A Framework for an In-depth Comparison of Scale-up and Scale-out Systems

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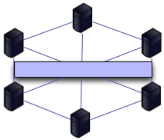
Scaling

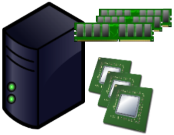
Q: *What do we do when there is too much data?*

A: Scale the system

- out
  - ++ nodes to the system
  - → modify applications



- up
  - ++ resources to a single node
  - → modify the system



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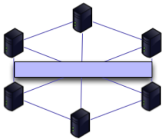
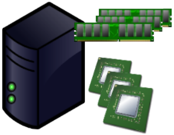




Q: *Which is better?*

Contributions

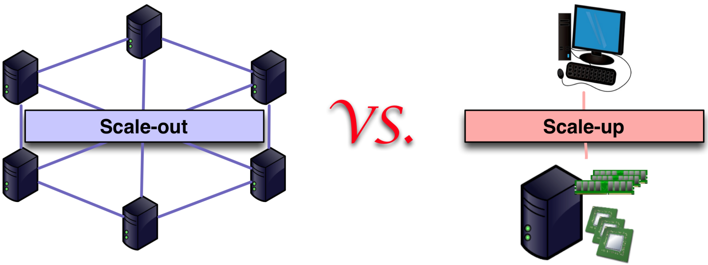
1. Comparison framework for scale-out/up
2. Achieve scale-out properties on scale-up
    - Parallelism limited by new job phases
    - Fault tolerance can make scale-up slower than scale-out
    - Scalable storage may be the ultimate bottleneck

We show:

- must consider properties when comparing scale-out/up
- limitations of a scale-up computation framework

Goal

Framework for comparing:

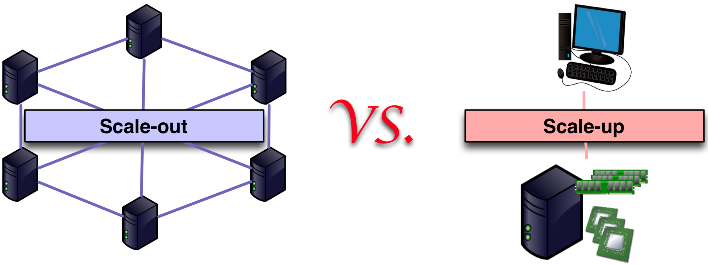


Why re-examine scale-up?

- new technology
- simplicity
- legacy applications

Goal

Framework for comparing:



Limit study to MapReduce

- standard for big data analytics
- goal is to make fair comparisons

Challenges - How do we:

Q: *compare algorithms?*

Q: *compare hardware?*

Q: *account for properties provided by scale-out by default?*

By design, scale-out provides:

- parallelism by automatically distributing load
- fault tolerance by rescheduling computation
- scalable storage with a distributed file system
- portability; Hadoop applications can run on any cluster
- availability because it can continually service clients
- scalability

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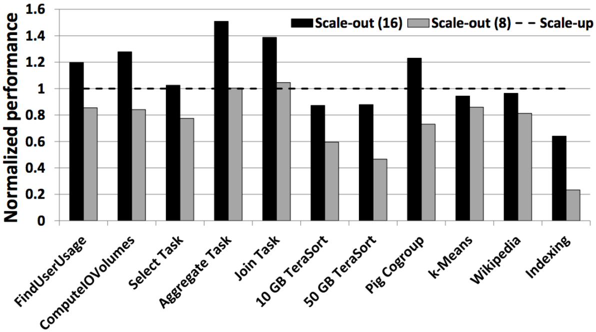
Related Work

Scale-up vs. Scale-out Hadoop: Time to Rethink?

