CloudDet: Interactive Visual Analysis of Anomalous Performances in Cloud Computing Systems

Ke Xu, Yun Wang, Leni Yang, Yifang Wang, Bo Qiao, Si Qin, Yong Xu, Haidong Zhang, Huamin Qu IEEE Transactions on Visualization and Computer Graphics, 2019



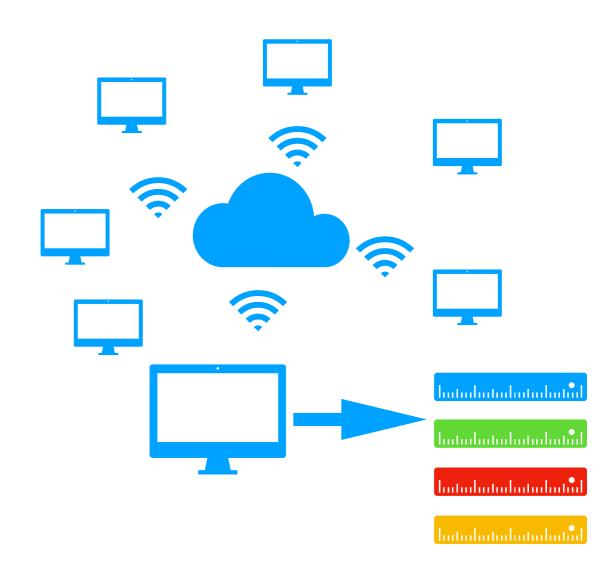
Amirhossein Abbasi Nov 2019

CloudDet



Motivation

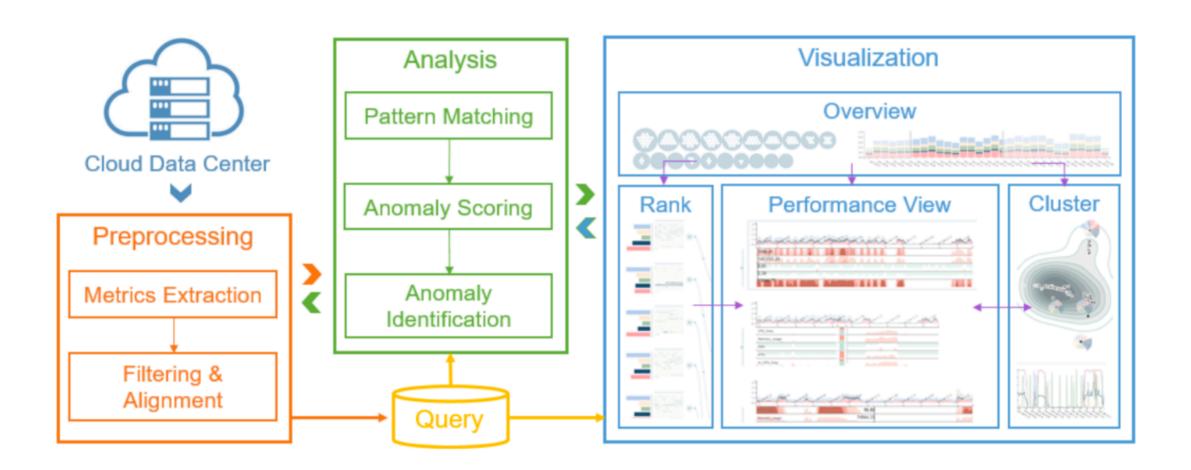
- Monitoring nodes instead of monitoring applications
- Too many false positives, scale problem.
- Visualization of anomalies:
 Intuitiveness, interaction.
- Research Contribution:
 Detection system, Visualization,
 Evaluation



Visualization Challenges

- Scale: Trade-off between system scalability and level-ofdetail(LoD)
- Multi-dimensionality: Temporal patterns, Relation between metrics
- Boundary normal/abnormal

System Overview



What is abnormal and what is not? How to detect?

