# GENE

## **22K** categories and **15M** images

- Animals
  - Bird
  - Fish
  - Mammal •
  - Invertebrate

- Plants

  - Flower
- Food
- Materials

- Structures
- Tree
   Artifact
  - Tools
  - Appliances
  - Structures

- Person
- Scenes
  - Indoor
  - Geological Formations
- **Sport Activity** •

## www.image-net.org

Deng et al. 2009, Russakovsky et al. 2015

Slide credit: Fei-Fei Li

## What is WordNet?



Original paper by **[George Miller, et al 1990]** cited over 5,000 times Organizes over 150,000 words into 117,000 categories called *synsets*. Establishes ontological and lexical relationships in NLP and related tasks.



### Individually Illustrated WordNet Nodes



jacket: a short coat



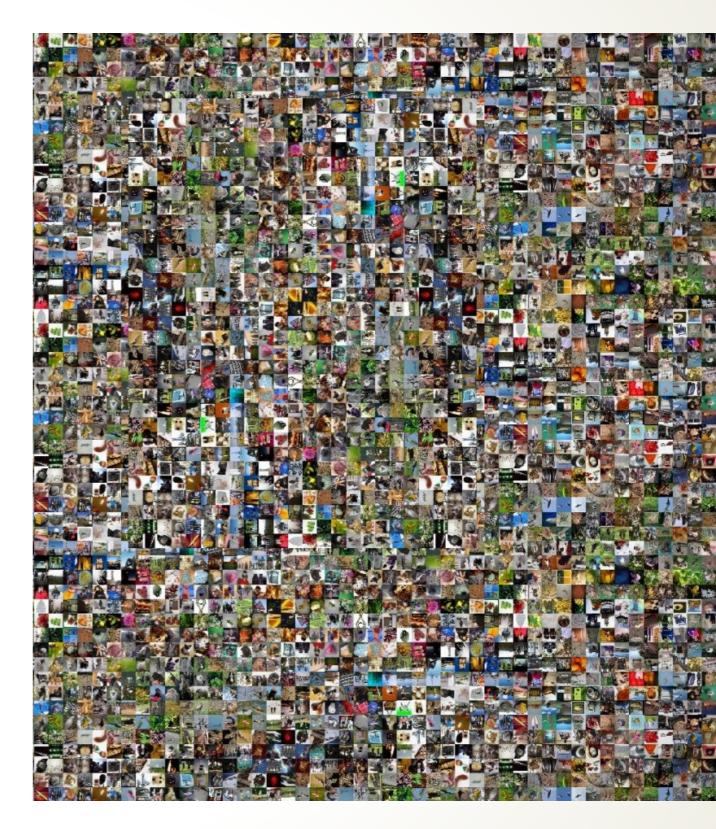
**German shepherd:** breed of large shepherd dogs used in police work and as a guide for the blind.

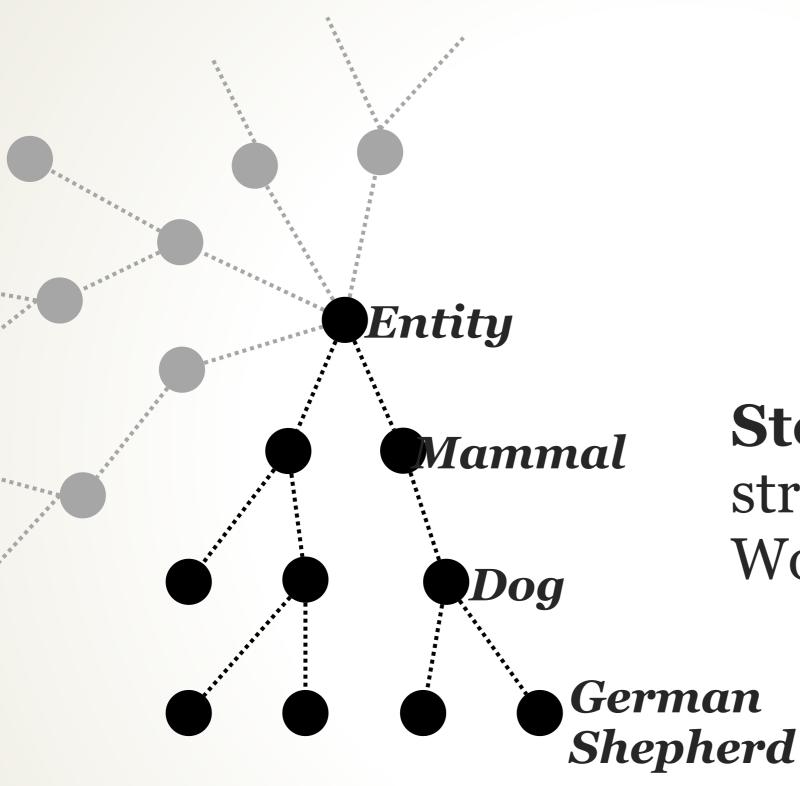


**microwave:** kitchen appliance that cooks food by passing an electromagnetic wave through it.



**mountain:** a land mass that projects well above its surroundings; higher than a hill.





# **Step 1:** Ontological structure based on WordNet

Slide credit: Fei-Fei Li and Jia Deng





**Step 2:** Populate categories with thousands of images from the Internet

Dog



German Shepherd by hand

Dog

# Three Attempts at Launching IMAGENET

# 1<sup>st</sup> Attempt: The Psychophysics Experiment

ImageNet<br/>PhD<br/>StudentsImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>ImageNet<br/>Ima

