

# **Machine Learning - Deep Learning fundamentals**

## (69152)

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*Master in Robotics, Graphics and Computer Vision*

Ana C. Murillo



# Faculty

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- **Ana C. Murillo** - faculty - acm@unizar.es

*Office hours in Google Meet or in person*

<https://directorio.unizar.es/?#/tutoria?colectivo=PDI&codCentro=110>

**M - 12.00-14.00h**

**J - 10.00-14.00h**

Please, send me an email to book a slot 24h in advance to confirm and specify if it's in person or online.

# Tentative program for the DL block

Hours	Day	Topic
	...	
M - 13-14h	2-Oct	<b>Fundamentals of DL</b>
Tu - 10-12h	3-Oct	<b>Fundamentals of DL</b>
M - 13-14h	16-Oct	<b>CNNs</b>
Tu - 10-12h	17-Oct	<b>CNNs</b>
LAB2	<b>18-20Oct</b>	CNNs - Basics. Clasification. (Detection. Segmentation). Sample CV application.
M - 13-14h	23-Oct	<b>Finish CNNs</b>
...	...	***** Bayesian & RL BLOCKS *****
Tu - 10-12h	21-Nov	<b>DRL</b>
		<i>Unsupervised</i>
	<b>24 &amp; 29 NOV</b>	Paper Reading lab
		<i>Unsupervised. GANs</i>
		<i>RNNs, Transformers</i>
LAB5	13-15 Dec	More CNNs. Unsupervised. DRL. (GANs). Sample Graphics and Robotics application.
		<i>More recent DL</i>
		<i>More recent DL</i>

