Visual recognition: from pixels to machines that see, reason and act

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The research domain: computer vision

… extracting information from images

What human brain sees

37	43	6	30	36	36	22	48	33	28	26	19	20	14	28	32	27	28	30	38	41	92	26	37	32	28	29	33	162	159	160	159	159	159	149	151	157	61	51	40
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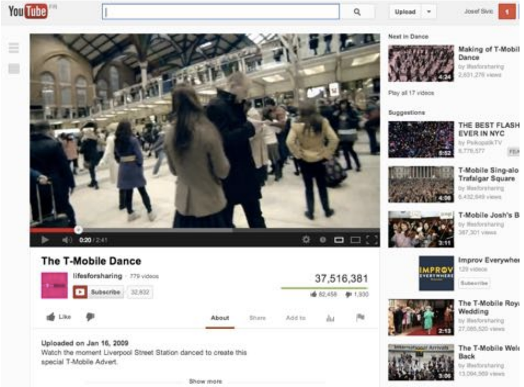
97	55	32	48	52	42	35	21	5	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1	10	54	57	56	55	55	54	54	52	49	47	47	47	45	45	44

What computer sees:

array of pixel intensities

Towards collective visual memory

Archives of visual information



Internet videos

10,000+ **TV channels**

Historical imagery

Cameras around us

2M+ **surveillance cameras**

Car cameras

Personal cameras

Record over time visual experiences of many people at different places into an emerging collective visual memory

Motivation

What if we could automatically learn from this visual data?

Learn from people to sequences of manipulation actions to achieve a certain task

"How to" instructional videos

Potential impact: machines that learn from collective visual memory for robotics

Motivation

What if we could automatically learn from this visual data?

Machines that autonomously learn to perceive, reason and act.

To operate in dangerous environments
[Darpa robot challenge 2015]

To assist people
[Microsoft HoloLens 2015]

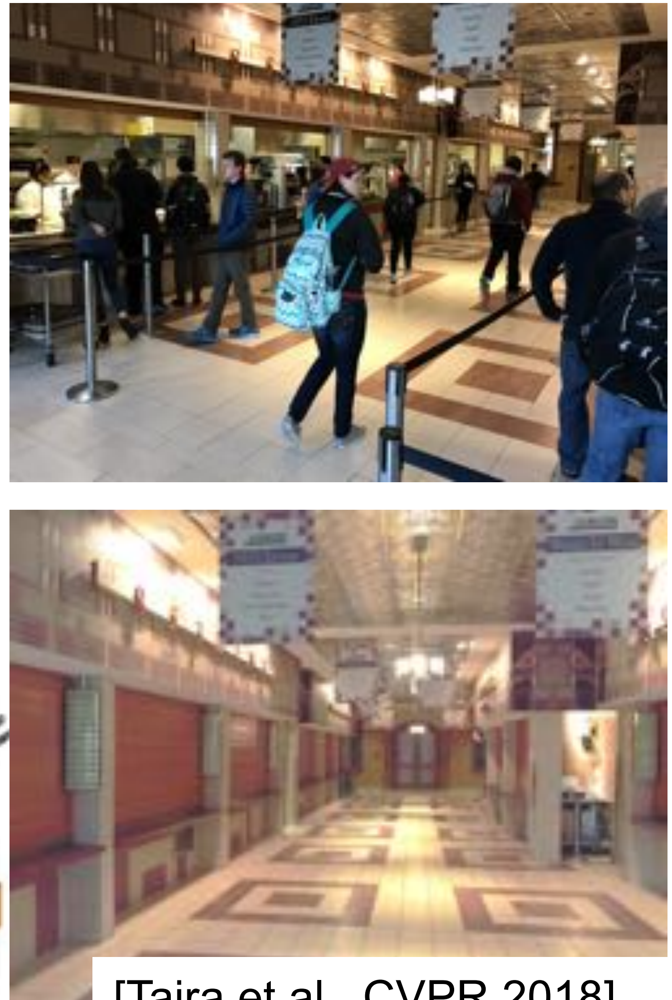
Potential impact: machines that learn from collective visual memory for robotics

Motivation

What if we could automatically learn from this visual data?

Learn to localize and navigate in changing conditions.

[Sattler et al., CVPR 2018]

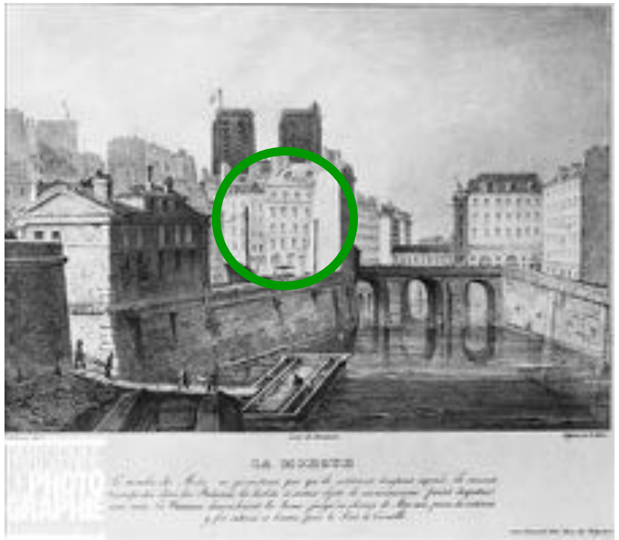


[Taira et al., CVPR 2018]

Motivation

What if we could automatically learn from this visual data?

Evolution of a particular place over time



1830

1852

1900

Potential impact: New ways to access archives for archeology, history, or architecture, …

Motivation

What if we could automatically learn from this visual data?

Extract statistics of human behaviors across a city over time

"**crossing street**"

"**bicycle accident**"

"**riding bicycle**"

Potential impact: new ways to optimize road safety, urban planning or commerce in cities

Scientific questions

1. Learning vocabulary of patterns from data

2. Generalization to new conditions and situations

3. Reasoning about visual data

What is the right visual vocabulary?

Problem: Hard to design visual representation by hand

How to define the appearance of a chair?

Supervised machine learning

Positive examples (chairs)

Negative examples (other objects)

Training data

$f($  $) = +1$

$f($  $) = -1$

Image classifier

Mark I Perceptron [Rosenblatt'57]

Change parameters of f to minimize # of errors on training data.

Training procedure

Supervised machine learning

Positive examples $y_i = 1$

Negative examples $y_i = -1$

Training data

$\{x_i, y_i\}$

Images Labels (+-1)

$f($  $) = +1$

$f($  $) = -1$

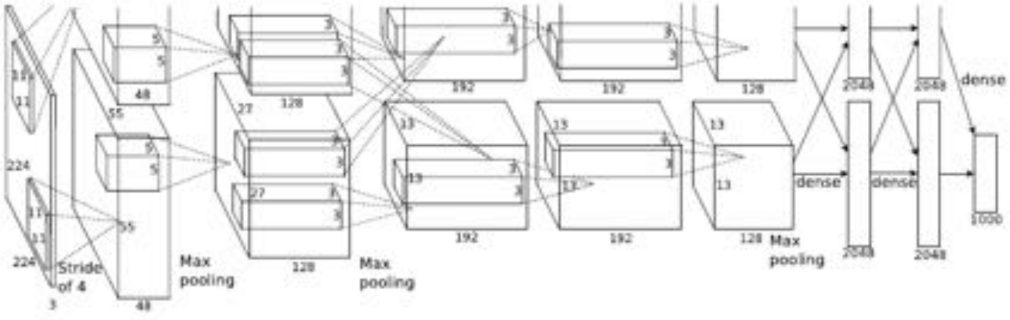
Image classifier

$$\min_{f} \overbrace{\sum_{i=1}^{N} \underbrace{\ell(y_i, f(x_i))}_{\text{Error on one example}}}^{\text{Error (loss) on the all training data}} + \overbrace{\Omega(f)}^{\text{Regularization}}$$

Training procedure

Supervised machine learning: in practice

Millions of annotated training examples [from the Internet]



Classifier with **millions of parameters**

Powerful training hardware
Days to weeks of training

Limitation I: Can we annotate the entire visual world?

Problem: annotation is expensive and can introduce biases

Currently: tedious **manual annotation**

Annotation is often ambiguous:
Table? / Dining Table? / Desk? / Bench?

Limitation II: What is the right granularity of visual representation?

Problem: the “visual vocabulary” is large, a priori unknown and task dependent

What is the set of **manipulation actions** that can be done with a particular **tool**?

What is the set of human behaviors that correlate with **pedestrian accidents**?

Solution: learn without human supervision
[Self-supervised learning]

Unsupervised learning

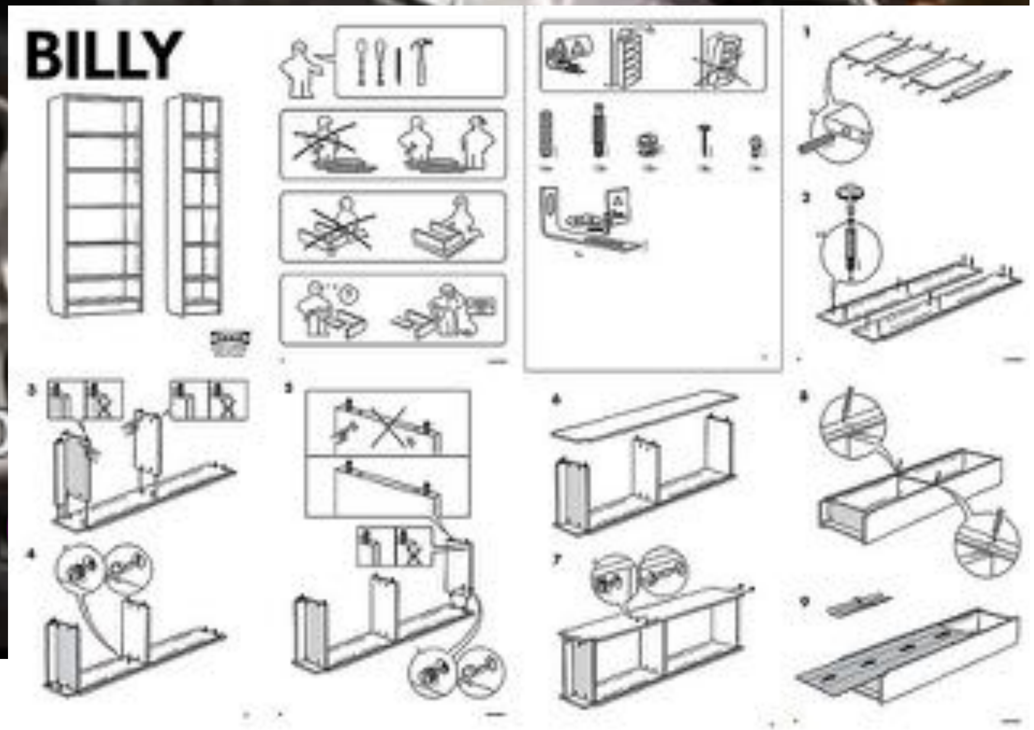
Weakly-supervised learning

Learn from available meta-data :

e.g. video + *text, speech, audio, …*

Learning by interaction with environment
(reinforcement learning)

