Properties of Datasets Predict the Performance of Classifiers

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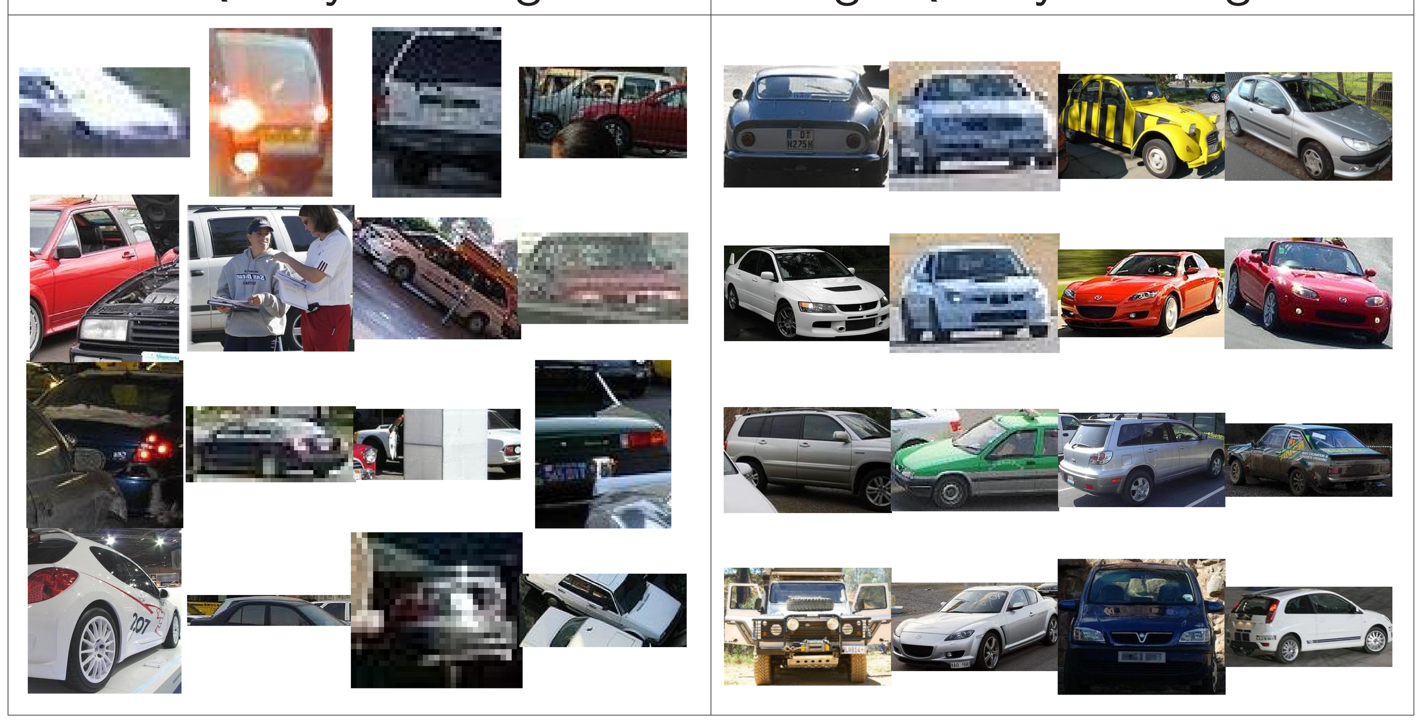
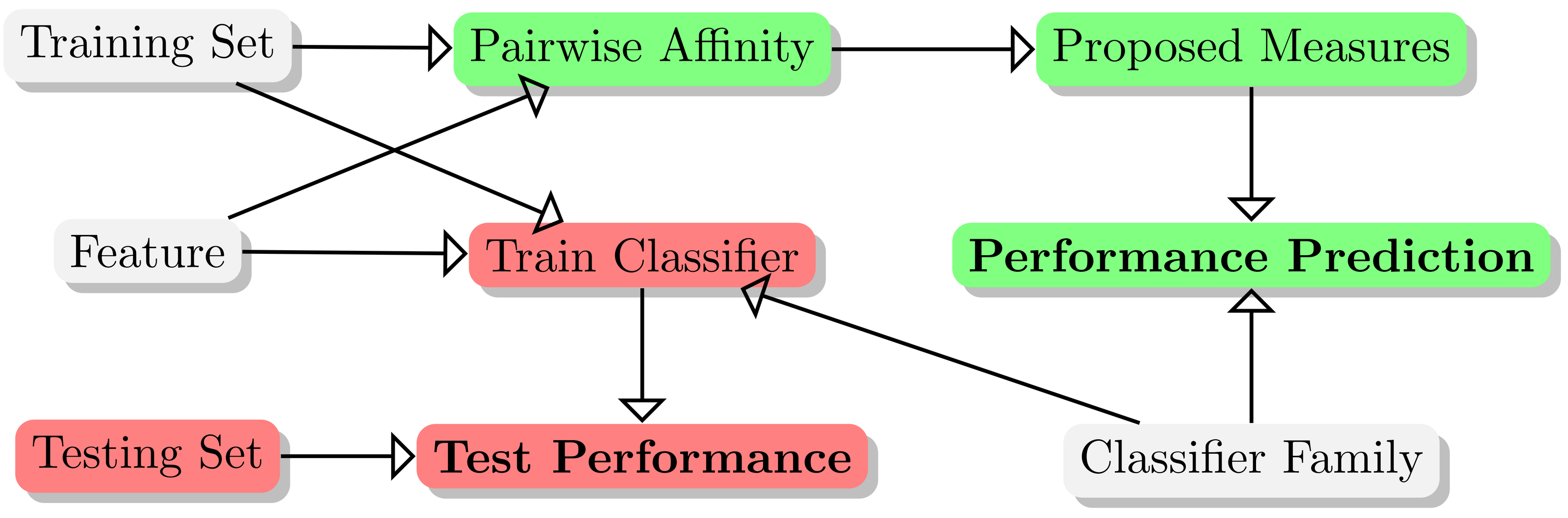
Introduction

