The world has over **6000** languages

Automated translation systems require **paired** data

[En] I think, therefore I am. <-> [Fr] Je pense, donc je suis.

Judge a man by his questions
rather than by his answers.

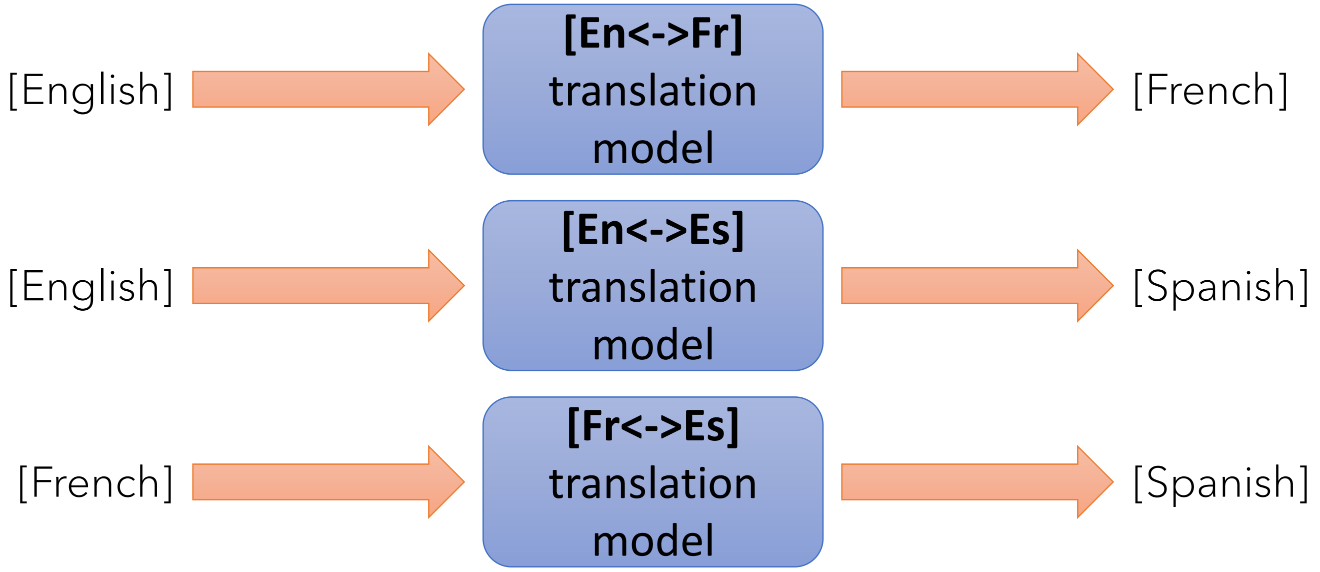
**paired** text corpus
**[En<->Fr]**

**[En<->Fr]**
translation
model

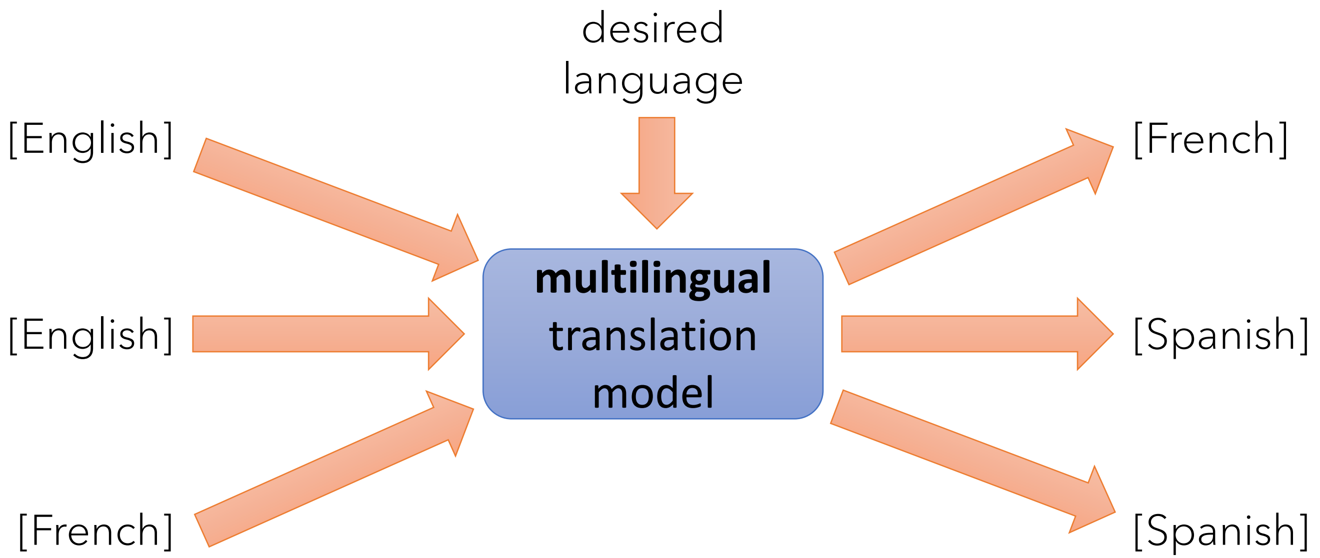
Il est encore plus facile de juger de l'esprit d'un
homme par ses questions que par ses réponses.

How many **paired** sentences are there for translating **Maltese** to **Tibetan**?

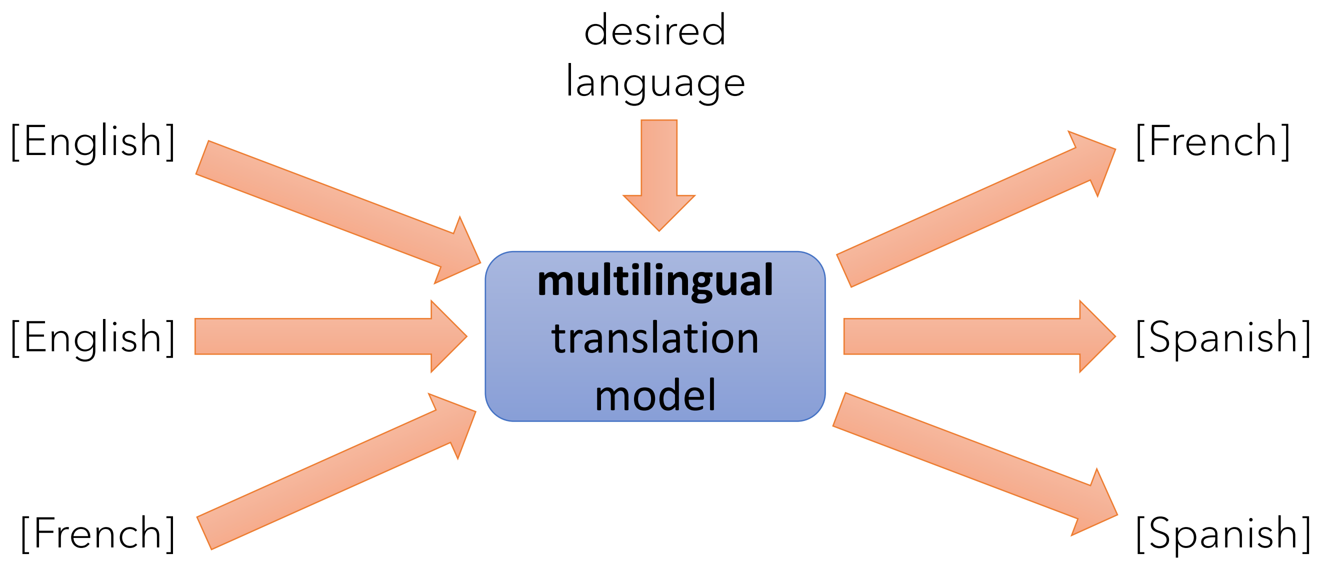
“Standard” machine translation:




“Multilingual” machine translation:




Johnson et al. **Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation.** 2016.

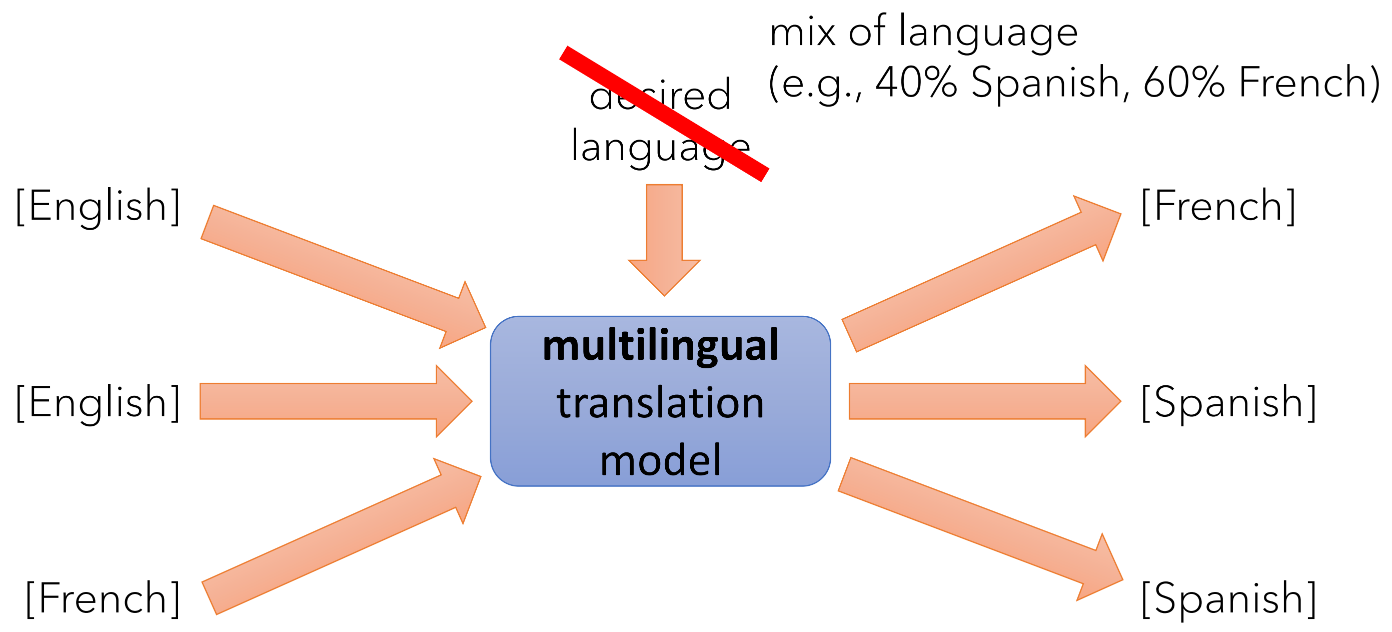



**What did they find?**

**Improved efficiency:**
Translating into and out of rare languages works **better** if the model is also trained on more common languages

**Zero-shot machine translation:**
E.g., train on **English -> French**, **French -> English**, and **English -> Spanish**, and be able to translate **French -> Spanish**

Johnson et al. **Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation.** 2016.

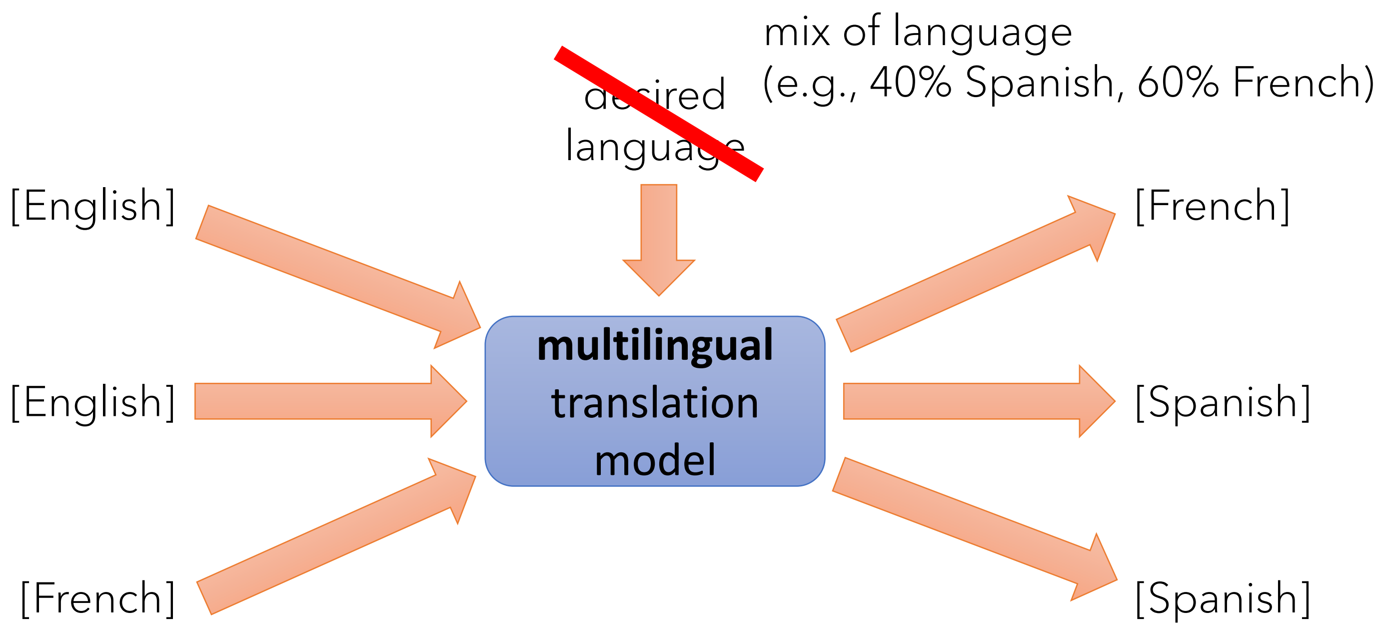



Translating **English** to **mix** of **Spanish** and **Portuguese**:

| Spanish/Portuguese: | Here the other guinea-pig cheered, and was suppressed. |
|---|---|
| $w_{pt} = 0.00$ | Aquí el otro conejillo de indias animó, y fue suprimido. |
| $w_{pt} = 0.30$ | Aquí el otro conejillo de indias animó, y fue suprimido. |
| $w_{pt} = 0.40$ | Aquí, o outro porquinho-da-índia alegrou, e foi suprimido. |
| $w_{pt} = 0.42$ | Aqui o outro porquinho-da-índia alegrou, e foi suprimido. |
| $w_{pt} = 0.70$ | Aqui o outro porquinho-da-índia alegrou, e foi suprimido. |
| $w_{pt} = 0.80$ | Aqui a outra cobaia animou, e foi suprimida. |
| $w_{pt} = 1.00$ | Aqui a outra cobaia animou, e foi suprimida. |

“Portuguese” weight
(Spanish weight = 1-w)

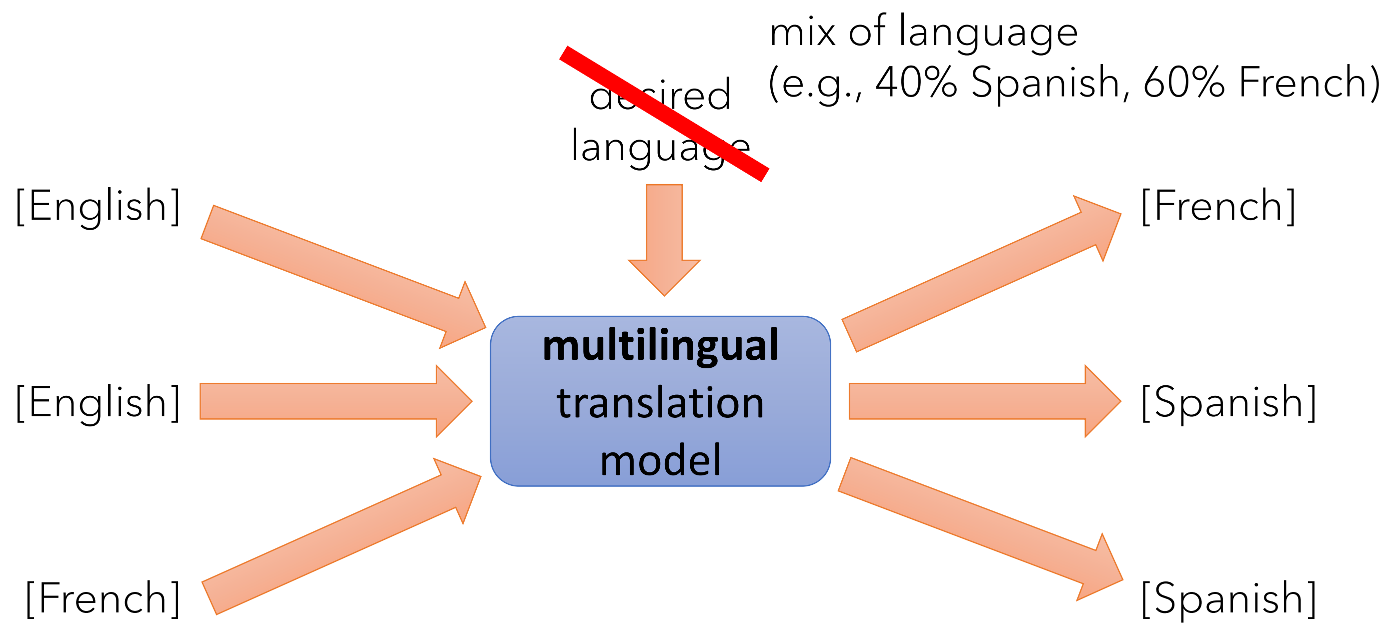
Johnson et al. **Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation.** 2016.




