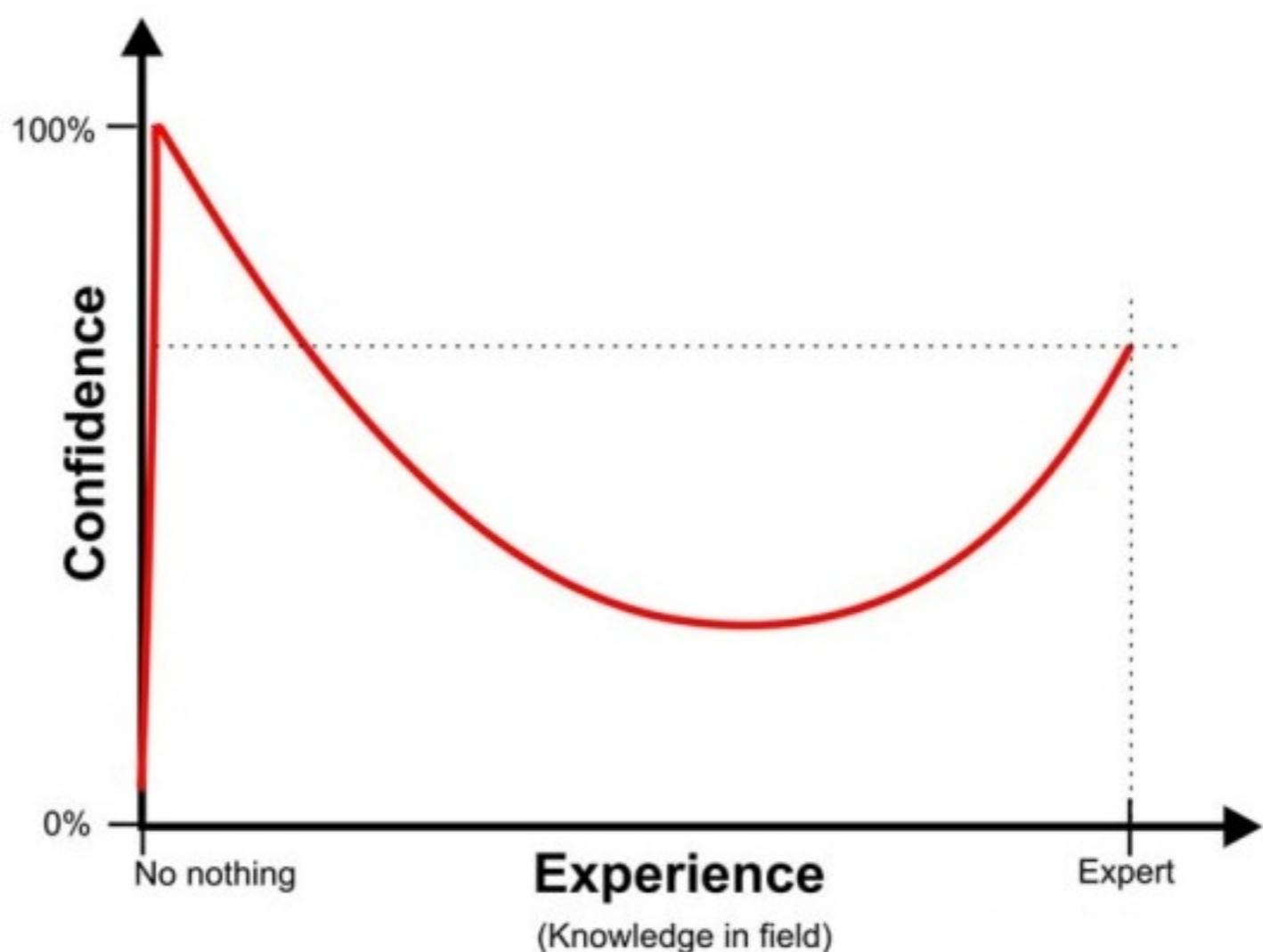


Work to Machine!

DIAS ML course by Martin Topinka

<https://github.com/toastmaker/ml-dias>



Introduce yourself and your goals



- Distinguish short GRBs flares from SGR flares
- Search for GRB afterglows in SDSS
- GRBs photometric redshift
- Clustering (minimal spanning tree) in the distance-from-templates space in DFBS
- Search for M-stars, Carbon stars in DFBS
- JWST high-z: galaxy morphology classification
- JWST high-z: search for bars in galaxies
- JWST high-z: mock up catalog generation

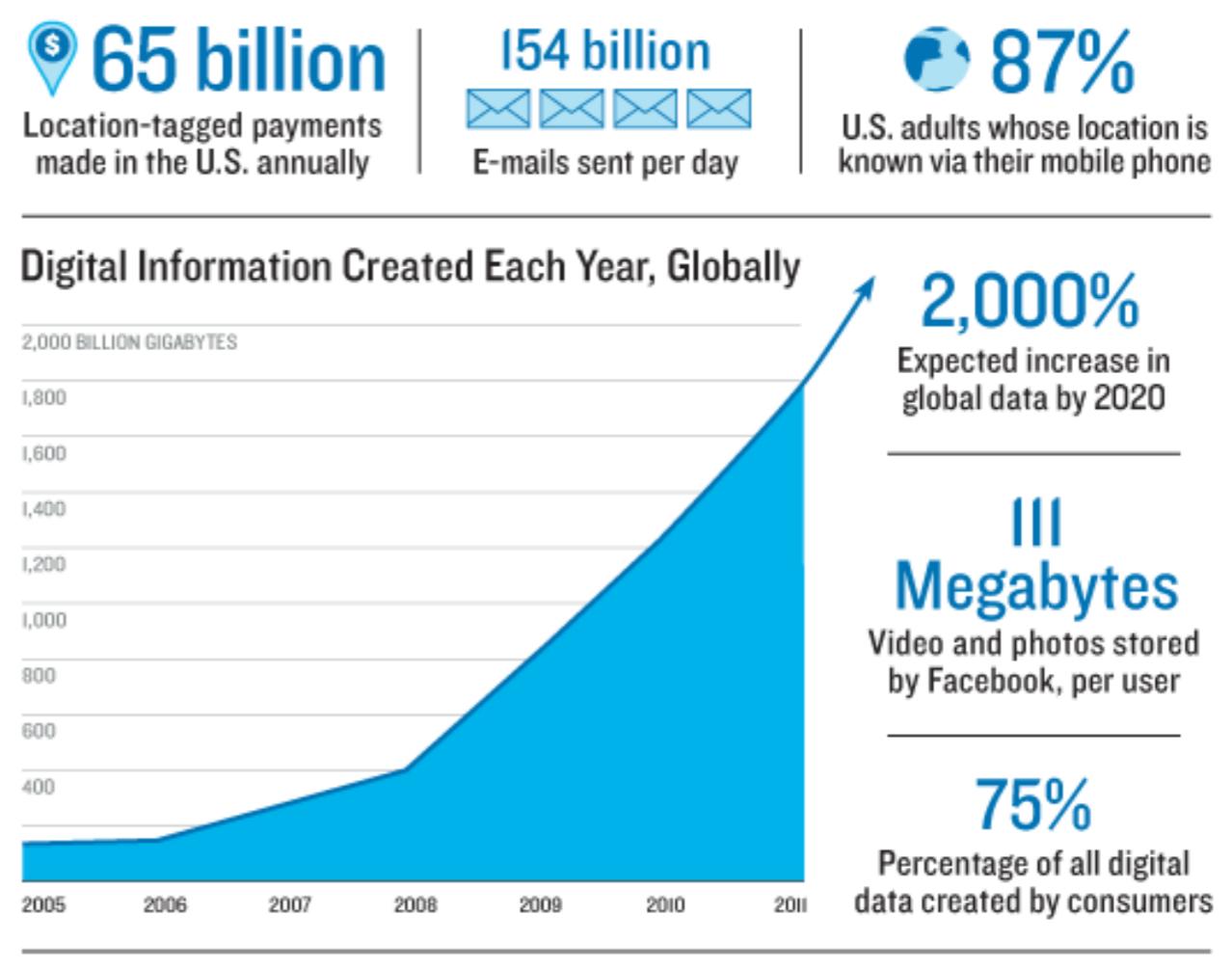
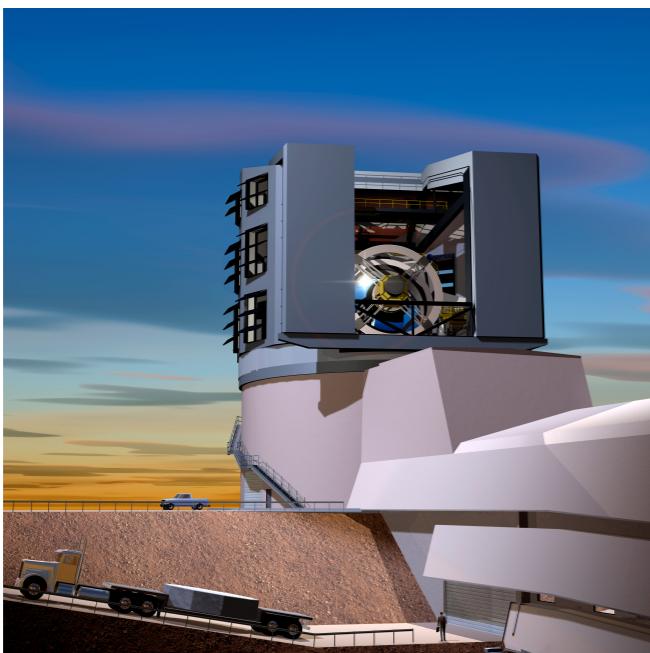
3Vs':

- **Volume (large archives)**
- **Velocity (continuous flow)**
- **Variety (complexity)**

LSST

DR11 37 10^9 objects, 7 10^{12} sources,
5.5 million 3.2 Gigapixel images
30 terabytes of data nightly

Final volume of raw image data = 60 PB
Final image collection (DR11) = 0.5 EB
Final catalog size (DR11) = 15 PB

