

CS 295B/CS 395B
Systems for Knowledge
Discovery

Under the hood of
query languages



The University of Vermont

FlumeJava: Easy, Efficient Data-Parallel Pipelines

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Abstract

MapReduce and similar systems significantly ease the task of writing data-parallel code. However, many real-world computations require a pipeline of MapReduces, and programming and managing such pipelines can be difficult. We present FlumeJava, a Java library that makes it easy to develop, test, and run efficient data-parallel pipelines. At the core of the FlumeJava library are a couple of classes that represent immutable parallel collections, each supporting a modest number of operations for processing them in parallel. Parallel collections and their operations present a simple, high-level, uniform abstraction over different data representations and execution strategies. To enable parallel operations to run efficiently, FlumeJava defers their evaluation, instead internally constructing an execution plan dataflow graph. When the final results of the parallel operations are eventually needed, FlumeJava first optimizes the execution plan, and then executes the optimized operations on appropriate underlying primitives (e.g., MapReduces). The combination of high-level abstractions for parallel data and computation, deferred evaluation and optimization, and efficient parallel primitives yields an easy-to-use system that approaches the efficiency of hand-optimized pipelines. FlumeJava is in active use by hundreds of pipeline developers within Google.

Categories and Subject Descriptors D.1.3 [Concurrent Programming]: Parallel Programming

General Terms Algorithms, Languages, Performance

Keywords data-parallel programming, MapReduce, Java

1. Introduction

Building programs to process massive amounts of data in parallel can be very hard. MapReduce [6–8] greatly eased this task for data-parallel computations. It presented a simple abstraction to users for how to think about their computation, and it managed many of the difficult low-level tasks, such as distributing and coordinating the parallel work across many machines, and coping robustly with failures of machines, networks, and data. It has been used very successfully in practice by many developers. MapReduce’s success in this domain inspired the development of a number of related systems, including Hadoop [2], LINQ/Dryad [20], and Pig [3].

MapReduce works well for computations that can be broken down into a map step, a shuffle step, and a reduce step, but for many real-world computations, a chain of MapReduce stages is required. Such data-parallel *pipelines* require additional coordination code to chain together the separate MapReduce stages, and require additional work to manage the creation and later deletion of the intermediate results between pipeline stages. The logical computation can become obscured by all these low-level coordination details, making it difficult for new developers to understand the computation. Moreover, the division of the pipeline into particular stages becomes “baked in” to the code and difficult to change later if the logical computation needs to evolve.

In this paper we present FlumeJava, a new system that aims to support the development of data-parallel pipelines. FlumeJava is a Java library centered around a few classes that represent *parallel collections*. Parallel collections support a modest number of *parallel operations* which are composed to implement data-parallel computations. An entire pipeline, or even multiple pipelines, can be implemented in a single Java program using the FlumeJava abstractions; there is no need to break up the logical computation into separate programs for each stage.

FlumeJava’s parallel collections abstract away the details of how data is represented, including whether the data is represented as an in-memory data structure, as one or more files, or as an external storage service such as a MySQL database or a Bigtable [5]. Similarly, FlumeJava’s parallel operations abstract away their implementation strategy, such as whether an operation is implemented as a local sequential loop, or as a remote parallel MapReduce invocation, or (in the future) as a query on a database or as a streaming computation. These abstractions enable an entire pipeline to be initially developed and tested on small in-memory test data, running in a single process, and debugged using standard Java IDEs and debuggers, and then run completely unchanged over large production data. They also confer a degree of adaptability of the logical FlumeJava computations as new data storage mechanisms and execution services are developed.

To achieve good performance, FlumeJava internally implements parallel operations using *deferred evaluation*. The invocation of a parallel operation does not actually run the operation, but instead simply records the operation and its arguments in an internal *execution plan* graph structure. Once the execution plan for the whole computation has been constructed, FlumeJava *optimizes* the execution plan, for example *fusing* chains of parallel operations together into a small number of MapReduce operations. FlumeJava then runs the optimized execution plan. When running the execution plan, FlumeJava chooses which strategy to use to implement each operation (e.g., local sequential loop vs. remote parallel MapReduce, based in part on the size of the data being processed), places remote computations near the data they operate on, and per-

Paper context

- Complement paper to Spark SQL
 - Why Spark SQL + CaRL pairing?
- DML SQL: what is it good for?
 - Ad hoc queries in SQL
 - Output of SQL query → input to s.t. else

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MapReduce: Simplified Data Processing on Large Clusters

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Abstract

MapReduce is a programming model and an associated implementation for processing and generating large data sets. Users specify a *map* function that processes a key/value pair to generate a set of intermediate key/value pairs, and a *reduce* function that merges all intermediate values associated with the same intermediate key. Many real world tasks are expressible in this model, as shown in the paper.

Programs written in this functional style are automatically parallelized and executed on a large cluster of commodity machines. The run-time system takes care of the details of partitioning the input data, scheduling the program's execution across a set of machines, handling machine failures, and managing the required inter-machine communication. This allows programmers without any experience with parallel and distributed systems to easily utilize the resources of a large distributed system.

Our implementation of MapReduce runs on a large cluster of commodity machines and is highly scalable: a typical MapReduce computation processes many terabytes of data on thousands of machines. Programmers find the system easy to use: hundreds of MapReduce programs have been implemented and upwards of one thousand MapReduce jobs are executed on Google's clusters every day.

1 Introduction

Over the past five years, the authors and many others at Google have implemented hundreds of special-purpose computations that process large amounts of raw data, such as crawled documents, web request logs, etc., to compute various kinds of derived data, such as inverted indices, various representations of the graph structure of web documents, summaries of the number of pages crawled per host, the set of most frequent queries in a

given day, etc. Most such computations are conceptually straightforward. However, the input data is usually large and the computations have to be distributed across hundreds or thousands of machines in order to finish in a reasonable amount of time. The issues of how to parallelize the computation, distribute the data, and handle failures conspire to obscure the original simple computation with large amounts of complex code to deal with these issues.

As a reaction to this complexity, we designed a new abstraction that allows us to express the simple computations we were trying to perform but hides the messy details of parallelization, fault-tolerance, data distribution and load balancing in a library. Our abstraction is inspired by the *map* and *reduce* primitives present in Lisp and many other functional languages. We realized that most of our computations involved applying a *map* operation to each logical "record" in our input in order to compute a set of intermediate key/value pairs, and then applying a *reduce* operation to all the values that shared the same key, in order to combine the derived data appropriately. Our use of a functional model with user-specified map and reduce operations allows us to parallelize large computations easily and to use re-execution as the primary mechanism for fault tolerance.

The major contributions of this work are a simple and powerful interface that enables automatic parallelization and distribution of large-scale computations, combined with an implementation of this interface that achieves high performance on large clusters of commodity PCs.

Section 2 describes the basic programming model and gives several examples. Section 3 describes an implementation of the MapReduce interface tailored towards our cluster-based computing environment. Section 4 describes several refinements of the programming model that we have found useful. Section 5 has performance measurements of our implementation for a variety of tasks. Section 6 explores the use of MapReduce within Google including our experiences in using it as the basis

To appear in OSDI 2004

Paper context: related work

- MapReduce (Google, OSDI 2004)

MapReduce: Simplified Data Processing on Large Clusters



The Apache™ Hadoop® project develops open-source software for reliable, scalable, distributed computing.

The Apache Hadoop software library is a framework that allows for the distributed processing of large data sets across clusters of computers using simple programming models. It is designed to scale up from single servers to thousands of machines, each offering local computation and storage. Rather than rely on hardware to deliver high-availability, the library itself is designed to detect and handle failures at the application layer, so delivering a highly-available service on top of a cluster of computers, each of which may be prone to failures.

