Project MagLev: NVIDIA's production-grade AI Platform

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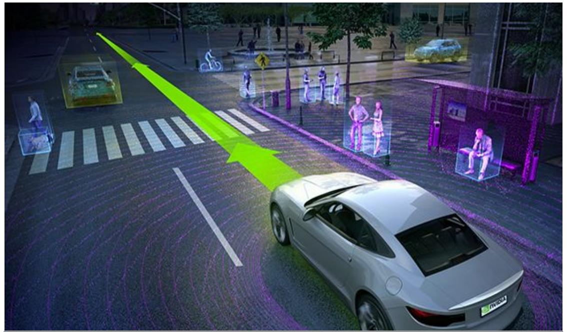
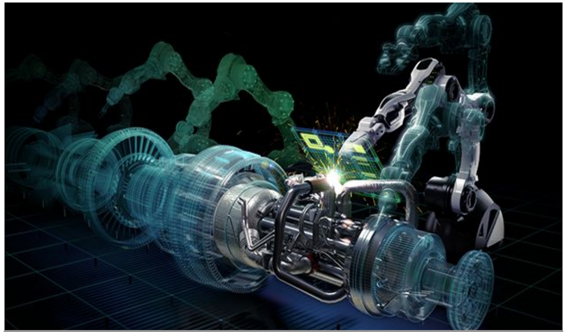
Agenda

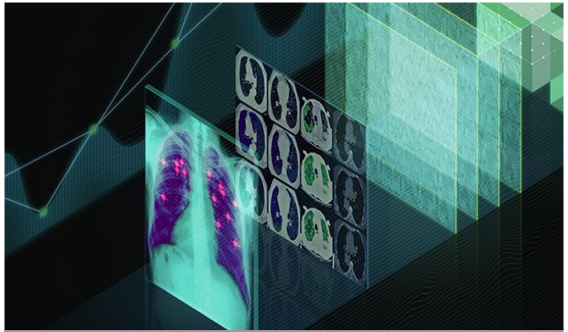
- AI inside of NVIDIA
- Constraints and scale
- AI Platform needs
- Technical solutions
- Scenario walkthrough
- Maglev architecture evolution

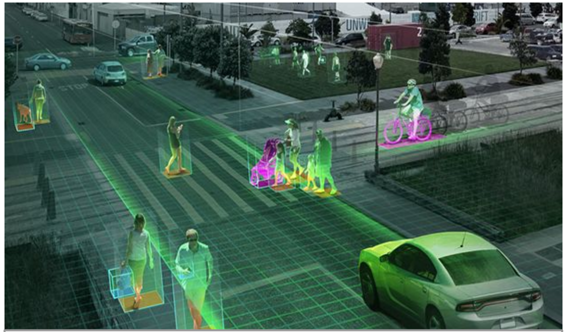
AI inside of NVIDIA

Deep Learning is fueling all areas of business


Self-Driving Cars


Robotics


Healthcare

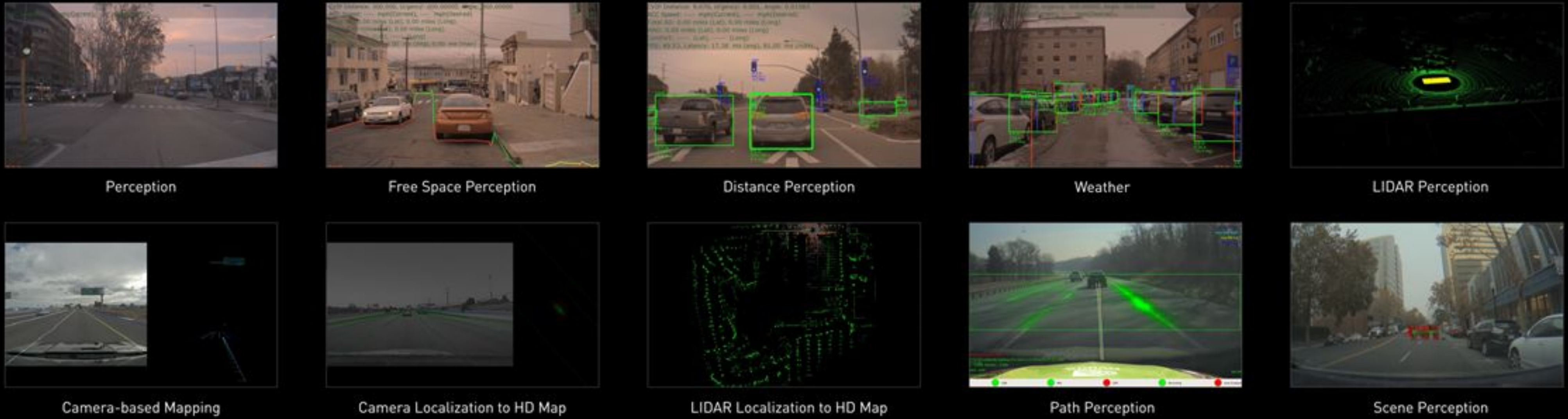

AI Cities


Retail


AI for Public Good

BUILDING AI FOR SDC IS HARD

Every neural net in our DRIVE Software stack needs to handle 1000s of conditions and geolocations



Constraints and scale

SDC Scale Today at NVIDIA

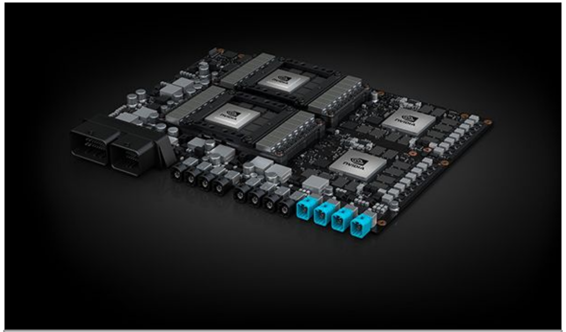
12-camera+Radar+Lidar RIG mounted on 30 cars	1,500 labelers	4,000 GPUs in cluster = 500 PFLOPs
> 1PB collected/month	20M objects labeled/mo	100 DRIVE Pegasus in cluster (Constellations)
15PB active training+test dataset	20 unique models 50 labeling tasks	1PB of in-rack object cache per 72 GPUs, 30PB provisioned

Constraints and scale

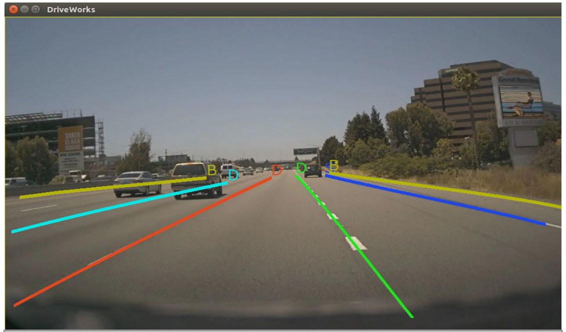
What are our requirements?

