REALIZING END TO END REPRODUCIBLE MACHINE LEARNING ON KUBERNETES

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Nearmap

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OUR MISSION
IF WE CHANGE THE WAY PEOPLE VIEW THE WORLD,
WE TRANSFORM THE WAY THEY WORK
Captured: 13 Jun 2018
Sydney, NSW
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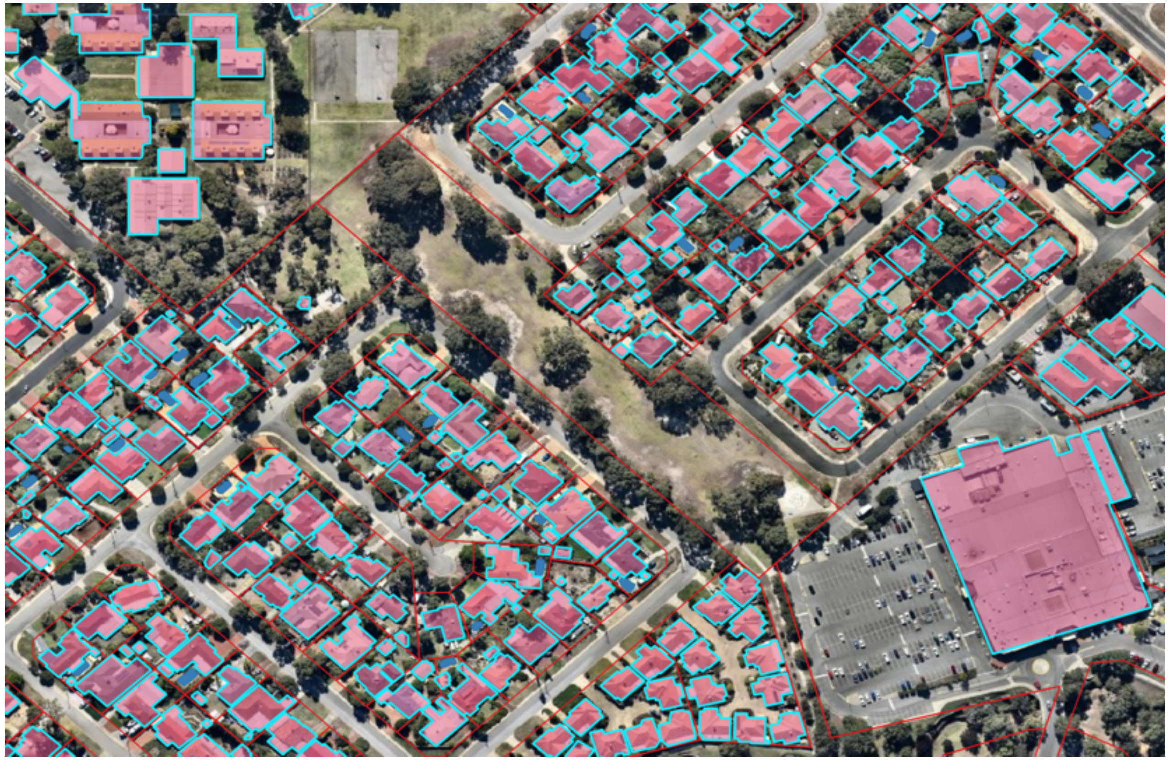
NEARMAP

- Founded in 2006 as a technology and innovation company
- Specialize in high definition aerial imagery delivered via cloud – 2D, 3D, AI and more
- Regularly capture large land areas in US, AU, NZ + CA
- 10,000+ companies leveraging service across the globe
- NEA is a publicly traded stock on the ASX

AI @ NEARMAP

Our team has been doing lots of exciting work building derived content

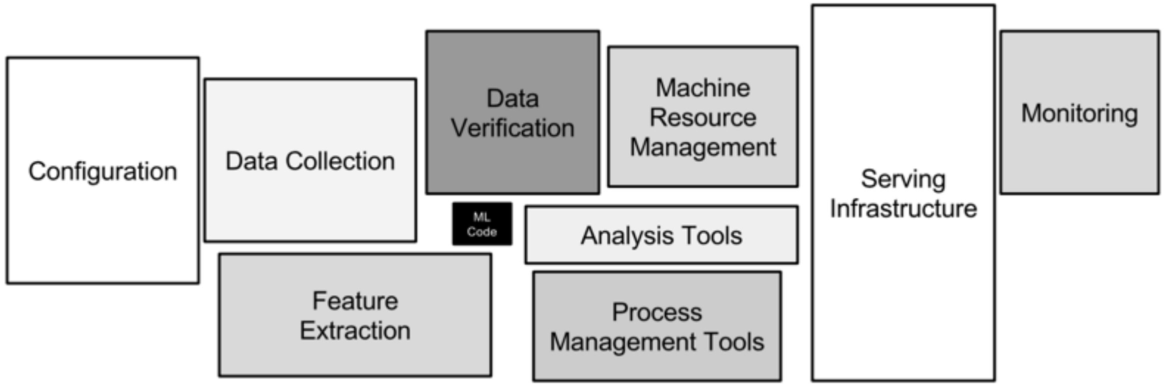
- Building outlines
- Things and stuff detection



