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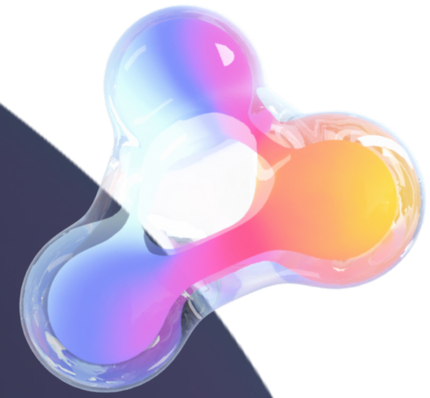
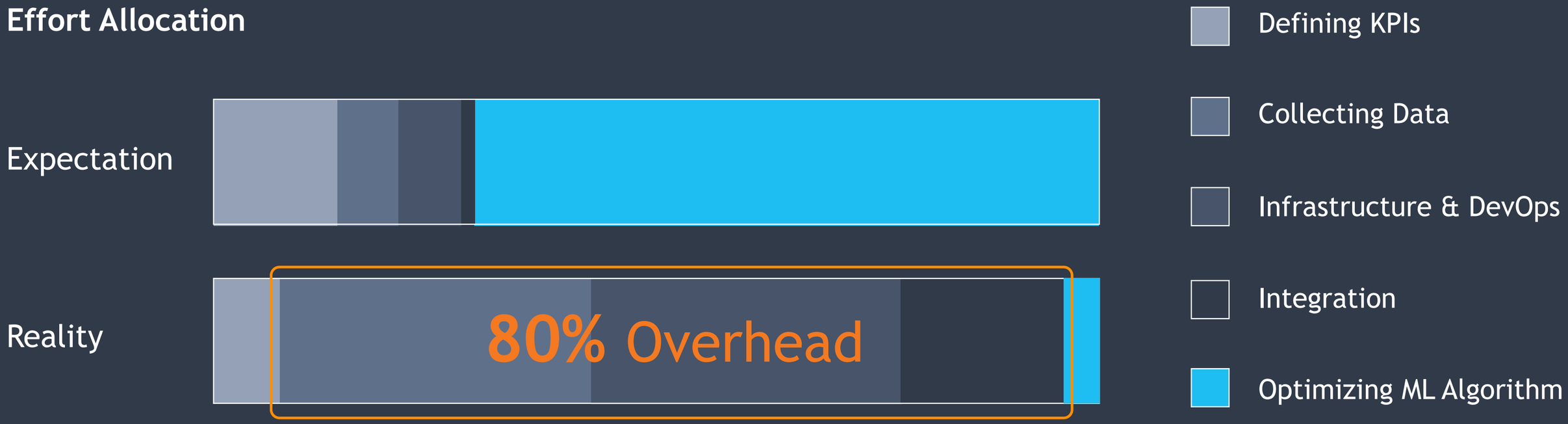
Data Science from Research to Production



Or Zilberman, Lead Data Scientist, Iguazio Nov 2020

Data-Scientists Don’t Do Data-Science !

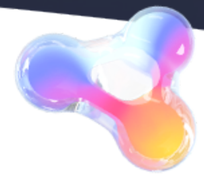
Effort Allocation



The need: Simpler Solutions, Better Data Integration

Source: Google Developers Launchpad

Goal



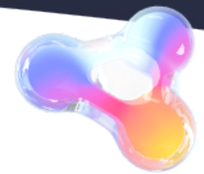
Help you Maximize your time focusing on the

Business Goal

instead of boilerplate related tasks

*focus on your business rather then Devops / Engineering

Goal



Help you Maximize your time focusing on the

Business Goal

instead of boilerplate related tasks

How?

Kubernetes
Cloud OS

Jupyter
DS IDE

Nuclio
Serverless Framework

Kubeflow
Orchestration

MLRun
Orchestration

~~DevOps~~ MLOps

And data-science

"Combine Dev and Ops to shorten the systems-development life cycle while delivering features, fixes, and updates frequently in close **alignment with business objectives**."

Or Zilberman

Lead Data Scientist @ Iguazio

Data Scientist @ Glispa Global Group:

Managed Glispa's Data Management Platform (User Personalization)
Owned Glispa's SSP Platform's Data Science efforts

RTB Process & Revenue Optimization
Ad serving network optimizations

Data Scientist @ Teddy Sagi's Group:

Supplied solutions to multiple companies in the group as part of a specialized AI team

E-Commerce: Recommendation engines based on Image, Text and user actions
Forex: Risk management,
Customer Life Time Value, Customer Churn
Automated lead generation

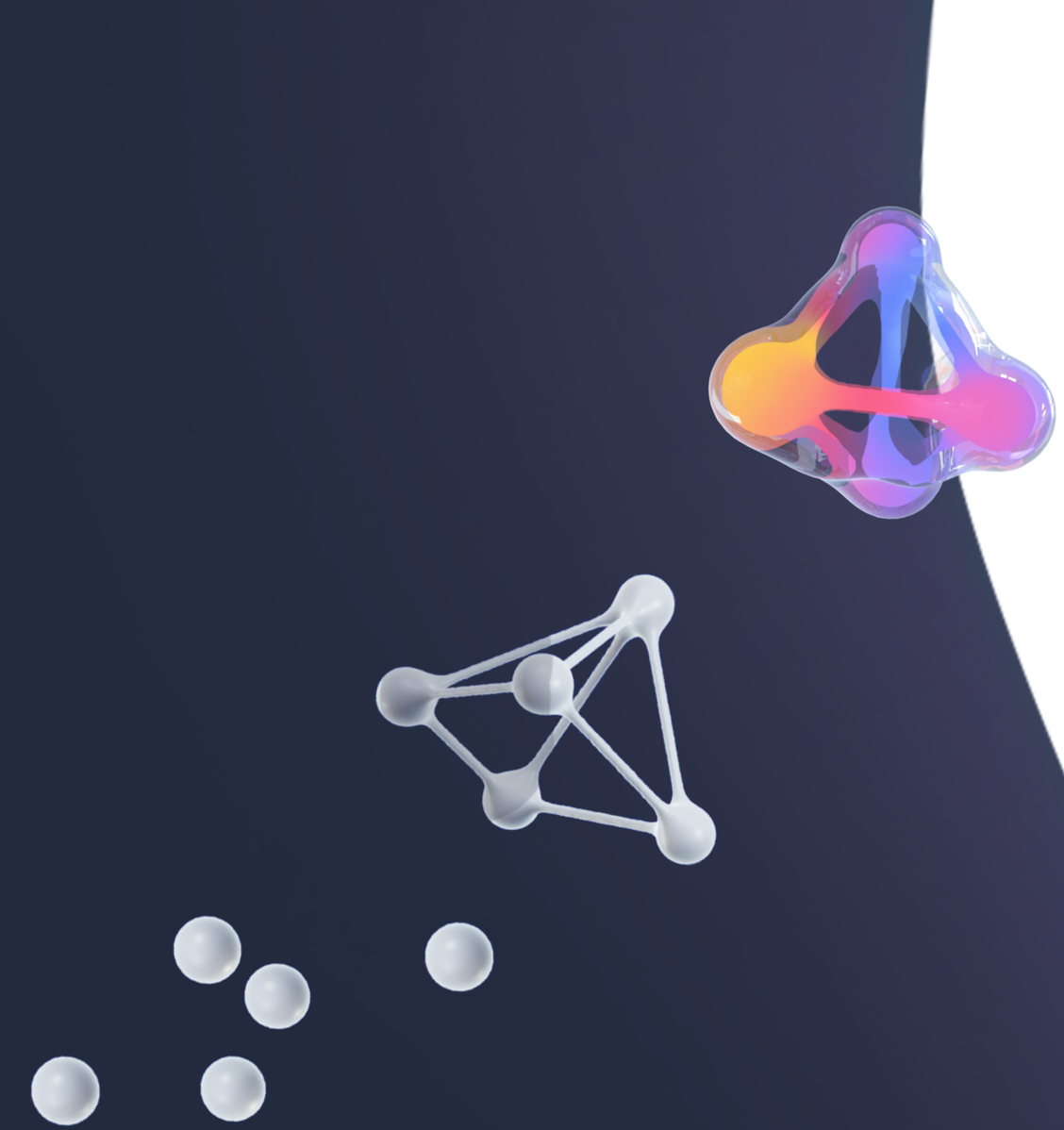
Patents: 3

Latest publication: An FPGA Scalable Parallel Viterbi Decoder @ IEEE MSOC 2018 Vietnam

Additional Experience:
- Head of SEO & CRO @ Dataworks
- VP Product @ NegevJobs
- Director @ Streamono/Gameono

Certifications:
- Google Analytics Certified Individual Qualification (01684861)
- iCDE (18012817THDUUZHU)

Education:
- University of Haifa

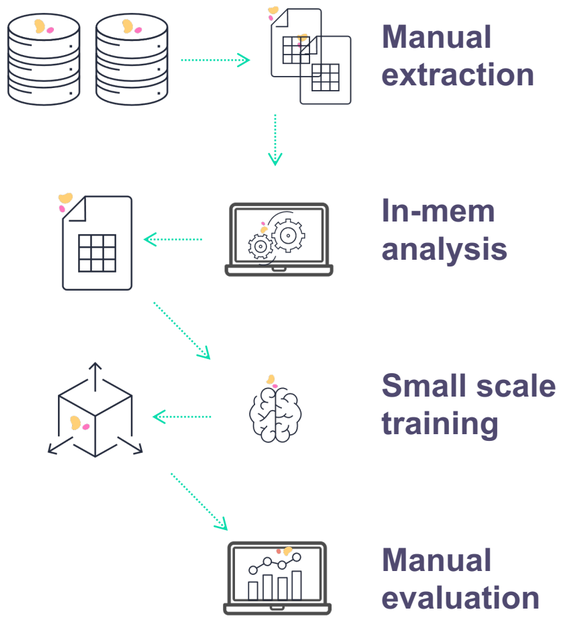


What will we do today?

