Next-generation alerting and fault detection

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SRECon16 Europe – Dublin, Ireland July 12, 2016

Alerting, fault & anomaly detection through:

Machine learning event & stream processing Alerting IDE's









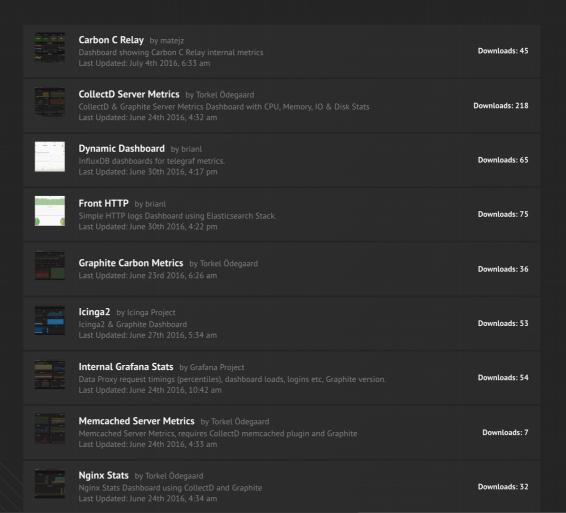
raintank





Dashboards.

Filter by: Data Source All Panel Type All Category All Search within this list Q Share your dashboards Sign up for a free Grafana.net account and share your creations with the community.





Plugins.

Plugin Type:





worldPing





Snap

APPLICATION



Example

IPSTUM by Grafana Project

Example app for Grafana





Kentik Connect Pro





NS1 for Grafana





Voxter VoIP Platform Metrics





Worldmap Panel



Zabbix

PANEL



Clock

PANEL



Pie Chart



Bosun

Open-Falcon

Also on Grafana.net

support for Graphite and Grafana

Also on 6 Grafana.net

- support for Graphite and Grafana
- hosted Graphite and Grafana

Presumptions

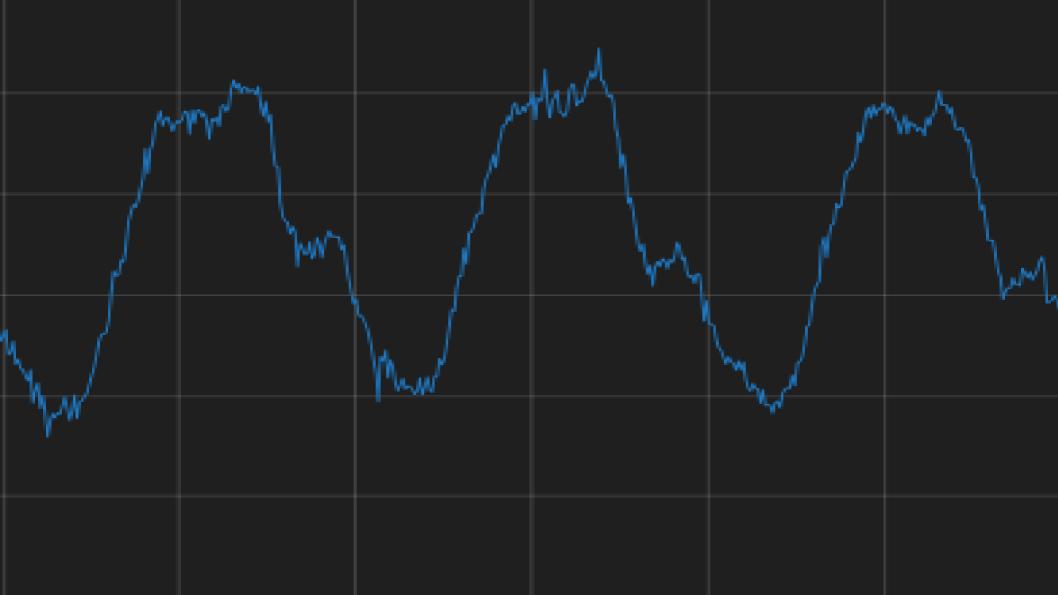
Monitoring using metrics in place

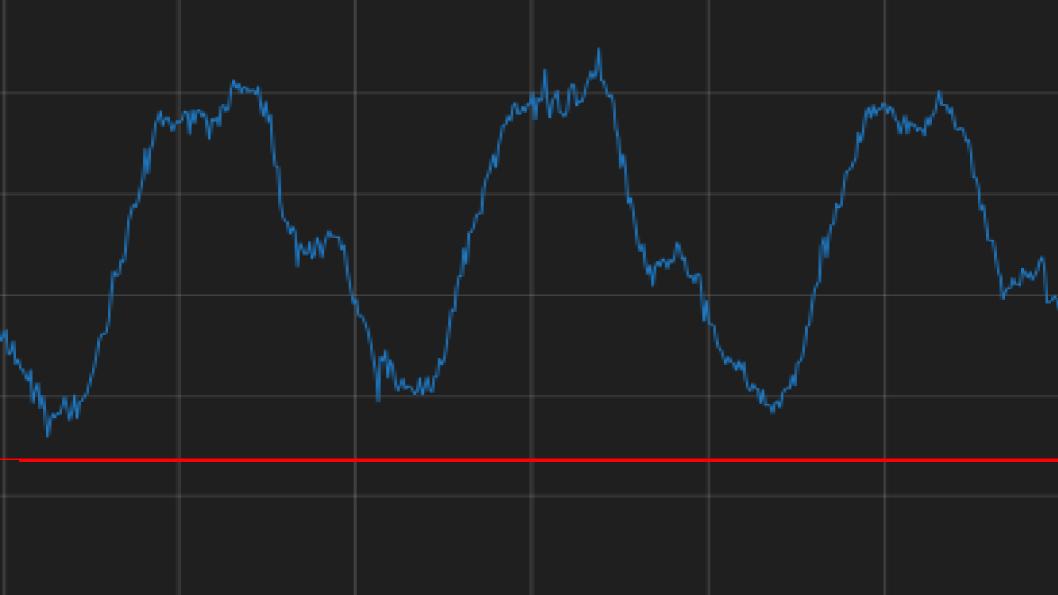
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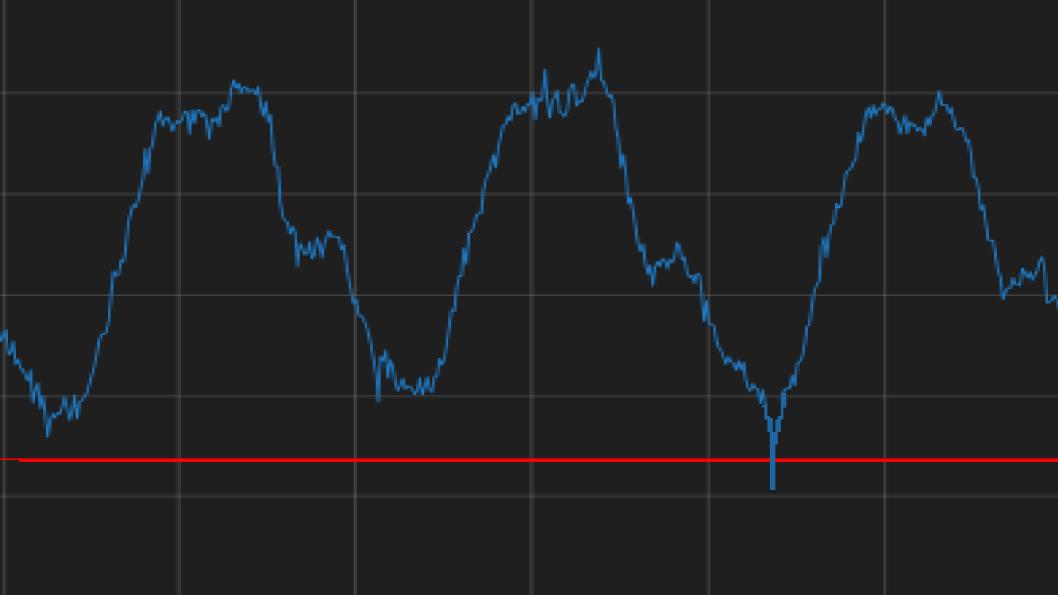
- Monitoring using metrics in place
- Alerting on metrics

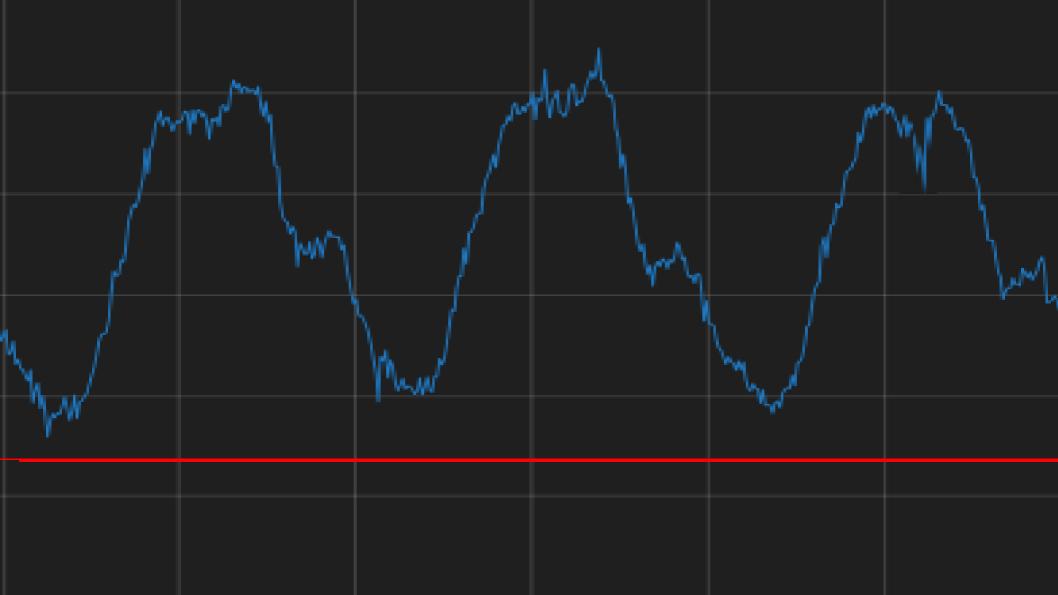
Presumptions

- Monitoring using metrics in place
- Alerting on metrics
- Alerts need high signal/noise ratio



