Course Logistics and Introduction

CS771: Introduction to Machine Learning

Piyush Rai

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- Q/A and announcements on Piazza. Please sign up

Course Team

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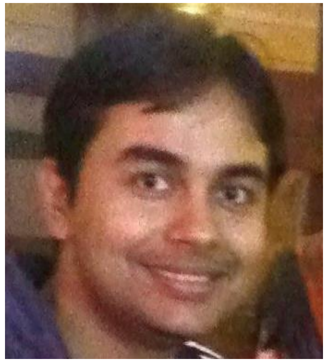

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  - Exact break-up of individual components will be announced in a few days

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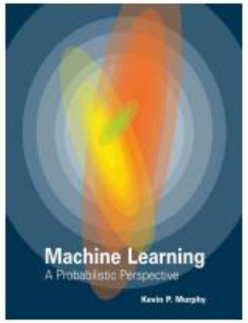

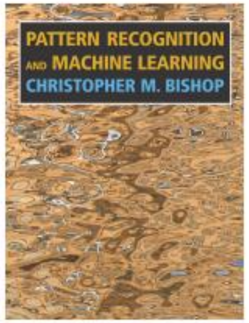

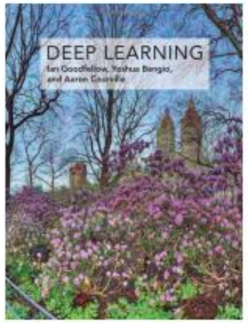

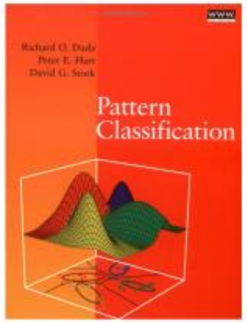

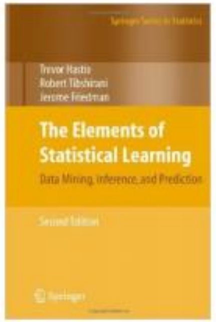

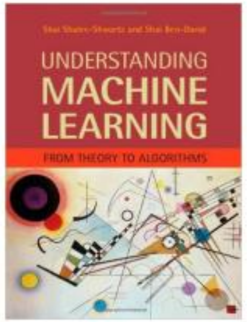

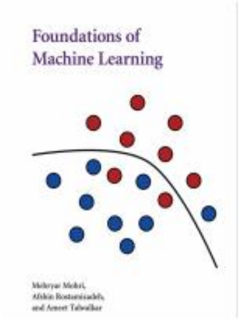

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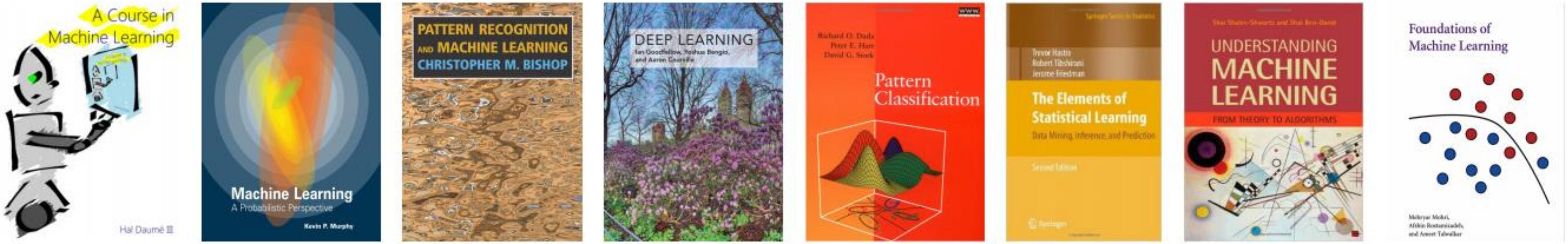

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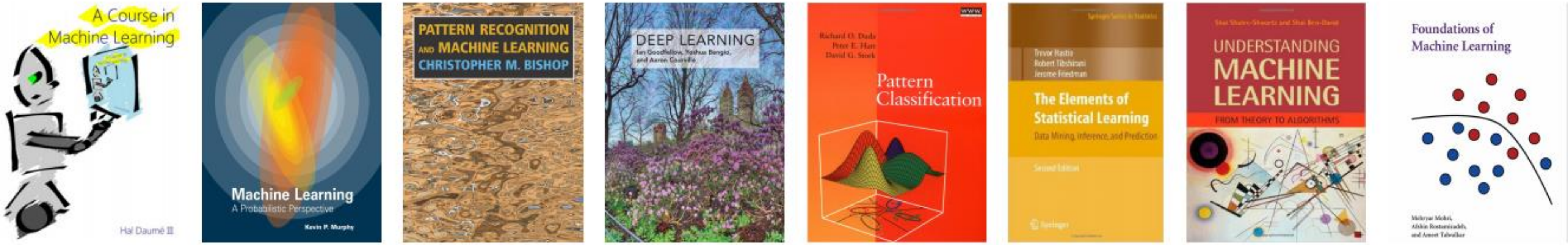

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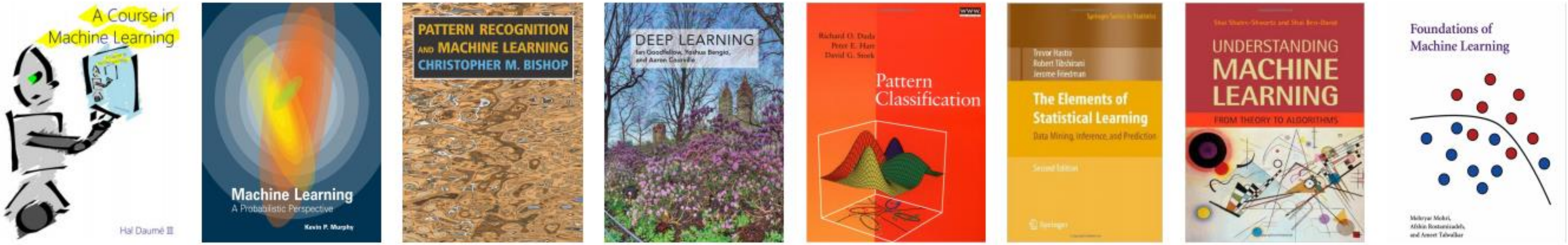

