## Machine Learning and the Curse of Highly-Variable Functions

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1. Machine Learning 2. Local generalization 3. The curse of highlyvariable functions 4. Inspiration from the brain: Distributed representations 1.



2. Deep architectures

### Statistical Learning

 New multi-disciplinary field





 Numerous applications



### What is Learning?

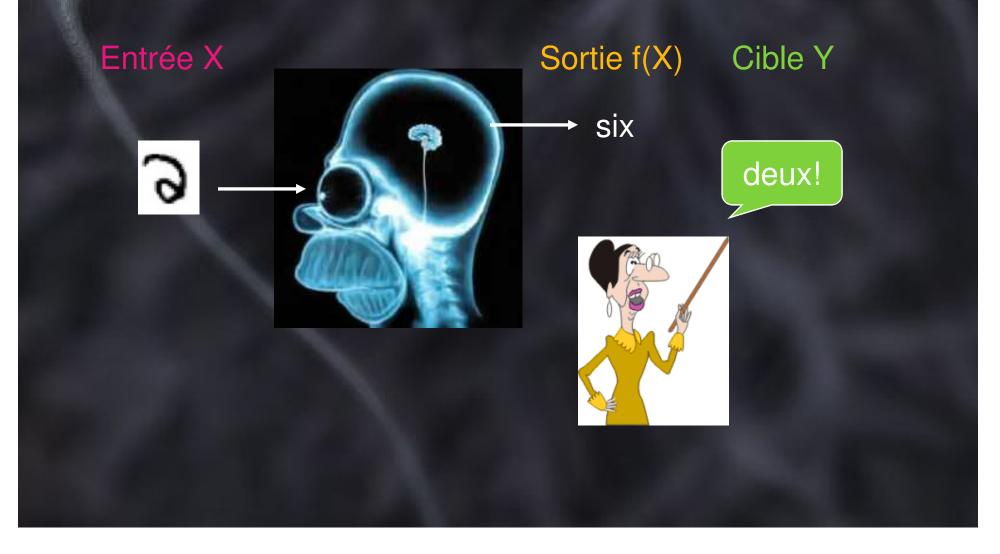
Learn underlying and previously unknown structure, from examples

= CAPTURE THE VARIATIONS

### Supervised Learning



### Supervised Training Example



#### Learn by heart

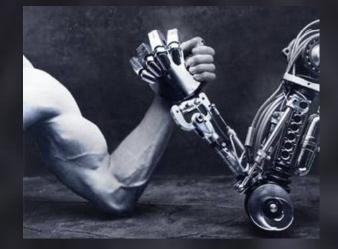
#### Generalize

or

- Easy for machines
- Hard for humans (!!???)

