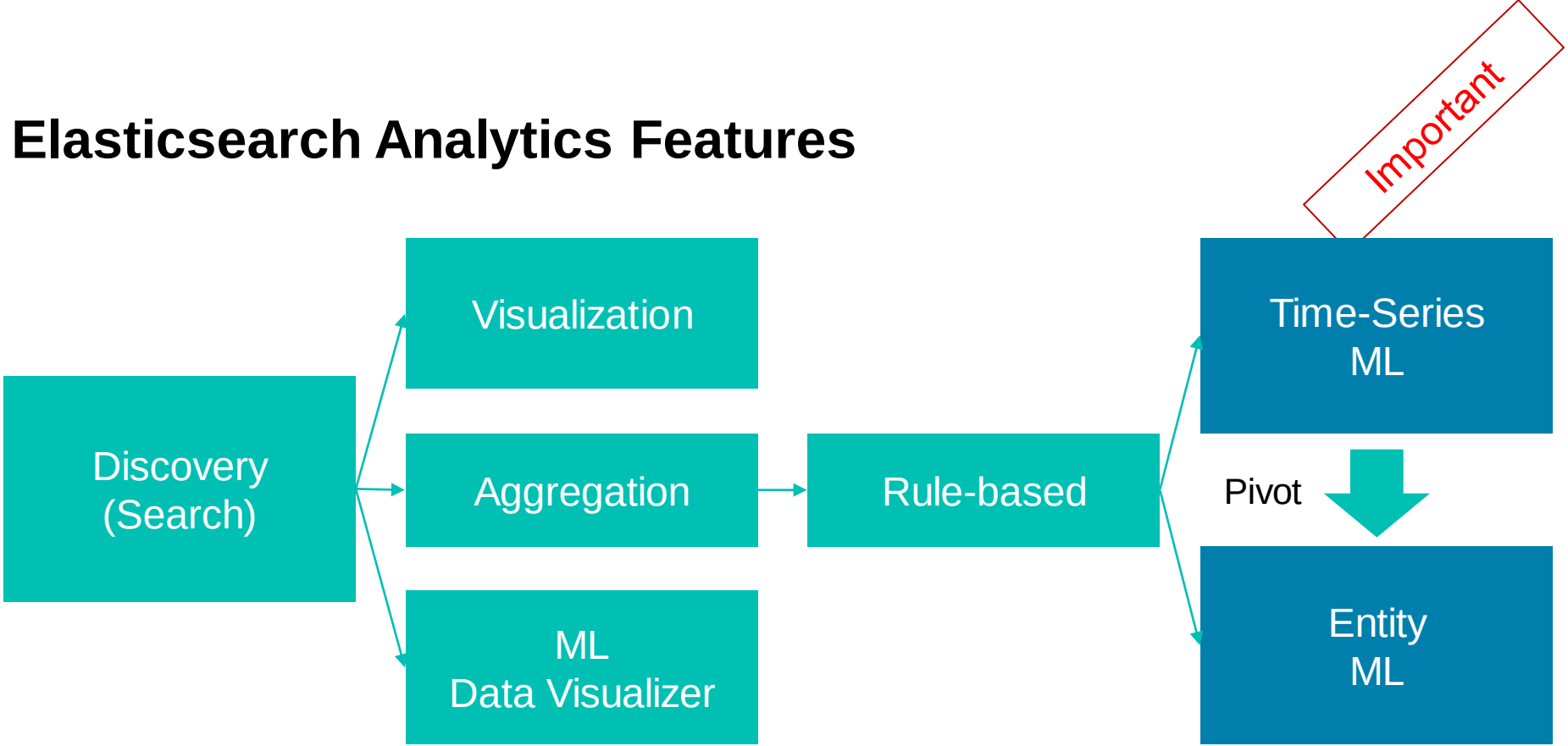
elastic

Elastic Machine Learning Workshop

Elastic
http://www.elastic.co

Understanding your DATA is Everything (Discussion)

Elasticsearch Analytics Features



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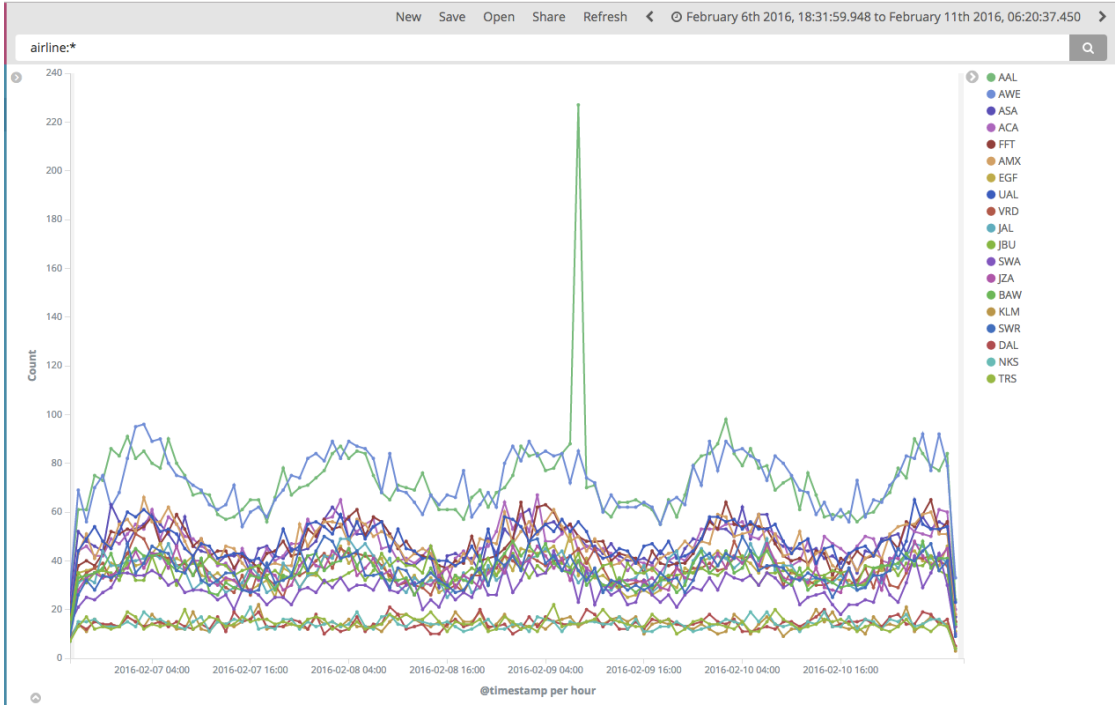
1. Times-Series based ML : Anomaly Detection Concepts

What is “Abnormal”

What is “Abnormal”?

What’s abnormal here?

Why?



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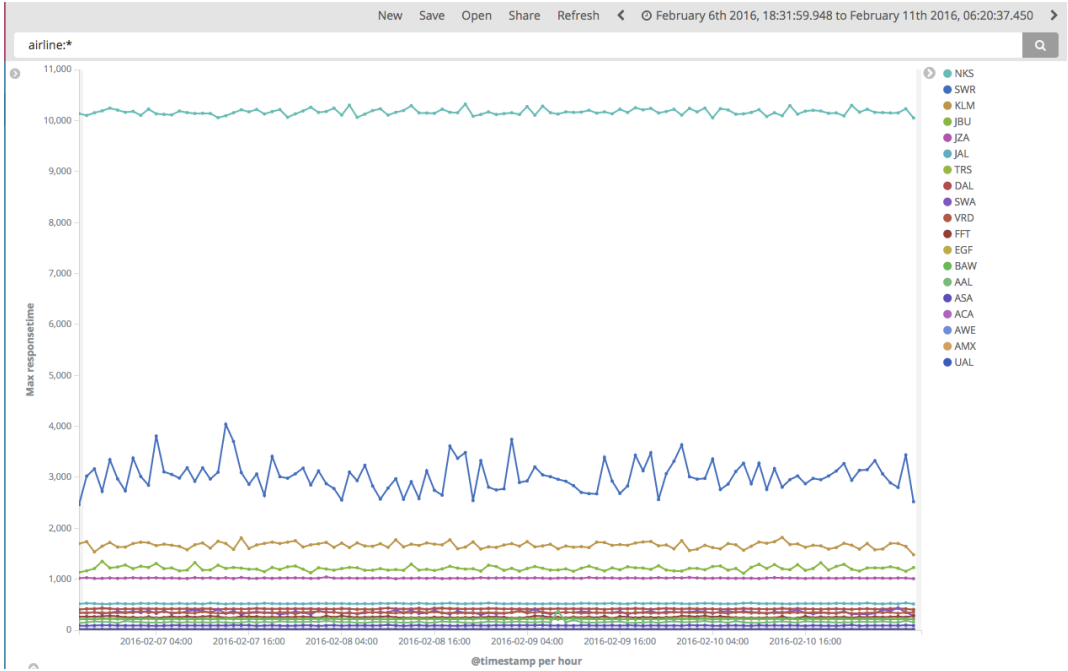
What is “Abnormal”?

What’s abnormal here?

Why?



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What is “Abnormal”?

What’s abnormal here?

Why?

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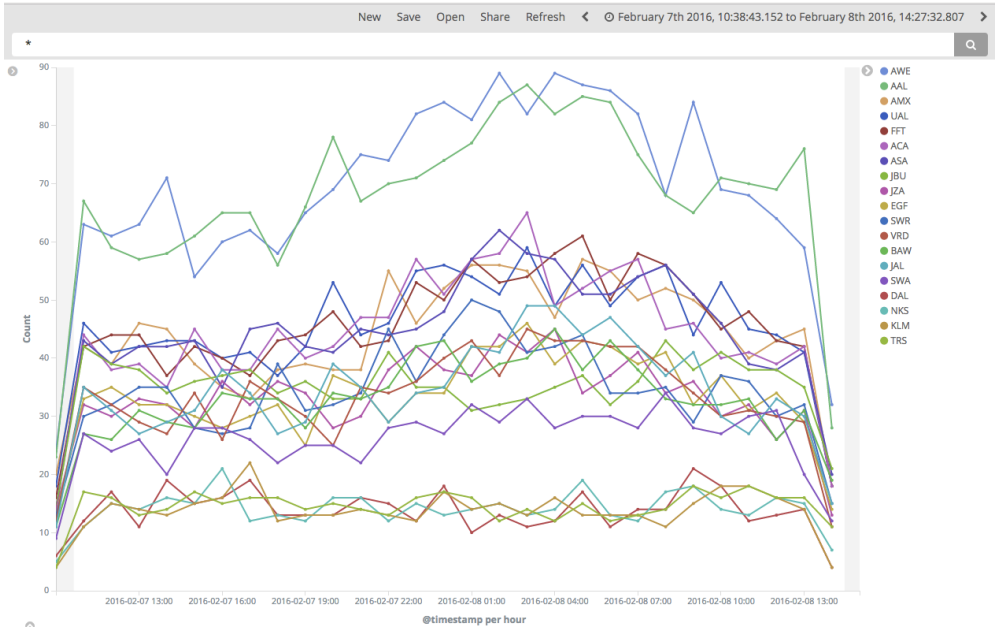
What is “Normal”?

In general, this question can be answered in two ways:

1) Something behaves in a consistent way with respect to itself, over time

2) Something behaves in a consistent way compared against similar entities



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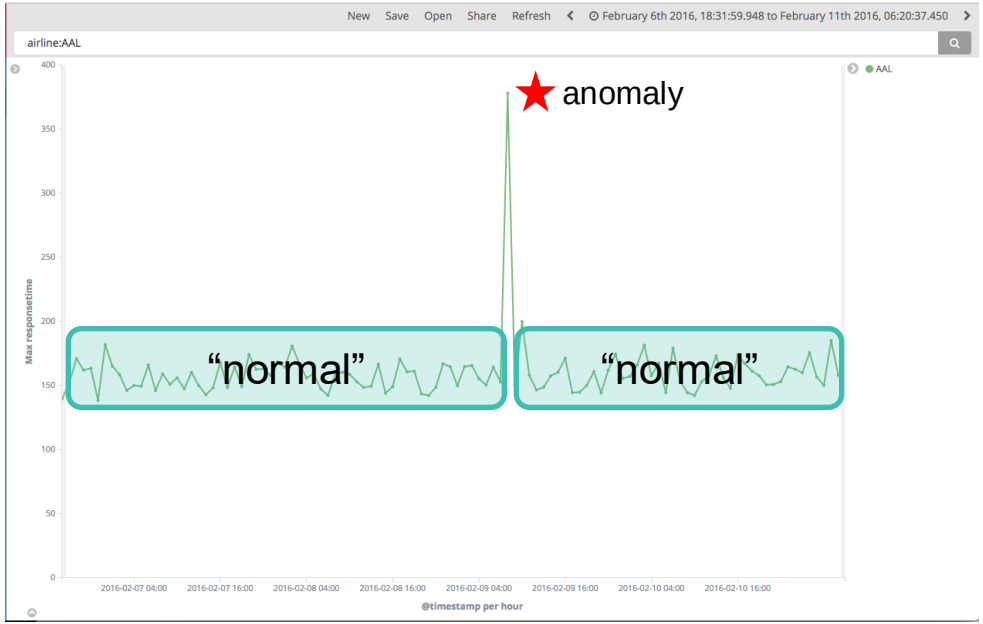
What is “Abnormal”?

1) If something changes its behavior, compared to its own history – that change is ***anomalous***.



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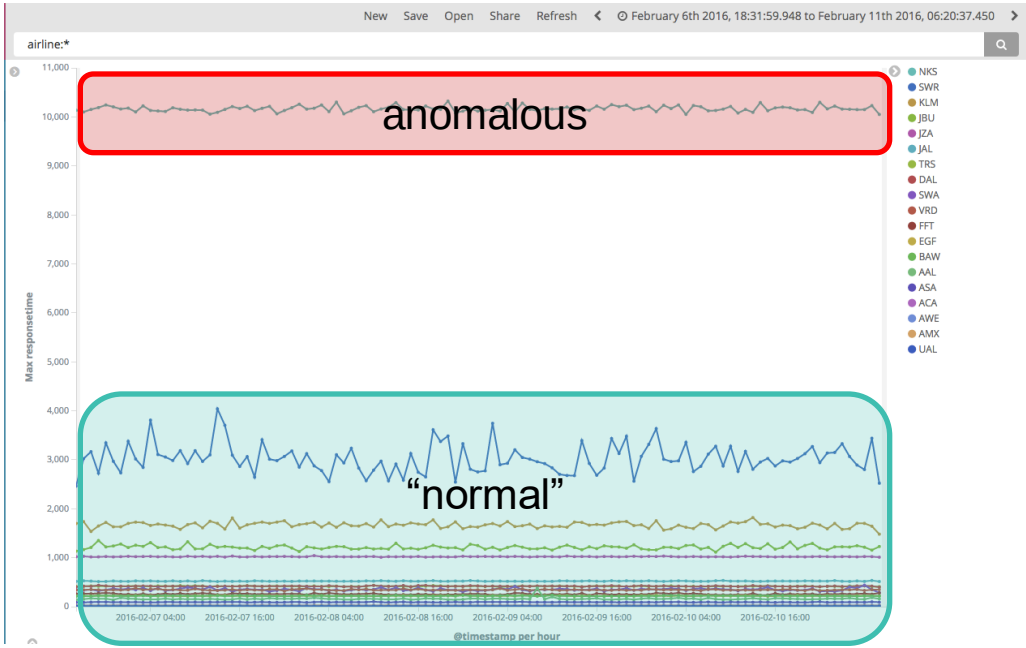
What is “Abnormal”?

2) If something is drastically different that others within a population, then that entity is ***anomalous***.



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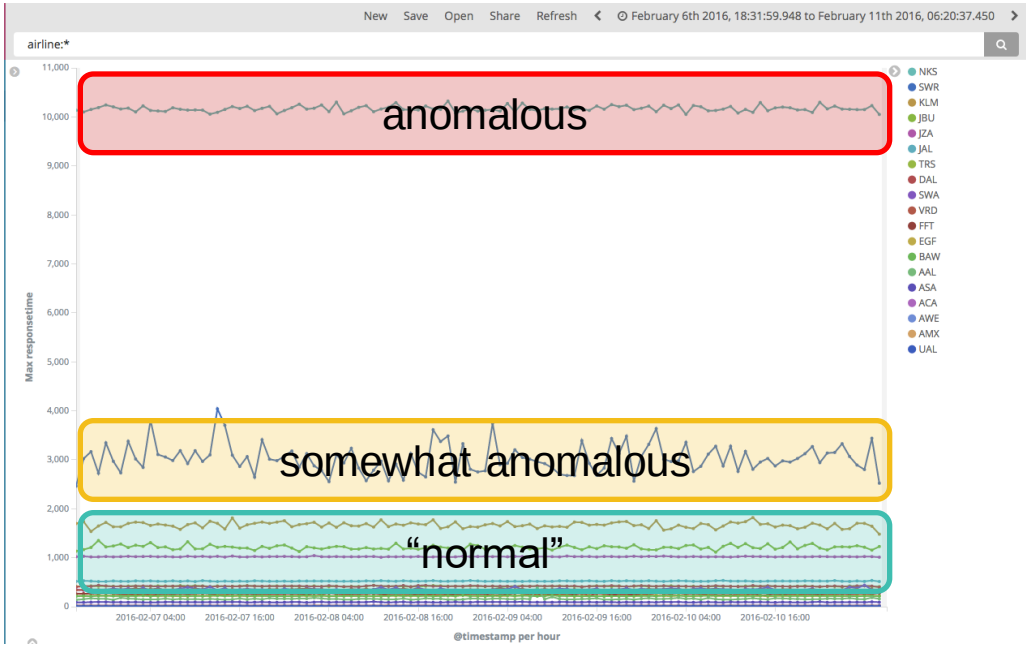
What is “Abnormal”?

