Outils pour l'analyse prédictive parallèle de multiples sources de données non structurées

Forum Ter@tec

Mercredi 25 juin 2015

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Challenges Businesses Are Facing Today

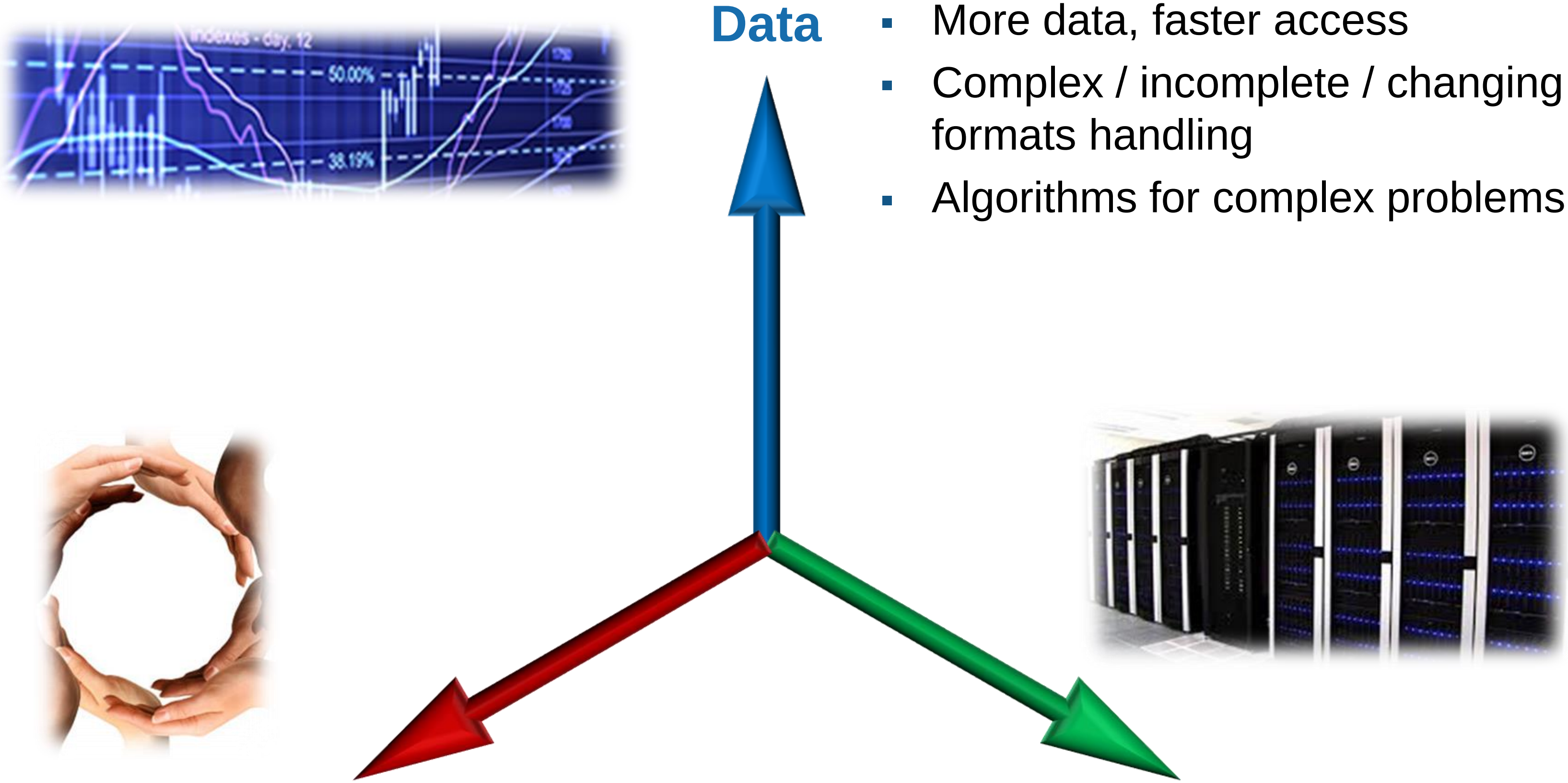
Big Data for evidence-based decision making

- **Goal**
  - Large (and increasing) amount of available data
  - Leverage data to make better decision

- **Organizational issues**
  - Rapid evolution
  - Data scientist need to share their algorithms and results efficiently

- **Technical issues**
  - Datasets do not fit in the memory of a single computer
  - Processing these data requires huge computing resources

How MATLAB Helps Tackling Big Data



Data

- More data, faster access
- Complex / incomplete / changing formats handling
- Algorithms for complex problems

