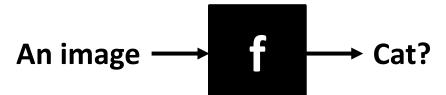
Course Overview

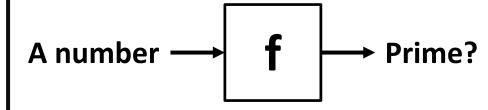
Trần Trung Kiên ttkien@fit.hcmus.edu.vn



Machine learning



Not machine learning



We KNOW f

Do you think you can write down a function to recognize cats?





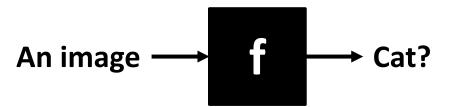




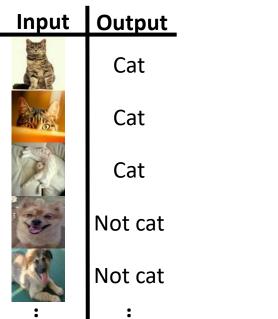


Image source: Fei-Fei Li's TED talk

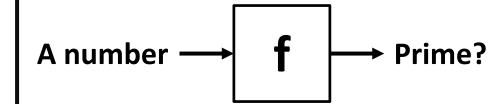
Machine learning



We do NOT KNOW f, but we have DATA which can be used to approximate f



Not machine learning

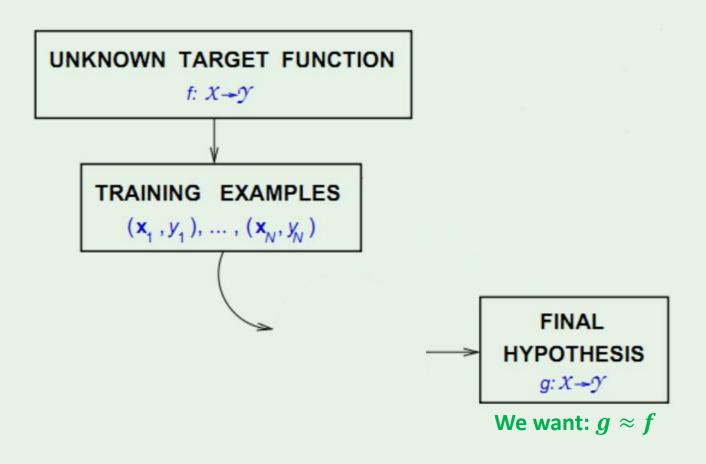


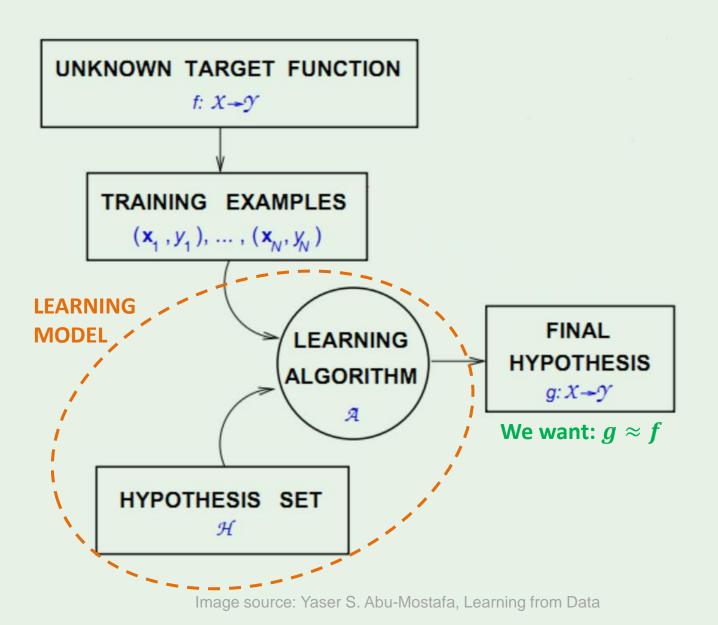
We KNOW f



Conditions to apply machine learning

- A pattern exists
- We cannot pin it down mathematically
- We have data on it







Examples: machine learning or not?

- Speech recognition
- Determining the time it would take a falling object to hit the ground
- Predicting whether you will pass this course or not



ML can be used in a lot of fields

- Computer vision
- □ NLP
- Medicine
- Economics
- ...

