Google

Principled Performance Analytics

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Site Reliability Engineering

Acknowledgements

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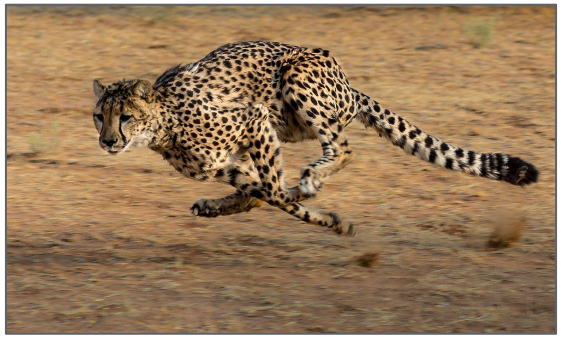
Is it working?

Reliability

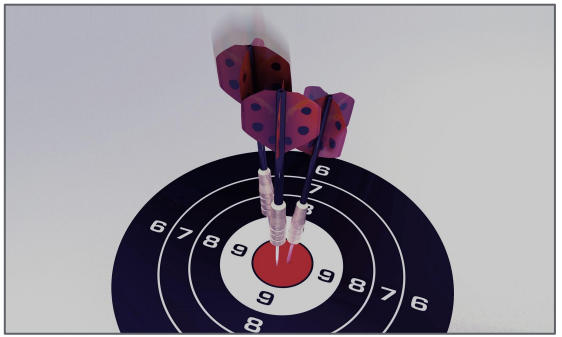
Availability

Is the service there when you need it?



Performance

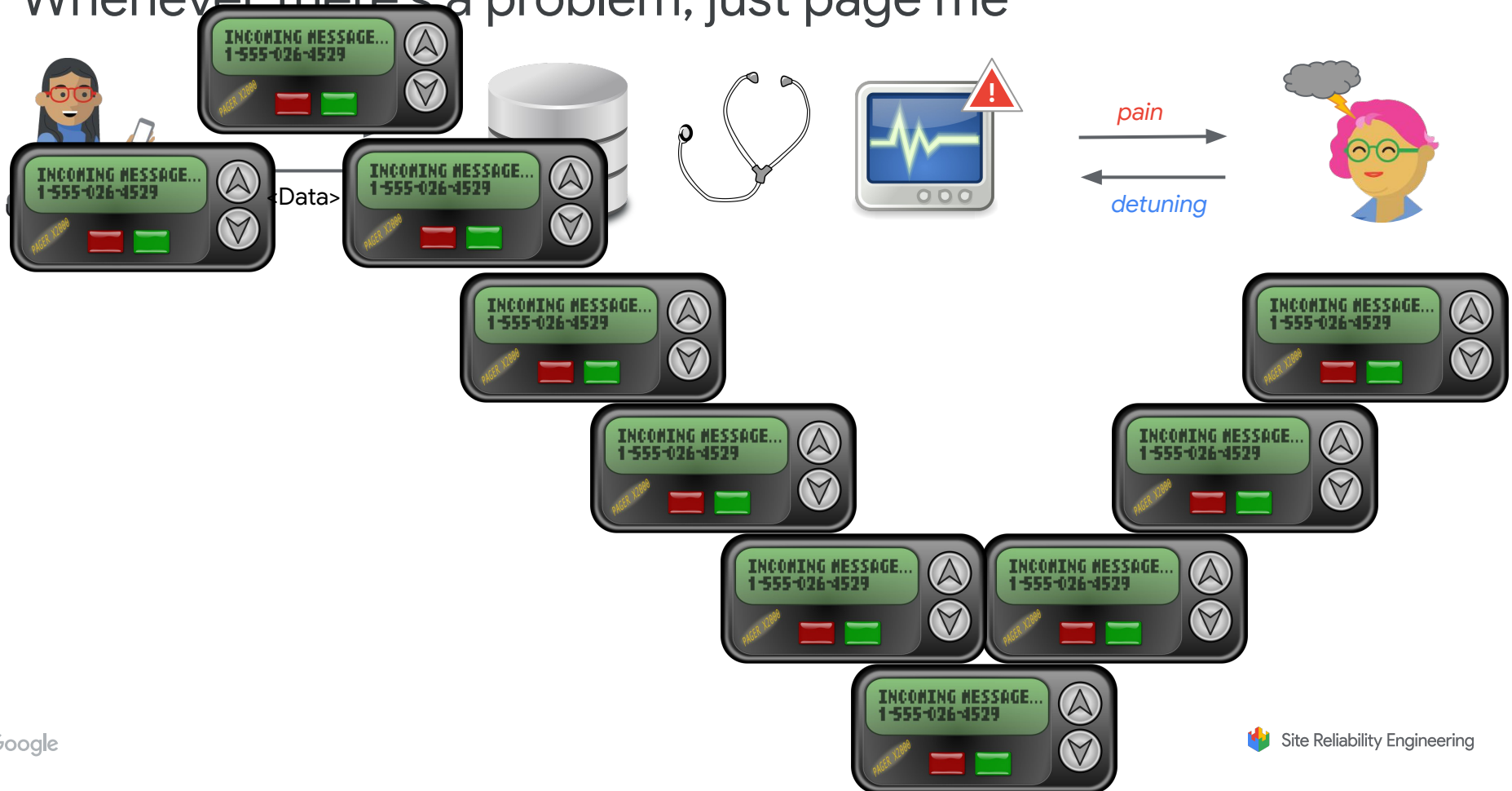
How effectively is work performed?



Correctness

Does a service do what's expected?

Whenever there's a problem, just page me

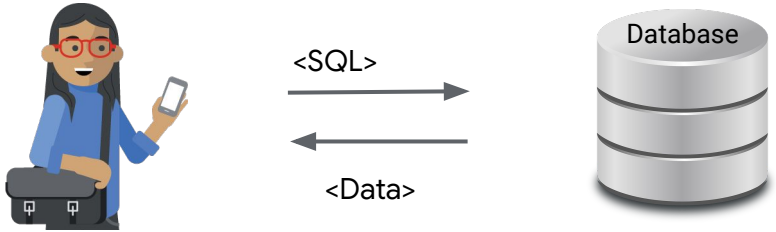


SLOs

1. Encode system goals
2. Specify behavior expectations
3. Determine when to page
4. Bound emergency behavior
5. Enable error budgets
6. Indemnify for dependency problems
7. Coordinate priorities between teams
8. Estimate outage magnitude
9. Signal service maturity
10. Bound supported behavior

HURRY: LIMITED TIME OFFER

Reliability in Practice



Availability

- ✔ Count the number of failed requests
- ✘ 400s vs 500s
- ✘ Deadlines
- ✘ Malformed Requests
- ✘ Retries Magnify Errors

Performance

- ✔ Set P99 latency SLO
- ✔ Create Probers
- ✘ Workload dependent
- ✘ Probers are narrow

Correctness

- ✔ Integration Tests
- ✔ Golden Datasets
- ✘ Limited, non-adaptive coverage
- ✘ Hope is not a strategy

Yo Dawg, I heard you like SLOs

Errors are shallow data

All happy families are alike; each unhappy family is unhappy in its own way.

