High Productivity Data Processing Analytics Methods with Applications

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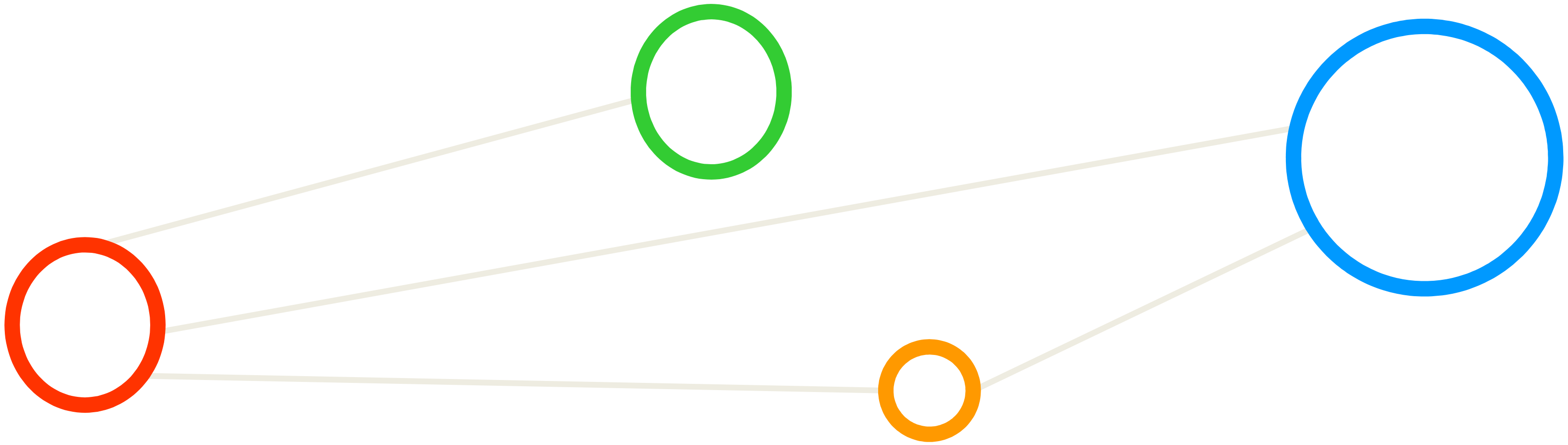
Outline



Outline

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- Smart Data Analytics Methods
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- Example Analytics Application
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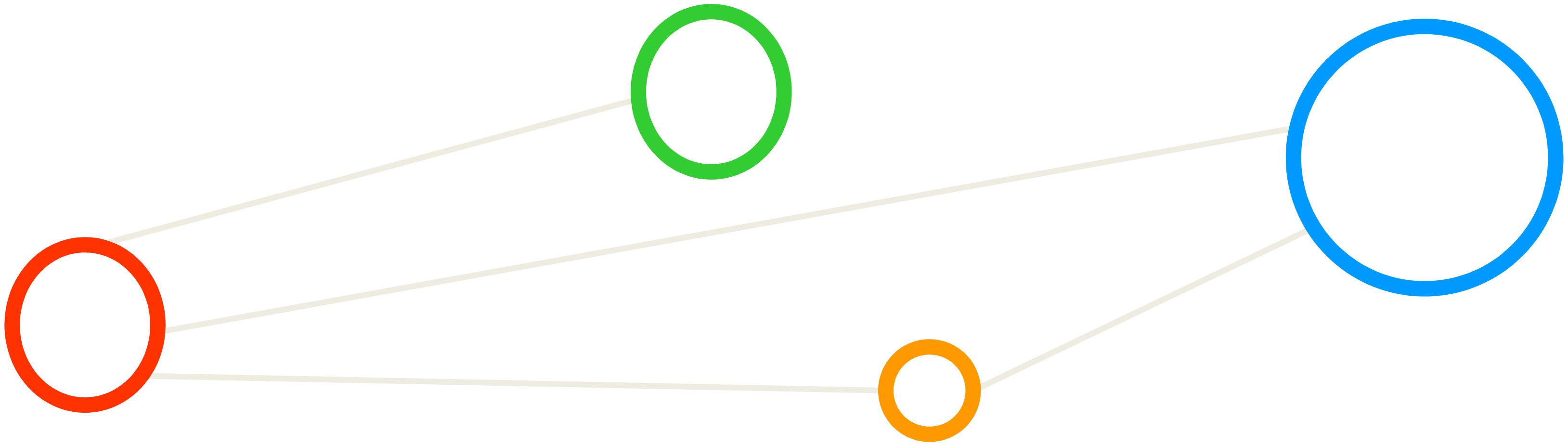
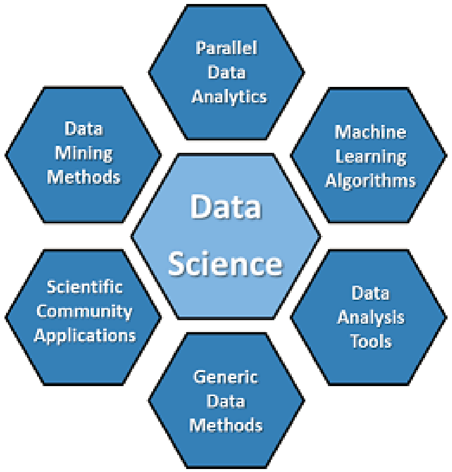
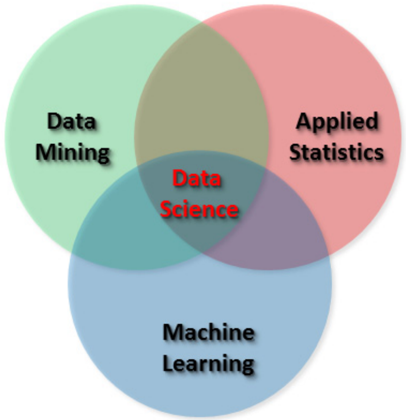
Introduction