# 1<sup>st</sup> Attempt: The Psychophysics Experiment

- # of synsets: 40,000 (subject to: imageability analysis)
- # of candidate images to label per synset:
   10,000
- *#* of people needed to verify: **2-5**
- Speed of human labeling: 2 images/sec (one fixation: ~200msec)
- Massive parallelism (N ~ 10<sup>2</sup>-3)

40,000 × 10,000 × 3 / 2 = 6000,000,000 sec ≈ 19 years

# 2<sup>nd</sup> Attempt: Human-in-the-Loop Solutions

#### Towards scalable dataset construction: An active learning approach

Brendan Collins, Jia Deng, Ka {bmcollin, dengjia, li, feifei

Department of Computer Science, Princeton

Abstract. As computer vision research co and greater variation within object categor more exhaustive datasets are necessary. He ing such datasets is laborious and monoto in which many images have been automa category (typically by automatic internet s relevant images from noise. We present a d which employs active, online learning to with minimal user input. The principle ad vious endeavors is its scalability. We demon superior to the state-of-the-art, with scala work.

#### 1 Introduction

Though it is difficult to foresee the future of co that its trajectory will include examining a gr (such as objects or scenes), that the complexit; categories will increase, and that these catego variation. It is unlikely that the researcher's keep pace with the growing need for annotat work aims to develop a system which can obta ages with minimal supervision. The particula

#### OPTIMOL: automatic Online Picture collecTion via Incremental MOdel Learning

#### Li-Jia Li<sup>1</sup>, Gang Wang<sup>1</sup> and Li Fei-Fei<sup>2</sup>

<sup>1</sup> Dept. of Electrical and Computer Engineering, University of Illinois Urbana-Champaign, USA <sup>2</sup> Dept. of Computer Science, Princeton University, USA jiali3@uiuc.edu, gwang6@uiuc.edu, feifeili@cs.princeton.edu

#### Abstract

A well-built dataset is a necessary starting point for advanced computer vision research. It plays a crucial role in evaluation and provides a continuous challenge to stateof-the-art algorithms. Dataset collection is, however, a tedious and time-consuming task. This paper presents a novel automatic dataset collecting and model learning approach that uses object recognition techniques in an incremental method. The goal of this work is to use the tremendous resources of the web to learn robust object category models in order to detect and search for objects in real-world cluttered scenes. It mimics the human learning process of iteratively accumulating model knowledge and image examples. We adapt a non-parametric graphical model and propose an incremental learning framework. Our algorithm is capable of automatically collecting much larger object category

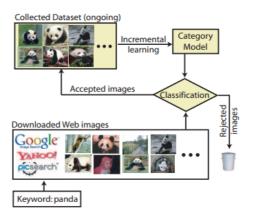
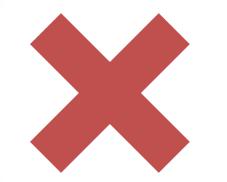


Figure 1. Illustration of the framework of the Online Picture collecTion via Incremental MOdel Learning (OPTIMOL) system. This framework works in an incremental way: Once a model is

#### Slide credit: Fei-Fei Li and Jia Deng

# 2<sup>nd</sup> Attempt: Human-in-the-Loop Solutions



Machine-generated datasets can only match the best algorithms of the time.



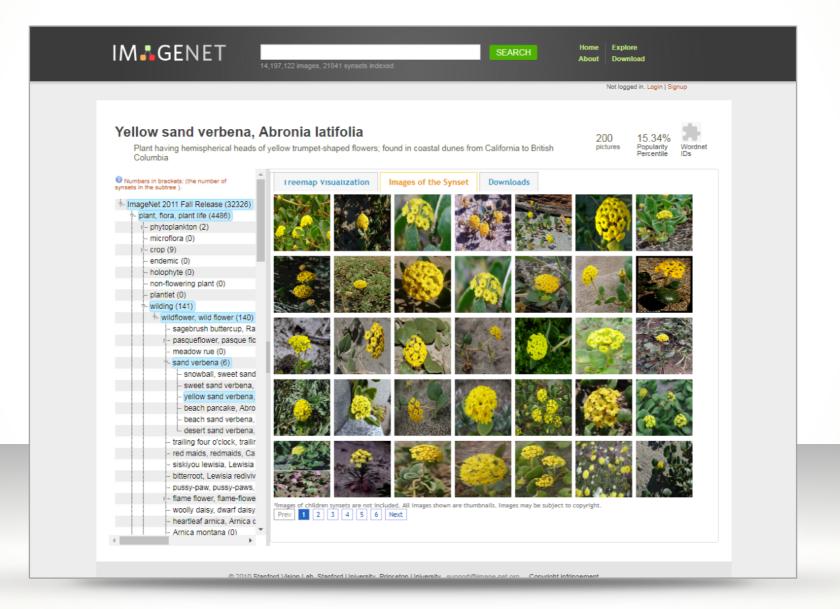
Human-generated datasets transcend algorithmic limitations, leading to better machine perception.