1. Review the Data Science process in production
2. Technological review - base & architecture
    1. Docker
    2. Kubernetes
    3. Serverless
3. Nuclio
    1. What is nuclio
    2. How to deploy serverless functions from our Jupyter notebook
    3. Training: Deploy a function
4. Kubeflow & MLRun
    1. What is kubeflow
    2. What is MLRun
    3. Training: Deploy functions
    4. Training: Deploy pipeline

87% of AI Projects Never Make it to Production

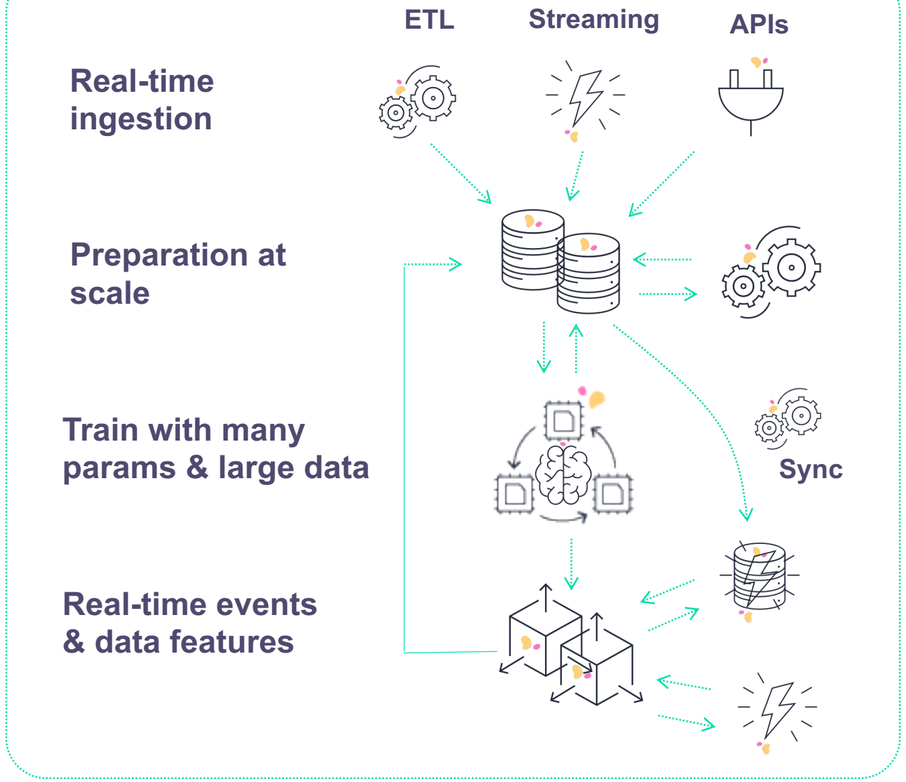
Research Environment



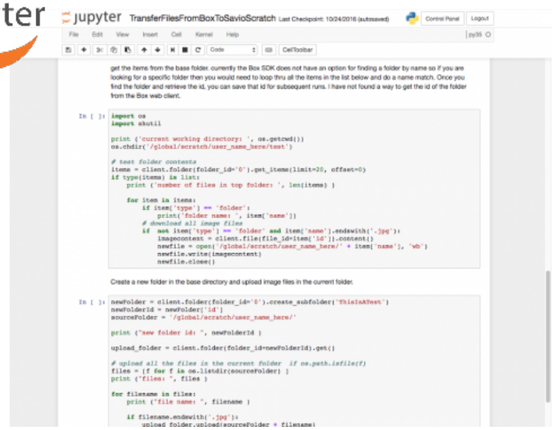
Build from Scratch

with a Large Team

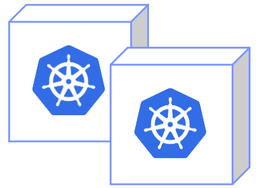
Production Pipeline



Did you Try Running Notebooks in Production?

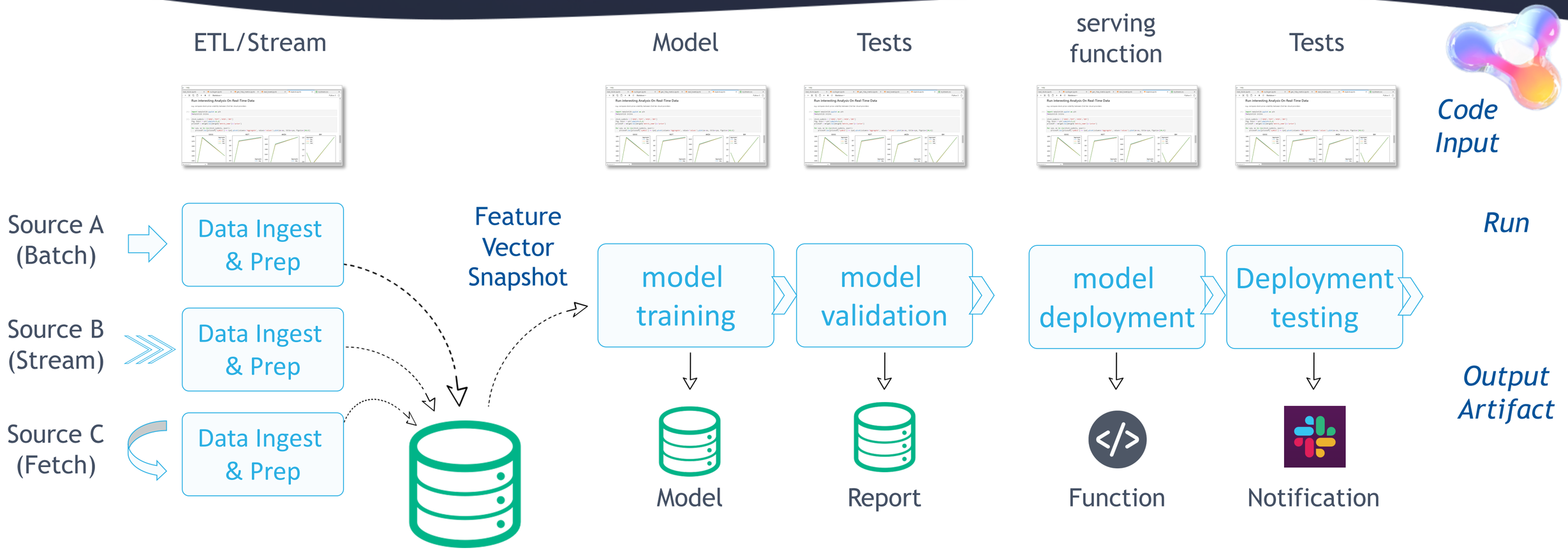


Refactor and operationalize



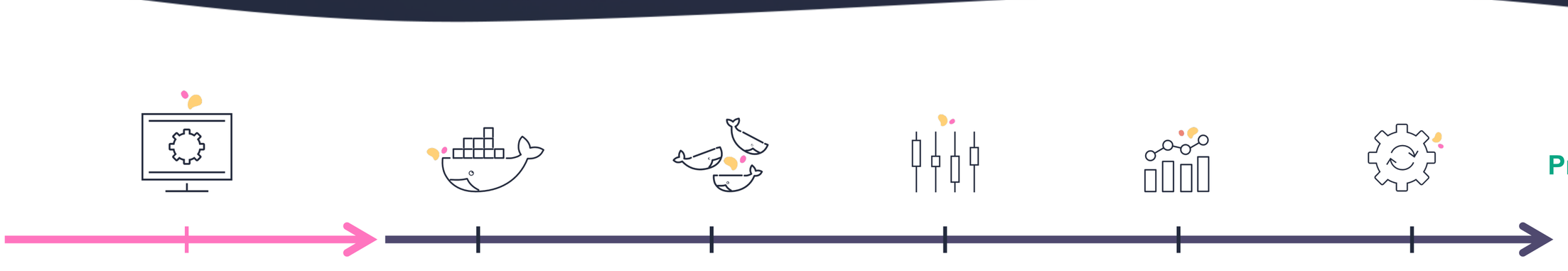
Micro-services

Typical Data Science Pipeline



Pipeline must be automated !

