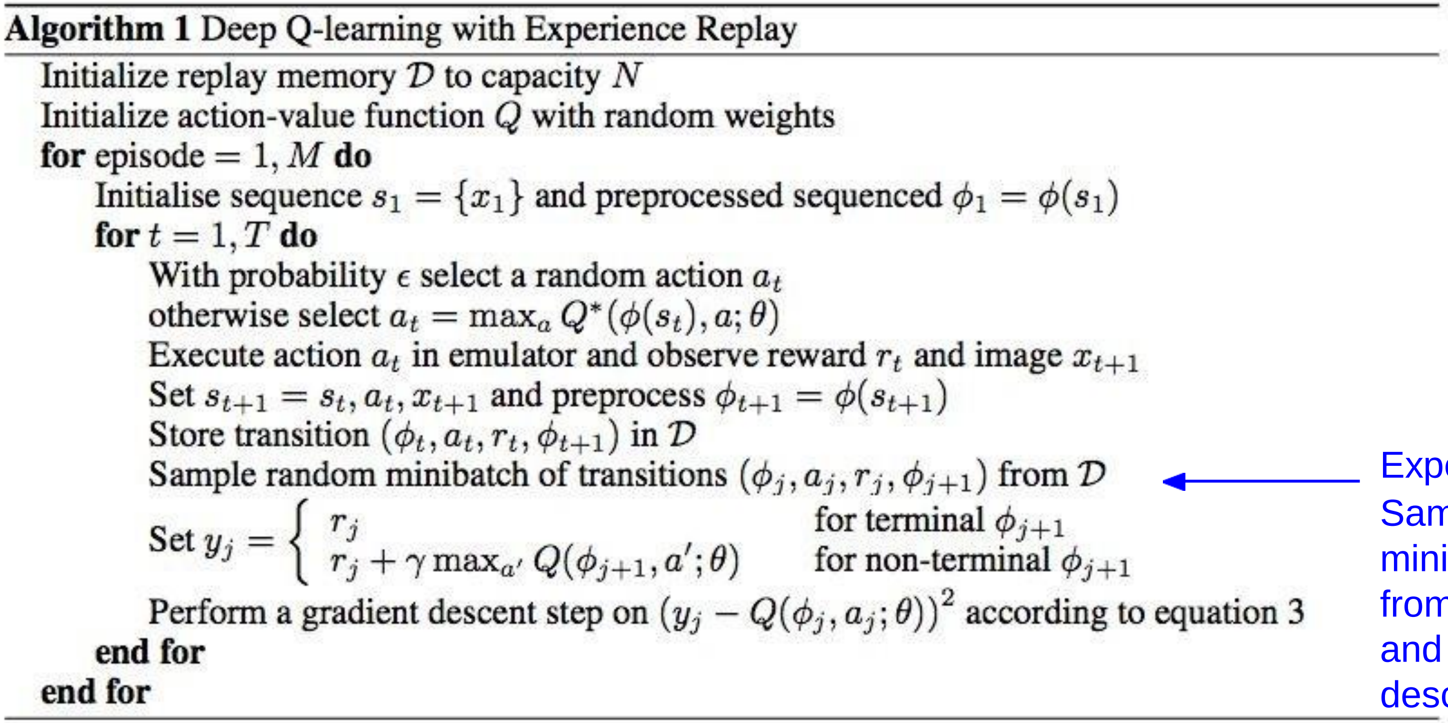
    end for
end for
```

Store transition in replay memory

[Mnih et al. NIPS Workshop 2013; Nature 2015]

Putting it together: Deep Q-Learning with Experience Replay



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    end for
end for
```

Experience Replay: Sample a random minibatch of transitions from replay memory and perform a gradient descent step

Policy Gradients

What is a problem with Q-learning?
The Q-function can be very complicated!

Example: a robot grasping an object has a very high-dimensional state => hard to learn exact value of every (state, action) pair

But the policy can be much simpler: just close your hand
Can we learn a policy directly, e.g. finding the best policy from a collection of policies?

Policy Gradients

Formally, let's define a class of parameterized policies: $\Pi = \{\pi_\theta, \theta \in \mathbb{R}^m\}$

For each policy, define its value:

$$J(\theta) = \mathbb{E}\left[\sum_{t\geq 0} \gamma^t r_t | \pi_\theta\right]$$

We want to find the optimal policy $\theta^* = \arg\max_\theta J(\theta)$

How can we do this?

Gradient ascent on policy parameters!

REINFORCE Algorithm (orig. Williams 1992)

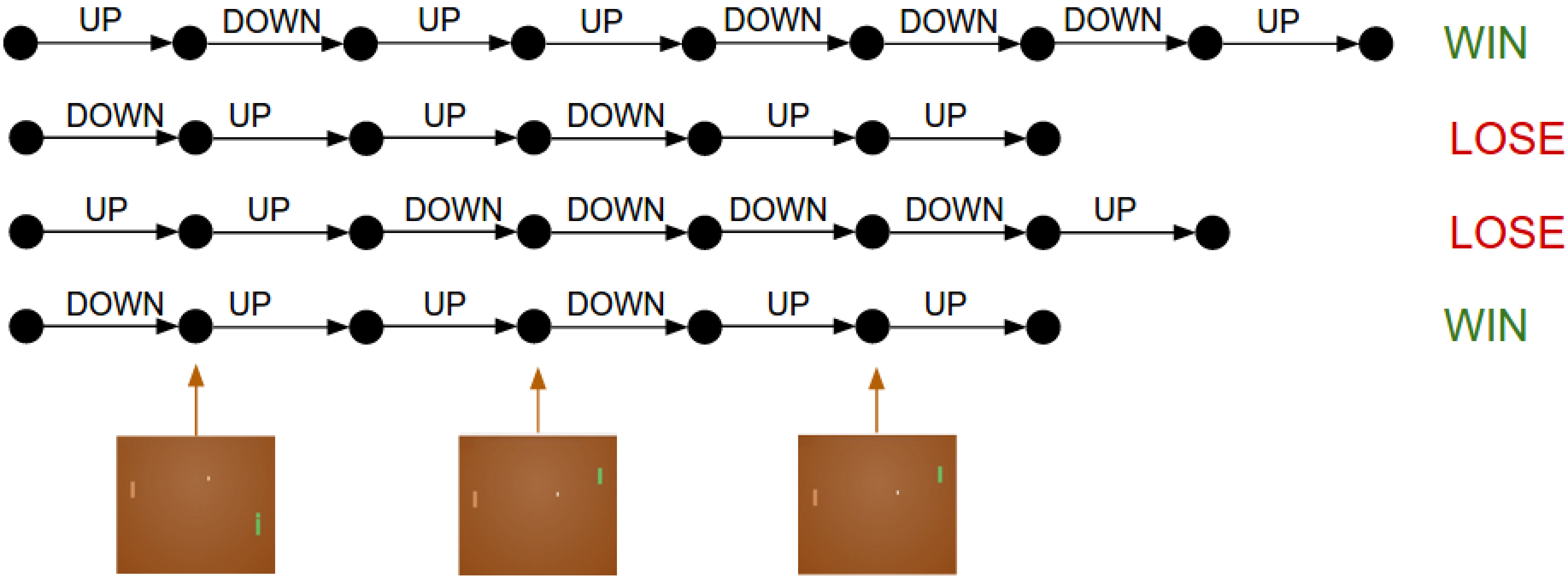
Gradient estimator: $$\nabla_\theta J(\theta) \approx \sum_{t \geq 0} r(\tau) \nabla_\theta \log \pi_\theta(a_t|s_t)$$

Interpretation:

- If r(r) is high, push up the probabilities of the actions seen
- If r(r) is low, push down the probabilities of the actions seen

Might seem simplistic to say that if a trajectory is good then all its actions were good. But in expectation, it averages out!

Policy Gradients



Andrej Karpathy

Policy Gradients

- Objective: $\sum_i A_i \log p(y_i|x_i)$
- x_i = state
- y_i = sampled action
- A_i = “advantage” e.g. +1/-1 for win/lose in simplest version, or discounted, or improvement over “baseline”

Adapted from Andrej Karpathy

Policy Gradients vs Q-Learning

- Policy gradients suffers from high variance and instability; might want to make gradients smaller (e.g. relative to a baseline)
- Policy gradients can handle continuous action spaces (Gaussian policy)
- Estimating exact value of state-action pairs vs choosing what actions to take (value not important)
- Step-by-step (did I correctly estimate the reward at this time) vs delayed feedback (run policy and wait until game terminates)

Actor-Critic Algorithm

We can combine Policy Gradients and Q-learning by training both an **actor** (the policy) and a **critic** (the Q-function).

- The actor decides which action to take, and the critic tells the actor how good its action was and how it should adjust
- Also alleviates the task of the critic as it only has to learn the values of (state, action) pairs generated by the policy
- Can also incorporate Q-learning tricks e.g. experience replay
- **Remark:** we can define by the **advantage function** how much an action was better than expected $A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$

RL for object detection

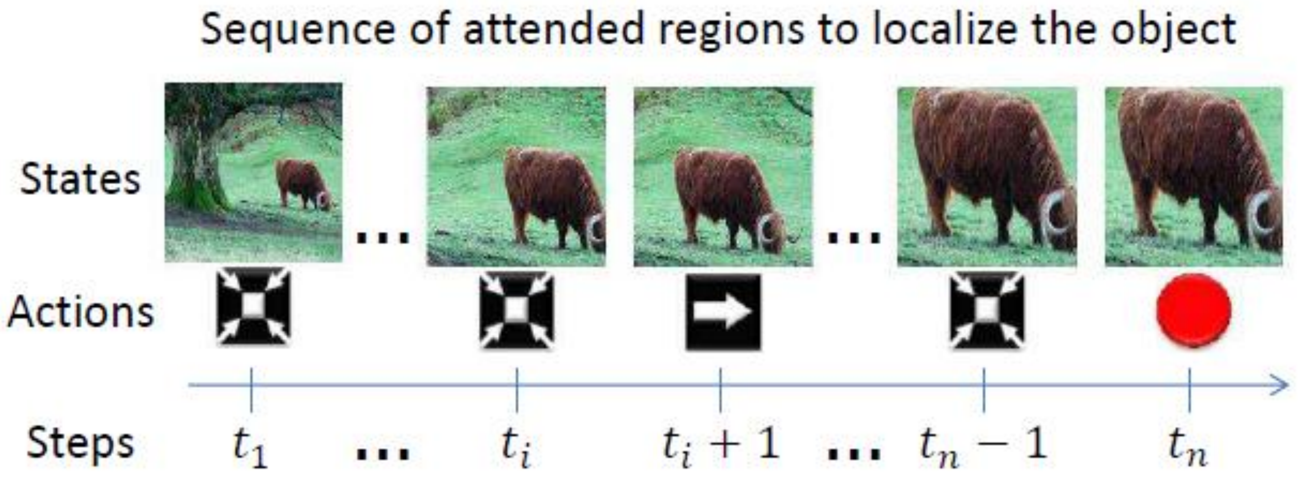


Figure 1. A sequence of actions taken by the proposed algorithm to localize a cow. The algorithm attends regions and decides how to transform the bounding box to progressively localize the object.

Caicedo and Lazebnik, "Active Object Localization with Deep Reinforcement Learning", ICCV 2015

RL for object detection

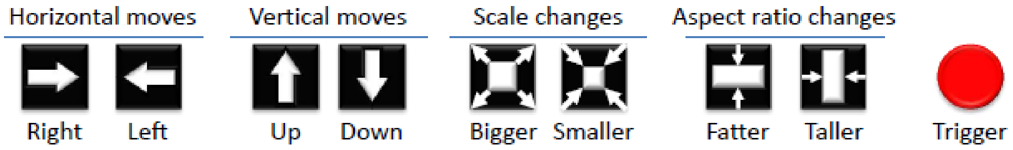
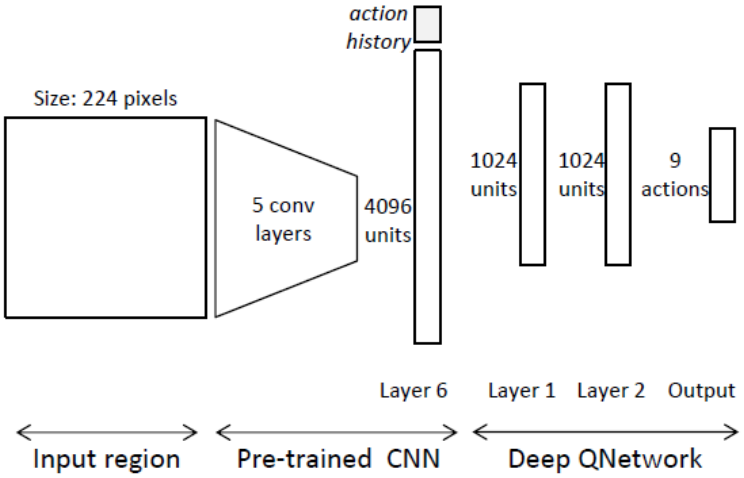


Figure 2. Illustration of the actions in the proposed MDP, giving 4 degrees of freedom to the agent for transforming boxes.

$$R_a(s, s') = sign\,(IoU(b', g) - IoU(b, g)) \qquad R_\omega(s, s') = \begin{cases} +\eta & \text{if } IoU(b, g) \geq \tau \\ -\eta & \text{otherwise} \end{cases}$$



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RL for navigation

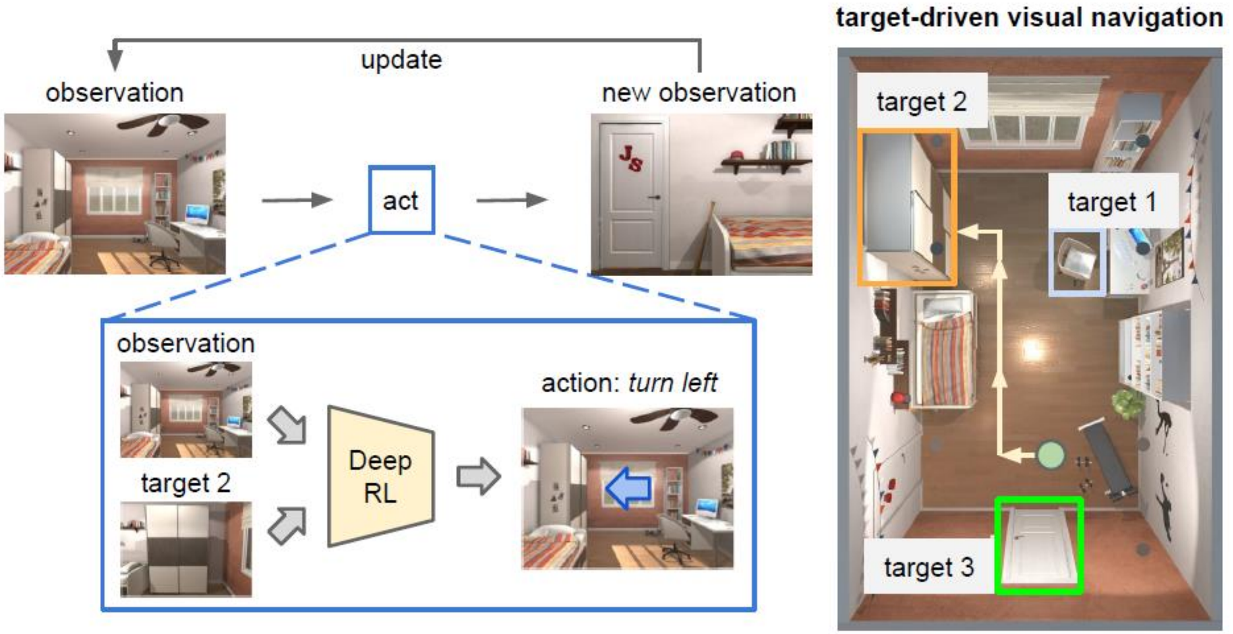


Fig. 1. The goal of our deep reinforcement learning model is to navigate towards a visual target with a minimum number of steps. Our model takes the current observation and the image of the target as input and generates an action in the 3D environment as the output. Our model learns to navigate to different targets in a scene without re-training.

Zhu et al., "Target-driven Visual Navigation in Indoor Scenes using Deep Reinforcement Learning", ICRA 2017

RL for navigation

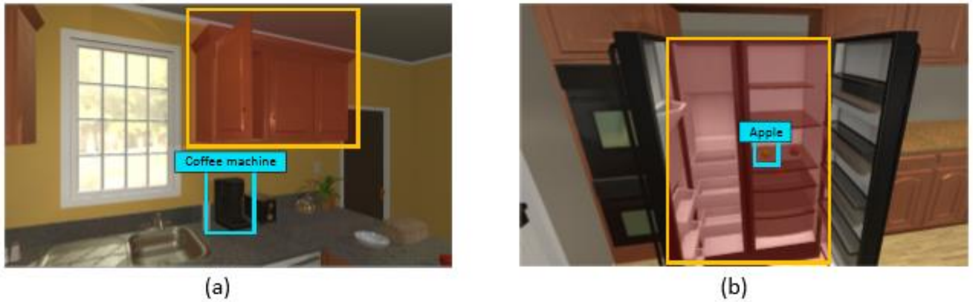


Figure 1: Our goal is to use scene priors to improve navigation in unseen scenes and towards novel objects. (a) There is no mug in the field of view of the agent, but the likely location for finding a mug is the cabinet near the coffee machine. (b) The agent has not seen a mango before, but it infers that the most likely location for finding a mango is the fridge since similar objects such as apple appear there as well. The most likely locations are shown with the orange box.

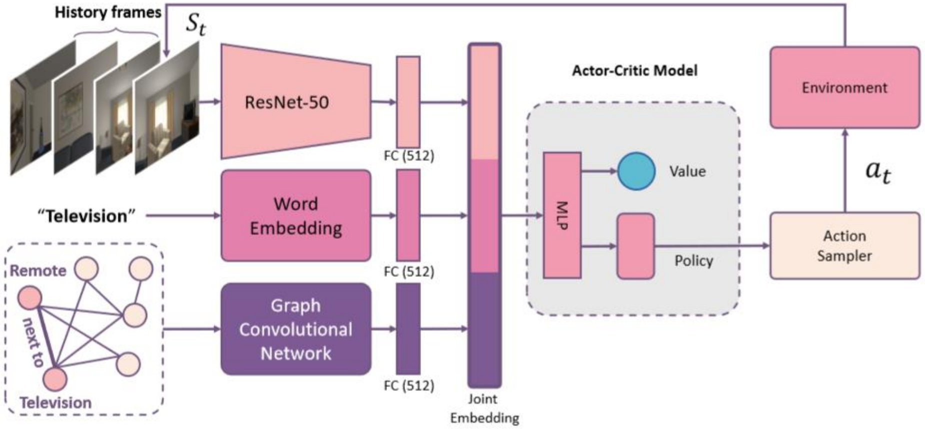


Figure 2: **Overview of the architecture.** Our model to incorporate semantic knowledge into semantic navigation. Specifically, we learn a policy network that decides an action based on the visual features of the current state, the semantic target category feature and the features extracted from the knowledge graph. We extract features from the parts of the knowledge graph that are activated.

Yang et al., "Visual Semantic Navigation using Scene Priors", ICLR 2019

RL for question-answering

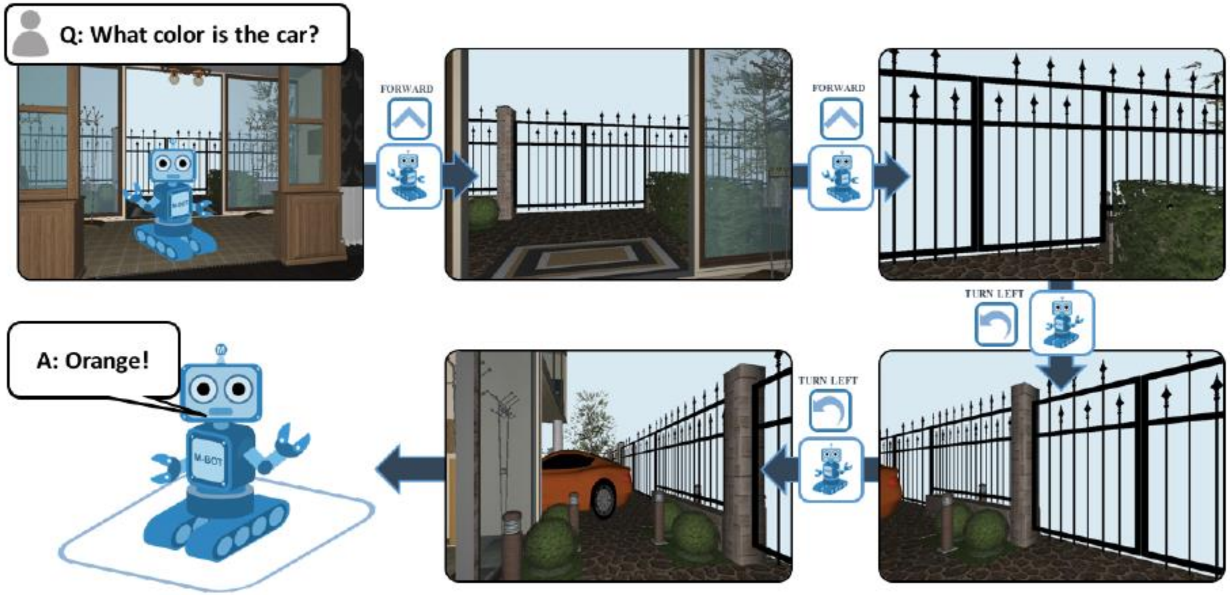


Figure 1: Embodied Question Answering – EmbodiedQA– tasks agents with navigating rich 3D environments in order to answer questions. These agents must jointly learn language understanding, visual reasoning, and goal-driven navigation to succeed.

Das et al., “Embodied Question Answering”, CVPR 2018

RL for question-answering

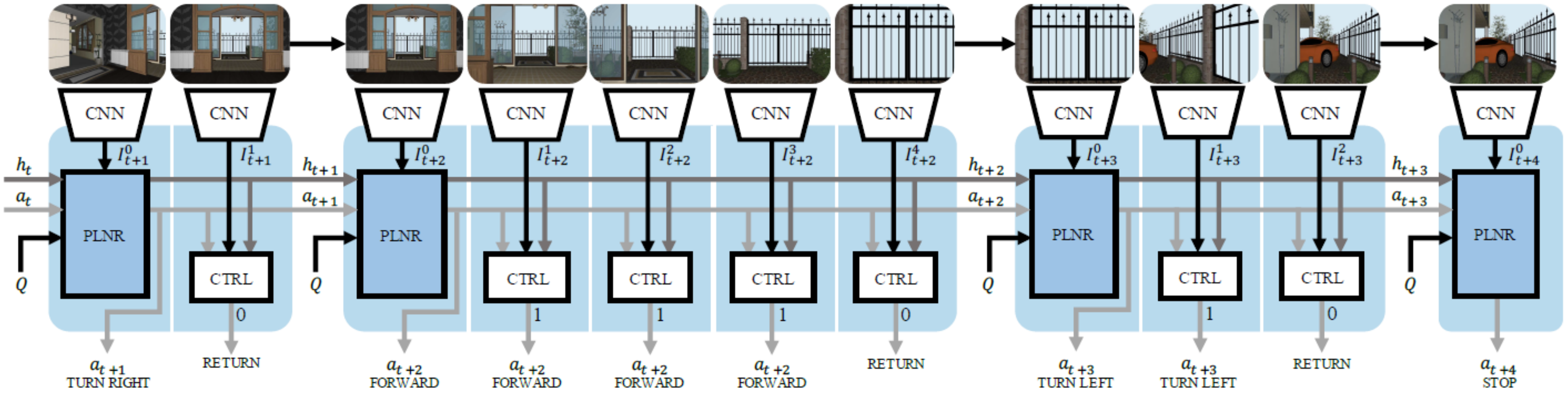


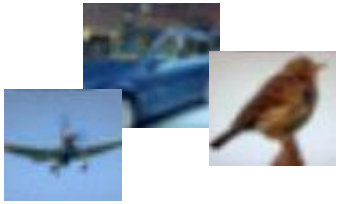
Figure 4: Our PACMAN navigator decomposes navigation into a planner and a controller. The planner selects actions and the controller executes these actions a variable number of times. This enables the planner to operate on shorter timescales, strengthening gradient flows.

Das et al., “Embodied Question Answering”, CVPR 2018

Part IV: Generation

- Motivation and taxonomy of methods
- Variational Autoencoders (VAEs)
- Generative Adversarial Networks (GANs)
- Applications and variants of GANs
- Dealing with sparse data, progressive training

Generative Models

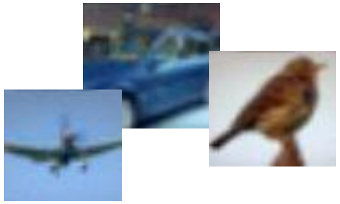


Training data ~ $p_{data}(x)$

Generated samples ~ $p_{model}(x)$

Want to learn $p_{model}(x)$ similar to $p_{data}(x)$

Generative Models



Training data ~ $p_{data}(x)$

Generated samples ~ $p_{model}(x)$

Want to learn $p_{model}(x)$ similar to $p_{data}(x)$

Addresses density estimation, a core problem in unsupervised learning

Several flavors:

- Explicit density estimation: explicitly define and solve for $p_{model}(x)$
- Implicit density estimation: learn model that can sample from $p_{model}(x)$ w/o explicitly defining it

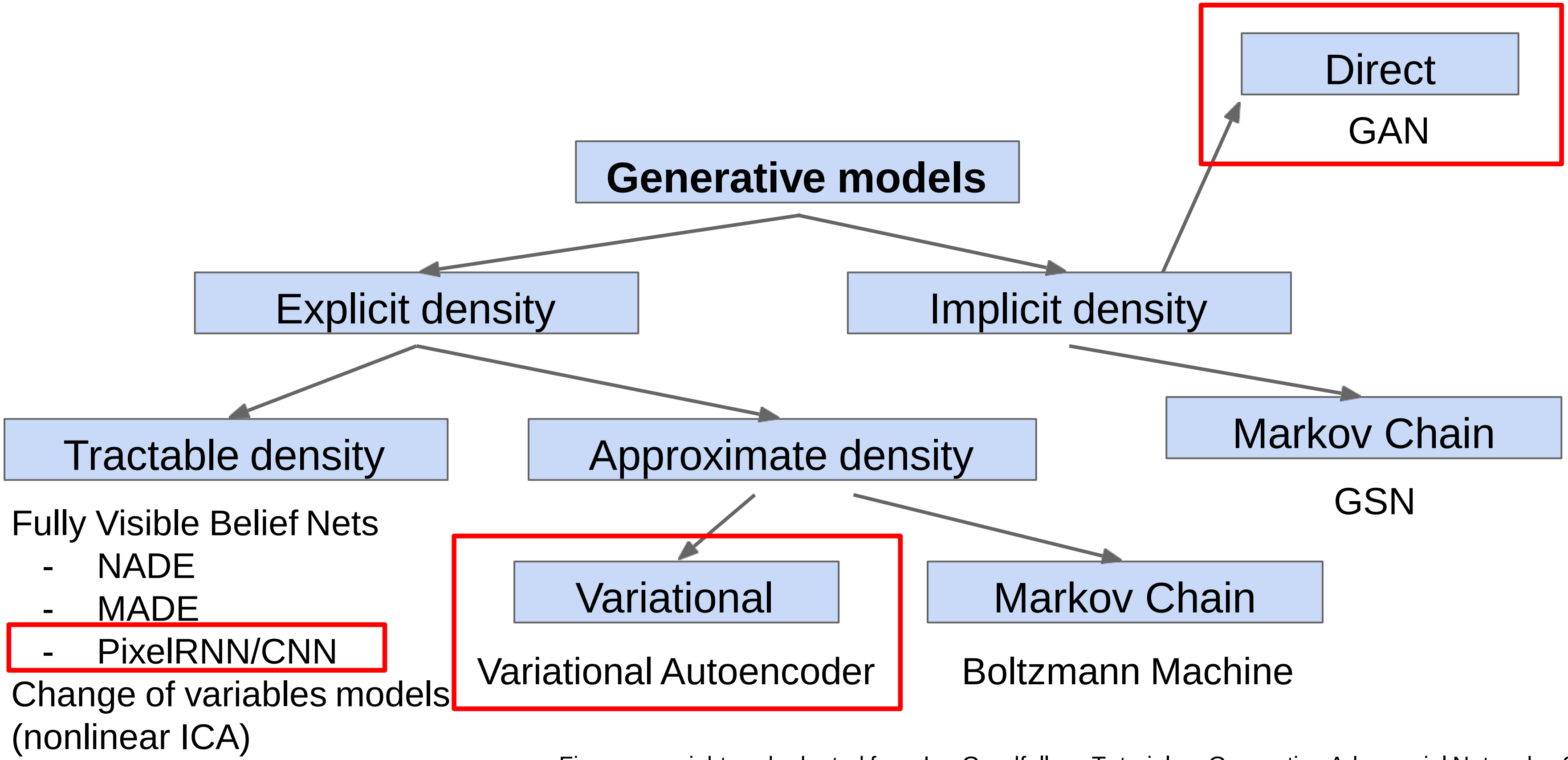
Why Generative Models?

- Realistic samples for artwork, super-resolution, colorization, etc.

- Generative models can be used to enhance training datasets with diverse synthetic data
- Generative models of time-series data can be used for simulation

Adapted from Serena Young

Taxonomy of Generative Models



Generative models

Explicit density

Implicit density

Direct

GAN

Tractable density

Approximate density

Markov Chain

GSN

Fully Visible Belief Nets
- NADE
- MADE
- PixelRNN/CNN

Change of variables models (nonlinear ICA)

Variational

Variational Autoencoder

Markov Chain

Boltzmann Machine

Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

PixelRNN and PixelCNN

Fully visible belief network

Explicit density model

Use chain rule to decompose likelihood of an image x into product of 1-d distributions:

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

Likelihood of image x

Probability of i’th pixel value given all previous pixels

Will need to define ordering of “previous pixels”

Complex distribution over pixel values => Express using a neural network!

Then maximize likelihood of training data

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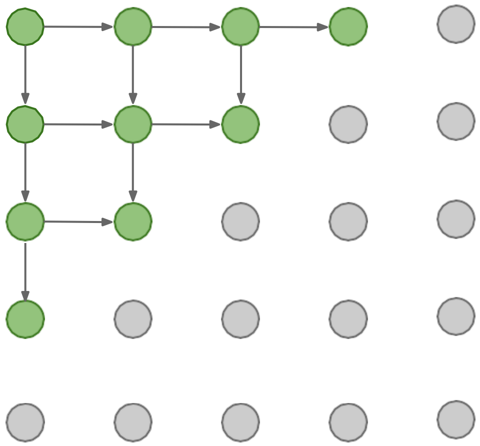
PixelRNN

[van der Oord et al. 2016]

Generate image pixels starting from corner

Dependency on previous pixels modeled using an RNN (LSTM)

Drawback: sequential generation is slow!



PixelCNN

[van der Oord et al. 2016]

Softmax loss at each pixel

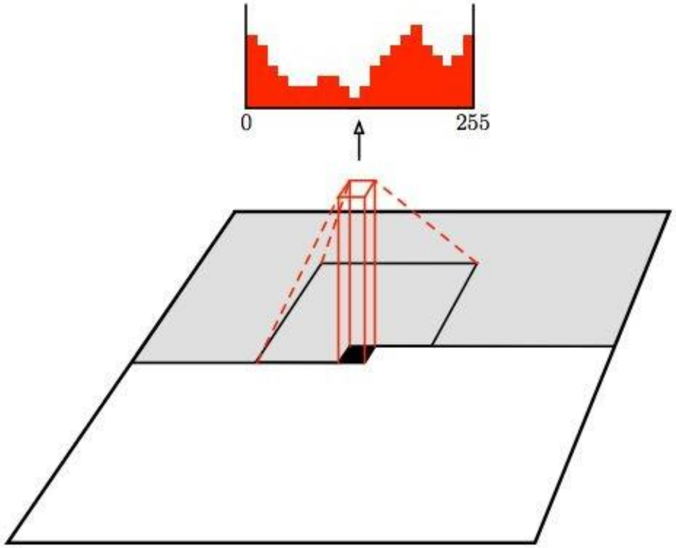


Figure copyright van der Oord et al., 2016. Reproduced with permission.

Still generate image pixels starting from corner

Dependency on previous pixels now modeled using a CNN over context region

Training: maximize likelihood of training images

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

Training is faster than PixelRNN (can parallelize convolutions since context region values known from training images)

Generation must still proceed sequentially => still slow

Variational Autoencoders (VAEs)

So far...

PixelCNNs define tractable density function, optimize likelihood of training data:

$$p_\theta(x) = \prod_{i=1}^{n} p_\theta(x_i | x_1, ..., x_{i-1})$$

VAEs define intractable density function with latent **z**:

$$p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$$

Cannot optimize directly, derive and optimize lower bound on likelihood instead

Some background: Autoencoders

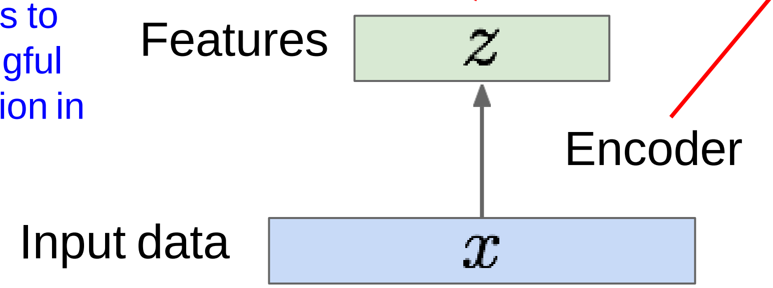
Unsupervised approach for learning a lower-dimensional feature representation from unlabeled training data

z usually smaller than **x** (dimensionality reduction)

Q: Why dimensionality reduction?

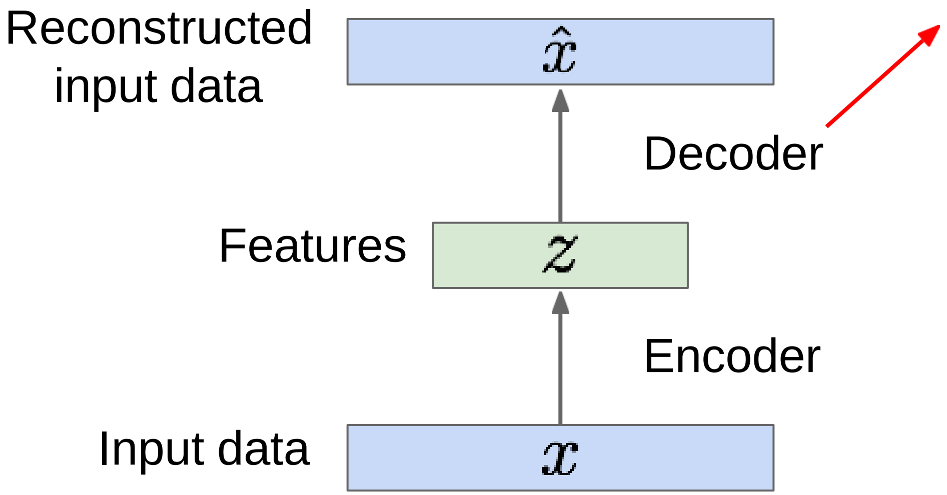
A: Want features to capture meaningful factors of variation in data

Originally: Linear + nonlinearity (sigmoid)
Later: Deep, fully-connected
Later: ReLU CNN



Some background: Autoencoders

How to learn this feature representation?
Train such that features can be used to reconstruct original data
"Autoencoding" - encoding itself



Reconstructed input data $\hat{x}$

Decoder

Features z

Encoder

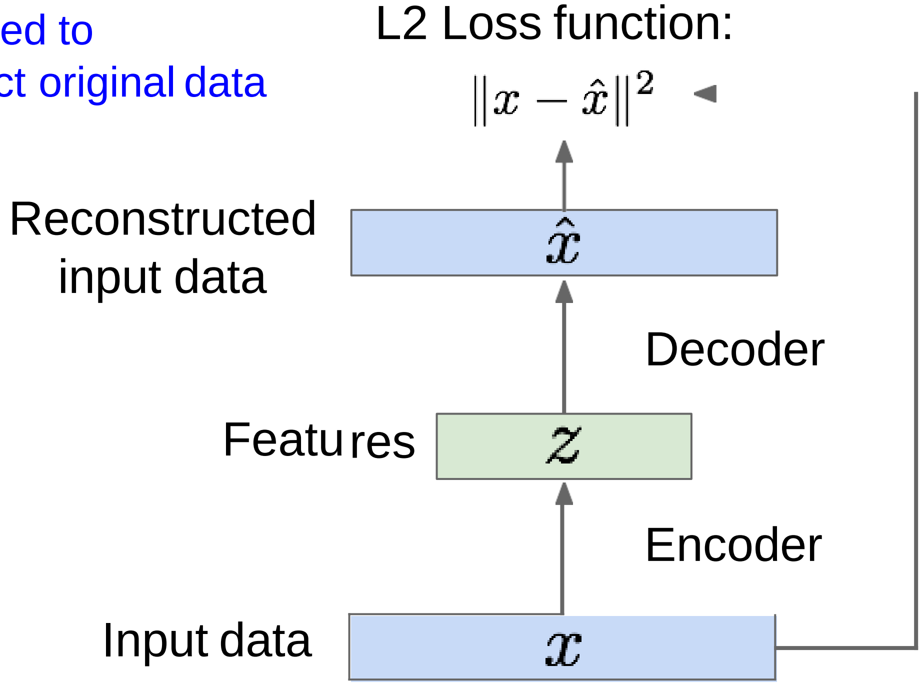
Input data x

Originally: Linear + nonlinearity (sigmoid)
Later: Deep, fully-connected
Later: ReLU CNN (upconv)

Some background: Autoencoders

Train such that features can be used to reconstruct original data

Doesn't use labels!



L2 Loss function:

$$\|x - \hat{x}\|^2$$

Reconstructed input data $\hat{x}$

Decoder

Features z

Encoder

Input data x

Reconstructed data

Encoder: 4-layer conv
Decoder: 4-layer upconv

Input data

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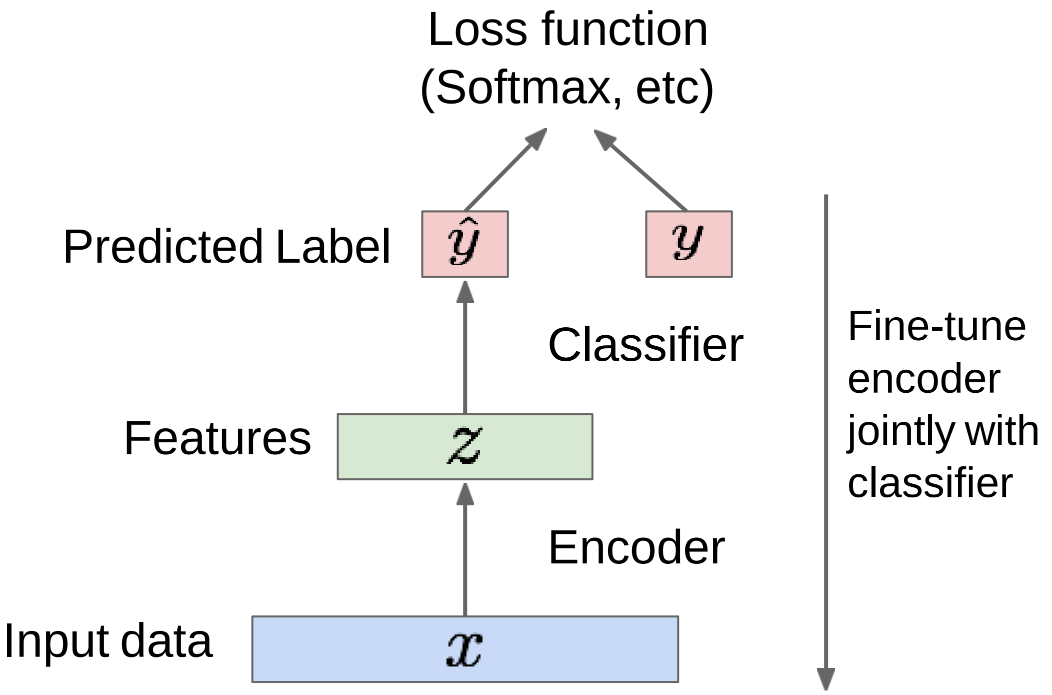
Some background: Autoencoders

Encoder can be used to initialize a **supervised** model



bird plane

dog deer truck

Train for final task (sometimes with small data)

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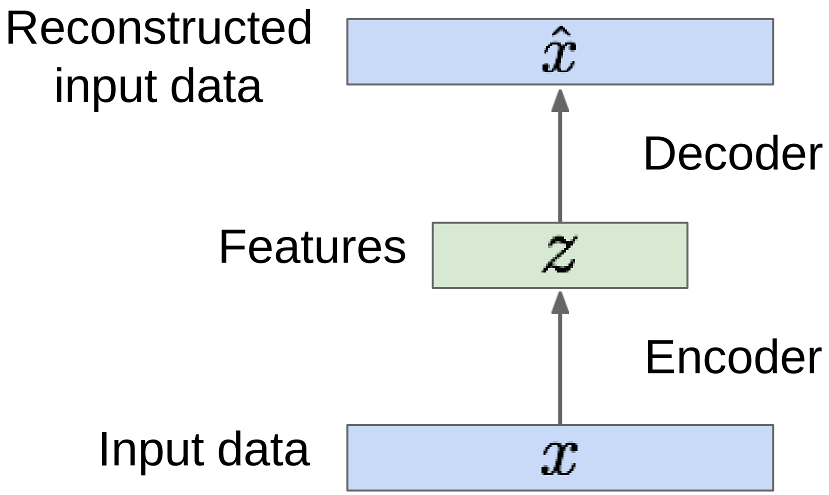
Some background: Autoencoders



Autoencoders can reconstruct data, and can learn features to initialize a supervised model

Features capture factors of variation in training data. Can we generate new images from an autoencoder?