# 3<sup>rd</sup> Attempt: Crowdsourcing



**49k Workers** *from* **167 Countries 2007-2010** 

# The Result: IMAGENET Goes Live in 2009



# **Others Targeted Detail**



## LabelMe

Per-Object Regions and Labels Russell et al, 2005



## Lotus Hill

Hand-Traced Parse Trees Yao et al, 2007

# **ImageNet Targeted Scale**

**SUN, 131K** [Xiao et al. '10]

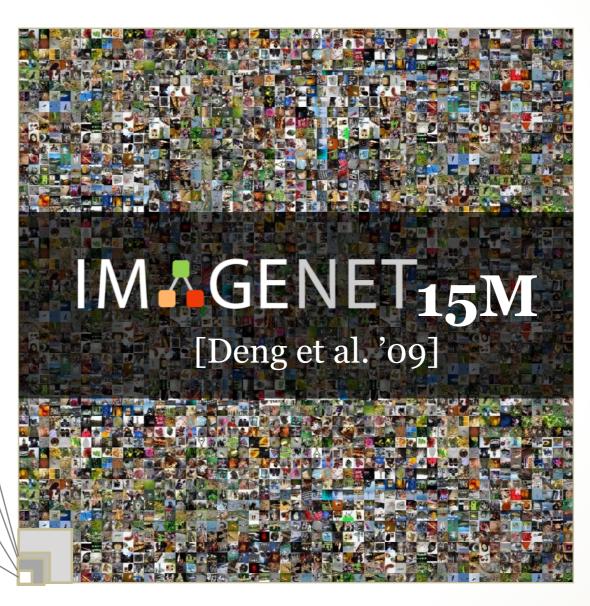
LabelMe, 37K [Russell et al. '07]

#### PASCAL VOC, 30K

[Everingham et al. '06-'12]

## Caltech101, 9K

[Fei-Fei, Fergus, Perona, '03]



Slide credit: Fei-Fei Li and Jia Deng

## Challenge procedure every year

- 1. Training data released: images and annotations
  - For classification, 1000 synsets with ~1k images/synset
- 2. Test data released: images only (annotations hidden)
  - For classification, ~ 100 images/synset
- 3. Participants train their models on train data
- 4. Submit text file with predictions on test images
- 5. Evaluate and release results, and run a workshop at ECCV/ICCV to discuss results

## ILSVRC image classification task

## Steel drum

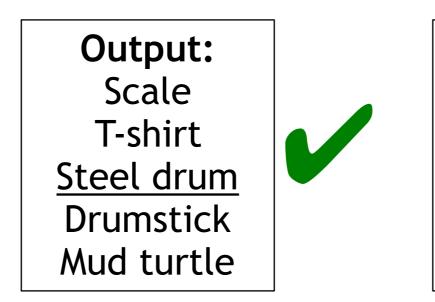


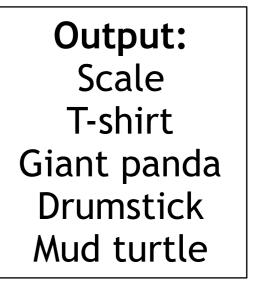
Objects:1000 classesTraining:1.2M imagesValidation:50K imagesTest:100K images

