Fingerprinting the datacenter: automated classification of performance crises

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Crisis identification is difficult, time consuming and costly

Frequent SW/HW failures cause downtime

Timeline of a typical crisis

3:00 AM – detection: automatic, easy

3:15 AM – identification: manual, difficult

- takes minutes to hours

4:15 AM – resolution: depends on crisis type

next day – root cause diagnosis, documentation

Web apps are complex and large-scale

– app used for evaluation: 400 servers, 100 metrics

Insight: performance metrics help identify recurring crises

Performance crises recur

- incorrect root cause diagnosis
- takes time to deploy the fix
  - other priorities, test new code

System state is similar during similar crises

- but not easily captured by fixed set of metrics
- 3 operator-selected metrics not enough

Contribution: crisis identification as it happens, via classification

1. Fingerprint = compact representation of system state
   - uniquely identifies a crisis
   - robust to noise
   - intuitive visualization

2. Using fingerprints to identify crises as they happen
   - goal: operator receives email about crisis
   - "Crisis similar to DB config error from 2 weeks ago"

3. Evaluation on data from a real commercial service deployed on hundreds of servers
   - 80% identification accuracy

Outline

- Definition of performance crises
- Crisis fingerprints
- Evaluation results
- Related work
- Conclusion

Definition and examples of performance crises

Performance crisis = violation of service-level objective (SLO)

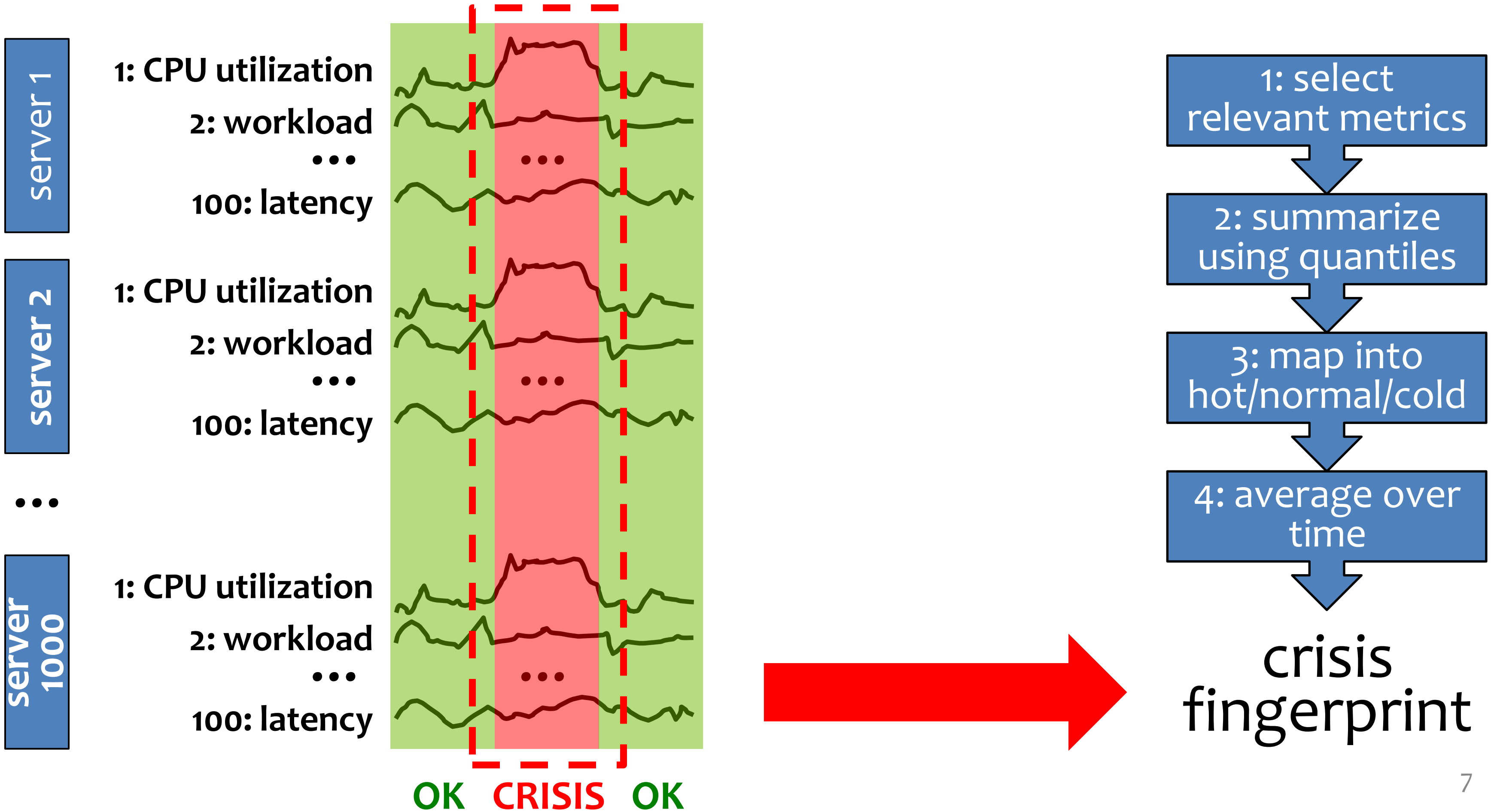
- based on business objectives
- captures performance of whole cluster
- example: >90% servers have latency < 100 ms during 15-minute epoch

