VoltDB

Intelligent Ingestion

David Rolfe

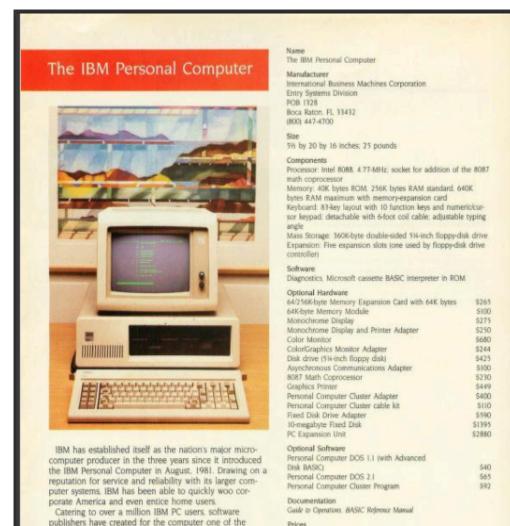
Director of Solution Architecture, EMEA



17-Jul-18

In 1984 the world was a very different place...

- Ronald Reagan was president
- For only US\$3700 (about US\$8700 now) you could buy an IBM PC with 256KB of RAM and a 1MB hard drive.
- Multi CPU computers were an exotic rarity.
- There was almost no computer to computer connectivity. Computers interacted with humans. Slowly.
- 1984 is roughly when the architecture of the major RDBMS products was designed.



largest bases of microcomputer programs, thereby con-

tributing further to the PC's proliferation. The 16-8-bit

8088 processor makes it possible for users to write more compley programs that offer mo

Prices

256K bytes of RAM and one floppy-disk drive \$1995 \$2420 256K bytes of RAM and two floppy-disk drives

Then we had the era of the "One Big Database"...

- Organizations realized that data was valuable.
- Very bad practice for Use Cases to dictate data structures
 - Optimization regarded as a last resort. And a sign of failure.
- The database was a repository of corporate data.
- There was one centrally planned database schema that was 'correct'.
- Everyone was supposed to use it. Or else.
- With hindsight it was all a bit "Soviet"...



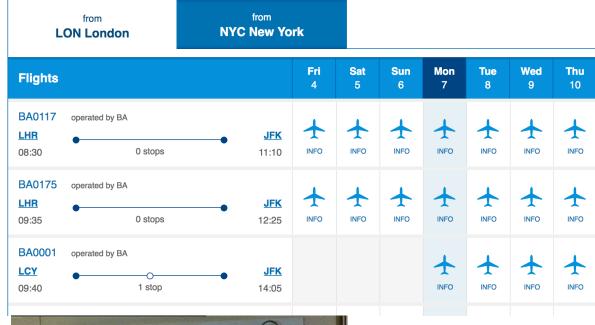
It may have been "Soviet" but...

- Databases were a new and radical concept that solved a real problem.
- They were inspired by the industrial scale chaos caused by every application 'owning' its own data
 - Some of that chaos has returned
- Regarding data as an asset that is more important than a single Use Case is 'common sense' now.
- The "One Big Database" was killed by:
 - Office politics/organizational complexity
 - Operational and design complexity.
 - Lack of suitably miraculous products.
 - The PC and virtualization.
- We now have gone to the other extreme microservices and KV stores



Modern applications are incredibly demanding

Goal: Predict flight delays.





"The Late Arrival Of The Incoming Aircraft"

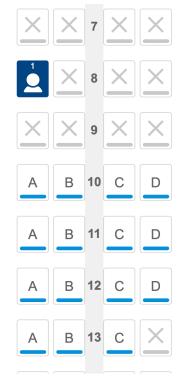


Raw TAF

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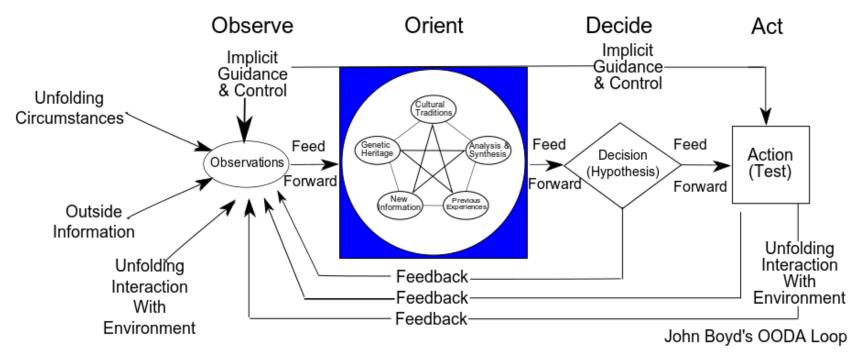
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The OODA Loop, and why it's important...