Leo Tolstoy
Anna Karenina

- SLOs require recognized errors
- Errors are ambiguous
- Bugs can result in over/undercounting
- Calibration errors result in over/undercounting
- Lots of room for problems
- No regular maintenance cycle
- Results in poor data products

$$\frac{\text{Errors}}{\text{Total}}$$

What now?

Reliability via Performance Analytics

Taking a Step Back

As a Customer:

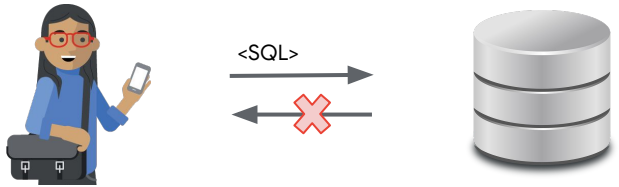
- Is service meeting expectations?

As a Service Provider:

- Is the system working as it should?

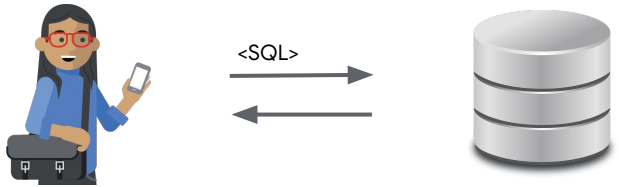
Shared Concerns:

- Is it you, is it me, or is it both of us?



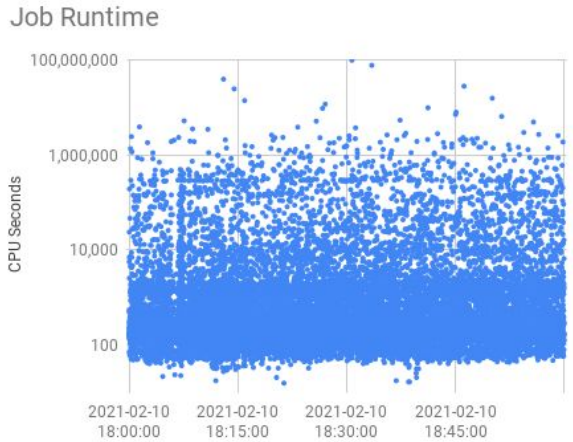
What do Service Providers See?

Workload performance ... across all customers



Complications:

- Mix shifts in workload
- Environmental factors like contention
- Mixed environments, job priorities, etc



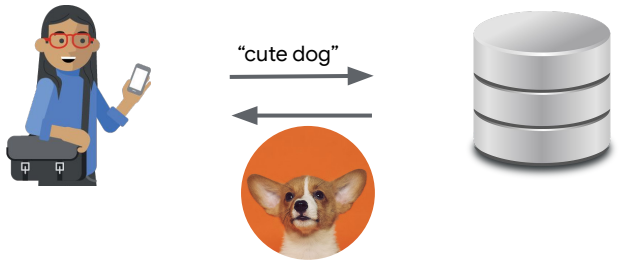
What do customers see?

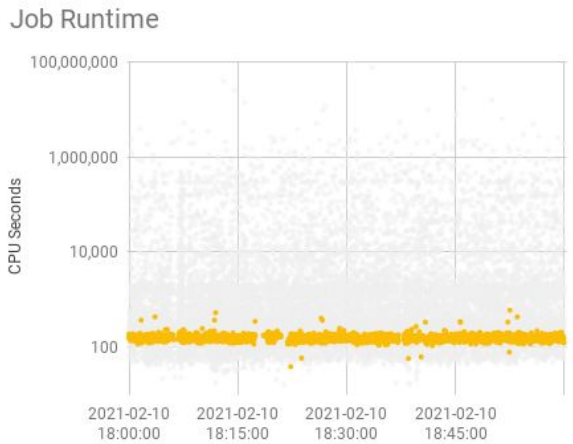
You may not know if a workload is performant

but your customers do

Services should be consistent

```
SELECT img
FROM DogPics AS DP
LEFT JOIN FriendsFavs AS FF
  USING (img_id)
WHERE DP.cute ='very'
  AND FF.stars >= 4
ORDER BY FF.favs DESC
LIMIT 1000
```