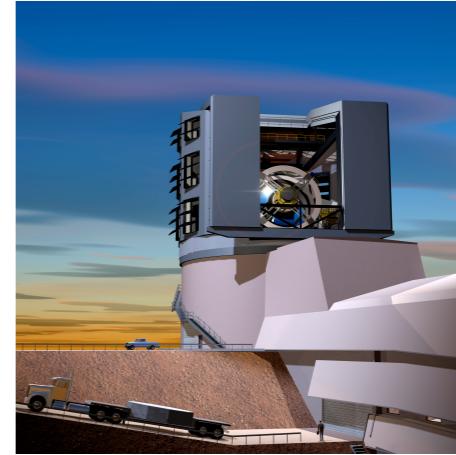


Big Data in a Nutshell

- Data volume doubles every 18 months (Moore's law)

- LSST:

- 10 years long movie of the sky
- 30'000 GB/night (size of entire SDSS)
- 1'000'000 transient alerts/night in differential imaging (faster and more reliable than catalog cross-matching)
- 50% rubbish
- Human time/attention does **not** scale :-)

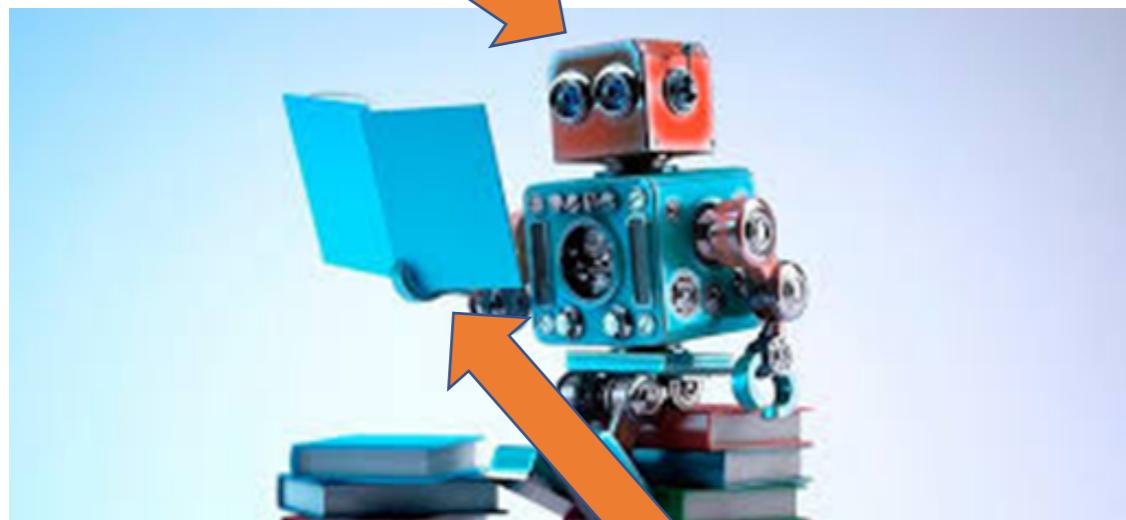


Automated real-time classification is needed!

The Fourth Paradigm: Data-Intensive Scientific Discovery

Era of “Data-driven discoveries”

Machine...



... Learning?!?

'AI IS THE NEW ELECTRICITY'



"Just as electricity transformed almost everything 100 years ago, today I actually have a hard time thinking of an industry that I don't think AI will transform in the next several years."

Andrew Ng

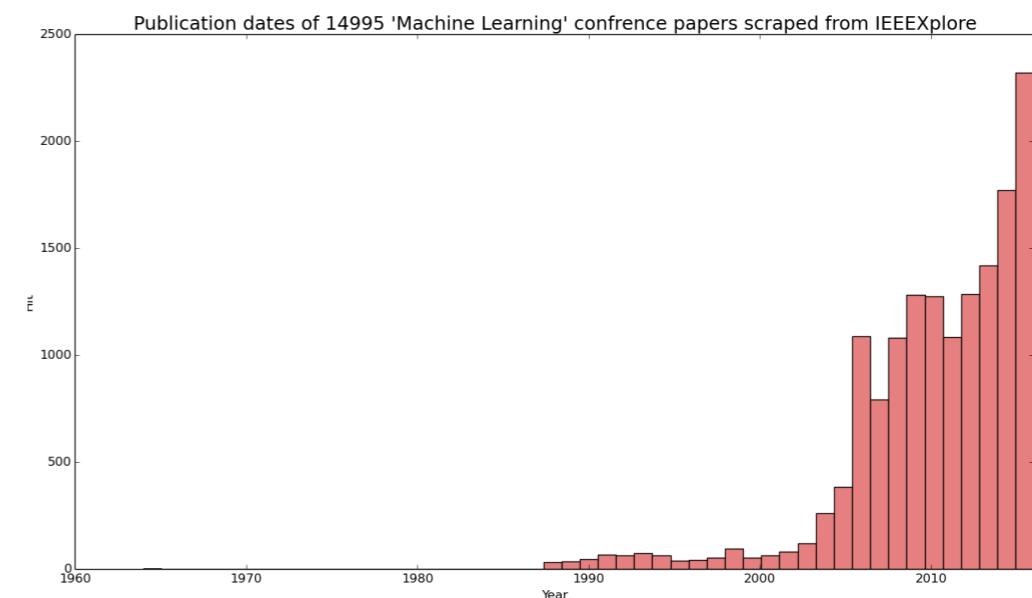
Former chief scientist at Baidu, Co-founder at Coursera

CBINSIGHTS

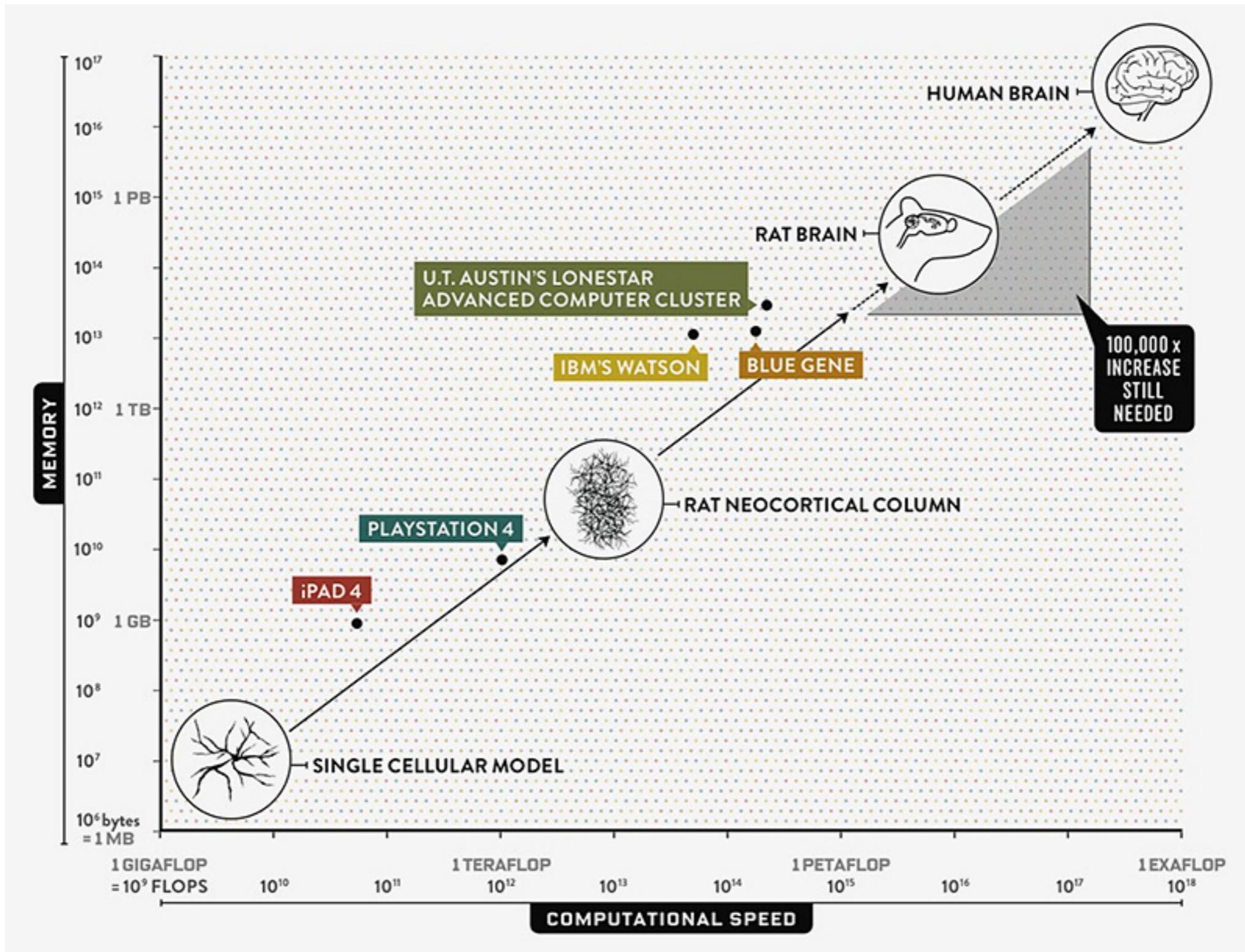
source: <https://www.gsb.stanford.edu/insights/andrew-ng-why-ai-new-electricity>

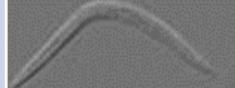
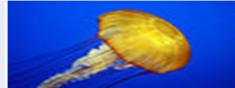
www.cbinsights.com

7



Machine learning algorithms can figure out how to perform tasks by generalising from examples (experience).