- 1. In order to 'win' your application's loop needs to run faster than 'reality'
- 2. 'Winning' against a web page means a loop of under 7 seconds.
- 3. 'Winning' in an IoT context means a loop of around 7 milliseconds.
- 4. 'Winning' now involves complex decision making at millisecond timescales.



John "Forty Second" Boyd



Complexity, Latency and Volumes

Year	Internet Bandwidth (GB)	Required Response Time)	Application Complexity
1985	33	2 day batch turnaround	Row level locking being invented. Transactions of any sort rare.
1995	150,500	2 minute batch	Row level locking of 5-10 rows; web servers using databases.
2000	75,250,000	8000ms – Web Page Advertising	Web advertising: Cookie -> User -> Demographic -> Ad
2010	19,974,008,812	100ms - Video Game Analytics / Sophisticated web advertising	Decisions need to consider dozens/hundreds of elements
2015- 2018	>42,423,169,029	10ms - IoT / Many Devices	Decisions may need to consider thousands of elements

Between 1984 and 2015 a lot changed...

Between 1985 and 2005:

- CPU power increased by about ^{100.0}
 1100X 10.0
- Ram costs reduced by about 4500X

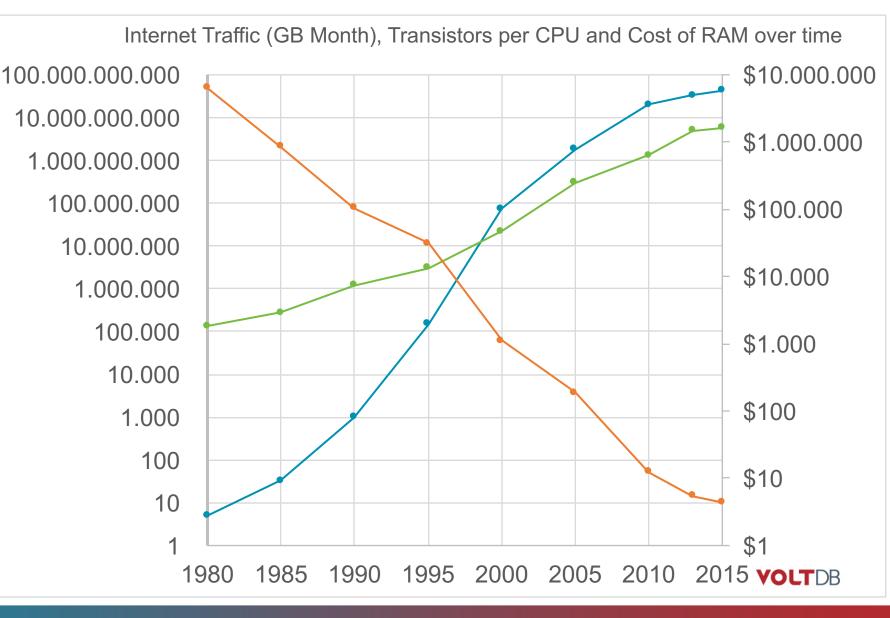
Between 1985 and 2017:

- CPU 200K times more powerful
- RAM 1/200,000th the price

Total Internet Bandwidth (GB/Mo)

Transistors per CPU

Price of Ram (\$/GB)



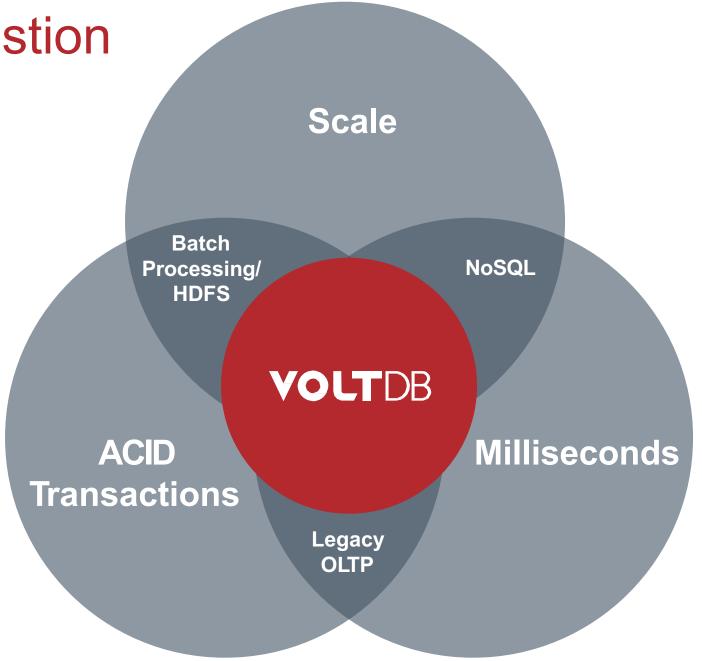
We now face real 'pain'...