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Latest news

Release 3.3.1 available 2021 Jun 15

This is the first stable release of Apache Hadoop 3.3.x line. It contains 697 bug fixes, improvements and enhancements since 3.3.0.

Users are encouraged to read the [overview of major changes](#) since 3.3.0. For details of 697 bug fixes, improvements, and other enhancements since the previous 3.3.0 release, please check [release notes](#) and [changelog](#) detail the changes since 3.3.0.

Ozone 1.1.0 is released 2021 Apr 17

General available(GA) release of Apache Hadoop Ozone with Volume/Bucket Quota Support, Security related enhancements, ofs/o3fs performance improvements, Recon improvements etc.

For more information check the [ozone site](#).

Modules

The project includes these modules:

- **Hadoop Common:** The common utilities that support the other Hadoop modules.
- **Hadoop Distributed File System (HDFS™):** A distributed file system that provides high-throughput access to application data.
- **Hadoop YARN:** A framework for job scheduling and cluster resource management.
- **Hadoop MapReduce:** A YARN-based system for parallel processing of large data sets.

Who Uses Hadoop?

A wide variety of companies and organizations use Hadoop for both research and production. Users are encouraged to add themselves to the Hadoop [PoweredBy wiki page](#).

Related projects

Other Hadoop-related projects at Apache include:

- **Ambari™:** A web-based tool for provisioning, managing, and monitoring Apache Hadoop clusters which includes support for Hadoop HDFS, Hadoop MapReduce, Hive, HCatalog, HBase, ZooKeeper, Oozie, Pig and Sqoop. Ambari also provides a dashboard for viewing cluster health such as heatmaps and ability to view MapReduce, Pig and Hive applications visually alongwith features to diagnose their performance characteristics in a user-friendly manner.
- **Avro™:** A data serialization system.
- **Cassandra™:** A scalable multi-master database with no single points of failure.
- **Chukwa™:** A data collection system for managing large distributed systems.
- **HBase™:** A scalable, distributed database that supports structured data storage for large tables.
- **Hive™:** A data warehouse infrastructure that provides data summarization and ad hoc querying.
- **Mahout™:** A Scalable machine learning and data mining library.

Paper context: related work

- MapReduce (Google, OSDI 2004)
- Hadoop (Yahoo! → Apache, 2006)



Pig Latin: A Not-So-Foreign Language for Data Processing

Christopher Olston*
Yahoo! Research

Benjamin Reed†
Yahoo! Research

Utkarsh Srivastava‡
Yahoo! Research

Ravi Kumar§
Yahoo! Research

Andrew Tomkins¶
Yahoo! Research

ABSTRACT

There is a growing need for ad-hoc analysis of extremely large data sets, especially at internet companies where innovation critically depends on being able to analyze terabytes of data collected every day. Parallel database products, e.g., Teradata, offer a solution, but are usually prohibitively expensive at this scale. Besides, many of the people who analyze this data are entrenched procedural programmers, who find the declarative, SQL style to be unnatural. The success of the more procedural *map-reduce* programming model, and its associated scalable implementations on commodity hardware, is evidence of the above. However, the map-reduce paradigm is too low-level and rigid, and leads to a great deal of custom user code that is hard to maintain, and reuse.

We describe a new language called *Pig Latin* that we have designed to fit in a sweet spot between the declarative style of SQL, and the low-level, procedural style of map-reduce. The accompanying system, Pig, is fully implemented, and compiles Pig Latin into physical plans that are executed over *Hadoop*, an open-source, map-reduce implementation. We give a few examples of how engineers at Yahoo! are using Pig to dramatically reduce the time required for the development and execution of their data analysis tasks, compared to using Hadoop directly. We also report on a novel debugging environment that comes integrated with Pig, that can lead to even higher productivity gains. Pig is an open-source, Apache-incubator project, and available for general use.

Categories and Subject Descriptors:

H.2.3 Database Management: Languages

General Terms: Languages.

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1. INTRODUCTION

At a growing number of organizations, innovation revolves around the collection and analysis of enormous data sets such as web crawls, search logs, and click streams. Internet companies such as Amazon, Google, Microsoft, and Yahoo! are prime examples. Analysis of this data constitutes the innermost loop of the product improvement cycle. For example, the engineers who develop search engine ranking algorithms spend much of their time analyzing search logs looking for exploitable trends.

The sheer size of these data sets dictates that it be stored and processed on highly parallel systems, such as shared-nothing clusters. Parallel database products, e.g., Teradata, Oracle RAC, Netezza, offer a solution by providing a simple SQL query interface and hiding the complexity of the physical cluster. These products however, can be prohibitively expensive at web scale. Besides, they wrench programmers away from their preferred method of analyzing data, namely writing imperative scripts or code, toward writing declarative queries in SQL, which they often find unnatural, and overly restrictive.

As evidence of the above, programmers have been flocking to the more procedural *map-reduce* [4] programming model. A map-reduce program essentially performs a group-by-aggregation in parallel over a cluster of machines. The programmer provides a map function that dictates how the grouping is performed, and a reduce function that performs the aggregation. What is appealing to programmers about this model is that there are only two high-level declarative primitives (map and reduce) to enable parallel processing, but the rest of the code, i.e., the map and reduce functions, can be written in any programming language of choice, and without worrying about parallelism.

Unfortunately, the map-reduce model has its own set of limitations. Its one-input, two-stage data flow is extremely rigid. To perform tasks having a different data flow, e.g., joins or n stages, inelegant workarounds have to be devised. Also, custom code has to be written for even the most common operations, e.g., projection and filtering. These factors

Paper context: related work

- MapReduce (Google, OSDI 2004)
- Hadoop (Yahoo! → Apache, 2006)
- Pig Latin (Yahoo!, SIGMOD 2008)



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Pig Latin: A Not-So-Foreign Language for Data Processing

Hive – A Petabyte Scale Data Warehouse Using Hadoop

Ashish Thusoo, Joydeep Sen Sarma, Namit Jain, Zheng Shao, Prasad Chakka, Ning Zhang, Suresh Antony, Hao Liu and Raghotham Murthy
Facebook Data Infrastructure Team

Abstract— The size of data sets being collected and analyzed in the industry for business intelligence is growing rapidly, making traditional warehousing solutions prohibitively expensive. Hadoop [1] is a popular open-source map-reduce implementation which is being used in companies like Yahoo, Facebook etc. to store and process extremely large data sets on commodity hardware. However, the map-reduce programming model is very low level and requires developers to write custom programs which are hard to maintain and reuse. In this paper, we present *Hive*, an open-source data warehousing solution built on top of Hadoop. Hive supports queries expressed in a SQL-like declarative language - *HiveQL*, which are compiled into map-reduce jobs that are executed using Hadoop. In addition, *HiveQL* enables users to plug in custom map-reduce scripts into queries. The language includes a type system with support for tables containing primitive types, collections like arrays and maps, and nested compositions of the same. The underlying IO libraries can be extended to query data in custom formats. Hive also includes a system catalog - *Metastore* - that contains schemas and statistics, which are useful in data exploration, query optimization and query compilation. In Facebook, the Hive warehouse contains tens of thousands of tables and stores over 700TB of data and is being used extensively for both reporting and ad-hoc analyses by more than 200 users per month.

