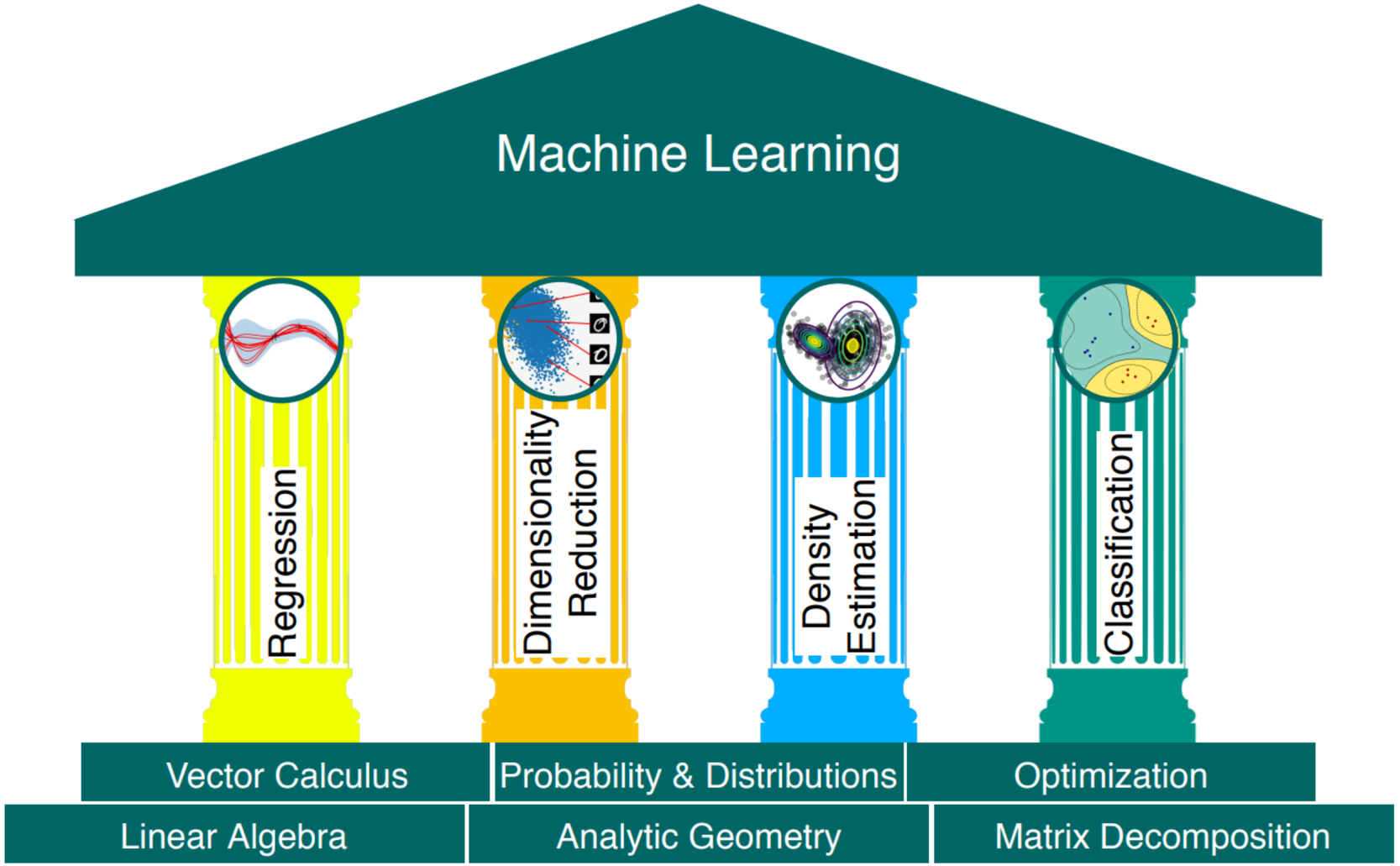
Review

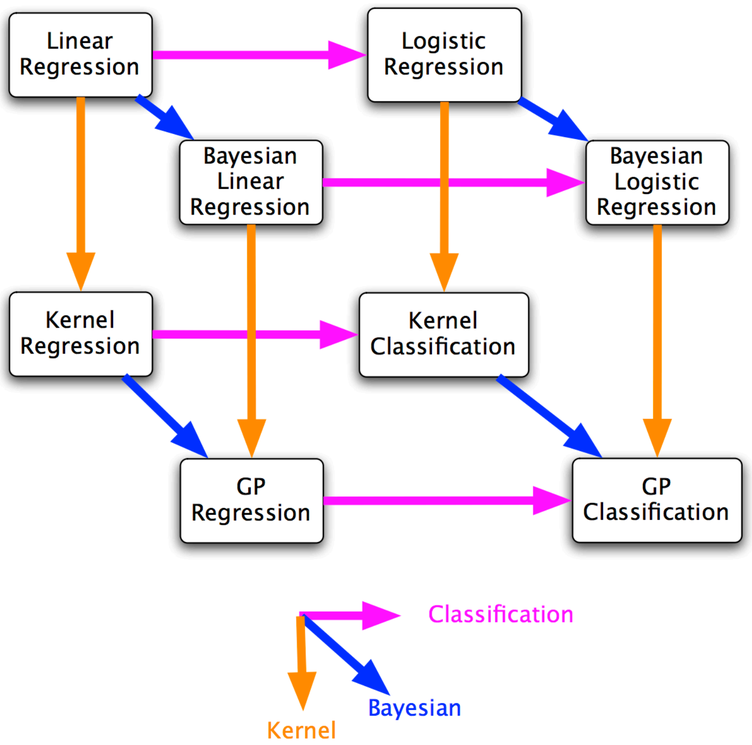
Week 12 - Introduction to ML / Jo Ciucă and Thang Bui / ANU / 2023 S2