# Today's class

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- **What's deep learning?**

- **Related topics**

- **DL pipeline**

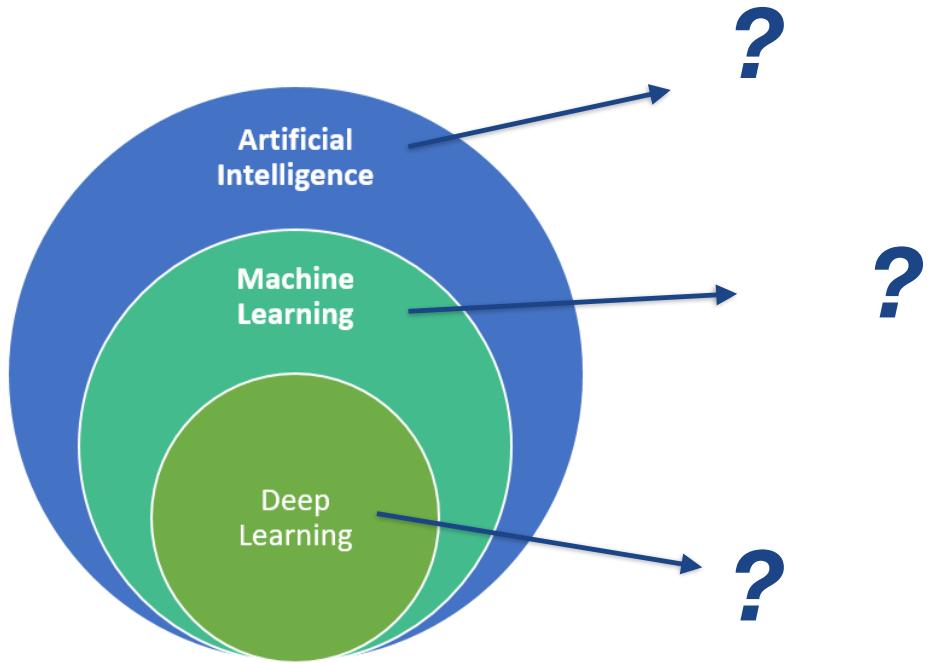
- Fundamentals of DL

- Review basic concepts

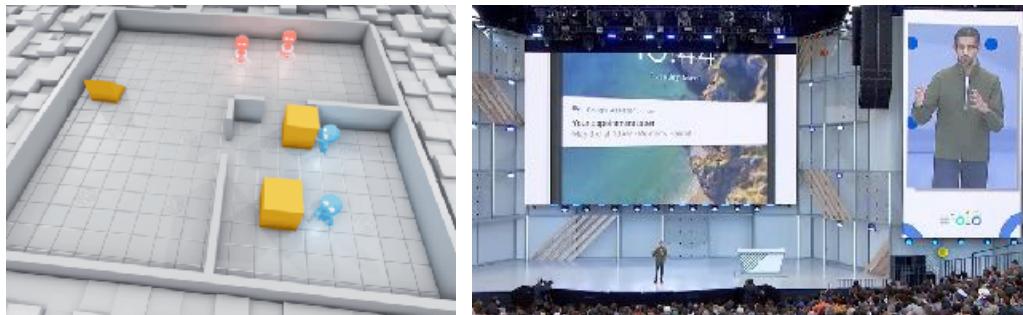
- NN and DNN

# What's *deep learning*? (and what's not ...?)

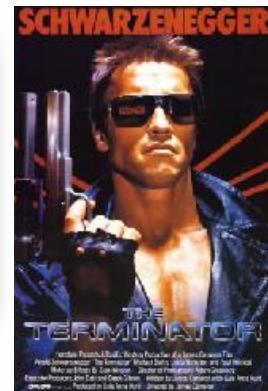
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# What can we do with deep learning?



*And what not ... :-)*



# What can we do with deep learning?

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- Some examples ...

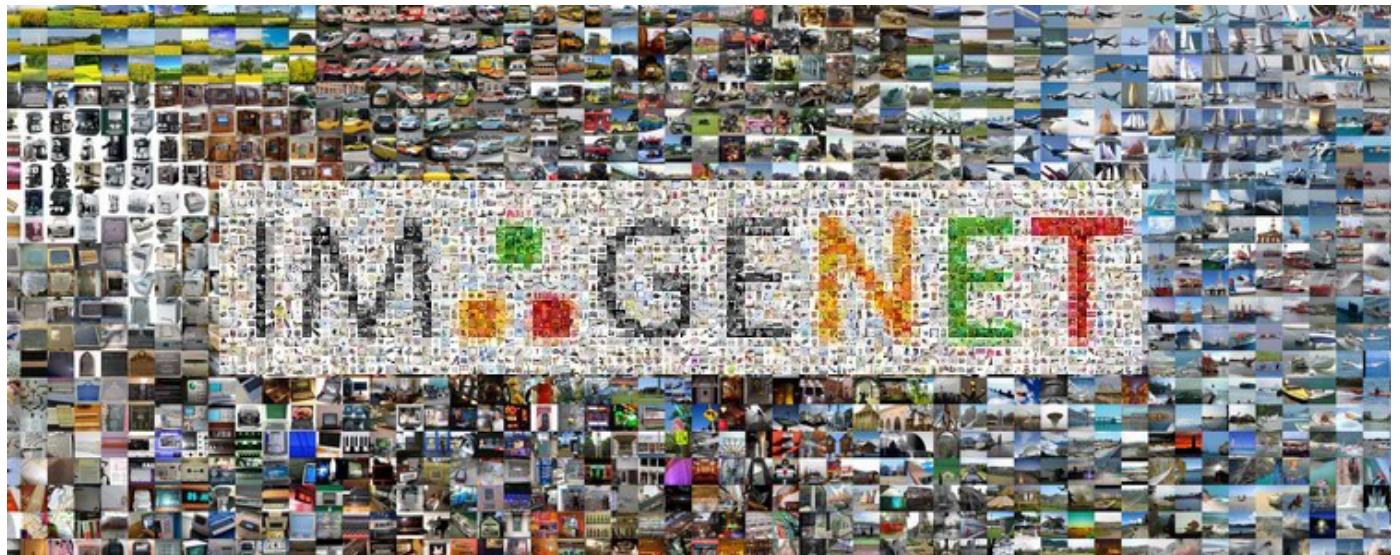
# Some examples of successful DL applications ...

