UVA CS 6316 / CS 4501 – Fall 2015 : Machine Learning

Lecture 1: Introduction

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University of Virginia
Department of
Computer Science

Welcome

- CS 6316/4501 Machine Learning
  - MoWe 3:30pm-4:45pm,
  - Olsson Hall 120

- http://www.cs.virginia.edu/yanjun/teach/2016f

- Your UVA collab: Course 6316-4501 page

Today

- ❑ **Course Logistics**
- ❑ My background
- ❑ Basics and rough content plan
- ❑ Application and History

Course Staff

- Instructor: Prof. Yanjun Qi
  - QI: /ch ee/
  - You can call me “professor”, “professor Jane”, “professor Qi”;
- TA office hours: Mon & Wed 5:30pm pm-6:30 pm @ Rice 504
- My office hours: Mon 5pm-6pm @ Rice 503

Course Logistics

- Course email list has been setup. You should have received emails already !

- Policy, the grade will be calculated as follows:
  - Assignments (55%, **Six** total, each ~9%)
  - Quizzes / Exam Sample Practices (5%)
  - Midterm exam (20%)
  - Final exam (20%)

Course Logistics

- Midterm: Oct, 75mins in class
- Final: Dec, 75mins in class

- Six assignments (each 9% to 10%)
  - **Three** extension days policy (check course website)

- In-class quizzes / Exam sample practice (total 5%)

Course Logistics

- Policy,
  - Homework should be submitted electronically through UVaCollab
  - Homework should be finished individually
  - Due at midnight on the due date
  - In order to pass the course, the average of your midterm and final must also be "pass".

Late Homework Policy

- Each student has **three** extension days to be used at his or her own discretion throughout the entire course. Your grades would be discounted by 15% per day when you use these 3 late days. You could use the 3 days in whatever combination you like. For example, all 3 days on 1 assignment (for a maximum grade of 55%) or 1 each day over 3 assignments (for a maximum grade of 85% on each). After you've used all 3 days, you cannot get credit for anything turned in late.

Course Logistics

- Text books for this class is:
  - NONE

- My slides – **if it is not mentioned in my slides, it is not an official topic of the course**

Course Logistics

- **Background Needed**
  - Calculus, Basic linear algebra, Basic probability and Basic Algorithm
  - Statistics is recommended.
  - Students should already have good programming skills, i.e. python is required for all programming assignments
  - We will review "linear algebra" and "probability" in class

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About Me

- Education:
  - PhD from School of Computer Science, Carnegie Mellon University (@ Pittsburgh, PA) in 2008
  - BS from Department of Computer Science, Tsinghua Univ. (@ Beijing, China)
    - My accent **PATTERN** : /l/, /n/,/ou/, /m/
- Research interests:
  - **Machine Learning, Biomedical applications**

About Me

- Five Years' of Industry Research Lab in the past :
  - 2008 summer – 2013 summer, **Research Scientist in IT** industry (Machine Learning Department, NEC Labs America @ Princeton, NJ)
  - 2013 Fall – Present, **Assistant Professor**, Computer Science, UVA

Industry + Academia

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OUR DATA-RICH WORLD

- Biomedicine
  - Patient records, brain imaging, MRI & CT scans, …
  - Genomic sequences, bio-structure, drug effect info, …
- Science
  - Historical documents, scanned books, databases from astronomy, environmental data, climate records, …
- Social media
  - Social interactions data, twitter, facebook records, online reviews, …
- Business
  - Stock market transactions, corporate sales, airline traffic, …
- Entertainment
  - Internet images, Hollywood movies, music audio files, …

BIG DATA CHALLENGES

- Data capturing (sensor, smart devices, medical instruments, et al.)
- Data transmission
- Data storage
- Data management
- High performance data processing
- Data visualization
- Data security & privacy (e.g. multiple individuals)
- ……

e.g. cloud computing

e.g. HCI

this course

- Data analytics
  - How can we analyze this big data wealth ?
  - E.g. Machine learning and data mining

BASICS OF MACHINE LEARNING

- "The goal of machine learning is to build computer systems that can learn and adapt from their experience." – Tom Dietterich
- "Experience" in the form of available data examples (also called as instances, samples)
- Available examples are described with properties (data points in feature space X)

e.g. SUPERVISED LEARNING

- Find function to map input space X to output space Y $f : X \longrightarrow Y$
- So that the difference between *y* and *f(x)* of each example ***x*** is small.

e.g.

x

I believe that this book is not at all helpful since it does not explain thoroughly the material . it just provides the reader with tables and calculations that sometimes are not easily understood …

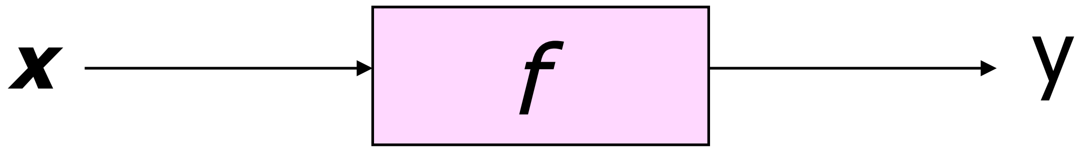
Input X : e.g. a piece of English text

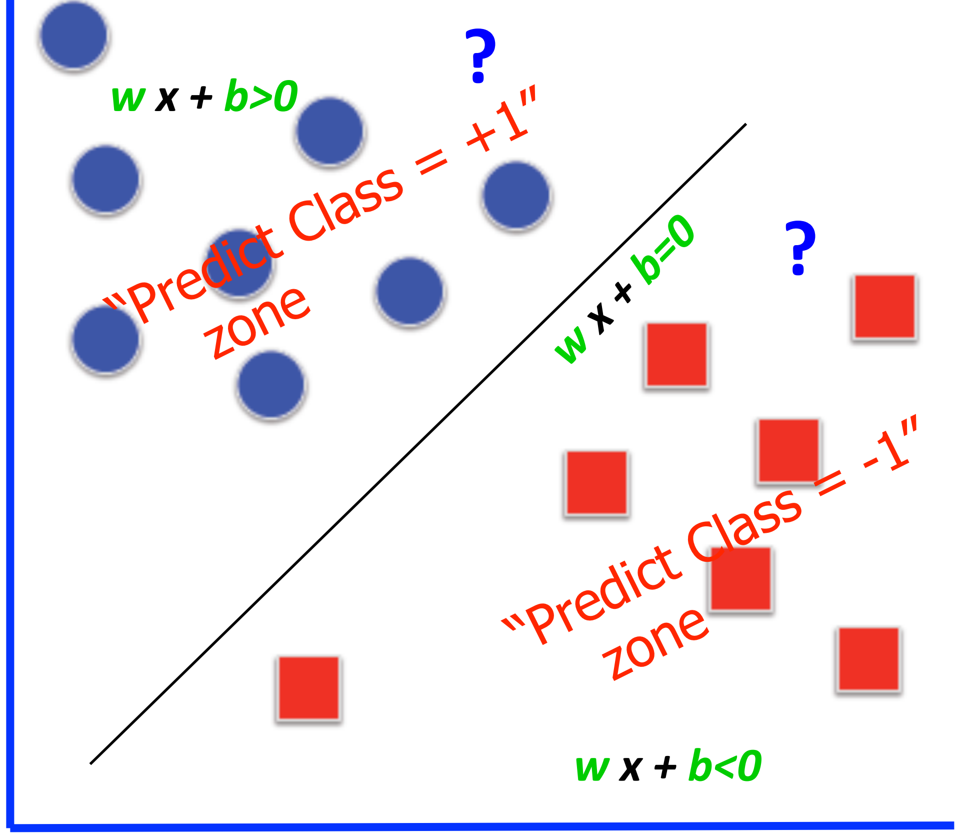
$\longrightarrow$

y -1

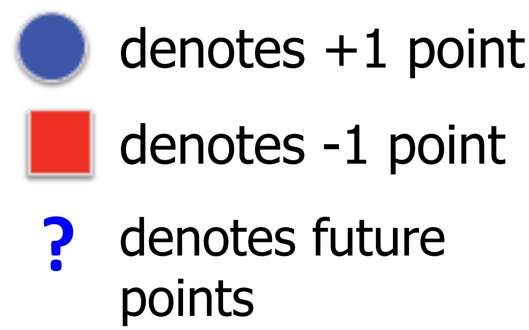
Output Y: {1 / Yes , -1 / No }
e.g. Is this a positive product review ?

