Introduction to Machine Learning

Introduction

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Making Intelligent Machines

Human Learning

Definition of Machine Learning Why Machine Learning?

Learning from (Past) Data

Overview of ML

Supervised Learning

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The world is woven from billions of lives, every strand crossing every other. What we call premonition is just movement of the web. If you could attenuate to every strand of quivering data, the future would be entirely calculable, as inevitable as mathematics.

Sherlock Holmes, 2017



- 1. Talk. See. Hear.
 - Natural Language Processing, Computer Vision, Speech Recognition
- 2. Store. Access. Represent. (Knowledge)
 - Ontologies. Semantic Networks. Information Retrieval.
- 3. Reason.
 - Mathematical Logic. Bayesian Inference.
- 4. Learn.
 - Improve with Experience

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- 4. Learn.
 - Improve with Experience
 - Machine Learning

What do we learn?

- Concepts (this is a chair, that is not a chair)
- Distinguishing concepts (this is a chair, that is a table)
- Other things (language, juggling, using a remote)
- How do we learn?
 - 1. Teaching (Passive).
 - 2. Experience (Active).
 - 2.1 Examples.
 - 2.2 Queries.
 - 2.3 Experimentation.

• Computers learn without being **explicitly programmed**.

Arthur Samuel (1959)

A computer program learns from experience E with respect to some task T, if its performance P while performing task T improves over E.

► Tom Mitchell (1989)

- Machines that know everything from the beginning?
 - Too bulky. Creator already knows everything. Fails with <u>new</u> experiences.
- Machines that learn?
 - Compact. Learn what is <u>necessary</u>.
 - Adapt.
 - Assumption: Future experiences are not too different from past experiences.
 - Have (structural) relationship.





Deductive Logic

- All birds can fly
- Dodo is a bird
- \blacktriangleright \Rightarrow Dodo can fly

Inductive Logic

- A stingray can swim
- Stingray is a fish
- $\blacktriangleright \Rightarrow \mathsf{All fish can swim}$

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Core Tenet

- Deduce Induce from past
- Generalize for future

- What do you want the ML algorithm to do?
 - ML tasks: classification, prediction, grouping, decision making
- How do you want to do it?
 - Supervised learning, unsupervised learning, and reinforcement learning

Supervised Learning

- Given a finite set of x's and corresponding y's, learn f()
- Infer y for a new x
 - y continuous (regression)
 - y discrete (classification)

Unsupervised Learning

- Given only x's, infer structure in data
 - hidden (latent) relationships among the objects
- e.g., clustering, embedding, dimensionality reduction, etc.

Reinforcement Learning

- Find the best mapping of situations to actions to maximize a numerical reward
- Agent learns to behave in an environment

Supervised Learning - Machine Learning meet Mother Nature

Data: A collection of data objects

- A representation of the object of interest or the state of the target system, and/or
- A label or a target value or a low-dimensional representation or an embedding or an action associated with the object/state
- Mother nature generates this data using an unknown generative process (secret recipe)
- ML problem given part of the information, infer the other part



Primary

- Given an individual's data (criminal and otherwise), predict risk of recidivism
- Given an email, determine if it is spam or normal
- Given an image, identify the object
- For a given day, predict the number of travelers that will pass through a subway station

Secondary

- Color a black and white image
- Translate English text to French
 - translate.google.com

True Test for Any Language System

 Buffalo buffalo Buffalo buffalo buffalo Buffalo buffalo.

True Test for Any Language System

 Buffalo buffalo Buffalo buffalo buffalo Buffalo buffalo.



Text excerpted from the Wikipedia articles Buffalo buffalo Buffalo buffalo buffalo buffalo buffalo buffalo. Hononym and Homophone. 26 March 2007

Buffalo buffalo, Buffalo buffalo buffalo, buffalo Buffalo buffalo.

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Learn hidden structure in the data

- No assumption of labels
- Examples
 - 1. Clustering (customers of Wegmans, set of magazine articles)
 - 2. Embedding any data into a metric space (\Re^d) (text, tweets, disease codes)
 - 3. Dimensionality reduction
 - 4. Factor analysis
 - 5. Dictionary learning

Isolating Music

https://vimeo.com/348102769

- An agent, operating in a changing environment, finds the best sequence of actions that maximize an end goal
- Key concepts: policy, reward, end-value, environment

Examples

- 1. Learning to play a game (Breakout, AlphaGo)
- 2. A robotic vaccum cleaner figures out the best time to recharge
- 3. Almost all robotic tasks
- 4. Traffic light control



https://www.youtube.com/v/V1eYniJORnk

ML as a generator - faces



Generating faces

- https://thispersondoesnotexist.com
- https://www.whichfaceisreal.com

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You will rejoice to hear that no disaster has overtaken you. If your heart is grieved, and your joy is swallowed up, you have the LORD to thank. You will rejoice to hear that no disaster has accompanied the commencement of an enterprise which you have regarded with such evil forebodings.

ML as a decision maker - criminal justice



References

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