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Unbiased Metric Learning

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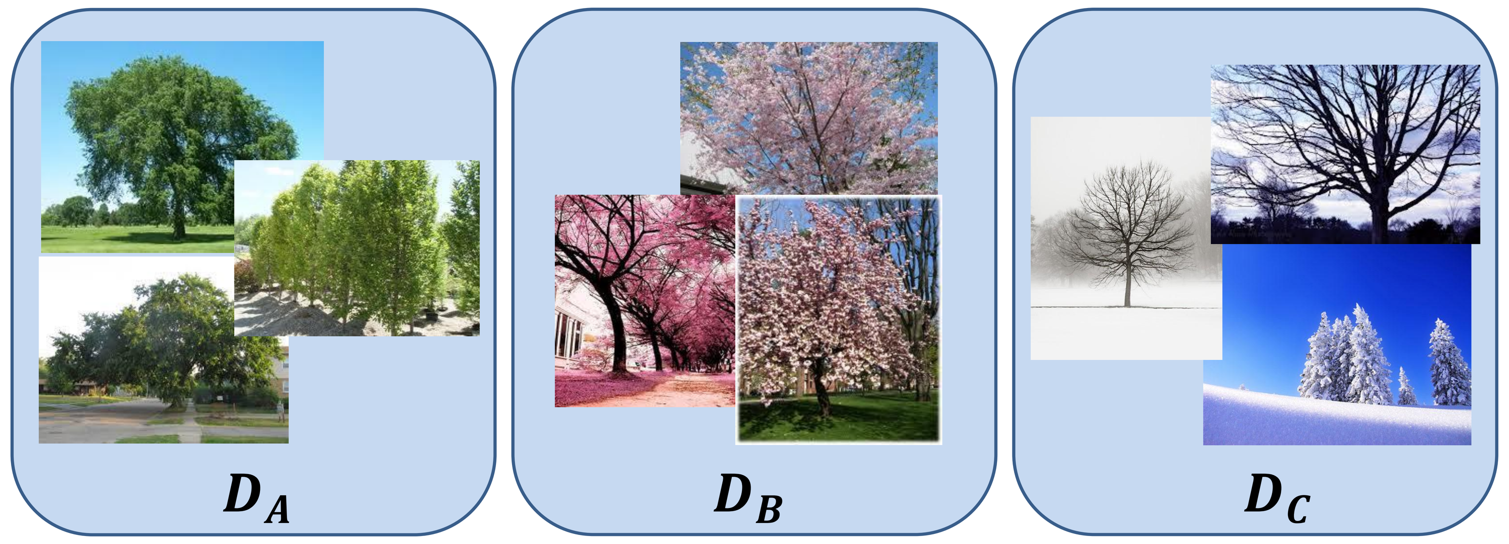
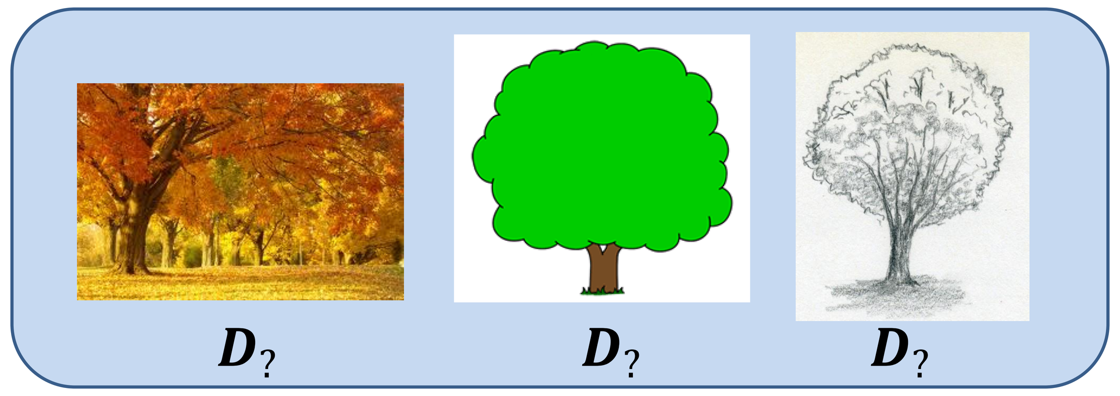
Issue: Data from different domains are *biased*



Learning

Target:
- Learn an *unbiased* recognition model from multiple domains
- Recognize data from *unseen* domains (generalization ability)