Safety

Tons of data!



Inference on edge

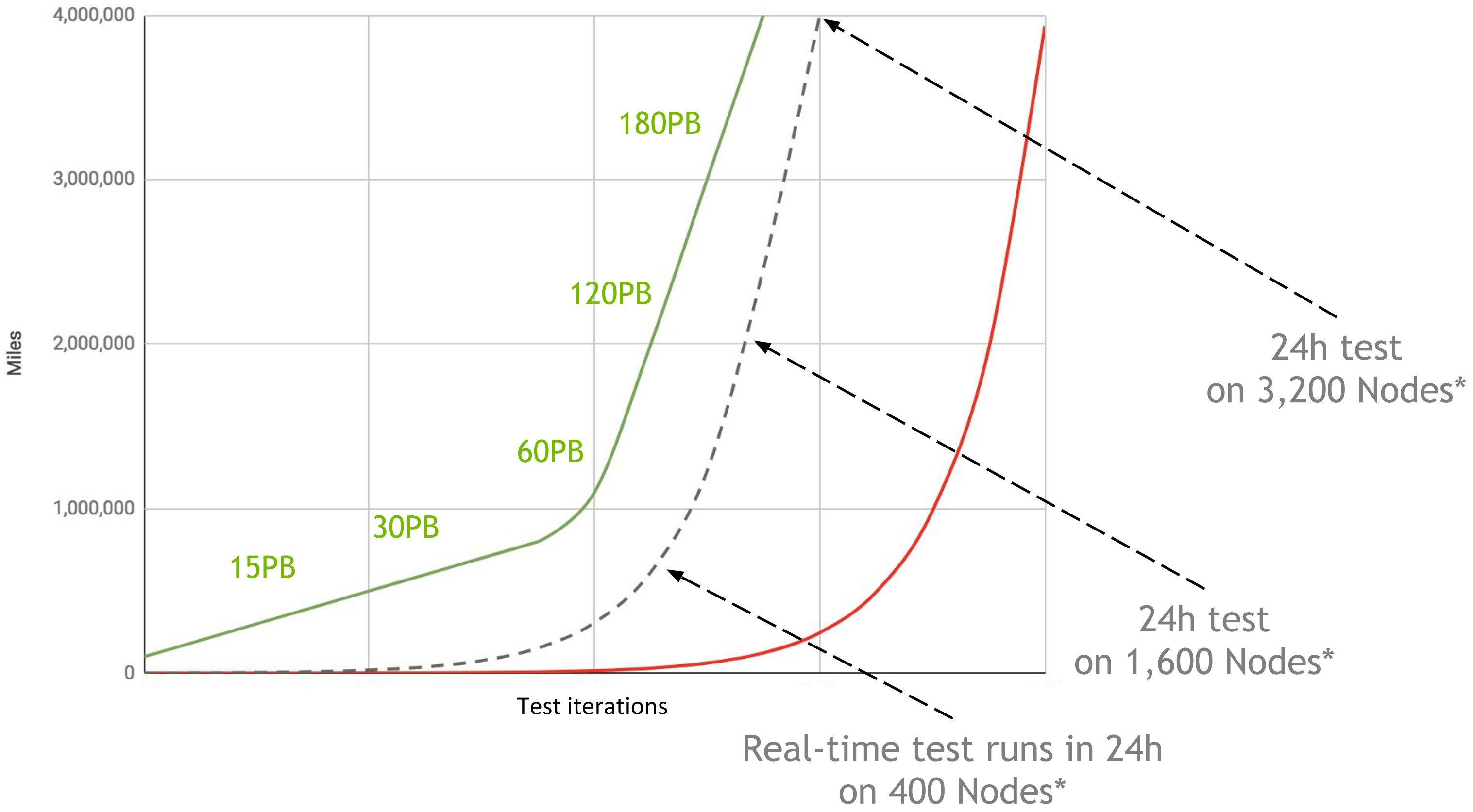


Reproducibility

What testing scale are we talking about?

We’re on our way to 100s PB of real test data = millions of real miles
+ 1,000s DRIVE Constellation nodes for offline testing alone
& billions of simulated miles

— NVIDIA’s data collection (miles)
-- Active testing to date (miles)
— Target robustness (miles)



