Universal Cross-Domain Retrieval: Generalizing Across Classes and Domains

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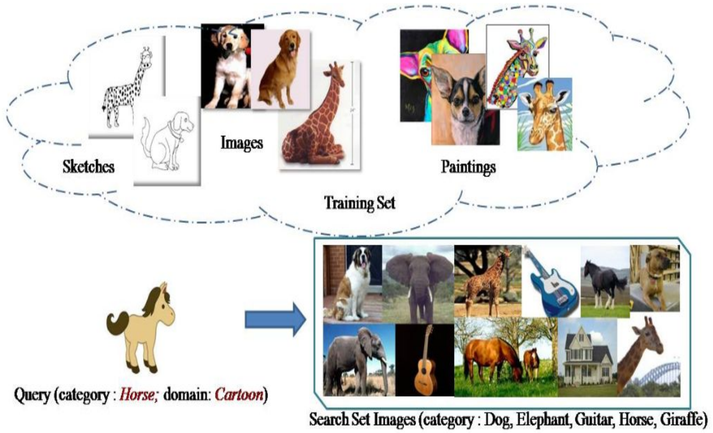
Universal Cross-domain Retrieval (UCDR)

- Cross-domain retrieval for truly generalized scenario
  - The query may belong to a seen or an unseen domain
  - The query may belong to any seen or unseen category
- First attempt in retrieval literature



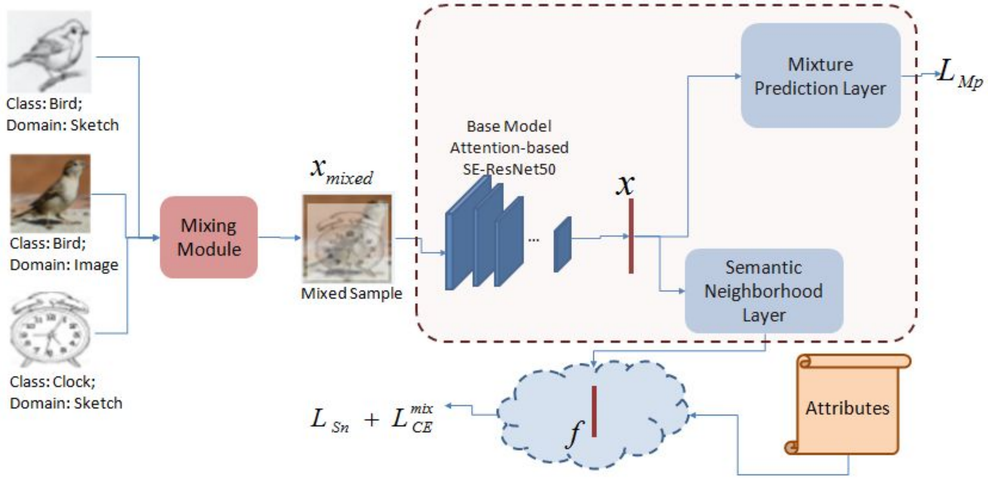
Existing Work & Challenges

- UCDR combines challenges of Domain Generalization with Zero-shot Cross-domain Retrieval
- Existing cross-domain retrieval algorithms assume prior knowledge about query and search-set domain
  - Domain-specific branch / architecture
  - Cannot be directly applied for generalized scenario, such as UCDR
- CuMix - classification network combining Zero-shot Learning with DG

Key Contributions

- Single-branch of network
- Reduction in trainable parameters
- Novel Loss function
  - (1) Mixture-prediction loss
  - (2) Semantic-neighbourhood embedding loss

Semantic Neighbourhood and Mixture Prediction Network (SnMpNet)



Learning Methodology

1. **Mixing Strategy across classea and domains**

$$x_{mixed} = \alpha x_1 + (1-\alpha)\left[\beta x_2 + (1-\beta)\, x_3\right]$$

$$\alpha \sim beta(\lambda, \lambda)$$

$$\beta \sim bernoulli(\gamma, \gamma)$$

2. **Predict Mixing Ratio - forgets domain information**

$$L_{MP} = \sum_x \sum_c l_c \log\left[Prob(x \in class - c)\right]$$

$$l_c = \begin{cases} \alpha, & if\ x \in class - b \\ (1-\alpha), & if\ x \in class - c \\ 0, & otherwise \end{cases}$$

3. **Align Semantic Neighbourhood - generalize to unseen classes**

$$L_{Sn} = \sum_x || D(f) - D_{gt}(f) ||^2$$

4. **Cross-entropy based classification loss for mixed-up data**

References

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[4] P. Sangkloy, N. Burnell, C. Ham and J. Hays, "The sketchy database: learning to retrieve badly drawn bunnies," *ACM TOG*, vol. 34, no. 4, pp. 1-12, 2016.

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- Code available at : https://github.com/mvp18/UCDR

Evaluation for UCDR

- Image Search Set from: (a) only unseen-class, (b) both seen and unseen class
- Leave-one-domain-out training strategy
- Comparable retrieval-version of SOTA methods - (a) EISNet-retrieval, (b) CuMix-retrieval

Query Domain	Method	Unseen-class Search set	Seen + Unseen class Search Set
		mAP@200	mAP@200
Sketch	EISNet-retrieval	0.2611	0.2286
	CuMix-retrieval	0.2736	0.2428
	SnMpNet	**0.3007**	**0.2624**
QuickDraw	EISNet-retrieval	0.1273	0.1101
	CuMix-retrieval	0.1304	0.1118
	SnMpNet	**0.1736**	**0.1512**
Painting	EISNet-retrieval	0.3599	0.3280
	CuMix-retrieval	0.3710	0.3400
	SnMpNet	**0.4031**	**0.3635**

Ablation Study

Sketchy-extended Dataset		
Model Variants	**mAP@200**	**Precision@200**
Base N/W	0.5218	0.4497
Base N/W + Semantic-Neighbourhood Loss	0.5613	0.5030
Base N/W + mixture CE-loss	0.5252	0.4530
Base N/W + Mixture CE-loss + Mixture Prediction Loss	0.5665	0.4989
SnMpNet	**0.5781**	**0.5155**

Retrieval Results