Parity Models

Erasure-Coded Resilience for Prediction Serving Systems

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Inference: using a trained ML model

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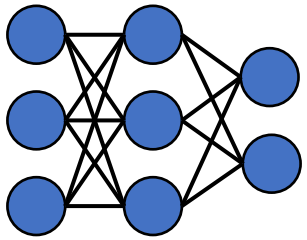

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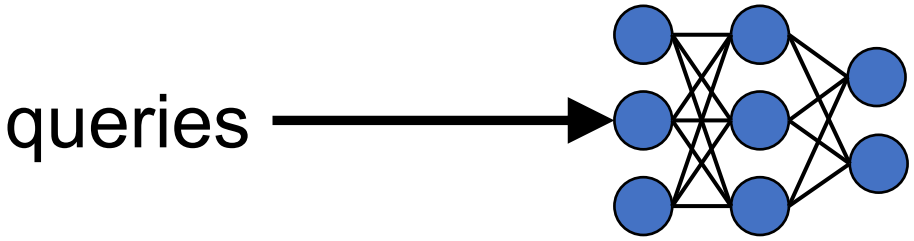

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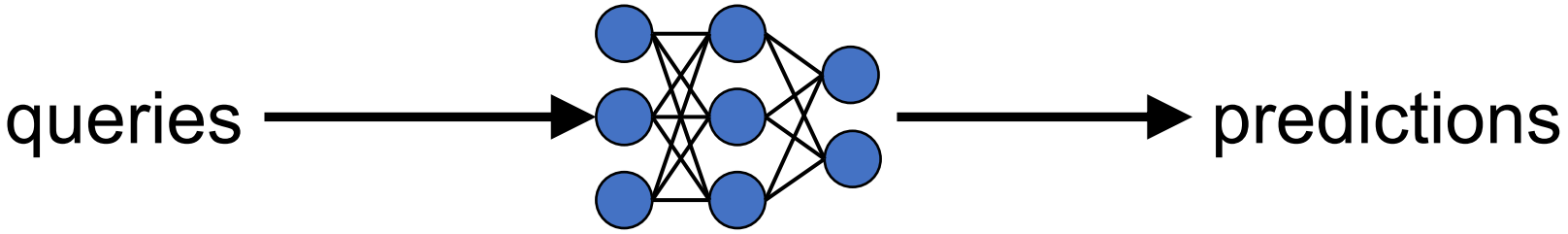

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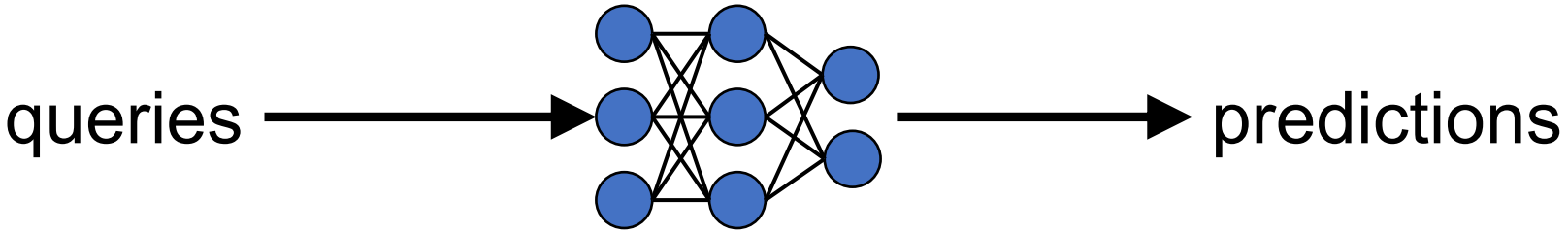

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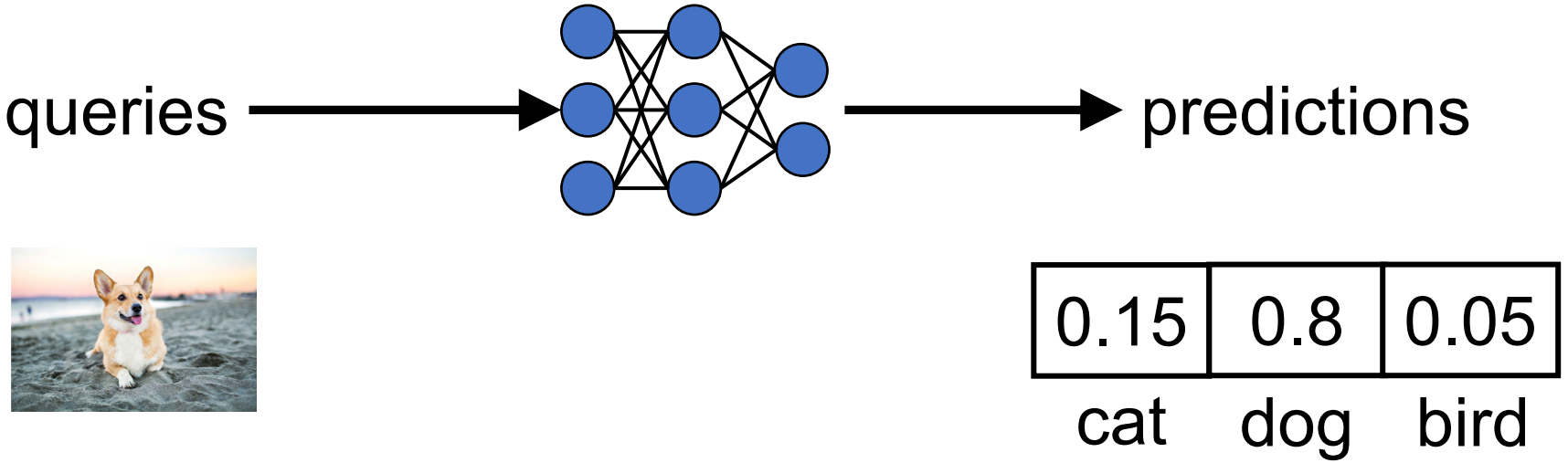

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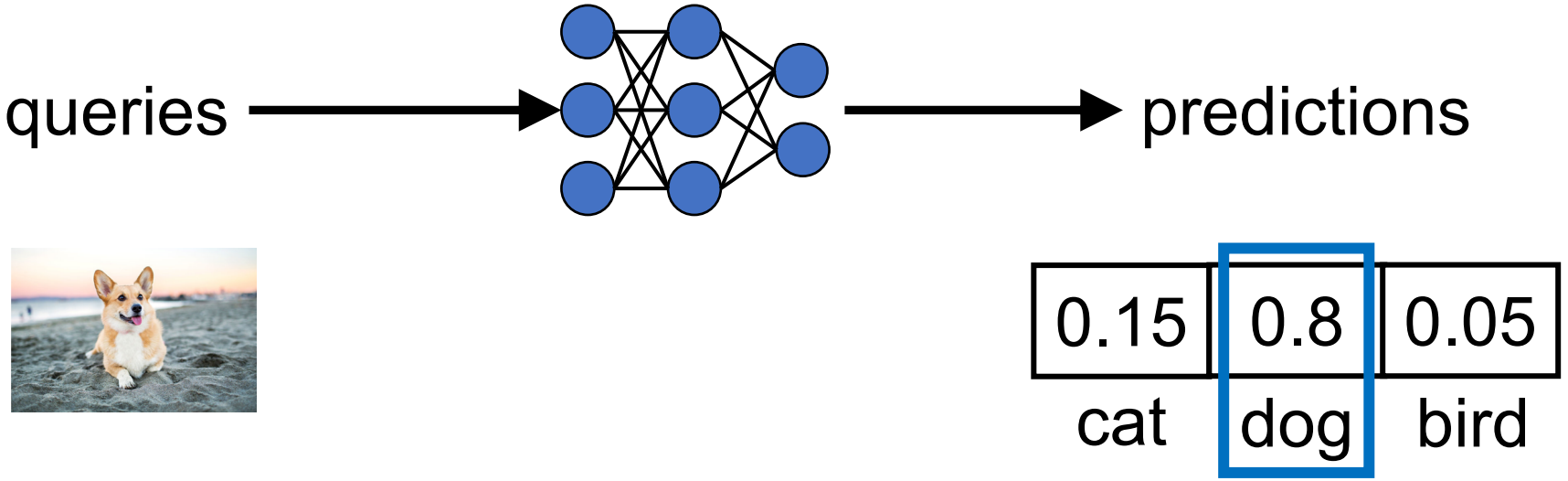


Inference used in latency-sensitive apps

Inference used in latency-sensitive apps

search

translation

ranking

Inference used in latency-sensitive apps

search

translation

ranking

Inference must operate with low, predictable latency

Prediction serving systems: inference in clusters

Prediction serving systems: inference in clusters

Open Source

Clipper

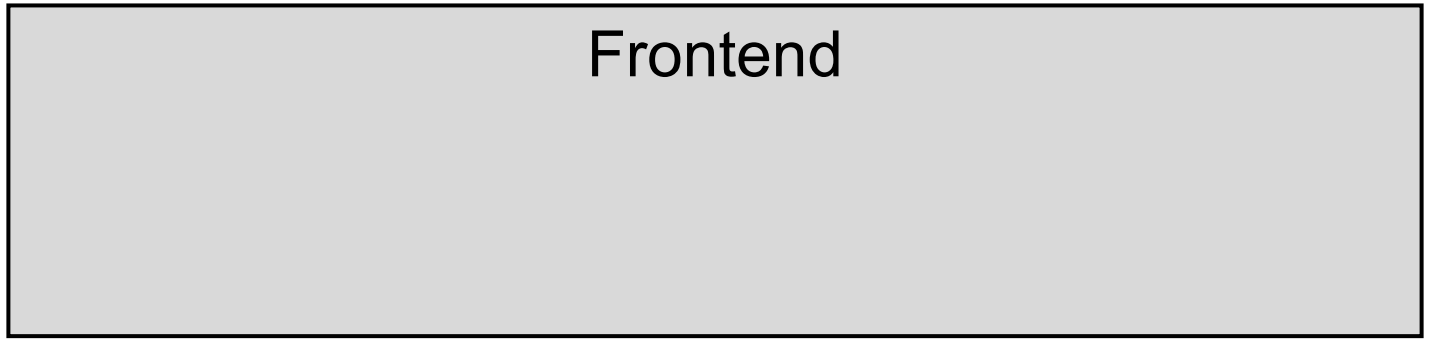
TensorFlow Serving

Cloud Services

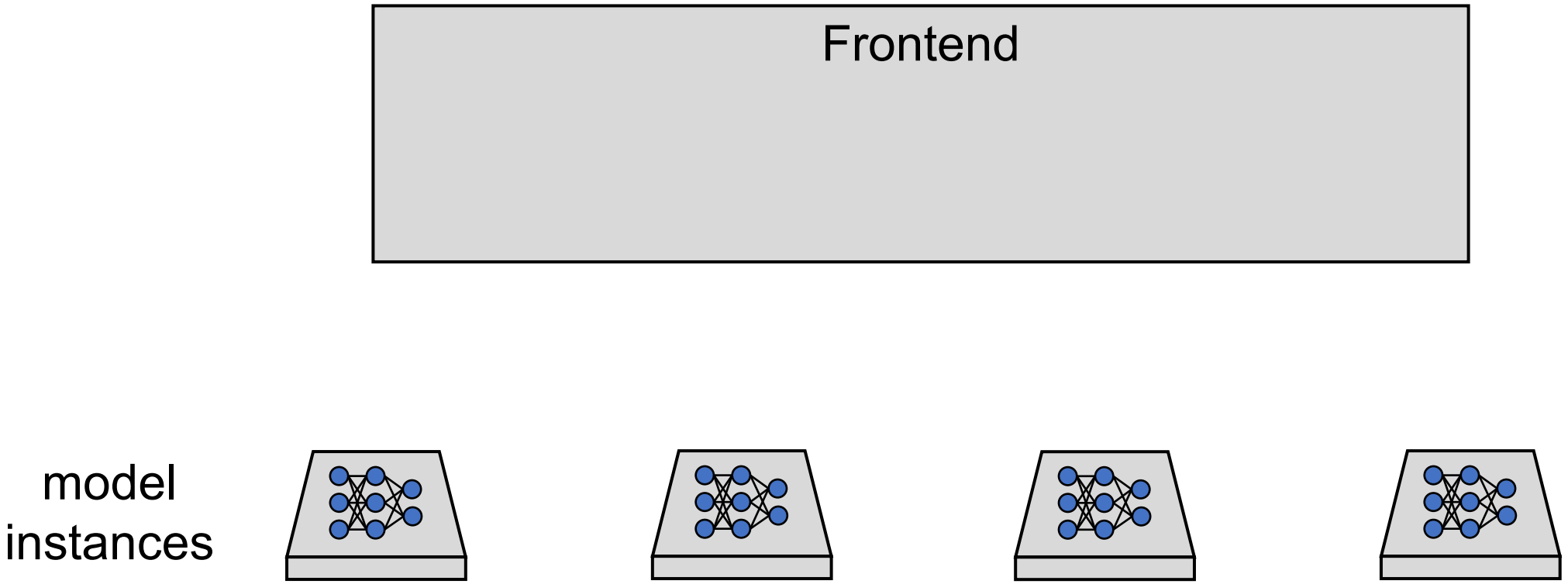
Microsoft Azure

Prediction serving systems: inference in clusters

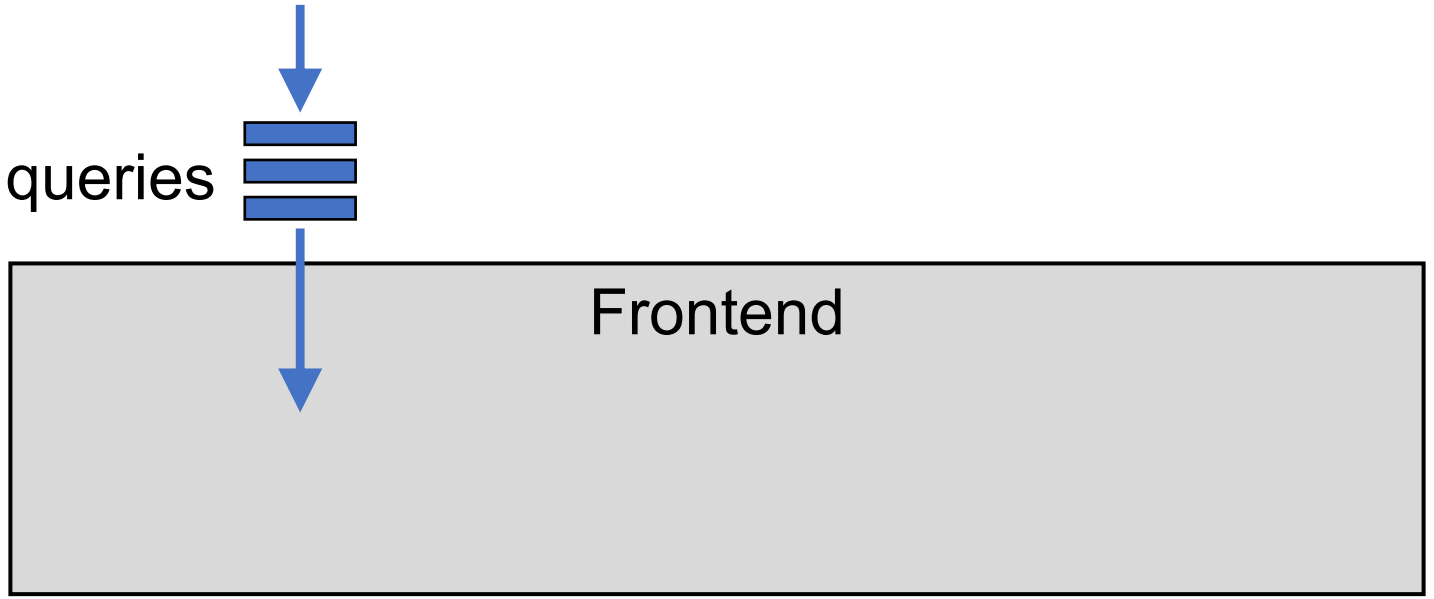
Prediction serving systems: inference in clusters



