Databricks Overview for MLOps

Clemens Mewald
Director of Product Management

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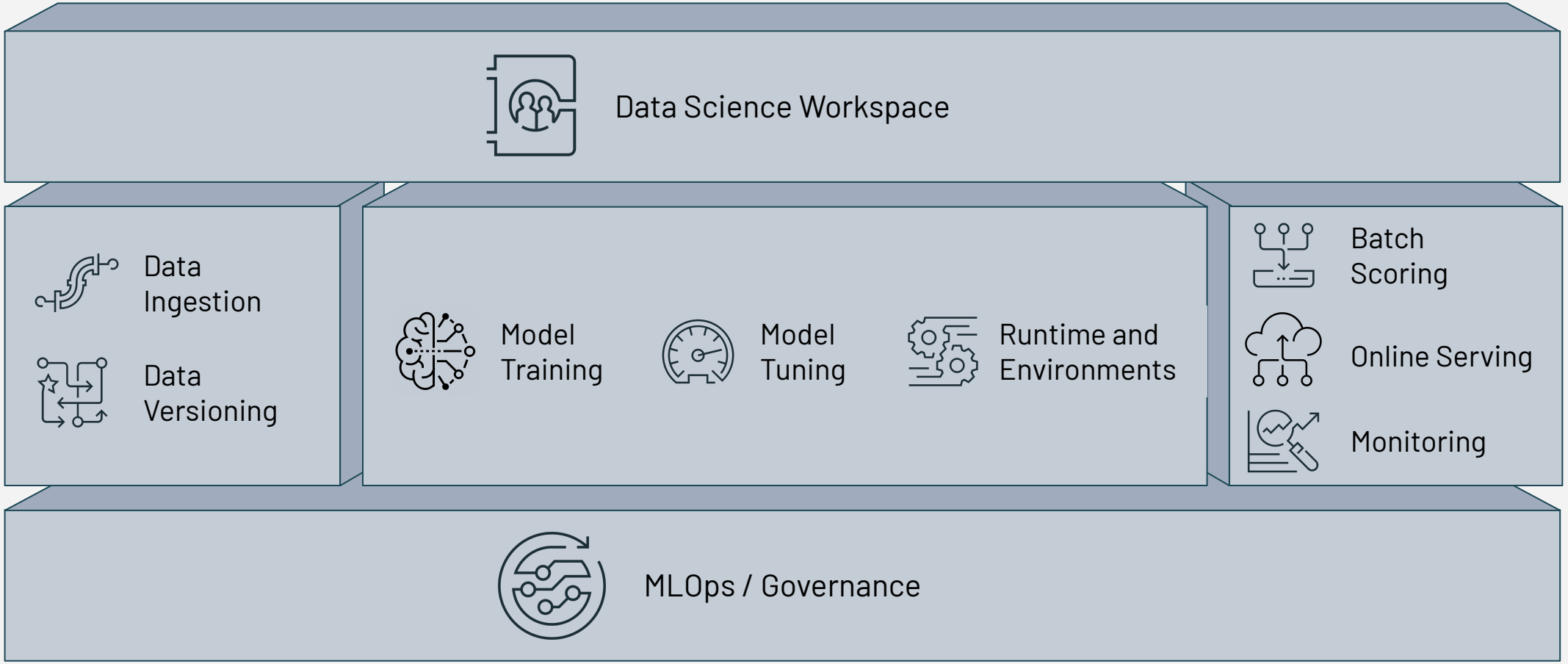
The Databricks ML Platform



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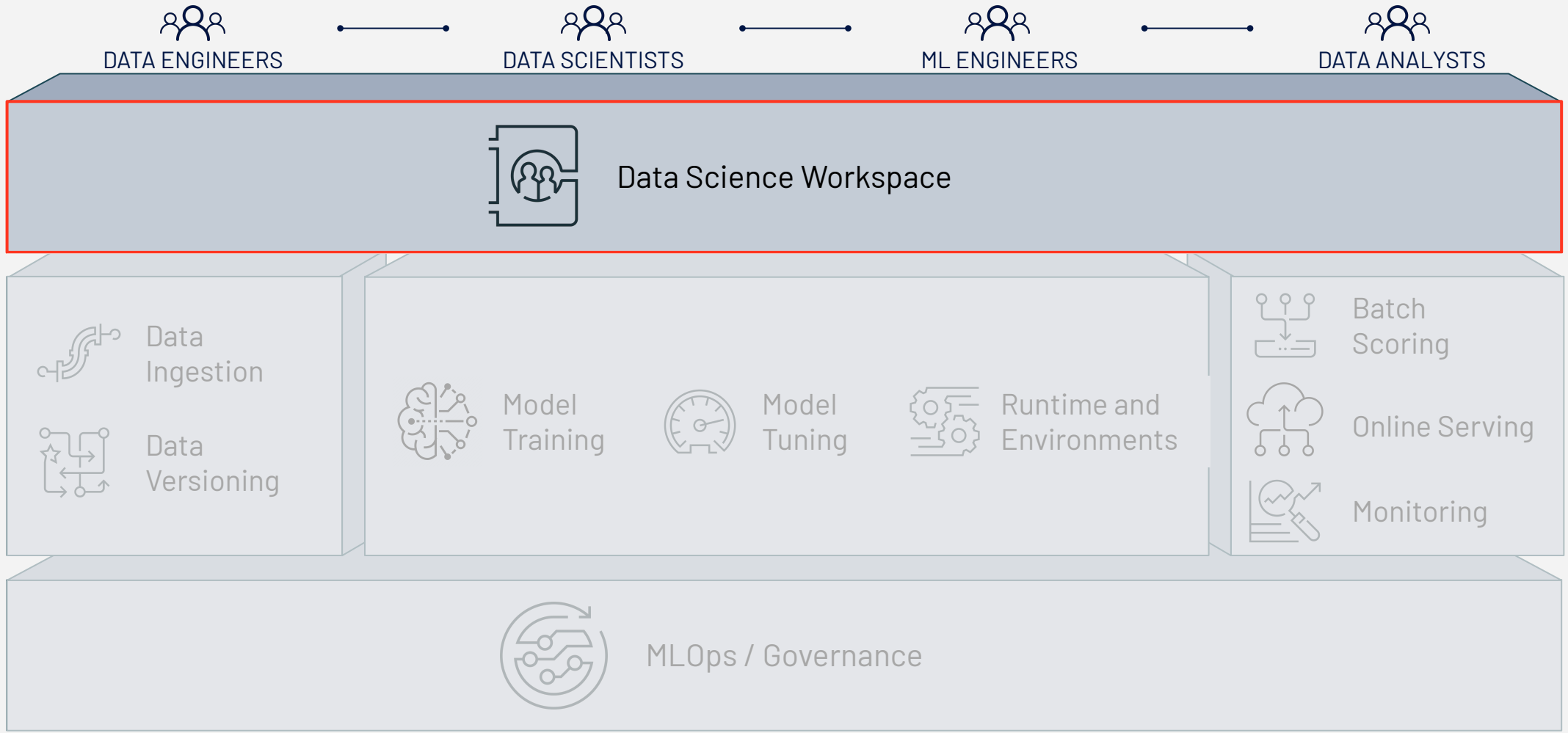
Collaborative Data Science Workspace



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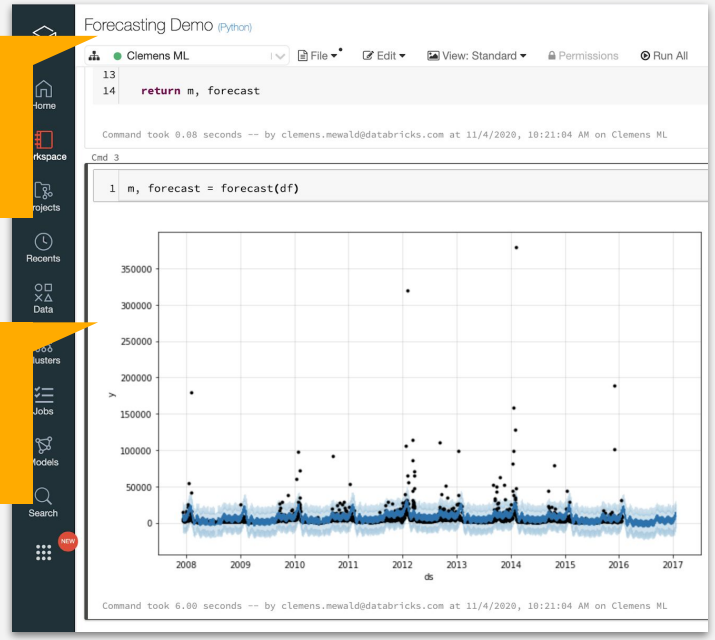
Databricks Notebooks

DATA ENGINEERS — DATA SCIENTISTS — ML ENGINEERS — DATA ANALYSTS

Data Science Workspace

Multi-Language
Scala, SQL, Python, R: All in one notebook.

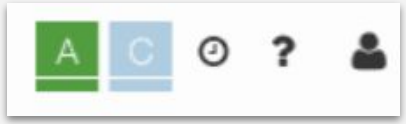
Collaborative
Realtime co-presence, co-editing, and commenting.



