RECOMMENDATION AND STARFISH

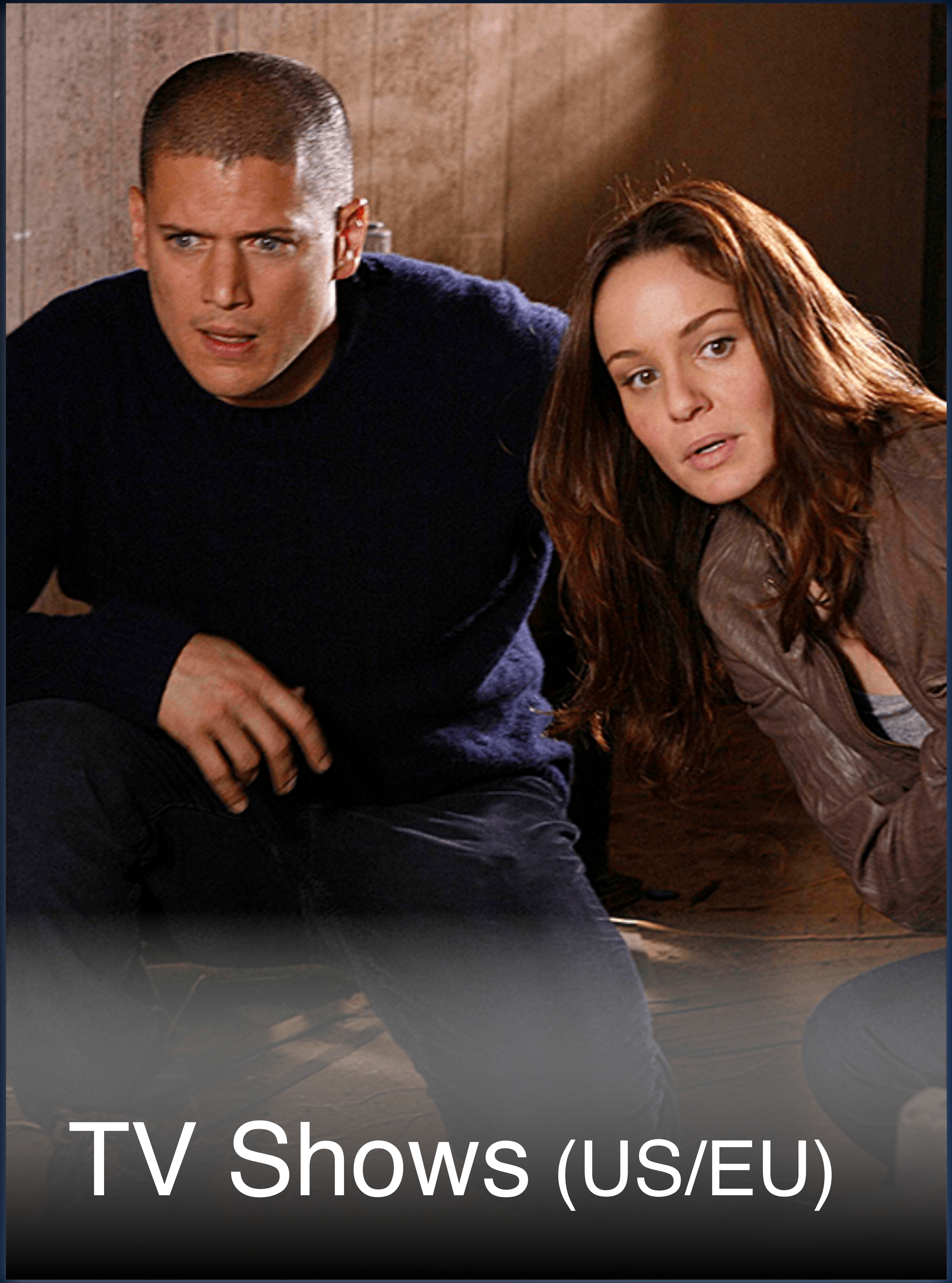
Shripad Deshmukh

U-NEXT

Watch, read, and listen. All of your entertainment in one place.

U-NEXT

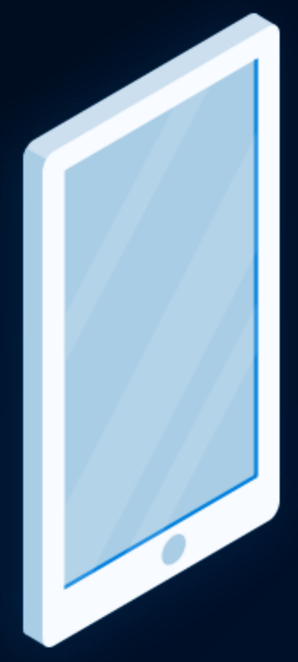
170,000+ films & TV shows



170,000+ films & TV shows

To all platforms

TVs



Smart devices

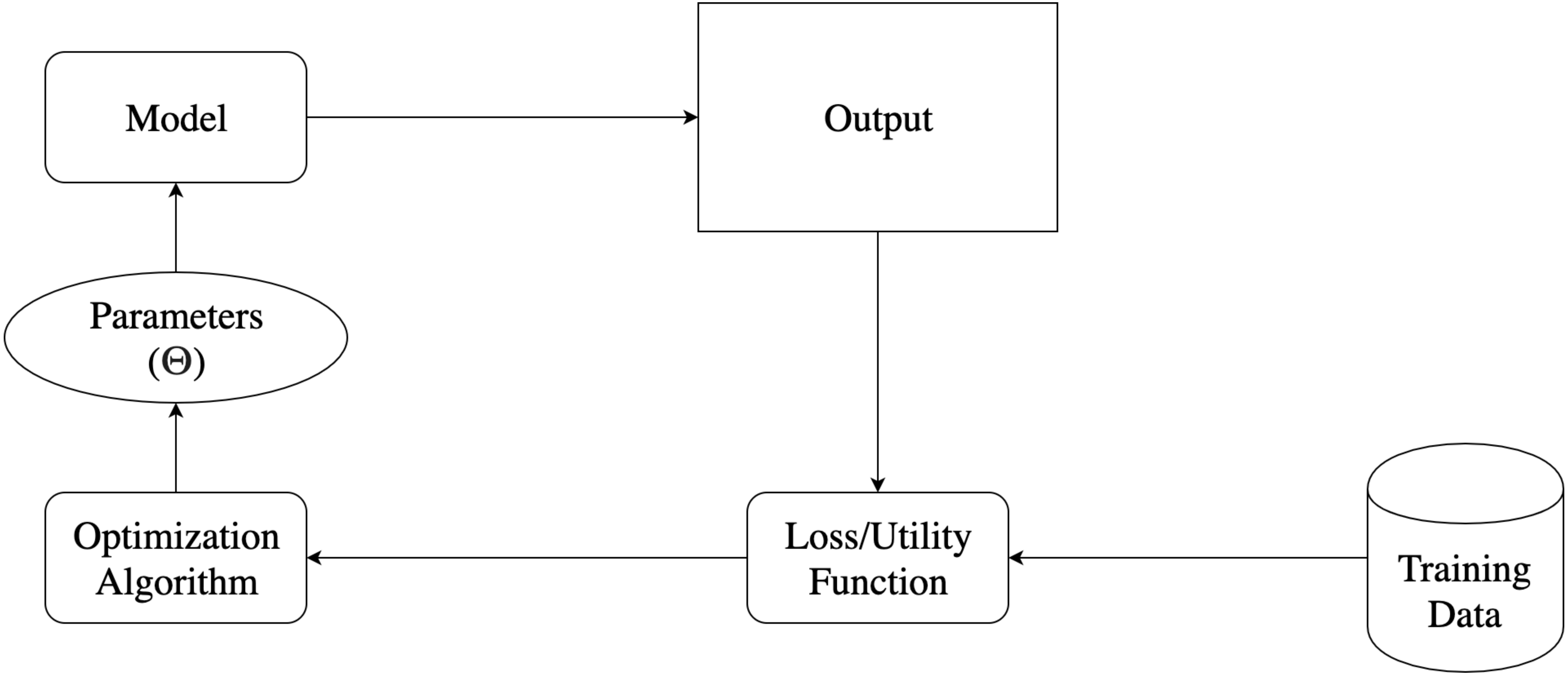
Gaming consoles

PCs

IMPLICIT DATA

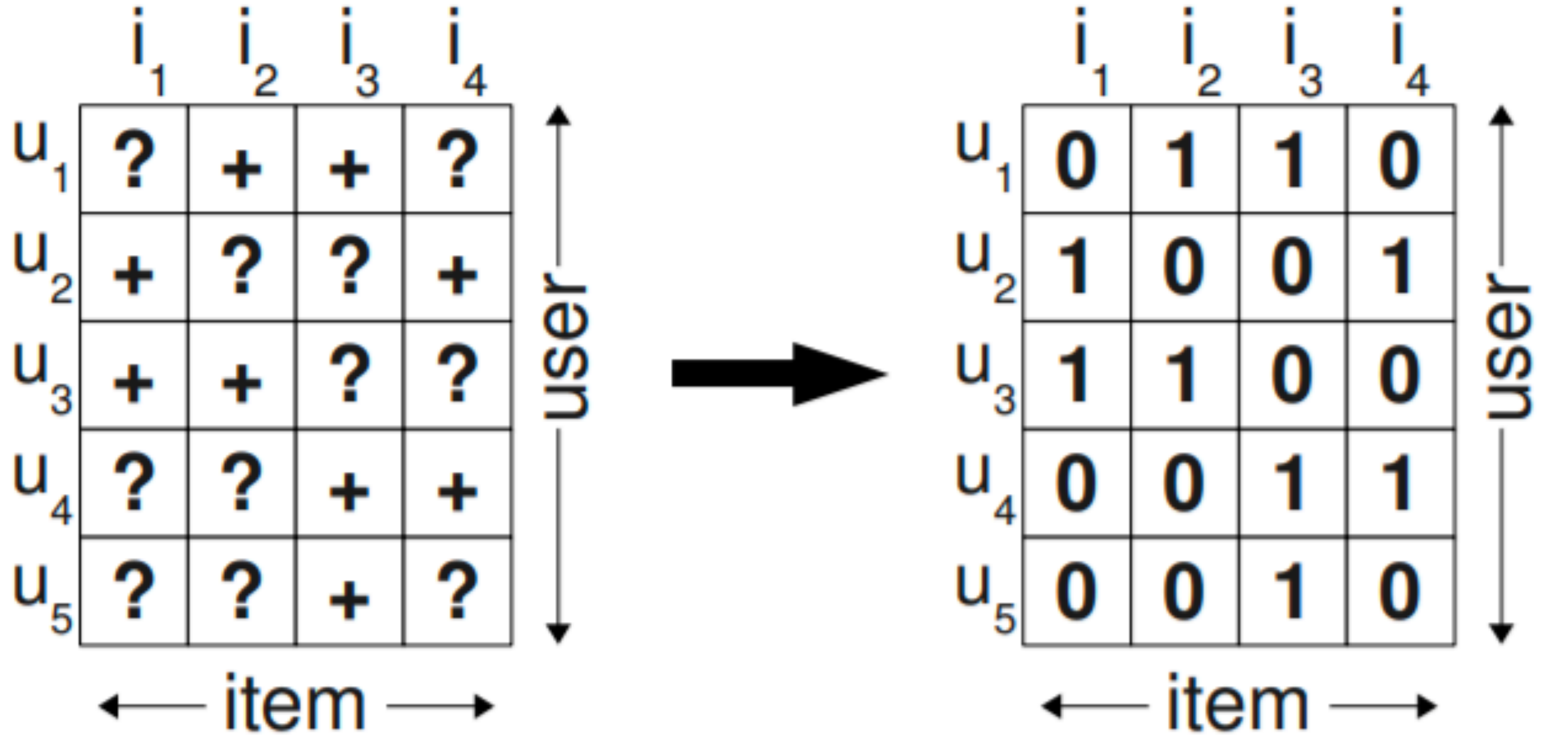
- Implicit Data:
  - No negative feedback
  - Inherently noisy
  - Preference vs Confidence

