CEE 501/494
Artificial Intelligence for Civil Engineers

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Lecture Overview

- Introduction to Machine Leaning
- Syllabus and logistics
- Doing some exercises reviewing necessary mathematical foundations (a formal review will continue in next set of slides next week).

Introduction to Machine Learning

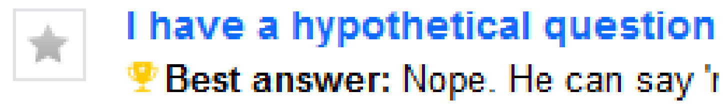
- You may find many definitions for "machine learning"
  - Some focus on prediction; Some focus on modeling; Some focus on algorithmic properties of a system. Some say it's just a rebranding of pattern recognition.
  - But all should involving learning by machines (computers)
- Definition of *learning* in a typical dictionary: "the acquisition of knowledge or skills through experience, study, or by being taught"
- Learning and adaptation

Sample Applications

- Many pattern recognition tasks
  - –Recognizing faces or voices
  - –Understanding the road signs in a cluttered background
  - –Detecting abnormal engine noise while driving
- Multimedia retrieval: e.g. search for a video clip in media databases or on the Internet.
- Credit risk assessment.
- Decision making in robotics.
- Recommendation systems (search engines, on-line shopping)

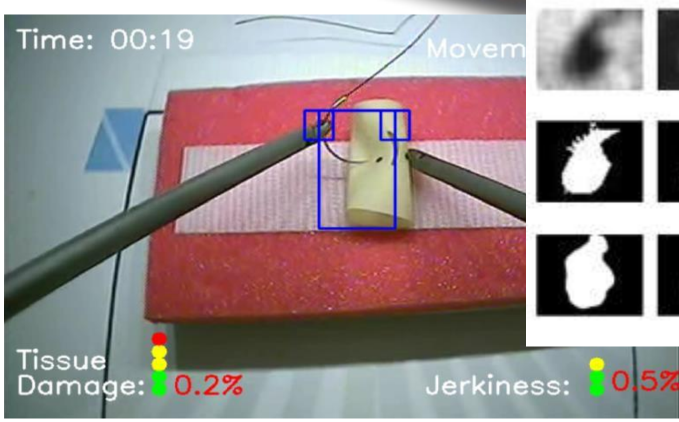
➔ Common to many diverse applications: learning typically results in a model that is tuned according to some feature representations of raw data; and how well learning was done is assessed by how well the model fits/explains/predicts new data.

Image splicing detection

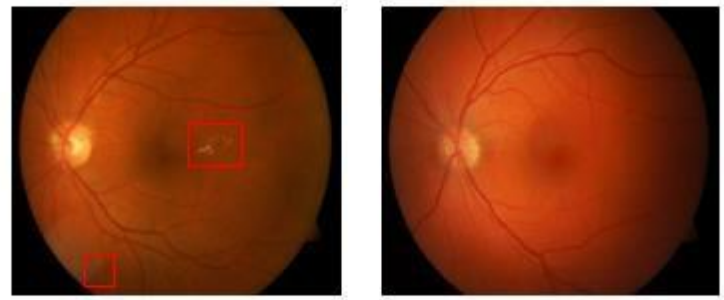


Learning to predict best answers in community Q & A

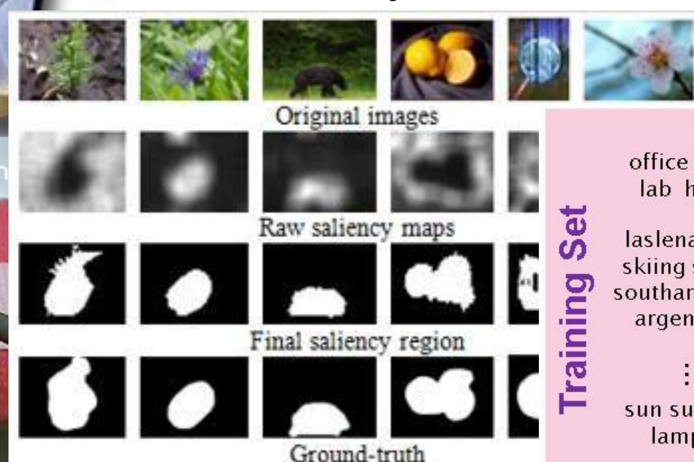
Learning to assess skills in simulation-based laparoscopic surgery training

