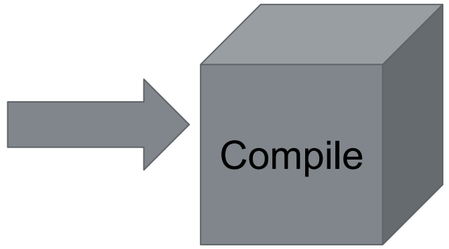
TFX Walkthrough

```
import kfp
```

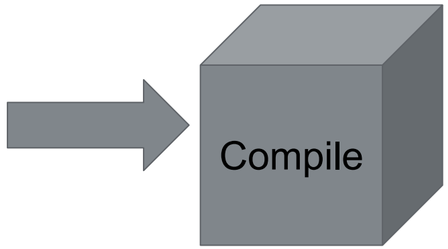
```
kfp_pipeline.py
```



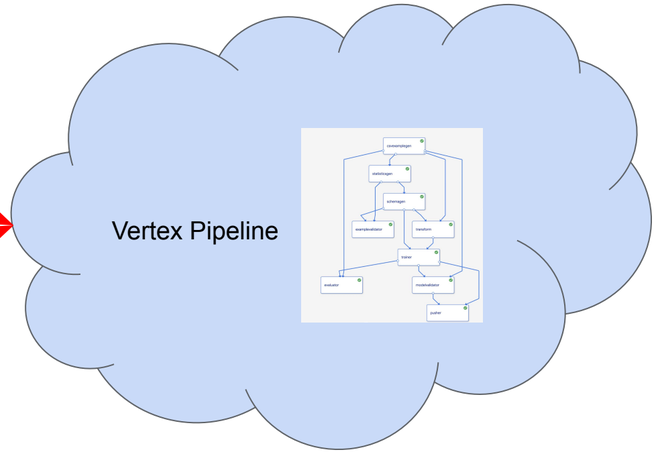

```
kfp_pipeline.json
```

```
import tfx
```

```
tfx_pipeline.py
```

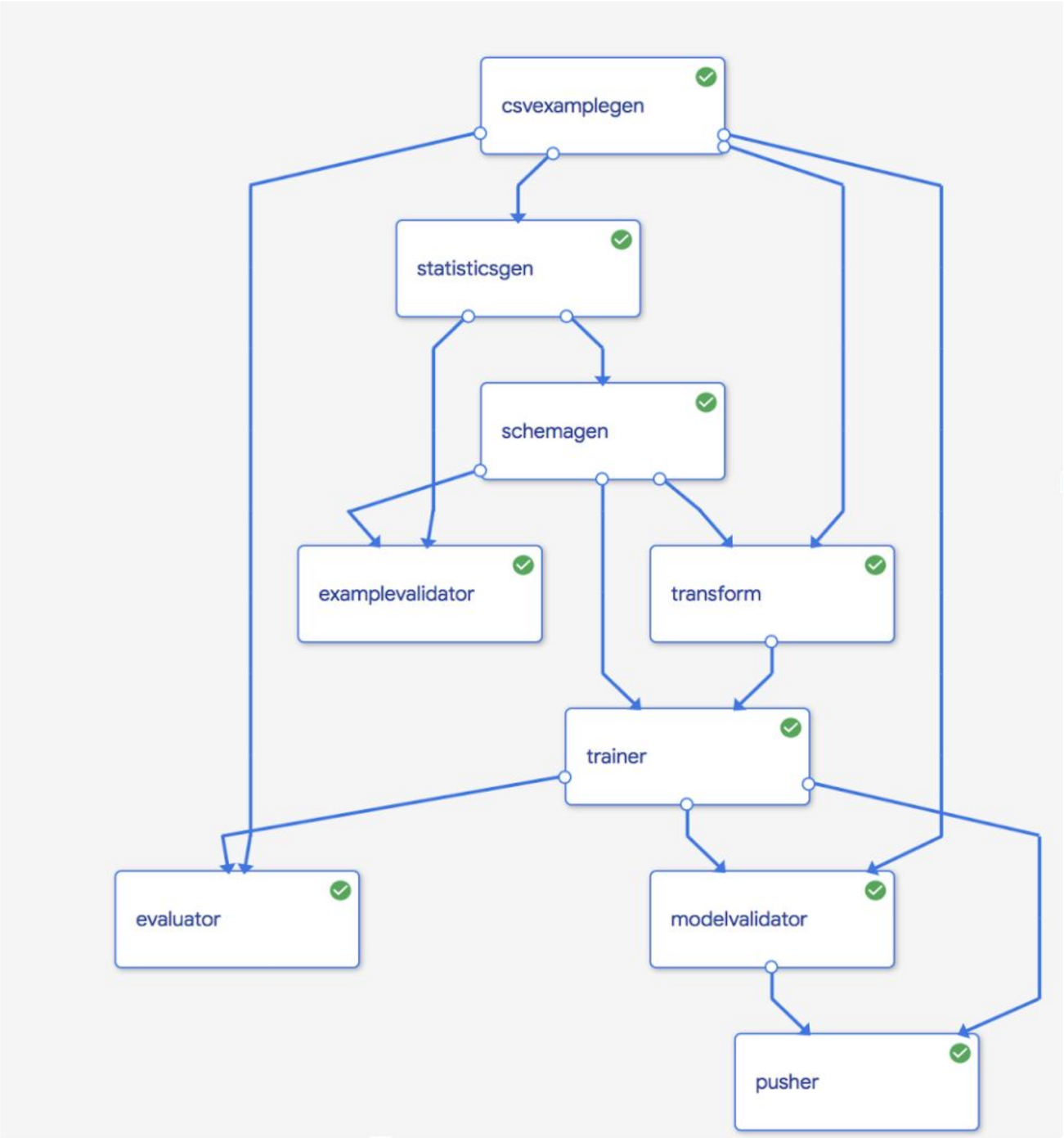



```
tfx_pipeline.json
```



Google Cloud

- Pre-built ML pipeline from Google Best Practices
- Each component can run individually in the notebook for debugging purposes!



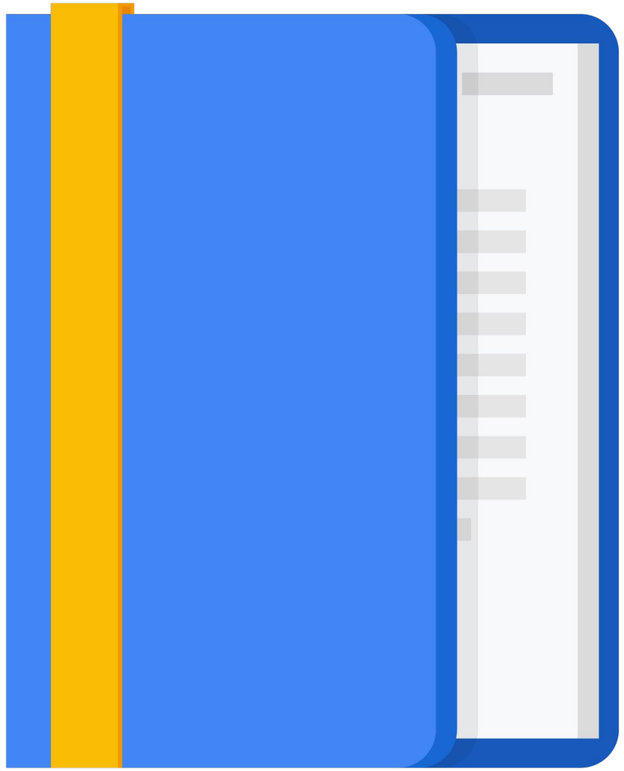
Google Cloud

Agenda

TensorFlow Extended (TFX)

