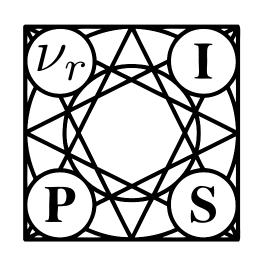
Failing Loudly: An Empirical Study of Methods for Detecting Dataset Shift





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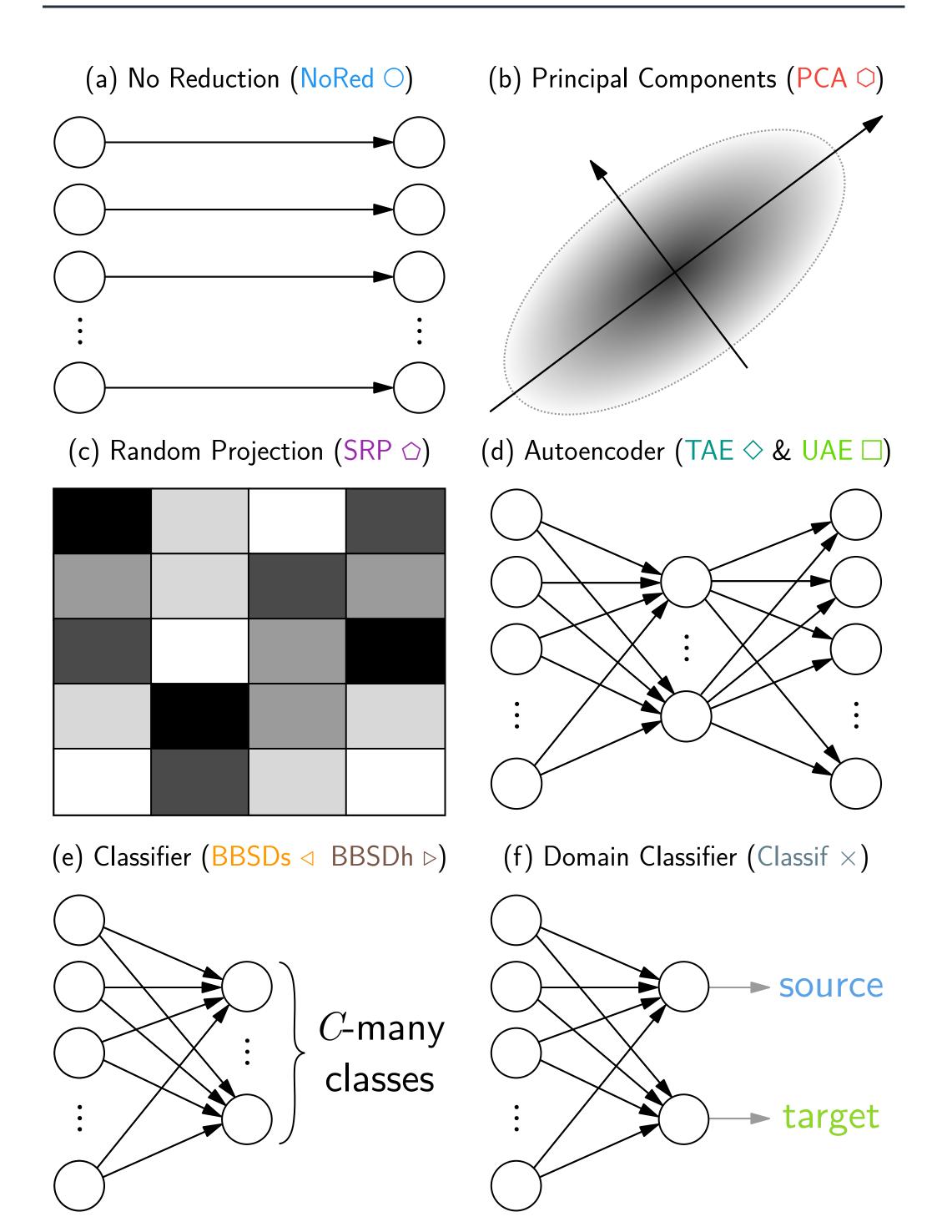


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Motivation

- The reliable functioning of software depends crucially on tests (unit tests, input validation).
- Despite their power, many machine learning models are sensitive to shifts in the data distribution.
- In practice, ML pipelines rarely inspect incoming data for any signs of distributional shift.
- Best practices for detecting shift in high-dimensional and real-life data have not yet been established.
- Existing solutions to addressing pure shifts like covariate shift or label shift $q(\boldsymbol{x},y) = q(\boldsymbol{x})p(y|\boldsymbol{x}) \quad \text{or} \quad q(\boldsymbol{x},y) = q(y)p(\boldsymbol{x}|y)$ often rely on strict preconditions, producing wrong results whenever these conditions are not met.

