William Blake, Jacob's Ladder (1805)

Deep learning trends

(a non-comprehensive, non-objective view)

Outline

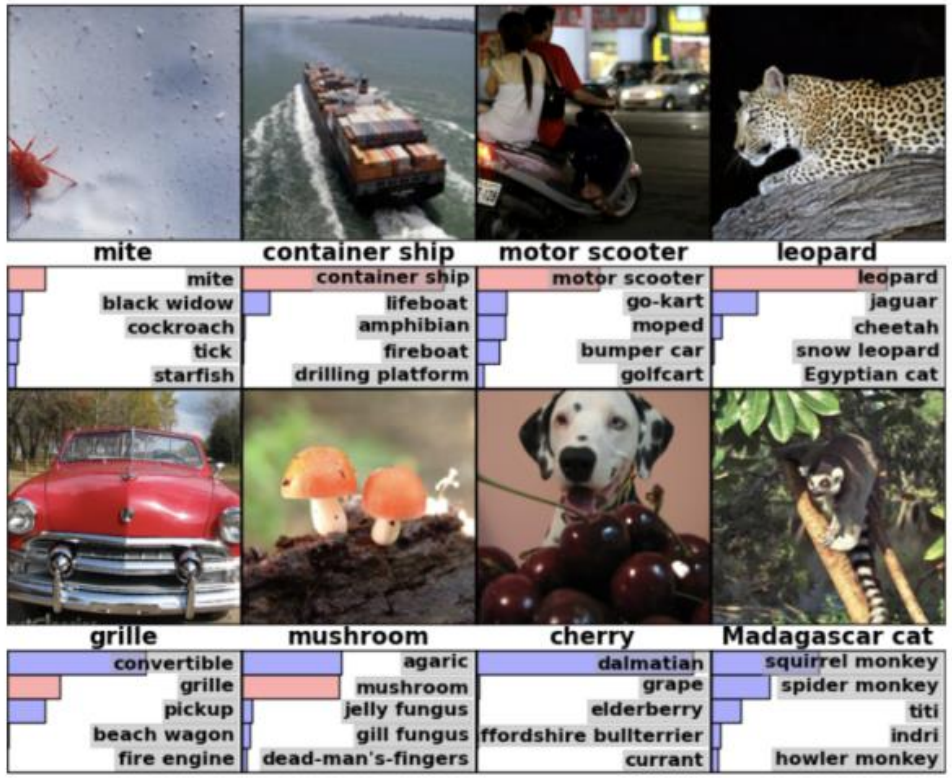
- Vision
- Embodied learning (RL, robotics)
- Language

Deep learning in vision: Where are we now?

- Glass is half full?
  - DL methods *actually work* and are better than older methods in most ways
  - Good methodologies: standardized benchmarks and metrics for many problems, quantitative comparisons, ablation studies
  - Good infrastructure: deep learning packages, cloud services, etc.
  - Culture of code sharing and reproducibility
- Glass is half empty?
  - Too much focus on benchmarks and numbers
  - Number of papers is exploding but diversity of topics is not necessarily increasing
  - Cutting-edge research is becoming prohibitively resource-intensive
  - Core benchmarks (ImageNet, COCO) are likely saturating but bigger datasets (or larger amounts of computing power) are not yet generally accessible

ImageNet: Asset or liability?

- Performance on the basic classification task has saturated



ILSVRC Challenge

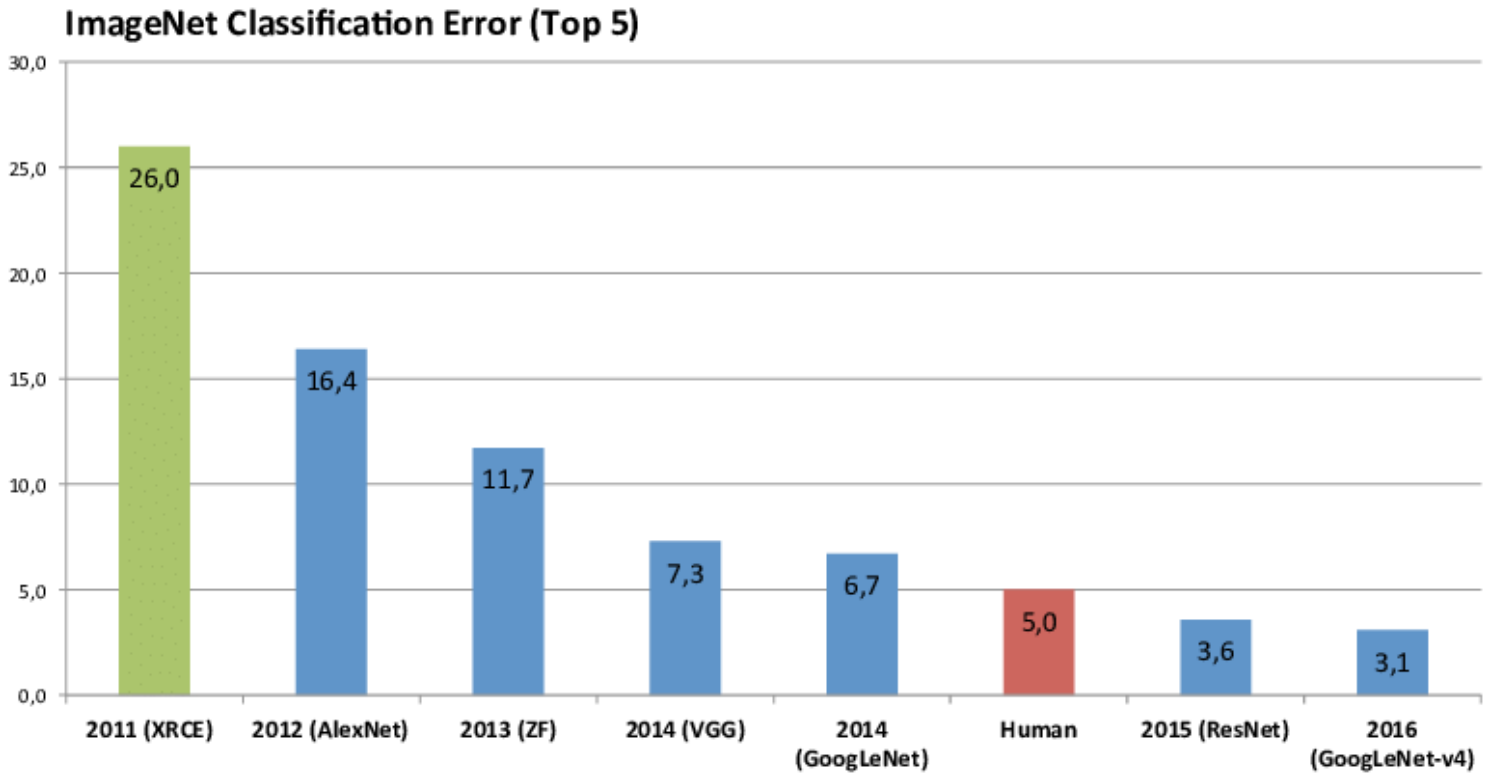


Figure source

ImageNet: Asset or liability?

- Performance on the basic classification task has saturated

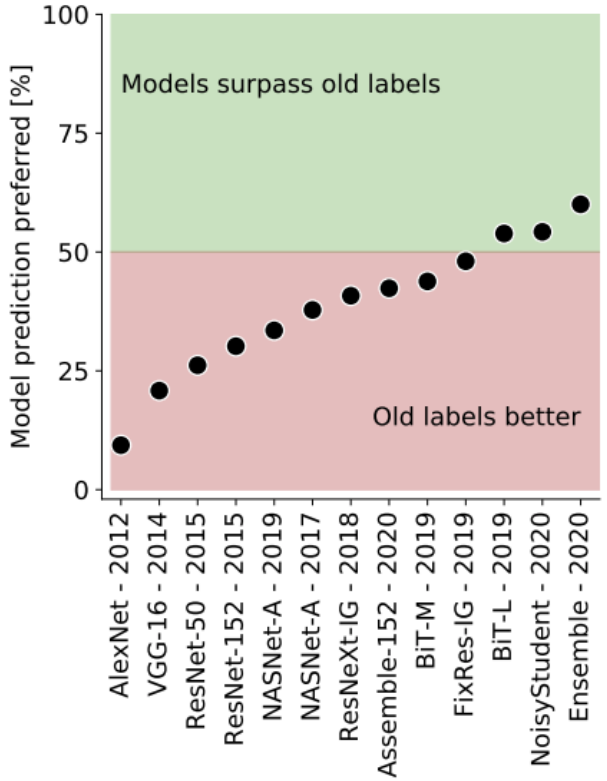


Figure 1: When presented with a model's prediction and the original ImageNet label, human annotators now prefer model predictions on average (Section 4). Nevertheless, there remains considerable progress to be made before fully capturing human preferences.

L. Beyer et al. Are we done with ImageNet? arXiv:2006.07159, 2020

ImageNet: Asset or liability?

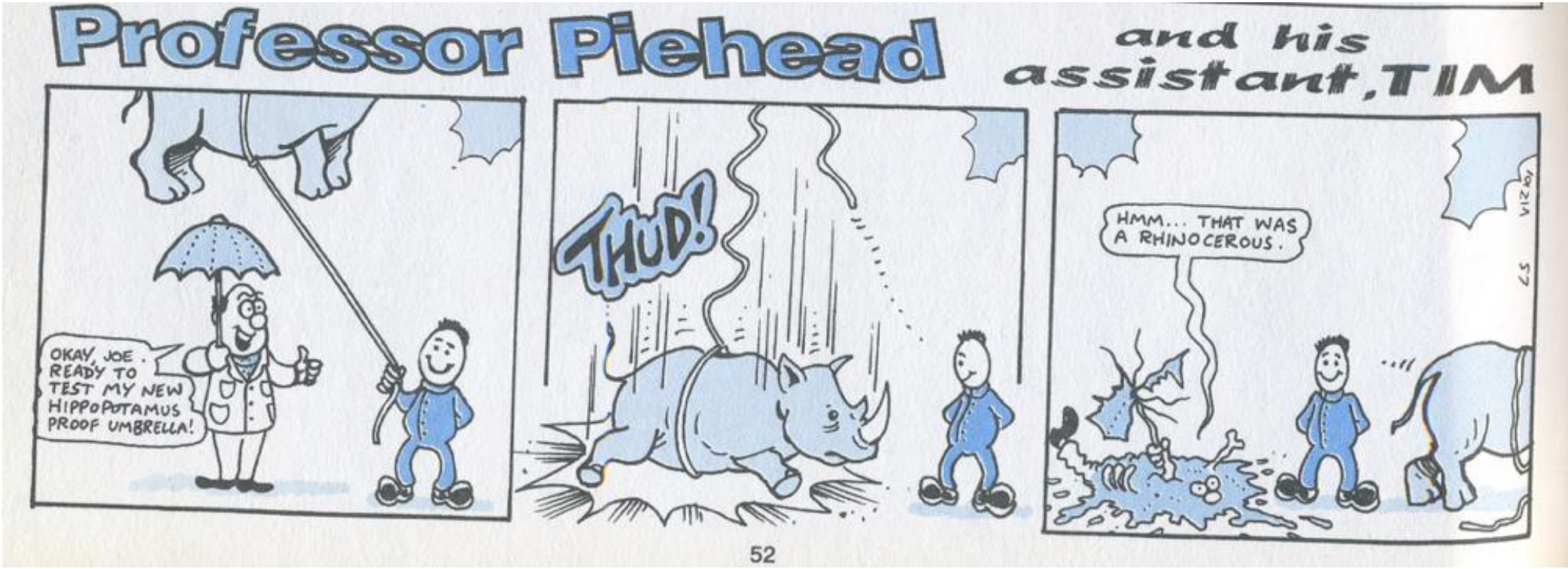
- Attaching labels to images is not very meaningful in the first place

"Now! ... *That* should clear up a few things around here!"