People & Systems

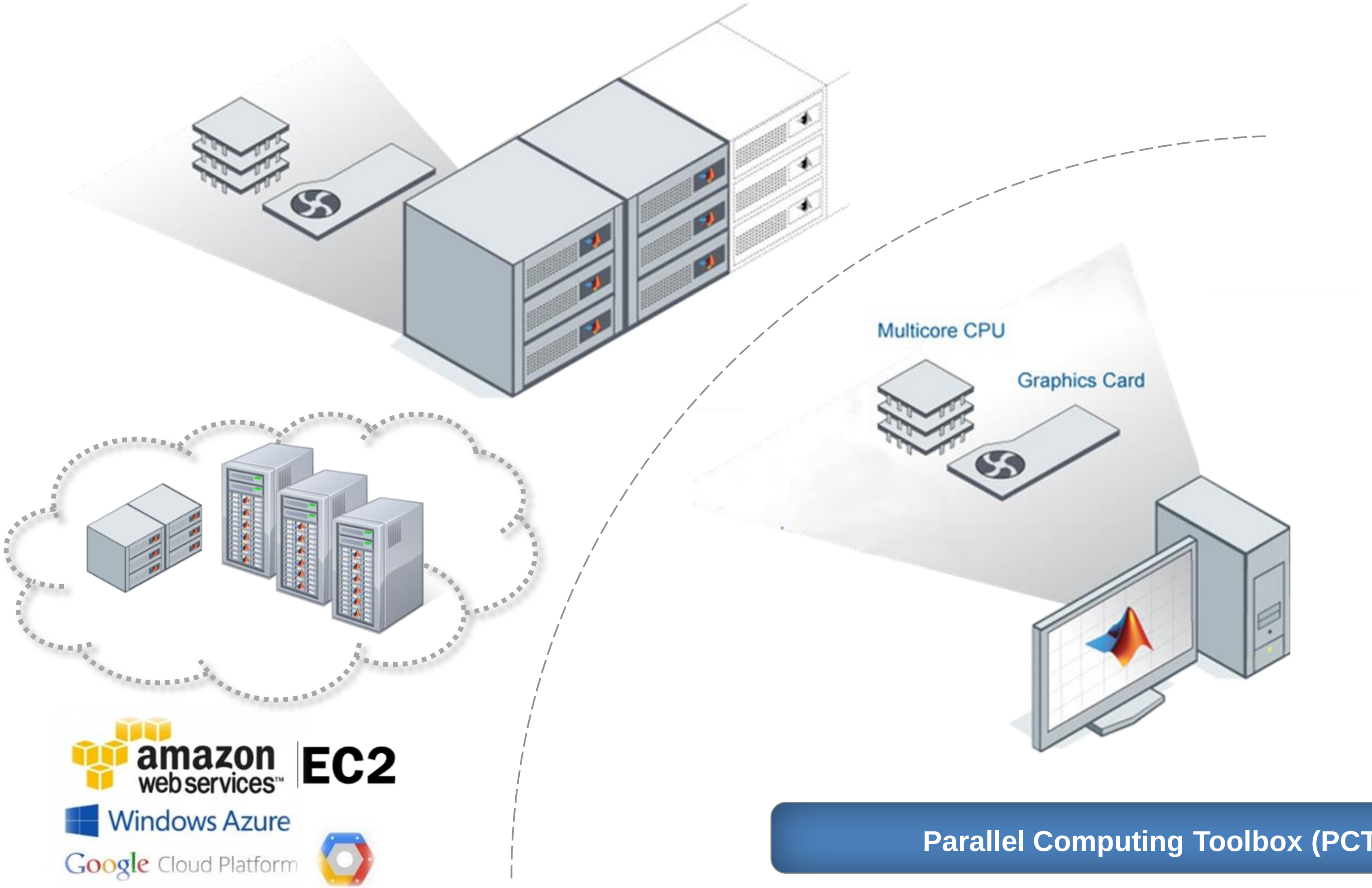
- Share algorithms & protect IP
- Real-time analytics