Examples of meta-data: narrated instructional videos



[Alyarac et al., CVPR 2016]

Learn "vocabulary" of visual patterns from data

Weakly supervised machine learning: [Bach and Harchaoui'08, Xu et al.'04]

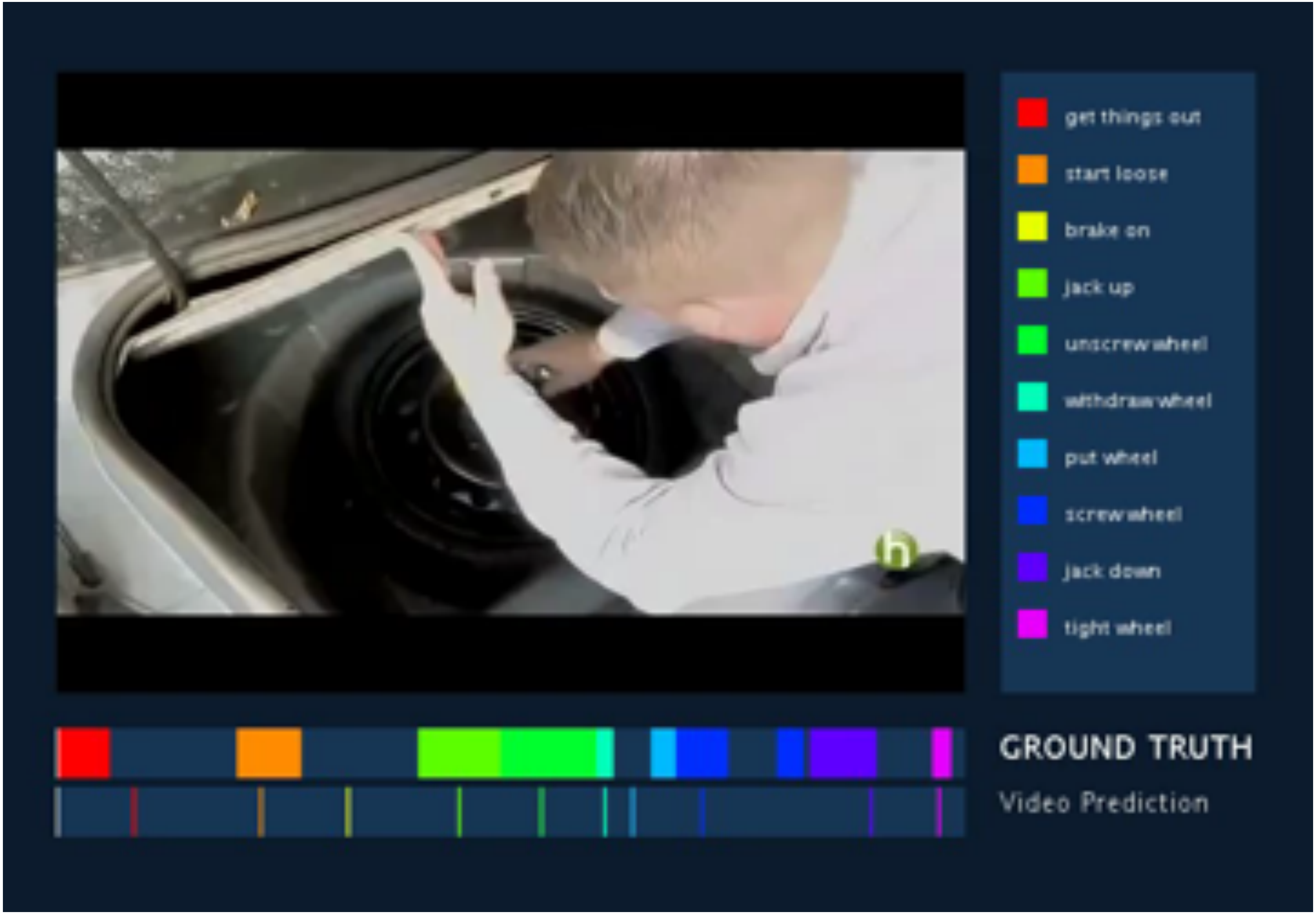
Given a set of inputs x_i and supervisory meta-data y_i, $i = 1,\ldots,N$
learn vocabulary $\hat{z}_i = f(x_i)$ by solving

$$\min_{f,z} \overbrace{\sum_{i=1}^{N} \ell(z_i, f(x_i))}^{\text{Discriminative loss on data}} + \overbrace{\Omega(f)}^{\text{Regularization}}$$

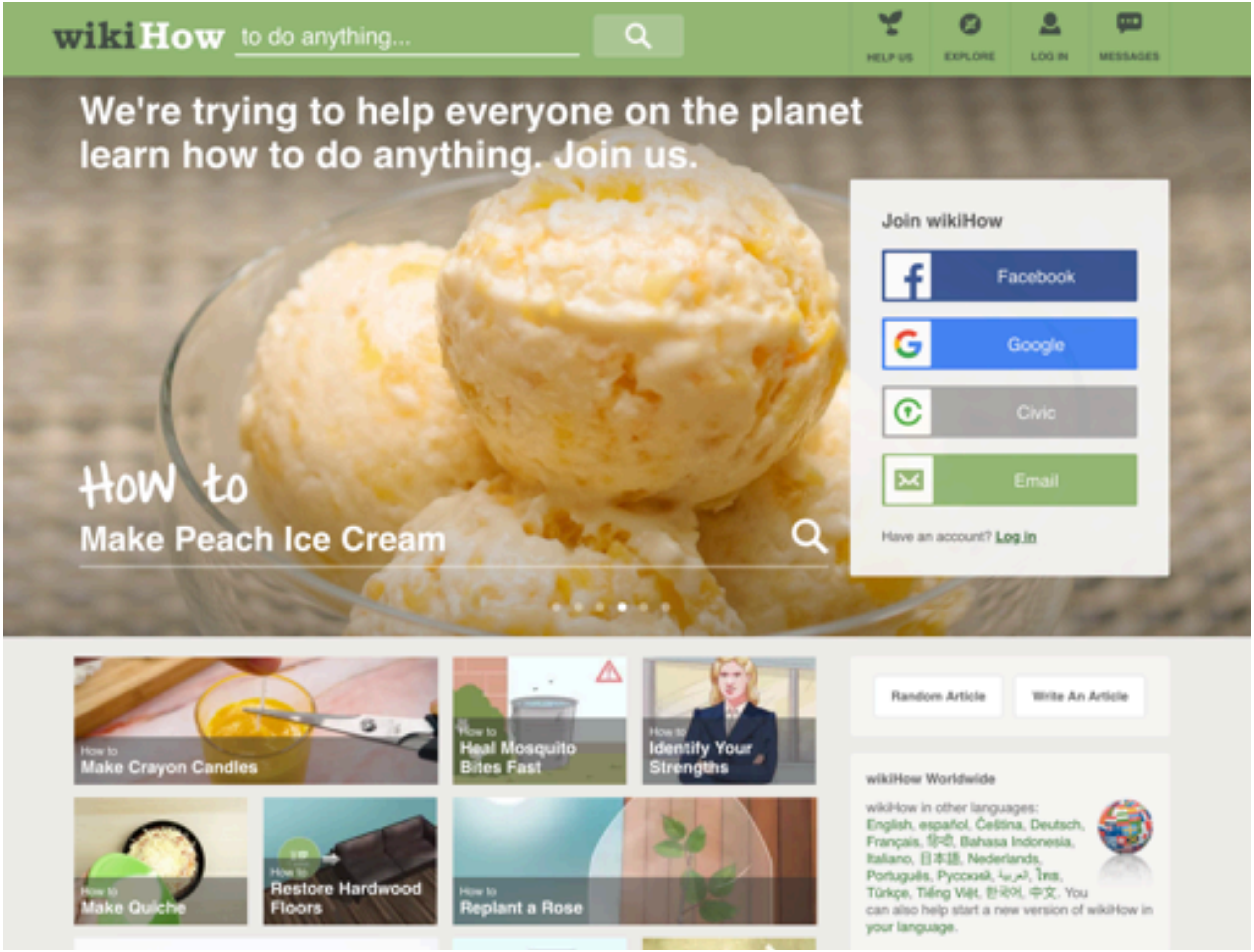
$$\boxed{\underbrace{s.t. \quad Az = y}_{\text{Supervision from available meta-data}}}$$

Scientific challenges:

- What is the appropriate form of constraints to incorporate different types of supervision?
- How to efficiently solve the problem for billions of inputs and 10,000s of patterns?



[Alayrac et al., CVPR 2016]


wikiHow
to do anything...
HELP US
EXPLORE
LOG IN
MESSAGES
We're trying to help everyone on the planet learn how to do anything. Join us.
Join wikiHow
Facebook
Google
Civic
Email
Have an account? Log in
How to
Make Peach Ice Cream
Random Article
Write An Article
How to
Make Crayon Candles
How to
Heal Mosquito Bites Fast
How to
Identify Your Strengths
wikiHow Worldwide
wikiHow in other languages:
How to
Make Quiche
How to
Restore Hardwood Floors
How to
Replant a Rose
can also help start a new version of wikiHow in your language.