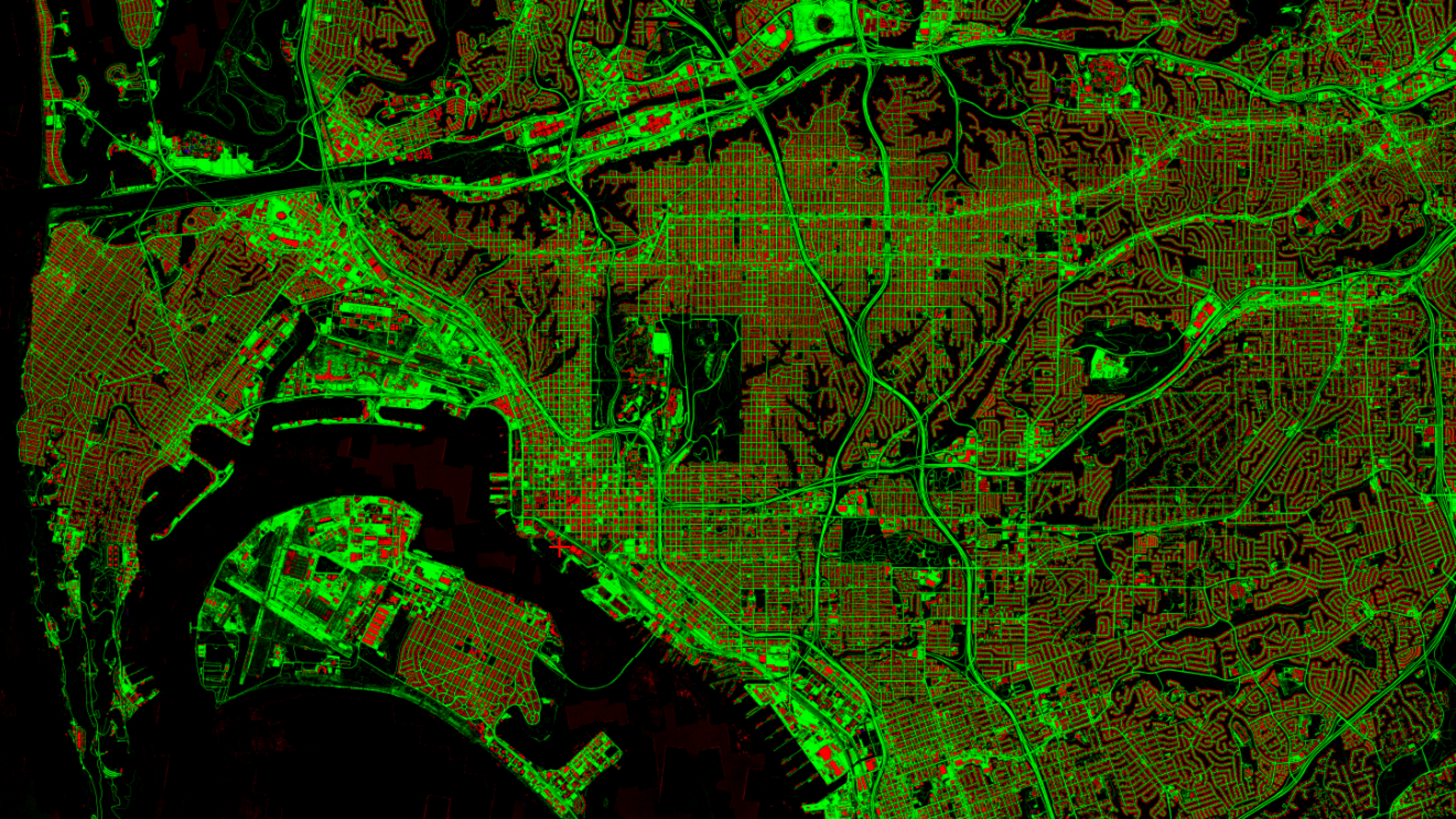
KUBERNETES: AI PLATFORM

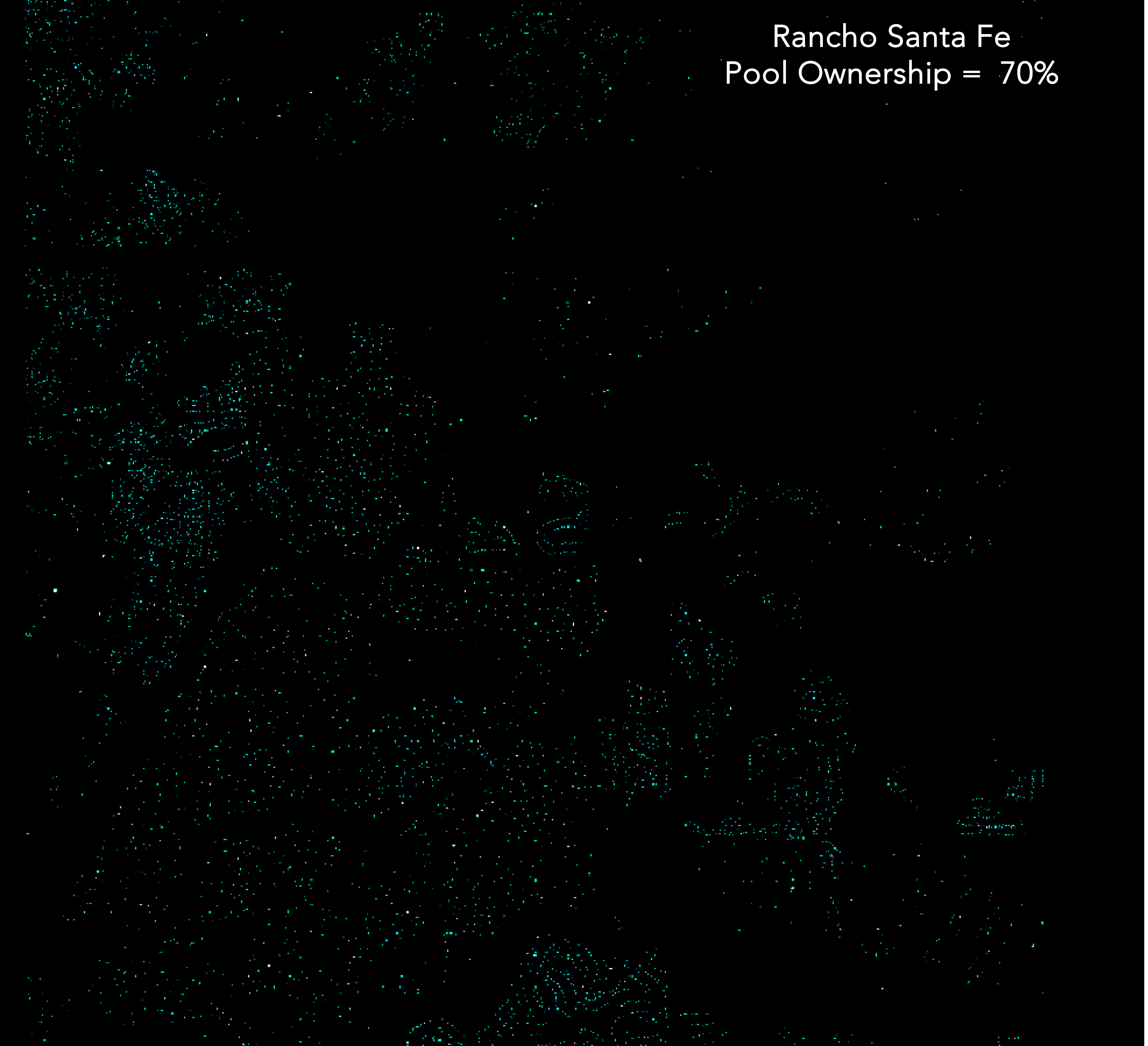
- AI system IS NOT just about model
- Joint effort of Data Scientists, Statisticians, Engineering, Devops & DataOps (MLOps)

- Resiliency, Scale, Platform abstraction and Agnosticism is desired
- Need to simplify orchestration & operations
- Need to provide a declarative ML platform



Sculley *et al.* Hidden Technical Debt in Machine Learning Systems. NIPS (2015)




Rancho Santa Fe
Pool Ownership = 70%


National City
Pool Ownership = 3%

AI @ SCALE

Crunching through petabytes size data, exhausting all K80 spot GPUs across all US data centers of AWS for weeks to produce semantic content on over a million km^2 area at resolution as high as 5cm/pixel in just 2 weeks.

Thursday, December 12 • 10:30 - 10:55

Running Massively Parallel Deep-learning Inference Pipelines on Kubernetes - Suneeta Mall & Martin Abeleda, Nearmap

Kubernetes Forum Sydney

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AGENDA

- Machine learning
- Why reproducibility
- Challenges in reproducible AI/ML
- How much reproducibility do we need
- What are some of the tools and techniques
- Realizing reproducible AI/ML seamlessly on K8s
- Robust models: replicability an extension to reproducibility
- Questions

New York, USA

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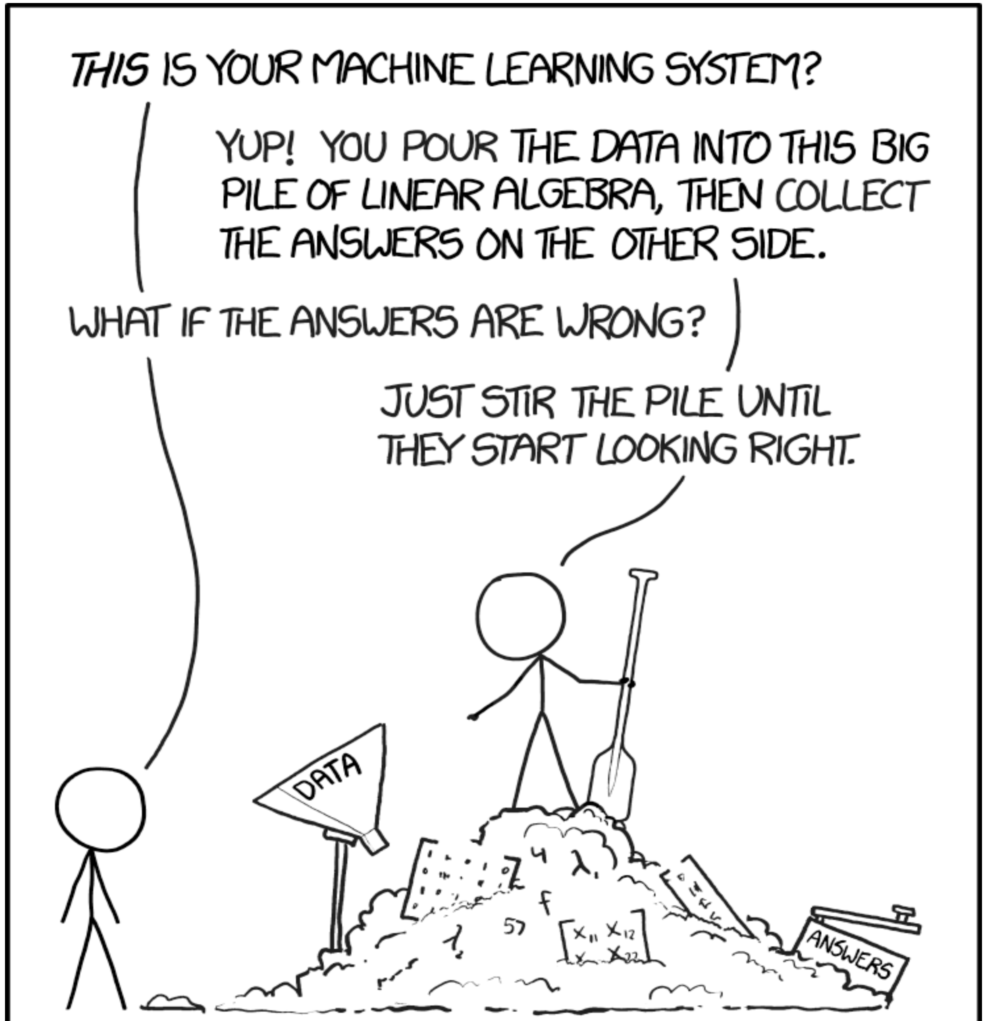
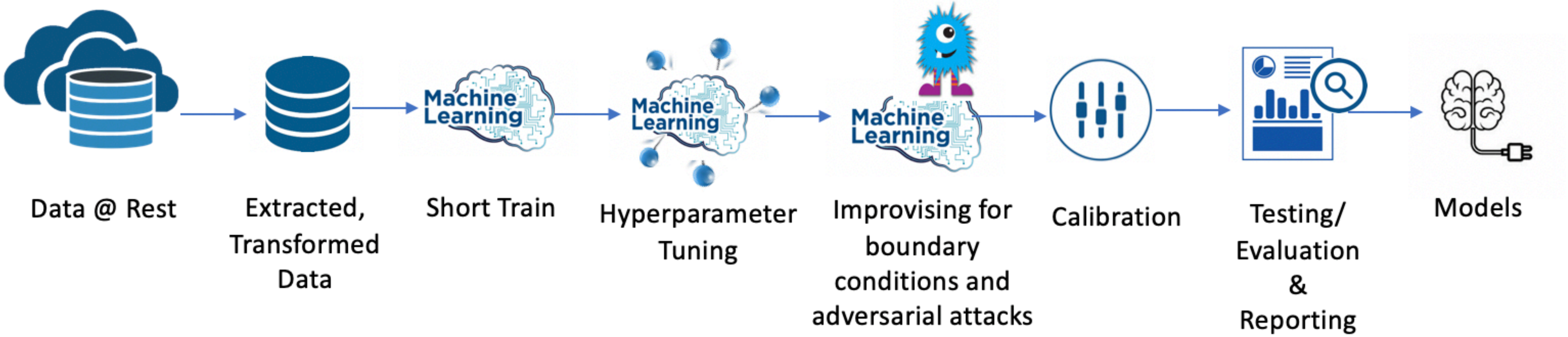
MACHINE LEARNING

