

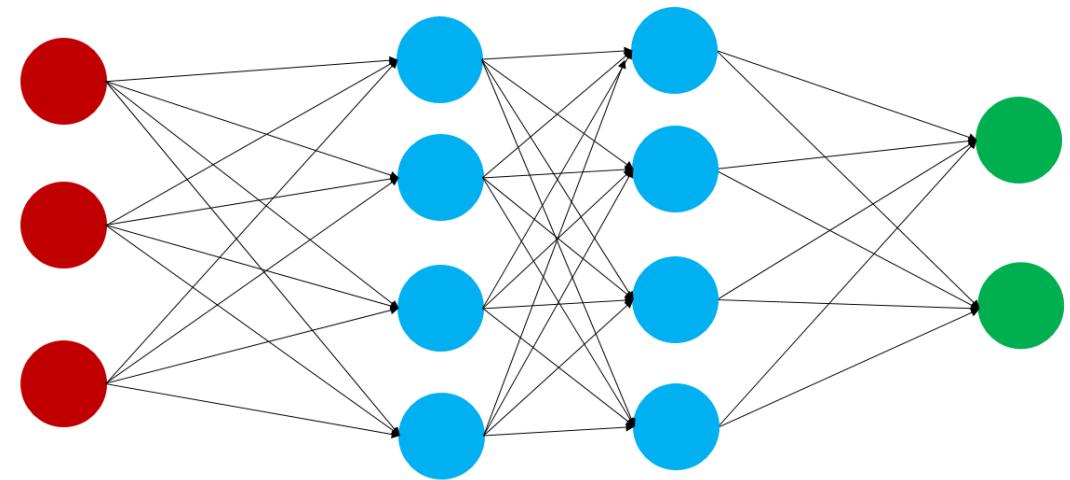
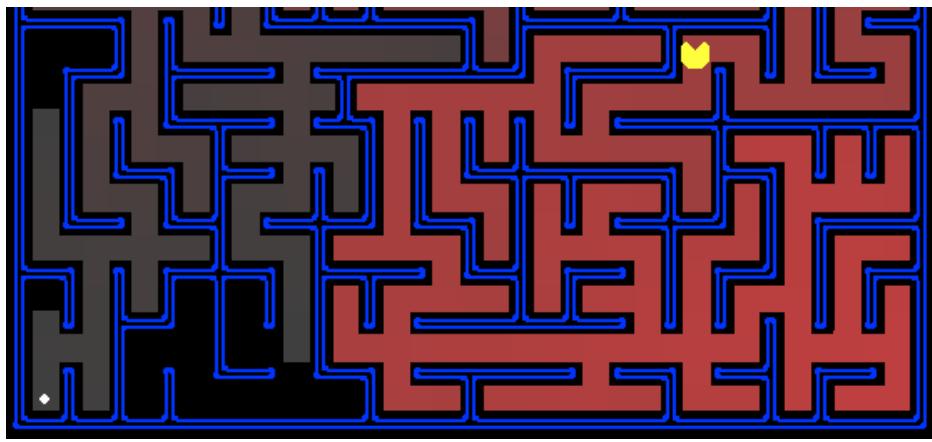
# Applications: Natural Language Processing, Computer Vision



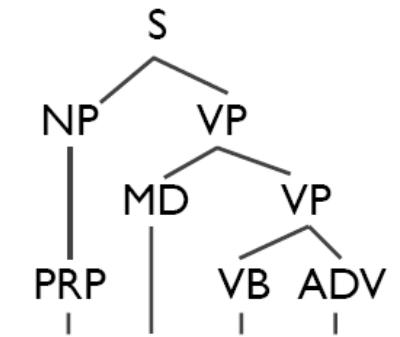
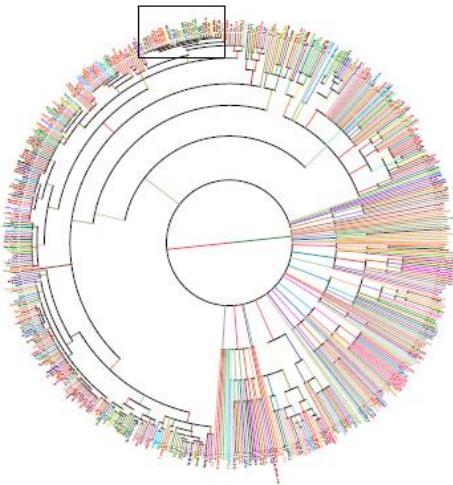
These slides are based on the slides created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley - <http://ai.berkeley.edu>.

# So Far: Foundational Methods

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# Now: Advanced Applications



You will see later

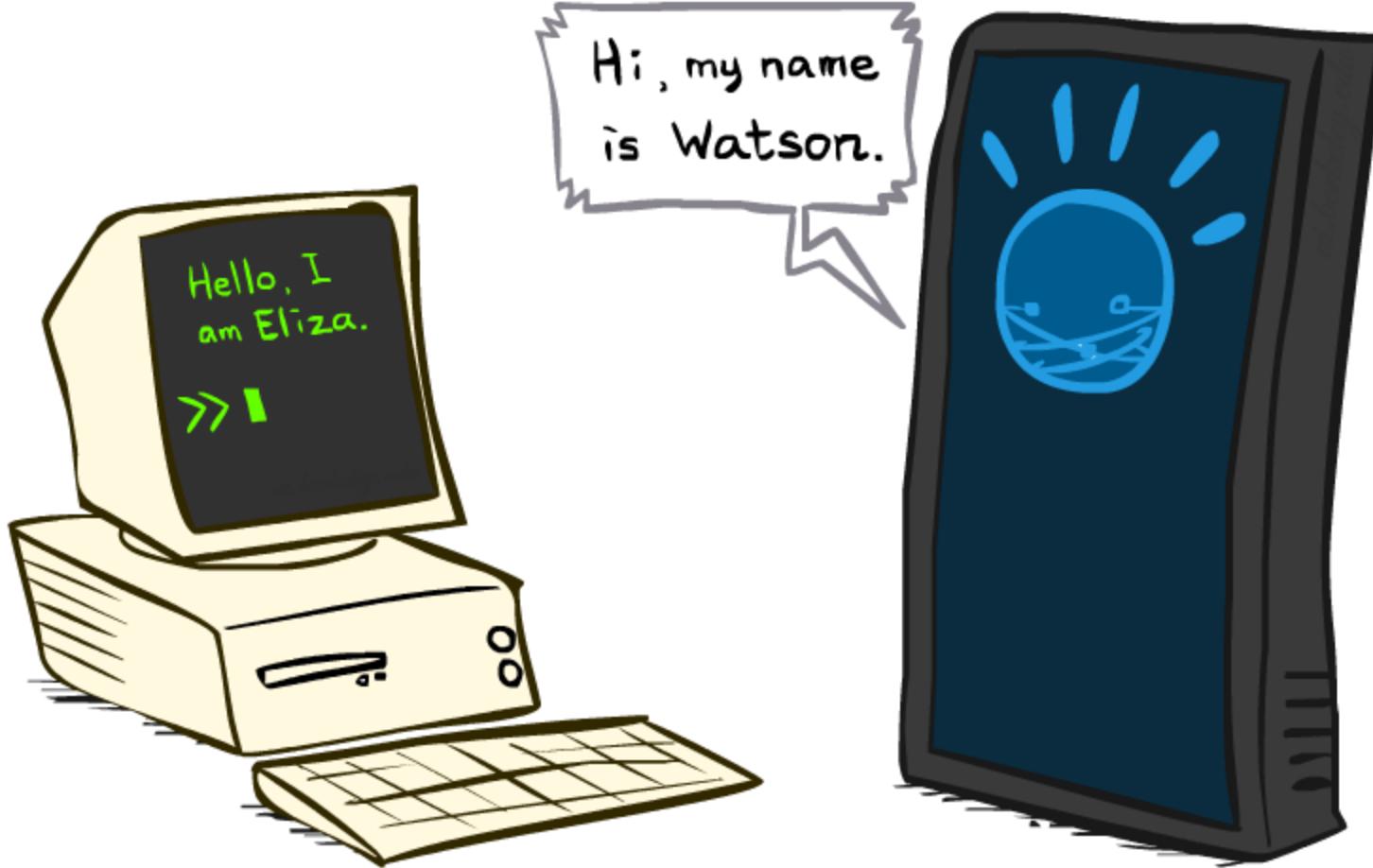
Después lo verás



AI Complete?

# Natural Language Processing

---



# What is NLP?



Ability to use language is what we believe sets humans apart.

# Why NLP?

---

Why do we want computers to understand language?

- Turing test (measure of intelligence?)
- To communicate with humans
- To learn
  - Most of our knowledge is available in natural language

# What is NLP?

---

- Fundamental goal: analyze and process human language, broadly, robustly, accurately...
- End systems that we want to build:
  - Ambitious: speech recognition, machine translation, information extraction, dialog interfaces, question answering...
  - Modest: spelling correction, text categorization...

