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Model Management and Delivery

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Welcome

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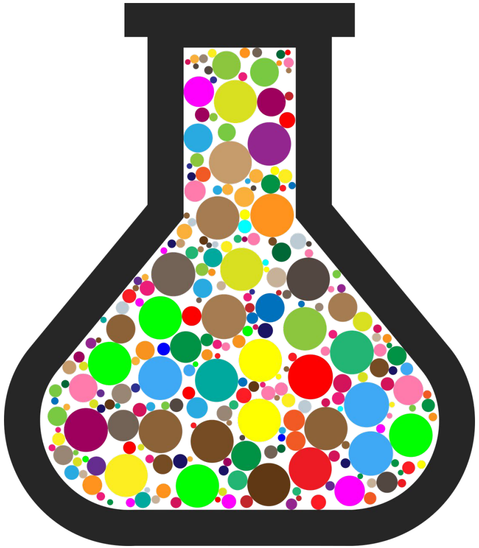
ML Experiments Management and Workflow Automation

Experiment Tracking

Why experiment tracking?

- ML projects have far more branching and experimentation
- Debugging in ML is difficult and time consuming
- Small changes can lead to drastic changes in a model’s performance and resource requirements
- Running experiments can be time consuming and expensive

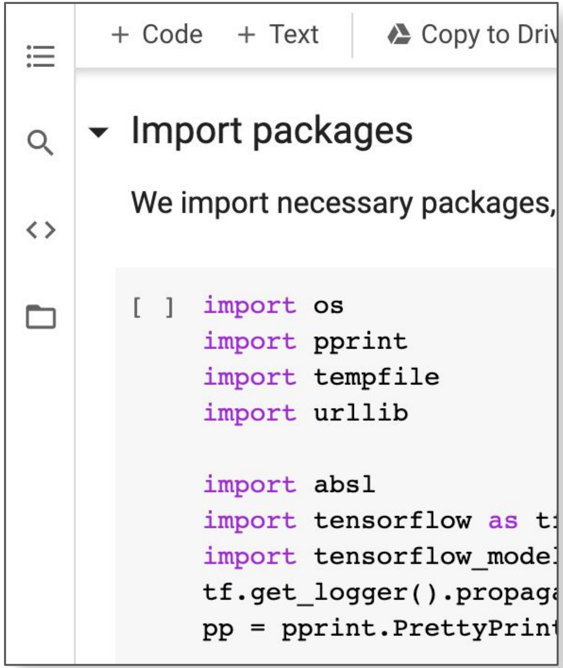


What does it mean to track experiments?

- Enable you to duplicate a result
- Enable you to meaningfully compare experiments
- Manage code/data versions, hyperparameters, environment, metrics
- Organize them in a meaningful way
- Make them available to access and collaborate on within your organization

Simple Experiments with Notebooks

- Notebooks are great tools
- Notebook code is usually not promoted to production
- Tools for managing notebook code
  - nbconvert (.ipynb -> .py conversion)
  - nbdime (diffing)
  - jupytext (conversion+versioning)
  - neptune-notebooks (versioning+diffing+sharing)



Smoke testing for Notebooks

```
jupyter nbconvert --to script train_model.ipynb python train_model.py;

python train_model.py
```

Not Just One Big File

- Modular code, not monolithic
- Collections of interdependent and versioned files
- Directory hierarchies or monorepos
- Code repositories and commits

Tracking Runtime Parameters

Config files

```yaml
data:
    train_path: '/path/to/my/train.csv'
    valid_path: '/path/to/my/valid.csv'

model:
    objective: 'binary'
    metric: 'auc'
    learning_rate: 0.1
    num_boost_round: 200
    num_leaves: 60
    feature_fraction: 0.2
```

Command line

```
python train_evaluate.py \
    --train_path '/path/to/my/train.csv' \
    --valid_path '/path/to/my/valid.csv' \
    -- objective 'binary' \
    -- metric 'auc' \
    -- learning_rate 0.1 \
    -- num_boost_round 200 \
    -- num_leaves 60 \
    -- feature_fraction 0.2
```

Log Runtime Parameters

```
parser = argparse.ArgumentParser()
parser.add_argument('--number_trees')
parser.add_argument('--learning_rate')
args = parser.parse_args()

neptune.create_experiment(params=vars(args))
...
# experiment logic
...
```

ML Experiments Management and Workflow Automation

Tools for Experiment Tracking

Data Versioning

- Data reflects the world, and the world changes
- Experimental changes include changes in data
- Tracking, understanding, comparing, and duplicating experiments includes data

Tools for Data Versioning

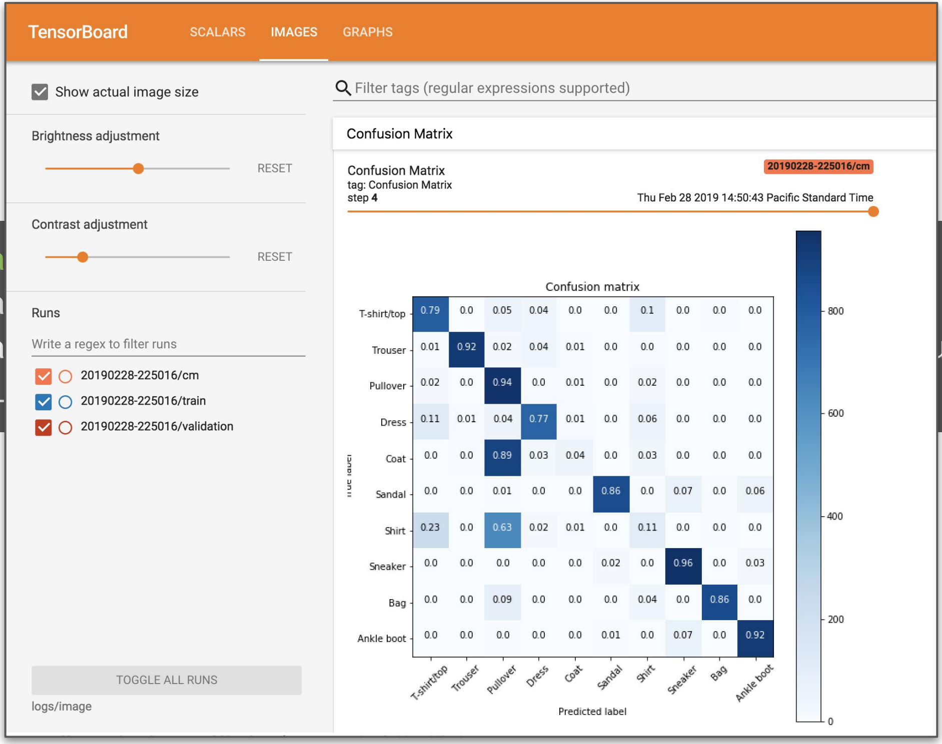
- Neptune
- Pachyderm
- Delta Lake
- Git LFS
- DoIt
- lakeFS
- DVC
- ML-Metadata

Experiment tracking to compare results

Name (50 visualized)	Tags	acc	Sweep	optimizer	epoch	batch_size	n_train	n_valid	n_conv_lay	loss	GPU
batch 64 4 GPU	4GPU b_64_c	0.4305	-	rmsprop	49	64	5000	800	1	1.632	-
batch 64 (V2, 5K train	2GPU b_64_c	0.4343	-	rmsprop	49	64	5000	800	1	1.63	-
50K examples (b 64)		0.4042	-	rmsprop	49	64	50000	8000	1	1.76	-
batch 32 4 GPU	4GPU b_32_c	0.4032	-	rmsprop	49	32	5000	800	1	1.714	-
batch 64 1 GPU	1GPU GCP	0.4465	-	rmsprop	49	64	5000	800	5	1.615	1
batch 128 (5K train)	2GPU b_128	0.4181	-	rmsprop	49	128	5000	800	1	1.658	-
batch 256 4 GPU	4GPU keras	0.3882	-	rmsprop	49	256	5000	800	1	1.751	-

Example: Logging metrics using TensorBoard

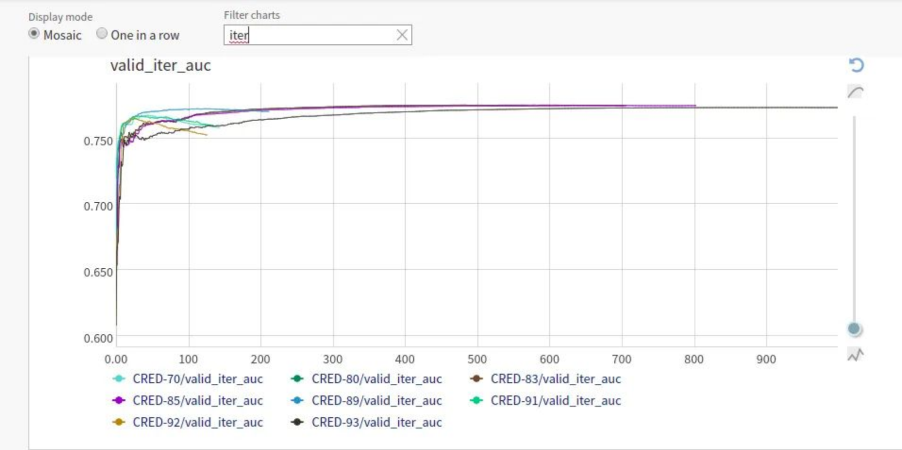
```
logdir = "logs/ima
tensorboard_callba                                  histogram_freq=1)
cm_callback = kera                                 usion_matrix)
model.fit(... call
```



Organizing model development

- Search through & visualize all experiments
- Organize into something digestible
- Make data shareable and accessible
- Tag and add notes that will be meaningful to your team

Tooling for Teams

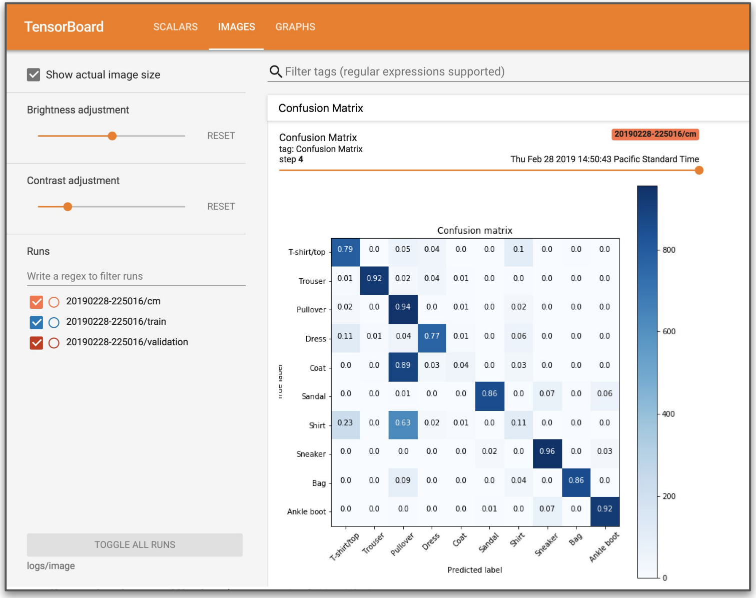


Short ID	Owner	Tags	valid_auc	train_auc	features_...	train_spli...	valid_spli...
CRED-93	kamil	lgbm features_v1	0.773536	0.807047	e1f5a473fe...	41bf231b7...	4b61d05c0...
CRED-92	kamil	lgbm features_v1	0.765647	0.790213	e1f5a473fe...	41bf231b7...	4b61d05c0...
CRED-91	kamil	lgbm features_v1	0.767254	0.78022	e1f5a473fe...	41bf231b7...	4b61d05c0...
CRED-89	kamil	lgbm features_v1	0.772704	0.788251	e1f5a473fe...	41bf231b7...	4b61d05c0...
CRED-85	jakub-czakon	lgbm features_v1	0.775187	0.797085	e1f5a473fe...	41bf231b7...	4b61d05c0...

Tooling for Teams

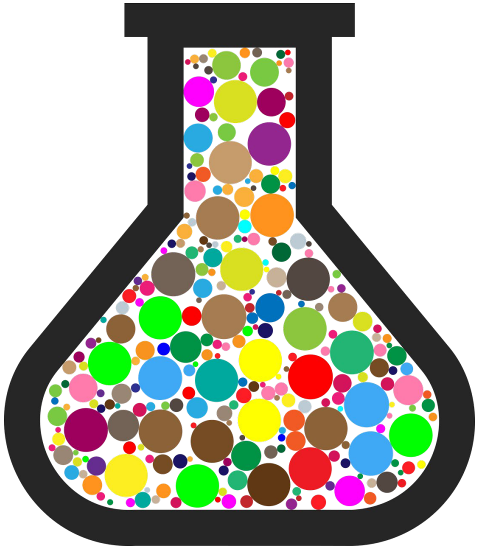
Vertex TensorBoard

- Managed service with enterprise-grade security, privacy, and compliance
- Persistent, shareable link to your experiment dashboard
- Searchable list of all experiments in a project



Experiments are iterative in nature

- Creative iterations for ML experimentation
- Define a baseline approach
- Develop, implement, and evaluate to get metrics
- Assess the results, and decide on next steps
- Latency, cost, fairness, etc.