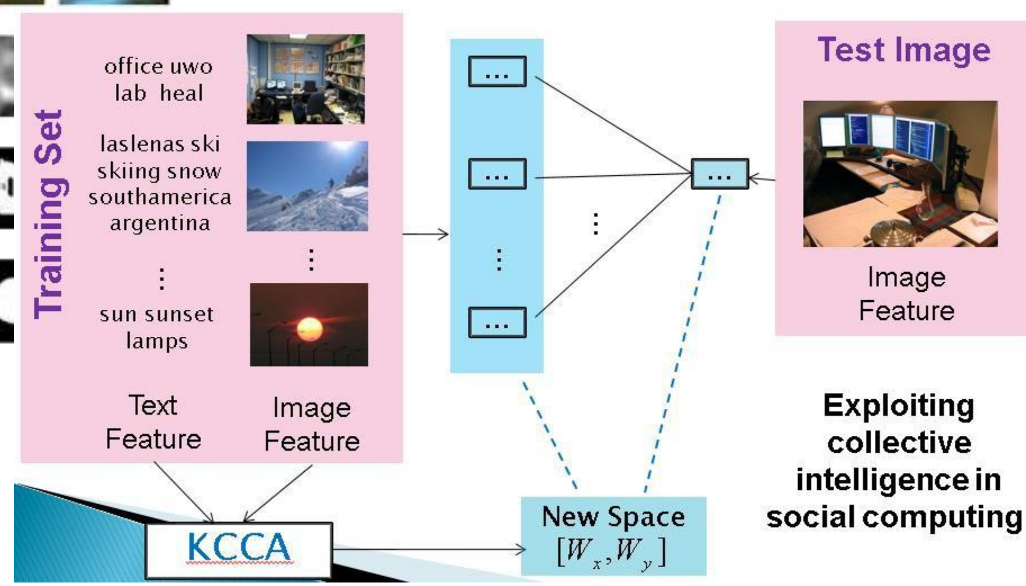


Diabetic retinopathy detection



Visual saliency detection





Exploiting collective intelligence in social computing

Tag prediction/recommendation

Importance of Statistical Models

Why we often reply on statistical methods in ML problems?

• Noisy Data
→ Measurement errors make features behave like random variables/vectors.
• Model Uncertainty
→ Approximate models introduce additional randomness.
• Real-World Ambiguity
→ Many problems have multiple valid outcomes or interpretations.

- ***Plus:*** Inherent ambiguity in many real-world problems.

An Illustrative Example

•**Task**: Classify the images into appropriate categories (e.g., cats vs. dogs).
•**Observation**: Real-world image data contains several sources of uncertainty.

Let's consider the sources of randomness in this problem.

Identify and Model the Differences

- From the given images, we identify possible differences between the two classes:

Color? Size of the eyes? Pointiness of the ears?

- Models, typically of mathematical form, are used to formalized and summarize the differences:

  - It is hypothesized that, with a proper model, different classes should be **distinguishable based on the features** used in the model.

  - The learning task is to **find a suitable model** and then **design classification algorithms** under that model, using features extracted from the images.

Preprocessing to Facilitate Feature Extraction

- ***Segmentation*** may be helpful: isolating the animals from one another and from the background.
  - Then a *feature extractor* will compute features from the segmented region.

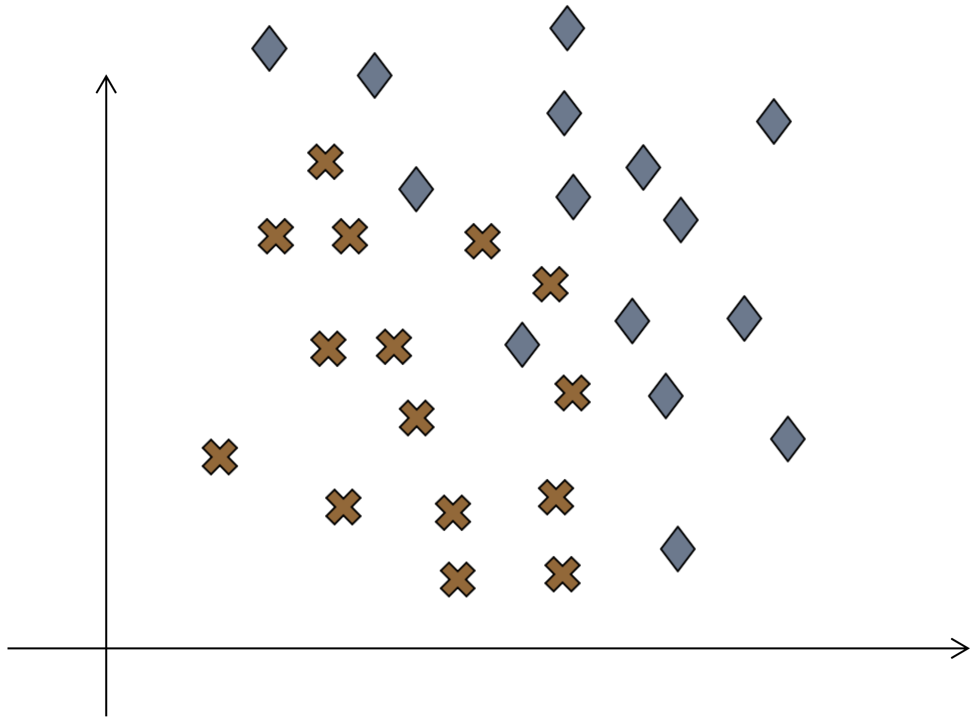
- In general, preprocessing involves various operations to facilitate feature extraction.
  - Segmentation
  - Filtering (noise reduction, smoothing, etc.)
  - Transformation (geometric, dimension-reduction, frequency analysis, etc.)