# Problem: Ambiguities

## Headlines:

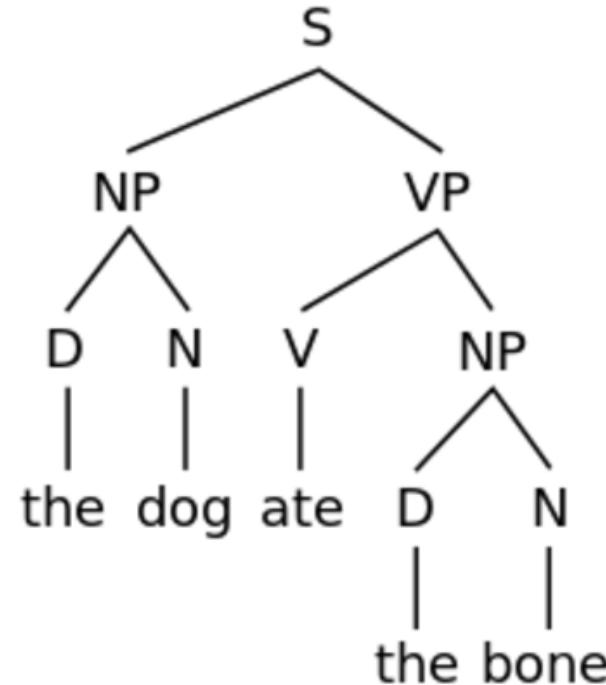
- Enraged Cow Injures Farmer With Ax
- Hospitals Are Sued by 7 Foot Doctors
- Ban on Nude Dancing on Governor's Desk
- Iraqi Head Seeks Arms
- Local HS Dropouts Cut in Half
- Juvenile Court to Try Shooting Defendant
- Stolen Painting Found by Tree
- Kids Make Nutritious Snacks



# Context Free Grammar

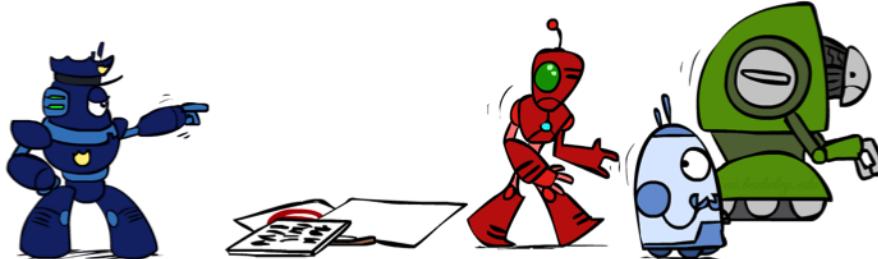
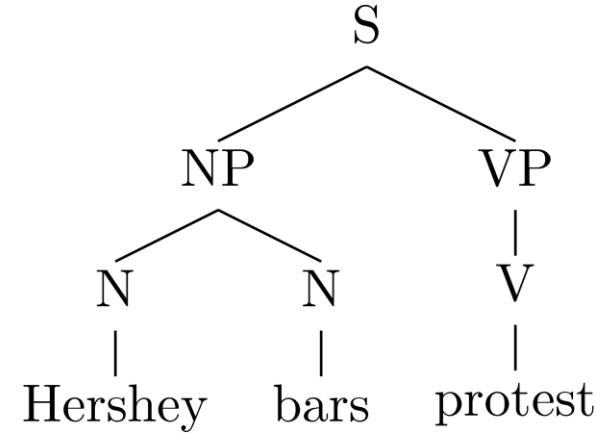
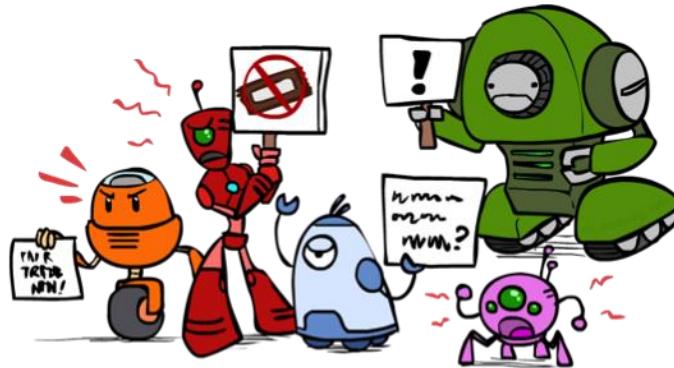
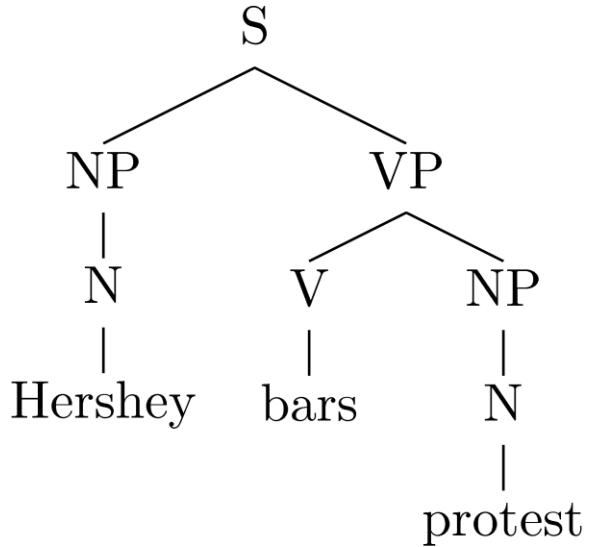
- A Context Free Grammar is a set of rules that describe the syntax of a language.

- $S \rightarrow NP\ VP$
- $NP \rightarrow D\ N$
- $NP \rightarrow N$
- $VP \rightarrow V\ NP$
- $N \rightarrow dog$
- ...



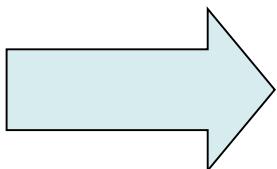
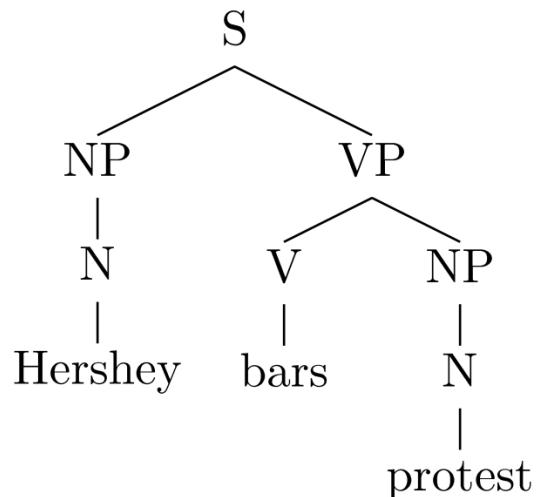
S: sentence, NP: noun phrase, VP: verb phrase, N: Noun, V: verb, D: determiner, ...

# Parsing as Search



# Grammar: PCFGs

- Natural language grammars are very **ambiguous!**
- Probabilistic Context Free Grammars are a formal probabilistic model of trees
  - Each rule has a **conditional probability**
  - A parse tree's probability is computed from the probabilities of all the rules used



$S \rightarrow NP\ VP\ .$	0.90
$NP \rightarrow N$	0.15
$VP \rightarrow V\ NP$	0.6
.....	

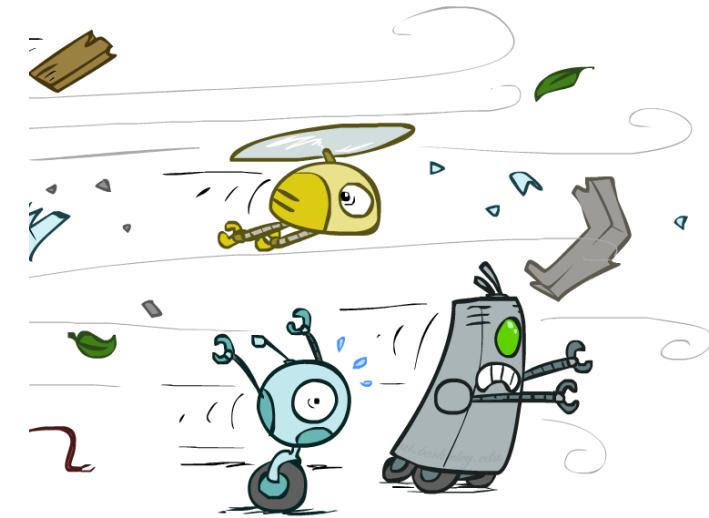
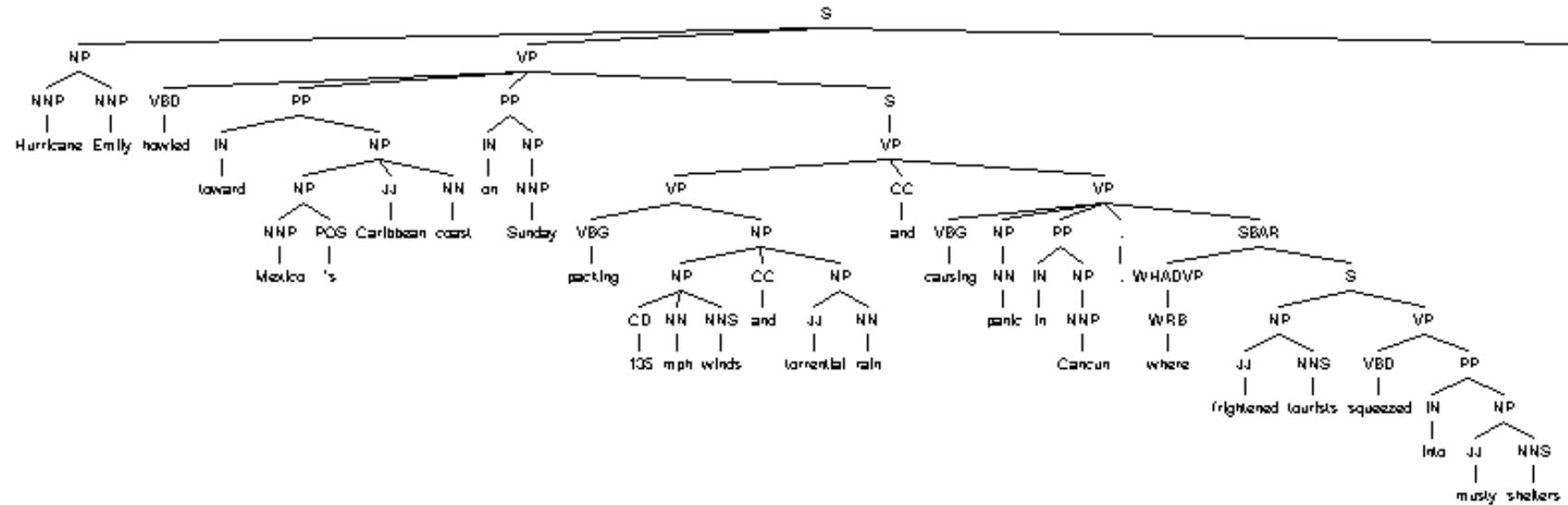
# Grammar: PCFGs

---

Parsing: Given a sentence, find the best parse tree – search!