Prediction serving systems: inference in clusters

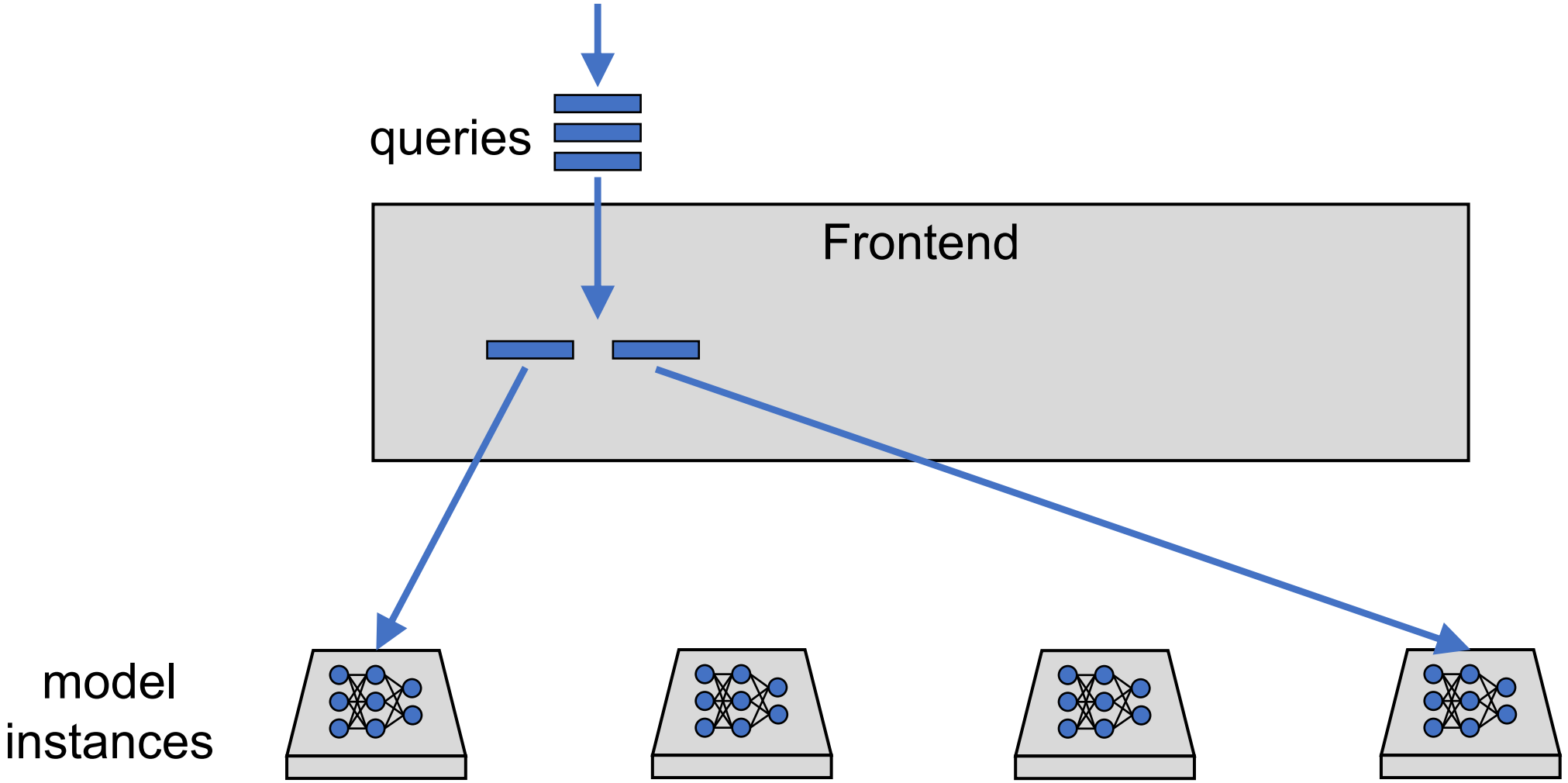


Prediction serving systems: inference in clusters

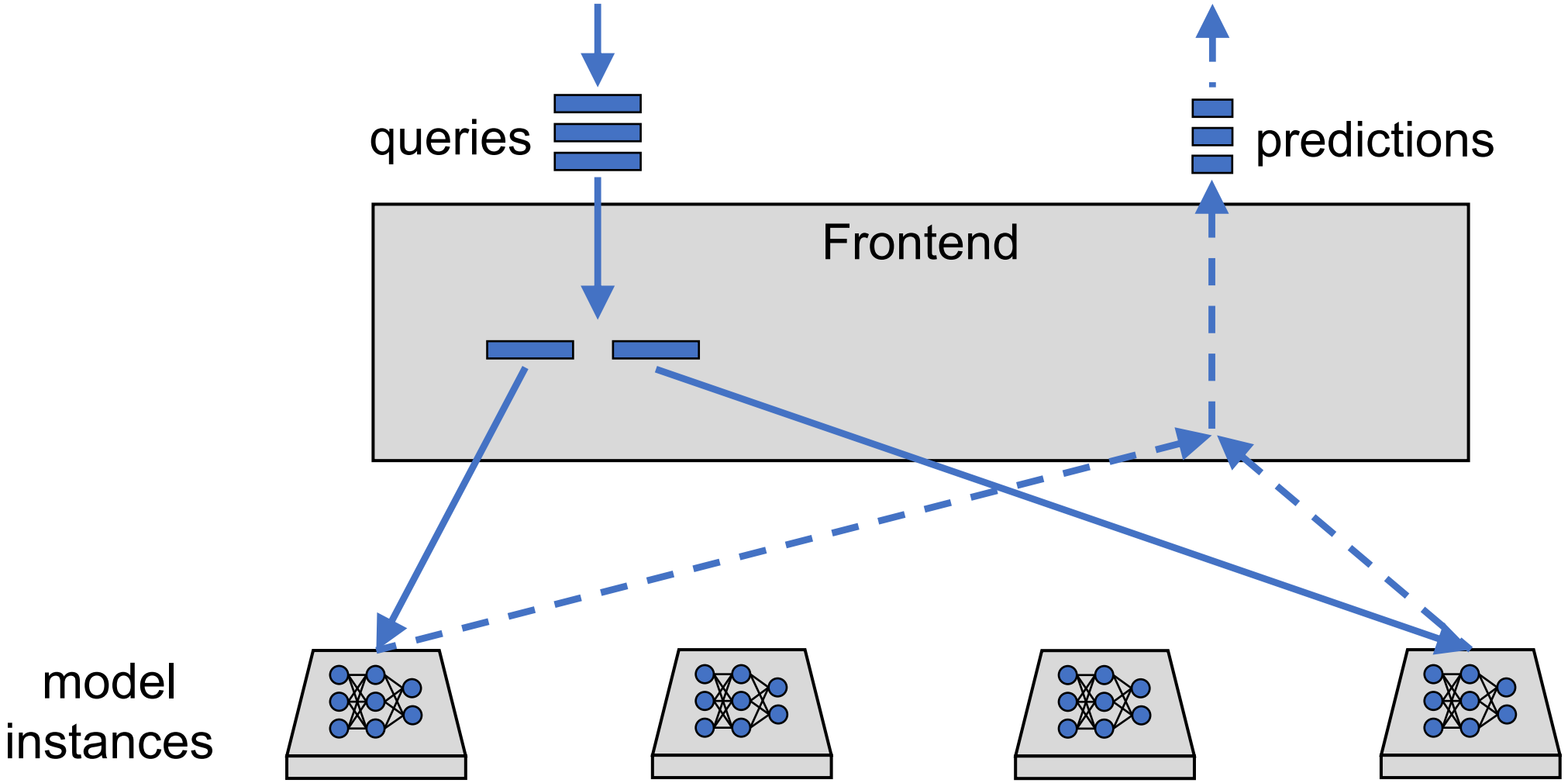


model instances

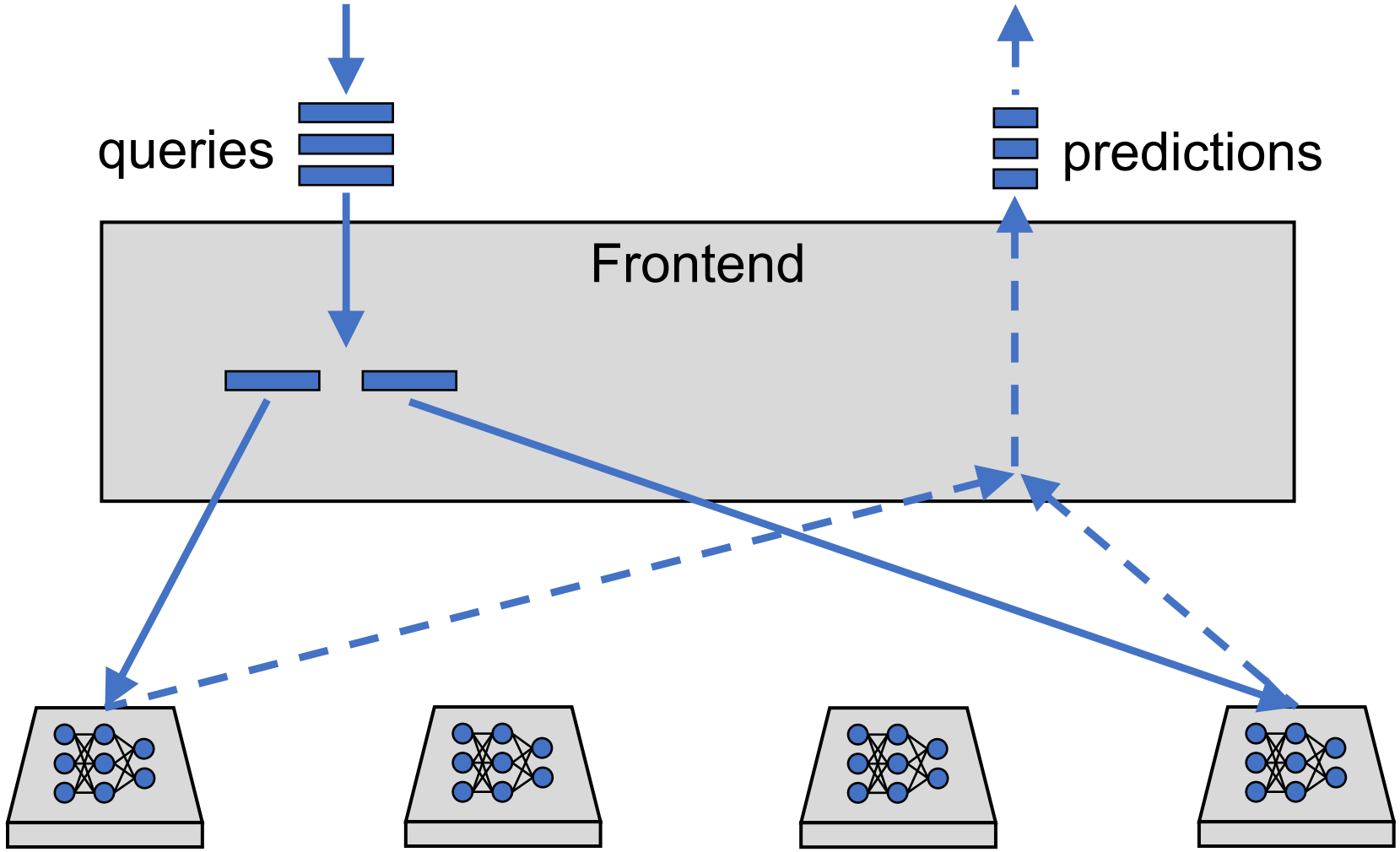
Prediction serving systems: inference in clusters



Prediction serving systems: inference in clusters



Slowdowns and failures in inference



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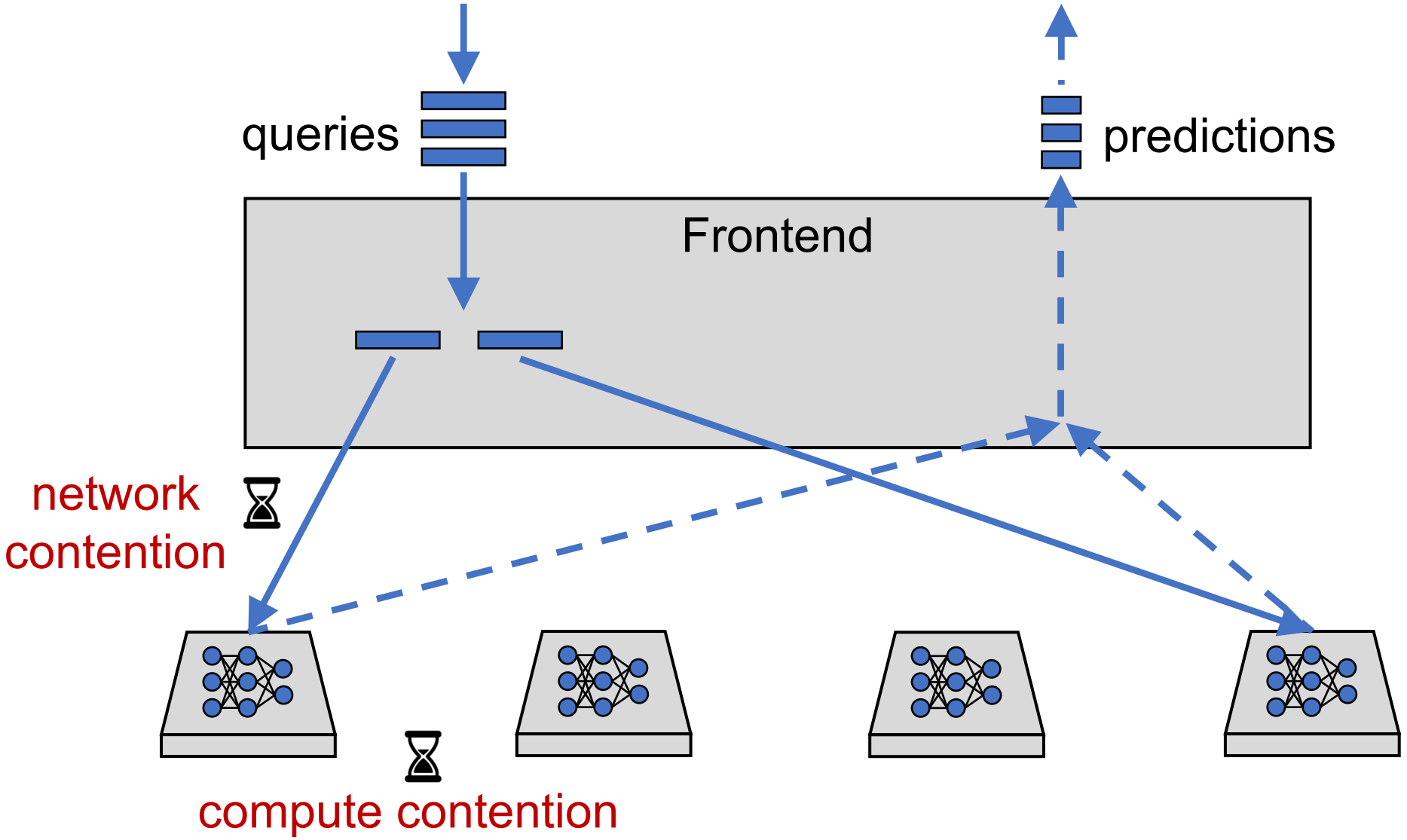

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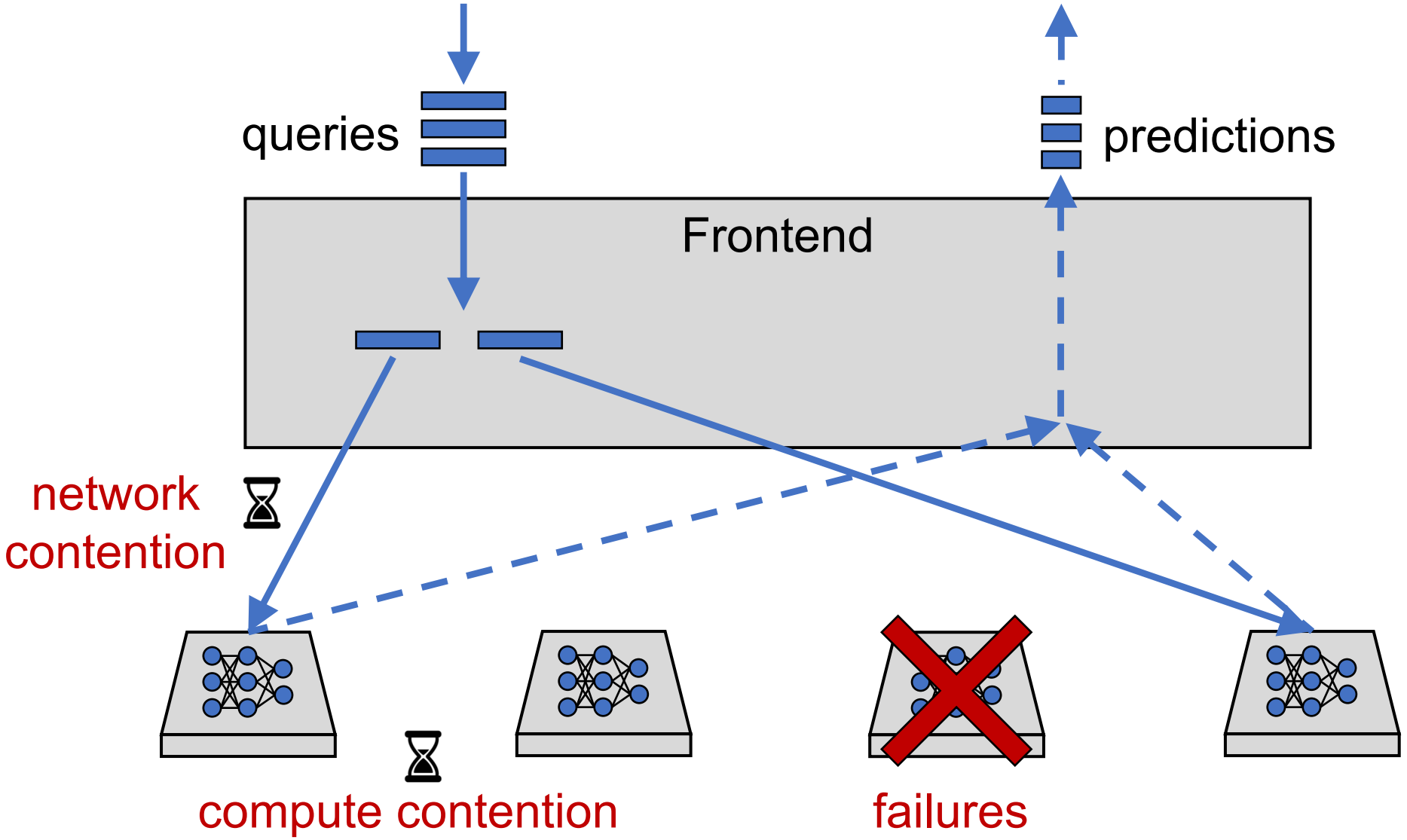

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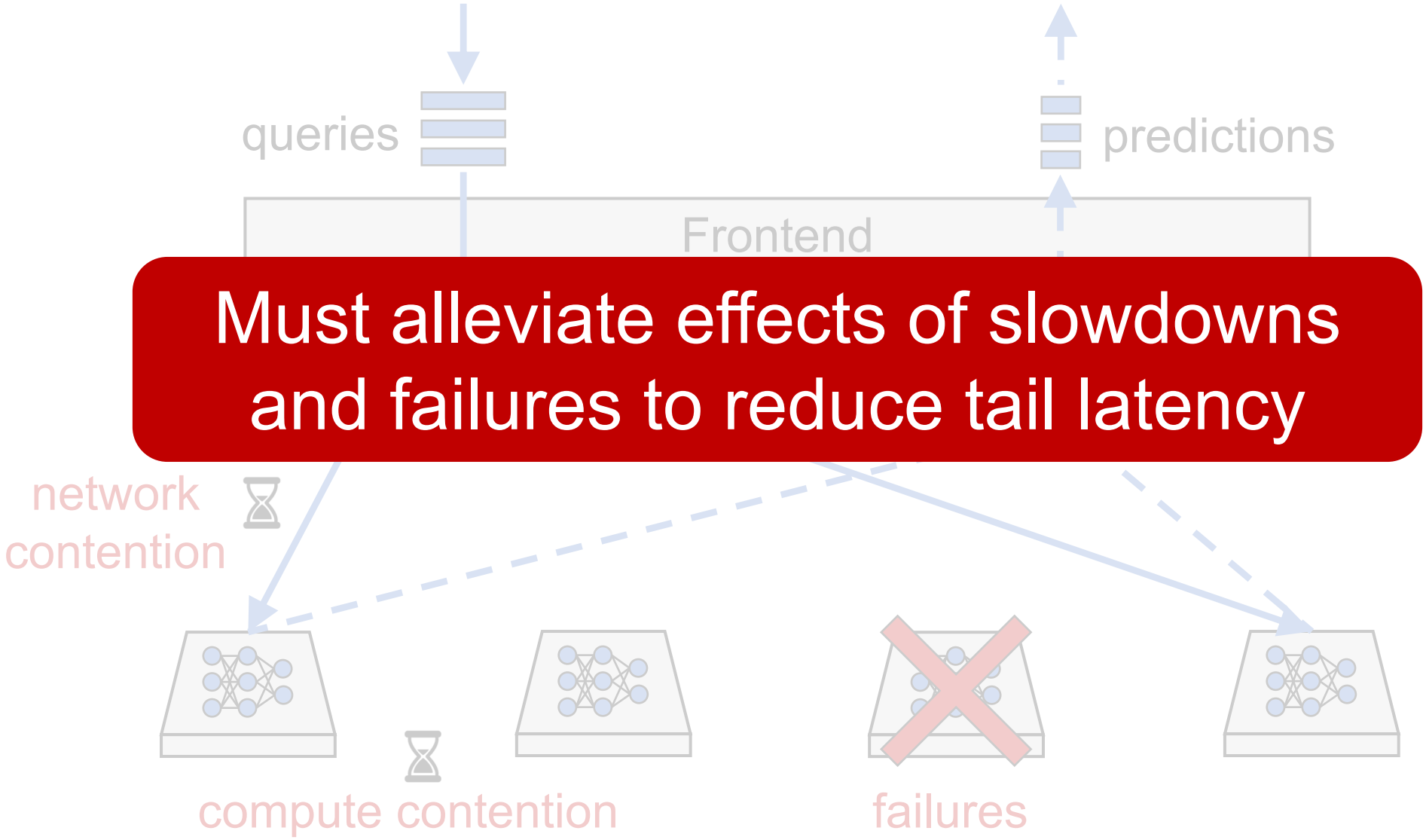

Erasure codes widely deployed in systems

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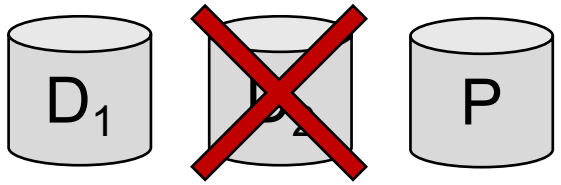
Storage systems

resource-efficient resilience



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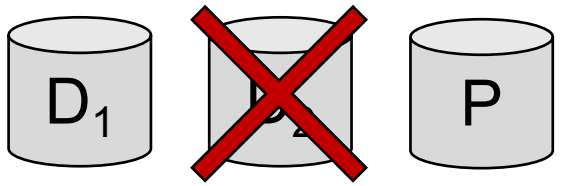
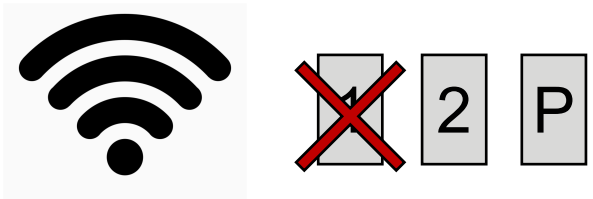


Communication systems

low-latency packet loss recovery



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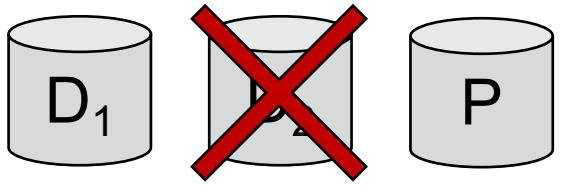

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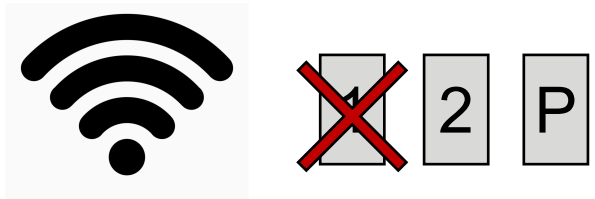

Erasure codes for systems that compute over data (e.g., serving systems)?

Erasure codes for resilient ML inference

This work: overcome fundamental challenges, use erasure codes for reducing tail latency in machine learning inference

Erasure codes for resilient ML inference

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Bring benefits of erasure codes to inference

- 👍 low recovery latency
- 👍 more resource-efficient than replication

End goal: erasure-coded prediction serving

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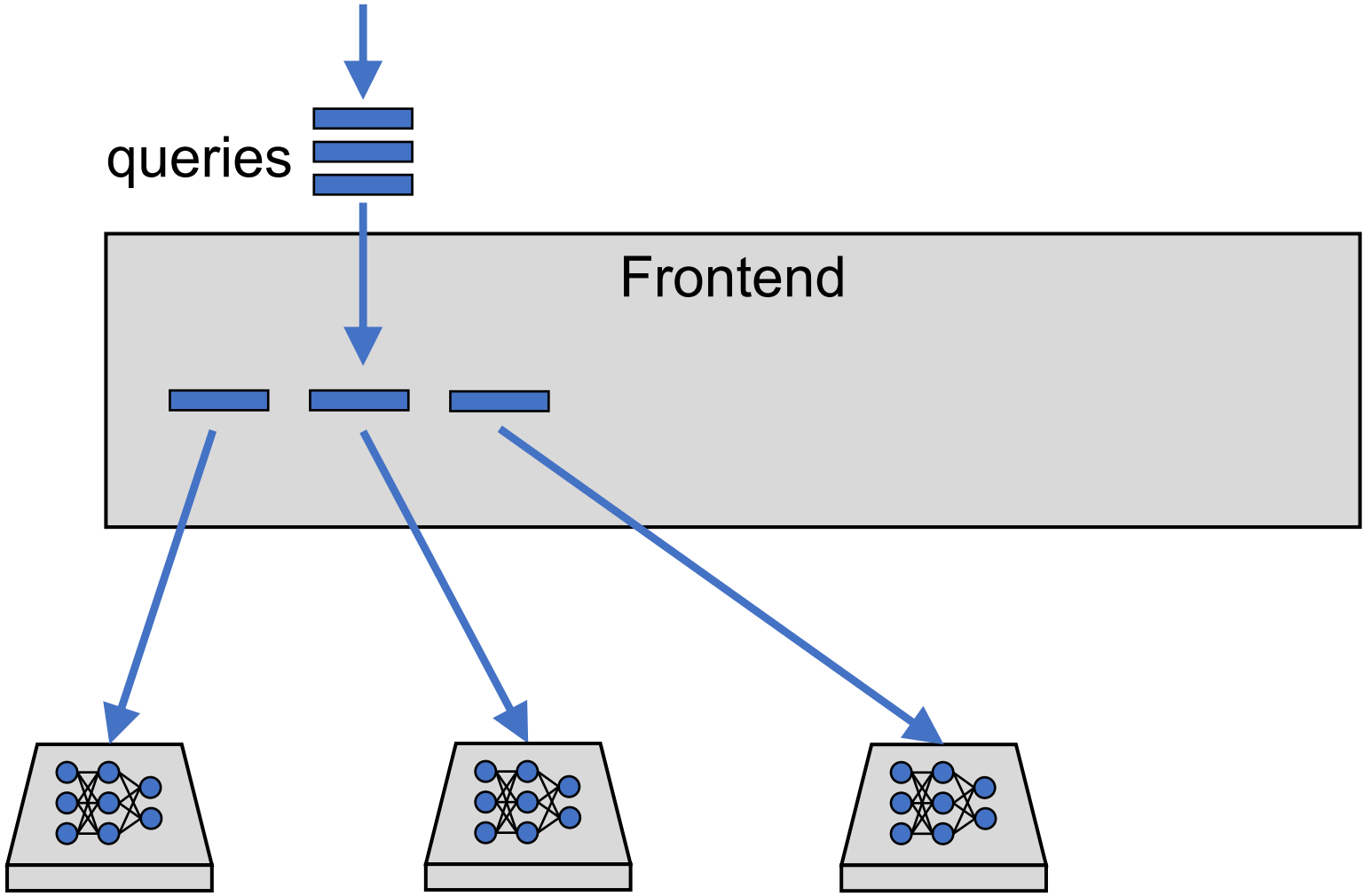

