COMP/EECE 7/8745 Machine Learning

Topics:

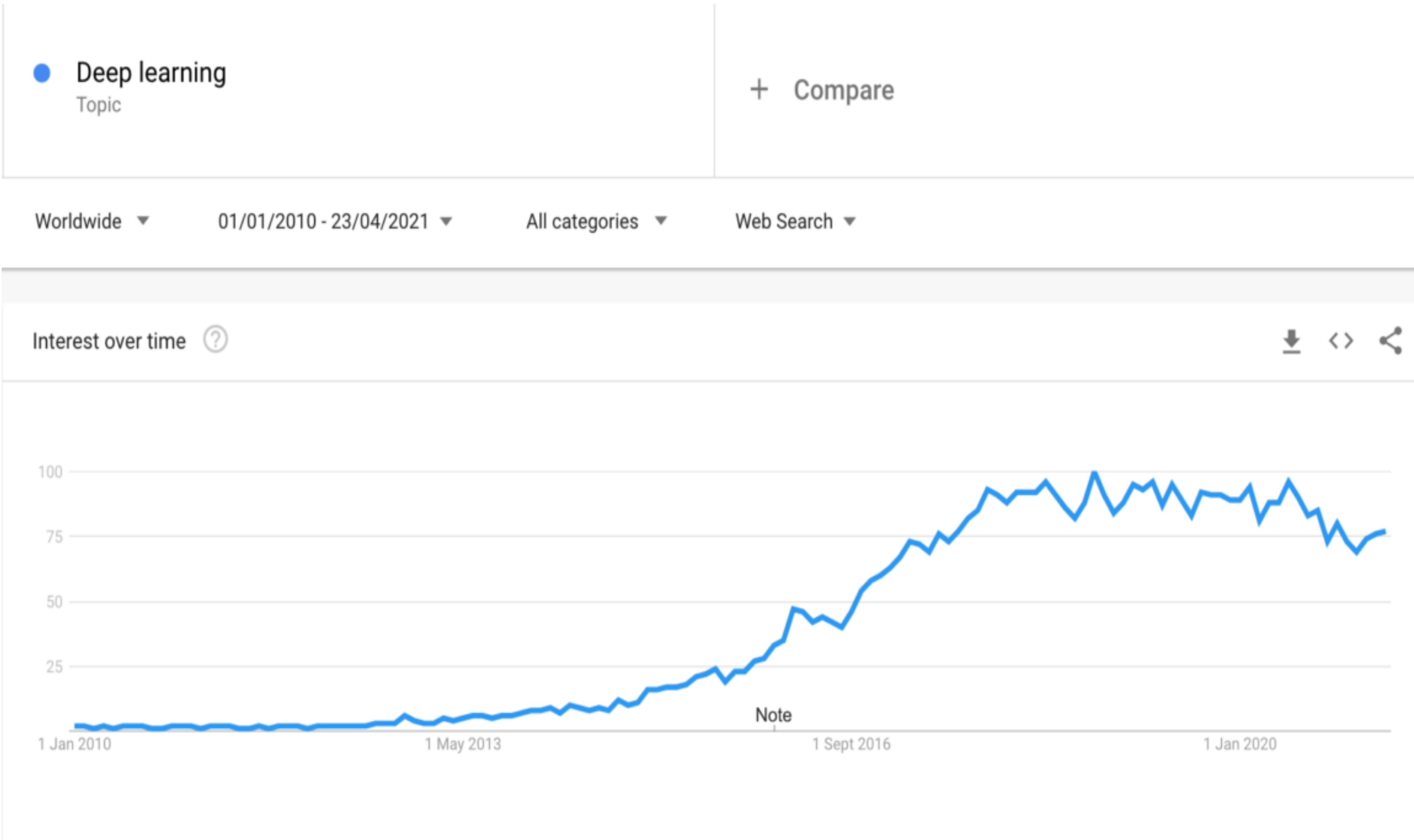
Introduction

- What is Machine Learning (ML)?
- Course organization & deliverables
  - Assignments, exams, projects
- Grading scheme

