Red Hat

Red Hat Dallas Emerging Tech Summit

December 5, 2019

AI and ML on Kubernetes

William Benton • Engineering Manager and Senior Principal Engineer

What is machine learning?

codifying problem and metrics

codifying problem and metrics ▶ data collection and cleaning ▶ feature engineering ▶ model training and tuning ▶ model validation ▶ model deployment ▶ monitoring, validation

codifying problem and metrics

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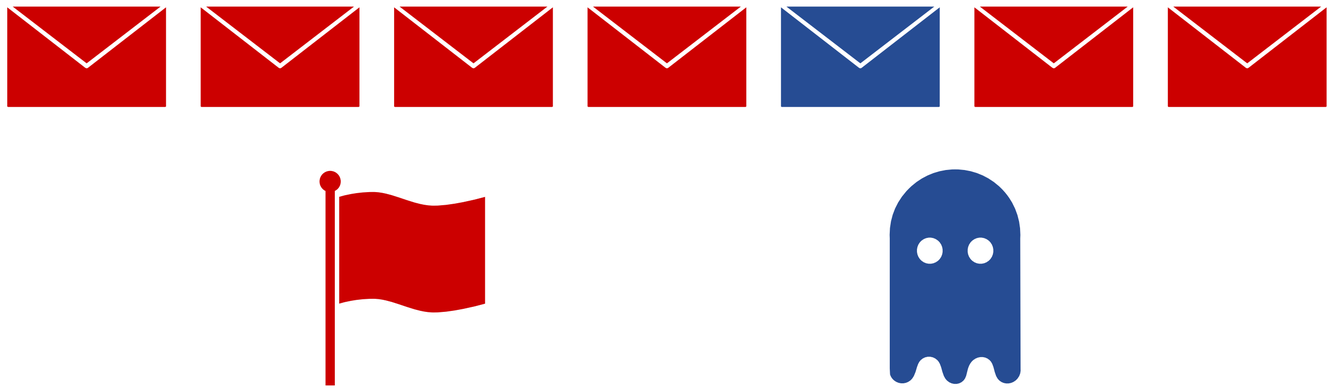
codifying problem and metrics



data collection and cleaning

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data collection and cleaning

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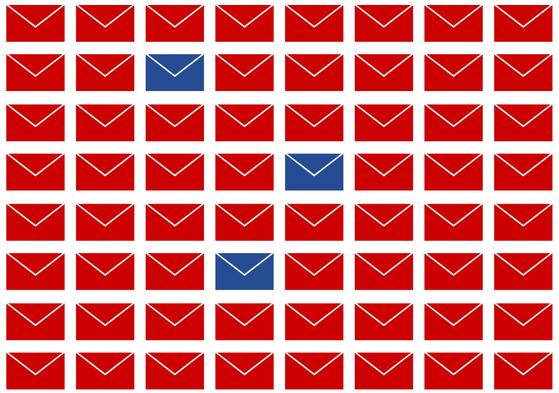

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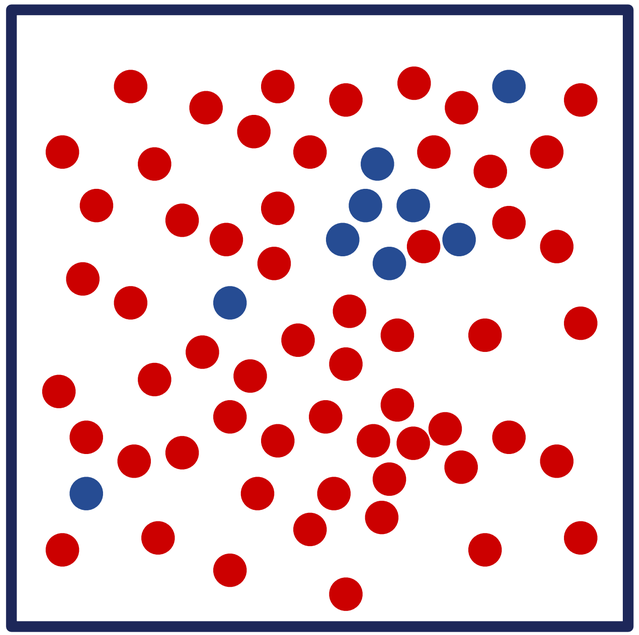
feature engineering



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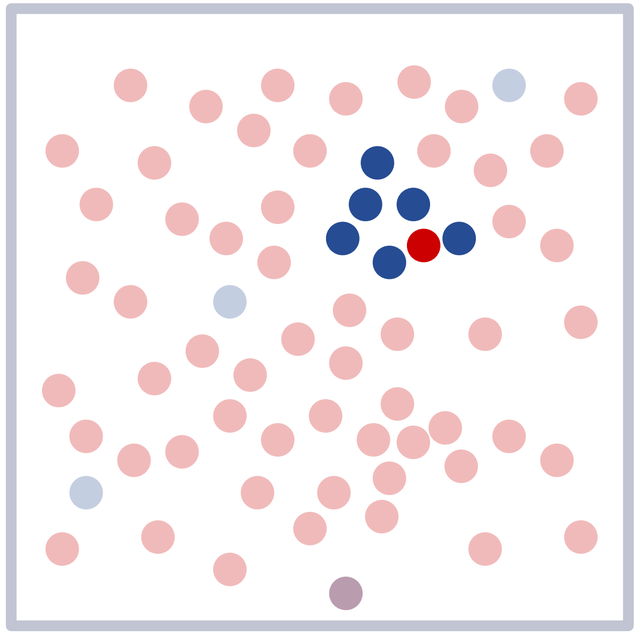

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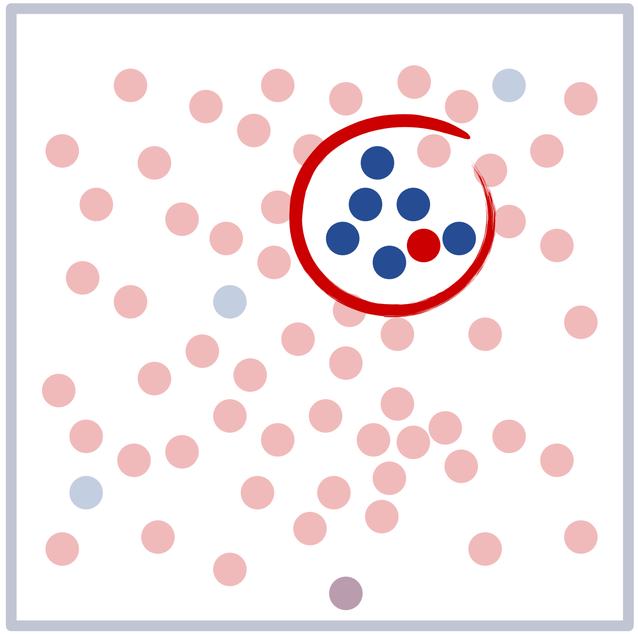

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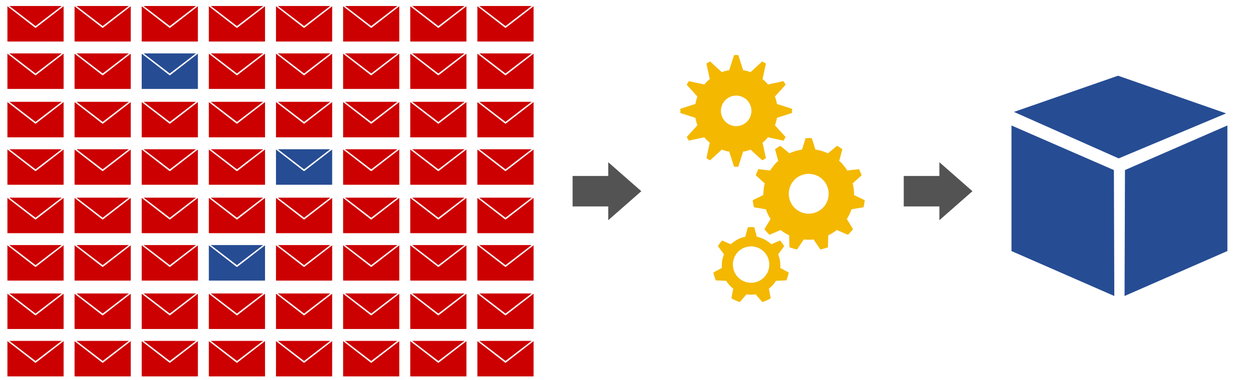
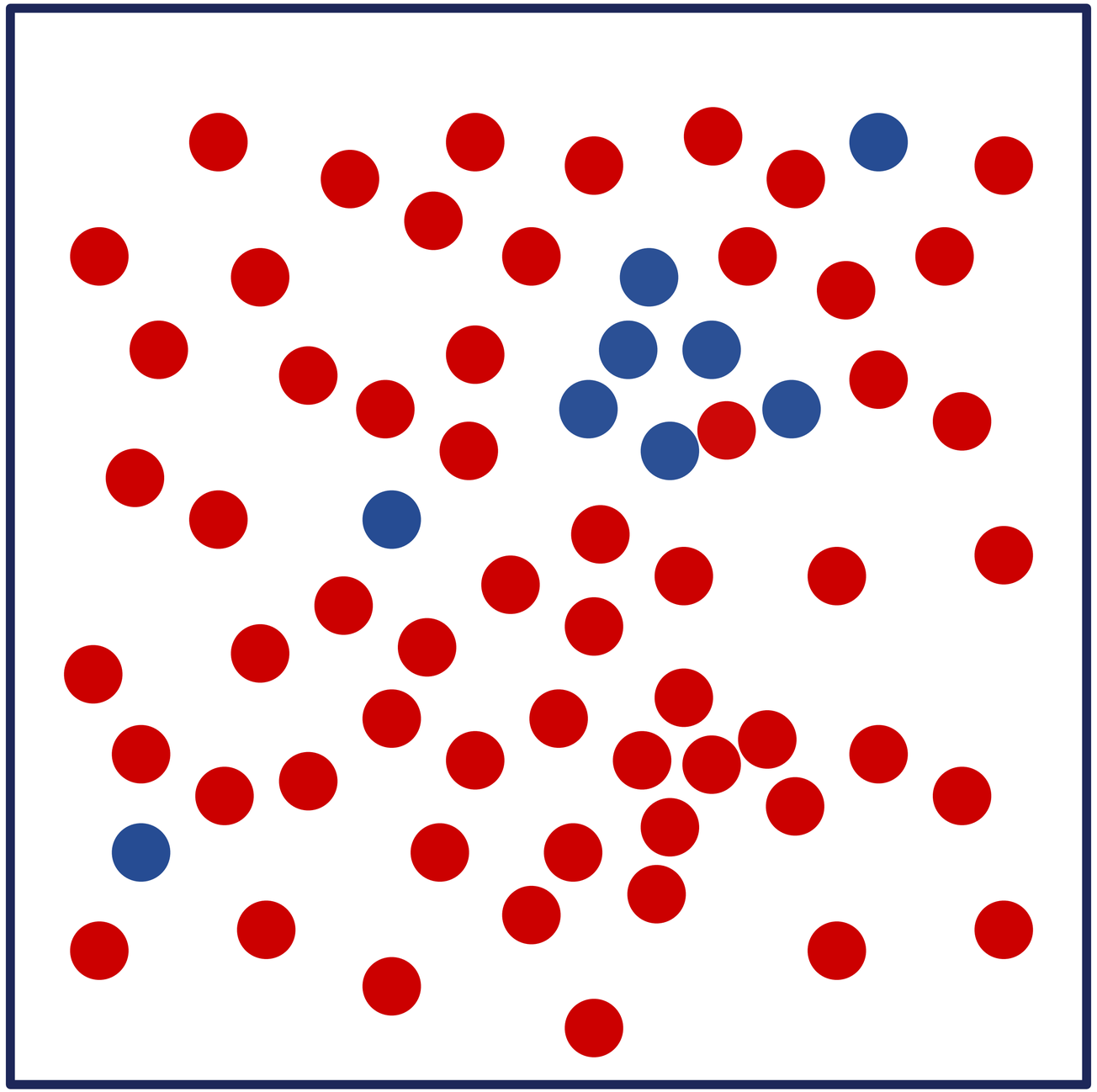
model training and tuning





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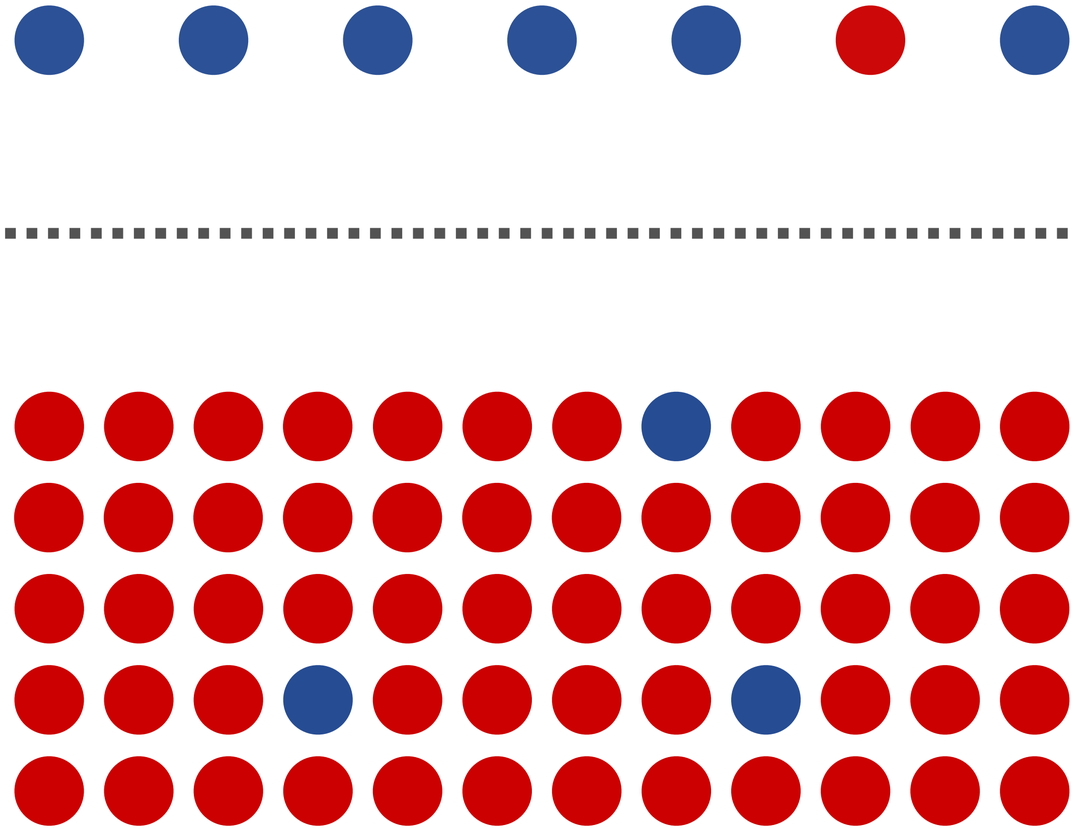

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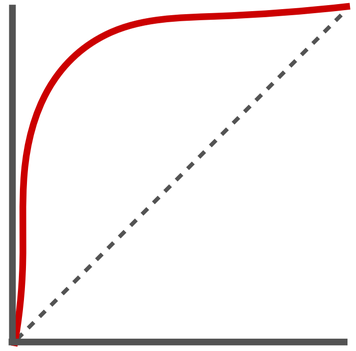
model validation



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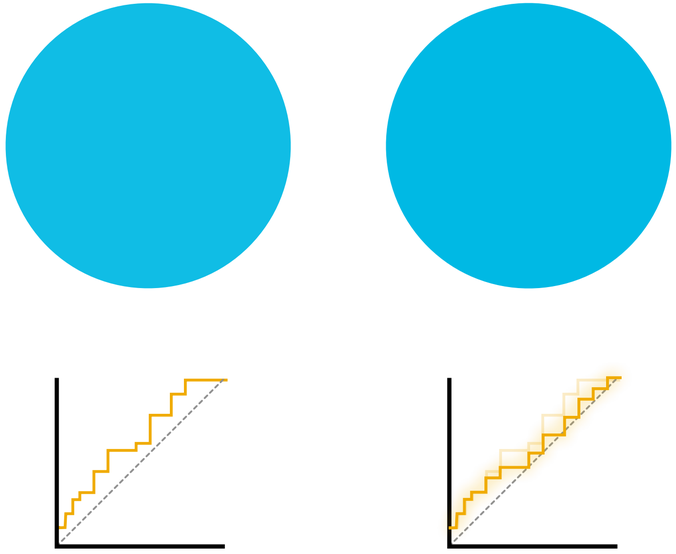
model deployment

monitoring, validation

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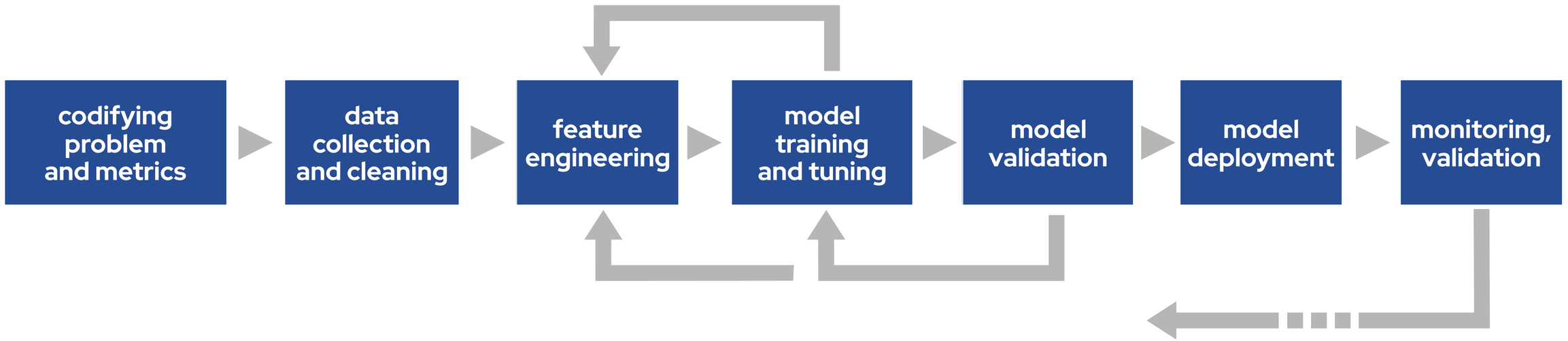
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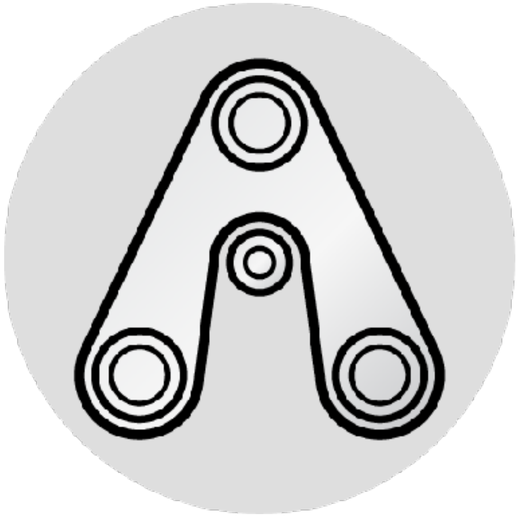
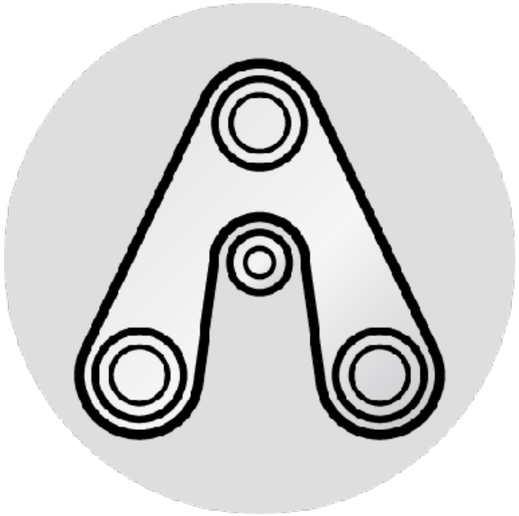
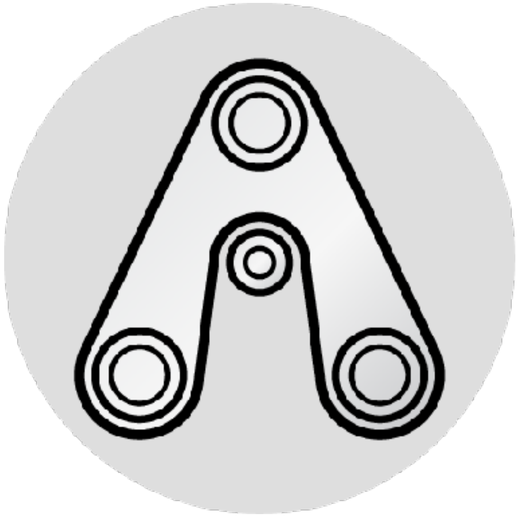
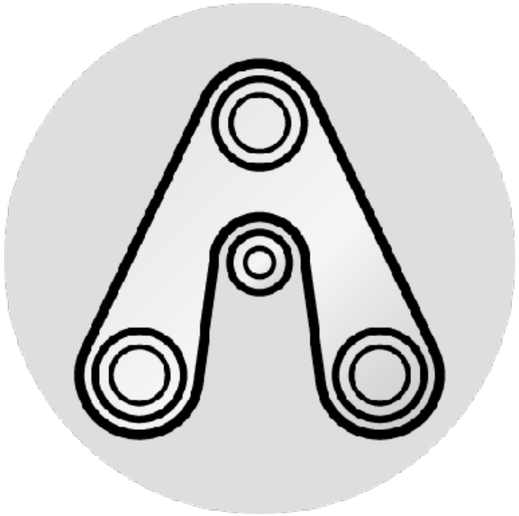


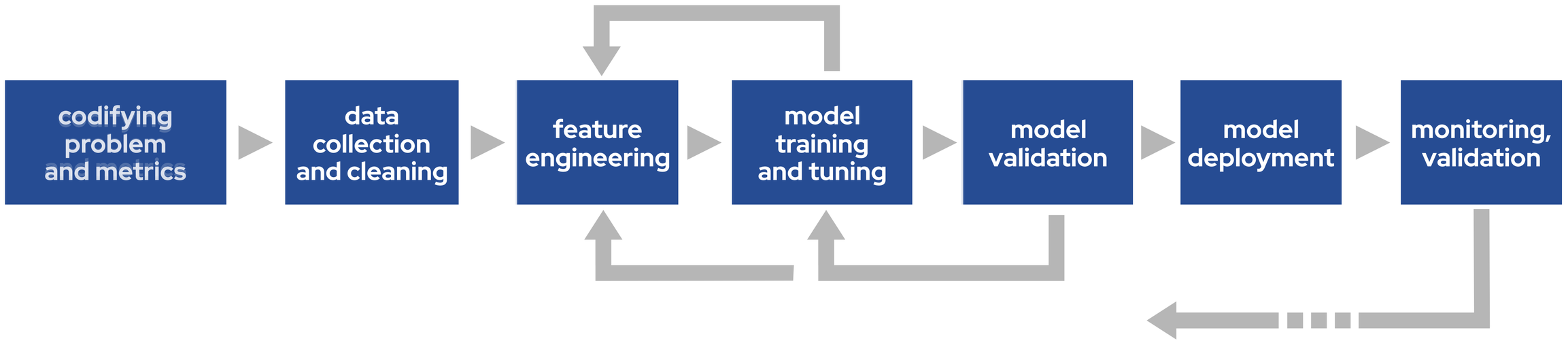




data as the foundation

Why “on Kubernetes?”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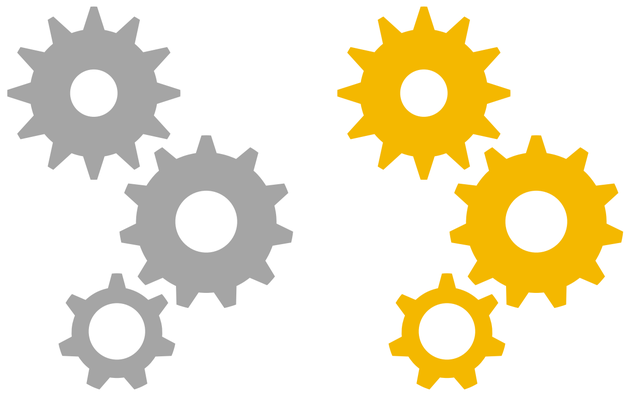

