# FIT1043 Introduction to Data Science Module 3: Data Types and Storage Lecture 6

Monash University

#### Unit Schedule: Modules

Module	Week	Content	
1.	1	overview and look at projects	
	2	(job) roles, and the impact	
2.	3	data business models	
	4	application areas and case studies	
3.	5	characterising data and "big" data	
	6	processing big data sources and case studies	
4.	7	resources and standards	
	8	resources case studies	
5.	9	data analysis theory	
	10	data analysis process	
6.	11	issues in data management	
	12	data management frameworks	

#### Discussion: R

- Powerful language for visualising and building predictive models of data
- Very easy to use with lots of inbuilt functionality.
- Great for exploratory data analysis
- ▶ Not as scalable as programming languages: Java, Python,

#### Discussion: Assessment

- First assignment due in Week 8.
- Are there any questions about the assignment?

## Big Data Processing (ePub section 3.4)

#### processing data at scale, especially for analysis

- databases
  - storing and accessing data
- distributed processing
  - breaking up computation to scale it up



#### **Business Context**

- businesses function in a continuously changing environment:
  - fixed formats as per Relational Database Management System (RDBMS) not suitable
- businesses function in a continuously changing environment:
  - usage varies, requires complex analytical queries
- need to reach insights faster and act on them in real time
  - stream processing

## Big Data Processing: Databases

storing and accessing data

#### **SQL** Review

- Relational Database Management Systems (RDBMS)
- SQL ::= structured query language

```
UPDATE clause - UPDATE country

SET clause - SET population = population + 1

MHERE clause - WHERE name = 'USA';

Predicts

Predicts
```

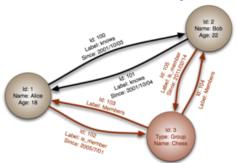
- rather like large scale set of Excel spreadsheets with better indexing and retrieval
- transaction oriented with support for throughput, correctness, distribution, ...

### JSON Example

```
"firstName": "John",
"lastName": "Smith",
"isAlive": true,
"age": 25,
"address": {
  "streetAddress": "21 2nd Street".
  "city": "New York",
  "state": "NY",
  "postalCode": "10021-3100"
"phoneNumbers": [
    "type": "home",
    "number": "212 555-1234"
    "type": "office".
    "number": "646 555-4567"
"children": [],
"spouse": null
```

- example from Wikipedia
- no fixed format
- semi-structured, key-value pairs, hierarchical
- "friendly" alternative to XML
- self-documenting structure
- example, EventRegistry file

#### Graph Database Example



- example graph
- example content FreeBase page for "Arnold Schwarzenegger"
- example content format <u>FreeBase extract</u>
- stores graph, commonly as triples, subject, verb, object
- commonly used to store Linked Open Data

## Database Background Concepts

in-database analytics: the analytics is done within the DB

in-memory database: the DB content resides memory

cache: data stored in-memory

key-value: value accessible by key, e.g., hash table

information silo: an insular information system incapable of reciprocal operation with other, related information systems

- if two big banks merge, then initially their RDBMSs will be siloed
- in a big insurance company, auto and home insurance customer RDBMSs may be siloed



# Database Background Concepts, cont.

#### Many NoSQL and SQL DBs offer:

- large scale, distributed processing
- robustness
- general query languages
- some notion of consistencye.g. "eventually" as nodes spread updates

## **Beyond SQL Databases**

Туре	Examples	Notes
RDBMS	MySQL,	SQL
	MSSQL Server	
Object DB	Zope,	navigate network
	<b>Objectivity</b>	
Doc. DB	MongoDB,	JSON like, Javascript like
	CouchDB	queries
key-val cache	Memcached,	in-memory
	<u>Coherence</u>	
key-val store	Aerospike,	not in-memory but highly opti-
	<i>HyperDex</i>	mised
tabular key-val	<u>Cassandra</u> ,	relational-like, "wide column
	<u>HBase</u>	store"
graph DB	<u>Neo4j</u> ,	RDF, SPARQL,
	OrientDB	

## Beyond SQL Databases (NoSQL)

- NoSQL databases offer a rich variety beyond traditional relational.
- Many target web applications.
- ► See blog post by Eric Knorr 19/11/2012 on Infoworld.com, "The wild, crazy world of databases"
- ► See blog post by Fabian Pascal 12/17/2015 on AllAnalytics.com,
  - "Data Fundamentals for Analysts: Documents and Databases".

