CISCO

You make **possible**

Machine Learning in Network Operations

Lessons Learned

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BRKOPS-2991

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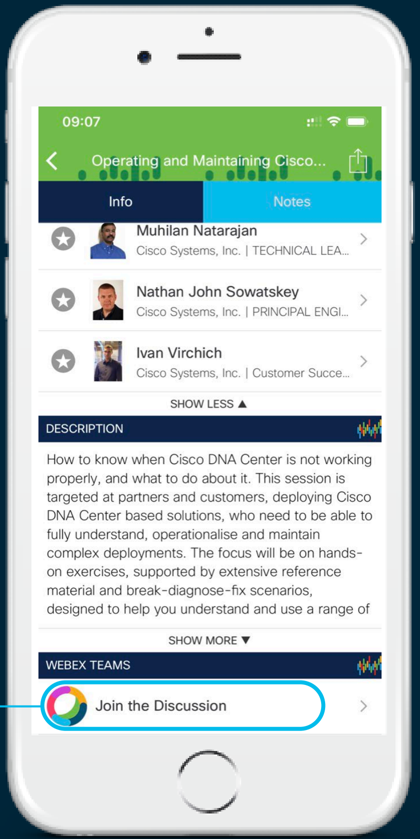


Objectives

Accelerate **Adoption of ML in Network Operations**

- What can it do
- How to start

Review **relevant ML considerations**

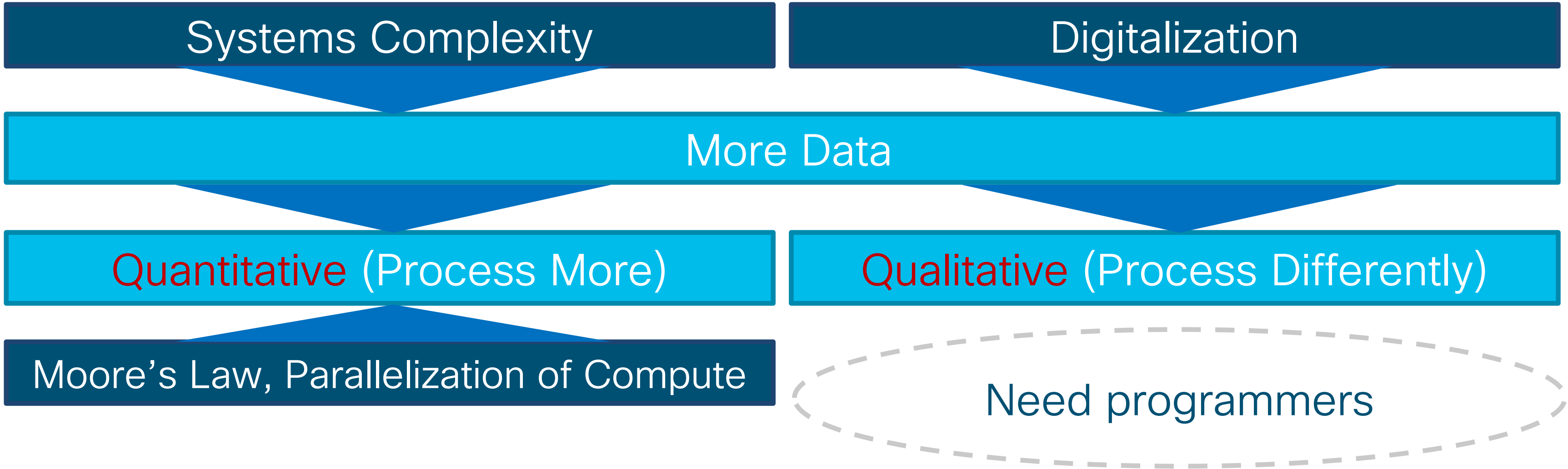
- Building, Running solutions with ML
- Maintain productive conversation with ML vendors

Agenda

- Intro: Network Operations + Machine Learning
- Building with ML
- ML in Production
- Use-case examples
- Conclusions

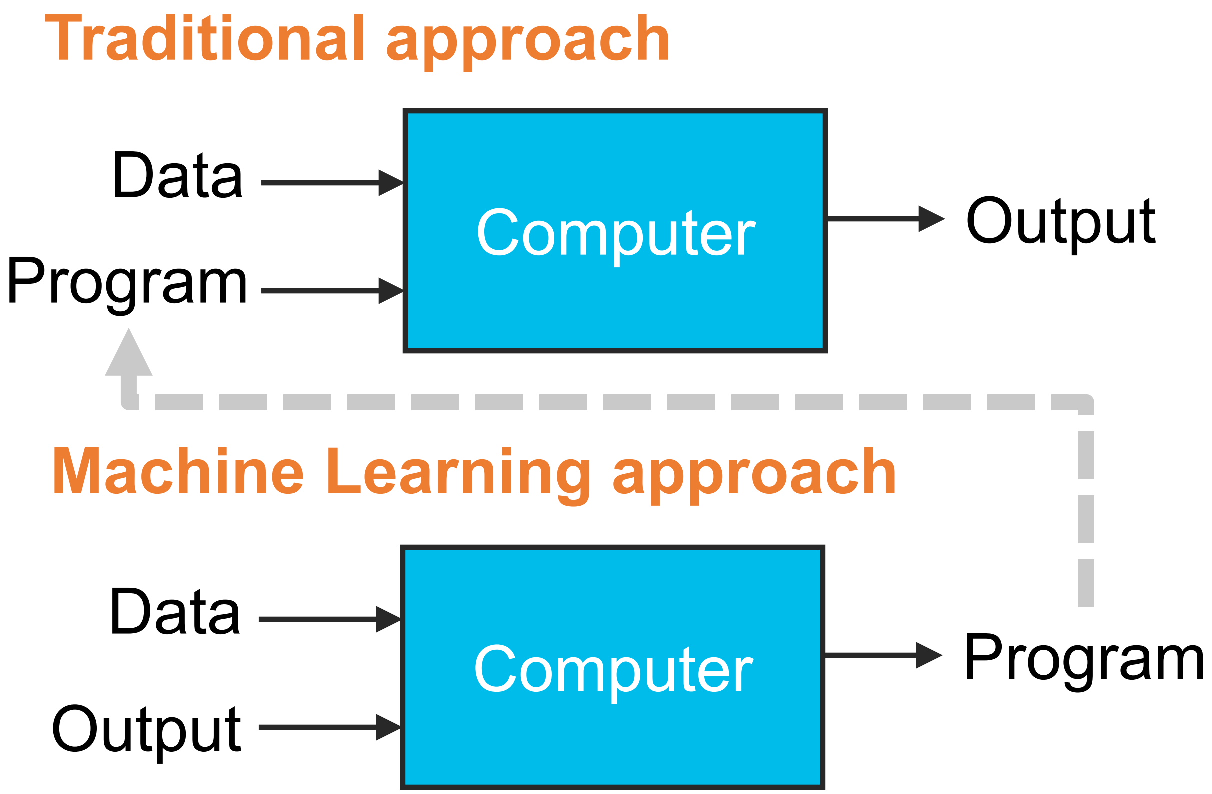
Introduction

Why now



ML helps to address the gap by changing how software is made

What is Machine Learning (in cartoon form)

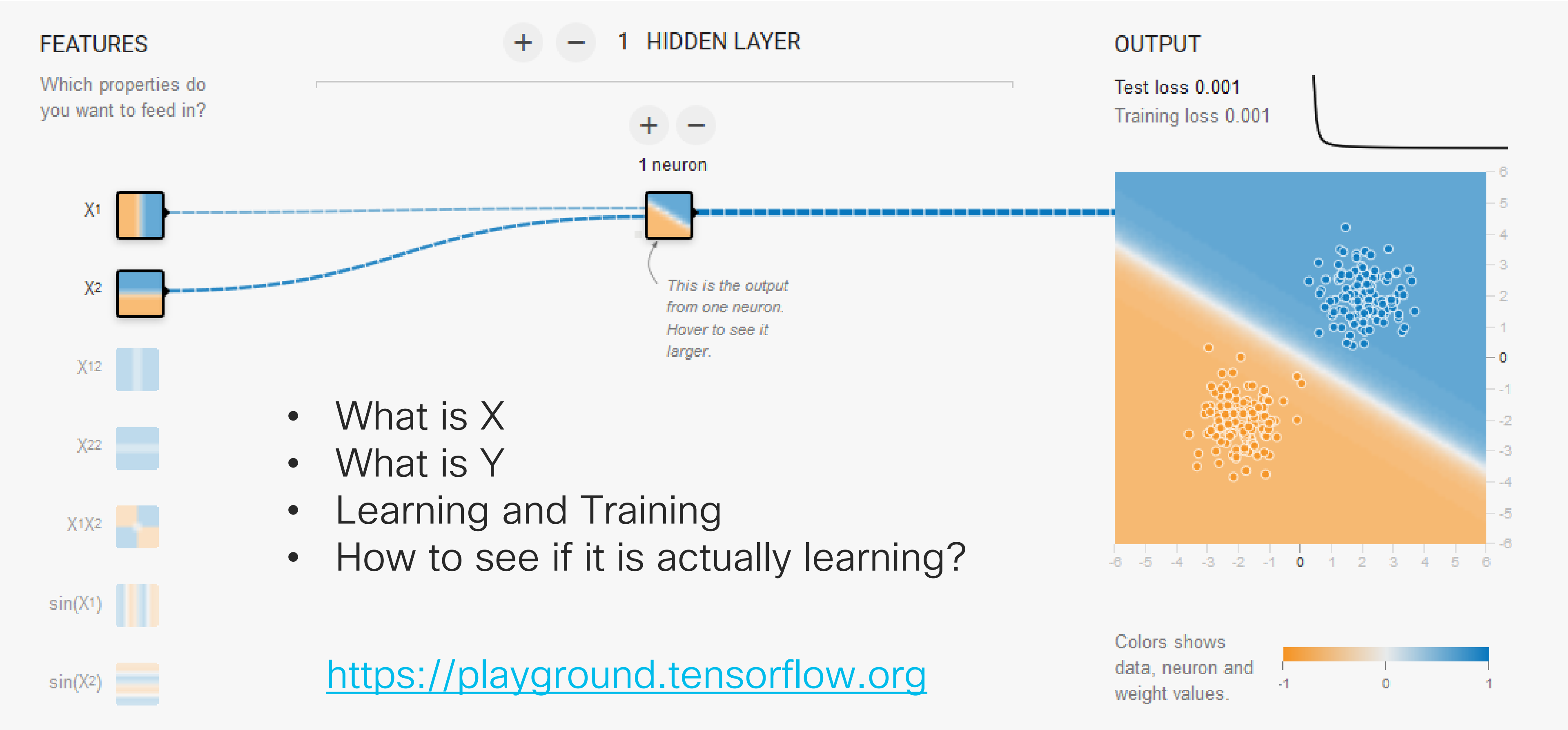


What is Machine Learning, by Way of Analogy

- Use examples to learn X to Y mapping
- X → input
- Y → output

X	Y
Picture	Objects in the picture
Voice Recording	Text transcription
Sales Figures for Last Week	Sales prediction for next week
Sensor Readings	Usual or Unusual?