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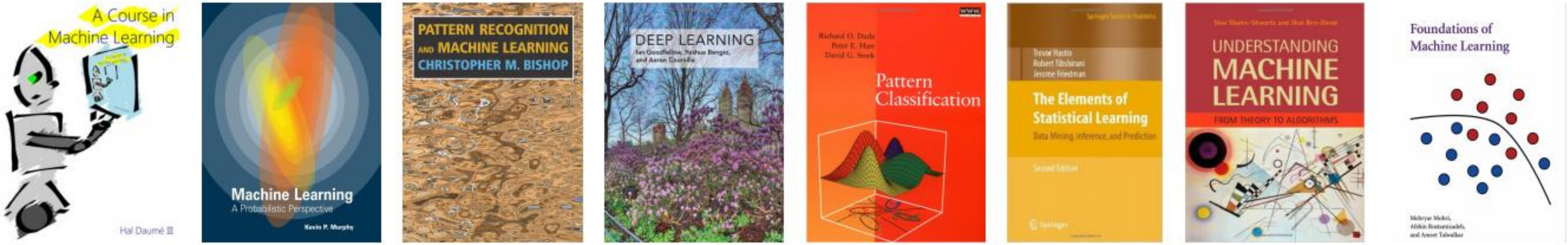

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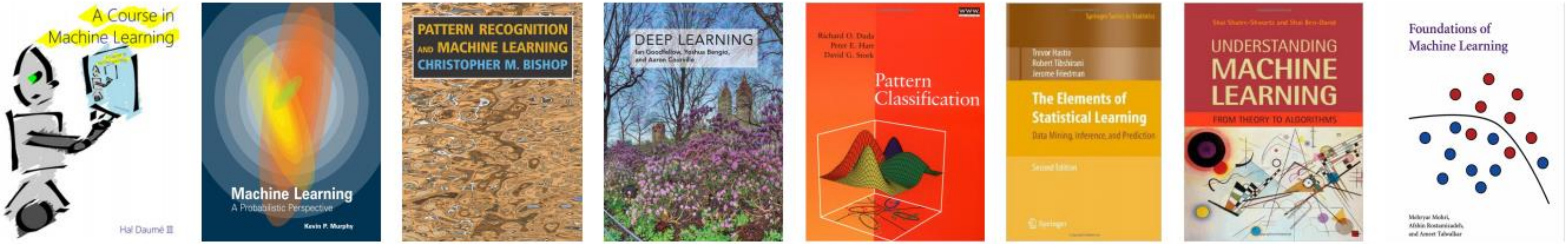

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- We will provide you the reading material from the relevant sources

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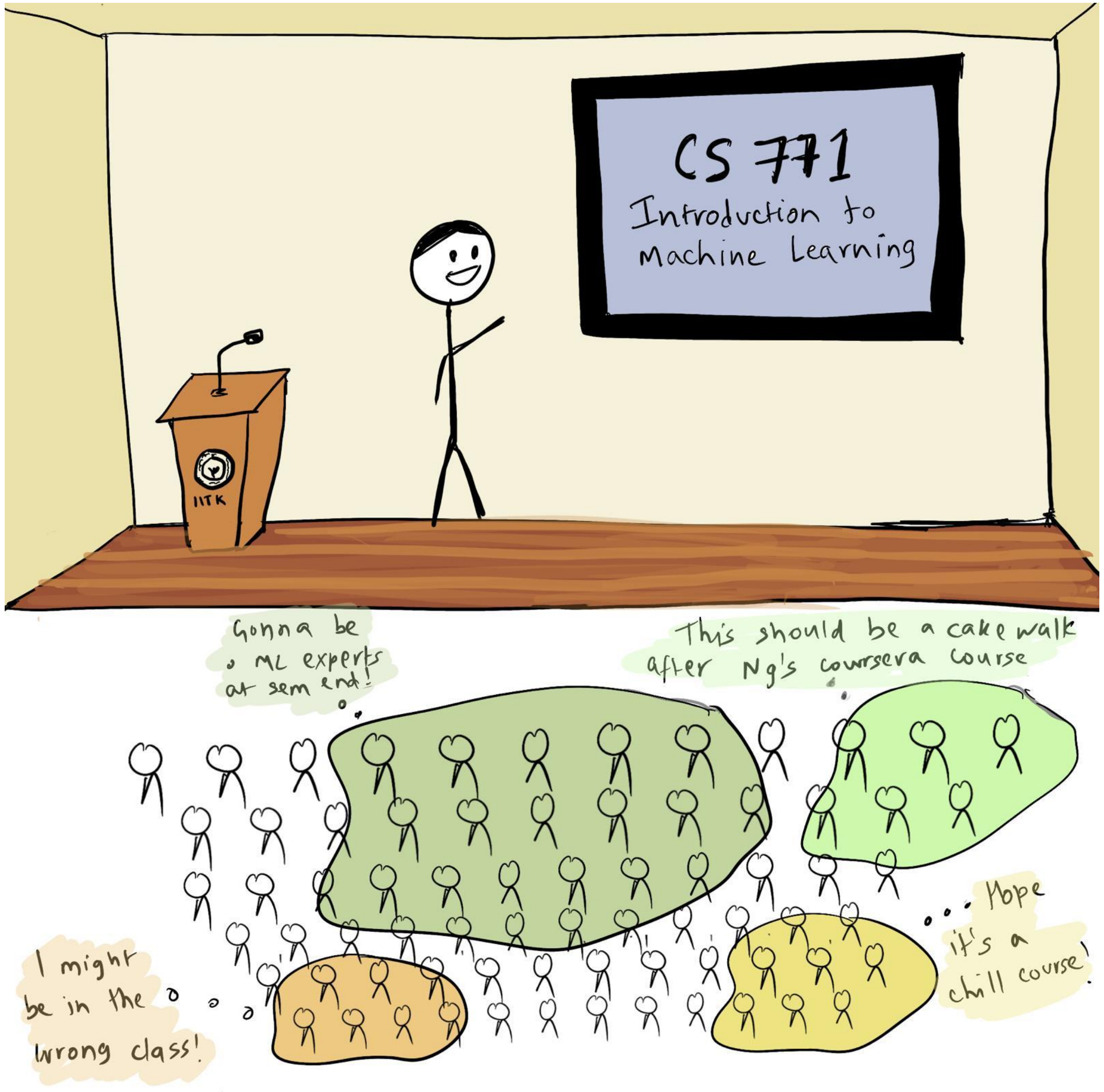