2) If something is drastically different that others within a population, then that entity is ***anomalous***.

There’s also the concept of being “somewhat anomalous”



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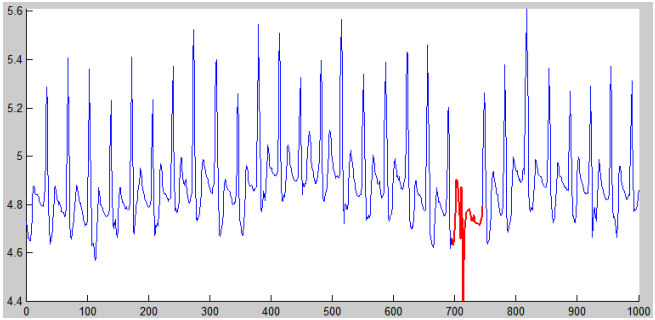
In Summary, Anomalousness is:

1) When an entities' ***behavior changes*** significantly and suddenly



2) When an entity is drastically ***different than others*** within a population

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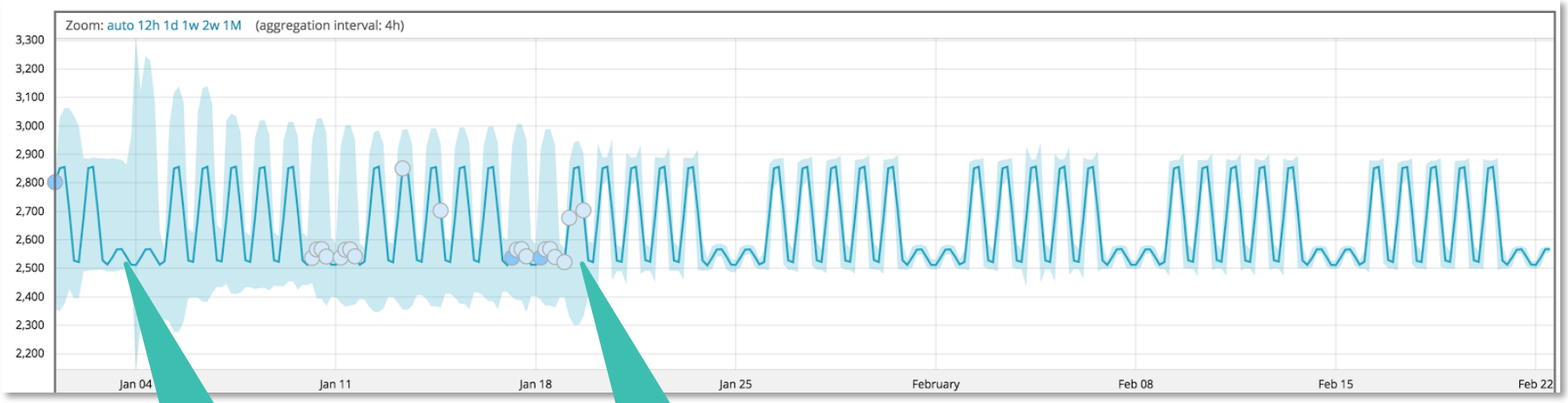
Also, model needs to account for any periodicity



After 2 full days, daily periodicity has been learned.

After 2 full weeks, weekly periodicity has been learned.

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Elastic ML Framework

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이상징후 탐지에 필수적인 16개의 알고리즘을 3 가지 방법론으로 구성해서 제안 – Elastic ML Framework

X축 : Single Metric, Multi Metric Time series – 과거와 다른 행동패턴(by)

Y축 : Population Analysis – 다른 것들과 비교해서 다른 행동패턴(over)

Z축 : Rare/Unusual Analysis – 보기 드문 행동패턴(rare)

* 몇 십년 경험을 가진 시스템 아키텍트/관리자 및 보안전문가의 노우하우(Know-How)를 시뮬레이션

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Lab 1: The Single Metric Job

Goal: Detect anomalies in a single time series

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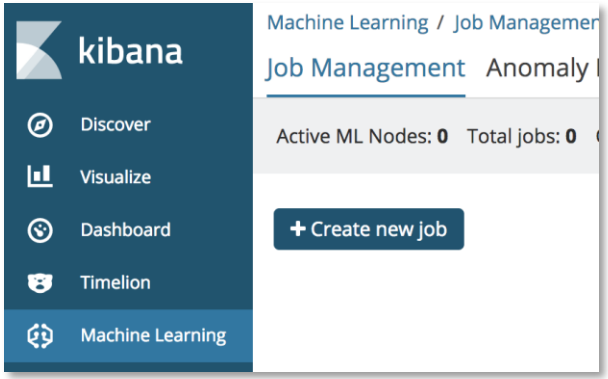
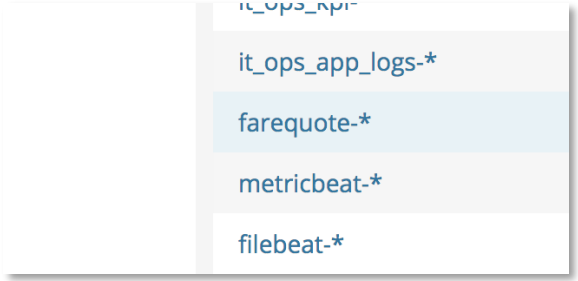
Steps to Complete

1) In Machine Learning, Create new job



2) Choose the “farequote-*” index pattern



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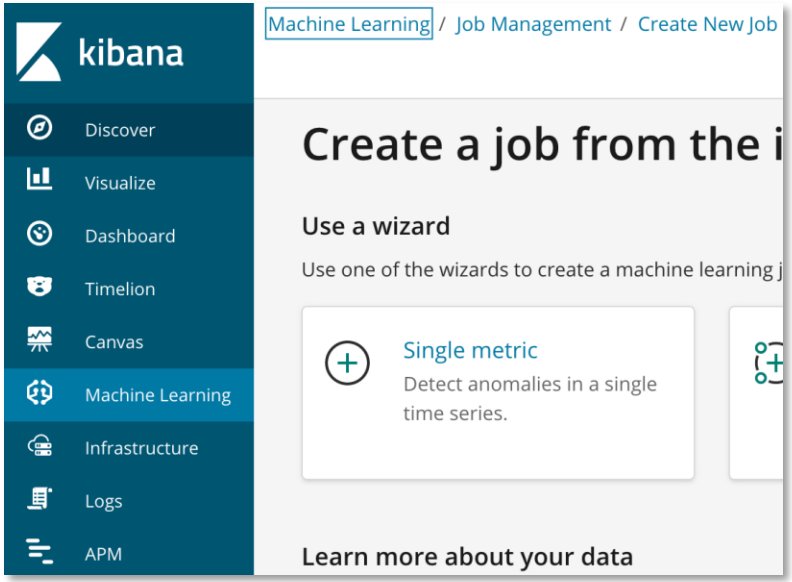
Steps to Complete

3) pick the Single Metric Wizard



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Steps to Complete

4) Aggregation: count

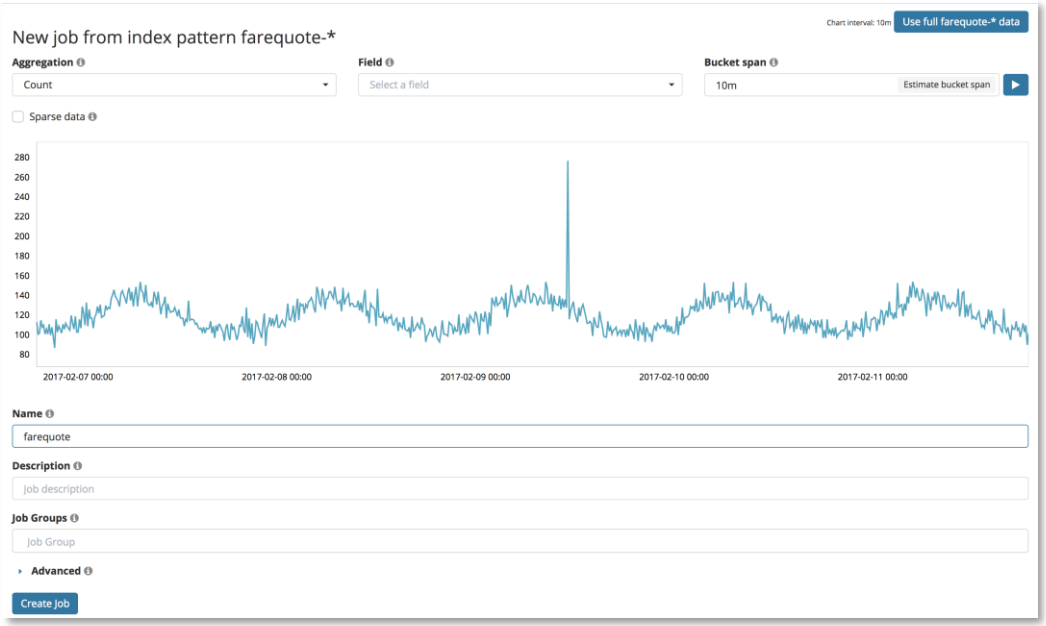
5) Field: <leave blank>

6) Bucket span: 10m

7) Click the “use full farequote data” button

8) Name: “farequote”

9) click “Create Job”



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Steps to Complete

10) See animated learning

11) click “View Results”

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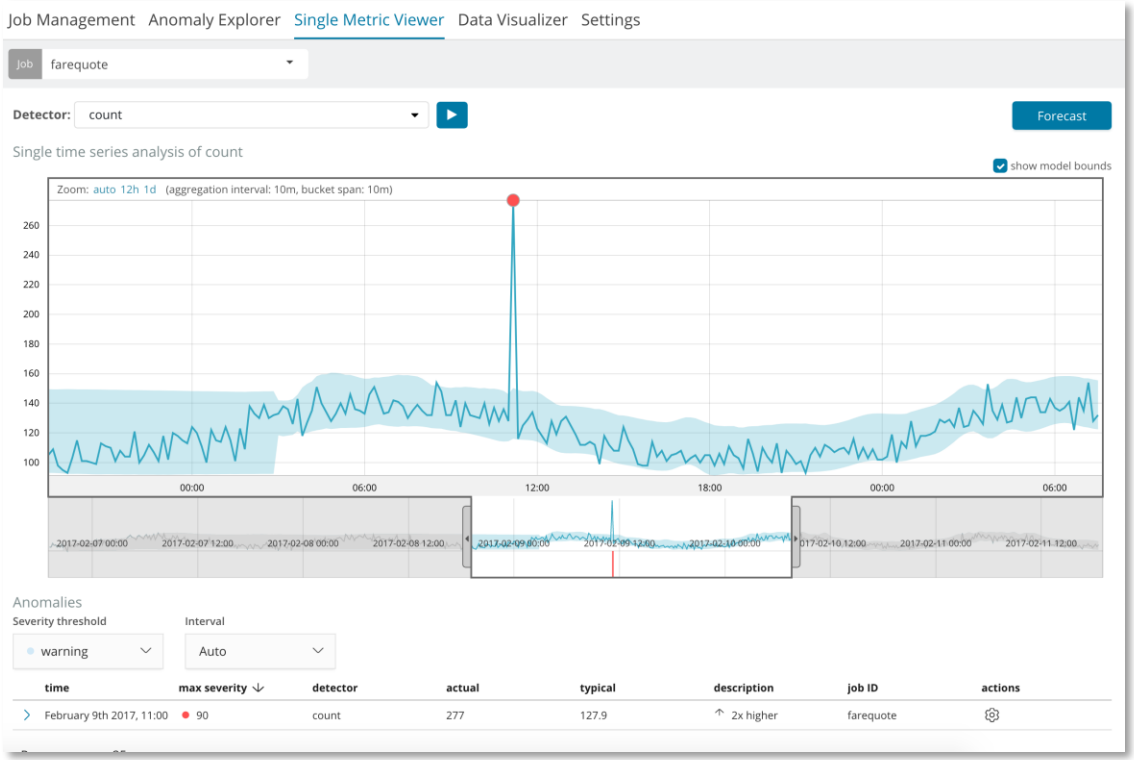
Steps to Complete

12) Zoom in on anomaly



Splitting the Analysis

Feature Selection and Selection

- Which attributes of a this data could be used to judge its unusualness?

raw logs

```
2016/02/08 06:20:43 INFO  [http-8680]: FareQuoteImpl - FareQuoteImpl.getFare(AAL): exiting: 92.5638
2016/02/08 06:20:44 INFO  [http-8680]: FareQuoteImpl - FareQuoteImpl.getFare(JZA): exiting: 990.4628
2016/02/08 06:20:46 INFO  [http-8680]: FareQuoteImpl - FareQuoteImpl.getFare(JBU): exiting: 877.5927
...
```

ingest

document


```
{
  "_index": "farequote",
  "_type": "response",
  "_id": "AVNQ1__XRcuaRiYtw-jH",
  "_score": 3.290889,
  "_source": {
    "sourcetype": "farequote",
    "airline": "AAL",
    "responsetime": "92.5638",
    "time": "2016-02-08T06:20:43+0000"
  }
}
```


“airline” (categorical)

“responsetime” (metric)

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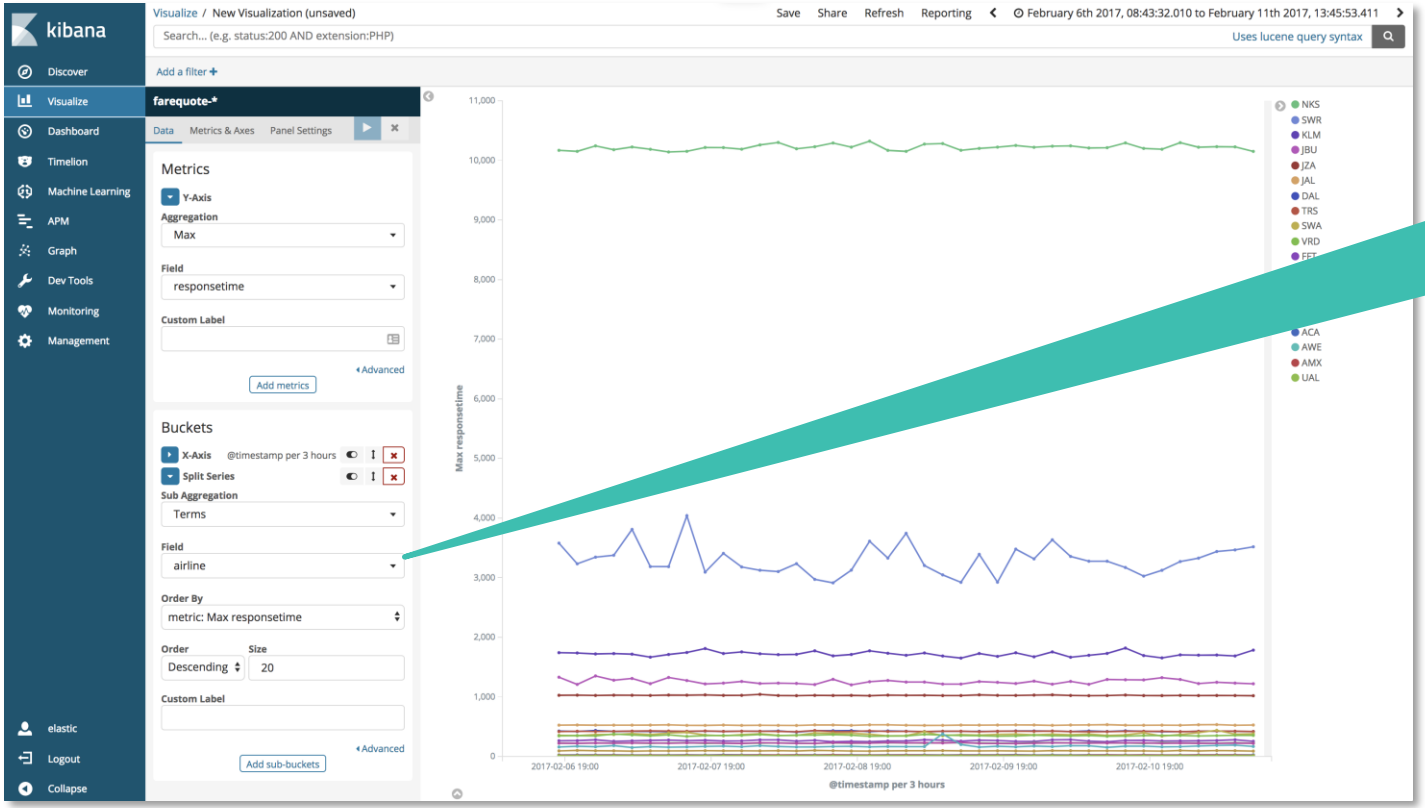
What Kinds of Questions Can be Answered?