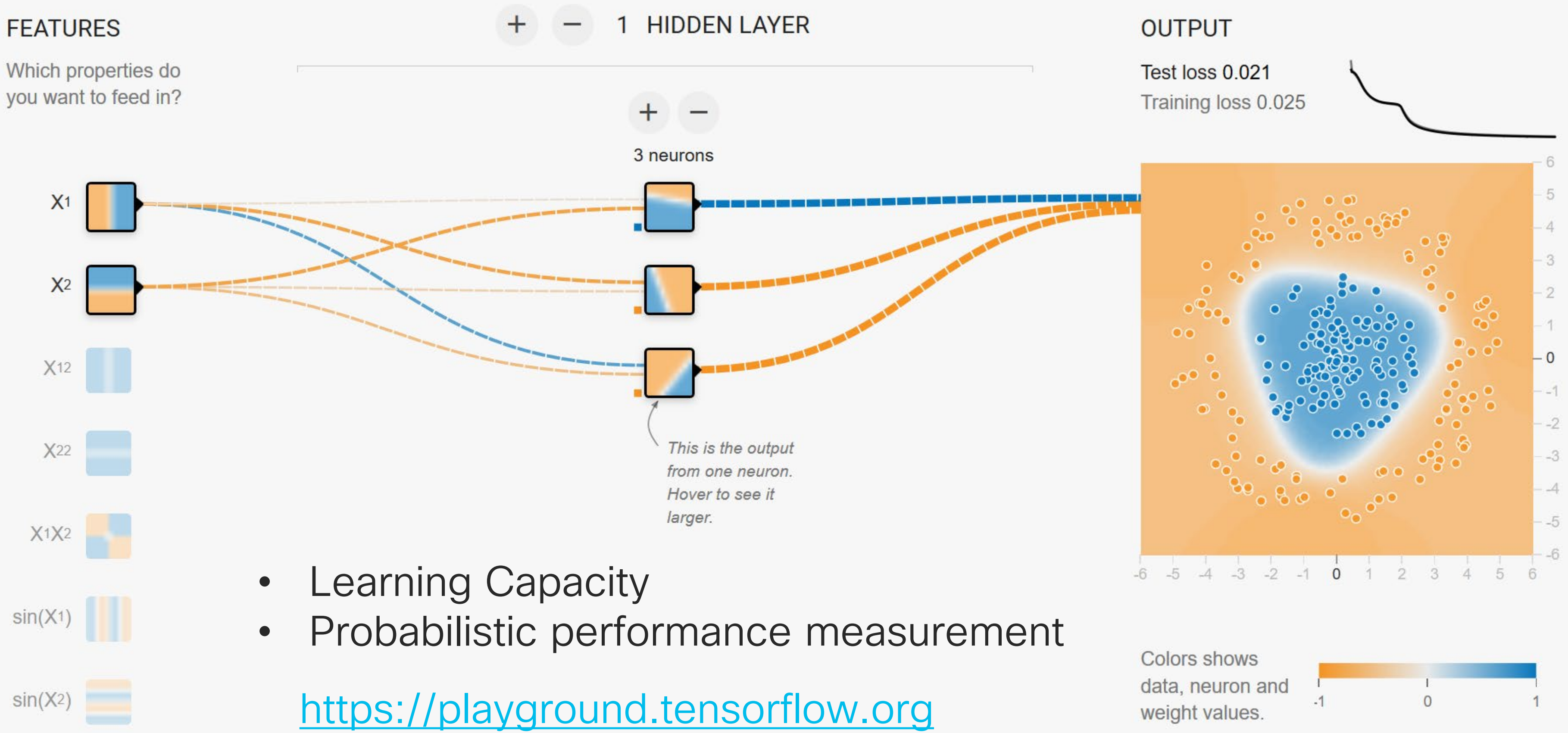
Learning about Machine Learning in the Browser



- What is X
- What is Y
- Learning and Training
- How to see if it is actually learning?

https://playground.tensorflow.org

Learning about Machine Learning in the Browser



- Learning Capacity
- Probabilistic performance measurement

https://playground.tensorflow.org

Supervised vs Unsupervised Learning

Supervised

- Labels (Y) are provided
- Classification: Will reload of router X impact flow Y?
- Regression: For how long the flow Y will be impacted by reload of router X

Unsupervised

- Transformations are done on data
- Clustering: Group routers by how many BGP prefixes and neighbors they know
- Dimensionality reduction: Compare the Uptime, CPU%, Memory% and Interface load of all devices in the network
  - Allows to find similar devices (small distance → more similar)
  - Also allows to do basic Anomaly Detection (far away from the rest → more unlikely)

- Often Supervised and Unsupervised Learning are used together

What ML can do for us

ML is very general capability. What are examples of problems seen in Network Operations well suited for todays ML capabilities

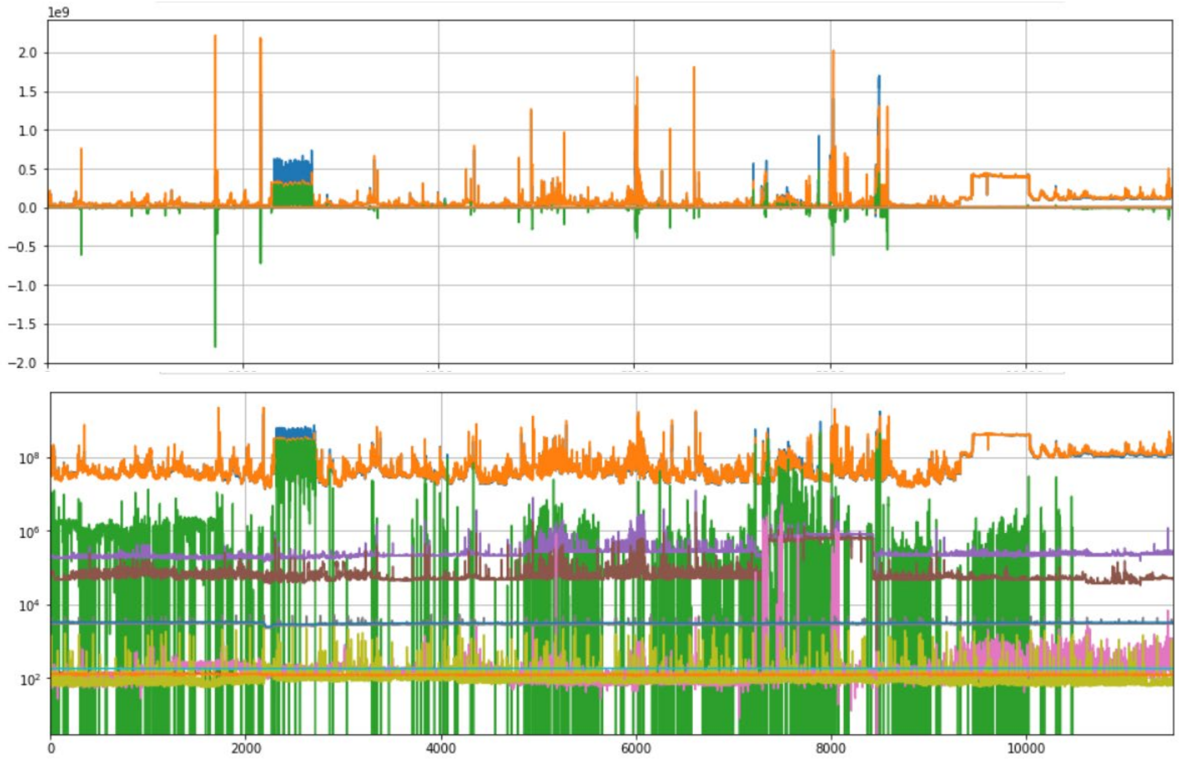
Problem Type	Description	How ML helps
Threshold problem	There is an error counter on each of 1000 devices, I need to do something when it is not normal.	ML can learn what ‘normal’ means 1000 times without having to manually set thresholds
Interaction problem	There is not one, but several counters. And they depend on each other. I need to do something when they are mutually not normal (each counter by itself can be normal)	ML can take multiple inputs and will learn their mutual correlations and dependencies

What ML can do for us

Problem Type	Description	How ML helps
Discovery problem	I have a lot of data about same events from different devices or components. There is too much to visually review, how do I find non-obvious things?	ML can ‘fuse’ data from different sources and represent it in a way easy to visualize
Maintenance problem	I carefully chosen thresholds, but now things have changed and I need to update 1000 of them	The other side of threshold problem – the fact that ML learns the threshold. It can do it every minute, hour, day, ….
Deluge problem	I have a combination of above problems in 1000, 100k, 100m instances…	ML scales very well, much better than writing individual code/config for each instance
Prediction problem	What if I wanted not to detect something, but rather predict (like have alert before failure happens)	ML can do detection very early (ns into events), as well as predict events*
…	…	…