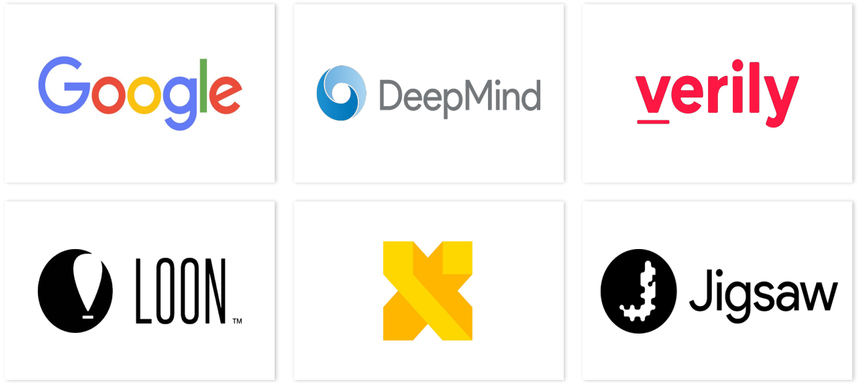
TFX standard components

TFX libraries

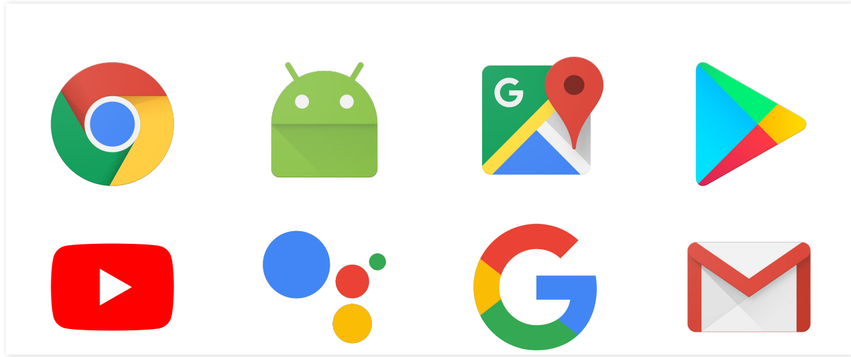


TFX powers Alphabets most important bets and products

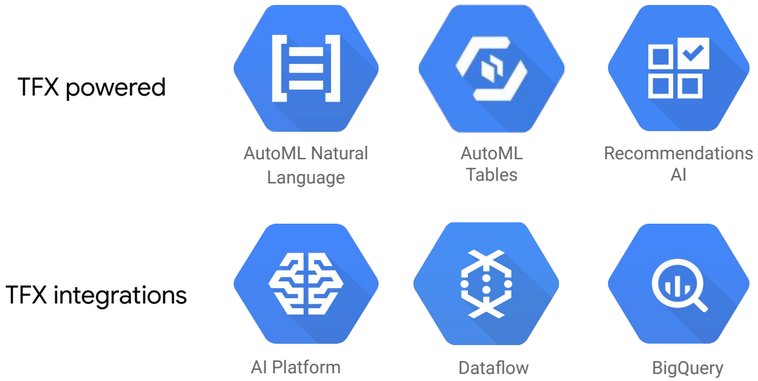
AlphaBets



Google Products

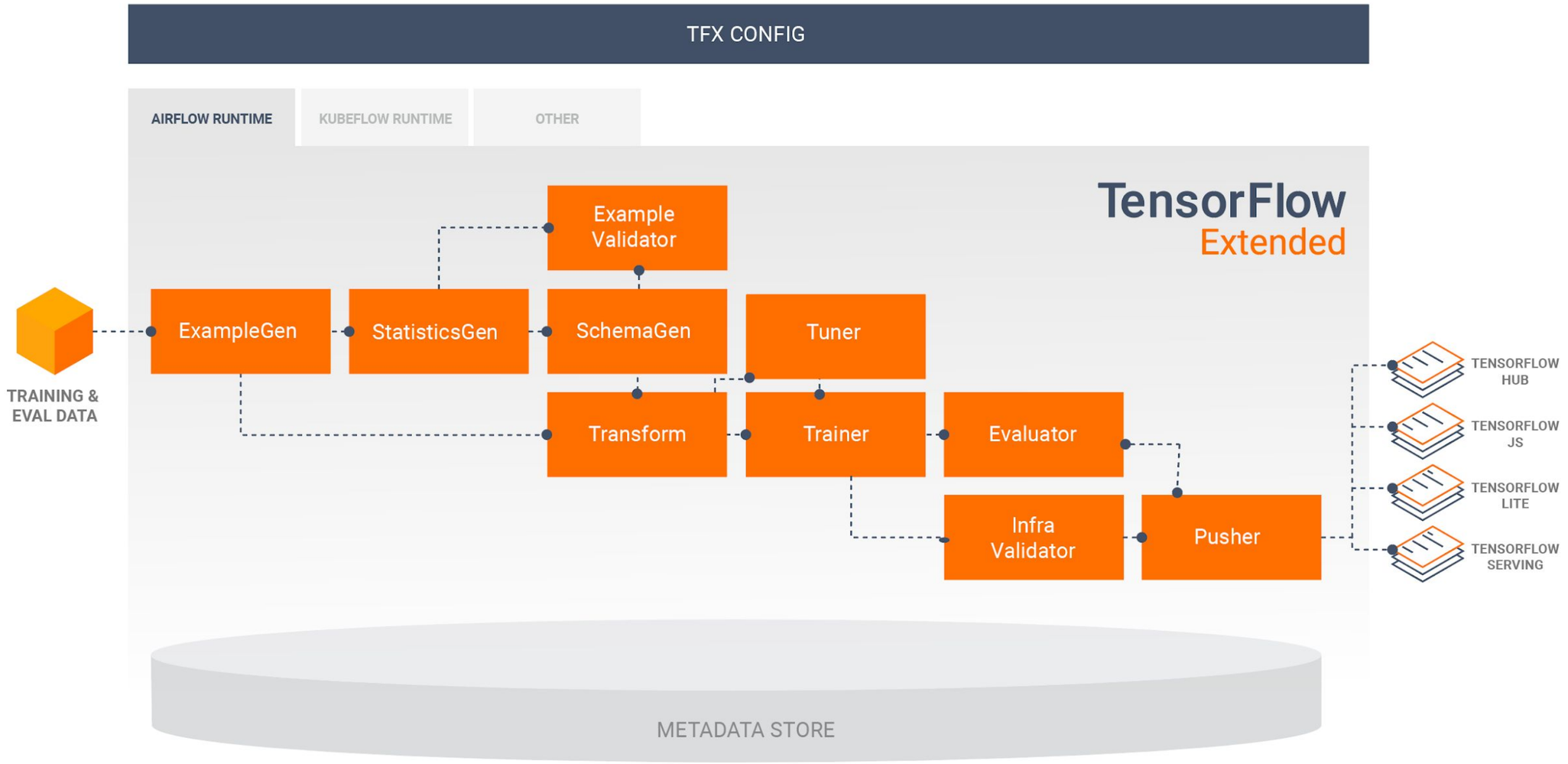


Google Cloud AI Products



Google Cloud

TFX: Google's production machine learning platform



OSS TFX enables global ML use cases

"... we have re-tooled our machine learning platform to use TensorFlow. This yielded significant productivity gains while positioning ourselves to take advantage of the latest industry research."

Ranking Tweets with TensorFlow - Twitter

https://goo.gle/tf-twitter-rank

Spotify	SAP Concur	Etsy
Airbus	Twitter	PayPal
Tencent	NetEase	Yahoo Japan
	JD.Com	

TFX's Lineage

Sibyl

(2007 - 2019) goo.gle/sibyl-video

User Focused, Production ML, Massive Scale, (Somewhat) Flexible.

Once upon a time, one of the most widely used E2E ML platforms at Google.

TFX

(2016 - Present) tensorflow.org/tfx

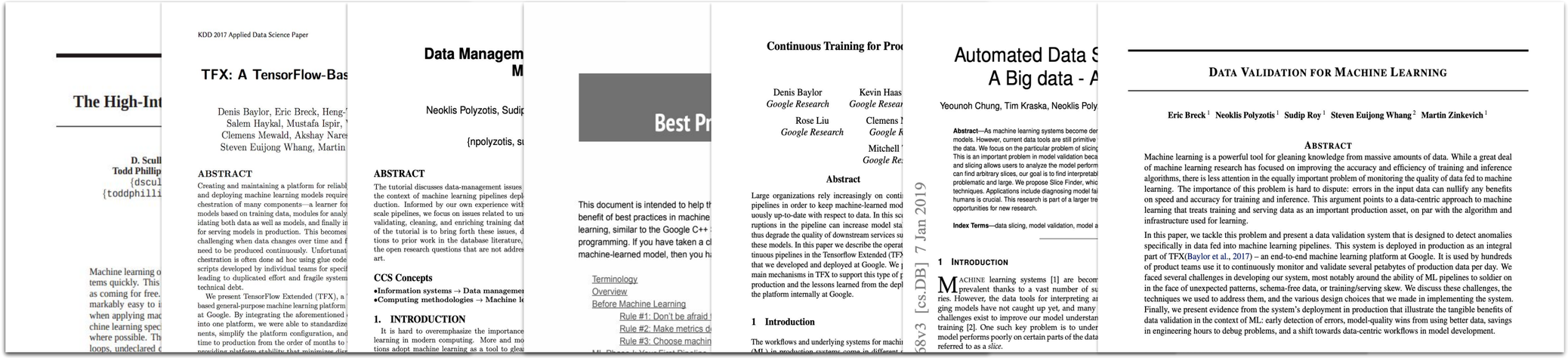
User Focused, Production ML, Massive Scale, **Flexible, Modular, Portable, Substrate-y.**

The most widely used E2E ML platform at **Alphabet** (including Google).

E2E OSS ML platform **OnPrem** and on **GCP**

TFX has Google's ML best practices built in

Machine Learning: The High Interest Credit Card of Technical Debt. NeurIPS (2015).
TFX: A TensorFlow-Based Production-Scale Machine Learning Platform. KDD (2017).
Data Management Challenges in Production Machine Learning. SIGMOD (2017).
Rules of Machine Learning: Best Practices for ML Engineering. Google AI Web (2017).
Continuous Training for Production ML in the TFX Platform. OpML (2019).
Slice Finder: Automated Data Slicing for Model Validation. ICDE (2019).
Data Validation for Machine Learning. SysML (2019).



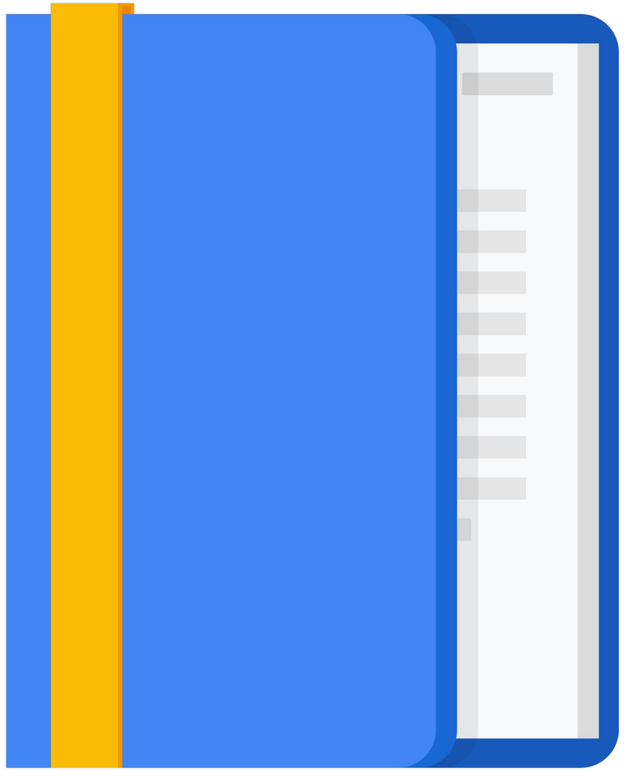
Google Cloud

Agenda

TensorFlow Extended (TFX)

