Tools Seminar

Week 7 - Machine Learning

Hongzheng Chen

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1

Introduction

Machine Learning Era

We witness the boom of ML:

- Face recognition
- Speech recognition
- Language translation
- Question-answering system
- Self-driving
- Games
- Healthcare
- Robots
- $\cdots$

Machine Learning

> *A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.*
>
> — *Mitchell, 1997*

Take exam as an example

- T: To obtain high score
- E: Do exercise
- P: Accuracy of exercise

Machine Learning Branches

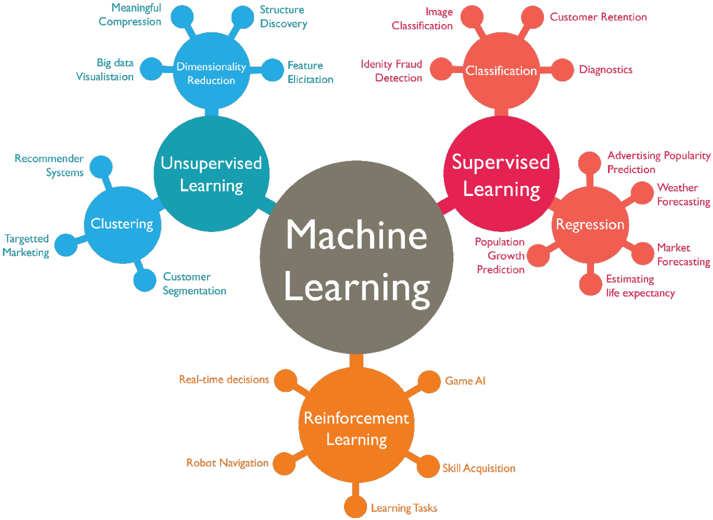


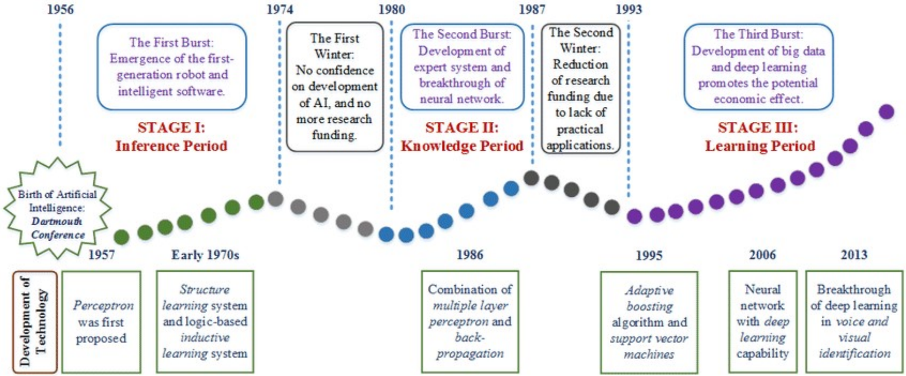
Fig source: https://askdatascience.com/13/

Some Ideas to Clarify

Artificial Intelligence (AI)
$>$ **Machine Learning (ML)**
$>$ **Deep Learning (DL)**

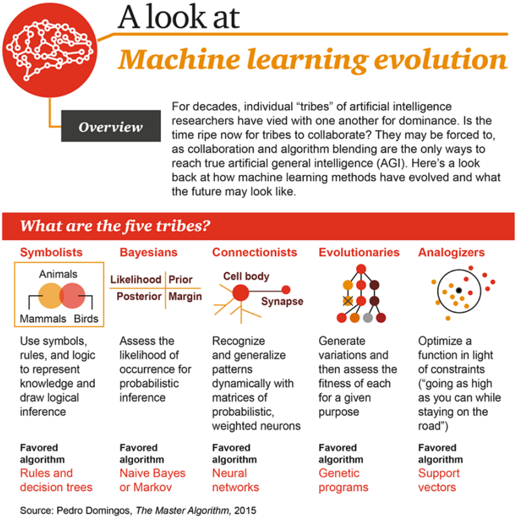
- ML is not the only way to achieve AI
- DL is just a method of ML
- Neural Network (NN) is the core of DL
- Computer Vision (CV) & Natural Language Processing (NLP) are two applications of DL