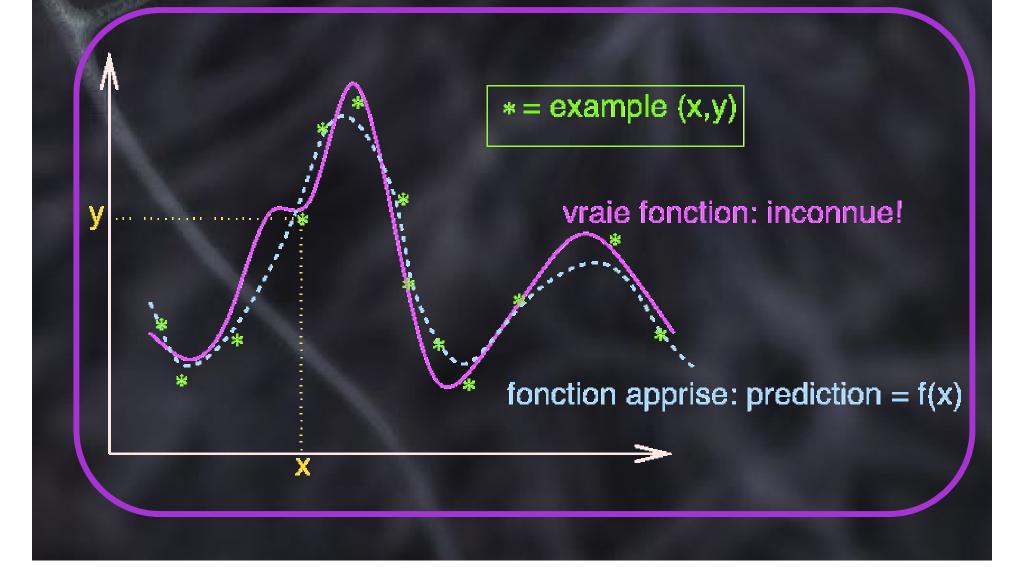


 Mathematically: fondamentally difficult

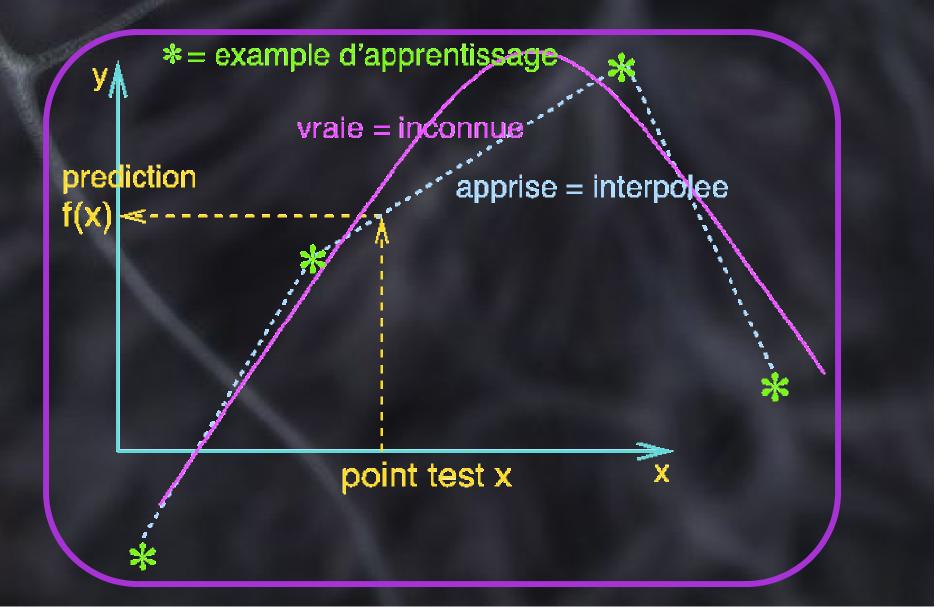


#### Easier for humans!!!!

#### Supervised Learning and Local Generalization



#### Locally capture the variations



# Easy when there are only a few variations

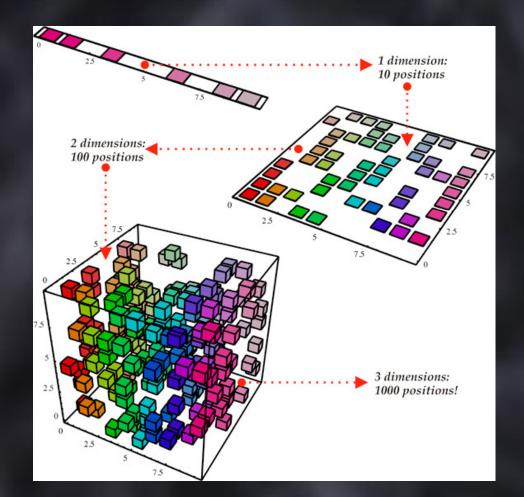
\* = example (x,y)

vraie fonction: inconnue!

fonction apprise: prediction = f(x)

### Curse of dimensionnality

To generalize locally, need examples representative of each possible variation.