QUESTION	ANSWERABLE?
Is there an unusual ***amount*** of requests per unit time (total)?	Yes
Is there any particular airlines with unusual ***amounts*** of requests per unit time?	Yes
Is the ***total*** response time of ***all*** API calls unusually long?	Yes
Is the response time of API calls ***per airline*** unusually long?	Yes
Are there any airlines with excessive take-off delays?	No

In Kibana: How to Answer that Question



ML has the same notion of "splitting" along a categorical field

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Lab 2: Multi-Metric Jobs

Goal: Detect anomalies in parallel time series

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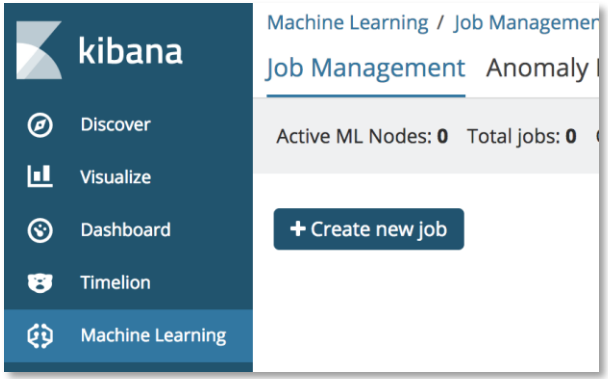
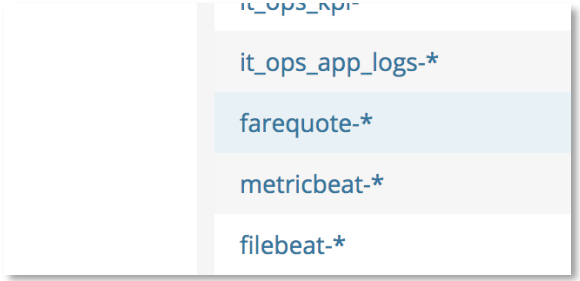
Steps to Complete

1) In Machine Learning, Create new job



2) Choose the “farequote-*” index pattern



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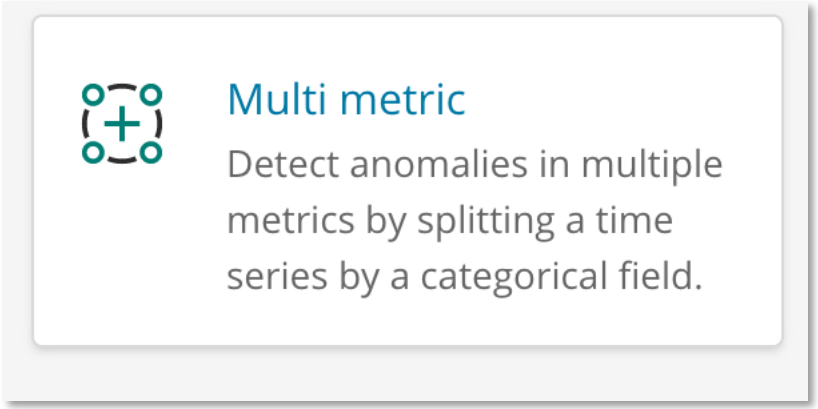
Steps to Complete

3) pick Multi metric Job Wizard



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Steps to Complete

4) choose
- event rate, count
- responsetime, max

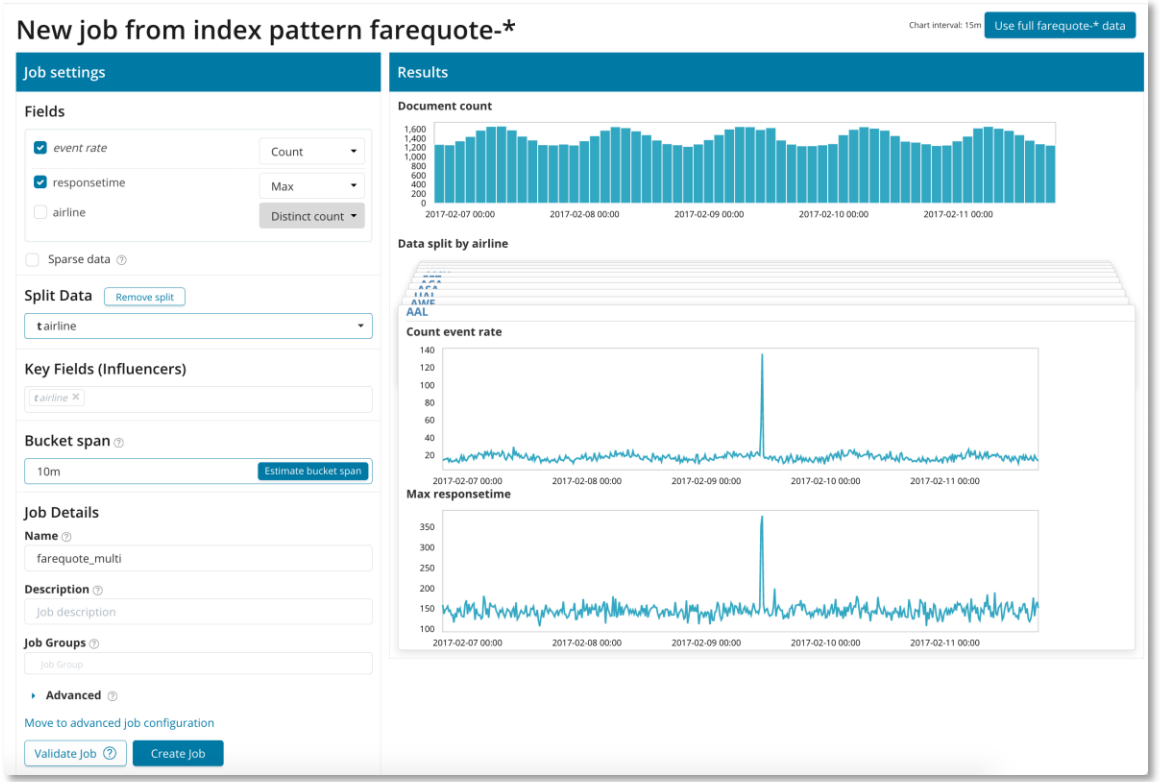
5) bucket span: 10m

6) Split Data: airline

7) click “use full farequote data”

8) Name: “farequote_multi”

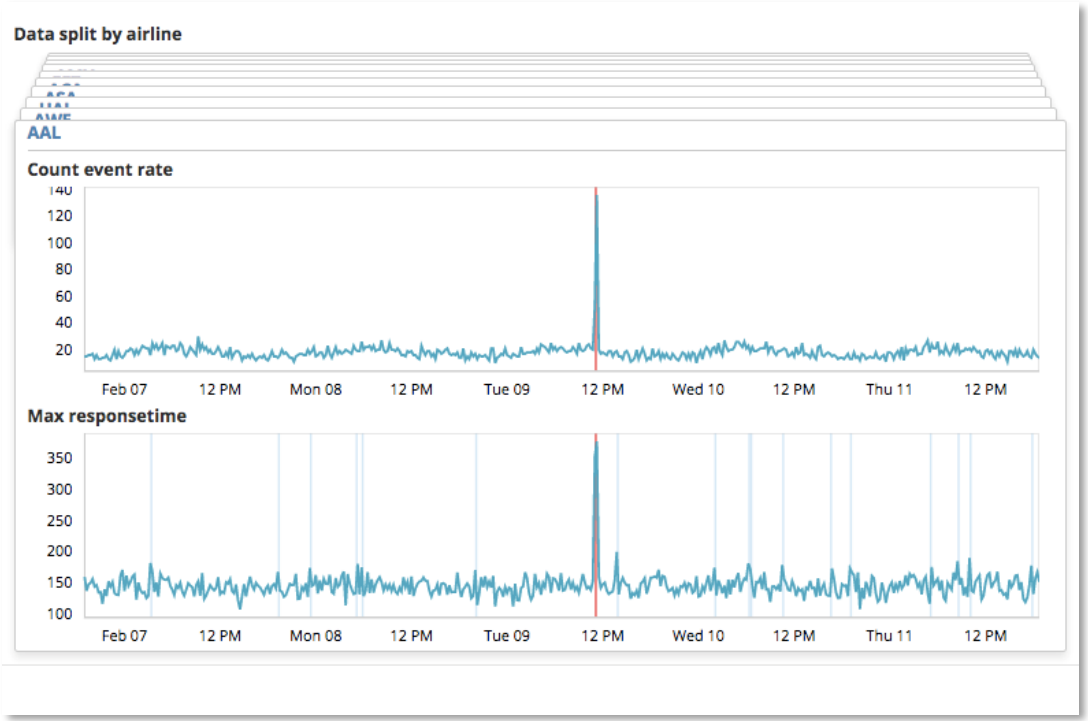
9) click “Create Job”



Steps to Complete

10) See animated learning

11) click “View Results”



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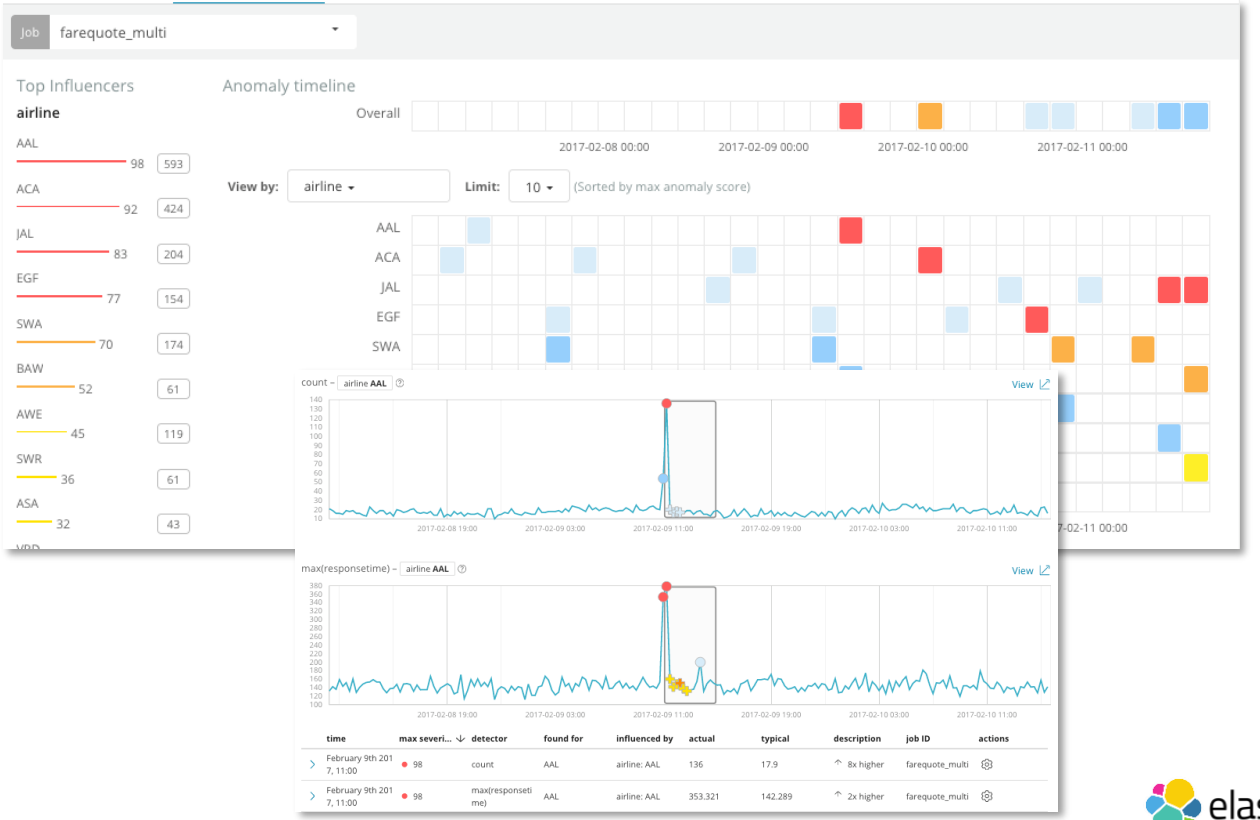
Steps to Complete

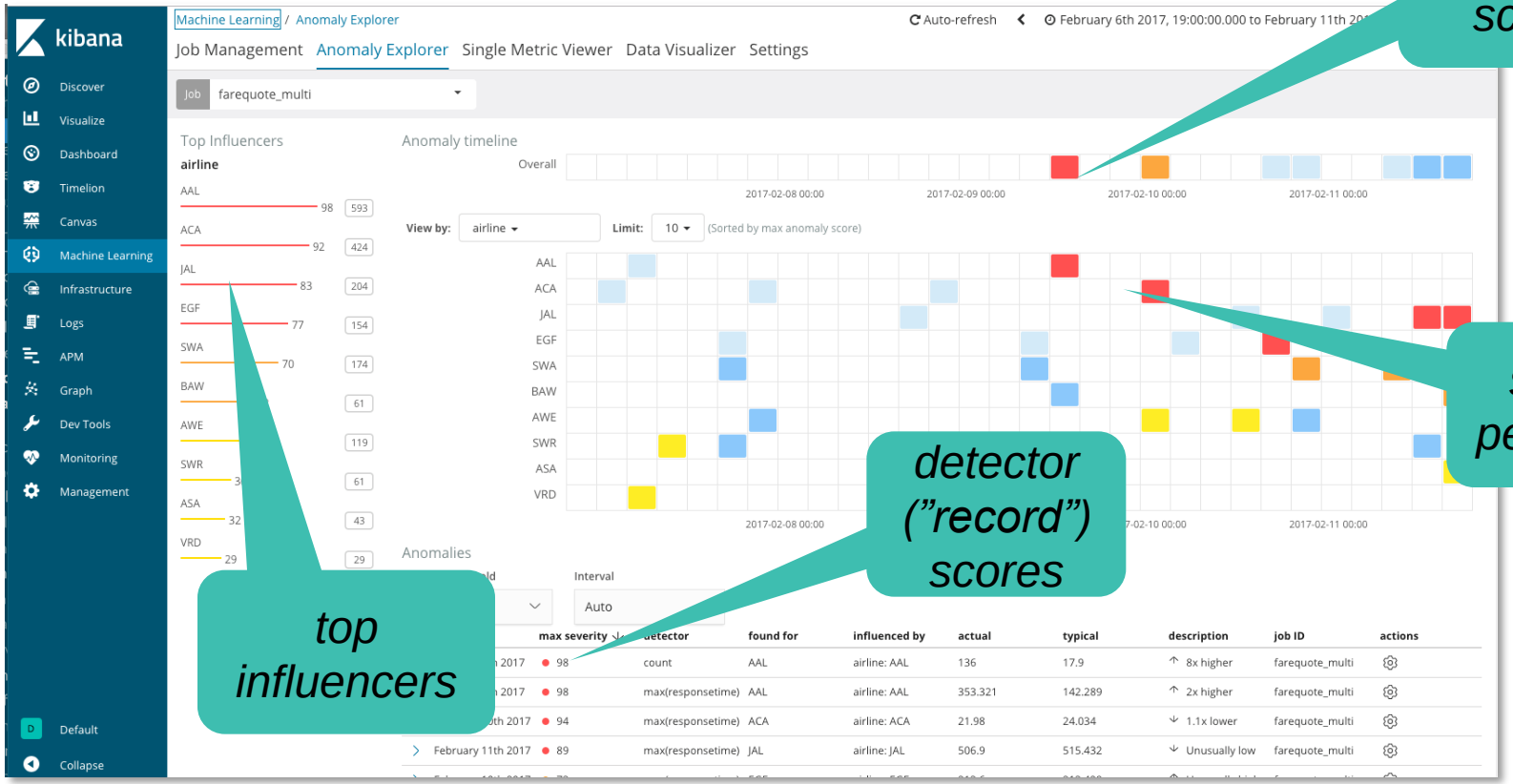
12) Result:

top unusual airline: AAL anomalies
in both count
and response time



The Anomaly Explorer View

Anomaly Explorer



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Concept: What is an Influencer?