Because Model Development is Just the First Step



Develop and Test Locally

Package

- Dependencies
- Parameters
- Run scripts
- Build

Scale-out

- Load-balance
- Data partitions
- Model distribution
- AutoML

Tune

- Parallelism
- GPU support
- Query tuning
- Caching

Instrument

- Monitoring
- Logging
- Versioning
- Security

Automate

- CI/CD
- Workflows
- Rolling upgrades
- A/B testing

Weeks

with **one** data scientist or developer

Months

with a **large team** of developers, scientists, data engineers and DevOps

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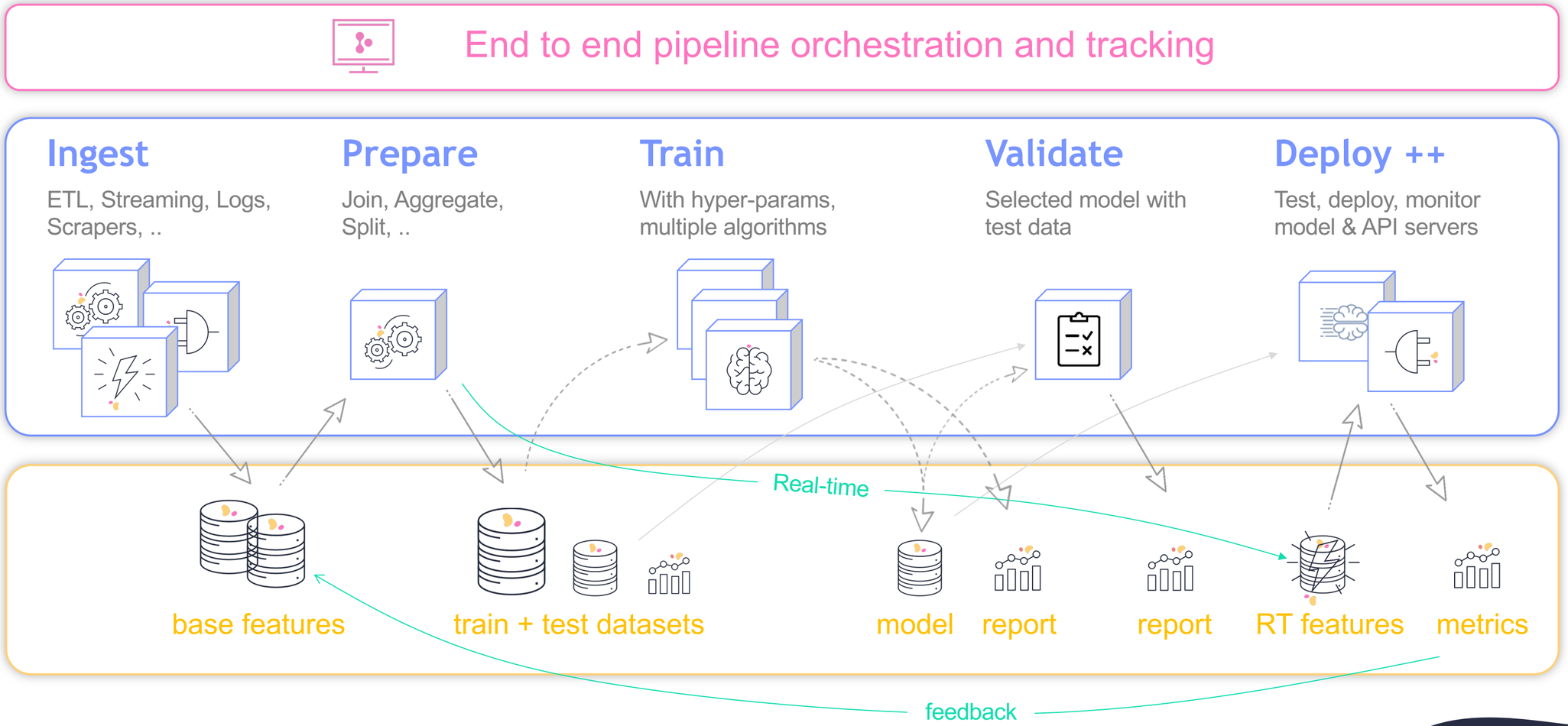
Typical Data Science Pipeline

Serverless:
ML & Analytics
Functions

Features/Data:
Fast, Secure,
Versioned



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Docker

Docker is a platform for developers and sysadmins to **build, share, and run** applications with containers. The use of containers to deploy applications is called *containerization*. Containers are not new, but their use for easily deploying applications is.
Containerization is increasingly popular because containers are:

Flexible: Even the most complex applications can be containerized.
Lightweight: Containers leverage and share the host kernel, making them much more efficient in terms of system resources than virtual machines.

Portable: You can build locally, deploy to the cloud, and run anywhere.
Loosely coupled: Containers are highly self sufficient and encapsulated, allowing you to replace or upgrade one without disrupting others.

Scalable: You can increase and automatically distribute container replicas across a datacenter.
Secure: Containers apply aggressive constraints and isolations to processes without any configuration required on the part of the user.

Docker

Docker Basics

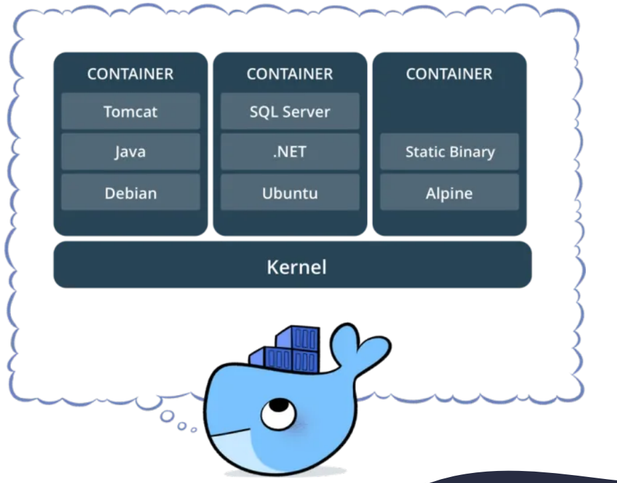
Image
The basis of a Docker container. The content at rest.

Container
The image when it is 'running.' The standard unit for app service

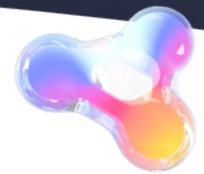
Engine
The software that executes commands for containers. Networking and volumes are part of Engine. Can be clustered together.

Registry
Stores, distributes and manages Docker images

Control Plane
Management plane for container and cluster orchestration



What is Kubernetes?



“Kubernetes” = Greek for governor, helmsman, captain

- open-source container orchestration system
- originally designed by Google, maintained by CNCF
- aim to provide "platform for automating deployment, scaling and operations of application containers across clusters of hosts"

Kubernetes - Pod

The basic, **atomically deployable unit** in Kubernetes.

A Pod consists of one or many *co-located containers*.
A Pod represents *a **single instance of an application***.

The containers in a Pod share the loopback interface (localhost) and can share mounted directories.

Each Pod has it's own, uniquely assigned and internal IP.

Pods are **mortal**, which means that if the node the Pod runs on becomes unavailable, the workload also goes unavailable.

```yaml
apiVersion: v1
kind: Pod
metadata:
  name: nginx
  namespace: default
  labels:
    app: nginx
spec:
  containers:
  - image: nginx:1.13.9
    name: nginx
    ports:
    - name: http
      containerPort: 80
```

Kubernetes - Deployment

With a Deployment, you can manage Pods in a ***declarative and upgradable*** manner.

Note the *replicas* field. Kubernetes will make sure that amount of Pods created from the template always are available.

When the Deployment is updated, Kubernetes will perform a **rolling update** of the Pods running in the cluster. Kubernetes will create one new Pod and remove an old until all Pods are new.

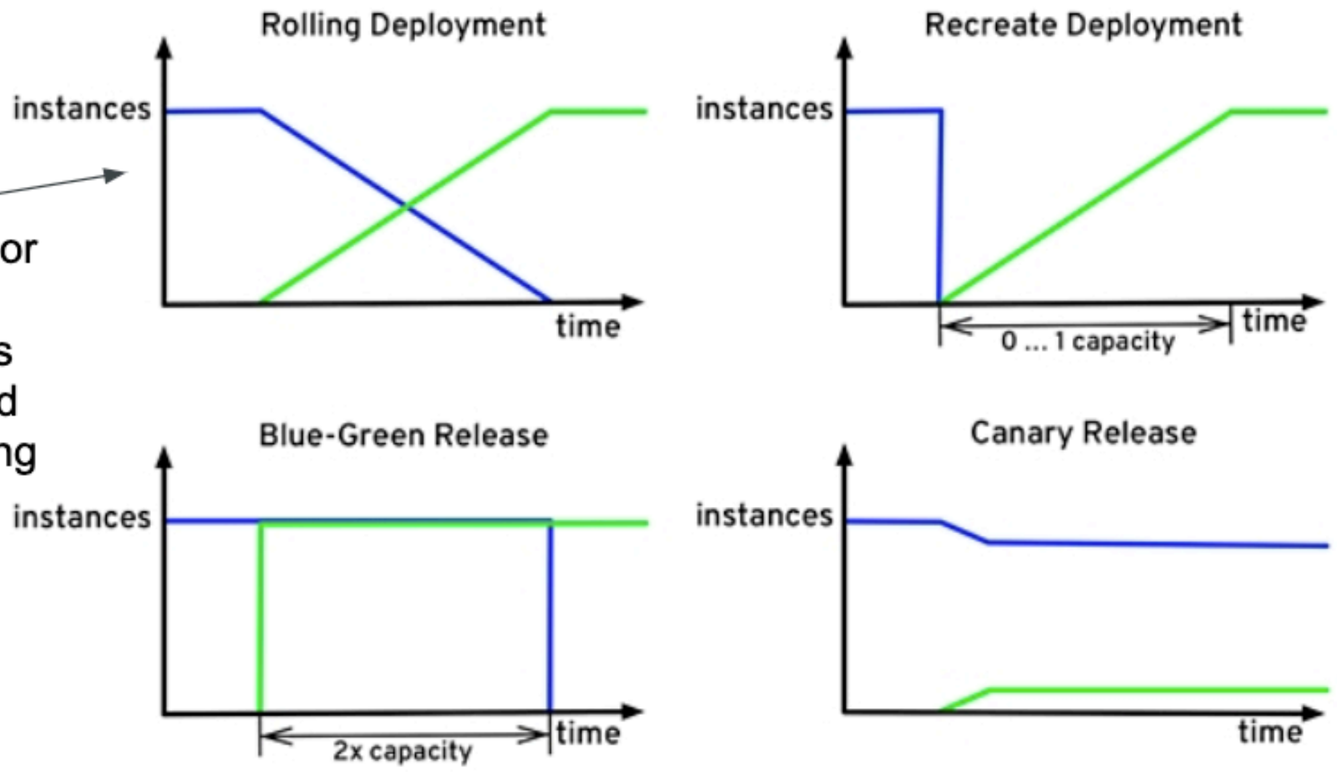
```yaml
apiVersion: apps/v1
kind: Deployment
metadata:
  labels:
    app: nginx
  name: nginx
spec:
  replicas: 3
  selector:
    matchLabels:
      app: nginx
  template:
    metadata:
      labels:
        app: nginx
    spec:
      containers:
      - image: nginx:1.13.9-alpine
        name: nginx
        ports:
        - name: http
          containerPort: 80
```

The Pod Template

Kubernetes – Deployment strategies

The built-in Deployment behavior

The other strategies can be implemented fairly easily by talking to the API.