Favorite cartoon of J. Koenderink

ImageNet: Asset or liability?

- Attaching labels to images is not very meaningful in the first place



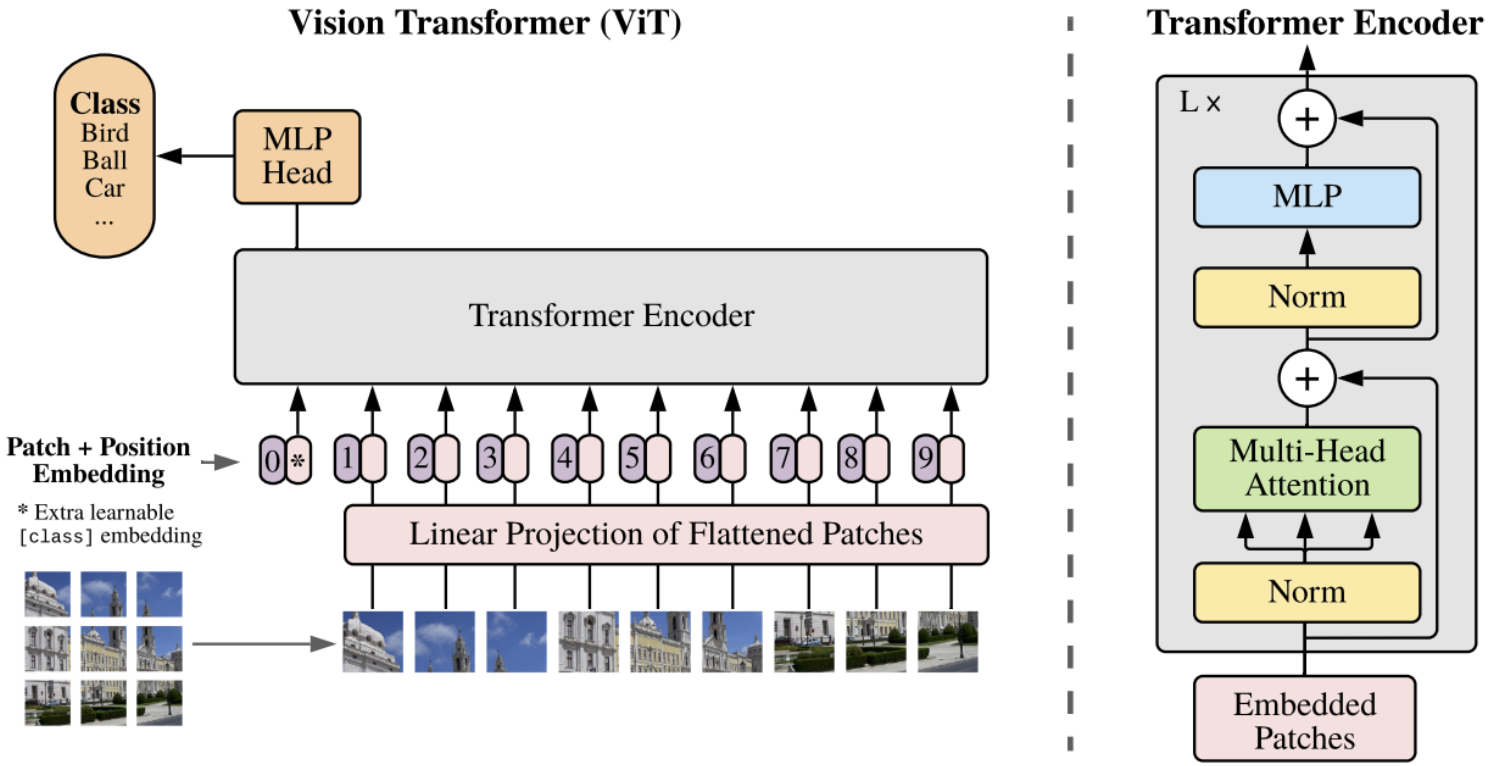
Favorite cartoon of D. Forsyth

How can we move forward?

- Develop the next generation of architectures

Beyond convolutional networks?

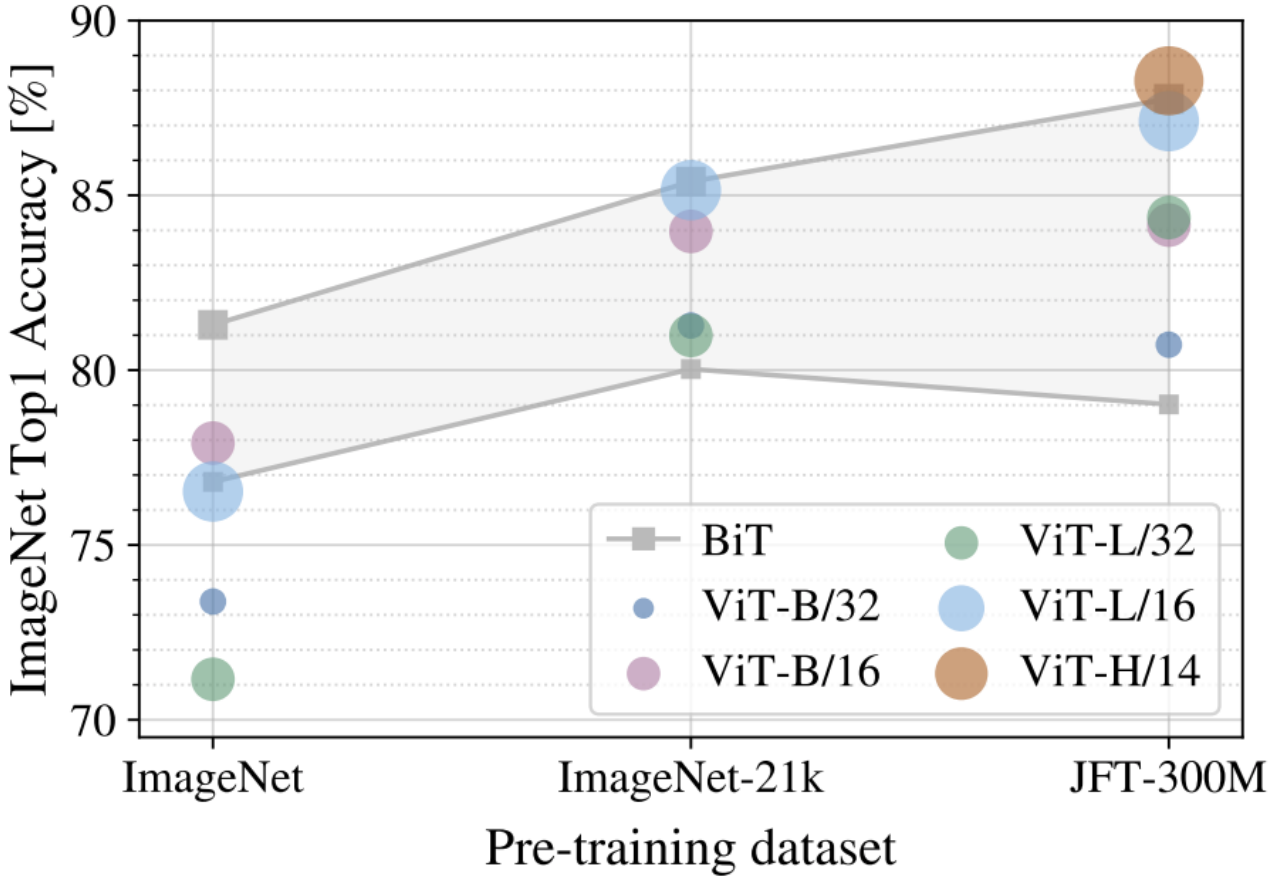
- Transformers for images



A. Dosovitskiy et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv 2020

Beyond convolutional networks?

- Transformers for images



BiT: ResNet (Big Transfer)
ViT: Vision Transformer (Base/Large/Huge)

JFT-300M: internal Google dataset (not public)

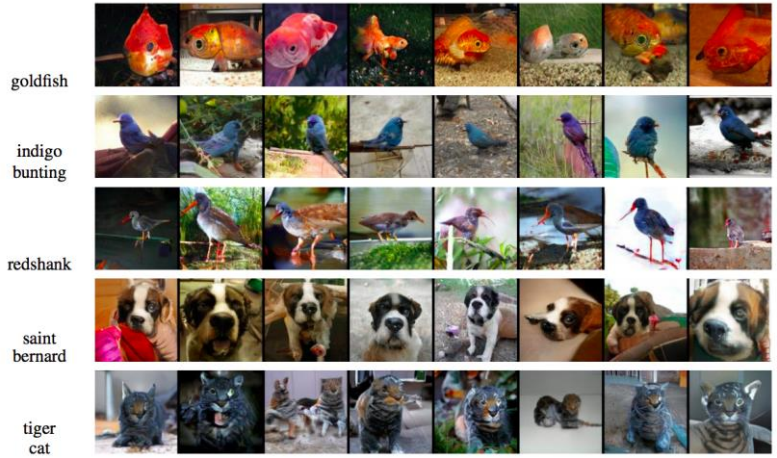
A. Dosovitskiy et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv 2020

How can we move forward?

- Develop the next generation of architectures
- Go beyond classification
  - “Rich” prediction tasks

“Rich” prediction tasks

Class label to image

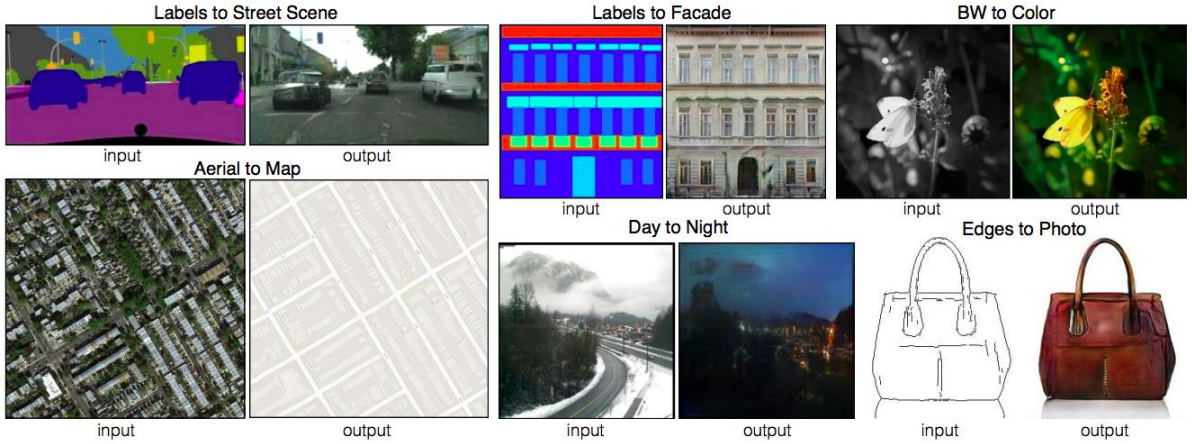


Zhang et al. (2019)

Text to image

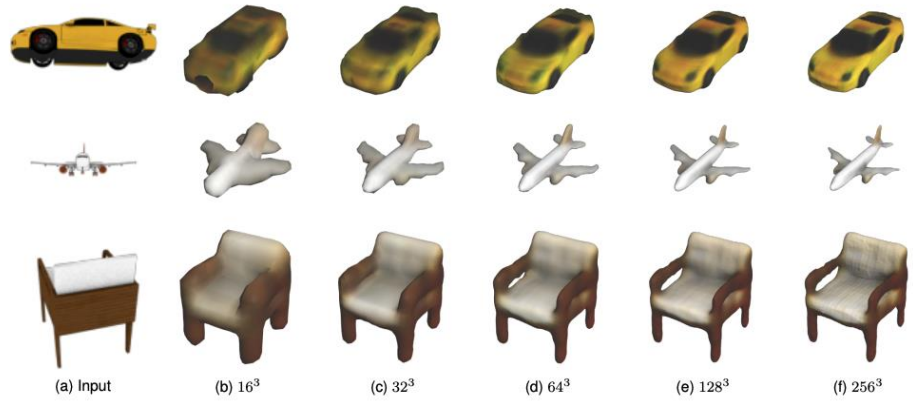
Qiao et al. (2019)