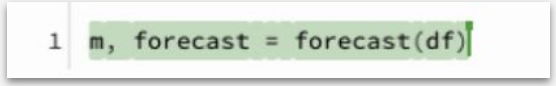
Cloud-native Collaboration Features

Commenting

Co-Presence



Co-Editing



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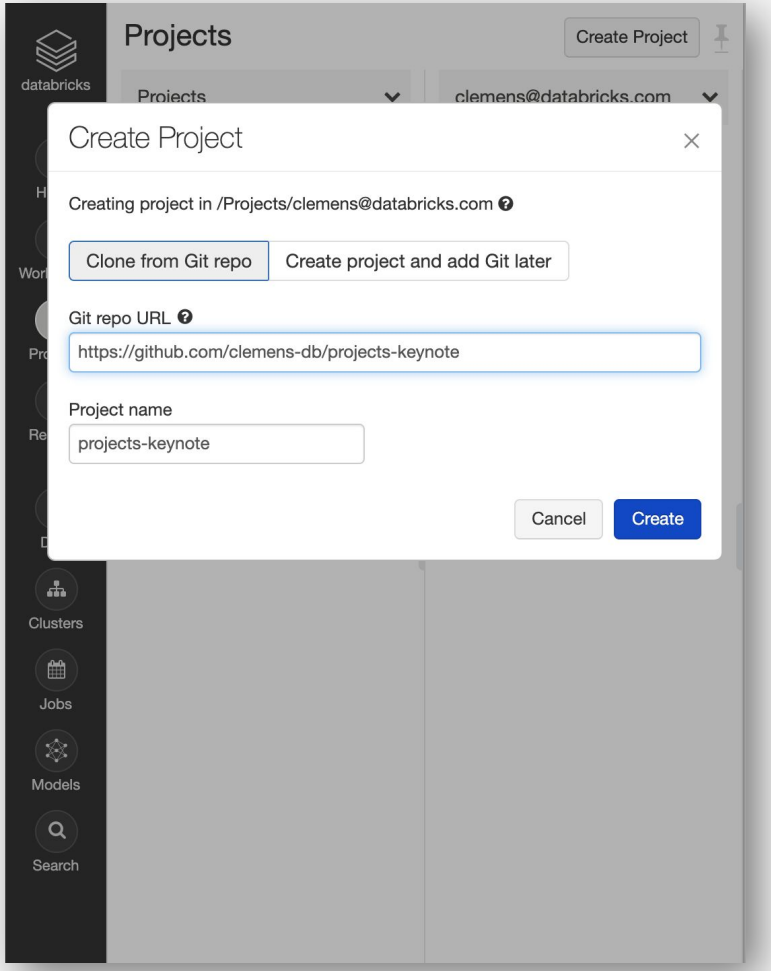
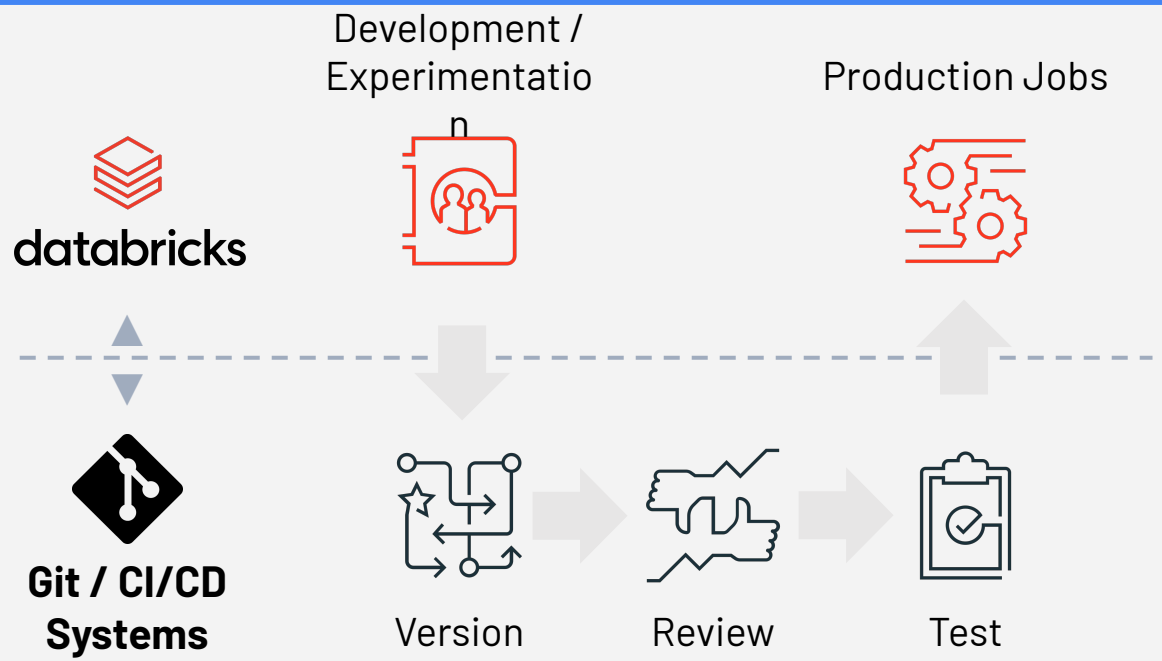
(Git-based) Projects



CI/CD Integration



Supported Git Providers

Azure DevOps GitHub GitLab Bitbucket

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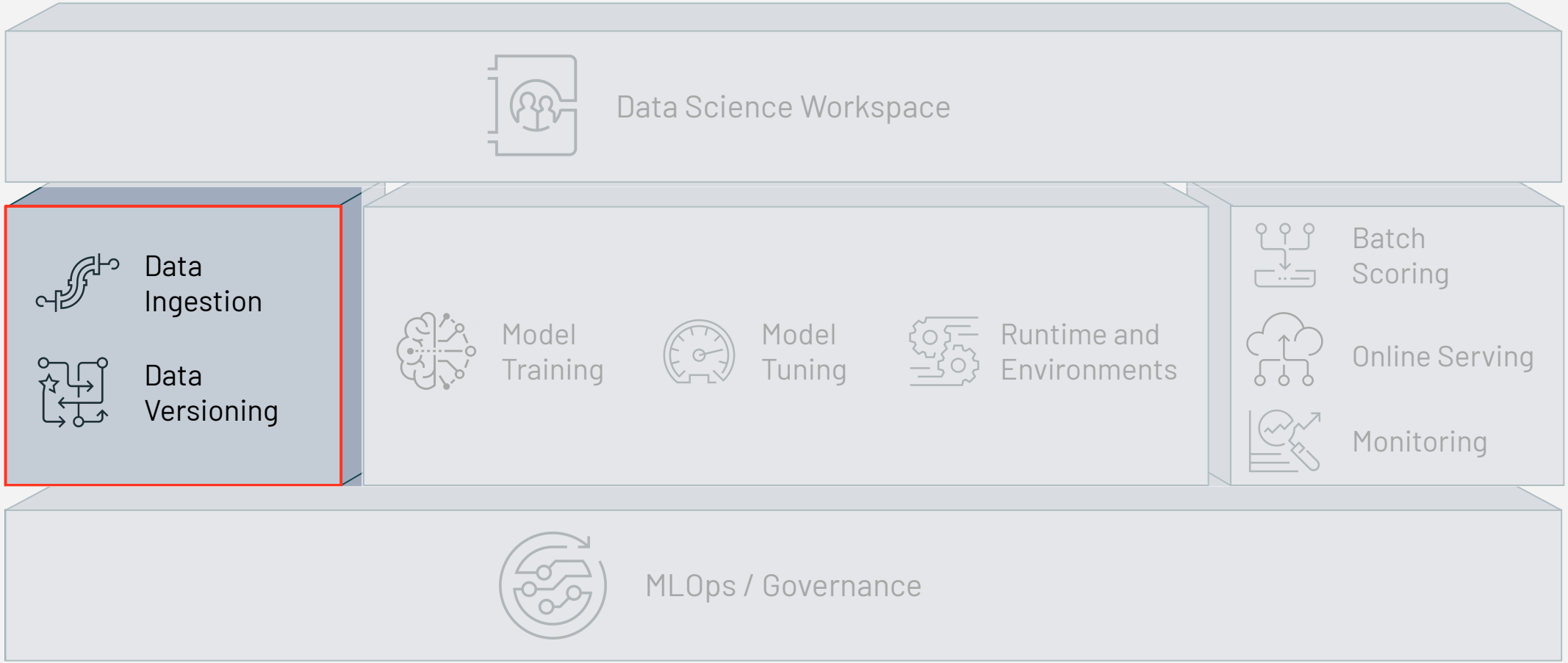
High Quality Data at Scale



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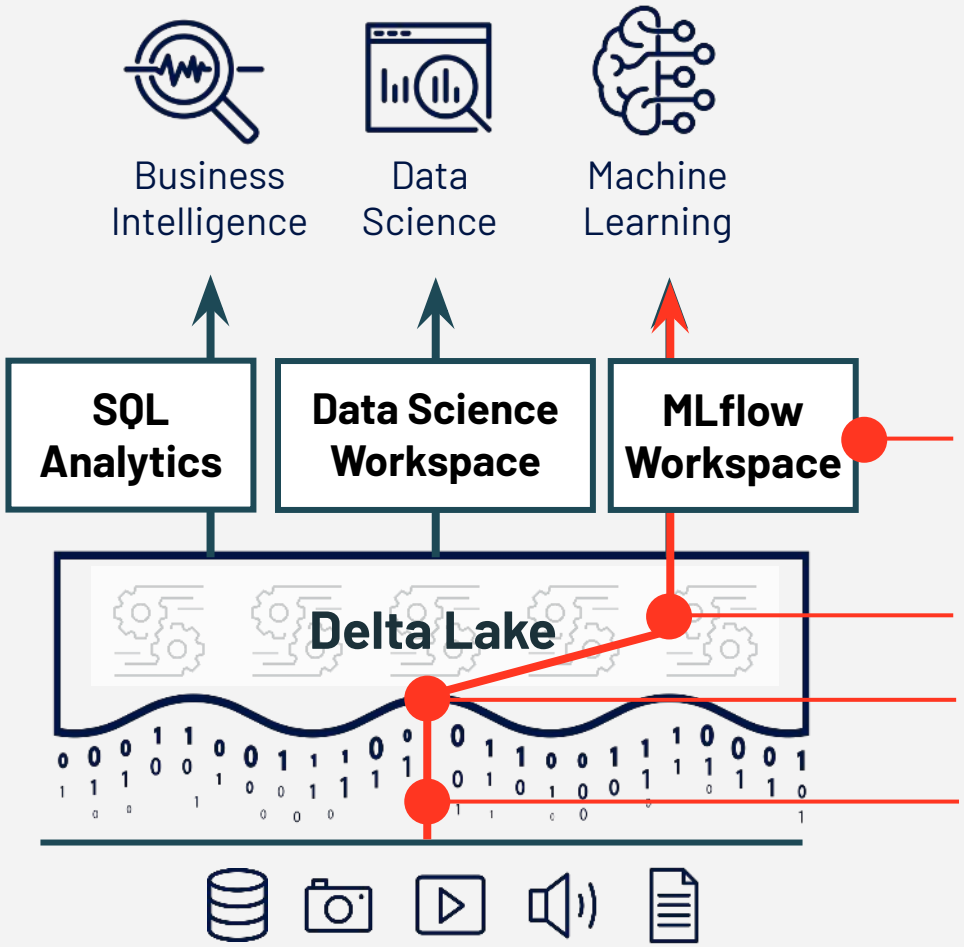
High Quality Data at Scale



DELTA LAKE

- Automated logging of data + version information
- Versioning and time-travel built-in
- ACID transactions guarantee data validity
- Ingest any format at any scale from any source