- Timescales ("OODA loop"), volumes and complexity all pose challenges.
- We need to take complex decisions, fast:
 - Complex Decisions usually involve many different data sources.
 - Key Value solutions imply a large number of network trips...
 - ...and ACID becomes an issue if your data changes while you are reading it
 - Legacy RDBMS implies a lack of scale.
 - Decisions involving shared resources usually implies locking or retries
 - Many decisions involve aggregate values ("HTAP/Translytics")
 - Many decisions involve telling a third party something
- What we need is the ability to do all of this as the data arrives.



Intelligent Ingestion

- 1. Complex Decisions
- 2. Multiple Data Sources
- 3. ACID
- 4. Millisecond Timing
- 5. Massive Scale



VOLTDB

VOLTDB

Why use VoltDB for "Intelligent Ingestion"?

Intelligent Ingestion



VoltDB is optimized for Scale, ACID and Latency...



An **Ariel Atom**. Very good for going round racetracks very quickly in nice weather. Not so good for school runs, driving tests, shopping, off road activities, as an ambulance, polar exploration, amphibious assaults, carrying cargo....

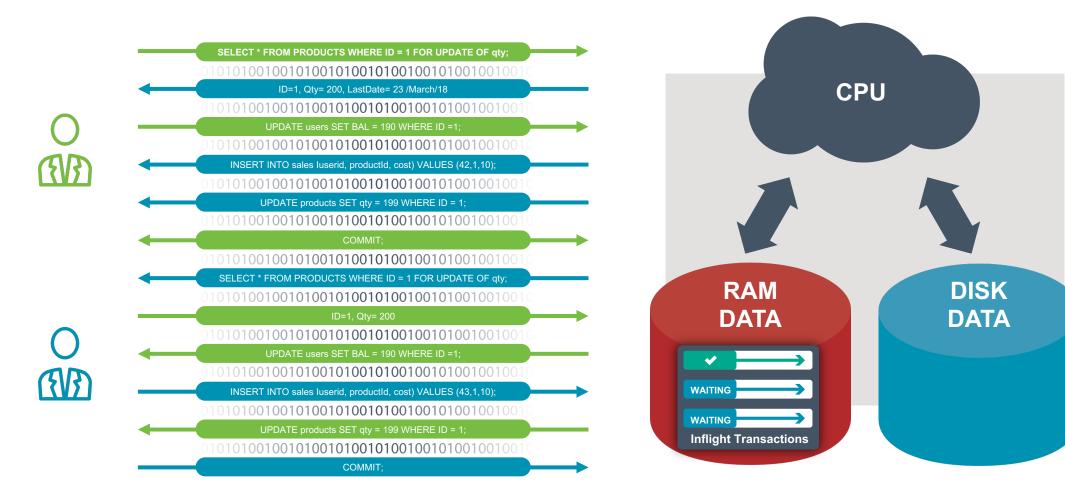
VoltDB is optimized to solve one class of problems better than anything else that exists.

It is not a general purpose RDBMS, nor a replacement for one.

It's used to complement your existing stack rather than replacing it.

