CSE 599 Empirical Foundations of Machine Learning

University of Washington, Autumn 2021

Normally class starts at 10 am, today 10:05 so people can find the room.

Welcome!

Introduction

Instructor: Ludwig Schmidt

MIT (PhD) → Berkeley (postdoc) → UW (faculty) - started this fall.

Research interests: exactly this class!

TA: Mitchell Wortsman

UW (3rd year PhD student advised by Ali Farhadi)

Research interests: still narrowing it down …

1. Logistics

2. Background & motivation

3. Course outline

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Basics

Room: CSE2 G04 (Gates building)

Time: Tuesday / Thursday 10 - 11:20 am

Website: https://mlfoundations.github.io/au21/   (announcements, material, etc.)

Registration: Now available! (see link on website)

Please provide feedback if you see things we can improve or suggestions for topics

Ask questions any time!

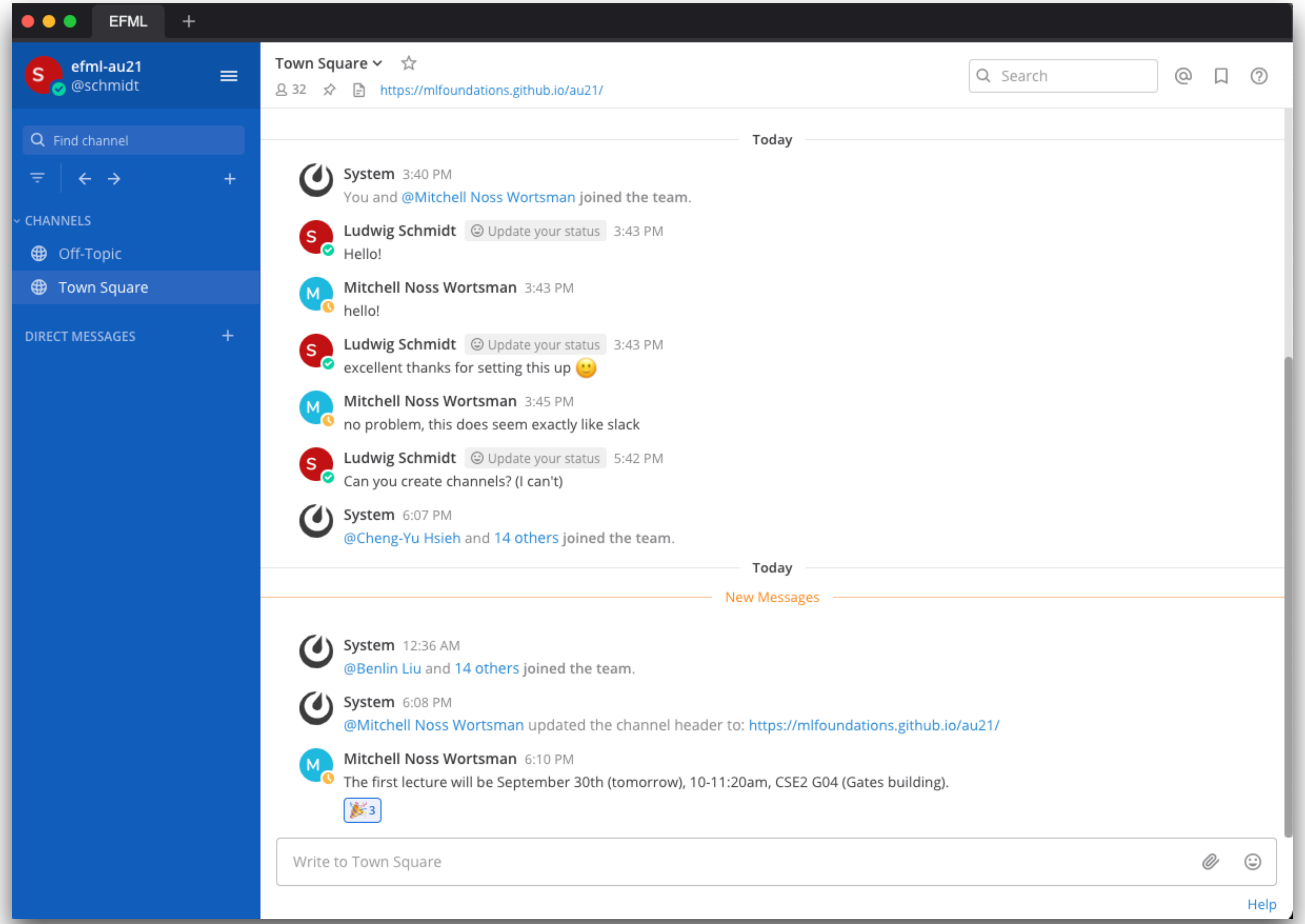
Communication: Mattermost

Similar to Slack but FERPA-compliant (Family Educational Rights and Privacy Act)

Should be accessible by anyone at UW (may require a request if not CSE)

Please log in if you have not already done so! (It's easy)

Feel free to ask any questions related to the course, post papers, etc.



(Remote) Attendance

In-person attendance is **strongly** encouraged.
→ Experience will be better, especially for discussions.

We have a Zoom link for a few people who cannot join in person, but the link is secret :-)

If you cannot join for a specific session, message Mitchell and me the day before and we will send you the link.

1. Logistics

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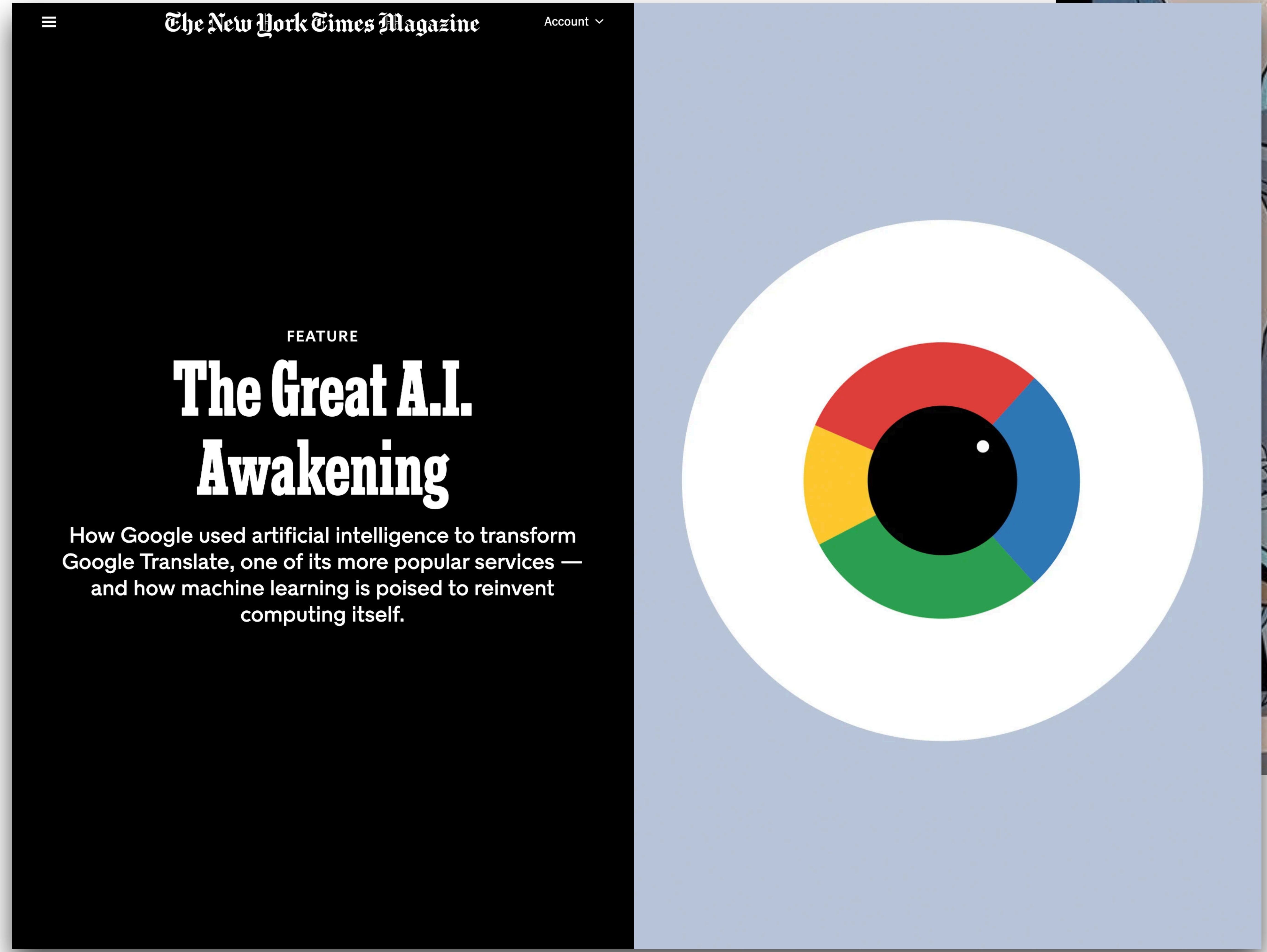
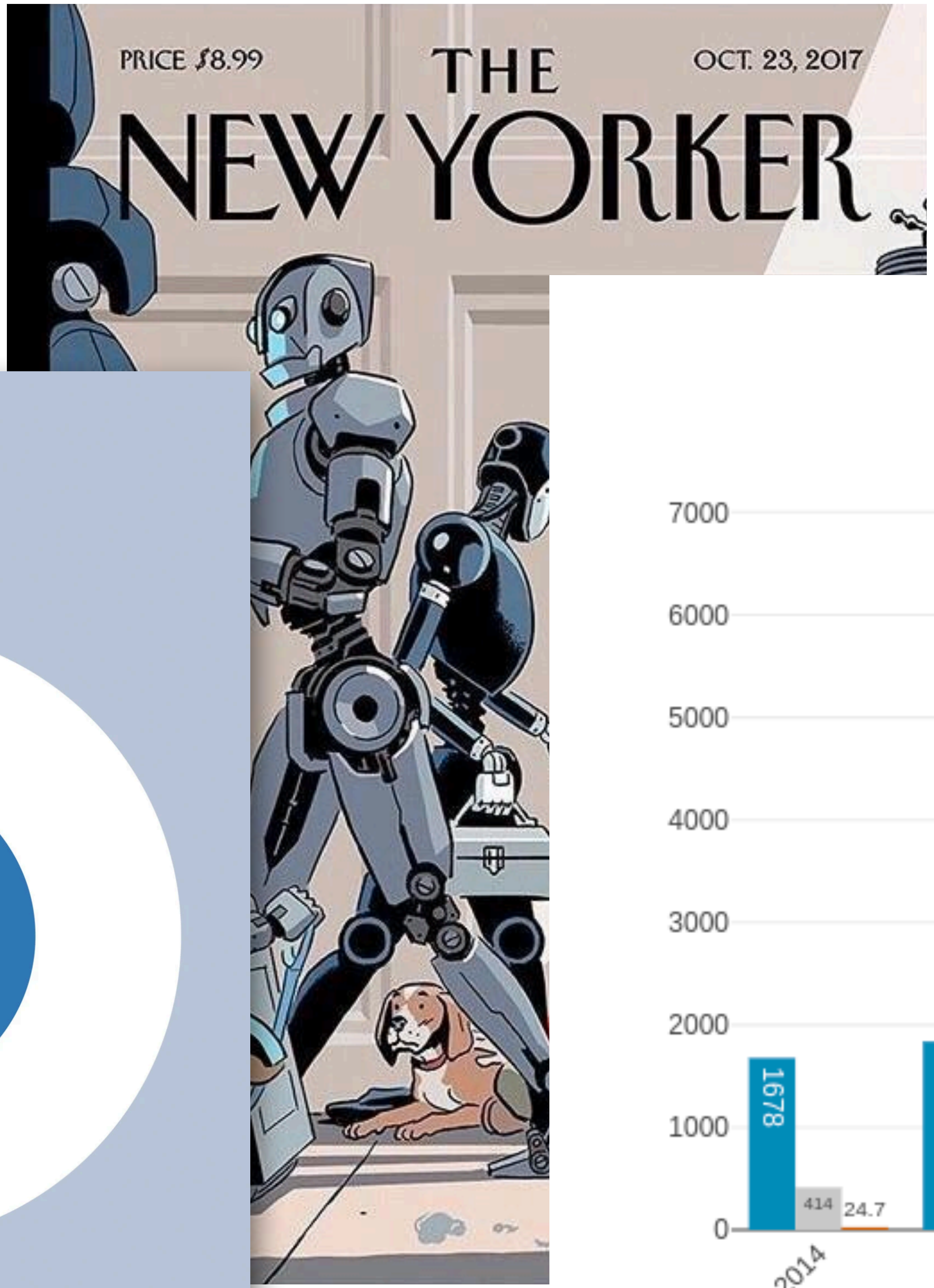
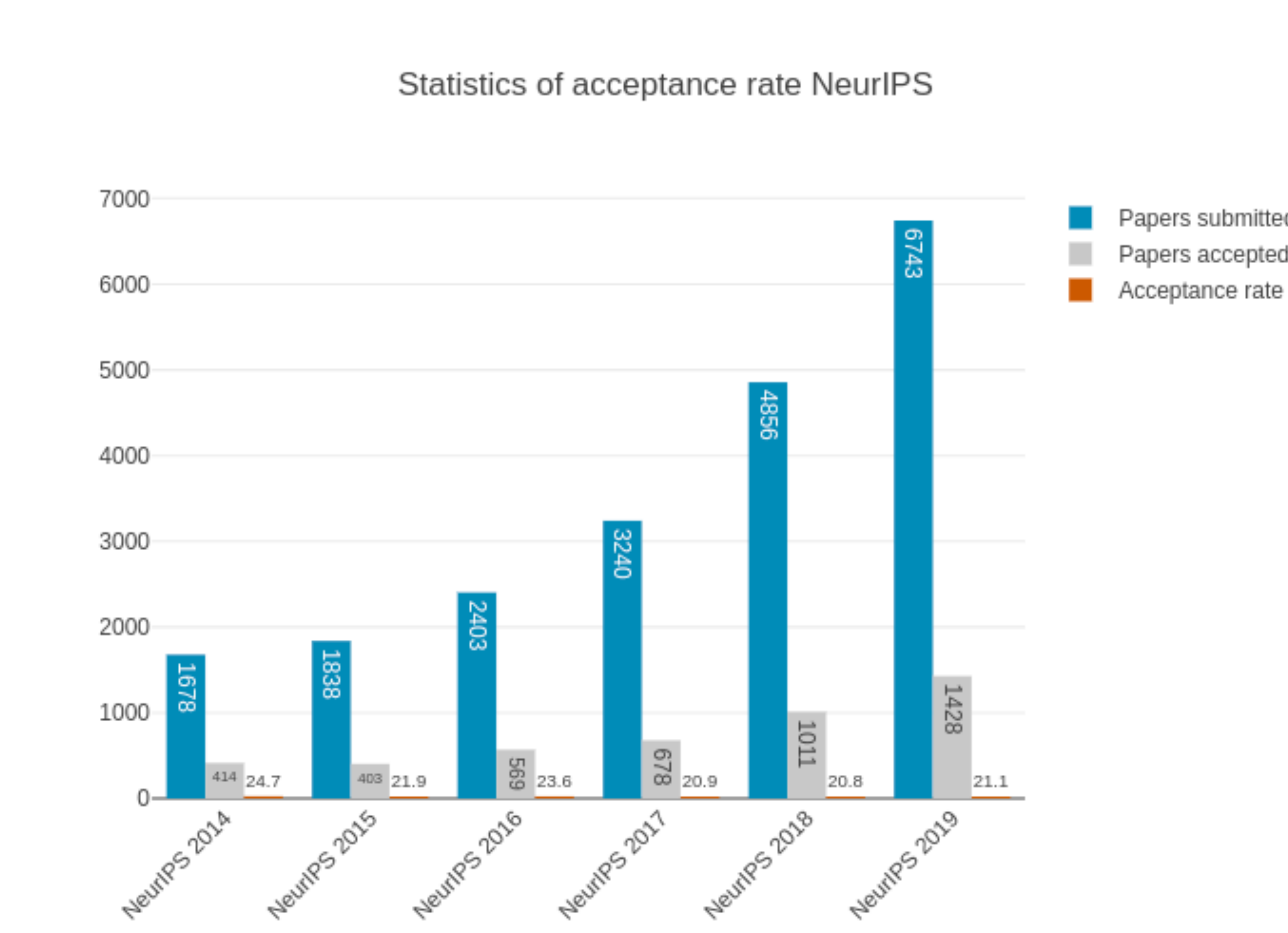
Explosive Growth in ML







Berkeley News

Research ▾ People ▾ Campus & community

CAMPUS & COMMUNITY, CAMPUS NEWS

Berkeley inaugurates Division of Data Science and Information, connecting teaching and research from all corners of campus

Berkeley News

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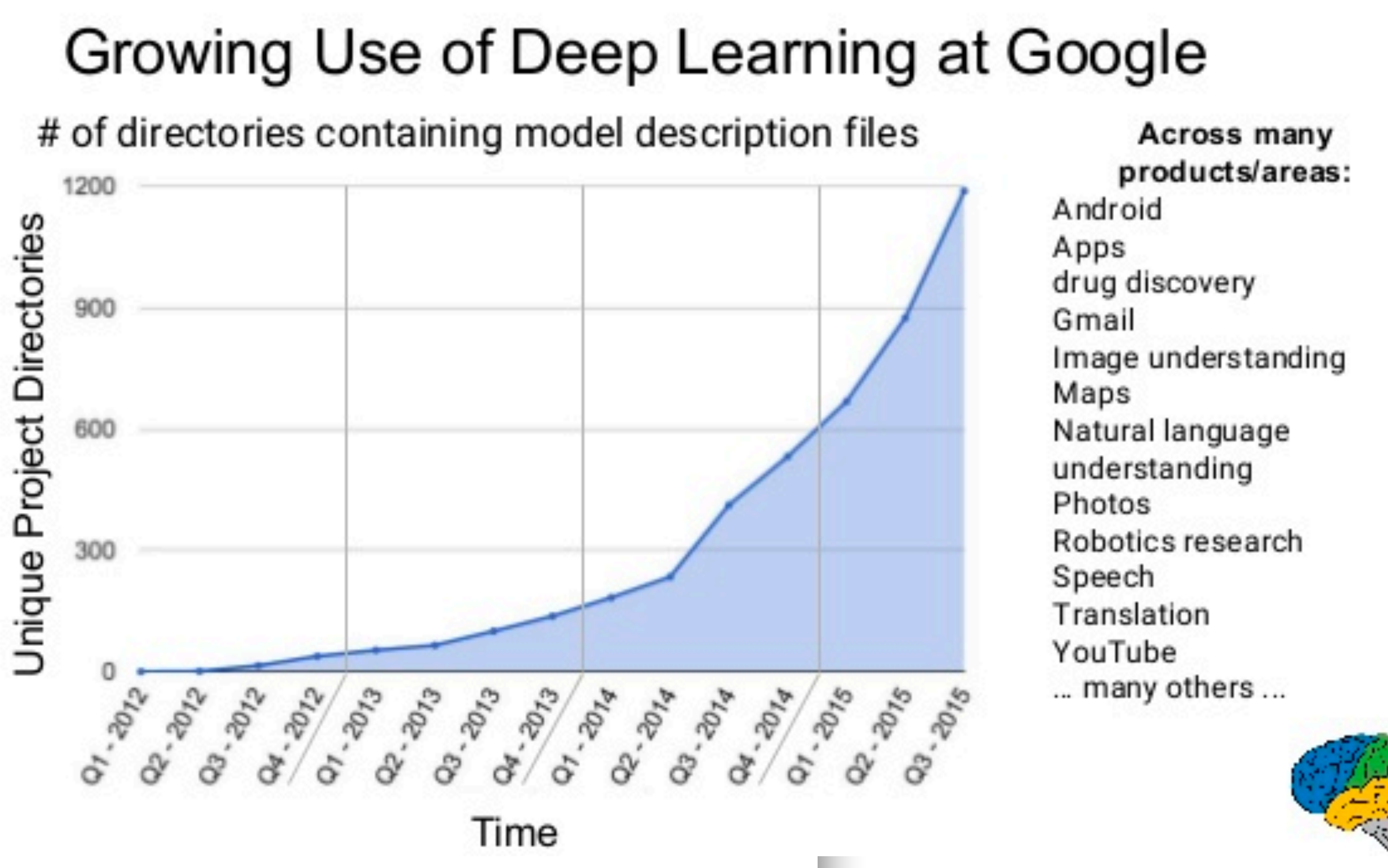
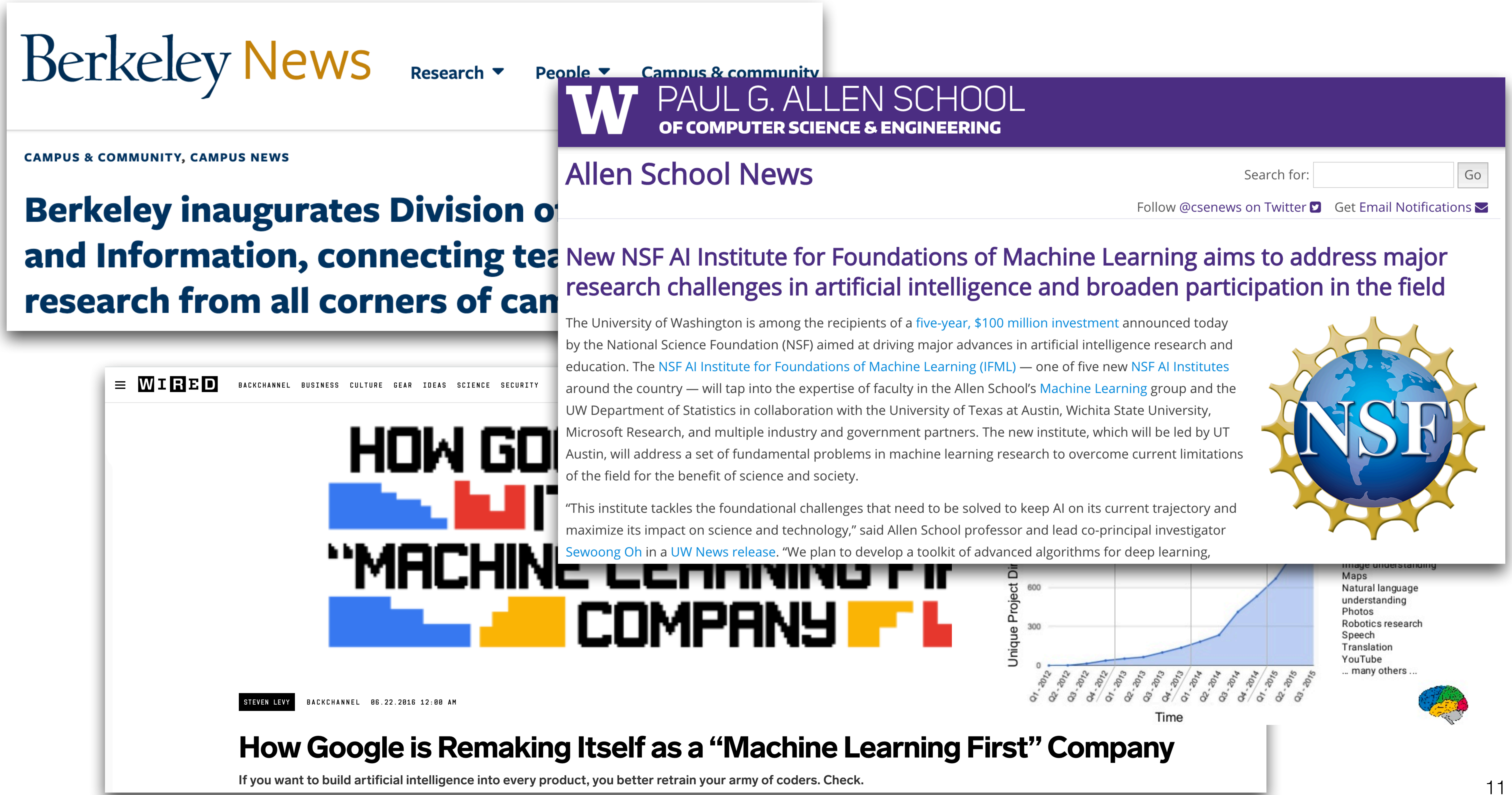


STEVEN LEVY BACKCHANNEL 06.22.2016 12:00 AM

How Google is Remaking Itself as a "Machine Learning First" Company

If you want to build artificial intelligence into every product, you better retrain your army of coders. Check.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Berkeley inaugurates Division o
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PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING
Allen School News
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New NSF AI Institute for Foundations of Machine Learning aims to address major research challenges in artificial intelligence and broaden participation in the field

The University of Washington is among the recipients of a five-year, $100 million investment announced today by the National Science Foundation (NSF) aimed at driving major advances in artificial intelligence research and education. The NSF AI Institute for Foundations of Machine Learning (IFML) — one of five new NSF AI Institutes around the country — will tap into the expertise of faculty in the Allen School's Machine Learning group and the UW Department of Statistics in collaboration with the University of Texas at Austin, Wichita State University, Microsoft Research, and multiple industry and government partners. The new institute, which will be led by UT Austin, will address a set of fundamental problems in machine learning research to overcome current limitations of the field for the benefit of science and society.

"This institute tackles the foundational challenges that need to be solved to keep AI on its current trajectory and maximize its impact on science and technology," said Allen School professor and lead co-principal investigator Sewoong Oh in a UW News release. "We plan to develop a toolkit of advanced algorithms for deep learning,

NSF

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Berkeley News

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Allen School Ne

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UW Department of Statistics in colla
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205

Senator Charles Schumer (D–NY) unveiled his artificial intelligence plan last week at a meeting of the National Security Commission on Artificial Intelligence. ALEX WONG/GETTY IMAGES

United States should make a massive investment in AI, top Senate Democrat says

By Jeffrey Mervis | Nov. 11, 2019 , 11:45 AM

The top Democrat in the U.S. Senate wants the government to create a new agency that would invest an additional $100 billion over 5 years on basic research in artificial intelligence (AI). Senator Charles Schumer (D–NY) says the initiative would enable the United States to keep pace with China and Russia in a critical research arena and plug gaps in what U.S. companies are unwilling to finance.

Go

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Time

Self-driving cars

Robotics

Self-driving cars

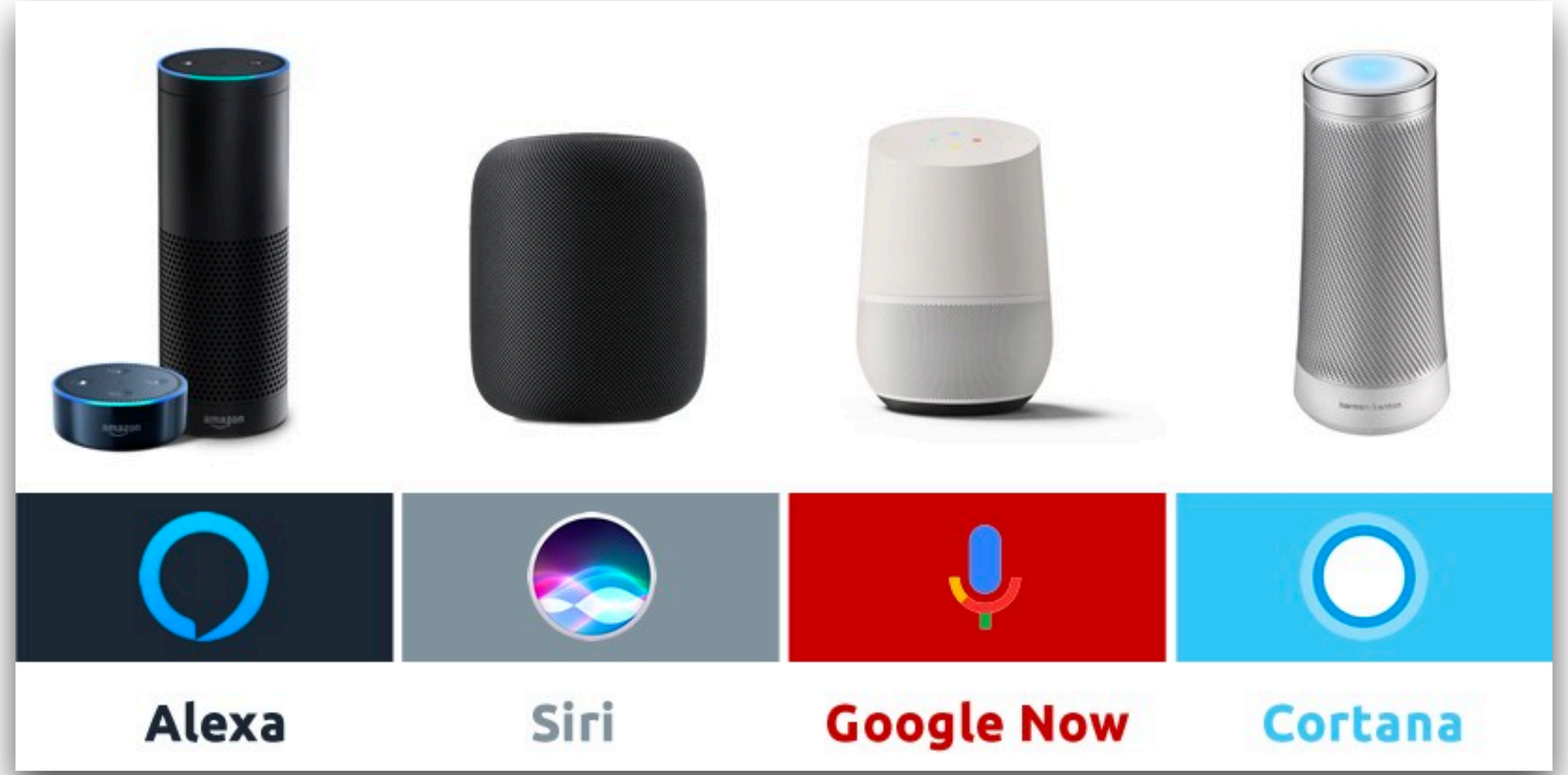
Robotics

Medical imaging

Self-driving cars

Robotics

Medical imaging



Voice assistants

What are the key advancements?

Progress in multiple areas of machine learning with similar approach: **deep learning**

- Computer vision
- Automatic speech recognition
- Natural language processing
- Game playing (Go, Atari, Starcraft, DotA)

Focus today: **computer vision**

[Deng, Dong, Socher, Li, Li, Fei-Fei'09]
[Russakovsky, Deng, Su, Krause, Satheesh, Ma, Huang, Karpathy, Khosla, Bernstein, Berg Fei-Fei'15]

ImageNet

Large **image classification** dataset: 1.2 mio training images, 1,000 image classes.

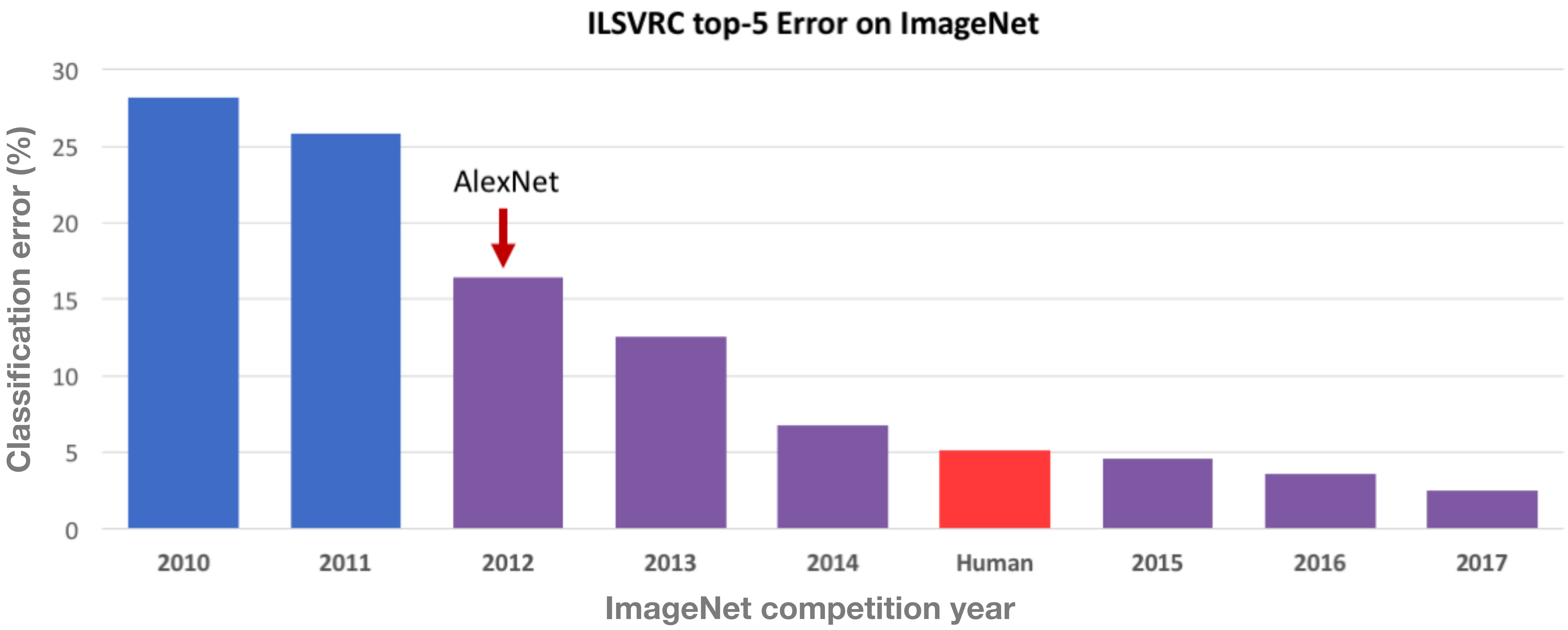
Golden retriever

Great white shark

Minibus

ImageNet

Progress over the past decade:



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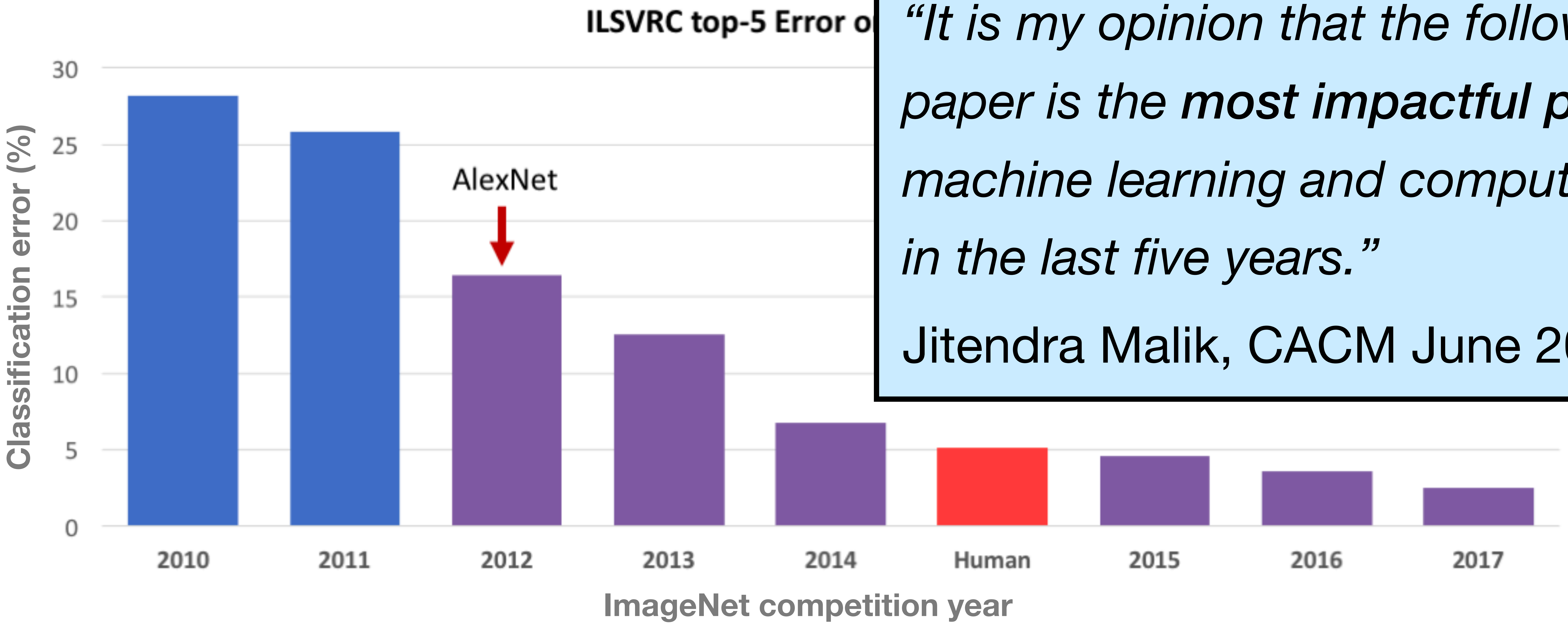

> *"It is my opinion that the following paper is the **most impactful paper** in machine learning and computer vision in the last five years."*
>
> Jitendra Malik, CACM June 2017

ImageNet

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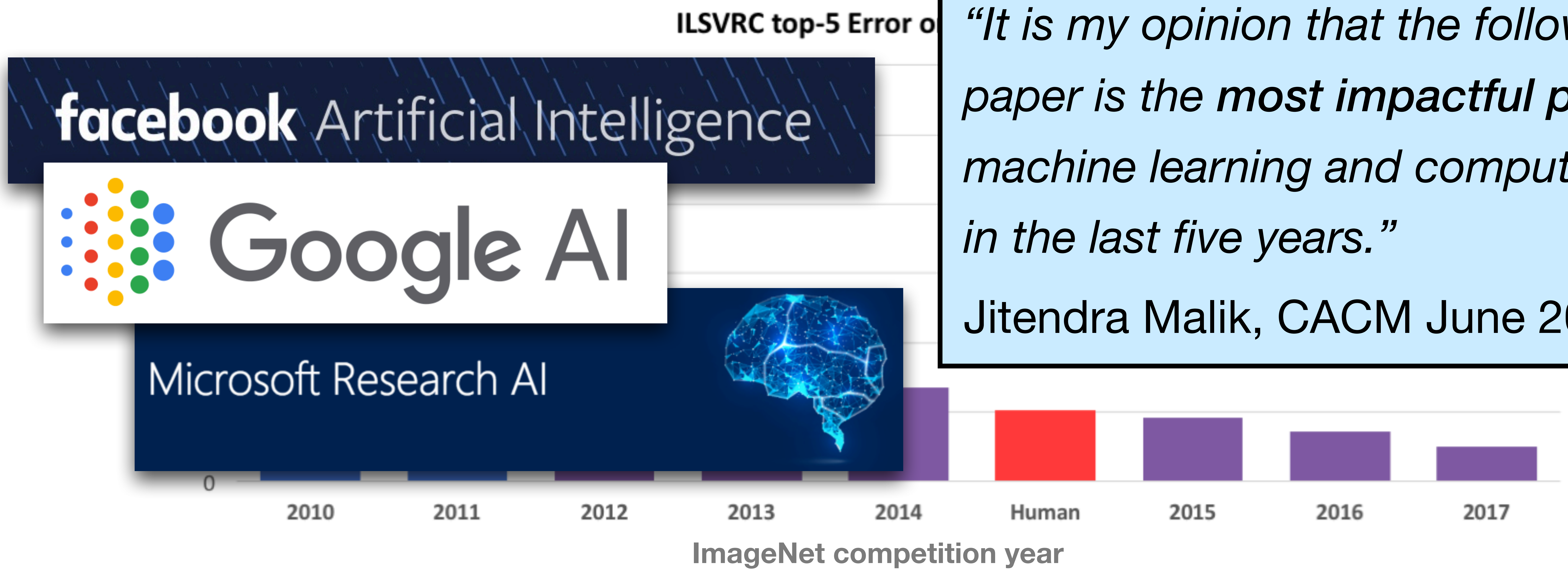

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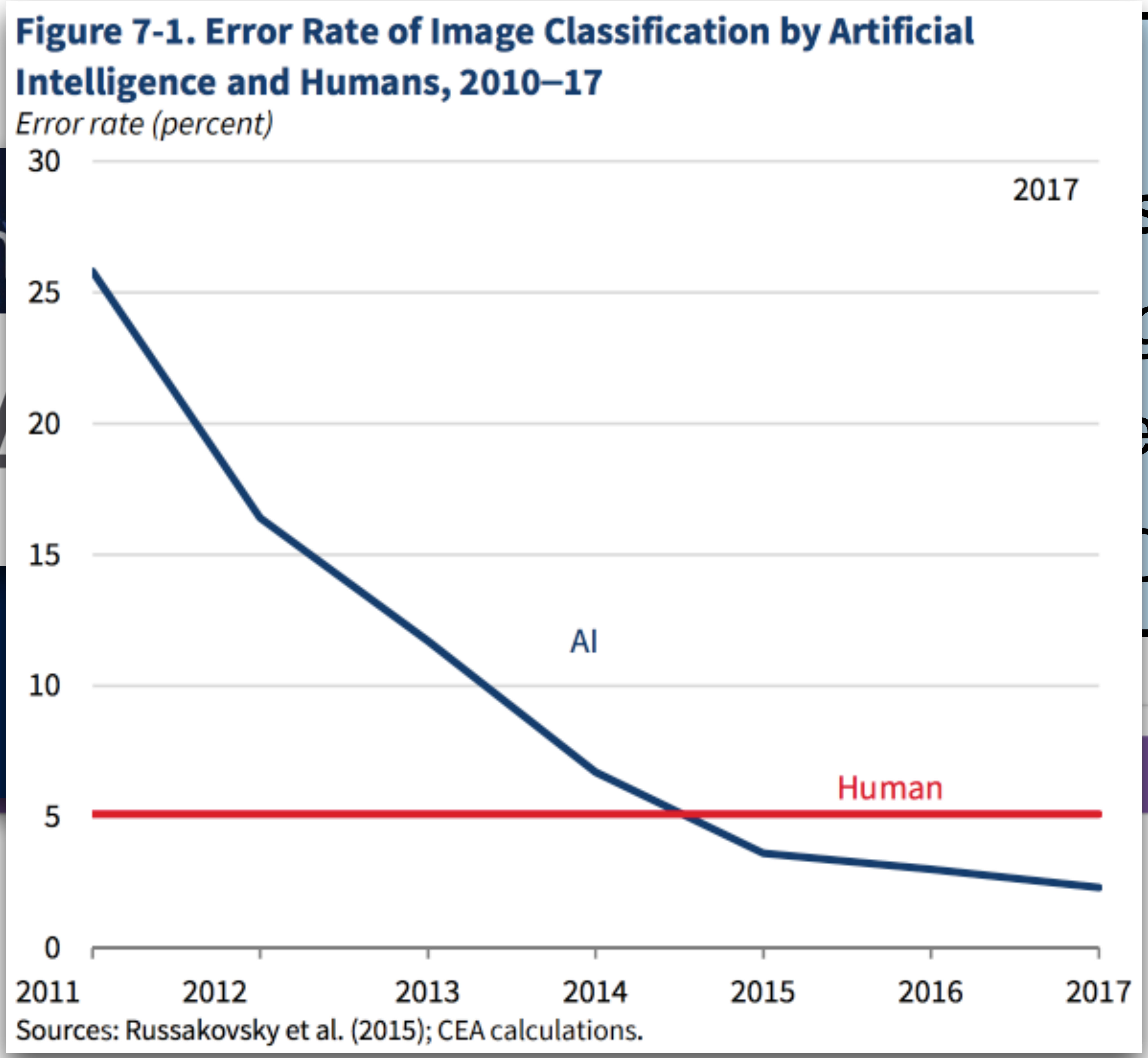

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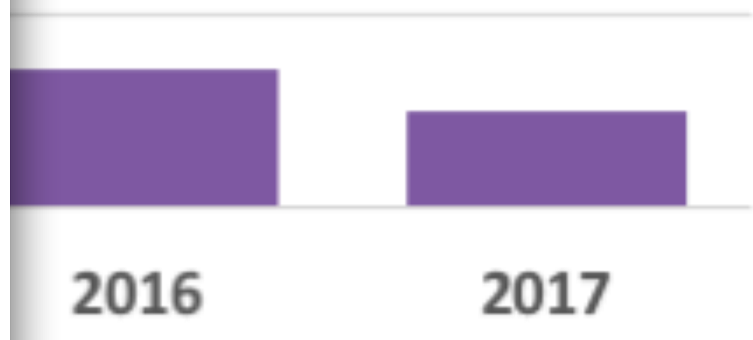

ImageNet History

Key person: **Fei-Fei Li**

Assistant prof at Princeton starting 2007

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Princeton is also home to the **WordNet** project

- Hierarchical database of words in English and other languages

dog, domestic dog, Canis familiaris
- canine, canid
  - carnivore
    - placental, placental mammal, eutherian, eutherian mammal
      - mammal
        - vertebrate, craniate
          - chordate
            - animal, animate being, beast, brute, creature, fauna
              - ...