ACM Symposium on Cloud Computing '13 [2, 5]

- 10 "typical" jobs
- for today's jobs, scale-up server > scale-out cluster



Methodology

input

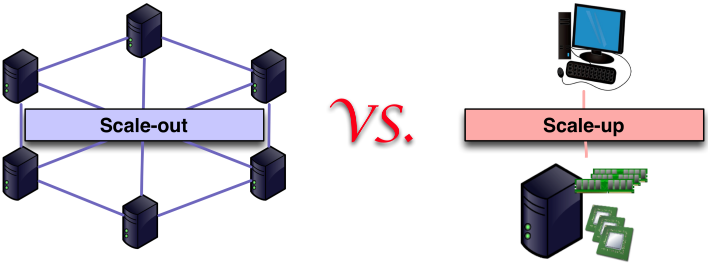
- →

software

- →
- →
- →

hardware

- →



Methodology

input

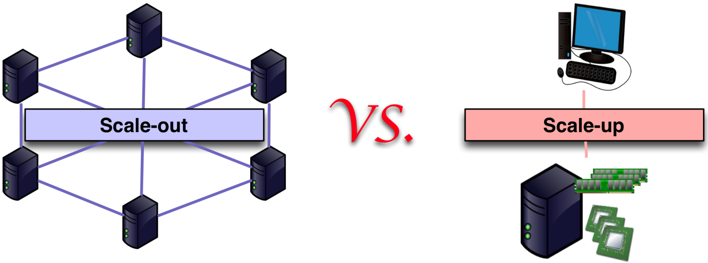
- workload, input size → same workload, scale data

software

- →
- →
- →

hardware

- →



Methodology

input

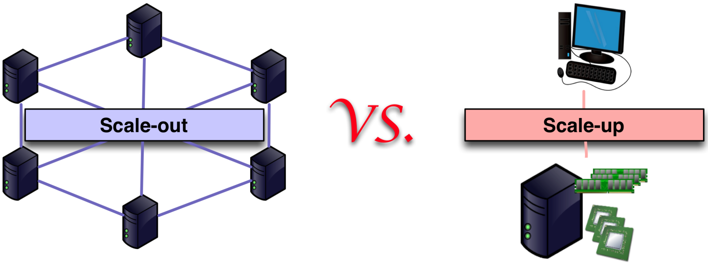
- workload, input size → same workload, scale data

software

- problem → word count, sort [3]
- →
- →

hardware

- →



Methodology

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- workload, input size → same workload, scale data

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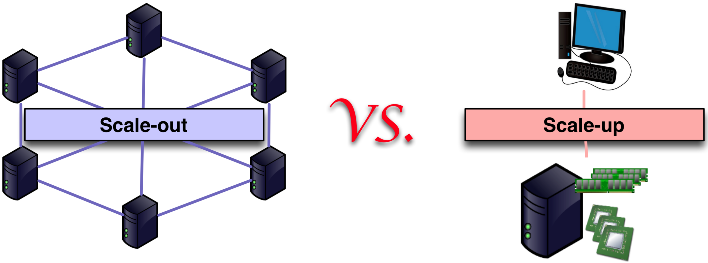
- problem → word count, sort [3]
- algorithm → methodology, functionality
- →

hardware

- →



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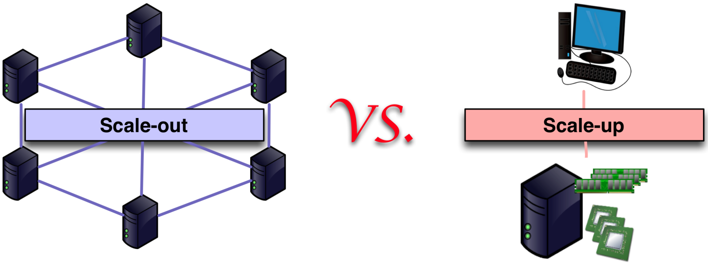
- scale-out properties → implementations

hardware

- →



Methodology

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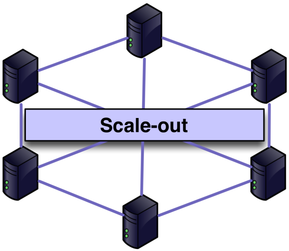
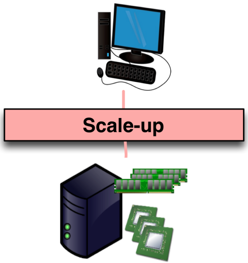
hardware

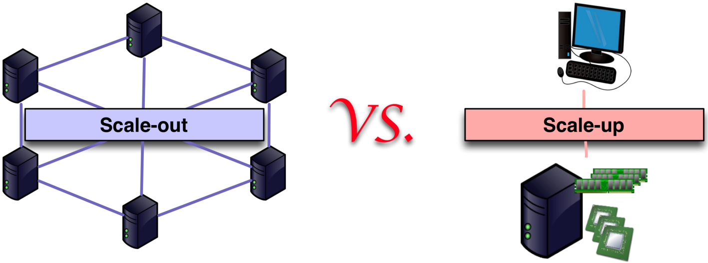
- processors, memory → ≡ compute contexts



VS.