Translating **English** to **mix** of **Japanese** and **Korean**:

| Japanese/Korean: | I must be getting somewhere near the centre of the earth. |
|---|---|
| $w_{ko} = 0.00$ | 私は地球の中心の近くにどこかに行っているに違いない。 |
| $w_{ko} = 0.40$ | 私は地球の中心近くのどこかに着いているに違いない。 |
| $w_{ko} = 0.56$ | 私は地球の中心の近くのどこかになっているに違いない。 |
| $w_{ko} = 0.58$ | 私は지구の中心의가까이에어딘가에도착하고있어야한다。 |
| $w_{ko} = 0.60$ | 나는지구의센터의가까이에어딘가에도착하고있어야한다。 |
| $w_{ko} = 0.70$ | 나는지구의중심근처어딘가에도착해야합니다。 |
| $w_{ko} = 0.90$ | 나는어딘가지구의중심근처에도착해야합니다。 |
| $w_{ko} = 1.00$ | 나는어딘가지구의중심근처에도착해야합니다。 |

Johnson et al. **Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation.** 2016.



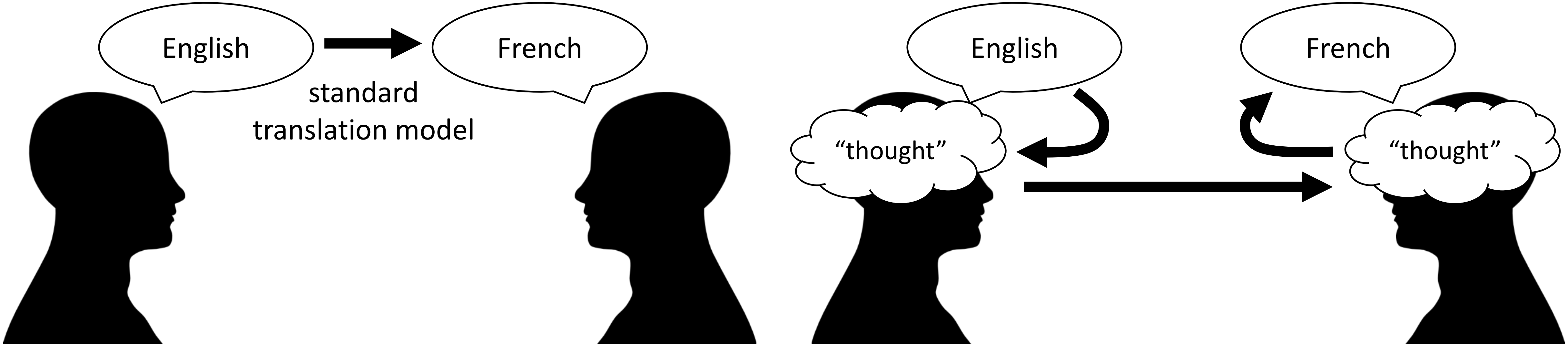

Translating **English** to **mix** of **Russian** and **Belarusian**:

| Russian/Belarusian: | I wonder what they'll do next! |
|---|---|
| $w_{be} = 0.00$ | Интересно, что они сделают дальше! |
| $w_{be} = 0.20$ | Интересно, что они сделают дальше! |
| $w_{be} = 0.30$ | Цікаво, что они будут делать дальше! |
| $w_{be} = 0.44$ | Цікаво, що вони будуть робити далі! |
| $w_{be} = 0.46$ | Цікаво, що вони будуть робити далі! |
| $w_{be} = 0.48$ | Цікаво, што яны зробяць далей! |
| $w_{be} = 0.50$ | Цікава, што яны будуць рабіць далей! |
| $w_{be} = 1.00$ | Цікава, што яны будуць рабіць далей! |

Neither Russian nor Belarusian!

Johnson et al. **Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation.** 2016.

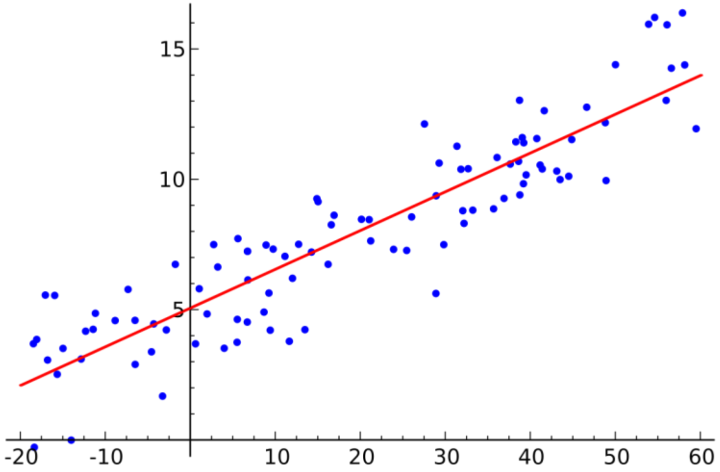
# What’s going on?



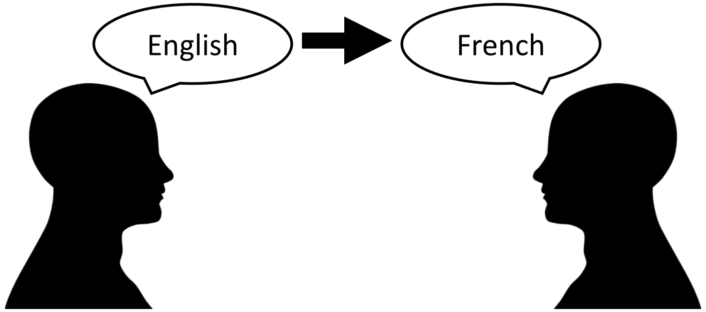

the “thought” is a **representation**!

# Representation learning

"Classic" view of machine learning:

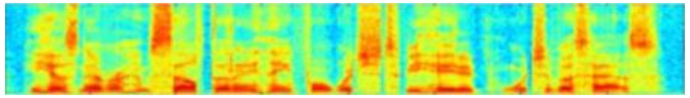



predict $y$ from $x$




but what is $x$?

Il est encore plus facile de juger de l'esprit d'un homme par ses questions que par ses réponses.

Handling such complex inputs requires **representations**


The power of deep learning lies in its ability to **learn** such **representations** automatically from data

# Deep Learning

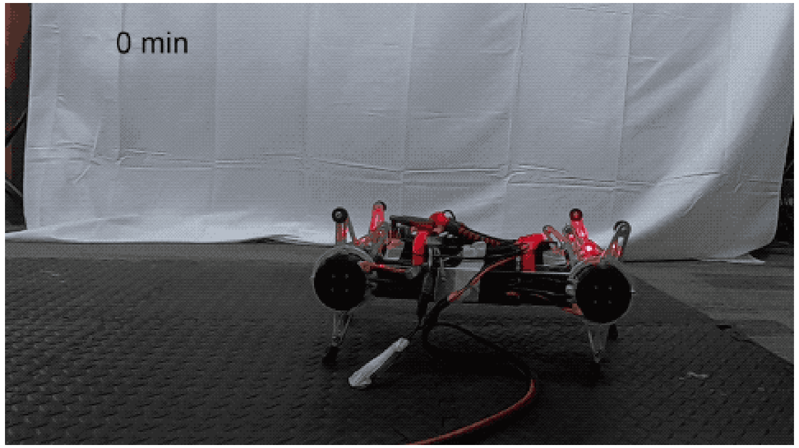
Designing, Visualizing and Understanding Deep Neural Networks

## CS W182/282A

Instructor: Sergey Levine
UC Berkeley

# Course overview

- **Broad** overview of deep learning topics
  - Neural network architectures
  - Optimization algorithms
  - Applications: vision, NLP
  - Reinforcement learning
  - Advanced topics
- **Four** homework programming assignments
  - Neural network basics
  - Convolutional and recurrent networks
  - Natural language processing
  - Reinforcement learning
- **Two** midterm exams
  - Format TBD, but most likely will be a take-home exam
- **Final project** (group project, 2-3 people)
  - Most important part of the course
  - CS182: choose vision, NLP, or reinforcement learning
  - CS282: self-directed and open-ended project

# Course policies

## Grading:

30% midterms

40% programming homeworks

30% final project

## Late policy:

5 slip days

strict late policy, no slack beyond slip days

no slip days for final project (due to grades deadline)

