



COMP [56]630– Machine Learning

Lecture 1 – Course Structure and ML Basics

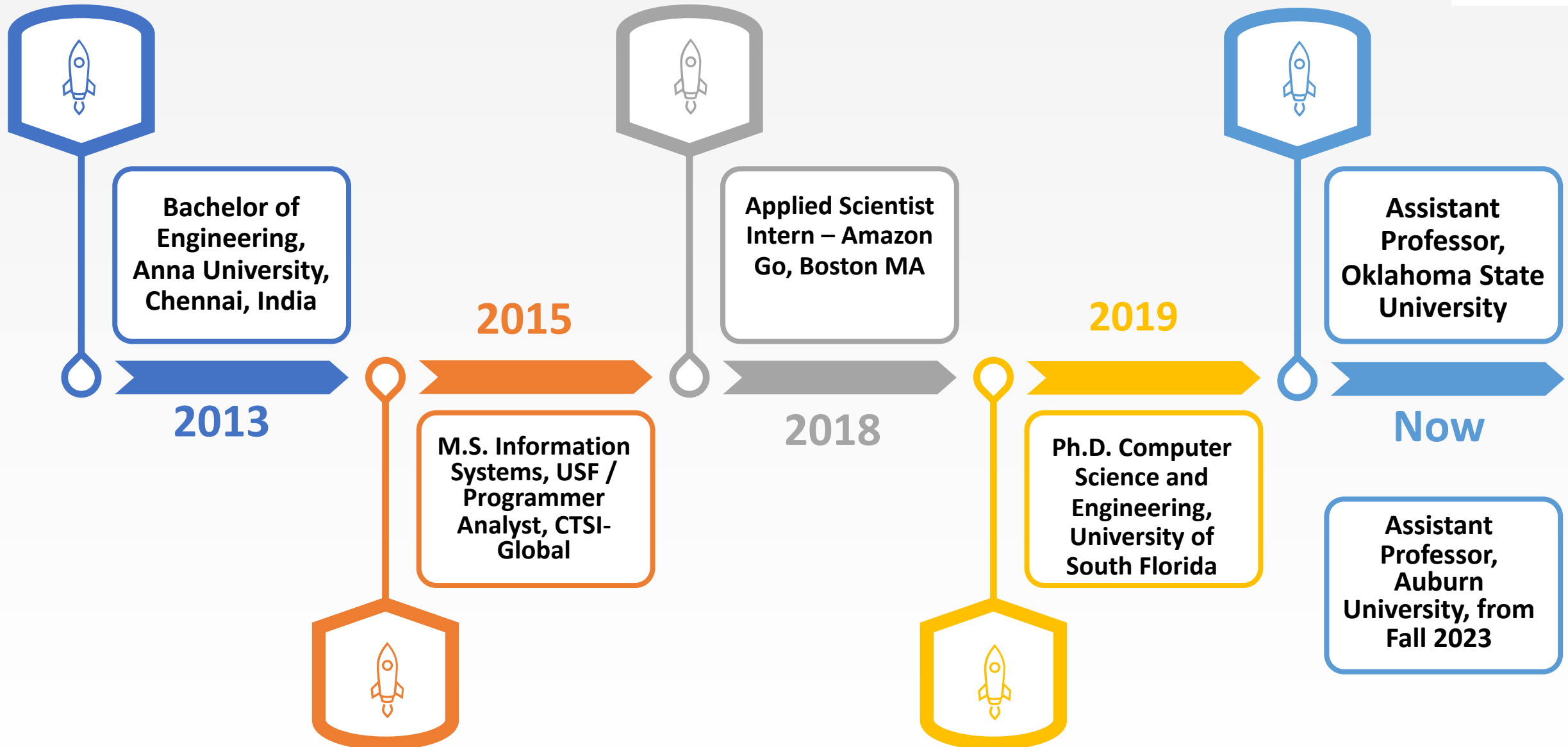
The Teaching Team

- Instructor:
 - Dr. Sathyanarayanan Aakur
 - Email: san0028@auburn.edu
 - Office hours: Monday/Wednesday 9:00 AM to 10:30 AM, 3101P Shelby Center, or by appointment.
- Teaching Assistant(s):
 - Shubham Trehan
 - Email: sz0113@auburn.edu
 - Office hours: TBD