WORDNET

ImageNet History

Fei-Fei's vision (2006 — 2007):

- Humans know thousands of visual categories (neuroscience).
- If we want human-like computer vision, we need correspondingly large datasets.

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Let's populate all of WordNet with around 1,000 images per node!

About 50 million images for about 50,000 classes (nouns in WordNet)

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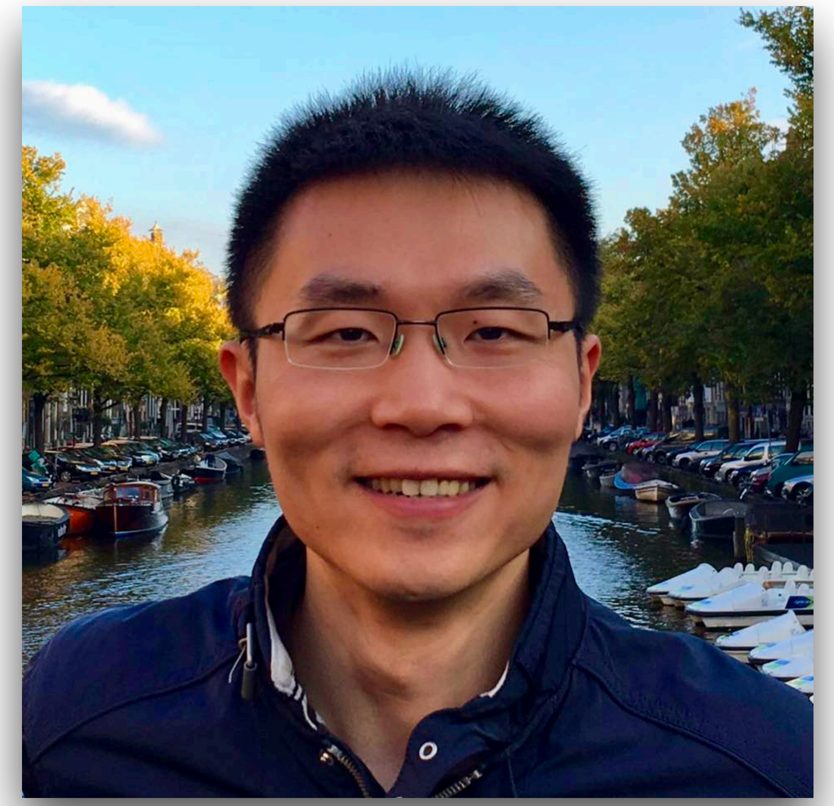
➡ About 50 million images for about 50,000 classes (nouns in WordNet)

(Planned) ImageNet is 1000x larger!

Context: **PASCAL VOC**

- Most active object detection / classification dataset from 2005 - 2012
- Largest version (2012): 12,000 images total for 20 classes

Building ImageNet



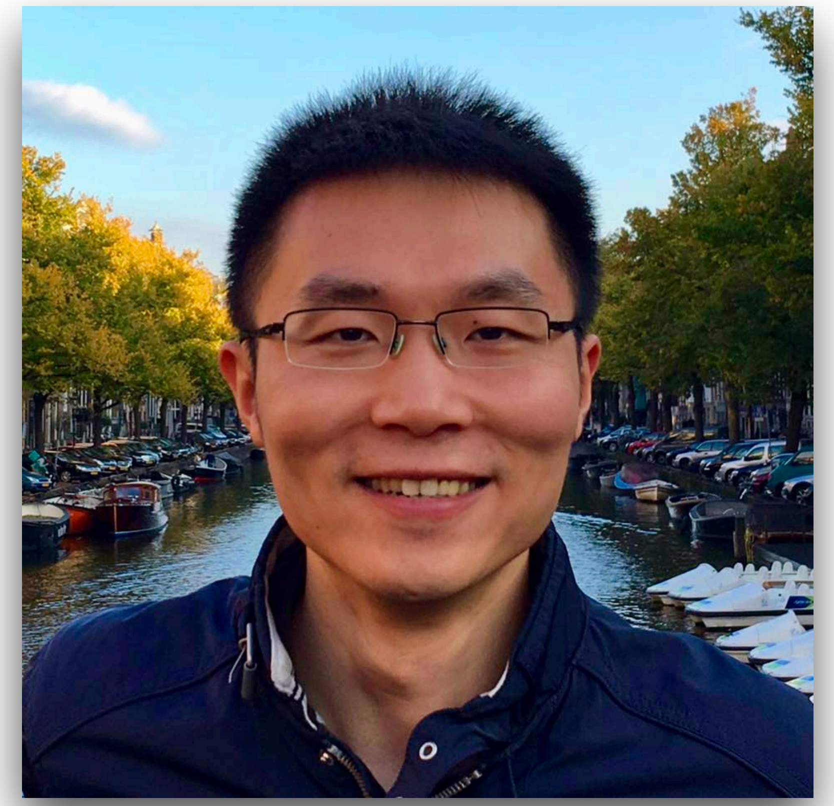
Main student: Jia Deng (now back at Princeton as faculty)

Where do you get 50 million images?

How do you label them?

[Deng, Dong, Socher, Li, Li, Fei-Fei'09]

Building ImageNet



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flickr

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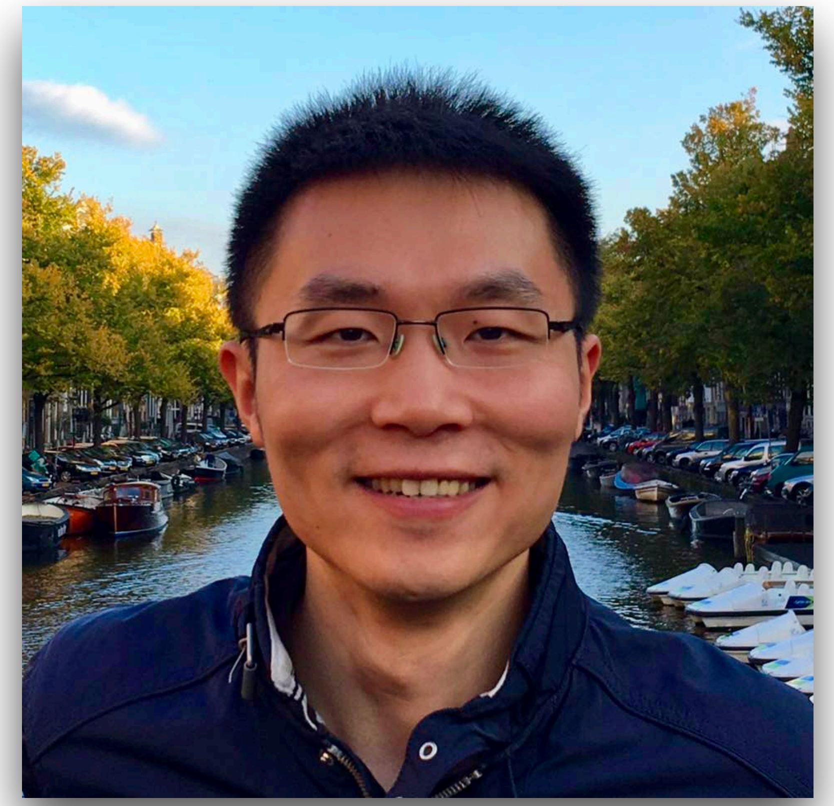

Where do you get 50 million images?

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How do you label them?

→ Internet! (Crowdsourcing platforms)

+ lots of **clever** task design

+ lots of **hard** work

amazon mechanical turk beta

[Deng, Dong, Socher, Li, Li, Fei-Fei'09]

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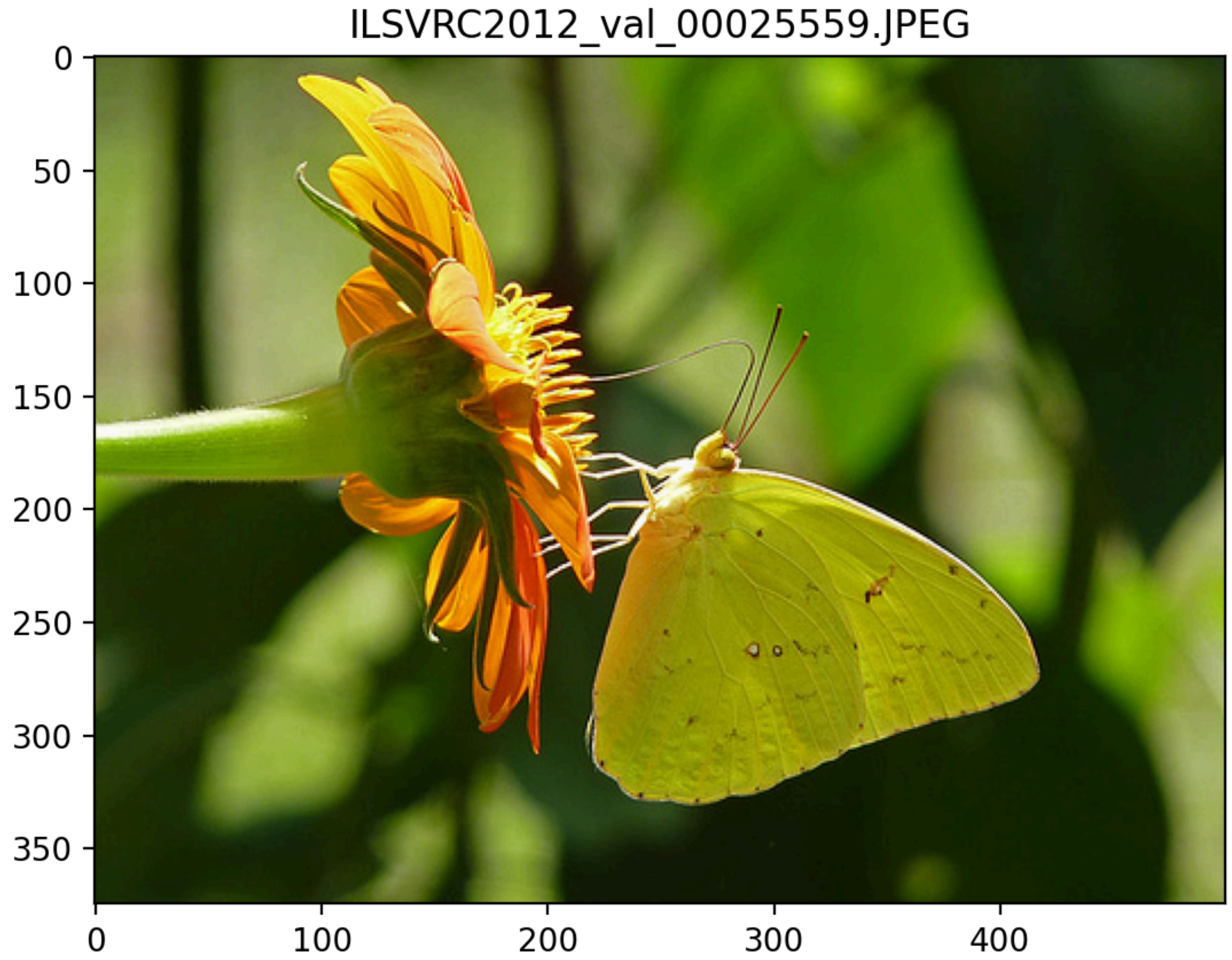
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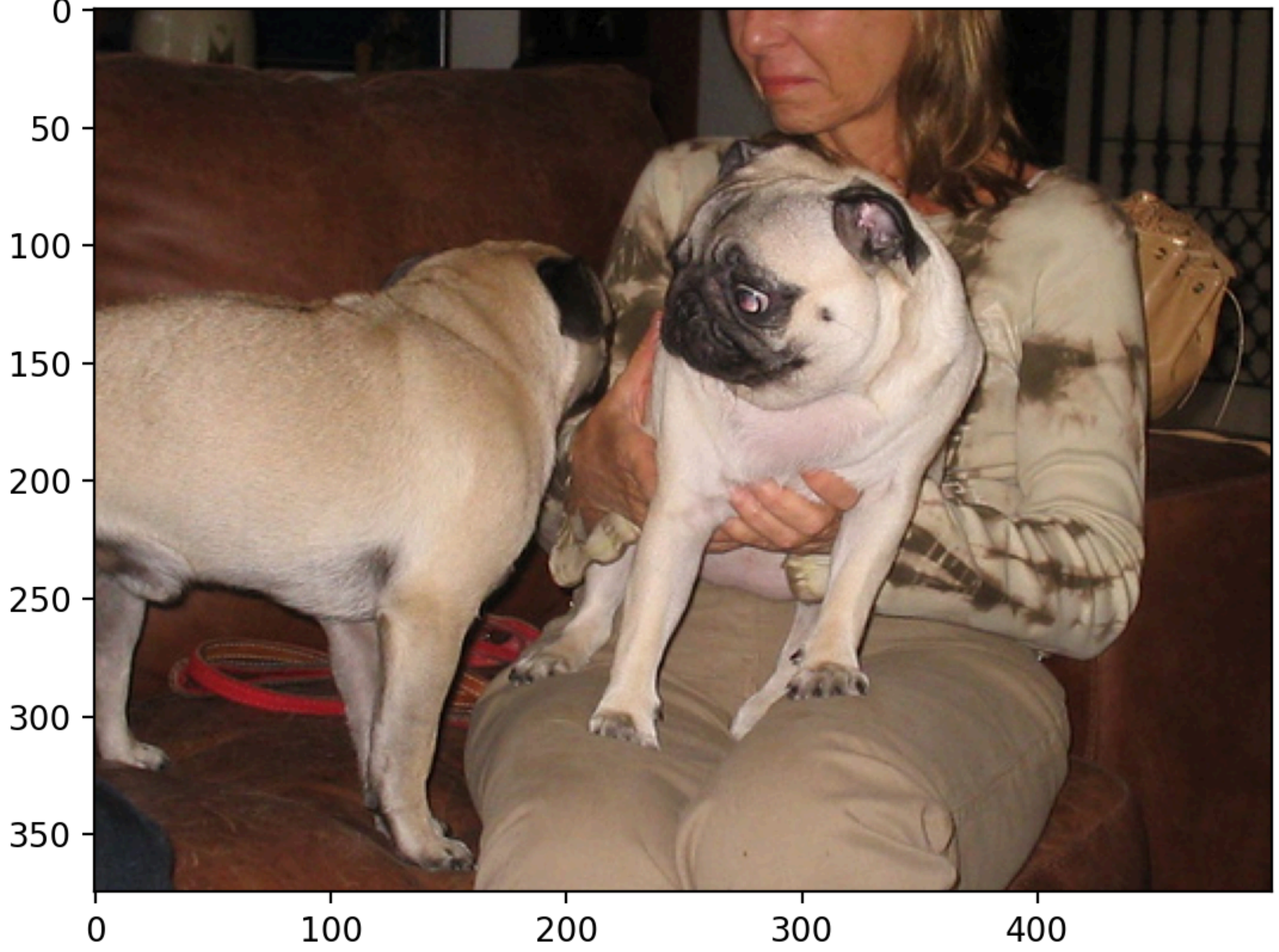

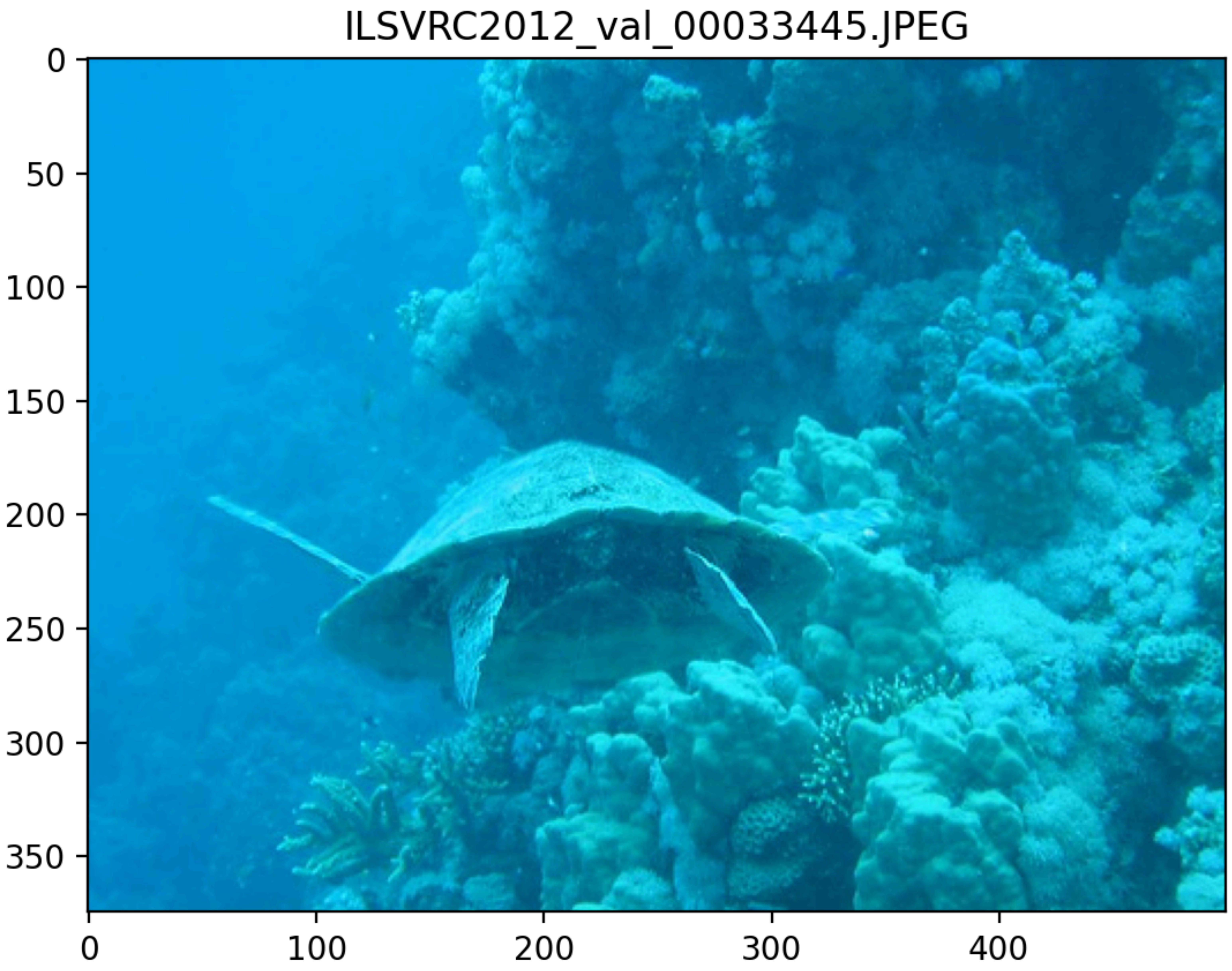
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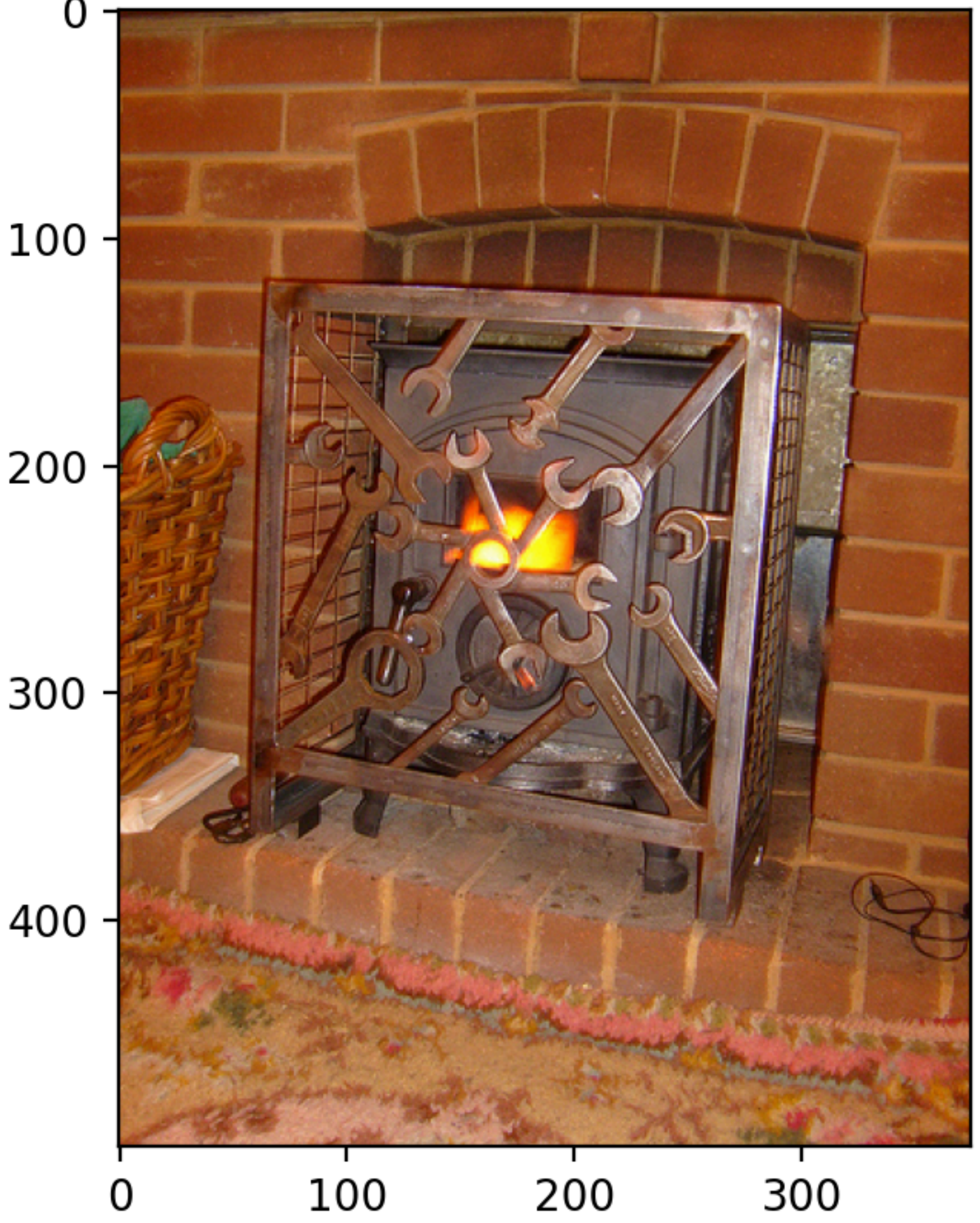

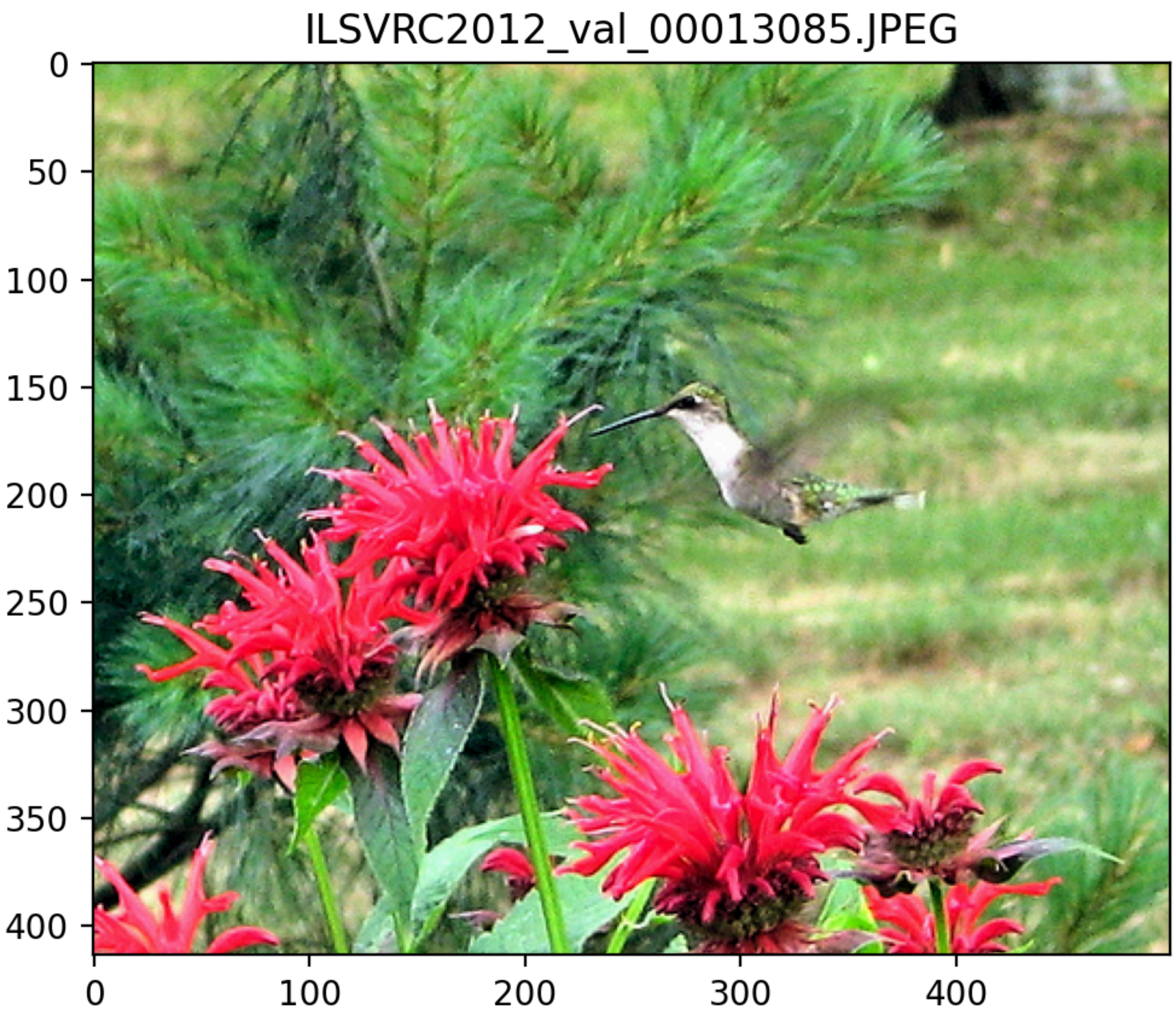
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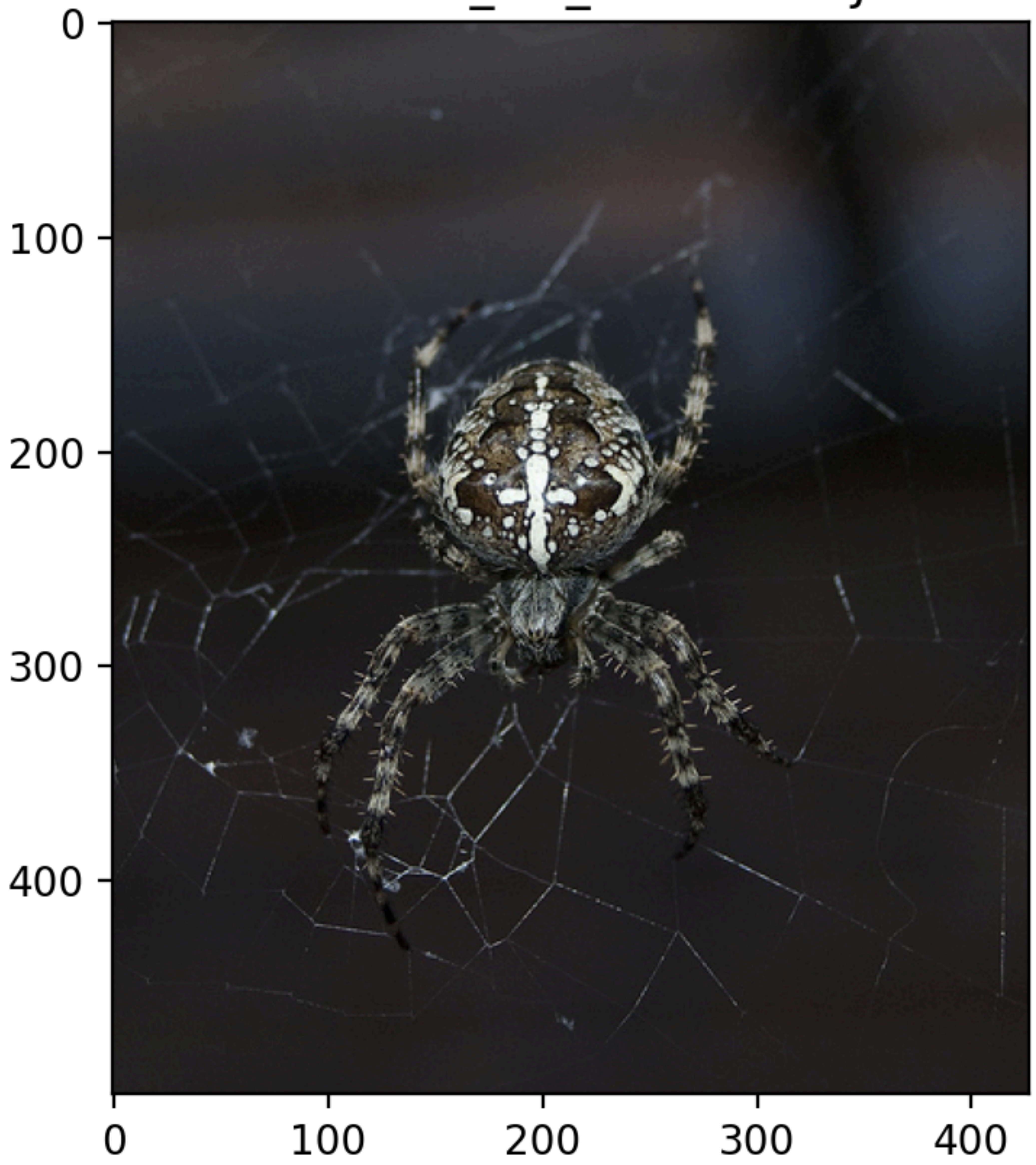

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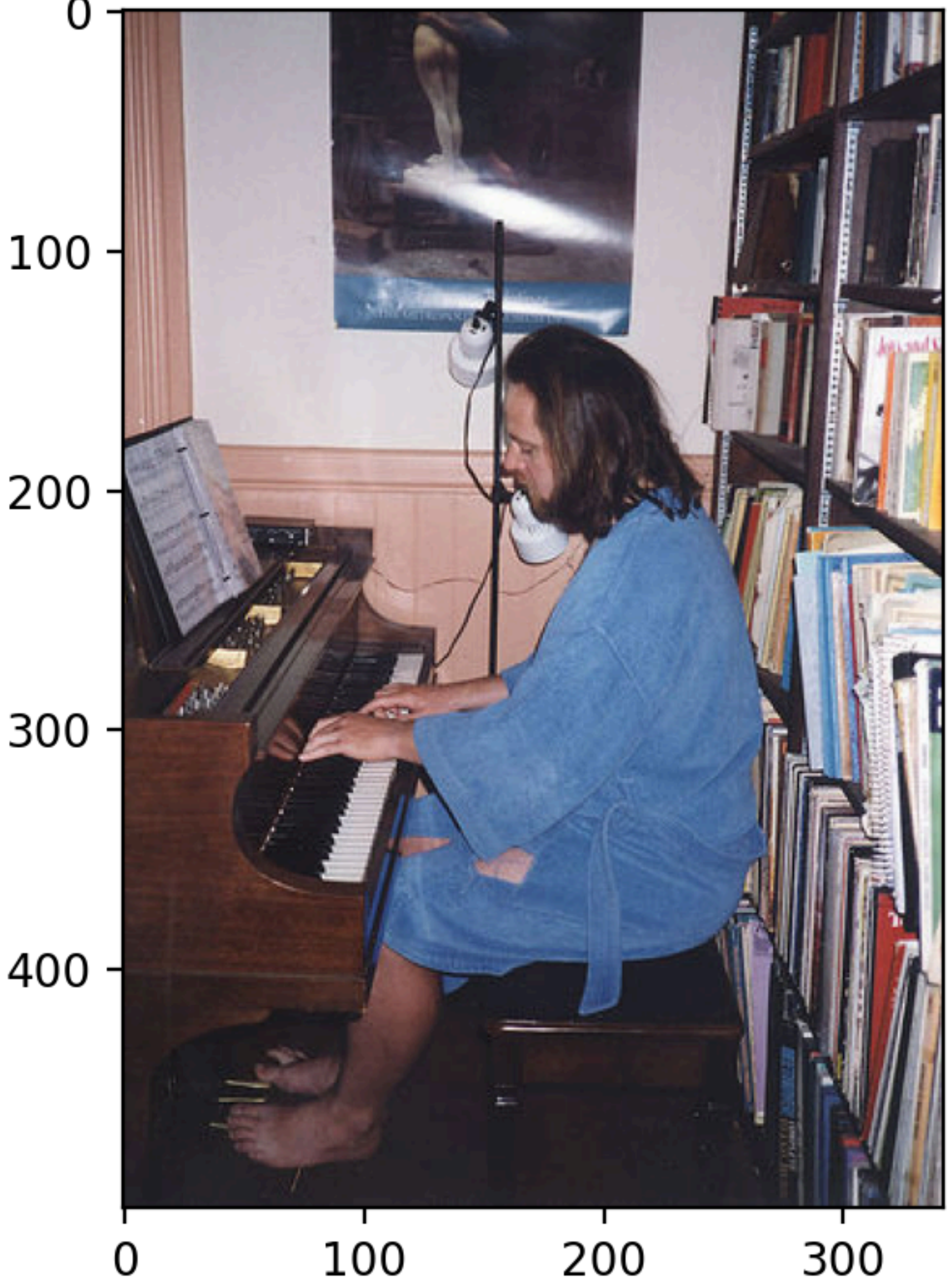