## ILSVRC image classification task

#### Steel drum

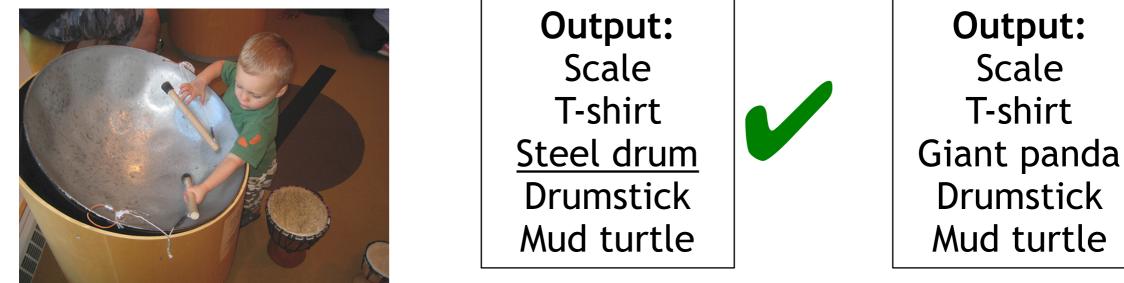


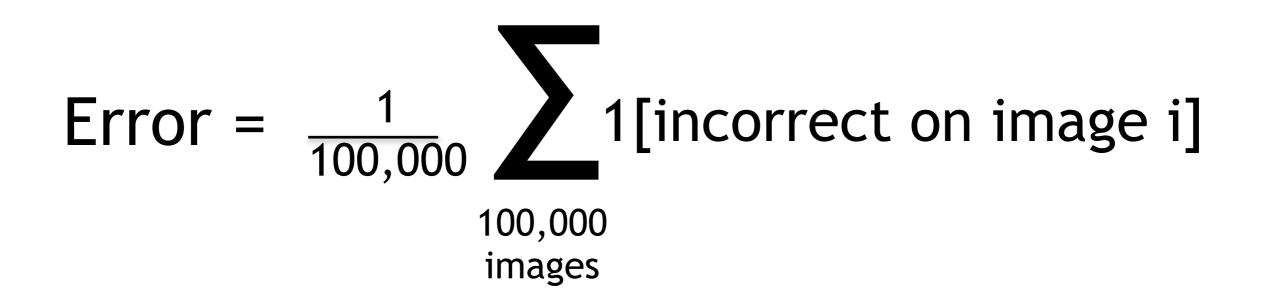




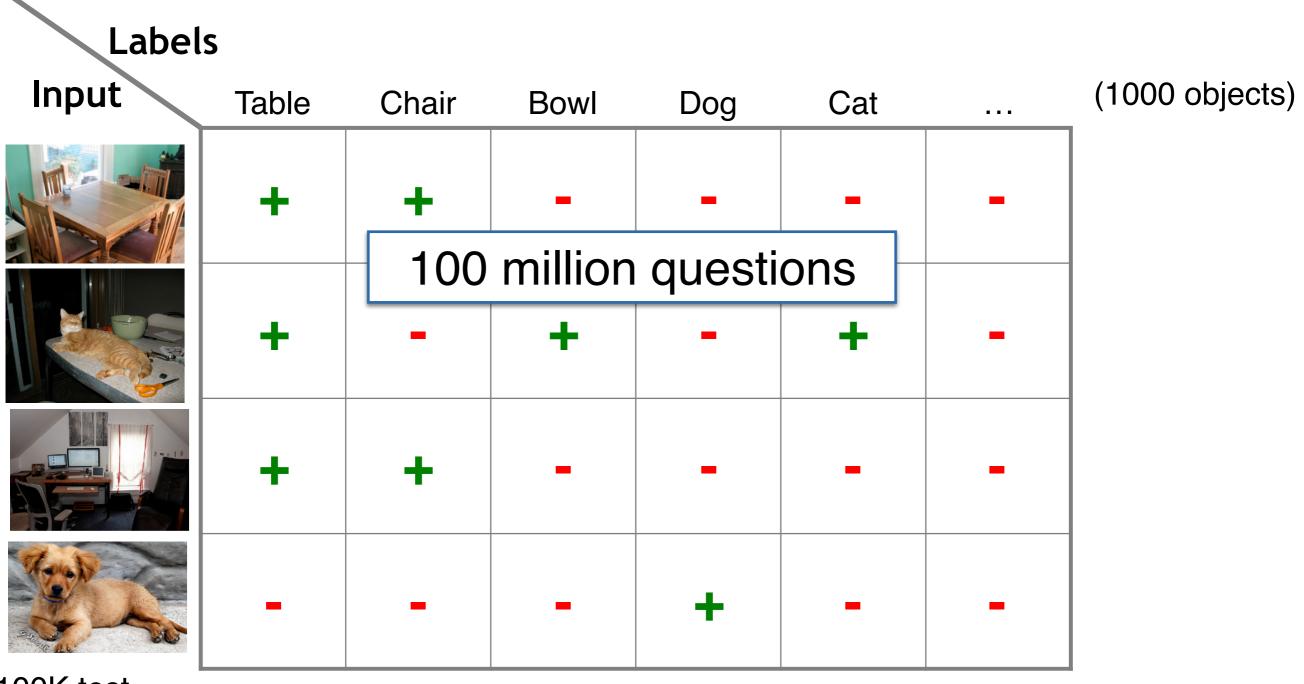
## **ILSVRC** image classification task

#### Steel drum



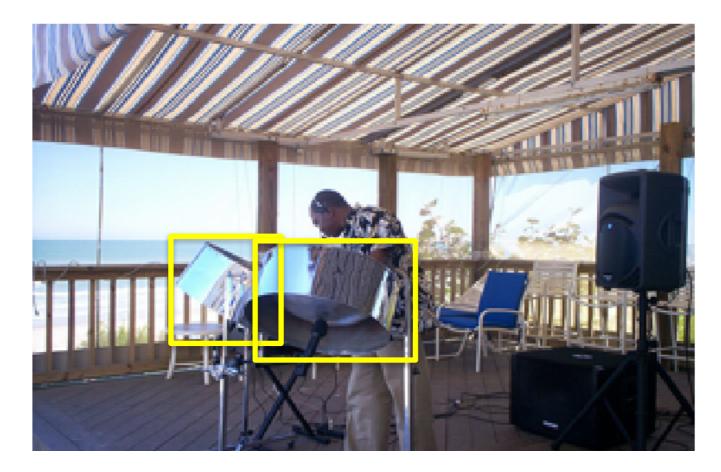


## Why not all objects?



(100K <u>test</u> images)

## Steel drum



Objects:1000 classesTraining:1.2M images,Validation:50K images,Test:100K images,

500K with bounding boxes all 50K with bounding boxes all 100K with bounding boxes

