Fault-Tolerant and Reproducible Input Processing for Machine Learning

Master Thesis

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ML Input Data Processing

- More data is a key factor in Deep Learning’s success
- Data is expensive
- Augmenting dataset needs compute intensive online processing
- Often pre-processing becomes a bottleneck
  - 20% of jobs spend 1/3 in input pipeline
  - 30% of total compute time for pre-processing

Alleviating Bottleneck by Scaling Out

- Industry agrees: Both Meta and Google scale out preprocessing using disaggregated service
- Right-size resources for training and pre-processing independently
- Exploit synergies between jobs by having a fleet-wide view within the service

Issues when Scaling Out

1) Fault-Tolerance

As more nodes are involved in a job failure probabilities become non-negligible

2) Reproducibility

Distributing the job introduces additional sources of non-determinism

(DRR is joint work with Zak; presented by him)

Issues when Scaling Out

This presentation

1) Fault-Tolerance

As more nodes are involved in a job failure probabilities become non-negligible

Motivation for Fault-Tolerance

- Only 35.9% ML jobs at Meta did not experience any fault [over course of a week]
- Use of transient cloud resources (i.e. SpotVMs)
  - At least 60% cheaper, but may be preempted at any time
- Live migration of nodes in datacenters

Requirements for Fault-Tolerant Processing

1. Disaggregated Distributed Pre-Processing
2. Correctness (Exactly-Once)
3. Performance (Bounded overhead; recover some progress)
4. Compatibility
5. Reproducibility

Platform to build on?

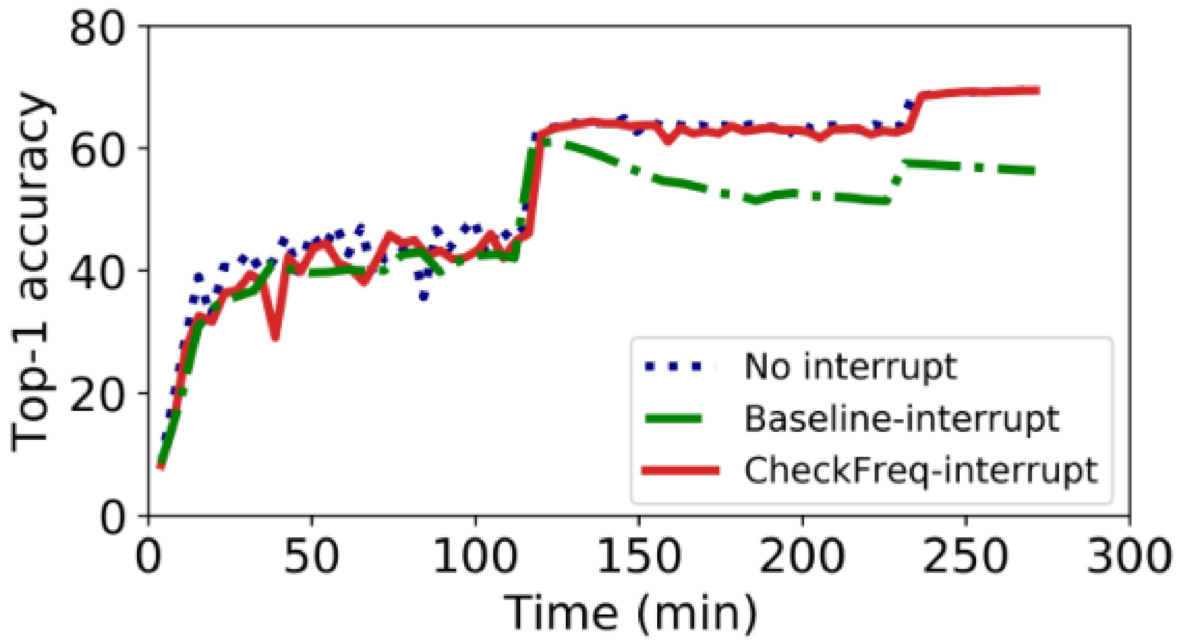
- Know of two disaggregated distributed preprocessing services: tf.data service and Meta's DPP
- Use Cachew (built on tf.data service) as it is open source
- Relieves ML users from the burden of managing compute, memory and storage infrastructure for ML input preprocessing
- Builds on top of tf.data service and provides:
  - Distributed disaggregated multi-tenant input pre-processing (Req1)
  - Supports tf.data pipelines (Req4)
  - Autocaching and autoscaling

Mitigating Worker Failure Impact on Accuracy

How often should a client see an example per epoch?

- No-guarantees, except for the same epoch size
  - See figure on next-slide, accuracy suffers, double-digit drop
- At-most-once
  - Could lead to some examples never being seen
  - Problematic with highly class-imbalanced datasets
- Exactly-once
  - No possibility of model performance degrading due to “invisible” pre-processing failures

CheckFreq Accuracy Drop



Mohan, J., Phanishayee, A., & Chidambaram, V. (2021, February). CheckFreq: Frequent, Fine-Grained DNN Checkpointing. In Proceedings of the USENIX Conference on File and Storage Technologies (FAST 2021).

Takeaway

Duplicated / missing examples lead to a 13% drop in accuracy

Cachew Illustrated

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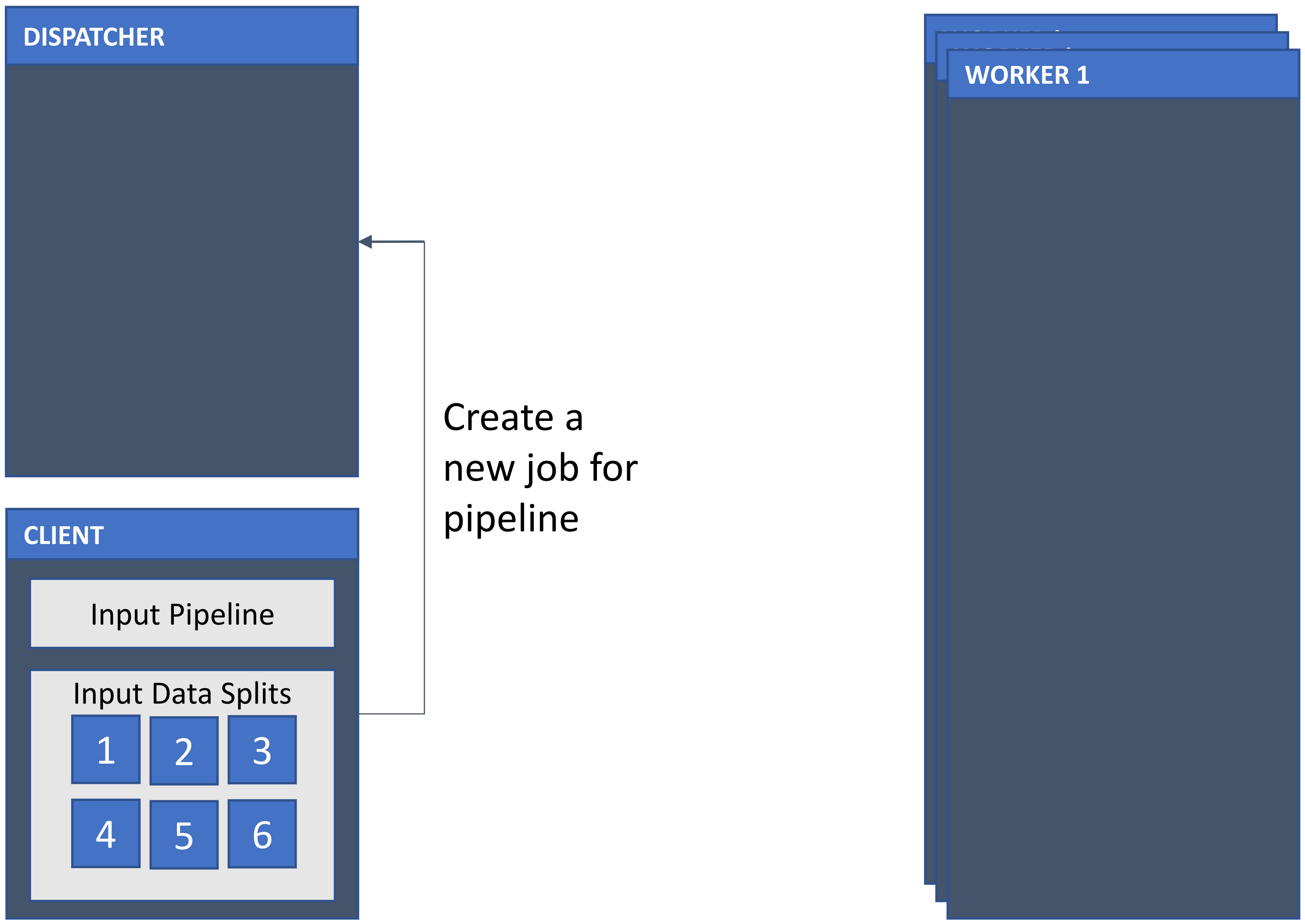

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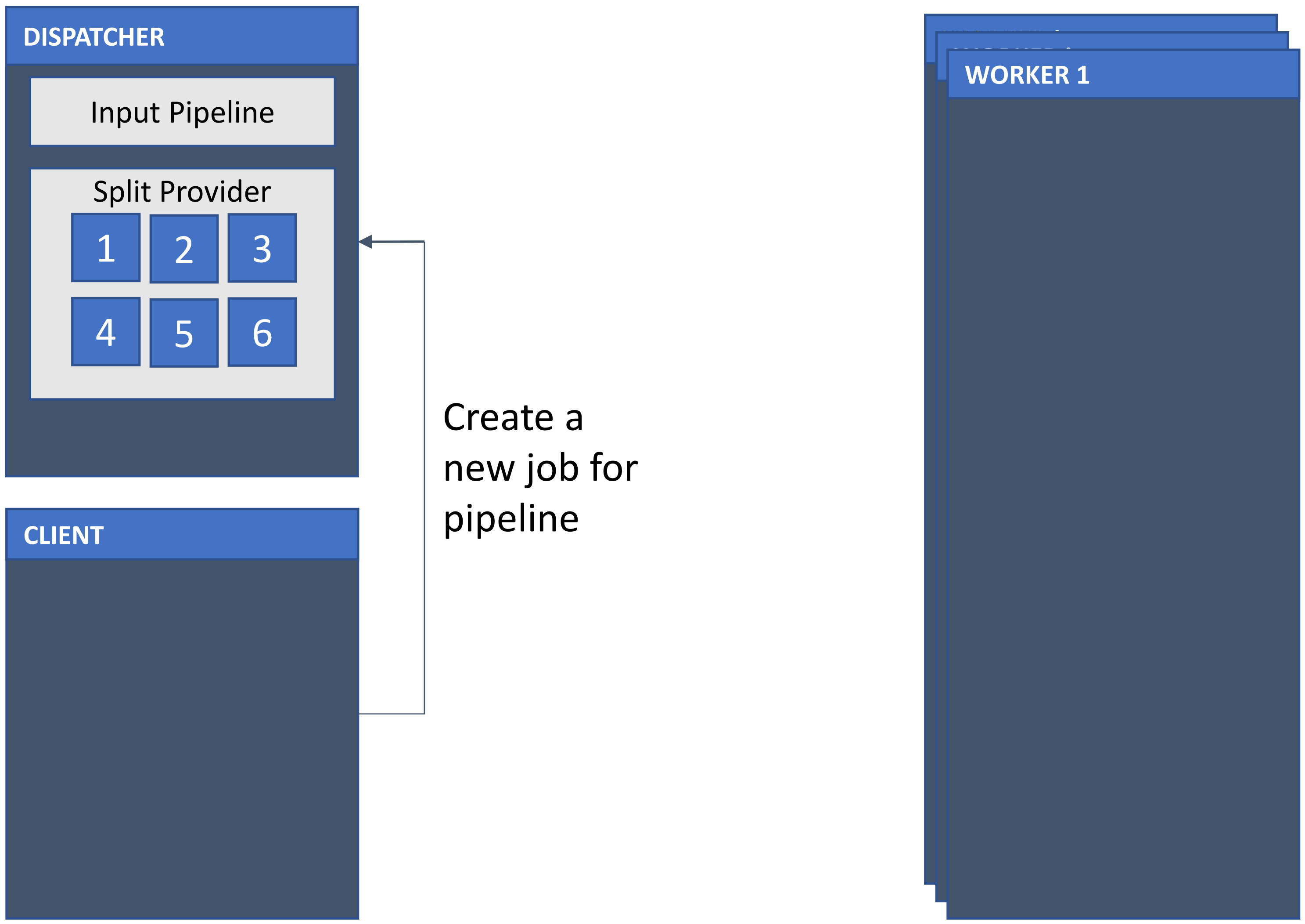