LEARNING RECOMMENDER SYSTEM



TRAINING DATA

Xui -> Score for an item that reflects
Users preference for that item



TRAINING DATA

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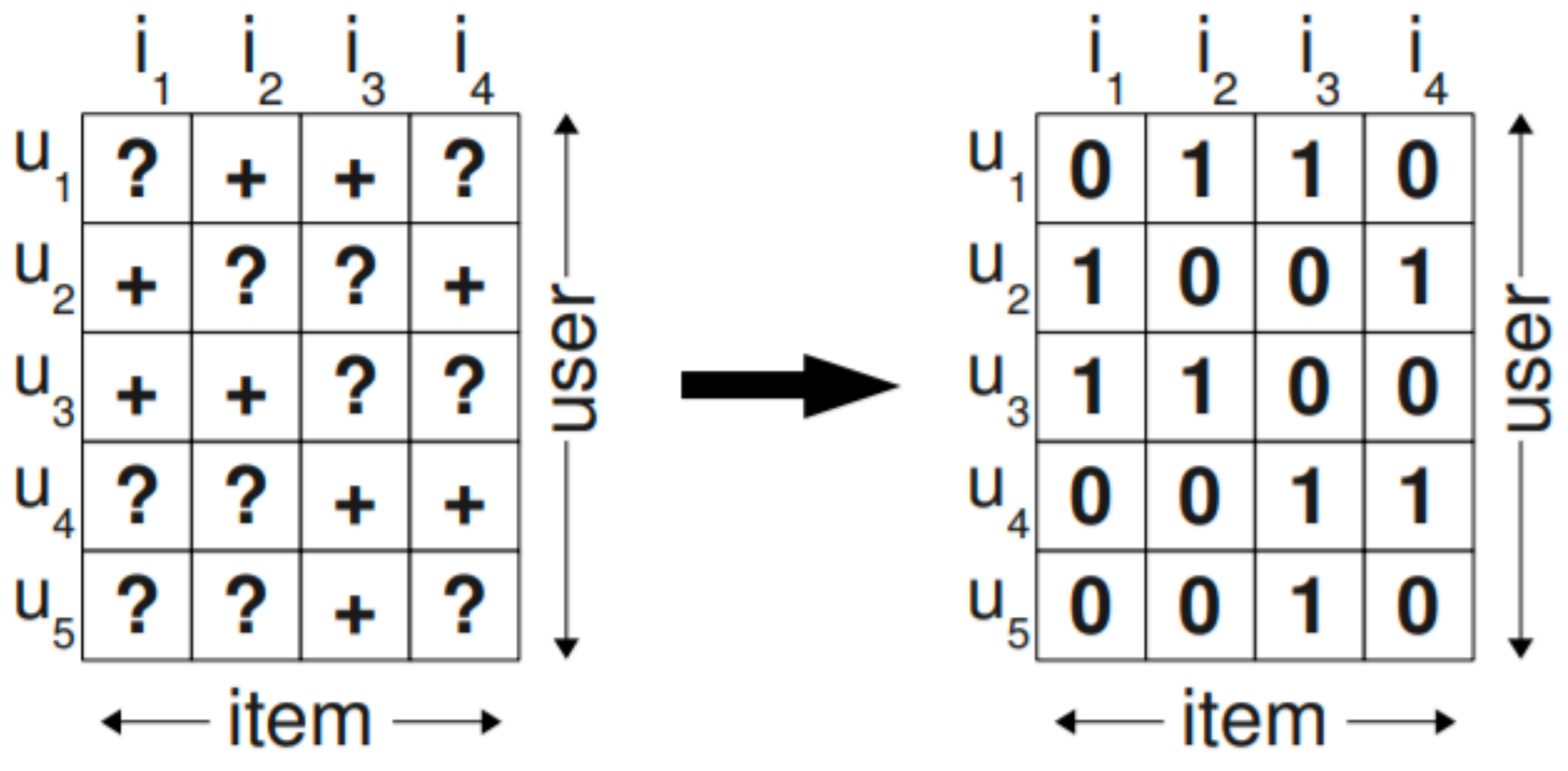
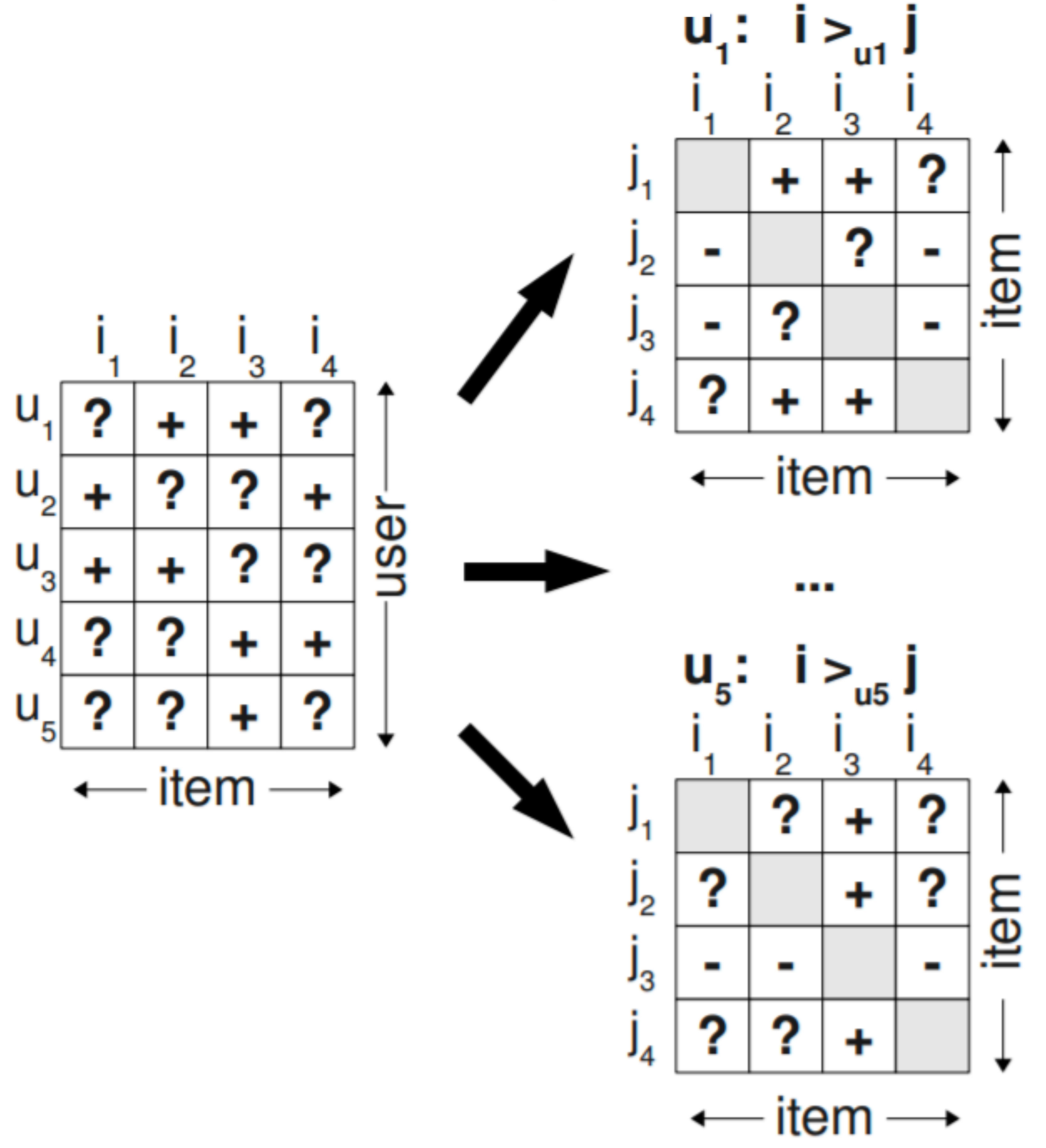
$(u, i, j) \in D_S$





BAYESIAN OPT

The Bayesian formulation of finding the correct personalized ranking for all items $i \in I$ is to maximize the following posterior probability where Θ represents the parameter vector of an arbitrary model class (e.g. matrix factorization).

$$p(\Theta | >_u) \propto p(>_u | \Theta)\, p(\Theta)$$

$>u$ is the desired but latent preference structure for user u
$p(>u \mid \theta)$ is a user specific likelihood function

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All users are presumed to act independently of each other. We also assume the ordering of each pair of items (i, j) for a specific user is independent of the ordering of every other pair, we can formulate the individual probability that a user prefers item i to item j as follows

$$p(i >_u j|\Theta) := \sigma(\hat{x}_{uij}(\Theta))$$

where σ is the logistic sigmoid:

$$\sigma(x) := \frac{1}{1+e^{-x}}$$

$$p(\Theta) \sim N(0, \Sigma_\Theta)$$

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BPR-Opt := ln p(Θ| >u)

$$= \sum_{(u,i,j)\in D_S} \ln \sigma(\hat{x}_{uij}) - \lambda_\Theta ||\Theta||^2$$

where λΘ are model specific regularization parameters.

ANALOGIES TO AUC OPTIMIZATION

$$\text{BPR-O}\textsc{pt} := \sum_{(u,i,j)\in D_S} \ln \sigma(\hat{x}_{uij}) - \lambda_\Theta ||\Theta||^2$$

$$\text{AUC}(u) = \sum_{(u,i,j)\in D_S} z_u \, \delta(\hat{x}_{uij} > 0)$$

The analogy between BPR-Opt and (1) is obvious. Besides the normalizing constant zu they only differ in the loss function.
The AUC uses the non-differentiable loss δ(x > 0) which is identical to the Heaviside function:

$$\delta(x > 0) = H(x) := \begin{cases} 1, & x > 0 \\ 0, & \text{else} \end{cases}$$

Optimizing for BPR-OPT criterion will be similar to optimizing for AUC which is a rank based metric as we can see from the above equation.