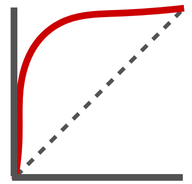

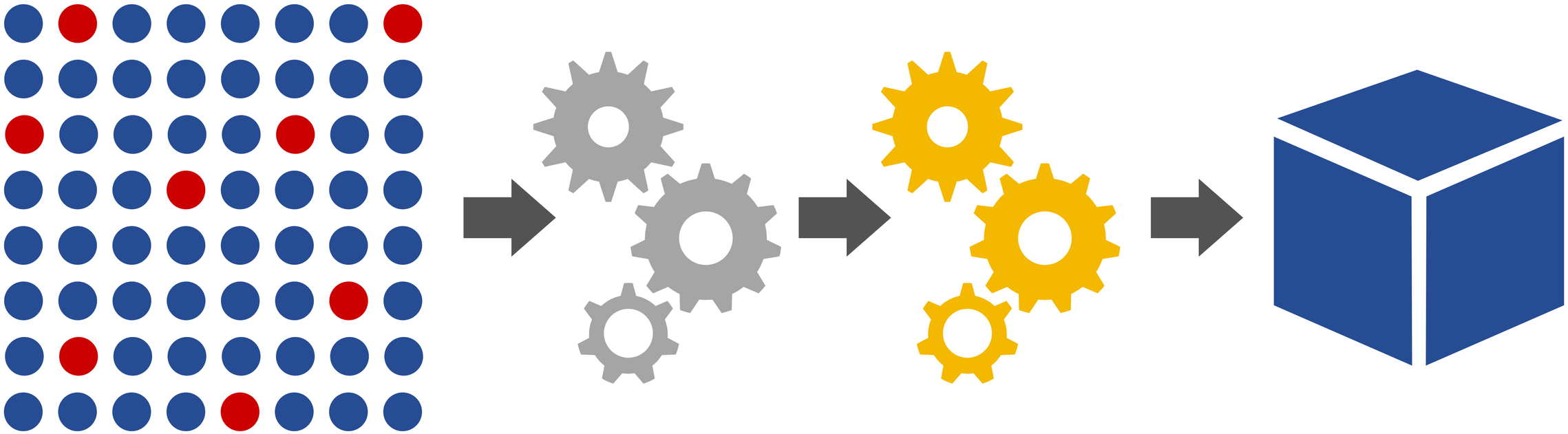

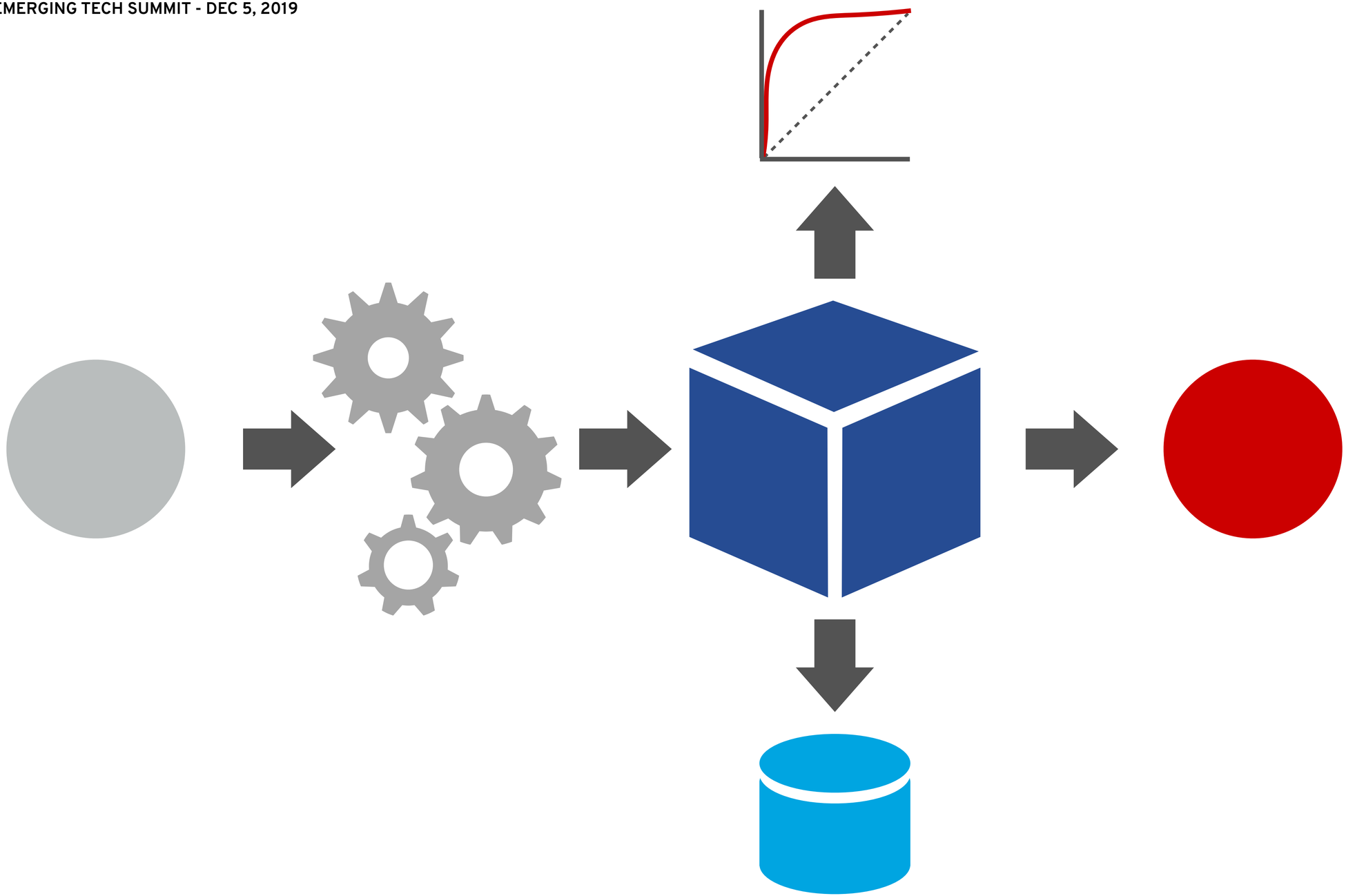

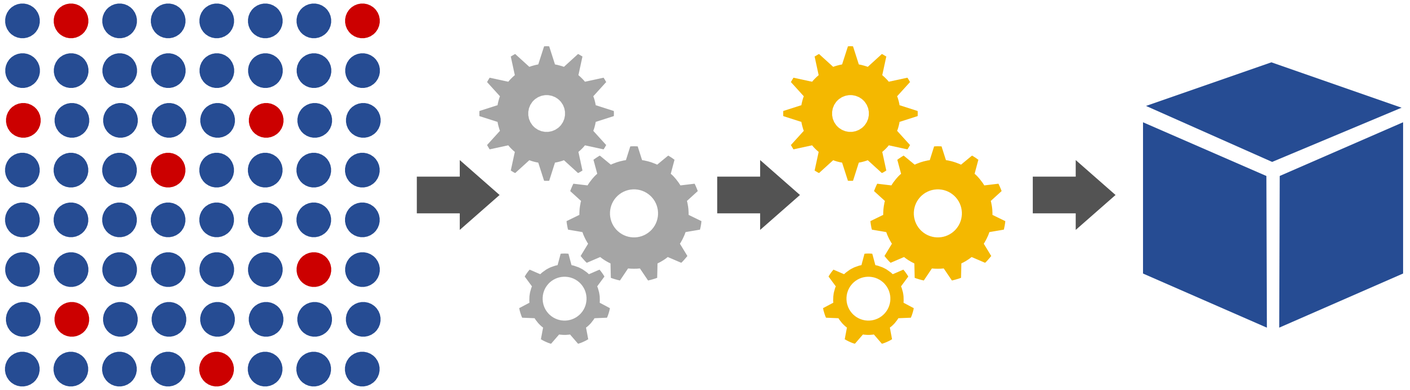

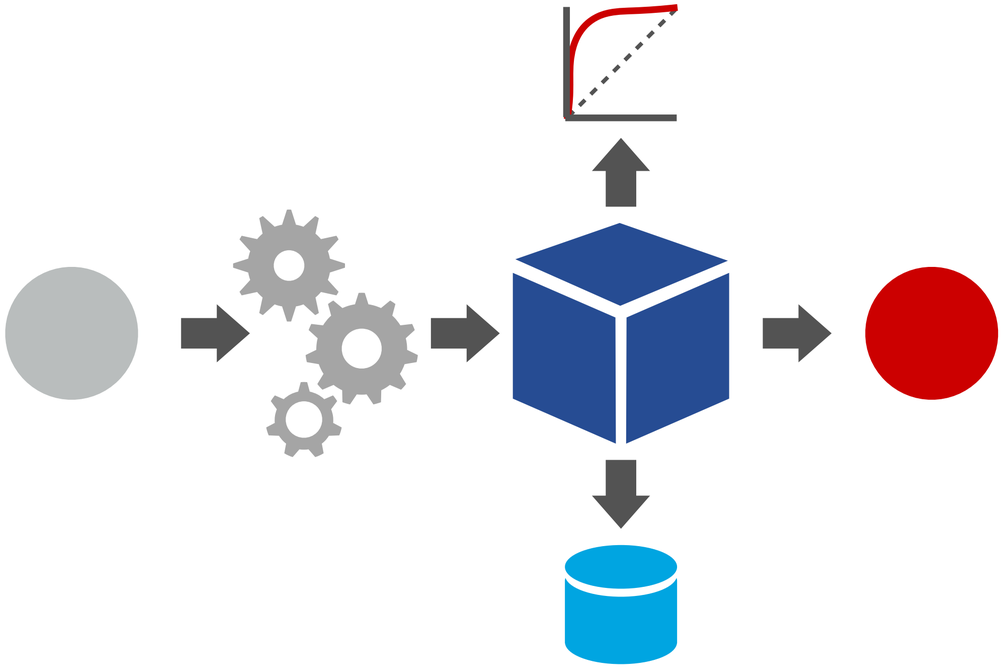

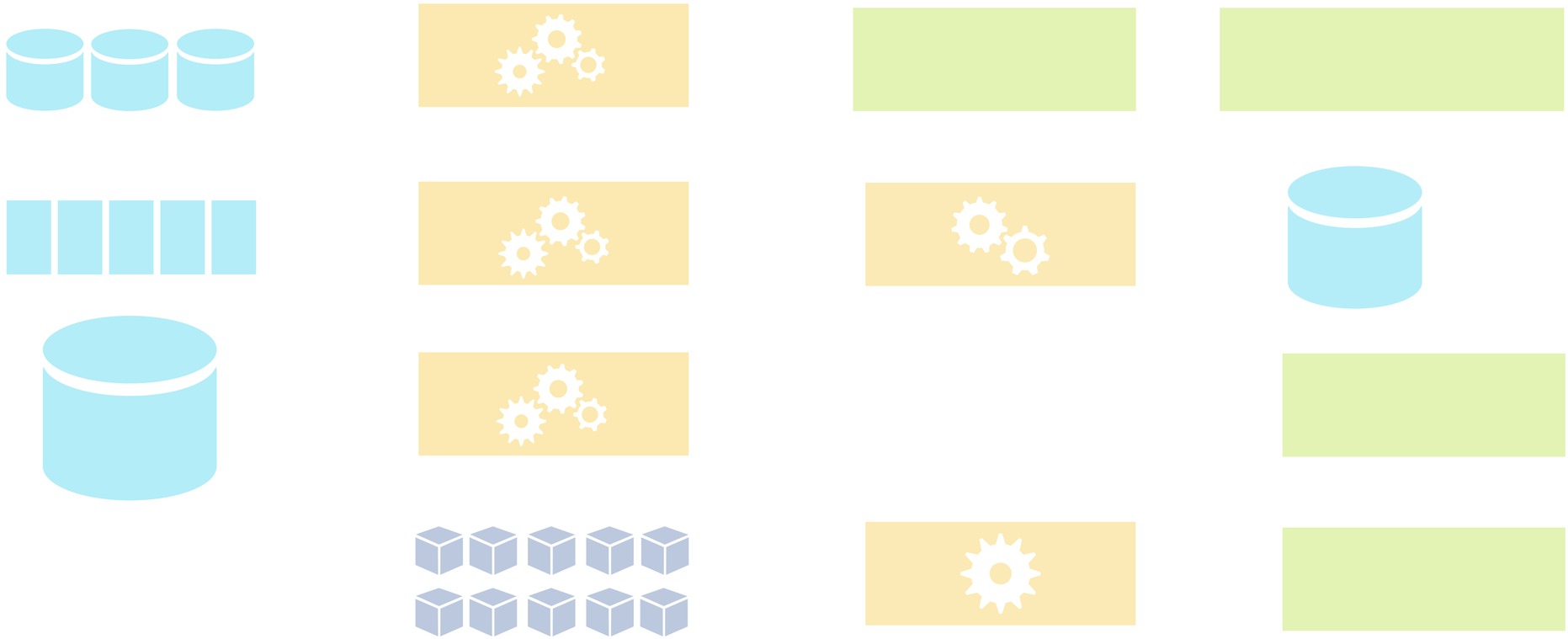

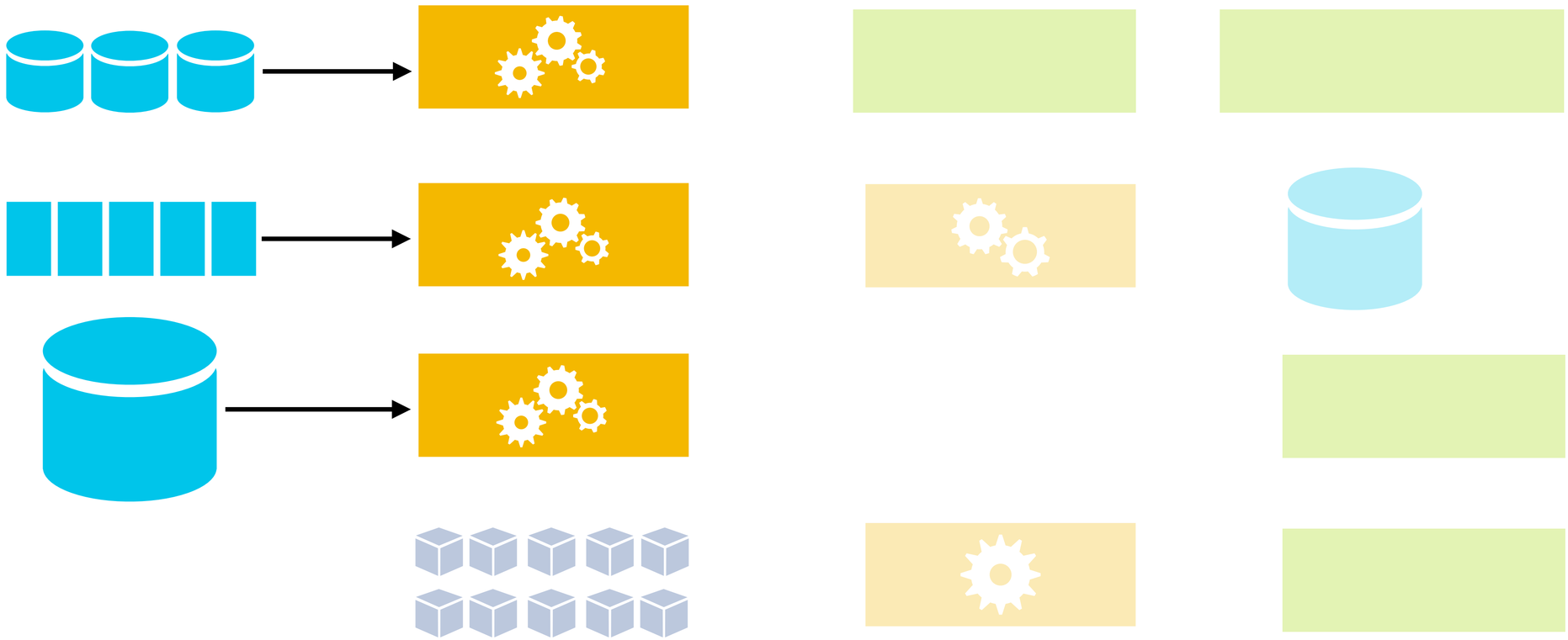

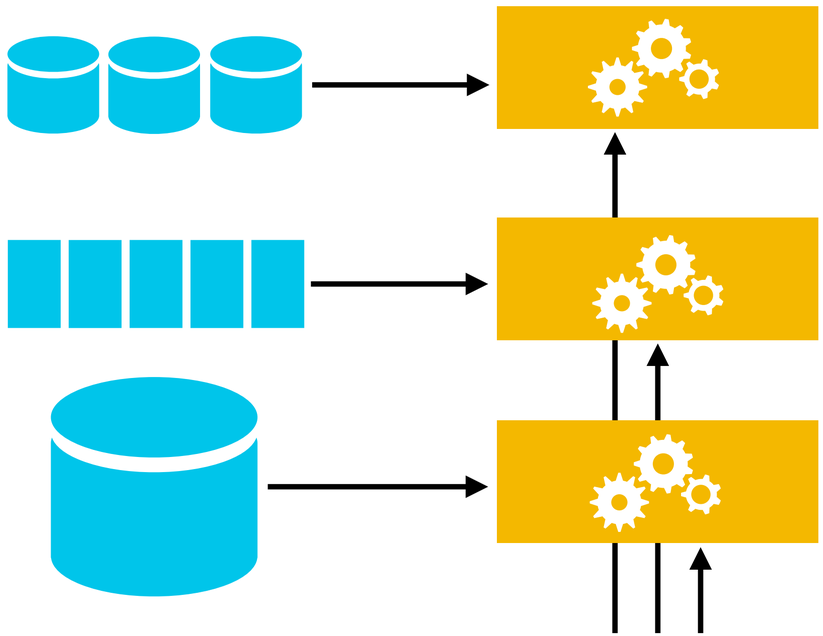

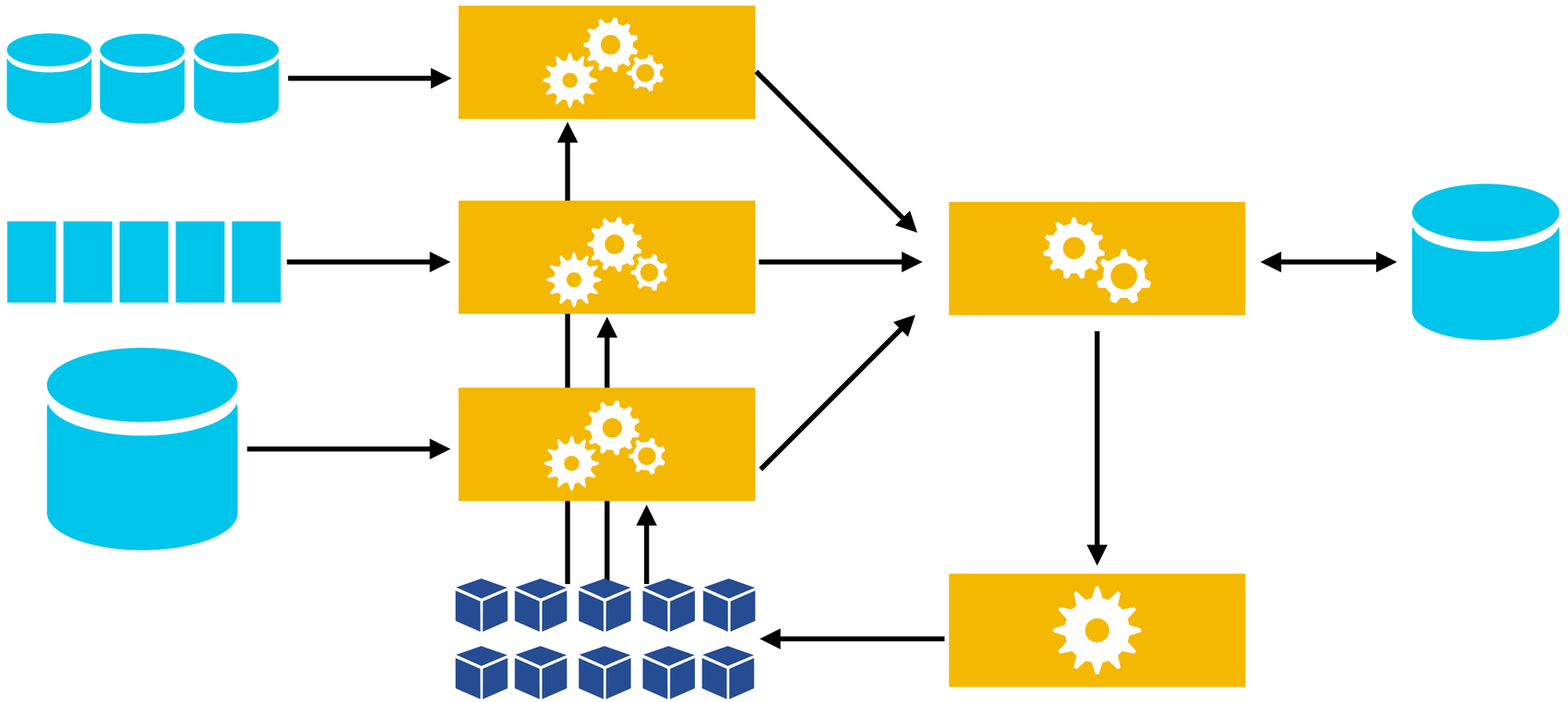

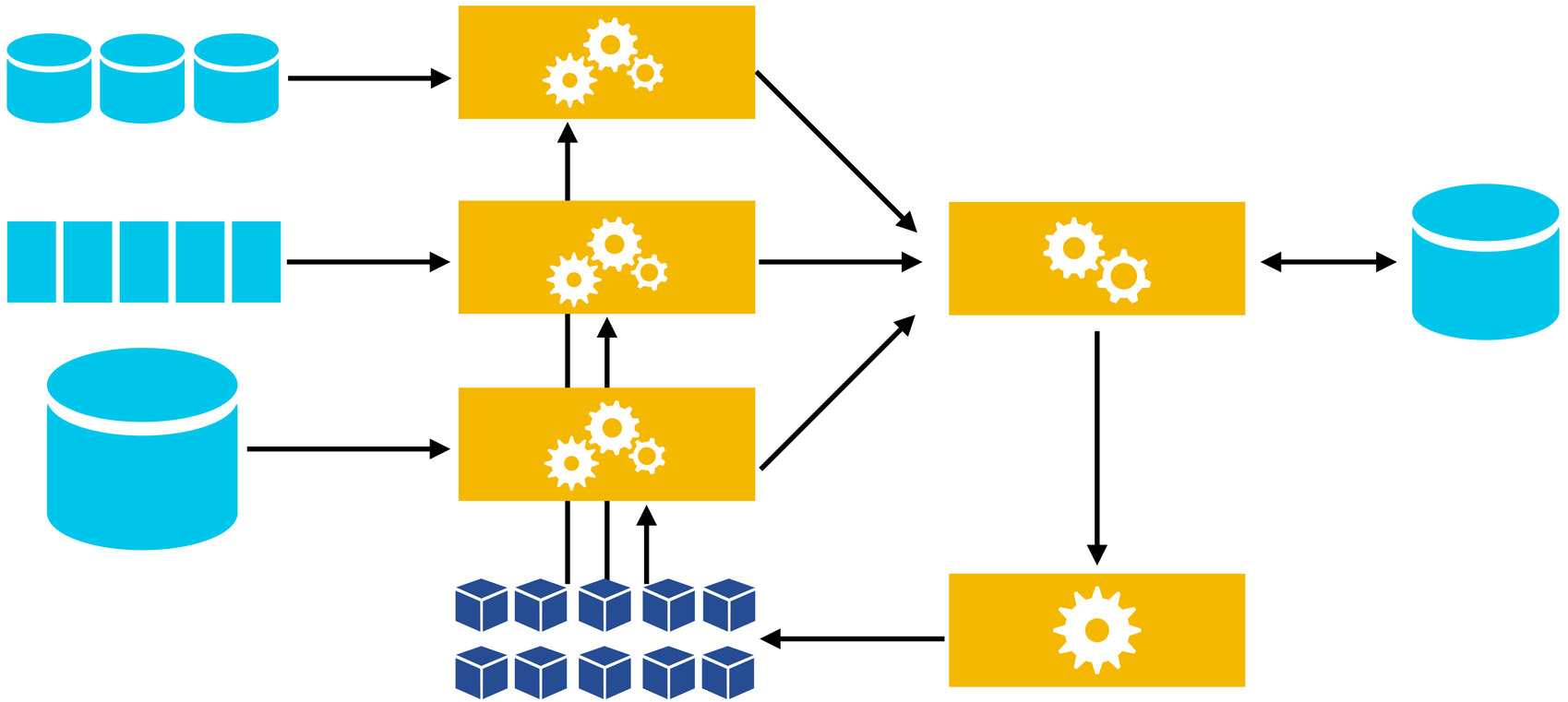

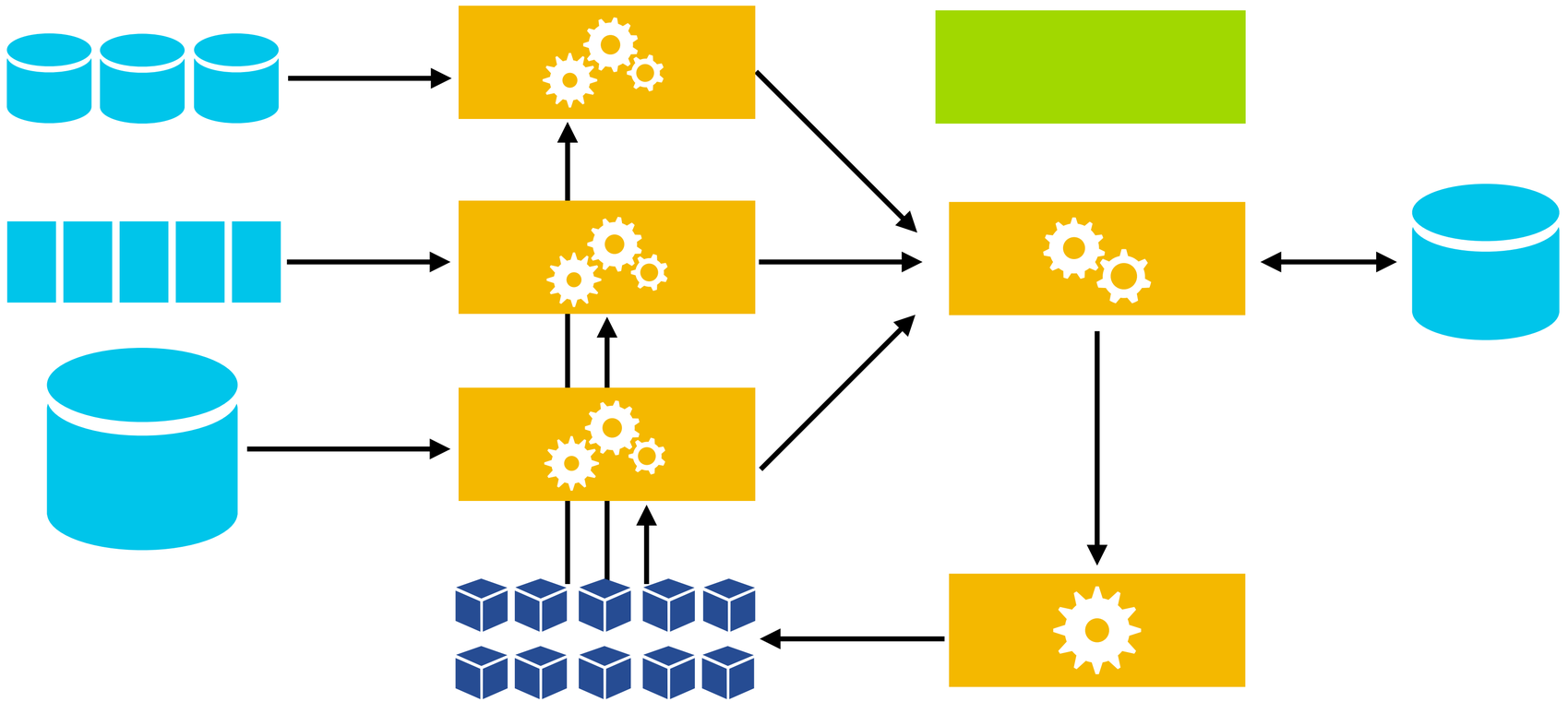

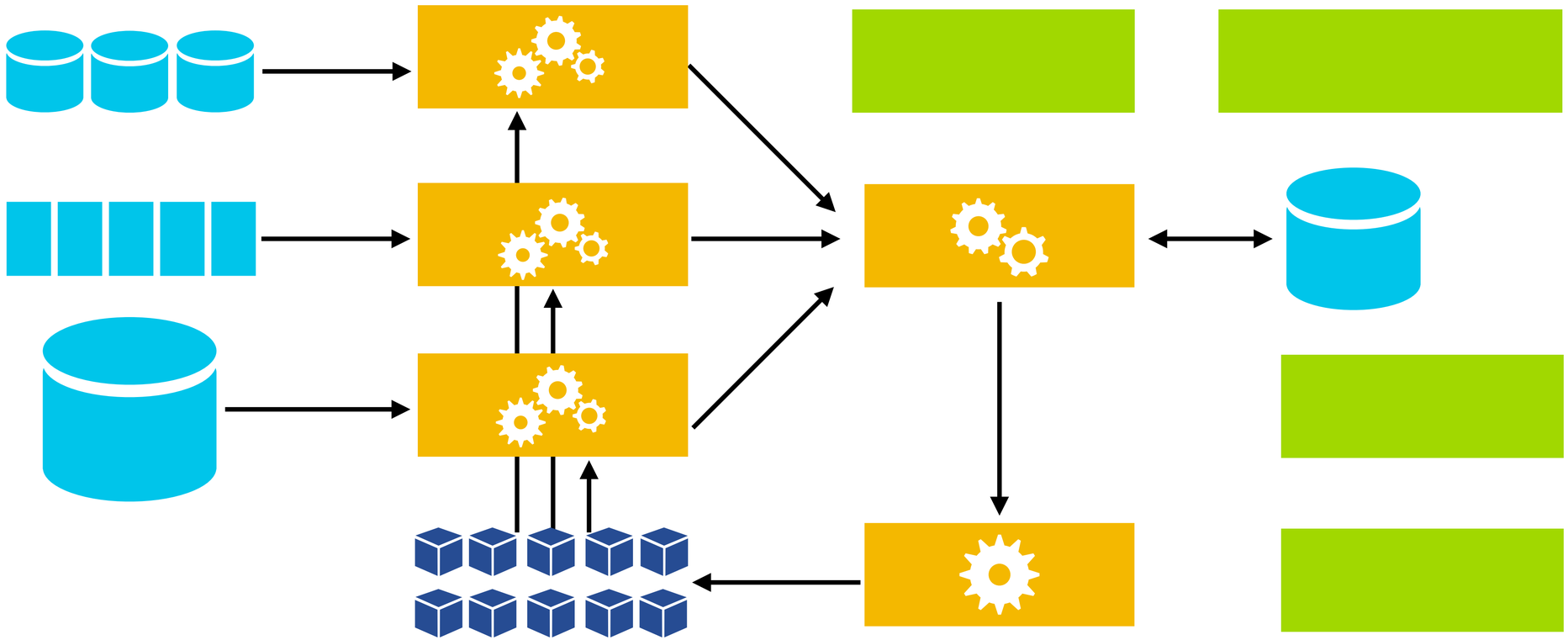

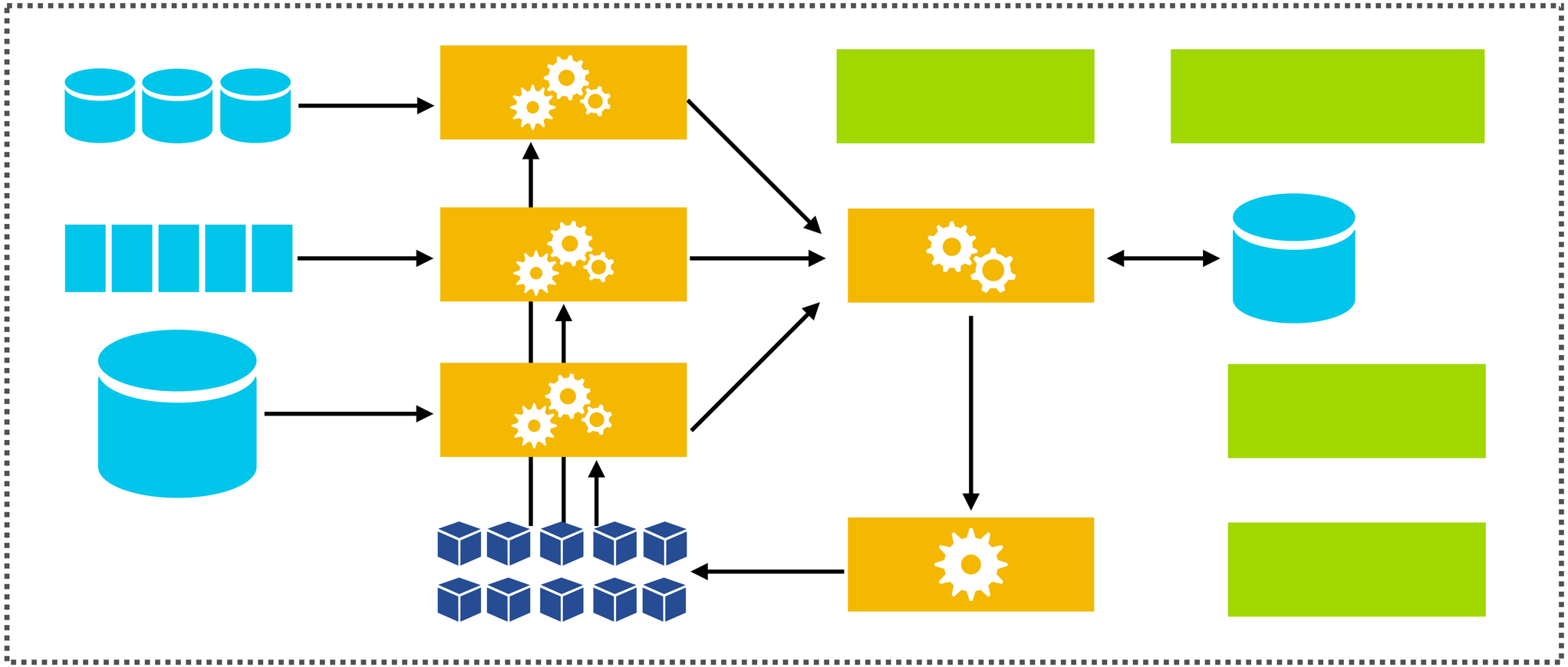

OpenShift is **enterprise Kubernetes** with a **great developer experience**.