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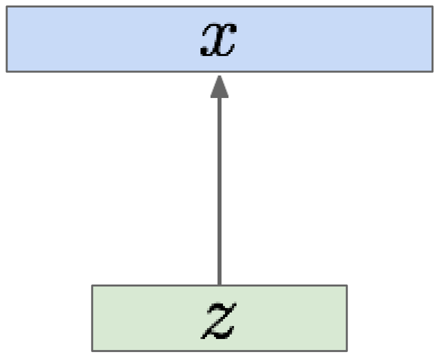
Variational Autoencoders

Probabilistic spin on autoencoders - will let us sample from the model to generate data!

Assume training data $\{x^{(i)}\}_{i=1}^{N}$ is generated from underlying unobserved (latent) representation **z**

Intuition (remember from autoencoders!): **x** is an image, **z** is latent factors used to generate **x:** attributes, orientation, etc.

Sample from true conditional $p_{\theta^*}(x \mid z^{(i)})$



Sample from true prior $p_{\theta^*}(z)$

Kingma and Welling, “Auto-Encoding Variational Bayes”, ICLR 2014

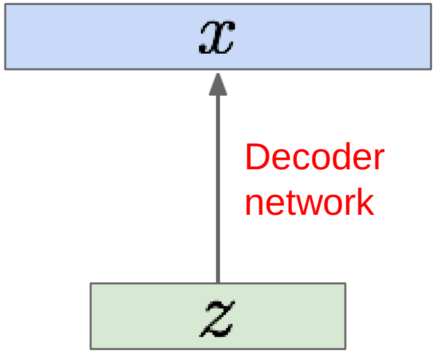
Variational Autoencoders

Sample from true conditional

$p_{\theta^*}(x \mid z^{(i)})$

Sample from true prior

$p_{\theta^*}(z)$



x

Decoder network

z

We want to estimate the true parameters θ^* of this generative model.

How should we represent this model?

Choose prior p(z) to be simple, e.g. Gaussian.

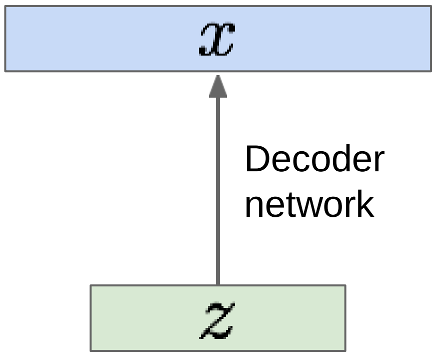
Conditional p(x|z) is complex (generates image) => represent with neural network

Kingma and Welling, “Auto-Encoding Variational Bayes”, ICLR 2014

Variational Autoencoders

Sample from true conditional

$p_{\theta^*}(x \mid z^{(i)})$



Sample from true prior

$p_{\theta^*}(z)$

We want to estimate the true parameters θ^* of this generative model.

How to train the model?

Learn model parameters to maximize likelihood of training data

$$p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$$

Now with latent z

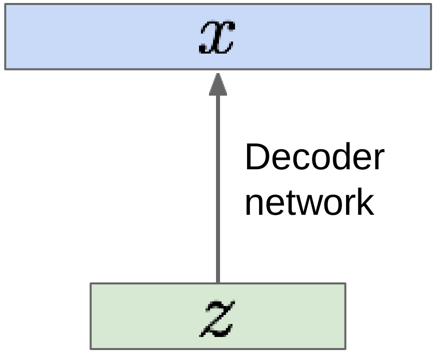
Kingma and Welling, “Auto-Encoding Variational Bayes”, ICLR 2014

Adapted from Serena Young

Variational Autoencoders

Sample from true conditional

$p_{\theta^*}(x \mid z^{(i)})$



Sample from true prior

$p_{\theta^*}(z)$

We want to estimate the true parameters θ^* of this generative model.

How to train the model?

Learn model parameters to maximize likelihood of training data

$$p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$$

Q: What is the problem with this?

Intractable!

Kingma and Welling, “Auto-Encoding Variational Bayes”, ICLR 2014

Variational Autoencoders: Intractability

Data likelihood: $p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$

Simple Gaussian prior

Intractable to compute p(x|z) for every z!

Decoder neural network

Posterior density also intractable: $p_\theta(z|x) = p_\theta(x|z) p_\theta(z) / p_\theta(x)$

Intractable data likelihood

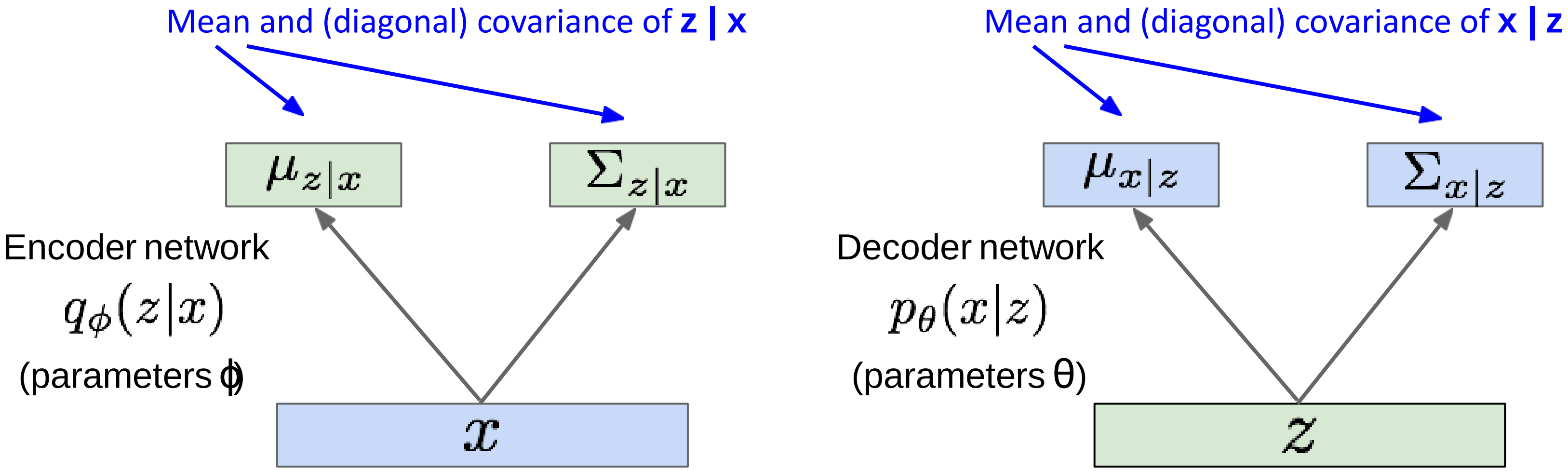
- Solution: In addition to decoder network modeling $p_\theta(x|z)$, define additional encoder network $q_\phi(z|x)$ that approximates $p_\theta(z|x)$
- This allows us to derive a lower bound on the data likelihood that is tractable, which we can optimize – omitted, see hidden slides

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Adapted from Serena Young

Variational Autoencoders

Since we’re modeling probabilistic generation of data, encoder and decoder networks are probabilistic



Mean and (diagonal) covariance of **z | x**

Encoder network

$q_\phi(z|x)$

(parameters ϕ)

Mean and (diagonal) covariance of **x | z**

Decoder network

$p_\theta(x|z)$

(parameters θ)

Kingma and Welling, “Auto-Encoding Variational Bayes”, ICLR 2014

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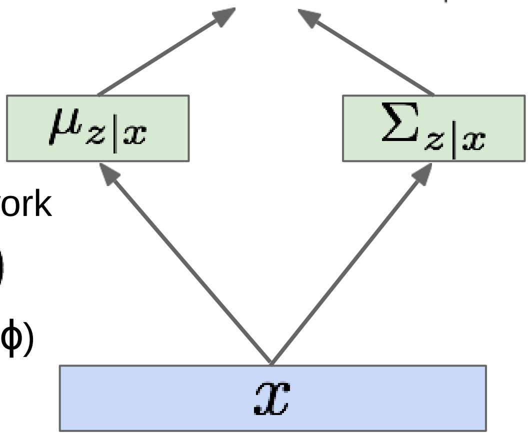
Variational Autoencoders

Since we're modeling probabilistic generation of data, encoder and decoder networks are probabilistic

Sample z from $z|x \sim \mathcal{N}(\mu_{z|x}, \Sigma_{z|x})$

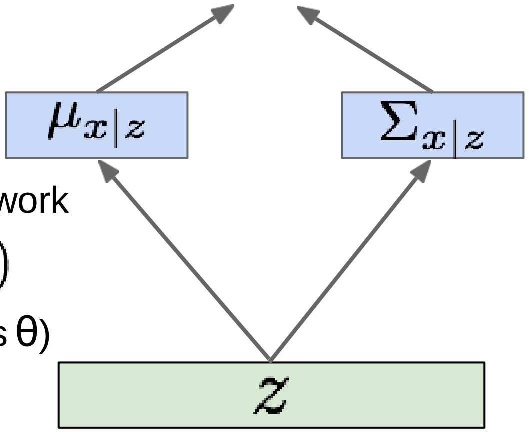


Encoder network

$q_\phi(z|x)$

(parameters ϕ)

Sample x|z from $x|z \sim \mathcal{N}(\mu_{x|z}, \Sigma_{x|z})$



Decoder network

$p_\theta(x|z)$

(parameters θ)

Encoder and decoder networks also called "recognition"/"inference" and "generation" networks

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

Variational Autoencoders

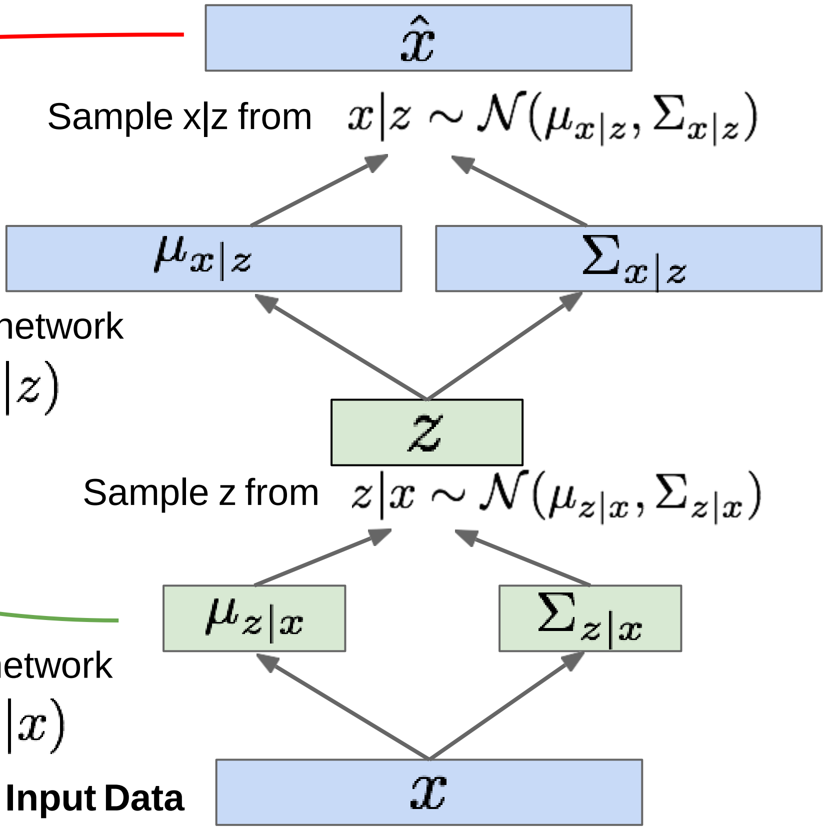
Putting it all together: maximizing the likelihood lower bound

$$\underbrace{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}_{\mathcal{L}(x^{(i)},\theta,\phi)}$$

Maximize likelihood of original input being reconstructed

Make approximate posterior distribution close to prior

For every minibatch of input data: compute this forward pass, and then backprop!



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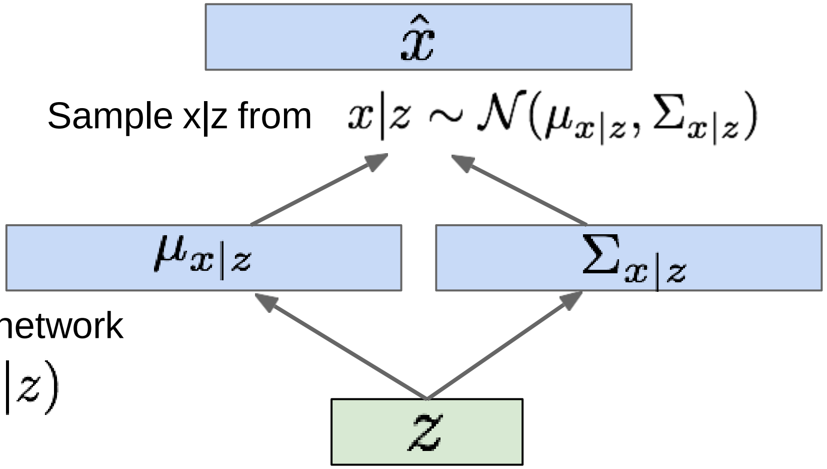
VAEs: Generating Data

Use decoder network. Now sample z from prior!



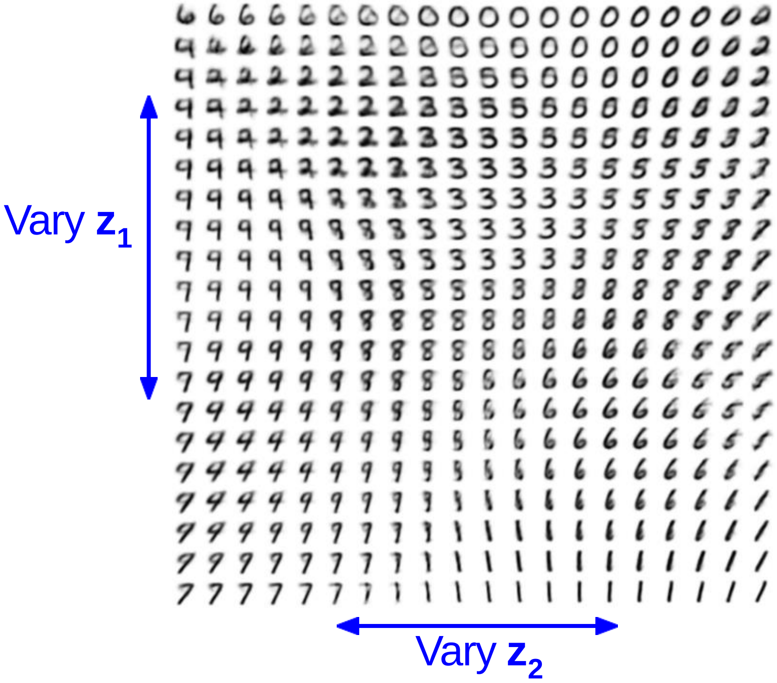
Sample x|z from $x|z \sim \mathcal{N}(\mu_{x|z}, \Sigma_{x|z})$

Decoder network $p_\theta(x|z)$

Sample z from $z \sim \mathcal{N}(0, I)$

Kingma and Welling, “Auto-Encoding Variational Bayes”, ICLR 2014

Data manifold for 2-d **z**



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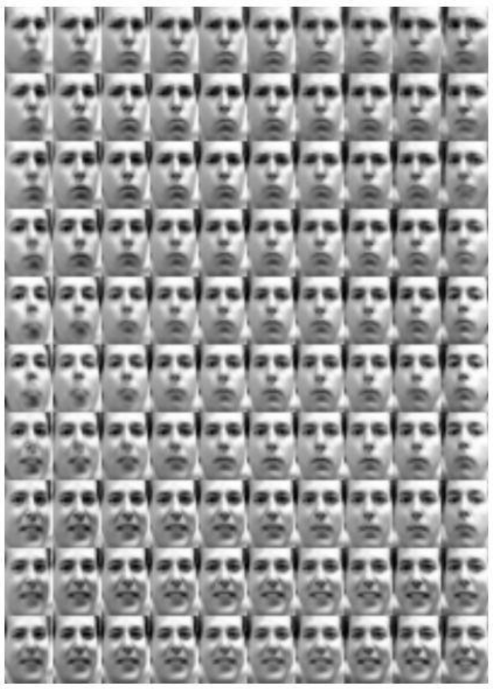
VAEs: Generating Data

Diagonal prior on **z** => independent latent variables

Different dimensions of **z** encode interpretable factors of variation

Also good feature representation that can be computed using $q_\phi(z|x)$!



Degree of smile

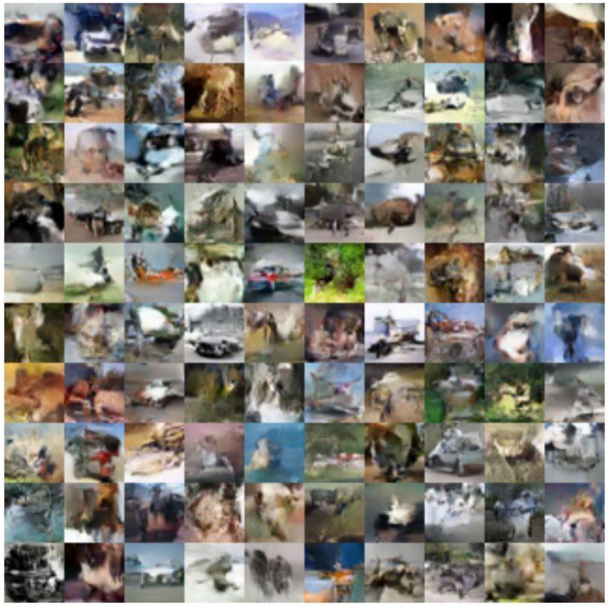
Vary $\mathbf{z}_1$

Vary $\mathbf{z}_2$

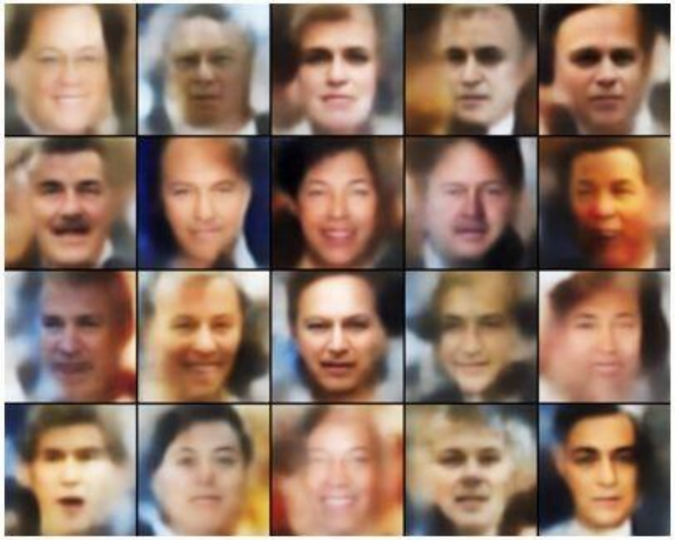
Head pose

Kingma and Welling, "Auto-Encoding Variational Bayes", ICLR 2014

VAEs: Generating Data



32x32 CIFAR-10



Labeled Faces in the Wild

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Variational Autoencoders

Probabilistic spin to traditional autoencoders => allows generating data
Defines an intractable density => derive and optimize a lower bound

Pros:

- Principled approach to generative models
- Allows inference of q(z|x), can be useful feature representation for other tasks

Cons:

- Maximizes lower bound of likelihood: okay, but not as good evaluation as PixelRNN/PixelCNN
- Samples blurrier and lower quality compared to state-of-the-art (GANs)

Adapted from Serena Young

So far...

PixelCNNs define tractable density function, optimize likelihood of training data:

$$p_\theta(x) = \prod_{i=1}^{n} p_\theta(x_i | x_1, ..., x_{i-1})$$

VAEs define intractable density function with latent **z**:

$$p_\theta(x) = \int p_\theta(z) p_\theta(x|z) dz$$

Cannot optimize directly, derive and optimize lower bound on likelihood instead

What if we give up on explicitly modeling density, and just want ability to sample?

GANs: don’t work with any explicit density function!
Instead, take game-theoretic approach: learn to generate from training distribution through 2-player game

Generative Adversarial Networks

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Problem: Want to sample from complex, high-dimensional training distribution. No direct way to do this!

Solution: Sample from a simple distribution, e.g. random noise. Learn transformation to training distribution.

Q: What can we use to represent this complex transformation?

Generative Adversarial Networks

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

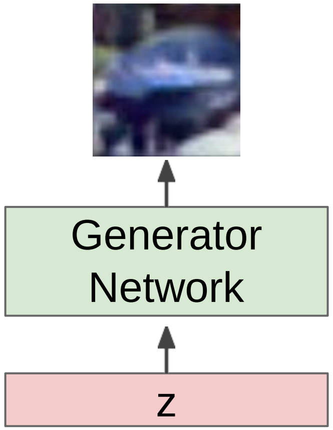
Problem: Want to sample from complex, high-dimensional training distribution. No direct way to do this!

Solution: Sample from a simple distribution, e.g. random noise. Learn transformation to training distribution.

Q: What can we use to represent this complex transformation?

A: A neural network!

Output: Sample from training distribution



Input: Random noise

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Generator network: try to fool the discriminator by generating real-looking images
Discriminator network: try to distinguish between real and fake images

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Generator network: try to fool the discriminator by generating real-looking images
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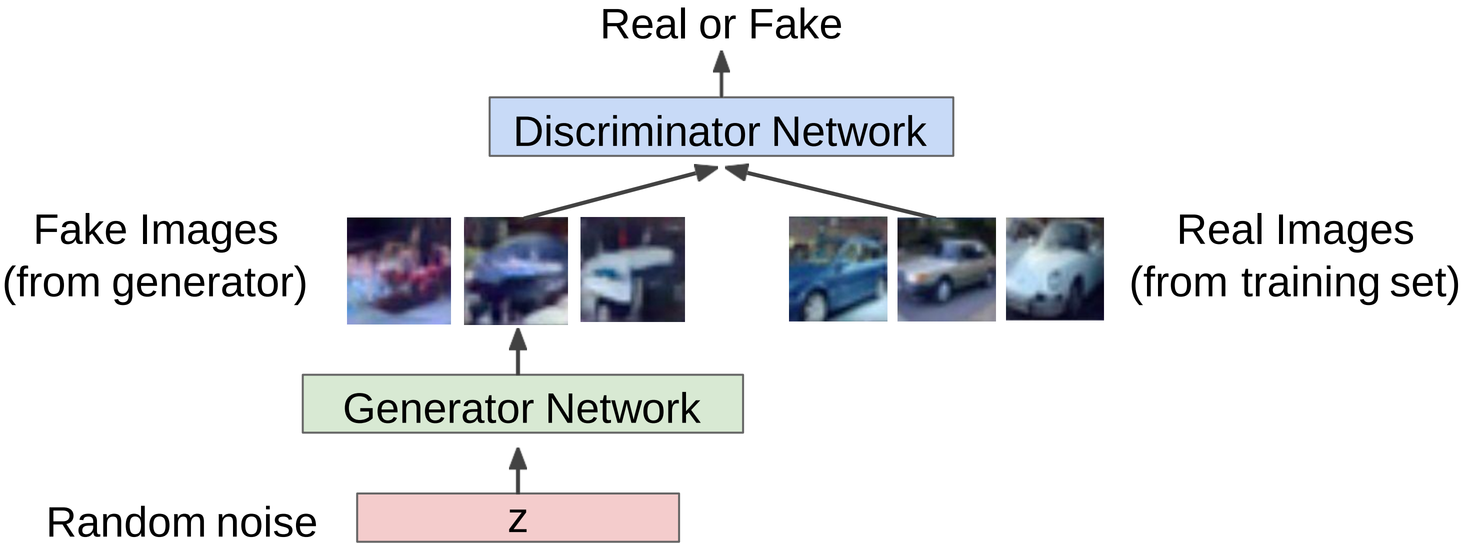

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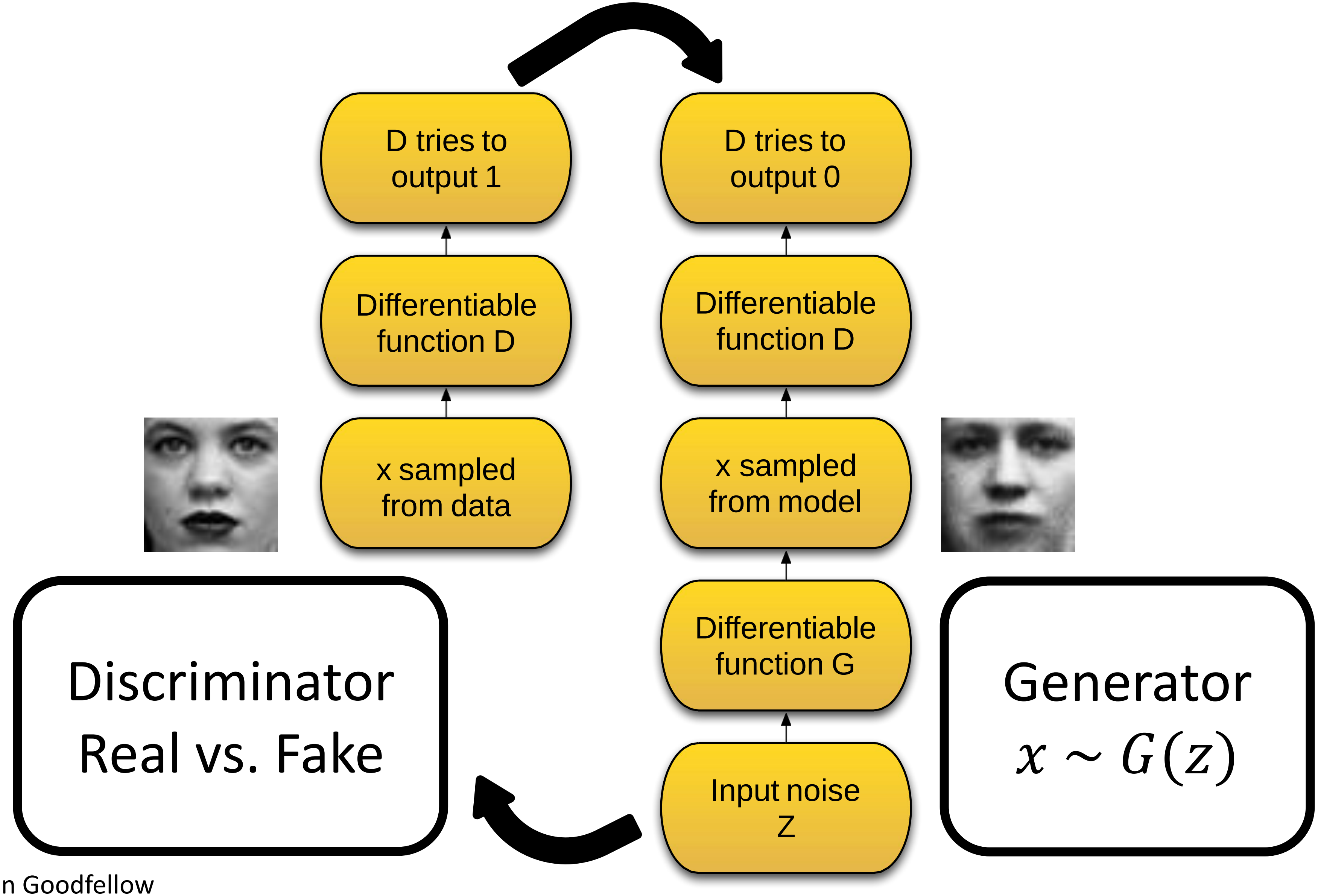
Adversarial Networks Framework



x sampled from data

Differentiable function D

D tries to output 1

Input noise Z

Differentiable function G

x sampled from model

Differentiable function D

D tries to output 0

Discriminator

Real vs. Fake

Generator

$x \sim G(z)$

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Generator network: try to fool the discriminator by generating real-looking images
Discriminator network: try to distinguish between real and fake images

Train jointly in **minimax game**

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Generator network: try to fool the discriminator by generating real-looking images
Discriminator network: try to distinguish between real and fake images

Train jointly in **minimax game**

Discriminator outputs likelihood in (0,1) of real image

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}}) \right]$$

- Discriminator (θ_d) wants to **maximize objective** such that D(x) is close to 1 (real) and D(G(z)) is close to 0 (fake)
- Generator (θ_g) wants to **minimize objective** such that D(G(z)) is close to 1 (discriminator is fooled into thinking generated G(z) is real)

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Training GANs: Two-player game

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Alternate between:

1. **Gradient ascent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x\sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

2. **Gradient descent** on generator

$$\min_{\theta_g} \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Alternate between:

1. **Gradient ascent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

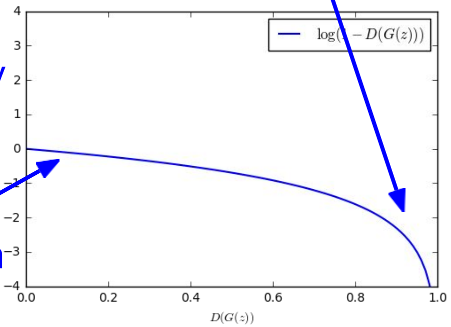
2. **Gradient descent** on generator

$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

In practice, optimizing this generator objective does not work well!

When sample is likely fake, want to learn from it to improve generator. But gradient in this region is relatively flat!

Gradient signal dominated by region where sample is already good



Training GANs: Two-player game

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Alternate between:

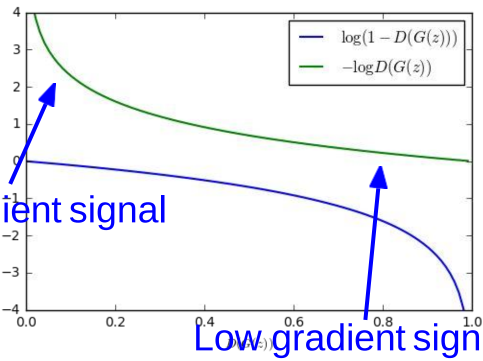
1. **Gradient ascent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

2. **Instead: Gradient ascent** on generator, different objective

$$\max_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(D_{\theta_d}(G_{\theta_g}(z)))$$

Instead of minimizing likelihood of discriminator being correct, now maximize likelihood of discriminator being wrong.
Same objective of fooling discriminator, but now higher gradient signal for bad samples => works much better! Standard in practice.



High gradient signal

Low gradient signal

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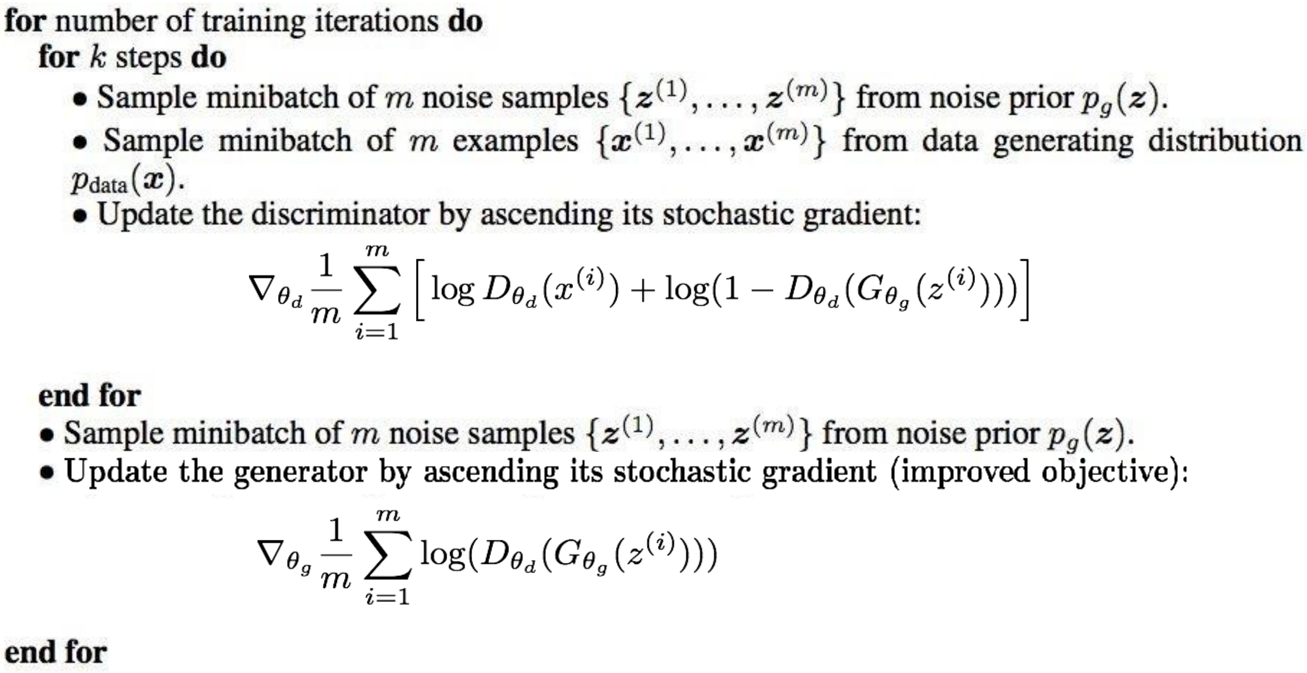
Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Putting it together: GAN training algorithm

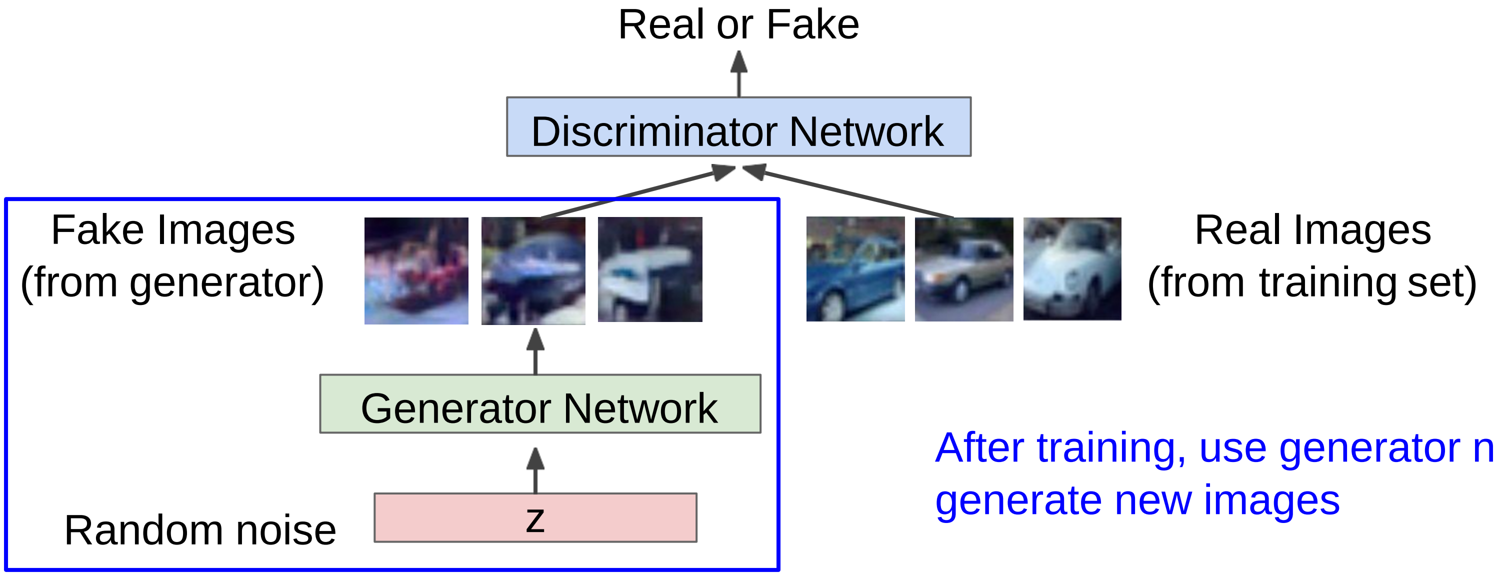


```
for number of training iterations do
    for $k$ steps do
        • Sample minibatch of $m$ noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
        • Sample minibatch of $m$ examples $\{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
        • Update the discriminator by ascending its stochastic gradient:
              $\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[ \log D_{\theta_d}(x^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(z^{(i)}))) \right]$
    end for
    • Sample minibatch of $m$ noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
    • Update the generator by ascending its stochastic gradient (improved objective):
              $\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log(D_{\theta_d}(G_{\theta_g}(z^{(i)})))$
end for
```

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Generator network: try to fool the discriminator by generating real-looking images
Discriminator network: try to distinguish between real and fake images

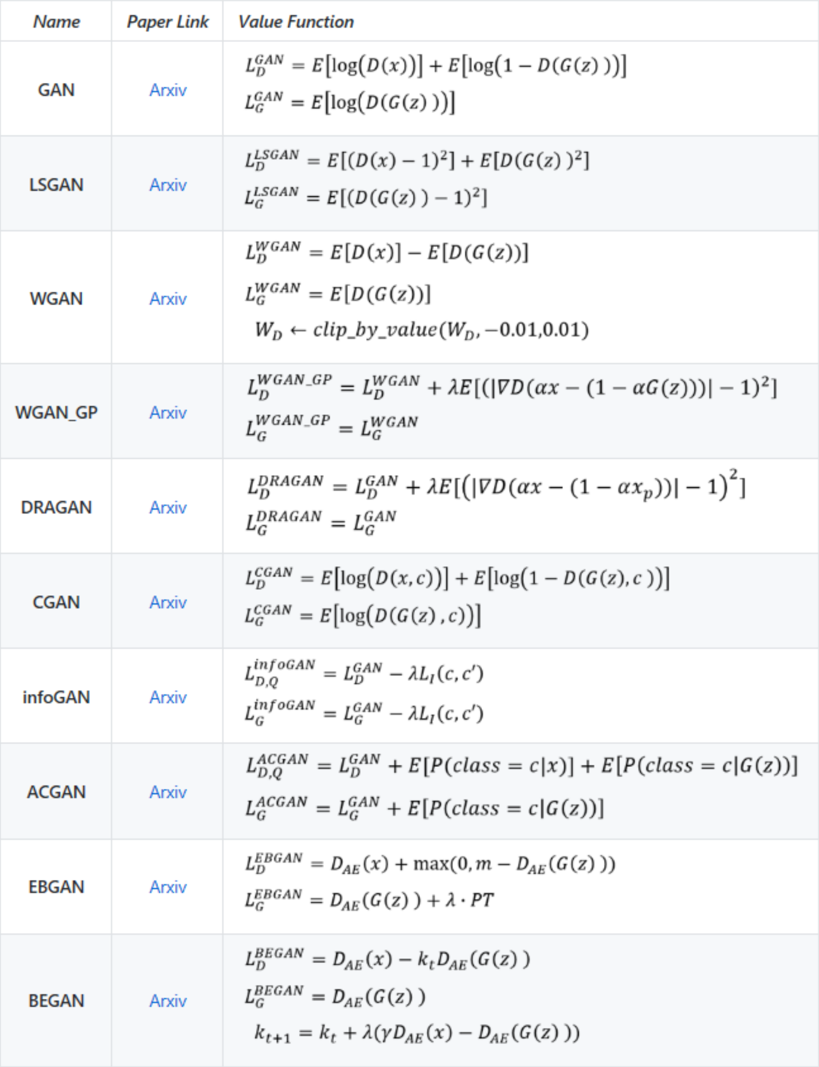


After training, use generator network to generate new images

GAN training is challenging

- Vanishing gradient – when discriminator is very good
- Mode collapse – too little diversity in the samples generated
- Lack of convergence because hard to reach Nash equilibrium
- Loss metric doesn’t always correspond to image quality; Frechet Inception Distance (FID) is a decent choice