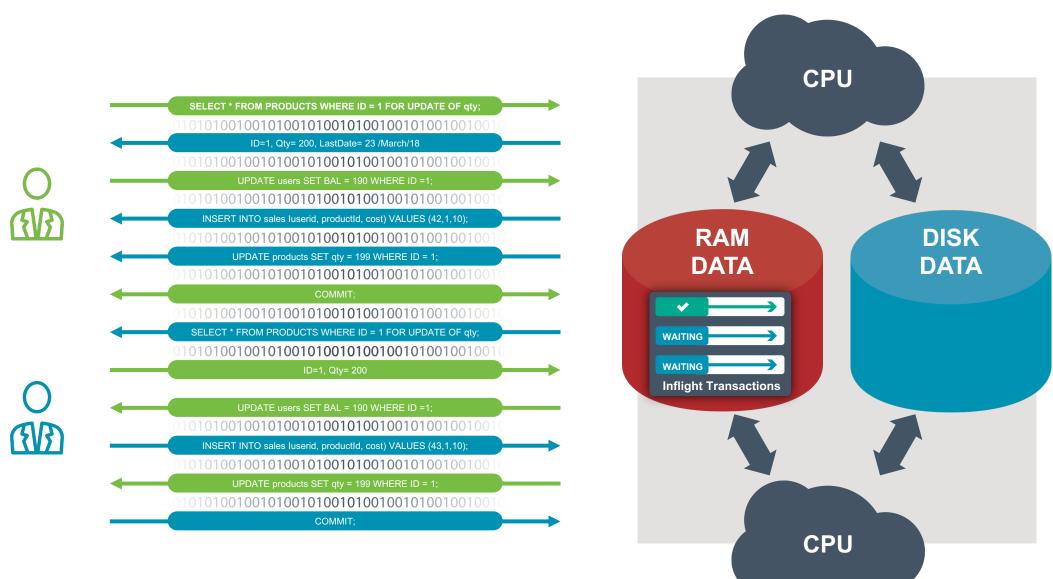


RDBMS - How We Thought an RDBMS Worked

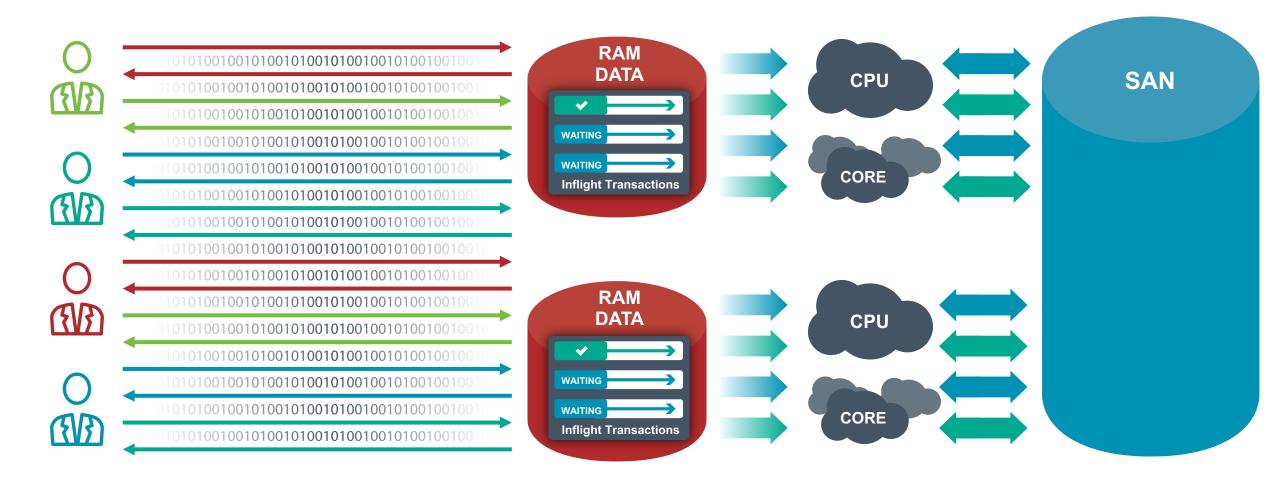




RDBMS - What Actually Happens – Part 1...



RDBMS - What Actually Happens – Part 2



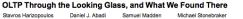


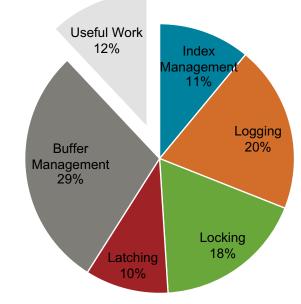
VoltDB was designed to solve this problem



