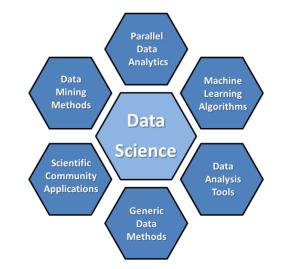
Data Sharing Experiences of Smart Data Analytics Tasks in Remote Sensing Research





Federated Systems and Data Division

**Research Group** 

#### **High Productivity Data Processing**

#### Dr. – Ing. Morris Riedel

Adjunct Associated Professor, University of Iceland Research Group Leader, Juelich Supercomputing Centre

Gabriele Cavallaro

University of Iceland

APARSEN – DPHEP – EUDAT – SCIDIP-ES Joint Data Preservation Workshop 'Safeguarding our Scientific, Educational and Cultural Heritage' 24 September 2014 Black Room, De Meervaart Conference Centre, Meer en Vaart 300, Amsterdam 1068

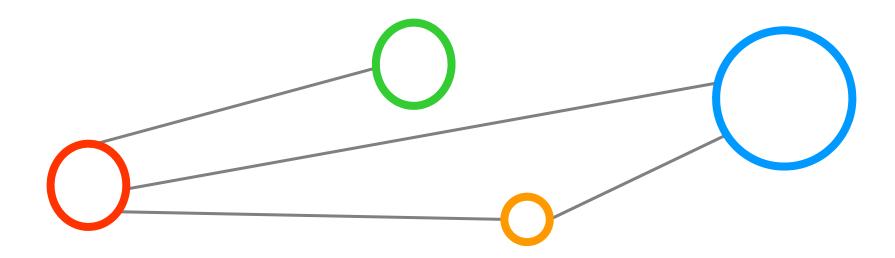




UNIVERSITY OF ICELAND SCHOOL OF ENGINEERING AND NATURAL SCIENCES

FACULTY OF INDUSTRIAL ENGINEERING, MECHANICAL ENGINEERING AND COMPUTER SCIENCE





## Outline

### Research Group High Productivity Data Processing

Smart Data Analytics & Daily Work Activities

## Smart Data Analytics in Remote Sensing Research

- Typical Example: Study on Land Cover Types Classification Using EUDAT B2SHARE
- Data sharing and Preserving Outcomes
- Practical Examples and Usage Models

### Summary

Selected Findings and Suggestions

References



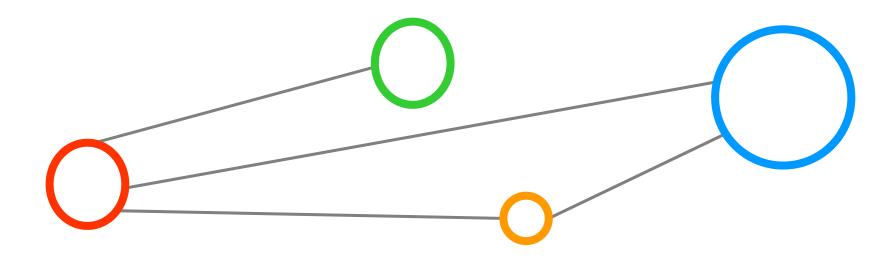


The work was performed under the umbrella of the **Research Data Alliance – Big Data Analytics Interest Group** 

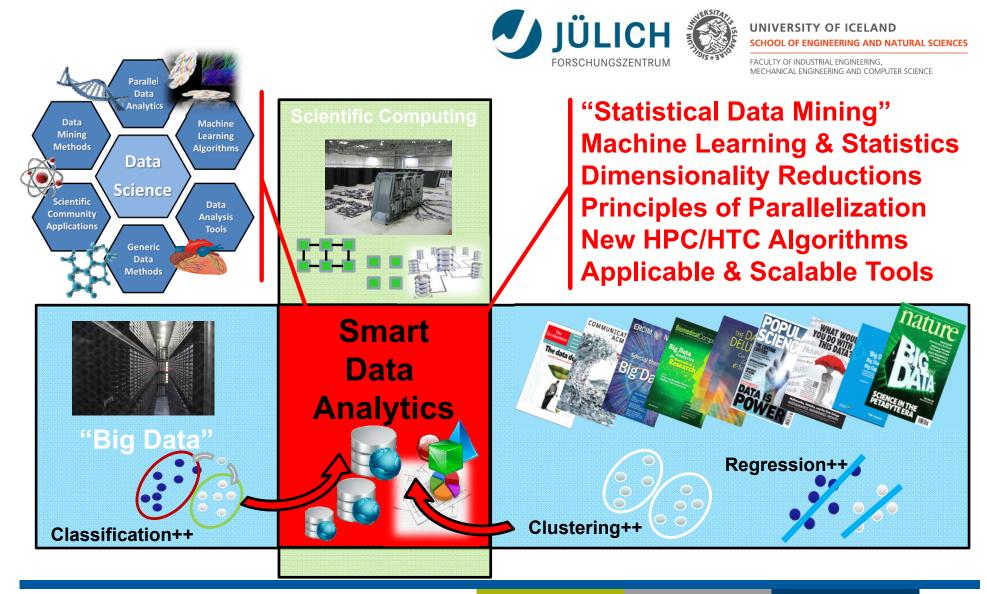
[1] RDA BDA IG Webpage



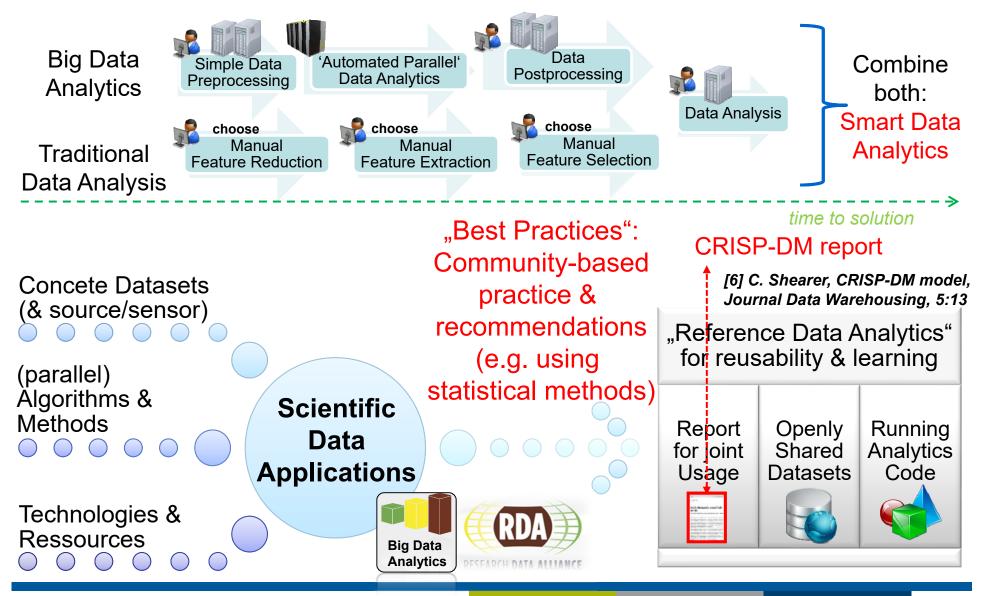
## Research Group High Productivity Data Processing