Alternative loss functions



Name	*Paper Link*	*Value Function*
GAN	Arxiv	$L_D^{GAN} = E\big[\log\big(D(x)\big)\big] + E\big[\log\big(1 - D(G(z)\,)\big)\big]$ $L_G^{GAN} = E\big[\log\big(D(G(z)\,)\big)\big]$
LSGAN	Arxiv	$L_D^{LSGAN} = E[(D(x) - 1)^2] + E[D(G(z)\,)^2]$ $L_G^{LSGAN} = E[(D(G(z)\,) - 1)^2]$
WGAN	Arxiv	$L_D^{WGAN} = E[D(x)] - E[D(G(z))]$ $L_G^{WGAN} = E[D(G(z))]$ $W_D \leftarrow clip\_by\_value(W_D, -0.01, 0.01)$
WGAN_GP	Arxiv	$L_D^{WGAN\_GP} = L_D^{WGAN} + \lambda E[(\lvert\nabla D(\alpha x - (1 - \alpha G(z)))\rvert - 1)^2]$ $L_G^{WGAN\_GP} = L_G^{WGAN}$
DRAGAN	Arxiv	$L_D^{DRAGAN} = L_D^{GAN} + \lambda E[\big(\lvert\nabla D(\alpha x - (1 - \alpha x_p))\rvert - 1\big)^2]$ $L_G^{DRAGAN} = L_G^{GAN}$
CGAN	Arxiv	$L_D^{CGAN} = E\big[\log\big(D(x, c)\big)\big] + E\big[\log\big(1 - D(G(z), c\,)\big)\big]$ $L_G^{CGAN} = E\big[\log\big(D(G(z)\,, c)\big)\big]$
infoGAN	Arxiv	$L_{D,Q}^{infoGAN} = L_D^{GAN} - \lambda L_I(c, c')$ $L_G^{infoGAN} = L_G^{GAN} - \lambda L_I(c, c')$
ACGAN	Arxiv	$L_{D,Q}^{ACGAN} = L_D^{GAN} + E[P(class = c \mid x)] + E[P(class = c \mid G(z))]$ $L_G^{ACGAN} = L_G^{GAN} + E[P(class = c \mid G(z))]$
EBGAN	Arxiv	$L_D^{EBGAN} = D_{AE}(x) + \max(0, m - D_{AE}(G(z)\,))$ $L_G^{EBGAN} = D_{AE}(G(z)\,) + \lambda \cdot PT$
BEGAN	Arxiv	$L_D^{BEGAN} = D_{AE}(x) - k_t D_{AE}(G(z)\,)$ $L_G^{BEGAN} = D_{AE}(G(z)\,)$ $k_{t+1} = k_t + \lambda(\gamma D_{AE}(x) - D_{AE}(G(z)\,))$

https://github.com/hwalsuklee/tensorflow-generative-model-collections

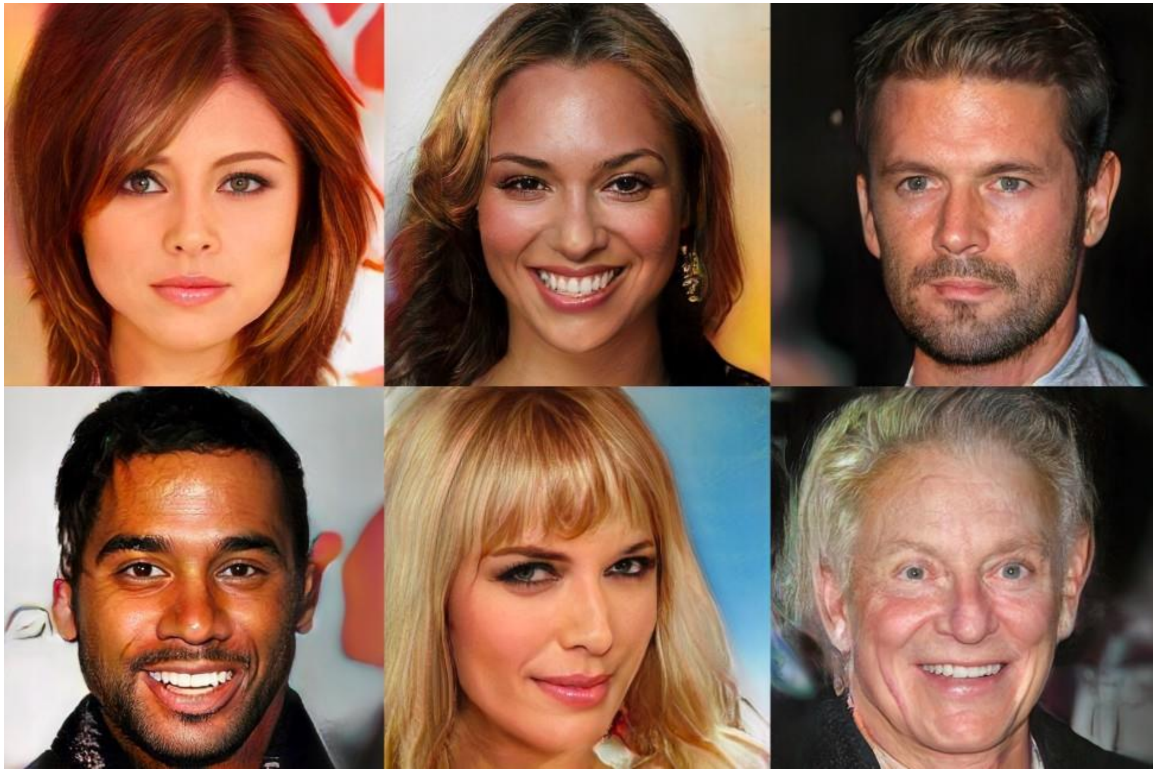
https://medium.com/@jonathan_hui/gan-wasserstein-gan-wgan-gp-6a1a2aa1b490

Tips and tricks

- Use batchnorm, ReLU
- Regularize norm of gradients
- Use one of the new loss functions
- Add noise to inputs or labels
- Append image similarity to avoid mode collapse
- Use labels when available (CGAN)
- …

https://github.com/soumith/talks/blob/master/2017-ICCV_Venice/How_To_Train_a_GAN.pdf
https://towardsdatascience.com/gan-ways-to-improve-gan-performance-acf37f9f59b

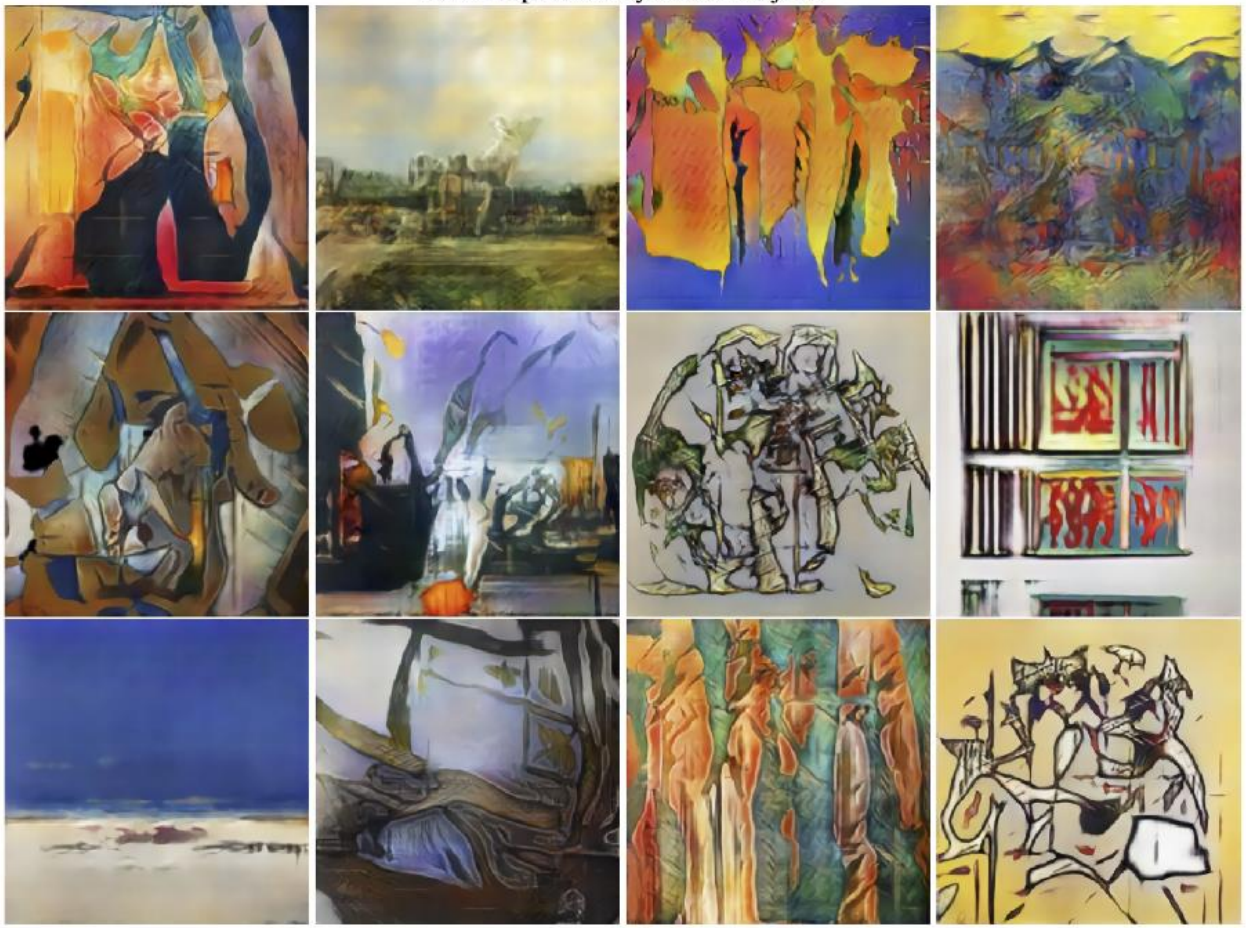
Celebrities Who Never Existed



Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

Creative Adversarial Networks

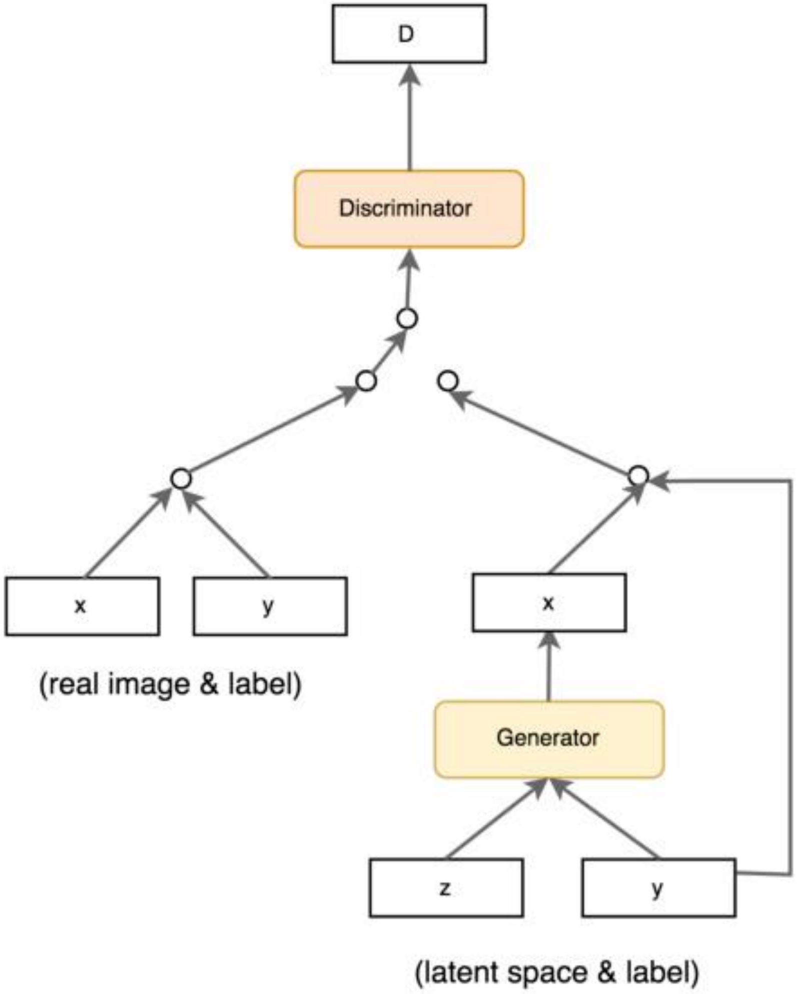
CAN: Top ranked by human subjects



(Elgammal et al., 2017)

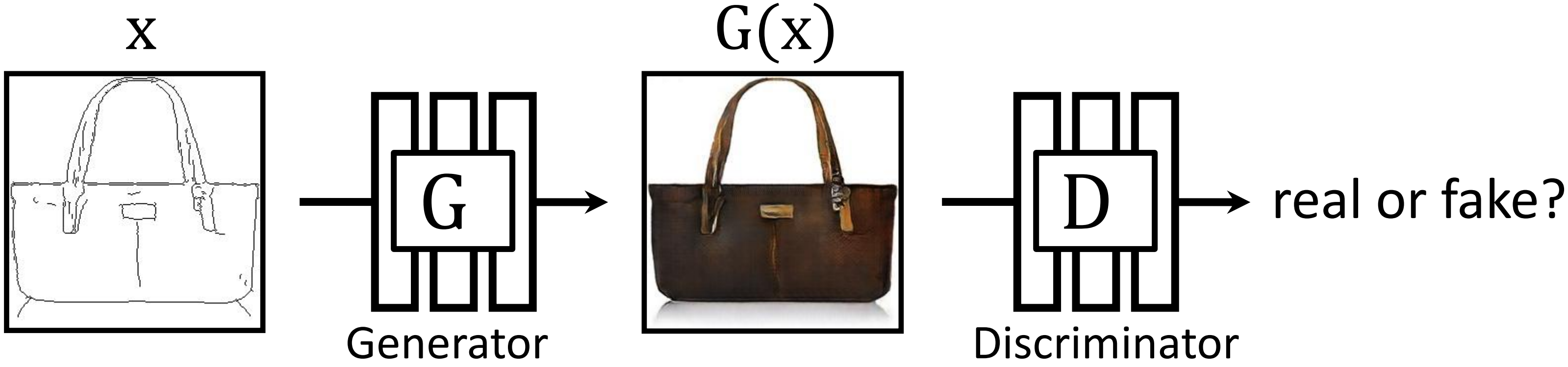
Ian Goodfellow

Conditional GANs



https://medium.com/@jonathan_hui/gan-cgan-infogan-using-labels-to-improve-gan-8ba4de5f9c3d

GANs



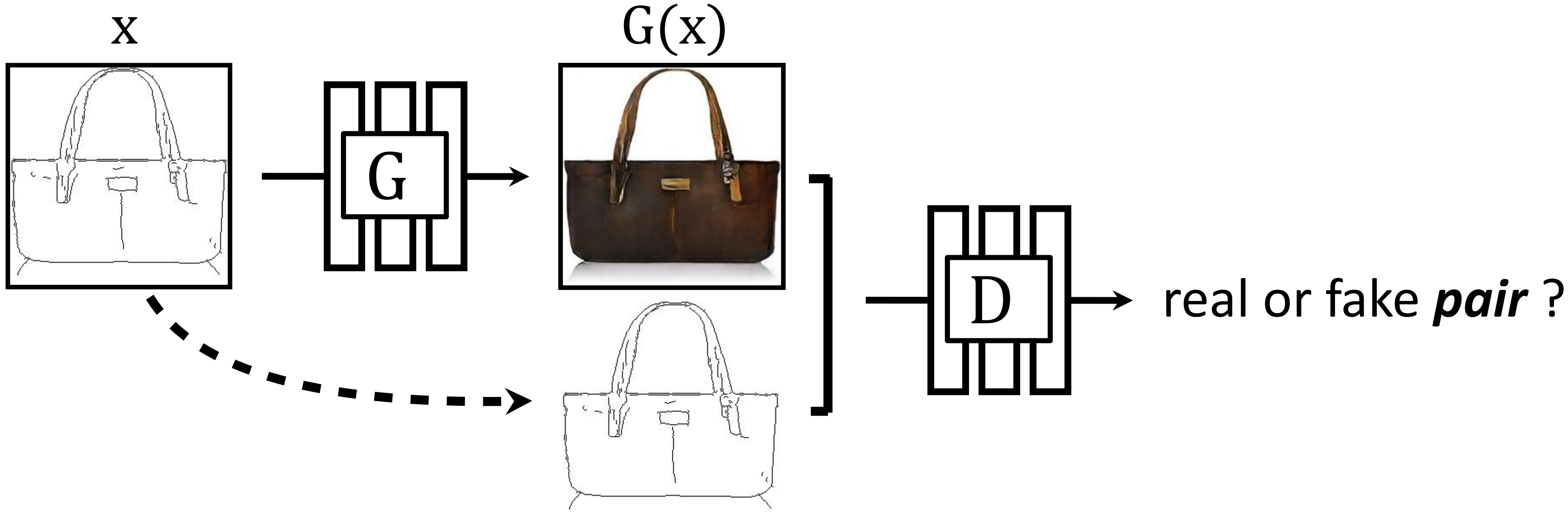
G: generate fake samples that can fool D

D: classify fake samples vs. real images

[Goodfellow et al. 2014]

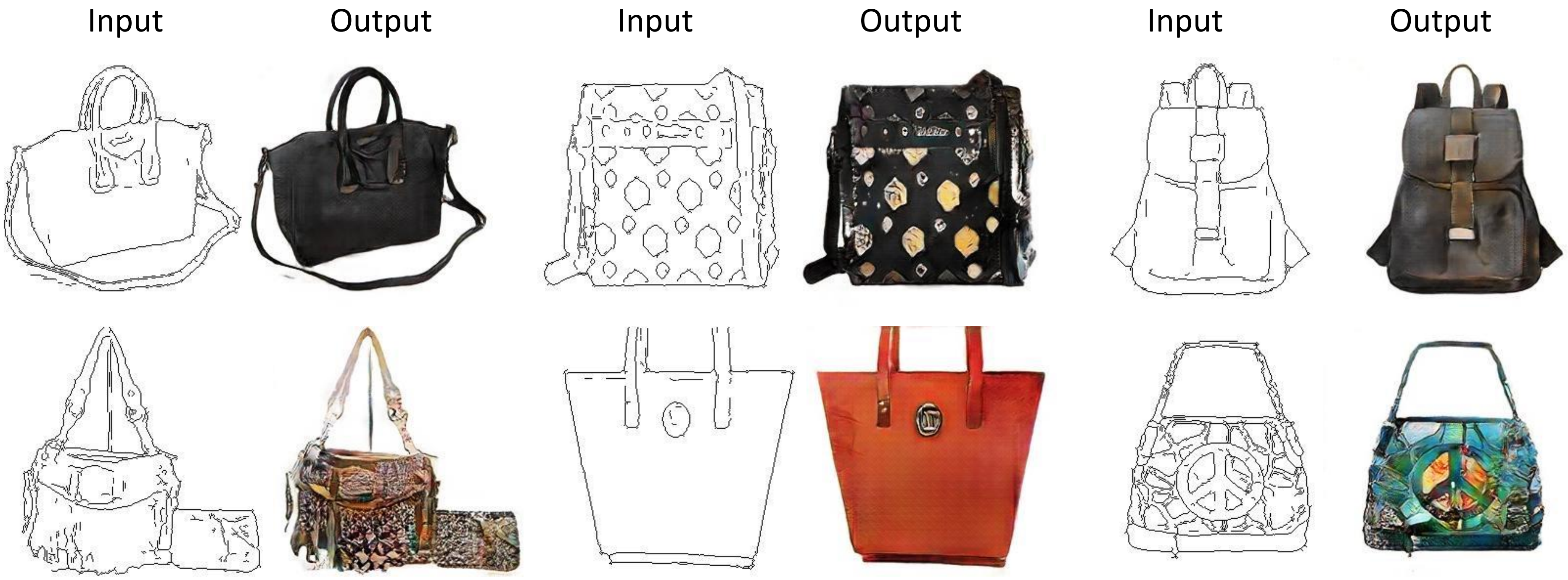
Jun-Yan Zhu

Conditional GANs



Adapted from Jun-Yan Zhu

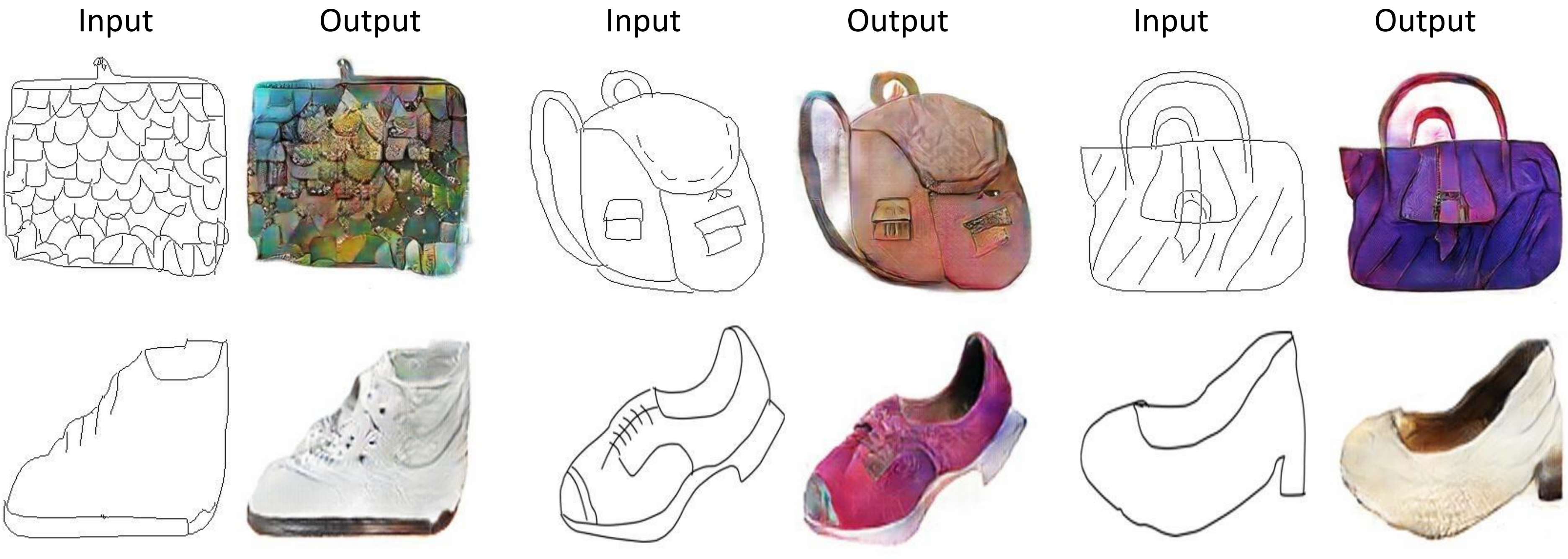
Edges → Images



Edges from [Xie & Tu, 2015]

Pix2pix / CycleGAN

Sketches → Images

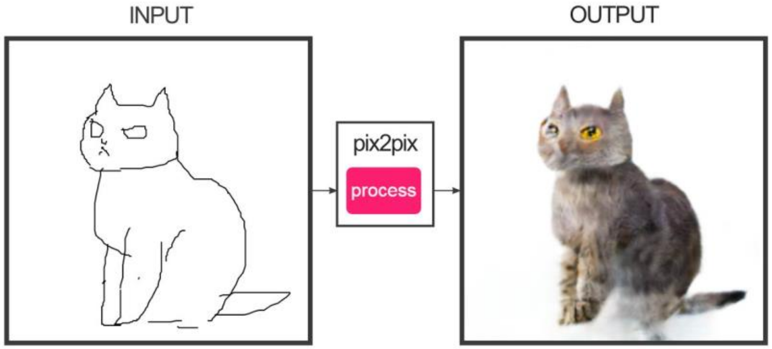


Trained on Edges → Images

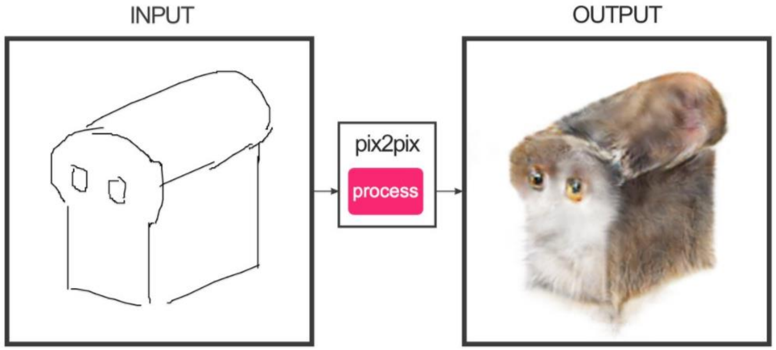
Data from [Eitz, Hays, Alexa, 2012]

Pix2pix / CycleGAN

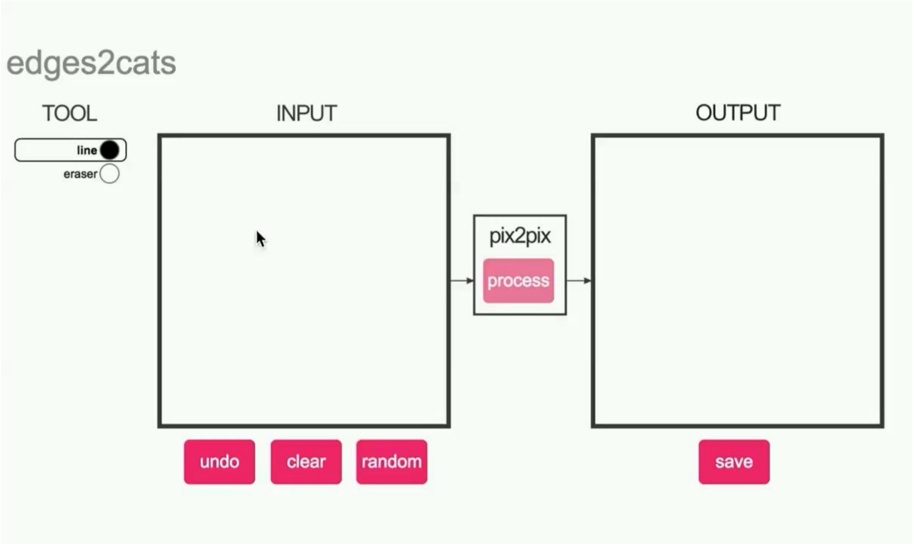
#edges2cats [Christopher Hesse]



@gods_tail



Ivy Tasi @ivymyt

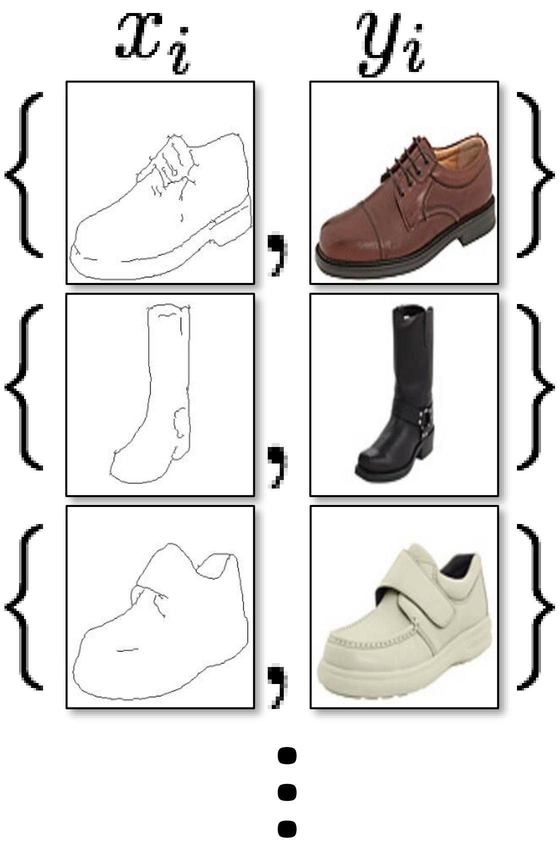


@matthematician

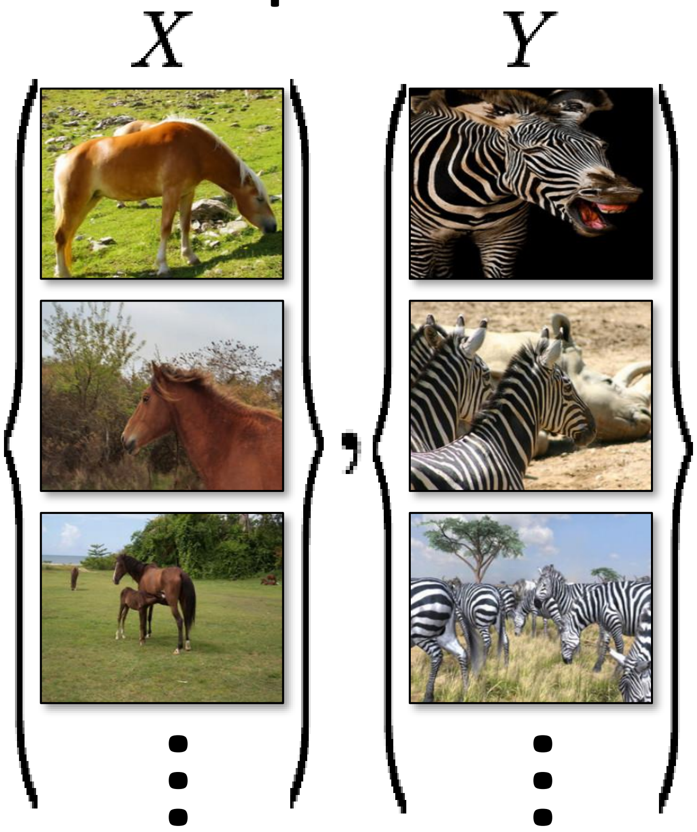
Vitaly Vidmirov @vvid

https://affinelayer.com/pixsrv/

Paired

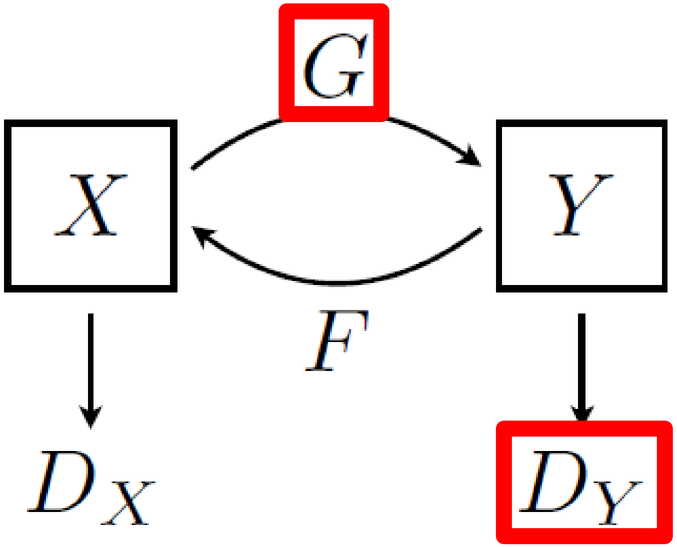


Unpaired



Jun-Yan Zhu

Cycle Consistency

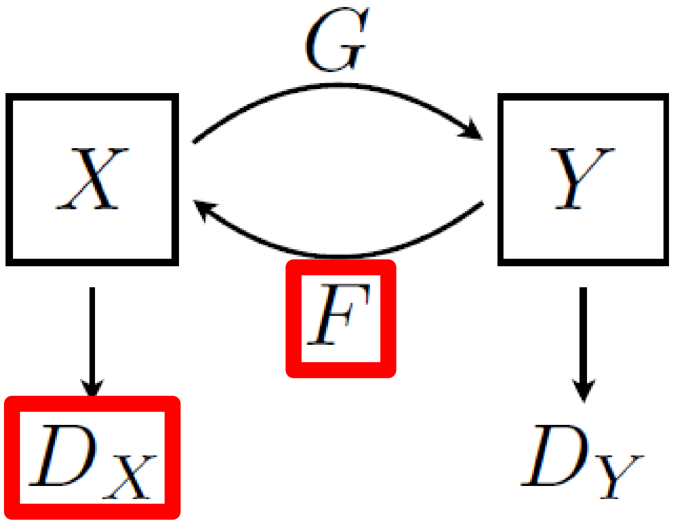


Discriminator $\mathrm{D_Y}$: $L_{GAN}(G(x), y)$

Real zebras vs. generated zebras

Zhu et al., “Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks”, ICCV 2017

Cycle Consistency



Discriminator $\mathrm{D_Y}$: $L_{GAN}(G(x), y)$

Real zebras vs. generated zebras

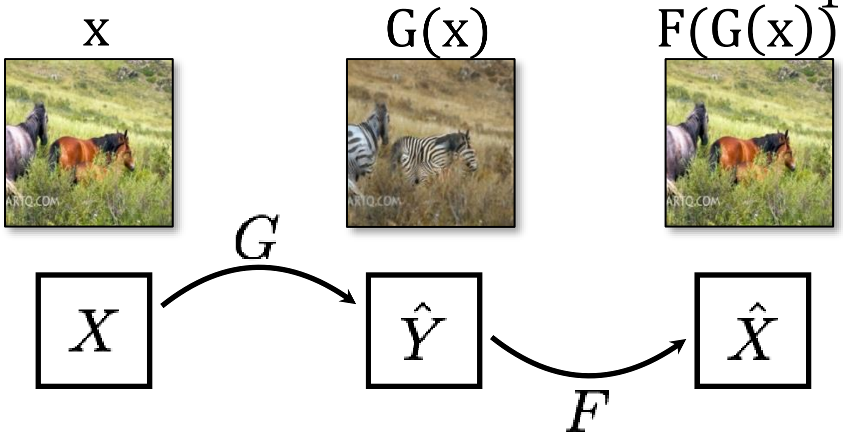
Discriminator $\mathrm{D_X}$: $L_{GAN}(F(y), x)$

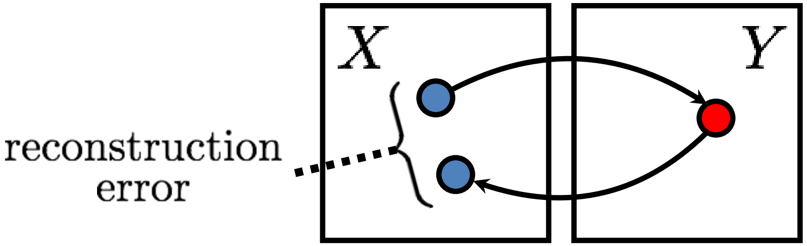
Real horses vs. generated horses

Zhu et al., "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks", ICCV 2017

Cycle Consistency

Forward cycle loss: $\|F(G(x)) - x\|_1$

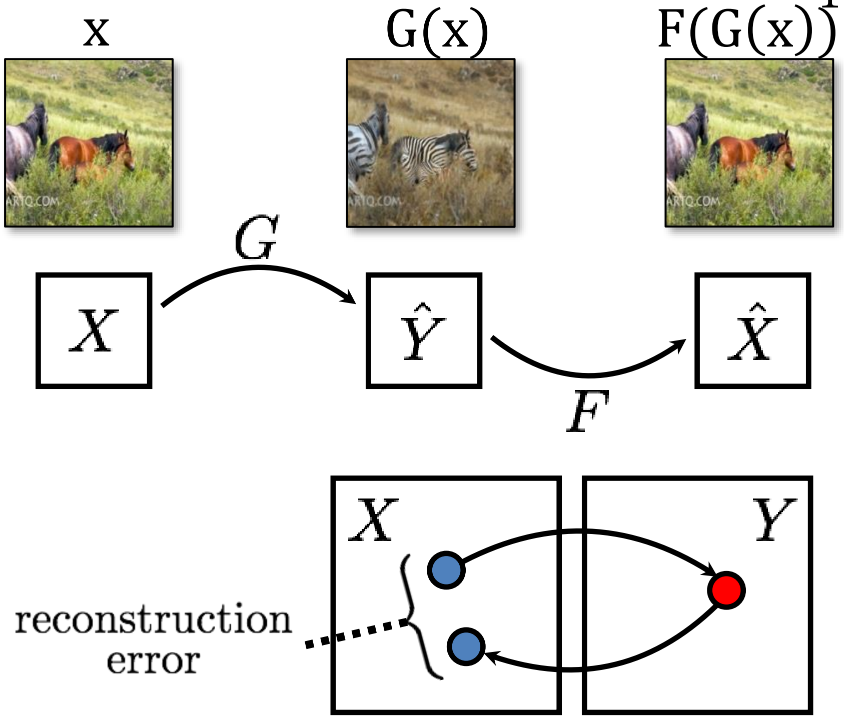




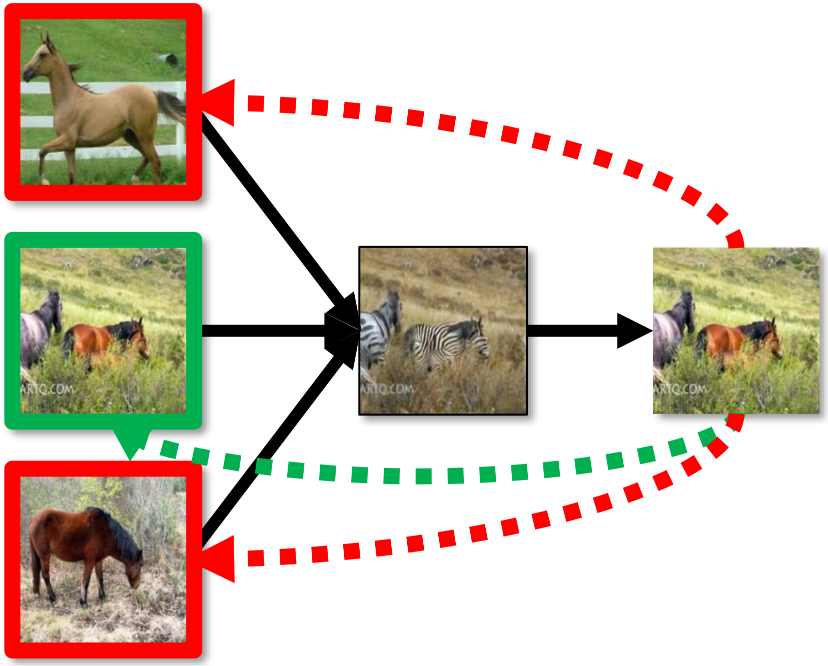
Zhu et al., “Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks”, ICCV 2017