I. INTRODUCTION

Scalable analysis on large data sets has been core to the functions of a number of teams at Facebook - both engineering and non-engineering. Apart from ad hoc analysis and business intelligence applications used by analysts across the company, a number of Facebook products are also based on analytics. These products range from simple reporting

data. As a result we started exploring Hadoop as a technology to address our scaling needs. The fact that Hadoop was already an open source project that was being used at petabyte scale and provided scalability using commodity hardware was a very compelling proposition for us. The same jobs that had taken more than a day to complete could now be completed within a few hours using Hadoop.

However, using Hadoop was not easy for end users, especially for those users who were not familiar with map-reduce. End users had to write map-reduce programs for simple tasks like getting raw counts or averages. Hadoop lacked the expressiveness of popular query languages like SQL and as a result users ended up spending hours (if not days) to write programs for even simple analysis. It was very clear to us that in order to really empower the company to analyze this data more productively, we had to improve the query capabilities of Hadoop. Bringing this data closer to users is what inspired us to build Hive in January 2007. Our vision was to bring the familiar concepts of tables, columns, partitions and a subset of SQL to the unstructured world of Hadoop, while still maintaining the extensibility and flexibility that Hadoop enjoyed. Hive was open sourced in August 2008 and since then has been used and explored by a number of Hadoop users for their data processing needs.

Right from the start, Hive was very popular with all users within Facebook. Today, we regularly run thousands of jobs on the Hadoop/Hive cluster with hundreds of users for a wide variety of applications starting from simple summarization jobs to business intelligence, machine learning applications and to also support Facebook product features.

Paper context: related work

- MapReduce (Google, OSDI 2004)
- Hadoop (Yahoo! → Apache, 2006)
- Pig Latin (Yahoo!, SIGMOD 2008)
- Hive (Facebook, IEEE ICDE 2010)





Pig Latin: A Not-So-Foreign Language for Data Processing

Hive – A Petabyte Scale Data Warehouse Using

FlumeJava: Easy, Efficient Data-Parallel Pipelines

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Abstract

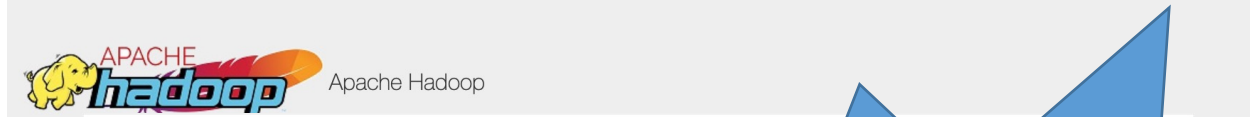
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- MapReduce (Google, OSDI 2004)
- Hadoop (Yahoo! → Apache, 2006)
- Pig Latin (Yahoo!, SIGMOD 2008)
- Hive (Facebook, IEEE ICDE 2010)
- FlumeJava (Google, PLDI 2010)
- ...
- Spark SQL (Academia, SIGMOD 2015)



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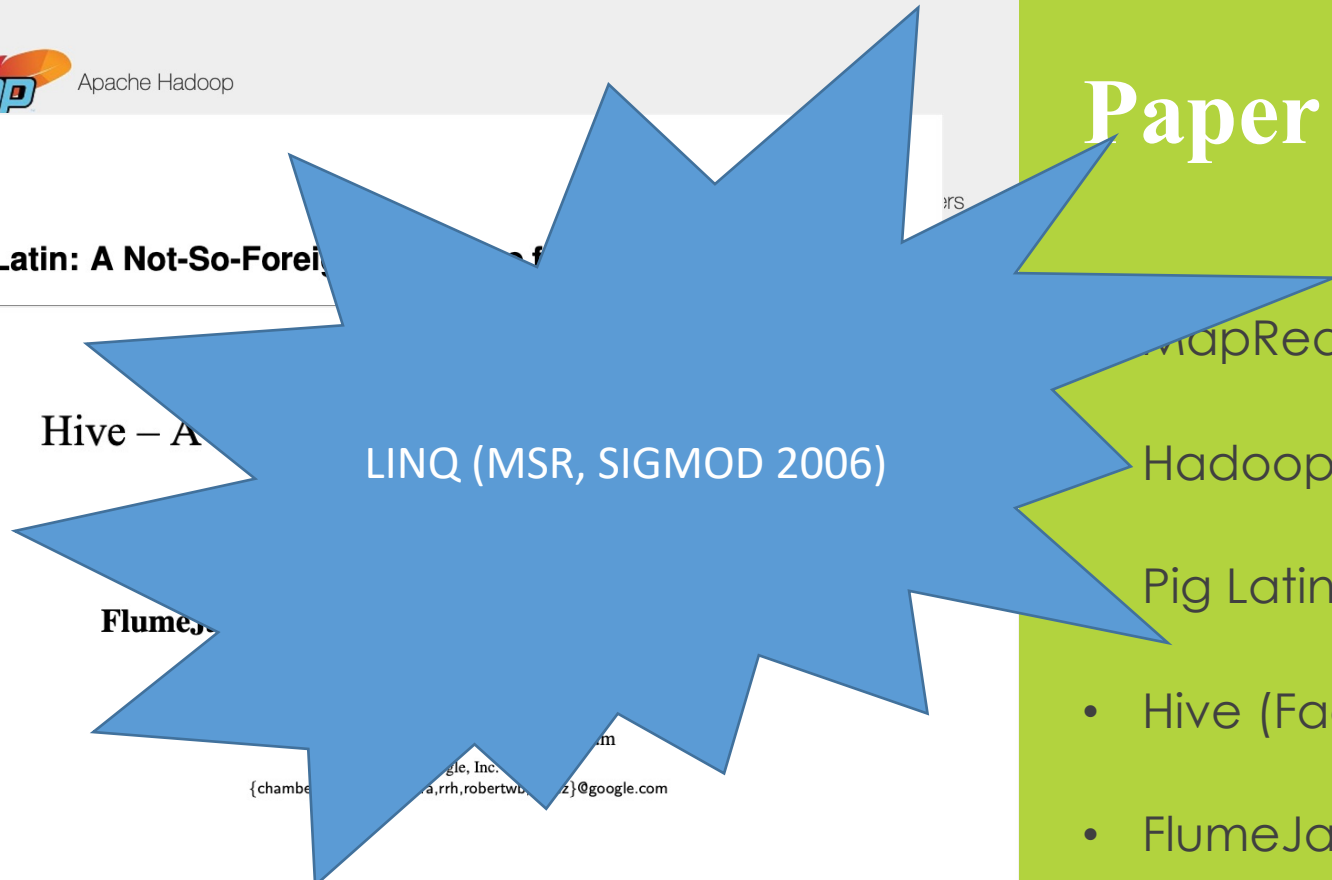
Pig Latin: A Not-So-Foreign Language

Hive – A Data Warehouse

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FlumeJava

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MapReduce (Google, OSDI 2004)

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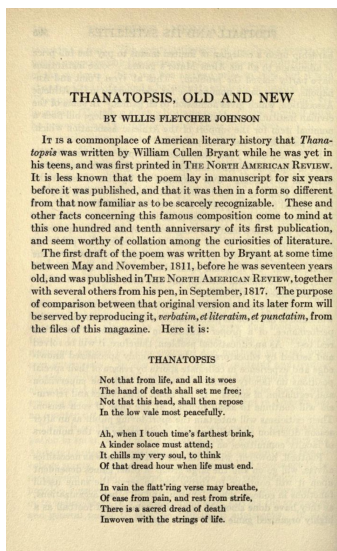
...