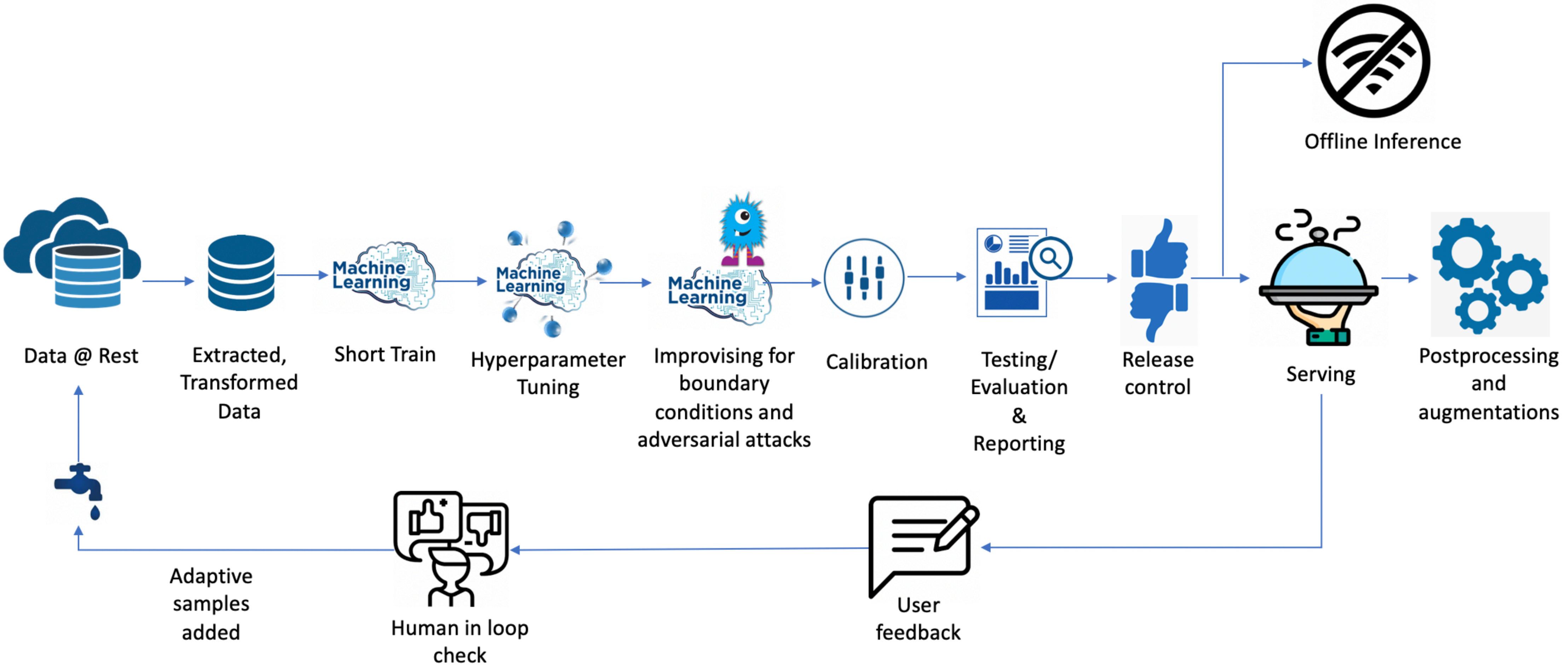


https://xkcd.com/1838/

STANDARD ML WORKFLOW



REALITY



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WHY REPRODUCIBILITY?

Sun City, Arizona, USA

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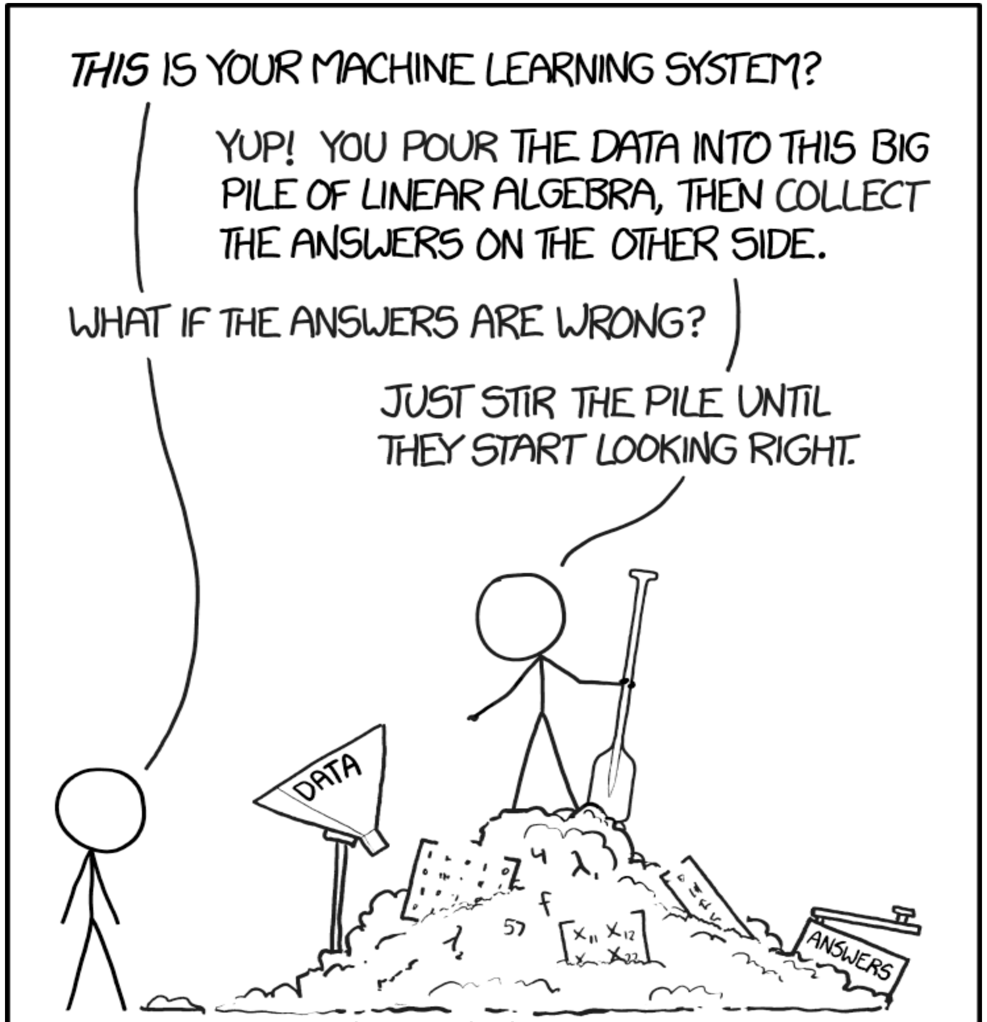
WHY REPRODUCIBILITY: TO UNDERSTAND

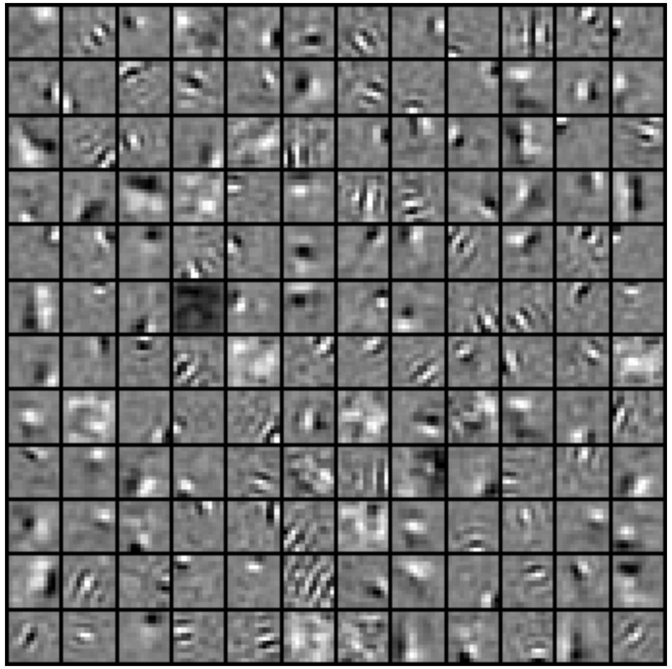


https://xkcd.com/1838/

To debug, understand and explain the deductions

WHY REPRODUCIBILITY: TO UNDERSTAND

- To <u>debug, understand and explain</u> the deductions
- Hello Deep learning



Erhan *et al.* “Visualizing higher-layer features of a deep network”
2009

10 Years of research

Olah *et al.* “The Building Blocks of Interpretability”
2018

WHY REPRODUCIBILITY: CREDIBILITY

- Users expectations: End user expects answers to <u>verifiable, reliable, unbiased and ethical</u>
- Governance: reproducible, traceable, and verifiable