Crises we analyzed

- app config, DB config, request routing errors
- overloaded front-end, overloaded back-end

Fingerprints capture state of performance metrics during crisis

- **Metrics as arbitrary time series**
  - OS, resource utilization, workload, latency, app, …



Step 1: Using feature selection to pick relevant metrics

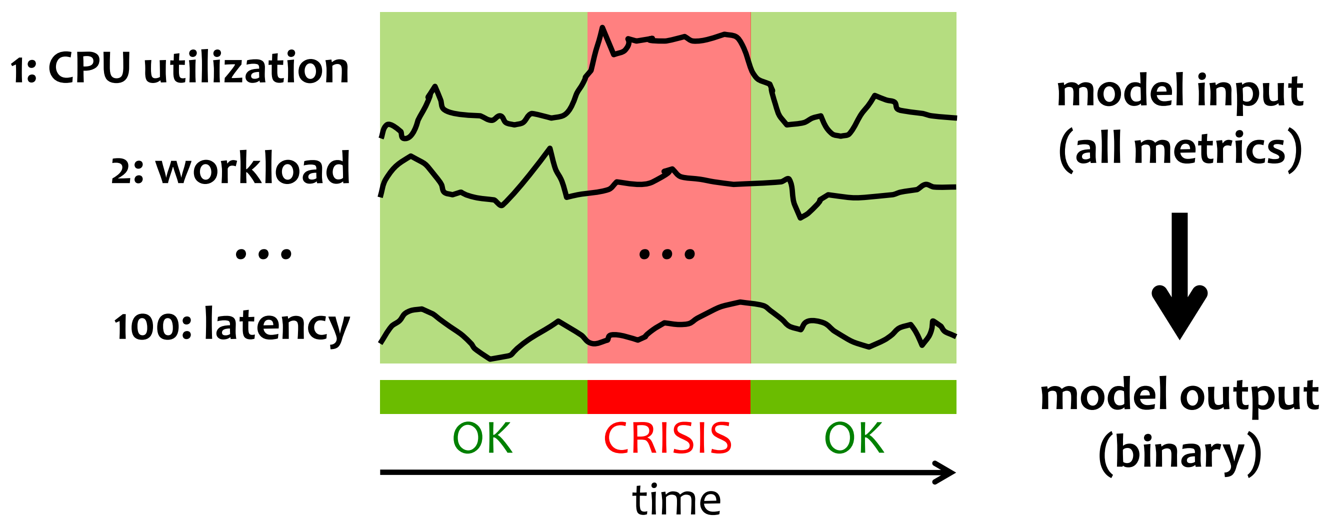
what would not work

- all 100 metrics
- 3 operator-selected metrics

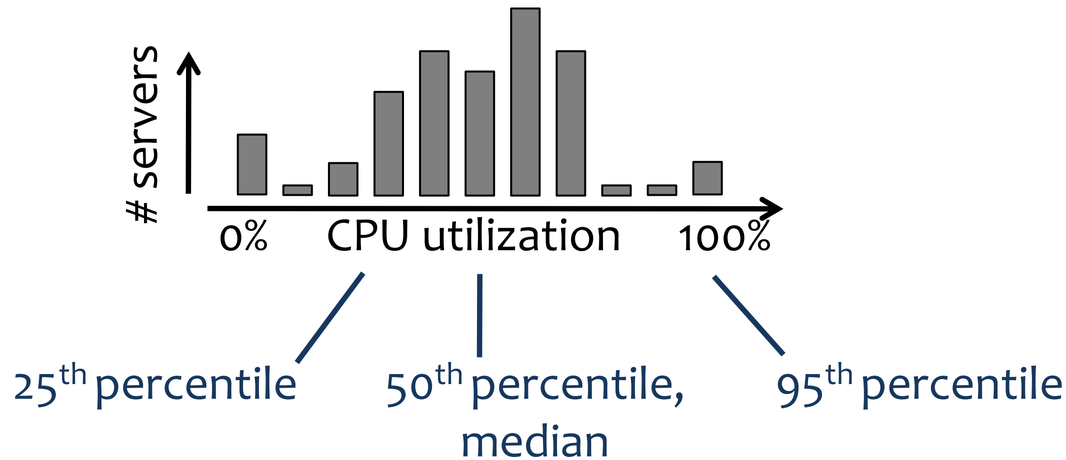
➡ low identification accuracy

Logistic regression with L1 constraints

– fit accurate linear more with only few metrics
– selected metrics that operators didn't consider



Step 2: Summarize selected metrics across servers using 3 quantiles



- **robust to outliers**
- **can efficiently compute even for datacenter-sized clusters**