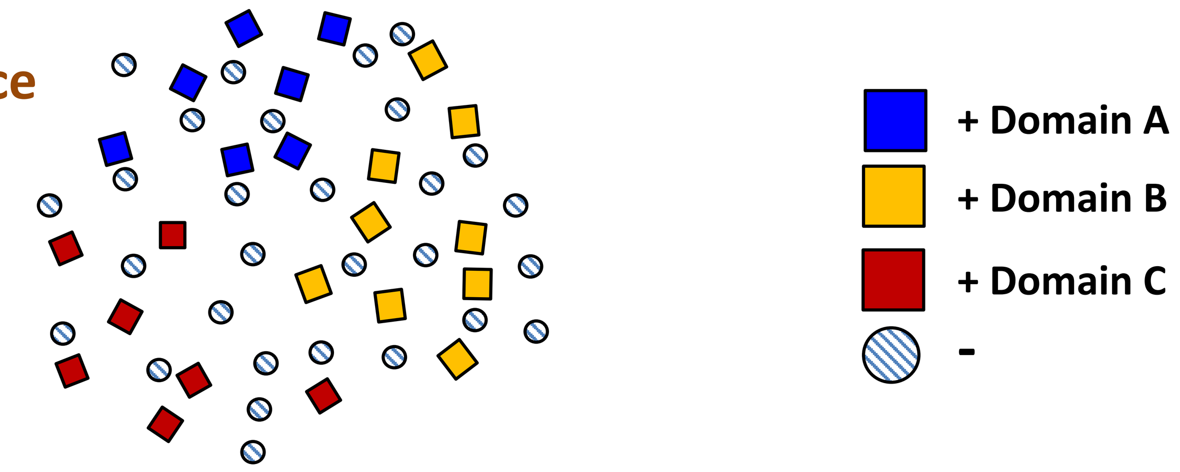
Testing



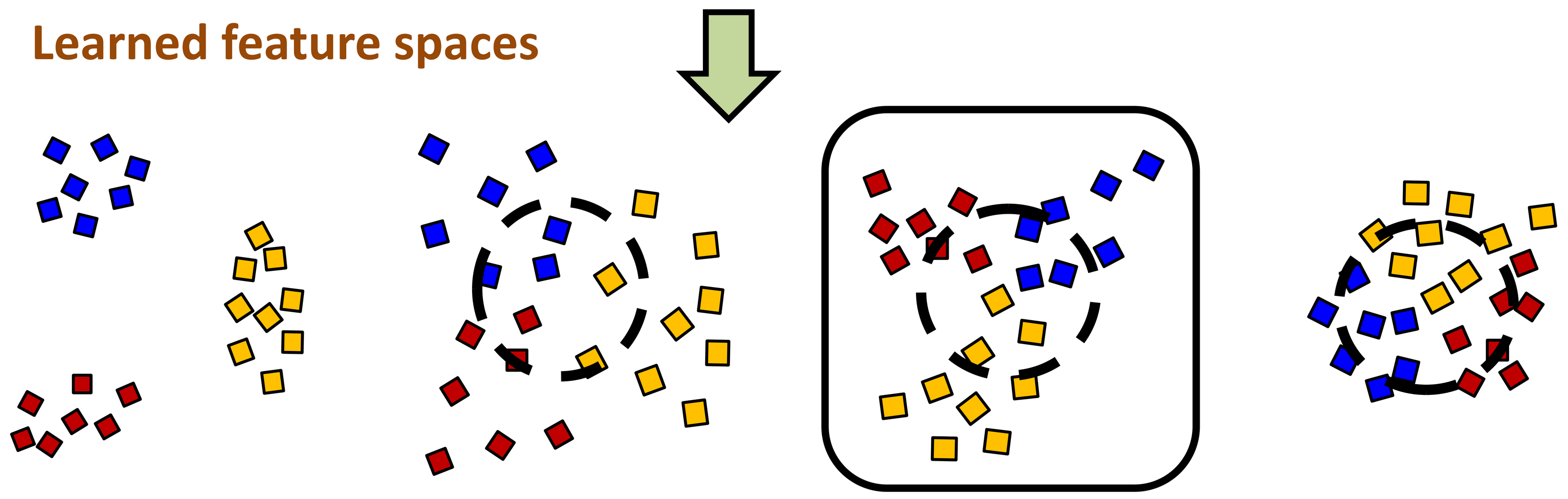
Approach Overview:

1. Learning feature spaces, where data from multiple domains are *bridged* together in different ways (capture common knowledge)
2. Validating out the best bridging using *web images*