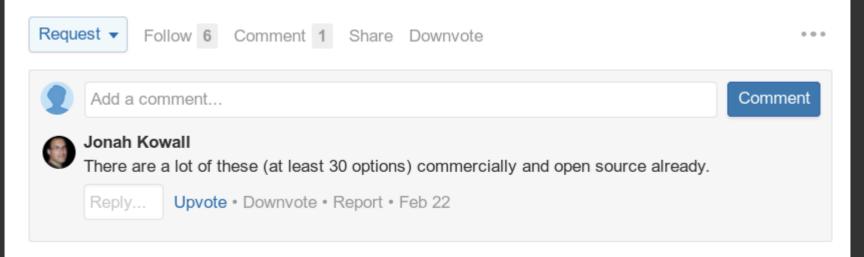


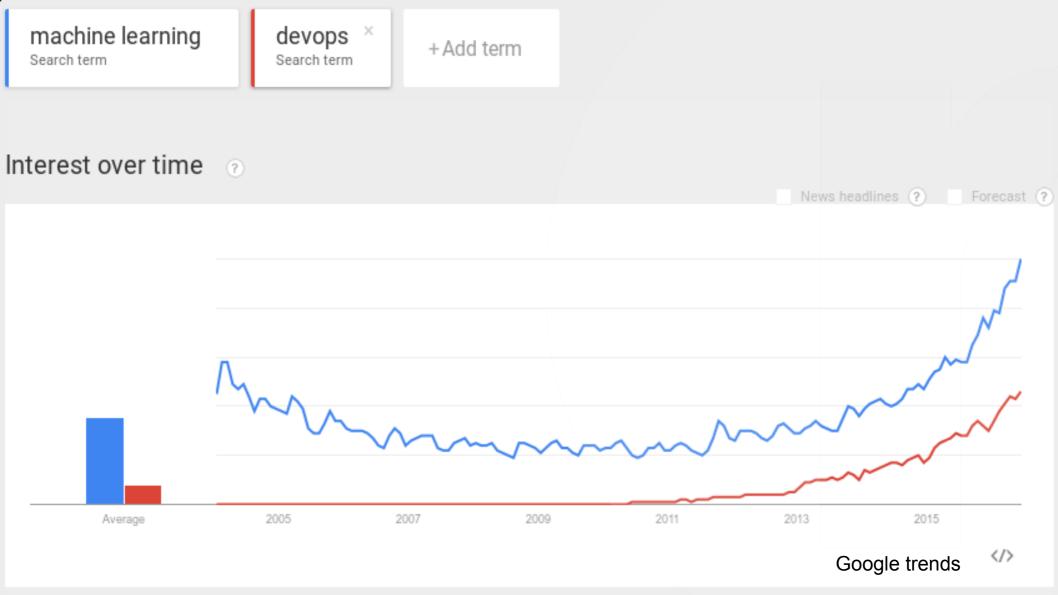




Are you facing a situation where your metric monitoring and alerting that uses static threshold rules is not scaling and you need an automated anomaly detection solution?

I would be happy to know your use case. We are building a solution in this space and researching use cases faced by real world companies.





Static thresholds → automated anomaly detection

Not scaling / too much data

Static thresholds → automated anomaly detection

- Not scaling / too much data
- Infrastructure complexity

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- Alerting on Patterns

Machine learning is a subfield of computer science that evolved from the study of pattern recognition and computational learning theory in artificial intelligence. In 1959, Arthur Samuel defined machine learning as a field of study that

gives computers the ability to learn without being explicitly programmed.

Machine learning explores the study and construction of

algorithms that can learn from and make predictions on data.

Such algorithms operate by building a **model** from an example training set of input observations in order to make data-driven predictions or decisions expressed as outputs, rather than following strictly static program instructions."



http://www.extremetech.com/extreme/224445-its-2-0-how-googles-deepmind-is-beating-the-best-in-go-and-why-that-matters



https://research.googleblog.com/2014/09/building-deeper-understanding-of-images.html



Using machine learning

for automated anomaly detection

a·nom·a·ly

/ə näməlē/ •0

noun

something that deviates from what is standard, normal, or expected.
 "there are a number of anomalies in the present system"
 synonyms: oddity, peculiarity, abnormality, irregularity, inconsistency, incongruity, aberration, quirk, rarity
 "the growth on the duck's bill is a harmless anomaly"

ASTRONOMY

the angular distance of a planet or satellite from its last perihelion or perigee.

Translations, word origin, and more definitions

fault

/fôlt/ •€)

noun

- an unattractive or unsatisfactory feature, especially in a piece of work or in a person's character.
 "my worst fault is impatience"
- 2. responsibility for an accident or misfortune.

"an ordinary man thrust into peril through no fault of his own" synonyms: responsibility, liability, culpability, blameworthiness, guilt "it was not my fault"

verb

criticize for inadequacy or mistakes.