Handwritten digit recognition

← → C 🕆 🗋 yann.lecun.com/exdb/mnist/							
Convolutional net LeNet-4	none	none				1.1	
Convolutional net LeNet-4 with K-NN instead of last layer MNIST Samples							1.1
Convolutional net LeNet-4 with local learni	IMINIST 3	ampies					1.1
Convolutional net LeNet-5, [no distortions]	10	4	9.	<			0.95
Convolutional net LeNet-5, [huge distortion		-/	3)			0.85
Convolutional net LeNet-5, [distortions]	2 1	1	2	0			0.8
Convolutional net Boosted LeNet-4, [distor) 1	ı)				0.7
Trainable feature extractor + SVMs [no dist	2 2	-1	0	A			0.83
Trainable feature extractor + SVMs [elastic	1 0	4	8	9			0.56
Trainable feature extractor + SVMs [affine	, –	,	4				0.54
unsupervised sparse features + SVM, [no di	45	ક	8	7			0.59
Convolutional net, cross-entropy [affine dis				•			0.6
Convolutional net, cross-entropy [elastic dis	7 7	ч	5	Ø			0.4
large conv. net, random features [no distorti	, .		\mathcal{L}	•			0.89
large conv. net, unsup features [no distortion	7 2	7	Ø	7			0.62
large conv. net, unsup pretraining [no distor	, –		0				0.60
large conv. net, unsup pretraining [elastic di							0.39
large conv. net, unsup pretraining [no distortions]			none Better		Better t	han	0.53
large/deep conv. net, 1-20-40-60-80-100-120-120-10 [elastic distortions]			e		human ©		0.35
committee of 7 conv. net, 1-20-P-40-P-150-10 [elastic dis	wid	width normalization				27 +-0.02	
committee of 35 conv. net, 1-20-P-40-P-150-10 [elastic distortions]			width normalization				0.23

The ILSVRC-2012 competition on ImageNet

- The dataset has 1.2 million highresolution training images.
- The classification task:
 - Get the "correct" class in your top 5 bets. There are 1000 classes.
- The localization task:
 - For each bet, put a box around the object. Your box must have at least 50% overlap with the correct box.

- Some of the best existing computer vision methods were tried on this dataset by leading computer vision groups from Oxford, INRIA, XRCE, ...
 - Computer vision systems use complicated multi-stage systems.
 - The early stages are typically hand-tuned by optimizing a few parameters.







University of Toronto (Alex Krizhevsky)

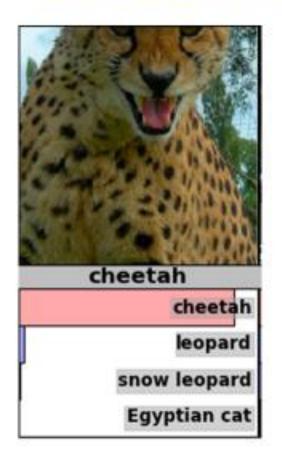
16.4%

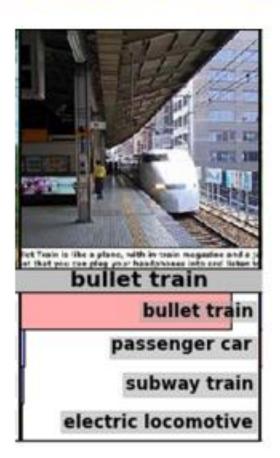
34.1%

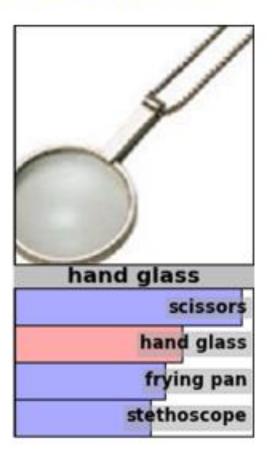
Error rates on the ILSVRC-2012 competition

		cla	essification	classification & localization
•	University of Tokyo	•	26.1%	53.6%
•	Oxford University Computer Vision Group	•	26.9%	50.0%
•	INRIA (French national research institute in CS) + XRCE (Xerox Research Center Europe)	•	27.0%	
•	University of Amsterdam	•	29.5%	

Examples from the test set (with the network's guesses)









Clarifai (ImageNet 2013 winner)

See how well computers can understand images



band stage concert music club rock show



garden kid flower woman child tree



dog winter snow



street alley old mexico italian



metal key door old lock wood



climb rock climber mountain sport



Go beyond object recognition: image captioning



"man in black shirt is playing guitar."



"construction worker in orange safety vest is working on road."



"two young girls are playing with lego toy."



"girl in pink dress is jumping in air."



