Robots learning about objects from the Web

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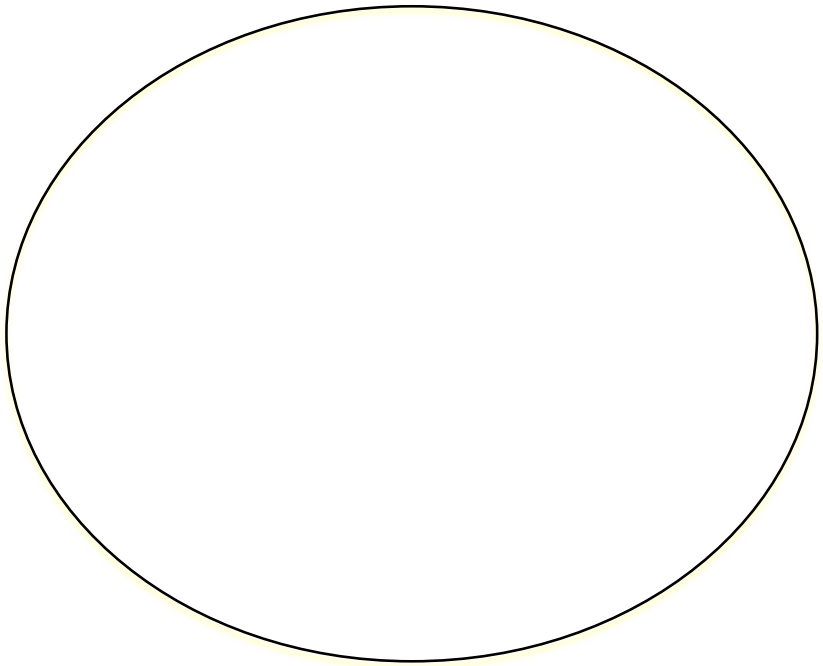
Barbara Caputo
Visual And Multimodal Applied Learning (VANDAL) Laboratory
Department of Computer, Control and Management Engineering

SAPIENZA
UNIVERSITÀ DI ROMA

Suppose you have a robot at home…



Suppose you have a robot at home…

What is this on the table??

Option A: asking a human

What is this on the table??
Let me ask Barbara…

Option A: asking a human

- Robots learn from own experience guided by humans
  - Human-robot interaction [Kjellstrom et al 2011,Billard&Grollman 2013]
  - Learning by demonstration [Argall et al 2009]

Option B: learning by itself

What is this on the table??
Let me try to figure it out
…

Option B: learning by itself

- Robots learn from own experience alone
  - Developmental robotics [Asada et al 2009, Tsai & Kujpers 2013, 2014..]

Option C: learning from the Web

What is this on the table??
Let me take a snapshot
and search on the Web…

..if the robot could learn from the Web like us….

Option C: learning from the Web

Let's see
on the Web..

http://www.marialiberati.com/2009/03/07/holy-cannoli/

aria Liberati.c...

Holy Cannoli !!

March 7th 2009 by **Maria Liberati**

Holy Cannoli!

Editor: Kate Hollinger

Copyright, 2009, Maria Liberati

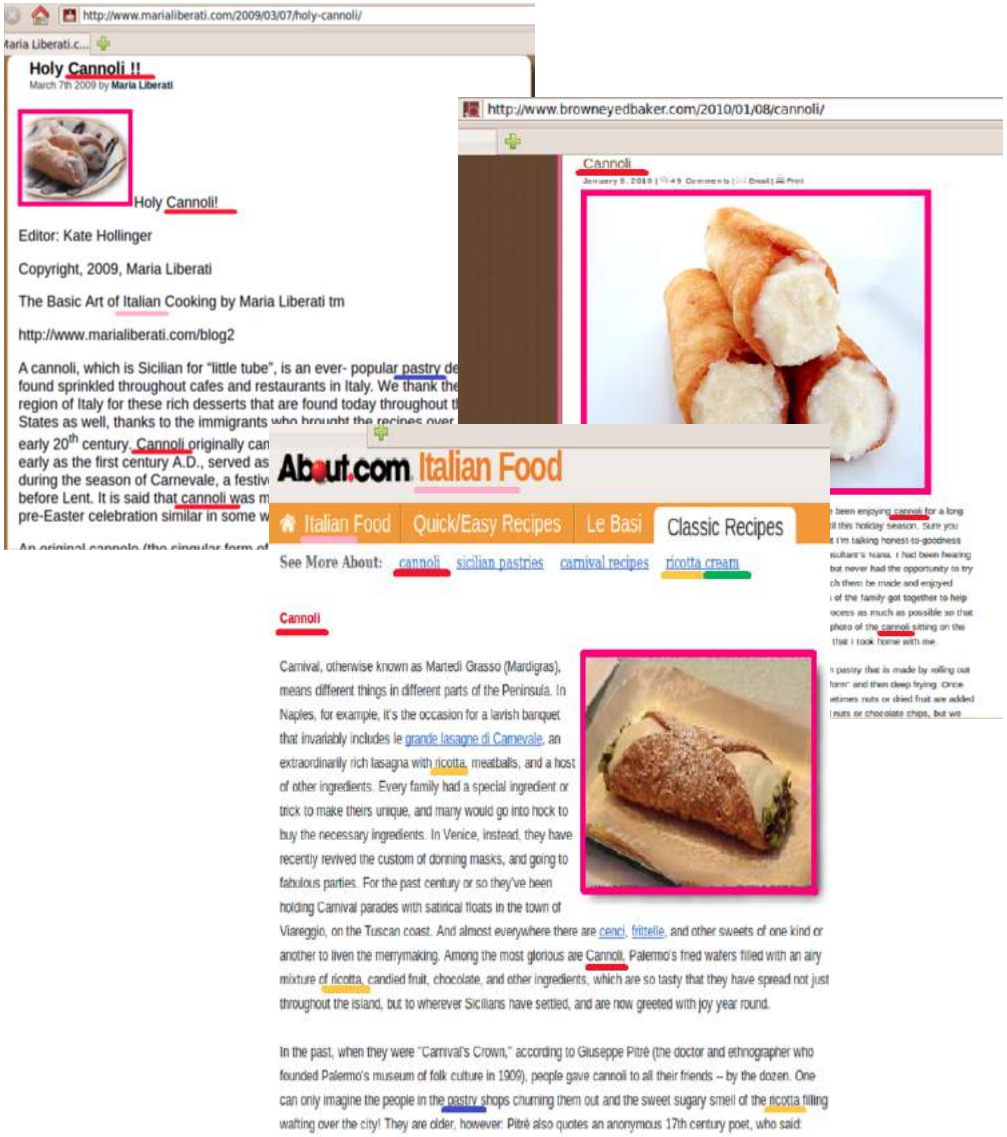
The Basic Art of Italian Cooking by Maria Liberati tm

http://www.marialiberati.com/blog2

A cannoli, which is Sicilian for "little tube", is an ever- popular pastry dessert found sprinkled throughout cafes and restaurants in Italy. We thank the Sicilian region of Italy for these rich desserts that are found today throughout the United States as well, thanks to the immigrants who brought the recipes over in the early 20th century. Cannoli originally came from the Palermo region of Sicily as early as the first century A.D., served as a treat and given to friends in dozens during the season of Carnevale, a festive European celebration held right before Lent. It is said that cannoli was most likely a symbol of fertility during the pre-Easter celebration similar in some ways to Mardi Gras.

Option C: learning from the Web

Let's see
on the Web..