Foundations of ML

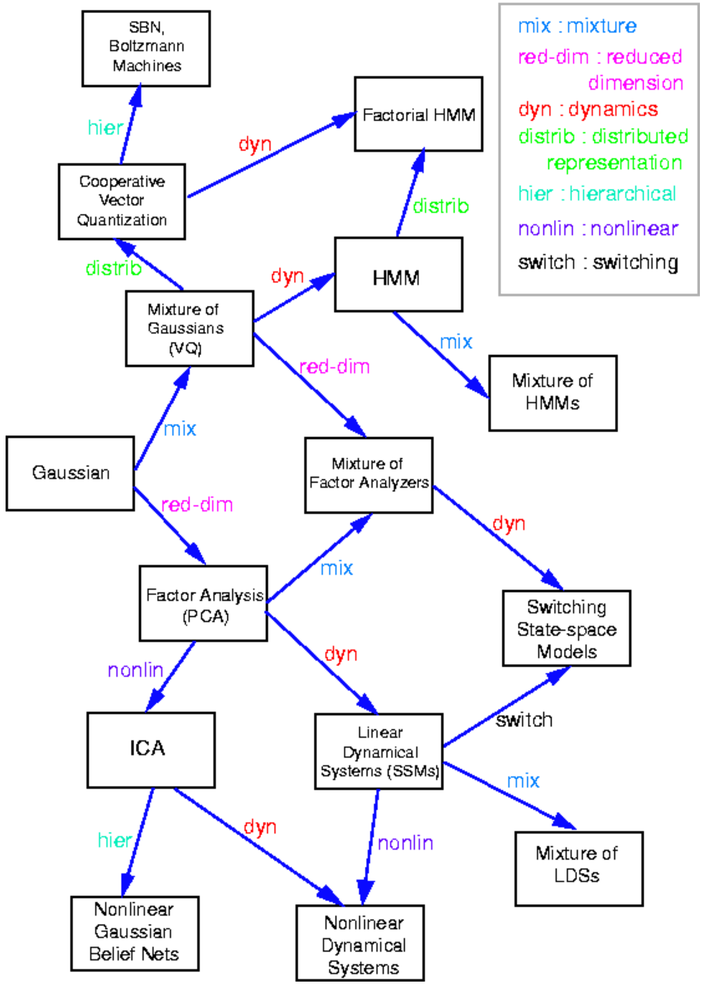


Source: Maths for ML Textbook

Beyond IML

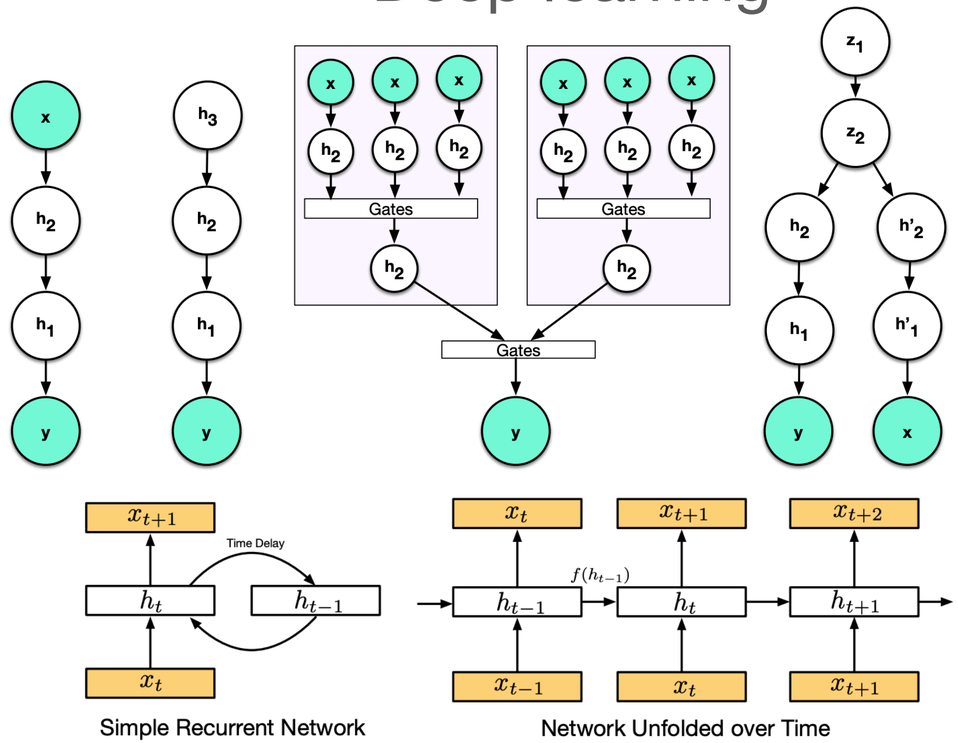


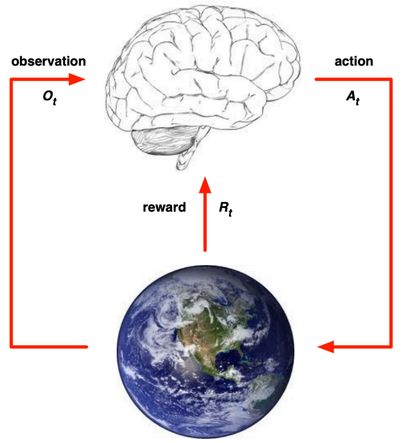
Kernels, probabilistic models, inference (SML)



Unsupervised learning, graphical models

Deep learning





Reinforcement learning

Final exam - logistics

- Time: next Friday. Check your exam timetable for exact time and location
- Reading time: 15 minutes
- Writing time: 180 minutes
- Total marks: 100. Weight: 60%
- Notes:
  - Answer the questions **on** the examination paper itself.
  - Partial marks will be given if intermediate steps are correct.
  - Permitted materials: Calculator (non-programmable, one A4 page with notes on both sides
  - Supplied materials: 20-page script book, one scribble paper.

Final exam - scope and question types

- Scope: **all** weeks (1-12), including the guest lecture
- Questions: a few multiple-choice (~20%), mathematical derivations (~40%), numerical calculations (~30%), short-answers (~10%). No programming.
- It is not a hurdle.

Classification

- Understand logistic regression
- Multi-class classification
- Differences and similarities between logistic regression and linear regression
- Logistic regression with regularization
- Perceptron for linearly separable data
- Confusion table and summary metrics

Linear regression

- What is linear regression?
- deriving the gradient and the closed-form solution of (regularised) linear regression
- What is linear regression with features? How can the features help linear regression?
- regularisation

GMMs and k-means

- Understanding EM algorithm for GMMs
- The differences between k-means and GMMs
- Understanding key parameters, the objective function, how to derive the updates

Model meets data