- Feature extraction is performed on the preprocessed data.
  - Good features should be ***invariant*** in some sense.

➔ As we will learn, many deep-learning approaches attempt to achieve all these together with classification in on shot.

Classification Models

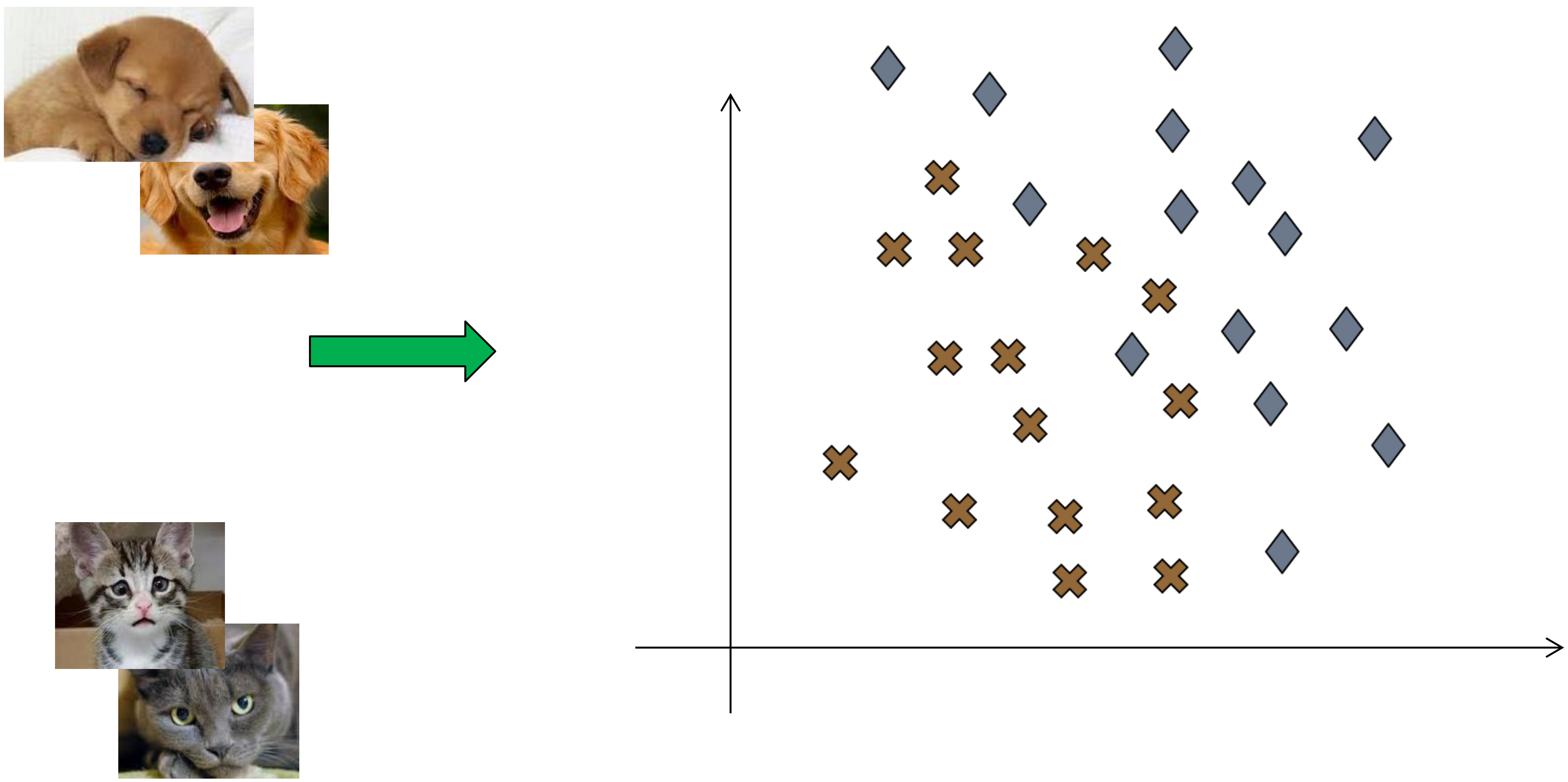
- Classification of the features into different categories.