## Prerequisites:

Excellent knowledge of calculus linear algebra

**especially:** multi-variate derivatives, matrix operations, solving linear systems

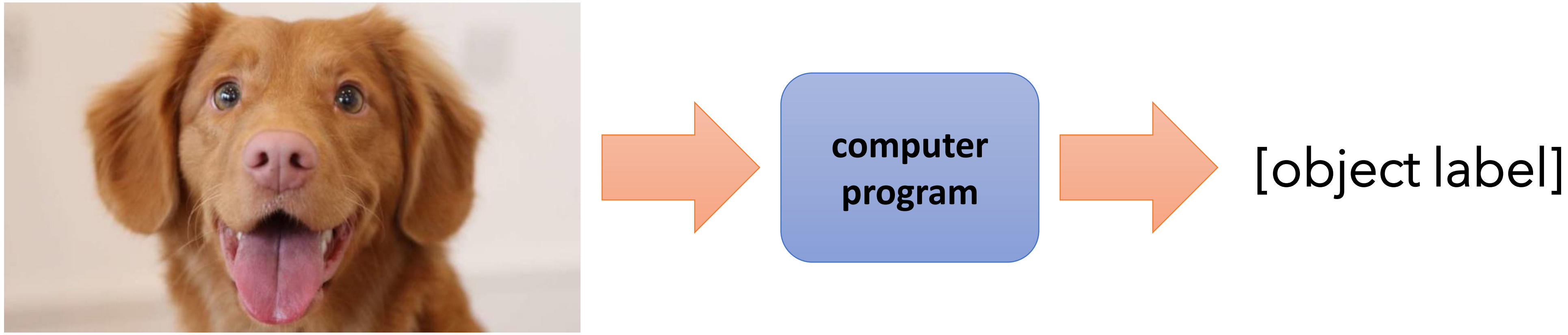
CS70 or STAT134, excellent knowledge of probability theory (including continuous random variables)

CS189, or a very strong statistics background

CS61B or equivalent, able to program in Python

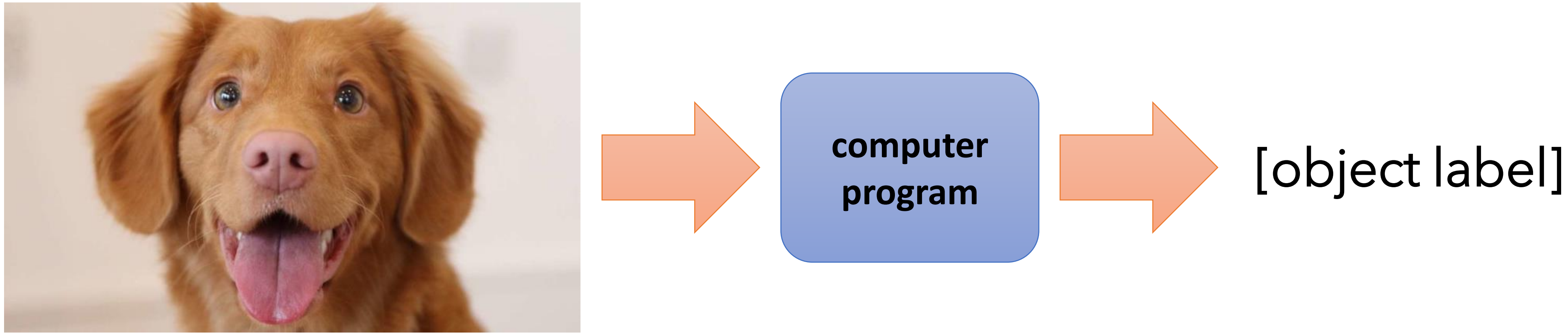
# What is machine learning?
# What is deep learning?

# What is machine learning?




- How do we implement this program?
- A function is a set of **rules** for transforming **inputs** into **outputs**
- Sometimes we can define the rules by hand – this is called programming
- What if we don't know the rules?
- What if the rules are too complex? Too many exceptions & special cases?

# What is machine learning?

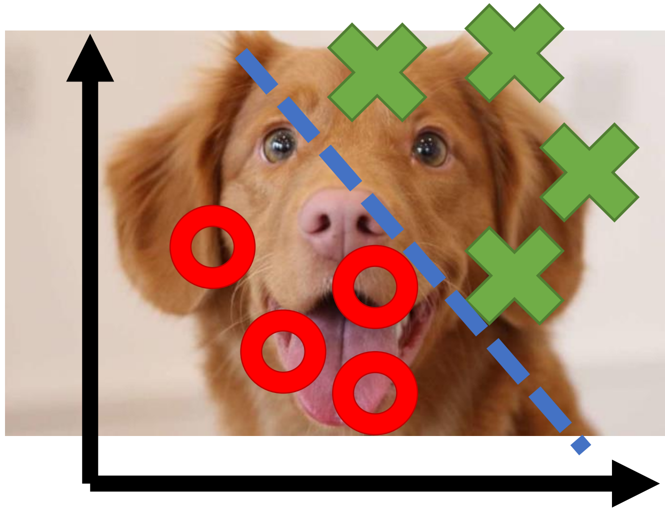



- Instead of defining the **input -> output** relationship by hand, define a program that acquires this relationship from **data**

- **Key idea:** if the rules that describe how **inputs** map to **outputs** are complex and full of special cases & exceptions, it is easier to provide **data** or **examples** than to implement those rules

- **Question:** Does this also apply to human and animal learning?

# What are we learning?



computer program

[object label]

$$\text{if below\_line(x) then:}$$
$$\text{else:}$$

this describes a line $\quad x_1\theta_1 + x_2\theta_2 + \theta_3 \leq 0$

learn $(\theta_1, \theta_2, \theta_3) = \vec{\theta} \qquad \vec{x}^T\vec{\theta} \leq 0$

so that our *parameterized* program (function) gives the right answer!

# In general...

if below_line(x) then: O
else: ✖

parameterized function

$f(x, \theta) = y$

the *input*

the *parameters*
these are learned

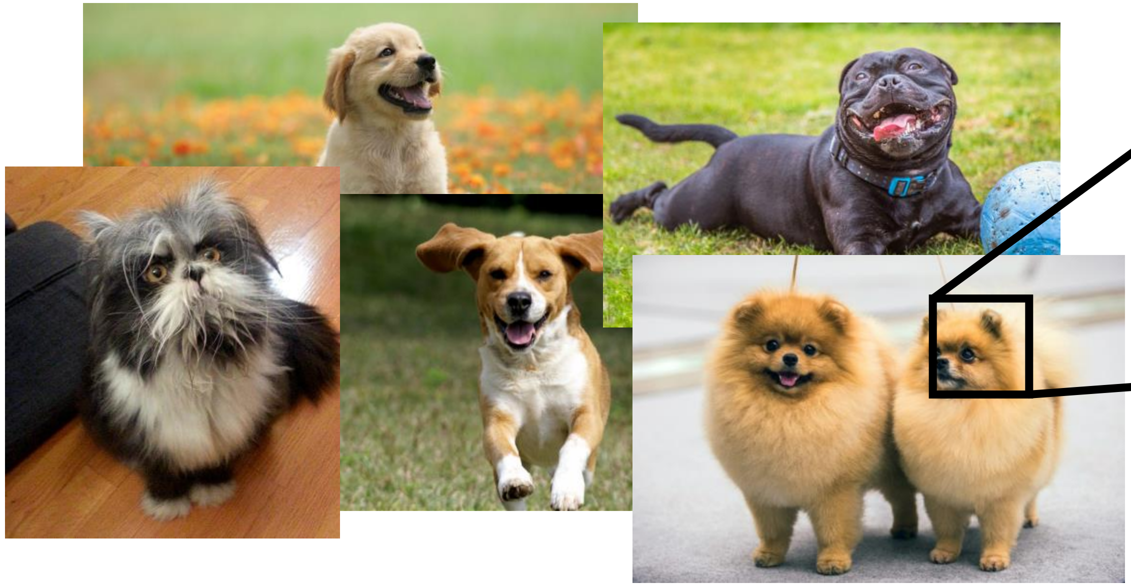
the *output*
e.g., label

can also write as: $f_\theta(x) = y$

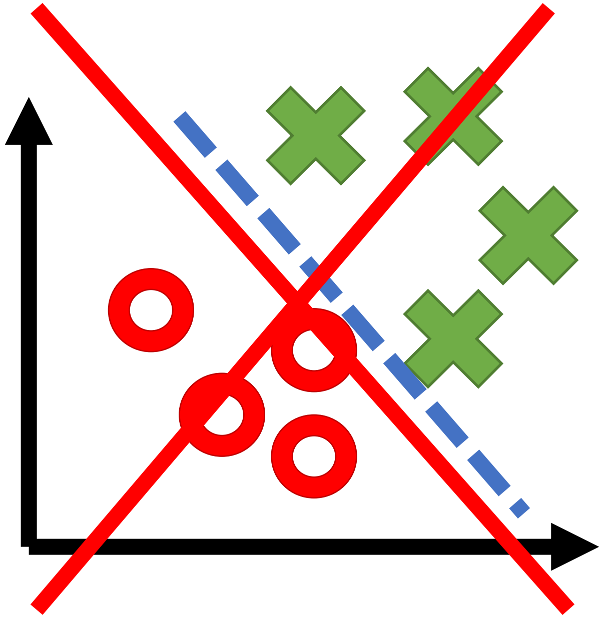
**crucially**, $f_\theta(x)$ can be almost any expression of $x$ and $\theta$!