AI History



Ref:
https://en.wikipedia.org/wiki/History_of_artificial_intelligence

AI Tribes



A look at

Machine learning evolution

Overview

For decades, individual “tribes” of artificial intelligence researchers have vied with one another for dominance. Is the time ripe now for tribes to collaborate? They may be forced to, as collaboration and algorithm blending are the only ways to reach true artificial general intelligence (AGI). Here’s a look back at how machine learning methods have evolved and what the future may look like.

What are the five tribes?

Symbolists	Bayesians	Connectionists	Evolutionaries	Analogizers
Animals / Mammals / Birds	Likelihood / Prior / Posterior / Margin	Cell body / Synapse		
Use symbols, rules, and logic to represent knowledge and draw logical inference	Assess the likelihood of occurrence for probabilistic inference	Recognize and generalize patterns dynamically with matrices of probabilistic, weighted neurons	Generate variations and then assess the fitness of each for a given purpose	Optimize a function in light of constraints (“going as high as you can while staying on the road”)
Favored algorithm Rules and decision trees	**Favored algorithm** Naive Bayes or Markov	**Favored algorithm** Neural networks	**Favored algorithm** Genetic programs	**Favored algorithm** Support vectors

Source: Pedro Domingos, *The Master Algorithm*, 2015

2

Some Introductory Books & Courses

Machine Learning

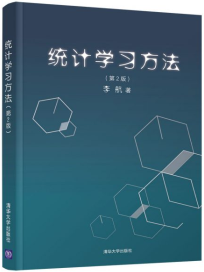
Prerequirement: Linear algebra, multivariable calculus, probability theory

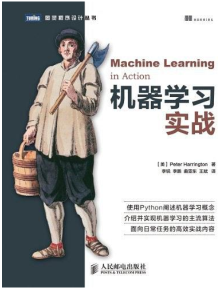
- Andrew Ng, Stanford CS229: Machine Learning
- Hsuan-Tien Lin, NTU: Machine Learning Foundations

You can find them on Bilibili!

* YJango, 《学习观》

Chinese Books





Other books

- Christopher M. Bishop, Pattern Recognition & Machine Learning (PRML)
- Stephen Boyd, Lieven Vandenberghe, Convex Optimization
- Ian Goodfellow, Yoshua Bengio, Aaron Courville, Deep Learning (flower book)
- Richard S. Sutton, Andrew G. Barto, Reinforcement Learning

Top-tier Conferences in AI Area

- General AI: AAAI, IJCAI
- NLP: ACL, EMNLP, NAACL
- CV: CVPR, ICCV, ECCV
- ML: NeurIPS/NIPS, ICML, ICLR
- Data mining: KDD, SIGMOD, ICDE, VLDB, SIGIR, WWW
- System: SysML

3

Machine Learning Basis

Machine Learning Basis

For **supervised learning** (classification & regression), we have

- Training set

$$\mathcal{D} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_m, y_m)\}$$

  - Sample: $(\mathbf{x}_i, y_i)$
  - Input/Feature/Attribute: $\mathbf{x}_i \in \mathcal{X} \subset \mathbb{R}^d$
  - Output/Label/Target: $y_i \in \mathcal{Y} \subset \mathbb{R}$
- Model: Want to learn a mapping from $\mathcal{X}$ to $\mathcal{Y}$

$$f : \mathcal{X} \mapsto \mathcal{Y}$$

For example, consider face recognition

- Input: Many students' faces in 2D figures
- Output: The name of the student
- Model: $f(\text{face}) = \text{student}$

