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