* DRIVE PEGASUS Nodes

The need for an AI platform

An end-to-end solution for industry-grade AI development

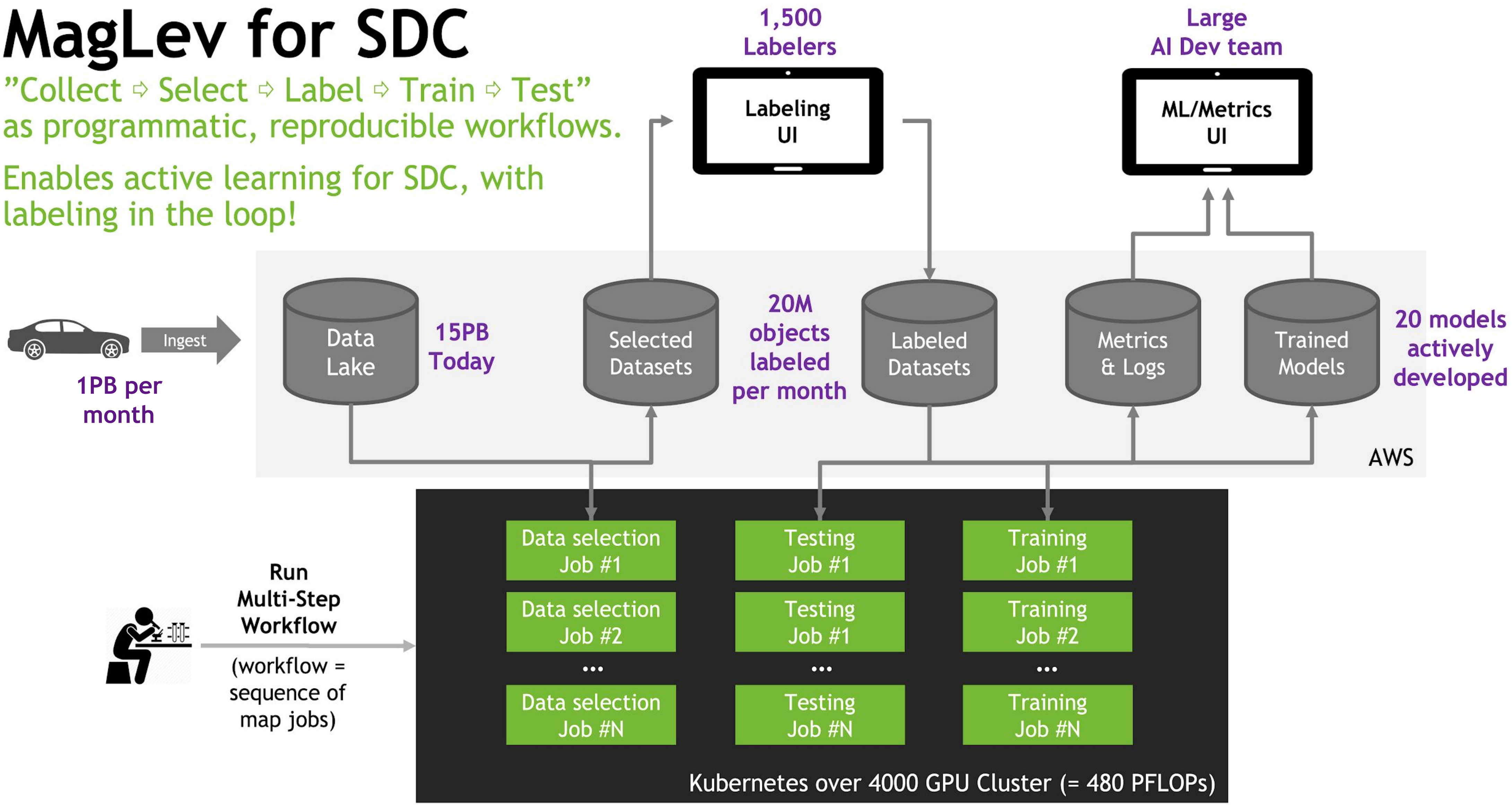
Enable the development of AV Perception, fully tested across 1000s of conditions, and yielding failure rates < 1 in N miles, N large

Scalable AI Training	PB-Scale AI Testing	AI-based Data Selection/Mining
Traceability: model=>code+data	Seamless PB-Scale Data Access	Workflow Automation

MagLev for SDC

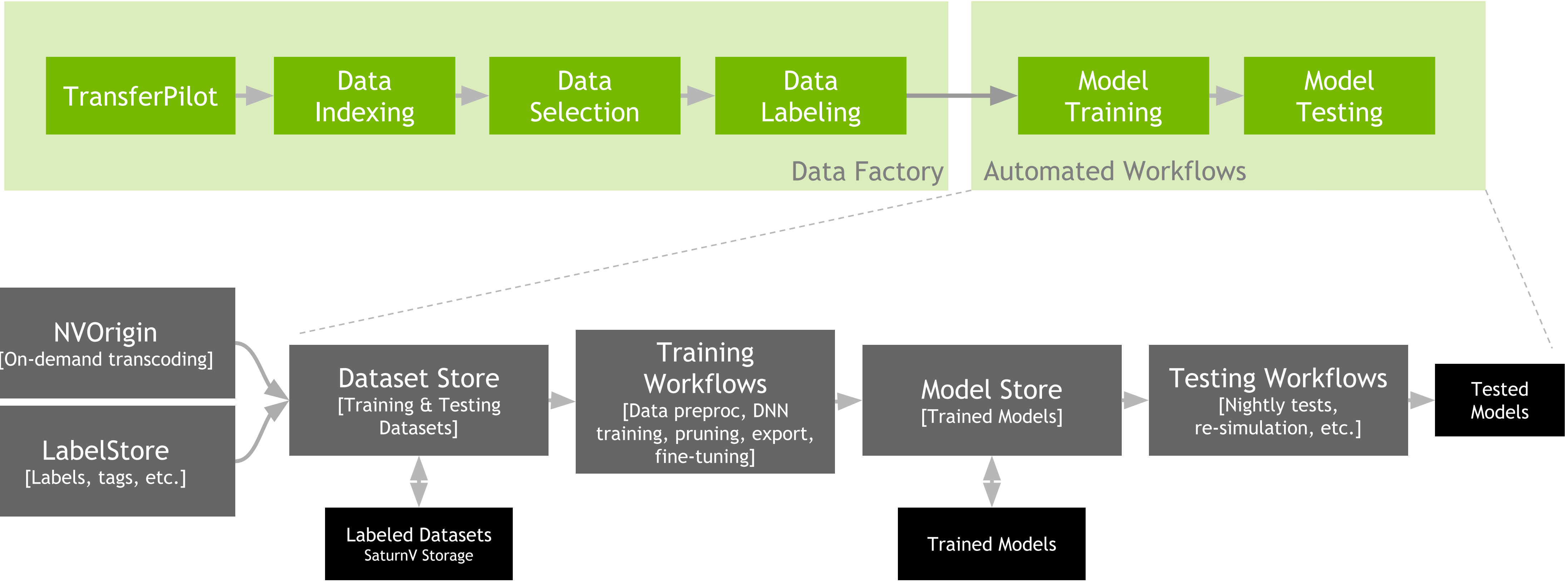
"Collect ⇨ Select ⇨ Label ⇨ Train ⇨ Test" as programmatic, reproducible workflows.

Enables active learning for SDC, with labeling in the loop!



The need for an AI platform

Enabling automation of training, and testing workflows



So how did we solve for this?