Kubernetes - Service

A Service exposes one or many Pods via a ***stable, immortal, internal IP address***.

It's also accessible via cluster-internal DNS:
{service}.{namespace}.svc.cluster.local, e.g.
nginx.default.svc.cluster.local

The Service selects Pods based on the **label key-value selectors** (here app=nginx)

A Service may expose multiple ports. This ClusterIP can be declaratively specified, or dynamically allocated.


```yaml
apiVersion: v1
kind: Service
metadata:
  name: nginx
  namespace: default
  labels:
    app: nginx
spec:
  type: ClusterIP
  ports:
  - name: http
    port: 80
    targetPort: 80
  selector:
    app: nginx
```

Serverless - Moving to Micro-Services

Application Modernization

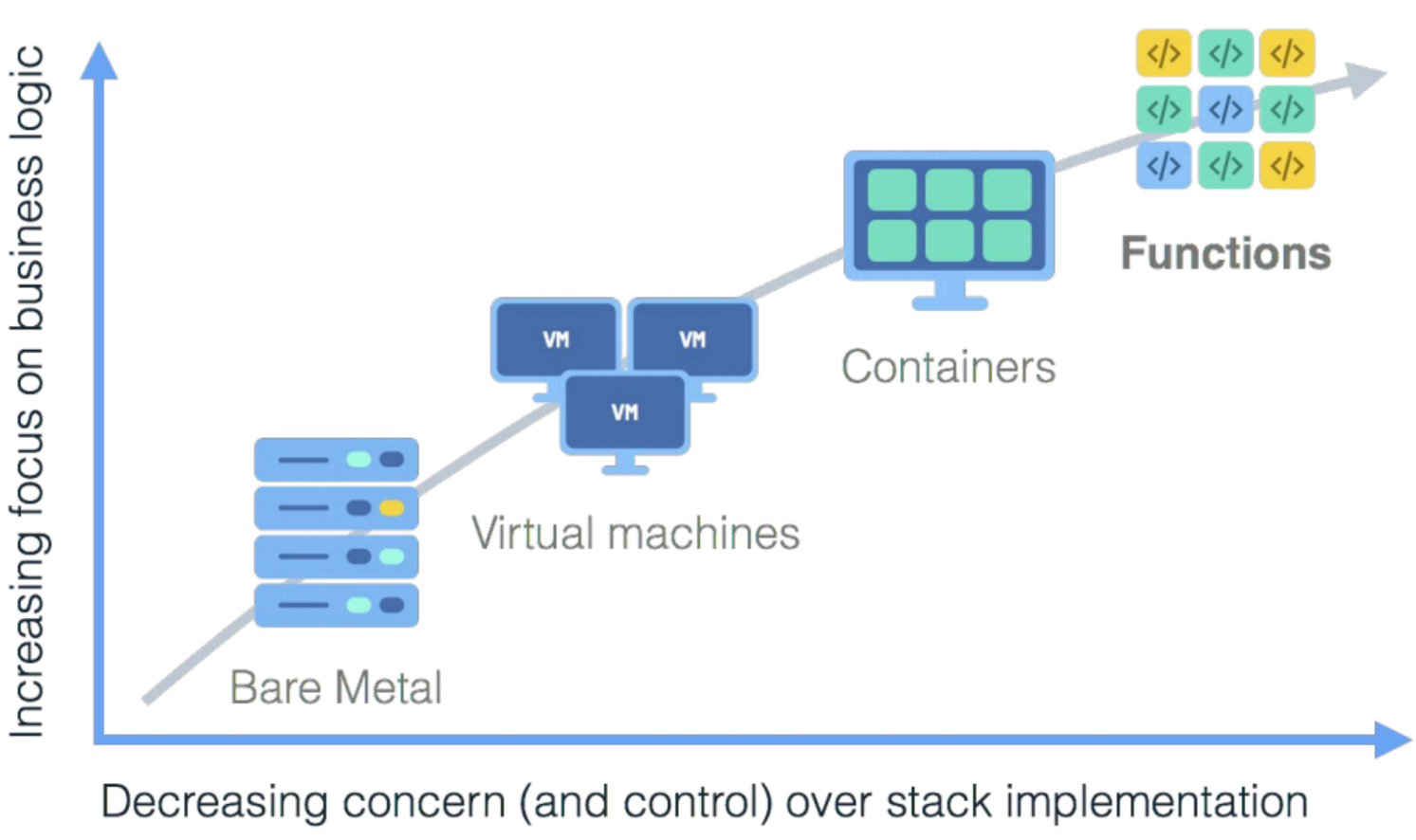
Developer Issues:

- Minor code changes require full re-compile and re-test
- Application becomes single point of failure
- Application is difficult to scale

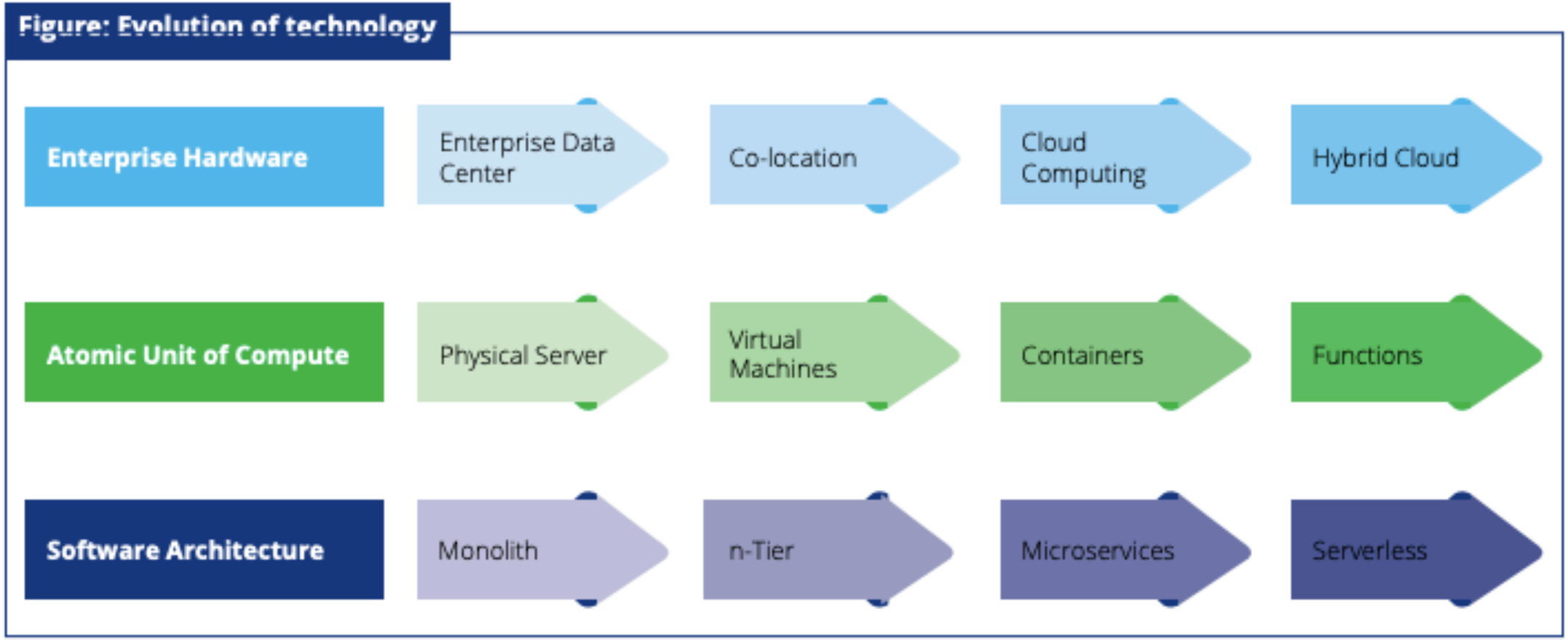
Microservices: Break application into separate operations

12-Factor Apps: Make the app independently scalable, stateless, highly available by design