e.g. SUPERVISED Linear Binary Classifier





$f(\mathbf{x},\mathbf{w},b) = sign(\mathbf{w}\ \mathbf{x} + b)$



Courtesy slide from Prof. Andrew Moore's tutorial

Basic Concepts

- Training (i.e. learning parameters $\boxed{\mathbf{w}, b}$)
  - Training set includes
    - available examples $\mathbf{x}_1, \ldots, \mathbf{x}_L$
    - available corresponding labels $y_1, \ldots, y_L$
  - Find $(\mathbf{w}, b)$ by minimizing loss (i.e. difference between y and $f(\mathbf{x})$ *on available examples in training set*)

$$(\mathbf{W}, b) = \underset{\mathbf{w},\, b}{\operatorname{argmin}} \sum_{i=1}^{L} \ell(f(x_i), y_i)$$

Basic Concepts

- Testing (i.e. evaluating performance on "future" points)
  - Difference between true $y_?$ and the predicted $f(\mathbf{x}_?)$ on a set of testing examples (i.e. *testing set*)
  - Key: example $\mathbf{x}_?$ not in the training set

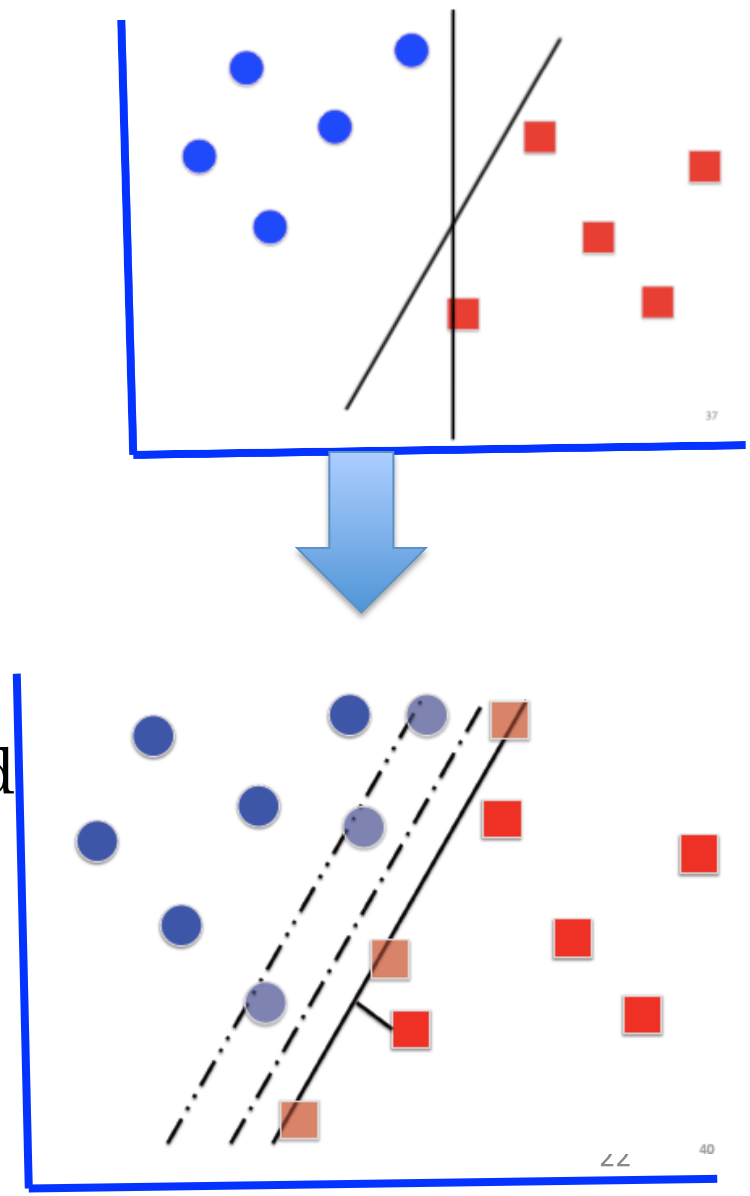
- Generalisation: learn function / hypothesis from past data in order to "explain", "predict", "model" or "control" new data examples

Basic Concepts

- Loss function
  - e.g. hinge loss for binary classification task

$$\sum_{i=1}^{L} \ell(f(x_i), y_i) = \sum_{i=1}^{L} \max(0, 1 - y_i f(x_i)).$$

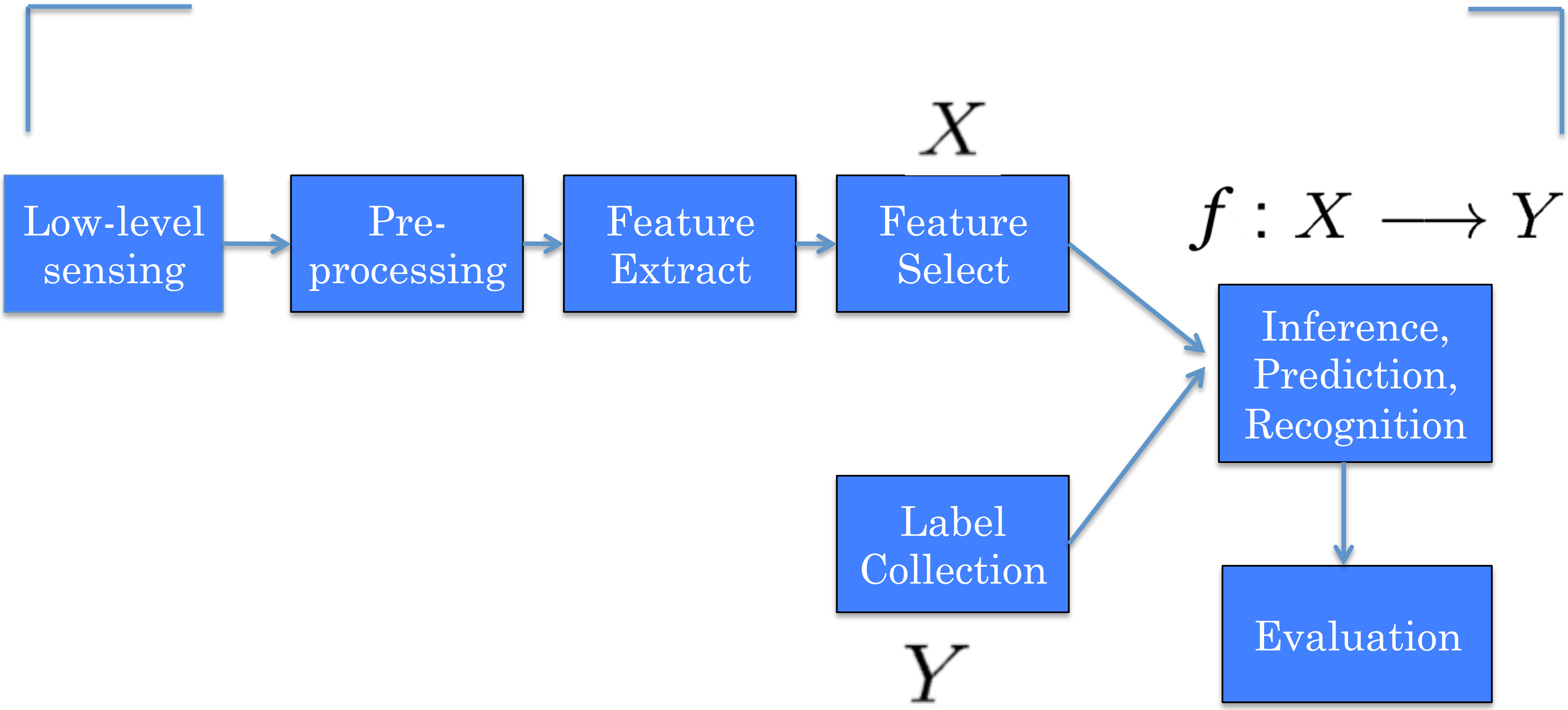
  - e.g. pairwise ranking loss for ranking task (i.e. ordering examples by preference)



- Regularization
  - E.g. additional information added on loss function to control model

$$C \sum_{i=1}^{L} \ell(f(x_i), y_i) + \frac{1}{2}\|w\|^2,$$

TYPICAL MACHINE LEARNING SYSTEM



"Big Data" Challenges for Machine Learning

✓Large size of samples
✓High dimensional features

Not the focus, will be covered in advanced-level course

Large-Scale Machine Learning: SIZE MATTERS

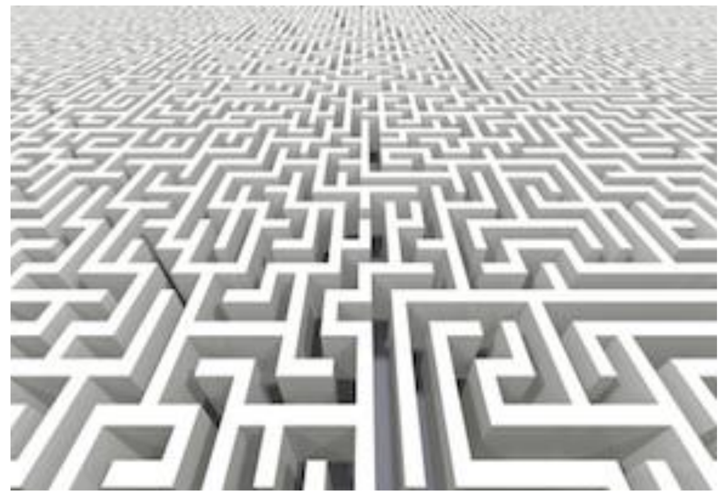
- One thousand data instances
- One million data instances
- One billion data instances
- One trillion data instances

Those are not different numbers, those are different mindsets !!!