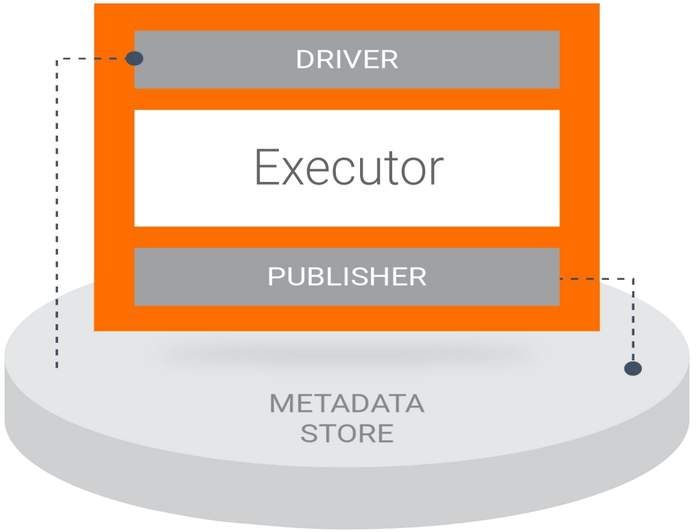
TFX standard components

TFX libraries



A TFX **component** implements a machine learning task

TFX standard components



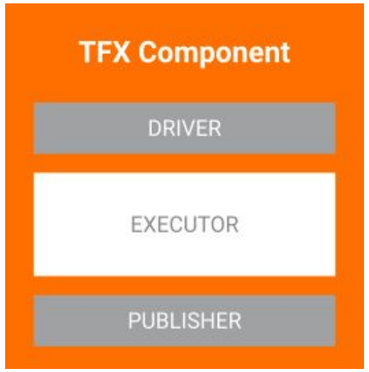
Compose ML pipelines faster with reusable components
pre-configured with production best practices

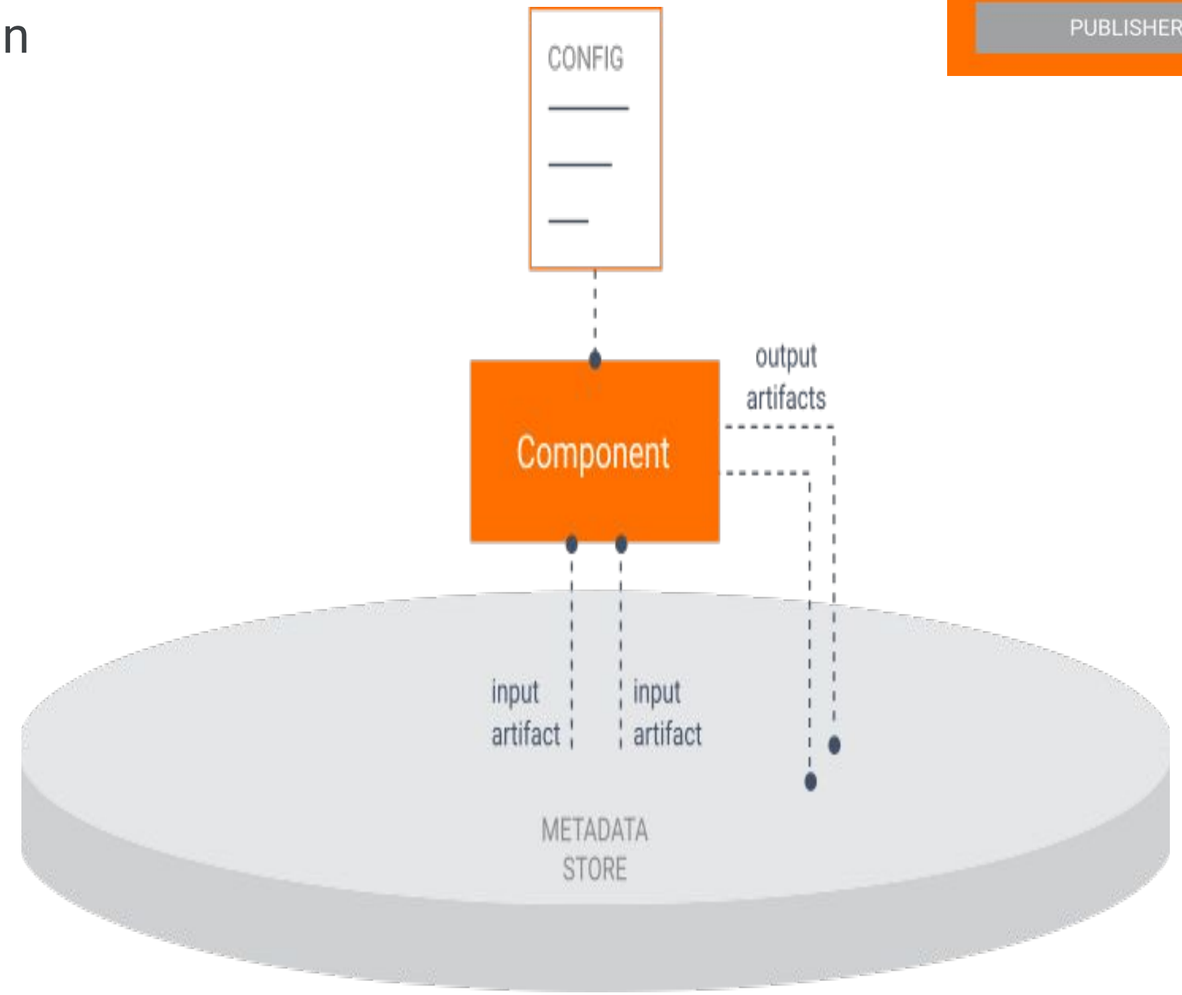
TFX **components** at runtime

1. **Driver** reads the component specification for parameters and artifacts and retrieves input artifacts from metadata store for the component.

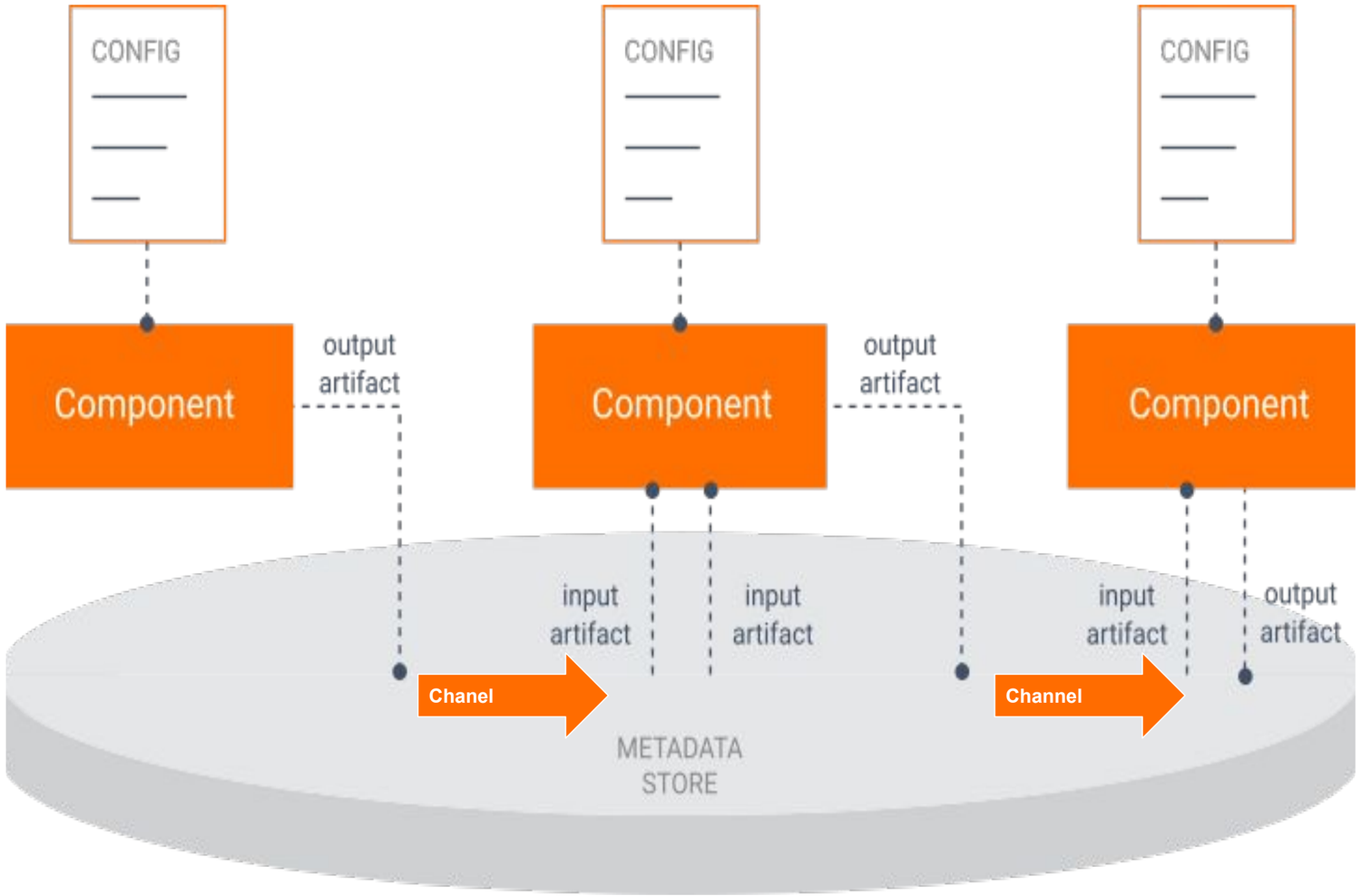
2. **Executor** performs computation on artifacts

3. **Publisher** uses the component specification and executor results to store component's output artifacts in metadata store.