Mathematics!

$$P(f_{k/N}) = ||X(f_{k/N})||^2, \quad k = 0, 1... \lceil \frac{N-1}{2} \rceil, \qquad (1) \qquad AS_{periodic} = min\left(\frac{|T_n - T_{n-1}|}{T_{n-1}}, 1\right), \qquad (4)$$

$$ACF(\tau) = \frac{1}{N} \sum_{n=0}^{N-1} d(\tau) \cdot d(n+\tau), \quad \tau = 0, 1 \dots \lceil \frac{N-1}{2} \rceil. \tag{2}$$

$$AS_{trend} = min\left(\left|\frac{K_n - K_{n-1}}{K_{n-1}}\right|, 1\right), \tag{5}$$

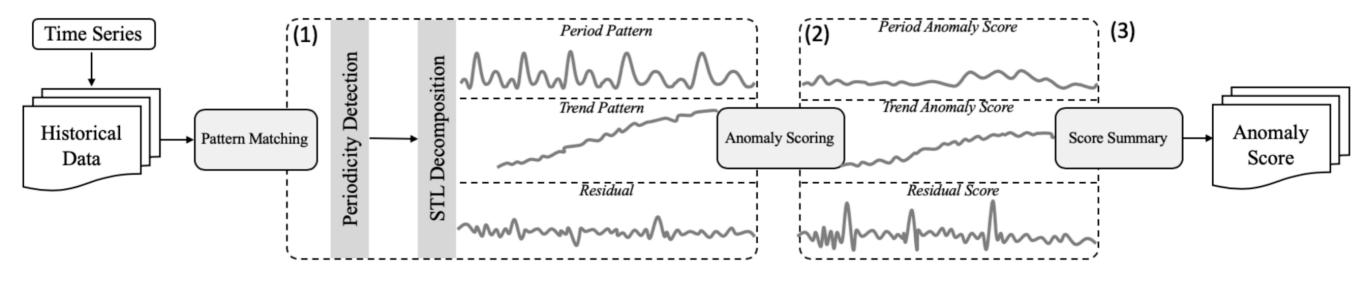
$$d_n = S_n + Tr_n + R_n, \quad n = 1, 2...N,$$

$$(3) \qquad AS_{spike} = min\left(\left|\frac{R_n - \mu_{n-1} - 3\sigma_{n-1}}{3\sigma_{n-1}}\right|, 1\right),$$

$$(6)$$

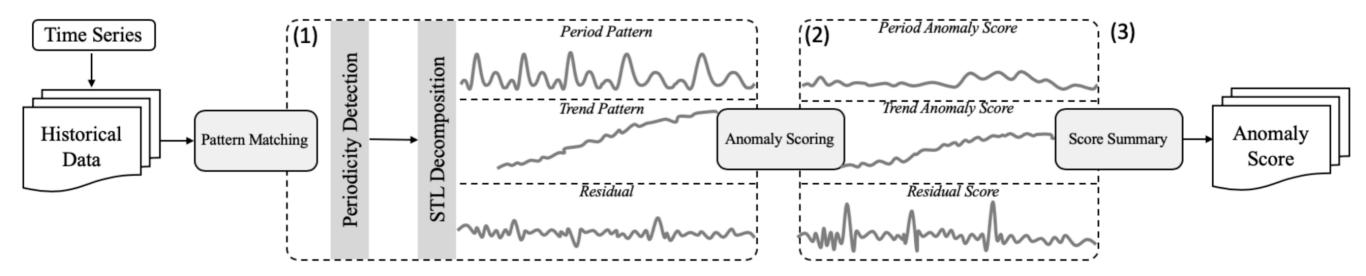
$$AS = f(AS_{periodic}, AS_{trend}, AS_{spike}), \tag{7}$$

Algorithm Flow



Algorithm Flow

Only utilizes the most recent data



Anomalies have patterns

Design Tasks

- Overview of anomalies for data query
- Ranking suspicious nodes dynamically
- Browse data flexibly
- Facilitate anomaly detection
- Similarities of nodes

Visualization

Encoding Protocol

Global Categorical Colors: performance metrics (CPU Frequency, Memory Usage,...)