Option C: learning from the Web

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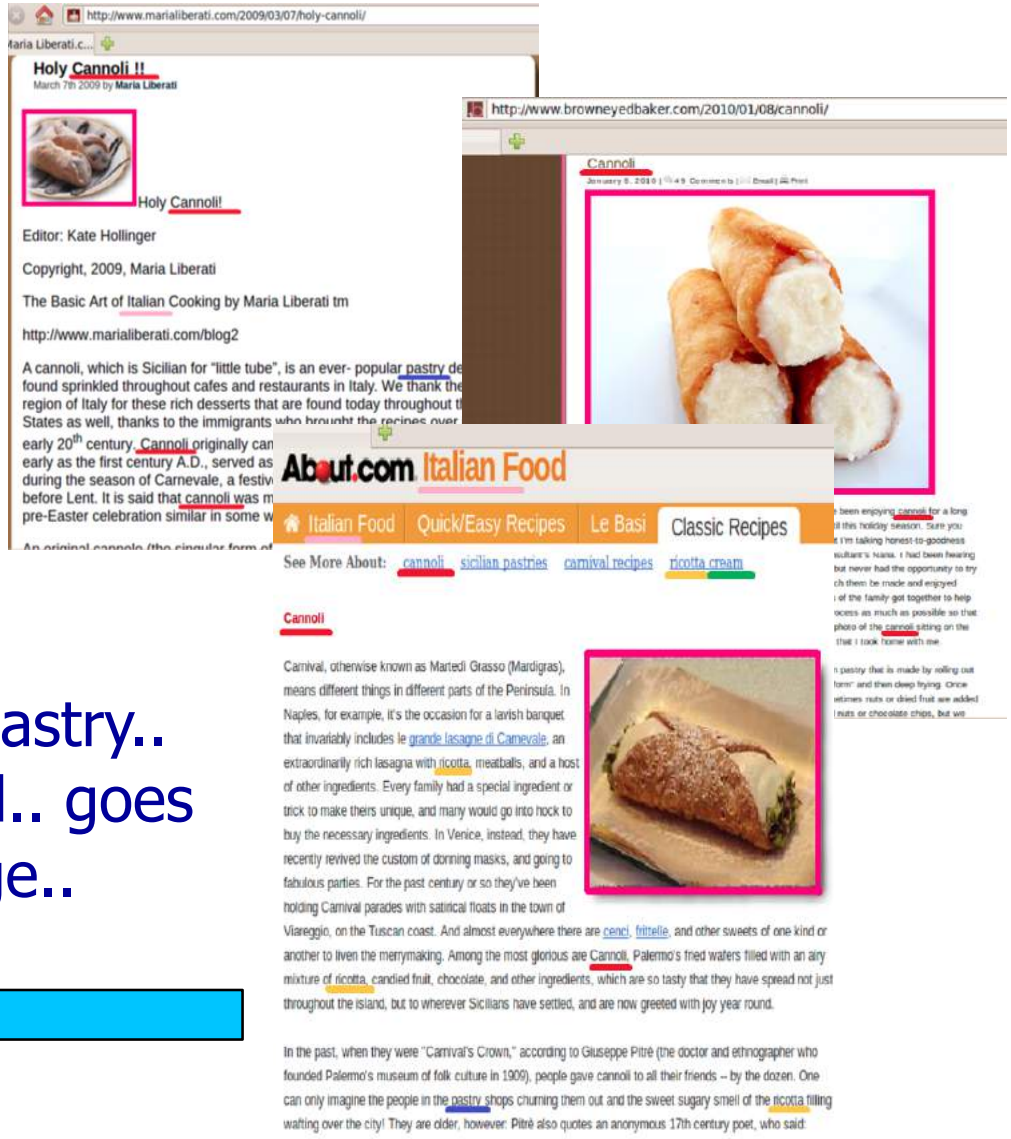


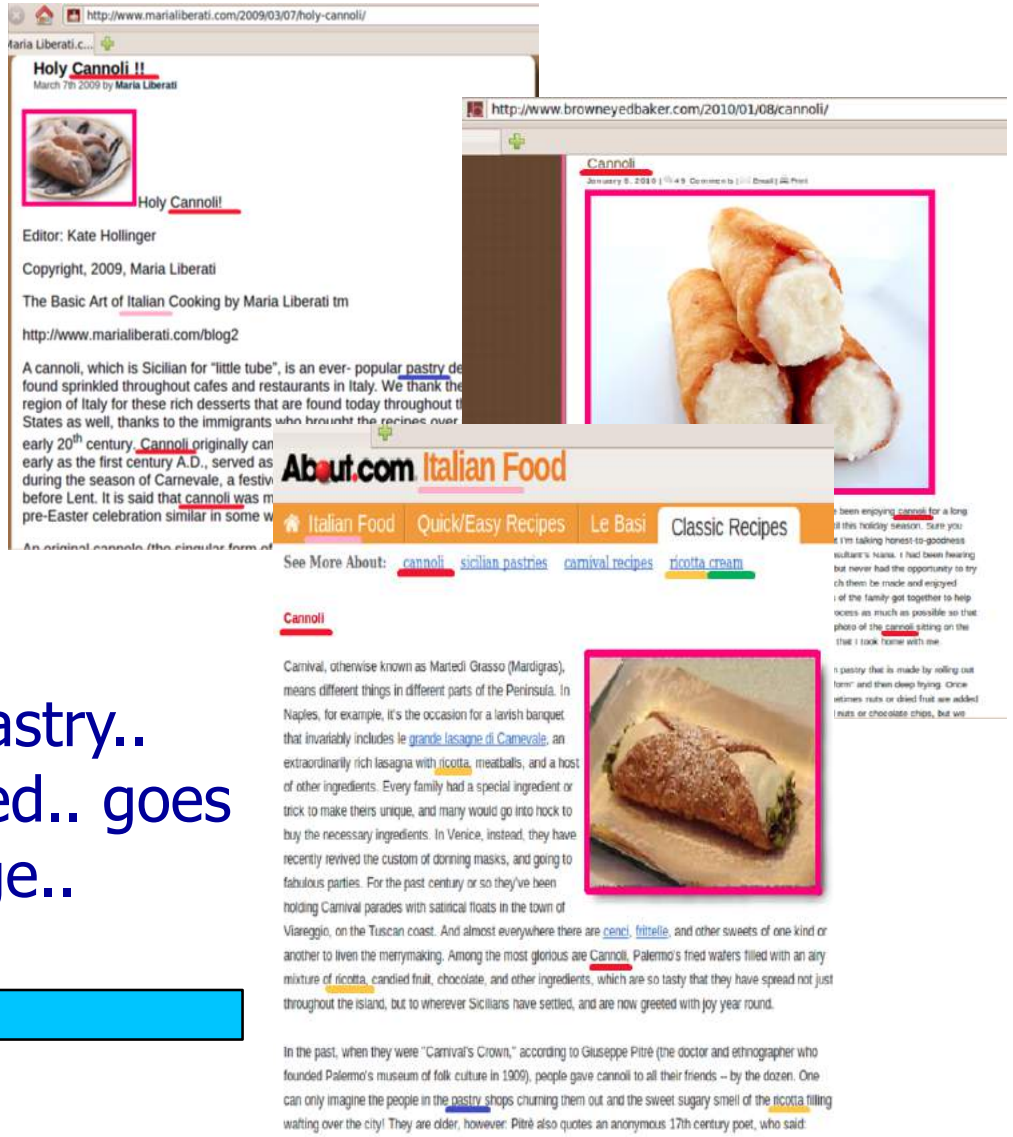
...cannoli..pastry..
ricotta filled.. goes
in the fridge..

Option C: learning from the Web

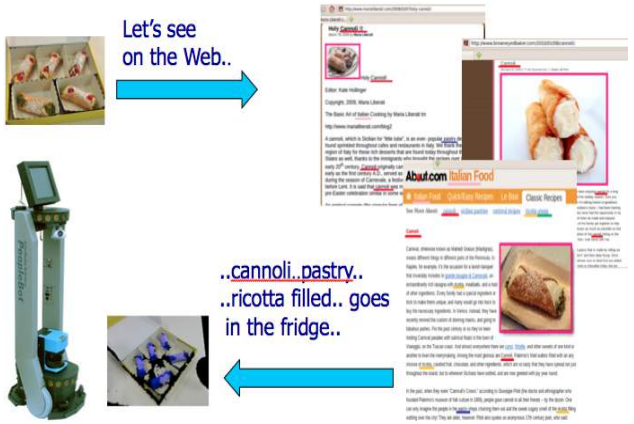
Let's see
on the Web..

Ok, now I
know what to
do with it

..cannoli..pastry..
..ricotta filled.. goes
in the fridge..



Option C: learning from the Web



To make this work, we have several challenges, such as:

1. How to extract from the Web information useful for a robot, from a robot query?
2. How to make such information usable by robots?
3. How to update continuously the perceptual and semantic Web -created knowledge bases?
4. ….

Focus on perceptual knowledge (images, depth); Visual learning tool of choice: deep learning

How to find usable perceptual knowledge on the Web?

How would a robot query the web?

Find a cannoli

What is this?

textual query

perceptual query

Rather than mining the Web on the fly, we might build clean Web-proxies, large enough to cover for most (any?) query

…but isn't this ImageNet????