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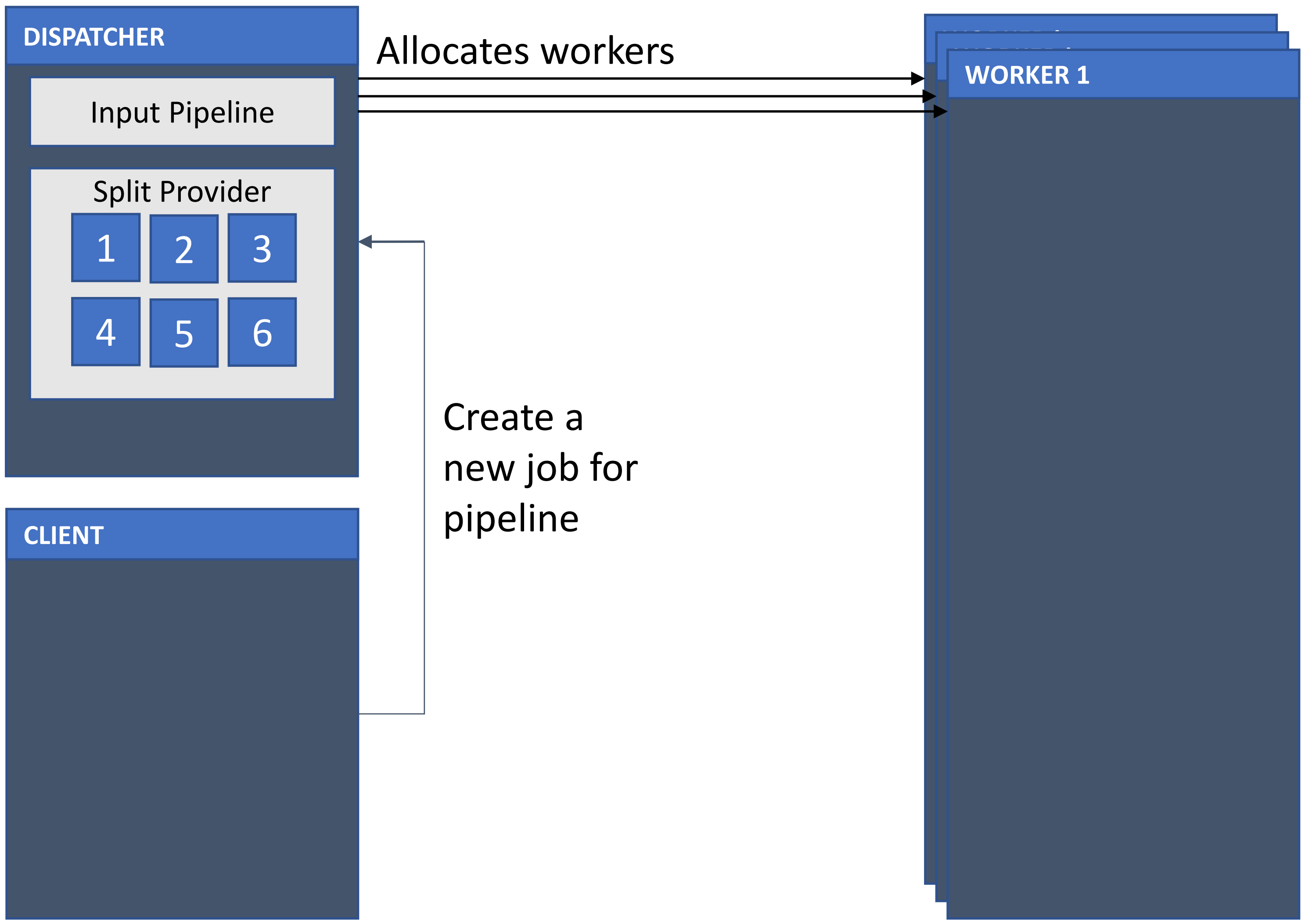

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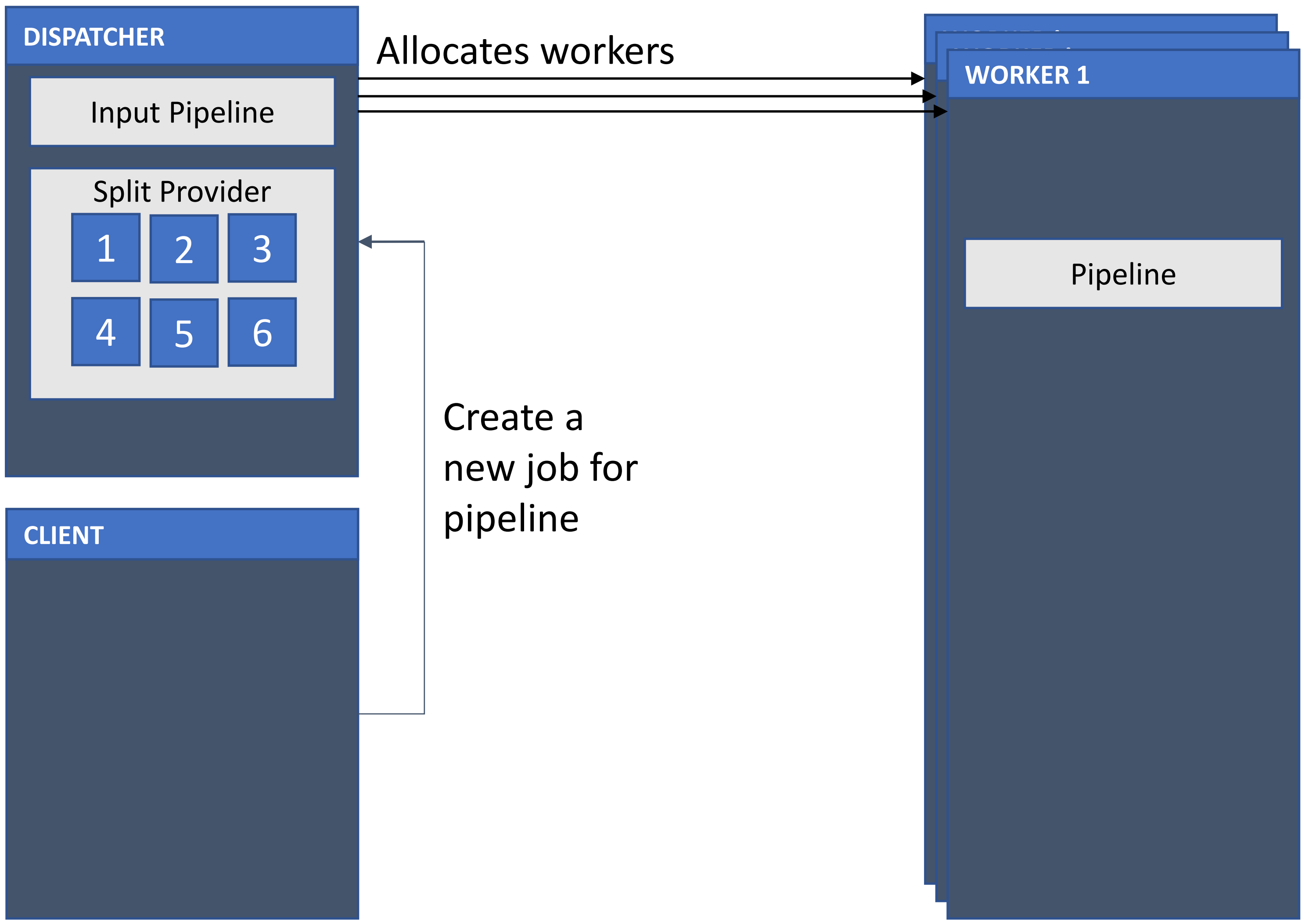

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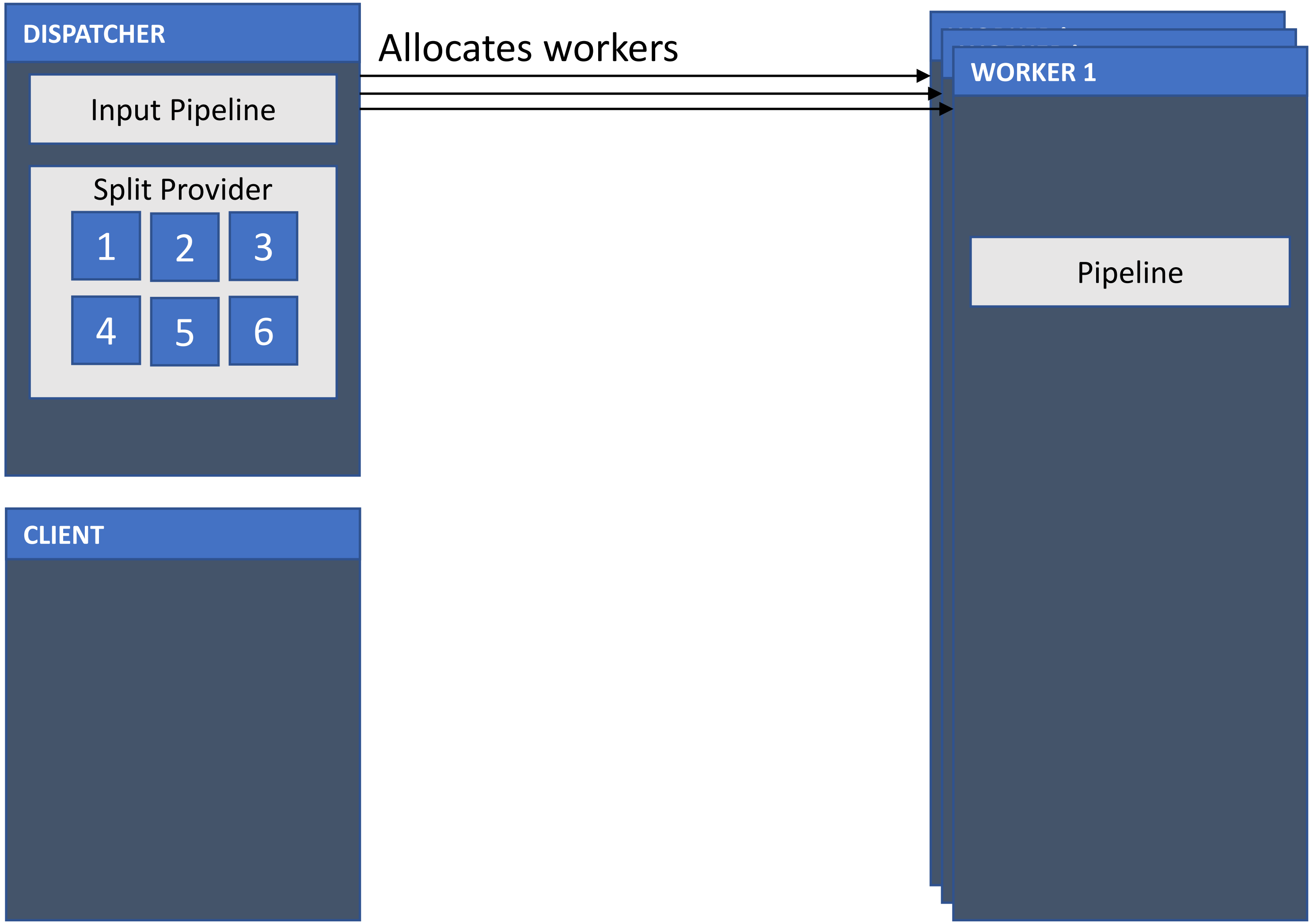

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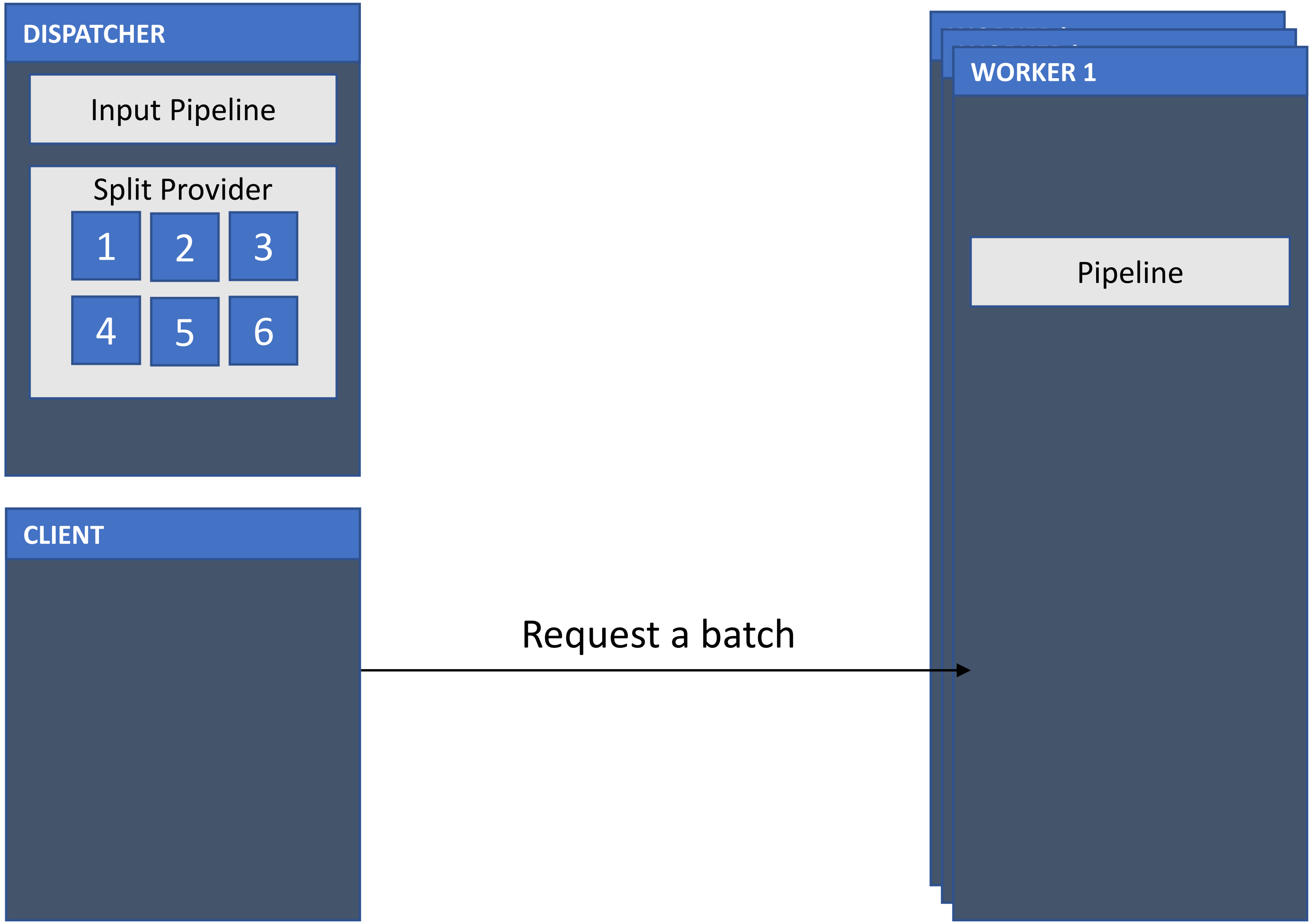