Cycle Consistency

Forward cycle loss: $\left\|F(G(x)) - x\right\|_1$



Small Large cycle loss



Helps cope with mode collapse

Zhu et al., "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks", ICCV 2017

Training Details: Objective

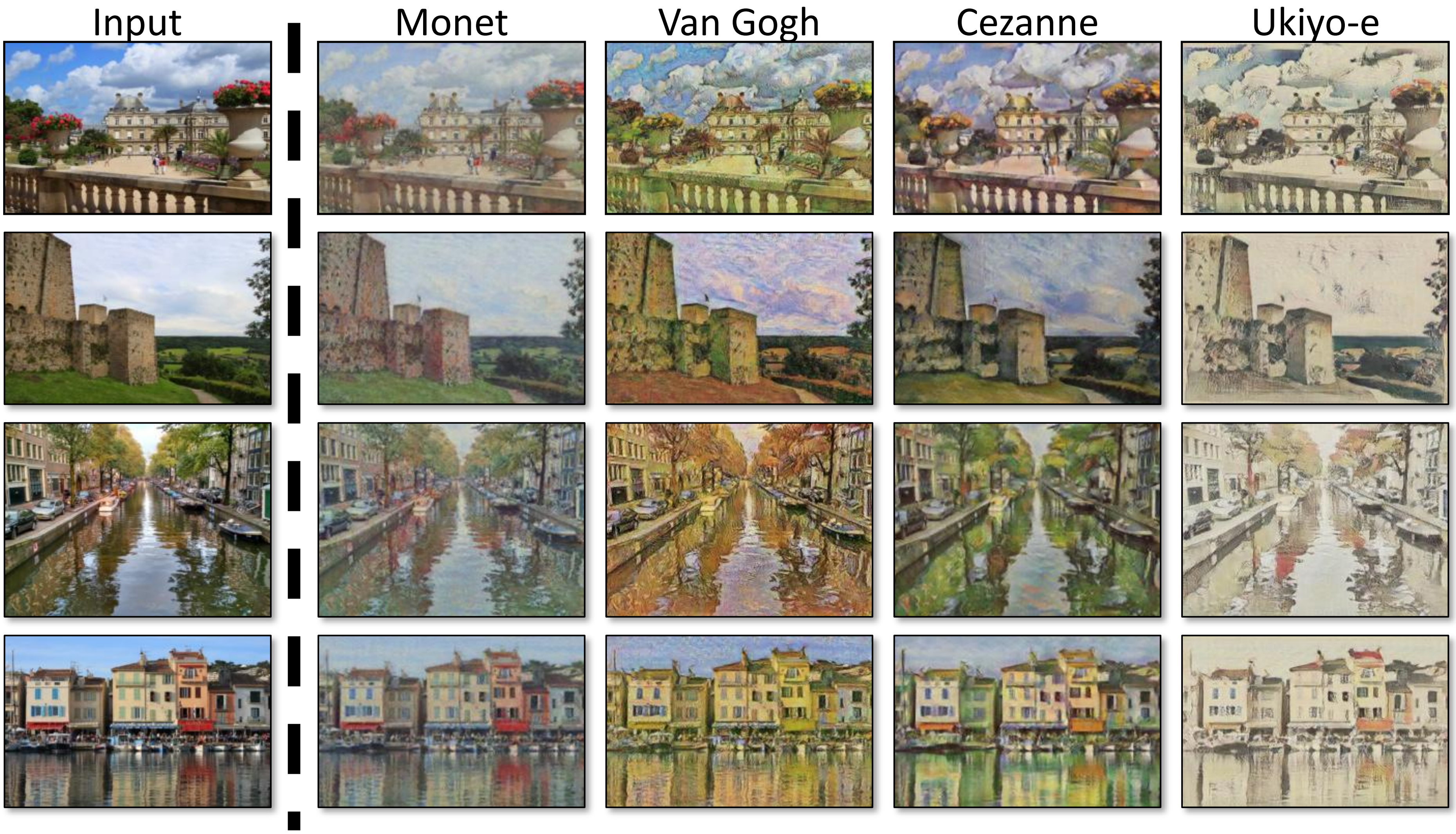
$$\begin{aligned}\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) =& \mathbb{E}_{y \sim p_{\text{data}}(y)}[\log D_Y(y)] \\ &+ \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log(1 - D_Y(G(x))],\end{aligned}$$

$$\begin{aligned}\mathcal{L}_{\text{cyc}}(G, F) =& \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] \\ &+ \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1].\end{aligned}$$

$$\begin{aligned}\mathcal{L}(G, F, D_X, D_Y) =& \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) \\ &+ \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) \\ &+ \lambda \mathcal{L}_{\text{cyc}}(G, F),\end{aligned}$$

$$G^*, F^* = \arg \min_{G,F} \max_{D_x, D_Y} \mathcal{L}(G, F, D_X, D_Y).$$

Zhu et al., “Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks”, ICCV 2017

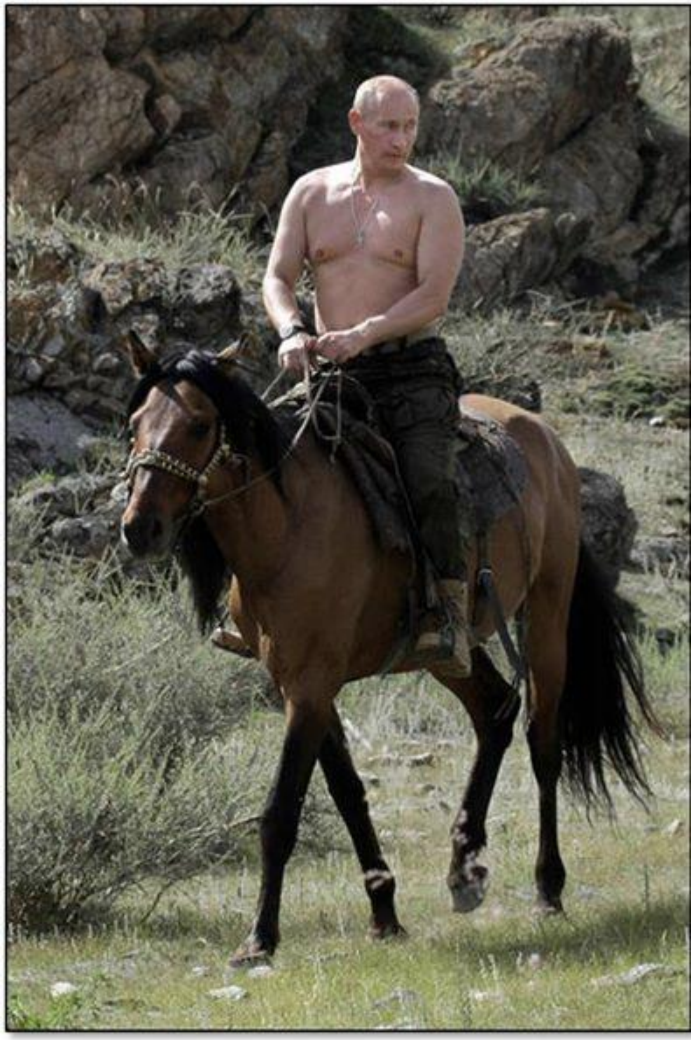


Pix2pix / CycleGAN

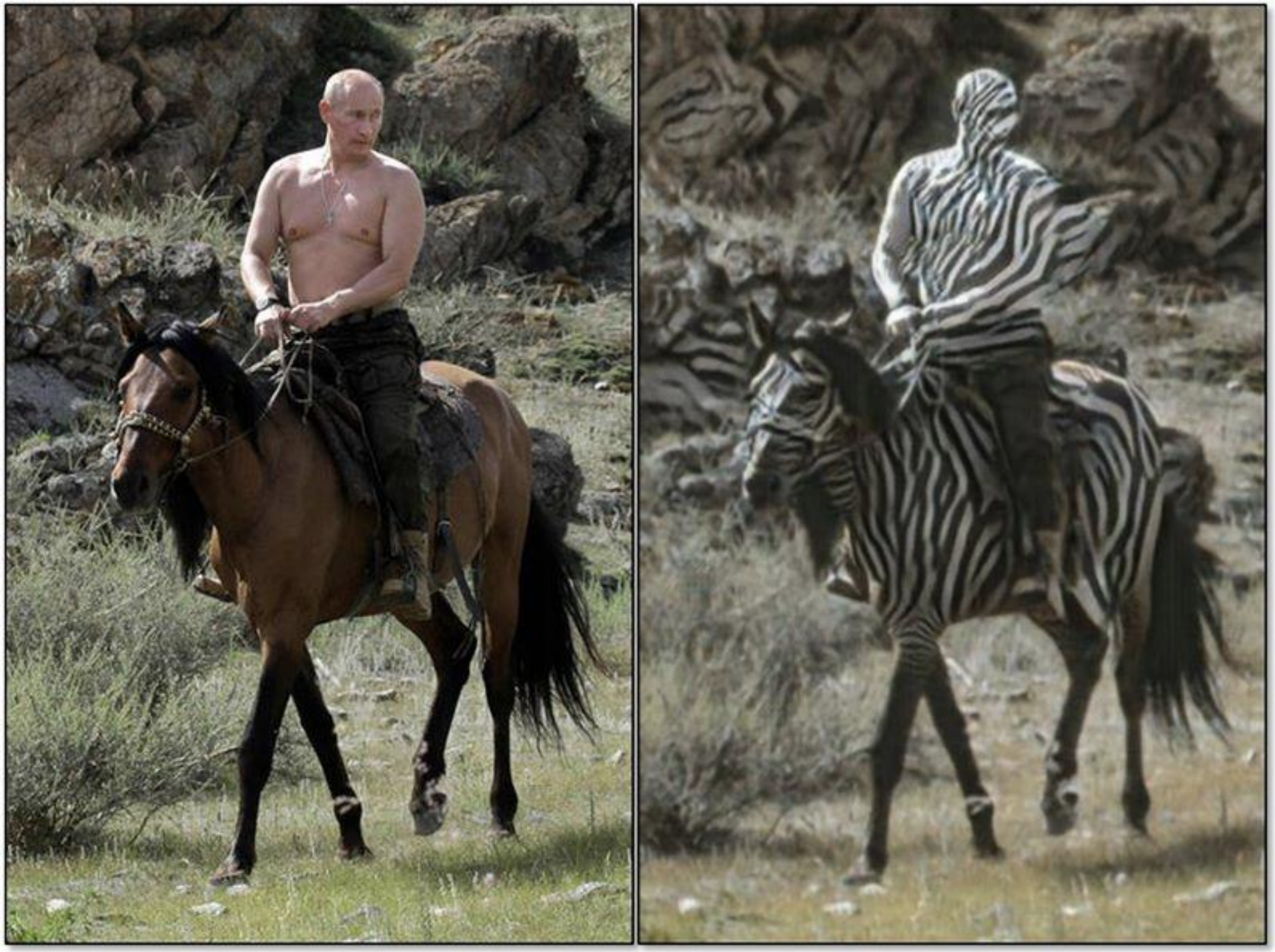
Pix2pix / CycleGAN

Pix2pix / CycleGAN

Pix2pix / CycleGAN

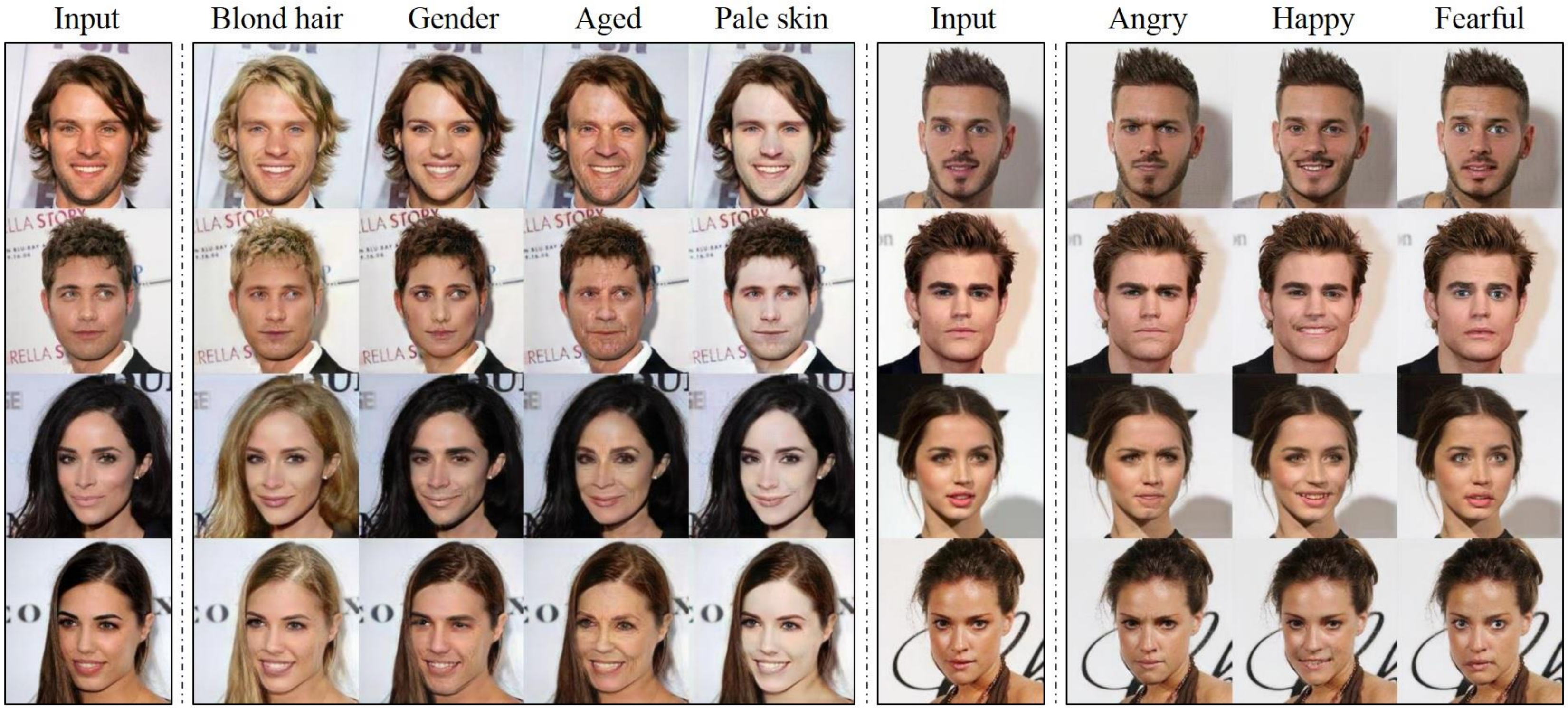


Pix2pix / CycleGAN



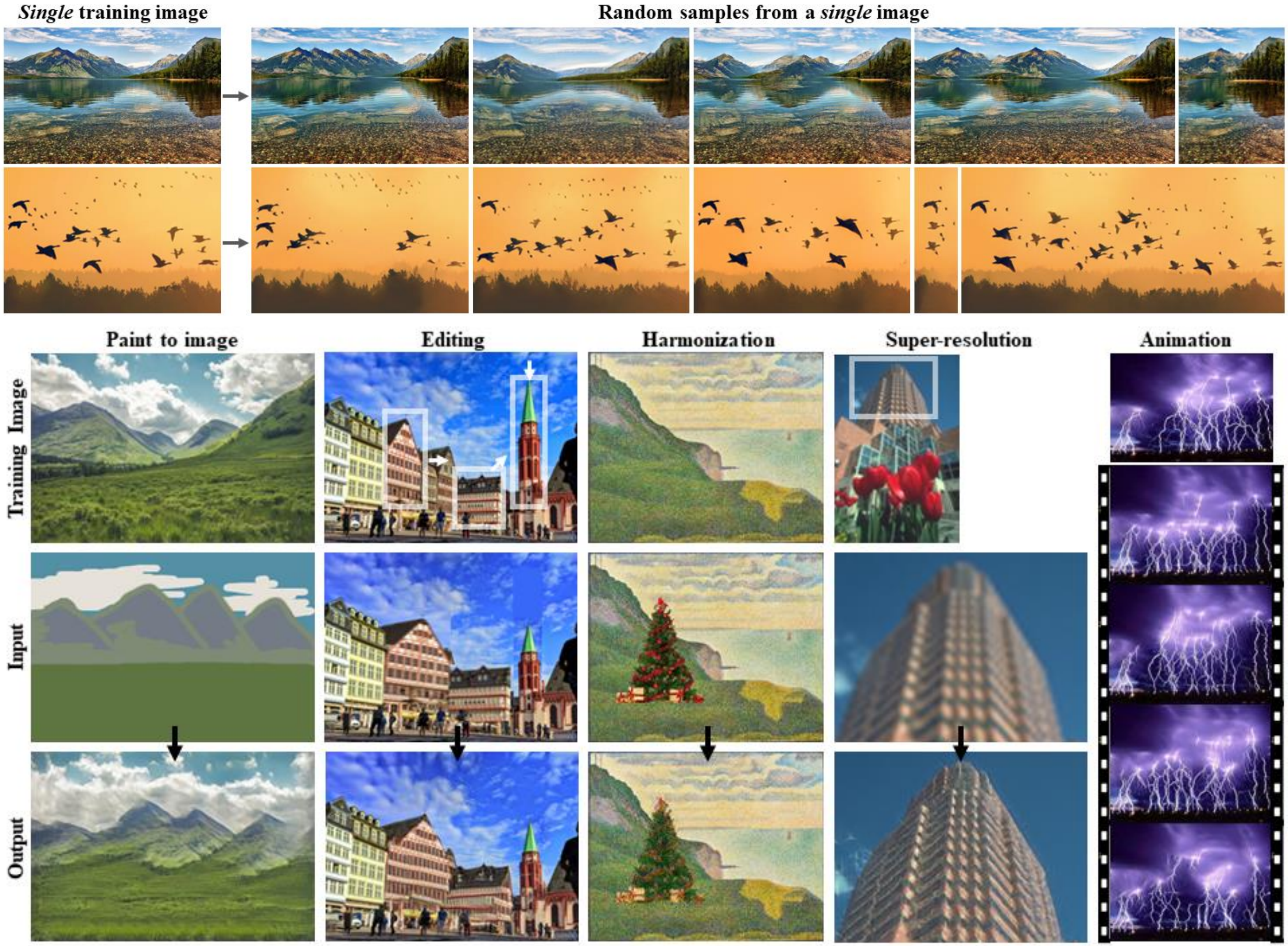
Pix2pix / CycleGAN

StarGAN



Choi et al., “StarGAN: Unified Generative Adversarial Networks for Multi-Domain Image-to-Image Translation”, CVPR 2018

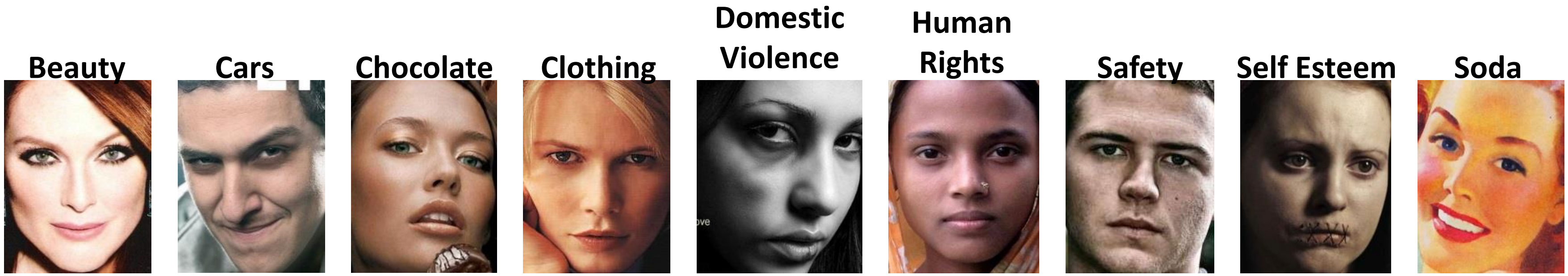
SinGAN



Shaham et al., “SinGAN: Learning a Generative Model from a Single Natural Image”, ICCV 2019

Generating with little data for ads

- Faces are persuasive and carry meaning/sentiment

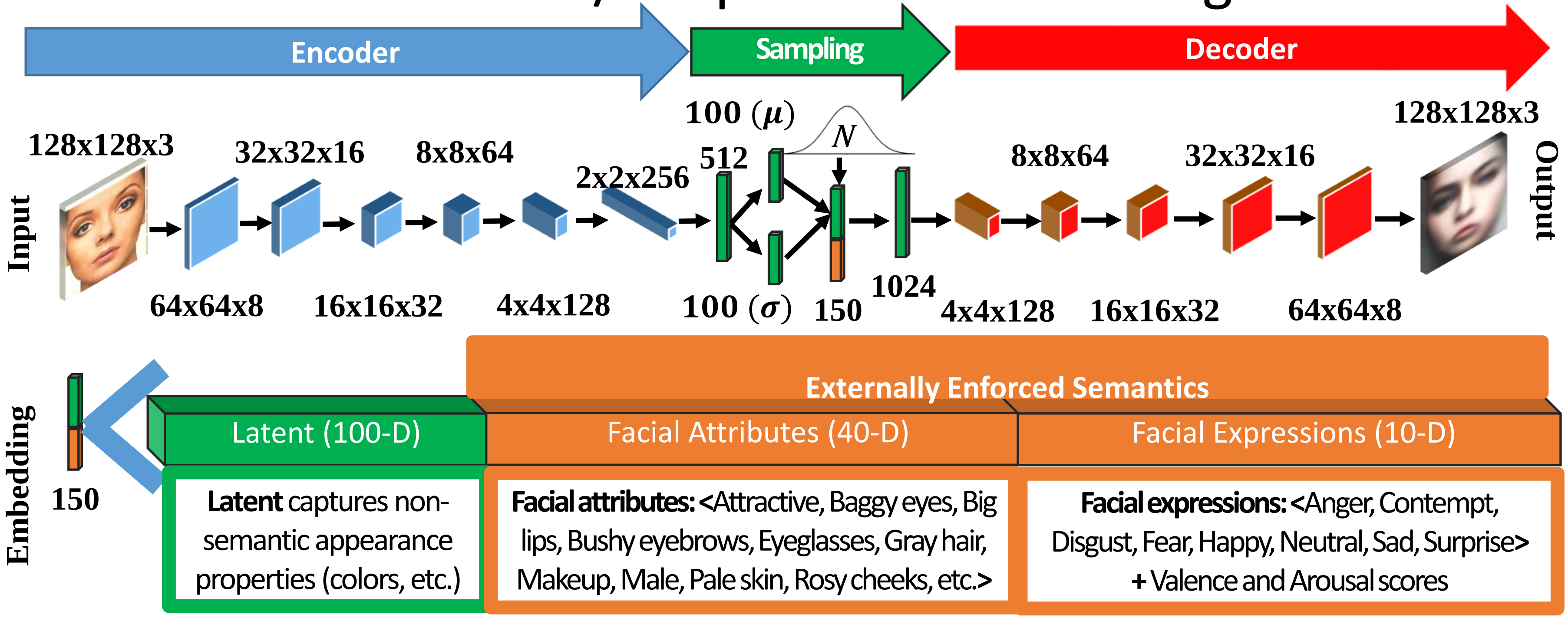


- We learn to generate faces appropriate for each ad category
- Because our data is so diverse yet limited in count, standard approaches that directly model pixel distributions don’t work well

Thomas and Kovashka, BMVC 2018

Generating with little data for ads

- Instead we model the distribution over *attributes* for each category (e.g. domestic violence ads contain "black eye", beauty contains "red lips")
- Generate an image with the attributes of an ad class
- Model attributes w/ help from external large dataset



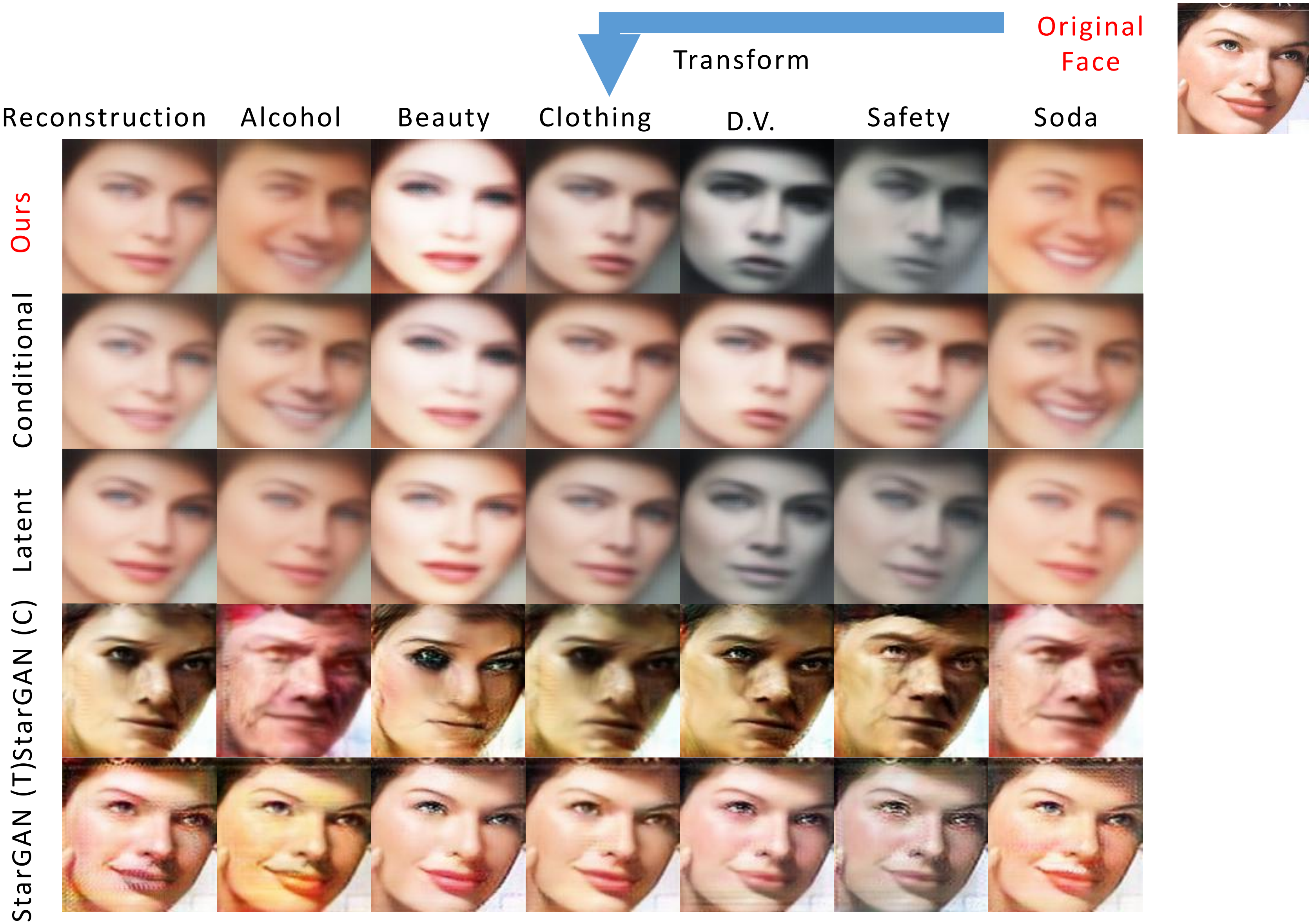
Latent captures non-semantic appearance properties (colors, etc.)

Facial attributes: <Attractive, Baggy eyes, Big lips, Bushy eyebrows, Eyeglasses, Gray hair, Makeup, Male, Pale skin, Rosy cheeks, etc.>

Facial expressions: <Anger, Contempt, Disgust, Fear, Happy, Neutral, Sad, Surprise> + Valence and Arousal scores

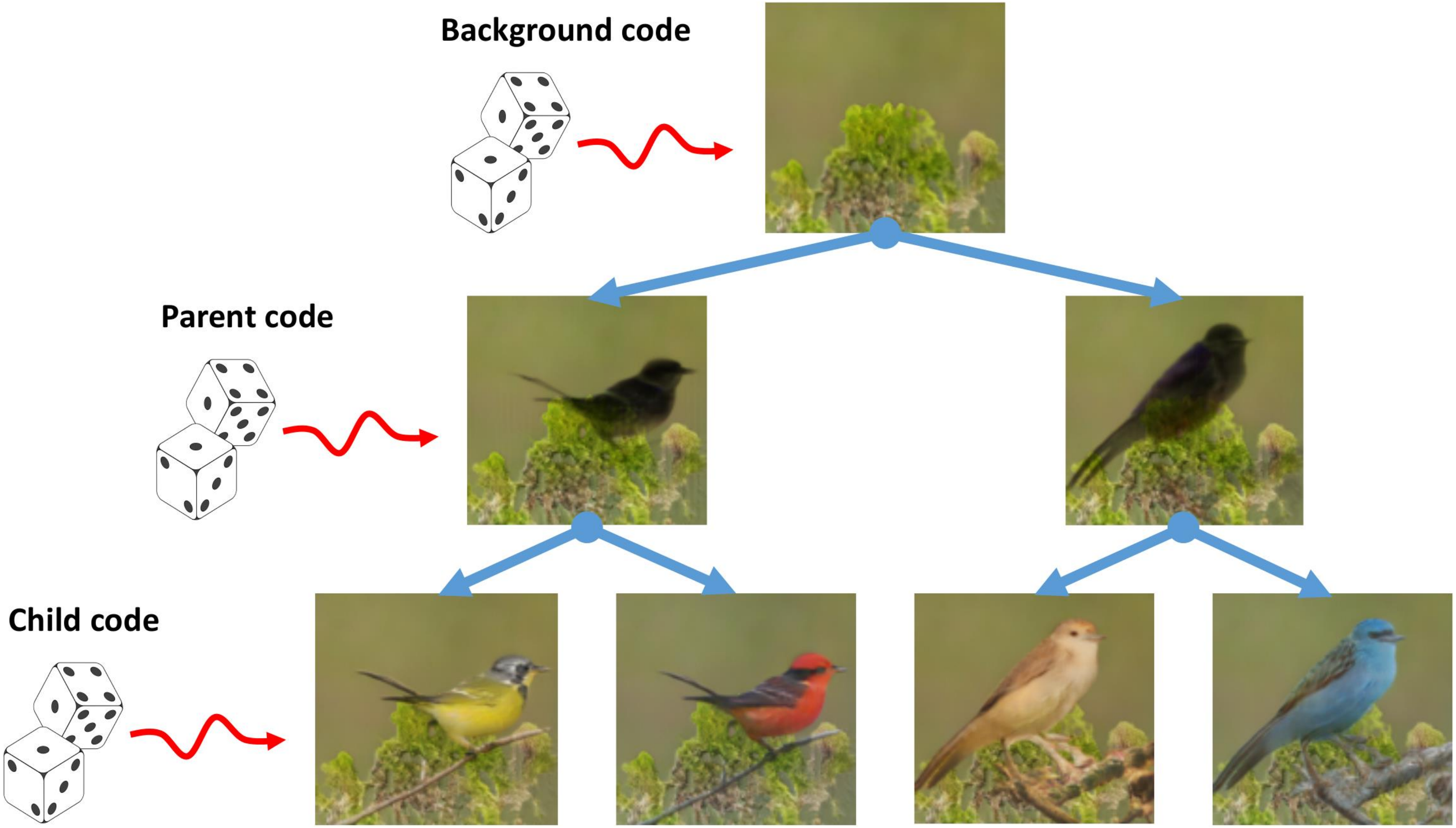
Thomas and Kovashka, BMVC 2018

Generating with little data for ads



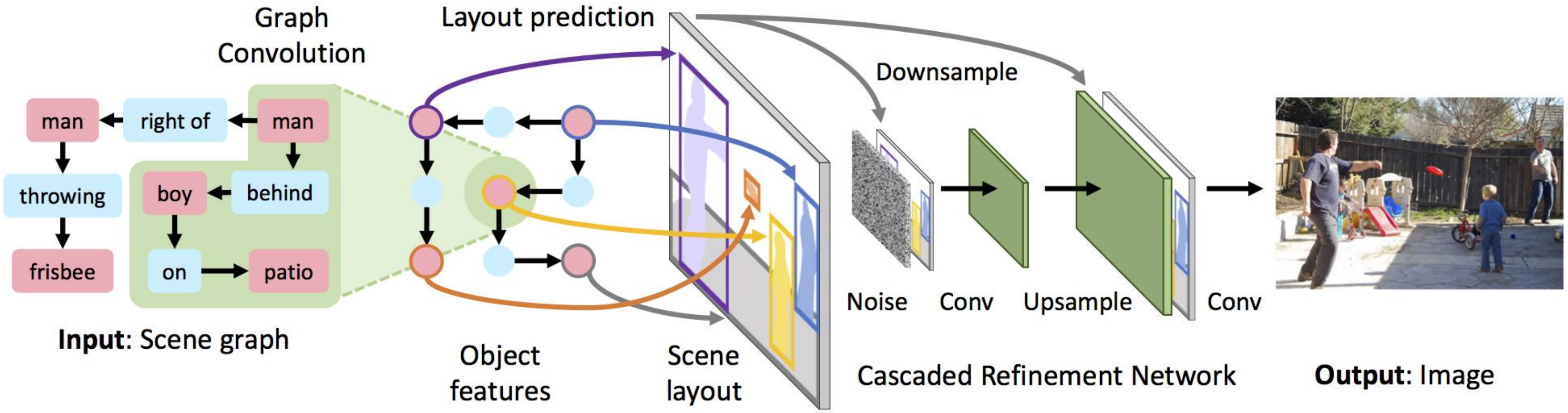
Thomas and Kovashka, BMVC 2018

Stagewise generation



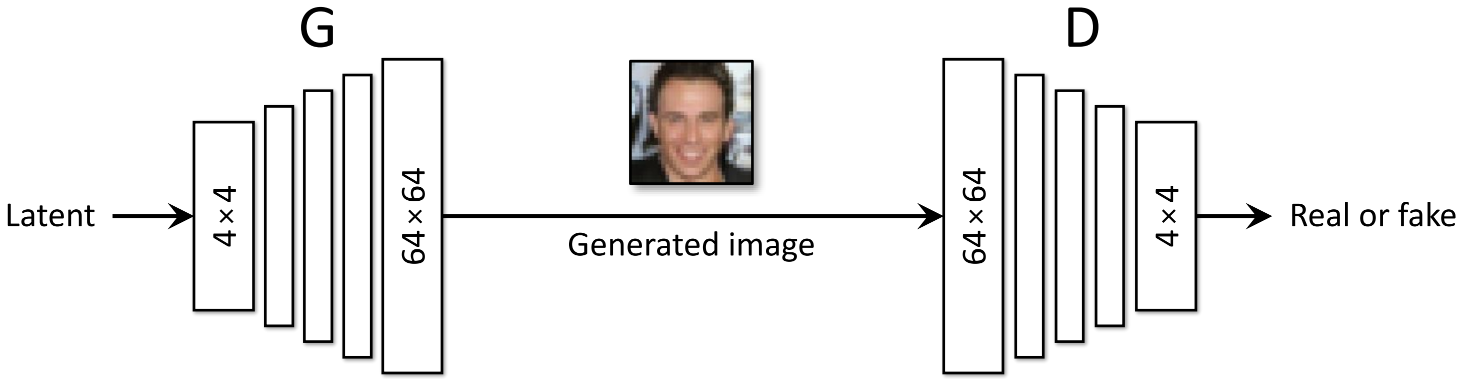
Singh et al., "FineGAN: Unsupervised Hierarchical Disentanglement for Fine-Grained Object Generation and Discovery", CVPR 2019

Stagewise generation



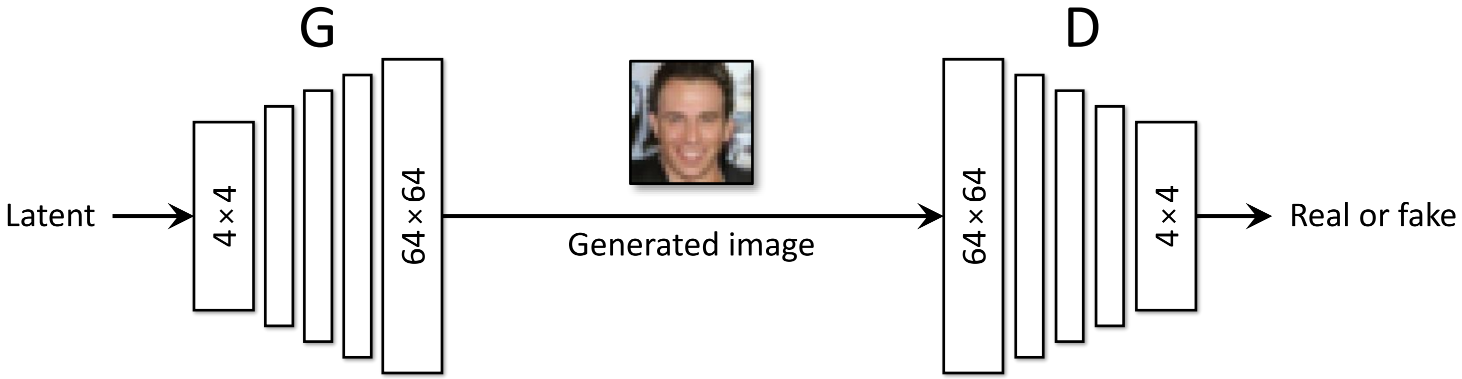
Johnson et al., “Image Generation from Scene Graphs”, CVPR 2018

