1. The TEDA-based Algorithms

- The proposed approach for anomaly detection in [a] uses Typicality and Eccentricity Data Analytics (TEDA), which works with the concepts of typicality and eccentricity of data samples, based on *spatial proximity in the data space*. In [a], TEDA is used for the first time in a fault detection application. In [b], *online* fault detection based on [a] is proposed. However, the TEDA-based algorithms [a, b] mainly focus on *spatial* anomalies, limiting their usefulness in applications with *temporal* dependencies [c].
- The comparison results (detected anomalies) of our algorithm and the TEDA-based algorithm [a, b] are presented in Fig. A and Fig. B, taking data file NT and AAPL from the Numenta Anomaly Benchmark (NAB) as examples respectively. As shown in Fig. A and Fig. B, our algorithm can detect the anomalies (red curves) effectively, while the TEDA-based algorithm [a, b] can *only* detect *spatial* anomalies (ignoring *context* of streaming data, as shown in Fig. A), with many *false positives* (such as the transient spatial points in Fig. B).

[a] P. Angelov, "Anomaly detection based on eccentricity analysis," in *Proc. IEEE Symp. Evolving Auton. Learn. Syst.*, pp. 1–8, 2014.

[b] B. S. J. Costa, C. G. Bezerra, L. A. Guedes, *et al.*, "Online fault detection based on typicality and eccentricity data analytics," in *Proc. Int. Joint Conf. Neural Netw.*, pp. 1–6, 2015.

[c] S. Ahmad, A. Lavin, S. Purdy, *et al.*, "Unsupervised real-time anomaly detection for streaming data," *Neurocomput.*, vol. 262, pp. 134–147, 2017.