(Some) Open Issues

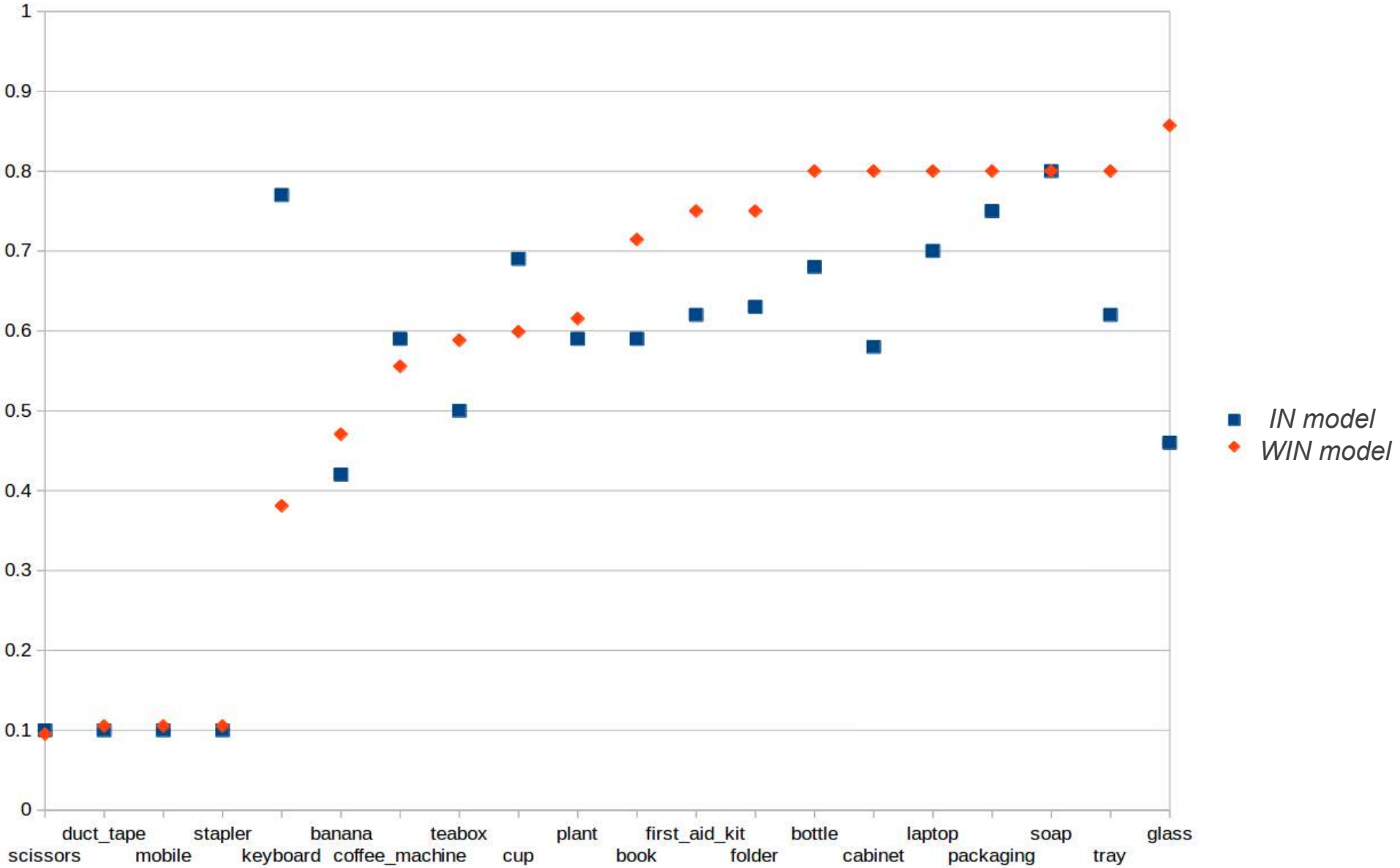
ImageNet is a db created in 2012 of 1K categories –**static, closed world assumption**

1. What if we could continuously update all its classes?
2. What if we could augment its classes (1k, 3K, ..10K)?
3. What if we could exploit prior knowledge on the task and build on demand task specific databases?

Can we automatically generate larger/task specific databases?

Proof of concept: generate a copy of ImageNet by downloading images using the class names as queries

Results with AlexNet(Web-ImageNet)



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Issues to deal with:

1. How to minimize noisily annotated images when harvesting the Web

2. What is the effect of noise on a given CNN architecture

Harvesting the Web –SEO Keywords

- We take advantage of the Search Engine Optimization (SEO) practice of keyword research.
- SEO professionals research keywords, which they use to achieve better rankings in search engines.

Tool of choice: MyKeyWorder

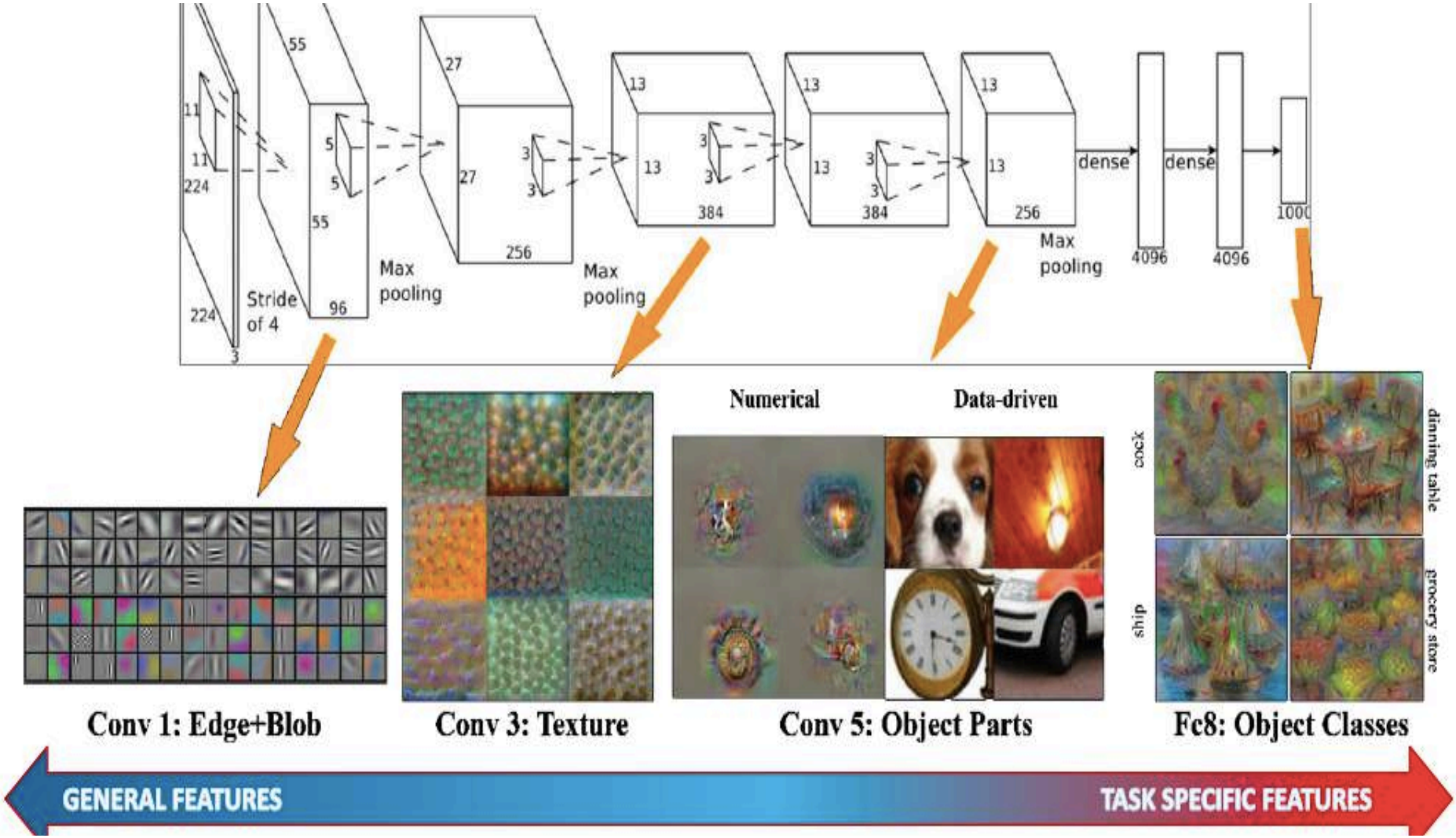
- It references language content from Princeton's Wordnet and Moby Thesaurus.
- It takes a query and returns lists of keywords associated with it, sorting them by relevance and frequency.

Harvesting the Web –SEO Keywords

Icecream - WIN

Icecream - WINC

How does noise affects CNNs?



How does noise affects CNNs?