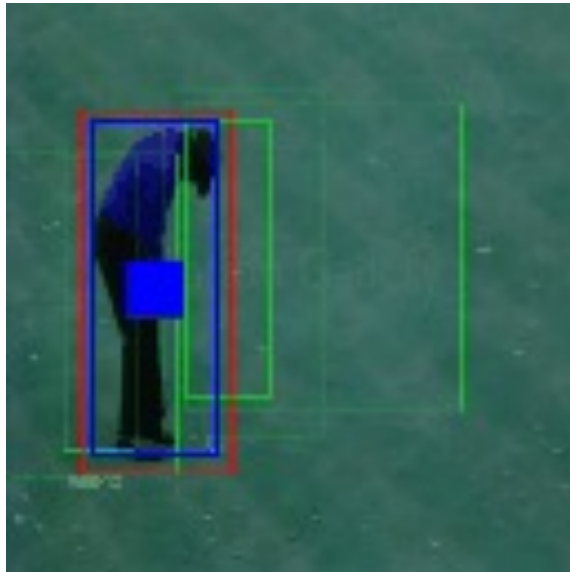




About Me

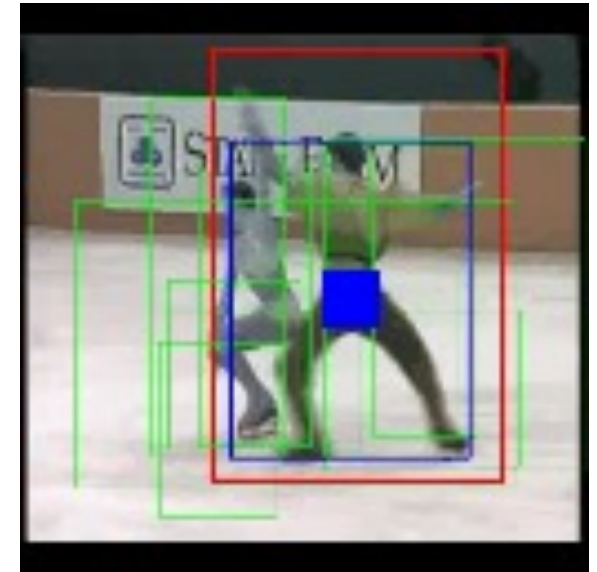
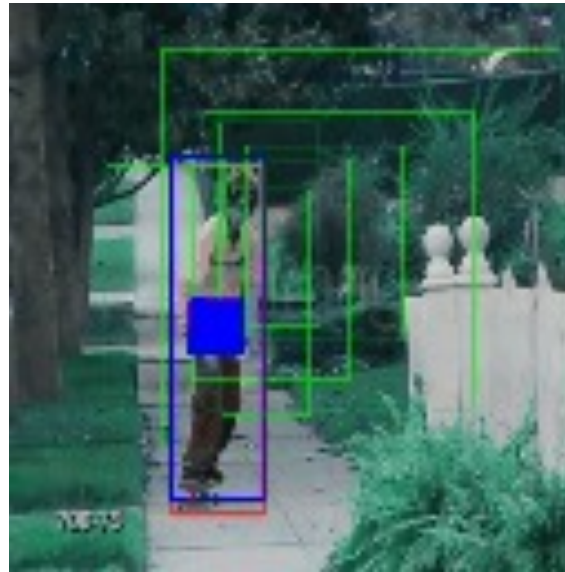
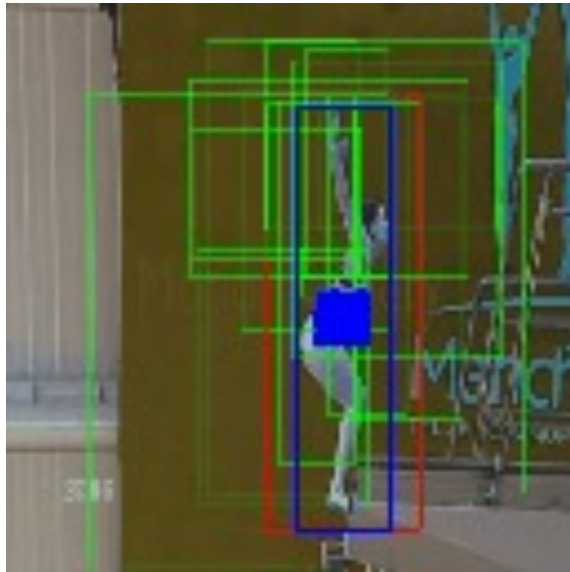