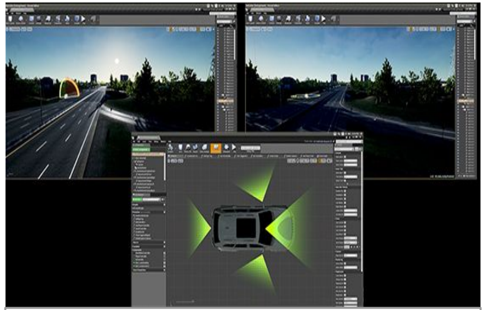
Technical solution(s)

Safety

- Non-compromisable primary objective for the passengers

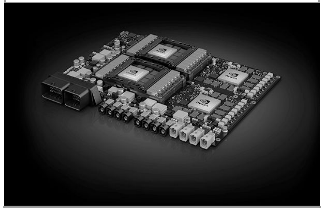
All other engineering requirements stem from this

- Models tested on huge datasets to be confident
- Faster iteration that aids in producing extremely good and well-tested models
- Reproducibility/Traceability



Safety

Tons of data!



Inference on edge

Reproducibility

NVIDIA.

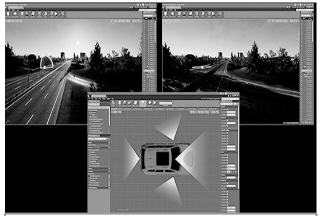
Technical solution(s)

Tons of data!

- Collecting enormous amounts of data under innumerable scenarios is key to building good AV models

- Now that we data, what next?
  - How do engineers access this data?
  - How do you make sure that the data:
    - can be preprocessed for each team’s need?
    - is not corrupted by other members of the team or across teams?

- Lifecycle management of data



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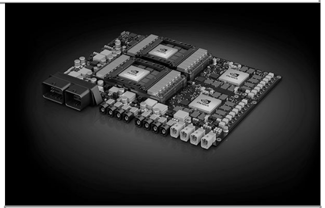


Inference on edge

Reproducibility

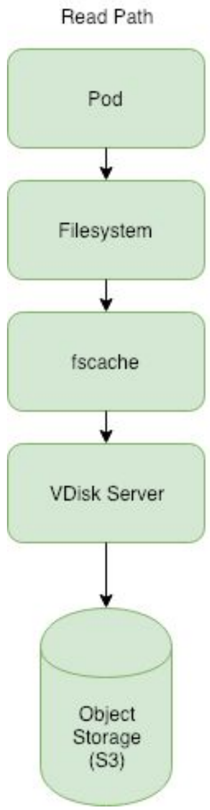
Technical solution(s)

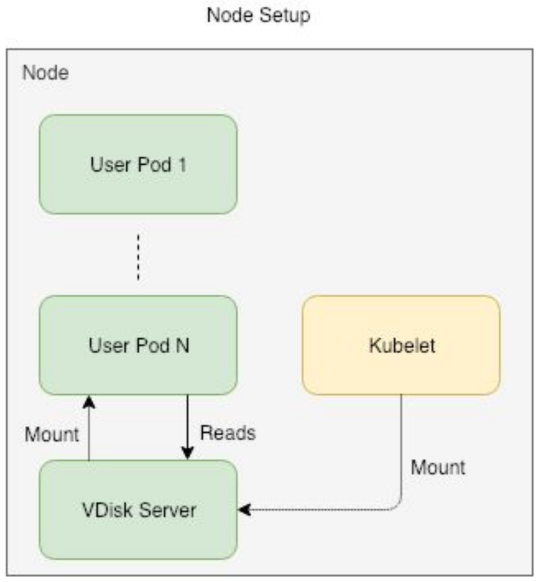
Tons of data!

What is the solution?

vdisk

- Virtualized Immutable file-system
- Offers broad platform support
- Structured to support data deduplication
- Inherently supports caching
- Provides kubernetes integration making it cloud-native

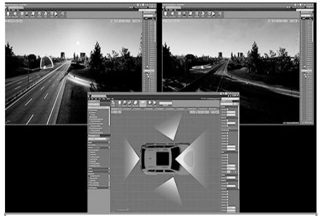




User sees: /in/training/file.ext

↓

Data lives: s3://bucket/prefix/file.ext



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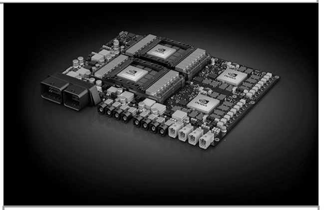


Inference on edge

Reproducibility

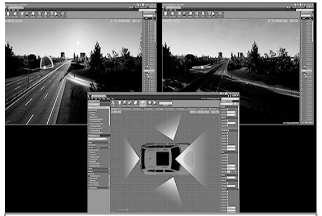
NVIDIA

Technical solution(s)

Inference on edge

- AV model inference is limited in terms of hardware capabilities

- So, finding a lighter model without losing performance is prudent and takes multiple and faster iterations



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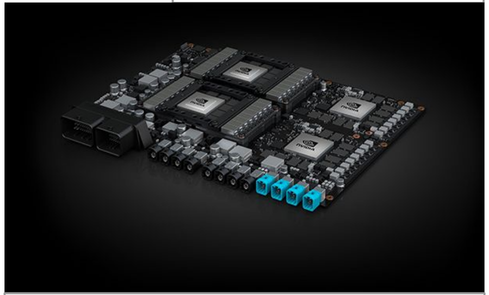


Inference on edge

Reproducibility

Technical solution(s)
Reproducibility

Why?

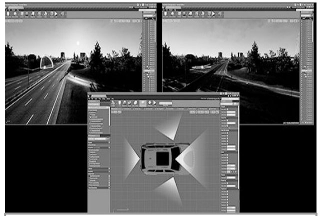
- Being able to run a 10 year old workflow and get the same results
- Faster iteration of model development
- Understand why a model behaved certain way

Requires:

- Proper version control of datasets, models and the experiments

Reproducibility

- … and traceability go hand in hand


Safety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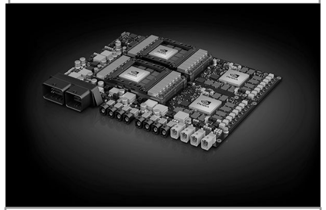
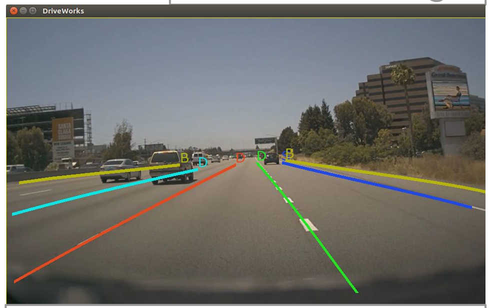