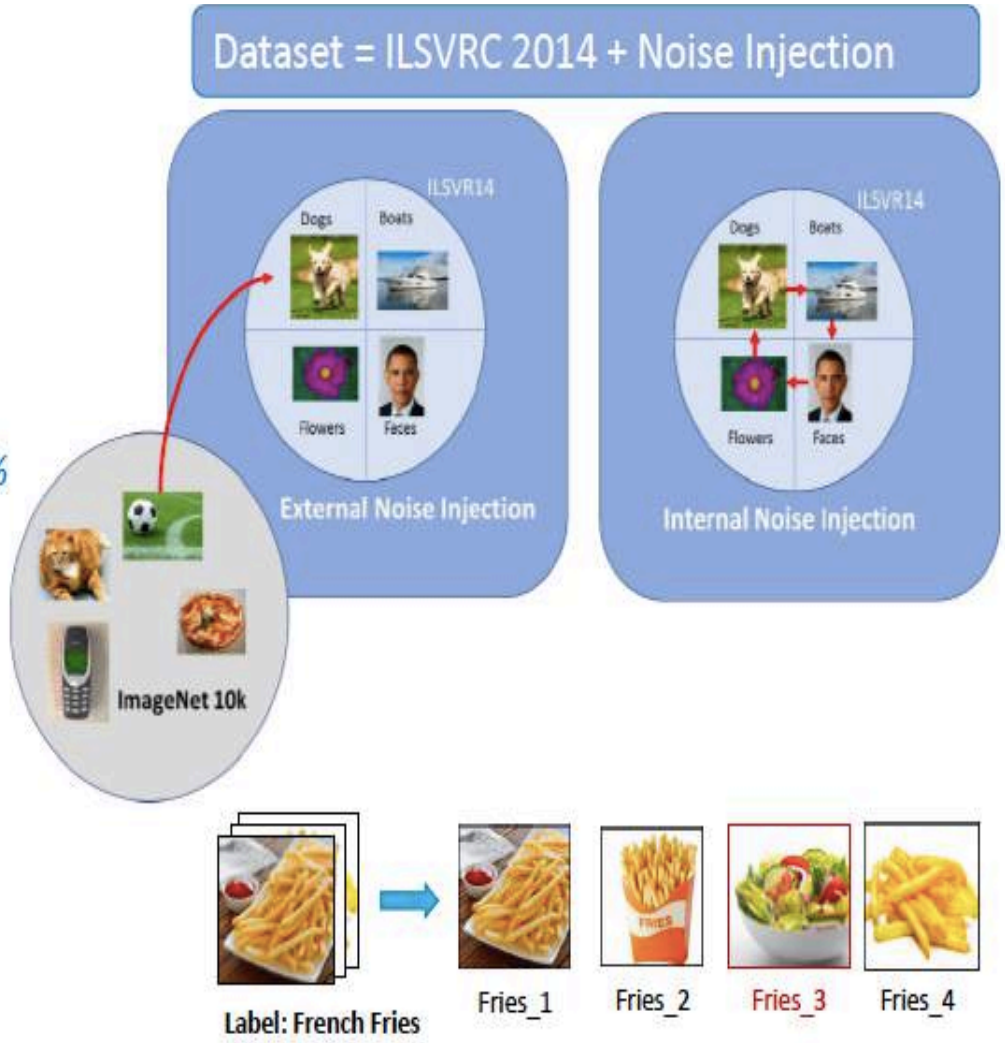
Original dataset	ILSVRC 2014 classification
Object Categories	1000
Number of images	1,281167 (700-1300 images per cat.)

DATASET

- 2 types of Noise Injection: *Internal and External*
- 9 percentages of Noise Injection: *5% 15% 25% ... 75% 85%*

TRAINING

- 2 different architectures: *AlexNet , GoogleNet*
- Training details
  - *60 Epochs*
  - *Stochastic Gradient descrent*
  - *Learning rate 0.01*
  - *Learning rate update: step*
  - *Momentum 0.9*



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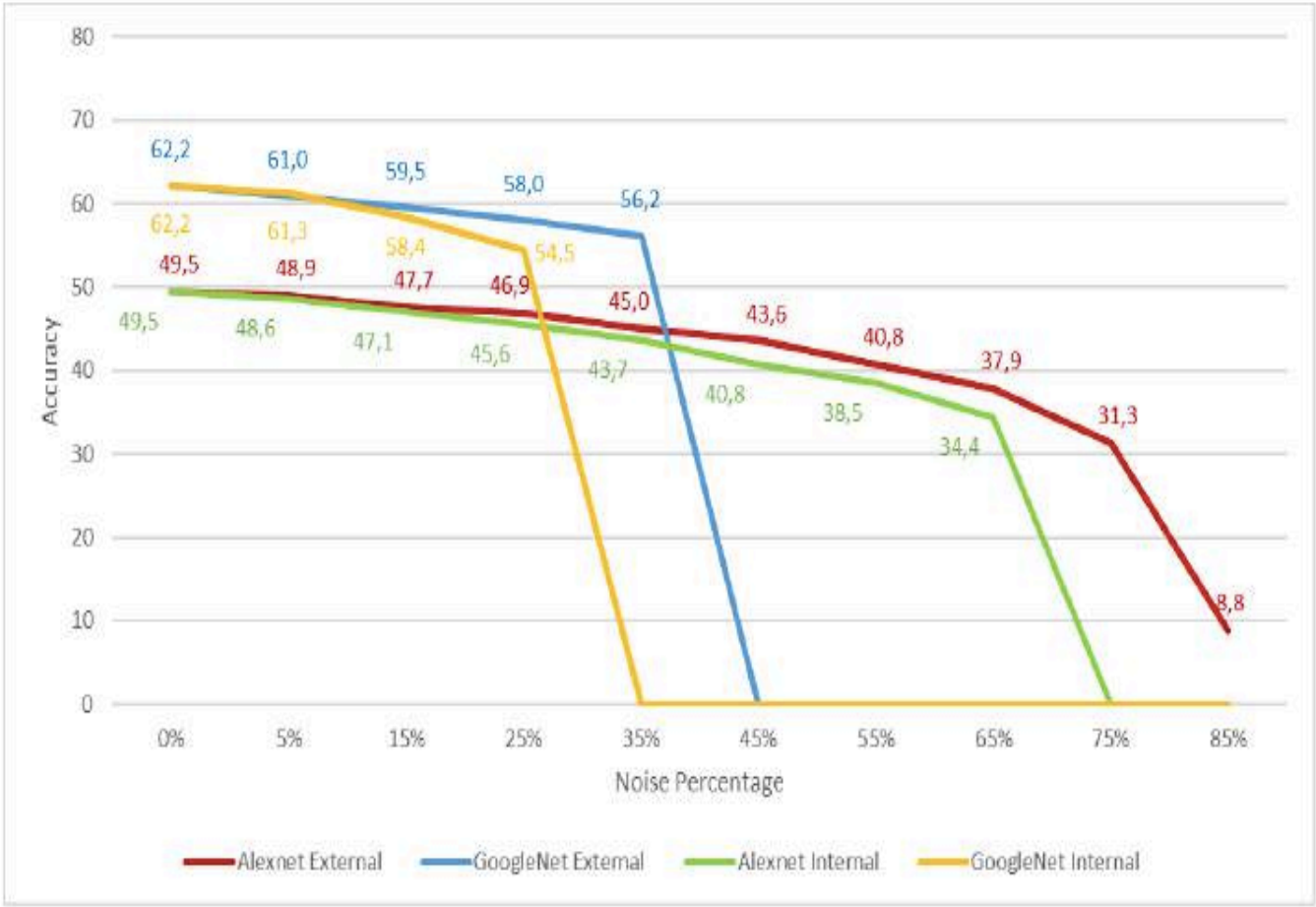
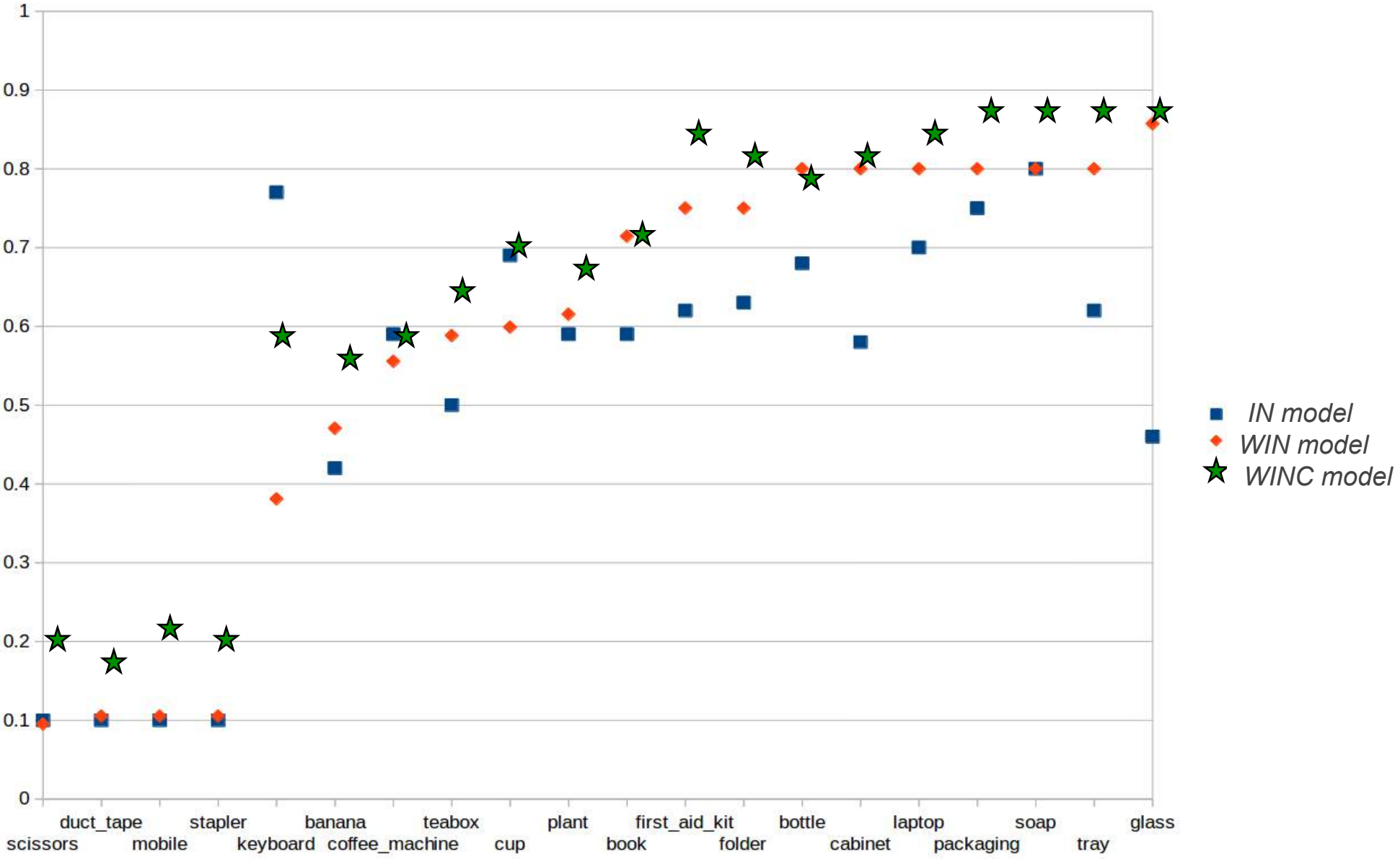