My Research – Computer Vision (Action Localization)



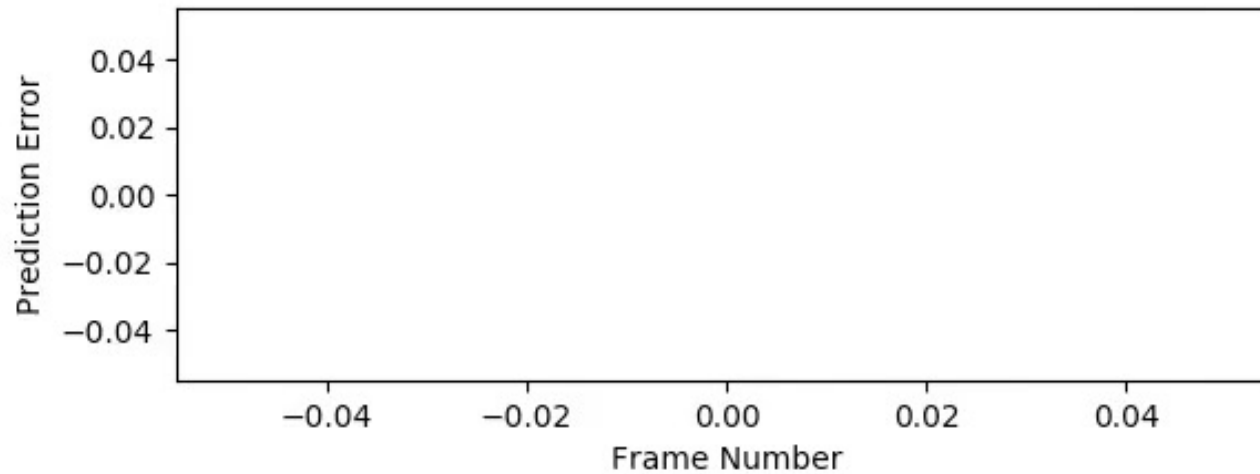
Blue BB: Prediction, Red BB: GT, Green BB: Other possible ROIs, Shaded Blue: Attention Location

My Research – Computer Vision (Action Localization)



Blue BB: Prediction, Red BB: GT, Green BB: Other possible ROIs, Shaded Blue: Attention Location

My Research – Computer Vision (Event Segmentation)