- **Object recognition**

**Objects**

- AlexNet. Competed in the ImageNet Large Scale Visual Recognition Challenge in 2012
- ImageNet: over 10 million annotated images

<http://image-net.org>

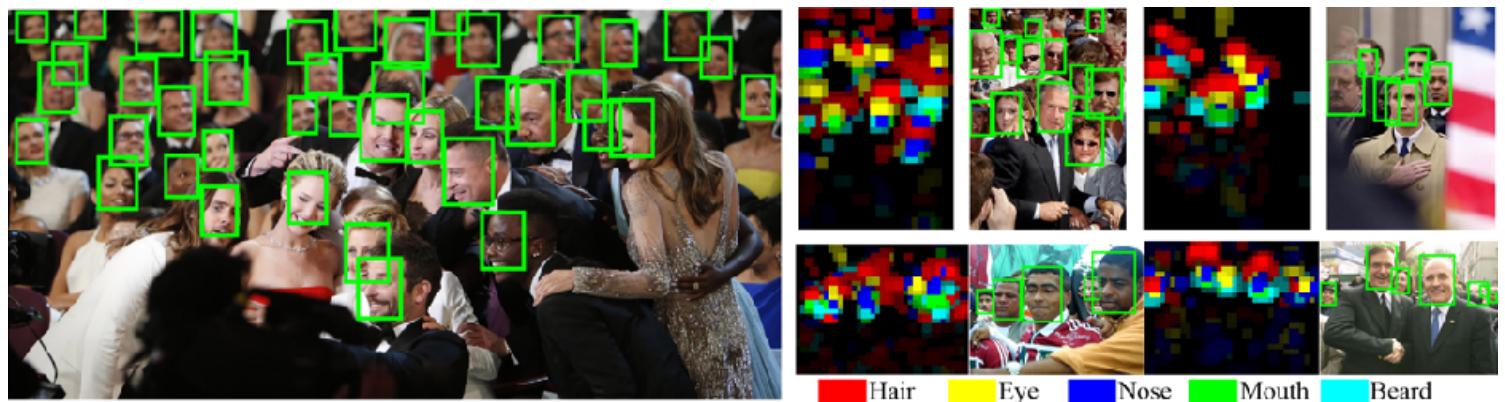


# Some examples of successful DL applications ...

- **Face detection**

**People**

- CelebFaces Attributes Dataset (CelebA). Large-scale face attributes dataset, more than 200K celebrity images



<https://www.youtube.com/watch?v=IMPjPQSb9g8&feature=youtu.be>

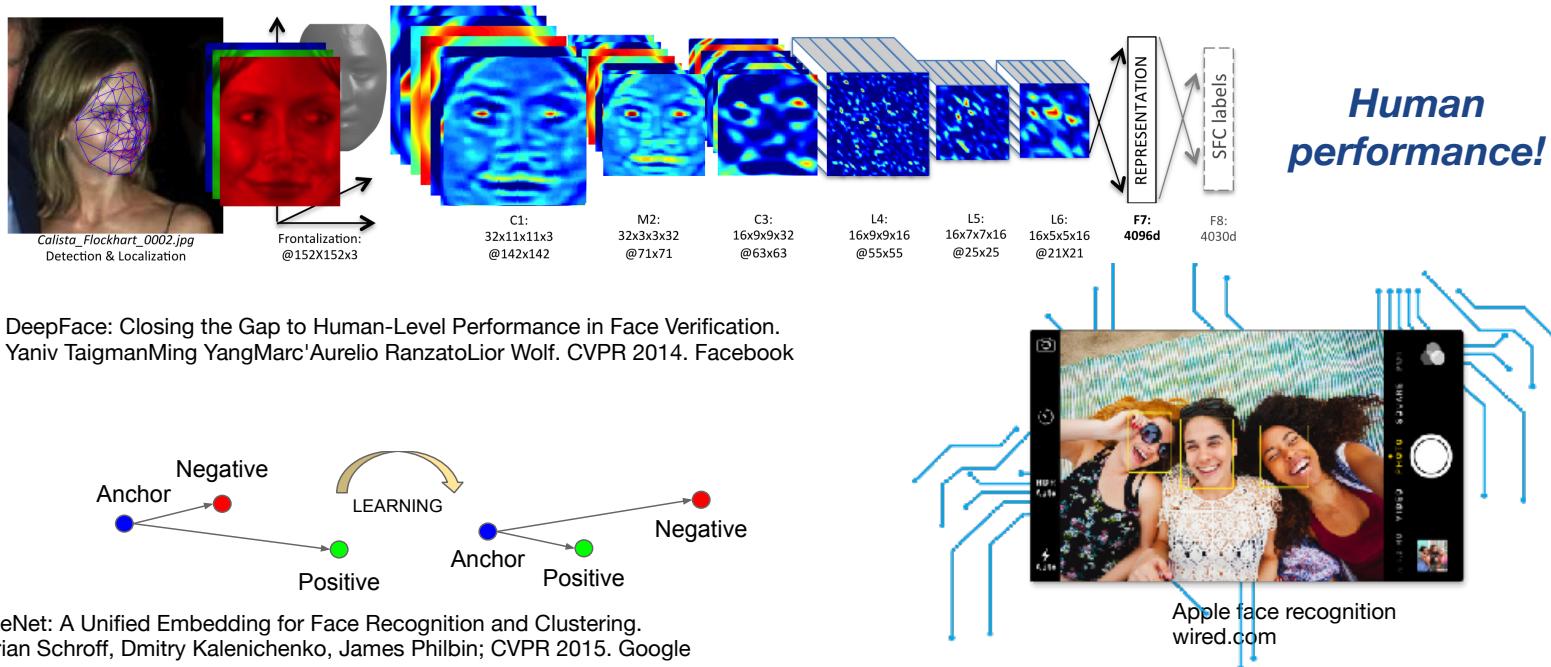
From Facial Parts Responses to Face Detection: A Deep Learning Approach  
Shuo Yang Ping Luo Chen Change Loy Xiaoou Tang  
International Conference on Computer Vision (ICCV) 2015.