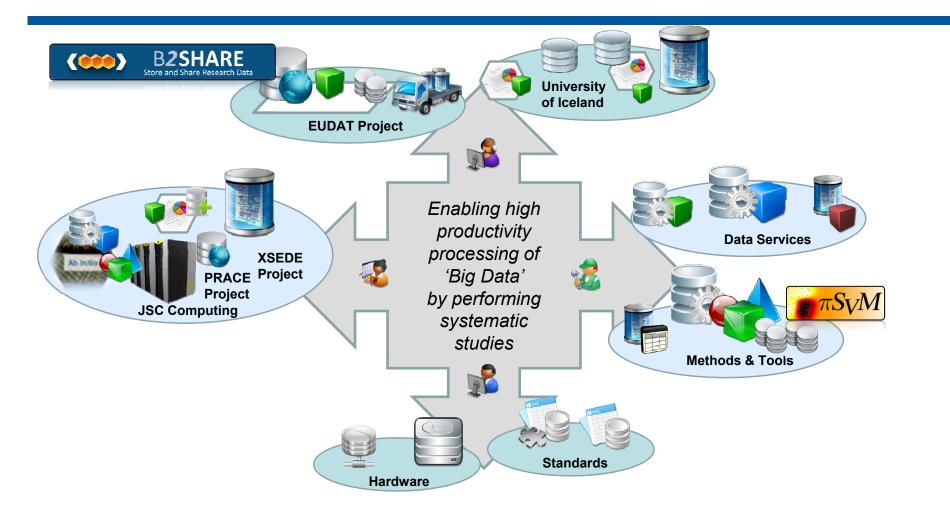
## Research Group High Productivity Data Processing



## **Smart Data Analytics**



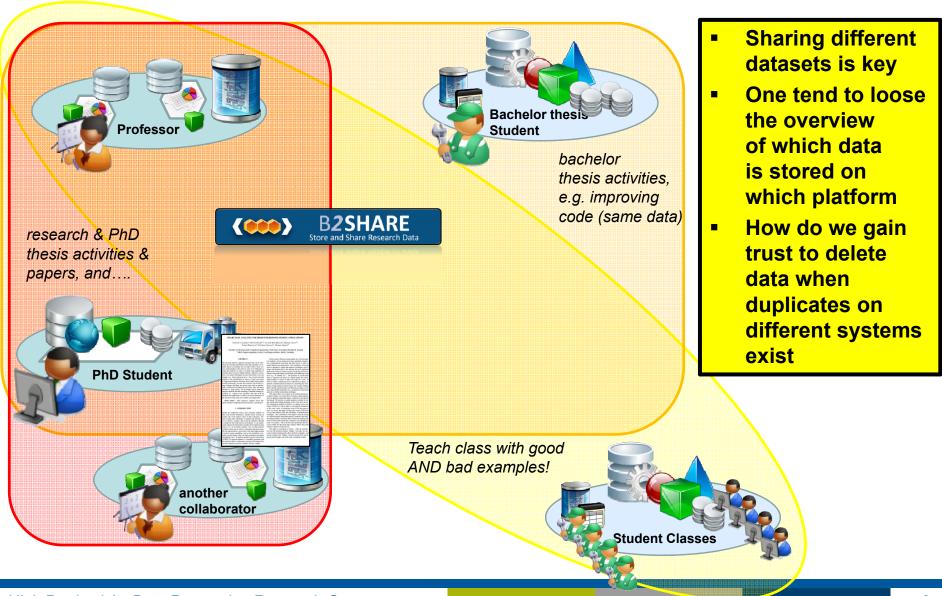
## Need for Sharing: Complex work environments



One tend to loose the overview of which data is stored on which platform

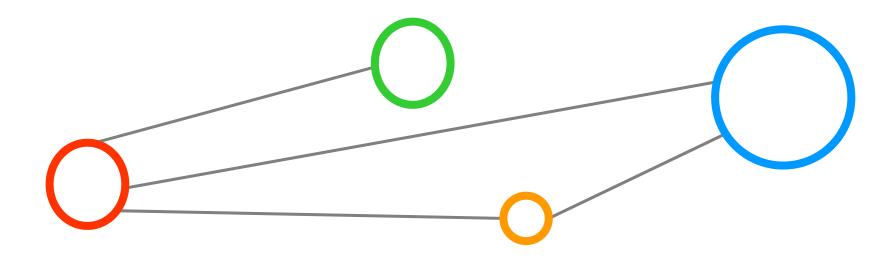
How do we gain trust to delete data when duplicates on different systems exist?