Differences between different ML alg. are how to determine f

Linear Regression

Consider sample with d features

$$\mathbf{x} = (x_1, x_2, \ldots, x_d)$$

Use **linear combination** of features as model

$$f(\mathbf{x}) = w_1 x_1 + w_2 x_2 + \cdots + w_d x_d + b = \mathbf{w}^{\mathrm{T}}\mathbf{x} + b \simeq y$$

where $\mathbf{w}$, b are the parameter needs to be learned
Loss function $J(\mathbf{w}, b)$: measure the performance of the model, we use **mean square error (MSE)** here

$$J(\mathbf{w}, b) = \|f(\mathbf{x}_i) - y_i\|_2^2$$

Then **objective** is to optimize

$$\min_{\mathbf{w},b} \left(\sum_{i=1}^{m} J(\mathbf{w}, b) \right) = \min_{\mathbf{w},b} \left(\sum_{i=1}^{m} \|f(\mathbf{x}_i) - y_i\|_2^2 \right)$$

Linear Regression

The best parameters are what we want

$$(\mathbf{w}^*, b^*) = \arg\min_{\mathbf{w},b} \left(\sum_{i=1}^{m} \| f(\mathbf{x}_i) - y_i \|_2^2 \right)$$

Commonly, we use gradient descent to optimize, which is an iterative process

$$\begin{cases} \mathbf{w}^{(k+1)} = \mathbf{w}^{(k)} - \alpha \frac{\partial J(\mathbf{w},b)}{\partial \mathbf{w}} & = \mathbf{w}^{(k)} - \alpha \nabla_{\mathbf{w}} J(\mathbf{w}, b) \\ b^{(k+1)} = b^{(k)} - \alpha \frac{\partial J(\mathbf{w},b)}{\partial b} & = b^{(k)} - \alpha \nabla_b J(\mathbf{w}, b) \end{cases}$$

If loss cannot be reduced more (converged), we find the optimal $\mathbf{w}^*$ and b^*
The final model becomes

$$f(\mathbf{x}) = (\mathbf{w}^*)^{\mathrm{T}} \mathbf{x} + b^*$$

Linear Regression

But for MSE of linear regression, you can easily find close-form solution by **least square method**

- Stack the samples

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1d} & 1 \\ x_{21} & x_{22} & \cdots & x_{2d} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{md} & 1 \end{bmatrix} = \begin{bmatrix} \mathbf{x}_1^{\mathrm{T}} & 1 \\ \mathbf{x}_2^{\mathrm{T}} & 1 \\ \vdots & \vdots \\ \mathbf{x}_m^{\mathrm{T}} & 1 \end{bmatrix}, \mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}, \hat{\mathbf{w}} = \begin{bmatrix} w_1 \\ \vdots \\ w_d \\ b \end{bmatrix}$$

- Optimize

$$\hat{\mathbf{w}}^* = \arg\min_{\hat{\mathbf{w}}} (\mathbf{y} - X\hat{\mathbf{w}})^{\mathrm{T}}(\mathbf{y} - X\hat{\mathbf{w}})$$

- Make derivative as 0

$$\frac{\partial J(\hat{\mathbf{w}})}{\partial \hat{\mathbf{w}}} = 2X^{\mathrm{T}}(X\hat{\mathbf{w}} - \mathbf{y}) = 0$$

- Solve for best $\hat{\mathbf{w}}$ (if $X^{\mathrm{T}}X$ has inverse)

$$\hat{\mathbf{w}}^* = (X^{\mathrm{T}}X)^{-1}X^{\mathrm{T}}\mathbf{y}$$

Summary

1. Obtain required training and testing data
2. Determine the objective of the task
3. Select a machine learning model to train
4. Use pre-trained model to predict

