Artificial intelligence, machine learning, machine intelligence, natural language processing, ...

- buzzwords, hype, real accomplishments, wishful thinking
  - big data, deep learning, neural networks, ...

- brief history
- examples
  - classification (spam detection)
  - prediction (future prices)
  - recommendation systems (Netflix, Amazon, Goodreads, ...)
  - natural language processing (sentiment analysis)
  - games (chess, Go)

- disclaimer: on this topic,

  I am even less of an expert than normal.

  Beware!

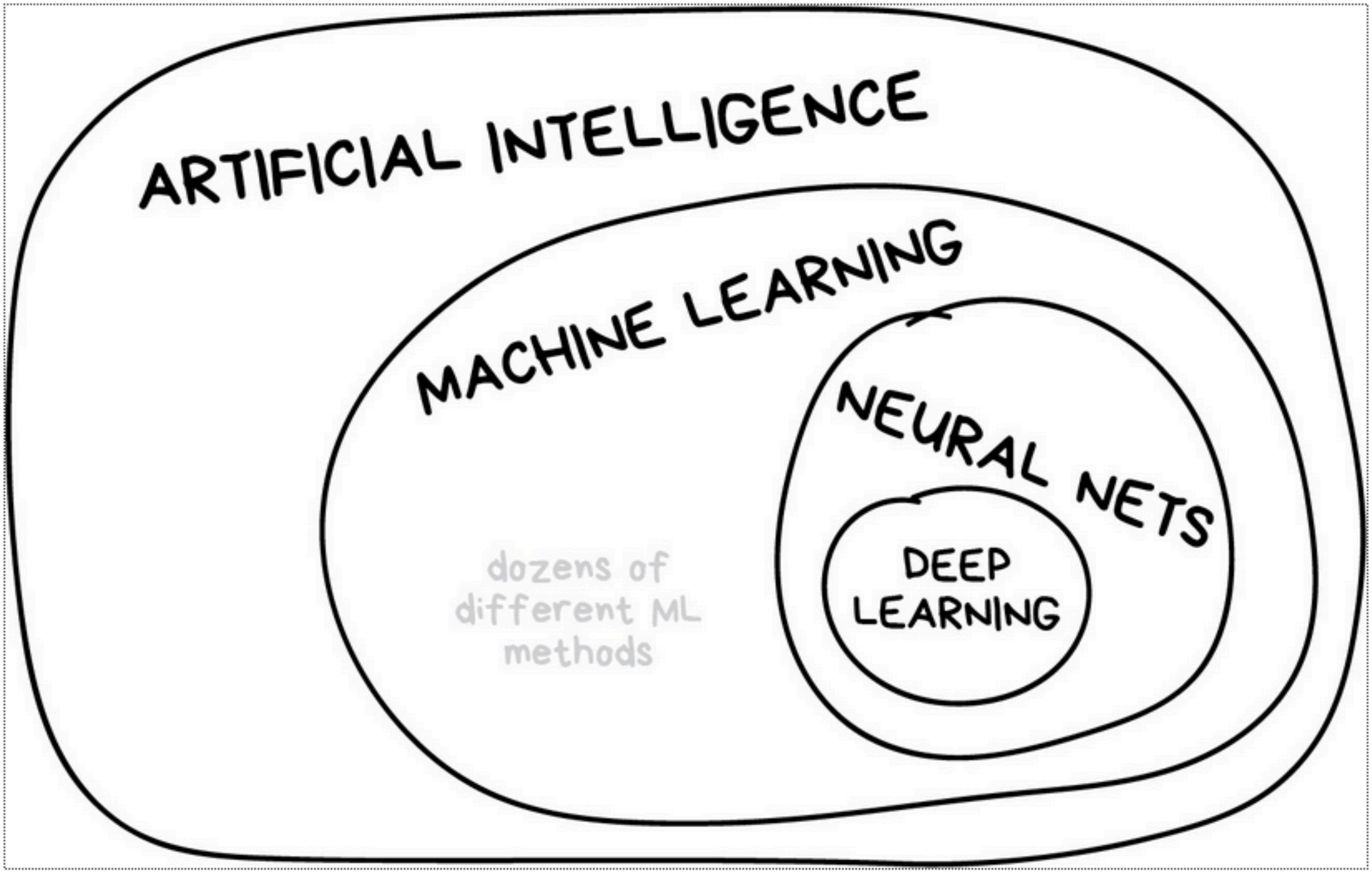
Revisionist history (non-expert perspective)

- **1950s, 1960s: naive optimism about artificial intelligence**
  - checkers, chess, machine translation, theorem proving, speech recognition, image recognition, vision, ...
  - almost everything proved to be much harder than was thought