- Spark SQL (Academia, SIGMOD 2015)



Paper context: data format

Raw non-digital text



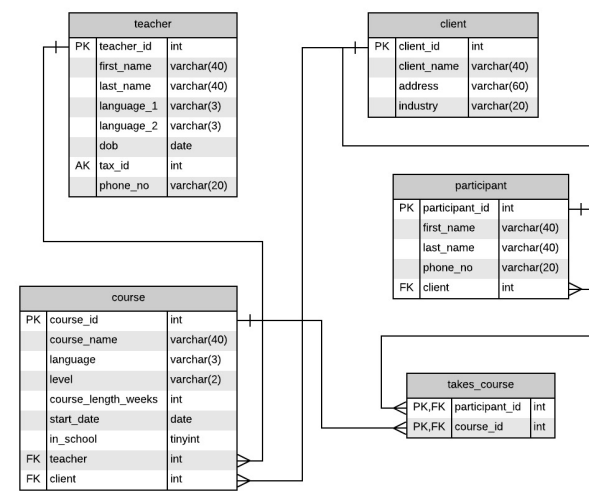
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  </head>
  <body>
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      <p class="paper_authors"></p>
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        <a href="http://graphics.stanford.edu/~kayof/kayof.html">Stanford University</a>
      </div>
      <div style="border-bottom: 1px solid #000; padding-bottom: 10px;">Jan 13, 2021</div>
      <div>
        
      </div>
      <p>Last quarter was, surprisingly, one of my most enjoyable quarters teaching. Lecture attendance was up, student-staff interaction was up, and my co-instructor " " and I felt we had a better handle than ever before on whether students were following the lecture. By the end of the quarter, a higher percentage of the class was attending live lectures than previous quarters. " "
      </p>
      <p>The main difference between this last quarter and my previous nine years of teaching? This 100+ student course took place in a new virtual classroom that I designed. I first taught on Zoom in Spring 2020 and got a sense of what worked and didn't work virtually. When it came time to teach " " Fall 2020, I decided to pitch my co-instructor Kuntle on a new, experimental format. " "
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      <p>After using my virtual classroom, I don't want to go back to vanilla in-person teaching. The virtual classroom has made it easy for me to experiment with different enhanced teaching mechanisms I'd been hearing about for years. Not only has it been easier to communicate with my students than ever before, I've also been interacting with a wider, more diverse set of students. " "
      </p>
      <p>To help other instructors during the pandemic and beyond, I've put together this blog post explaining how I translated the main elements of an in-person classroom to video-and what enhancements I added. Note that all
```

Pandas Dataframe

```
In [10]: df.iloc[3400]
Out[10]:
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seed            127525
t               1585
right          False
missed_ball    160.862
xpos_ball      48.1418
xpos_ball_prev 159.235
ypos_ball_prev 51.796
xpos_pad       160
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is_far_left    False
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score         270
small         fast
ball_down     False
xdist_ball_pad 0.862097
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num_bricks_left 54
bricks_in_col_00 2
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Relational Database



Text Formatting

Nested markup tags

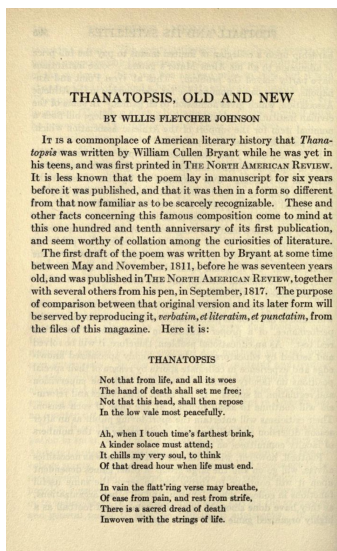
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Typed records/objects + Relations

Structure

Paper context: data format

Raw non-digital text



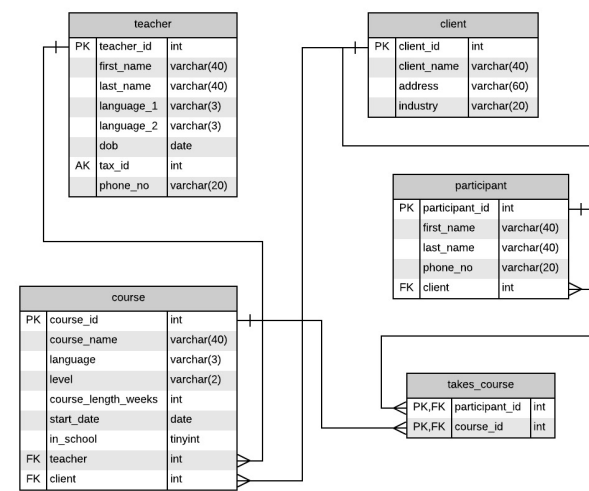
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        <a href="https://arsenalfc.stanford.edu/kunle">Kunle Oluokun</a>
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is_far_left    False
is_far_right   False
score          270
small          fast
ball_down      False
xdist_ball_pad 0.862097
ydist_ball_pad 94.8582
l2_ball_pad    94.8621
num_bricks_left 54
bricks_in_col_00 2
bricks_in_col_01 0
bricks_in_col_02 2
bricks_in_col_03 3
bricks_in_col_04 3
bricks_in_col_05 1
bricks_in_col_06 1
bricks_in_col_07 4
```

Relational Database



Text Formatting

Nested markup tags

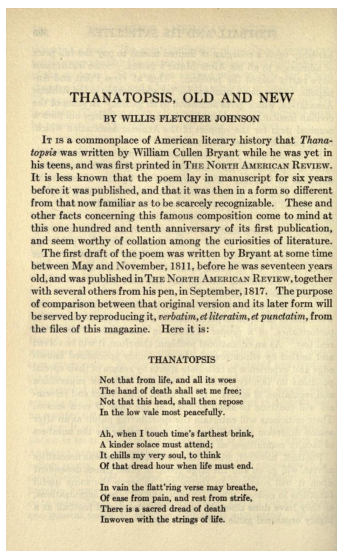
Typed records/objects

Typed records/objects + Relations

Pre-Processing

Paper context: data format

Raw non-digital text



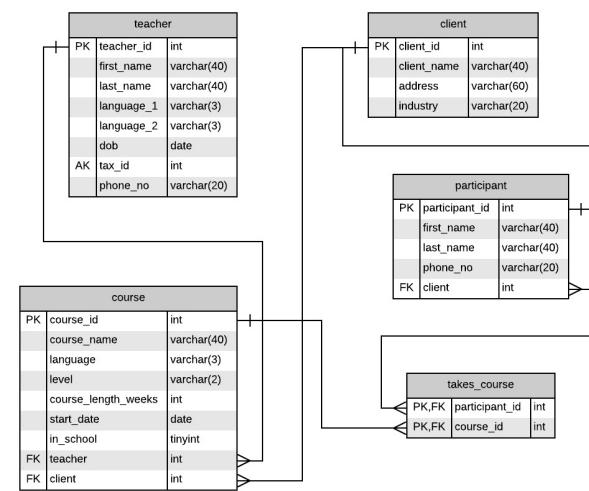
Webpage source

```
<!DOCTYPE html>
<html>
  <head>
    <title>Virtual Teaching Doesn't Mean Giving Up on the Live Lectures</title>
    <link rel="preconnect" href="https://fonts.gstatic.com">
    <link href="https://fonts.googleapis.com/css2?family=Crimson+Text:wght@400;600&display=swap" rel="stylesheet">
    <link rel="stylesheet" type="text/css" href="style.css">
  </head>
  <body>
    <div class="home_container">
      <div class="paper_title">Virtual Teaching Doesn't Mean Giving Up on the Live Lectures</div>
      <p class="paper_authors"></p>
      <div>
        <a href="http://graphics.stanford.edu/~kayvonf">Kayvon Fatahalians</a>
        <a href="https://arsenalfc.stanford.edu/kunle">Kunle Oluokotun</a>
        </div>
      <div style="border-bottom: 1px solid #000; padding-bottom: 10px;">Jan 13, 2021</div>
      