- An Influencer is a field, selected at configuration time, that would be a logical entity ”to blame” if an anomaly were to exist
- Doesn’t have to be a field in the actual detector, but fields used to split the data are often good candidates
- Will get its own score based upon how influential that entity is on the anomaly

Scoring

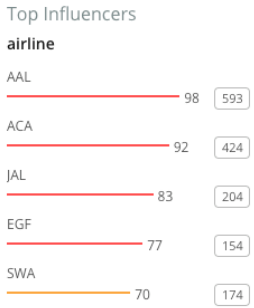
- Overall Job score is 90
  - How unusual is that bucket, given all airlines?
- Detector scores are 98
  - How unusual is the response time and count of airline=AAL?
- airline=AAL is the top influencer in this time range
  - 98 is the max score
  - 593 is the sum of all scores over the time range

Anomalies

Severity threshold: warning

Interval: Auto

time	max severity	detector	found for	influenced by	actual	typical	description	job ID	actions
February 9th 2017	98	count	AAL	airline: AAL	136	17.9	8x higher	farequote_multi	
February 9th 2017	98	max(responsetime)	AAL	airline: AAL	353.321	142.289	2x higher	farequote_multi	



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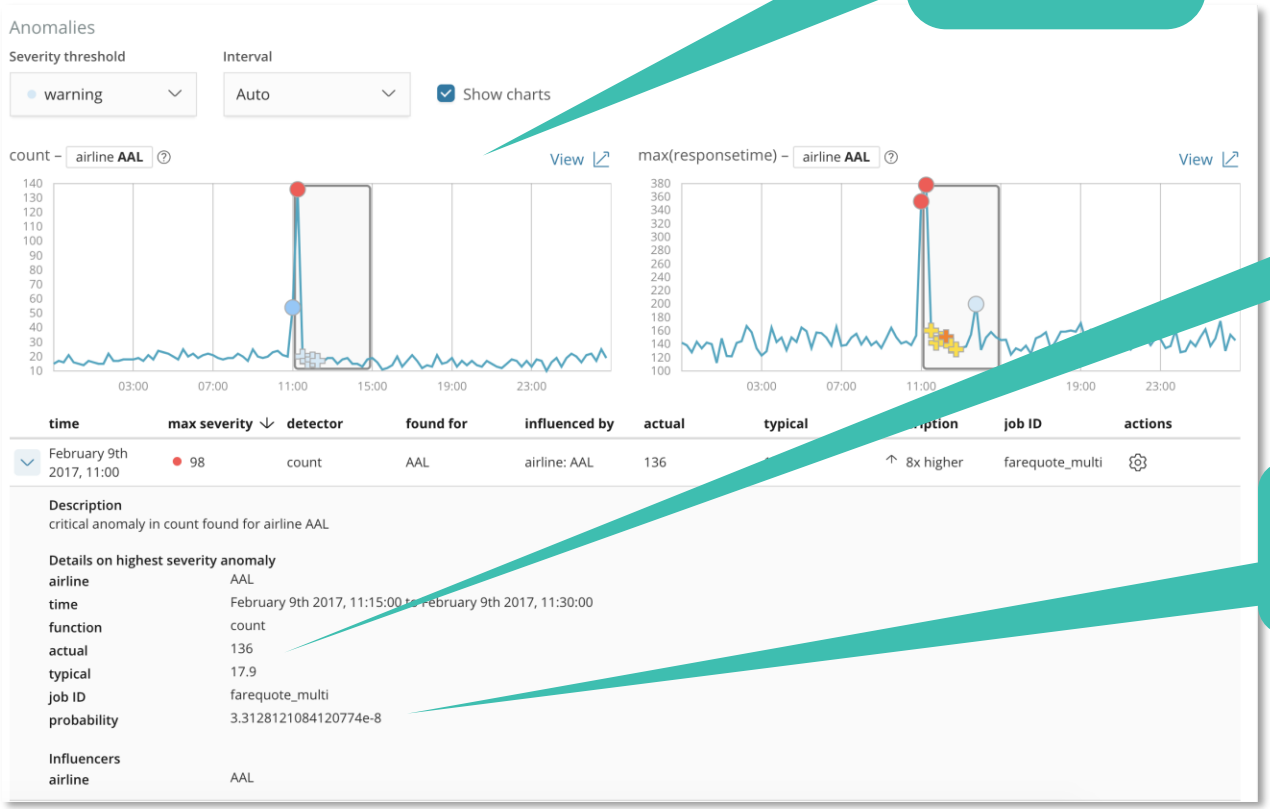
Anomaly Details



view individual anomalies

actual vs. "typical"

raw probability

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Forecasting

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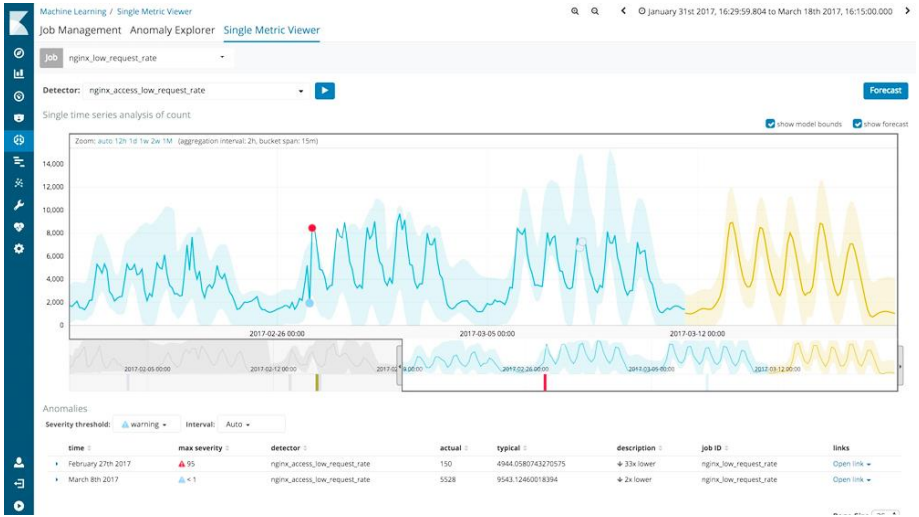
Extrapolate into the future with forecasting



Example use cases

- I want to know when capacity will exceed 80%

- What is my expected visitor count next Saturday at 8am?

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Lab 3: Forecasting

Goal: Extrapolate into the future

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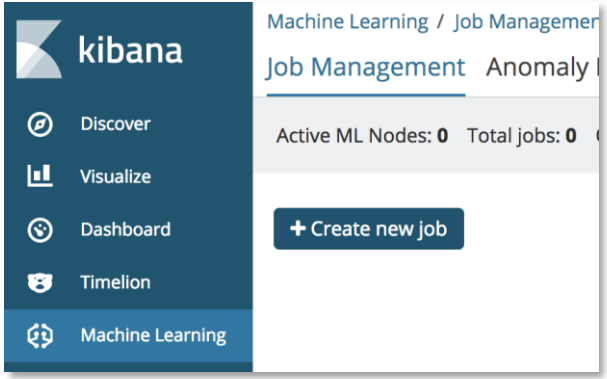
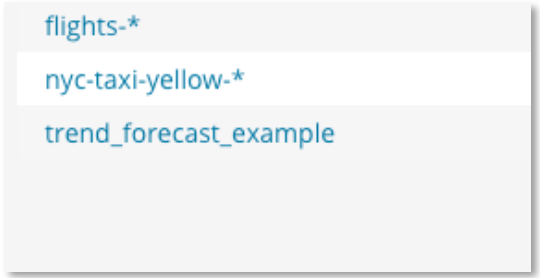
Steps to Complete

1) In Machine Learning, Create new job



2) Choose the “trend_forecast_example” index pattern



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Steps to Complete

3) single metric job

4) sum of field “amount”

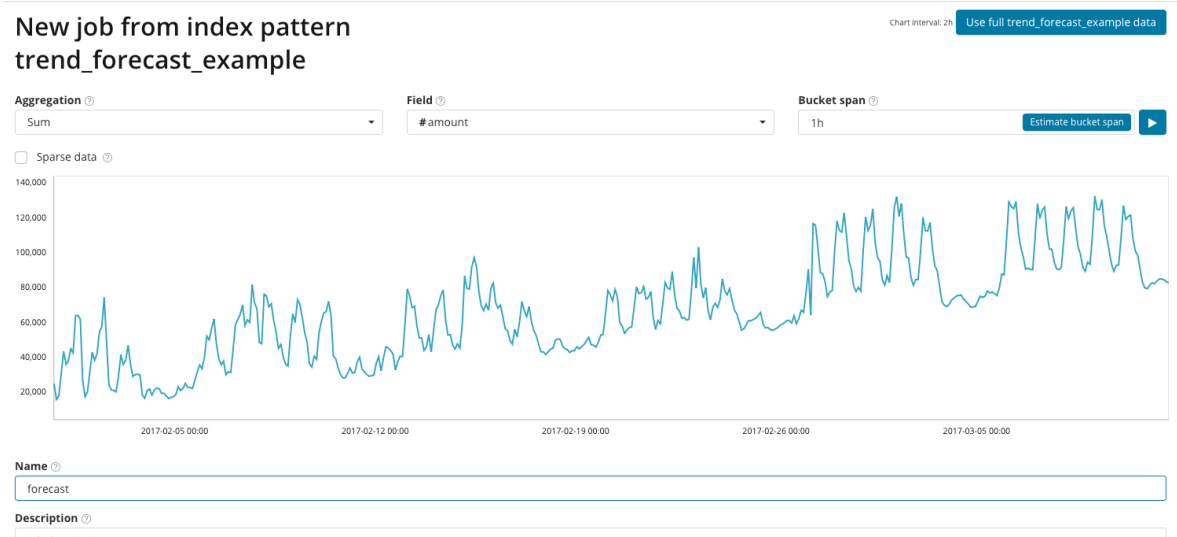
5) bucket span: 1h

6) click “use full data”

7) Name: “forecast”

8) click “Create Job”

9) click “View Results”



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Steps to Complete

10) click “Forecast” button

11) Enter “7d” for duration

12) click “Run” button

13) see forecast in UI
(results also available via API)

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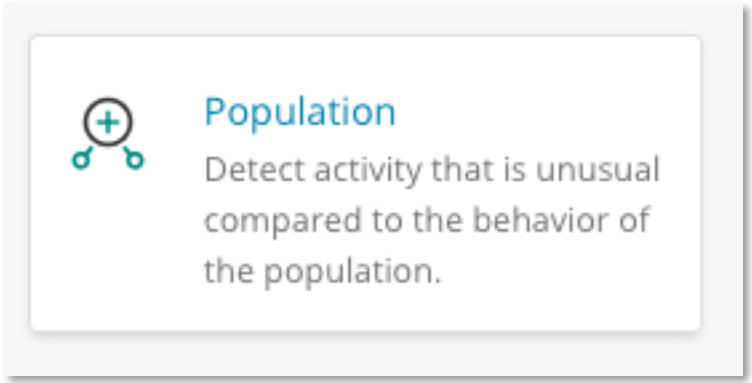
Population Analysis

Population Analysis

- Use when:
  - Compare entities against peers
  - Not against own history
- Helpful when:
  - Entities have high-cardinality (i.e. external IP addresses)
  - Data for specific entities may be sparse in time (individual customers placing orders)
  - The behavior of the population as a whole is mostly homogeneous
- Not appropriate when:
  - Members of the population have vastly different behavior inherently.



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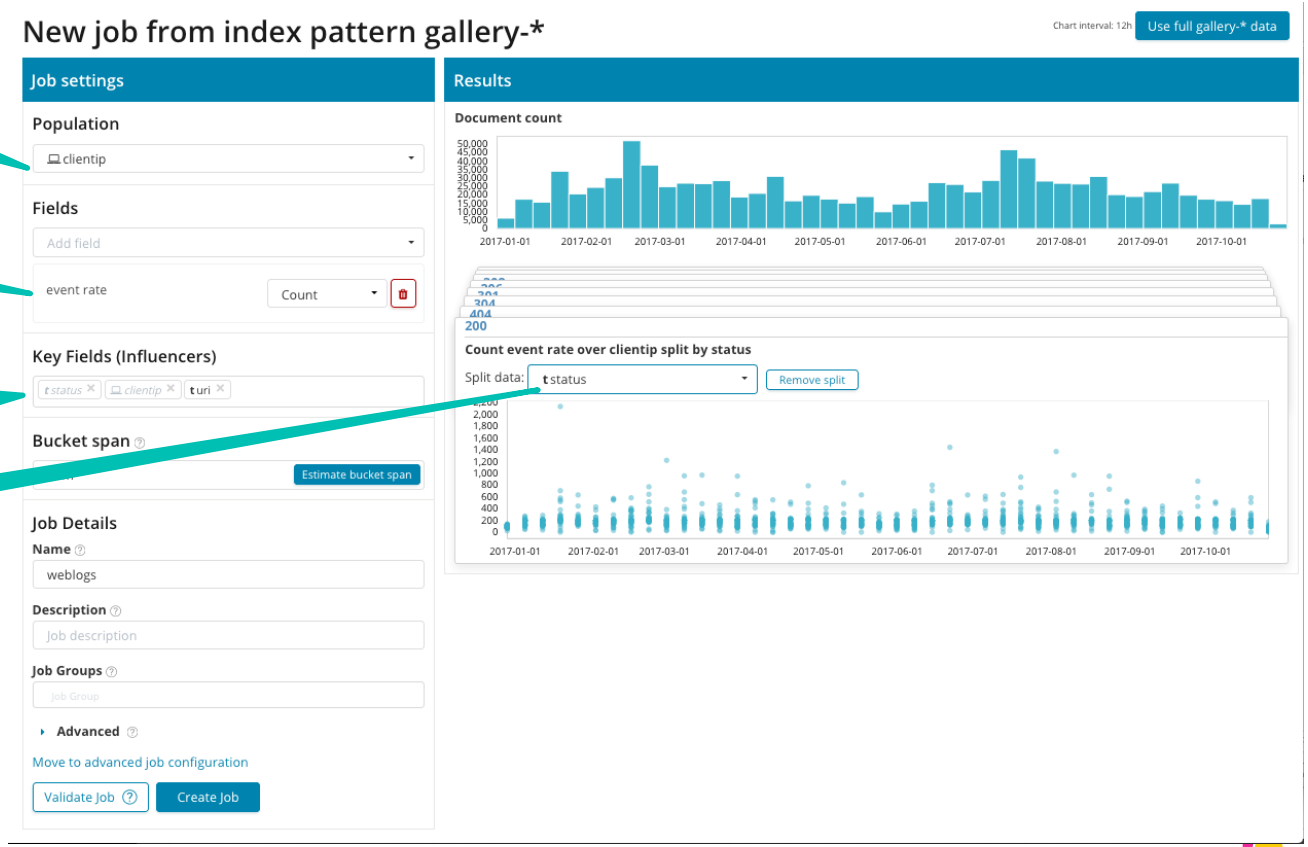
Population Analysis

population field

the detector

influencers

optional split



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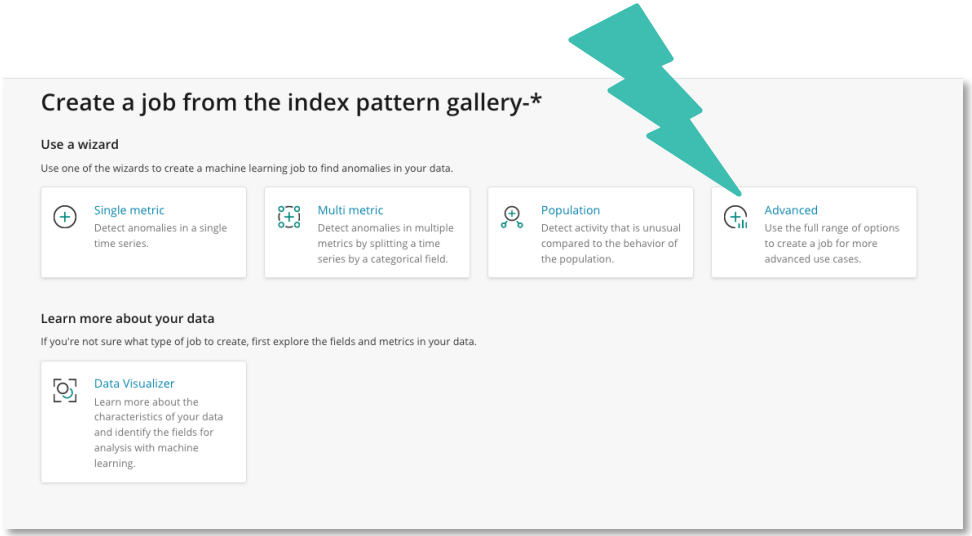
Population Analysis

clientip: 173.203.78.60
status: 404
uri: /wp-login.php

Advanced Jobs

Advanced Jobs

- Gives more flexibility
- Access to additional capabilities
- Requires more understanding of configuration parameters



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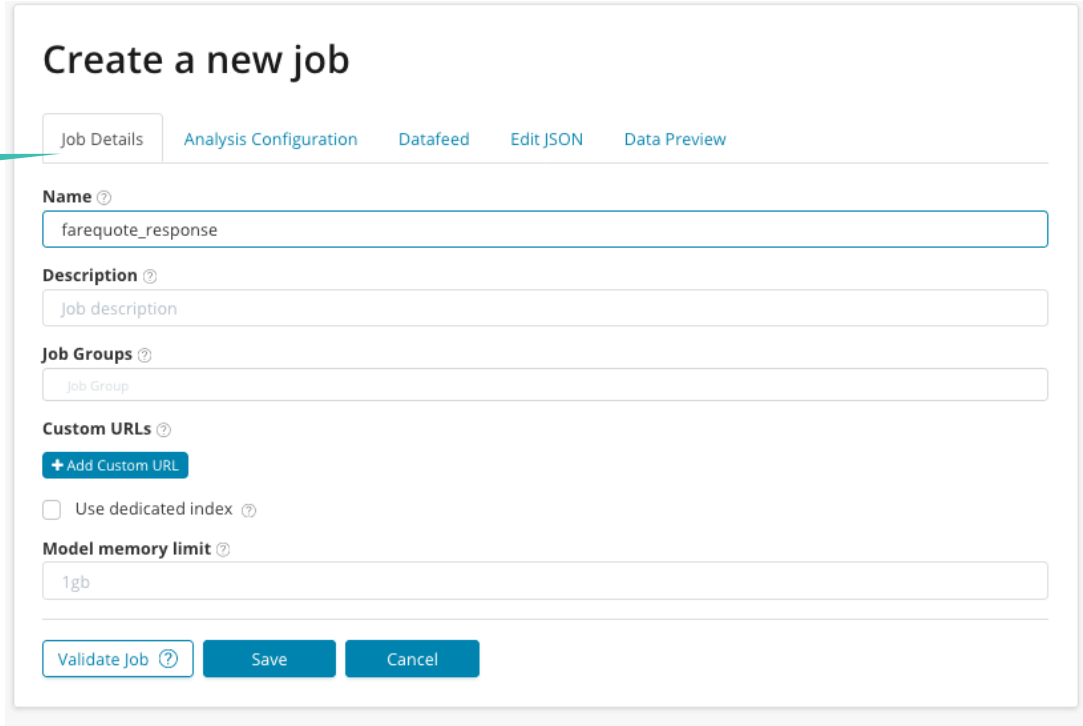
Configuration of Advanced Job