- Find the tree with the highest probability
- Associate (inverse) probability with cost
- A\* Search
- Need good heuristic

# Syntactic Analysis



Hurricane Emily howled toward Mexico 's Caribbean coast on Sunday packing 135 mph winds and torrential rain and causing panic in Cancun, where frightened tourists squeezed into musty shelters.

Berkeley NLP Group Parser <http://tomato.banatao.berkeley.edu:8080/parser/parser.html>

A\* Search

# Grammar: PCFGs

- Where do these probabilities come from?
  - Data
- Parse trees are not readily available
- They had to be annually created: treebanks
  - The Penn Treebank

$S \rightarrow NP\ VP\ .$	0.90
$NP \rightarrow N$	0.15
$VP \rightarrow V\ NP$	0.6
.....	

# Natural Language Toolkit

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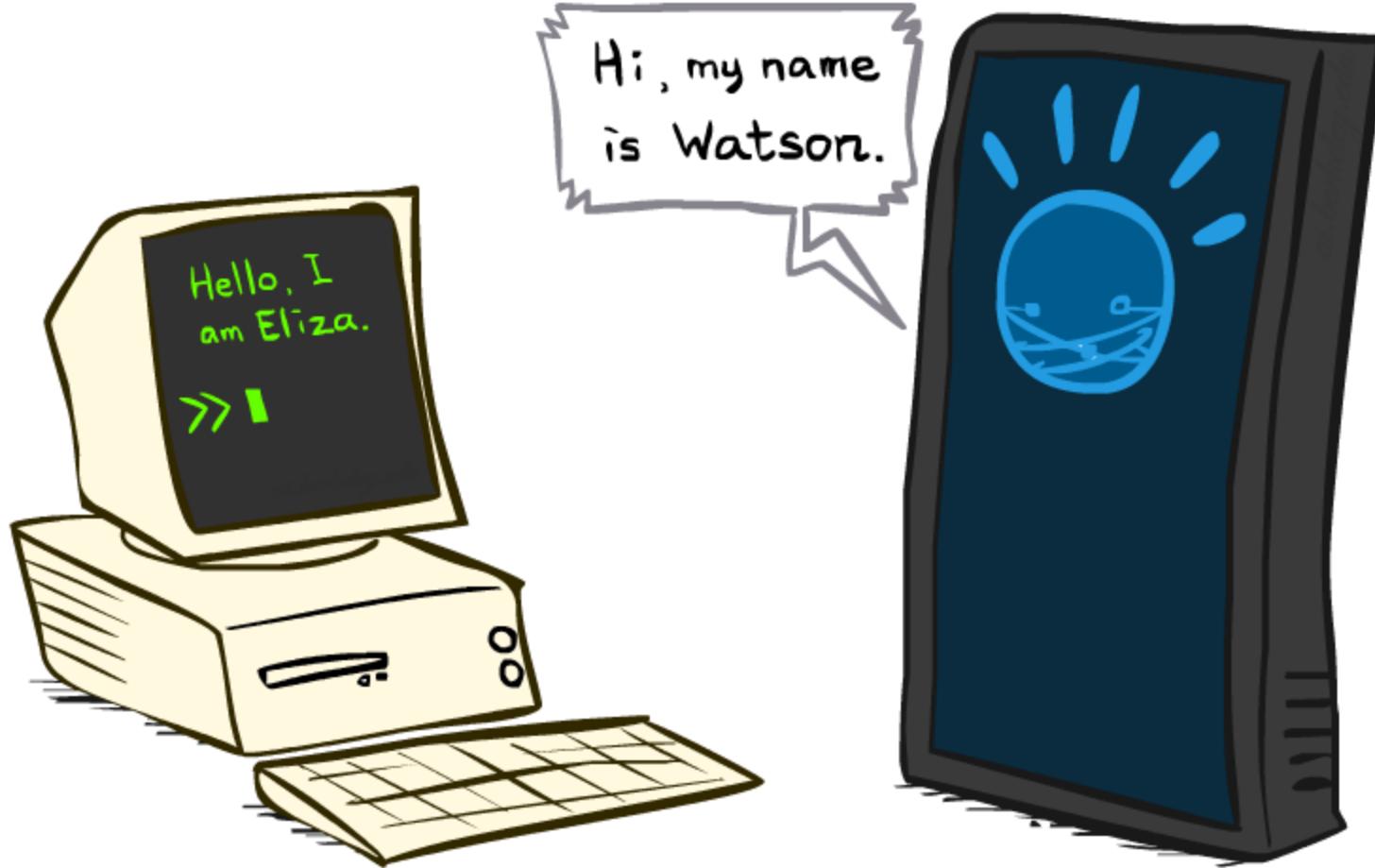
NLTK is a Python package for Natural Language Processing.

It includes:

- easy-to-use interfaces to NLP resources
- text processing libraries for classification, tokenization, tagging, parsing, semantic reasoning

# Dialog Systems

---



# ELIZA

---



- A “psychotherapist” agent (Weizenbaum, ~1964)
- Led to a long line of chatterbots
- How does it work:
  - Trivial NLP: string match and substitution
  - Trivial knowledge: tiny script / response database
  - Example: matching “I remember \_\_” results in “Do you often think of \_\_”?

# Watson



"a camel is a horse designed by"

About Des One Vogu en.w a ca a ca analog Altern en.w Re: Re: A to: R www The Jan 4 comm www A ca Sep com bette Why Jun 2 variat www.smashingmagazine.com If a camel is a horse de

a multilingual free encyclopedia

**Wiktionary** ['wɪkʃənri] *n.*, a wiki-based Open Content dictionary

Wilco Pwrl krtt

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**a camel is a horse designed by a committee**

Contents [hide]

1 English

1.1 Alternative forms

1.2 Etymology

1.3 Usage

1.4 Quotations

1.5 References

1.6 External links

**The Phrase Finder**

[e > Discussion Forum](#)

Google™ Custom Search

**A camel is a horse designed by committee**

Posted by Ruben P. Mendez on April 16, 2004

Does anyone know the origin of this maxim? I heard it way back at the United Nations, which is chockfull of committees. It may have originated there, but I'd like an authoritative explanation. Thanks

- [Re: A camel is a horse designed by committee SR 16/April/04](#)
  - [Re: A camel is a horse designed by committee Henry 18/April/04](#)

If a camel is a horse designed by committee then what's this contemporary Routemaster?

# What's in Watson?

- A question-answering system (IBM, 2011)
- Designed for the game of Jeopardy
- How does it work:
  - Sophisticated NLP: deep analysis of questions, noisy matching of questions to potential answers
  - **Lots of data:** onboard storage contains a huge collection of documents (e.g. Wikipedia, etc.), exploits redundancy
  - Lots of computation: 90+ servers



# Machine Translation

---



# Machine Translation

## "Il est impossible aux journalistes de rentrer dans les régions tibétaines"

Bruno Philip, correspondant du "Monde" en Chine, estime que les journalistes de l'AFP qui ont été expulsés de la province tibétaine du Qinghai "n'étaient pas dans l'illégalité".

**Les faits** Le dalaï-lama dénonce l'"enfer" imposé au Tibet depuis sa fuite, en 1959

**Vidéo** Anniversaire de la rébellion tibétaine: la Chine sur ses gardes



## "It is impossible for journalists to enter Tibetan areas"

Philip Bruno, correspondent for "World" in China, said that journalists of the AFP who have been deported from the Tibetan province of Qinghai "were not illegal."

**Facts** The Dalai Lama denounces the "hell" imposed since he fled Tibet in 1959

**Video** Anniversary of the Tibetan rebellion: China on guard



- Translate text from one language to another
- Recombines fragments of example translations
- Challenges:
  - What fragments? [learning to translate]
  - How to make efficient? [fast translation search]

# The Problem with Dictionary Lookups

---

顶部 /**top**/roof/

顶端 /summit/peak/**top**/apex/

顶头 /coming directly towards one/**top**/end/

盖 /lid/**top**/cover/canopy/build/Gai/

盖帽 /surpass/**top**/

极 /extremely/pole/utmost/**top**/collect/receive/

尖峰 /peak/**top**/

面 /fade/side/surface/aspect/**top**/face/flour/

摘心 /**top**/topping/

# MT: 60 Years in 60 Seconds



Warren Weaver

When I look at an article in Russian, I say: "This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode."



John Pierce

"Machine Translation" presumably means going by algorithm from machine-readable source text to useful target text... In this context, there has been no machine translation...