# Some examples of successful DL applications ...

- Face recognition

People

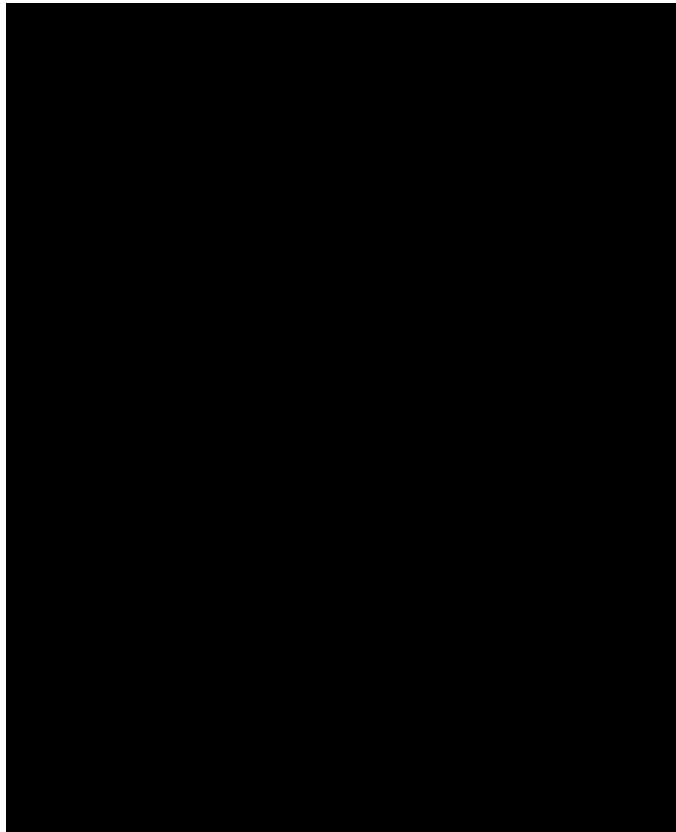
- 4 million images of 4,000 persons



# Some examples of successful DL applications ...

- Learn by watching how to play?! → DRL

**Behaviours**



*Google's Deep Mind*

# Some examples of successful DL applications ...

- Self-driving car

**Behaviours**



# Some examples of successful DL applications ...

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- DeepMind AI ***Not only visual tasks ...***
- Reduces Google Data Centre Cooling Bill by 40%
- “*Using a system of neural networks trained on different operating scenarios and parameters within our data centres, we created a more efficient and adaptive framework to understand data centre dynamics and optimize efficiency.*”

***Google's Deep Mind***

# Some examples of successful DL applications ...

- **Voice** recognition and Natural **Language** Processing



Hi, how can I help?



***Not only visual tasks ...***

Jeff Bezos: "Alexa, buy me something from Whole Foods."

Alexa: "Sure, Jeff. Buying Whole Foods now."

Jeff Bezos: "WHA- ahh go ahead."