Tabs of different information



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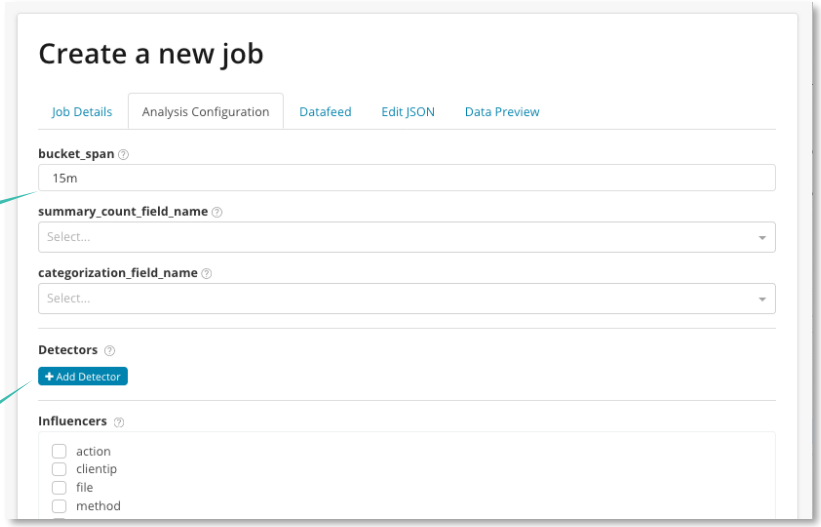
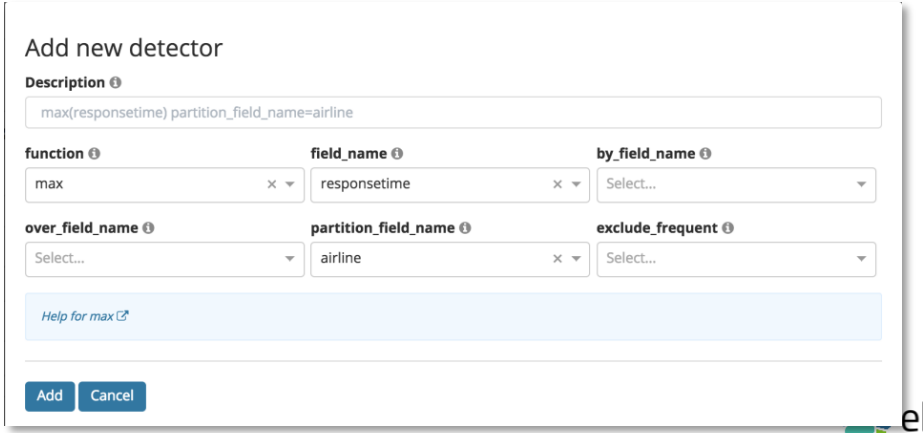
Analysis Configuration

Settting of bucket_span

Creation of "detector"





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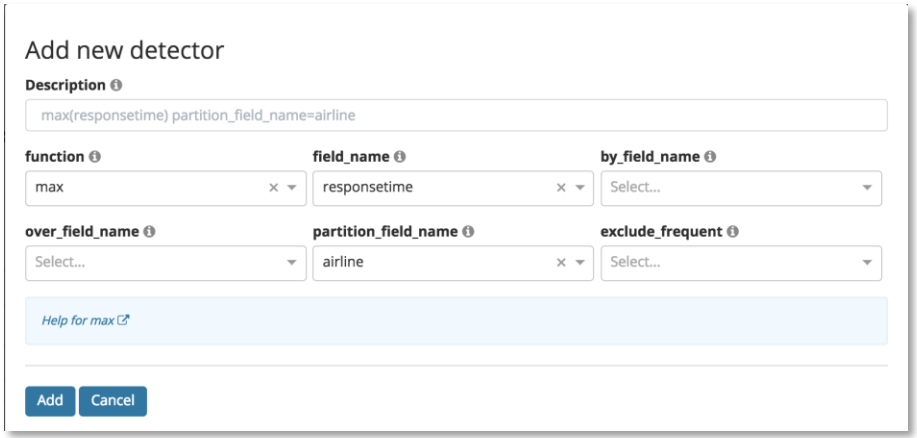
Detector Details

- **function** – min, max, mean, etc.
- **field_name** –field **function** “operates on”
- **by_field_name** –“dependent” split
- **partition_field_name** –“independent” split
- **over_field_name** – defines a population



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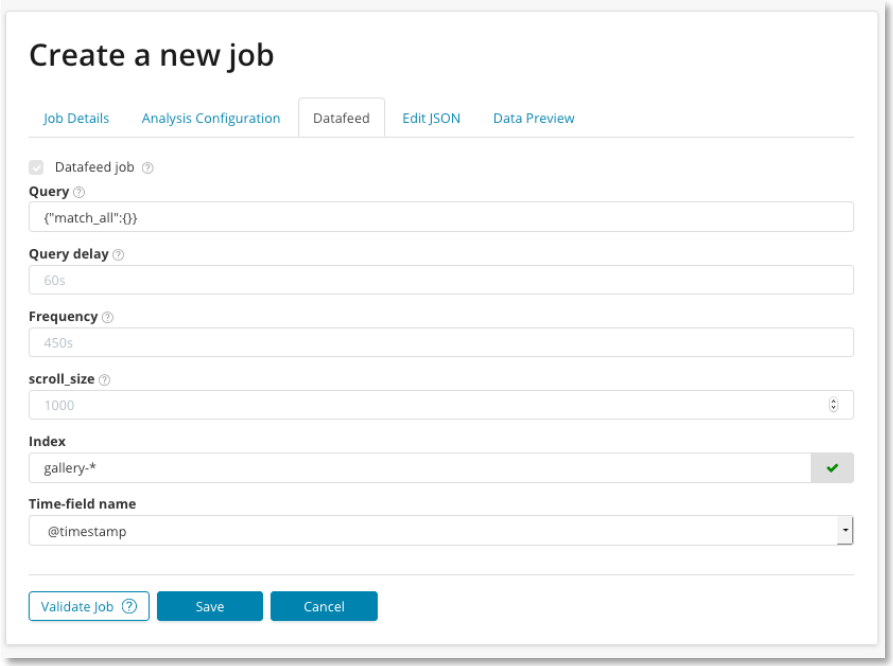
Datafeed Details

- Datafeed manages how ML queries Elasticsearch
- See ML docs for configuration options



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Rarity Analysis

Rare Analysis

- Finding items that rarely occur is also often useful
  - Rarely occurring log messages
  - Rare running process names
  - Rare connection destinations
- ML has a rare function, but it should be noted that:
  - It is relative, i.e. it takes into account the frequency of other field values

A,B,A,B,A,C,B,A,B,A,C,A,B,C,A,C,B,A,C,B,A,C,X <=X is rare
A,B,C,D,E,F,G,H,I,J,K,L,M,N,O,P,Q,R,S,T,U,V,W,X <= X is not rare

  - Therefore it works best when there are plenty of routine messages to contrast the rare ones

Example of Rare Analysis

- Use Case: Security team @ services company
- Wanted to profile typical processes on each host using netstat

```
Active Internet connections (servers and established)
(index=netstat host="ids01-dc2" State=LISTEN (7/16/13 1:32:51AM))
Proto Recv-Q Send-Q Local Address               Foreign Address             State       PID/Program name
tcp        0      0  10.220.174.41:561         0.0.0.0:*                   LISTEN      8776/argus
tcp        0      0  0.0.0.0:22                0.0.0.0:*                   LISTEN      2033/sshd
tcp        0      0  0.0.0.0:1241              0.0.0.0:*                   LISTEN      4472/nessusd
tcp        0      0  0.0.0.0:8089              0.0.0.0:*                   LISTEN      4238/splunkd
tcp        0      0  127.0.0.1:25              0.0.0.0:*                   LISTEN      4194/master
tcp        0      0  0.0.0.0:8000              0.0.0.0:*                   LISTEN      4361/python
tcp        0      0  0.0.0.0:8834              0.0.0.0:*                   LISTEN      4472/nessusd
tcp        0      0  127.0.0.1:199             0.0.0.0:*                   LISTEN      2022/snmpd
```

- Goal was to identify rare processes that “start up and communicate” for each host, individually

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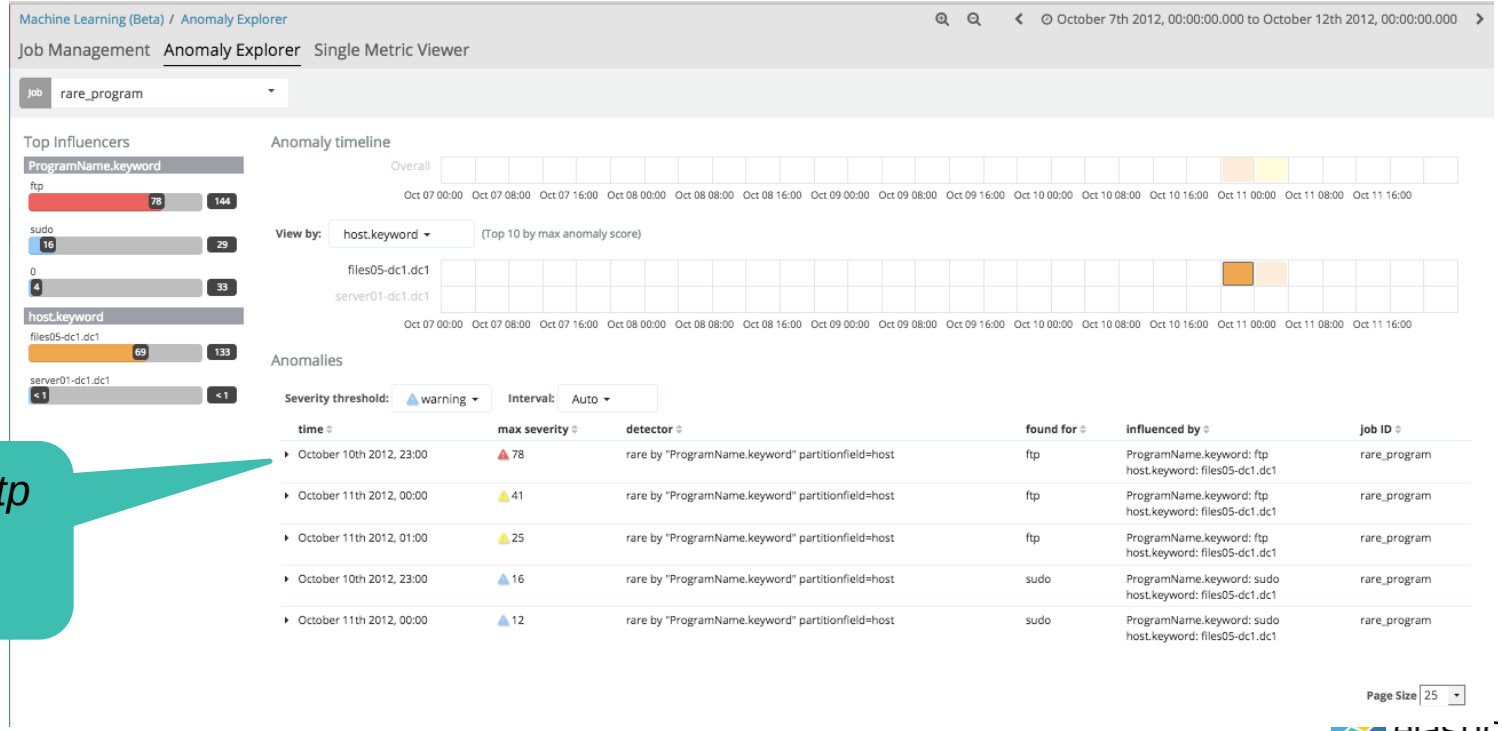
Example of Rare Analysis

detector: *rare by ProgramName partition_field=host*



ProgramName: ftp
host: files05
rarely occurs

ML Categorization

Categorization

- What is it?
  - Automatically grouping similar log messages into the same “category”
- How?
  - Via an algorithm that looks at string similarity and clusters similar log lines
- Why?
  - Bring structure to semi-structured data so that it can be analyzed

Benefit: Find anomalies in logs without knowing what they contain

Example

```
Oct 22 18:17:58 localhost sshd[8903]: Invalid user admin from 41.43.112.199 port 41805
Oct 22 18:17:58 localhost sshd[8903]: input_userauth_request: invalid user admin [preauth]
Oct 22 18:17:59 localhost sshd[8903]: Connection closed by 41.43.112.199 port 41805 [preauth]
Oct 22 20:58:03 localhost sshd[2074]: Received disconnect from 72.93.85.203 port 53552:11: disconnected by user
Oct 22 20:58:03 localhost sshd[2074]: Disconnected from 72.93.85.203 port 53552
Oct 22 20:58:03 localhost sshd[2072]: pam_unix(sshd:session): session closed for user ec2-user
Oct 22 21:32:54 localhost sshd[8944]: pam_unix(sshd:session): session opened for user ec2-user by (uid=0)
Oct 22 21:35:15 localhost runuser: pam_unix(runuser-l:session): session closed for user ec2-user
Oct 22 21:35:15 localhost runuser: pam_unix(runuser-l:session): session opened for user ec2-user by ec2-user(uid=0)
Oct 22 21:35:16 localhost runuser: pam_unix(runuser-l:session): session closed for user ec2-user
```

Step 1 – remove mutable text

```
Oct 22 18:17:58 localhost sshd[8903]: Invalid user admin from 41.43.112.199 port 41805
Oct 22 18:17:58 localhost sshd[8903]: input_userauth_request: invalid user admin [preauth]
Oct 22 18:17:59 localhost sshd[8903]: Connection closed by 41.43.112.199 port 41805 [preauth]
Oct 22 20:58:03 localhost sshd[2074]: Received disconnect from 72.93.85.203 port 53552:11: disconnected by user
Oct 22 20:58:03 localhost sshd[2074]: Disconnected from 72.93.85.203 port 53552
Oct 22 20:58:03 localhost sshd[2072]: pam_unix(sshd:session): session closed for user ec2-user
Oct 22 21:32:54 localhost sshd[8944]: pam_unix(sshd:session): session opened for user ec2-user by (uid=0)
Oct 22 21:35:15 localhost runuser: pam_unix(runuser-l:session): session closed for user ec2-user
Oct 22 21:35:15 localhost runuser: pam_unix(runuser-l:session): session opened for user ec2-user by ec2-user(uid=0)
Oct 22 21:35:16 localhost runuser: pam_unix(runuser-l:session): session closed for user ec2-user
```

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Step 2 – cluster similar messages together

Oct 22 18:17:58 localhost sshd[8903]: Invalid user admin from 41.43.112.199 port 41805

Oct 22 18:17:58 localhost sshd[8903]: input_userauth_request: invalid user admin [preauth]

Oct 22 18:17:59 localhost sshd[8903]: Connection closed by 41.43.112.199 port 41805 [preauth]