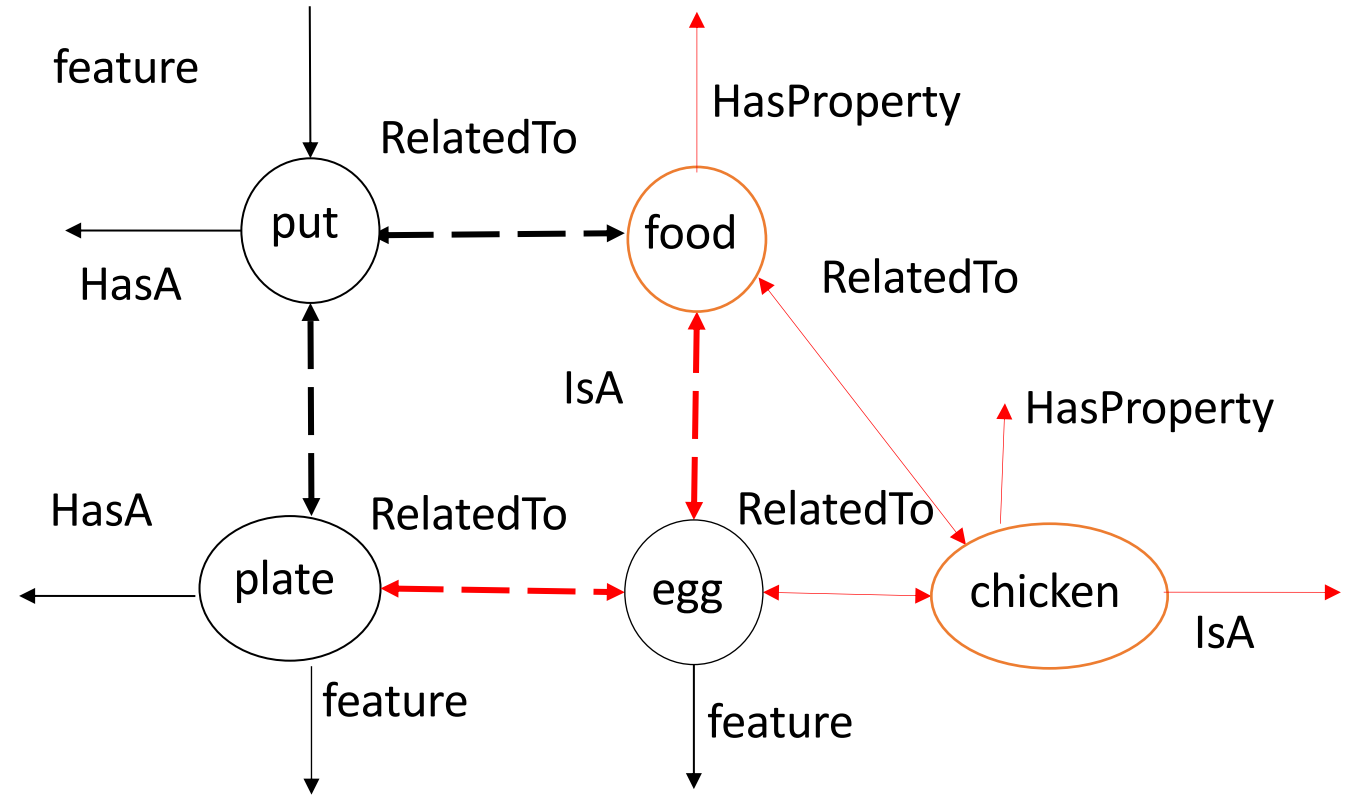


S. Aakur, S. Sarkar. A Perceptual Prediction Framework for Self- Supervised Event Segmentation. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019.*

My Research – Computer Vision (Active Vision)

