<table>
<thead>
<tr>
<th>Program</th>
<th>Support Vector Machines and Regularized Learning</th>
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</table>
| **1. Introduction:** | • Modelling, optimization and regularization.  
• Classical unconstrained optimization.  
• Examples in constrained optimization.  
• Linear classifiers, margins and generalization.  
• Linear Support Vector Machines: primal problem.  
• Lagrangian formulation and dual problem.  
• KKT conditions and optimal solution.  
• Linear classifiers revisited: Cover's theorem. |
| **2. SVM models:** | • Kernelization and non-linear SVMs:  
  ◦ Non-linear classification in feature spaces.  
  ◦ Mercer's Theorem. Kernel trick.  
  ◦ Common kernel choices.  
  ◦ Parameter tuning.  
• Support Vector Regression:  
  ◦ Regression problems.  
  ◦ epsilon-insensitive loss.  
  ◦ Primal and dual formulations, kernelization.  
• One-class Support Vector Machine:  
  ◦ Density estimation problems.  
  ◦ Primal and dual formulations, kernelization.  
  ◦ Kernels for non-vector data.  
• Other SVM-related models. |
| **3. SVM learning algorithms:** | • Brief introduction to convex optimization.  
• Non-linear SVM learning algorithms:  
  ◦ Chunking and decomposition methods. SVMlight.  
  ◦ Sequential Minimal Optimization. LIBSVM.  
• Linear SVM learning algorithms:  
  ◦ Primal solver: Pegasos.  
  ◦ Dual solver: LIBLINEAR. |
| **4. Regularized learning:** | • Regularization and usual regularization functions.  
• Regularized linear models:  
  ◦ Lasso.  
  ◦ Elastic-Net.  
  ◦ Fused Lasso, group variants.  
• Other regularized models. |
| **5. Convex optimization for regularized learning:** | • Proximal optimization and proximal methods.  
• The ISTA and FISTA algorithms.  
• Application to regularized learning.  
• Application to denoising and projection problems. |
| **6. Practical sessions:** | • Python with scikit-learn, Jupyter notebooks. |
Bibliography