- **1980s, 1990s: expert or rule-based systems**
  - domain experts write down lots of rules, computers apply them to make decisions
  - it's too hard to collect the rules, and there are too many exceptions
  - doesn't scale to large datasets or new problem domains

- **2010s: machine learning, big data, ...**
  - provide a "training set" with lots of examples correctly characterized
  - define "features" that might be relevant
  - write a program that "learns" from its successes and failures on the training data (basically by figuring out how to combine feature values)
  - turn it loose on new data

The big picture (vas3k.com/blog/machine_learning)



Examples of ML applications (tiny subset)

- **classification**
  - spam detection, digit recognition, optical character recognition, authorship, ...
  - image recognition, face recognition, ...
- **prediction**
  - house prices, stock prices, credit scoring, ...
  - tumor probabilities, intensive care outcomes, ...
- **recommendation systems**
  - e.g., Netflix, Amazon, Goodreads, ...
- **natural language processing (NLP)**
  - language translation
  - text to speech; speech to text
  - sentiment analysis
- **games**
  - checkers, chess, Go

Types of learning algorithms

- supervised learning (labeled data)
  - teach the computer how to do something with training examples
  - then let it use its new-found knowledge to do it on new examples
- unsupervised learning (unlabeled data)
  - let the computer learn how to do something without training data
  - use this to determine structure and patterns in data
- reinforcement learning
  - some kind of "real world" system to interact with
  - feedback on success or failure guides/teaches future behavior
- recommender systems
  - look for similarities in likes and dislikes / behaviors / ...
  - use that to predict future behaviors

Classification example: spam detection

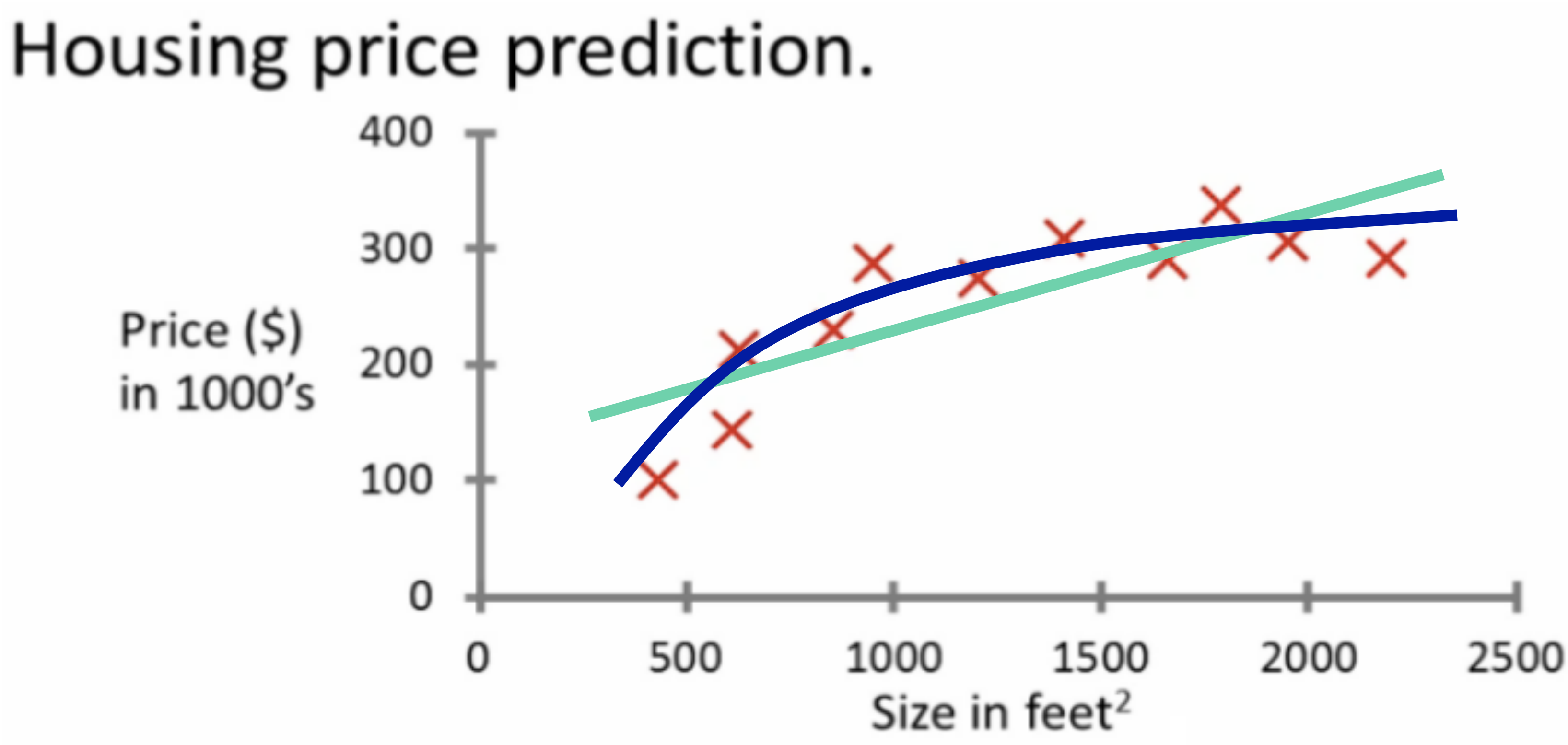
- rule-based: look for odd words & spellings, known bad sources, etc.
  - V1/\6R/\, M0N\E`/, spamRus.com, ...