what would not work

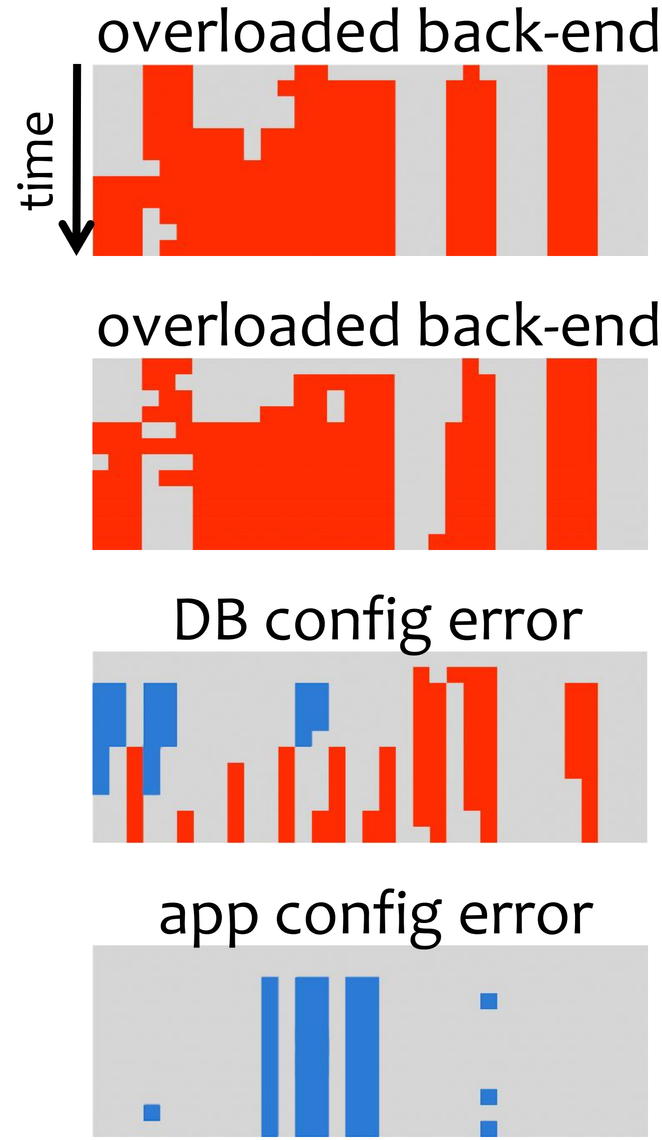
- **mean, variance**
- **only median**

Step 3: Map metric quantiles into hot/normal/cold

Based on historic values

Epoch fingerprints

- differentiate among crises
- compact
- intuitive



what would not work

- raw metric values
- time series model

Step 4: Averaging over time

Different crises have different durations

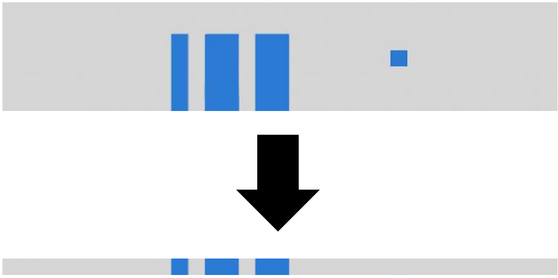
what would not work
- all epoch fingerprints
- 1 epoch fingerprint

Crisis fingerprint

– average epoch fingerprints over time

– compare by computing Euclidean distance

epoch fingerprints



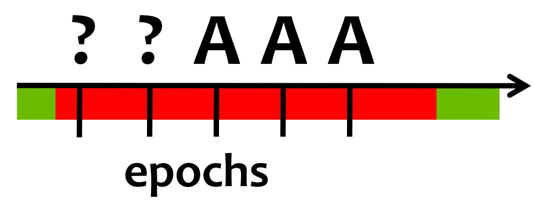
crisis fingerprint is a vector

Crisis identification in operational setting

Crisis detected automatically via SLO violation

During first hour of crisis

- update fingerprint of current crisis
- if found similar crisis P, emit label P
  else emit ? – "previously-unseen crisis"



When crisis is over

- automatically update relevant metrics, fingerprints
- ideally, operators enter supplied label into crisis DB

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- Crisis fingerprints
- **Evaluation results**
- **Related work**
- **Conclusion**

System under study

24 x 7 enterprise-class user-facing application at Microsoft
- 400 machines
- 100 metrics per machine, 15-minute epochs
- operators: "Correct label useful during first hour"

Definition of a crisis
- operators supplied 3 latency metrics and thresholds