Name	# of neurons / # of synapses	Visuals
<i>Caenorhabditis elegans</i>	302	
<i>Hydra vulgaris</i>	5,600	
<i>Homarus americanus</i>	100,000	
<i>Blatta Orientalis</i>	1,000,000	
Nile Crocodile	80,500,000	
Digital Reasoning NN (2015)	~86,000,000 (est.) / 1.6E11	
<i>Rattus Rattatouillensis</i>	200,000,000	
Blue and yellow macaw	1,900,000,000	
Chimpanzee	28,000,000,000	
<i>Homo Sapiens Sapiens</i>	86,000,000,000 / 1.5E14	
African Elephant	257,000,000,000	

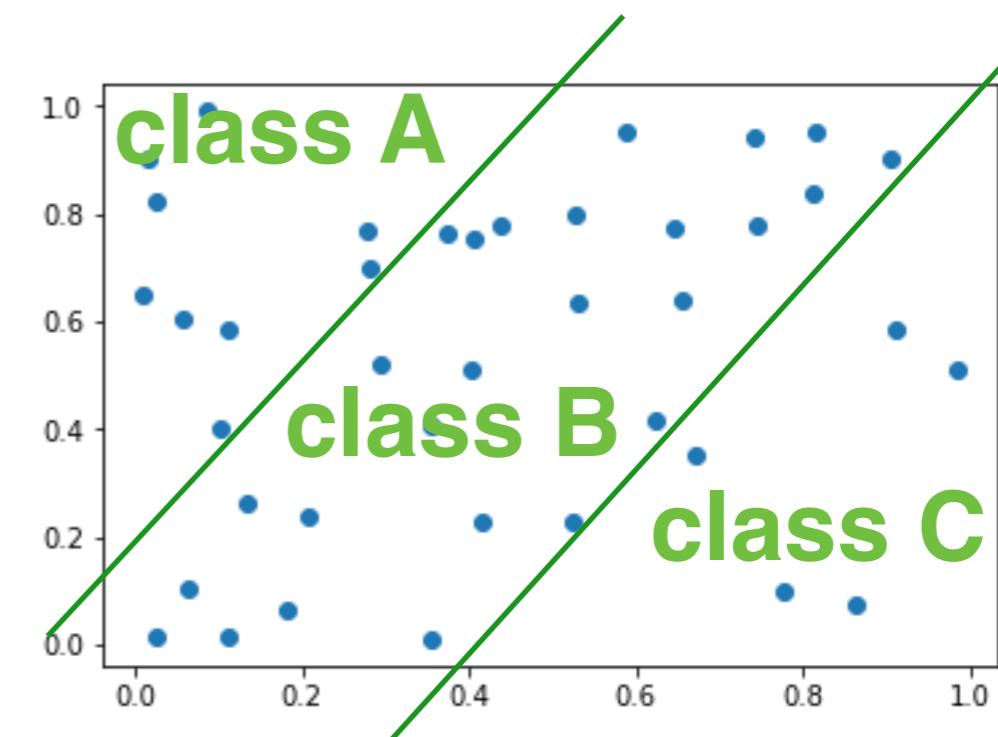
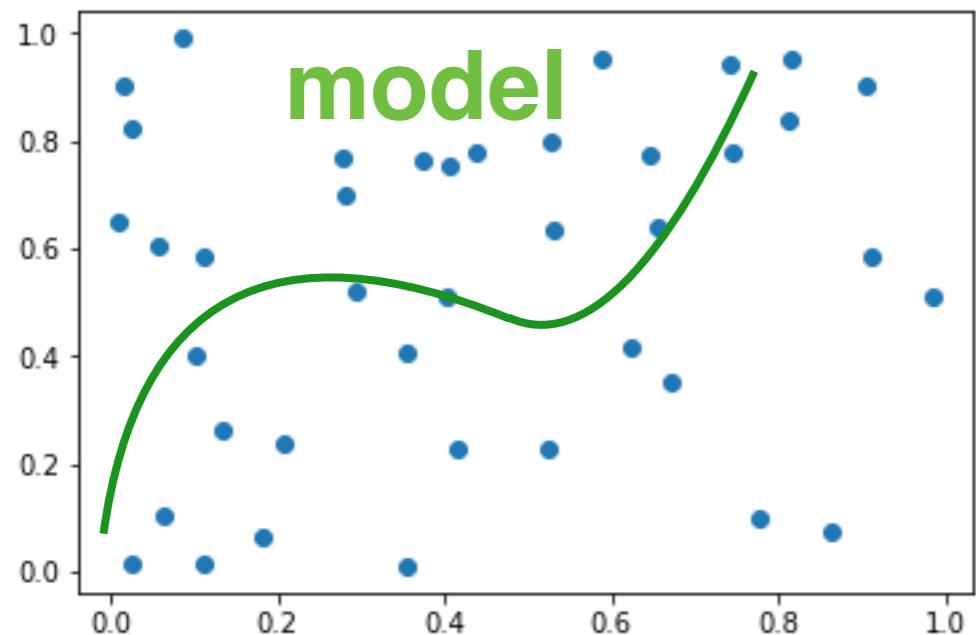
- **Supervised** - classification, regression (fitting)
- **Unsupervised** - clustering, graphs/trees, transformations, typically in multi-dim
- **Semi-supervised**, genetic algorithms, GANs...

The difference between a physicist and an astronomer:

The physicist sees random 2D data and draws a curved line in it saying it's the model that describes the data.

The astronomer draws two parallel lines, saying these points belong to class A, these to class B and this is class C.

