Faculty Development Program

on

Machine Learning and Image Processing

Course structure

- **Lectures**
- **Introduction to ML, Linear regression**
- **Logistic regression, SVM**
- **PCA, ANN**
- **DNN, CNN**
- **Advanced topics on IP**

- **Hands-on sessions**
- **Introduction to Colab & Python**
- **Hands-on using Python**
- **Hands-on using Keras**
- **Hands-on using Keras**
- **Demo on image processing**

Introduction to Machine Learning

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- **Primary focus will be in second category problems**

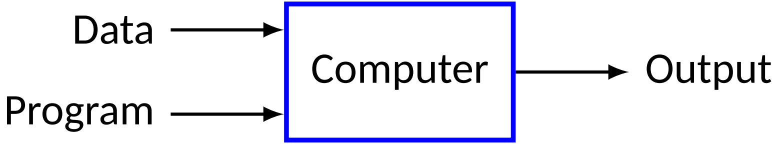
Problem Solving Strategies for Big Data

- Need to solve problems efficiently and accurately when the input data is huge ($\sim$ GB, TB order)

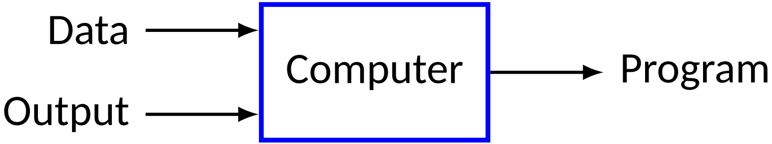
- Finding a deterministic algorithm is difficult
  - Need to find out features
  - Formal description of features are not easy
  - Requires significant effort for model building
  - Need to have domain knowledge

- Statistical inference is found to be suitable
  - Feature selection is not crucial
  - Model will learn from past data

Traditional programming vs ML



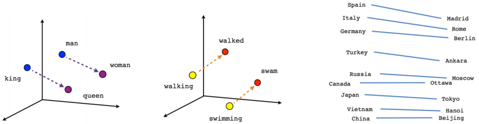
Traditional programming



Machine learning

Application domains

- Computer vision
- Natural language processing
- E-commerce, finance
- Weather prediction
- Genomics
- Drug discovery
- Particle physics
- Surveillance
- Cryptography
- Self driving car
- Games
- Intelligent control systems
- Speech processing
- *many others*



Male-Female Verb tense Country-Capital

Image source: Internet

Learning algorithm

- A ML algorithm is an algorithm that is able to learn from data
- Mitchelle (1997)
  - A computer program is said to learn from experience **E** with respect to some class of task **T** and performance measure **P**, if its performance at task in **T** as measured by **P**, improves with experience **E**.

- Task - A ML task is usually described in terms of how ML system should process an example
  - Example is a collection of features that have been quantitatively measured from some objects or events that we want the learning system process
    - Represented as $\boldsymbol{x} \in \mathbb{R}^n$ where x_i is a feature
    - Feature of an image — pixel values

Common AI/ML/DL Tasks

- **Classification**
  - Need to predict which of the k categories some input belongs to
  - Need to have a function $f : \mathbb{R}^n \rightarrow \{1, 2, \ldots, k\}$
  - $y = f(\boldsymbol{x})$ input $\boldsymbol{x}$ is assigned a category identified by y
  - Examples
    - Object identification
    - Face recognition
- **Regression**
  - Need to predict numeric value for some given input
  - Need to have a function $f : \mathbb{R}^n \rightarrow \mathbb{R}$
  - Examples
    - Energy consumption
    - Amount of insurance claim

Common AI/ML/DL Tasks (contd.)

- Classification with missing inputs
  - Need to have a set of functions
  - Each function corresponds to classifying x with different subset of inputs missing
  - Examples
    - Medical diagnosis (expensive or invasive)

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  - Need to convert relatively unstructured data into discrete, textual form
    - Optical character recognition
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- Machine translation
  - Conversion of sequence of symbols in one language to some other language
    - Natural language processing (English to Spanish conversion)

Common AI/ML/DL Tasks (contd.)