BIG DATA CHALLENGES FOR MACHINE LEARNING

LARGE-SCALE

Highly Complex

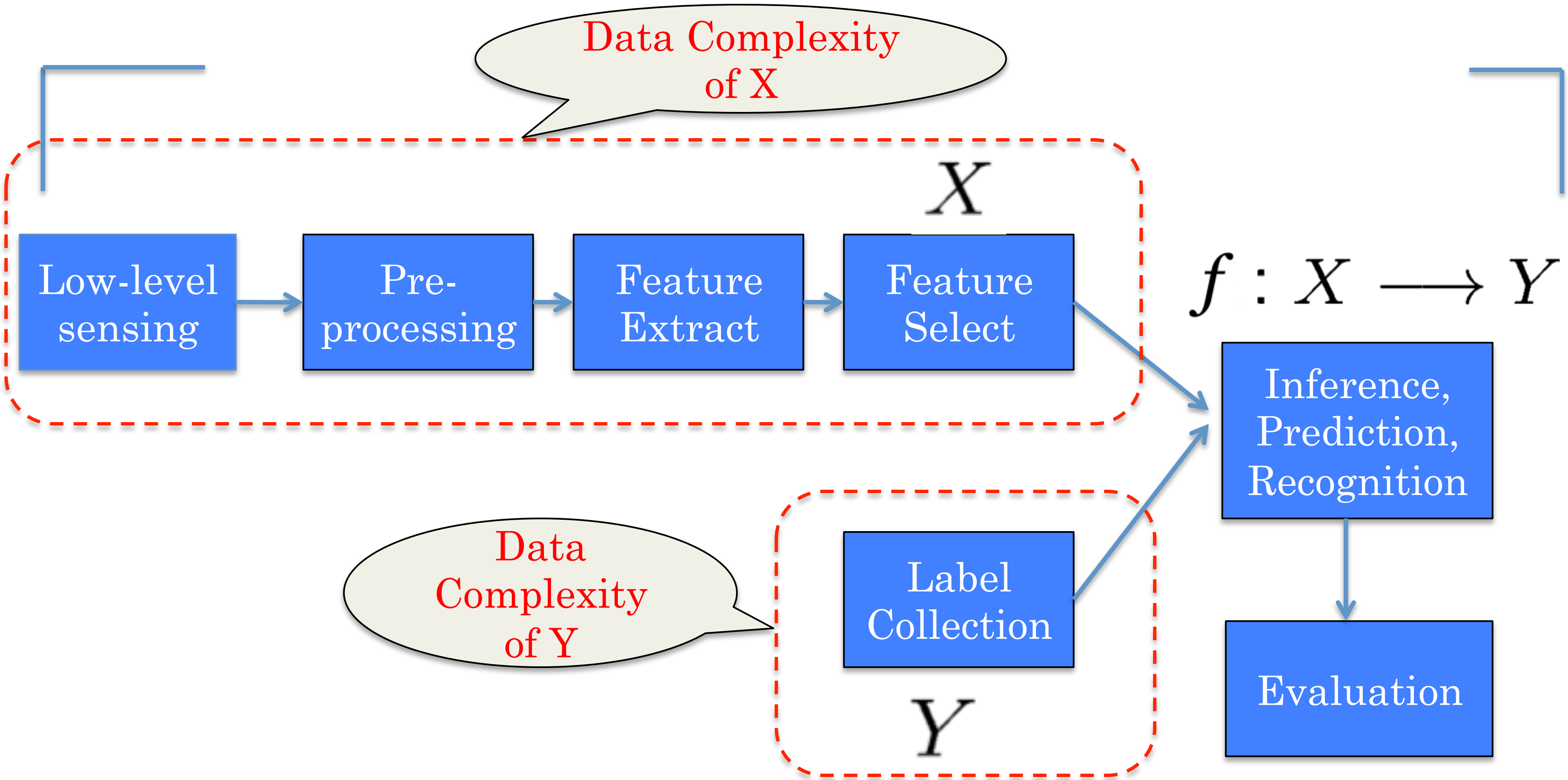


Most of this course

The variations of both X (feature, representation) and Y (labels) are complex !

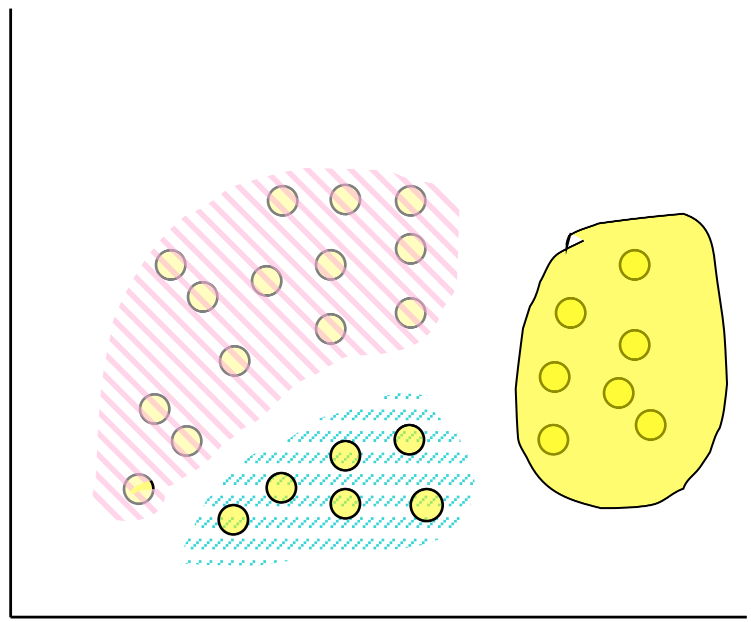
- ✓Complexity of X
- ✓Complexity of Y

TYPICAL MACHINE LEARNING SYSTEM



UNSUPERVISED LEARNING : [COMPLEXITY OF Y]

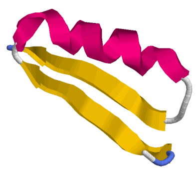
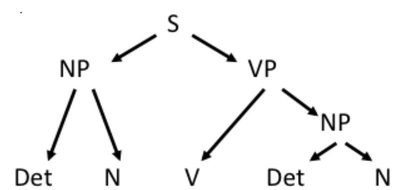
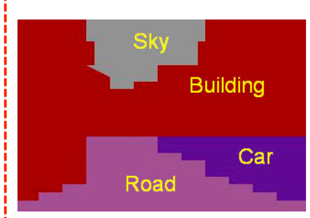
- No labels are provided (e.g. No Y provided)
- Find patterns from unlabeled data, e.g. clustering



e.g. clustering => to find "natural" grouping of instances given un-labeled data

STRUCTURAL OUTPUT LEARNING : [COMPLEXITY OF Y]

