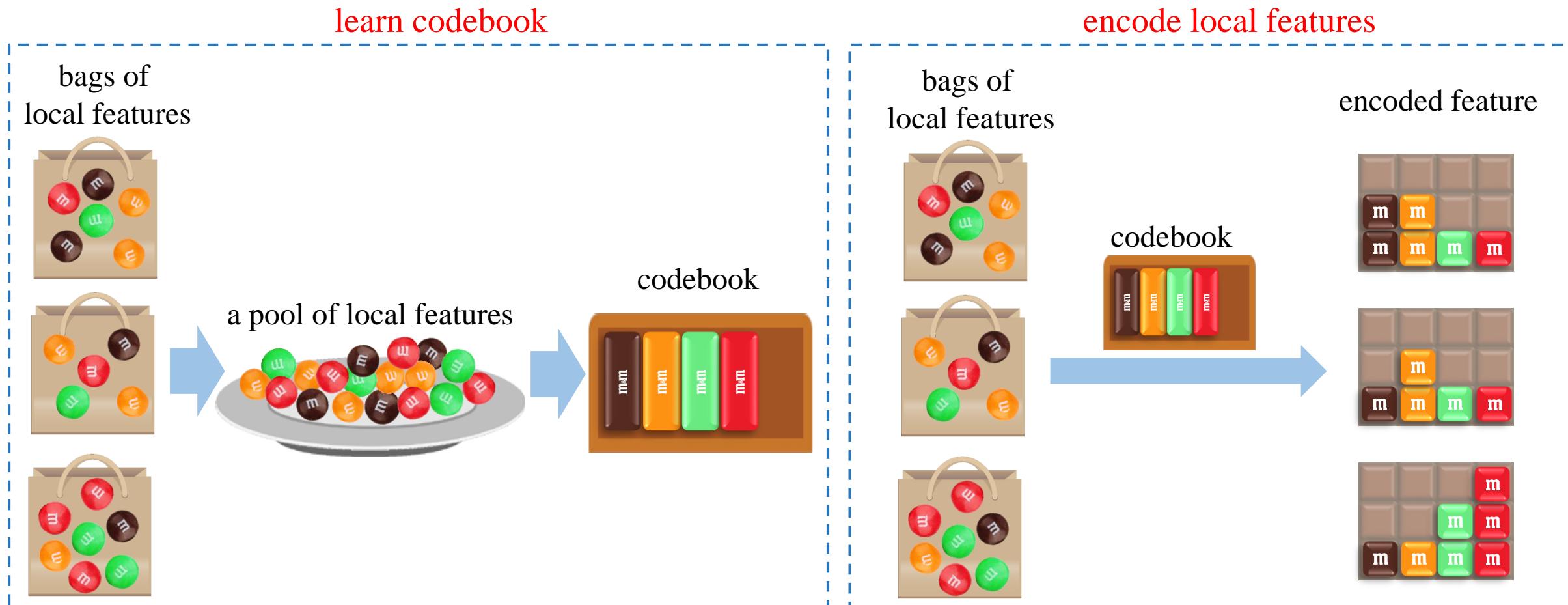


# Domain Adaptive Fisher Vector

Li Niu

# Feature Encoding

**Feature encoding:** encode each bag of local features into feature vector based on codebook.

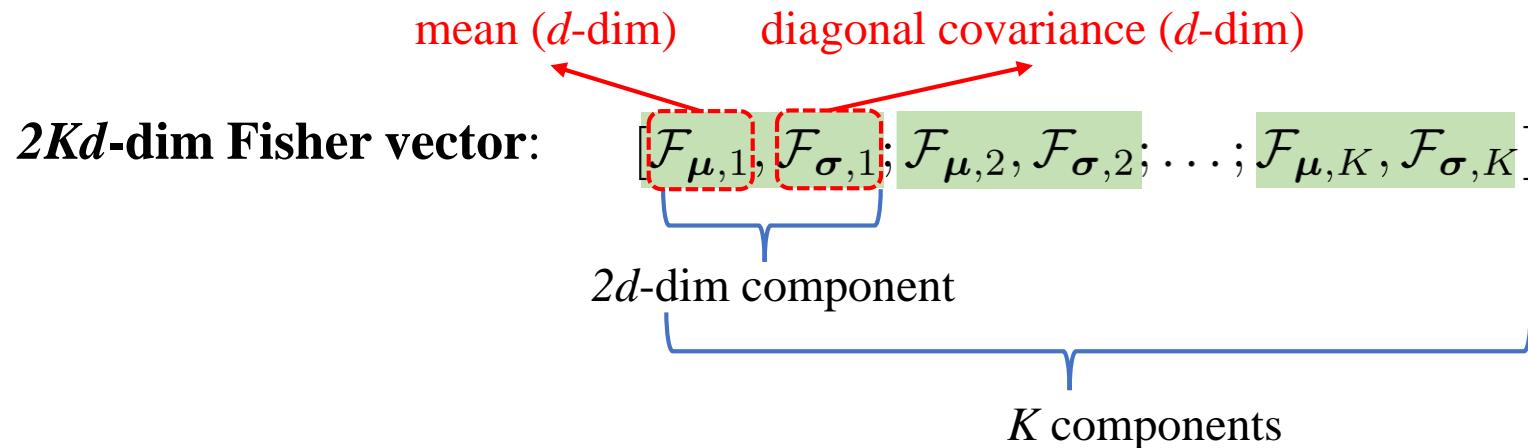
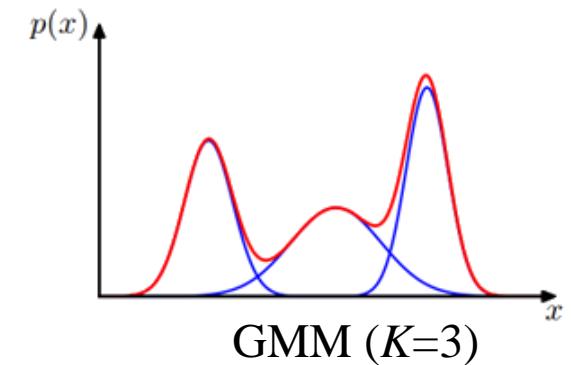


# Fisher Vector

**Fisher vector:** a powerful feature encoding method. [15]

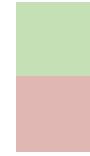
**Local feature:**  CNN feature of image proposals  
 trajectory feature of video trajectories

**Codebook:**  $K$ -component Gaussian Mixture Model (GMM)  
trained on  $d$ -dim local features.



# Our Method

**$2Kd$ -dim Fisher vector  $\mathbf{X}$ :**  $[\mathcal{F}_{\mu,1}, \mathcal{F}_{\sigma,1}; \mathcal{F}_{\mu,2}, \mathcal{F}_{\sigma,2}; \dots; \mathcal{F}_{\mu,K}, \mathcal{F}_{\sigma,K}]$

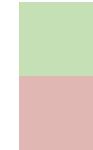


domain invariant component  
domain variant component

**domain invariant component:** capture the common data distribution across domains.

# Our Method

**$2Kd$ -dim Fisher vector  $\mathbf{X}$ :**  $[\mathcal{F}_{\mu,1}, \mathcal{F}_{\sigma,1}; \mathcal{F}_{\mu,2}, \mathcal{F}_{\sigma,2}; \dots; \mathcal{F}_{\mu,K}, \mathcal{F}_{\sigma,K}]$