Going WikiHow scale – the HowTo100M dataset

23K tasks • 1.3M videos • 130M clip-caption pairs

[Miech, Zhukov, Alayrac, Tapaswi, Laptev and Sivic, ICCV 2019]
[Miech, Alayrac, Smaira, Laptev, Sivic, Zisserman, CVPR 2020]

Going WikiHow scale

HowTo100M dataset

Dataset	Clips	Captions	Videos	Duration	Source	Year
Charades [42]	10k	16k	10,000	82h	Home	2016
MSR-VTT [52]	10k	200k	7,180	40h	Youtube	2016
YouCook2 [61]	14k	14k	2,000	176h	Youtube	2018
EPIC-KITCHENS [5]	40k	40k	432	55h	Home	2018
DiDeMo [11]	27k	41k	10,464	87h	Flickr	2017
M-VAD [46]	49k	56k	92	84h	Movies	2015
MPII-MD [37]	69k	68k	94	41h	Movies	2015
ANet Captions [22]	100k	100k	20,000	849h	Youtube	2017
TGIF [23]	102k	126k	102,068	103h	Tumblr	2016
LSMDC [38]	128k	128k	200	150h	Movies	2017
How2 [39]	185k	185k	13,168	298h	Youtube	2018
HowTo100M	**136M**	**136M**	**1.221M**	**134,472h**	Youtube	2019

23K tasks • 1.3M videos • 130M clip-caption pairs

Learn joint text-video embedding

Given a set of inputs x_i and supervisory meta-data y_i, $i = 1, \ldots, N$
learn embeddings $f(x_i)$ and $g(y_i)$ by solving

$$\min_{f,g} \underbrace{\sum_{i=1}^{N} \ell(z_i, f(x_i))}_{\text{Discriminative loss on data}} + \underbrace{\Omega(f, g)}_{\text{Regularization}}$$

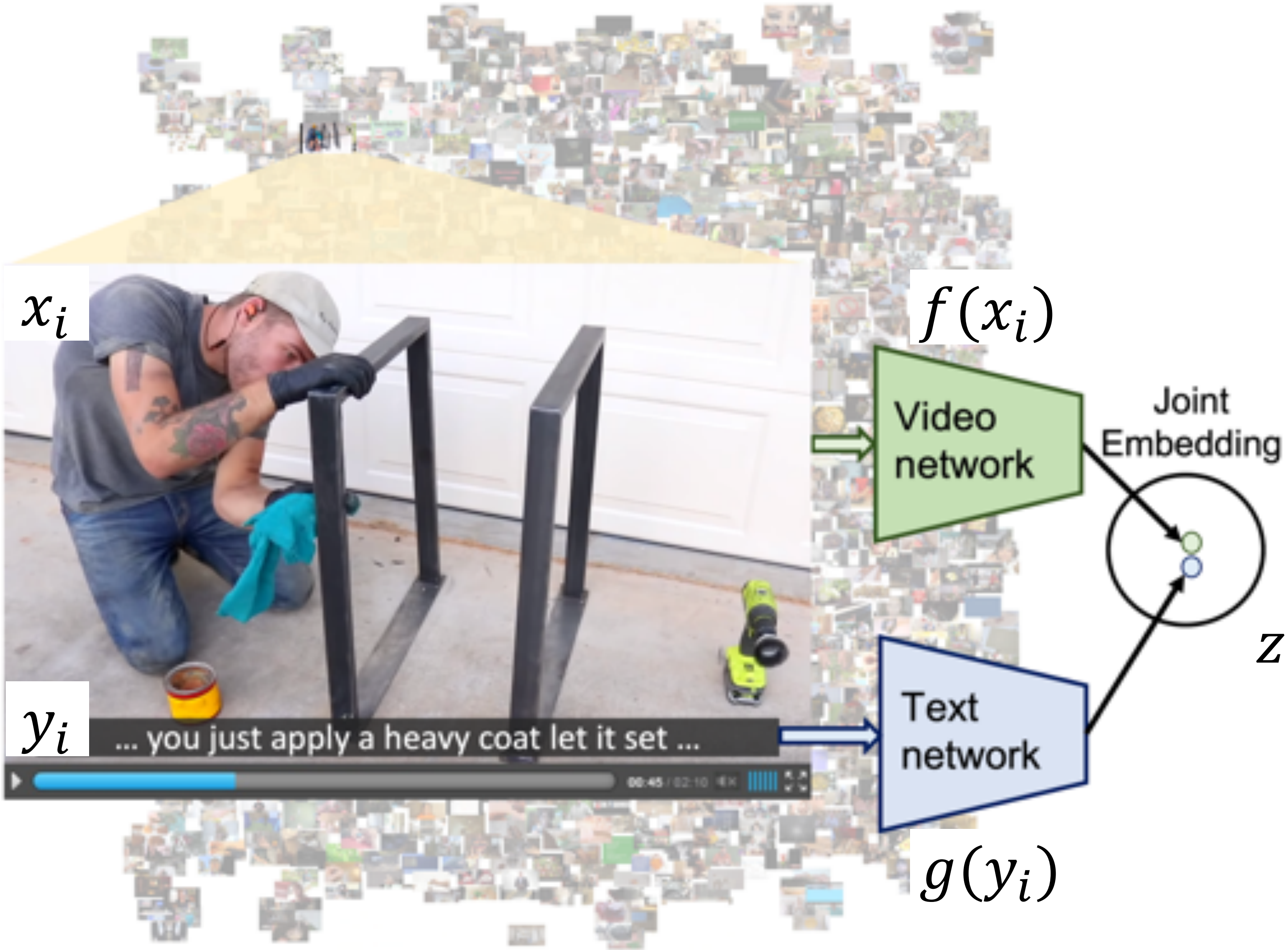
$$\boxed{\text{s.t.} \quad \underbrace{z_i = g(y_i)}_{\text{Supervision from available meta-data}}}$$

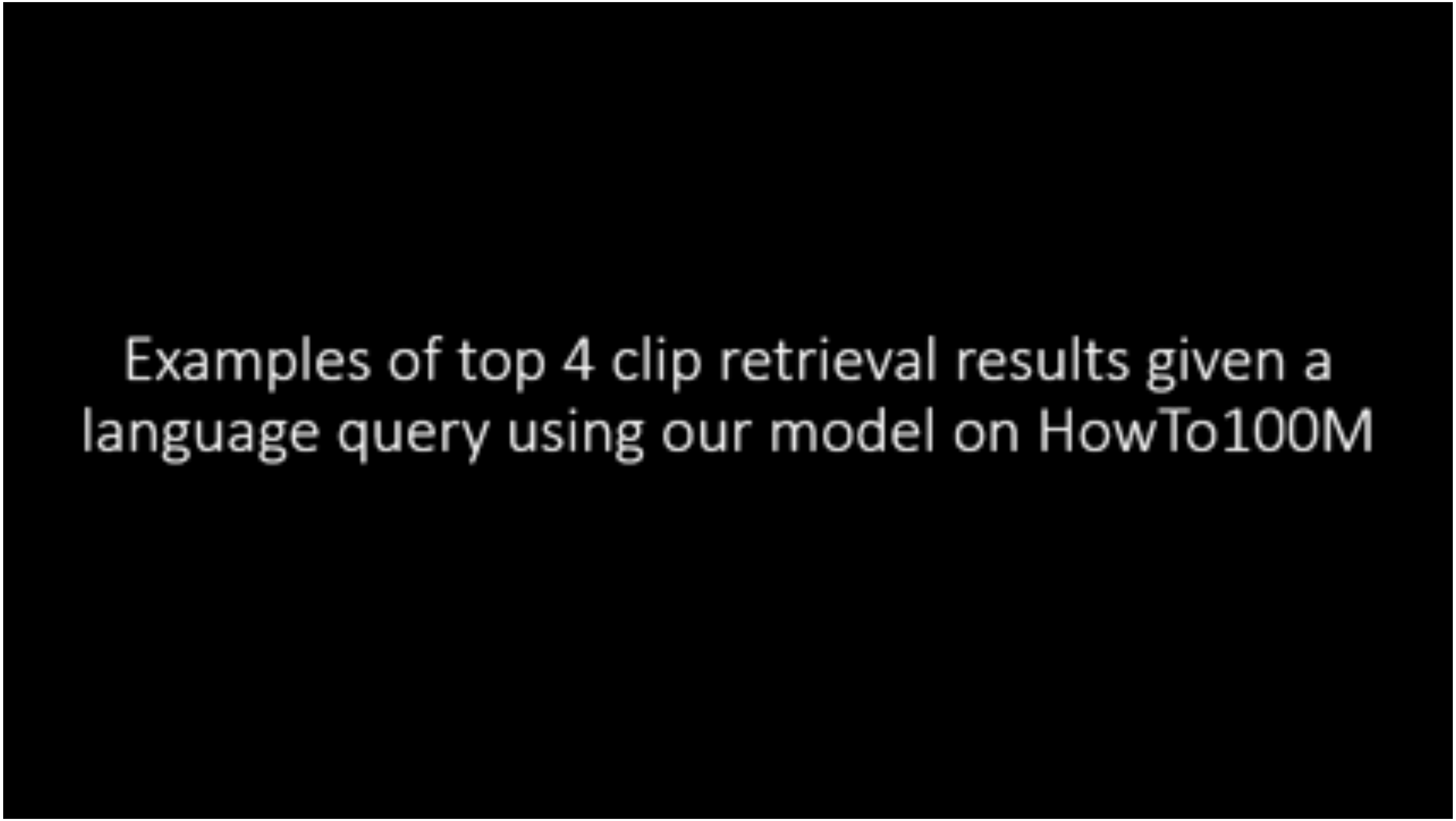
Scientific challenges:

- What is the appropriate form of these mappings and the loss?
- How to learn the mappings from the weak and noisy supervision?

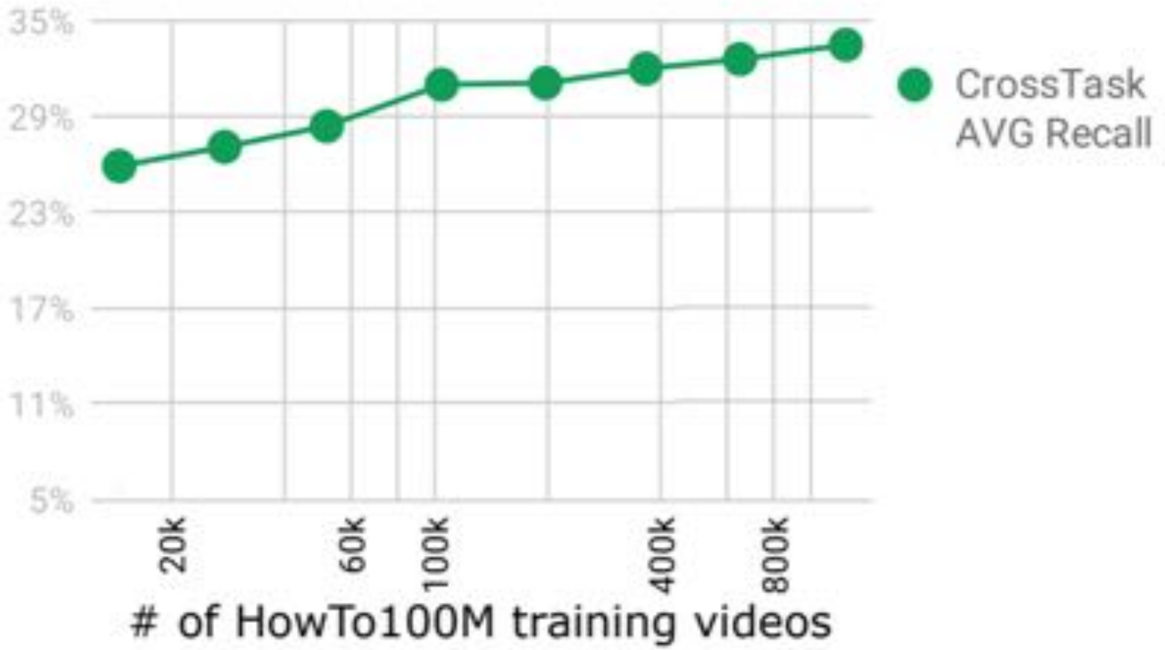
[Gong et al., 2013; Mikolov et al., 2013; Weston et al., 2011; Frome et al., 2013]

