

## Multi-Modal Image Retrieval for Complex Queries using Small Codes





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## **Text2semantic** Represent object configurations as an MRF. Sketches approximated by bounding boxes. Sample MRF to generate most likely sketches. ree left road and of grass road car building sky and right of grass sky grass Hash code ground, sky and sky and tree **Multi-View Hashing** Semantic Representations from each modality differ. Project different modalities (views) of the data to common low-dimensional subspace. Partial Least Squares (PLS) learns projection from each modality to the common subspace. $\succ$ Given two views X, Y; PLS decomposes them as: $X = TP^T + E; \quad Y = UQ^T + F; \quad U = TD + H$ $\succ$ Iteratively maximizes: $[\operatorname{cov}(t_i, u_i)]^2 = \max_{|w_{xi}|=1, |w_{yi}|=1} [\operatorname{cov}(Xw_{xi}, Yw_{yi})]^2$ Object Masks PLS Red car to the left of a yellow car $\succ$ Map vectors in the subspace to binary codes to reduce memory burden and enable fast matching (Hamming dist.). Randomly rotate projection matrix to uniformly distribute information across all dimensions. $\tilde{W}_x = W_x R$ Iterative Quantization (ITQ) to compute optimal rotation matrix that minimizes the quantization error (Gong et al.): $\mathcal{Q}(H,R) = ||H - XW_x R||_F^2$