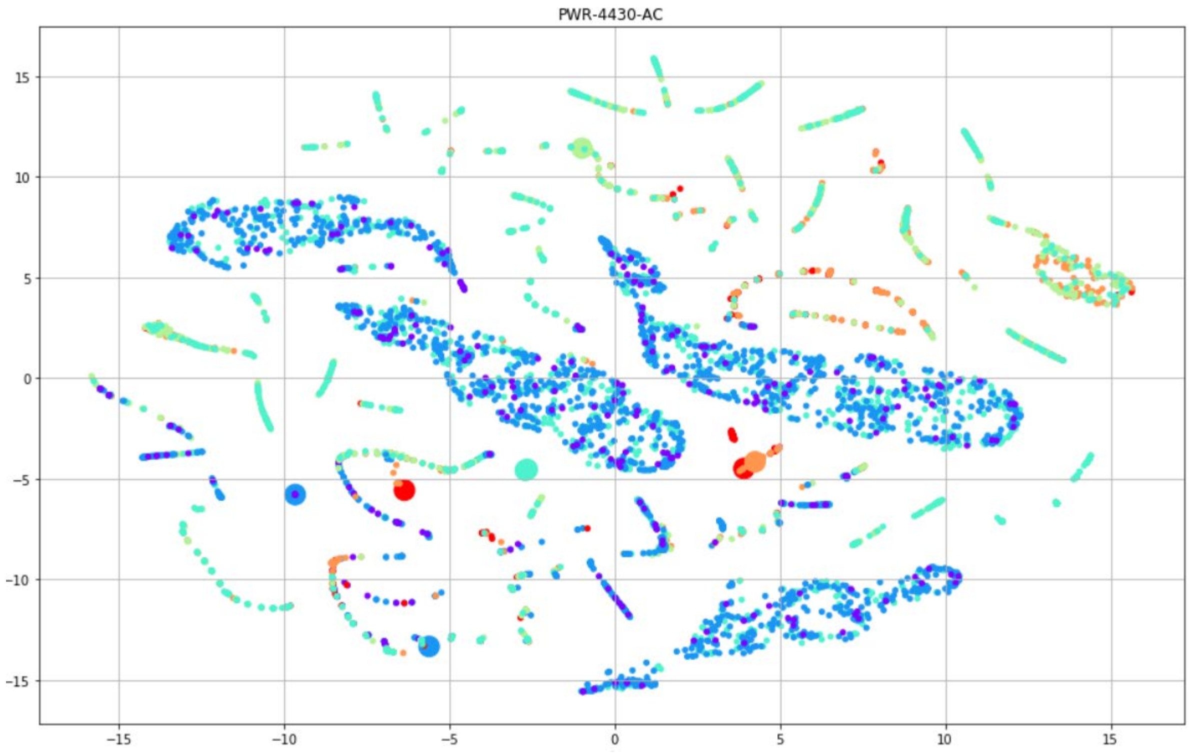
Example

ML is good at finding patterns, thresholds and anomalies in multidimensional data that is difficult to visualize



Example

- Dimensionality reduction
- Similarity
- Visualizing 15 dimensions of sensor data in 2 dimensions
- Useful for visual pattern discovery



Various ways to use ML

- Consume within a product
- Use trained models with new data
- Use existing pipelines with new data
- Create new pipelines with ML framework
- Create/Enhance ML framework
- Design new ML algorithms

Sophistication

Do we need ML when we have statistics?

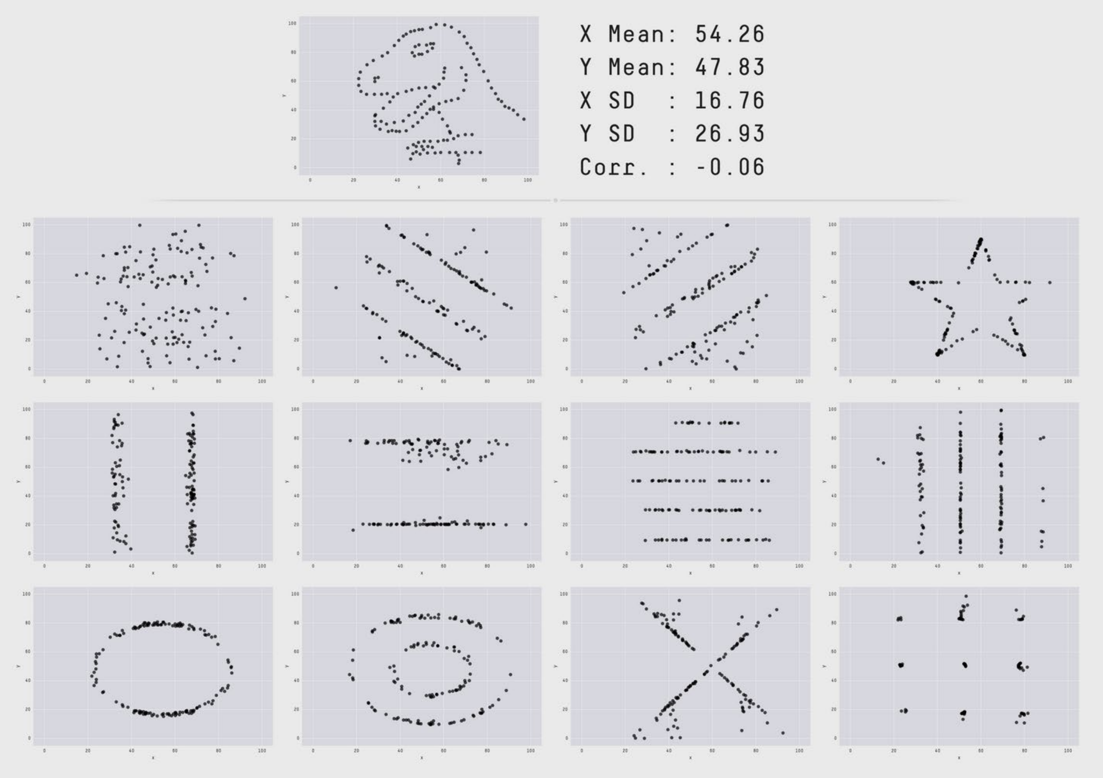
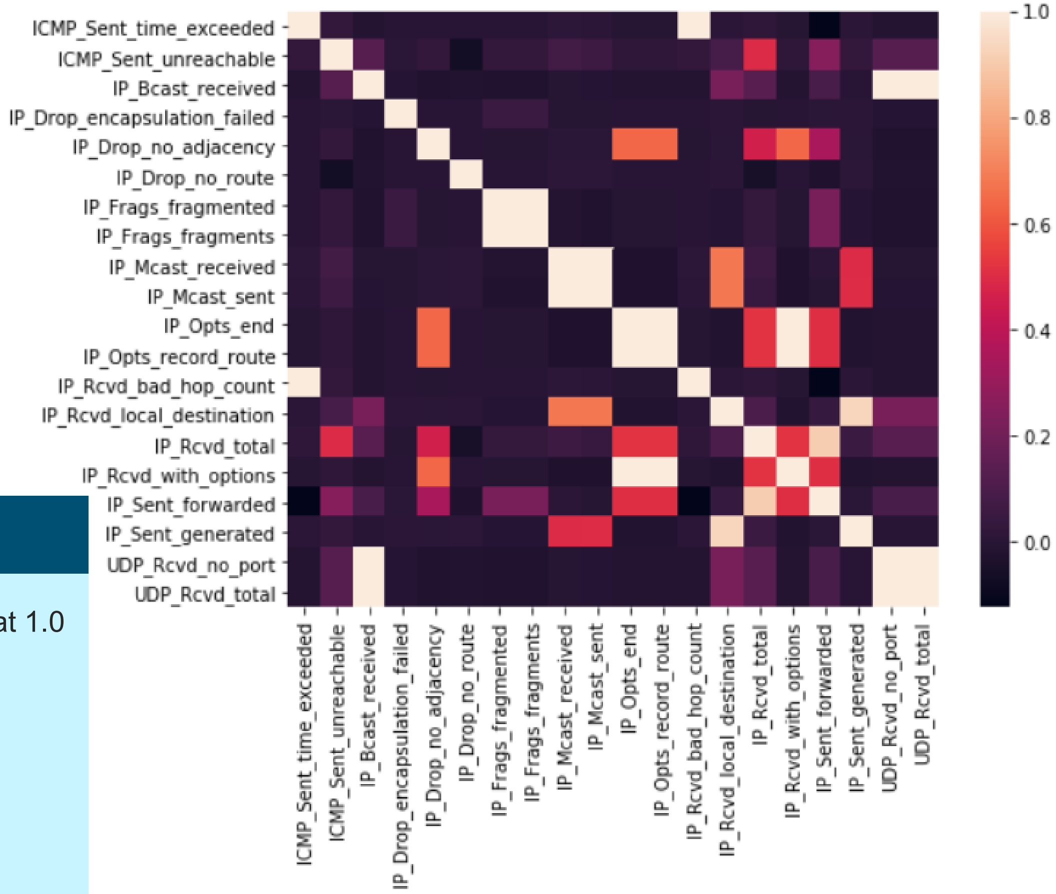


Fig 2. The ***Datasaurus Dozen****. While different in appearance, each dataset has the same summary statistics (mean, standard deviation, and Pearson's correlation) to two decimal places.*

https://www.autodeskresearch.com/publications/samestats

Correlation & Causation



Causal or coincidental?

ICMP_Sent_time_exceeded ←→ IP_Rcvd_bad_hop_count at 1.0

IP_Frags_fragmented ←→ IP_Frags_fragments at 1.0

IP_Sent_forwarded ←→ IP_Rcvd_total at 0.91

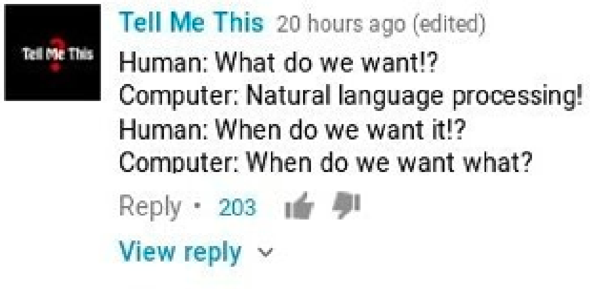
IP_Sent_generated ←→ IP_Rcvd_local_destination at 0.94

UDP_Rcvd_no_port ←→ IP_Bcast_received at 1.0

UDP_Rcvd_total ←→ IP_Bcast_received at 1.0

Limitations of today's Machine Learning

- X → Y mapping is not AI
  - Statistical Learning, Correlation / Matching
- Moravec Paradox + Narrow AI creates impression of intelligence
  - Easy to confuse proficiency at narrow task (answering specific question by voice) with general skill (answering any question)



an airplane is parked on the tarmac at an airport

Note about predictions

- Model outputs are often called predictions
- But not all predictions are about the future
- X→Y (calculate Y given X)
- If at time T anomaly detector sees strange sensor value, it will **detect** anomaly at time T
- To predict (foretell) an anomaly we need leading indicators