Linear classifier?

Classification Models

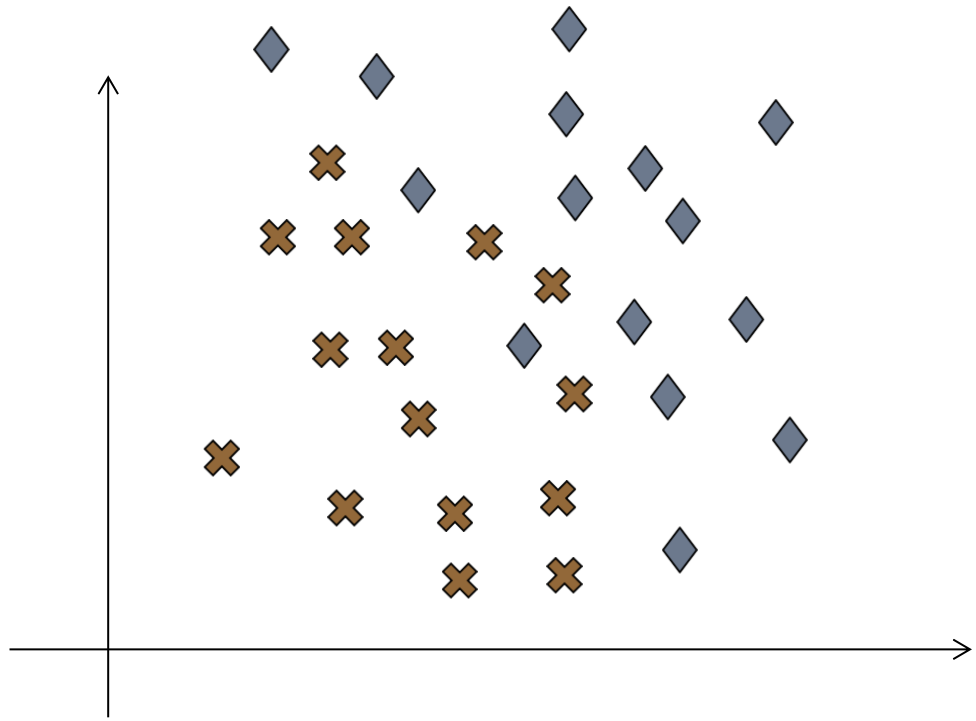
- Classification of the features into different categories.



Non-linear classifier?

Classification Models

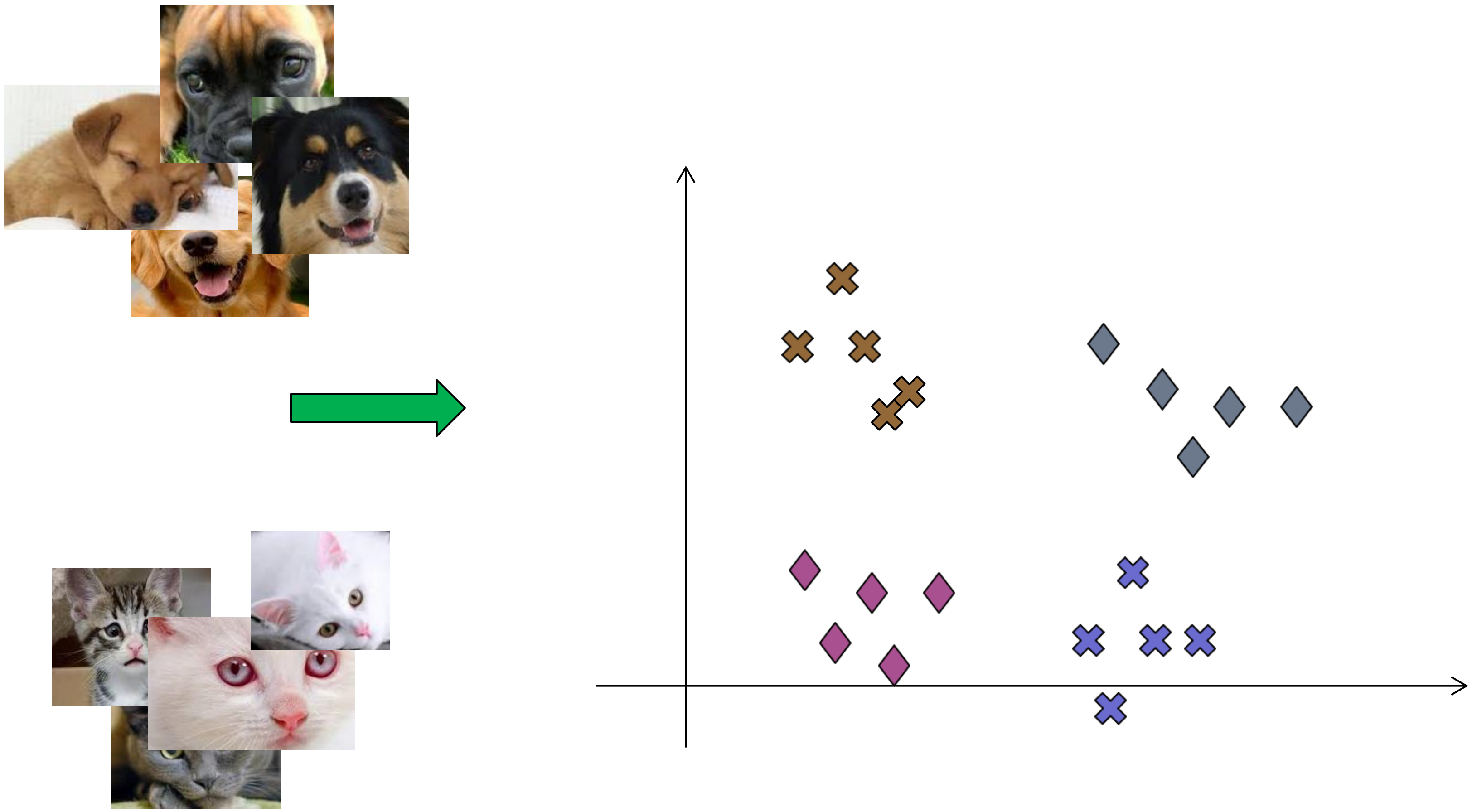
- Classification of the features into different categories.