 domain invariant component  
domain variant component

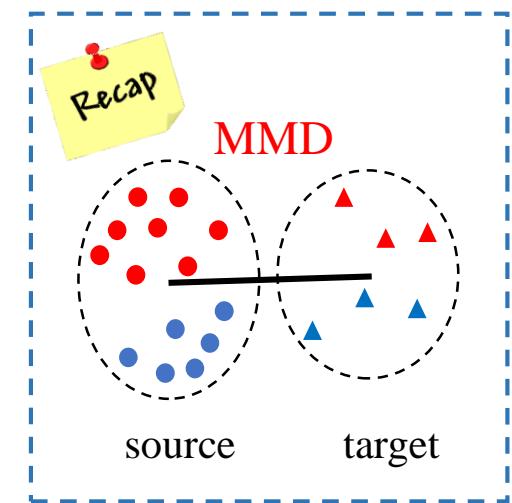
**domain invariant component:** capture the common data distribution across domains.

**Motivation:** learn projection  $\mathbf{R}$  to identify domain invariant components by minimizing domain distance.

$$\begin{array}{ll} \min_{\mathbf{W}, \mathbf{R}} & \|\mathbf{WRX}^s - \mathbf{Y}\|_F^2 + \|\mathbf{W}\|_F^2 + \boxed{\|\tilde{\mathbf{R}}\|_{2,1}} + \boxed{\left\| \frac{1}{n_s} \mathbf{RX}^s \mathbf{1} - \frac{1}{n_t} \mathbf{RX}^t \mathbf{1} \right\|^2} \\ \text{s.t.} & \mathbf{RXHX'R'} = \mathbf{I} \end{array}$$