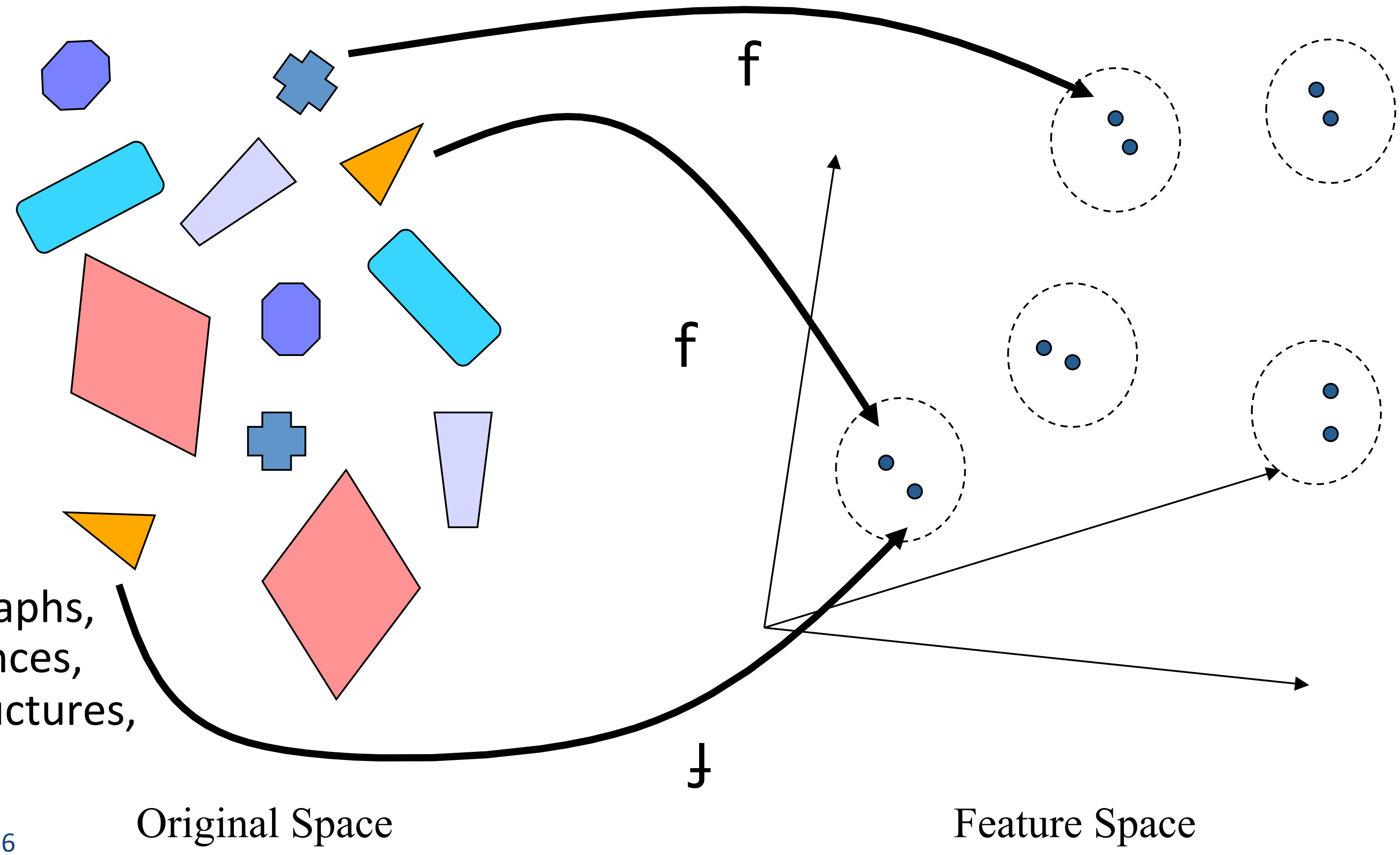
- Many prediction tasks involve output labels having structured correlations or constraints among instances

Structured Dependency between Examples	Sequence	Tree	Grid
Input X	APAFSVSPASGACGPECA…	The dog chased the cat	
Output Y	 CCEEEEECCCCCHHHCCC…		

Many more possible structures between y_i , e.g. spatial , temporal, relational …

STRUCTURAL INPUT : Kernel Methods
[COMPLEXITY OF X]

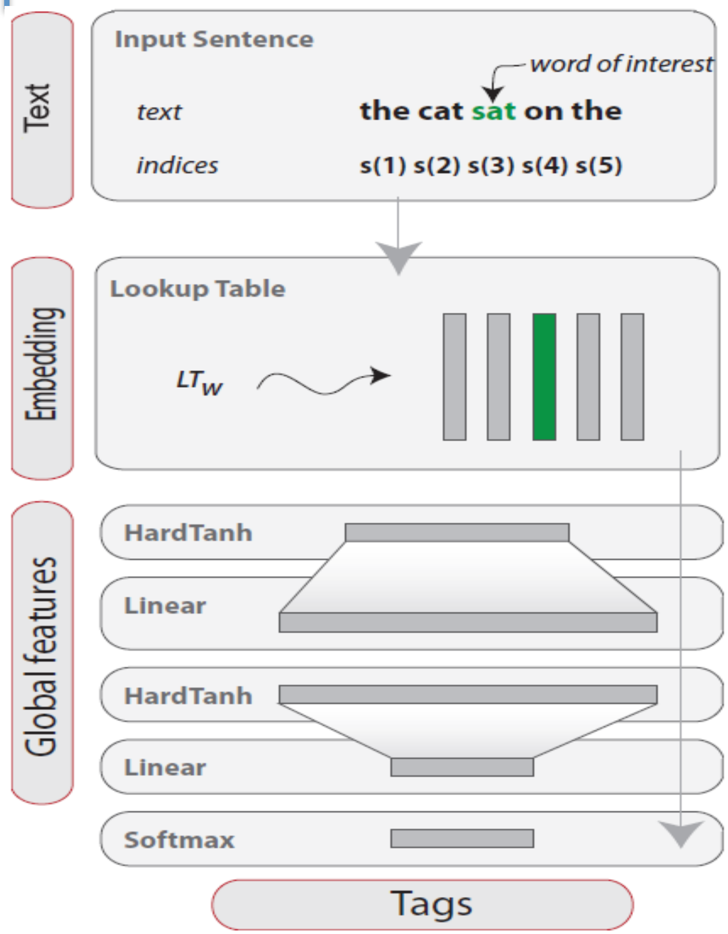
Vector vs. Relational data



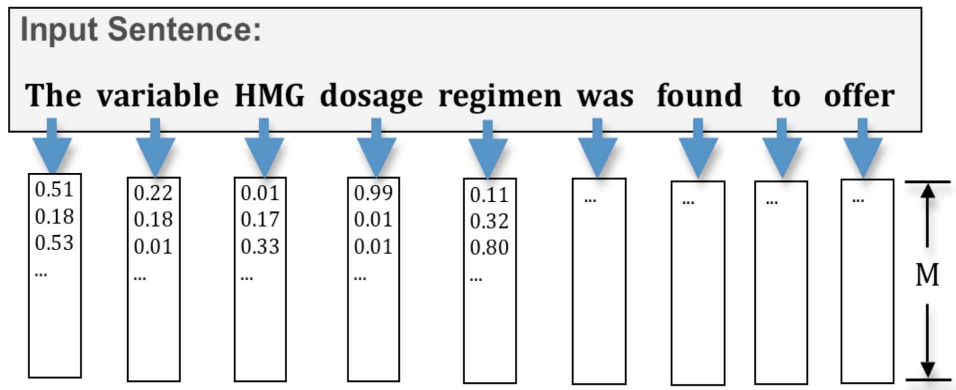
e.g. Graphs,
Sequences,
3D structures,

MORE RECENT: FEATURE LEARNING
[COMPLEXITY OF X]

