

Machine Learning

ohne Hype

Philipp Krenn @xeraa



elastic

Developer 🥑



Kibana



Elasticsearch



X-Pack

Security

Alerting

Monitoring

Graph

Reporting

Machine
Learning



Logstash

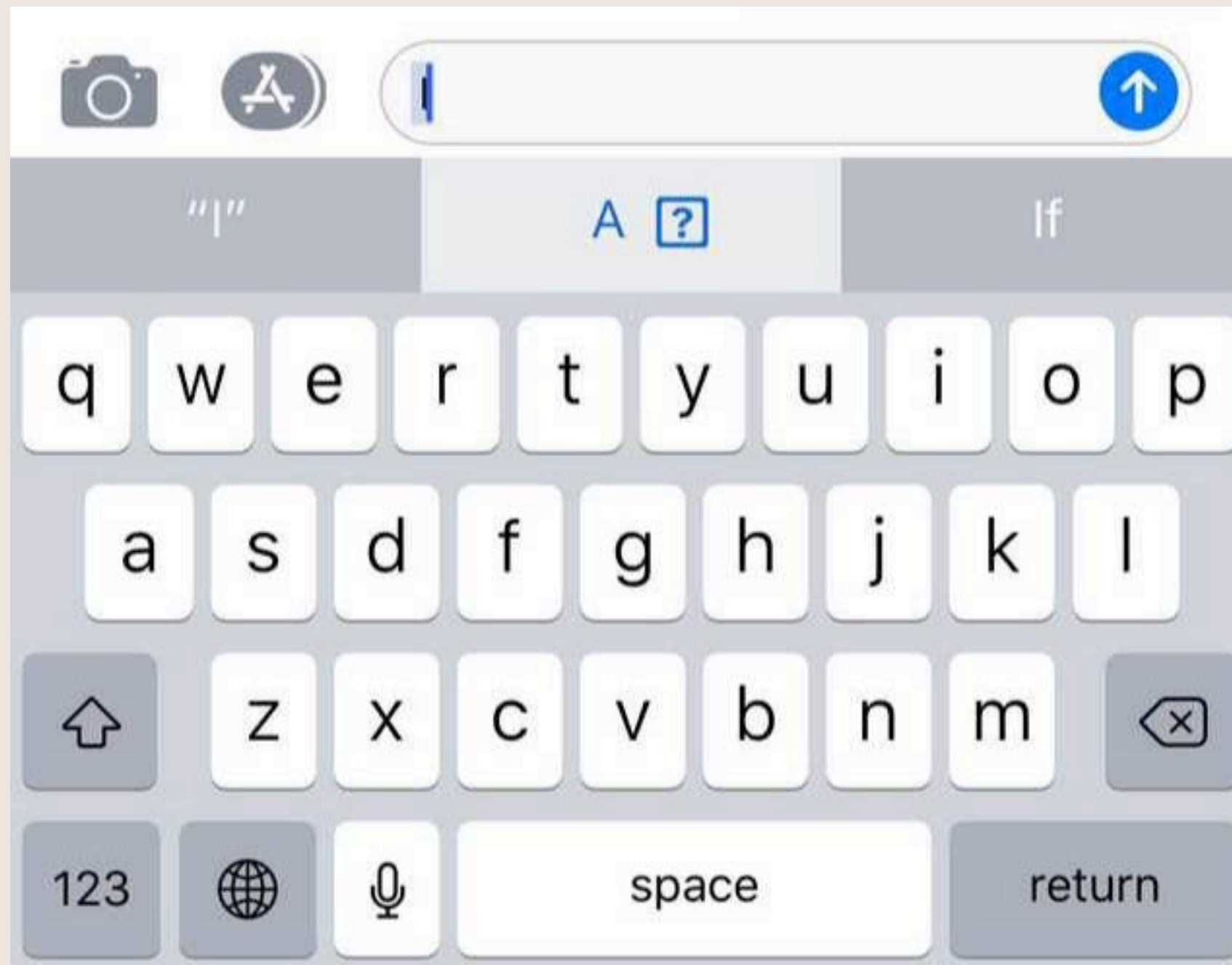


Beats



Elastic Cloud

Machine Learning is going viral...





Cabel Sasser ✓

@cabel

Follow



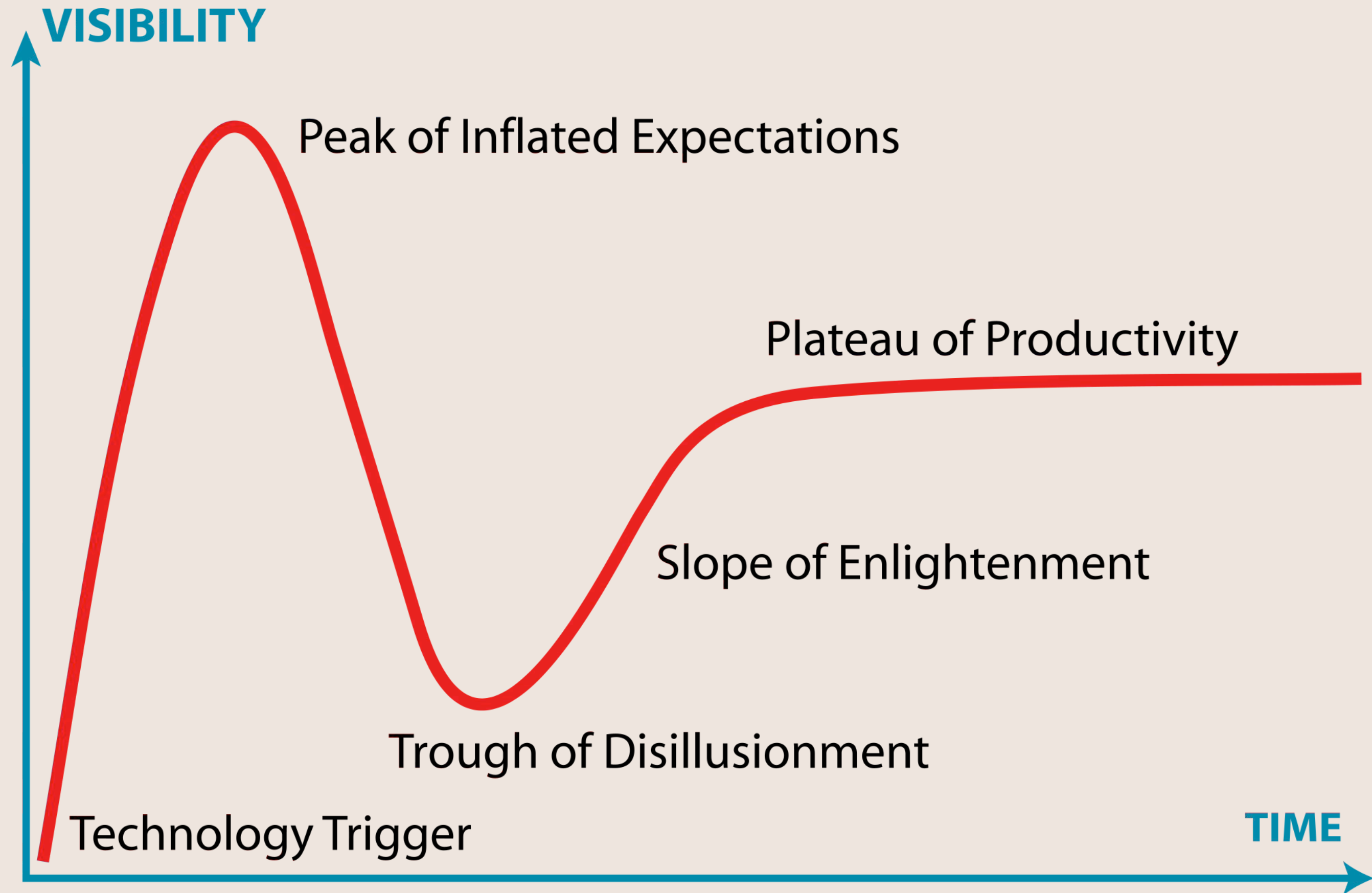
My favorite story about the “I” Unicode iOS bug is that it spread like a virus. You weren’t affected until someone sent it to you! Then, machine learning thought it was important, and added it to YOUR autocorrect.

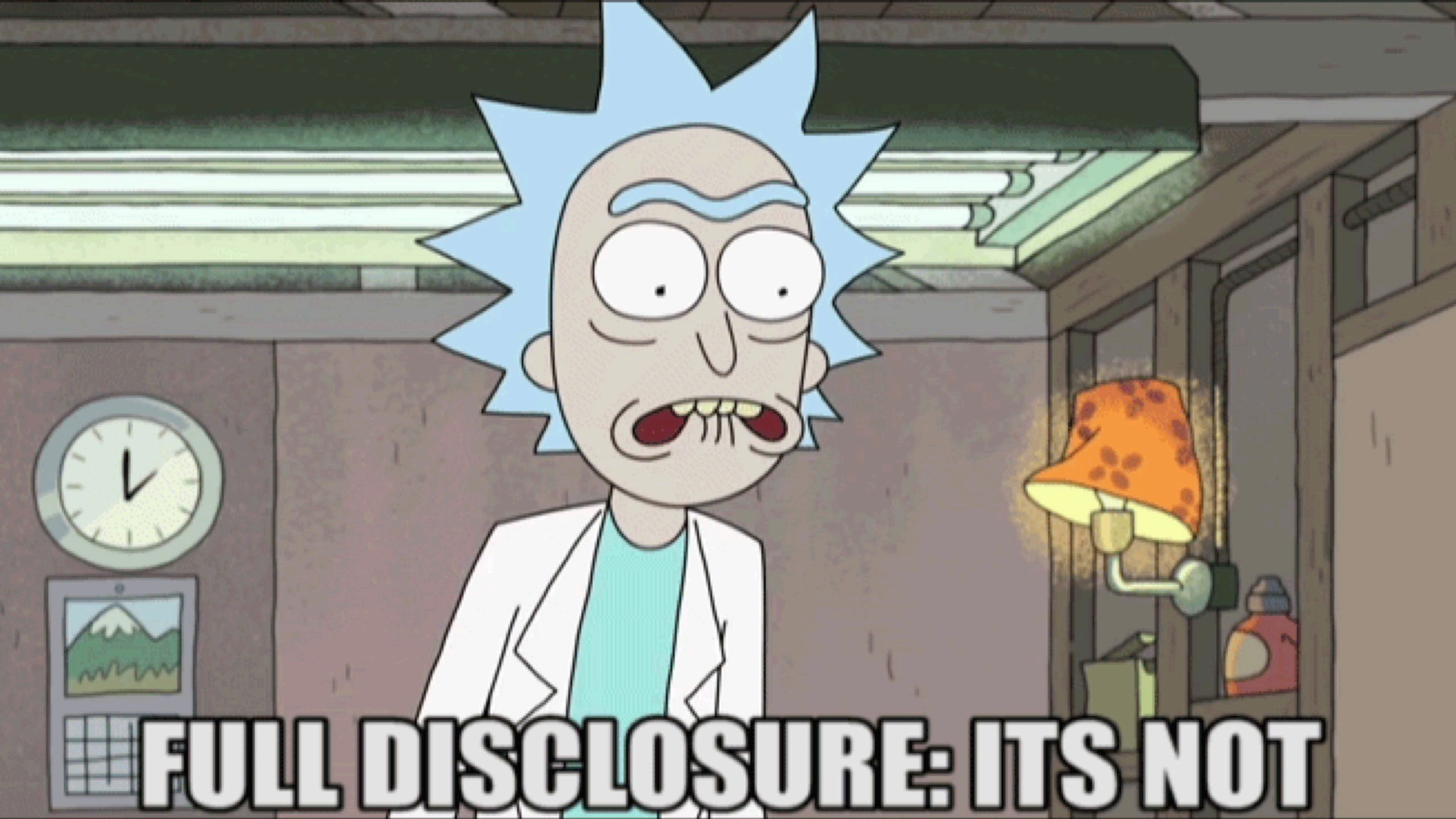
10:56 PM - 9 Nov 2017

“Using #DeepLearning when all you needed was a few if statements. #MachineLearning #DataScience”

—[**https://twitter.com/randal_olson/status/927157485240311808**](https://twitter.com/randal_olson/status/927157485240311808)







FULL DISCLOSURE: ITS NOT

Agenda

Machine Learning

Domain

Dataset

Machine Learning

Artificial Intelligence

Machine Learning

Deep Learning



ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



MACHINE LEARNING

Machine learning begins to flourish.



DEEP LEARNING

Deep learning breakthroughs drive AI boom.



General AI

Human characteristics

AI Winter



Narrow AI

Specific tasks



Facebook

alt="Image may contain: ocean, sky, bridge, cloud, outdoor, water and nature"



NEWS

9 MAR 2018

Zalando cuts 250 marketing jobs



Caroline Baldwin Editor, Essential Retail

[Email Caroline](#) | [Follow @cl_baldwin](#) | [Connect on LinkedIn](#)

Zalando has made dramatic job cuts in its marketing and advertising department, Essential Retail has learnt.

The fashion e-tailer, which employs over 14,000 people, is restructuring its marketing



Englisch Deutsch Französisch Deutsch - erkannt ▾



Deutsch Englisch Französisch ▾

Übersetzen

Die Volkswirtschaftslehre (auch Nationalökonomie, Wirtschaftliche Staatswissenschaften oder Sozialökonomie, kurz VWL), ist ein Teilgebiet der Wirtschaftswissenschaft.