# But what **parameterization** do we use?

$f_\theta(x) = y$ → [object label]



| | | | |
|---|---|---|---|
| 0.2 | 0.1 | 0.3 | 0.3 |
| 0.2 | 0.5 | 0.3 | 0.3 |
| 0.3 | 0.1 | 0.2 | 0.2 |
| 0.3 | 0.1 | 0.2 | 0.2 |

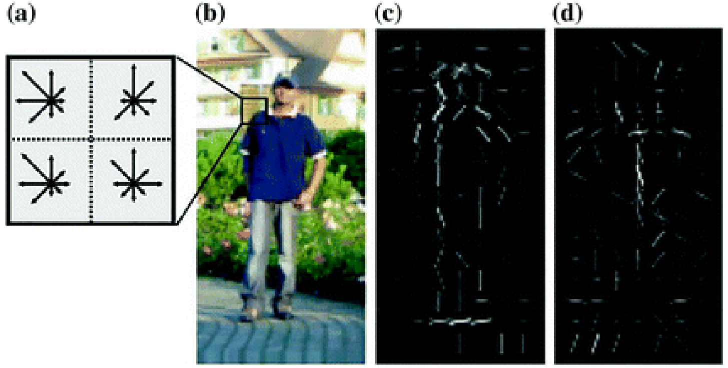


# “Shallow” learning

$$f_\theta(x) = y$$ [object label]

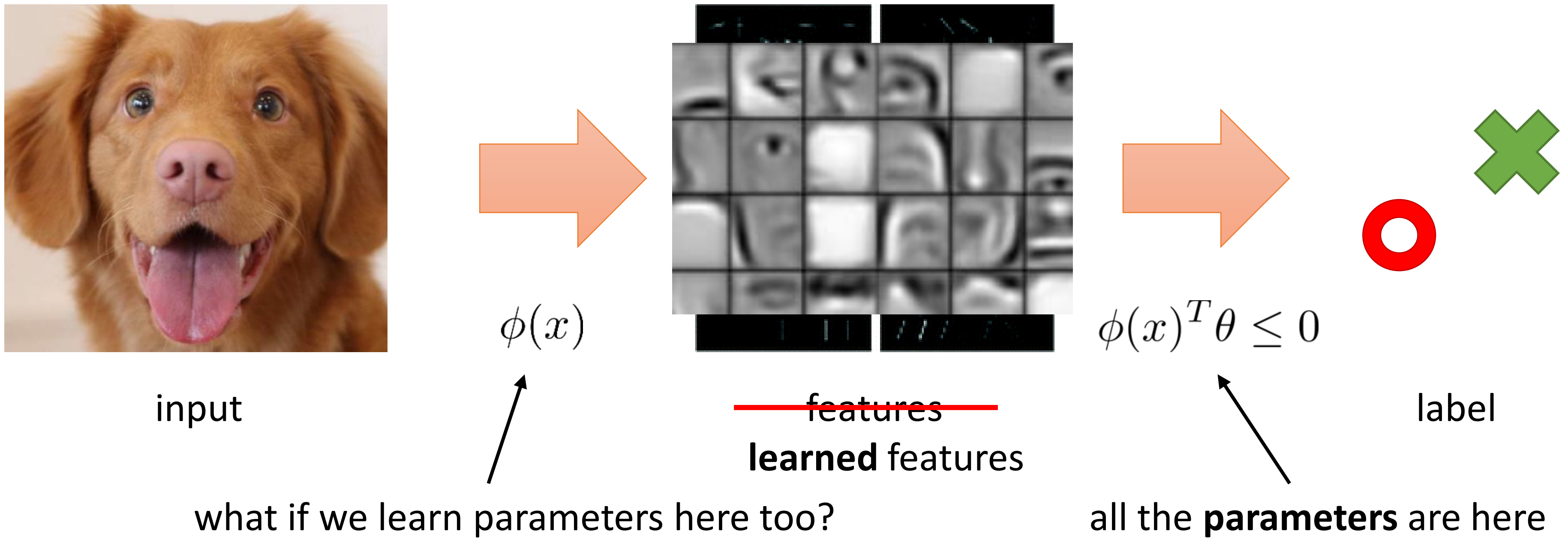
fixed function for extracting *features* from $x$

$$\phi(x)^T \theta \leq 0$$



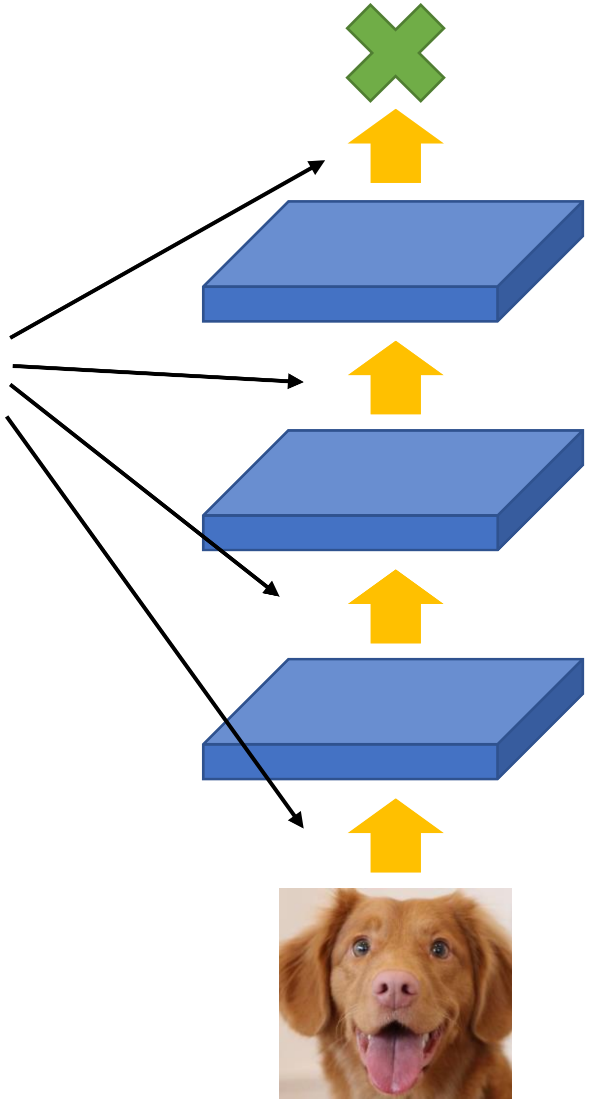

- Kind of a “compromise” solution: don’t hand-program the rules, but hand-program the features
- Learning on top of the features can be simple (just like the 2D example from before!)
- Coming up with good features is very hard!

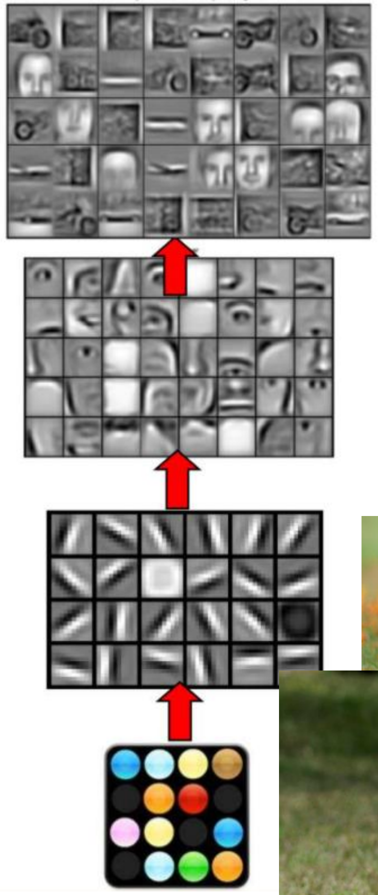
# From shallow learning to deep learning



# Multiple layers of representations?

each arrow represents a simple **parameterized** transformation (function) of the preceding layer