Compute Power

- Leverage HPC facilities & clouds
- Distributed memory framework

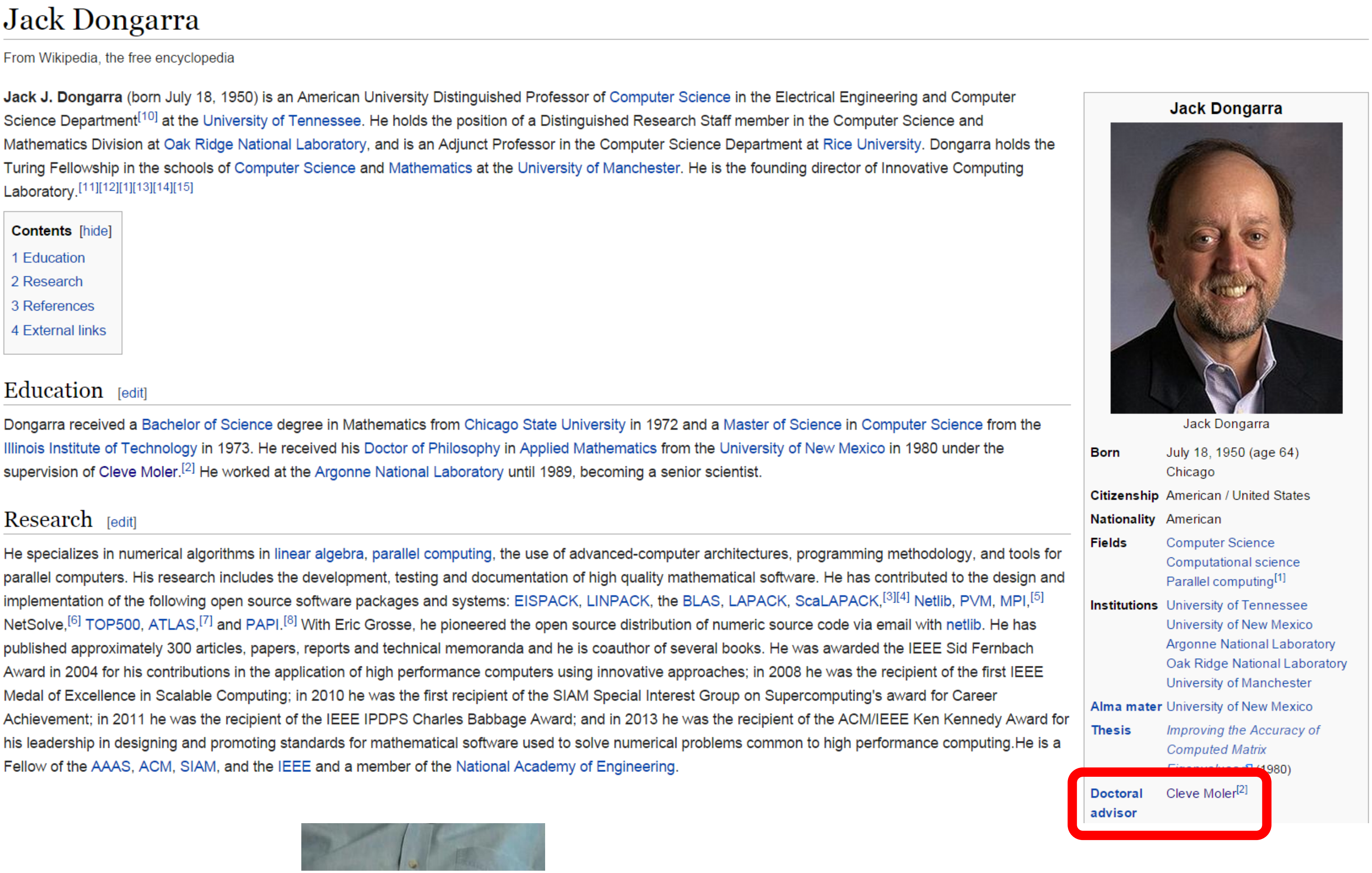
Scaling Out Calculations

MATLAB Distributed Computing Server (MDCS)



Parallel Computing Toolbox (PCT)

MATLAB & High Performance Computing?



Jack Dongarra

From Wikipedia, the free encyclopedia

Jack J. Dongarra (born July 18, 1950) is an American University Distinguished Professor of Computer Science in the Electrical Engineering and Computer Science Department[10] at the University of Tennessee. He holds the position of a Distinguished Research Staff member in the Computer Science and Mathematics Division at Oak Ridge National Laboratory, and is an Adjunct Professor in the Computer Science Department at Rice University. Dongarra holds the Turing Fellowship in the schools of Computer Science and Mathematics at the University of Manchester. He is the founding director of Innovative Computing Laboratory.[11][12][1][13][14][15]

Contents [hide]

Education [edit]

Dongarra received a Bachelor of Science degree in Mathematics from Chicago State University in 1972 and a Master of Science in Computer Science from the Illinois Institute of Technology in 1973. He received his Doctor of Philosophy in Applied Mathematics from the University of New Mexico in 1980 under the supervision of Cleve Moler.[2] He worked at the Argonne National Laboratory until 1989, becoming a senior scientist.