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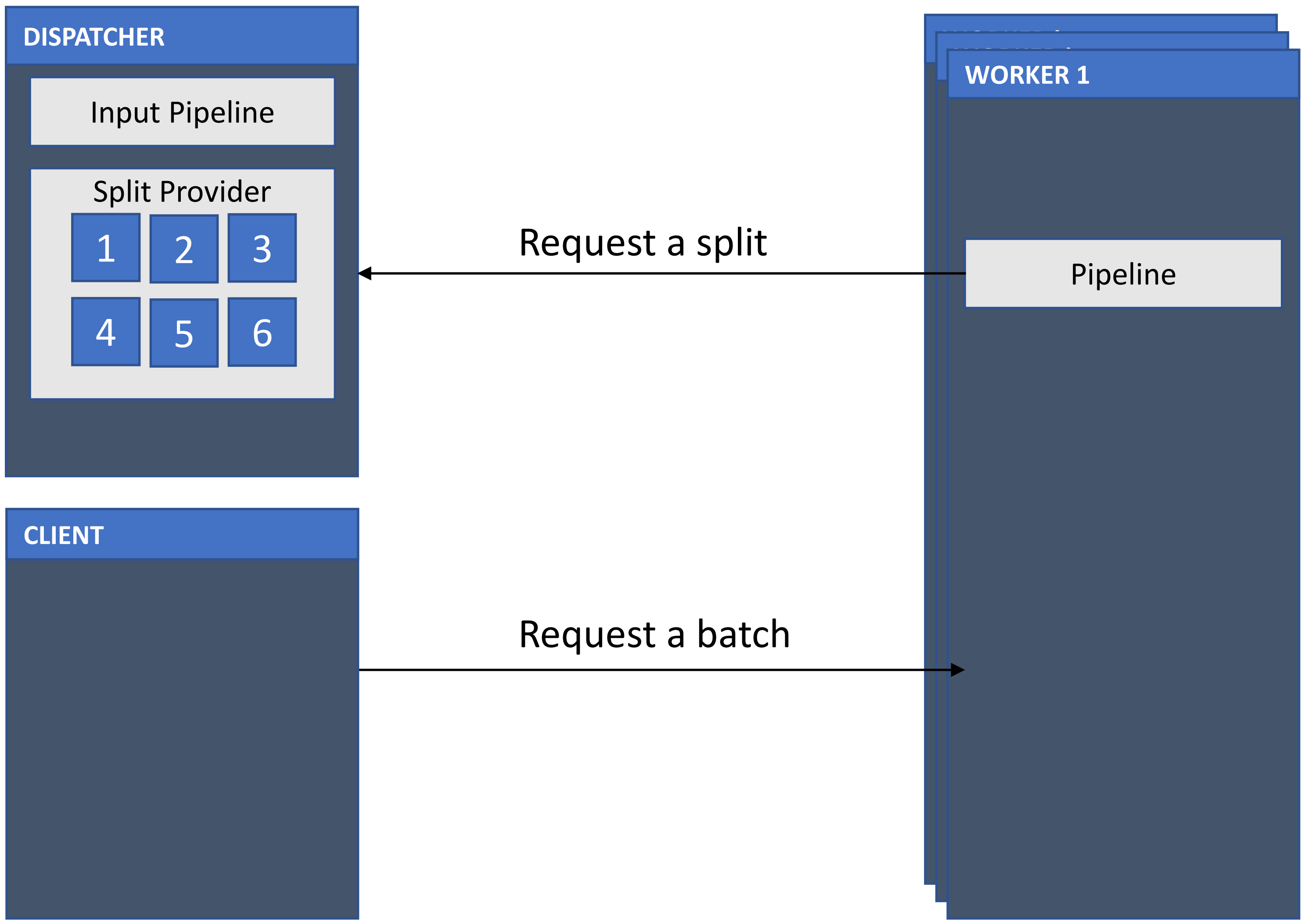

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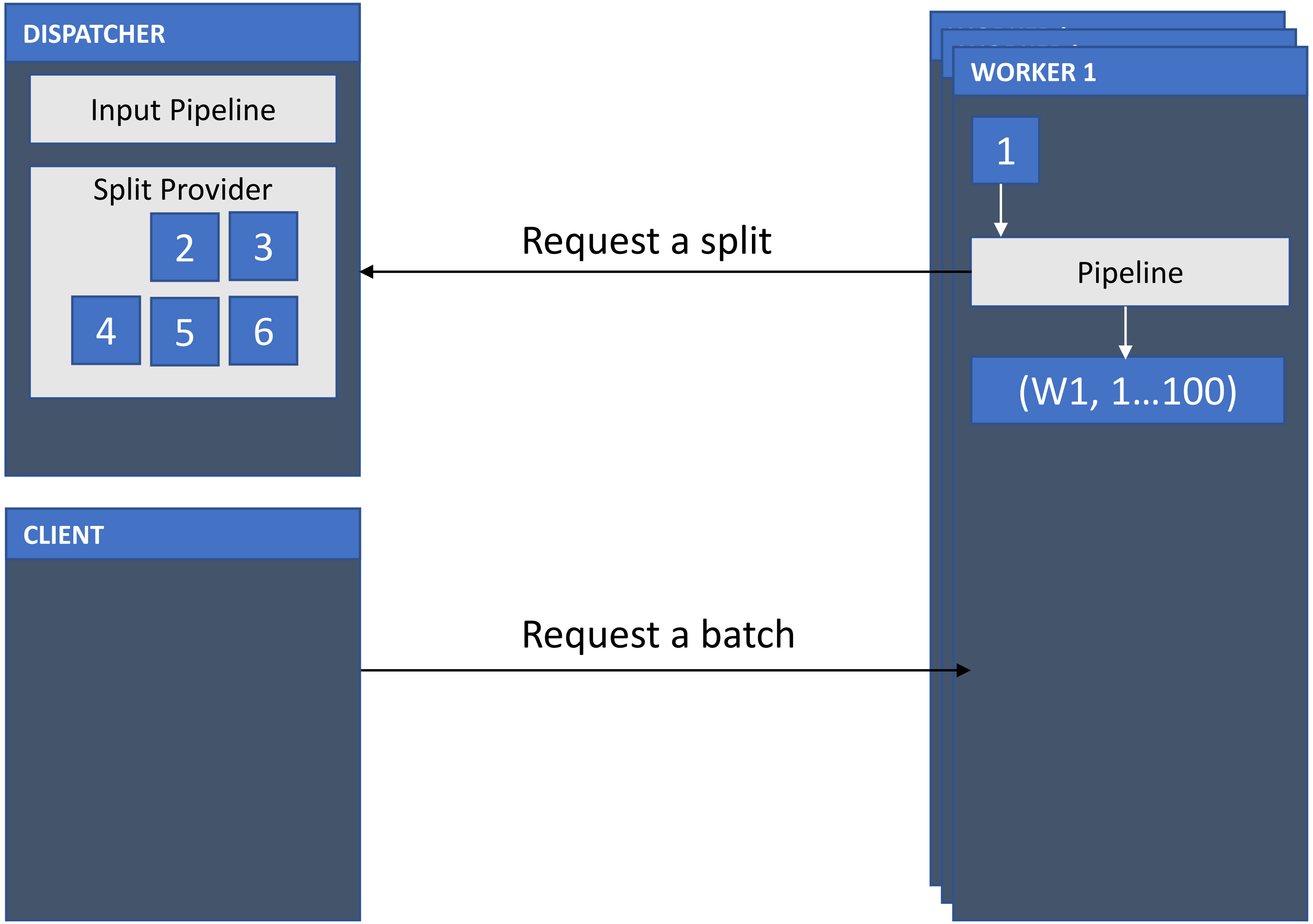

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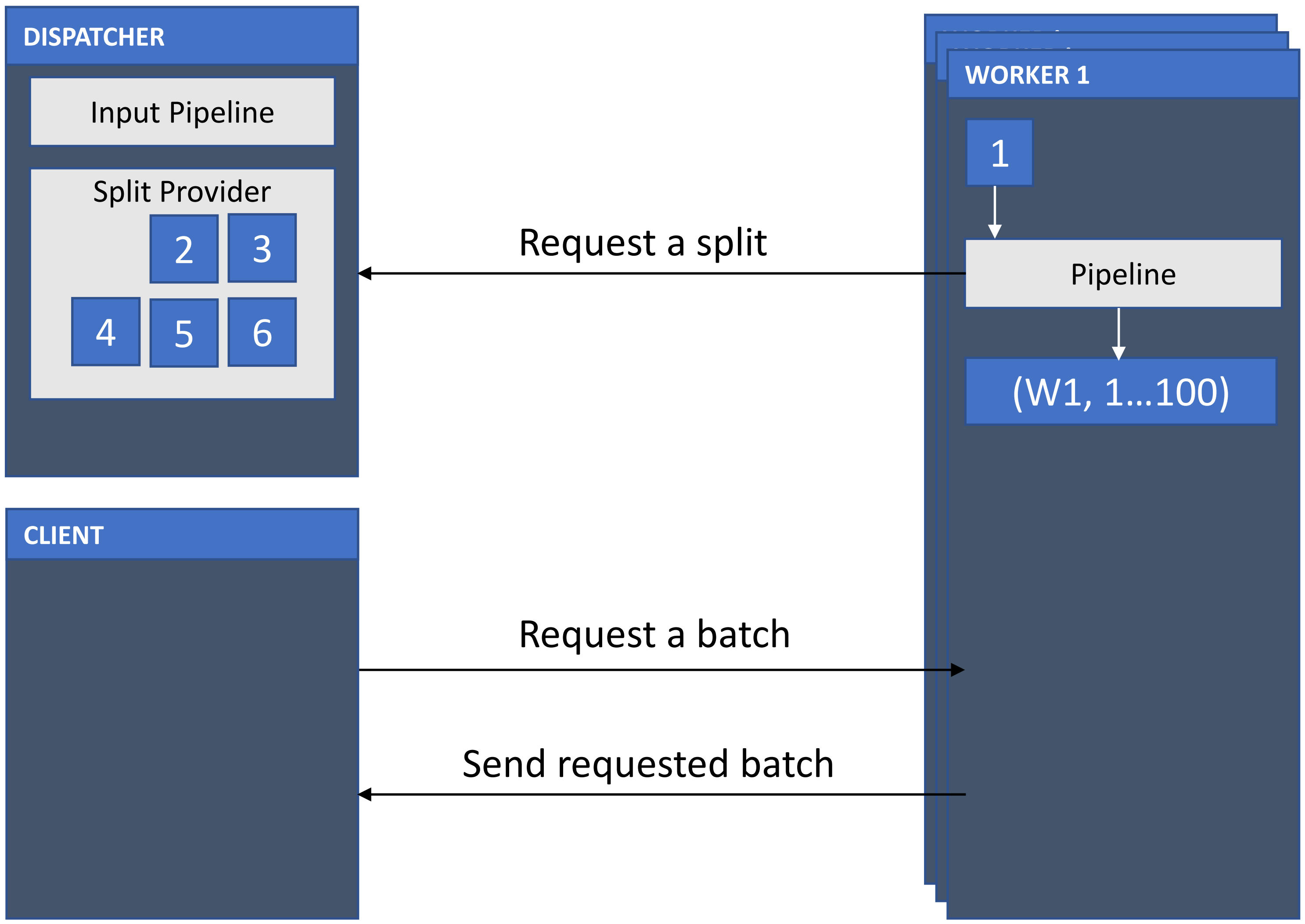

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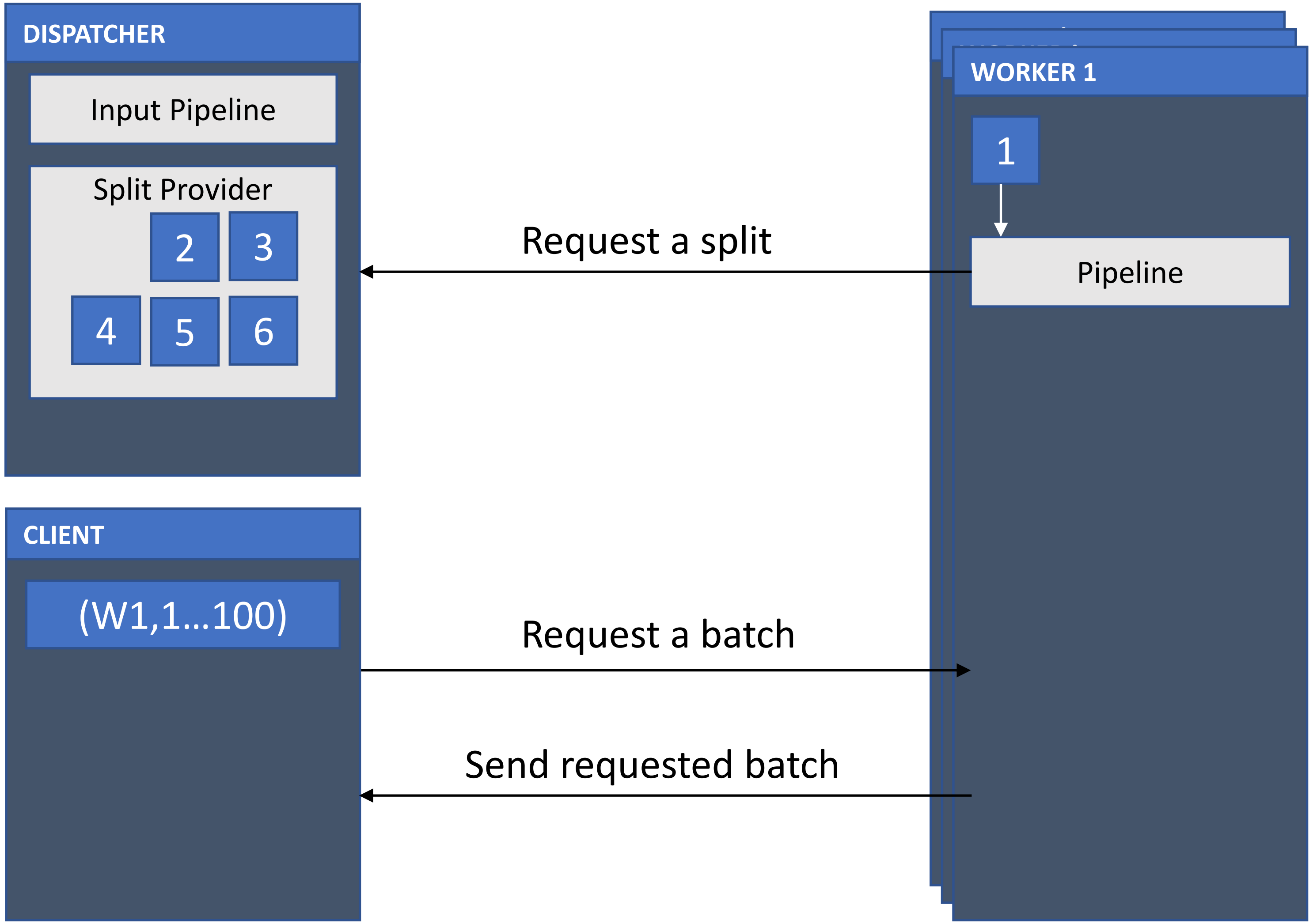