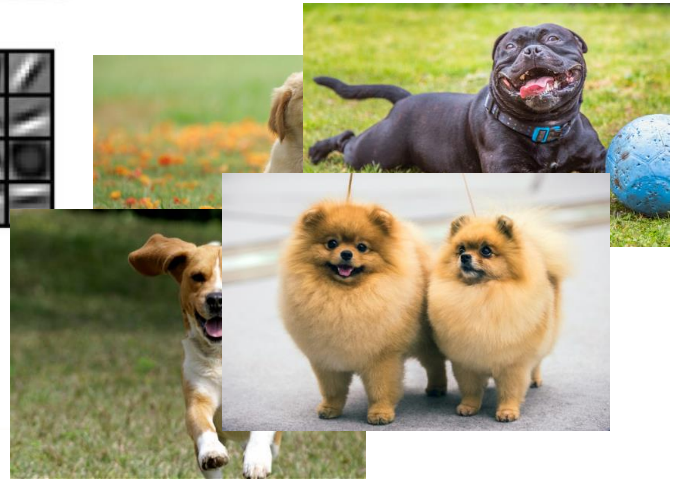




Higher level representations are:

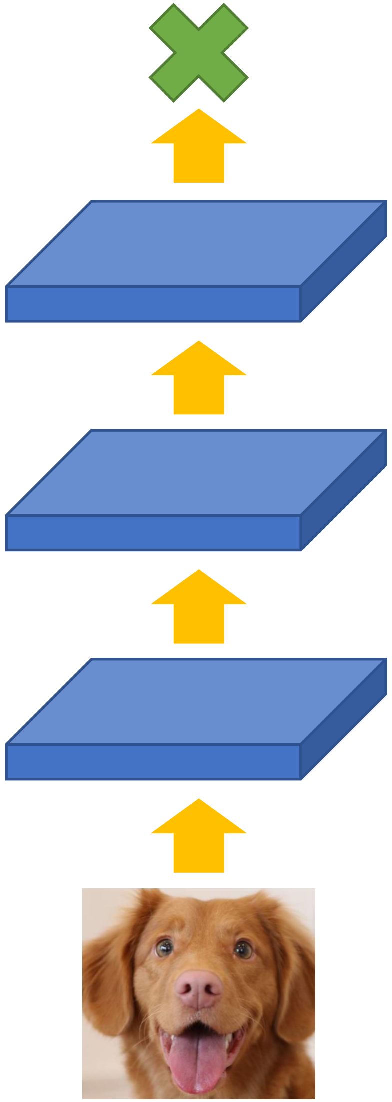
things, people, or situations that cause annoyance, inconvenience, or bother.
"NEW-suhn-siz"

- More abstract
- More invariant to nuisances
- Easier for predicting label



Coates, Lee, Raina, Ng.

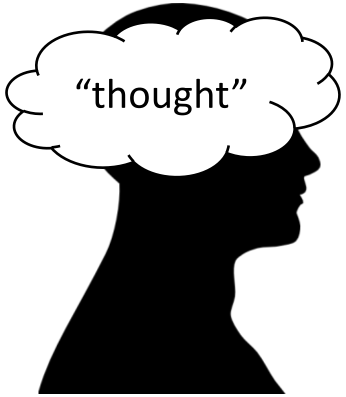
# So, what is deep learning?



- Machine learning with **multiple layers** of **learned representations**

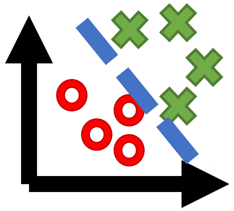
- The **function** that represents the transformation from input to internal representation to output is usually a deep neural network
  - This is a bit circular, because almost all **multi-layer parametric** functions with **learned parameters** can be called neural networks (more on this later)

- The parameters for every layer are usually (**but not always!**) trained with respect to the overall task objective (**e.g., accuracy**)
  - This is sometimes referred to as **end-to-end** learning



# What makes deep learning work?

1950 — 1950: Turing describes how learning could be a path to machine intelligence



1957: Rosenblatt's **perceptron** proposed as a practical learning method

1960

1970 — 1969: Minsky & Papert publish book describing fundamental limitations of neural networks

most (but not all) mainstream research focuses on "shallow" learning

1980

1986: Backpropagation as a practical method for training deep nets

1990 — 1989: LeNet (neural network for handwriting recognition)

*what the heck happened here?*

Huge wave of interest in ML community in probabilistic methods, convex optimization, but mostly in shallow models

2000

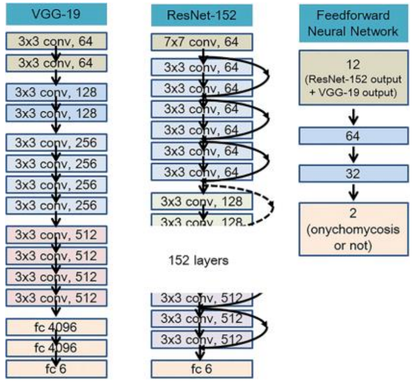
~2006: deep neural networks start gaining more attention

2010

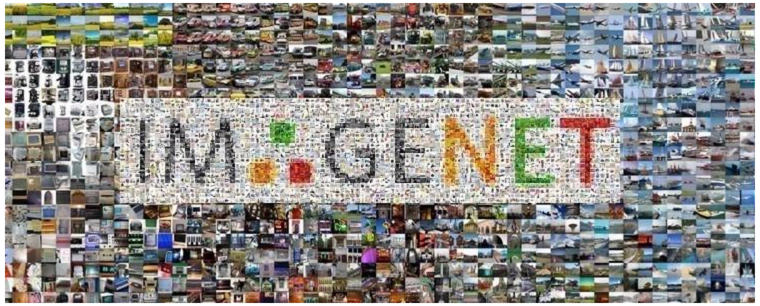
2012: Krizhevsky's AlexNet paper beats all other methods on ImageNet

# What makes deep learning work?

1) **Big** models with many layers

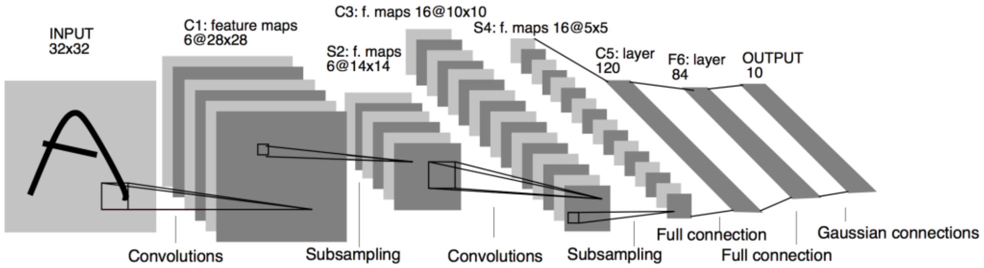



2) **Large** datasets with many examples

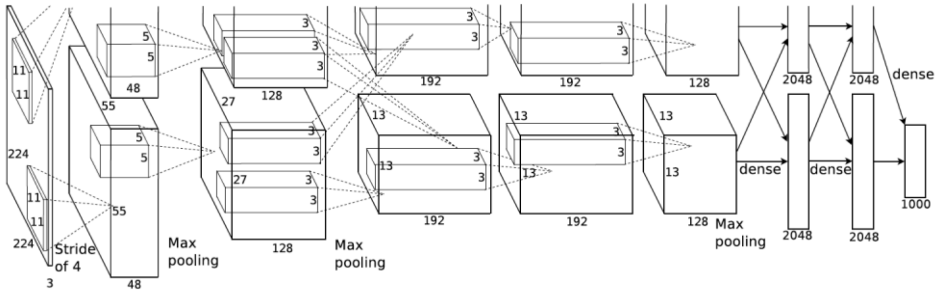


3) Enough **compute** to handle all this

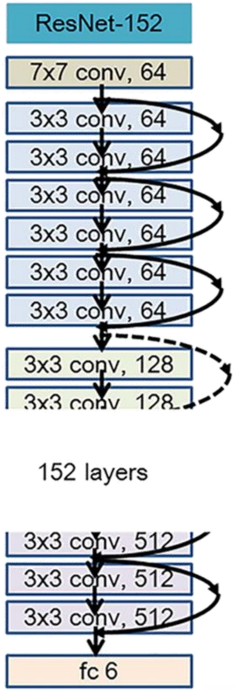
# Model scale: is more layers better?