Research [edit]

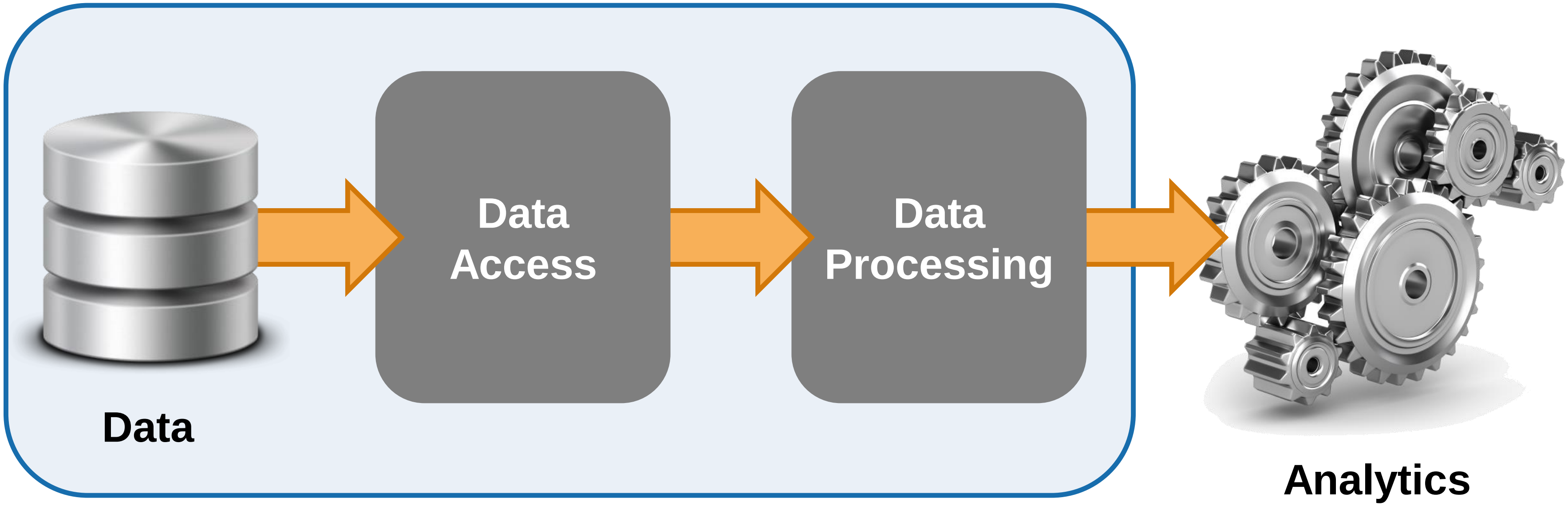
He specializes in numerical algorithms in linear algebra, parallel computing, the use of advanced-computer architectures, programming methodology, and tools for parallel computers. His research includes the development, testing and documentation of high quality mathematical software. He has contributed to the design and implementation of the following open source software packages and systems: EISPACK, LINPACK, the BLAS, LAPACK, ScaLAPACK,[3][4] Netlib, PVM, MPI,[5] NetSolve,[6] TOP500, ATLAS,[7] and PAPI.[8] With Eric Grosse, he pioneered the open source distribution of numeric source code via email with netlib. He has published approximately 300 articles, papers, reports and technical memoranda and he is coauthor of several books. He was awarded the IEEE Sid Fernbach Award in 2004 for his contributions in the application of high performance computers using innovative approaches; in 2008 he was the recipient of the first IEEE Medal of Excellence in Scalable Computing; in 2010 he was the first recipient of the SIAM Special Interest Group on Supercomputing's award for Career Achievement; in 2011 he was the recipient of the IEEE IPDPS Charles Babbage Award; and in 2013 he was the recipient of the ACM/IEEE Ken Kennedy Award for his leadership in designing and promoting standards for mathematical software used to solve numerical problems common to high performance computing.He is a Fellow of the AAAS, ACM, SIAM, and the IEEE and a member of the National Academy of Engineering.

Jack Dongarra

Jack Dongarra

Born	July 18, 1950 (age 64) Chicago
Citizenship	American / United States
Nationality	American
Fields	Computer Science Computational science Parallel computing[1]
Institutions	University of Tennessee University of New Mexico Argonne National Laboratory Oak Ridge National Laboratory University of Manchester
Alma mater	University of New Mexico
Thesis	*Improving the Accuracy of Computed Matrix Eigenvalues* (1980)
Doctoral advisor	Cleve Moler[2]