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ML Experiments Management and Workflow Automation

Introduction to MLOps

Data Scientists vs. Software Engineers

Data Scientists

- Often work on fixed datasets
- Focused on model metrics
- Prototyping on Jupyter notebooks
- Expert in modeling techniques and feature engineering
- Model size, cost, latency, and fairness are often ignored

Data Scientists vs. Software Engineers

Software Engineers

- Build a product
- Concerned about cost, performance, stability, schedule
- Identify quality through customer satisfaction
- Must scale solution, handle large amounts of data
- Detect and handle error conditions, preferably automatically
- Consider requirements for security, safety, fairness
- Maintain, evolve, and extend the product over long periods

Growing Need for ML in Products and Services

- Large datasets
- Inexpensive on-demand compute resources
- Increasingly powerful accelerators for ML
- Rapid advances in many ML research fields (such as computer vision, natural language understanding, and recommendations systems)
- Businesses are investing in their data science teams and ML capabilities to develop predictive models that can deliver business value to their customers

Key problems affecting ML efforts today

We've been here before

- In the 90s, Software Engineering was siloed
- Weak version control, CI/CD didn't exist
- Software was slow to ship; now it ships in minutes
- Is that ML today?

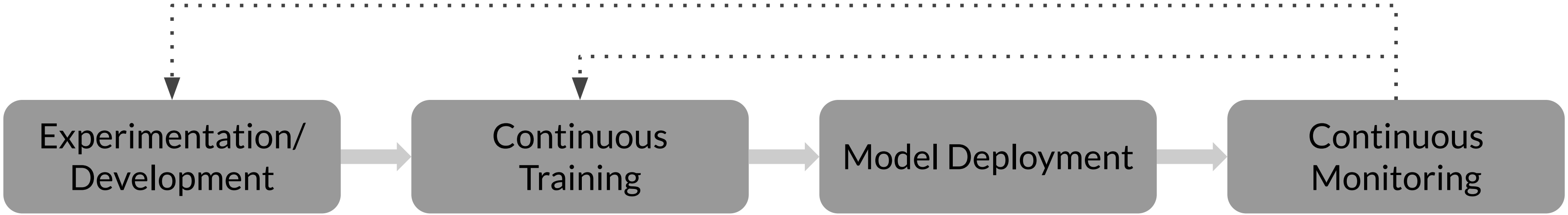
Today's perspective

- Models blocked before deployment
- Slow to market
- Manual tracking
- No reproducibility or provenance
- Inefficient collaboration
- Unmonitored models

Bridging ML and IT with MLOps

- **Continuous Integration (CI):** Testing and validating code, components, data, data schemas, and models
- **Continuous Delivery (CD):** Not only about deploying a single software package or a service, but a system which automatically deploys another service (model prediction service)
- **Continuous Training (CT):** A new process, unique to ML systems, that automatically retrains candidate models for testing and serving
- **Continuous Monitoring (CM):** Catching errors in production systems, and monitoring production inference data and model performance metrics tied to business outcomes

ML Solution Lifecycle



Data Scientist/ML Engineering

ML Engineering/Data Scientist

ML Engineering/DevOps Engineer

ML Engineering/DevOps Engineer

Standardizing ML processes with MLOps

- ML Lifecycle Management
- Model Versioning & Iteration
- Model Monitoring and Management
- Model Governance
- Model Security
- Model Discovery

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MLOps Methodology

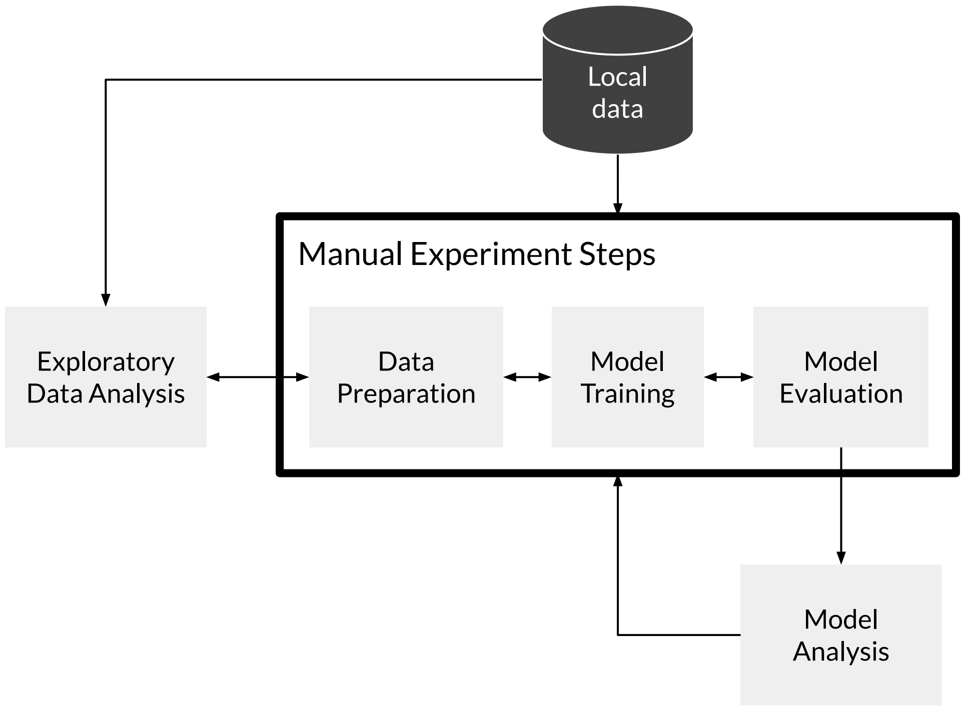
MLOps level 0

What defines an MLOps process' maturity?

- The level of **automation** of ML pipelines determines the maturity of the MLOps process
- As maturity increases, the available velocity for the training and deployment of new models also increases
- Goal is to automate training and deployment of ML models into the core software system, and provide monitoring

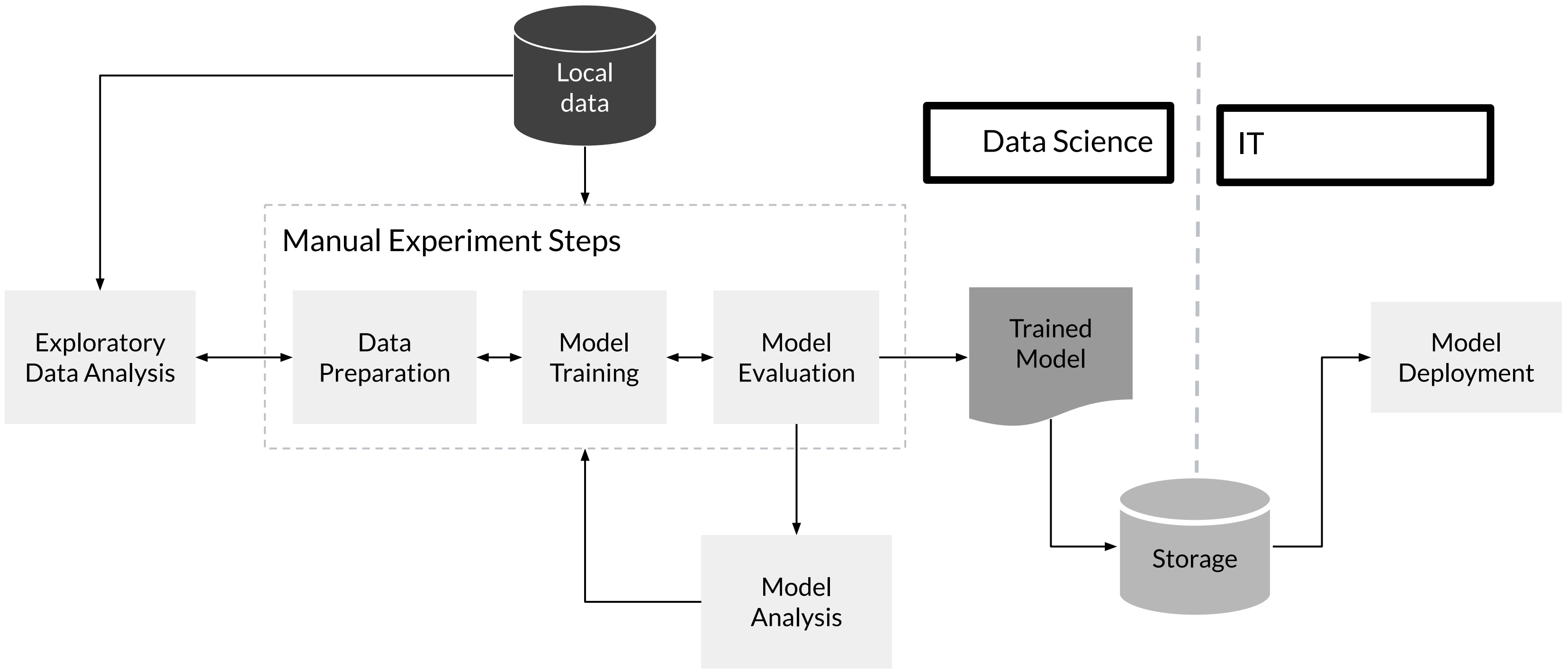
MLOps level 0: Manual process

Manual, script-driven, interactive



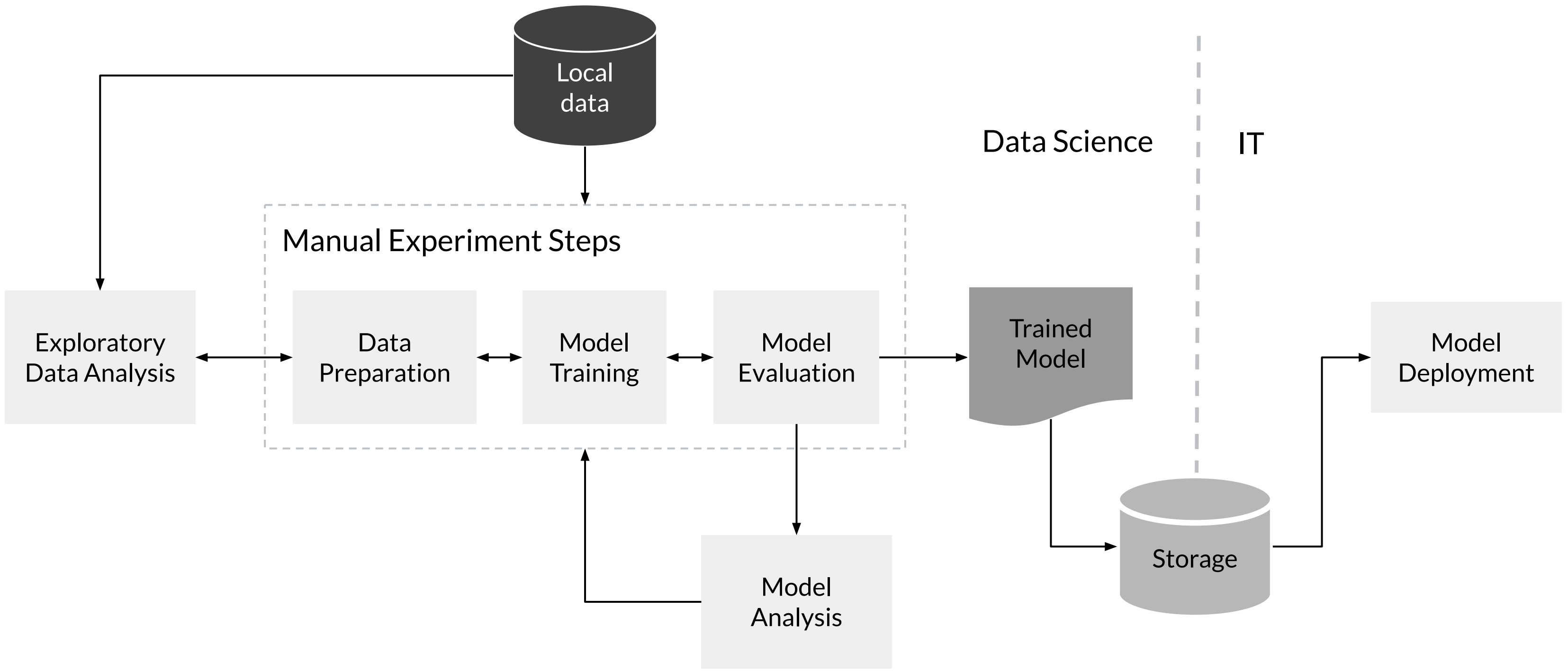
MLOps level 0: Manual process

Disconnection between ML and operations



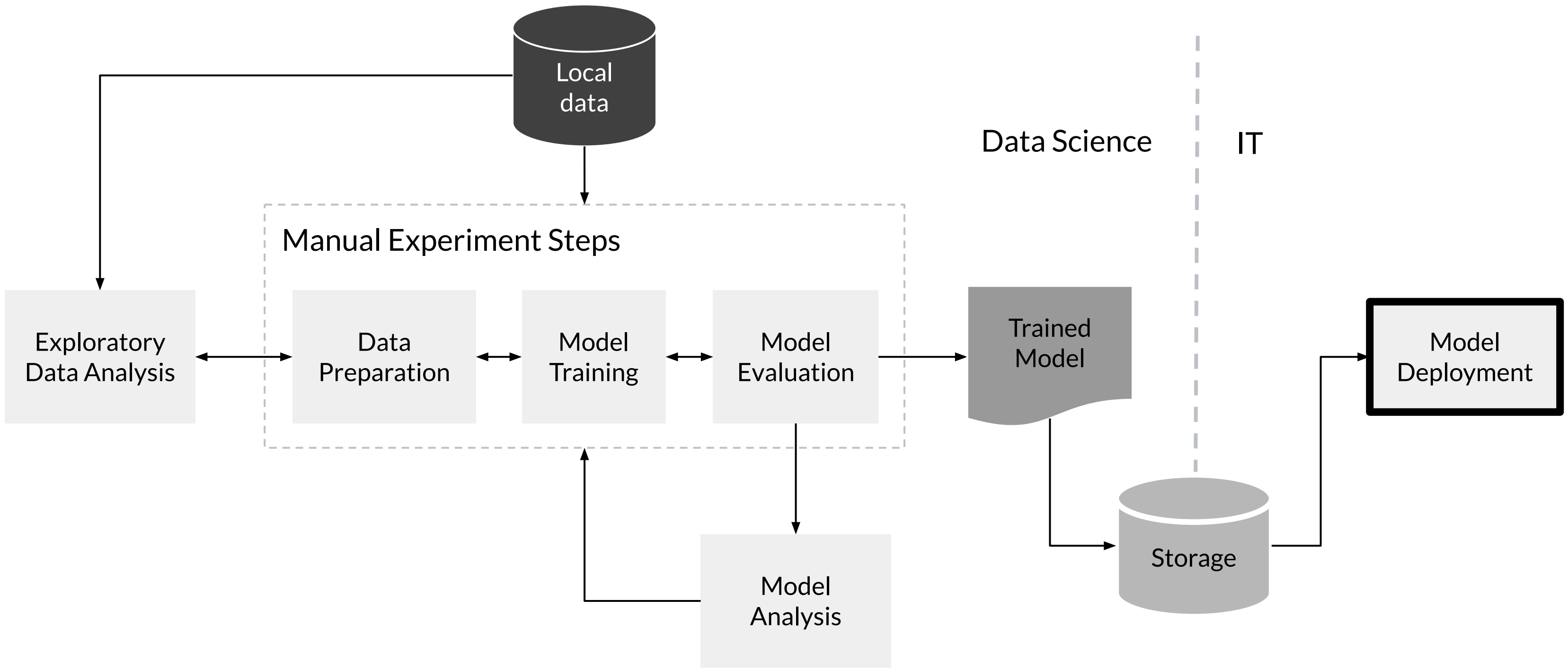
MLOps level 0: Manual process

Less frequent releases, so no CI/CD



How do you scale?

