

# ARCHITECTURAL DESIGNS AND SERVICES FOR BIG DATA

ScaDS – Competence Center for Scalable Data Services and Solutions Dresden/Leipzig

> Dr. René Jäkel ZIH, Technische Universität Dresden





### **Increasing Data Sizes**

#### Brontobyte **10**<sup>27</sup> Sensor Data from IOT **10**<sup>21</sup> 1024 Zettabyte Yottabyte Network Traffic 2016 250 trillion DVDs **10**<sup>18</sup> **10**<sup>15</sup> Petabyte Exabyte CERN - 1PB/Second Gigabyte Terabyte Facebook - 500 TB per Day Megabyte

+Veracity, Velocity, Variety

## +Technology proliferation



Source: http://api.ning.com



### **Increasing Data Sizes**

Long tail of "Science"





https://www.semrush.com/blog/community-manager-a-jack-of-all-trades/



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# ScaDS AND ASSOCIATED PARTNERS

Specialists from computer & domain sciences

DRESDEN LEIPZIG

Focal point for new research activities





#### Life Sciences

**Material and Engineering Sciences** 

**Environmental and Traffic Sciences** 

**Digital Humanities** 

**Business Data** 

### Big Data Life Cycle Management und Workflows

Data Quality/ Data Integration

Knowledge Extraction

Visual Analysis

Service

Center

Efficient Big Data Architecture



- Efficient Big Data Infrastructure
  - Hardening computation infrastructure (Security)
  - Flexible cluster management
  - Big Data Framework Execution & Monitoring on HPC
  - Geo-temporal data storage
  - Cloud-based service support for analysis of travel data
- Big Data Lifecycle and Workflows
  - Execution of large data-driven workflows (KNIME-workflow integration @HPC)
  - Time series management and forecasting
- Holistic data integration
  - Privacy-Preserving Data Matching
  - Deduplication (in Graphs)
- Visual Analysis
  - Improve visualization of large particle data
  - Multi-scale visualization for engineering data
- Knowledge Extraction
  - Porting computer vision algorithms on GPUs
  - Knowledge Extraction on biological and environmental data
  - Deep Learning & structure recognition in spatial planning

#### See Talk of Prof. Rahm

# SCADS SERVICE CENTER AS FOCAL POINT



- 10 new projects contributing directly to ScaDS Dresden/Leipzig (new colleagues in ScaDS labs in Dresden and Leipzig)
- 13 further ScaDS-associated project acquisitions: 26 positions



- Goal: open services for scientific communities
- Starting as demonstration services
  - Visualization for multiscale simulations in engineering
  - Focus and context methods for point-based data
  - ECAST service
  - Entity-Augmentation
  - Binary image segmentation
  - Sierra Platinum: Peak-Calling
  - Imputation service
  - Analytics service for time series
  - Innoplan service
  - Wind anomaly detection
  - Text repository & mining services for Digital Humanities (CTS)
  - Graph Analytics Service

See Talk of Jan Frenzel

# ScaDS CONTACTS TO INDUSTRY AND WORKSHOPS



2<sup>nd</sup> Big Data All-Hands-Meeting, Karlsrune 11... – 12... October 2017



- 3 Big Data in Business (BiDiB) Workshops
- 3 successful international summer schools (Dresden, Leipzig, Munich)
  - more than 250 national/international guests
- Big Data All-Hands-Meeting in Dresden, June 2016
- 30 renowned experts in guest program (21 short-term, 6 mid-term, 3 long-term)



# ScaDS INTERNATIONAL VISIBILITY& OUTREACH

- >120 of publications, > 200 talks worldwide
- Industry talks: i.e. Data2Day, Bitkom Big Data Summit, Fosdem, Flink Forward



- Awards:
  - Best Science Paper Award der British Machine Vision Conference (BMVC) (Cooperation Prof. G. Myers und Prof. Carsten Rother)
  - Winner of SciVis-Contest IEEE VIS (Group of Prof. Gumhold)
  - Best Demo Award BTW 2017 (Gradoop), 3rd place Data Science Challenge
  - Staatspreis für Innovation, Category "Transfer" Dr. Stefan Kühne