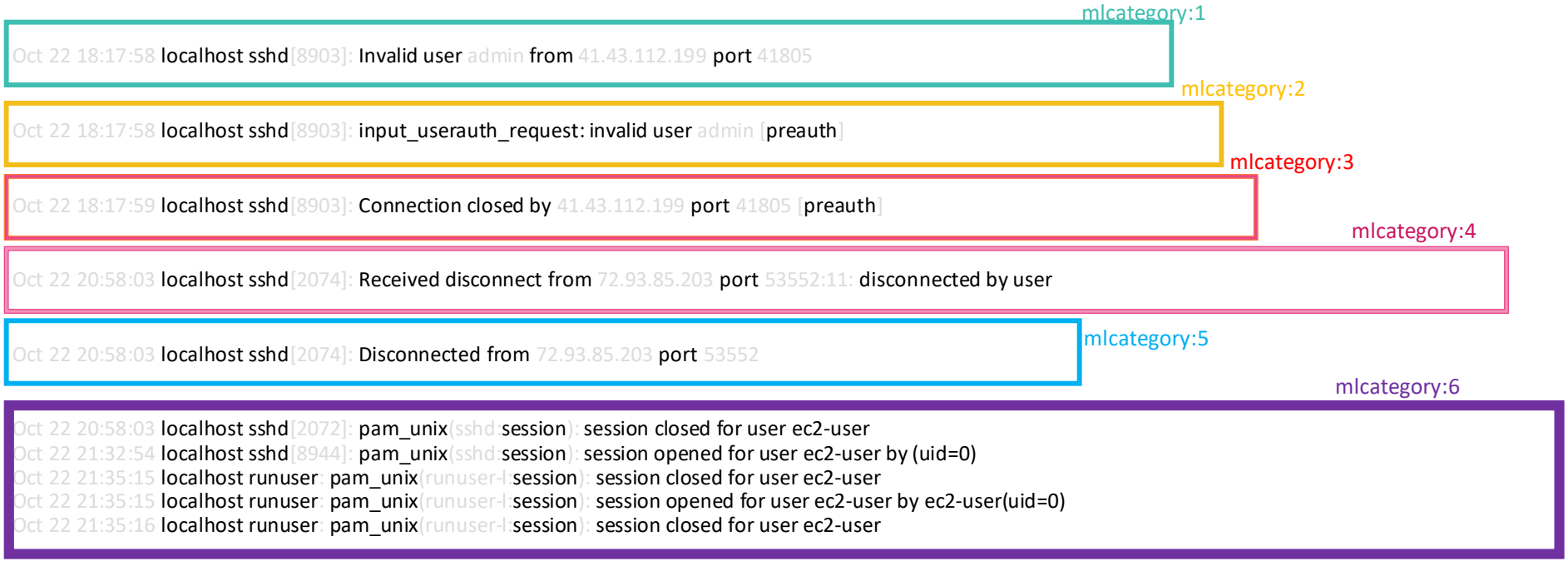
Oct 22 20:58:03 localhost sshd[2074]: Received disconnect from 72.93.85.203 port 53552:11: disconnected by user

Oct 22 20:58:03 localhost sshd[2074]: Disconnected from 72.93.85.203 port 53552

Oct 22 20:58:03 localhost sshd[2072]: pam_unix(sshd:session): session closed for user ec2-user
Oct 22 21:32:54 localhost sshd[8944]: pam_unix(sshd:session): session opened for user ec2-user by (uid=0)
Oct 22 21:35:15 localhost runuser: pam_unix(runuser-l:session): session closed for user ec2-user
Oct 22 21:35:15 localhost runuser: pam_unix(runuser-l:session): session opened for user ec2-user by ec2-user(uid=0)
Oct 22 21:35:16 localhost runuser: pam_unix(runuser-l:session): session closed for user ec2-user

elastic

Step 2 – cluster similar messages together



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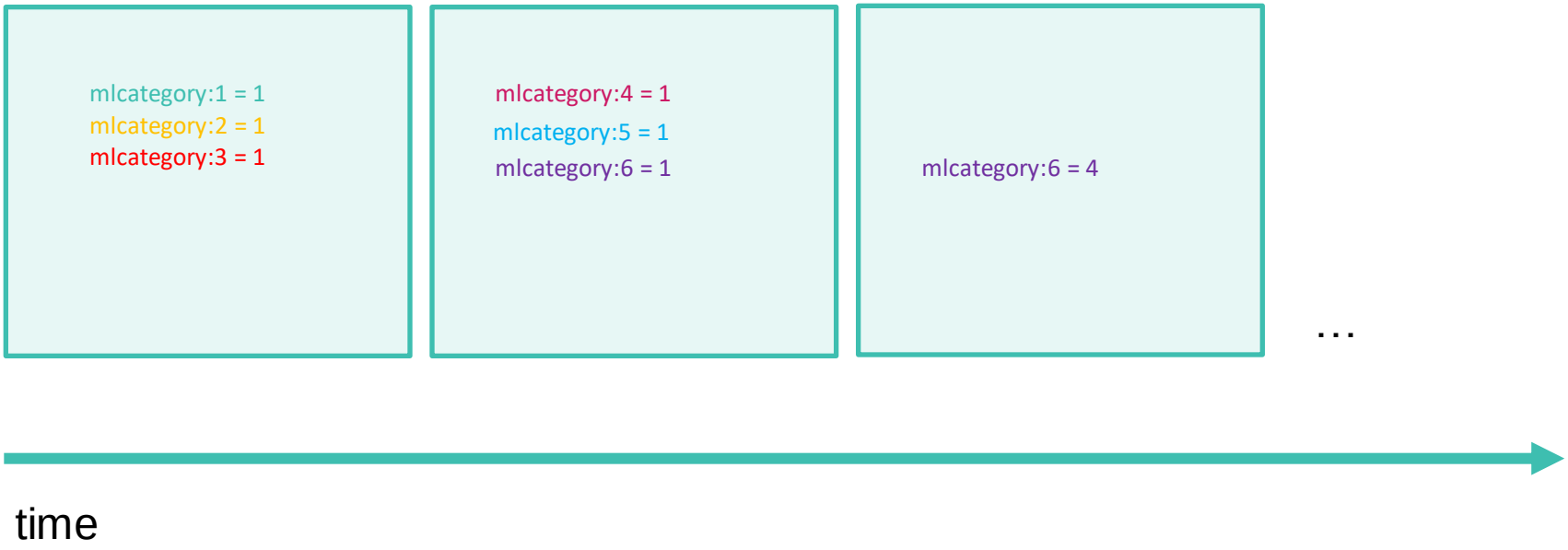
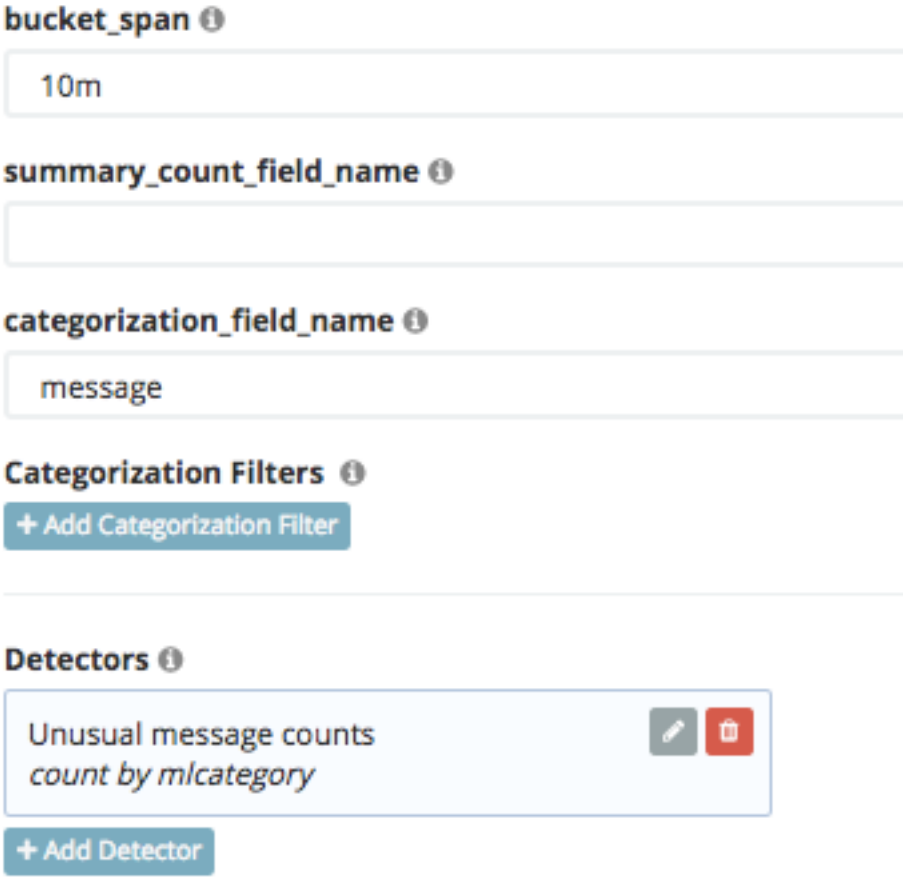
Step 3 – count per time bucket

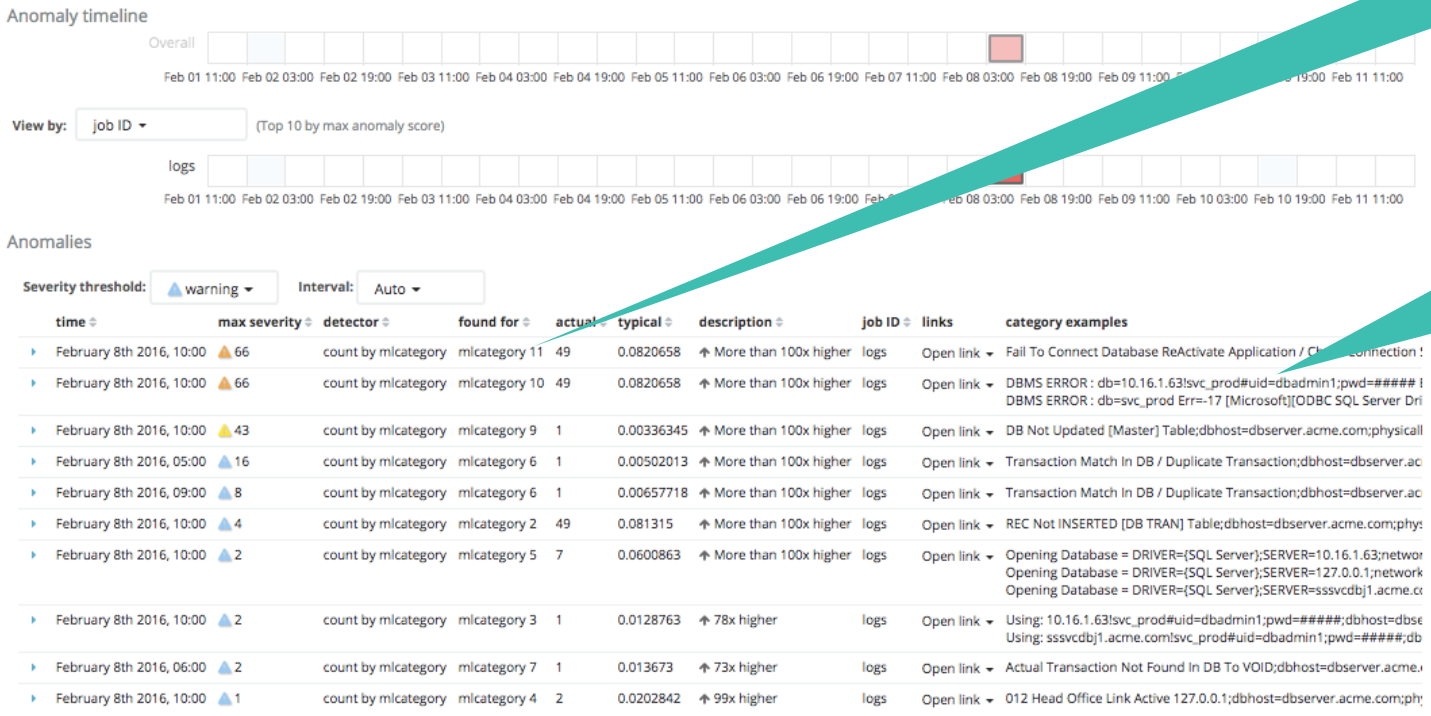


Categorization Example

- Configure an ML job to use:
  - “message” as the categorization_field_name
  - there will be a new, “magic” field called “mlcategory” that is dynamically created by ML to group similar messages together



Categorization Example – count by mlcategory



category name

example matching log messags

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Lab 4, Track 1: Root Cause Analysis

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Lab 4: Track 1 - Problem

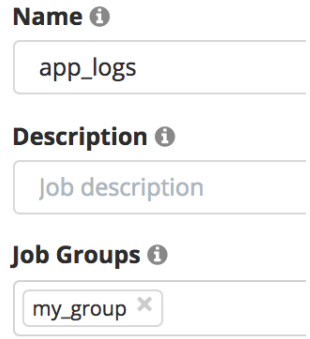
- Transaction processing app records # transactions per minute in an index called “it_ops_kpi-*”. Find the anomaly in it.
- Also, SQL Database and Network performance metrics were gathered for the application environment (it_ops_network-* and it_ops_sql-*). Use multi-metric jobs to see what might be going on in there.
- Lastly, there’s an index (it_ops_app_logs-*) that has the application’s log lines in them. See if there’s anything anomalous in there as well.
- View all jobs correlated together in the Anomaly Explorer

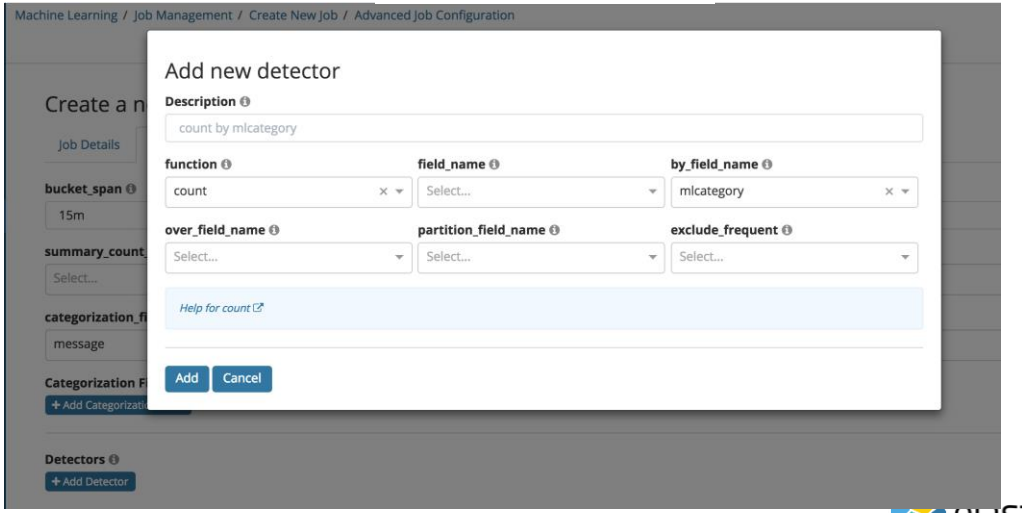
Lab 4: Track 1 - Solution

- Create and Advaned job for:
  - “it_ops_app_logs-*”
  - Create a “count by mlcategory” job for the log events
    - use “message” as the categorization_field_name
- Create Multi-Metric jobs for the following indices:
  - it_ops_sql-*
  - it_ops_network-*
- Create a “low_sum” Single-Metric job for the following :
  - it_ops_kpi-*
- Group all jobs into the same Job Group name
- View all jobs overlaid in the Explorer View

Lab 4: Track 1 - Solution

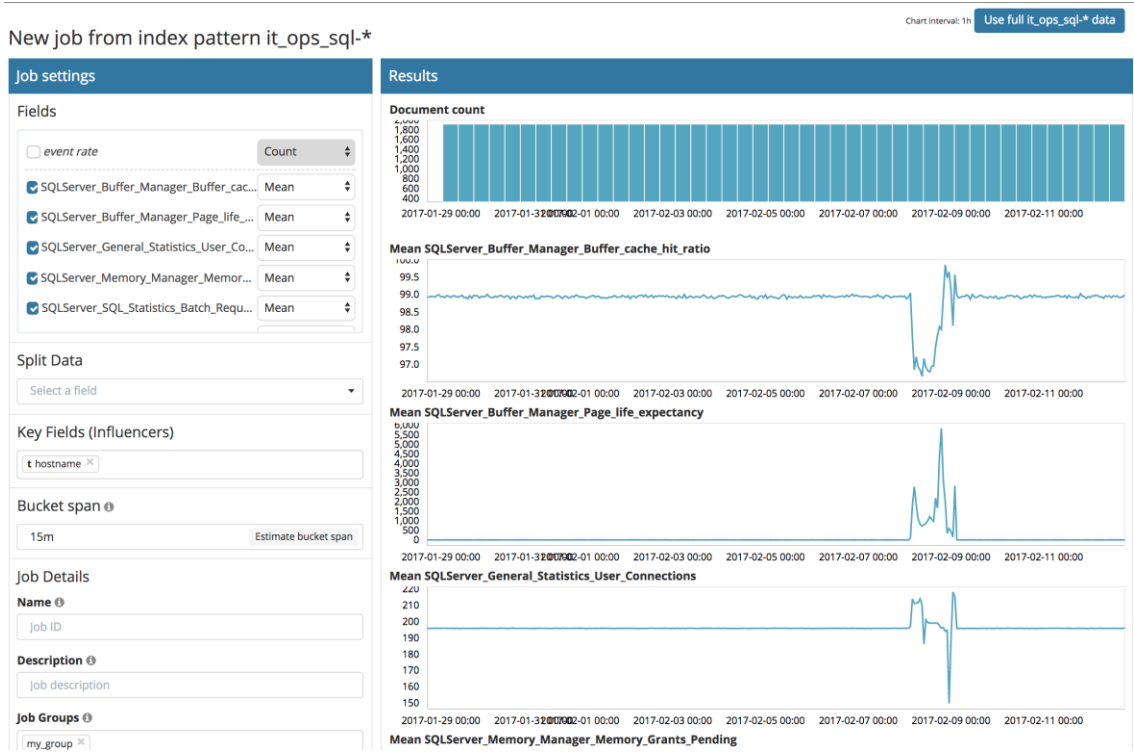
- For index:it_ops_app_logs
  - create an advanced job
  - put job in a group
  - make sure you choose “message” for categorization_field_name
  - detector is: count with by_field_name of “mlcategory”