declarative deployments;
resource management
for apps and compute

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efficient isolation,
secure by default

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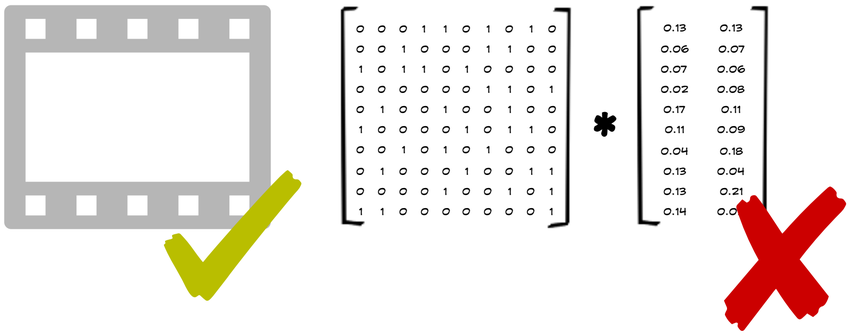
workflows to accelerate discovery

Some common concerns for AI/ML systems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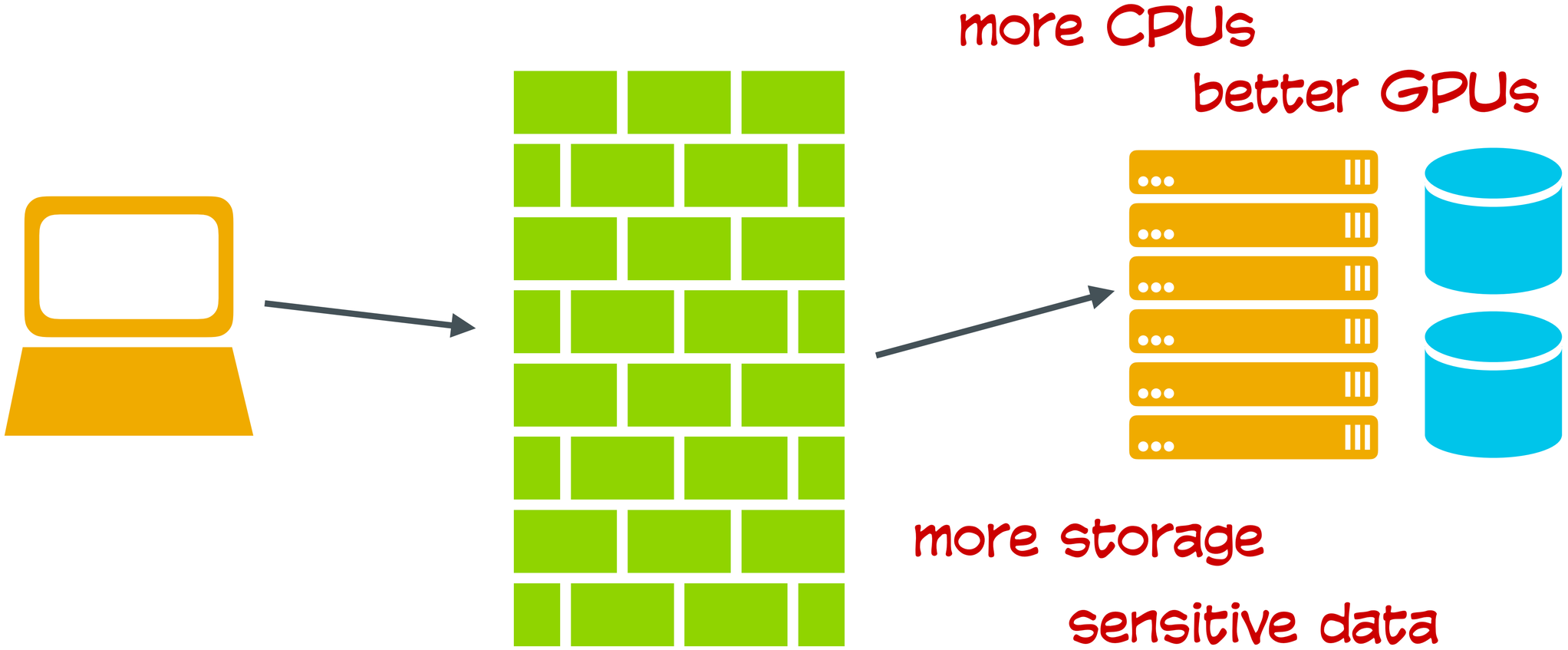
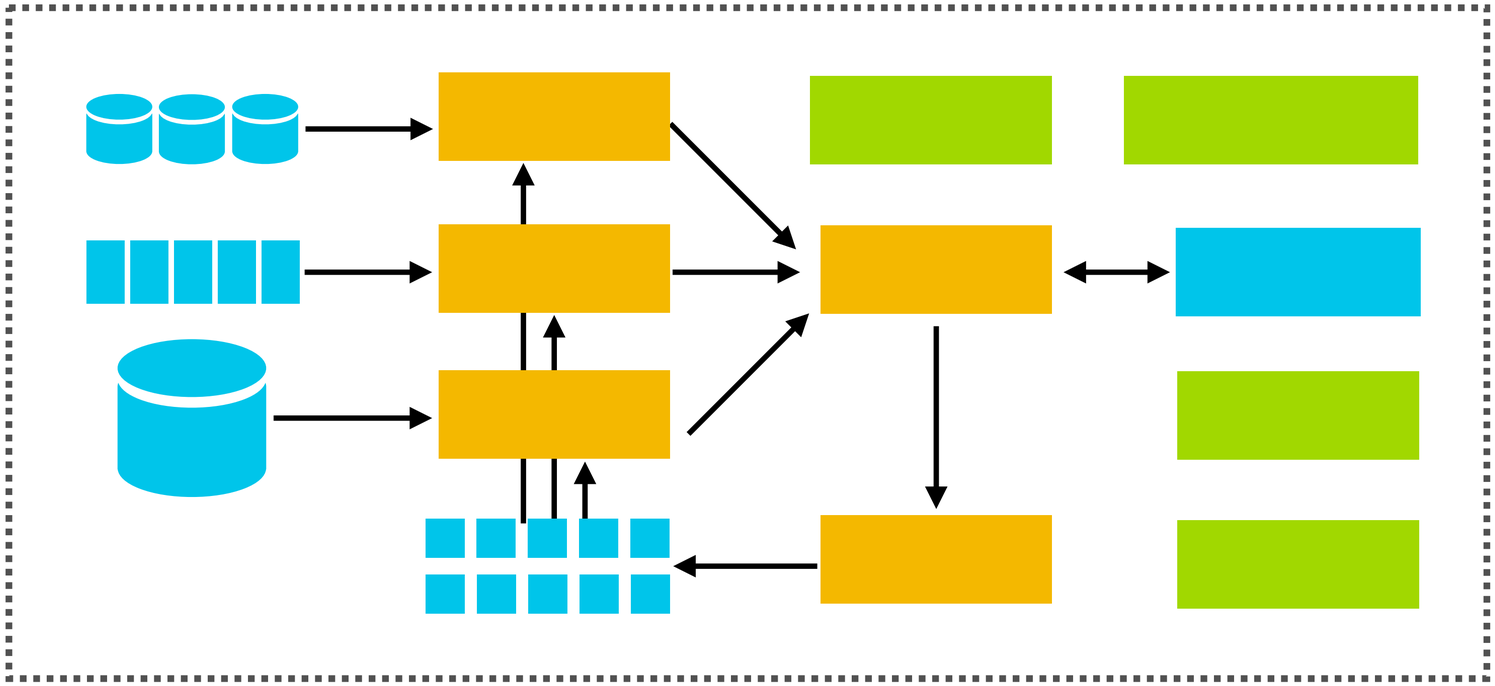
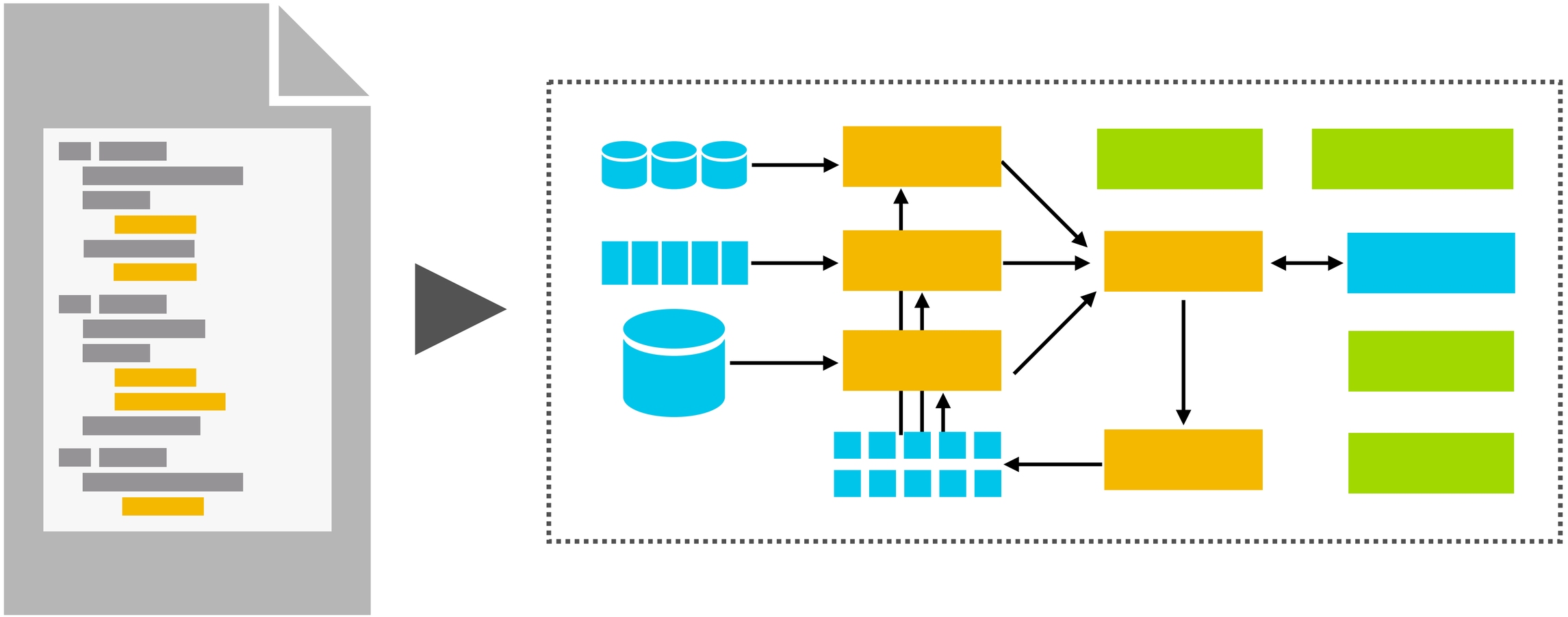
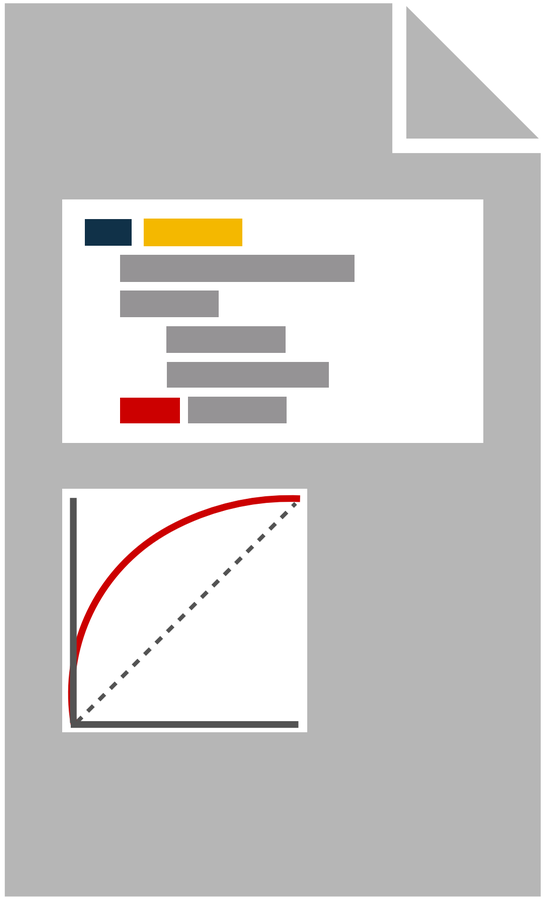
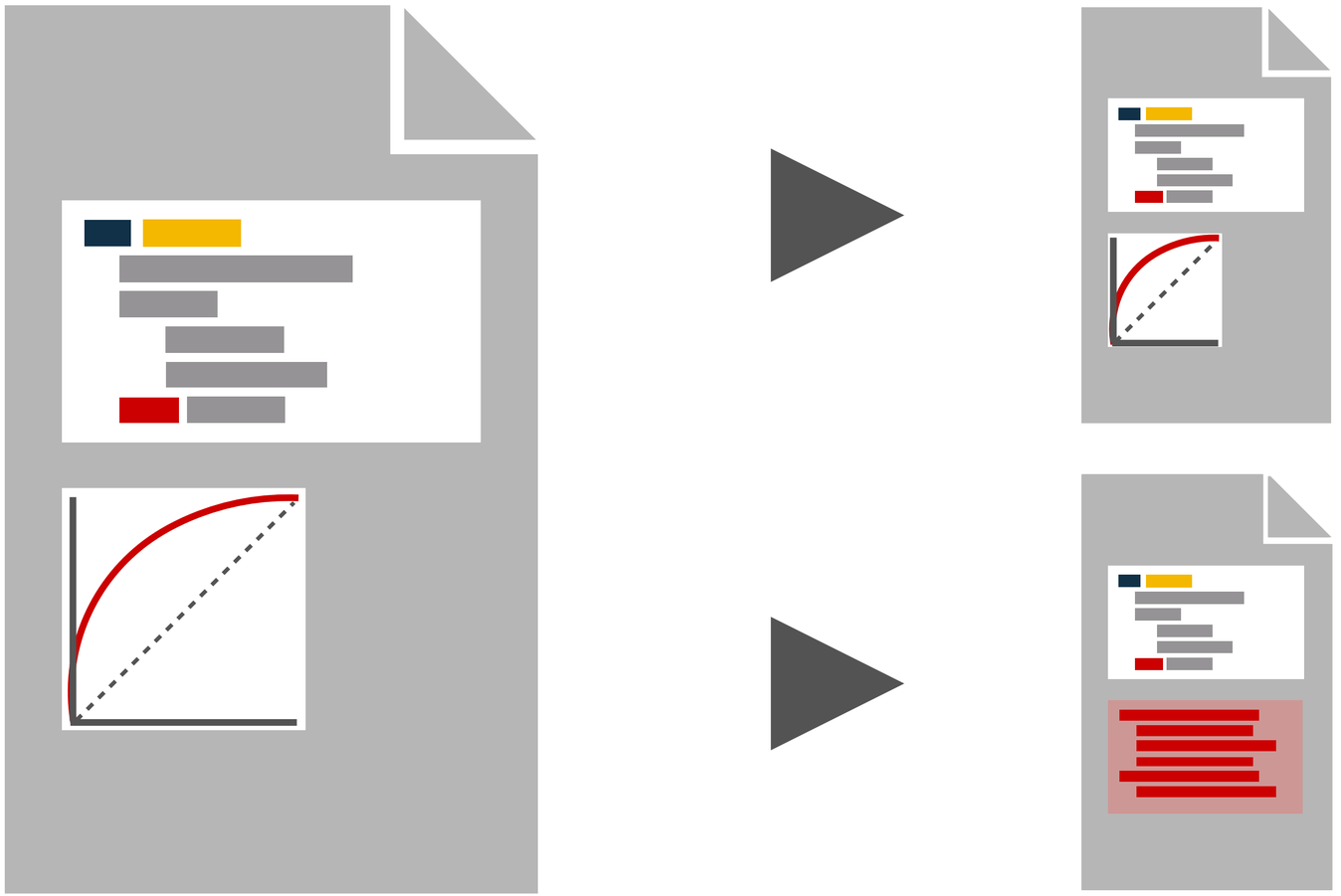
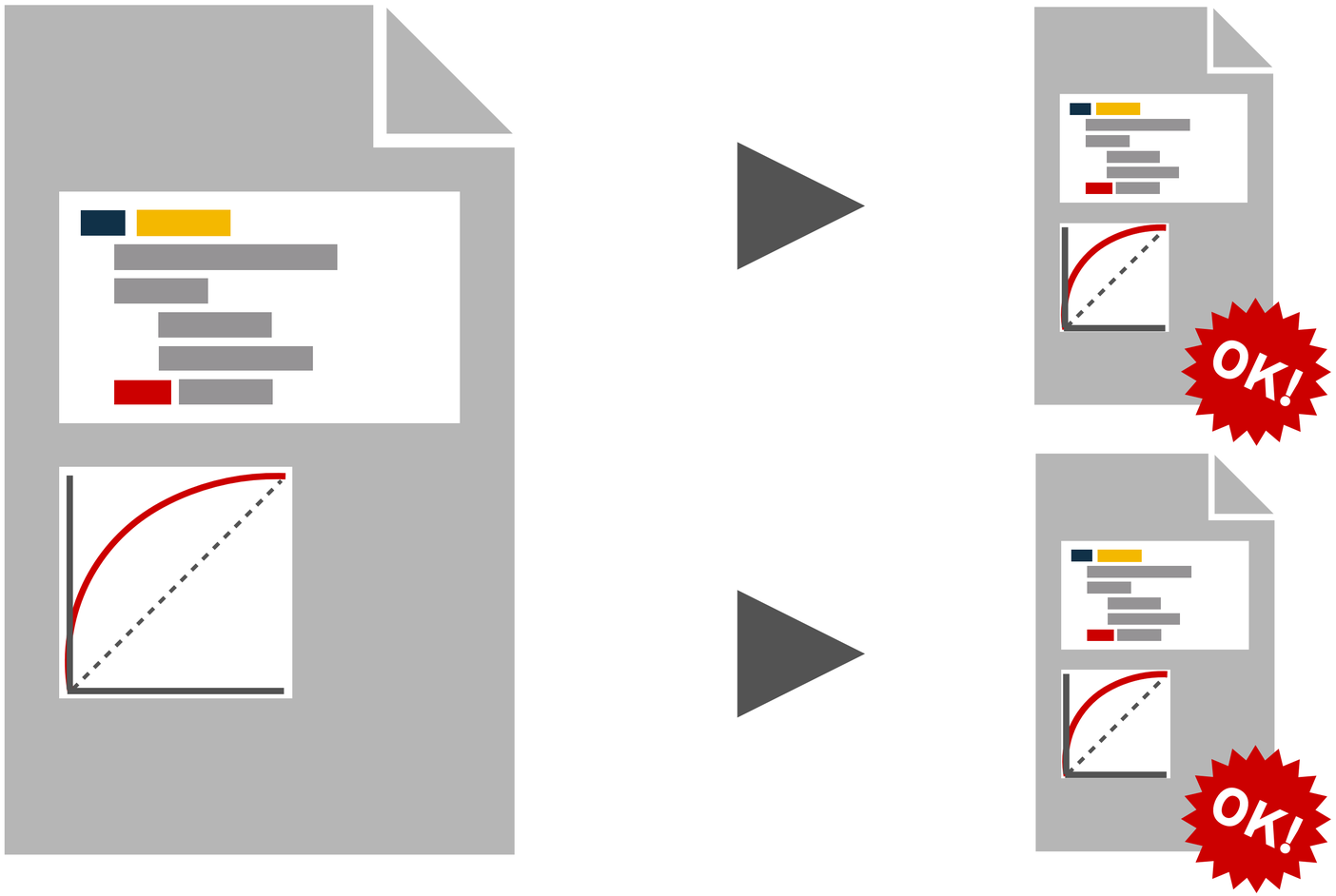