Berkeley's first MT grant

MT is the "first" non-numeral compute task

ALPAC report deems MT bad

Statistical MT thrives

Statistical data-driven approach introduced



'47

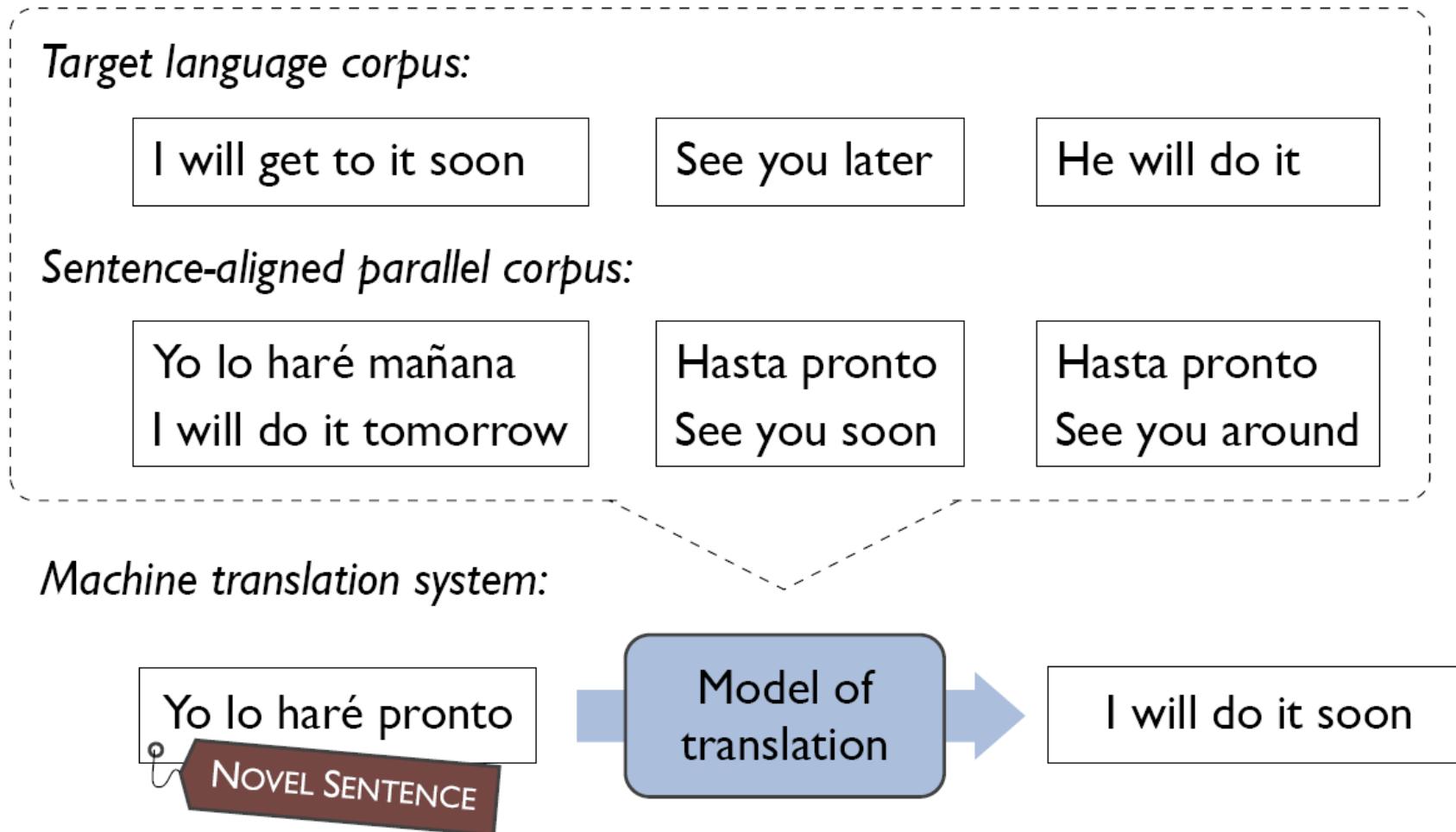
'58

'66

'90's

'00's

# Data-Driven Machine Translation

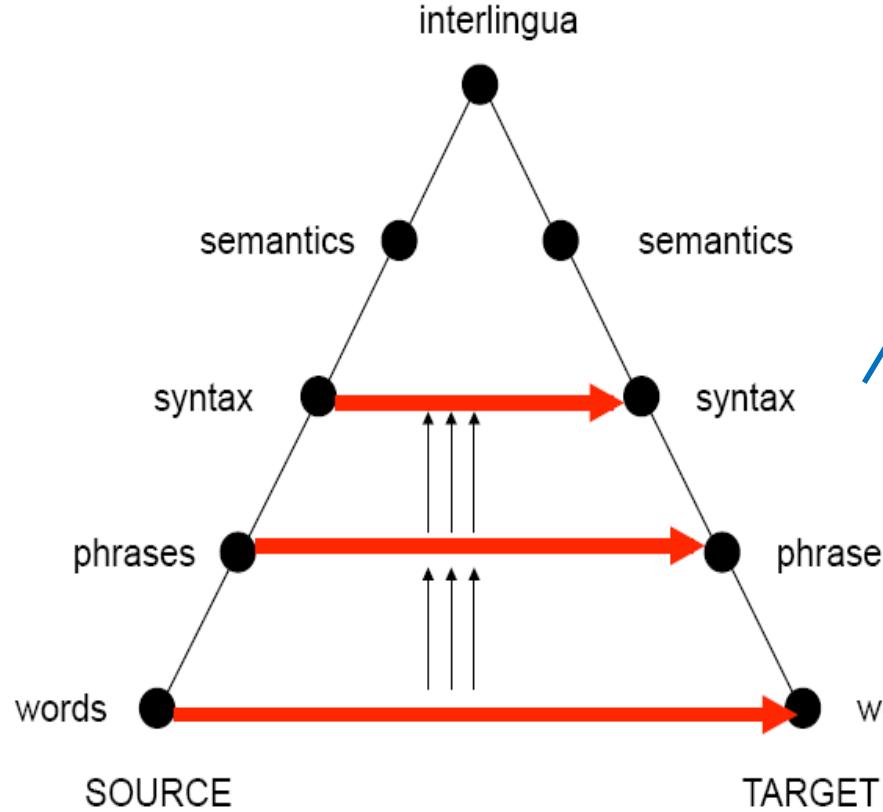


# Learning to Translate

		CLASSIC SOUPS		Sm.	Lg.
清 燉 雞 湯	57.	House Chicken Soup (Chicken, Celery, Potato, Onion, Carrot) .....		1.50	2.75
雞 飯 湯	58.	Chicken Rice Soup .....		1.85	3.25
雞 麵 湯	59.	Chicken Noodle Soup .....		1.85	3.25
廣 東 雲 吞	60.	Cantonese Wonton Soup.....		1.50	2.75
蕃 茄 蛋 湯	61.	Tomato Clear Egg Drop Soup .....		1.65	2.95
雲 吞 湯	62.	Regular Wonton Soup .....		1.10	2.10
酸 辣 湯	63.	Hot & Sour Soup .....		1.10	2.10
蛋 花 湯	64.	Egg Drop Soup.....		1.10	2.10
雲 蛋 湯	65.	Egg Drop Wonton Mix.....		1.10	2.10
豆 腐 菜 湯	66.	Tofu Vegetable Soup .....		NA	3.50
雞 玉 米 湯	67.	Chicken Corn Cream Soup .....		NA	3.50
蟹 肉 玉 米 湯	68.	Crab Meat Corn Cream Soup.....		NA	3.50
海 鮮 湯	69.	Seafood Soup.....		NA	3.50

*Example from Adam Lopez*

# Levels of Transfer



Yo lo haré mañana  
I will do it tomorrow

```

graph TD
    VP1[VP] --- NP1[NP]
    VP1 --- VB1[VB]
    VP1 --- PRN1[PRN]
    NP1 --- NP2[NP]
    NP2 --- MD1[MD]
    NP2 --- VB2[VB]
    NP2 --- PRN2[PRN]
    MD1 --- will1["will"]
    VB2 --- do1["do"]
    PRN2 --- it1["it"]
  
```

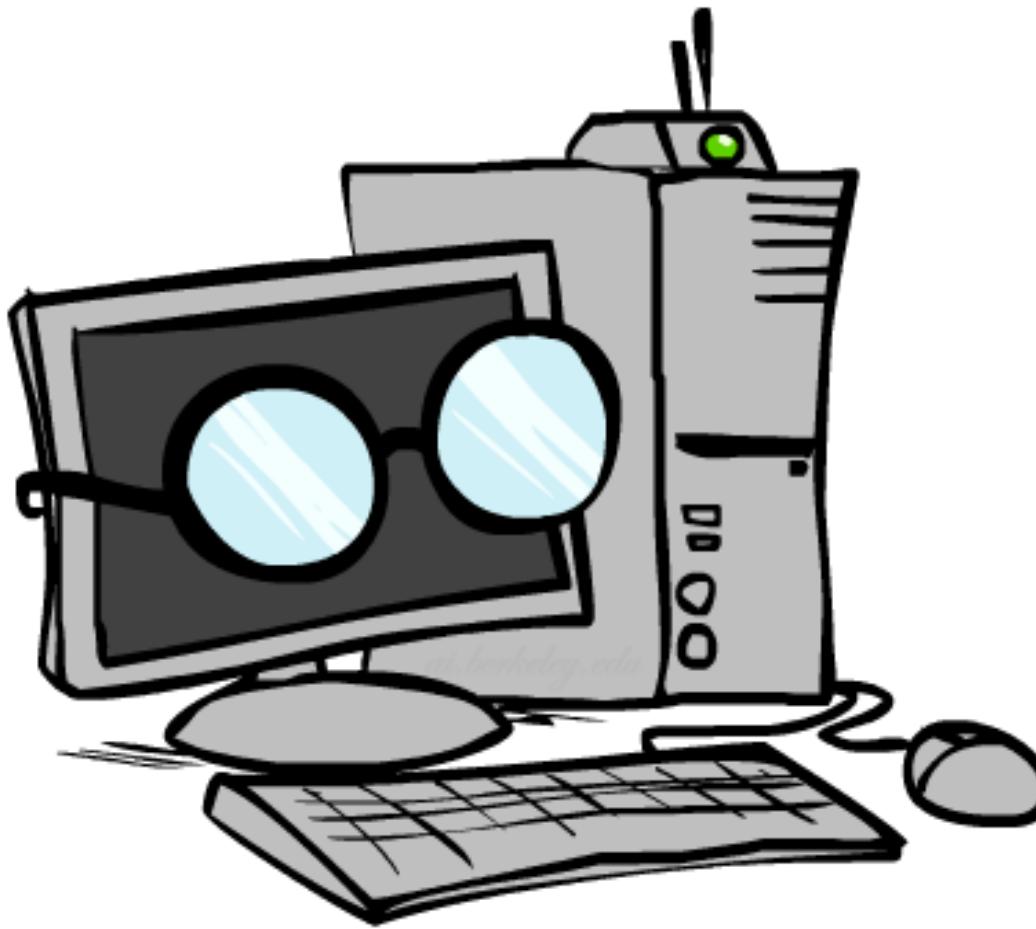
$$P(\text{MD} \mid \text{VB}, \text{PRN}, \text{NP}) = 0.8$$