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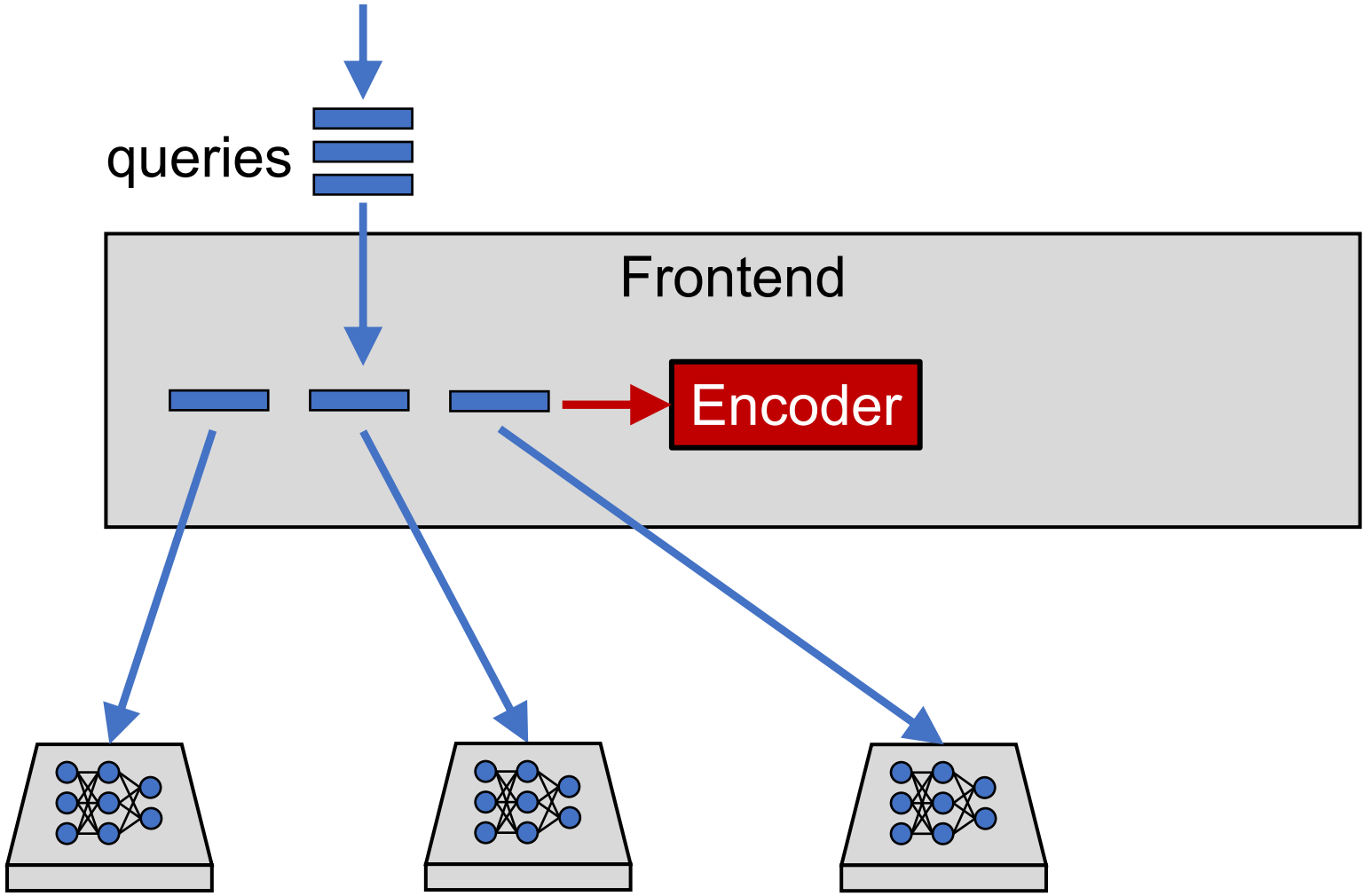

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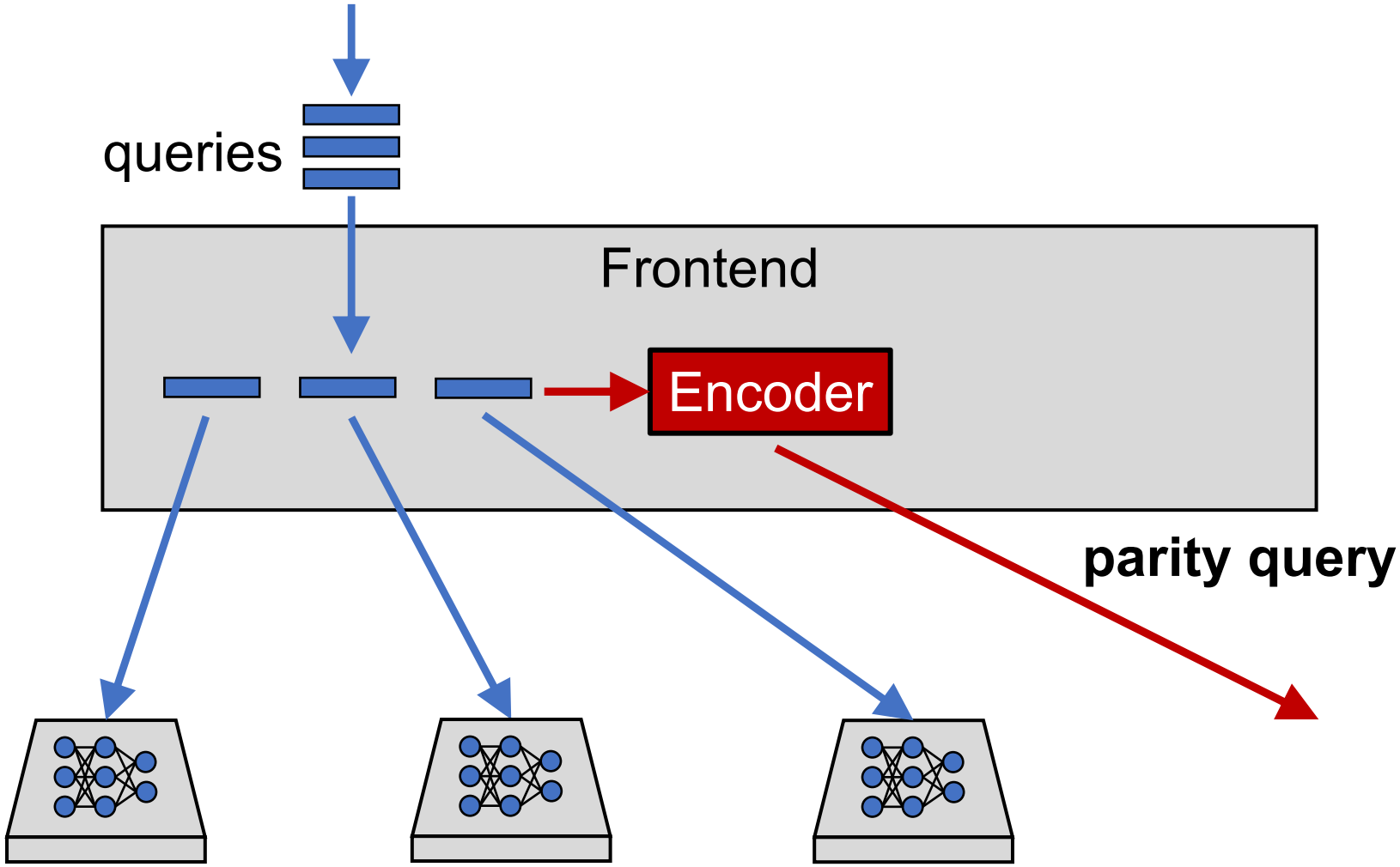

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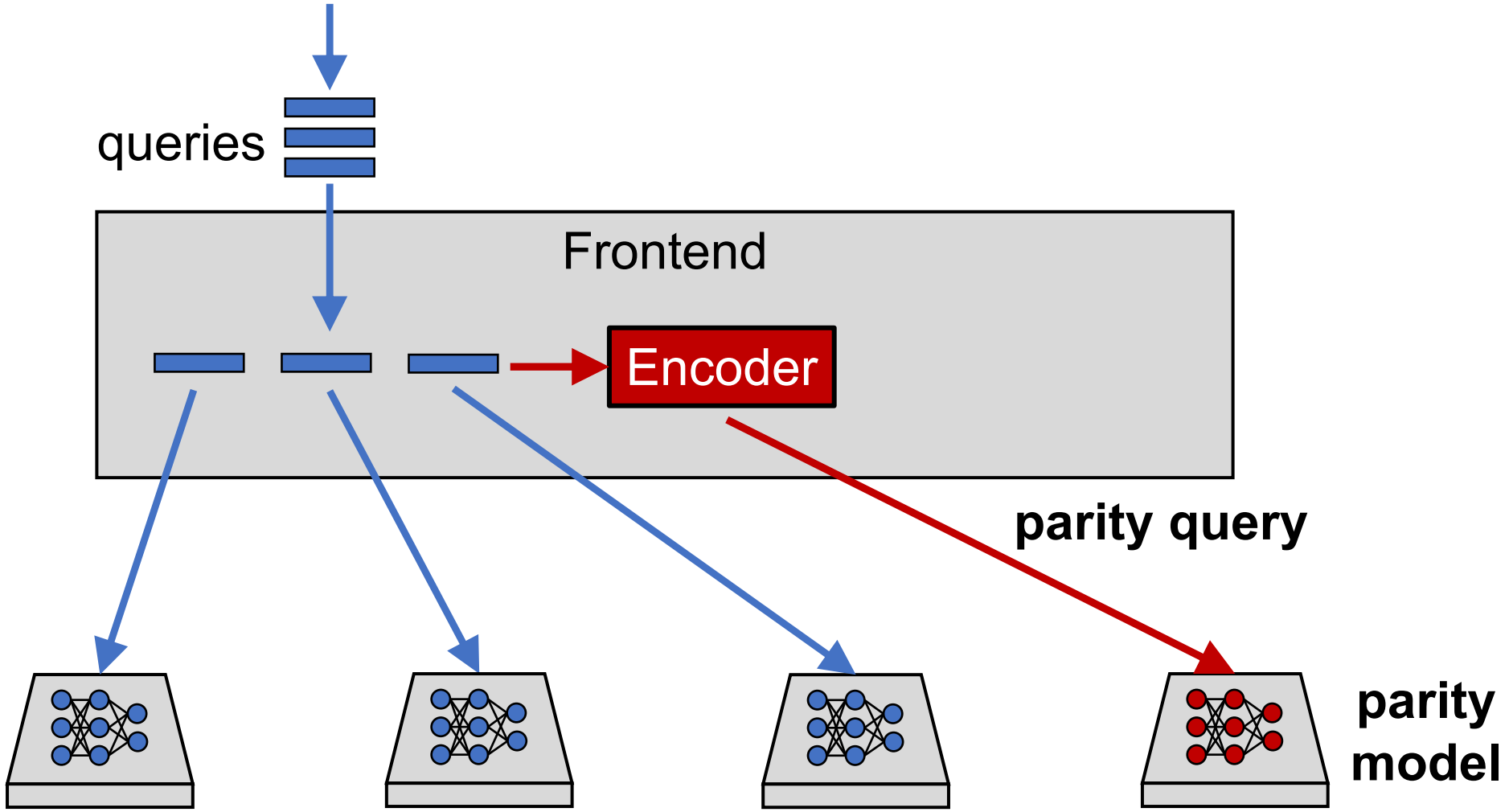

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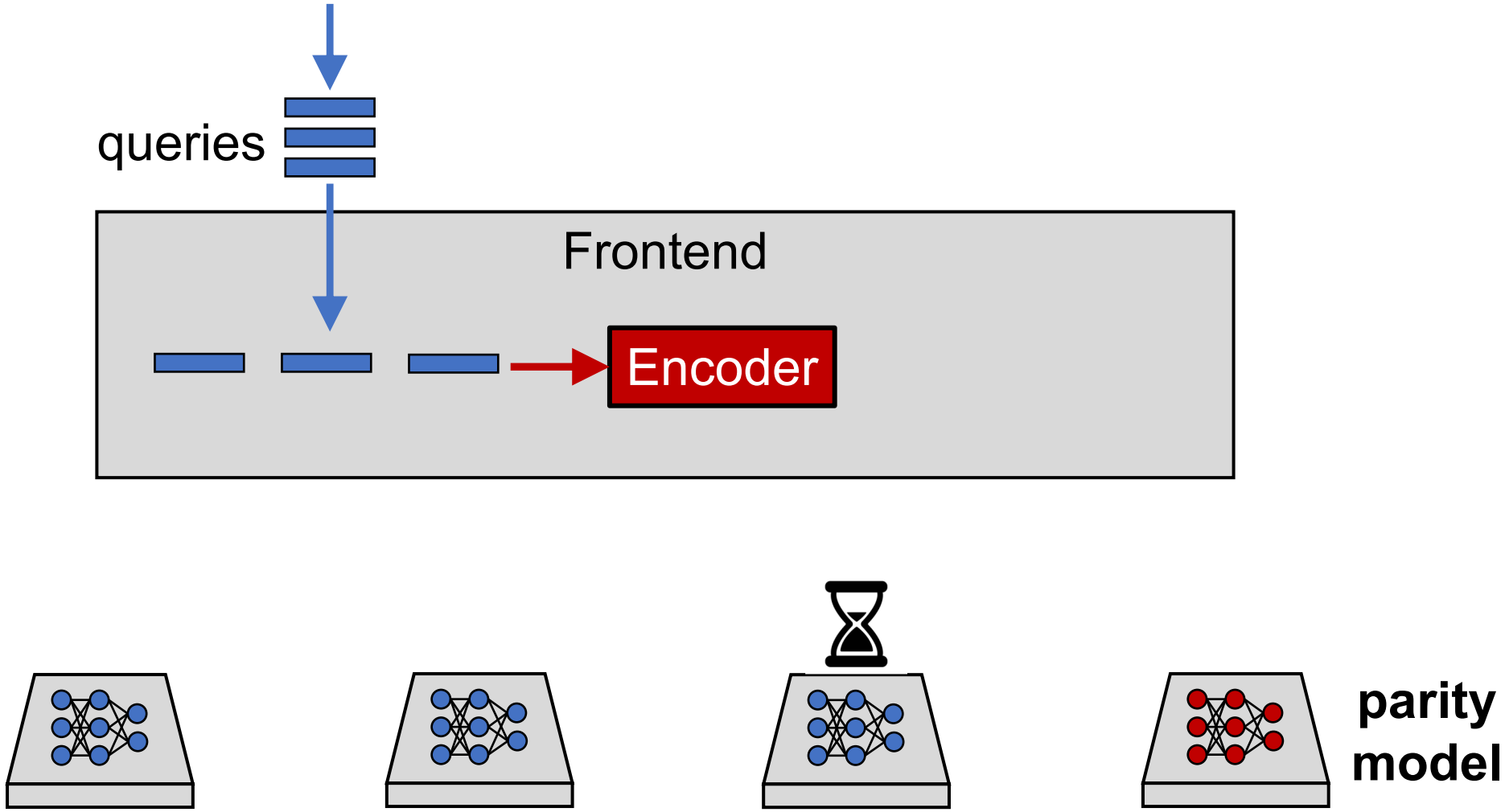

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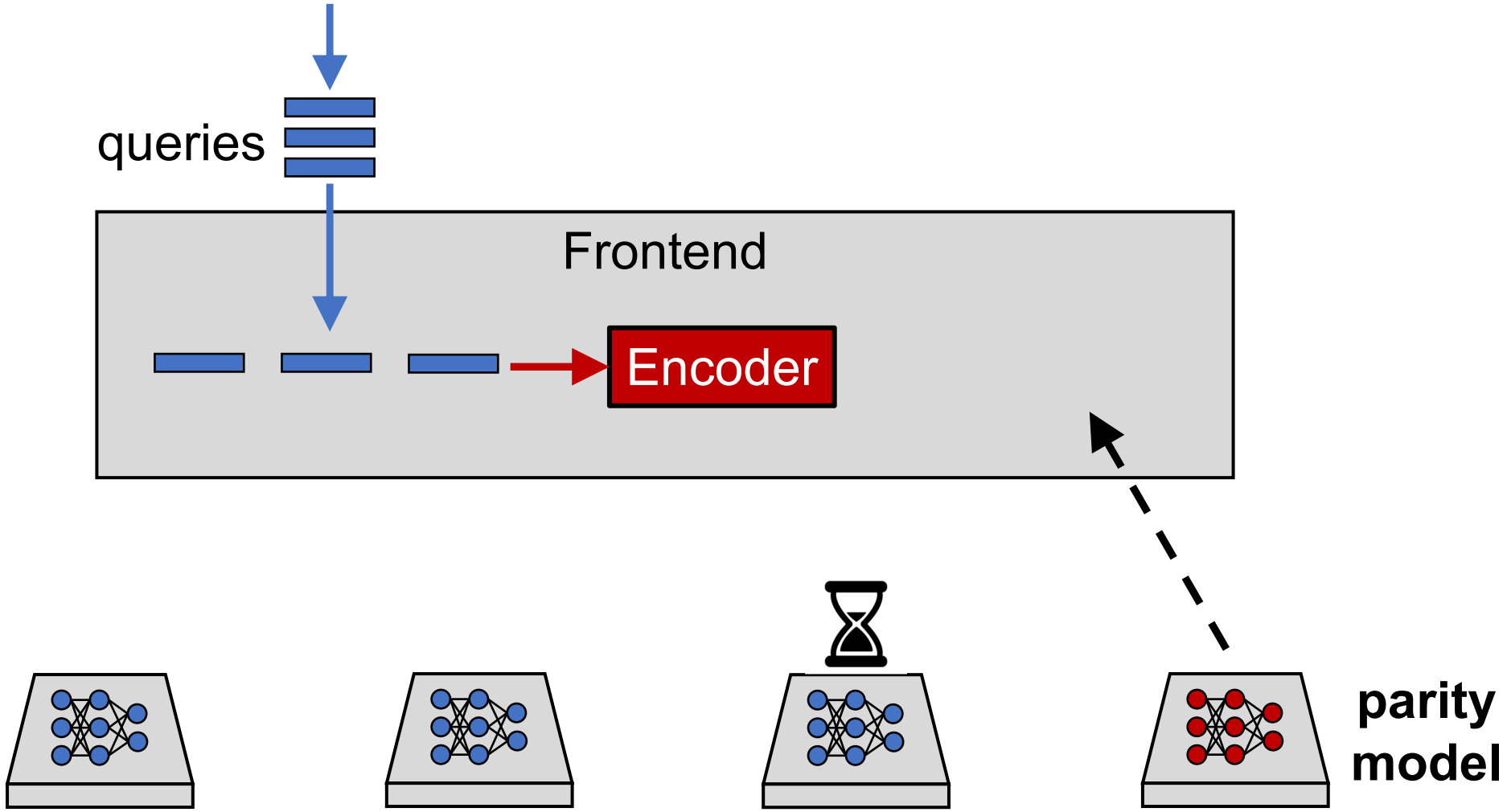

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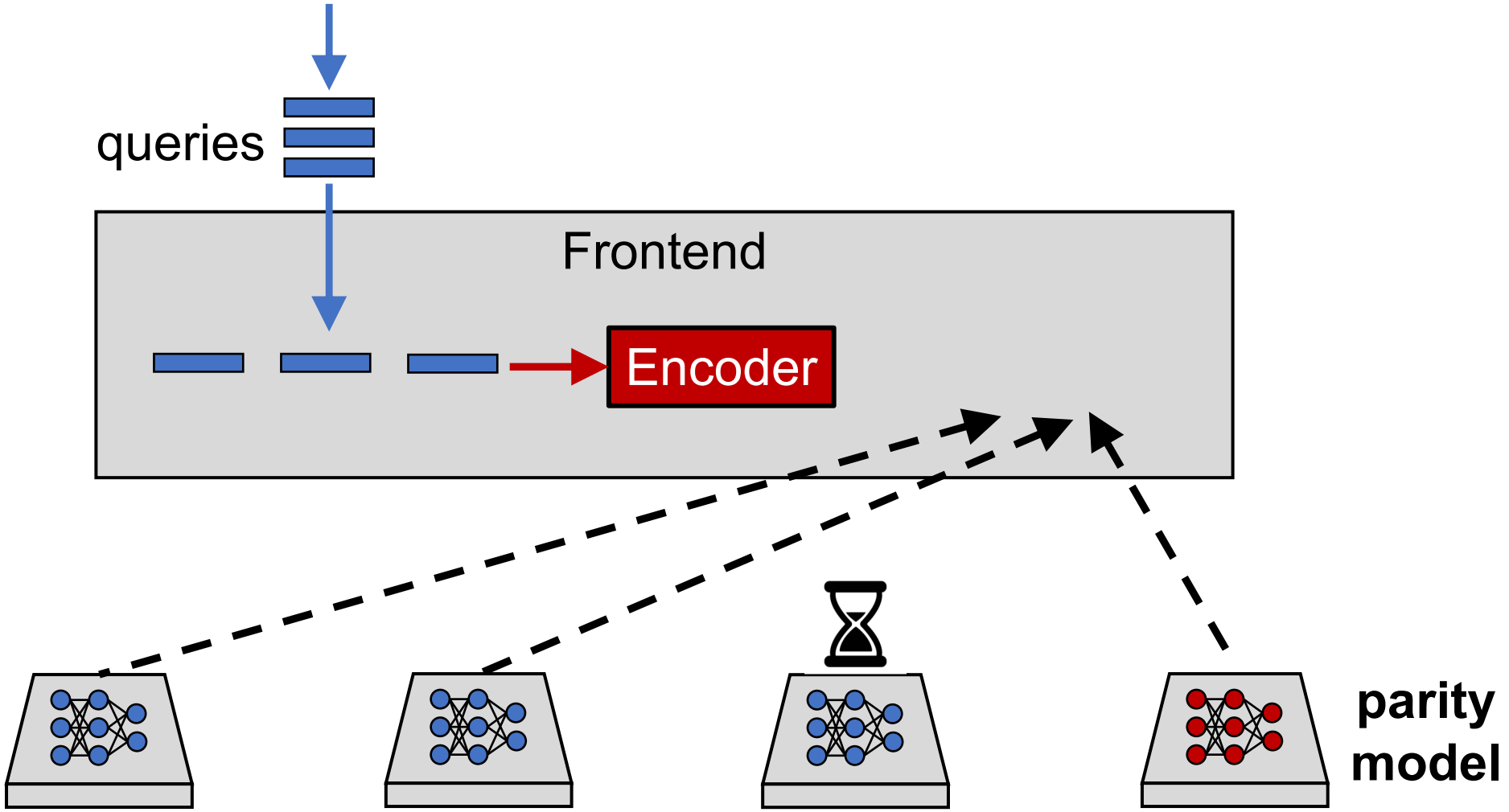