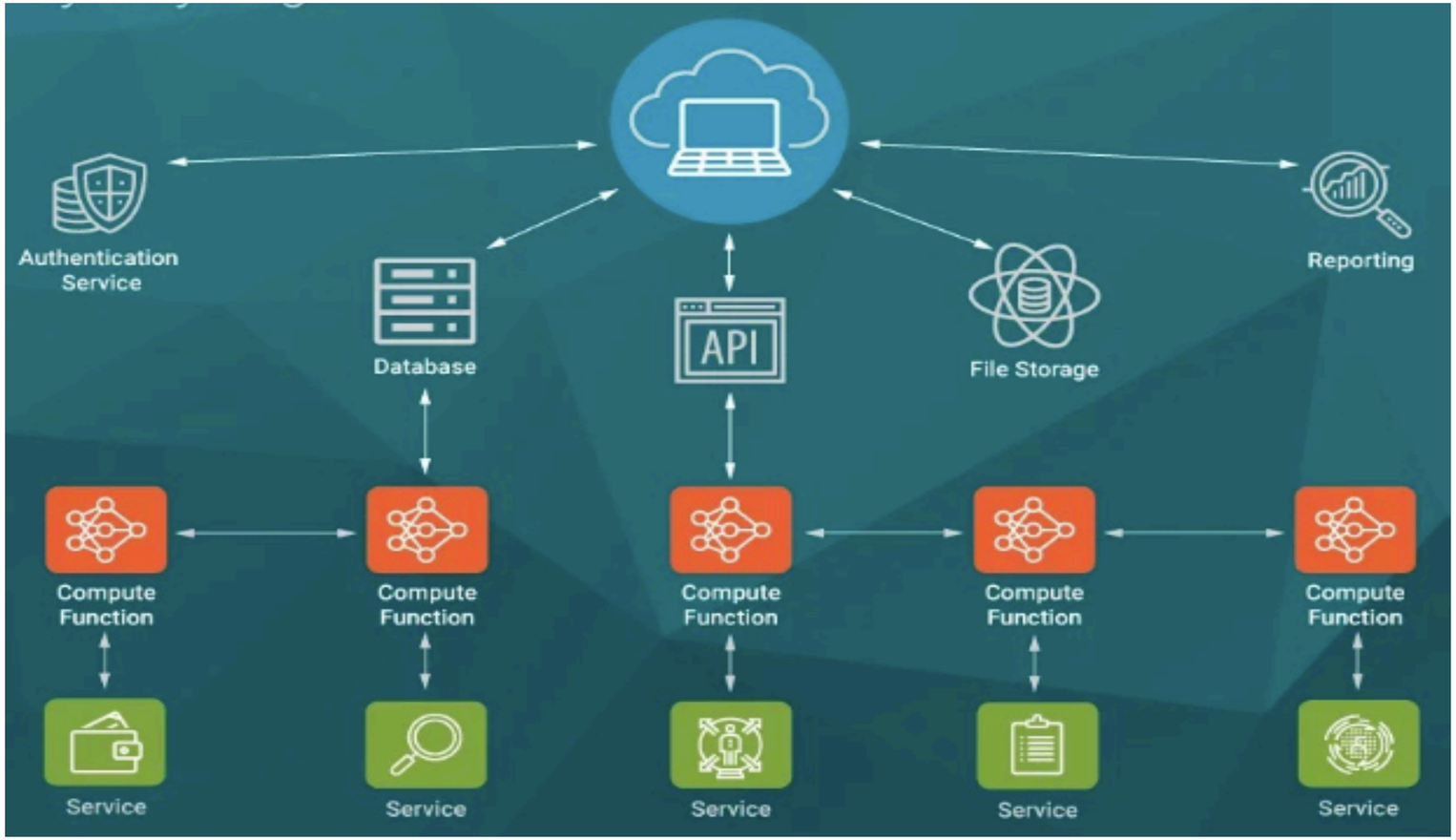
Serverless


Increasing focus on business logic
Bare Metal
VM
VM
VM
Virtual machines
Containers
Functions
Decreasing concern (and control) over stack implementation

Serverless



Serverless Architecture



Nuclio & MLRun:
Serverless Simplicity, Maximum Performance

- **Automated** code to production
- **Elastic** resource scaling (zero to N)
- **Effortless** logging, monitoring, and versioning
- **High-performance** runtimes + fast data access
- **Glue-less** pipeline and tracking integration
- **Reusable** internal/public function marketplace

”Moving from Hadoop/Java to Nuclio reduce 90% of our code footprint and got us much better performance”

Why Not Use Serverless for Training and Data Prep?

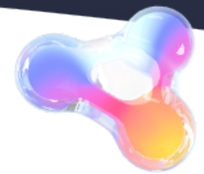
Serverless: resource elasticity (to Zero), automated deployment and operations

What about Training and data prep ?

	Serverless Today	Data Prep and Training
Task lifespan	Millisecs to mins	Secs to hours
Scaling	Load-balancer	Partition, shuffle, reduce, Hyper-params
State	Stateless	Stateful
Input	Event	Params, Datasets

Nuclio ML Functions, Expands Serverless to data-science !

The Agility Challenge:
How to Innovate & Iterate Faster, Deploy Everywhere



Modern Apps Today:

Complex, Long Development

- Many moving parts, lack of skilled developers, scientists, and DevOps

Production readiness

- Error-handling, security, logging, auto-scaling, live updates, ..

Slow to respond or act

- High-latency, or fast but inaccurate
- Cloud latency/bandwidth barriers

The Need:

Serverless
Automate dev and ops

High-performance
Data, AI and app services

Federated
In the cloud, on-prem or edge

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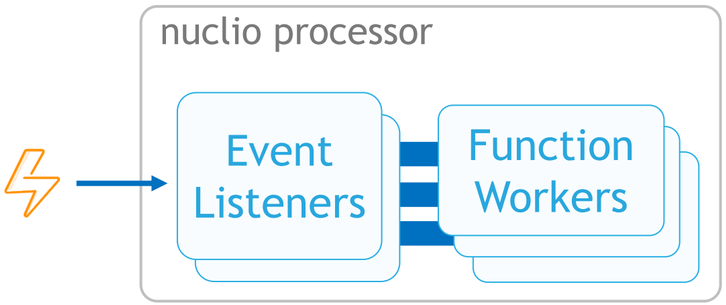
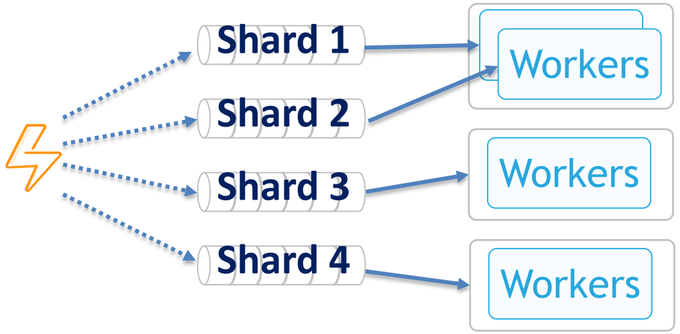
Nuclio: Taking Serverless to The Next Level

Extreme Performance



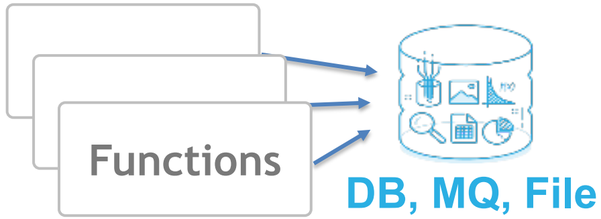
- Non-blocking, parallel
- Zero copy, buffer reuse
- Up to 400K events/sec/proc
- **GPU** Support

Advanced Data & AI Features



- Auto-rebalance, checkpoints
- Any source: Kafka, NATS, Kinesis, event-hub, iguazio, pub/sub, RabbitMQ, Cron, ..
- Jupyter, Spark, Rapids integration

Statefulness



- Data bindings
- Shared volumes
- Context cache

Open-source Serverless for compute and data intensive tasks, **100x faster** than AWS Lambda !

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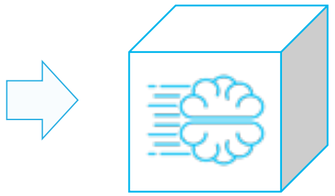
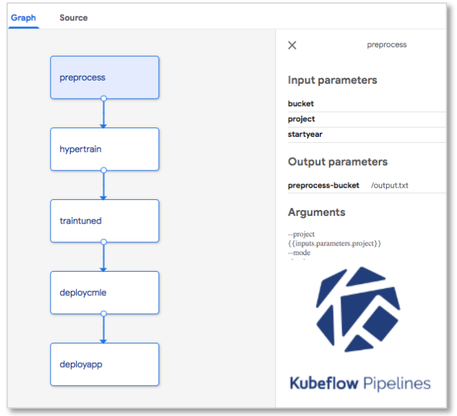
Nuclio: Fast Serverless for Data Science & RT Analytics



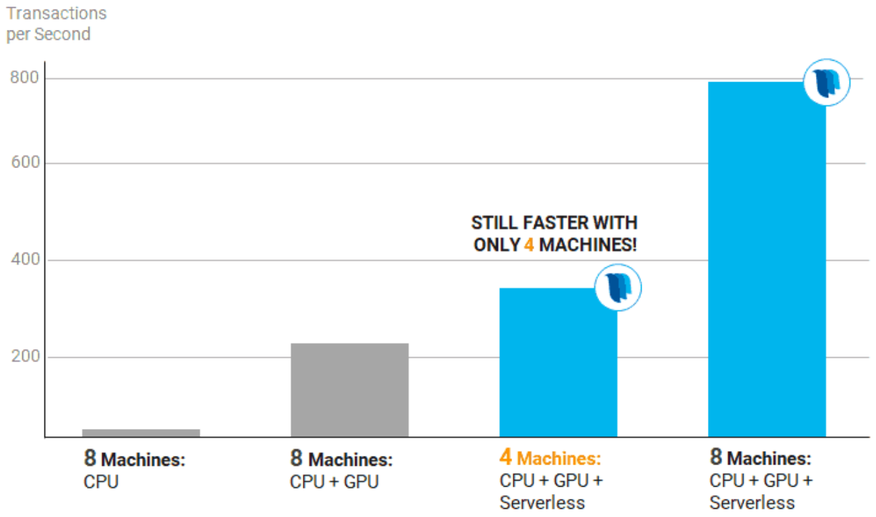
magic commands from notebook to function



Extending ML Pipelines from batch:

1. **Parallel** processing
2. Code **build**/deployment
3. **Stream** processing
4. API/Model **Serving**

High-performance IO and Computation + GPU Optimizations



Code + DevOps Automation:

1. Auto-scaling (to zero)
2. Automated logging & monitoring
3. Security hardening
4. Auto-build and CI/CD
5. Workload mobility (cloud/edge/..)