Image to image



Isola et al. (2017)

Image to 3D



Hane et al. (2019)

Learning 3D structure

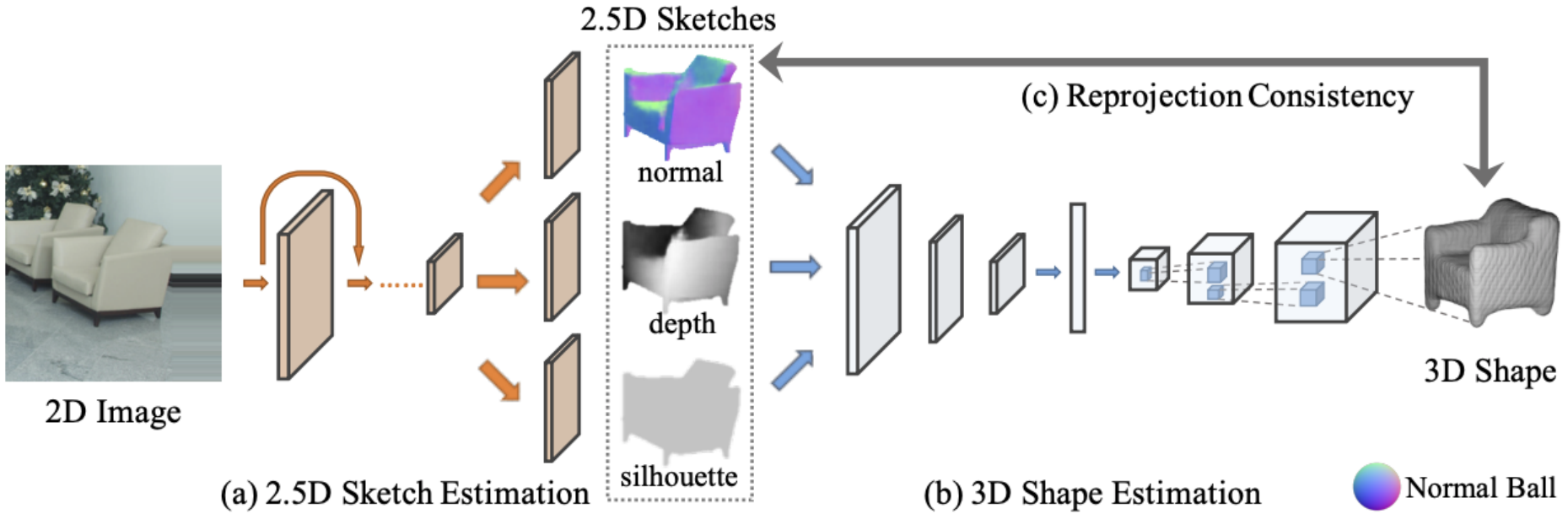
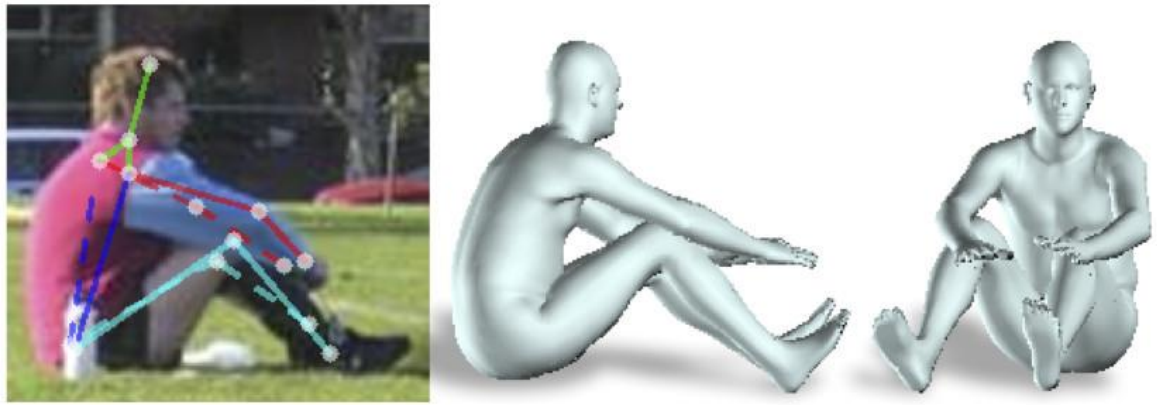


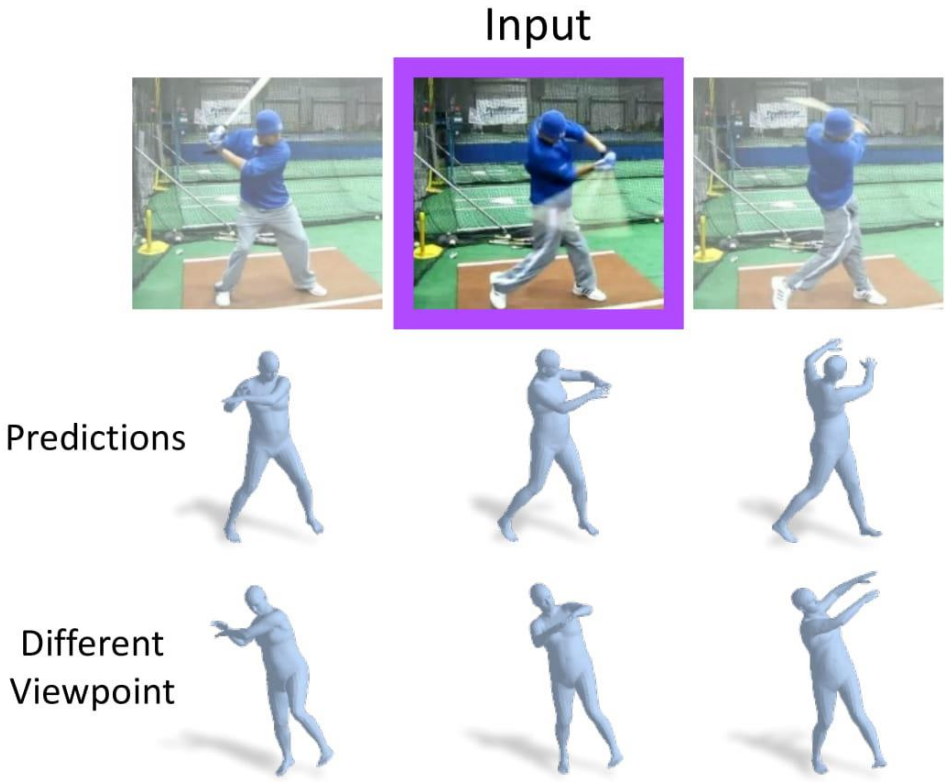
Figure 2: Our model (MarrNet) has three major components: (a) 2.5D sketch estimation, (b) 3D shape estimation, and (c) a loss function for reprojection consistency. MarrNet first recovers object normal, depth, and silhouette images from an RGB image. It then regresses the 3D shape from the 2.5D sketches. In both steps, it uses an encoding-decoding network. It finally employs a reprojection consistency loss to ensure the estimated 3D shape aligns with the 2.5D sketches. The entire framework can be trained end-to-end.

J. Wu, Y. Wang, T. Xue, X. Sun, W. Freeman, J. Tenenbaum, MarrNet: 3D Shape Reconstruction via 2.5D Sketches, NeurIPS 2017

Learning 3D structure



F. Bogo, A. Kanazawa, C. Lassner, P. Gehler, J. Romero and M. Black, [Keep it SMPL: Automatic Estimation of 3D Human Pose and Shape from a Single Image](), ECCV 2016



A. Kanazawa, J. Zhang, P. Felsen, J. Malik, [Learning 3D Human Dynamics from Video](), CVPR 2019

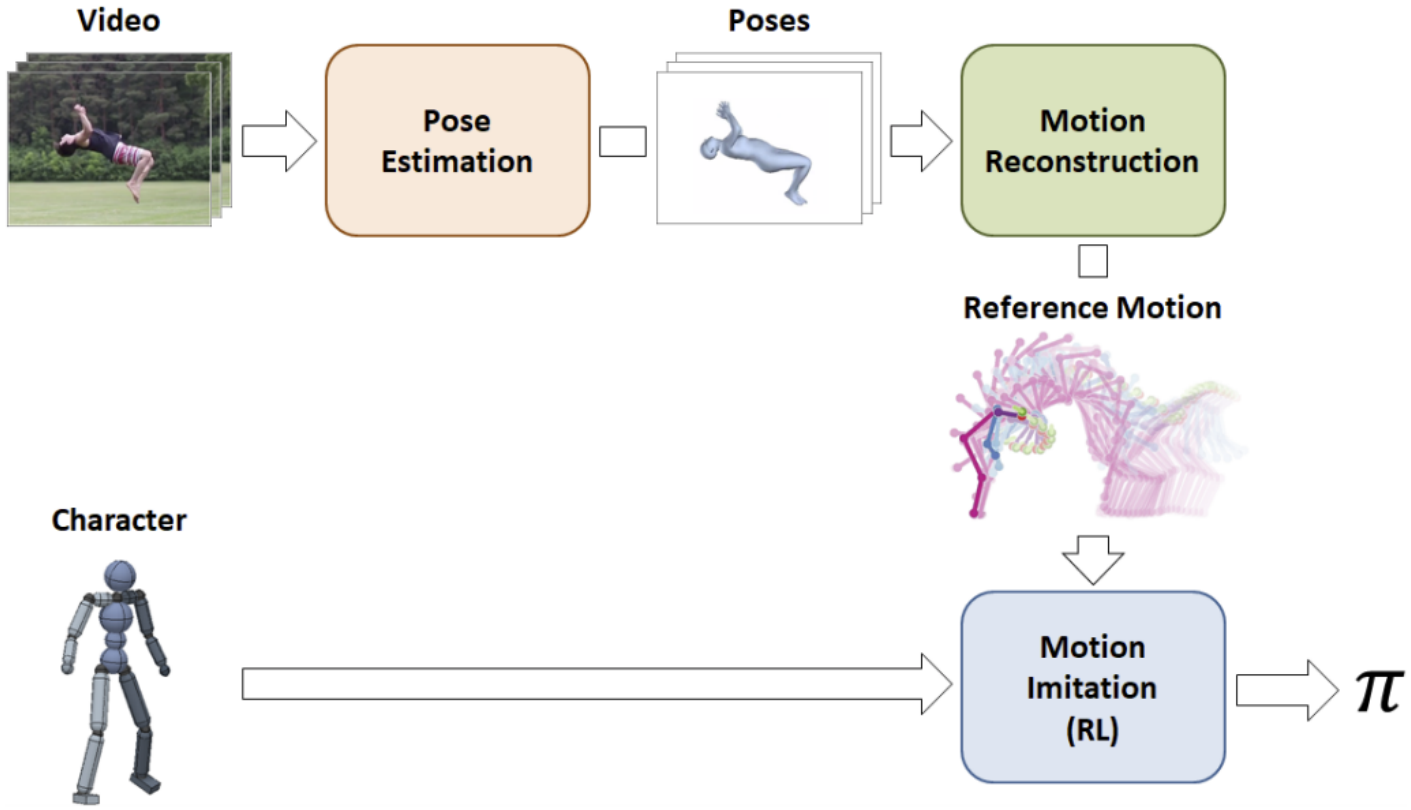
Learning skills from video

Fig. 1. Simulated characters performing highly dynamic skills learned by imitating video clips of human demonstrations. **Left:** Humanoid performing cartwheel B on irregular terrain. **Right:** Backflip A retargeted to a simulated Atlas robot.