# ScaDS ORGANIZED WORKSHOPS & SUMMERSCHOOLS





1. Big Data All-Hands-Meeting in Dresden

Fachgespräch "BigData – Konzepte zur Analyse komplexer Infrastrukturen"







#### ScaDS Big Data Industry Forum

Overview I Agenda I Blending Tools and Data in KNIME I Linked Big Data Analytics using IBM System G





Life-Sciences

**Material Sciences** 

**Environmental and Traffic Sciences** 

**Digital Humanities** 

**Business Data** 

Big Data Life Cycle Management und Workflows

Data Quality/ Data Integration

Knowledge Extraction

Visual Analysis

Service-

Center

Efficient Big Data Architecture



# ARCHITECTURES FOR DATA ANALYTICS



- New machine room and HPC-infrastructure: HRSK-2 inauguration May 13<sup>th</sup> 2015
- Current HPC installation:
  > 1 PetaFlop/s, > 5 PB HDD, > 40 TB SSD
  > 130 TB main memory
- Further systems suited for various purposes:
  - SGI UV 2000 (Venus)
  - "Galaxy" cluster @Leipzig+Dresden;
    90 nodes "Shared-Nothing" architecture
  - Research-Cloud: 13 nodes with OpenStack (64 cores, 64GB RAM, 250GB lokal disk)







# ScaDS III BIG DATA ARCHITECTURES - MOTIVATION

### **Big Data / Data Analytics**

- Active research field for almost all scientific domains
  - What insights can we get out of broad data base?
  - Usually only prototypic ideas/solutions
- Limited technological and methodical knowledge in domains present
- High potential to characterize value within data by using state-of-the-art methods within frameworks (Hadoop-Ecosystem, deep learning, statistics, ...)

## HPC

- Highly specialized hardware; efficient use requires special knowledge
- Traditional batch system based interaction, hardly to be integrated into complex workflows – good for large parallel applications
- "fixed system": no standard methods to shape environments for special needs
- Often mainly centralized storage

## MOTIVATION: HOW TO SUPPORT USERS WITH INFRASTRUCTURES

- HPC vs. Data Analytics
  - Bring computing to data, or data to computing (data mover)?
  - Systems and infrastructure should support users, not forcing them to follow rigid regiments
  - Let user pick up approach, which is best for individual use case
  - HPC: traditional rather monolithic usage, e.g simulations
  - Big Data analytics: more data centric, but not all and every analysis is embarrassingly parallel, iterative models still induce large data movements
- There is no unique Big Data blueprint!
- From the users perspective which way to follow? more HPC like approach or dynamic possibilities of big data frameworks?

# ScaDS BIG DATA AND HPC – CONVERGENCE PATTERNS

Requirements to support Big Data workloads on HPC

- Support frameworks: more versatile software stacks
- Fast access to data: not just self-production of data (simulation), but also use 3<sup>rd</sup>-party data (open data, domain repositories)
- Support different data processing paradigms on very same system:
  - Batch vs. Streaming
  - In-Memory and iterations
- Better support of evaluation of (temporary) results, e.g. visualization frontends
- Service orientation (working environments)





# ScaDS HRSK-II HARDWARE EXTENSIONS (PHASE 1 + 2)





- Provisioning of required environments (Hadoop, Spark, Flink, ML-frameworks ...)
- Big Data session created on demand
- Run directly as analytics service at HPC site
- Adoptable to other frameworks/applications







# ANALYTICS USE CASES



 Use Case: processing pipeline for cell tracking (bacteria E.coli) over time



- Challenge: support execution of data-intensive user workflows in HPC environment
  - No prior HPC-knowledge required on user side
  - Formulation of workload directly in workflow environment
- Solution: combination of well-known and widely used tools
  - KNIME for workflow formulation
  - Middleware UNICORE used for HPC interaction

# ScaDS EXECUTION OF LARGE DATA-DRIVEN WORKFLOWS

- First: export of workflow and its input data
- Second: automatic generation of compute jobs and execution





Evaluation data set:

'untime [s]