## Need for Sharing: One Example from Daily Research

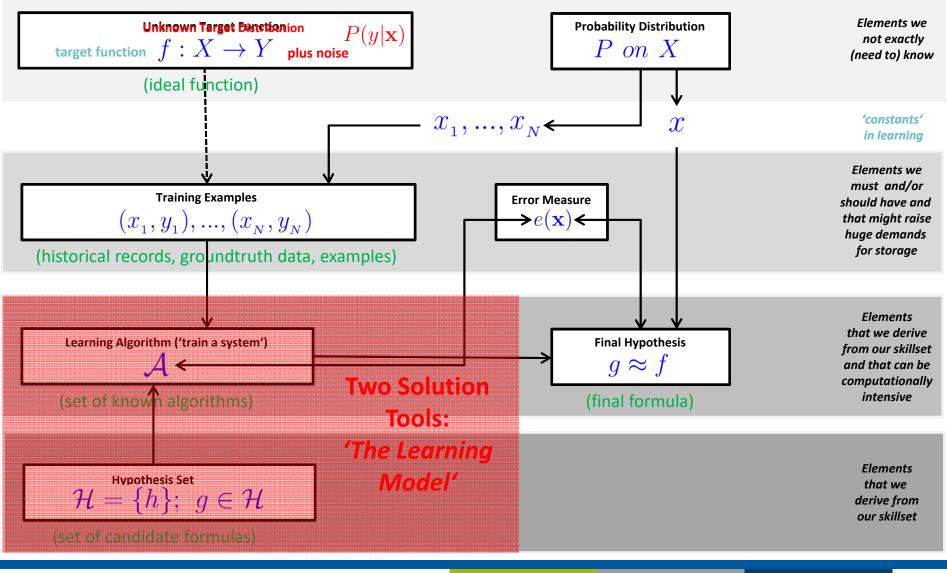


High Productivity Data Processing Research Group

## Smart Data Analytics in Remote Sensing Research



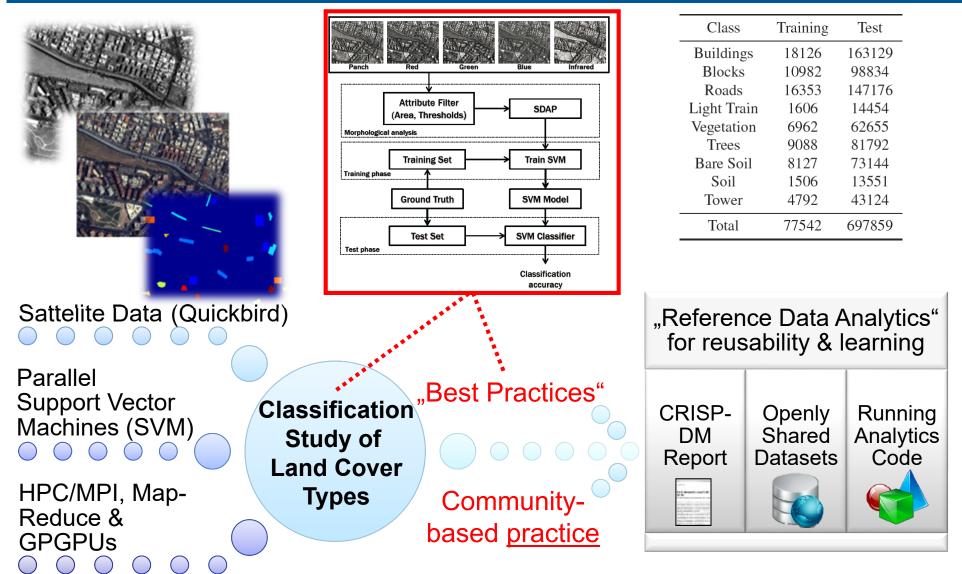
## Supervised Learning from Data – Data Inputs & Outputs

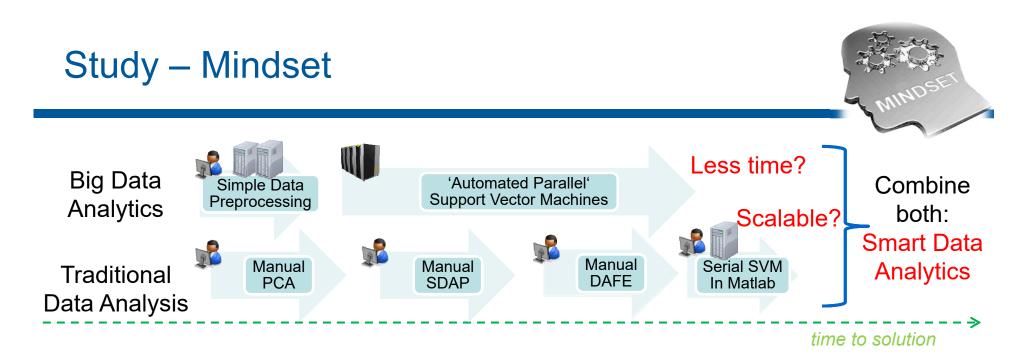


High Productivity Data Processing Research Group

## Use parallel Support Vector Machines (SVMs)







#### Big Data Analytics $\rightarrow$ [processing power++, time scientists-]

- Working on 'big data' by an automated process on computing machinery
- Scalable to 'big data volumes' (e.g. high dimensions), image time-series

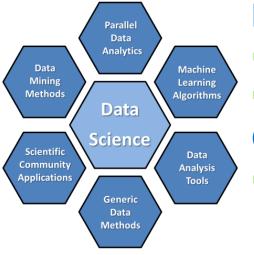
### Traditional Data Analysis → [time scientists+++, processing power-]

- Data reduction by manual intervention  $\rightarrow$  'small data' (e.g. low dimensions)
- Not necessarily needs ,large-scale computing environments' scalable?



## Smart Data Analytics: Clever mix of both approaches

- Apply parallel and distributed computing techniques where feasible
- Take advantage of semi-automated statistical techniques from data science



## Examples to reduce 'big dataset dimensions'

- Principle Component Analysis (PCA)
- Discriminant Analysis Feature Extraction (DAFE)

## **Classification optimization technique**

Self-Dual Attribute Profile (SDAP)



Area



Std Dev

Moment of Inertia

[9] G. Cavallaro, M. Mura, J.A. Benediktsson, L. Bruzzone 'A Comparison of Self-Dual Attribute Profiles based on different filter rules for classification', IEEE IGARSS2014, Quebec, Canada

### Open Questions remains for the study...

- Can we perhaps 'speed-up' some of the statistical techniques?
- How can we preserve outcomes of the process for re-use & sharing?

## Study – Toolset



ΤοοΙ	Platform Approach	Findings when using Tool
Twister/ParallelSVM	Java; Apache Hadoop 1.0 (map- reduce); Twister (iterations), HTC	Much dependencies on other software: Hadoop, Messaging: stability needs to improve; slightly outdated move to HARP (Hadoop 2.0 SVM plug-in)
piSVM	C code; Message Passing Interface (MPI); HPC	Works stable; speed-up only when computing is really required (make no sense for small dataset dimensions), optimizations in code (load imbalance with increasing cores, collectives, etc.)
GPU accelerated LIBSVM	CUDA language	Easy to install, but relatively hard to program, no standard language (CUDA); but promising for future tests

## 'HTC Approach'

- Used FutureGrid cluster with Twister/ParallelSVM
- Uses map-reduce & messaging

[10] Sun Z., and Fox G., 'Study on Parallel SVM Based on MapReduce', In Proceedings of the international conference on parallel and distributed processing techniques and applications, 2012.

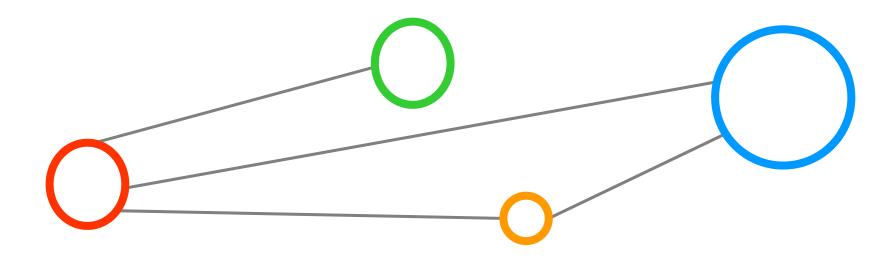
### 'HPC Approach'

- Used JUDGE cluster at Juelich Supercomputing Centre
- MPI was installed; piSVM ported

[11] piSVM Website, 2011 code



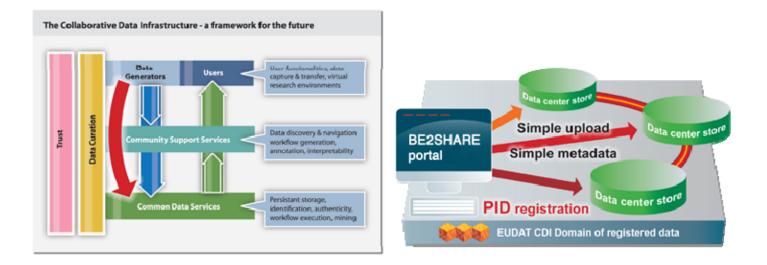
## Using EUDAT B2SHARE in Research



## **EUDAT B2SHARE**







- Having this tool available on the Web helps tremendously to save time for no research tasks
- Using the tool enables to focus better on the research tasks