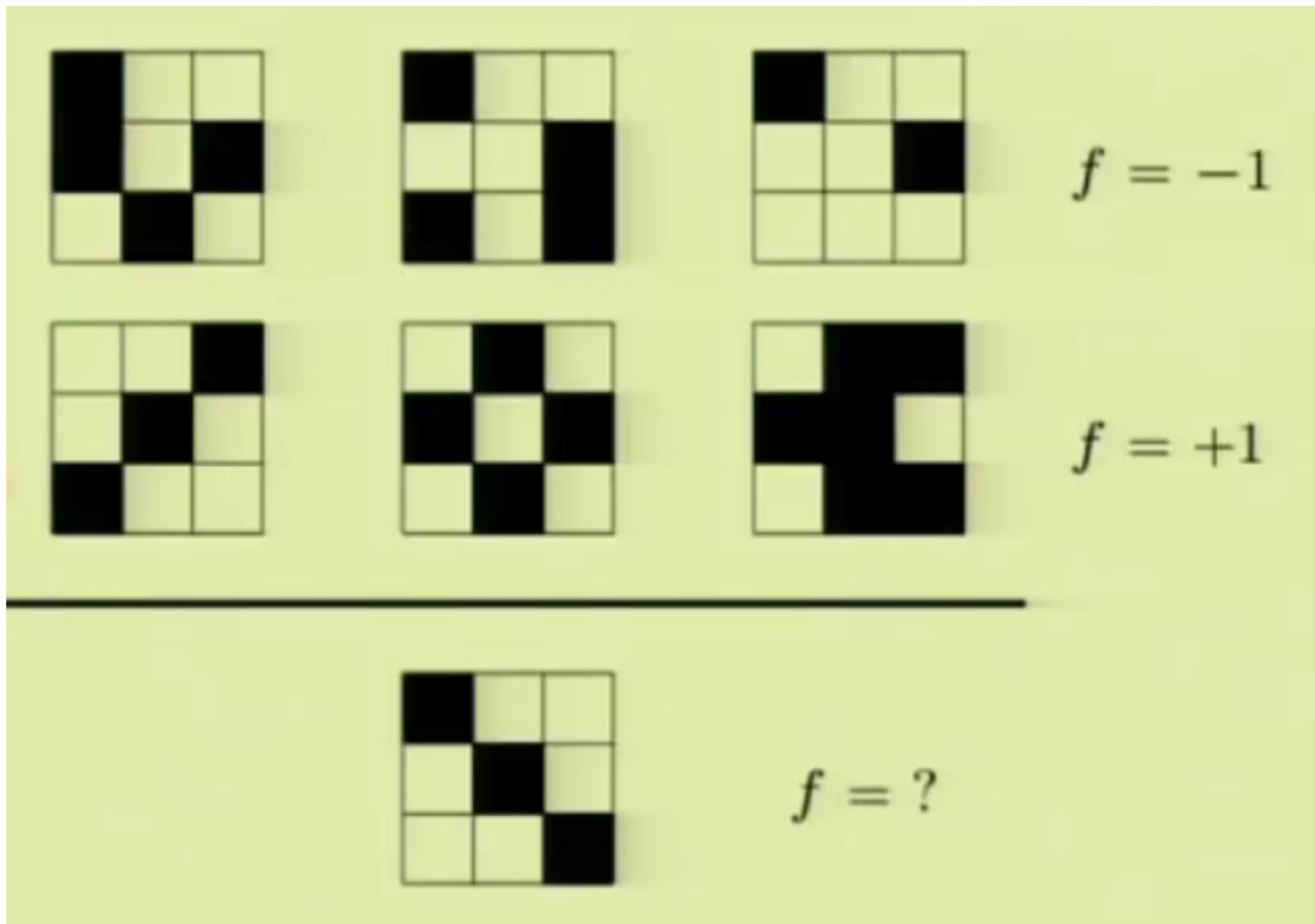
— Andy Lawrence, private communication



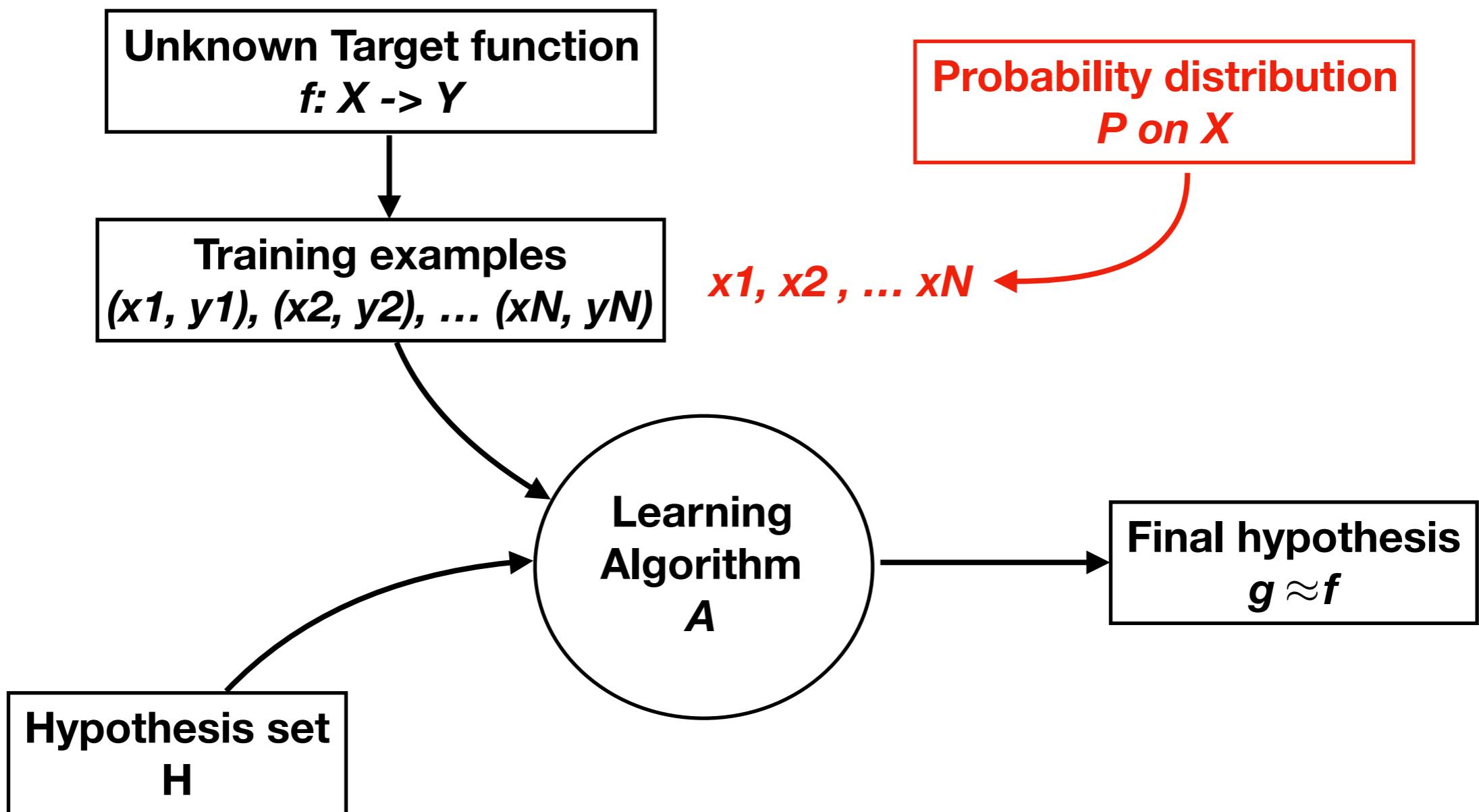
Essentials of Learning

- Pattern must exist
- Mapping “target function” is unknown or expensive to calculate
- We have the data (and computing resources...)
- Data sample is representative

Target function...

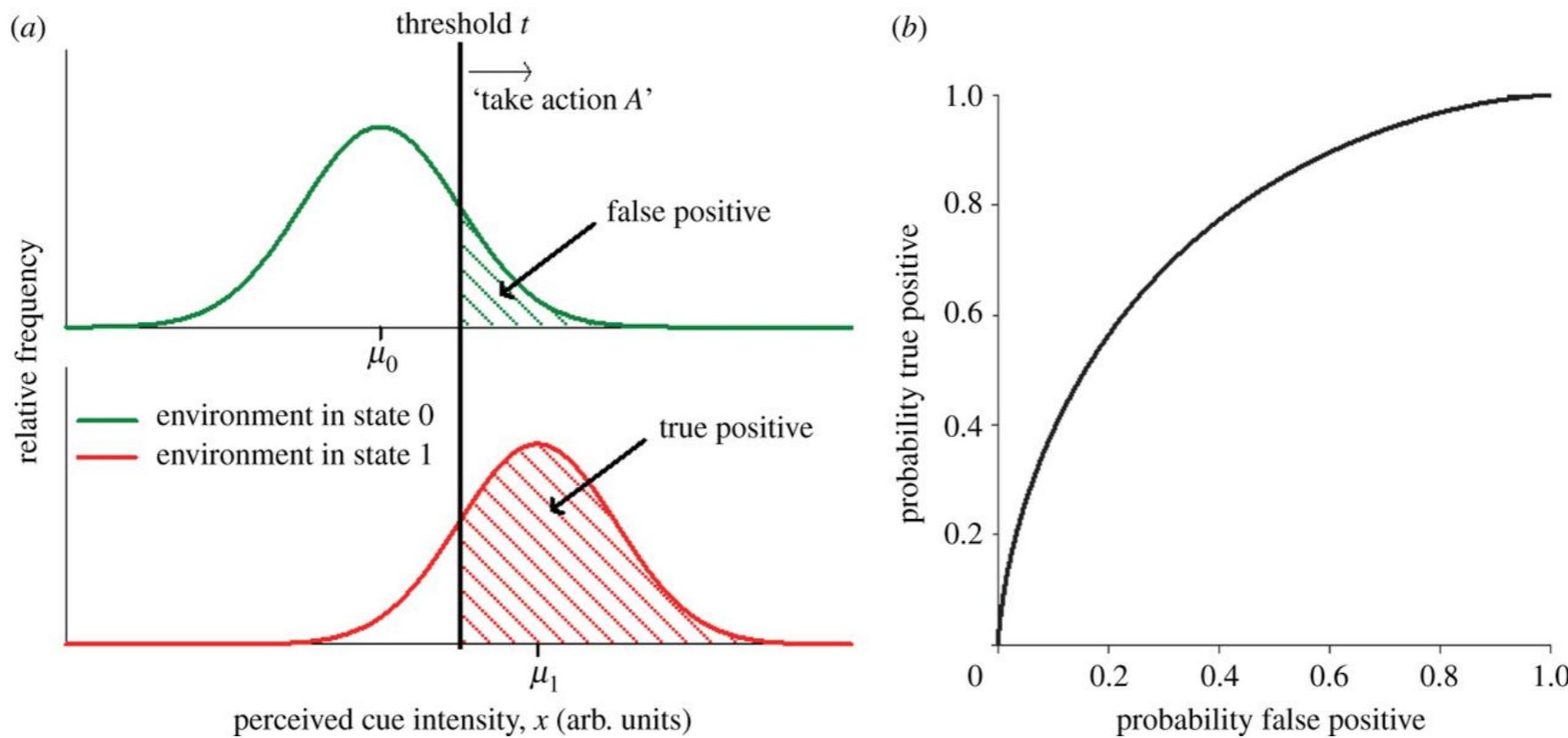


Learning Diagram



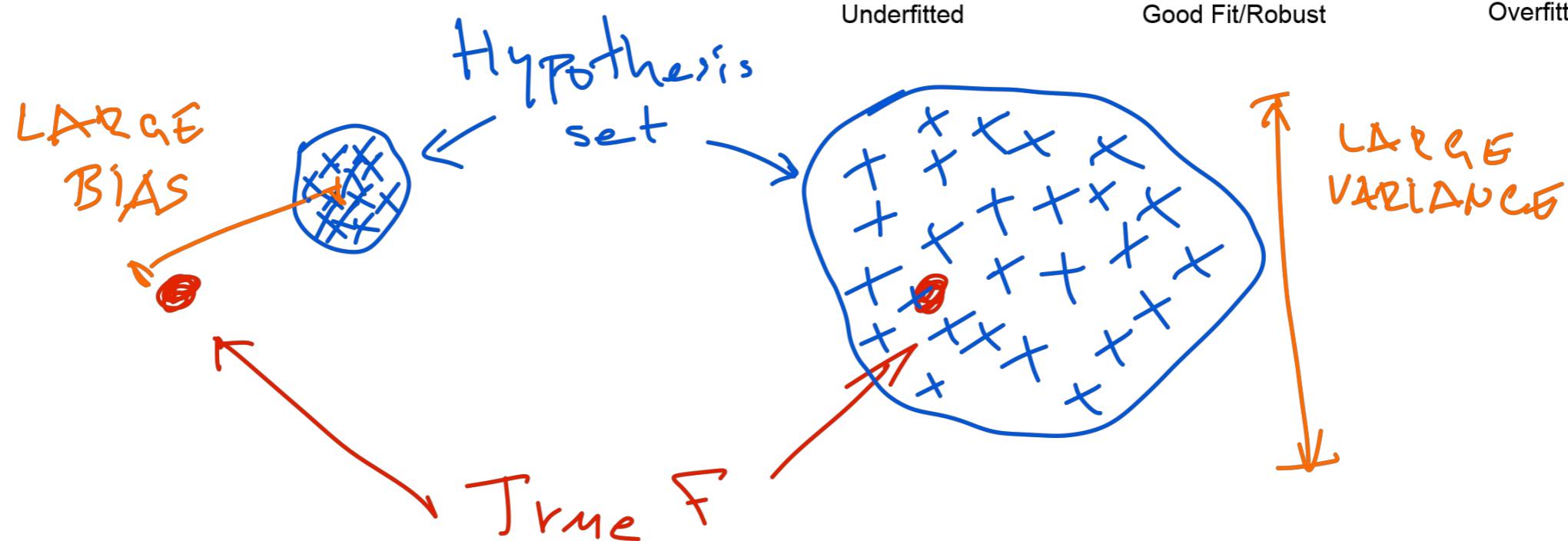
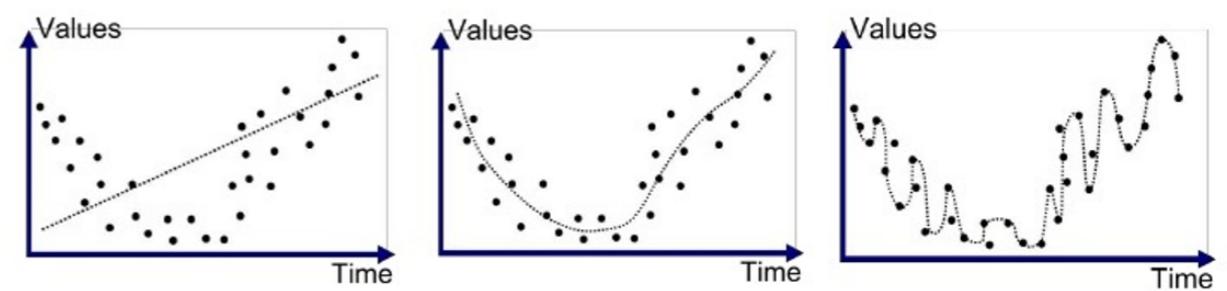
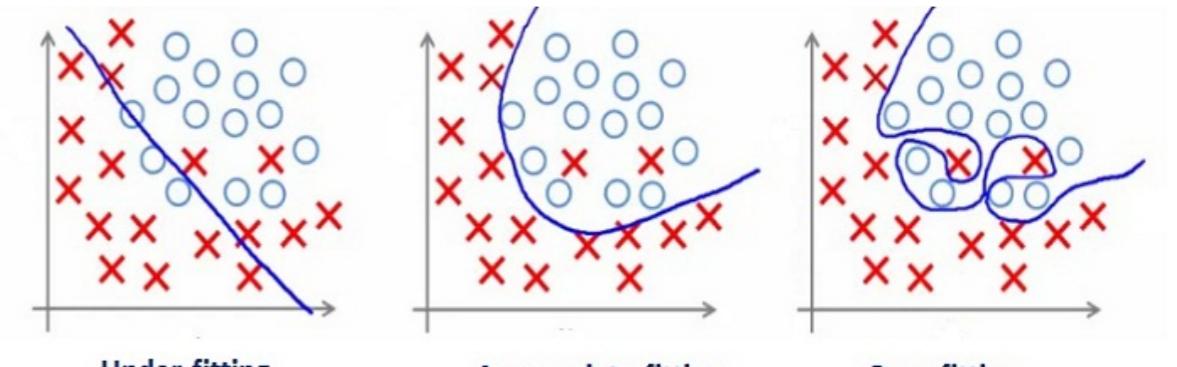
Loss function