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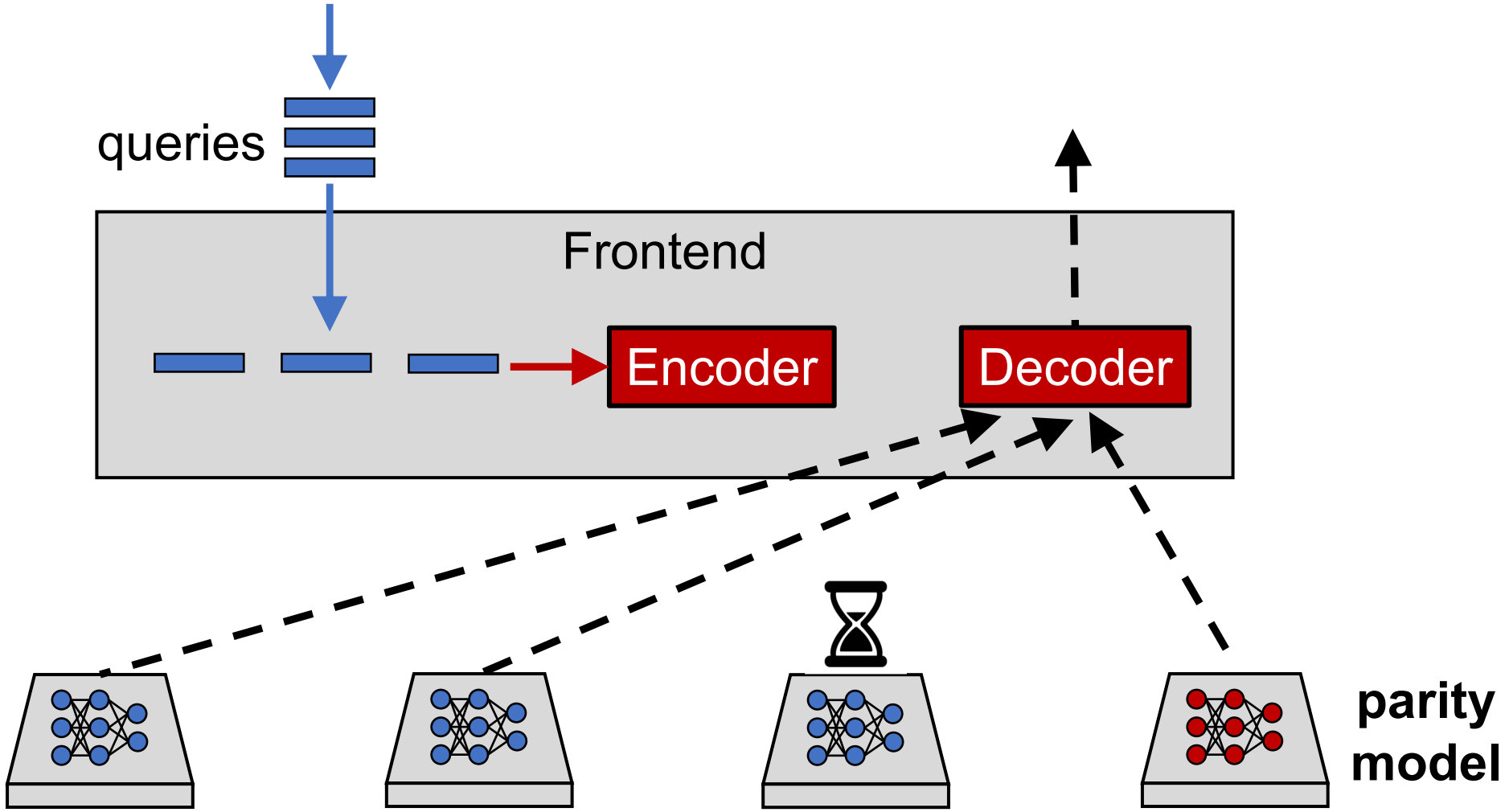

What does it mean to use erasure codes for ML inference?

Why is this hard?

Quick recap of erasure codes

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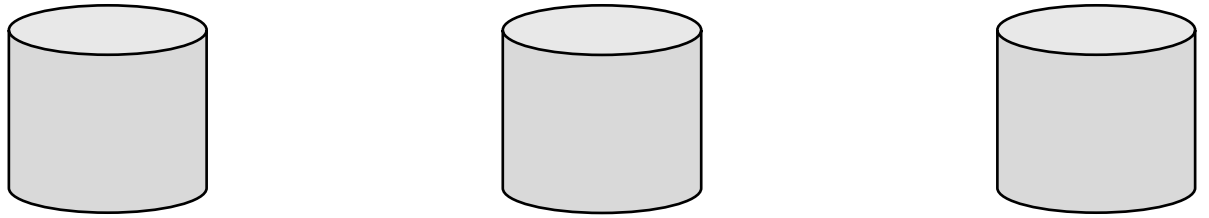

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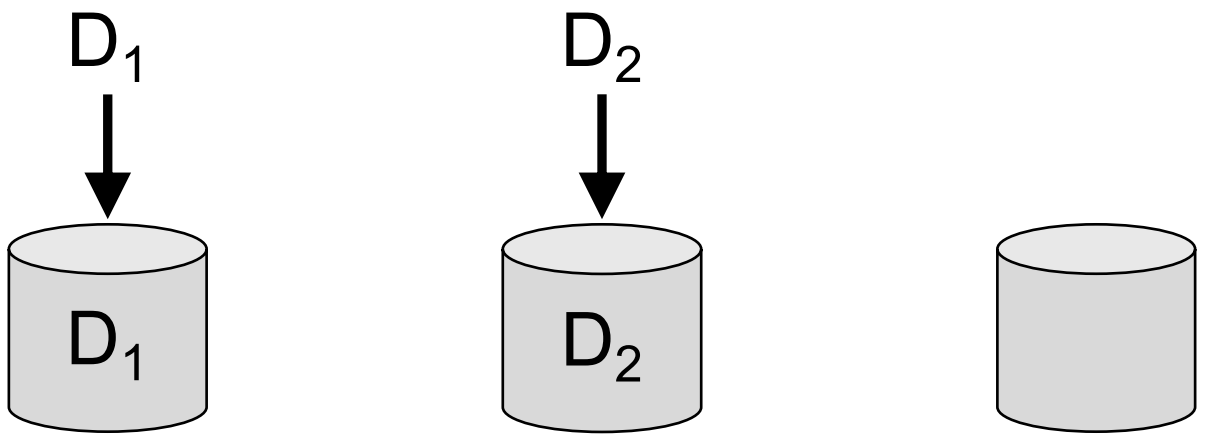

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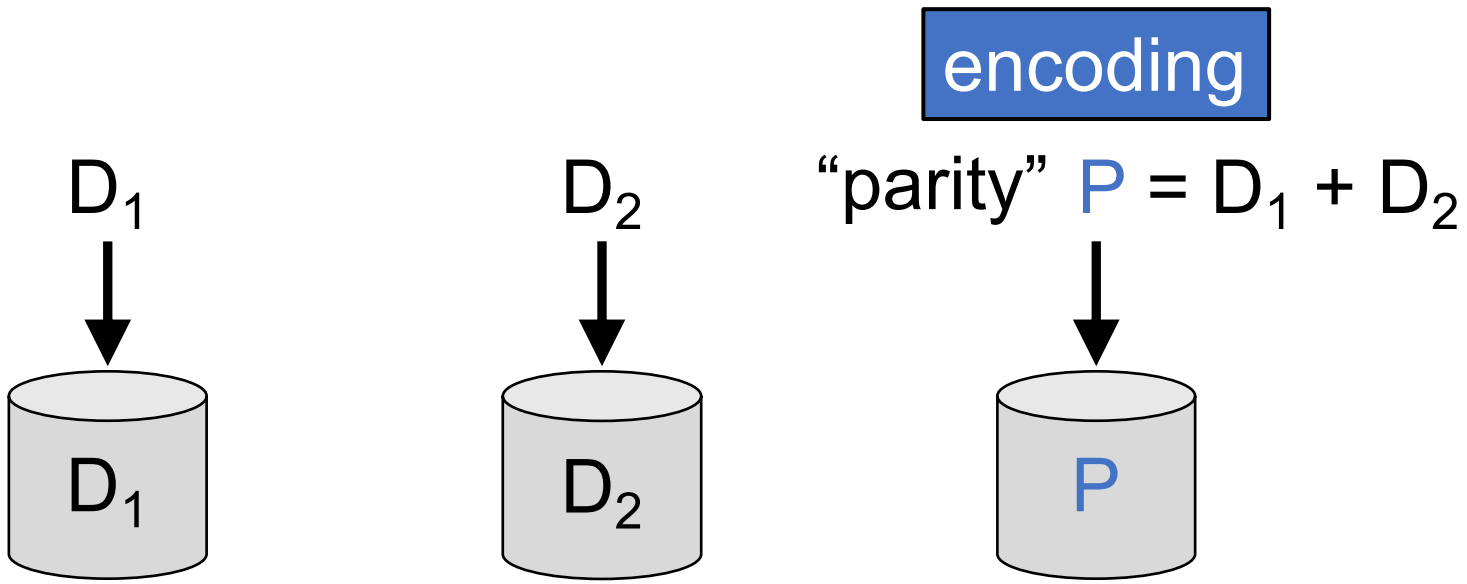

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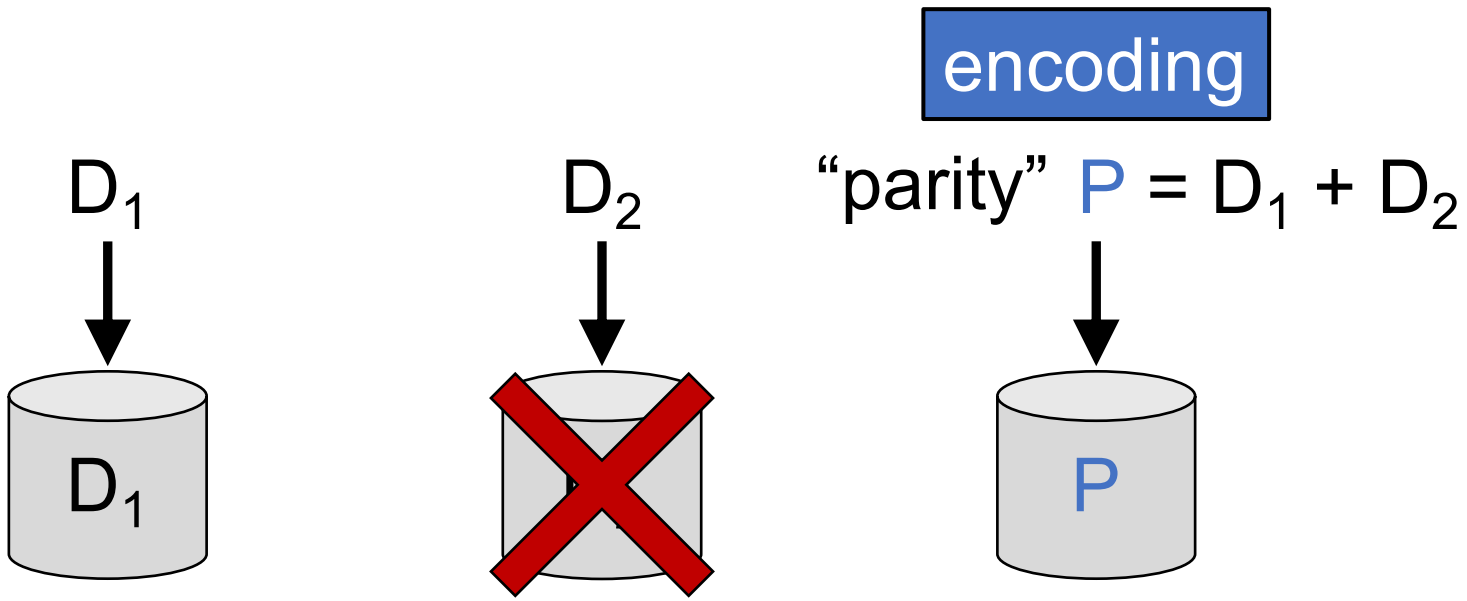

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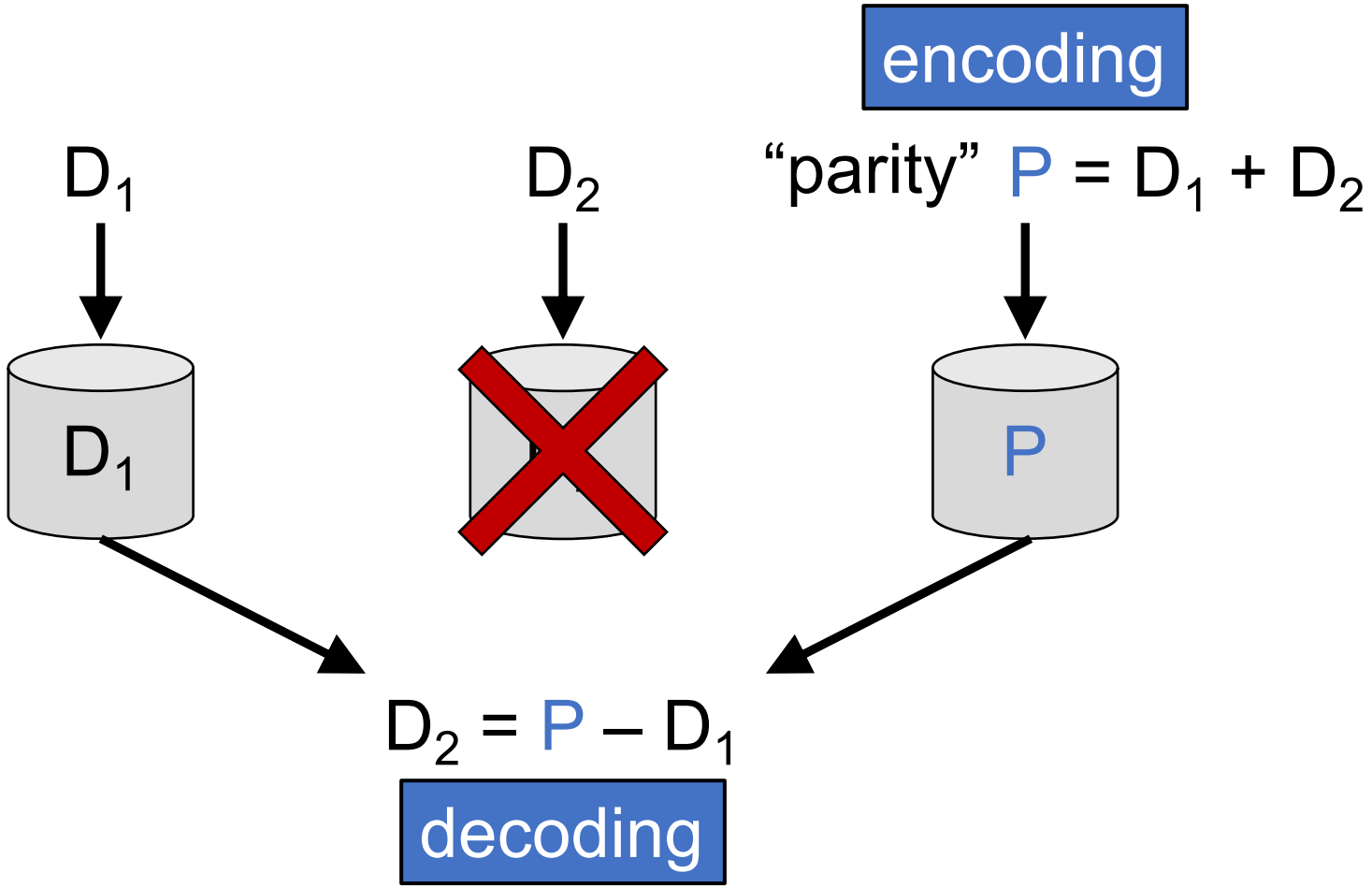
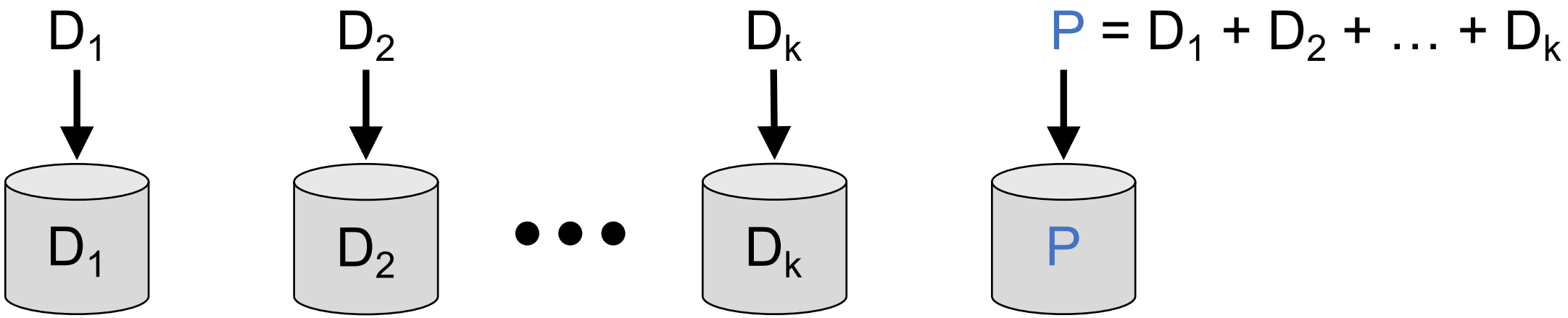
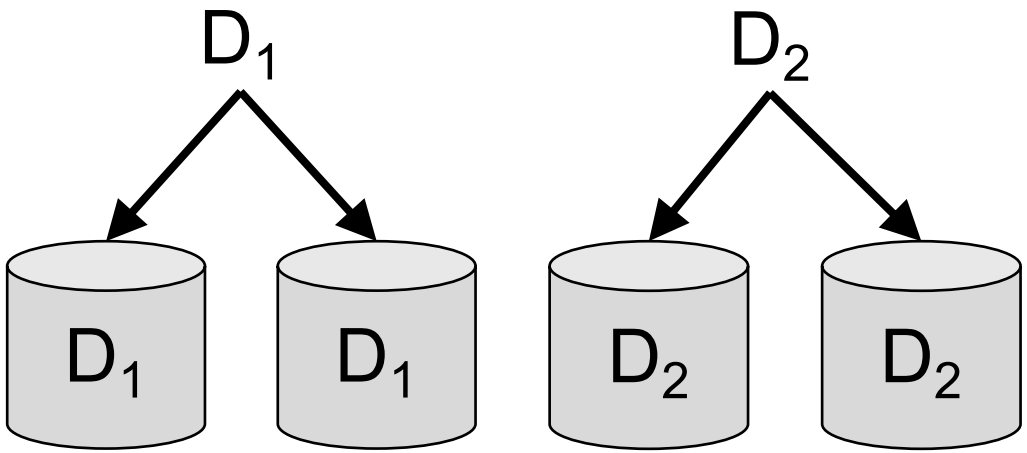


Quick recap of erasure codes: parameter k

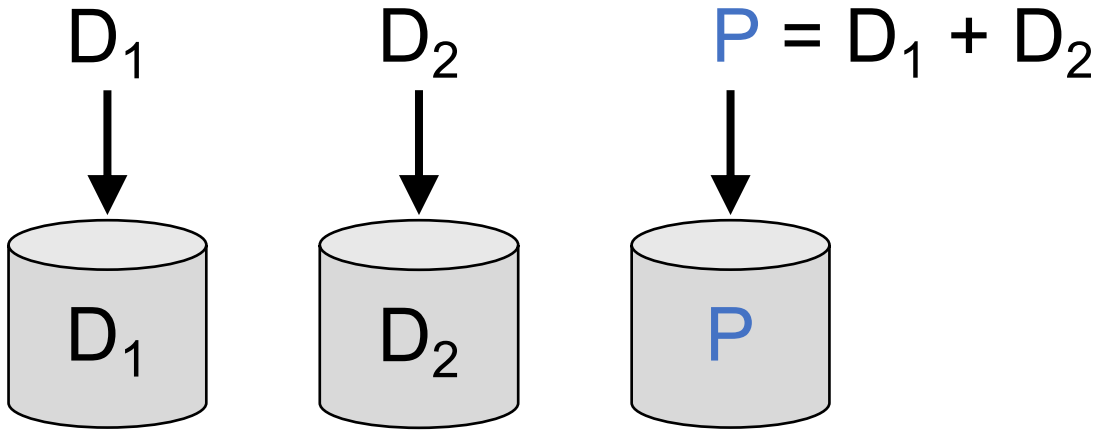


Quick recap of erasure codes: benefits

Replication



Erasure Coding



- same resilience
- lower resource-overhead

Using erasure codes for inference

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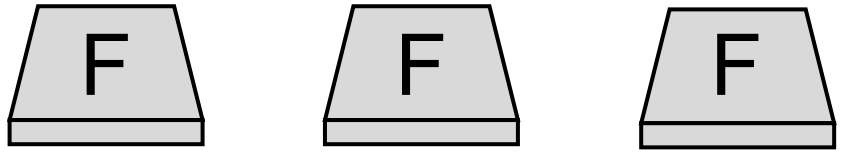

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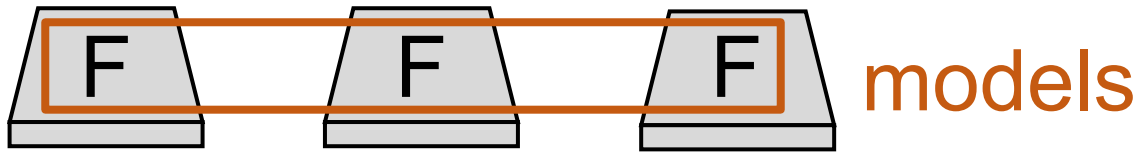

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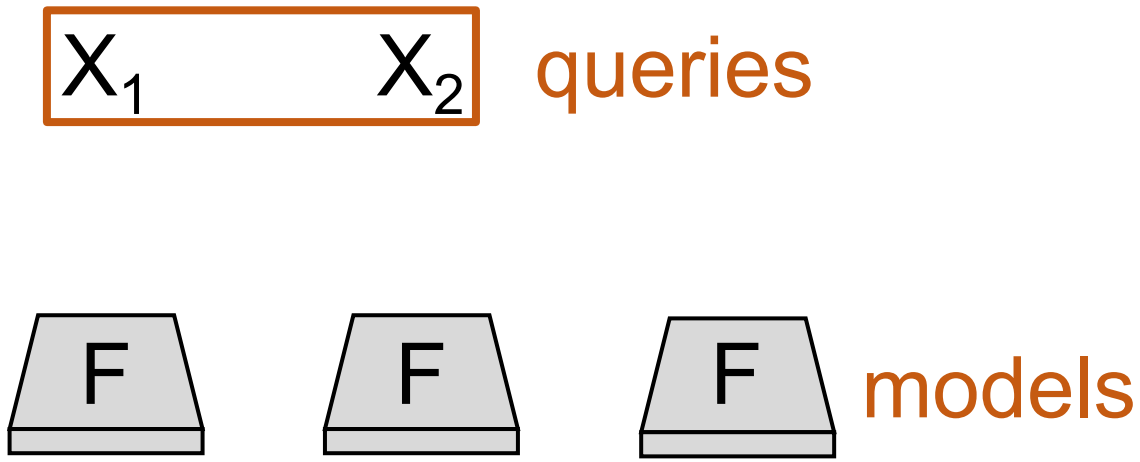