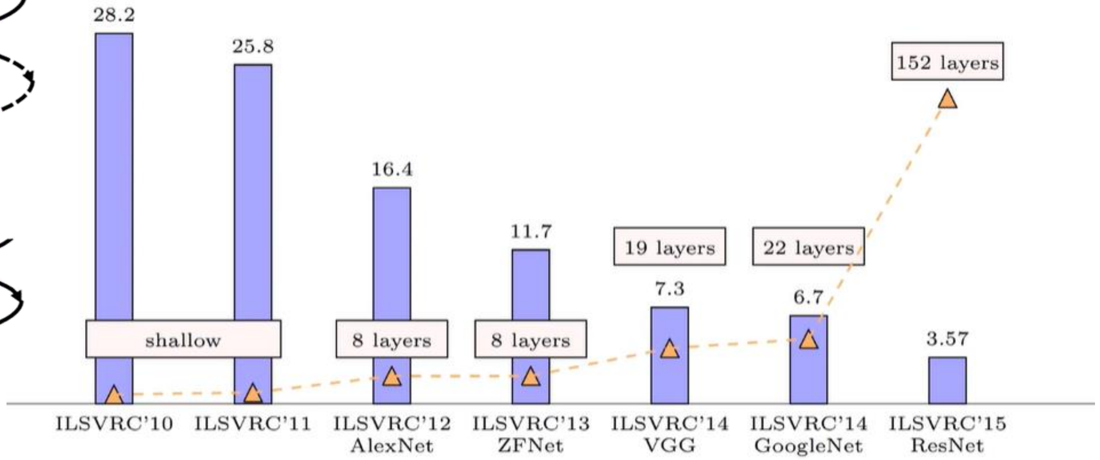

LeNet, 7 layers (1989)



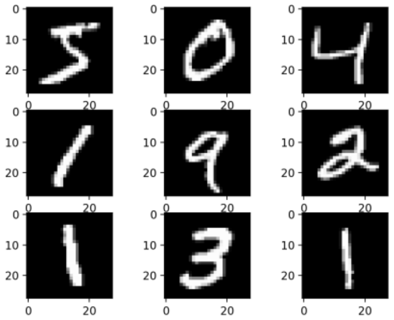

Krizhevsky's model (AlexNet) for ImageNet, 8 layers (2012)




ResNet-152: 152 layers (2015)



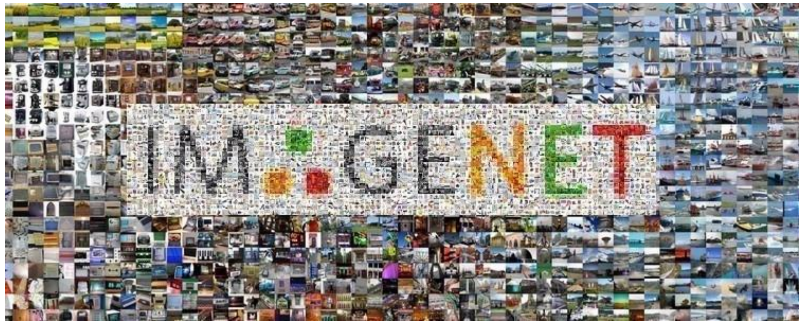
# How big are the datasets?



**MNIST (handwritten characters), 1990s - today:** 60,000 images

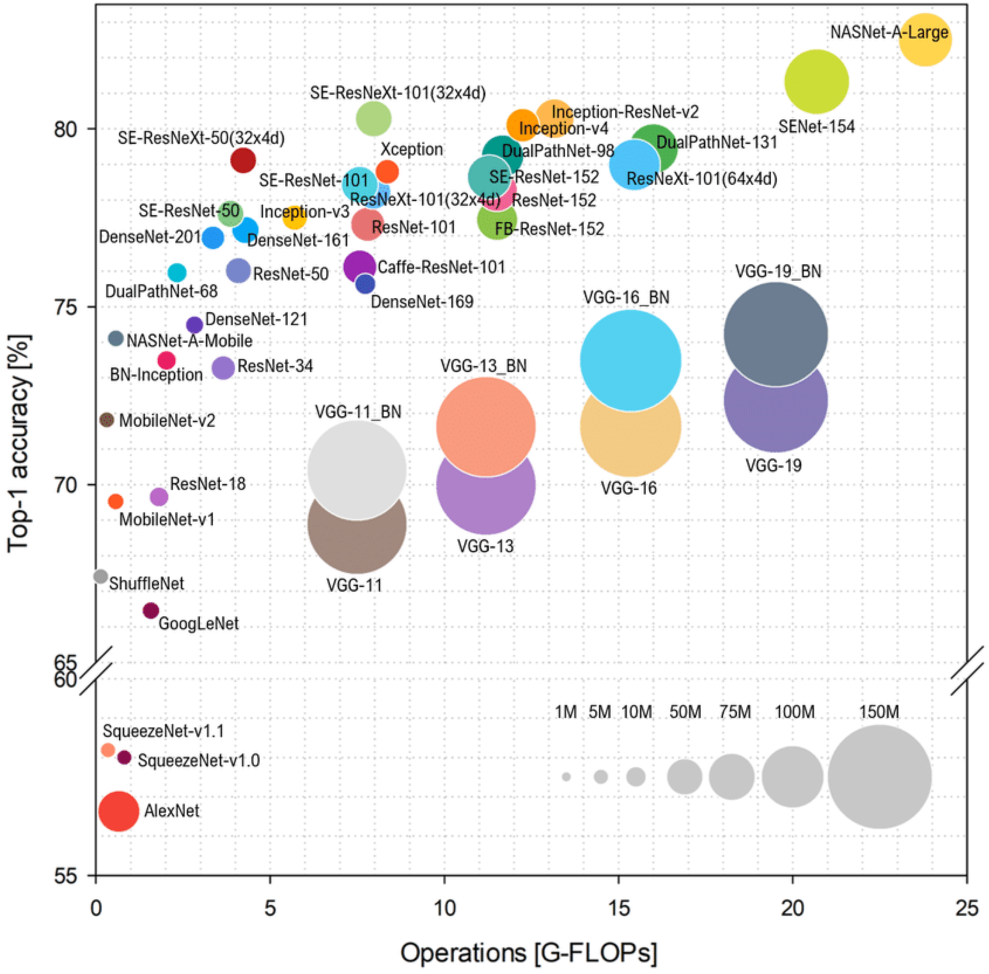

**CalTech 101, 2003:** ~9,000 images

**CIFAR 10, 2009:** ~60,000 images

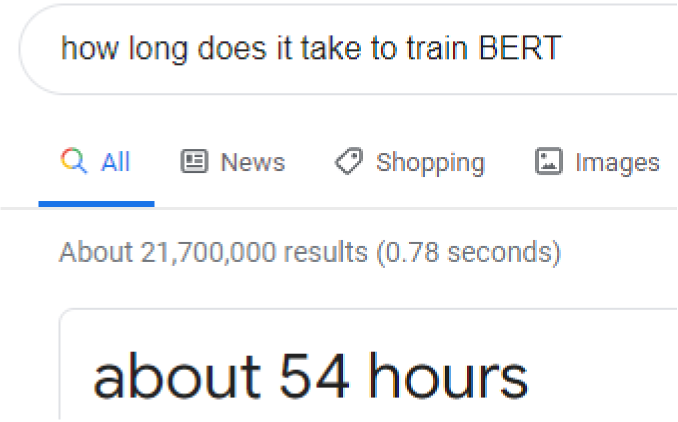


**ILSVRC (ImageNet), 2009:** 1.5 **million** images

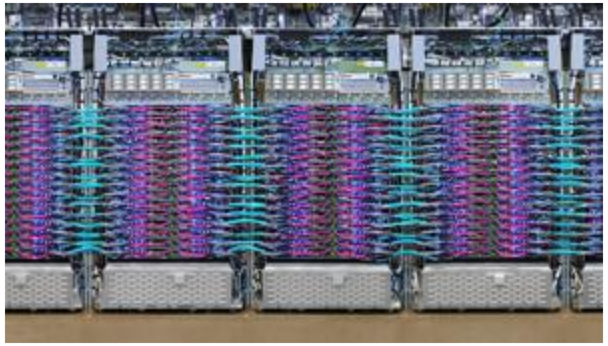
# How does it scale with compute?