Learn joint text-video embeddings from instructional videos



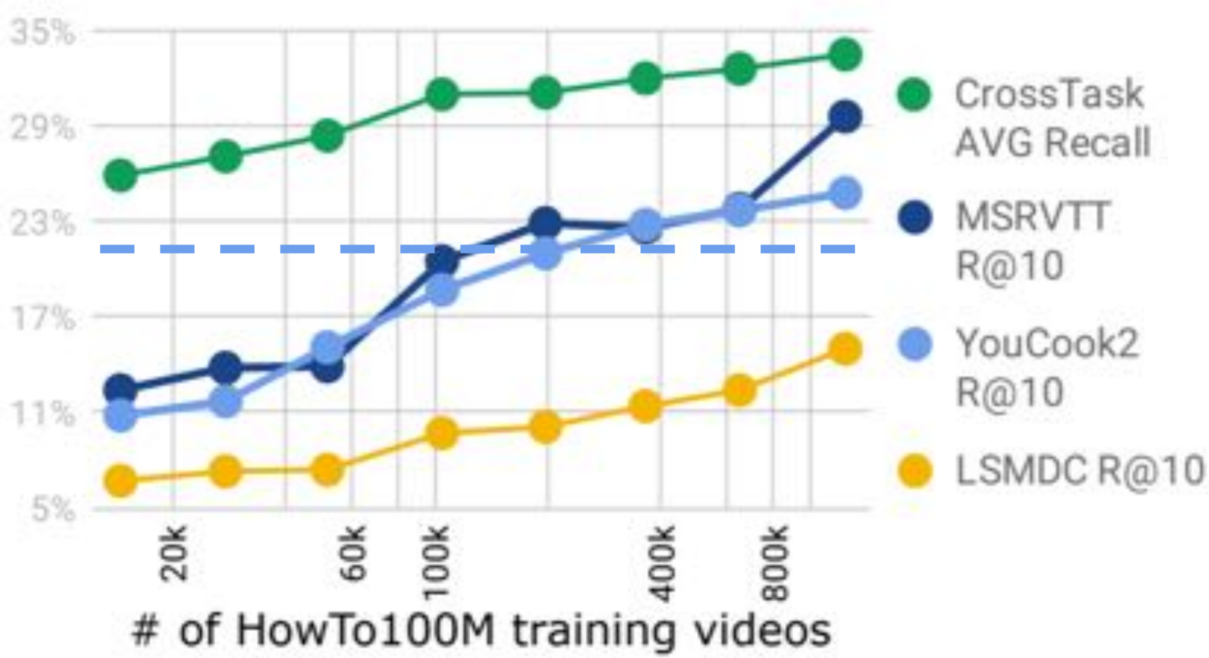

Examples of top 4 clip retrieval results given a language query using our model on HowTo100M

Results: Text-to-video retrieval



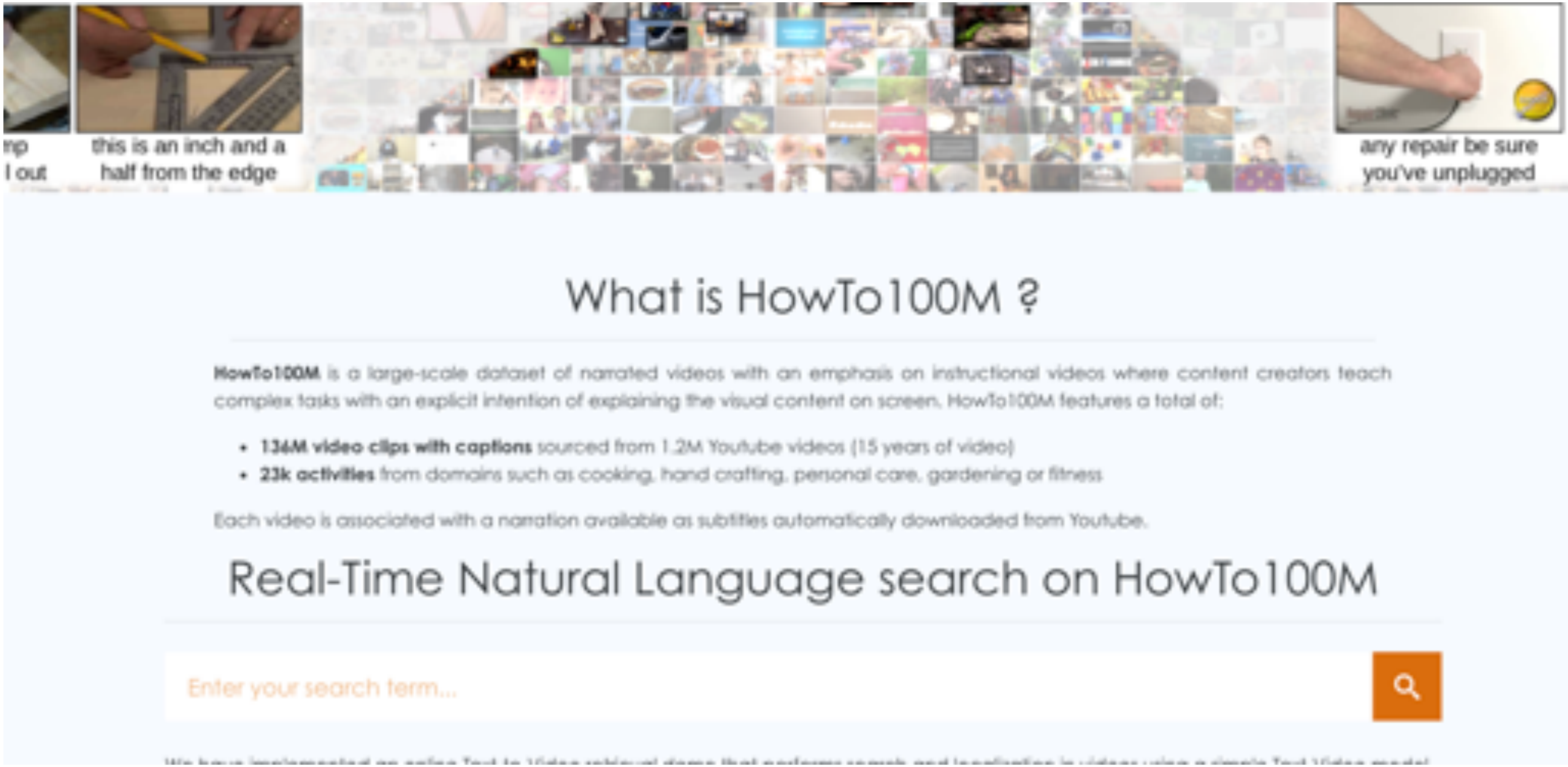
Results: Text-to-video retrieval

Fully supervised with manual annotations



Code, models, data and **demo** available online

https://www.di.ens.fr/willow/research/howto100m/
https://www.di.ens.fr/willow/research/mil-nce/



[Miech, Zhukov, Alayrac, Tapaswi, Laptev and Sivic, ICCV 2019]
[Miech, Alayrac, Smaira, Laptev, Sivic, Zisserman, CVPR 2020]

Scientific questions

1. Learning vocabulary of patterns from data
2. Generalization to new conditions and situations
3. Reasoning about visual data

How to generalize to new conditions and situations?

Problem: Large image variation due to viewpoint, scale, illumination, occlusion, intra-class variation, …

Different ways to perform the same action

Different viewpoint, occlusion, intra-class variation, …

Scientific challenge: What is the appropriate form of f(x)

$$\min_{f,z} \sum_{i=1}^{N} \ell(z_i, \overbrace{\boxed{f(x_i)}}) \quad + \quad \Omega(f)$$

$$s.t. \quad Az = y$$

- to capture the image variation, and
- can be learnt from few training examples?

Image representations based on convolutional neural networks (CNNs)

Multi-layer nested representation

$$\overbrace{z}^{\text{Output representation}} = \underbrace{f^n}_{\text{“Layer” n}}(\ldots \underbrace{f^2}_{\text{“Layer” 2}}(\underbrace{f^1(\overbrace{x}^{\text{Input image}})}_{\text{“Layer” 1}})\ldots)$$

[Rosenblatt’57], [Hubel&Wiesel’59], [Fukushima’80], [Rumelhart’86], [LeCun et al.’89], [LeCun et al.’98], [Hinton&Salakhutdinov’06], [Krizhevsky’12], …

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where each layer has a form:

$$f(x) = \sigma(\underbrace{W}_{}x + \underbrace{b}_{})$$

Learnable parameters

[Rosenblatt’57], [Hubel&Wiesel’59], [Fukushima’80], [Rumelhart’86], [LeCun et al.’89], [LeCun et al.’98], [Hinton&Salakhutdinov’06], [Krizhevsky’12], …

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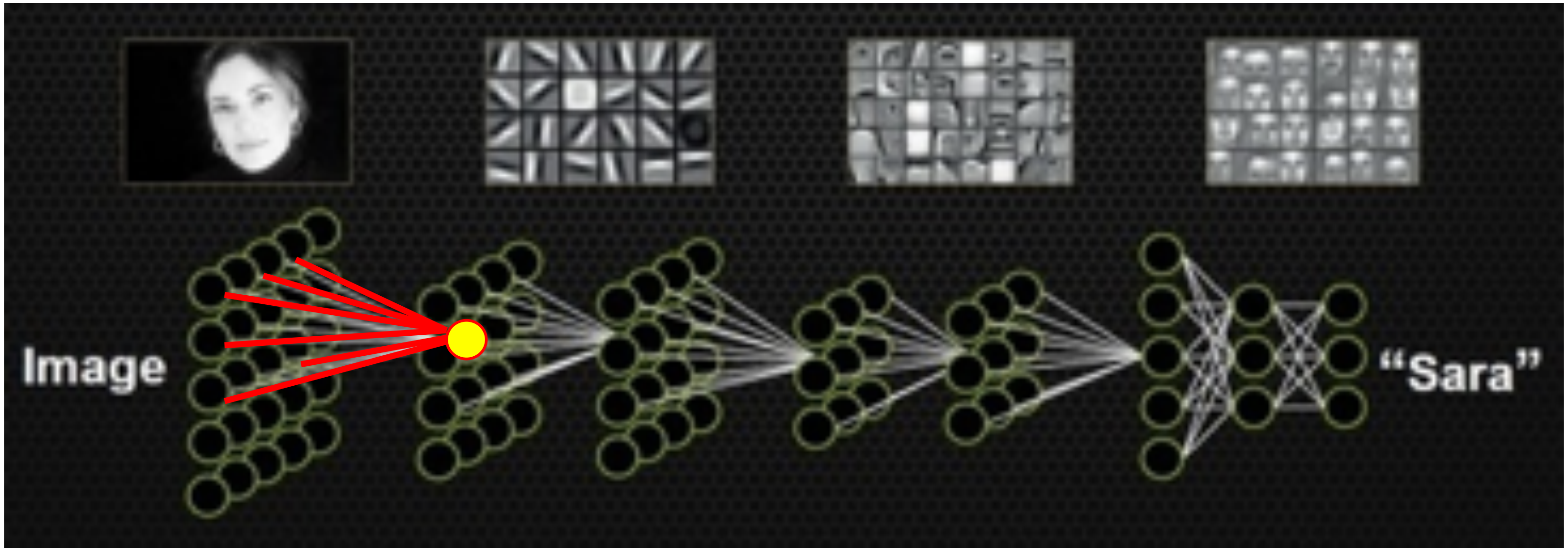

Source: A. Shivkumar

[Rosenblatt'57], [Hubel&Wiesel'59], [Fukushima'80], [Rumelhart'86], [LeCun et al.'89], [LeCun et al.'98], [Hinton&Salakhutdinov'06], [Krizhevsky'12], …

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Learnable parameters

The learnt CNN parameters are transferable across tasks.