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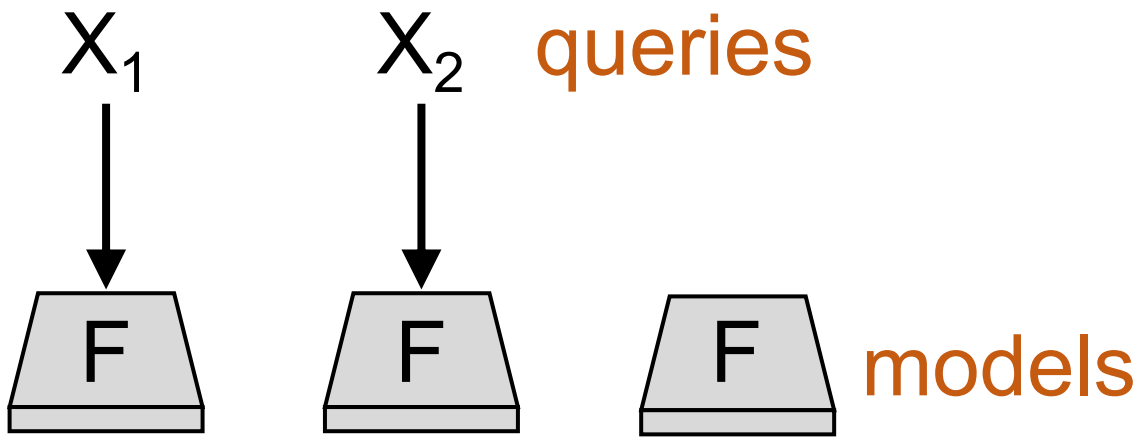

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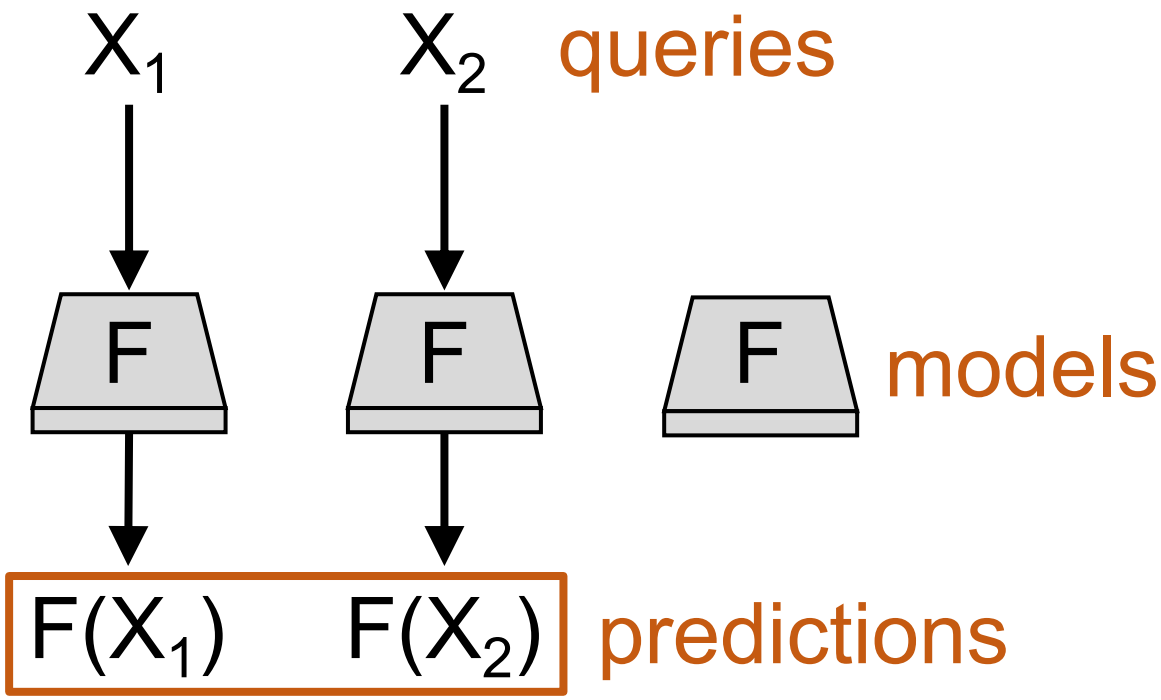

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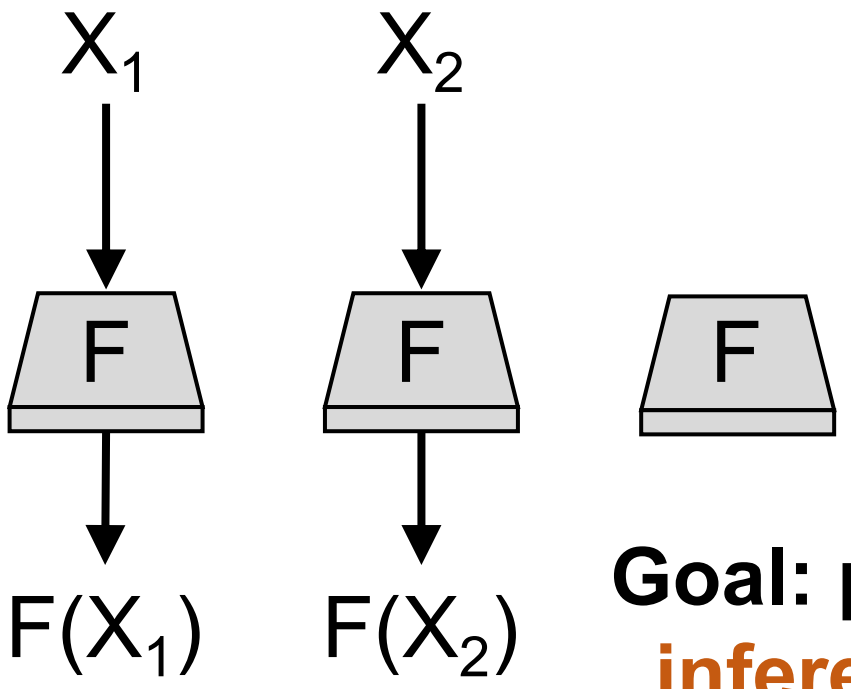
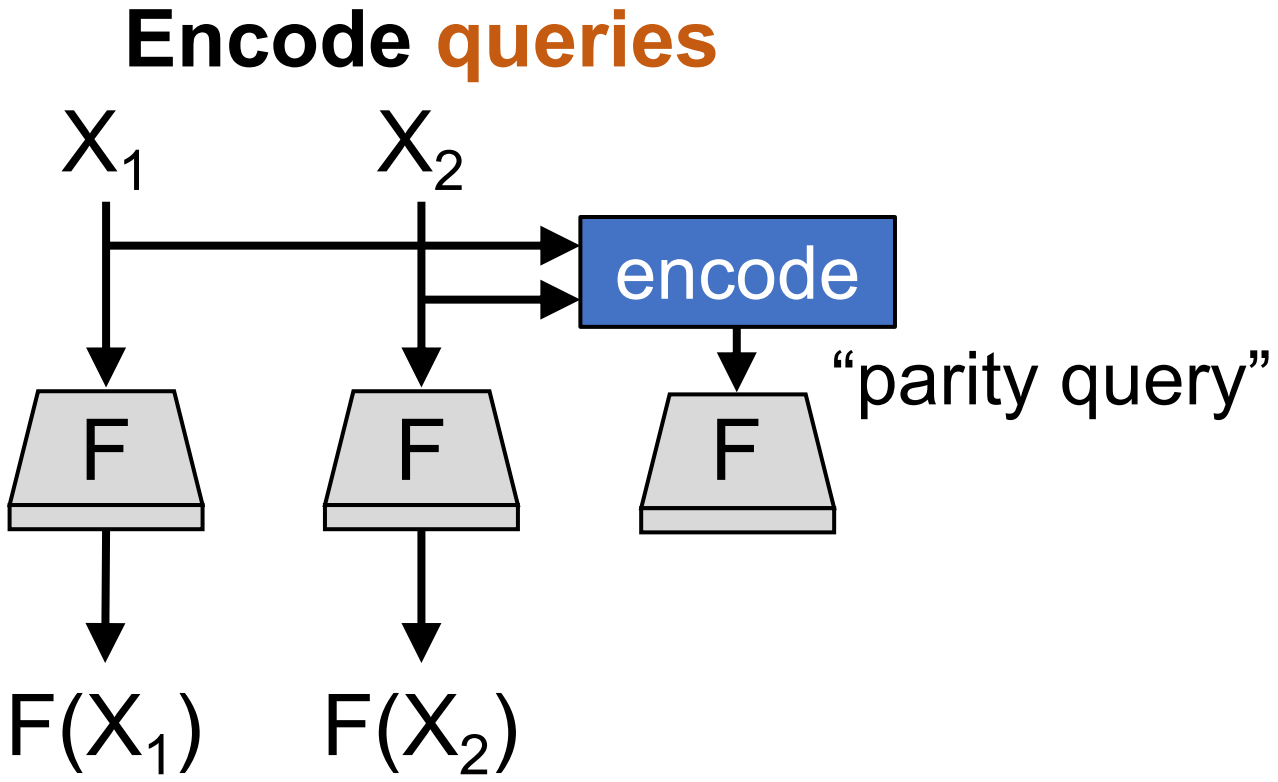


Goal: preserve results of inference over queries

Using erasure codes for inference



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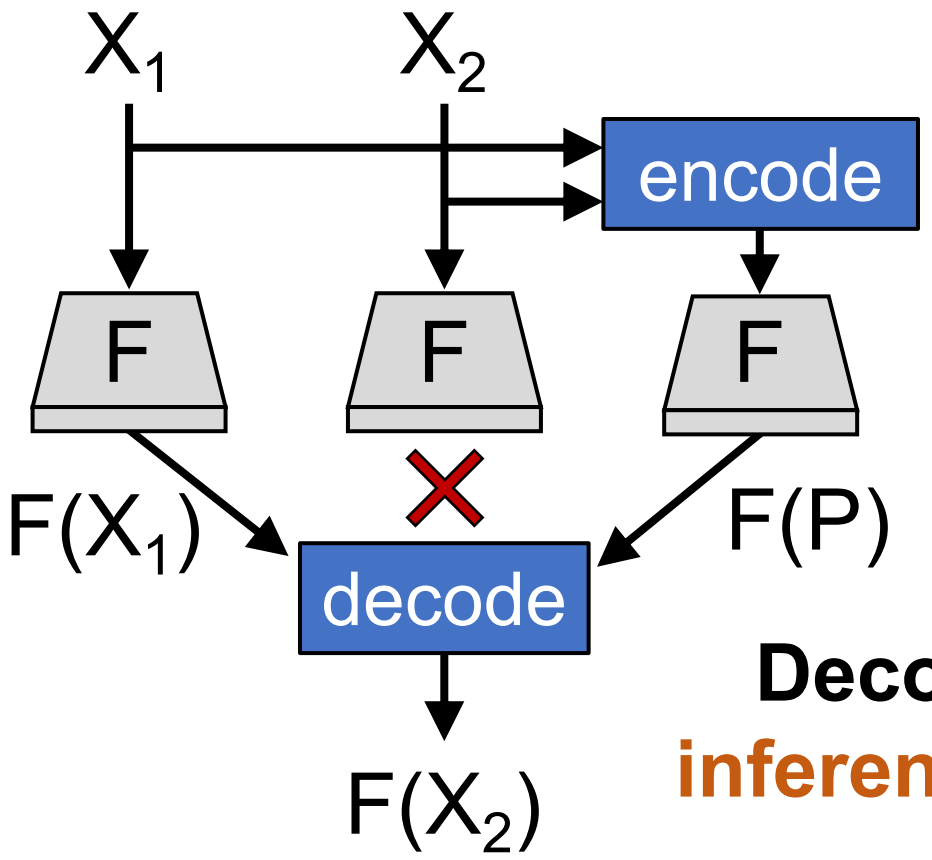
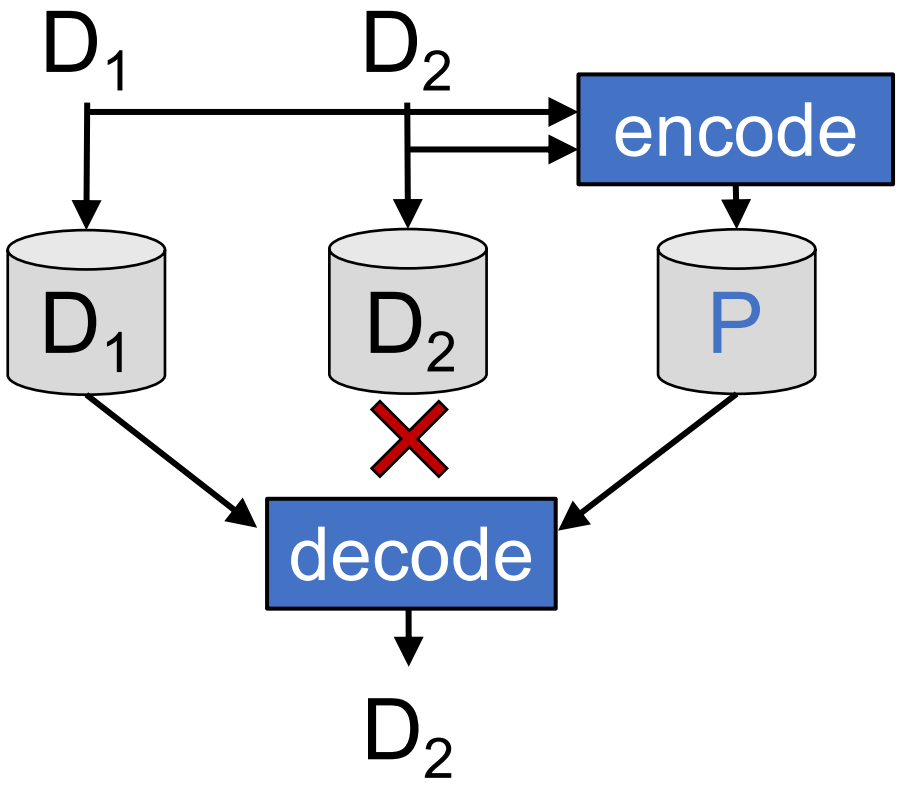


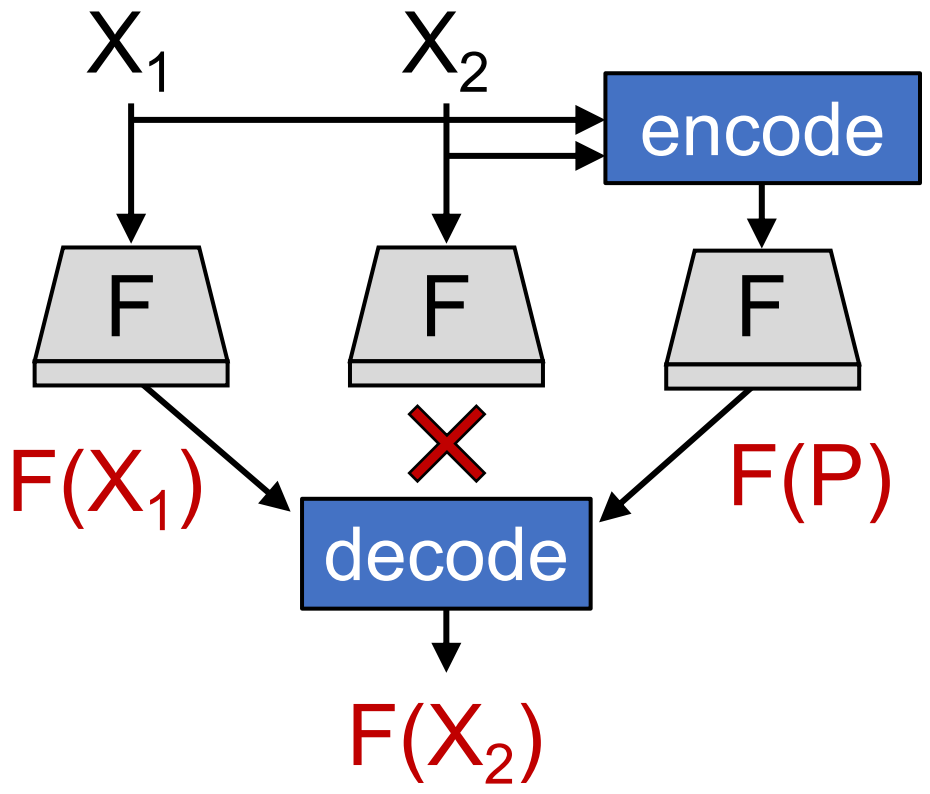
Decode results of inference over queries

Traditional coding vs. codes for inference

Codes for storage

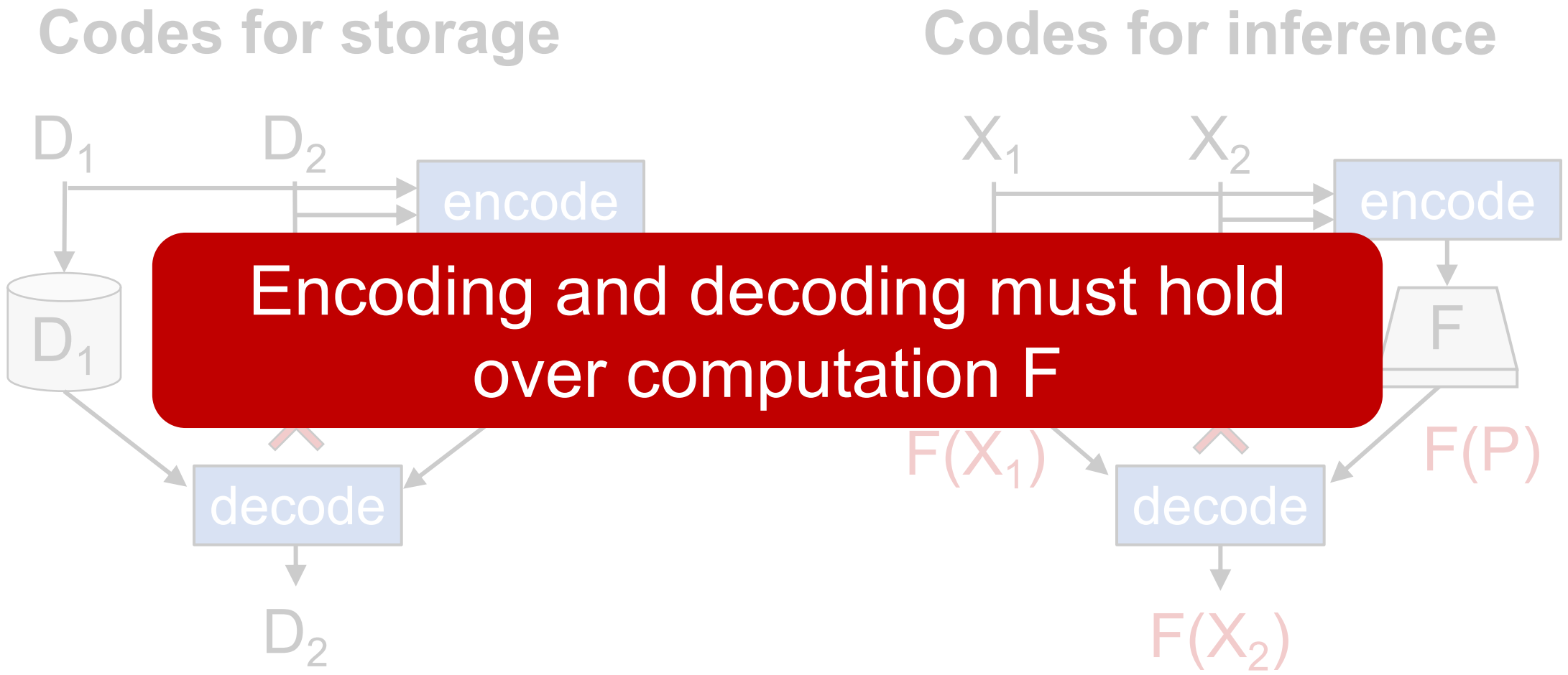


Codes for inference



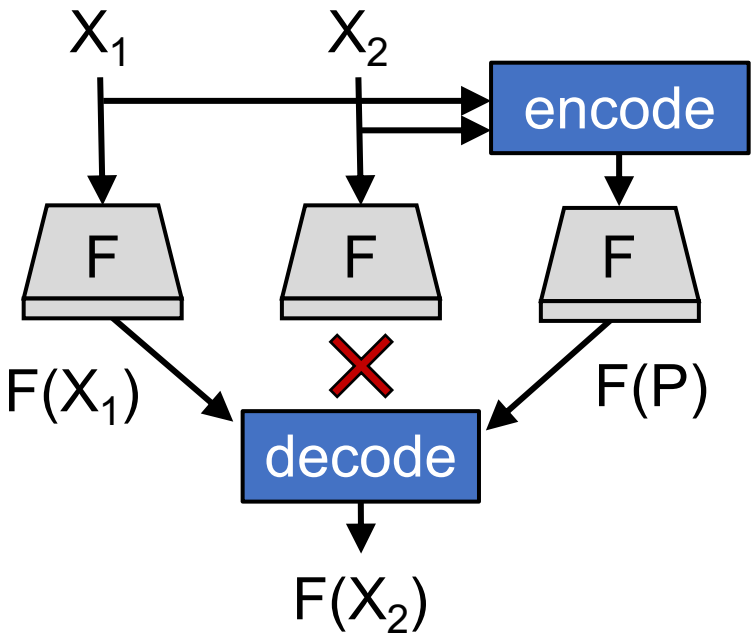
Need to handle **computation over inputs**