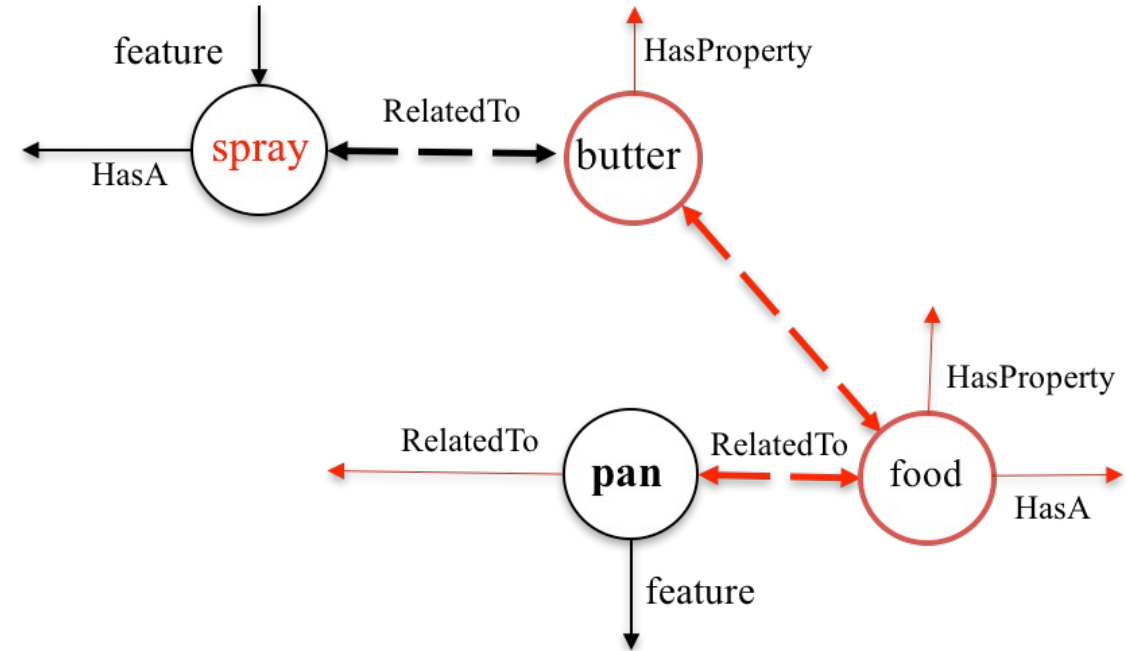


My Research – Computer Vision (Learning from Experience)



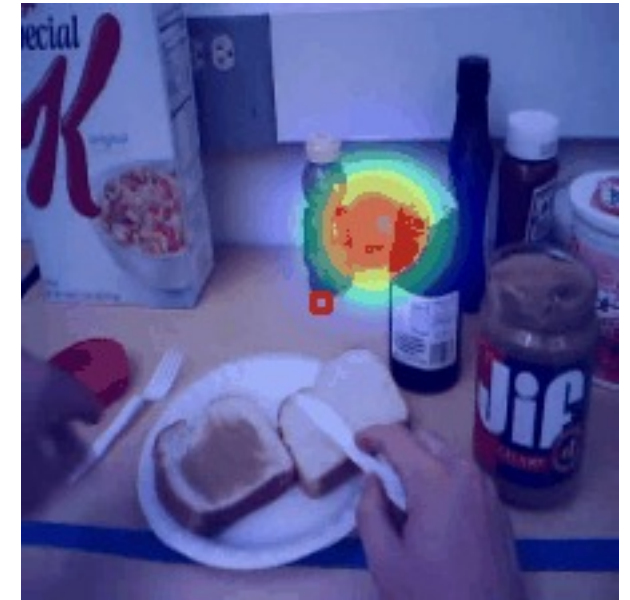
Aakur, S., de Souza, F., & Sarkar, S. (2019). Generating open world descriptions of video using common sense knowledge in a pattern theory framework. *Quarterly of Applied Mathematics*, 77(2), 323-356.

My Research – Computer Vision (Learning from Experience)



Aakur, S., de Souza, F., & Sarkar, S. (2019). Generating open world descriptions of video using common sense knowledge in a pattern theory framework. Quarterly of Applied Mathematics, 77(2), 323-356.

My Research – Computer Vision (Gaze Prediction)





Course Administration

- Textbook:
 - No particular book is required for this course. However, I would recommend the following books for reference.
 - Textbook 1: Christopher M Bishop, Pattern Recognition and Machine Learning
 - Textbook 2: Introduction to Machine Learning, Third Edition by Ethem Alpaydin.
- Supplementary material will be posted on Canvas as needed.



Grading Information (5600)

Exams (20%)

- One Midterm Exam

Quizzes (25%)

- One quiz at the end of every week on Canvas.
- Open book and open notes

Assignments (35%)

- Five (5) assignments – One every two weeks
- Typically contains two (2) to three (3) problems and one (1) bonus problem

Final Exam (20%)

- A Comprehensive final exam at the end of the semester
- Talk to us about any concerns about projects/exams



Grading Information (6600)

Midterm (20%)

- One Midterm Exam

Quizzes (20%)

- One quiz at the end of every week on Canvas.
- Open book and open notes

Assignments (25%)

- Four (4) assignments – One every two weeks
- Typically contains two (2) to three (3) problems and one (1) bonus problem

Final Project (15%)

- Team effort (2-3 students per team)
- Proposal due at the end of 6th week
- Project report and presentation due at the end of the course
 - Only for graduate section (6600)

Final Exam (20%)

- A Comprehensive final exam at the end of the semester
- Talk to us about any concerns about projects/exams



More details

Assignments

- Do them to truly understand the material, not to get the grade
- All homework write-ups **must** be your own work, written up individually and independently
 - Peer discussions are encouraged. Please don't share solutions!
- No late submissions will be accepted

Quizzes and Exams

- Will cover material from each week lectures, reading assignments and supplementary material.
- Only one attempt per quiz