[Oquab et al. ’13, Oquab et al.‘14],
See also: [Girshick et al.’14, Sermanet et al.’14, Zeiler&Fergus’13, Donahue et al.’13]

Image representations based on convolutional neural networks (CNNs)

Multi-layer nested representation

$$\overbrace{z}^{\text{Output representation}} = \underbrace{f^n}_{\text{"Layer" n}}(\ldots \underbrace{f^2}_{\text{"Layer" 2}}(\underbrace{f^1(\overbrace{x}^{\text{Input image}})}_{\text{"Layer" 1}})\ldots)$$

where each layer has a form:

$$f(x) = \sigma(\underbrace{W}_{}x + \underbrace{b}_{})$$

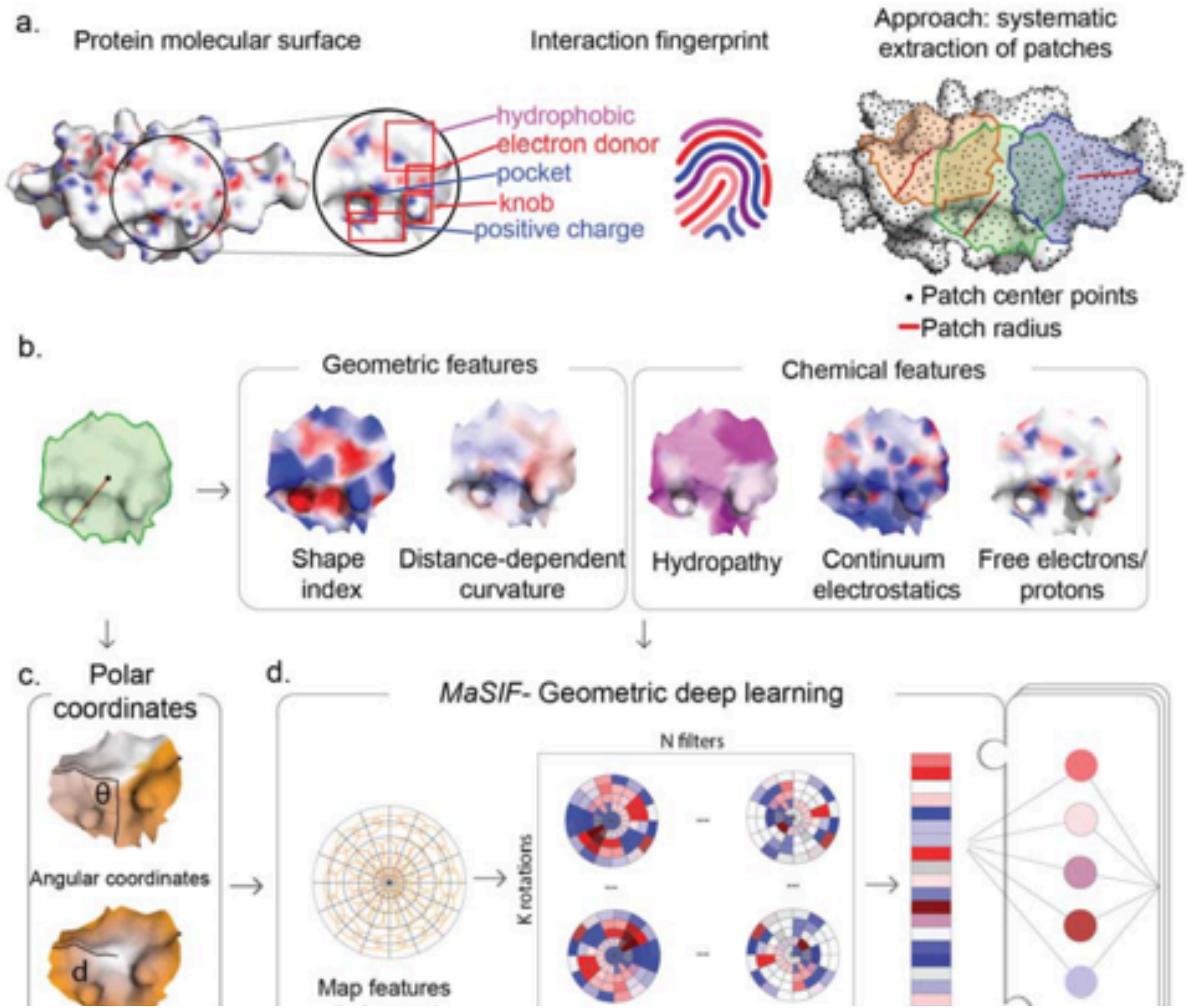
Learnable parameters

But: good for 2D images. Video and 3D objects are still open.

[Oquab et al. ’13, Oquab et al.‘14],
See also: [Girshick et al.’14, Sermanet et al.’14, Zeiler&Fergus’13, Donahue et al.’13]

Input: 3D point cloud
Output: 3D object segmentation

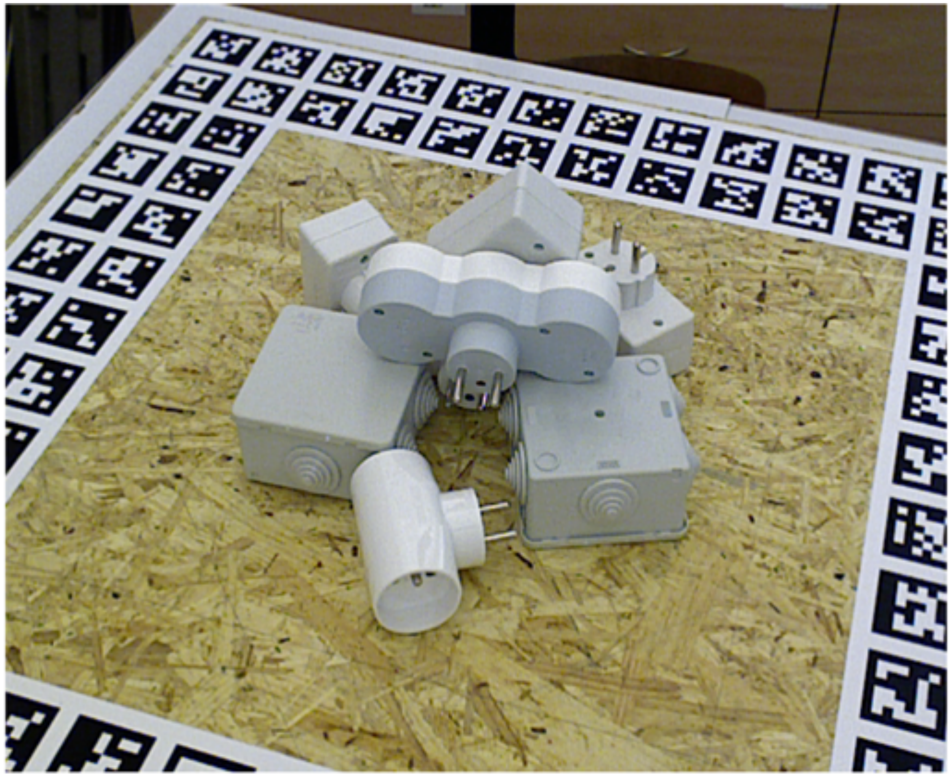
[Engelmann et al., CVPR 2020]



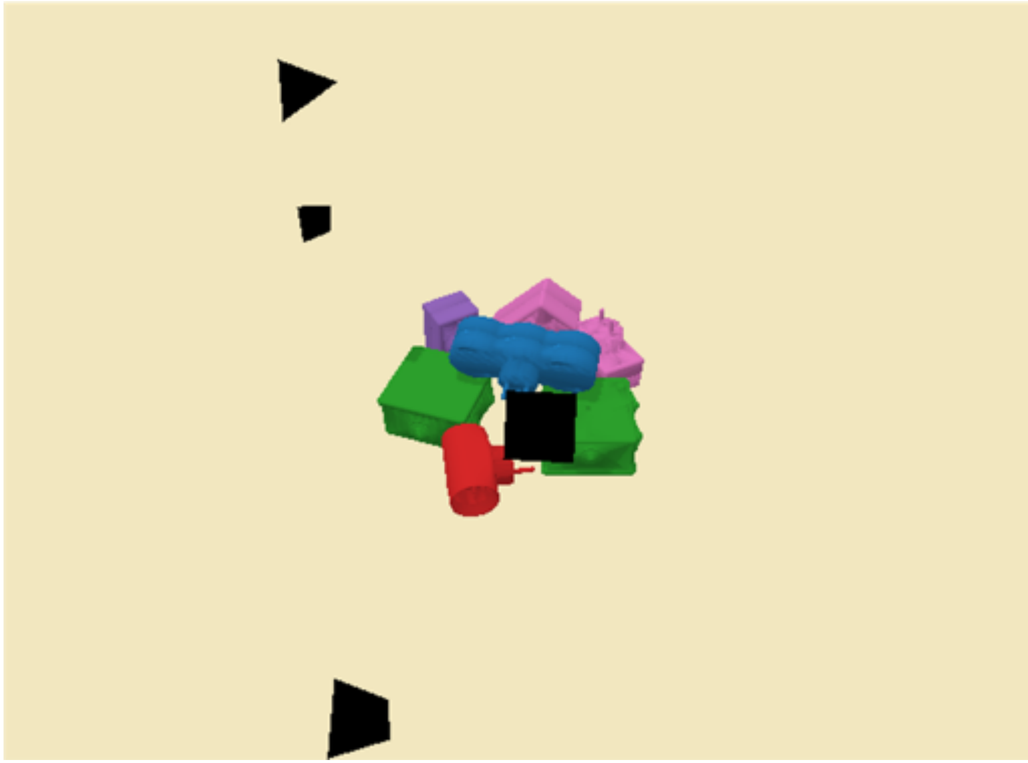
Gainza et al., 2020, Deciphering interaction fingerprints from **protein molecular surfaces using geometric deep learning**, Nature methods.