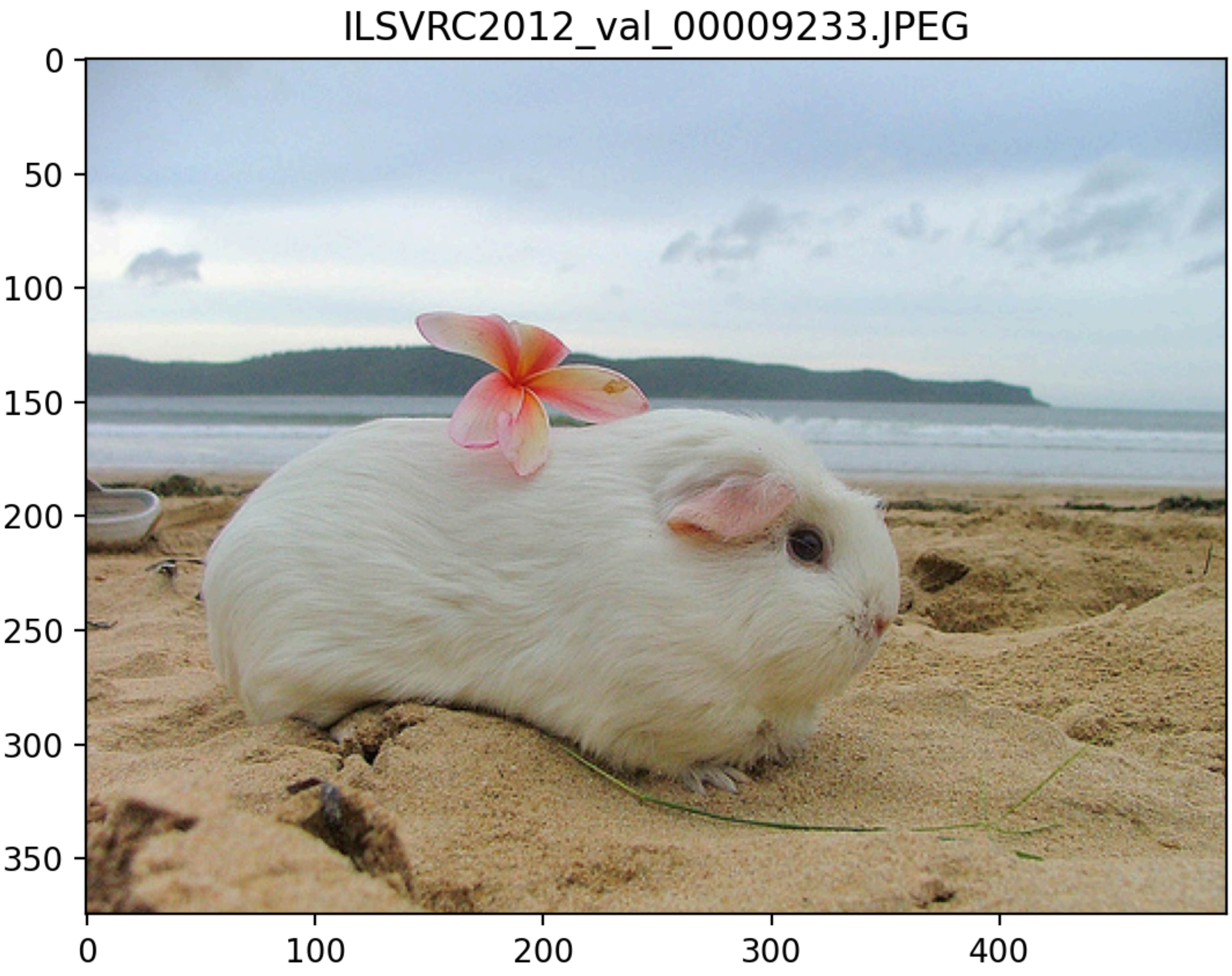
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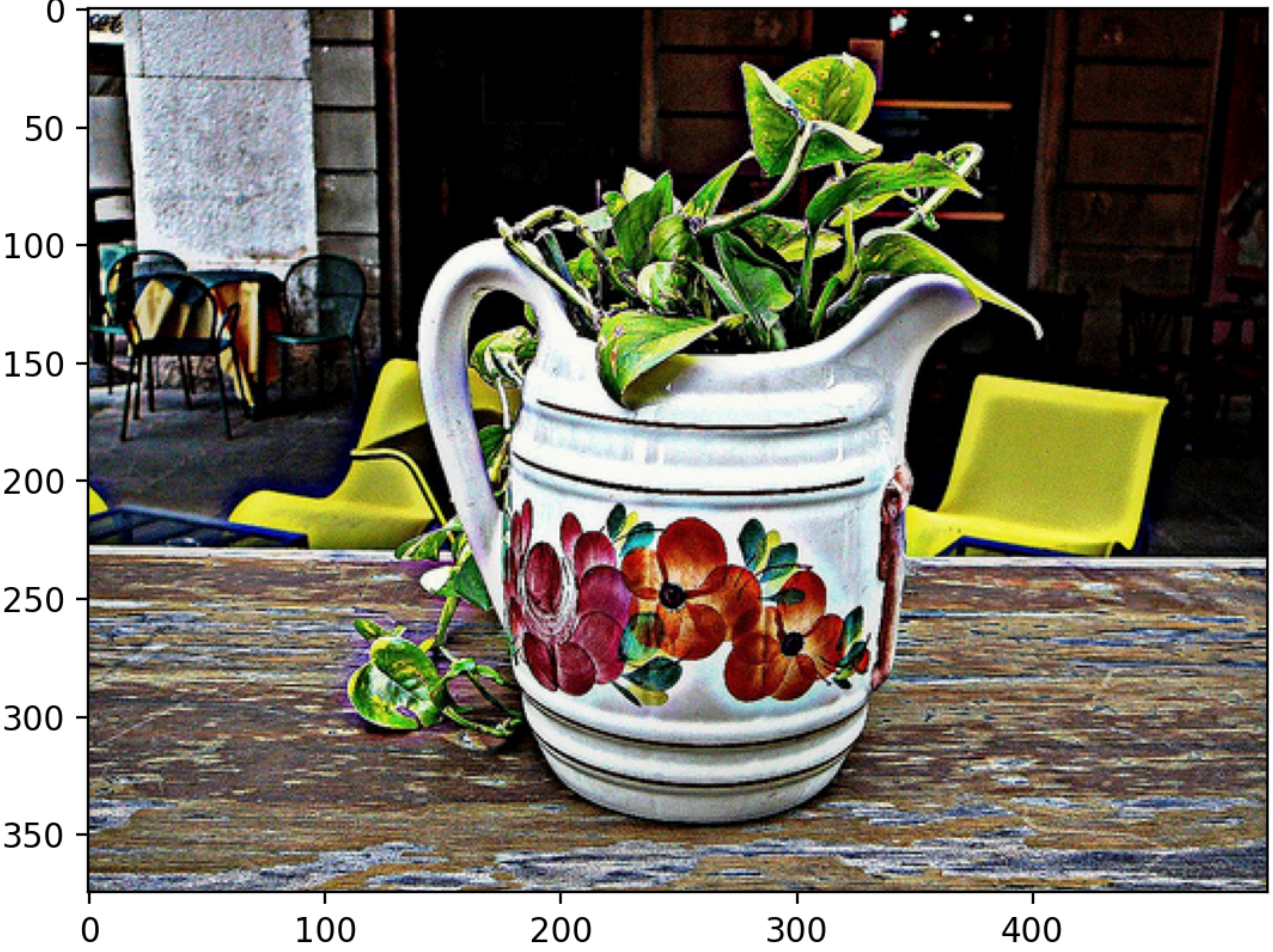

ImageNet Competition

ImageNet was about 10% done (already 5 million images!)

Alex Berg (prof at UNC and research scientist at FAIR)

→ Let's make it a competition!

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➡ Let's make it a competition!

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

Olga Russakovsky (student then postdoc at Stanford)

"Small" version of ImageNet: 1,000 classes, 1.2 million images

➡ "ImageNet" has become equivalent to ILSVRC 2012

IMAGENET Large Scale Visual Recognition Challenge 2010 (ILSVRC2010)

Held as a "taster competition" in conjunction with PASCAL Visual Object Classes Challenge 2010 (VOC2010)

News

- September 2, 2014: A new paper which describes the collection of the ImageNet Large Scale Visual Recognition Challenge dataset, analyzes the results of the past five years of the challenge, and even compares current computer accuracy with human accuracy is now available. *Please cite it when reporting ILSVRC2010 results or using the dataset.*
- For latest challenge, please visit here.
- September 16, 2010: Slides for overview of results are available, along with slides from the two winning teams:

  Winner: NEC-UIUC
  Yuanqing Lin, Fengjun Lv, Shenghuo Zhu, Ming Yang, Timothee Cour, Kai Yu (NEC). LiangLiang Cao, Zhen Li, Min-Hsuan Tsai, Xi Zhou, Thomas Huang (UIUC). Tong Zhang (Rutgers).
  [PDF] NB: This is unpublished work. Please contact the authors if you plan to make use of any of the ideas presented.

  Honorable mention: XRCE
  Jorge Sanchez, Florent Perronnin, Thomas Mensink (XRCE)
  [PDF] NB: This is unpublished work. Please contact the authors if you plan to make use of any of the ideas presented.

- September 3, 2010: Full results are available. Please join us at the VOC workshop at ECCV 2010 on 9/11/2010 at Crete, Greece. At the workshop we will provide an overview of the results and invite winning teams to present their methods. We look forward to seeing you there.
- August 9, 2010: Submission deadline is extended to 4:59pm PDT, August 30, 2010. There will be no further extensions.
- August 8, 2010: Submission site is up.
- June 16, 2010: Test data is available for download!.
- May 3, 2010: Training data, validation data and development kit are available for download!.
- May 3, 2010: Registration is up!. Please register to stay updated.
- Mar 18, 2010: We are preparing to run the ImageNet Large Scale Visual Recognition Challenge 2010 (ILSVRC2010)

ImageNet Classification Task

Training data: 1.2 million images for 1,000 classes (roughly class-balanced)

Validation set: 50,000 images for 1,000 classes (exactly class-balanced)

Test set: 150,000 images for 1,000 classes (exactly class-balanced, hidden labels)

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- Five predictions per image
- Prediction counts as correct if the image label is among the five predictions

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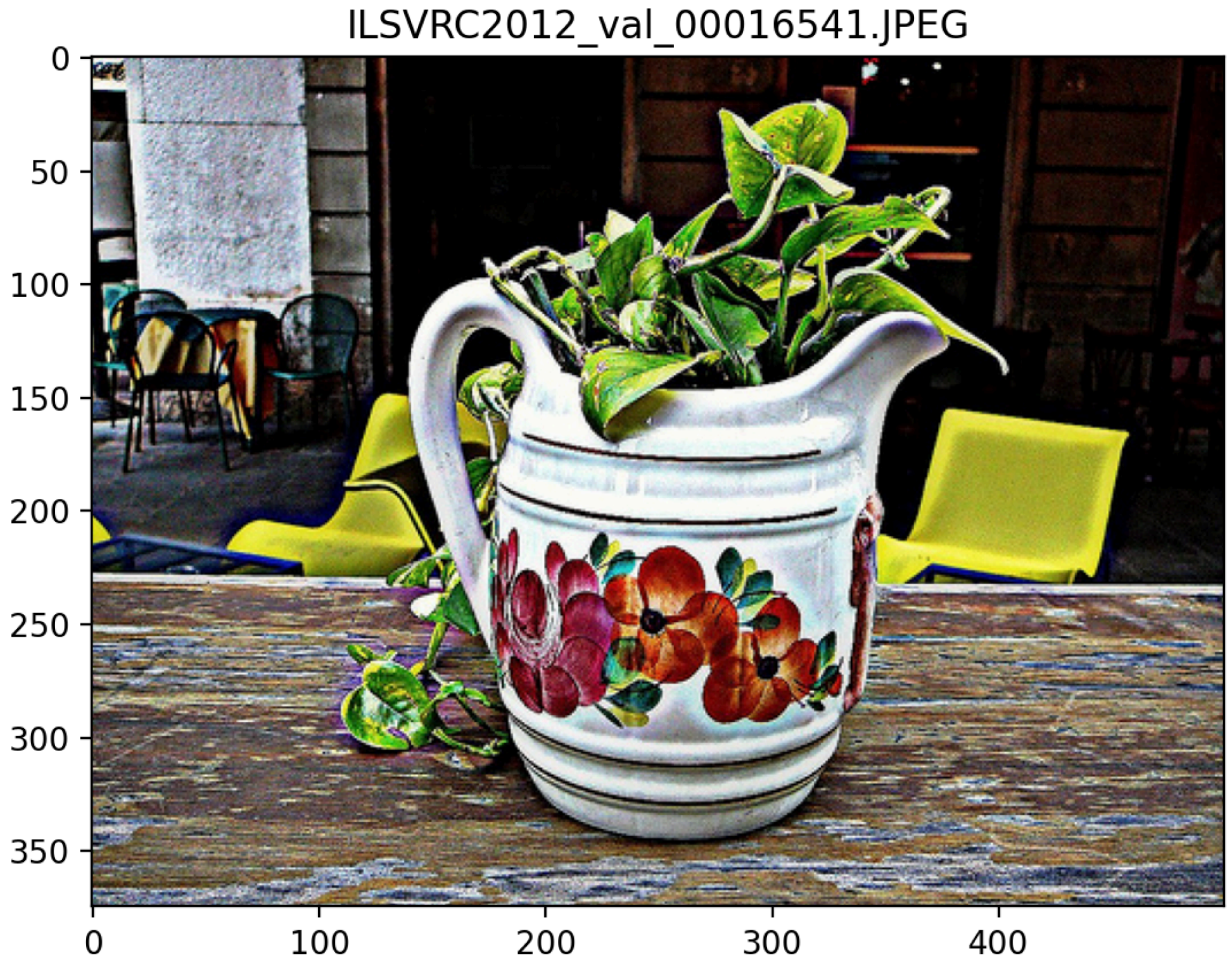
Why? Sometimes multiple labels per image, sometimes unclear class boundaries.
+ task is already hard enough



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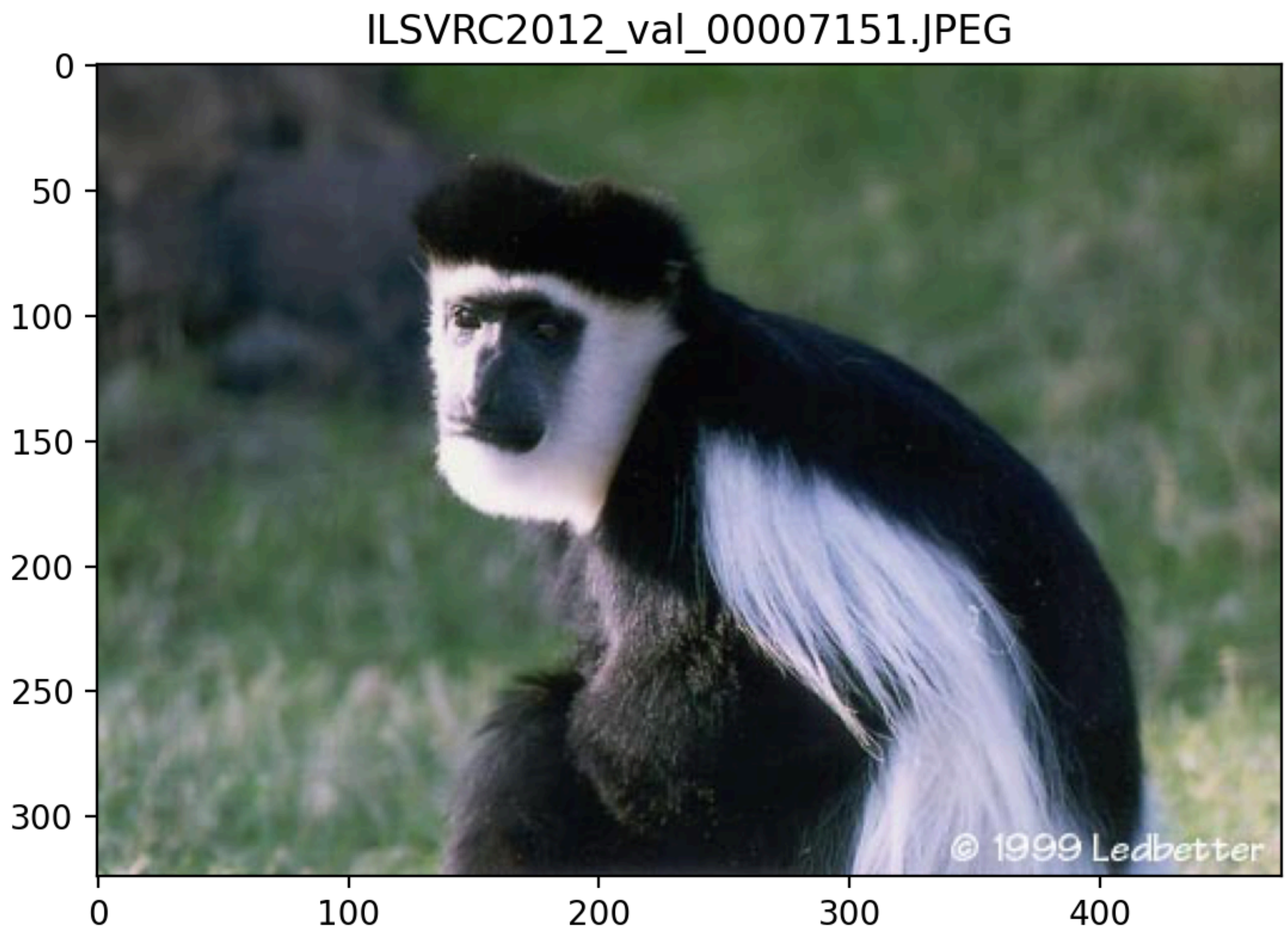
WordNet ID (wnid) Synonym set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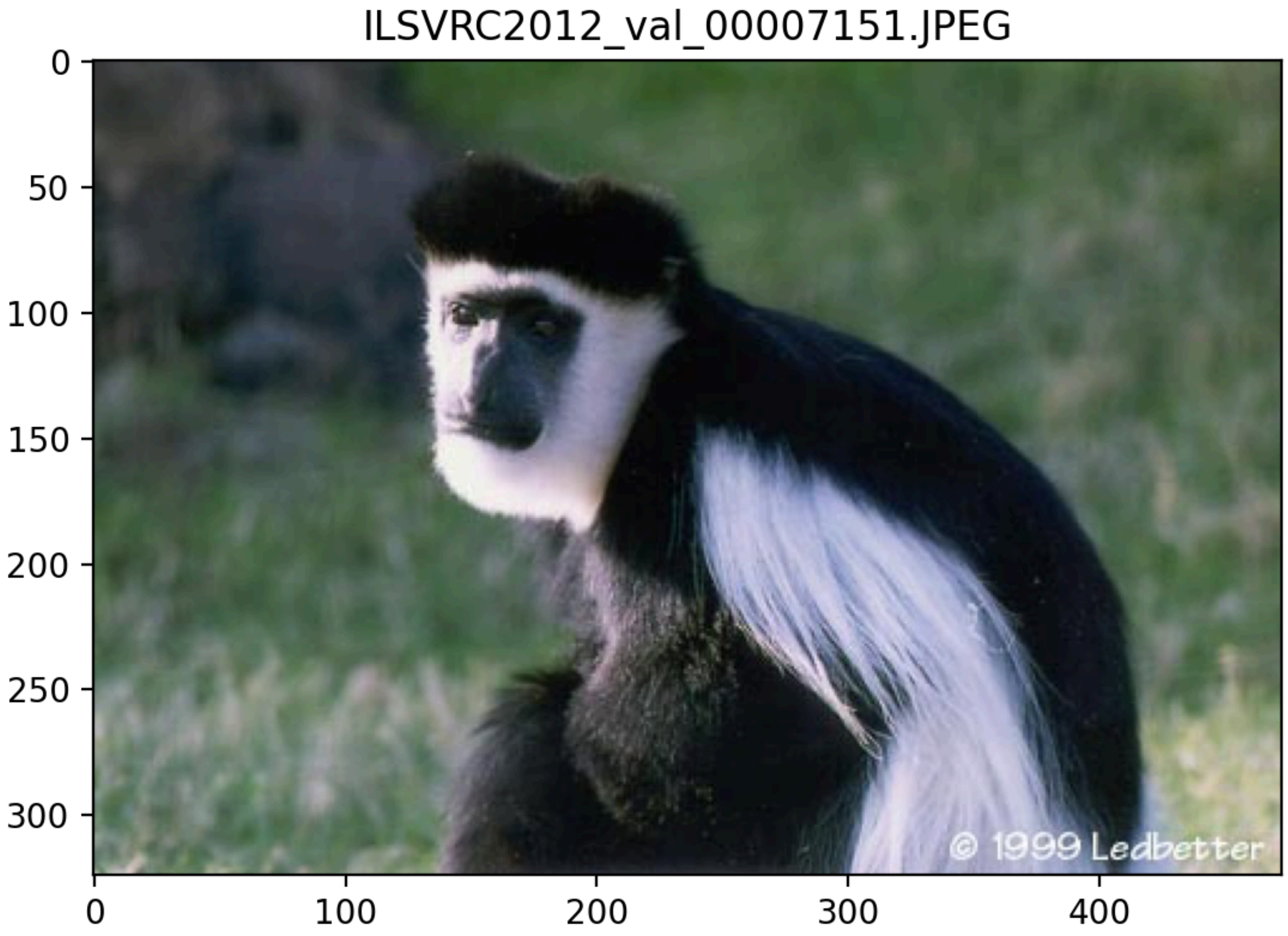

n02488702   colobus, colobus monkey

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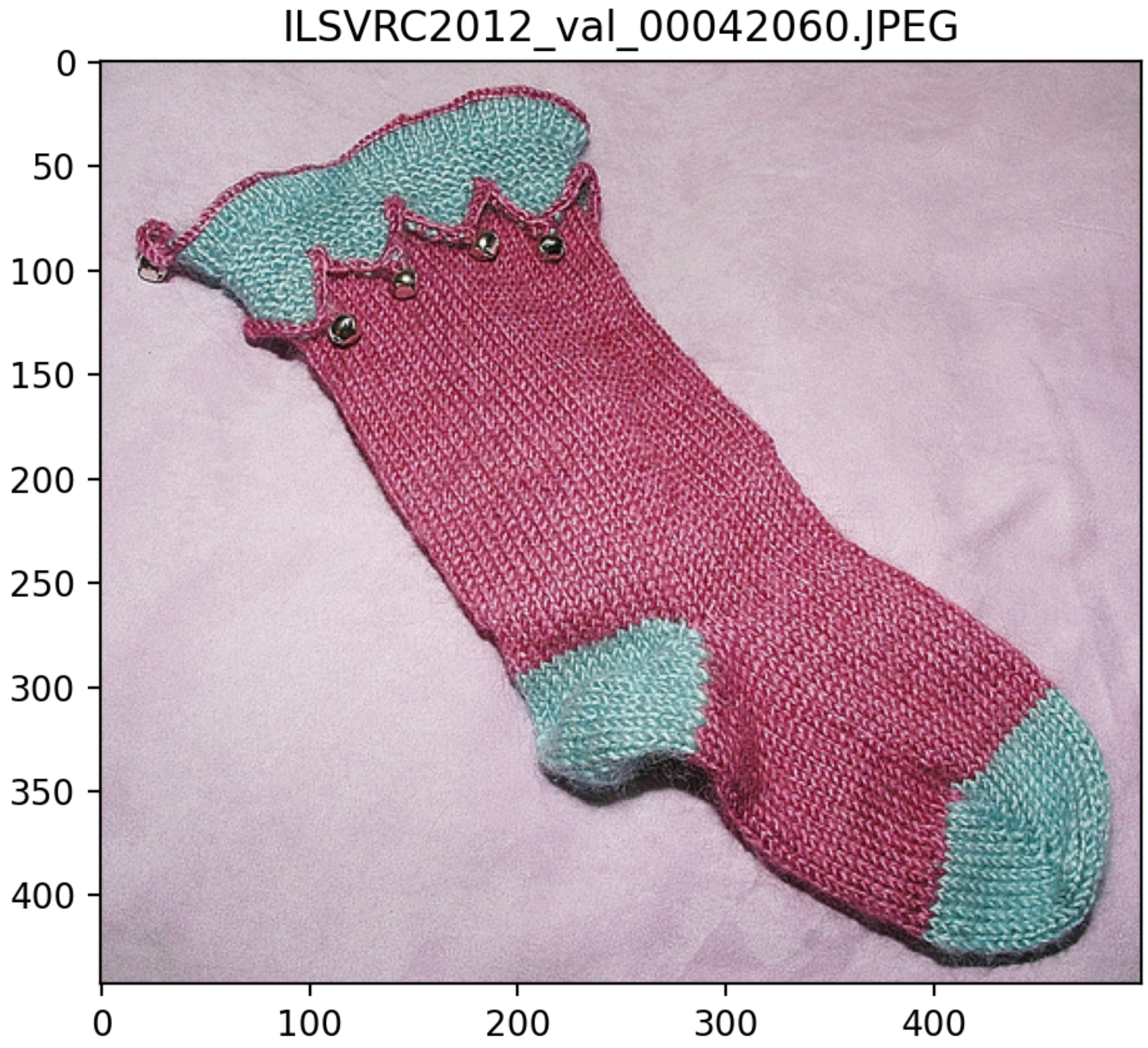

n03026506 Christmas stocking

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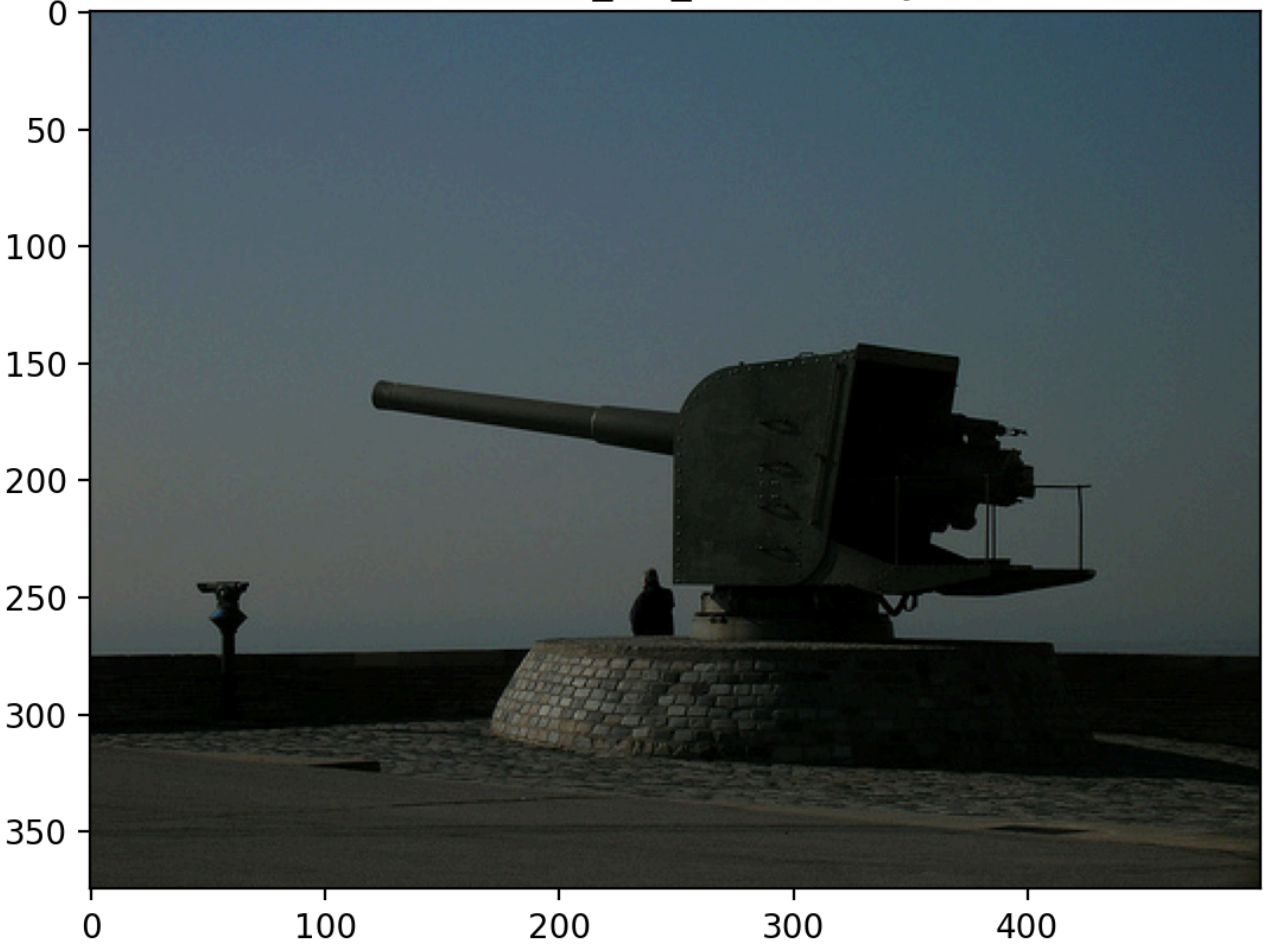

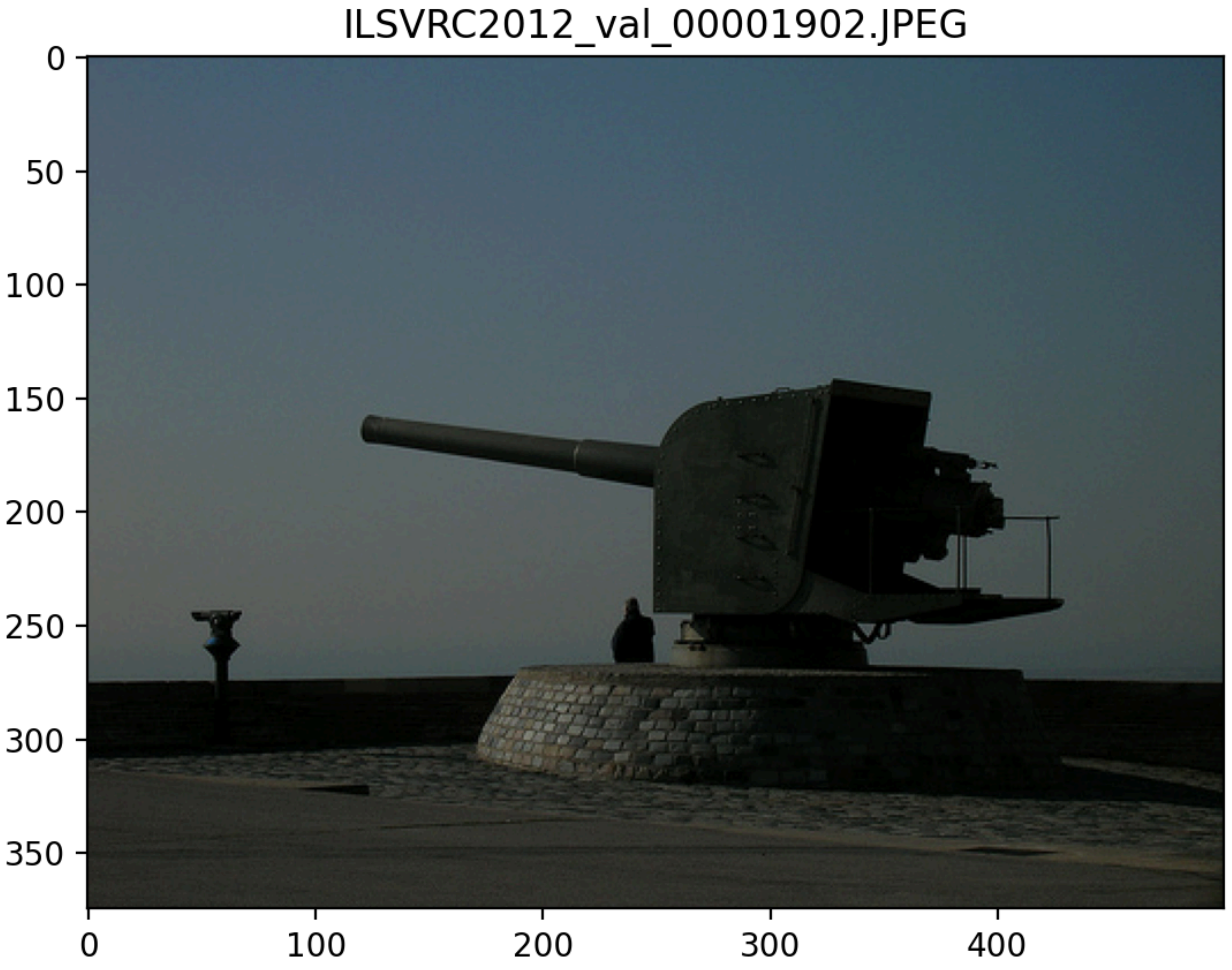

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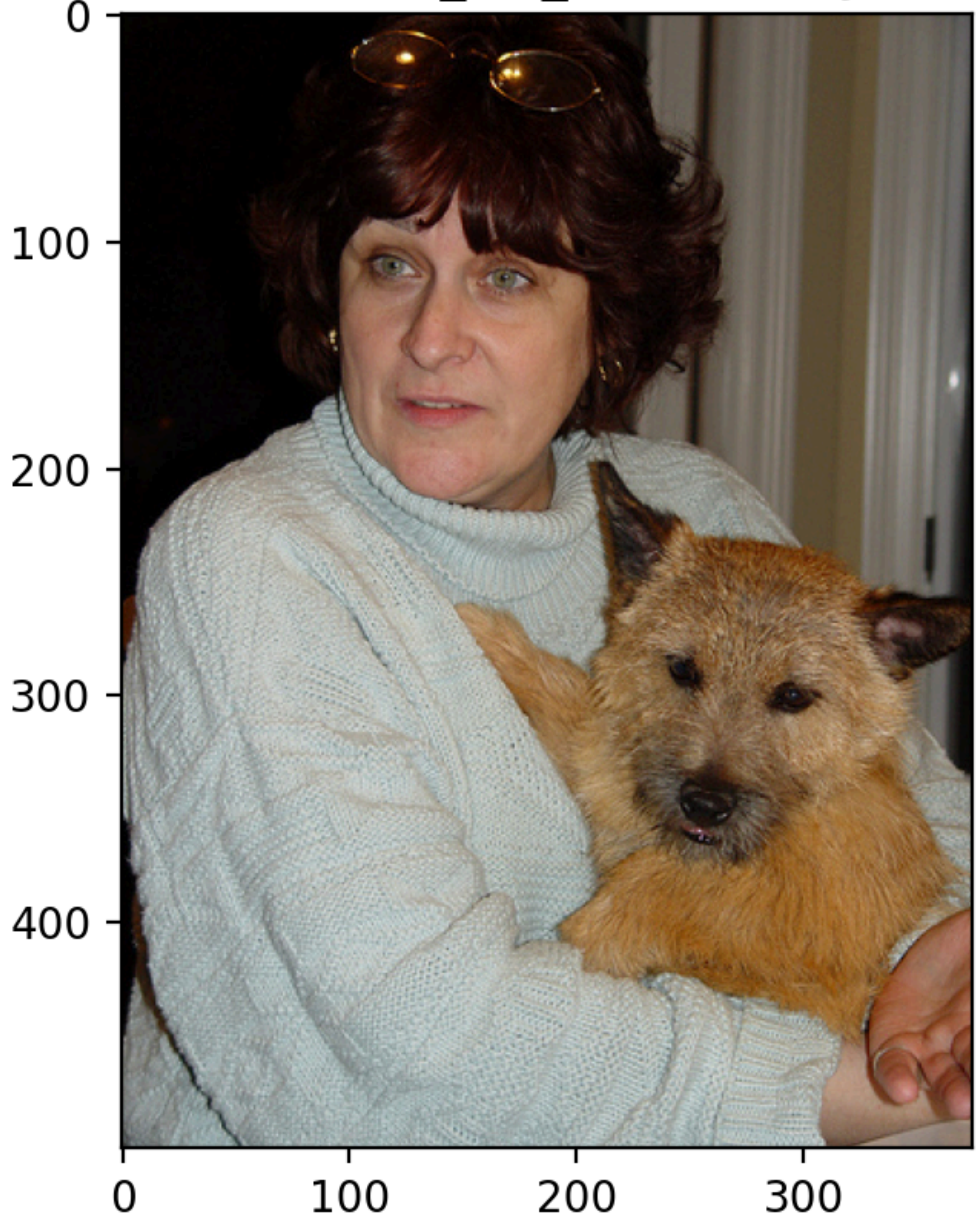