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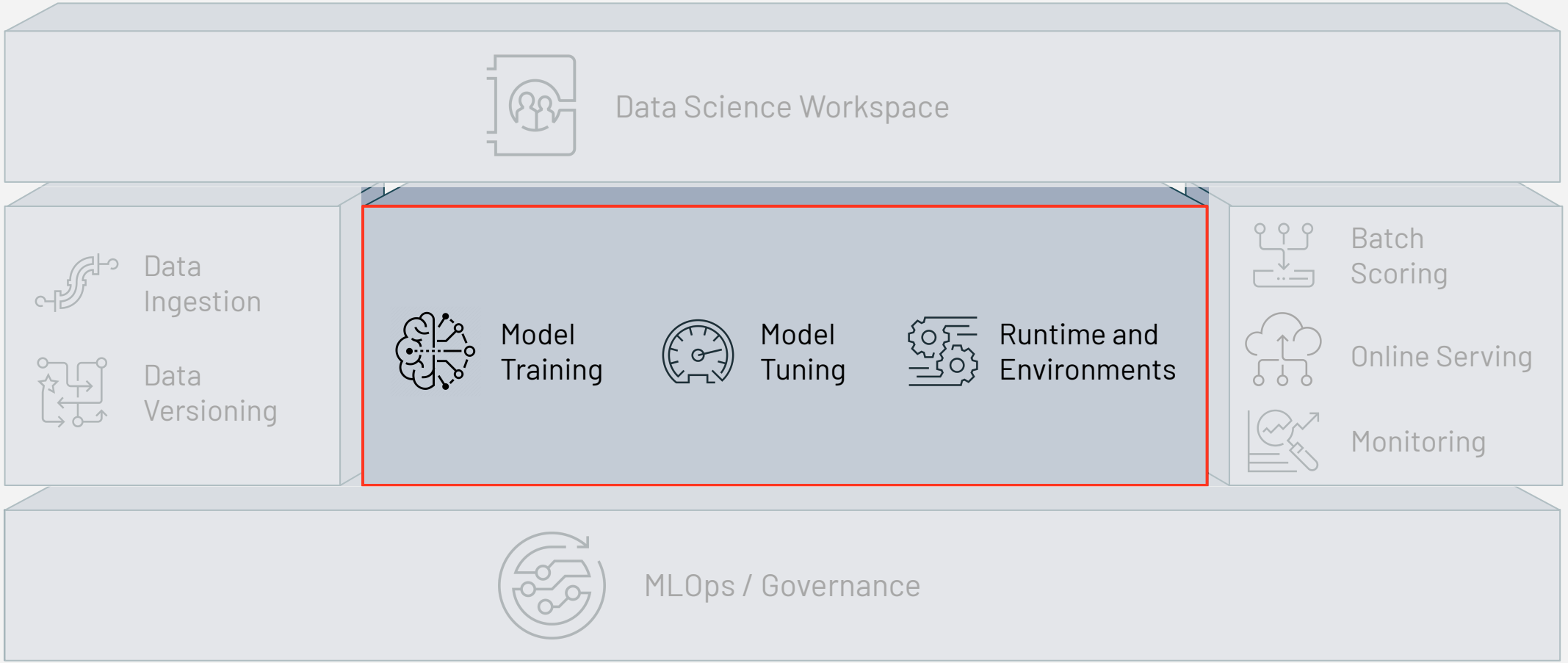
Turnkey ML Training at Scale



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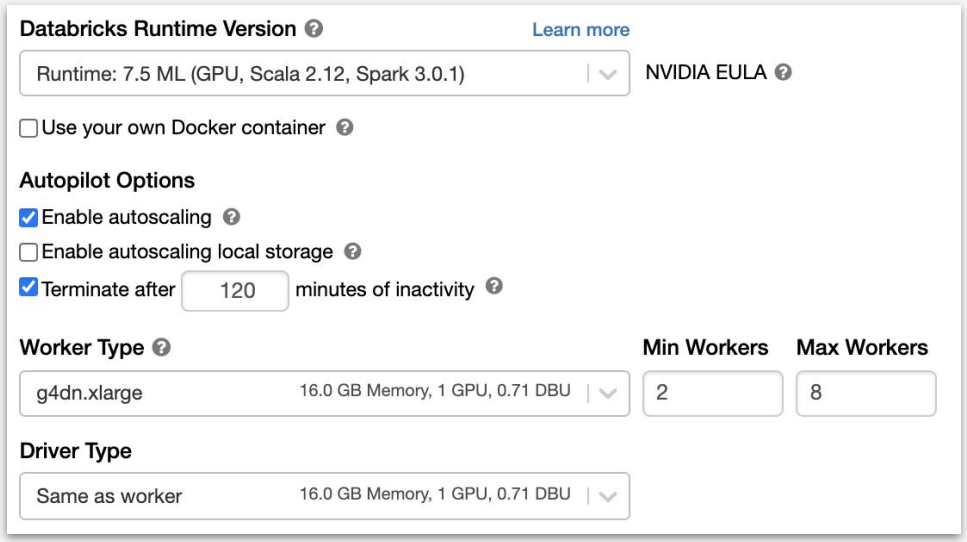
Turnkey ML Training at Scale

ML Runtime: DevOps-free Environment optimized for Machine Learning



Packages up the most popular ML Toolkits

Simplifies Distributed ML/DL

Distribute and scale any single-machine ML code to 1,000's of machines.

Built-in AutoML and Auto-Logging

Hyperparameter tuning, AutoML, automated tracking, and visualizations with MLflow

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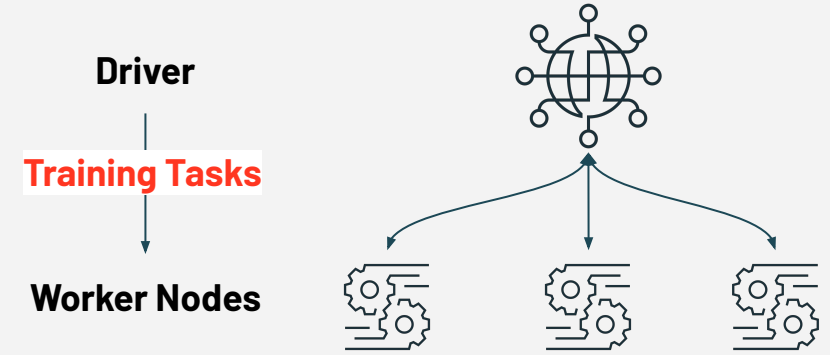
Distributed Training

- Built-in support in the ML Runtime



HorovodRunner (Keras, TensorFlow, and PyTorch)

```
hr = HorovodRunner(np=2)
hr.run(train)
```

TensorFlow native Distribution Strategy (Spark TensorFlow Distributor)

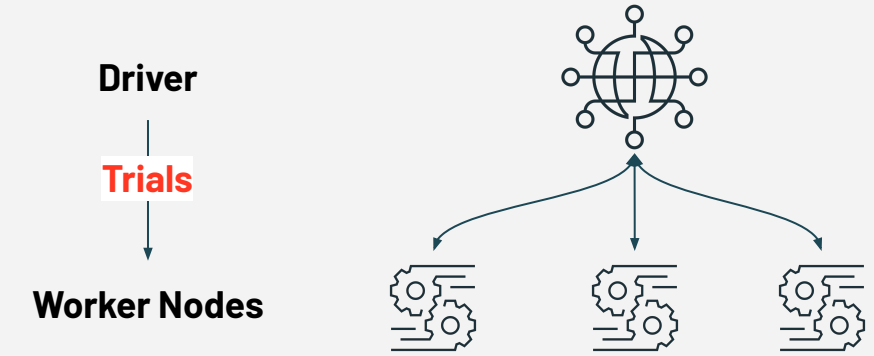
```
runner = MirroredStrategyRunner(num_slots=1, local_mode=True, use_gpu=USE_GPU)
runner.run(train)
```

Distributed Tuning

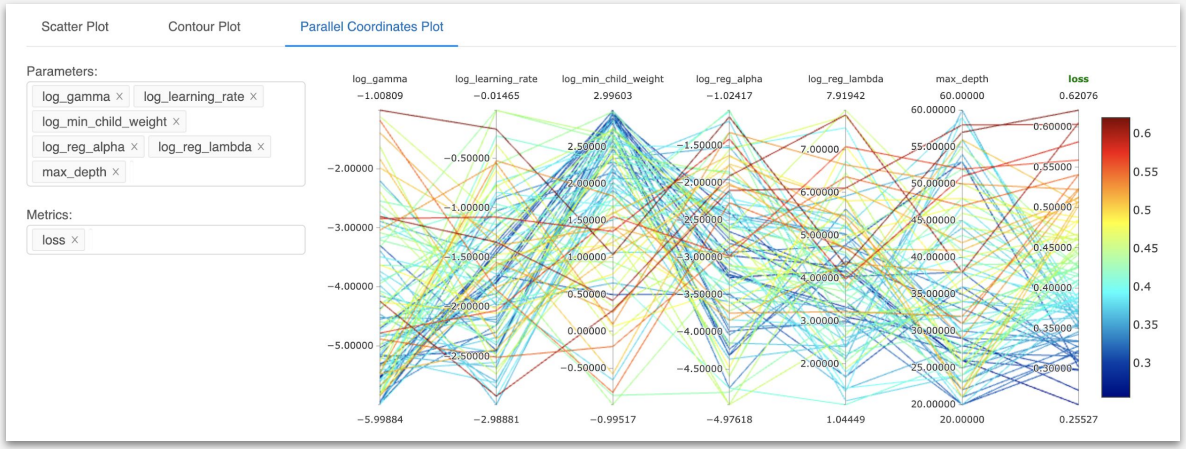
- Built-in support in the ML Runtime

```
search_space = {
  'max_depth':            hp.quniform('max_depth', 20, 60, 1),
  'log_learning_rate':    hp.uniform('log_learning_rate', -3, 0),
  'log_reg_alpha':        hp.uniform('log_reg_alpha', -5, -1),
  'log_reg_lambda':       hp.uniform('log_reg_lambda', 1, 8),
}

best_params = fmin(fn=train_model,
                   space=search_space,
                   algo=tpe.suggest,
                   max_evals=96,
                   trials=SparkTrials(parallelism=6))
```