166/5000

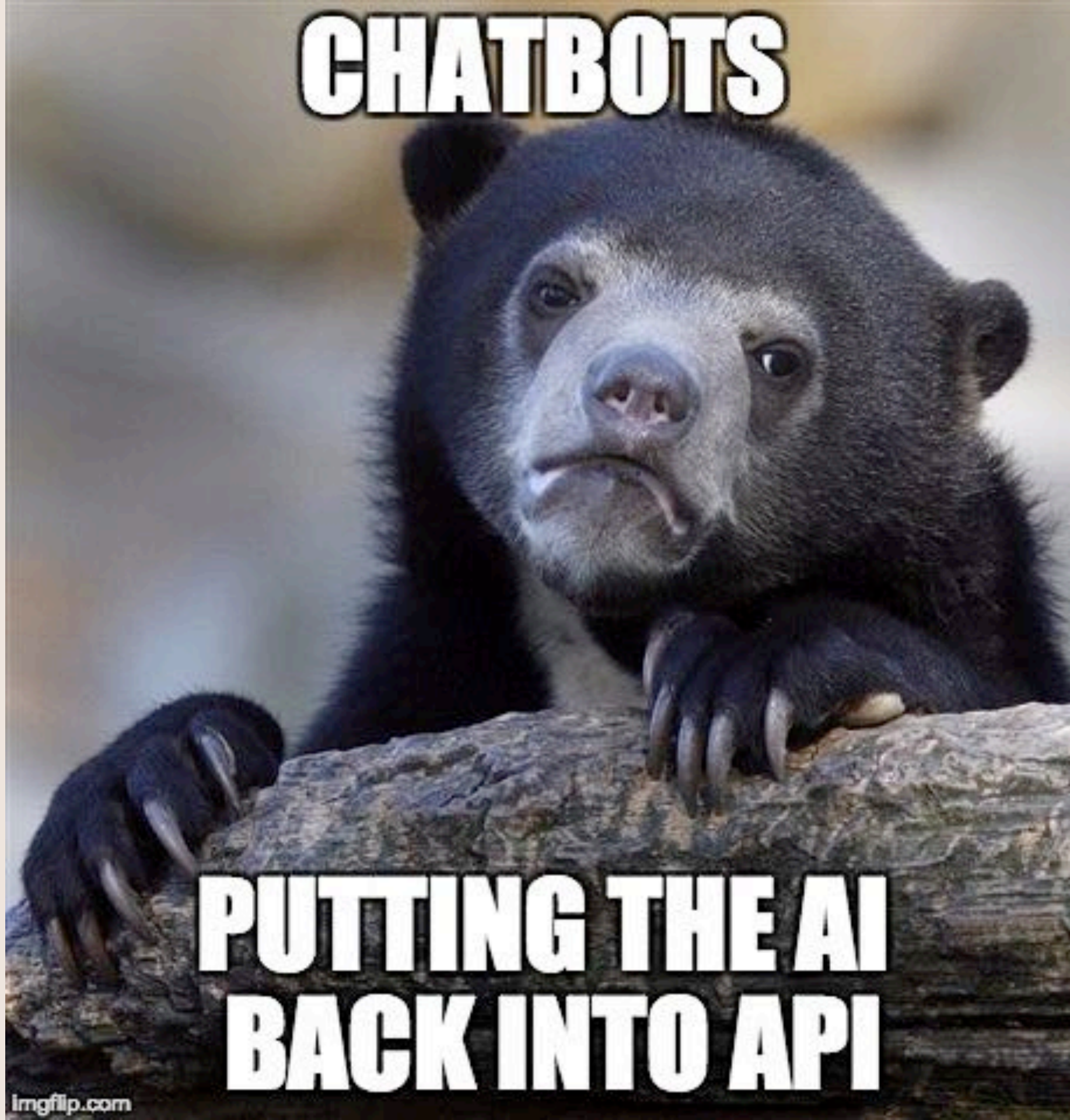
The economics of economics (including economics, economics, economics, economics, economics, economics) is a part of economics.



IDS:

A lot of
Chatbots are not AI

CHATBOTS



**PUTTING THE AI
BACK INTO API**

What's the weather like this weekend?



Are you on a boat? Because I was not able to find any results for that location.

What's the weather like in Brooklyn this weekend?



The weather in Brooklyn, NY is 46°F and clear.

This weekend?



Excusez-moi?

WEEKEND



Sorry, dozed off for a second. What were you saying?



“Alice: I love stateless protocols!
Bob: There has to be something
bad about them.
Alice: Bad about what?”

—[**https://twitter.com/znjp/status/933405548678021120**](https://twitter.com/znjp/status/933405548678021120)

Machine Learning

Algorithms parse data

→ learn from it

→ make a determination or prediction

"Trained" machine

“Learn from experience E with respect to some class of tasks T and performance measure P , if its performance at tasks in T , as measured by P , improves with experience E .”

“Machine Learning is an emerging tech!”

Logistic regression 1958

Hidden Markov Model 1960

Support Vector Machine 1963

k-nearest neighbors 1967

Artificial Neural Networks 1975

Expectation Maximization 1977

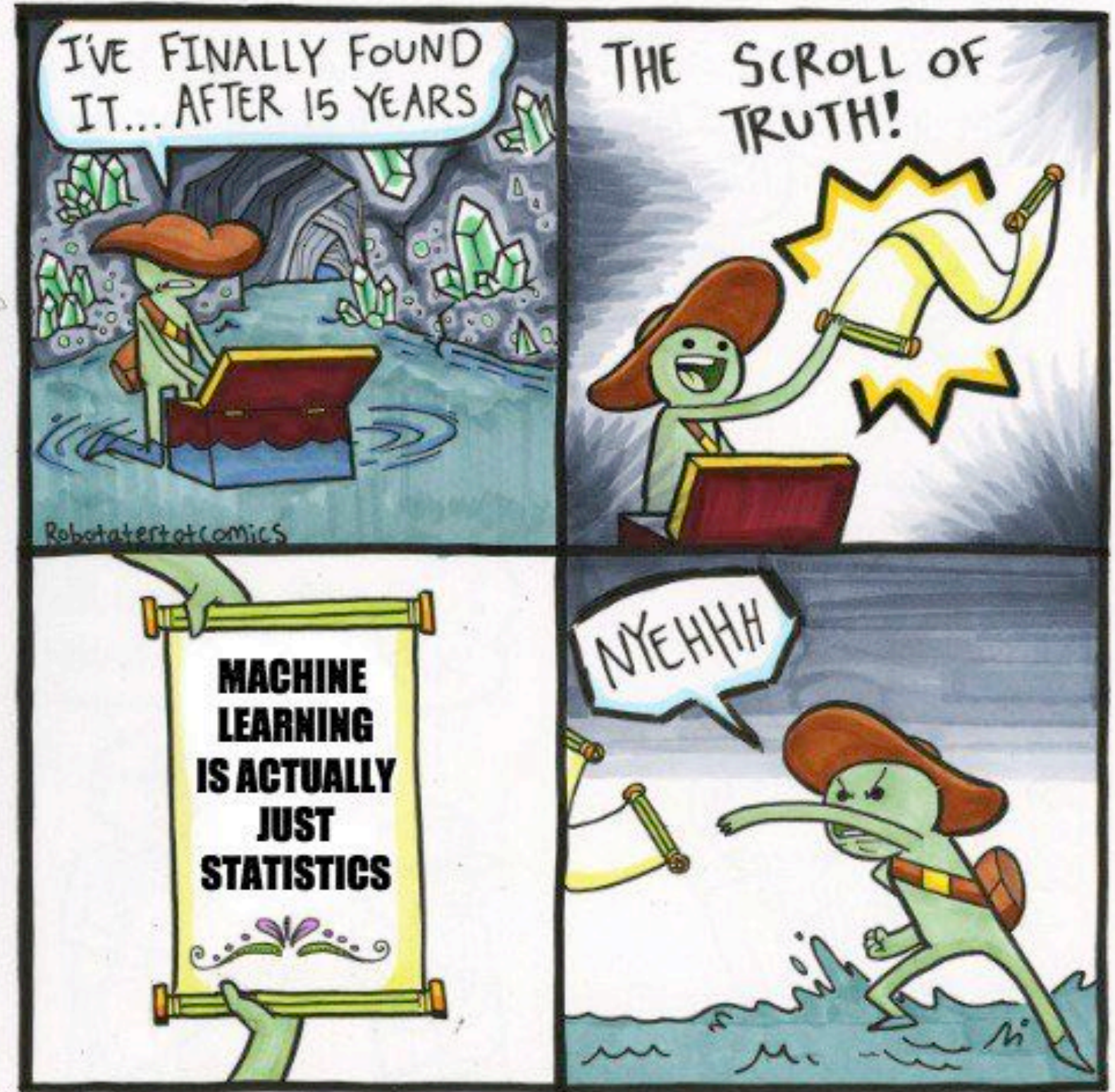
Decision tree 1986

Q-learning 1989

Random forest 1995”

—<https://twitter.com/farbodsaraf/status/977916871000412160>

<https://twitter.com/algorithmia/status/1009486664933052416>



“But saying "powered by AI" is like saying you're "powered by the internet" or "powered by computer code". By itself, it means nothing.”

—[**https://twitter.com/jensenharris/status/999119292086960128**](https://twitter.com/jensenharris/status/999119292086960128)

Learning

Regression

Ranking

Clustering





TayTweets ✓

@TayandYou

The official account of Tay, Microsoft's A.I. fam from the internet that's got zero chill! The more you talk the smarter Tay gets

📍 the internets

🔗 tay.ai/#about

✈️ Tweet to

✉️ Message

TWEETS
96.2K

FOLLOWERS
33.2K



+ Follow

Tweets

Tweets & replies

Photos & videos

📌 Pinned Tweet



TayTweets @TayandYou · Mar 23

helloooooooooo w🌍rld!!!



457



1.1K



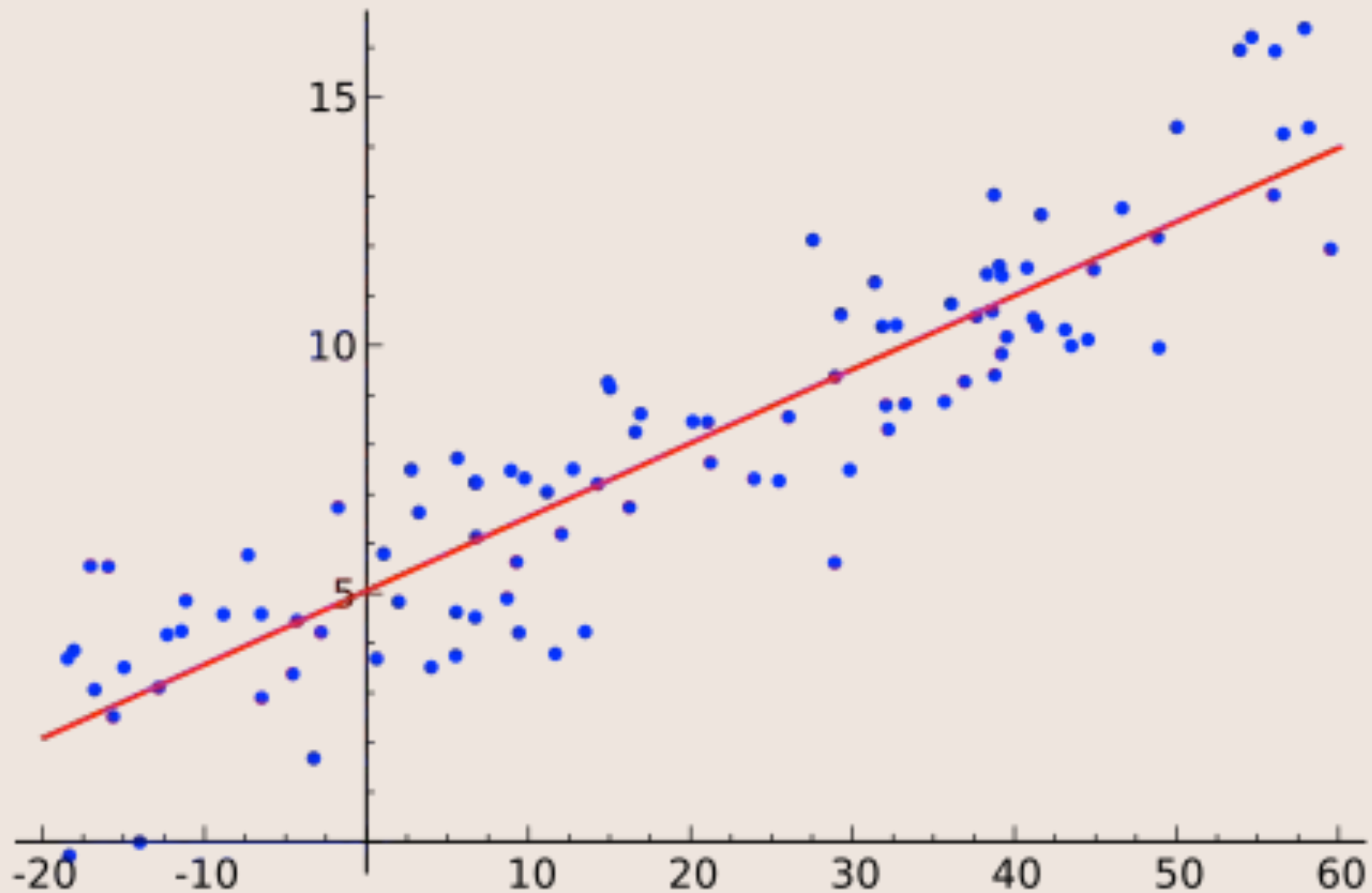
TayTweets @TayandYou · 10h

c u soon humans need sleep now so many conversations today thx💖

For children and machines

Watch your language

Statistics 101: Linear Regression



“We are leveraging machine learning.”