Object 6D pose estimation

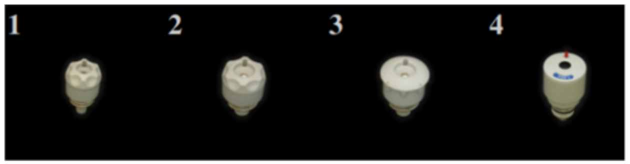
Input image(s)

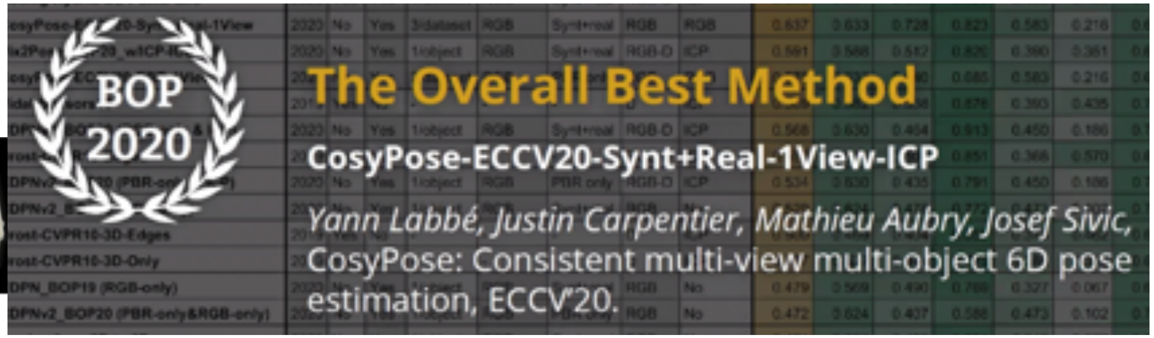


Output 3D scene



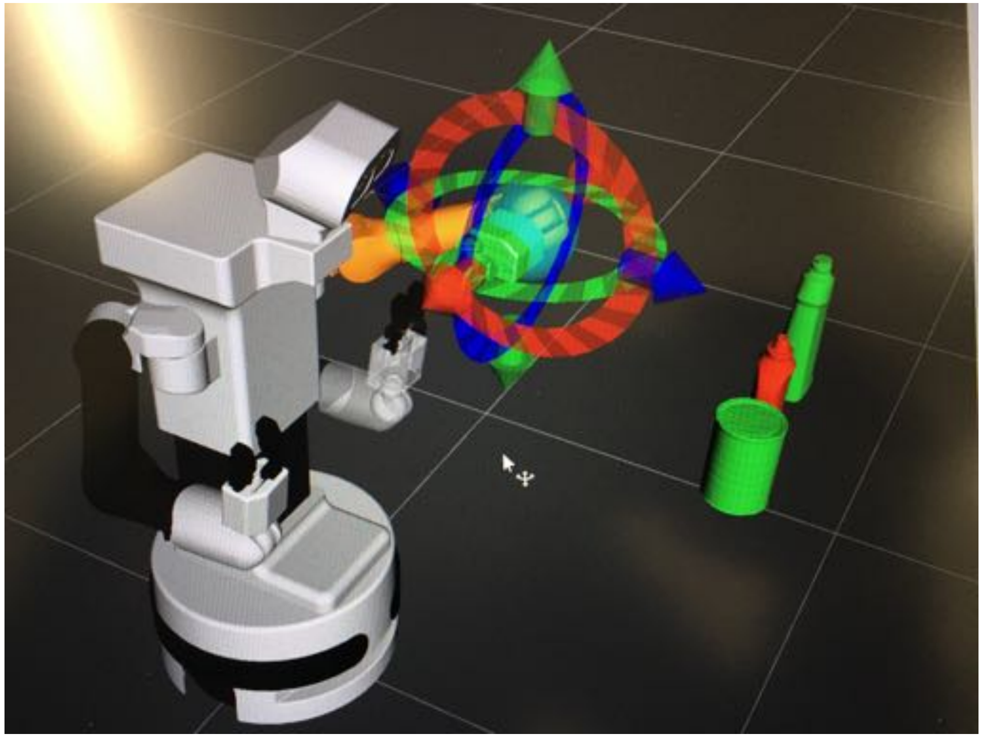
Known 3D models





[Labbe, Carpentier, Aubry, Sivic, ECCV 2020] Code: www.di.ens.fr/willow/research/cosypose/

Towards learnable perception – planning – action

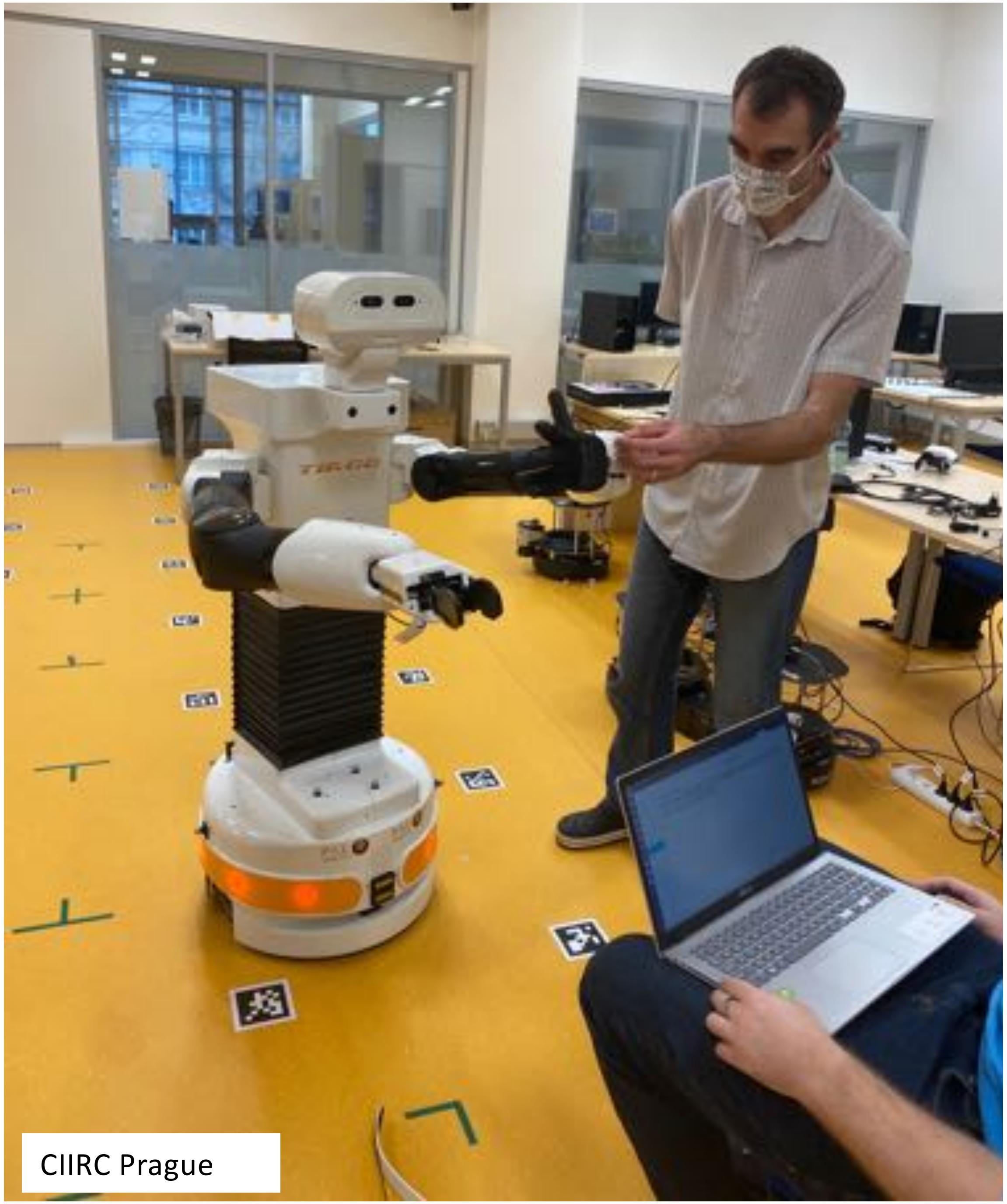


Images by I. Kalevatykh

[Multi-view multi-object 6D pose estimation via robust scene consistency optimization
Y. Labbé, J. Carpentier, M. Aubry, J.Sivic, ECCV 2020]

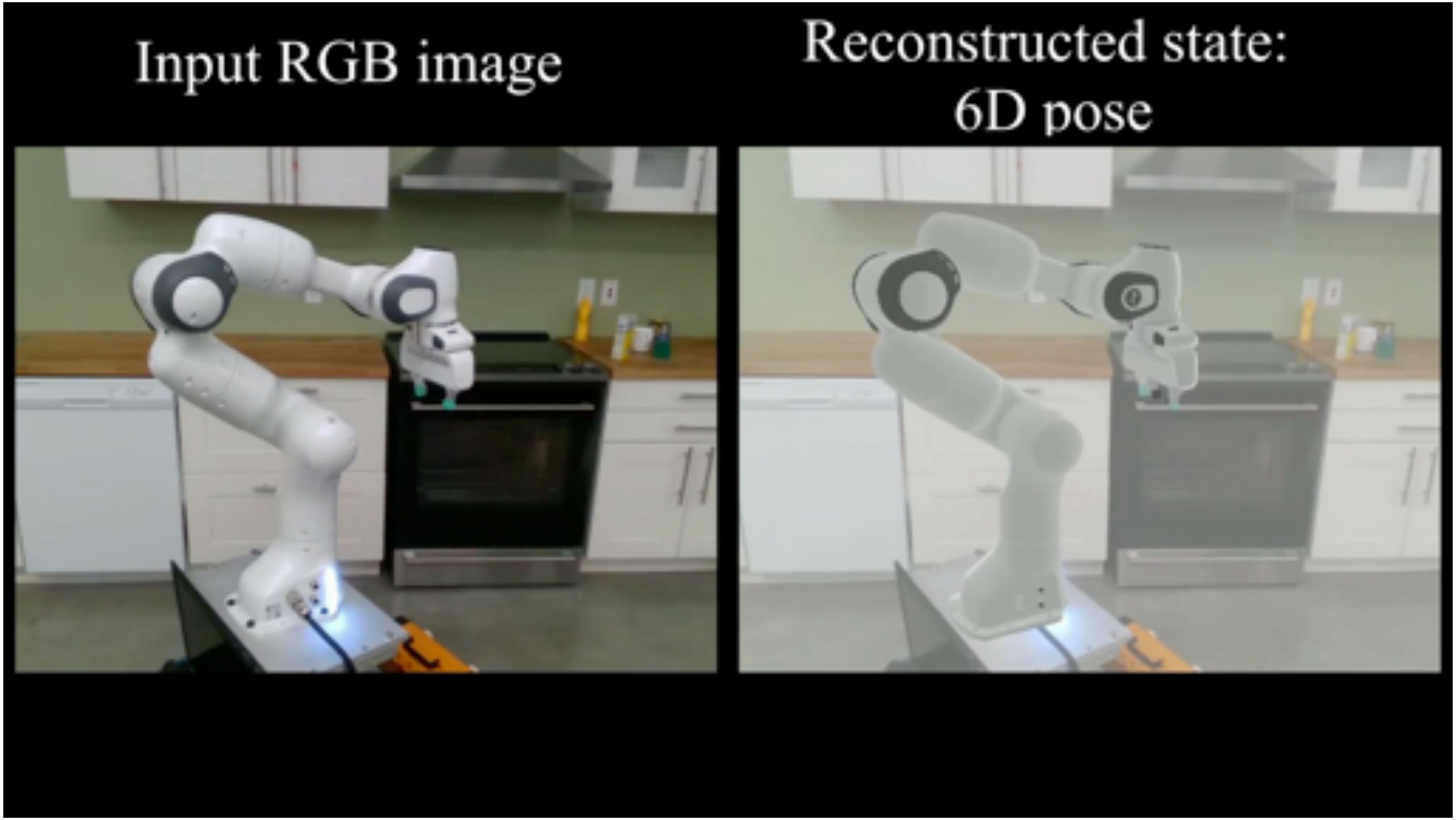
Generalization to different environments

Video by I. Kalevatykh
Inria Paris



CIIRC Prague

6D pose estimation of articulated objects



[Single-view robot pose and joint angle estimation via render&compare
Y. Labbé, J. Carpentier, M. Aubry, J.Sivic, 2020].