Big Data Analytics

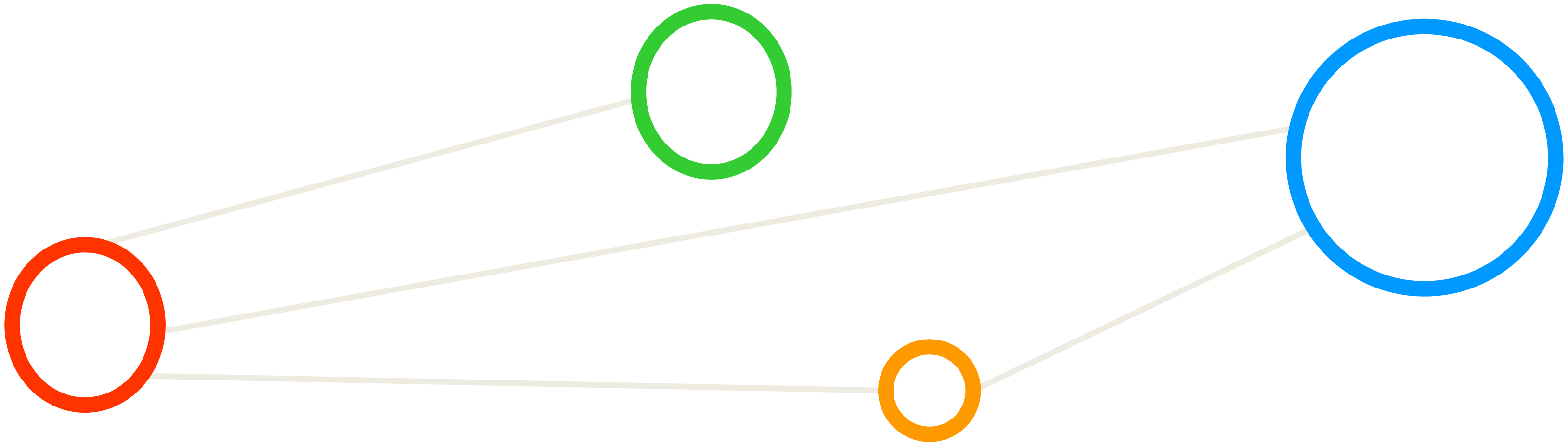
- (Automatically) examine large quantities of scientific ('big') data
  - Uncover hidden patterns
  - Reveal unknown correlations
  - Extract information in cases where there is no exact formula
- Intersection of traditional methods from a wide variety of fields





- **Use of parallelization techniques (MPI, Map-reduce, GPGPUs) offers scalability to big data sets**