Building with ML

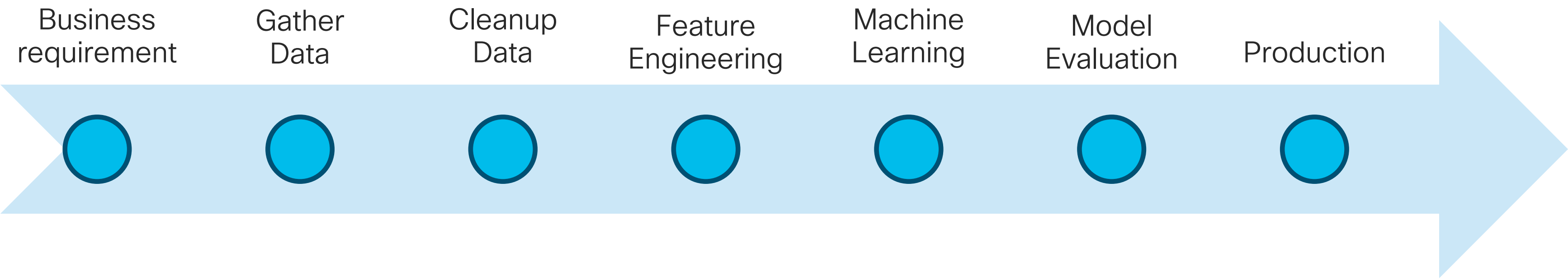
Evolution of ML use

- Consume within a product
- Use trained models
- Use existing pipelines with new data
- Create new pipelines with ML framework
- Create/Enhance ML framework
- Design new ML algorithms

Platforms with ML capabilities → Experiments in applying APIs to solve domain problems → Domain-specific solutions emerge

- Domain Expertize is Critical

Uncertainties



- Uncertainties will lead to adjustments and iterations
- MVP or RAT
  - Aligning priorities with risk allows to learn the most with the least investment
- Scaling is often seen as (and is) a challenge in many networking projects, but in ML use-cases it is very rarely a riskiest assumption
  - Proving that ML creates enough value with existing data

Intuition in applying ML to problems

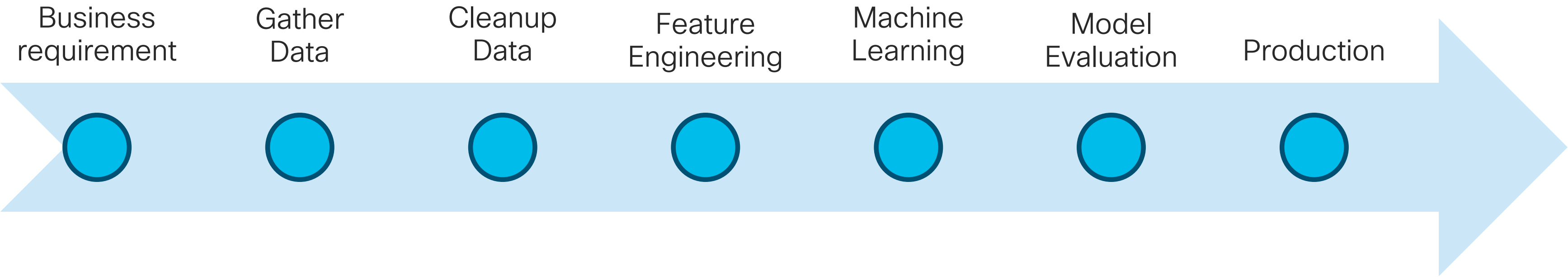
- Can ML help detect memory leak early?
- Data Scientist: Yes! .... If you have training data. Do you have training data?

upTime	FreeMem	Label
1	100	No Leak
2	90	Leak
3	80	Leak

- Even with leak the free memory could temporarily increase, how does one know if the memory just taken wouldn't be soon released?
- Collect data per-process? Per allocator?
- How many instances of leak we need to see before a reasonably good model can be trained?
- How long it will take to collect this data?

- What if we tried to predict uptime (Y) by freeMemory (X)
  - If there is no leak – the error of prediction should be high
  - With leak – the error should be visibly lower
- Just need the error threshold → can use few known examples of leak to set

Uncertainties



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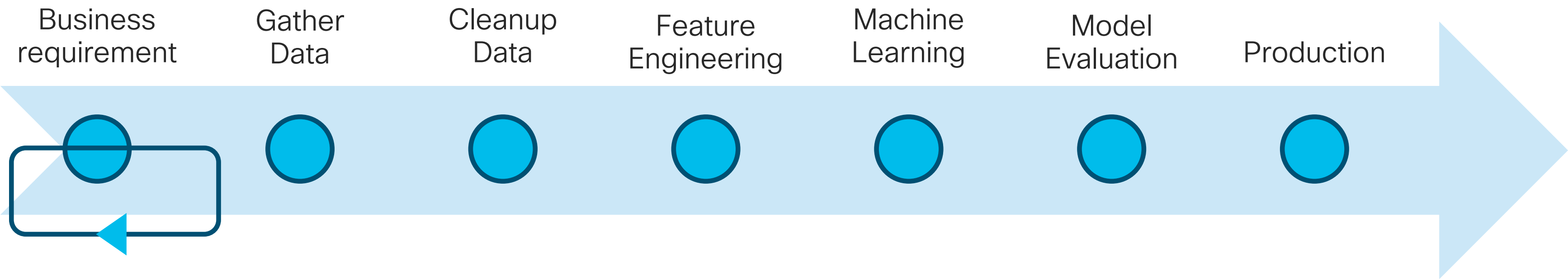
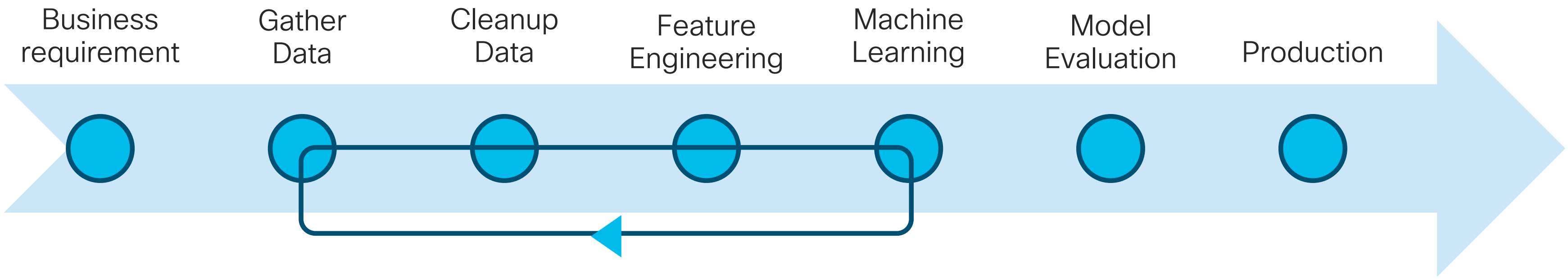
Uncertainties



- More interesting opportunity with existing data
- Data required cannot be obtained in requisite quantity or quality

Update Requirements	Update Data Collection

Uncertainties



- Available data does not permit Machine Learning pipeline to be efficient: too few samples, too biased, hard to extract features, …

Update
Data Collection

Robin Hanson
@robinhanson

Follow

Good CS expert says: Most firms that thinks they want advanced AI/ML really just need linear regression on cleaned-up data.

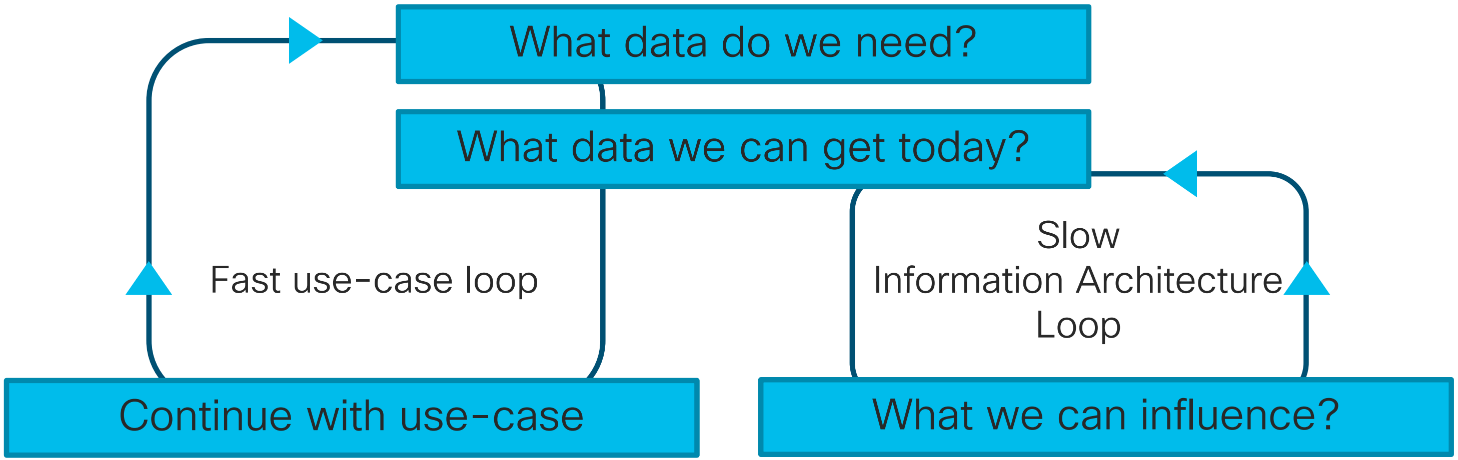
10:19 AM - 28 Nov 2016

https://twitter.com/robinhanson

Data lessons

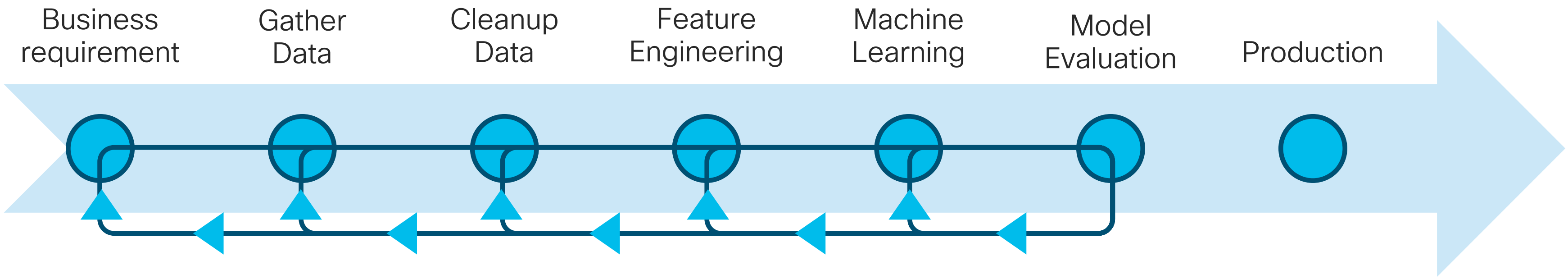
- Is Data really a New Oil?
- More data beats better algorithm
- Better data beats more data
- Data labeling is very large discipline in itself for organization to master (type systems, scale, consistency, maintenance)
  - If there is a way to sidestep labeling on the 1st ML use-case, there are good reasons to consider it
    - Race to production