more CPUs
better GPUs
more storage
sensitive data







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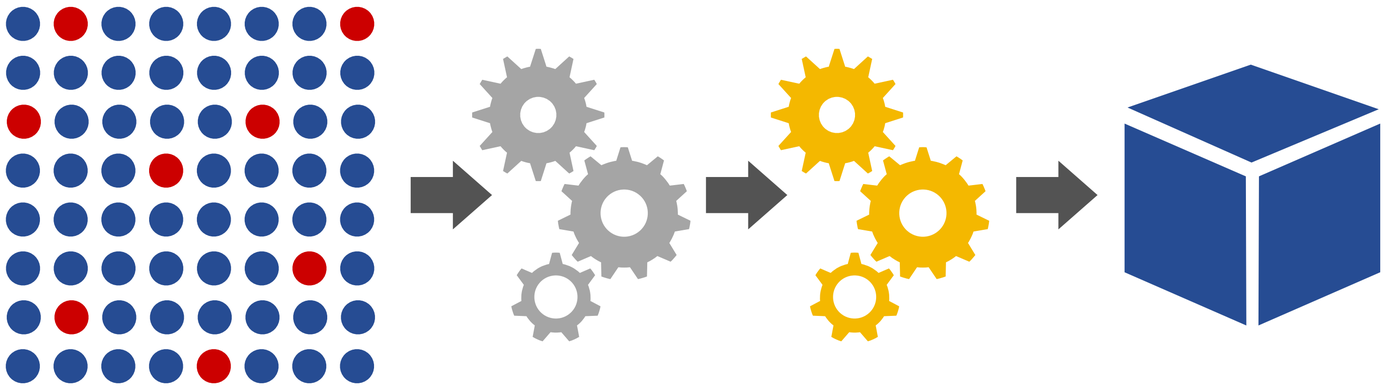