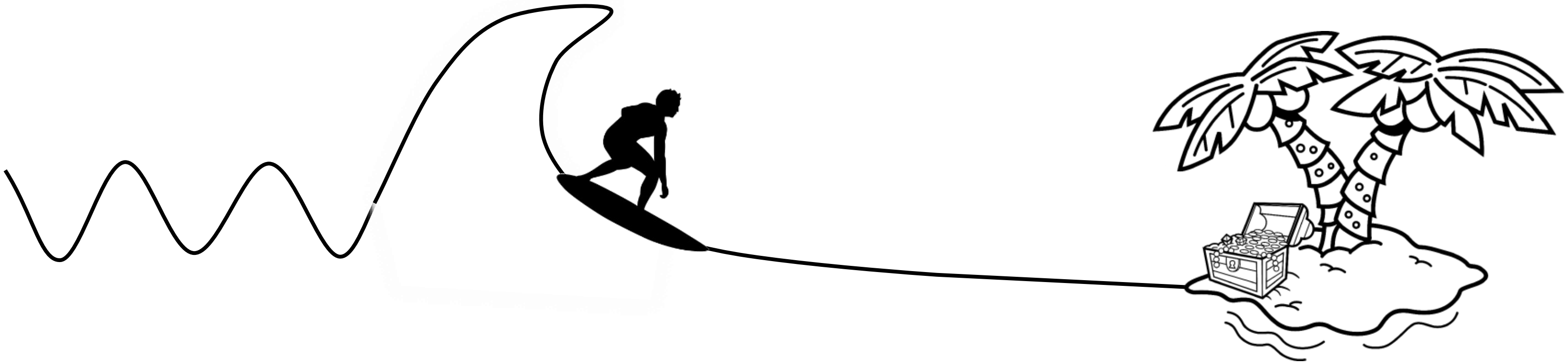
Progressive generation



Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

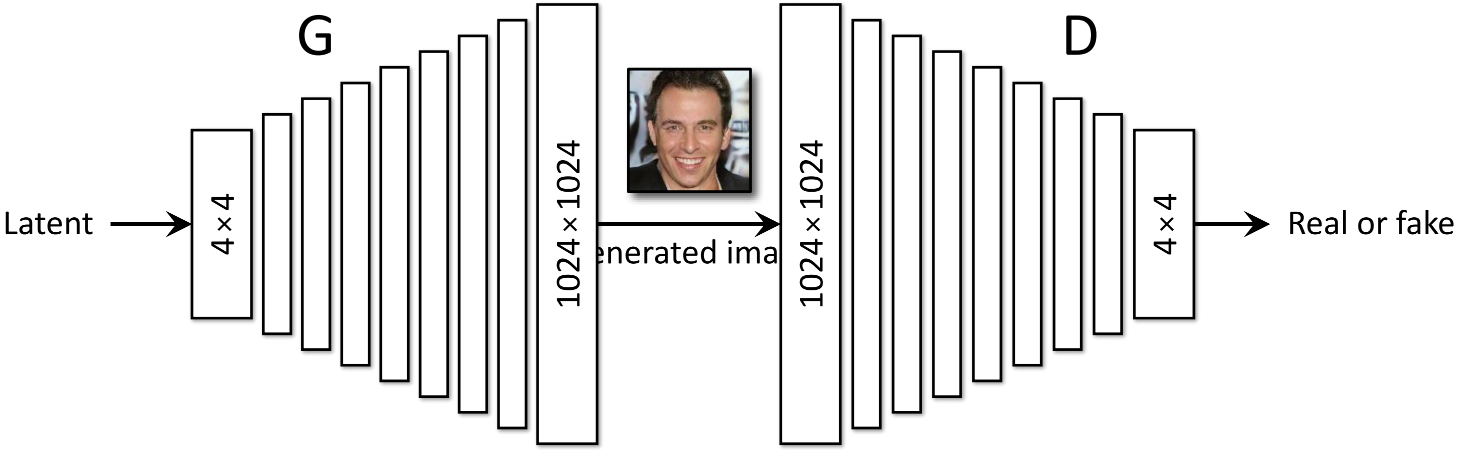
Progressive generation

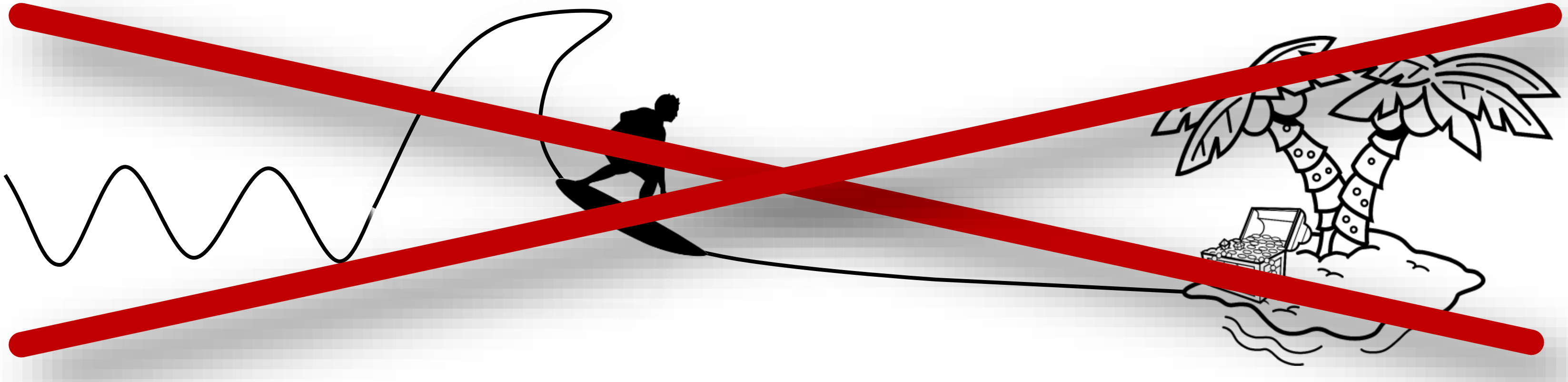




Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

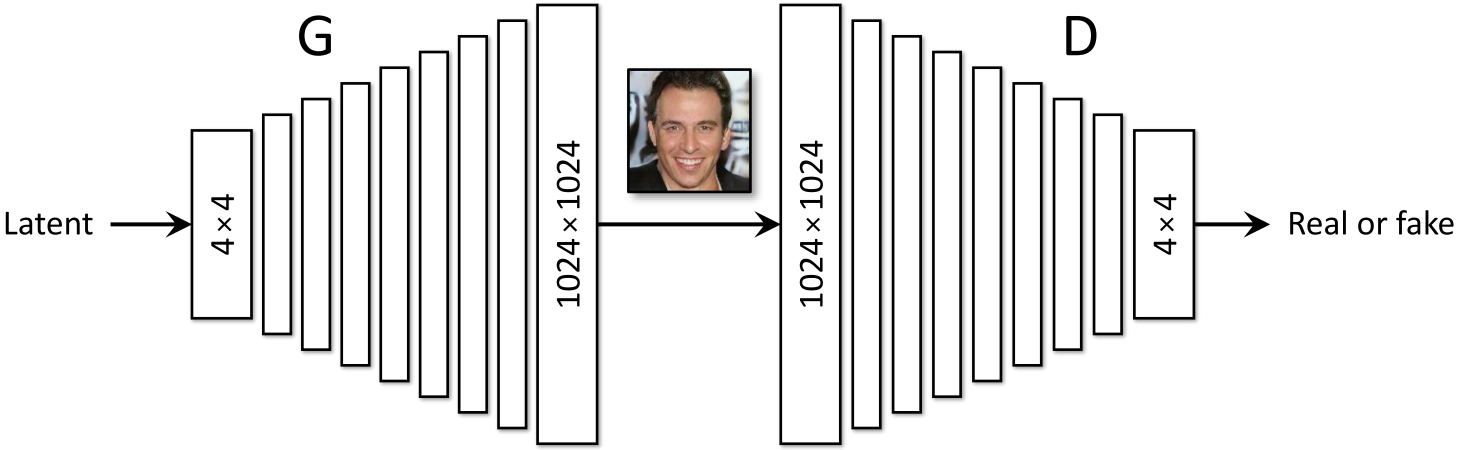
Progressive generation

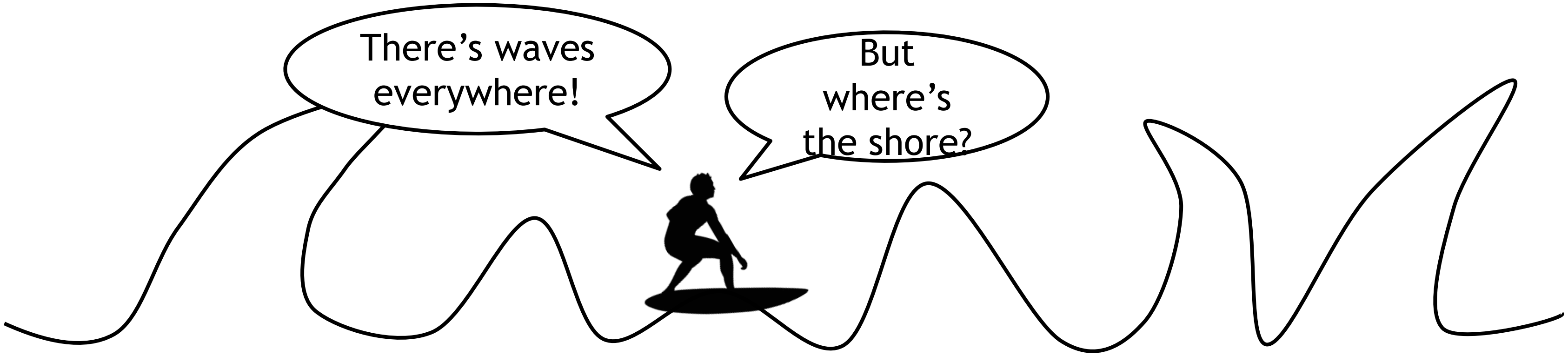




Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

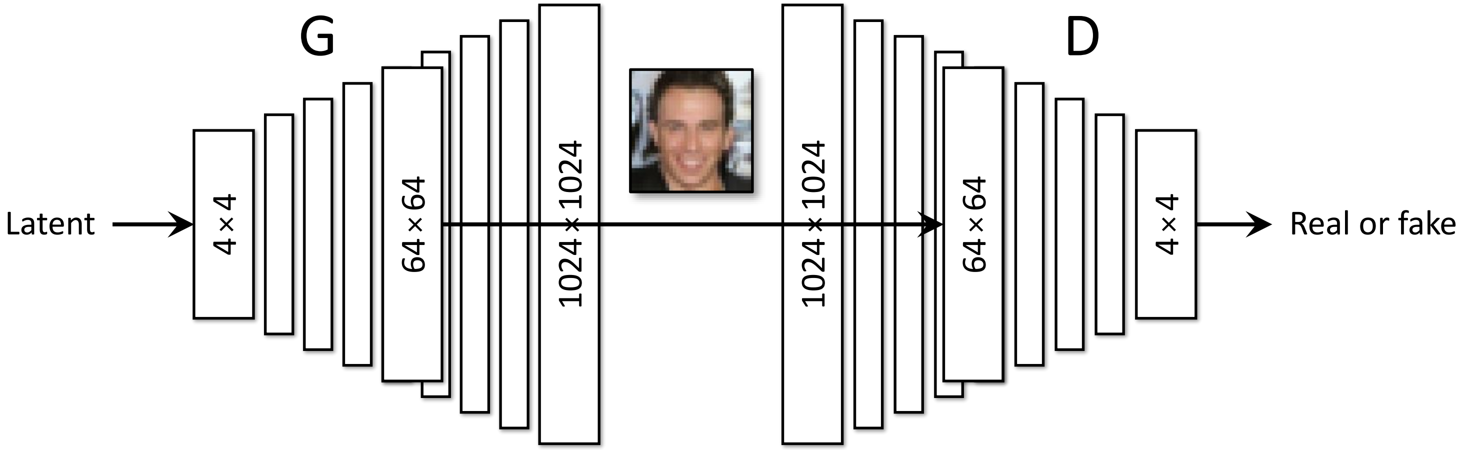
Progressive generation

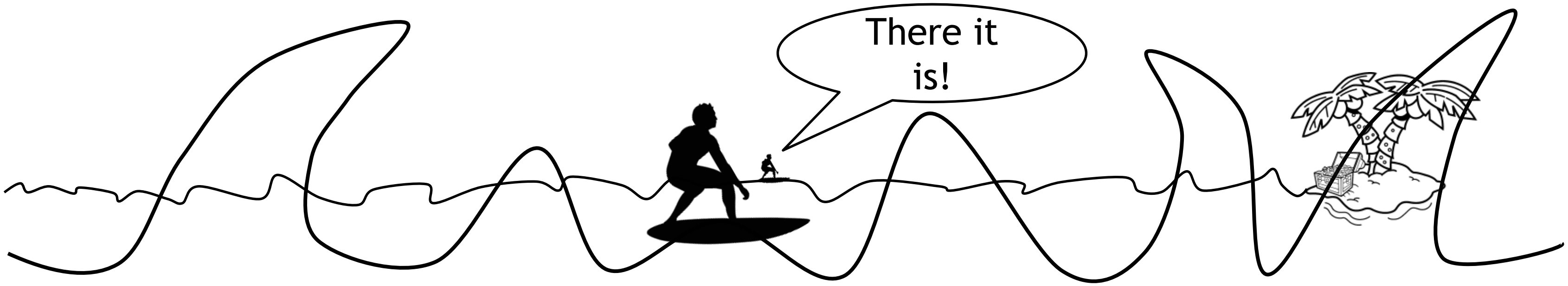




Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

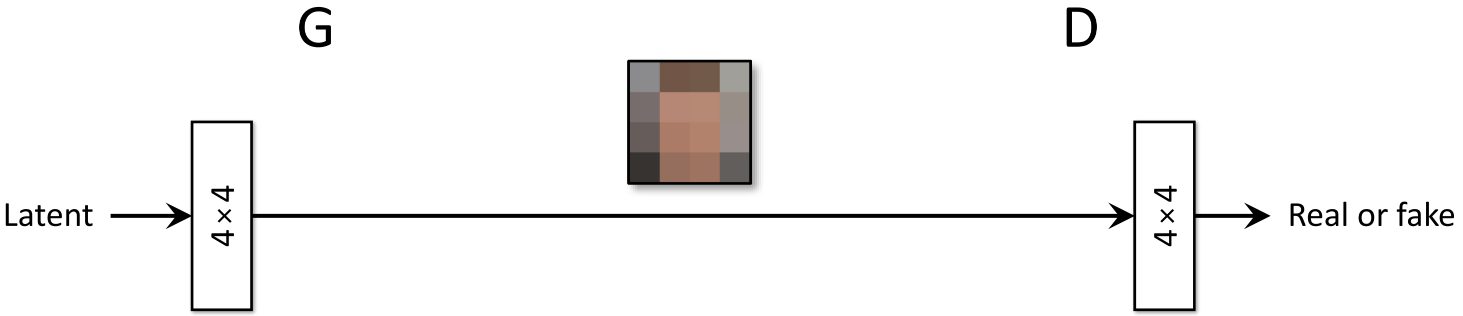
Progressive generation





Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

Progressive generation



G

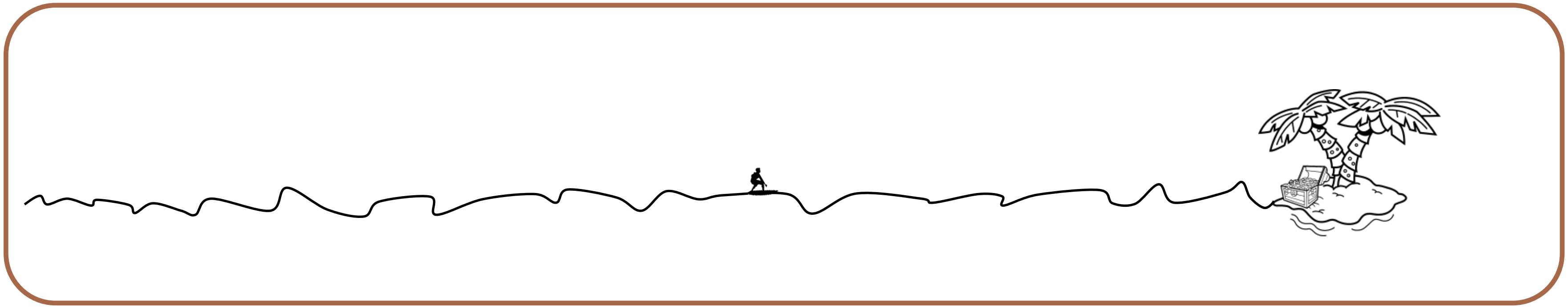
D

Latent

4×4

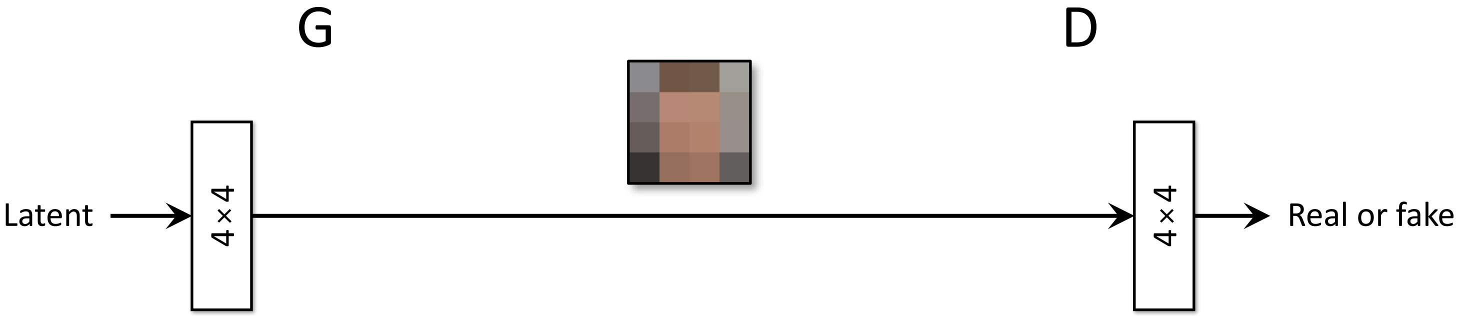
4×4

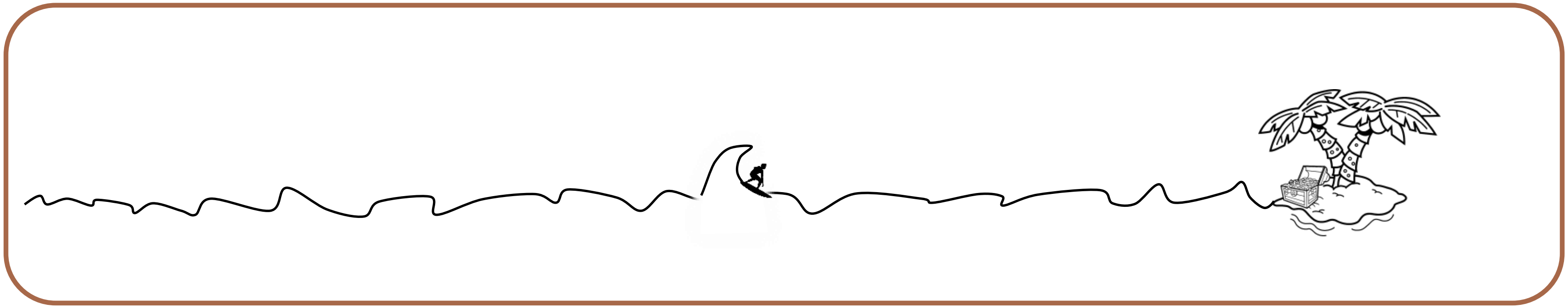
Real or fake



Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

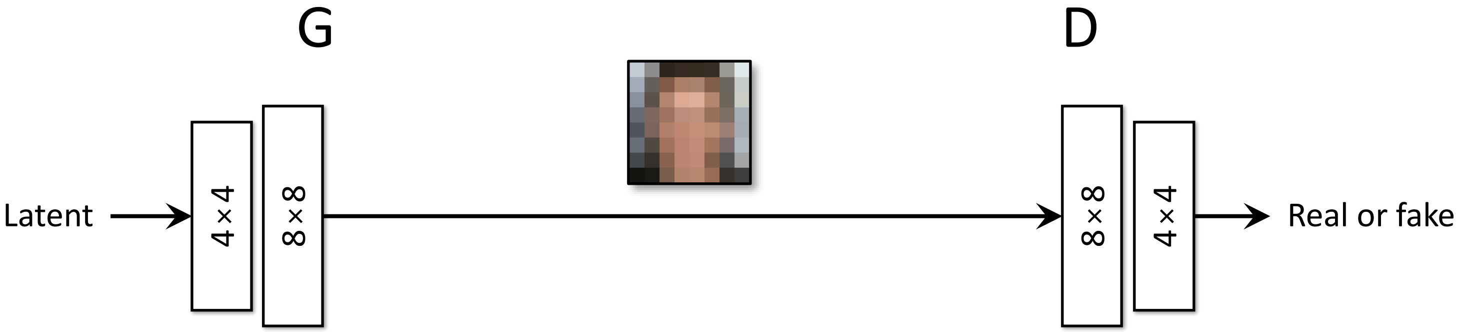
Progressive generation

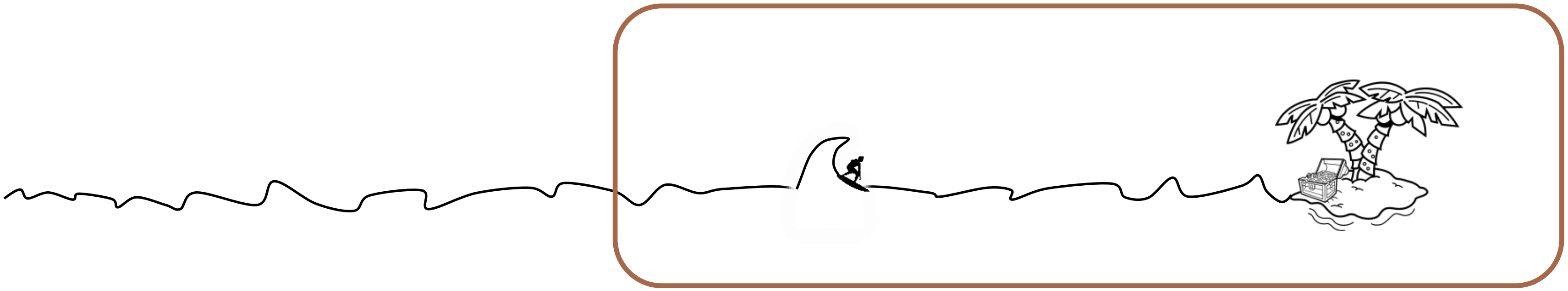




Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

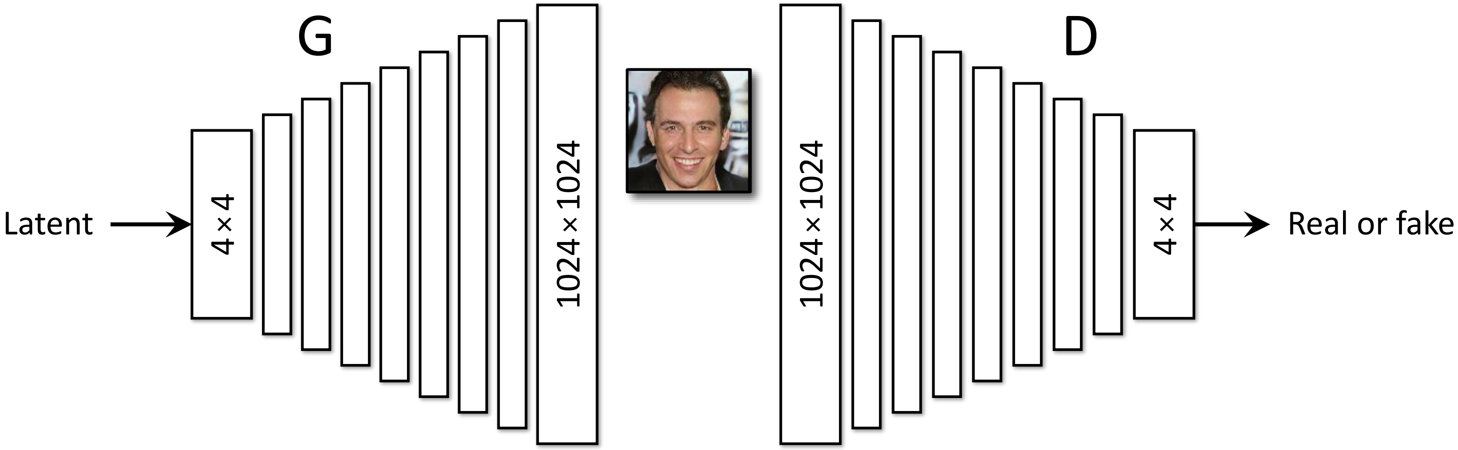
Progressive generation

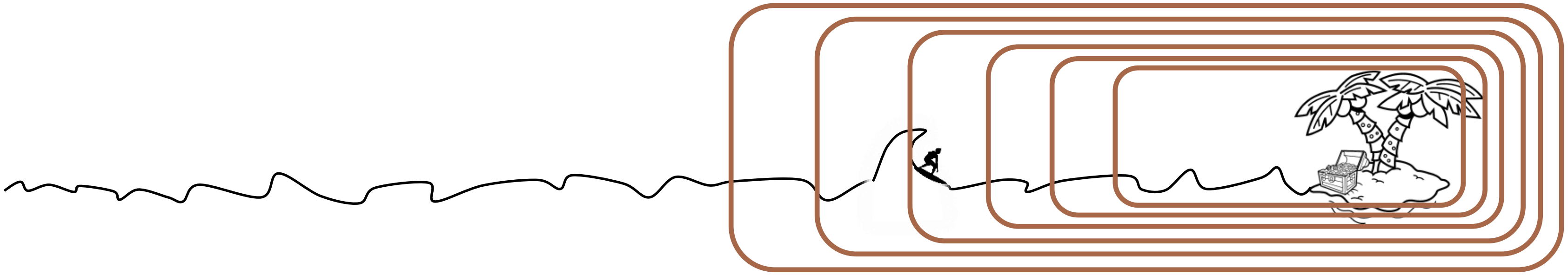




Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

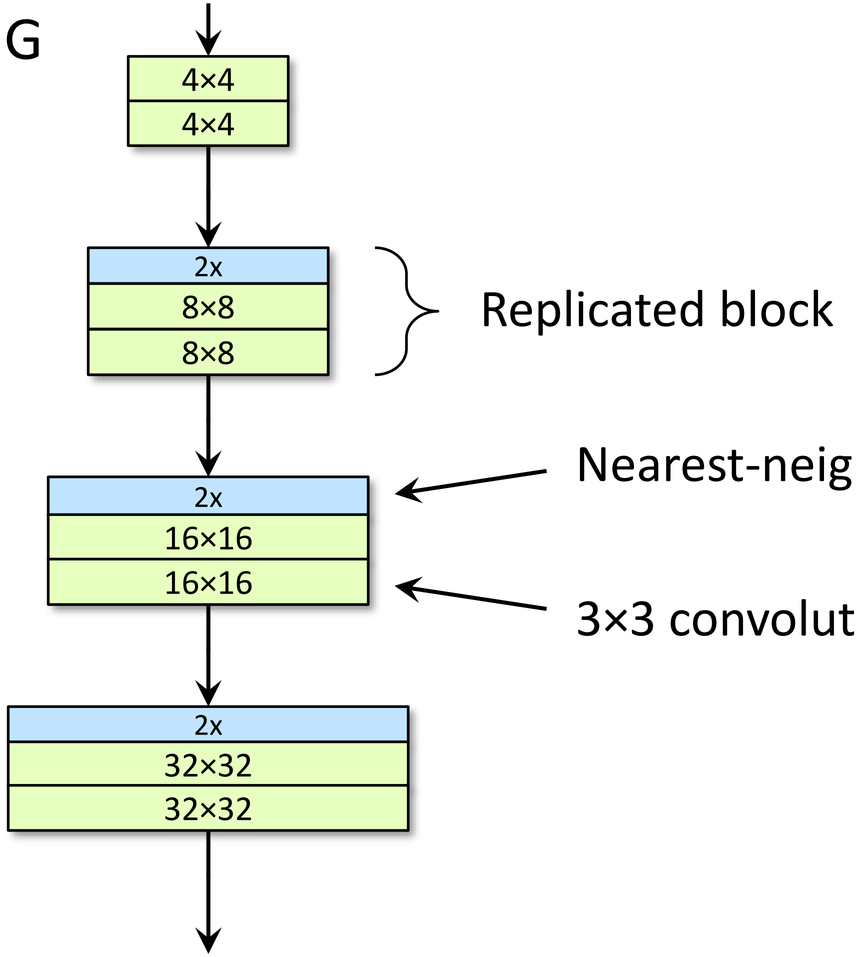
Progressive generation





Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation", ICLR 2018

Progressive generation



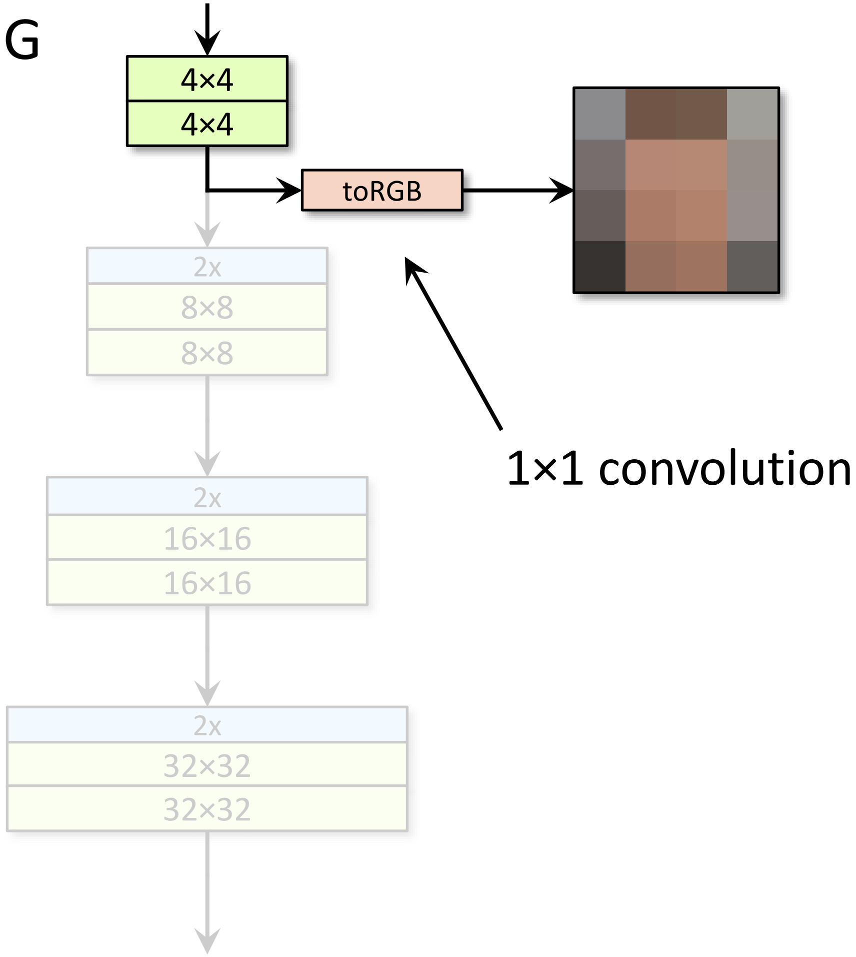
Replicated block

Nearest-neighbor upsampling

3×3 convolution

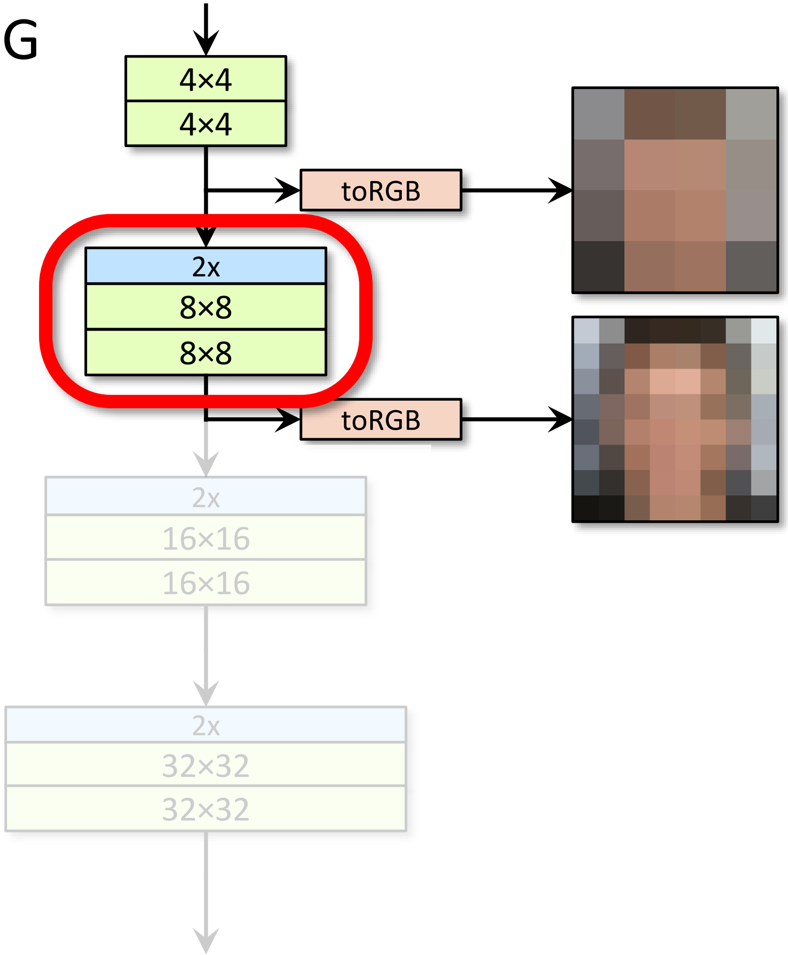
Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

Progressive generation



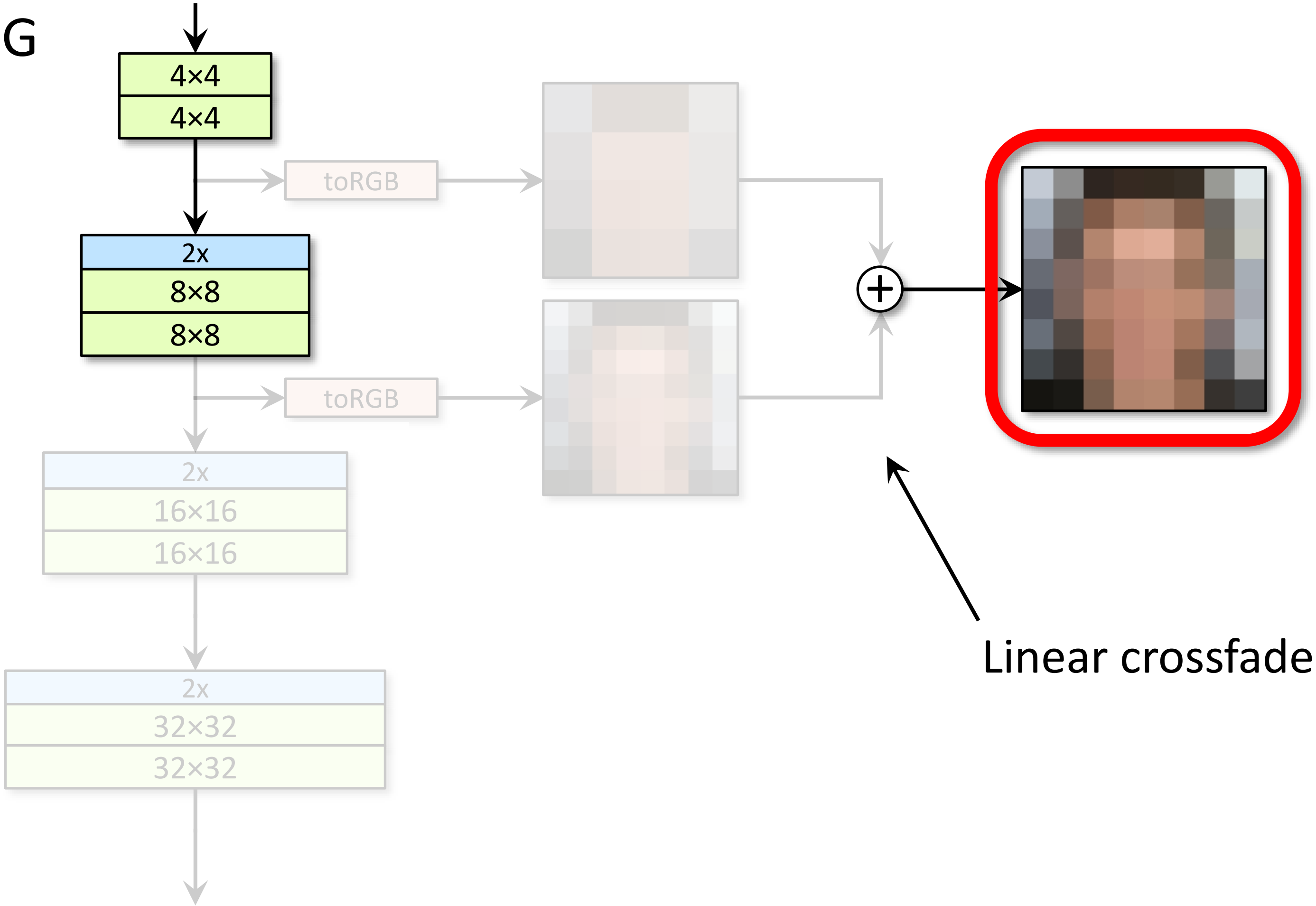
Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

Progressive generation



Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

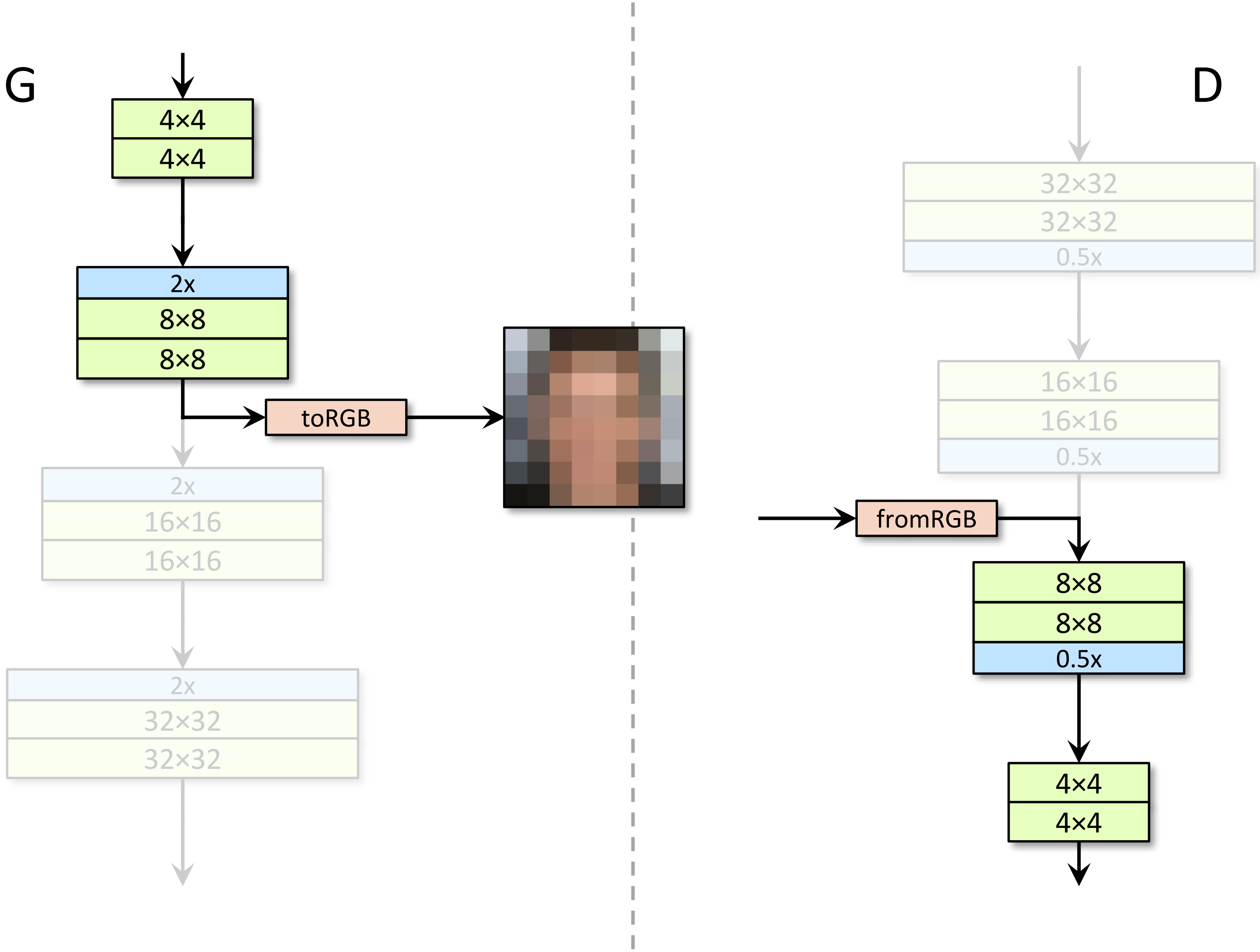
Progressive generation



Linear crossfade

Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

Progressive generation

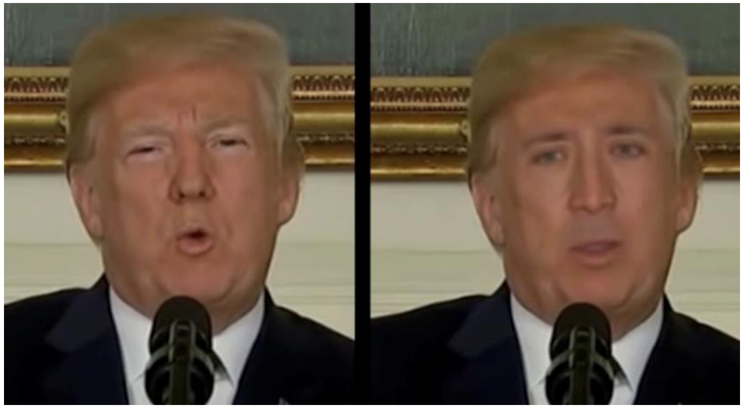


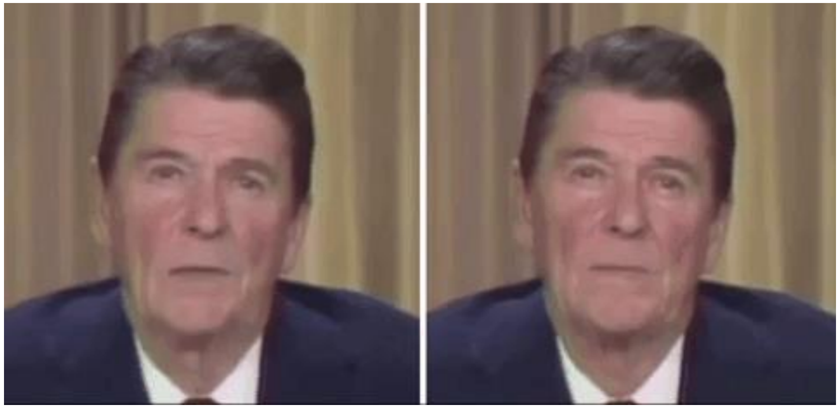
Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”, ICLR 2018

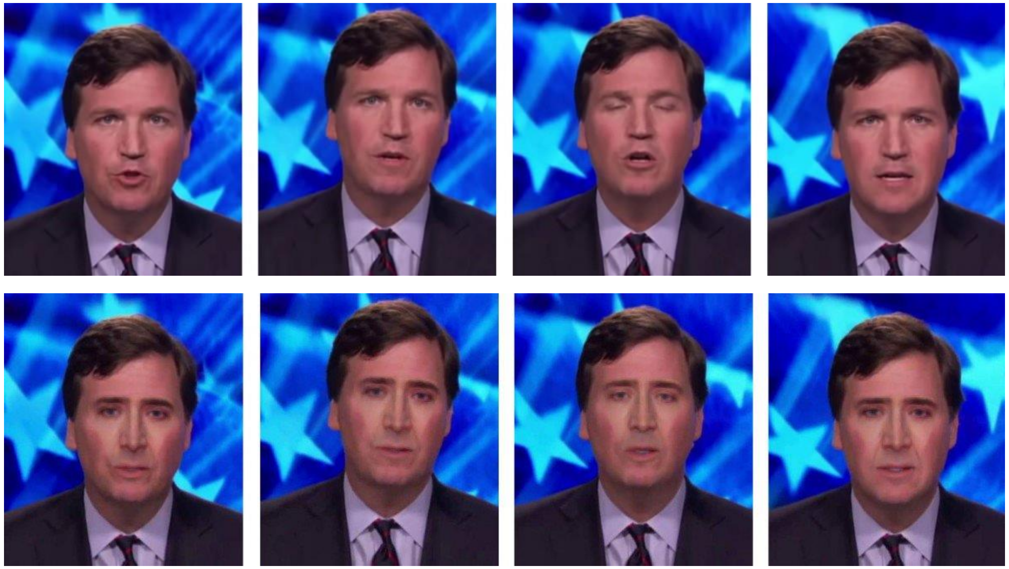
Part V: Ethics (Politics, Privacy, Bias)

- Politics and deep fakes
  - Examples from DARPA
  - Detection methods
- Privacy
  - GANs for anonymity in the cloud
  - What can be reconstructed
- Security
  - Adversarial perturbations
- Bias
  - What models show
  - How to cope
- AI for the people

“Deepfakes”

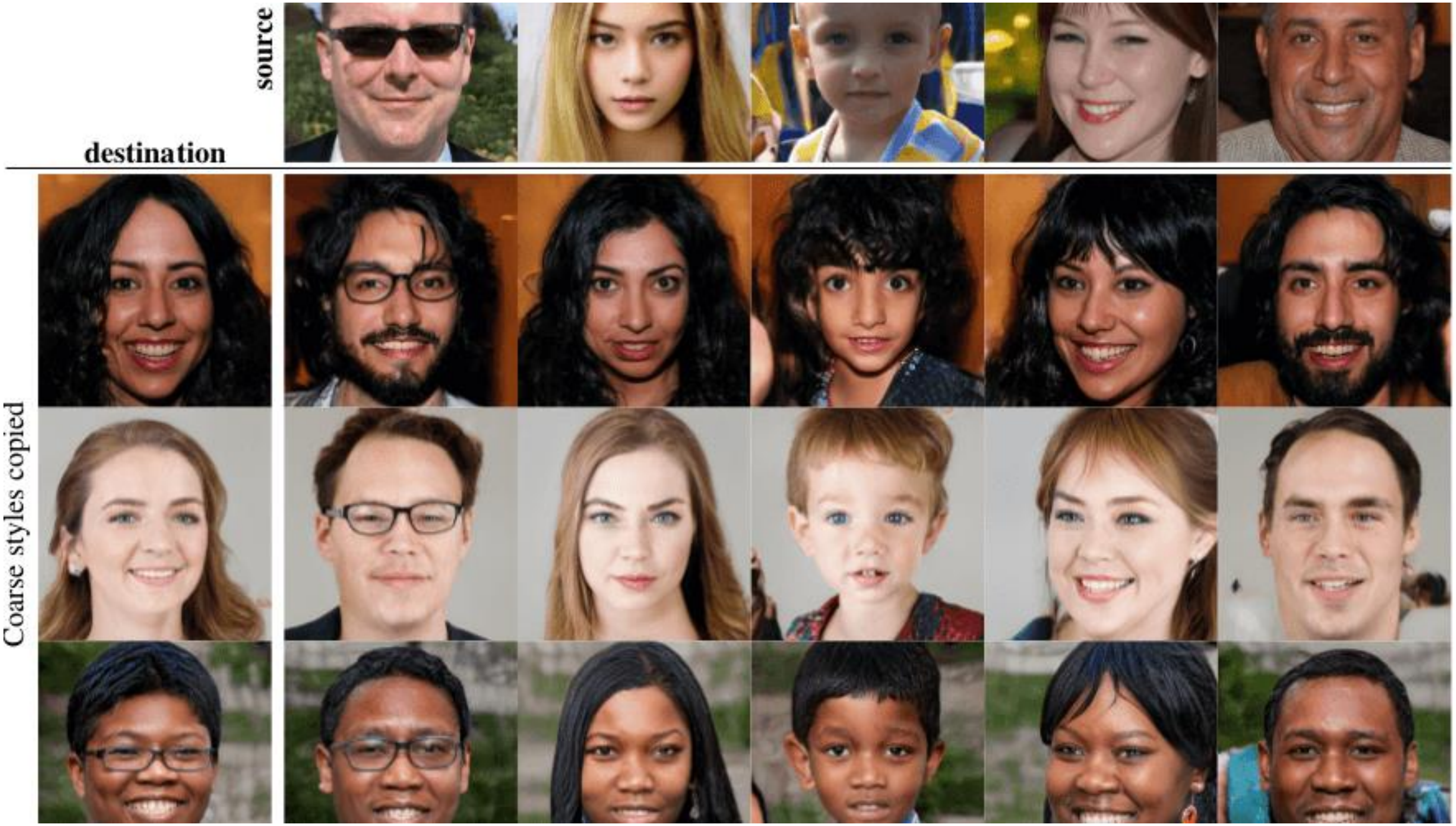






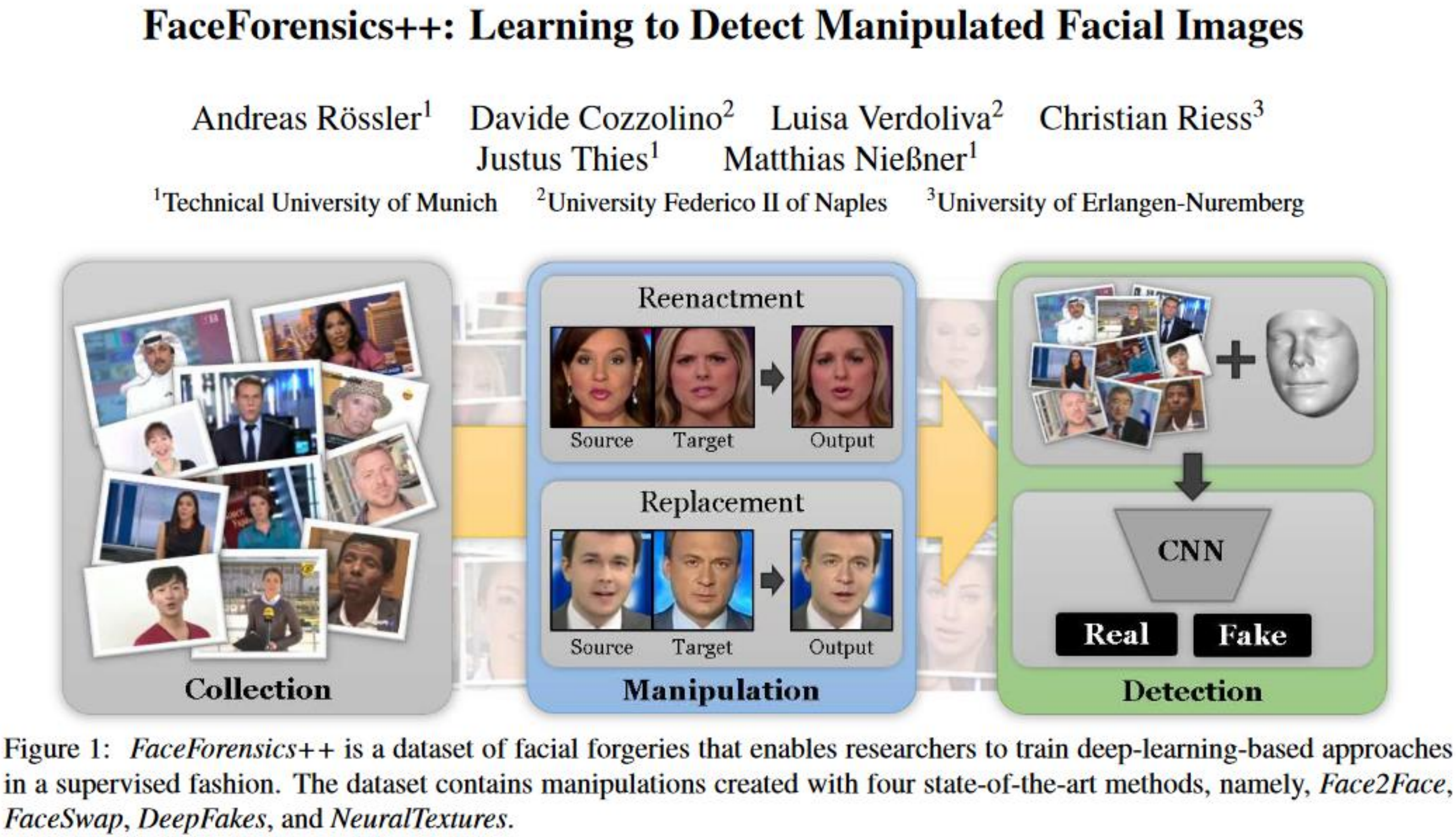
https://www.technologyreview.com/s/611726/the-defense-department-has-produced-the-first-tools-for-catching-deepfakes/
https://www.niemanlab.org/2018/11/how-the-wall-street-journal-is-preparing-its-journalists-to-detect-deepfakes/

You can be anyone you want…



Karras et al., “A Style-Based Generator Architecture for Generative Adversarial Networks”, CVPR 2019, https://arxiv.org/pdf/1812.04948.pdf

Detection methods



FaceForensics++: Learning to Detect Manipulated Facial Images

Andreas Rössler[1] Davide Cozzolino[2] Luisa Verdoliva[2] Christian Riess[3]
Justus Thies[1] Matthias Nießner[1]
[1]Technical University of Munich [2]University Federico II of Naples [3]University of Erlangen-Nuremberg

Figure 1: *FaceForensics++* is a dataset of facial forgeries that enables researchers to train deep-learning-based approaches in a supervised fashion. The dataset contains manipulations created with four state-of-the-art methods, namely, *Face2Face*, *FaceSwap*, *DeepFakes*, and *NeuralTextures*.