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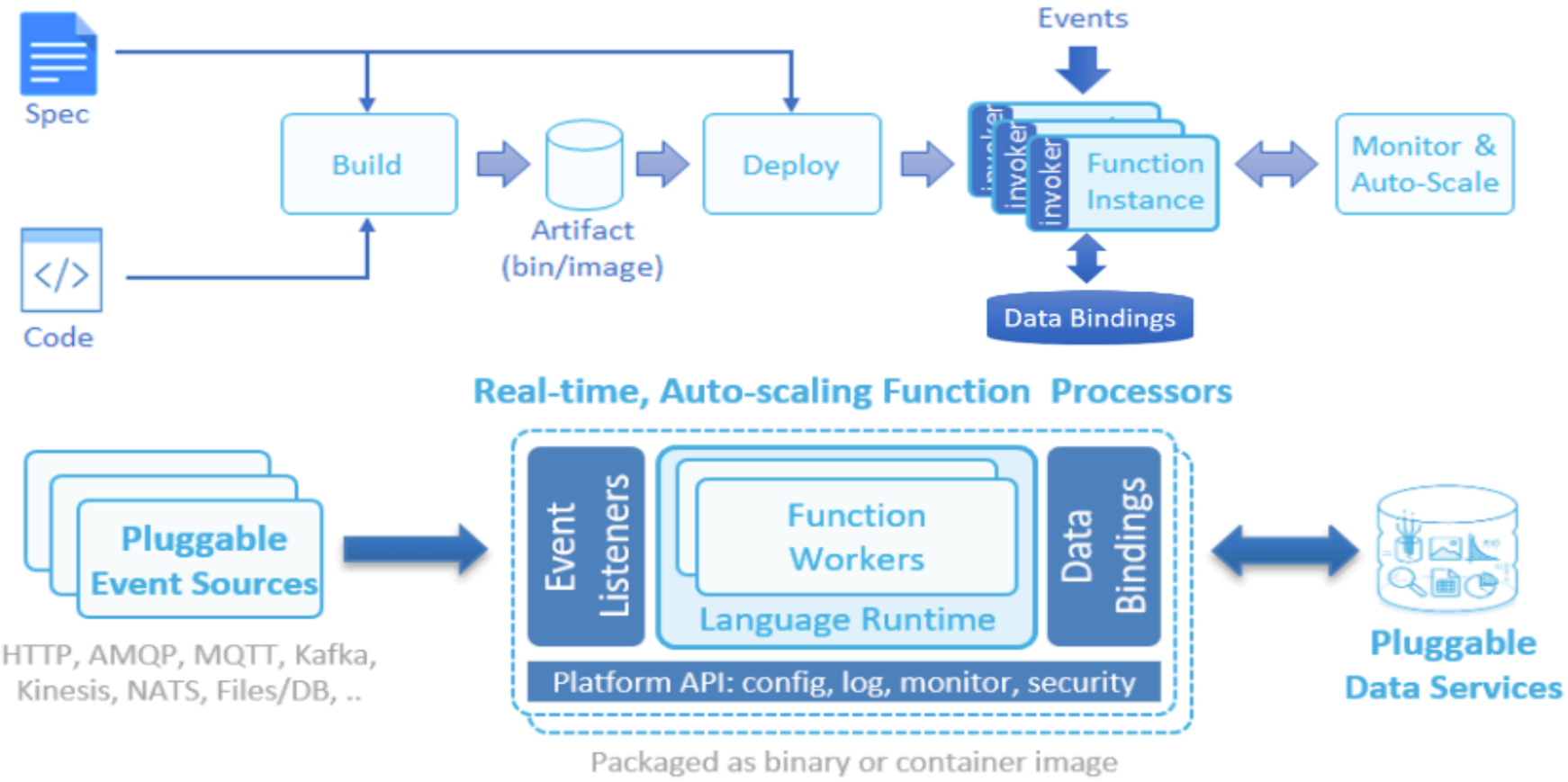
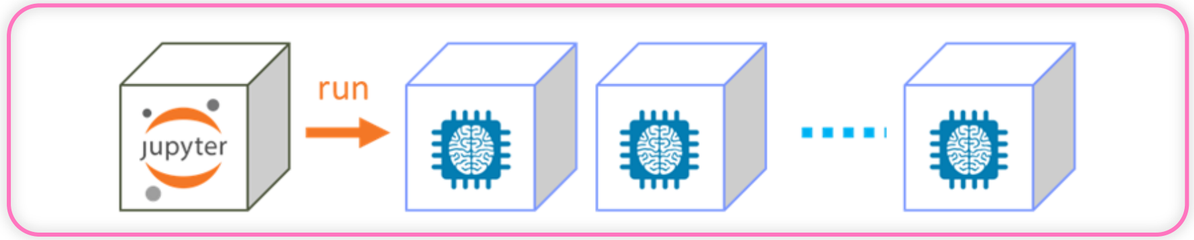
Nuclio – Under the hood



Dynamic Scaling for Intensive Workloads

- Scale + Performance for intensive ML & Data processing tasks
- Seamless transition from user code to elastic, auto tracked jobs + data
- AutoML & Hyper-params are built-in
- Make frameworks “Serverless”
  - Spark, Dask
  - MPI/Horovod
  - SQL (via Presto)
  - Nuclio

Dynamically Scaled Containers + Distributed Tracking

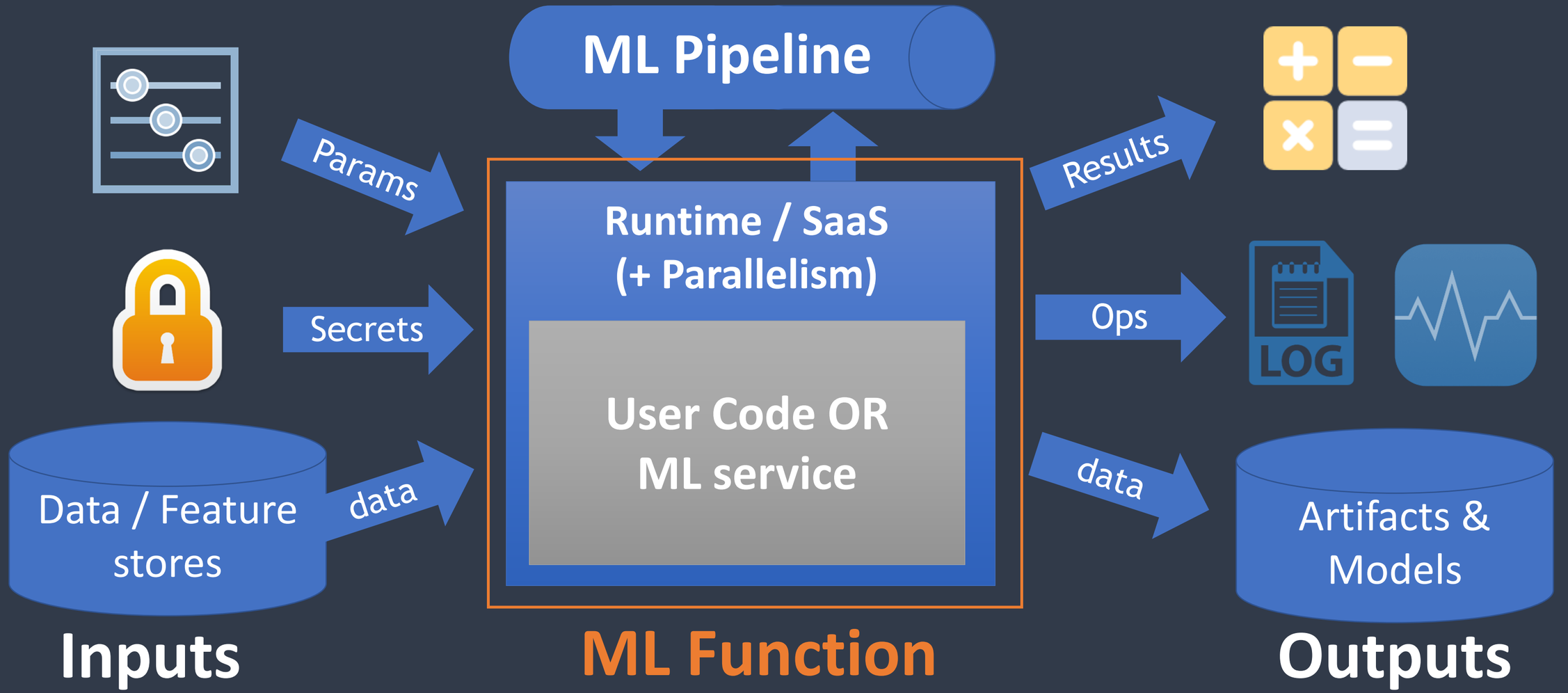


Fast inter cluster messaging (MPI, Dask, Spark, ..)