Results with AlexNet(Web-ImageNet-Cleaned)



Putting all the pieces together

1. We generate WINC (Web-ImageNet-Cleaned) and train a GoogLeNet on it

2. We use this CNN to make predictions on Bob and Betty

3. We further use semantic context as a heuristic to indicate our preferences from the CNN list of predictions

4. From this preferred subset we rank by the CNN's confidence and pick the highest

[Massouh, Babiloni, Tommasi, Young, Hawes and Caputo, IROS 2017]
[Young, Basile, Cabrio, Caputo, Kunze and Hawes, ICRA 2017]

???
1.

Merging visual and semantic cues

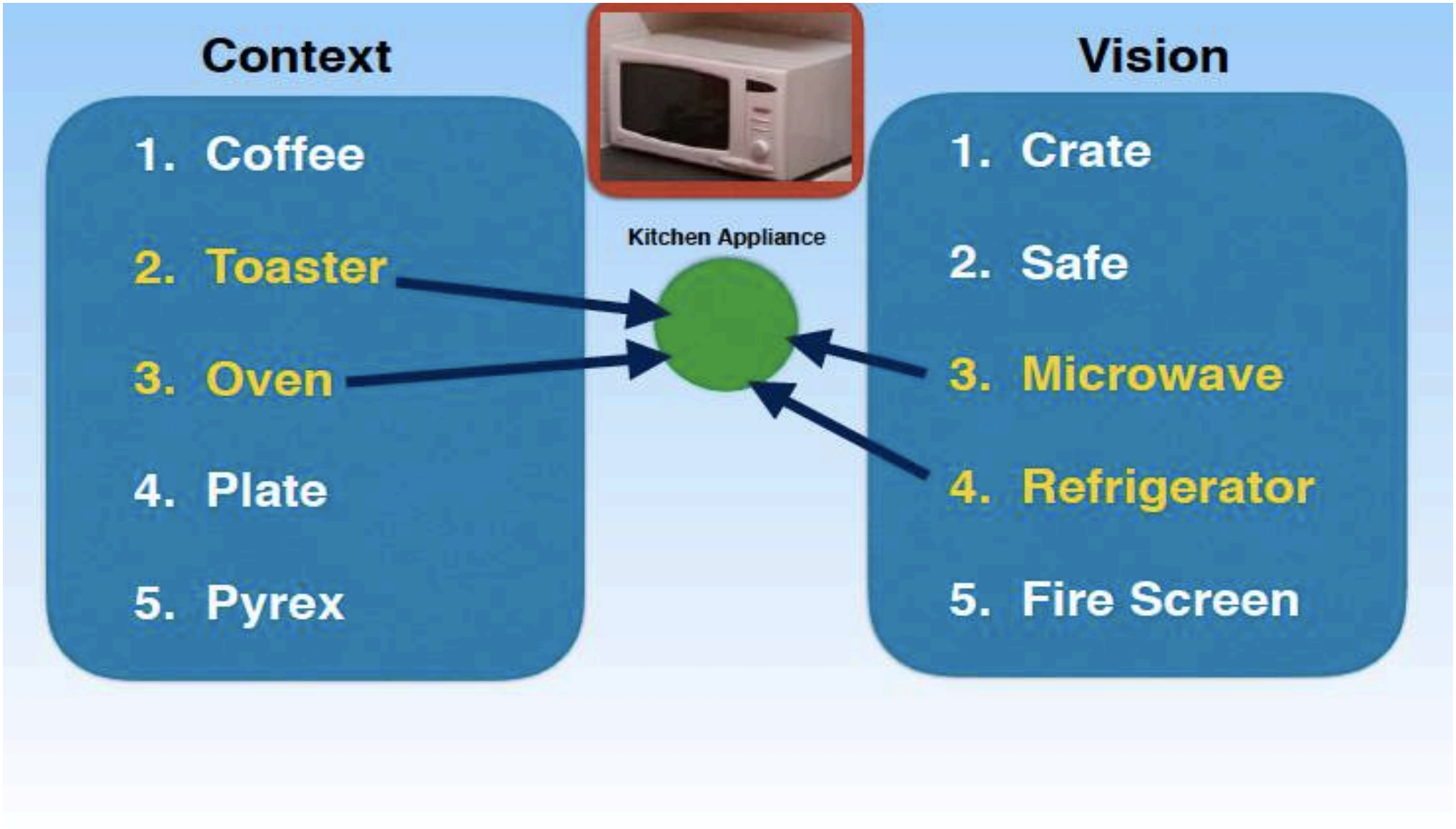
Context

1. Coffee
2. Toaster
3. Oven
4. Plate
5. Pyrex

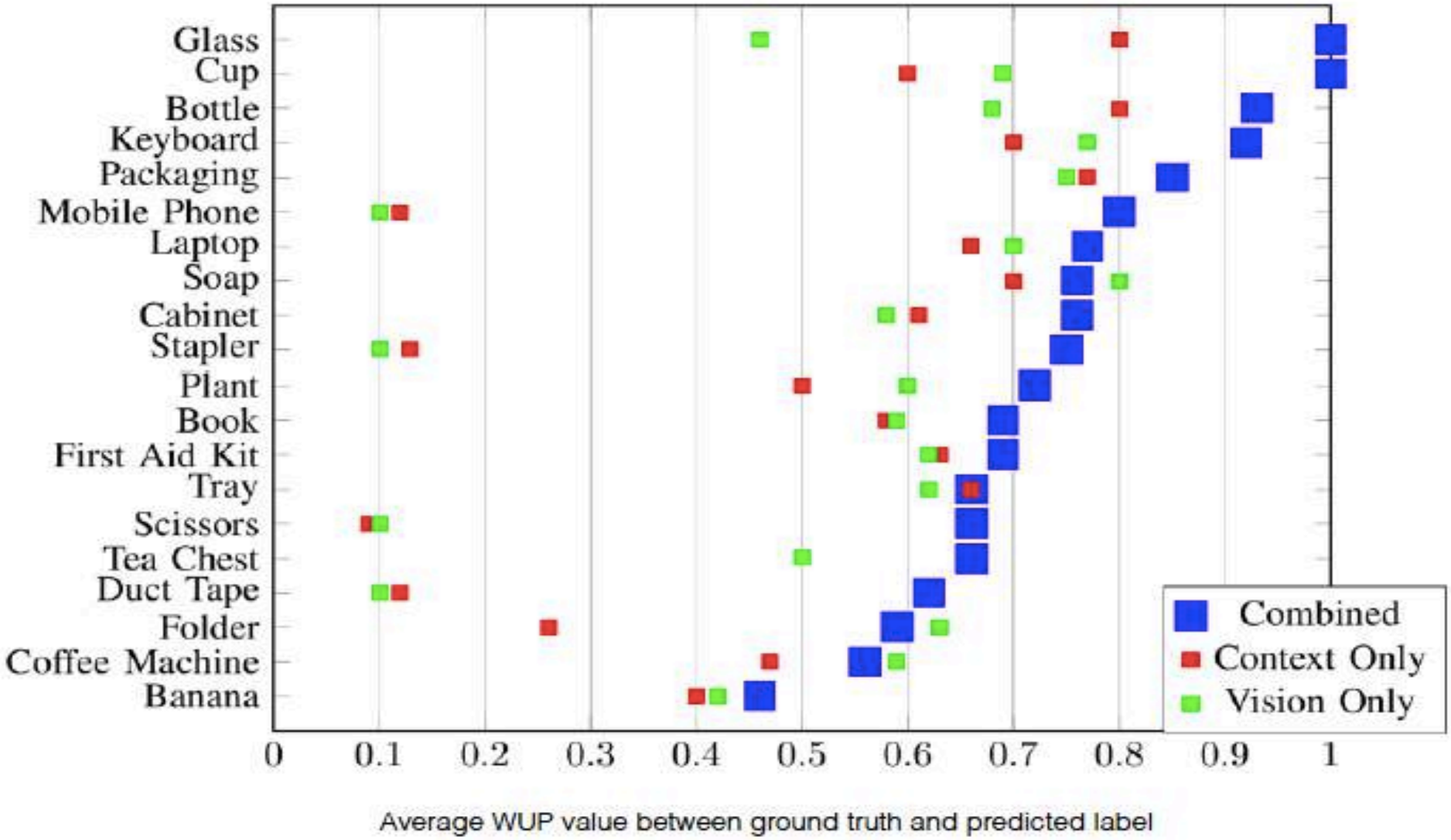