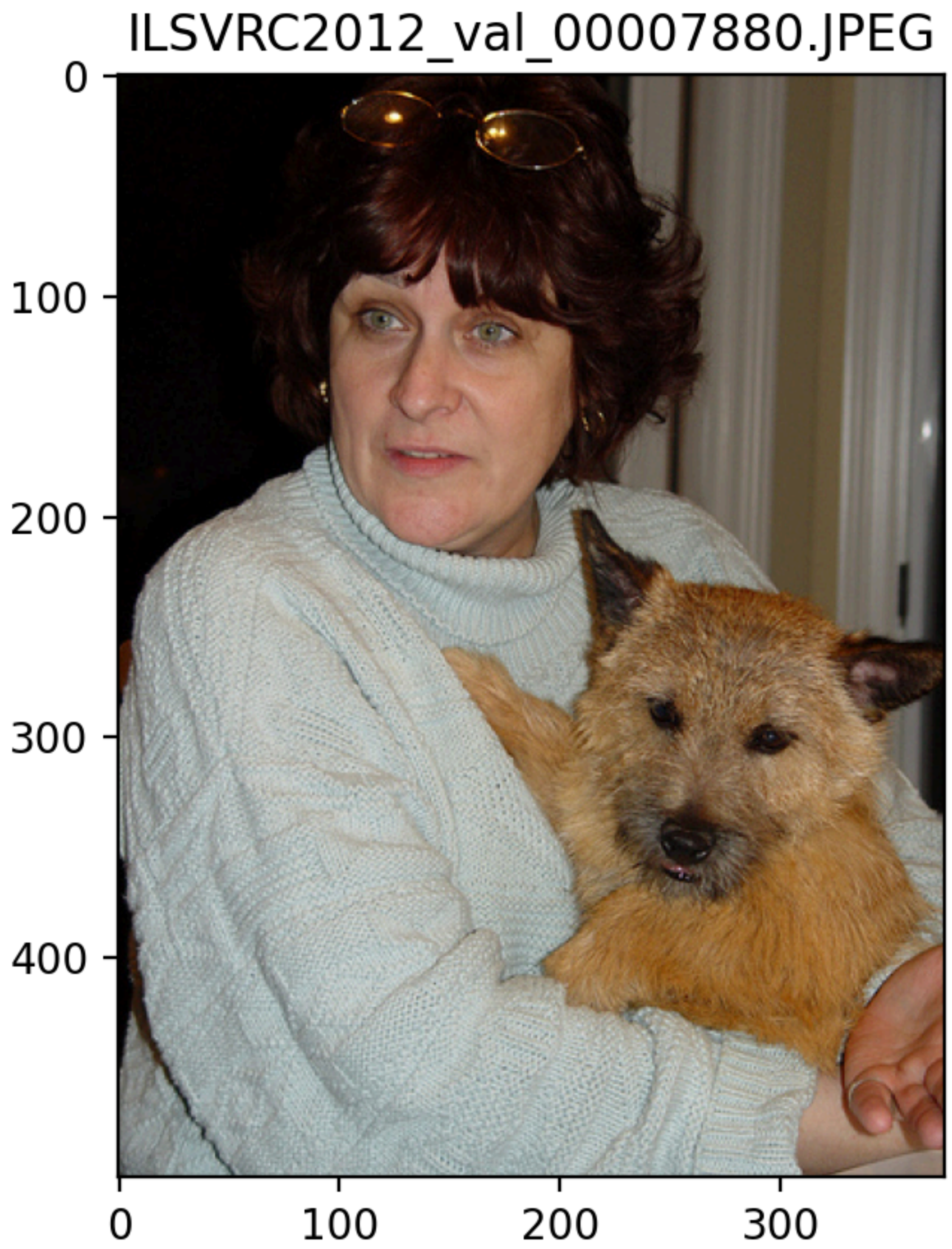

n02094258 Norwich terrier

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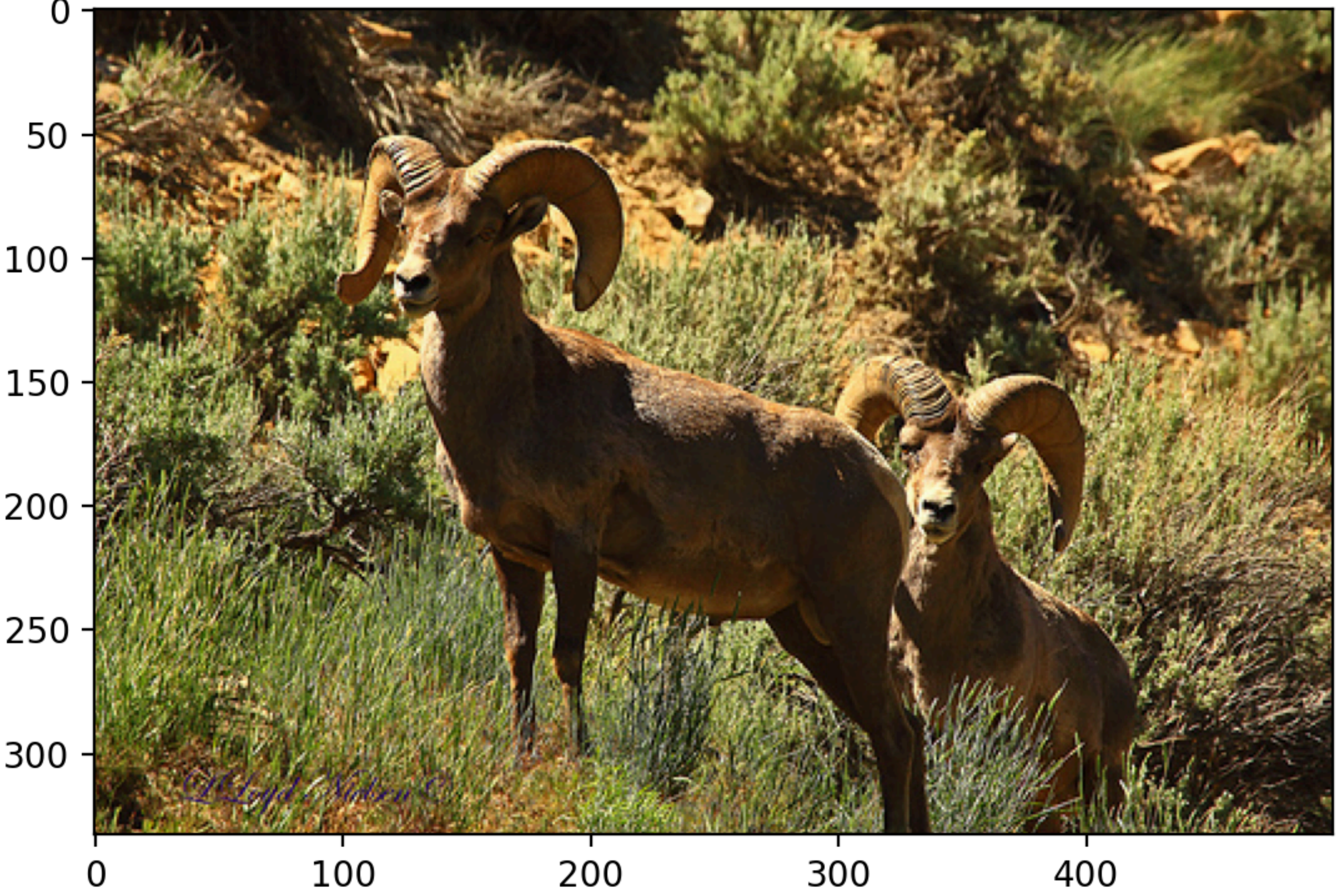

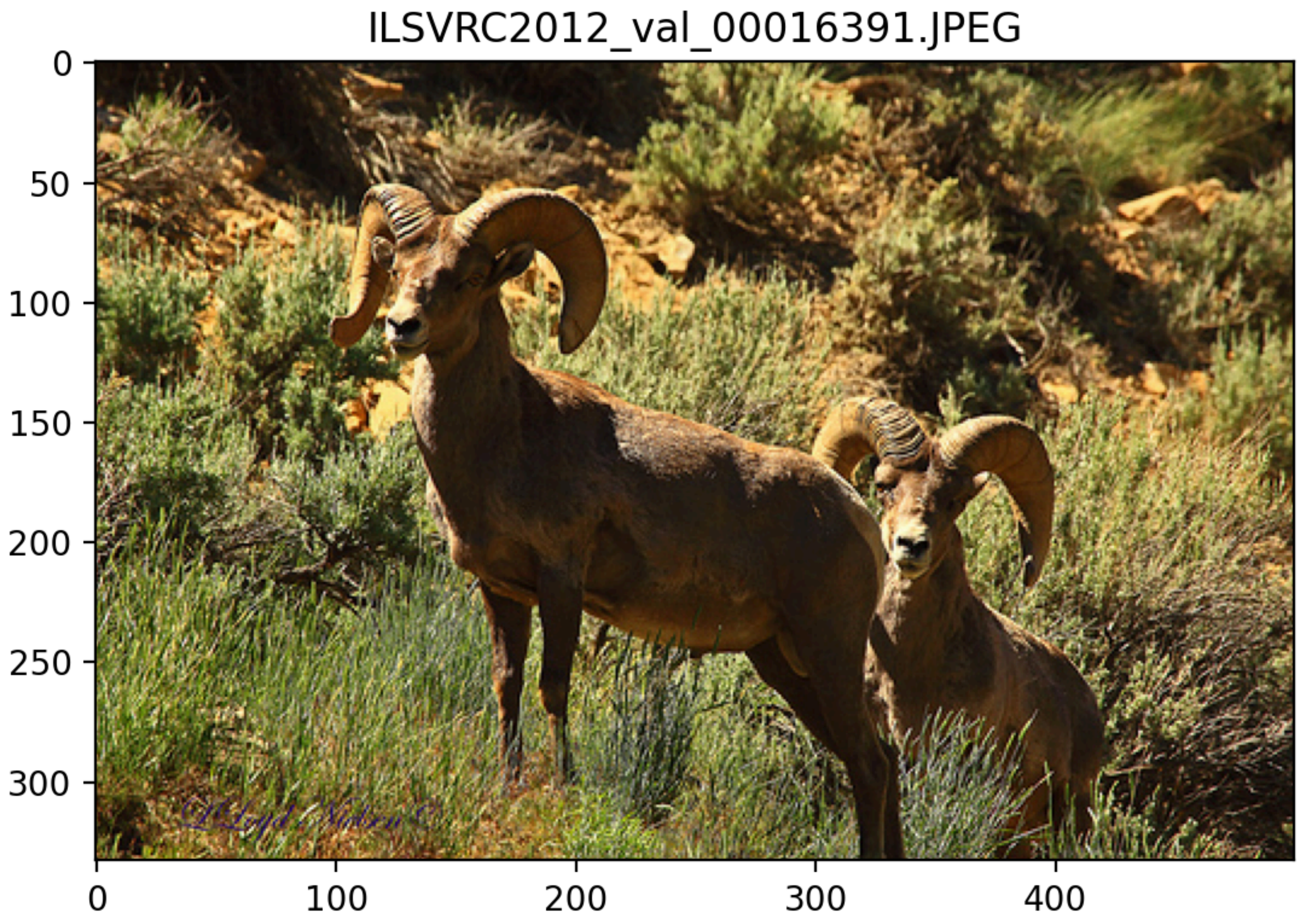

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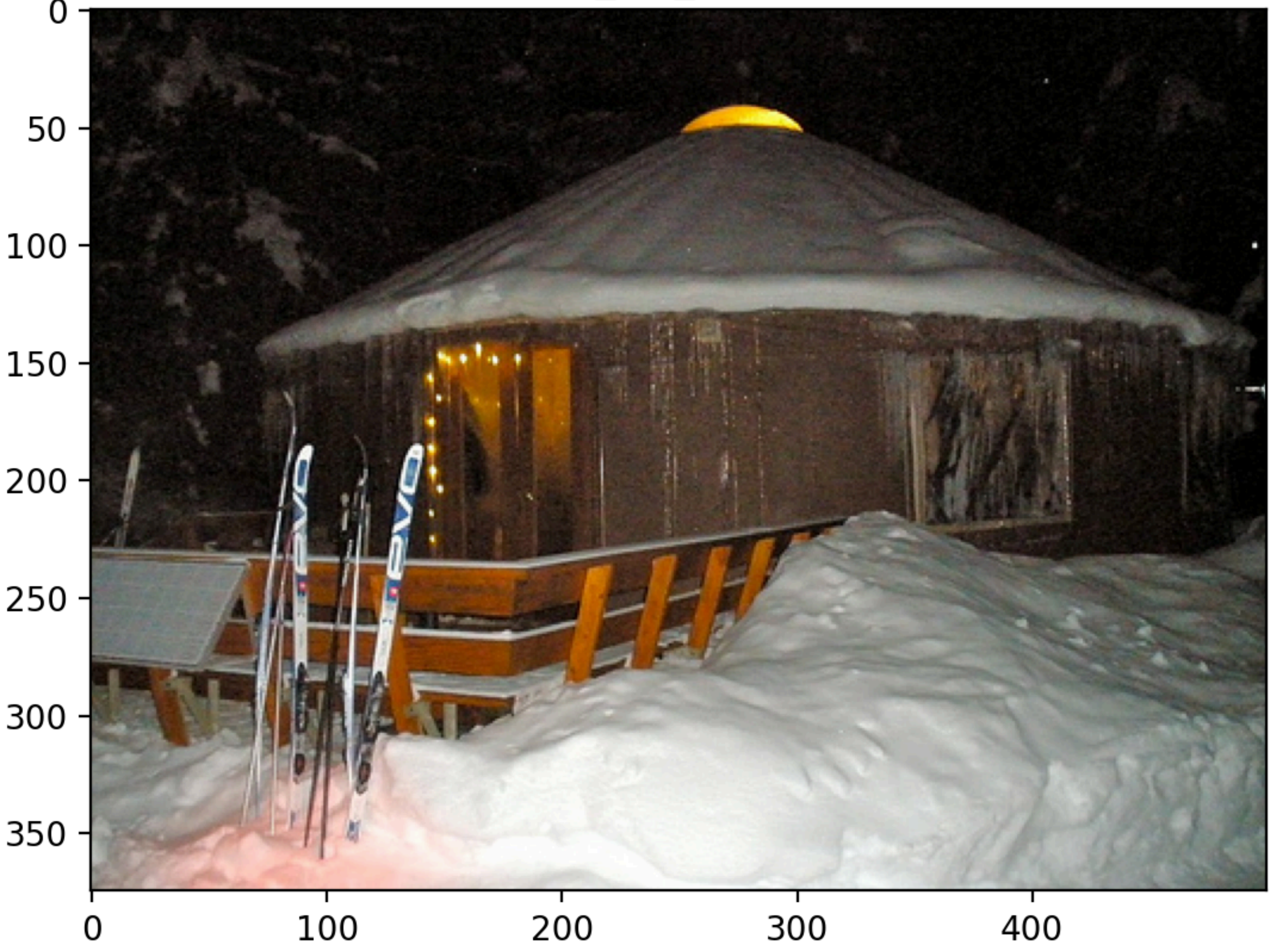

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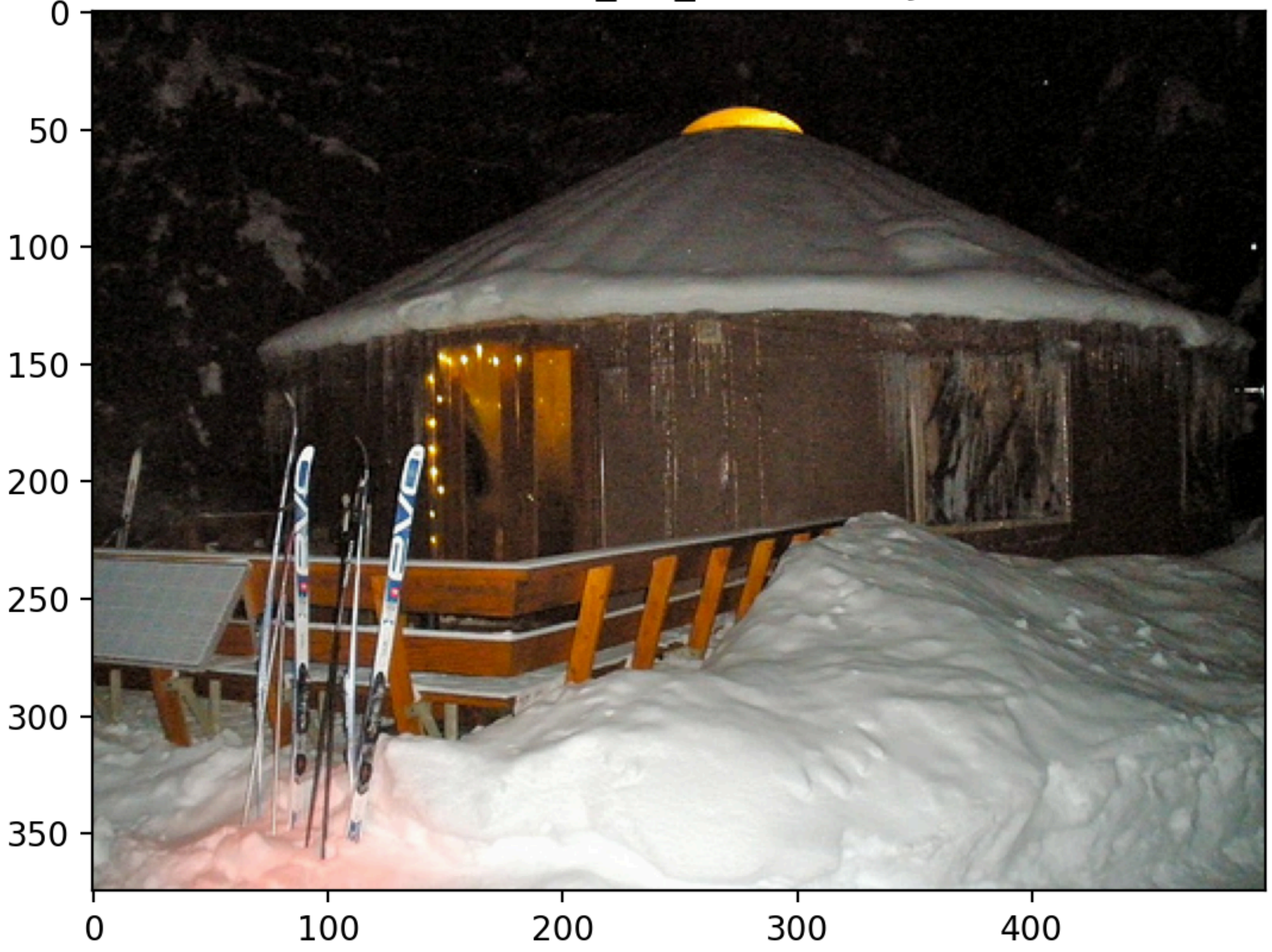

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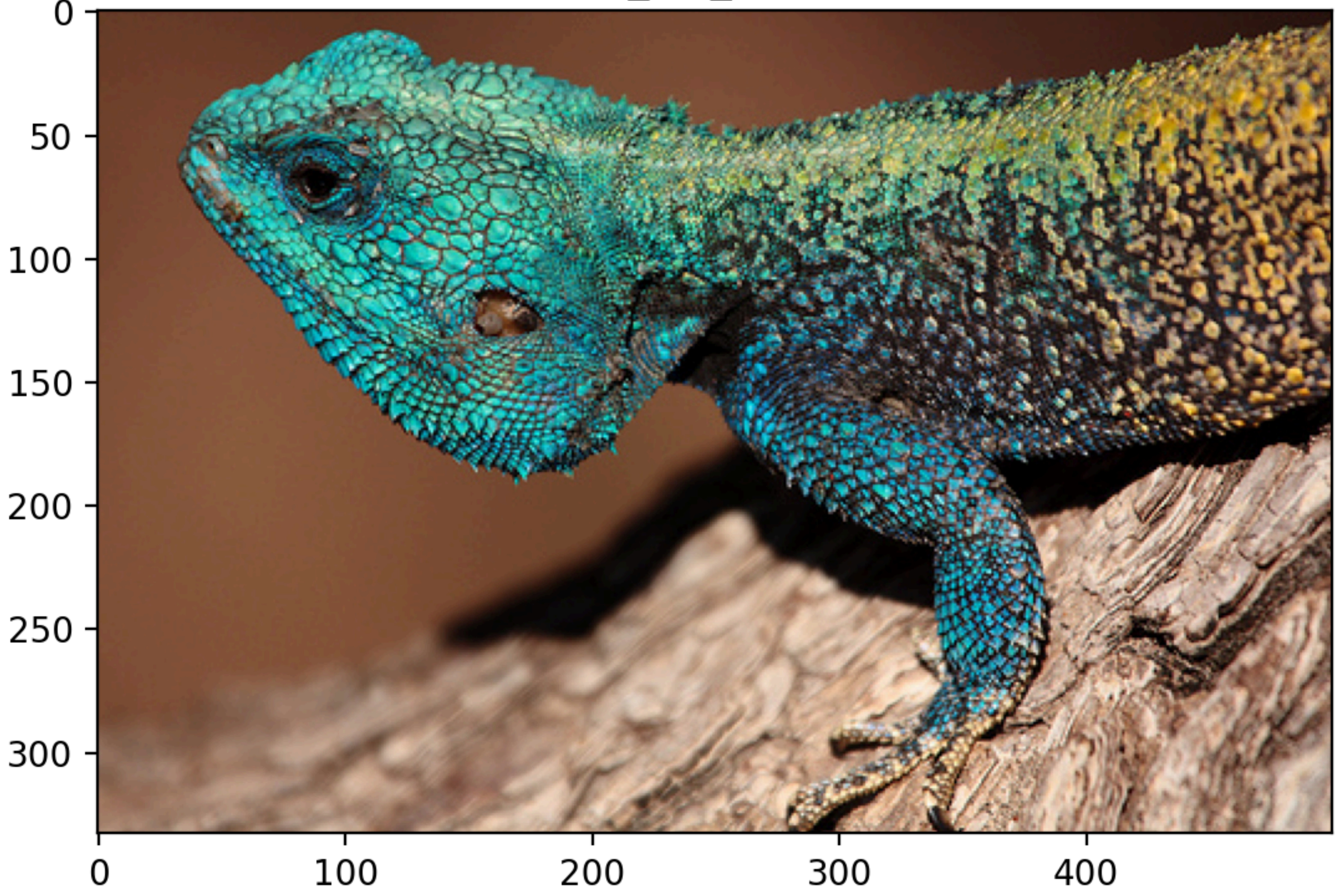

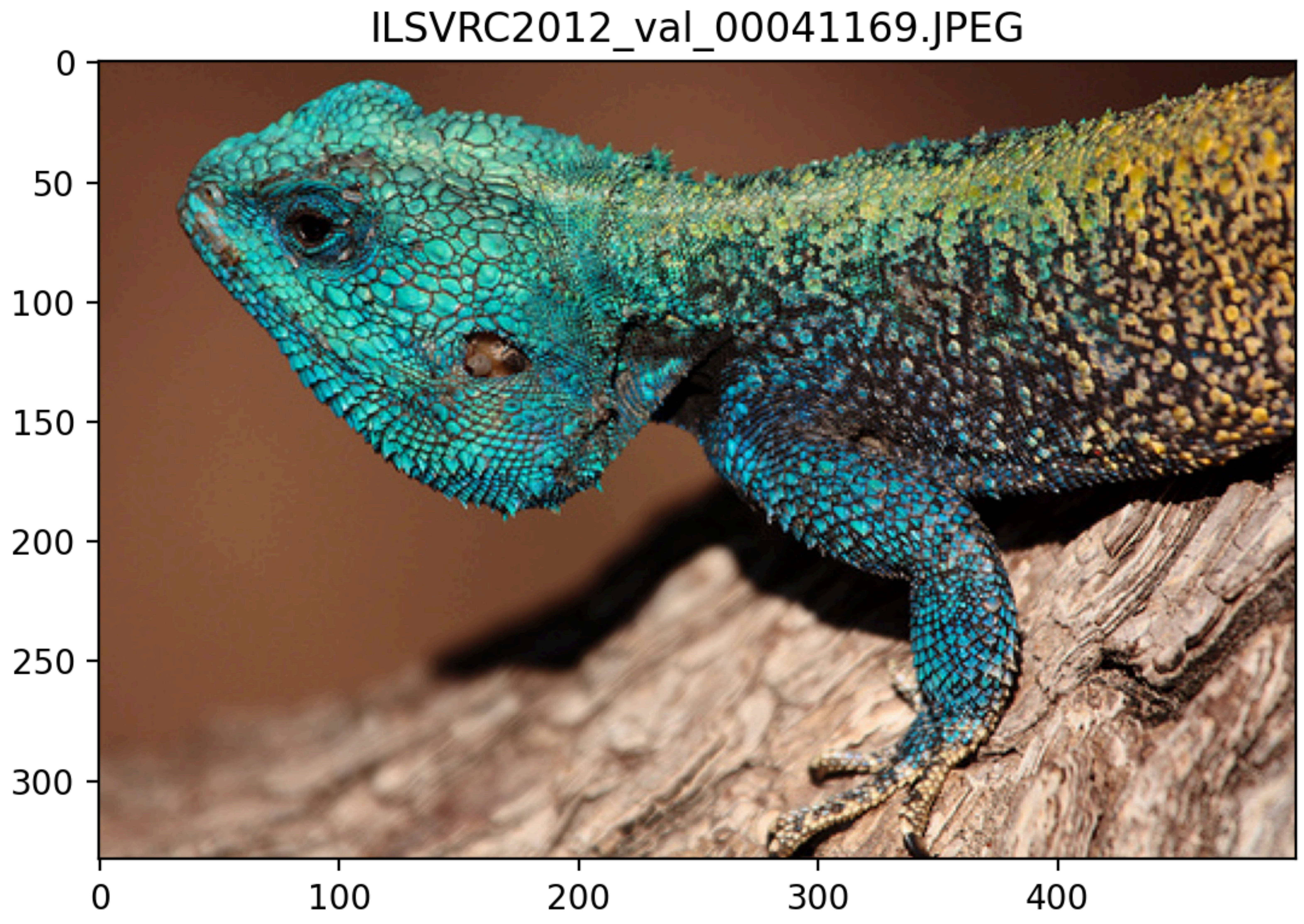

n01687978 agama

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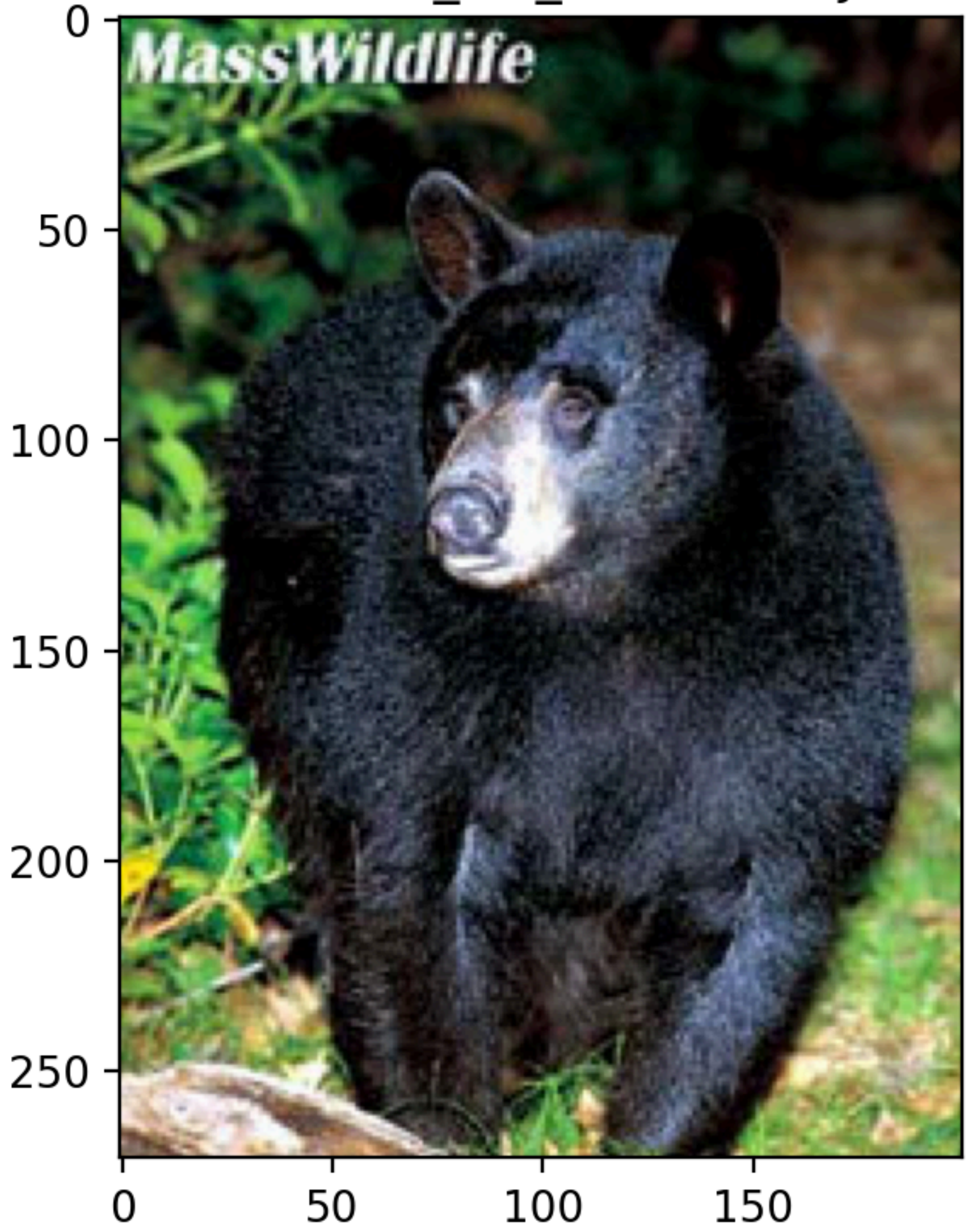
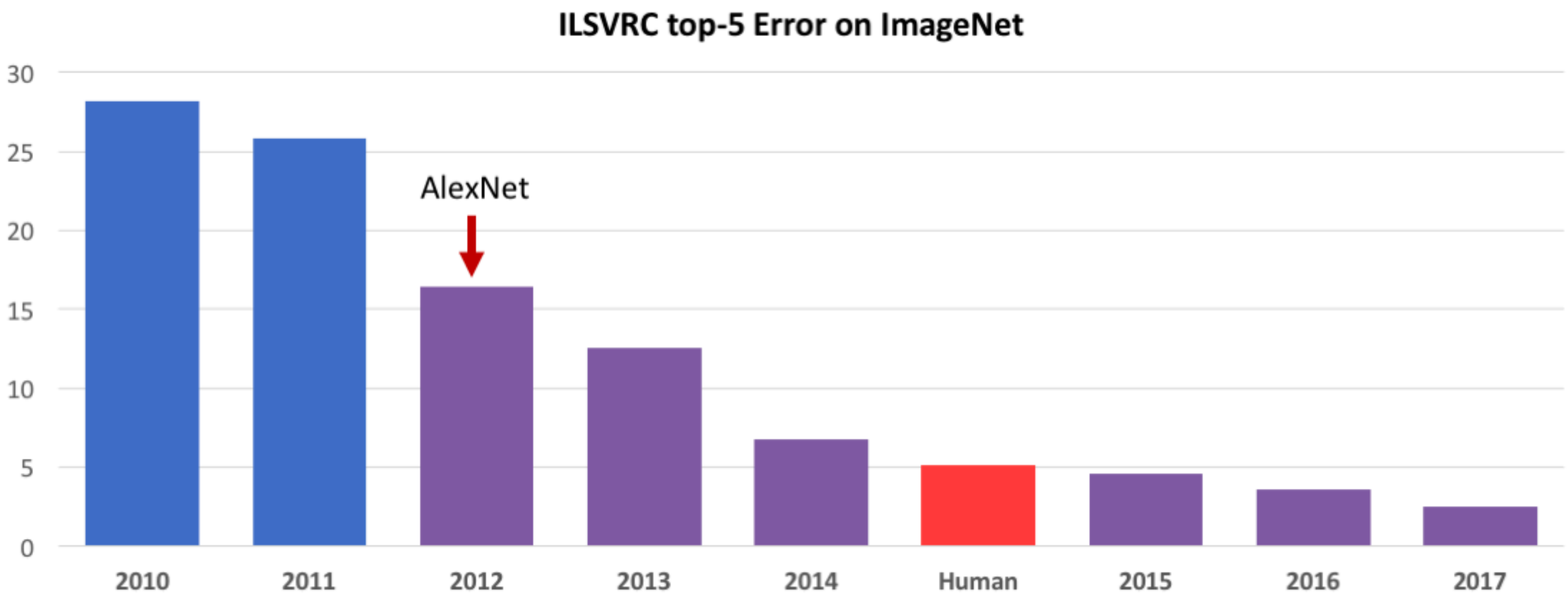


n02134418 sloth bear, Melursus ursinus, Ursus ursinus

ILSVRC2012_val_00013247.JPEG

n04591713 wine bottle



11 teams 4 teams 6 teams

AlexNet

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

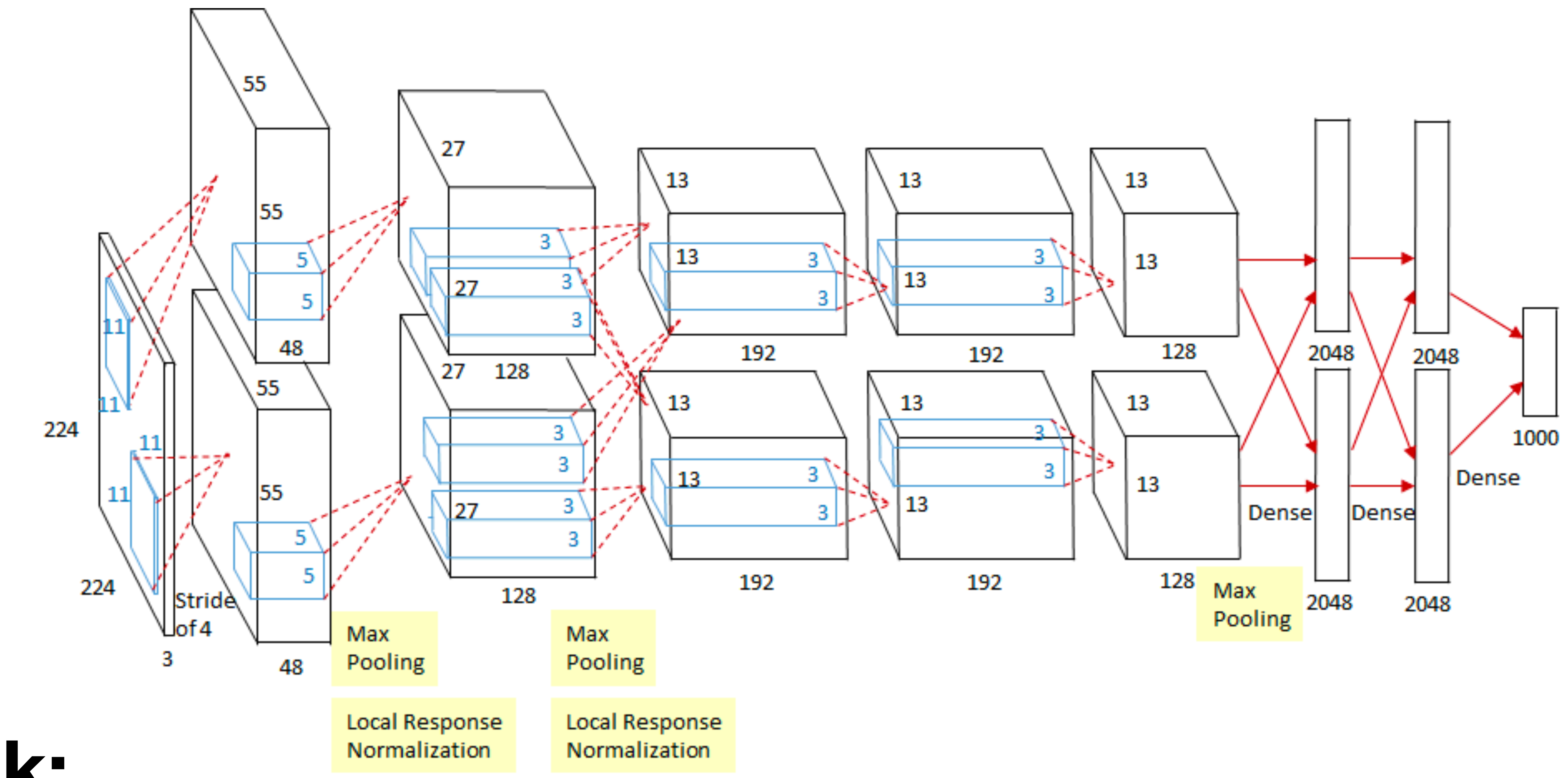
Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

AlexNet

Large **convolutional neural network** (CNN)

Basic idea like in the late 80s, many “tricks” to get it to work on ImageNet



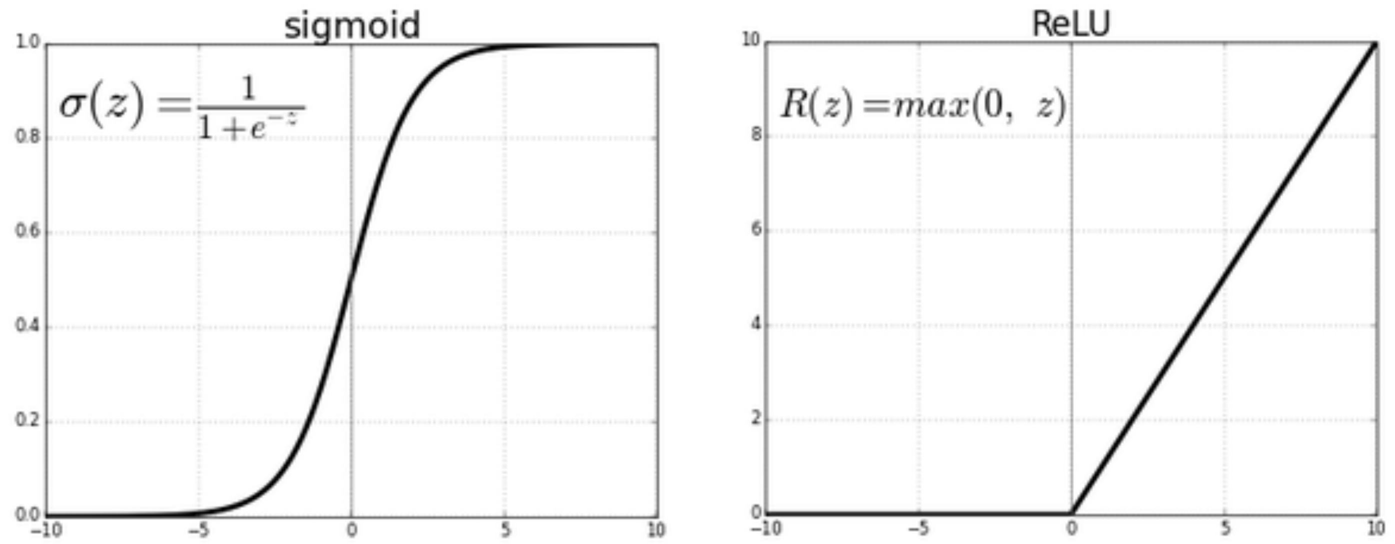
Basic building block:

Structured, learnable linear layer followed by a simple element-wise non-linearity

Repeat the building block several times, add a classification loss at the end.

AlexNet Ingredients

ReLU (rectified linear unit) non-linearity

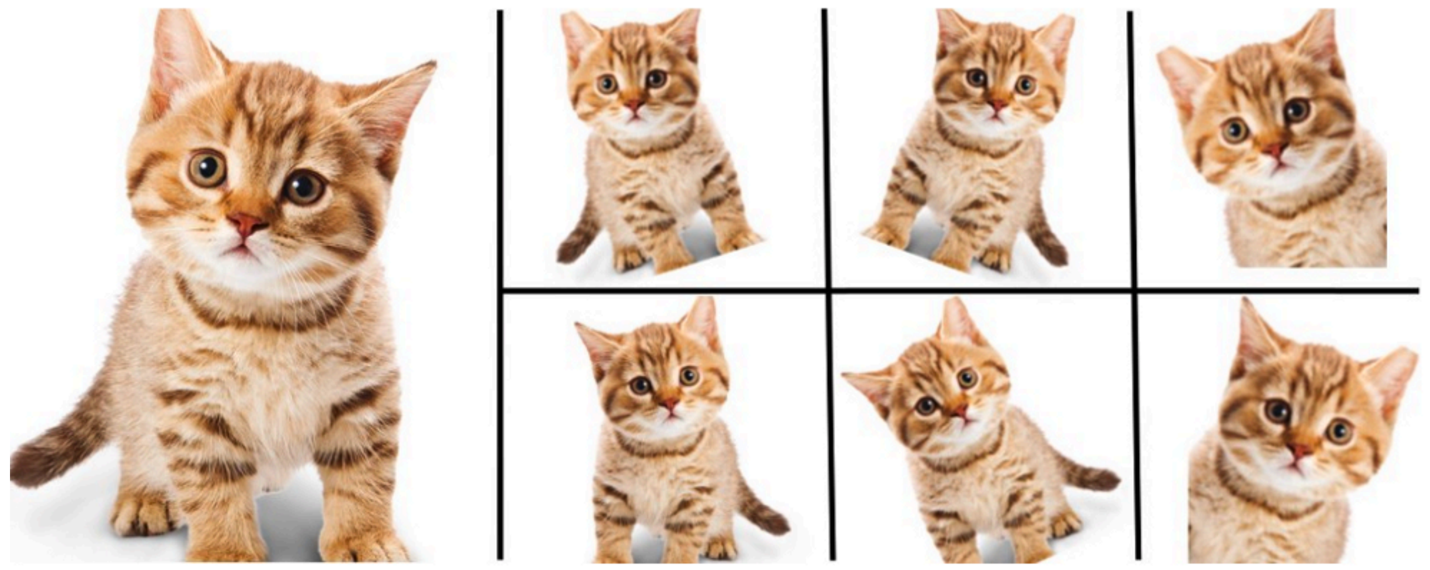


Local response normalization

Training on GPUs

Overlapping pooling

Dropout



Data augmentation

Why these? Each change lead to 0 - 2 percentage points of accuracy improvement.