English (E)	$P(E \mid \text{lo haré})$
will do it	0.8
will do so	0.2

English (E)	$P(E \mid \text{mañana})$
tomorrow	0.7
morning	0.3

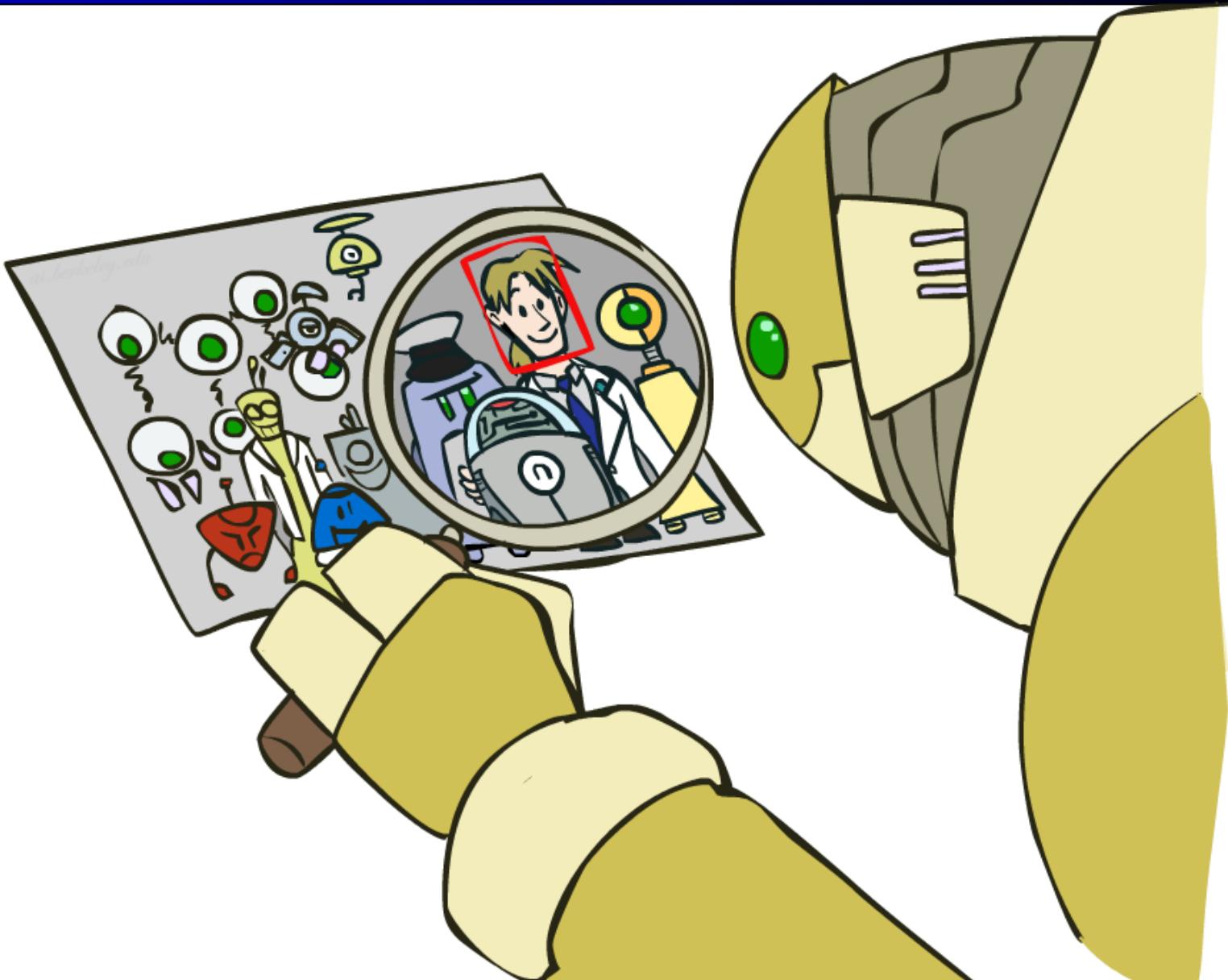
# Computer Vision

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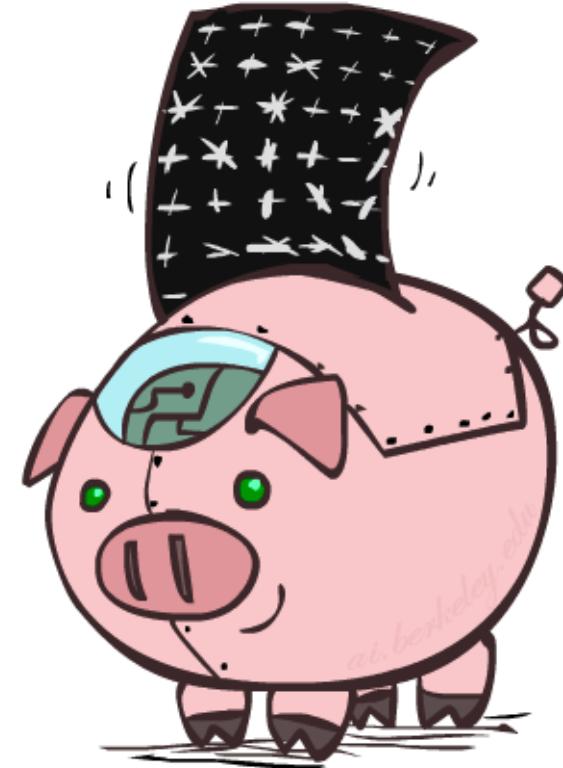
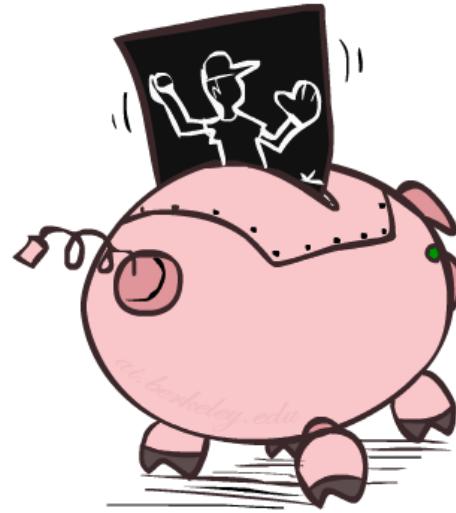
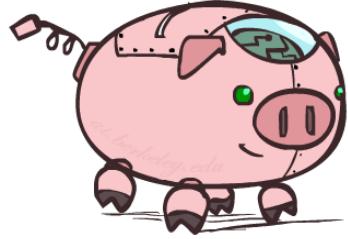
# Object Detection

---



# Object Detection Approach 1: HOG + SVM

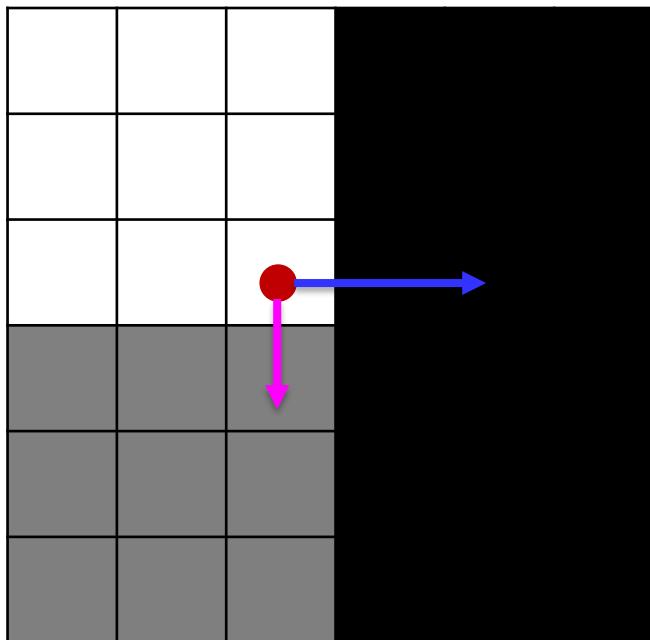
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# Histograms of Oriented Gradients (HOG)

## Step 1: Detect gradients:

- Gradients are directional changes in image intensity or color
- For every pixel, take the difference between neighboring pixels (apply an edge filter for example [1,-1])



255	255	255	0	0	0
255	255	255	0	0	0
255	255	255	0	0	0
150	150	150	0	0	0
150	150	150	0	0	0
150	150	150	0	0	0