- Structured output
  - Output is a vector with important relationship between the different elements
    - Mapping natural language sentence into a tree that describes grammatical structure
    - Pixel based image segmentation (eg. identify roads)

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- Synthesis and sampling
  - Generate new example similar to past examples
    - Useful for media application
    - Text to speech

Performance measure

- Accuracy is one of the key measures
  - The proportion of examples for which the model produces correct outputs
  - Similar to error rate
    - Error rate often referred as expected 0-1 loss
- Mostly interested how ML algorithm performs on unseen data
- Choice of performance measure may not be straight forward
  - Transcription
    - Accuracy of the system at transcribing entire sequence
    - Any partial credit for some elements of the sequence are correct

Types of learning

- Supervised learning
  - Labeled data, outcomes are known for training data, Regression/Classification
  - A set of labeled examples $\langle x_1, x_2, \ldots, x_n, y \rangle$
    - x_i are input variables, y output variable
  - Need to find a function $f : X_1 \times X_2 \times \ldots X_n \rightarrow Y$
  - Goal is to minimize error/loss function
    - Like to minimize over all dataset
    - We have limited dataset
- Unsupervised learning
  - Unlabeled data, outcomes are not known for training data, Clustering
- Reinforcement learning
  - Need to learn from experience, no immediate outcome is known, Control/Game
- Semi-supervised learning
  - Missing lables for some training examples

Issue of Representation

- Representation of data in an efficient/structured manner is crucial for solving problems more effectively
  - Searching of a set of elements in a given list (sorted/unsorted)
  - Arithmetic operations on Arabic and Roman numerals
  - Primality test of n when n is represented as $11111\ldots111$ (n-number of one)

- Structured representation can help in predicting future values

Choice of Representation

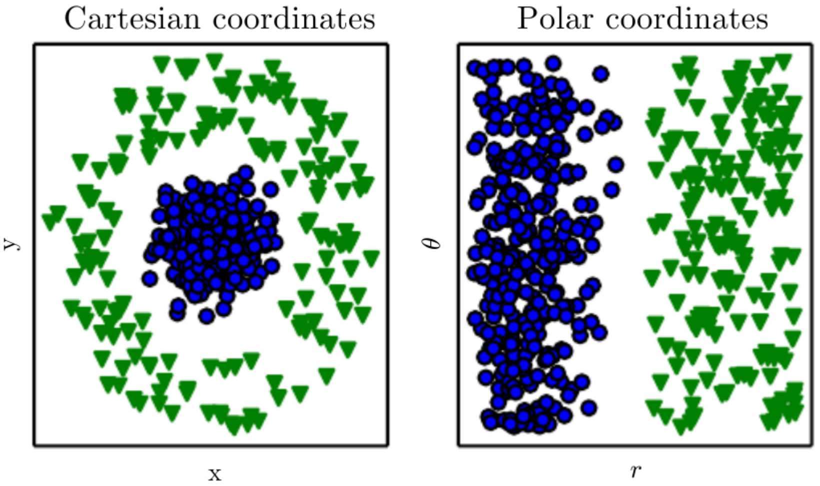


Image source: Deep Learning book

Learning representation/feature

- Traditional approaches
  - Pattern recognition
    - Input, output of the problem
- End to end learning
  - System automatically learns internal representation

AI-ML Tasks

- Heavily depends on features
- Requires good domain knowledge
- Feature extraction is not easy job
  - Identify a car
    - How to describe wheel
    - Shadow/brightness
    - Obscuring element

Representation Learning

- Learned representation often results in better performance compared to hand design
- Allows the system to rapidly adapt to new task
- Need to discover a good set of features
- Manual design of features is nearly impossible

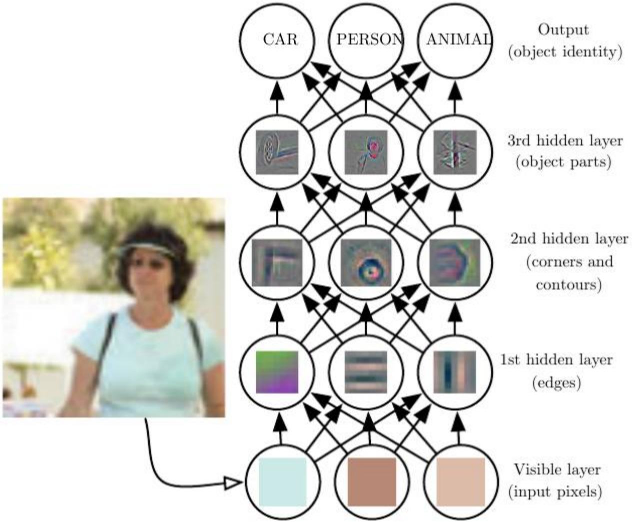
Design of Features

- Goal is to separate out variation factors
- These factors are separate sources of influence
- It may exist as unobserved object or unobserved forces that affect observable quantity
  - Speech - Factors are age, sex, accent, etc
  - Image - Position, color, brightness, etc.