STOCHASTIC GRADIENT DESCENT USING BOOTSTRAPPING

$$\frac{\partial \text{BPR-Opt}}{\partial \Theta} = \sum_{(u,i,j) \in D_S} \frac{\partial}{\partial \Theta} \ln \sigma(\hat{x}_{uij}) - \lambda_\Theta \frac{\partial}{\partial \Theta} ||\Theta||^2$$

$$\propto \sum_{(u,i,j) \in D_S} \frac{-e^{-\hat{x}_{uij}}}{1 + e^{-\hat{x}_{uij}}} \cdot \frac{\partial}{\partial \Theta} \hat{x}_{uij} - \lambda_\Theta \Theta$$

$$\Theta \leftarrow \Theta + \alpha \left(\frac{e^{-\hat{x}_{uij}}}{1 + e^{-\hat{x}_{uij}}} \cdot \frac{\partial}{\partial \Theta} \hat{x}_{uij} + \lambda_\Theta \Theta \right)$$

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$$\propto \sum_{(u,i,j)\in D_S} \frac{-e^{-\hat{x}_{uij}}}{1+e^{-\hat{x}_{uij}}} \cdot \frac{\partial}{\partial \Theta}\hat{x}_{uij} - \lambda_\Theta \Theta$$

$$\Theta \leftarrow \Theta + \alpha \left(\frac{e^{-\hat{x}_{uij}}}{1+e^{-\hat{x}_{uij}}} \cdot \frac{\partial}{\partial \Theta}\hat{x}_{uij} + \lambda_\Theta \Theta \right)$$

procedure LearnBPR(D_S, Θ)
  initialize Θ
  repeat
    draw (u, i, j) from D_S
    $\Theta \leftarrow \Theta + \alpha \left(\frac{e^{-\hat{x}_{uij}}}{1+e^{-\hat{x}_{uij}}} \cdot \frac{\partial}{\partial \Theta}\hat{x}_{uij} + \lambda_\Theta \cdot \Theta \right)$
  until convergence
  return $\hat{\Theta}$
end procedure

LEARNING MODELS WITH BPR

Matrix Factorization and learned k-nearest-neigbhor both try to model the hidden preferences of a user on an item but Matrix factorization shows better result.

$$\hat{x}_{uij} := \hat{x}_{ui} - \hat{x}_{uj}$$

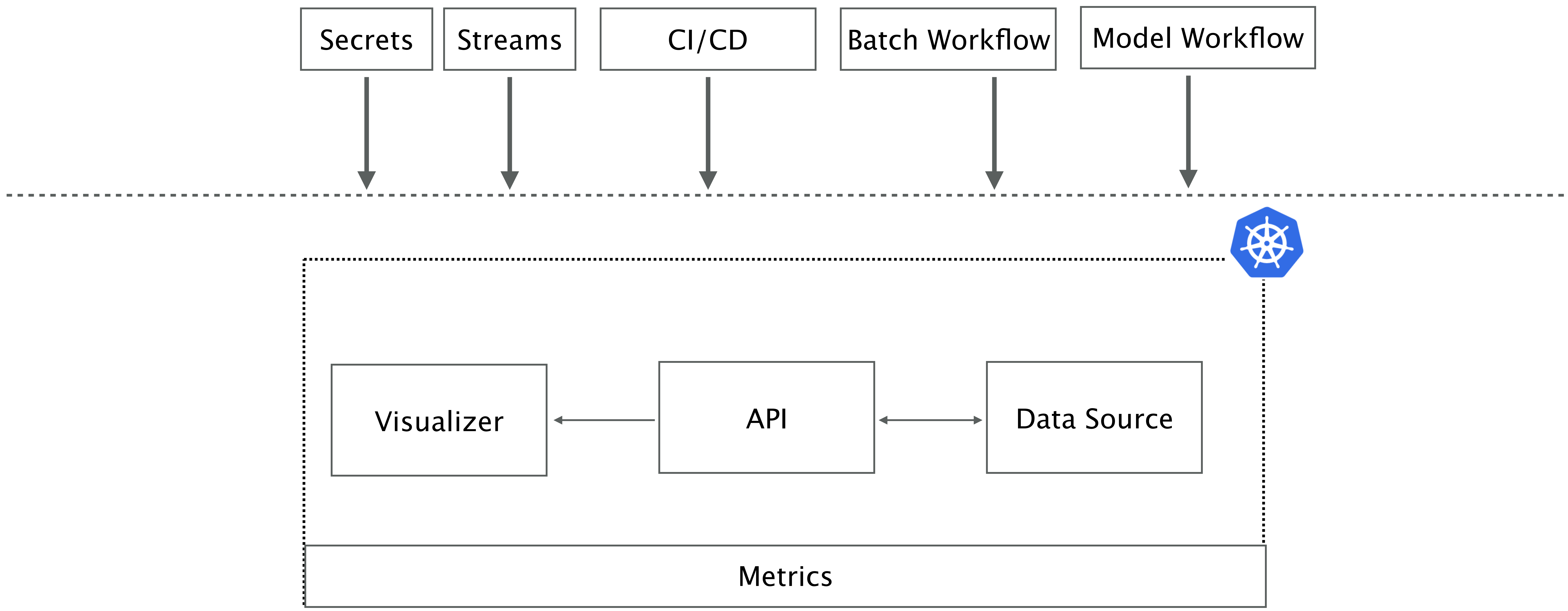
PAIN POINTS

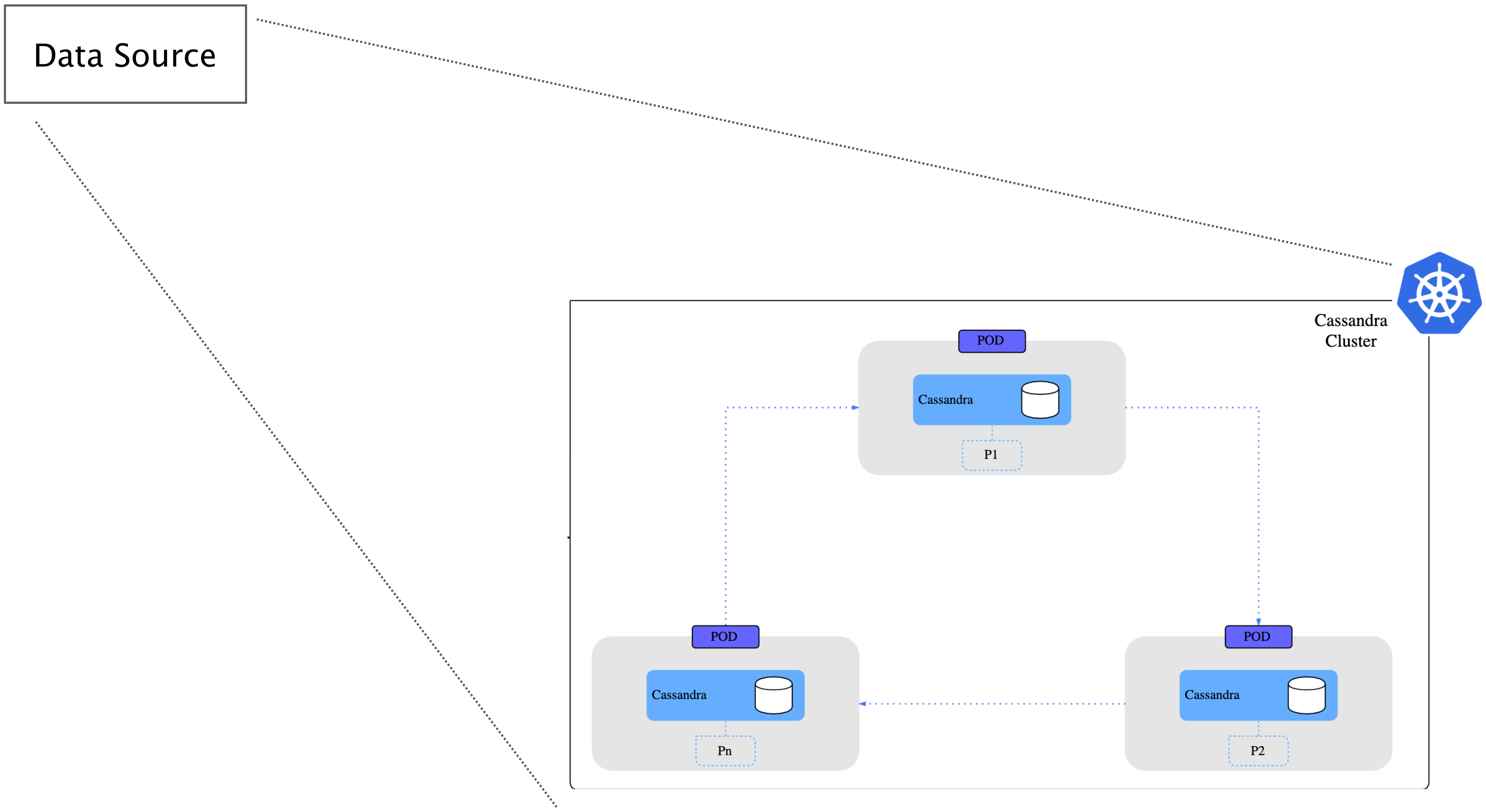
End-to-end orchestration of idea to production

- Easier experimentation
- Scaling backend computation
- Serving precomputed data
- Serving model in real-time

STARFISH

- Platform of Data Science services
- Supports;
  - Precomputed big data
  - Support realtime models
  - A/B


Secrets
Streams
CI/CD
Batch Workflow
Model Workflow
Visualizer
API
Data Source
Metrics


Data Source
Cassandra Cluster
POD
Cassandra
P1
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Cassandra
Pn
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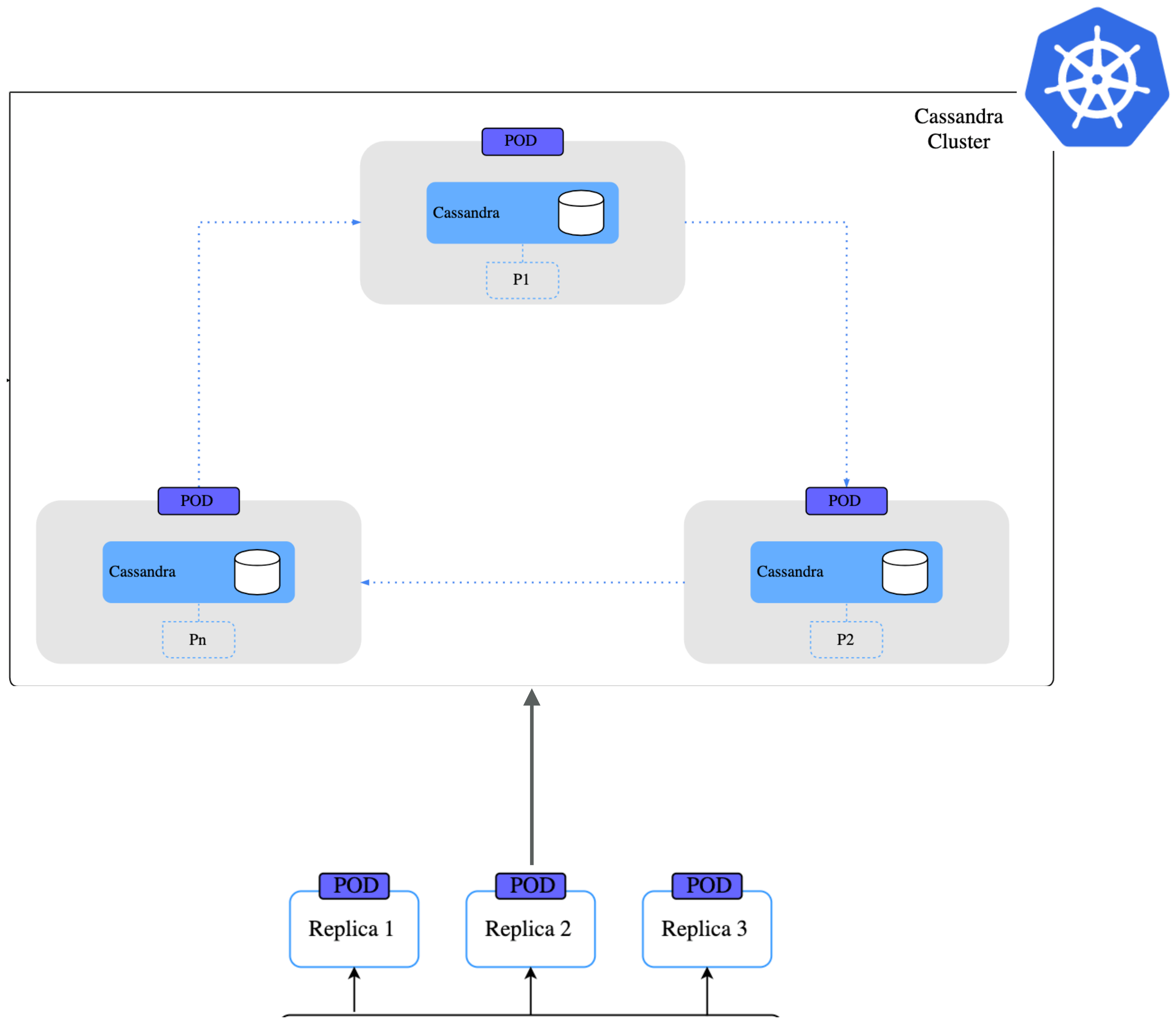
Cassandra
P2