AlexNet Background

Alex' Masters thesis: "Learning Multiple Layers of Features from Tiny Images"

Built a smaller image classification dataset **CIFAR-10**

- 50,000 images
- 10 classes
- 32x32 pixels
- Subset of a large dataset TinyImages (80 million images)

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➡ Good results, so they decided to scale up the approach

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➡ Good results, so they decided to scale up the approach

➡ Alex tuned the model for **one year** on ImageNet

AlexNet Results

Model	Top-1	Top-5
Sparse coding [2]	*47.1%*	*28.2%*
SIFT + FVs [24]	*45.7%*	*25.7%*
CNN	**37.5%**	**17.0%**

Table 1: Comparison of results on ILSVRC-2010 test set. In *italics* are best results achieved by others.

Model	Top-1 (val)	Top-5 (val)	Top-5 (test)
SIFT + FVs [7]	—	—	*26.2%*
1 CNN	40.7%	18.2%	—
5 CNNs	38.1%	16.4%	**16.4%**
1 CNN*	39.0%	16.6%	—
7 CNNs*	36.7%	15.4%	**15.3%**

Table 2: Comparison of error rates on ILSVRC-2012 validation and test sets. In *italics* are best results achieved by others. Models with an asterisk* were "pre-trained" to classify the entire ImageNet 2011 Fall release. See Section 6 for details.

About 9 percentage points improvement over previous state-of-the art

Immediate Controversy in 2012

Yann LeCun ▸ Public Oct 13, 2012

+Alex Krizhevsky's talk at the ImageNet ECCV workshop yesterday made a bit of a splash. The room was overflowing with people standing and sitting on the floor. There was a lively series of comments afterwards, with +Alyosha Efros, Jitendra Malik, and I doing much of the talking.

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Too bad I couldn't be there! Any take-away points for those of us who couldn't attend? +Alyosha Efros , I'd love to get your take as well!

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Yann LeCun — Oct 13, 2012

+Svetlana Lazebnik: Our friend +Alyosha Efros said that ImageNet is the wrong task, wrong dataset, wrong everything. You know him ;-)

Still, he likes the idea of feature learning.

Alyosha Efros +11

Oct 14, 2012

Something like that... :) I do like feature learning, the less supervised --- the better. So, I am excited that people are working in this direction, but I am not ready to declare success until they can show improvement on PASCAL detection. Basically, I think ImageNet is just too easy (+Yann LeCun did confirm that it's easier than PASCAL in terms of objects being more centered and little scale variation). In my view, the important thing to look at is chance performance. Chance on PASCAL detection is something like 1 in a million. Chance on Imagenet classification is 1 in 200 (easier than Caltech-256!!!). Chance on ImageNet detection is lower but still maybe around 1 in a thousand or so. When chance is so high, the temptation for a classifier to overfit to the bias is in the data is too great. The fact that "t-short" category turned out to be one of the easiest ones for all the classifiers in the competition should give us pause as to whether the task is indeed modeling the complexity of our visual world. What was agreed upon is that, even if deep learning can't be applied to PASCAL detection directly (although I still don't see why not), it should still be possible to use the features learned from ImageNet and then use them on PASCAL instead of HOG. I do think it will give some sort of a boost, but I suspect it won't be a huge one.

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Geoffrey Hinton +31

Oct 15, 2012

I predicted that some vision people would say that the task was too easy if a neural net was successful. Luckily I know Jitendra so I asked him in advance whether this task would really count as doing proper object recognition and he said it would, though he also said it would be good to do localization too. To his credit, Andrew Zisserman says our result is impressive.

I think its pretty amazing to claim that a vision task is "just too easy" when we succeed even though some really good vision people tried hard at it and failed to do nearly as well. I also think that trying to discredit a system that gets about 84% correct by saying you could get 0.5% correct by chance is a bit desperate.

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This is not a religious war between deep learning and computer vision. Everyone wins when someone improves a result on some benchmark. No one should feel "defeated", and no one should give up unless they no longer believe in what they are doing. Progress is always exciting, particularly when it comes from a brand new way of doing things, rather than from a carefully tweaked combination of existing methods.

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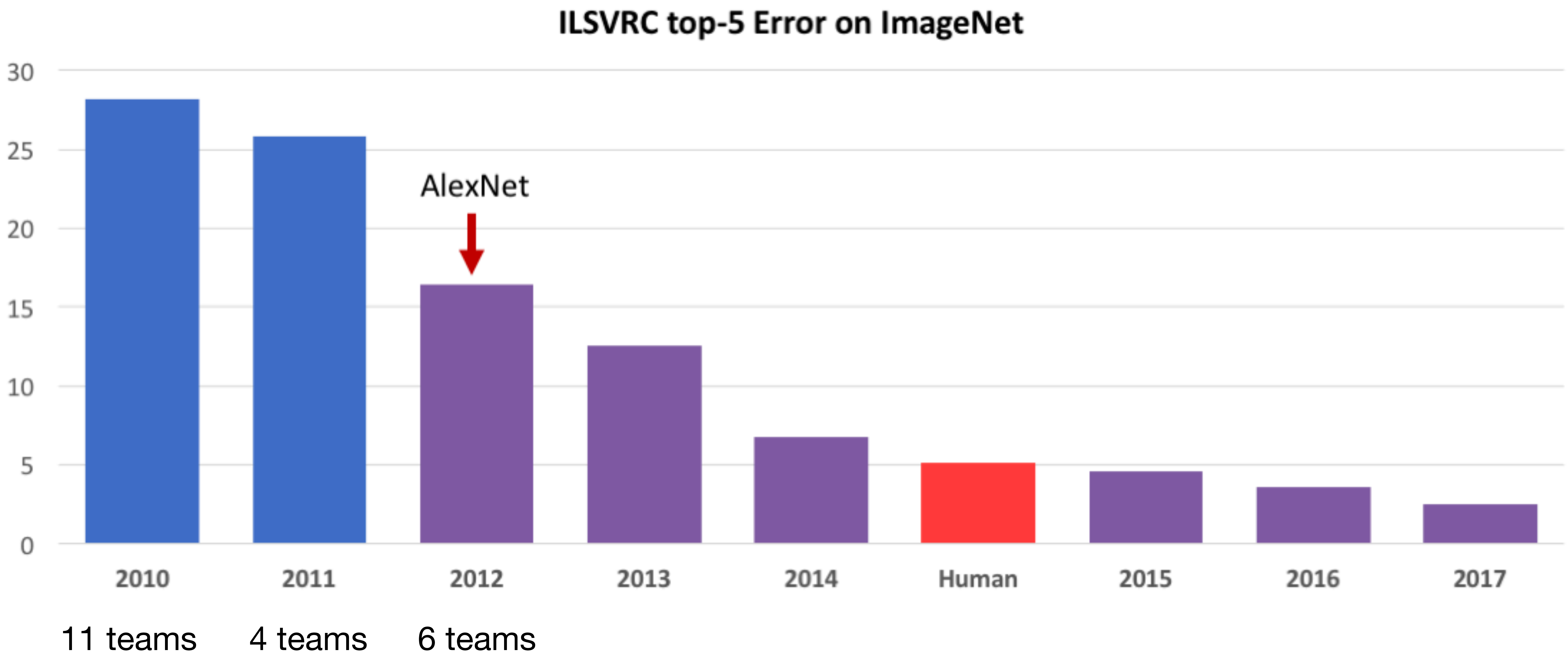
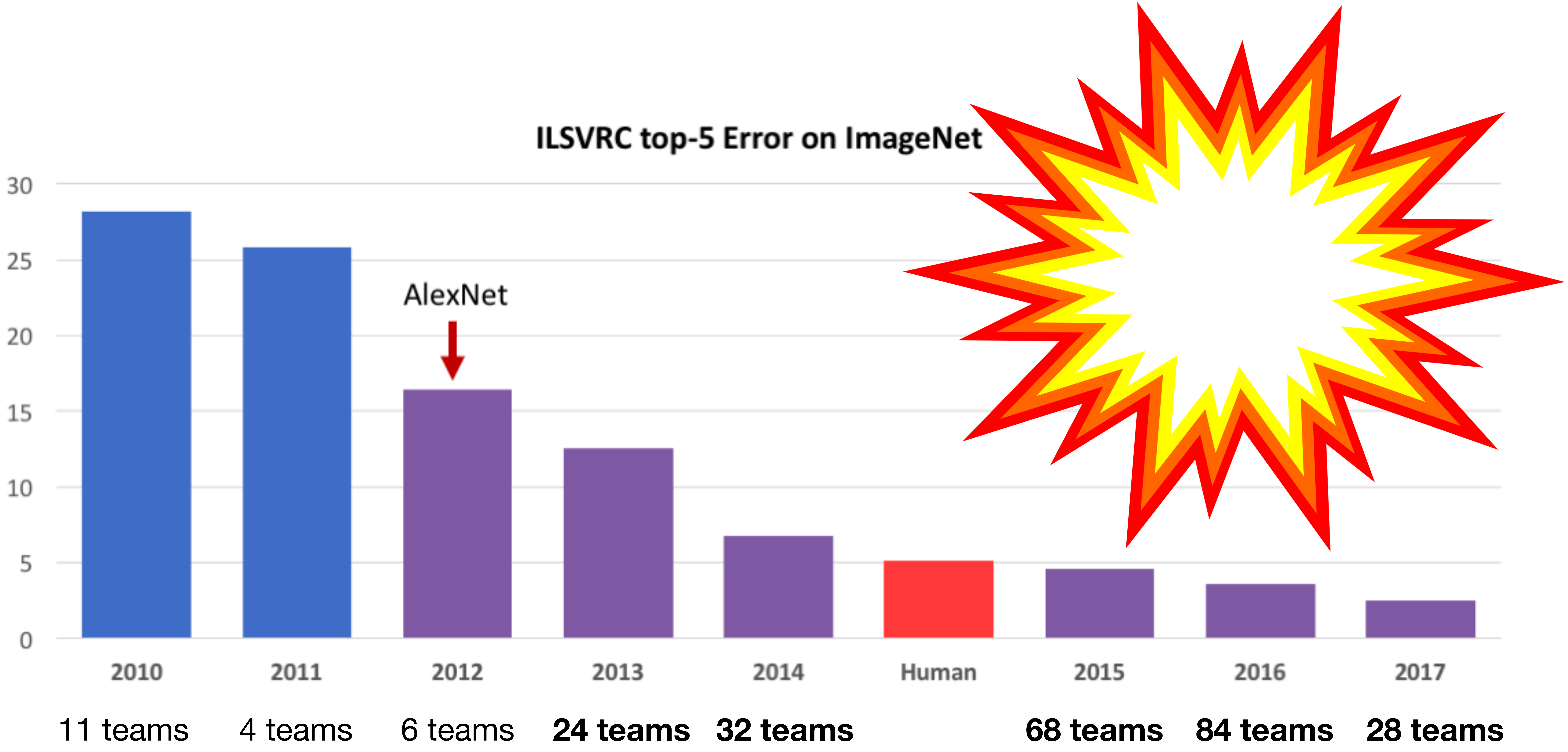
NOTE: Alyosha is a great scientist.

When he's wrong, he's happy to admit it and he is wrong in interesting ways.


ILSVRC top-5 Error on ImageNet
30
25
20
15
10
5
0
AlexNet
2010
2011
2012
2013
2014
Human
2015
2016
2017
11 teams
4 teams
6 teams



Large improvement, new method ➡ Tremendous interest from the community

Impact on ImageNet

Effectively every team switches to convolutional neural networks.

Subsequent networks

Impact on ImageNet

Effectively every team switches to convolutional neural networks.

Subsequent networks

- VGG (2014): up to 19 layers (AlexNet: 8 layers), more parameters

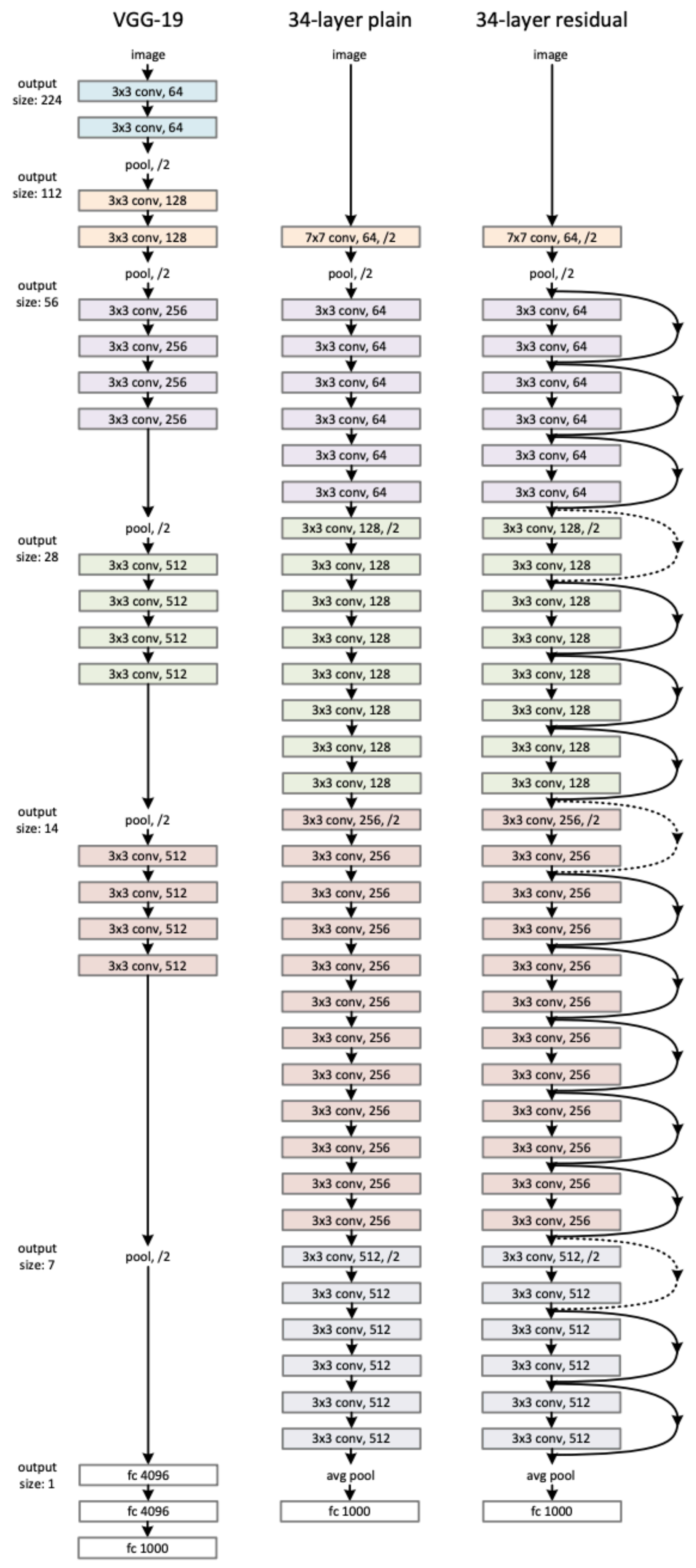


Figure 3. Example network architectures for ImageNet. **Left**: the VGG-19 model [41] (19.6 billion FLOPs) as a reference. **Middle**: a plain network with 34 parameter layers (3.6 billion FLOPs). **Right**: a residual network with 34 parameter layers (3.6 billion FLOPs). The dotted shortcuts increase dimensions. **Table 1** shows more details and other variants.

Impact on ImageNet

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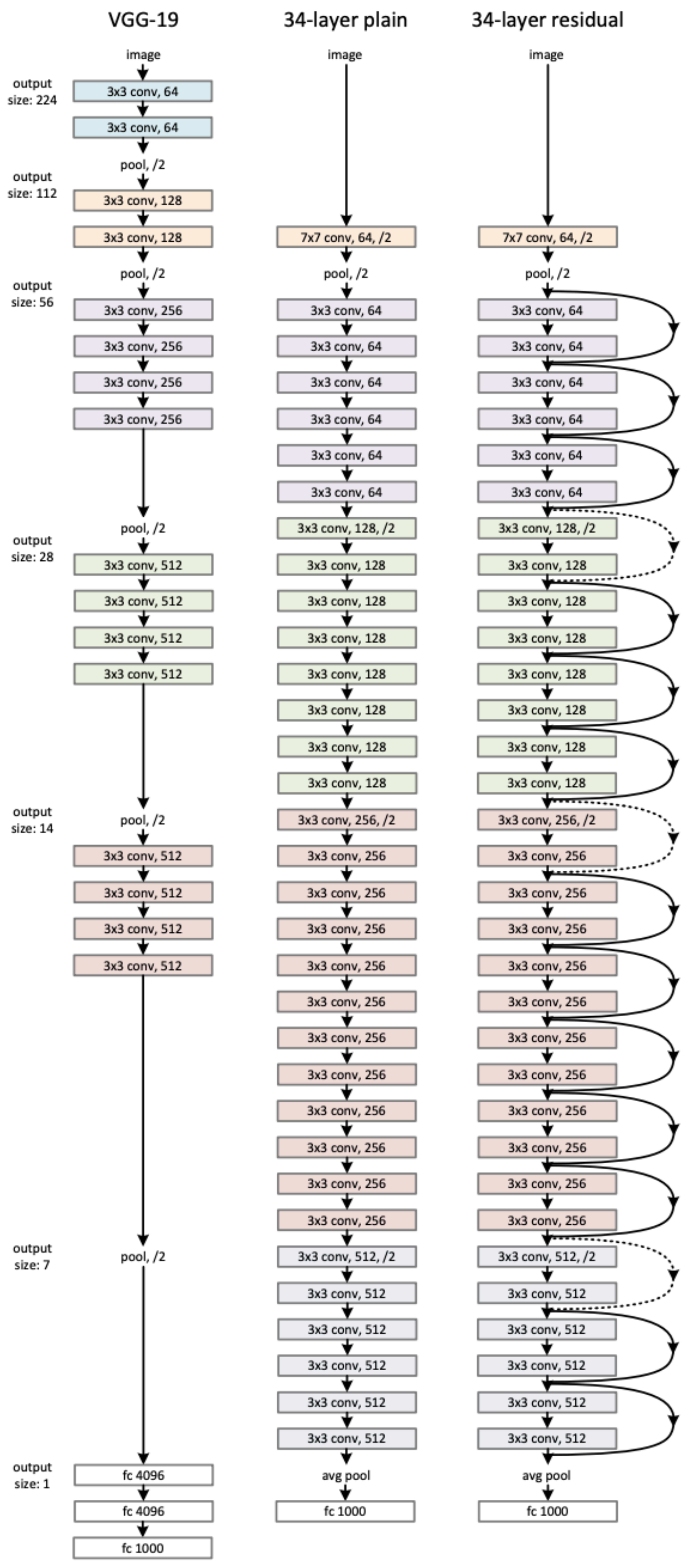
- VGG (2014): up to 19 layers (AlexNet: 8 layers), more parameters
- ResNet (2015): 150 layers, more parameters



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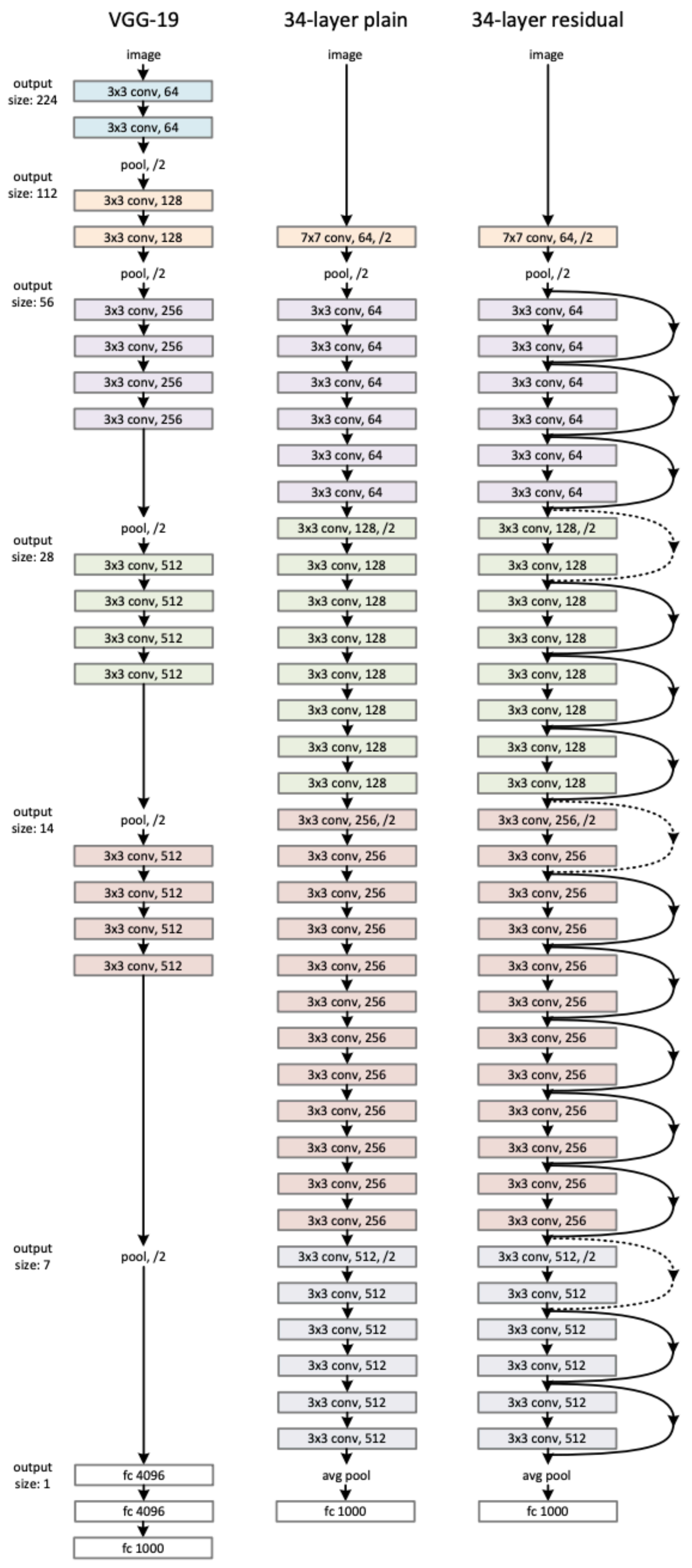

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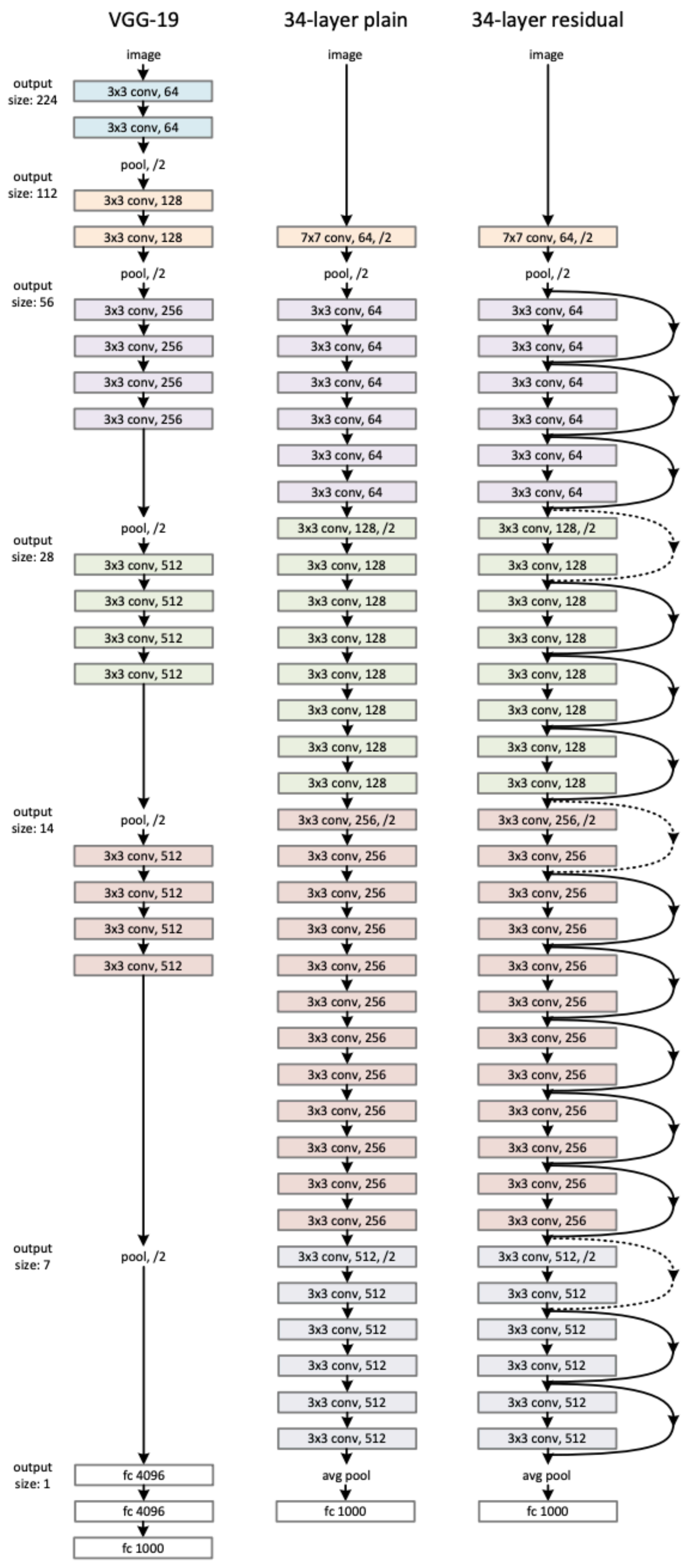
Training times **increase** to weeks on dozens of GPUs ($30k) …

… and decrease by orders of magnitude ($100 for a ResNet)



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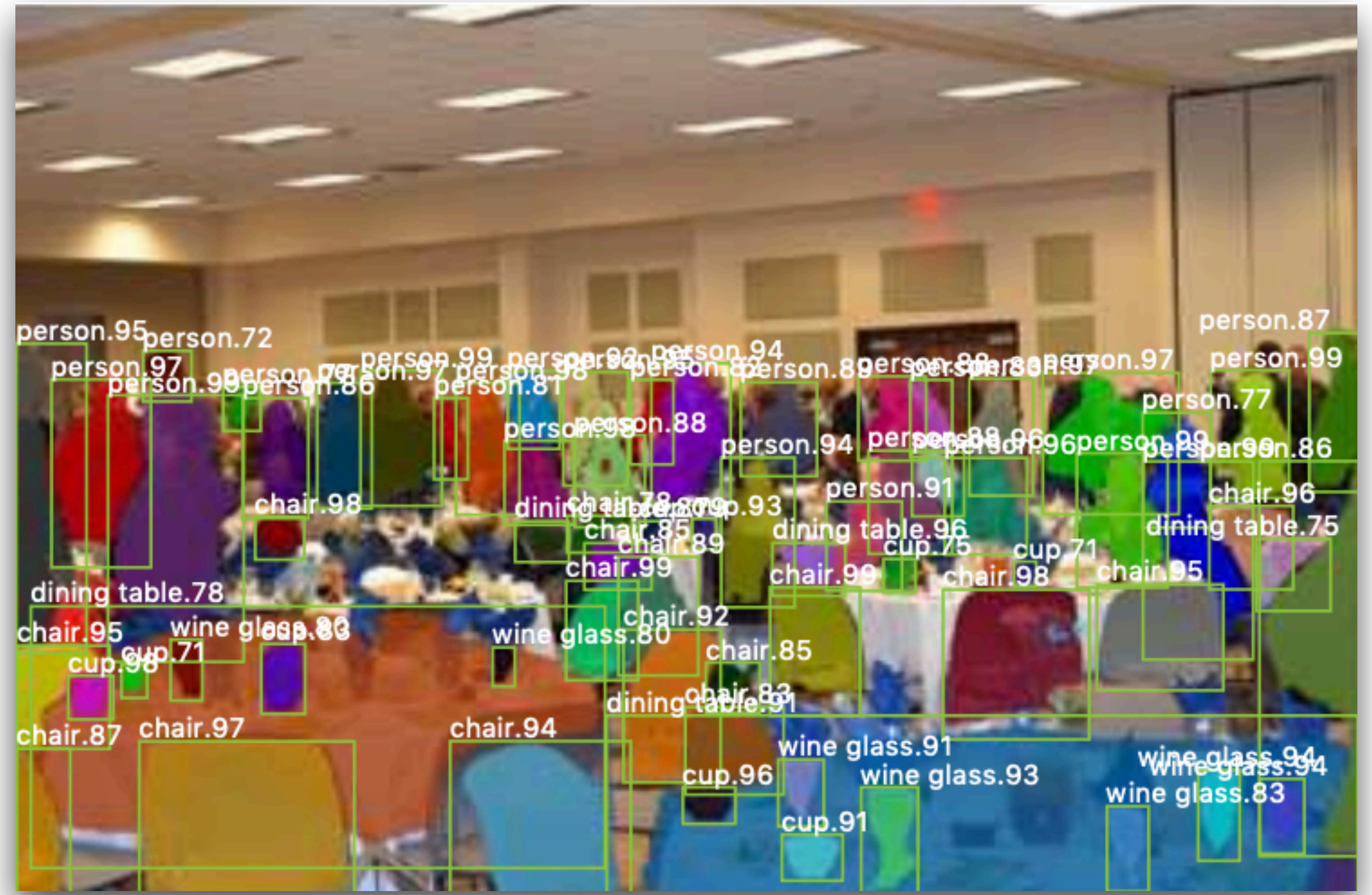
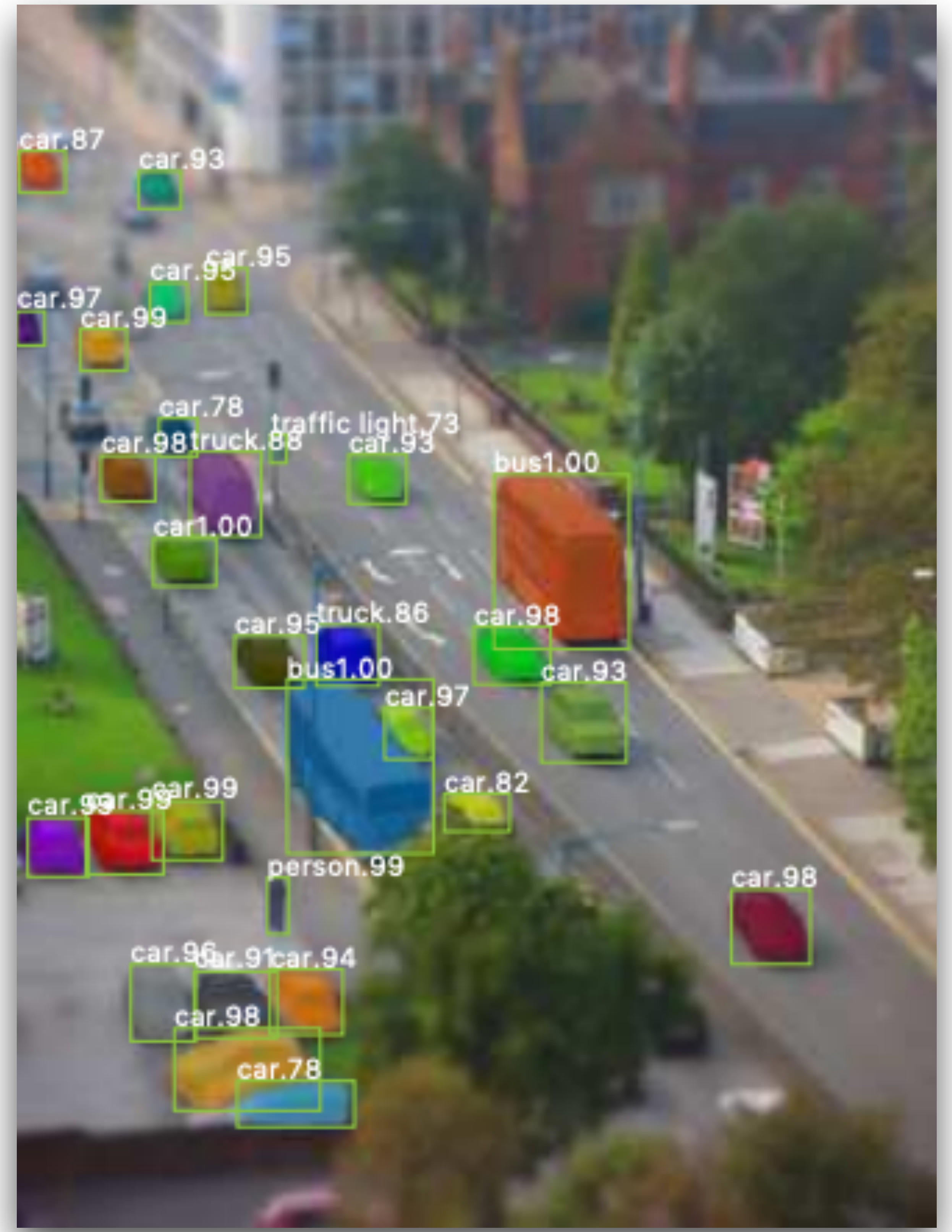
Impact on Computer Vision

Effectively the entire field switches to convolutional neural networks.

- Object detection
- Image segmentation
- Pose estimation
- 3D reconstruction
- Image inpainting
- Generative models
- etc.





Deep learning revolution in computer vision

Historical Comparison - Revolutions

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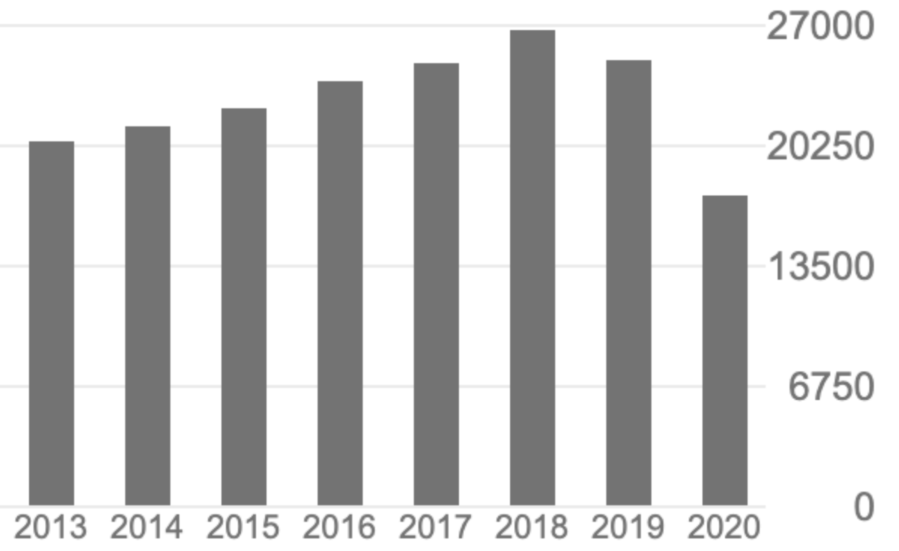

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The communist manifesto K Marx, F Engels Penguin	11661	2002
The german ideology K Marx, F Engels International Publishers Co	11652	1970
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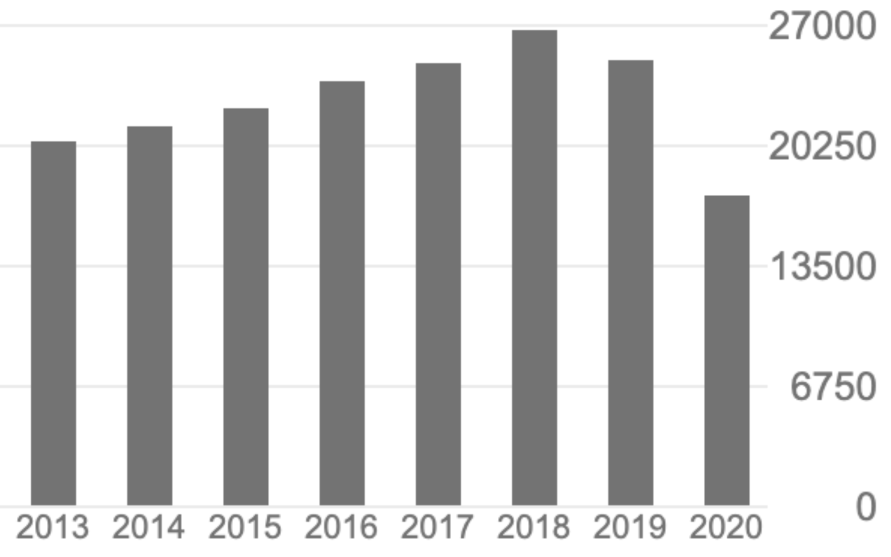

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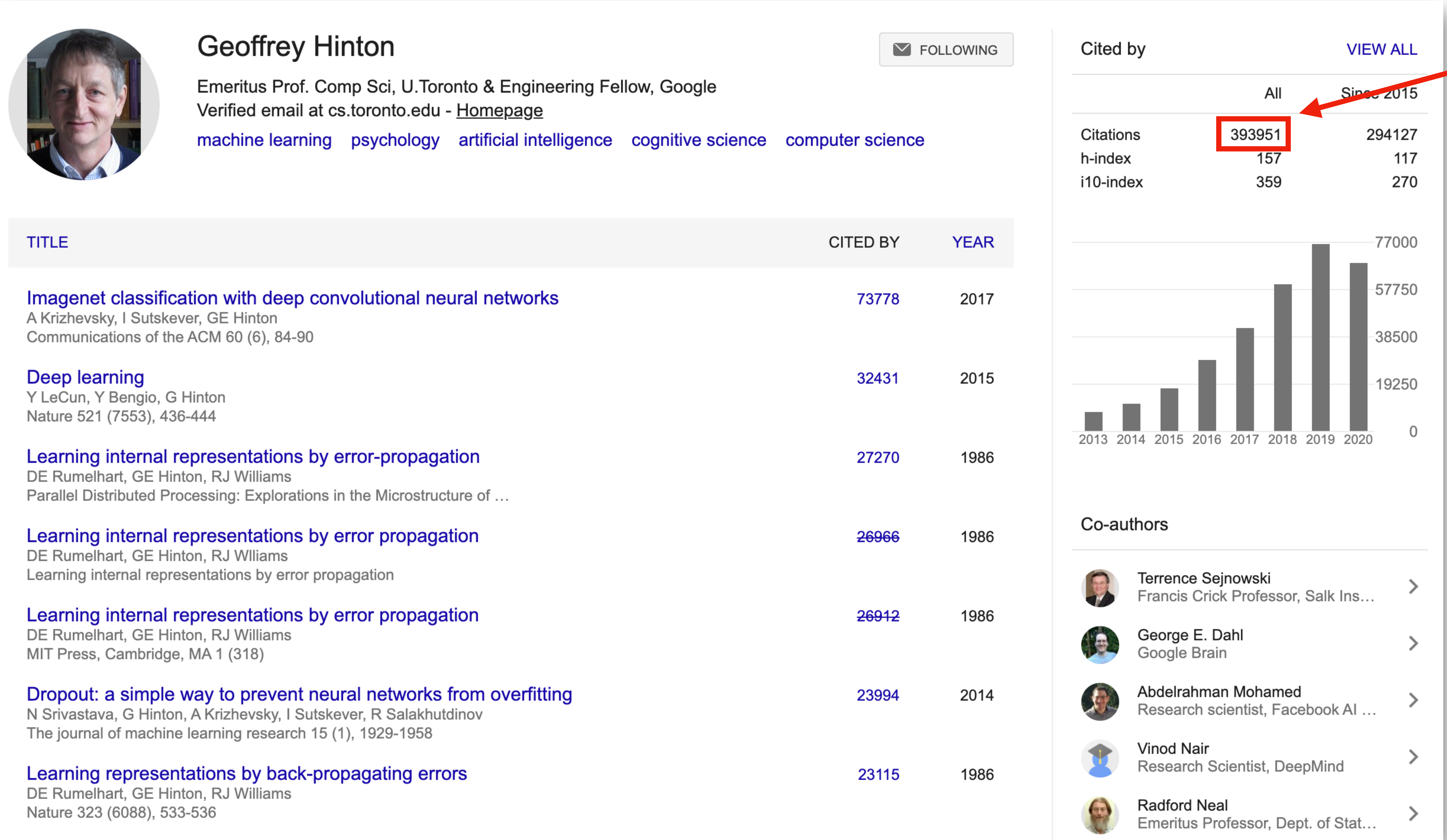

10k more than Marx!