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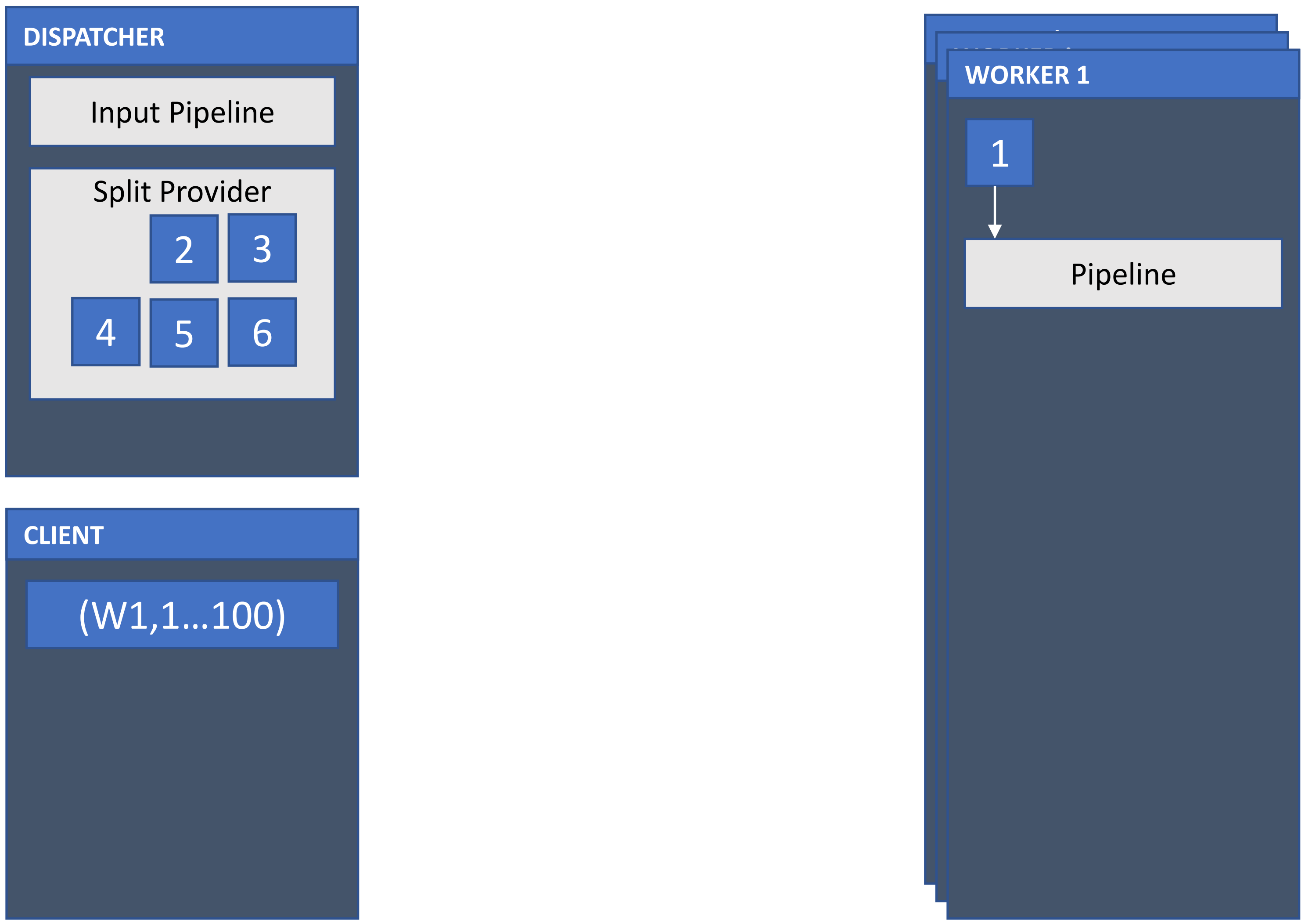

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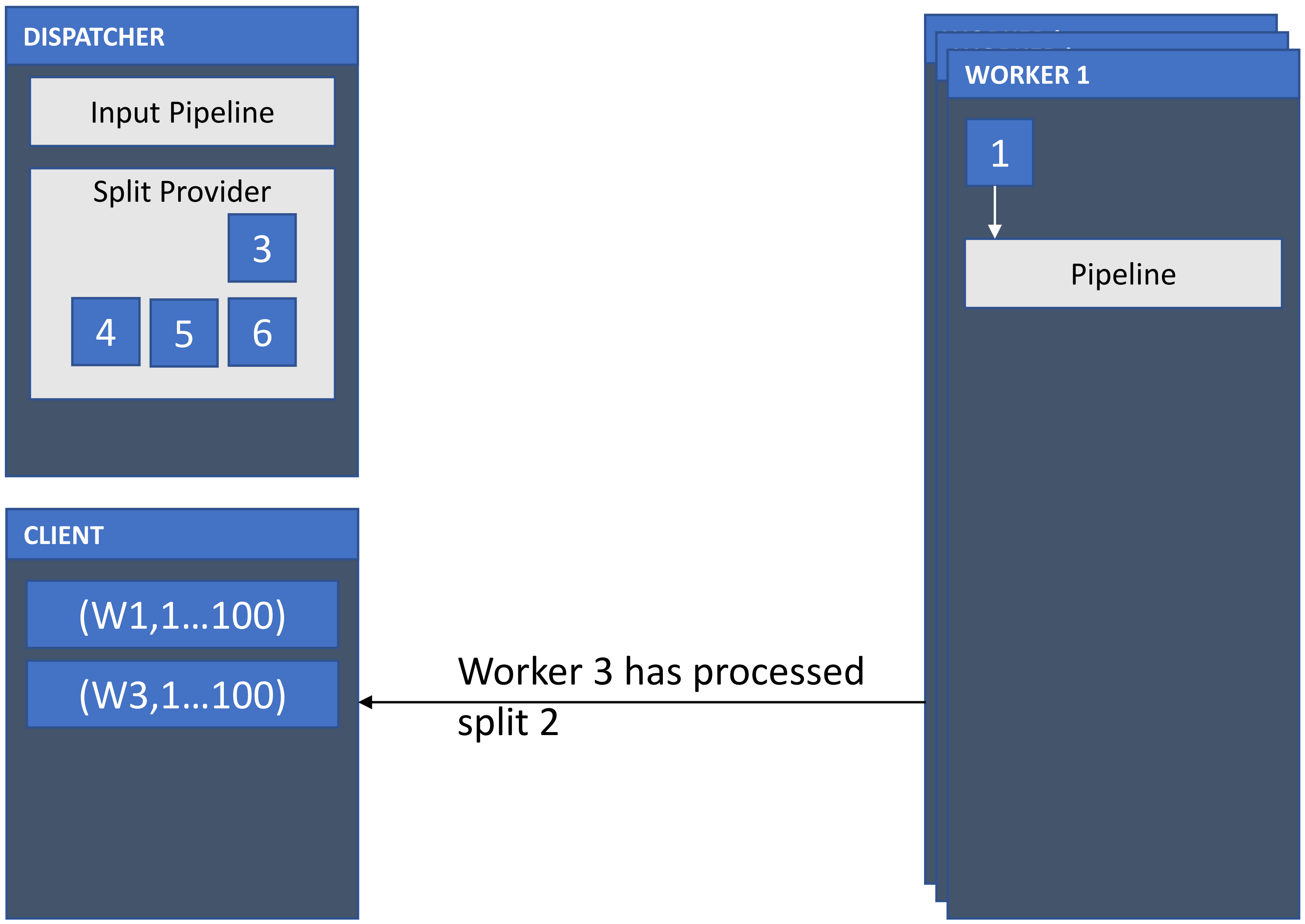

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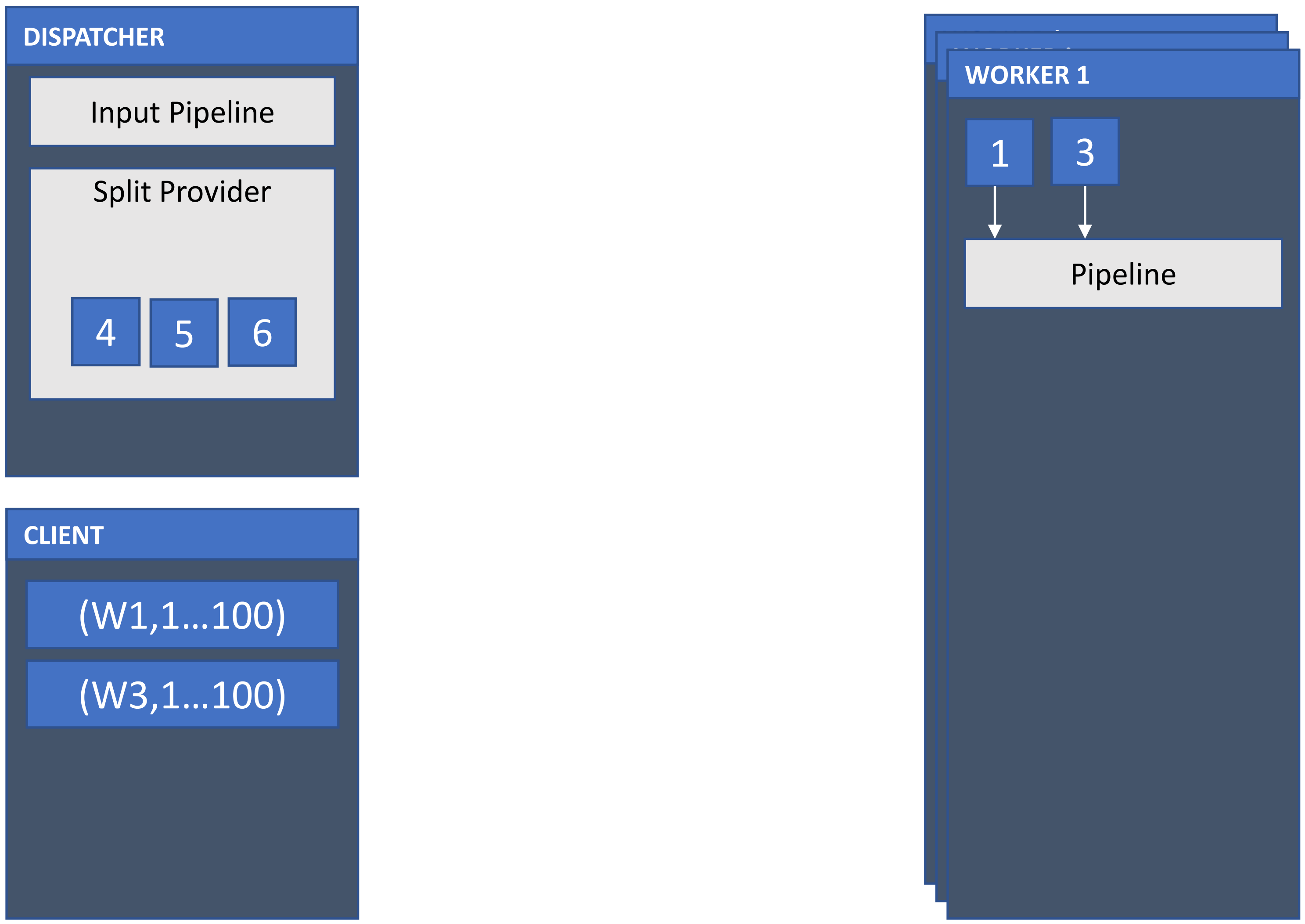

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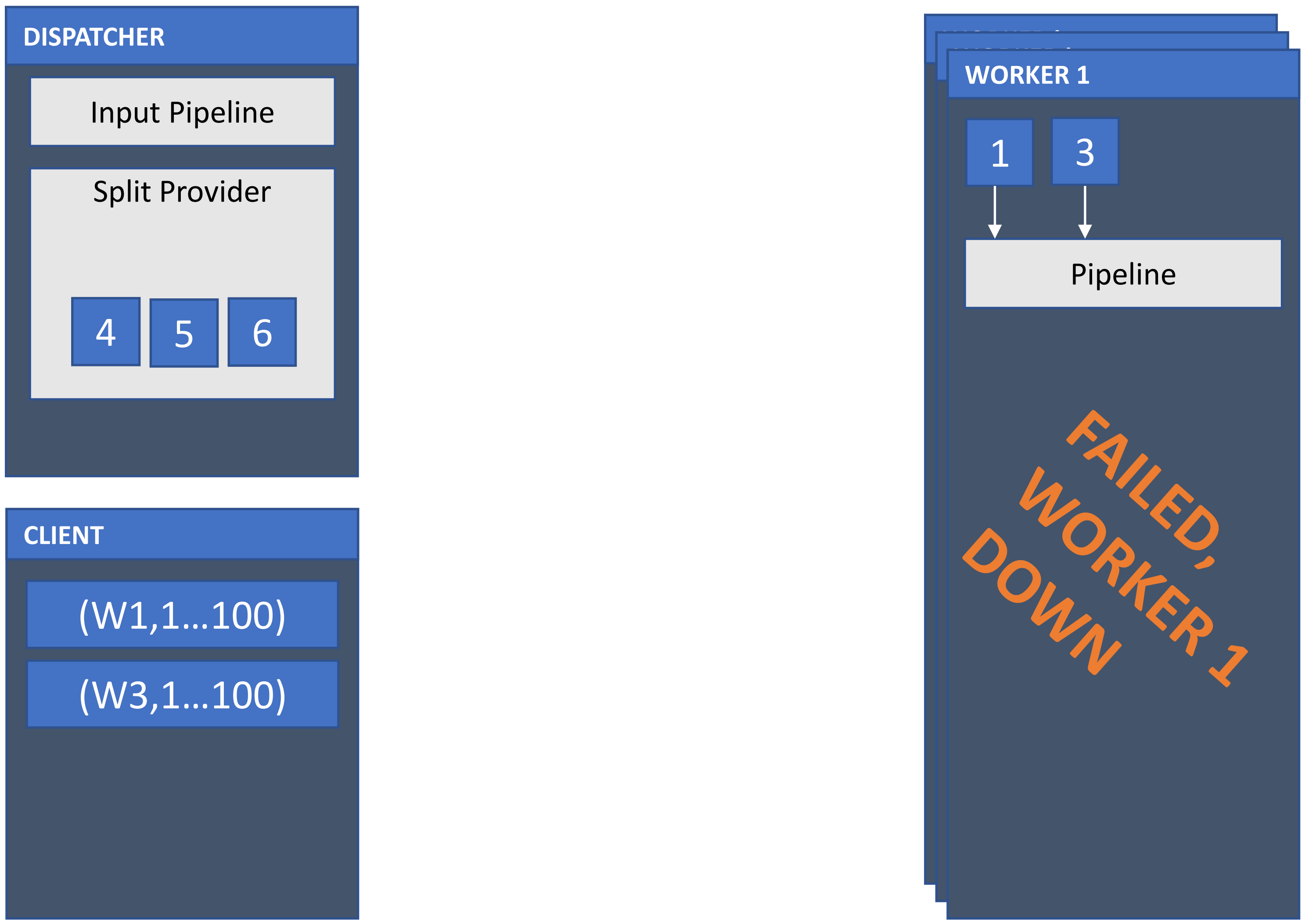