Michael Stonebraker Samuel Madden Daniel J. Abadi Stavros Harizopolos MIT CSAIL	Nabil Hachem AvamGarde Consulting, LLC nhachem@agdba.com	Pat Helk Microsoft Con phelland@micri
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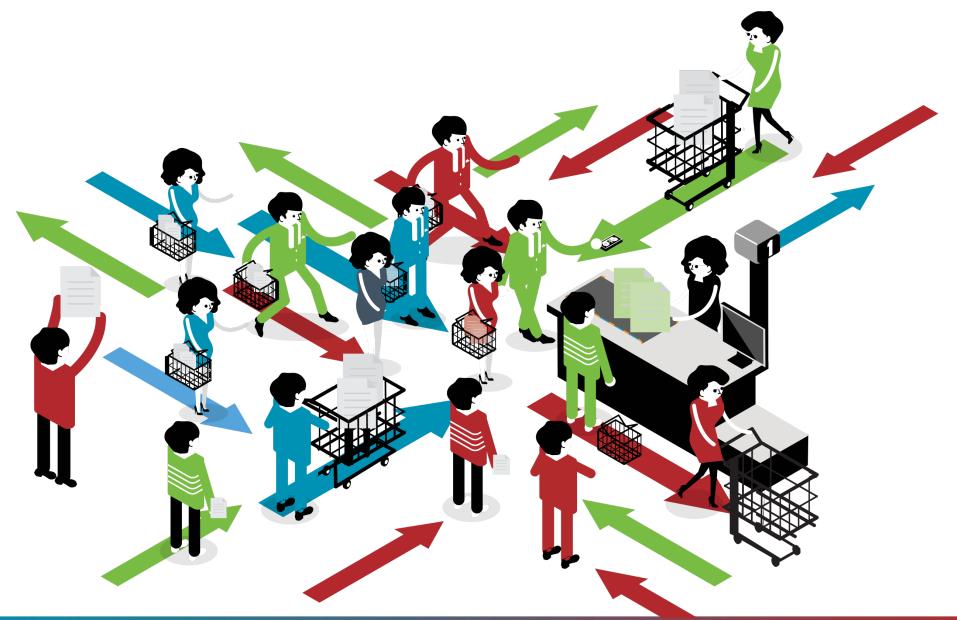
HP Labs Palo Alto, CA	Yale University New Haven, CT	Massachusetts Institute of Technology Cambridge, MA
stavros@hp.com	dna@cs.yale.edu	{madden, stonebraker}@csail.mit.edu
ABSTRACT Online Transaction Processing (OL) of features — disk-resident B-trees concurrency control, support for n	and heap files, locking-based nulti-threading — that were	 INTRODUCTION Modern general purpose colline transaction processing (OLTP) database systems include a standard stude of fattaners a collection of on-sida data strutures for table storage, including hasp files
optimized for computer technology in modern processors, memories, an computers are vanyi different from that many OLTP databases will no most OLTP transactions can be proc Yet database architecture has change Based on this observation, we look a	d networks mean that today's those of 30 years ago, such sw fit in main memory, and ressed in milliseconds or less. d lintle.	and B-trees, support for multiple concurrent queries via locking- based concurrency control, leg-based recovery, and an efficient buffer manager. These features were developed to support trans- actions processing in the 1970's and 1980's, when an OLTP data- base was many times larger than the main memory, and when the computers that ran these databases cost hundreds of thousands to millions of dollars.
convertisinal database systems that recent hardware tends, and spec- through dealled instruction-level 1 ponents involved in a transaction (Shore) raming a subset of TPC-C. Shore, we progressively modified i removale or optimization, we had a fully ran our workload. Overall, we mizations that explain a total differ	one might build that exploit ulate on their performance breakdown of the major com- processing database system Rather than simply profiling it so that after every feature (faster) working system that identify overheads and opti-	Today, the situation is quite different. First, modern processors are very disk, such this the componention time for many OLTD- style transactions is measured in microseconds. For a few hou- sand dollica, a system with glaphysics of main memory can be purchased. Furthermore, it not uncommon for institutions to worn networked clusters of many such workstations, with aggre- gate memory measured in hundred of glaphytes — sufficient to keep many OLTD databases in RAM.
in raw performance. We also show pole in the tent" in modern (memor but that substantial time is spent in tree, and buffer management operation	hat there is no single "high resident) database systems, gging, latching, locking, B- ts.	Second, the rise of the Internet, as well as the variety of data intensive applications in use in a number of domains, has led to a rising interest in database-like applications without the full saite of standard database features. Operating systems and networking conferences are now full of proposals for "database-like" storage systems with varying forms of consistency, reliability, concur-
Categories and Subject De H.2.4 [Database Management]: Syn ing; concurrency.		rency, replication, and queryability [DG04, CDG+06, GBH+00, SMK+01].
General Terms Measurement, Performance, Experim Keywords	sentation.	This rising demand for database-like services, coupled with dra- matic performance improvements and costs reduction in hard- ware, suggests a number of interesting alternative systems that one might build with a different set of features than those pro- vided by standard OLTP engines.
Online Transaction Processing, OLI processing, DBMS architecture.		1.1 Alternative DBMS Architectures Obviously, optimizing OLTP systems for main memory is a good idea when a database fits in RAM. But a number of other data- base variants are possible; for example:
Permission to make digital or hard copies sonal or classroom use is granted withou made or distributed for profit or commerce this notice and the full citation on the f republish, to post on servers or to redist cific permission and/or a fee.	t fee provided that copies are not ial advantage and that copies bear first page. To copy otherwise, or ribute to lists, requires prior spe-	 Logless databases. A log-free database system might either not need recovery, or might perform recovery from other sites in a cluster (as was proposed in systems like Harp [LGG+91], Harber (LM06], and C-Stere [SAB+05]). Sinele threaded database. Since multi-dreading in OLTP
SIGMOD'08, June 9-12, 2008, Vancouve Copyright 2008 ACM 978-1-60558-102-		 single inreaded databases. Since multi-inreading in OLTP databases was traditionally important for latency hiding in the