## Study – Datasource & Sensors

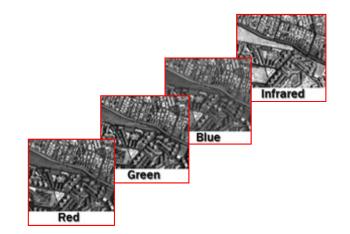
### Geographical location: Image of Rome, Italy

Remote sensor data obtained by Quickbird satellite

High-resolution (0.6m) panchromatic image



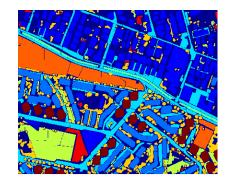
Pansharpened (UDWT) low-resolution (2.4m) multispectral images



## Study – Training vs. Test Data Generation

### Labelled data available

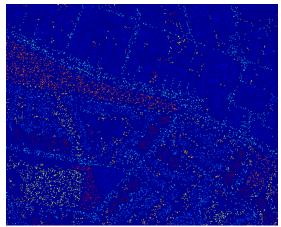
 Groundtruth data of 9 different land-cover classes available



### Data preparation

- We generated a set of training samples by randomly selecting 10% of the reference samples (with labelled data)
- Generated set of test samples from the remaining labels (labelled data, 90% of reference samples)

Class	Training	Test
Buildings	18126	163129
Blocks	10982	98834
Roads	16353	147176
Light Train	1606	14454
Vegetation	6962	62655
Trees	9088	81792
Bare Soil	8127	73144
Soil	1506	13551
Tower	4792	43124
Total	77542	697859

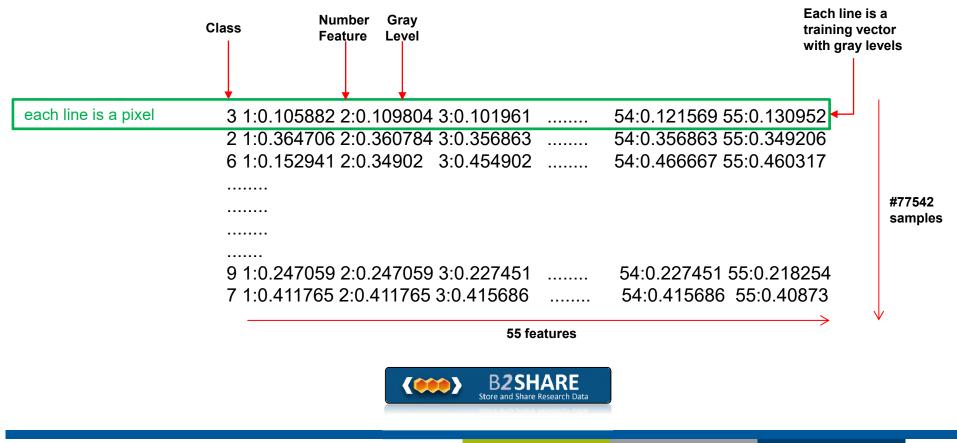


## Training Image (10% pixels/class)

## Data structure required for Data Analytics

### Based on 'LibSVM data format'

• E.g. 'SDAP on area' on all images training file





- Sharing pre-processed data
- LibSVM format

- **Training and Testing Datasets**
- **Different setups** for analysis (SDAP on All or **SDAP** on **Panchromatic**)

EUDAT	Store and Share Research Data
Information Comments Reviews Usage statistics	
	Rome data set OK
	22 May 2014 http://b2share.eudat.eu
Abstract: Attribute area	
The record appears in these collections:	
Generic	

iles 🔻			
Name	Date	Size	
sdap_area_panch_training.el	22 May 2014	12.7 MB	Download
sdap_area_all_training.el	22 May 2014	46.7 MB	Download
sdap_area_panch_test.el	22 May 2014	114.8 MB	Download
sdap_area_all_test.el	22 May 2014	420.0 MB	Download

Export								
Export as	<u>BibTeX</u> ,	MARC,	MARCXML,	<u>DC</u> ,	EndNote,	NLM,	RefWorks	
-								

PID:	http://hdl.handle.net/11304/4615928c-e1a5-11e3-
	8cd7-14feb57d12b9
Publication:	http://b2share.eudat.eu
Publication Date:	2014-05-22
Uploaded by:	cavallaro.gabriele@gmail.com
Domain:	generic
Checksum:	16ba6c2e80c98859d0f9c044c73d1ec976b68c788e0
	681e3932d91e5a2a029c1





(Not yet reviewed) Report abuse

## Sharing and Downloading Dataset on Cluster JUDGE

### Simple download from http using the wget command

mriedel@judg	ae:∼/biqdat	a> ls	-al				
total 640	, <u>.</u>						
drwxrwxrwx 2	21 mriedel	zam	32768	2014-09-17	22:20		
drwxr-xr-x 1	.9 mriedel	zam	32768	2014-09-18	11:49	T	
drwxr-xr-x	2 mriedel	zam	32768	2014-06-19	07:17	102-salinasindian	
drwxr-xr-x	2 mriedel	zam	512	2014-06-19	20:11	107-salinasrescaled	
drwxr-xr-x	2 mriedel	zam	512	2014-07-08	17:14	111-romemultispectra	1other
drwxr-xr-x	2 mriedel	zam	512	2014-07-10	11:46	112-romeoriginalband	s open
drwxr-xr-x	2 mriedel	zam	512	2014-09-17	22:31	120-indianpine	B2SHARE
drwxr-xr-x	2 mriedel	zam	512	2014-09-17	22:14	121-salinas	datasets
drwxr-xr-x	2 mriedel	zam	512	2014-09-17	22:19	122-salinas2	
drwxr-xr-x	2 mriedel	zam	512	2014-09-17	22:24	123-indianpine2	
drwxr-xr-x	2 mriedel	zam		2014-07-09			
drwxr-xr-x		zam				bigindianpines	
Simple	mriedel	zam		2014-05-28			
· · · · · · · · · · · · · · · · · · ·	mriedel	zam				indianpinesreduced	
Download	mriedel	zam				mnist-576-rbf	
from http	skoehnen			2014-07-29			
· · · · · · · · · · · · · · · · · · ·	mriedel	zam		2014-06-25			
using wget	mriedel	zam				rome-ok-copy	
Well defined	mriedel	zam		2014-06-03			before adopting
	mriedel	zam				salinasindianrev	B2SHARE regularly
directory	mriedel	zam	32/68	2014-06-10	15:47	salinas-new	
structures							

## Link back to B2SHARE fosters Trust

#### Make a short note in your directory linking back to B2SHARE

total 580320 drwxr-xr-x 2 mriedel zam 512 2014-07-09 11:03 . drwxrwxrwx 21 mriedel zam 32768 2014 00 17 22:20 <b>10</b>	
-rw-rr 1 mriedel zam 35 2014-07-09 11:01 b2share.txt	
-rw-rr 1 mriedel zam 46652874 2014-05-22 13:36 sdap_area_all_training.el -rw-rr 1 mriedel zam 114763982 2014-05-22 13:36 sdap_area_panch_test.el -rw-rr 1 mriedel zam 12745692 2014-05-22 13:36 sdap area panch training.el	
mriedel@judge:~/bigdata/86-romeok> more b2share.txt https://b2share.eudat.eu/record/86 mriedel@judge:~/bigdata/86-romeok>	

