

Big Data & Hadoop

4/24/2019





What is Big Data?

- Big data essentially means datasets that are too large for traditional data processing systems, and therefore require new processing technologies.
- Datasets whose characteristics size, data type and frequency - are beyond efficient, accurate and secure processing, as well as storage and extraction, by traditional database management tools.
- Big data technologies (such as Hadoop, HBase, and MongoDB) have received considerable media attention recently.







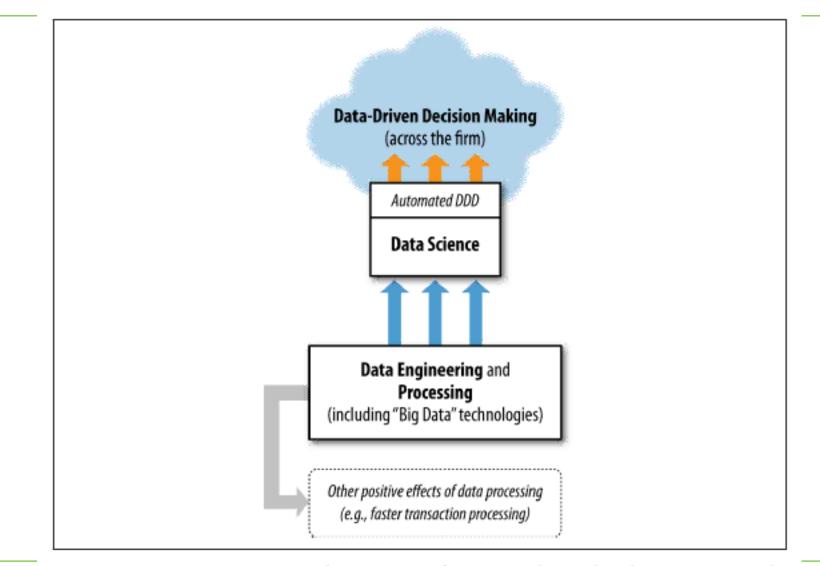


Figure 1-1. Data science in the context of various data-related processes in the organization.

The Four Vs

- Volume how much data is captured, stored, and processed.
- Velocity how fast the data is received, and how fast it needs to be processed and extracted.
- Variety how different and complex the data elements are.
- Value how effectively the data can be processed for business benefit.





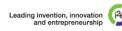


Big Data Challenges in the financial markets

- While the actual volume of data for financial markets applications compared to generalized Big Data applications, such as social media and retail – is usually not large, the complexity and frequency of data pose significant challenges.
- Data types within financial applications can vary considerably. Relevant data might be unstructured text (such as news stories and social media updates), semi structured text (such as XML), or structured text or binary data (price updates for securities).
- The frequency of updates of data can be extreme, up to several million per second for some markets at peak periods. This requires very specialized processing architectures, comprising complex hardware, software and networking. Techniques such as massively parallel processing and in-memory data storage are generally required, and extremely efficient software coding.







Big Data Challenges in financial markets (Continue)

- The analytical performance required for many applications in terms
 of response times for queries is also challenging, with responses
 required in fractions of a second milliseconds for many applications
 to be useful.
- Unlike many Big Data applications, those in the financial markets require data elements to be accurate and high precision. For example, a record of a trade price needs to be exact, and its timestamp needs to be resolved within nanoseconds.
- The security requirements of the financial markets, including the need for 24*7 uptime, access controls, audit trails and rollbacks, are beyond many common Big Data technologies, which tend to suffer from their open source origins and lack enterprise-grade functionality.







A variety of trading and risk data for Big Data

- Time series price data
 - as granular as every single tick (trade report) and every order to buy or sell, over an extended period of hours, days, weeks or years.
 - Structured price and associated data, for each transaction .
 - Both manual and automated trade executions.
- Unstructured real-time data, including news stories and social media updates.
- Both structured and unstructured reference data, varying from records of corporate actions, counterparty and legal entity information, contracts and income flows related to derivatives and structured products.
- Audio recordings of transactions negotiated and executed via phone.





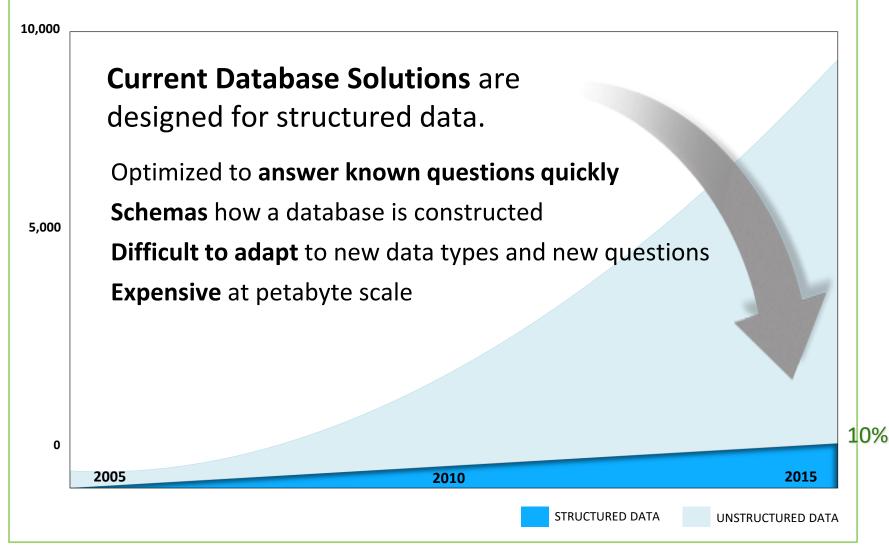
Structured vs Unstructured Data

- Structured data refers to data that is formatted into records and fields that have pre-defined (or self defining) meanings, usages and formats. Such records might be fixed format, where fields are a defined number of characters, bytes, or bits (binary digits), or they might be in an XML format.
 - Typical structured data in the financial markets includes pricing updates – trade reports and quotes – as well as end of day snapshot pricing, and historical time series of prices.
- Unstructured data relates to data that has no predefined structure, so that it needs to be parsed using techniques such as natural language processing before it becomes useful for analysis.
 - Such data is most commonly text-based, though audio and video also qualifies as unstructured.
 - Key reference data, such as corporate actions, is also often provided in unstructured text format.













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Main Big Data Technologies

Hadoop

- Low cost, reliable scale-out architecture
- Distributed computing Proven success in Fortune 500 companies
- Exploding interest

Hadoop



NEW YORK UNIVERSITY

NoSQL Databases

- Huge horizontal scaling and high availability
- Highly optimized for retrieval and appending
- Types
 - Document stores
 - Key Value stores
 - Graph databases

NoSQL Databases



Analytic RDBMS

- Optimized for bulkload and fast aggregate query workloads
- Types
 - Column-oriented
 - MPP
 - In-memory

Analytic Databases











Hadoop & Databases

Databases

"Schema-on-Write"

- Schema must be created before any data can be loaded
- An explicit load operation has to take place which transforms data to DB internal structure
- New columns must be added explicitly before new data for such columns can be loaded into the database

Hadoop

"Schema-on-Read"

- Data is simply copied to the file store, no transformation is needed
- A SerDe (Serializer/Deserlizer) is applied during read time to extract the required columns (late binding)
- New data can start flowing anytime and will appear retroactively once the SerDe is updated to parse it

- Reads are Fast
- Standards and Governance



- Loads are Fast
- Flexibility and Agility









The Apache Hadoop projects

The Apache Hadoop projects provide a series of tools designed to solve big data problems. The Hadoop cluster implements a parallel computing cluster using inexpensive commodity hardware. The cluster is partitioned across many servers to provide a near linear scalability. The philosophy of the cluster design is to bring the computing to the data. So each datanode will hold part of the overall data and be able to process the data that it holds. The overall framework for the processing software is called MapReduce.