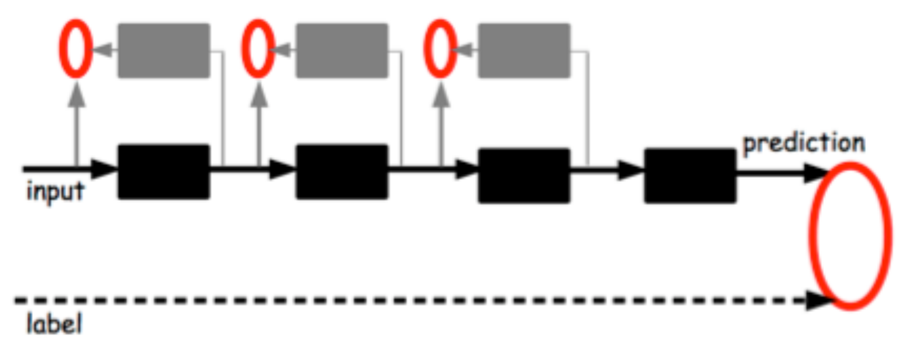
Deep Learning



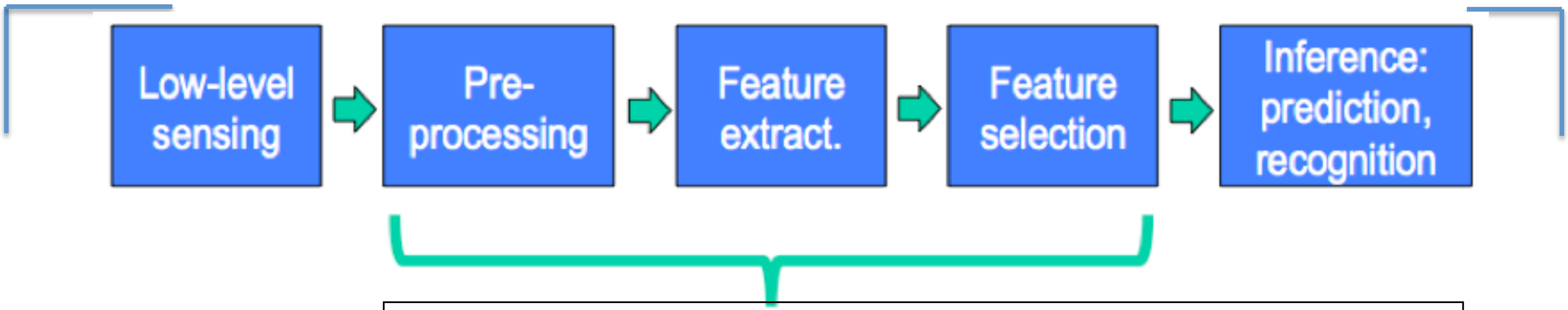
Supervised Embedding



Layer-wise Pretraining



DEEP LEARNING / FEATURE LEARNING : [COMPLEXITY OF X]

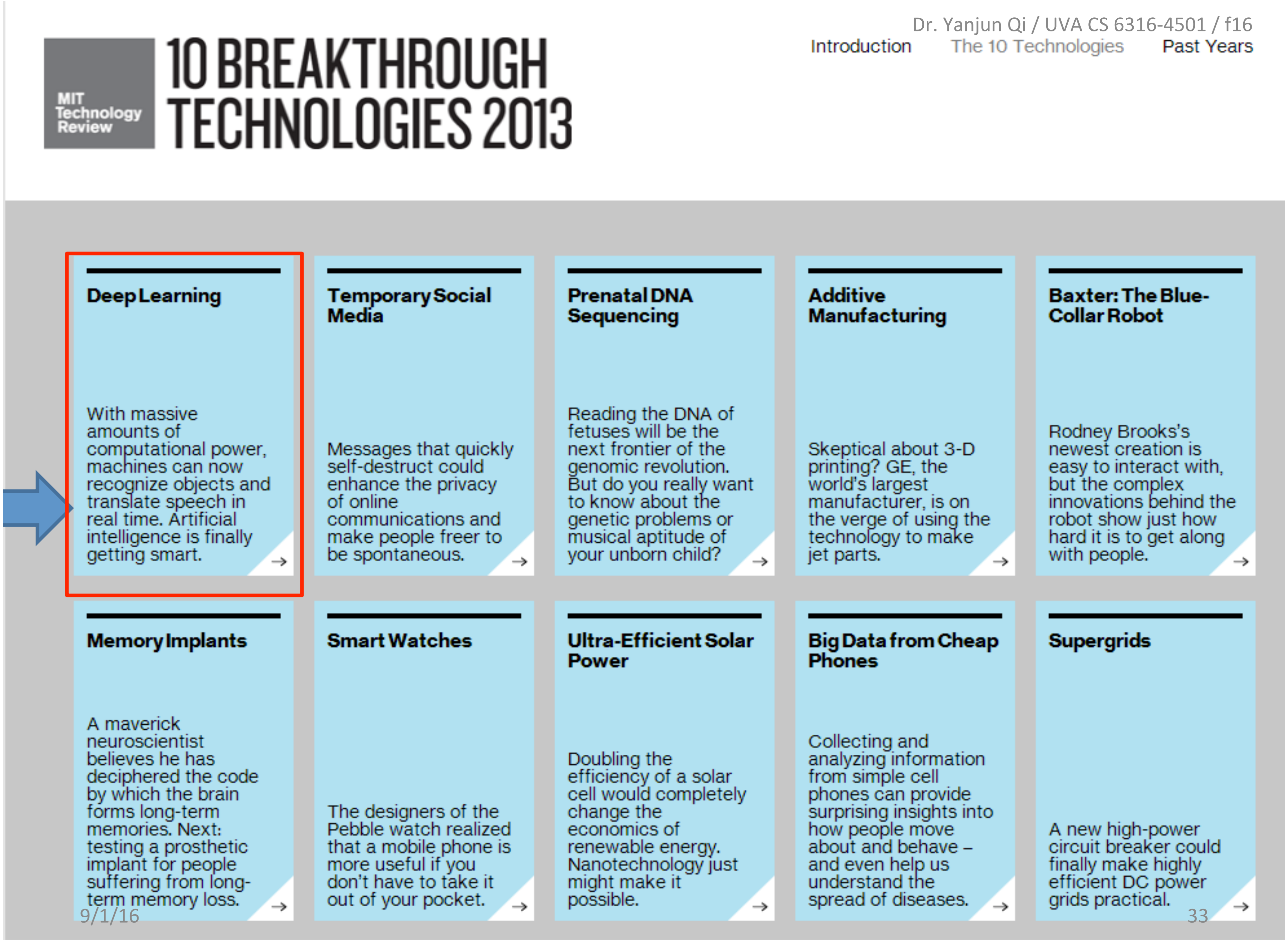


Feature Engineering

- ✓ Most critical for accuracy
- ✓ Account for most of the computation for testing
- ✓ Most time-consuming in development cycle
- ✓ Often hand-craft and task dependent in practice

Feature Learning

- ✓ Easily adaptable to new similar tasks
- ✓ Layerwise representation
- ✓ Layer-by-layer unsupervised training
- ✓ Layer-by-layer supervised training

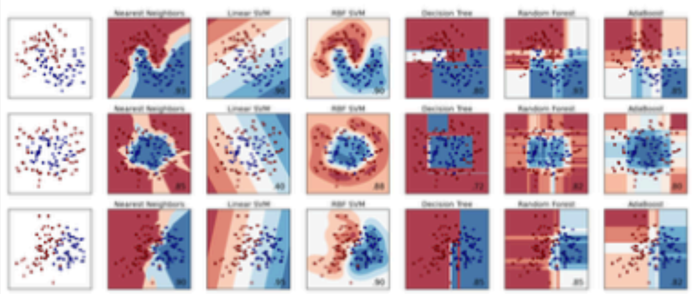


MIT Technology Review
10 BREAKTHROUGH TECHNOLOGIES 2013
Introduction
The 10 Technologies
Past Years
Deep Learning
With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart.
Temporary Social Media
Messages that quickly self-destruct could enhance the privacy of online communications and make people freer to be spontaneous.
Prenatal DNA Sequencing
Reading the DNA of fetuses will be the next frontier of the genomic revolution. But do you really want to know about the genetic problems or musical aptitude of your unborn child?
Additive Manufacturing
Skeptical about 3-D printing? GE, the world's largest manufacturer, is on the verge of using the technology to make jet parts.
Baxter: The Blue-Collar Robot
Rodney Brooks's newest creation is easy to interact with, but the complex innovations behind the robot show just how hard it is to get along with people.
Memory Implants
A maverick neuroscientist believes he has deciphered the code by which the brain forms long-term memories. Next: testing a prosthetic implant for people suffering from long-term memory loss.
Smart Watches
The designers of the Pebble watch realized that a mobile phone is more useful if you don't have to take it out of your pocket.
Ultra-Efficient Solar Power
Doubling the efficiency of a solar cell would completely change the economics of renewable energy. Nanotechnology just might make it possible.
Big Data from Cheap Phones
Collecting and analyzing information from simple cell phones can provide surprising insights into how people move about and behave – and even help us understand the spread of diseases.
Supergrids
A new high-power circuit breaker could finally make highly efficient DC power grids practical.

Course Content Plan → Five major sections of this course

- ❑ Regression (supervised)
- ❑ Classification (supervised)
- ❑ Unsupervised models
- ❑ Learning theory
- ❑ Graphical models

http://scikit-learn.org/



scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which set of categories a new observation belong to.

Applications: Spam detection, Image recognition.
Algorithms: *SVM*, *nearest neighbors*, *random forest*, ... — *Examples*

Regression

Predicting a continuous value for a new example.