- Quality of the training set $\rightarrow$ Test performance of classifiers

Low Quality Training Set | High Quality Training Set



- This work attempts to quantify the quality of the training set



Visual Structural Similarity

- Pairwise Visual Structural Similarity measure (K^E_{MMI} [1])

$$K^E_{\text{MMI}}(x, y) = \max_i \min\left(E_i(x), E_i(y)\right)$$

$$E_i(x) = \max_{z \in \mathcal{Z}(x)} \left\{1 + \exp(-\alpha_i(\mathbf{w}_i \cdot \Phi(x, z) - \gamma_i))\right\}^{-1}$$

- Feature selection via discriminative reasoning
- Measuring affinity of positives $\rightarrow$ negatives modelled implicitly via discriminative reasoning

Multi Scale Data Describing Measures

- Local scale: measures similarity to nearest neighbors
  $\mu_L = \frac{1}{n}\sum_{i=1}^{n} \max_{p_j \neq p_i} K(p_i, p_j)$
- Semi-Global scale: measures similarity between all positive pairs
  $\mu_S = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} K(p_i, p_j)$
- Global scale: links multiple local steps to measure global similarity
  - Construct a full graph with $w_{ij} = 1 - K(p_i, p_j)$ and find the shortest path between all pairs
  - $D_G(p_i, p_j)$ and $P_G(p_i, p_j)$: cost and length of the shortest path.
  - $\mu_G = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} D_G(p_i, p_j)$ and $\mu_P = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} P_G(p_i, p_j)$
- Semantics of the first order moments

Measure	Scale	Semantic	Measure	Scale	Semantic
μ_L	Local	Connectivity	μ_S	Semi-Global	Lack of Variation
μ_G	Global	Intra-Class Variation	μ_P	Global	Connected Variation

Predicting Test Performance

- Traditional training+test procedure:

$$AP^{(\mathcal{C})}_{\mathcal{M}} = \tau\left(M(\mathcal{C}_{TR}), \mathcal{C}_{TST}\right)$$

- Assumption: training set and test set are outcomes of the same distribution
- Let $\mu^{(\mathcal{C}_{TR})}$ describe the training set:

$$AP^{(\mathcal{C})}_{\mathcal{M}} = \tilde{f}_{\mathcal{M}}\left(\mu^{(\mathcal{C}_{TR})}\right) + \epsilon_{\tilde{f}_{\mathcal{M}}}$$

- Assume a sigmoid shape for $\tilde{f}$:

$$\tilde{f}_{\mathcal{R}}(\mathbf{w}_{\mathcal{R}}; \mathbf{v}) = \left(1 + \exp\left\{-\mathbf{w}^T_{\mathcal{R}}\mathbf{v}\right\}\right)^{-1}$$