API
Data Source


Cassandra
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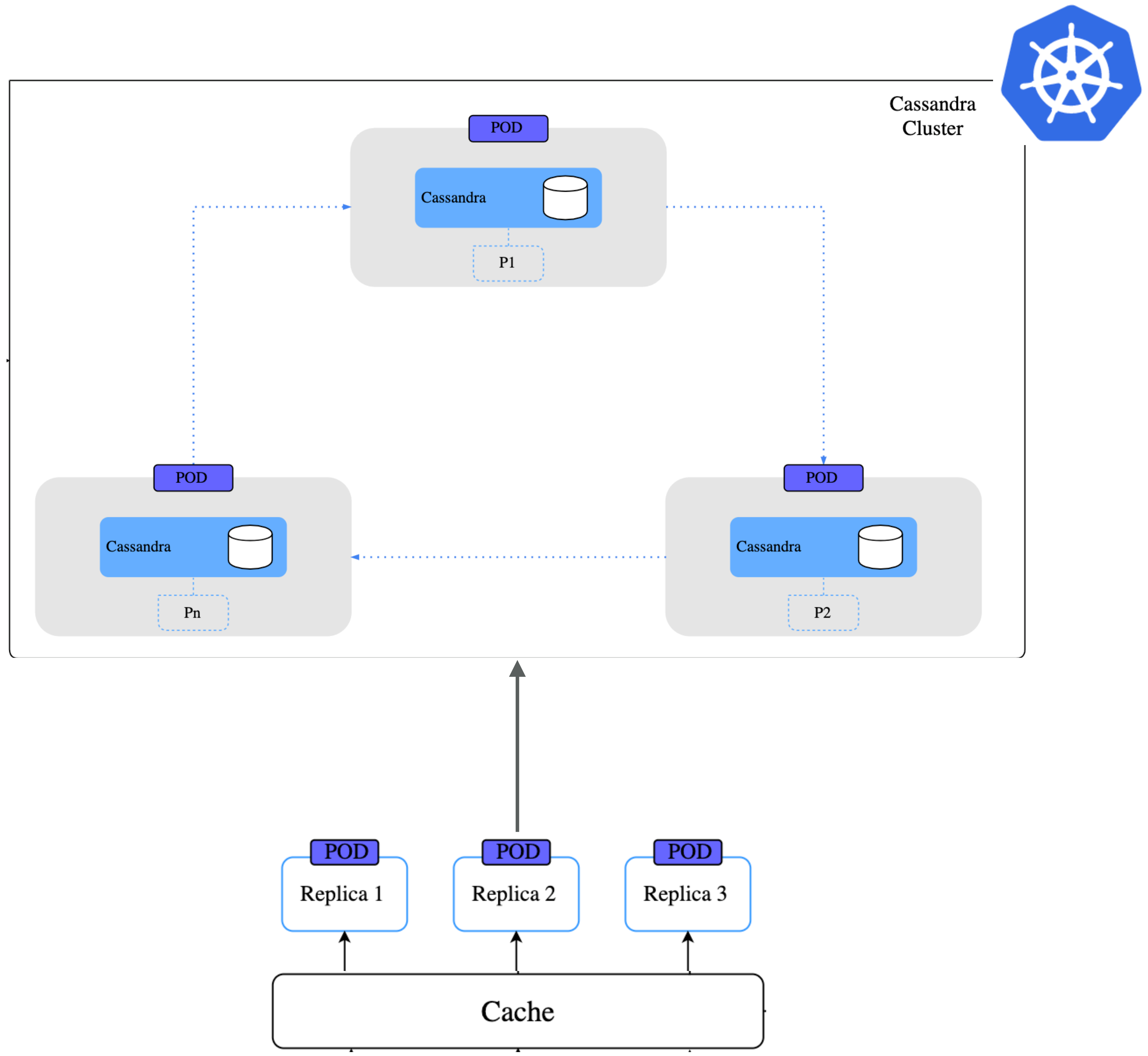
Replica 3


API
Data Source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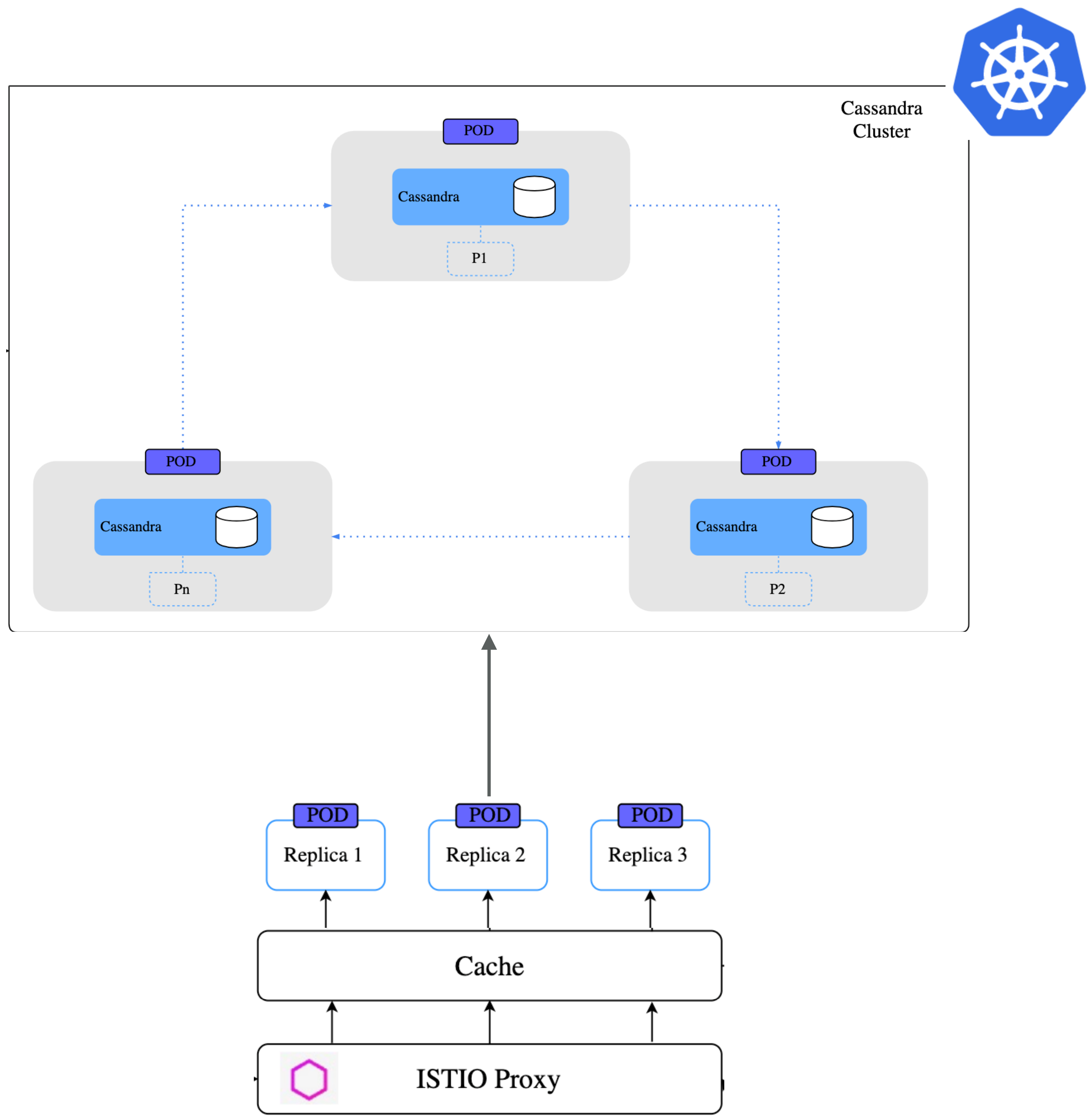
Cache


API
Data Source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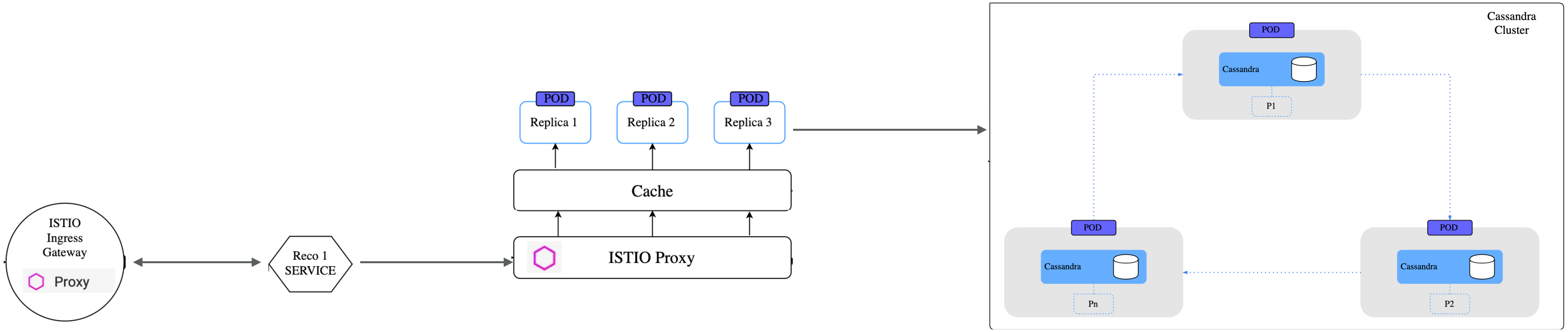
Replica 3
Cache
ISTIO Proxy