Applications: Drug response, Stock prices.
Algorithms: *SVR*, *ridge regression*, *Lasso*, ... — *Examples*

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: *k-Means*, *spectral clustering*, *mean-shift*, ... — *Examples*

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: *PCA*, *feature selection*, *non-negative matrix factorization*. — *Examples*

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: *grid search*, *cross validation*, *metrics*. — *Examples*

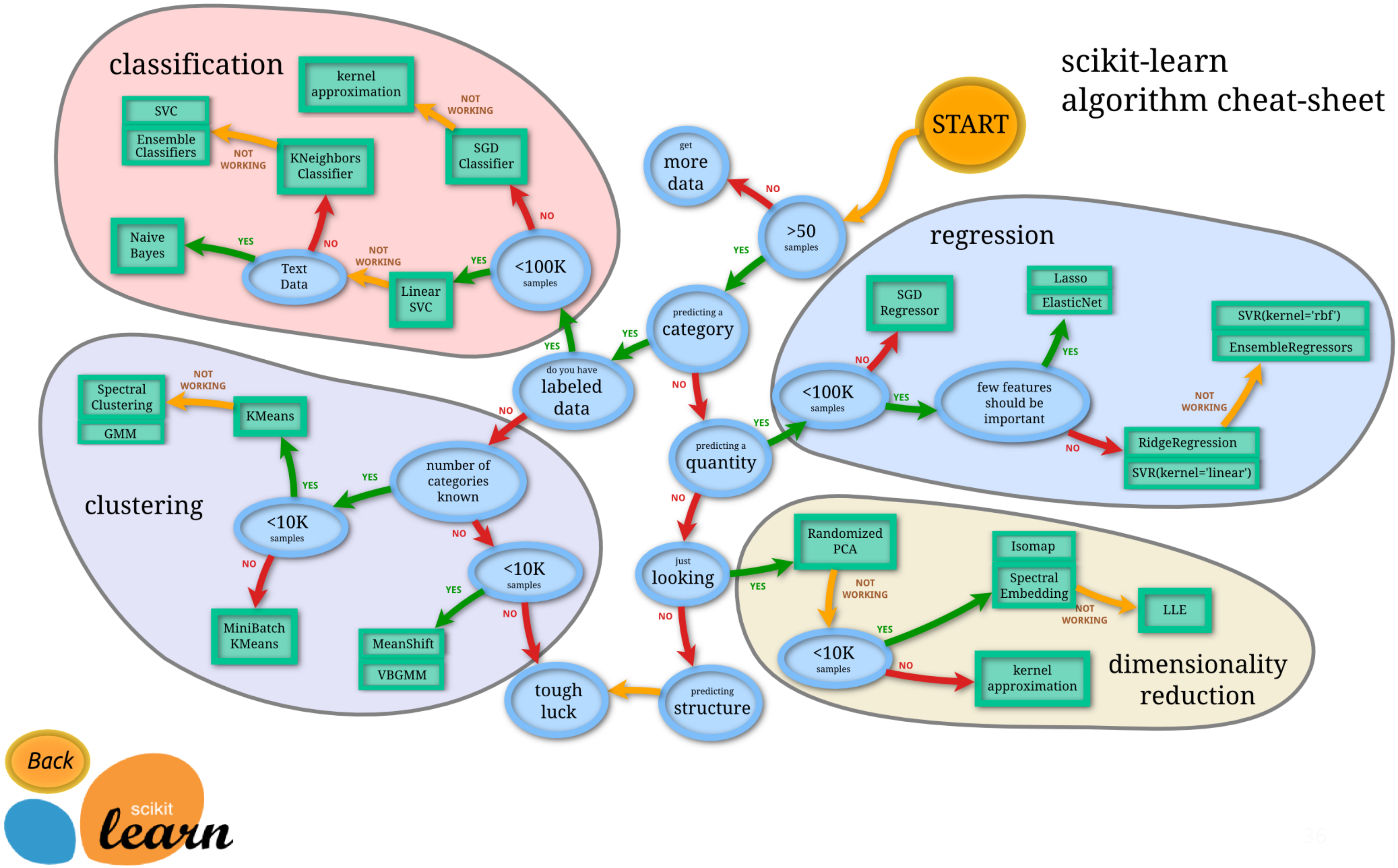
Preprocessing

Feature extraction and normalization.

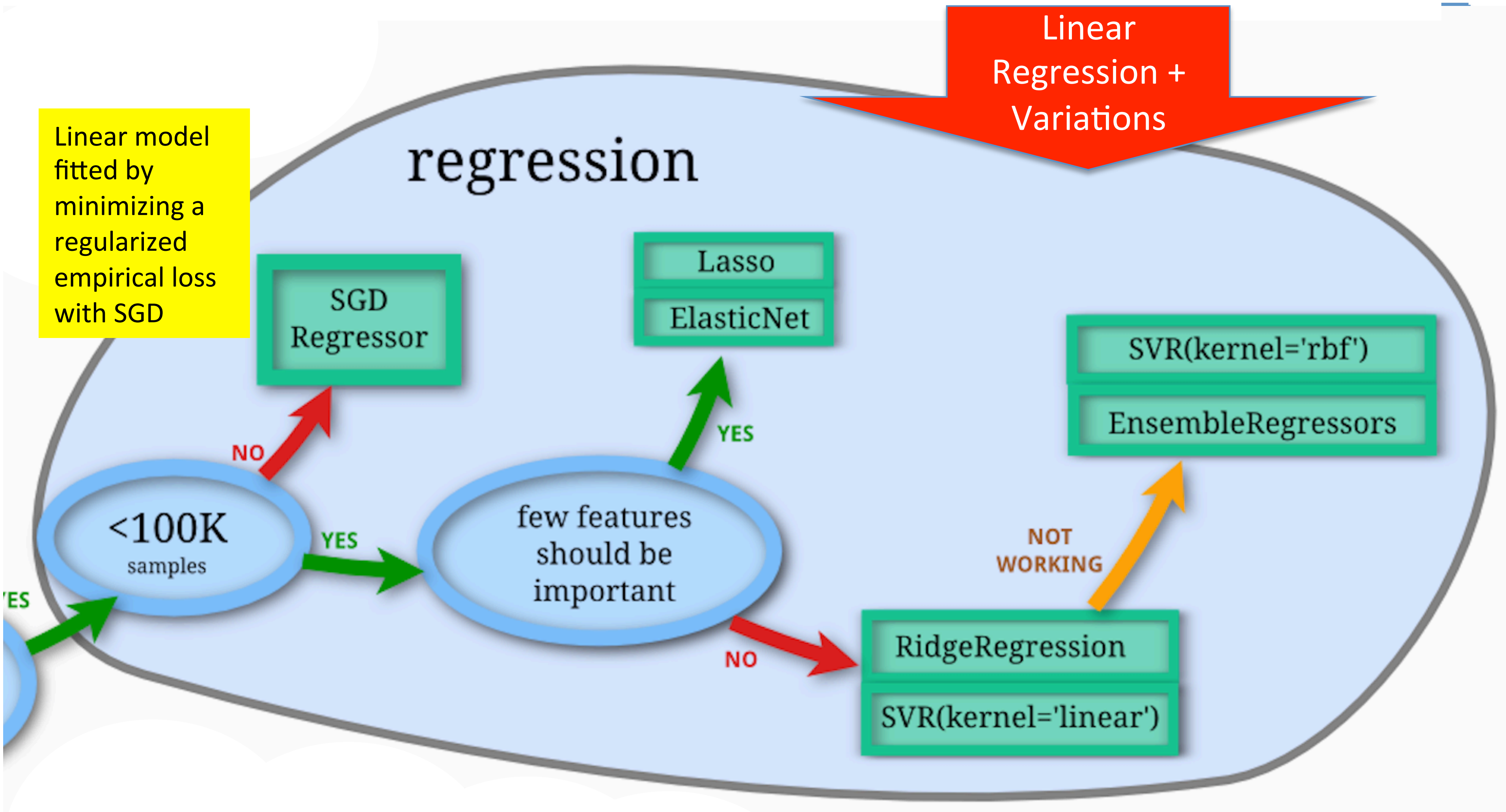
Application: Transforming input data such as text for use with machine learning algorithms.
Modules: *preprocessing*, *feature extraction*. — *Examples*