6/16/17, 9:23 AM

Tweet your reply



# Some examples of successful DL applications ...

- **Recommendation** systems

*Not only visual  
tasks ...*

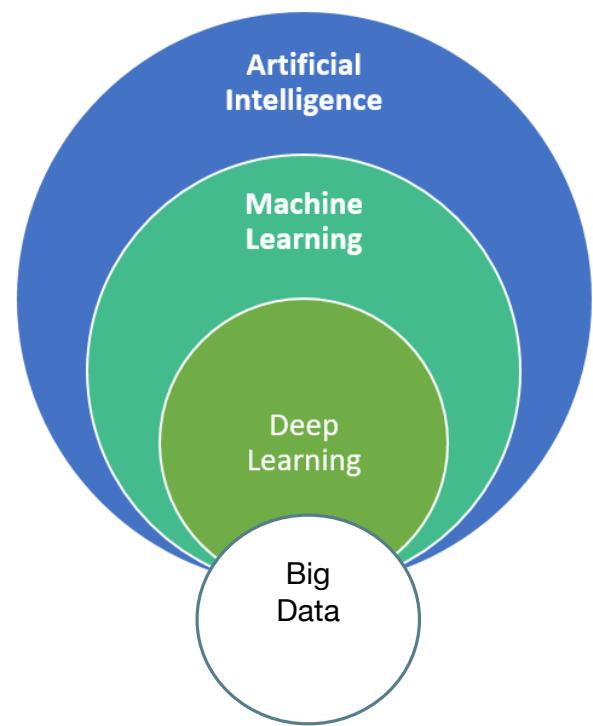


# Deep Learning and Big Data

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- Related topics to DL

- Big data
- Data science
- Business Intelligence
- ...

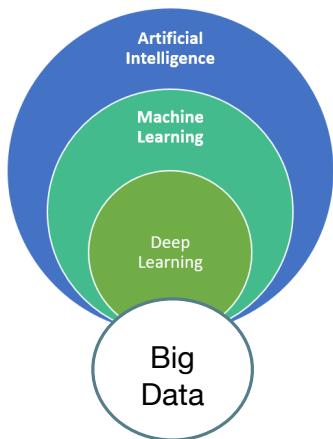


# Deep Learning and Big Data

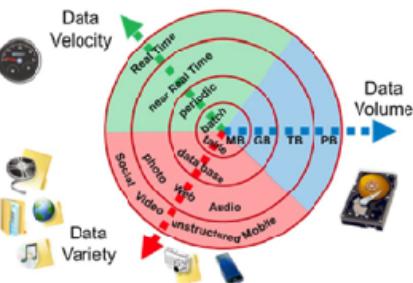
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- Related topics to DL

- **Big data:** “data sets that are so large or complex that traditional data processing application software is inadequate to deal with them” (Wikipedia)
- **Data science:** Scientific field with the aim of extracting knowledge from raw data (usually “big data”)
- **Business Intelligence:** Set of techniques to extract information from business data, that will be used to improve its performance.
- *Data mining:* The exploration of raw data in the search for patterns (usually in the context of **databases**).



# Machine Learning + Big Data



- **Cons:**

- *Torture the numbers, and they'll confess to anything — Gregg Easterbrook (and probably many others ... )*
- *So it's like having billions of monkeys typing. One of them will write Shakespeare. — Michael Jordan*
- **Pros:** New opportunities, challenges, and amazing results and applications!!

# Deep Learning vs general ML pipeline

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# Deep Learning vs general ML pipeline

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- Same methodology you saw the first day. Certain steps/ideas get particularly important: data selection, avoid overfitting, ...

1. Frame problem

2. Get data

3. Explore data

4. Prepare data

5. Explore promising models

6. Fine tune the best

7. Present/**analyze** the solution and results

*It may sound you just  
“throw” as much data as  
you can ... but not just that!*