      <p>Last quarter was, surprisingly, one of my most enjoyable quarters teaching. Lecture attendance was up, student-staff interaction was up, and my co-instructor " " and I felt we had a better handle than ever before on whether students were following the lecture. By the end of the quarter, a higher percentage of the class was attending live lectures than previous quarters. " "
      <p>The main difference between this last quarter and my previous nine years of teaching? This 100+ student course took place in a new virtual classroom that I designed. I first taught on Zoom in Spring 2020 and got a sense of what worked and didn't work virtually. When it came time to teach " " Fall 2020, I decided to pitch my co-instructor Kunle on a new, experimental format. " "
      <p>After using my virtual classroom, I don't want to go back to vanilla in-person teaching. The virtual classroom has made it easy for me to experiment with different enhanced teaching mechanisms I'd been hearing about for years. Not only has it been easier to communicate with my students than ever before, I've also been interacting with a wider, more diverse set of students. " "
      <p>To help other instructors during the pandemic and beyond, I've put together this blog post explaining how I translated the main elements of an in-person classroom to video-and what enhancements I added. Note that all
```

Pandas Dataframe

```
In [10]: df.iloc[3400]
Out[10]:
agent_name      Target
seed            127525
t               1585
right          False
missed_ball     160.862
xpos_ball       48.1418
xpos_ball_prev  159.235
ypos_ball_prev  51.796
xpos_pad        160
ypos_pad        143
xpos_pad_prev  160
ypos_pad_prev  143
board_alive     60877497971844372295859610308414
is_far_left     False
is_far_right    False
score           270
small           fast
ball_down       False
xdist_ball_pad  0.862097
ydist_ball_pad  94.8582
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num_bricks_left 54
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bricks_in_col_04 3
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bricks_in_col_06 1
bricks_in_col_07 4
```

Relational Database



Text Formatting

Nested markup tags

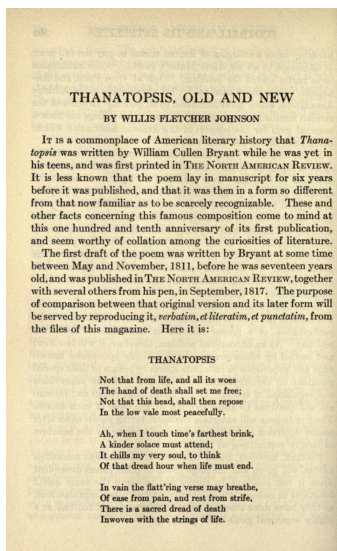
Typed records/objects

Typed records/objects + Relations

Domain knowledge

Discussion: How might structure encode domain knowledge?

Paper context: data format



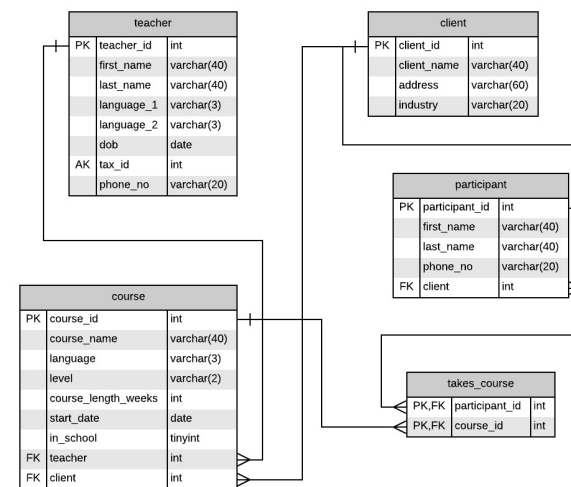
Text Formatting

```
<!DOCTYPE html>
<html>
  <head>
    <title>Virtual Teaching Doesn't Mean Giving Up on the Live Lecture</title>
    <link rel="preconnect" href="https://fonts.gstatic.com">
    <link href="https://fonts.googleapis.com/css2?family=Crimson+Text:wght@400;600&display=swap" rel="stylesheet">
    <link rel="stylesheet" type="text/css" href="style.css">
  </head>
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        </div>
      <div style="border-bottom: 1px solid #000; padding-bottom: 10px;">Jan 13, 2021</div>
      <div>
        
      </div>
      <p>Last quarter was, surprisingly, one of my most enjoyable quarters teaching. Lecture attendance was up, student-staff interaction was up, and my co-instructor " and I felt we had a better handle than ever before on whether students were following the lecture. By the end of the quarter, a higher percentage of the class was attending live lectures than previous quarters. "
      </p>
      <p>The main difference between this last quarter and my previous nine years of teaching? This 100+ student course took place in a new virtual classroom that I designed. I first taught on Zoom in Spring 2020 and got a sense of what worked and didn't work virtually. When it came time to teach "
      <a href="http://cs149.stanford.edu/fall20">Parallel Computing</a>
      </p>
      <p>Fall 2020, I decided to pitch my co-instructor Kunte on a new, experimental format. "
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is_far_left    False
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score          270
small         94.8582
pad_width     94.8621
ball_speed    54
ball_down     2
xdist_ball_pad 0
ydist_ball_pad 0
12_ball_pad   2
num_bricks_left 3
bricks_in_col_00 3
bricks_in_col_01 3
bricks_in_col_02 3
bricks_in_col_03 3
bricks_in_col_04 1
bricks_in_col_05 1
bricks_in_col_06 1
bricks_in_col_07 4
```

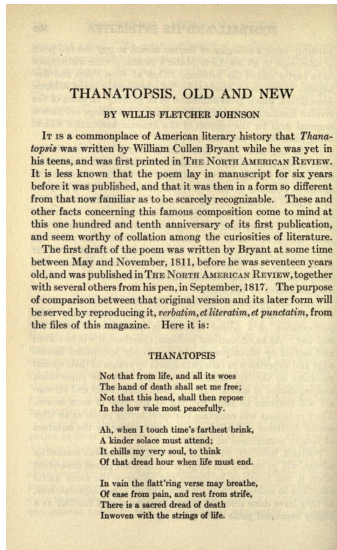
Typed records/objects



Typed records/objects + Relations

Paper context: data format

Text Formatting



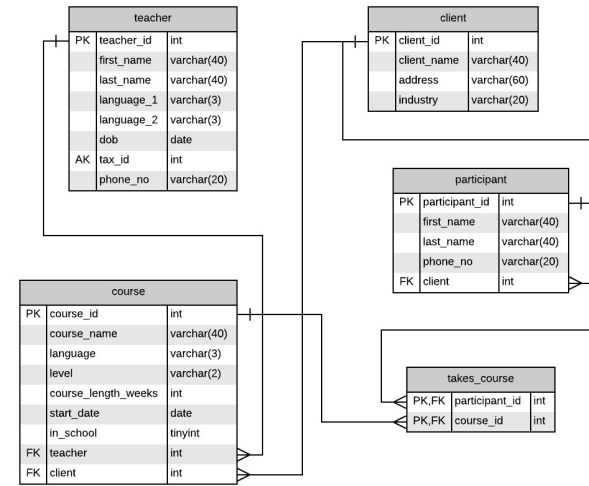
Nested markup tags

```
<!DOCTYPE html>
<html>
  <head>
    <title>Virtual Teaching Doesn't Mean Giving Up on the Live Lectures</title>
    <link rel="preconnect" href="https://fonts.gstatic.com">
    <link href="https://fonts.googleapis.com/css2?family=Crimson+Text:wght@400;600&display=swap" rel="stylesheet">
    <link rel="stylesheet" type="text/css" href="style.css">
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        <a href="http://cs149.stanford.edu/fall20">Parallel Computing</a>
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    </div>
  </body>
</html>
```

Typed records/objects