Original feature space



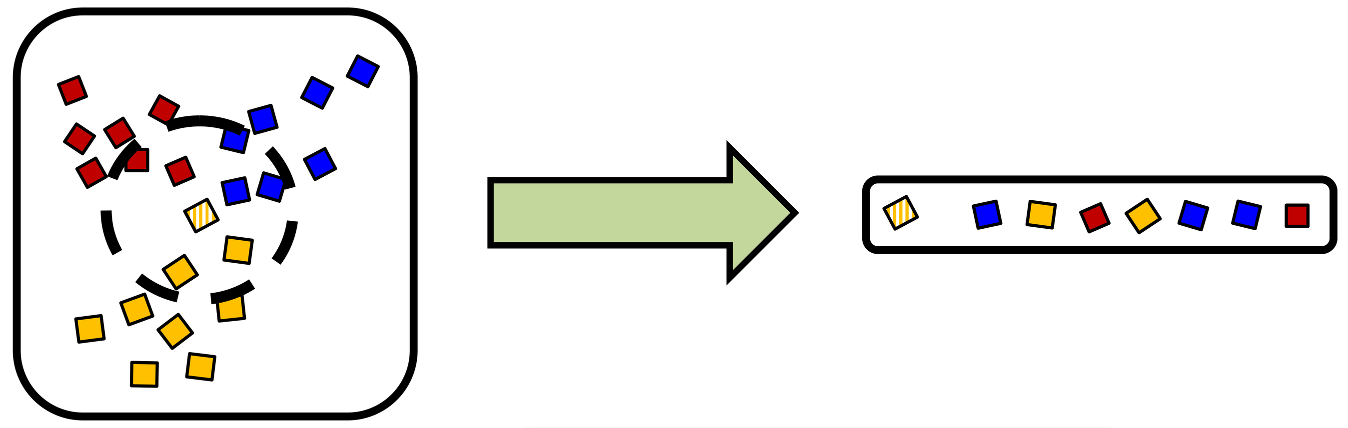
Learned feature spaces



Feature Space Learning:

- *Label Coherence* and *Domain Diversity* within Neighborhood
  - Examples of the same label to be close
  - "+ examples" from multiple domains to be close
- Metric Learning to Rank

Neighborhood perspective — Ranking perspective



- Goal: $d_W(i,j) = \sqrt{(x_i - x_j)^T W (x_i - x_j)}$
- Formulation:

$$\min_{W\succeq 0,\xi\geq 0} tr(W) + \frac{C_1}{n}\sum_{q\in\mathcal{X}}\xi_q + \frac{C_2}{n}\sum_{q\in\mathcal{X}}\xi_q^+$$

$$\forall q\in\mathcal{X}, \forall y\in\mathcal{Y}\backslash y_q^*:$$

Label Coherence Constraint

$$\langle W, \psi_{po}(q,y_q^*) - \psi_{po}(q,y)\rangle_F \geq \Delta(y,y_q^*) - \xi_q$$

$$\forall q\in\mathcal{X}, \forall y^+\in\mathcal{Y}^+\backslash y_q^{+*}:$$

Domain Diversity Constraint

$$\langle W, \psi_{po}(q,y_q^{+*}) - \psi_{po}(q,y^+)\rangle_F \geq \hat{\Delta}(y^+,y_q^{+*}) - \xi_q^+$$

- Optimization: Alternating-Direction Method of Multipliers

Validation with Web Images:

- Difficulty
  - I. Test data can from unseen domains
  - II. Test data can from multiple domains
  - III. No domain knowledge of test data
- Assumption: web images are less biased
- Potential Issue: web images are only weakly-labeled

Experiments:

- Existence of bias

Table 1. K-nearest neighbor classification accuracy on all datasets. Metrics are learned on each dataset individually. The left-most column specifies the training dataset, while the up-most row specifies the test dataset.