Data lessons



- Information Architecture contributes to economics of every use-case
- How data is acquired can be different for MVP and production – it affects the scale and iteration cost, but not the business relevance (substrate independence)

Uncertainties



- Model doesn't achieve acceptable KPI levels

Update Requirements

Gather / Tag More Data

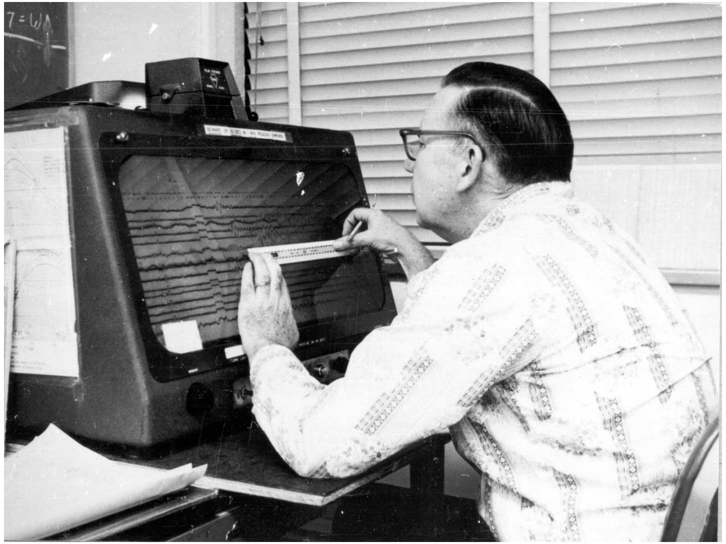
Update Data Preparation

Add / Change Features

Update ML HyperParameters

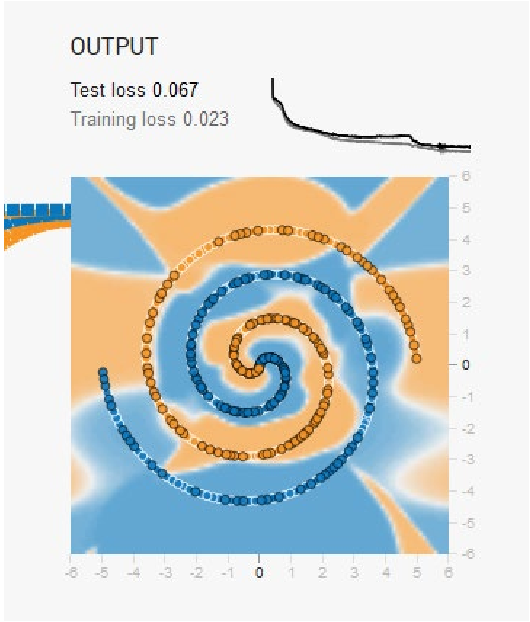
Evaluation

- **Never by a single number** (as in this model has 98% accuracy)
  - Graph: Predicted vs Reality, Residuals, …
- Does **feature importance make sense** to domain experts?
- **Review of the prediction errors** drives data and model improvement
  - Tradeoffs: False positives and False negatives often don’t have the same importance
  - Are we optimizing right goal (i.e. less large errors or lower average error)
  - Cluster all errors, review all clusters
- **Model interpretability (introspection)**
  - Explain individual predictions
  - Do correct predictions have right explanations
  - Data / Feature improvements



Importance of evaluation

- The evaluation numbers may look reasonable
- But what the model has learned is of little value to the task



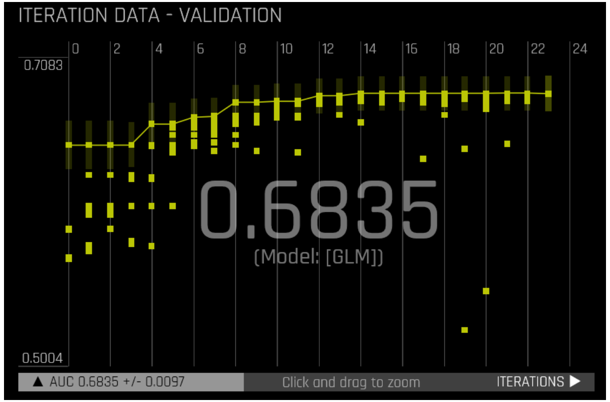
Machine Learning

- Getting away from 'what algorithm' question
  - If data is useful and clean – many algorithms can be evaluated very quickly
    - Start simple (~linear models etc.), establish baseline
    - Sophistication has costs
    - Speed & Cost of iteration matters a lot

Speed of iteration	Progress
Minutes to Hours	Fast progress
Day to 4-5 Days	Slower progress
Week and more	Very few iterations can be made, chances of evaluating many solutions small. Still works for simple, high value cases

Machine Learning automation (Auto ML)

- ML optimizes values of parameters for given task (for example weights in neural network)
- HyperParameters are set by engineer (for example size of the neural network)
- AutoML makes many iterations of normal ML and optimizes also HyperParameters – the faster the iteration the more thorough the search
  - Augments Data Scientists / Engineers and speeds up progress – very aligned with MVP / RAT ideas



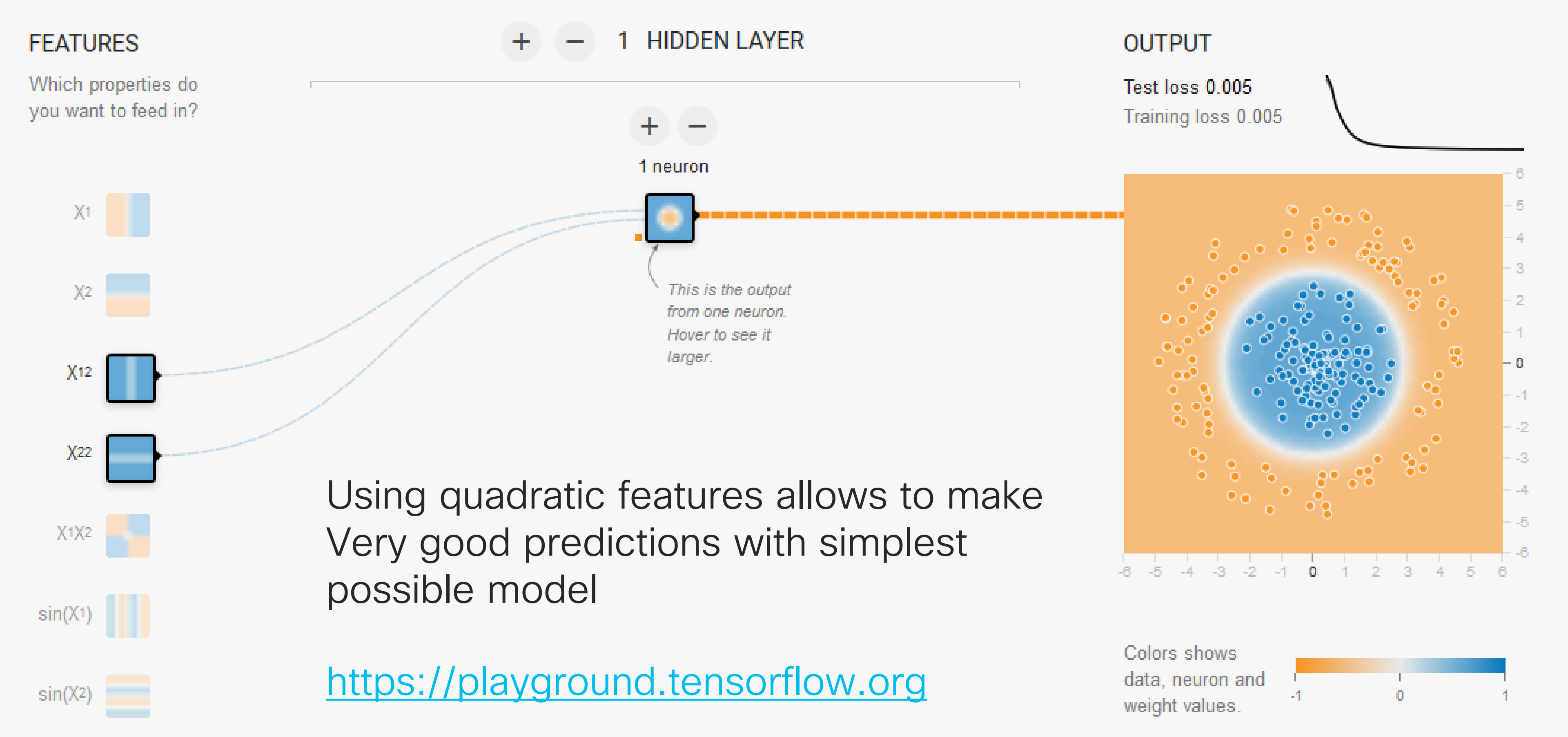
On features

- This is yet another place where T-shaped expertise has huge impact
- Domain expert would know what is important in data
  - But needs ML knowledge to turn these insights into features playing on strengths of ML algorithms

Feature Example (Animal Classification)	Feature Example (IGP monitoring)
Walks like a duck (Y/N)	Number of LSPs in database
Quacks like a duck (Y/N)	Minimum Age of LSP
….	…