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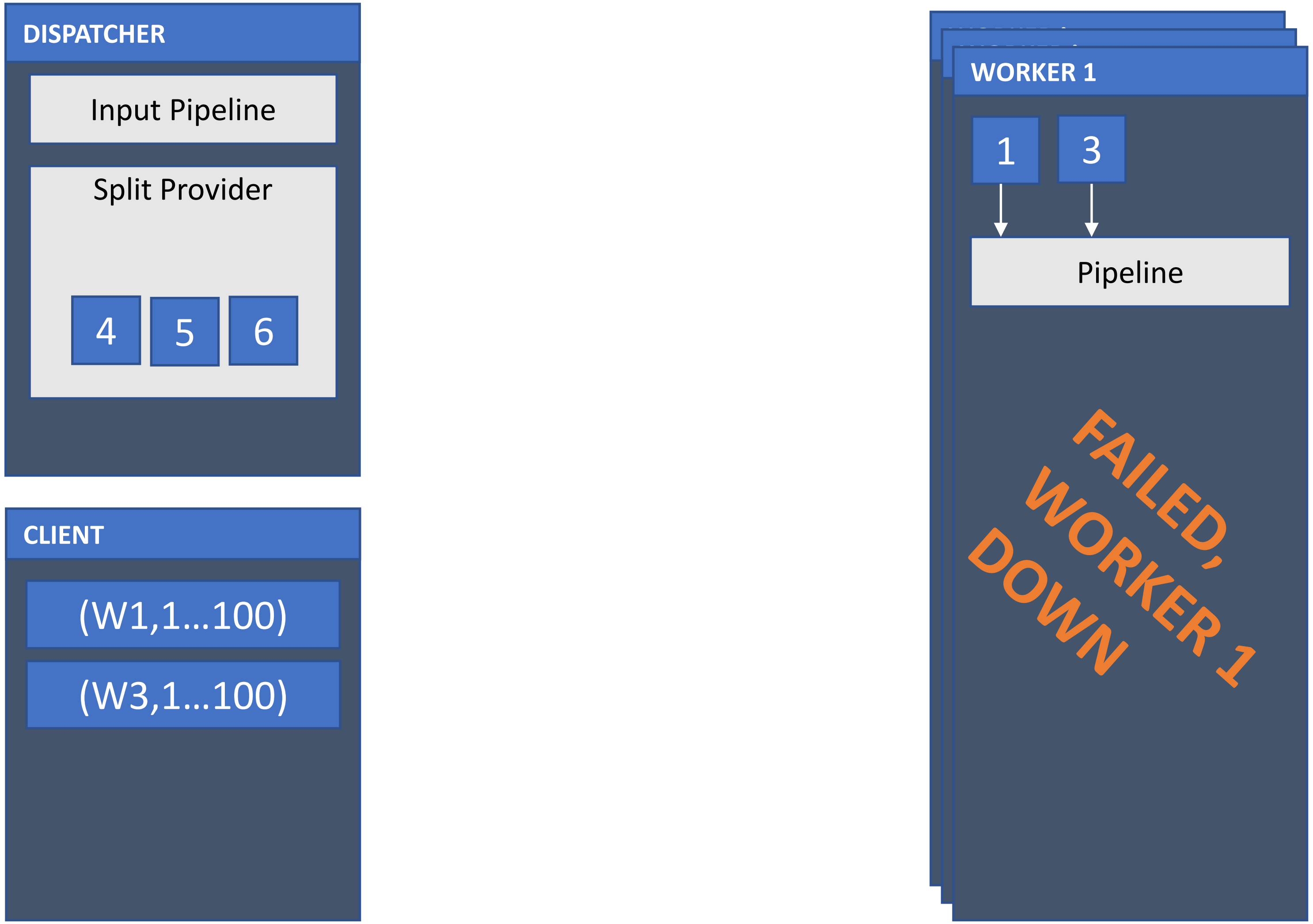
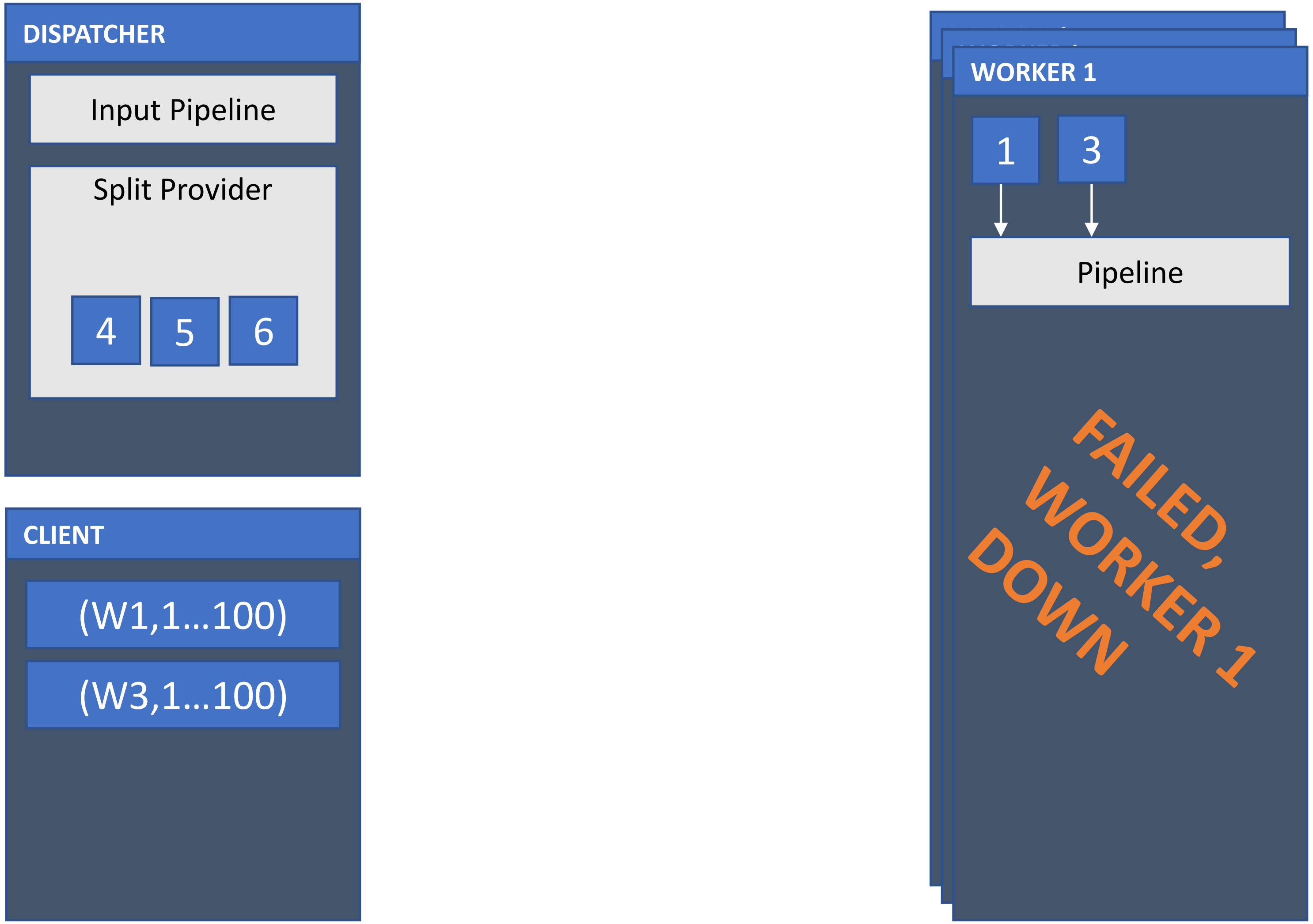


How can we react?

- Skip 3: at-most-once
- Recompute 1 & 3, transmit everything: at-least-once
- Recompute 1 & 3, but skip 1 at the client: exactly-once

Cachew Illustrated



How can we react?

- Skip 3: at-most-once
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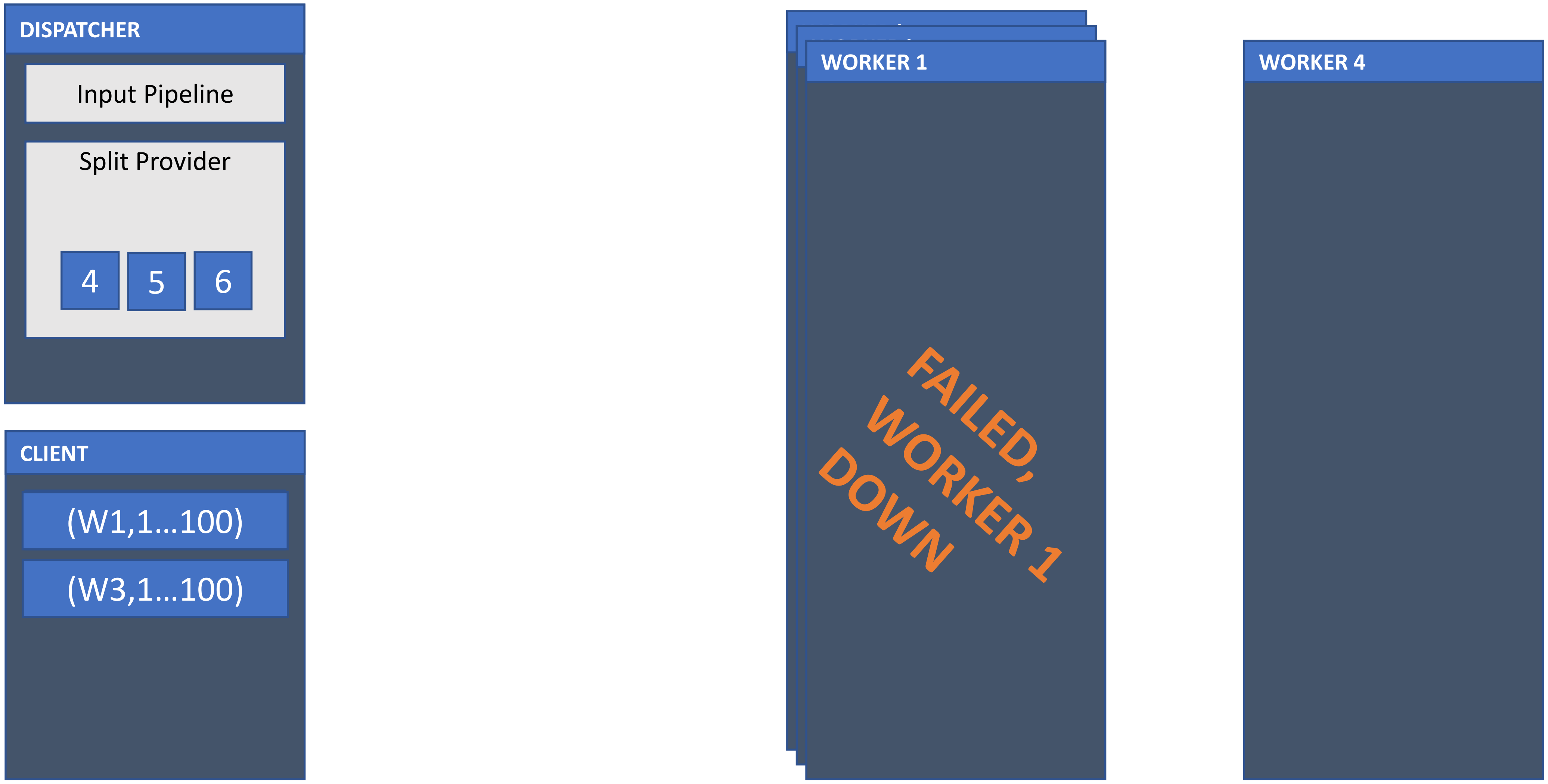
What do we need?

- Dispatcher: Remember split <-> worker association
- Client: Remember expected Batch ID
- Detect failure, failover task to a different worker
- Deterministic ordering

Failover Illustrated



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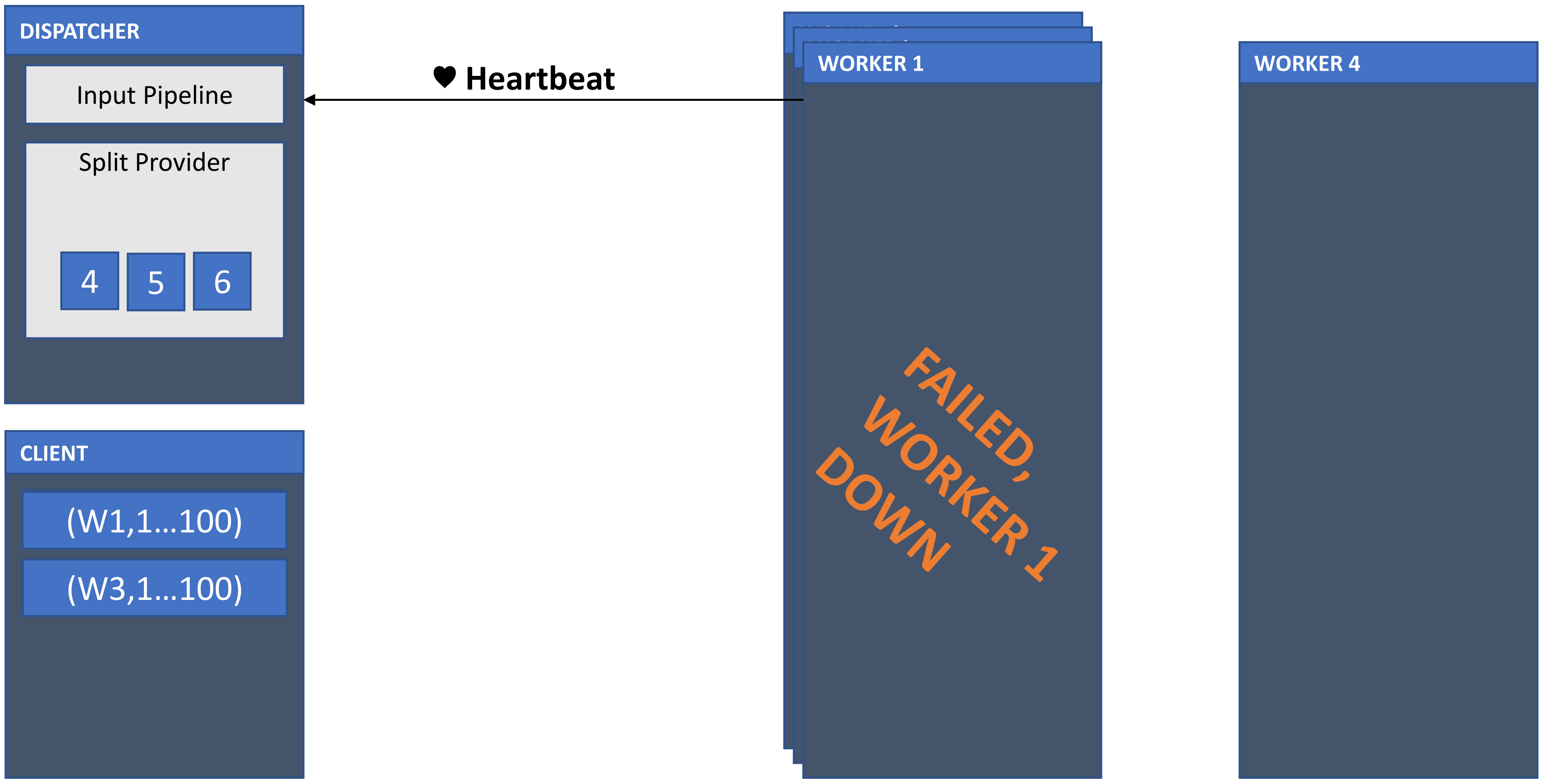