Video

X. B. Peng, A. Kanazawa, J. Malik, P. Abbeel, S. Levine, SFV: Reinforcement Learning of Physical Skills from Videos, SIGGRAPH Asia 2018

Learning skills from video



Video

X. B. Peng, A. Kanazawa, J. Malik, P. Abbeel, S. Levine, SFV: Reinforcement Learning of Physical Skills from Videos, SIGGRAPH Asia 2018

How can we move forward?

- Develop the next generation of architectures
- Go beyond classification
  - “Rich” prediction tasks
  - Generation

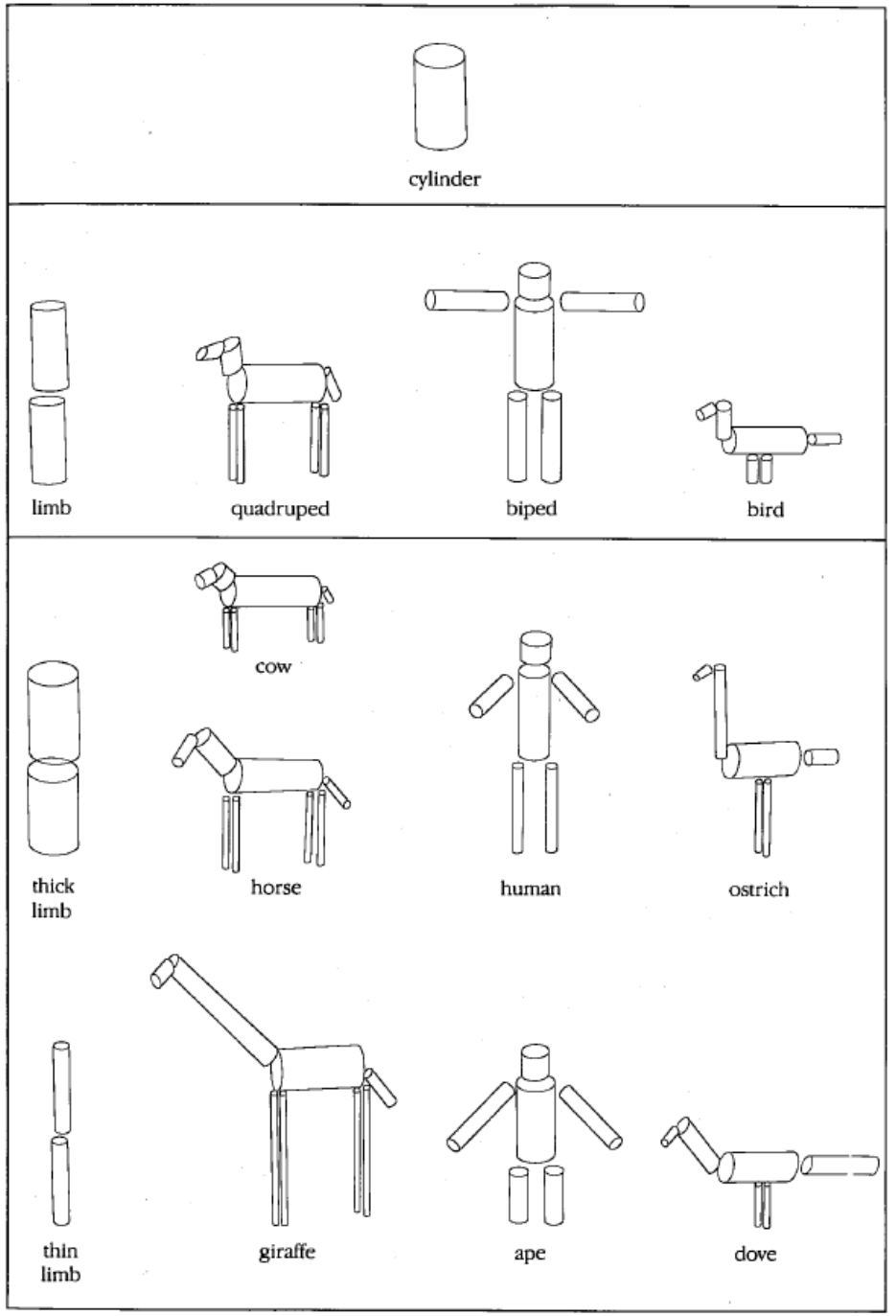
Generation

- State of the art: StyleGAN

T. Karras, S. Laine, T. Aila. A Style-Based Generator Architecture for Generative Adversarial Networks. CVPR 2019

Generation

- May shed light on important open questions, such as:
  - Do we need explicitly compositional (part-based) object representations?



Source: D. Marr, Vision, 1982

Generation

- May shed light on important open questions, such as:
  - Do we need explicitly compositional (part-based) object representations?
- BigGAN proves that we don't?

A. Brock, J. Donahue, K. Simonyan, Large scale GAN training for high fidelity natural image synthesis, ICLR 2019

Generation

- May shed light on important open questions, such as:
  - Do we need explicitly compositional (part-based) object representations?
- Or maybe we do?

A. Brock, J. Donahue, K. Simonyan, Large scale GAN training for high fidelity natural image synthesis, ICLR 2019

Generation

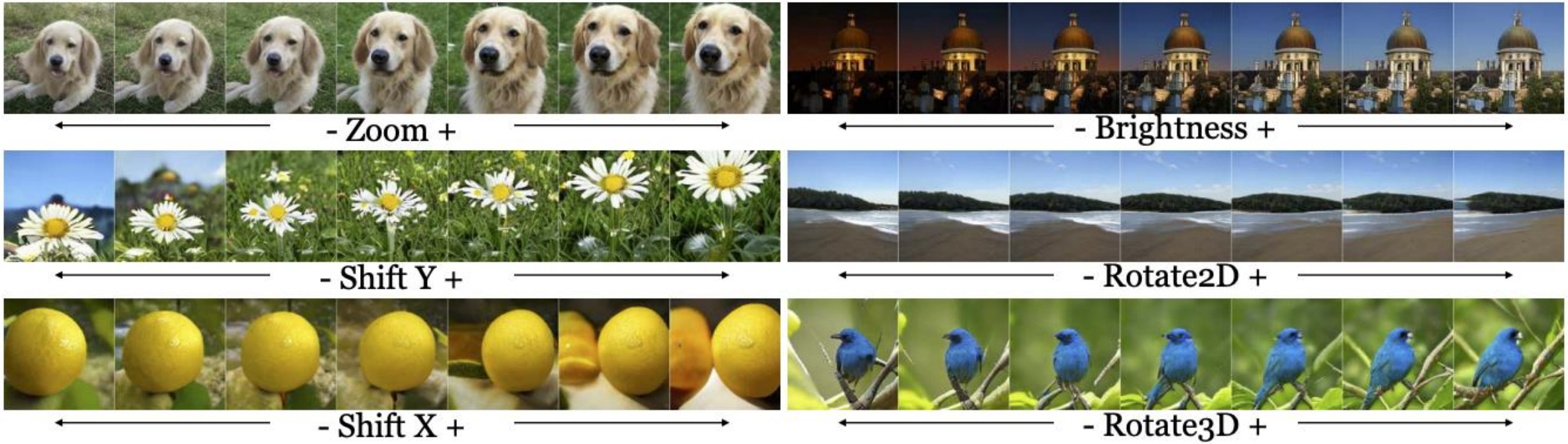
- May shed light on important open questions, such as:
  - Do we need explicitly compositional (part-based) object representations?

S. Azadi, D. Pathak, S. Ebrahimi, T. Darrell, Compositional GAN: Learning Conditional Image Composition, arXiv 2019

Generation

- May shed light on important open questions, such as:
  - Do we need explicit 3D object representations?

Maybe we don't?



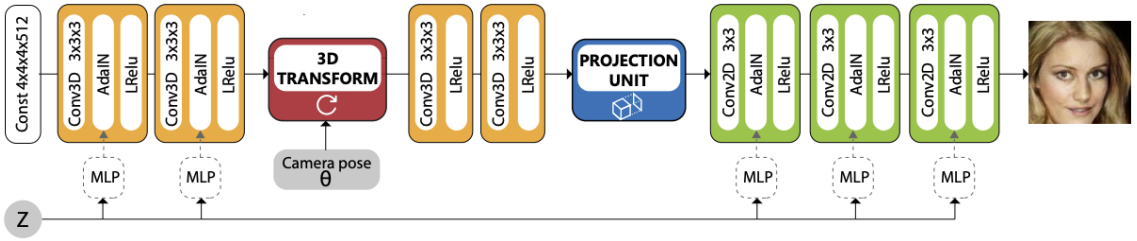
A. Jahanian, L. Chai, and P. Isola. On the "steerability" of generative adversarial networks. ICLR 2020

Generation

- May shed light on important open questions, such as:
  - Do we need explicit 3D object representations?

Or maybe we do?

Figure 1. HoloGAN learns to separate pose from identity (shape and appearance) only from unlabelled 2D images without sacrificing the visual fidelity of the generated images. All results shown here are sampled from HoloGAN for the same identities in each row but in different poses.



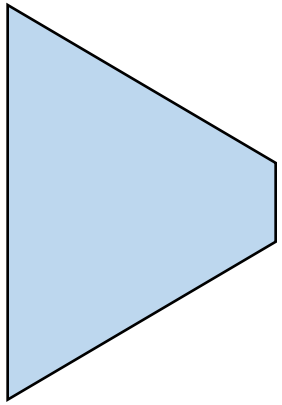
T. Nguyen-Phuoc et al., HoloGAN: Unsupervised Learning of 3D Representations From Natural Images, 2019

Possible ways forward

- Develop the next generation of architectures
- Go beyond classification
  - “Rich” prediction tasks
  - Generation
- Work on integrating discriminative and generative models

Integrating discriminative and generative models?

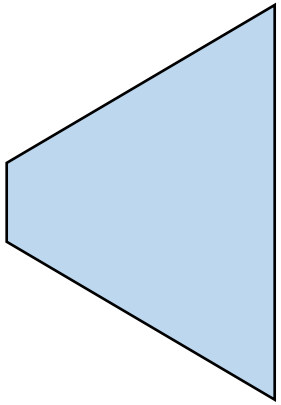
Discriminative model



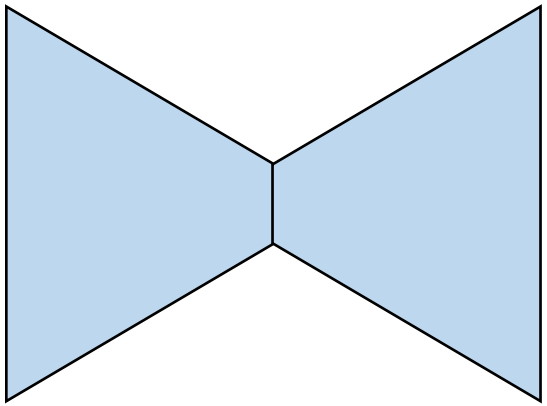
Label

Generative model

Noise/
latent
variable

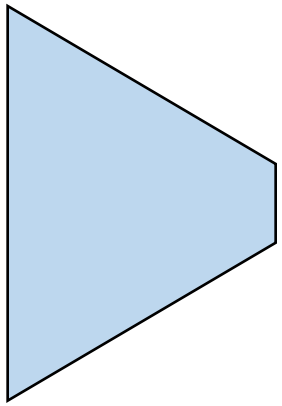


Encoder-decoder architecture



Integrating discriminative and generative models?