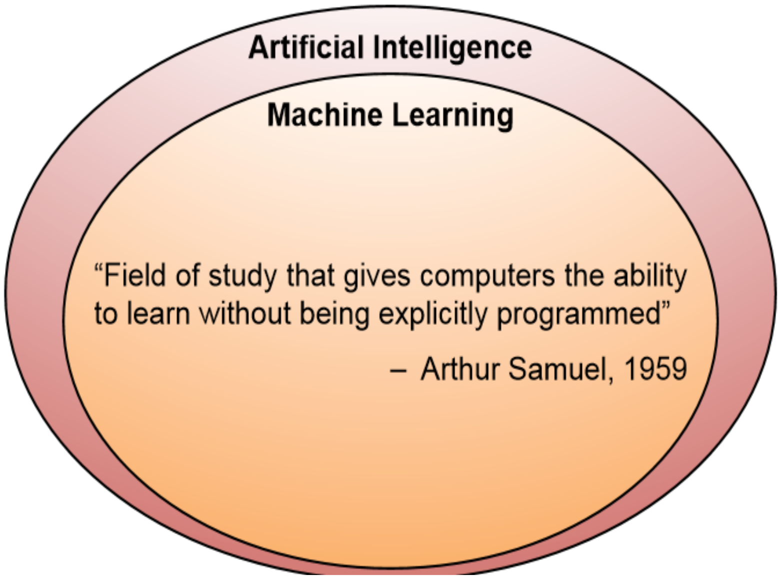
Md Zahangir Alom
Department of Computer Science
University of Memphis, TN

Machine or Deep learning: got lots of attention.

- Google Trends :



What is Machine Learning?



"Learning is any process by which a system improves performance from experience."
- Herbert Simon

Definition by Tom Mitchell (1998):

Machine Learning is the study of algorithms that

- improve their performance P
- at some task T
- with experience E.

A well-defined learning task is given by <P, T, E>.

- "Machine learning is programming computers to optimize a performance criterion using example data or past experience." Intro to Machine Learning, Alpaydin, 2010
- Examples of ML system:
  - Facial recognition
  - Digit recognition
  - Molecular classification
  - Many more ….

Traditional programming vs ML

Traditional Programming

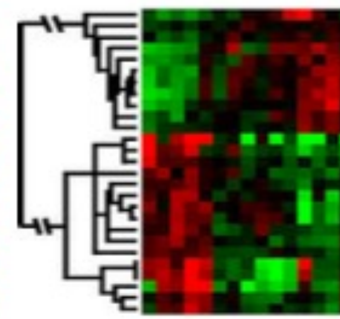
Machine Learning

When Do We Use Machine Learning?

ML is used when:

- Human expertise does not exist (navigating on Mars)
- Humans can't explain their expertise (speech recognition)
- Models must be customized (personalized medicine)
- Models are based on huge amounts of data (genomics)



Learning isn't always useful:

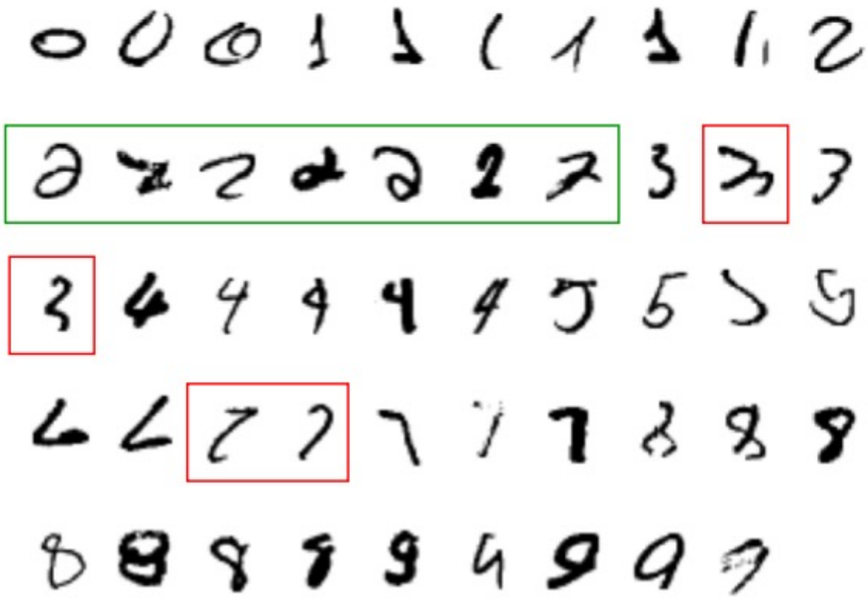
- There is no need to "learn" to calculate payroll

Based on slide by E. Alpaydin

Example up-close

- Problem: Recognize images representing digits 0 through 9
- Input: High dimensional vectors representing images
- Output: 0 through 9 indicating the digit the image represents
- Learning: Build a model from “training data”
- Predict “test data” with model

A classic example of a task that requires machine learning:
It is very hard to say what makes a 2