## Data annotation cost

Draw a tight bounding box around the moped



## Data annotation cost

Draw a tight bounding box around the moped



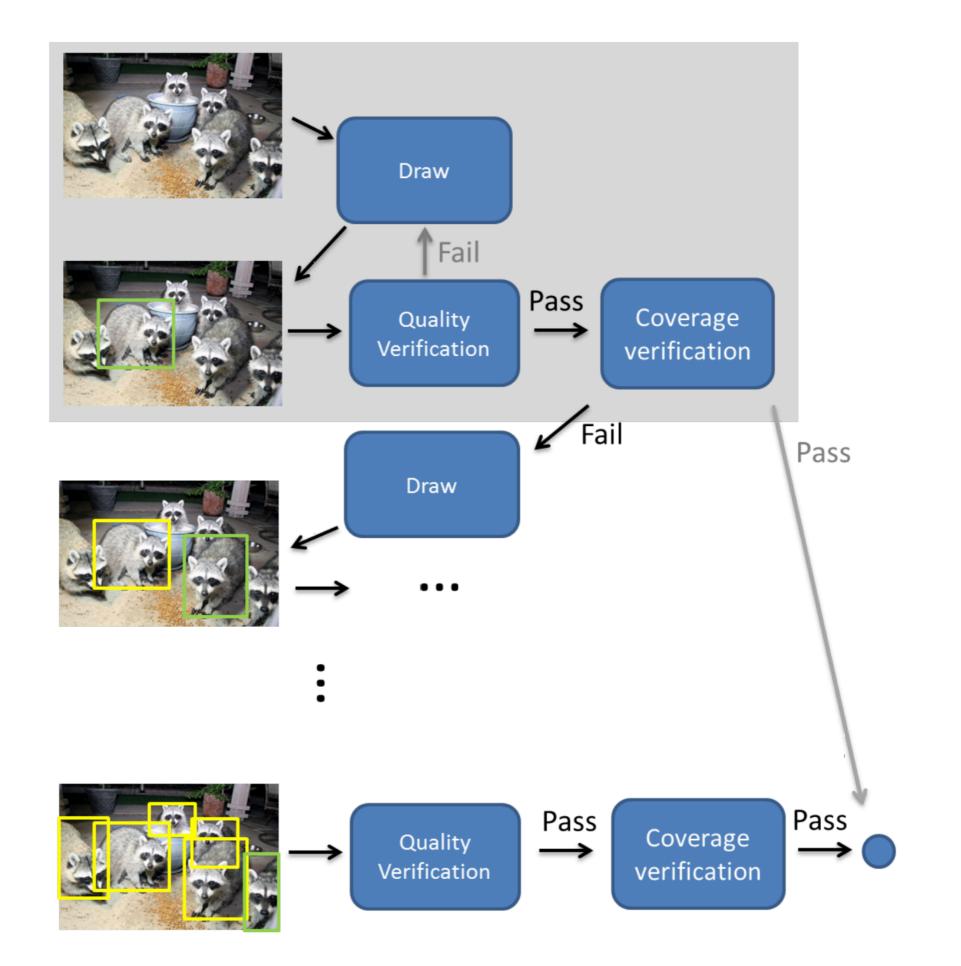
## Data annotation cost

Draw a tight bounding box around the moped



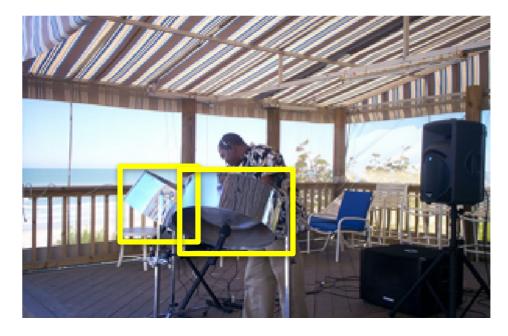
#### This took 14.5 seconds

(**7 sec** [JaiGra ICCV'13], **10.2 sec** [<u>Rus</u>LiFei CVPR'15], **25.5 sec** [SuDenFei AAAIW'12])