- penalty for being wrong
- imbalanced classes

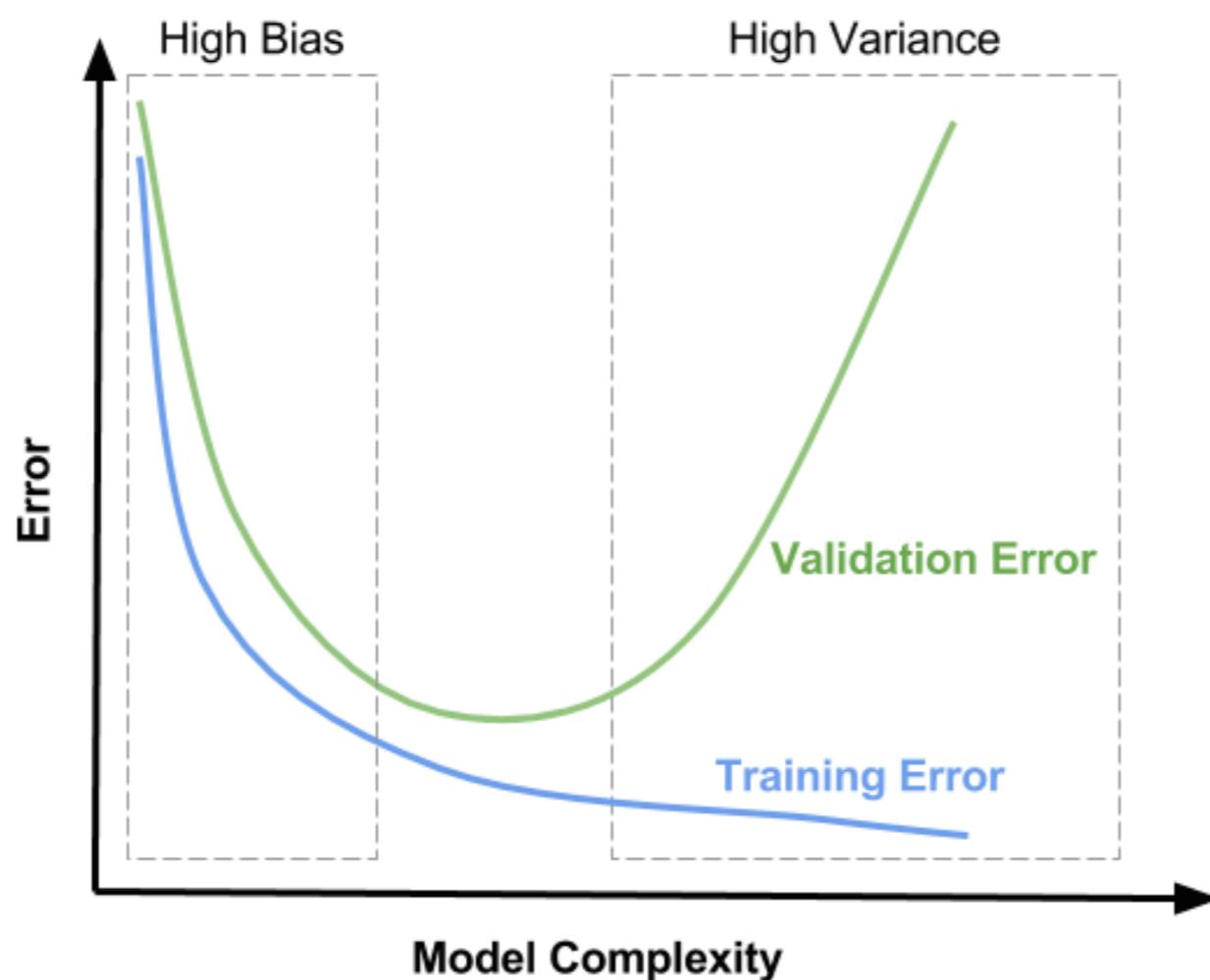


Bias - Variance Trade-off

- Under-fitting/over-fitting
- in sample error vs out of sample error
- VC dimension

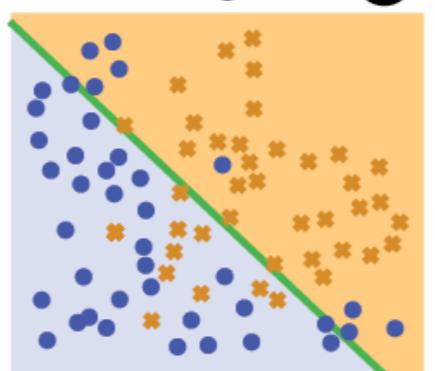


(cross)-Validation



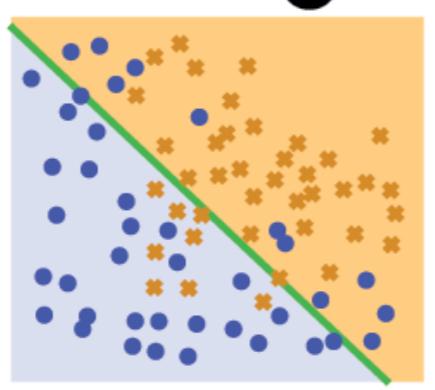
Model 1...

...on Training data. ①



* 30 * 10 error: 22.5%
● 32 ● 8 acc.: 77.5%

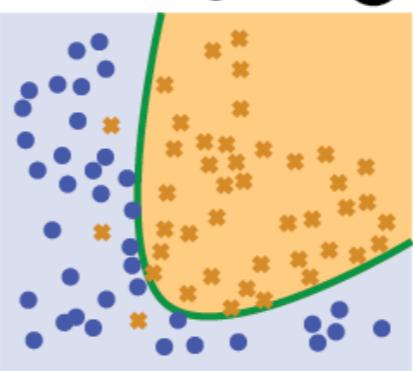
...on Test data. ④



* 32 * 8 error: 23.8%
● 29 ● 11 acc.: 76.2%

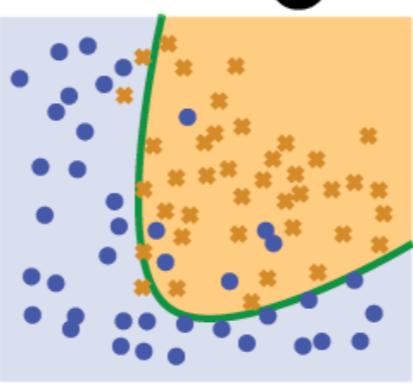
Model 2...

...on Training data. ②



* 37 * 3 error: 7.5%
● 37 ● 3 acc.: 92.5%

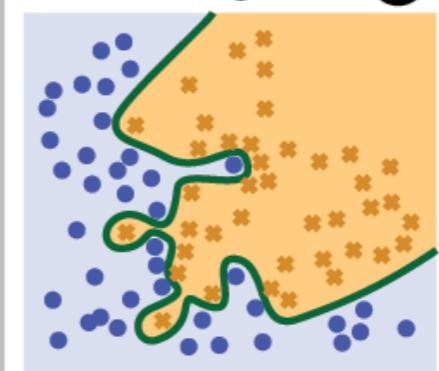
...on Test data. ⑤



* 37 * 3 error: 11.3%
● 34 ● 6 acc.: 88.7%

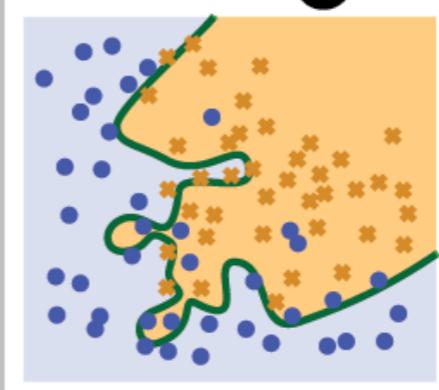
Model 3...