Credit: Rishika Agarwal (EE, graduated 2017)

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Introduction to Machine Learning

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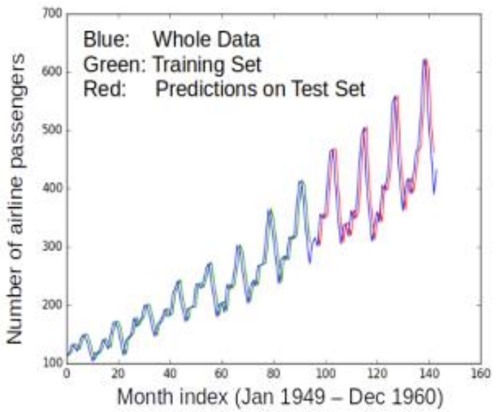

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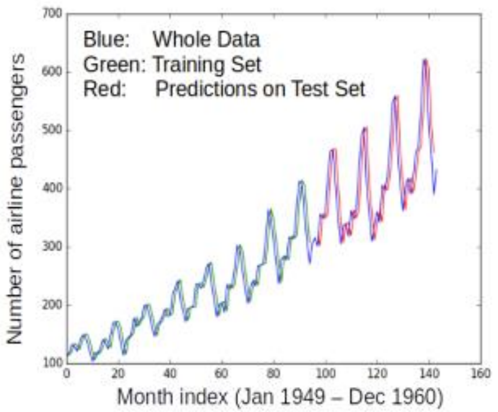

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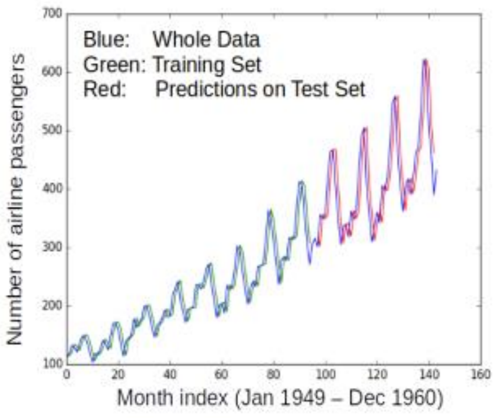

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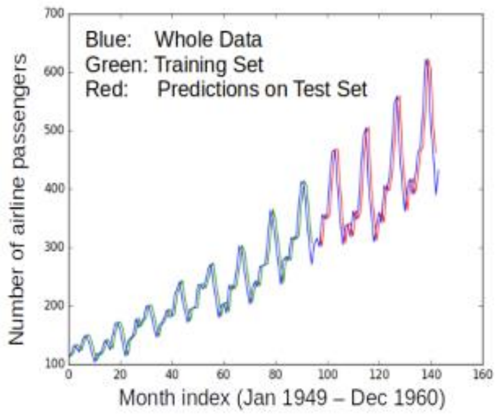

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  - No need to pre-define and hard-code all the rules (infeasible/impossible anyway)
  - The rules are not "static"; can adapt as the ML algo ingests more and more data

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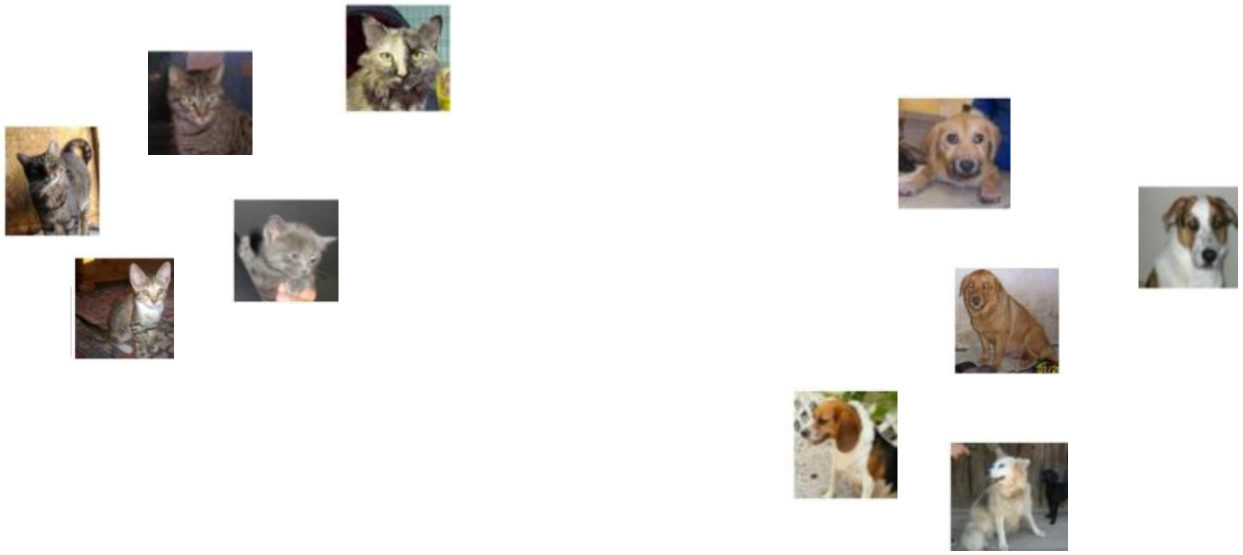