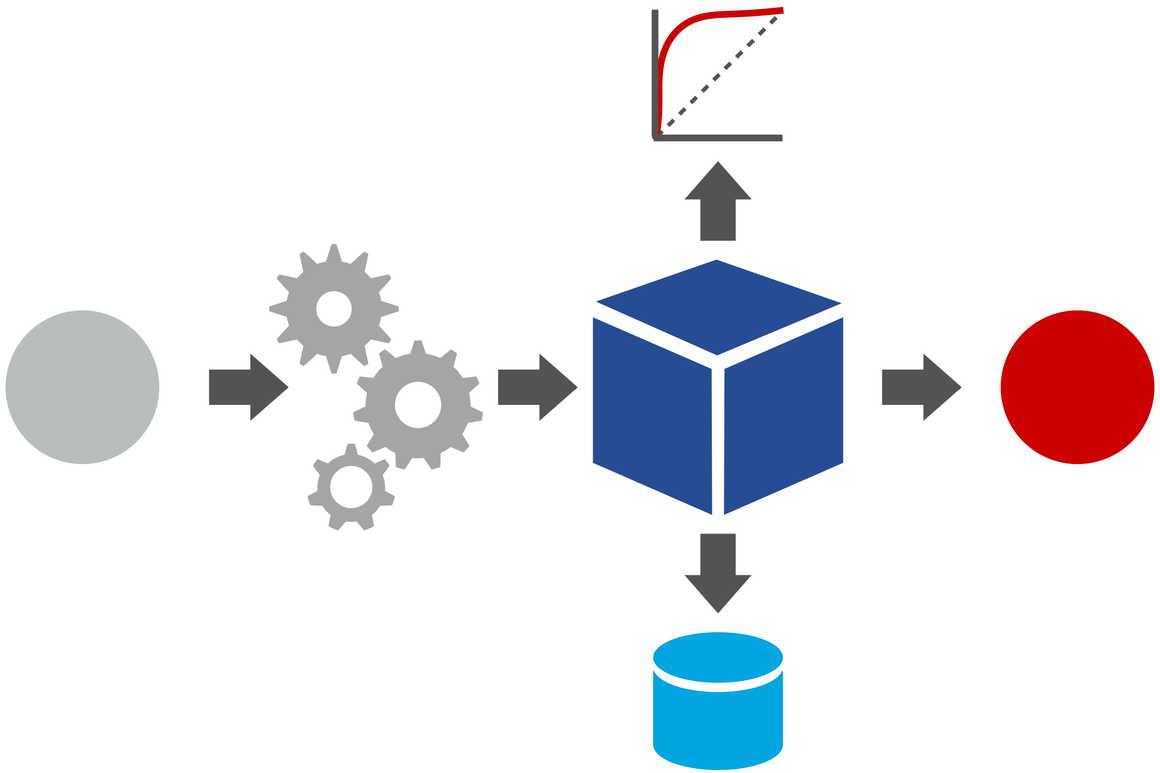

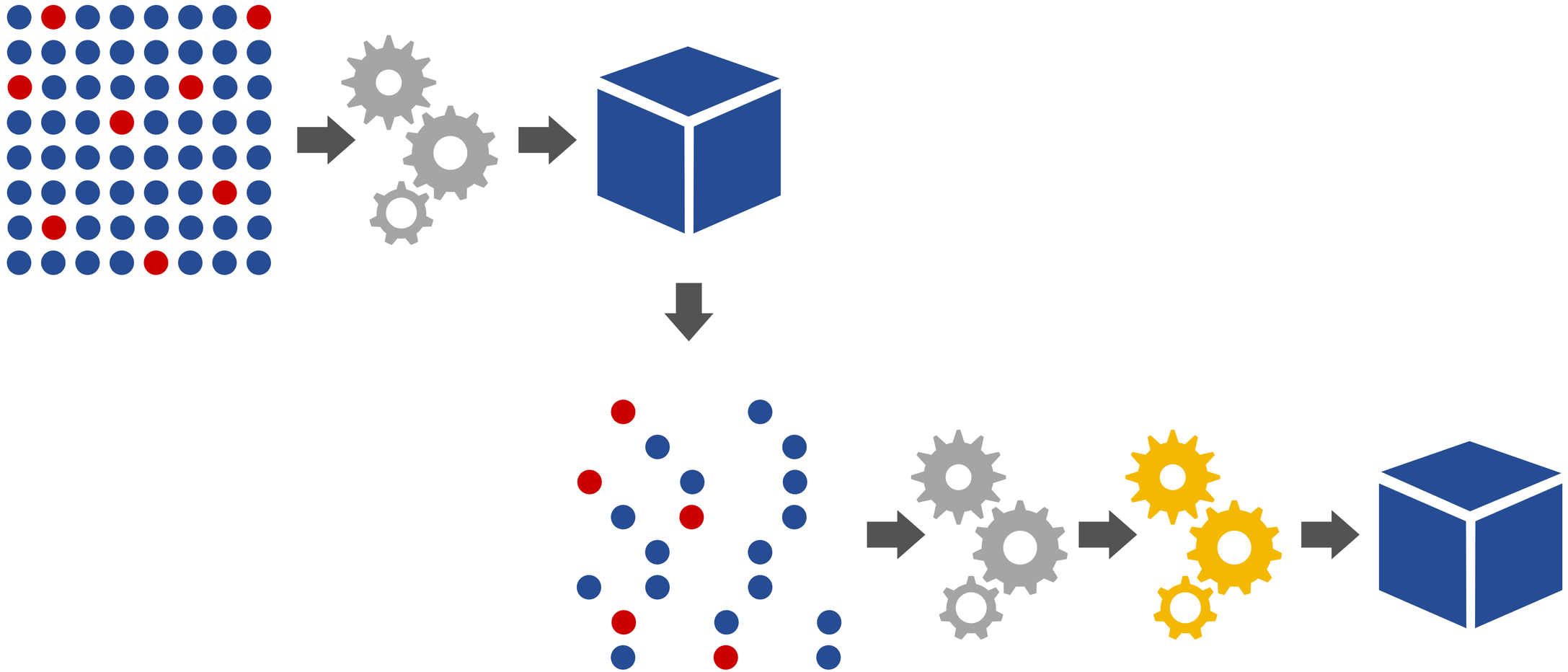

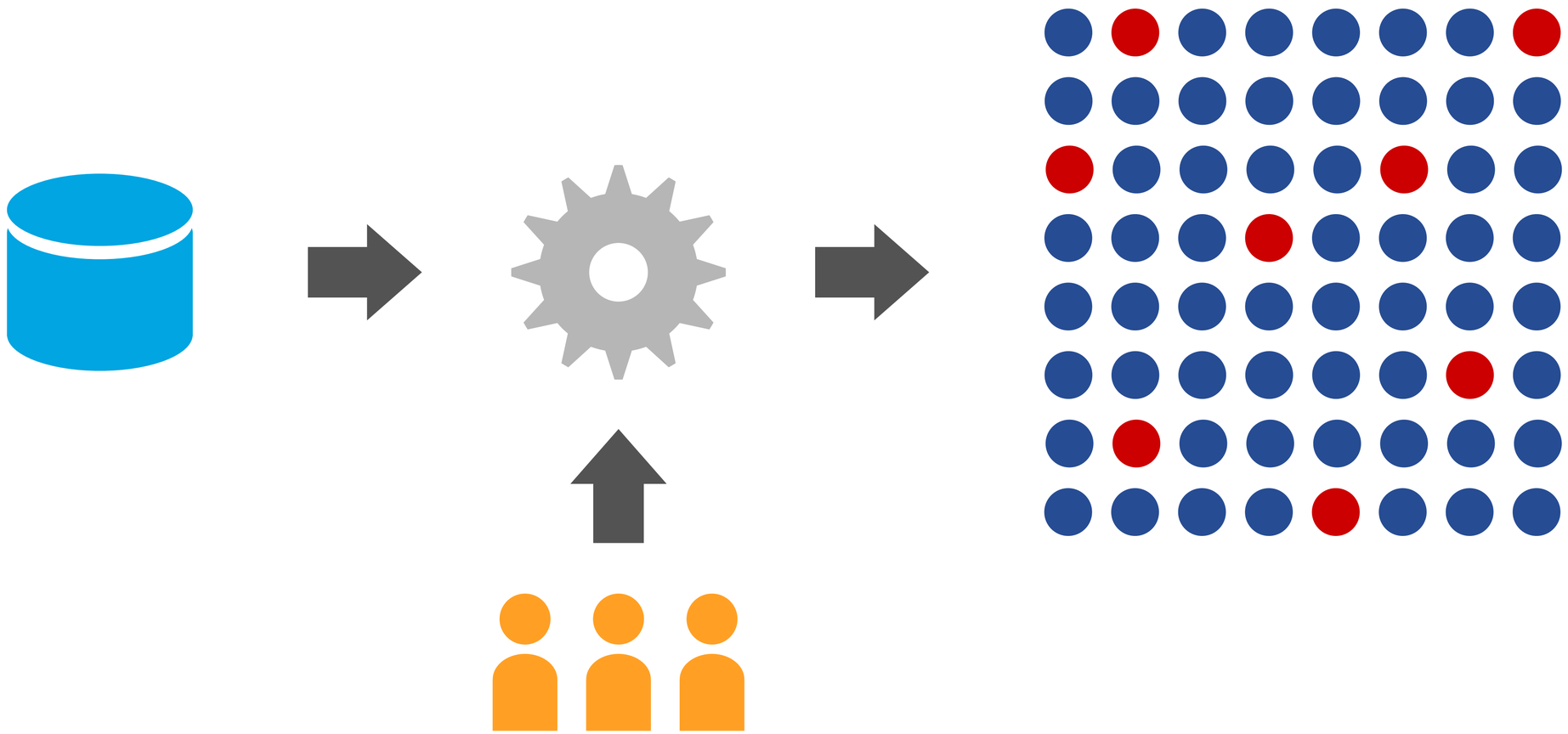

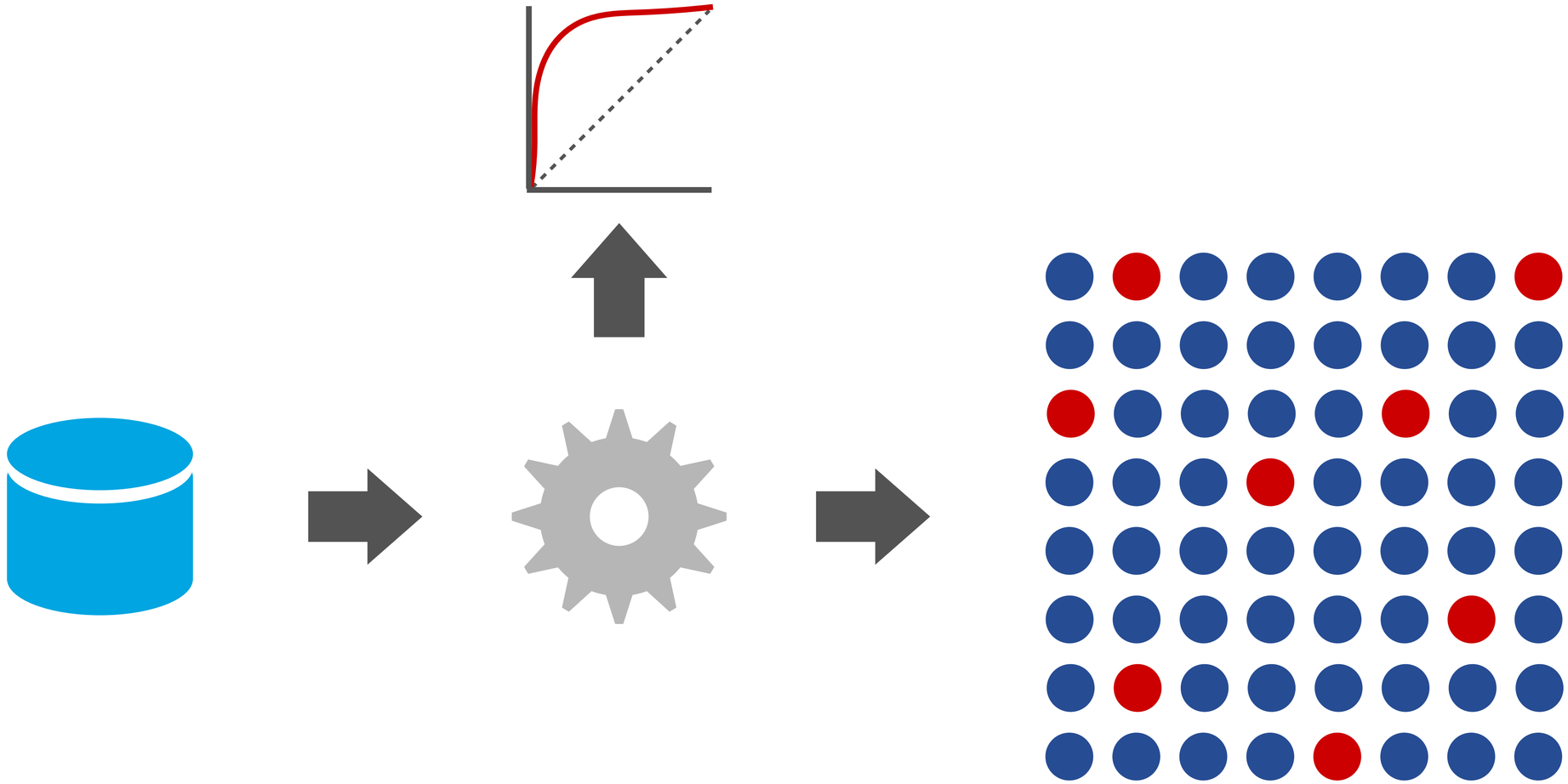

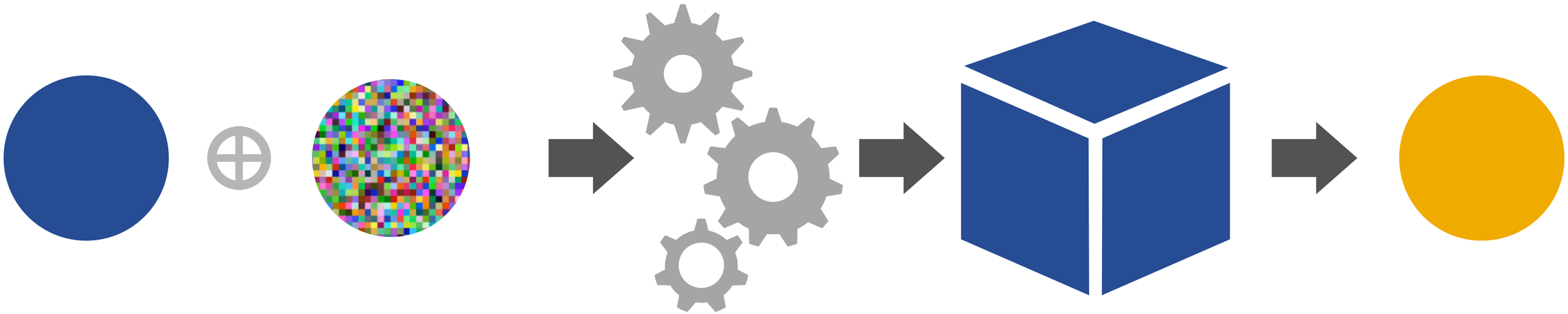

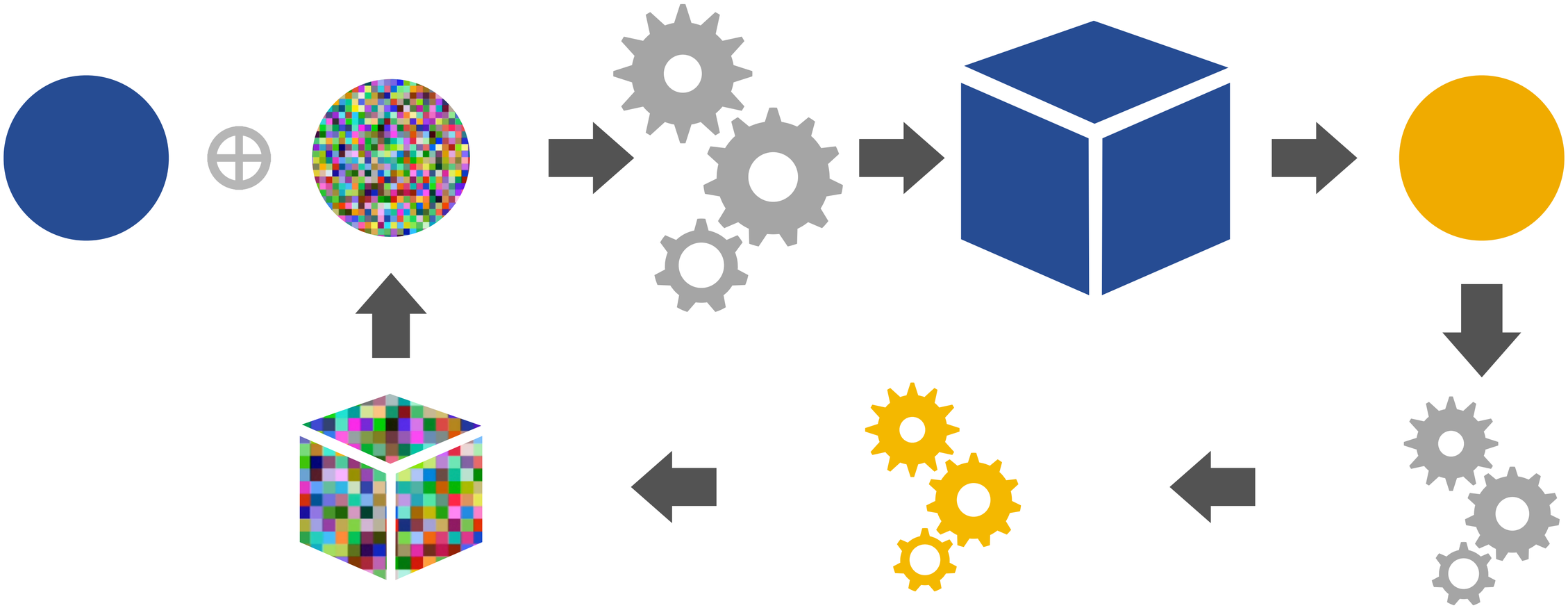

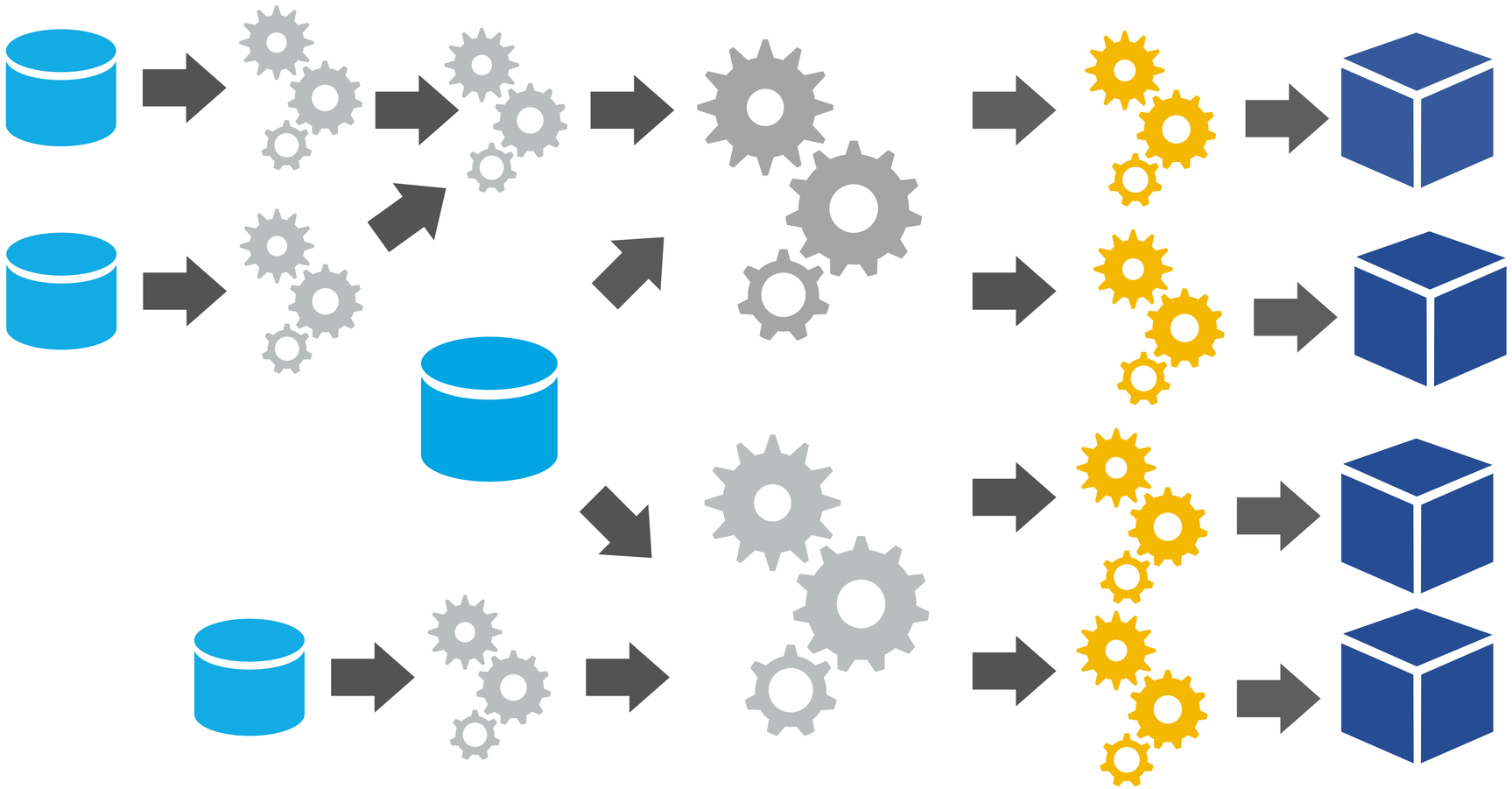

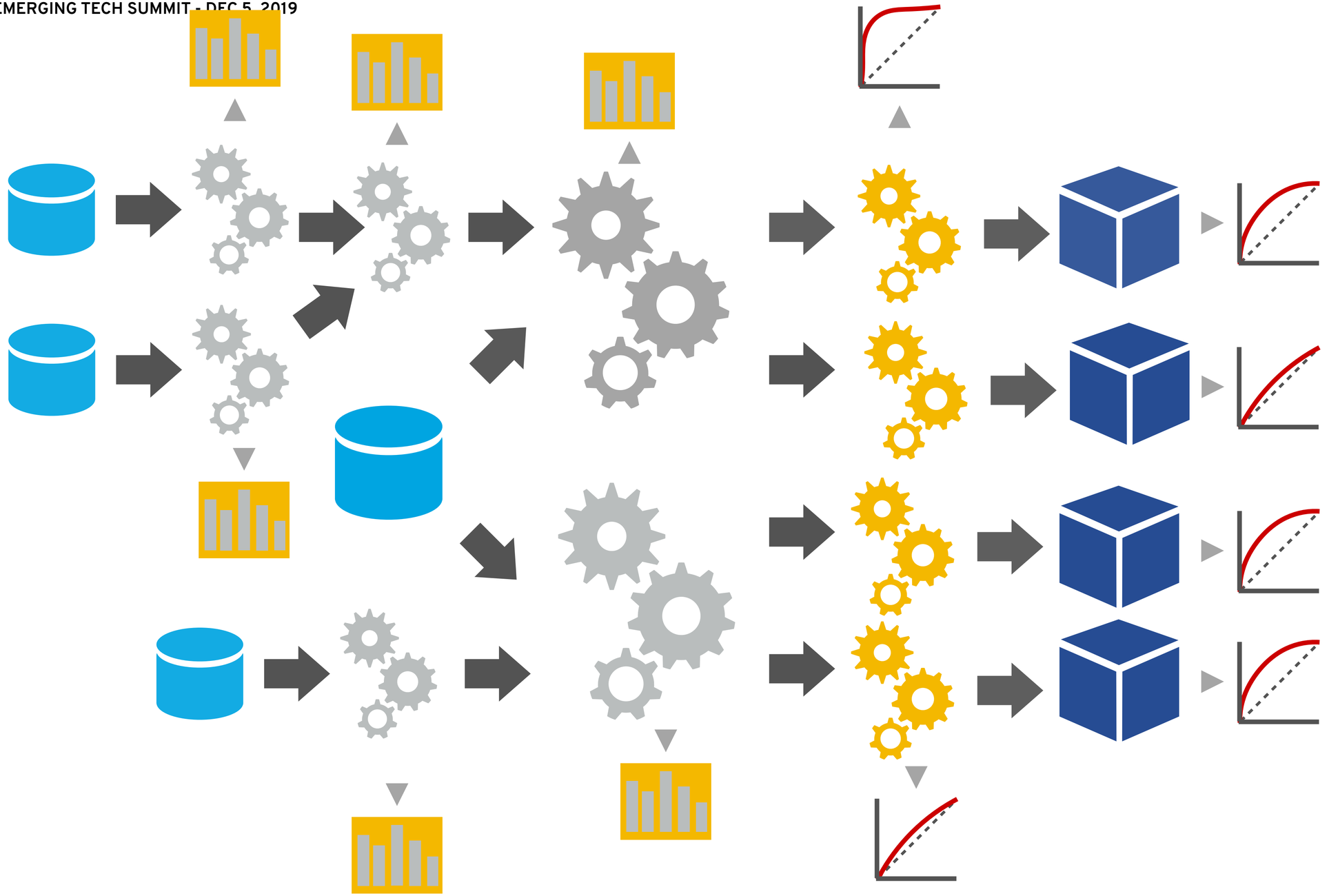

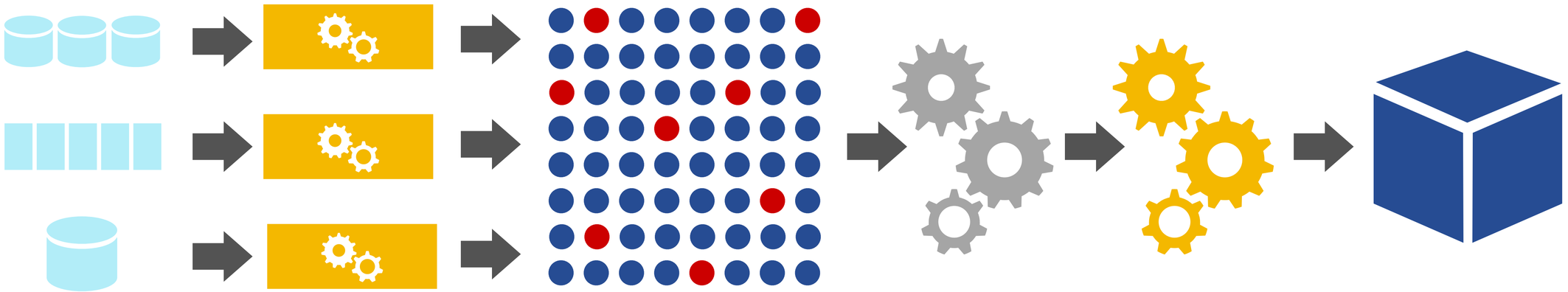


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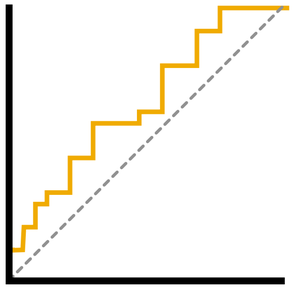


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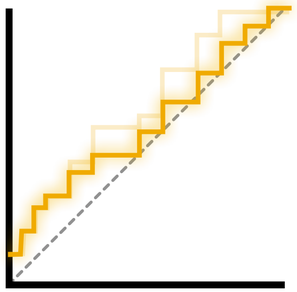
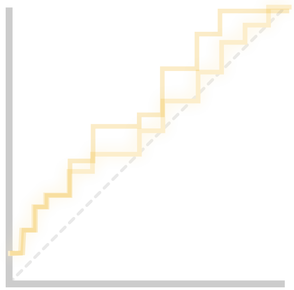
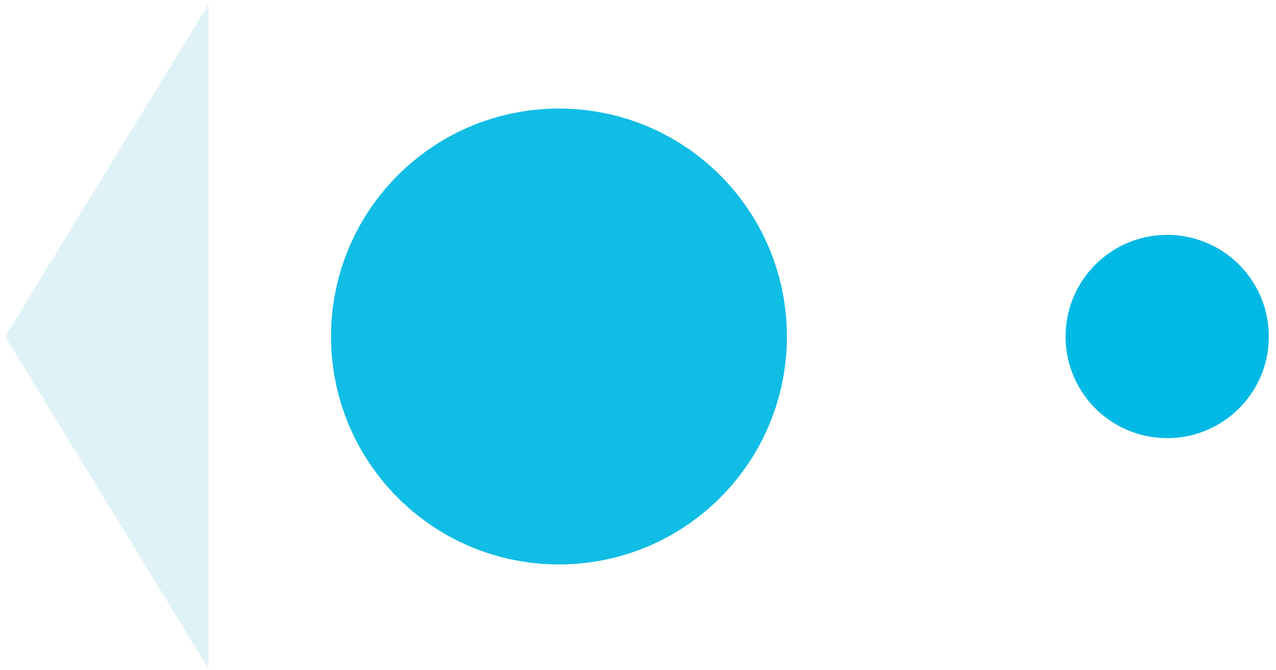


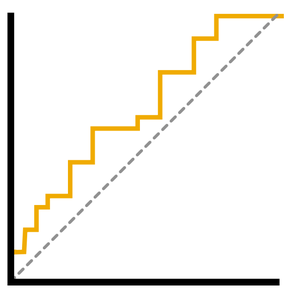
(joint) distribution of input data?

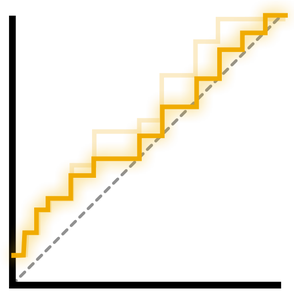
distribution of predictions?



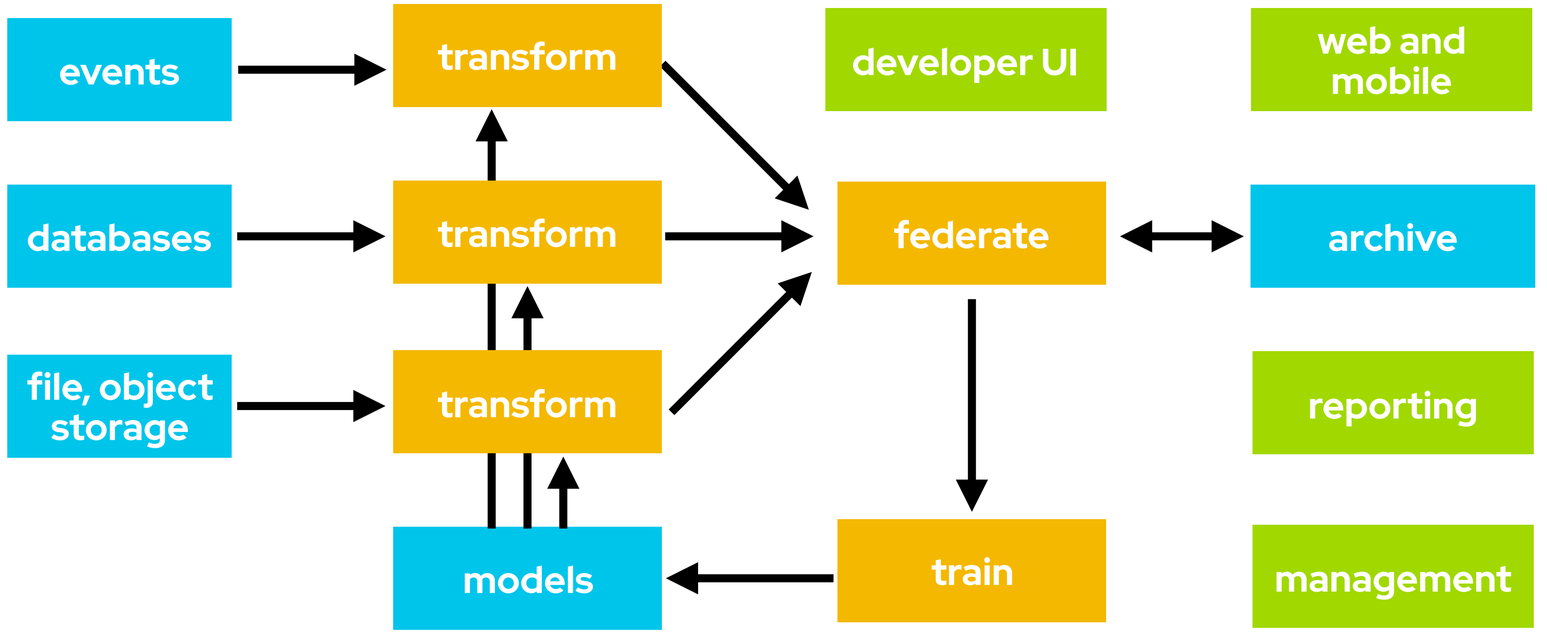
distribution of number of multiplications while scoring?