Low-latency data layer (shared code, files, dataframes)

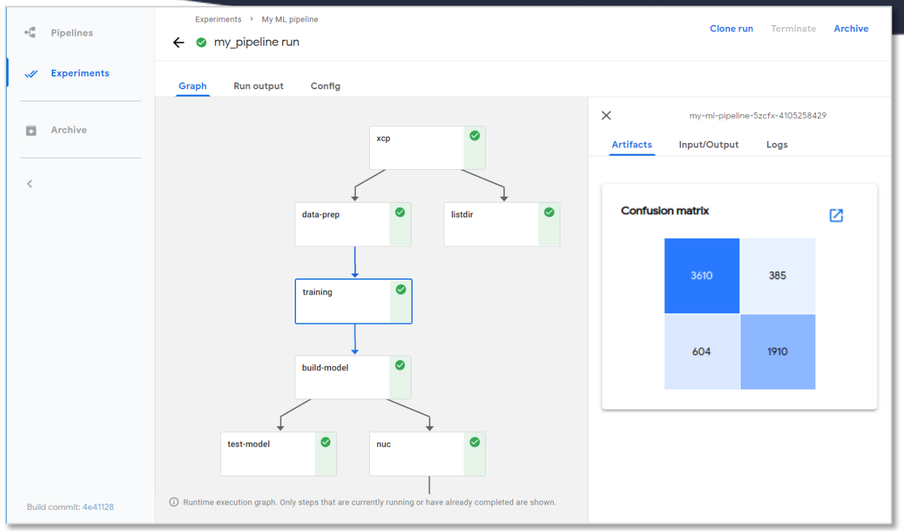
https://github.com/mlrun/mlrun

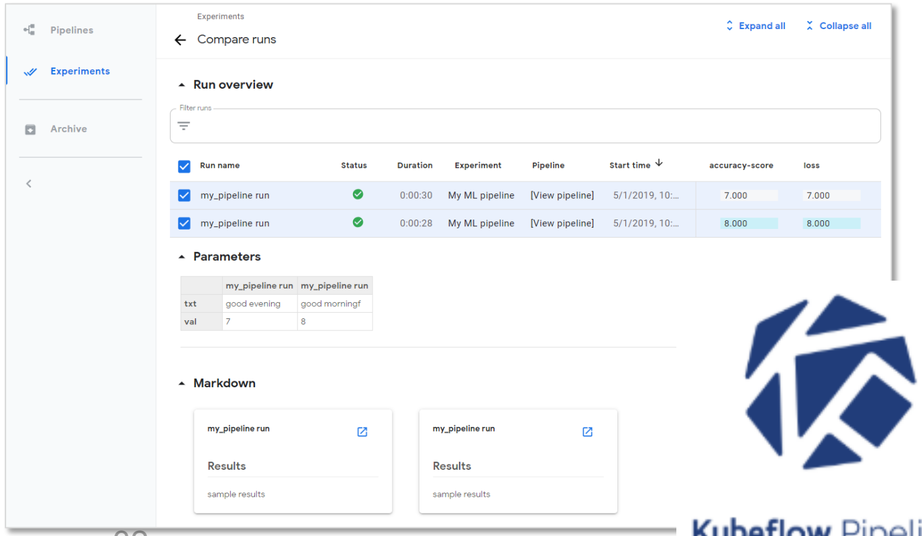
ML & Analytics Functions Architecture



https://github.com/mlrun/mlrun

KubeFlow: Automated ML Pipelines & Tracking





Kubeflow Pipelines

Integrating and Extending KubeFlow Pipelines

Manage experiments, runs, and artifacts

Build workflows using code or reusable components

(across many cloud/3rd party ML and data framework)

With MLRun & Nuclio:

Automated code to serverless function

Glueless data access and parallelism

Distributed training and GPU Acceleration

Code + execution + data tracking and versioning

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Simple, Production-Ready Development Process

Data-Scientist / Developer

1. Write and test functions locally

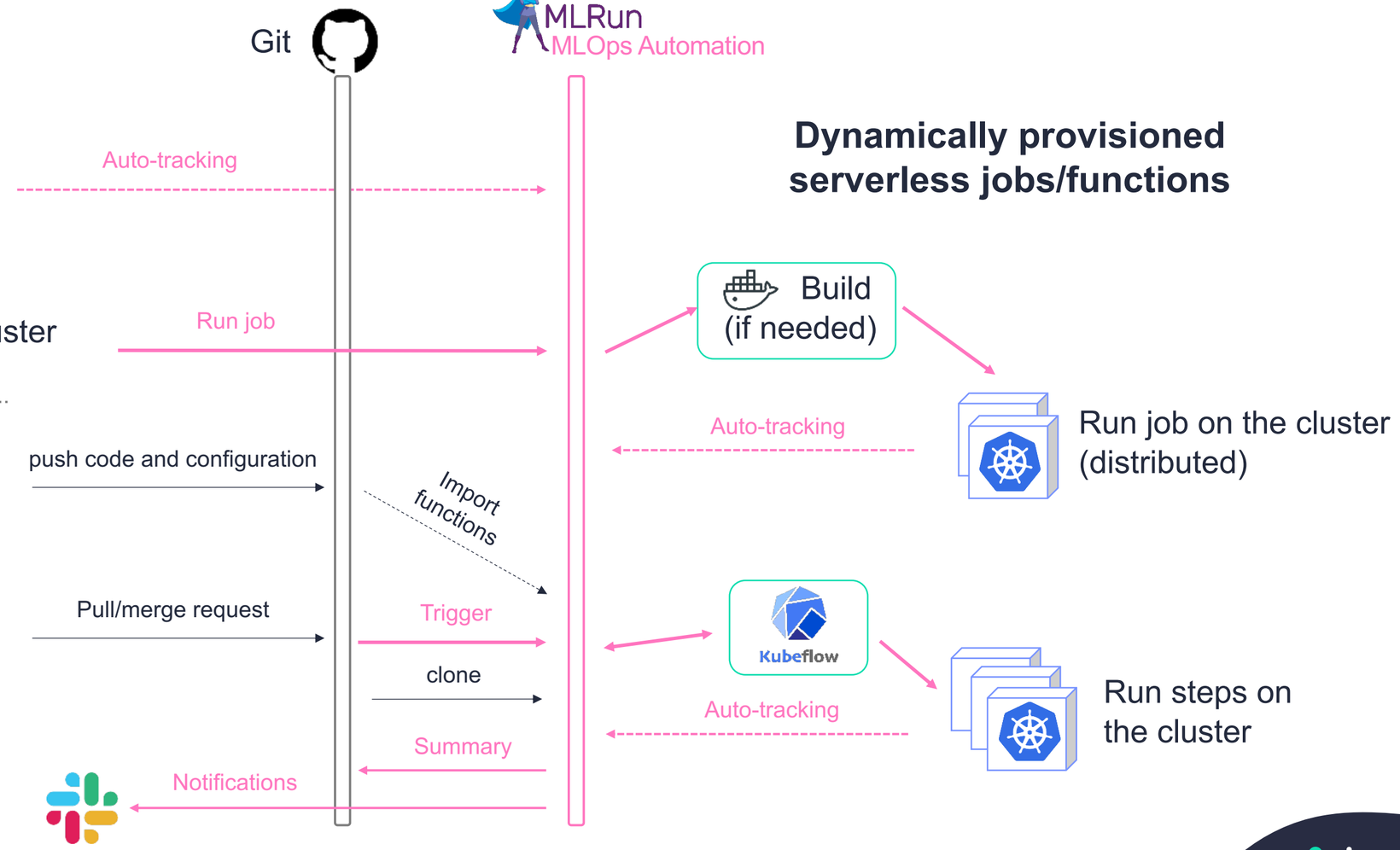
2. Add requirements, run on the cluster

Specify image, packages, cpu/gpu/mem, data, ..
Requirements via annotation or function spec

```
%nuclio cmd -c pip install pandas
%nuclio config spec.build.baseImage = "mlrun/mlrun"
```