Hadoop Distributed File System (HDFS)

Massive redundant storage across a commodity cluster

MapReduce

- Map: distribute a computational problem across a cluster
- Reduce: Master node collects the answers to all the sub-problems and combines them.









Core Hadoop: HDFS

• Self-healing, high bandwidth *clustered storage*.



HDFS breaks incoming files into blocks and stores them redundantly across the cluster.





Core Hadoop: MapReduce

Distributed computing framework



Processes large jobs in parallel across many nodes and combines the results.





Addressing the Scale Issue

- Single machine cannot serve all the data: you need a distributed special (file) system
- Large number of commodity hardware disks: 1000 disks 1TB each
 - Issue: With Mean time between failures (MTBF) or failure rate of 1/1000, then at least 1 of the above 1000 disks would be down at a given time.
 - Thus failure is norm and not an exception.
 - File system has to be fault-tolerant: replication, checksum
 - Data transfer bandwidth is critical (location of data)
- Critical aspects: fault tolerance + replication + load balancing, monitoring
- Exploit parallelism afforded by splitting parsing and counting









Major Hadoop Utilities

SQL-like language and metadata repository

Apache Hive

Hue

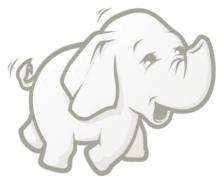
Browser-based desktop interface for interacting with Hadoop

Oozie

Server-based workflow engine for Hadoop activities

Apache Pig

High-level language for expressing data analysis programs



Apache HBase

The Hadoop database. Random, real -time read/write access

Apache Zookeeper

Highly reliable distributed coordination service

Flume

Distributed service for collecting and aggregating log and event data

Sqoop

Integrating Hadoop with RDBMS

Apache Whirr

Library for running Hadoop in the cloud





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What is MapReduce?

- MapReduce is a programming model Google has used successfully in processing its "big-data" sets (~ 20000 peta bytes per day)
 - Users specify the computation in terms of a map and a reduce function;
 - Underlying runtime system automatically parallelizes the computation across large-scale clusters of machines, and
 - Underlying system also handles machine failures, efficient communications, and performance issues.
 - -- Reference: Dean, J. and Ghemawat, S. 2008. **MapReduce: simplified data processing on large clusters.** *Communication of ACM* 51, 1 (Jan. 2008), 107-113.





From CS Foundations to MapReduce

Consider a large data collection:

 {web, weed, green, sun, moon, land, part, web, green,...}

Problem:

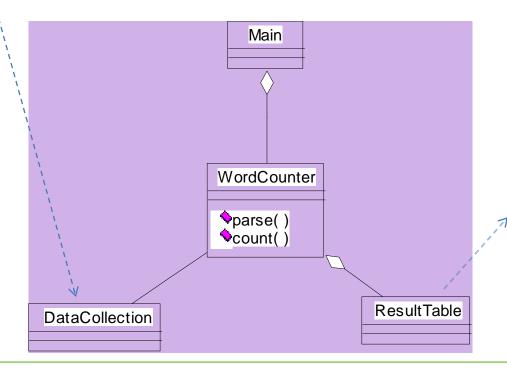
Count the occurrences of the different words in the collection.



Word Counter and Result Table

{web, weed, green, sun, moon, land, part, web, green,...}

Data collection



web	2
weed	1
green	2
sun	1
moon	1
land	1
part	1

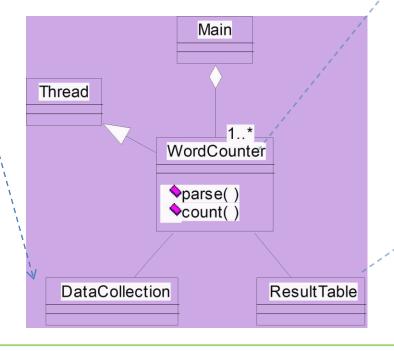




Multiple Instances of Word Counter

{web, weed, green, sun, moon, land, part, web, green,...}

Data collection

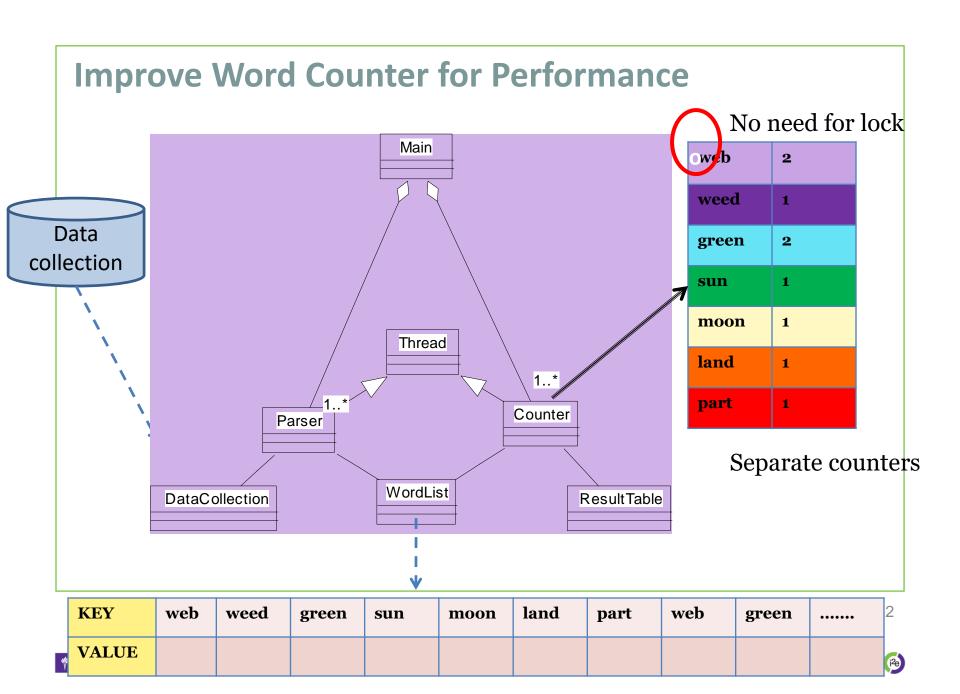


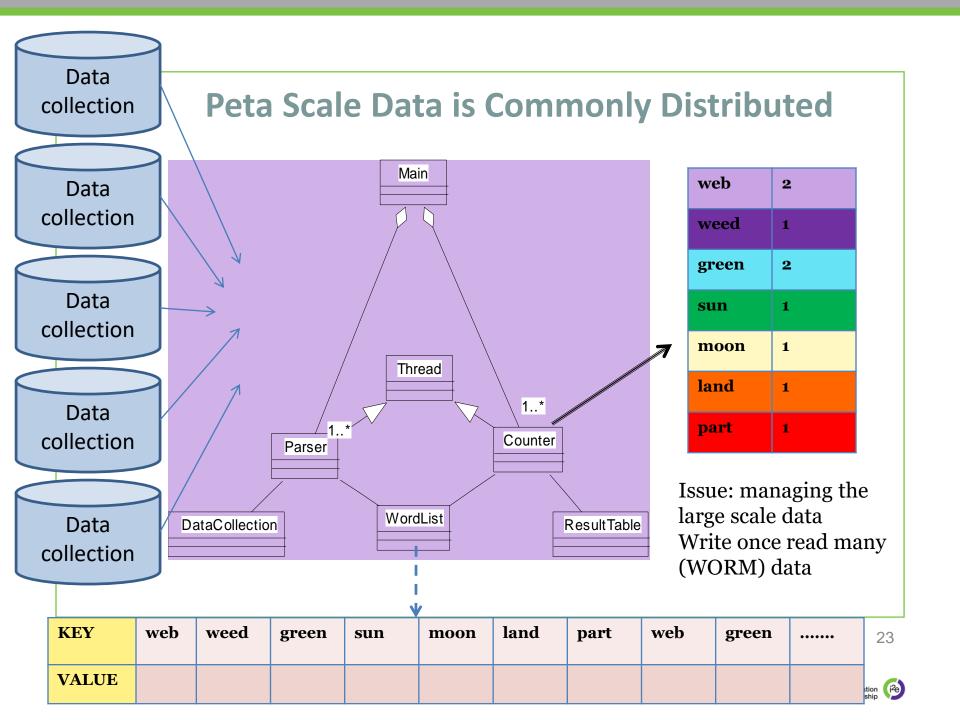
Ω	
web	2
weed	1
green	2
sun	1
moon	1
land	1
part	1