Grading Policies

Percentage	Grade	GPA Quality Points
90 - 100	A	4.0
80 - 89	B	3.0
70 - 79	C	2.0
60 - 69	D	1.0



Tentative Schedule

Week 1	Syllabus, Course policies, What is ML?, ML Basics
Week 2	Linear Regression
Week 3	Logistic Regression, Model Selection, Evaluation Metrics
Week 4	Neural Networks
Week 5	Deep Learning - Convolutional Neural Networks
Week 6	Deep Learning - Sequence Learning
Week 7	Deep Learning - Recent Advances, Bayesian Learning
Week 8	Midterm 1, Probabilistic Graphical Models
Week 9	Spring Break

Week 10	Support Vector Machines
Week 11	Decision Trees
Week 12	Unsupervised Learning
Week 13	Expectation Maximization and Gaussian Mixture Models
Week 14	Hidden Markov Models and Dimensionality Reduction
Week 15	Reinforcement Learning and ML Applications
Week 16	Bias, Fairness and Ethics in AI
Week 17	Final Exam Week



Software Requirements

- We will use Python as the major language in this course
 - Intermediate level is a pre-requisite
- Different packages/libraries will be used to create ML applications.
 - NumPy
 - Tensorflow
 - Sci-kit Learn
- A short intro will be given in class
 - Some self-study is expected to learn the intricacies of using these libraries.



Expectations from You

- **Work Hard!**
 - This is a heavy course that covers ML fundamentals.
 - A little heavy on mathematics to provide the foundations of each algorithm
 - Exciting and stimulating topics
- Attend all lectures (I try to keep it engaging and interactive!)
- Ask questions, participate in discussions
- Exams are comprehensive. Study all materials posted.
- Complete all assignments
 - Try to understand the algorithm, usage and implementation



Academic Dishonesty

- **Absolutely no form of cheating will be tolerated**
- See syllabus, AU Policy, and CSSE Academic Integrity Policy
- Cheating → Failing grade (no exceptions)



Tips to succeed in the course

- Read any supplementary material posted in addition to the lectures
- Do the assignments and quizzes on your own to understand the concepts
- Don't be discouraged by errors!
 - Learning is a repetitive process!
 - Mistakes are your keys to success! 😊
- Ask thorough questions to understand the concepts
- Balance your time!
 - I understand that you have several things to do. Allot at least 2-3 hours per week.
 - Remember. Hard work always pays off!



Have you ever used machine learning?
How? Where?



Laptop: Biometrics auto-login (face recognition, 3D), OCR

Smartphones: QR codes, computational photography (Android Lens Blur, iPhone Portrait Mode), panorama construction (Google Photo Spheres), face detection, expression detection (smile), Snapchat filters (face tracking), FaceID (iPhone), Night Sight (Pixel), iPhone 12 Pro (LiDAR)

Web: Image search, Google photos (face recognition, object recognition, scene recognition, geolocalization from vision), Facebook (image captioning), Google maps aerial imaging (image stitching), YouTube (content categorization)

VR/AR: Outside-in tracking (HTC VIVE), inside out tracking (simultaneous localization and mapping, HoloLens), object occlusion (dense depth estimation)

Motion: Kinect, full body tracking of skeleton, gesture recognition, virtual try-on

Medical imaging: CAT / MRI reconstruction, assisted diagnosis, automatic pathology, connectomics, endoscopic surgery

Industry: Vision-based robotics (marker-based), machine-assisted router (jig), automated post, ANPR (number plates), surveillance, drones, shopping

Transportation: Assisted driving (everything), face tracking/iris dilation for drunkenness, drowsiness, automated distribution (all modes)

Media: Visual effects for film, TV (reconstruction), virtual sports replay (reconstruction), semantics-based auto edits (reconstruction, recognition)