Overfitting

Classification Models

- Classification of the features into different categories.

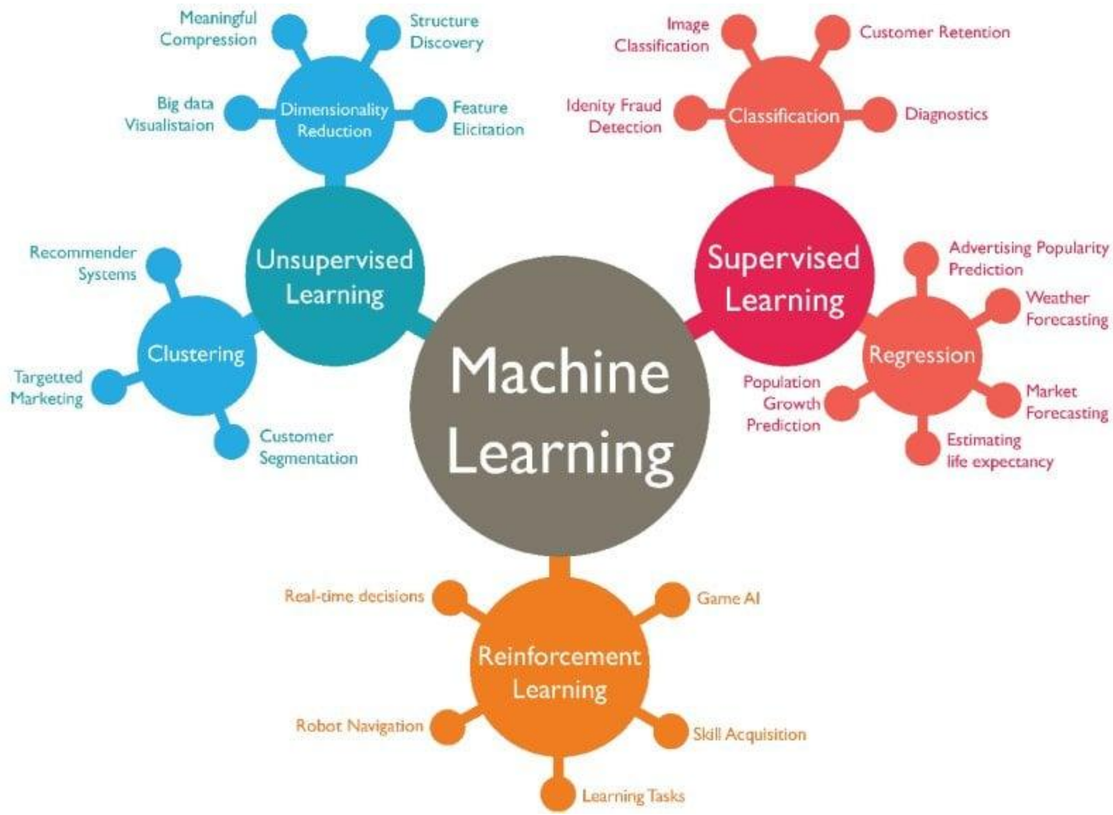


Cost of Decision, Priors, etc.