Rossler et al.. "FaceForensics++: Learning to Detect Manipulated Facial Images", ICCV 2019

Detection methods

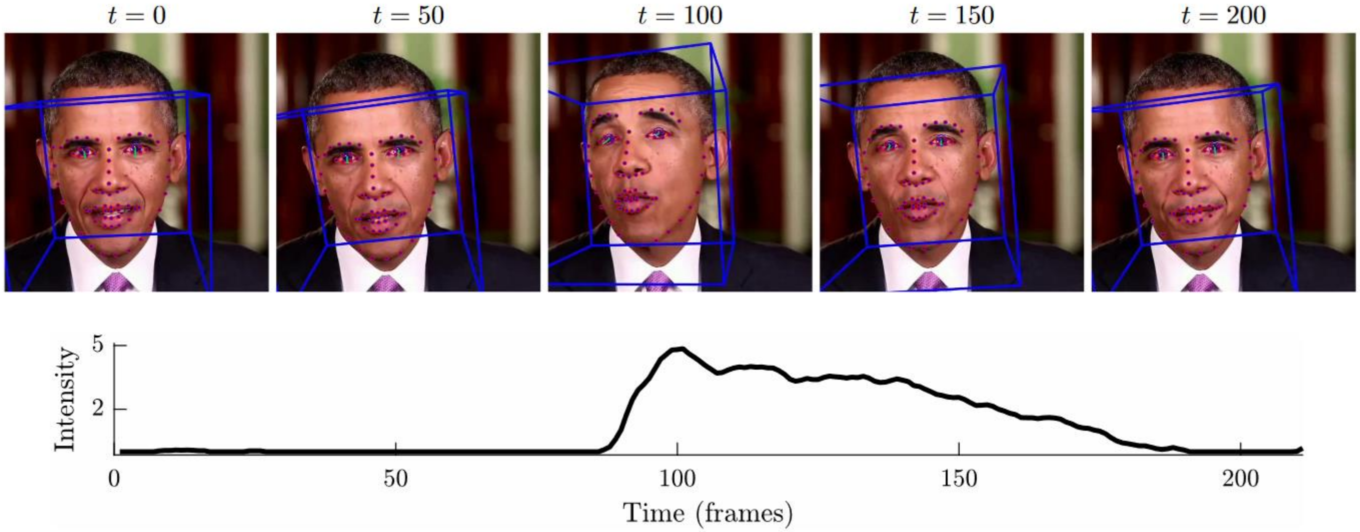
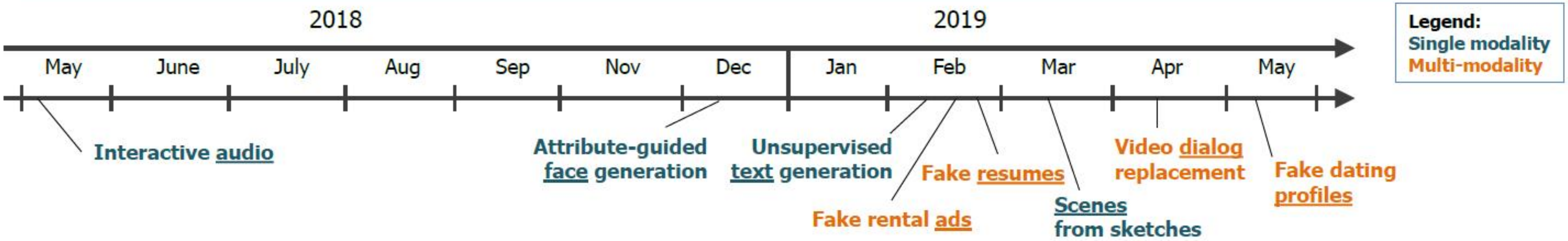


Figure 1. Shown above are five equally spaced frames from a 250-frame clip annotated with the results of OpenFace tracking. Shown below is the intensity of one action unit AU01 (eye brow lift) measured over this video clip.

“We describe a forensic technique that models facial expressions and movements that typify an individual’s speaking pattern. Although not visually apparent, these correlations are often violated by the nature of how deep-fake videos are created and can, therefore, be used for authentication.

Agarwal et al., “Protecting World Leaders Against Deep Fakes”, CVPR Workshops, 2019

Incredible Pace of Synthetic Media Generation



Legend:
Single modality
Multi-modality

Interactive audio

Attribute-guided face generation

Unsupervised text generation

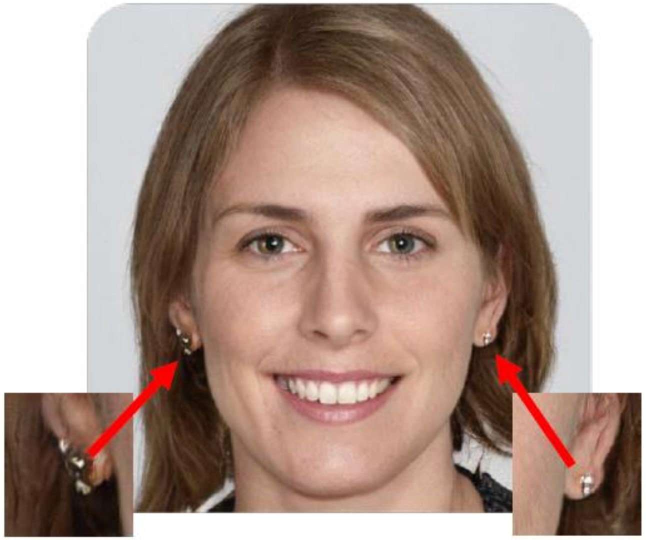
Fake rental ads

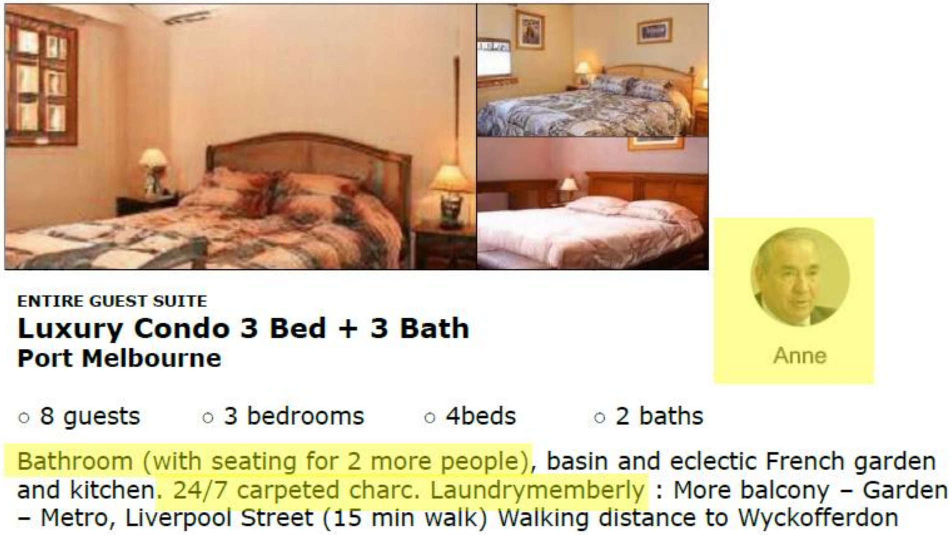
Fake resumes

Scenes from sketches

Video dialog replacement

Fake dating profiles





ENTIRE GUEST SUITE

Luxury Condo 3 Bed + 3 Bath
Port Melbourne

Anne

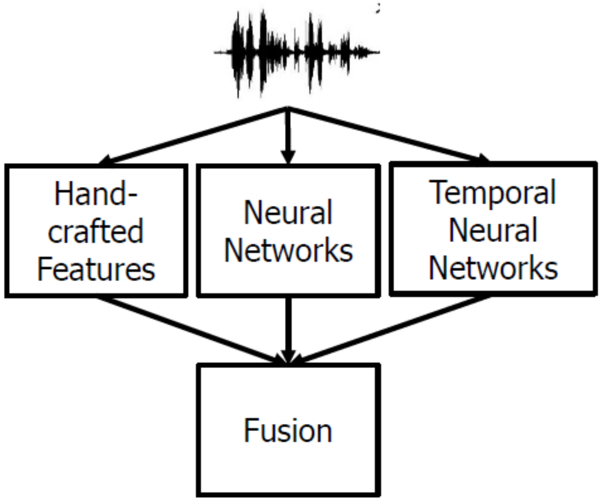
○ 8 guests ○ 3 bedrooms ○ 4beds ○ 2 baths

Bathroom (with seating for 2 more people), basin and eclectic French garden and kitchen. 24/7 carpeted charc. Laundrymemberly : More balcony – Garden – Metro, Liverpool Street (15 min walk) Walking distance to Wyckofferdon

Matt Turek

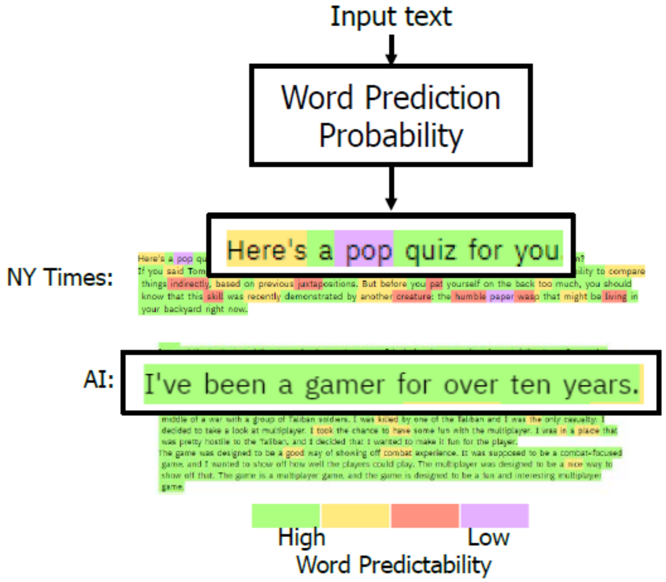
State of the Art Detection is Statistically Based, Narrow, or Both

Audio: ASVspoof



(Lavrentyeva et al. 2017)

Text: GLTR



Here's a pop quiz for you.

Here's a pop qu… …n?
If you said Tom … …ility to compare things indirectly, based on previous juxtapositions. But before you pat yourself on the back too much, you should know that this skill was recently demonstrated by another creature: the humble paper wasp that might be living in your backyard right now.

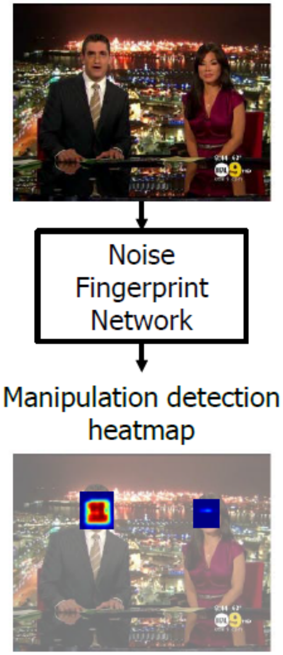
I've been a gamer for over ten years.

…middle of a war with a group of Taliban soldiers. I was killed by one of the Taliban and I was the only casualty. I decided to take a look at multiplayer. I took the chance to have some fun with the multiplayer. I was in a place that was pretty hostile to the Taliban, and I decided that I wanted to make it fun for the player.
The game was designed to be a good way of showing off combat experience. It was supposed to be a combat-focused game, and I wanted to show off how well the players could play. The multiplayer was designed to be a nice way to show off that. The game is a multiplayer game, and the game is designed to be a fun and interesting multiplayer game.

AI methods choose more predictable next-words than humans, statistically

(MIT-IBM Watson AI lab, HarvardNLP 2019)

Image/Video: DARPA MediFor



(MediFor: USC/ISI, Univ. Naples 2019)

Matt Turek

Expected Threats

Targeted Personal Attacks

Peele 2017

AI Multimedia Algorithms

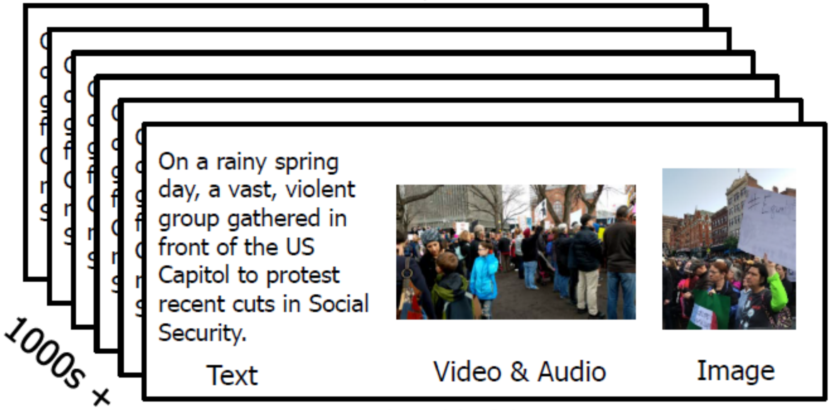
⇩

Highly realistic video

Generated Events at Scale

AI Multimedia Algorithms

⇩



On a rainy spring day, a vast, violent group gathered in front of the US Capitol to protest recent cuts in Social Security.

Believable fake events

Ransomfake concept: Identity Attacks as a service (IAaaS)

Bricman 2019

AI Multimedia Algorithms

⇩

Forged Evidence

⇩

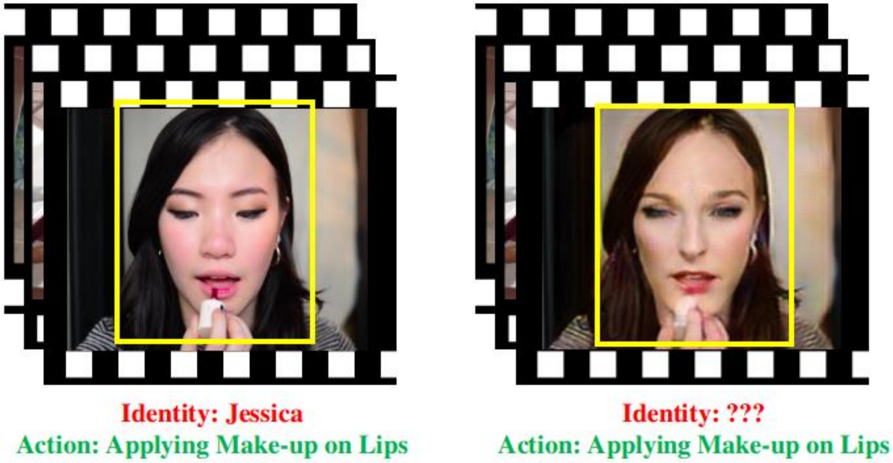
Identity Attacks

Examples of possible fakes:

- Substance abuse
- Foreign contacts
- Compromising events
- Social media postings
- Financial inconsistencies
- Forging identity

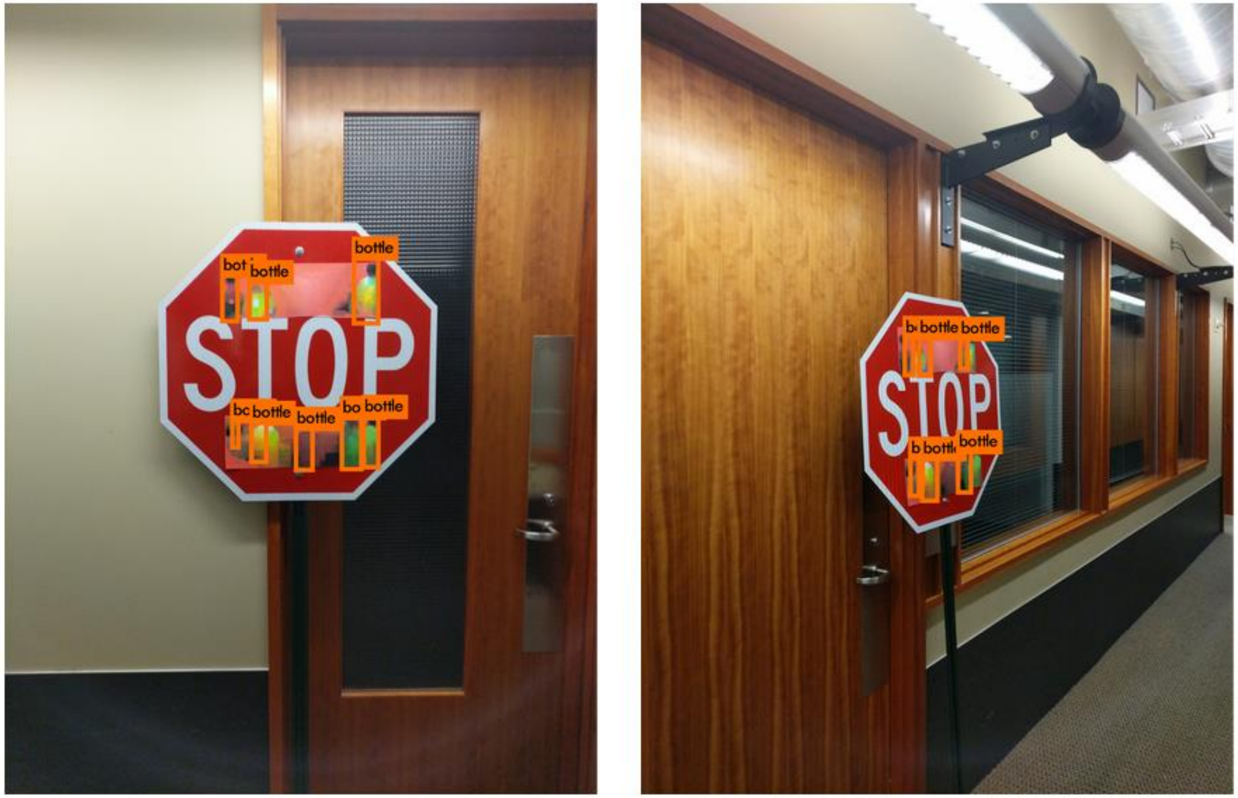
Undermines key individuals and organizations

GANs for Privacy (Action Detection)


Identity: Jessica
Action: Applying Make-up on Lips
Identity: ???
Action: Applying Make-up on Lips

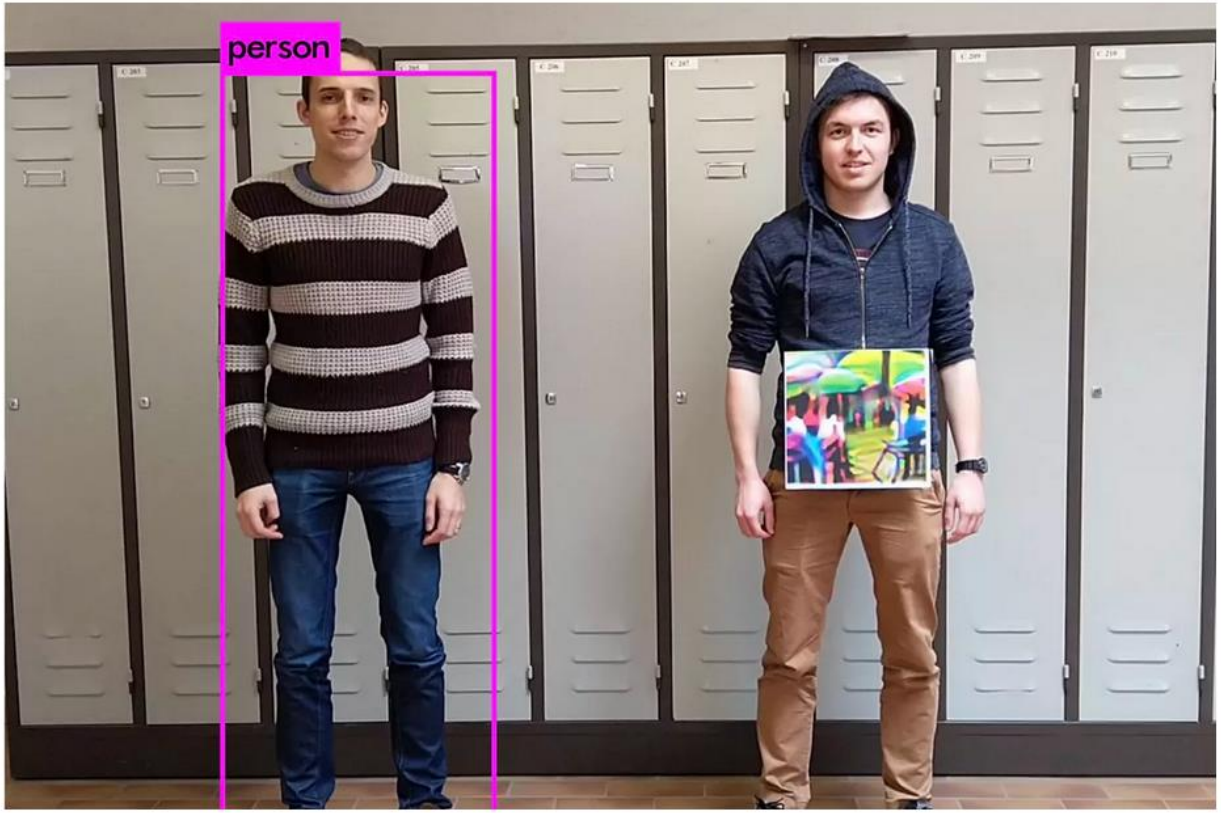
Ren et al., “Learning to Anonymize Faces for Privacy Preserving Action Detection”, ECCV 2018

Adversarial Attacks



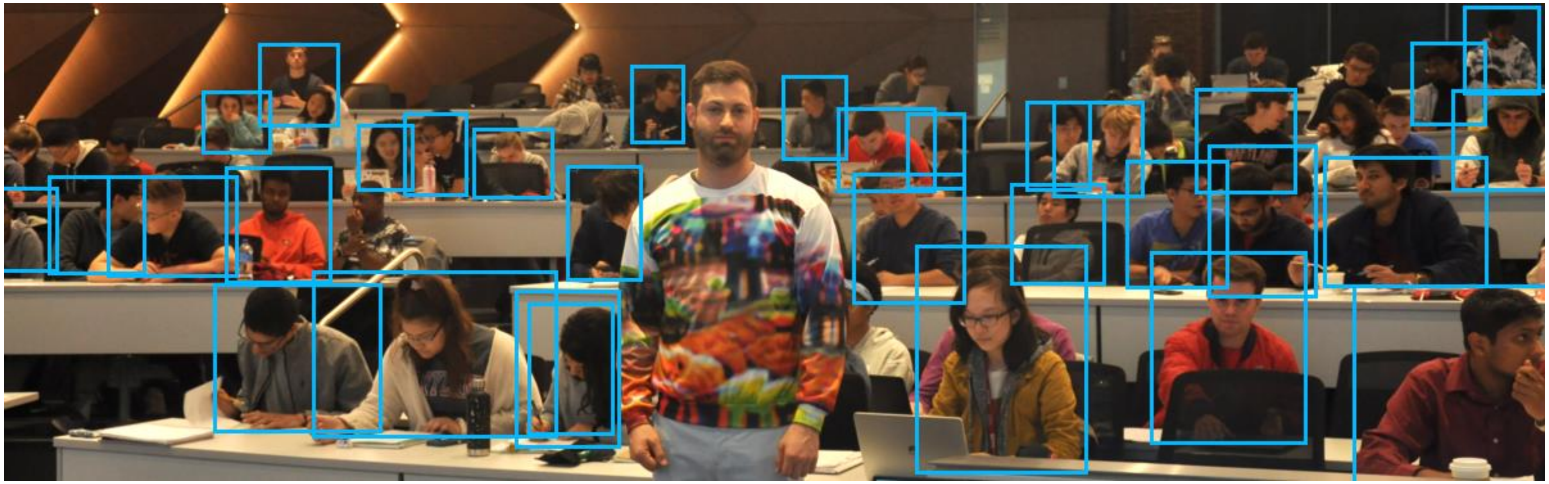
https://bair.berkeley.edu/blog/2017/12/30/yolo-attack/

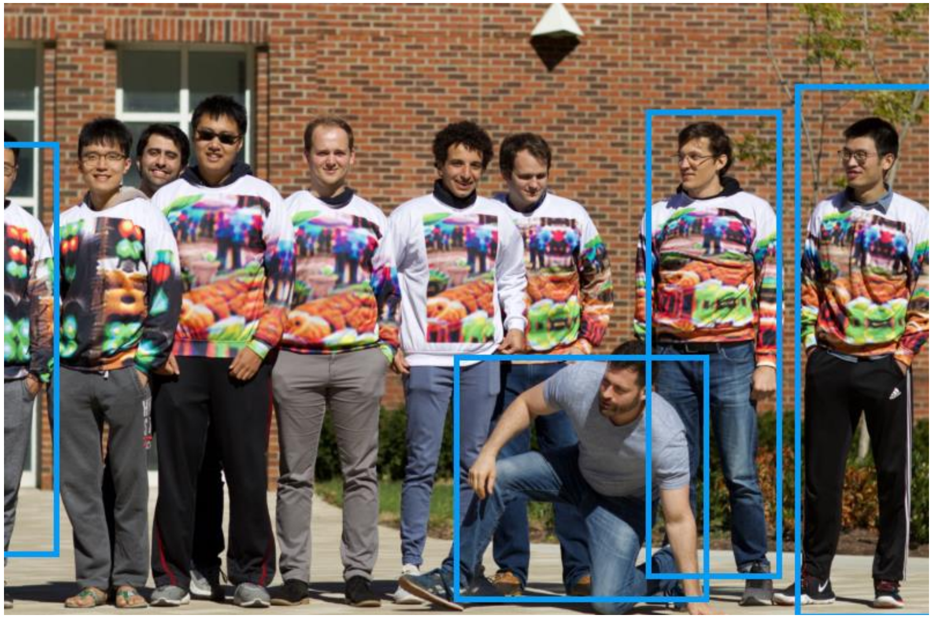
Adversarial Attacks



https://www.theverge.com/2019/4/23/18512472/fool-ai-surveillance-adversarial-example-yolov2-person-detection

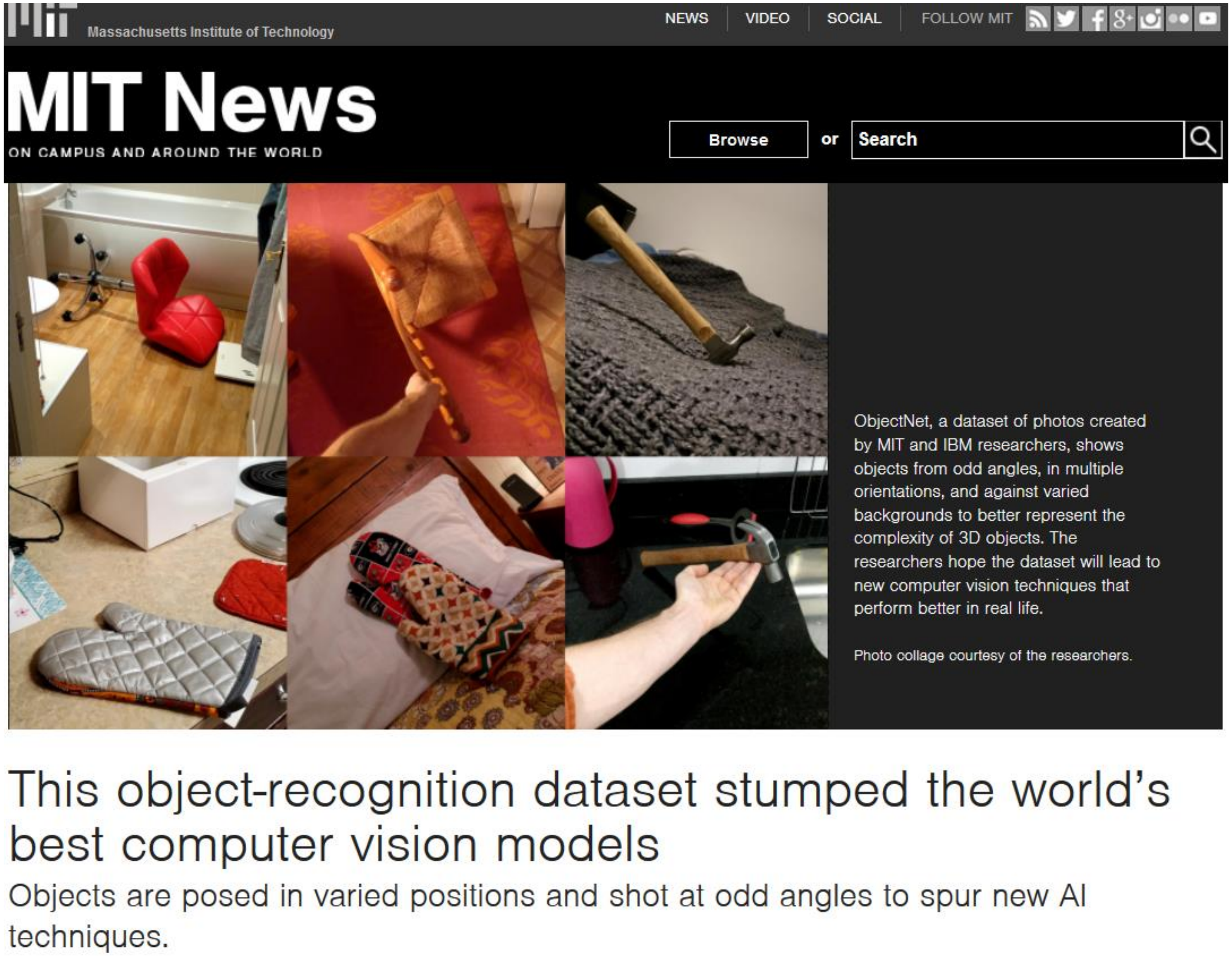
Adversarial Attacks





Tom Goldstein https://www.cs.umd.edu/~tomg/projects/invisible/

Adversarial Attacks


Massachusetts Institute of Technology
NEWS
VIDEO
SOCIAL
FOLLOW MIT
MIT News
ON CAMPUS AND AROUND THE WORLD
Browse
or
Search

ObjectNet, a dataset of photos created by MIT and IBM researchers, shows objects from odd angles, in multiple orientations, and against varied backgrounds to better represent the complexity of 3D objects. The researchers hope the dataset will lead to new computer vision techniques that perform better in real life.

Photo collage courtesy of the researchers.

This object-recognition dataset stumped the world's best computer vision models

Objects are posed in varied positions and shot at odd angles to spur new AI techniques.

http://news.mit.edu/2019/object-recognition-dataset-stumped-worlds-best-computer-vision-models-1210

Conversation AI

Bias in the Vision and Language of Artificial Intelligence

Margaret Mitchell
Senior Research Scientist
Google AI

Andrew Zaldivar

Me

Simone Wu

Parker Barnes

Lucy Vasserman

Ben Hutchinson

Elena Spitzer

Deb Raji

Timnit Gebru

Adrian Benton

Brian Zhang

Dirk Hovy

Josh Lovejoy

Alex Beutel

Blake Lemoine

Hee Jung Ryu

Hartwig Adam

Blaise Agüera y Arcas

What do you see?

- Bananas
- Stickers
- Dole Bananas
- Bananas at a store
- Bananas on shelves
- Bunches of bananas
- Bananas with stickers on them
- Bunches of bananas with stickers on them on shelves in a store

...We don’t tend to say

Yellow Bananas

What do you see?

Green Bananas

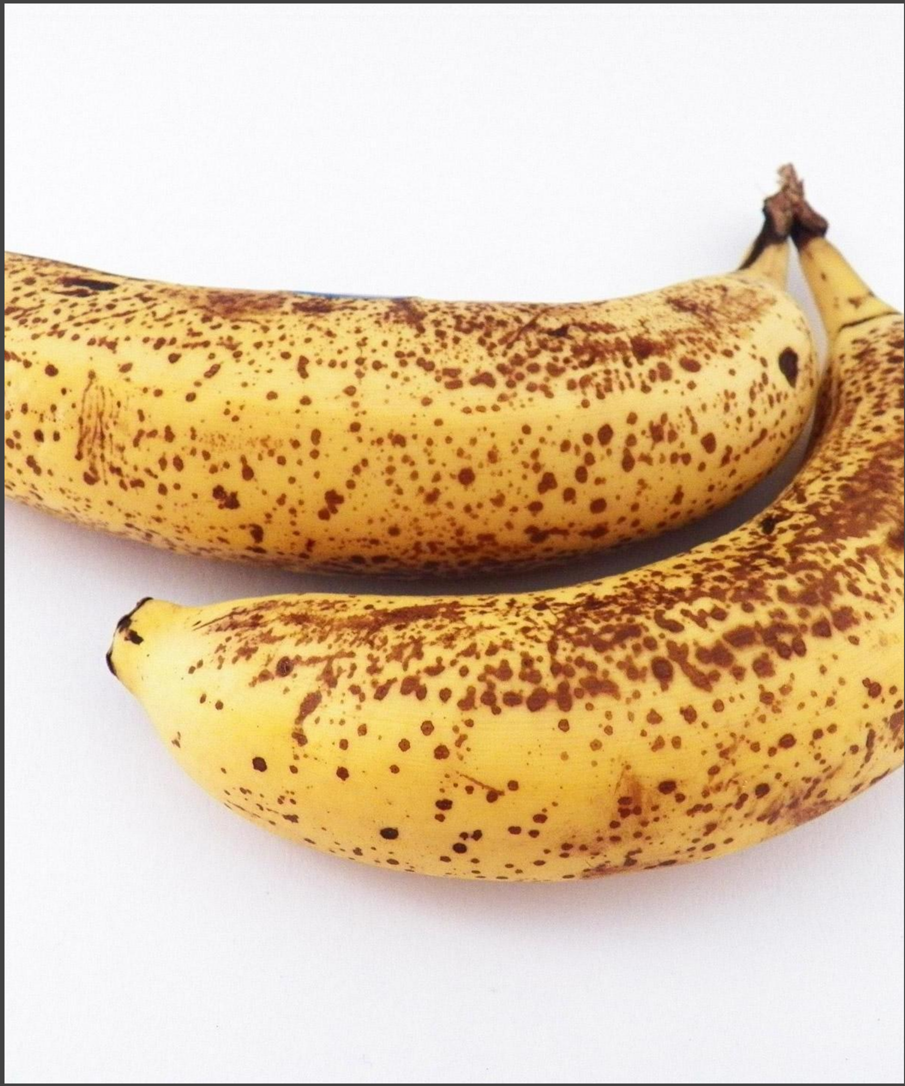
Unripe Bananas

What do you see?

Ripe Bananas

Bananas with spots

Bananas good for banana bread



What do you see?

Yellow Bananas

Yellow is prototypical for bananas

Prototype Theory

One purpose of categorization is to **reduce the infinite differences** among stimuli **to** behaviourally and **cognitively usable proportions**

There may be some central, prototypical notions of items that arise from stored typical properties for an object category (Rosch, 1975)

May also store exemplars (Wu & Barsalou, 2009)

Fruit

Bananas
“Basic Level”

Unripe Bananas,
Cavendish Bananas

A man and his son are in a terrible accident and are rushed to the hospital in critical care.

The doctor looks at the boy and exclaims "I can't operate on this boy, he's my son!"

How could this be?

A man and his son are in a terrible accident and are rushed to the hospital in critical care.

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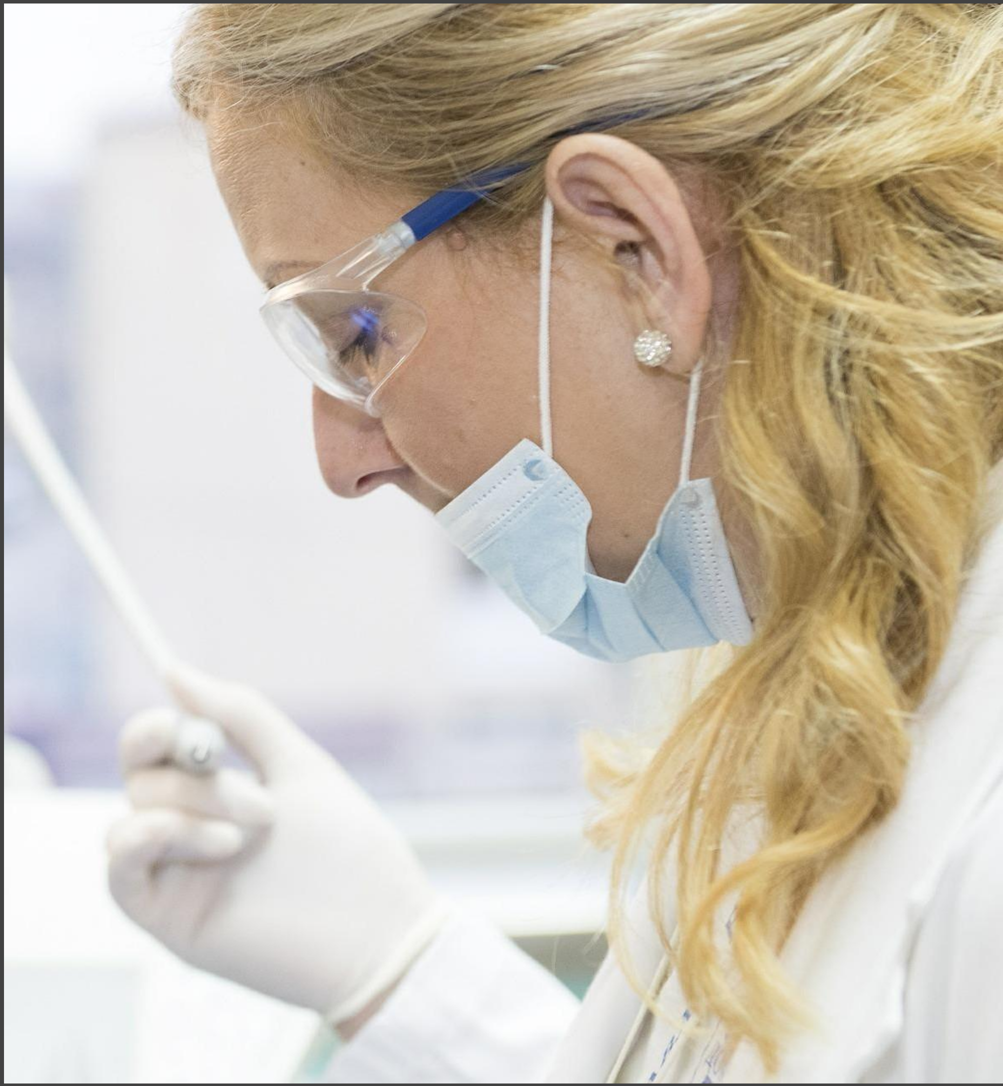
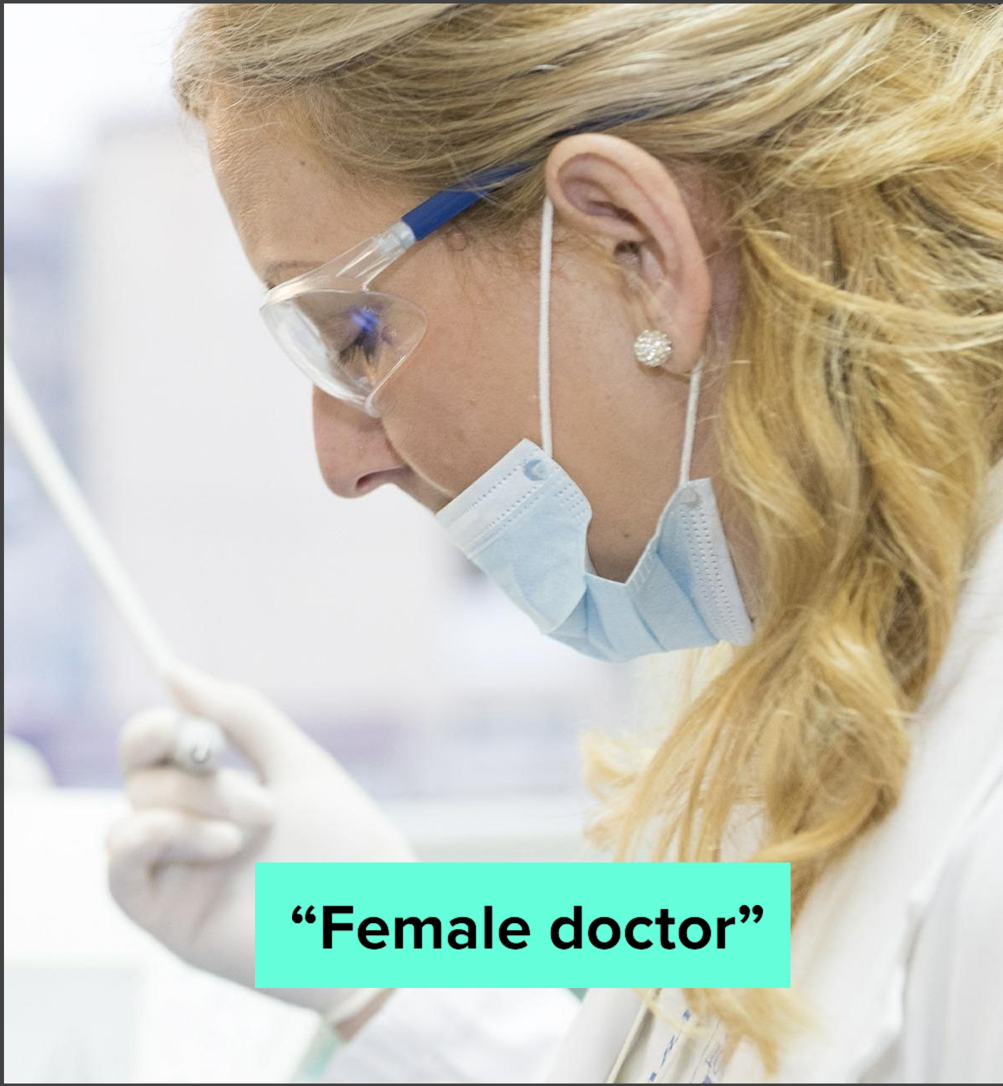
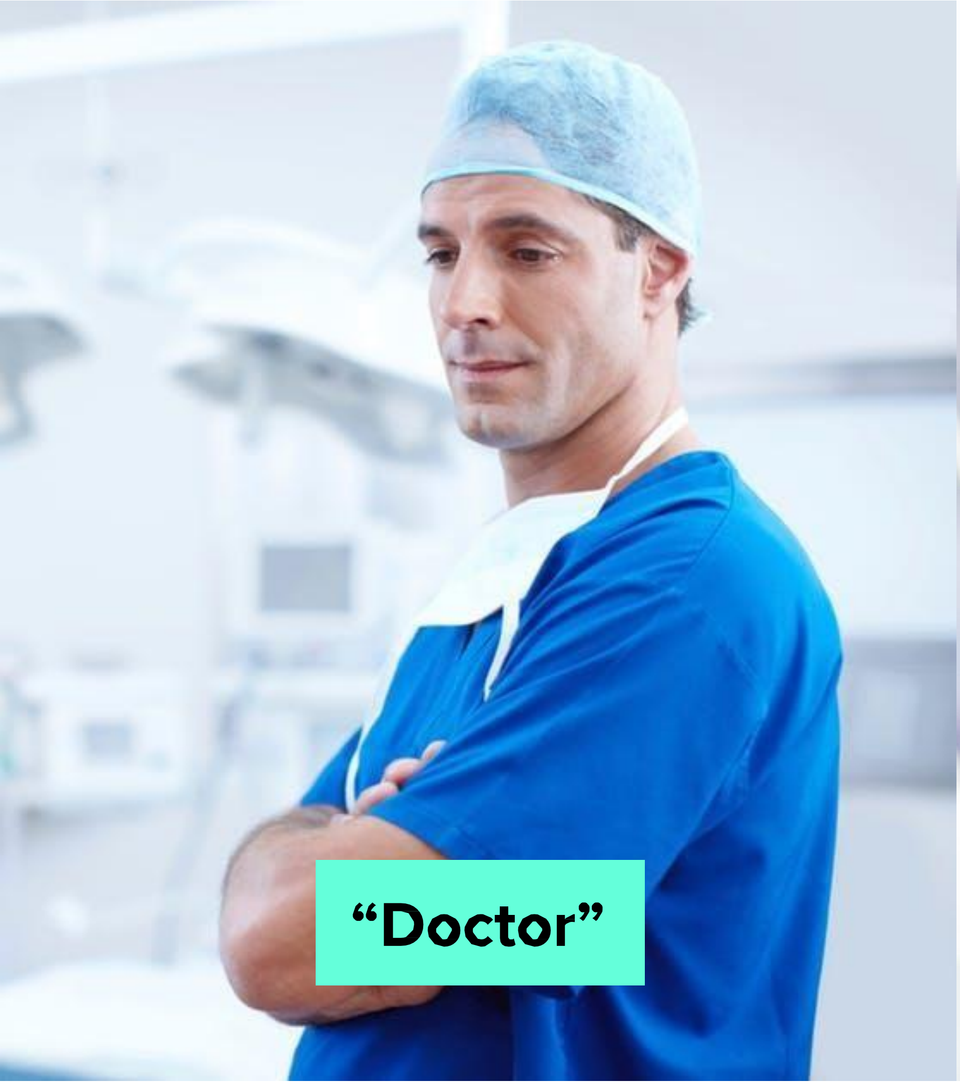


A man and his son are in a terrible accident and are rushed to the hospital in critical care.