API
Data Source


ISTIO
Ingress
Gateway
Proxy
Reco 1
SERVICE
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Cassandra
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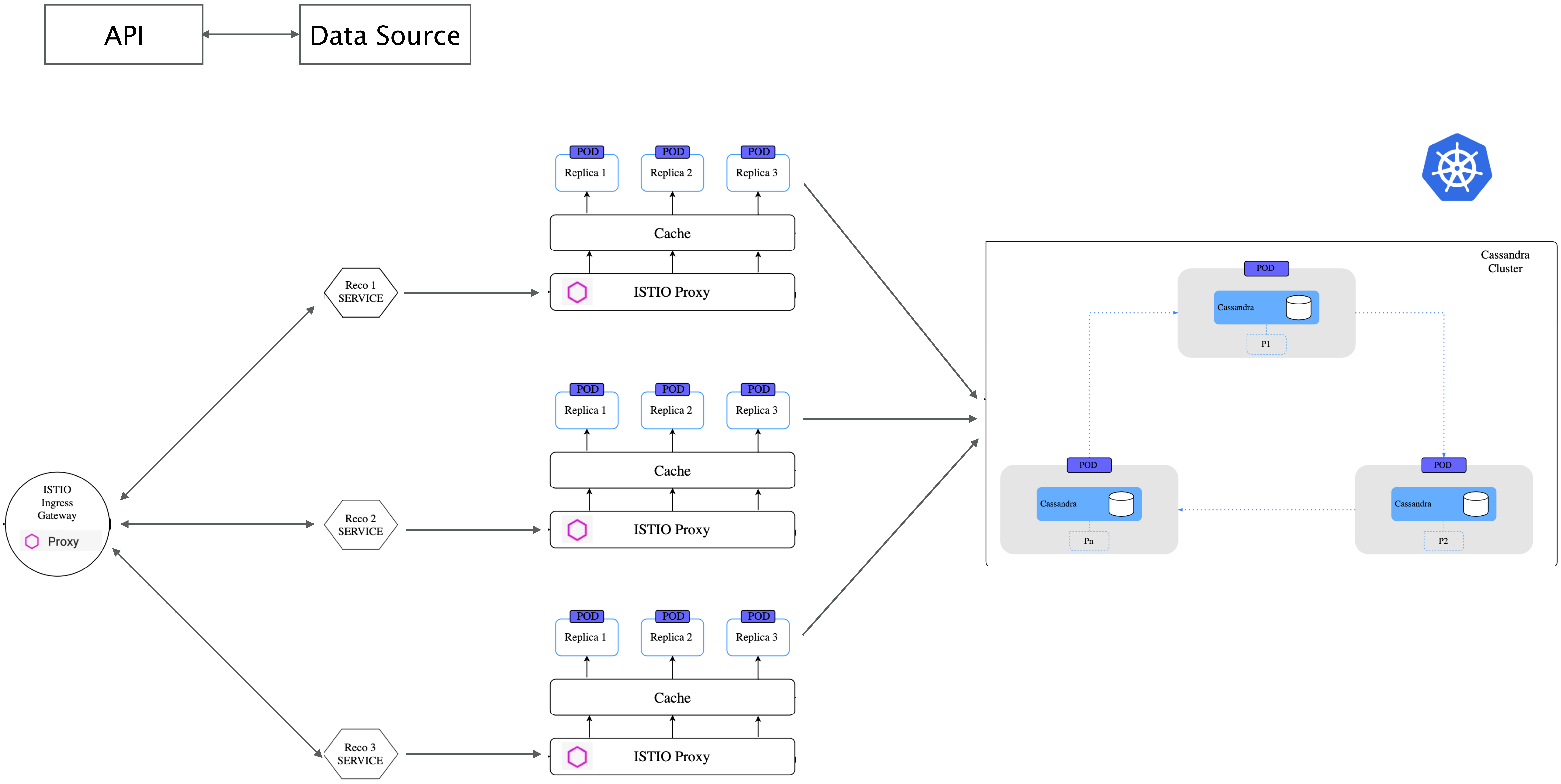

API
Data Source
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Replica 1
POD
Replica 2
POD
Replica 3
Cache
ISTIO Proxy
Reco 1 SERVICE
Reco 2 SERVICE
Reco 3 SERVICE
ISTIO Ingress Gateway
Proxy
Cassandra Cluster
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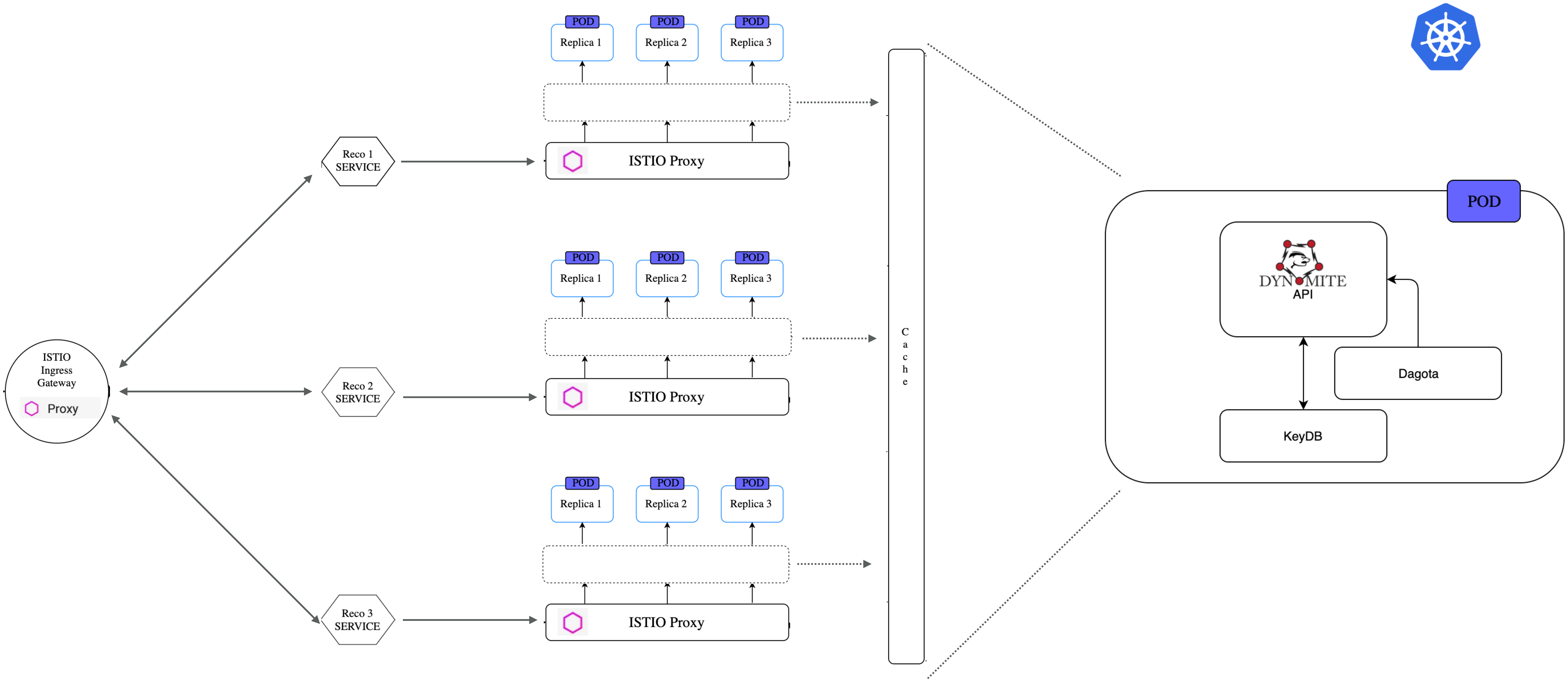
API
Data Source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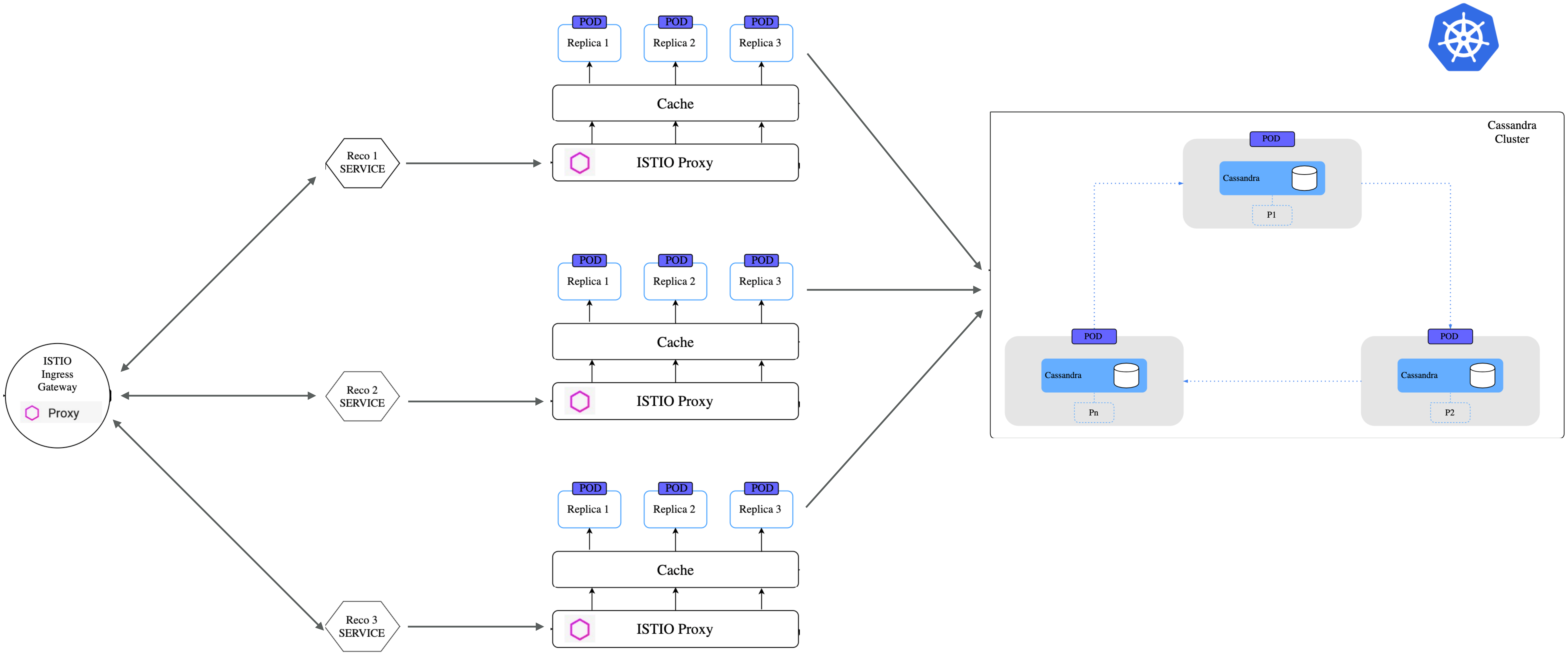
Reco 3
SERVICE
ISTIO Proxy
Cache
POD
DYNOMITE
API
Dagota
KeyDB