Deployment and lack of active performance monitoring



Challenges for MLOps level 0

- Need for actively monitoring the quality of your model in production
- Retraining your production models with new data
- Continuously experimenting with new implementations to improve the data and model

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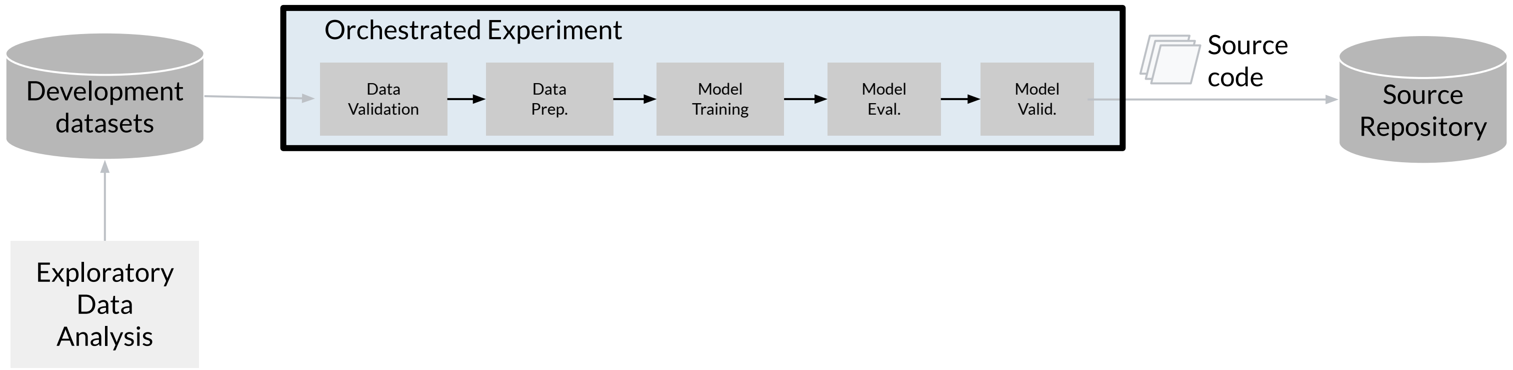
MLOps Methodology

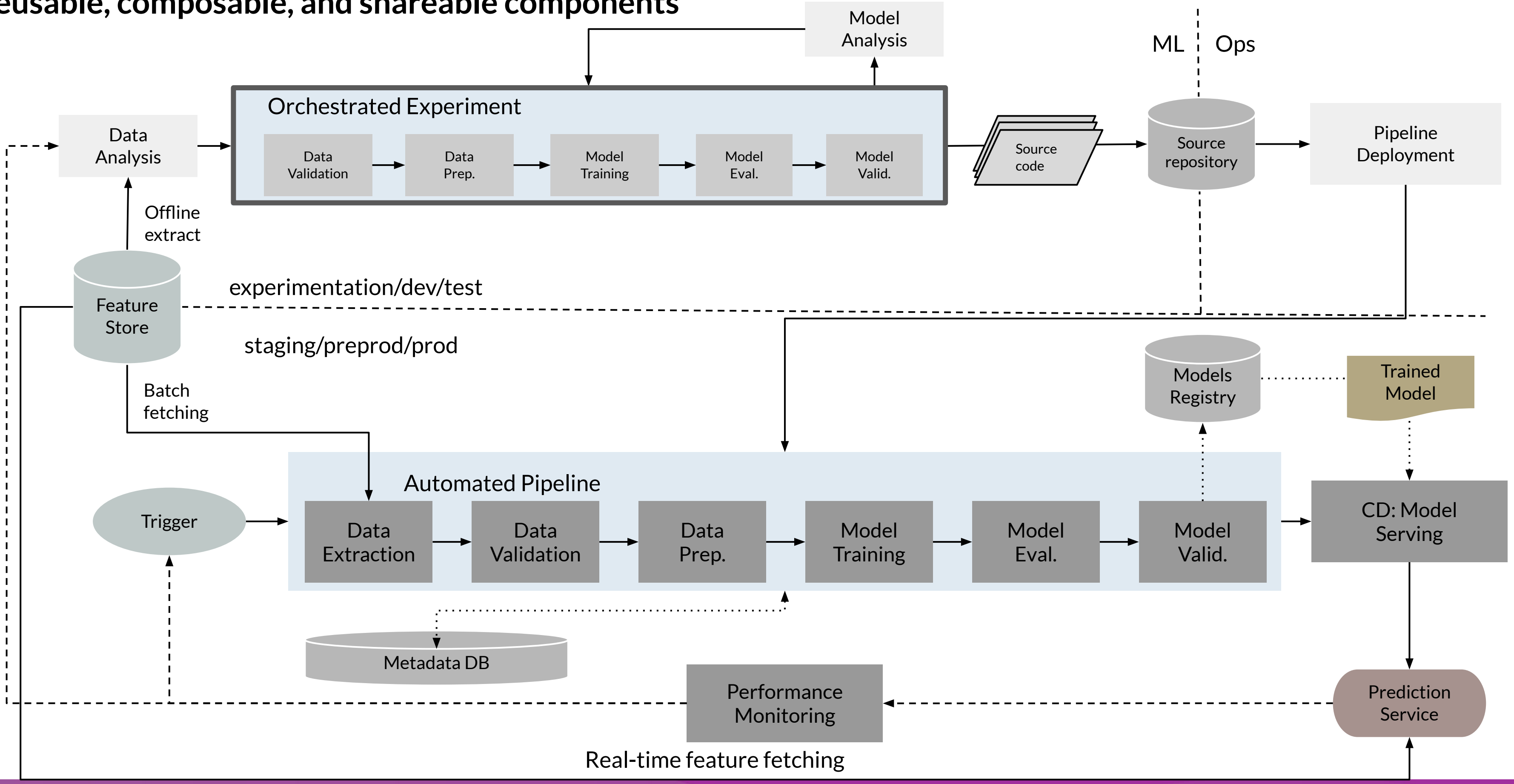
MLOps levels 1 and 2

MLOps level 1: ML pipeline automation

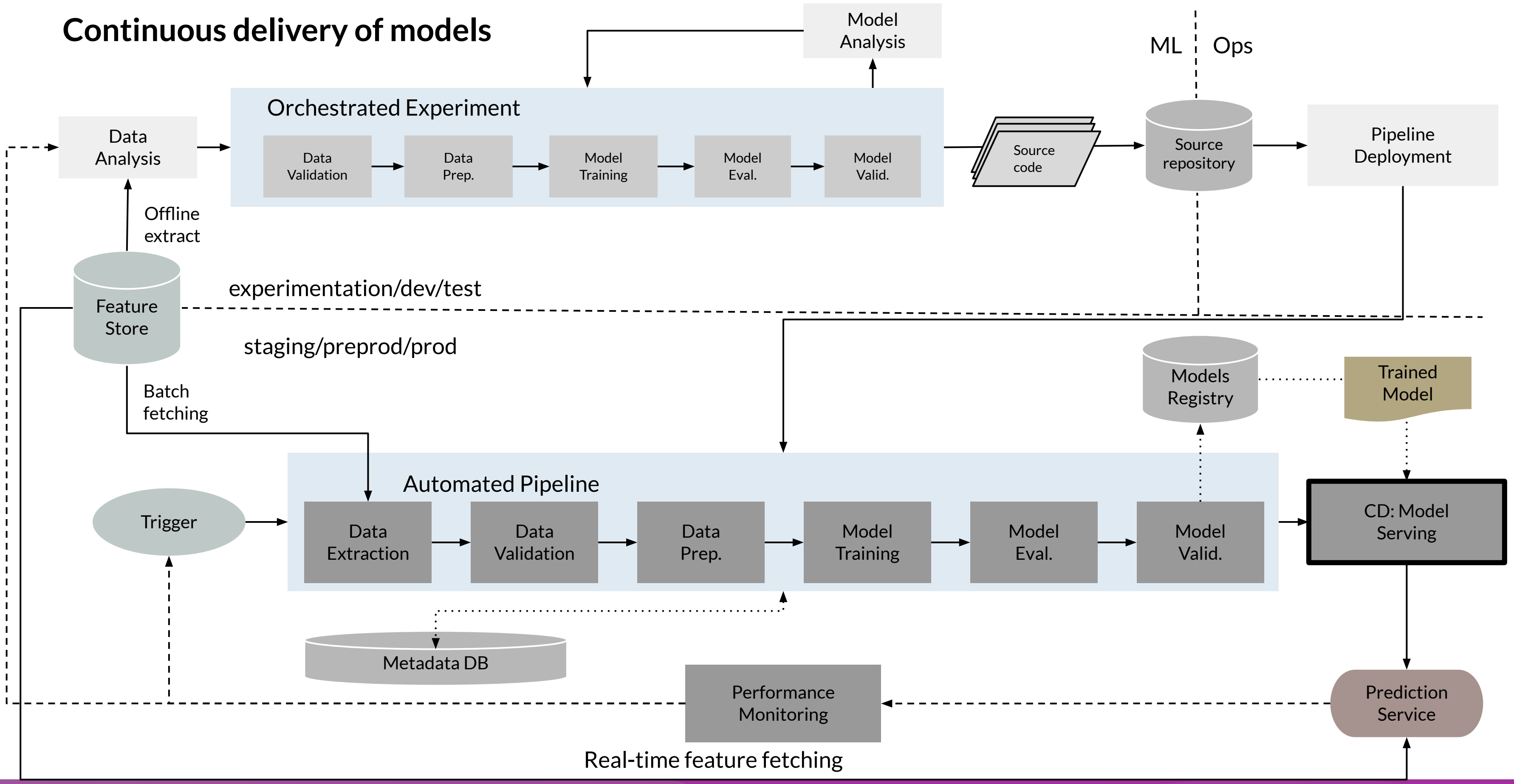
Rapid experimentation



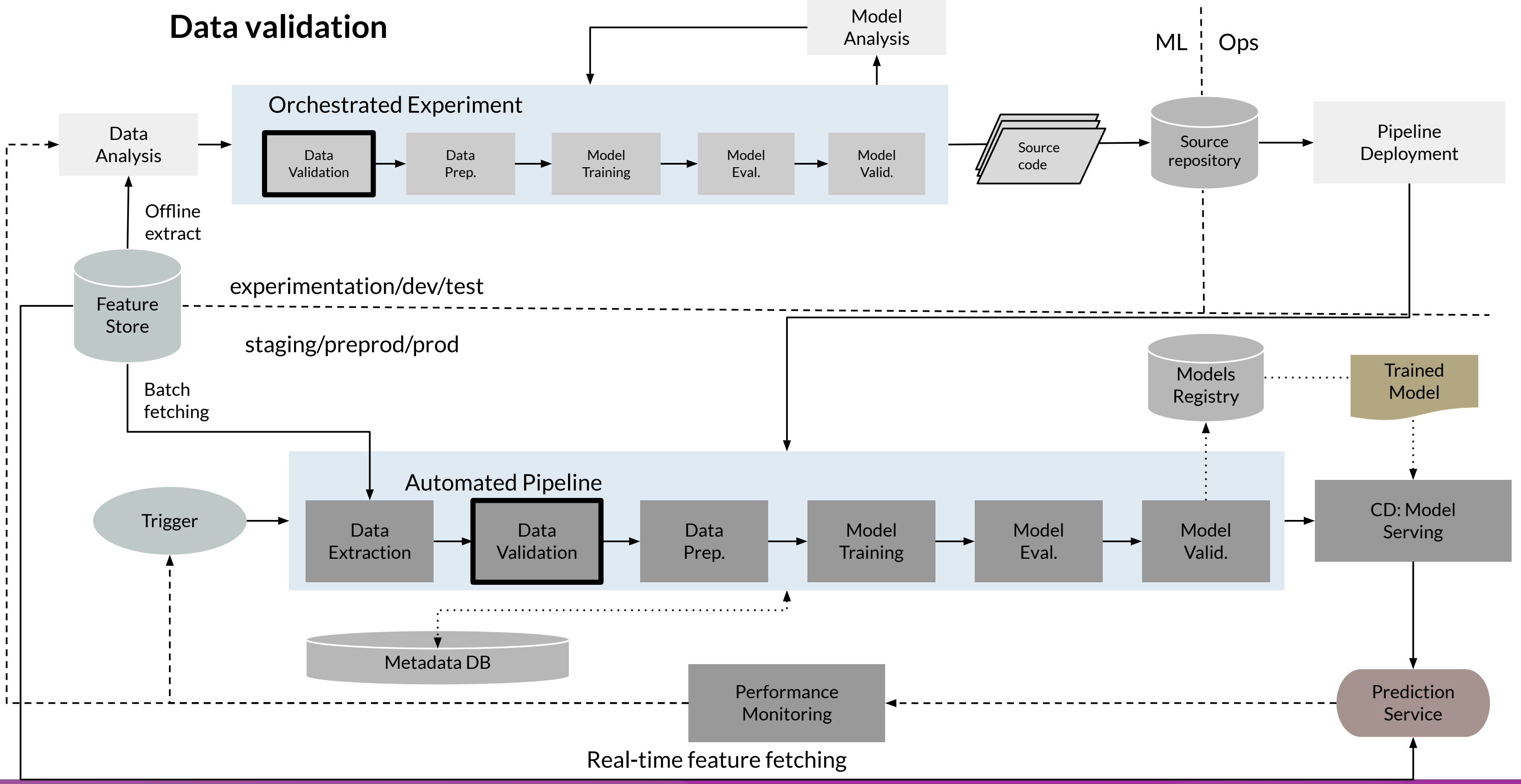
Reusable, composable, and shareable components