Slide credit: Geoffrey Hinton

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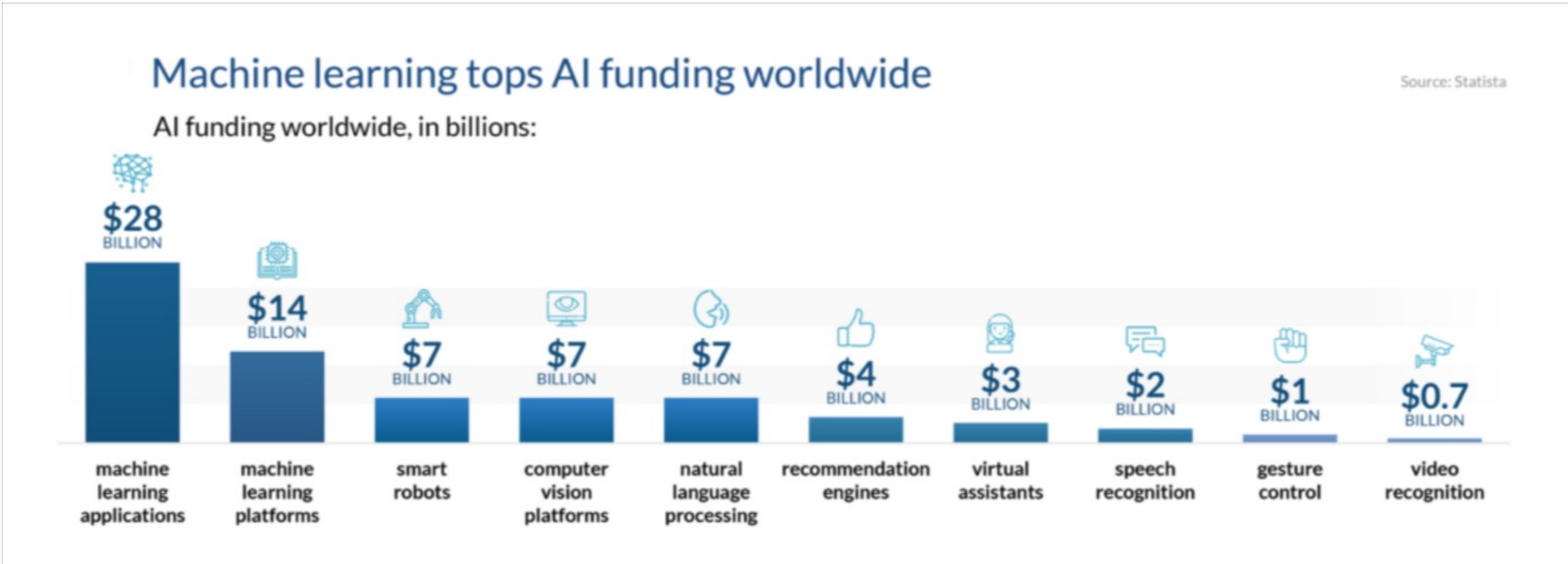
Machine Learning funding trends and opportunities



History of Machine Learning (ML)

- 1950s
  - Samuel's checker player
  - Selfridge's Pandemonium
- 1960s:
  - Neural networks: Perceptron
  - Pattern recognition
  - Learning in the limit theory
  - Minsky and Papert prove limitations of Perceptron
- 1970s:
  - Symbolic concept induction
  - Winston's arch learner
  - Expert systems and the knowledge acquisition bottleneck
  - Quinlan's ID3
  - Michalski's AQ and soybean diagnosis
  - Scientific discovery with BACON
  - Mathematical discovery with AM

Slide credit: Ray Mooney

History of Machine Learning (ML)

- 1980s:
  - Advanced decision tree and rule learning
  - Explanation-based Learning (EBL)
  - Learning and planning and problem solving
  - Utility problem
  - Analogy
  - Cognitive architectures
  - Resurgence of neural networks (connectionism, backpropagation)
  - Valiant's PAC Learning Theory
  - Focus on experimental methodology
- 1990s
  - Data mining
  - Adaptive software agents and web applications
  - Text learning
  - Reinforcement learning (RL)
  - Inductive Logic Programming (ILP)
  - Ensembles: Bagging, Boosting, and Stacking
  - Bayes Net learning

Slide credit: Ray Mooney

History of Machine Learning (ML)

- 2000s
  - Support vector machines & kernel methods
  - Graphical models
  - Statistical relational learning
  - Transfer learning
  - Sequence labeling
  - Collective classification and structured outputs
  - Computer Systems Applications (Compilers, Debugging, Graphics, Security)
  - E-mail management
  - Personalized assistants that learn
  - Learning in robotics and vision
- 2010s
  - Deep learning systems
  - Learning for big data
  - Bayesian methods
  - Multi-task & lifelong learning
  - Applications to vision, speech, social networks, learning to read, etc.
  - ???