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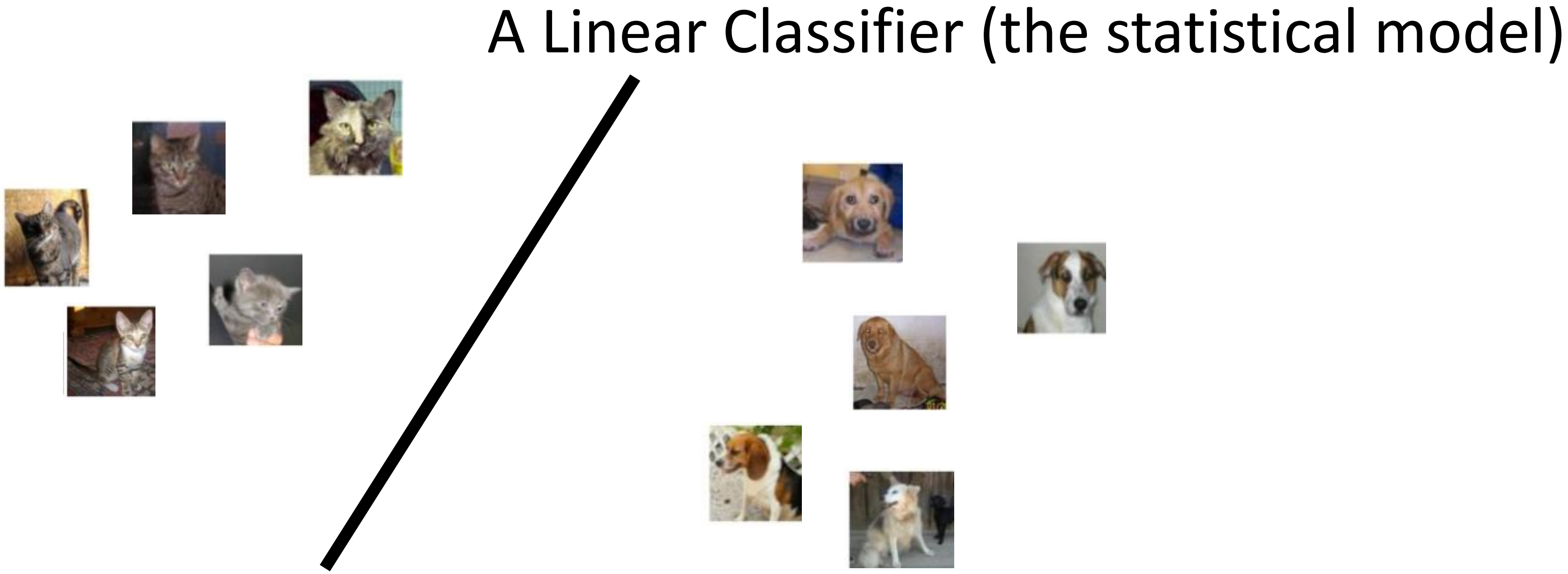

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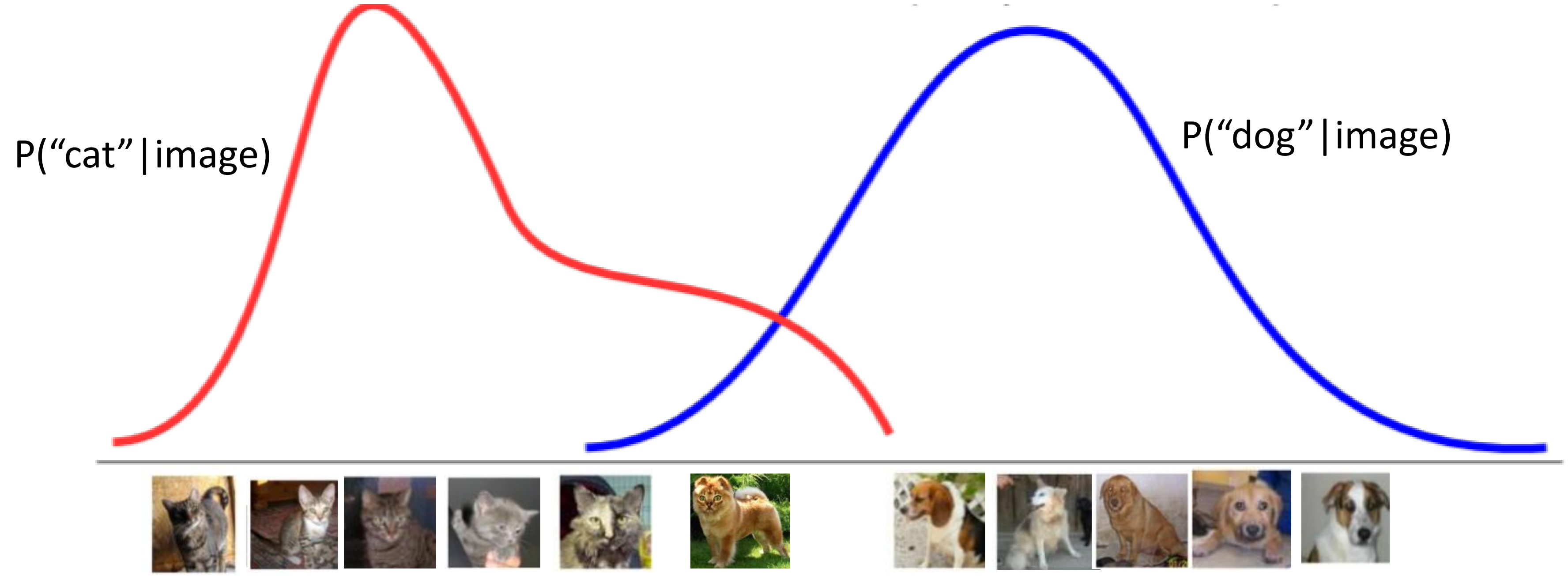
A Probabilistic Classifier (the statistical model)



