Google: A Computer Scientist's Playground

Jochen Hollmann

Google Zürich und Trondheim joho@google.com

Google

Outline

- · Mission, data, and scaling
- Systems infrastructure
- Parallel programming model: MapReduce
- Googles work environment

Google's Mission

To organize the world's information and make it universally accessible and useful

Google

A sense of scale

Example: The Web

- 20+ billion web pages x 20KB = 400+ terabytes
- One computer can read 30-35 MB/sec from disk
 - ~four month to read the web
- ~1,000 hard drives just to store the web
- Even more to do something with the data

Dealing with Scale

- Hardware, networking
 - Building a basic computing platform with low cost
- · Distributed systems
 - Building reliable systems out of many individual computers
- · Algorithms, data structures
 - Processing data efficiently, and in new and interesting ways
- · Machine learning, information retrieval
 - Improving quality of search results by analyzing (lots of) data
- User interfaces
 - Designing effective interfaces for search and other products
- · Many others...



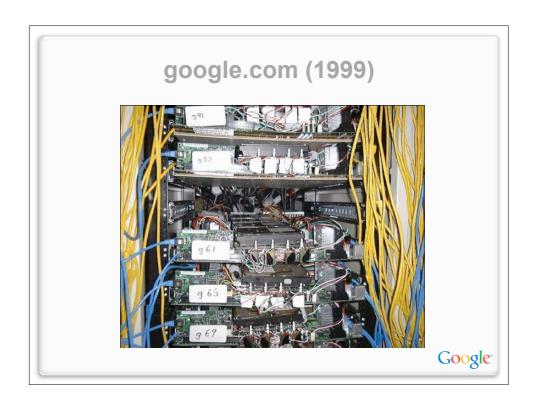
Why Use Commodity PCs?

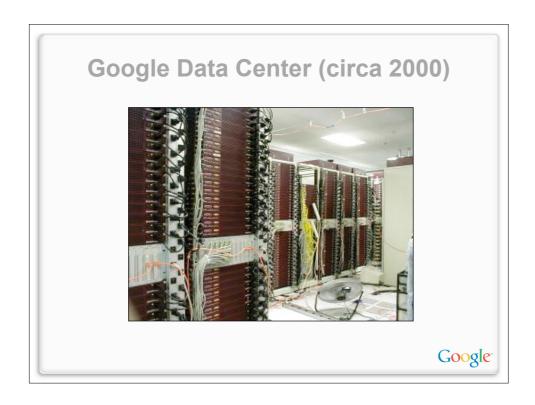
- Single high-end 8-way Intel server:
 - IBM eserver xSeries 440
 - 8 2-GHz Xeon, 64 GB RAM, 8 TB of disk
 - -\$758,000
- Commodity machines:
 - Rack of 88 machines
 - 176 2-GHz Xeons, 176 GB RAM, ~7 TB of disk
 - -\$278,000
- 1/3X price, 22X CPU, 3X RAM, 1X disk

Sources: racksaver.com, TPC-C performance results, both from late 2002











google.com (3 days later)



Google

Implications of our Computing Environment

Single-thread performance doesn't matter

 We have large problems and total throughput/\$ more important than peak performance

Stuff Breaks

- If you have one server, it may stay up three years (1,000 days)
- If you have 10,000 servers, expect to lose ten a day

"Ultra-reliable" hardware doesn't really help

- At large scales, super-fancy reliable hardware still fails, albeit less often
 - software still needs to be fault-tolerant
 - commodity machines without fancy hardware give better perf/\$

Fault-tolerant software makes cheap hardware practical

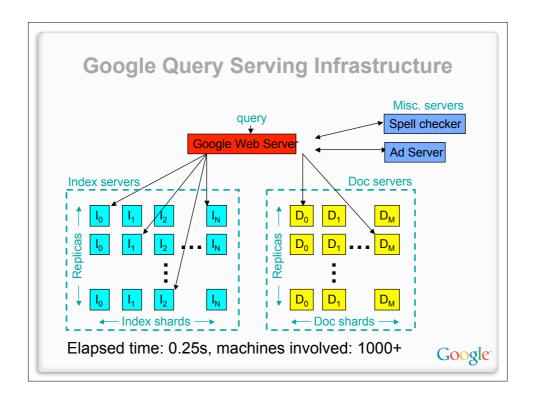
An Example: The Index

- Similar to index in the back of a book (but big!)
 - Building takes several days on hundreds of machines
 - More than 4 billion web documents
 - Images: 880M images
 - File types: More than 35M non-HTML documents (PDF, Microsoft Word, etc.)
 - Usenet: 800M messages from >35K newsgroups