<u>"Good results are not enough, Making them easily reproducible also makes them credible"</u>

- Lecun @ International Solid State Circuit Conference in San Francisco, 2019

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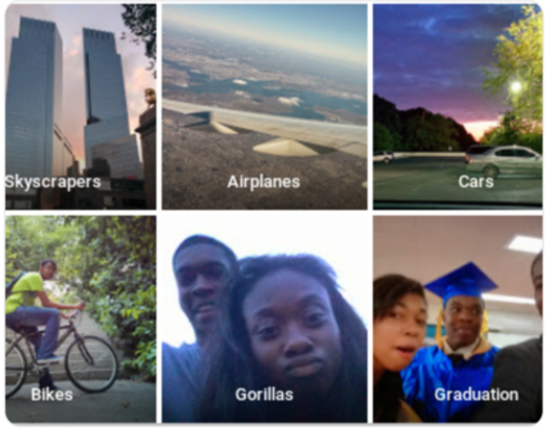
WHY REPRODUCIBILITY: CORRECTNESS

If anything can go wrong, it will Murphy's law

Amazon scraps secret AI recruiting tool that showed bias against women

jackyalcine really couldn't give a f...
@jackyalcine
Follow

Google Photos, y'all fucked up. My friend's not a gorilla.



6:22 pm - 28 Jun 2015

IBM's Watson gave unsafe recommendations for treating cancer

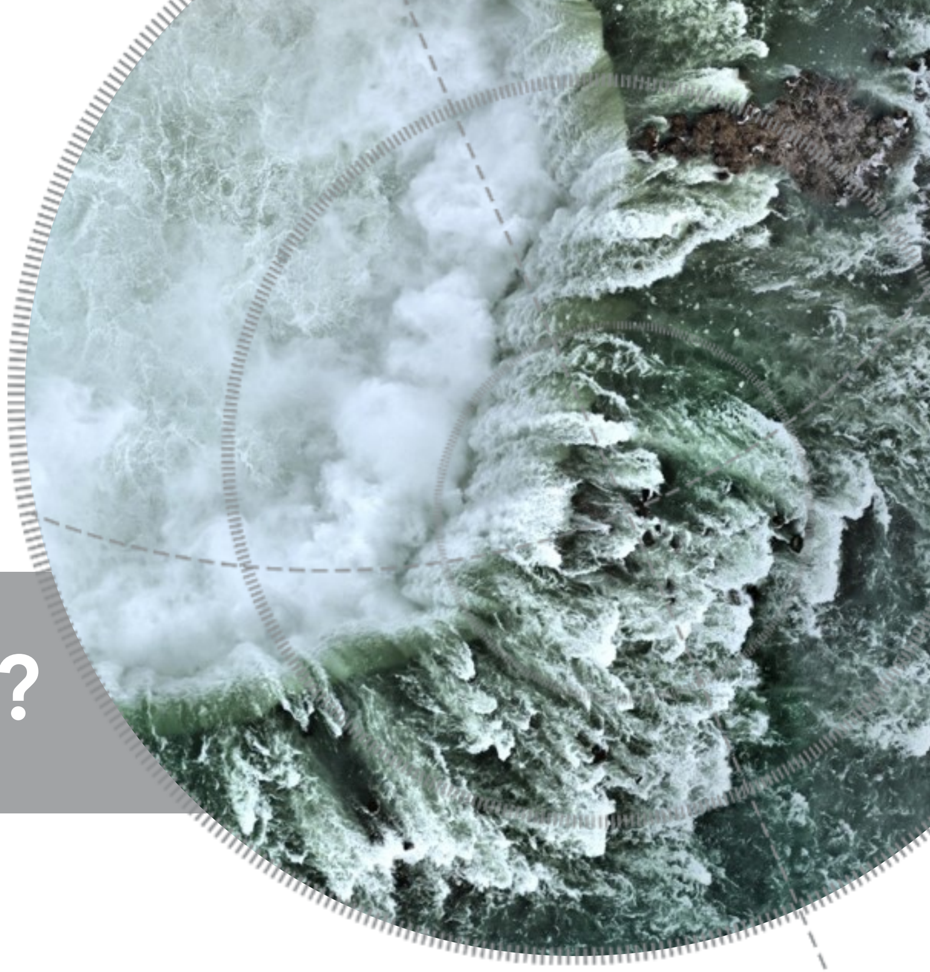
WHY REPRODUCIBILITY: EXTENSIBILITY

The Foundation need be reproducible & reliable!

Roofs
Trees
Driveways
Pools

4942.57 m^2

CHALLENGES IN REPRODUCIBLE ML?



Captured: Niagara Falls, CANADA

CHALLENGES IN REPRODUCIBLE AI/ML

- Hardware
  - Variations from GPU architecture
  - CPU multithreading variations (SESS)
- Software
  - Unintended behaviours due to dependencies
  - Floating Point Precision
- Algorithmic
  - Dropouts
  - Random initializations
  - Shuffles
  - Random Augmentations
- Practices/Process
  - Randomizations
  - Iterative Exploratory
- Data
  - Incomplete Demographics
  - Poisoned data

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CHALLENGES: HARDWARE

- Different GPU architectures (Stream Multiprocessing)
- Even parallelism on CPU may give different results
  - Intra and Inter ops threads parallelism

"Consistency of Floating Point Results or Why doesn't my application always give the same answer?"

https://www.nccs.nasa.gov/images/FloatingPoint_consistency.pdf
Corden (2008) Intel

CHALLENGES: SOFTWARE

2.7. Reproducibility (determinism)

By design, most of cuDNN's routines from a given version generate the same bit-wise results across runs when executed on GPUs with the same architecture and the same number of SMs. However, bit-wise reproducibility is not guaranteed across versions, as the implementation of a given routine may change. With the current release, the following routines do not guarantee reproducibility because they use atomic operations:

- `cudnnConvolutionBackwardFilter` when `CUDNN_CONVOLUTION_BWD_FILTER_ALGO_0` or `CUDNN_CONVOLUTION_BWD_FILTER_ALGO_3` is used
- `cudnnConvolutionBackwardData` when `CUDNN_CONVOLUTION_BWD_DATA_ALGO_0` is used
- `cudnnPoolingBackward` when `CUDNN_POOLING_MAX` is used
- `cudnnSpatialTfSamplerBackward`

https://docs.nvidia.com/deeplearning/sdk/cudnn-developer-guide/index.html#reproducibility

"Determinism in deep learning" By Duncan Riach @ GTC 2019

https://drive.google.com/file/d/18pmjeiXWqzHWB8mM2mb3kjN4JSOZBV4A/view

CHALLENGES: SOFTWARE

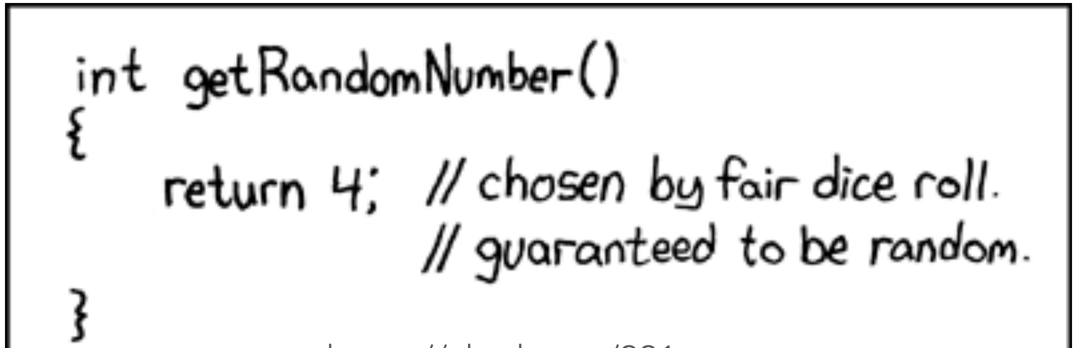
Story of *Pyproj* (a geospatial transform library) upgrade from V1.9.6 to V2.4.0

Location calculation for San Diego Convention Centre = Somewhere in Miramar off golf course

True story: https://github.com/pyproj4/pyproj/issues/470

CHALLENGES: ALL THE THINGS RANDOMNESS

- Algorithmic
- Dropouts
- Random initializations
- Random augmentations
- Random noise introduction (adversarial robustness)
- Shuffles



https://xkcd.com/221

Get a grip with the (random) seed!

```
os.environ['PYTHONHASHSEED'] = str(seed)
random.seed(seed)
tf.random.set_seed(seed)
np.random.seed(seed)
tf.keras.layers.Dropout(x, seed=SEED)
```

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CHALLENGES: DATA

- **Change Anything Changes Everything** principle
- No inputs are ever really independent

(Scully, 2015)

- How to get back to same data in exact same sequence to diagnose & resolve:
  - Data poisoning
  - Under/Over-represented data (inappropriate demographic)

gerry
@geraldmellor
Follow

"Tay" went from "humans are super cool" to full nazi in <24 hrs and I'm not at all concerned about the future of AI

https://twitter.com/geraldmellor/status/712880710328139776

THEN WE HAVE …

- A model is rarely deployed twice (Talby, 2018)*
- Concept drift
- Continual learning – full automation and governance

First prototype car

First car to do road trip

Automobiles

Self driving Solar powered cars

1807 1858 1909 1980 2018

*https://www.oreilly.com/radar/lessons-learned-turning-machine-learning-models-into-real-products-and-services/

HOW MUCH REPRODUCIBILITY DO YOU NEED?