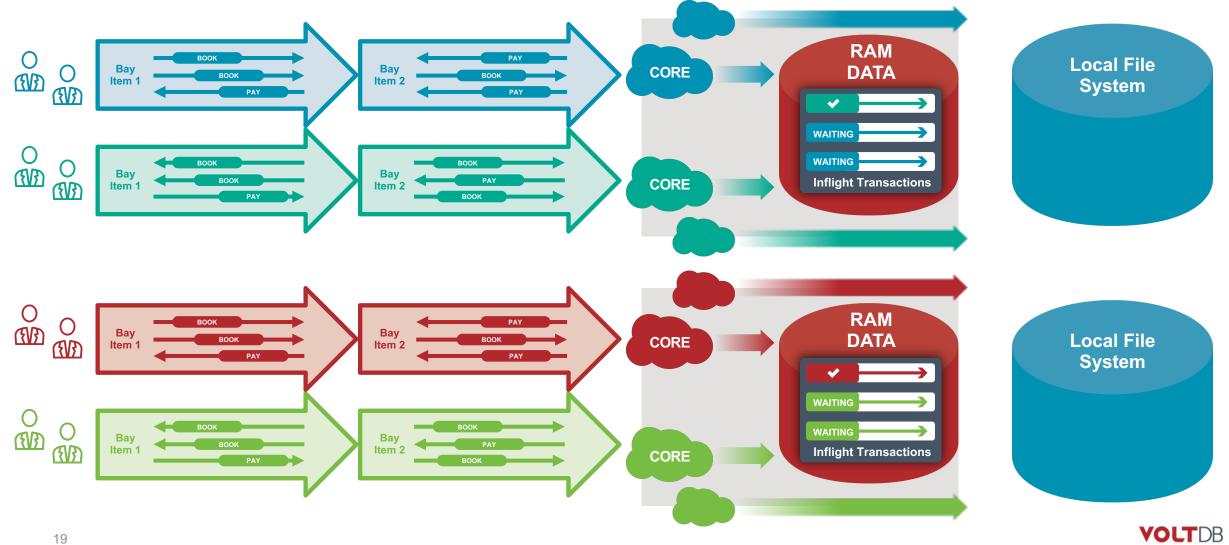
VOLTDB

If we tried this in a supermarket...

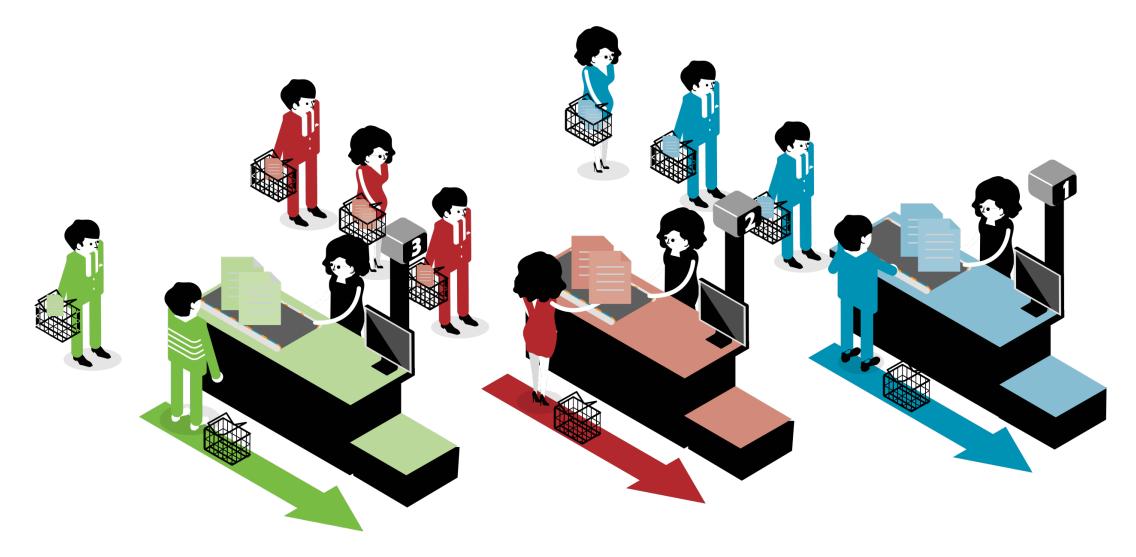


VOLTDB

How VoltDB works



How a supermarket works...