Enables the trust to delete data if necessary (working against big data)

Link back to B2SHARE for quick checks and file that links back fosters trust

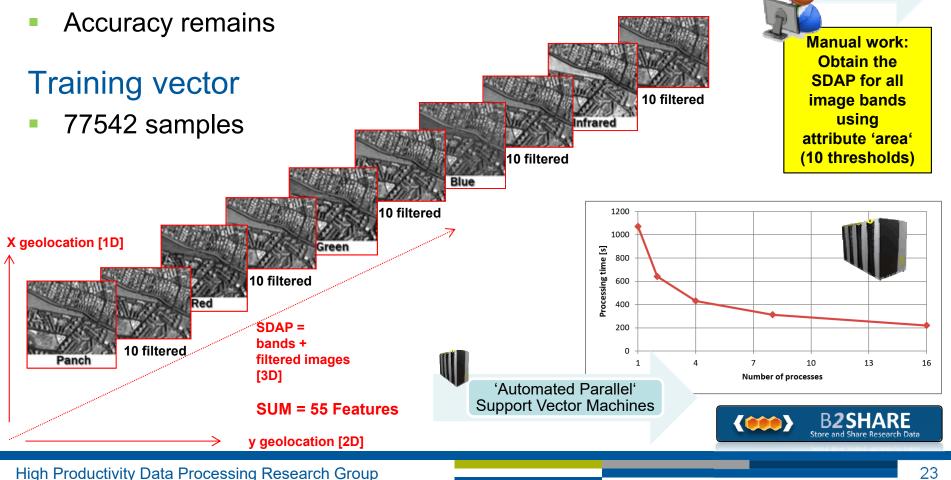
## Data analysis using Cluster Judge and Share Results

### Training speed-up is possible when number of features is 'high'

Manual

SDAP

- Serial Matlab: ~1277 sec (~21 minutes)
- Parallel (16) Analytics: 220 sec (3:40 minutes)







#### piSVM Analytics Runtimes JUDGE Cluster Rome Images 55 Features

Morris Riedel ; Gabriele Cavallaro

; 30 May 2014

http://b2share.eudat.eu

Abstract: piSVM version 1.2; configuration: -o 1024 -q 512 -c 10000 -g 16 -t 2 -m 1024 -s 0; 55 features; SDAP build on high-resolution (0.6m) panchromatic image and on pansharpened (UDWT) low-resolution (2.4m) multispectral images using attribute area (10 threshold values)

Supplemental material for paper study.

Keyword(s): parallel SVM ; analytics ; MPI ; multi-spectral images

The record appears in these collections: Generic





#### Files 🔻

Name	Date	Size	
1797203-all-1-1.txt	30 May 2014	1.1 kB	Download
1797253-all-8-1.txt	30 May 2014	1.2 kB	Download
1797240-all-4-1.txt	30 May 2014	1.2 kB	Download
1797267-all-32-1.txt	30 May 2014	1.5 kB	Download
1797230-all-2-1.txt	30 May 2014	1.2 kB	Download
1797258-all-16-1.txt	30 May 2014	1.3 kB	Download

Rate this document:

(Not yet reviewed)

Report abuse

#### Export

Export as BibTeX, MARC, MARCXML, DC, EndNote, NLM, RefWorks

PID:	http://hdl.handle.net/11304/69430fd2-e7d6-11e3-
	b2d7-14feb57d12b9
Publication:	http://b2share.eudat.eu
Publication Date:	2014-05-30
Uploaded by:	m.riedel@fz-juelich.de
Contact email:	m.riedel@fz-juelich.de
Domain:	generic
Checksum:	3dbc215b81f342cba96752026694c449824d99644c

### Cluster runtimes preserved and shared: Unstable runtimes, so re-try with newer code version needed





#### piSVM Analytics Joboutputs JUDGE Cluster Rome Images 55 Features

Morris Riedel ; Gabriele Cavallaro

23 June 2014

http://b2share.eudat.eu

Abstract: piSVM version 1.2; configuration: -o 1024 -q 512 -c 10000 -g 16 -t 2 -m 1024 -s 0;

55 features;

SDAP build on high-resolution (0.6m) panchromatic image and on pansharpened (UDWT) low-resolution (2.4m) multispectral images using attribute area (10

threshold values)

Supplemental material for paper study.

Correspondent job outputs for the job run times given in B2SHARE entry:

http://hdl.handle.net/11304/69430fd2-e7d6-11e3-b2d7-14feb57d12b9

Keyword(s): parallel SVM; analytics; MPI; multi-spectral images

The record appears in these collections: Generic





#### Files 🔻

Name	Date	Size	
Train-rome-all-32-1.01797267.01797267	25 Jun 2014	262.4 kB	Download
Train-rome-all-1-1.01797203.01797203	25 Jun 2014	110.9 kB	Download
Train-rome-all-16-1.01797258.01797258	25 Jun 2014	183.7 kB	Download
Train-rome-all-8-1.01797253.01797253	25 Jun 2014	145.7 kB	Download
Train-rome-all-4-1.01797240.01797240	25 Jun 2014	124.8 kB	Download
Train-rome-all-2-1.01797230.01797230	25 Jun 2014	115.4 kB	Download

#### Export

×

Export as BibTeX, MARC, MARCXML, DC, EndNote, NLM, RefWorks

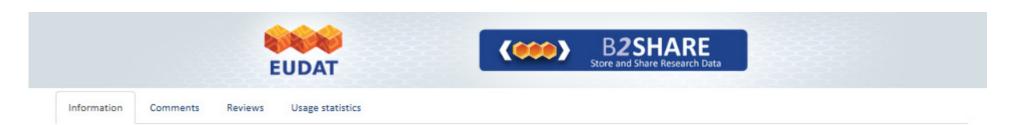
PID:	http://hdl.handle.net/11304/d02f34e6-0117-11e4-
	81ac-dcbd1b51435e
Publication:	http://b2share.eudat.eu
Publication Date:	2014-06-23
Uploaded by:	m.riedel@fz-juelich.de
Contact email:	m.riedel@fz-juelich.de
Domain:	generic
Checksum:	cde1a6fcb3b5f31d7283e273120e46135dbf95d8c07
	680d269ff21b1921095d4

#### Rate this document:



(Not yet reviewed) Report abuse  Improved stable code version runtimes shared and used in publication and to create runtime figures





#### piSVM1.2 Analytics JUDGE Cluster Rome Images 55 Features

Morris Riedel

, 03 August 2014 http://b2share.eudat.eu

Abstract: piSVM version 1.2; configuration: -0 1024 -q 512 -c 10000 -g 16 -t 2 -m 1024 -s 0;

55 features;

SDAP build on high-resolution (0.6m) panchromatic image and on pansharpened (UDWT) low-resolution (2.4m) multispectral images using attribute area (10

threshold values)

Supplemental material for paper study.