- So far we have assumed that the costs of erroneous decisions are equal.
  - Not always a valid assumption.
  - Consider “False Alarm” and “Miss of Detection” in military radar.
- Also, we might have implicitly assumed that equal number of the two classes appear in our inputs
  - Not always a valid assumption.
  - Again, consider the radar example.
- The goal: to design a classifier that can minimize the overall cost
  - ➢ Task of decision theory ➔ Optimal solution exists if enough information is given.

Basic Modes of Learning

- Supervised learning: the training set is labeled.
- Unsupervised learning: the training set is not labeled.
- Reinforcement learning

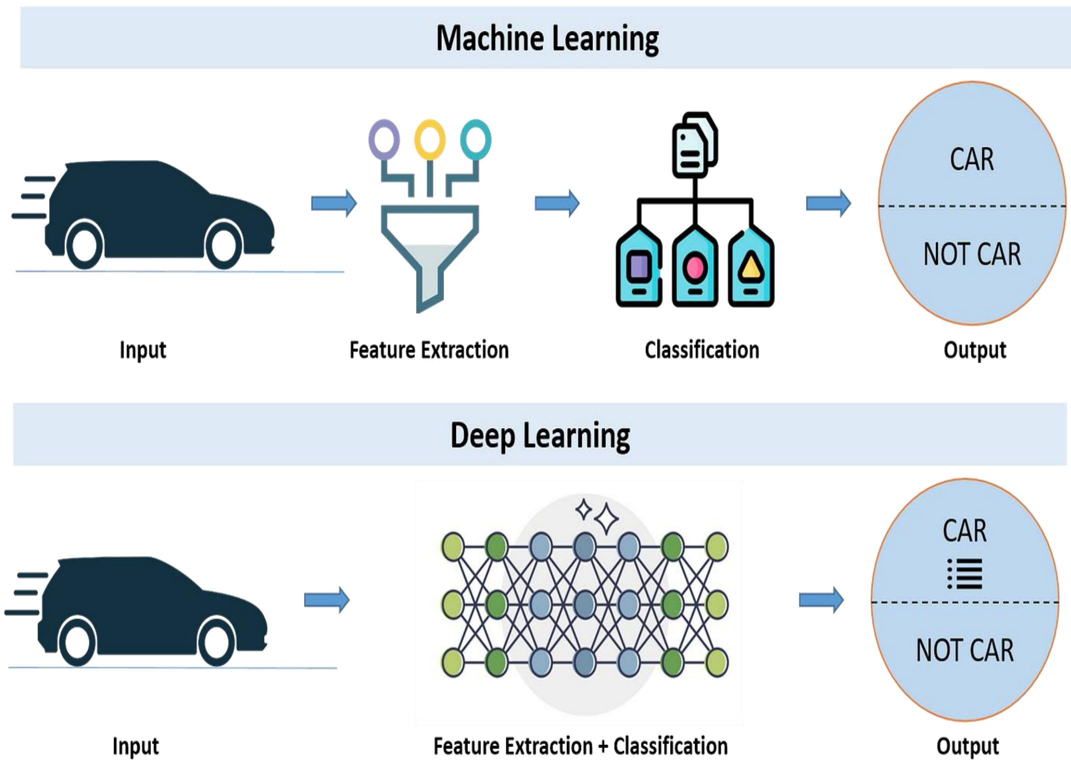


- As we have seen earlier, learning from a particular training set has potentially the generalization problem.
  - Performance on new (test) data.

Image source: Data Science Dojo. (n.d.). Machine Learning 101.

Introduction to Deep Learning

•Deep Learning is a specialized branch of Machine Learning
•Utilizes artificial neural networks with multiple layers ("deep")
•Designed to learn from vast amounts of data
•Inspired by human brain's structure
•Can automatically learn complex patterns and features



They power many modern AI applications:

- ➢ Image Recognition
- ➢ Speech-to-Text
- ➢ Language Translation
- ➢ Autonomous Vehicles

Image source: Arun P. (2021). *Deep Learning Fundamentals.* Retrieved from [Medium]

Rise of Generative AI

•A type of AI that creates new content and applies knowledge creatively to solve new problems - *text, images, videos, music, and more*
•Learns from complex data: *language, code, art, science, etc.*

Why is Everyone Talking About It?

Tools like **ChatGPT**, **DALL·E**, **Midjourney**, and **Gemini** are reshaping:

- Writing
- Design
- Coding
- Engineering

It's powering automation, creativity, and intelligent decision- making in every domain.