Train	Test: Cal	Pas	SUN	Lab
Cal	**0.87**	0.33	0.24	0.39
Pas	0.31	**0.40**	0.32	0.30
SUN	0.11	0.23	**0.37**	0.22
Lab	0.24	0.25	0.18	**0.47**

Experiments:

- Cross-dataset classification: leave one dataset out as test set, learn from the other datasets

I. Feature Space Learning

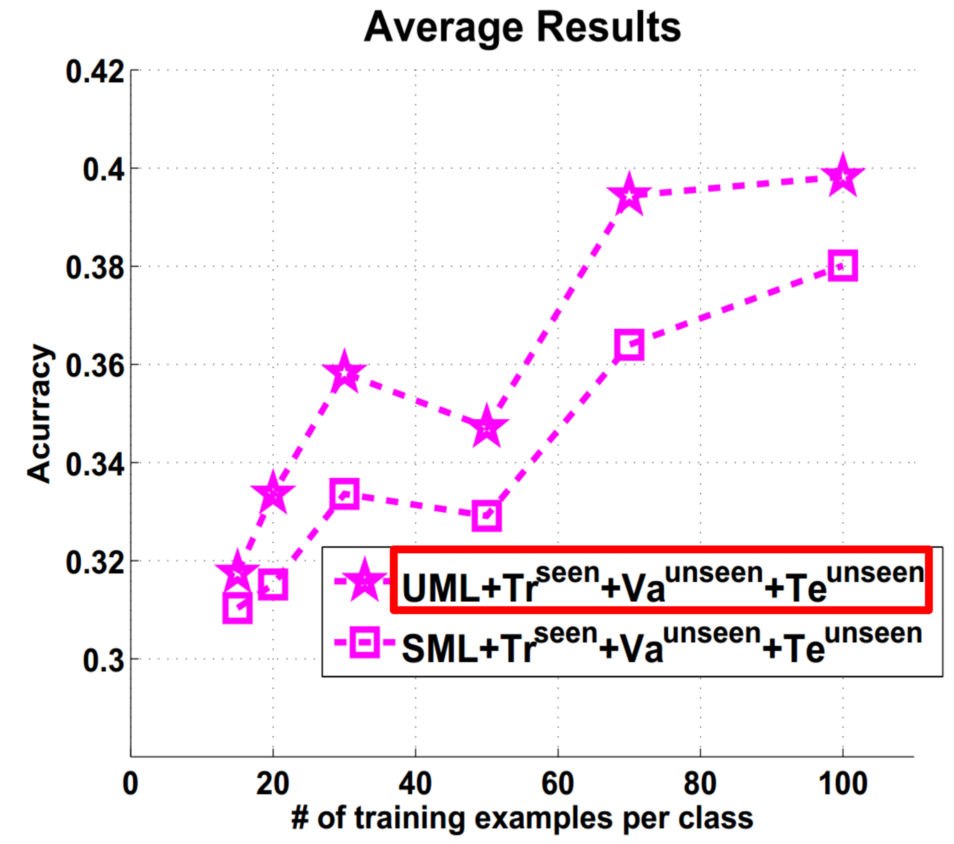


Figure 1. Cross-dataset classification accuracy on Te^{unseen} with validation on Va^{unseen}. This figure shows the learning is able to produce model with better generalization ability.