#### Overview: Databases

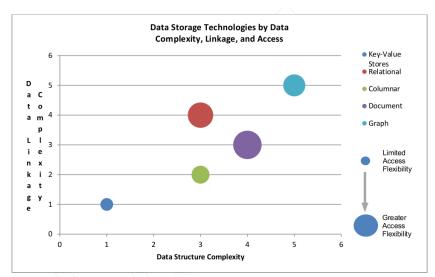


Figure 4: Data Storage Technologies

#### Overview: Processing

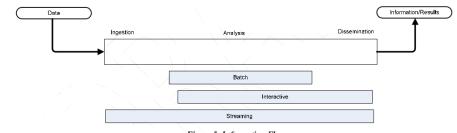


Figure 5: Information Flow

Interactive: bringing humans into the loop

Streaming: massive data streaming through system with little

storage

Batch: data stored and analysed in large blocks,

"batches," easier to develop and analyse

## Big Data Processing: Distributed processing

breaking up computation to scale it up



## Processing Background Concepts

in-memory: in RAM, i.e., not going to disk

parallel processing: performing tasks in parallel

distributed computing: across multiple machines

multi-threaded processing: multiple threads on the one

machine (usually shared memory)

scalability: to handle a growing amount of work; to be

enlarged to accommodate growth (not just "big")

data parallel: processing can be done independently on

separate chunks of data

yes: process all documents in a collection to extract

names

no: convert a wiring diagramme into a physical design

(optimisation)



#### Distributed Analytics

- legacy systems provide powerful statistical tools on the desktop
  - SAS, R, Matlab

but often-times without distributed or multi-processor support

- supporting distributed/multi-processor computation requires special redesign of algorithms
- in-database analytics systems intended to support this
- e.g. MADLib from Pivotal and MLLib from Spark integrates with their distributed SQL;



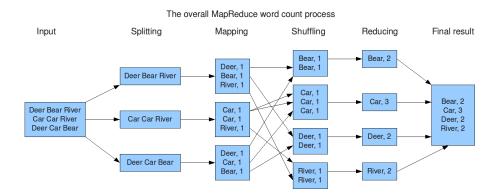
#### Map-Reduce

Simple distributed processing framework developed at Google

- published by Dean and Ghemawat of Google in 2004
- intended to run on commodity hardware; so has fault-tolerant infrastructure
- from a distributed systems perspective, is quite simple



#### Map-Reduce Example



for a simple word-count task: (1) divide data across machines (2) map() to key-value pairs (3) sort and merge() identical keys

#### Map-Reduce, cont.

- requires simple data parallelism followed by some merge ("reduce") process
- stopped using by Google probably in 2005
- ▶ Google now uses <u>"Cloud Dataflow"</u> (and <u>here</u>), available commercially, as open source

#### Hadoop

#### Open-source Java implementation of Map-Reduce

- originally developed by Doug Cutting while at Yahoo!
- architecture:

Common: Java libraries and utilities

YARN: job scheduling and cluster management

HDFS: Hadoop Distributed File System

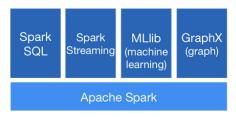
MapReduce: core paradigm

- huge tool ecosystem
- well passed the peak of the hype curve



#### Spark

- another (open source) Apache top-level project at *Apache Spark*
- developed at <u>AMPLab</u> at UC Berkeley
- builds on Hadoop infrastructure (HDFS, etc.)
- interfaces in Java, Scala, Python, R
- provides in-memory analytics
- works with some of the Hadoop ecosystem



# Next: Module 4 Data Resources, Processes, Standards and Tools