Data Analytics Workflow



Data

Data Access

Data Processing

Analytics

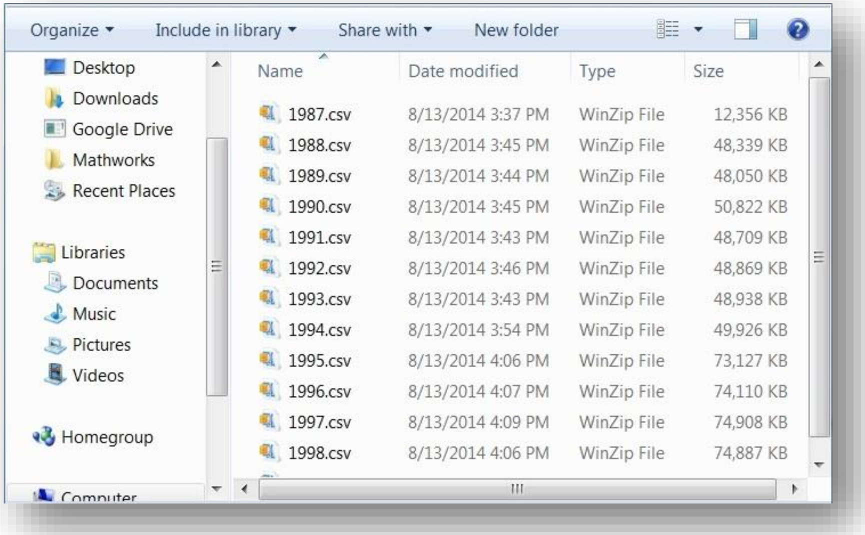
Today’s presentation

- Descriptive Statistics
- Machine Learning
- Neural Networks
- MapReduce

Access Large Datasets

`datastore`

- Data container that allows to easily read data that are **too large to fit in the computer's memory**



Name	Date modified	Type	Size
1987.csv	8/13/2014 3:37 PM	WinZip File	12,356 KB
1988.csv	8/13/2014 3:45 PM	WinZip File	48,339 KB
1989.csv	8/13/2014 3:44 PM	WinZip File	48,050 KB
1990.csv	8/13/2014 3:45 PM	WinZip File	50,822 KB
1991.csv	8/13/2014 3:43 PM	WinZip File	48,709 KB
1992.csv	8/13/2014 3:46 PM	WinZip File	48,869 KB
1993.csv	8/13/2014 3:43 PM	WinZip File	48,938 KB
1994.csv	8/13/2014 3:54 PM	WinZip File	49,926 KB
1995.csv	8/13/2014 4:06 PM	WinZip File	73,127 KB
1996.csv	8/13/2014 4:07 PM	WinZip File	74,110 KB
1997.csv	8/13/2014 4:09 PM	WinZip File	74,908 KB
1998.csv	8/13/2014 4:06 PM	WinZip File	74,887 KB

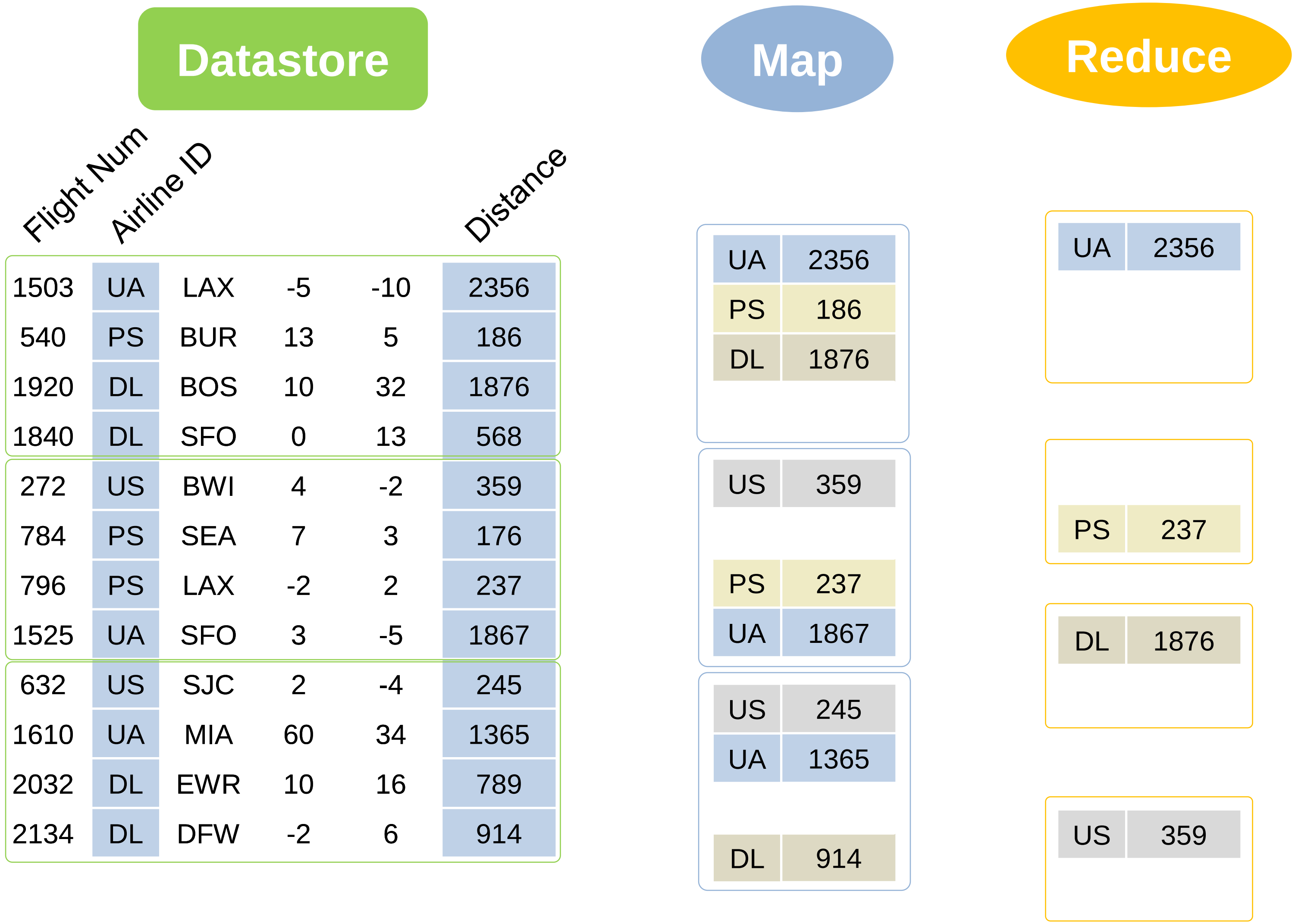
- Incremental read: data loaded in memory by parts