Dimensionality Reduction



Our Framework

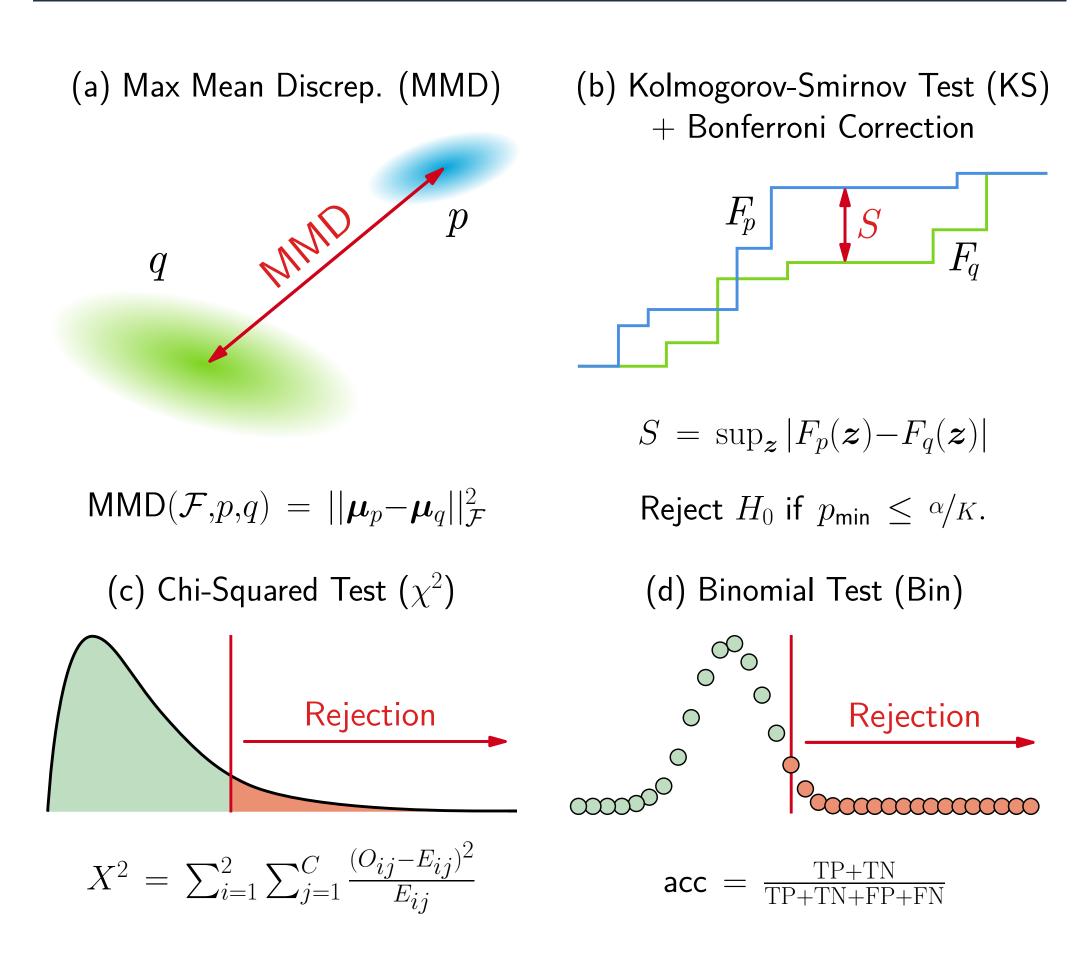
Given labeled data $\{(\boldsymbol{x}_1,y_1),...,(\boldsymbol{x}_n,y_n)\} \sim p$ and unlabeled data $\{\boldsymbol{x}_1',...,\boldsymbol{x}_m'\} \sim q$, our task is to determine whether $p(\boldsymbol{x})$ equals $q(\boldsymbol{x}')$:

$$H_0: p(\boldsymbol{x}) = q(\boldsymbol{x}')$$
 vs $H_A: p(\boldsymbol{x}) \neq q(\boldsymbol{x}')$.