Attribute 1Attribute 2Attribute 3Attribute 4Attribute 5

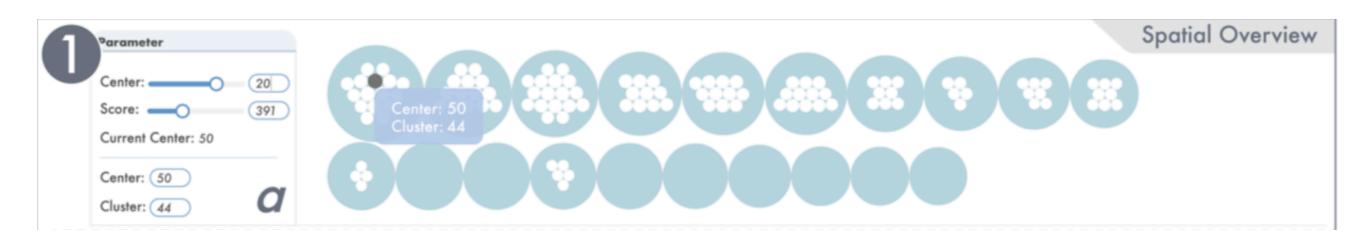
Linear Color Scheme: Anomaly score

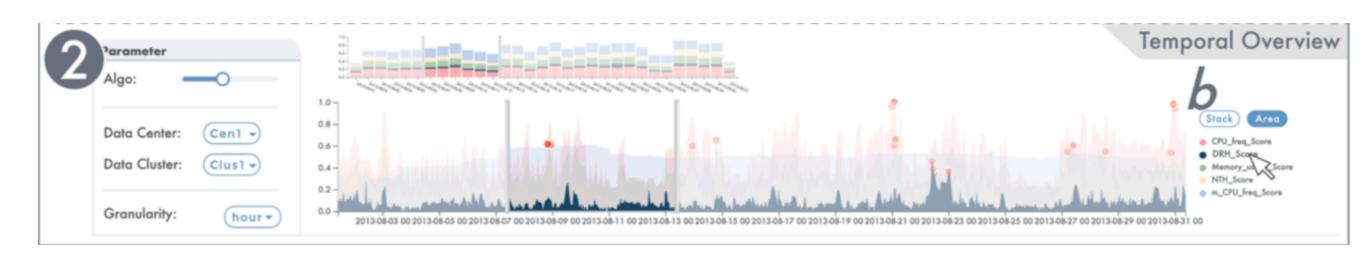
low

Diverging Color Scheme: Difference of performance metrics to average