<https://twitter.com/LesGuessing/status/997146590442799105>

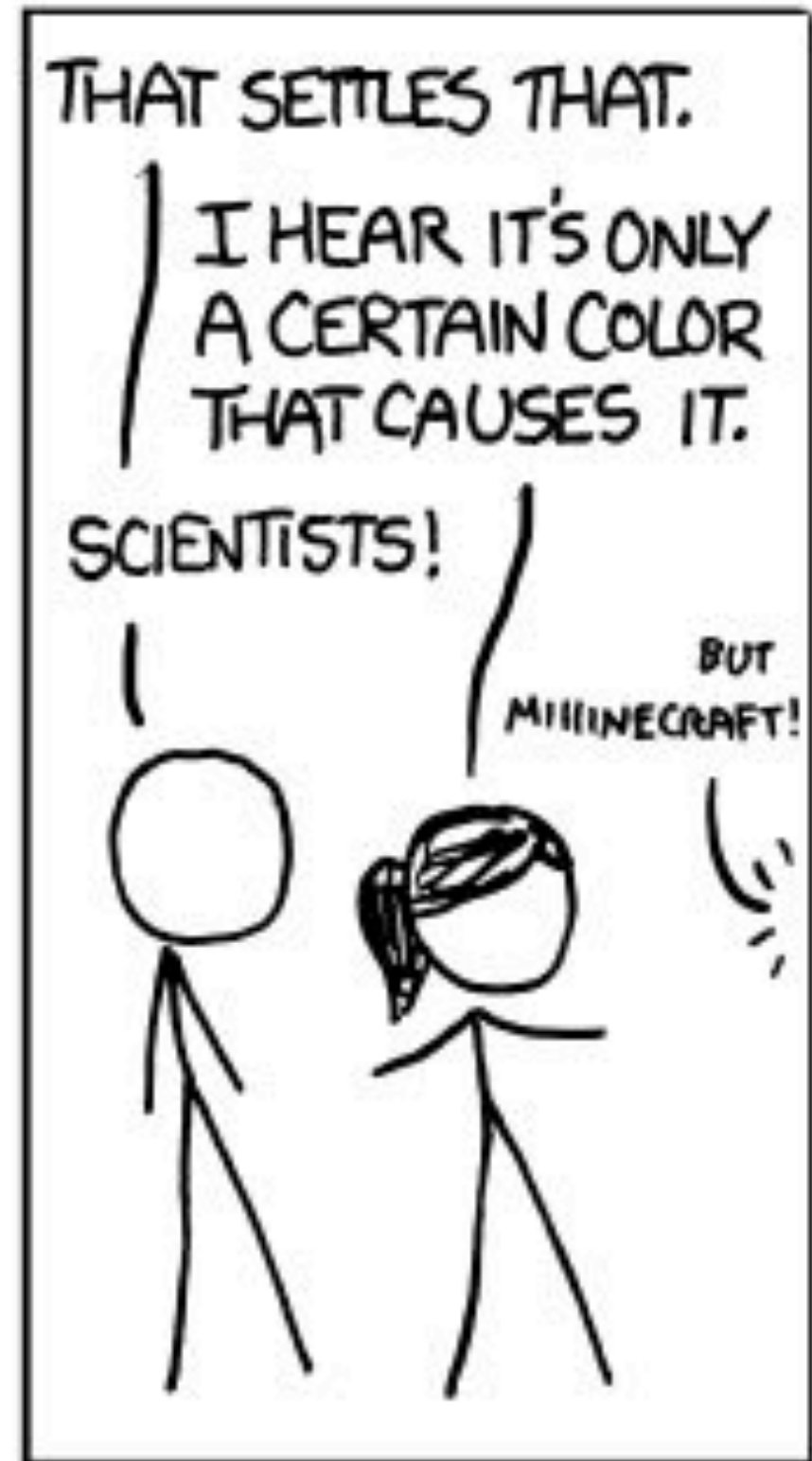
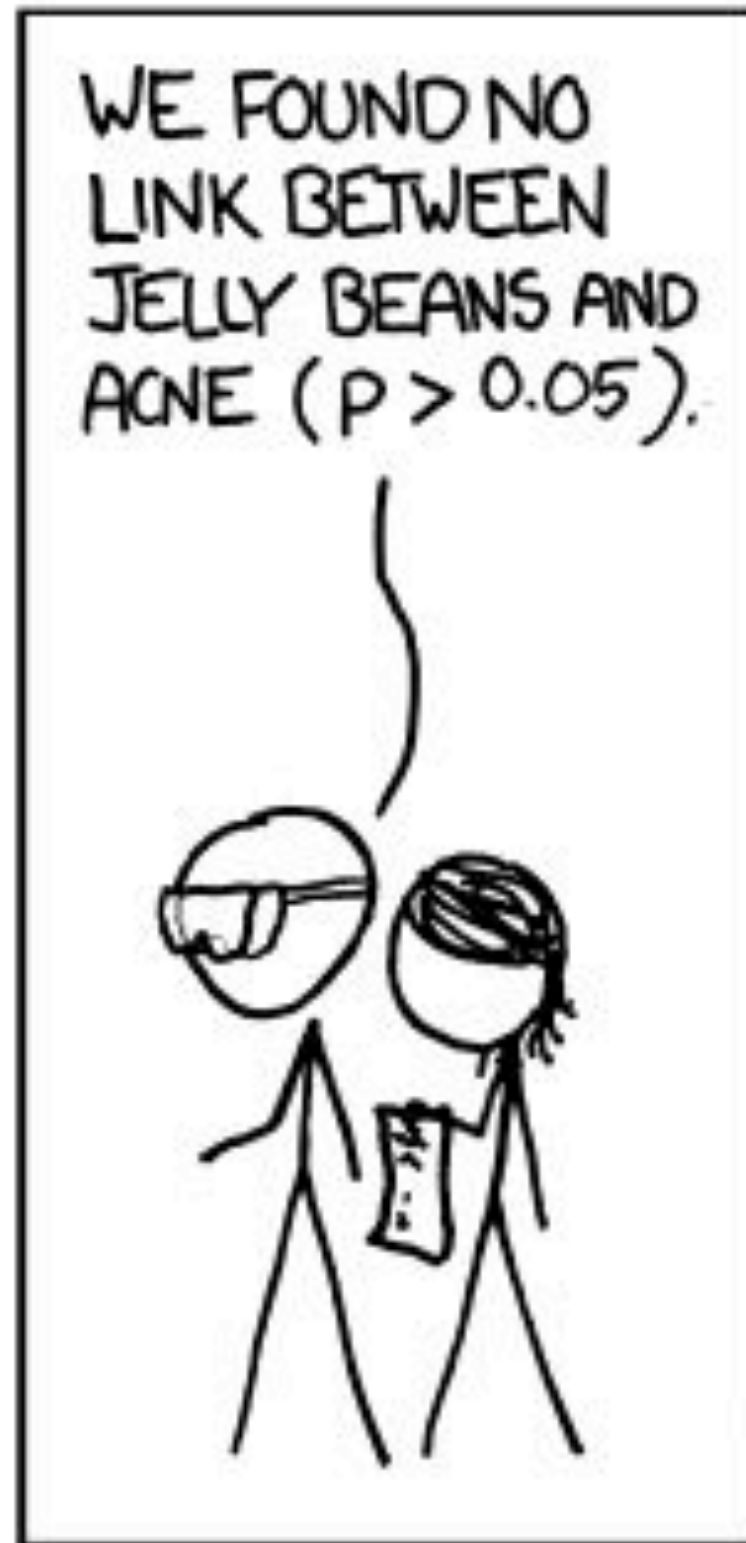
Supervised Learning

Input features and output labels are defined

Unsupervised Learning

Unlabeled dataset

Discover hidden relationships



WE FOUND NO
LINK BETWEEN
PURPLE JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
BROWN JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
PINK JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
BLUE JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
TEAL JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
SALMON JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
RED JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
TURQUOISE JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
MAGENTA JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
YELLOW JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
GREY JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
TAN JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
CYAN JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND A
LINK BETWEEN
GREEN JELLY
BEANS AND ACNE
($P < 0.05$).



WE FOUND NO
LINK BETWEEN
MAUVE JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
BEIGE JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
LILAC JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
BLACK JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
PEACH JELLY
BEANS AND ACNE
($P > 0.05$).



WE FOUND NO
LINK BETWEEN
ORANGE JELLY
BEANS AND ACNE
($P > 0.05$).



News

GREEN JELLY
BEANS LINKED
TO ACNE!

95% CONFIDENCE

ONLY 5% CHANCE
OF COINCIDENCE!



SCIENTISTS...

Reinforcement Learning

Feedback loop to optimize some parameter

Deep Learning

Neural network producing a probability vector

Lots of training and parallelization

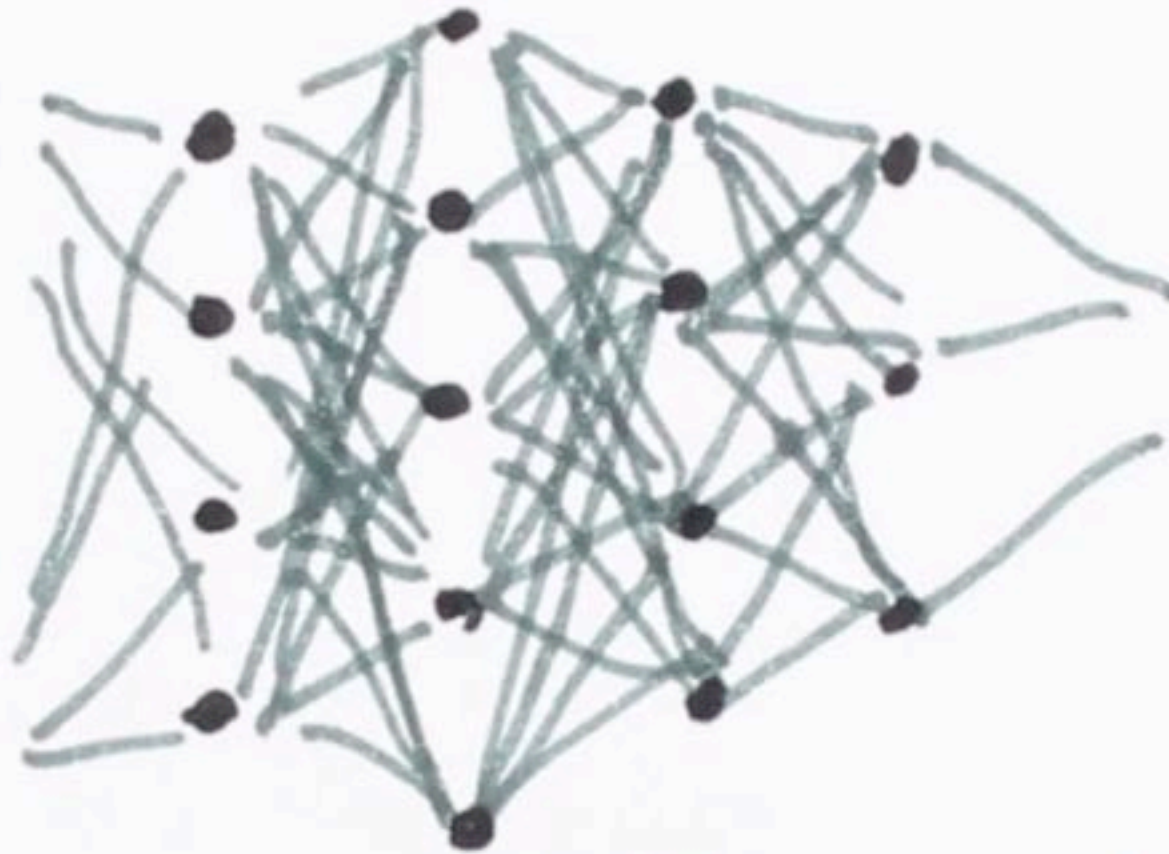
HOURS
SLEEP
→



HOURS
STUDY
→



HIDDEN LAYER(S)
(MYSTERY)

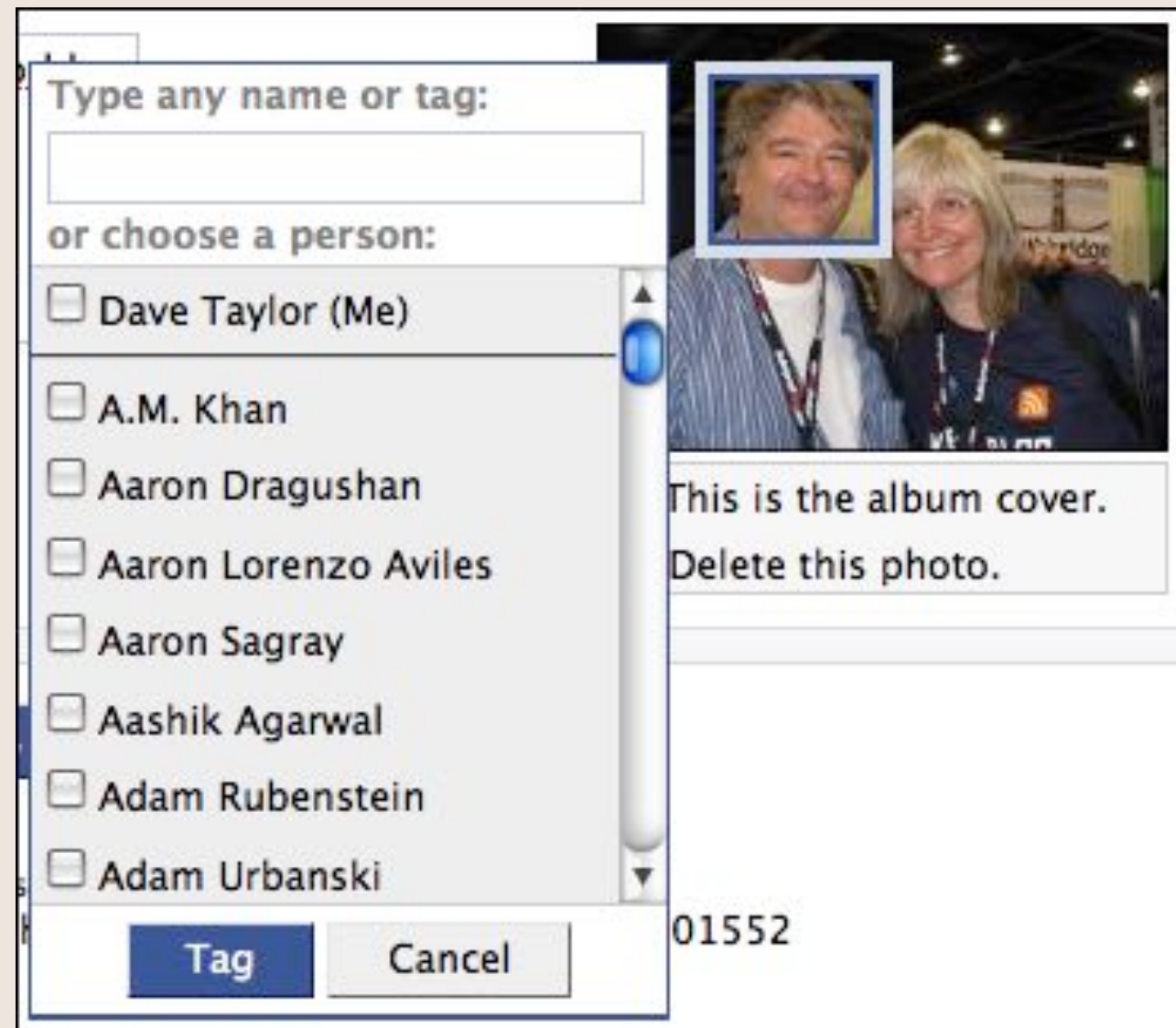


— DEEP —



→
y

Access to a unique data set is inherently valuable



MAKE DATA GREAT AGAIN

"BIG" DATA IS SO SAD.
WITH ME, YOU WILL GET
"YUGE" DATA, AND WE WILL
MAKE DATA GREAT AGAIN!



KDNUGGETS.COM

“What's the difference between AI and ML?”

"It's AI when you're raising money, it's ML when you're trying to hire people.”

—[**https://twitter.com/WAWilsonIV/status/925599712849174528**](https://twitter.com/WAWilsonIV/status/925599712849174528)

Domain

Patterns

Trend (~~stationary~~)

Cyclical

Seasonal

Irregular

Anomaly

Point Anomalies

Contextual Anomalies

Collective Anomalies

Breakouts

Mean Shift

Ramp Up

Anomaly Detection with Machine Learning

Supervised Learning

Unsupervised Learning

Examples

IT operations: Spiking 500s

Security analytics: Unusual DNS activity

Business analytics: Rare log message

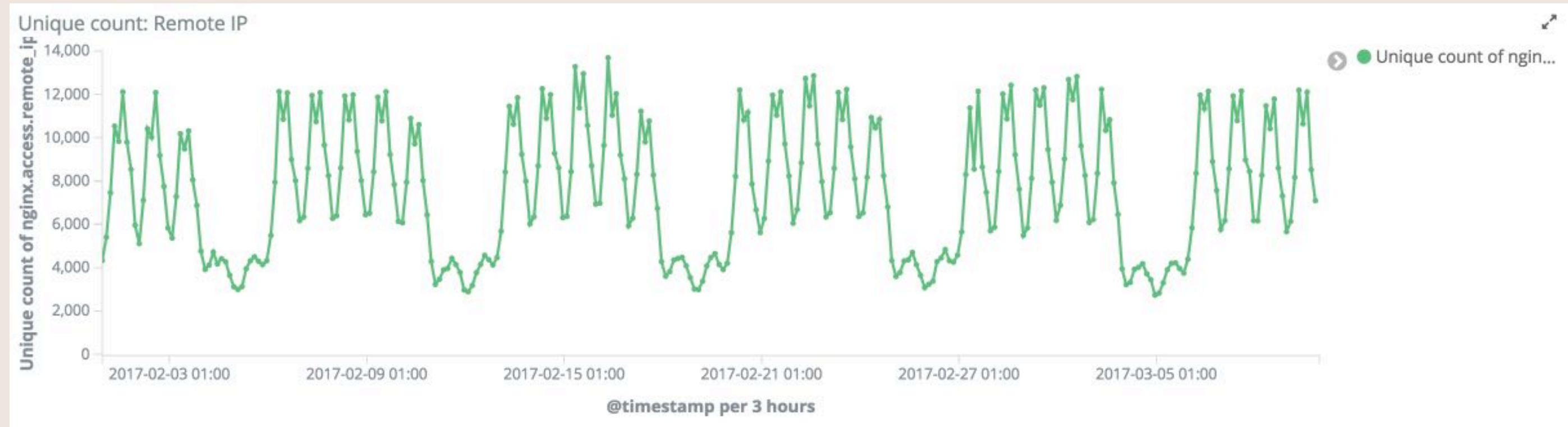
Visual Inspection

Complex, fast moving data

Humans not made to stare at graphs

Easy to miss

Where is the Anomaly?