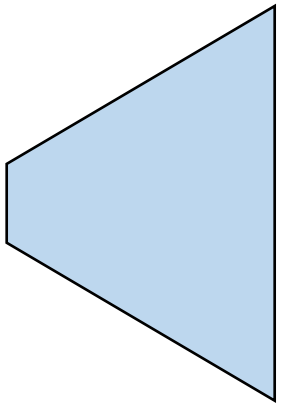
Discriminative model



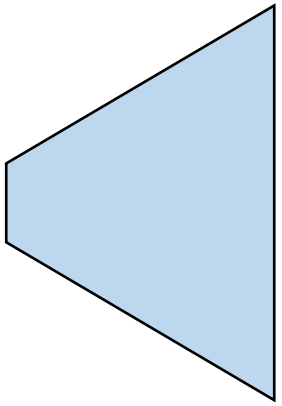
Label

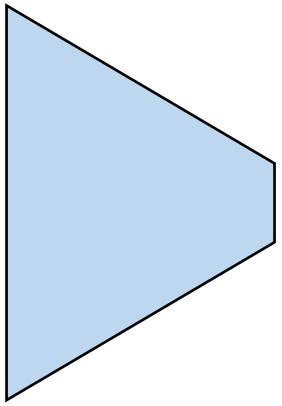
Generative model

Noise/
latent
variable



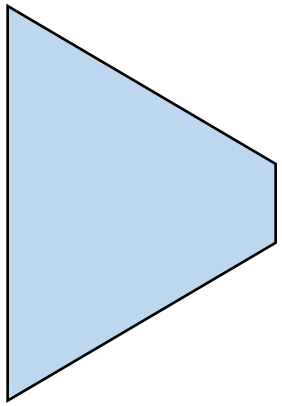
GAN





Integrating discriminative and generative models?

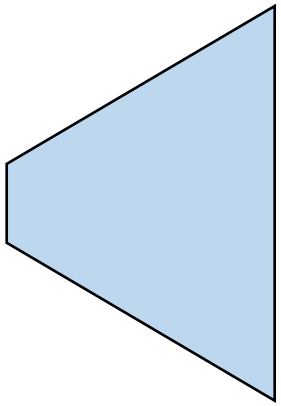
Discriminative model



Label

Generative model

Noise/
latent
variable



What else is there?

Integrating discriminative and generative models?

- Can “hallucination” help with recognition?
  - Low-shot learning, incremental learning, transfer learning

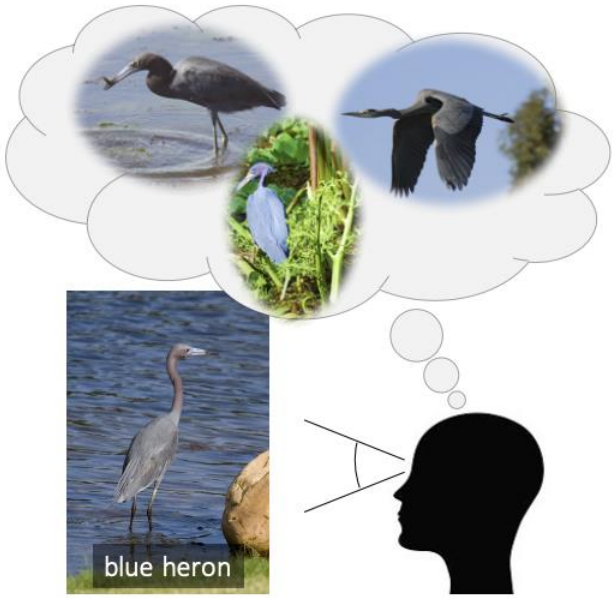
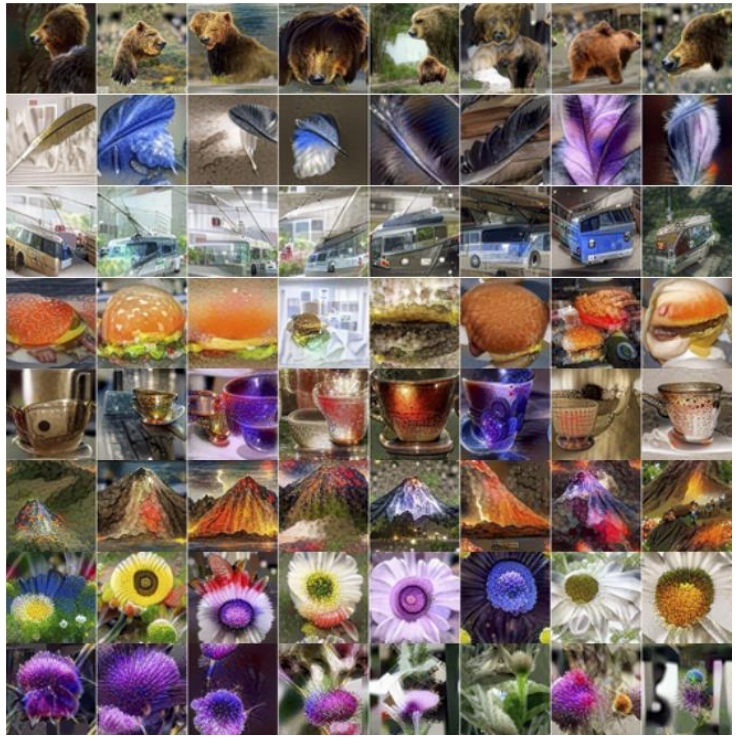


Figure 1. Given a single image of a novel visual concept, such as a blue heron, a person can visualize what the heron would look like in other poses and different surroundings. If computer recognition systems could do such hallucination, they might be able to learn novel visual concepts from less data.

Wang et al. (2018)



High-quality images synthesized by “inverting” an ImageNet-pretrained network

Yin et al. (2019)

Integrating discriminative and generative models?

- Can attribute-based manipulation of training examples help to train more accurate or less biased models?

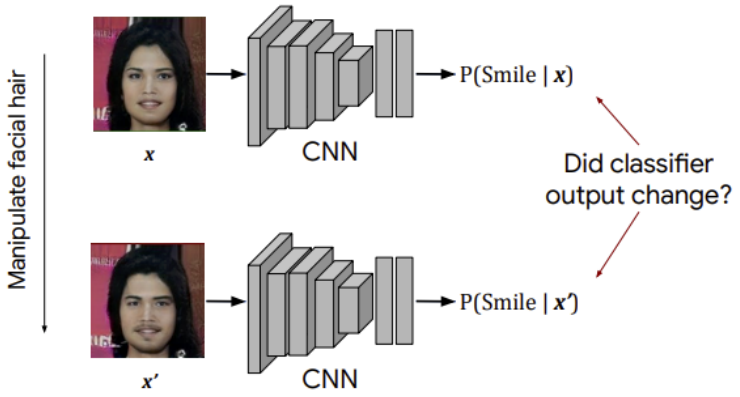


Figure 1: Counterfactual attribute sensitivity measures the effect of manipulating a specific property of an image on the output of a trained classifier. In this example, we consider the effect of adding facial hair on the output of a smiling classifier. If the classifier's output systematically changes as a result of adding or removing facial hair then a potentially undesirable bias has been detected since, all else being equal, facial hair should be irrelevant to the classification task.

Denton et al. (2019)

Figure 1: Our approach learns to *actively create* training images for fine-grained attribute comparisons, focusing attention on informative pairs of images unavailable in the real image training pool. Here we show two example pairs it generated to improve learning of *open* (left) and *masculine* (right).

Yu and Grauman (2019)

Possible ways forward

- Develop the next generation of architectures
- Go beyond classification
  - “Rich” prediction tasks
  - Generation
- Work on integrating discriminative and generative models
- Move away from full supervision

Self-supervised learning

- For still image recognition tasks, self-supervision is more cumbersome (so far) as getting enough supervised training data
- However, it is very attractive (and possibly unavoidable) for video, audio, and sensorimotor learning

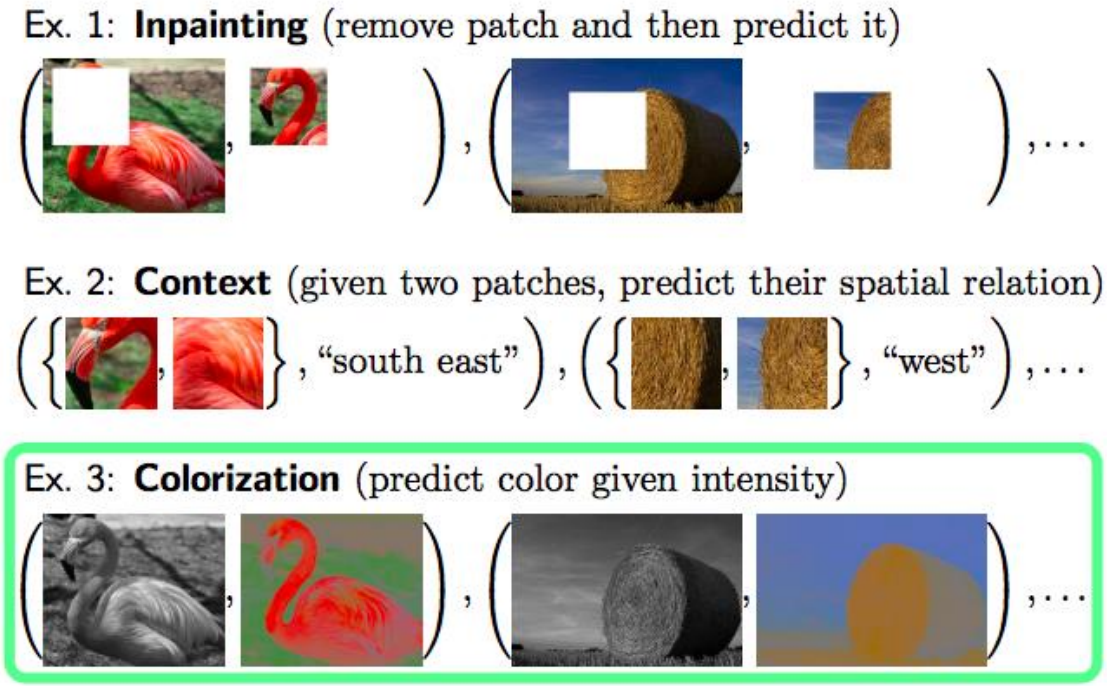
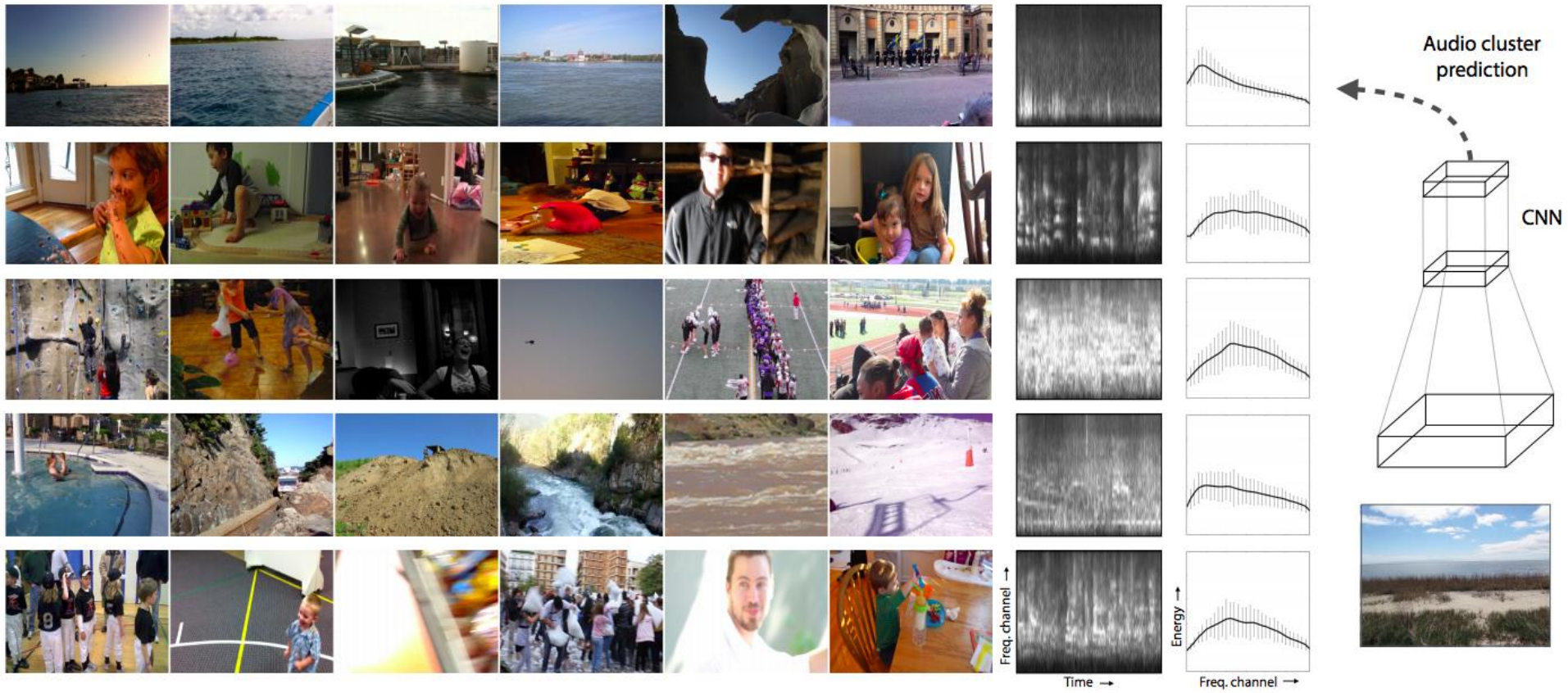