"her colleagues and superiors could not fault her dedication to the job" synonyms: find fault with, criticize, attack, censure, condemn, reproach; More

GEOLOGY

(of a rock formation) be broken by a fault or faults.

"rift valleys where the crust has been stretched and faulted"





Daniel Kibblesmith 🕏 @kibblesmith





Amazon is a \$250 billion dollar company that reacts to you buying a vacuum by going THIS GUY LOVES BUYING VACUUMS HERE ARE SOME MORE VACUUMS

RETWEETS 7.124

LIKES 11,417

















1 context

• e.g. Amazon, Facebook, LinkedIn

1 context

- e.g. Amazon, Facebook, LinkedIn
- e.g. infrastructure change

2 Changing rules

Games vs your infra

2 Changing rules

- Games vs your infra
- Trained model doesn't work on new scenarios

3Signal strength

Image recognition, security
vs
ops metrics

4 relevancy

• e.g. super fast to fast

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- e.g. redundancy failover

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operator knows best

5 Effort

- data prep: filtering, selection, cleaning
- statistical modeling, model selection
- training, testing
- track performance & maintenance
- operate infrastructure
- fitting UX/UI

6 Complexity

• Intrinsic

6 Complexity

- Intrinsic
- Incidental https://engineering.quora.com/Avoiding-Complexityof-Machine-Learning-Systems

ML/AD for operations has merits
BUT:

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Anomalies != Faults. Signal/noise trap

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- Significant effort & complexity

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BUT:

- Anomalies != Faults. Signal/noise trap
- Significant effort & complexity
- Limited use cases

• Enrich metric metadata (metrics20.org)

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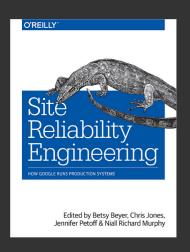
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 awareness of infrastructure
 awareness of infrastructure change

HOW do THEY do it?







"it's important that monitoring systems - especially the critical path from the onset of a production problem, through a page to a human, through basic triage and deep debugging - be kept simple and comprehensible by everyone on the team."

"Similarly, to keep noise low and signal high, the elements of your monitoring system that direct to a pager need to be **very simple and robust**. Rules that generate alerts for humans should be **simple to understand and represent a clear failure**."

https://www.oreilly.com/ideas/monitoring-distributed-systems

Conclusion



CEP

& Stream processing

e.g. storm, riemann.io, spark streaming

in → logic → out

```
(where (service "thumbnailer rate")
 ; Convert build numbers from strings to longs
 (adjust [:build #(Long. %)]
   ; Compute a throughput for each specific build
   (by :build
      (smap #(assoc % :service (str (:service %) " build " (:build %)))
        (rate 5 index)))
   ; Or maybe an old version reported numbers that were 2x larger than they
   : should have been
    (where (< (:build event) 1055)
     (scale 1/2 index)
     (else index))))
```

Compared to query-based alerting systems:

Good scheduling guarantees/execution timeliness

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- Unfamiliar paradigm (maybe)

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- Unfamiliar paradigm (maybe)
- Performance/scalability (maybe)
- operational complexity (maybe)

Conclusion

Not a bad idea...

But doesn't get to the root of the alerting problems.

Aha!



Bosun



IDE for alerting

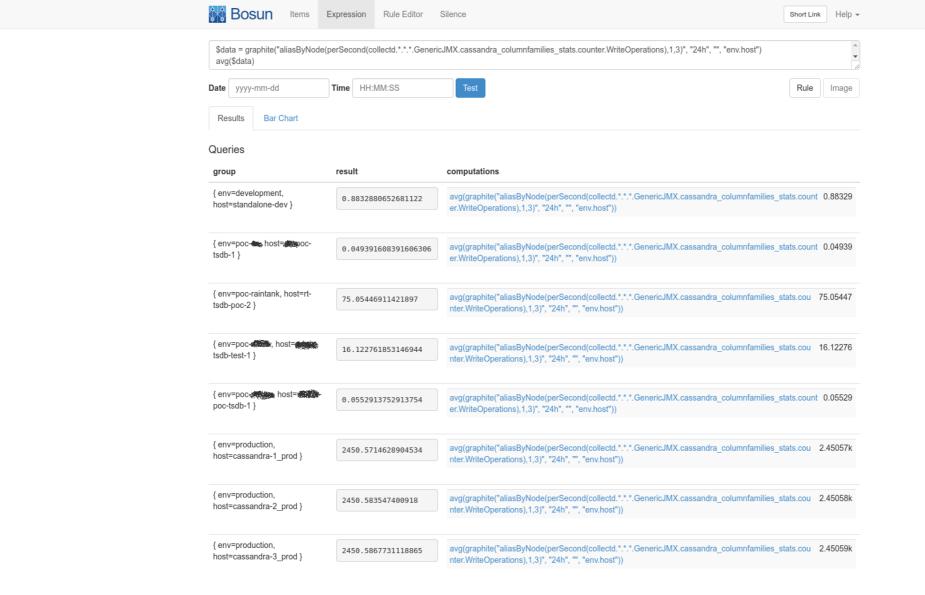
Support **programmers** building and maintaining **software**