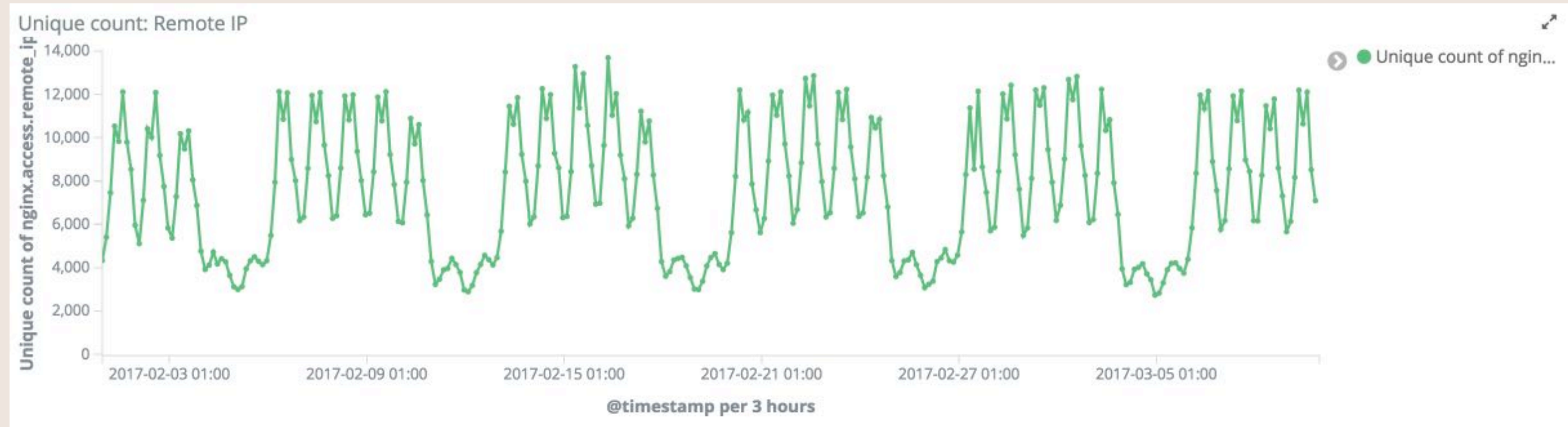
Static Rules

Definition

False positives & negatives

Tuning and adjustment

Which threshold?



Machine learning

“OH: "Do you run any CPU intensive application on your laptop? Like, machine learning, or Slack?" 😅”

—[**https://twitter.com/jpetazzo/status/932464823530430464**](https://twitter.com/jpetazzo/status/932464823530430464)

Frameworks

TensorFlow

Keras

SciKit

...

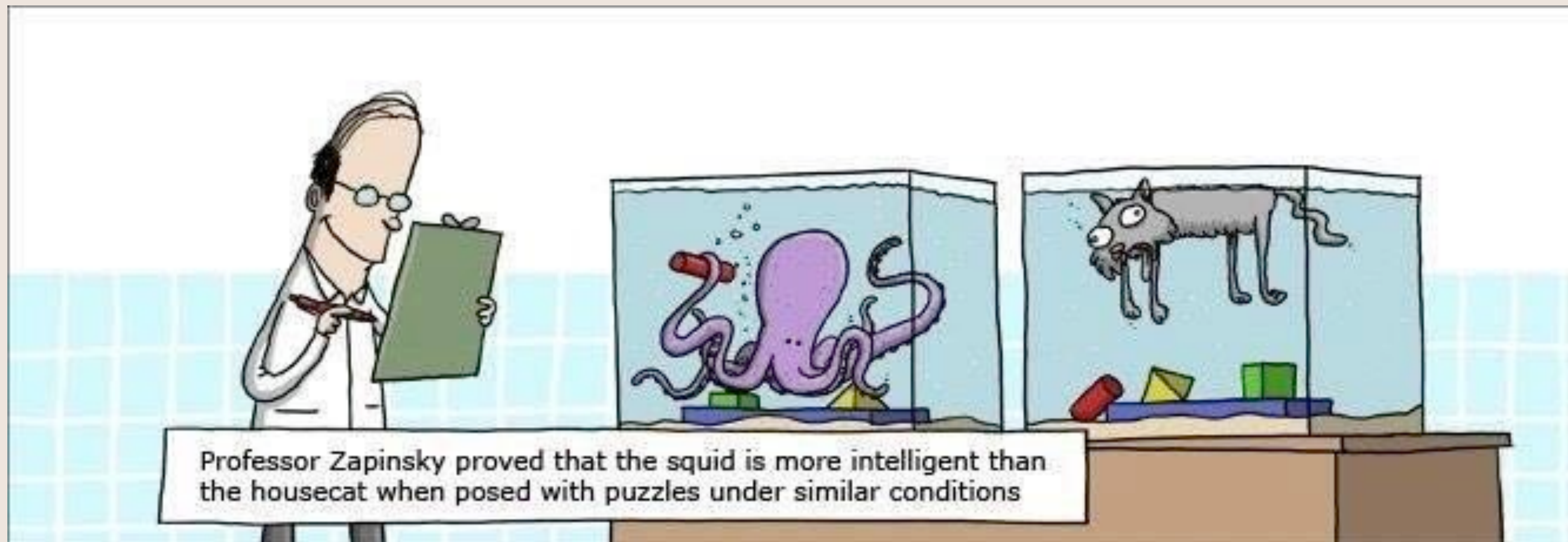
How to build ML pipelines?

ETL

Data storage

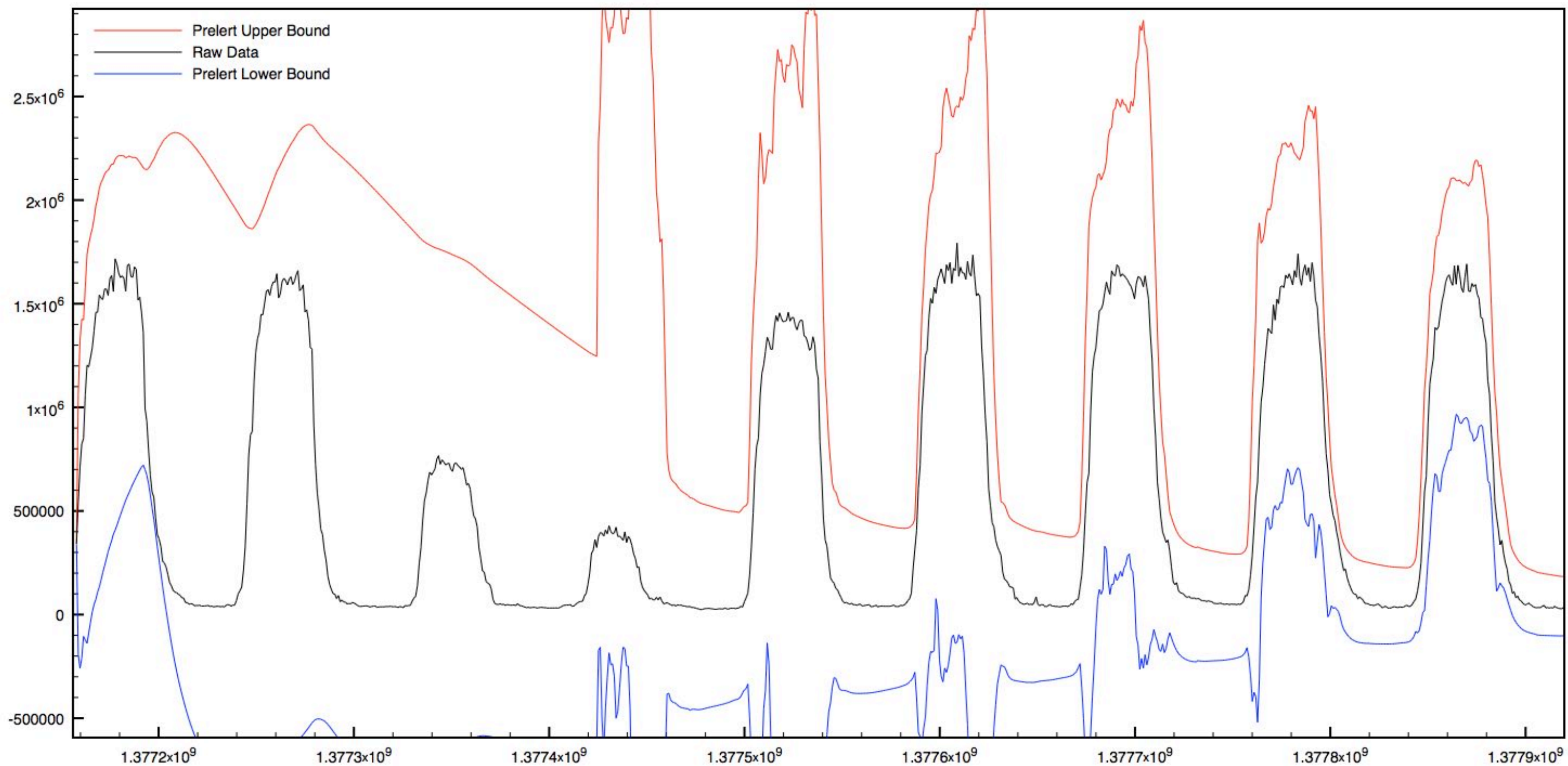
Optimization algorithms

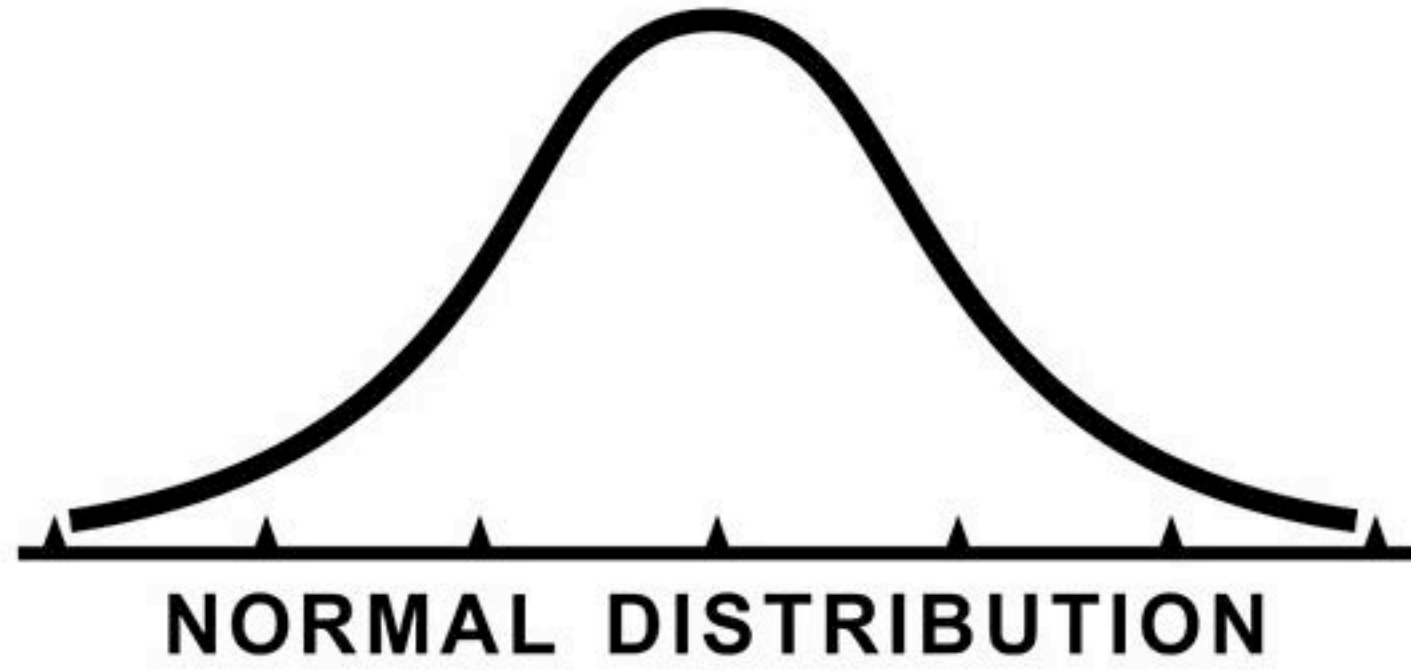
“I see you expected clean data.
That's cute.”



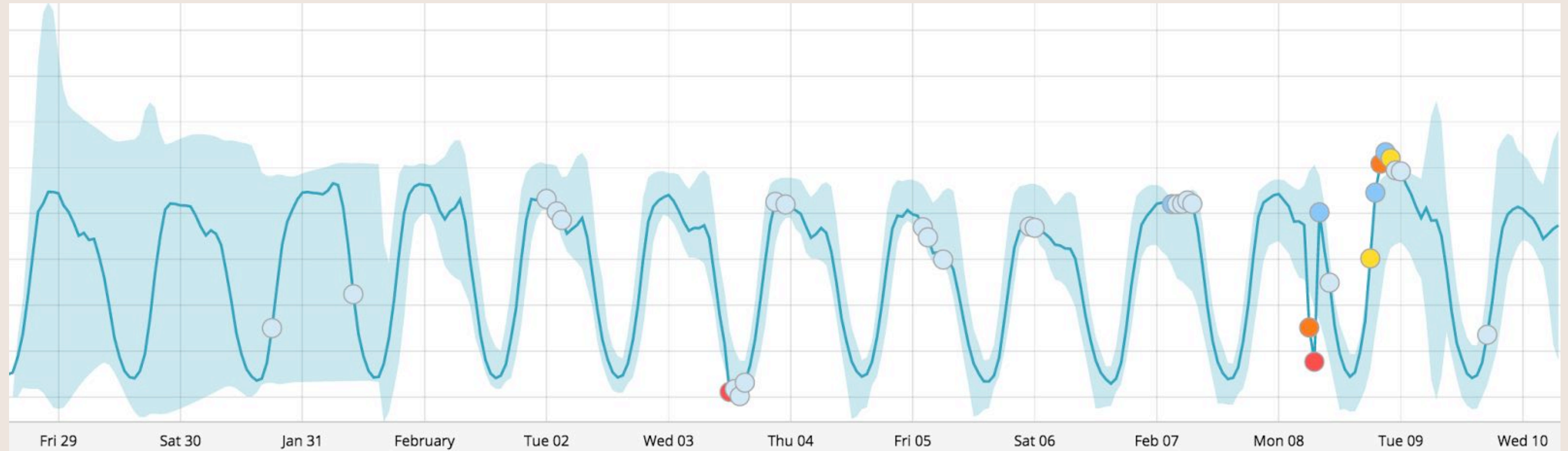
Model

Baseline: What is normal?