## What about NLP?




## On what?? on this:



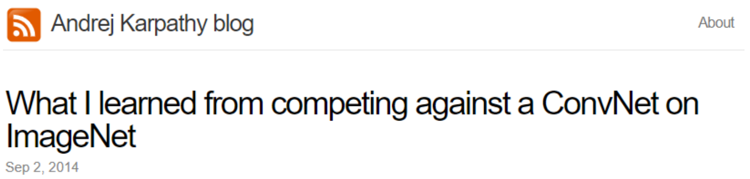
about 16 TPUs
(this photo shows a few
thousand of these)

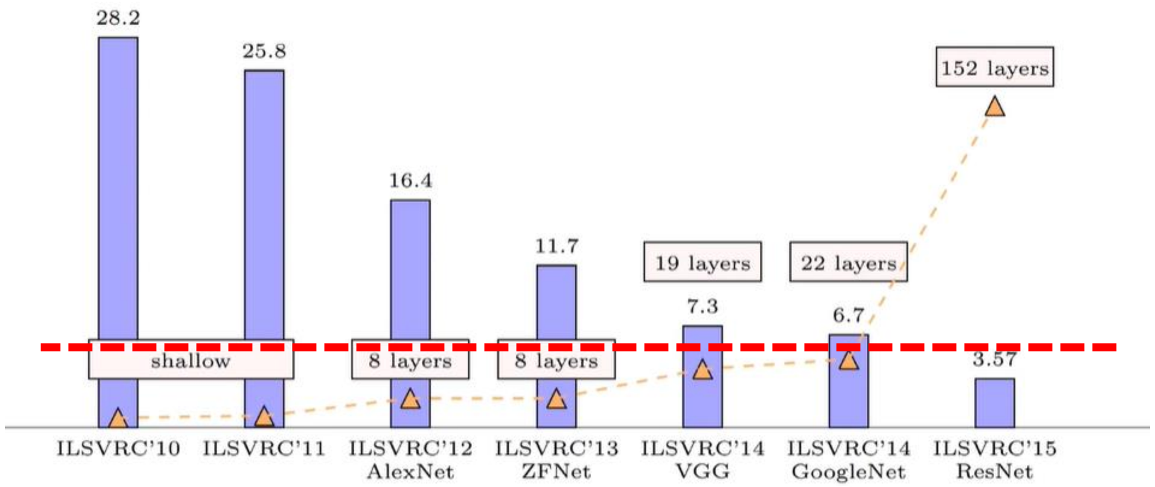
# So… it’s really expensive?

- **One perspective:** deep learning is not such a good idea, because it requires huge models, huge amounts of data, and huge amounts of compute

- **Another perspective:** deep learning is great, because as we add more data, more layers, and more compute, the models get better and better!

…which human?




**human performance:**
about 5% error

# The underlying themes

- **Acquire representations** by using **high-capacity** models and lots of **data**, without requiring manual engineering of features or representations
  - Automation: we don't need to **know** what the good features are, we can have the model figure it out from data
  - Better performance: when representations are learned end-to-end, they are better tailored to the current task
- **Learning vs. inductive bias** ("nature vs. nurture"): models that get most of their performance from their data rather than from designer insight
  - **Inductive bias:** what we build into the model to make it learn effectively (we can never fully get rid of this!)
  - Should we build in **knowledge**, or better machinery for learning and scale?
- **Algorithms that scale:** This often refers to methods that can get better and better as we add more data, representational capacity, and compute

**Model capacity**: (informally) how many different functions a particular model class can represent (e.g., all linear decision boundaries vs. non-linear boundaries).

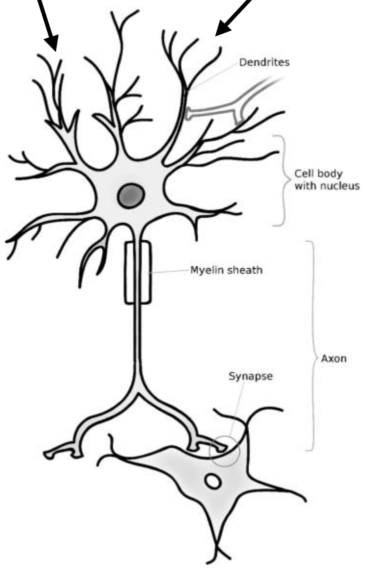
**Inductive bias**: (informally) built-in knowledge or biases in a model designed to help it learned. All such knowledge is "bias" in the sense that it makes some solutions more likely and some less likely.

**Scaling**: (informally) ability for an algorithm to work better as more data and model capacity is added.

# Why do we call them **neural** nets?

Early on, neural networks were proposed as a rudimentary model of neurons in the brain

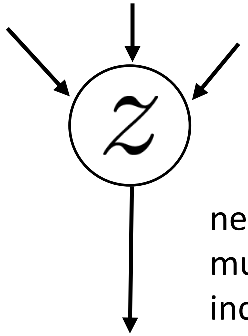
dendrites receive signals from other neurons




neuron "decides" whether to fire based on incoming signals

axon transmits signal to downstream neurons

artificial "neuron" sums up signals from upstream neurons (also referred to as "units")




neuron "decides" how much to fire based on incoming signals

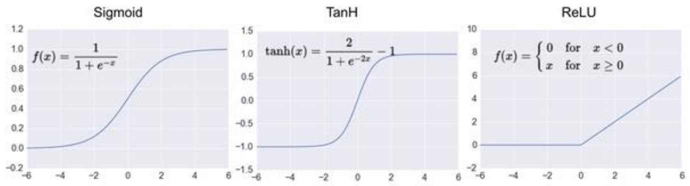
activations transmitted to downstream units

$$z = \sum_i a_i$$

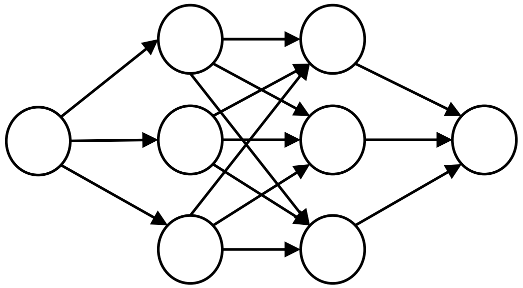
upstream activations

$$a = \sigma(z)$$

"activation function"




layer 1 layer 2



Is this a good model for real neurons?

- Crudely models *some* neuron function
- Missing many other important anatomical details
- Don't take it too seriously

# What does deep learning have to do with the brain?

**Unsupervised learning models of primary cortical receptive fields and receptive field plasticity**

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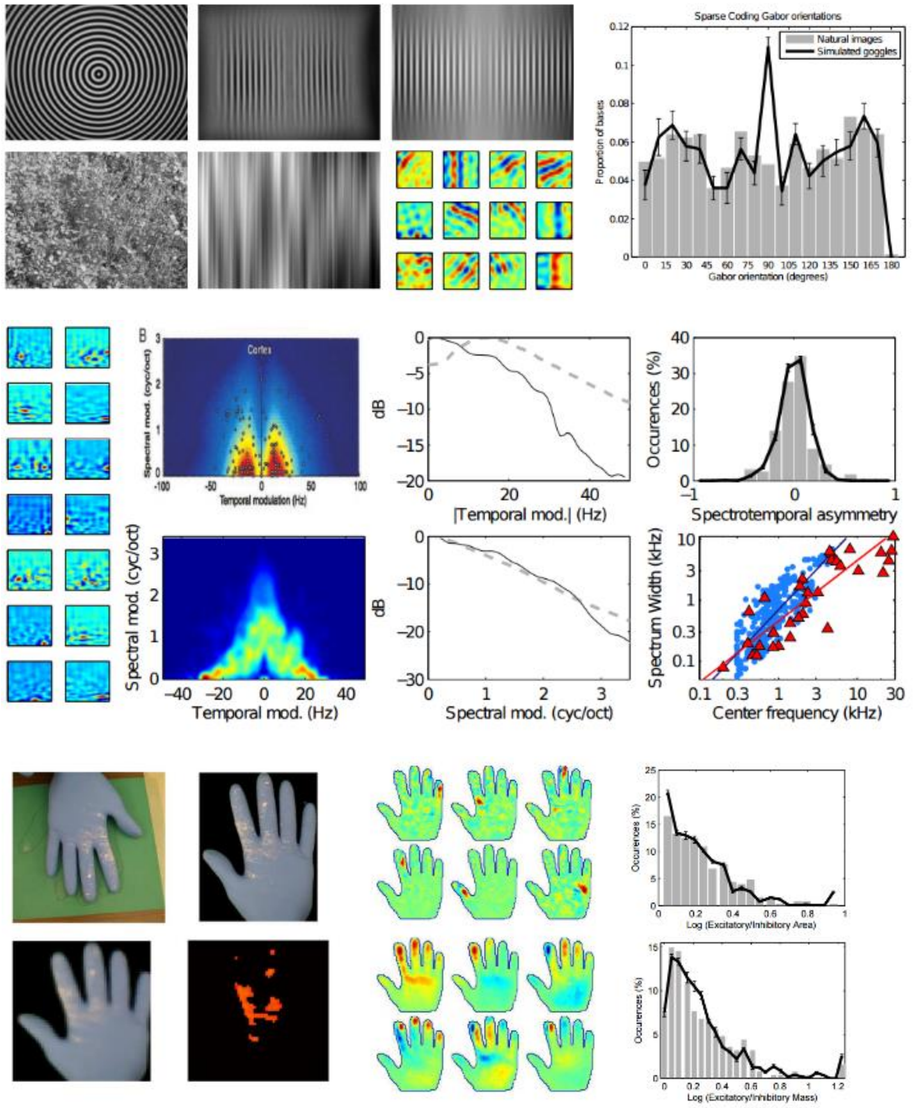


Does this mean that the brain does deep learning?

Or does it mean that any sufficiently powerful learning machine will basically derive the same solution?