Intelligent applications are machine learning systems


events
databases
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developer UI
web and mobile
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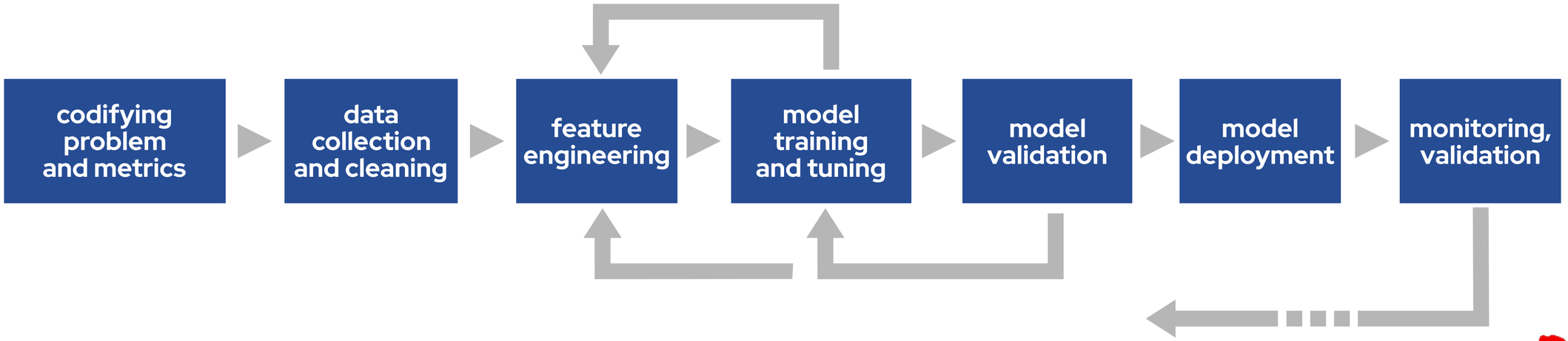
codifying problem and metrics
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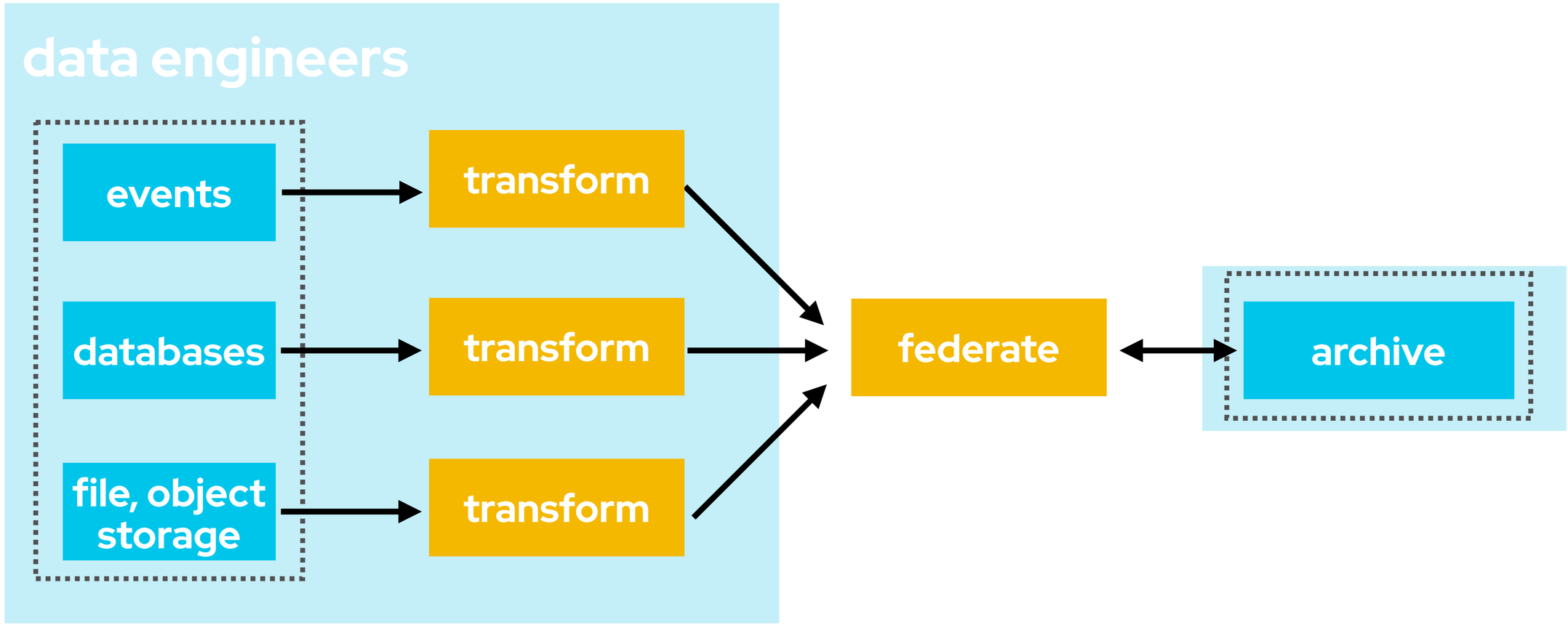
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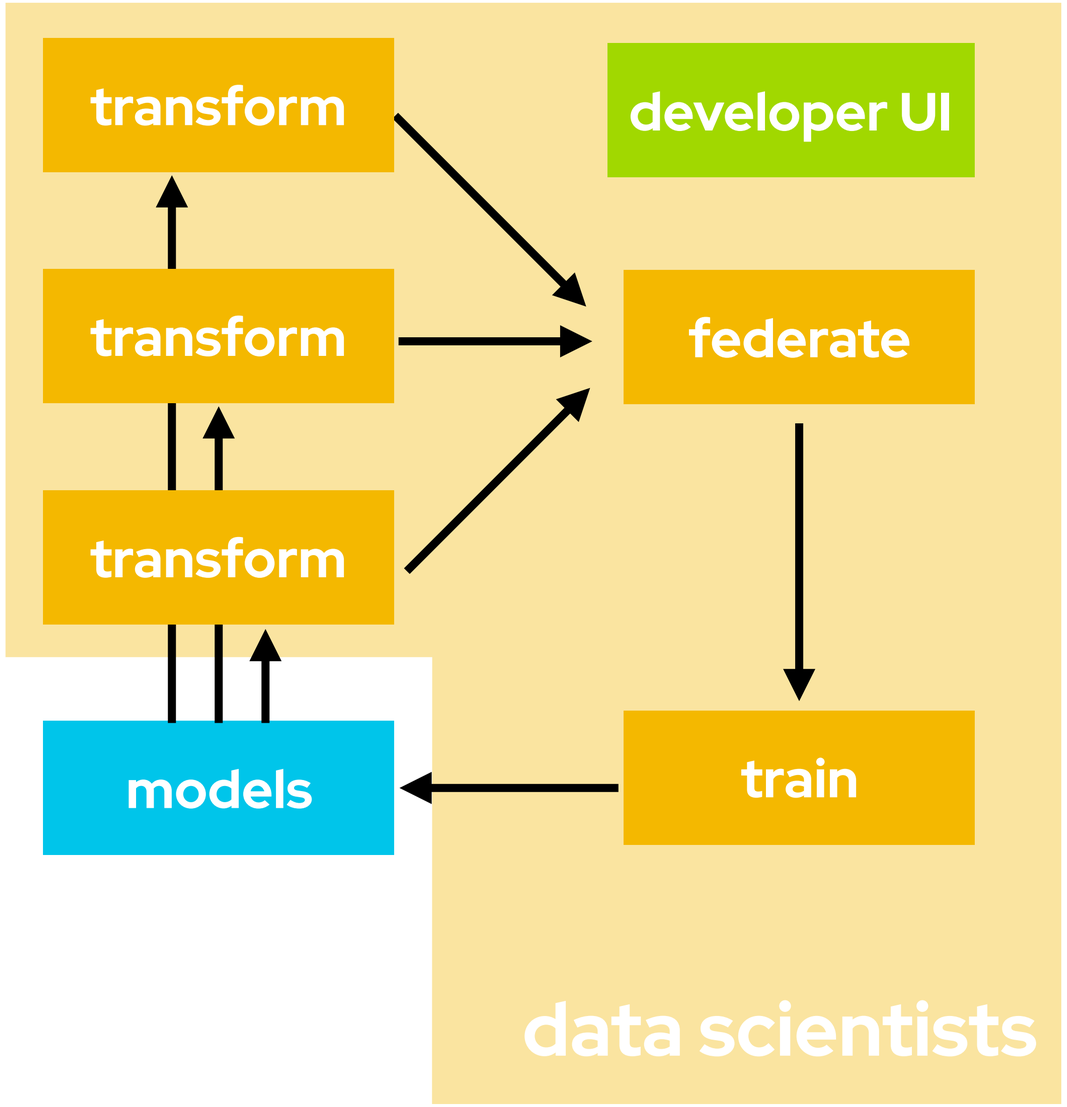
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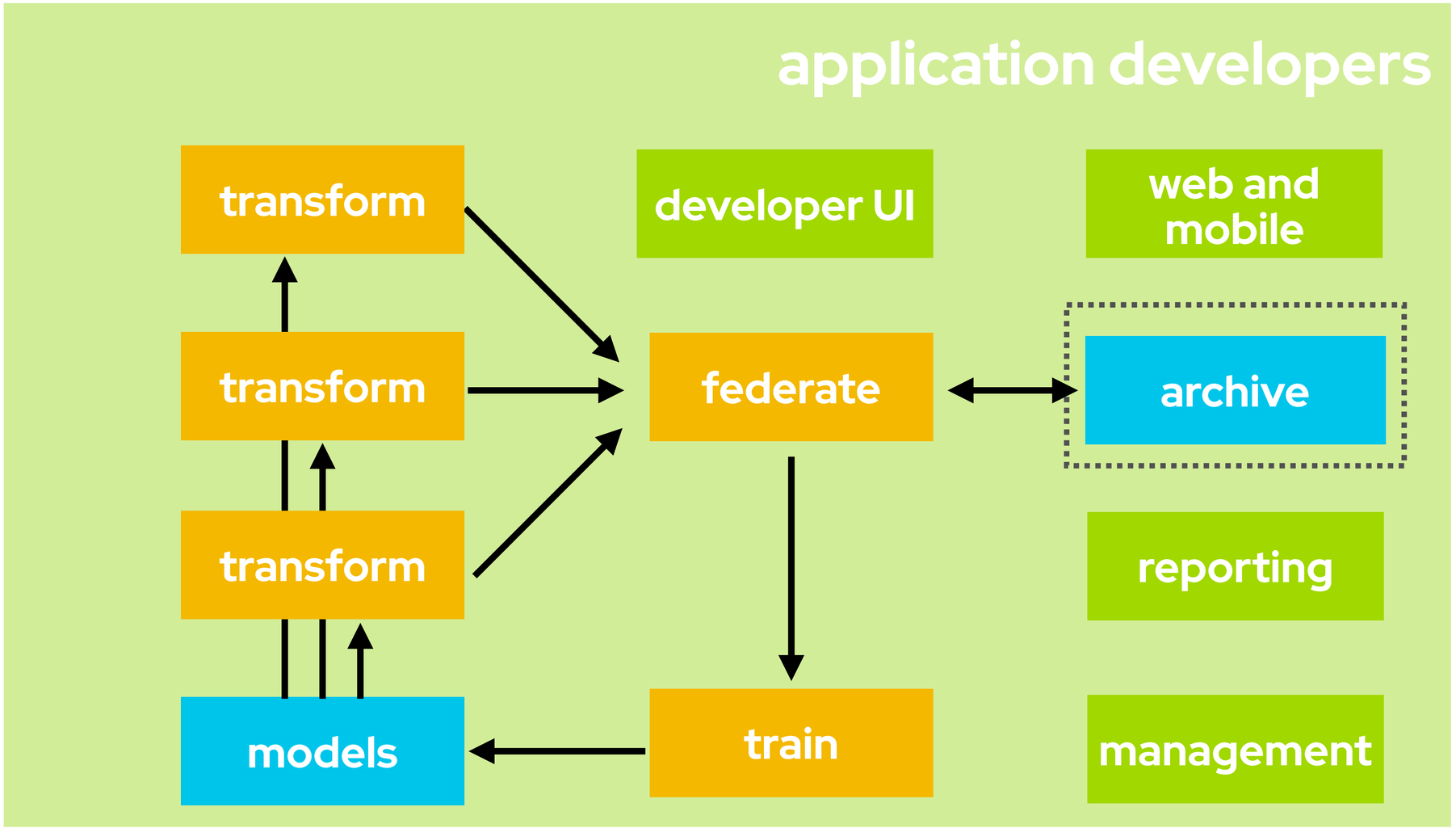
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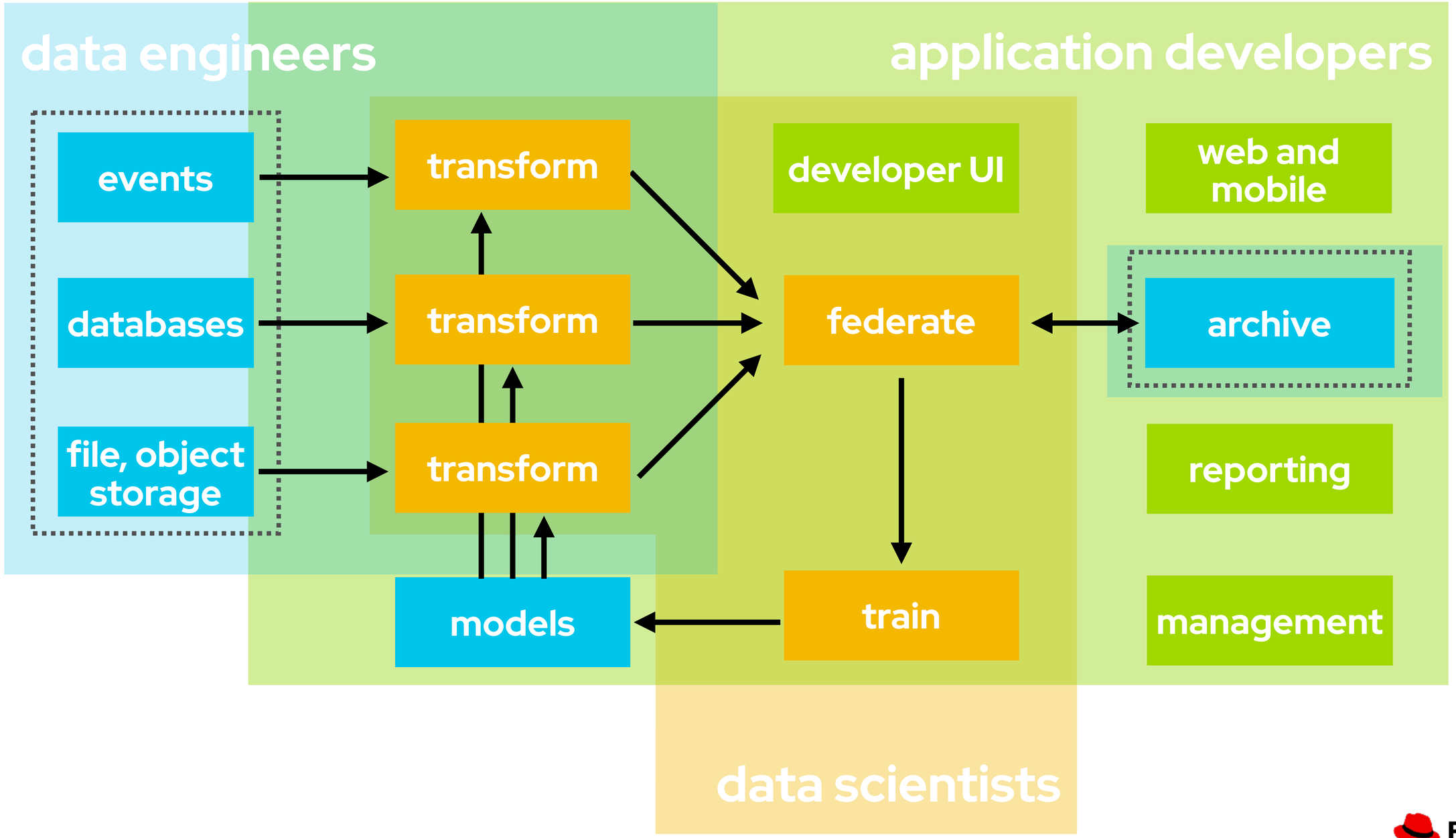
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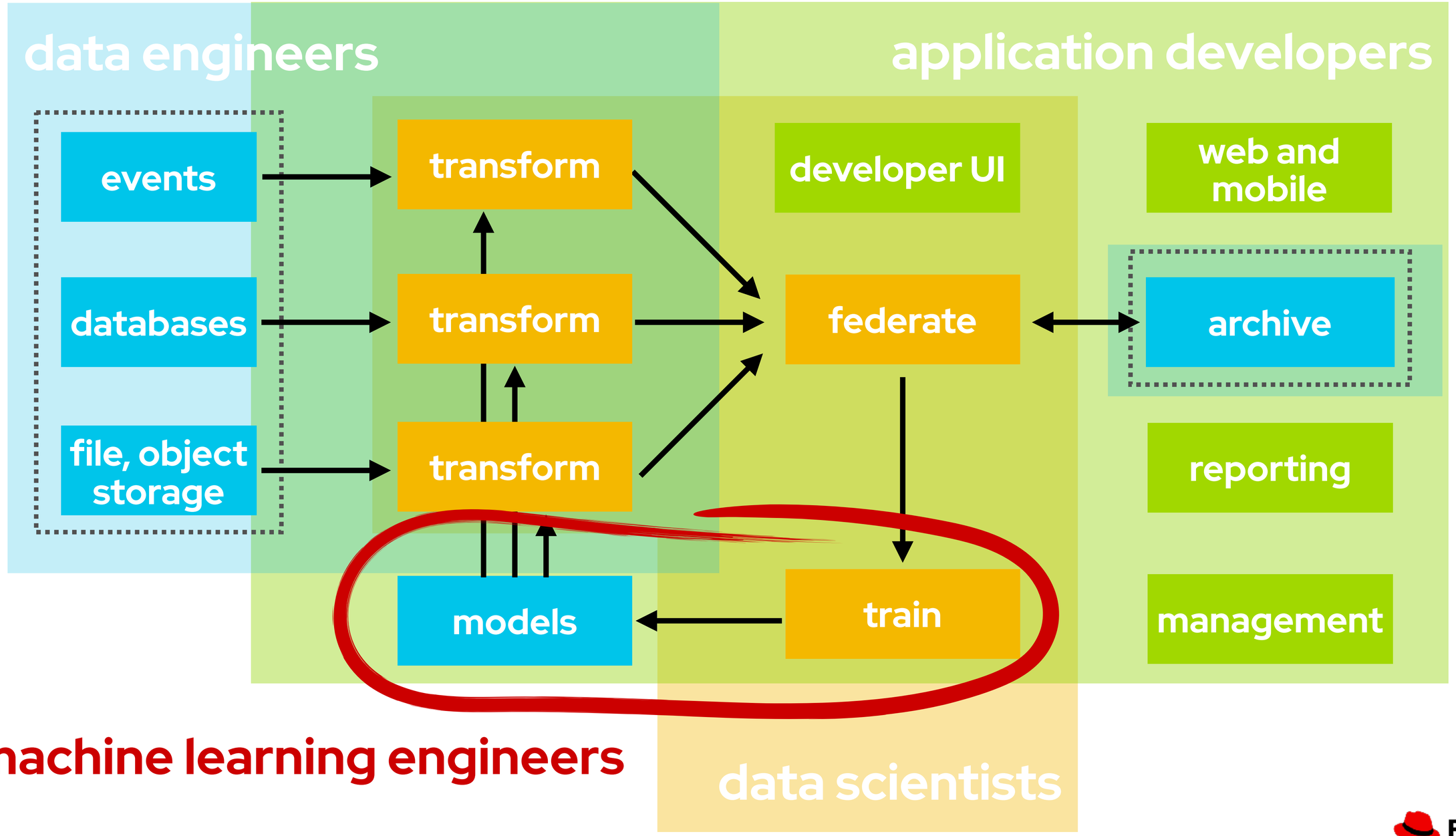
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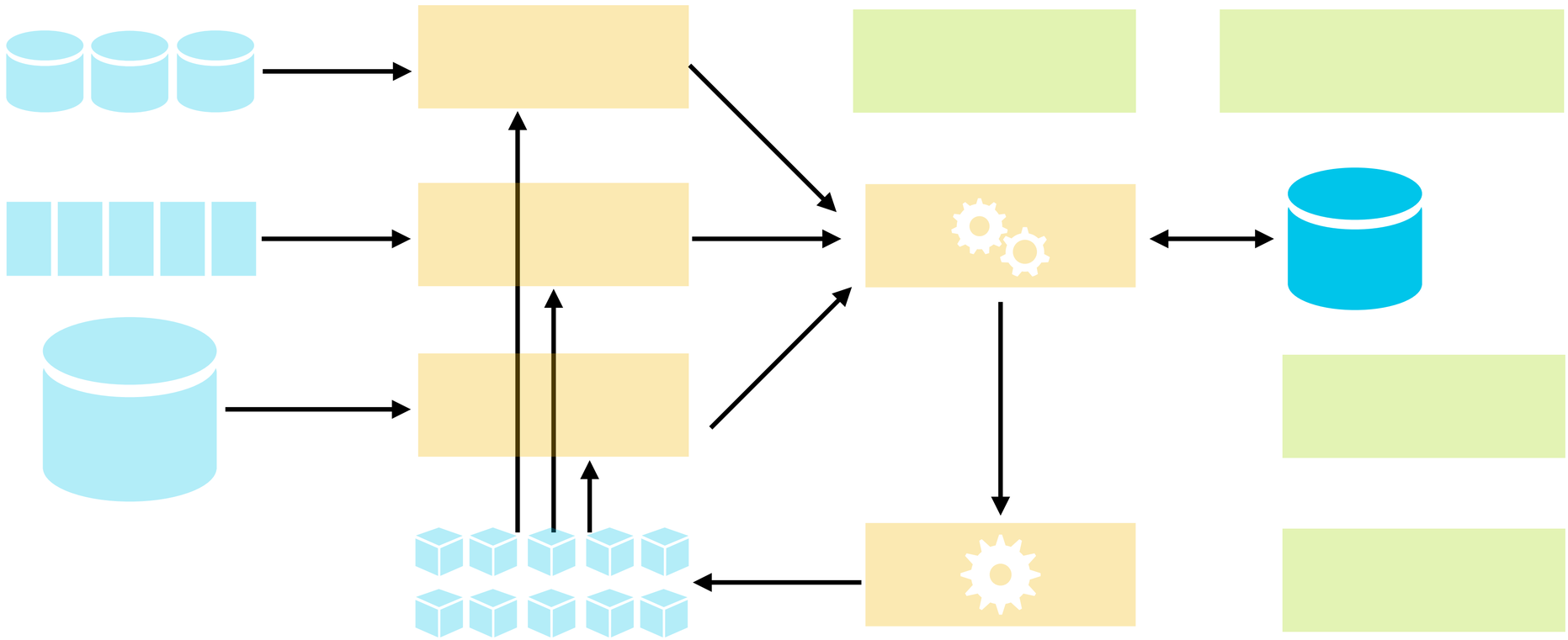
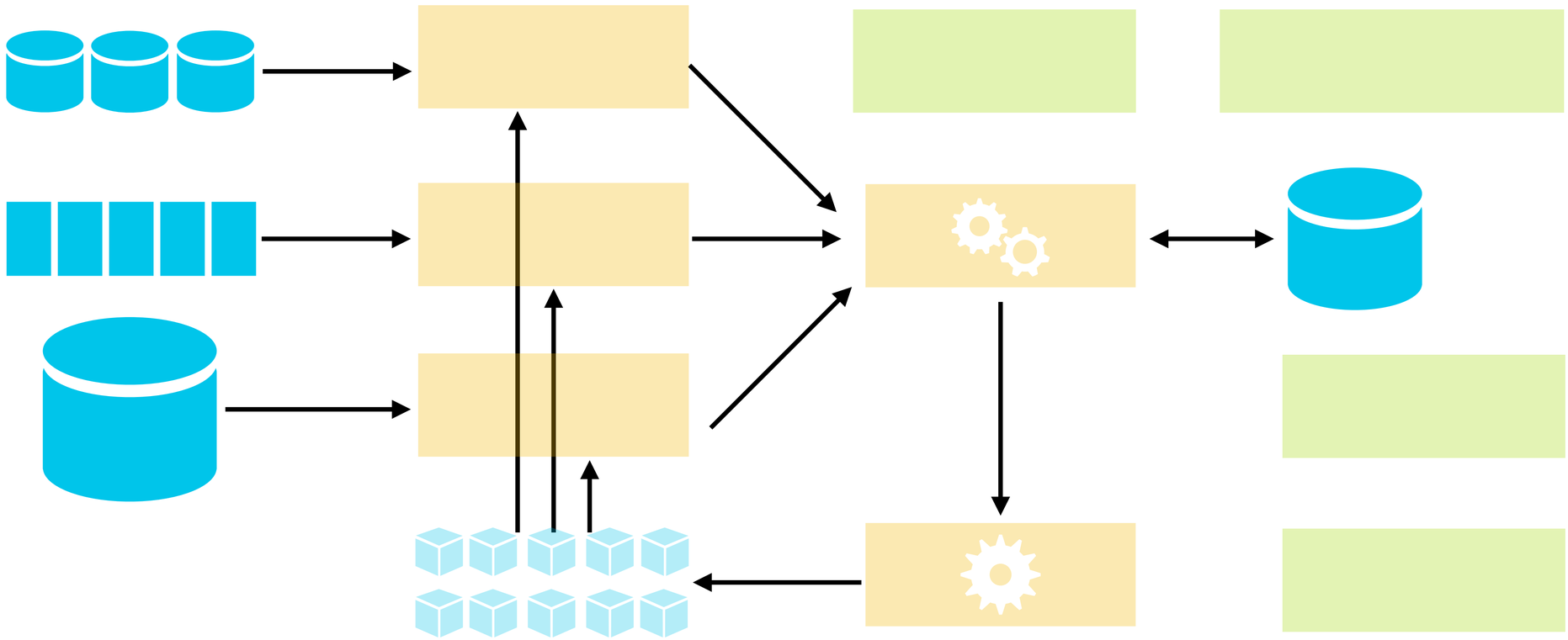
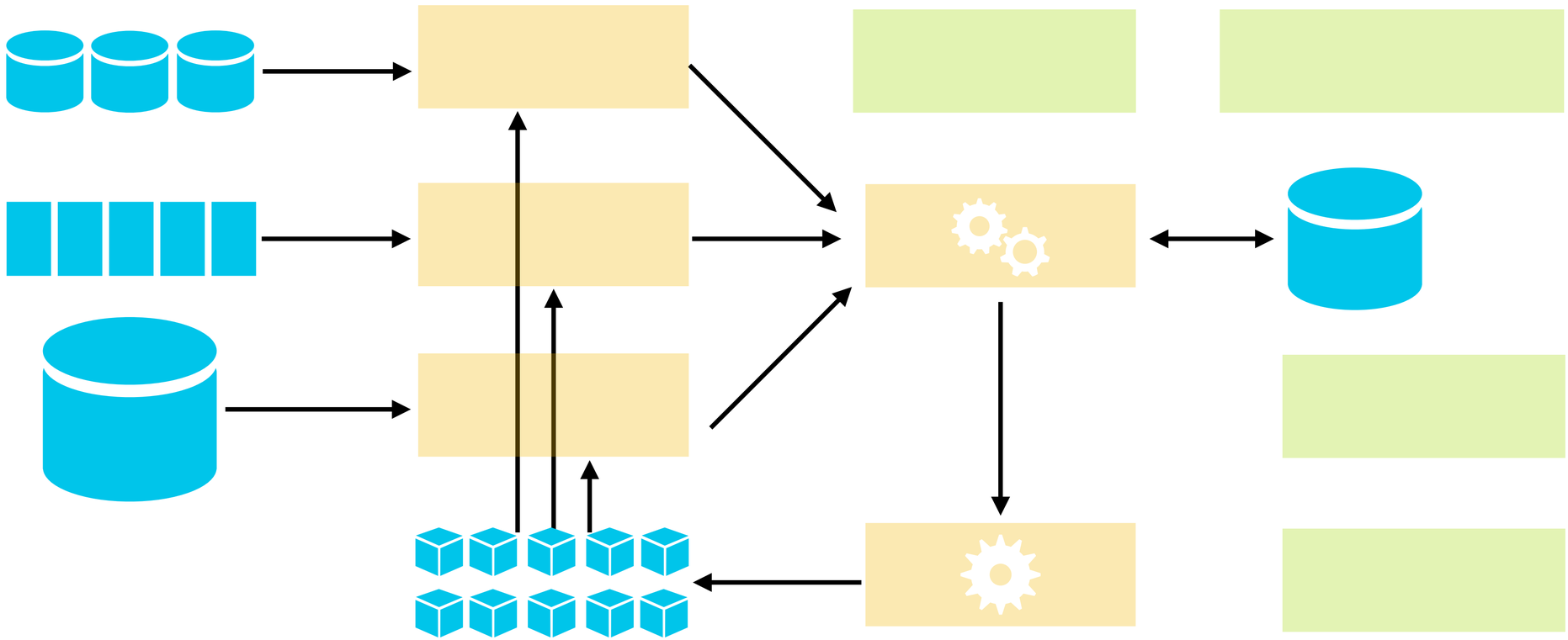
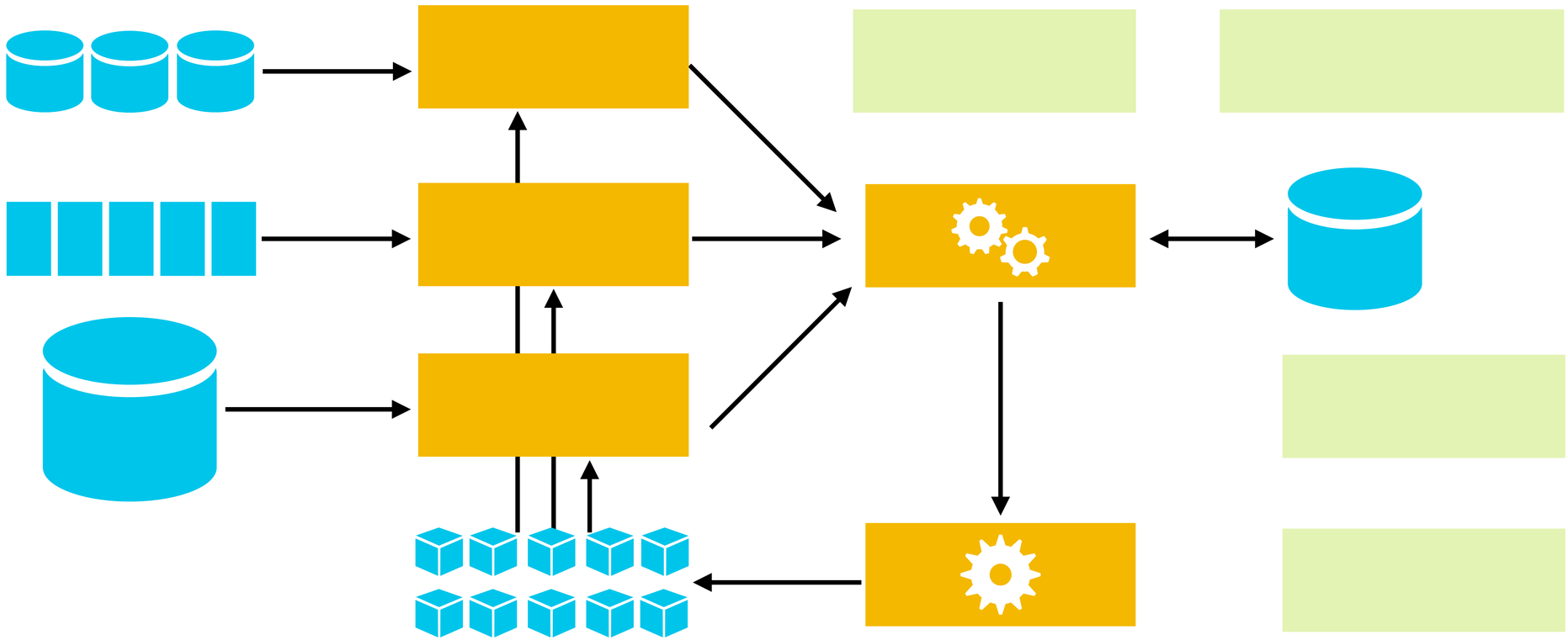
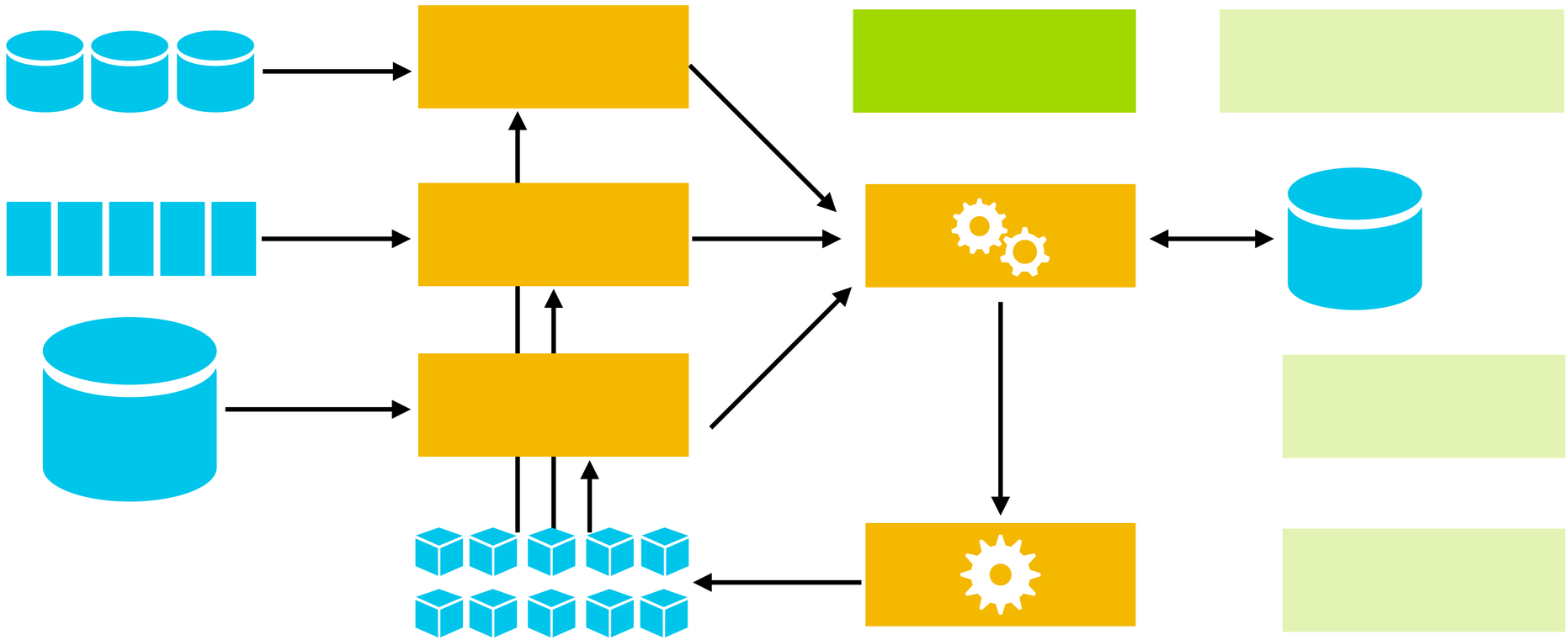
Managing compute and data in a shared discovery environment