Inference on edge


Reproducibility

MagLev
Scenario walkthrough

- Predicting 12 month mortgage delinquency using Fannie Mae Single family home loan data

Key points:

Immutable dataset creation

Specifying workflows and launching them

End-to-traceability

MagLev

Scenario walkthrough

- Creating an immutable dataset

```
>> maglev volumes create --name <my-volume> --path
</some/local/directory/path> [--resume-version <version>]
    Creating volume: Volume(name = my-volume, version =
    449c8efa-eaef-4d9b-81b9-3a59fe269e9b)
    Uploading '<local-file>'...
    …
    Successfully created new volume.
    Volume(name = my-volume, version = 449c8efa-eaef-4d9b-81b9-3a59fe269e9b)
```

- Creates a ISO image

- ISO image only contains the metadata for the dataset while the actual dataset resides in S3

MagLev

Scenario walkthrough

```yaml
defaults:
  gpus: 1
  image: 'nvcr.io/nvidian_general/chrisg:d196974e8541'
image_pull_secrets: ["nvcrio"]
tasks:
  - name: rapids-data-preprocessing…

  - name: dnn-experiment…

  - name: xgboost-experiment…

  - name: dnn-train…

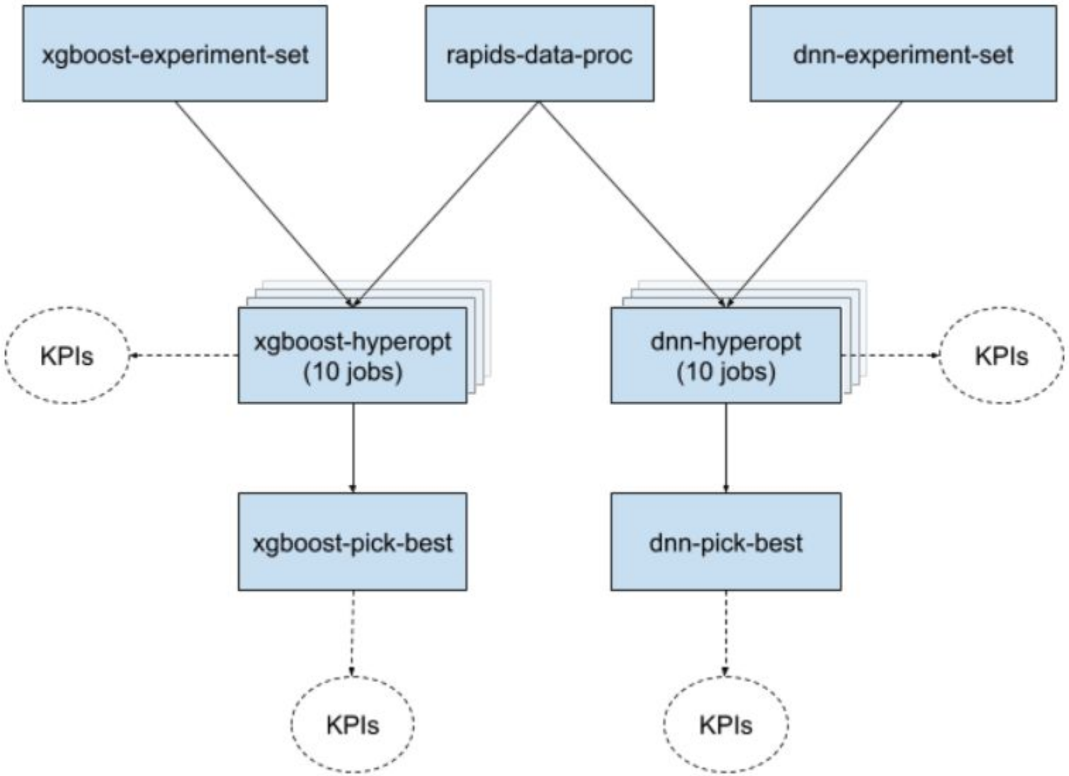
  - name: dnn-evaluate…

  - name: xgboost-train…

  - name: xgboost-pick…

  - name: xgboost-retrain…

  - name: xgboost-test…
```



MagLev

Scenario walkthrough

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  - name: dnn-evaluate…
  - name: xgboost-train…
  - name: xgboost-pick…
  - name: xgboost-retrain…
  - name: xgboost-test…
```

```yaml
- name: rapids-data-preprocessing
  args:
    - '0.05'
  inputs:
    volumes:
      - mount_path: /in/mortgage/
        name: artifact-rapids-mortgage-2000Q1-tiny
        version: 0df2b082-24fd-4934-9e18-2c3ed3d70cb2
  outputs:
    volumes:
      - mount_path: /out/dnn/
        name: dnn-data
      - mount_path: /out/xgboost/
        name: xgboost-data
```

MagLev

Scenario walkthrough

```yaml
defaults:
  gpus: 1
  image: 'nvcr.io/nvidian_general/chrisg:d196974e8541'
image_pull_secrets: ["nvcrio"]
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  - name: dnn-evaluate…
  - name: xgboost-train…
  - name: xgboost-pick…
  - name: xgboost-retrain…
  - name: xgboost-test…
```

```yaml
- name: dnn-experiment
  command: >-
    maglev experiment-sets create -f
    viaduct/rapids/mortgage/small/torch/experiments/adam_hyperopt.yaml
  outputs:
    volumes:
      - mount_path: /out/
        name: out
```

MagLev

Scenario walkthrough

```yaml
defaults:
  gpus: 1
  image: 'nvcr.io/nvidian_general/chrisg:d196974e8541'
image_pull_secrets: ["nvcrio"]
tasks:
  - name: rapids-data-preprocessing…
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  - name: dnn-train…
  - name: dnn-evaluate…
  - name: xgboost-train…
  - name: xgboost-pick…
  - name: xgboost-retrain…
  - name: xgboost-test…
```

