KDD2020- Workshop

Robust, Deep and Inductive Anomaly Detection

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Application

Anomaly Detection: Video Surveillance.

- Detecting: **Background activities.**

Definition

Anomaly Detection

- Anomalies are objects : **different from most other objects.**

Anomaly Detection: By Spectral Techniques

- Analysis based on **Eigen-Decomposition** of data.

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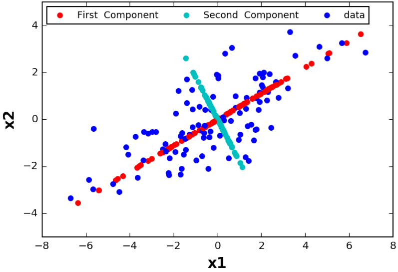
- **Key Idea:**
  - Find combination of attributes **capturing bulk of variability**.
  - Reduced set of attributes can **explain only normal data well**.
- Several methods use Principal Component Analysis.
  - **Top few principal components** capture variability: normal data.
  - **Outliers have variability** in the smallest component.

Motivation and Challenges

Anomaly Detection: PCA

- PCA is highly sensitive to **data perturbation.**



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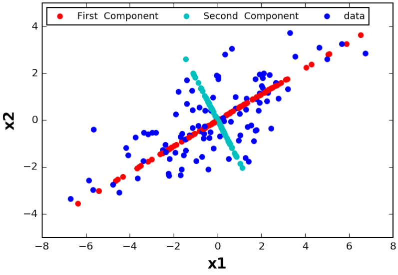

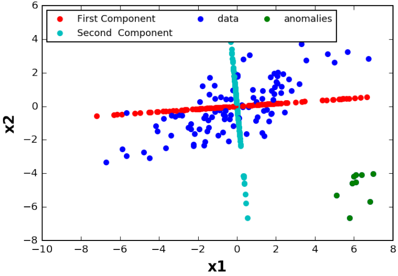

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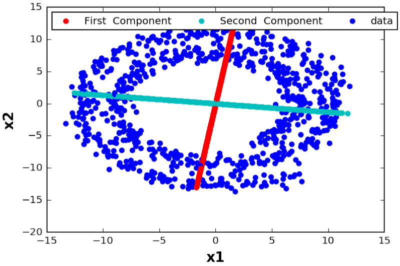

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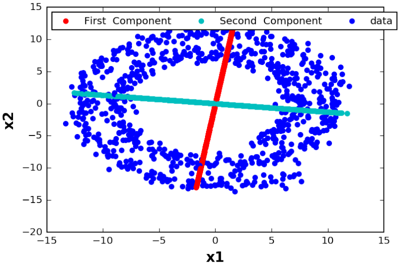
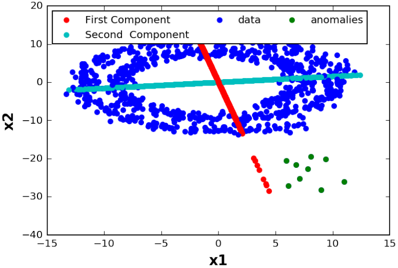
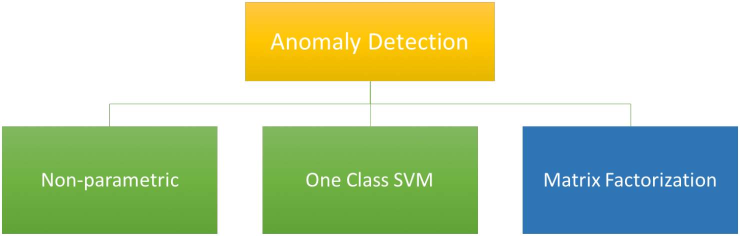




- We propose **Robust (Convolutional) Auto-encoder** to overcome these limitations.

Related Work

Conventional Anomaly Detection Techniques



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- Factorise $\mathbf{X} \in \mathbb{R}^{N \times D}$ into $\mathbf{Z} \in \mathbb{R}^{N \times K}$ and $\mathbf{W} \in \mathbb{R}^{K \times D}$

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Limitations:

- **Does not handle data perturbations.**
- **Does not capture nonlinear projections.**

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Robust (Convolutional) Autoencoders

Auto-encoders for anomaly detection.