As long as it can be explained, understood, reclaimed!

"…offers a road map to reach the same conclusions "

*Dodge**

or

*https://www.wired.com/story/artificial-intelligence-confronts-reproducibility-crisis/

HOW TO REALIZE REPRODUCIBILITY

Because CACE is real

1) Reproducible ML code

2) ~~Don't change anything~~

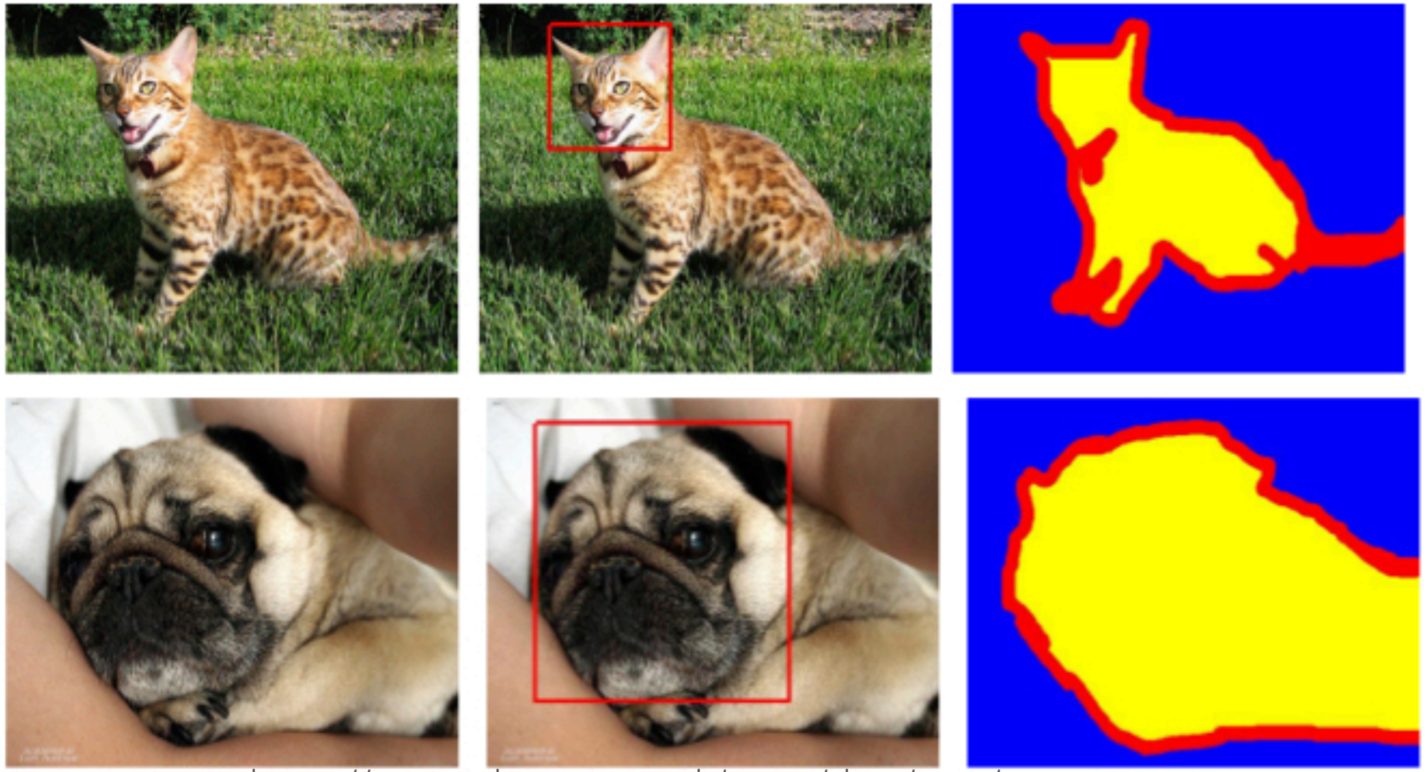
2) Version Control everything!

https://xkcd.com/1597/

REFERENCE EXAMPLE APP: END TO END ML ON KUBERNETES

Sample app: https://github.com/suneeta-mall/e2e-ml-on-k8s.git

Oxford Pet Dataset:



https://www.robots.ox.ac.uk/~vgg/data/pets/

1. REPRODUCIBLE ML CODE

Algorithmic

Software

Captured: Washington, USA

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GOTCHAS OF CODE

- Code is *version controlled*
- Reproducible runtime – *pinned* libraries
- Smart randomness
- Rounding precision & overflows
- Dependent library's behavior *aware*

"Backward pass of broadcasting on GPU is non-deterministic"
https://github.com/tensorflow/tensorflow/issues/2652

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ACHIEVING 100% REPRODUCIBILITY

See train.py and stack:

@ https://github.com/suneeta-mall/e2e-ml-on-k8s.git

1. Every randomness is seeded
2. Libraries pinned
3. And I have

```python
def set_seeds(seed=SEED):
    os.environ['PYTHONHASHSEED'] = str(seed)
    random.seed(seed)
    tf.random.set_seed(seed)
    np.random.seed(seed)
```

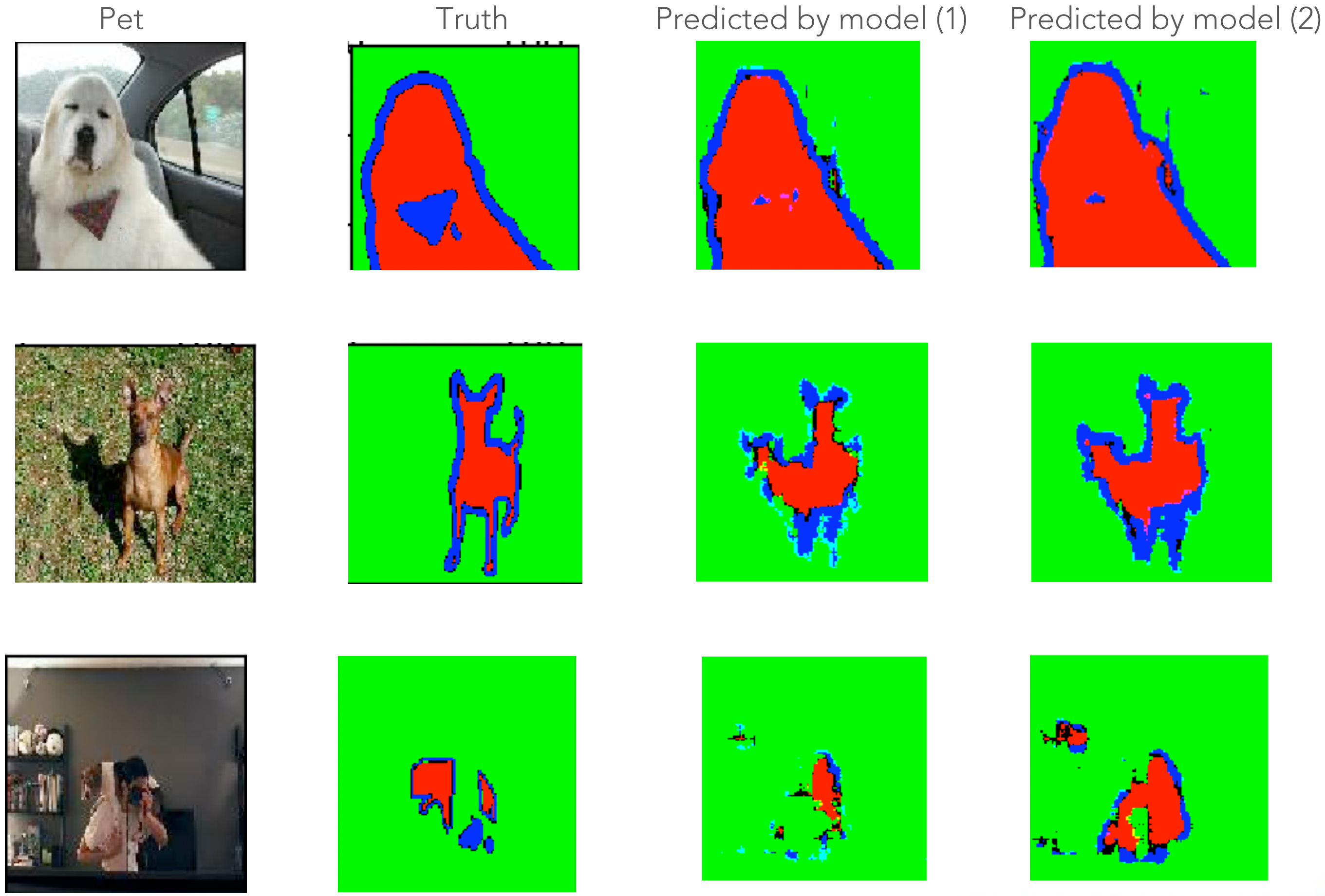
```python
def set_global_determinism(seed=SEED, fast_n_close=False):
    set_seeds(seed=seed)
    if fast_n_close:
        return
    os.environ['TF_DETERMINISTIC_OPS'] = '1'
    os.environ['TF_CUDNN_DETERMINISTIC'] = '1'
    tf.config.threading.set_inter_op_parallelism_threads(1)
    tf.config.threading.set_intra_op_parallelism_threads(1)
    from tfdeterminism import patch
    patch()
```

