

# CS 360/530: Foundations of Machine Learning

Spring 2020

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## Course overview

This course will give a broad introduction to foundations of machine learning and statistical learning.

**Prerequisites.** Familiarity with the following is required.

- Basic computer programming—we use R/Python.
- Probability theory (CS 215, MA 605)
- Multivariable calculus and linear algebra (MA 105, MA 106, EE 611)

If you do not have the necessary background, please meet me before registering this course.

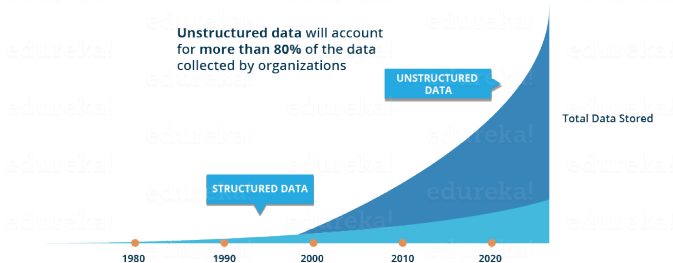
## Course page and other resources

- [www.iitgoa.ac.in/~clint/courses/ml-spring-2020.html](http://www.iitgoa.ac.in/~clint/courses/ml-spring-2020.html)
- We use Google Classroom
- Readings will be assigned for every lecture.

# Data science

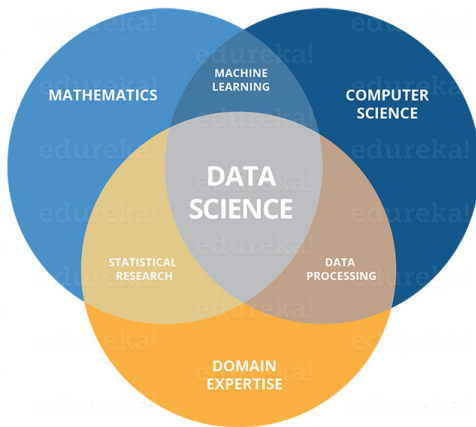
Data science—a field of study that aims to use a scientific approach to extract meaning and insights from data

Why do we need data science?—edureka.co



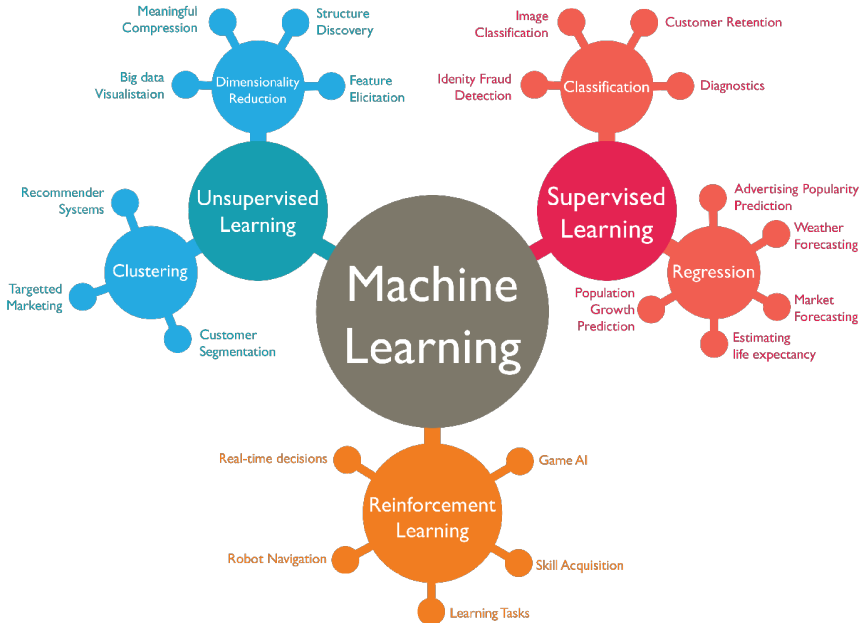
- sources: financial logs, text files, multimedia forms, sensors, and instruments
- Simple BI tools are incapable of processing the data

# Skills required for data science



(edureka.co)

- Data science: focus is on the **data**
- Machine learning: focus is on **learning methods**



# Data science — outline

Learn how to load data into **R** (or Python), get it into the most useful structure, transform it, visualize it, and model it.

- Data visualization—e.g. via `ggplot2` in **R** and Exploratory data analysis
- Expected value, variance, the Central Limit Theorem
- Hypothesis Testing—a method that is used in making statistical decisions using experimental data. E.g. A/B testing
- High-dimensional space and problems, Dimensionality reduction—e.g. Principal Component Analysis (PCA)

# Machine learning — outline

## Supervised learning

- Linear regression, logistic regression, Perceptron (review)
- Generative learning algorithms, Gaussian discriminant analysis
- Maximum likelihood estimation (MLE)
- Support Vector Machines (SVMs)



# Machine learning in practice

- Bias–Variance tradeoff and error analysis
- Regularization and model selection
- Experimental evaluation of learning algorithms, cross-validation
- Learning Theory, Generalization errors + model selection, VC dimension — if time permits.

# Machine learning — outline

## Unsupervised learning

- Mixture models and mixture of Gaussians
- The expectation maximization (EM) algorithm
- Probabilistic topic models

# Deep learning — outline

- Multilayer neural networks
- Back-propagation algorithm
- Auto-encoders