Merging visual and semantic cues

Merging visual and semantic cues

Merging visual and semantic cues



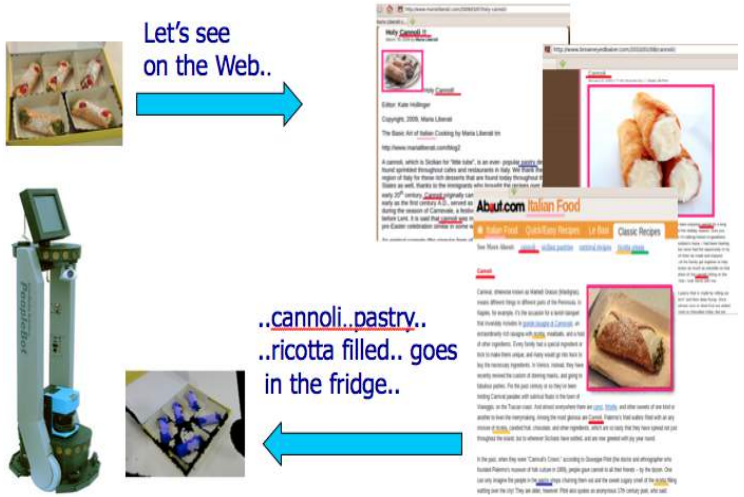
Merging visual and semantic cues



Learning about objects from the Web

Q:

1. How to find usable perceptual knowledge from the Web?



A:

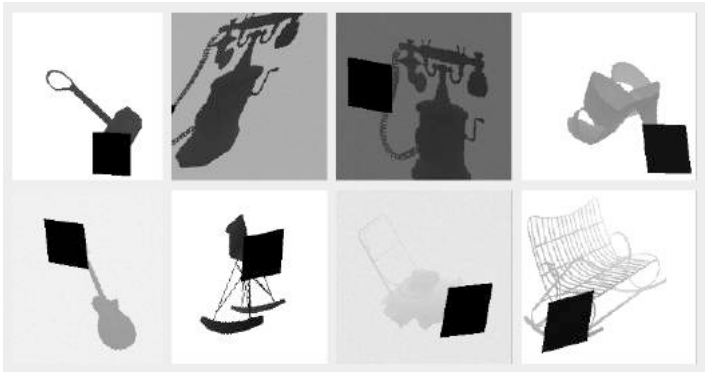
1. Build automatically Web-based perceptual knowledge bases, generic and task specific

Moving forward

Harvesting 3D percepts from the Web

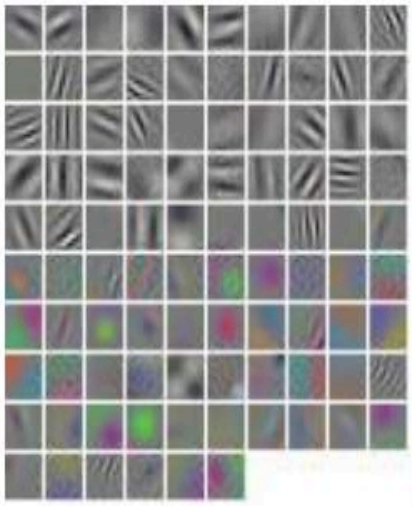
From 3D CAD models to synthetic depth → the VANDAL database

- 4.1 millions depth views
- 9.383 different CAD models (counting morphs)
- 319 object classes (ILSVRC 2014 subset)