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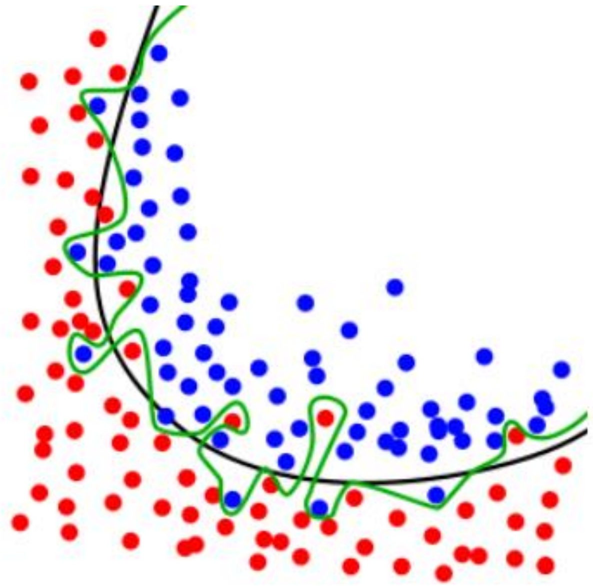

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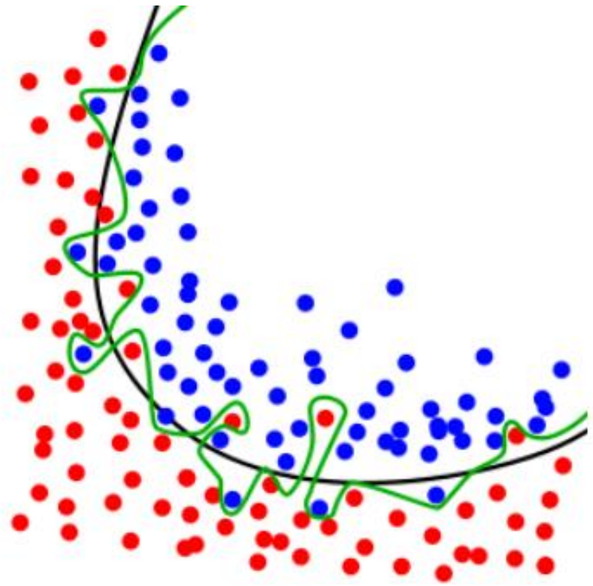

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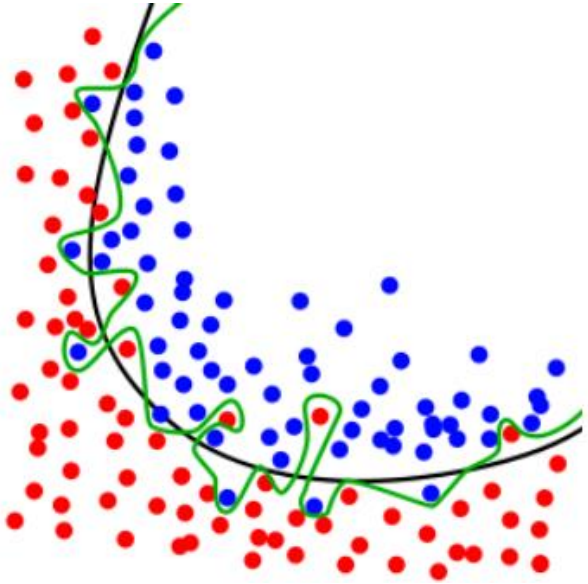

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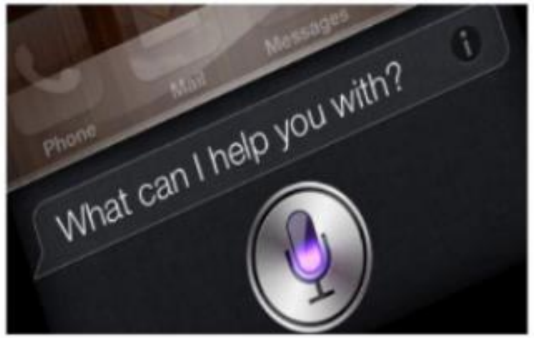
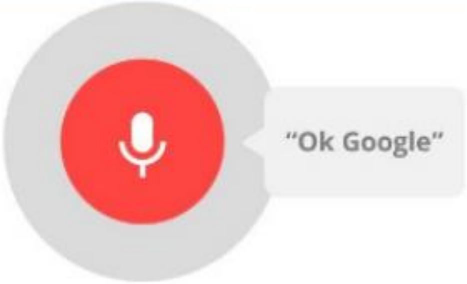
- Simpler models should be preferred over more complex ones!

ML Applications Abound..