Lab 4: Track 1 - Solution

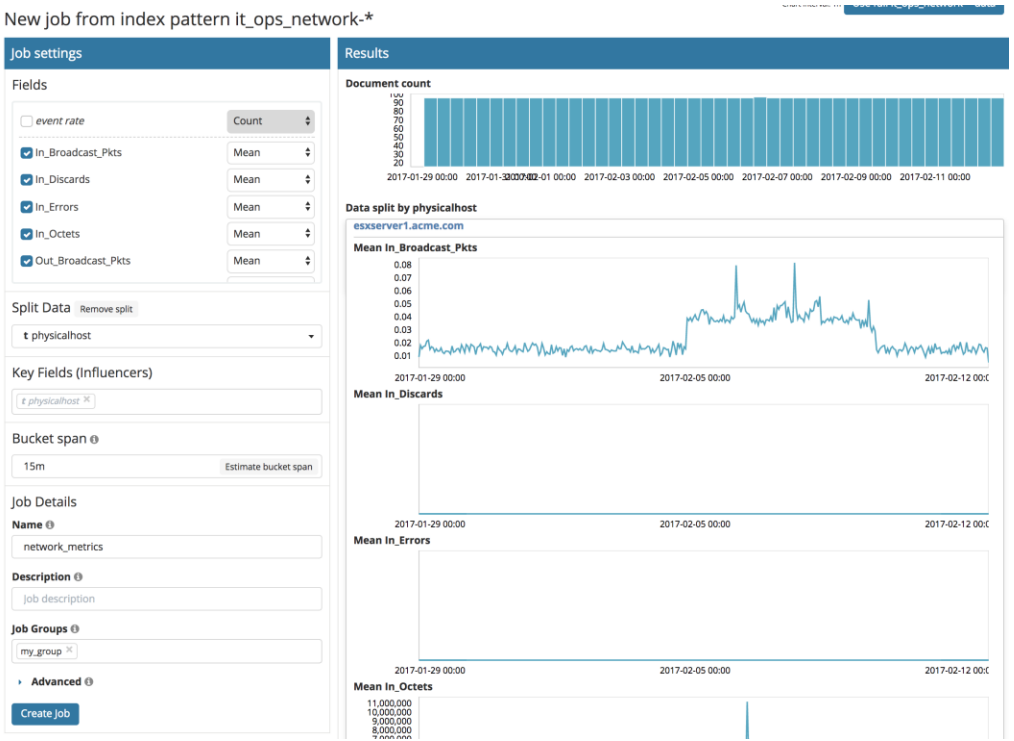
- For index:it_ops_sql-*
  - create multi-metric job
  - “mean” for all SQL metrics
- Also put job in same Job Group as the app logs job



Lab 4: Track 1 - Solution

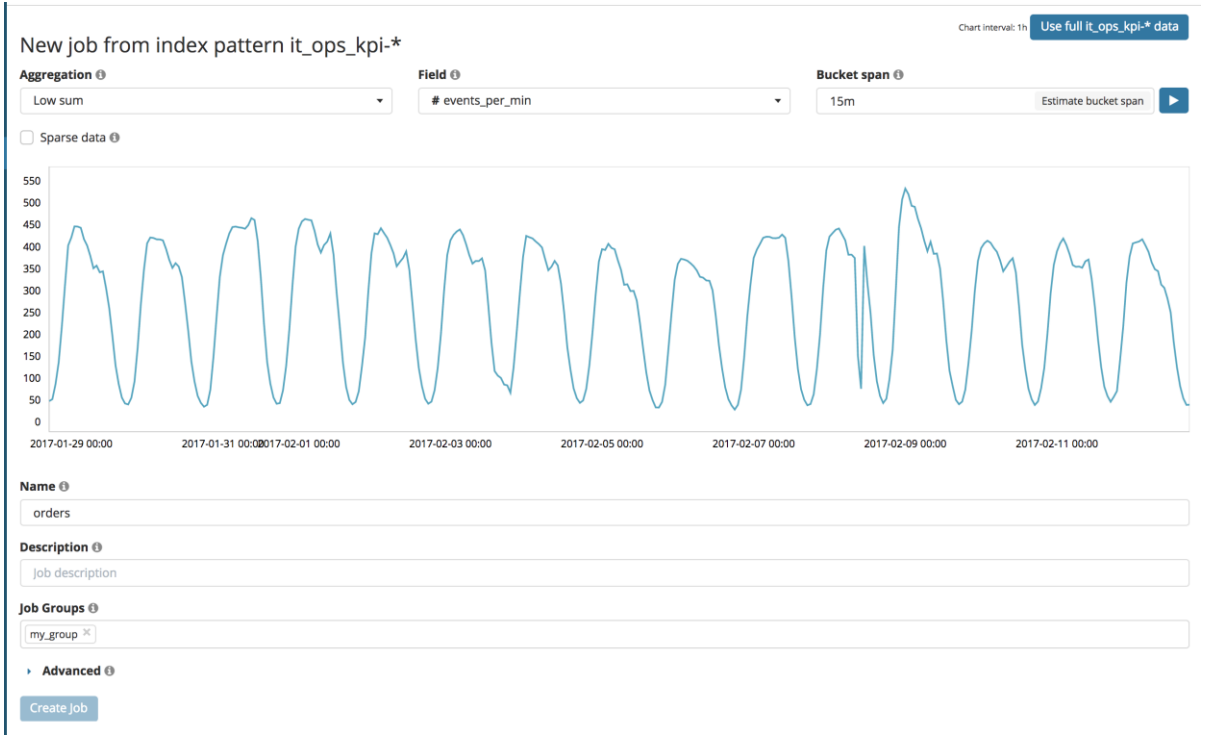
- For index:it_ops_network-*
  - create multi-metric job
  - “mean” for all metrics

- Also put job in same Job Group as the app logs job



Lab 4: Track 1 - Solution

- For index:it_ops_kpi-*
  - create single-metric job
  - “low_sum” for field “events_per_min”
- Also put job in same Job Group as the app logs job



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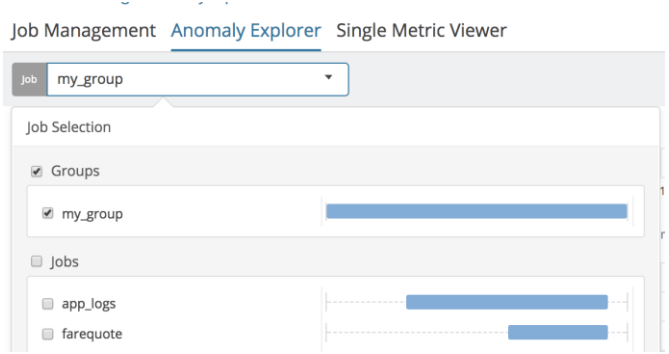
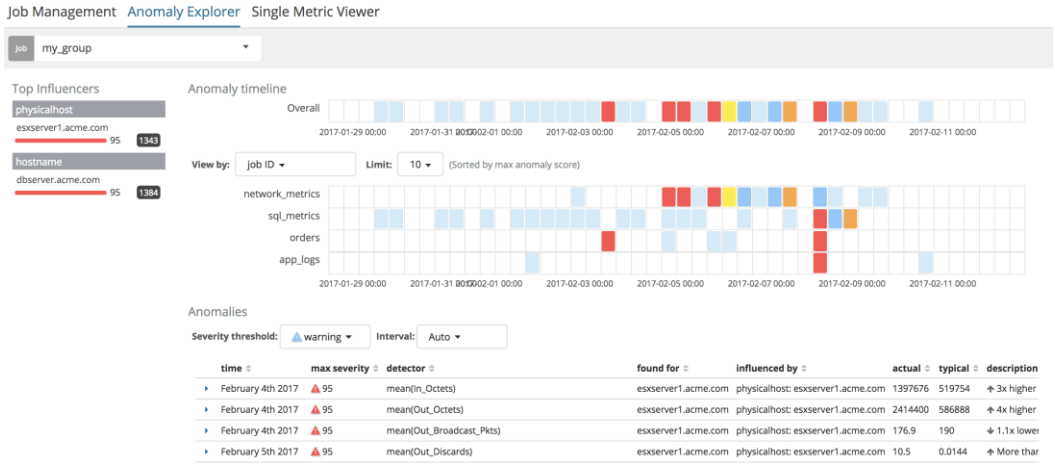
Lab 4: Track 1 - Solution

- View all jobs in Group



- See correlated anomalies



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Lab 4, Track 2: Analyze Web Logs

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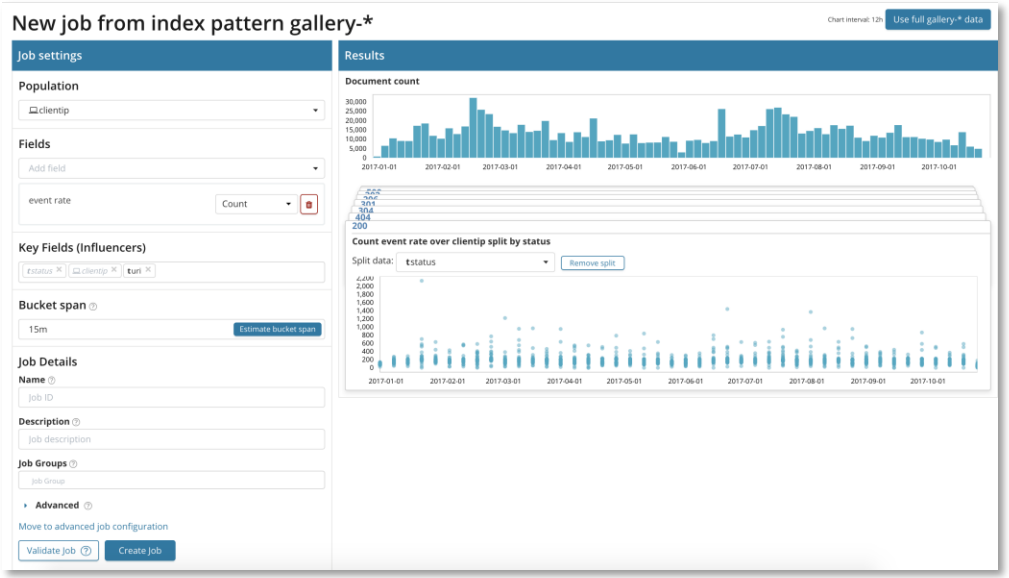
Lab 4: Track 2 - Problem

- There’s been suspicion that automated bots are slamming the web site from time to time.
- Use a population analysis job to find any rogue IPs and see what URIs were being requested
- Data is in gallery-* index

Lab 4: Track 2 - Solution

- Create and population job for:
  - “gallery-*”
  - count by status over clientIP
  - uri as additional Influencer



Lab 4: Track 2 - Solution

- See rogue IP 173.203.78.60
- Thousands of requests for URI: wp-login.php
- This is a low-intelligence brute force attack
- Fortunately, that web page doesn't exists on webserver, hence 404 status code

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ML Recipes

Complex Detector Example

- **high_count by ErrorCode over Host partition_field=App**
  - Partition: App
    - Split the data into separate data sets for each App. Create a model (and population) for each.
  - Over: Host
    - For each App, create a population model out of all the Hosts and detect when a Host stands out.
  - By: ErrorCode
    - When modeling and evaluating Hosts, baseline each ErrorCode separately.
  - Function: High_Count
    - Measure the number of times an ErrorCode is observed in the time bucket.

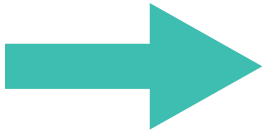
https://www.elastic.co/kr/what-is/elasticsearch-machine-learning/recipes

2. Entity based ML : Data Frame Analytics Concepts

Elastic Data frames transforms

1st Transform: Pivot

```
Original Data:
{
    index: reviews,
    user: rich,
    vendor: acme,
    review: 4,
    timestamp: 2019-04-26T10:12:01
},
{
    index: reviews,
    user: rich,
    vendor: transpop,
    review: 3,
    timestamp: 2019-04-28T10:17:42
},
…
```



```
Output stream:
{
    index: reviews,
    user: rich,
    avg_review: 3.5,
    num_reviews: 2
}
```

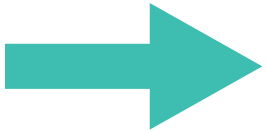
Entity-centric indexing/summarization from a data stream

elastic

Elastic Data frames transforms

1st Transform: Pivot

```
Original Data:
{
    index: reviews,
    user: rich,
    vendor: acme,
    review: 4,
    timestamp: 2019-04-26T10:12:01
},
{
    index: reviews,
    user: rich,
    vendor: transpop,
    review: 3,
    timestamp: 2019-04-28T10:17:42
},
{
    index: reviews,
    user: rich,
    vendor: vcentrix,
    review: 5,
    timestamp: 2019-04-29T09:27:12
},
…
```



```
Output stream:
{
    index: reviews,
    user: rich,
    avg_review: 4,
    num_reviews: 3
}
```

Entity-centric indexing/summarization from a data stream

elastic

“DataFrames”

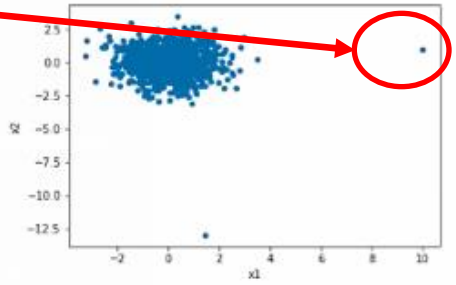
What do people do with it?

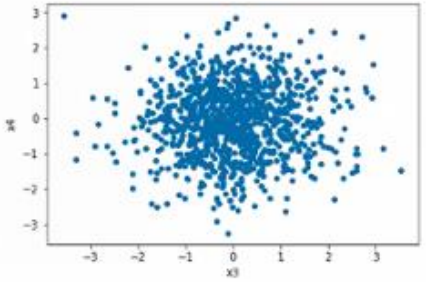
- Analyze multiple variables together
- Model real-world situations
- Find outliers
- Make predictions

```
In [5]: import pandas as pd
        from matplotlib import pyplot as plt

In [15]: dfx = pd.read_csv('/Users/thomasveasey/data/x')
         dfx.head()

Out[15]:
```

	id	x1	x2	x3	x4	x5	x6
0	1	10.000000	0.988253	-1.279285	0.373475	-0.829858	-1.530520
1	2	1.452591	-13.000000	0.266071	-0.067993	0.109710	0.780813
2	3	-1.387421	-1.380247	-0.982101	-1.150864	-0.425088	0.999819
3	4	-0.310192	-0.638912	-0.939306	1.544084	-0.933099	0.167036
4	5	-0.305223	-1.793177	2.122106	0.522571	0.455539	-0.312145

```
In [11]: dfx = pd.read_csv('/Users/thomasveasey/data/x')
         dfx.plot.scatter(x = 'x1', y = 'x2')
         dfx.plot.scatter(x = 'x3', y = 'x4')

Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x121f42eb8>
```





Use Cases

- Sales Analysis (House prices, etc.)
- Unusual Transactions (Fraud, etc.)
- User Behavior (Customer churn, etc.)

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“DataFrames”

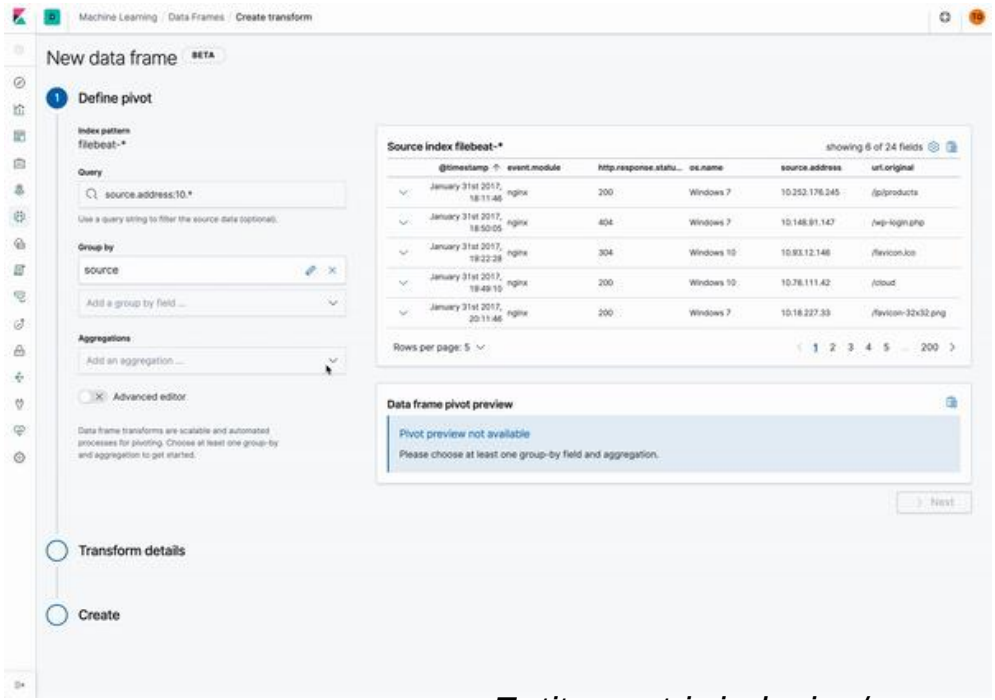
Common Challenges?