"black and white dog jumps over bar."



"young girl in pink shirt is swinging on swing."



Machine learning (ML) is hot nowadays

- ☐ Why?
 - Data get bigger and bigger
 - Computers get faster and faster
- If you want to be in academia, ML is a good place for you.
- If you want to be in industry, ML is a good place for you too.
 - In big IT companies like Google, Facebook, ..., ML is one of the most important skills.
 - □ In Viet Nam, recently some ML companies have emerged ☺.



Types of learning

- The type of learning we have talked about so far is called supervised learning
 - data have the form: (input, correct output)
 - It'll be the main focus in this course
- There are other types of learning out there
 - Unsupervised learning
 - (input)
 - Reinforcement learning
 - (input, some output, grade for this output)
 - **-** ...

Course contents:

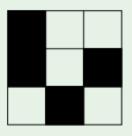
After successful completion of this course, you will be able to:

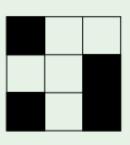
What is machine learning? —> Explain what machine learning is

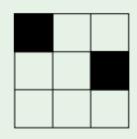
Can a machine learn?



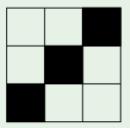
Can a machine learn?

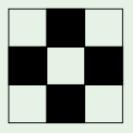


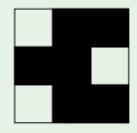




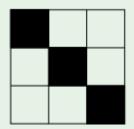
$$f = -1$$







$$f = +1$$



$$f = ?$$

Course contents:

- What is machine learning?
- Can a machine learn?
- How to learn?
- How to learn well?

After successful completion of this course, you will be able to:

Explain what machine learning is

Explain why a machine can learn

Explain learning models and implement them (in Python)

Analyze results when applying a learning model to a dataset, and propose solutions to improve results

Listen and read provided English materials



How do we teach and learn?

- We will follow the excellent online course taught by Caltech Professor Yaser Abu-Mostafa
 - Why excellent?



A ML jungle out there

1				
semi-supervised learning	overfitting	stochastic gradient d	descent SVM	Q learning
Gaussian p istribution-free	C :		snooping	earning curves
collaborative filtering	nonlinear transform	C dimension sampling		mixture of expe
decision trees	RBF tra	aining versus testing	noisy targets	no free Bayesian prior
active learnin	J Illical Illouels	bias-variance tra	adeoff weak	learners
ordinal regression	cross validation	logistic regression	data contamination	
ensemble learning		types of learning	perceptrons 1	hidden Markov mo
ploration versus exploitat	error measures tion	kernel methods	~ .	cal models
	is learning feasible	? soft	t-order constrain	
clustering	regularization	weight decay	Occam's razor	Boltzmann maci

Caltech course teaches the foundations of ML so that you can go further in the future easily



How do we teach and learn?

- We will follow the excellent online course taught by Caltech Professor Yaser Abu-Mostafa
- There are 18 video lectures and we have 15 weeks
 - Weeks 01 → 02: video lecture 01 + Python
 - \square Weeks 03 \rightarrow 15: video lectures 02 \rightarrow 14
 - □ You'll drink coffee and watch video lectures 15 → 16 at home
 - □ Video lectures 17 → 18 are optional



How do we teach and learn?

- Before class, you will watch the video lecture I require, and post to the forum at least one question
- In class, I will explain this video lecture and answer some questions
 - □ If you don't watch the video before, you may find it difficult to follow
- After class, you will pick at least one question and post your answer to the forum



How are students assessed?

- Exercises (40% of the grade)
 - 1 exercise / 2 video lectures
 - Total: 6 exercises / 12 video lectures (01→12)
 - Each exercise includes both theoretical and programming questions
 - Programming language: Python (+ NumPy)
 - It allows us to implement ML models very quickly
 - Jupyter Notebook is awesome (text + live code + latex)



How are students assessed?

- □ Final project (50% of the grade)
 - Train SVM (a state-of-the-art learning model) to classify images of hand-written digits
 - ☐ Group?
 - Present on the final exam day
- □ Forum Q & A (10% of the grade)
 - ☐ Easy to get this 10%
 - Penalize spam



How are students assessed?

- Remember: the main goal is to learn, truly learn
- You can discuss ideas with others, but your writing and code must be your own, based on your own understanding
- □ If you violate this rule, you will get 0 score for the course



Last slide

This course will be difficult (3)

But if you can enjoy difficulties, focus on your own learning, eliminate noise, ...

... you will be able to grasp the foundations of ML ©