Correspondending dataset available at>

http://hdl.handle.net/11304/4615928c-e1a5-11e3-8cd7-14feb57d12b9

Keyword(s): SVM ; remote sensing ; analytics ; MPI

The record appears in these collections: Generic



Name	Date	Size	
1949513-checkjobinfo.el	08 Aug 2014	1.2 kB	Download
1949516-sdap_area_all_training.el.model.model	08 Aug 2014	18.7 MB	Download
Train-tune-rec86-1-16-8.o1949514.o1949514	08 Aug 2014	145.6 kB	Download
1949518-sdap_area_all_training.el.model.model	08 Aug 2014	18.7 MB	Download
1949509-submit-train-tune-record86.sh	08 Aug 2014	572 Bytes	Download
1949513-sdap_area_all_training.el.model.model	08 Aug 2014	18.7 MB	Download
Train-tune-rec86-2-16-16.o1949516.o1949516	08 Aug 2014	183.7 kB	Download
1949513-submit-train-tune-record86.sh	08 Aug 2014	572 Bytes	Download
Train-tune-rec86-8-16-64.e1950870.e1950870	08 Aug 2014	210 Bytes	Download
Train-tune-rec86-1-8-4.o1949513.o1949513	08 Aug 2014	124.7 kB	Download
1949510-submit-train-tune-record86.sh	08 Aug 2014	572 Bytes	Download
Train-tune-rec86-1-2-1.o1949509.o1949509	08 Aug 2014	110.9 kB	Download
1949514-checkjobinfo.el	08 Aug 2014	1.2 kB	Download
1949510-checkjobinfo.el	08 Aug 2014	1.2 kB	Download

#### Export

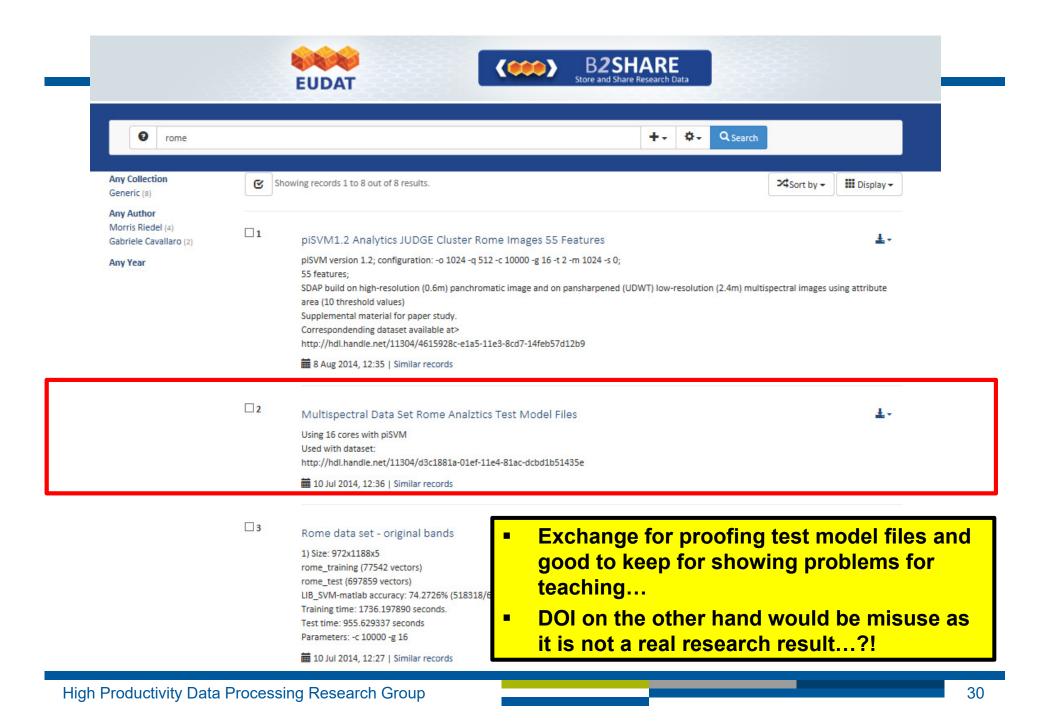
×

Export as BibTeX, MARC, MARCXML, DC, EndNote, NLM, RefWorks

#### Metadata

PID:	http://hdl.handle.net/11304/6880662c-1edf-11e4-		
	81ac-dcbd1b51435e		
Publication:	http://b2share.eudat.eu		
Publication Date:	2014-08-03		
Uploaded by:	m.riedel@fz-juelich.de		
Contact email:	m.riedel@fz-juelich.de		
Domain:	generic		
Checksum:	d89cc21553d3dbecc8c0f2e2c53fcf012e46c5113038		
	b3f6a991850b369ff78e		

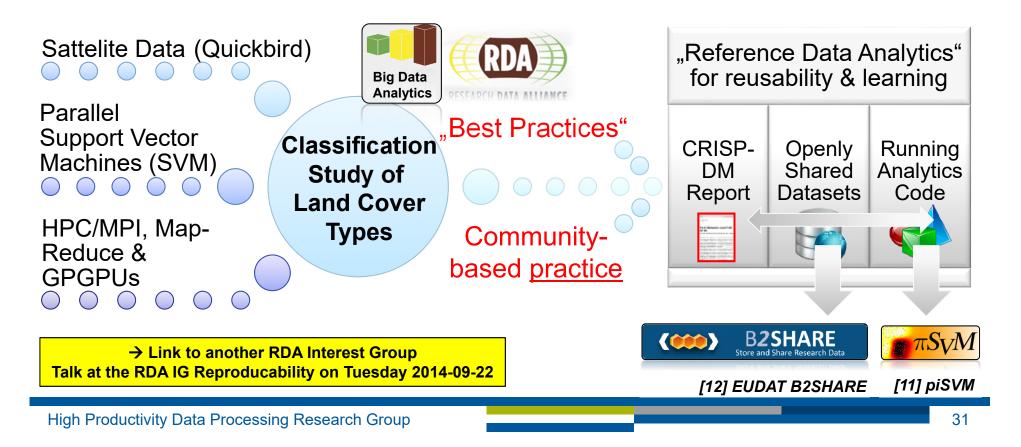
- Preserving the outcomes: the trained model
- Towards reproducability: job scribts are stored too



## Study – Addressing Reproducability Aspects

### Inline with emerging publishing requirements

- Running analytics code and used datasets openly available
- Datasets have a 'persistent identifier (PIDs)' based on the handle system
- CRISP-DM reports helps binding both together (e.g. which parameters)



## Next: Publishing results and linking B2SHARE

#### SMART DATA ANALYTICS METHODS FOR REMOTE SENSING APPLICATIONS

Gabriele Cavallaro<sup>a</sup>, Morris Riedel<sup>a,b</sup>, Jon Atli Benediktsson<sup>a</sup>, Markus Goetz<sup>a,b</sup>, Tomas Runarsson<sup>a</sup>, Kristjan Jonasson<sup>a</sup>, Thomas Lippert<sup>b</sup>

<sup>a</sup> Faculty of Electrical and Computer Engineering, University of Iceland, Reykjavik, Iceland <sup>b</sup> Julich Supercomputing Center, Forschungszentrum, Julich, Germany

#### ABSTRACT

The big data analytics approach emerged that can be interpreted as extracting information from large quantities of scientific data in a systematic way. In order to have a more concrete understanding of this term we refer to its refinement as smart data analytics in order to examine large quantities of scientific data to uncover hidden patterns, unknown correlations, or to extract information in cases where there is no exact formula (e.g. known physical laws). Our concrete big data problem is the classification of classes of land cover types in image-based datasets that have been created using remote sensing technologies, because the resolution can be high (i.e. large volumes) and there are various types such as panchromatic or different used bands like red, green, blue, and nearly infrared (i.e. large variety). We investigate various smart data analytics methods that take advantage of machine learning algorithms (i.e. support vector machines) and state-of-the-art parallelization approaches in order to overcome limitations of big data processing using non-scalable serial approaches.