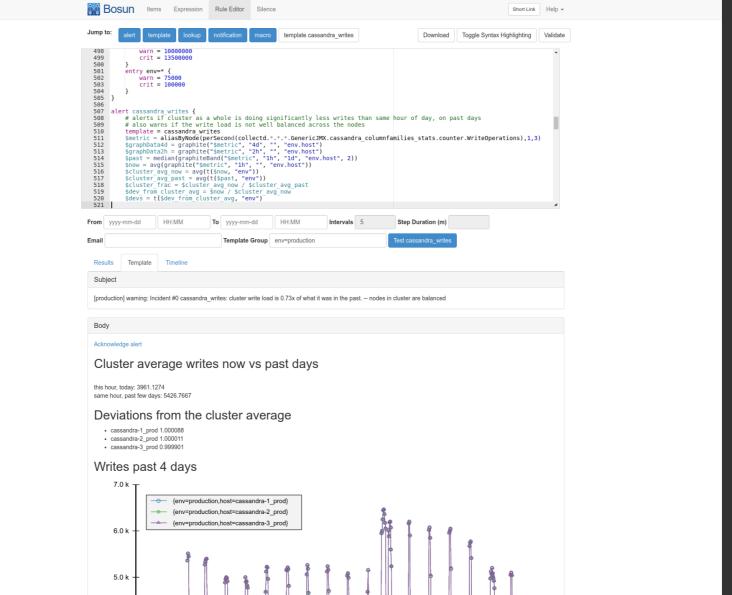
IDE for alerting

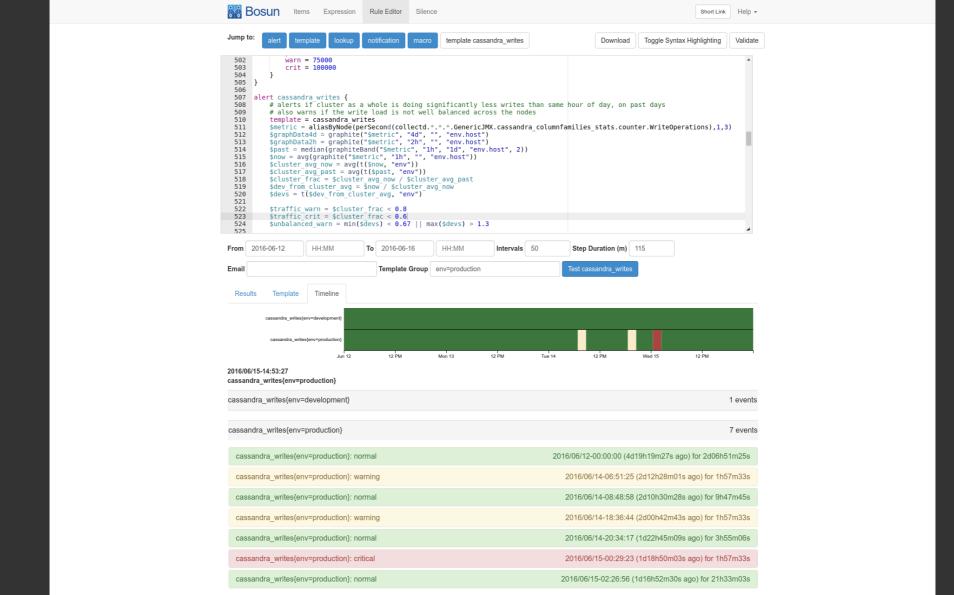
Support **programmers** building and maintaining **software**

Support operators building and maintaining alerting









1 [historical] testing

vs traditional alerting, machine learning

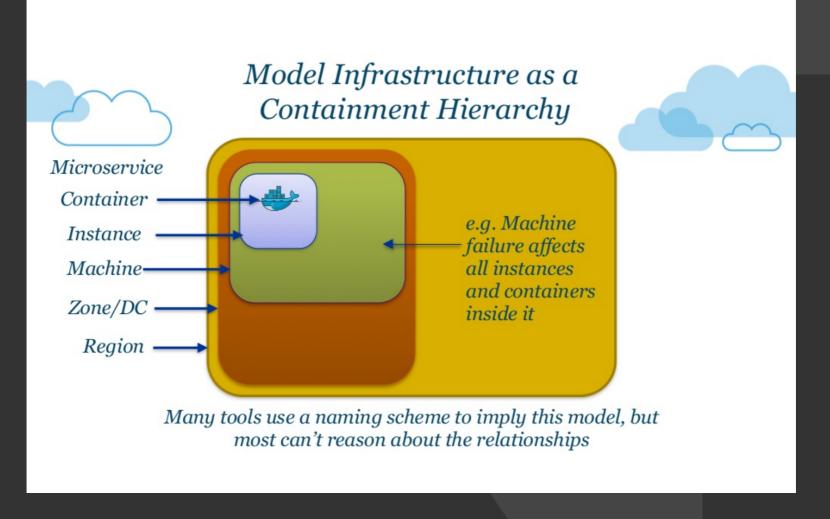
2 data juggling

Arbitrary scope

2 data juggling

Arbitrary scope Arbitrary data

3 dependencies



http://www.slideshare.net/adriancockcroft/gluecon-monitoring-microservices-and-containers-a-challenge