- ML interpretability helps see how features transform into predictions

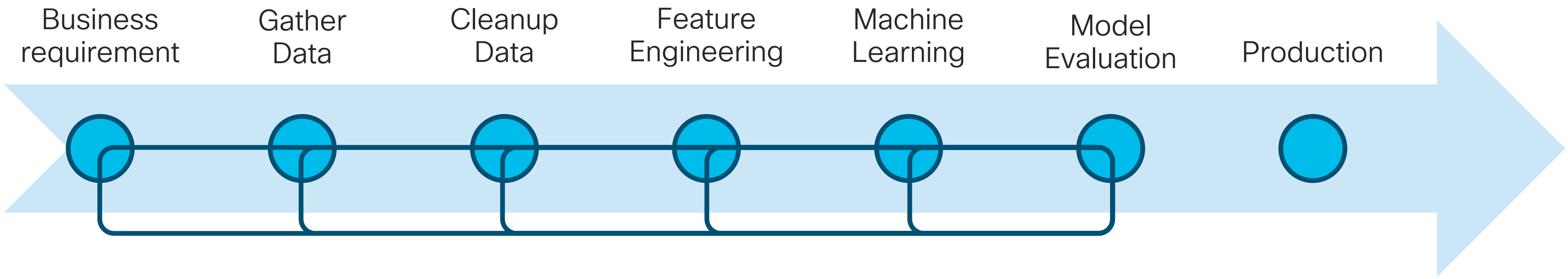
Importance of features



Using quadratic features allows to make Very good predictions with simplest possible model

https://playground.tensorflow.org

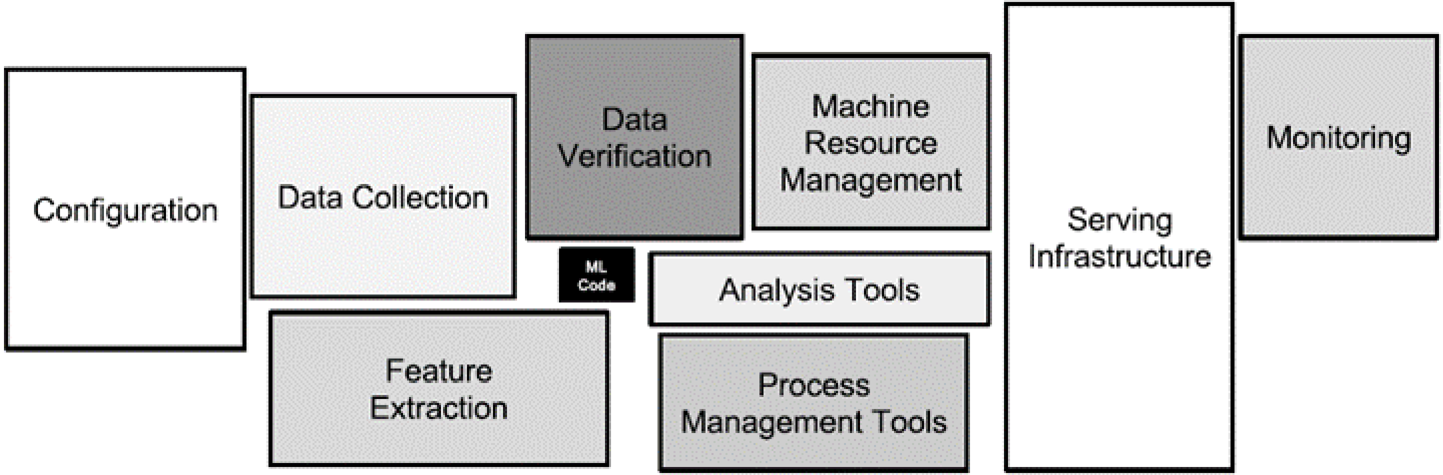
Uncertainties



- Model is acceptable but Business Impact is not proven

Update Requirements

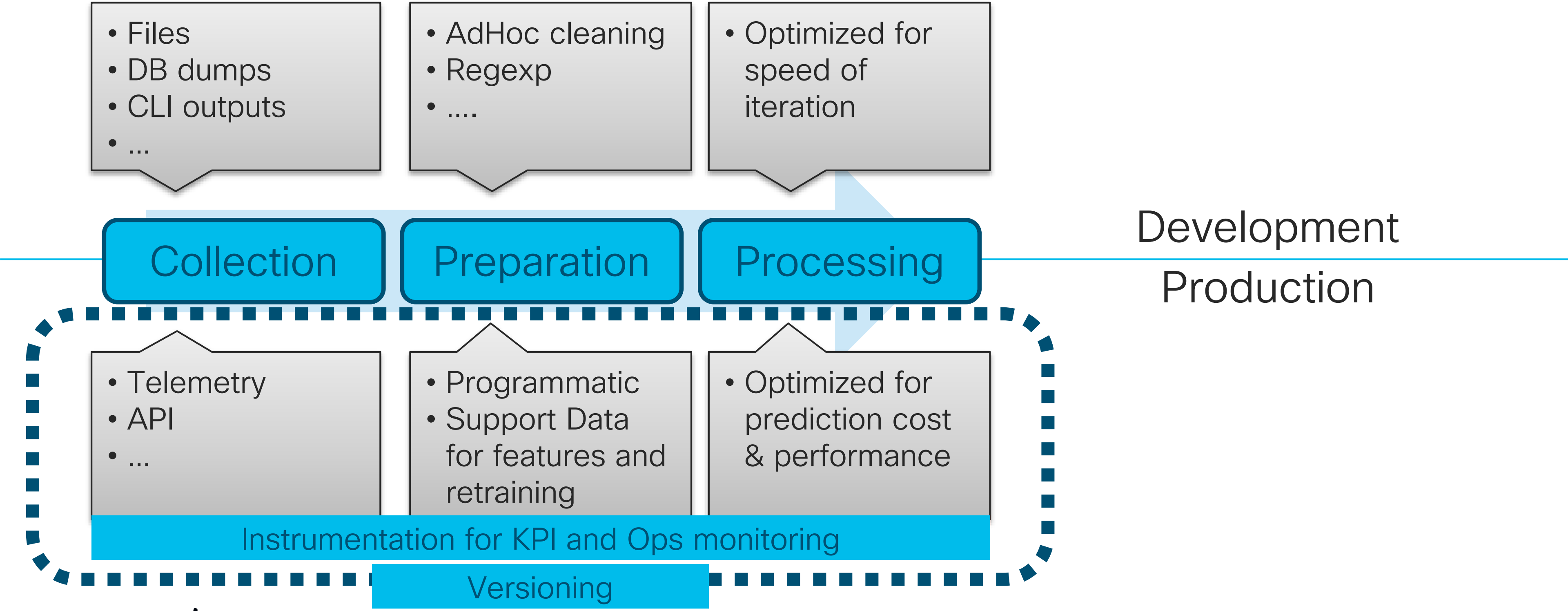
Relative Scale of ML



https://papers.nips.cc/paper/5656-hidden-technical-debt-in-machine-learning-systems.pdf

ML in Production

Highlights



Files
DB dumps
CLI outputs
...
AdHoc cleaning
Regexp
....
Optimized for speed of iteration
Collection
Preparation
Processing
Development
Production
Telemetry
API
...
Programmatic
Support Data for features and retraining
Optimized for prediction cost & performance
Instrumentation for KPI and Ops monitoring
Versioning

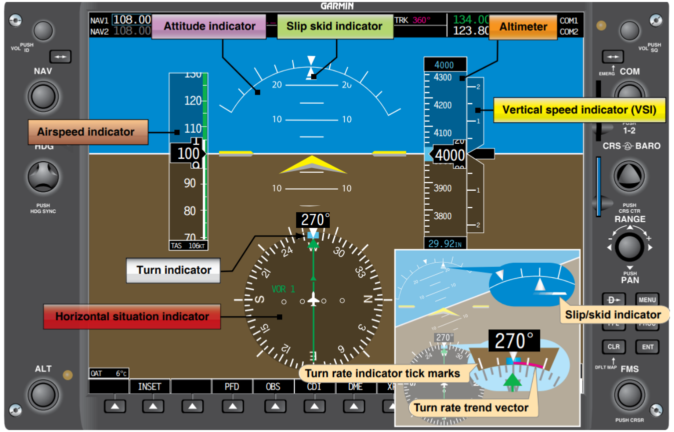
Where to run

Where	Pro	Contra
On Board	Lowest latency, Reuse existing compute, Survives network issues	Limited resources Availability Data scope
On Premises	Wide choice of options, Private	Needs Infrastructure May not be reachable during network issues
In the Cloud	Easy to Start Elastic resource management,	May need certification / approval for Data Added Latency May not be reachable during network issues

- Data goes to Model or Model goes to Data?
- Hybrid and Federated options could be viable
  - Economic considerations
  - Privacy considerations
  - Survivability considerations

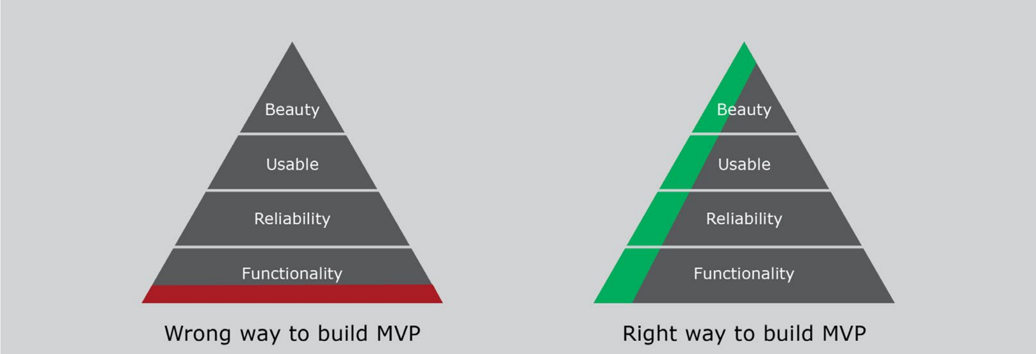
User Interface

- Present information to the user or operator
  - Mindful of cognitive overload, unnecessary clicks, scrolling, …
  - Help deal with ambiguities
    - Present multiple options, make suggestion & allow correction
- Collect implicit data and explicit feedback
- Present prediction interpretations
- Provide tools to deal with overload
  - (feedback, pause, macros, filter, sort, …)
- Integrate with Workflow and other Systems



In-Workflow testing

- Having alternative workflow may complicate adoption
  - While system improves from ‘cold start’ it maybe be objectively less convenient or efficient and users may prefer old workflow
- Alternative workflow should be available as fallback, with careful tracking of exceptions
  - Only works if new workflow is sufficiently usable