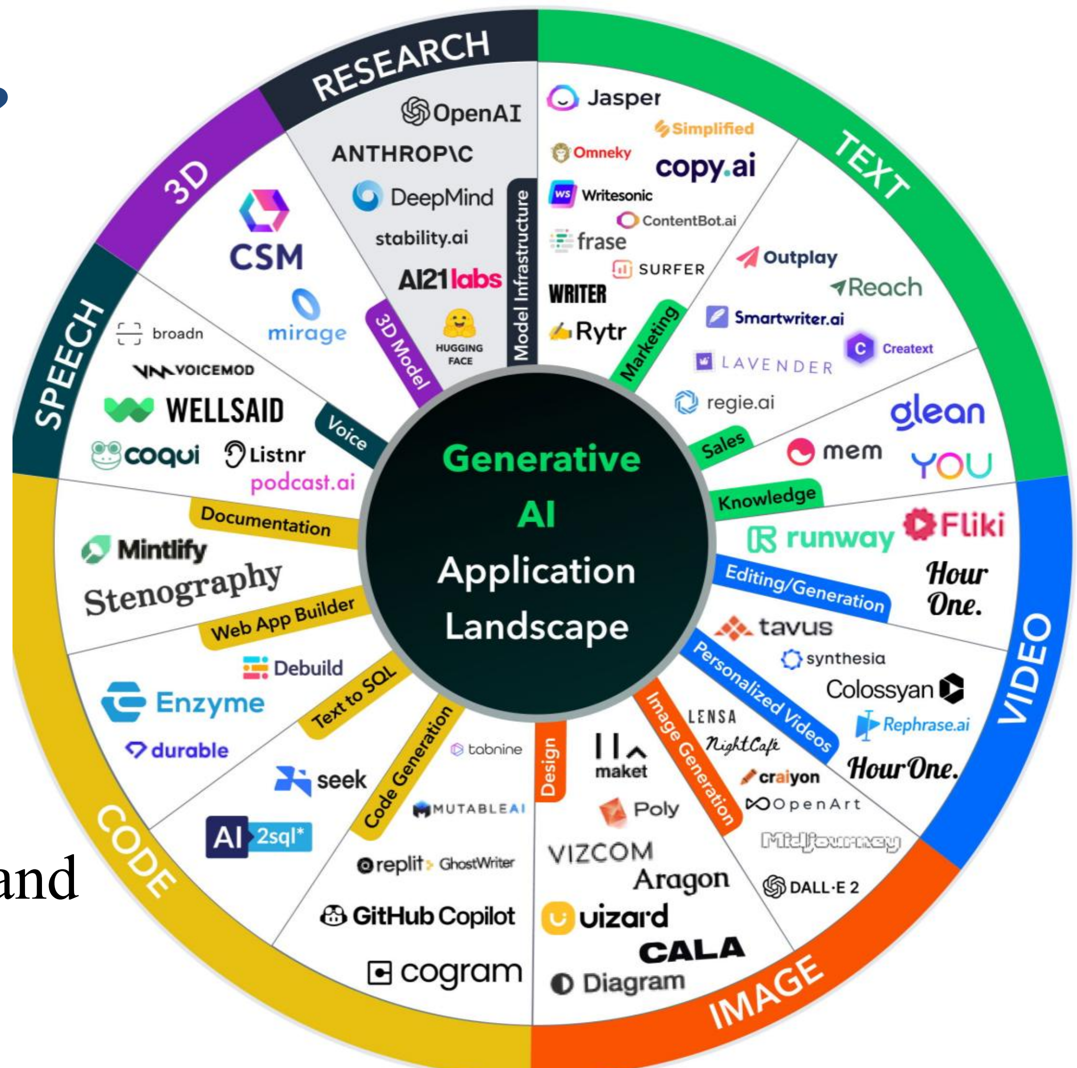


Image Source: RapidOps. (n.d.). *Top Generative AI Tools.*

Course Objectives & Major Topics to Cover

- **To provide an *introductory* yet *comprehensive* coverage of these many facets of machine learning.**

- Basics of Bayesian decision theory

- Supervised learning: Linear Regression, Logistic regression; Generative models vs. discriminative model; Kernel methods for classification (Support vector machines); Cross validation; Introduction to concepts of cost functions, regularization, hyper parameters; Intro. Intro. to decision trees.

- Unsupervised learning: Data clustering and description; Dimensionality reduction and Principal Component Analysis.

- Neural networks & deep learning: Basics of neural learning via multi- layer feedforward networks; Back prop, Stochastic Gradient descent; Overview of hyper parameter tuning & training techniques; Convolutional neural networks;

- Advanced topics: Transformers and Self-Attention,Transfer Learning,Large Language Models (LLMs),Generative AI, Prompt Engineering

… in Addition

- Time permitting, some relevant research presentations.
- Guest lectures

About This Course

The first undergraduate machine learning course in CEE @ ASU.