II. Validation with Web Images

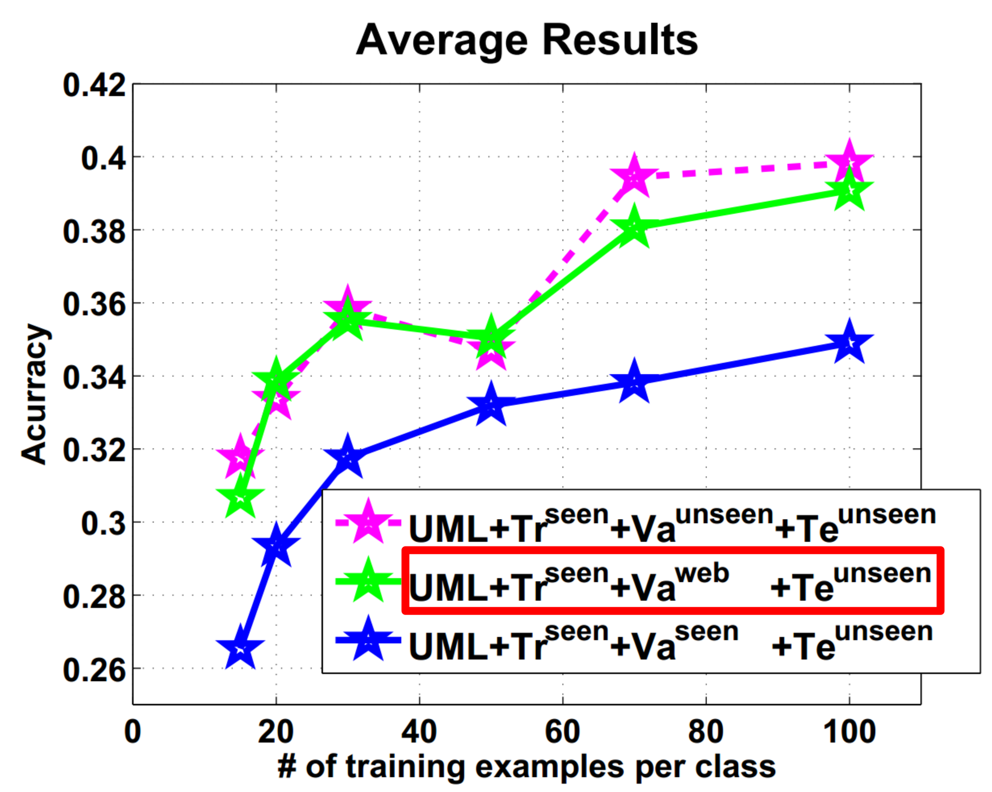


Figure 2. Cross-dataset classification accuracy on Te^{unseen} with validation on different set. This figure shows that web image, when being used as validation set, is able to identify model with better generalization ability, which is produced in learning stage.

iii. Full Evaluation

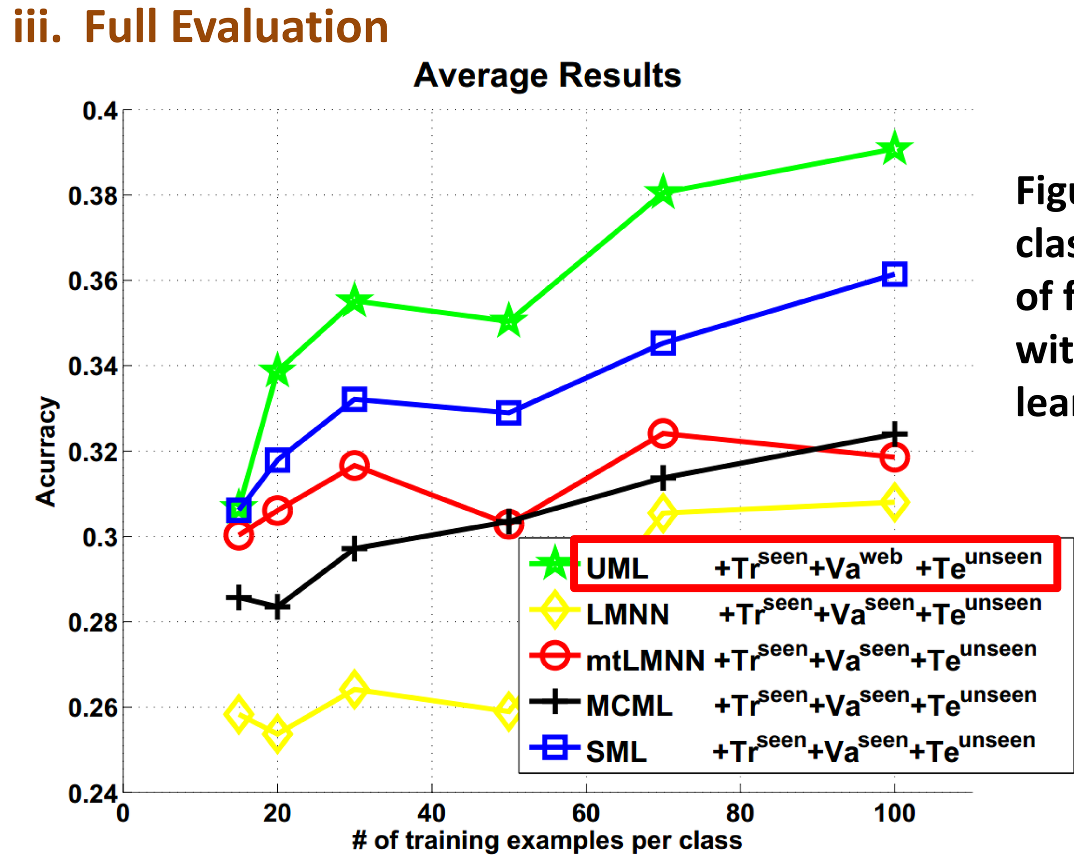


Figure 3. Cross-dataset classification accuracy of full model, compared with other metric learning approaches.

References
[1] A. Torralba and A. Efros. Unbiased look at dataset bias. In CVPR, 2011
[2] A. Khosla, T. Zhou, T. Malisiewicz, A. Efros, and A. Torralba. Undoing the damage of dataset bias. In ECCV, 2012
[3] B. Mcfee and G. Lanckriet. Metric learning to rank. In ICML, 2010