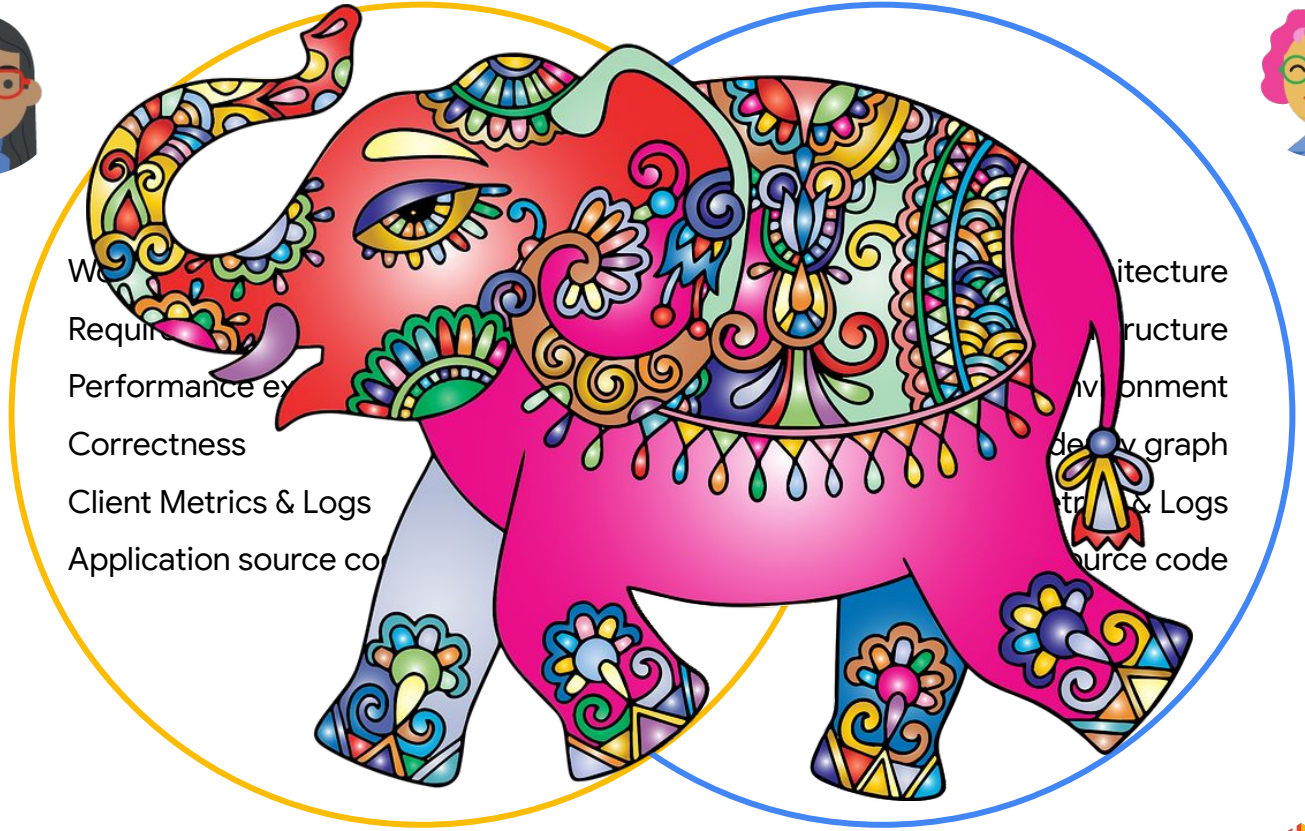


A High Level Model

Workload → Performance ← Service

Performance → Reliability

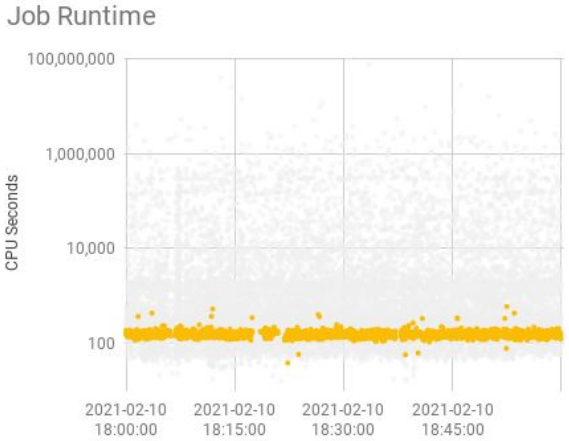
No Consensus Elephant



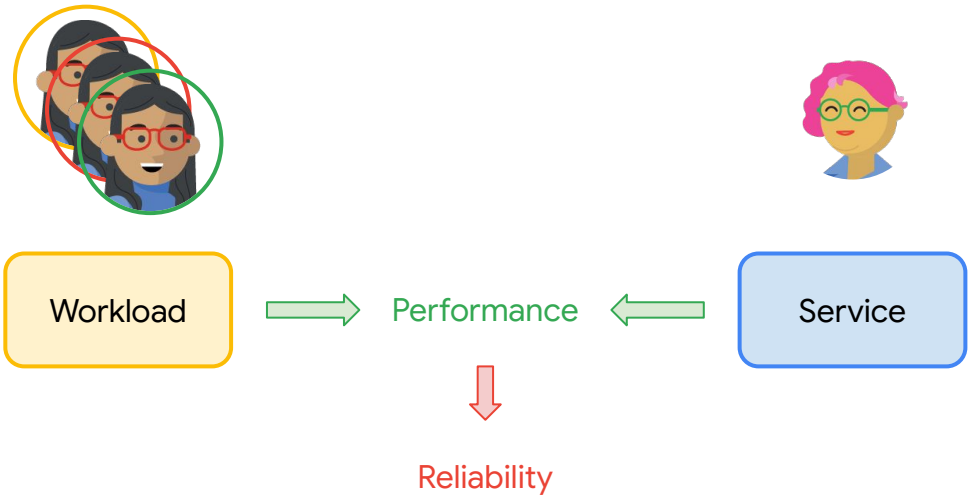
Applying to the Model

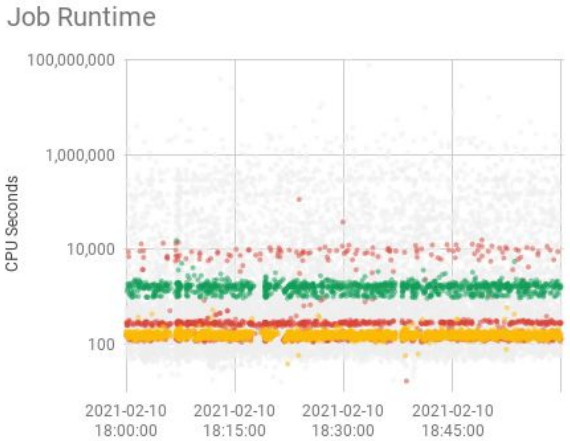
Workload → Performance ← Service

Performance → Reliability



Applying to the Model

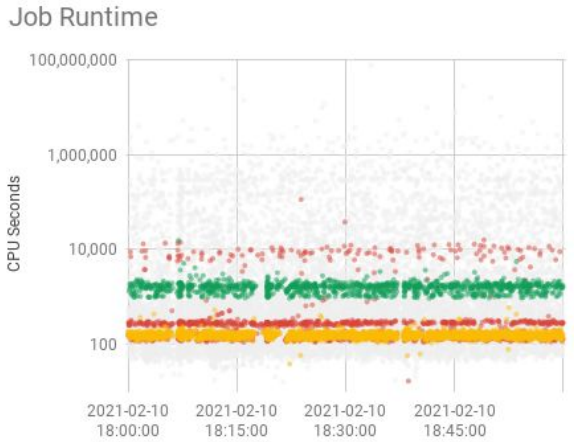




It’s Just That Easy™

Steps to Solve Service Reliability:

1. Partition Workloads by Intent
2. Analyze Performance
3. Profit!



2σ Technique

2σ Technique

Hypothesis:

Self-Similar Workloads Should Have Consistent Performance

Technique Overview:

- Partition workloads into Cohorts ⟵ *Approximate Intent via Workload Features*
- Build Performance Baselines ⟵ *Estimate Distributional Form (e.g. Normal)*
- Estimate Likelihood of Delivered Performance ⟵ *Test For Stationary*

Result:

- Set of Events with Predicted Likelihoods
- Time-series of summary statistics describing concentration of extreme outliers

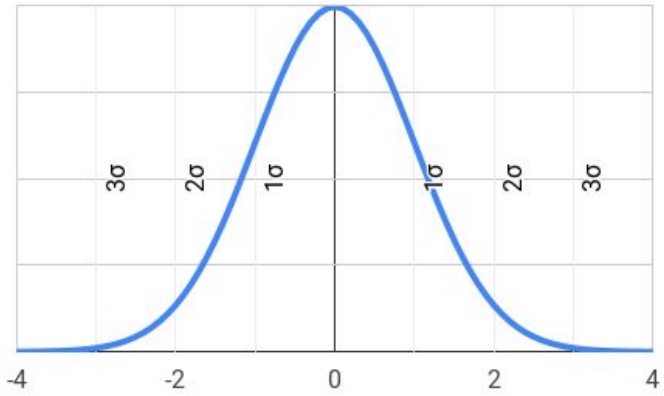
Approximations Unlock Leverage

Assume:

- Metric distributions can be approximated by Normal distribution
- Modeling errors excluded via baseline qualification

Then:

- Workload z-scores are a proxy for likelihood
- Workload performance should be IID
- Z-scores follow a standard Normal distribution
- Baseline distribution computation is “embarrassingly parallelizable”
- Z-scores are combinable (across cohorts!)

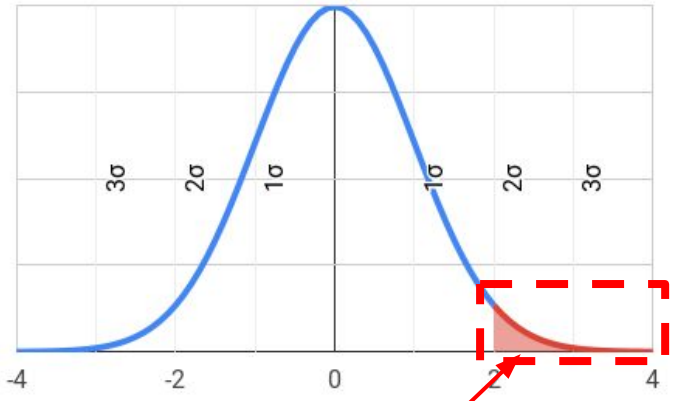


$$\mathrm{z-score} = \frac{\text{obs. workload} - \text{baseline mean}}{\text{baseline std}}$$

Mechanics

Strategy:

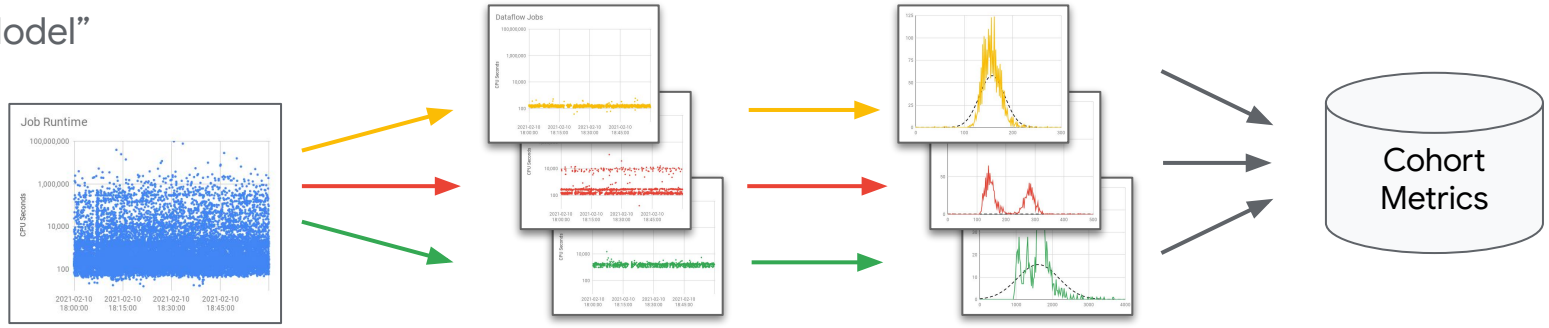
- Aggregate z-scores across workloads
- Monitor fraction of workloads with z-scores ≥ 2, in windows
- Expect 2-5% 2σ outliers in any given window
- When >10% of workloads are >2\sigma, BE AFRAID.



Detection is based on fraction of workloads exhibiting regression

Leveraging Structure: 2σ Technique

“Model”