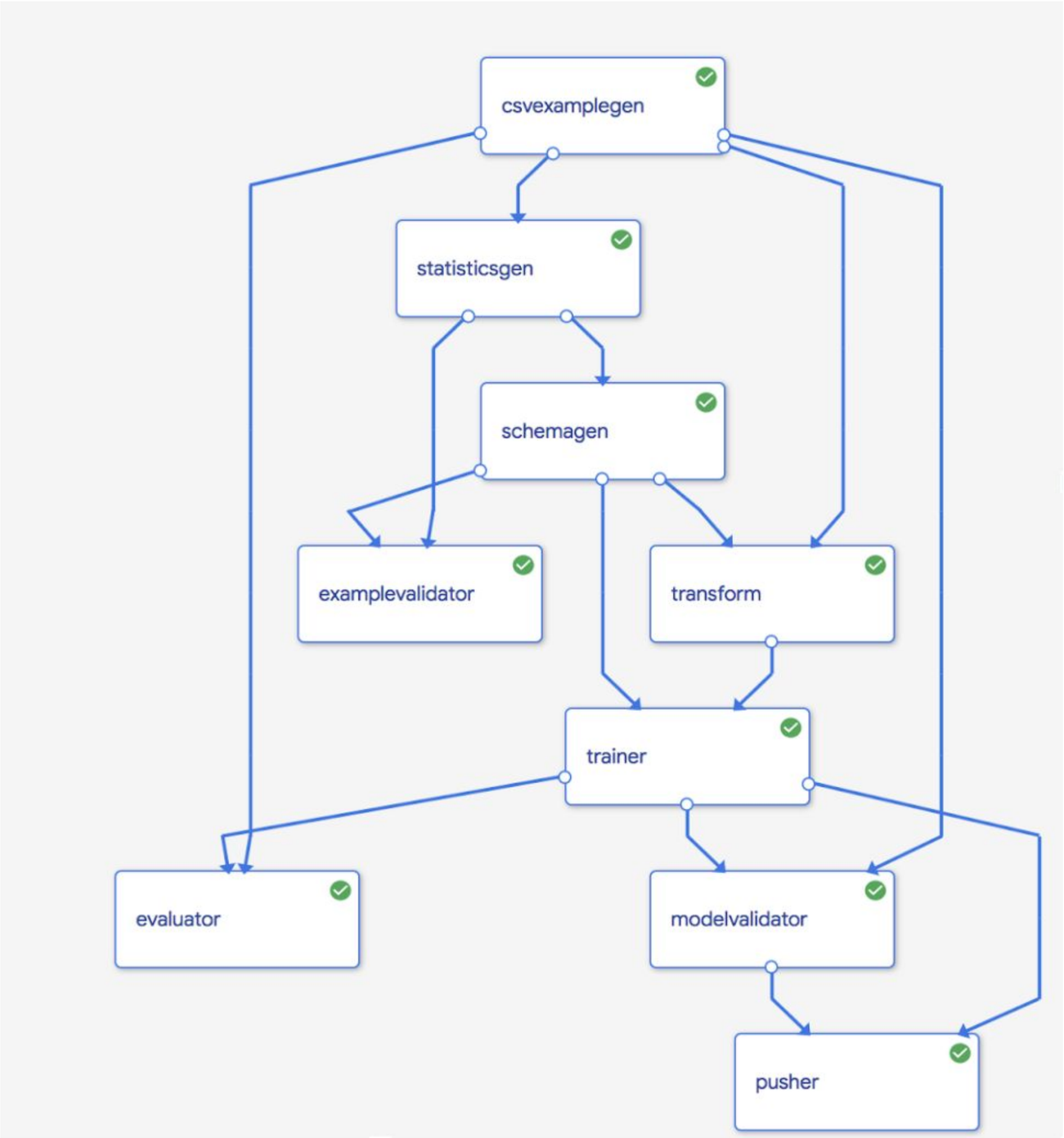


A TFX **pipeline** is a sequence of **components** connected by **channels** in a directed acyclic graph (DAG) of **artifact** dependencies



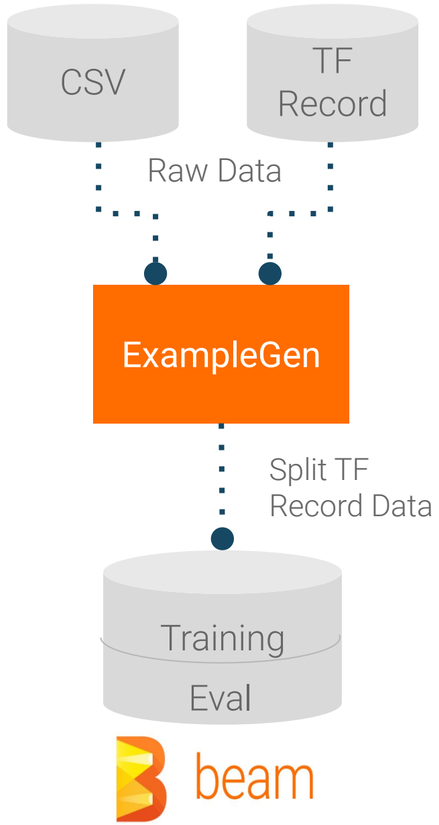
Google Cloud

There is a fixed number of TFX components.



Component: **ExampleGen**

Inputs and Outputs



Configuration

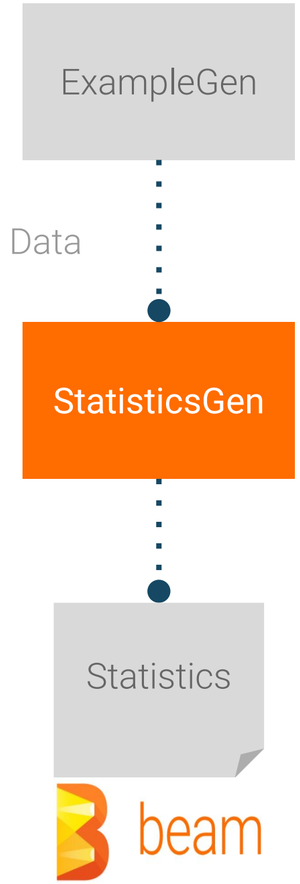
```
output_config = example_gen_pb2.Output(
    split_config=example_gen_pb2.SplitConfig(splits=[
        example_gen_pb2.SplitConfig.Split(name='train', hash_buckets=4),
        example_gen_pb2.SplitConfig.Split(name='eval', hash_buckets=1)
    ])
)


example_gen = tfx.components.CsvExampleGen(
    input=external_input(DATA_ROOT),
    output_config=output_config
).with_id("CsvExampleGen")
```

ML project lifecycle benefits

- Reproducible and configurable data partitioning and shuffling into common data representation
- External CSV, Avro, Parquet, BigQuery, and TFRecord ingestion
- Apache Beam supported for scalable data ingestion
- Customizable to new input data formats and ingestion methods

Component: **StatisticsGen**

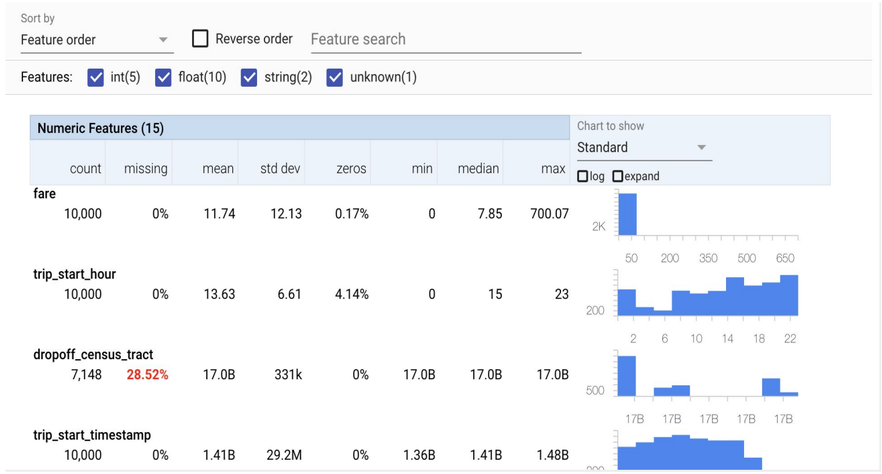
Inputs and Outputs



Configuration

```
statistics_gen = tfx.components.StatisticsGen(
    examples=example_gen.outputs['examples']).with_id("StatisticsGen")
```

TFDV Feature Statistics Visualization



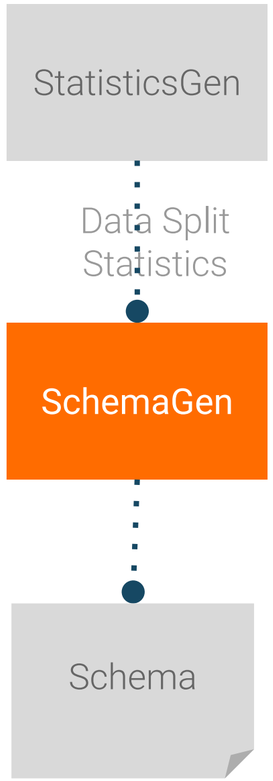
ML project lifecycle benefits

- TensorFlow Data Validation (TFDV) library for calculating feature statistics
- Scalable full-pass dataset feature statistics processing with Apache Beam

Google Cloud

Component: **SchemaGen**

Inputs and Outputs



Configuration

```
schema_gen = tfx.components.SchemaGen(
    statistics=statistics_gen.outputs['statistics'],
    infer_feature_shape=False).with_id("SchemaGen")
```