Observe: Multi-thread Lock on shared data











Data collection

One node

Data

For our example,

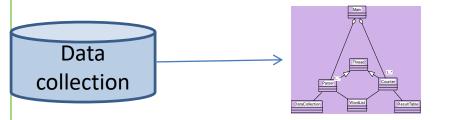
#1: Schedule parallel parse tasks

#2: Schedule parallel count tasks

This is a particular solution; Lets generalize it:

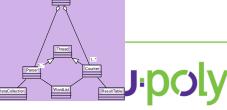
Our parse is a mapping operation: MAP: input → <key, value> pairs

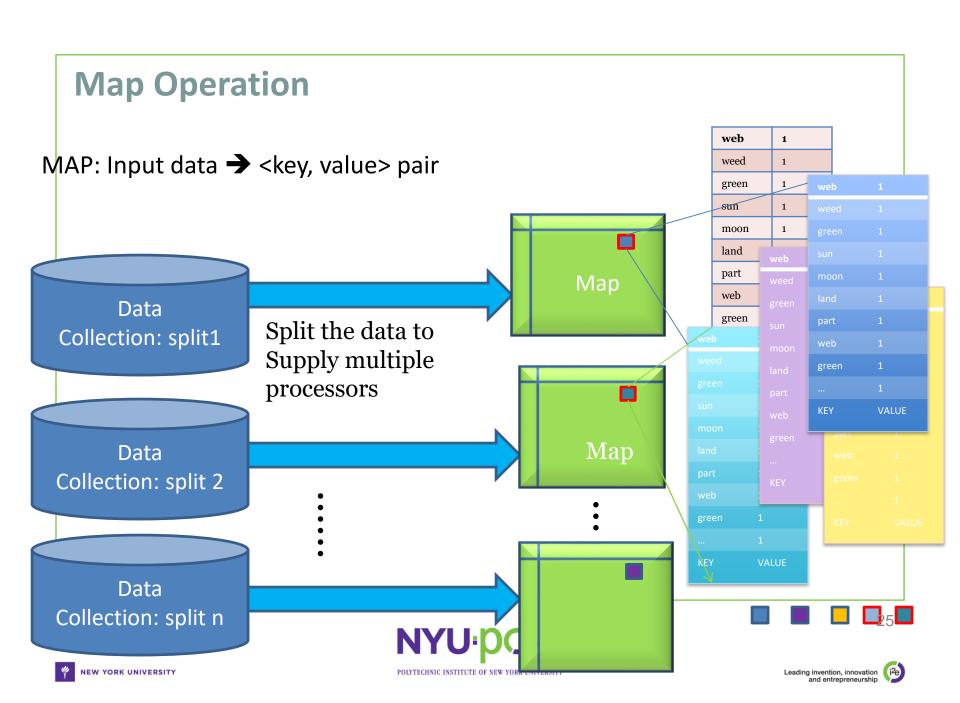
Our count is a reduce operation: REDUCE: <key, value> pairs reduced