- TA: Madumita Karthikeyan
  Email: mkarthi5@asu.edu
  Office: Virtual Zoom meet
  Tuesday: 2:00 pm - 3:00 pm
  Thursday: 2:00 pm -3:00 pm

Prerequisites

- You need to have a working knowledge of calculus, linear algebra and basic probability theory.
  - ➢ You will work on some exercise later today as a refresher.
  - ➢ We will do a formal review next week.
- Proficiency in Python programming (ideally in MATLAB too)

plus

- You will need some physical vigor for sitting here for 2.5 hours, **actively learning**.
- We will plan on using the last ~35 min of most lectures for more interactive learning activities.

Course Information

- Course materials will be available only through the Canvas on MyASU.

- Textbook: No required textbook. We will try to make the notes self-contained. But you should use additional recourses for study, including on-line sources, whenever you feel the notes are not detailed enough.
  - Some reference books of interest are listed in the posted syllabus.

- There are also many on-line courses on machine learning.
  - You are encouraged to refer to those to help your study

Course Information

- Lecture notes will be posted before each class.
  - ➢ May be updated throughout the semester. You need to update your version accordingly.
  - ➢ Only PDF version will be posted
  - – Lecture notes may not include examples that are worked out during the lectures.

- Homework, project, and supplemental reading materials will all be posted on the Canvas.

Course Information

- Some of the homework assignments and the project will require programming work.

- **In general, late submissions of the assignments will not be accepted.**

- The major topics to be covered (subject to adjustment) and a tentative timeline have been included in the posted syllabus.

Assessment

- Homework – 45 points
  - There will be 5 homework assignments. All problems require programming.
- One Project 30 points
  - The project will be based on a proposal from you. Proposal presentation- 10 points
  - Final Presentation - 10 points
  - Working final code- 10 points

Assessment

- Classwork: 5 points

To encourage to complete and submit in-class programming assignments

- Bonus : 5 points

Assessment

- Exams 20 points
  - Two midterms (TBD): 10 points each; covering only the respective period preceding the exams. (We probably will use only 1.5 hour for each of the midterms.)
  - Exams will have theory & coding components

Submission of HWs and Projects

- Submissions of homework and project related (reports, code, etc.) need to be electronic.

- **Any grade appeal must happen within one week of the grade's posting. Later appeal will not be considered.**

Email Policy

All email correspondence related to this course must adhere to the following rules:

•**Subject Line Format**

Always include the course prefix in your subject line:

`CEE 501/494:` (e.g., `CEE 494: Question about HW1`)

•**CC the TA**

Every email to the instructor must also CC the TA, unless there is a specific and valid reason not to.

Note: The TA and Grader are official course staff with full access to the Canvas Grade Center.

•**Response Policy**

Emails will be read once daily, Monday through Friday.

TA will respond directly unless the issue requires the instructor's input.

•**Email Quality:**

Keep emails clear, self-contained, and concise.

Avoid asking questions that are already answered in syllabus, lecture notes, or Canvas.

Email Policy (continued)

- Avoid asking questions in email that should be raised either in class, or in individual consultation with the TA during office hours.
    - These include questions of an excessively conceptual nature, and questions that require an unreasonable amount of time from the instructor/TA.
    - A good rule of thumb: if your question cannot be answered in a short paragraph, then it is not appropriate for email.

- Emails that do not follow these guidelines may not be replied by the TAs/instructor.
    - If your email goes unanswered more than one day after you sent it, check if you forgot following these guidelines.

Academic Integrity

- A perceived lack of academic integrity undermines a school's reputation, and devalues your degree.
- ASU Academic Integrity Policy:
  http://provost.asu.edu/academicintegrity
- All violations for which a penalty is assigned must be reported to the Dean's office. <u>This is NOT a matter of faculty discretion</u>, but a university-mandated legal requirement.
- **All the assignments/project and exams are individual work except stated otherwise.**

Some efforts to ensure Academic Integrity

- During exams, your seat may be assigned. You have to sit on the seat that we ask you to sit.

- We will use different versions of exam papers in the same exam.

- We may run your code and report through plagiarism detection software.
  - Such software has gotten very smart.

Common Qs & As

- I missed the exam. Can I have a make-up one?

  ➔ No, unless you have official documents supporting a genuine emergency.

- I have multiple assignments due this week and thus I couldn’t finish the assignment. Can I get an extension to turn in this homework?

  ➔ No. Deadlines are announced ahead, and thus please plan ahead far enough to avoid the last minute crisis.