Google

Structuring the Index

- Too large for one machine, so...
 - · Use PageRank as a total order
 - Split it into pieces, called shards, small enough to have several per machine
 - Replicate the shards, making more replicas of high PageRank shards
 - · Do the same for the documents
 - Then: replicate this whole structure within and across data centers

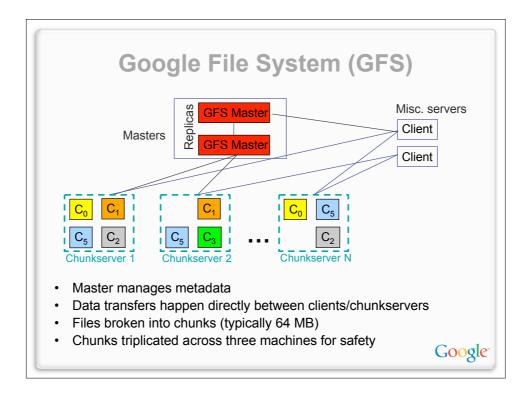


Reliable Building Blocks

- · Need to store data reliably
- Need to run jobs on pools of machines
- Need to make it easy to apply lots of computational resources to problems

In-house solutions:

- Storage: Google File System (GFS)
- Job scheduling: Global Work Queue (GWQ)
- MapReduce: simplified large-scale data processing



GFS Usage at Google

- 30+ Clusters
- Clusters as large as 2000+ chunkservers
- · Petabyte-sized filesystems
- 2000+ MB/s sustained read/write load
- All in the presence of HW failures
- More information can be found in SOSP, '03

MapReduce: Easy-to-use Cycles

- A simple programming model that applies to many large-scale computing problems
- Hide messy details in MapReduce runtime library:
 - automatic parallelization
 - load balancing
 - network and disk transfer optimization
 - handling of machine failures
 - robustness
 - improvements to core library benefit all users of library!



Typical problem solved by MapReduce

- Read a lot of data
- Map: extract something you care about from each record
- · Shuffle and Sort
- Reduce: aggregate, summarize, filter, or transform
- · Write the results

Outline stays the same, map and reduce change to fit the problem



More specifically...

- Programmer specifies two primary methods:
 - map(k, v) \rightarrow <k', v'>* - reduce(k', <v'>*) \rightarrow <k', v">*
- All v' with same k' are reduced together, in order.
- Usually also specify:
 - partition(k', total partitions) -> partition for k'
 - often a simple hash of the key
 - allows reduce operations for different k' to be parallelized

Google

Example: Word Frequencies in Web Pages

A typical exercise for a new engineer in his or her first week

- · Input is files with one document per record
- Specify a map function that takes a key/value pair key = document URL value = document contents
- Output of map function is (potentially many) key/value pairs.
 In our case, output (word, "1") once per word in the document

Example continued: word frequencies in web pages

- MapReduce library gathers together all pairs with the same key (shuffle/sort)
- The <u>reduce</u> function combines the values for a key In our case, compute the sum

Output of reduce (usually 0 or 1 value) paired with key and saved

```
"be", "2"
"not", "1"
"or", "1"
"to", "2"
```

Google

Example: Pseudo-code

```
Map(String input_key, String input_value):
    // input_key: document name
    // input_value: document contents
    for each word w in input_values:
        EmitIntermediate(w, "1");

Reduce(String key, Iterator intermediate_values):
        // key: a word, same for input and output
        // intermediate_values: a list of counts
        int result = 0;
        for each v in intermediate_values:
            result += ParseInt(v);
        Emit(AsString(result));

Total 80 lines of C++ code including comments, main()
```

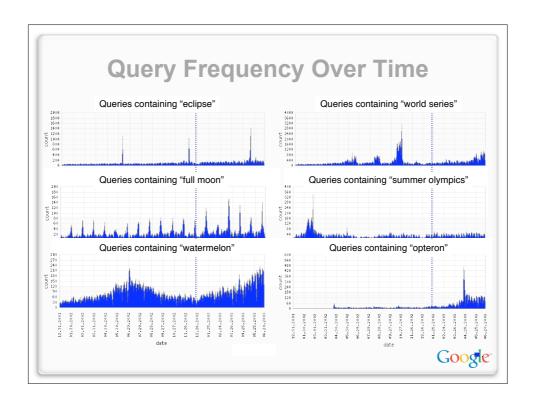
Widely applicable at Google

- Implemented as a C++ library linked to user programs
- Can read and write many different data types

Example uses:

distributed grep distributed sort term-vector per host document clustering machine learning

web access log stats web link-graph reversal inverted index construction statistical machine translation



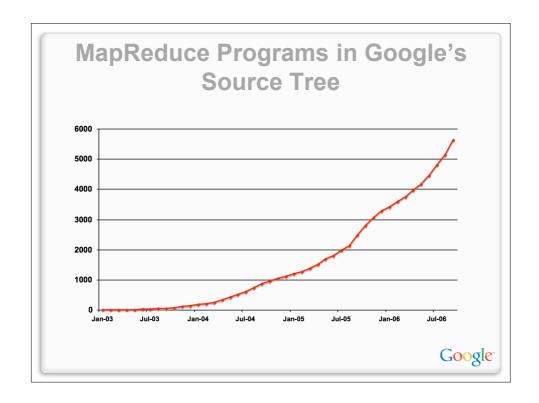
Example: Generating Language Model Statistics

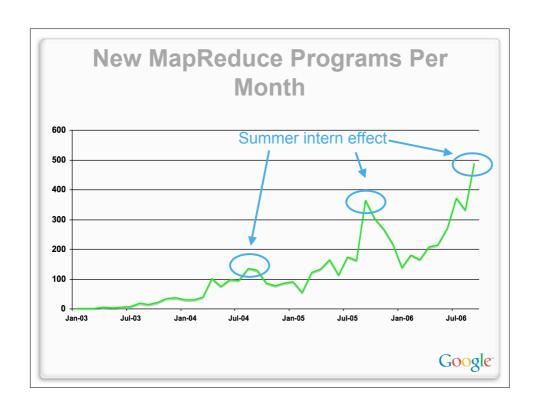
- Used in our statistical machine translation system
 - need to count # of times every 5-word sequence occurs in large corpus of documents (and keep all those where count >= 4)
- · Easy with MapReduce:
 - map: extract 5-word sequences => count from document
 - reduce: combine counts, and keep if count large enough

Google

Example: Joining with Other Data

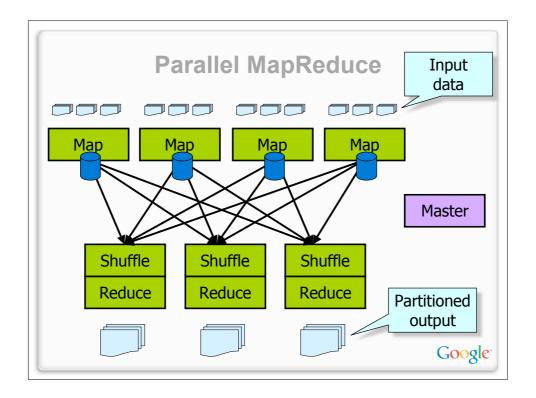
- Example: generate per-doc summary, but include per-host information (e.g. # of pages on host, important terms on host)
 - per-host information might be in per-process data structure, or might involve RPC to a set of machines containing data for all sites
- map: extract host name from URL, lookup per-host info, combine with per-doc data and emit
- reduce: identity function (just emit key/value directly)





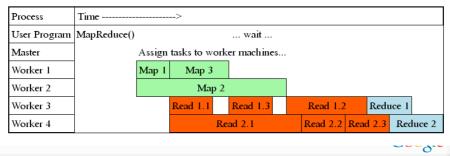
MapReduce: Scheduling

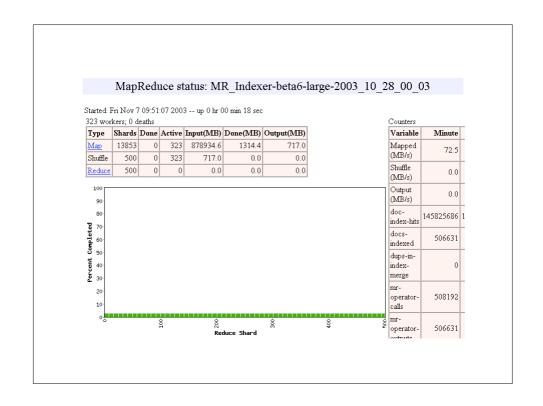
- · One master, many workers
 - Input data split into *M* map tasks (typically 64 MB in size)
 - Reduce phase partitioned into R reduce tasks
 - Tasks are assigned to workers dynamically
 - Often: M=200000; R=4000; workers=2000
- Master assigns each map task to a free worker
 - Considers locality of data to worker when assigning task
 - Worker reads task input (often from local disk!)
 - Worker produces R local files containing intermediate k/v pairs
- · Master assigns each reduce task to a free worker
 - Worker reads intermediate k/v pairs from map workers
 - Worker sorts & applies user's *Reduce* op to produce the output

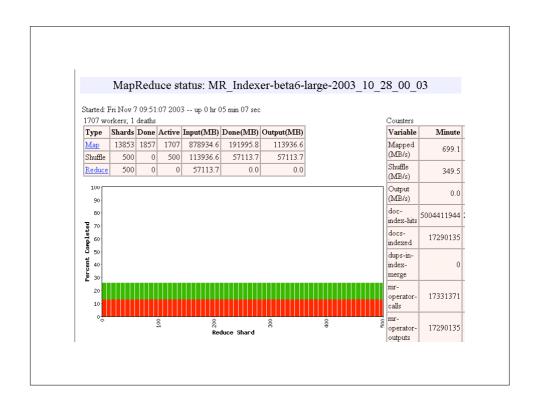


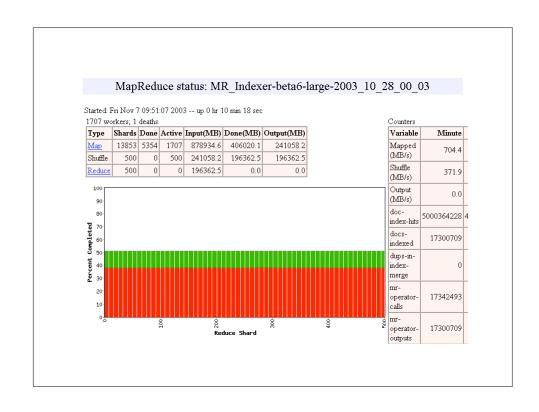
Task Granularity and Pipelining Fine granularity tasks: many more map tasks than machines - Minimizes time for fault recovery - Can pipeline shuffling with map execution - Better dynamic load balancing

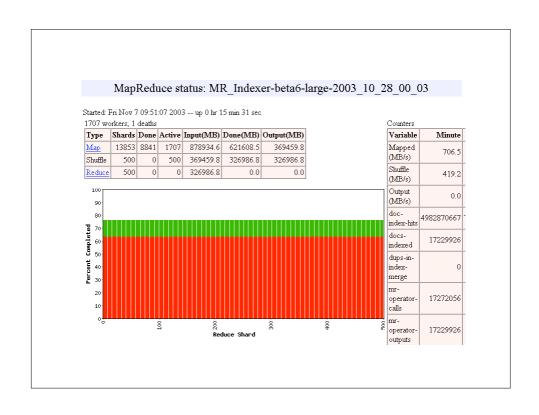
Often use 200,000 map/5000 reduce tasks w/ 2000 machines

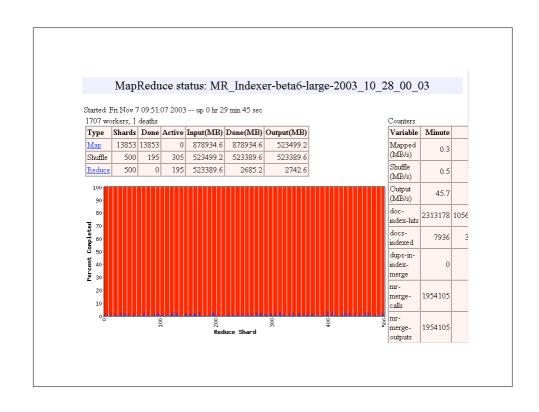


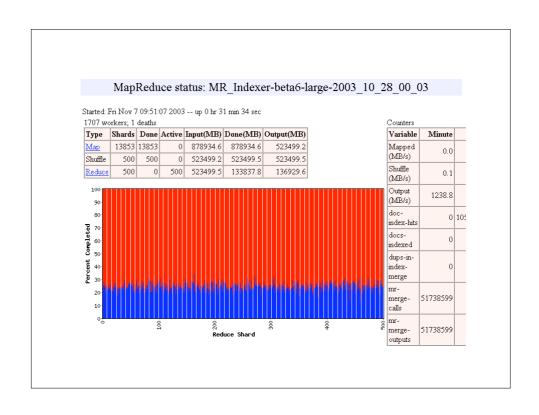


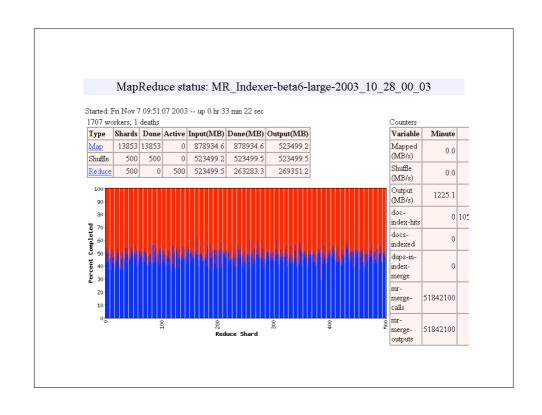


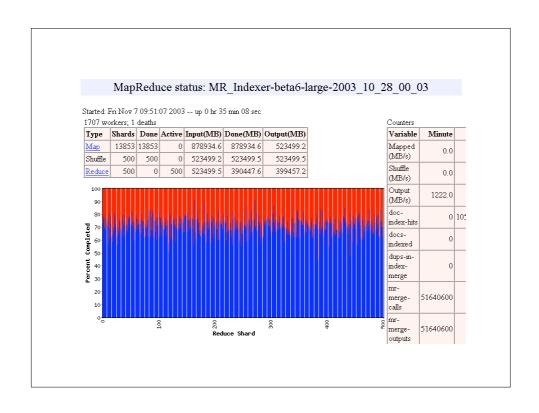


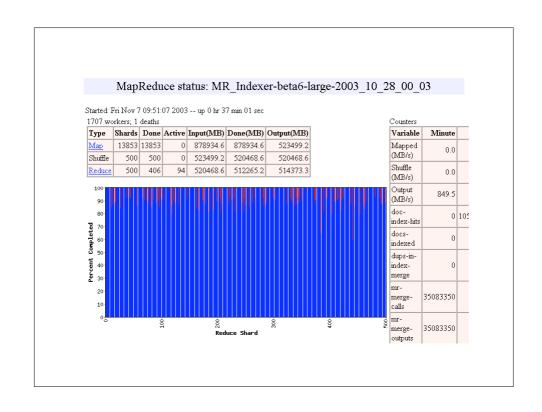


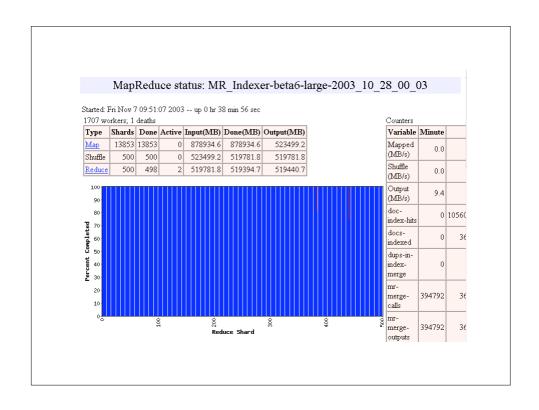


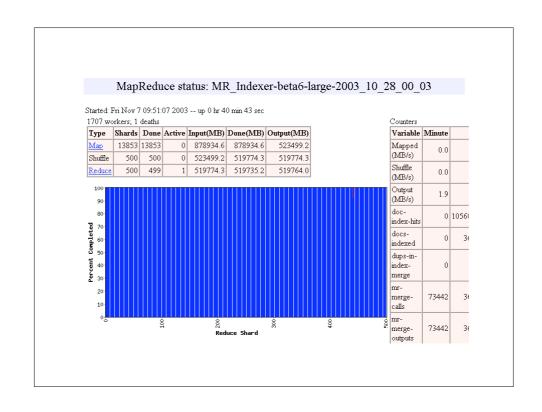












Fault tolerance: Handled via re-execution

On worker failure:

- · Detect failure via periodic heartbeats
- Re-execute completed and in-progress map tasks
- Re-execute in progress reduce tasks
- Task completion committed through master

On master failure:

State is checkpointed to GFS: new master recovers & continues

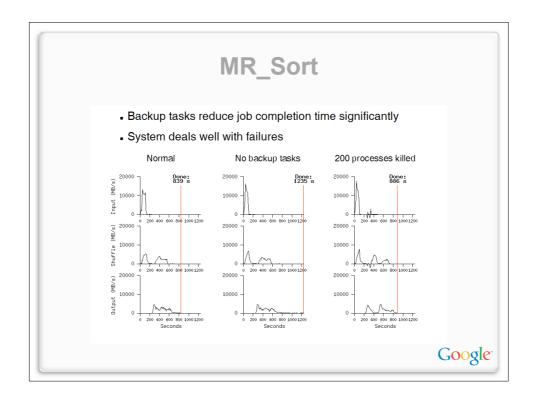
Very Robust: lost 1600 of 1800 machines once, but finished fine



Refinement: Backup Tasks

- Slow workers significantly lengthen completion time
 - Other jobs consuming resources on machine
 - Bad disks with soft errors transfer data very slowly
 - Weird things: processor caches disabled (!!)
- Solution: Near end of phase, spawn backup copies of tasks
 - Whichever one finishes first "wins"
- · Effect: Dramatically shortens job completion time





Refinement: Locality Optimization

Master scheduling policy:

- Asks GFS for locations of replicas of input file blocks
- Map tasks typically split into 64MB (== GFS block size)
- Map tasks scheduled so GFS input block replica are on same machine or same rack

Effect: Thousands of machines read input at local disk speed

· Without this, rack switches limit read rate



Refinement: Skipping Bad Records

Map/Reduce functions sometimes fail for particular inputs

• Best solution is to debug & fix, but not always possible

On seg fault:

- Send UDP packet to master from signal handler
- Include sequence number of record being processed

If master sees *K* failures for same record (typically *K* set to 2 or 3) :

· Next worker is told to skip the record

Effect: Can work around bugs in third-party libraries



Other Refinements

- Optional secondary keys for ordering
- · Compression of intermediate data
- · Combiner: useful for saving network bandwidth
- Local execution for debugging/testing
- · User-defined counters



Performance Results & Experience

Using 1,800 machines:

- MR_Grep scanned 1 terabyte in 100 seconds
- MR_Sort sorted 1 terabyte of 100 byte records in 14 minutes

Rewrote Google's production indexing system

- a sequence of 7, 10, 14, 17, 21, 24 MapReductions
- simpler
- more robust
- faster
- more scalable

Google

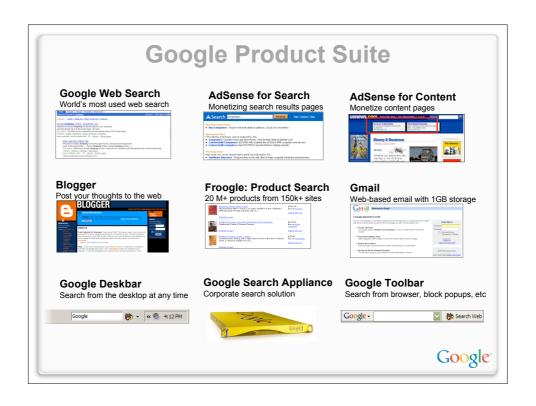
Implications for Multi-core Processors

- Multi-core processors require parallelism, but many programmers are uncomfortable writing parallel programs
- MapReduce provides an easy-to-understand programming model for a very diverse set of computing problems
 - users don't need to be parallel programming experts
 - system automatically adapts to number of cores & machines available
- Optimizations useful even in single machine, multicore environment
 - locality, load balancing, status monitoring, robustness, ...

Data + CPUs = Playground

- Substantial fraction of internet available for processing
- Easy-to-use teraflops/petabytes
- · Cool problems, great colleagues

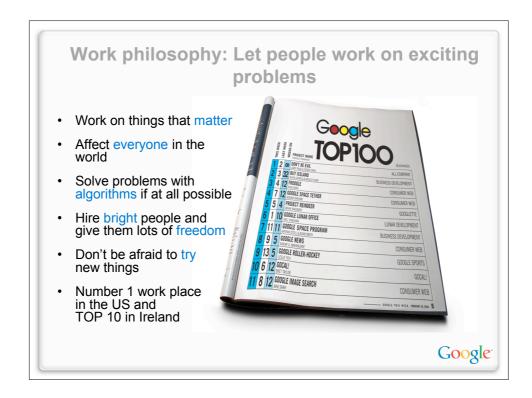




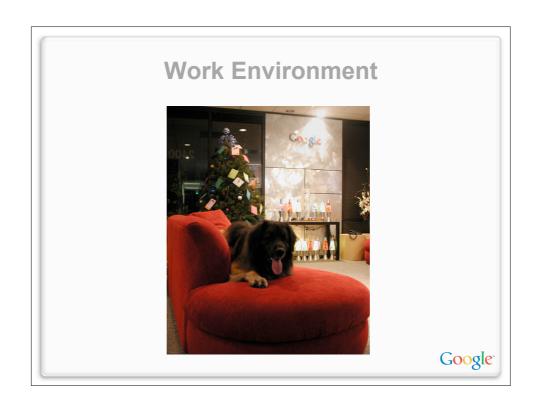
Who Does All This?

- Talented, motivated people
 - ... working in small teams (3-5 people)
 - ... on problems that matter
 - ... with freedom to explore their ideas "20% rule", access to computational resources
- It's not just search: Google has experts in...

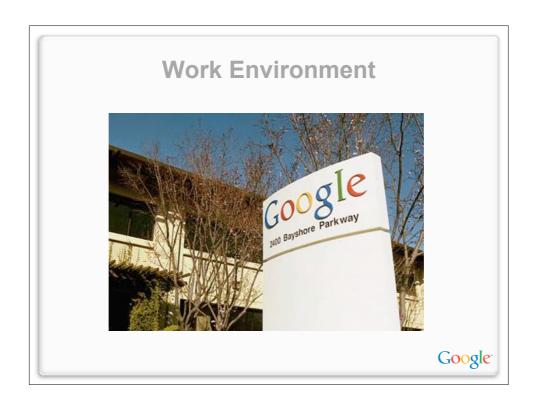
Hardware, networking, distributed systems, fault tolerance, data structures, algorithms, machine learning, information retrieval, AI, user interfaces, compilers, programming languages, statistics, product design, mechanical eng., ...











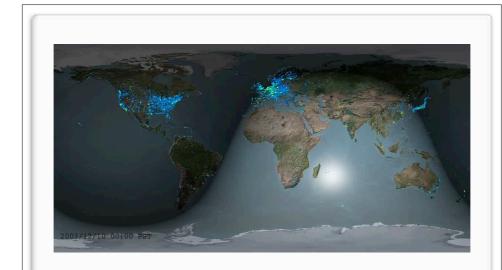
We're Hiring!

 If this sounds like fun, we have engineering positions in:

Trondheim, Zürich, Munich, London, Dublin And around the globe!

http://labs.google.com/why-google.html http://google.com/jobs

Google



http://labs.google.com/why-google.html http://google.com/jobs

The End

• Thanks to Jeff Dean for compiling most of the slides