- machine learning: choose a set of features like
  - odd spelling, weird characters, language and grammar, origin, length, ...
  - provide a training set of messages that are marked "spam" or "not spam"
- ML algorithm figures out parameter settings that let it do the best job of separating spam from not spam in the training set
- then apply that to real data

- potential problems:
  - training set isn't good enough or big enough
  - creating it is probably done manually
  - "over-fitting": does a great job on training set but little else
  - spammers keep adapting so we always need new training material

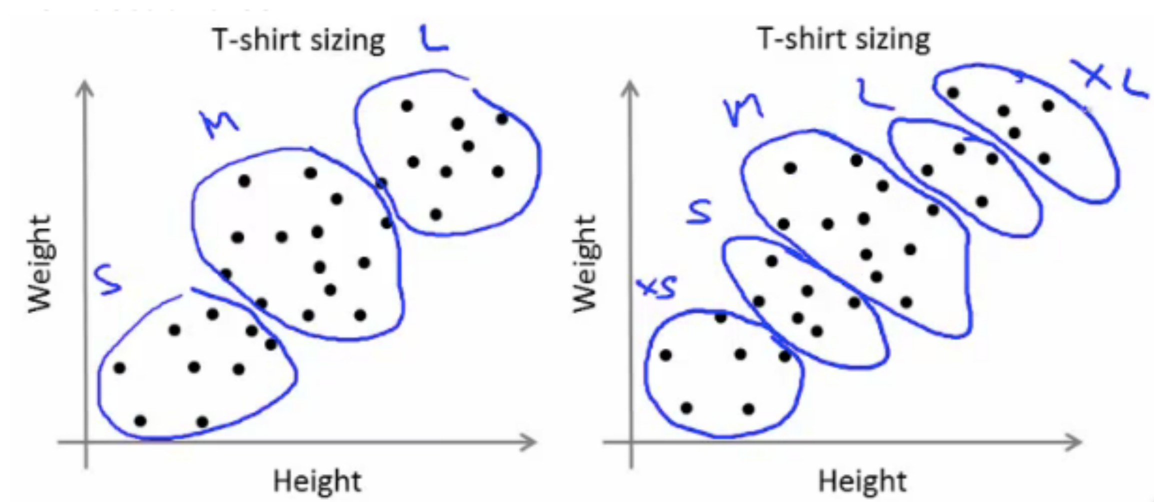
Prediction example: house prices

- only one feature here: square footage
- straight line? ("linear regression")
- some kind of curve?



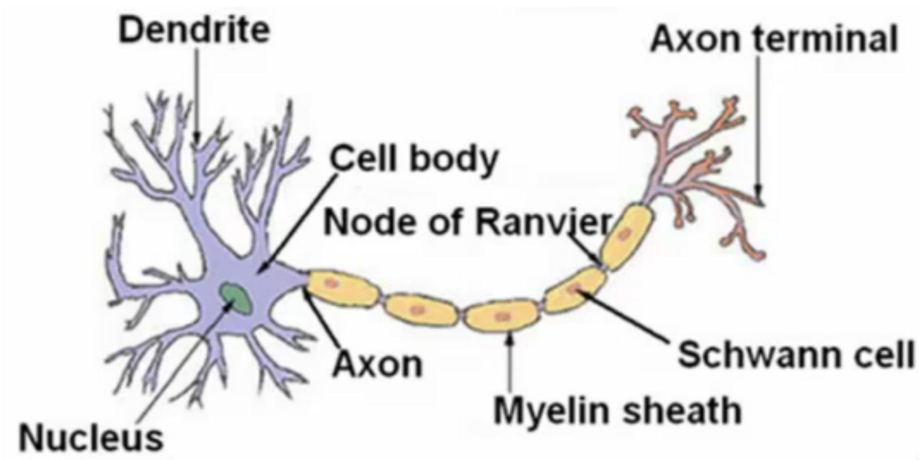
Clustering (learning from unlabeled data)