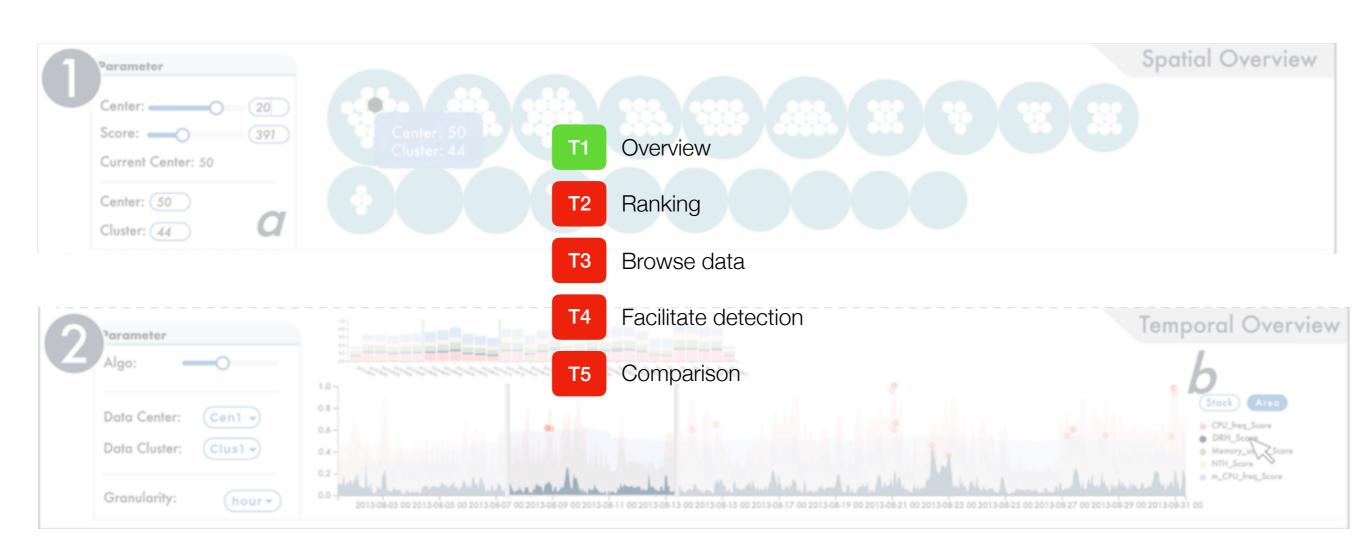


Spatial and Temporal Views





Spatial and Temporal Views



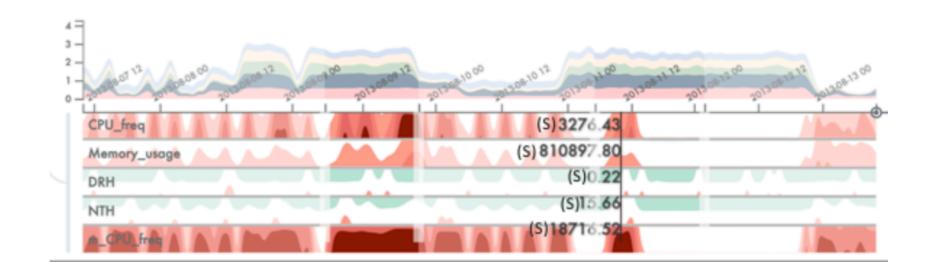
Rank and Performance View

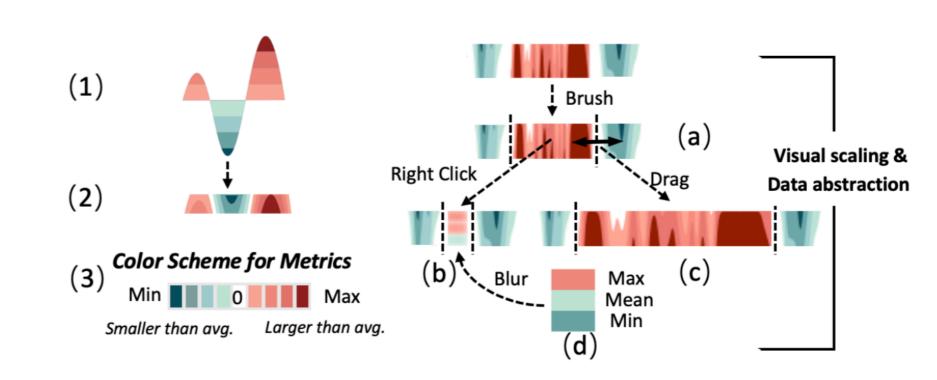


Horizon Chart

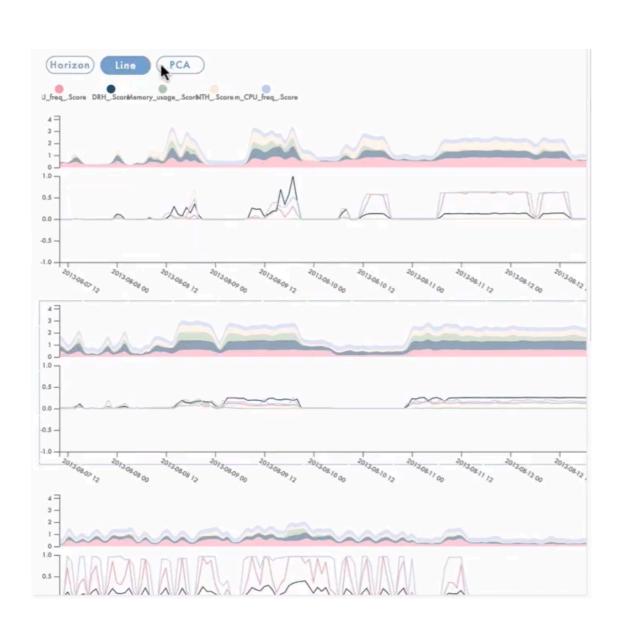
Interactions:

- Brushing
- Collapsing
- Stretching



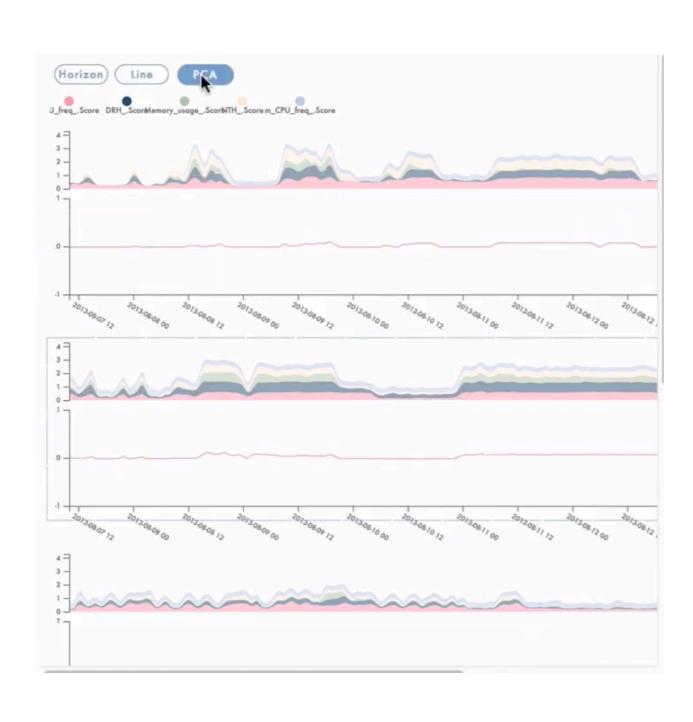


Line mode



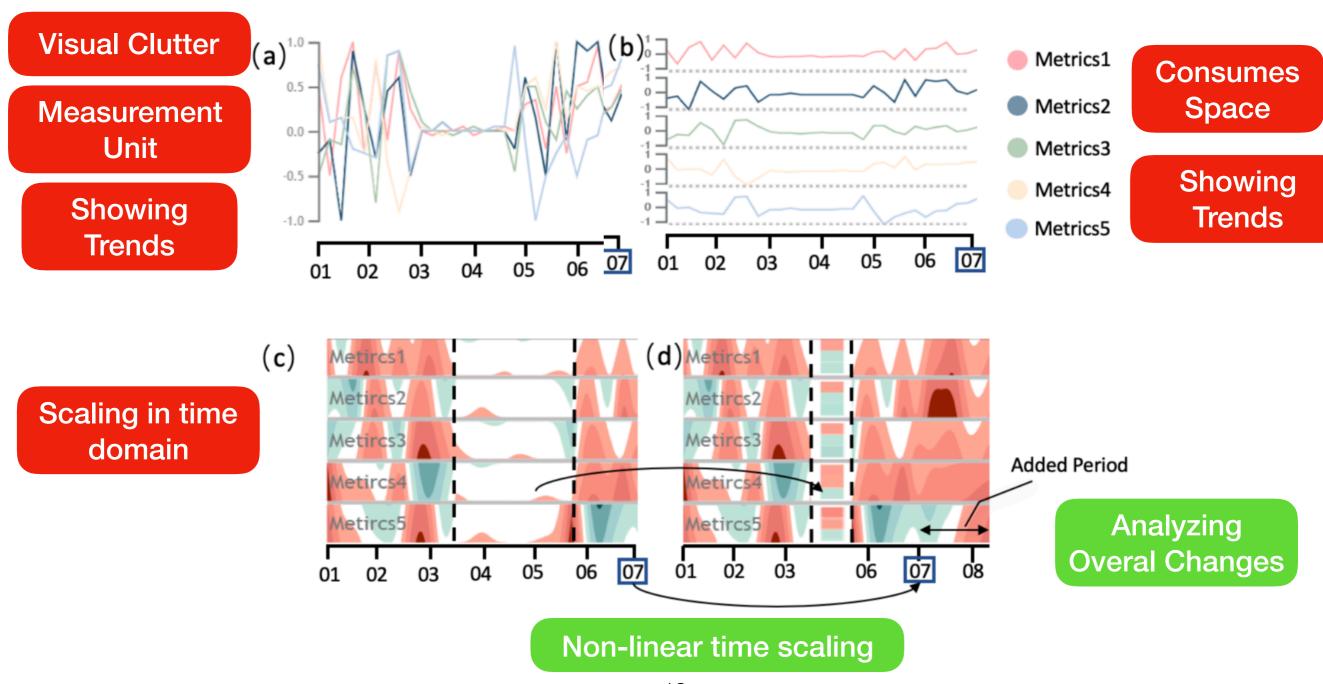
- Each line for one metric
- More conventional
- Normalize data to [-1,1]