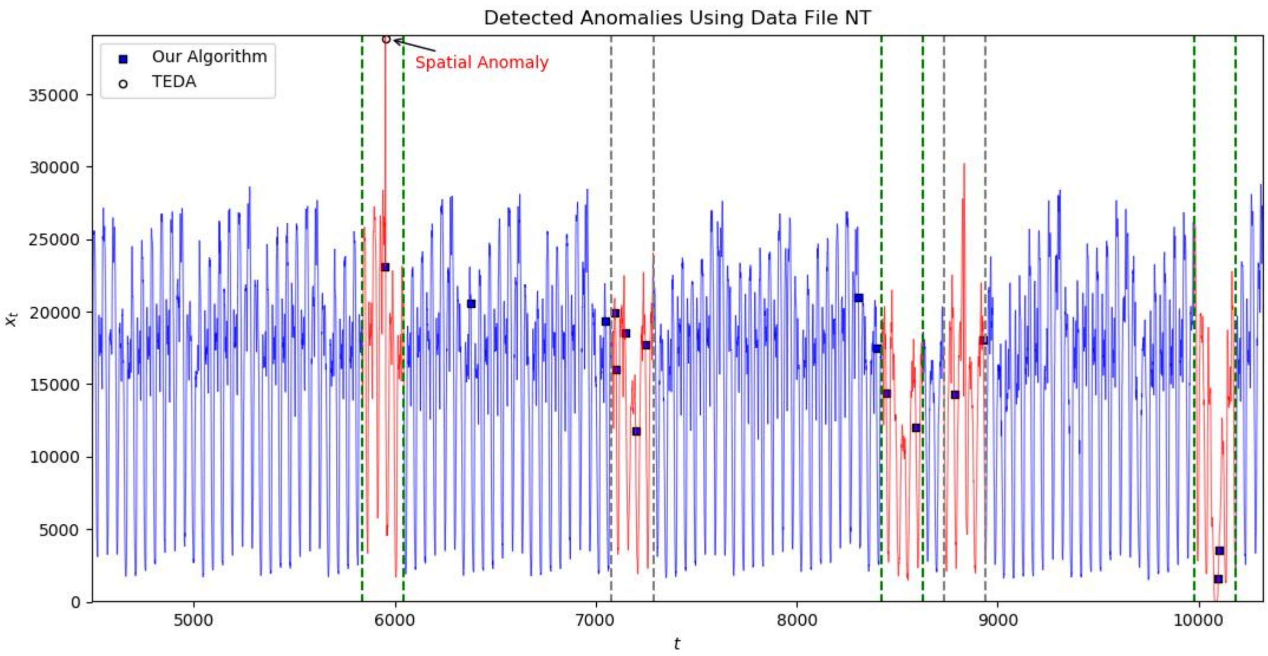

Fig. A

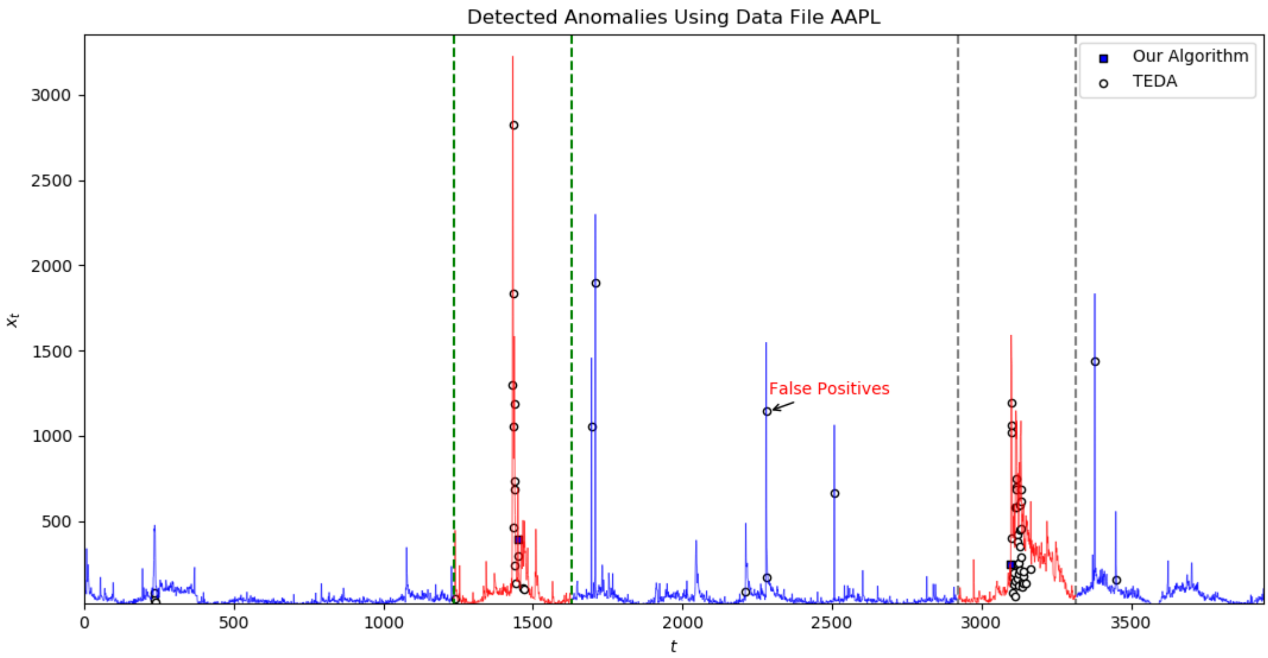

Fig. B

2. The RDE-based Algorithm

- The proposed approach for anomaly detection in [d] (you mentioned) is based on the concept of density in data space using Recursive Density Estimation (RDE), which differs from the probability density function.
- The RDE-based algorithm [d] is to identify if the system is working in a normal operating state or in a faulty mode, i.e., to identify the *beginning* and the *end* of faulty states, respectively.
- The RDE-based algorithm [d] tries to ignore transient signals and is sensitive to *abrupt changes*, which presents an oscillatory (not dense) behavior.
- The comparison results (detected anomalies) of our algorithm and the RDE-based algorithm [d] are presented in Fig. C and Fig. D, taking data file NT and AAPL from the Numenta Anomaly Benchmark (NAB) as examples respectively. As shown in Fig. C and Fig. D, our algorithm can detect the anomalies (between two dotted lines) effectively, while the RDE-based algorithm [d] can *only* detect *abrupt changes*, with many *false positives* (such as the regular abrupt changes in Fig. D, ignoring *context* of streaming data).

[d] B. S. J. Costa, P. P. Angelov, and L. A. Guedes, "Fully unsupervised fault detection and identification based on recursive density estimation and self-evolving cloud-based classifier," *Neurocomput.*, vol. 150, pp. 289–303, 2015.