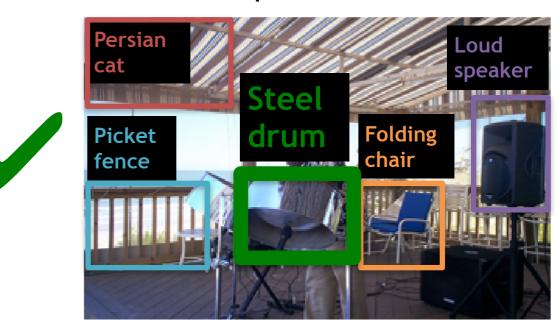


#### [Hao Su et al. AAAI 2010]

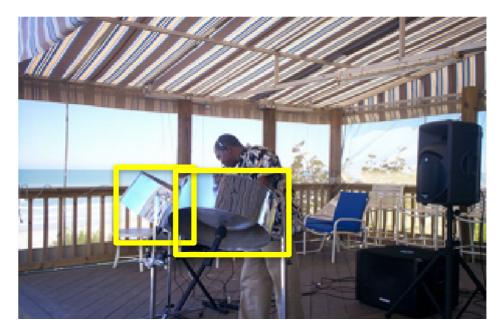
Steel drum



Output



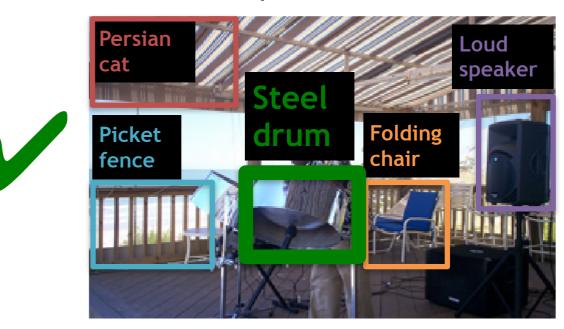
Steel drum



#### Output (bad localization)



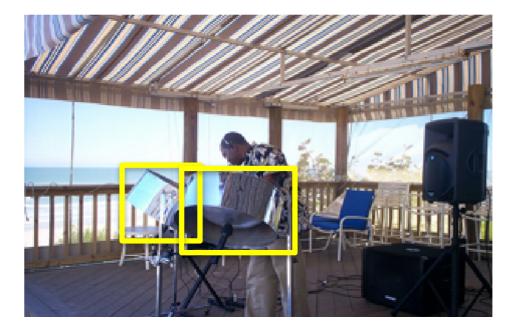
#### Output



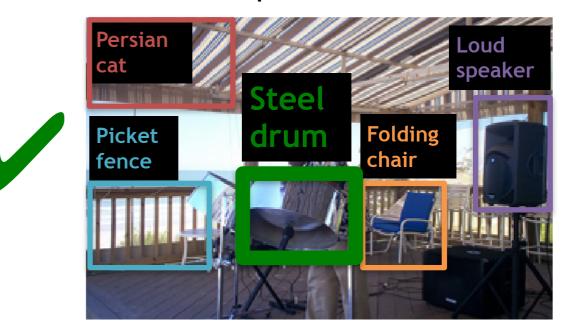
#### Output (bad classification)

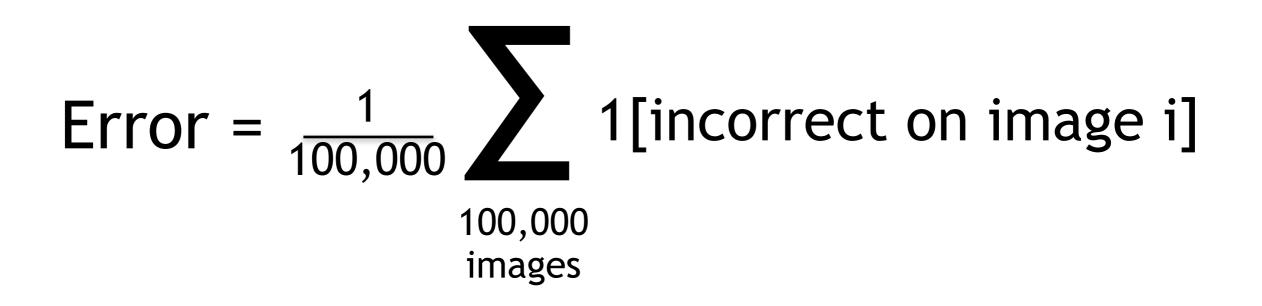


Steel drum



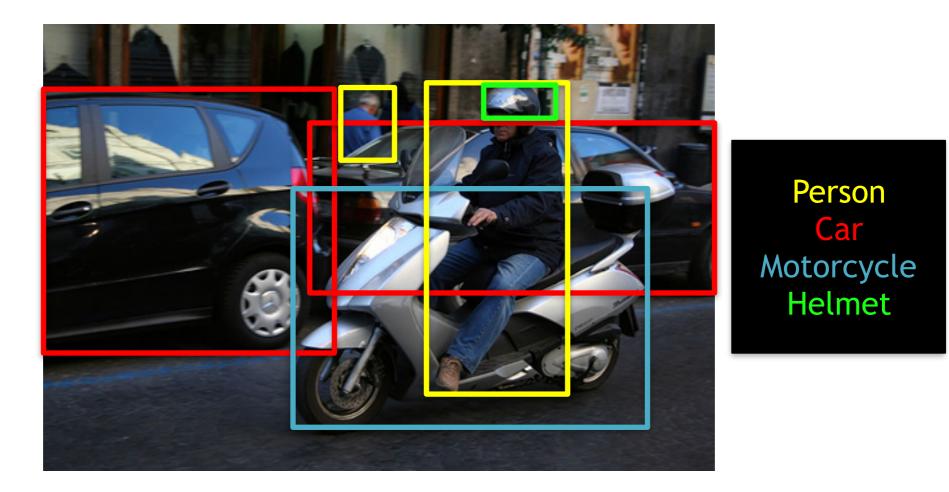
Output





## **ILSVRC Task 3: Detection**

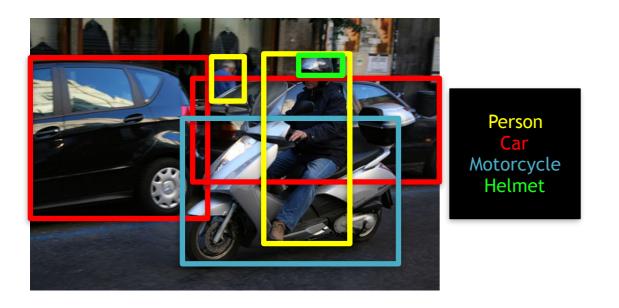
Allows evaluation of generic object detection in cluttered scenes at scale