4 transcience

5 DRY

remove hassle wrt improving signal/noise

Tremove hassle wrt improving signal/noise

ongoing maintenance & tuning is critical

Tremove hassle wrt improving signal/noise

- ongoing maintenance & tuning is critical
- code for UI and logic > knobs

Tremove hassle wrt improving signal/noise

- ongoing maintenance & tuning is critical
- code for UI and logic > knobs
- leveraging additional data

2 communication

Author to recipient

2 communication

- Author to recipient
- Alert often primary UI

3Human > computer

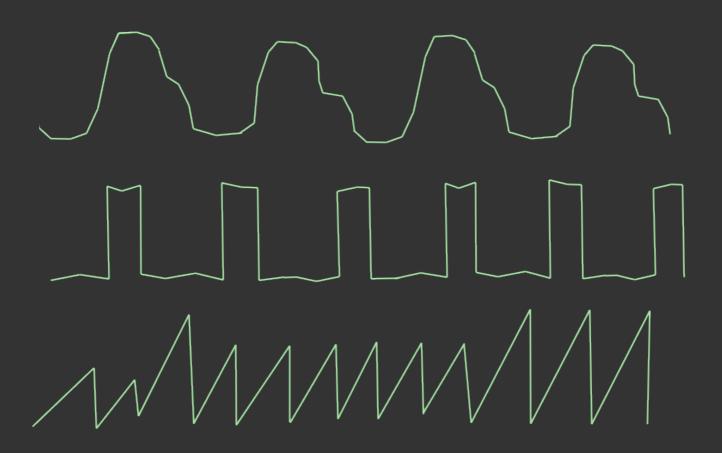
4 attention is scarce, expensive

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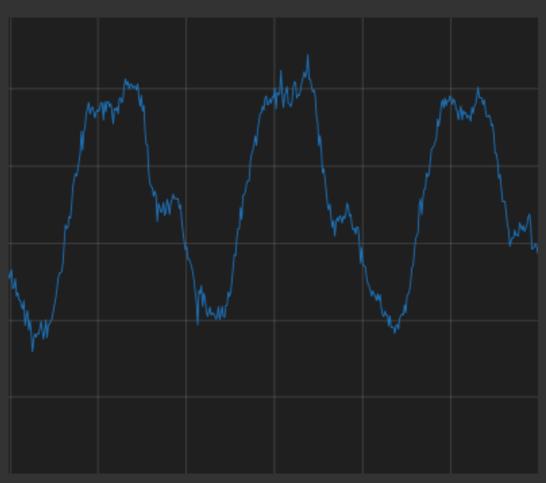
"provide monitoring platform that enables operators to efficiently utilize their attention"