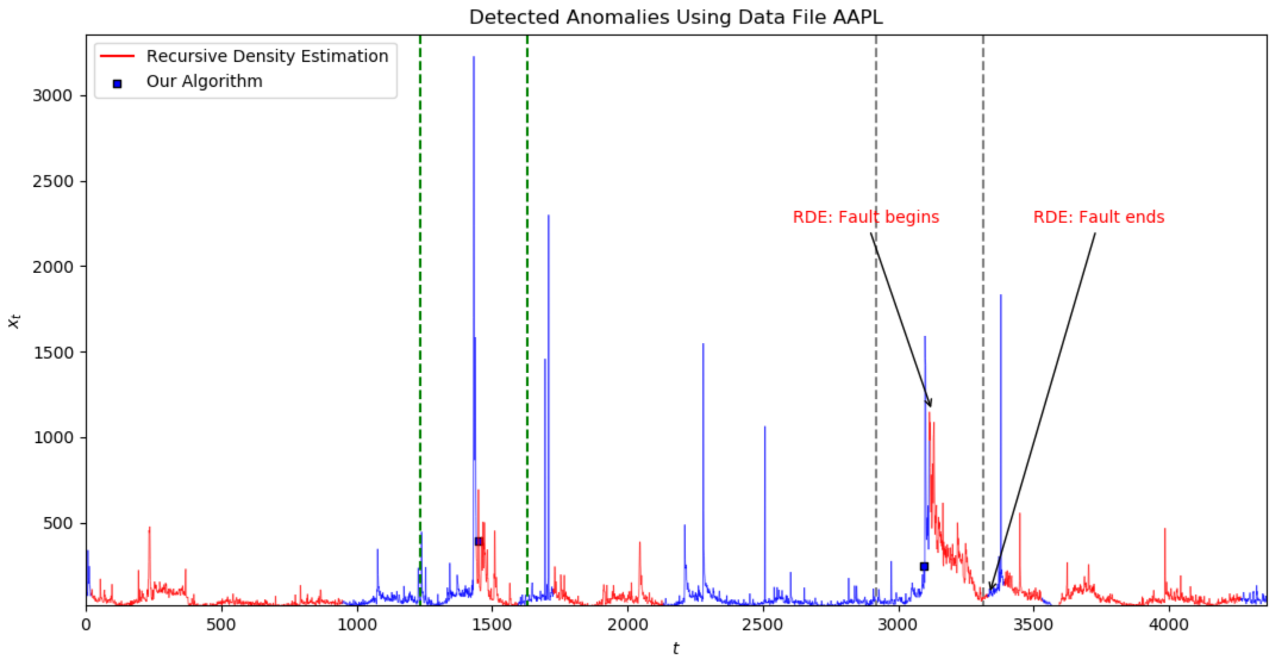

Fig. C

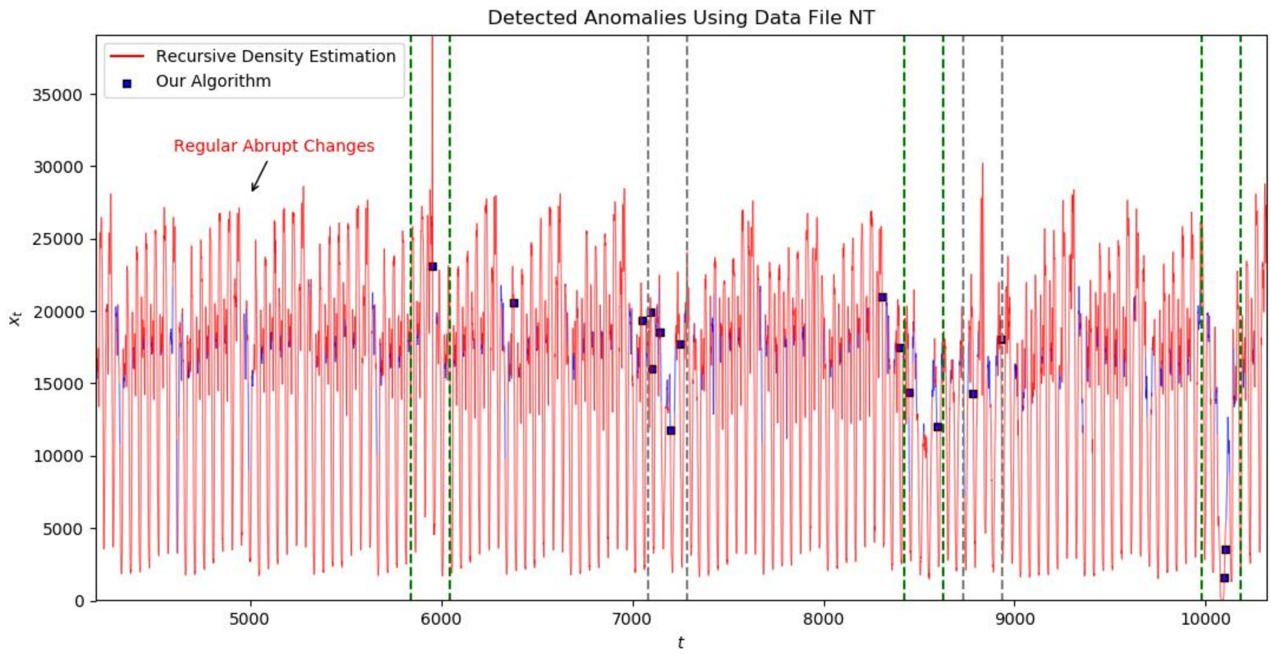

Fig. D

3. Bayesian Online Changepoint Detection

- *Bayesian Online Changepoint Detection* [e] makes strong assumptions regarding data, and [e] can easily detect spikes. Subtle changes may occur in data preceding obvious anomalies, but it is hard for [e] to detect them.

[e] R. P. Adams and D. J. MacKay, “Bayesian online changepoint detection,” Stat., 2012.

4. Multinomial Relative Entropy

- *Multinomial Relative Entropy* [f] is based on relative entropy, and capable of detecting temporal anomalies in complex scenarios.

[f] C. Wang, K. Viswanathan, L. Choudur, et al., "Statistical techniques for online anomaly detection in data centers," in Proc. Int. Symp. Integr. Netw. Manag., pp. 385–392, 2011.

5. Scores of [b, e, f]

Tables A-C illustrate the comparison results after all experiments have been done based on the NAB, and the results show that scores of our algorithm are generally higher than that of the other algorithms on most of the data files. We have implemented all of them on the same hardware and software platform.

Table A