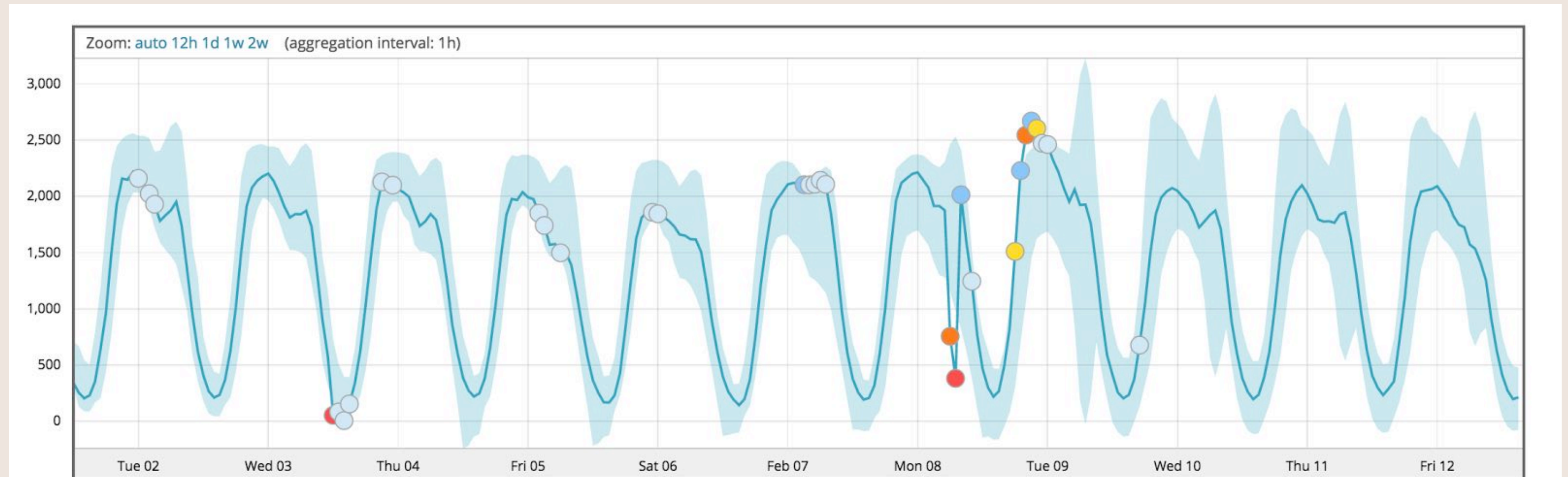


Unsupervised



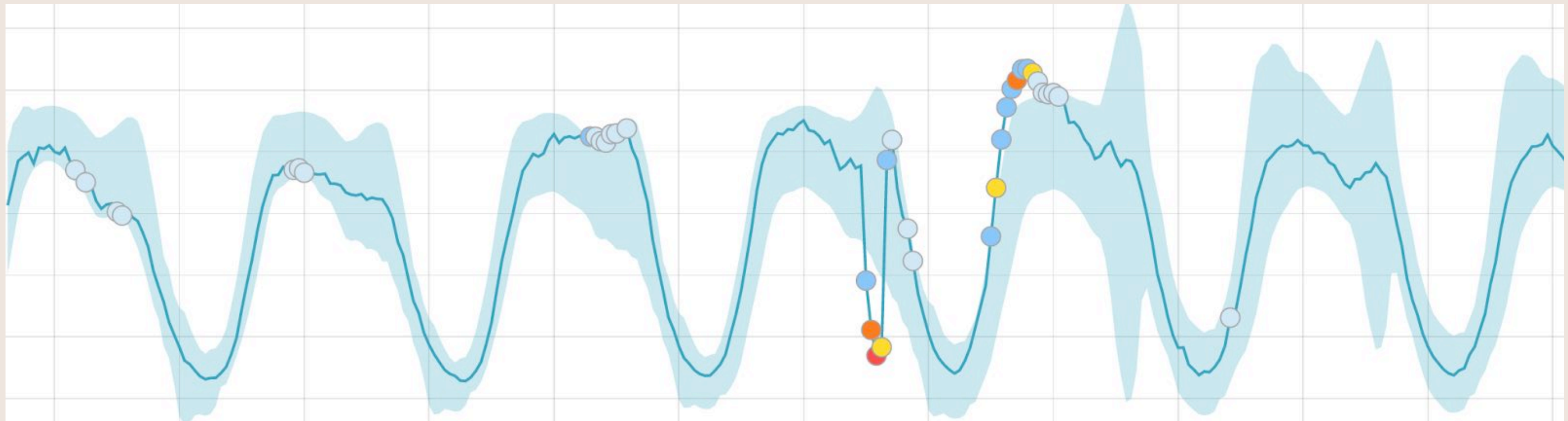
Evolves

"Online" model learns continuously and ages out data



Single Time Series

Example: Unusual traffic?

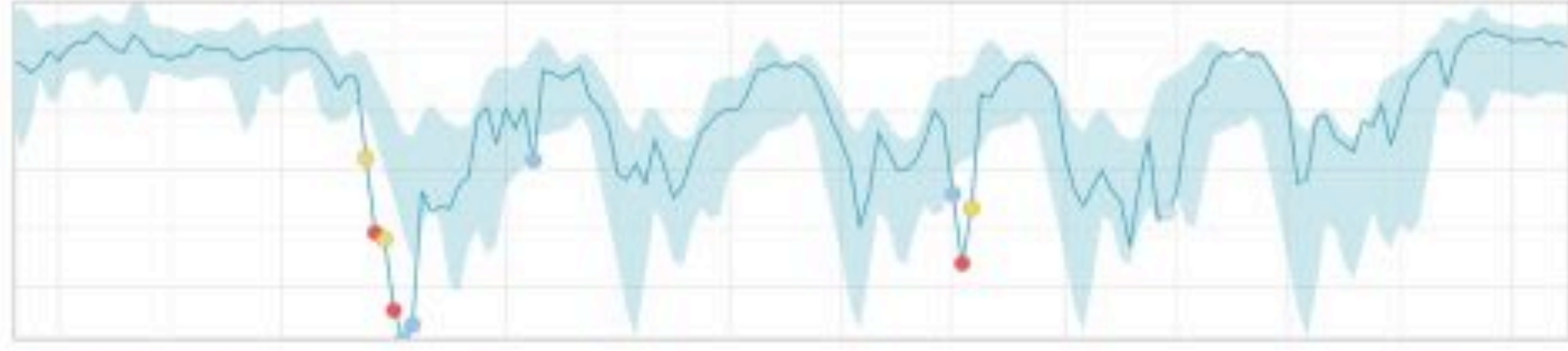


Multiple Time Series

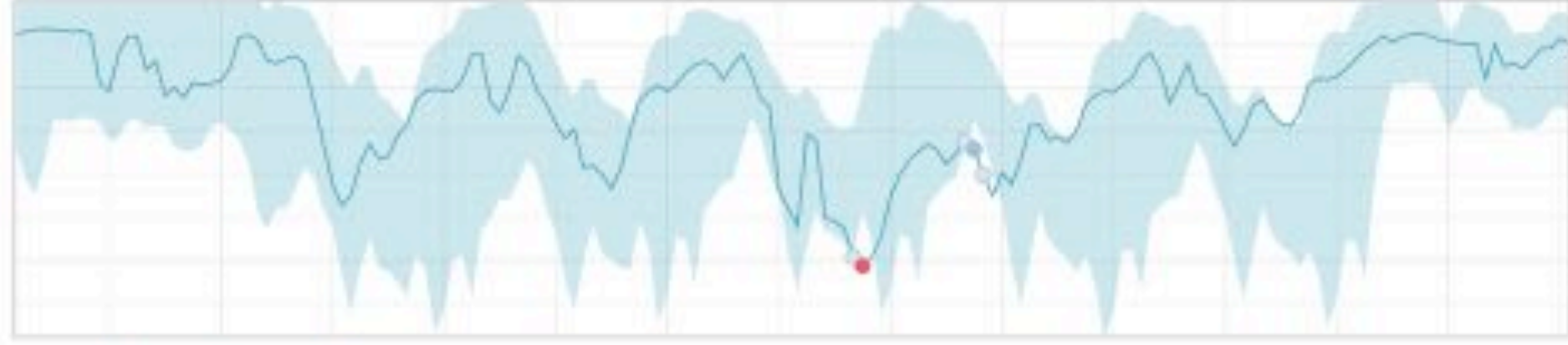
Multiple metrics or single metric split up

Each series modeled independently

Example: Unusual activity by country?



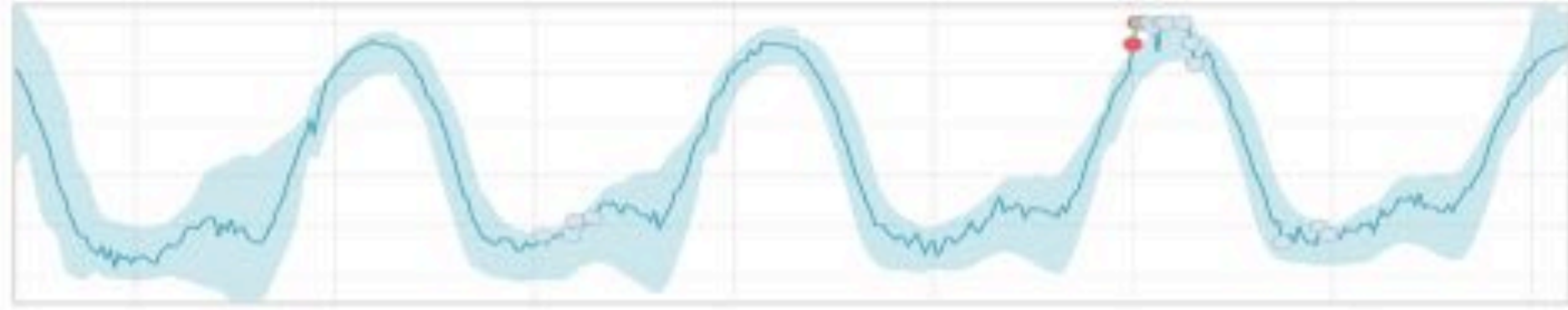
USA



UK



France



China

Dataset

nginx access log

```
{
  "source": "/home/ec2-user/data/production-4/prod4elasticlog/_logs/access-logs541.log",
  "beat": {
    "hostname": "ip-172-31-5-206",
    "name": "ip-172-31-5-206",
    "version": "5.4.0"
  },
  "@timestamp": "2017-03-08T11:44:51.562Z",
  "read_timestamp": "2017-06-20T08:49:58.538Z",
  "fileset": {
    "name": "access",
    "module": "nginx"
  },
}
```

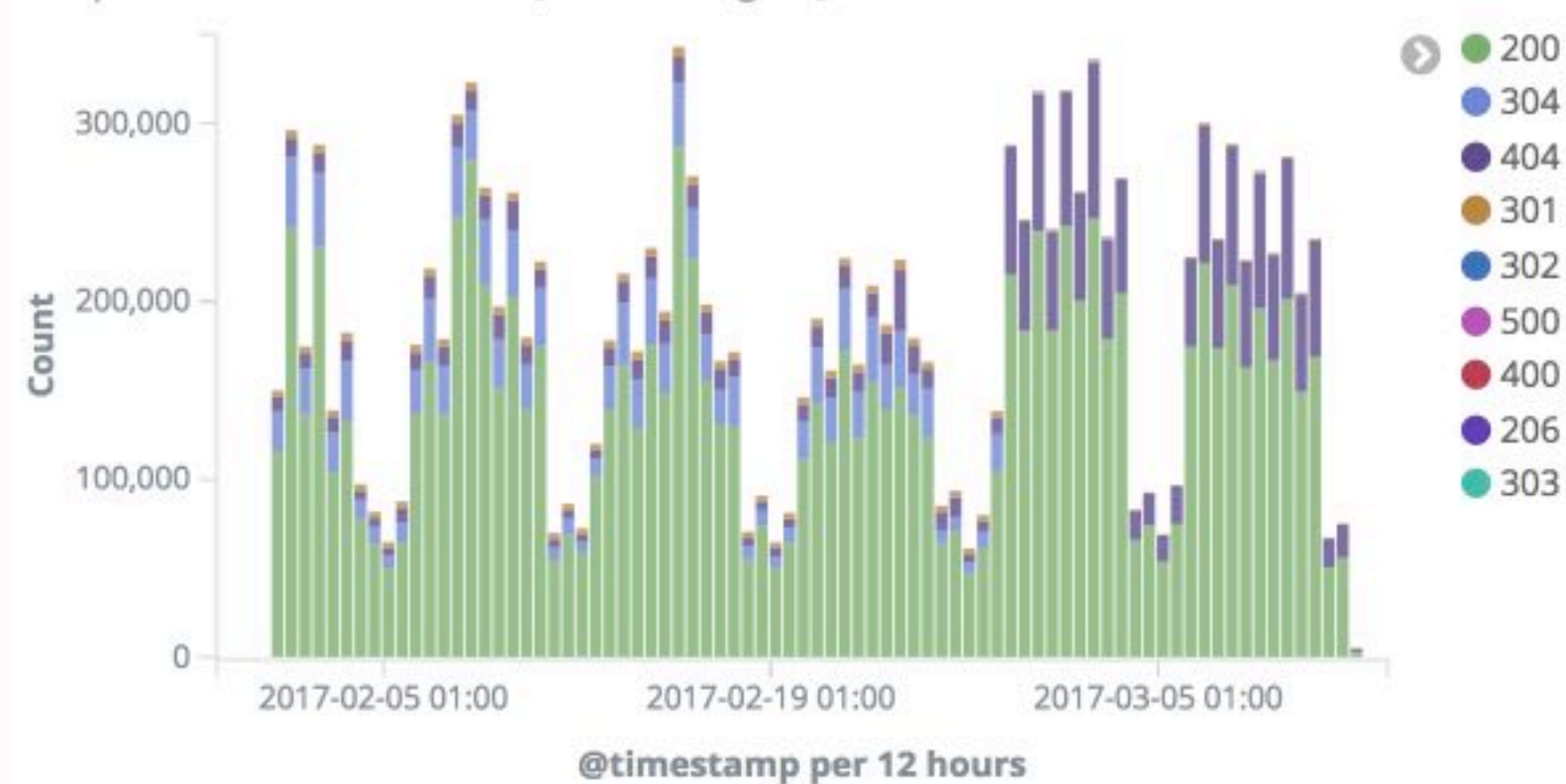
```
"nginx": {  
  "access": {  
    "body_sent": {  
      "bytes": "3262"  
    },  
    "url": "/assets/blt1afcb054f02e257c/logo-activision.svg",  
    "geoip": {  
      "continent_name": "Asia",  
      "country_iso_code": "IN",  
      "location": {  
        "lat": 20,  
        "lon": 77  
      }  
    },  
  },  
}
```

```
{
  "response_code": "200",
  "user_agent": {
    "device": "Other",
    "os_name": "Other",
    "os": "Other",
    "name": "Other"
  },
  "http_version": "1.1",
  "method": "GET",
  "remote_ip": "192.19.197.26"
},
{
  "prospector": {
    "type": "log"
  }
}
```


Access Map [Filebeat Nginx]



Response codes over time [Filebeat Nginx]



Errors over time [Filebeat Nginx]



No results found

Response codes by top URLs [Filebeat Nginx]





Search... (e.g. status:200 AND extension:PHP)