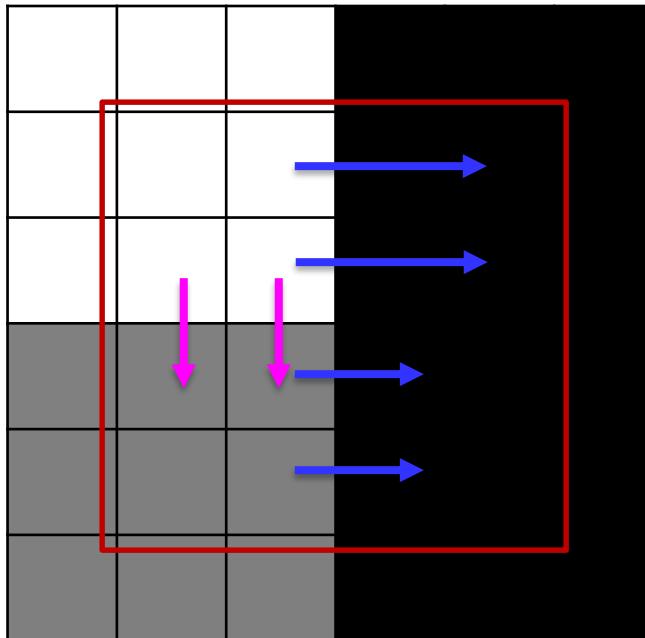
$$dx = 255 - 0 = 255$$

$$dy = 255 - 150 = 155$$

# Histograms of Oriented Gradients HOG

## Step 2: Binning (Generalization)

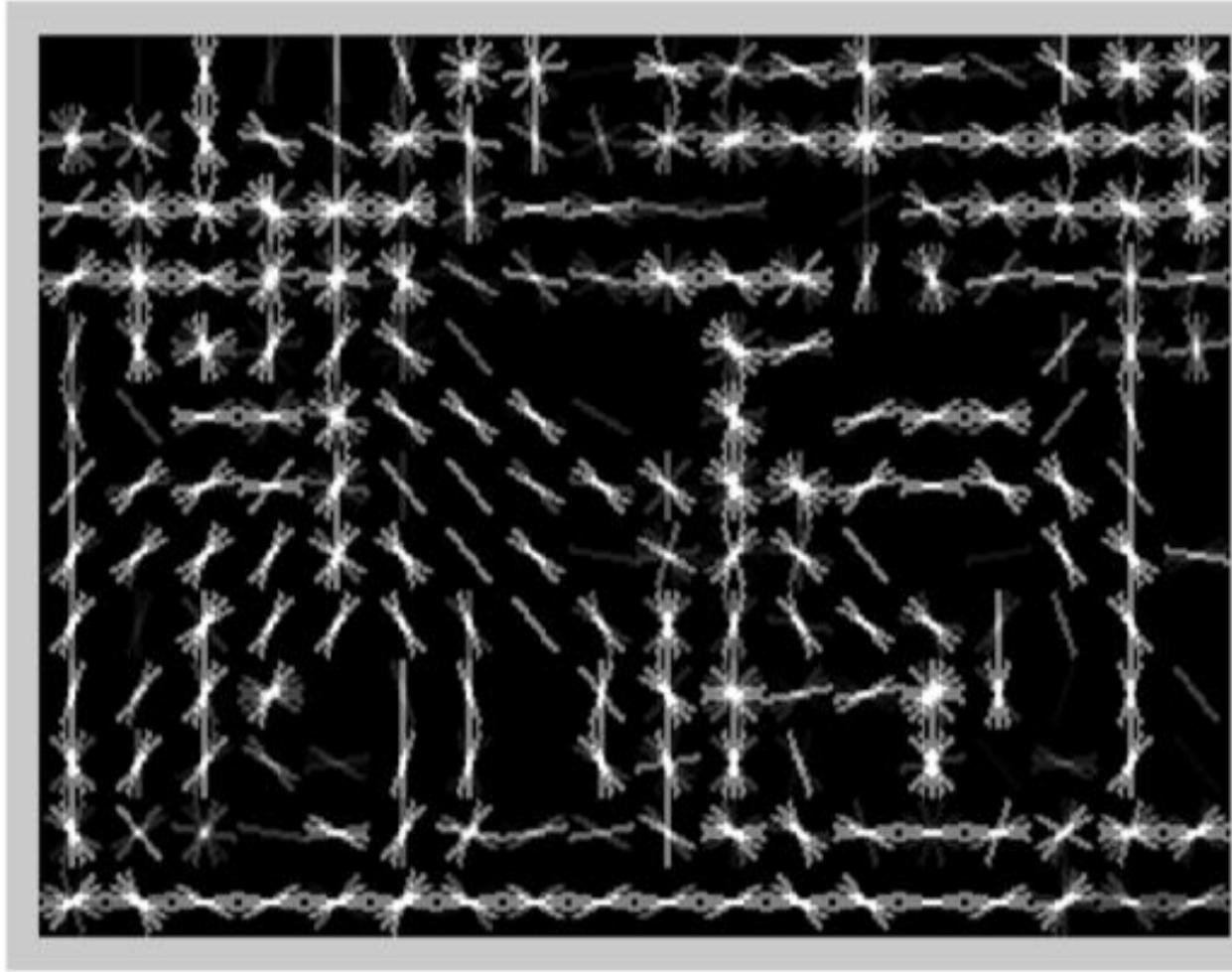
- Combine gradients from several pixels
- Divide image into small sub-images (cells)
- Accumulate a histogram of gradients within that cell
- The combined histogram entries are used as the feature vector



255	255	255	0	0	0
255	255	255	0	0	0
255	255	255	0	0	0
150	150	150	0	0	0
150	150	150	0	0	0
150	150	150	0	0	0

# Features and Generalization

---



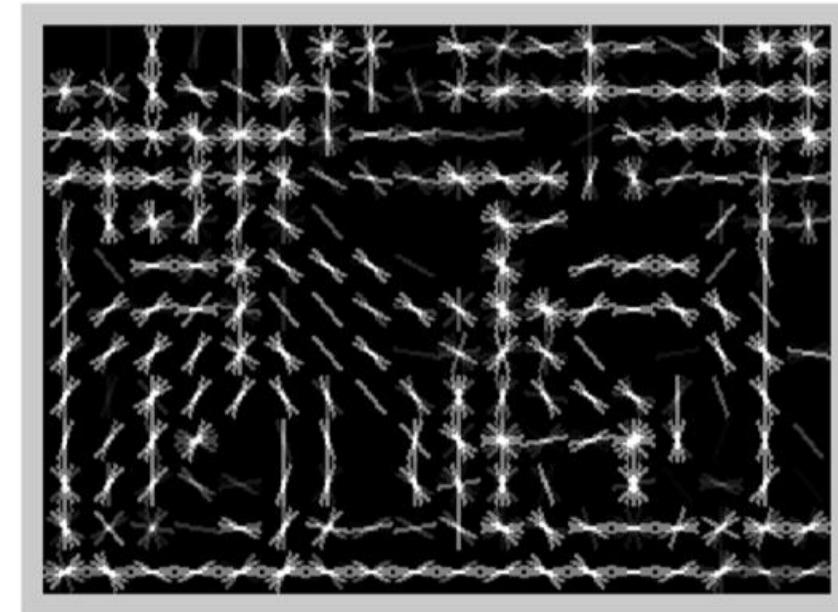
[Dalal and Triggs, 2005]

# Features and Generalization

---



Image



HoG

# Training

---

## Round 1

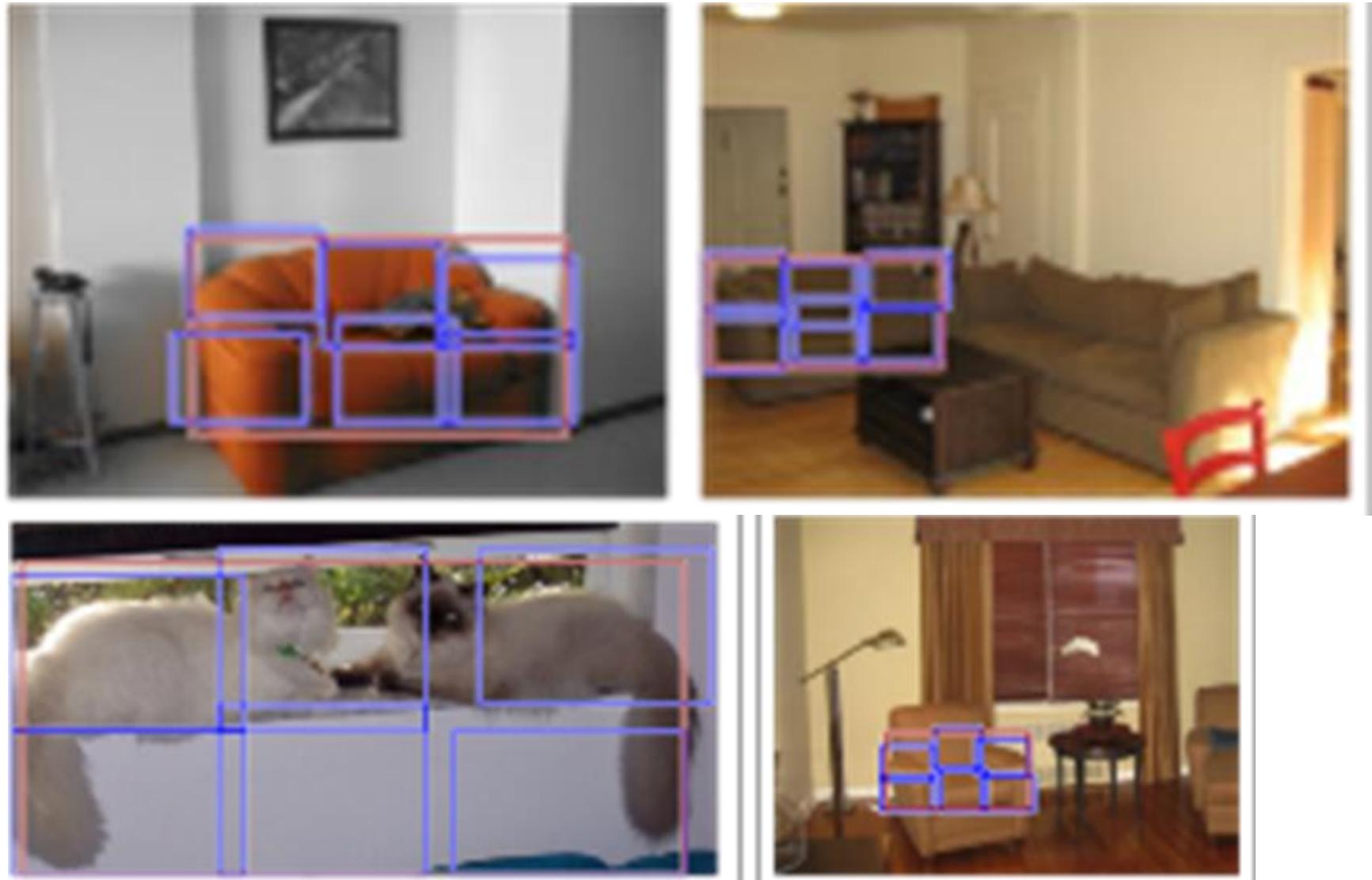
- Training set =
  - Positive examples: from labeling
  - Negative examples: random patches
- preliminary SVM

## Round 2 (“bootstrapping” or “mining hard negatives”)

- Training set =
  - Positive examples: from labeling
  - Negative examples: hard negatives and close calls (patches that have score  $\geq -1$ )
- final SVM

# Results

Sofa: we use 6 classifiers – one for each part of the sofa.