- Data sources of various natures
  - Database (using Database Toolbox)
  - Single text file or collection of text files
  - MATLAB is generally able to read and write data directly from/to HDFS

- `datastore` can be partitioned using the `partition` function
  - Allows **parallel** data access
  - Take advantage of parallel file systems

MapReduce Programming Model

Example with air traffic dataset: find the longest flight for each carrier



Datastore

Flight Num	Airline ID				Distance
1503	UA	LAX	-5	-10	2356
540	PS	BUR	13	5	186
1920	DL	BOS	10	32	1876
1840	DL	SFO	0	13	568
272	US	BWI	4	-2	359
784	PS	SEA	7	3	176
796	PS	LAX	-2	2	237
1525	UA	SFO	3	-5	1867
632	US	SJC	2	-4	245
1610	UA	MIA	60	34	1365
2032	DL	EWR	10	16	789
2134	DL	DFW	-2	6	914

Map

UA	2356
PS	186
DL	1876

US	359
PS	237
UA	1867

US	245
UA	1365
DL	914

Reduce

UA	2356

PS	237

DL	1876

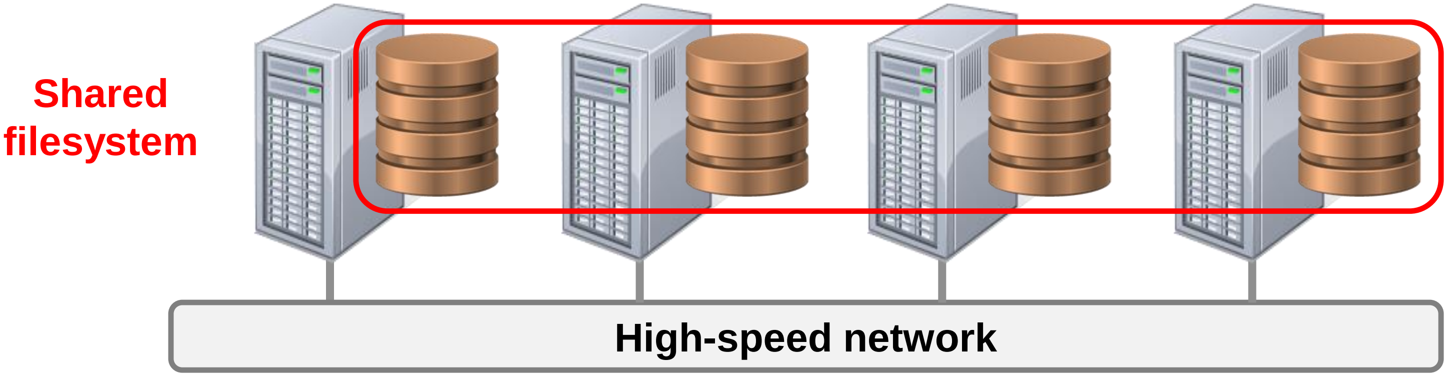
US	359

MapReduce Programming Model

Strengths and limitations

- `mapreduce` has been introduced in MATLAB R2014b

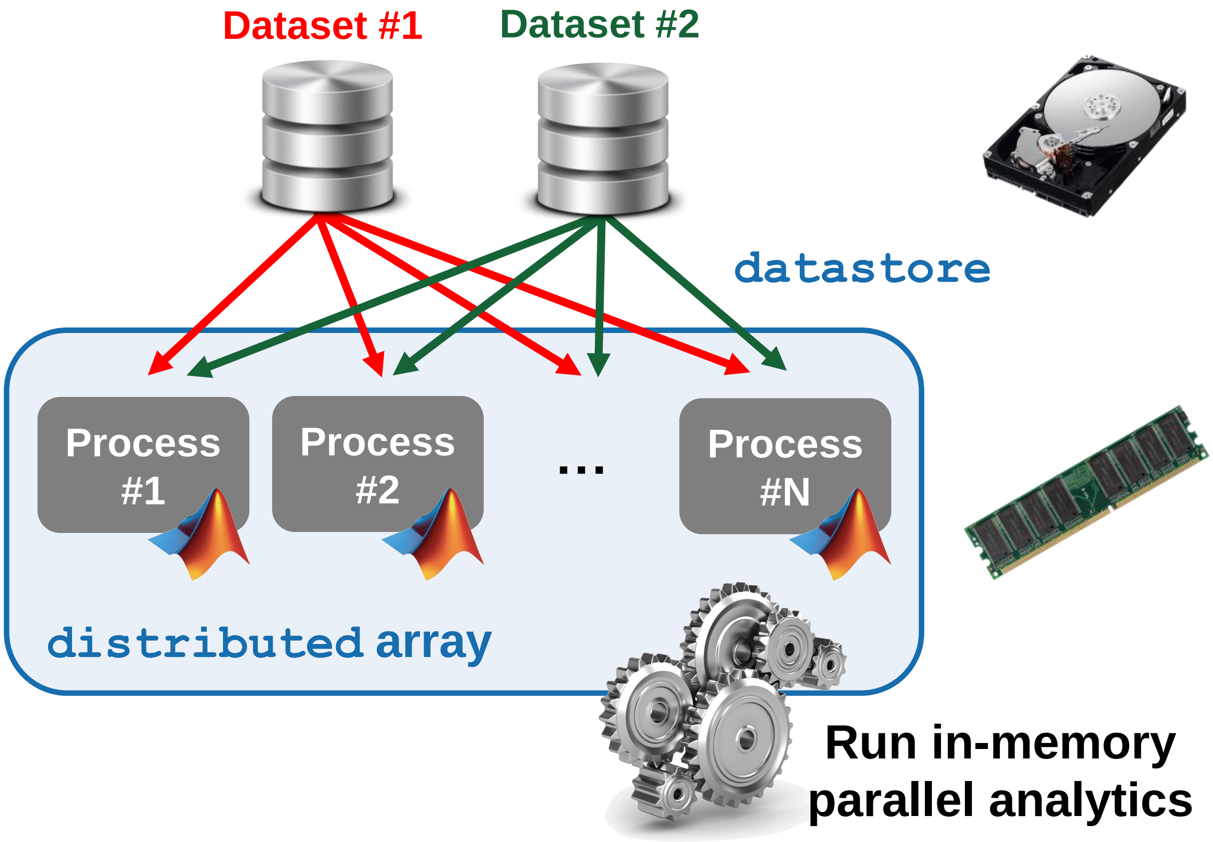
- **Strengths**
  - Analytics are made easy when they fit in the MapReduce framework
  - MapReduce on Hadoop can take advantage of data locality in HDFS



- **Limitations**
  - Subset-by-subset data processing, no vision of the whole dataset
  - Scalability issues in some cases

A Parallel Programming Model for Predictive Analytics

- Parallel computing implementation in MATLAB
  - Capabilities all based on MPI
  - MATLAB offers a transparently distributed data structure: `distributed`



Dataset #1

Dataset #2

`datastore`

Process #1

Process #2

...