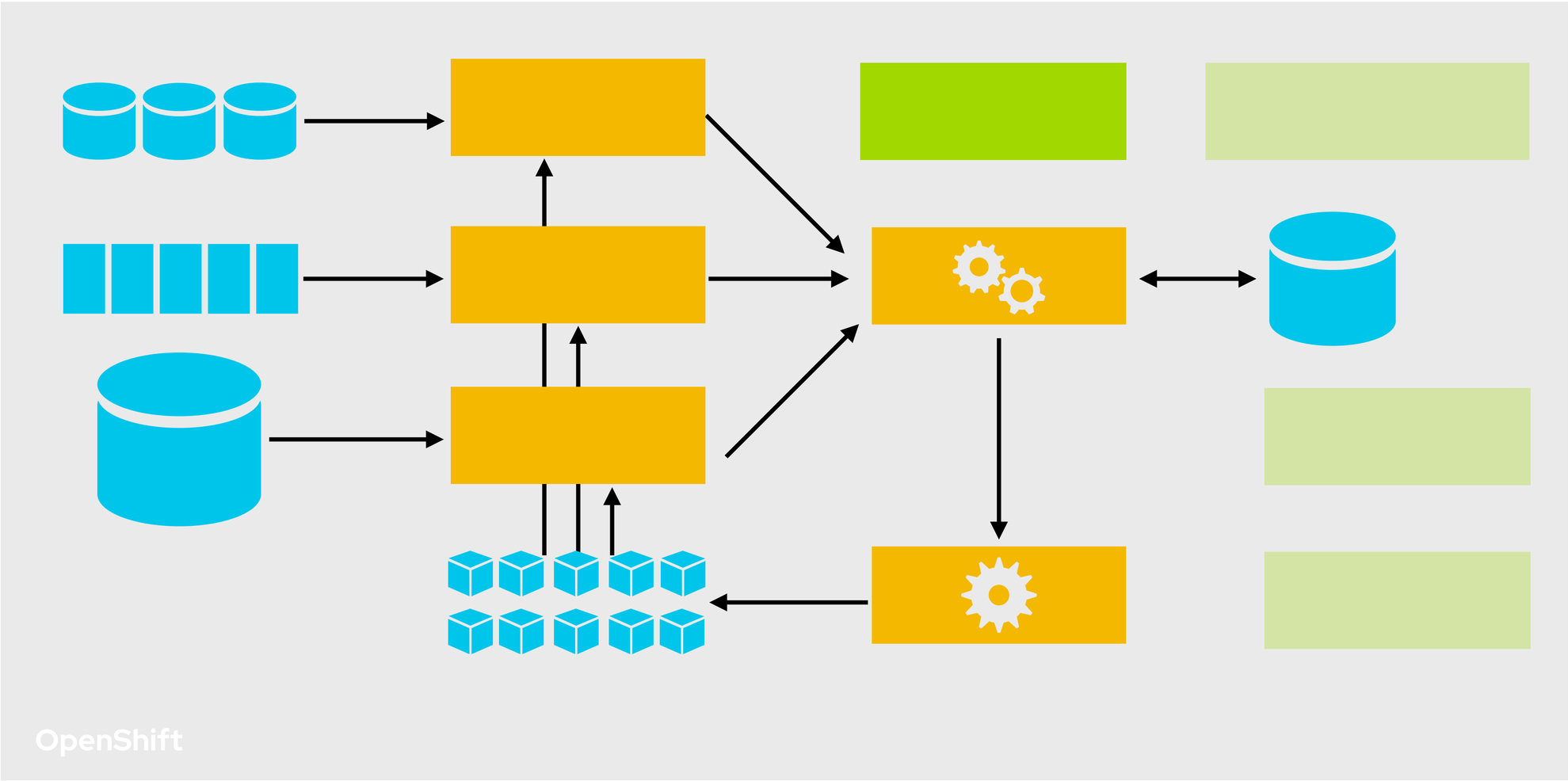








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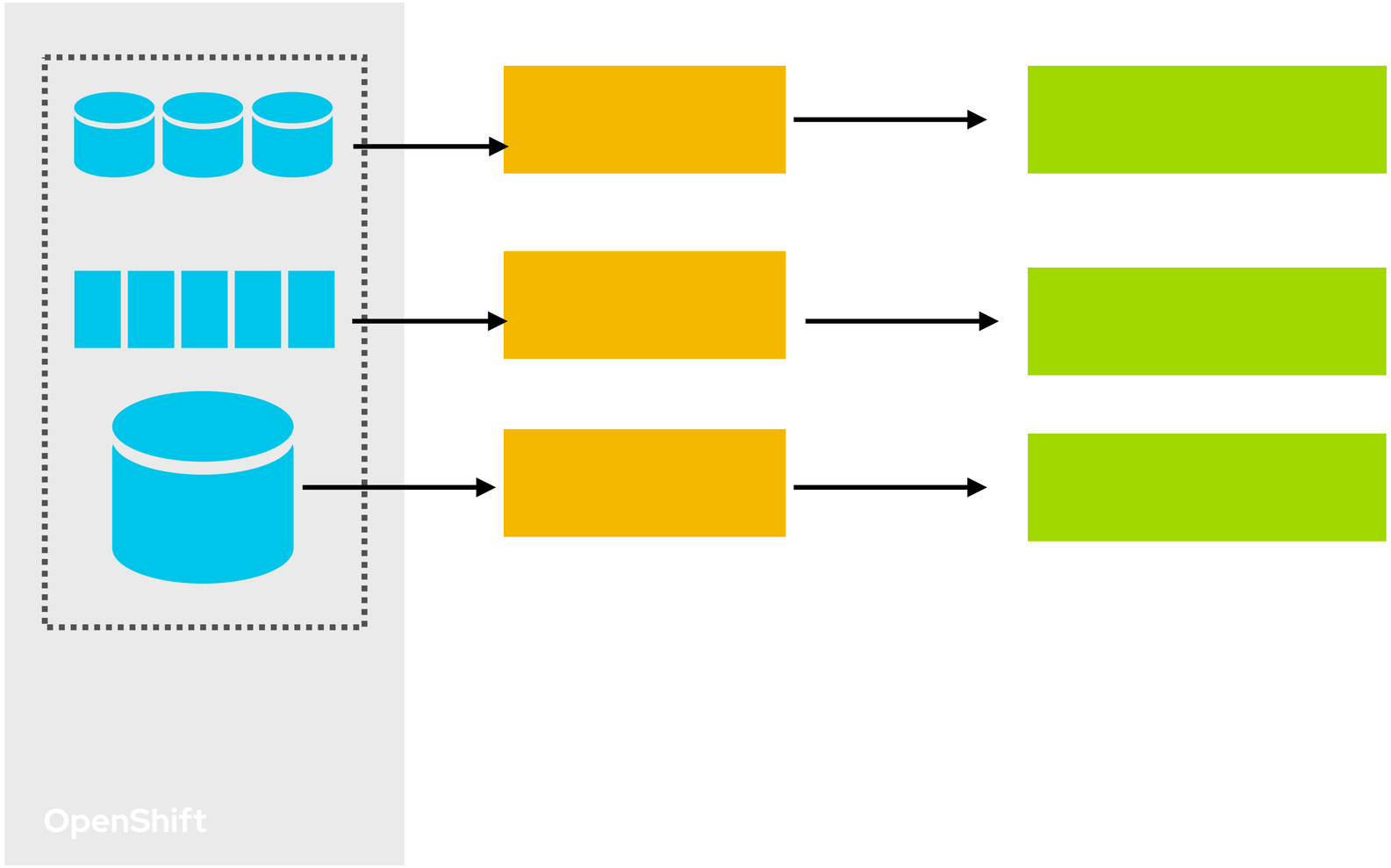
There's no one-size-fits-all architecture for AI/ML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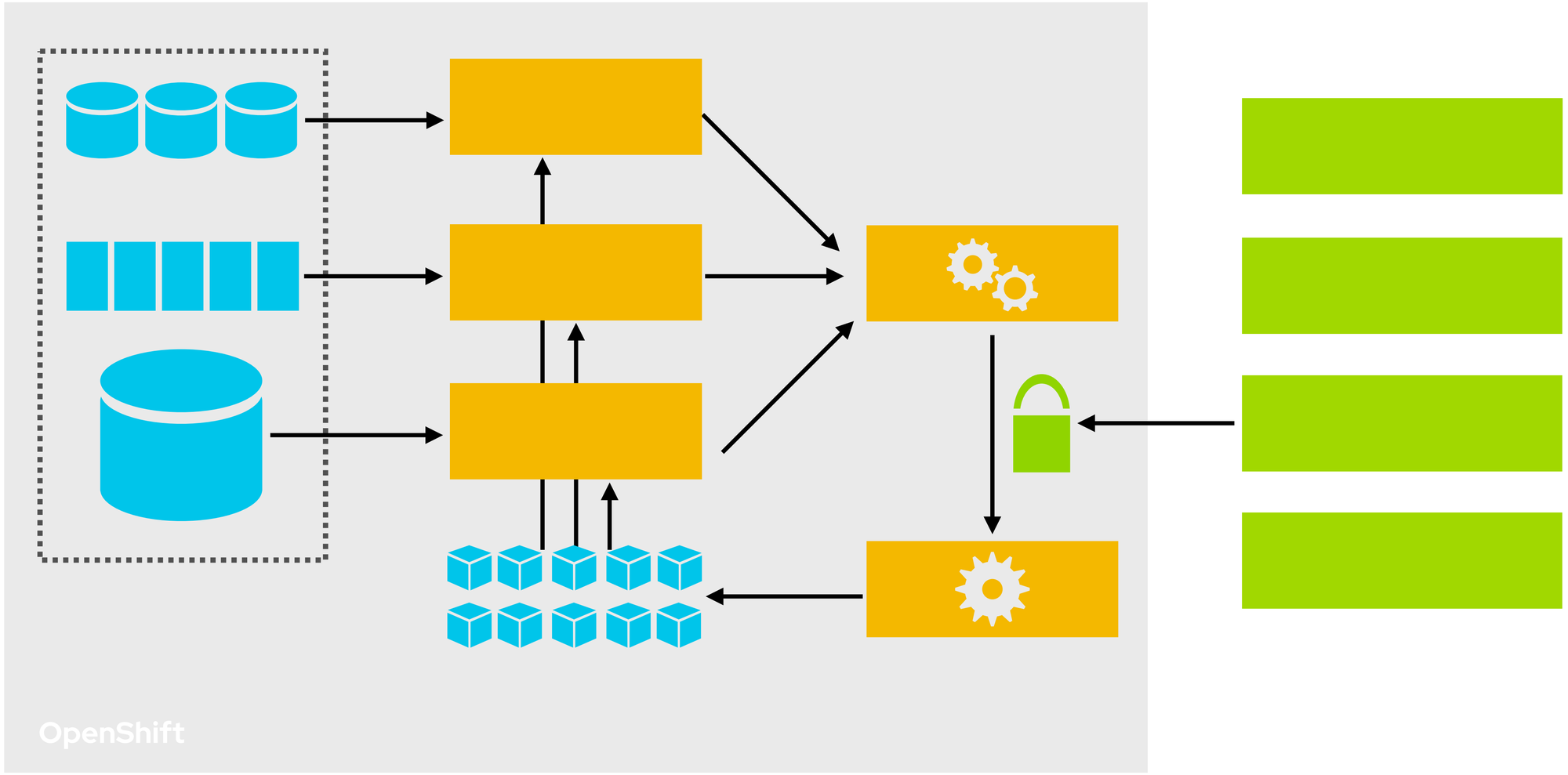
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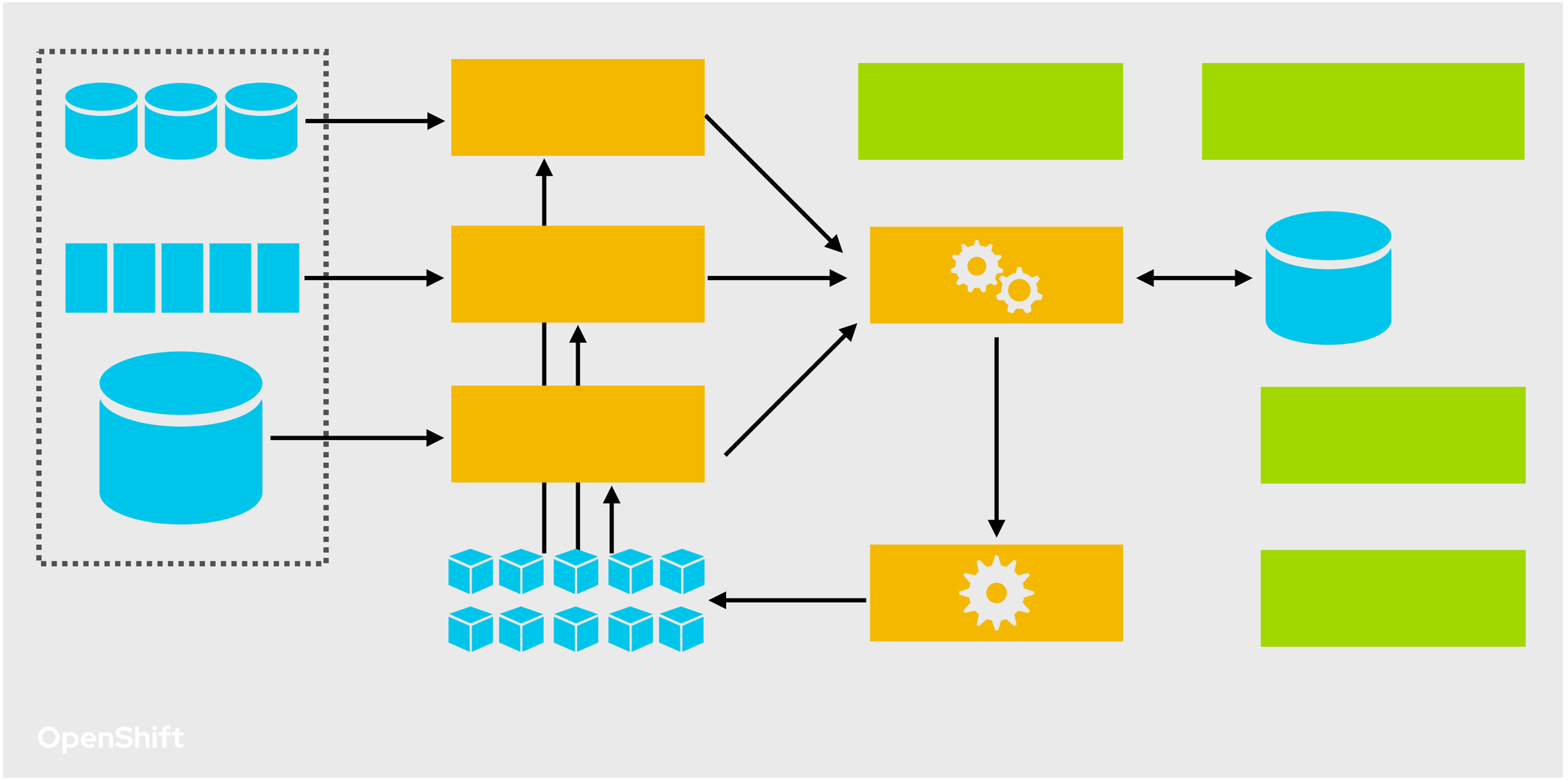
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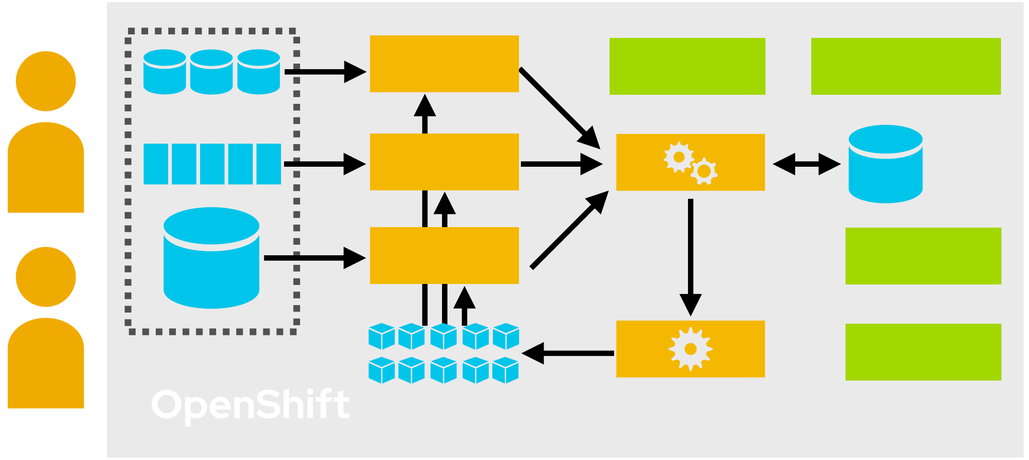
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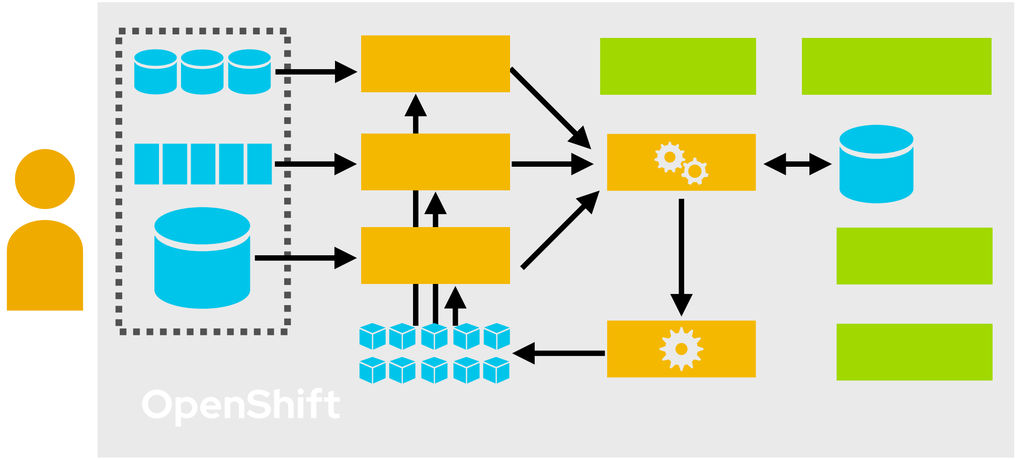
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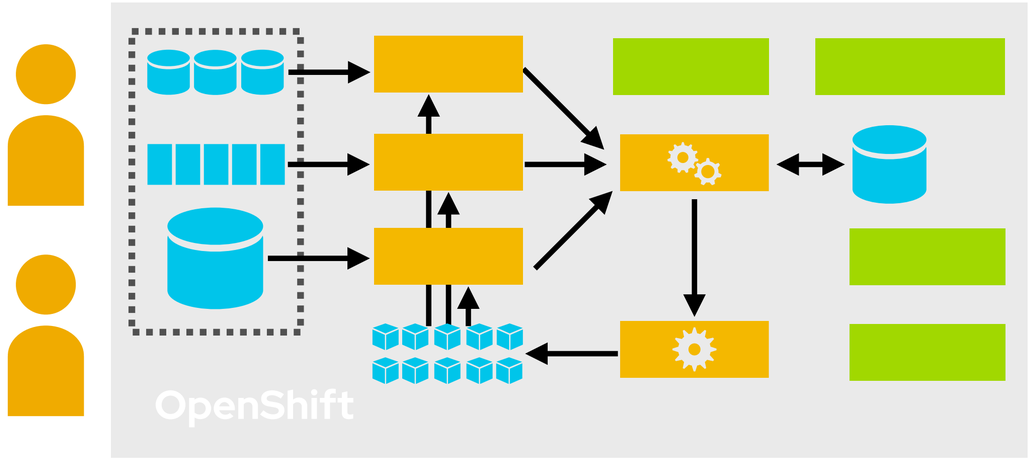
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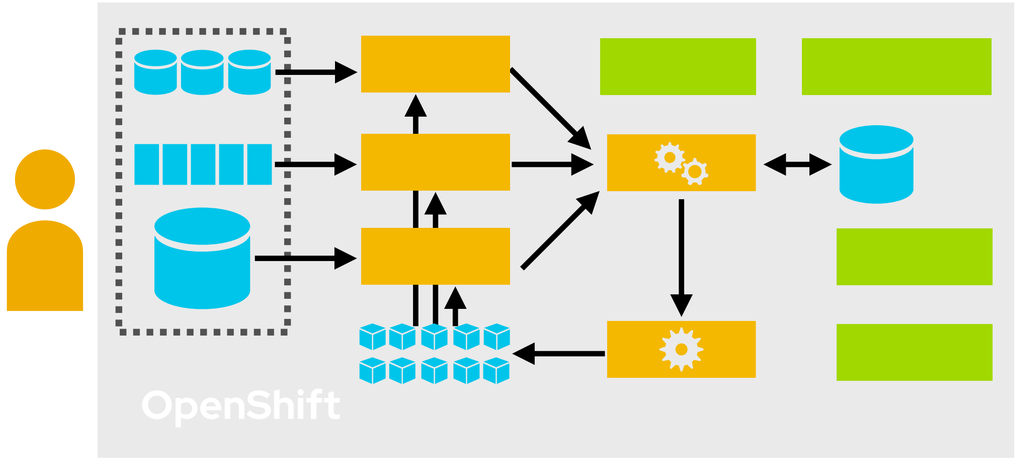
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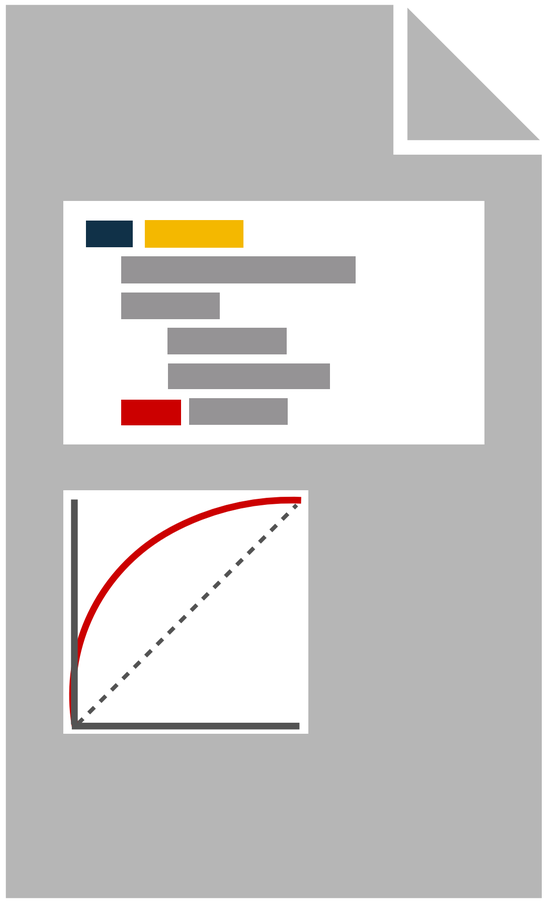