Traditional coding vs. codes for inference



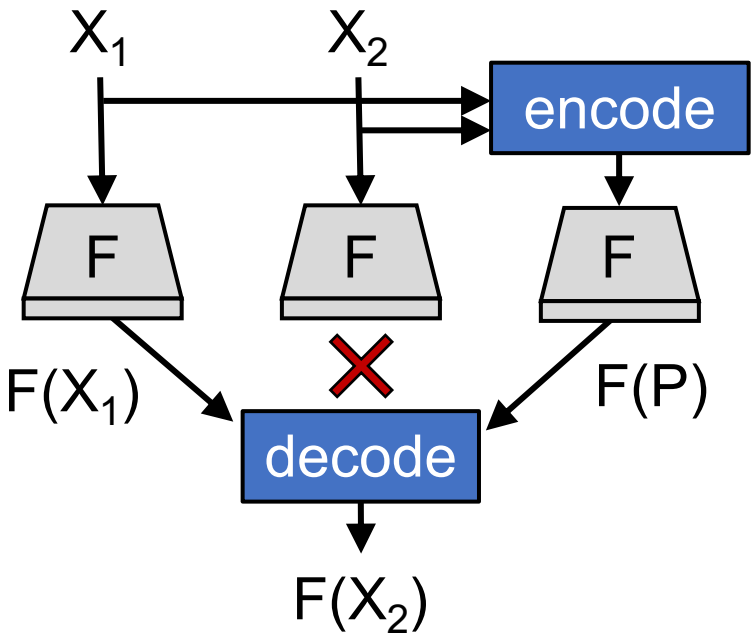
Need to handle **computation over inputs**

Designing erasure codes for inference is hard



Designing erasure codes for inference is hard

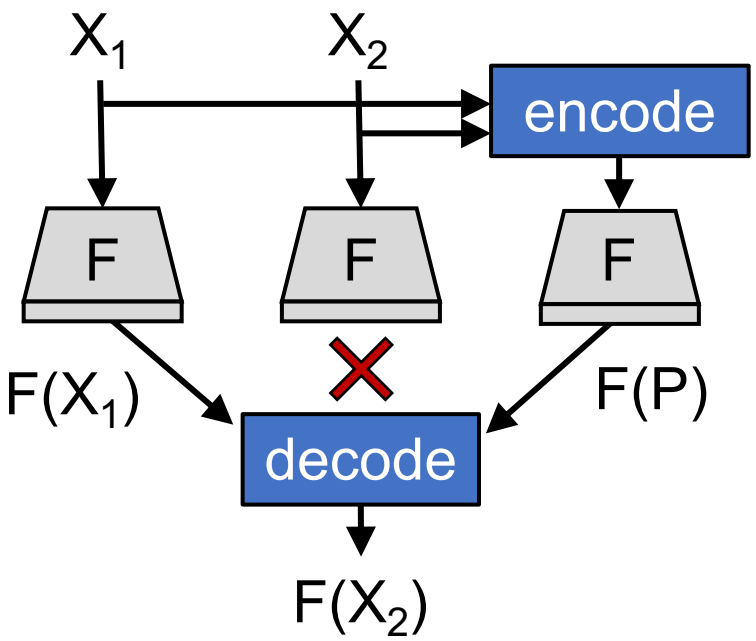
Theoretical framework: “coded-computation”



Designing erasure codes for inference is hard

Theoretical framework: “coded-computation”

Currently: handcraft erasure code



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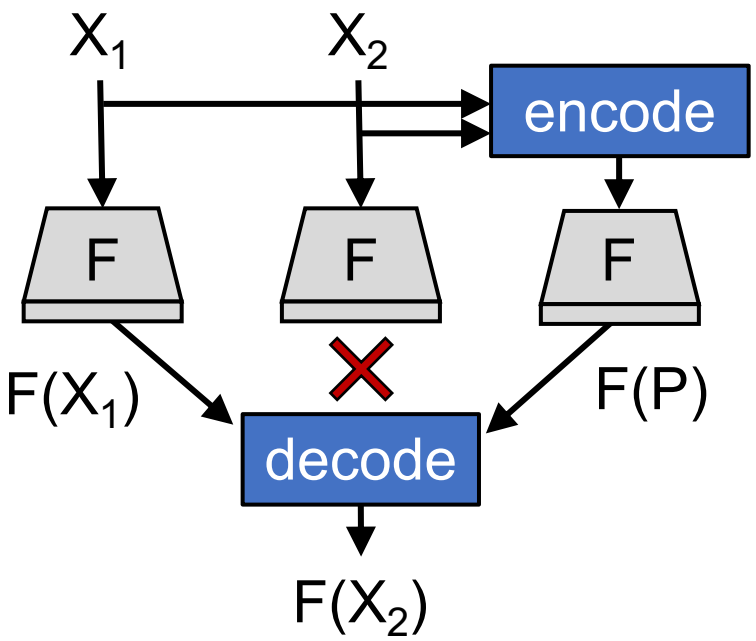
Currently: handcraft erasure code

- Straight-forward for **linear** F

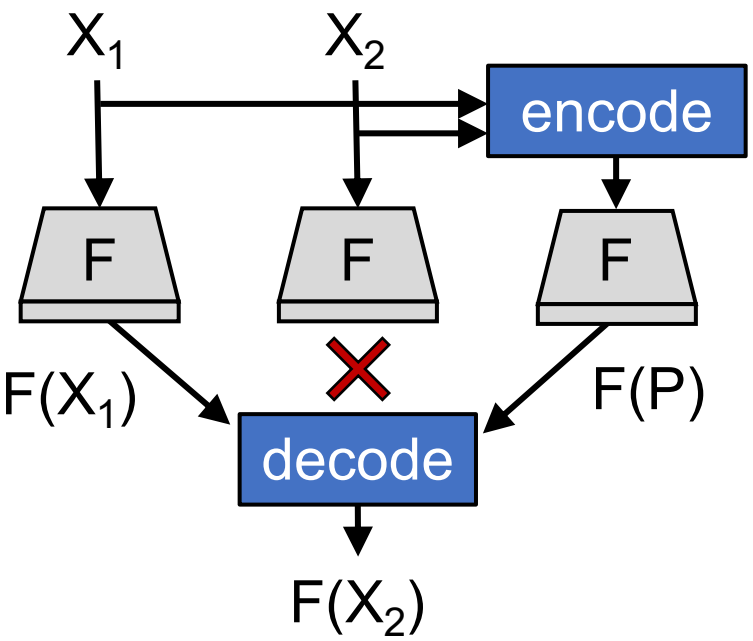


Designing erasure codes for inference is hard

Theoretical framework: "coded-computation"

Currently: handcraft erasure code

- Straight-forward for **linear** F
- Far more challenging for **non-linear** F
  - Apply to only restricted functions (polynomials)
  - Require 2x resource-overhead



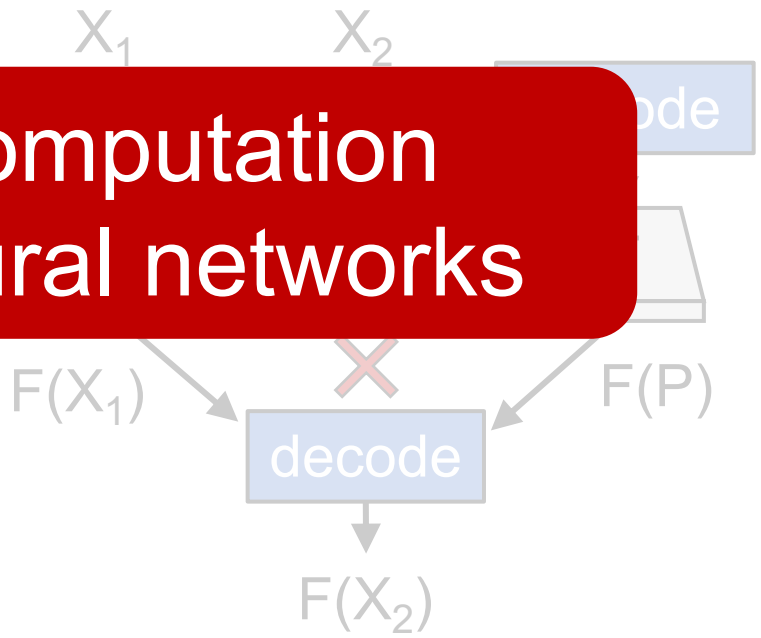
Designing erasure codes for inference is hard

Theoretical framework: “coded-computation”

Currently: handcraft erasure code

Current handcrafted coded-computation approaches cannot support neural networks

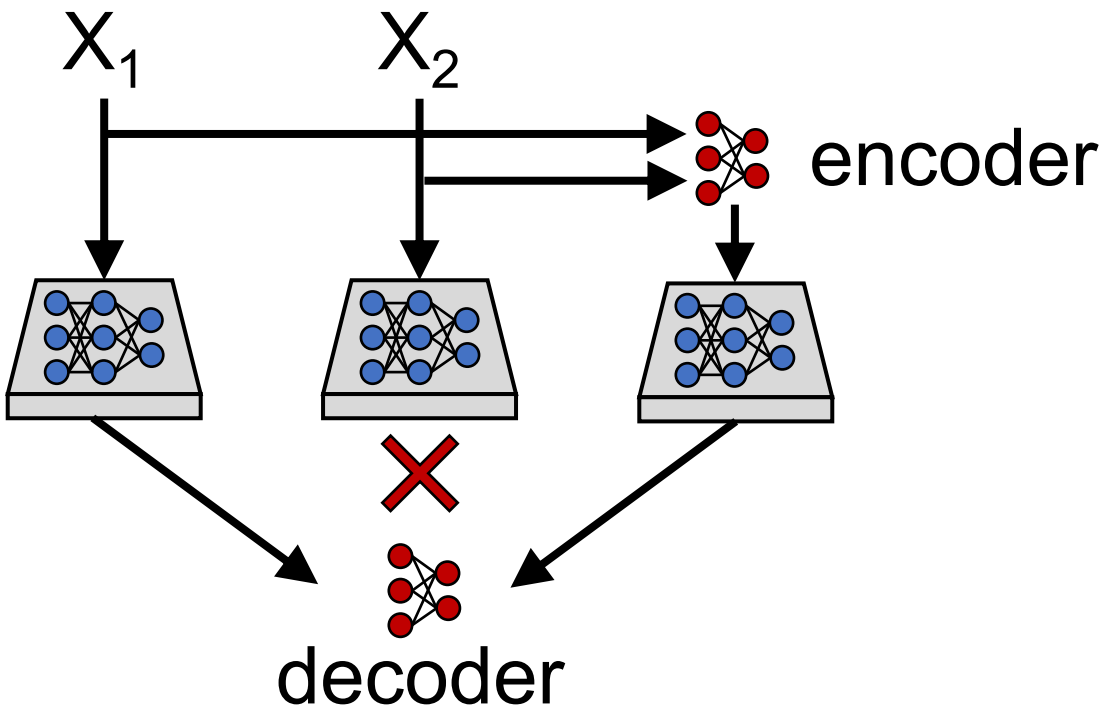
- Apply to only restricted functions (polynomials)
- Require 2x resource-overhead



This work:
overcome challenges of handcrafting erasure codes for coded-computation by taking a **learning-based** approach to erasure-coded resilience

Learning an erasure code?

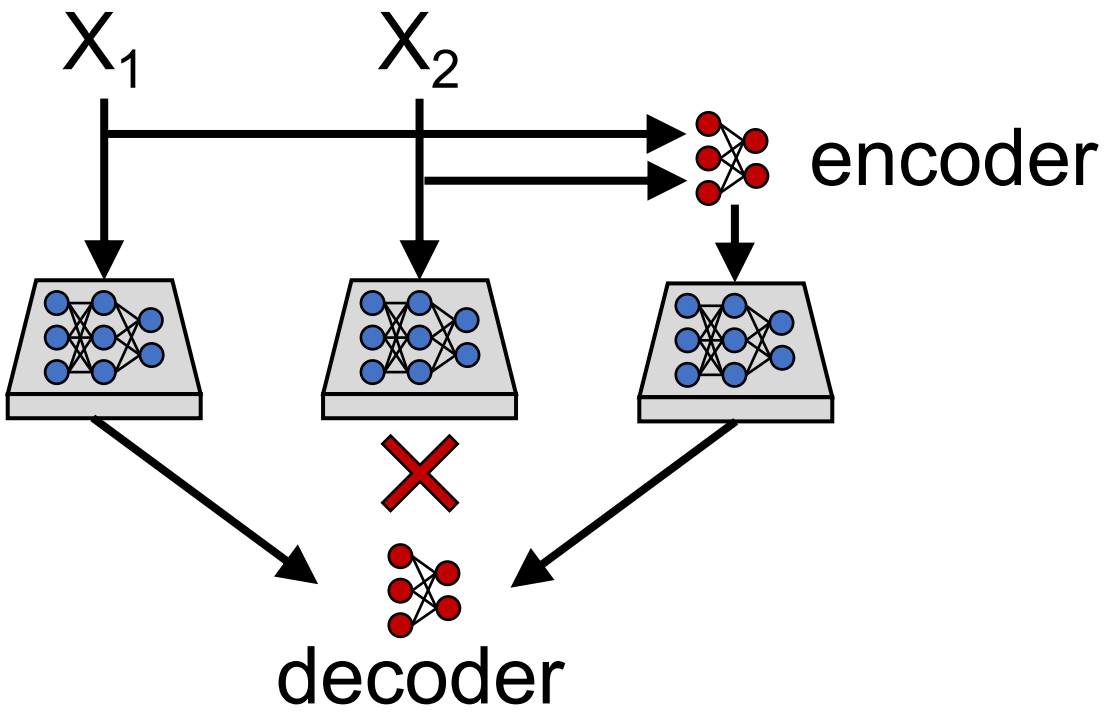
Design encoder and decoder as neural networks



Learning an erasure code?

Design encoder and decoder as neural networks

Accurate

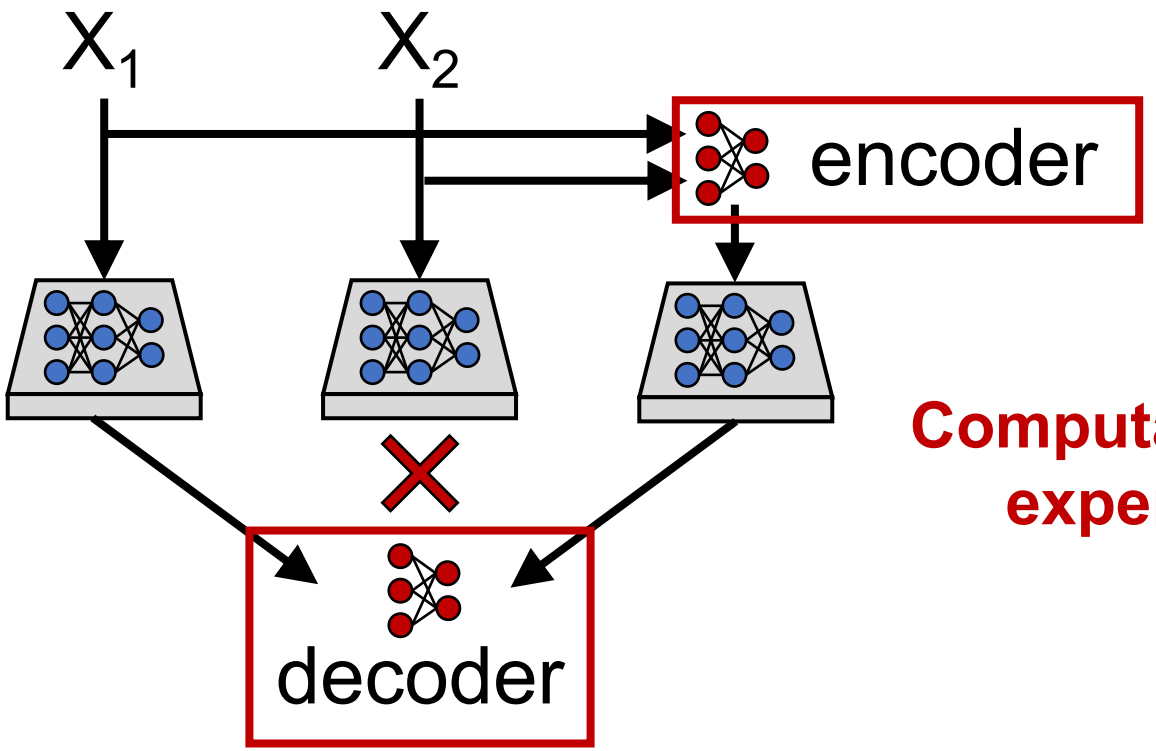


Learning an erasure code?

Design encoder and decoder as neural networks

Accurate

Expensive encoder/decoder



Computationally expensive

Learn computation over parities

Learn computation over parities

Use simple, fast encoders and decoders
Learn computation over parities: **“parity model”**

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Use simple, fast encoders and decoders
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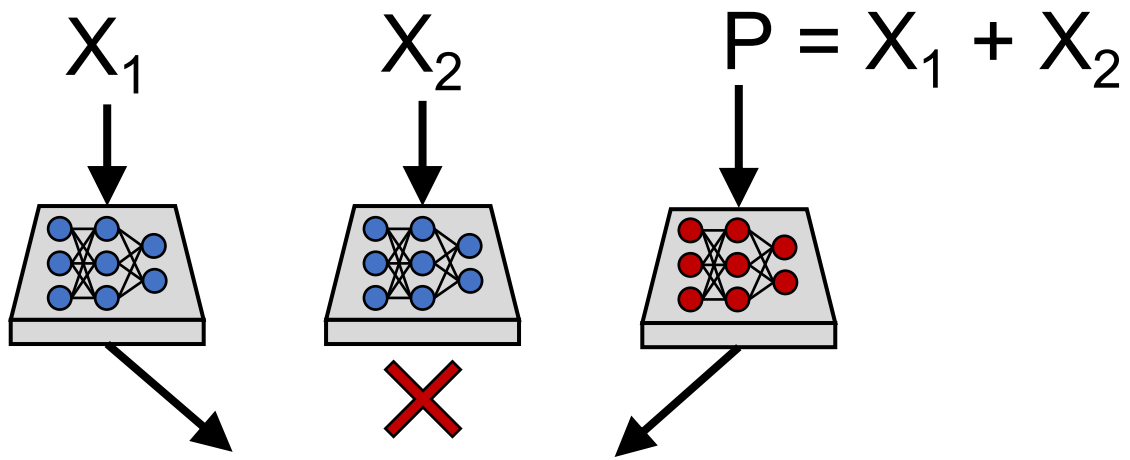

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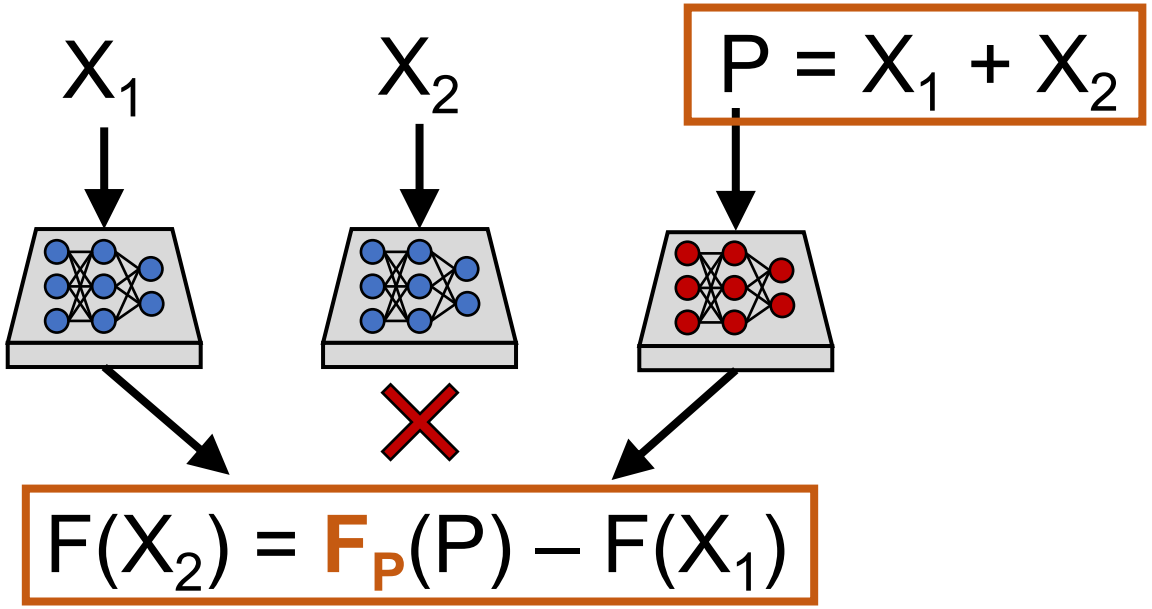

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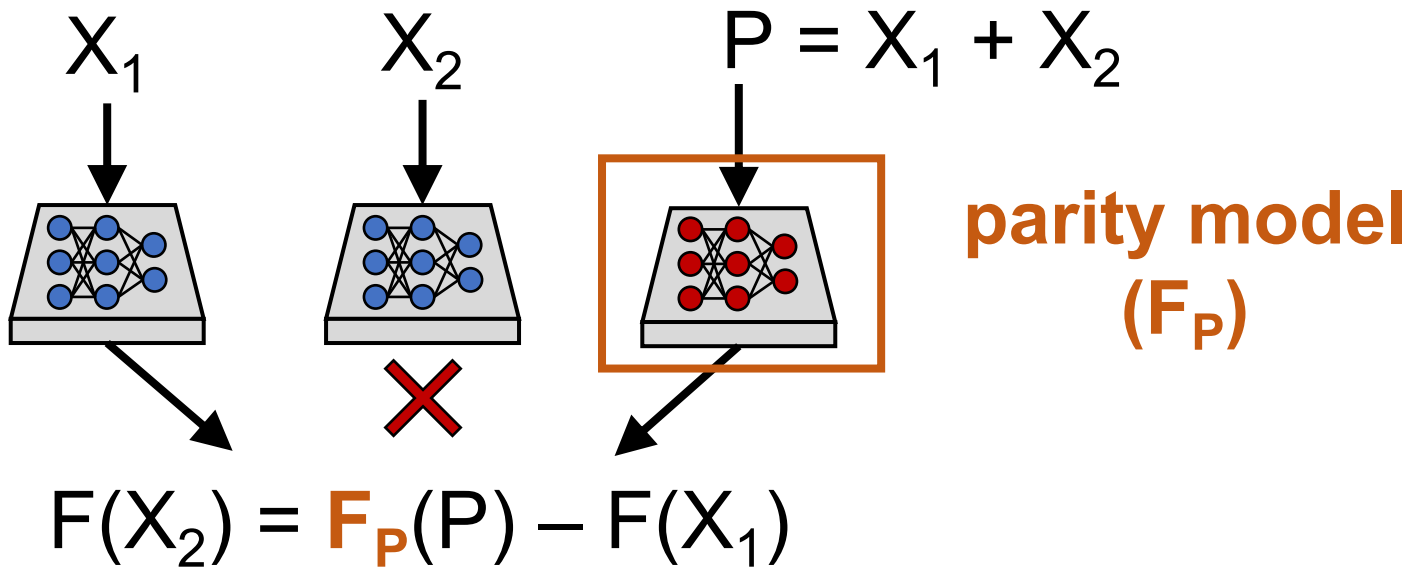
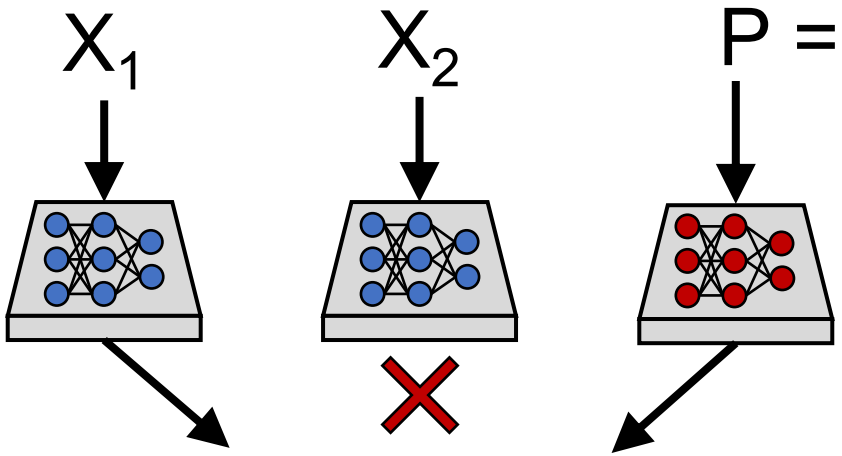