We explore the following design considerations:

- what representation to run the test on;
- which two-sample test to run;
- when the representation is multidimensional;
 whether to run a single multivariate test or multiple univariate two-sample tests; and
- how to combine their results.

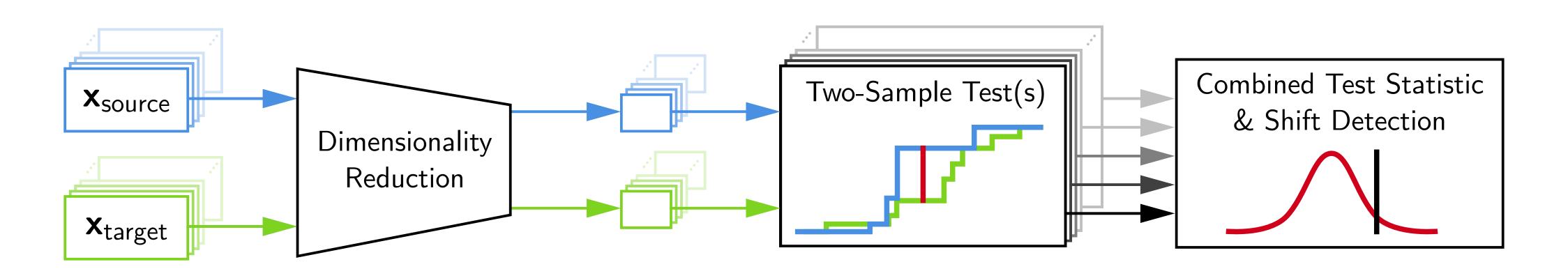
Statistical Two-Sample Testing



Key Observations

- Multiple univariate tests and multivariate kernel tests offer comparable detection performance.
- BBSDs < (univariate) and UAE □ (multivariate) are the best-performing shift detectors, respectively.
- Top different samples from Classif \times are helpful in characterizing a shift's nature and malignancy.
- MNIST original split is not i.i.d., but harmless.

Shift Detection Pipeline Overview



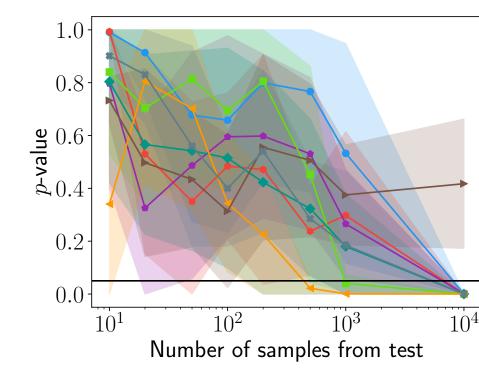
Key Results

(a) Detection accuracy of different dimensionality reduction techniques across all simulated shifts on MNIST and CIFAR-10. **Green bold** entries indicate the best DR method at a given sample size, *red italic* the worst.

Test	DR	Number of samples from test								
1651		10	20	50	100	200	500	1,000	10,000	
	NoRed	0.03	0.15	0.26	0.36	0.41	0.47	0.54	0.72	
ts	PCA	0.11	0.15	0.30	0.36	0.41	0.46	<u>0.54</u>	<u>0.63</u>	
tests	SRP	0.15	0.15	0.23	0.27	0.34	0.42	<u>0.55</u>	<u>0.68</u>	
Univ.	UAE	0.12	0.16	0.27	0.33	0.41	0.49	<u>0.56</u>	<u>0.77</u>	
U	TAE	0.18	0.23	0.31	0.38	0.43	0.47	<u>0.55</u>	<u>0.69</u>	
	BBSDs	0.19	0.28	0.47	0.47	<u>0.51</u>	<u>0.65</u>	<u>0.70</u>	0.79	
χ^2	BBSDh	0.03	0.07	0.12	0.22	0.22	0.40	0.46	<u>0.57</u>	
Bin	Classif	0.01	0.03	0.11	0.21	0.28	0.42	<u>0.51</u>	<u>0.67</u>	
	NoRed	0.14	0.15	0.22	0.28	0.32	0.44	0.55	_	
tests	PCA	0.15	0.18	0.33	0.38	0.40	0.46	<u>0.55</u>	_	
	SRP	0.12	0.18	0.23	0.31	0.31	0.44	<u>0.54</u>	_	
Multiv.	UAE	0.20	0.27	0.40	0.43	0.45	<u>0.53</u>	<u>0.61</u>	_	
${\sf M}$	TAE	0.18	0.26	0.37	0.38	0.45	0.52	0.59	_	
	BBSDs	0.16	0.20	0.25	0.35	0.35	0.47	0.50		

(b) Detection accuracy of different shifts on MNIST and CIFAR-10 using the best DR techniques. **Green bold** shifts are identified as harmless, *red italic* shifts as harmful.