Deep Learning

- Try to address the problem of representation learning
- Representation are expressed in terms of other simpler representation
- Develop complex concept using simpler concept

Simple to Complex Features



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Simple to Complex Features

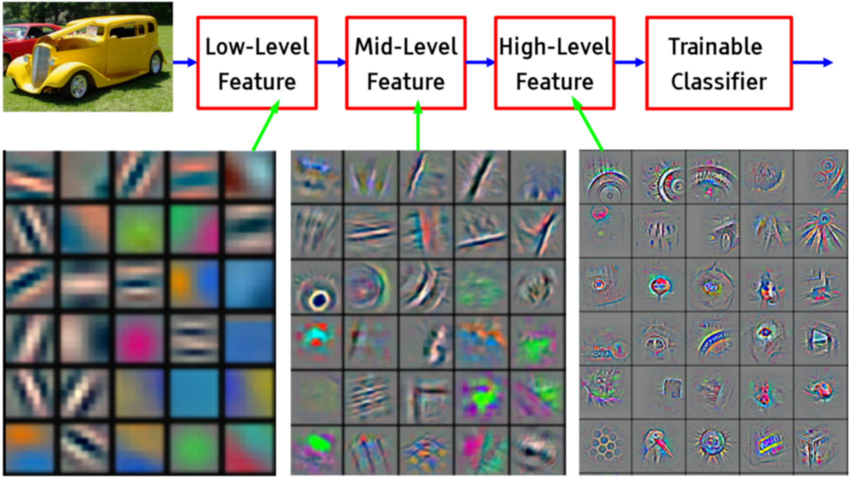
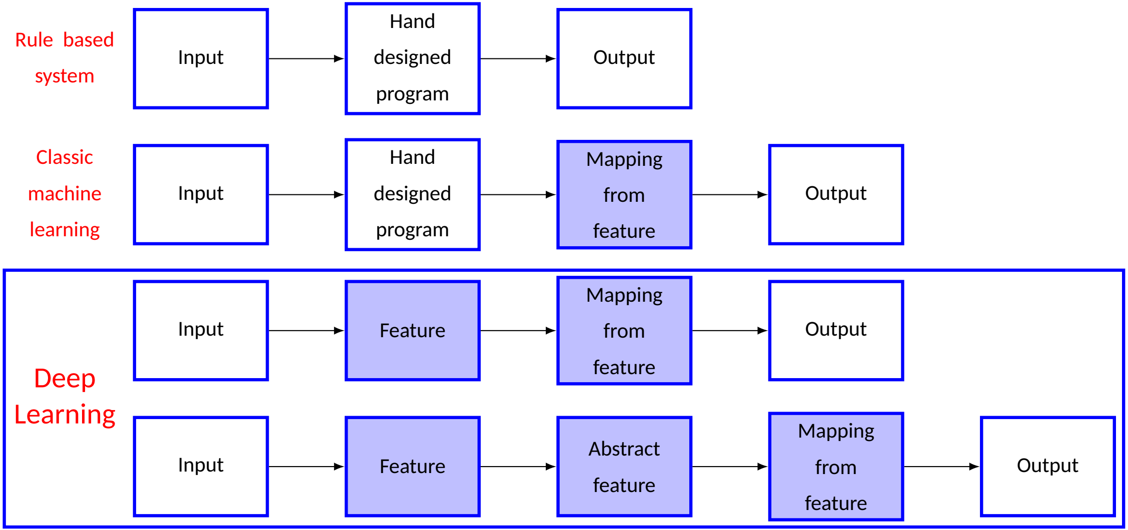


Image source: Deep Learning Tutorial by Yann LeCun Marc'Aurelio Ranzato, ICML, 2013

Conventional Machine Learning

Image source: Deep Learning by Yann LeCun, Yoshua Bengio & Geoffrey Hinton

Representation learning



History

- Has many names and view point
  - Cybernetics (1940-1960)
  - Connectionism (1980-1990) (neural net)
  - Deep learning (2006+)

- More useful as the amount of data is increased
- Models have grown in size as increase in computing resources
- Solving complex problem with increasing accuracy

Popularization of Neural Network

- **Most of the theory of neural network was developed in the 1980s**
- **Started gaining popularity around 2012**
  - **Geoffrey Hinton and Alex Krizhevsky winning the ImageNet competition where they beat the nearest competitor by a huge margin (2012)**

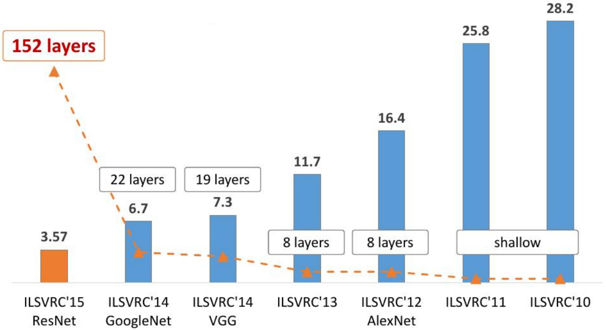


Image source: Deep Residual Learning by Kaiming He, et.al.