- Learn the parameters of $\tilde{f}_{\mathcal{R}}$ via regression

Results

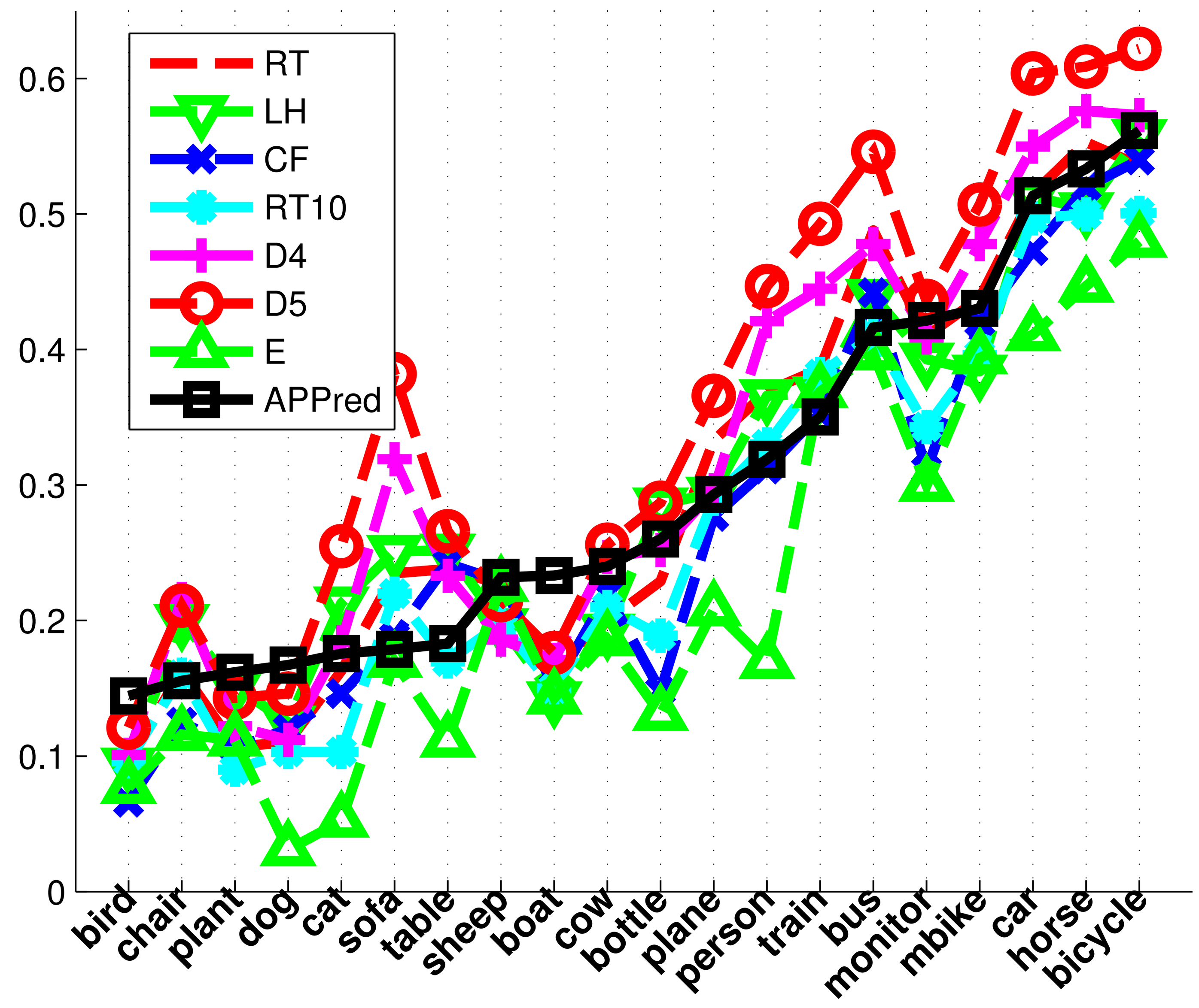
- Correlation of the measured moments to the reference methods

f	D4	D5	RT	RT10	E	CF	LHSL	mean	min
μ_S	71	70	71	75	68	71	68	70.5	67.5
μ_G	-75	-73	-74	-80	-74	-75	-71	-74.6	-71.1
μ_L	88	85	86	90	90	86	85	87.2	85.0
μ_P	90	89	89	93	90	90	87	**89.6**	**87.1**

- Test performance prediction based on all reference methods

Criterion \ $\mathbf{v}$	$\mathbf{m}_L$	$\mathbf{m}_S$	$\mathbf{m}_G$	$\mathbf{m}_P$	$\mathbf{m}_{PL}$	$\mathbf{m}_{SG}$	$\mathbf{m}_{SL}$	$\mathbf{m}_{GP}$	$\mathbf{m}_{LSGP}$	n	1
10^3 RMSE	79	86	77	63	64	80	80	**62**	65	171	159
Corr to AP	87	84	89	88	89	88	86	**92**	92	-82	-97