mlflow Integration



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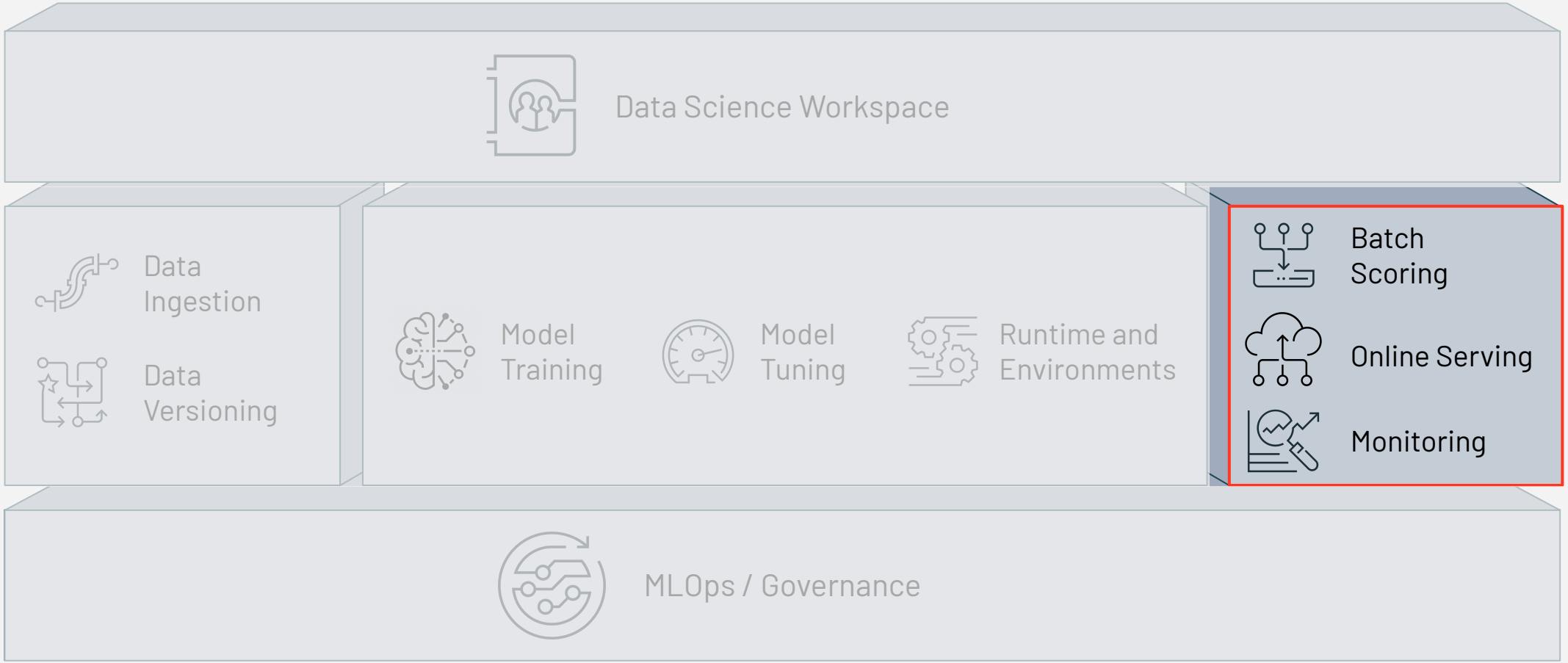
Support for all Deployment Modes



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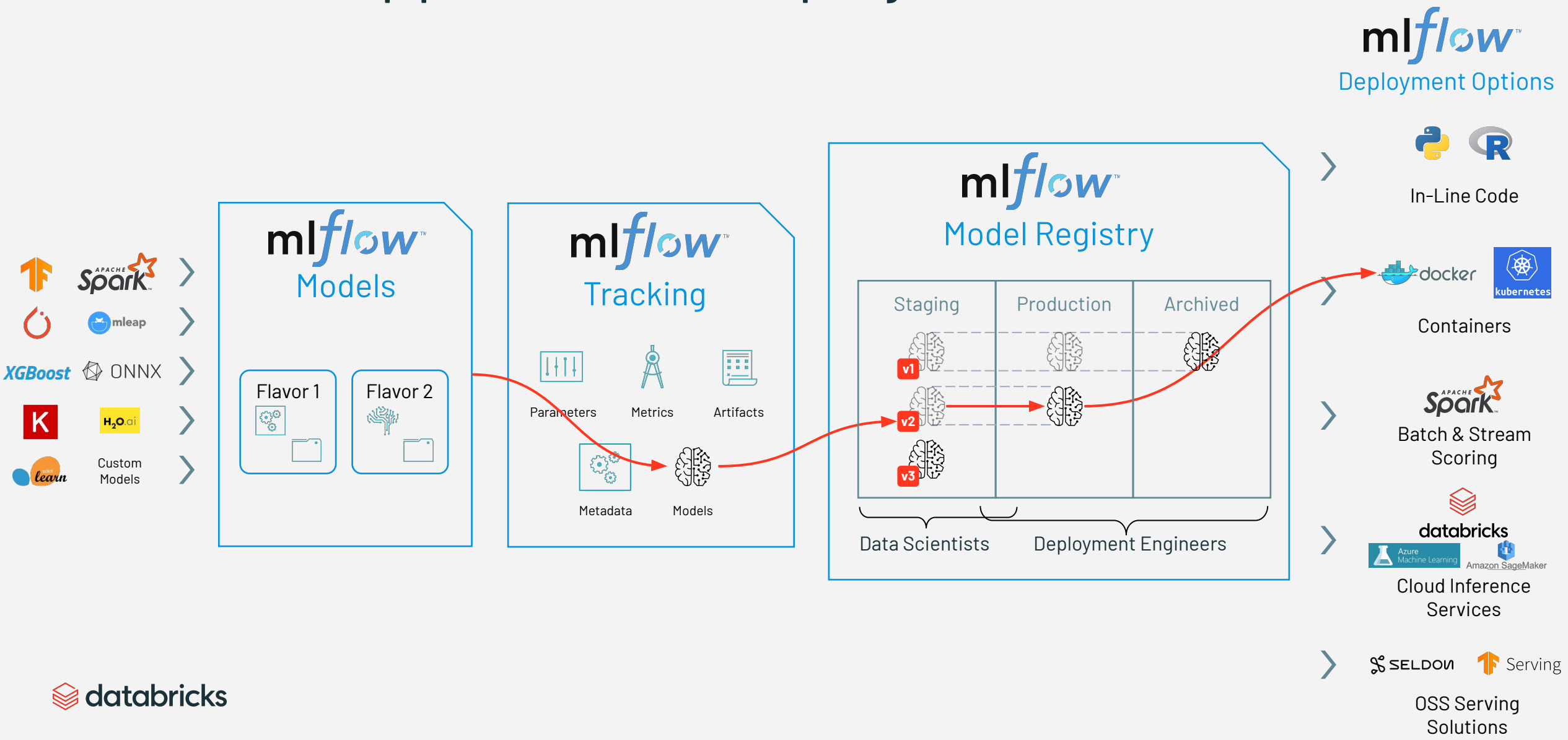
Support for all Deployment Modes



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Support for all Deployment Modes

Deploying an MLLib model as a Spark UDF

```
model_udf = mlflow.pyfunc.spark_udf(spark, model_uri='models:/clemens-windfarm-signature/production')
df.with_column('prediction', model_udf)
```

Support for all Deployment Modes

Deploying an MLLib model as a Spark UDF

Deploying a Scikit Learn model as a Spark UDF

```
model_udf = mlflow.pyfunc.spark_udf(spark, model_uri='models:/clemens-windfarm-signature/production')
df.with_column('prediction', model_udf)
```

Support for all Deployment Modes

Deploying an MLLib model as a Spark UDF

Deploying a Scikit Learn model as a Spark UDF

Deploying a TensorFlow model as a Spark UDF

```
model_udf = mlflow.pyfunc.spark_udf(spark, model_uri='models:/clemens-windfarm-signature/production')
df.with_column('prediction', model_udf)
```

Support for all Deployment Modes

Deploying an MLLib model as a Spark UDF

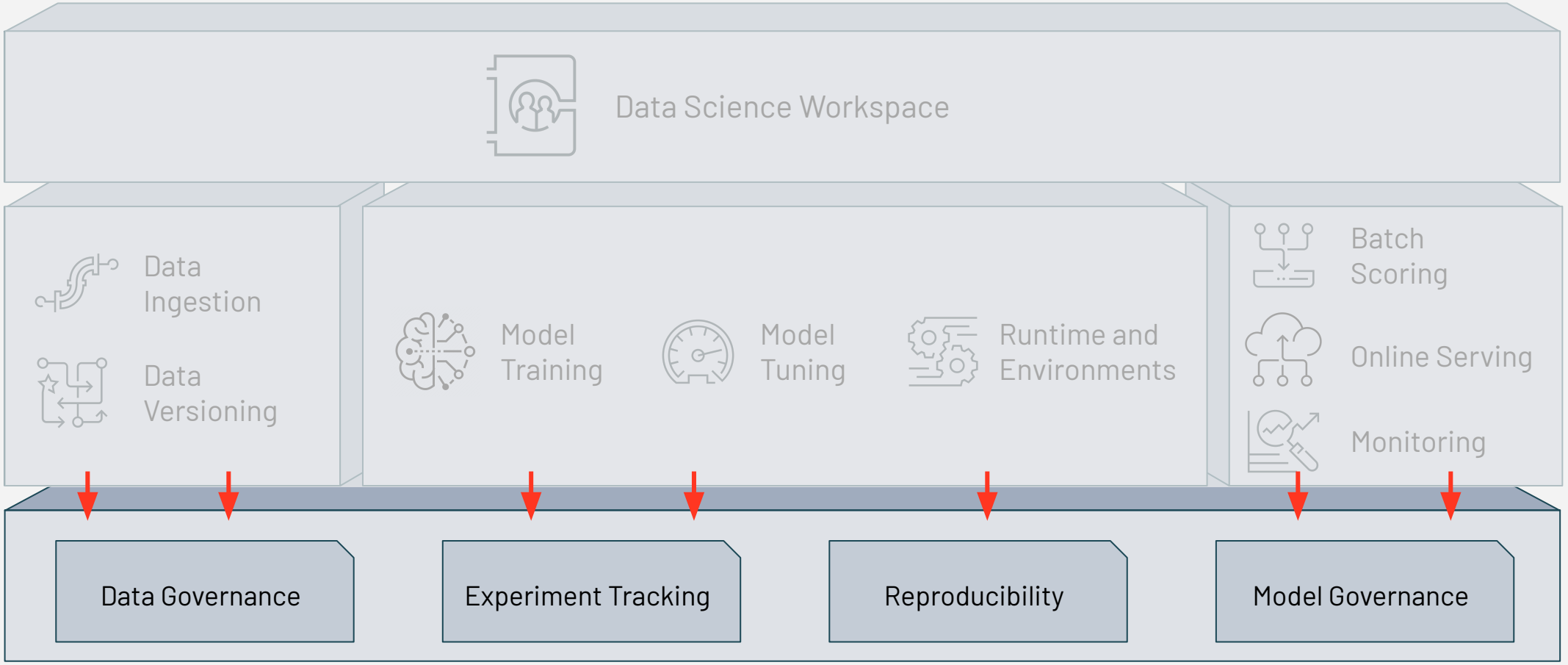
Deploying a Scikit Learn model as a Spark UDF

Deploying a TensorFlow model as a Spark UDF

```
model_udf = mlflow.pyfunc.spark_udf(spark, model_uri='models:/clemens-windfarm-signature/production')
df.with_column('prediction', model_udf)
```

Yes, they're all the same! As are the commands to deploy these models as Docker containers, etc.