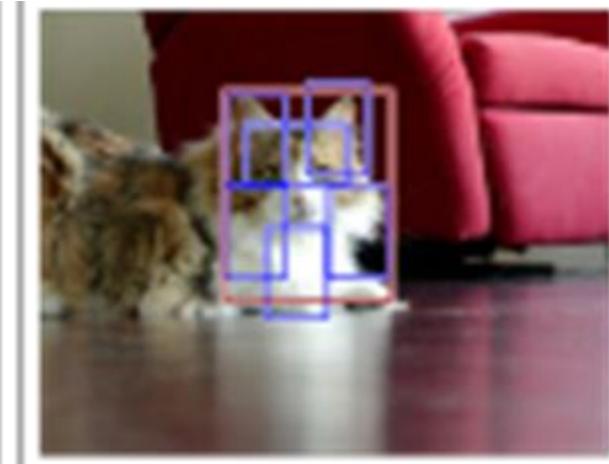
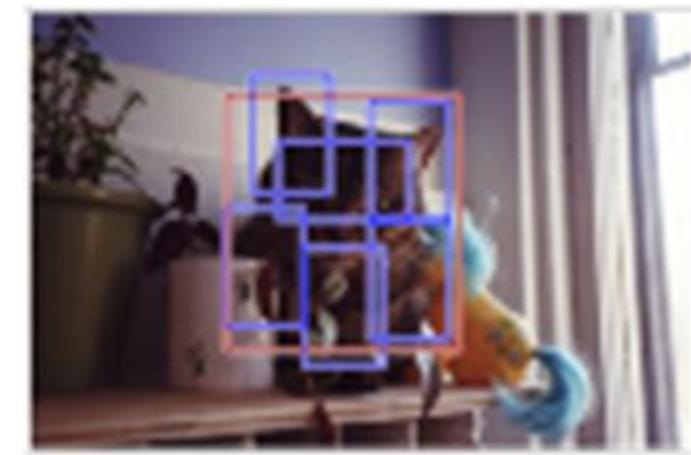
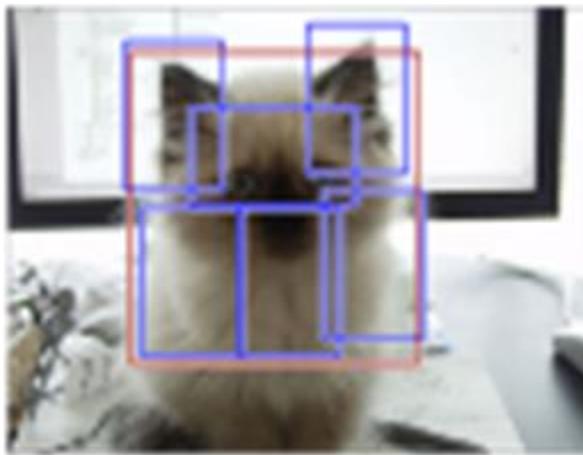
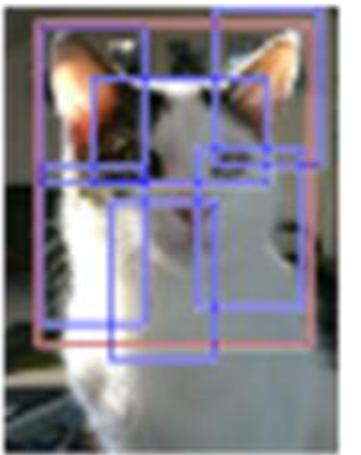


# Results

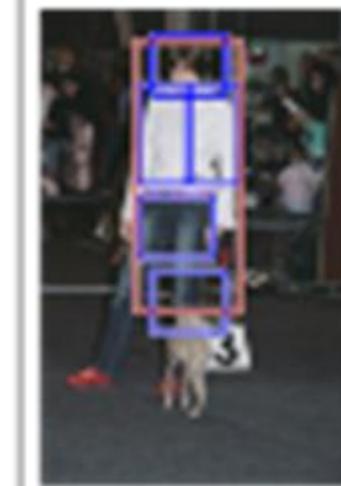
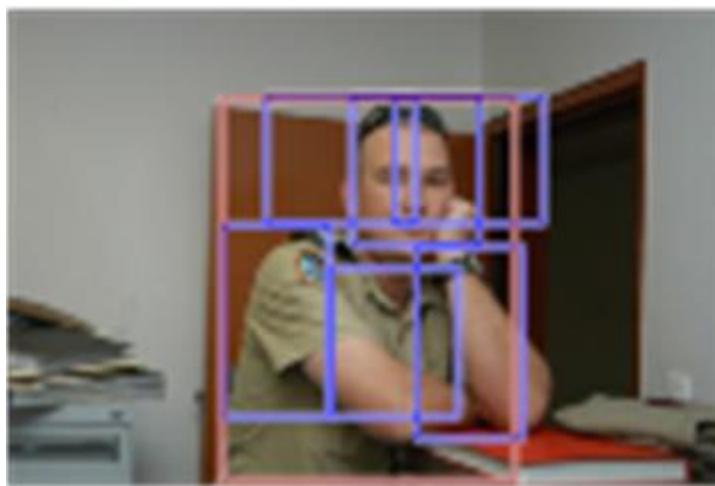


[Girschik, Felzenswalb, McAllester]