THE PERFORMANCES OF THE ALGORITHMS ACROSS DATA FROM REALTWEETS: BAYESIAN, TYPICALITY AND ECCENTRICITY, AND RELATIVE ENTROPY

Data File	Bayesian Score	Typicality and Eccentricity Score	Relative Entropy Score
AAPL	42.83	56.63	69.80
AMZN	61.97	68.11	46.52
CRM	0.00	86.79	31.03
CVS	0.00	51.91	63.85
FB	20.82	22.79	93.01
GOOG	20.49	33.60	62.98
IBM	49.17	57.52	87.53
KO	0.00	61.89	31.01
PFE	0.00	41.02	67.01
UPS	0.00	53.76	54.57

Table B

THE PERFORMANCES OF THE ALGORITHMS ACROSS DATA FROM REALKNOWNCAUSE: BAYESIAN, TYPICALITY AND ECCENTRICITY, AND RELATIVE ENTROPY

Data File	Bayesian Score	Typicality and Eccentricity Score	Relative Entropy Score
ATSF	0.00	0.00	15.01
CUAM	0.00	0.00	71.21
ERLSF	67.19	83.69	83.93
MTSF	42.12	0.00	38.55
NT	0.00	18.15	88.33
RAKH	84.74	12.89	12.10
RAKU	51.14	27.59	0.00

Table C

THE PERFORMANCES OF THE ALGORITHMS ACROSS DATA FROM REALAWSCLOUDWATCH (AWS) WITH 8 DATA FILES AND ARTIFICIALWITHANOMALY (AWA) WITH 6 DATA FILES: BAYESIAN, TYPICALITY AND ECCENTRICITY, AND RELATIVE ENTROPY

Data File	Bayesian Score	Typicality and Eccentricity Score	Relative Entropy Score
AWS	55.89	39.57	63.25
AWA	11.56	13.54	56.65