- Test performance prediction using global measures

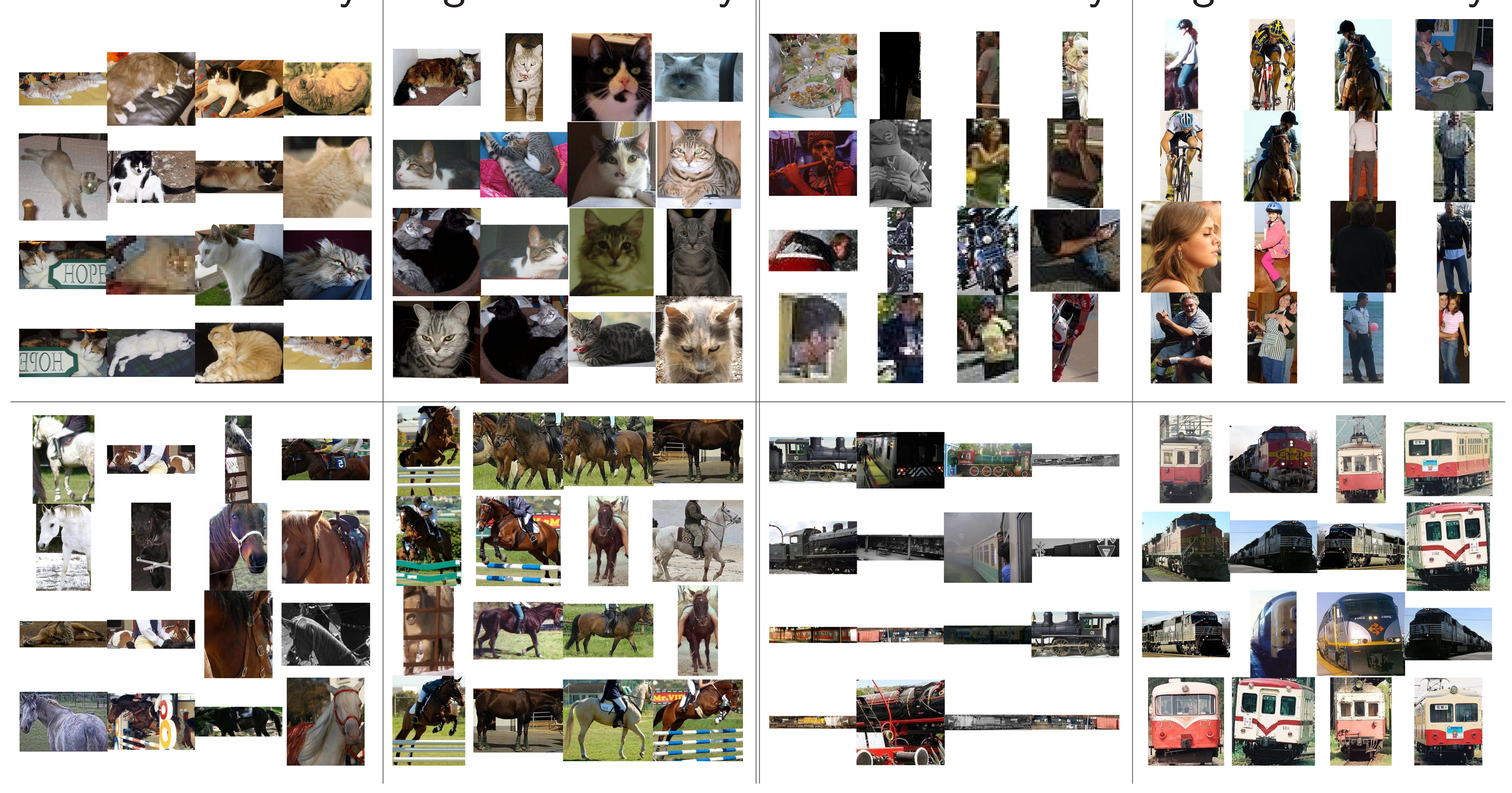


- Test performance prediction specific to each reference method

	D4	D5	RT	RT10	E	CF	LHSL
10^2 MAE	4.5	5.3	3.5	3.3	4.2	3.6	4.0
Corr	89.7	92.3	93.3	93.6	89.5	93.7	89.6

- Sampling according to Local Connectivity

Low Connectivity | High Connectivity | Low Connectivity | High Connectivity



Conclusions

- The data describing measures quantify the quality of the training set
- *Big Connected Data* might rectify the effects of intra-class variation

References

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This work was supported by the Swedish Foundation for Strategic Research and by the European Commission KIC: EIT ICT labs.