- Differentiate prediction, training and hyperparameter tuning.
- The role of cross validation
- Difference between parameters and hyperparameters
- Empirical risk minimisation
- Evaluation metrics and loss functions
- The role of training data, testing data and validation data

Probability and distributions

- Being able to calculate discrete/continuous probability
- Being able to apply Bayes' Theorem
- Familiar with Gaussian distributions
- Understand mean, variance, expectation, covariance…

Principal Component Analysis

- dimensionality reduction
- Understand the steps of PCA
- How PCA relates variance preservation with eigenvalues?
- PCA in high dimensions

Vector calculus

- Being able to calculate the gradient / partial derivatives of a function (with respect to vectors or matrices) and apply them to optimize machine learning problems.
- Being able to use identities in lectures without proofs.

Matrix decomposition

- Understand determinant and its properties
- Being able to calculate determinant
- Eigenvalues, eigenvectors, eigen-decomposition and SVD

Analytic geometry

- Understand norms, dot product and the more general inner product
- Lengths and distances are related to the inner product you choose
- Angles and orthogonality
- Orthogonal matrices and rotations
- Orthonormal Basis
- Orthogonal projections and Gram-Schmidt Orthogonalisation

Linear algebra

- Matrix operations
- Systems of linear equations (e.g., Gaussian elimination)
- Vector subspaces
- Linear combination and linear independence
- Basis of a vector space, rank
- Linear mappings and matrix

Thank you!

Hope the course has been interesting/useful/fun/rewarding/challenging!

We welcome constructive feedback - good things/areas of improvement?

Good luck with the final exam!

Questions?