Learn computation over parities

Use simple, fast encoders and decoders
Learn computation over parities: **“parity model”**

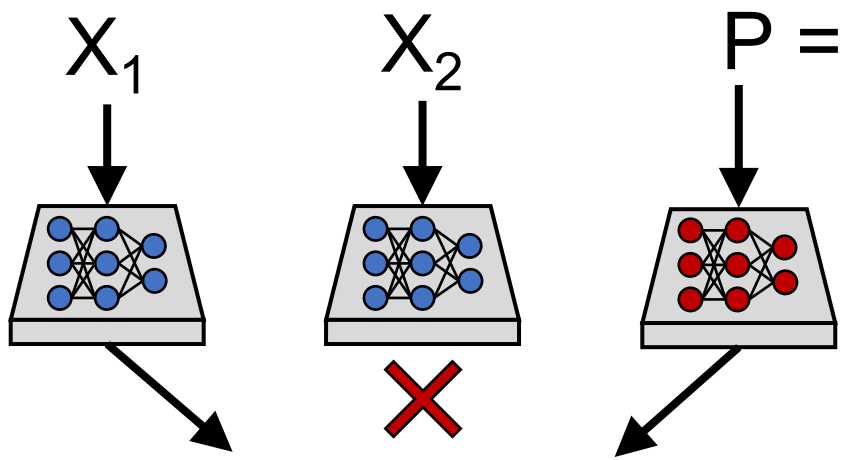
Accurate

Efficient encoder/decoder



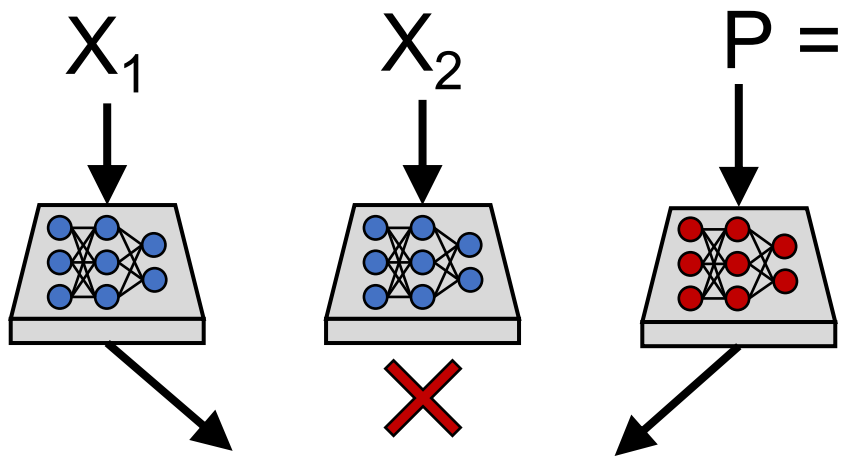
parity model (F_P)

Designing parity models



Designing parity models

Goal: transform parities into a form that enables decoder to reconstruct unavailable predictions



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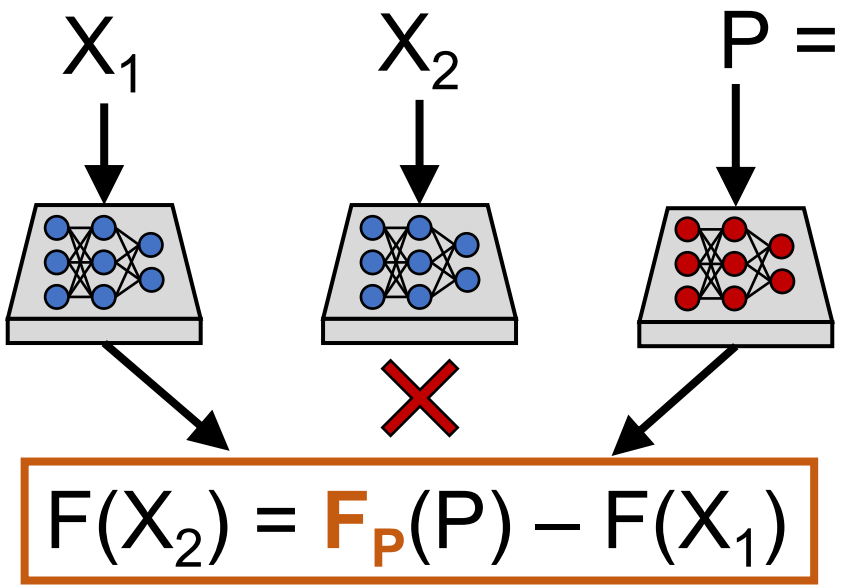

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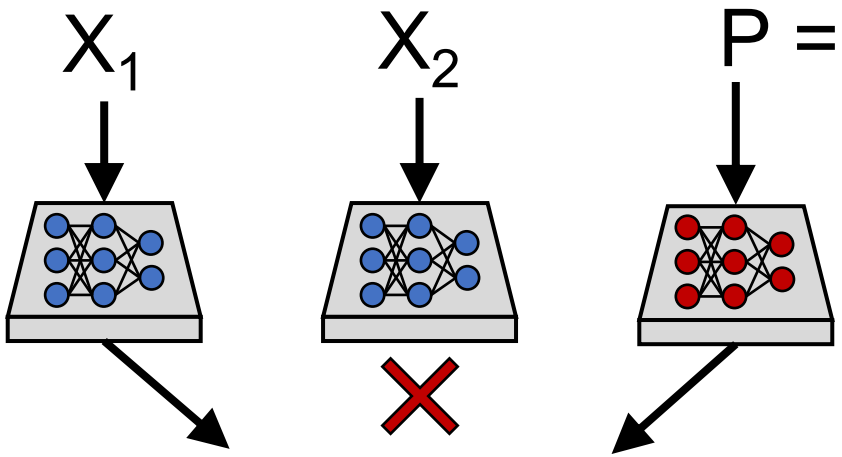

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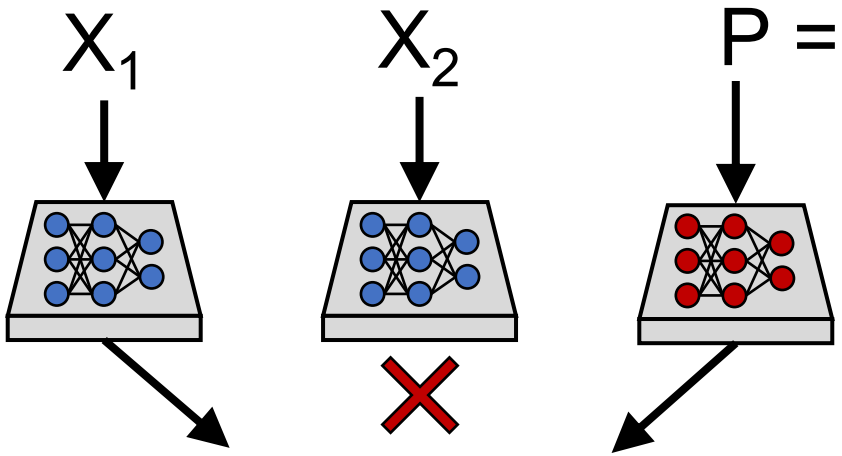


parity model (F_P)

$F(X_2) = F_P(P) - F(X_1)$

$F_P(P) = F(X_1) + F(X_2)$

Learn a parity model

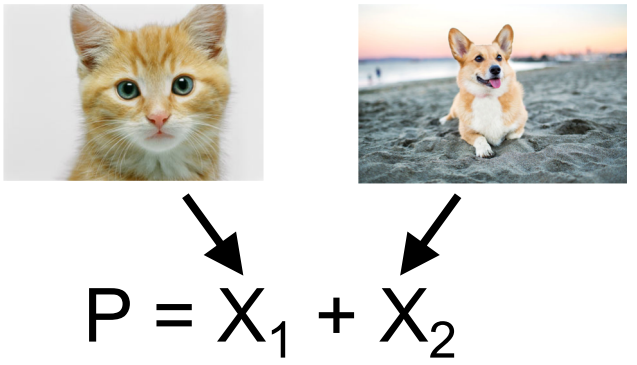
Training a parity model

$$P = X_1 + X_2$$

Desired output: $F(X_1) + F(X_2)$

Training a parity model

1. Sample inputs and encode

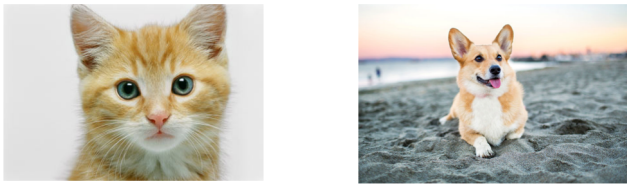


queries

Desired output: $F(X_1) + F(X_2)$

Training a parity model

1. Sample inputs and encode



queries

$P = X_1 + X_2$

Desired output: $F(X_1) + F(X_2)$

predictions

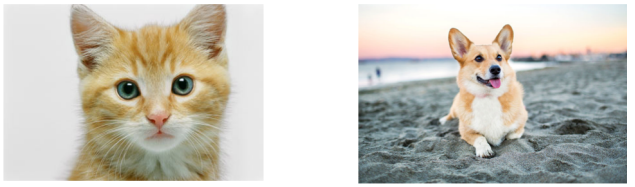
0.8	0.15	0.05

0.2	0.7	0.1

Training a parity model

1. Sample inputs and encode

2. Perform inference with parity model



queries

$P = X_1 + X_2$

$F_P(P)_1$

Desired output: $F(X_1) + F(X_2)$

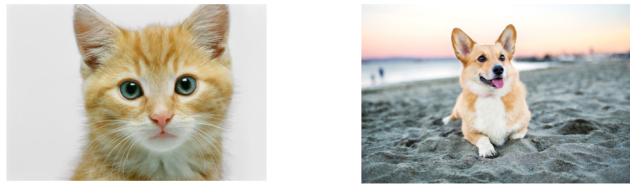
predictions

0.8	0.15	0.05

0.2	0.7	0.1

Training a parity model

1. Sample inputs and encode
2. Perform inference with parity model
3. Compute loss



queries

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Desired output: $F(X_1) + F(X_2)$

compute loss

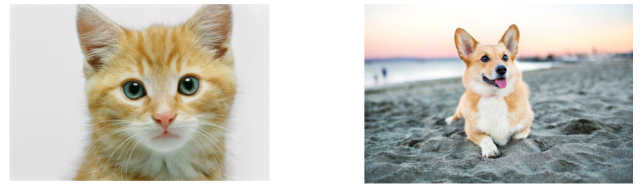
predictions

0.8	0.15	0.05

0.2	0.7	0.1

Training a parity model

1. Sample inputs and encode
2. Perform inference with parity model
3. Compute loss
4. Backpropogate loss



queries

$P = X_1 + X_2$

$F_P(P)_1$

Desired output: $F(X_1) + F(X_2)$

compute loss

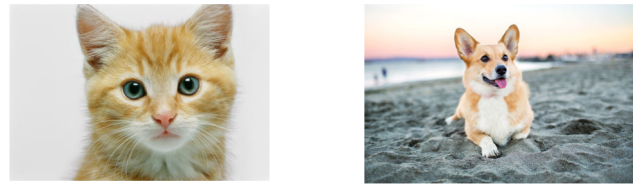
predictions

0.8	0.15	0.05

0.2	0.7	0.1

Training a parity model

1. Sample inputs and encode
2. Perform inference with parity model
3. Compute loss
4. Backpropogate loss
5. Repeat



queries

$P = X_1 + X_2$

$F_P(P)_1$

Desired output: $F(X_1) + F(X_2)$

compute loss

predictions

0.8	0.15	0.05

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Training a parity model

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2. Perform inference with parity model
3. Compute loss
4. Backpropogate loss
5. Repeat

queries

$P = X_1 + X_2$

$F_P(P)_2$

compute loss

Desired output: $F(X_1) + F(X_2)$

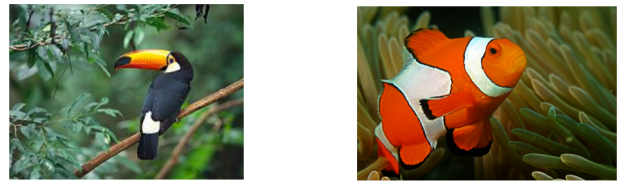
predictions

0.15	0.8	0.05

0.3	0.5	0.2

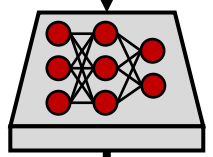
Training a parity model

1. Sample inputs and encode
2. Perform inference with parity model
3. Compute loss
4. Backpropogate loss
5. Repeat



queries

$P = X_1 + X_2$



$F_P(P)_3$

compute loss

Desired output: $F(X_1) + F(X_2)$

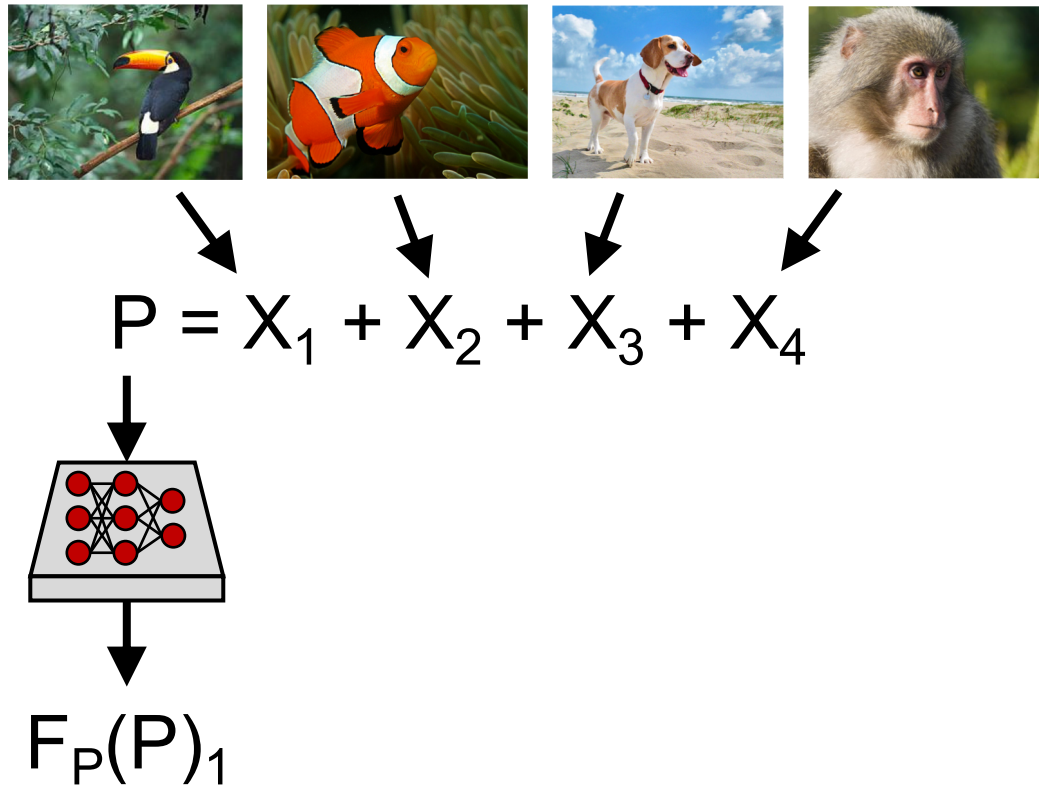
predictions

0.03	0.02	0.95

0.3	0.3	0.4

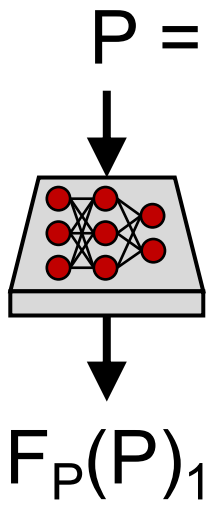
Training a parity model: higher parameter k

Can use higher code parameter k

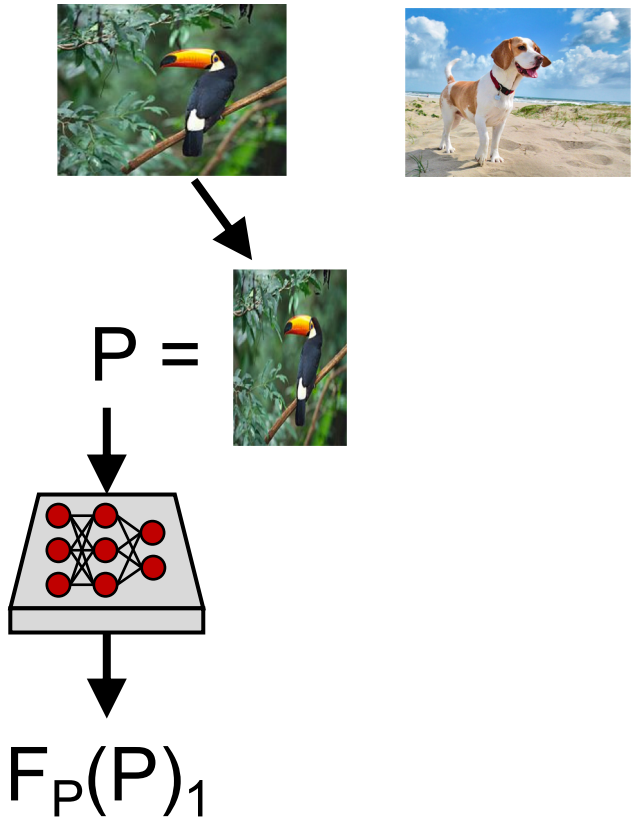


Desired output: $F(X_1) + F(X_2) + F(X_3) + F(X_4)$

Training a parity model: different encoders



Training a parity model: different encoders



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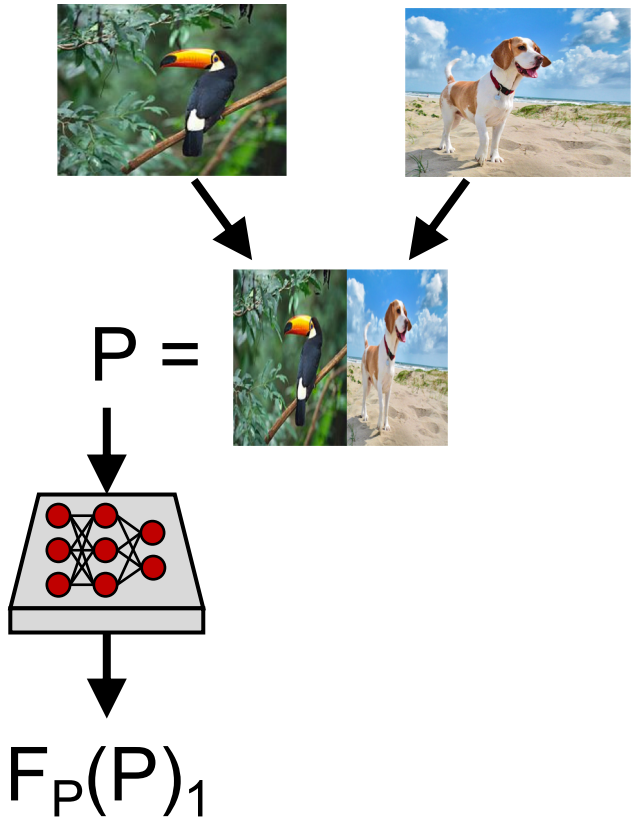
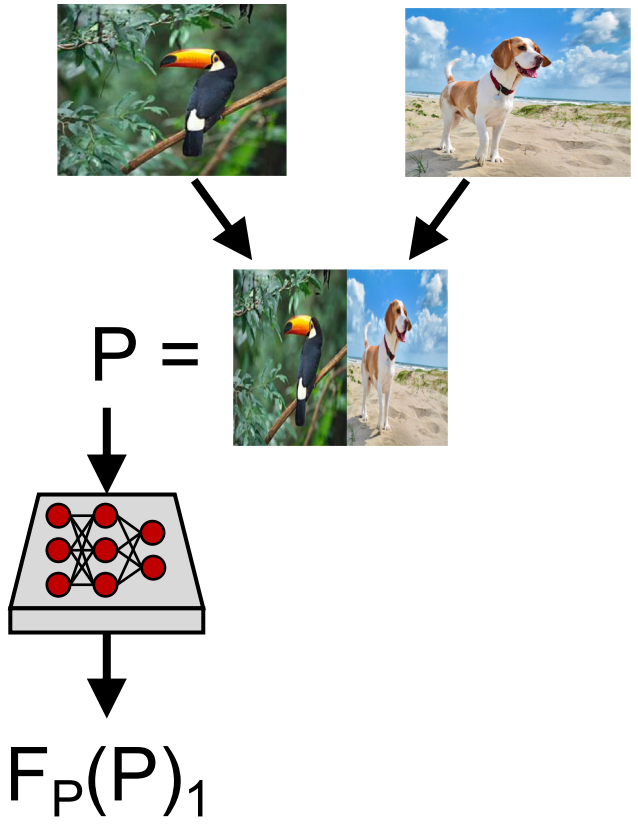


Training a parity model: different encoders

Can specialize encoders and decoders to inference task at hand



Learning results in approximate reconstructions

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Appropriate for machine learning inference

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1. Predictions resulting from inference are approximations