- Auto encoder with single **hidden layer**

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  - activation function: $f : \mathbb{R} \rightarrow \mathbb{R}$
- **XU** projects $\mathbf{X}$ into K dimensional space
  $\mathbf{U} \in \mathbf{R}^{\mathbf{D}\times\mathbf{K}}$, $\mathbf{V} \in \mathbf{R}^{\mathbf{K}\times\mathbf{D}}$.
- Non linear projection: **sigmoid** $f(\cdot) := (1 + \exp(-a))^{-1}$

Comparison: Conventional Anomaly Detection Methods

- Deep (convolution) Robust Auto encoder **are versatile.**

	Handles Data Perturbation	Captures Non-linear Structure	Learns Non-linear Structure from data
PCA	No	No	No
RPCA	Yes	No	No
RKPCA	Yes	Yes	No
RCAE	Yes	Yes	Yes

Robust (convolution) Auto-Encoders [RCAE]

- For activation function $f : \mathbb{R} \to \mathbb{R}$

$$\min_{\mathbf{U},\mathbf{V},\mathbf{N}} \|\mathbf{X} - \mathbf{f}(\mathbf{X}\mathbf{U})\mathbf{V} + \mathbf{N}\|_{\mathbf{F}}^{\mathbf{2}} + \frac{\mu}{\mathbf{2}} \cdot (\|\mathbf{U}\|_{\mathbf{F}}^{\mathbf{2}} + \|\mathbf{V}\|_{\mathbf{F}}^{\mathbf{2}}) + \lambda \|\mathbf{N}\|_{\mathbf{1}} \tag{3}$$

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- $\mathbf{N}$ captures **gross outliers.**
- $0 < \lambda < +\infty$, models a standard auto encoder robust to noise.

RCAE Vs Robust PCA (1)

- **RPCA objective** function with basic equality constraints:

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- Conceptual Similarity between **Equation** 4 and **Equation** 5 established [5].

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- More generally objective could be rewritten as below.

$$\min_{\theta,\mathbf{N}} \|\mathbf{X} - \hat{\mathbf{X}}(\theta) + \mathbf{N}\|_{\mathbf{F}}^{\mathbf{2}} + \frac{\mu}{\mathbf{2}} \cdot \mathbf{\Omega}(\theta) + \lambda\|\mathbf{N}\|_{\mathbf{1}} \quad (7)$$

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- Equation 7 is **non-convex but unconstrained and sub-differentiable**

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- Applying **Soft-thresholding**[1] to compute **N**

$$N_{ij} = \begin{cases} (\mathbf{X} - \hat{\mathbf{X}}(\theta))_{ij} - \frac{\lambda}{2} & \text{if } (\mathbf{X} - \hat{\mathbf{X}}(\theta))_{ij} > \frac{\lambda}{2} \\ (\mathbf{X} - \hat{\mathbf{X}}(\theta))_{ij} + \frac{\lambda}{2} & \text{if } (\mathbf{X} - \hat{\mathbf{X}}(\theta))_{ij} < -\frac{\lambda}{2} \\ 0 & \text{else.} \end{cases} \tag{9}$$

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Dataset	# instances	# anomalies	# features
restaurant	200	Unknown (foreground)	19200
usps	231	11 ('7')	256
cifar-10	5000	50 (cats)	1024

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- **AUPRC and AUROC** measure ranking performance.
- **P@10** measures classification performance.(actual anomalies among top-10 scored instances).

Results

Non Inductive: Top anomalous Images Detected

- USPS : 220 images of ‘1’s, and 11 images of ‘7’(anomalous)

(a)RCAE

(b) RPCA

- CIFAR: 5000 images of ‘dog’s, and 50 images of ‘cat’s(anomalous)

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Non Inductive Anomaly Detection: Performance

- The **Robust convolution autoencoder** outperforms the state of the art methods.

(a) usps

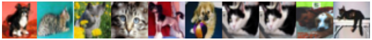
Methods	AUPRC	AUROC	P@10
RCAE	0.9614 ± 0.0025	0.9988± 0.0243	0.9108 ± 0.0113
CAE	0.7003 ± 0.0105	0.9712 ± 0.0002	0.8730 ± 0.0023
AE	0.8533 ± 0.0023	0.9927 ± 0.0022	0.8108 ± 0.0003
RKPCA	0.5340 ± 0.0262	0.9717 ± 0.0024	0.5250 ± 0.0307
DRMF	0.7737 ± 0.0351	0.9928 ± 0.0027	0.7150 ± 0.0342
RPCA	0.7893 ± 0.0195	0.9942 ± 0.0012	0.7250 ± 0.0323
SVD	0.6091 ± 0.1263	0.9800 ± 0.0105	0.5600 ± 0.0249