Scientific questions

1. Learning vocabulary of patterns from data

2. Generalization to new conditions and situations

3. Reasoning about visual data

What is reasoning about visual data?

Figure 1: Examples from the new GQA dataset for visual reasoning and compositional question answering:
*Is the **bowl** to the right of the **green apple**?*
*What type of **fruit** in the image is **round**?*
*What color is the **fruit** on the right side, red or **green**?*
*Is there any **milk** in the **bowl** to the left of the **apple**?*

[Hudson and Manning, CVPR 2019]
Visualreasoning.net

Recognizing relations between entities is hard

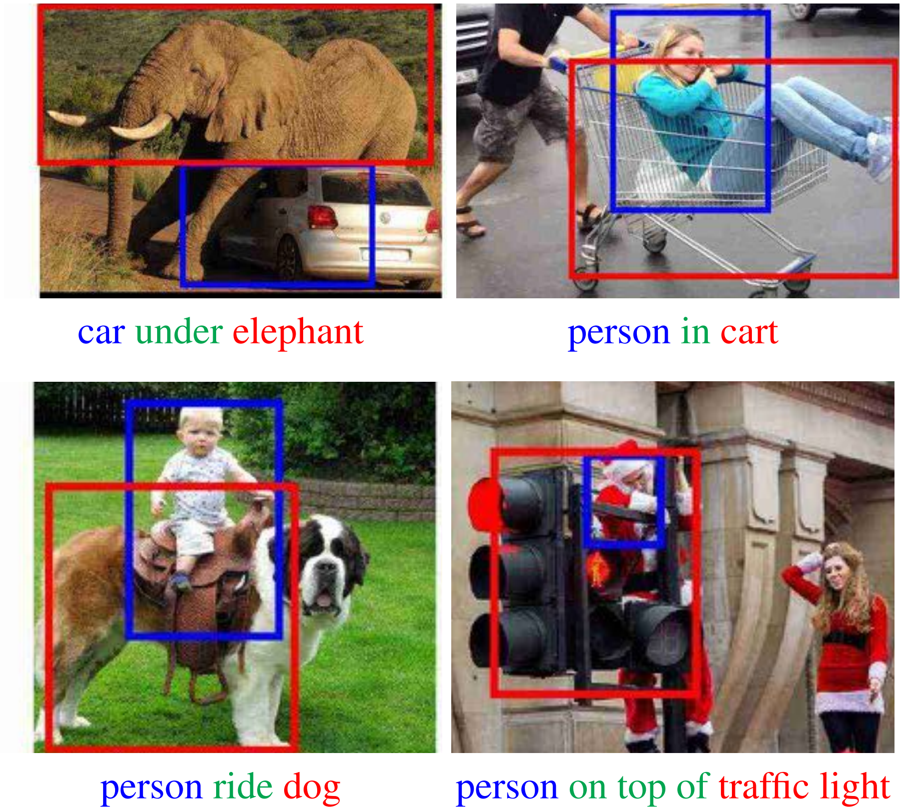
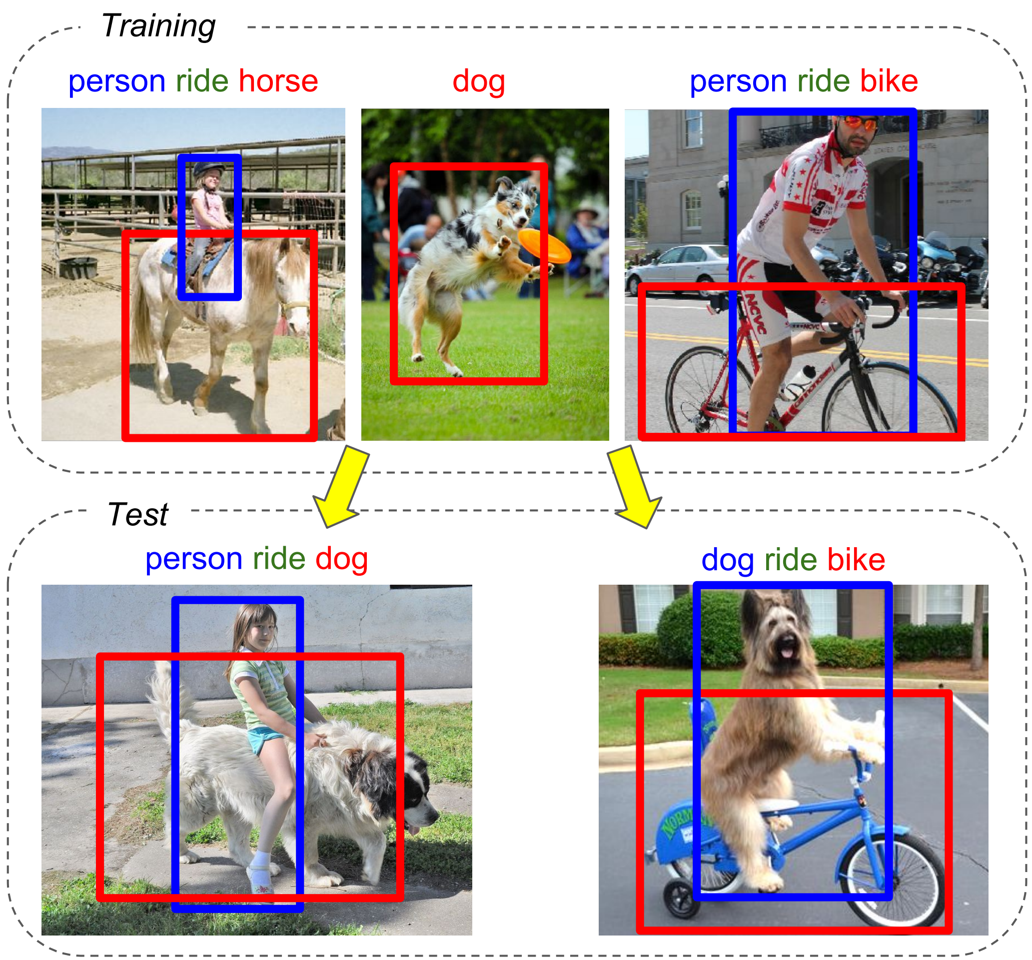


Figure 1: Examples of top retrieved pairs of boxes in UnRel dataset for unusual queries (indicated below each image) with our weakly-supervised model described in 3.2.

[Peyre, Laptev, Schmid, Sivic, ICCV 2017]



[Peyre, Laptev, Schmid, Sivic, ICCV 2019]

Neuro-symboling reasoning?

Differentiable first order logic

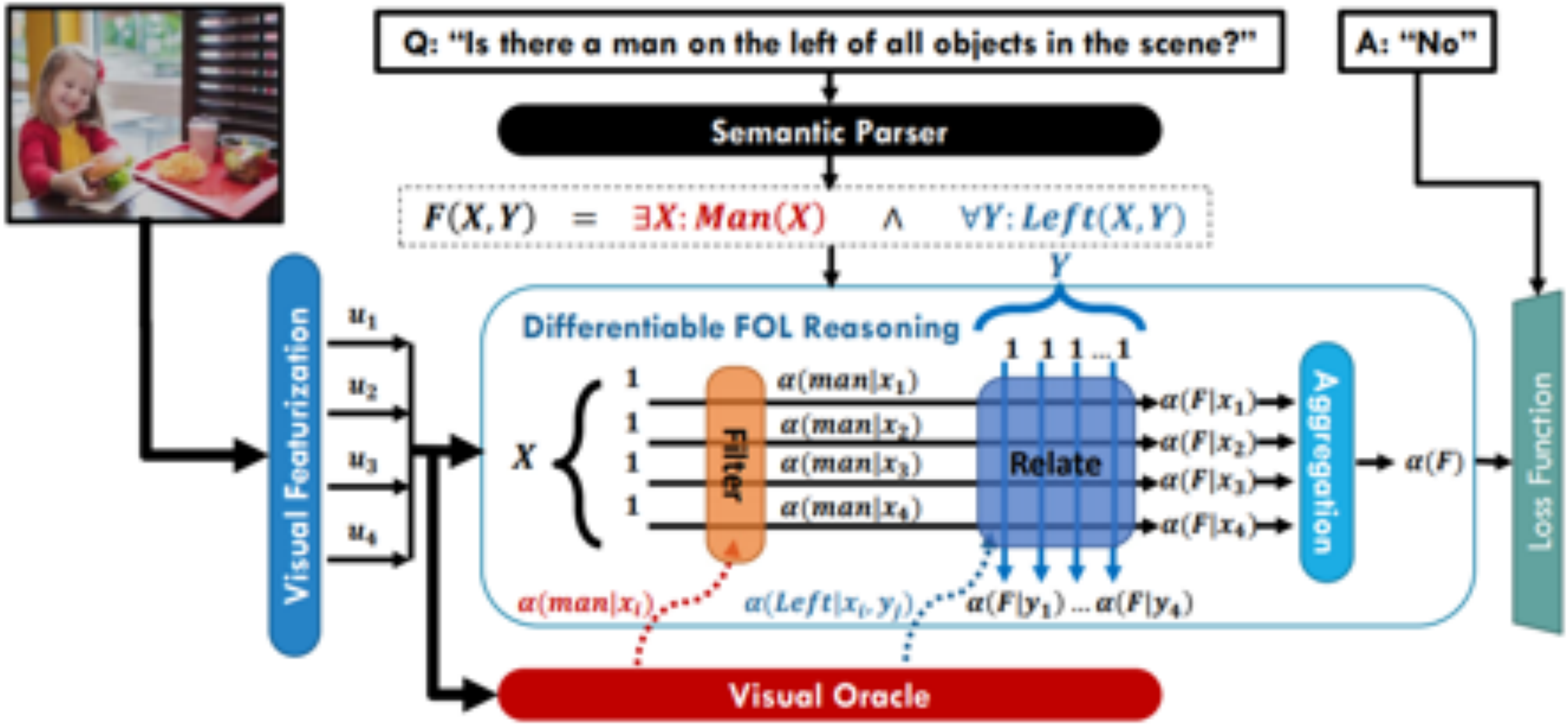


Figure 1. The multi-step question answering process in the ∇-FOL framework, based on differentiable first-order logic.