Experimental Setup



Scale-out

- 32 nodes, 2-dual core processors, 8GB RAM

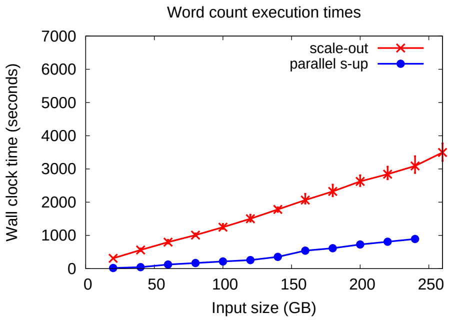
Scale-up

- 1 node, 2 $\times$ 8-core processors (HT), 256GB RAM

= 32 compute contexts, 256GB RAM

* node $\in$ scale-out gets the same work as a thread $\in$ scale-up

Scale-up can Perform Better than Scale-out



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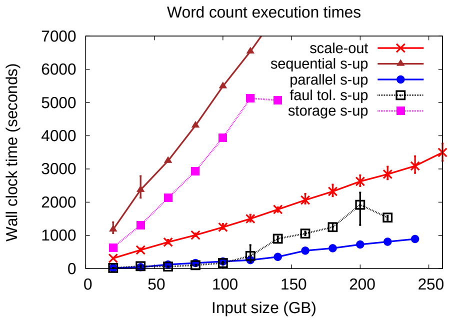


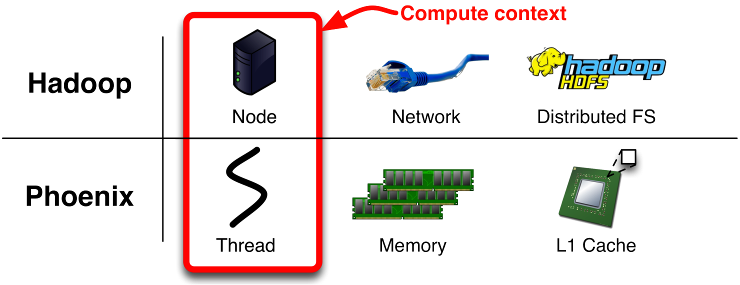
... but achieving scale-out properties changes the story!

- Other properties must be considered in comparison

Achieving Scale-out Properties on Scale-up

Phoenix: MapReduce runtime for multicore systems [4, 7, 6]

→ parallelism, port for methodology



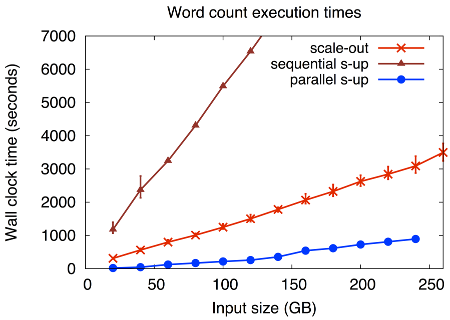
Distributed MultiThreaded Checkpointing (DMTCP) [1]

→ fault tolerance

Hadoop Distributed File System (HDFS)

→ scalable storage

Achieving Scale-out Properties on Scale-up



Properties must be considered when comparing scale-out/up

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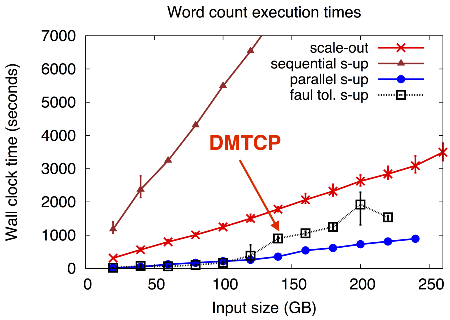