```yaml
- name: dnn-train
  command: >-
    main --maglev --patience 4 --dataset_id
    0df2b082-24fd-4934-9e18-2c3ed3d70cb2 --num_features 2048  --hidden_dims
    512 512 512 512 --optimizer adam --data_dir /in/data/ --epochs 5
    --ignore_bad_pr_auc
  completions: 10
  inputs:
    volumes:
      - from: rapids-data-preprocessing
        mount_path: /in/data
        name: dnn-data
      - from: dnn-experiment
        mount_path: experiment-set
        name: out
  outputs:
    volumes:
      - mount_path: out
        name: out
```

MagLev

Scenario walkthrough

```yaml
defaults:
  gpus: 1
  image: 'nvcr.io/nvidian_general/chrisg:d196974e8541'
image_pull_secrets: ["nvcrio"]
tasks:
  - name: rapids-data-preprocessing…
  - name: dnn-experiment…
  - name: xgboost-experiment…
  - name: dnn-train…
  - name: dnn-evaluate…
  - name: xgboost-train…
  - name: xgboost-pick…
  - name: xgboost-retrain…
  - name: xgboost-test…
```

```yaml
- name: dnn-evaluate
  command: >-
    evaluate --dataset_id 0df2b082-24fd-4934-9e18-2c3ed3d70cb2 --num_features
    2048 --hidden_dims 512 512 512 512 --test_dataset
    /in/data/encoded_test_discrete.csv.gz
  inputs:
    volumes:
      - from: rapids-data-preprocessing
        mount_path: /in/data
        name: dnn-data
      - from: dnn-experiment
        mount_path: experiment-set
        name: out
```

PyTorch DNN vs XGBoost with RAPIDS on MagLev

```
%matplotlib inline

import maglev
import matplotlib.pyplot as plt
```

Workflow Metadata

```
# Update this with your workflow id
WORKFLOW_ID = "c4254540-76e1-5460-9e87-c4801c791a28"
```

```
DNN_MODEL_ID = "d1c8673b-a258-48e6-9360-fb758d8f134c"
XGBOOST_MODEL_ID = "c31d4b39-b86e-4c61-81db-dab979d96b8b"

# Used to track performance of models over time
DATASET_ID = "10ccd8e0-f172-443a-ad29-f52711fff9e3"

client = maglev.Client.default_service_client()
```

```
print(client.get_workflow(WORKFLOW_ID))
```

```
Workflow(workflow_id=u'c4254540-76e1-5460-9e87-c4801c791a28',
         namespace=u'maglev-849d16e8-3f2d-4615-b508-ba7f08925d0d',
         name=u'maglev-workflow-r6g5v',
         project_id=u'cebca8ba-5865-11e8-9c2d-fa7ae01bbebc'.
         creation_date=datetime.datetime(2019, 1, 26, 16, 29, 34, 470722))
```

Hyperparameter Experiments

Let's load and inspect the experiments created by the `dnn-experiment` and `xgboost-experiment` tasks.

```
experiment_sets = client.list_experiment_sets(workflow_id=WORKFLOW_ID)
```

XGBoost

```
xgboost_es = list(filter(lambda x: 'xgboost' in x.get_description().lower(), experiment_sets))[0]
print("Description:\n\n\t{}".format(xgboost_es.get_description()))
```

```
Description:

	FNMA Mortgage Dataset Small XGBoost Hyperopt
```

Experiment Parameters

```
xgboost_es.get_parameters()[["exp_id", "alpha", "eta", "gamma", "lambda", "max_depth"]].sort_values('exp_id')
```

	exp_id	alpha	eta	gamma	lambda	max_depth
9	0	4.518904	0.007317	7.288823	3.532960	9
8	1	2.655062	0.107846	4.022320	3.569992	10
7	2	5.863257	0.019554	7.396898	5.197621	5
6	3	4.923602	0.159066	4.052578	1.768556	4
5	4	8.972206	0.214875	9.208735	1.234819	7

Model Comparison on Test Set

Our workflow includes tasks to pick the best XGBoost and DNN models and then evaluate them on the holdout test set created in `rapids-data-preprocessing`. During this evaluation we create MagLev experiment metrics and mark them as optimum for easier fetching, which we do below.

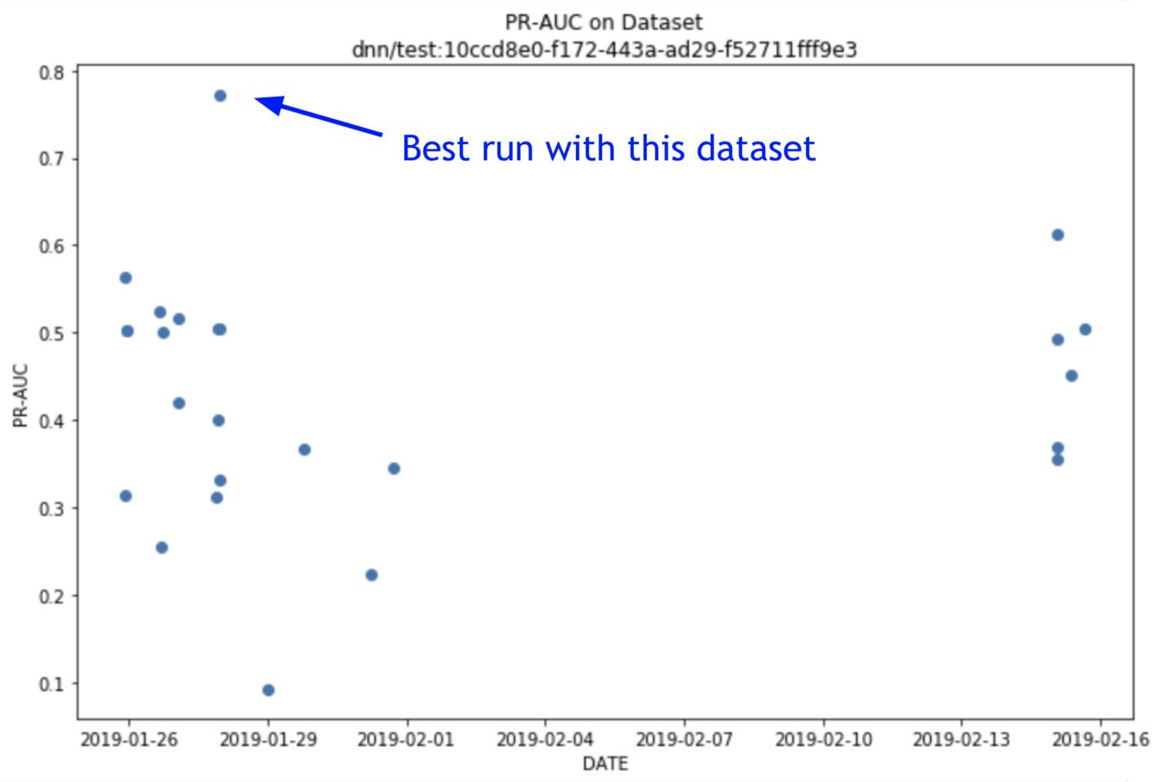
```
# Get the metrics created for this workflow
xgboost_metrics = client.list_metrics(workflow_id=WORKFLOW_ID, model_id=XGBOOST_MODEL_ID)
dnn_metrics = client.list_metrics(workflow_id=WORKFLOW_ID, model_id=DNN_MODEL_ID)