fault detection with bosun

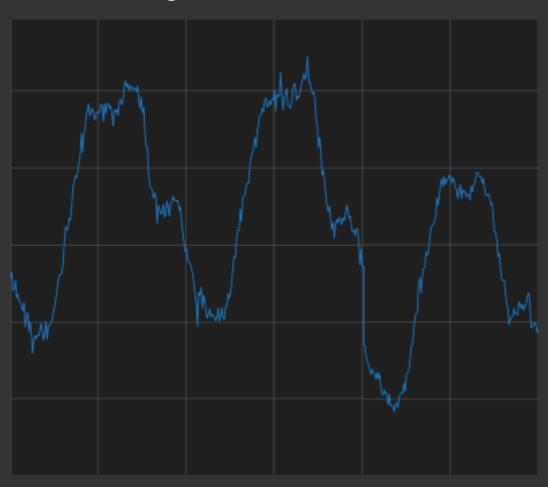
Classify series & find KPI's



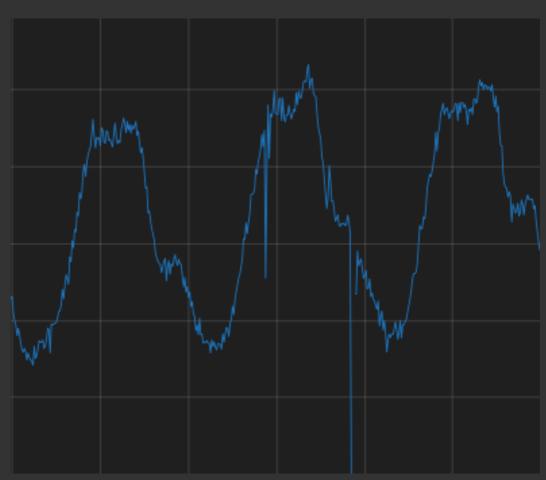
Smoothly seasonal: good



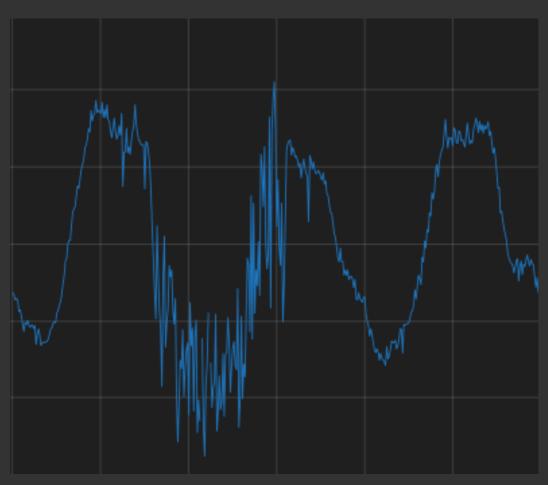
Smoothly seasonal: offset



Smoothly seasonal: spikes



Smoothly seasonal: erratic

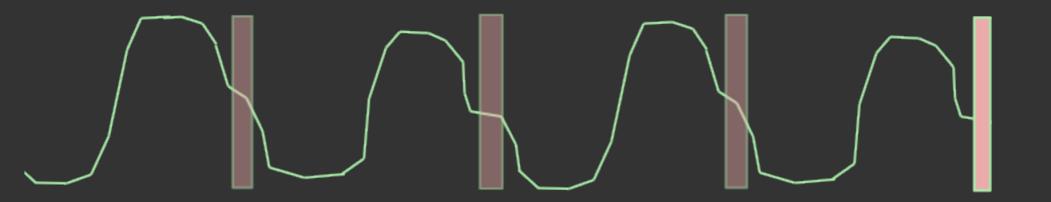


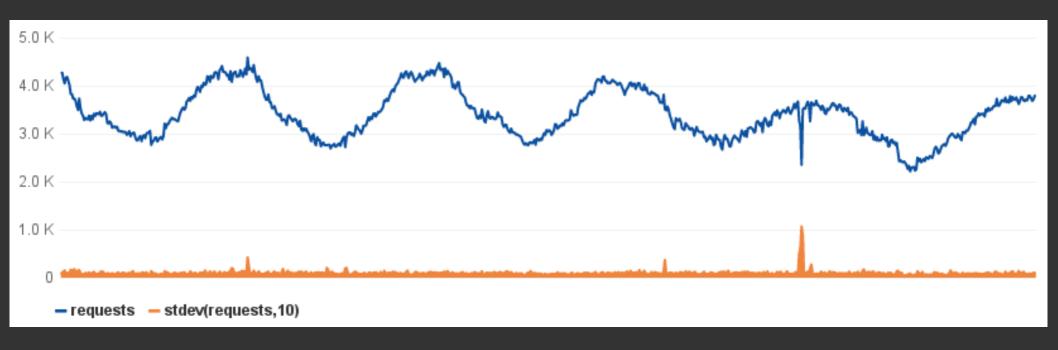
Solution 1/2: strength

Band(), graphiteBand()

bosun.org/expressions.html

Solution 1/2: strength





Deviation-now

Erraticness now = ---
Deviation-historical

```
Deviation-now median-historical

Erraticness now = -----

Deviation-historical median-now
```

```
deviation-now * median-historical

Erraticness now = -----

(deviation-historical * median-now) + 0.01
```

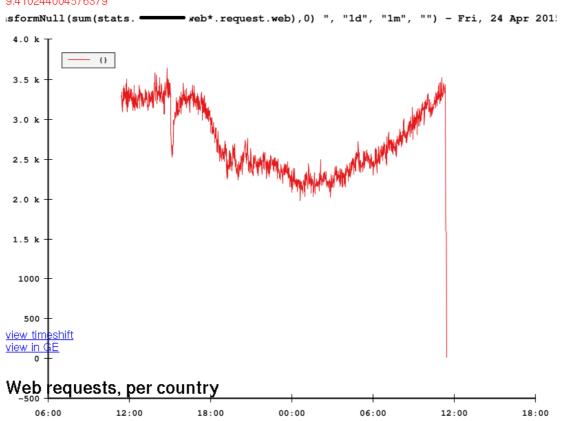
Web requests, Global

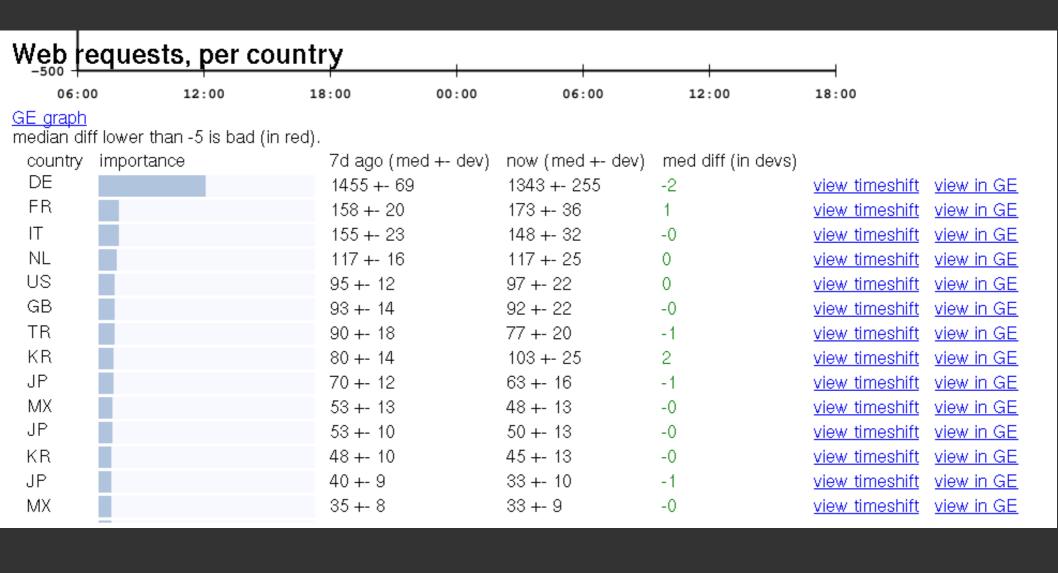
Total amount now should not be much less than in the past 7d ago 12485