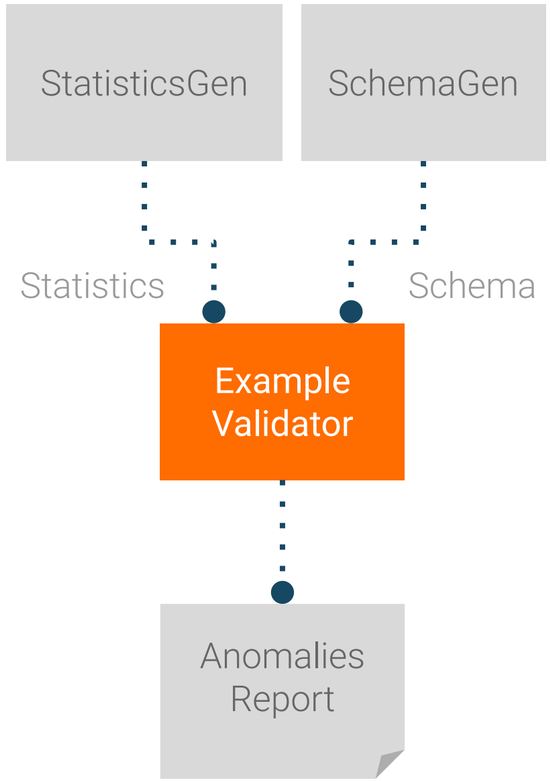
Feature name	Type	Presence	Valency	Domain
'fare'	FLOAT	required	single	-
'trip_start_hour'	INT	required	single	-
'pickup_census_tract'	BYTES	optional		-
'dropoff_census_tract'	FLOAT	optional	single	-
'company'	STRING	optional	single	'company'

ML project lifecycle benefits

- **TensorFlow Data Validation (TFDV)** creates common data description for pipeline components
- A Schema enables continuous data monitoring and validation during pipeline training

Component: **ExampleValidator**

Inputs and Outputs



Configuration

```
example_validator = tfx.components.ExampleValidator(
    statistics=statistics_gen.outputs['statistics'],
    schema=schema_importer.outputs['result'],
).with_id("ExampleValidator")
```

Visualization

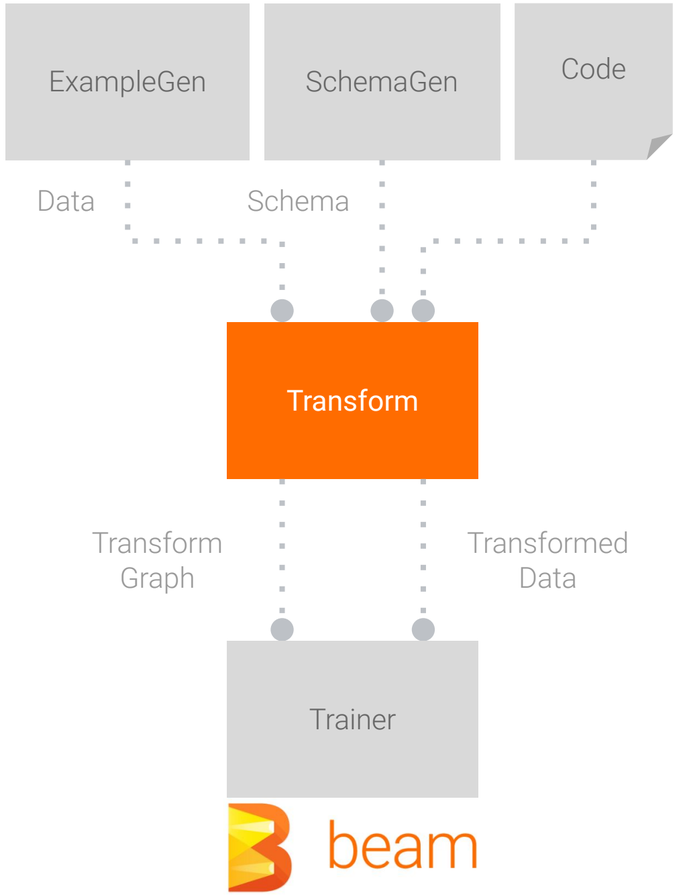
Feature name	Anomaly short description	Anomaly long description
'payment_type'	Unexpected string values	Examples contain values missing from the schema: Prcard (<1%).
'company'	Unexpected string values	Examples contain values missing from the schema: 2092 - 61288 Sbeih company (<1%), 2192 - 73487 Zeymane Corp (<1%), 2192 - Zeymane Corp (<1%), 2823 - 73307 Seung Lee (<1%), 3094 - 24059 G.L.B. Cab Co (<1%), 3319 - CD Cab Co (<1%), 3385 - Eman Cab (<1%), 3897 - 57856 Ilie Malec (<1%), 4053 - 40193 Adwar H. Nikola (<1%), 4197 - Royal Star (<1%), 585 - 88805 Valley Cab Co (<1%), 5874 - Sergey Cab Corp. (<1%), 6057 - 24657 Richard Addo (<1%), 6574 - Babylon Express Inc. (<1%), 6742 - 83735 Tasha ride inc (<1%).

ML project lifecycle benefits

- Data monitoring for detection of anomalies, train-serving skew, and data drift

Component: **Transform**

Inputs and Outputs



Configuration

```
transform = tfx.components.Transform(
    examples=example_gen.outputs['examples'],
    schema=schema_importer.outputs['result'],
    module_file=TRANSFORM_MODULE).with_id("Transform")
```

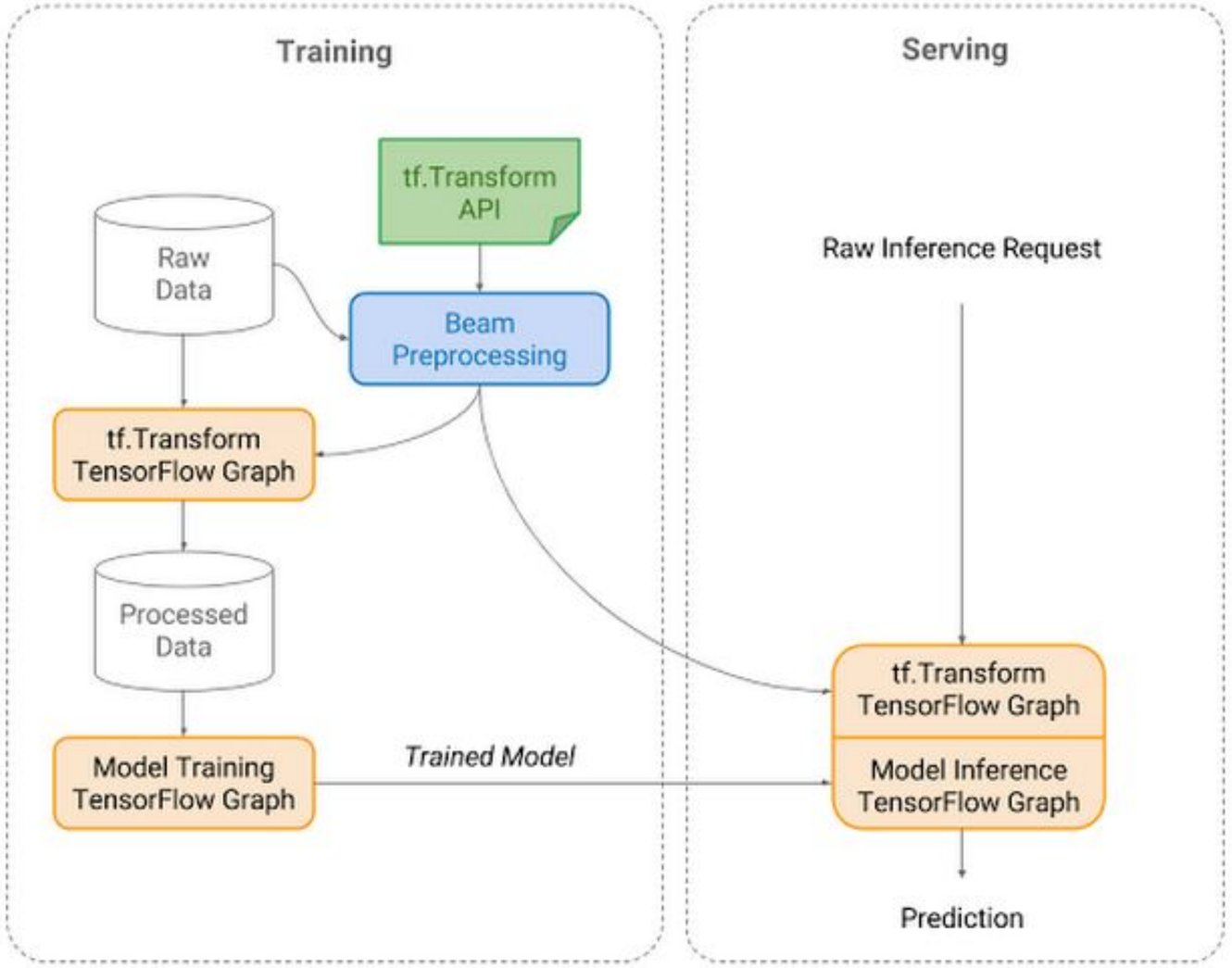
TRANSFORM_MODULE='preprocessing.py'

```
def preprocessing_fn(inputs):

  outputs = {}

  # Scale numerical features
  for key in features.NUMERIC_FEATURE_KEYS:
    outputs[features.transformed_name(key)] = tft.scale_to_z_score(
        _fill_in_missing(inputs[key]))

  # Generate vocabularies and maps categorical features
  for key in features.CATEGORICAL_FEATURE_KEYS:
    outputs[features.transformed_name(key)] = tft.compute_and_apply_vocabulary(
        x=_fill_in_missing(inputs[key]), num_oov_buckets=1, vocab_filename=key)

  outputs[features.transformed_name(features.LABEL_KEY)] = _fill_in_missing(
      inputs[features.LABEL_KEY])

  return outputs
```