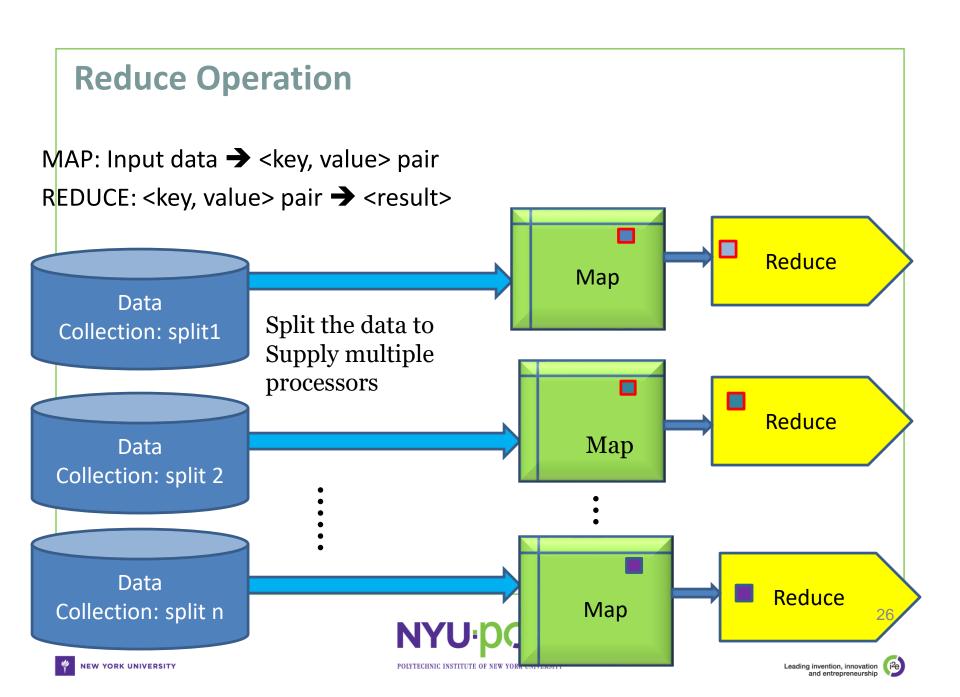


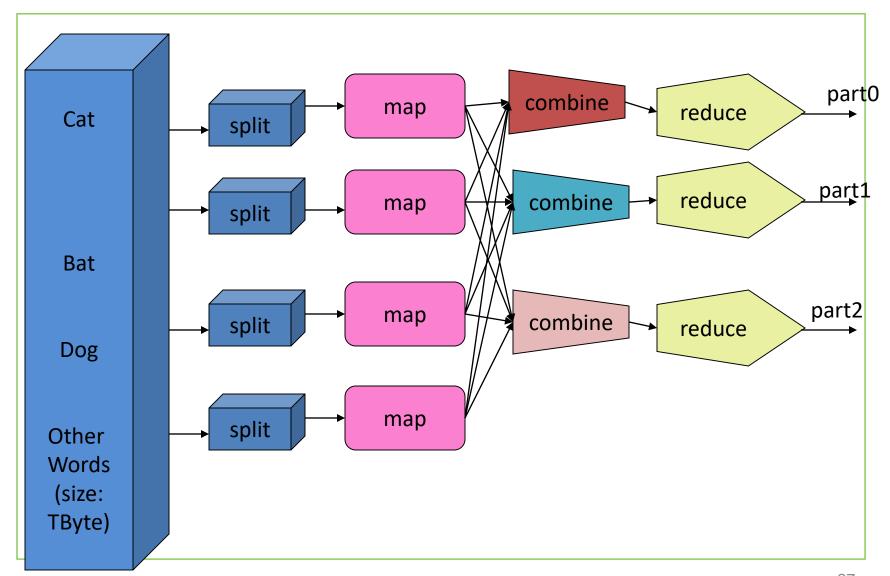
Data collection

collection





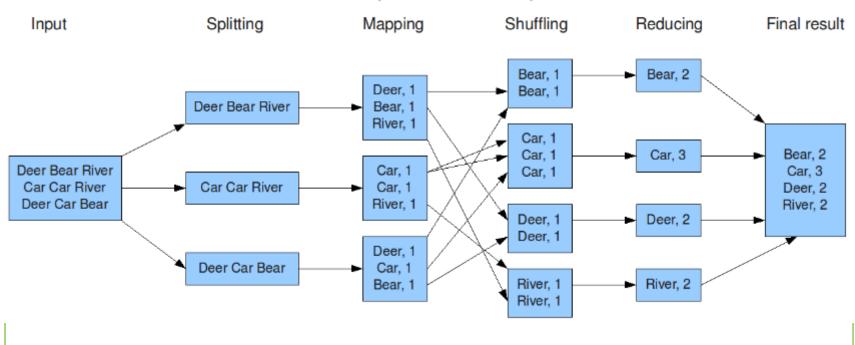








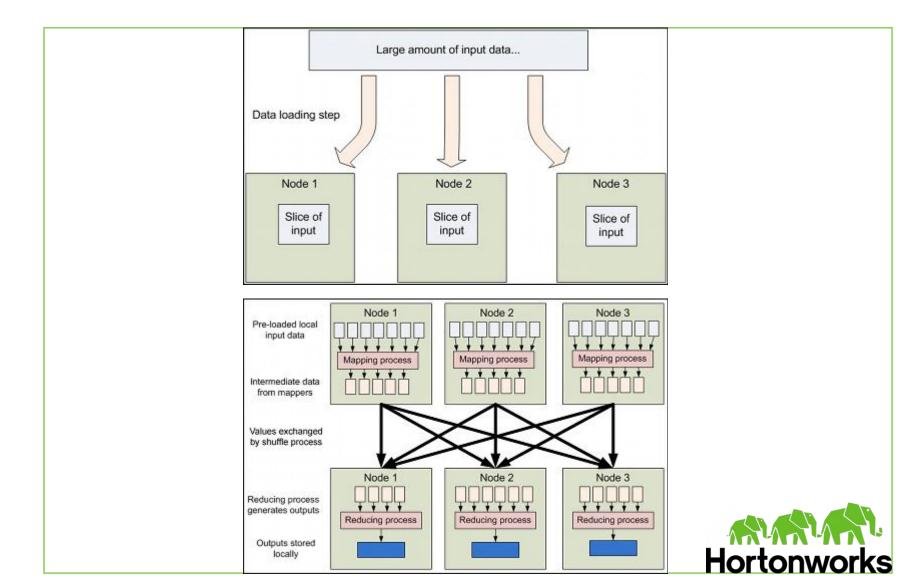
The overall MapReduce word count process



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Hortonworks Sandbox and HDP

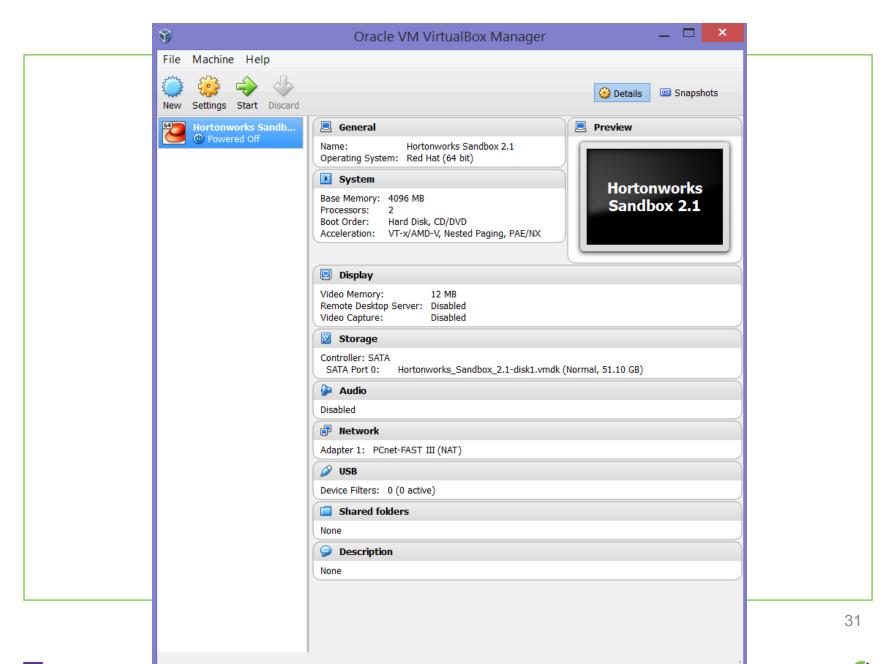
- The Hortonworks Sandbox is a single node implementation of the Hortonworks Data Platform(HDP). It is packaged as a virtual machine to make evaluation and experimentation with HDP fast and easy.
- Latest Releases of HDP Sandbox: HDP 2.1 Sandbox on Oracle VirtualBox.
 - System Requirements
 - Now runs on 32-bit and 64-bit OS (Windows XP, Windows 7, Windows 8 and Mac OSX)
 - Minimum 4GB RAM; 8Gb required to run Ambari and Hbase
 - Virtualization enabled on BIOS
 - Browser: Chrome 25+, IE 9+, Safari 6+ recommended. (Sandbox will not run on IE 10)