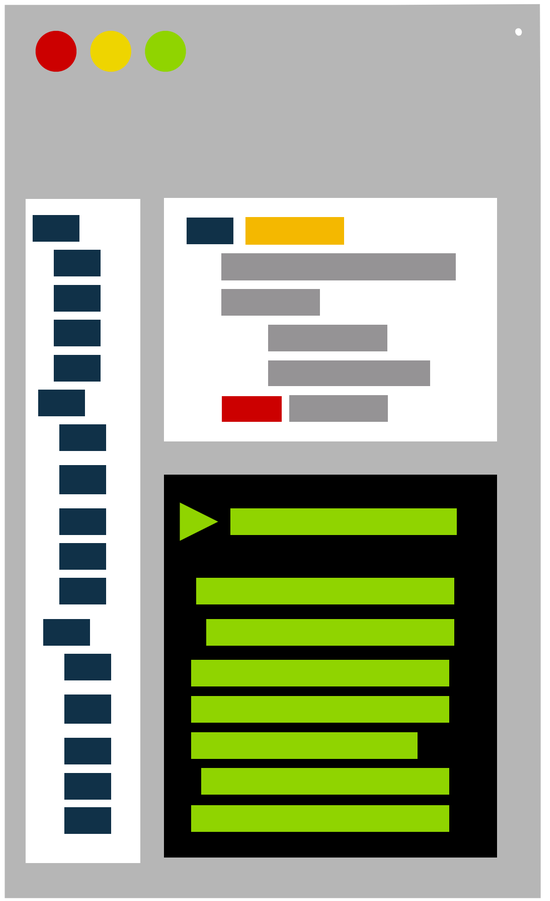

From developer experience to data scientist experience(s)


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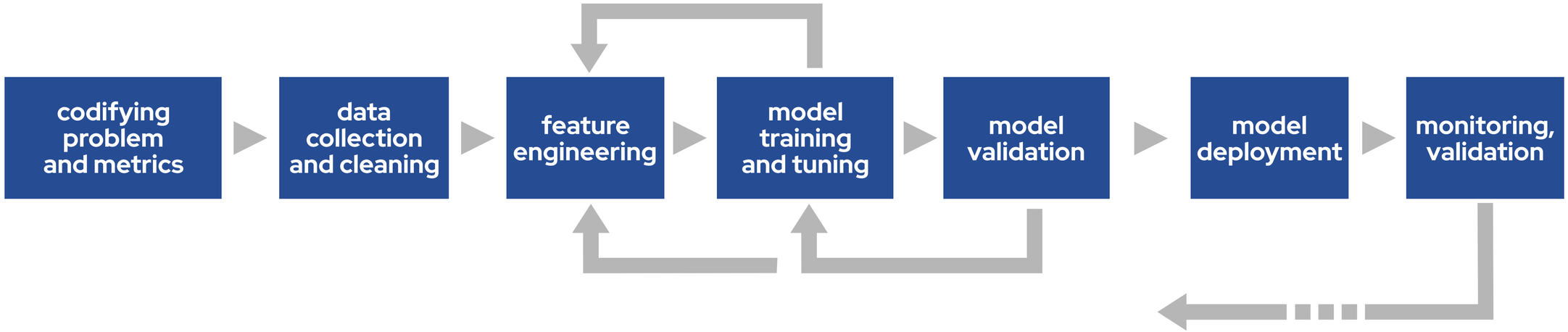
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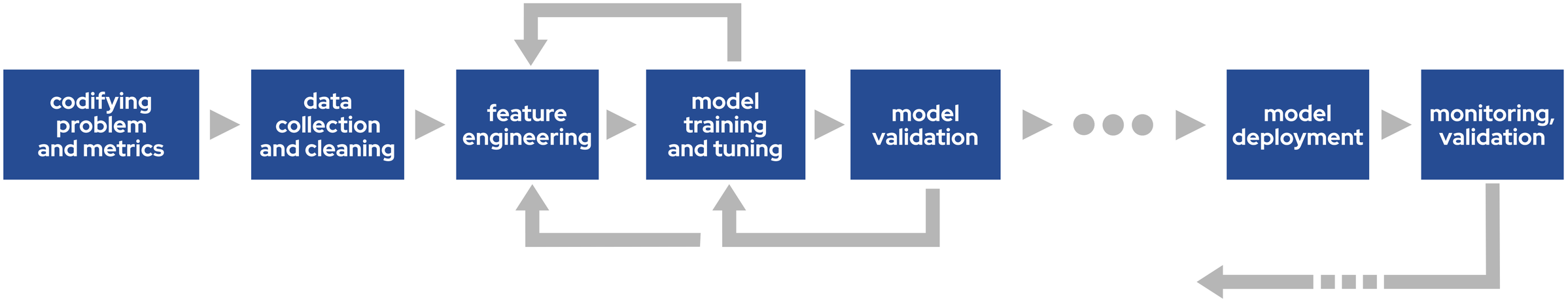
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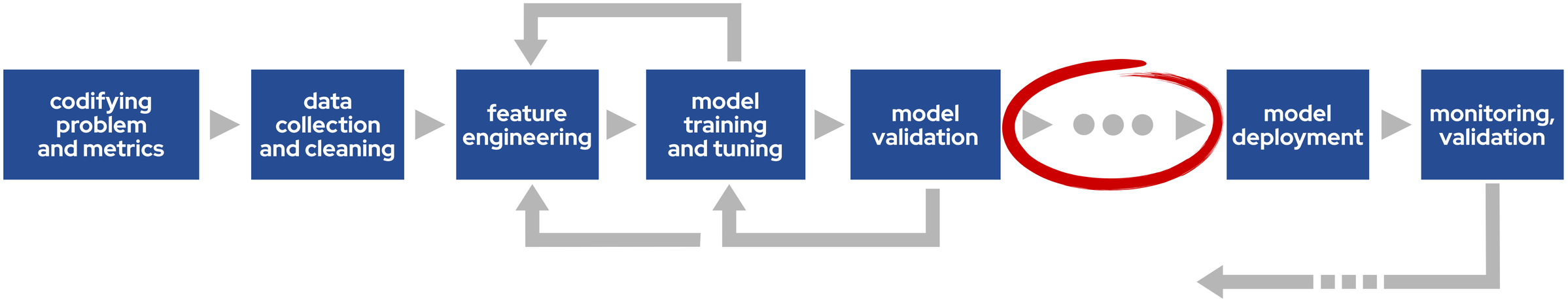
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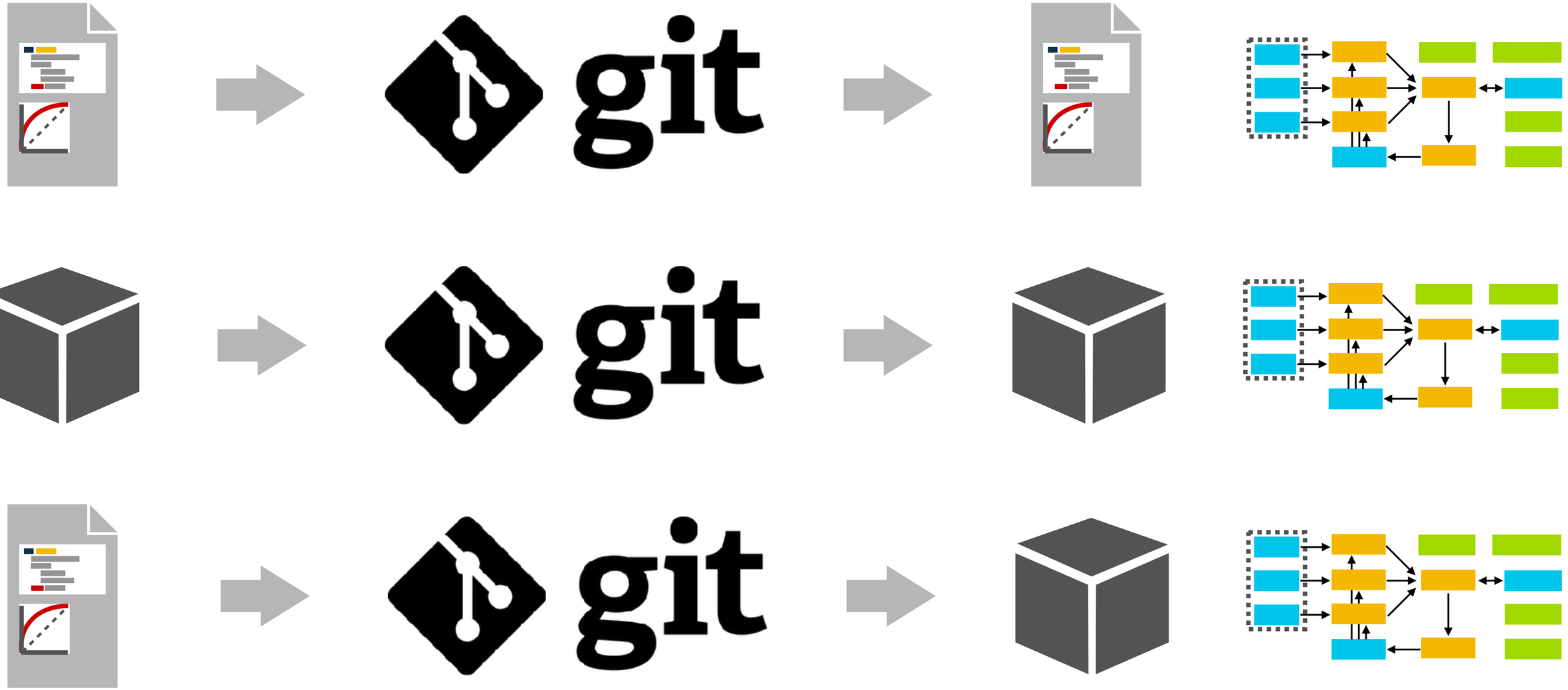
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In this notebook we will process the synthetic Austen/food reviews data and convert it into feature vectors. In later notebooks these feature vectors will be the inputs to models which we will train and eventually use to identify spam.

This notebook uses term frequency-inverse document frequency, or tf-idf, to generate feature vectors. Tf-idf is commonly used to summarise text data, and it aims to capture how important different words are within a set of documents. Tf-idf combines a normalized word count (or term frequency) with the inverse document frequency (or a measure of how common a word is across all documents) in order to identify words, or terms, which are 'interesting' or important within the document.

We begin by loading in the data:

In [1]:
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import pandas as pd

df = pd.read_parquet("data/training.parquet")
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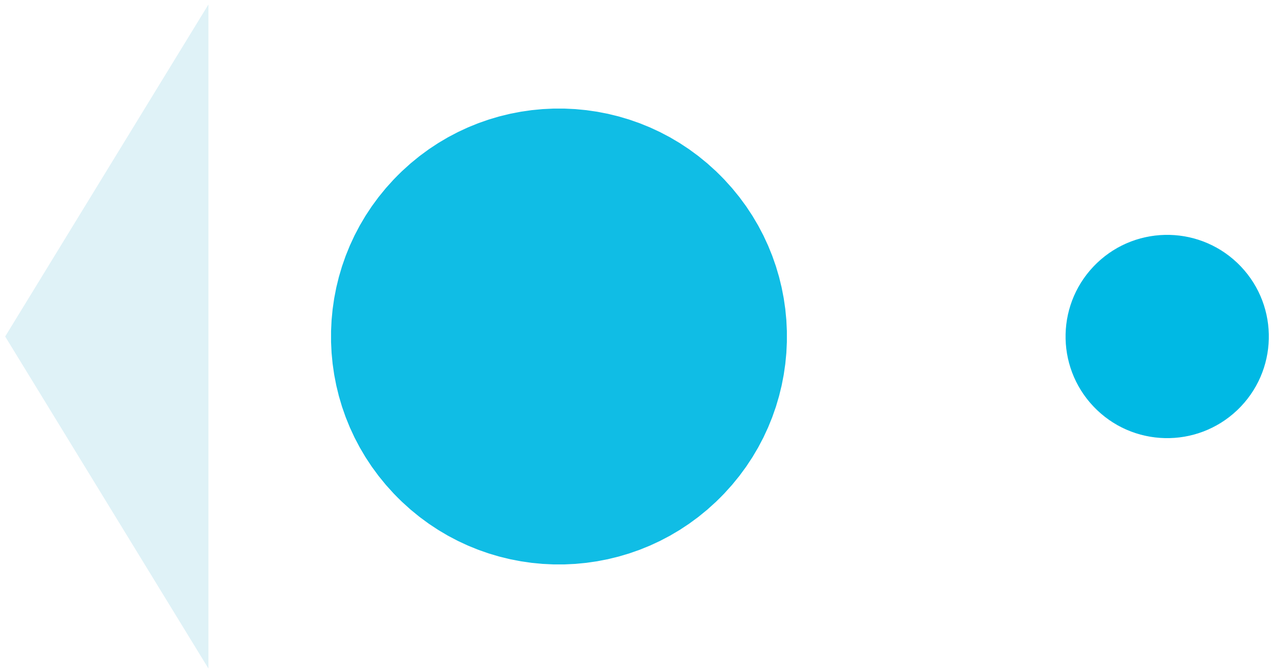

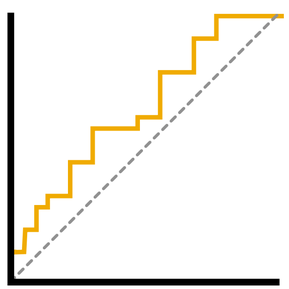

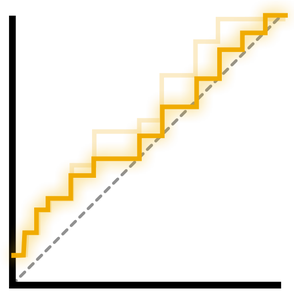

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Running our models as services gives us an interesting opportunity to detect data drift by publishing the distribution of our predictions as metrics. If the distribution of predictions shifts over time, we can use that as an indication that the distribution of the data we're evaluating has shifted as well, and that we should re-train our model.
In this example, our pipeline service publishes metrics related to the predictions made by the model (keys beginning with `pipeline_predictions_`) as well as metrics related to the computational performance of our pipeline service (keys beginning with `pipeline_processing_seconds_`).

In [ ]:
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get_metrics()
```

Since our service publishes Prometheus metrics, we can define alerting rules or visualize how our metric values change over time.

In [ ]:
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def experiment(data, size, **kwargs):
    for k, v in kwargs.items():
        sample = data[data.label == k].sample(int(size * v))
        score_text(sample["text"].values.tolist())
```

In [ ]:
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experiment(data, 20000, legitimate=.05, spam=.95)
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```

In [ ]:
```
experiment(data, 20000, legitimate=.25, spam=.75)
```

In [ ]:
```
experiment(data, 20000, legitimate=1)
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Exercises

1. What would a REST API for serving multiple versions of multiple pipelines look like? (Hint: consider the verbs and nouns involved.)
2. While we don't have a monitoring stack enabled for this workshop, you can certainly install and configure one in your own OpenShift cluster. What sort of alerting rules might you install to identify data drift in this application?

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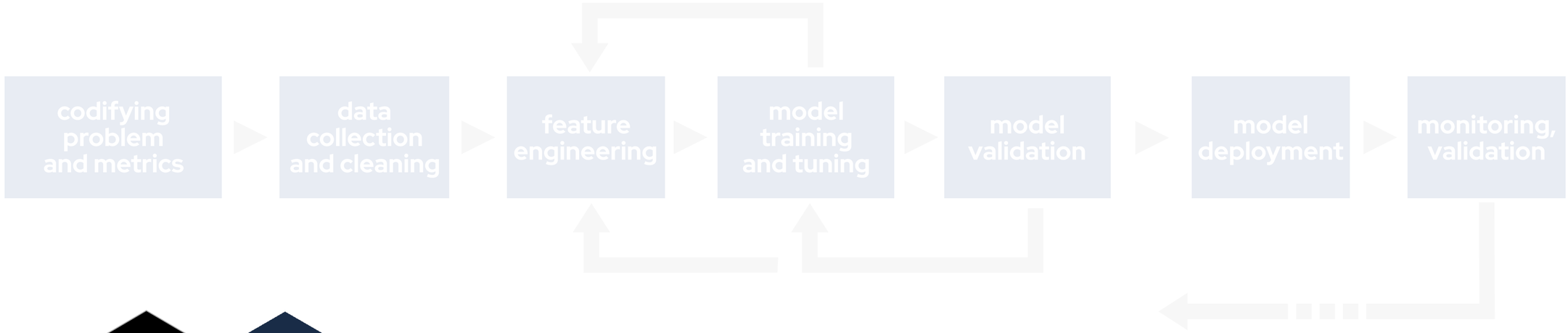
Conclusions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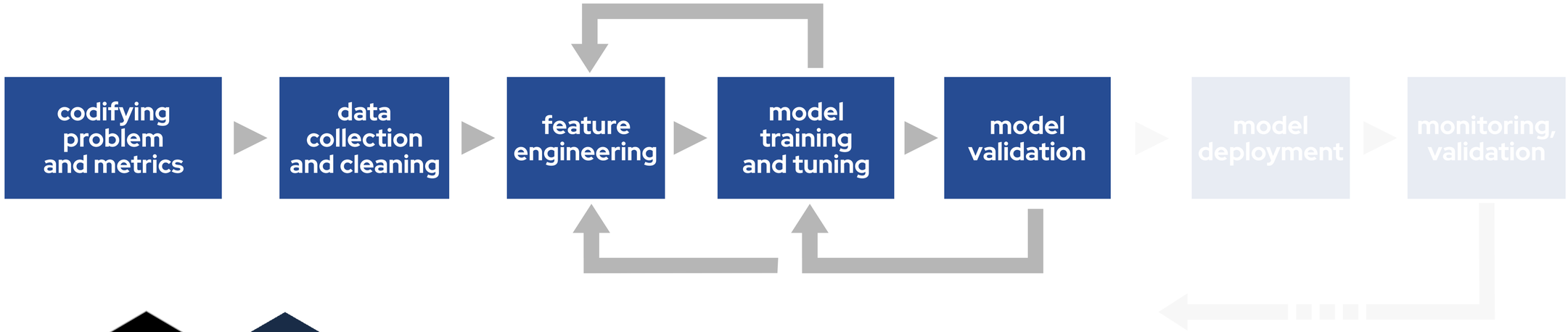

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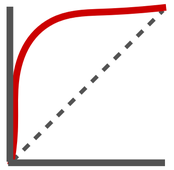

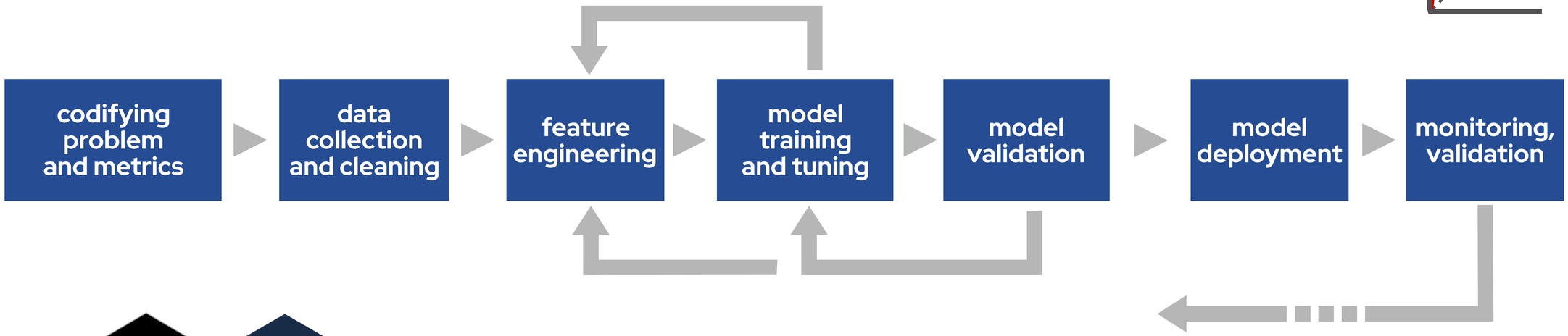

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