Component: **Transform**

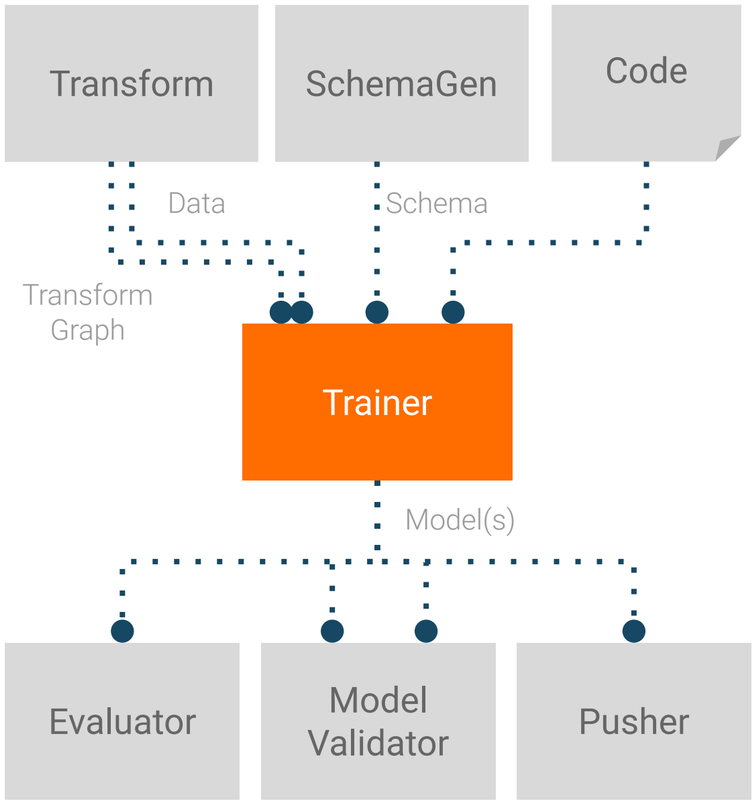
ML project lifecycle benefits

- Generates SavedModel for consistent training and serving feature engineering
- Backed by Apache Beam for scalable distributed data processing to large datasets



Component: **Trainer**

Inputs and Outputs



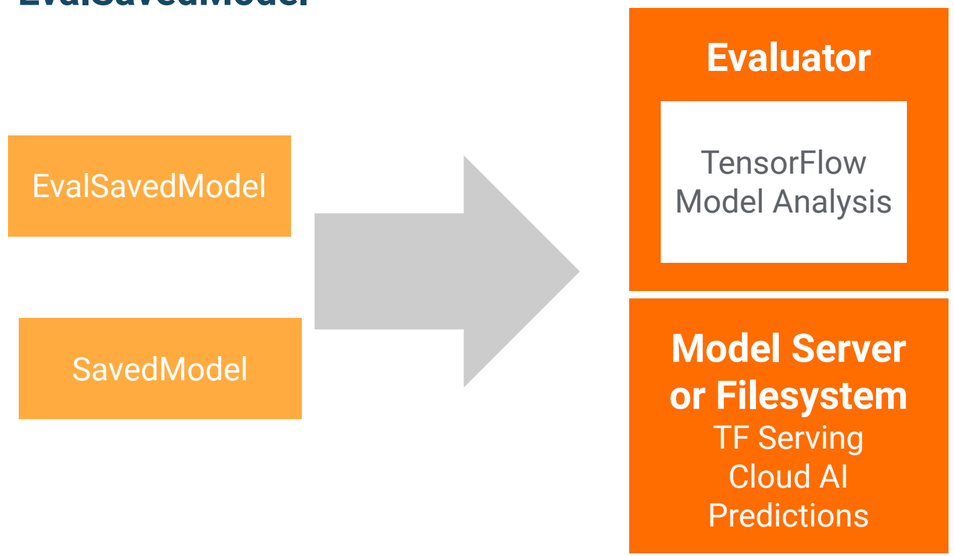

```
executor =
executor_spec.ExecutorClassSpec(trainer_executor.GenericExecutor)


trainer = tfx.components.Trainer(
    custom_executor_spec=executor,
    module_file=model.py,
    transformed_examples=transform.outputs["transformed_examples"],
    schema=schema_importer.outputs["result"],
    transform_graph=transform.outputs["transform_graph"],
    train_args=trainer_pb2.TrainArgs(num_steps=5000),
    eval_args=trainer_pb2.EvalArgs(num_steps=1000)
).with_id("Trainer")
```

Code -> your TensorFlow code in a pipeline/models/model.py

Google Cloud

Component: **Trainer**

Trainer outputs a trained **SavedModel** and **EvalSavedModel**

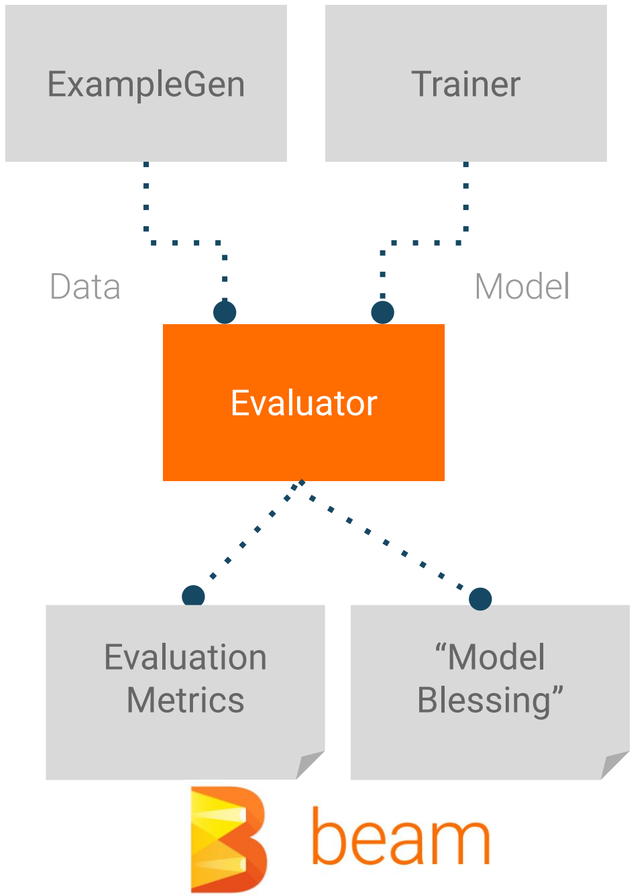


ML project lifecycle benefits

- Produces standardized TensorFlow SavedModel model artifact for sharing and easier deployment
- Configurable with Generic Trainer for any TensorFlow model API such Estimator, tf.Keras, and TFLite

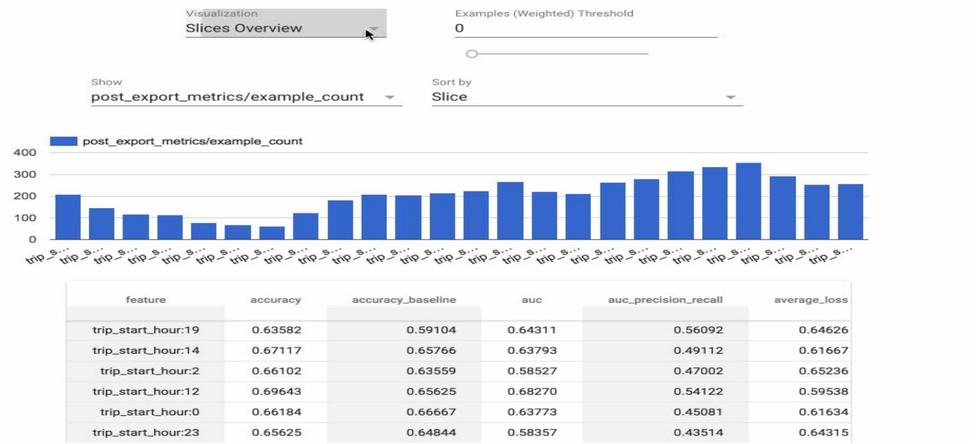
Component: **Evaluator**

Inputs and Outputs




```
model_analyzer = tfx.components.Evaluator(
    examples=example_gen.outputs[“examples”],
    model=trainer.outputs[“model”],
    baseline_model=model_resolver.outputs[“model”],
    eval_config=eval_config).with_id("ModelEvaluator")
```

TensorFlow Model Analysis (TFMA) library for visualizing model evaluation



feature	accuracy	accuracy_baseline	auc	auc_precision_recall	average_loss
trip_start_hour:19	0.63582	0.59104	0.64311	0.56092	0.64626
trip_start_hour:14	0.67117	0.65766	0.63793	0.49112	0.61667
trip_start_hour:2	0.66102	0.63559	0.58527	0.47002	0.65236
trip_start_hour:12	0.69643	0.65625	0.68270	0.54122	0.59538
trip_start_hour:0	0.66184	0.66667	0.63773	0.45081	0.61634
trip_start_hour:23	0.65625	0.64844	0.58357	0.43514	0.64315

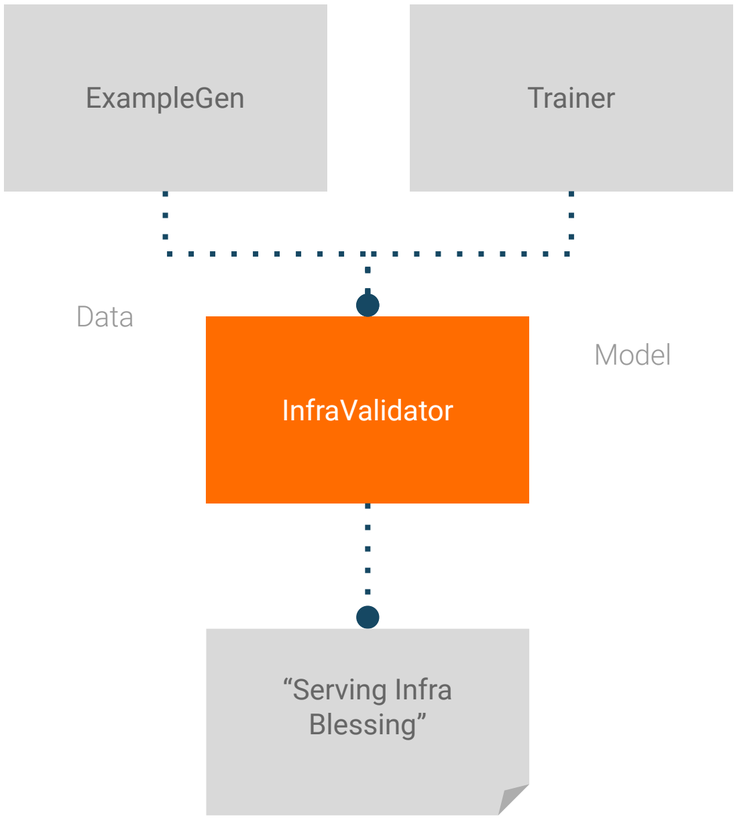
ML project lifecycle benefits

- Uses TensorFlow Model Analysis (TFMA) and Apache Beam for scalable model evaluation across data splits and slices.
- Validate model performance “good enough” to be pushed to production