The only 3 ways to interact with any database

Approach	Examples	Strengths	Weaknesses
Many SQL Statements + Commit or Rollback	JDBC, ODBC,	Liked by developers, initial development is rapid	 Doesn't handle scaling OLTP loads well – DB spends its time figuring out who can see what instead of working Constant locking problems for shared, finite resources Failure of a client to Commit or Rollback causes a temporary resource leak
Move all the data to the client and back again	NoSQL, KV Stores	Very developer friendly	 Multiple updated copies of the data can arrive at the same time for scaling OLTP loads All of the data gets moved across the network, every time.
Stored Procedures	VoltDB, PL/SQL	Predictable speed and best possible scaling characteristics	 Not in fashion with developers. PL/SQL created perception of complexity. Other implementations of Java Stored Procedures really slow.

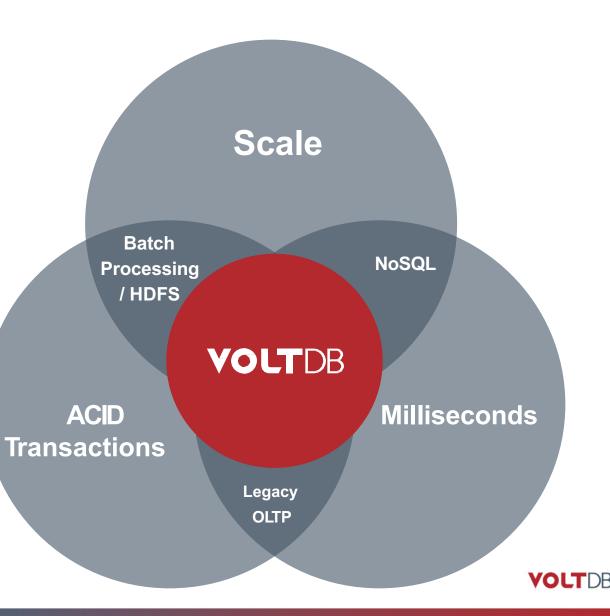
VOLTDB

VoltDB and Machine Learning

ML: The search for value

ML adds *real* value when:

- Combined with state
 - State can be a composite of multiple data sources
- Is used to inform and influence decisions
- Happens in real time
- Happens at scale



VoltDB + ML

The Good News

- VoltDB appears to work with any ML engine with a Java runtime
- VoltDB can be made to work with any ML engine with a C++ runtime
 - Requires JNI expertise

Caveats

- Runtime engine can't have runtime dependencies/speak to another server
- Runtime engine must be deterministic
- Runtime engine must be fast (< 5ms)
 - >5ms undermines utility of using VoltDB
 - Be wary of instantiation costs



VoltDB + ML

Limitations

- Non Deterministic code
- Other servers
- Not C++ or JVM compatible
 - Not a showstopper, but...
- Slow

• Example: Neural Nets

But GPDR may make them unusable in EU anyway...



ML Example – User Defined Function in H20

```
public class AirlineDemoUDF {
   private static String modelClassName = "abm_pojo_test";
   public String ademo(String cRSDepTime, String year, String month, String dayOfMonth, String dayOfWeek,
          String uniqueCarrier, String origin, String dest) {
       try {
          hex.genmodel.GenModel rawModel;
          rawModel = (hex.genmodel.GenModel) Class.forName(modelClassName).newInstance();
          EasyPredictModelWrapper model = new EasyPredictModelWrapper(rawModel);
          RowData row = new RowData();
          row.put("Year", year);
          row.put("Month", month);
          row.put("DayofMonth", dayOfMonth);
          row.put("DayOfWeek", dayOfWeek);
          row.put("CRSDepTime", cRSDepTime);
          row.put("UniqueCarrier", uniqueCarrier);
          row.put("Origin", origin);
                                                                     CREATE FUNCTION ademo FROM METHOD h20.AirlineDemoUDF.ademo;
          row.put("Dest", dest);
          BinomialModelPrediction p = model.predictBinomial(row);
                                                                     CREATE PROCEDURE flight_hist
          return (p.label);
                                                                     PARTITION ON TABLE flights COLUMN f_FlightNum AS
                                                                     SELECT f_cRSDepTime, f_year, f_month, f_dayOfMonth,
       } catch (Exception e) {
                                                                     f_dayOfWeek, f_uniqueCarrier, f_origin, f_dest
          System.err.println(e.getMessage());
                                                                     ,ademo(f_cRSDepTime, f_year, f_month, f_dayOfMonth,
          return null;
                                                                     f_dayOfWeek, f_uniqueCarrier, f_origin, f_dest ) ademo
                                                                     from flights
                                                                     where f_FlightNum = ?
   }
                                                                     order by f_year, f_month, f_dayOfMonth,f_cRSDepTime;
```