```
In [10]: df.iloc[3400]
Out[10]:
agent_name      Target
seed            127525
t               Right
action          False
missed_ball     160.862
xpos_ball       48.1418
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ypos_ball_prev  51.796
xpos_pad        160
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is_far_left     False
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score           270
pad_width       small
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xdist_ball_pad  0.862097
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bricks_in_col_04 3
bricks_in_col_05 1
bricks_in_col_06 1
bricks_in_col_07 4
```

Typed records/objects + Relations



MapReduce

FlumeJava

Spark

Hive

Indri: A language-model based search engine for complex queries (extended version)

Trevor Strohman, Donald Metzler, Howard Turtle and W. Bruce Croft
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Amherst, MA, 01003, USA
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Keywords: Search and Retrieval, Question Answering

Abstract

Search engines are a critical tool for intelligence analysis. A number of innovations for search have been introduced since research with an emphasis on analyst needs began in the TIPSTER project. For example, the Inquery search engine introduced support for specification of complex queries in a probabilistic inference network framework. Recent research on language modeling has led to the development of Indri, a search engine that combines the best features of inference nets and language modeling in an architecture designed for large-scale applications. In this paper, we describe the Indri system and show how the query language is designed to support modern language technologies. We also present results demonstrating that Indri is both effective and efficient.

1. Introduction

Search and detection technology has been a focus of DARPA and ARDA research programs since the TIPSTER program began in the early 1990s (Harman 1992). A number of innovations have been developed in this research, resulting in very significant improvements in the effectiveness of search tools. The Inquery search engine (Callan *et al.* 1995), developed at the University of Massachusetts for the TIPSTER project, provided a query language capable of representing complex queries in a probabilistic framework and was used in a number of government and commercial applications.

In the years since Inquery was developed, there has been significant progress, both in terms of information retrieval (IR) research and in the development of other language technologies and applications, such as information extraction and question answering. These new technologies interact with search and provide new requirements for a search engine. In addition, the ever-increasing volume of searchable data requires that search engines be scalable to the level

of multi-terabytes. In response to these requirements, we have recently developed Indri, a scalable search engine that combines the advantages of the inference net framework used in Inquery with the language modeling approach to retrieval that has been the subject of much recent IR research (Croft and Lafferty 2003). Indri is part of the ARDA-sponsored Lemur project¹.

The Indri search engine is designed to address the following goals:

- The query language should support complex queries involving evidence combination and the ability to specify a wide variety of constraints involving proximity, syntax, extracted entities, and document structure.
- The retrieval model should provide superior effectiveness across a range of query and document types (e.g. Web, cross-lingual, ad-hoc²).
- The query language and retrieval model should support retrieval at different levels of granularity (e.g. sentence, passage, XML field, document, multi-document).
- The system architecture should support very large databases, multiple databases, optimized query execution, fast indexing, concurrent indexing and querying, and portability.

In this paper, we describe the most important aspects of the Indri retrieval model, query language, and system architecture. We give some examples of the types of complex queries that can be supported, and illustrate the effectiveness and efficiency of the system using results from the 2004 TREC Terabyte track.

¹ <http://www.lemurproject.org>. Indri is available as a download from this site.

² “ad-hoc” refers to the TREC track that focuses on finding as many relevant documents as possible using queries of varying complexity

Paper context

- Venue – not top-tier
- Authors: big names in IR
 - Have many other, better papers
 - 650 citations – not bad!
- Writing not most accessible
 - Very short
 - Highly specialized target audience

So why I did I choose this paper?

Few papers document the intermediate DSL

Operator	Name	Description
#uwN(<i>t</i> ₁ <i>t</i> ₂ ...)	Unordered Window	Matches unordered text
#odN(<i>t</i> ₁ <i>t</i> ₂ ...)	Ordered Window	Matches ordered text
#any: <i>field</i>	Any operator	Finds any text appearing in a field named <i>field</i>
term. <i>field</i>	Field restriction	Finds the word <i>term</i> appearing in a field named <i>field</i>
#combine(<i>q</i> ₁ <i>q</i> ₂ ...)	Combine operator	Combines beliefs from other operators to form a single score for a document
#weight(<i>w</i> ₁ <i>q</i> ₁ <i>w</i> ₂ <i>q</i> ₂ ...)	Weight operator	Combines beliefs from other operators to form a single score for a document, using weights to indicate which operators should be trusted most
#greater(<i>field</i> <i>n</i>)	Numeric range operators	Finds any occurrence of <i>field</i> with a numeric value less than, greater than, or equal to <i>n</i>
#less(<i>field</i> <i>n</i>)		
#equal(<i>field</i> <i>n</i>)		
#date:before(<i>d</i>)	Date range operators	Finds any occurrence of a date occurring before or after a date, or between two dates.
#date:after(<i>d</i>)		
#date:between(<i>b</i> <i>a</i>)		
#operator[<i>field</i>](<i>q</i> ₁ <i>q</i> ₂ ...)	Extent retrieval	Evaluates <i>operator</i> on every occurrence of <i>field</i> ; useful for passage retrieval
#filrej(<i>c</i> <i>s</i>)	Filter reject	Evaluate the expression <i>s</i> only if <i>c</i> is not satisfied
#filreq(<i>c</i> <i>s</i>)	Filter require	Evaluate the expression <i>s</i> only if <i>c</i> is satisfied

Table 1: Indri query language operators

Consider the following information need: “I want paragraphs from news feed articles published between 1991 and 2000 that mention a person, a monetary amount, and the company InfoCom.”

This need can be expressed in the following Indri query:

```
#filreq(  
  #band( NewsFeed.doctype  
    #date:between(1991 2000) )  
  #combine[paragraph] (  
    #any:person  
    #any:money InfoCom ) )
```

How does this differ from SQL?

Operator	Name	Description
#uwN(<i>t</i> ₁ <i>t</i> ₂ ...)	Unordered Window	Matches unordered text
#odN(<i>t</i> ₁ <i>t</i> ₂ ...)	Ordered Window	Matches ordered text
#any: <i>field</i>	Any operator	Finds any text appearing in a field named <i>field</i>
term. <i>field</i>	Field restriction	Finds the word <i>term</i> appearing in a field named <i>field</i>
#combine(<i>q</i> ₁ <i>q</i> ₂ ...)	Combine operator	Combines beliefs from other operators to form a single score for a document
#weight(<i>w</i> ₁ <i>q</i> ₁ <i>w</i> ₂ <i>q</i> ₂ ...)	Weight operator	Combines beliefs from other operators to form a single score for a document, using weights to indicate which operators should be trusted most
#greater(<i>field</i> <i>n</i>)	Numeric range operators	Finds any occurrence of <i>field</i> with a numeric value less than, greater than, or equal to <i>n</i>
#less(<i>field</i> <i>n</i>)		
#equal(<i>field</i> <i>n</i>)		
#date:before(<i>d</i>)	Date range operators	Finds any occurrence of a date occurring before or after a date, or between two dates.
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#date:between(<i>b</i> <i>a</i>)	Extent retrieval	Evaluates <i>operator</i> on every occurrence of <i>field</i> ; useful for passage retrieval
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    #date:between(1991 2000) )  
  #combine[paragraph] (  
    #any:person  
    #any:money InfoCom ) )
```

Not bound by schema

e.g., don't need to know column names

use ML to select relevant documents

An Introduction to Neural Information Retrieval

Suggested Citation: Bhaskar Mitra and Nick Craswell (2018), "An Introduction to Neural Information Retrieval", : Vol. xx, No. xx, pp 1–18. DOI: 10.1561/XXXXXXXXXX.