Historical Comparison - Revolutions

10k more than Marx!

CAVEAT: DO NOT MEASURE SCIENCE BY CITATION COUNT

Similar Performance Trends for Many Other Datasets

Object detection (PASCAL VOC)

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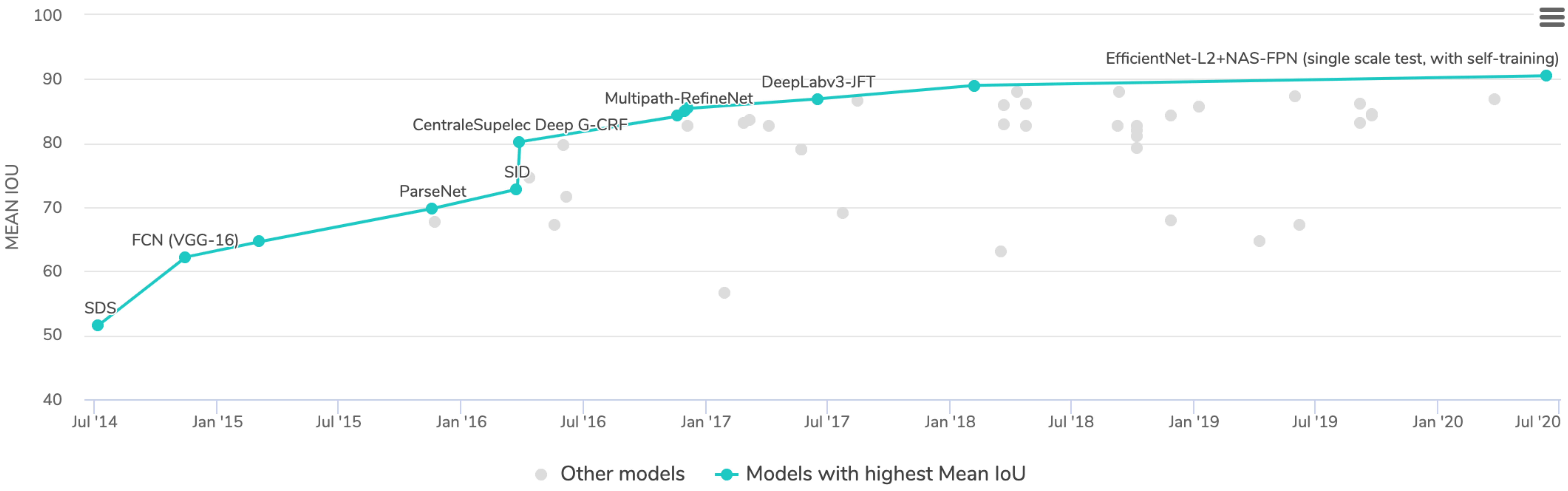
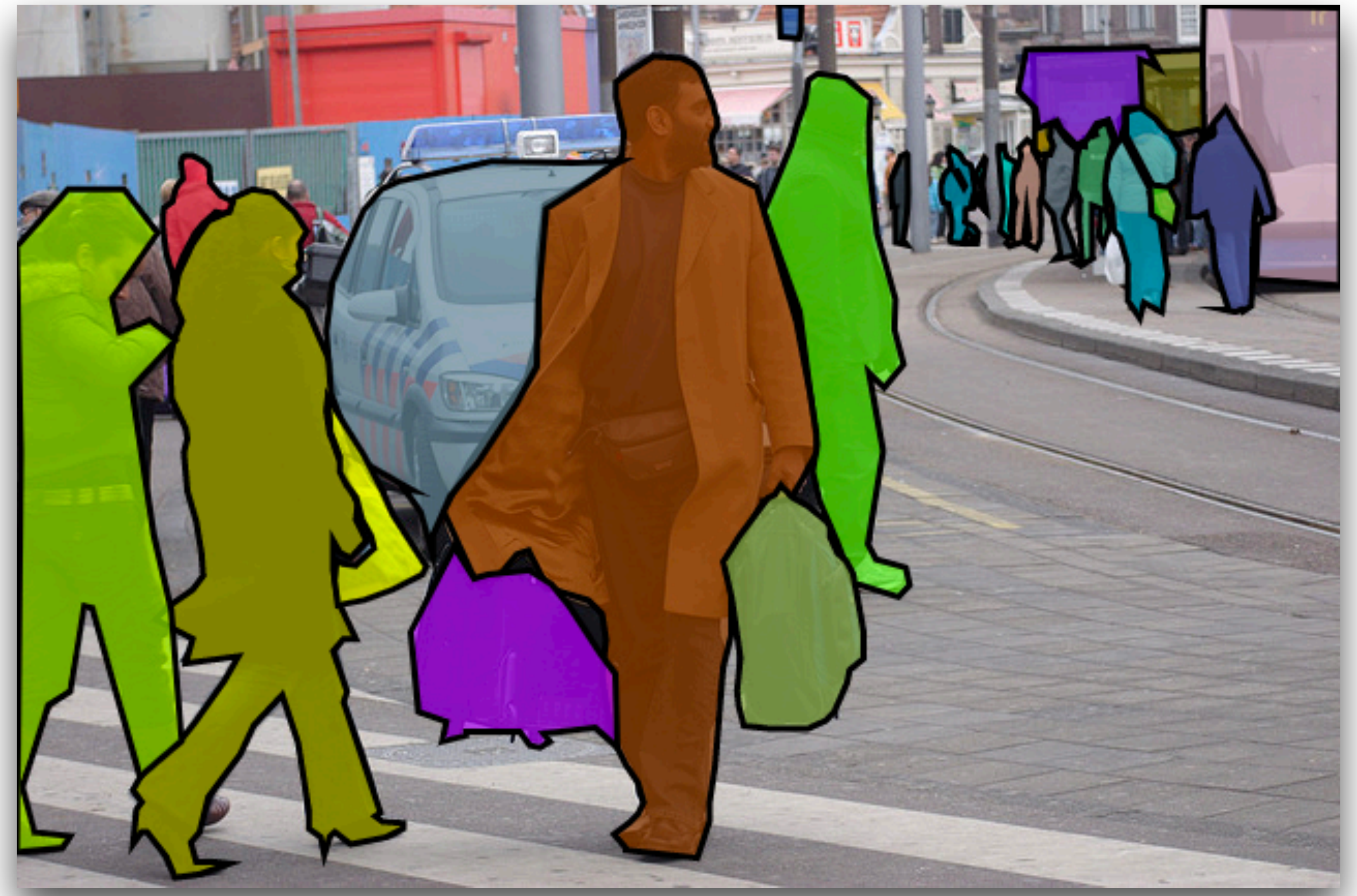


Object Detection (MS COCO)



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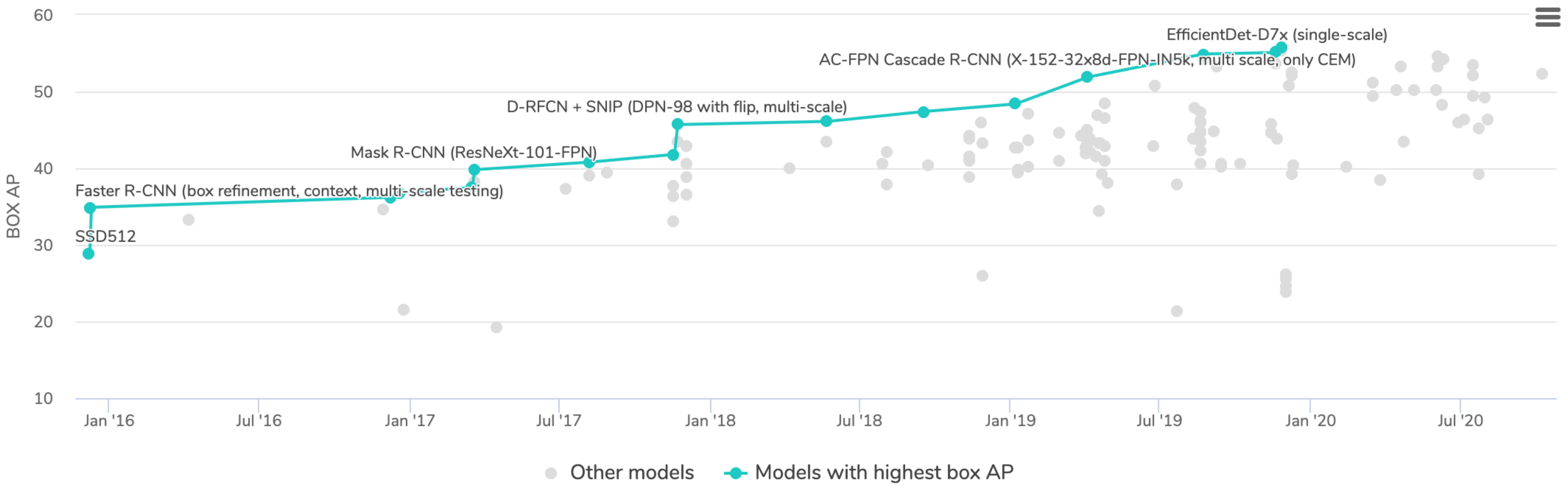

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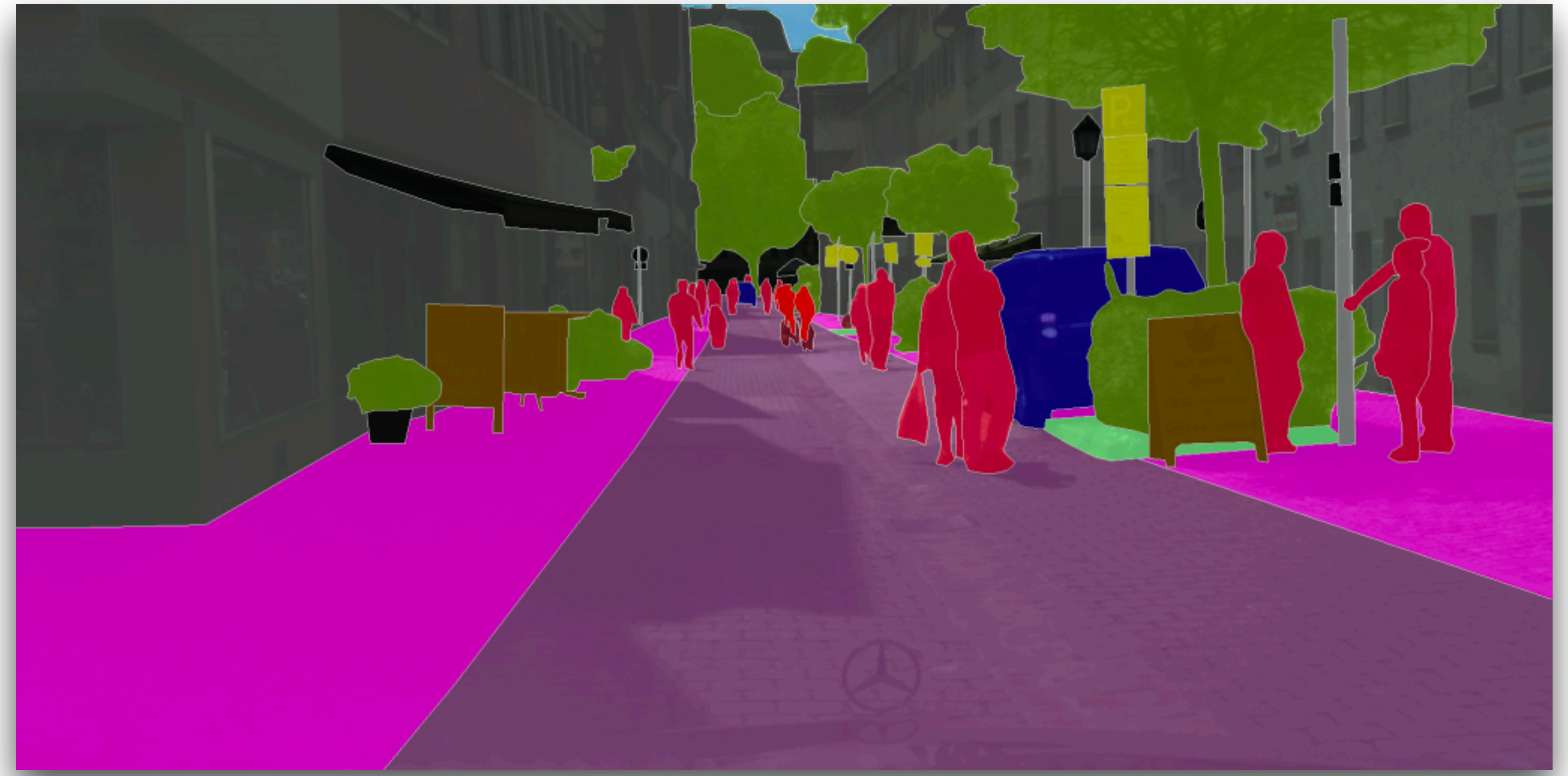
Semantic Segmentation (Cityscapes)



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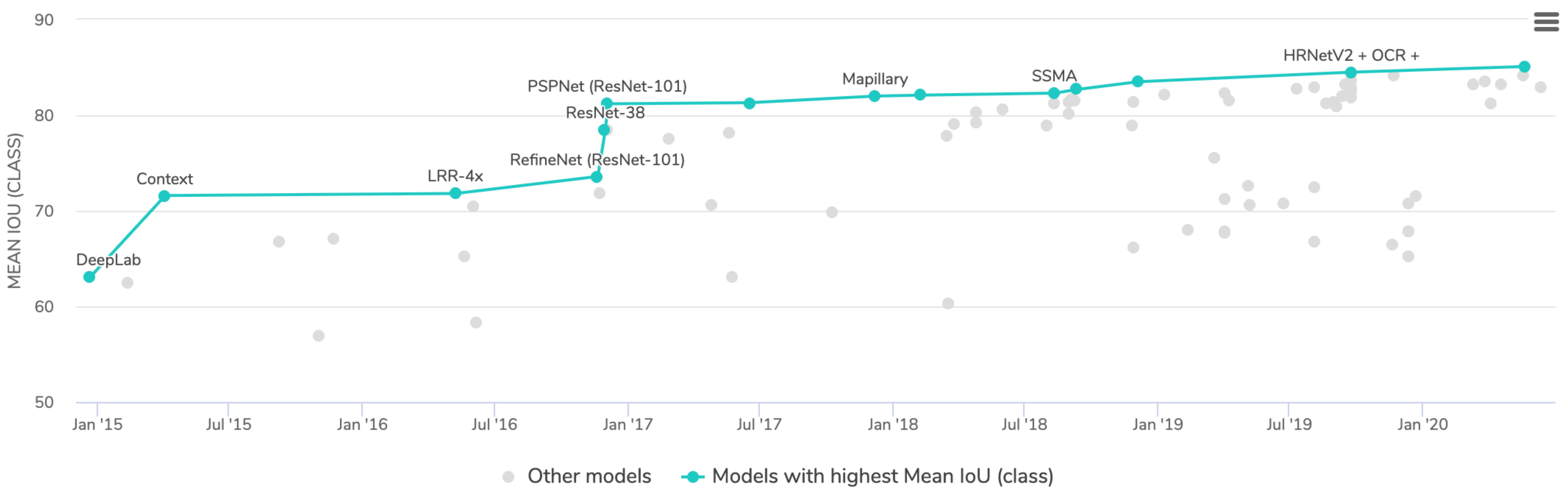
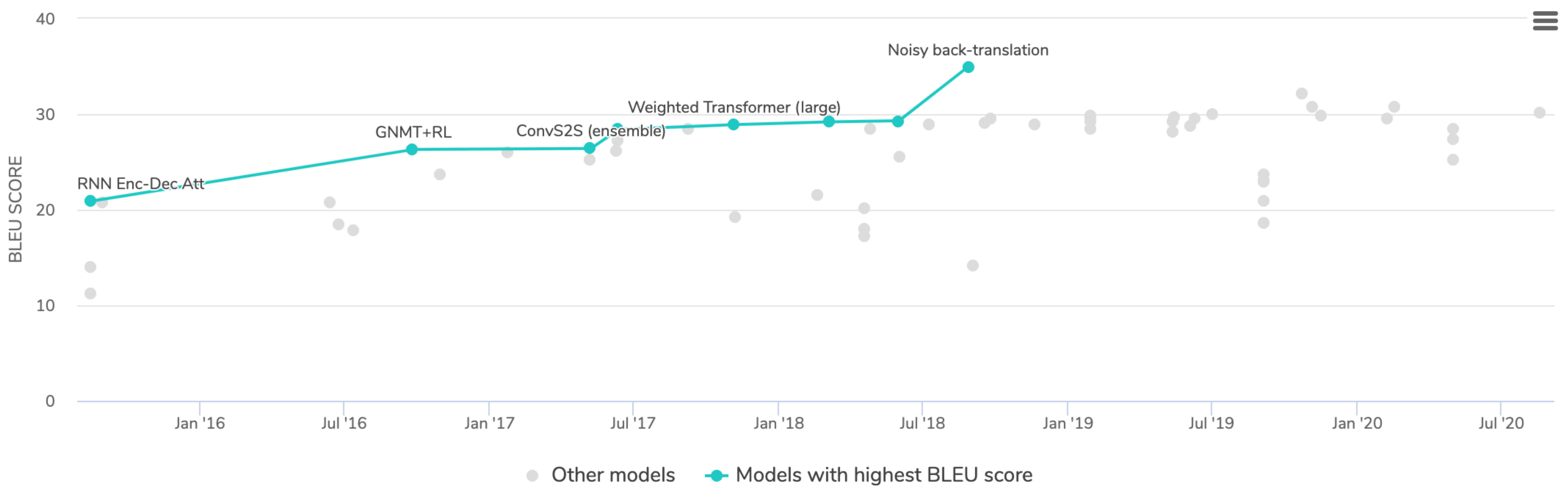


Machine Translation (WMT EN-DE)



Question Answering (SQuAD 1.1)

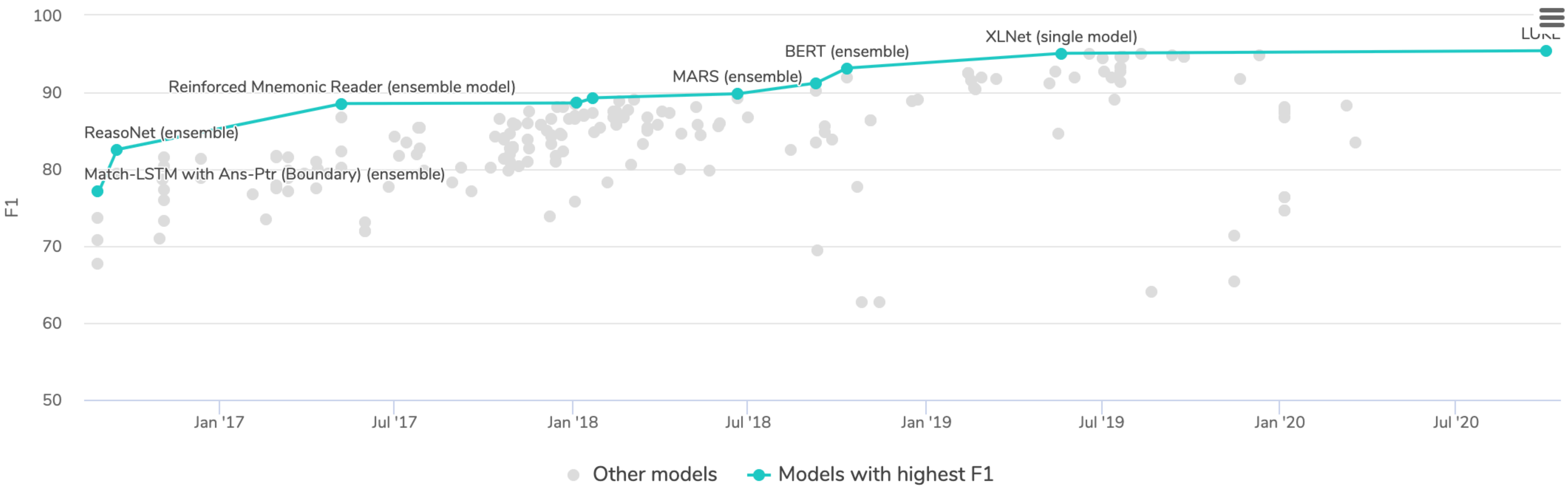
In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under **gravity**. The main forms of precipitation include drizzle, rain, sleet, snow, **graupel** and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals **within a cloud**. Short, intense periods of rain in scattered locations are called “showers”.

What causes precipitation to fall?
gravity

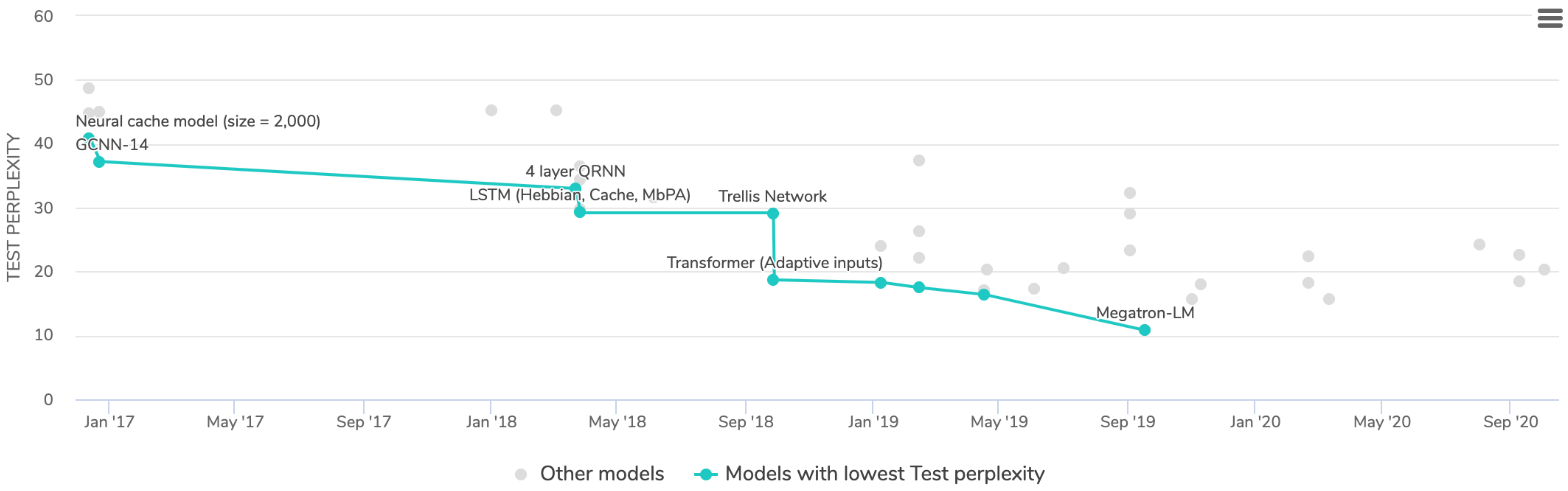
What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
graupel

Where do water droplets collide with ice crystals to form precipitation?
within a cloud

Question Answering (SQuAD 1.1)



Language Modeling (WikiText-103)



Key points

Field largely guided by **benchmarks**

Small number of **key datasets** for each task (image classification, detection, etc.)

Algorithmic / model innovations justified by improvements on benchmarks

Algorithmic innovations usually tested on **multiple datasets**

Little to no **mathematical theory**

Substantial **progress** on a wide range of benchmarks

Culture shift

2000 - 2010

- Support vector machines & kernels
- Boosting
- Matrix factorization and tensor methods
- Compressed sensing / high-dim stats
- Convex optimization

Empirical progress usually goes

hand in hand with theoretical results

2010 - 2020

- Convolutional neural networks
- Recurrent neural networks
- Transformers (NLP)
- Network architecture improvements
- Zoo of different architectures

Empirical progress usually comes

without mathematical theory

Culture shift

2000 - 2010	2010 - 2020
Empirical progress usually goes hand in hand with theoretical results	Empirical progress usually comes without mathematical theory
Emphasis on **provable guarantees**	Emphasis on **benchmarks**
Optimization problems often **convex**	**Non-convexity** is fine
No specialized hardware	**Large-scale** purely experimental work

Still major caveats with benchmarks

Excitement about experimental results, rapid growth in machine learning

But: even results on datasets like ImageNet remained controversial until recently.

One common criticism: **overfitting from test set re-use**

Ideal ML Workflow

1. Collect data

Ideal ML Workflow

1. Collect data

2. Split data

Training set

Validation set

Test set

Ideal ML Workflow

1. Collect data

2. Split data

Training set

Validation set

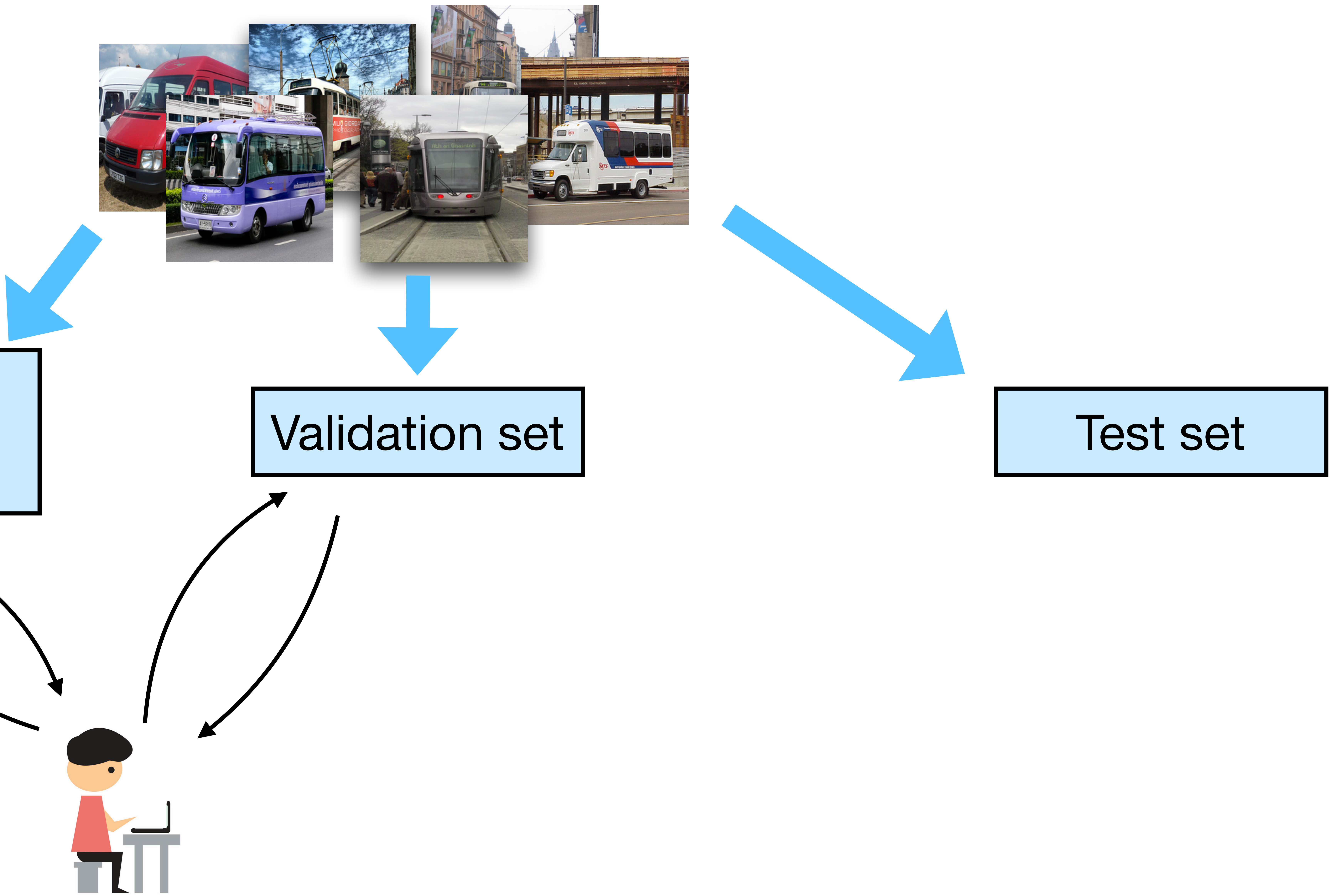
Test set

3. Train and tune model

Ideal ML Workflow

1. Collect data

2. Split data



3. Train and tune model

Ideal ML Workflow

1. Collect data

2. Split data

Training set

Validation set

Test set

3. Train and tune model

Ideal ML Workflow

1. Collect data

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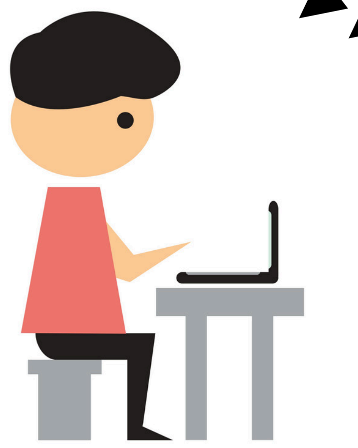
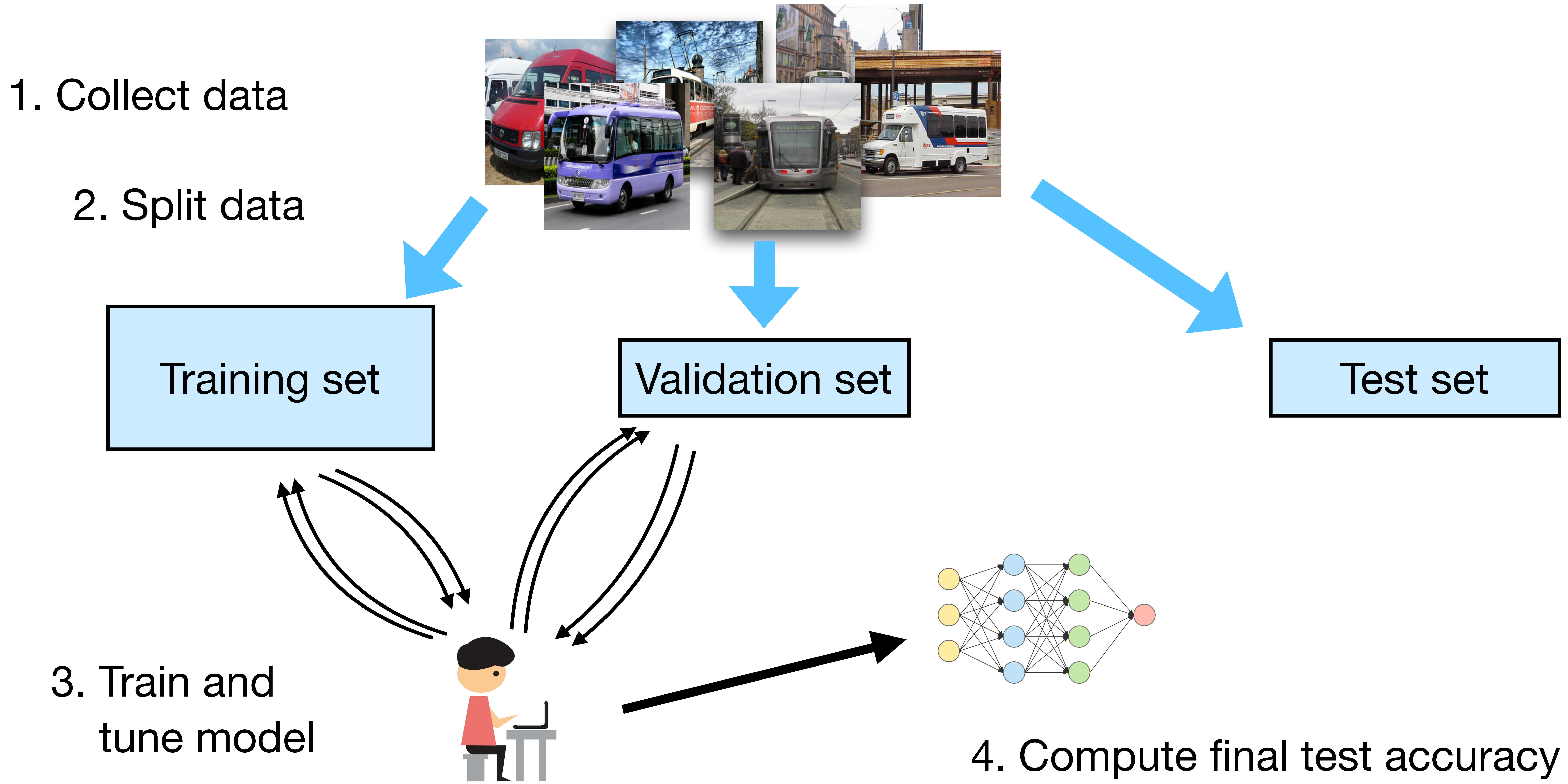
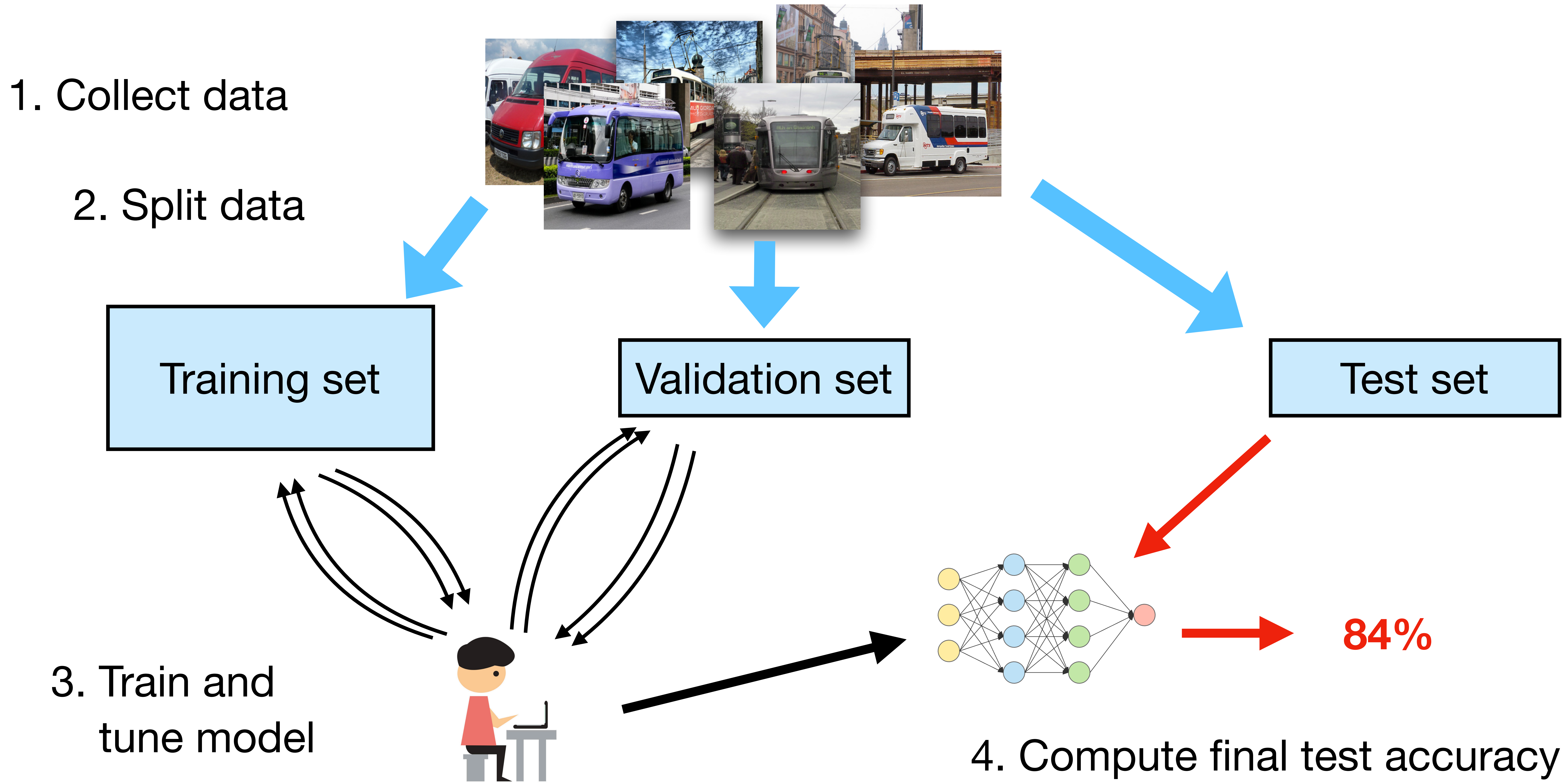


Ideal ML Workflow



Ideal ML Workflow



Ideal ML Workflow

1. Collect data

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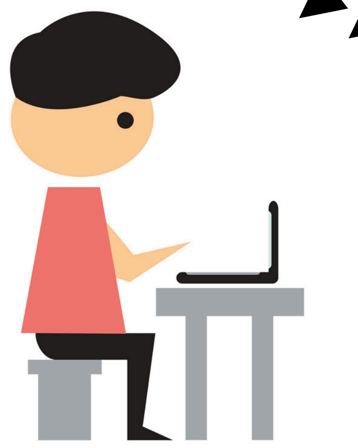
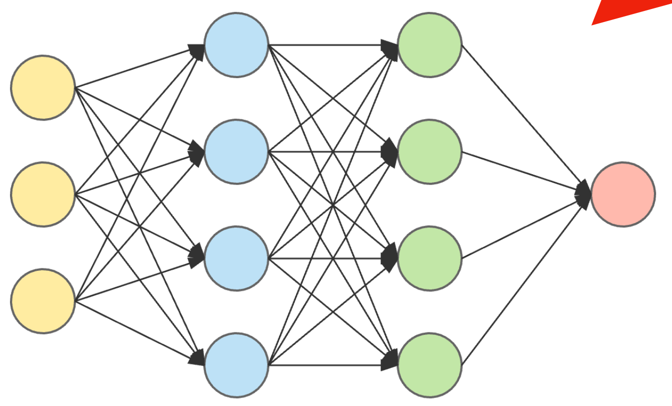