Properties must be considered when comparing scale-out/up

- fault tolerance can make scale-up slower than scale-out

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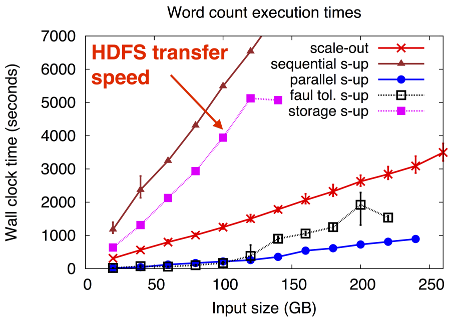
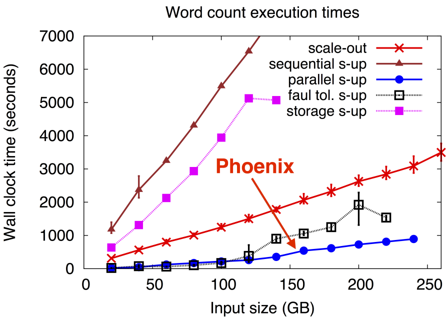


Properties must be considered when comparing scale-out/up

- fault tolerance can make scale-up slower than scale-out
- scalable storage may be the ultimate bottleneck

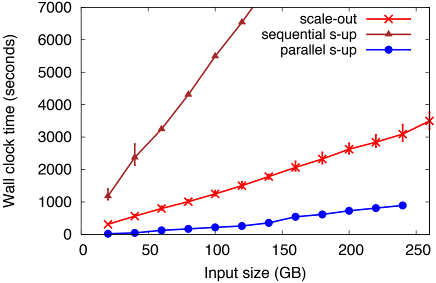
Achieving Scale-out Properties on Scale-up



Properties must be considered when comparing scale-out/up

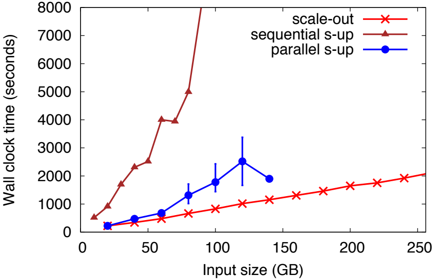
- fault tolerance can make scale-up slower than scale-out
- scalable storage may be the ultimate bottleneck
- parallelism limited by new job phases

Achieving Parallelism



← Word count

Sort →



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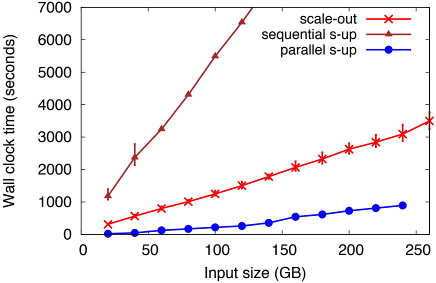

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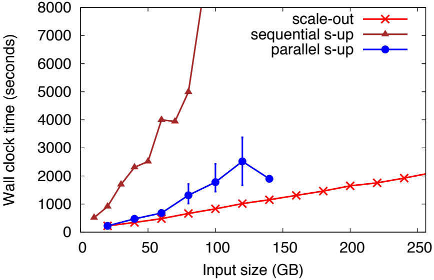
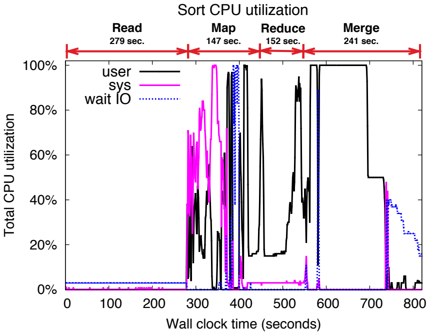


Why is sort slower?!

CPU Utilization of Parallel Sort



Parallelism is limited by new job phases

- read: move data from disk into memory
- merge: sort the data

Sort is slower on scale-up because

1. new job phases
2. more key-value pairs

Conclusion

Compare scaling architectures (scale-up/out)

- comparison framework
  - $\rightarrow$ encompasses {input, software, hardware} parameters
- achieving scale-out properties on scale-up

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Questions?

Special thanks to our anonymous reviewers for their helpful comments and suggestions.

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