API
Data Source


ISTIO
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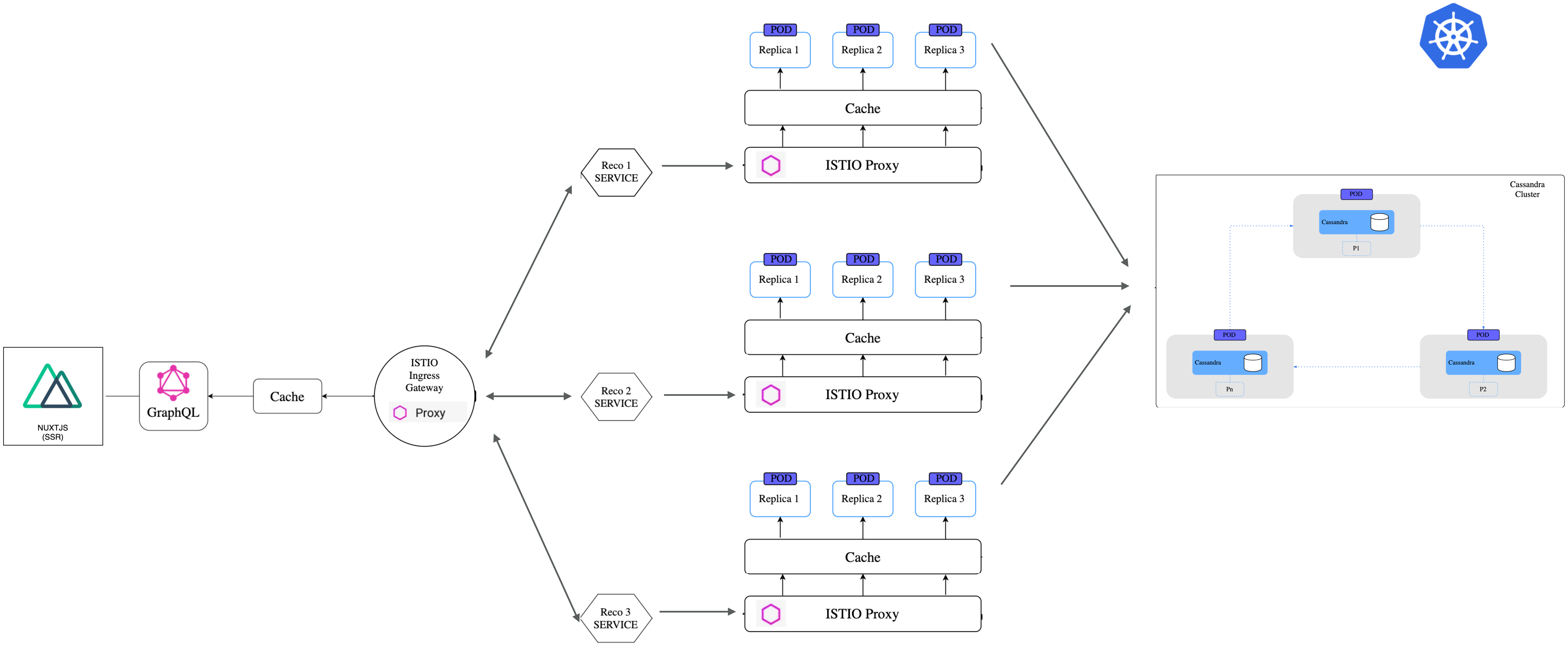
Visualizer
API
Data Source


NUXTJS
(SSR)
GraphQL
Cache
ISTIO
Ingress
Gateway
Proxy
Reco 1
SERVICE
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Cassandra
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Cassandra
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Batch Workflow
Model Workflow
Visualizer
API
Data Source
Data Source
Airflow Cluster
Models/Data
S3/SQS
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Replica 1
Replica 2
Replica 3
Cache
ISTIO Proxy
Reco 1 SERVICE
Reco 2 SERVICE
Reco 3 SERVICE
ISTIO Ingress Gateway
Proxy
Cache
GraphQL
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Cassandra Cluster
Cassandra
P1
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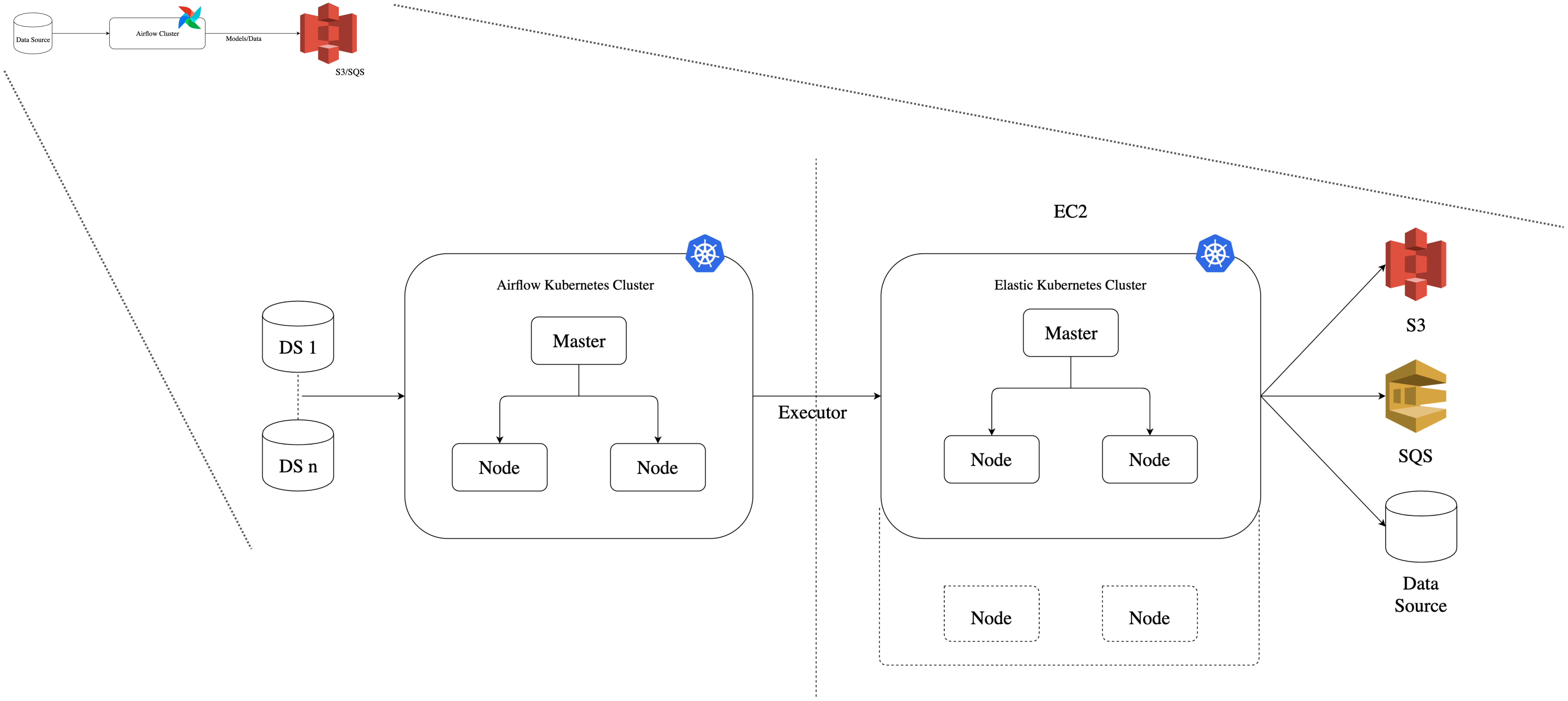
Batch Workflow

Model Workflow




Batch Workflow
Model Workflow
Visualizer
API
Data Source
Data Source
Airflow Cluster
Models/Data
S3/SQS
HELM
argo events
argo workflow
Cassandra Cluster
POD
Cassandra
P1
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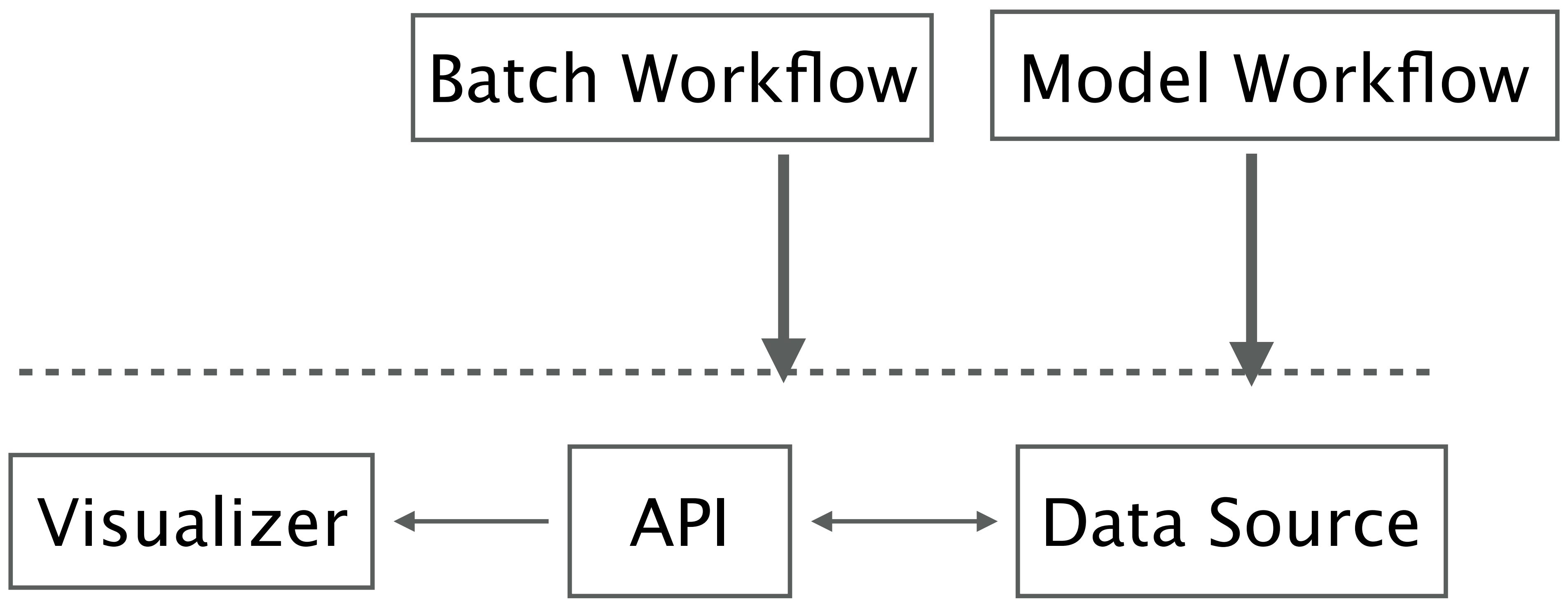
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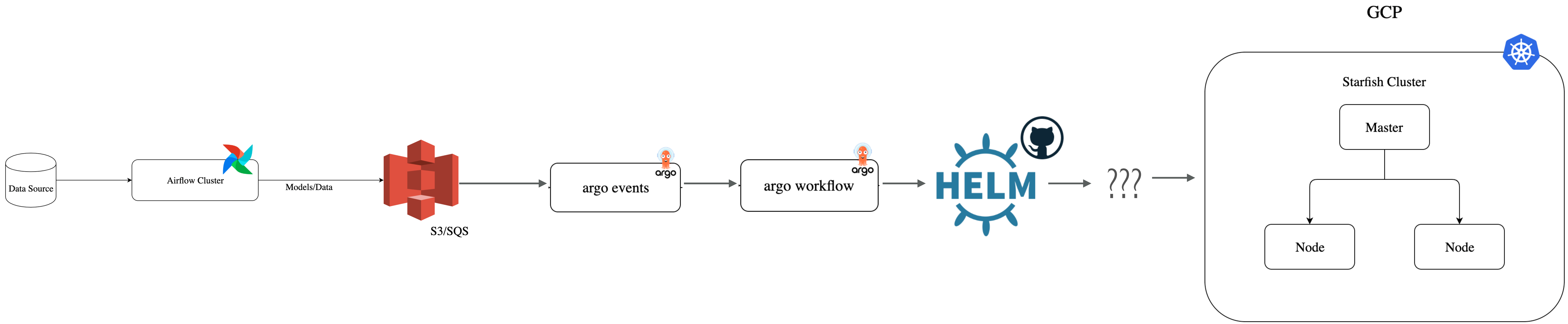
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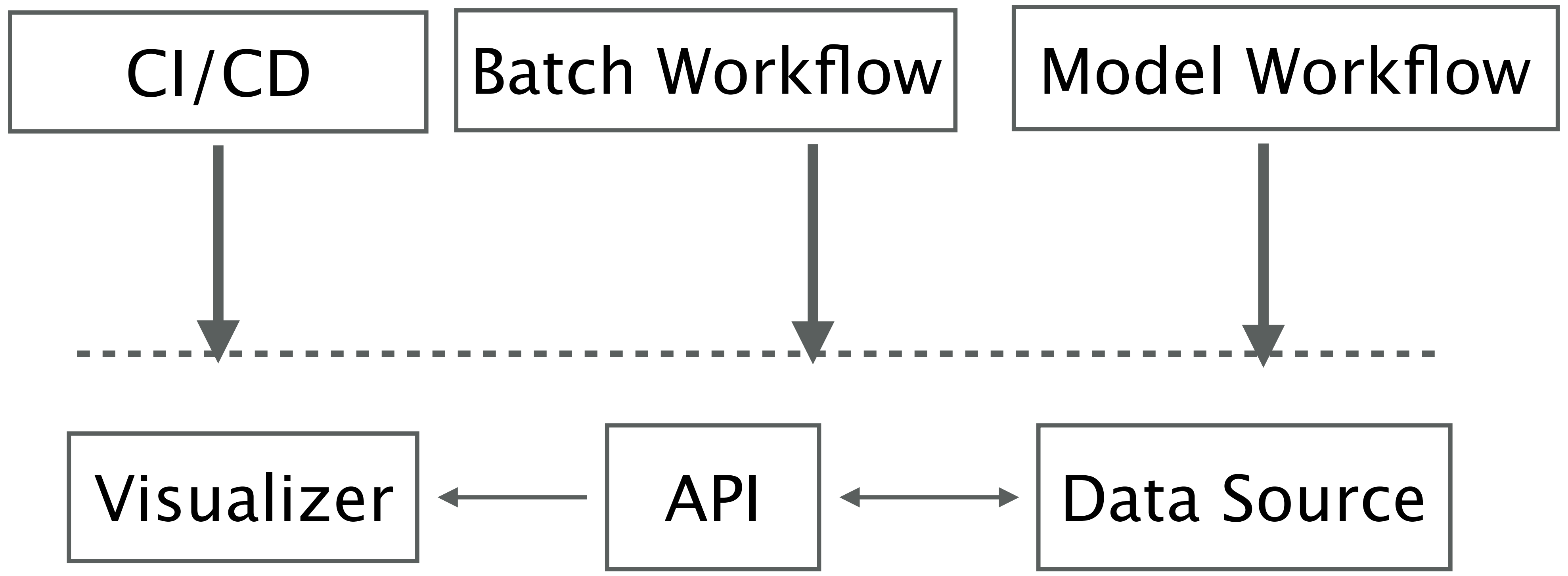
GCP
Starfish Cluster
Master
Node
Node