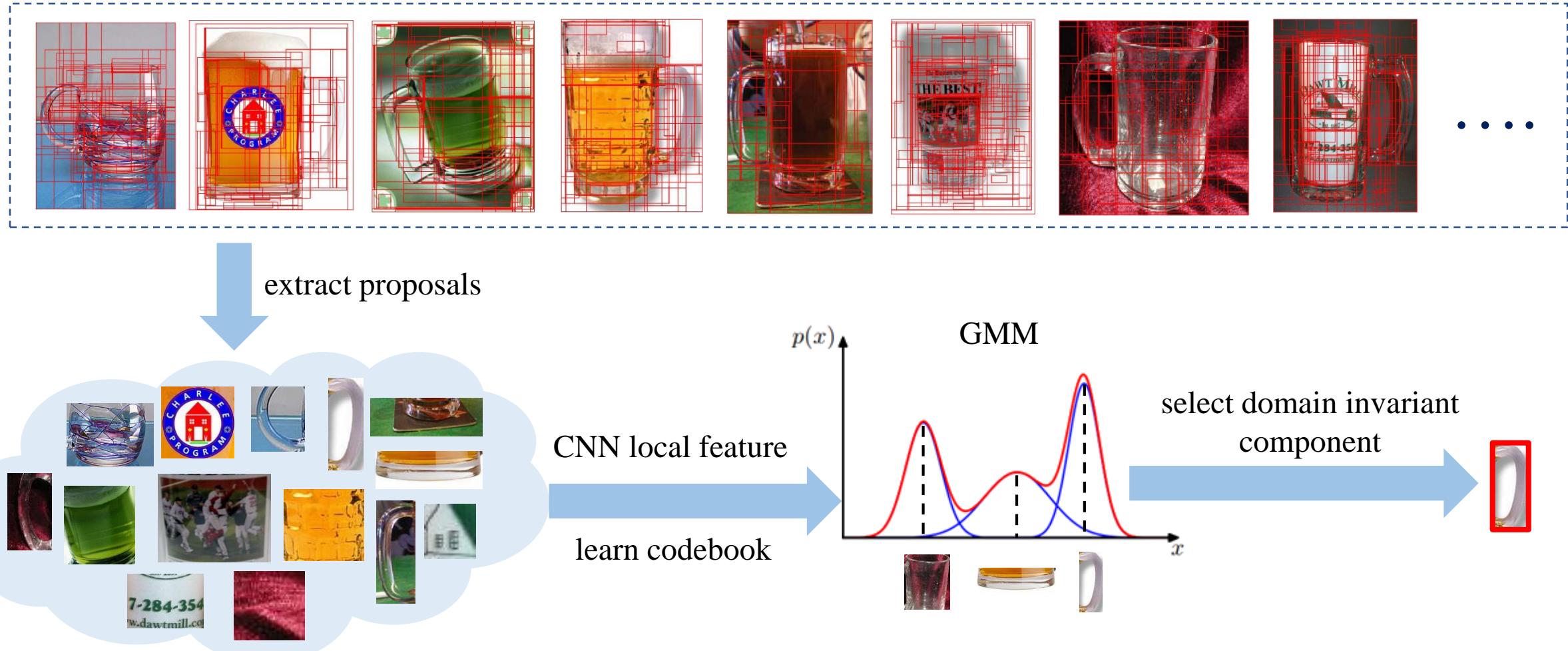
group lasso

MMD



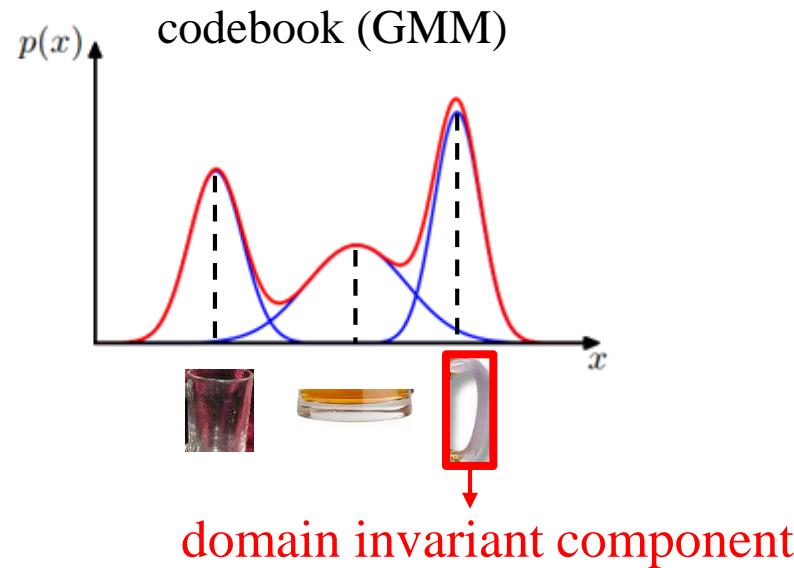
# Experiments

## Domain Adaptive Fisher Vector for Classifying “Beer Mug”



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## Domain Adaptive Fisher Vector for Classifying “Beer Mug”

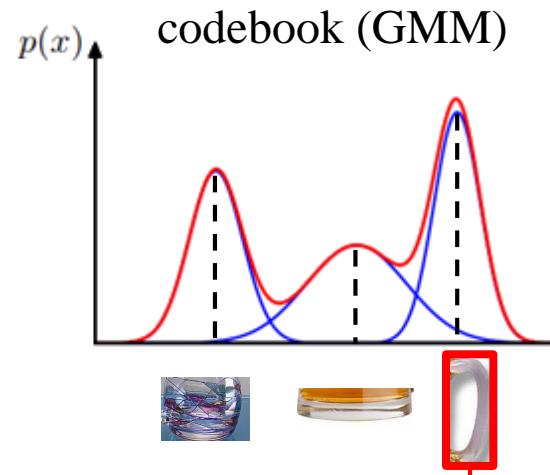


top proposals corresponding to domain invariant component



# Experiments

## Domain Adaptive Fisher Vector for Classifying “Beer Mug”



top proposals corresponding to domain invariant component



Accuracies (%) on the Bing-Caltech256 dataset

AGMM	EM_RGMM	KMM	GFK	TCA	SA	SDDL	LTSI	CORAL	Ours
76.8	77.4	73.6	73.6	74.8	74.2	62.4	77.6	75.2	<b>79.4</b>