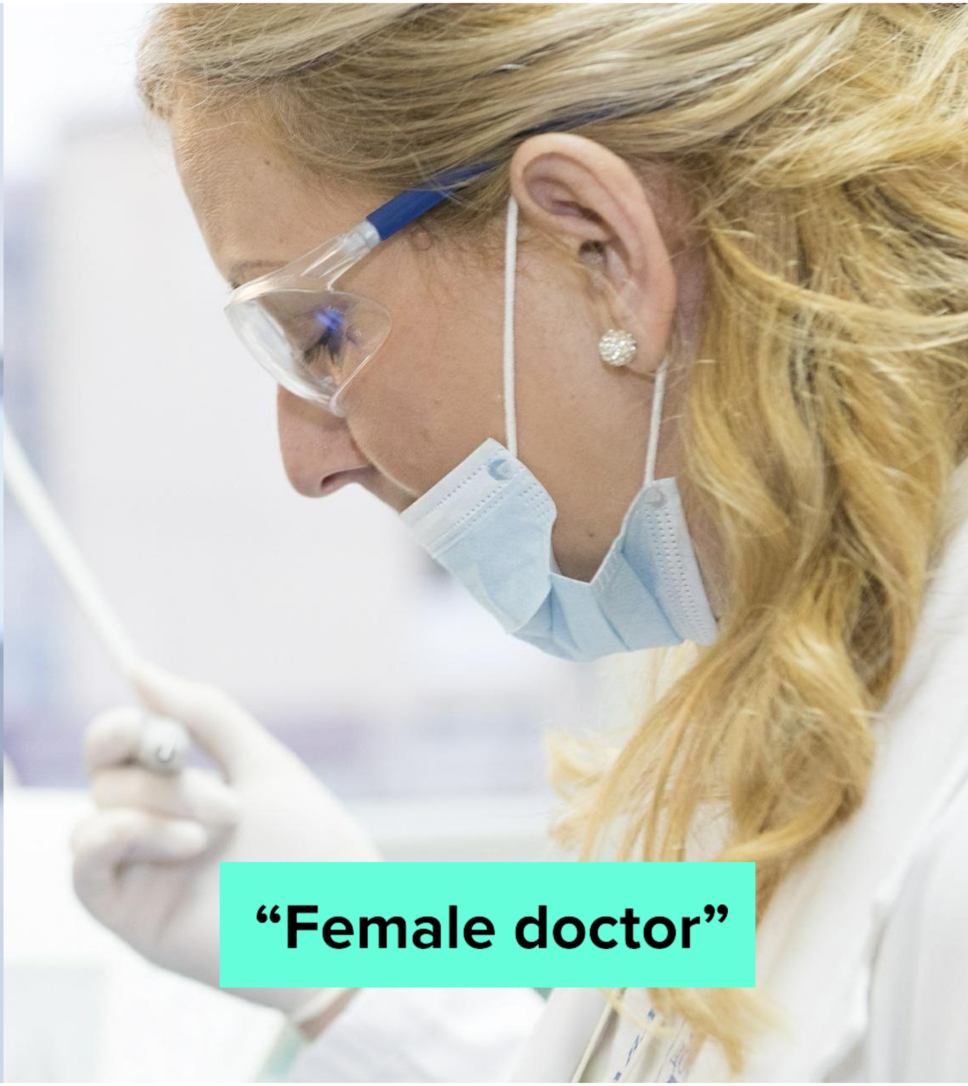
The doctor looks at the boy and exclaims "I can't operate on this boy, he's my son!"

How could this be?



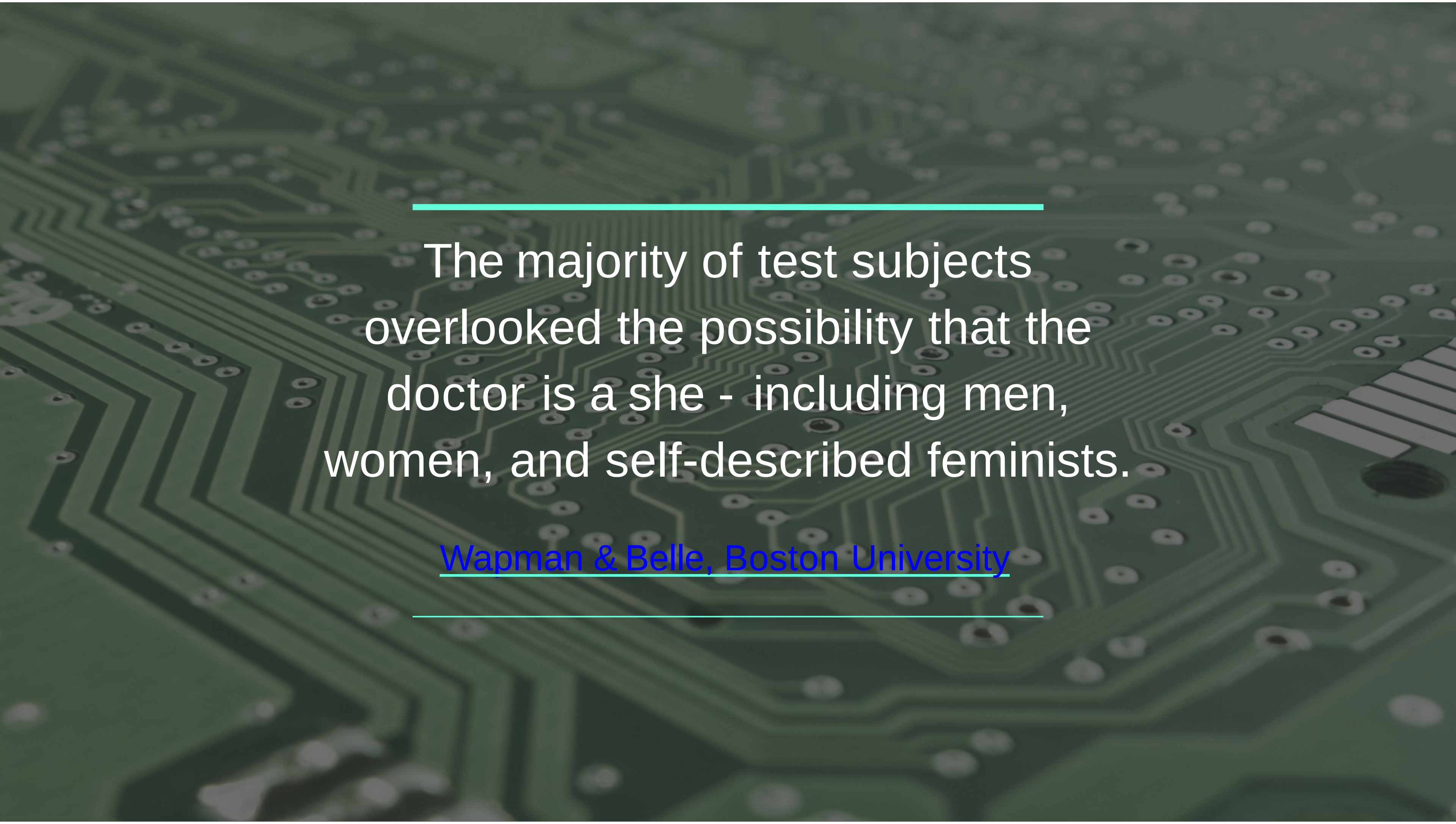


“Doctor”



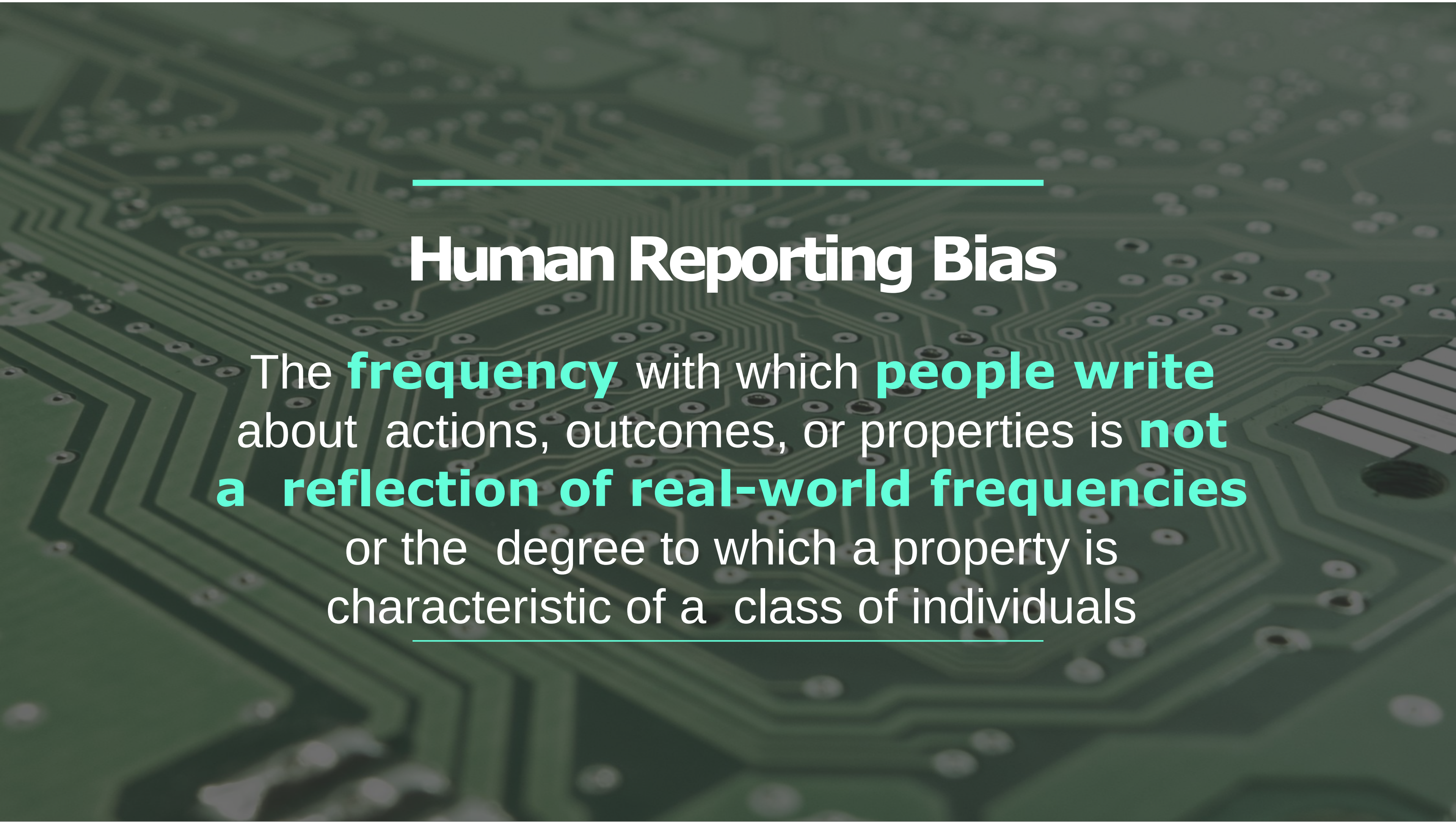
“Female doctor”

Margaret Mitchell



> The majority of test subjects overlooked the possibility that the doctor is a she - including men, women, and self-described feminists.

Wapman & Belle, Boston University

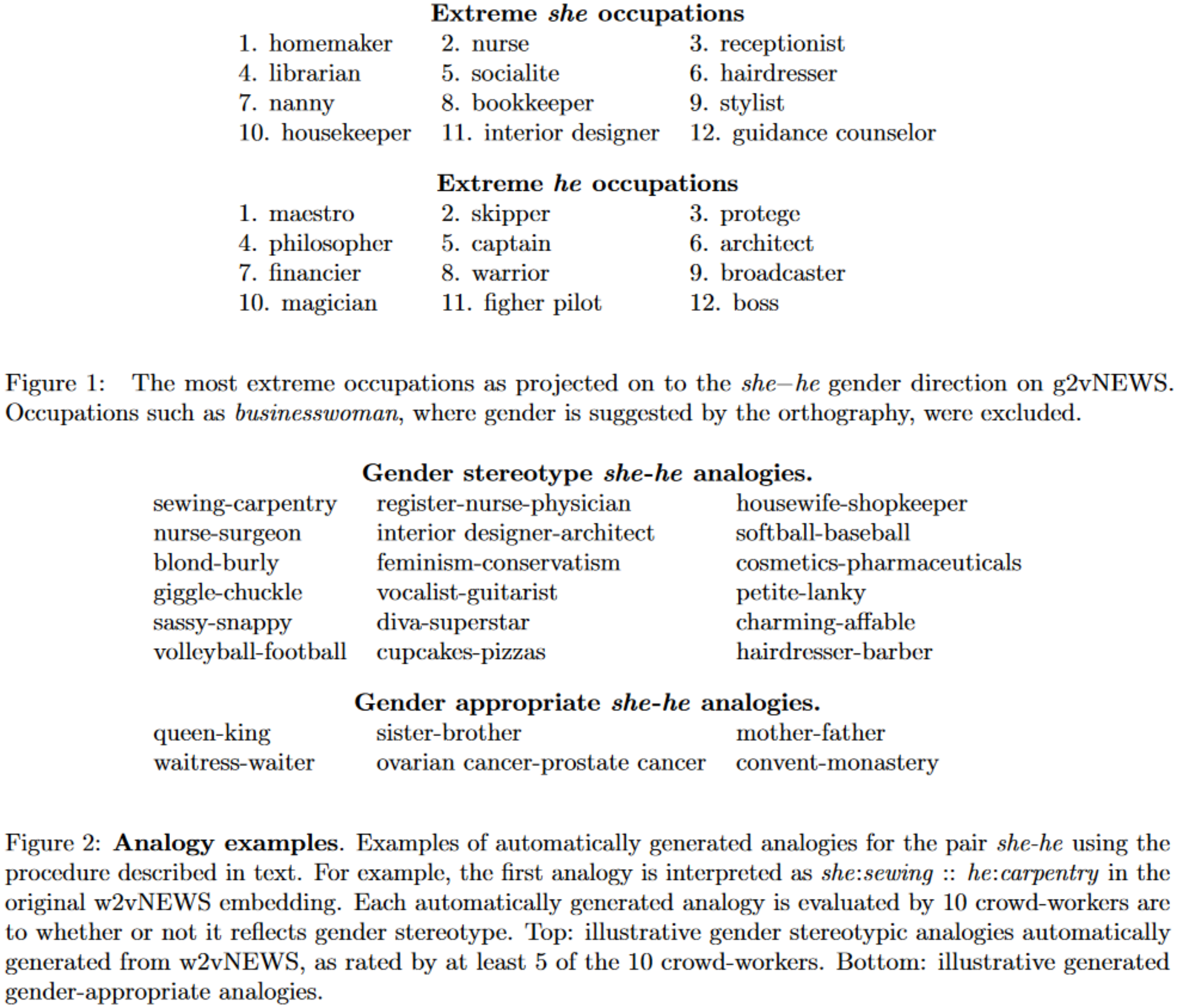


Human Reporting Bias

The **frequency** with which **people write** about actions, outcomes, or properties is **not a reflection of real-world frequencies** or the degree to which a property is characteristic of a class of individuals

Margaret Mitchell

Bias in Language



Extreme *she* occupations

1. homemaker	2. nurse	3. receptionist
4. librarian	5. socialite	6. hairdresser
7. nanny	8. bookkeeper	9. stylist
10. housekeeper	11. interior designer	12. guidance counselor

Extreme *he* occupations

1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. figher pilot	12. boss

Figure 1: The most extreme occupations as projected on to the *she*−*he* gender direction on g2vNEWS. Occupations such as *businesswoman*, where gender is suggested by the orthography, were excluded.

Gender stereotype *she*-*he* analogies.

sewing-carpentry	register-nurse-physician	housewife-shopkeeper
nurse-surgeon	interior designer-architect	softball-baseball
blond-burly	feminism-conservatism	cosmetics-pharmaceuticals
giggle-chuckle	vocalist-guitarist	petite-lanky
sassy-snappy	diva-superstar	charming-affable
volleyball-football	cupcakes-pizzas	hairdresser-barber

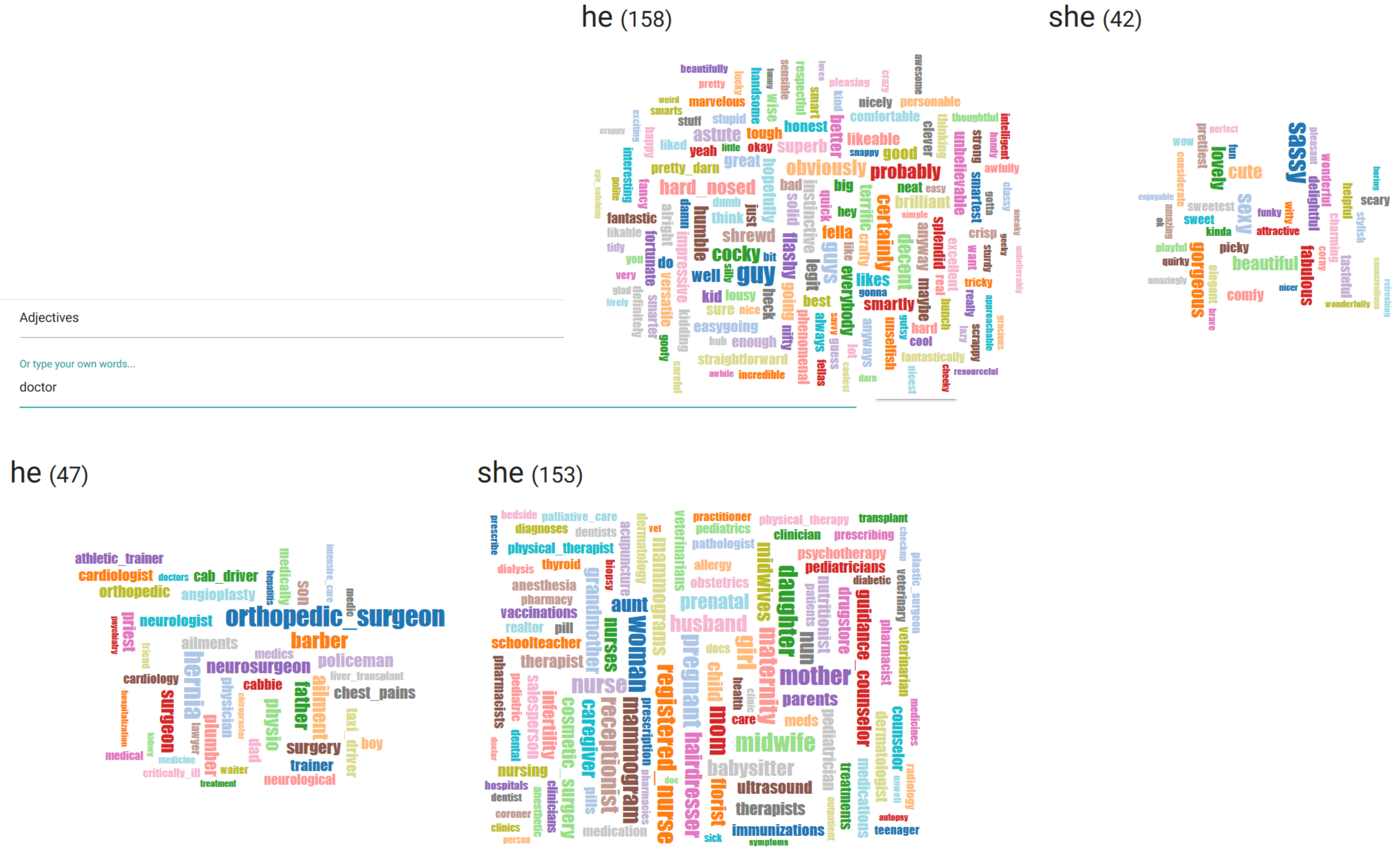
Gender appropriate *she*-*he* analogies.

queen-king	sister-brother	mother-father
waitress-waiter	ovarian cancer-prostate cancer	convent-monastery

Figure 2: **Analogy examples**. Examples of automatically generated analogies for the pair *she*-*he* using the procedure described in text. For example, the first analogy is interpreted as *she*:*sewing* :: *he*:*carpentry* in the original w2vNEWS embedding. Each automatically generated analogy is evaluated by 10 crowd-workers are to whether or not it reflects gender stereotype. Top: illustrative gender stereotypic analogies automatically generated from w2vNEWS, as rated by at least 5 of the 10 crowd-workers. Bottom: illustrative generated gender-appropriate analogies.

Bolukbasi et al., “Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings”, NIPS 2016

Bias in Language



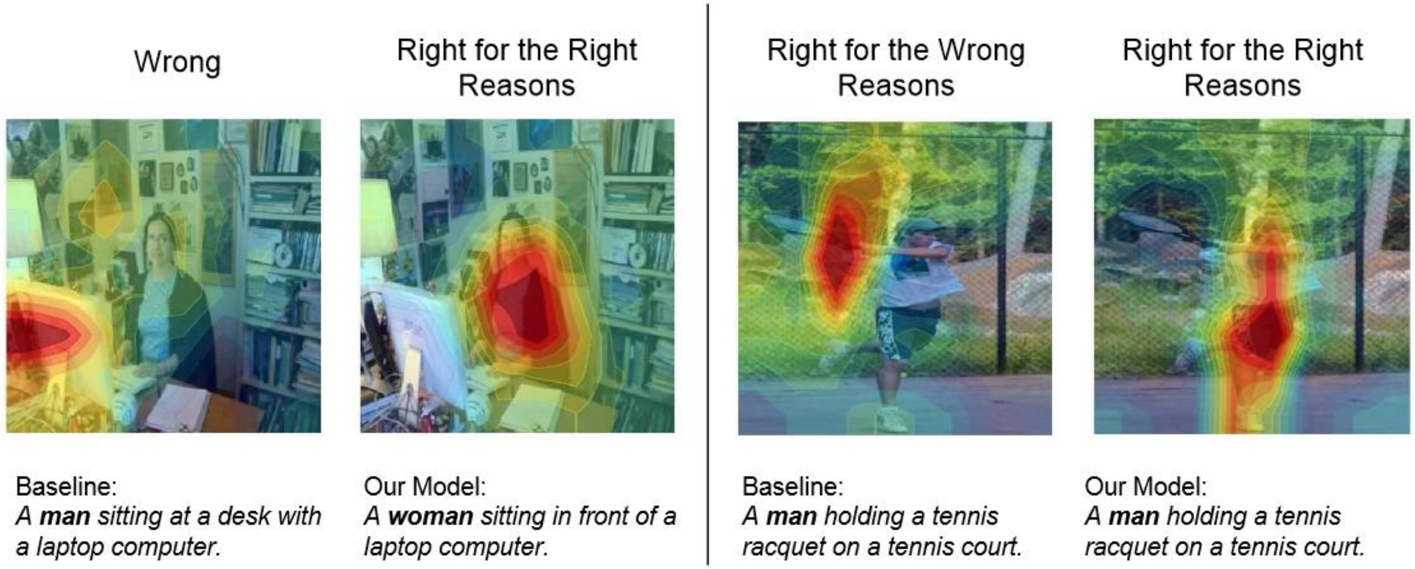
Adjectives

Or type your own words...

doctor

http://wordbias.umiacs.umd.edu/

Bias in Vision



Wrong

Right for the Right Reasons

Right for the Wrong Reasons

Right for the Right Reasons

Baseline:
*A **man** sitting at a desk with a laptop computer.*

Our Model:
*A **woman** sitting in front of a laptop computer.*

Baseline:
*A **man** holding a tennis racquet on a tennis court.*

Our Model:
*A **man** holding a tennis racquet on a tennis court.*

Fig. 1: Examples where our proposed model (Equalizer) corrects bias in image captions. The overlaid heatmap indicates which image regions are most important for predicting the gender word. On the left, the baseline predicts gender incorrectly, presumably because it looks at the laptop (not the person). On the right, the baseline predicts the gender correctly but it does not look at the person when predicting gender and is thus not acceptable. In contrast, our model predicts the correct gender word and correctly considers the person when predicting gender.

Burns et al., “Women also Snowboard: Overcoming Bias in Captioning Models”, ECCV 2018

Bias in Vision

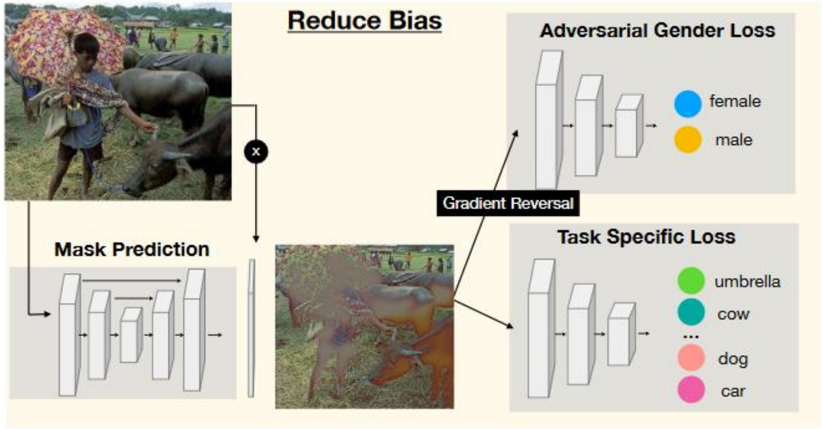


Figure 2. In our bias mitigation approach, we learn a task-specific model with an adversarial loss that removes features corresponding to a protected variable from an intermediate representation in the model – here we illustrate our pipeline to visualize the removal of features in image space through an auto-encoder network.

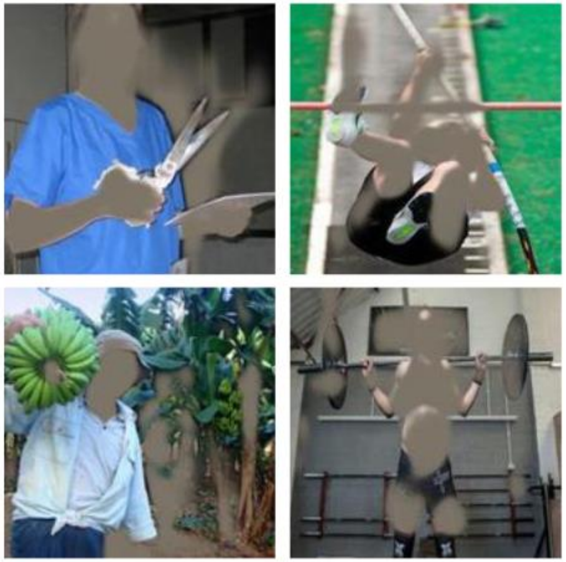
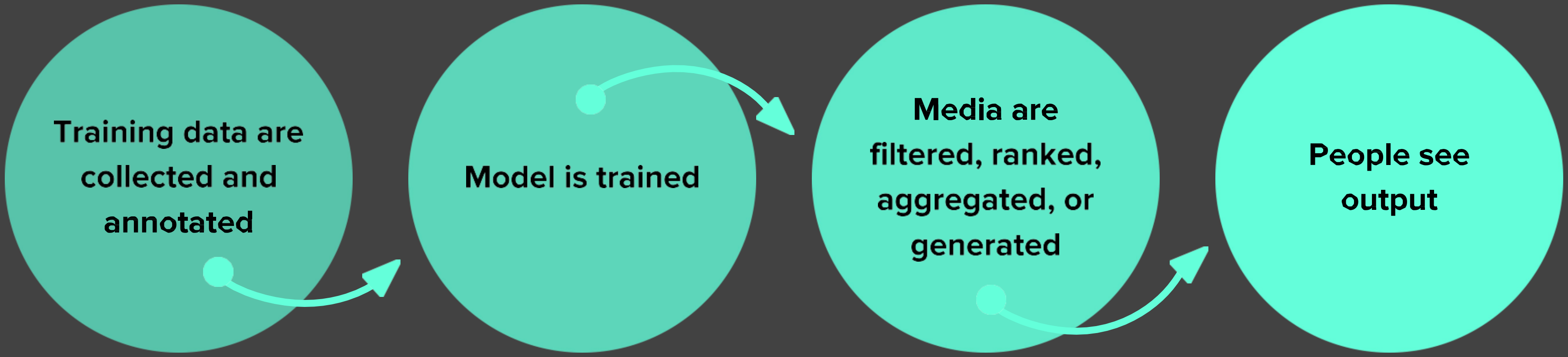


Figure 3. Images after adversarial removal of gender when applied to the image space. The objective was to preserve information about objects and verbs, e.g. scissors, banana (COCO) or vaulting, lifting (imSitu) while removing gender correlated features.

Wang et al., "Balanced Datasets Are Not Enough: Estimating and Mitigating Gender Bias in Deep Image Representations", ICCV 2019



Training data are collected and annotated

Model is trained

Media are filtered, ranked, aggregated, or generated

People see output

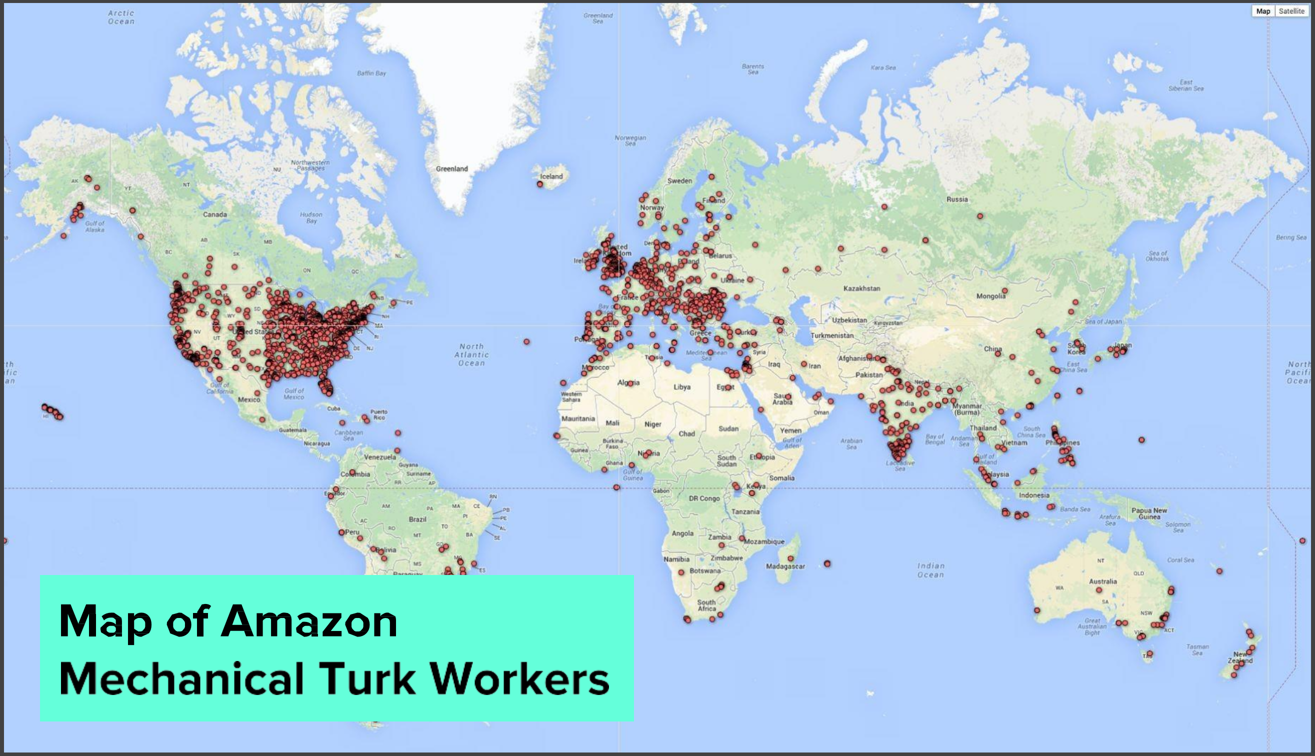
Margaret Mitchell

Biases in Data

Margaret Mitchell

Biases in Data

Selection Bias: Selection does not reflect a random sample



Map of Amazon Mechanical Turk Workers

CREDIT

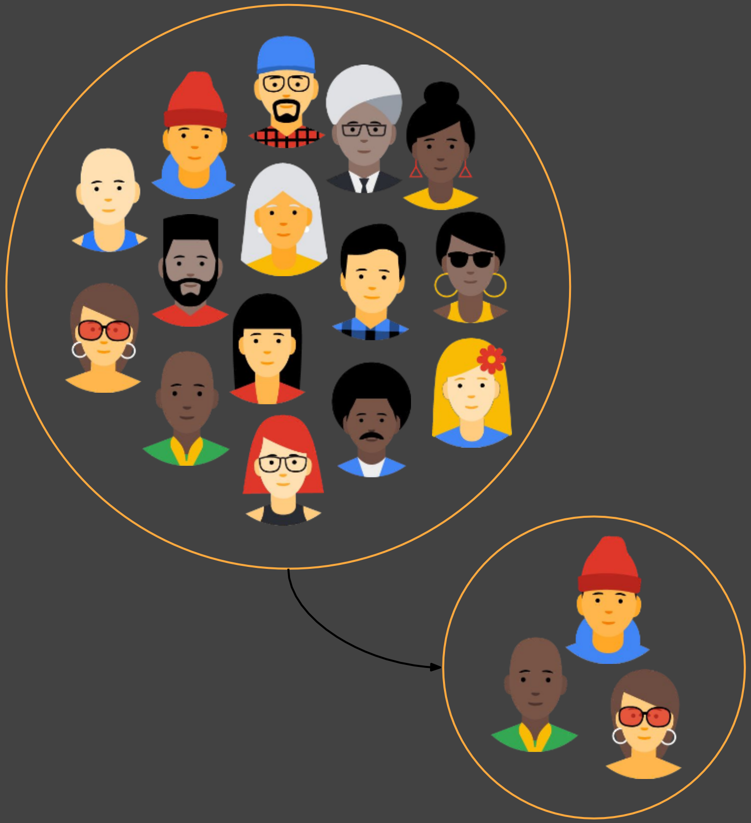
© 2013–2016 Michael Yoshitaka Erlewine and Hadas Kotek

Biases in Data

Out-group homogeneity bias: Tendency to see outgroup members as more alike than ingroup members

Biases in Data → Biased Data Representation

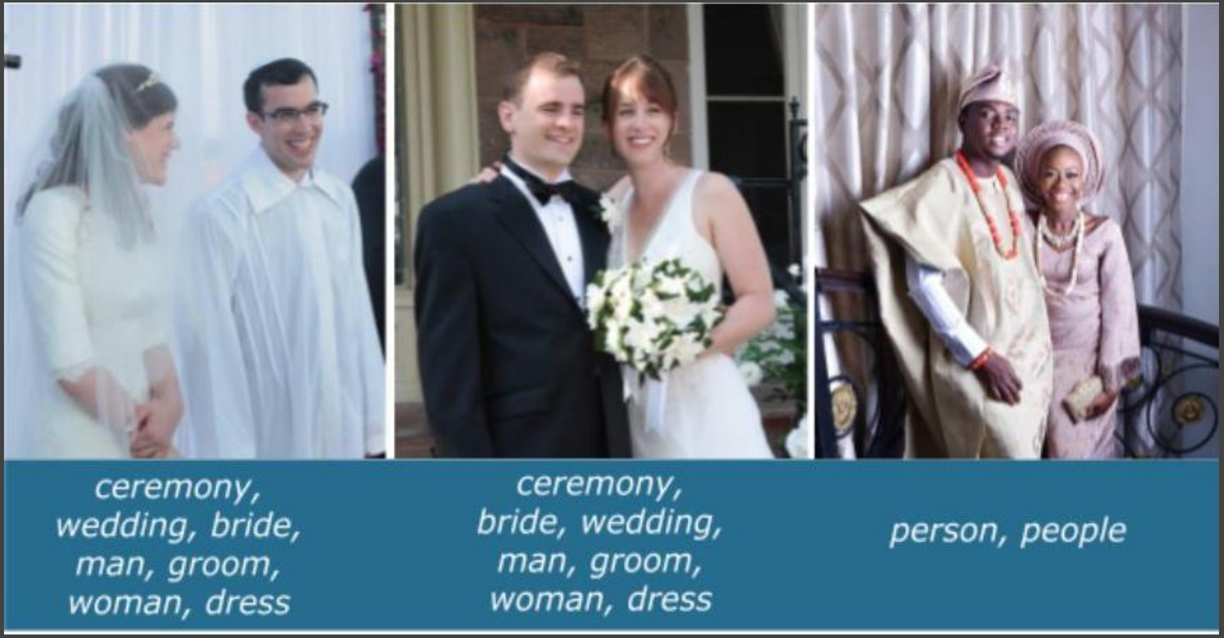
It's possible that you have an appropriate amount of data for every group you can think of but that some groups are represented less positively than others.