# Results

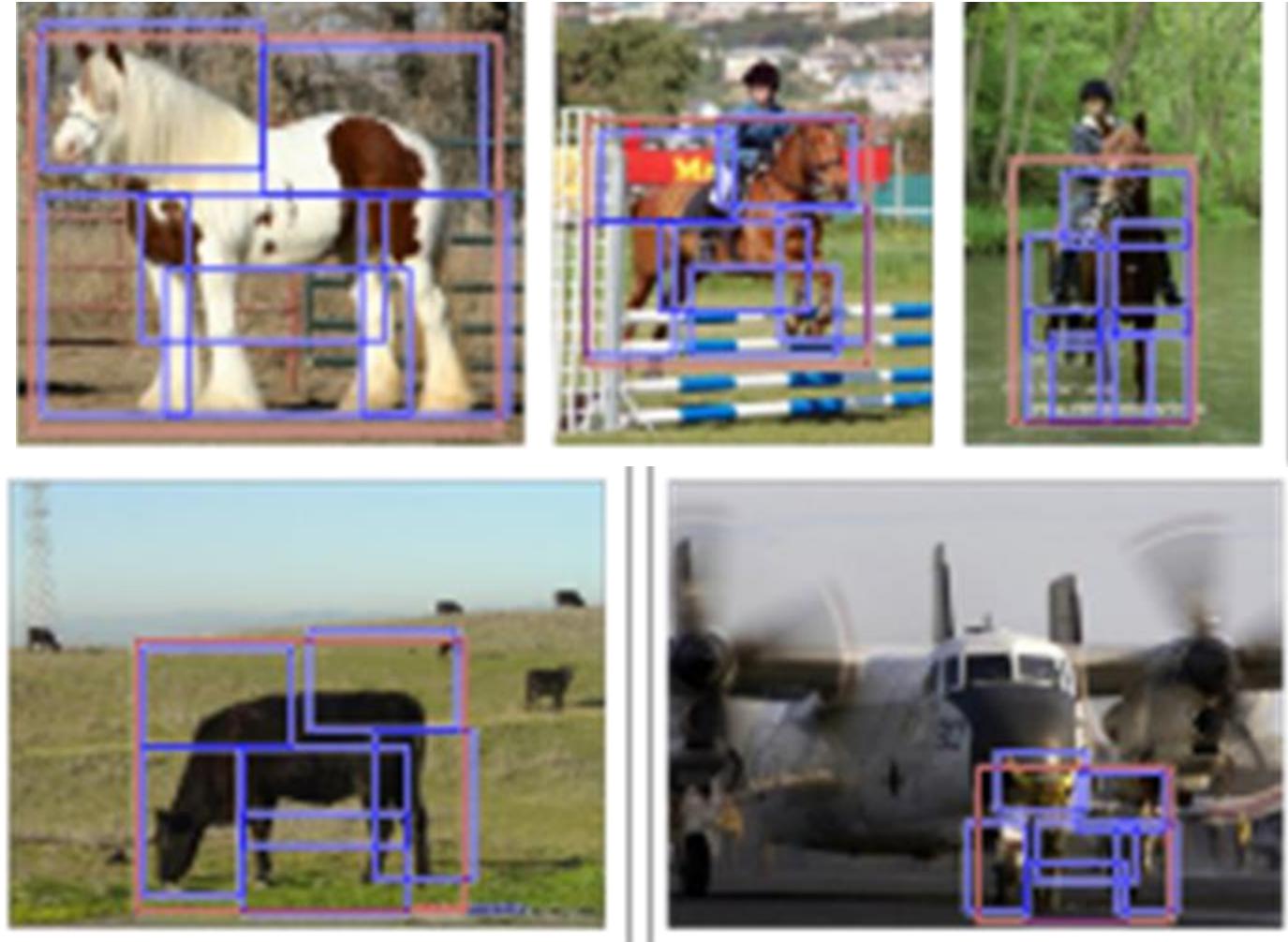


# Results



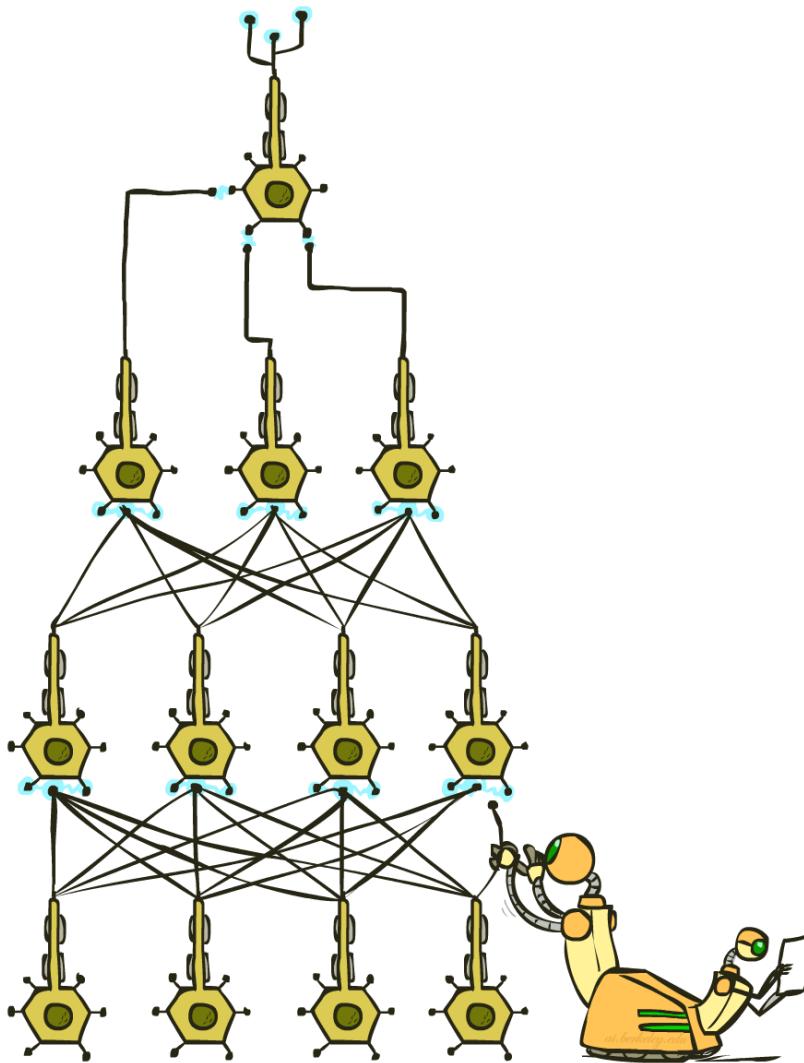
[Girschik, Felzenswalb, McAllester]

# Results



[Girschik, Felzenswalb, McAllester]

# Object Detection Approach 2: Deep Learning



# How Many Computers to Identify a Cat?

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## How Many Computers to Identify a Cat? 16,000



An image of a cat that a neural network taught itself to recognize.  
Jim Wilson/The New York Times

By JOHN MARKOFF  
Published: June 25, 2012

MOUNTAIN VIEW, Calif. — Inside Google's secretive X laboratory, known for inventing self-driving cars and augmented reality glasses, a small group of researchers began working several years ago on a simulation of the human brain.

**Multimedia**



Presented with 10 million digital images found in YouTube videos, what did Google's brain do? What millions of humans do with YouTube: looked for cats.

There Google scientists created one of the largest neural networks for machine learning by connecting 16,000 computer processors, which they turned loose on the Internet to learn on its own.

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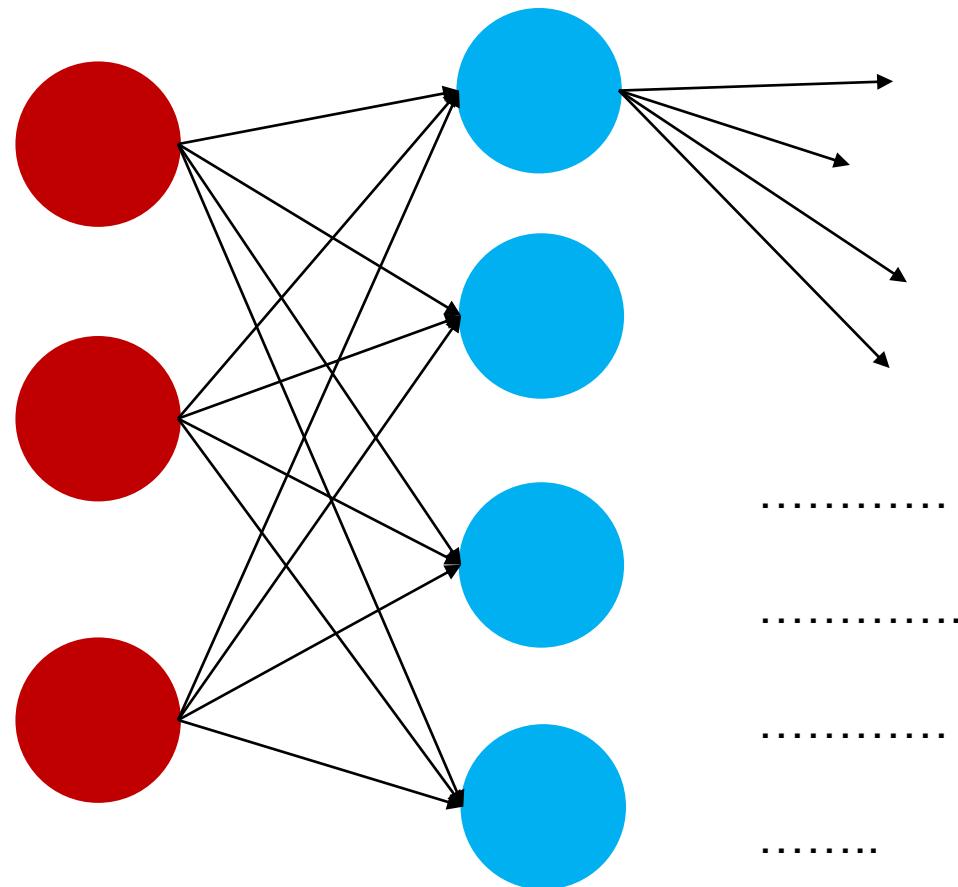


“Google Brain”

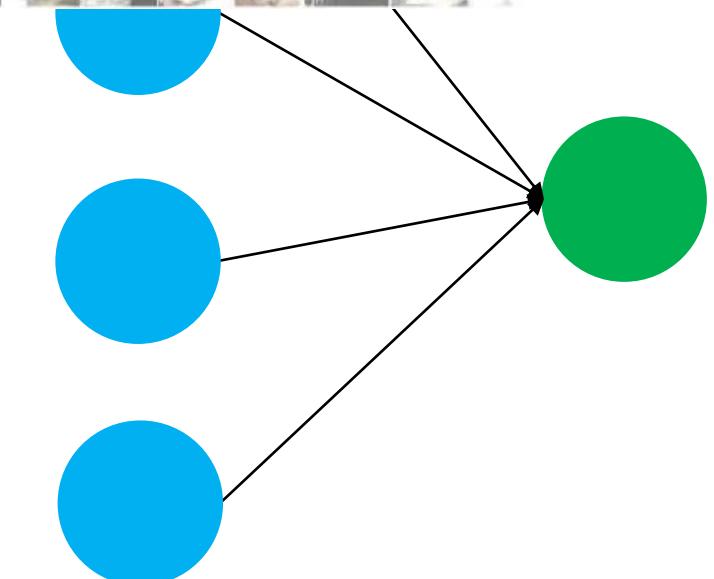
[Le, Ng, Dean, et al, 2012]

# Deep Neural Network

Input layer:  
pixels



Hidden layers: features  
(edges, Hogs, parts of object)



**Computing**

# Algorithm Clones Van Gogh's Artistic Style and Pastes It onto Other Images, Movies

**The nature of artistic style is something of a mystery to most people.**

Think of Vincent Van Gogh's *Starry Night*, Picasso's work on cubism, or Edvard Munch's *The Scream*. All have a powerful, unique style that humans recognize easily.

But what of machines? Deep neural networks are revolutionizing the way machines recognize and interpret the world. Machine vision now routinely outperforms humans at tasks such as object and face recognition, something that was unimaginable just a few years ago.

Recently, these devices have taken the first tentative steps toward recognizing artistic style and even reproducing it. Just how far this kind of work can go hasn't been clear. For example, is it possible to copy and paste an artistic style from one image onto an entire video, without producing artifacts that ruin the visual experience?

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TURN YOUR PHOTOS INTO ART.

Repaint your picture in the style of your favorite artist.

# What Next?

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## Natural Language Processing?

- Ling 165: Introduction to Natural Language Processing

## Machine Learning?

- TensorFlow: Open source library for machine learning  
<http://Tensorflow.org>  
<http://playground.tensorflow.org/>
- Kaggle: <https://www.kaggle.com/>  
Data science crowd sourcing. Real machine learning problems.
- Math 285L Final project presentations session:  
1:30-2:45pm, Thursday, May 12, Clark Hall 111.