Based on slide by Ray Mooney

Machine learning resources

- Data
  - NIPS and other contest
  - mldata.org
  - UCI machine learning repository
- Contests
  - Kaggle
- Software
  - Python sci-kit
  - R
  - Tensorflow
  - Your own code

What We'll cover in this course

- **Introduction**
  - Data acquisition and preparation
  - Model validation and evaluation
- **Supervised learning:**
  - Least squares
  - Logistic regression
  - Support vector machines & Kernel methods
  - Neural Network
    - Auto-encoder
    - Deep Belief Network (DBN)
    - Recurrent Neural Networks (RNN)
  - Model ensembles
  - Bayesian learning
  - Graph learning
  - Decision trees, random forests, and boosting
- **Unsupervised learning**
  - Dimensionality reduction:
    - PCA, Fisher discriminant Maximum margin criterion
  - Clustering : tSNE, UMAP etc.
- **Reinforcement learning**
  - Temporal difference learning
  - Q learning

Explainable AI (XAI)

Statistics for ML

Ethics and regulations for ML

Applications

Background requirements

- Basic linear algebra and probability
  - Vectors
  - Dot products
  - Eigenvector and eigenvalue
- See Appendix of textbook for probability background
  - Mean
  - Variance
  - Gaussian/Normal distribution
  - Probability

– Also see basic and applied stats (from onlines)

– **Programming background with Python**

Course organization & deliverables

- 5 ~ 6 Assignments (50%)
  - Mix of theory and applications
  - Ref. codes will be available in : https://github.com/zahangircse/COMP-EECE-7-8745
  - **First one goes out end of next week**
    - Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early

Topics for assignments

- ML algorithms implementation with Python
  - Linear regression
  - Support Vector Machine (SVM) and Kernel methods
  - Gradient descent for least squares, hinge loss, and logistic loss
  - Neural Networks (NN) and its variants , and ensembling
  - Bagged decision stumps
  - Unsupervised analysis
    - K-means clustering, tSNE, UMAP, etc.
  - Learned with Less labeled samples and Explainable AI (XAI)

Our focus will be on applying machine learning to real applications

Exams

- Examinations (20%)
  - MID-TERM
  - FINAL

  – **What to expect on the exams**:
    - Basic conceptual understanding of machine learning techniques
    - Deep drive into the theory of ML (sometimes)

- Progress reports (10%)
- Final project (20%)
  - Group project (at most 3 members in each group)

Final project

- **Goal**
  - To explore Machine Learning(ML) methods
  - Encouraged to apply on Computer vision, Speech, NLP, Medical imaging, Robotics, Bioinformatics and so on.
  - Must be done this semester.
- You will be asked to form group **(not more than 3 member in a group)** and submitting project proposal
- Main categories
  - Application/Survey
    - Compare a bunch of existing algorithms on a new application of your interest
  - Formulation/Development
    - Formulate a new model or algorithm for a new or old problem
  - Theory
    - Theoretically analyze an existing machine learning approaches

Computing

- Major bottleneck (May require)
  - GPUs
- Options
  - Your own / group / advisor's resources
  - Google COLAB for free : https://towardsdatascience.com/getting-started-with-google-colab-f2fff97f594c
  - Google Cloud Credits
    - $50 credits to every registered student courtesy Google
  - UM / CS Department GPU cluster (if available)

Textbooks

- **Not required but highly recommended for beginners**

- **Introduction to Machine Learning** by Ethem Alpaydin (2nd edition, 2010, MIT Press). Written by computer scientist and material is accessible with basic probability and linear algebra background

- **Foundations of Machine Learning** by Afshin Rostamizadeh, Ameet Talwalkar, and Mehryar Mohri (2012, MIT Press)

- **Learning with Kernels** by Scholkopf and Smola (2001, MIT Press)

- **Applied predictive modeling** by Kuhn and Johnson (2013, Springer). This book focuses on practical modeling.

- **Deep Learning by Ian Goodfellow**, Yoshua Bengio, and Aaron Courville (available at http://www.deeplearningbook.org/).

Summary

- What is machine learning?
- History of machine learning
- What We'll cover in this course
- Course organization & deliverables
- Examinations and projects
- Grade breakdown

- What's next:
  - Different Machine Learning(ML) approaches
  - How and what does machine learn?
  - Ecosystem for Machine Learning (DL)