...on Training data. ③

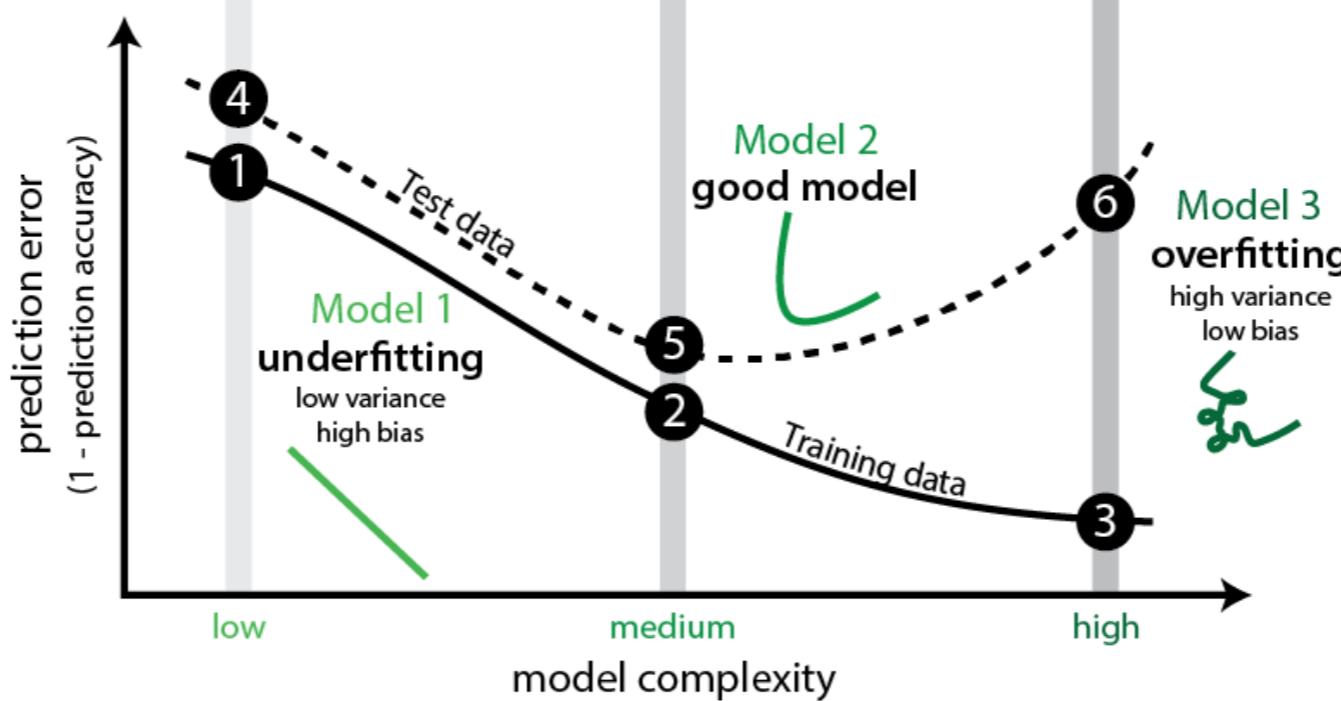


* 37 * 0 error: 0%
● 37 ● 0 acc.: 100%

...on Test data. ⑥



* 34 * 6 error: 21.3%
● 29 ● 11 acc.: 78.7%



	Remedies
High Bias	<ul style="list-style-type: none"> • Train longer • Increase model complexity <ul style="list-style-type: none"> • more features • more parameters, • richer architecture
High Variance	<ul style="list-style-type: none"> • Get more data • Decrease model complexity <ul style="list-style-type: none"> • less features • less parameters, • simpler architecture • Regularization • Early stopping • Drop-out

Data Augmentation:

- When more data are needed, make up new ones! (The way of the god.)
- Translate, rotate, flip, crop, lighten/darken, add noise, dephase, etc.



Cats



Dogs



Machines are lazy and love shortcuts



Dog?



50% dog, 50% cat?

Correlations != Reasoning



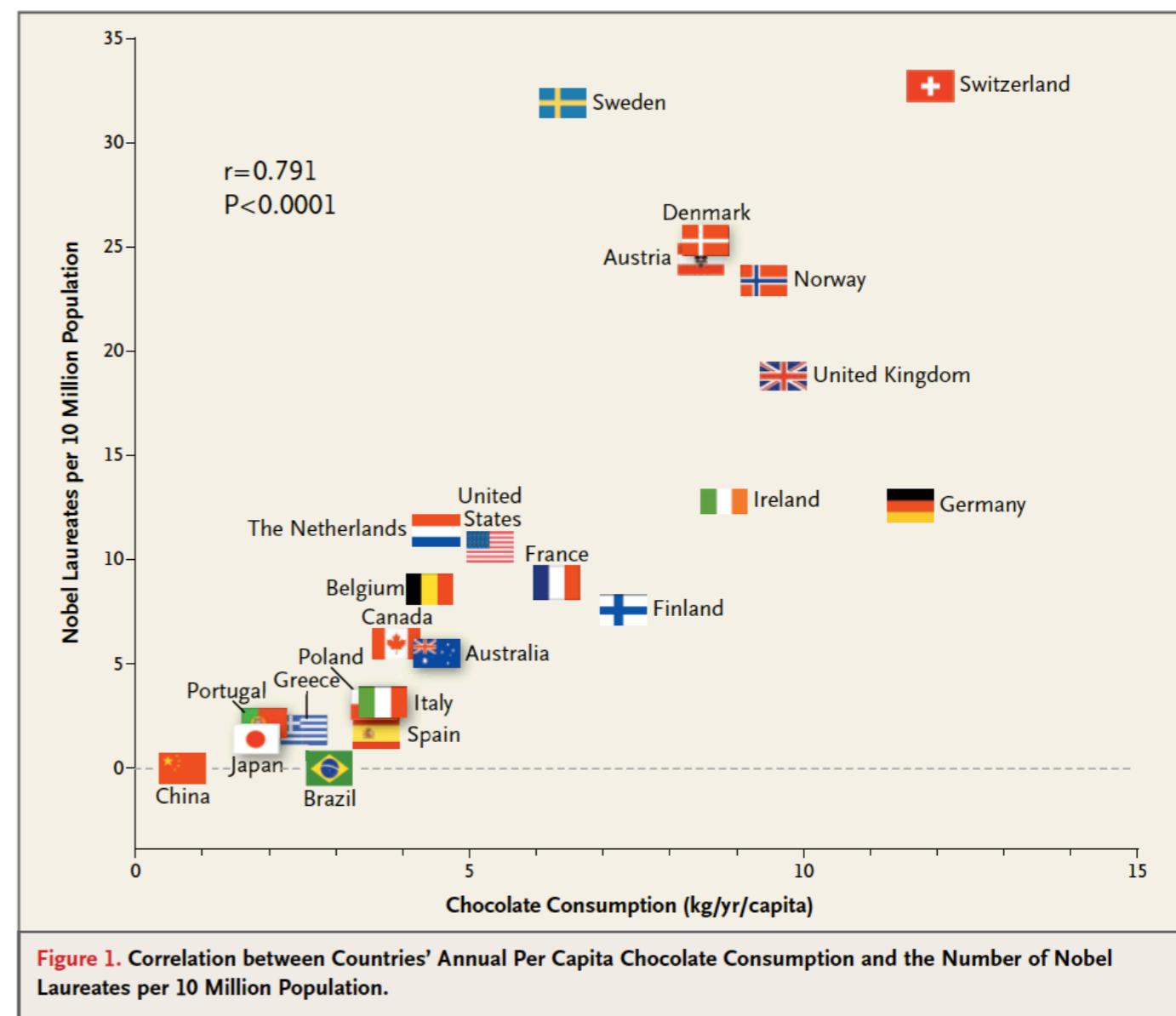
Justin King

@Justinkingnews

Headline: "Women who own horses live longer"

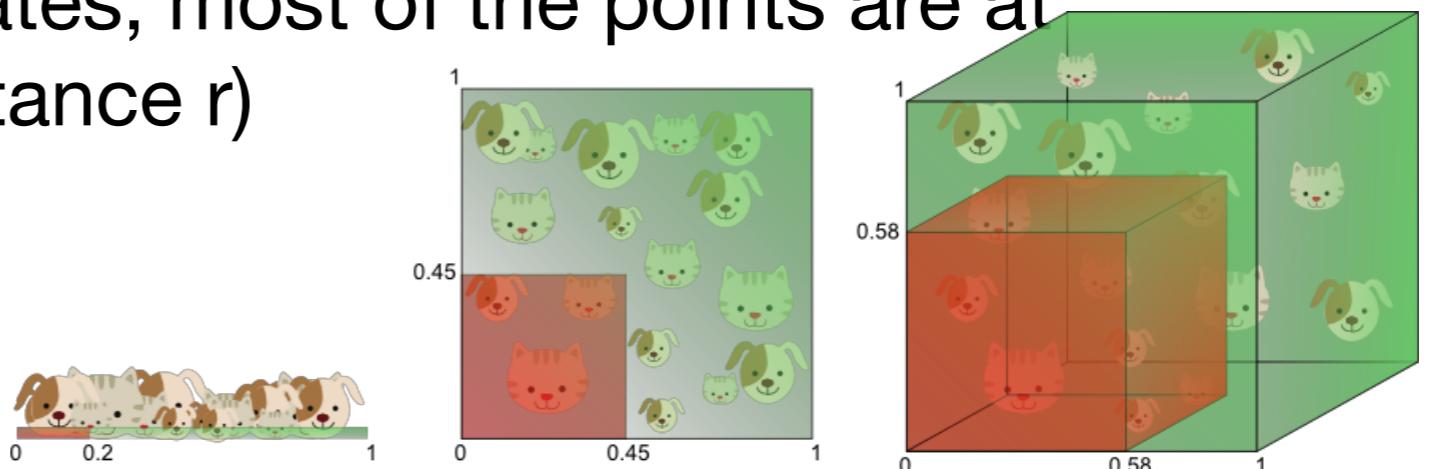
Implied correlation: horses make you live longer.

Reality: if you own a horse, you can probably afford health insurance.