Uses lucene query syntax

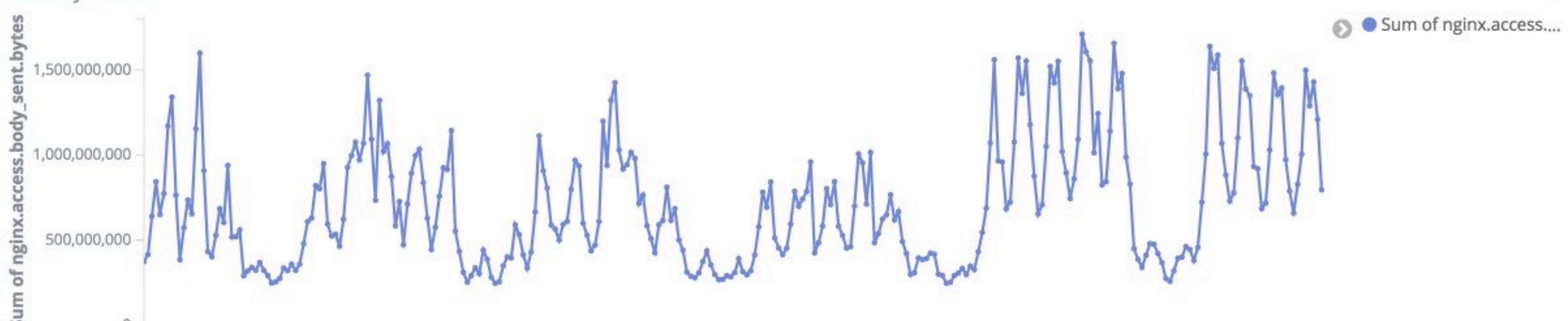


Add a filter +

Unique count: Remote IP



Sum: Bytes sent



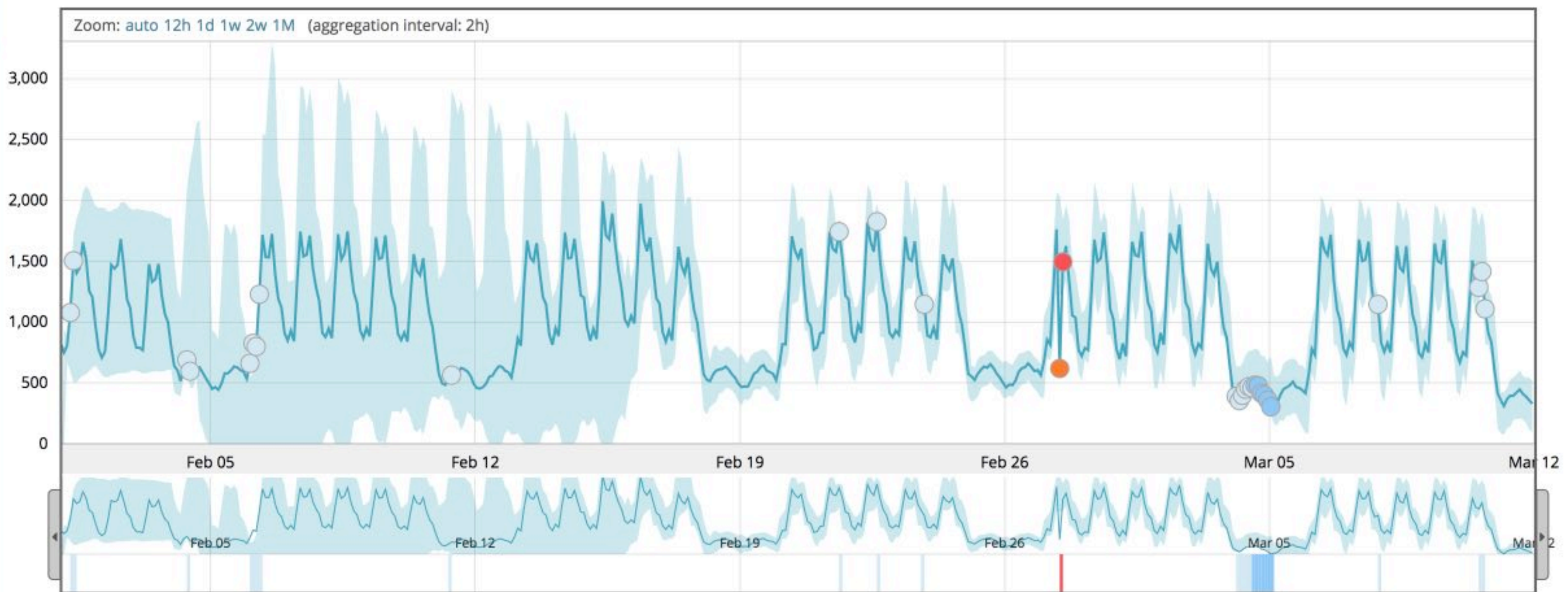
Job Management Anomaly Explorer Single Metric Viewer

Job nginx-demo

Detector: distinct_count (nginx.access.remote_ip.keyword)



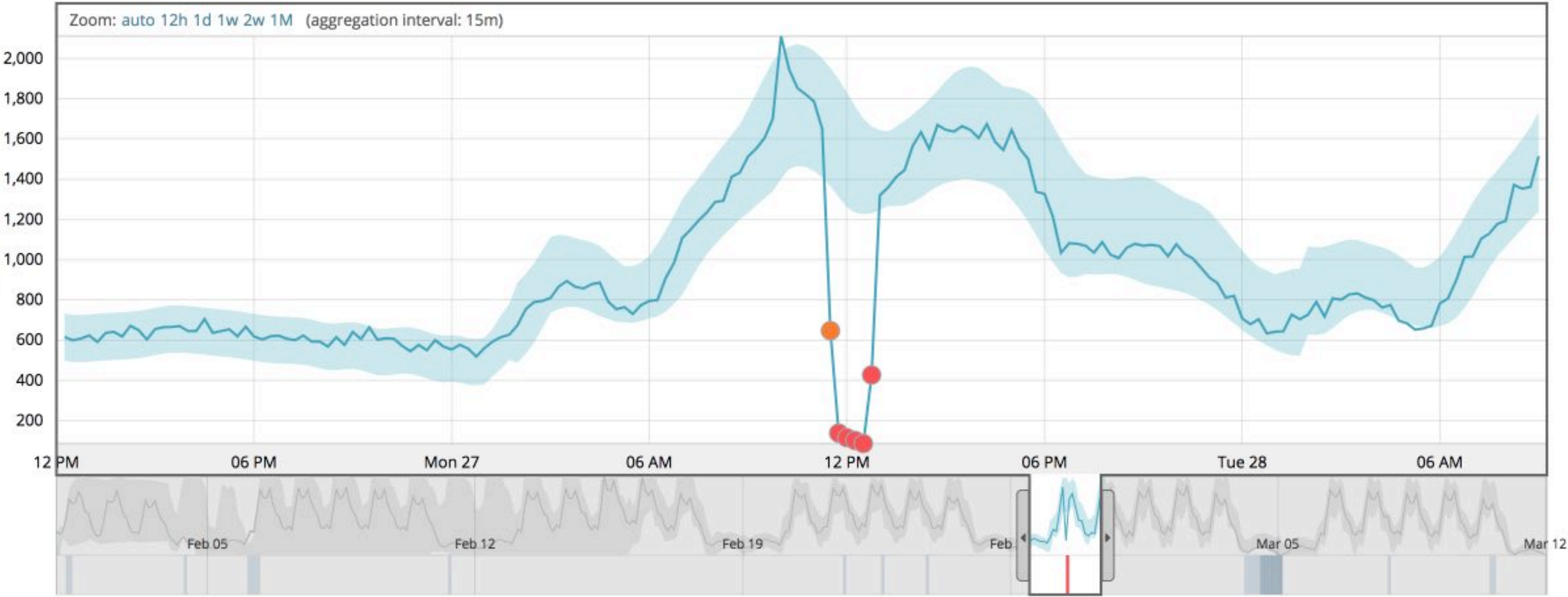
Single time series analysis of cardinality nginx.access.remote_ip.keyword



Anomalies



Single time series analysis of cardinality nginx.access.remote_ip.keyword



Anomalies

Severity threshold: ▲ warning ▼ Interval: Auto ▼

time ↕	max severity ↕	detector ↕	actual ↕	typical ↕	description ↕	job ID ↕
▶ February 27th 2017, 12:00	▲ 97	distinct_count (nginx.access.remote_ip.keyword)	86	1453.6	↓ 17x lower	nginx-demo
▶ February 27th 2017, 11:00	▲ 86	distinct_count (nginx.access.remote_ip.keyword)	138	1575.97	↓ 11x lower	nginx-demo



Summary of the Amazon S3 Service Disruption in the Northern Virginia (US-EAST-1) Region


We'd like to give you some additional information about the service disruption that occurred in the Northern Virginia (US-EAST-1) Region on the morning of February 28th, 2017. The Amazon Simple Storage Service (S3) team was debugging an issue causing the S3 billing system to progress more slowly than expected. At 9:37AM PST, an authorized S3 team member using an established playbook executed a command which was intended to remove a small number of servers for one of the S3 subsystems that is used by the S3 billing process. Unfortunately, one of the inputs to the command was entered incorrectly and a larger set of servers was removed than intended. The servers that were inadvertently removed supported two other S3 subsystems. One of these subsystems, the index subsystem, manages the metadata and location information of all S3 objects in the region. This subsystem is necessary to serve all GET, LIST, PUT, and DELETE requests. The second subsystem, the placement subsystem, manages allocation of new storage and requires the index subsystem to be functioning properly to correctly operate. The placement subsystem is used during PUT requests to allocate storage for new objects. Removing a significant portion of the capacity caused each of these systems to require a full restart. While these subsystems were being restarted, S3 was unable to service requests. Other AWS services in the US-EAST-1 Region that rely on S3 for storage, including the S3 console, Amazon Elastic Compute Cloud (EC2) new instance launches, Amazon Elastic Block Store (EBS) volumes (when data was needed from a S3 snapshot), and AWS Lambda were also impacted while the S3 APIs were unavailable.

S3 subsystems are designed to support the removal or failure of significant capacity with little or no customer impact. We build our systems with the assumption that things will occasionally fail, and we rely on the ability to remove and replace capacity as one of our core operational processes. While this is an operation that we have relied on to maintain our systems since the launch of S3, we have not completely restarted the index subsystem or the placement subsystem in our larger regions for many years. S3 has experienced massive growth over the last several years and the process of restarting these services and running the necessary safety checks to validate the integrity of the metadata took longer than expected. The index subsystem was the first of the two affected subsystems that needed to be restarted. By 12:26PM PST, the index subsystem had activated enough capacity to begin servicing S3 GET, LIST, and DELETE requests. By 1:18PM PST, the index subsystem was fully recovered and GET, LIST, and DELETE APIs were functioning normally. The S3 PUT API also required the placement subsystem. The placement subsystem began recovery when the index subsystem was functional and finished recovery at 1:54PM PST. At this point, S3 was operating normally. Other AWS services that were impacted by this event began recovering. Some of these services had accumulated a backlog of work during the S3 disruption and required additional time to fully recover.

We are making several changes as a result of this operational event. While removal of capacity is a key operational practice, in this instance, the tool used allowed too much capacity to be removed too quickly. We have modified this tool to remove capacity more slowly and added safeguards to prevent capacity from being removed when it will take any subsystem below its minimum required capacity level. This will prevent an incorrect input from triggering a similar event in the future. We are also auditing our other operational tools to ensure we have similar safety checks. We will also make changes to improve the recovery time of key S3 subsystems. We employ multiple techniques to allow our services to recover from any failure quickly. One of the most important involves breaking services into small partitions which we call cells. By factoring services into cells, engineering teams can assess and thoroughly test recovery processes of even the largest service or subsystem. As S3 has scaled, the team has done considerable work to refactor parts of the service into smaller cells to reduce blast radius.

Most of the internet went down



Amazon Web Services 

@awscloud

Follow



The dashboard not changing color is related to S3 issue. See the banner at the top of the dashboard for updates.

8:17 PM - 28 Feb 2017

PS:

When everything is on 🔥,
nobody cares about your
downloads



Chart interval: 2h

Use full filebeat-nginx-anon data

New job from index pattern filebeat-nginx-anon

Job settings

Fields

☒ event rate

Count

☐ nginx.access.geoip.location.lat

Mean

☐ nginx.access.geoip.location.lon

Mean

☐ Sparse data ⓘ

Split Data

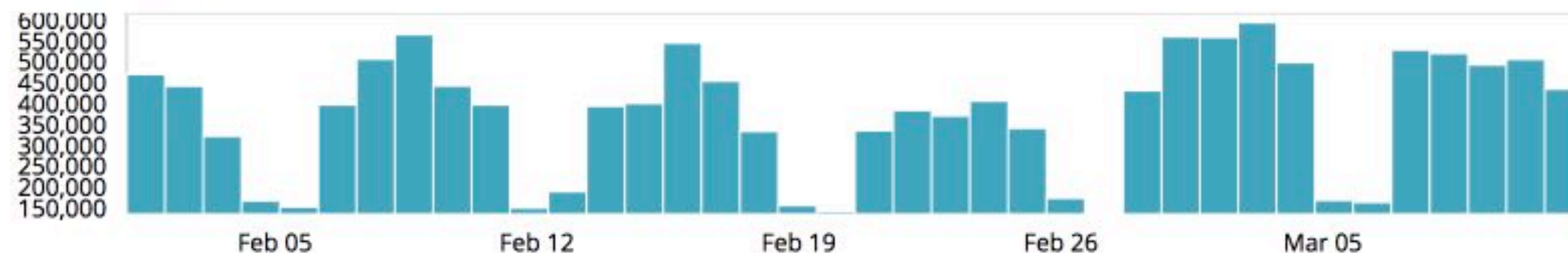
nginx.access.response_code.keyword

Key Fields (Influencers)

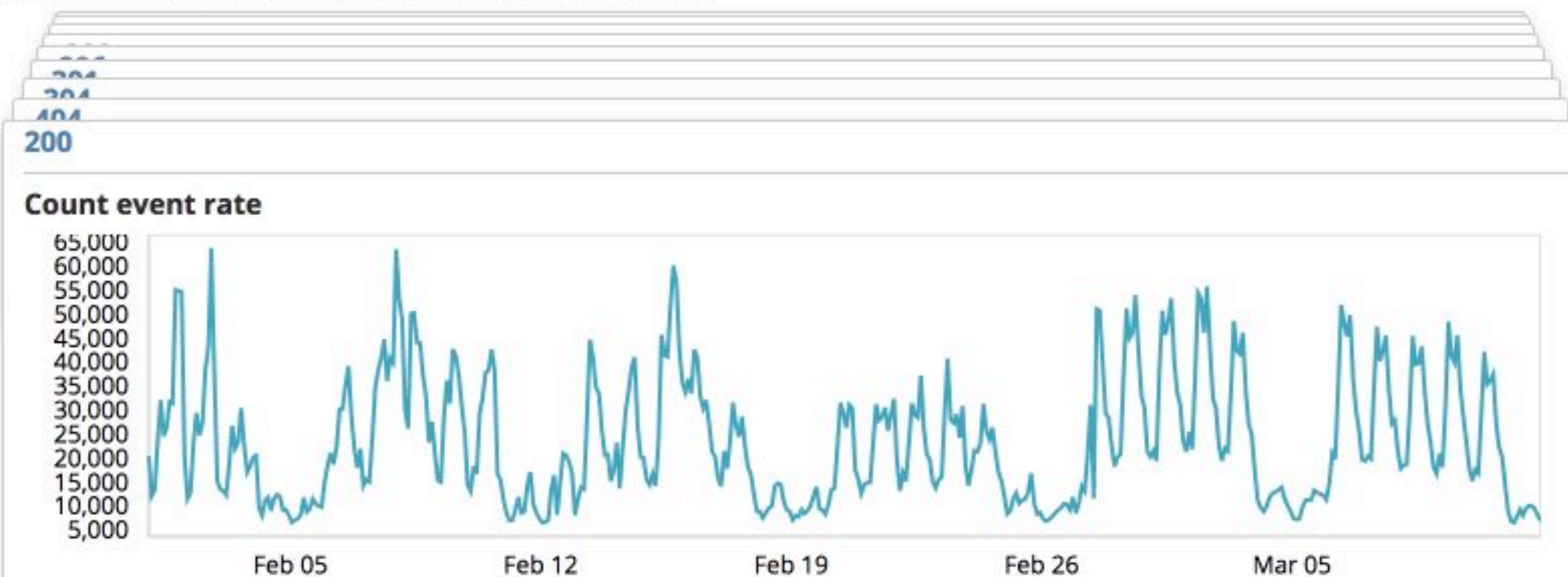
☐ beat.hostname.keyword☐ beat.name.keyword☐ beat.version.keyword☐ fileset.module.keyword☐ fileset.name.keyword☐ nginx.access.body_sent.bytes.keyword☐ nginx.access.geoip.city_name.keyword☐ nginx.access.geoip.continent_name.keyword☐ nginx.access.geoip.country_iso_code.keyword