Index Terms— Data Analytics, Support Vector Machines, Parallel Computing, Remote Sensing, Classification

#### 1. INTRODUCTION

Besides the traditional sources and collection methods of data, with all their limitations, satellite remote sensing [1] remains one of the largest source of data collections. Remote sensing takes advantage of satellite and airborne sensors to observe, measure, and record the radiation reflected or emitted by the Earth and its environment. It can significantly enhance the information available from traditional data sources (i.e., by providing synoptic views of large portions of Earth), which can be used for subsequent data processing. The big data problem is given due to the rapid improvement of remote sensing capabilities such as the availability of remotely sensed images with very high geometrical resolution (QuickBird 0.6m). In addition detailed spectral information (AVIRIS 224 spectral channels) is constantly increasing, and the amount of data is continuously growing with images more and more numerous, precise, frequent, but also complex.

In this context, Remote sensing makes use of several analysis methods, such as image processing, automatic classification, multitemporal processing and data fusion, in order to handle different real applications. The availability of the data raises a demand for smart data analytics techniques such as image classification that is one amongst the most significant application worlds for remote sensing, but facing serious limitations when performing classification with traditional serial tools (e.g. R, Matlab, etc.). The problem of classification aims to categorize all pixels in a digital image into meaningful features or classes of land cover types in a scene. In order to obtain a satisfactory level of detection accuracy, we perform a detailed physical analysis by exploiting the availability of high spatial resolution image. We consider attribute filters, flexible operators that can transform an image according to many different attributes (e.g., geometrical, textural and spectral) as further optimization technique.

This paper offers one solution to the aforementioned described scientific case in the field of remote sensing applications by applying smart data analytics methods to one specific big dataset. We provide a scalable analytics solution for image classification taking advantage of one of the most succesful classification methods referred to as support vector machines (SVMs) [2]. But in order to overcome the limitations of the wide variety of traditional serial SVM data analysis tools, we survey and apply existing open source SVM tools for big data analytics that take advantage of parallelization techniques. The contribution of this paper is thus the design of a tailored parallel smart data analytics method to the aforedescribed scientific case that is able to reduce the training time of the SVM classifier under the constraints of not dropping in terms of accuracy. The work has been performed and discussed within the Research Data Alliance (RDA) Big Data Analytics Interest Group (IG)[3].

This paper is structured as follows. After the introduction into the problem domain, Chapter 2 provides the necessary technical background, offers methods summaries, and surveys related work. Chapter 3 presents results from our approach and the paper ends with some concluding remarks. Beta: not linked handles yet, but will be soon possible (long list at the paper end?)

This significant reduction in training time was not affecting the training accuracy that we obtained by running also SVM predictions in parallel being always roughly 97% like the serial Matlab approach. The implementation of piSVM for basic smart analytic applications is stable enough, but we observed some limitations with respect to scaling to higher number of cores and I/O limits.

In order to support the more and more emerging approaches towards 'reproducable science' we have uploaded all datasets and the runtimes into the B2SHARE EUDAT service. Hence, the data and the piSVM implementation can be thus used to reproduce our findings in the paper. Finally, the described approach with concrete application in this paper contributes to the findings of the RDA Big Data Analytics Interest Group.

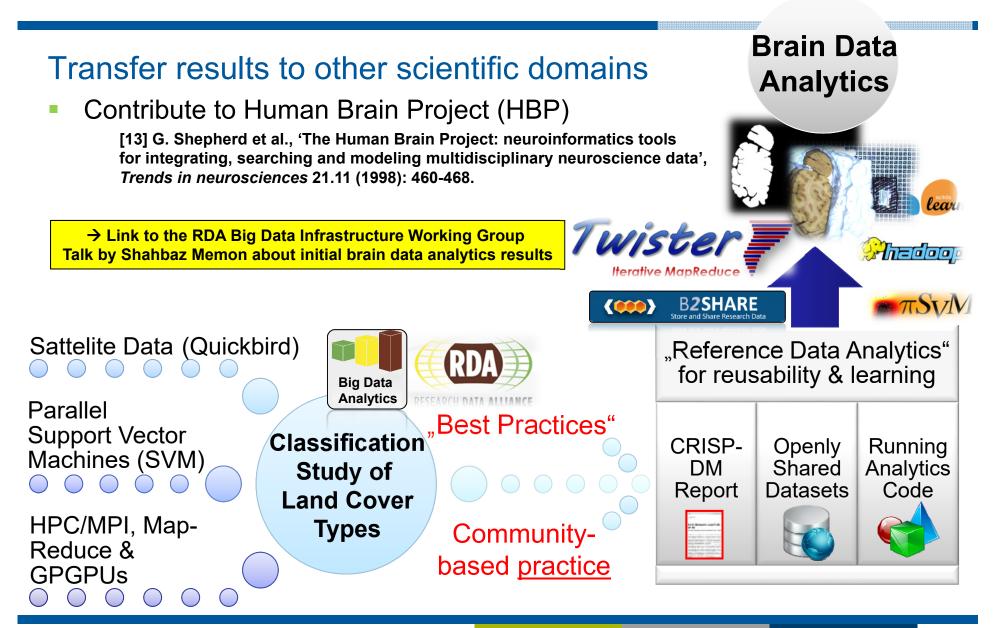
Finally future work will be the detailed investigation of other parallel implementations with a focus on the GPU-LibSVM library.

[14] G. Cavallaro and M. Riedel, 'Smart Data Analytics Methods for Remote Sensing Applications', IGARSS 2014

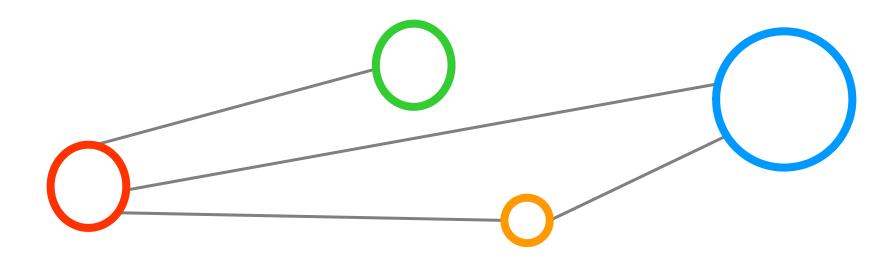
## Unsolved: Sharing different versions of software?!