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now
the essence of knowledge
Boston — Delft

What kind of ML do we use?

Today: whatever is hot in ML

- Neural nets
 - Vanilla deep networks
 - GANs
 - Attention networks
- Word embeddings

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Montreal, Canada
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Improvements That Don't Add Up: Ad-Hoc Retrieval Results Since 1998

Timothy G. Armstrong, Alistair Moffat, William Webber, Justin Zobel
Computer Science and Software Engineering
The University of Melbourne
Victoria 3010, Australia
{tgar,alistair,wew,jz}@cse.unimelb.edu.au

ABSTRACT

The existence and use of standard test collections in information retrieval experimentation allows results to be compared between research groups and over time. Such comparisons, however, are rarely made. Most researchers only report results from their own experiments, a practice that allows lack of overall improvement to go unnoticed. In this paper, we analyze results achieved on the TREC Ad-Hoc, Web, Terabyte, and Robust collections as reported in SIGIR (1998–2008) and CIKM (2004–2008). Dozens of individual published experiments report effectiveness improvements, and others claim statistical significance. Dozens of individual experiments report effectiveness improvements, but the original TREC systems. And in only a handful of experiments is the score of the best TREC automatic run exceeded. Given this finding, we question the value of ad-hoc experimentation over the long-term, and propose that the community adopt a practice of regular longitudinal comparison on measurable progress, or at least prevent the lack of it from going unnoticed. We describe an online database of retrieval runs that facilitates such a practice.

the 1960s (Cleverdon, 1967, 1991). These established the standard methodology for assessment of retrieval effectiveness: a test collection consisting of a fixed document corpus, a set of topics or queries, and judgments indicating which documents are relevant to each topic. To measure a retrieval system, the queries are run against the corpus, returning a ranked list of documents or runs for each query. The group of runs a system returns for a set of topics will be referred to here as a system's *retrieval*. The runs are ranked using a measure such as mean average precision (MAP) or recall at precision (R@P) (Harman, 1995; Moffat and Zobel, 2008). In collaborative experiments, multiple groups submit systems that are compared against each other. But in laboratory work, a typical scenario considered in this paper, as few as one system may be used, one implementing a new technique, the other providing a baseline for comparison. The validity of the new technique is tested by comparing its score to the baseline, and any apparent improvement is then tested with a statistical significance test (Zobel, 1998; Sanderson and Zobel, 2005; Smucker et al., 2007). Creating test collections is costly. The document corpus must be collected; topics must be formulated, and most expensive of all, relevance judgments must be performed. However, once a test collection has been created, using and reusing it is cheap, as no further human involvement is required in the evaluation process. This there is a strong incentive for researchers to reuse existing test data, it does offer one great advantage: it allows us to compare the results of different research experiments; it allows us to compare experiments on the same collection; it allows us to compare scores across different, privately-formatted collections, comparing scores is straightforward and informative. However, if researchers scores is straightforward and informative. However, if researchers scale, high-quality test collections are available to it several large-scale, high-quality test collections created through collaborative effort (Voth and Harman, 2005). Founded at the start of the 1990s, TREC is an annual experiment involving many research groups working on a range of retrieval tasks. The TREC effort collects sizeable document corpora, formulates many research tasks, and provides a rich resource for multi-gigabyte document sets (Zobel, 1998). The document sets are used in test collection construction and comparative evaluation of subsequent retrieval innovations. As a result, the community is in the enviable position of being able to conduct experiments that are deterministic, completely repeatable,

Categories and Subject Descriptors: H.3.4 Information Storage and Retrieval: Systems and software—performance evaluation.
General Terms: Experimentation, Measurement, Standardization.
Keywords: Retrieval experiment, evaluation, system measurement, survey.

1. INTRODUCTION
Information retrieval (IR) research has a strong tradition of empirical evaluation, stretching back to the Cranfield experiments of

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purpose of research, teaching, or systematic downloading is prohibited without ex-



What kind of ML do we use?

Today: whatever is hot in ML

- Neural nets
- Vanilla deep networks
- GANs
- Attention networks
- Word embeddings

But does it really work?

An Introduction to Neural Information Retrieval

Suggested Citation: Bhaskar Mitra and Nick Craswell (2018), "An Introduction to Neural Information Retrieval", : Vol. xx, No. xx, pp 1–18. DOI: 10.1561/XXXXXXX.

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bmitra@microsoft.com

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Bellevue, USA

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Computer Science and Software Engineering
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Victoria 3010, Australia
{tgar,alistair,webb,jz}@case.unimelb.edu.au

ABSTRACT

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Categories and Subject Descriptors:
H.3.4 Information Storage and Retrieval: Systems and software—performance evaluation.

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OPINION

The Neural Hype and Comparisons Against Weak Baselines

Jimmy Lim
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1 Introduction

Recently, the machine learning community paused in a moment of self-reflection. In a widely-discussed paper at ICLR 2018, Sculley et al. [13] wrote: “We observe that the rate of empirical advancement may not have been matched by consistent increase in the level of empirical rigor across the field as a whole.” Their primary complaint is the development of a “research and publication culture that emphasizes wins” (emphasis in original), which typically means “demonstrating that a new method beats previous methods on a given task or benchmark”. An apt description might be “leaderboard chasing”—and for many vision and NLP tasks, this isn’t a metaphor. There are literally centralized leaderboards that track incremental progress, down to the fifth decimal point, some persisting over years, accumulating dozens of entries.

Sculley et al. remind us that “the goal of science is not wins, but knowledge”. The structure of the scientific enterprise today (pressure to publish, pace of progress, etc.) means that “winning” and “doing good science” are often not fully aligned. To wit, they cite a number of papers showing that recent advances in neural networks could very well be attributed to mundane issues like better hyperparameter optimization. Many results can’t be reproduced, and some observed improvements might just be noise.

I’d like to suggest that similar self-examination is needed in our own community, especially with respect to the hype surrounding neural IR approaches. They are new, shiny, and have enchanted our youngest members—new students, many of whom find it hard to believe that anything even existed before neural networks. Yet it is unclear to me, at least for “classic” *ad hoc* retrieval problems without vast quantities of training data from behavior logs, whether neural techniques are actually more effective in absolute terms. As Sculley et al. suggest, (at least some) progress

What kind of ML do we use?

Today: whatever is hot in ML

- Neural nets
- Vanilla deep networks
- GANs
- Attention networks
- Word embeddings

But does it really work?

Bayesian Statistics Without Tears: A Sampling–Resampling Perspective

A. F. M. SMITH and A. E. GELFAND*

Even to the initiated, statistical calculations based on Bayes's Theorem can be daunting because of the numerical integrations required in all but the simplest applications. Moreover, from a teaching perspective, introductions to Bayesian statistics—if they are given at all—are circumscribed by these apparent calculational difficulties. Here we offer a straightforward sampling–resampling perspective on Bayesian inference, which has both pedagogic appeal and suggests easily implemented calculation strategies.

KEY WORDS: Bayesian inference; Exploratory data analysis; Graphical methods; Influence; Posterior distribution; Prediction; Prior distribution; Random variate generation; Sampling–resampling techniques; Sensitivity analysis; Weighted bootstrap.