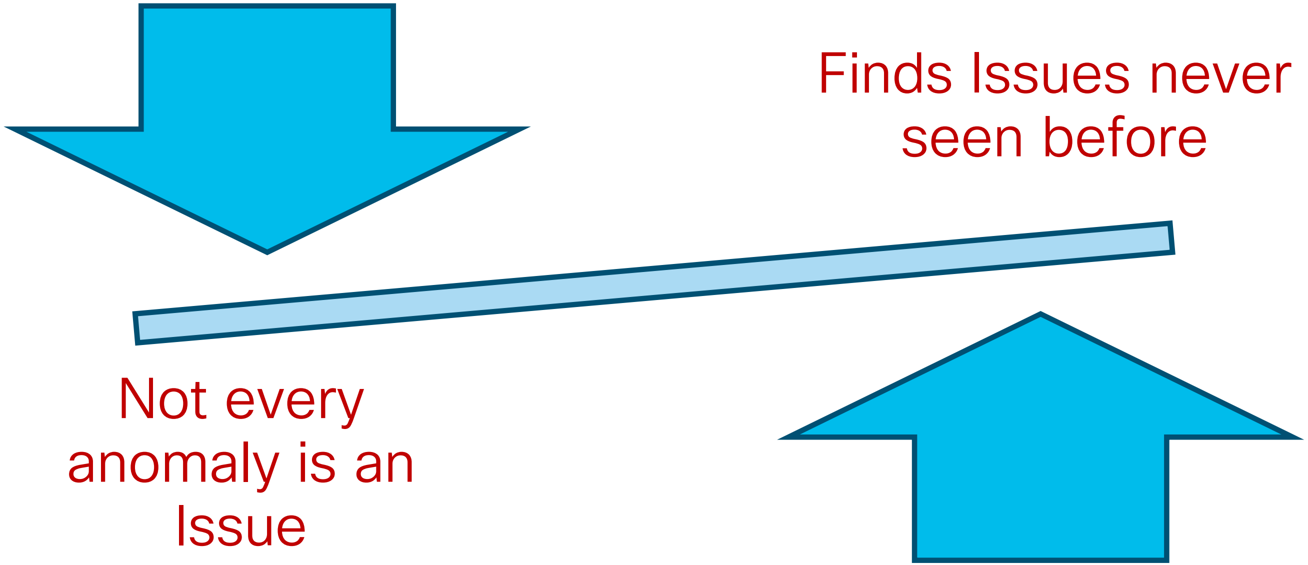
https://medium.com/tokopedia-product-team/minimum-viable-product-mvp-101-5192bc5c2a2

Cognitive Overload

- Alert storms: more Alerts then the operator can process
  - Cognitive overload
  - Default reaction: Curiosity → Indifference
    - Boy that cried wolf
- Produce less alerts (make system less sensitive), or
- Match Alert volume to Attention Budget
  - What are X most important alerts?

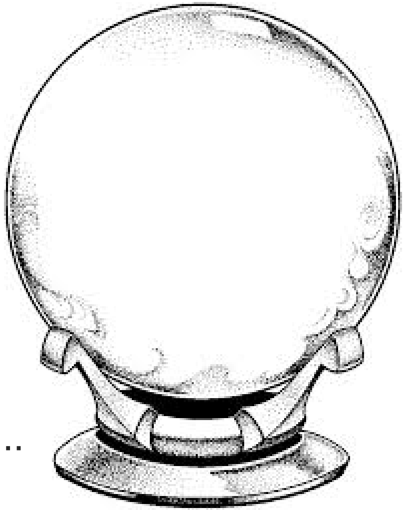
Source	Meaning
Information Theory	Rare, New, …
User Feedback	Was useful before
Context	Goes with …

Anomaly Detection

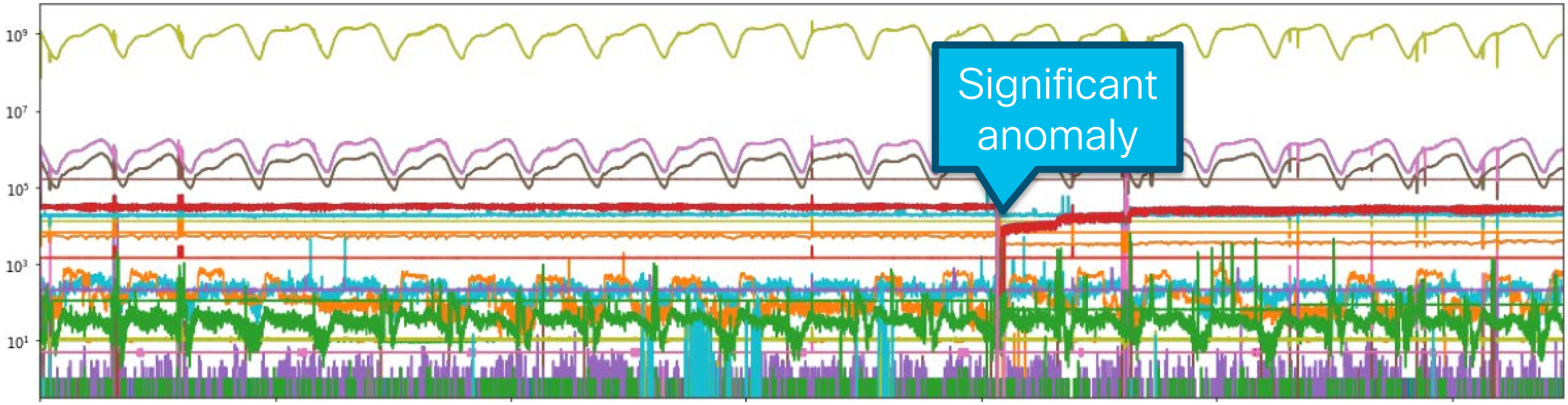


Interpretability

- Even a single Alert maybe overwhelming to understand
  - Large input: Decision made based on 1000 factors
    - https://en.wikipedia.org/wiki/The_Magical_Number_Seven,_Plus_or_Minus_Two
  - Black box algorithms
- Translate for the operator
  - What from input was responsible for most of the decision?
  - What are most important variables that went into decision? (Not the model)
- Critical ingredient to build trust and ensure fast follow-up
- Growing number of methods: PDP, LIME, Anchors, LOCO, Shapley, …
  - Can be more compute expensive than predictions themselves



Interpretability




```
DROP_FRM_CRC_ERR_SGMII1 > 3.00', -0.03.
```

CRC Drops on internal DataPath links, HW failure

- Explanations require domain expertize to understand, but
  - can be points of crystallization for new knowledge in Operations
  - can be interpreted loosely
  - can serve as basis for ranking

Retraining

- **Model Drift**: Models start to degrade as soon as they are put in production (for example traffic patterns change in the network) – model may need to be retrained from time to time

How soon, How often

- Can the model performance be evaluated directly (i.e. predictions and ground truth are both available)
- Or, detect significant difference between training data and new input data
  - Use ML model to estimate the difference between the training and inference sets (in AUC / feature)
- Because of CACE – new issues could be introduced with retraining – retest known failure modes & issues to be fixed, every model is like new release (**Often, the real modeling work starts in production**)

On what data

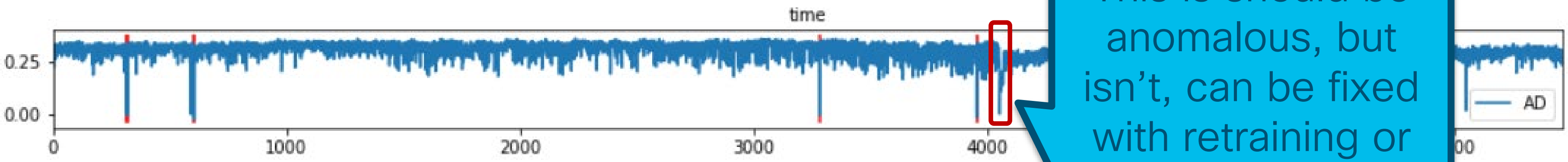
- Limit the size of training? How much old data to keep / How much new to add
  - Rare cases, Low-Variance, Decorrelation
- User feedback – at times too noisy and/or too small to use to train models directly

Model Assertions

Rules overlaid on top of predictions

- Assurance against 'this should never happen' cases (high cost errors)
- One of the ways to integrate important user feedback, when it is not sufficient to directly train on…

- Example use with anomaly detection: when score floats very near anomaly for long time – declare anomaly (threshold setting is tricky)



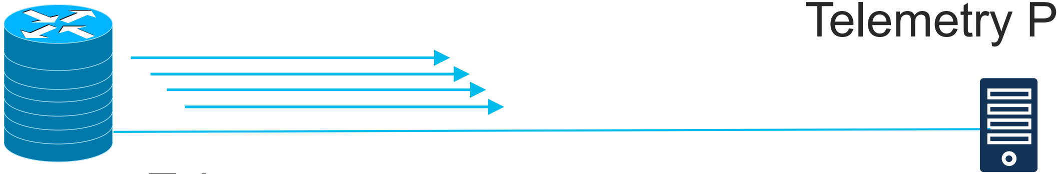
This is should be anomalous, but isn't, can be fixed with retraining or model assertion

Use-case examples

Use-case: Predict Hardware Failures

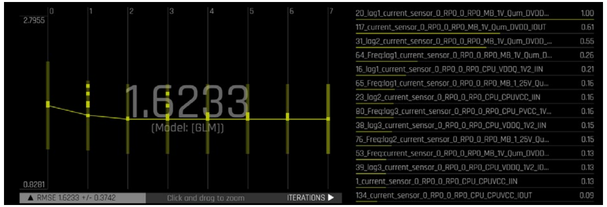
- Stream device component sensor data via telemetry
- Continuously Monitor each module / part
- Detect Marginal Hardware