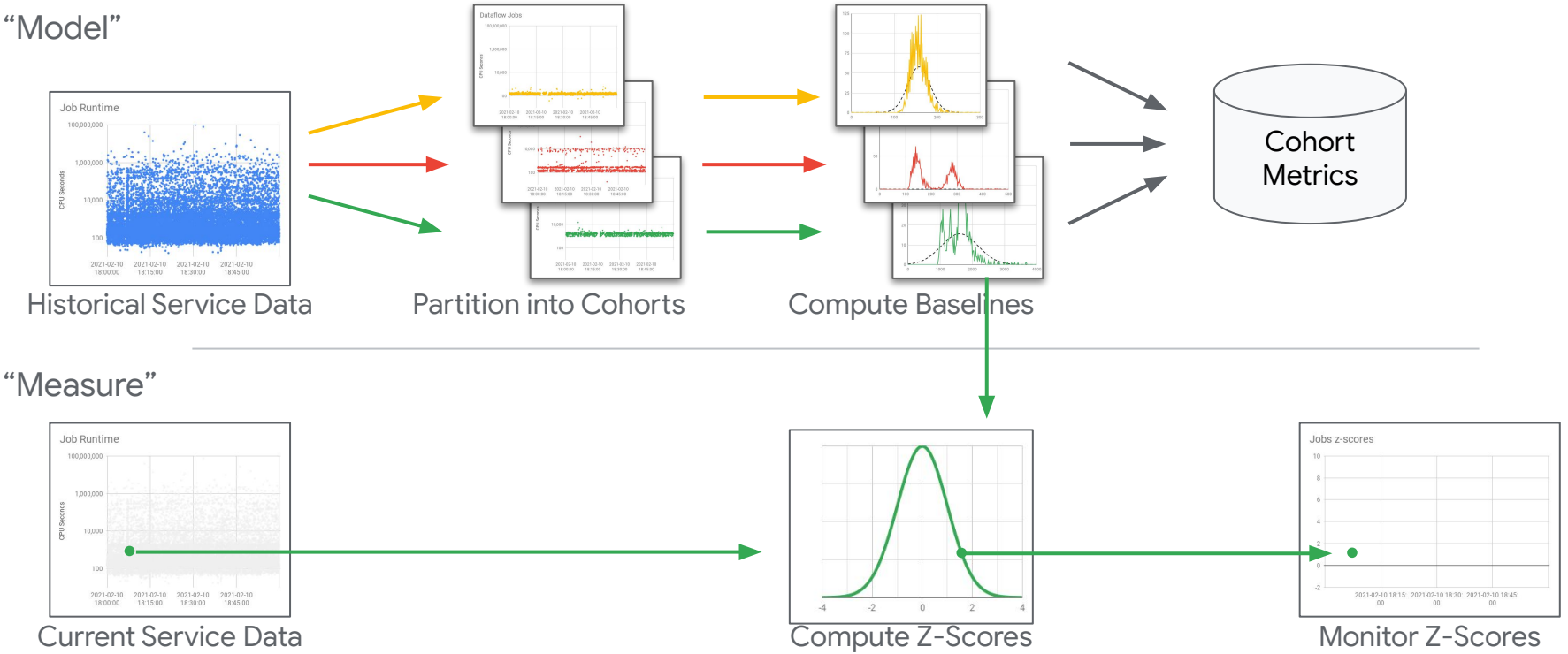


Historical Service Data

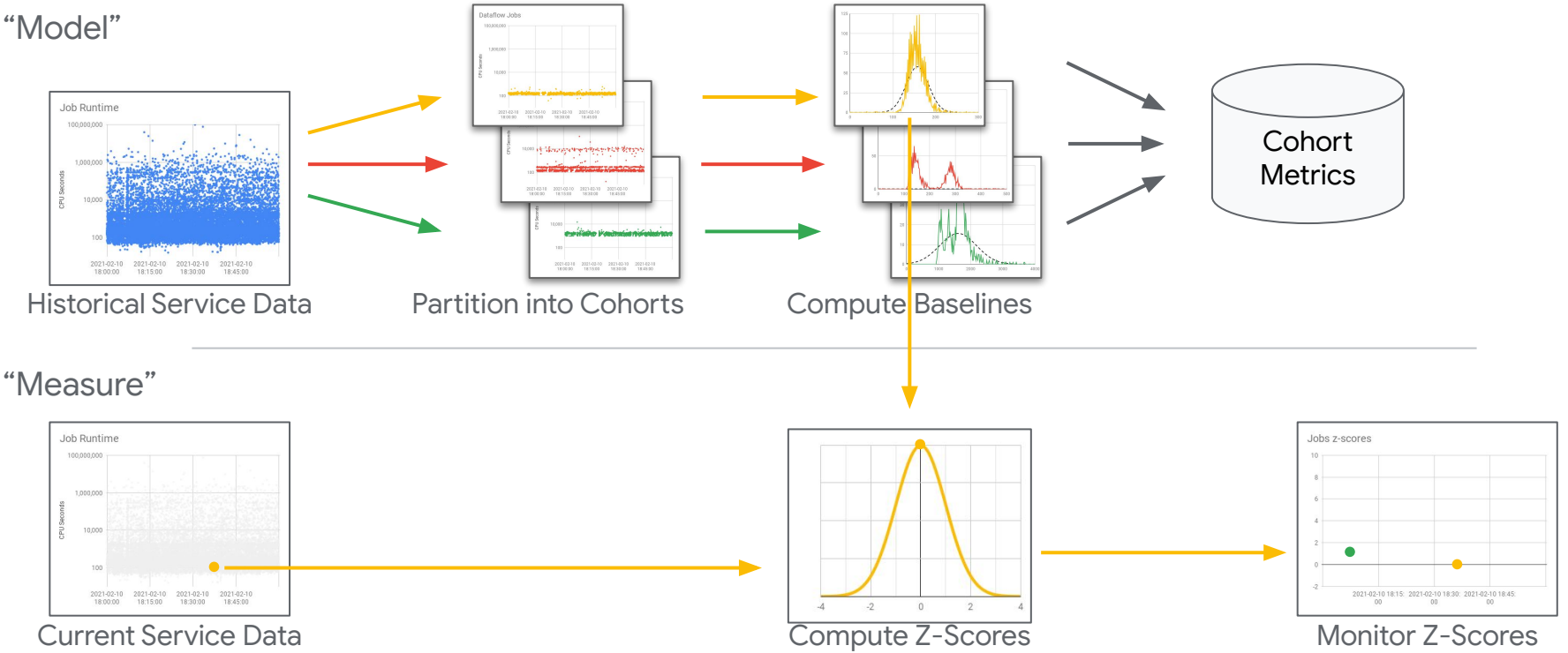
Partition into Cohorts

Compute Baselines

Leveraging Structure: 2σ Technique



Leveraging Structure: 2σ Technique



Leveraging Structure: 2σ Technique

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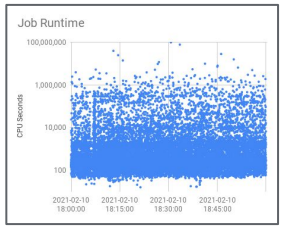

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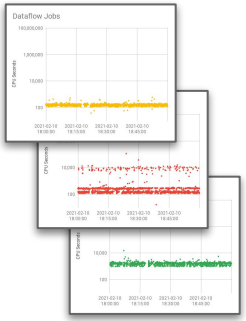
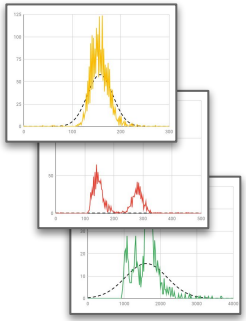
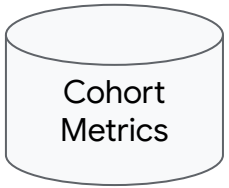