- 10% servers have latency > threshold during 1 epoch

19 operator-labeled crises of 10 types
- 9 of type A, 2 of type B, 1 each of 8 more types
- 4-month period

Evaluation results

Identification stability = stick to first label

- unstable: ??A??, AABBB
- stable: ?????, AAAAA, ??AAA

Previously-seen crises:

- identification accuracy: 77%
- identified when detected or one epoch later

For 77% of crises, average time to ID 10 minutes

- could potentially save up to 50 minutes
- more with shorter epochs

Accuracy for previously-unseen crises: 82%

More results in the paper

Comparison to other approaches

- using all metrics
- 3 operator-specified metrics
- failure signatures [SOSP ‘05]

Updating fingerprints

Sensitivity analysis

Online-clustering approach

- model evolution of fingerprint during crisis
- doesn’t assume 100% correct labeling of crises

Closest related work

- Capturing, indexing, clustering, and retrieving system history, SOSP ’05
  – authors: Cohen, Zhang, Goldszmidt, Symons, Kelly, Fox

- Failure signatures
  – signature for individual servers
  – build and manage per-crisis classification models
  – detailed comparison in the paper

Conclusion

Crisis fingerprint

– compact representation of system state
– scales to large clusters
– intuitive visualization

Use of Machine Learning crucial for metric selection

Correct identification for 80% crises

– on average after 10 minutes
– rigorous evaluation on production data

Selection of relevant metrics used at Microsoft

Thank you!