CI/CD
Batch Workflow
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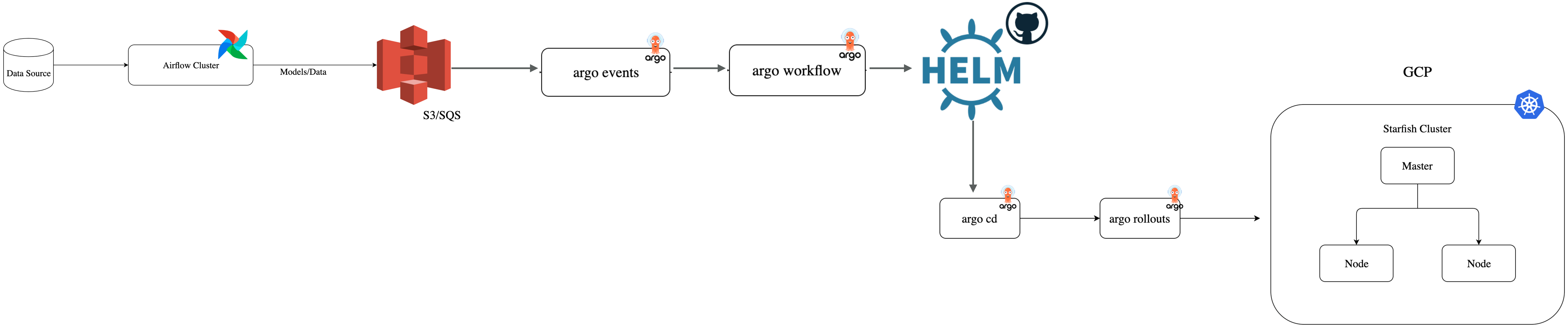
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argo rollouts
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Starfish Cluster
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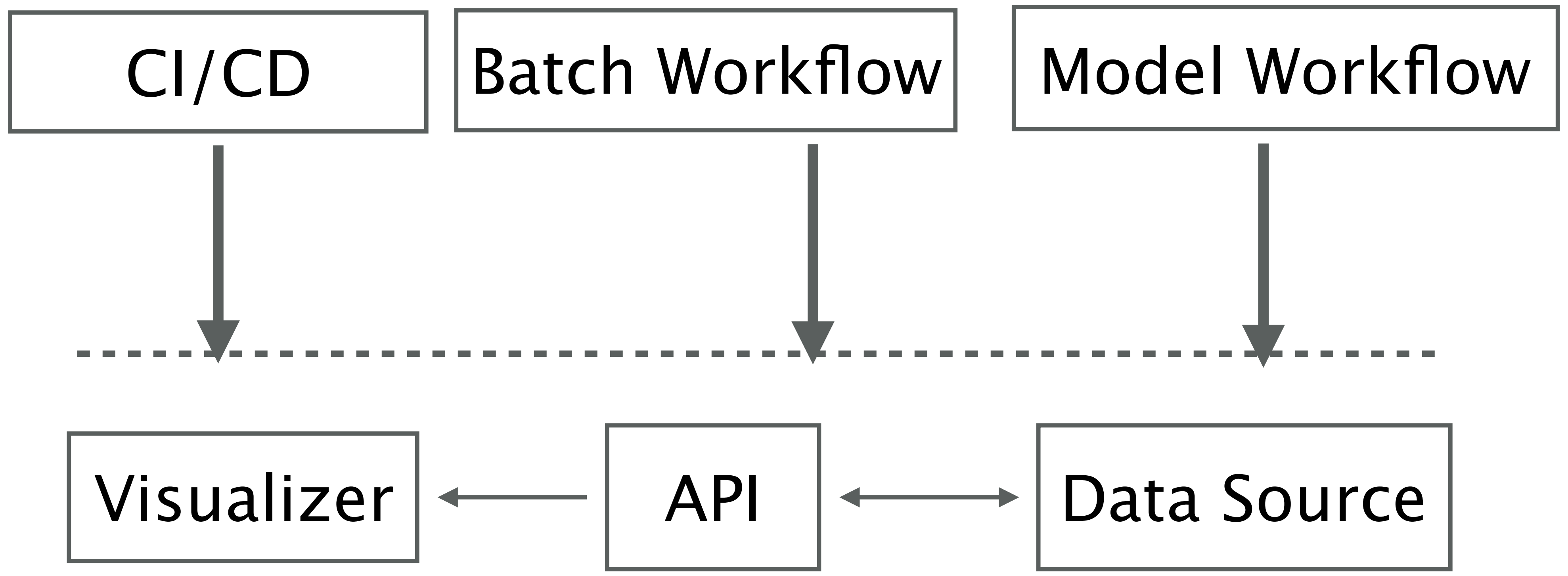
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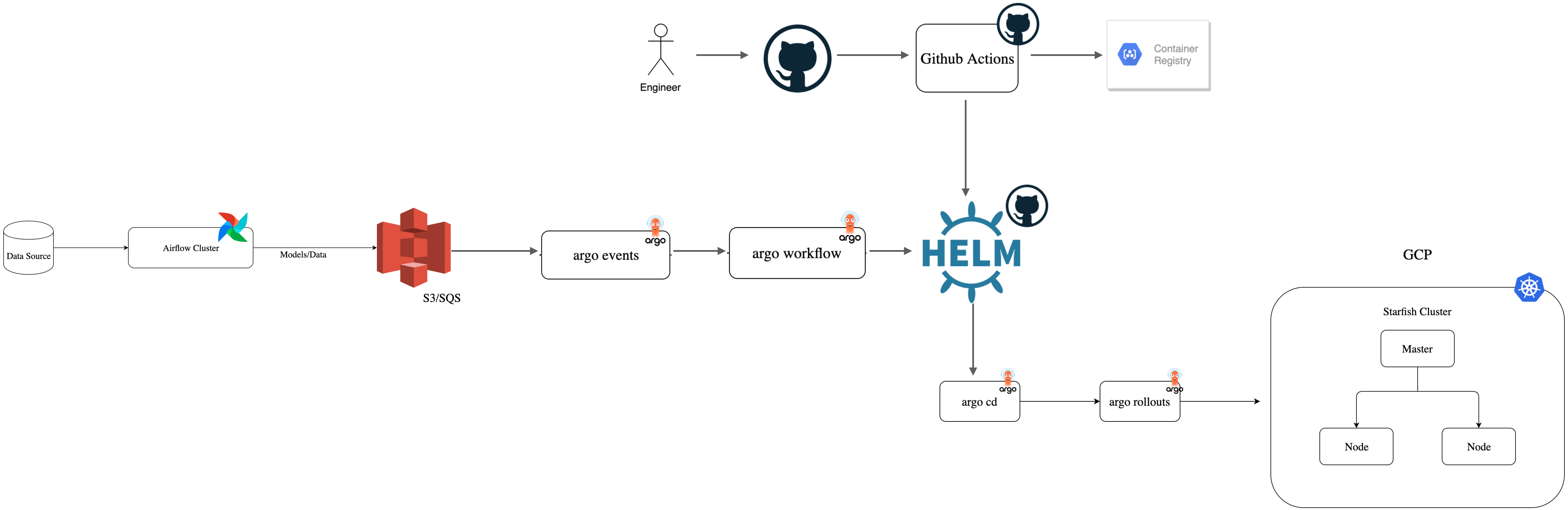
Engineer
Github Actions
Container
Registry
Data Source
Airflow Cluster
Models/Data
S3/SQS
argo events
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HELM
argo cd
argo rollouts
GCP
Starfish Cluster
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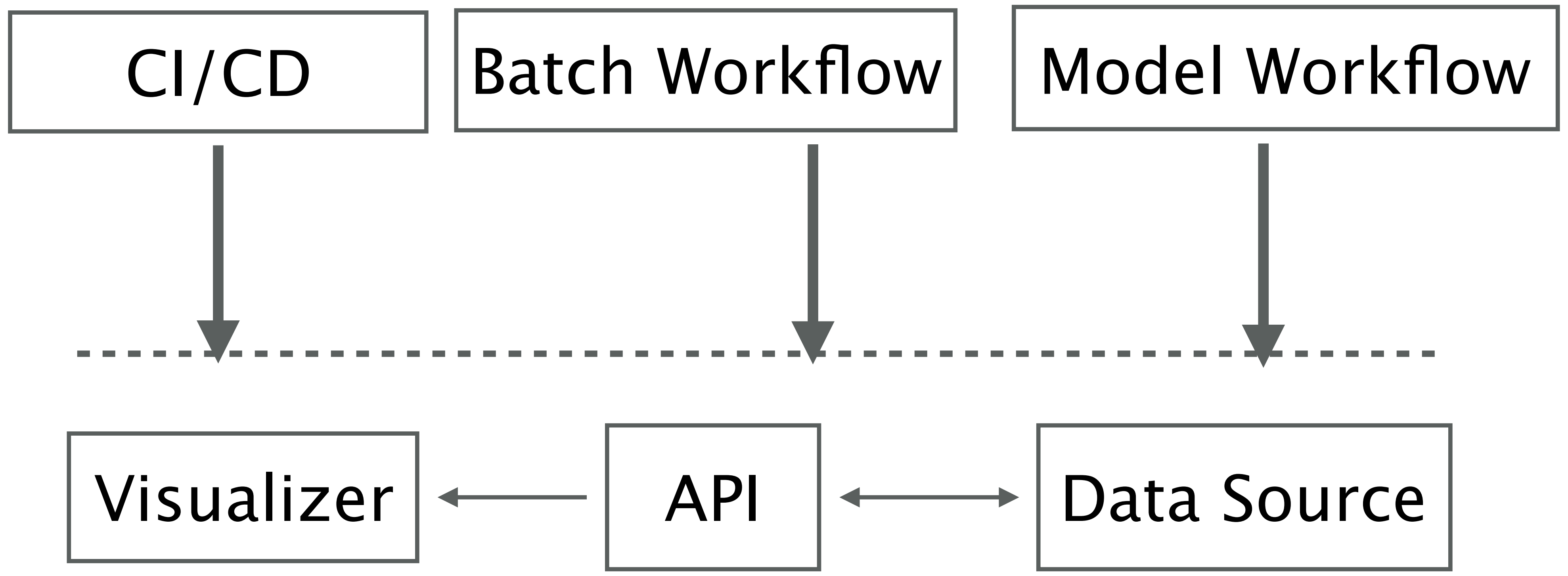
Node