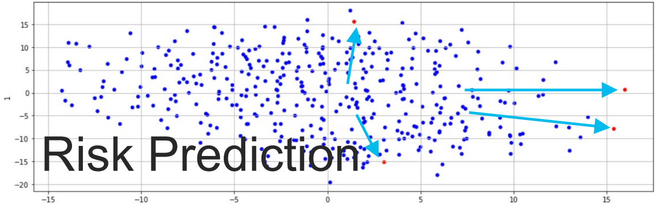
Telemetry Pipeline



Telemetry

ML pipeline





Learnings on use-cases

Priming the use-case generation pipeline

- Support development of local T-shaped experts
  - Enable local tinkering / experiments with ML
  - Ensure that overhead doesn't eat 100% of enthusiast's time
- Data Science Competitions & Hackathons on own data & Use-cases
- Relevant Data (cleaned and cleared to be used in experiments)
- Experimentation Infrastructure Reachable by Users and Workflows
  - Viability of Data Science part on real data even if prototype not scalable

Toy example: monitor CPU load

- EEM script to collect 'show process cpu' every 10 minutes

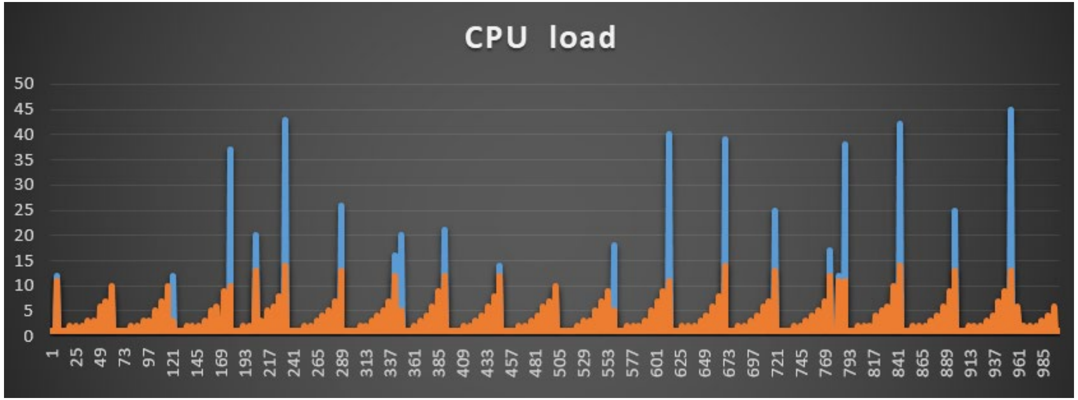
```
CPU utilization for five seconds: 0%/0%; one minute: 1%; five minutes: 1%
 PID Runtime(ms)     Invoked      uSecs   5Sec   1Min   5Min TTY Process
   1         158       20130          7  0.00%  0.00%  0.00%   0 Chunk Manager
   2      369610     1563845        236  0.00%  0.00%  0.00%   0 Load Meter
   3           0           4          0  0.00%  0.00%  0.00%   0 Process to do EH
   4          69         179        385  0.00%  0.00%  0.00%   0 RF Slave Main Th
...
```

- Parse collected outputs and convert to a table form

A	B	C	D
timestamp	cpu5	cpu60	cpu300
04-05-19 08:16	0	1	1
04-05-19 08:36	1	1	1
04-05-19 08:56	1	1	1
04-05-19 09:16	1	1	1
04-05-19 09:36	2	22	10
04-05-19 09:56	44	12	12
04-05-19 10:16	1	1	2
04-05-19 10:36	1	1	1

CPU load

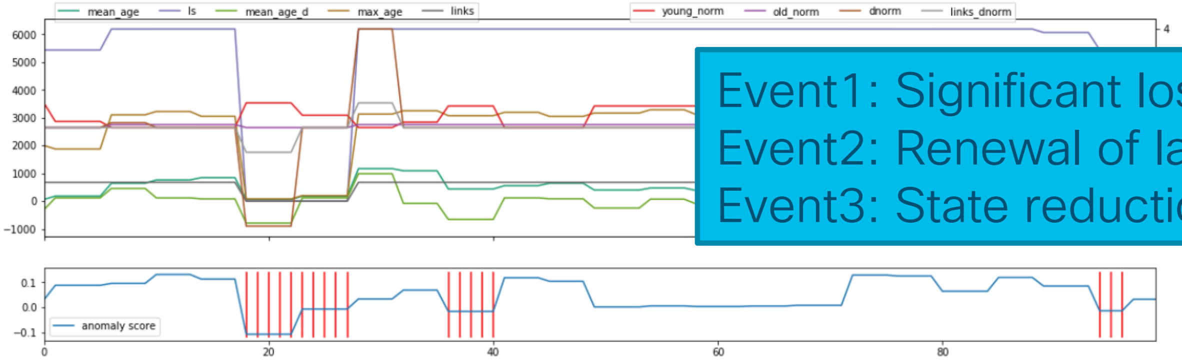
- Review collected data



- Collecting every 10 minutes, but longest average is 5 minutes
  - → Losing information
    - Either collect more frequently can try add up Runtime delta
- Do we see examples of things we want to detect?
  - 5-Min average never higher than 50% → can be 2.5min at 100%
    - Then 60-Sec average could be high
  - There is some periodicity, we may want to take that into account
    - Use CPU load at previous time as features
- Do we have enough information to understand it (have 'show proc cpu')
  - And to follow up (perhaps collect additional information automatically)

Use-case: IGP monitoring at Network Level

- State of link-state IGP is represented in link-state database
- Collect LSDB periodically
- Transform it into features, for example ‘number of LSPs’
- Use ML to find anomalies



Event1: Significant loss of state (# of LSPs)
Event2: Renewal of large part of LSPs
Event3: State reduction

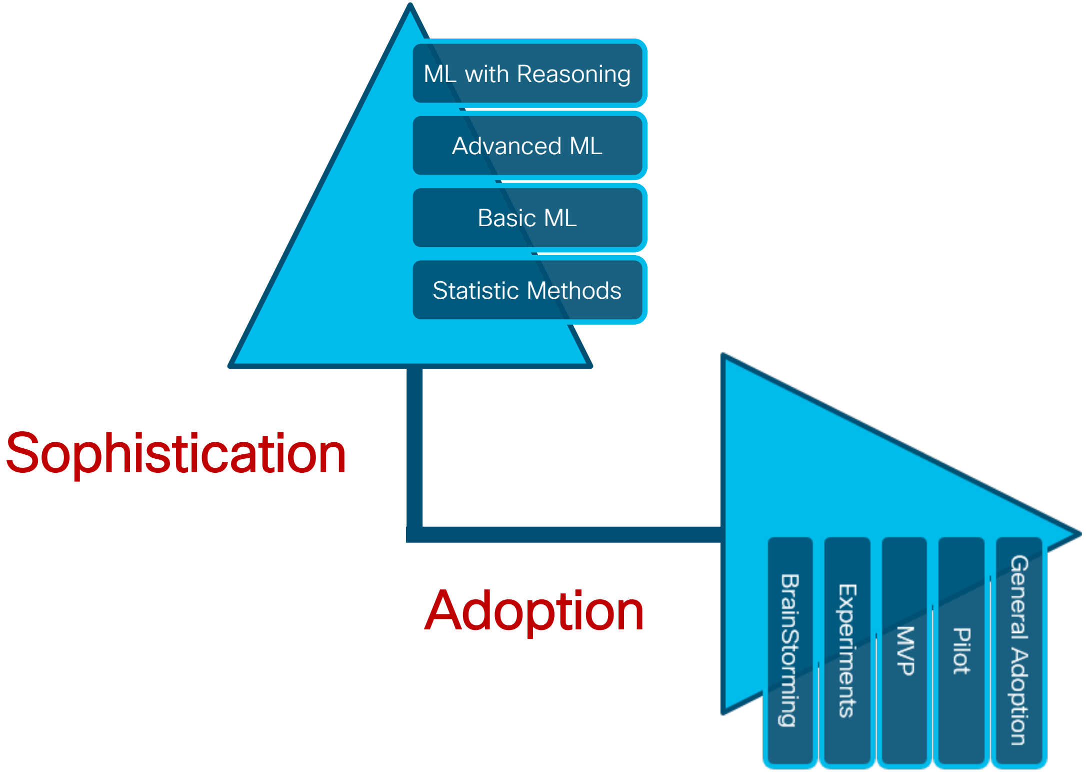
```
anomaly score on last sample: 0.03
```

Learn and experiment with this use-case at
LTRRST-2548 Machine Learning for Routers and Switches

Demo: Making Of IGP monitoring

Summary

… it is a journey, measuring progress is important



This is not the 1st time when technology is about to change everything ☺

. . .
Some factory owners did replace steam engines with electric motors, drawing clean and modern power from a nearby generating station.

Revolutionary impact

But given the huge investment this involved, they were often disappointed with the savings. Until about 1910, plenty of entrepreneurs looked at the new electrical drive system and opted for good old-fashioned steam.

Why? Because to take advantage of electricity, factory owners had to think in a very different way. They could, of course, use an electric motor in the same way as they used steam engines. It would slot right into their old systems. . . .

Taken from

- Why didn't electricity immediately change manufacturing? https://www.bbc.com/news/business-40673694

Summary

- Many challenges in Network Operations benefit from Machine Learning
  - Network Operations generates a lot of 2ndary Data
  - If not underway start ASAP: both technical and organizational learning
- T-Shaped expertize (ML + NetOps) – effective way to accelerate progress
- Data, User Interfaces, Production management are to be paid equal attention as ML
- Viability of ML approach on exact data is the high-priority uncertainty

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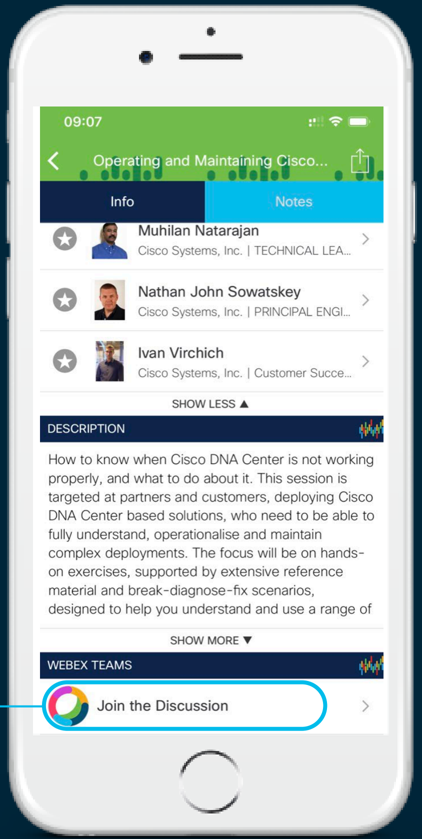

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