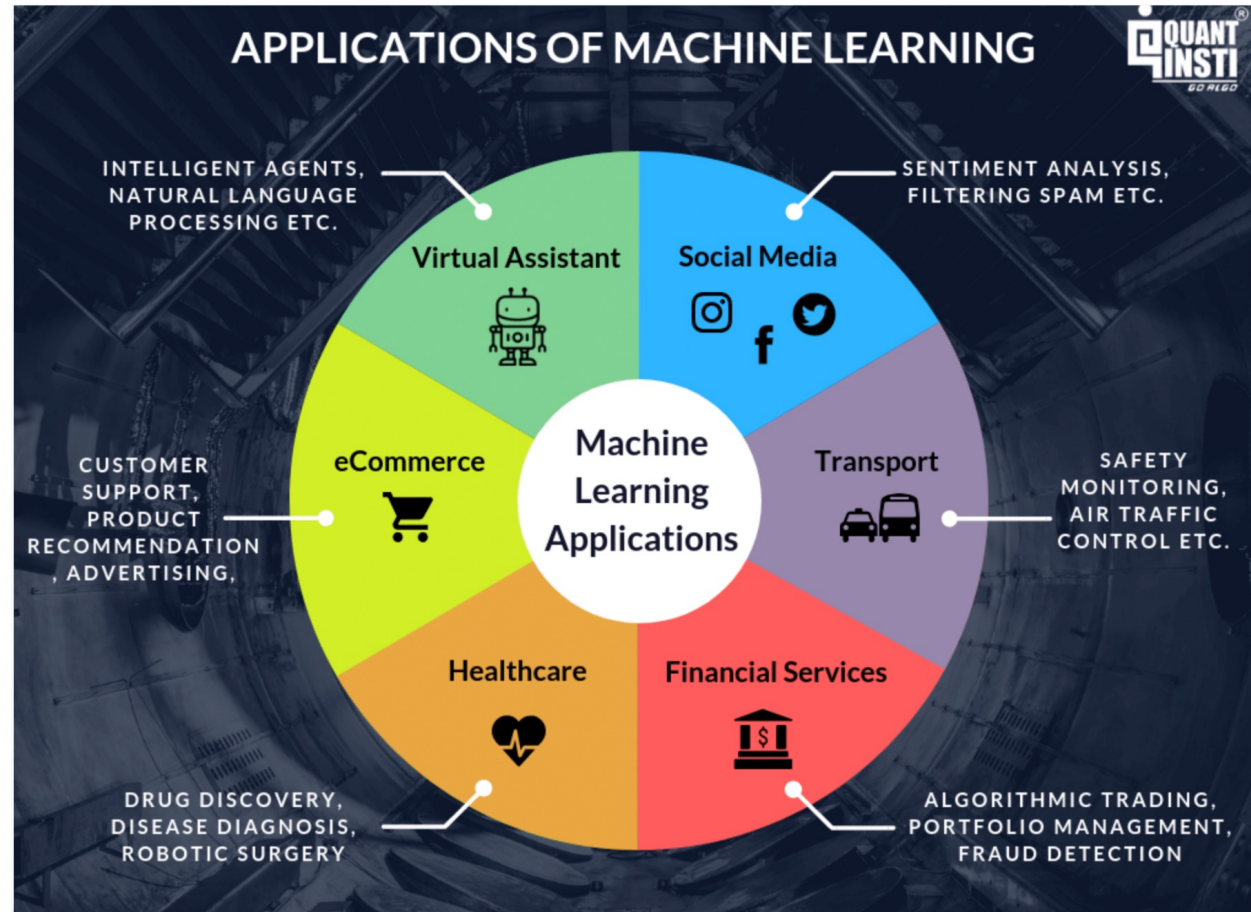
What is Machine Learning anyway?

No, Really. What is it?

A close-up of a Terminator robot head, showing its metallic, skull-like face with glowing red eyes. The background is a blurred, industrial setting.