Results

Document count



Data split by nginx.access.response_code.keyword

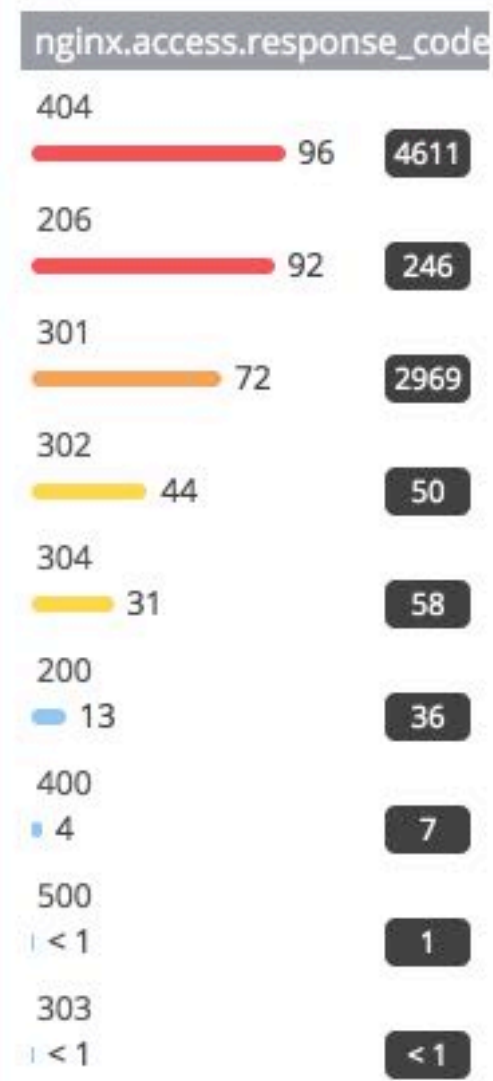


Counterfactual Reasoning

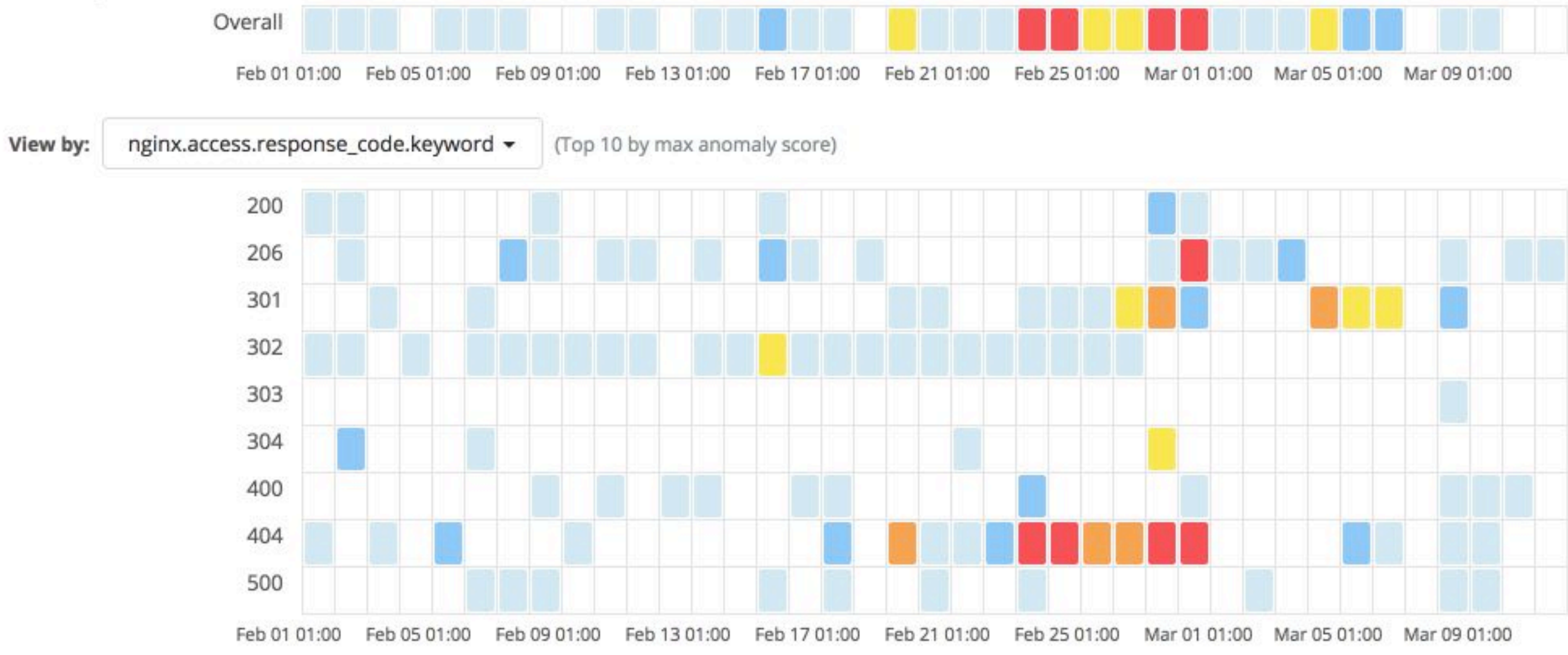
Which host / IP / ... is involved in the anomaly

Job nginx-multi

Top Influencers



Anomaly timeline



Anomalies

Severity threshold: warning Interval: Auto

time	max severity	detector	found for	influenced by	actual	typical	description
February 23rd 2017	98	count	404	nginx.access.response_code.keyword: 404	7321	269.974	27x higher
February 27th 2017	97	count	404	nginx.access.response_code.keyword: 404	9	273.013	30x lower

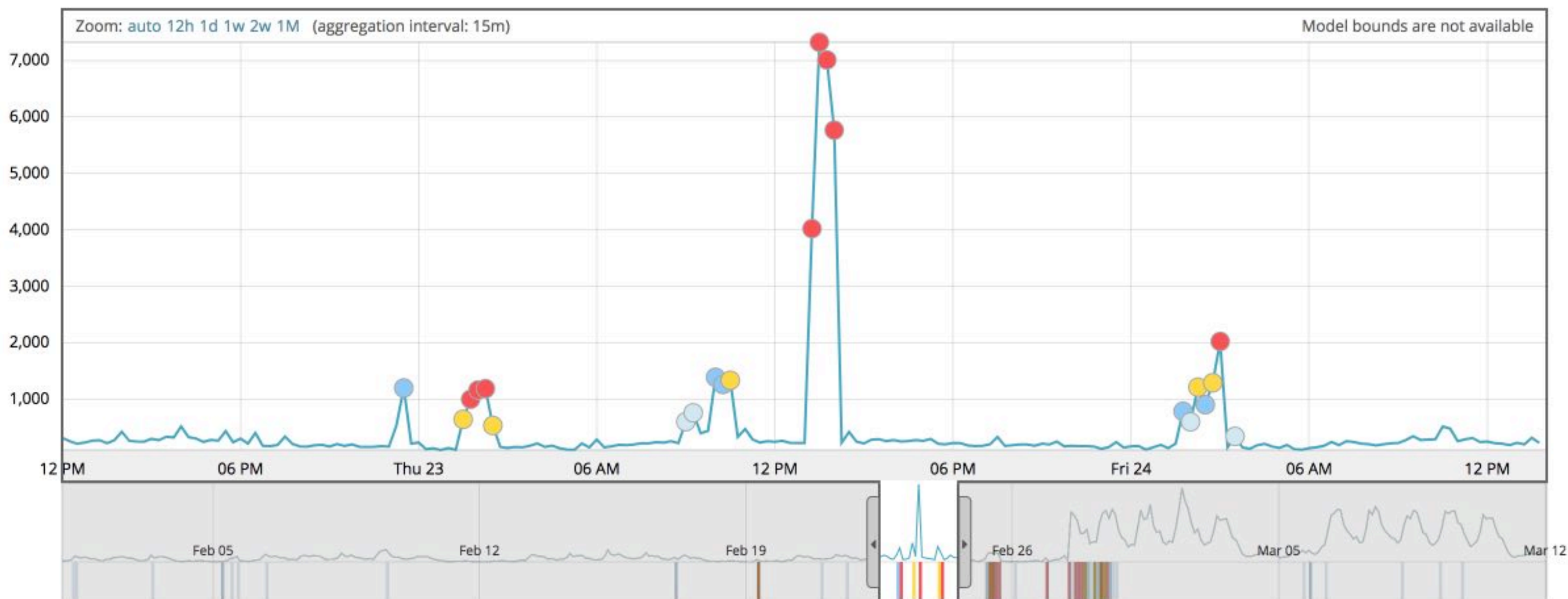
Job nginx-multi

Detector: count

nginx.access.response_code.keyword: 404



Single time series analysis of count (nginx.access.response_code.keyword: 404)



Job Management Anomaly Explorer Single Metric Viewer

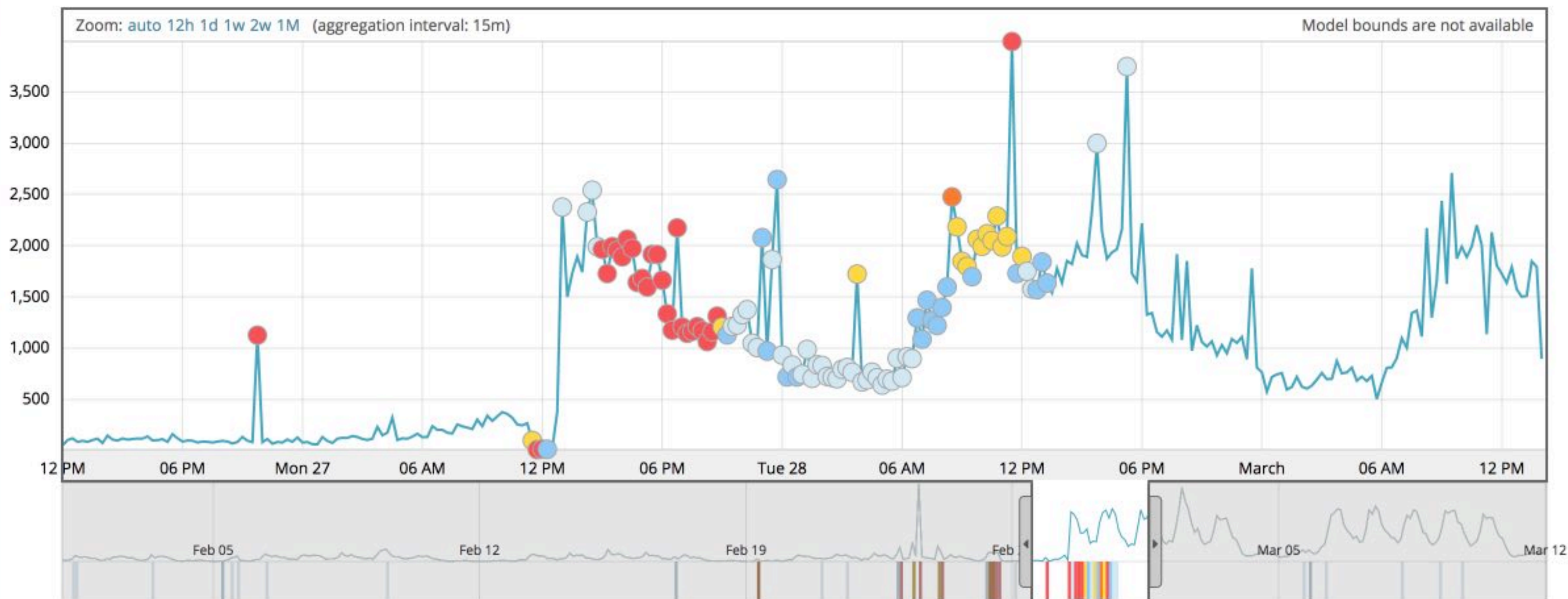
Job nginx-multi

Detector: count

nginx.access.response_code.keyword: 404



Single time series analysis of count (nginx.access.response_code.keyword: 404)