Popularity

- Increase data size
  - Computing resources are available
  - Accepting performance 5000 labeled example per category
  - 10 million for human performance
- Increasing model size
- Increasing accuracy, complexity, real world impact
- Used by many companies
  - Google, Microsoft, Facebook, IBM, Baidu, Apple, Adobe, Nvidia, NEC, etc.
- Availability of good commercial & open-source tools
  - Theano, Torch, DistBelief, Caffe, TensorFlow, Keras, etc.

DL Trend

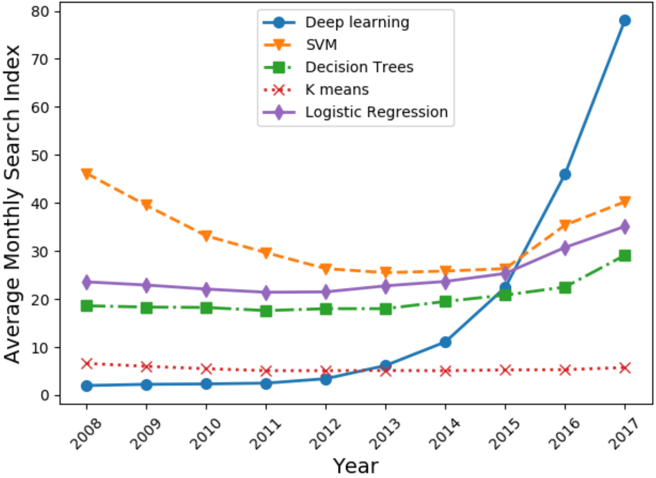


Image source: Internet

Search trend in Google

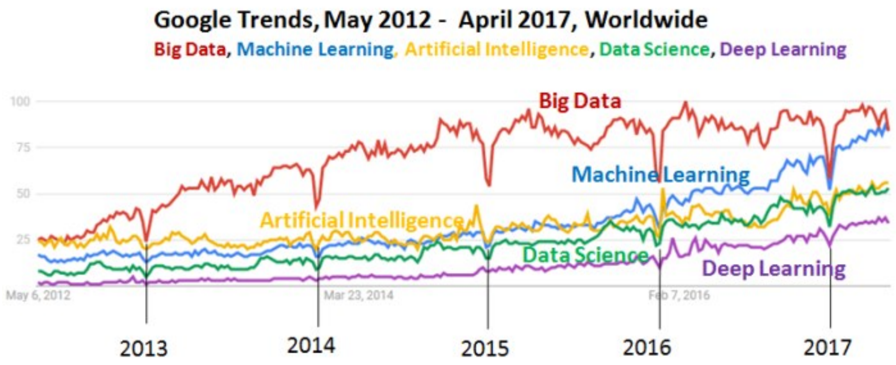
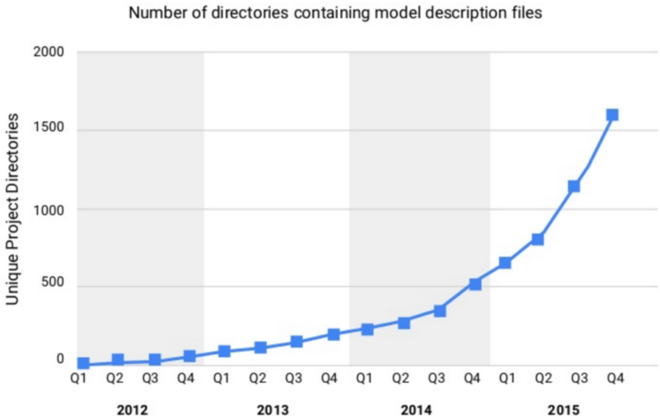


Image source: Internet

AI/DL in Google



Across many products/areas

- Apps
- Maps
- Photos
- Gmail
- Speech
- Android
- YouTube
- Translation
- Robotics Research
- Image Understanding
- Natural Language Understanding
- Drug Discovery

Google

Image source: Internet

Artificial Intelligence is the New Electricity — Andrew Ng

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Thank you!