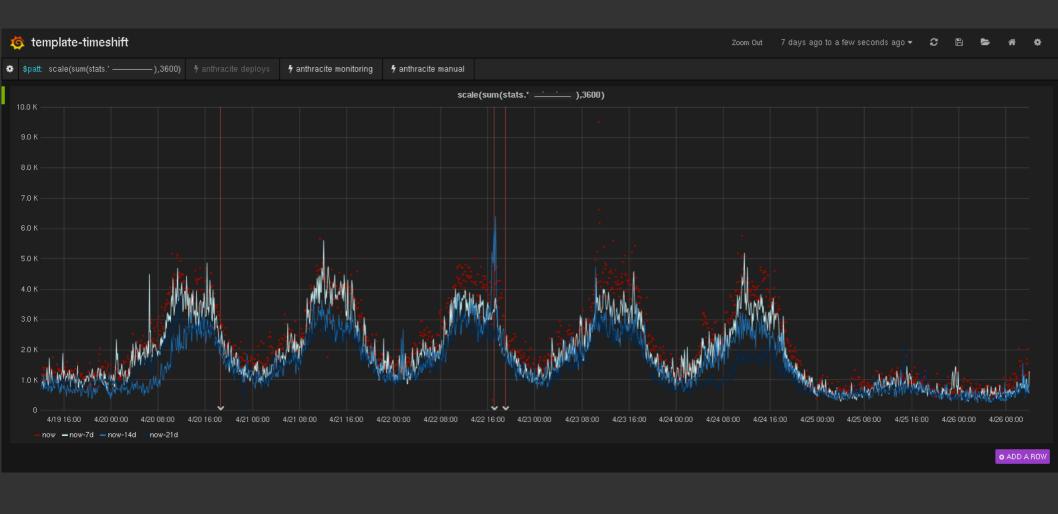
Now 13102

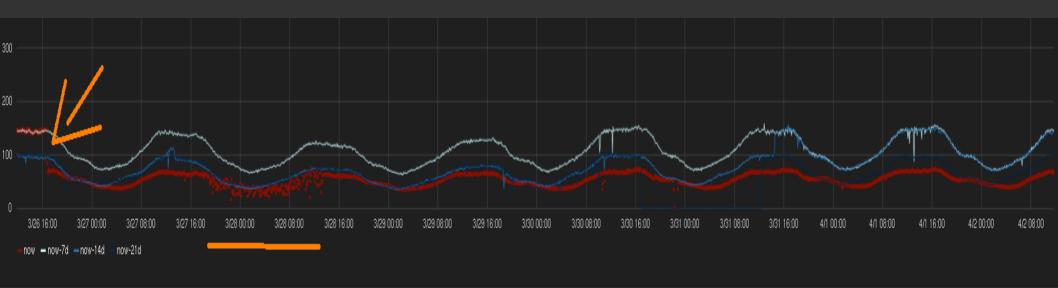
Erraticness of Web requests, Global

Erraticness - increased deviation - could be indicative of a spike or drop. Low values up to 6 are ok. 9 are critical 9.410244004576379









dieter.plaetinck.be/post/practical-fault-detection-on-timeseries-part-2

More details
Bosun macro, template & example
Grafana dashboard

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• All about the workflow

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- An IDE like bosun exponentially boosts ability to maintain high signal/noise alerting

- All about the workflow
- An IDE like bosun exponentially boosts ability to maintain high signal/noise alerting
- Build & share!

Want more?

- bosun.org/resources presentations by Kyle Brandt (LISA 2014 + Monitorama 2015)
- "my philosophy on alerting" by Rob Ewaschuk
- kitchensoap.com/2015/05/01/openlettertomonitoringproducts
- kitchensoap.com/2013/07/22/owning-attention-considerations-for-alert-design
- "monitoring microservices" by Adrian Cockroft
- (dieter.plaetinck.be/post/practical-fault-detection-alerting-dont-need-to-be-datascientist)
- dieter.plaetinck.be/post/practical-fault-detection-on-timeseries-part-2
- metrics20.org/media
- mabrek.github.io
- iwringer.wordpress.com
 @Dieter_be @raintanksaas slack.raintank.io raintank.io bosun.org grafana.org