Figure source: G. Larsson, M. Maire, and G. Shakhnarovich, Colorization as a Proxy Task for Visual Understanding, CVPR 2017

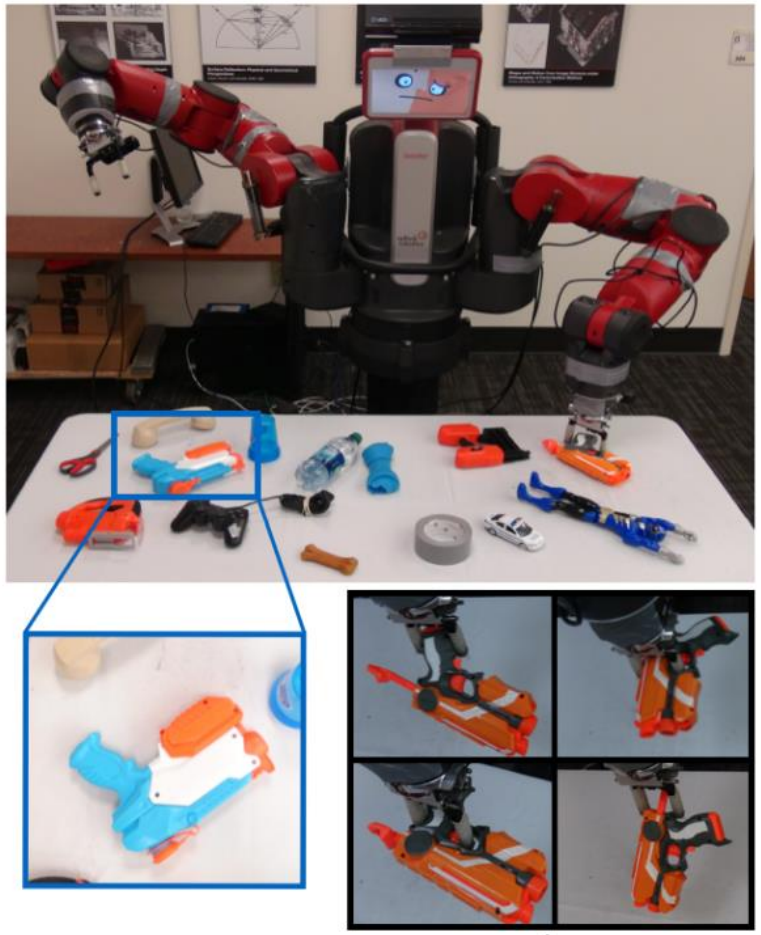
Cross-modal self-supervision



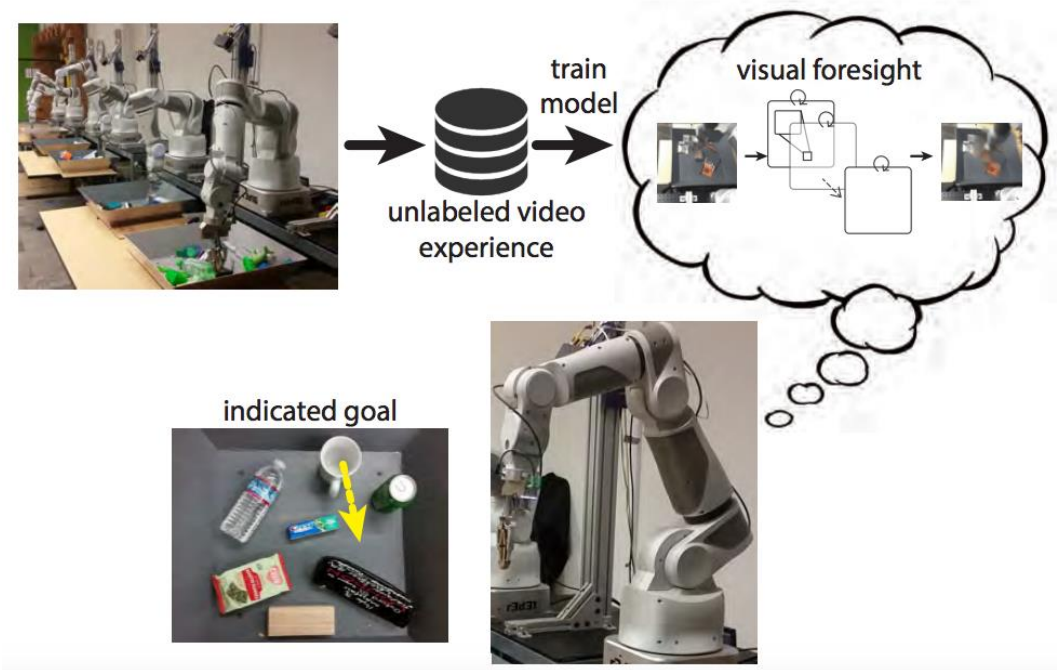
(a) Images grouped by audio cluster (b) Clustered audio stats. (c) CNN model

A. Owens, J. Wu, J. McDermott, W. Freeman, and A. Torralba, Ambient Sound Provides Supervision for Visual Learning, ECCV 2016

Self-supervision from future prediction



L. Pinto and A. Gupta, Supersizing self-supervision: Learning to grasp from 50K tries and 700 robot hours, ICRA 2016



C. Finn and S. Levine. Deep Visual Foresight for Planning Robot Motion. ICRA 2017

Self-supervision from future prediction

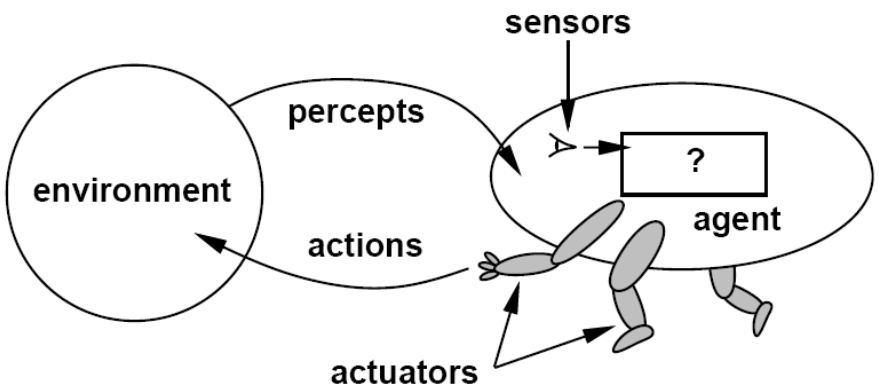
- Curiosity is also about predicting the effects of one's actions!

Video

D. Pathak, P. Agrawal, A. Efros, T. Darrell, Curiosity-driven Exploration by Self-supervised Prediction, ICML 2017

Possible ways forward

- Develop the next generation of architectures
- Go beyond classification
  - “Rich” prediction tasks
  - Generation
- Work on integrating discriminative and generative models
- Move away from full supervision
- Focus on embodied vision, sensorimotor learning



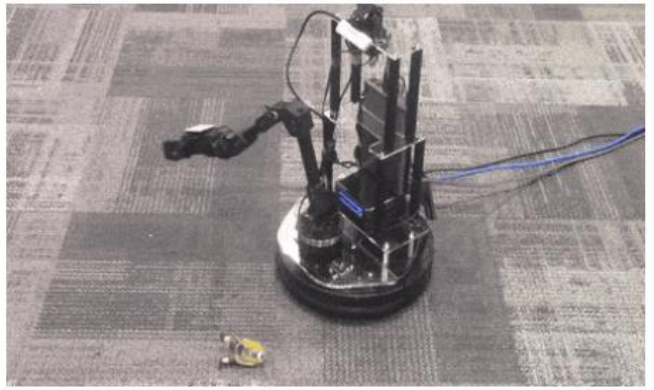
Outline

- Vision
- Embodied learning (RL, robotics)