http://scikit-learn.org/stable/tutorial/machine_learning_map/

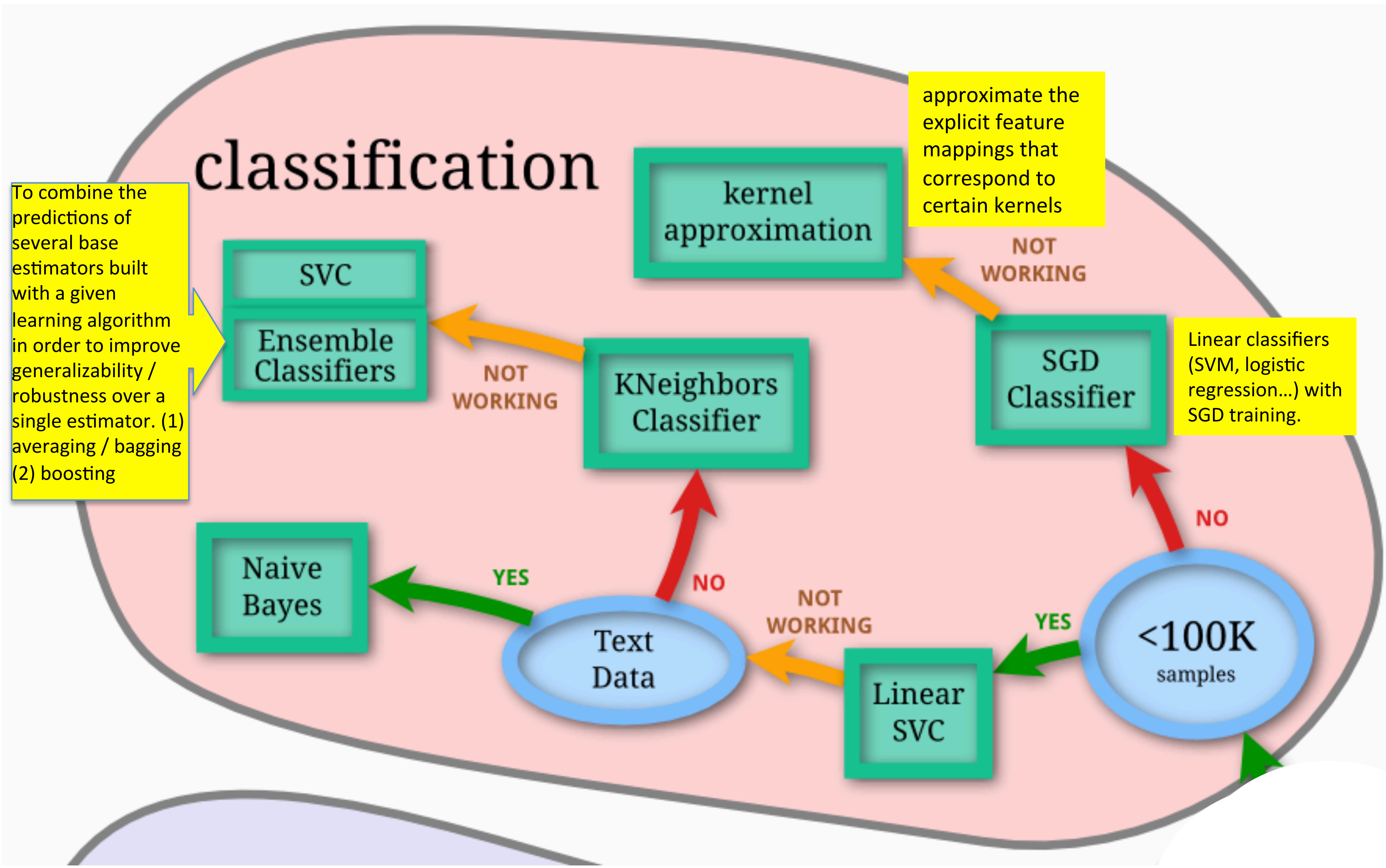
Scikit-learn algorithm cheat-sheet



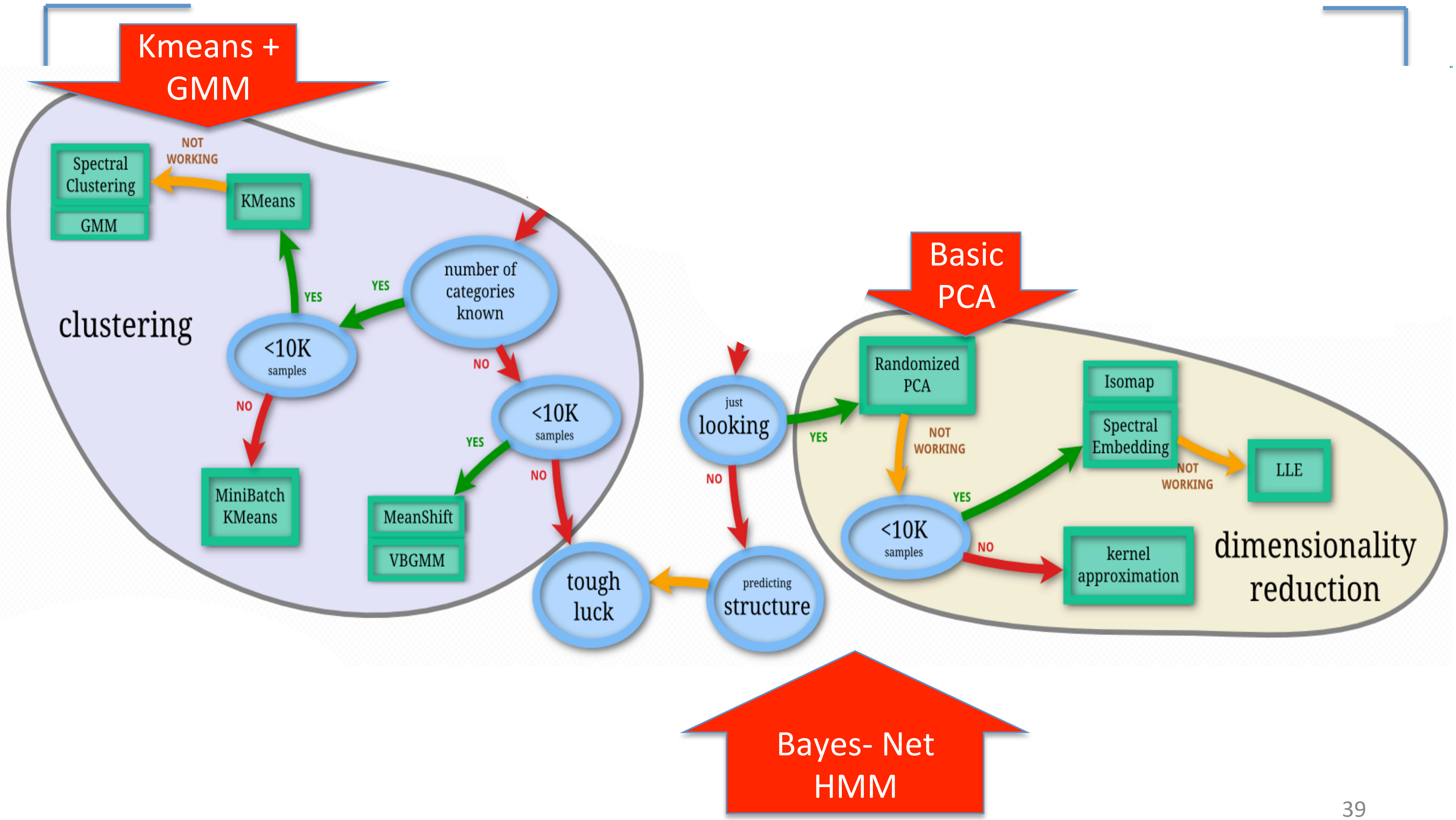
Scikit-learn : Regression



Scikit-learn : Classification



Unsupervised Models



Summary

- This is not a course about learning to use toolbox

- We focus on learning principles, mathematical formulation, algorithm design and learning theory.

Today

- ❑ Course Logistics
- ❑ My background
- ❑ Basics and rough content plan
- ❑ **Application and History**

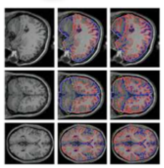
What can we do with the data wealth?

→ REAL-WORLD IMPACT

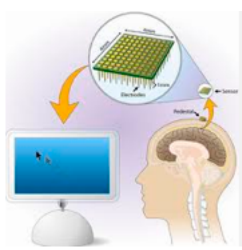
Transportation Data

Genomic Data

Medical Images



Brain computer interaction (BCI)



Device sensor data

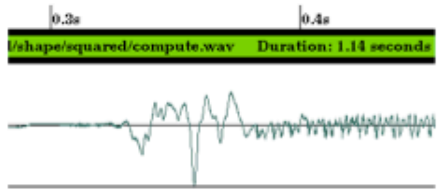
- Business efficiencies
- Scientific breakthroughs
- Improve quality-of-life:
  - healthcare,
  - energy saving / generation,
  - environmental disasters,
  - nursing home,
  - transportation,
  - …

When to use Machine Learning (Adapt to / learn from data) ?

