Incremental Multiple Kernel Learning for Object Detection

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Motivation

- Components of a visual categorization system:
 Representative training dataset
 Efficient and effective feature extraction methods
- Powerful classifier
- Obtaining a generic training dataset is relatively easy
- > Obtaining a scene specific training dataset for a given application is harder
 - □ Fair amount of manual labor required for every new scene



Scene specific characteristics of a traffic intersection:
 Camera location and typical vehicle paths restrict observed poses
 Camera location restricts the negative class (background)
 Images of vehicles and background change over time

 Changing illumination conditions

- Shadows cast by the buildings



- > Our Incremental Multiple Kernel Learning (IMKL) based approach initializes with a generically obtained training database
- It tunes itself automatically towards the classification task
 Updates the training dataset, tailoring it towards the scene
- Updates the weights used to combine multiple information sources
 Tunes the classifier in an online fashion
- > Ability to remove training examples over time
 - Useful when dealing with changing illumination conditions
- ➤ IMKL approach is a fusion of:
 - In Multiple Kernel Learning (MKL) [†]
 - Incremental Support Vector Machine (ISVM) *
 - † A. Rakotomamonjy, F.R. Bach, S. Canu and Y. Grandvalet
 - More efficiency in multiple kernel learning. ICML 2007
 - * G. Cauwenberghs and T. Poggio. Incremental and decremental support vector machine learning NIPS 2000

- IMKL Algorithm

 KKT conditions

 IMKL Optimization Problem

 $min \sum_{i} \frac{1}{d_k} w_k w_k^T + C \sum_{i} \xi_i$ $\sum_{j} k a_i a_j O_{ij}^k + y_i b 1 =$
 $\sum_{j} \frac{1}{d_k} \sum_{k} o_i O_{ij}^k + y_i b 1 =$
 $\sum_{j} \sum_{k} d_k a_j O_{ij}^k + y_i b 1 =$
 $\sum_{j} \sum_{k} 0 a_i O_{ij}^k + y_i b 1 =$
 $\sum_{j} \sum_{k} 0 a_i O_{ij}^k + y_i b 1 =$
- $\sum_{i=1}^{k} a_{i}g_{i} = 0$ $\xi_{i} \ge 0 \quad \forall i, \quad d_{k} \ge 0 \quad \forall k, \quad \sum_{k} d_{k} = 1$ $p_{k}d_{k} = 0$ $\sum_{k} d_{k} = 1$ $\sum_{k=1}^{k} d_{k} = 1$
- Optimization problem is convex

such that $y_i \sum \phi_k(x_i) + y_i b \ge 1 - \xi_i \quad \forall i$

- \square KKT conditions and necessary and sufficient
- > When a new point x_{new} is added, we need to calculate its Lagrange multiplier α_{new} :
 - Bounded by 0 and C
 - Begin with 0 and keep incrementing till solution is reached

 \square Every time we increment $\alpha_{new},$ we must update the remaining Lagrange multipliers, kernel weights and bias to maintain the KKT conditions

□ These changes are given by the differential forms of the KKT conditions



- > Differential equations hold when α_{new} is small enough to ensure that there is no change in set membership
 - u When set membership changes, equations are updated



Termination Conditions:



