Scalable Text Processing with MapReduce

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2008 New Frontiers in Computing Technology

Introduction

- In text processing, we've seen the emergence and dominance of:
  - Empirical techniques
  - Data-driven research
- Must scale up to larger datasets, or else:
  - Uninteresting conclusions on "toy" datasets
  - Ad hoc workarounds (e.g., approximations)
  - Unreasonably long experimental turnaround
- How do we *practically* scale up?
  - Managing concurrency is difficult
  - Clusters are expensive

How much data?

- Wayback machine has ~2 PB (2006)
- Google processes 20 PB a day (2008)
- “all words ever spoken by human beings” ~ 5 EB
- CERN’s LHC will generate 15 PB a year (2008)
- NOAA has ~1 PB climate data (2007)

What to do with more data?

- Answering factoid questions
  - Pattern matching on the Web
  - Works amazingly well

Who shot Abraham Lincoln? → X shot Abraham Lincoln

- Learning relations
  - Start with seed instances
  - Search for patterns on the Web
  - Using patterns to find more instances

Wolfgang Amadeus Mozart (1756 - 1791)
Einstein was born in 1879

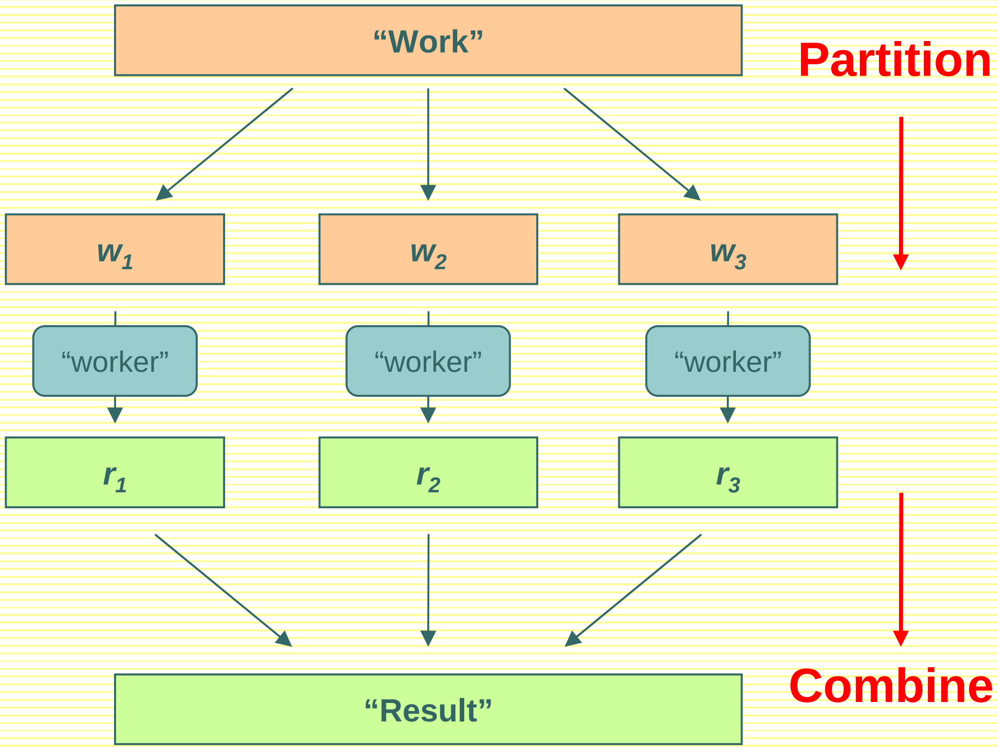
PERSON (DATE –
PERSON was born in DATE

Birthday-of(Mozart, 1756)
Birthday-of(Einstein, 1879)

(Brill et al., TREC 2001; Lin, ACM TOIS 2007)
(Agichtein and Gravano, DL 2000; Ravichandran and Hovy, ACL 2002; …)

Scaling Up: Present Solution

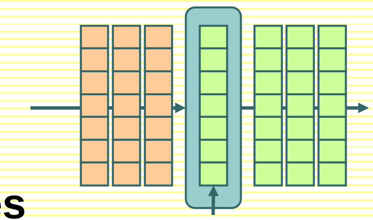
- Divide and conquer
- Throw more machines at it



It's a bit more complex…

Fundamental issues

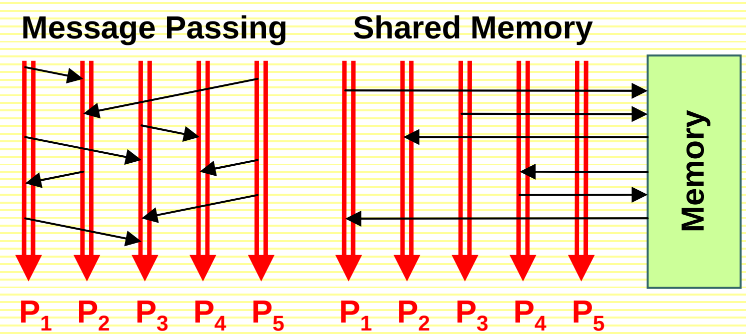
scheduling, data distribution, synchronization, inter-process communication, robustness, fault tolerance, …



Architectural issues

Flynn's taxonomy (SIMD, MIMD, etc.), network typology, bisection bandwidth UMA vs. NUMA, cache coherence

Different programming models



Different programming constructs

mutexes, conditional variables, barriers, …
masters/slaves, producers/consumers, work queues, …

Common problems

livelock, deadlock, data starvation, priority inversion…
dining philosophers, sleeping barbers, cigarette smokers, …

The reality: programmer shoulders the burden of managing concurrency…

MapReduce in a Nutshell

- What's different?
  - Runtime transparently handles system-level issues
  - Programmer focuses on solving the problem
- General problem structure:
  - Iterate over a large number of records
  - Extract something of interest from each
  - Shuffle and sort intermediate results
  - Aggregate intermediate results
  - Generate final output

Map

Reduce

- MapReduce provides a functional abstraction:
  - Programmer supplies "Mapper" and "Reducer"
  - Runtime automatically handles everything else!

MapReduce Runtime

- Handles scheduling
  - Assigns workers to map and reduce tasks
- Handles data distribution
  - Gets map workers to the data
- Handles synchronization
  - Shuffles intermediate key-value pairs to reduce workers
- Handles faults
  - Detects worker failures and restarts
- Everything happens on top of distributed FS
  - GFS = Google File System

From MapReduce to Hadoop

- Google's proprietary MapReduce implementation is in C++
- Hadoop is an open-source MapReduce reimplementation in Java (lead by Yahoo)
  - HDFS is a reimplementation of GFS
  - Growing number of associated open source projects…

"Cloud Computing" Initiative

- Google/IBM's Academic Cloud Computing Initiative (October 2007)
  - Initial pilot institutions: Washington, Berkeley, CMU, MIT, UMD
- IBM provides UMD a Hadoop cluster
  - 20 machines (40 processors)
  - Couple of TB storage
  - Associated infrastructure support
- Maryland does good work with the cluster!
  - Use it to tackle open research problems
  - Use it in the classroom

Statistical Machine Translation

Chris Dyer (Ph.D. student, Linguistics)
Aaron Cordova (undergraduate, Computer Science)
Alex Mont (undergraduate, Computer Science)

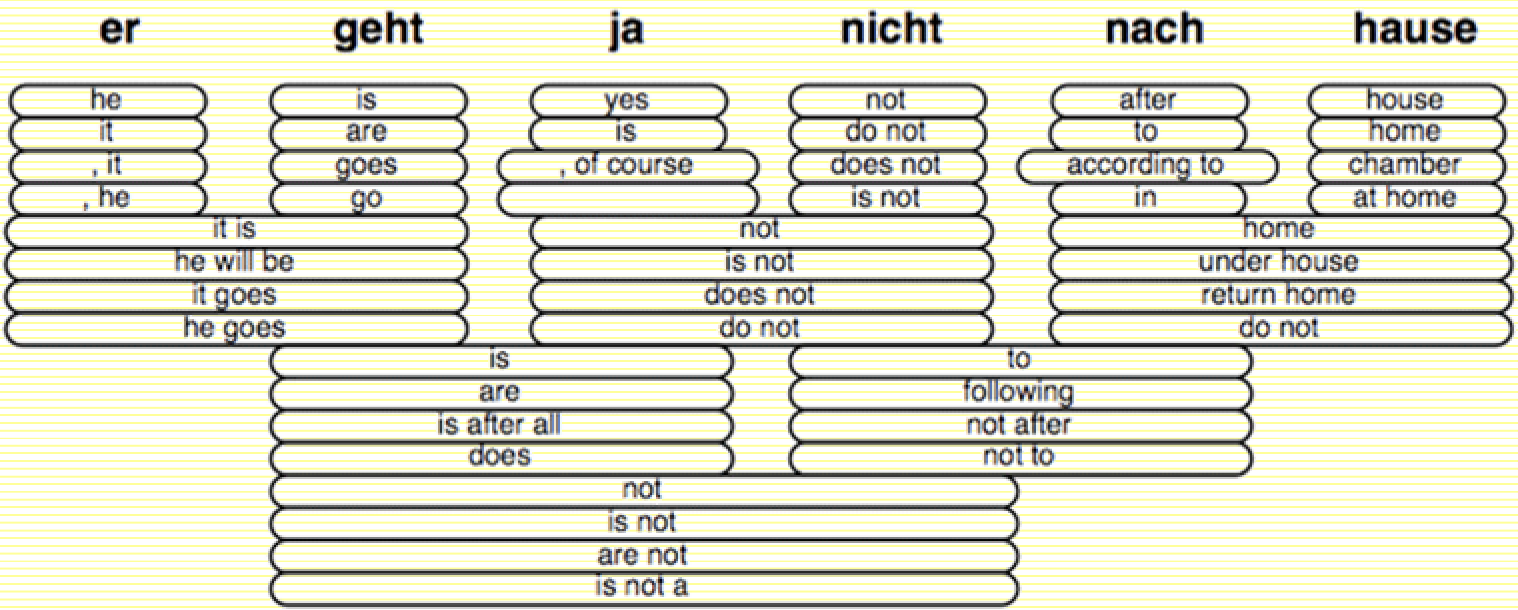
- Conceptually simple:
  (translation from foreign *f* into English *e*)

$$\hat{e} = \arg\max_{e} P(e \mid f)$$

$$\hat{e} = \arg\max_{e} P(f \mid e) P(e)$$

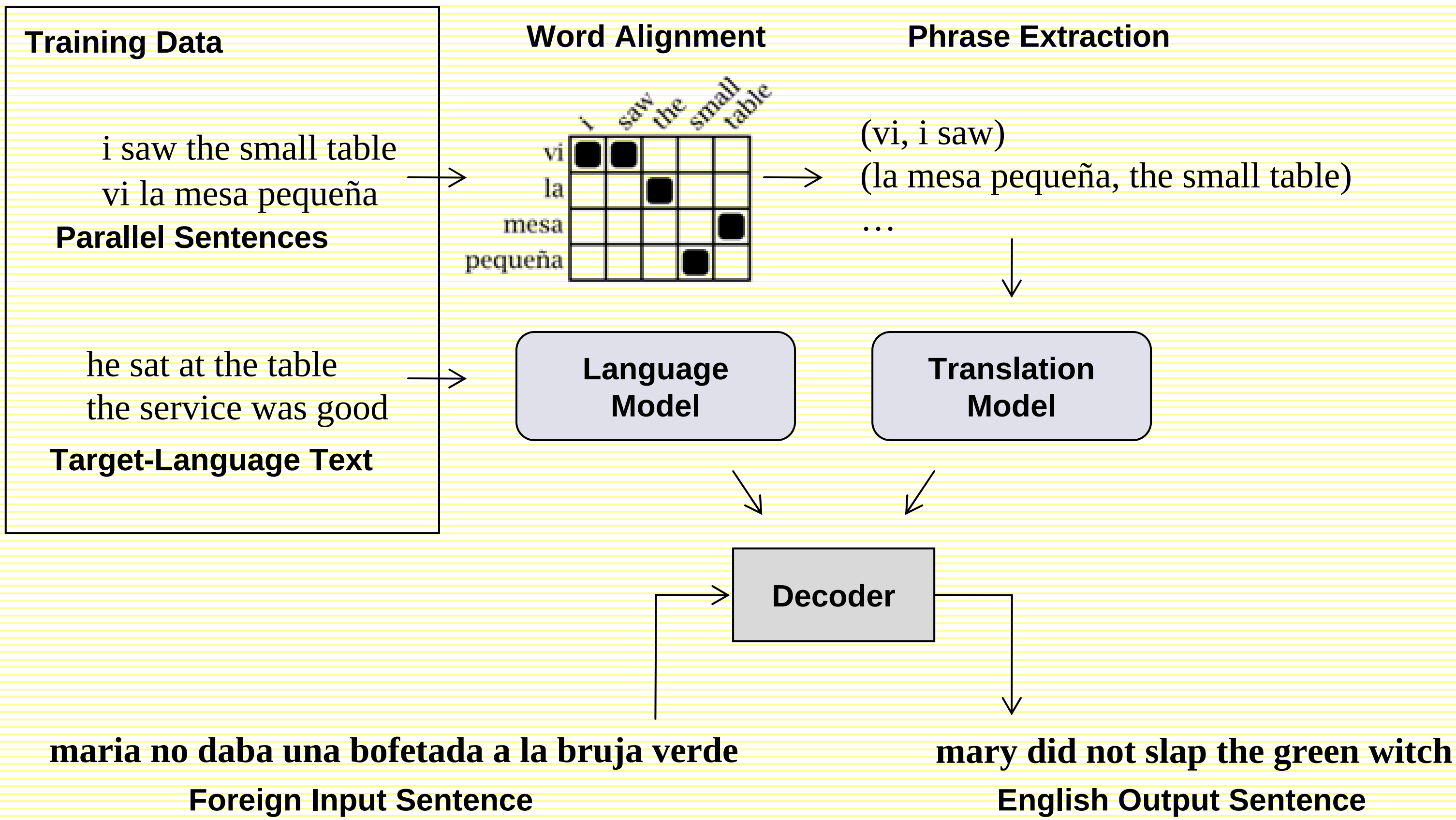
- Difficult in practice!
- Phrase-Based Machine Translation (PBMT) :
  - Break up source sentence into little pieces (phrases)
  - Translate each phrase individually

Phrasal Decomposition

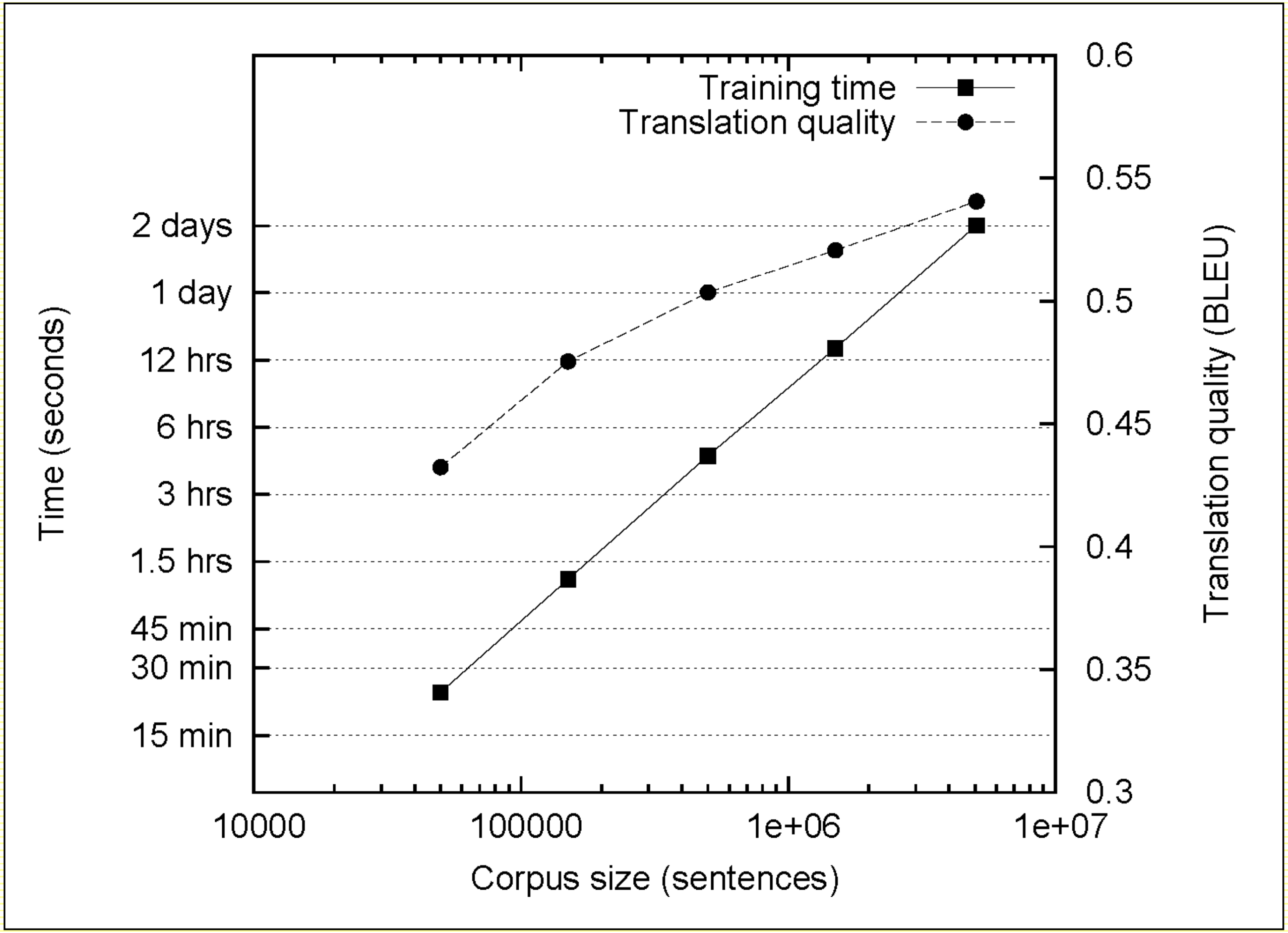


Example from Callison-Burch (2007)

MT Architecture



The Data Bottleneck



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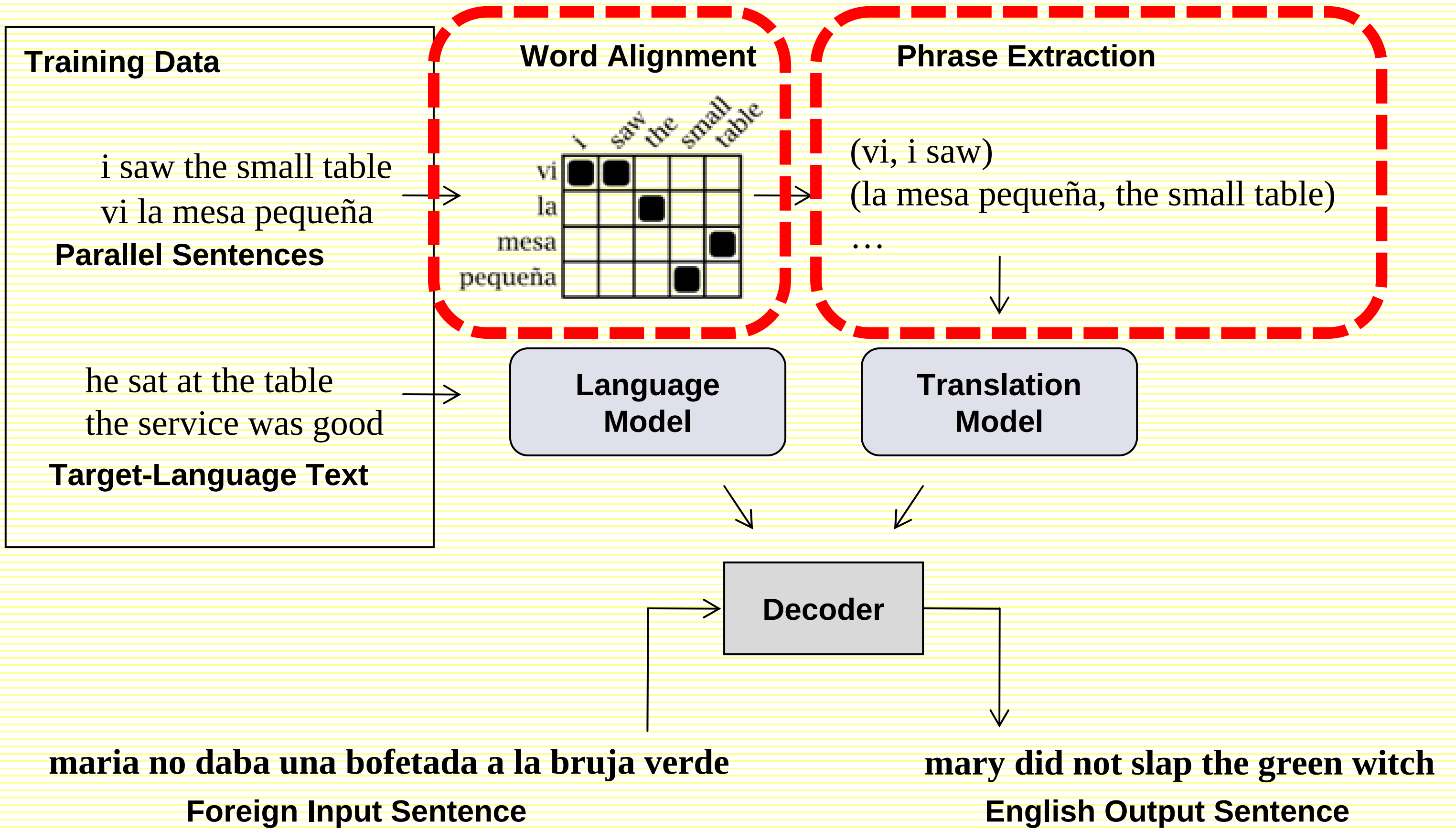
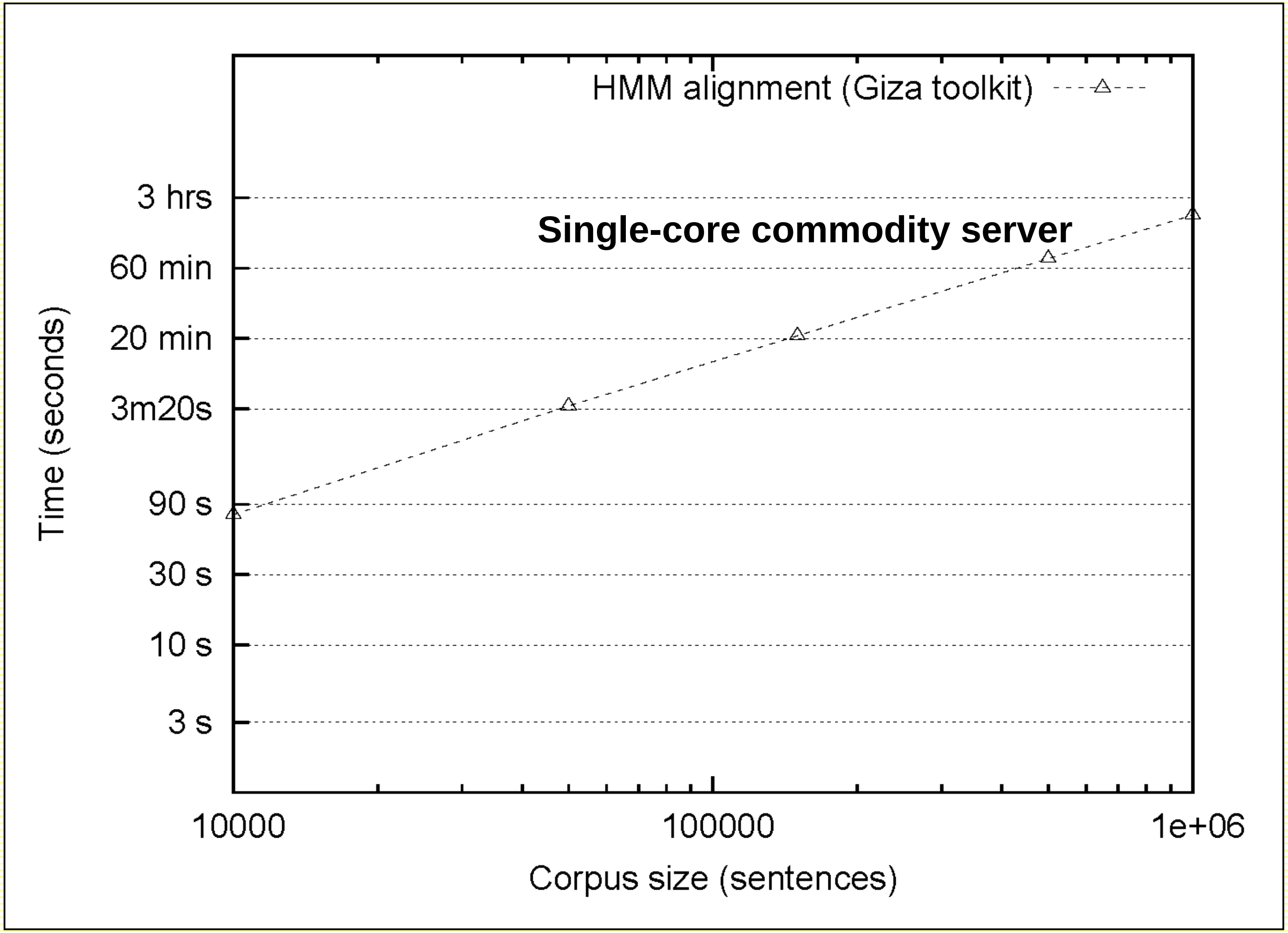
MT Architecture

We've built MapReduce Implementations of these two components!



HMM Alignment: Giza



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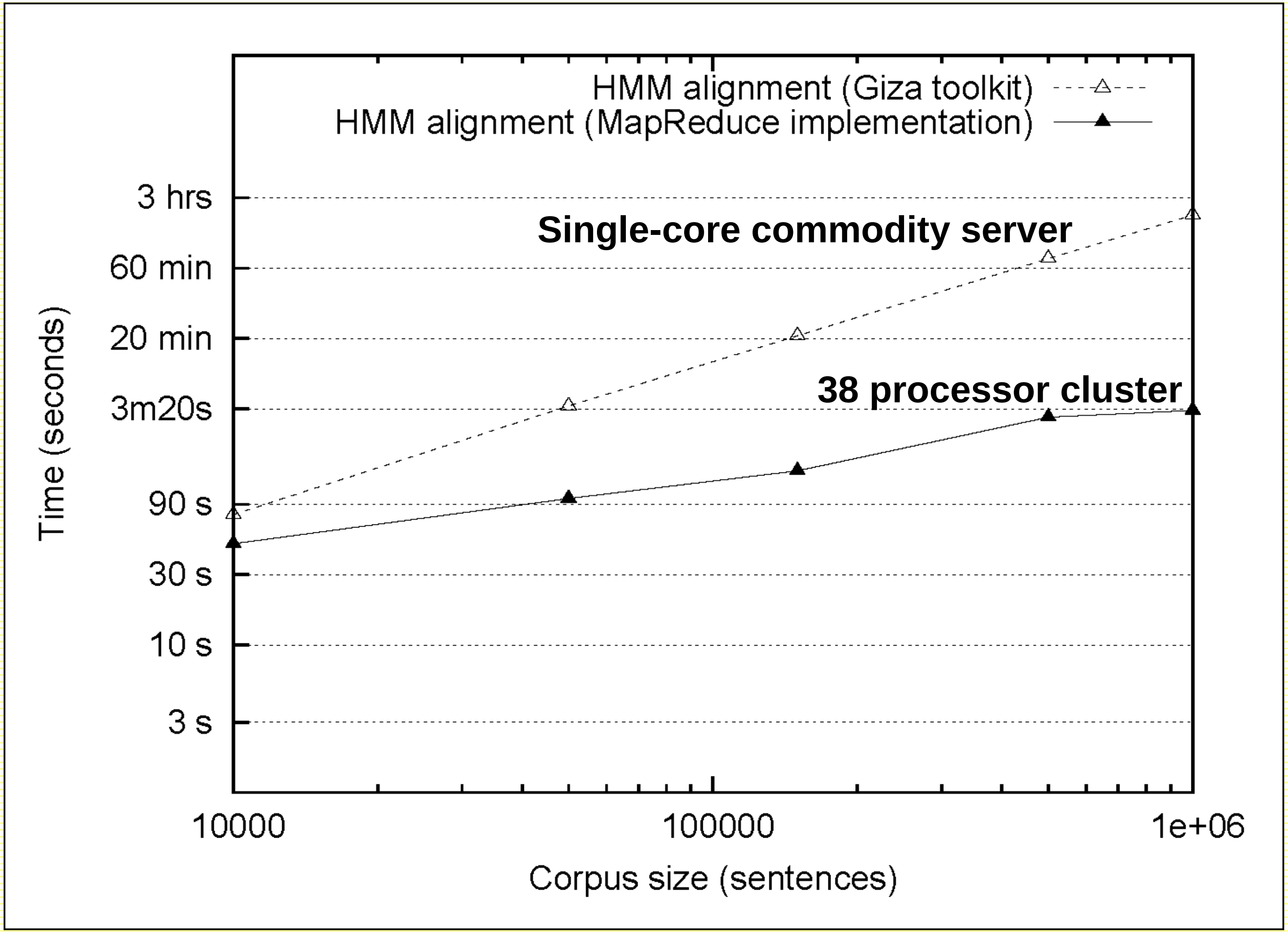
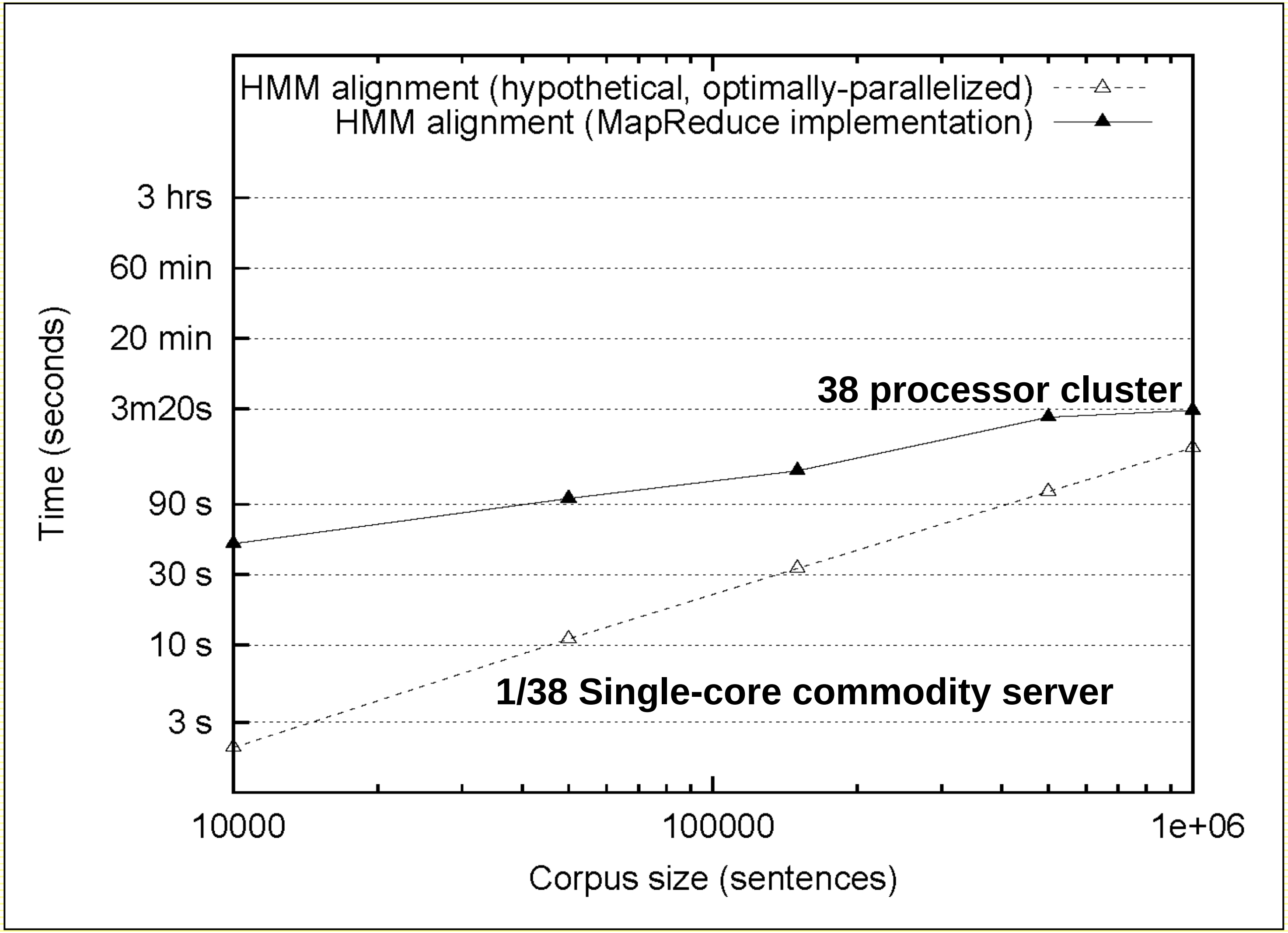
HMM Alignment: MapReduce



HMM Alignment: MapReduce



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What's the point?

- The hypothetical, optimally-parallelized version doesn't exist!
- MapReduce occupies a sweet spot in the design space for a large class of problems:
  - **Fast**… in terms of running time
  - **Easy**… in terms of programming effort
  - **Cheap**… in terms of hardware costs

Chris Dyer, Aaron Cordova, Alex Mont, and Jimmy Lin. **Fast, Easy, and Cheap: Construction of Statistical Machine Translation Models with MapReduce.** Proceedings of the Third Workshop on Statistical Machine Translation at ACL 2008, June 2008, Columbus, Ohio.

Beyond MapReduce

- Hadoop and HDFS provides a good start
- Everybody can play:
  - Different applications
    (e.g., from stat MT to biological sequence alignment)
  - Extensions to the programming model
    (e.g. MapReduceMerge)
  - Different hardware substrates
    (e.g., MapReduce on multicore, CELL, and GPU's)
- Development of a vibrant community
  - Academic-Industrial collaborations are the key
  - Government involvement: e.g., NSF's Cluster Exploratory (CLuE)
- Education plays a critical role!

(Yang et al., SIGMOD 2007; Ranger et al., HPCA 2007; Kruijf and Sankaralingam, 2007; He et al., 2007)

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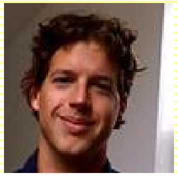

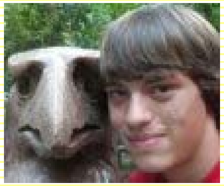

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