End-to-end MLOps / Governance



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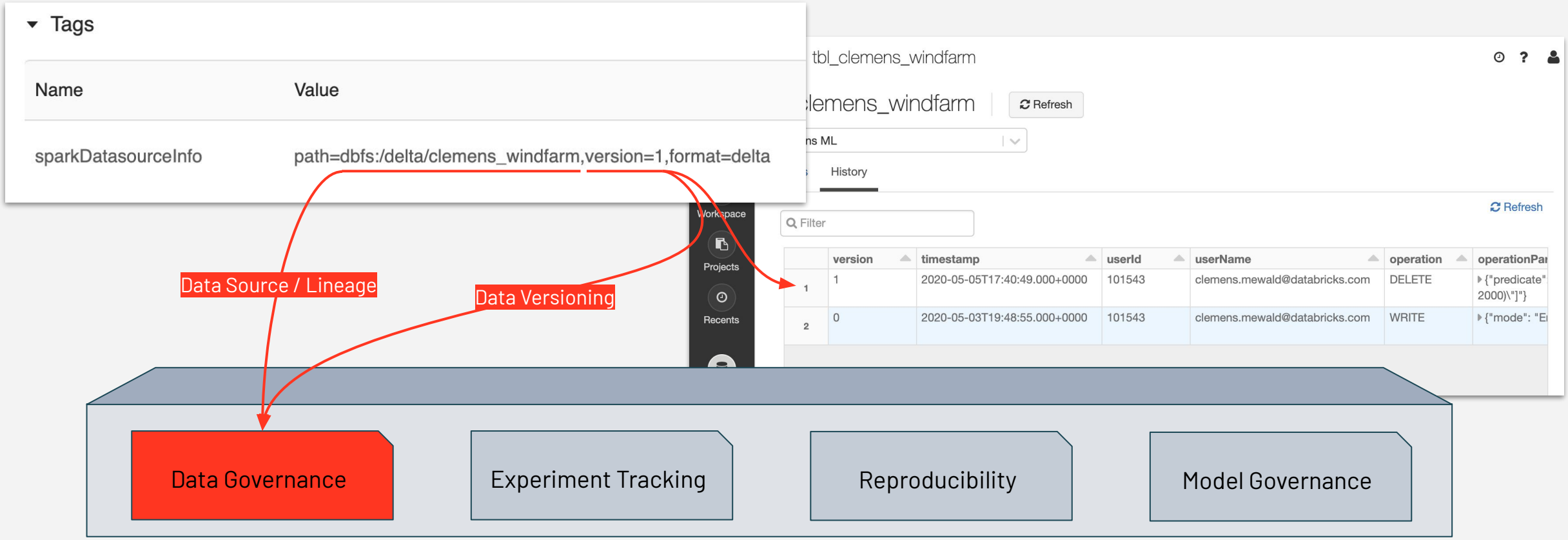
Automated Data Source capture and Versioning



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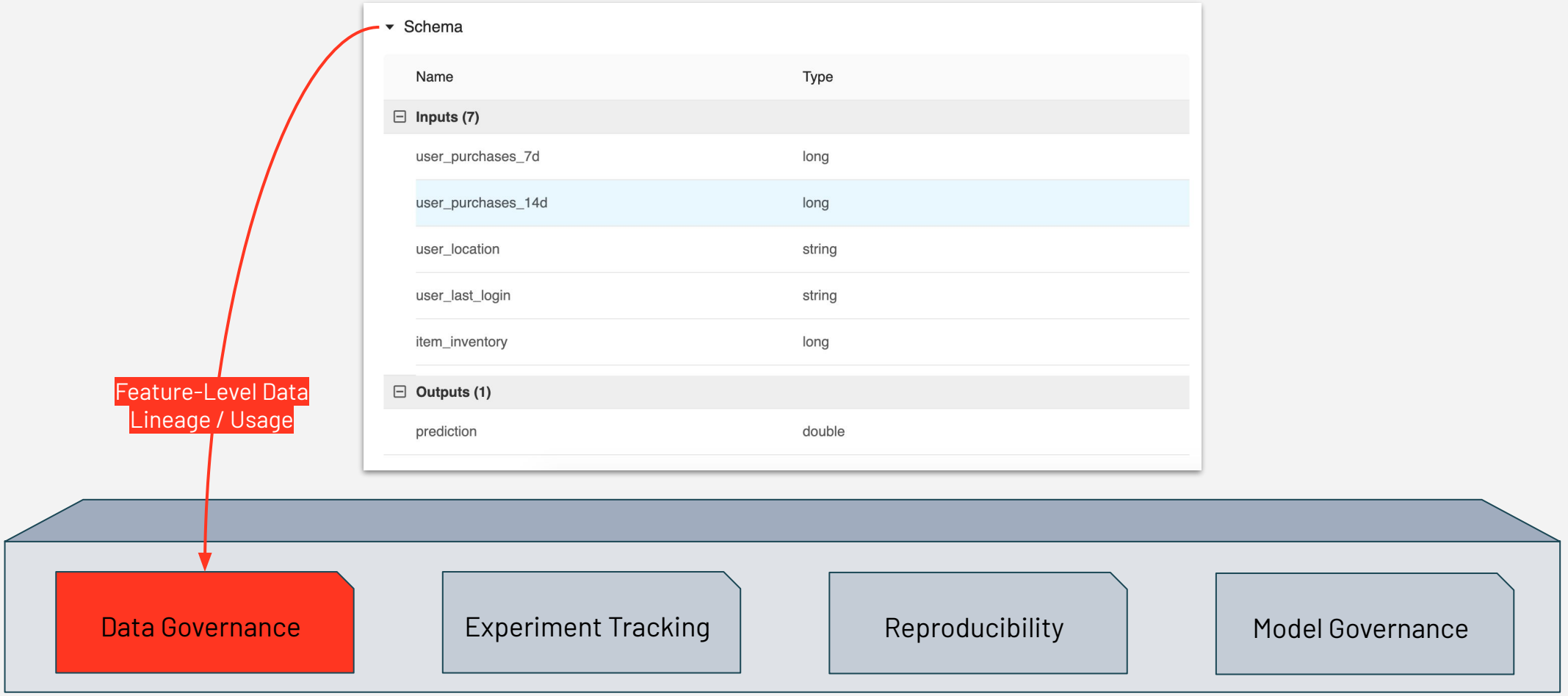
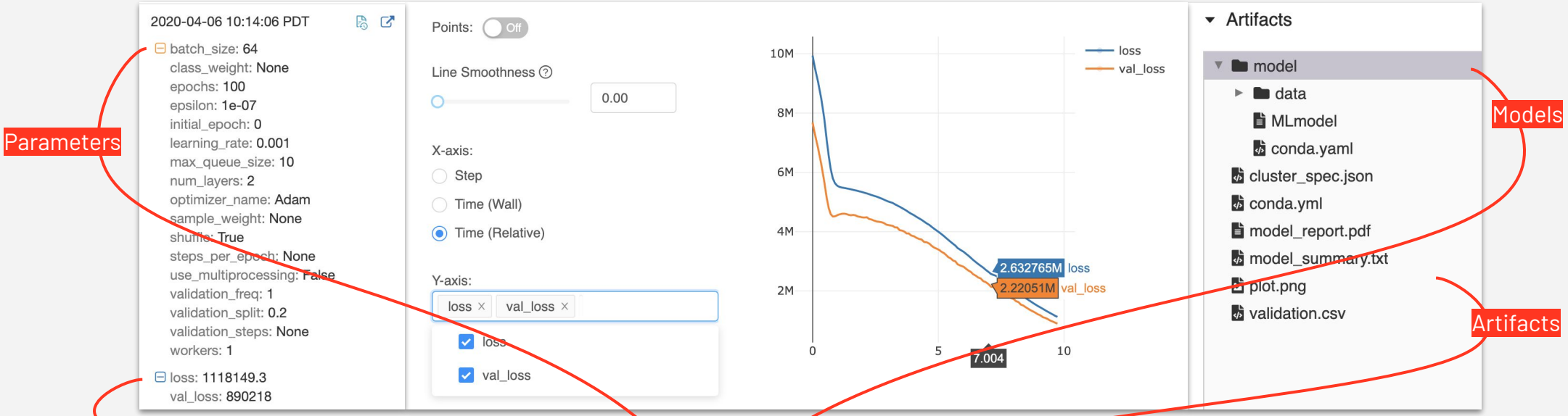
Automated capture of Feature Usage



Automated capture of ML metrics, parameters, artifacts, etc.