Google Cloud

Component: **InfraValidator**

Inputs and Outputs




```
infra_validator = tfx.components.InfraValidator(
    model=trainer.outputs['model'],
    examples=example_gen.outputs['examples'],
    serving_spec=infra_validator_pb2.ServingSpec(...),
    validation_spec=infra_validator_pb2.ValidationSpec(...),
    request_spec=infra_validator_pb2.RequestSpec(...)
).with_id("ModelInfraValidator")
```

Configuration options

ServingSpec: Type of model server and infrastructure to test with e.g. TF Serving

ValidationSpec: Adjusts the infra validation criteria or workflow.

RequestSpec: Which model signature, how many examples to test.

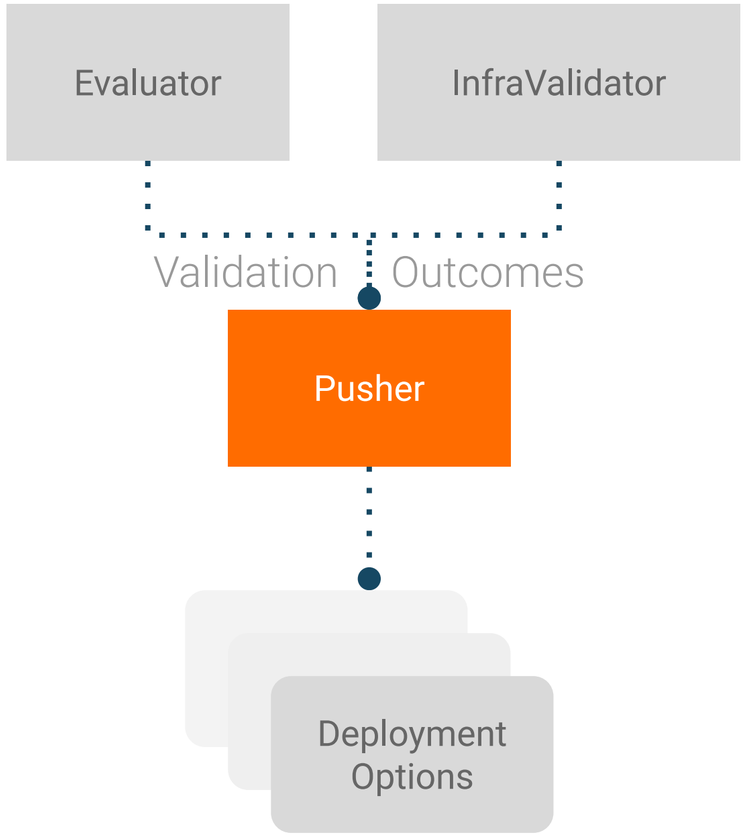
ML project lifecycle benefits

- Validate model in model serving environment before pushing to production
- Configurable to mirror different model serving environments such as Kubernetes and TF Serving

Google Cloud

Component: **Pusher**

Inputs and Outputs

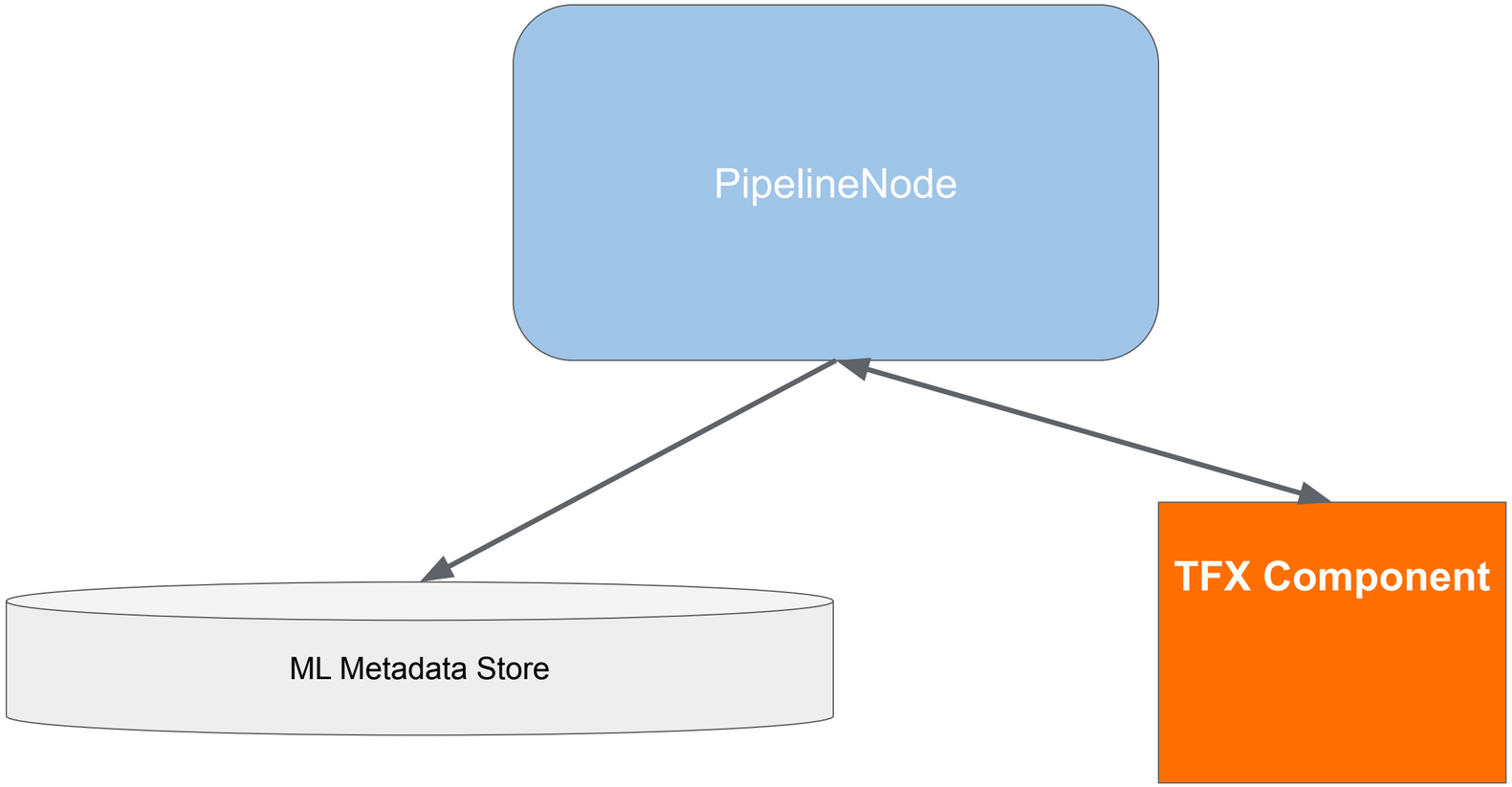



```
pusher = tfx.components.Pusher(
    model=trainer.outputs['model'],
    model_blessing=model_analyzer.outputs['blessing'],
    infra_blessing=infra_validator.outputs['blessing'],
    push_destination=pusher_pb2.PushDestination(
        filesystem=pusher_pb2.PushDestination.Filesystem(
            base_directory=SERVING_MODEL_DIR))
).with_id("ModelPusher")
```

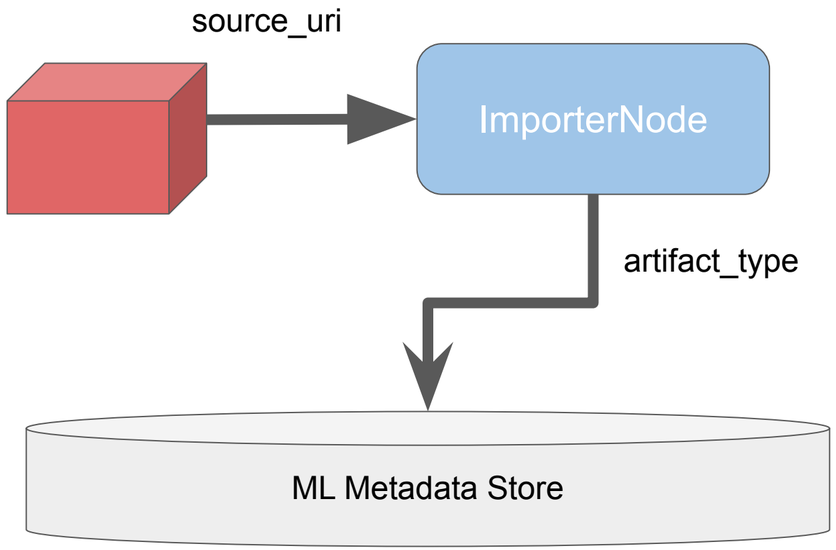
ML project lifecycle benefits

- Validation checks on model performance and serving ability before pushing to production.
- Reusable model export code that is configurable for different push destinations:
  - Filesystem (TensorFlow Lite, TensorFlow JS)
  - Model Server (TensorFlow Serving)

What are Pipeline Nodes?