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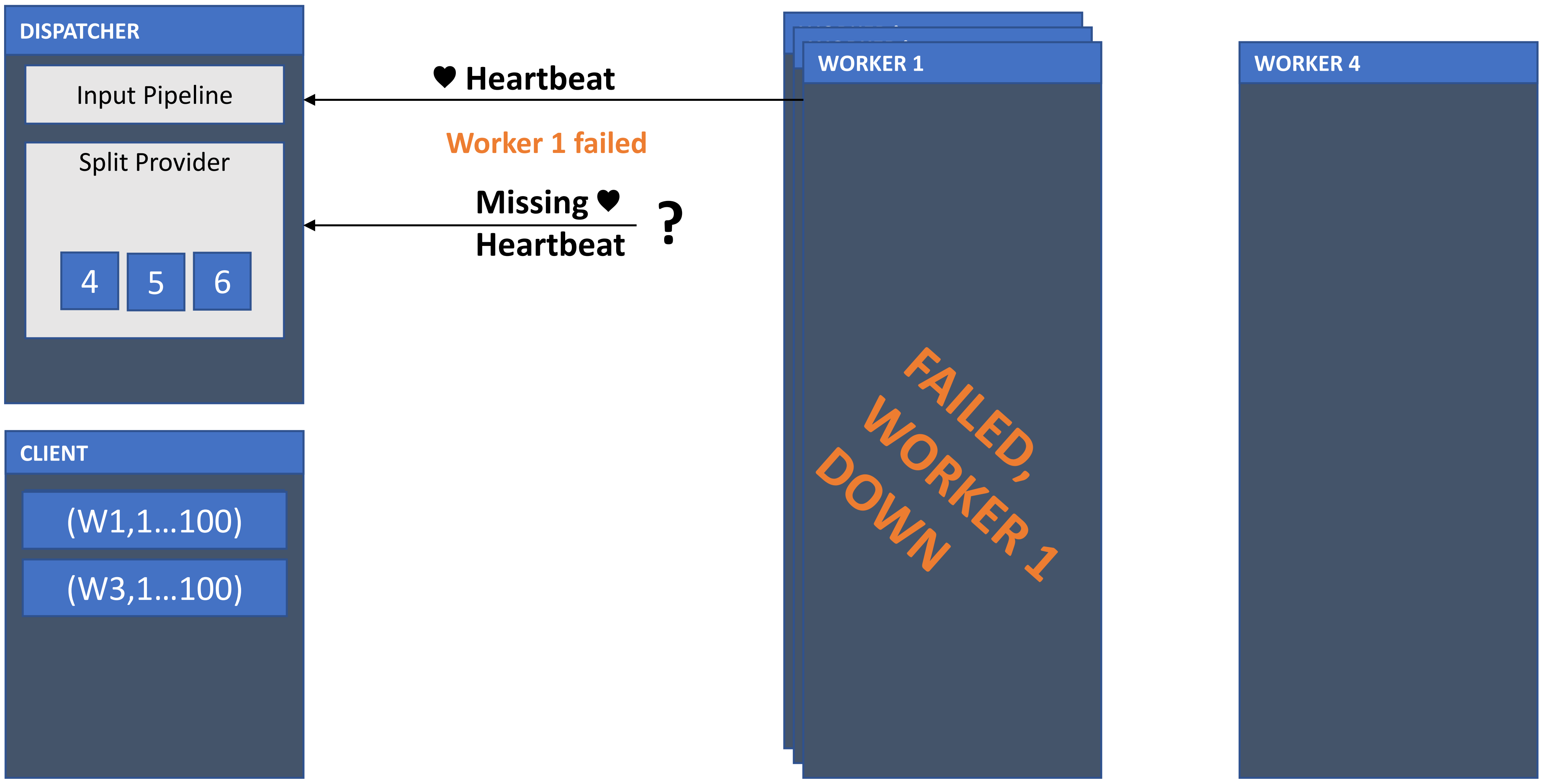

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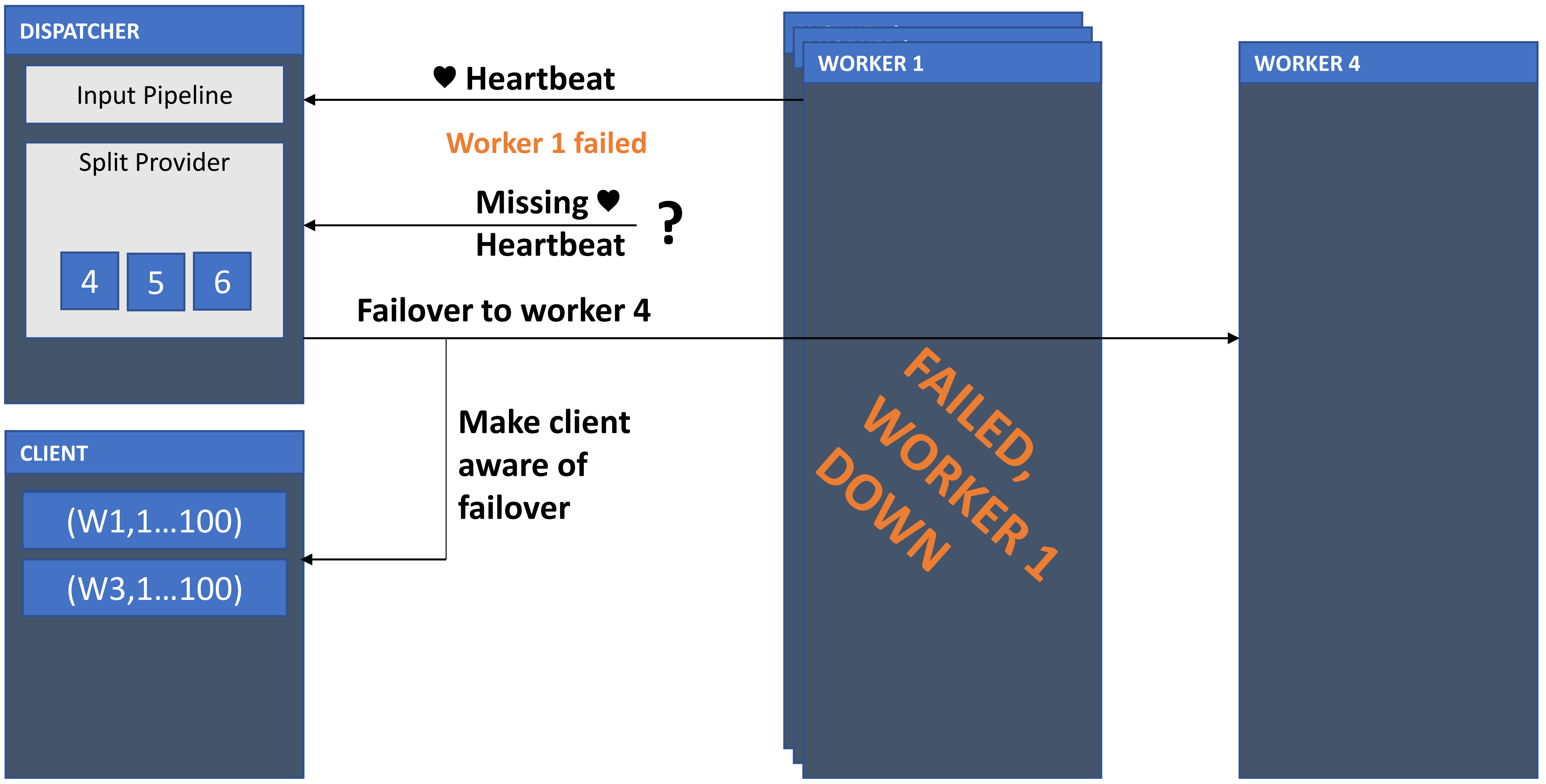

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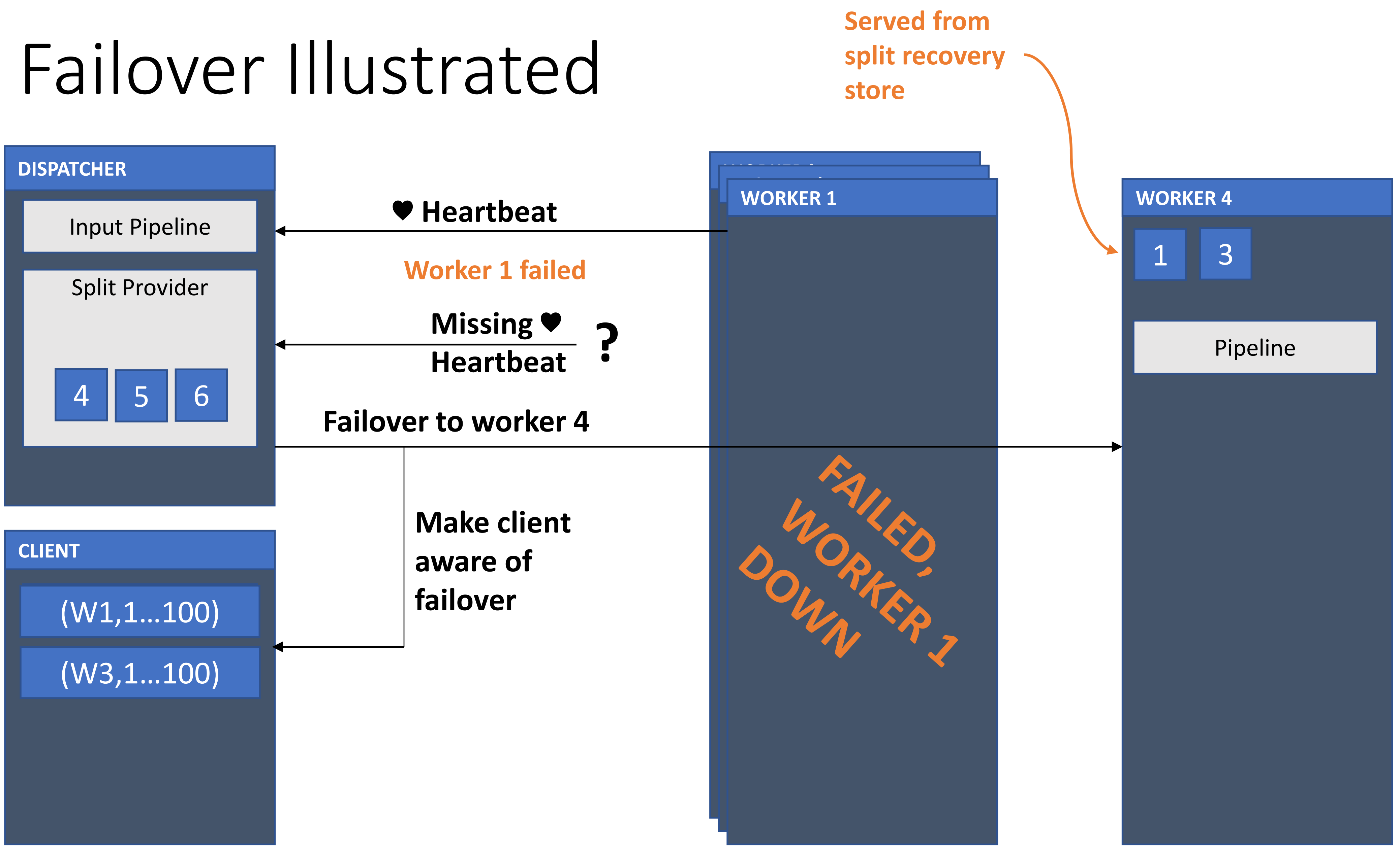