# Find the optimum metrics that have names starting with 'test/'
def best_metrics(metrics):
    return {m.name: m for m in metrics if m.optimum_is_maximum and 'test/' in m.name }

# Compare!
best_xgboost_metrics = best_metrics(xgboost_metrics)
best_dnn_metrics = best_metrics(dnn_metrics)
for m in ['test/pr_auc', 'test/roc_auc']:
    print("{}:\n\txgb:\t{:.4f}\n\tdnn:\t{:.4f}".format(m.upper(), best_xgboost_metrics[m].value, best_dnn_metrics[m].va

print("\n\nBest XGBoost Model Version:\t{}".format(best_xgboost_metrics['test/pr_auc'].model_version_id))
print("Best PyTorch DNN Model Version:\t{}".format(best_dnn_metrics['test/pr_auc'].model_version_id))
```

```
TEST/PR_AUC:
        xgb:    0.6591
        dnn:    0.2556
TEST/ROC_AUC:
        xgb:    0.9509
        dnn:    0.8729


Best XGBoost Model Version:     3ec0be68-3cee-55d1-8650-c07f5e0fb65a
Best PyTorch DNN Model Version: ac07d7c8-c26d-5366-8d4b-cff48ae4f8b2
```

DNN Models Performance on Test Dataset Over Time

During creation of the evaluation metrics of the PyTorch model on the test set we've also assign datasets to these metrics. This allows us to track over time how models perform on a particular dataset:

```
all_dnn_metrics = client.list_metrics(model_id=DNN_MODEL_ID)

def filter_dnn_metric(m):
    if m.name != 'test/pr_auc': return False
    if m.datasets is None: return False
    if not isinstance(m.datasets, dict): return False
    if 'dnn/test' not in m.datasets: return False
    if m.datasets['dnn/test'] != DATASET_ID: return False

    return True

test_pr_auc = list(filter(filter_dnn_metric,
                          all_dnn_metrics))
test_pr_auc = sorted(test_pr_auc,
                     key=lambda m: m.creation_date)

x = [m.creation_date for m in test_pr_auc]
y = [m.value for m in test_pr_auc]