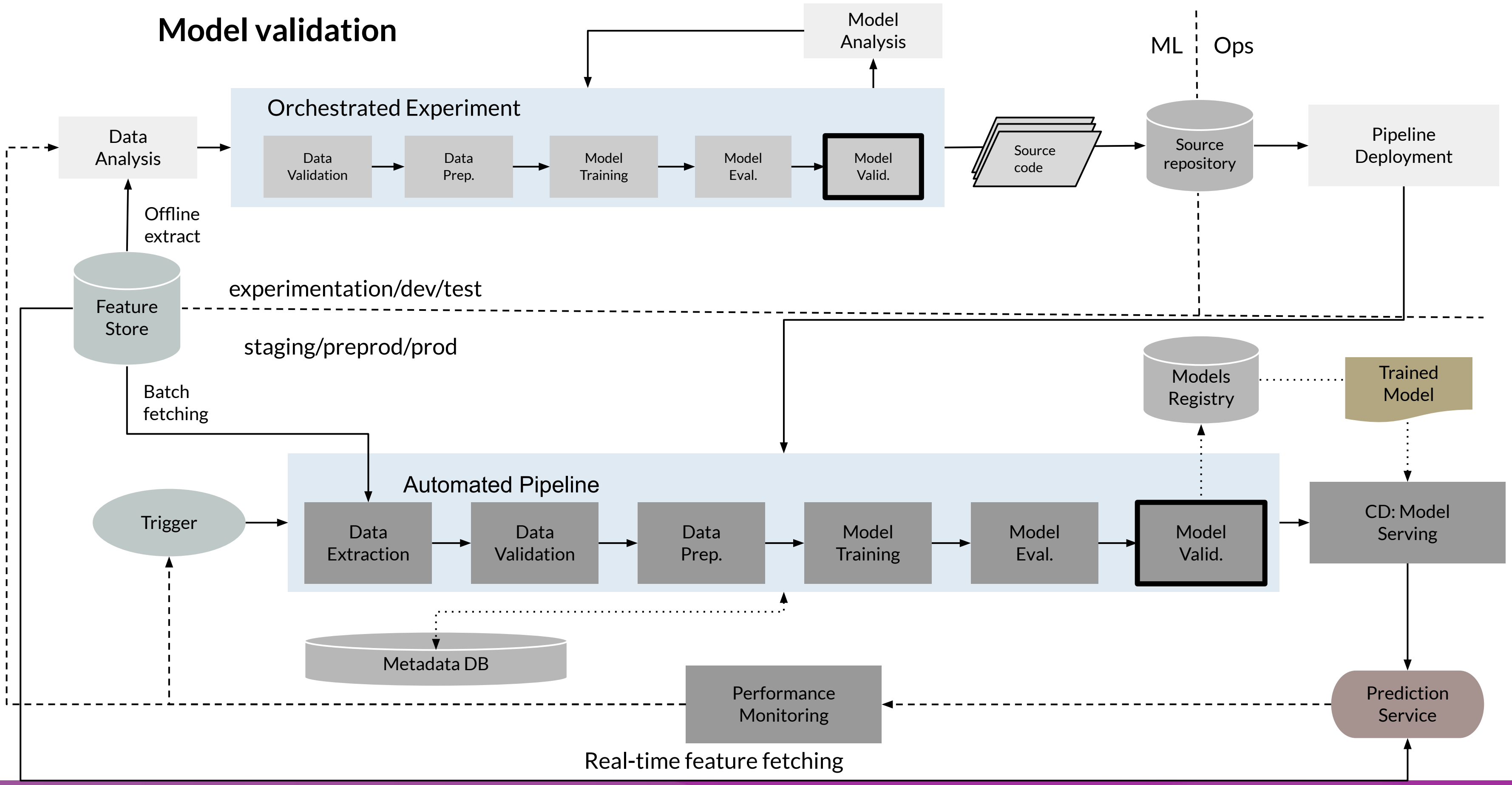
Continuous delivery of models



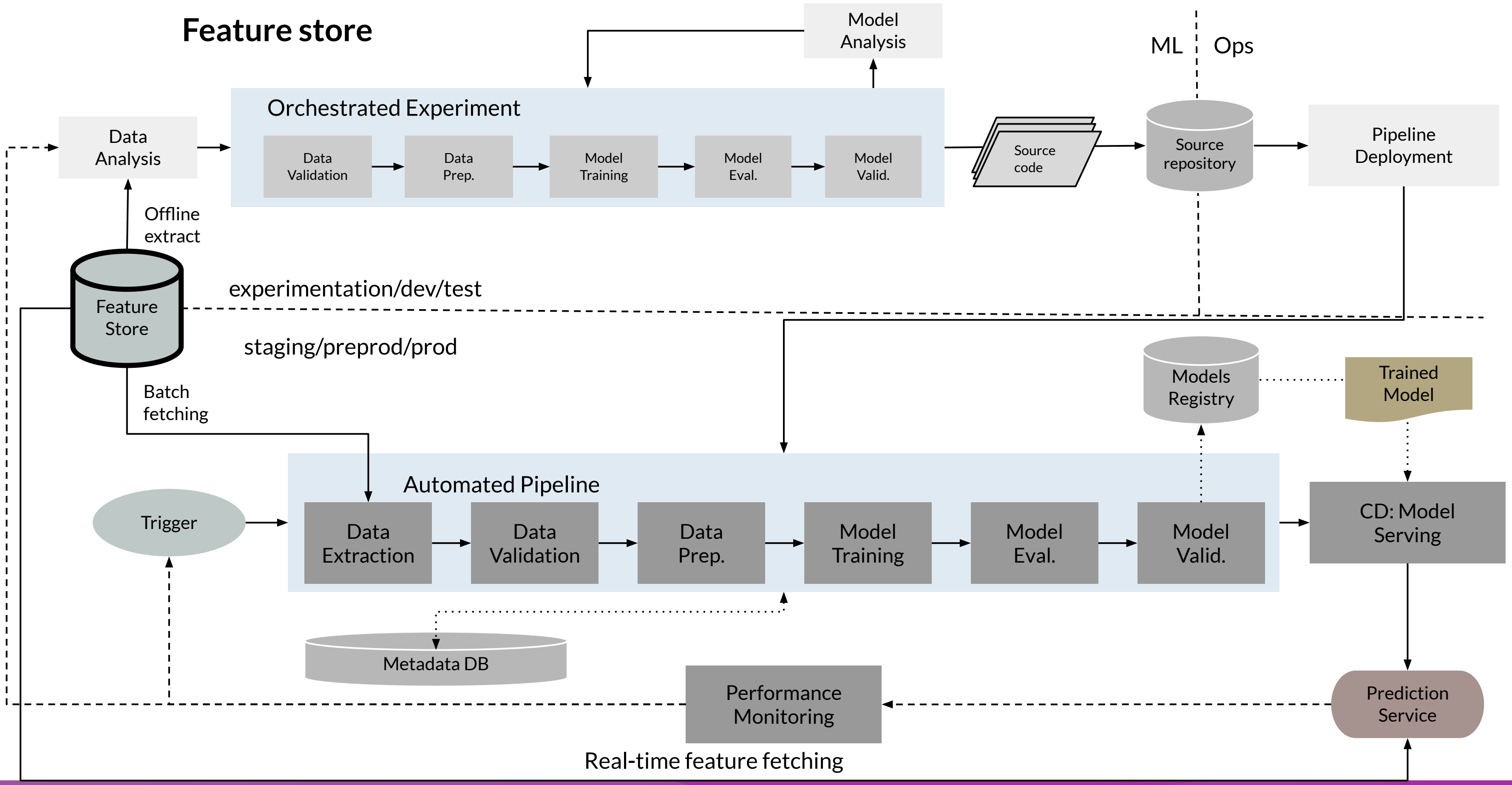
Data validation



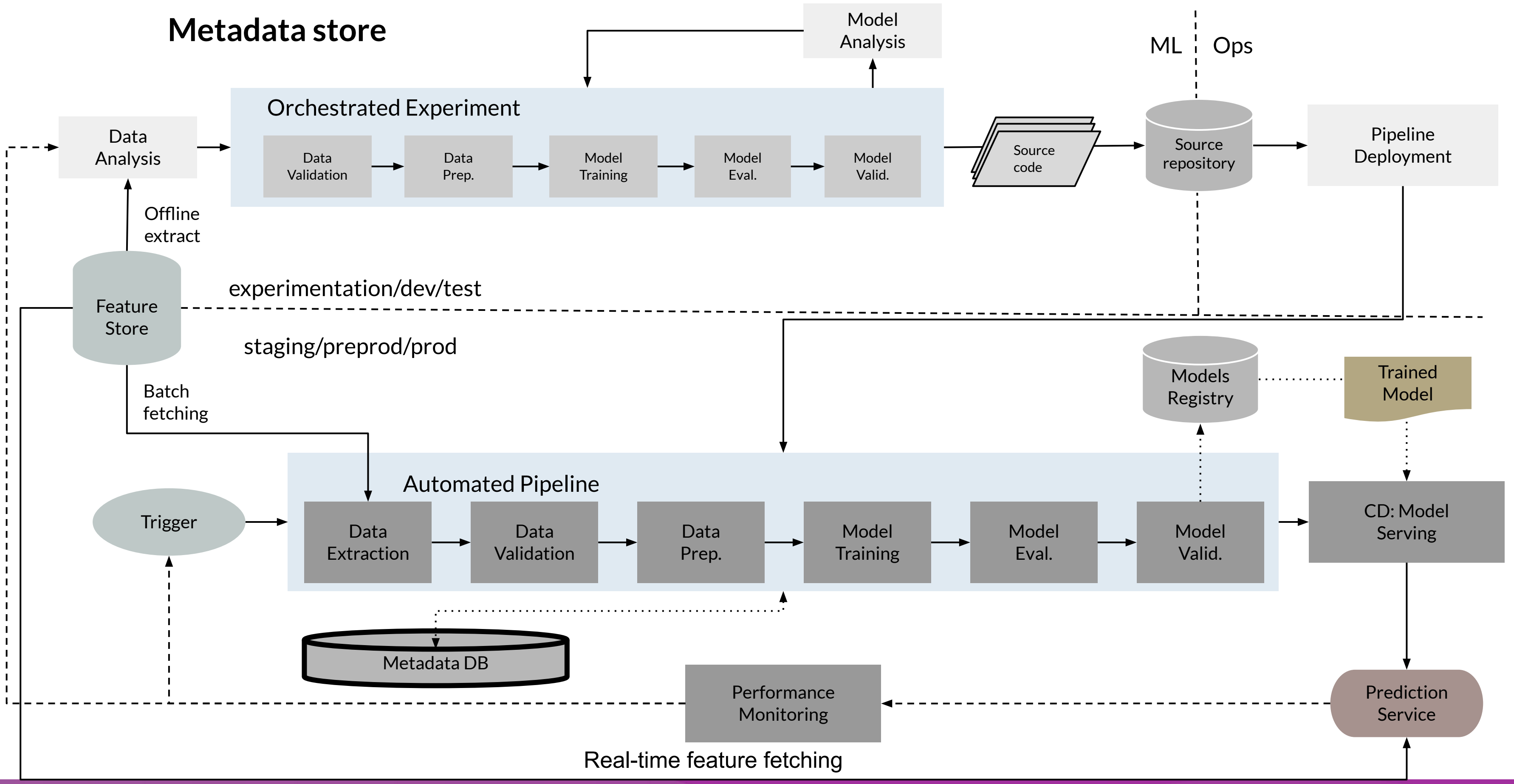
Model validation



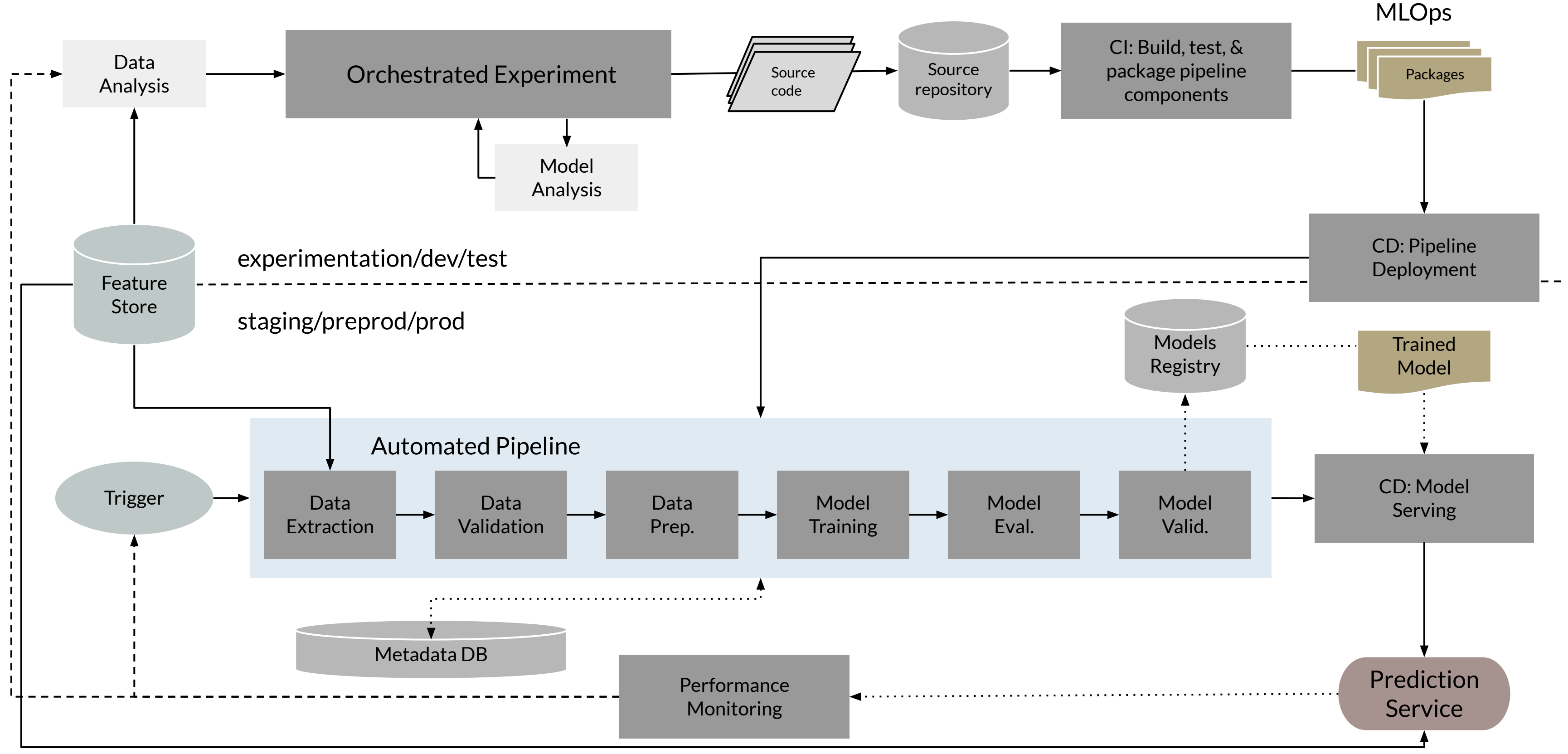
Feature store

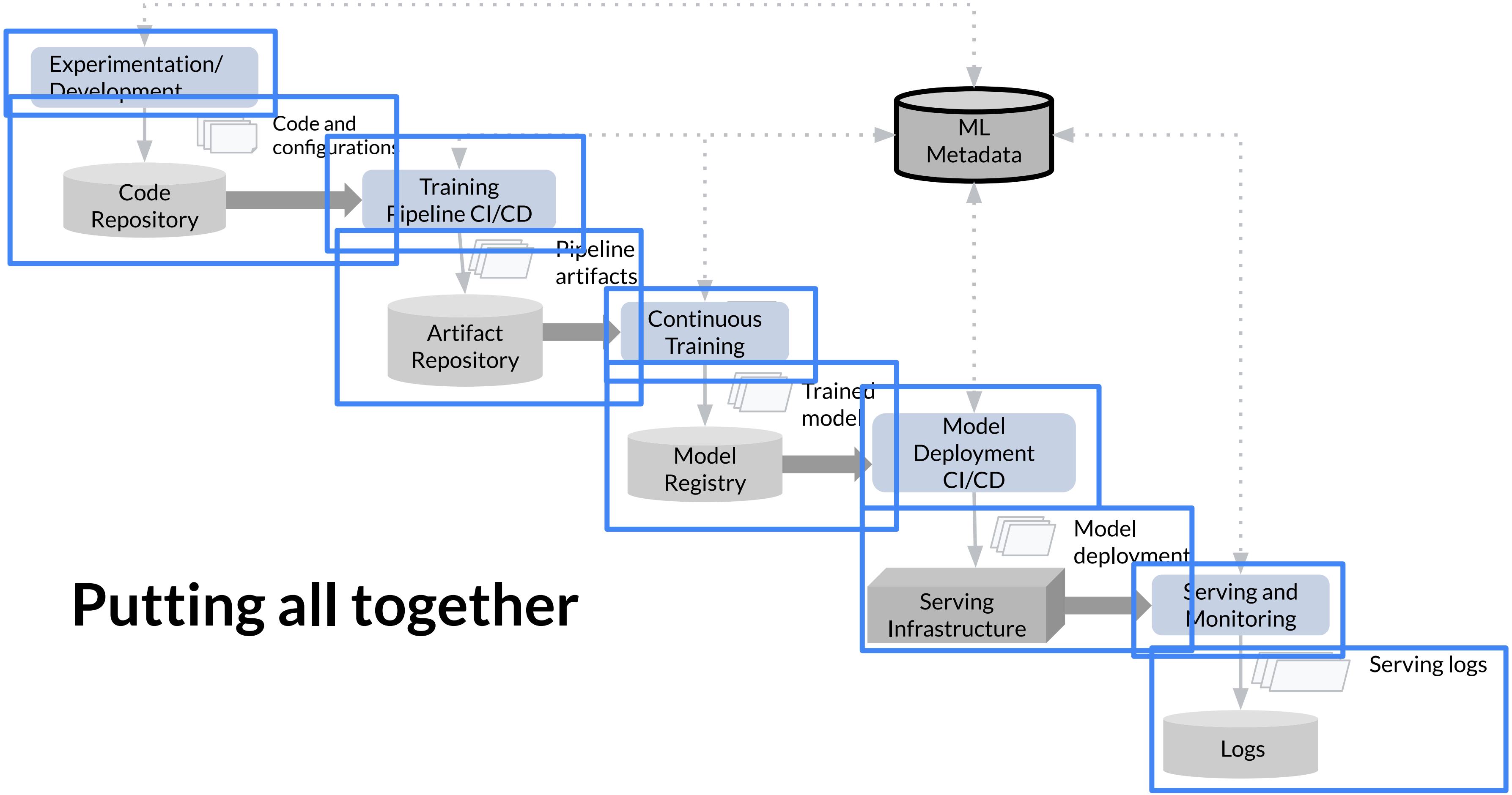


Metadata store



MLOps level 2: CI/CD pipeline automation





Putting all together

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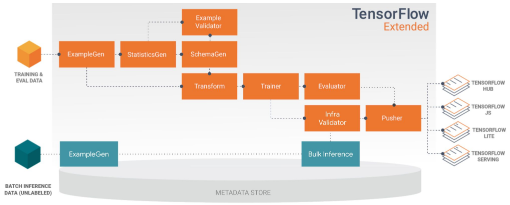
MLOps Methodology

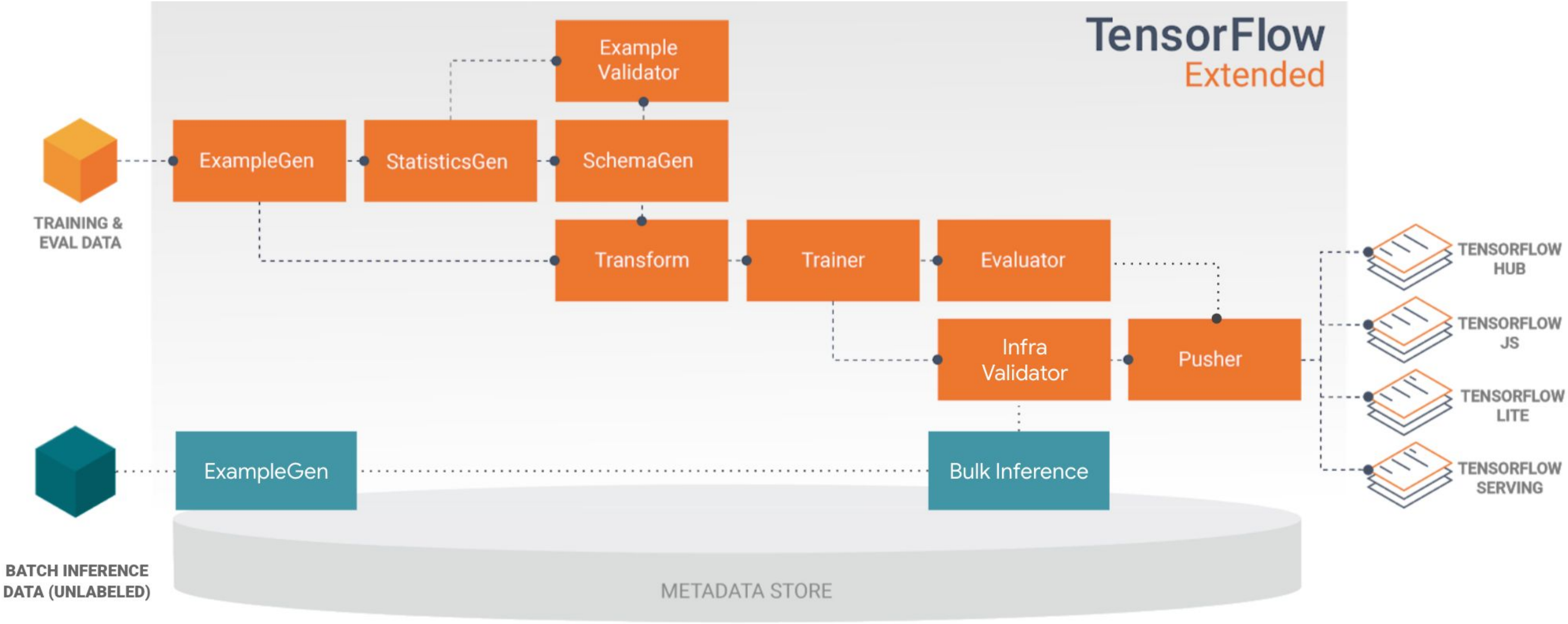
Developing components for an orchestrated workflow

Orchestrate your ML workflows with TFX

- Pre-built and standard components, and 3 styles of custom components
- Components can also be containerized
- Examples of things you can do with TFX components:
    - Data augmentation, upsampling, or downsampling
    - Anomaly detection based on confidence intervals or autoencoder reproduction error
    - Interfacing with external systems like help desks for alerting and monitoring
    - … and more!



Hello TFX



TensorFlow
Extended
TRAINING &
EVAL DATA
ExampleGen
StatisticsGen
Example
Validator
SchemaGen
Transform
Trainer
Evaluator
Infra
Validator
Pusher
TENSORFLOW
HUB
TENSORFLOW
JS
TENSORFLOW
LITE
TENSORFLOW
SERVING
BATCH INFERENCE
DATA (UNLABELED)
ExampleGen
Bulk Inference
METADATA STORE

Anatomy of a TFX Component

Component Specification