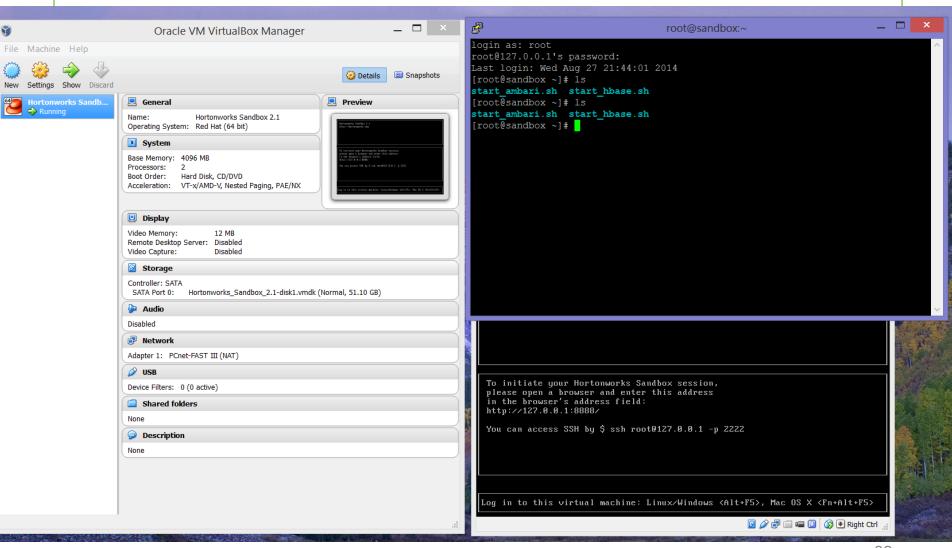










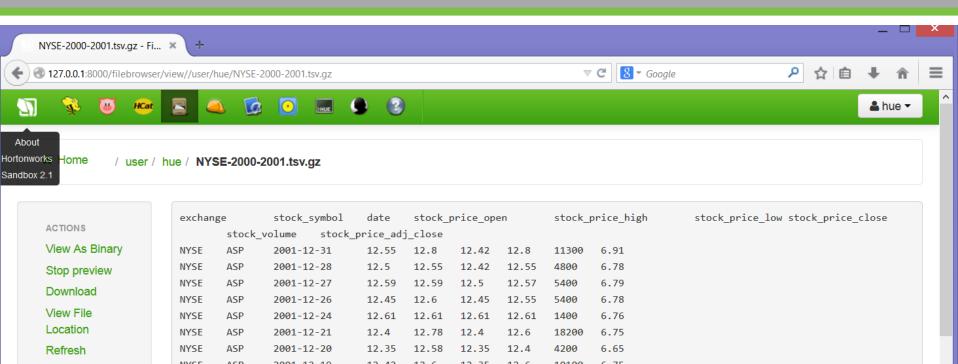




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ACTIONS		stock	_volume stock_	price_ad	j_close						
View As Binary	NYSE	ASP	2001-12-31	12.55	12.8	12.42	12.8	11300	6.91		
Stop preview	NYSE	ASP	2001-12-28	12.5	12.55	12.42	12.55	4800	6.78		
Download	NYSE NYSE	ASP ASP	2001-12-27 2001-12-26	12.59 12.45	12.59 12.6	12.5 12.45	12.57 12.55	5400 5400	6.79 6.78		
View File	NYSE	ASP	2001-12-26	12.45	12.61	12.45	12.55	1400	6.76		
Location	NYSE	ASP	2001-12-21	12.4	12.78	12.4	12.6	18200	6.75		
Refresh	NYSE	ASP	2001-12-20	12.35	12.58	12.35	12.4	4200	6.65		
	NYSE	ASP	2001-12-19	12.42	12.6	12.35	12.6	10100	6.75		
INFO	NYSE	ASP	2001-12-18	12.37	12.5	12.37	12.41	10100	6.65		
Last Modified	NYSE	ASP	2001-12-17	12.4	12.52	12.4	12.52	8000	6.71		
Aug. 27,	NYSE	ASP	2001-12-14	12.54	12.54	12.32	12.4	283000	6.65		
2014 9:16	NYSE	ASP	2001-12-13	12.4	12.55	12.4	12.54	13700	6.72		
p.m.	NYSE	ASP	2001-12-12	12.55	12.55	12.4	12.4	6900	6.65		
User	NYSE	ASP	2001-12-11	12.6	12.6	12.45	12.55	8900	6.73		
hue	NYSE	ASP	2001-12-10	12.5	12.6	12.43	12.6	4400	6.75		
Group	NYSE	ASP	2001-12-07	12.6	12.65	12.43	12.6	9600	6.75		
hue	NYSE	ASP	2001-12-06	12.7	12.71	12.65	12.65	3400	6.78		
Size	NYSE	ASP	2001-12-05	12.63	12.81	12.45	12.7	15800	6.81		
10.8 MB	NYSE	ASP	2001-12-04	12.79	12.79	12.6	12.65	10800	6.78		
Mode	NYSE	ASP	2001-12-03	12.72	12.79	12.65	12.79	8500	6.85		
100755	NYSE	ASP	2001-11-30	12.75	12.81	12.7	12.79	14600	6.8		
	NYSE	ASP	2001-11-29	12.7	12.82	12.7	12.82	3300	6.82		
	NYSE	ASP	2001-11-28	12.52	12.79	12.52	12.79	11100	6.8		
	NYSE	ASP	2001-11-27	12.53	12.6	12.42	12.42	12300	6.61		
	NYSE	ASP	2001-11-26	12.6	12.65	12.53	12.65	8200	6.73		
	NYSE	ASP	2001-11-23	12.5	12.5	12.5	12.5	3600	6.65		
7.0.0.1:8000/about	NYSE	ASP	2001-11-21	12.65	12.65	12.57	12.57	4400	6.69		~
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From Raw Data to Insight

- We will using HDP and Microsoft Business Intelligence to:
 - Cleaning and aggregating 10 years of stock price and dividend data.
 Enriching the data model by looking up additional attributes from Wikipedia
 - Creating an interactive visualization on the model



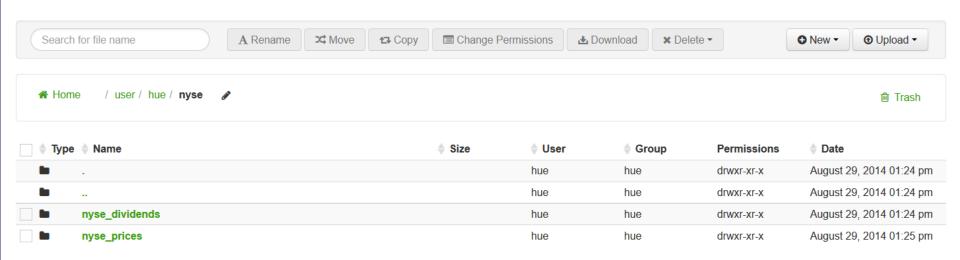




Staging the data on HDFS



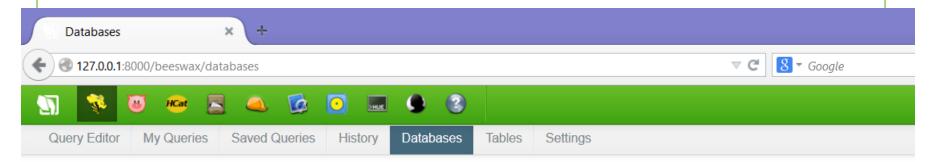
File Browser







Create the database NYSE



Databases

Create a new database

Search for database name

Drop

Database Name

default

nyse





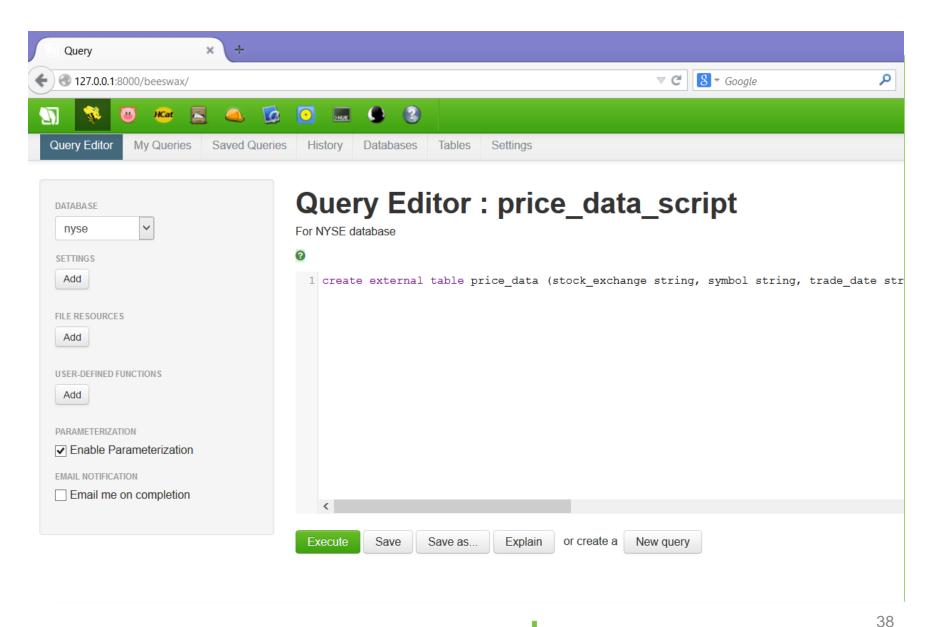
Creating a Hive schema on the raw data

- Use the Beeswax UI of Hive to execute the DDL queries:
 - create external table price_data (stock_exchange string, symbol string, trade_date string, open float, high float, low float, close float, volume int, adj_close float) row format delimited fields terminated by ',' stored as textfile location '/user/hue/nyse/nyse_prices';
 - create external table dividends_data (stock_exchange string, symbol string, trade_date string, dividend float) row format delimited fields terminated by ',' stored as textfile location '/user/hue/nyse/nyse_dividends';
- Test your results:
 - select * from price_data where symbol = 'IBM';
 - select * from dividends_data where symbol = 'IBM';

