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