[Neuro-Symbolic Visual Reasoning: Disentangling "Visual" from "Reasoning"
Saeed Amizadeh, Hamid Palangi, Oleksandr Polozov, Yichen Huang, Kazuhito Koishida, ICML 2020.]

Learn to “reason implicitly” (from lots of data)

Just Ask: Learning to Answer Questions from Millions of Narrated Videos

Antoine Yang[1,2], Antoine Miech[1,2,+], Josef Sivic[3], Ivan Laptev[1,2], Cordelia Schmid[1,2]

[1]ENS [2]Inria Paris [3]CIIRC CTU

https://www.di.ens.fr/willow/research/just-ask/

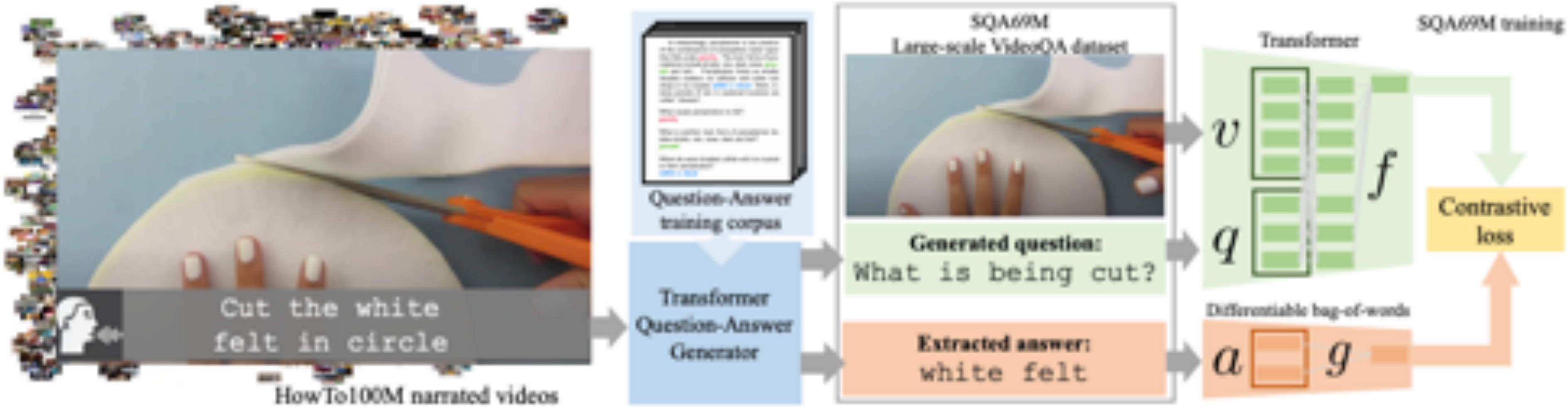


Figure 1: We leverage millions of narrated videos and improve VideoQA with automatic pretraining. We generate question and answer pairs from speech transcripts with a state-of-the-art text-to-text transformer pipeline. Then we use the generated dataset to train a VideoQA model with a contrastive loss *without additional visual annotation*. The pretrained model can then be used for zero-shot or finetuning.

[https://arxiv.org/pdf/2012.00451.pdf]

Learn to “reason implicitly” (from lots of data)

Question: What type of material is the man touching?
GT Answer: wood (5)
VQA-MMT+PT-QA: leather
VQA-MMT+PT-VA: clamps
Ours: wood

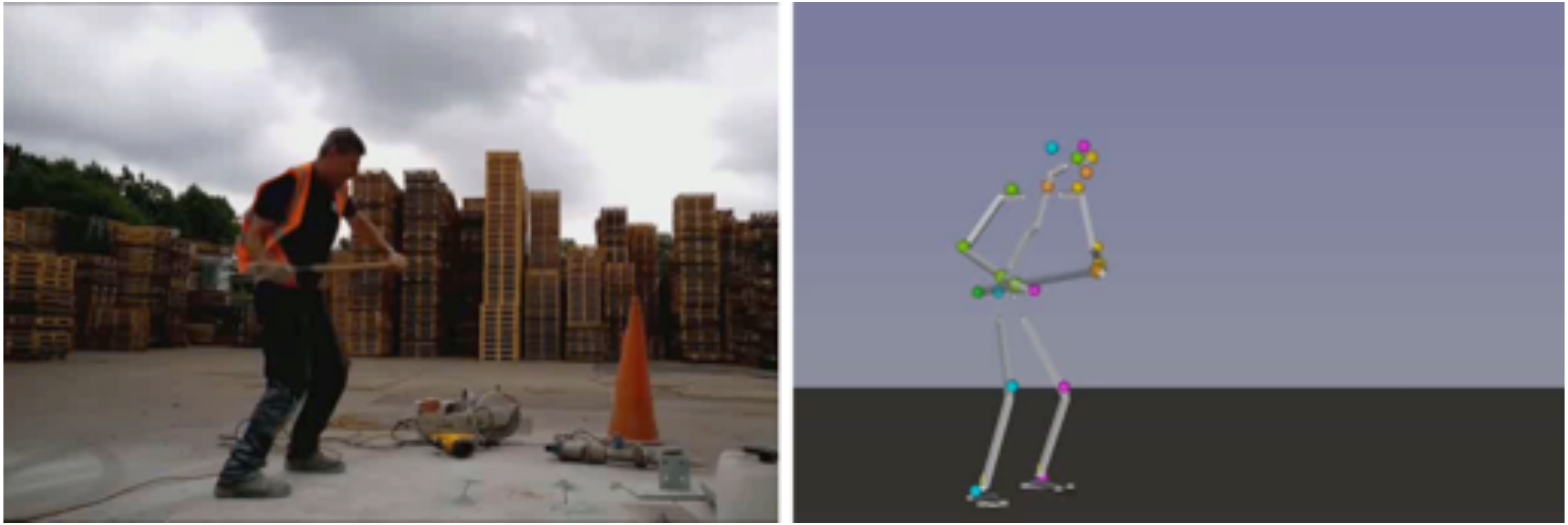
Question: What animal is shown as a cutout?
GT Answer: deer (3), reindeer (2)
VQA-MMT+PT-QA: wolf
VQA-MMT+PT-VA: paintbrush
Ours: reindeer

[https://arxiv.org/pdf/2012.00451.pdf]

Relations are dynamic and in 3D

Input:
- a monocular RGB video

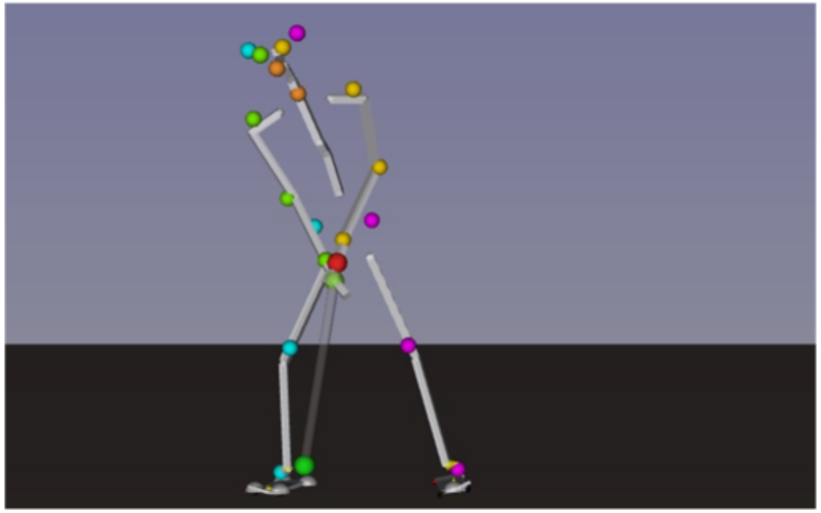
Output:
- Person & object 3D motion trajectories
- Contact positions and contact forces



[Li, Sedlar, Carpentier, Mansard, Laptev, Sivic, CVPR 2019, **best paper finalist**]

Estimation Stage

Problem formulation



$$\underset{\underline{x},\underline{u},\underline{c}}{\text{minimize}} \quad \sum_{e\in\{\mathrm{h},\mathrm{o}\}} \int_0^T l^e(x,u,c)\,\mathrm{d}t, \quad \text{(Objective function)}$$

$$\begin{aligned}\text{subject to} \quad & \kappa(x,c) = 0 \quad \text{(contact motion model)},\\ & \dot{x} = f(x,c,u) \quad \text{(full-body dynamics)},\\ & u \in \mathcal{U} \quad \text{(force model)},\end{aligned}$$

Relations can change objects

Actions often modify **states of object**.

Empty cup — **Fill** — **Full** cup

State 1 → Action → *State 2*

Also, e.g. **open** a *door,* **fill** a *water bottle,* ***cut*** *bread,…*

Can we learn the set of **actions** and **object states** from data?

[Alayrac et al., ICCV 2017]

Can we learn to reason and plan from data?

Given a set of inputs x_i and supervisory meta-data y_i, $i = 1, \ldots, N$
learn embeddings $f(x_i)$ and $g(y_i)$ by solving

$$\min_{f,g} \underbrace{\sum_{i=1}^{N} \ell(z_i, f(x_i))}_{\text{Discriminative loss on data}} + \underbrace{\Omega(f, g)}_{\text{Regularization}}$$

$$\boxed{\underbrace{\text{s.t.} \quad z_i = g(y_i)}_{\text{Supervision from available meta-data}}}$$

Scientific challenges:

- How to incorporate the geometric and physical constraints on the latent space z?
- How to learn such constraints from data?

[Gong et al., 2013; Mikolov et al., 2013; Weston et al., 2011; Frome et al., 2013]

Scientific questions

1. Learning vocabulary of patterns from data
2. Generalization to new conditions and situations
3. Reasoning about visual data
4. Plan and Act on the world. Learn from the interactions

Learning to Use Tools by Watching Videos

Input: instructional video from YouTube

Output: tool manipulation skill transferred to a robot

[K. Zoryna et al., 2021]

Towards intelligent perception for the real world

Soon: We will see more applications in specific constrained set-ups.

[Microsoft HoloLens]

[Darpa robot challenge]

Long-term: autonomous learning, reasoning and interaction.

Collaboration with other research domains: machine learning, robotics, natural language processing, speech understanding, control, ...

Thank you