Parameters

Metrics

Models

Artifacts

Data Governance

Experiment Tracking

Reproducibility

Model Governance

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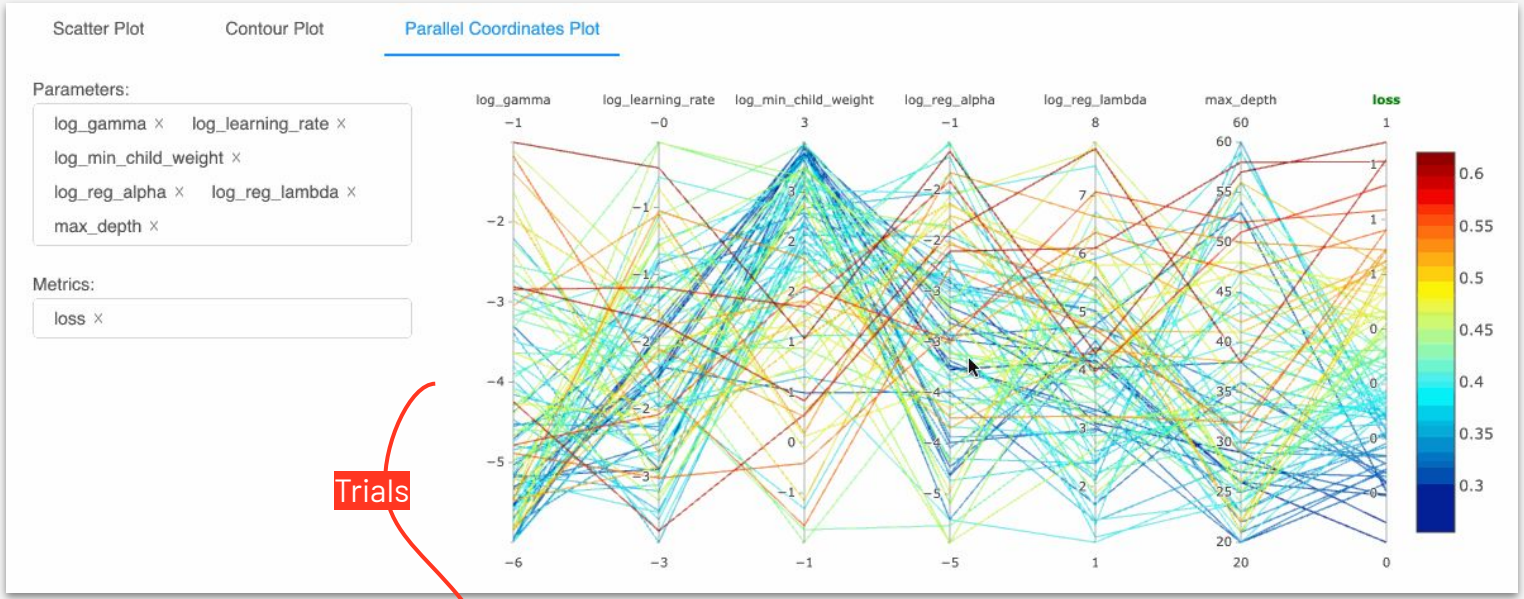
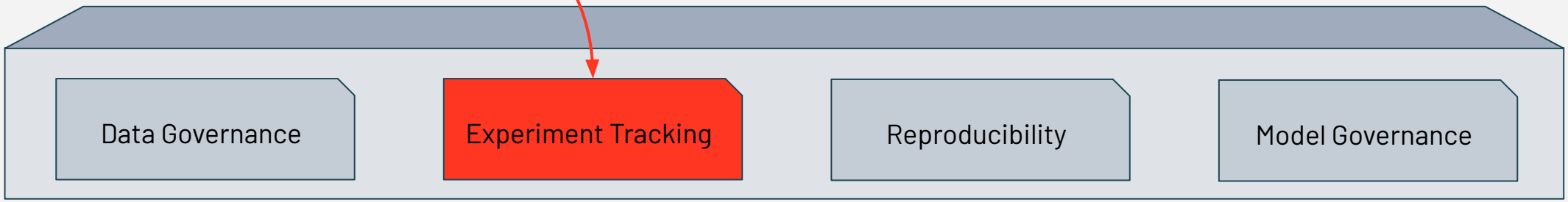
Automated capture of Hyperparameter Search





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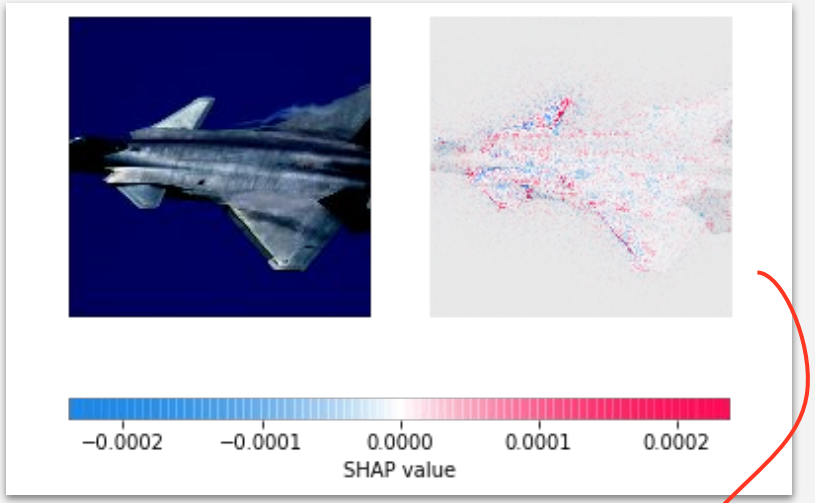
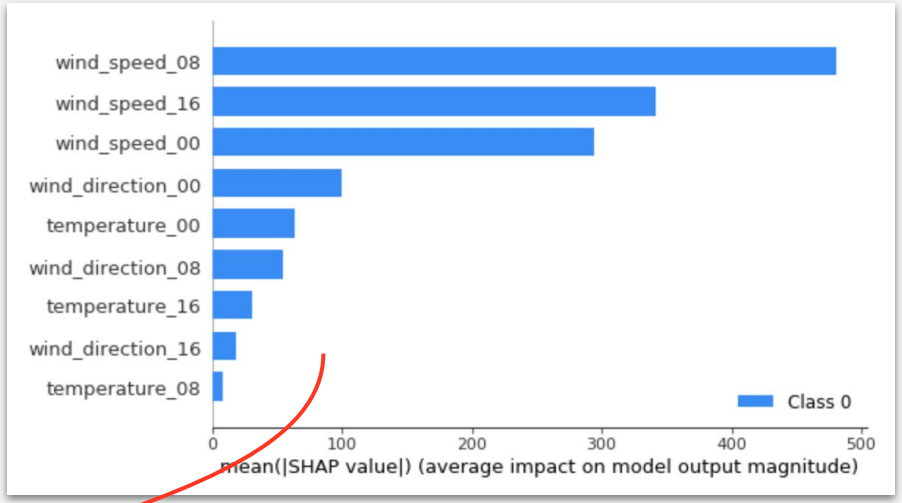
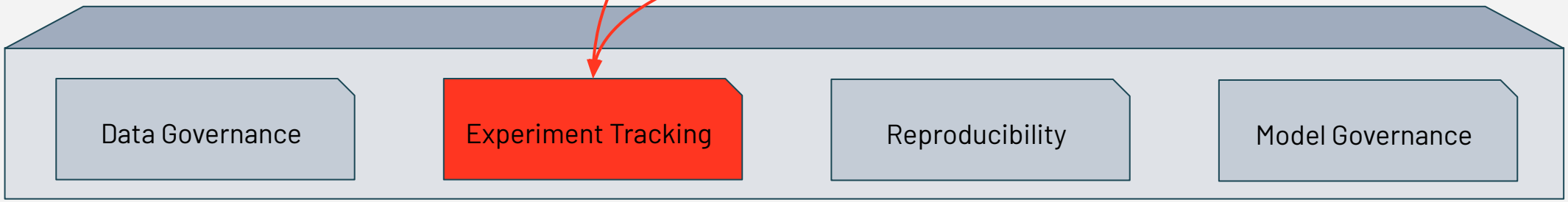
Automated Model Interpretability