Predictive Policing

Online Fraud Detection

Picture courtesy: gizmodo.com,rcdronearena.com,www.wiseyak.com,www.charlesdong.com

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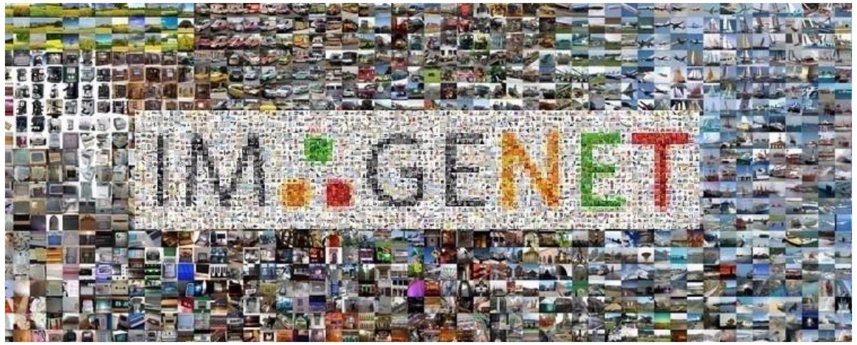

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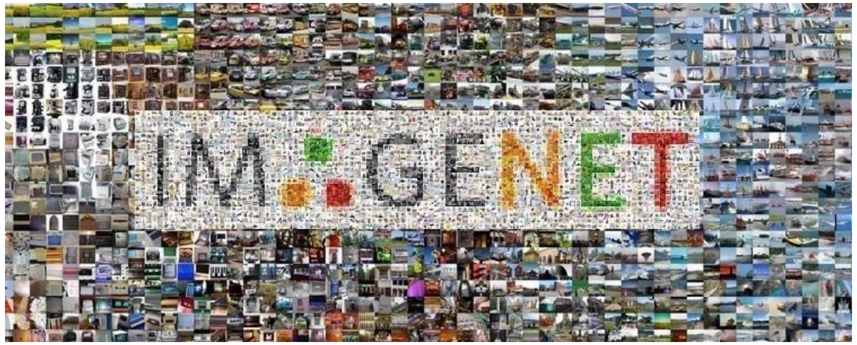

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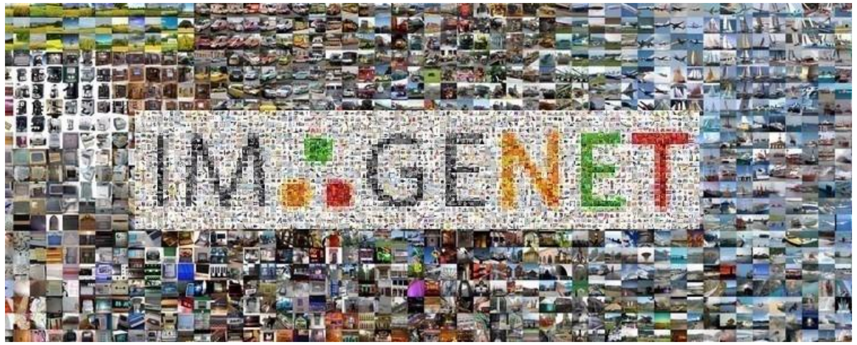