1. INTRODUCTION

Given data x obtained under a parametric model indexed by finite-dimensional θ , the Bayesian learning process is based on

$$p(\theta|x) = \frac{l(\theta; x)p(\theta)}{\int l(\theta; x)p(\theta) d\theta}, \quad (1.1)$$

the familiar form of Bayes's Theorem, relating the posterior distribution $p(\theta|x)$ to the likelihood $l(\theta; x)$, and the prior distribution is $p(\theta)$. If $\theta = (\phi, \psi)$, with interest centering on ϕ , the joint posterior distribution is marginalized to give the posterior distribution for ϕ ,

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for suitable choices of $m(\cdot)$.

Thus, in the continuous case, the integration operation plays a fundamental role in Bayesian statistics, whether it is for calculating the normalizing constant in

(1.1), the marginal distribution in (1.2), or the expectation in (1.3). However, except in simple cases, explicit evaluation of such integrals will rarely be possible, and realistic choices of likelihood and prior will necessitate the use of sophisticated numerical integration or analytic approximation techniques (see, for example, Smith et al. 1985, 1987; Tierney and Kadane, 1986). This can pose problems for the applied practitioner seeking routine, easily implemented procedures. For the student, who may already be puzzled and discomforted by the intrusion of too much calculus into what ought surely to be a simple, intuitive, statistical learning process, this can be totally off-putting.

In the following sections, we address this problem by taking a new look at Bayes's Theorem from a sampling–resampling perspective. This will open the way to both easily implemented calculations and essentially calculus-free insight into the mechanics and uses of Bayes's Theorem.

2. FROM DENSITIES TO SAMPLES

As a first step, we note the essential duality between a sample and the density (distribution) from which it is generated. Clearly, the density generates the sample; conversely, given a sample we can approximately recreate the density (as a histogram, a kernel density estimate, an empirical cdf, or whatever).

Suppose we now shift the focus in (1.1) from densities to samples. In terms of densities, the inference process is encapsulated in the updating of the prior density $p(\theta)$ to the posterior density $p(\theta|x)$ through the medium of the likelihood function $l(\theta; x)$. Shifting to samples, this corresponds to the updating of a sample from $p(\theta)$ to a sample from $p(\theta|x)$ through the likelihood function $l(\theta; x)$.

In Section 3, we examine two resampling ideas that provide techniques whereby samples from one distribution may be modified to form samples from another distribution. In Section 4, we illustrate how these ideas may be utilized to modify prior samples to posterior samples, as well as to modify posterior samples arising under one model specification to posterior samples arising under another. An illustrative example is provided in Section 5.

3. TWO RESAMPLING METHODS

Suppose that a sample of random variates is easily generated, or has already been generated, from a continuous density $g(\theta)$, but that what is really required is a sample from a density $h(\theta)$ absolutely continuous with

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What kind of ML do we use?

Then: probabilistic language models

- Famous, highly influential paper
- Bayesian approaches are quite old
- Needed hardware to catch up to actually be useful
- Peak Bayesian language modeling
 - 1962 – first year over 100 papers
 - Steady increase until 2008 (~12k → 24k)
 - Overall trend: still increasing, more fluctuation

(has "cooled off")

https://app.dimensions.ai/discover/publication?search_mode=content&search_text=probabilistic%20language%20models%20&search_type=kws&search_field=full_search

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What is a language model?

Probabilistic model that takes text input:

$P(\text{query} \mid \text{document})$

$P(\text{query} \mid \text{passage})$

$P(\text{tag} \mid \text{document})$

We use the LM for prediction, classification, etc.

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What is tf-idf?

tf-idf: “term frequency – inverse document frequency”

- statistical, not probabilistic
- old and still shockingly good

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Bayesian modeling

Important concepts:

- “Bayesian” is more than Bayes Rule
- Belief vs. probability
- Joint vs. conditional probabilities



Bayesian modeling

Important concepts:

- **“Bayesian” is more than Bayes Rule**
 - Frequentist – counts
 - Philosophical – some underlying true phenomenon
 - Assumptions – constant or equally likely
 - Bayesian -- belief
 - Easier to encode domain-specific knowledge



Bayesian modeling

Important concepts:

- “Bayesian” is more than Bayes Rule
- **Belief vs. Probability**
 - Belief encodes possible worlds



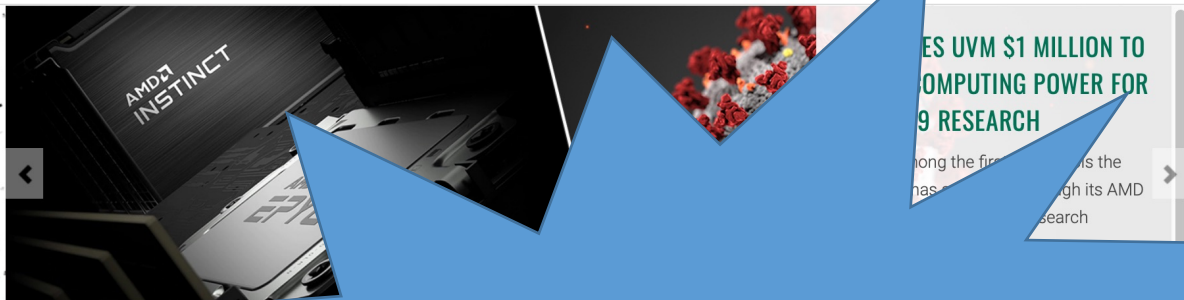
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- **Joint vs. conditional probabilities**
 - Posterior is may not have closed form
 - May still need to marginalize



MENU VERMONT ADVANCED COMPUTING CORE



Who here has had a job time out, cancelled, or fail on them?

Three high performance computing systems: BlackDiamond, Bluemoon, and ... computation, low-latency ... through ...

Various de ...

- VACC account h ...
- UVM facu ...

connecting to the ... running a job, and ...

more ...

Dashboard
For account owners (Pis), not sponsored users

Services
Onboarding for those new to performance computing

SchedMD

ENHANCED BY Google

slurm
workload manager
Version 21.08

Documentation

NOTE: This documentation is for Slurm version 21.08.
Documentation for older versions of Slurm are distributed with the source, or may be found in the

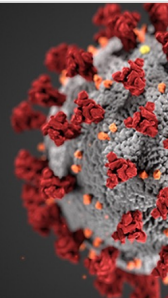
Why this all might matter to you

- Using slurm directly = pre-MapReduce
 - Benefits: 100% freedom
 - Not tied to tech. or data format



MENU

VERMONT ADVANCED COMPUTING CORE



AMD GIVES UVM \$1 MILLION TO BOOST COMPUTING POWER FOR COVID-19 RESEARCH

UVM is among the first 21 schools the company has supported through its AMD HPC Fund for COVID-19 Research program.

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Three high performance computing (HPC) clusters – BlackDiamond, Bluemoon, DeepGreen – which support large-scale computation, low-latency networking for MPI workloads, and high-throughput AI and machine learning workflows.

Data Management

Various data storage plans to meet the needs of our:

- VACC account holders
- UVM faculty

Services

Onboarding for those new to high performance computing

JOIN THE VACC

Cost / Payment

VACC account holders join one of three tiers on a yearly basis.

Request Account

Principal Investigators (PIs) or IT support working with PIs may request an account.

USE THE VACC

Knowledge Base

Help topics include connecting to the cluster, moving files, running a job, and more.

Dashboard

For account owners (PIs), not sponsored users

Tweets by @uvmvacc

Vermont Advanced Computi @uvmvacc

Bluemoon cluster about to bring online 5000 new compute cores!!!



17h

Vermont Advanced Computi @uvmvacc

We're thrilled to receive funding from

Why this all might matter to you

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 - Composing tasks? Probably manual
 - Need to serialize? Probably manual



ENHANCED BY Google



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