84%

4. Compute final test accuracy

Typical ML Workflow

1. Download data
   (fixed split)

Training set

Test set

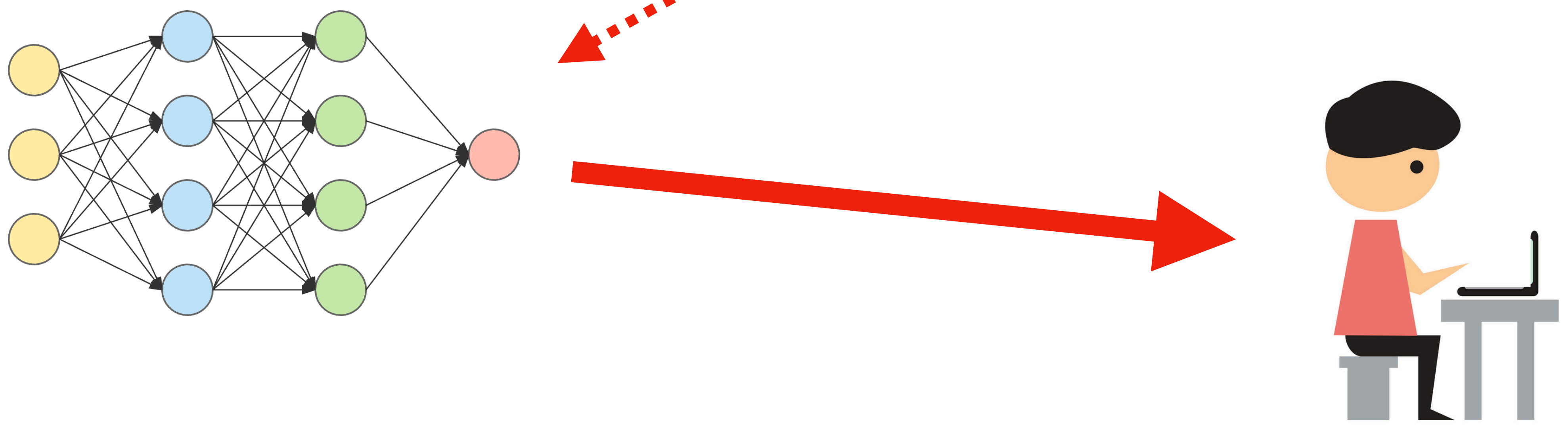
Typical ML Workflow

1. Download data
(fixed split)

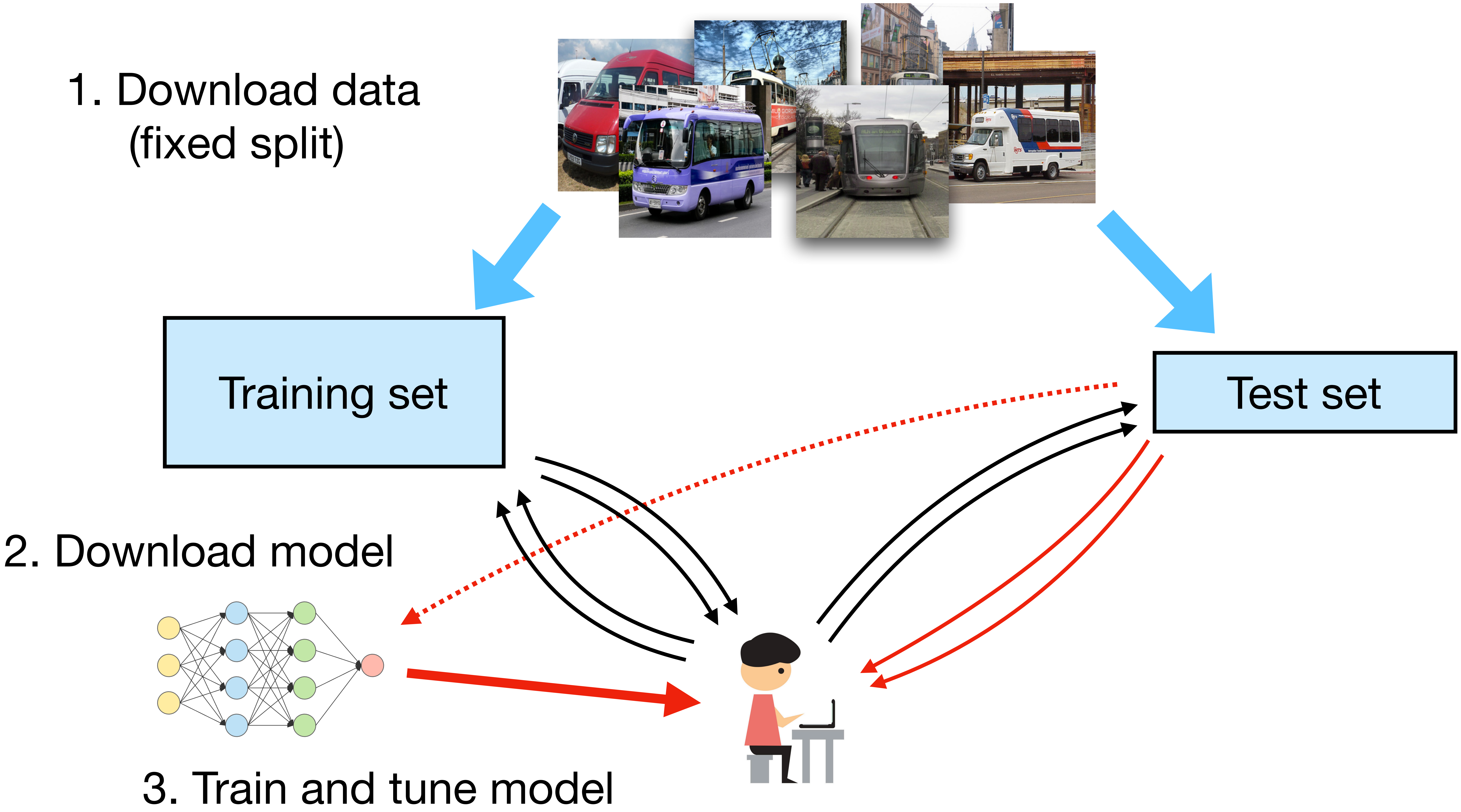
Training set

Test set

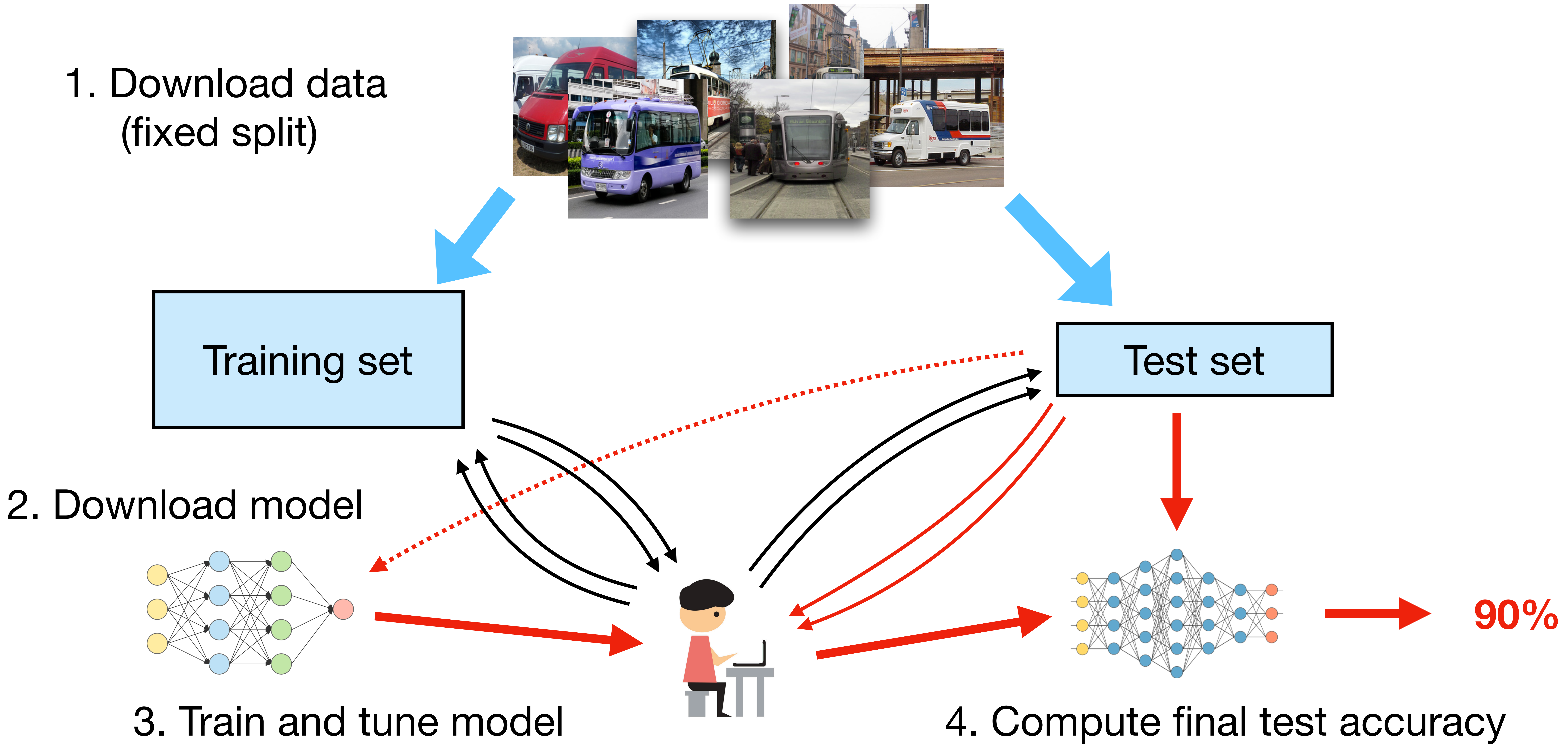
2. Download model



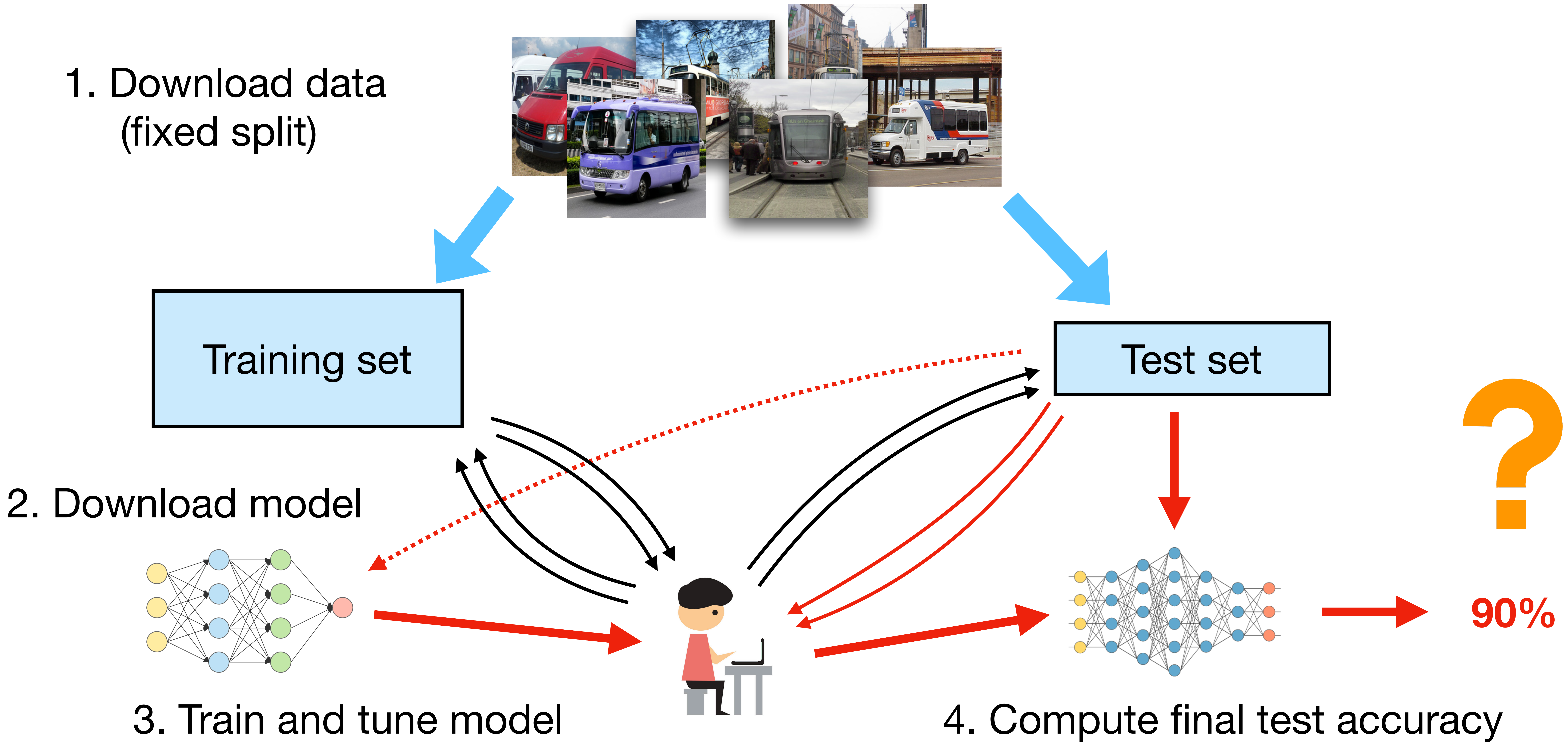
Typical ML Workflow



Typical ML Workflow

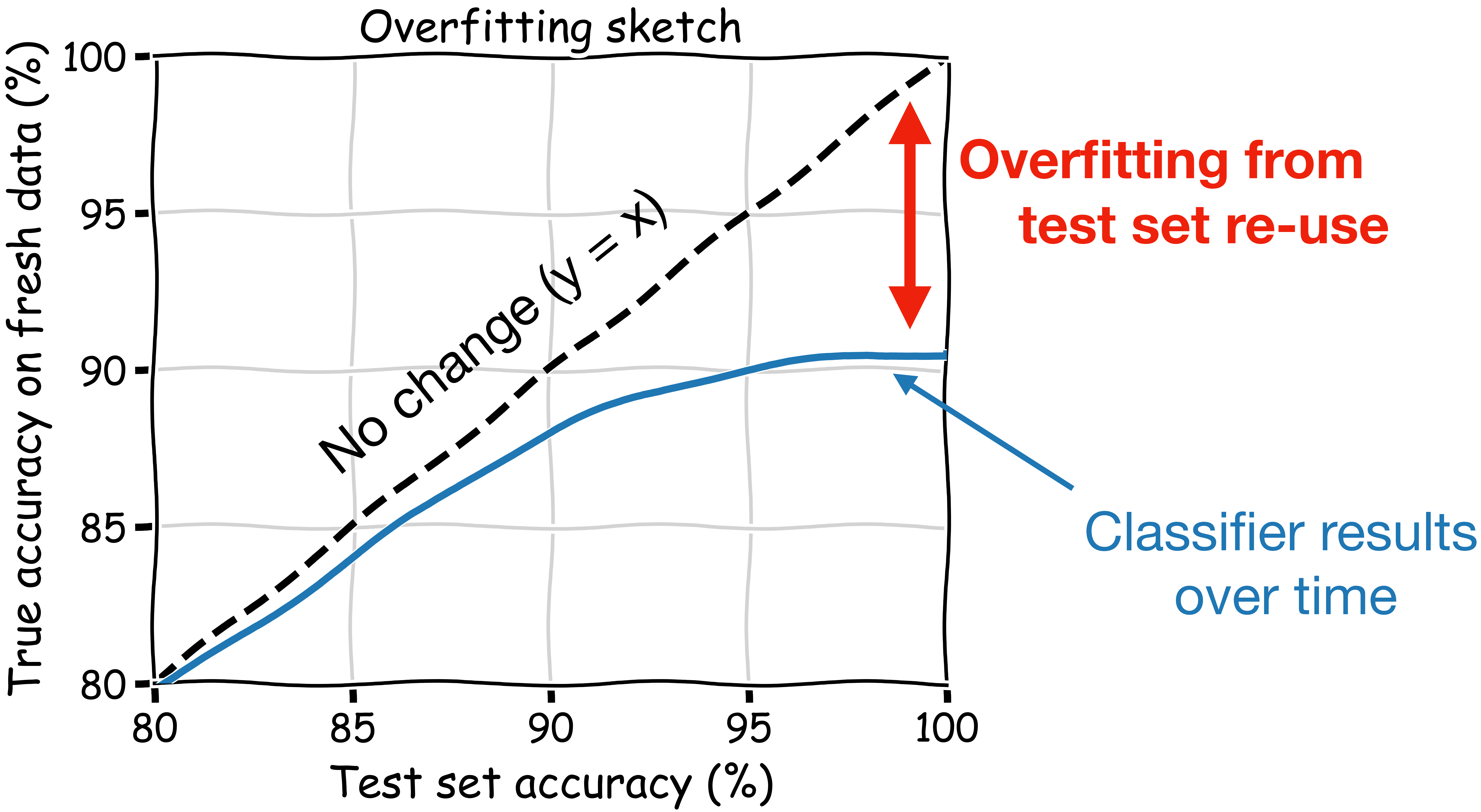


Typical ML Workflow



Danger with Test Set Re-Use: Overfitting

Maybe we are just incrementally fitting to more and more random noise.

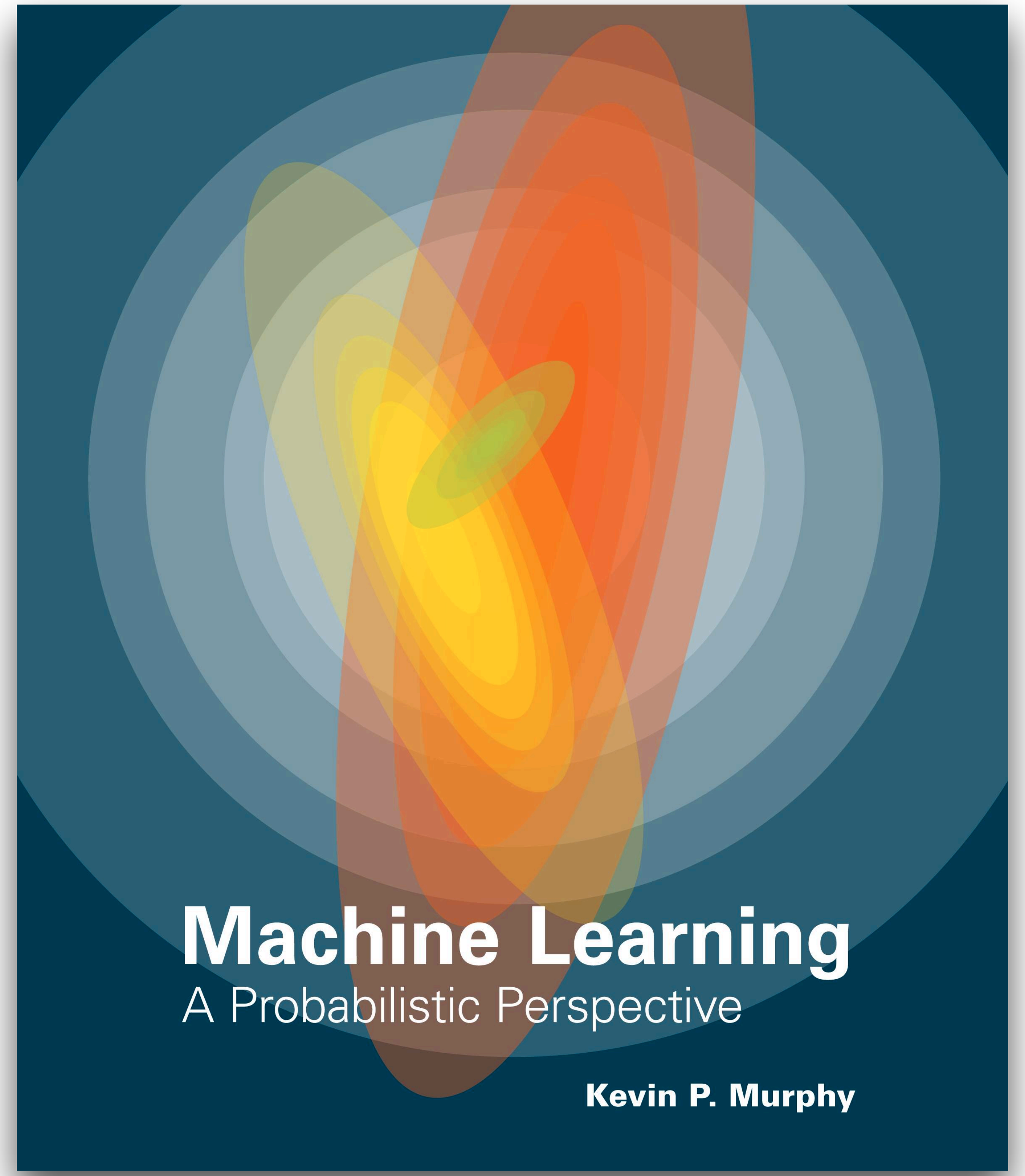


To be clear: We now know that there is no evidence of overfitting through test set re-use on many contemporary ML benchmarks (e.g., ImageNet)

However, the community was majorly confused about this.

We can learn from this story.

Textbooks



Chapter 1:

*[…] we should not use [the test set] for model fitting or model selection, otherwise we will get an unrealistically optimistic estimate of performance of our method. This is one of the “**golden rules**” of machine learning research.*

Slides from a Stanford NLP Class

Training models and pots of data

- The **train**, **tune**, **dev**, and **test** sets need to be completely distinct
- It is invalid to test on material you have trained on
  - You will get a falsely good performance. We usually overfit on train
- You need an independent tuning set
  - The hyperparameters won't be set right if tune is same as train
- If you keep running on the same evaluation set, you begin to overfit to that evaluation set
  - Effectively you are "training" on the evaluation set … you are learning things that do and don't work on that particular eval set and using the info
- To get a valid measure of system performance you need another untrained on, **independent** test set … hence dev2 and final test

Research Papers, e.g., PASCAL VOC

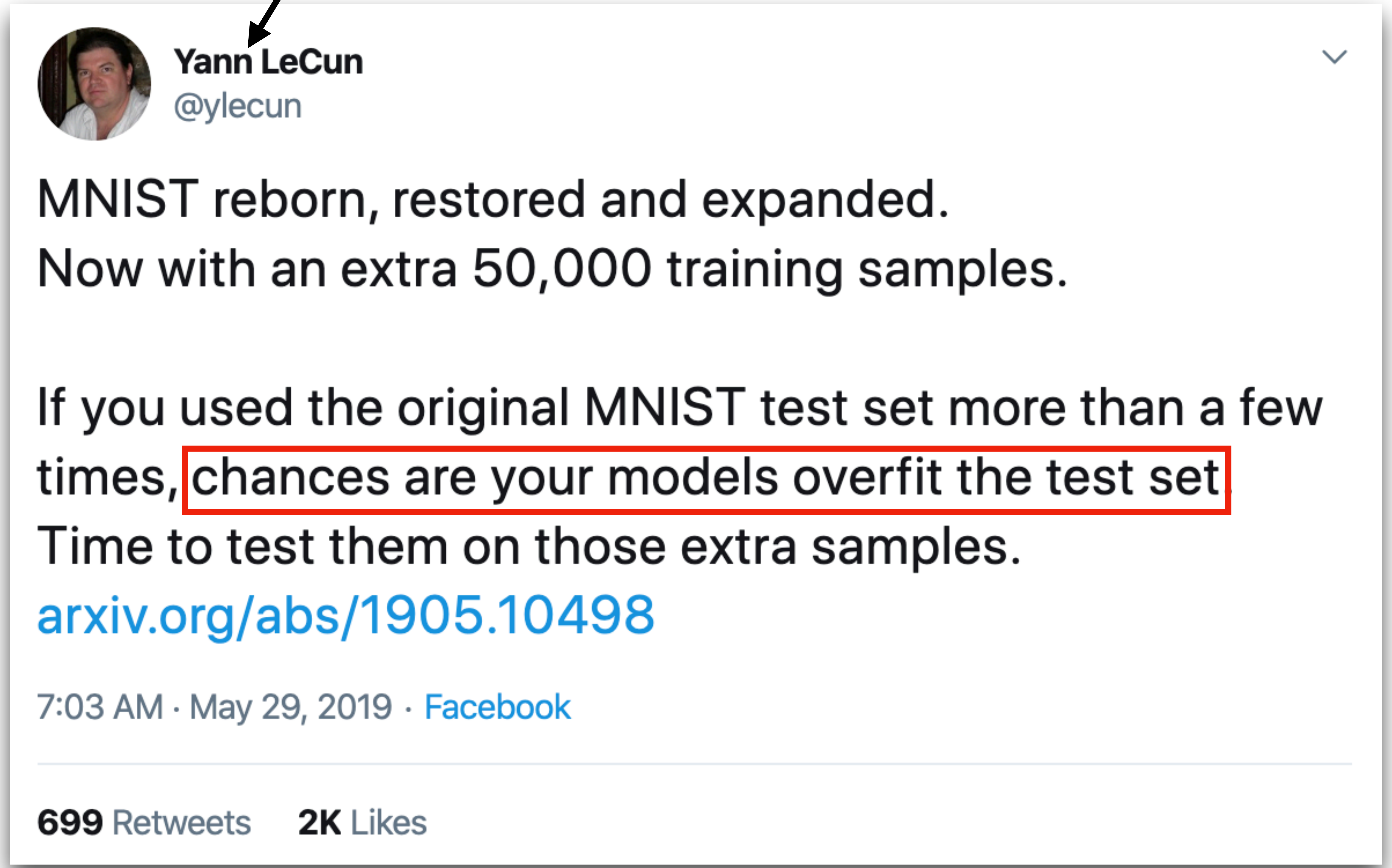
"Withholding the annotation of the test data until completion of the challenge played a significant part in ***preventing over-fitting*** *of the parameters of classification or detection methods. In the VOC2005 challenge, test annotation was released and this led to some* ***"optimistic" reported results, where a number of parameter settings had been run on the test set, and only the best reported****. This danger emerges in any evaluation initiative where ground truth is publicly available."*

+ several more mentions of "danger of overfitting" in the various PASCAL papers.

(Note: I searched for a while, there is not a single documented case of overfitting through test set re-use on PASCAL VOC. Alyosha helped with this.)

Context: a group had just released a new test set for MNIST

Invented CNNs, won a Turing award

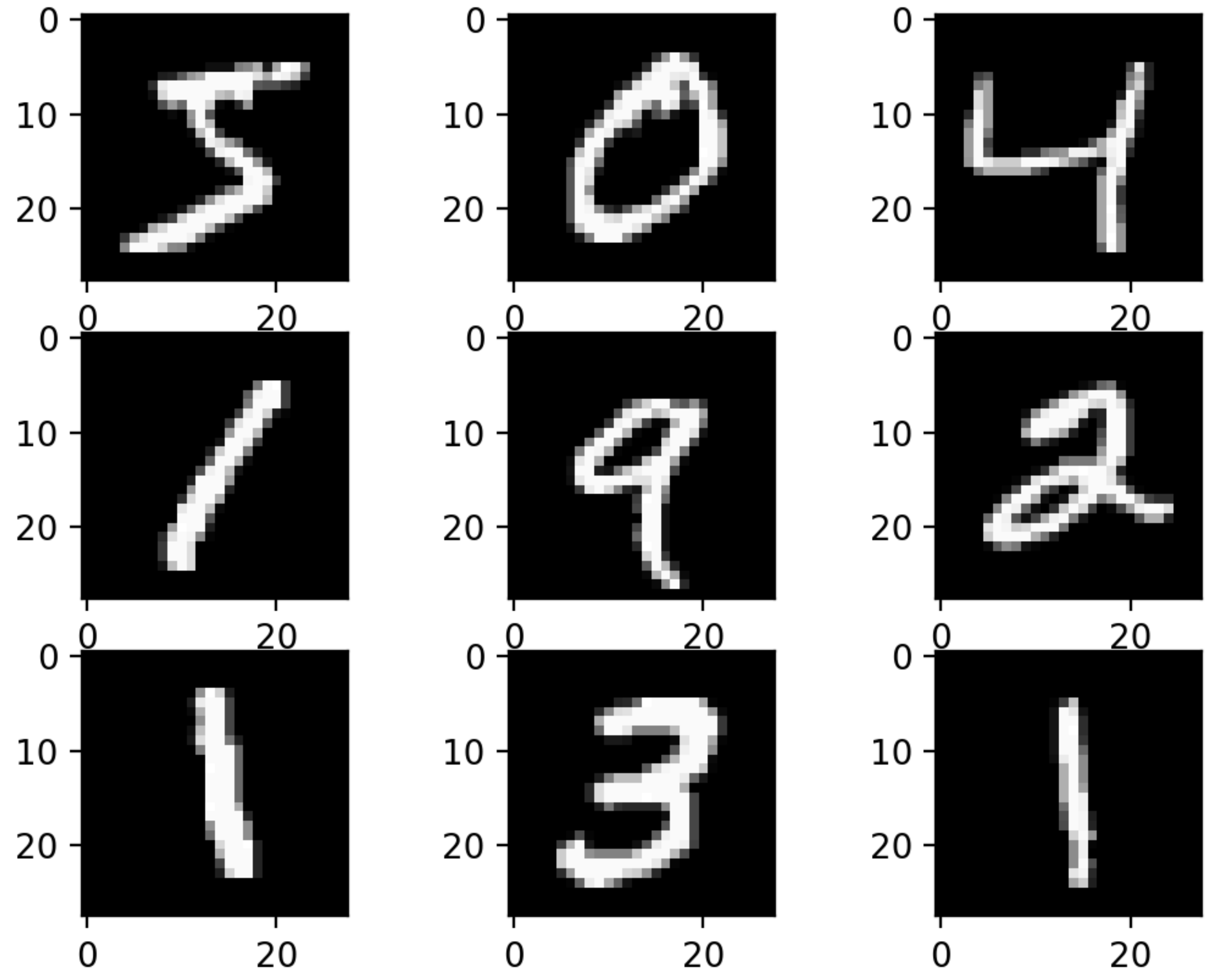

Yann LeCun
@ylecun

MNIST reborn, restored and expanded.
Now with an extra 50,000 training samples.

If you used the original MNIST test set more than a few times, chances are your models overfit the test set. Time to test them on those extra samples.
arxiv.org/abs/1905.10498

7:03 AM · May 29, 2019 · Facebook

699 Retweets **2K** Likes



MNIST: digit classification

60k train, 10k test

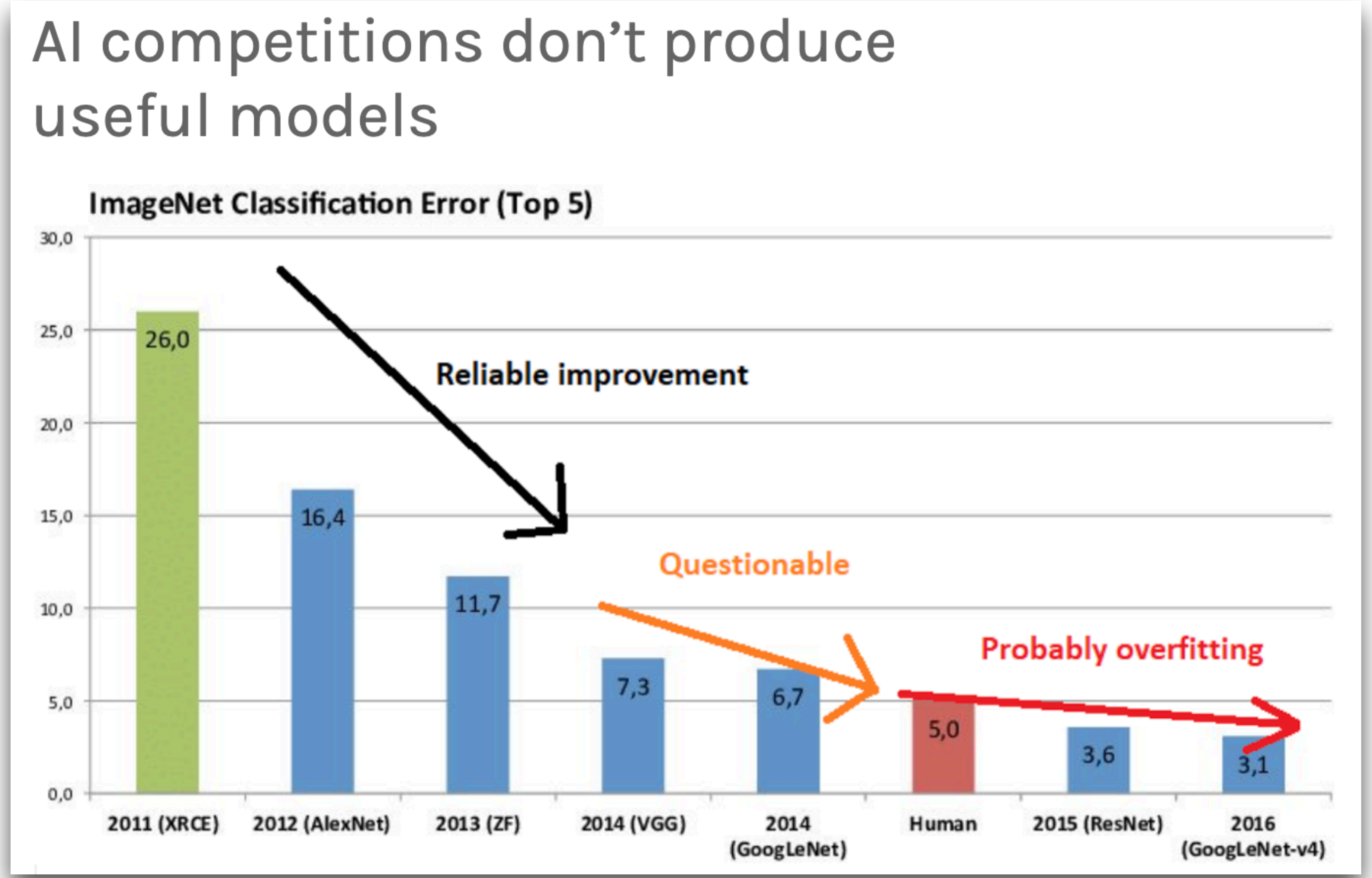
10 classes

Released in 1998

Oldest widely used dataset

Now considered “easy”

https://lukeoakdenrayner.wordpress.com/2019/09/19/ai-competitions-dont-produce-useful-models/



I can't really estimate the numbers, but knowing what we know about multiple testing does anyone really believe the SOTA rush in the mid 2010s was anything but crowdsourced overfitting?

We tested for Overfitting

Do ImageNet Classifiers Generalize to ImageNet?

Benjamin Recht, UC Berkeley | Rebecca Roelofs, UC Berkeley | Ludwig Schmidt, UC Berkeley | Vaishaal Shankar, UC Berkeley

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Outcome: There is actually no overfitting from test set re-use at all on ImageNet.

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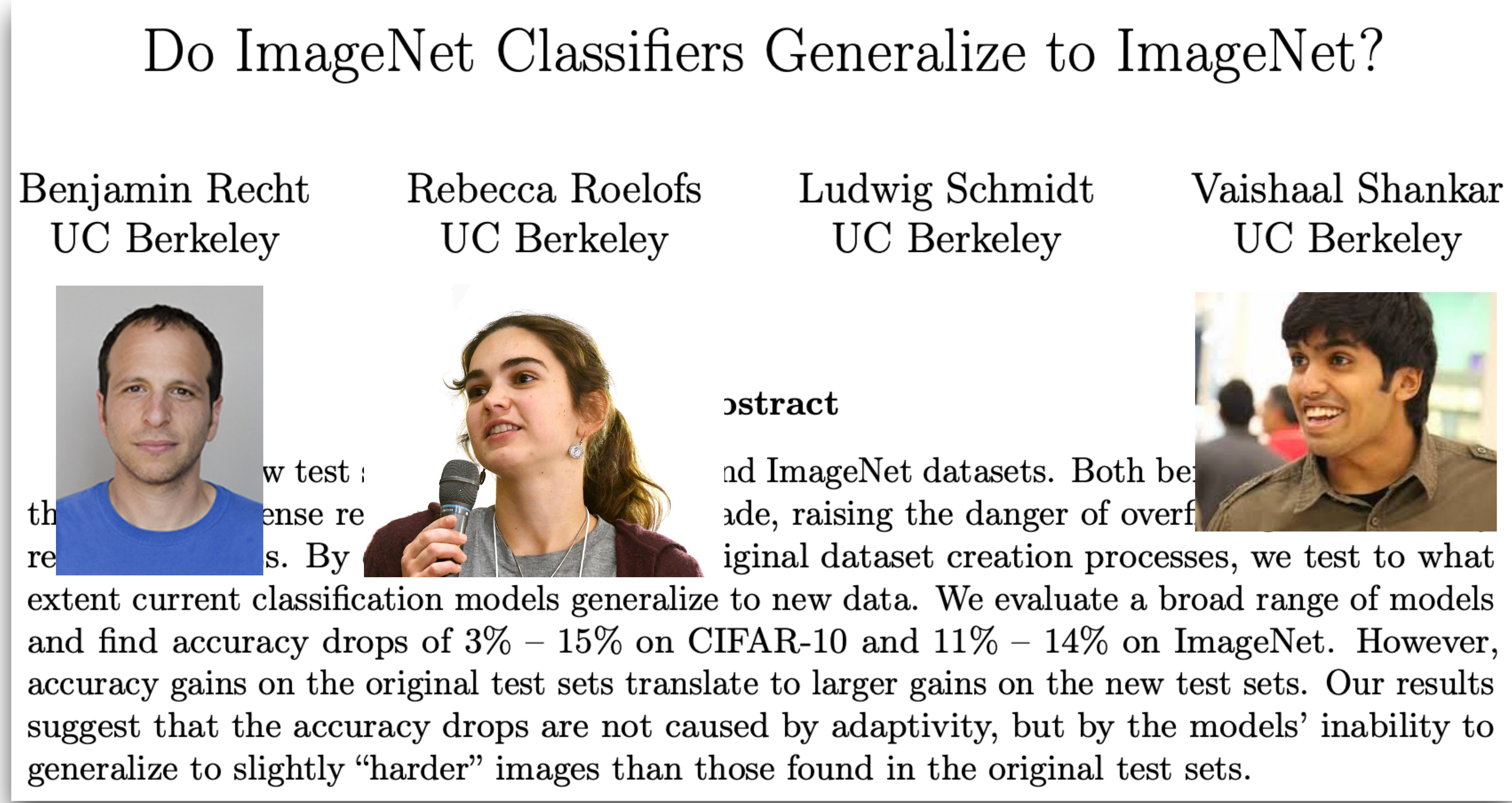

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Outcome: There is actually no overfitting from test set re-use at all on ImageNet.

Meta-outcome: A lot of people were really confused about this.

AlexNet Results

Model	Top-1	Top-5
Sparse coding [2]	*47.1%*	*28.2%*
SIFT + FVs [24]	*45.7%*	*25.7%*
CNN	**37.5%**	**17.0%**

Table 1: Comparison of results on ILSVRC-2010 test set. In *italics* are best results achieved by others.

Model	Top-1 (val)	Top-5 (val)	Top-5 (test)
SIFT + FVs [7]	—	—	*26.2%*
1 CNN	40.7%	18.2%	—
5 CNNs	38.1%	16.4%	**16.4%**
1 CNN*	39.0%	16.6%	—
7 CNNs*	36.7%	15.4%	**15.3%**

Table 2: Comparison of error rates on ILSVRC-2012 validation and test sets. In *italics* are best results achieved by others. Models with an asterisk* were "pre-trained" to classify the entire ImageNet 2011 Fall release. See Section 6 for details.

About 9 percentage points improvement over previous state-of-the art

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- About 9 percentage points improvement over previous state-of-the art
- 88,000 citations, Turing award, transformation of computer science

???

An analogy to complexity theory

P vs NP is one of the core problems in theoretical computer science - why?

Quick complexity recap

A lot of important computational problems are in either P or NP.

P: set of problems solvable in polynomial time
(Sorting, shortest paths, linear programming, matrix multiplication, etc.)