Curse of Dimensionality

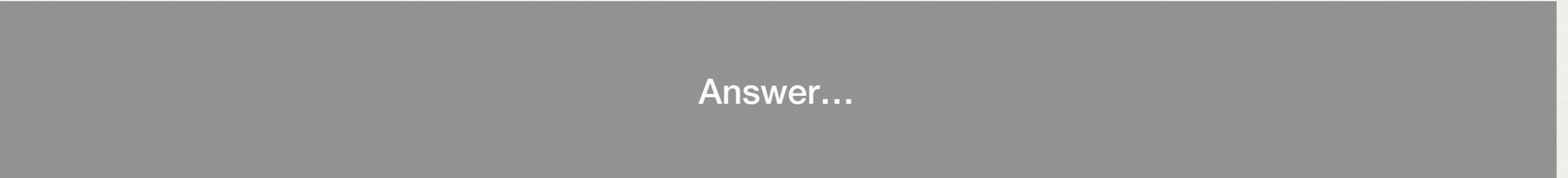
- Too many features
 - Expensive to store
 - Slowing down computation
 - Subject to *Dimensionality curse*
 - Sample space gets harder and harder to fill as dimensions grow
 - A reason why too many features lead to overfitting as data become **sparse**
-
- “*If people can see in multi-dimensions we would not need machine learning*”
 - More and more data needed to fill the same % of space
 - Distance measure degenerates, most of the points are at the surface of a sphere (distance r)



How Many Shades of Gray Can you Distinguish?



Answer...

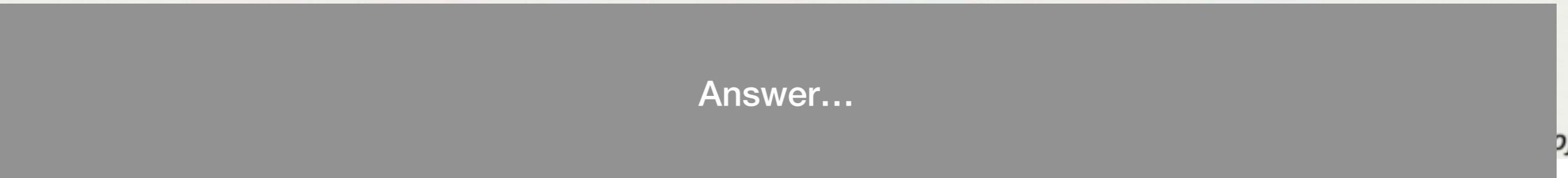


Value encodes continuous variables (less well)

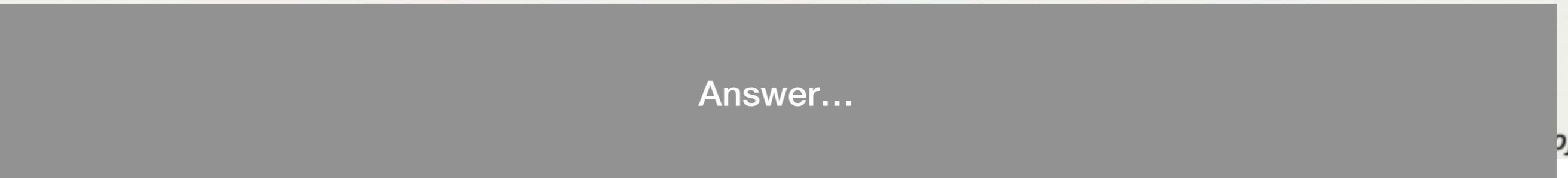
How Many Colors?



Hue encodes nominal variables

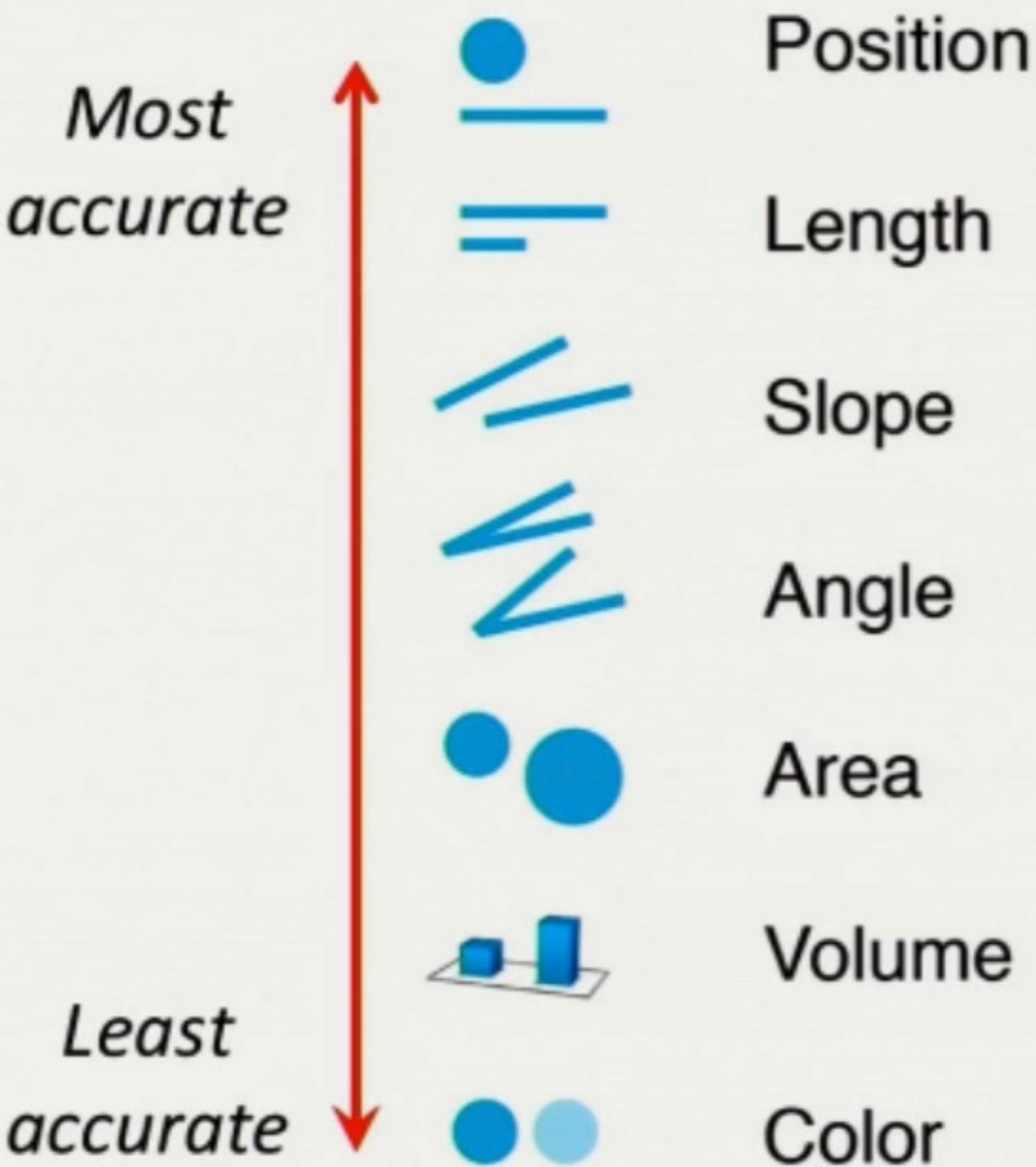


Answer...



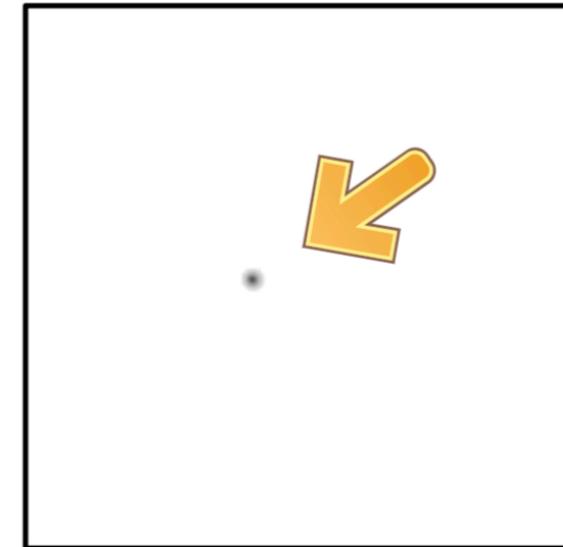
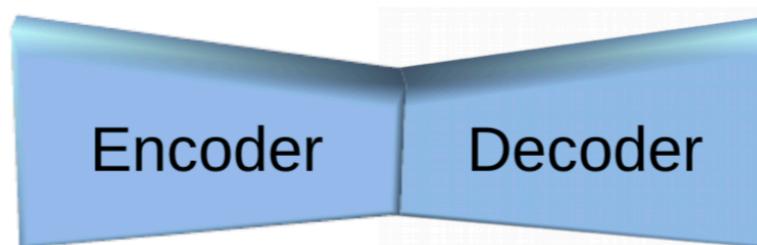
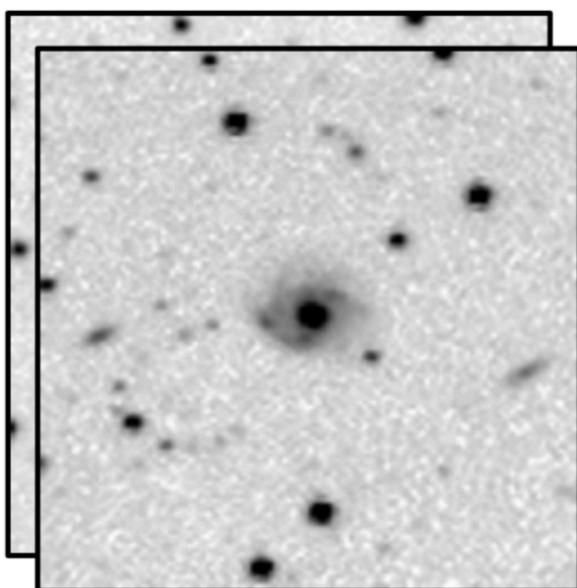
(off)