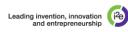


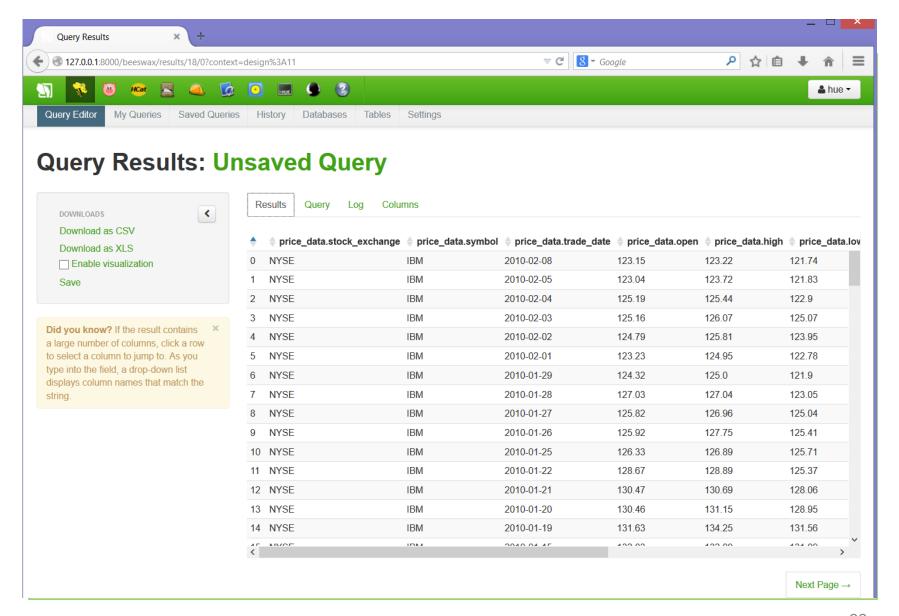






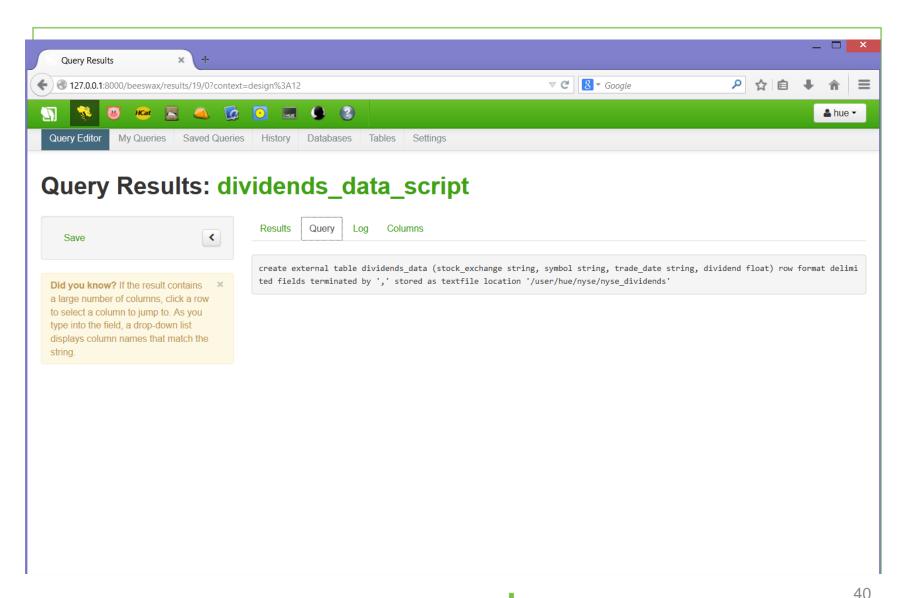








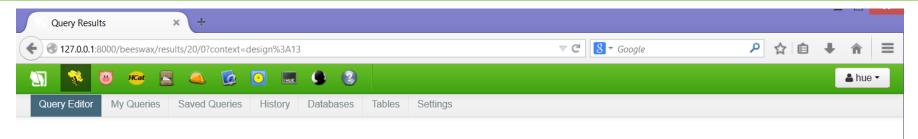












Query Results: Unsaved Query



Did you know? If the result contains a large number of columns, click a row to select a column to jump to. As you type into the field, a drop-down list displays column names that match the

R	esults Query Log Columns			
*	dividends_data.stock_exchange	dividends_data.symbol	dividends_data.trade_date	dividends_data.dividend
0	NYSE	IBM	2010-02-08	0.55
1	NYSE	IBM	2009-11-06	0.55
2	NYSE	IBM	2009-08-06	0.55
3	NYSE	IBM	2009-05-06	0.55
4	NYSE	IBM	2009-02-06	0.5
5	NYSE	IBM	2008-11-06	0.5
6	NYSE	IBM	2008-08-06	0.5
7	NYSE	IBM	2008-05-07	0.5
8	NYSE	IBM	2008-02-06	0.4
9	NYSE	IBM	2007-11-07	0.4
10	NYSE	IBM	2007-08-08	0.4
11	NYSE	IBM	2007-05-08	0.4
12	NYSE	IBM	2007-02-07	0.3
13	NYSE	IBM	2006-11-08	0.3
14	NYSE	IBM	2006-08-08	0.3
15	NYSE	IBM	2006-05-08	0.3

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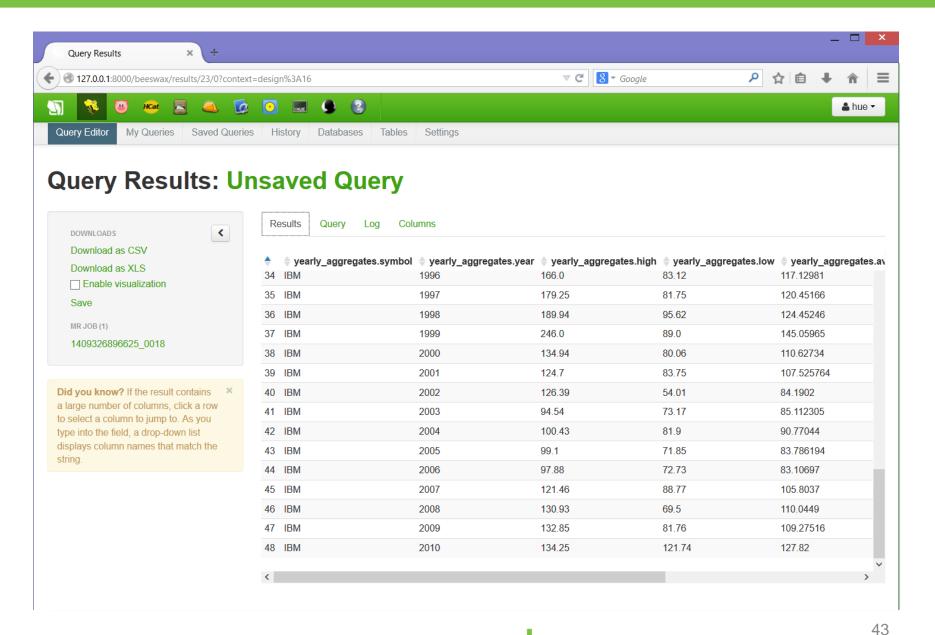
Aggregating the stocks and dividend data

- The DDL statement to create the table 'yearly_aggregates':
 - create table yearly_aggregates (symbol string, year string, high float, low float, average_close float, total_dividends float) row format delimited fields terminated by ',' stored as textfile location '/user/hue/nyse/stock_aggregates';
- Populate the table with data using the following query:
 - insert overwrite table yearly_aggregates select a.symbol, year(a.trade_date), max(a.high), min(a.low), avg(a.close), sum(b.dividend) from price_data a left outer join dividends_data b on (a.symbol = b.symbol and a.trade_date = b.trade_date) group by a.symbol, year(a.trade_date);



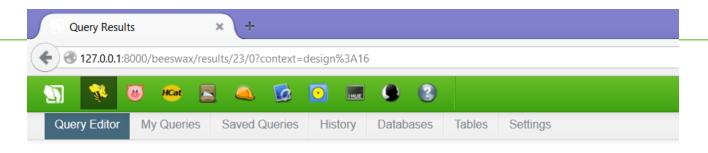




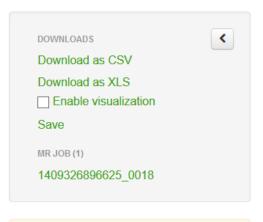








Query Results: Unsaved Query



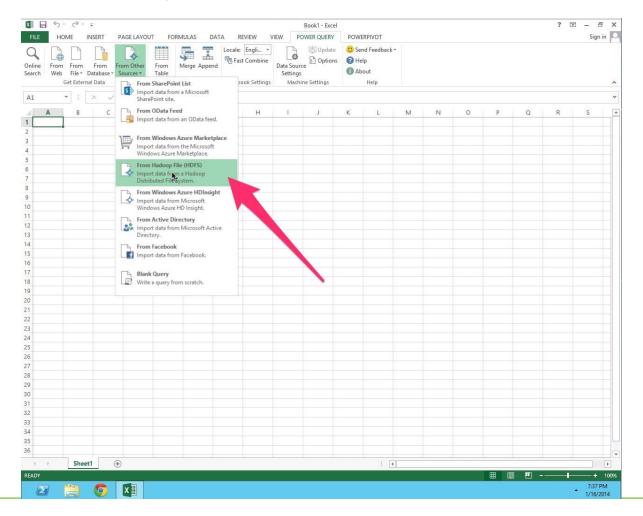
Did you know? If the result contains a large number of columns, click a row to select a column to jump to. As you type into the field, a drop-down list displays column names that match the string.