plt.figure(figsize=(11, 7))
plt.xlabel("DATE")
plt.ylabel("PR-AUC")
plt.title("PR-AUC on Dataset\n{}:{}".format('dnn/test', DATASET_ID))
plt.plot_date(x, y);
```



MagLev Architecture Evolution

Version 1 - Technical viability

Compute and data on public cloud

- Mostly for technical evaluation
- Costs skyrocketing
- Poor performance
    - clash between functionality and efficiency

Image source: shuttershock.com

Early decisions

- Cloud native platform
- General purpose services/ETL pipelines hosted on public cloud allows us to elastically scale based on requirements

MagLev Architecture Evolution

Version 2 - Minimize costs

Compute on internal data-center for GPU workloads

- Minimize costs
- Take advantage of innovation on GPUs before it hits the market
- Huge compute cluster that is always kept busy by the training/testing workflows

What needed to improve:

- Performance due to lack of data locality

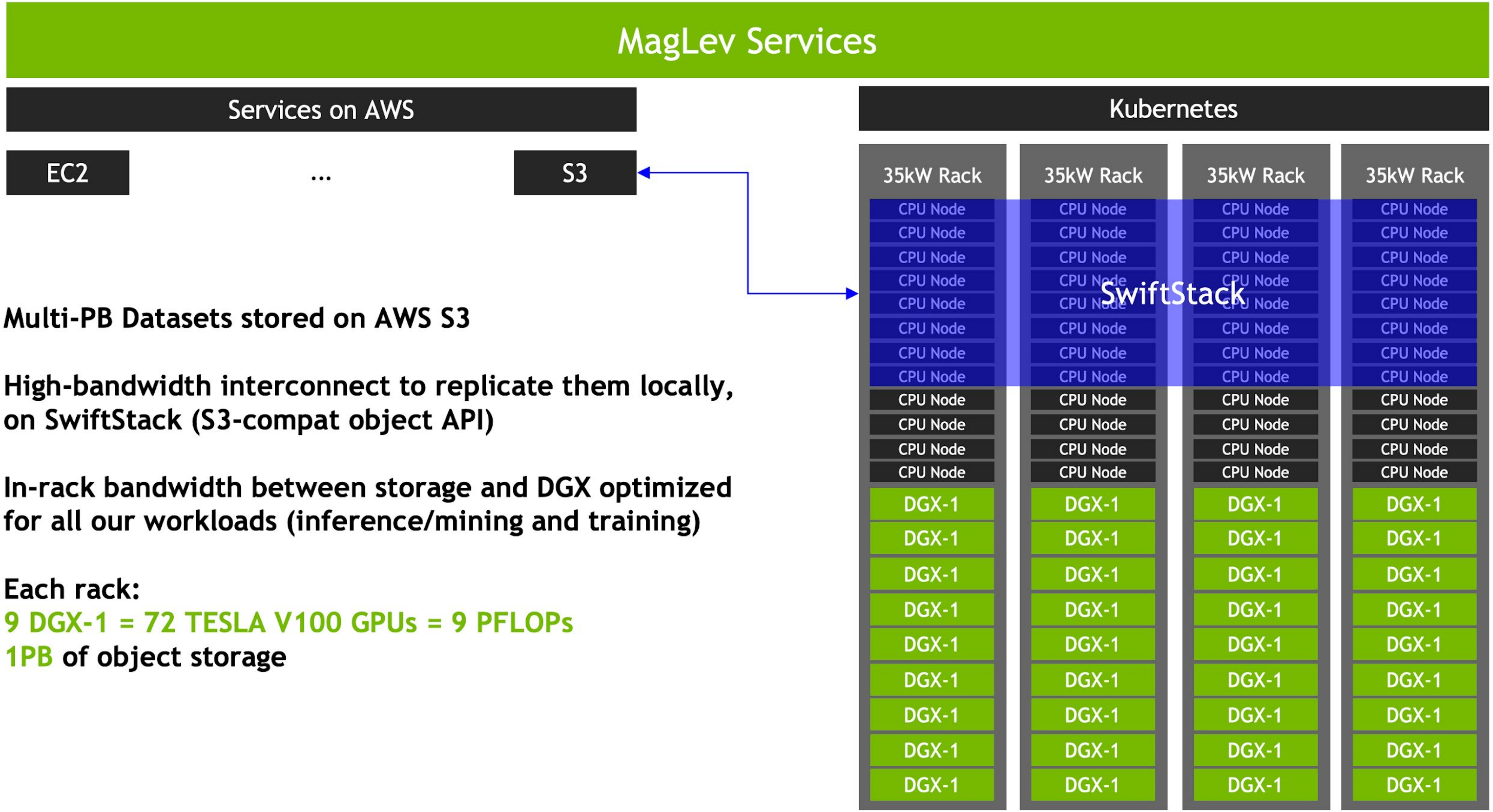
MagLev Architecture Evolution

Version 3 - High performance

Internal data center specialized for both compute and data performance

- High performance due to data locality
- Better UX for data scientists
    - Programmatically create workflows

MagLev Data Center Architecture



Multi-PB Datasets stored on AWS S3

High-bandwidth interconnect to replicate them locally, on SwiftStack (S3-compat object API)

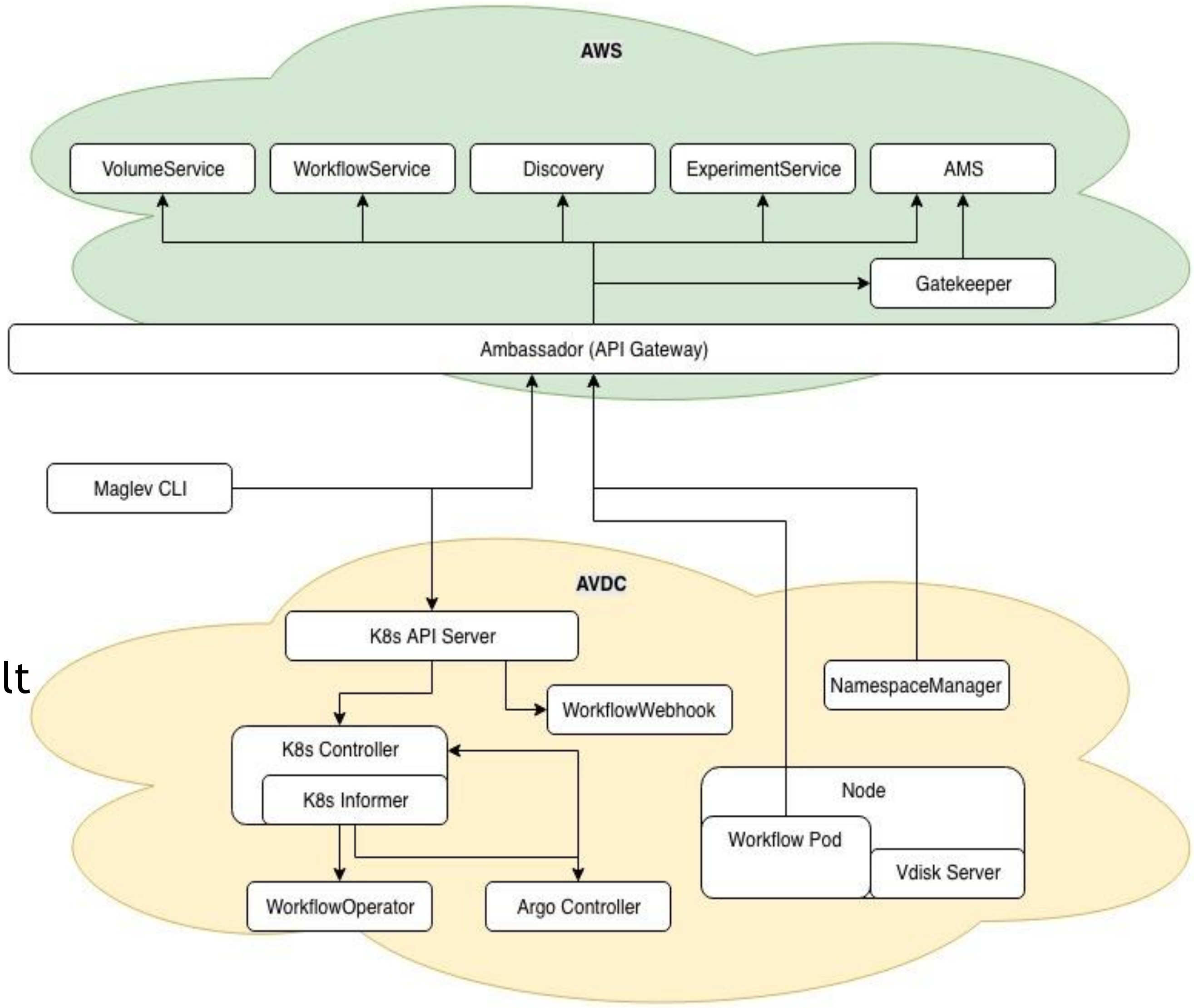
In-rack bandwidth between storage and DGX optimized for all our workloads (inference/mining and training)

Each rack:
9 DGX-1 = 72 TESLA V100 GPUs = 9 PFLOPs
1PB of object storage

MagLev Service Architecture

- General service cluster on public cloud
  - Authentication
  - Volume management
  - Workflow traceability
  - Experiment/Model management
- Compute cluster on internal NGC cloud

- Both clusters are cloud-native built on top of Kubernetes



Questions