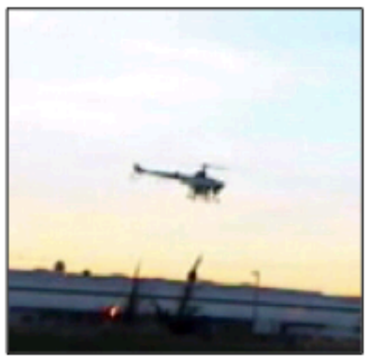
- 1. Extract knowledge from data
  - Relationships and correlations can be hidden within large amounts of data
  - The amount of knowledge available about certain tasks is simply too large for explicit encoding (e.g. rules) by humans
- 2. Learn tasks that are difficult to formalise
  - Hard to be defined well, except by examples, e.g., face recognition
- 3. Create software that improves over time
  - New knowledge is constantly being discovered.
  - Rule or human encoding-based system is difficult to continuously re-design "by hand".

MACHINE LEARNING IS CHANGING THE WORLD

Mining Databases



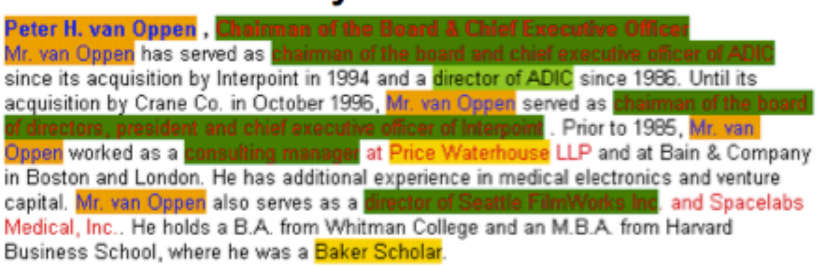
Speech Recognition



Control learning

Object recognition

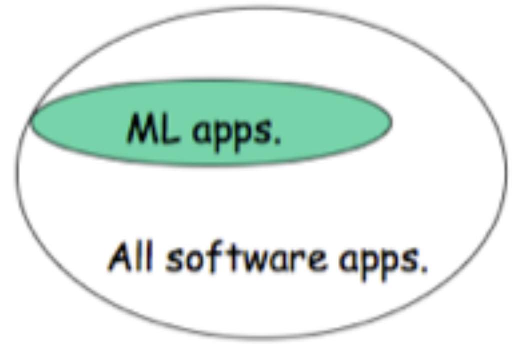
Text analysis



Many more !

MACHINE LEARNING IN COMPUTER SCIENCE

- Machine learning is already the preferred approach for
  - Speech recognition, natural language processing
  - Computer vision
  - Medical outcome analysis
  - Robot control …



- Why growing ?
  - Improved machine learning algorithm
  - Increased data capture, new sensors, networking
  - Systems/Software too complex to control manually
  - Demand to self-customization for user, environment, ….

RELATED DISCIPLINES

- Artificial Intelligence
- Data Mining
- Probability and Statistics
- Information theory
- Numerical optimization
- Computational complexity theory
- Control theory (adaptive)
- Psychology (developmental, cognitive)
- Neurobiology
- Linguistics
- Philosophy

What are the goals of AI research?

Artifacts that THINK like HUMANS	Artifacts that THINK RATIONALLY
Artifacts that ACT like HUMANS	Artifacts that ACT RATIONALLY

From: M.A. Papalaskar

How can we build more intelligent computer / machine ?

- Able to
  - **perceive the world**
  - **understand the world**

- This needs
  - Basic speech capabilities
  - Basic vision capabilities
  - Language/semantic understanding
  - User behavior / emotion understanding
  - Able to think ??

How can we build more intelligent computer / machine ?

R2-D2 and C-3PO

@ Star Wars – 1977

to serve human beings, and fluent in "over six million forms of communication"

How can we build more intelligent computer / machine ?

Jeopardy Game

➔ Requires a Broad Knowledge Base

IBM Watson

➔ an artificial intelligence computer system capable of answering questions posed in natural language developed in IBM's DeepQA project.

IBM WATSON

How can we build more intelligent computer / machine ?

Apple Siri / Amazon Echo

➔ an intelligent personal assistant and knowledge navigator

How can we build more intelligent computer / machine ? : Objective Recognition / Image Labeling

ImageNet: an image database organized according to the **WordNet**

LSVRC: Large Scale Visual Recognition Challenge based on ImageNet.

72%, 2010

74%, 2011

85%, 2012

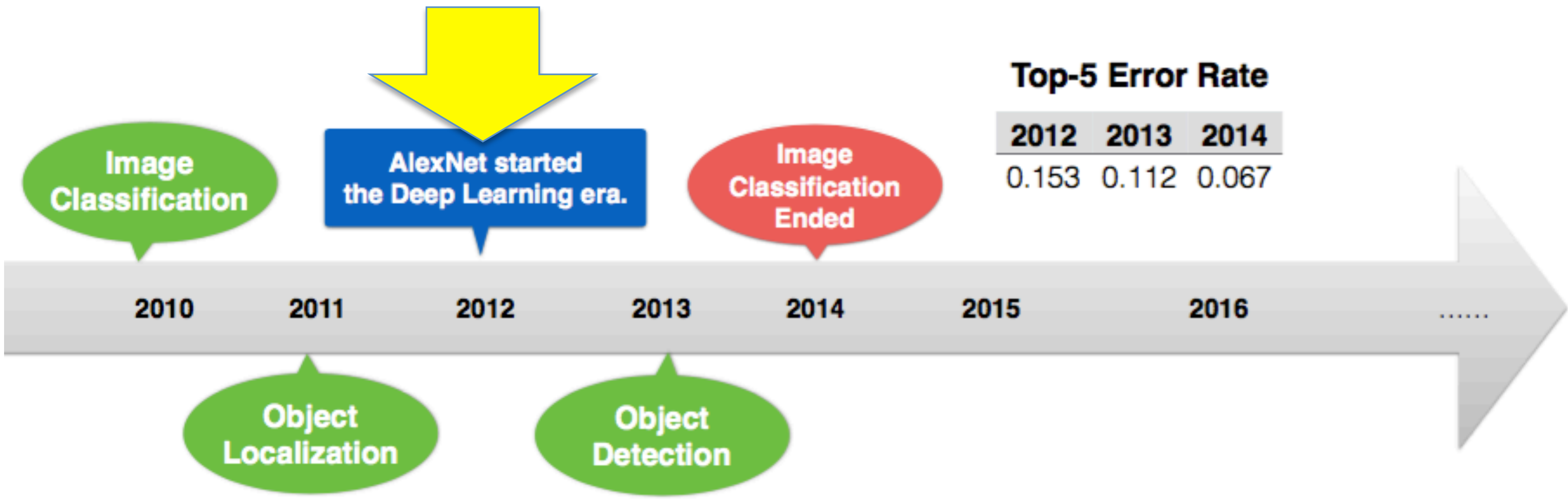
89%, 2013

93%, 2014

[training on 1.2 million images [X] vs. 1000 different word labels [Y]]

Deep Convolution Neural Network (CNN) won (as Best systems) on "very large-scale" ImageNet competition 2012 / 2013 / 2014

How can we build more intelligent computer / machine ? : Objective Recognition / Image Labeling



Top-5 Error Rate

2012	2013	2014
0.153	0.112	0.067

- 2013, Google Acquired Deep Neural Networks Company headed by Utoronto “Deep Learning” Professor Hinton
- 2013, Facebook Built New Artificial Intelligence Lab headed by NYU “Deep Learning” Professor LeCun
- 2016, Google's DeepMind defeats legendary Go player Lee Se-dol in historic victory

Detour: planned programming assignments

- HW: Semantic language understanding (sentiment classification on movie review text)
- HW: Visual object recognition (labeling images about handwritten digits)
- HW: Audio speech recognition (unsupervised learning based speech recognition task)

Today Recap

- Course Logistics
- My background
- Basics and rough content plan
- Application and History

Next lesson: Machine Learning in a Nutshell

Task
↓
Representation
↓
Score Function
↓
Search/Optimization
↓
Models, Parameters

ML grew out of work in AI

Optimize a performance criterion using example data or past experience,

Aiming to generalize to unseen data

Next lesson: Review of linear algebra and basic calculus

References

- Prof. Andrew Moore's tutorials
- Prof. Raymond J. Mooney's slides
- Prof. Alexander Gray's slides
- Prof. Eric Xing's slides
- http://scikit-learn.org/
- Hastie, Trevor, et al. The elements of statistical learning. Vol. 2. No. 1. New York: Springer, 2009.
- Prof. M.A. Papalaskar's slides