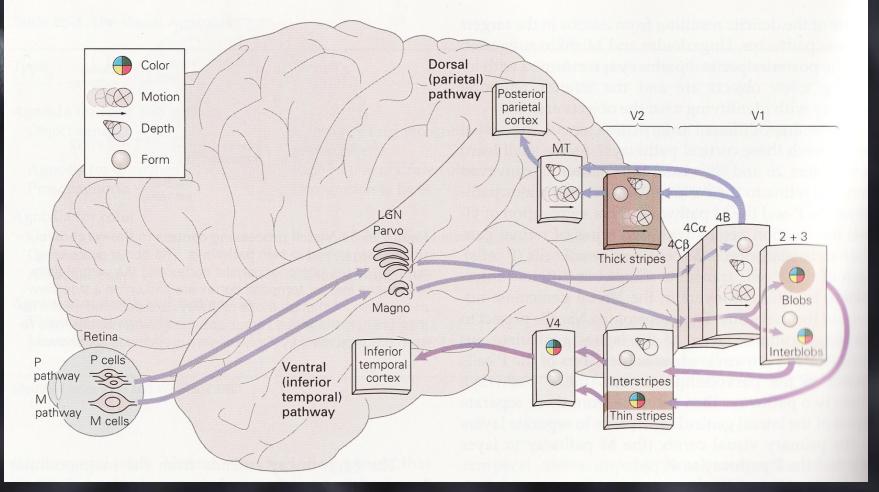
### Learning Brains

10<sup>11</sup> neurons,
 10<sup>14</sup> synapses

- Complex neural network
- Learning: modify synapses



### Visual System



**Sequence of transformations / abstraction levels** 

#### Deep Architecture in the Brain

Area V4

Area V2

Higher level visual abstractions

Primitive shape detectors

Area V1

Edge detectors

Retina

pixels

### **Distributed Representations**

Many neurons active simultaneously in the brain: around 1%

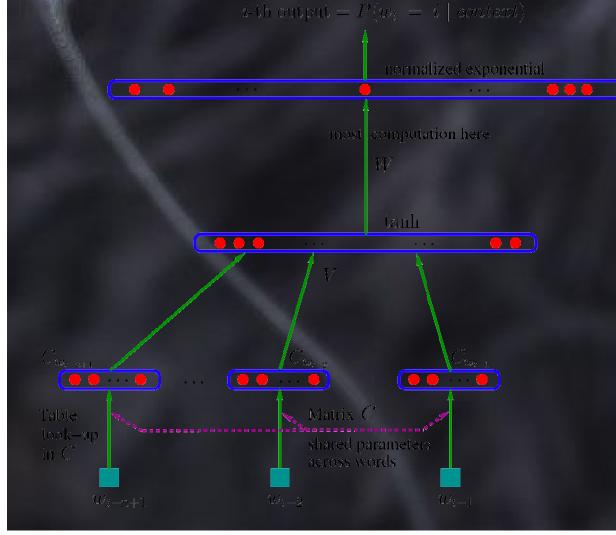
The input is represented by the activation of a set of features that are not mutually exclusive.

Can be exponentially more efficient than local representations

### Neurally Inspired Language Models

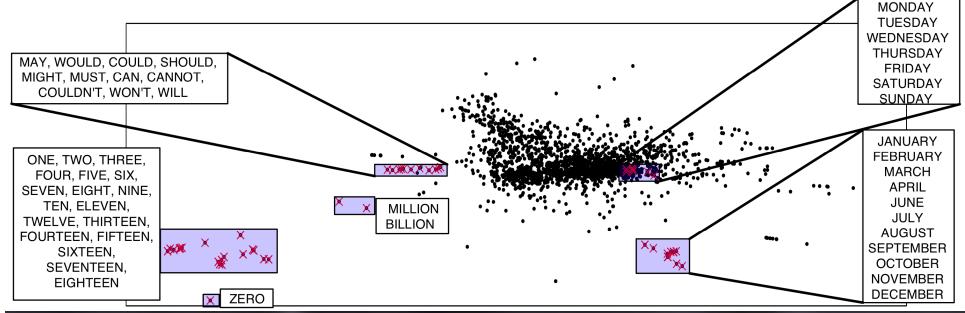
- Classical statistical models of word sequences: local representations
- Input = sequence of symbols, each element of sequence = 1 of N possible words
- Distributed representations: learn to embed the words in a continuous-valued low-dimensional semantic space

### Neural Probabilistic Language Models Successes of



Successes of this architecture and its descendents: beats localist state-of-the-art in NLP in most tasks (language model, chunking, semantic role labeling, POS)

### **Embedding Symbols**





#### Nearby Words in Semantic Space

France	Jesus	XBOX	Reddish	Scratched
Spain	Christ	Playstation	Yellowish	Smashed
Italy	God	Dreamcast	Greenish	Ripped
Russia	Resurrection	PS###	Brownish	Brushed
Poland	Prayer	SNES	Bluish	Hurled
England	Yahweh	WH	Creamy	Grabbed
Denmark	Josephus	NES	Whitish	Tossed
Germany	Moses	Nintendo	Blackish	Squeezed
Portugal	Sin	Gamecube	Silvery	Blasted
Sweden	Heaven	PSP	Greyish	Tangled
Austria	Salvation	Amiga	Paler	Slashed

### **Insufficient Depth**

#### Insufficient depth = May require exponentialsize architecture

#### Sufficient depth = Compact representation

Ö(n)

#### **Breakthrough!**



#### Before 2006 Failure of deep architectures

#### After 2006

Train one level after the other, **unsupervised**, extracting abstractions of gradually higher level



# Success of deep distributed neural networks

#### Since 2006

- Record broken on MNIST handwritten
  characer recognition benchmark
- A component of winning NetFlix entry
- State-of-the-art beaten in language modeling
- NSF et DARPA are interested...

### Challenges and Ongoing Research

#### Challenge:

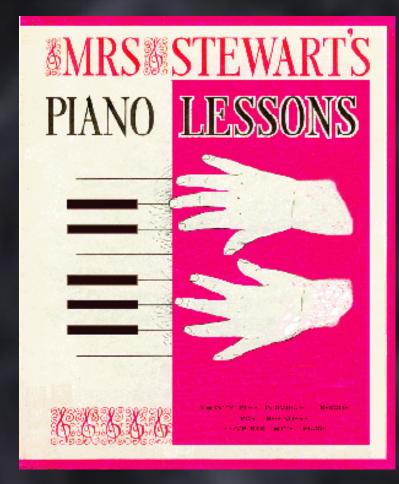
- Non-convex optimization
- Deep: huge number of local minima
- Recurrent nets / context learning

#### Humans as inspiration:

- Curriculum: first show easy examples, like teachers with students
- Collective computation: genetic-like parallel search
  through many communicating individuals
- Learning context: multiple time scales

### **Musical Curriculum Project**

- Digitize scores in a musical teaching method
- Train a model, one lesson at a time, each time rehearsing only the past lessons
- Hypothesis: can get better model then training with everything in one go



#### Conclusions

- Intelligence knowledge learning
  Curse of dimensionality / highly varying functions: limitations of local generalization
- 3. Solution: distributed + deep architectures
- 4. Challenge: local minima
- Cognitively inspired solutions: guide training to learn intermediate concepts