4

Data Processing

Machine Learning Today

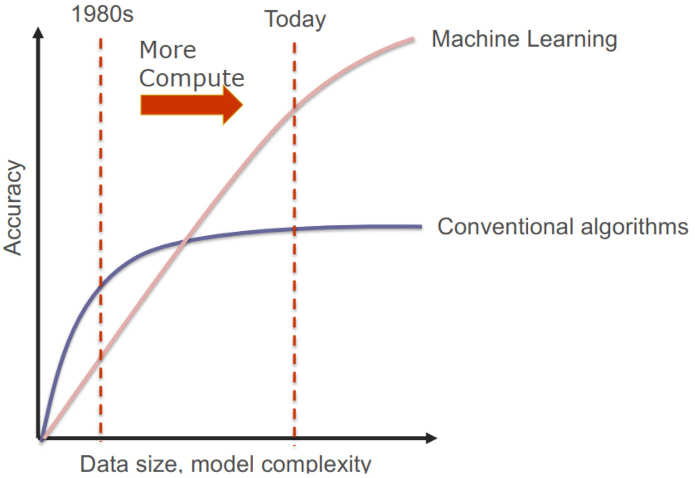
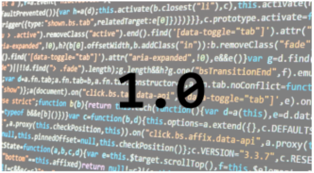


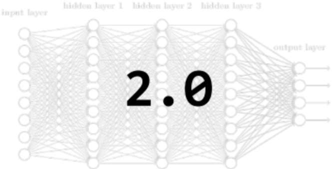
Fig source: Jeff Dean, HotChips 2017

Software 2.0 Era

Training data: The new input to software 2.0



- Input: Algorithms in code
- Compiled to: Machine instructions



- Input: Training data
- Compiled to: Learned parameters

Fig source: Kunle Olukutun, ISCA, 2018

Thus, **quality & quantity** of the data determine performance!

Common Data Science Steps

1. Data collection
2. Feature engineering (Data cleaning/preprocessing)
3. Model selection
4. Training
5. Evaluation

Data Collection

In competitions, we commonly have official datasets
But what if no collected datasets available in some specific tasks?
(e.g. face mask recognition)

Data Collection

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But what if no collected datasets available in some specific tasks?
(e.g. face mask recognition)
Design a web crawler!

1. Crawl the webpages (`requests`, `urllib`)
2. Parse html (`bs4`)
3. Retrieve useful data (text, figure, or other specific content)
4. Organize the data
5. Store them into files (`mysql`, `json`)

A Dataset Example

	Feat 1	Feat 2	$\cdots$	Feat d	Label
Sample 1	x_{11}	x_{12}			y_1
$\vdots$					$\vdots$
Sample m					y_m

Many ML tasks need to predict the label (classification/regression), e.g.

- Kaggle Titanic
- Tianchi Happiness
- ICM/MCM/CUMCM

Data Cleaning

Data cleaning or feature engineering is **the first step** of most ML tasks!
Most datasets are troublesome: (think about questionnaires)

- Data missing
- Redundant data
- Data not in same scale
- Useless features
- Too many features
- ...

ML is also called **representative learning**
Good data and good features benefit learning process

5

Pandas & Sklearn

Some Hints

Hint Use jupyter notebook for interactive operations, see demo

- You should carefully deal with the data which may be very dirty
- You can select any features you like, do transformation, and discard others
- For models with hyperparameters, use grid search to fine-tune
- Moreover, you can even stack two models, i.e. ensemble learning

6

Summary

Summary

- Introduction
- Machine learning basis: Linear regression
- Data processing: pandas
- Training & Testing: sklearn

Assignments

Use pandas & sklearn to predict
whether the income of a person exceeds $50K/yr (two-class classification)

- Dataset: http://archive.ics.uci.edu/ml/datasets/Adult
- `adult.data` is the train set and `adult.test` is the test set, i.e. you need not separate train and test set manually
- `adult.names` gives descriptions of the features
- Present the classification **accuracy** and try to get close to the official accuracy (85%)
- You can use any ML model you like, see https://scikit-learn.org/stable/supervised_learning.html
- Try to figure out why some models are better than others
- All the works need to be done in a Jupyter notebook
- Preserve your results in the notebook and submit your `.ipynb` to Github

Assignments

Hint:

- Remember the proposed hints in the former slide, and you can try several methods and compare the accuracy
- Classification can be viewed as a special case of regression, thus common regression methods can be used