- Analysis often limited by RAM of single machine
- Data Scientists cannot/don’t want to design and manage a scalable architecture for analysis
- Data may already be collected and centralized in a ”Big Data” tool, but cannot “use it there”
- Data may exist in a time-series format and would need to be transformed

Lab 5, Transforms

Elastic Data frames transforms

1st Transform: Pivot



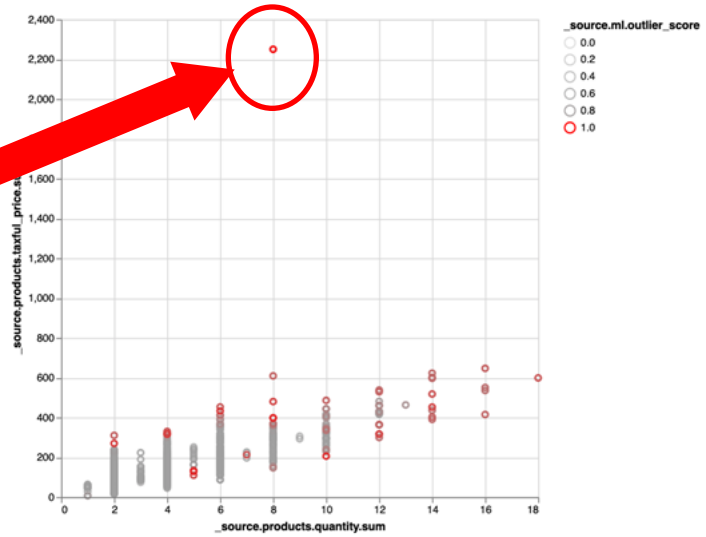
Entity-centric indexing/summarization from a data stream

elastic

Elastic “Data frames analytics”

2st Analysis – Multi-dimensional outlier detection, Regression, Classification…


```
"customer_full_name" : {
  "keyword" : "Wagdi Shaw"
},
"ml__id_copy" : "Vyu9e08pKNasT-9TLV9p3k0AAAAAAAAA",
"products" : {
  "taxful_price" : {
    "sum" : 2250.0
  },
  "quantity" : {
    "sum" : 8.0
  }
},
"ml" : {
  "outlier_score" : 0.9848338961601257,
  "feature_influence.products.quantity.sum" : 0.007586637046188116,
  "feature_influence.products.taxful_price.sum" : 0.992413341999054
}
```

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Topics in Production

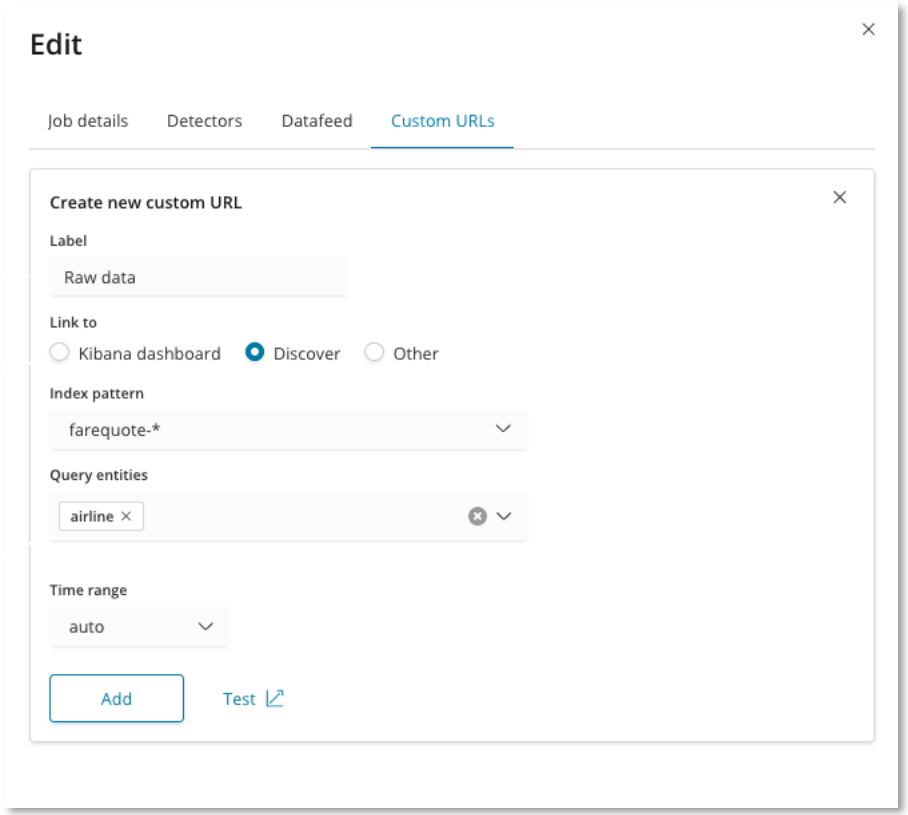
Custom URLs: Linking to other places, in context

Custom URLs in Job config

Name the label

where to link

fields for filtering



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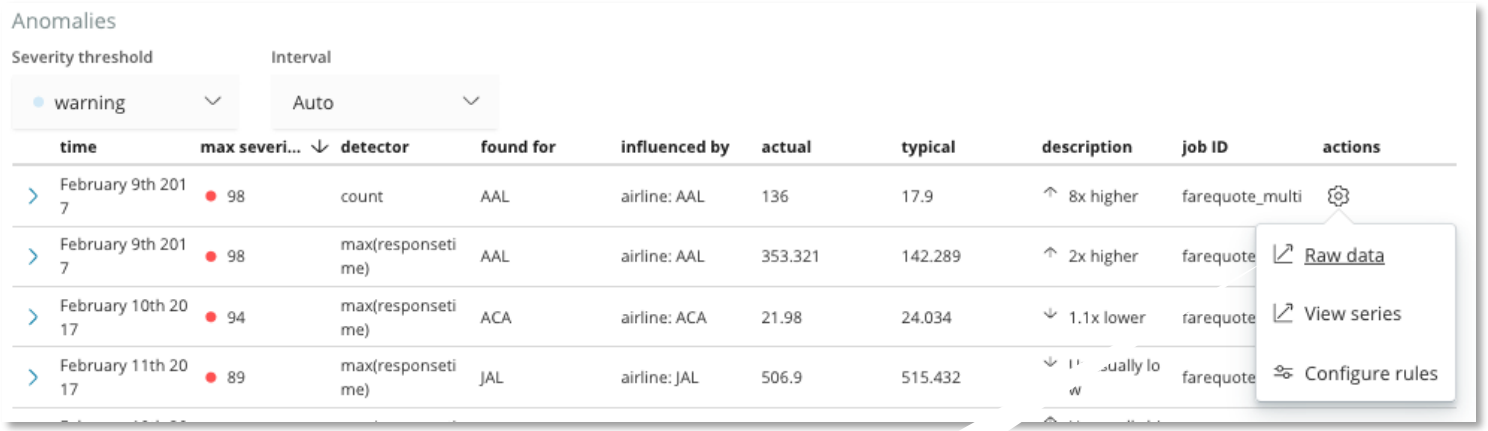
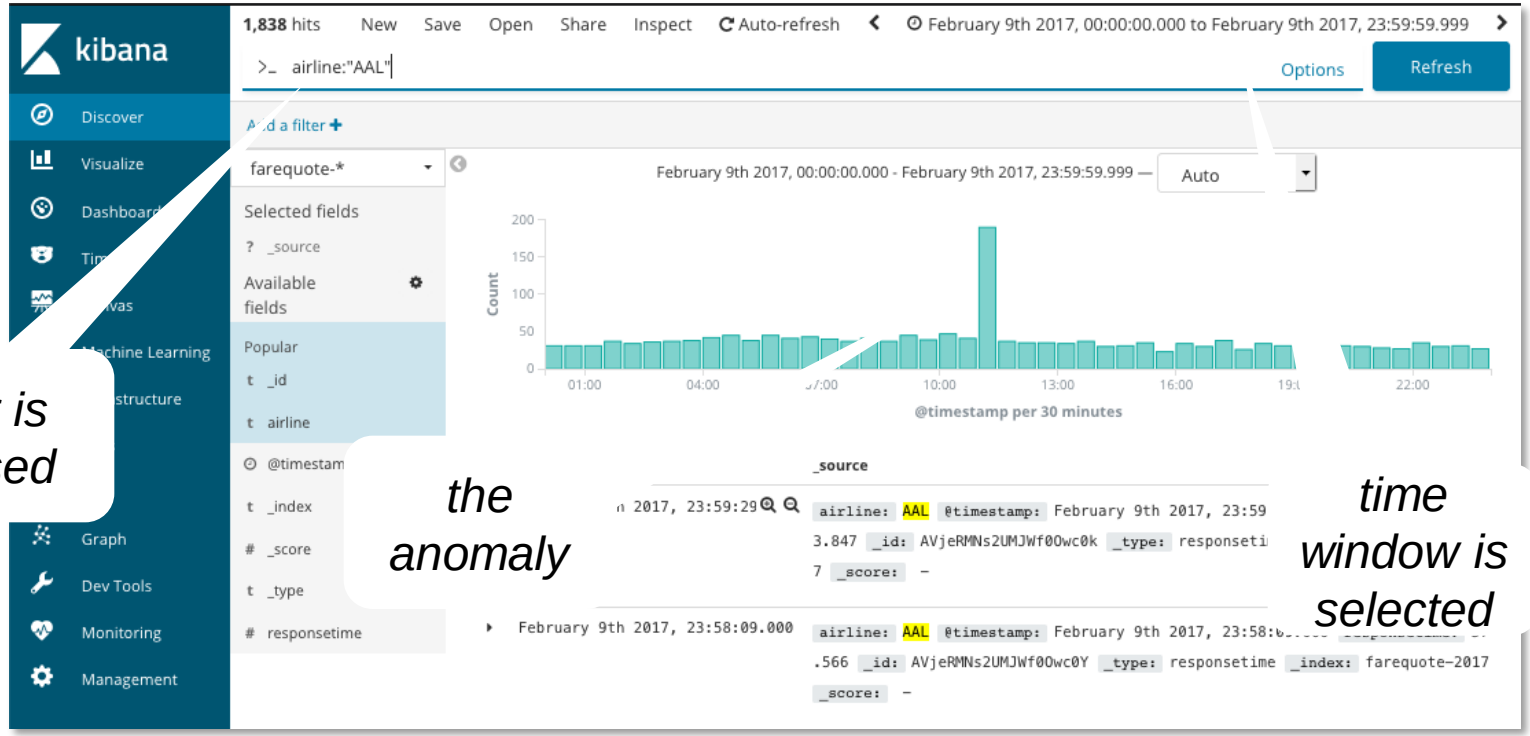
In Anomaly Explorer



Link now available

elastic

Clicking on Custom URL, passing context



elastic

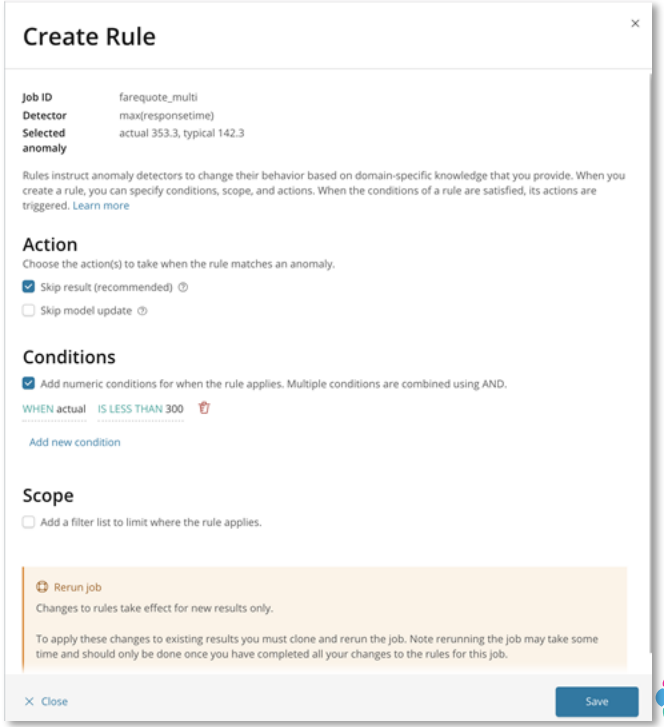
Custom Rules

Adding Custom Rules to ML
(v6.4+)

Define rules that:
- Ignore the creation of anomalies
- Disqualify data from being modeled

Meet certain conditions:
- on “actual”, ”typical” or difference

Optional scoping
- limit when rule is applied



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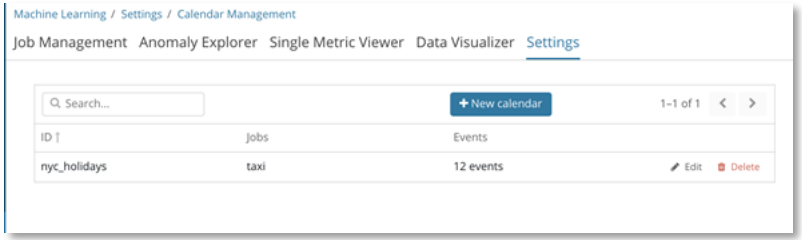
Calendars

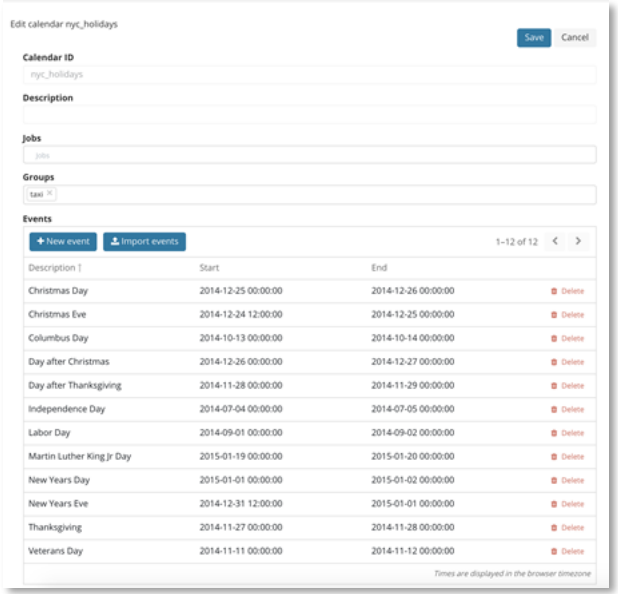
Ignoring Timeframes with Calendars

Define timeframes for ML to
- not create anomalies
- not allow model to see new data

Good for known, upcoming times

Calendars can apply to individual jobs or job groups





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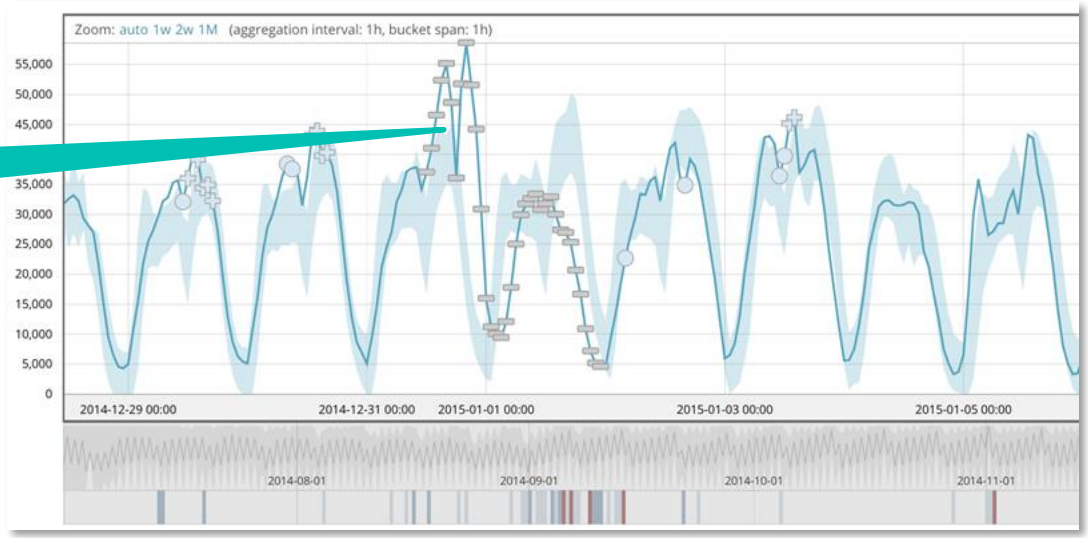
Ignoring Timeframes with Calendars

Ignored times marked with "—" symbol



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Let’s apply ML to your DATA!!!

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Thank you

https://www.elastic.co/kr/what-is/elasticsearch-machine-learning

elastic