**expensive!**

# ML pipeline & DL

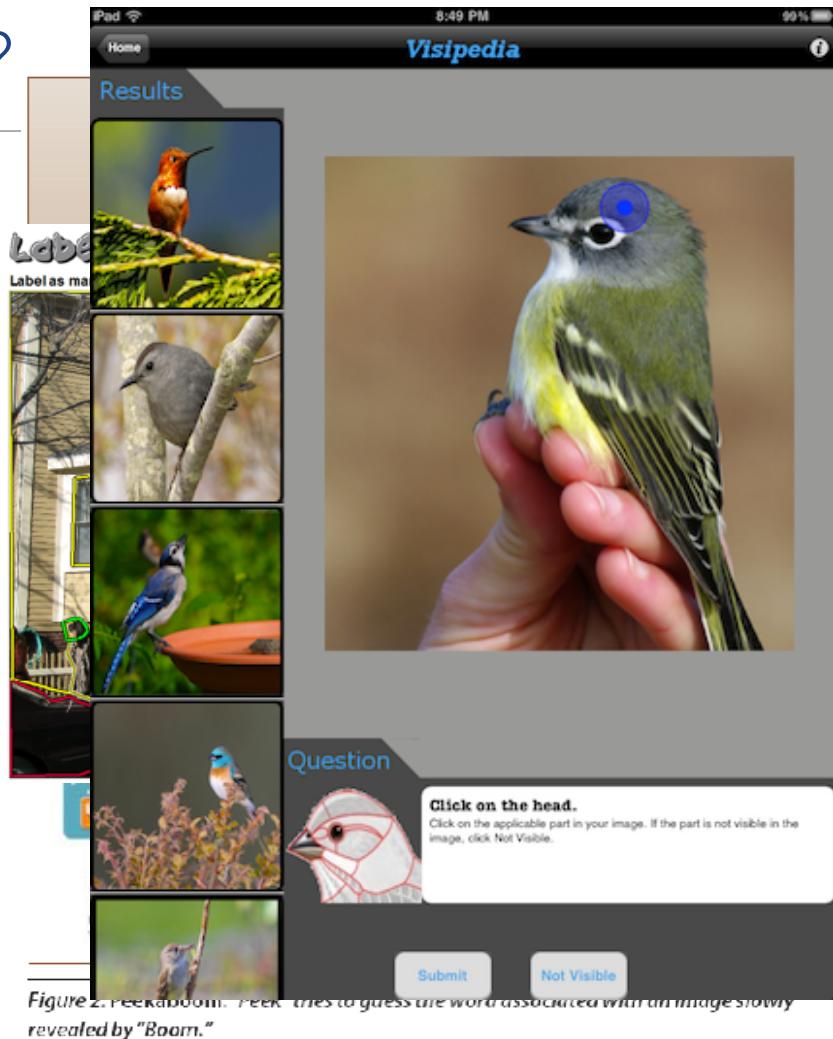
- Collect **data** (labeled?) choose how to **represent** it?
- **Learn:** organize the sample data (training data): fit/learn a **model**
- **Classify: evaluate** new data with regard to the model learnt (classify/recognize new content)



# How to get training data?

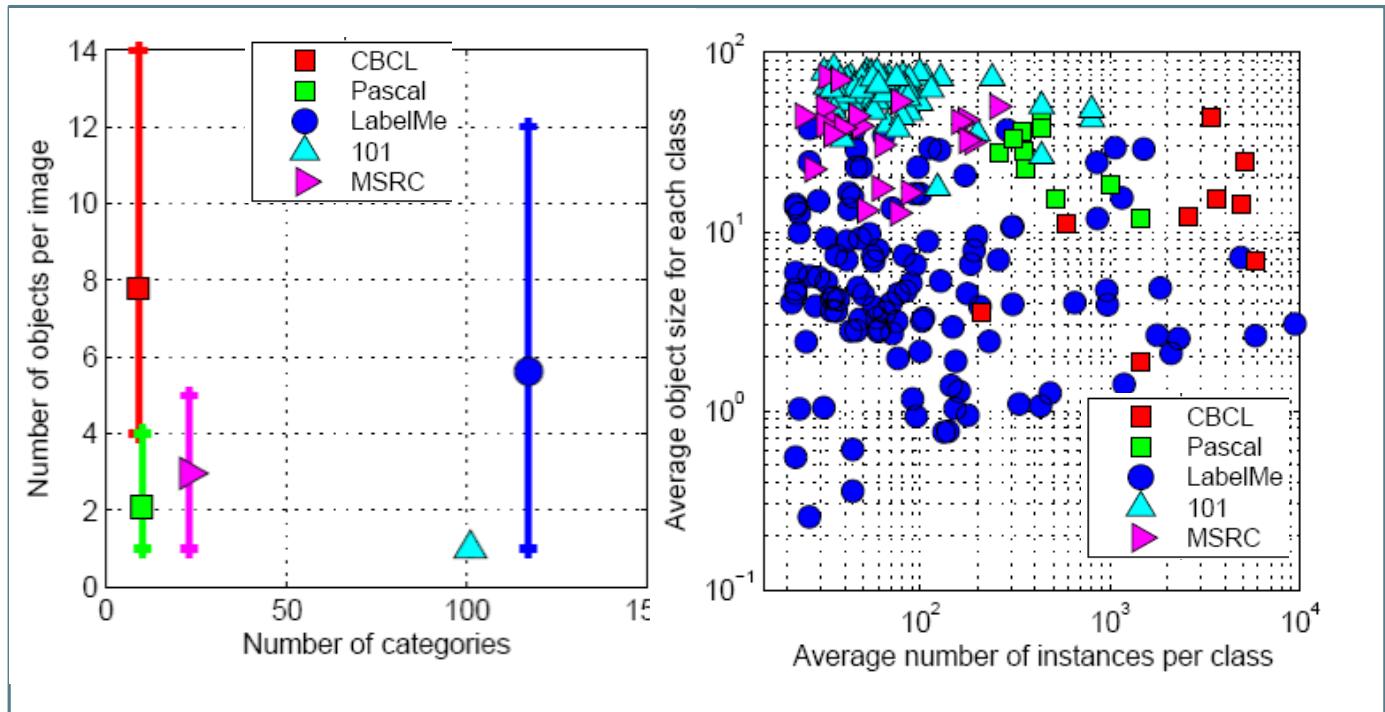
Lots of strategies. Crowdsourcing is a common ingredient lately