Model Interpretability



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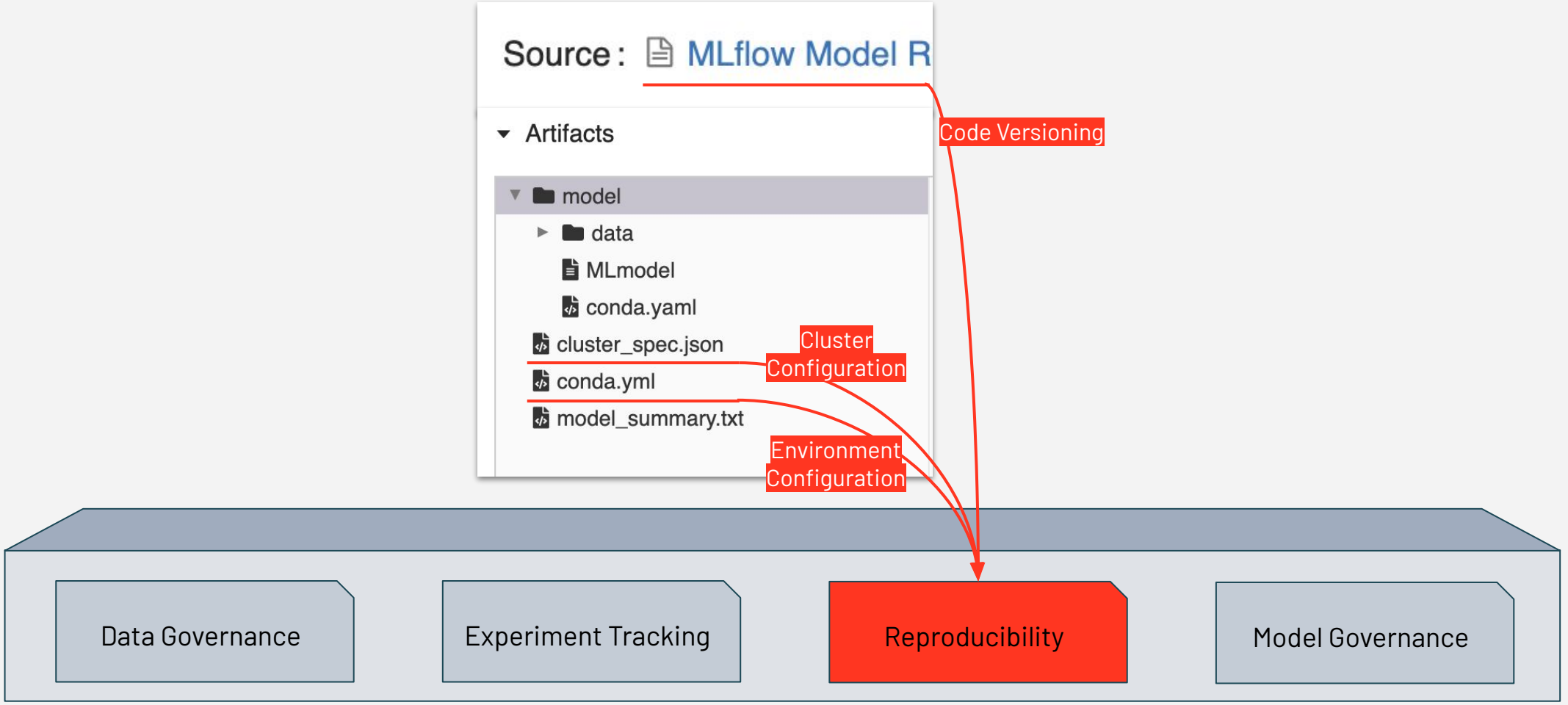
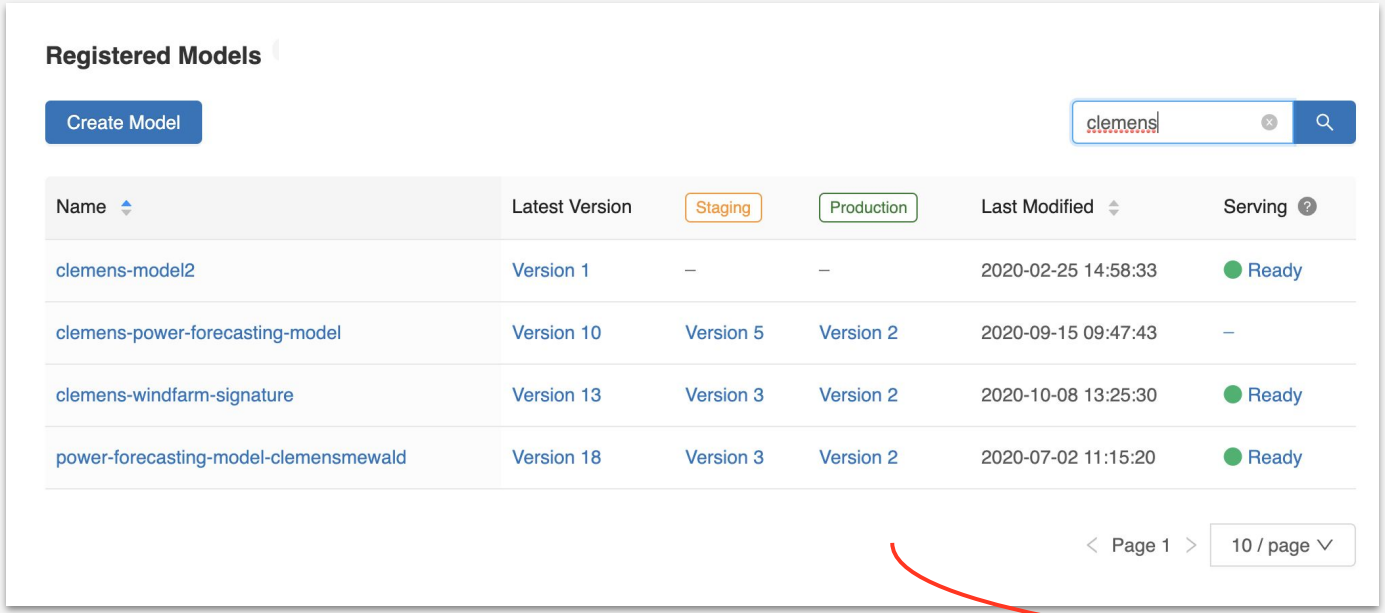
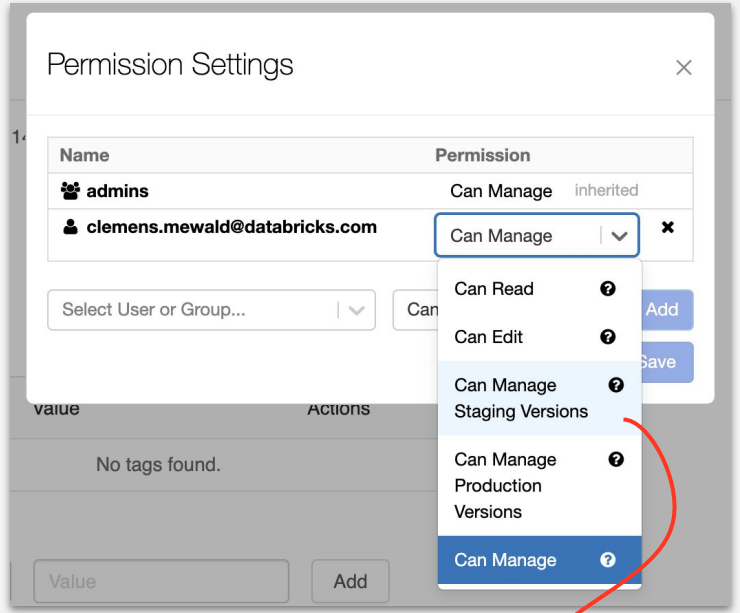
Automated capture of Code, Environment and Cluster Specification



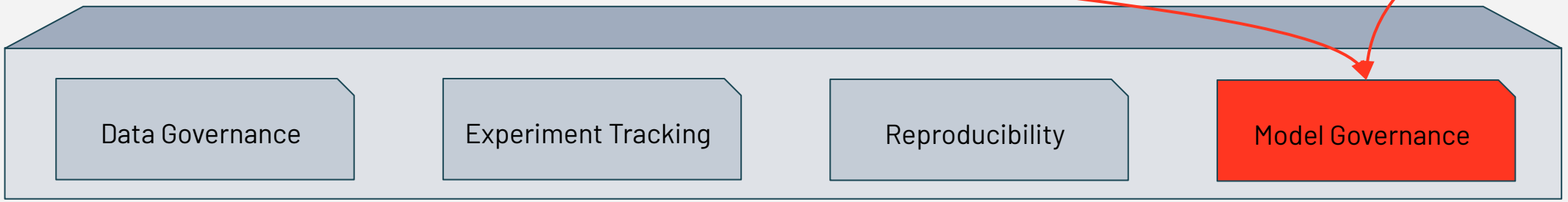
Model Sharing, Reuse, and ACLs





Model Discoverability

Model Stage-Based ACLs



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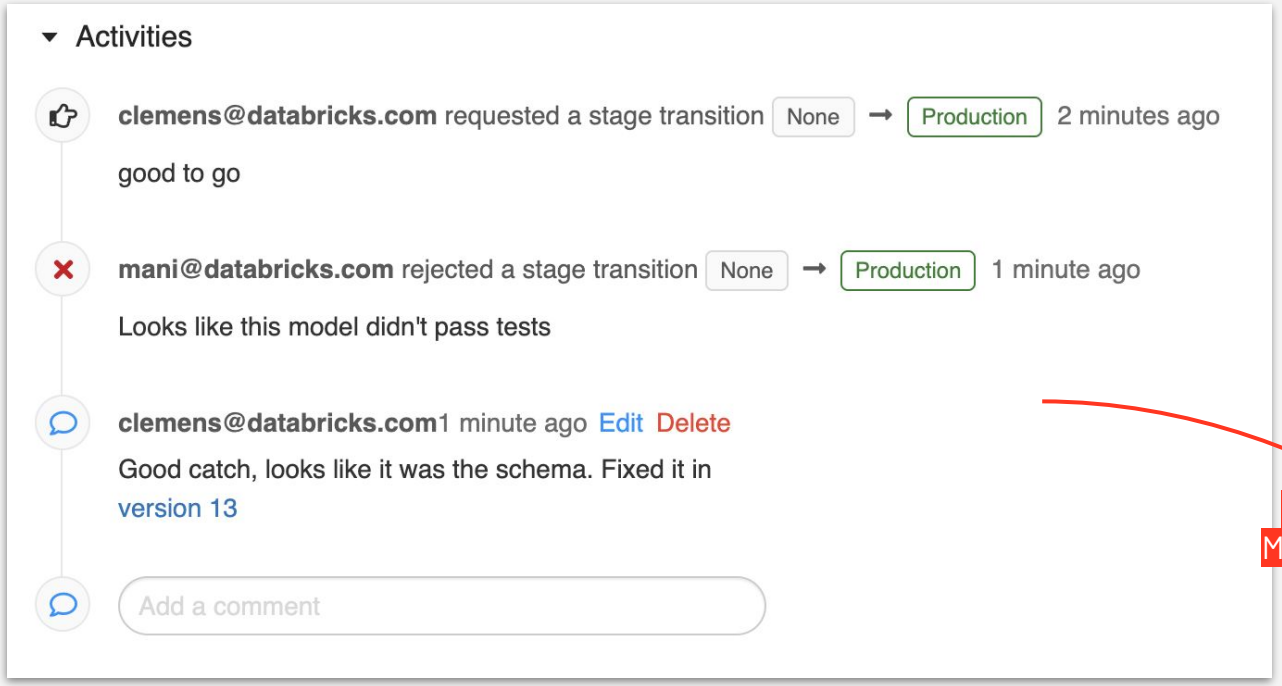
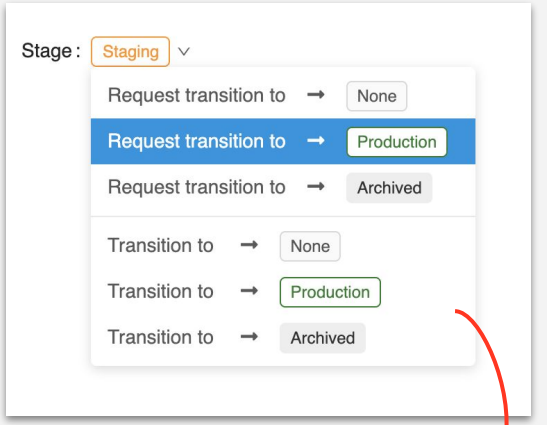
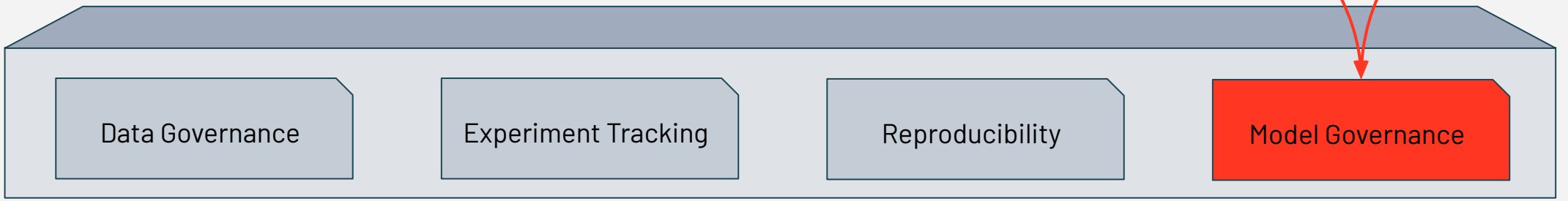
Automated Model Lineage and Governance