PCA mode

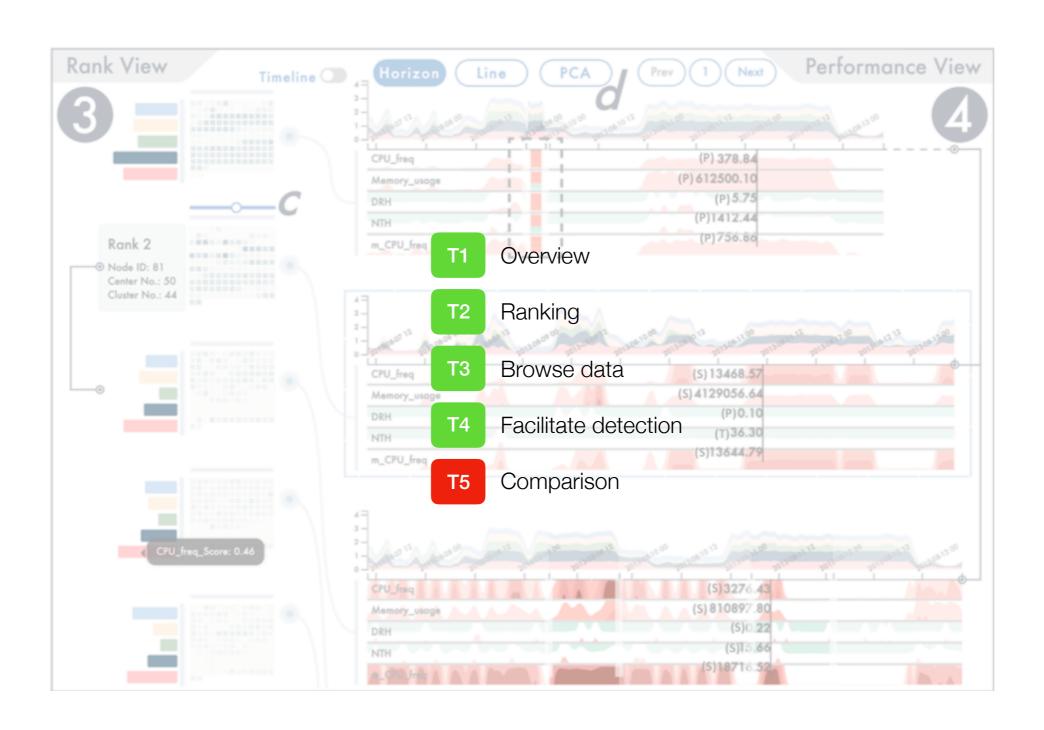


- Project a multivariate data to a one-dimensional time-series data
- Major Trend

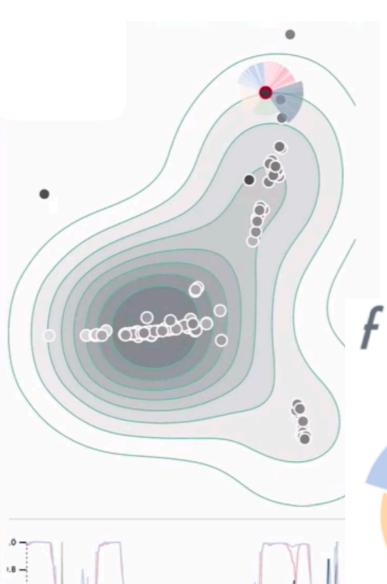
Alternative Designs



Rank and Performance View

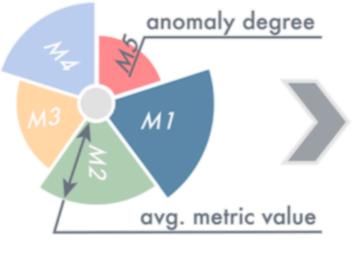


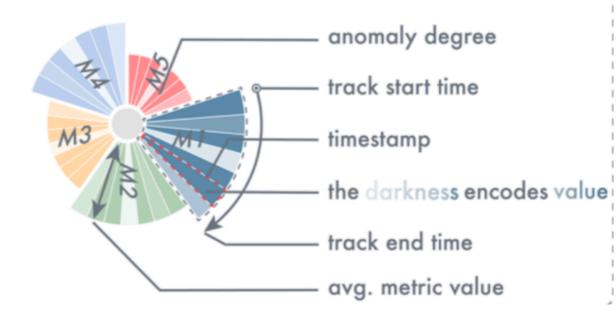
The Cluster View



- Dimensionality reduction.
- Another perspective for anomaly diagnosis
 - White contour: most probably anomaly
 - Gray contour:normal.

Each arc represents one metric





The Cluster View

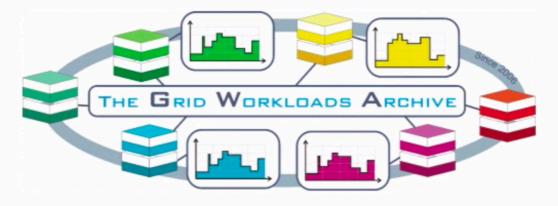


Official Video (1:05 min)

CloudDet: Interactive Visual Analysis of Anomalous Performances in Cloud Computing Systems







Bitbrains Datacenter Traces

1720 VMs, 10 performance metrics, one month...





What-Why-How Summary

What

Multi-variate timeseries quantitative performance data from compute nodes. Why

- Anomaly Ranking
- Anomaly inspection
- Anomaly Clustering

How

- Colors and brightness
- horizontal and line chart
- Special glyphs
- Spatial positions of nodes and charts.
- Interactivity: Scrolling, Brushing, and setting parameters