- 1,8 TB in ~7,5 M files
- Runtime improvement: previously 17d on 4 cores now 2h on 800 cores
- 200x faster parallel execution
- Next steps: fully automated pipeline connecting microscope with HPC environment and research data repository



data size





- Application area: low delay operation support using thermal imaging processing
- Quasi real-time data processing required in decision support during surgery – University Hospital Dresden (UKD)
  - Neural activity monitoring require long-term intraoperative measurements (~10 minutes)
  - Fast preprocessing required to decrease delay for subsequent analysis workflows and result presentations
     => minimize overall OP delay
  - Iterative process: 3000 frames
    (5.4 GB) have to be processed every minute
    (50 Hz sampling rate)





hematoma



- Application area: low delay operation support using thermal imaging processing
- Quasi real-time data processing required in decision support during surgery – University Hospital Dresden (UKD)
- Solution: Provision of Spark-Cluster @HPC
  - Fast SSD-backend to speed-up IO; fail-safe storage of imaging data
- Runtime improvement:
  - UKD-workstation: ~7000s/30.000 images

Soark

- Spark cluster @Taurus: ~32s/30.000 images
- $\rightarrow$  ~220x faster





- Application area: environmental sciences and urban modelling
- Challenges:
  - Analysis of maps to trace the development of settlement areas and their internal structure over time





### Settlement area detection, Messtischblaetter 1875-1943



Collaboration between:

Computer Vision Lab Dresden (CVLD) ZIH, TU-Dresden IOER



- Application area: environmental sciences and urban modelling
  - Scenario:
    - Analysis of historic maps ("Messtischblätter"): Good coverage of Germany in 1:25000 scale (1875-1945)
    - Thorough evaluation is desired (over time)
    - Accurate training sets required
  - Solution
    - Usage of image segmentation algorithms in data processing
    - Avoid previously required labor intensive manual work

Example settlement areas





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### Results:

- Automatic and new method for settlement detection in historic maps available using Random Forest (RF) + Conditional Random Field (CRF)
- Scalable data processing of large quantity of input maps possible



- Results:
  - Automatic and new method for settlement detection in historic maps available
  - Scalable data processing of large quantity of input maps possible
- Runtime improvement:
  - serial processing on ordinary workstation: ~780 minutes (13 hours)
  - Parallel execution: <4min  $\rightarrow$  ~200x faster



Input

Correct output labels

## MULTI-SCALE VISUALIZATION OF ENGINEERING DATA



- Follow simulation of processes over time on different scales
- Easy user-interface for direct interaction with data (webbrowser based)
- Preparation of simulations on different scales at HPC-site and output presentation via visual analysis



Methods:

- Time-dependent finite element simulation of complete component on 3 scales
- 200 time steps per scale using Abaqus tool; simulations need to be aligned





## Multi-scale visualization – The key for a deeper understanding of materials







GEFÖRDERT VOM



Bundesministerium für Bildung und Forschung





## SUMMARY AND OUTLOOK

# SCADS SUCCESS STORY SCADS DRESDEN/LEIPZIG



### Strong scientific output and competence (>120 publications)

i.a. Big Graph Analytics, Sierra Platinum , CTS, data intensive workflows for HPC, settlement recognition in historic maps, Interactive Multi-Scale Visualization...



#### **Service Center for Big Data with high impact** Numerous interdisciplinary big data application projects and industry collaborations & transfer in industry



### Many project aquisitions

> 11 Mio Euro (Exploids, BIGGR, TIQ-Graph, KOBRA, MASI, GERDIE, EMUDIG4.0..)



### National & international outreach & visibility

200 keynotes/talks worldwide, 3 successful summer schools, 30 proven experts in guest program, 3 successful Big Data in Industry workshops



### Successful training and education program "Big-Data-Schwerpunkt": lectures/ seminars/ trainings/ PhD seminars Hundreds of Graduates with Big Data Expertise (Master)

>10 PhDs in Big Data close to finishing



- Convergence of HPC and Big Data offers great opportunities in data analysis
- There is no unique big data usage pattern
  - Many different aspects are of interest (not just "volume")
  - But: transparency for users is very important
- HPC systems will support an extremely large main memory, which will result in huge input/output data (size and/or number of files)
- Other, more distributed approaches still valid, e.g. for Hadoop-like workloads, but more iterative methods needed (machine learning)
- Still depending on use-case requirements user needs to adopt current workloads
  - Big Data Analytics at the push of a button ... will take a while







## THANK YOU





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