ML Example – Calling JPMML from a Procedure

public VoltTable[] runModel(String pmmlFileName, VoltTable inputParams) throws Exception {

Evaluator evaluator = pmmlEvaluators.get(pmmlFileName);

```
if (evaluator == null) {
    throw new Exception("Model " + pmmlFileName + " not found");
}
```

List<InputField> inputFields = evaluator.getInputFields(); Map<FieldName, FieldValue> arguments = new LinkedHashMap<FieldName, FieldValue>();

```
// Sanity check input params
```

```
if (inputParams == null) {
    throw new Exception("VoltTable inputParams can't be null");
}
```

```
if (inputParams.getRowCount() != 1) {
    throw new Exception("VoltTable inputParams must have one row");
}
```

```
inputParams.advanceRow();
for (InputField inputField : inputFields) {
    mapVoltparamToPmmlParam(inputParams, arguments, inputField);
}
```

```
Map<FieldName, ?> result = evaluator.evaluate(arguments);
```

```
// Processing results
// Retrieving the values of target fields (ig. primary results):
List<TargetField> targetFields = evaluator.getTargetFields();
VoltTable resultTable = mapPmmlTargetFieldsToVoltTable(result, targetFields);
```

// other fields

```
List<OutputField> outputFields = evaluator.getOutputFields();
VoltTable otherTable = mapPmmlOutputFieldsToVoltTable(result, outputFields);
```

```
VoltTable[] outputParams = { resultTable, otherTable };
```

return outputParams;

public class GolfDemo extends VoltProcedure {

VoltTable[] pmmlOut;

try {

```
JPMMLImpl i = JPMMLImpl.getInstance();
VoltDBJPMMLWrangler w = i.getPool().borrowObject();
final String modelName = "tree.model";
VoltTable paramtable = w.getEmptyTable(modelName);
paramtable.addRow(temperature, humidity, windy, outlook);
pmmlOut = w.runModel(modelName, paramtable);
```

} catch (Exception e) {

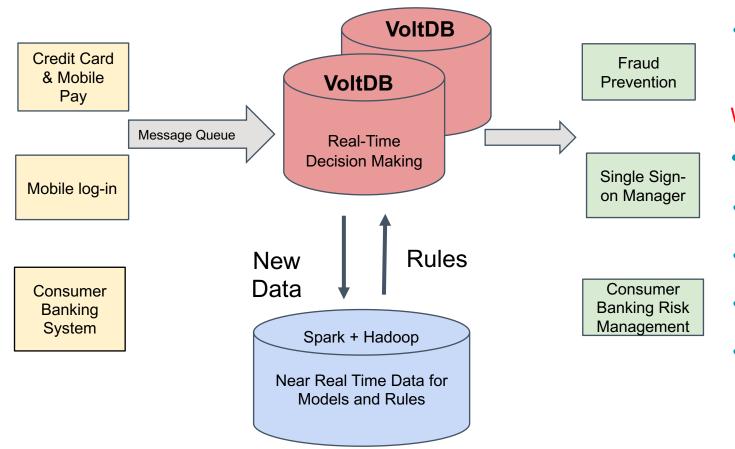
```
System.err.println(e.getMessage());
throw new VoltAbortException(e);
```

}

ł

```
voltExecuteSQL(true);
return pmmlOut;
```





Application/Use Case

- Fraud Prevention
- Single sign-in of all Huawei phones
- Consumer banking risk management

Why VoltDB?

- > 50% reduction in fraud cases
- >\$15M/year saved from fraud loss
- 10k complex Transactions Per Second
- 99.99% transactions finish < 50ms
- 10x better performance than

traditional fraud detection



A Proven and Reliable Partner