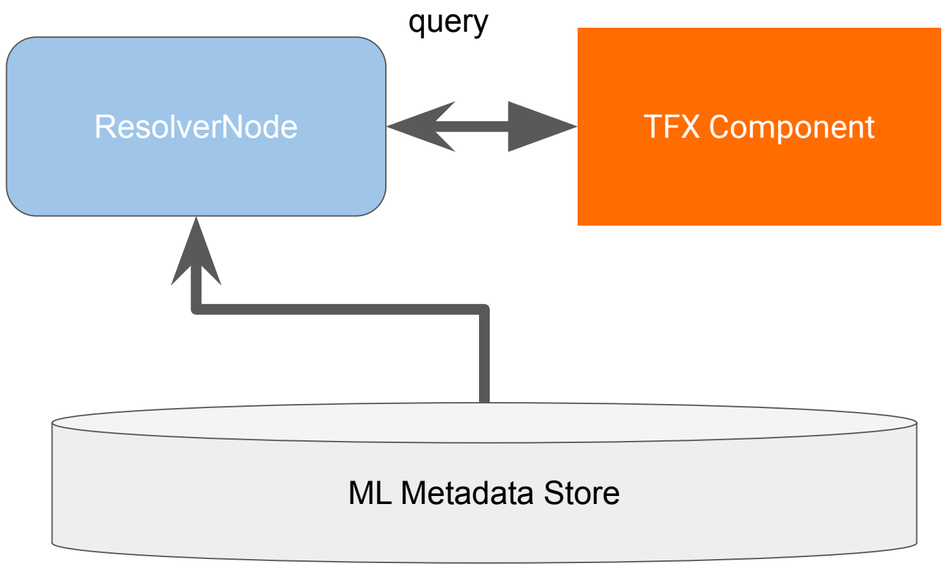


Importer imports an external data object into ML Metadata



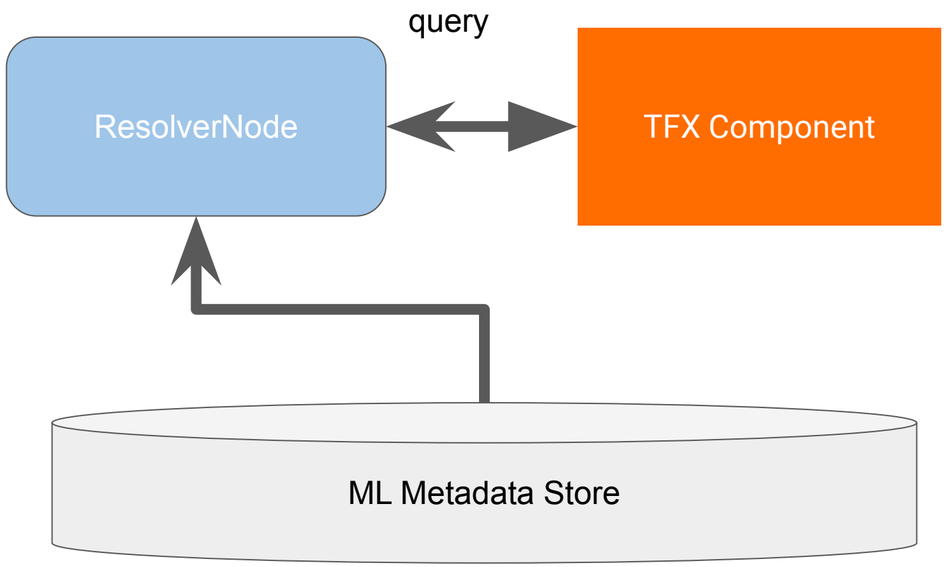

```
importer = tfx.dsl.components.common.importer.Importer(
      source_uri='uri/to/schema'
      artifact_type=standard_artifacts.Schema,
).with_id("SchemaImporter")
```

Resolver performs metadata queries




```
latest_blessed_model = tfx.dsl.components.common.resolver.Resolver(
    strategy_class=LatestBlessedModelStrategy,
    model=Channel(type=tfx.types.standard_artifacts.Model),
    model_blessing=Channel(type=tfx.types.standard_artifacts.ModelBlessing),
).with_id("LatestBlessedModelResolver")
```

Current Resolver



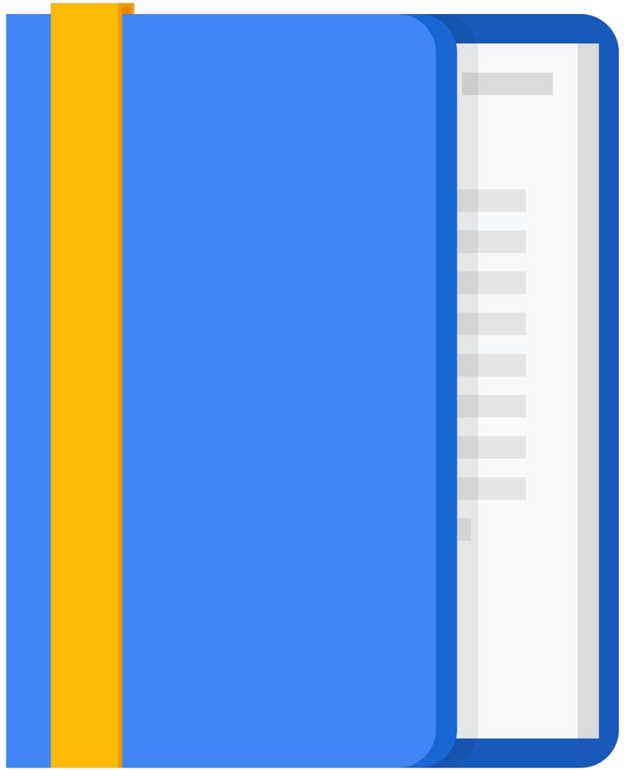
- **LatestBlessedModelStrategy**

Agenda

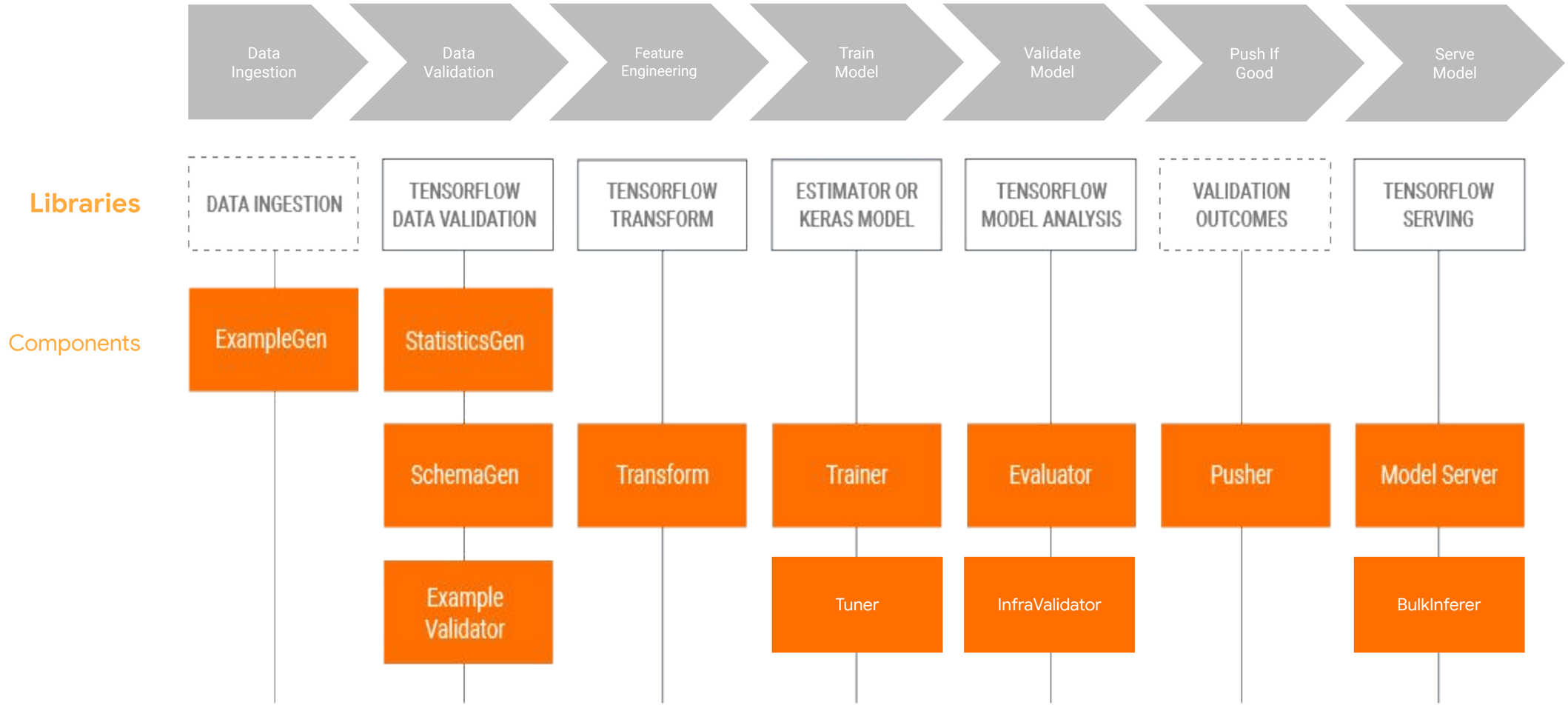
TensorFlow Extended (TFX)

TFX standard components

TFX libraries



TFX libraries integrate with ml pipeline each phase



Google Cloud

Lab

TFX Walkthrough

In this lab, you will walk through the configuration and execution of the key TFX components.

tfx_pipelines/walkthrough/labs/tfx_walkthrough_vertex.ipynb

Google Cloud