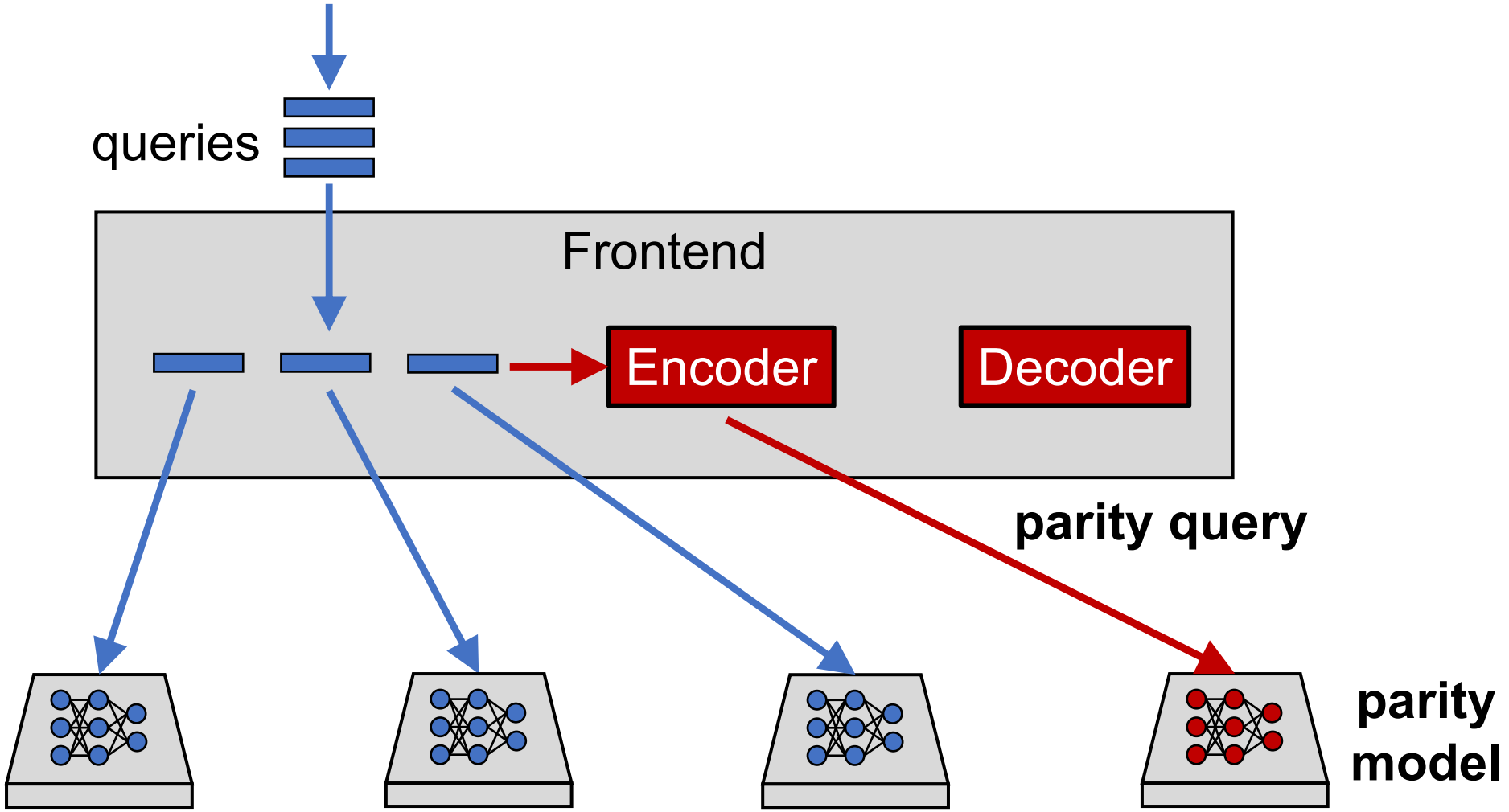
Learning results in approximate reconstructions

Appropriate for machine learning inference

1. Predictions resulting from inference are approximations

2. Inaccuracy only at play when predictions otherwise slow/failed

Parity models in action in Clipper

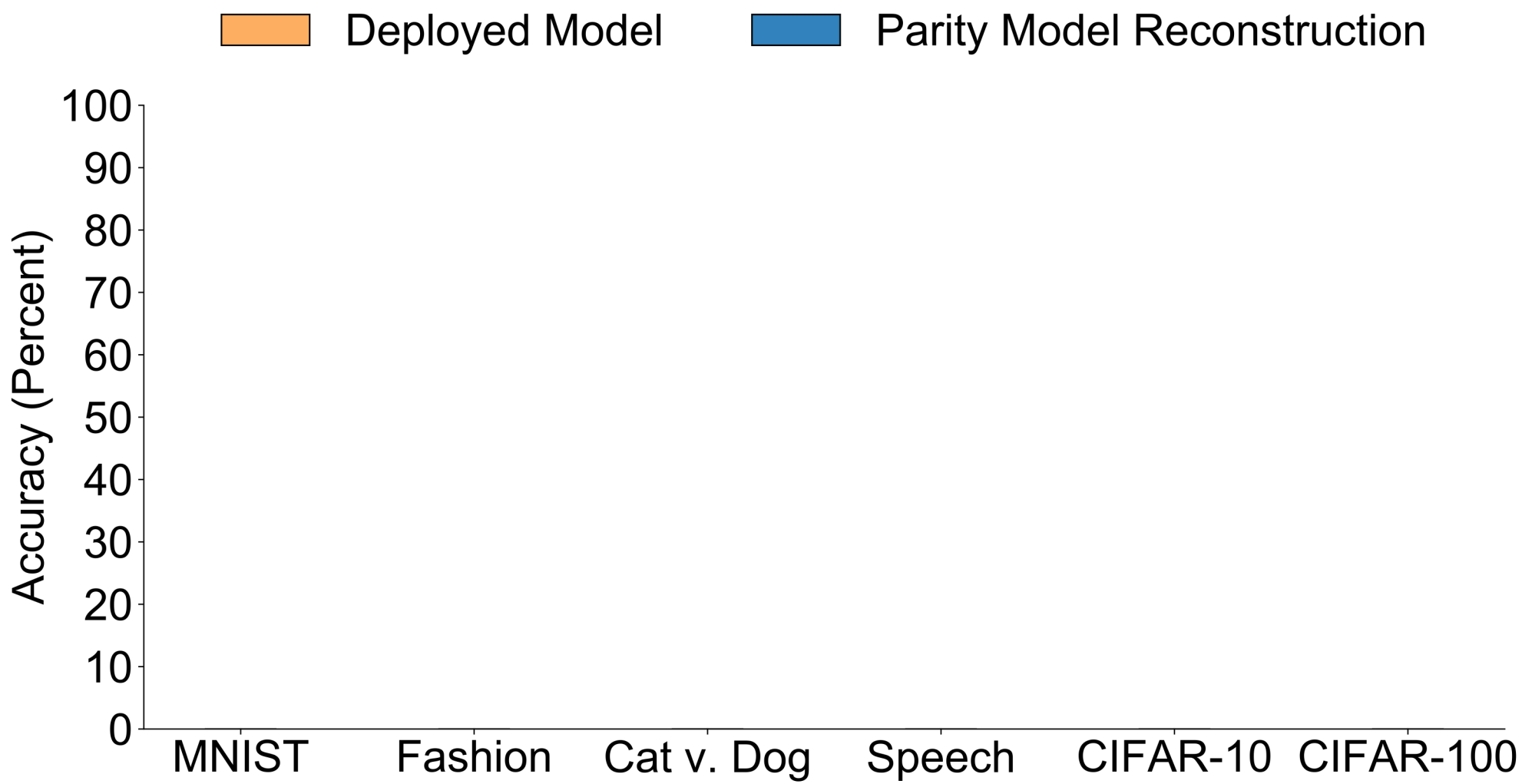


Evaluation

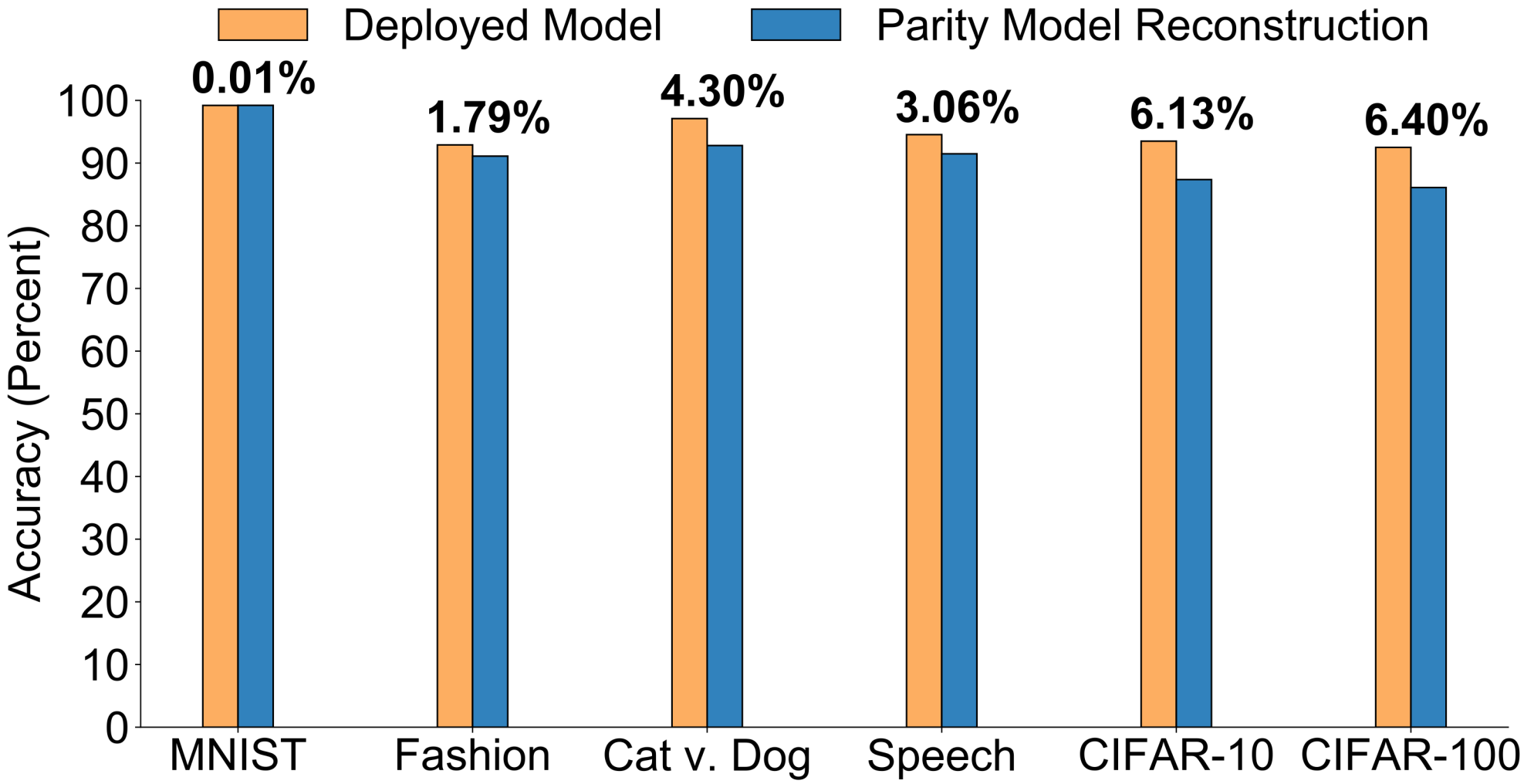
1. How **accurate** are reconstructions using parity models?

2. By how much can parity models help reduce **tail latency**?

Accuracy of parity models



Accuracy of parity models



Accuracy of parity models

Reconstructed output only comes into play when original predictions are slow/failed

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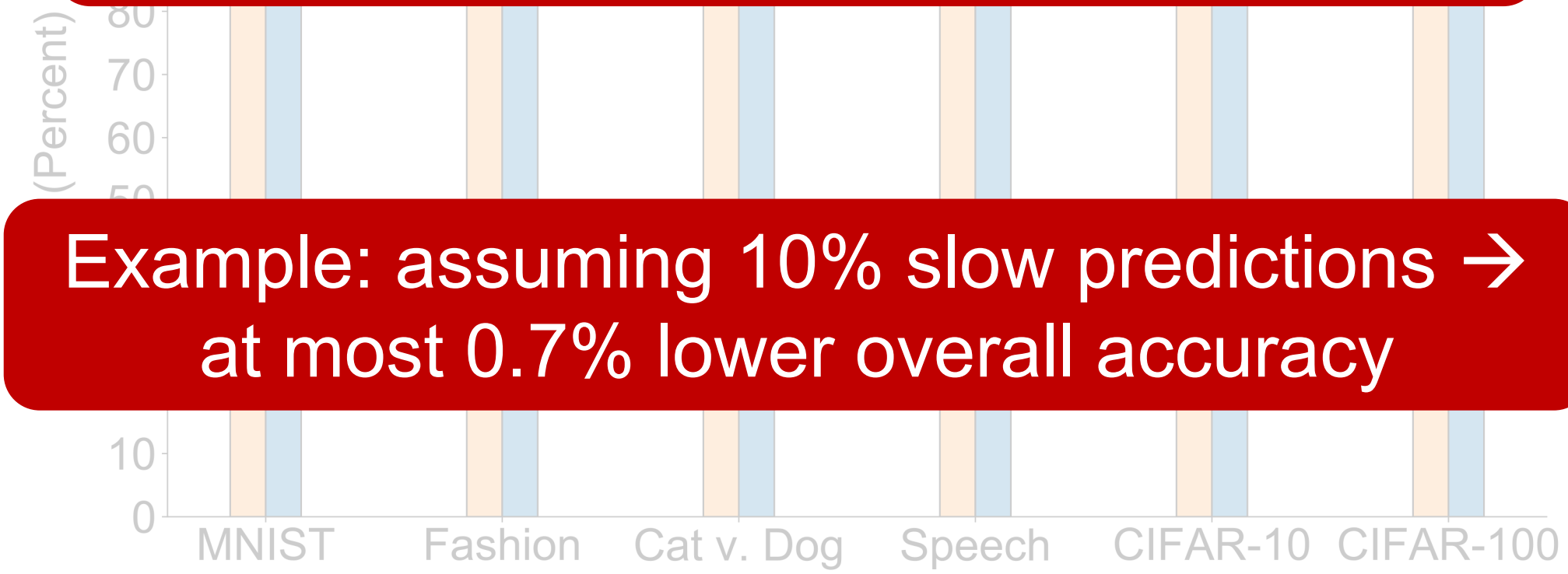
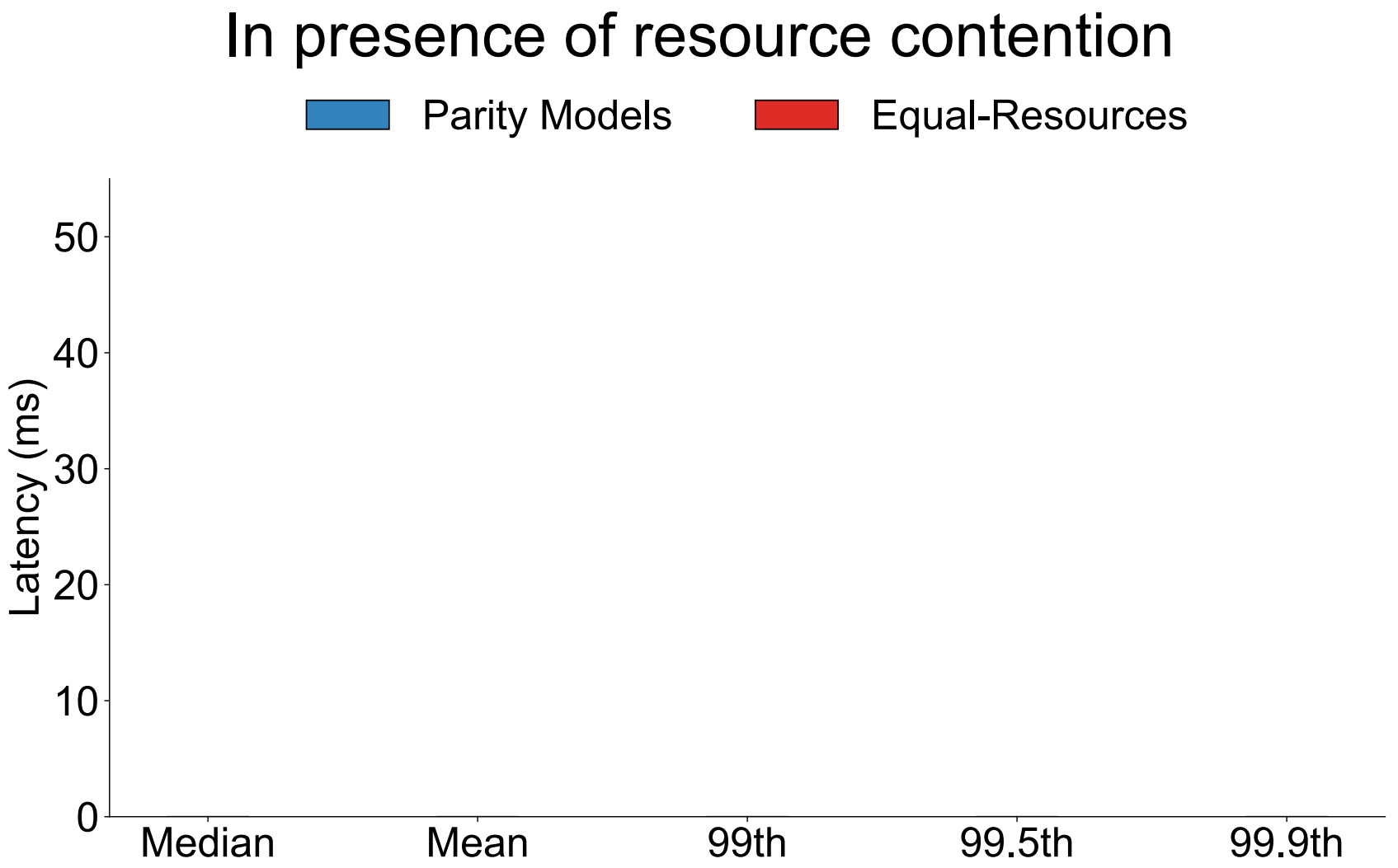


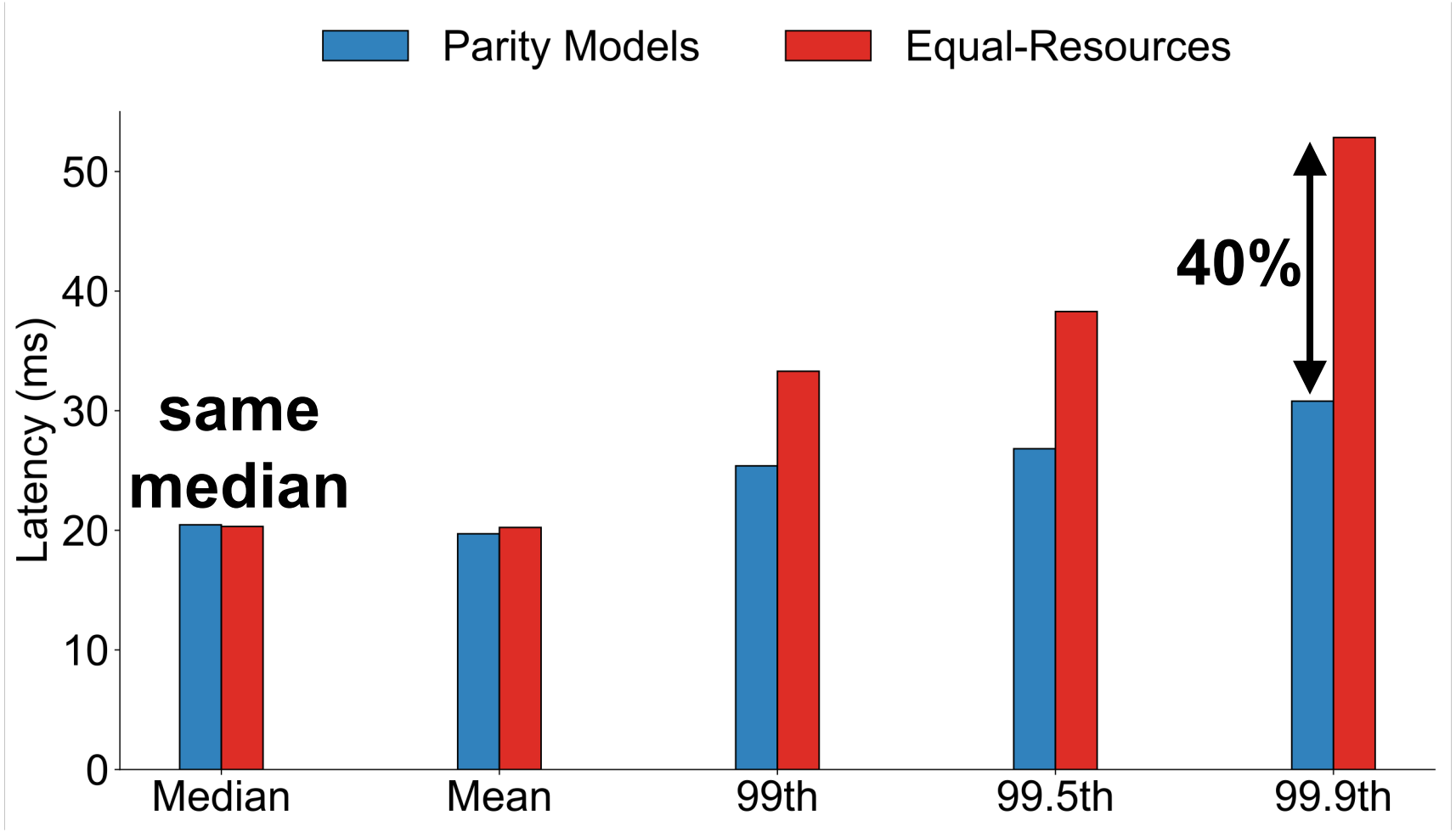
Example: assuming 10% slow predictions → at most 0.7% lower overall accuracy

Tail latency reduction



Tail latency reduction

In presence of resource contention



Extensive evaluation in paper

- Evaluate accuracy with different:
  - Different encoders
  - Inference tasks (image classification, object localization, speech)
  - Neural network architectures (ResNets, VGG, LeNet, MLP)
  - Code parameters (k = 3, k = 4)

- Evaluate tail latency with different:
  - Inference hardware (GPUs, CPUs)
  - Query arrival rates
  - Batch sizes
  - Levels of load imbalance
  - Amounts of redundancy
  - Baseline approaches

Parity models summary

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- Overcome challenges of handcrafting erasure codes for coded-computation through learning-based coded-resilience

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Project: pdl.cmu.edu/MLCodedComputation/

Code: github.com/Thesys-lab/parity-models