(b) cifar-10

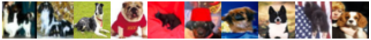
Methods	AUPRC	AUROC	P@10
RCAE	0.9934 ± 0.0003	0.6255 ± 0.0055	0.8716 ± 0.0005
CAE	0.9011 ± 0.0000	0.6191 ± 0.0000	0.0000 ± 0.0000
AE	0.9341 ± 0.0029	0.5260 ± 0.0003	0.2000 ± 0.0003
RKPCA	0.0557 ± 0.0037	0.5026 ± 0.0123	0.0550 ± 0.0185
DRMF	0.0034 ± 0.0000	0.4847 ± 0.0000	0.0000 ± 0.0000
RPCA	0.0036 ± 0.0000	0.5211 ± 0.0000	0.0000 ± 0.0000
SVD	0.0024 ± 0.0000	0.5299 ± 0.0000	0.0000 ± 0.0000

Inductive: Top anomalous Images Detected

- First train model on **only normal** 5000 dog images.
- Evaluate it on a test set 500 dogs and 50 ‘cat’s(anomalous).



(a) RCAE



(b) CAE

Inductive: Top anomalous Images Detected

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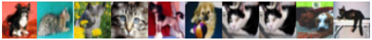
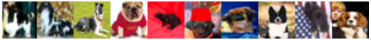


(a) RCAE



(b) CAE

	SVD	RKPCA	AE	CAE	RCAE
AUPRC	0.1752 $\pm$ 0.0051	0.1006 $\pm$ 0.0045	0.6200 $\pm$ 0.0005	0.6423 $\pm$ 0.0005	0.6908 $\pm$ 0.0001
AUROC	0.4997 $\pm$ 0.0066	0.4988 $\pm$ 0.0125	0.5007 $\pm$ 0.0010	0.4708 $\pm$ 0.0003	0.5576 $\pm$ 0.0005
P@10	0.2150 $\pm$ 0.0310	0.0900 $\pm$ 0.0228	0.1086 $\pm$ 0.0001	0.2908 $\pm$ 0.0001	0.5986 $\pm$ 0.0001

Image De-noising Capability: RCAE vs RPCA

- Top anomalous images in original form (first row), noisy form (second row), image denoising task on `cifar-10`.

(a) RCAE

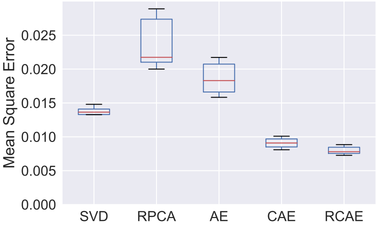
(b) RPCA

Image De-noising Capability: RCAE vs RPCA

- Top anomalous images in original form (first row), noisy form (second row), image denoising task on `cifar-10`.

(a) RCAE

(b) RPCA



Conclusion

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- Our approach is **robust, deep and inductive.**
- Not oversensitive besides captures **subtle anomalies**.
- Extend deep autoencoders for **outlier description**.

References

- [1] Clevert, D.A., Unterthiner, T., Hochreiter, S.: Fast and accurate deep network learning by exponential linear units (elus). arXiv preprint arXiv:1511.07289 (2015)
- [2] Goodfellow, I., Bengio, Y., Courville, A. Deep Learning. MIT Press (2016), http://www.deeplearningbook.org
- [3] Xiong, L., Chen, X., Schneider, J. Direct robust matrix factorization for anomaly detection. In International Conference on Data Mining (ICDM). IEEE (2011)
- [4] Zhao, M., Saligrama, V. Anomaly detection with score functions based on nearest neighbor graphs. In Advances in Neural Information Processing Systems (NIPS). pp. 2250 2258 (2009)
- [5]Chalapathy, Raghavendra, Aditya Krishna Menon, and Sanjay Chawla. Robust, Deep and Inductive Anomaly Detection.arXiv:1704.06743 (2017).
- [6] Candes, E., Li, X., Ma, Y., Wright, J.: Robust principal component analysis: Recovering low-rank matrices from sparse errors. In: Sensor Array and Multichannel Signal Processing Workshop (SAM), 2010 IEEE. pp. 201204. IEEE (2010)


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