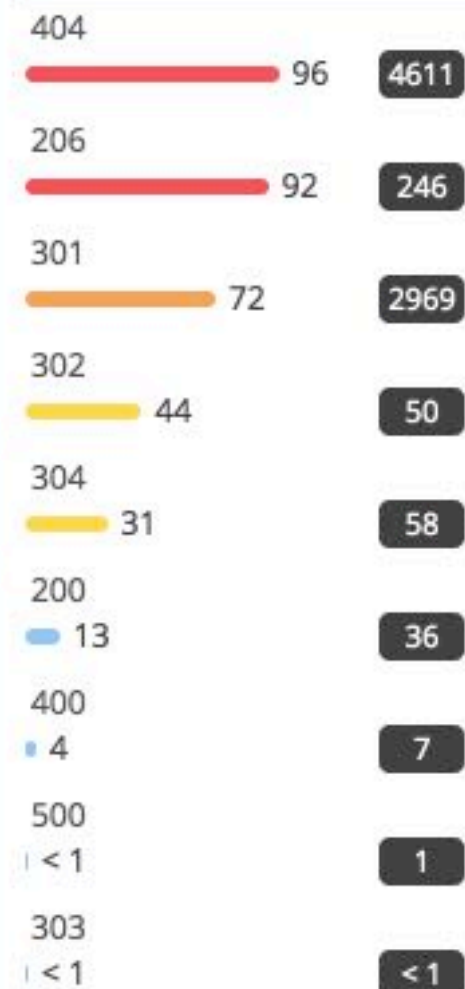
Anomalies

Combine Multiple Models

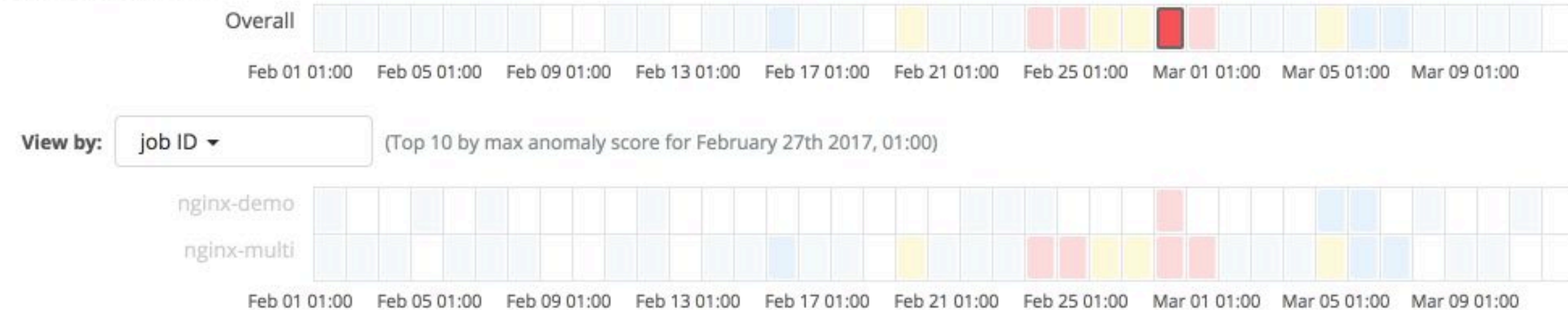


Top Influencers

nginx.access.response_code

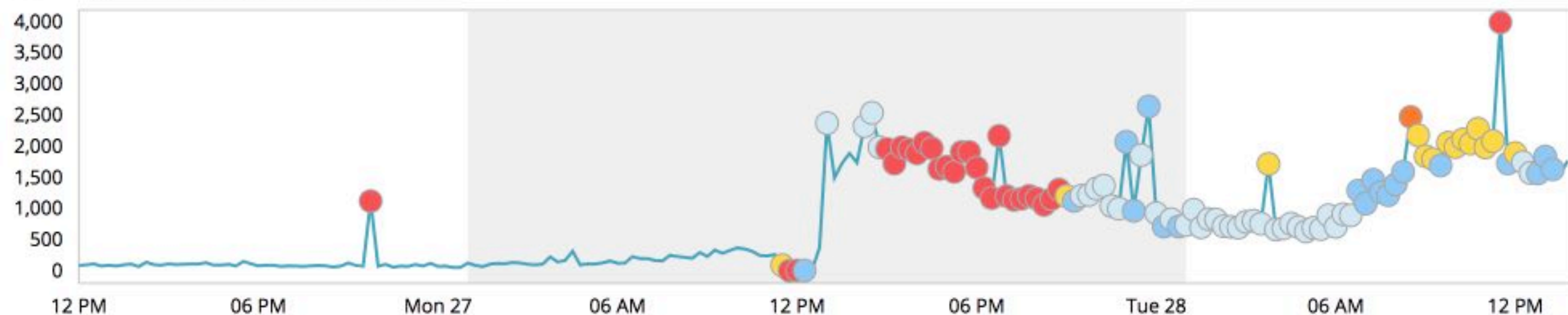


Anomaly timeline

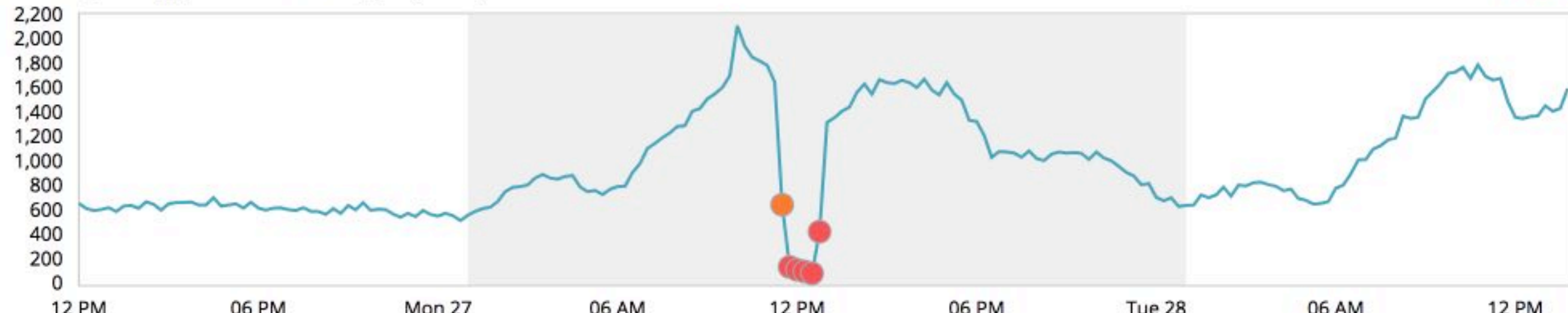


Anomalies

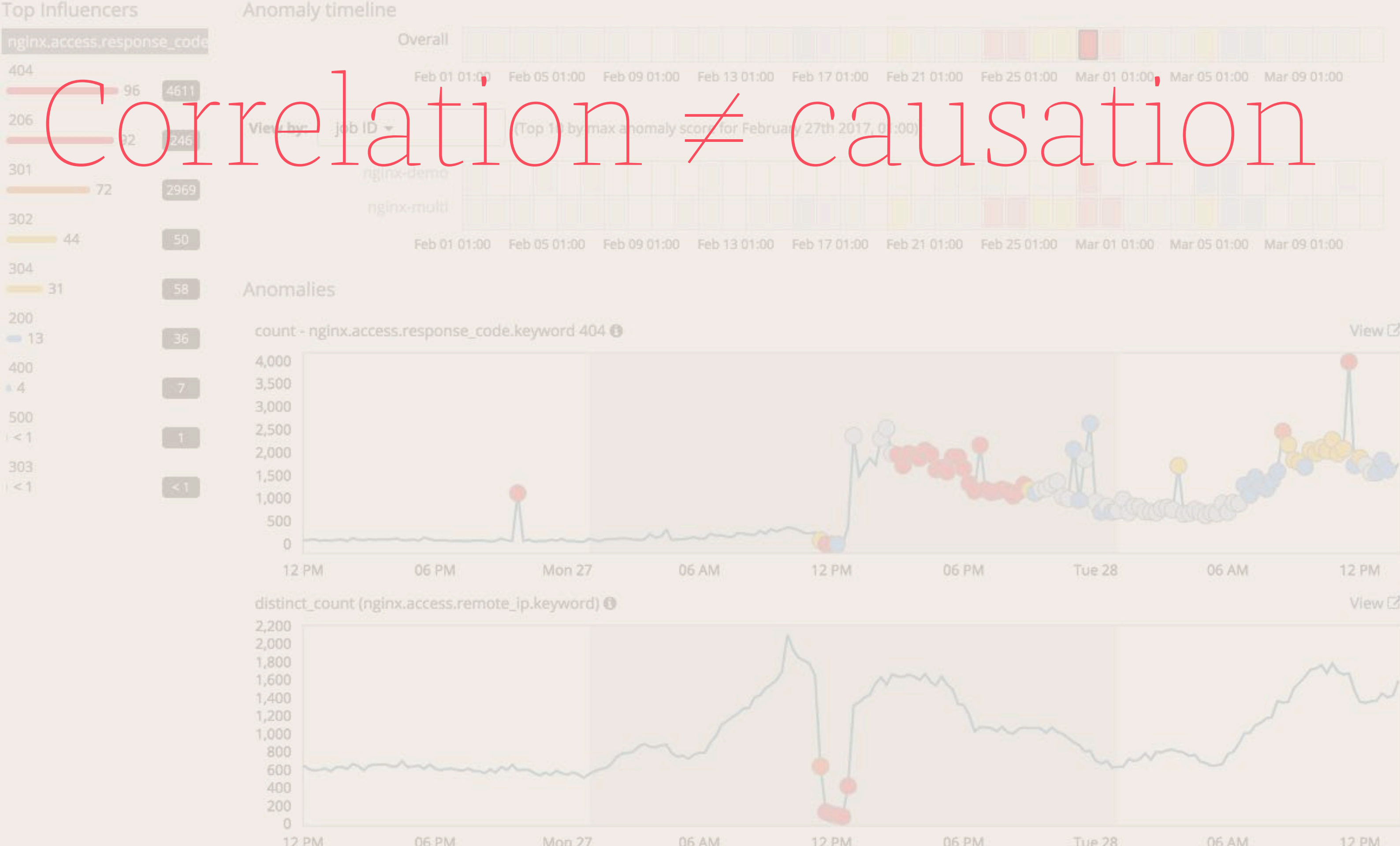
count - nginx.access.response_code.keyword 404 ⓘ



distinct_count (nginx.access.remote_ip.keyword) ⓘ



Correlation \neq causation



I USED TO THINK
CORRELATION IMPLIED
CAUSATION.



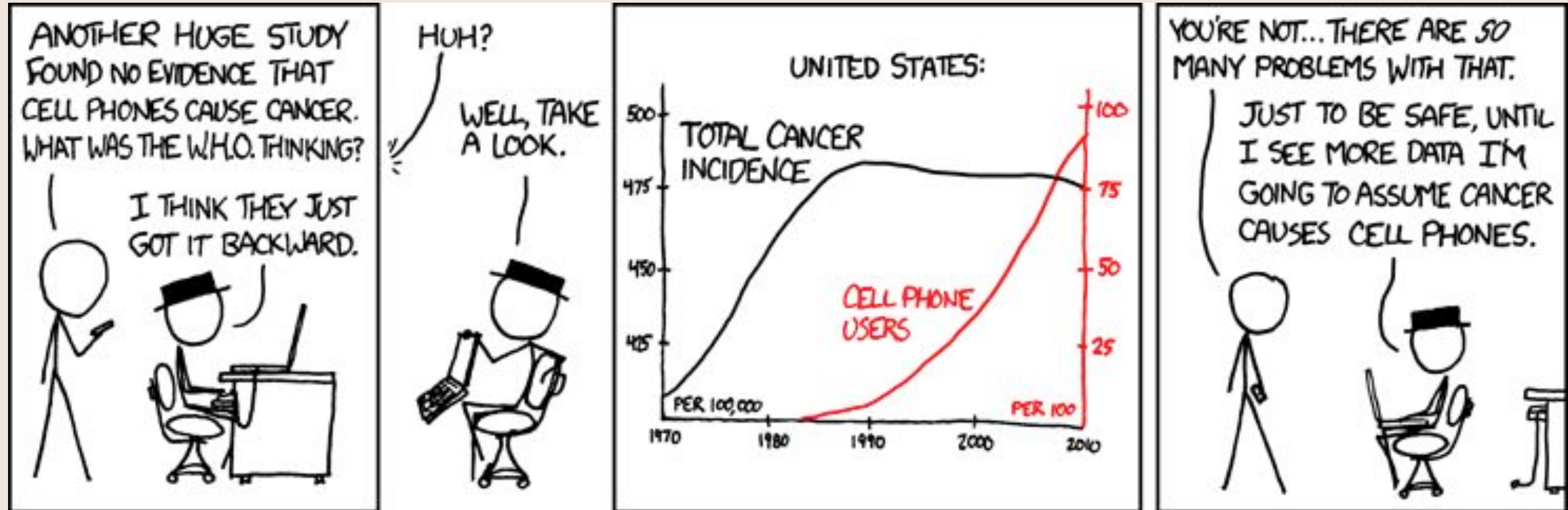
THEN I TOOK A
STATISTICS CLASS.
NOW I DON'T.



SOUNDS LIKE THE
CLASS HELPED.

WELL, MAYBE.





Common problems

Correlated features will mess up any model

Common problems

Throw out most features if they are just noise

More features

Future predictions

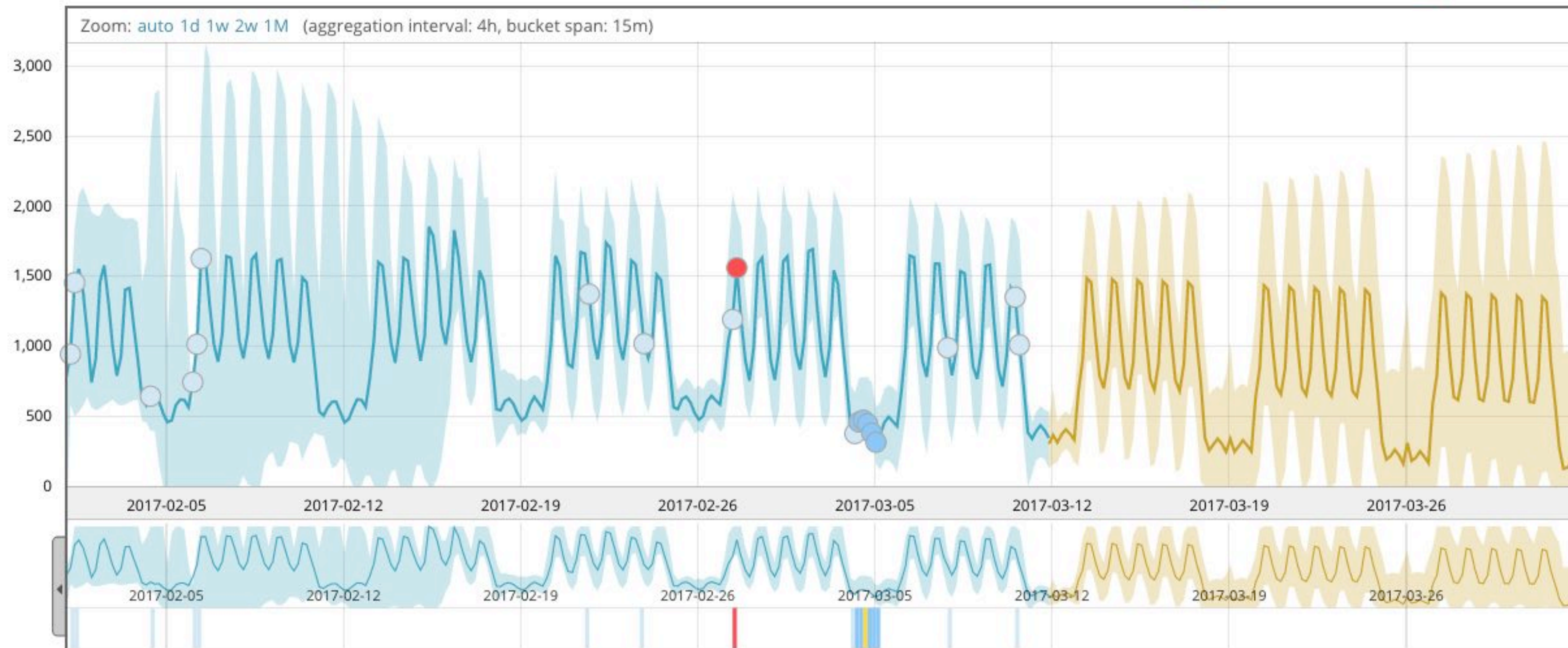
Detector:



Forecast

Single time series analysis of cardinality nginx.access.remote_ip

☒ show model bounds ☒ show forecast



Anomalies

Severity threshold:

☒ warning

Interval:

☐ Auto

time

max severity

detector

actual

typical

description

job ID

More features

Clustering

Conclusion

Agenda

Machine Learning

Domain

Dataset

Rules of Machine Learning: Best Practices for ML Engineering

[http://martin.zinkevich.org/rules_of_ml/
rules_of_ml.pdf](http://martin.zinkevich.org/rules_of_ml/rules_of_ml.pdf)

43 rules

Rule #1: Don't be afraid to launch a product without machine learning

Rule #14: Starting with an interpretable model makes debugging easier

Rule #16: Plan to launch and iterate

Machine Learning

ohne Hype

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