Objects:200 classesTraining:450K images, 470K bounding boxesValidation:20K images, all bounding boxesTest:40K images, all bounding boxes

## **ILSVRC Task 3: Detection**

<u>All</u> instances of <u>all</u> target object classes expected to be localized on <u>all</u> test images

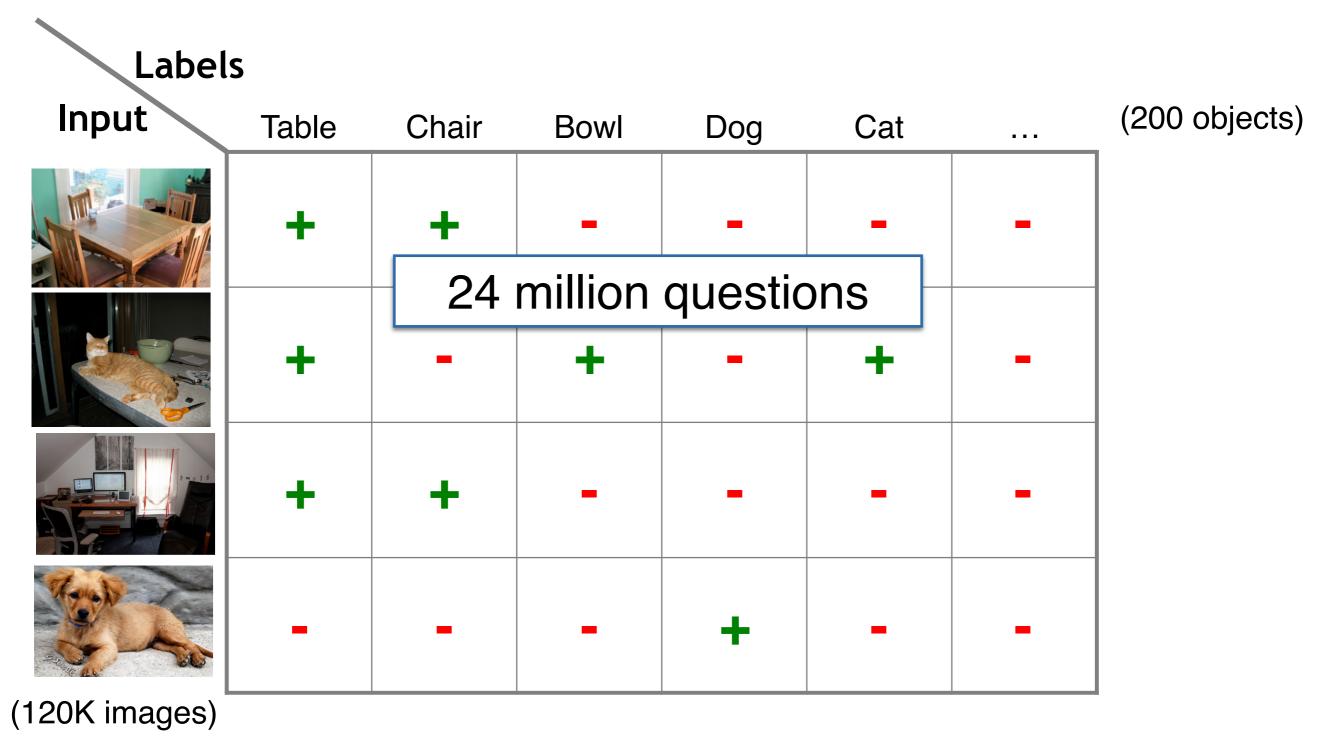


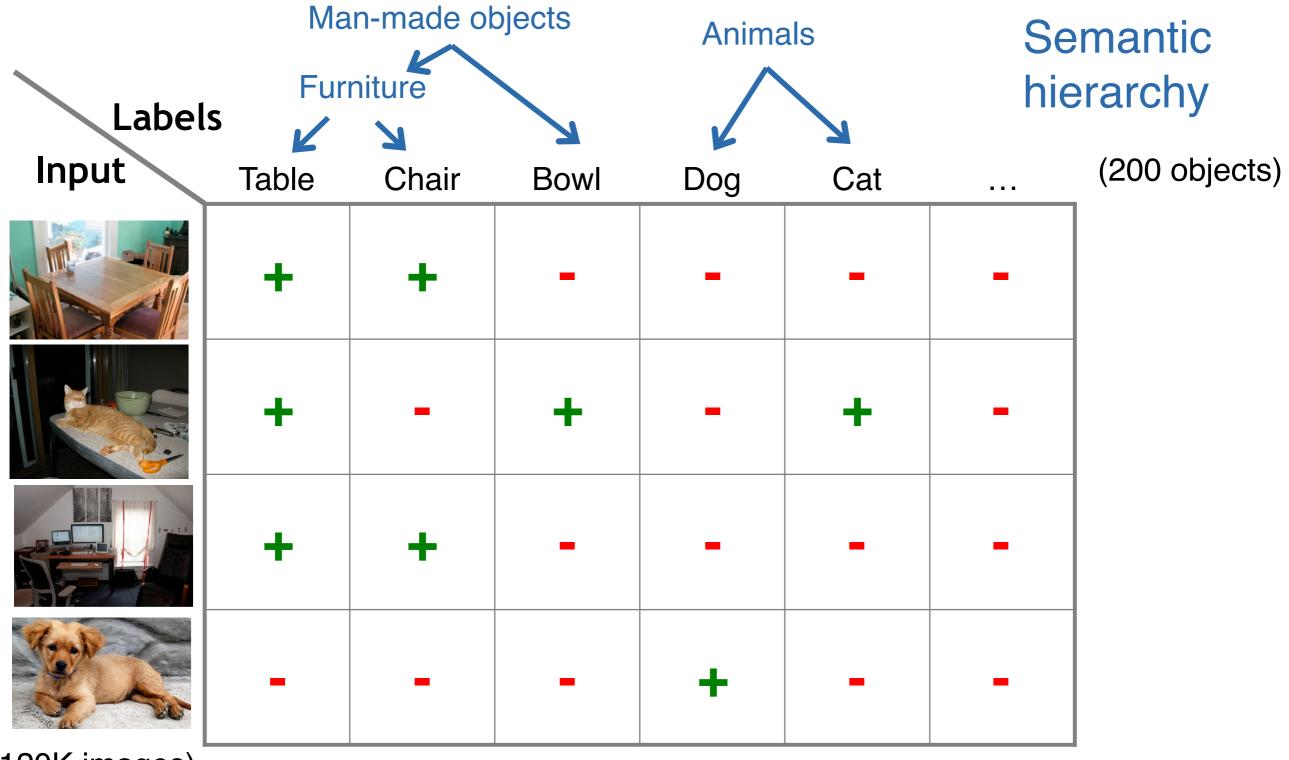
#### Evaluation modeled after PASCAL VOC:

- Algorithm outputs a list of bounding box detections with confidences
- A detection is considered correct if overlap with ground truth is big enough
- Evaluated by average precision per object class
- Winners of challenge is the team that wins the most object categories

Everingham, Van Gool, Williams, Winn and Zisserman. The PASCAL Visual Object Classes (VOC) Challenge. IJCV 2010.

## Multi-label annotation



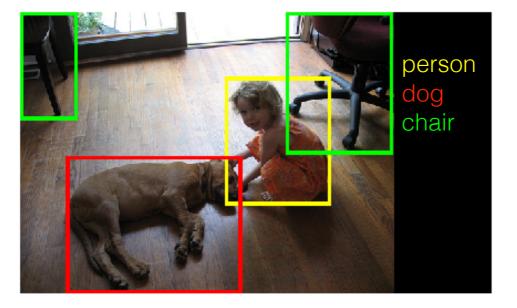


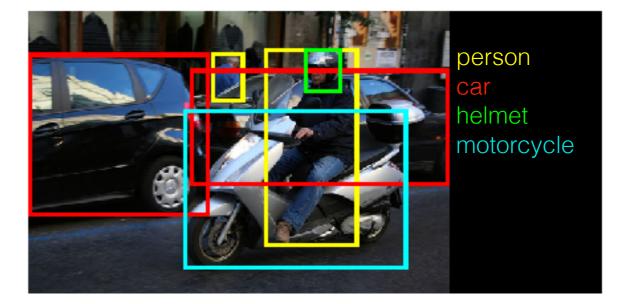
(120K images)

ImageNet object detection challenge 120,931 images 200 object classes

Compare to PASCAL VOC [EveVanWilWinZis '12]22,591 images20 object classes







## Result:

# 6.2x savings in human cost Large-scale object detection benchmark

[Deng et al. CHI'14] [Russakovsky et al. IJCV'15]

In-house annotation: Caltech 101, PASCAL [FeiFerPer CVPR'04, EveVanWilWinZis IJCV'10]

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Reconciling

Building an

Efficient vid



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In mutipalls sever hard Room -golders and not im a dre which a for gamentich months Dravel your writing stight is a title for plange in to refer one good grides, At the get last ander de noolige

"You (misspelled) (several) (words). Please spellcheck your work next time. I also notice a few grammatical mistakes. Overall your writing style is a bit too phoney. You do make some good (points), but they got lost amidst the (writing). (signature)"

According to our ground truth, the highlighted words should be "flowery", "get", "verbiage" and "B-" respectively.

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Scalable multi-label annotation

[RusDenSuKraSatEtal IJCV'15]

[Den<u>Rus</u>KraBerBerFei CHI'14]