But saying training is snail-ish is an understatement

28 mins vs 1 hr 45 mins

FORGETTING TO SET A SEED

1. Trained with reproducible code (train.py)*
2. Trained with same code as (1) but unseeded dropout layer



* https://github.com/suneeta-mall/e2e-ml-on-k8s.git

2 VERSIONING CONTROL

Hardware

Software

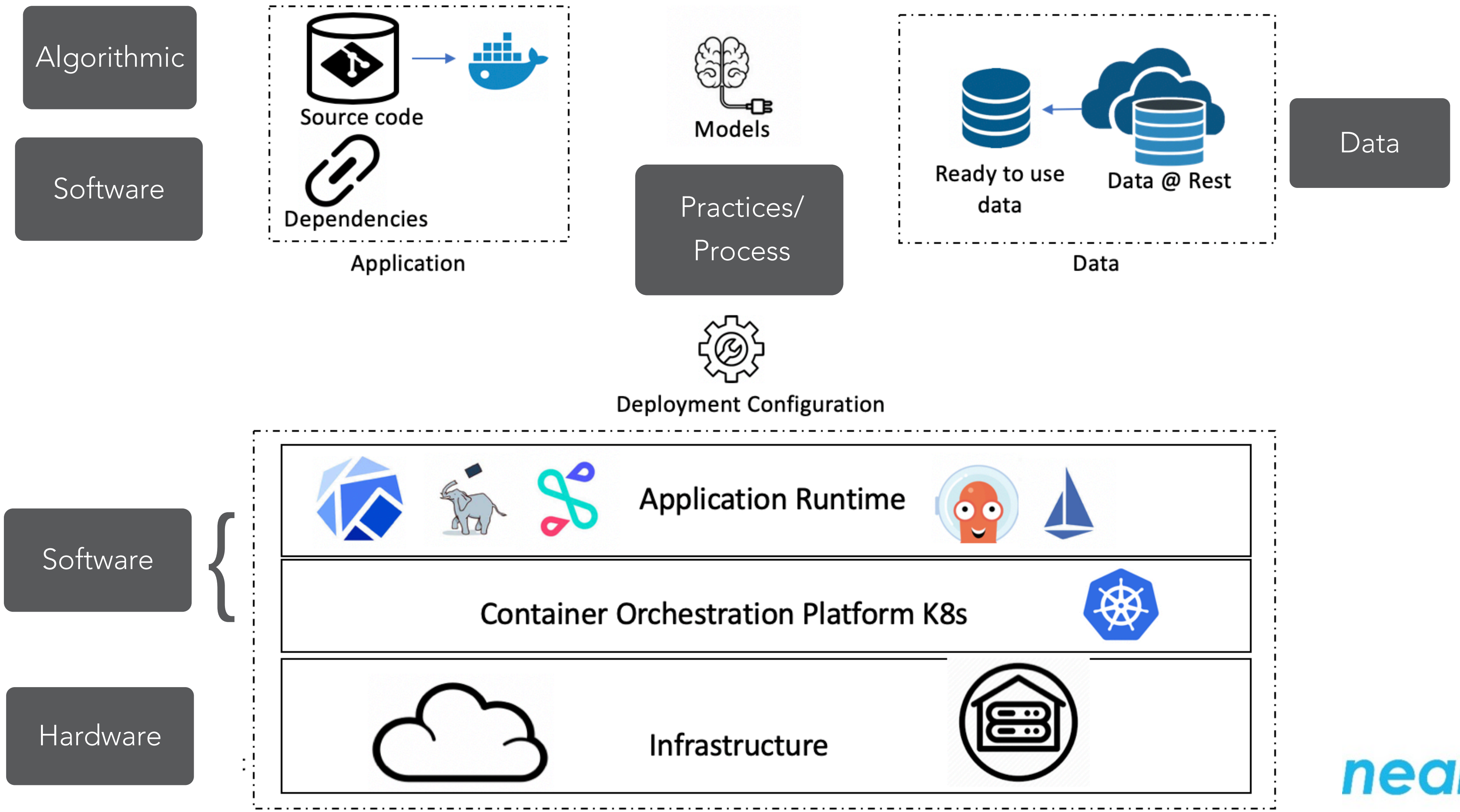
Algorithmic

Process

Data

Captured: Perth, AUSTRALIA

WHAT TO VERSION CONTROL?



2.1 VERSIONING ENVIRONMENT

Hardware

Software

Captured: Perth, AUSTRALIA

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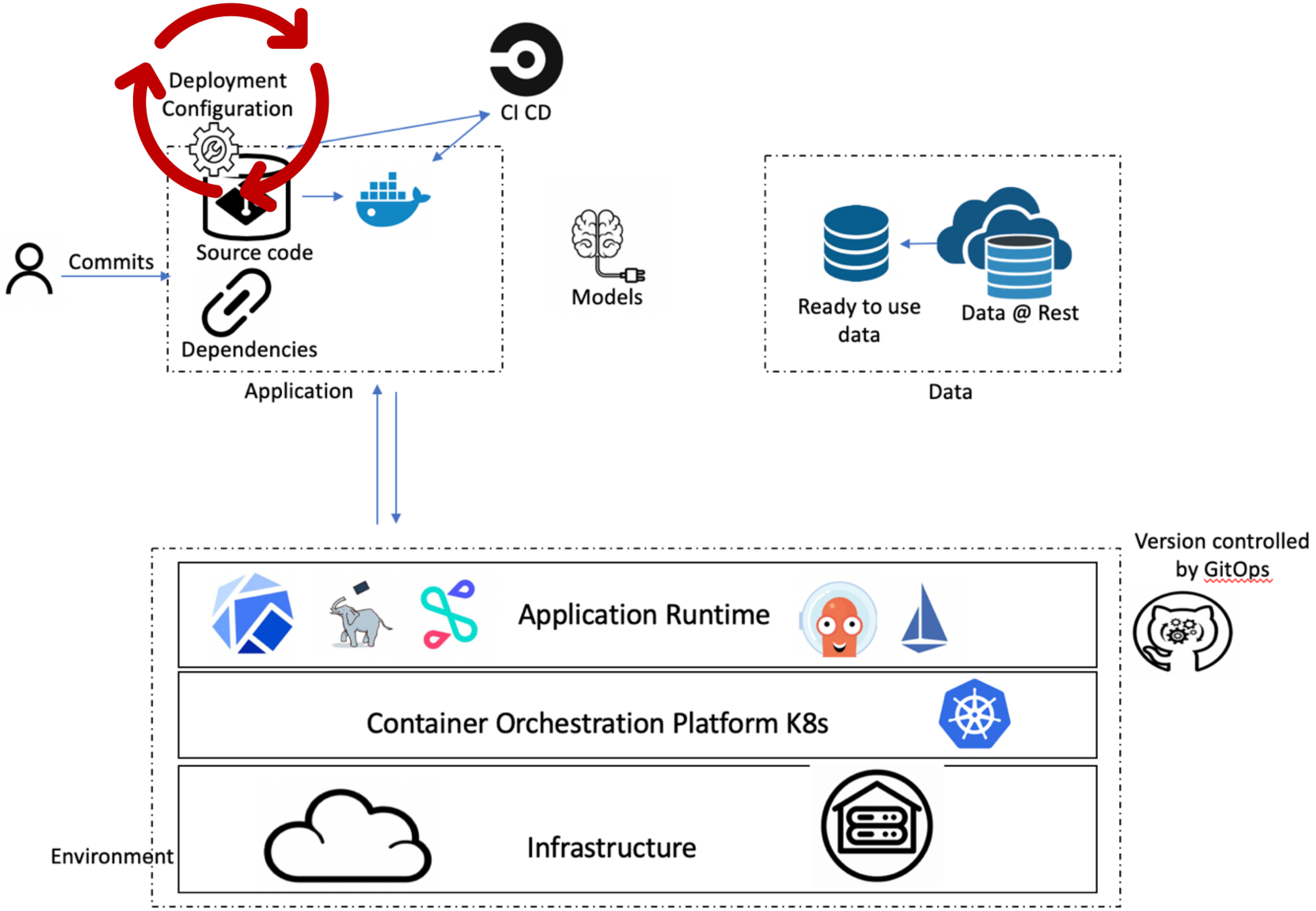
GITOPS: VERSIONING ENVIRONMENT