Results	Query	Log	Columns			
Name						
yearly_agg	early_aggregates.symbol					
yearly_aggregates.year						
yearly_agg	yearly_aggregates.high yearly_aggregates.low					
yearly_agg						
yearly_aggregates.average_close						
yearly_aggregates.total_dividends						

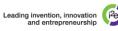


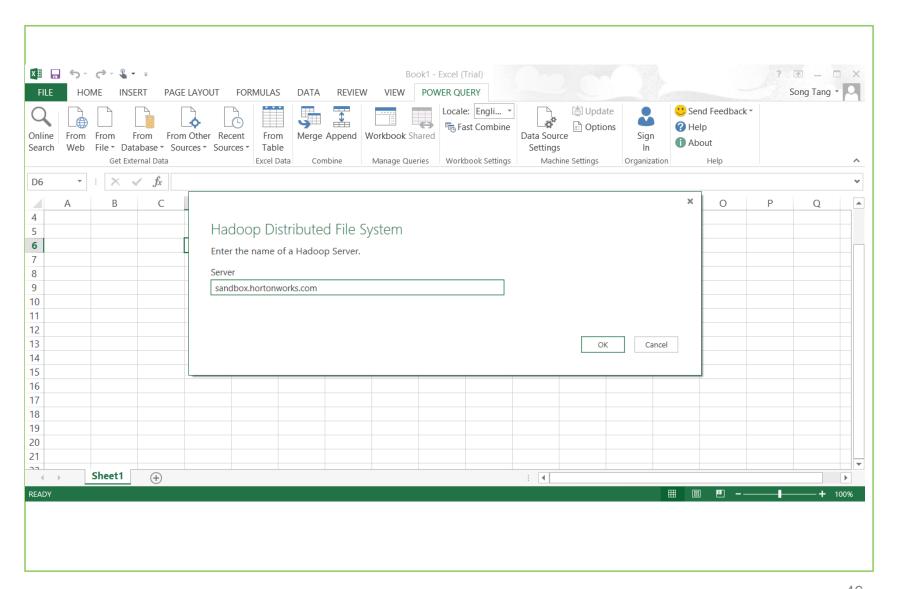


Export Hadoop resultset to Excel Power Query



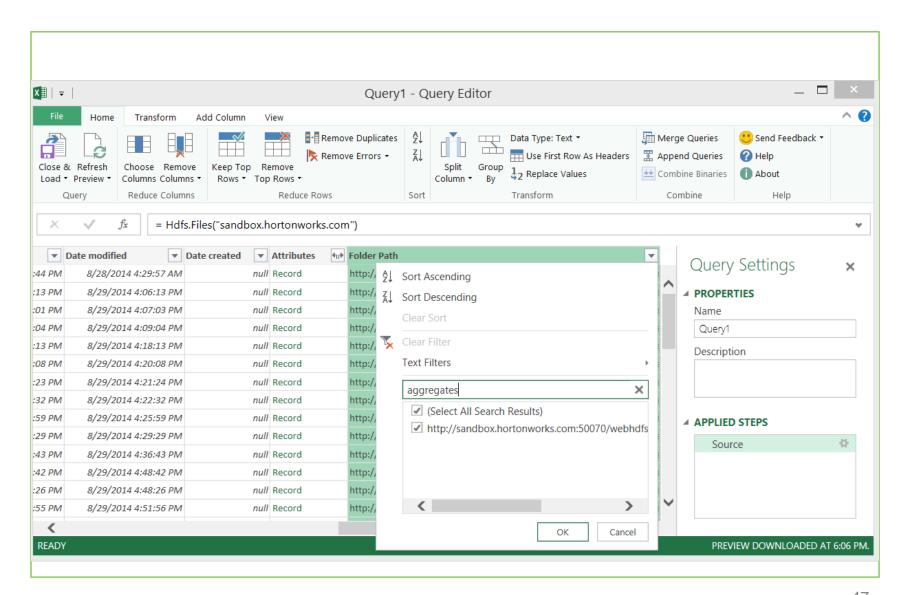








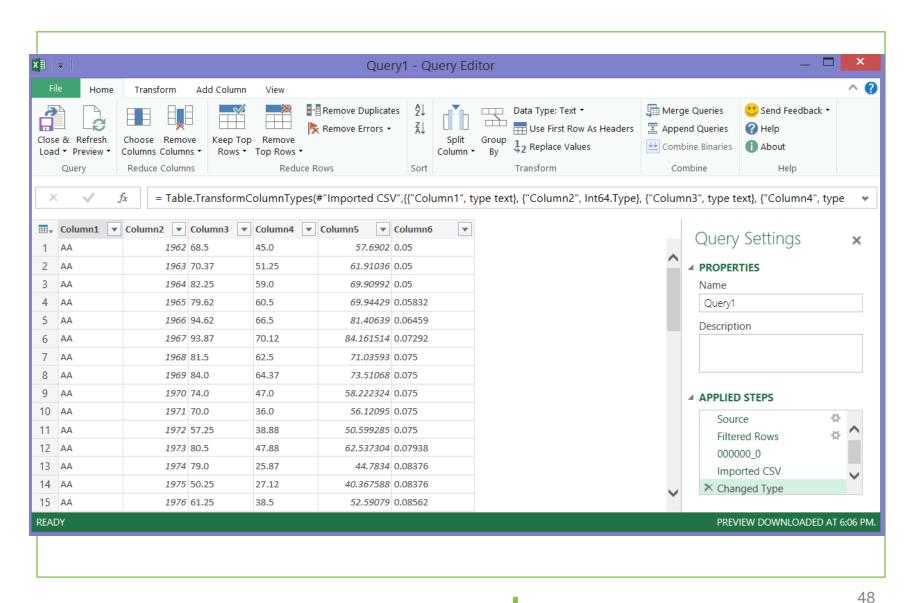










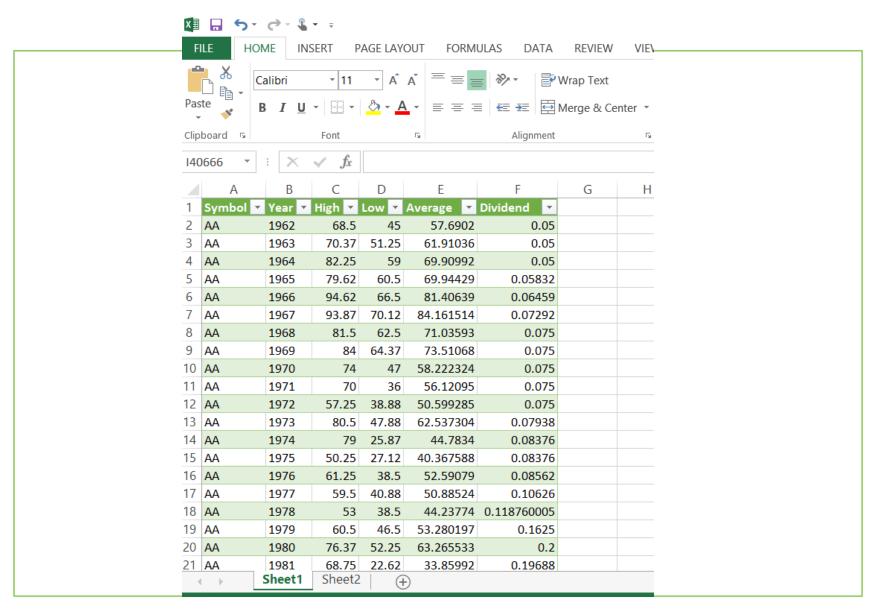








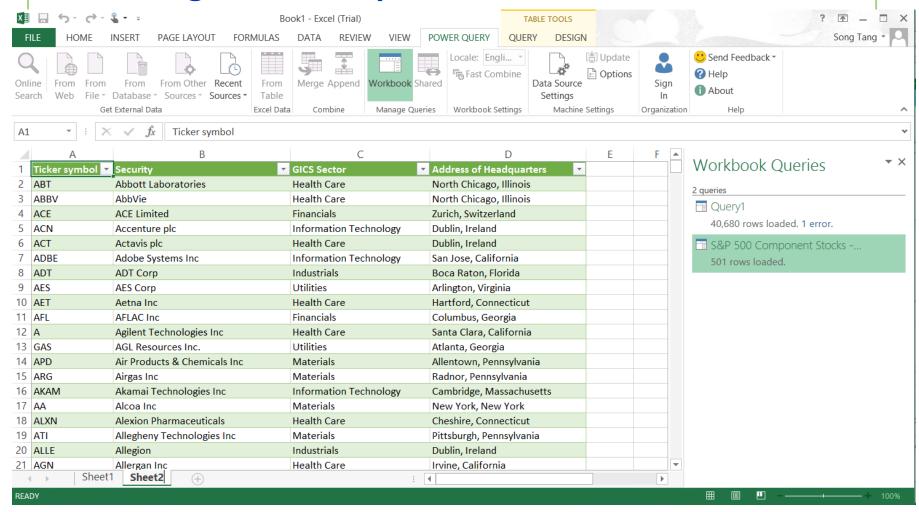
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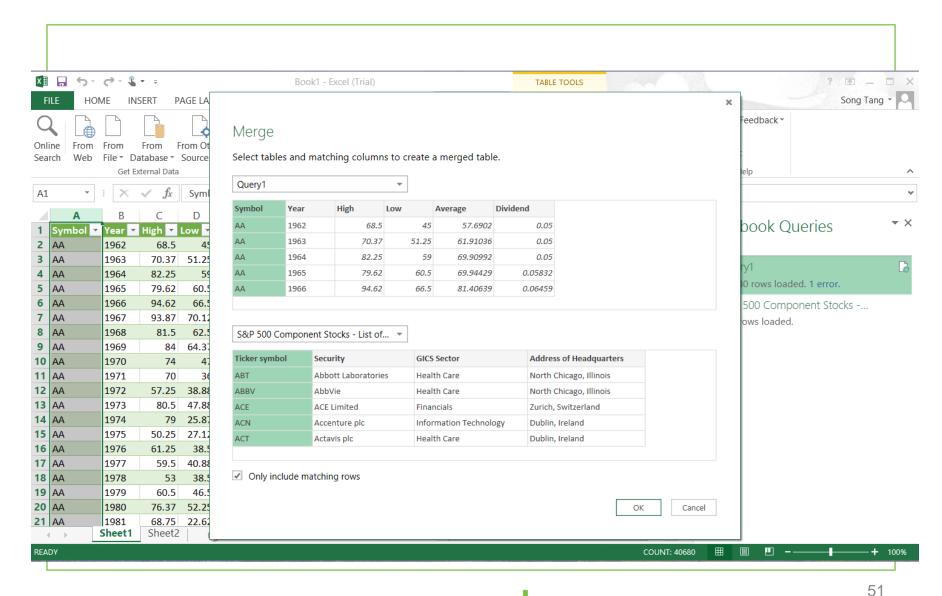


Enhancing the Hadoop resultset with Internet Data