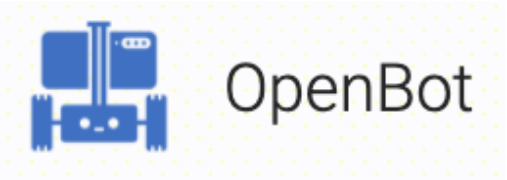
Embodied platforms

- Simulation: AI2Thor, Habitat

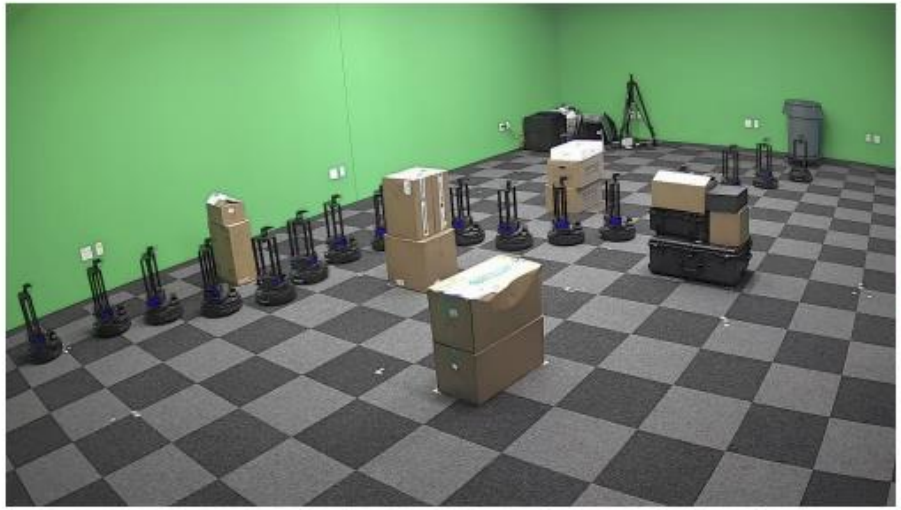
- Real robots: PyRobot



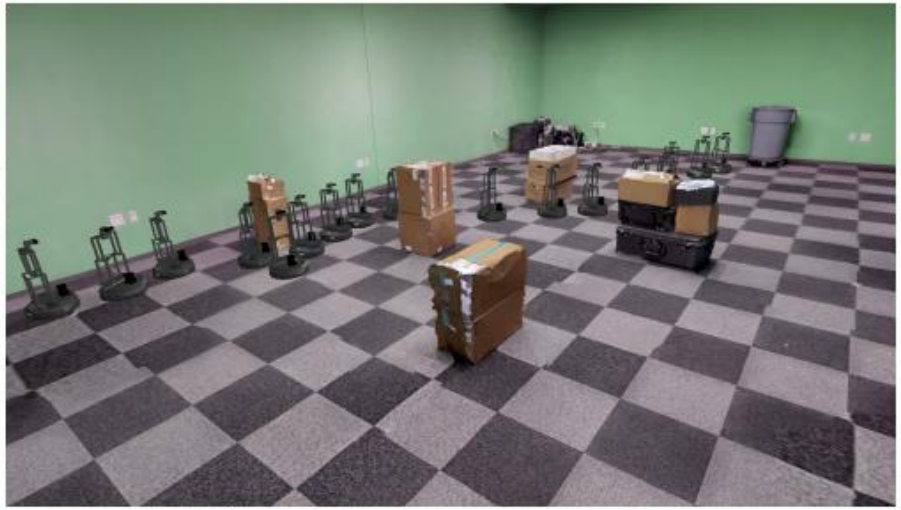
- Robot on your smartphone: OpenBot



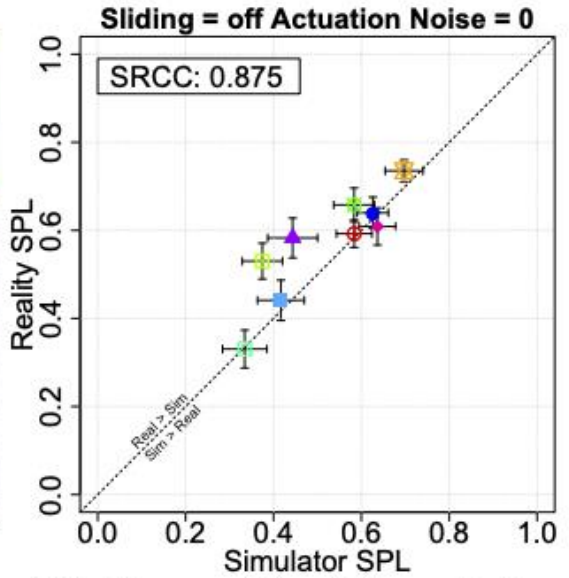
Can we trust simulators?



(a) Reality.



(b) Simulation.



(c) Sim-vs-Real Correlation.

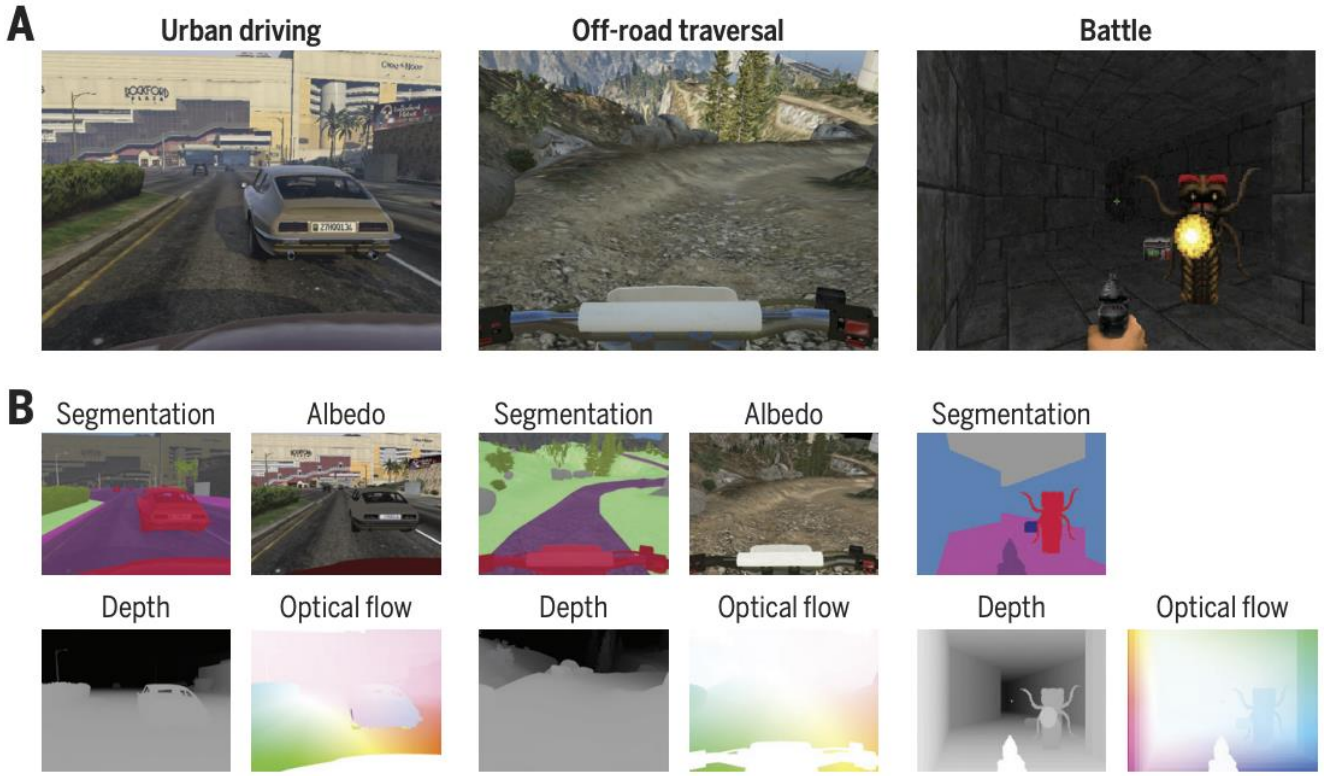
A. Kadian, J. Truong, A. Gokaslan, A. Clegg, E. Wijmans, S. Lee, M. Savva, S. Chernova, D. Batra, Are We Making Real Progress in Simulated Environments? Measuring the Sim2Real Gap in Embodied Visual Navigation, arXiv 2019

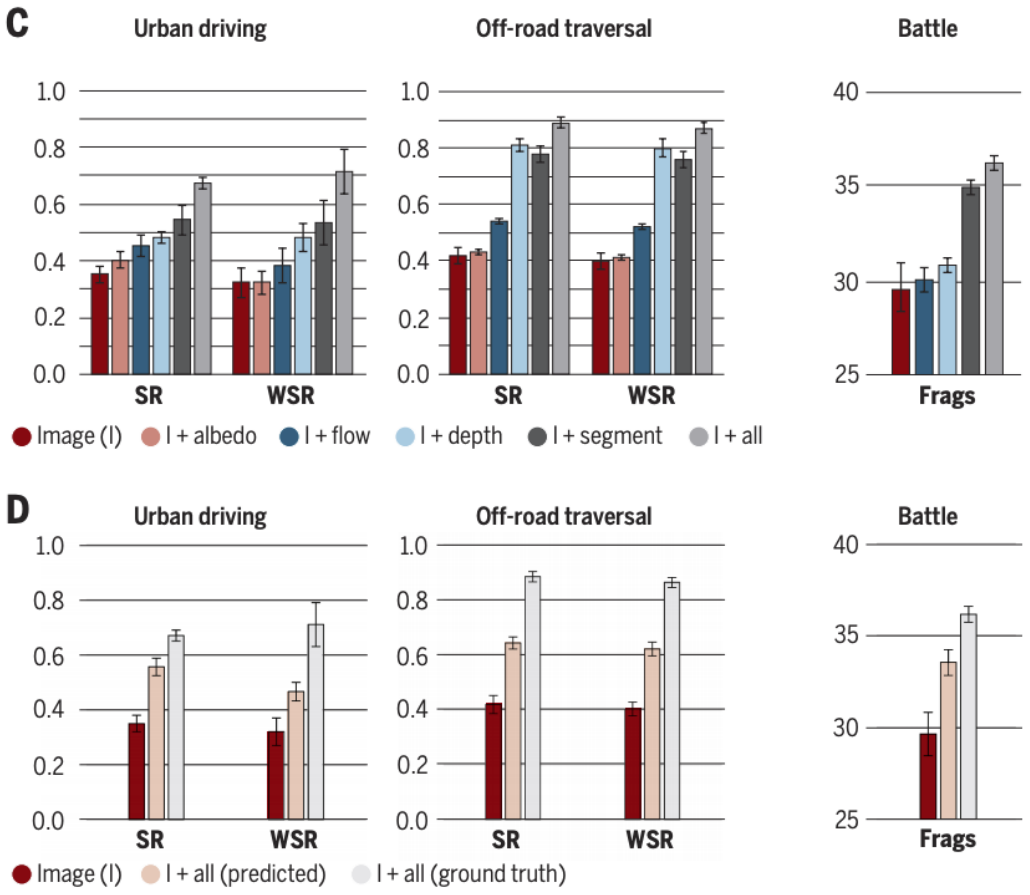
Can we scale up robot learning?

Figure 1. Our large-scale data collection setup, consisting of 14 robotic manipulators. We collected over 800,000 grasp attempts to train the CNN grasp prediction model.

S. Levine et al., Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection, *International Symposium on Experimental Robotics*, 2017

What internal representations are needed for embodied tasks?





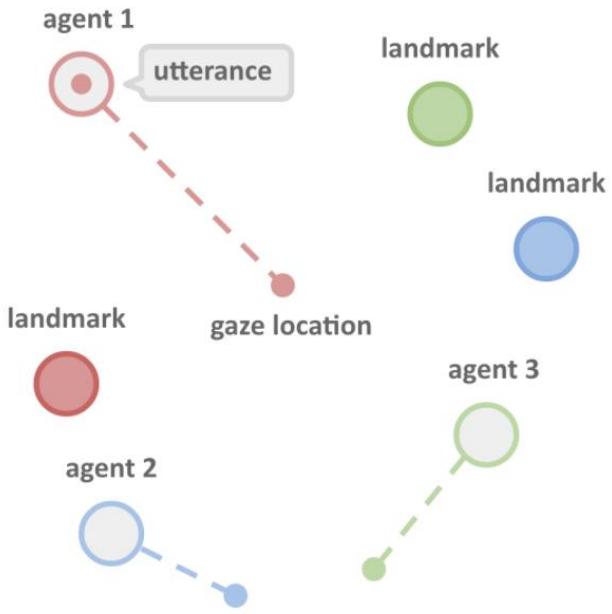
"Our main finding is that computer vision does matter. Models equipped with intermediate representations train faster, achieve higher task performance, and generalize better to previously unseen environments."