Node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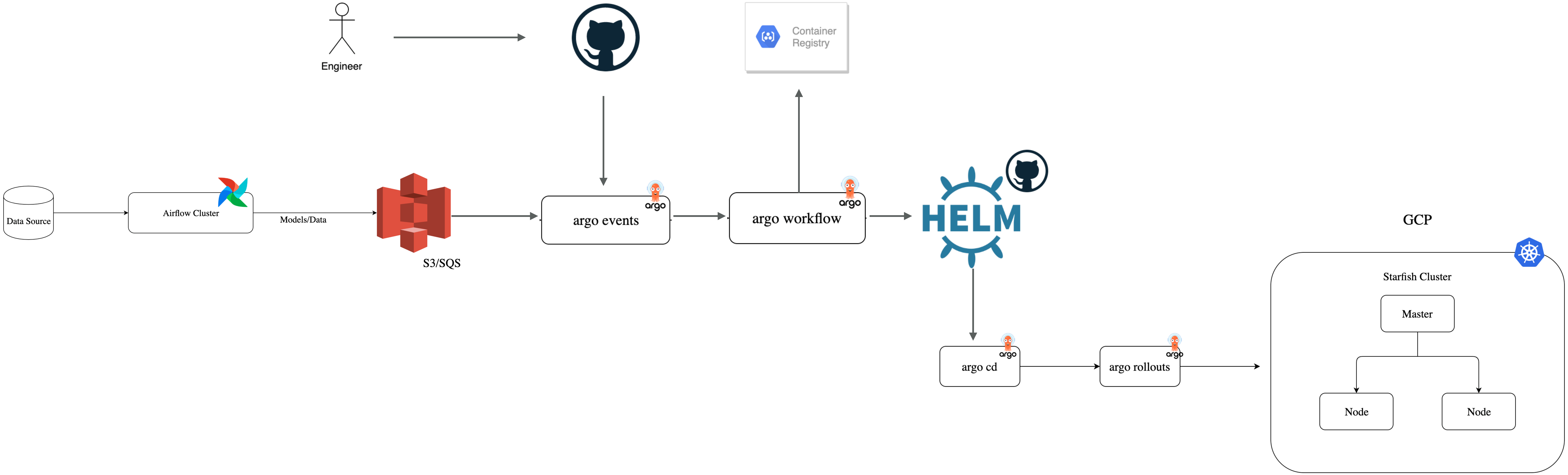
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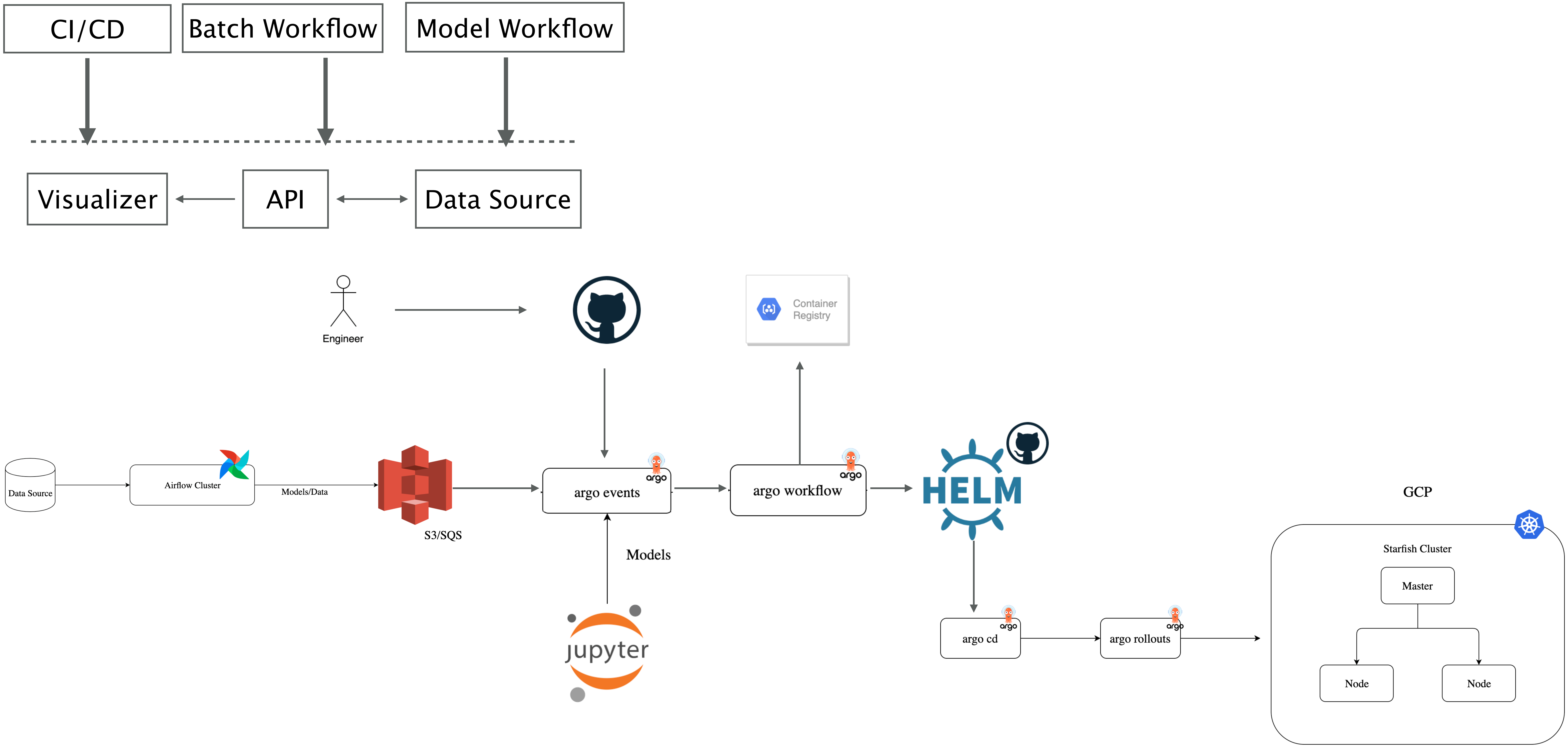
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Engineer
Container Registry
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Airflow Cluster
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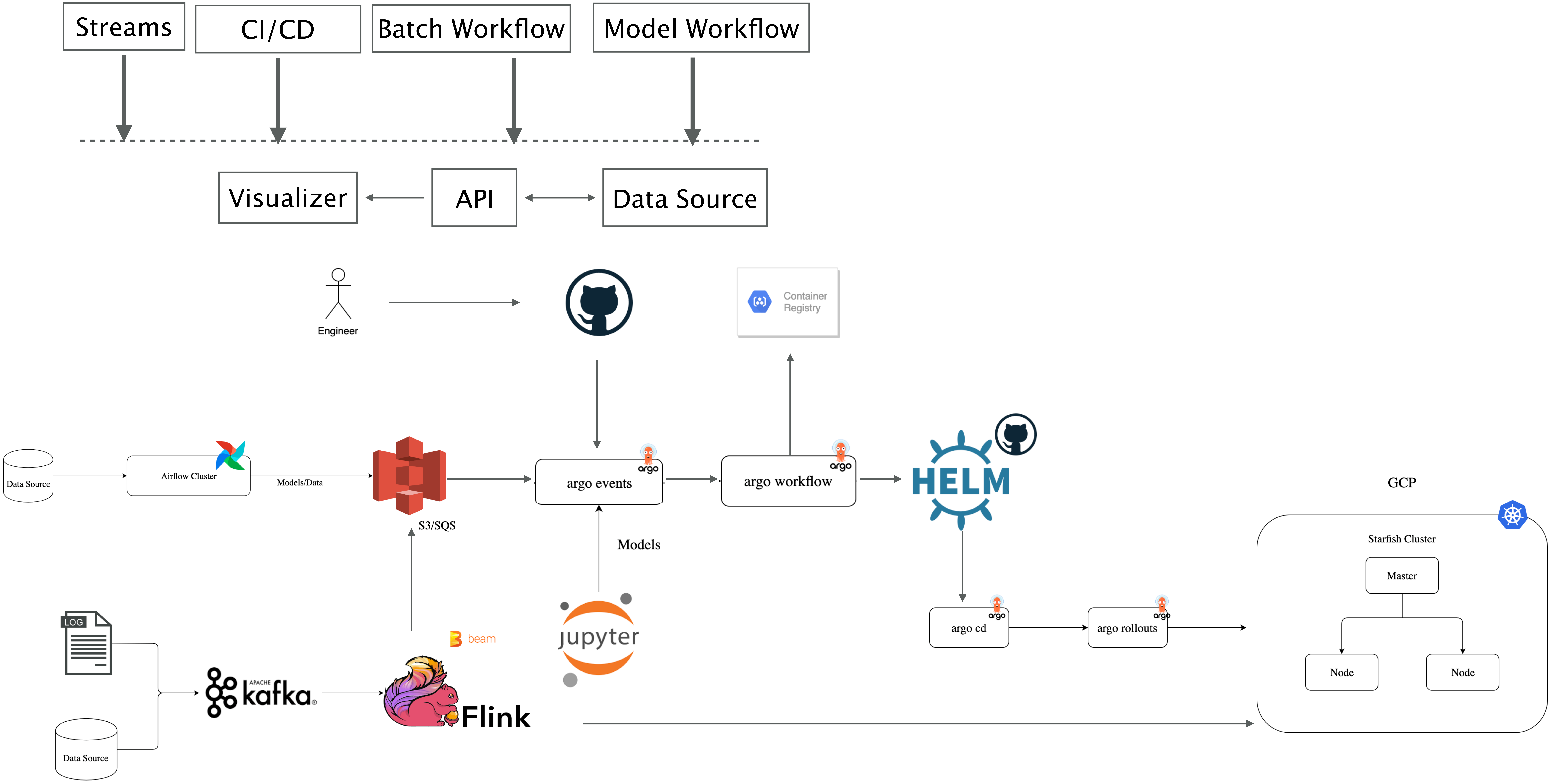
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Container Registry
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Airflow Cluster
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HELM
GCP
Starfish Cluster
Master
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Node
Models
LOG
APACHE kafka
beam
Flink
jupyter
Data Source
argo cd
argo rollouts

Thank You