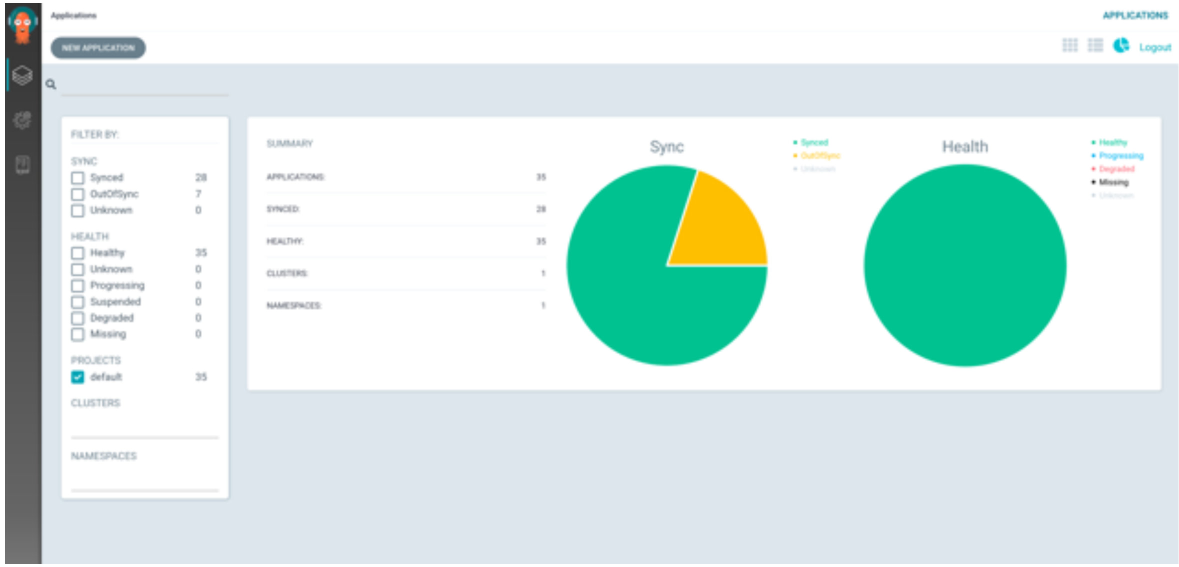
Standard continuous integration and continuous delivery flow with gitops



GITOPS WITH ARGOCD

BYO Kubernetes cluster, install Argo CD & then:

$ kubectl apply –f cluster-conf/e2e-ml-argocd-app.yaml*



Using Kustomize, configures cluster for:

- Jupyter
- Training frameworks TFJob, TorchJob etc.
- DAG pipelines Kubeflow, Pachyderm, Argo
- HP Tuning: Katib, Ray
- Serving (Seldon, TFServe etc.)
- Istio (Service Mesh)

* https://github.com/suneeta-mall/e2e-ml-on-k8s.git

2.2 VERSIONING: WORKFLOW & DATA

Algorithmic

Software

Process

Data

Captured: Dallas, USA

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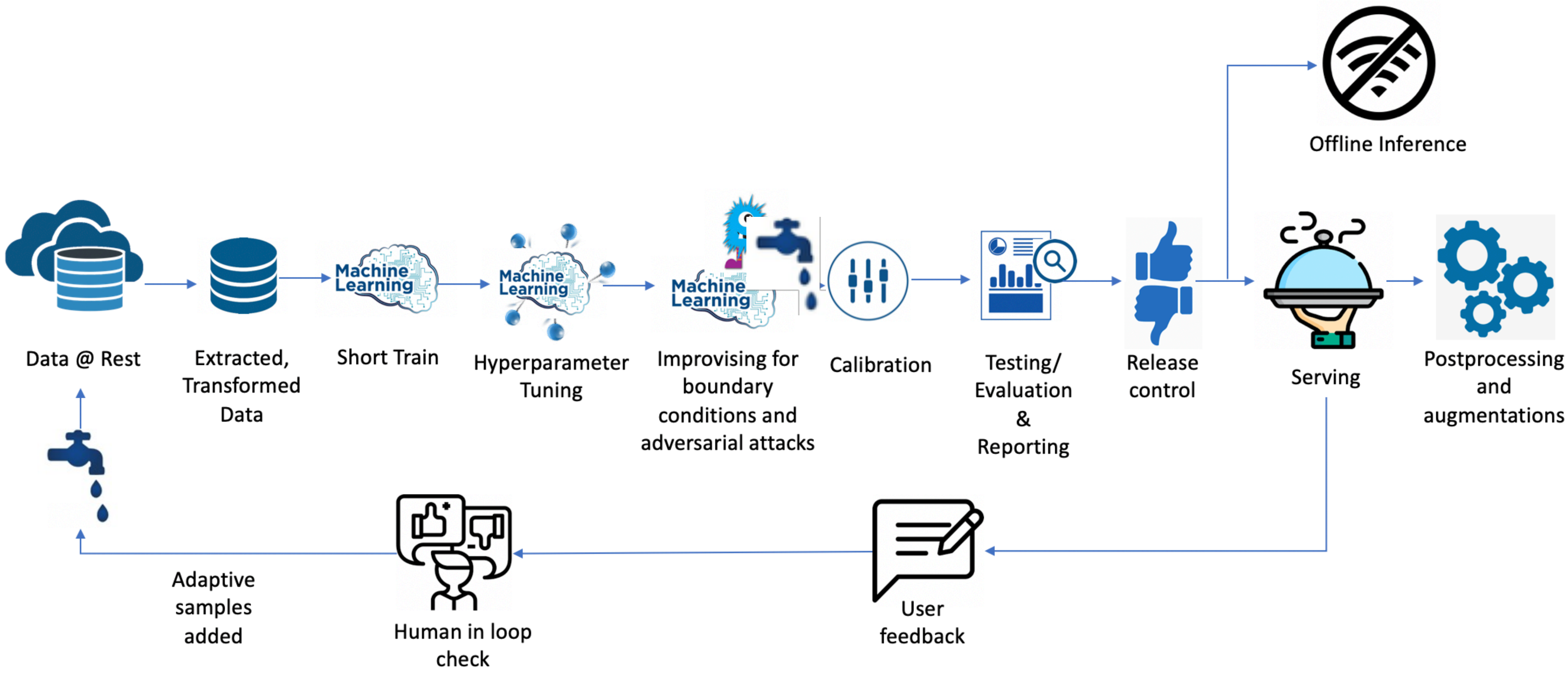
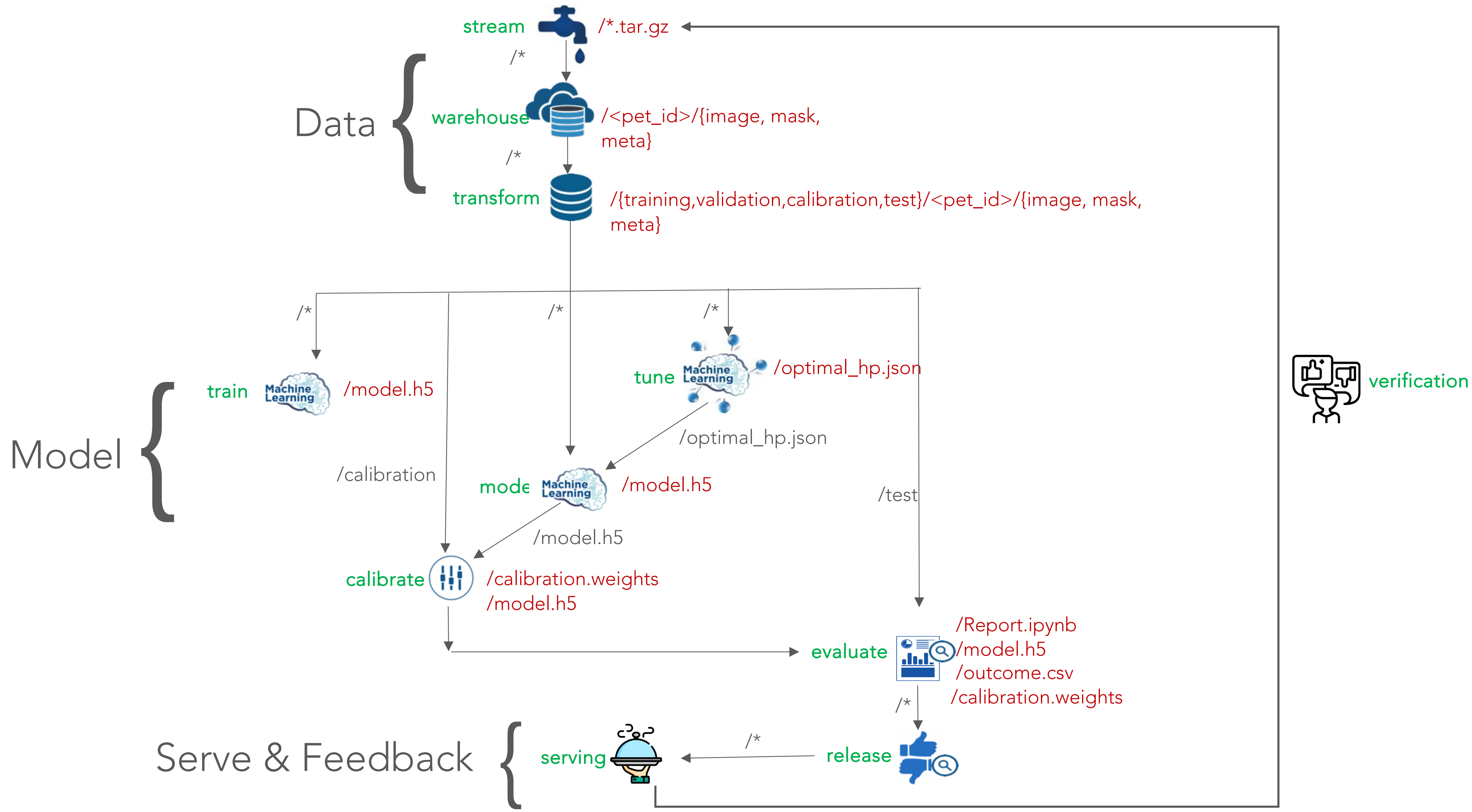
REALITY