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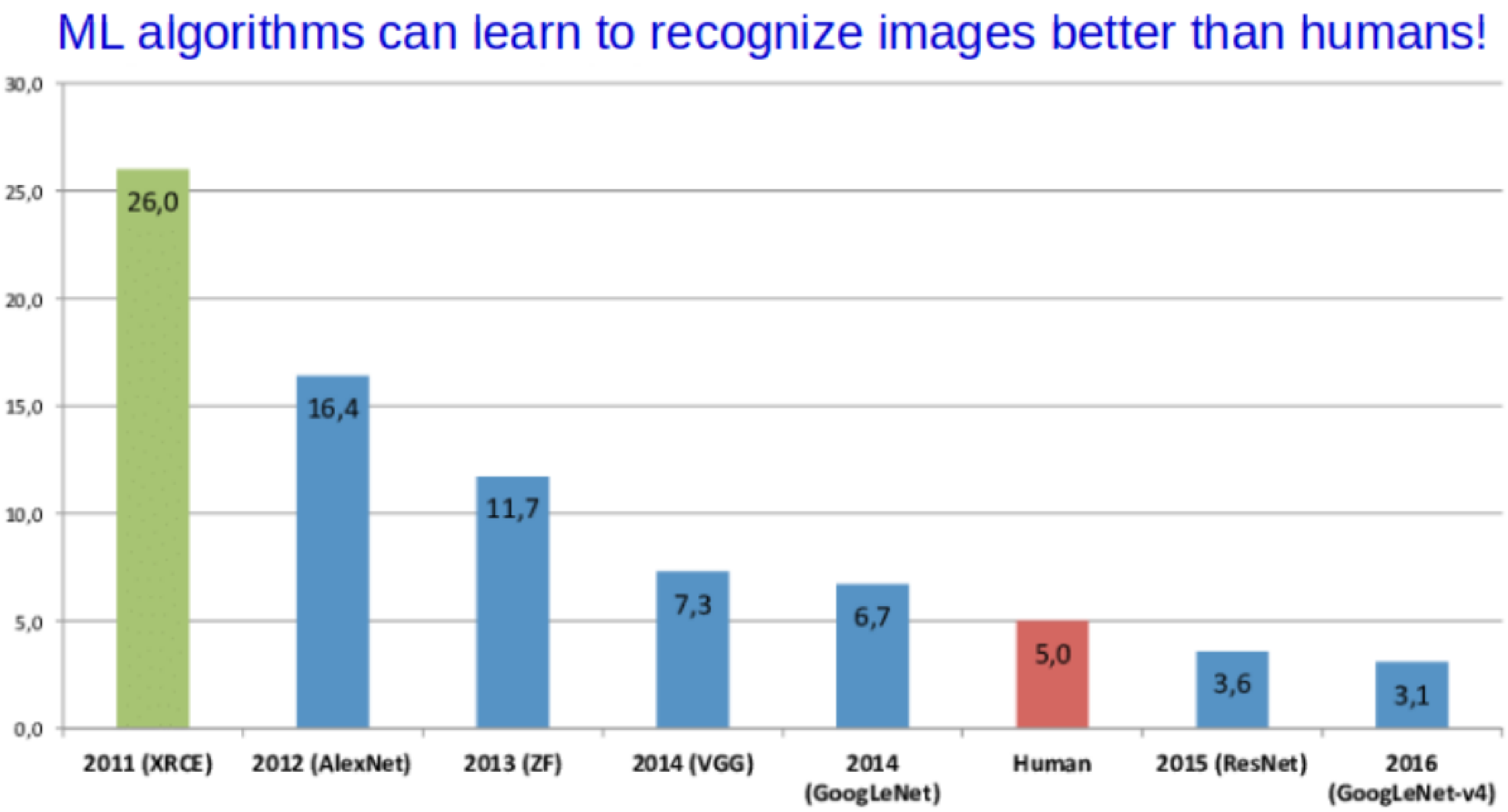
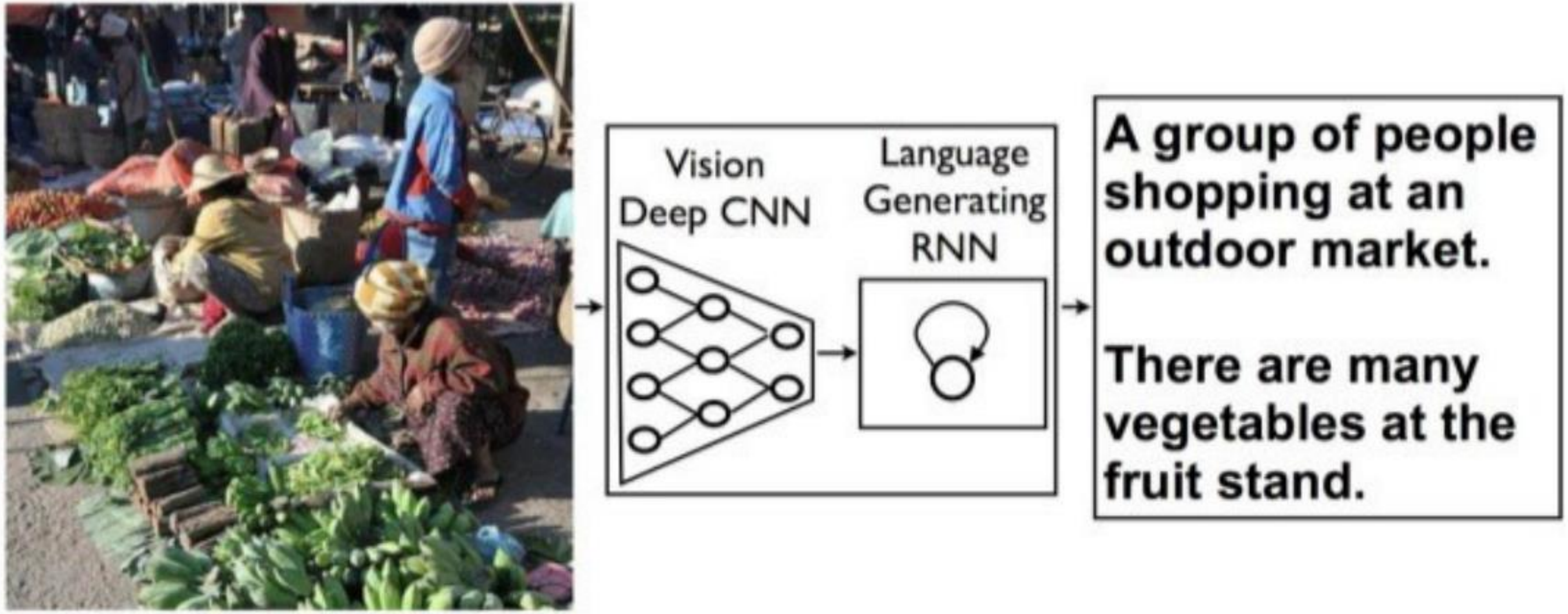
ML: Some Success Stories



ML: Some Success Stories

ML algorithms can learn to generate captions for images



http://arxiv.org/abs/1411.4555 "Show and Tell: A Neural Image Caption Generator"

ML: Some Success Stories

ML algorithms can learn to translate speech in **real time**

Picture courtesy: https://news.microsoft.com/

ML: Some Success Stories

- Automatic Program Correction

```
#include<stdio.h>
int main(){
 int a;
 scanf("%d", a );
 printf("ans=%d",
  a+10);
 return 0;
}
```

```
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int main(){
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Figure 1: Left: erroneous program, Right: fix by TRACER. The compiler message read: *Line-4, Column-9: warning: format '%d' expects argument of type 'int *', but argument 2 has type 'int'.*