Test	Shift	Number of samples from test								
TESL	JIIIIL	10	20	50	100	200	500	1,000	10,000	
	s_gn	0.00	0.00	0.03	0.03	0.07	0.10	0.10	0.10	
	m_gn	0.00	0.00	0.10	0.13	0.13	0.13	0.23	0.37	
Ds	l_gn	0.17	0.27	<u>0.53</u>	0.63	<u>0.67</u>	0.83	<u>0.87</u>	<u>1.00</u>	
BBSDs	s_img	0.00	0.00	0.23	0.30	0.40	<u>0.63</u>	<u>0.70</u>	<u>0.93</u>	
	m_img	0.30	0.37	0.60	<u>0.67</u>	<u>0.70</u>	<u>0.80</u>	<u>0.90</u>	<u>1.00</u>	
Univariate	l_img	0.30	0.50	<u>0.70</u>	<u>0.70</u>	<u>0.77</u>	<u>0.87</u>	<u>0.97</u>	<u>1.00</u>	
	adv	0.13	0.27	0.40	0.43	<u>0.53</u>	<u>0.77</u>	<u>0.83</u>	<u>0.90</u>	
U	ko	0.00	0.00	0.07	0.07	0.07	0.33	0.40	<u>0.70</u>	
	m_img+ko	0.13	0.40	0.87	0.93	0.90	<u>1.00</u>	<u>1.00</u>	<u>1.00</u>	
	oz+m_img	<u>0.67</u>	<u>1.00</u>							
	s_gn	0.03	0.03	0.03	0.03	0.03	0.07	0.07	_	
	m_gn	0.03	0.03	0.03	0.03	0.17	0.27	0.30	_	
UAE	l_gn	0.50	<u>0.57</u>	<u>0.67</u>	<u>0.70</u>	<u>0.80</u>	<u>0.90</u>	<u>1.00</u>	_	
	s_img	0.17	0.20	0.27	0.30	0.40	0.47	<u>0.63</u>	_	
ate	m_img	0.23	0.33	0.37	0.40	0.47	0.60	<u>0.70</u>	_	
Multivariate	l_img	0.30	0.30	0.37	0.47	0.60	<u>0.77</u>	<u>0.87</u>	_	
u l ti	adv	0.03	0.20	0.27	0.27	0.33	0.40	0.40	_	
Σ	ko	0.10	0.13	0.13	0.13	0.17	0.17	0.30	_	
	${\sf m_img}{+}{\sf ko}$	0.20	0.30	0.37	0.53	<u>0.54</u>	0.63	<u>0.87</u>	_	
	$oz + m _img$	0.27	<u>0.63</u>	0.77	<u>1.00</u>	<u>1.00</u>	<u>1.00</u>	<u>1.00</u>	_	



(a) Test w/ 10% pert.

(e) Acc. w/ 10% pert.

- 0.8

 9.0.6

 0.2

 0.0

 101

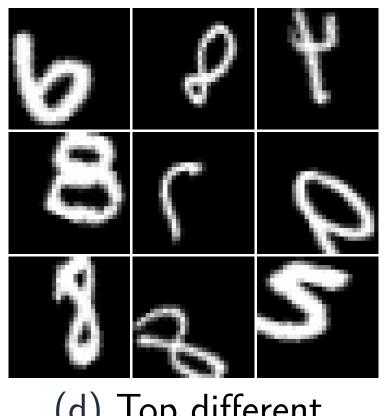
 102

 103

 Number of samples from test

 (b) Test w/ 50% pert.
- NoRed
 PCA
 SRP
 UAE
 TAE
 BBSDs
 BBSDh
 Classif

 Number of samples from test



(c) Test w/ 100% pert. (d) Top different.

(f) Acc. w/ 50% pert.

37(h) Top similar.

(g) Acc. w/ 100% pert. (h) Top sin