ML Engineer

3. Build/run ML pipeline
   (interactive or via triggers)



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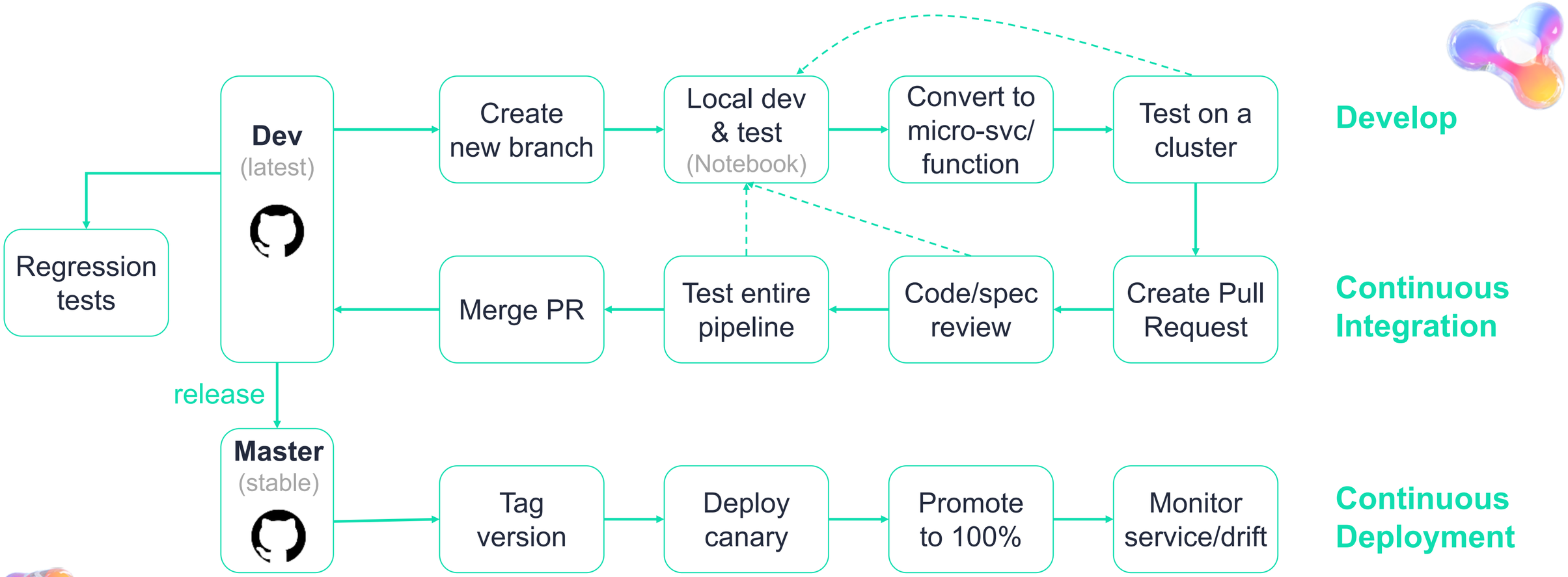
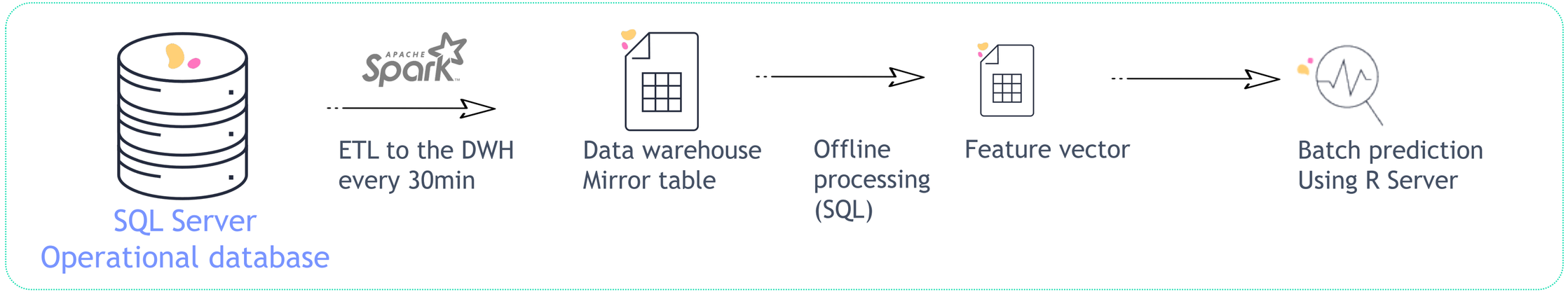
Building CI/CD Process for ML(Ops)



Traditional Fraud-Detection Architecture (Hadoop)

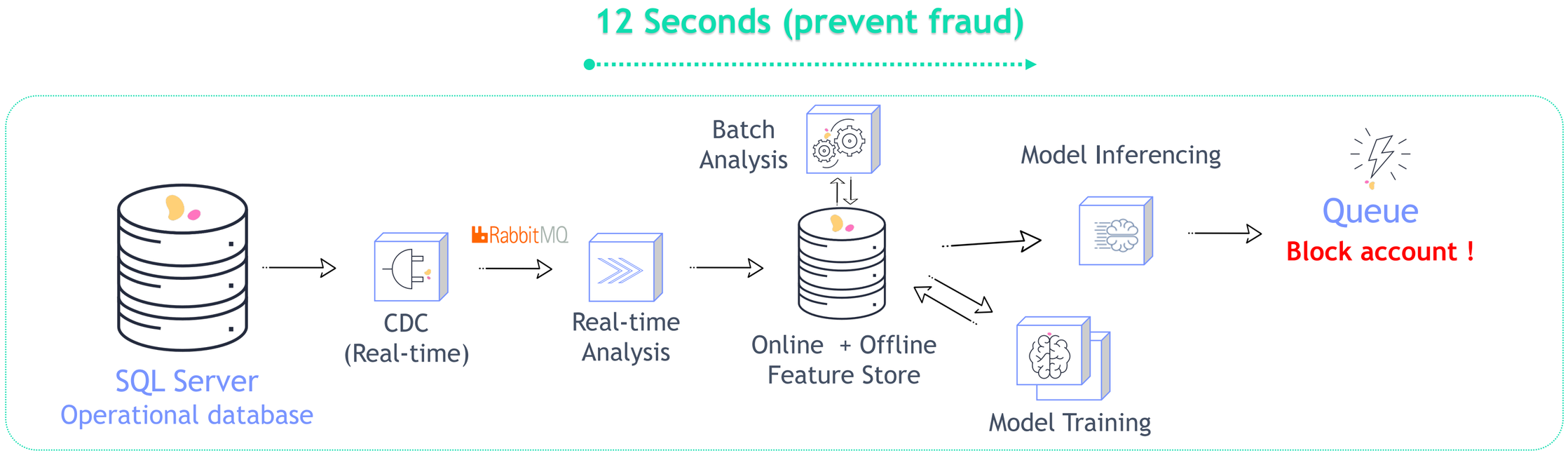
40 Precious Minutes (detect fraud after the fact)



40 minutes to identify suspicious money laundering account

Long and complex process to production

Real-Time Fraud Prediction & Prevention



12 Seconds to detect and prevent fraud !

Automated dev to production using a serverless approach

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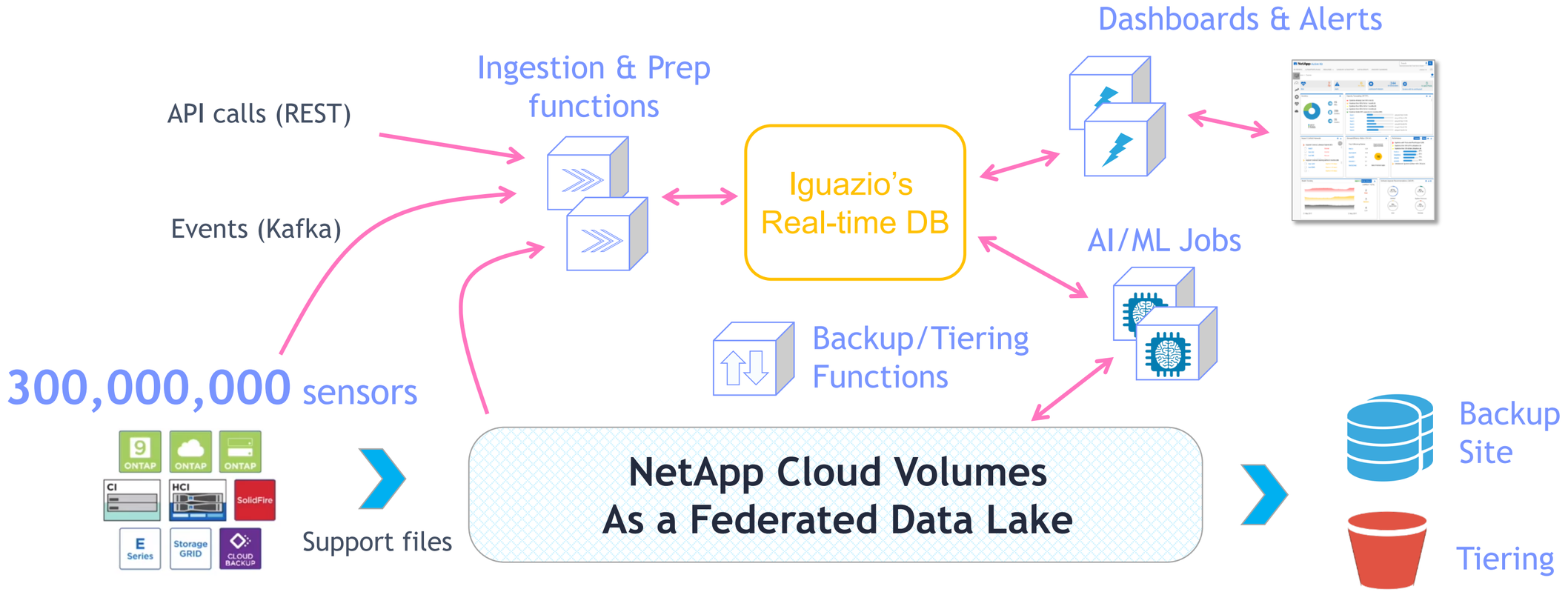
Example: Real-Time Intelligent Ops (NetApp ActiveIQ)



80% Lower Costs

Real-time Performance

90% Less Code & DevOps

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Biren Fondekar • 2nd
Chief Transformation Officer at NetApp
3d •

Check out this new partnership with #NetApp and #Iguazio – the collaboration enables us to simplify the life of our customers' data science teams, allowing them to bring AI projects to market much faster by automating the entire process and deploying data pipelines at scale.

Shankar Pasupathy, Manikandan R and Gaurav Singh who are my colleagues on the #NetAppActiveIQ Team, led our effort to adopt Iguazio – given our strong desire to move away from Hadoop. AIQ offers a fantastic reference architecture - AIQ Data Hub - for a modern date analytics platform. Since moving from a traditional data warehouse/Hadoop data lake to a serverless, event-driven, Kubernetes-powered hybrid cloud architecture, we've been able to drive:

- 50% improvement in operating costs
- 16x storage capacity reduction
- 3-6x fewer compute nodes
- 6-12x improvement in time to develop and deploy new AI services

Our AIQ Team operates now in real time vs. a batch model approach under Hadoop.

Demos !