COMS30035, Machine learning: Introduction

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Unit Outline (see Blackboard)

1	Introduction [stream]Machine learning concepts [stream]	L1: Revision of Jupyter Notebook, ML libraries and regression.	Revisiting regression [stream], Classification and neural networks [stream]
2	Kernel machines [Kernels 1, stream] [Kernels 2, stream] [Kernels 3, stream]	L2: Classification, nnets and SVMs	Introduction to graphical models [Prob revision, stream] [PGM 1, stream] [Netica demo, stream] [PGM 2, stream] [PGM 3, stream]
3	Bayesian ML using graphical models [PGM 4, stream] [PGM 5, stream] [Notebook, stream]	L3: Probabilistic graphical models	k-means and mixtures of Gaussians [k-means, Gaussmix stream] [Running k-means, k-means problems , stream]
4	[The EM algorithm stream]	L4: k-means and EM	PCA [PCA stream] Eigenfaces stream] [Probabilistic PCA, stream]
5	ICA [ICA, stream]	L5: PCA and ICA	Seqential data [Markov Models stream] [Hidden Markov Models, stream]
6	**Reading week**		
7	Sequential data [EM for HMMs stream] [Linear Dynamical Systems, stream] [Quick Visual example of an LDS, stream]	L6: Hidden Markov Models	Selection and Combination [Model selection and averaging stream] [Ensembles: bagging and boosting, stream]
8	Trees, Mixtures and Crowds [Trees stream] [Conditional mixtures, stream] [Crowdsourcing, stream]	L7: Trees and Ensemble methods	
9-11	**Coursework weeks**		
12	**Review week**		

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- Teams: Please post any questions here! We will try to reply or answer in the lectures

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- Discussion with others is encouraged, but submissions need to be unique [**plagiarism is taken seriously!**]

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- It is typically grounded in Statistics and seen as a subfield of Artificial Intelligence.

Machine learning interest [Google trends]

Examples:

What kind of tasks can we learn from data?

Examples: Linear regression

Observe one numerical variable and use it to predict another using a linear model.
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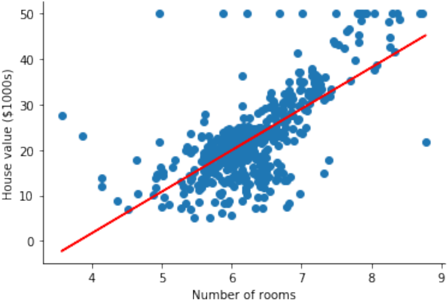

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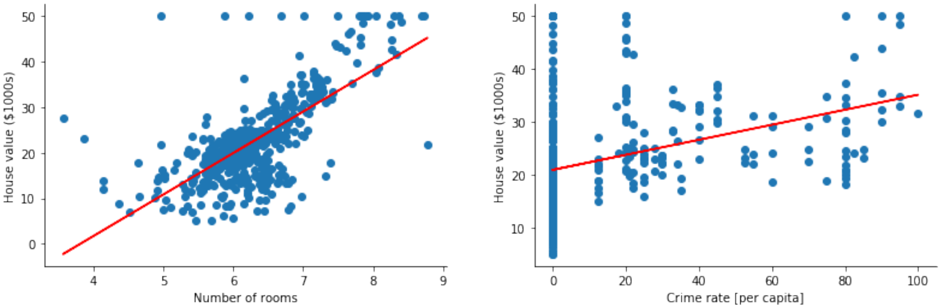

Examples: Classification

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Example: Is it a dog or a bagel?

Examples: Dimensionality reduction

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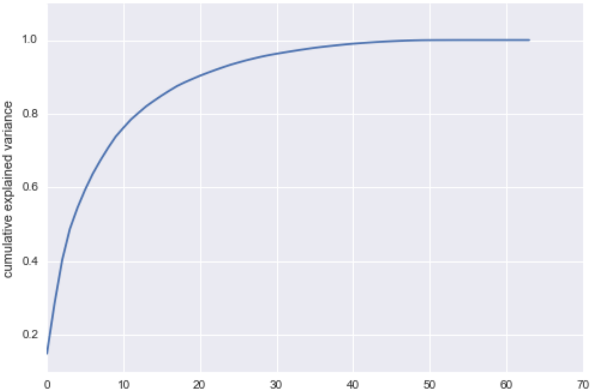
Example: How many features/components are enough to explain 80% of the variance in a given dataset? More here.



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Input: "Machine Learning is the study of computer algorithms that learn a model of data."

Output/completion: "Traditional AI, such as natural language processing, machine translation, image recognition, and machine translation relies heavily on well-defined data, and can perform well without much further manipulation of the data. Typically, a machine learning system recognizes patterns of data and then uses those patterns to predict outcomes of a given scenario. (see prediction)"

Try it out **app.inferkit.com/demo**!

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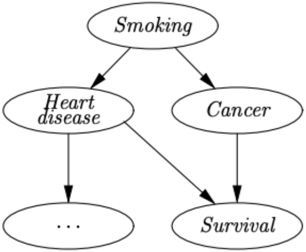
Example: What are the changes of survival for a smoker?



$\Pr(cancer \mid smoking)$	$\Pr(cancer \mid \neg smoking)$
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  - Individual Project (e.g., on applications or ML or advanced ML)

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- Murphy, K., Machine learning a probabilistic perspective (2012). The book is also freely available here.

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