- The component's input and output contract

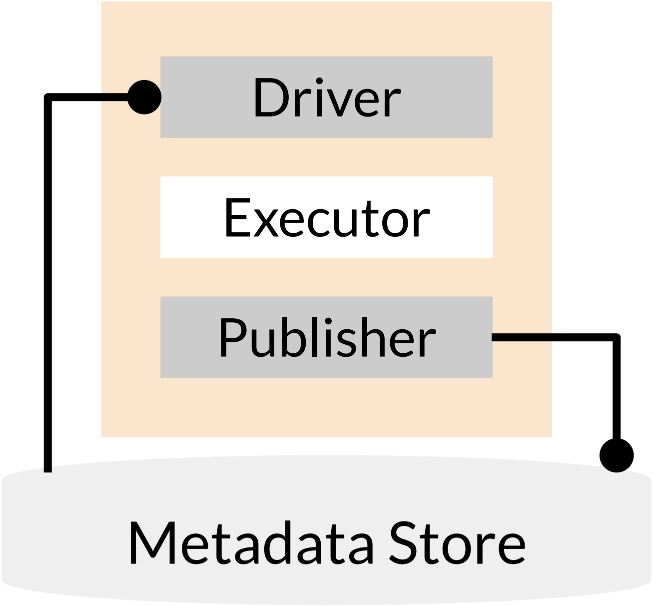
Executor Class

- Implementation of the component’s processing

Component Class

- Combines the specification with the executor to create a TFX component

TFX components at runtime



Types of custom components

- Fully custom components combine the specification with the executor
- Python function-based components use a decorator and argument annotations
- Container-based components wrap the component inside a Docker container

Python function-based components

```python
@component
def MyValidationComponent(
    model: InputArtifact[Model],
    blessing: OutputArtifact[Model],
    accuracy_threshold: Parameter[int] = 10,
    ) -> OutputDict(accuracy=float):
  '''My simple custom model validation component.'''

  accuracy = evaluate_model(model)
  if accuracy >= accuracy_threshold:
    write_output_blessing(blessing)

  return {
    'accuracy': accuracy
  }
```

Container-based components

```
from tfx.dsl.component.experimental import container_component
from tfx.dsl.component.experimental import placeholders
from tfx.types import standard_artifacts

grep_component = container_component.create_container_component(
    name='FilterWithGrep',
    inputs={'text': standard_artifacts.ExternalArtifact},
    outputs={'filtered_text': standard_artifacts.ExternalArtifact},
    parameters={'pattern': str},
    ...
)
```