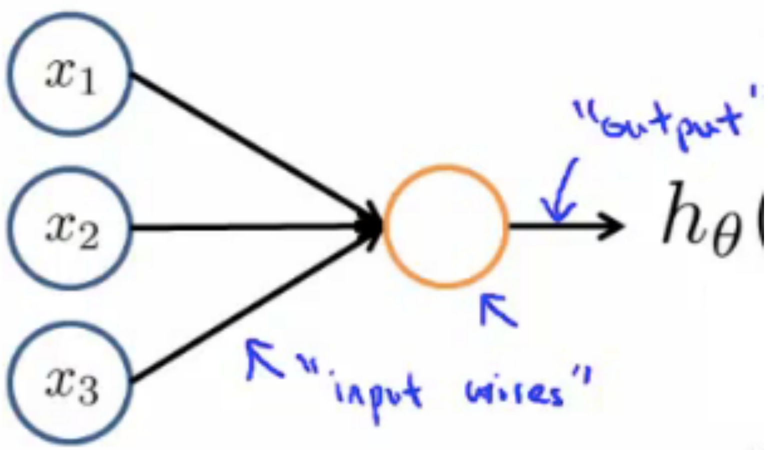
- **contrast with supervised learning**
  - supervised learning
    given a set of labels, fit a hypothesis to it
  - unsupervised learning
    try and determine structure in the data
    clustering algorithm groups data together based on data features
- **good for**
  - market segmentation - group customers into different market segments
  - social network analysis - Facebook "smartlists"
  - topic analysis
  - authorship

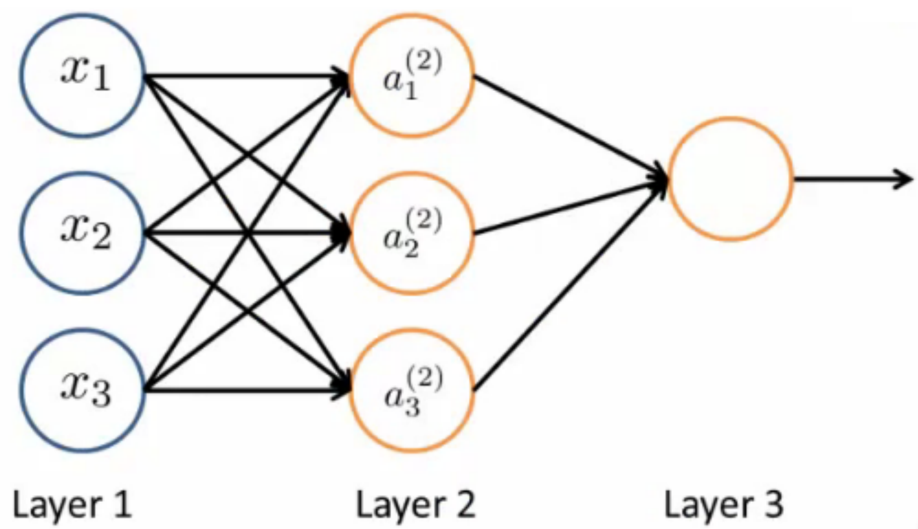


Neural networks, deep learning

- simulate human brain structure
  with artificial neurons
  in simple connection patterns







Natural language processing (NLP)

- understanding text
  - parsing, syntactic structure
  - topic modeling
  - sentiment analysis
  - text generation
- text to speech
- speech to text
- translation

ML / AI issues

- **algorithmic fairness**
  - results can't be better than training data
  - if that has implicit or explicit biases, results are biased
- **accountability**
  - what is the algorithm really doing?
  - can its results be explained
- **appropriate uses?**
  - prison sentencing
  - drone strikes
  - weapon systems
  - resume evaluation
  - medical decisions
  - ...
- **limitations**
  - can ML algorithms be better than their data?

You might like…

- COS 126 General Computer Science (Dan Leyzberg)
- APC 199 Math Alive
- AST 203 The Universe
- CEE 262B Structures ("Bridges") (Maria Garlock; STL)
- EGR 277 Technology and Society (ITP certificate; David Reinecke; SA)
- CLA 208 Origins and Nature of English Vocabulary (Joshua Katz; LA)

- FRS 106 Art and Science of Motorcycle Design (Mike Littman; STL)
- FRS 116 The Evolution of Human Language (Christiane Fellbaum; EC)
- FRS 118 Life on Mars–or Maybe Not (Michael Lemonick, Ed Turner; SA)
- FRS 122 Connection & Communication in the Digital Bazaar (Swati Bhatt; SA)
- FRS 134 Scientists against Time (Hal Feiveson; HA)
- FRS 162 Bioethics: Public Policy, Ethics and the Law (Harold Shapiro; SA)
- FRS 166 What to Read and Believe in the Digital Age (Joe Stephens, Council of the Humanities; SA)