```
#include<stdio.h>
int main(){
    int x,x1,d;
    // ...
    d=(x-x1)(x-x1);
    return d;
}
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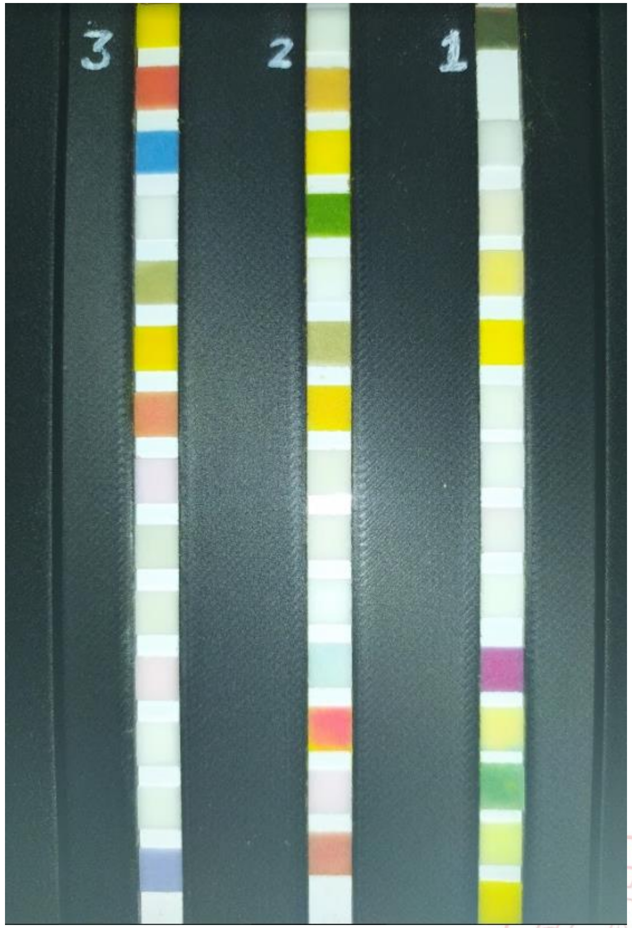
    int x,x1,d;
    // ...
    d=(x-x1)*(x-x1);
    return d;
}
```

Figure 2: Left: erroneous program, Right: fix by TRACER. The compiler message read: *Line-5, Column-11: error: called object type 'int' is not a function or function pointer.*

Example from "Compilation error repair: for the student programs, from the student programs", Ahmed et al (2018)

ML: Some Success Stories

- ML based colorimetry for water quality assessment
- Take uncontaminated water sample
- Spike it with known concentration of various compounds (e.g., lead, iron, fluoride, etc)
- Dip a test strip (one square to measure each compound) in the contaminated water for some time.
- Take a picture of the strip using a phone camera to capture how the colors have changed
- Train an ML model to predict concentration levels of various compounds based on color levels in the images



(work being done at IITK in collaboration with two startups - Earthface Analytics Pvt Ltd and Kritsnam Technologies Pvt Ltd)

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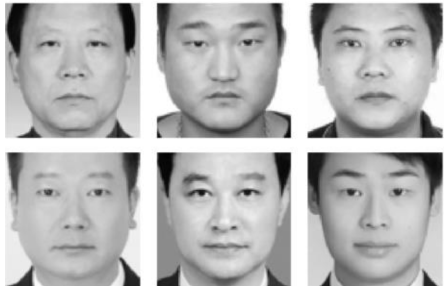

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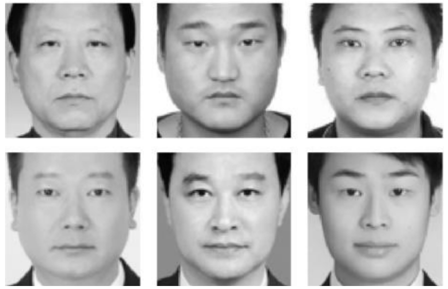

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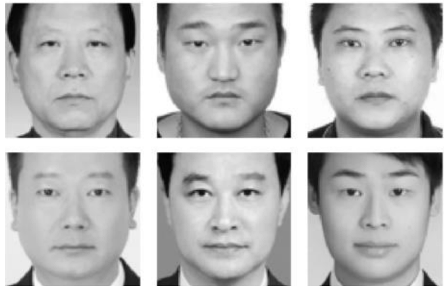

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Picture courtesy: Bhargava and Forsyth (2019), https://www.thestranger.com/, Xiaolin Wu and Xi Zhang, "Automated Inference on Criminality Using Face Images"

Looking Back Before We Start: History of ML

1750-1900
- Origins of Bayes Theorem: Thomas Bayes and Pierre-Simon Laplace (~1800)
- Least Squares method: Legendre (1805)

1900-1950
- Early works on PCA (Peason), Factor Analysis (Spearman), CCA (by Hotelling), for exploratory data analysis
- Early works on Discriminant Analysis methods (Fisher) for classification
- McCulloch-Pitts model of the artificial neuron (1943)
- Turing predicted that Machine Learning is possible (1947)
- Design of the "Turing Test" (1950)

1950-1960
- Minsky & Edmonds' neural net machine (SNARC)
- Arthur Samuels' Checkers Player based on Machine Learning
- Rosenblatt's Perceptron algo
- Widrow-Hoff's ADALINE algo
- K-means clustering algo (Lloyd)
- Early origins of Reinforcement Learning (Bellman and others)

1960-1970
- Multi-layer ADALINE (called MADALINE)
- Nearest Neighbors algorithm
- Early works on Genetic Algorithms inspired by natural evolution (John Holland)

1970-1980
- Minsky-Papert showed that Perceptron can't learn XOR function (and nonlinear functions in general). Led to the so-called "AI Winter"
- Automatic Differentiation (later rediscovered as Backprop)

1980-1990
- Fukushima's Neurocognitron model for visual recognition
- Multi-layer Perceptrons (can learn nonlinear functions). Sunny days of AI are back!
- The Backpropagation algorithm to train deep neural nets
- Decision Trees, ID3 (Quinlan)
- NetTalk: Neural nets that can learn to pronounce English words
- Modern Reinforcement Learning

1990-2000
- Neural nets slumber due to lack of compute power
- Support Vector Machines (SVM), Kernel methods, Bayesian methods
- Random Forests, Boosting
- Continued work on neural nets for images, sequences (CNN, LSTM, etc)
- Deep Blue beats Kasparov

2000-2010
- Continued focus on classical statistical and probabilistic models, connections b/w learning & cognition
- Areas like vision, NLP, speech embrace data-driven ML methods as opposed to rule-based methods
- ML based algorithm wins the Netflix Challenge
- Neural nets re-emerged and rebranded as Deep Learning (Hinton, Bengio, LeCun, Ng, and others), thanks to improved training, GPUs

2010-2020
- Watson beats Humans in Jeopardy!
- Advances in ML/deep learning result in breakthroughs in areas like vision, NLP, speech, etc.
- Software frameworks (e.g., Tensorflow, PyTorch, ease implementing ML algos)
- Drones, self-driving cars, etc.
- **Human-like text generators (GPT-3)**
- A lot of industry/media focus, excitement, and hype
- Focus on Fairness, Accountability, and Transparency in ML algorithms

Road Ahead

Another **AI Winter** ?

Next Class

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- Various Flavors of ML problems

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- Data and features

Next Class

- Various Flavors of ML problems
- Data and features
- Basic mathematical operations on data and features