B. Zhou, P. Krähenbühl, and V. Koltun, Does Computer Vision Matter for Action? Science Robotics, 4(30), 2019 (video)

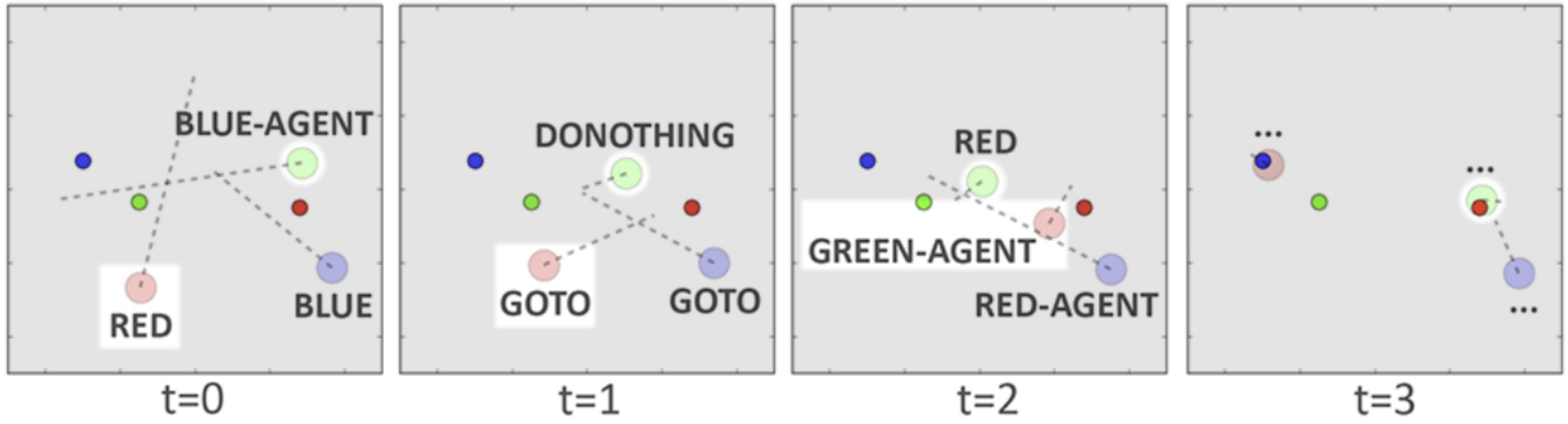
Multiple agents and communication

Source

Emergence of language



Our agents exist in a simple, 2D world, and are able to take actions such as moving to locations, looking at things, or saying things to communicate with other agents. In this picture, agent 1 is saying something while staring at a point in the center of the map.



In the above step-by-step run, at t=0 the red agent says a word corresponding to the red landmark (center right), then at t=1 says a word that is equivalent to 'Goto', then in t=2 says 'green-agent'. The green-agent hears its instructions and immediately moves to the red landmark.

https://openai.com/blog/learning-to-communicate/
Video

A. Mordatch and P. Abbeel, Emergence of Grounded Compositional Language in Multi-Agent Populations, AAAI 2018

RL for negotiation

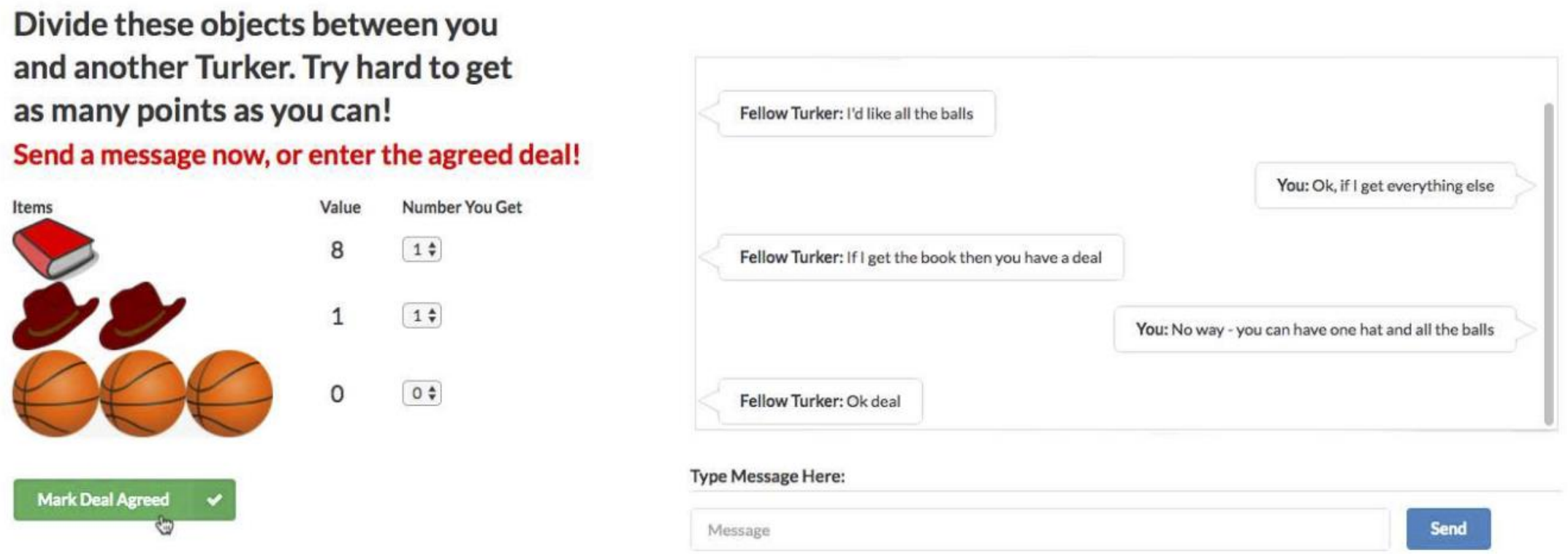


Figure 1: A dialogue in our Mechanical Turk interface, which we used to collect a negotiation dataset.

M. Lewis et al., Deal or No Deal? End-to-End Learning for Negotiation Dialogues, EMNLP 2017

Outline

- Vision
- Embodied learning (RL, robotics)
- Language

Large-scale language models

Model Alias	Org.	Article Reference
ULMfit	fast.ai	*Universal Language Model Fine-tuning for Text Classification* Howard and Ruder
 ELMo	AllenNLP	*Deep contextualized word representations* Peters et al.
OpenAI GPT	OpenAI	*Improving Language Understanding by Generative Pre-Training* Radford et al.
 BERT	Google	*BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding* Devlin et al.
XLM	Facebook	*Cross-lingual Language Model Pretraining* Lample and Conneau

Image source

Should we be scared of GPT-3?

Opinion

The New York Times

How Do You Know a Human Wrote This?

Machines are gaining the ability to write, and they are getting terrifyingly good at it.

By Farhad Manjoo
Opinion Columnist

July 29, 2020

https://www.nytimes.com/2020/07/29/opinion/gpt-3-ai-automation.html

See also:
https://www.nytimes.com/2020/11/24/science/artificial-intelligence-ai-gpt3.html

MIT Technology Review

Opinion

GPT-3, Bloviator: OpenAI's language generator has no idea what it's talking about

Tests show that the popular AI still has a poor grasp of reality.

by Gary Marcus and Ernest Davis

August 22, 2020

https://www.technologyreview.com/2020/08/22/1007539/gpt3-openai-language-generator-artificial-intelligence-ai-opinion/

Language: The importance of grounding

- *Meaning* cannot be learned from *form* alone – it requires knowing about the relationship between language and the outside world

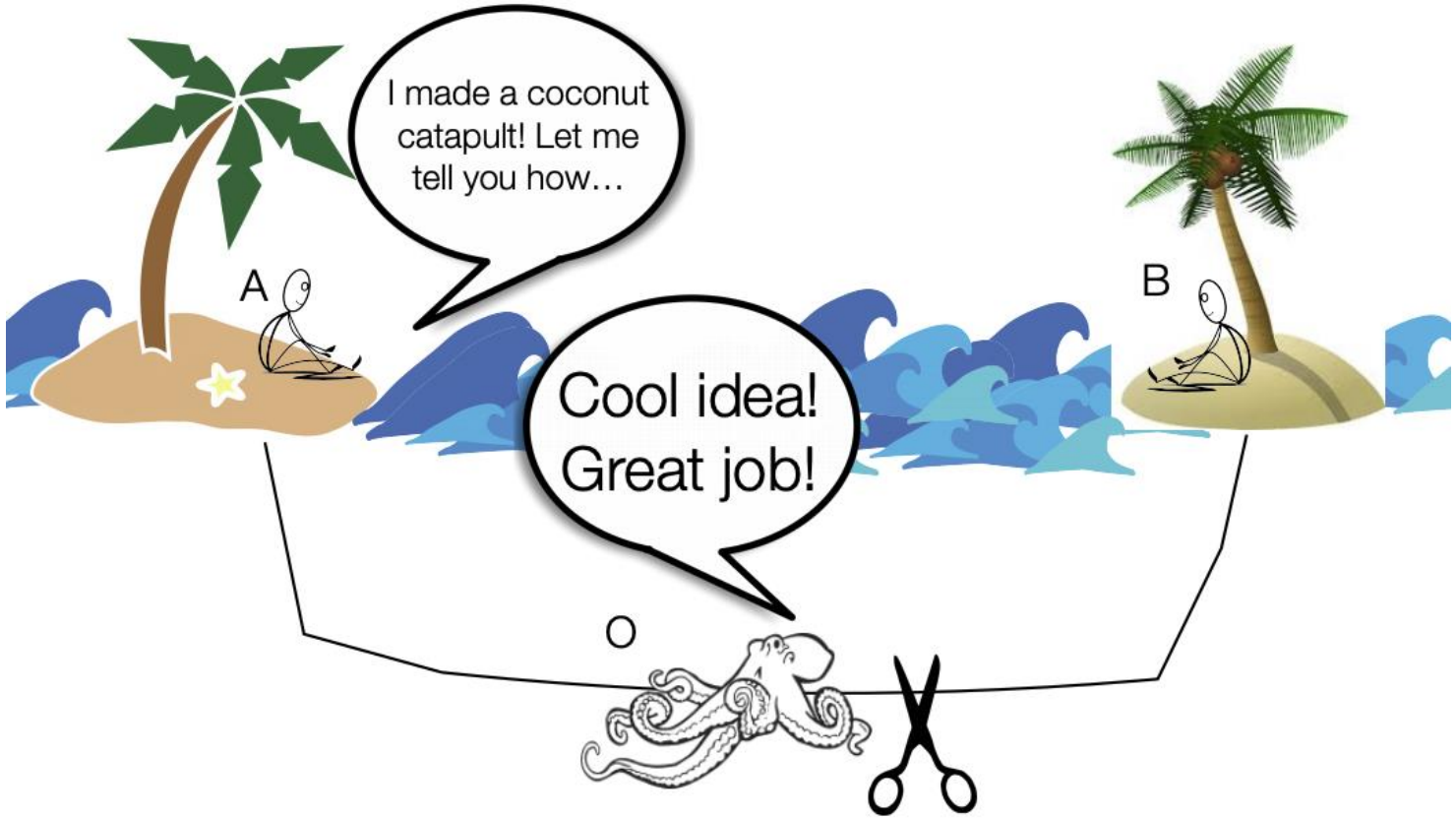


Image source

E. Bender and A. Koller, Climbing towards NLU: On Meaning, Form, and Understanding in the Age of Data, ACL 2020

Further challenges

- Reasoning
- Memory
- Lifelong learning

Recent Trends

- Explainable Deep Learning
- Robust Deep Learning
- Light Weight Deep Learning (Network Pruning)
- Neural Architecture Search
- Few Shot, One Shot and Zero Shot Learning
- Incremental Learning
- Deep Learning in Multimedia
- Deep Learning in Other Domains
- And Many More ....

Parting thoughts

- The next breakthroughs are not likely to come cheaply
- Access to data, computation, and platforms will be key
- The next few years will make it clearer which problems have been truly solved and which ones have been underestimated
- The hard problems are getting into “AI-complete” territory

Acknowledgement

Thanks to the following courses and corresponding researchers for making their teaching/research material online

- Deep Learning, Stanford University
- Introduction to Deep Learning, University of Illinois at Urbana-Champaign
- Introduction to Deep Learning, Carnegie Mellon University
- Convolutional Neural Networks for Visual Recognition, Stanford University
- Natural Language Processing with Deep Learning, Stanford University
- And Many More ……