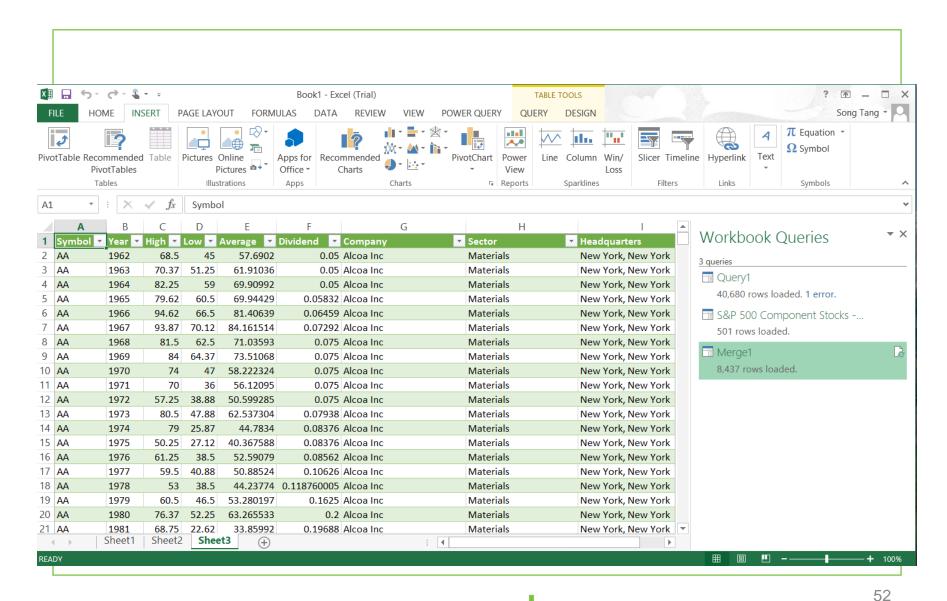








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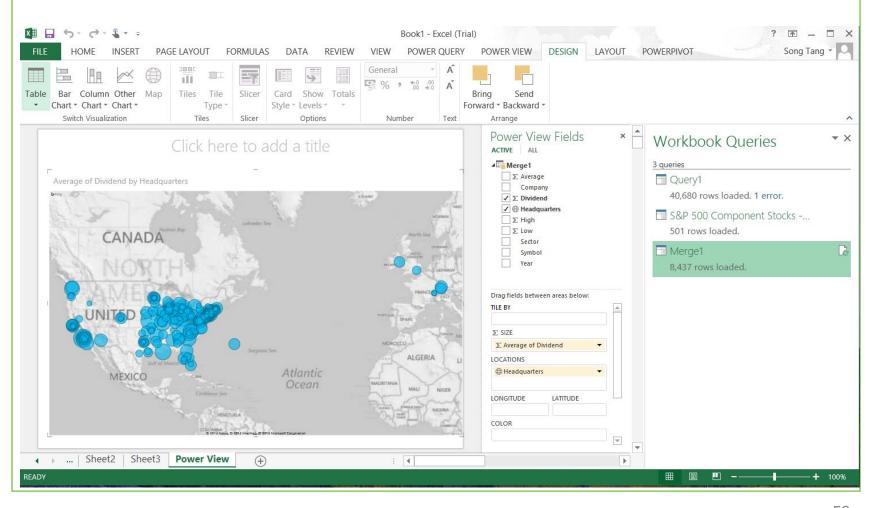








Visualizing S & P 500 dividend geographic distribution









Stock Price Prediction using Hadoop MapReduce

- Using Technical Indicators SMA (Simple moving average), EMA (Exponential moving average) and OBV (On Balance Volume).
- Normalizing the stock data and performing BPNN (Back-Propagation Neural Networks) algorithm.
- Using Hadoop MapReduce to develop virtual data nodes for parallel processing of the data using Neural Network for time efficient forecasting of the stock price movement.







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