Process #N

`distributed` array

Run in-memory parallel analytics

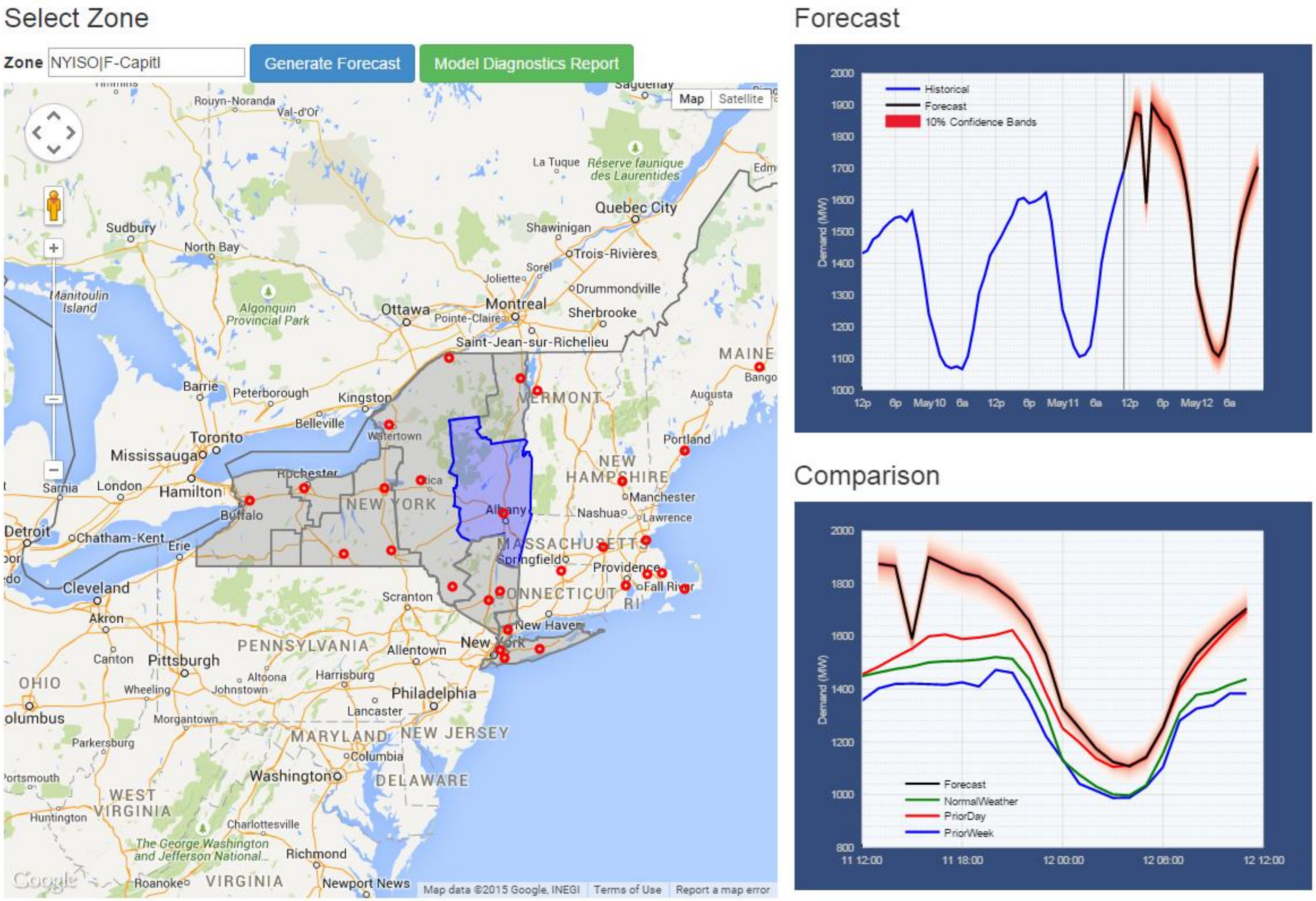
A Parallel Programming Model for Predictive Analytics

Scalability analysis

	Does it scale?	Does it require to store the complete dataset on a single process?
1. Read data from one or multiple datasets and preprocess it	✓	✓
2. Store the preprocessed data in a distributed array	✓ (up to 100s of processes)	✓
3. Run in-memory analytics on the distributed array	✓ (depends on the algorithm)	✓ (depends on the algorithm)

A Parallel Programming Model for Predictive Analytics

Example: power load forecasting



Select Zone

Zone NYISO|F-Capitl

Generate Forecast

Model Diagnostics Report

Forecast

Comparison

http://ec2-54-165-201-58.compute-1.amazonaws.com:8080/DemandForecastWeb/

A Parallel Programming Model for Predictive Analytics

Example: power load forecasting

- **Goal**
  - Develop a predictive model to forecast electrical power consumption
  - Deploy the prediction tool in power plants to adjust production
- **Predictors from different datasets**
  - Power consumption over the previous days
  - Calendar information: day of the week? holiday period?
  - Climate data
- **Challenges**
  - Multiple data sources with different formatting
  - Datasets have different samplings
- **Final result**
  - Predictive model based on Neural Networks
  - Deployed in production using MATLAB Production Server

Key Takeaways

- Access large datasets with MATLAB
  - `datastore` allows to read datasets that do not fit in memory
  - `partition` allows parallel data access
- Tools for easily developing algorithms and scaling out computations
  - No need to be an expert in computer science
  - No need to be an expert in parallel computing
- MathWorks development teams heavily involved
  - Continuous development and improvement
  - New features in each release

Thank you!

Q & A session