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 Brushing, and Querying

Scalability

What

Why

How

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- horizontal and line chart
- Special glyph
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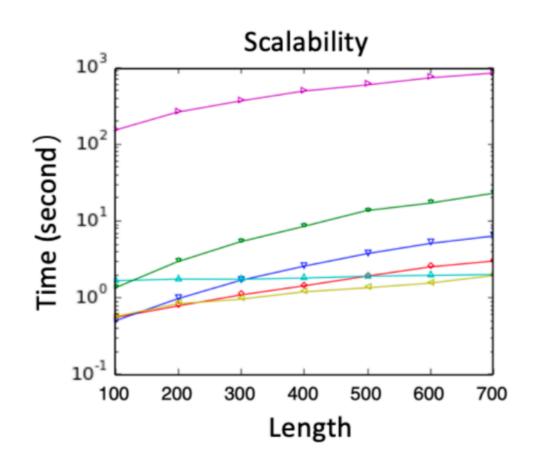
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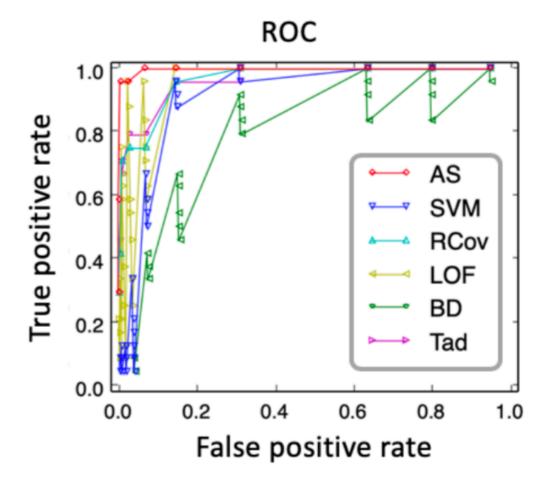
Scale

Very Scalable: scale **linearly** with time-series input data size

Evaluation

Quantitative Evaluation





Case Studies

Case Study 1: Bitbrains Datacenter Traces

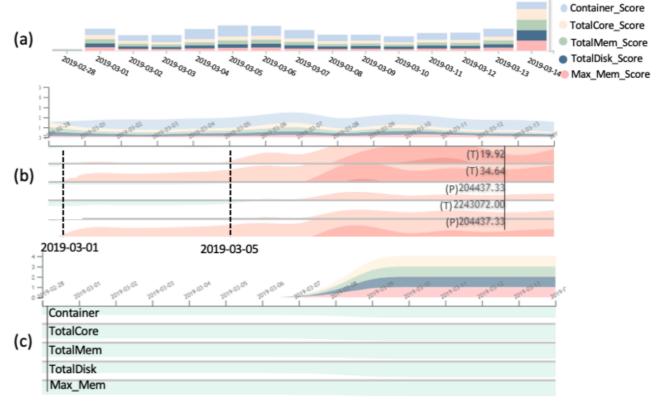
500 VMs, One month



Case Study 2: Live Cloud System Data

1,000,000 nodes, Two weeks

[100 data centers with 20 data clusters with 500 nodes each]



User Feedback

- Automated Anomaly Detection: Trust in algorithm,
- System: Useful and User-friendly, Consistent, too comprehensive and Overwhelming, Need Tutorial
- Visualization and Interaction: Helpful, new perspective for overall trend, clear comparison, Confess that they use chaotic line charts before.

Critique

Positive

- Alternative designs
- Super-scalable
- Perfect evaluation
- Very Accurate
- Special Glyphs

Negative

- Better to use non-diverging colors for horizon charts.
- Minor occlusion in the clustering.
- Make use of global colors in horizontal chart.
- Bad way for Assigning the ranks to performance.
- Empty clusters in spatial overview.
- Limitation: Just consider recent data and one metric.
- Limitation: Don't discuss why using those performance metrics for anomaly.

Question?