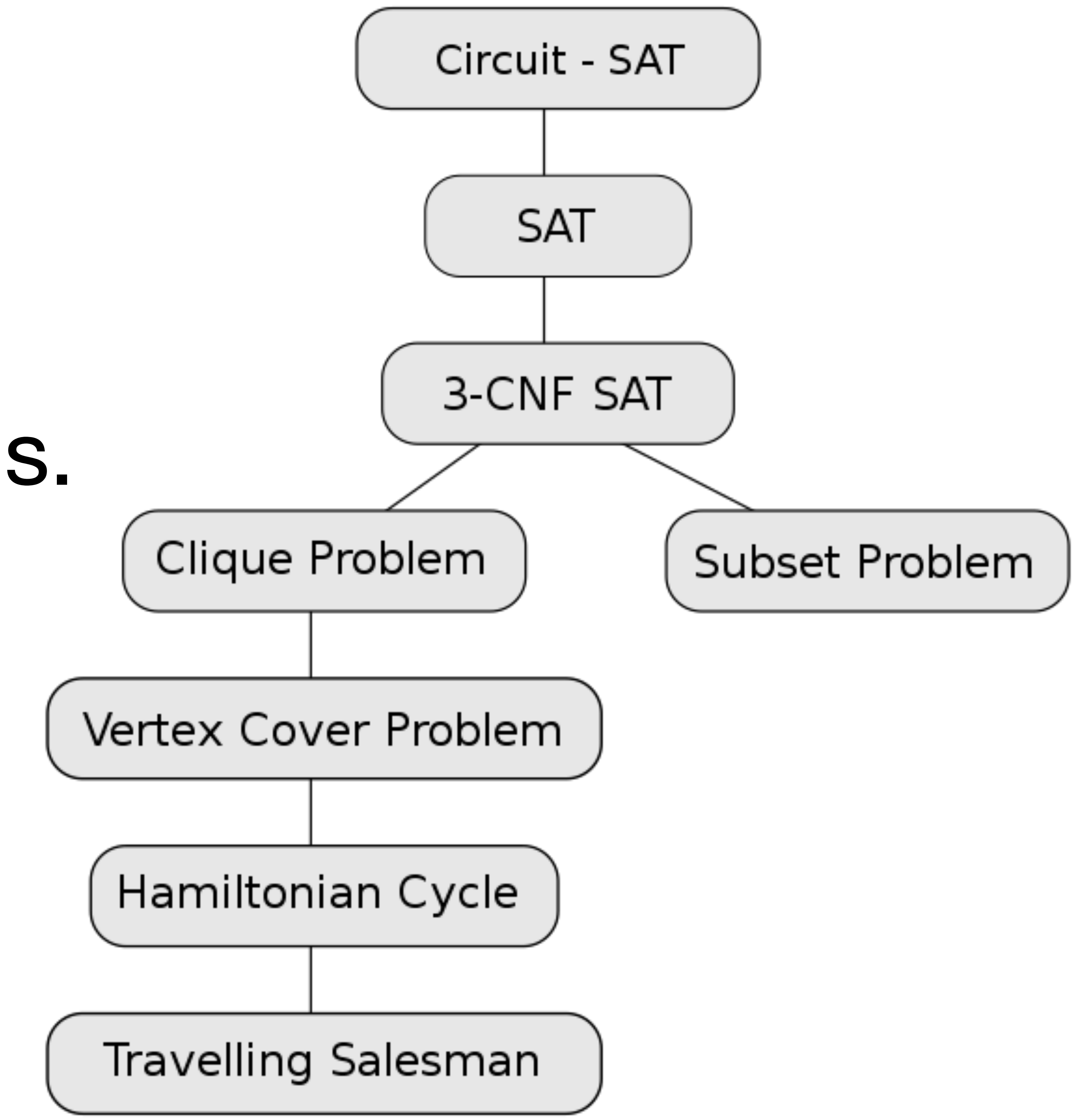
NP: set of problems solvable in polynomial time on a non-deterministic Turing machine
(Satisfiability, traveling salesman problem, vertex cover, etc.)

NP-Completeness

A key property of many important problems in NP: they are **NP-complete**.

➡ If you can solve a single NP-complete problem in polynomial time, you can solve **all** problems in NP in polynomial time.

This is formally established via **reductions** between problems.

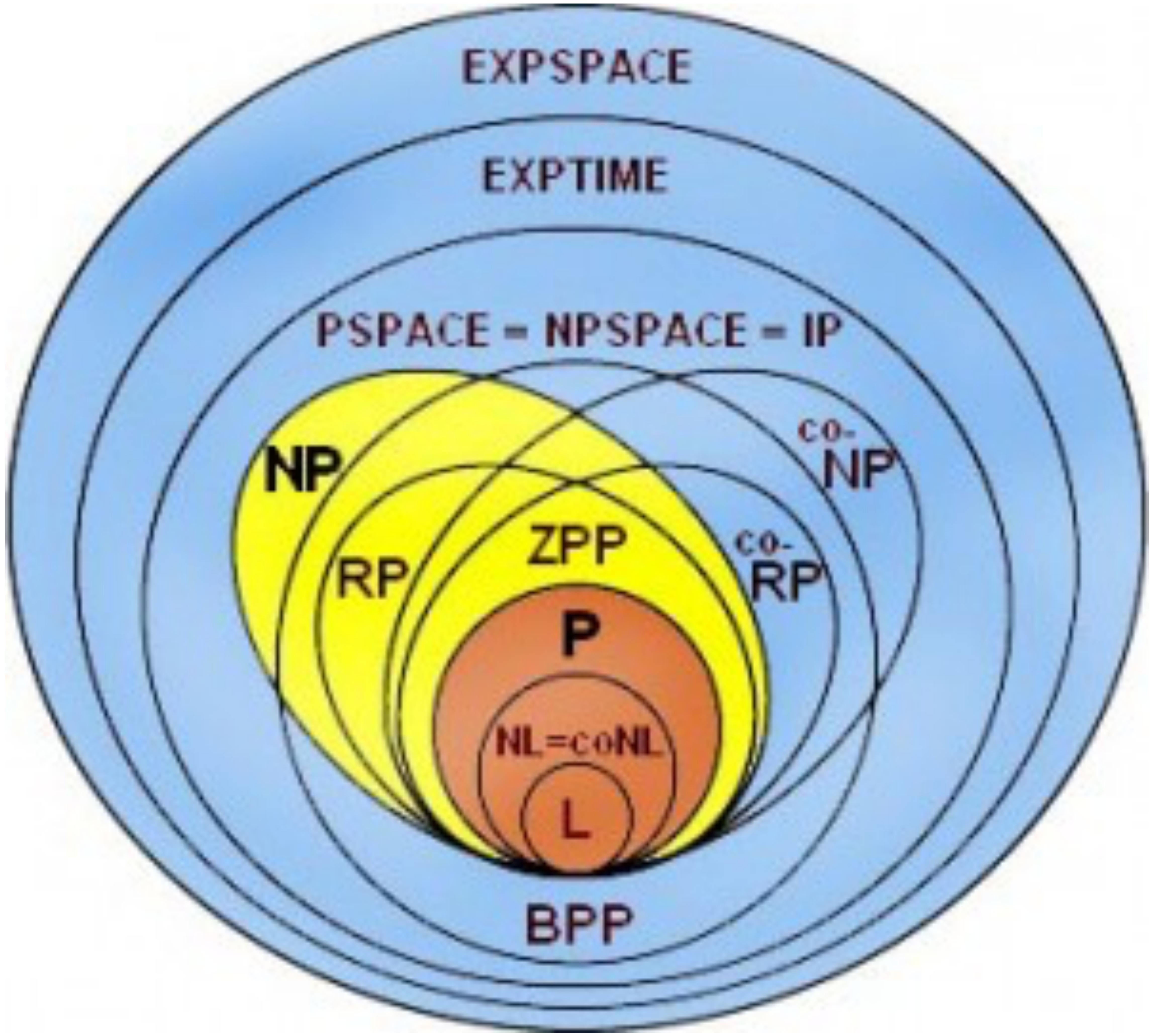


By now there are **thousands** of NP-complete problems.

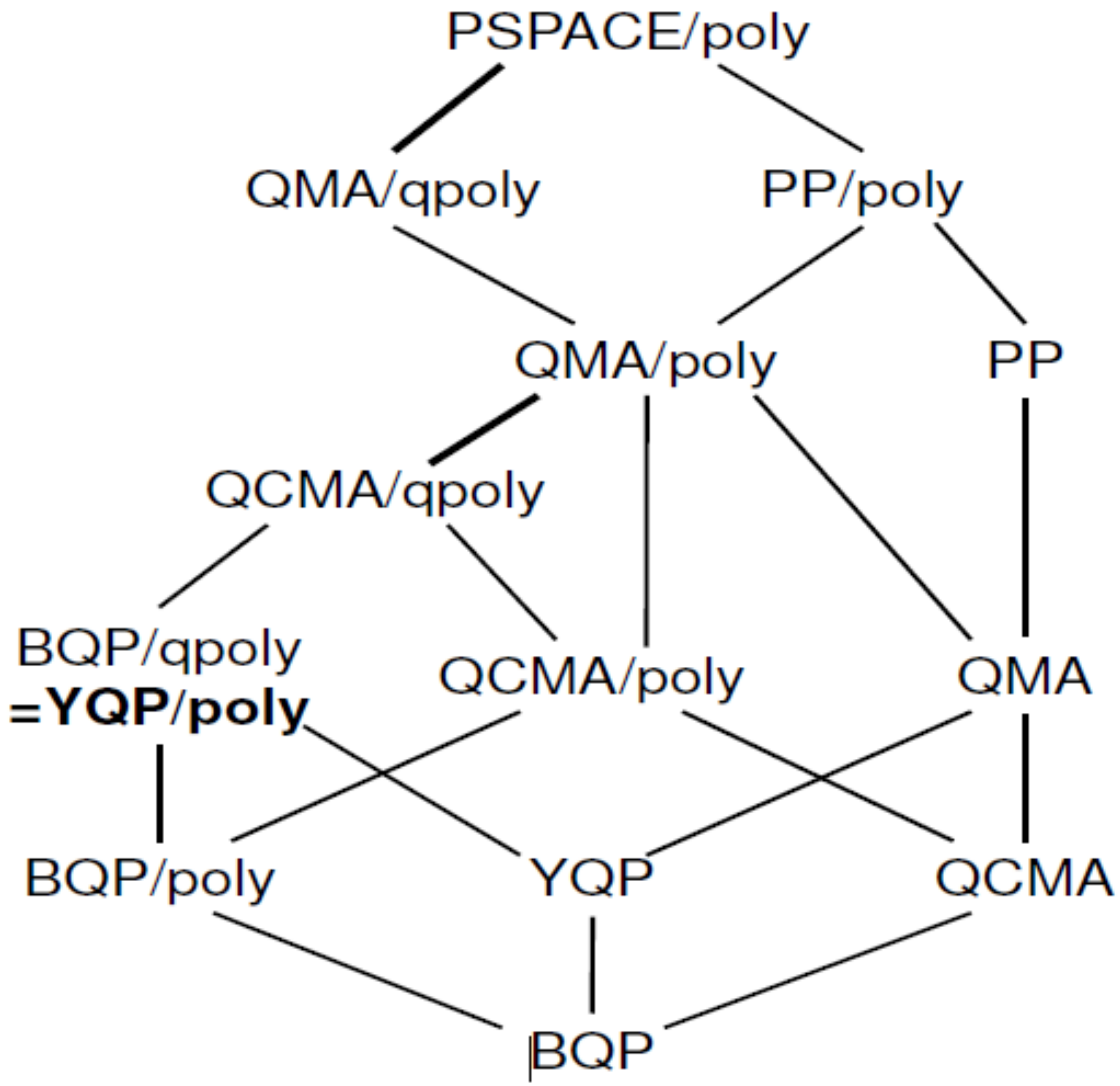
➡ All of them have the same computational hardness, up to polynomial factors in the running time.

Big open question (P vs NP): is there a poly-time algorithm for any of these problems?

Complexity theory beyond P vs NP



Complexity theory beyond P vs NP



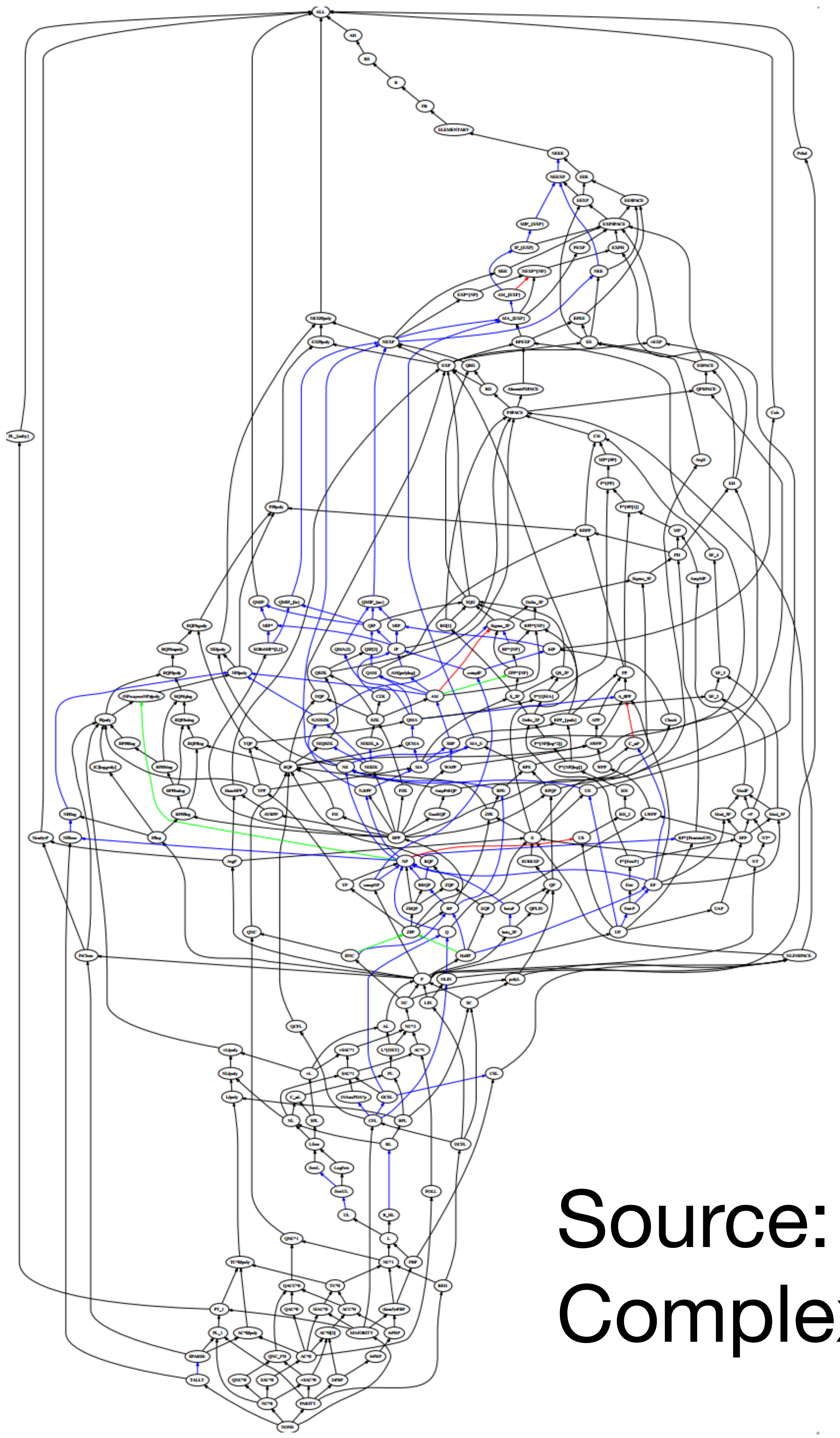
Complexity theory beyond P vs NP

Complexity theory has built a rich hierarchy of computational problems.

➡ Many advantages, e.g., can quickly put a new computational problem in context.

Similar story in optimization: linear programs, quadratic programs, semi-definite programs, etc.

How does a similar problem hierarchy for data distributions and tasks in machine learning (across vision, NLP, etc.) look?



Source: Complexity Zoo

Not all is well: failures of benchmarks

Different field: recommender systems

On the Difficulty of Evaluating Baselines

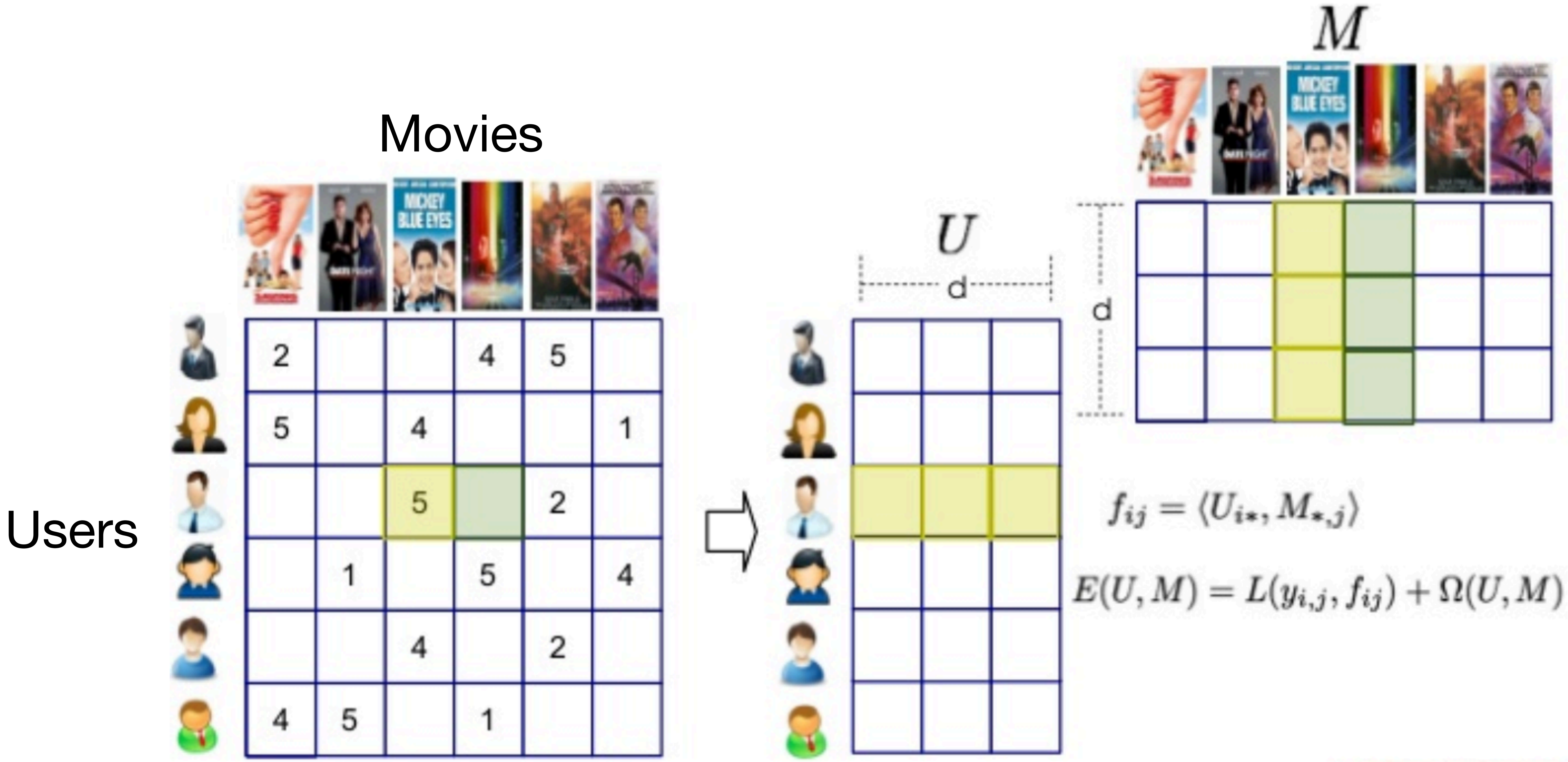
A Study on Recommender Systems

Steffen Rendle* srendle@google.com
Li Zhang* liqzhang@google.com
Yehuda Koren† yehuda@google.com

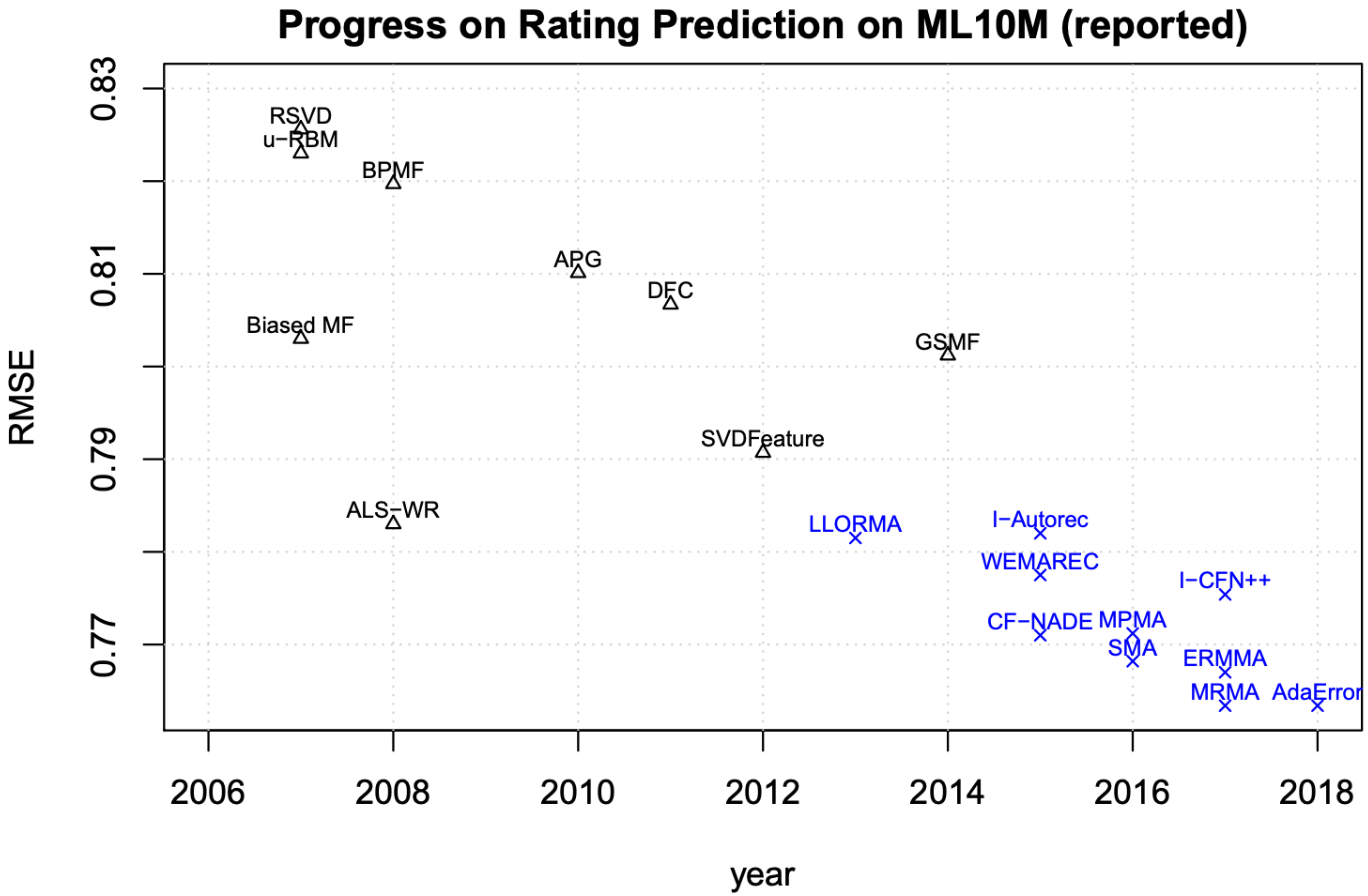
Abstract

Numerical evaluations with comparisons to baselines play a central role when judging research in recommender systems. In this paper, we show that running baselines properly is difficult. We demonstrate this issue on two extensively studied datasets. First, we show that results for baselines that have been used in numerous publications over the past five years for the Movielens 10M benchmark are suboptimal. With a careful setup of a vanilla matrix factorization baseline, we are not only able to improve upon the reported results for this baseline but even outperform the reported results of any newly proposed method. Secondly, we recap the tremendous effort that was required by the community to obtain high quality results for simple methods on the Netflix Prize. Our results indicate that empirical findings in research papers are questionable unless they were obtained on standardized benchmarks where baselines have been tuned extensively by the research community.

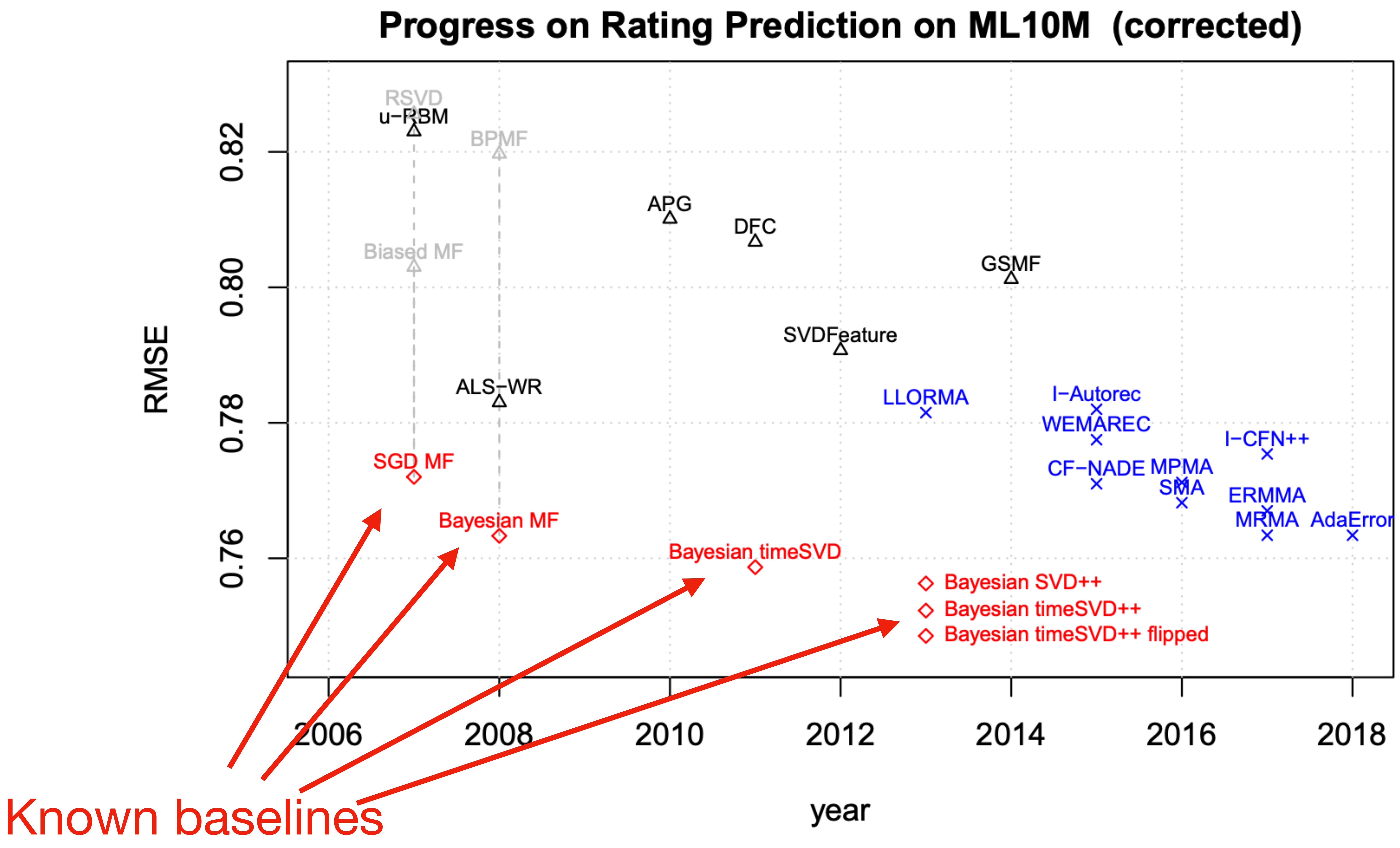
Recommender Systems & Matrix Factorization



“State of the Art”



Actual State of the Art



Danger with Empirical Evaluations

Difficulty of properly running baselines

Variations in tasks (exact dataset, evaluation metric, etc.)

Incentives around baselines

➡ **Standardized, competitive** benchmarks address these points

Standard computer vision benchmarks (CIFAR-10, ImageNet, COCO) are so competitive that missed baselines seem unlikely by now.

What makes a good ML evaluation?

Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans

Michael Roberts, Derek Driggs, Matthew Thorpe, Julian Gilbey, Michael Yeung, Stephan Ursprung, Angelica I. Aviles-Rivero, Christian Etmann, Cathal McCague, Lucian Beer, Jonathan R. Weir-McCall, Zhongzhao Teng, Effrossyni Gkrania-Klotsas, AIX-COVNET, James H. F. Rudd, Evis Sala & Carola-Bibiane Schönlieb

Nature Machine Intelligence **3**, 199–217 (2021) | Cite this article

Abstract

Machine learning methods offer great promise for fast and accurate detection and prognostication of coronavirus disease 2019 (COVID-19) from standard-of-care chest radiographs (CXR) and chest computed tomography (CT) images. Many articles have been published in 2020 describing new machine learning-based models for both of these tasks, but it is unclear which are of potential clinical utility. In this systematic review, we consider all published papers and preprints, for the period from 1 January 2020 to 3 October 2020, which describe new machine learning models for the diagnosis or prognosis of COVID-19 from CXR or CT images. All manuscripts uploaded to bioRxiv, medRxiv and arXiv along with all entries in EMBASE and MEDLINE in this timeframe are considered. Our search identified 2,212 studies, of which 415 were included after initial screening and, after quality screening, 62 studies were included in this systematic review. Our review finds that none of the models identified are of potential clinical use due to methodological flaws and/or underlying biases. This is a major weakness, given the urgency with which validated COVID-19 models are needed. To address this, we give many recommendations which, if followed, will solve these issues and lead to higher-quality model development and well-documented manuscripts.

Questions

How reliable are performance measurements on ML benchmarks?

Why does progress on ImageNet lead to progress on many other tasks and datasets?

What tasks and datasets does ImageNet progress **not** help on?

How well do models with 90% top-1 accuracy on ImageNet really work?

What is the role of ImageNet in this story? What makes a good ML dataset?

➡ What kind of answers am I looking for?

Why empirical foundations?

It’s interesting! Lots of progress over the past years, still not well understood.

People expect more: reliability, fairness, security, etc.

Are the investments in ML going to the right problems?

Not all is well: many papers with failed evaluations, etc.

It leads to better methods!

Google Scholar

Alec Radford

FOLLOW

OpenAI
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Deep Learning Machine Learning

TITLE	CITED BY	YEAR
Unsupervised representation learning with deep convolutional generative adversarial networks A Radford, L Metz, S Chintala arXiv preprint arXiv:1511.06434	10311	2015
Improved techniques for training gans T Salimans, I Goodfellow, W Zaremba, V Cheung, A Radford, X Chen Advances in neural information processing systems 29, 2234-2242	5659	2016
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Openai baselines P Dhariwal, C Hesse, O Klimov, A Nichol, M Plappert, A Radford, ...	710	2017

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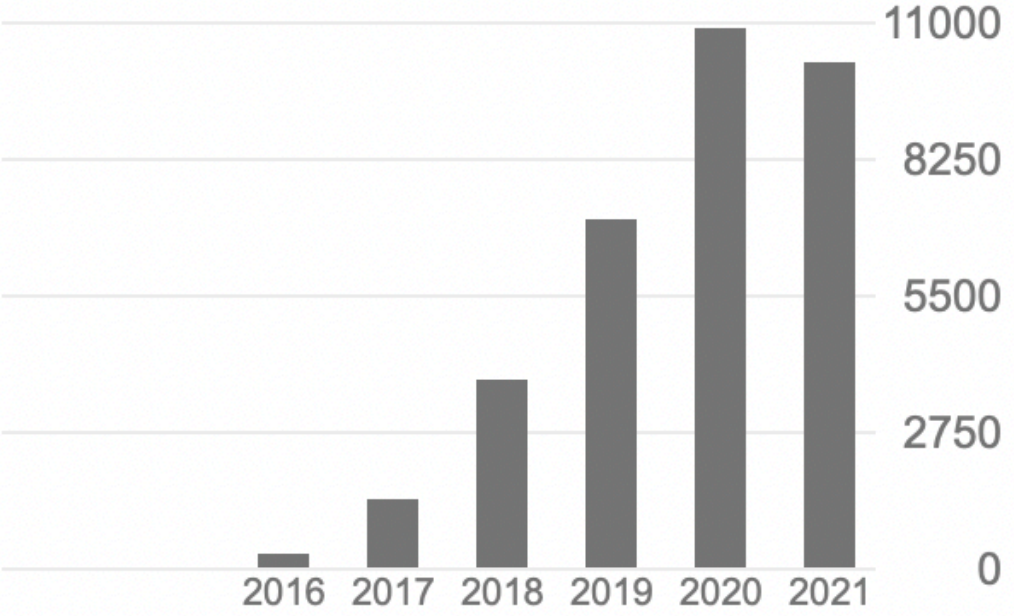
Citations	34065	33801
h-index	25	25
i10-index	27	27



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Kaiming He

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Research Scientist, Facebook AI Research (FAIR)
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Computer Vision   Machine Learning

TITLE	CITED BY	YEAR
Deep Residual Learning for Image Recognition K He, X Zhang, S Ren, J Sun Computer Vision and Pattern Recognition (CVPR), 2016	91640	2016
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Focal Loss for Dense Object Detection TY Lin, P Goyal, R Girshick, K He, P Dollár International Conference on Computer Vision (ICCV), 2017	9302	2017
Feature Pyramid Networks for Object Detection TY Lin, P Dollár, R Girshick, K He, B Hariharan, S Belongie Computer Vision and Pattern Recognition (CVPR), 2017	8881	2017
Learning a Deep Convolutional Network for Image Super-Resolution C Dong, CC Loy, K He, X Tang European Conference on Computer Vision (ECCV), 2014	7813 *	2014

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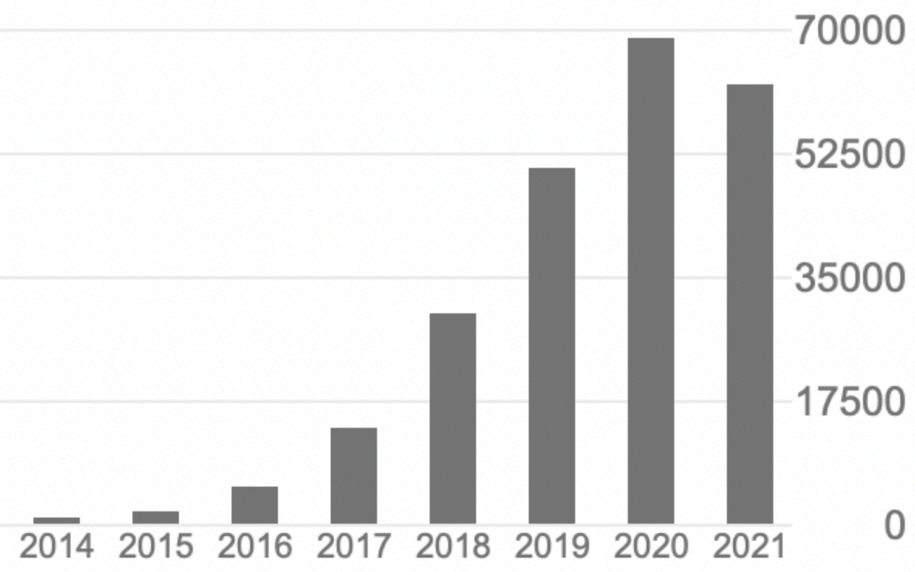
Citations	238421	231788
h-index	58	57
i10-index	66	66



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Ross Girshick

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Research Scientist, Facebook AI Research (FAIR)
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computer vision machine learning

TITLE	CITED BY	YEAR
Faster R-CNN: Towards real-time object detection with region proposal networks S Ren, K He, R Girshick, J Sun Advances in neural information processing systems, 91-99	34254	2015
Rich feature hierarchies for accurate object detection and semantic segmentation R Girshick, J Donahue, T Darrell, J Malik Proceedings of the IEEE conference on computer vision and pattern …	21344	2014
You only look once: Unified, real-time object detection J Redmon, S Divvala, R Girshick, A Farhadi Proceedings of the IEEE conference on computer vision and pattern …	18571	2016
Microsoft coco: Common objects in context TY Lin, M Maire, S Belongie, J Hays, P Perona, D Ramanan, P Dollár, ... European conference on computer vision, 740-755	18536	2014
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Mask R-CNN K He, G Gkioxari, P Dollár, R Girshick arXiv preprint arXiv:1703.06870	14051	2017

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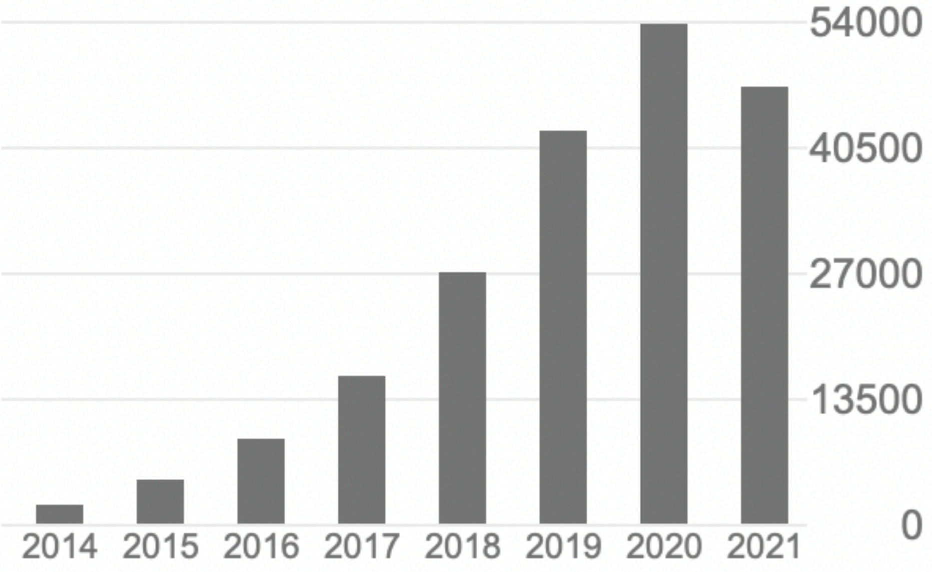

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Co-authors VIEW ALL

Kaiming He
Research Scientist, Facebook AI…

Caveats

This class takes a technical perspective on ML.

A narrow technical focus can obscure ethical questions.

But: research on ethical questions in machine learning needs solid foundations, too.

A course on empirical foundations of ML is largely new.

(It still rests on decades of work in other fields - research validity is not new.)

➡ We're going to figure some things out as we go through the quarter.

1. Logistics

2. Background & motivation

3. Course outline

Course Outline

Main parts of the class

1. Fundamentals: applied stats, causality, a bit of philosophy of science (5 lectures)

2. Paper discussions: both “classical” and recent papers (5 lectures)

3. Guest speakers (Alec Radford 🤞, Nicholas Carlini, and more) (3 lectures)

4. Student project presentations: initial overview and final presentations (3 lectures)

5. Practical tooling for empirical ML (favorite Python packages, etc.) (1 lecture)

Grading & project

Grading: 20% participation in class discussions, 80% research project.

Project

Theme: broadly around datasets, evaluation, robustness

Can be research you are already doing

Team size 1 - 3

Proposals due at the beginning of the 4th lecture (October 12)

Next lecture: some inspiration

Thanks!

Questions?