- ESP game. Luis Von Ahn and Laura Dabbish 2004
- LabelMe (MIT) - researchers and volunteers Russell, Torralba, Freeman, 2005
- Birds-200-2011 - fans of certain topic. Caltech-UCSD. Wah, Branson, Welinder, Perona, Belongie, 2011



# Is my dataset good?

- Enough classes? Enough examples? Enough variability?  
Good labels?

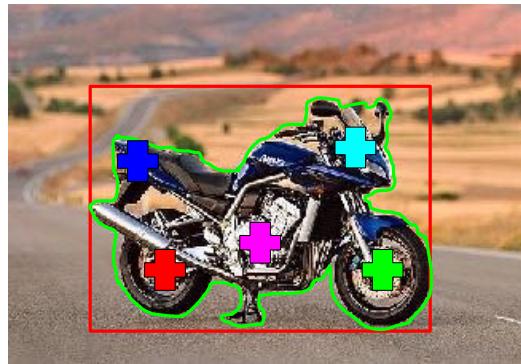


# How to label training data?

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- Depends on the application/problem

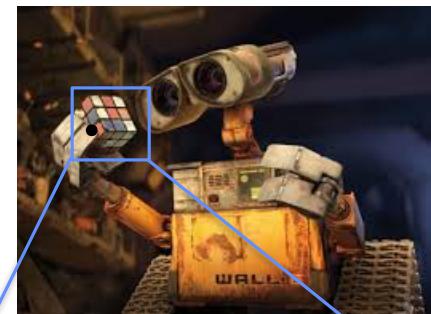
*Contains a motorbike*



# ML pipeline & DL

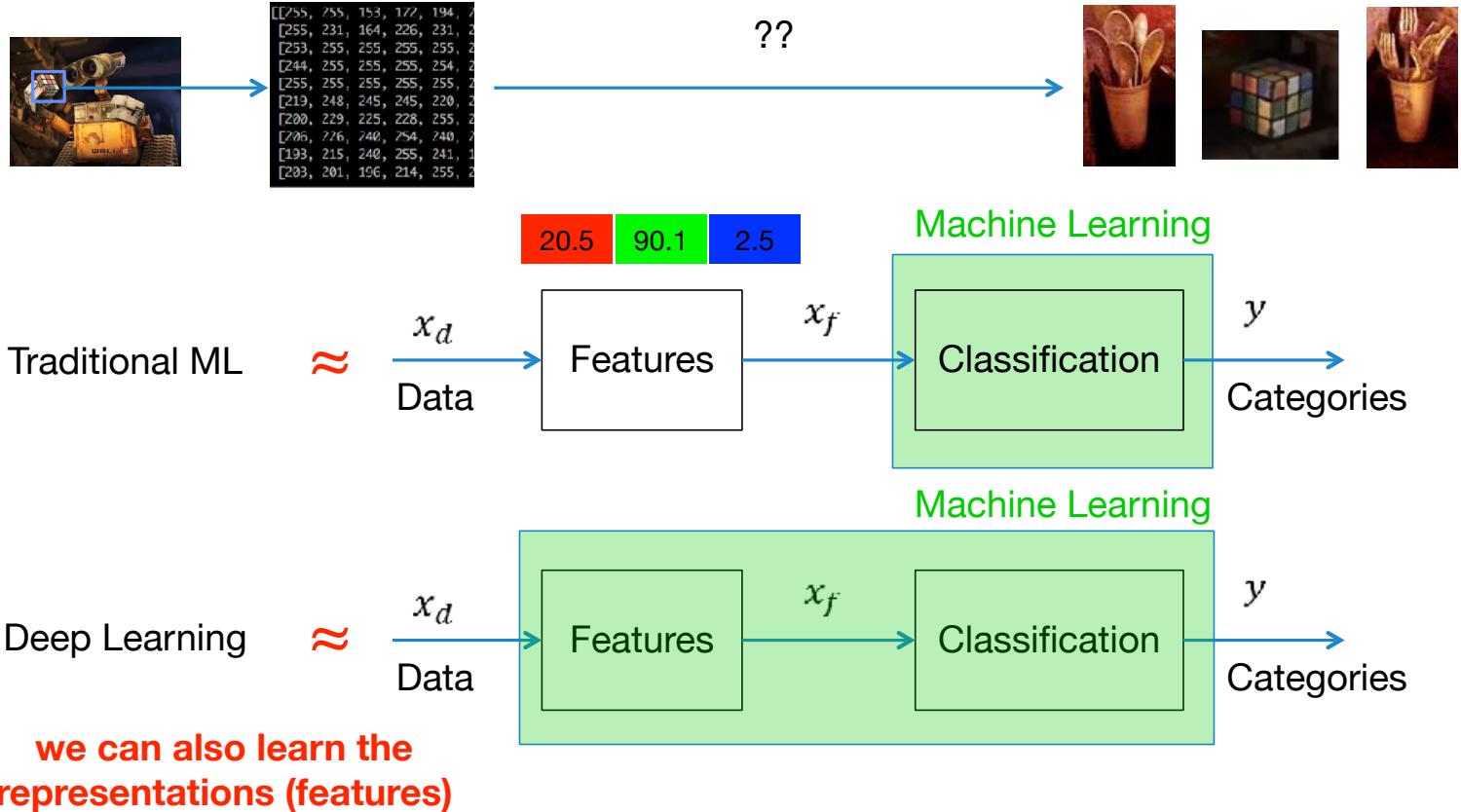
- **Collect** data (labeled?), choose how to **represent** it?
- **Learn**: organize the sample data (training data): fit/learn a model
- **Classify: evaluate** new data with regard to the model learnt (classify/recognize new content)

features: **VERY complicated and important *design* decision!!**



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[[255, 255, 153, 172, 194, 206, 205, 214, 121, 45, 53, 54],  
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 [203, 201, 196, 214, 255, 210, 180, 176, 254, 249, 243, 216]]
```

# ML pipeline & DL pipeline



# Next

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- What's deep learning?
  - Related topics
  - DL pipeline
- **Fundamentals of DL**
  - **Review basic concepts**
  - NN and DNN

## Bibliography - Resources for some of the materials today

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- Stanford classes on deep learning for Computer Vision (<http://cs231n.stanford.edu>)
- Ian Goodfellow, Yoshua Bengio, Aaron Courville. **Deep Learning**. MIT Press, 2016. <http://www.deeplearningbook.org>
- Book: **Computer Vision: Algorithms and Applications** ([http://szeliski.org/ Book/](http://szeliski.org/Book/)). Richard Szeliski, Steve Seitz.  
Computer vision course slides. CSE 576 (Graduate Computer Vision)  
University of Washington ([http:// courses.cs.washington.edu/courses/cse576/08sp/](http://courses.cs.washington.edu/courses/cse576/08sp/))
- Fei-Fei, Fergus, Torralba: short course “recognising objects” (<http://people.csail.mit.edu/torralba/shortCourseRLOC>)