Container-based components

```
grep_component = container_component.create_container_component(
    ...
    image='google/cloud-sdk:278.0.0',
    command=[
        'sh', '-exc',
        '''
          ...
        ''',
        '--pattern', placeholders.InputValuePlaceholder('pattern'),
        '--text', placeholders.InputUriPlaceholder('text'),
        '--filtered-text',
placeholders.OutputUriPlaceholder('filtered_text'),
    ],
)
```

Fully custom components

- Define custom component spec, executor class, and component class
- Component reusability
  - Reuse a component spec and implement a new executor that derives from an existing component

Defining input and output specifications

```
class HelloComponentSpec(types.ComponentSpec):
  INPUTS = {
      # This will be a dictionary with input artifacts, including URIs
      'input_data': ChannelParameter(type=standard_artifacts.Examples),
  }
  OUTPUTS = {
      # This will be a dictionary which this component will populate
      'output_data': ChannelParameter(type=standard_artifacts.Examples),
  }
  PARAMETERS = {
      # These are parameters that will be passed in the call to create an instance of this component
      'name': ExecutionParameter(type=Text),
  }
```

Implement the executor

```
class Executor(base_executor.BaseExecutor):
  def Do(self, input_dict: Dict[Text, List[types.Artifact]],
         output_dict: Dict[Text, List[types.Artifact]],
         exec_properties: Dict[Text, Any]) -> None:
    ...
```

Implement the executor

```
class Executor(base_executor.BaseExecutor):
    ...
    split_to_instance = {}
    for artifact in input_dict['input_data']:
      for split in json.loads(artifact.split_names):
        uri = os.path.join(artifact.uri, split)
        split_to_instance[split] = uri
    for split, instance in split_to_instance.items():
      input_dir = instance
      output_dir = artifact_utils.get_split_uri(
          output_dict['output_data'], split)
      for filename in tf.io.gfile.listdir(input_dir):
        input_uri = os.path.join(input_dir, filename)
        output_uri = os.path.join(output_dir, filename)
        io_utils.copy_file(src=input_uri, dst=output_uri, overwrite=True)
```

Make the component pipeline-compatible

```
from tfx.types import standard_artifacts
from hello_component import executor


class HelloComponent(base_component.BaseComponent):
  SPEC_CLASS = HelloComponentSpec
  EXECUTOR_SPEC = ExecutorClassSpec(executor.Executor)
```

Completing the component class

```
class HelloComponent(base_component.BaseComponent):
  ...
  def __init__(self,
               input_data: types.Channel = None,
               output_data: types.Channel = None,
               name: Optional[Text] = None):
    if not output_data:
      examples_artifact = standard_artifacts.Examples()
      examples_artifact.split_names = input_data.get()[0].split_names
      output_data = channel_utils.as_channel([examples_artifact])

    spec = HelloComponentSpec(input_data=input_data, output_data=output_data, name=name)
    super(HelloComponent, self).__init__(spec=spec)
```

Assemble into a TFX pipeline

```
def _create_pipeline():
  ...
  example_gen = CsvExampleGen(input_base=examples)

  hello = component.HelloComponent(
      input_data=example_gen.outputs['examples'],
      name='HelloWorld')

  statistics_gen = StatisticsGen(
      examples=hello.outputs['output_data'])
  ...
  return pipeline.Pipeline(
      ...
      components=[example_gen, hello, statistics_gen, ...],
      ...
  )
```

Model Management and Deployment Infrastructure

Managing Model Versions

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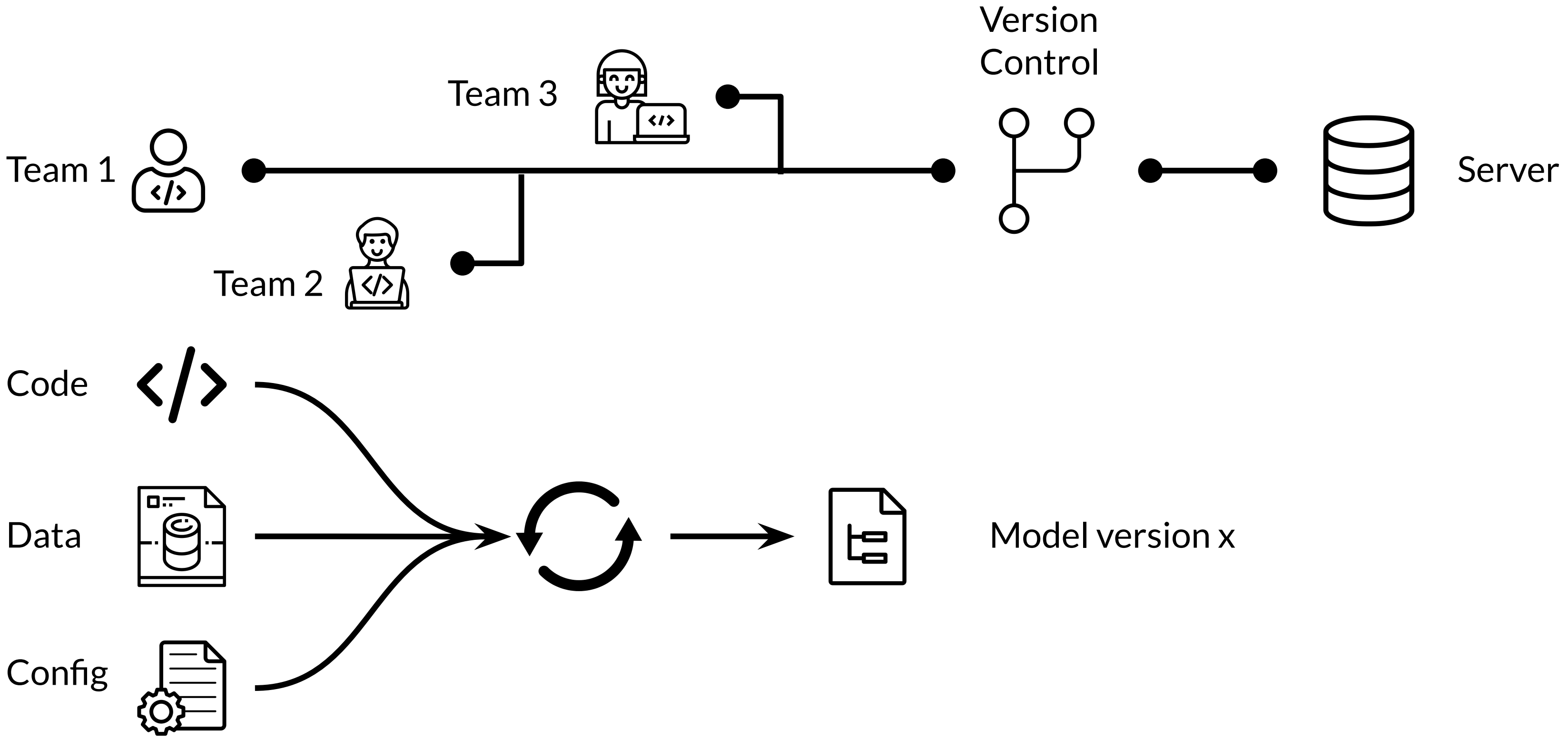
Why versioning ML Models?



How ML Models are versioned?

How software is versioned?

Version: MAJOR.MINOR.PATCH

- MAJOR: Contains incompatible API changes
- MINOR: Adds functionality in a backwards compatible manner
- PATCH: Makes backwards compatible bug fixes

ML Models versioning

- No uniform standard accepted yet
- Different organizations have different meanings and conventions

A Model Versioning Proposal

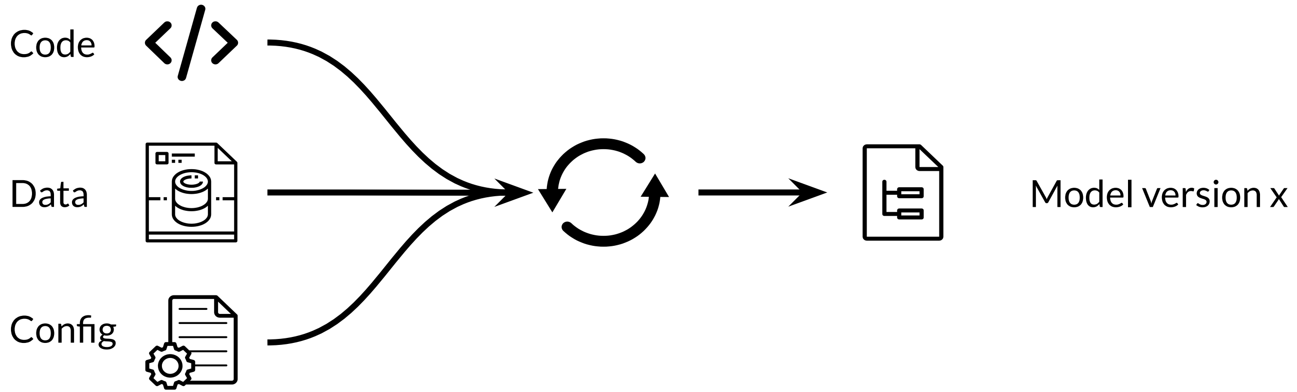
Version: MAJOR.MINOR.PIPELINE

- MAJOR: Incompatibility in data or target variable
- MINOR: Model performance is improved
- PIPELINE: Pipeline of model training is changed

Retrieving older models

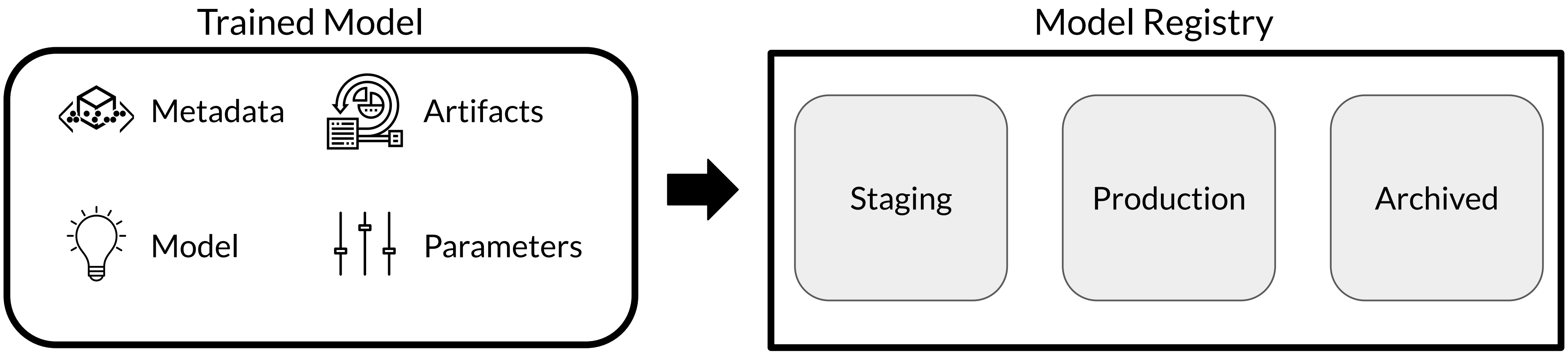
- Can ML framework be leveraged to retrieve previously trained models?
- ML framework may internally be versioning models

What is model lineage?



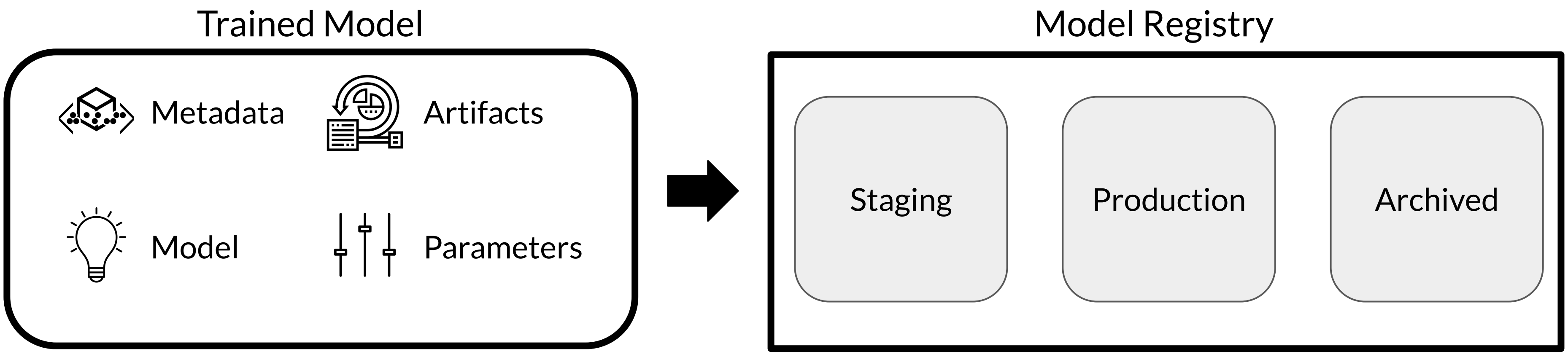
- Artifacts: information needed to preprocess data and generate result (code, data, config, model)
- ML orchestration frameworks may store operations and data artifacts to recreate model
- Post training artifacts and operations are usually not part of lineage

What is a model registry?