Audit Log of Model Changes

Approval Process for Stage Transitions



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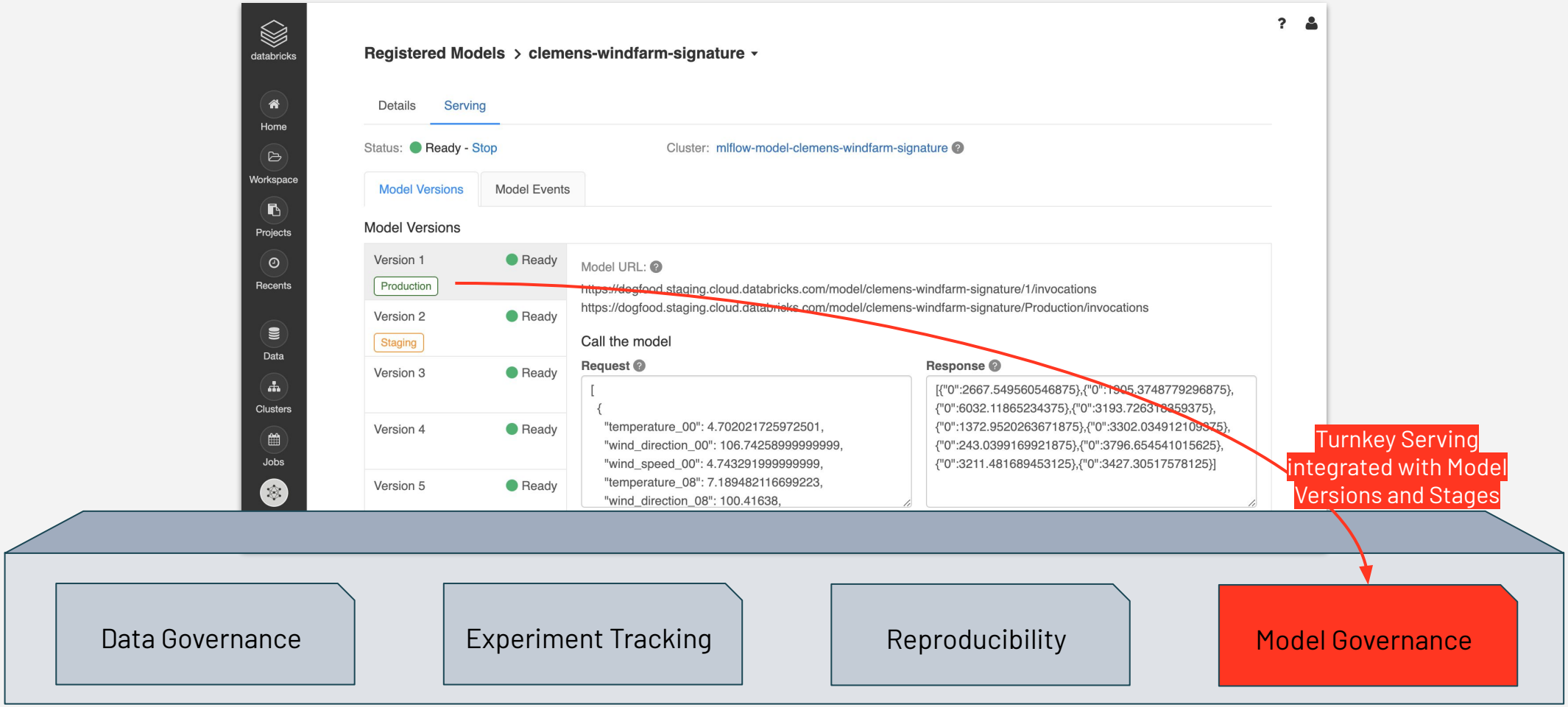
Turnkey Model Serving



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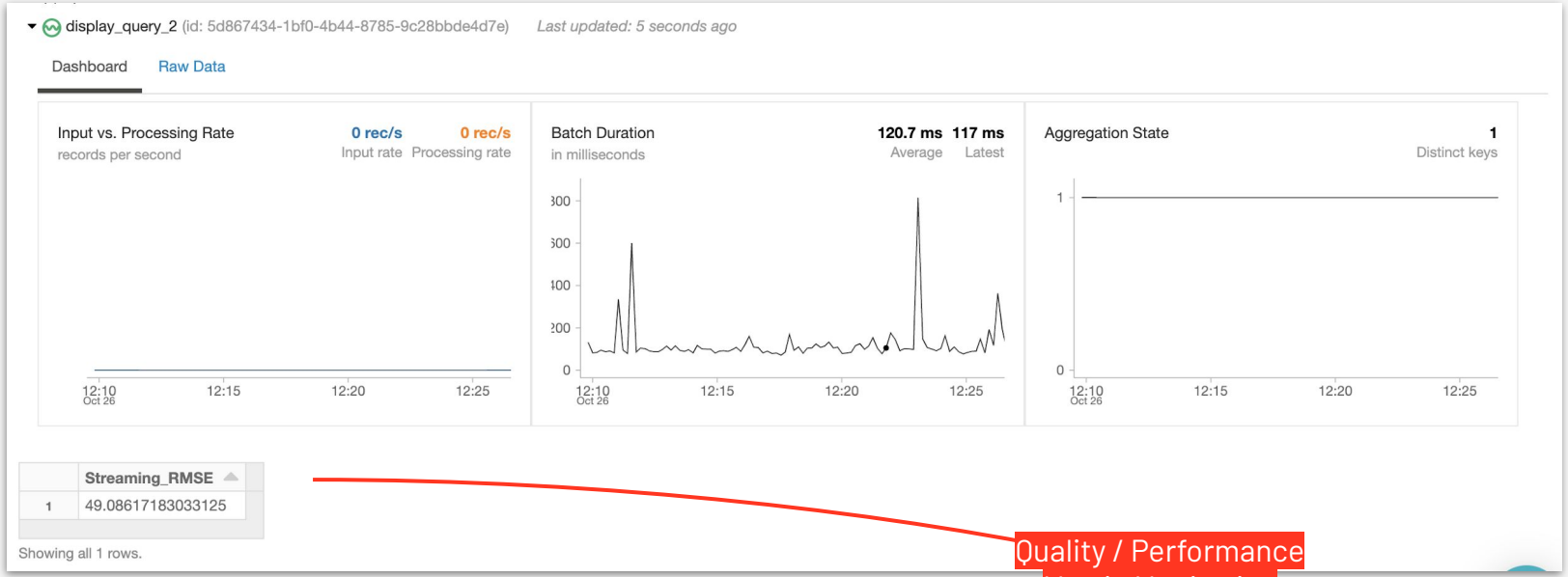
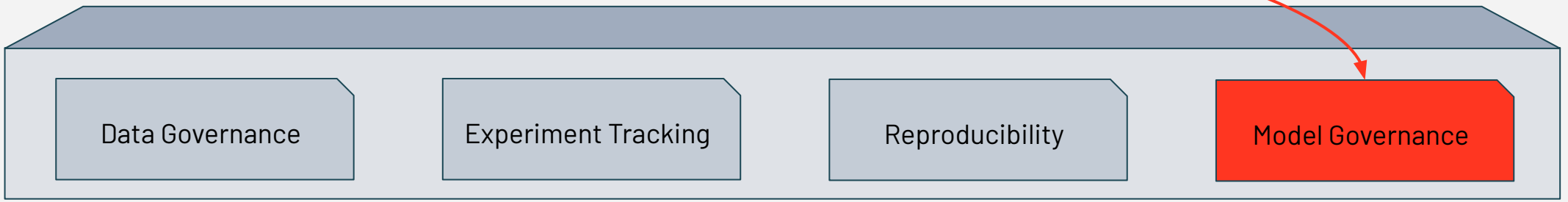
Model Quality monitoring



Quality / Performance Metric Monitoring



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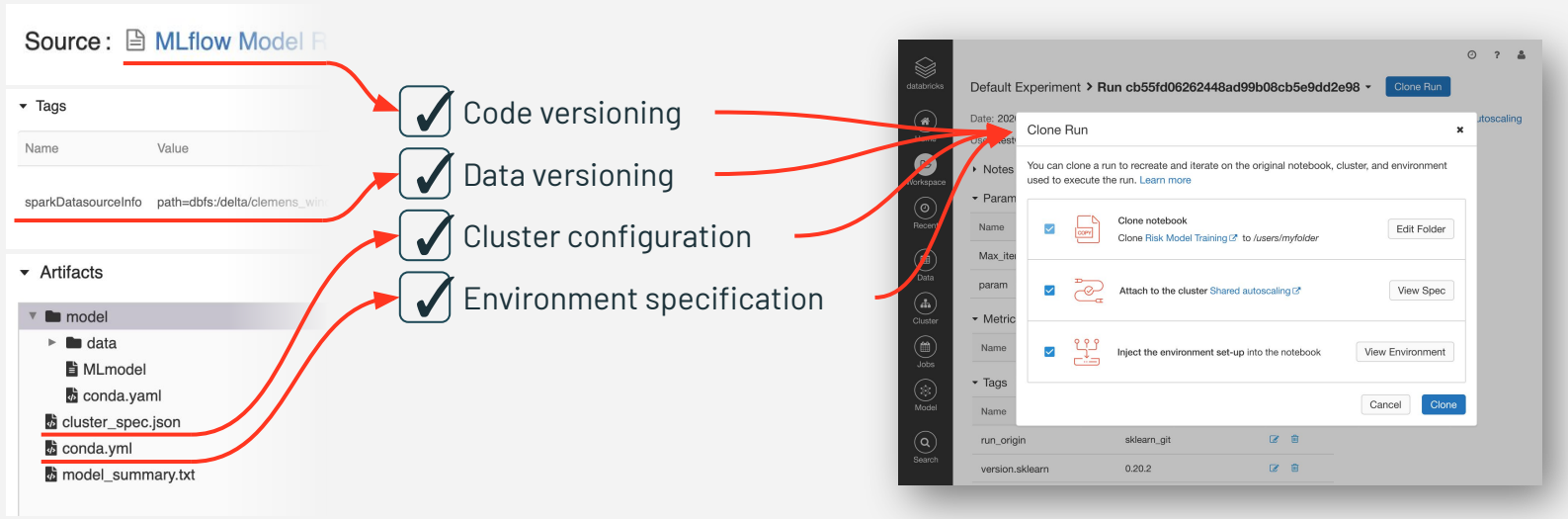
The Result: Full End-to-End Governance and Reproducibility

Auto-Logging | **Reproducibility Checklist** | **Reproduce Run Feature**



Data Governance | Experiment Tracking | Reproducibility | Model Governance

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The Databricks ML Platform