

Suggested Syllabus 1: Machine learning in machine vision

1. Introduction
2. Introduction to probability
 - 2.1 Random variables
 - 2.2 Joint probability
 - 2.3 Marginalization
 - 2.4 Conditional probability
 - 2.5 Bayes' rule
 - 2.6 Independence
 - 2.7 Expectation
3. Common probability distributions
 - 3.1 Bernoulli distribution
 - 3.2 Beta distribution
 - 3.3 Categorical distribution
 - 3.4 Dirichlet distribution
 - 3.5 Univariate normal distribution
 - 3.6 Normal-scaled inverse gamma distribution
 - 3.7 Multi-variate normal distribution
 - 3.8 Normal inverse Wishart distribution
 - 3.9 Conjugacy
4. Fitting probability models
 - 4.1 Maximum likelihood
 - 4.2 Maximum a posteriori
 - 4.3 The Bayesian approach
 - 4.4 Worked example 1: univariate normal
 - 4.5 Worked example 2: categorical distribution
5. The normal distribution
 - 5.1 Types of covariance matrix
 - 5.2 Decomposition of covariance
 - 5.3 Linear transforms of variables
 - 5.4 Marginal distributions
 - 5.5 Conditional distributions
 - 5.6 Product of two normals
 - 5.7 Change of variable
6. Learning and inference in vision
 - 6.1 Computer vision problems
 - 6.2 Types of model
 - 6.3 Example 1: regression
 - 6.4 Example 2: binary classification
 - 6.5 Which type of model should we use?
 - 6.6 Applications
7. Modeling complex data densities
 - 7.1 Normal classification model
 - 7.2 Hidden variables
 - 7.3 Expectation maximization
 - 7.4 Mixture of Gaussians
 - 7.5 The t-distribution
 - 7.6 Factor analysis
 - 7.7 Combining models
 - 7.8 Expectation maximization in detail
 - 7.9 Applications
8. Regression models
 - 8.1 Linear regression
 - 8.2 Bayesian linear regression
 - 8.3 Non-linear regression
 - 8.4 Kernels and the kernel trick
 - 8.5 Gaussian process regression
 - 8.6 Sparse linear regression
 - 8.7 Dual linear regression
 - 8.8 Relevance vector regression
 - 8.9 Regression to multivariate data
 - 8.10 Applications
9. Classification models
 - 9.1 Logistic regression
 - 9.2 Bayesian logistic regression
 - 9.3 Non-linear logistic regression
 - 9.4 Dual logistic regression
 - 9.5 Kernel logistic regression
 - 9.6 Relevance vector classification
 - 9.7 Incremental fitting and boosting
 - 9.8 Classification trees
 - 9.9 Multi-class logistic regression
 - 9.10 Random trees, forests, and ferns
 - 9.11 Relation to non-probabilistic models
 - 9.12 Applications
10. Graphical models
 - 10.1 Conditional independence
 - 10.2 Directed graphical models
 - 10.3 Undirected graphical models
 - 10.4 Comparing directed and undirected graphical models
 - 10.5 Graphical models in computer vision
 - 10.6 Inference in models with many unknowns
 - 10.7 Drawing samples
 - 10.8 Learning
11. Models for chains and trees
 - 11.1 Models for chains
 - 11.2 MAP inference for chains
 - 11.3 MAP inference for trees
 - 11.4 Marginal posterior inference for chains
 - 11.5 Marginal posterior inference for trees
 - 11.6 Learning in chains and trees
 - 11.7 Beyond chains and trees
 - 11.8 Applications
12. Models for grids
 - 12.1 Markov random fields
 - 12.2 MAP inference for binary pairwise MRFs
 - 12.3 MAP inference for multi-label pairwise MRFs
 - 12.4 Multi-label MRFs with non-convex potentials
 - 12.5 Conditional random fields
 - 12.6 Higher order models
 - 12.7 Directed models for grids
 - 12.8 Applications
13. Image preprocessing and feature extraction
 - 13.1 Per-pixel transformations
 - 13.2 Edges, corners, and interest points
 - 13.3 Descriptors
 - 13.4 Dimensionality reduction
14. Models for geometry
 - 14.1 The pinhole camera
 - 14.2 Three geometric problems
 - 14.3 Homogeneous coordinates
 - 14.4 Learning extrinsic parameters
 - 14.5 Learning intrinsic parameters
 - 14.6 Inferring 3D world points
 - 14.7 Applications
15. Models for transformations
 - 15.1 2D transformation models
 - 15.2 Learning transformation models

- 15.3 Inference in transformation models
- 15.4 Three geometric problems for planes
- 15.5 Transformations between images
- 15.6 Robust learning of transformations
- 15.7 ApplicationsModel
- 16. Multiple cameras
 - 16.1 Two-view geometry
 - 16.2 The essential matrix
 - 16.3 The fundamental matrix
 - 16.4 Two-view reconstruction pipeline
 - 16.5 Rectification
 - 16.6 Multi-view reconstruction
 - 16.7 Application
- 17. Models for shape
 - 17.1 Shape and its representation
 - 17.2 Snakes
 - 17.3 Shape templates
 - 17.4 Statistical shape models
 - 17.5 Subspace shape models
 - 17.6 Three-dimensional shape models
 - 17.7 Statistical models for shape and appearance
 - 17.8 Non-Gaussian statistical shape models
 - 17.9 Articulated models
 - 17.10 Application
- 18. Models for style and identity
 - 18.1 Subspace identity model
 - 18.2 Probabilistic linear discriminant analysis
 - 18.3 Non-linear identity models
 - 18.4 Asymmetric bilinear models
 - 18.5 Symmetric bilinear and multilinear models
 - 18.6 Application
- 19. Temporal models
 - 19.1 Temporal estimation framework
 - 19.2 Kalman filter
 - 19.3 Extended Kalman filter
 - 19.4 Unscented Kalman filter
 - 19.5 Particle filtering
 - 19.6 Applications
- 20. Models for visual words
 - 20.1 Images as collections of visual words
 - 20.2 Bag of words
 - 20.3 Latent Dirichlet allocation
 - 20.4 Single author-topic model
 - 20.5 Constellation models
 - 20.6 Scene models
 - 20.7 Applications