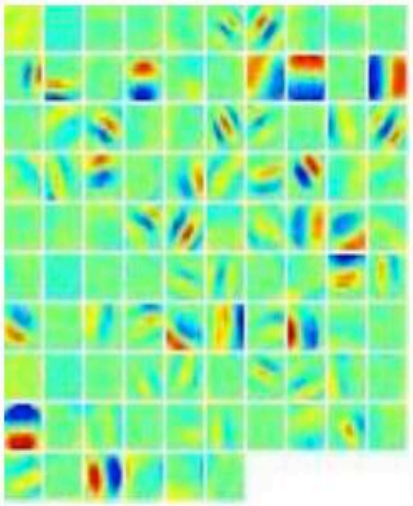


Sample renderings with data augmentation

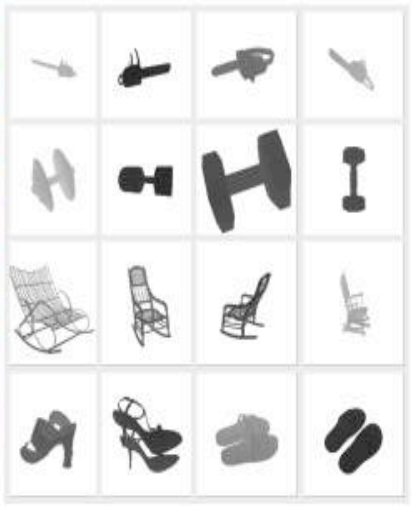
Imagenet samples



Imagenet filters



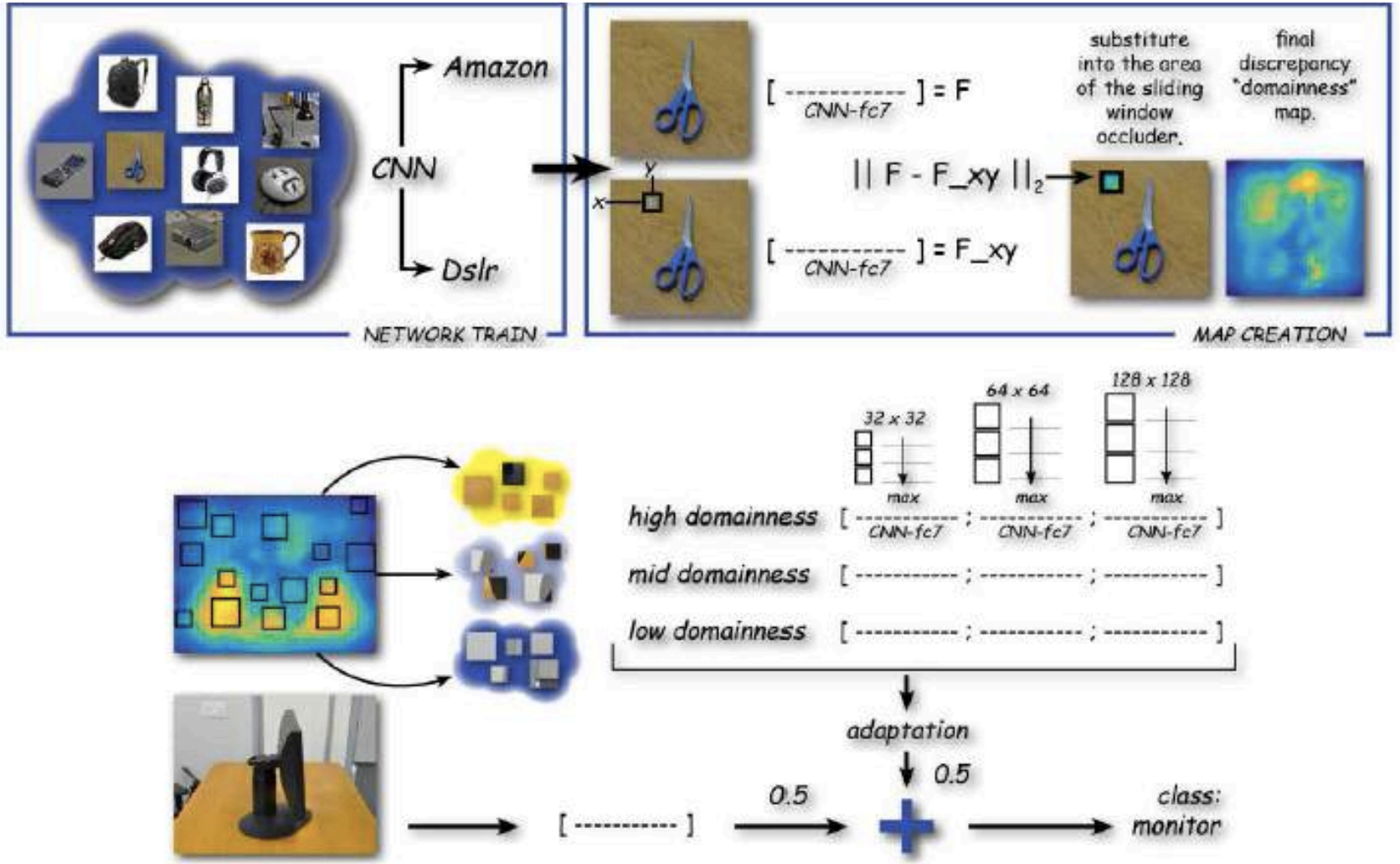
DepthNet samples



Vandal samples

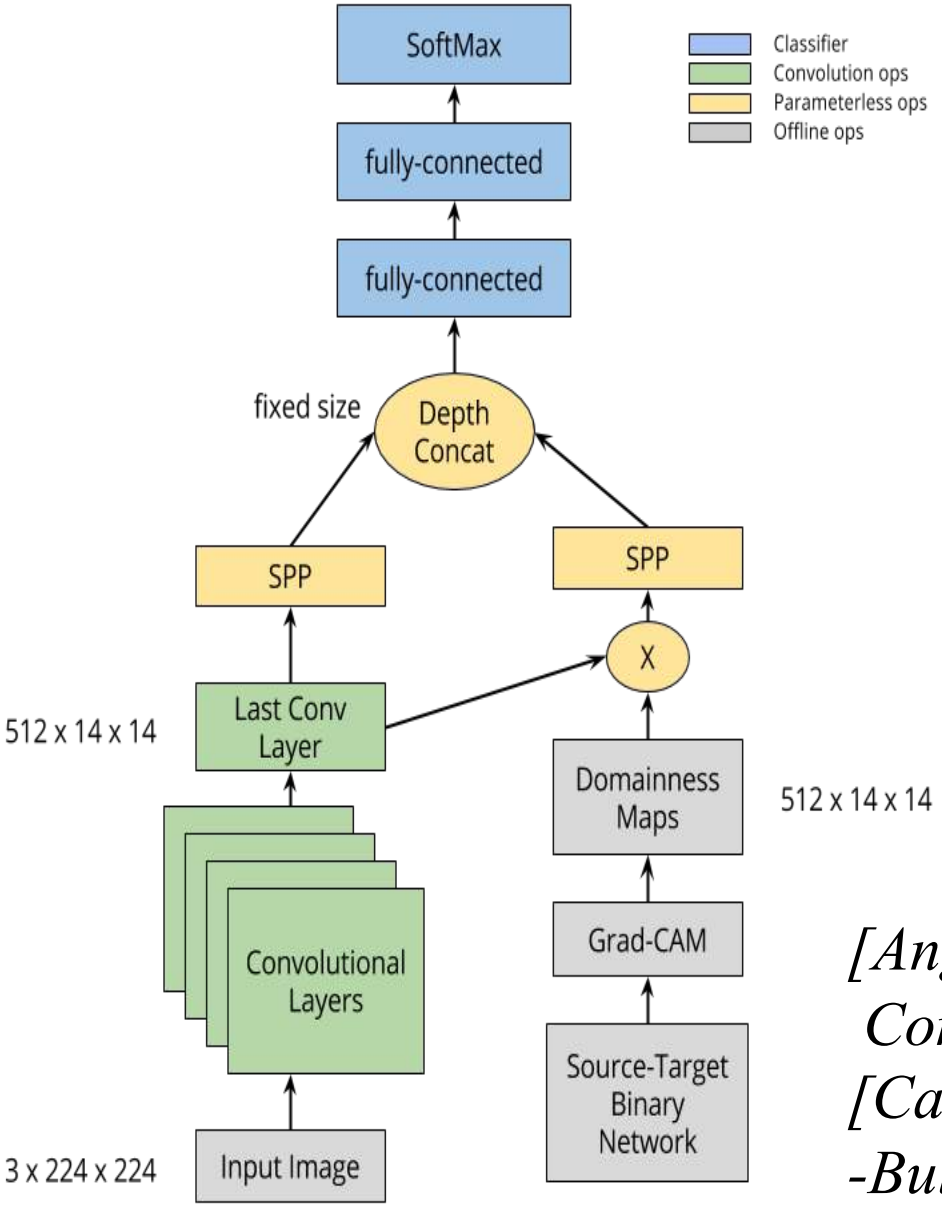
[Carlucci, Russo and Caputo, ICRA 2017]

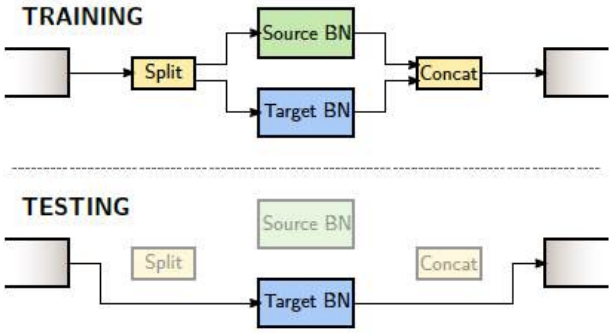
Can we localize the domain shift?

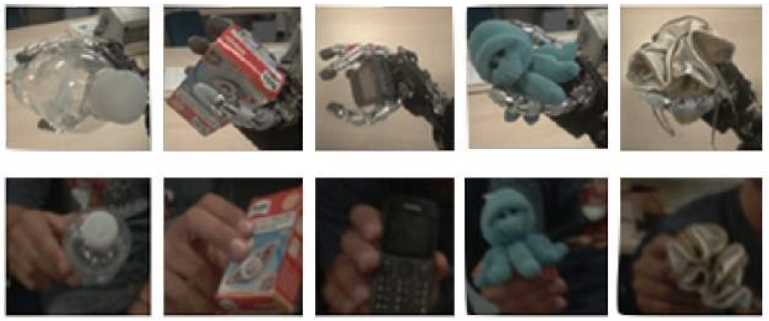


[Tommasi, Russo, Lanzi and Caputo, ECCV-W 2016]

Can we embed domainness maps in a CNN?