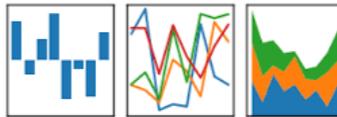
Relative accuracy of the visualisation space axes:

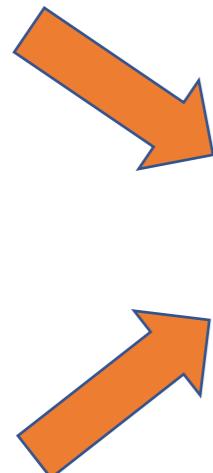


Hands on Sessions

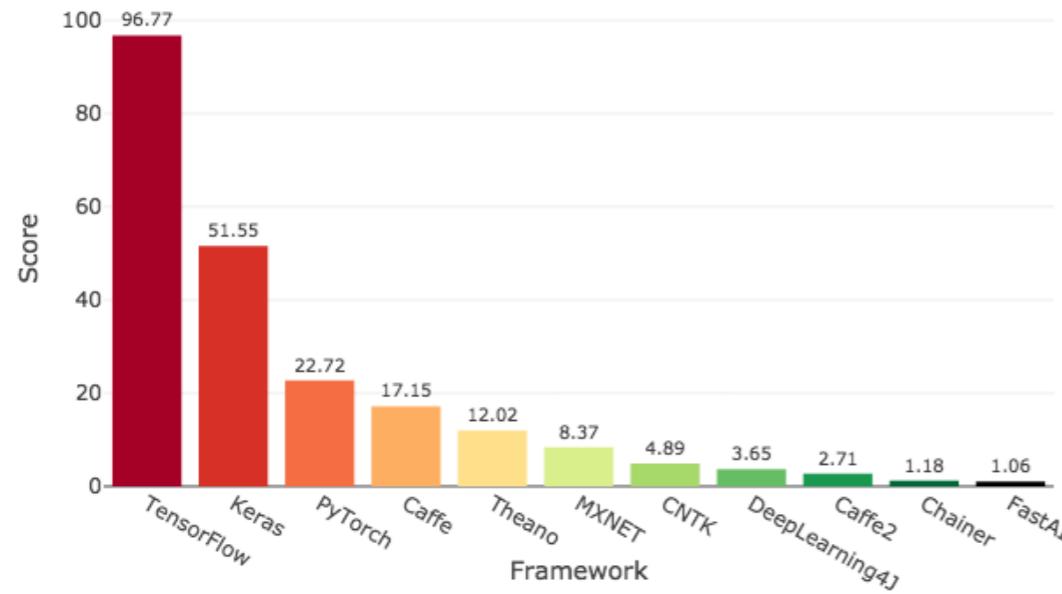
- Galaxy/Star classification (with PCA)
- Regression Photometric redshift with Random Forests
- “voodoo lecture” on Deep Learning with Convolutional Neural Networks on denoising/transient finding



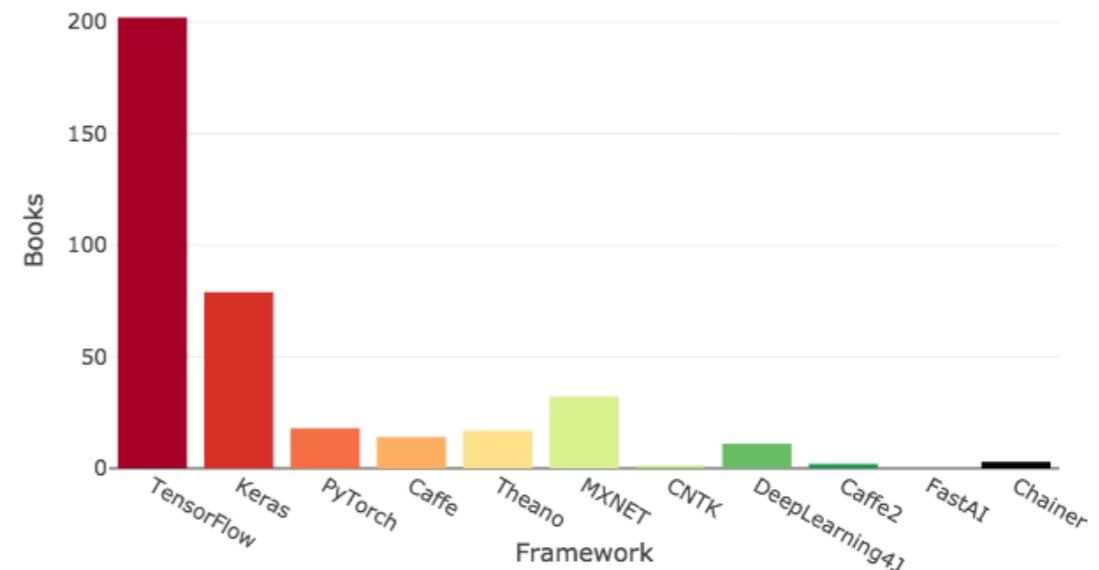
Name	Use	Logo
Pandas	Data Analysis $y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$	pandas 
Spark	Distributed Computing	
Scikit-learn	Machine Learning Toolbox	
Keras	Deep Learning	
TensorFlow	Deep Learning	
Open-cv	Computer Vision	



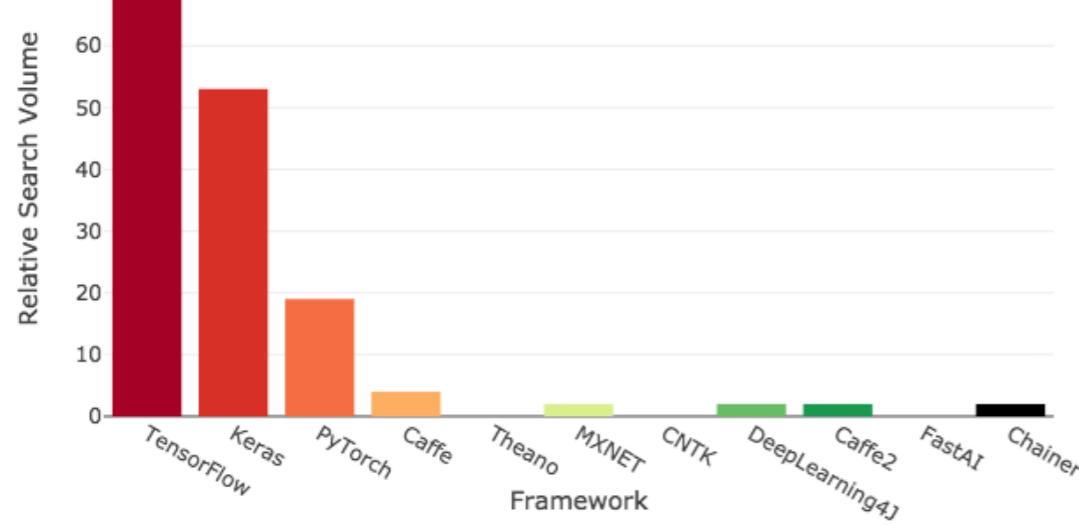
Deep Learning Framework Power Scores 2018



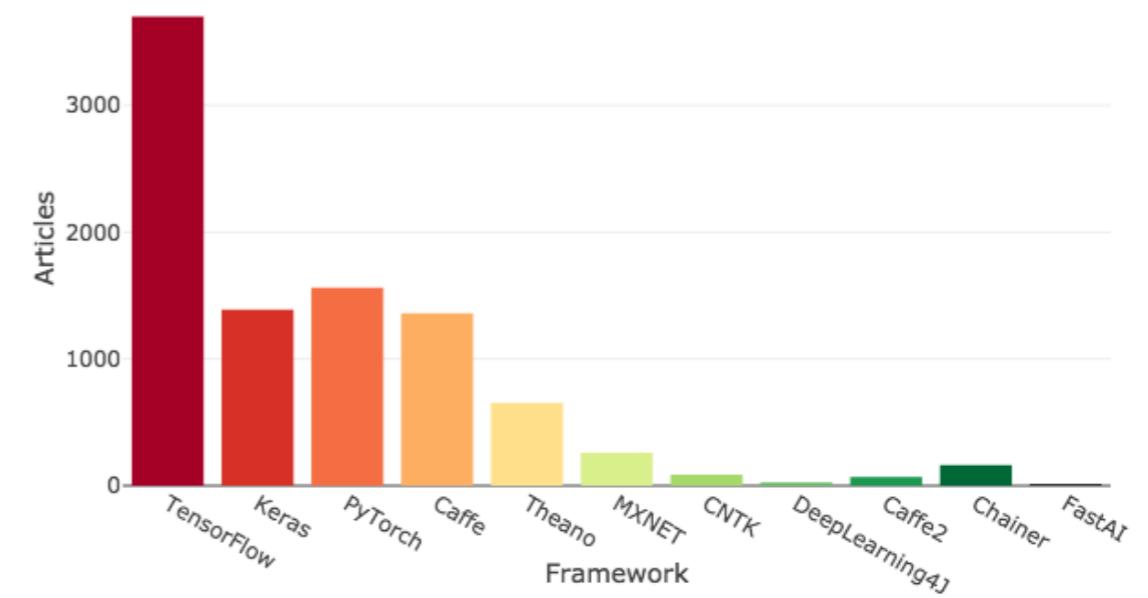
Amazon Books



Google Search Volume



ArXiv Articles



Software prerequisites

- Python 3
- Anaconda anaconda.org with Python 3.7
- You may create an environment
`conda create --name=ml python=3.6`
- *scikit-learn, pandas, scikit-image, seaborn, tensorflow, keras* (anaconda may suggest to downgrade some of the libraries to Python 3.6, but it's ok, the environment works as an independent container)
`conda install xxx or conda install -c conda-forge xxx`
- `conda update conda ; conda update anaconda ; conda update xxx`
- Cheat sheets...

Intel...

- conda create -n intelpython --override-channels --channel intel python=3.5 intelpython scipy pydaal anaconda scikit-learn

ML seminar

- Aka astro-ph
- an algorithm overview, usage
- publications together?
- 1x every 2 weeks or month?