- Central repository for storing trained ML models
- Provides various operations of ML model development lifecycle
- Promotes model discovery, model understanding, and model reuse
- Integrated into OSS and commercial ML platforms

Metadata stored by model registry



- Model versions
- Model serialized artifacts
- Free text annotations and structured properties
- Links to other ML artifact and metadata stores

Capabilities Enabled by Model Registries

- Model search/discovery and understanding
- Approval/Governance
- Collaboration/Discussion
- Streamlined deployments
- Continuous evaluation and monitoring
- Staging and promotions

Examples of Model Registries

- Azure ML Model Registry
- SAS Model Manager
- MLflow Model Registry
- Google AI Platform
- Algorithmia

Model Management and Deployment Infrastructure

Continuous Delivery

What is Continuous Integration (CI)

Continuous Integration

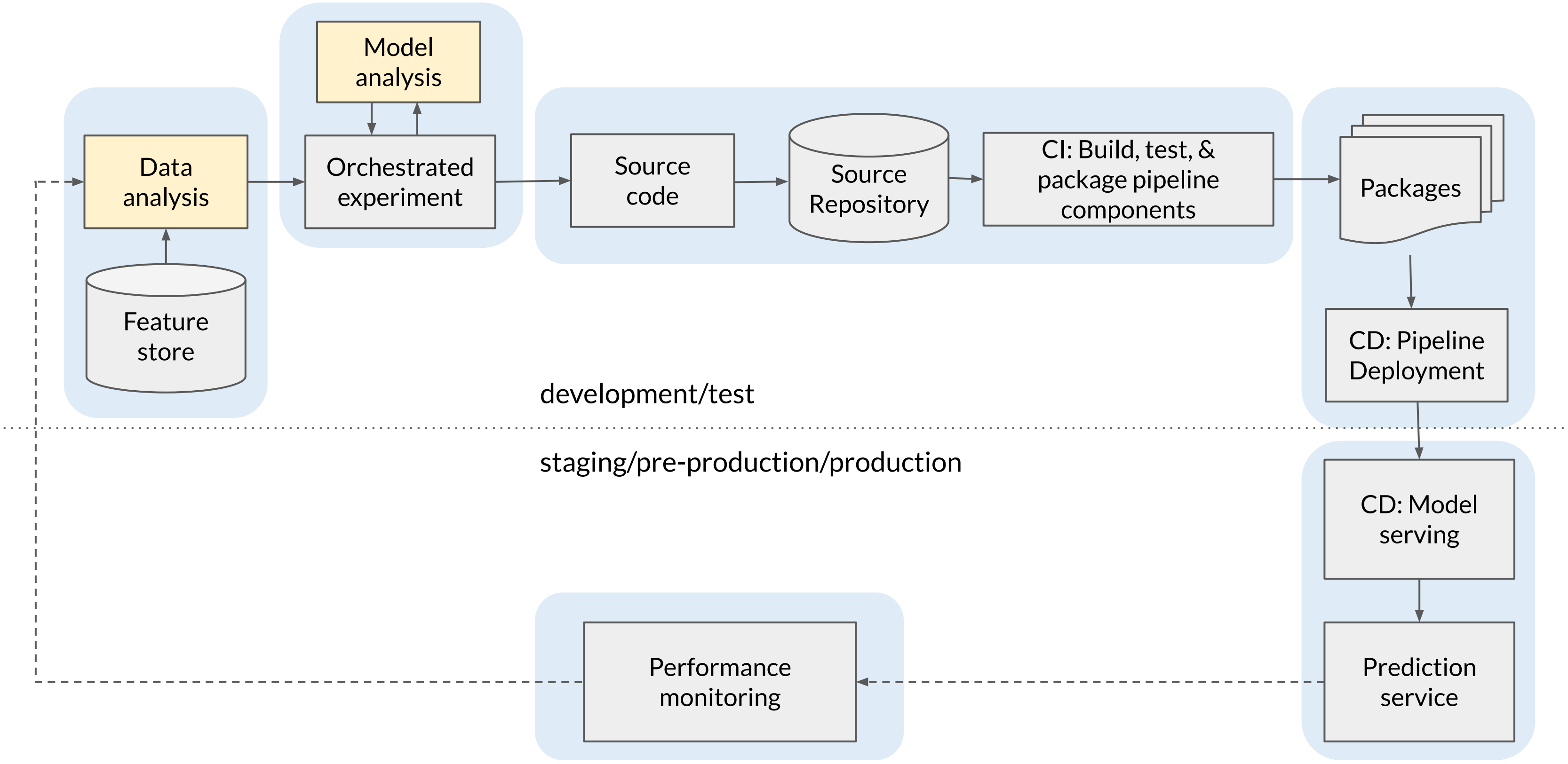
- Triggered when new code is pushed or committed
- Build packages, container images, executables etc
- Performs unit and integration tests for the components
- Delivers the final packages to Continuous Delivery pipeline

What is Continuous Delivery (CD)

Continuous Delivery

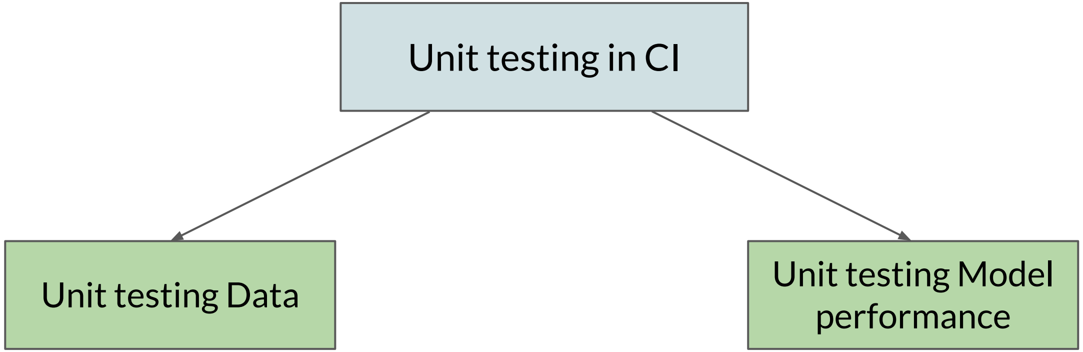
- Deploys new code and trained models to the target environment
- Ensures compatibility of code and models with the target environment
- Checks the prediction service performance of the model before deploying

CI/CD Infrastructure

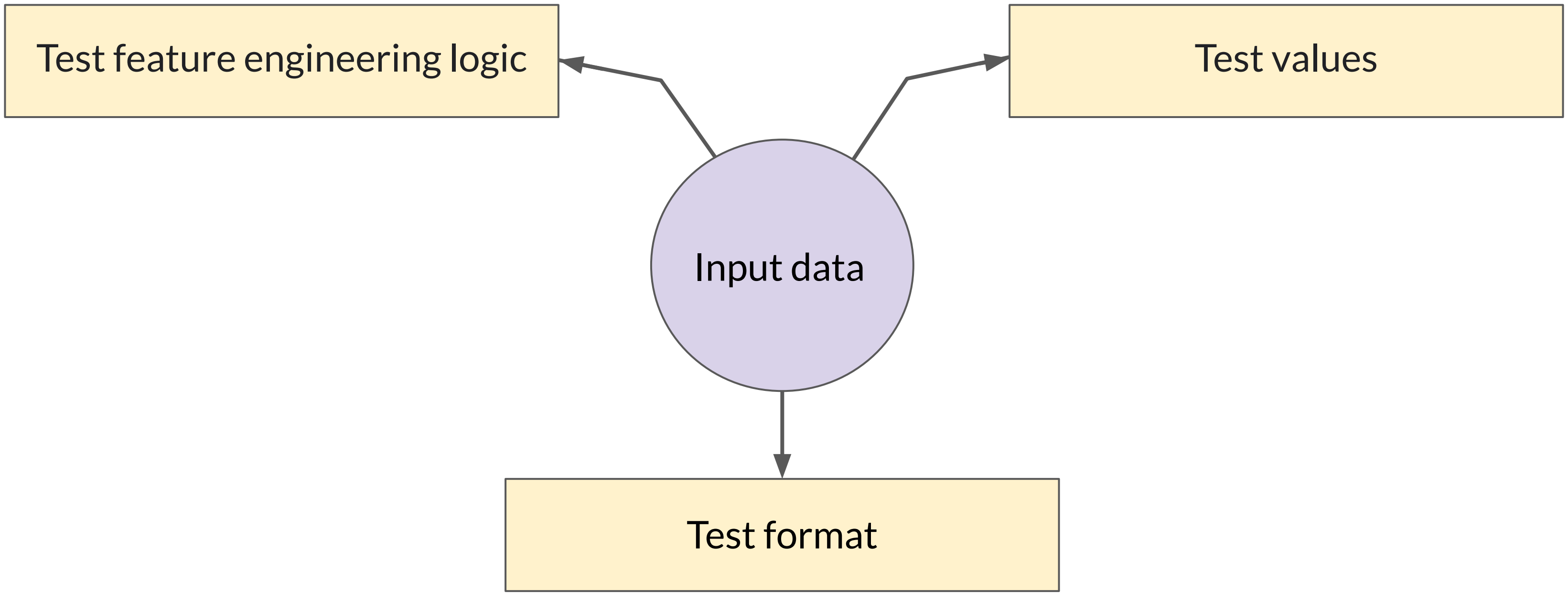


Unit Testing in CI

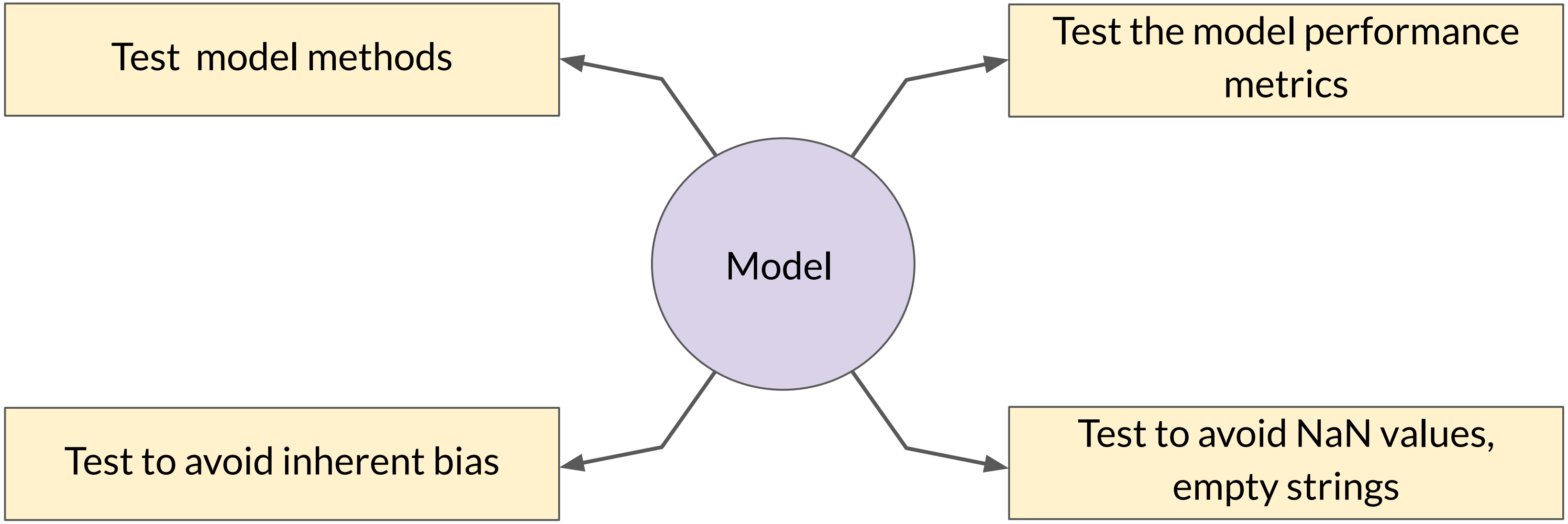
- Testing that each component in the pipeline produces the expected artifacts.



Unit Testing Input Data



Unit Testing Model Performance



ML Unit Testing Considerations

Mocking	Data Coverage	Code Coverage
Mocks of datasets are especially important for ML. They should cover edge and corner cases.	Your mocks should sparsely cover the same space as your data, but with a much smaller dataset.	Use code coverage libraries to make sure that you are not missing unit tests for any part of our code.