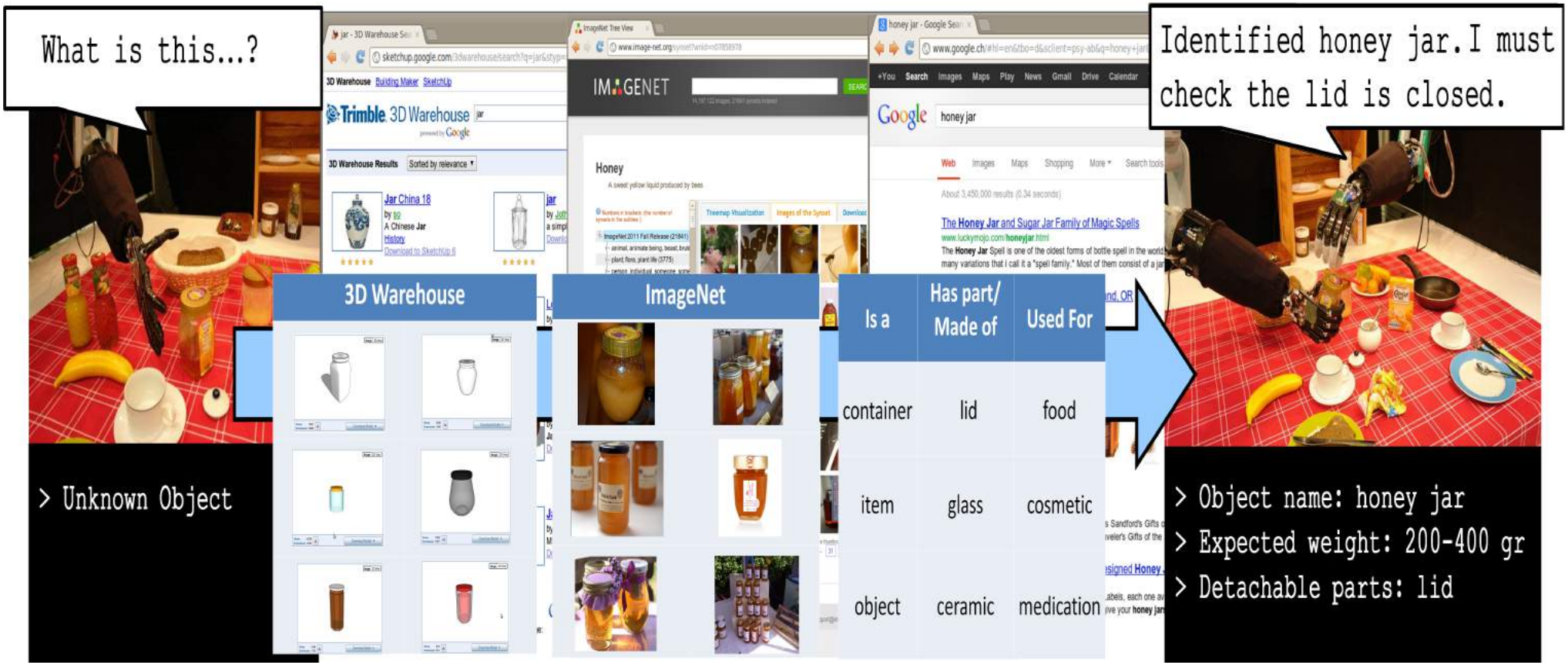




[Angeletti, Tommasi and Caputo, ComingSoon 2018]
[Carlucci, Porzi, Ricci, Caputo and Rota -Bulo', ICCV17 sub]

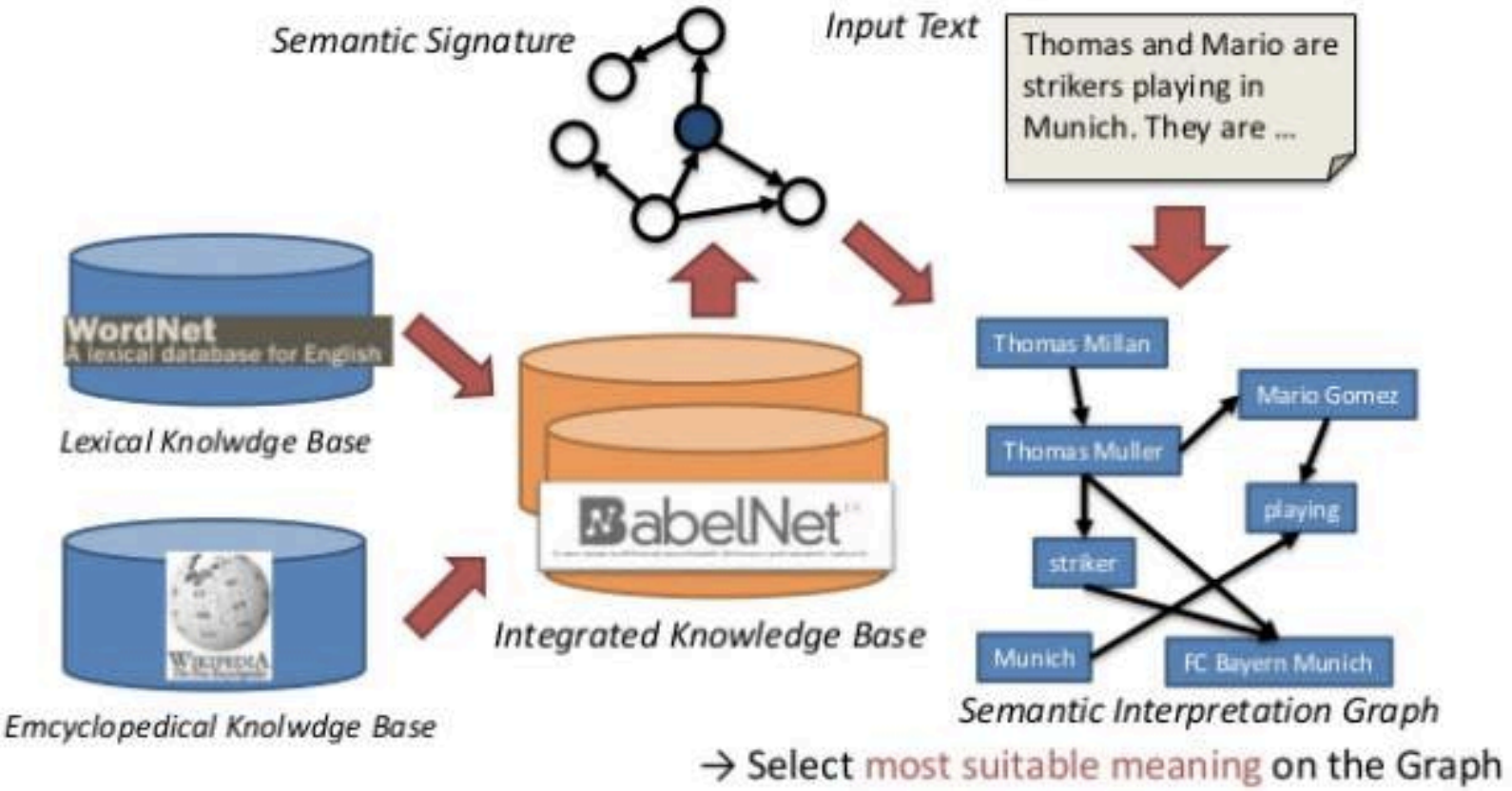
Learning about objects from the Web: where does manipulation fit in?

An object is far more than its name…



Leveraging over 3D and 2D perceptual data freely available from the Web, linking it to structured semantic knowledge about objects

An object is far more than its name…



Leveraging over 3D and 2D perceptual data freely available from the Web, linking it to structured semantic knowledge about objects

A final though

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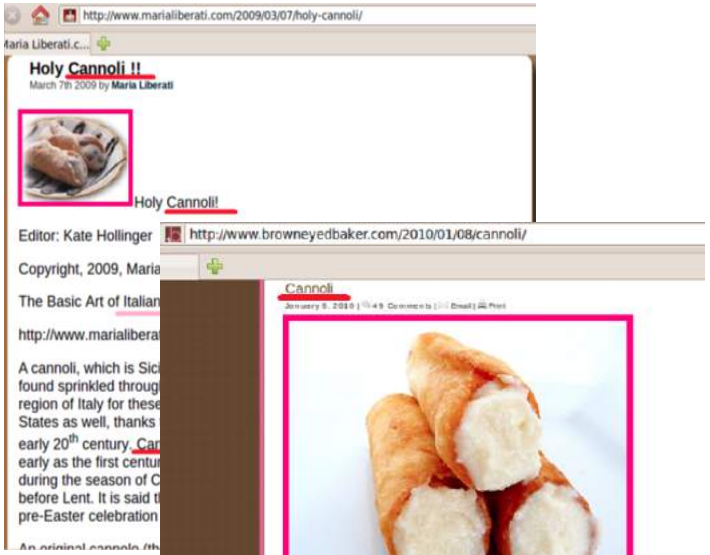
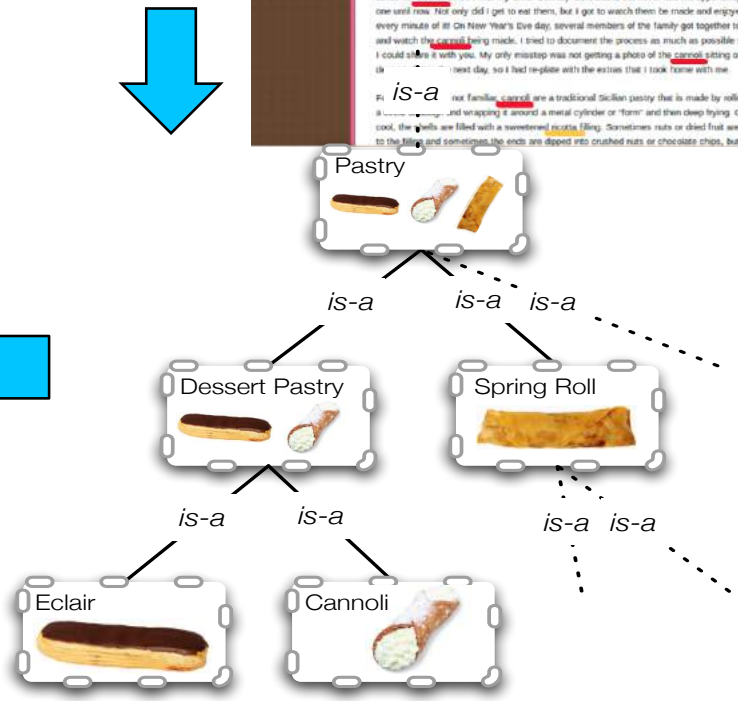
- **Embodied cognition** has been the leading principle in artificial cognitive system research over the last 10 years
- ***BUT*** **we humans learn also from externalized knowledge –like books, the Web, virtual reality….**

..this is what this is about!

chist-era

erc

Thanks for your attention