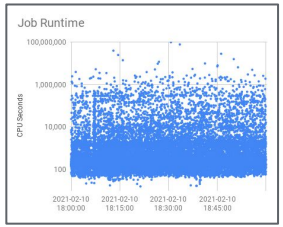
Partition into Cohorts



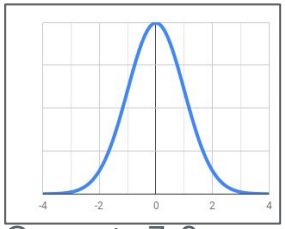
Compute Baselines



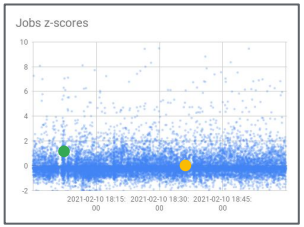
"Measure"



Current Service Data



Compute Z-Scores



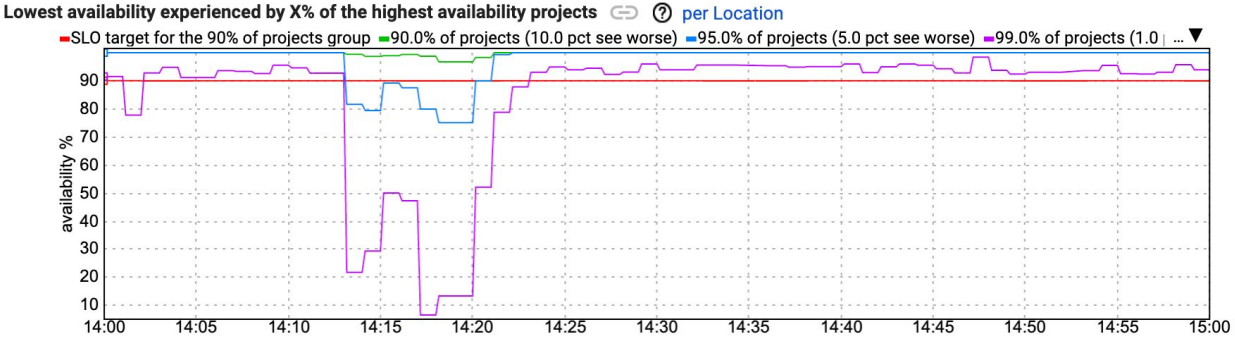
Monitor Z-Scores

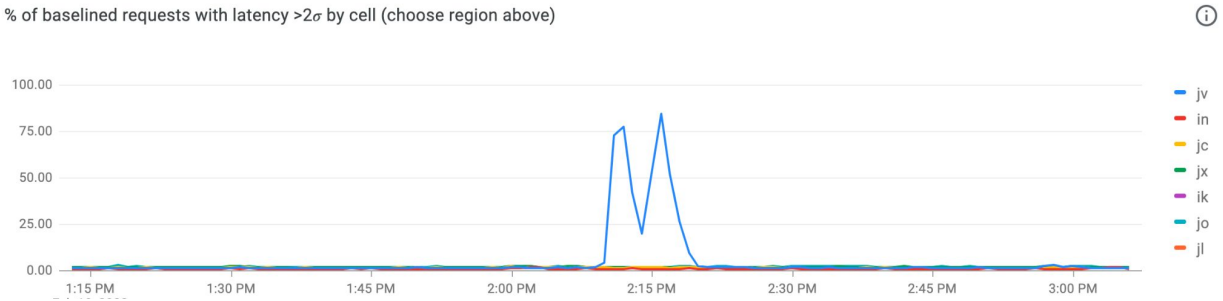
Frequently Asked Questions

- Do performance metrics actually follow Normal distributions?
- How do you know if approximations hold?
- How do you define cohorts?
- How do deal with “singleton” / infrequent workloads?
- Aren’t there a *lot* of singleton workloads?

- Ok, but does this *really* work?