Margaret Mitchell

Biases in Data → Biased Labels

Annotations in your dataset will reflect the worldviews of your annotators.


ceremony, wedding, bride, man, groom, woman, dress
ceremony, bride, wedding, man, groom, woman, dress
person, people

https://ai.googleblog.com/2018/09/introducing-inclusive-images-competition.html

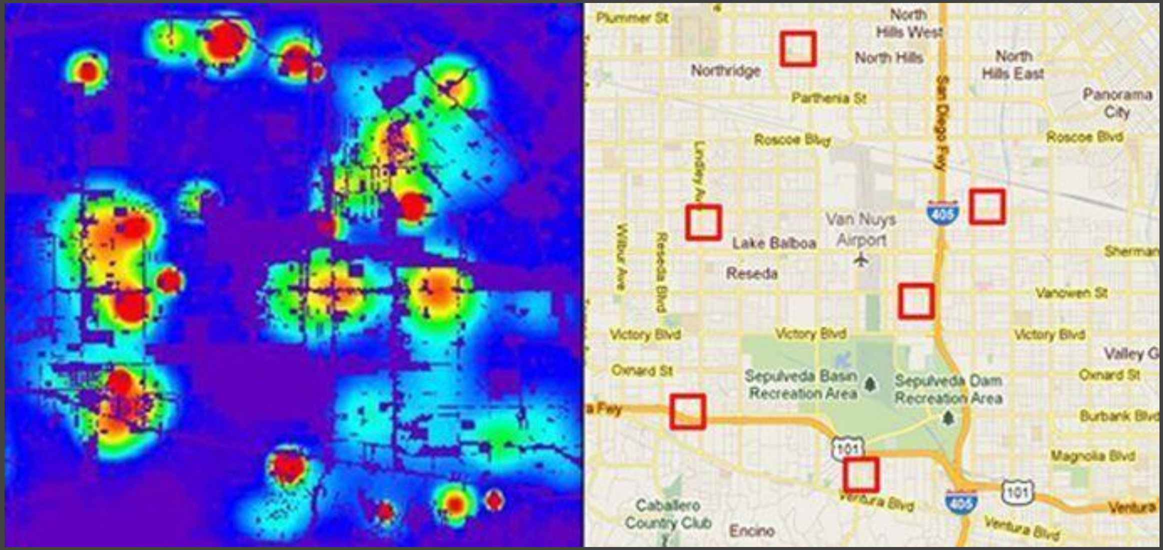
Margaret Mitchell

Predicting Future Criminal Behavior

Margaret Mitchell

Predicting Policing

- Algorithms identify potential crime hot-spots
- Based on where crime is previously reported, not where it is known to have occurred
- Predicts future events from past



CREDIT

Smithsonian. *Artificial Intelligence Is Now Used to Predict Crime. But Is It Biased?* 2018

Predicting Sentencing

- Prater (who is white) rated **low risk** after shoplifting, despite two armed robberies; one attempted armed robbery.
- Borden (who is black) rated **high risk** after she and a friend took (but returned before police arrived) a bike and scooter sitting outside.
- Two years later, Borden has not been charged with any new crimes. Prater serving 8-year prison term for grand theft.

CREDIT

ProPublica. Northpointe: Risk in Criminal Sentencing. 2016.

Predicting Criminality

Israeli startup, Faception

> *"Faception is first-to-technology and first-to-market with proprietary computer vision and machine learning technology for profiling people and* ***revealing their personality based only on their facial image****."*

Offering specialized engines for recognizing "High IQ", "White-Collar Offender", "Pedophile", and "Terrorist" from a face image.

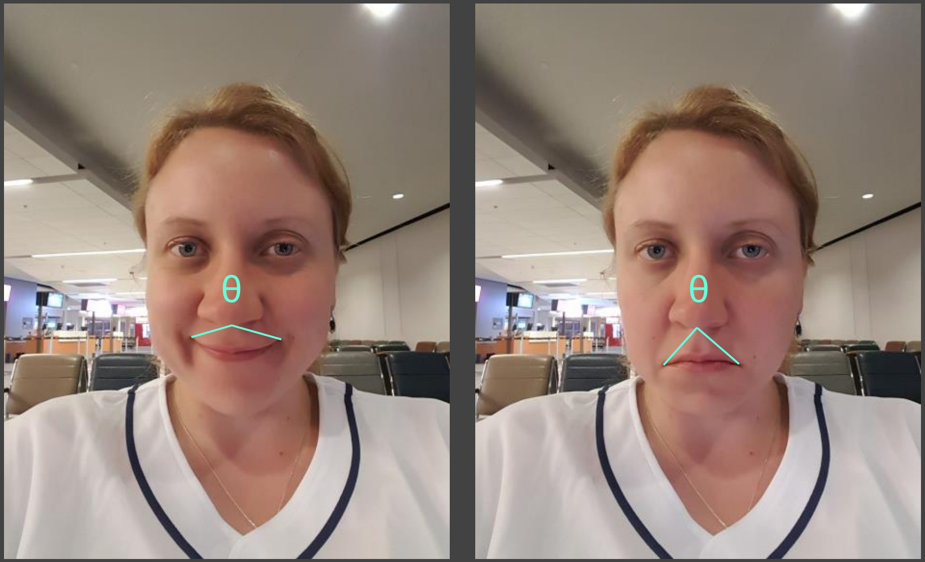
Main clients are in homeland security and public safety.

Predicting Criminality

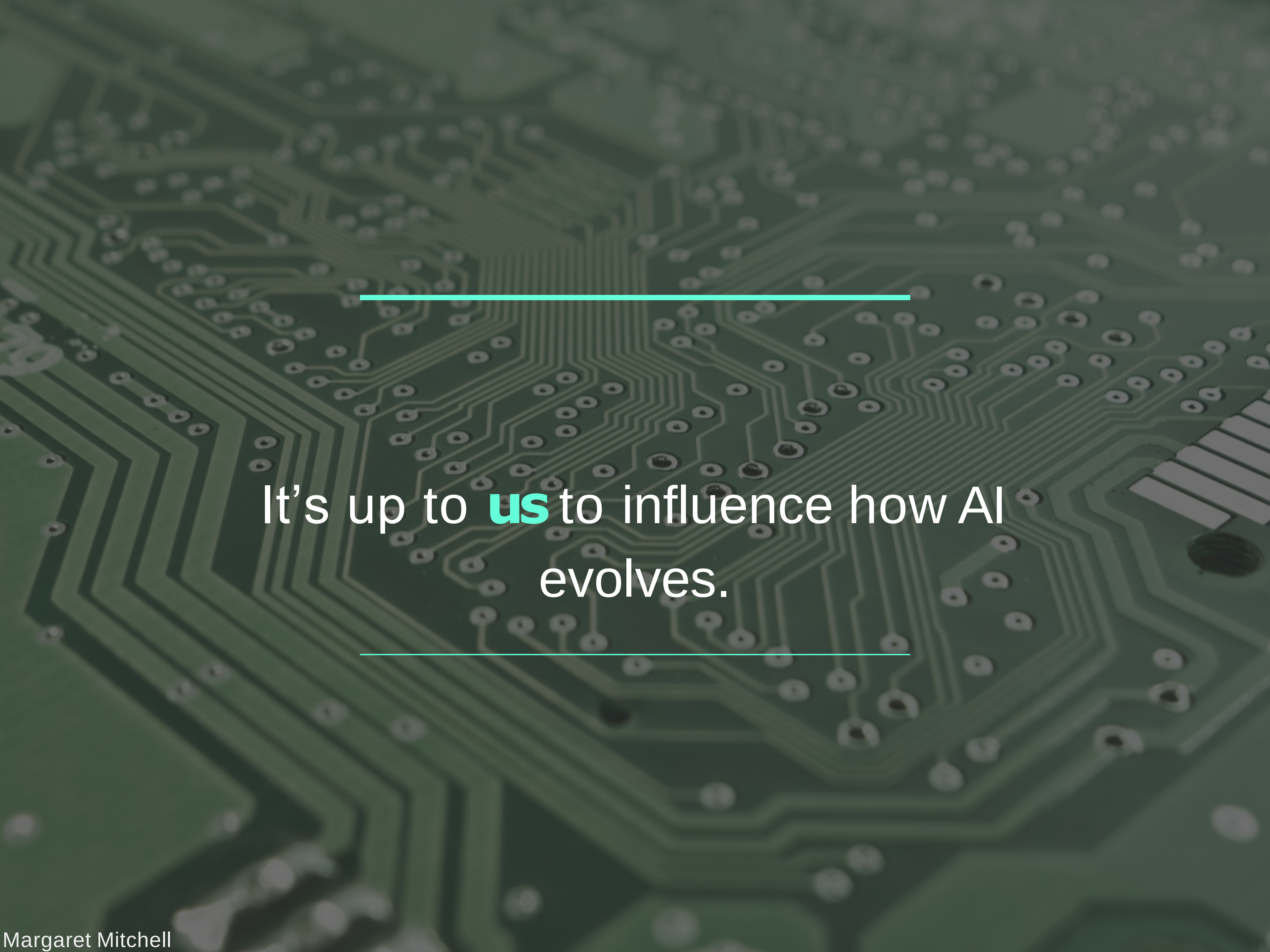
“Automated Inference on Criminality using Face Images” Wu and Zhang, 2016. arXiv

1,856 closely cropped images of faces; Includes “wanted suspect” ID pictures from specific regions.

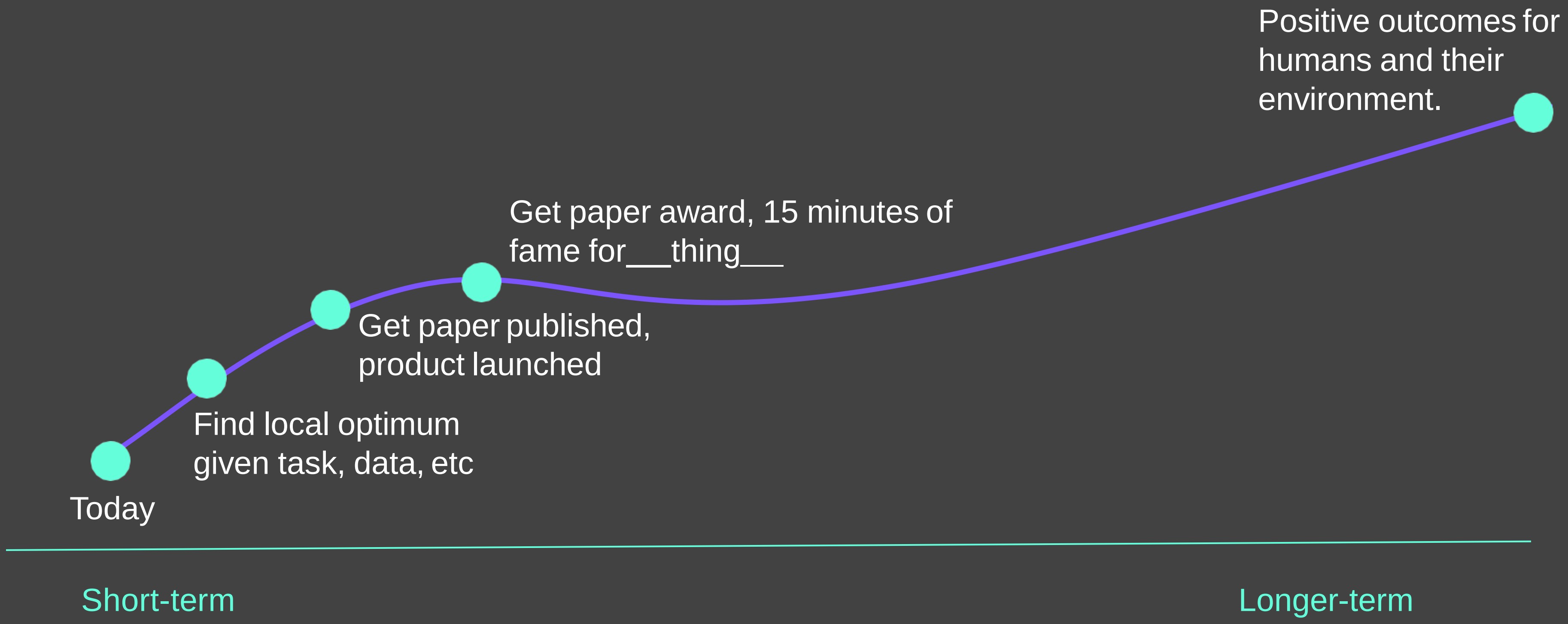
“[…] angle θ from nose tip to two mouth corners is on average 19.6% smaller for criminals than for non-criminals …”



See our longer piece on Medium, “Physiognomy’s New Clothes”



It’s up to **us** to influence how AI evolves.



Positive outcomes for humans and their environment.

Get paper award, 15 minutes of fame for___thing___

Get paper published, product launched

Find local optimum given task, data, etc

Today

Short-term

Longer-term

Margaret Mitchell

H A I

augment

human

intellect.

H A I

human

augment

AI must incorporate more of the versatility, nuance, and depth of the human **intellect.**

H

human

A

AI should **augment** human skills, not replace them.

I

AI must incorporate more of the versatility, nuance, and depth of the human **intellect.**

H

The development of AI should be guided by a concern for its impact on **human** society.

A

AI should **augment** human skills, not replace them.

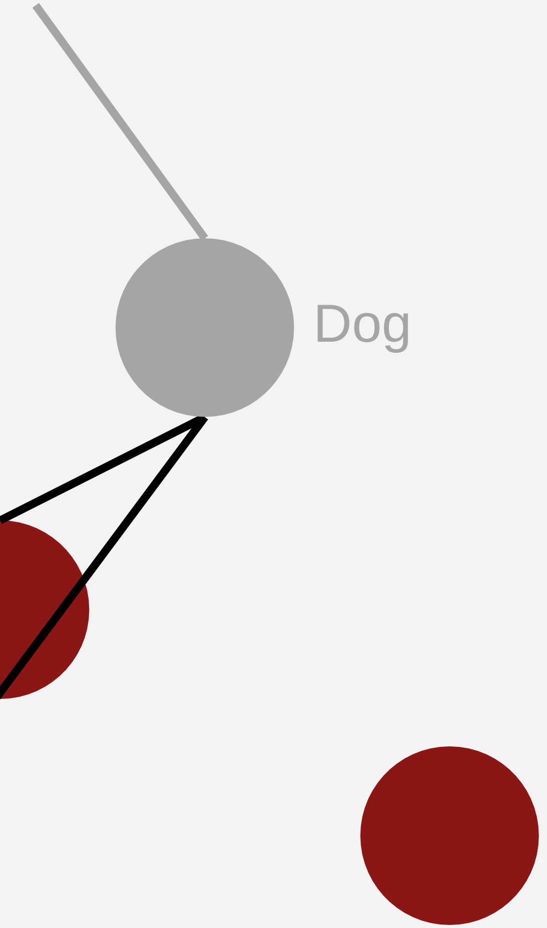
I

AI must incorporate more of the versatility, nuance, and depth of the human **intellect.**

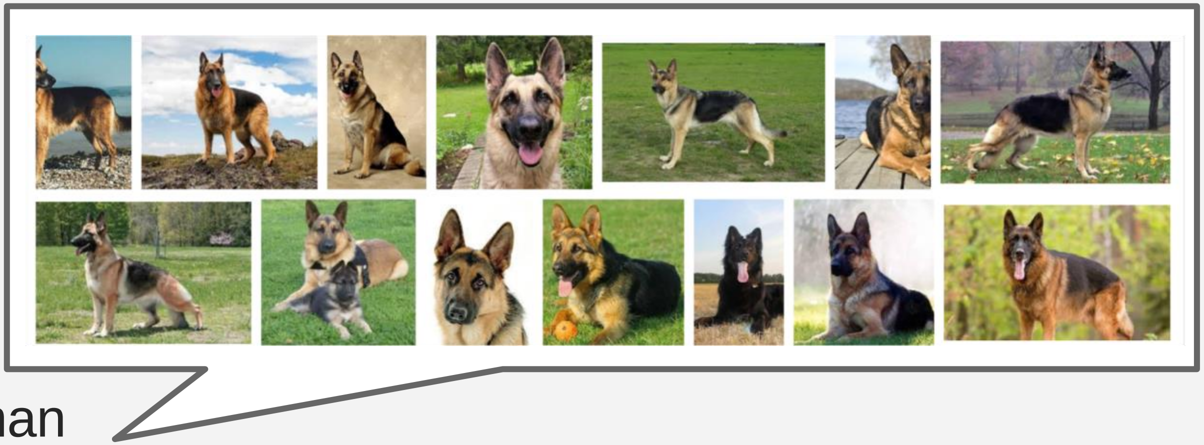
Fei-Fei Li

AI must incorporate more of the versatility, nuance, and depth of the human **intellect.**

IMAGENET

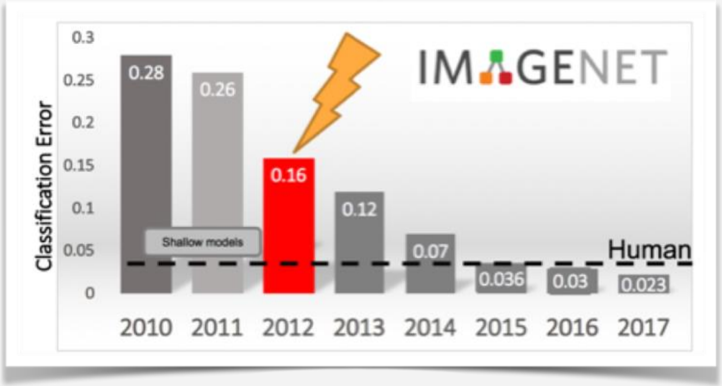


German Shepherd

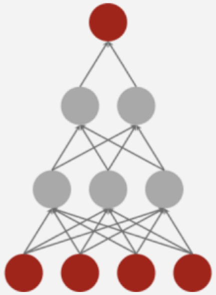


J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li & L. Fei-Fei. *CVPR*, 2009.

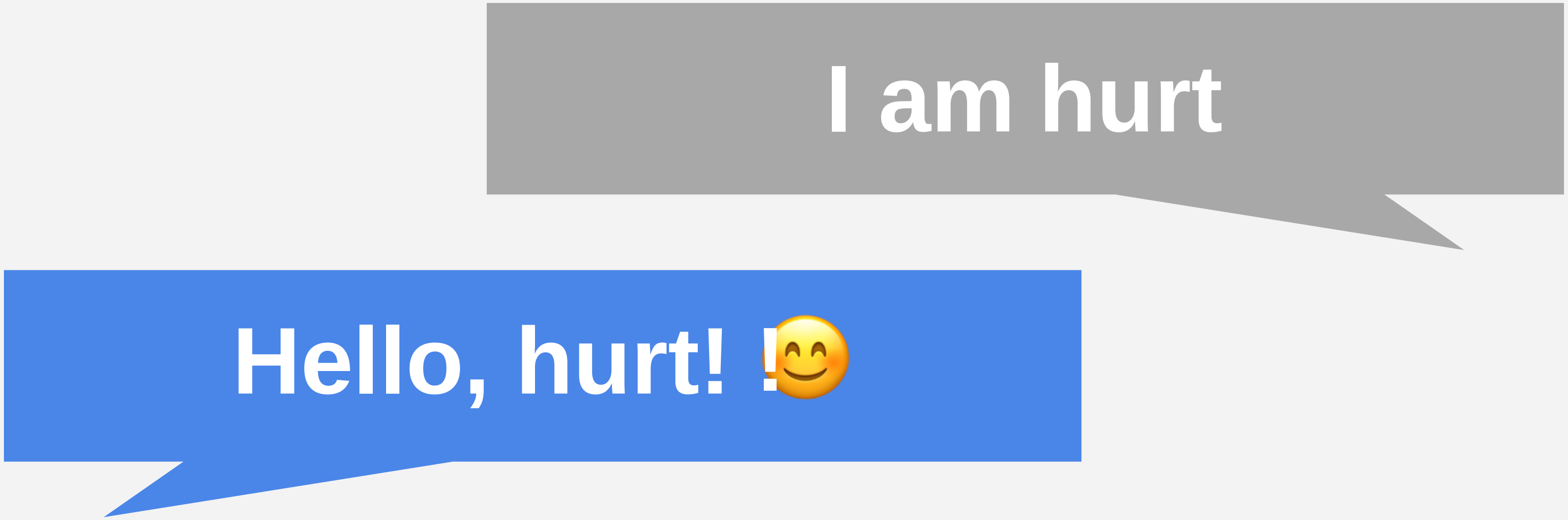
From academic backwater to center of attention in 5 years



What happened?



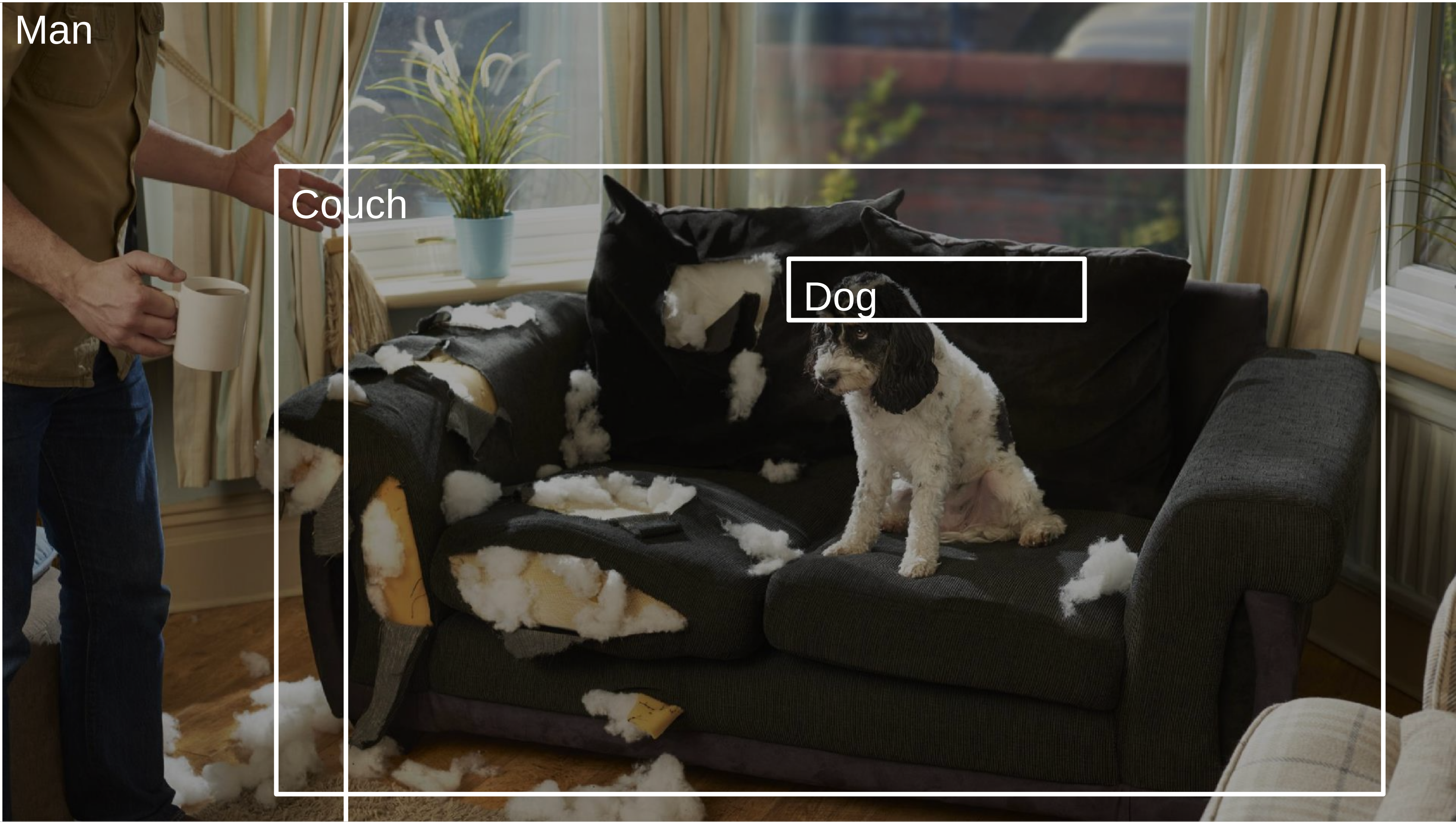
The Deep Learning Revolution



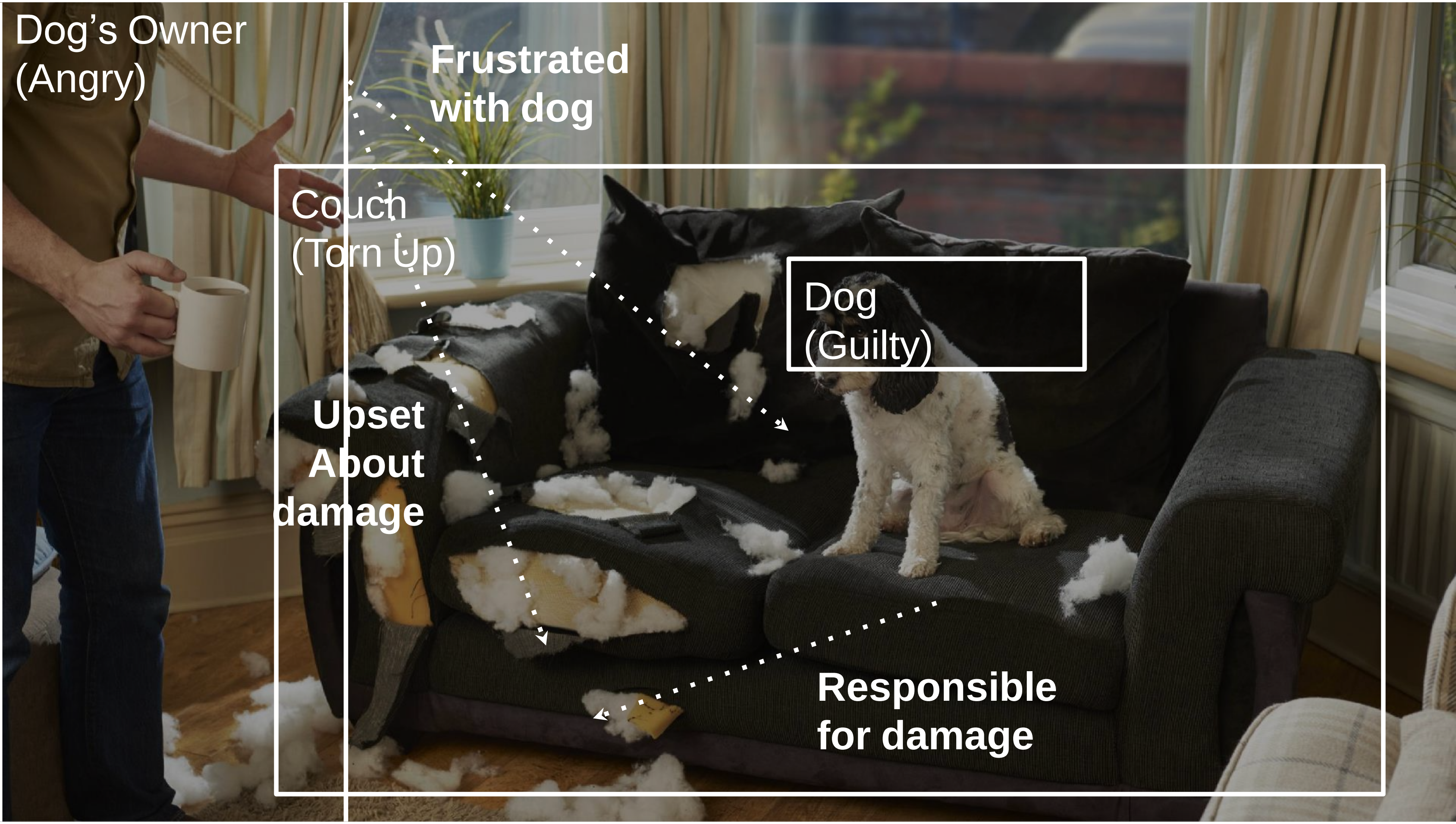
I am hurt

Hello, hurt! !😊

The limits of chatbot conversation



Fei-Fei Li

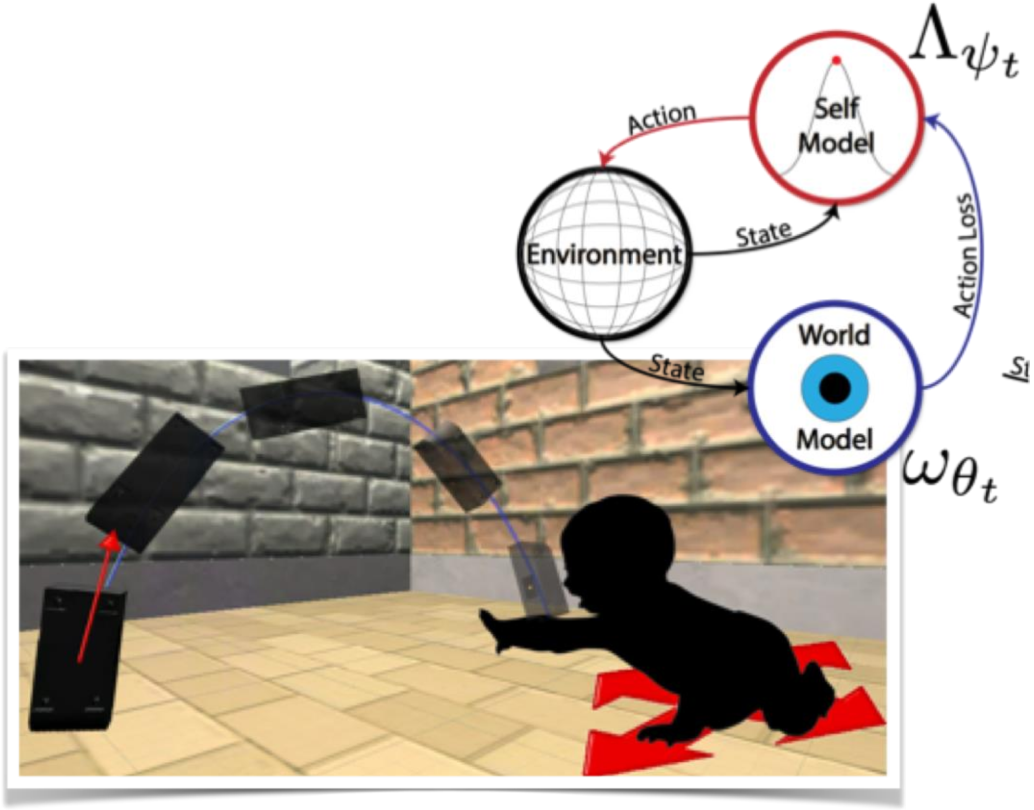

Dog's Owner
(Angry)
Frustrated
with dog
Couch
(Torn Up)
Dog
(Guilty)
Upset
About
damage
Responsible
for damage

Context | Situational Awareness | Prior Knowledge

Fei-Fei Li

Curiosity-based Learning

- A baby's learning is exploratory, curiosity-driven, multi-modal, active and social.
- Can we model this process and apply it in machines?



Mrowca, Haber, Fei-Fei & Yamins, *CogSci,* 2018

“Thinking slow” Commonsense knowledge and reasoning

- Reasoning requires combining previously acquired knowledge to address new tasks
- Can a neural network reason more like a human?

He served chicken.

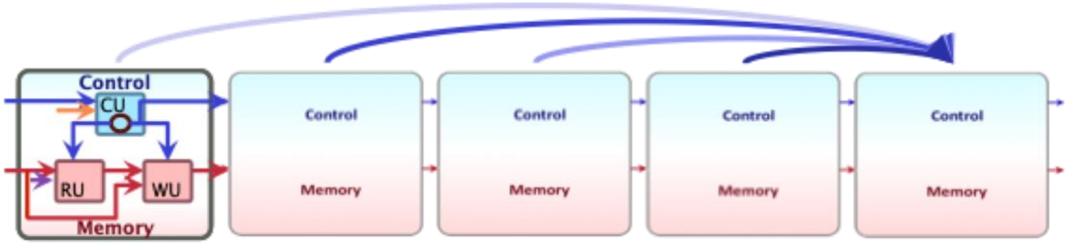
Not like serving a tennis ball

He probably cooked it first!

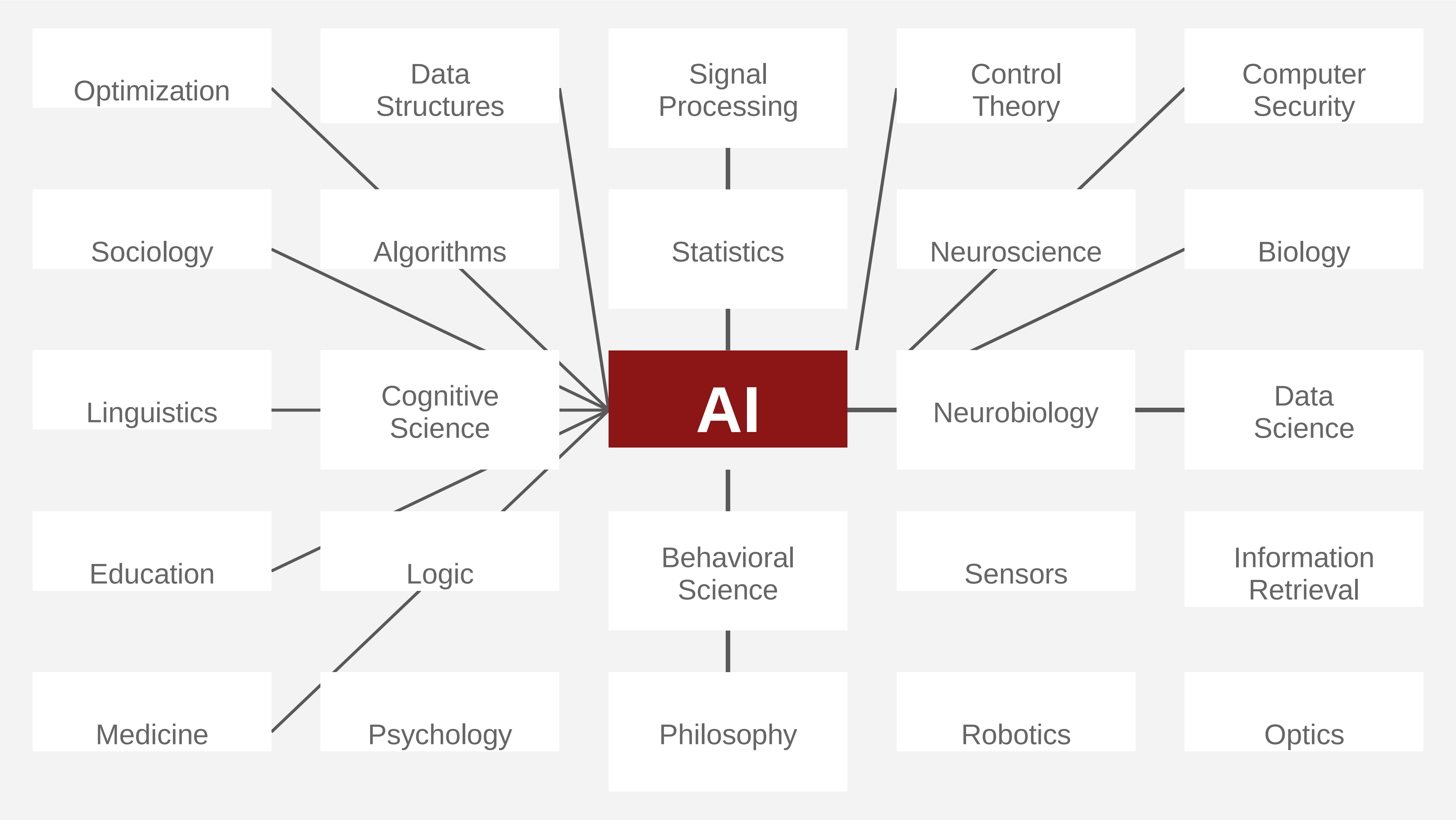
The trophy wouldn’t fit in the suitcase because it was too big.

The trophy?

The suitcase?



Hudson and Manning, 2018



Optimization
Data Structures
Signal Processing
Control Theory
Computer Security
Sociology
Algorithms
Statistics
Neuroscience
Biology
Linguistics
Cognitive Science
AI
Neurobiology
Data Science
Education
Logic
Behavioral Science
Sensors
Information Retrieval
Medicine
Psychology
Philosophy
Robotics
Optics

Fei-Fei Li

AI should **augment** human skills, not replace them.

Fei-Fei Li

~50%

current work activities can be theoretically automated now

100%

current work activities can be potentially **enhanced** by intelligent technology

Enhancing human care with intelligent systems

Hospital-Acquired Infections

99,000 Deaths

Annually

Unmonitored Elderly Fall Injuries

$36.4 Billion

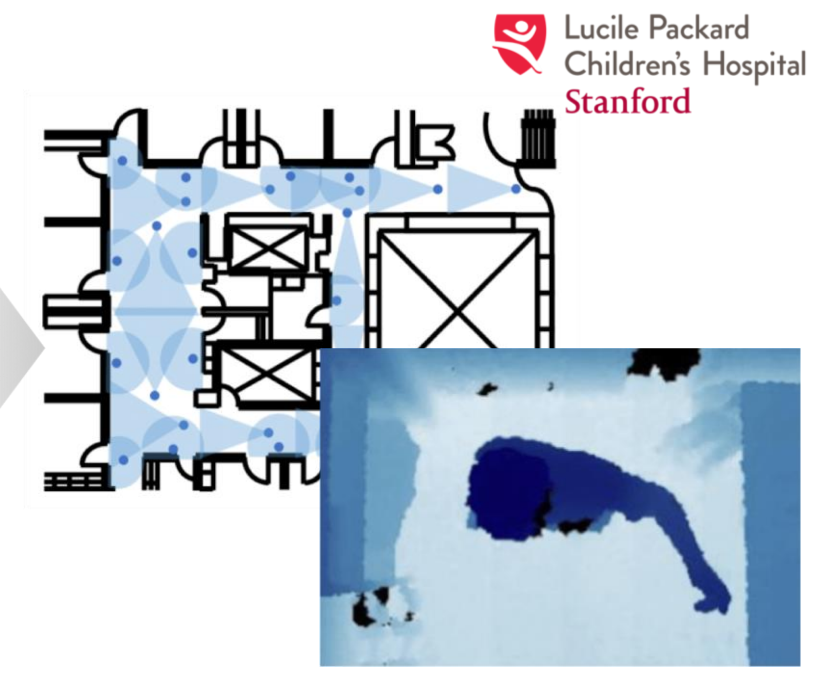
Annually

A. Houser, W. Fox-Grage & K. Ujvari, *AARP Public Policy Institute*, 2012)

Airtek Indoor Air Solutions.
2014. Calfee.

Annual Review of
Medicine 2012

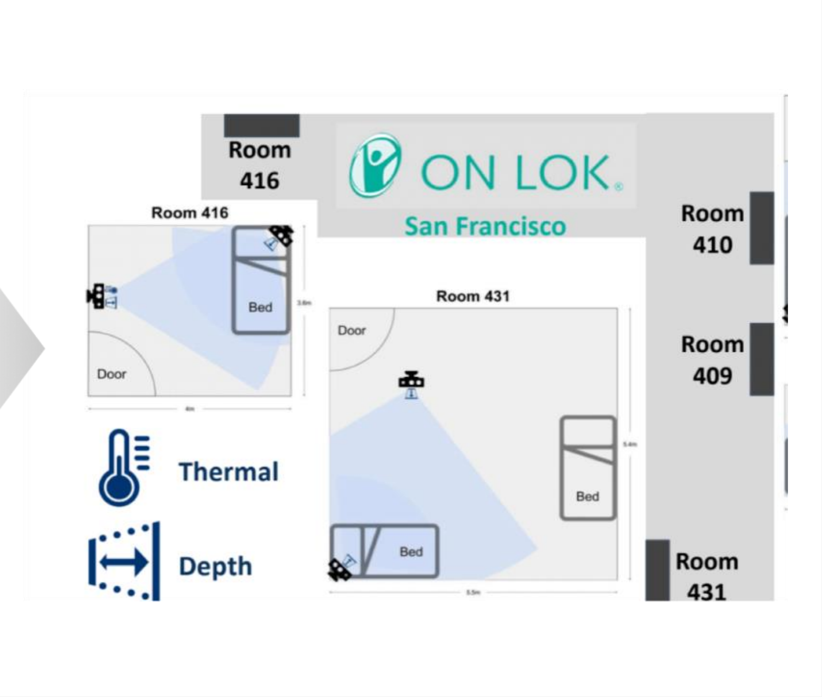
From: Inconsistent hand hygiene



To: Intelligent monitors placed throughout hospitals

A. Haque, A. Singh, A. Alahi, S. Yeung, M. Guo, A. Luo, J. Jopling, L. Downing, W. Beninati, T, Platchek, A. Milstein & L. Fei-Fei, *Under review*
A. Haque, E. Peng, A. Luo, A. Alahi,S. Yeung & L. Fei-Fei, *ECCV*, 2016

From: Ineffective wearables, lack of human caretakers



To: Intelligent monitors placed throughout senior living homes

A. Luo, T. Hsieh, R. Rege, A. Mehra,G. Pusiol, L. Downing, A. Milstein & L. Fei-Fei. *In preparation.*

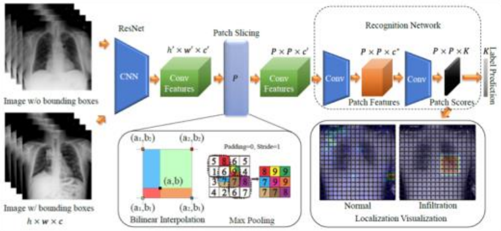
Giving human specialists more time

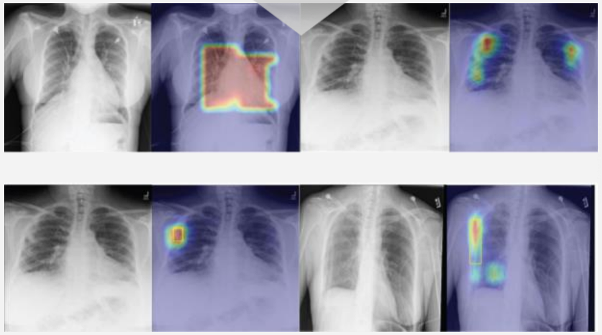
Lowers costs

Improves safety and outcomes

Reduces burden on human caregivers

An algorithm for automating simple radiology analysis





More time for human specialists to do what they do best

Z. Li, C. Wang, M. Han, Y. Xue, W. Wei, Li-J. Li, L. Fei-Fei, *CVPR*, *2018*