mriedel@judge:~> ls -al total 111840	L			
drwxr-xr-x 19 mriedel	zam 3276	8 2014-09-18 11:4	9 ,	
drwxr-xr-x 214 root		8 2014-09-12 09:0	2	
-rw-rr 1 mriedel		0 2014-08-08 10:3	5 115-RunsMatthiasStable.tar a bachelor project	
drwxr-xr-x 3 mriedel	zam 3276	8 2014-06-03 16:2	4 ann-0.1	
drwxr-xr-x 3 mriedel	zam 3276	8 2014-06-03 17:0	2 ann-0.2	
drwxr-xr-x 3 mriedel	zam 3276	8 2014-06-04 14:4	2 ann-0.3 different versions of a	
drwxr-xr-x 2 mriedel	zam 3276	8 2014-06-16 19:1	2 ann-0.4 parallel neural network code	
drwxr-xr-x 2 mriedel	zam 3276	8 2014-06-16 19:2	4 ann-0.4-orig (another classification	
drwxr-xr-x 2 mriedel	zam 3276	8 2014-06-19 08:3	8 ann-0.5 technique)	
drwxr-xr-x 6 mriedel	zam 3276	8 2014-06-25 00:5		
drwxr-xr-x 4 mriedel	zam 3276	8 2014-06-19 16:3	1 ann-0.6-scal	
drwxr-xr-x 2 mriedel	zam 3276	8 2014-06-24 17:0	2 ann-0.7	
-rw 1 mriedel	zam 179	7 2014-05-12 13:5	1 .bashrc	
drwxrwxrwx 21 mriedel	zam 3276	8 2014-09-17 22:2	0 <mark>bigdata</mark>	
drwxr-xr-x 3 mriedel	zam 51	2 2014-06-19 09:3	4 .config	
drwxr-xr-x 3 mriedel	zam 3276	8 2014-06-03 14:3	8 .emacs.d	
-rw 1 mriedel	zam 186	4 2014-05-12 13:5		
drwxr-xr-x 3 mriedel	zam 3276	8 2014-05-12 14:5		
drwxr-xr-x 5 mriedel	zam 3276	8 2014-09-18 11:4		
drwxr-xr-x 3 mriedel	zam 51	2 2014-07-09 14:5	1 pisvm-1.2-refactored support vector machine	
-rw 1 mriedel		6 2014-05-12 13:5		
-rw 1 mriedel		0 2014-09-18 11:5		
drwx 2 mriedel		8 2014-05-12 14:3		
drwxr-xr-x 2 mriedel		8 2014-05-12 <u>14:3</u>	9 transfers	
-rw 1 mriedel		6 2014-09-18	True reproducability needs: (1) datasets;	
-rw 1 mr <u>i</u> edel	zam 20	4 2014-09-17		
mriedel@judge:~>				
			and (3) correct versions of algorithm code	

## Future Work









## **Scientific Smart Data Analytics**

- Often different & more complex as industrial 'big data analytics' cases
- Need for sharing of 'intermediate results' that may become the final result
- Demand for uploading of 'different data versions' on same original data
- Challenge: Upload all data from all analytics run well with metadata time?!

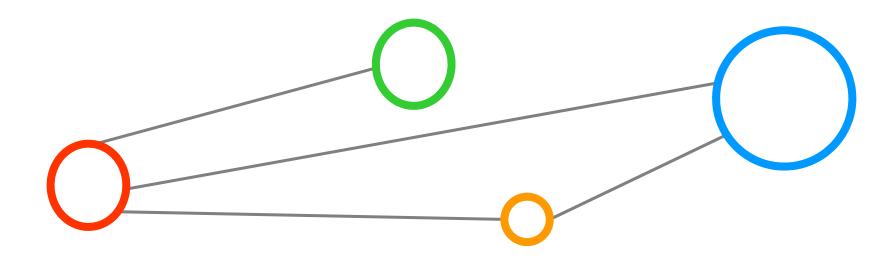
## **Experiences with B2SHARE**

- Ideal sharing service for research groups and teaching purposes
- Assigned PID very useful (e.g. in papers) as well as unique record Ids
- Enabled <u>trust</u> to 'delete data' & brings order to 'messy big data' directories
- Using the handle is convenient (but on directory structure not required...)

## Suggestions for B2SHARE

- Requirement of more flexible metadata schemes ('communities >1 types')
- Recommender system integration ('you might be also interested in...')
- Where is the boundary to say 'analytics code is also data'?





## References

- [1] RDA BDA IG Webpage, online: https://rd-alliance.org/group/big-data-analytics-ig.html
- [2] John Wood et al., 'Riding the Wave How Europe can gain from the rising tide of scientific data', EC Report, 2010
- [3] KE Partners, 'A Surfboard for Riding the Wave Towards a four country action programme on research data', November 2012
- [4] DOE ASCAC Data Subcommittee Report, 'Synergistic Challenges in Data-Intensive Science and Exascale Computing', 2013
- [5] D. Lazer et al. 'The Parable of Google Flu Traps in Big Data Analysis', Science 03/2014, Vol. 343
- [6] Shearer C., 'The CRISP-DM model: the new blueprint for data mining', J Data Warehousing (2000); 5:13-22.
- [7] A. J. Plaza and C. Chang, 'High Performance Computing in Remote Sensing', CRC Press, 2007
- [8] J. Munoz-Man, A. J. Plaza, J.A. Gualtiers, G. Camps-Valls 'Parallel Implementations of SVM for Earth Observation', Parallel Programming, Models and Applications in Grid and P2P Systems, 2009, pages 292-312
- [9] G. Cavallaro, M. Mura, J.A. Benediktsson, L. Bruzzone 'A Comparison of Self-Dual Attribute Profiles based on different filter rules for classification', IEEE IGARSS2014, Quebec, Canada
- [10] Sun Z., and Fox G., 'Study on Parallel SVM Based on MapReduce', In Proceedings of the international conference on parallel and distributed processing techniques and applications, 2012.
- [11] piSVM Website, 2011 code, online: http://pisvm.sourceforge.net/
- [12] EUDAT European Data Infrastructure, B2SHARE Tool, Online: https://b2share.eudat.eu/
- [13] Shepherd, Gordon M., et al. "The Human Brain Project: neuroinformatics tools for integrating, searching and modeling multidisciplinary neuroscience data." *Trends in neurosciences* 21.11 (1998): 460-468.
- [14] G. Cavallaro and M. Riedel, 'Smart Data Analytics Methods for Remote Sensing Applications', IGARSS 2014

## Acknowledgements

Gabriele Cavallaro, University of Iceland Tomas Philipp Runarsson, University of Iceland

#### **EUDATB2SHARE** Team



Selected Members of the Research Group on High Productivity Data Processing

Ahmed Shiraz Memon Mohammad Shahbaz Memon Markus Goetz Christian Bodenstein Philipp Glock Matthias Richerzhagen











Thanks for your attention



# **RESEARCH DATA ALLIANCE** FOURTH PLENARY MEETING

22 – 24 September 2014 Amsterdam, the Netherlands | Meervaart conference centre

www.rd-alliance.org/rda-fourth-plenary-meeting.html

# Talk available at:

www.morrisriedel.de/talks

# **Contact:**

## m.riedel@fz-juelich.de