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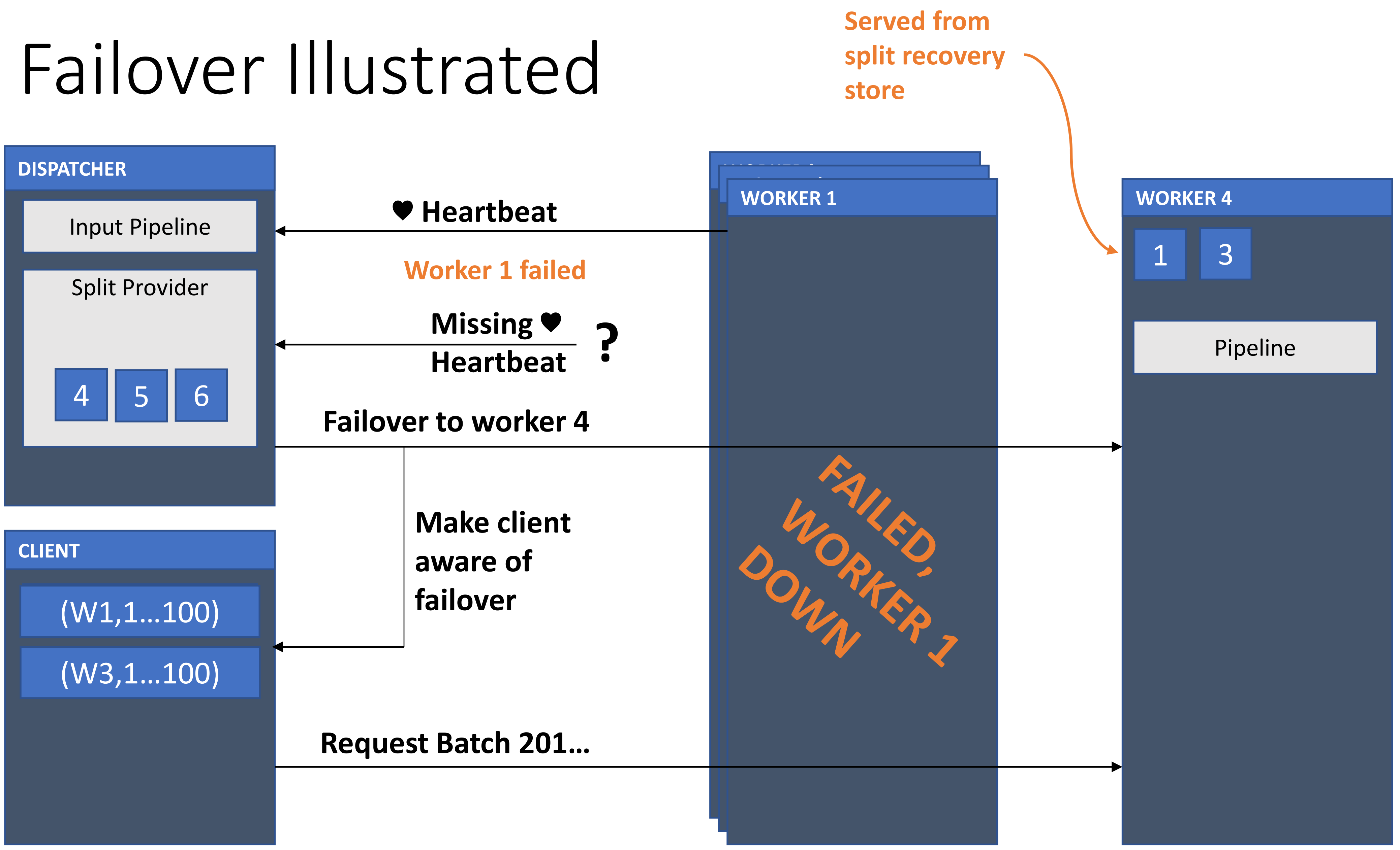

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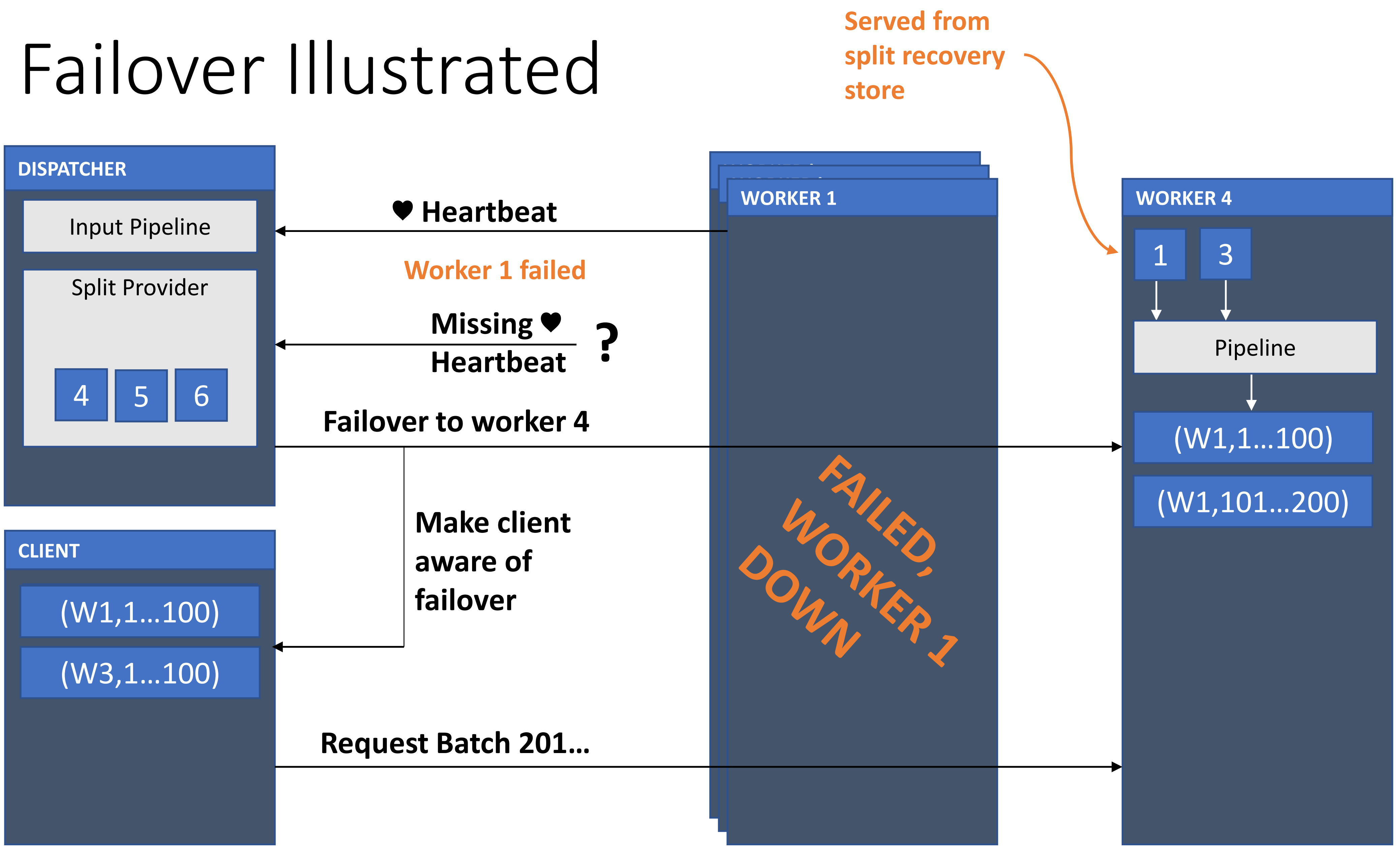

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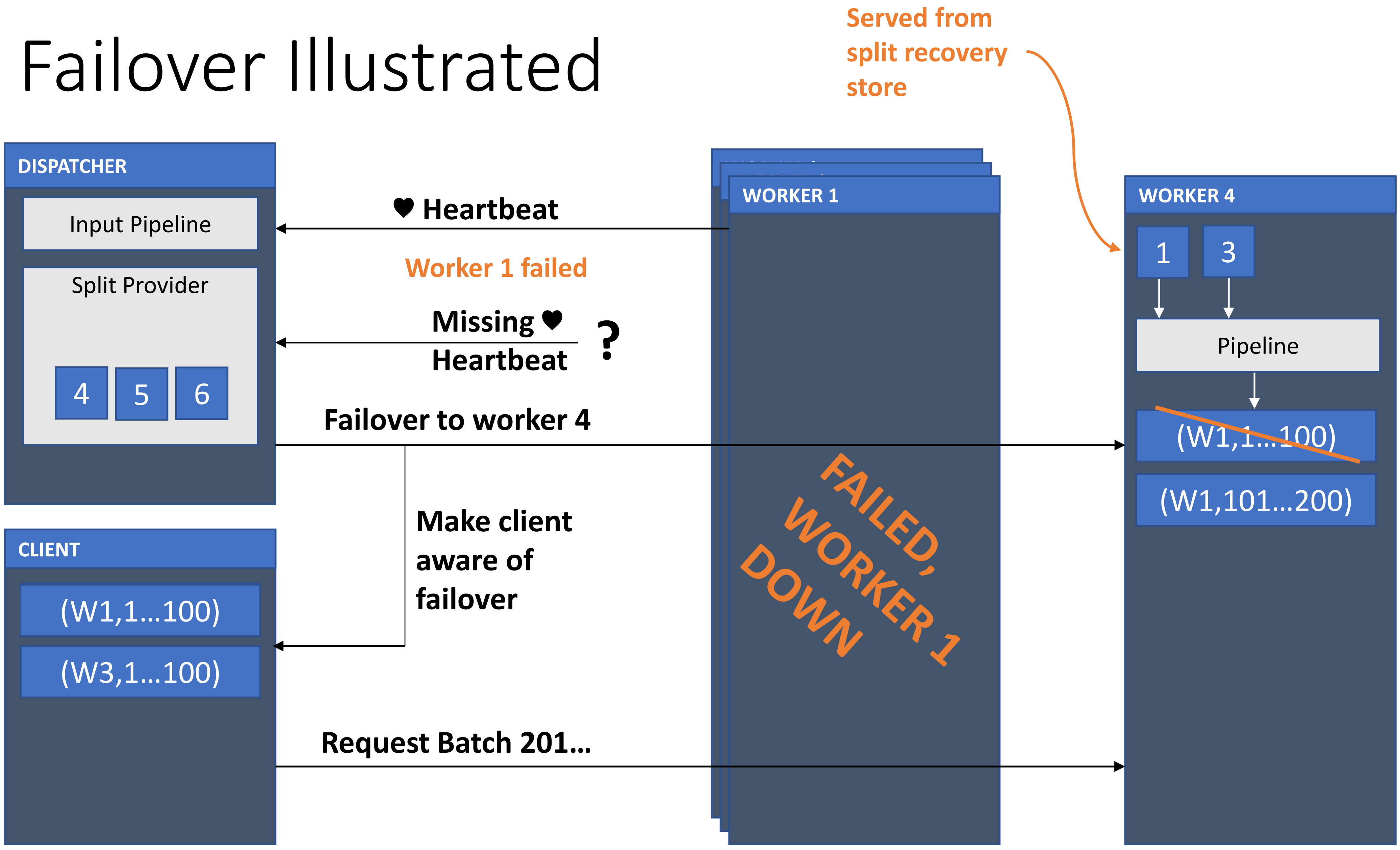

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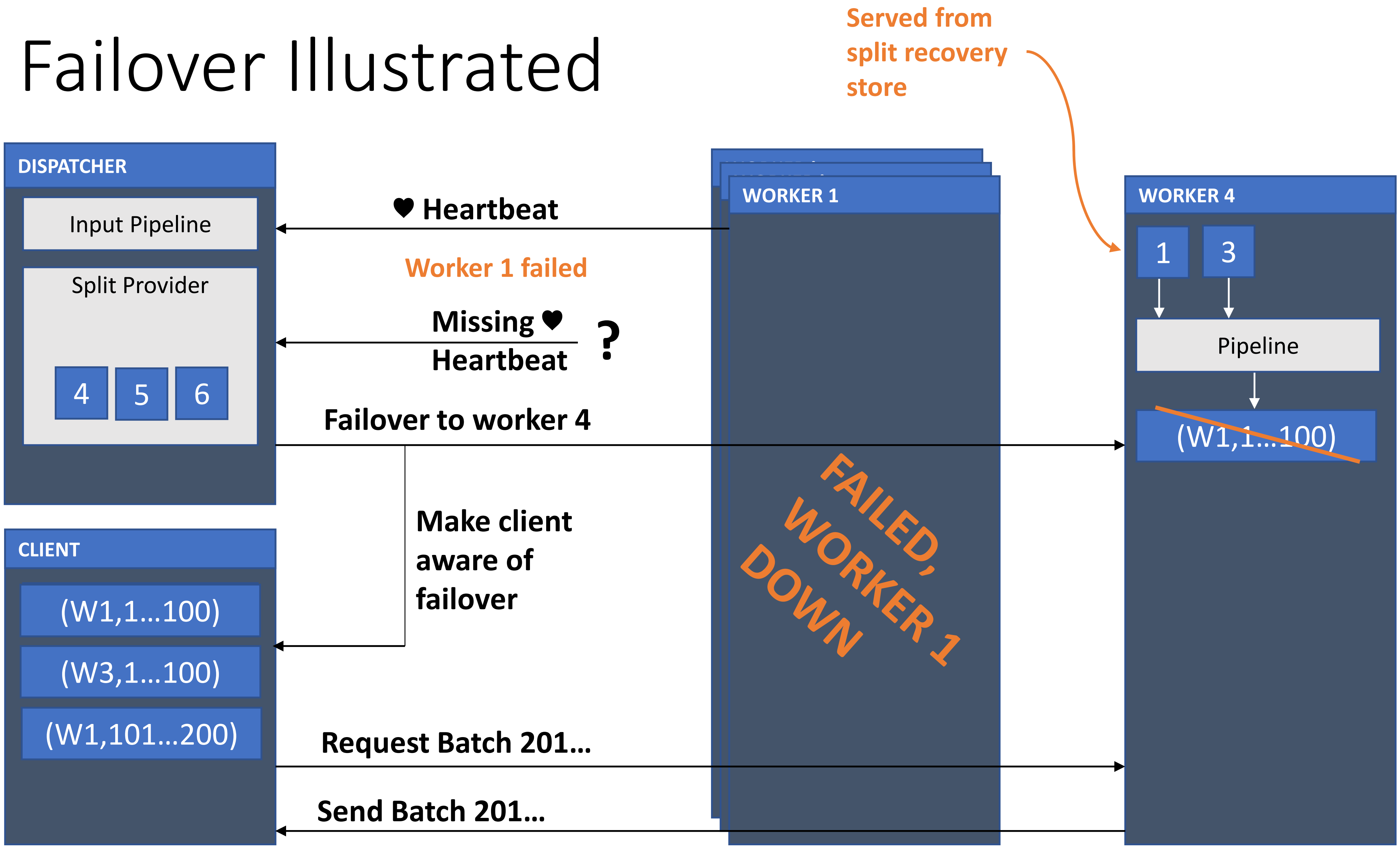


Reducing Overhead

overhead = detection + failover + recomputation

Detection

Fine-tune heartbeat detection mechanisms

~ 1-10s

Failover

Have nodes in hot-standby

Implement “express” messages (circumvent heartbeat-based protocols)