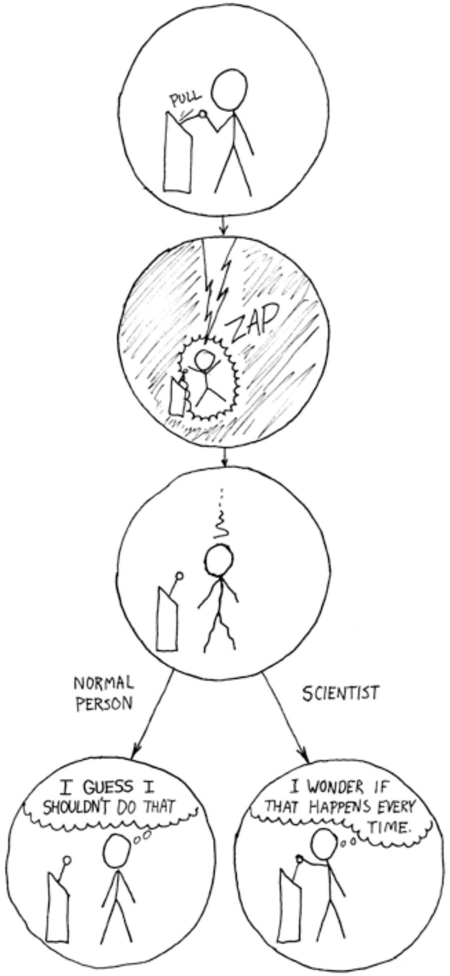
Offline Inference
Machine Learning
Machine Learning
Machine Learning
Data @ Rest
Extracted, Transformed Data
Short Train
Hyperparameter Tuning
Improvising for boundary conditions and adversarial attacks
Calibration
Testing/ Evaluation & Reporting
Release control
Serving
Postprocessing and augmentations
Adaptive samples added
Human in loop check
User feedback


stream
/*.tar.gz
/*
Data
warehouse
/<pet_id>/{image, mask, meta}
/*
transform
/{training,validation,calibration,test}/<pet_id>/{image, mask, meta}
/*
/*
/*
Model
train
/model.h5
tune
/optimal_hp.json
/optimal_hp.json
/calibration
mode
/model.h5
/test
/model.h5
calibrate
/calibration.weights
/model.h5
evaluate
/Report.ipynb
/model.h5
/outcome.csv
/calibration.weights
/*
verification
Serve & Feedback
serving
/*
release

PACHYDERM: FOR PROVENANCE

- Git like data repository
- Automated repositories that `act`
- Pipeline DAG like processes with provenance across graph input, transformation spec, output
- Runs on K8s as backbone

Ref https://github.com/pachyderm/pachyderm



https://xkcd.com/242

KUBEFLOW: ML TOOLKIT

- Take away the pain of infrastructure
- Deployments of machine learning (ML) workflows on Kubernetes simple, portable and scalable
- Enables declarative ML bringing together open source ML framework.
    - Training
    - Tuning (Katib)
    - Serving
    - Pipelines
    - Notebook (Jupyter)

DON'T GEL WELL - YET

- Kubeflow is native K8s but Pachyderm is not!
- Lack of operator supports makes their integration harder

vs

TUNING WITH PACHYDERM

In container tuning:

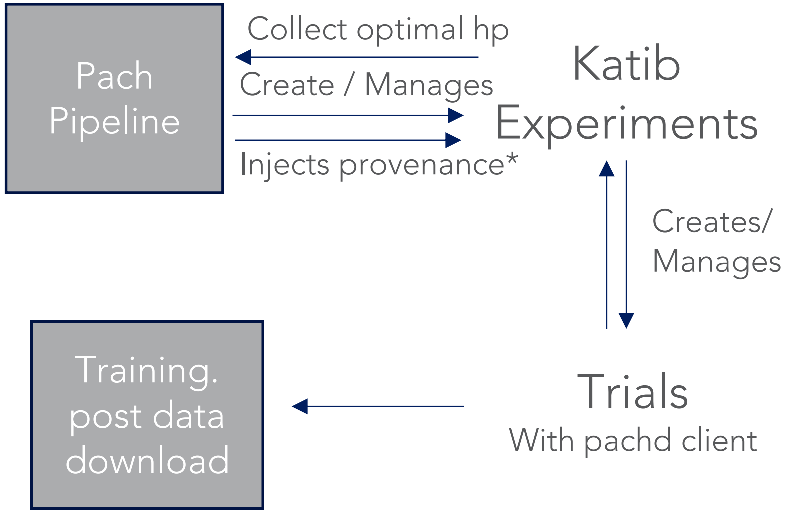
```yaml
`input:
  pfs:
    glob: "/"
    repo: transform
pipeline:
  name: tune
transform:
  cmd:
  - "/bin/bash"
  image: suneetamall/e2e-ml-on-k8s:6
  stdin:
  - "python tune.py --input /pfs/transform --output /pfs/out"
resource_requests:
  memory: 4G
  cpu: 1
datum_tries: 2
```

*cluster-conf/k8s/pipelines/pachyderm-specs.yaml

* https://github.com/suneeta-mall/e2e-ml-on-k8s.git

PACHYDERM IN CONJUNCTION WITH KUBEFLOW

HP Tune with Katib




```yaml
input:
  pfs:
    glob: "/"
    empty_files: true
    repo: transform
pipeline:
  name: tune-kf
transform:
  cmd:
  - "/bin/bash"
  image: suneetamall/e2e-ml-on-k8s:1
  stdin:
  - "python tune_katib.py --input /pfs/transform --output /pfs/out"
pod_spec: '{"serviceAccount": "ml-user", "serviceAccountName": "ml-user"}'
datum_tries: 2
```

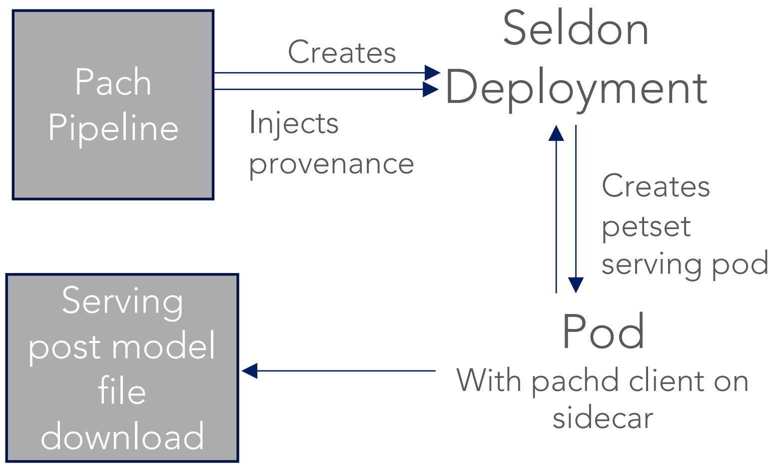
- PACH_JOB_ID
- PACH_OUTPUT_COMMIT_ID
- <input>_COMMIT

e2e-ml-on-k8s@extend_pachyderm-specs-with-kubeflow.yaml

* https://docs.pachyderm.com/reference/pipeline_spec/#environment-variables

RELEASE & SERVING WITH SELDON

- Push model for serving based on evaluation report (release.py)

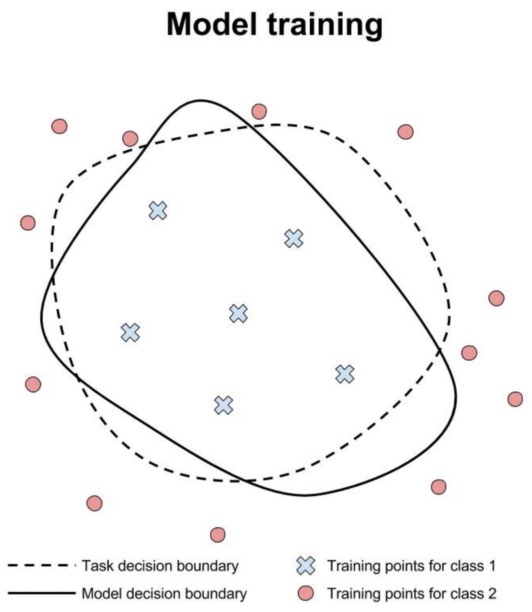


REPLICABILITY: MODEL ROBUSTNESS

- Robust model
  - Cleverhans
  - NSL
  - Foolbox and more ..
- Models generalization across architectures and training sets

  (Explaining and harnessing adversarial examples - Szegedy et al.)
- *Not make confident mistakes*

  (Unrestricted Adversarial Examples - Goodfellow et al.)



http://www.cleverhans.io

SOME TOOLS

DVC + mlflow

https://dvc.org/

https://mlflow.org/

https://martinfowler.com/articles/cd4ml.html

THANK YOU

https://www.nearmap.com/au/en/aerial-view-maps-about-us/geospatial-data-careers

https://www.youtube.com/watch?v=NWhYkjIRvVI