Infrastructure validation

When to apply infrastructure validation

- Before starting CI/CD as part of model training
- Can also occur as part of CI/CD as a last check to verify that the model is deployable to the serving infrastructure

TFX InfraValidator

- TFX InfraValidator takes the model, launches a sand-boxed model server with the model, and sees if it can be successfully loaded and optionally queried
- InfraValidator is using the same model server binary, same resources, and same server configuration as production

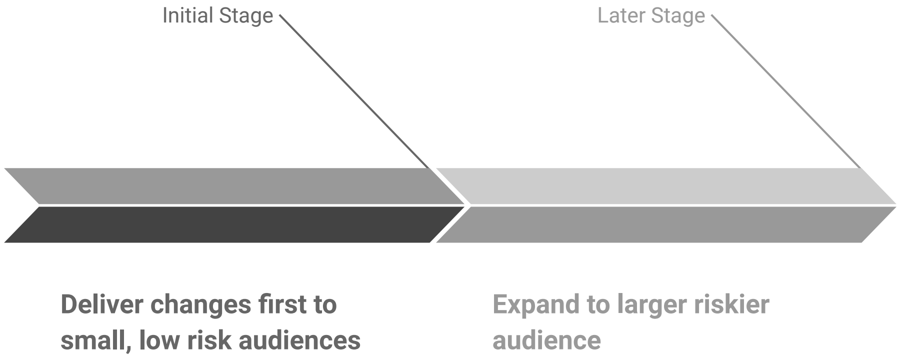
Model Management and Deployment Infrastructure

DeepLearning.AI

Progressive Delivery

Progressive Delivery

Progressive Delivery is essentially an improvement over Continuous Delivery

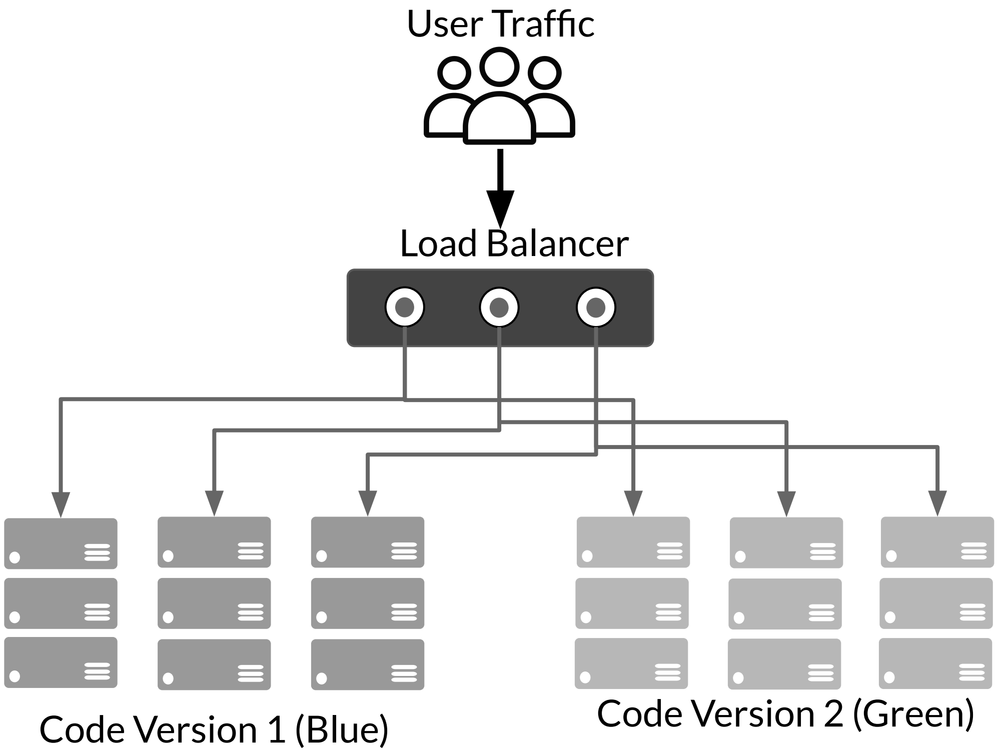


- Decrease deployment risk
- Faster deployment
- Gradual rollout and ownership

Complex Model Deployment Scenarios

- You can deploy multiple models performing same task
- Deploying competing models, as in A/B testing
- Deploying as shadow models, as in Canary testing

Blue/Green deployment

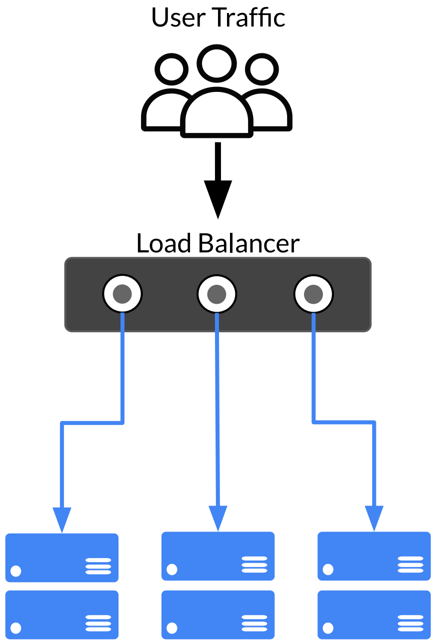


- No downtime
- Quick rollback & reliable
- Smoke testing in production environment

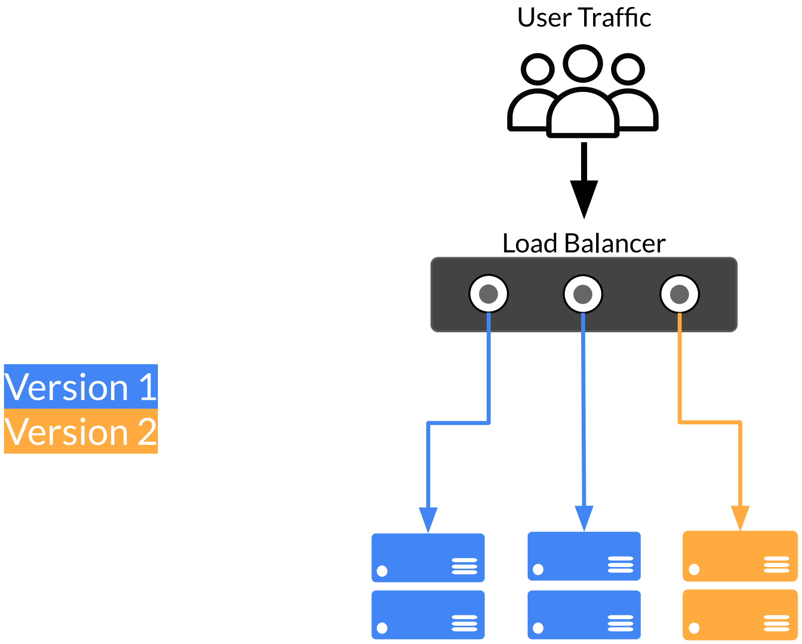
The diagrams are illustrations based on:
https://dev.to/mostlyjason/intro-to-deployment-strategies-blue-green-canary-and-more-3a3#

Canary deployment

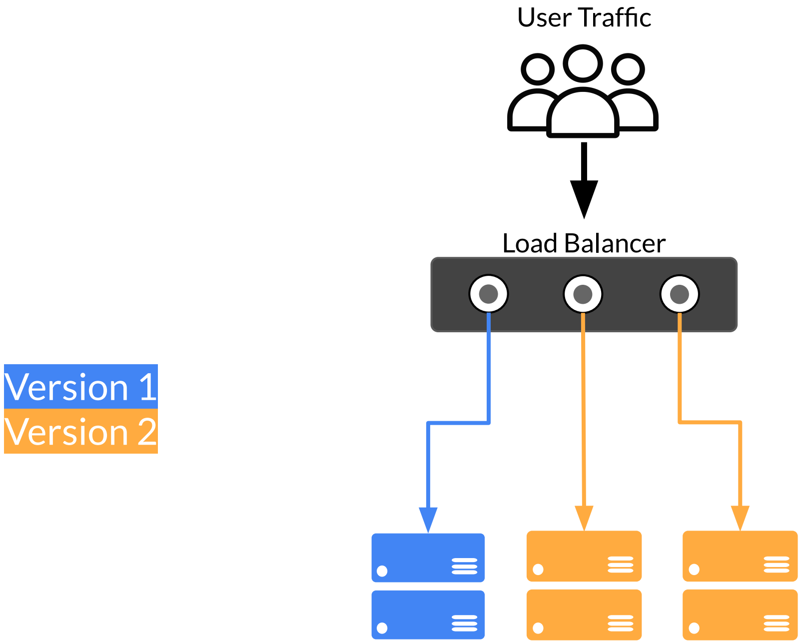
Version 1
Version 2



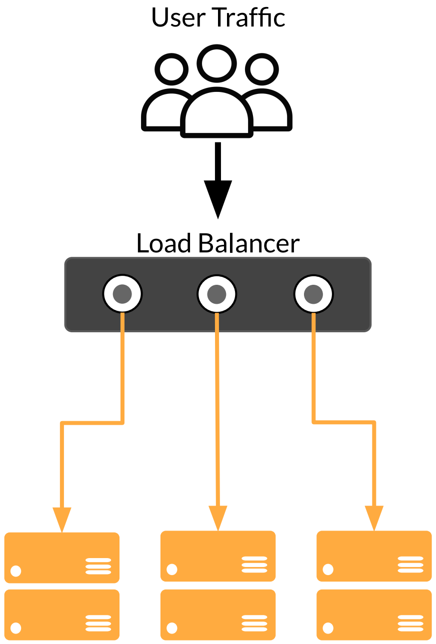
Canary deployment



Canary deployment



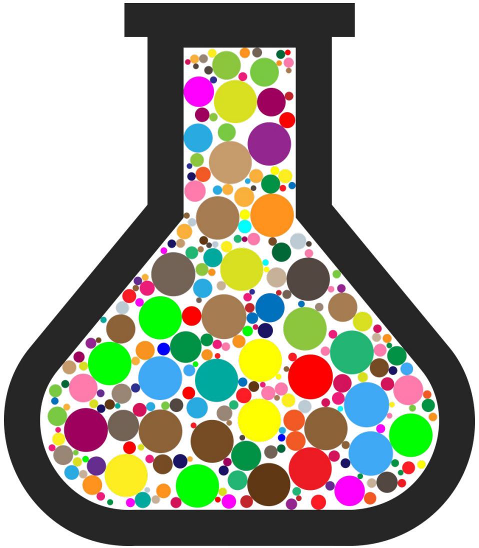
Canary deployment



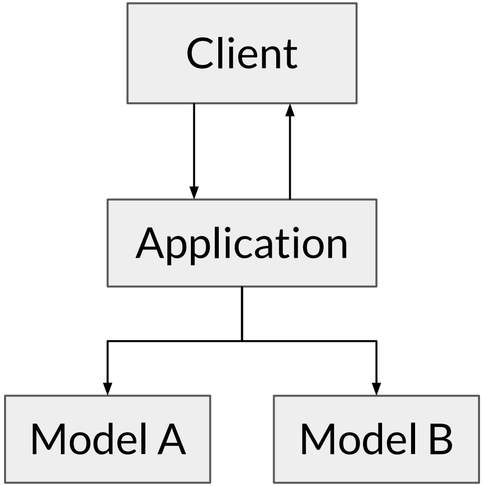
Version 1
Version 2

Live Experimentation

- Model metrics are usually not exact matches for business objectives
- Example: Recommender systems
    - Model trained on clicks
    - Business wants to maximize profit
    - Example: Different products have different profit margins

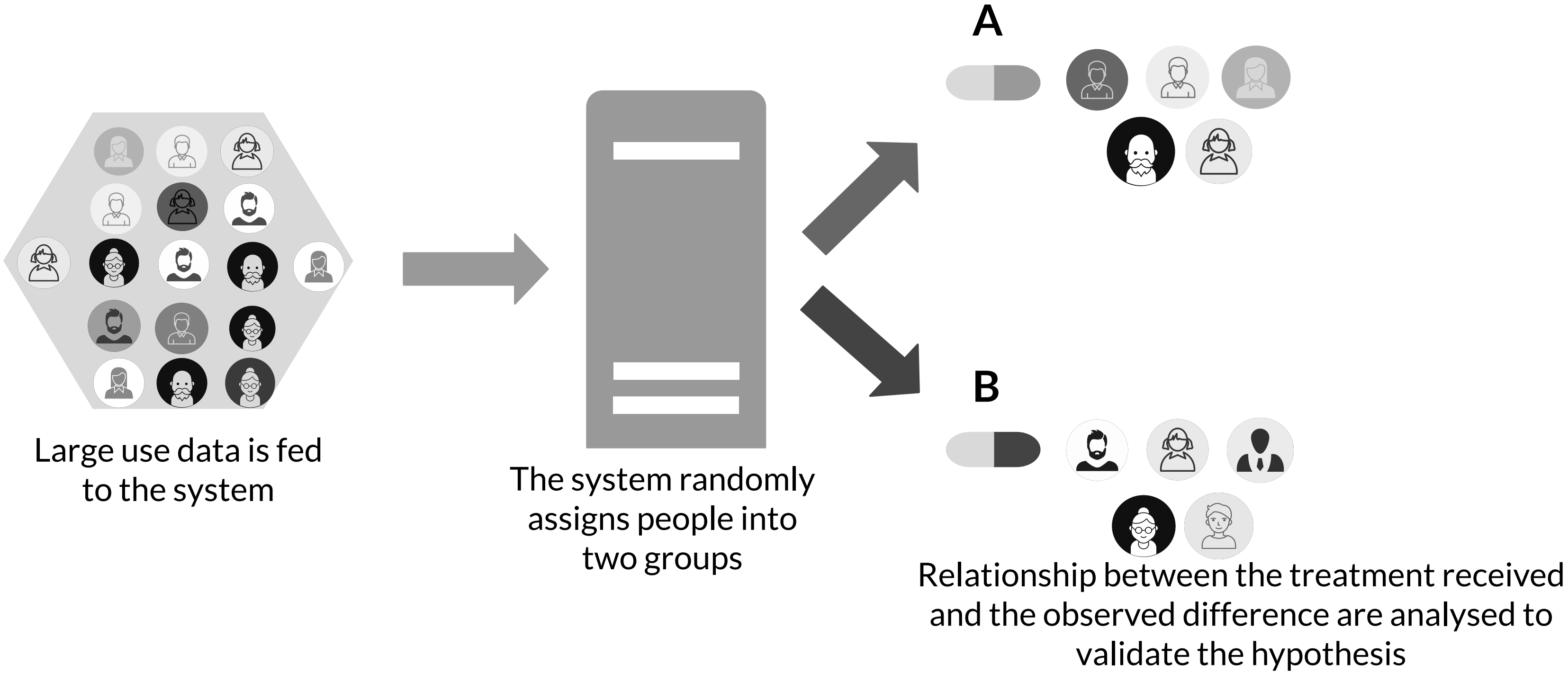


Live Experimentation: A/B Testing



- Users are divided into two groups
- Users are randomly routed to different models in environment
- You gather business results from each model to see which one is performing better

Live Experimentation: A/B Testing



Live Experimentation: Multi-Armed Bandit (MAB)

- Uses ML to learn from test results during test
- Dynamically routes requests to winning models
- Eventually all requests are routed to one model
- Minimizes use of low-performing models

Live Experimentation: Contextual Bandit

- Similar to multi-armed bandit, but also considers context of request
- Example: Users in different climates