

Automatic Model Evaluation

Given a trained classifier, the overall goal is to estimate its accuracy on various test datasets without labels



Motivation

- Distribution shift degrades classifier accuracy Reduce the shift to make model generalizable to the target domain
- Meta-dataset (dataset of datasets)

It contains many datasets from different distributions **Data synthesis:** 1) image transform and 2) background change

sample set 1

seed set

sample set 2



Are Labels Always Necessary for Classifier Accuracy Evaluation? Weijian Deng and Liang Zheng Australian National University

Correlation Study

• Negative Linear Correlation between Test Accuracy and Distribution Shift



Classifier tends to have a *low accuracy* on the sample set which has a *high distribution shift* from the training set

Dataset-level Regression

Predict classifier accuracy from *distribution-related statistics* on an unlabeled test set

• Linear regression

 $a_{linear} = A_{linear}(\mathbf{f}) = w_1 f_{linear} + w_0$ Model Feature: $f_{linear} = FD(\mathcal{D}_{ori}, \mathcal{D}) = \|\boldsymbol{\mu}_{ori} - \boldsymbol{\mu}\|_2^2$

Fréchet distance (FD) measures the difference between training and test distributions

Neural network regression

 $a_{neural} = A_{neural}(f_{neural})$ Model $f_{neural} = [f_{linear}; \boldsymbol{\mu}; \boldsymbol{\sigma}]$ Feature:

Network regression uses *mean*, *co-variance*, and *FD* to represent each test set

$$+ Tr(\boldsymbol{\Sigma}_{ori} + \boldsymbol{\Sigma} - 2(\boldsymbol{\Sigma}_{ori}\boldsymbol{\Sigma}))^{\frac{1}{2}}$$

Experiment

	Digits			Natural images			
Method	SVHN	USPS	RMSE↓	Pascal	Caltech	ImageNet	RMSE↓
Ground-truth accuracy	25.46	64.08	-	86.13	93.40	88.83	-
Predicted score ($\tau = 0.8$)	7.97	37.22	22.66	84.32	90.78	86.50	2.28
Predicted score ($\tau = 0.9$)	7.03	32.94	25.59	78.61	87.71	81.33	6.96
Linear reg.	26.28	50.14	9.87	83.87	79.77	83.19	8.62
Neural network reg.	27.52	64.11	1.46	87.76	89.39	91.82	3.04

Predicted score-based baseline is sensitive to the threshold; *Our regression methods gain promising estimations*



Comparing linear regression and neural network regression when test data undergo new image transformations: A) Cutout and Shear; B) Equalize and ColorTemperature

Network regression is more robust than linear regression

Reference

A. Torralba and A. A. Efros. Unbiased look at dataset bias. In CVPR, 2011 Ben-David, Shai, et al. "A theory of learning from different domains." Machine learning, 2010

The code is available at https://weijiandeng.xyz/AutoEval