~ 1-10s

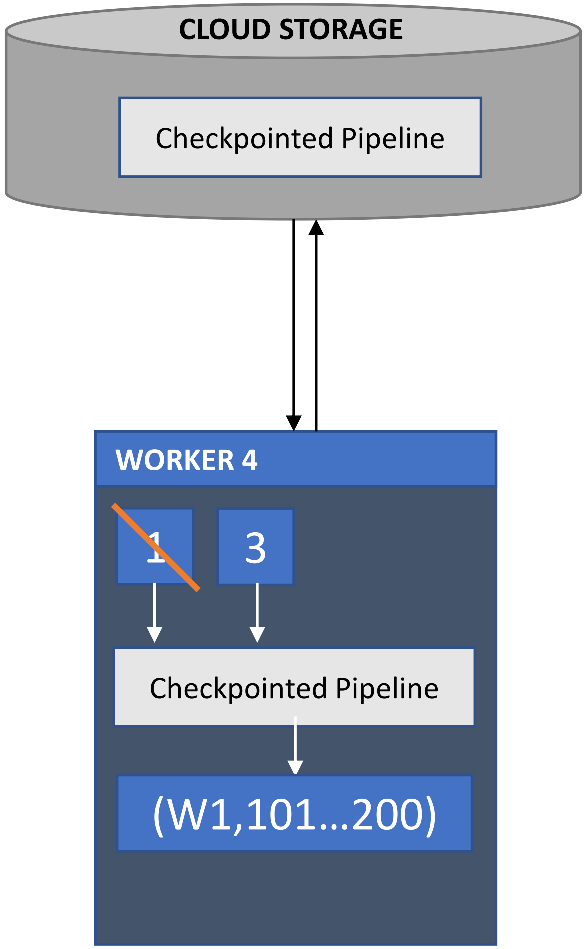
Recomputation

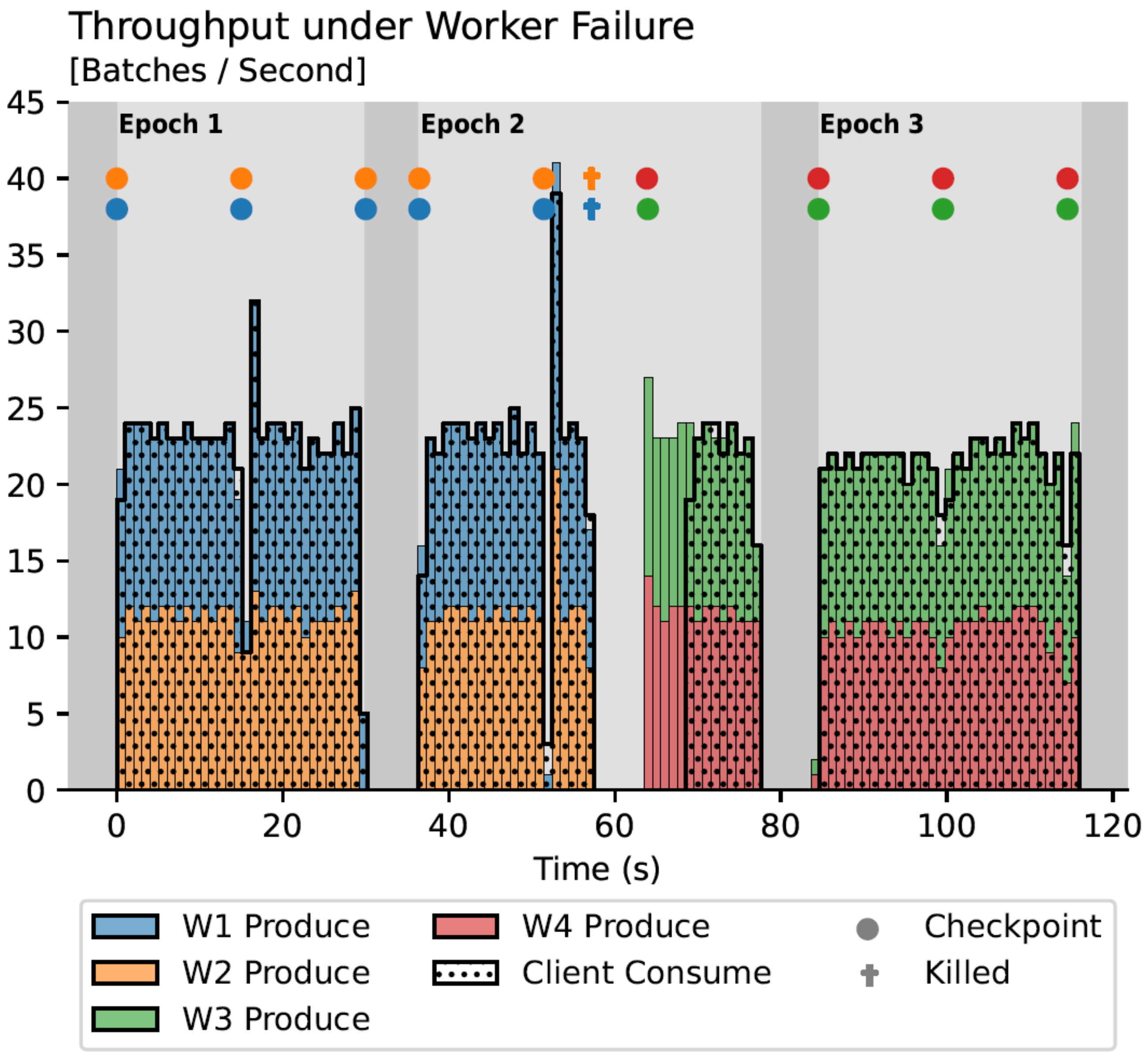
Checkpoint worker state to recompute less

~ ½ epoch

Checkpointing

- Workers regularly checkpoint their pipeline state to GlusterFS (cloud storage)
- This reduces the overhead because we need not recompute everything from scratch (Req3)
- The pipeline needs to be locked to arrive at a consistent state (checkpoint stall)
- Implementation builds on top of existing tf.data checkpointing mechanism

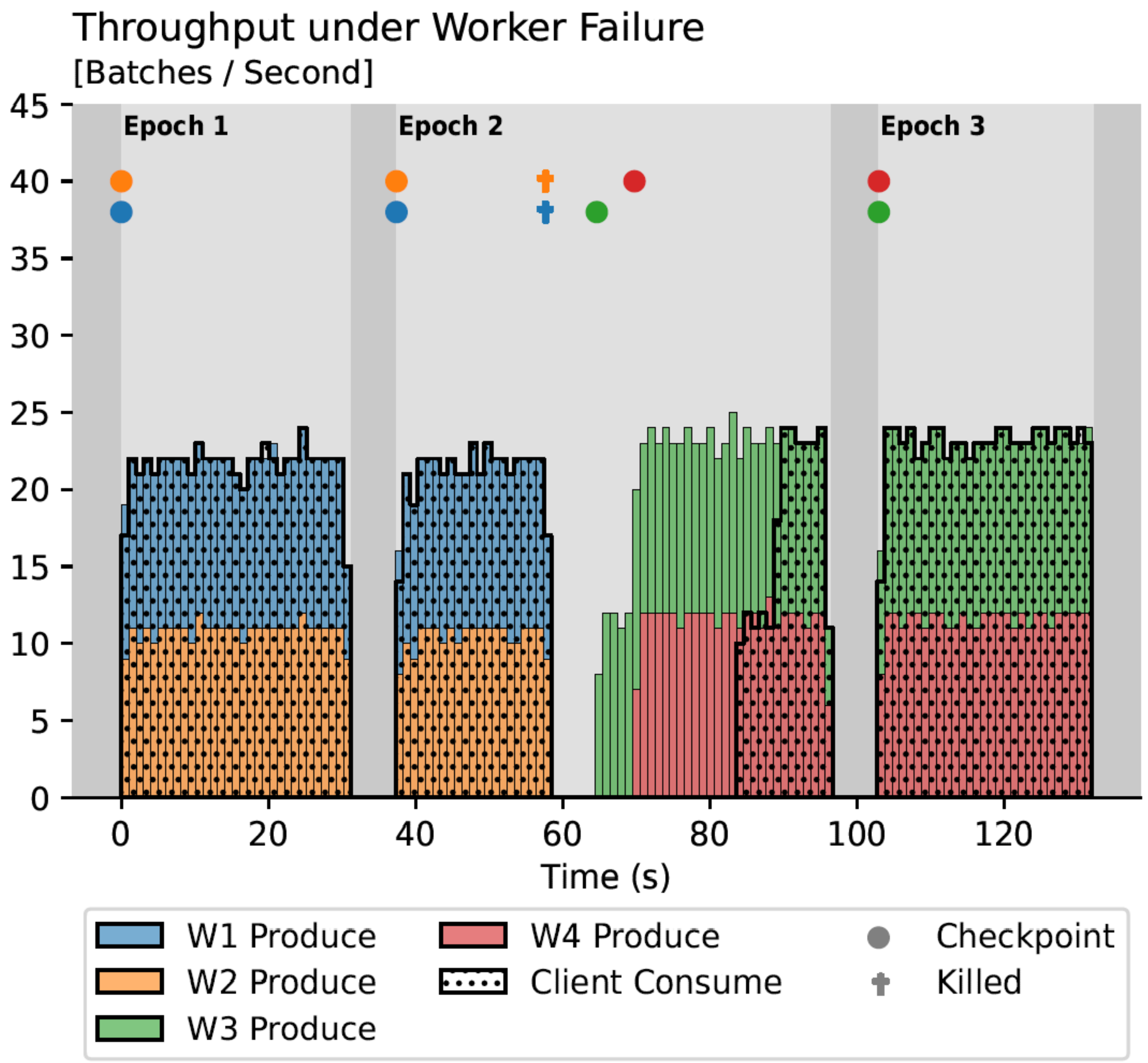




Takeaways

1) Throughput is constant; important characteristic used for scaling/profiling

2) Checkpointing introduced overhead



Takeaways

1) Without any worker checkpointing we have more recomputation

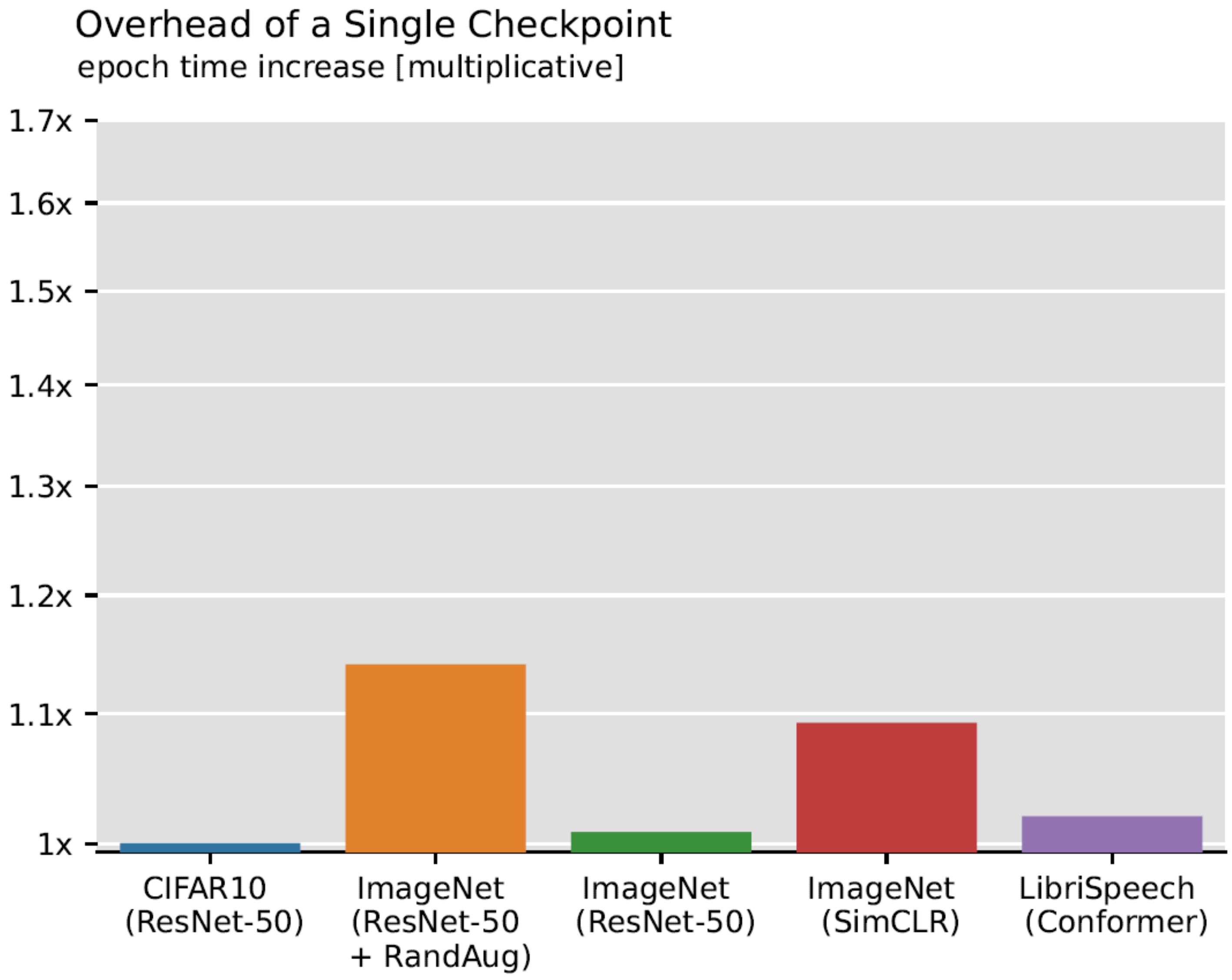
2) Worker checkpoints recover some of the progress (Req3)

Overhead Revisited

overhead = detection + failover + checkpointing + recomputation

Checkpointing Overhead

- Pipeline needs to be checkpointed in a consistent state (so it is locked)
- This will result in a drop in throughput
- Overhead is highly dependent on the structure and contents of individual pipelines
- Tradeoff between checkpointing and recomputation overhead
- Depends highly on the failure pattern



Questions

How does checkpointing overhead compare for different pipelines?

Is it feasible for all pipelines to make even just a single checkpoint?

Takeaways

1) Overhead varies with pipeline

2) Sometimes no checkpoint is better

Conclusion

- Built a system which satisfies all requirements (distributed, exactly-once, performant, bounded overhead and reproducible randomness) in the C++ layer maintaining full compatibility with all tf.data input pipelines
- Evaluation shows that worker checkpoints are not always feasible

Further Work

- Optimal checkpointing frequency
- Optimize checkpointing overhead (e.g. specific Ops)
- Use small independent sets of work (like Meta's DPP)
- Try to flush out pipelines (as in Meta's Check-N-Run)

References

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Convoluted Pipeline Example