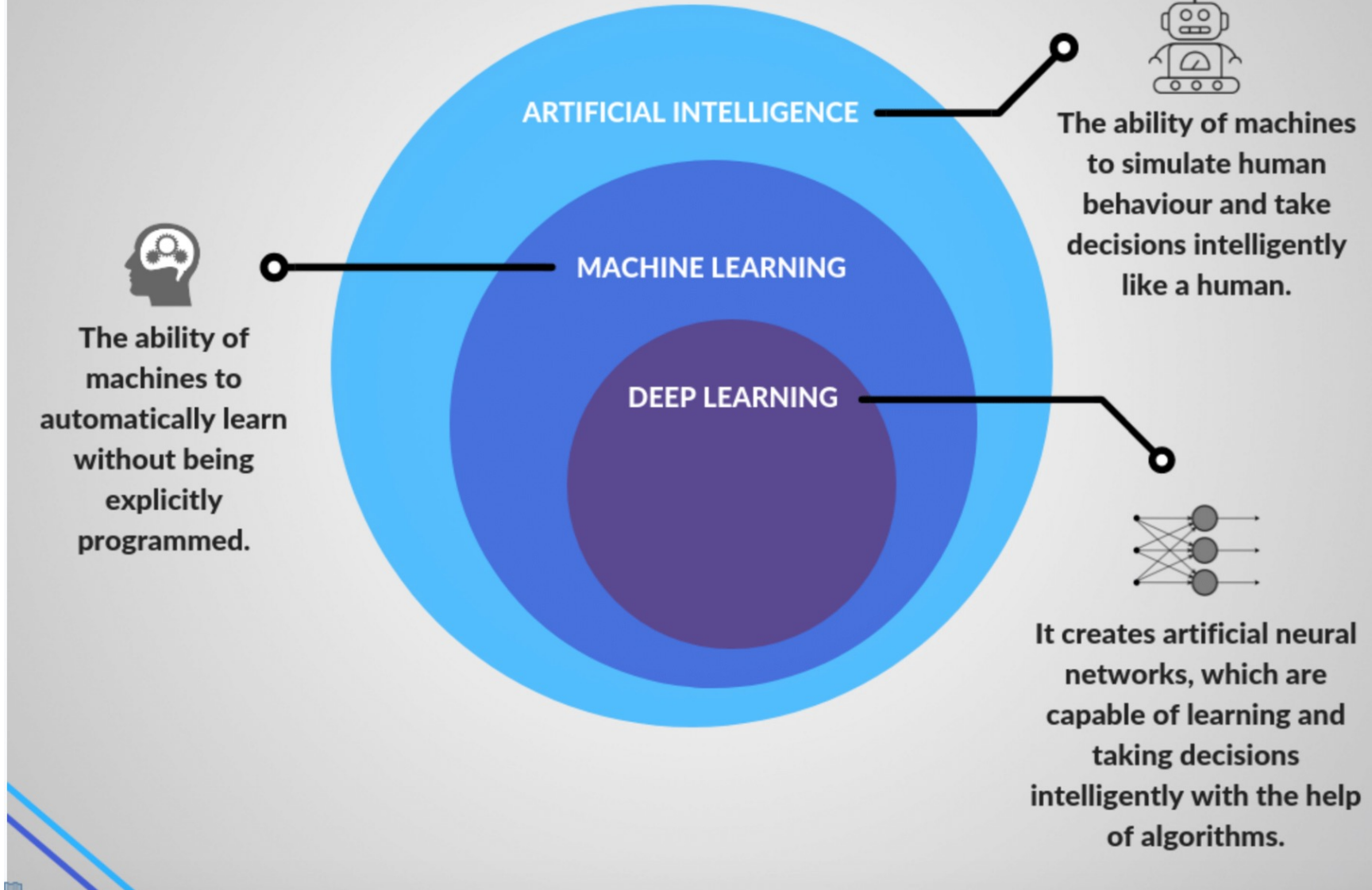
What you think it is

What it actually is





Artificial Intelligence (AI)
≠ Machine Learning (ML)
≠ Deep Learning (DL)





What is Machine Learning?

- **Definition:** study of computer algorithms that improve automatically through experience i.e. developing computational methods that use experience to improve performance, e.g., making accurate predictions.
- **What is Experience?**
 - Data! ML is a data-driven task,
- **Interdisciplinary!**
 - **Computer science:** need to design efficient and accurate algorithms, analysis of complexity, theoretical guarantees.
 - **Mathematics:** ML is based on the ideas from linear algebra, statistics and probability
- **Example application:** use words from an email, sender information, etc. to determine if it is a spam email



ML Objectives

- **Algorithms:**
 - Efficient, accurate, and general
 - Scalability
- **Theoretical questions:**
 - What can be learned?
 - How to model learning computationally?

scikit-learn algorithm cheat-sheet