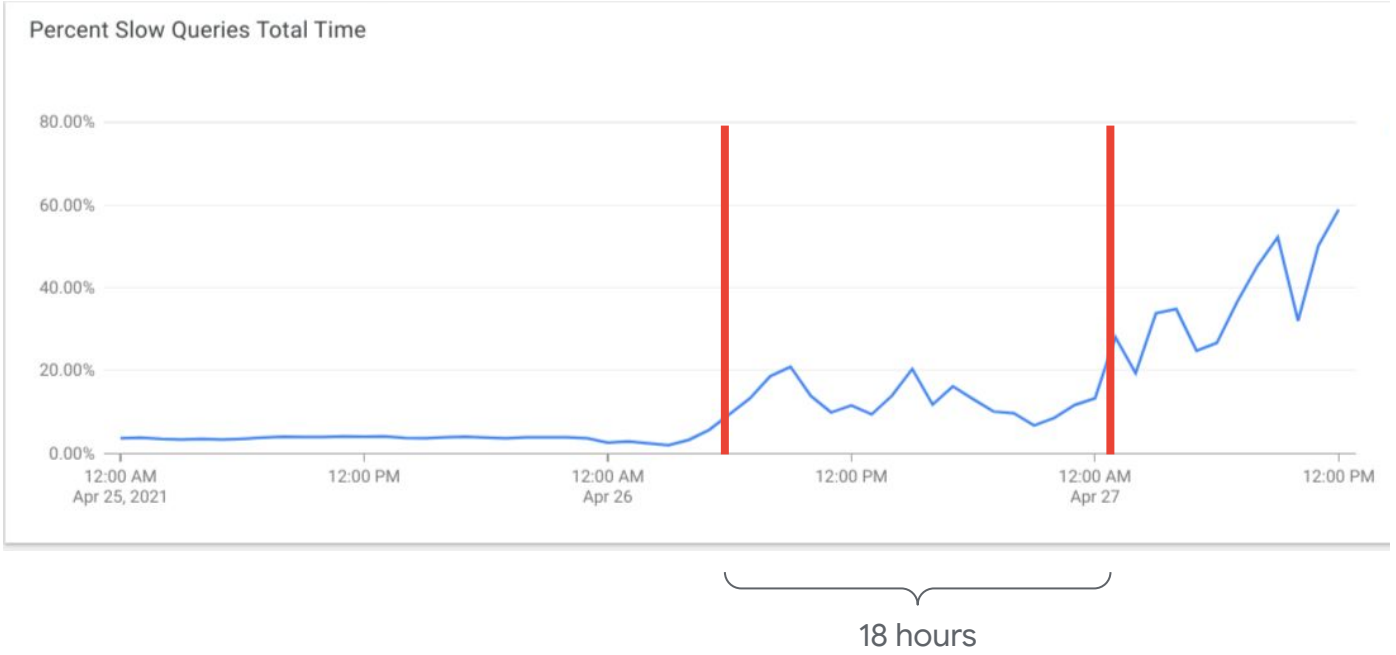
Backtesting



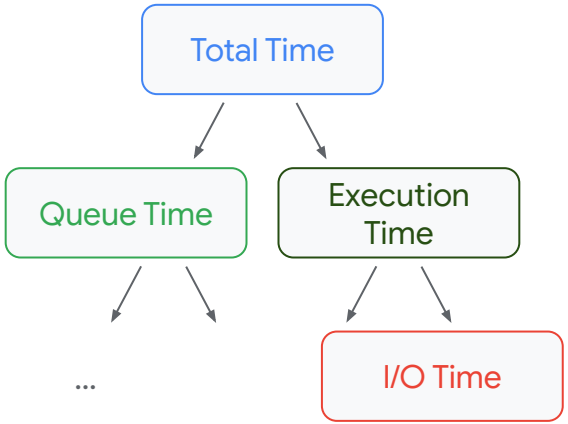


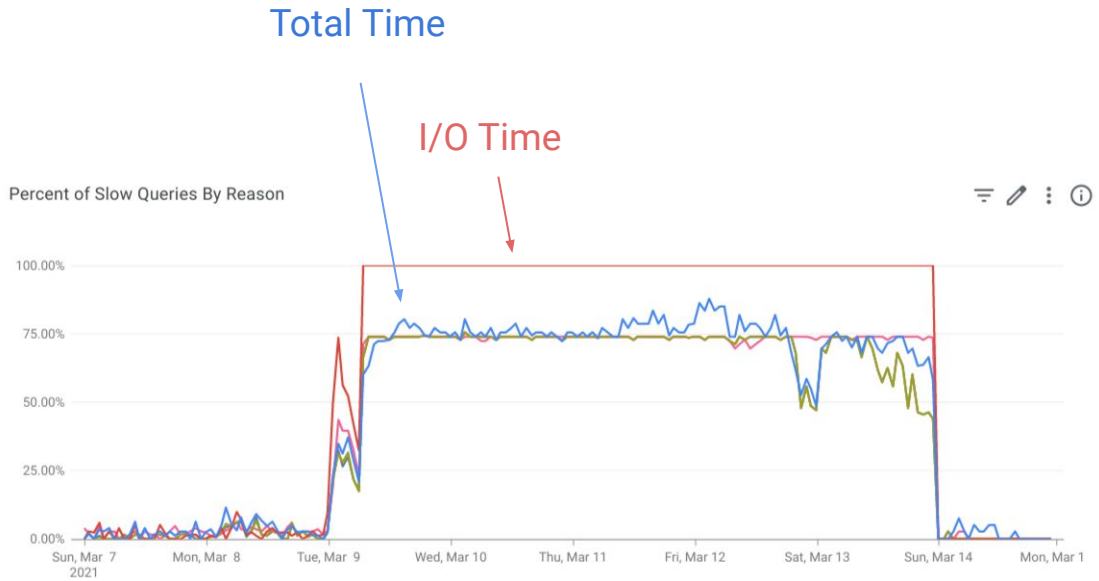
Applications

Sensitive Detection of Service Problems

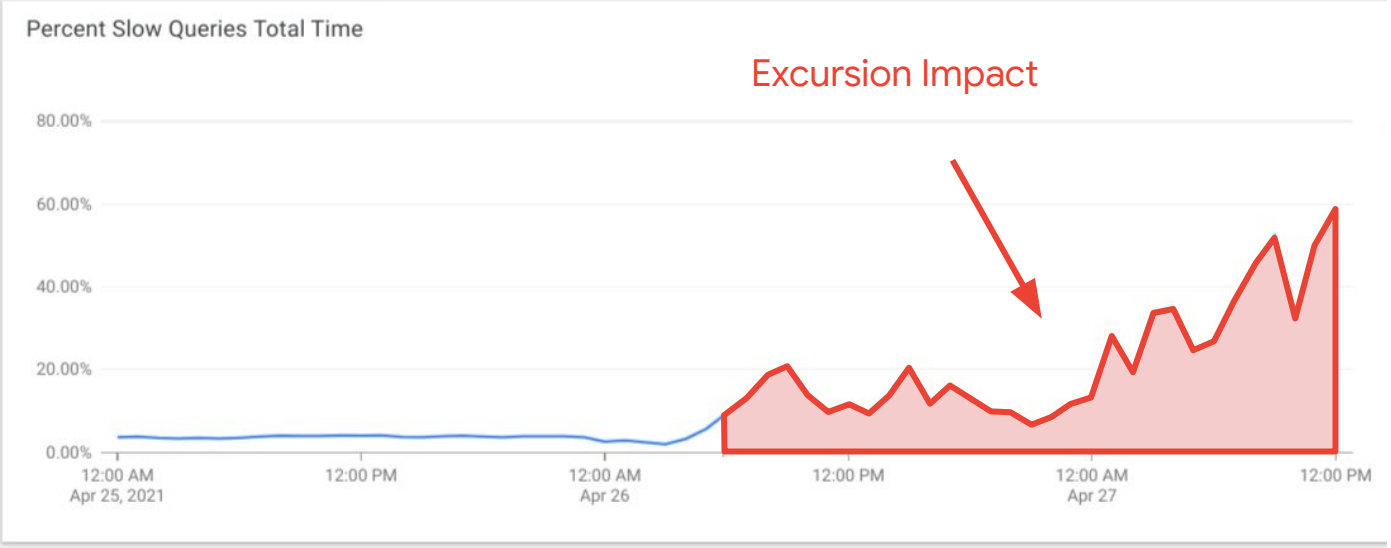


Streamlined Diagnosis

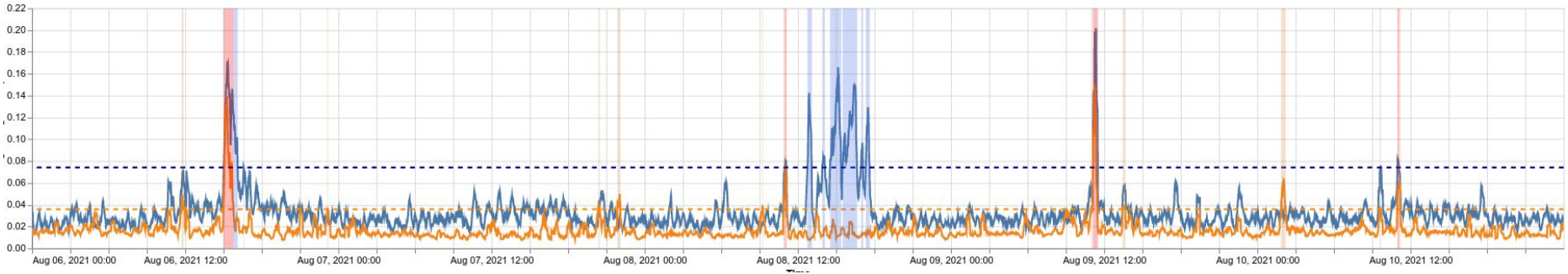




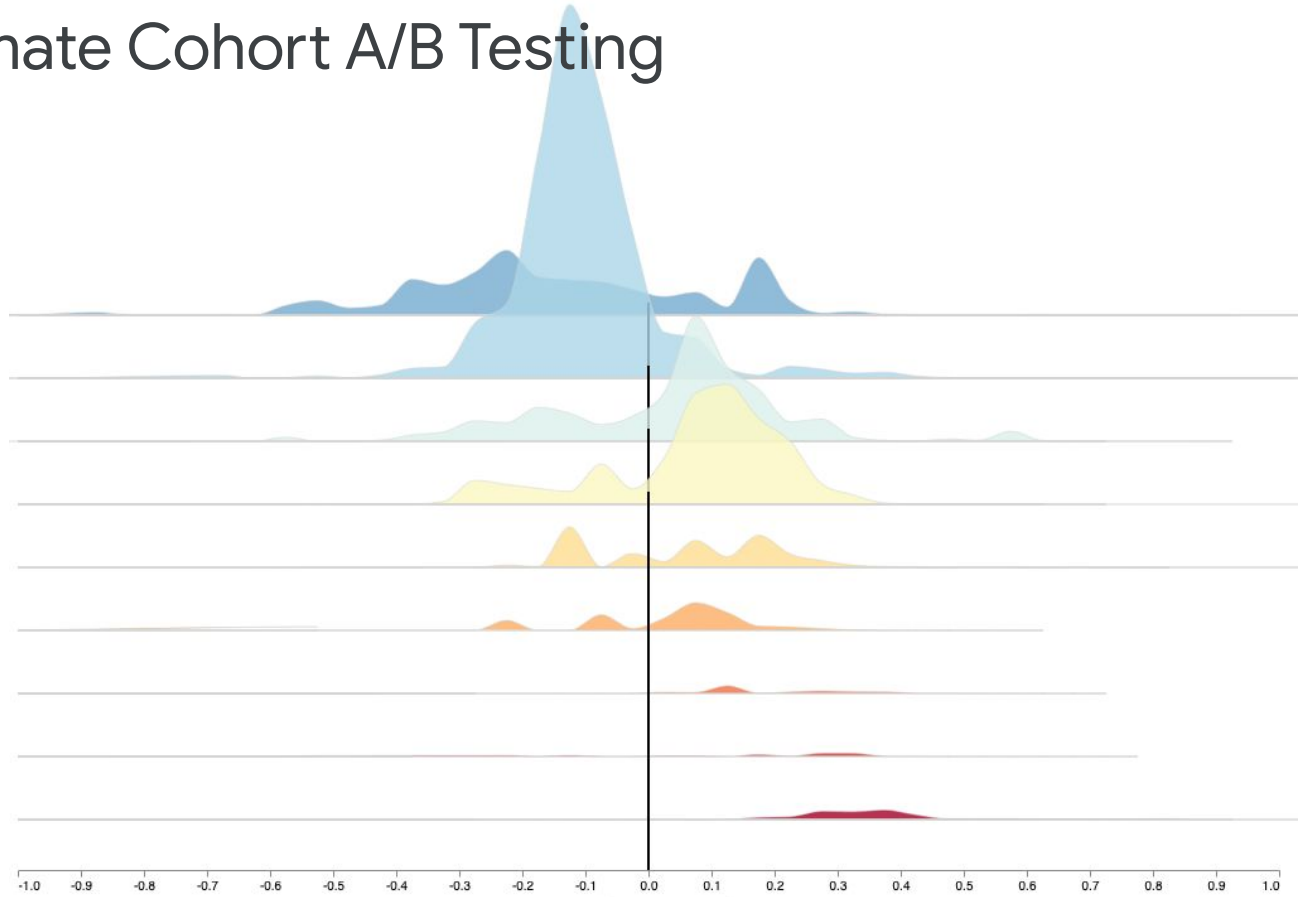
Excursion Impact Assessment



Measuring unexpected correlations



Approximate Cohort A/B Testing



Conclusions

Key Observations

- Reliability is a shared property (between customer & service)
  - Reconstruction of end to end behavior is critical
- Variability is what customers actually care about
- Distributed systems often produce decorrelation
  - We can measure it, and its absence
- Workload correlation can identify proximate causes
- Metric combinability is critical for analysis
- Error recognition is a gestalt of human judgements over time
- Due to the unrecognized problems in error recognition, SLOs aren't feasible

Contributions

2σ is a method that:

- Incorporates user intent in order to model expected performance
- Tests an IID hypothesis to infer when systems diverge from expected behavior
- To produce data products that are comparable and combinable

We use these data products in order to:

- Perform change point detection when systems diverge from expectations
- Estimate the duration, severity, and specific impact of these excursions
- Localize subsystem performance problems
- Compare relative and absolute performance over time and arbitrary workload dimensions
- Directly measure correlation across subsystems and isolation domains

Resulting in:

- Calibration-free insights that characterize the consistency of a system
- The ability to test system invariants continuously
- Data building blocks that can be reprocessed to answer many questions

Closing Thoughts

- We can do a lot better than SLOs, and we must
- Performance data >> Availability data
- We need more models
- We need help!
  - (and have openings, talk to me or Brent)

Questions