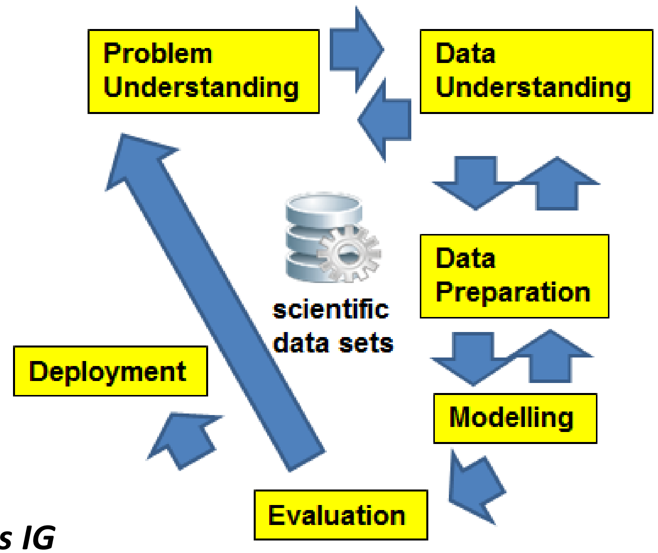
Smart Data Analytics Methods



Systematic Analytics with CRISP - DM

- Performed survey of ‘reference models‘ that enable data analytics in structured way
- Cross Industry Standard Process for Data Mining
  - Used in Research Data Alliance
  - BigData Analytics Interest Group

[7] P. Chapman et al., CRISP-DM Guide

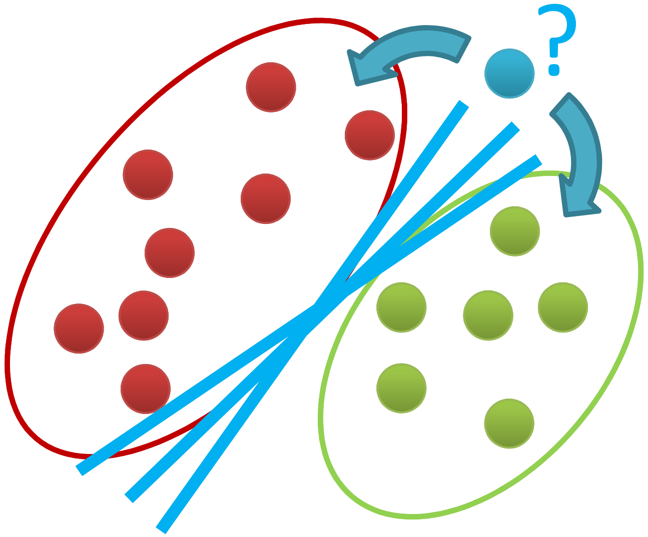


[10] RDA Big Data Analytics IG

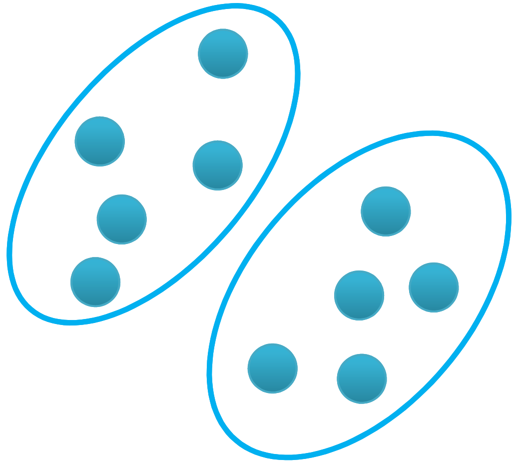
Support Vector Machines Analytics

Classification

Support Vector Machines

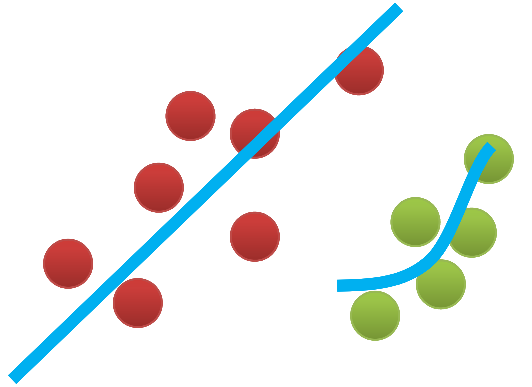


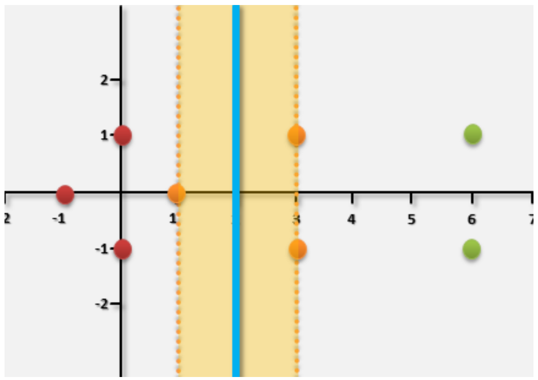
Clustering



Regression

Support Vector Machines





Quadratic Programming

$$\mathcal{L}(\alpha) = \sum_{n=1}^{N} \alpha_n - \frac{1}{2} \sum_{n=1}^{N} \sum_{m=1}^{N} y_n y_m \alpha_n \alpha_m \mathbf{x}_n^T \mathbf{x}_m$$

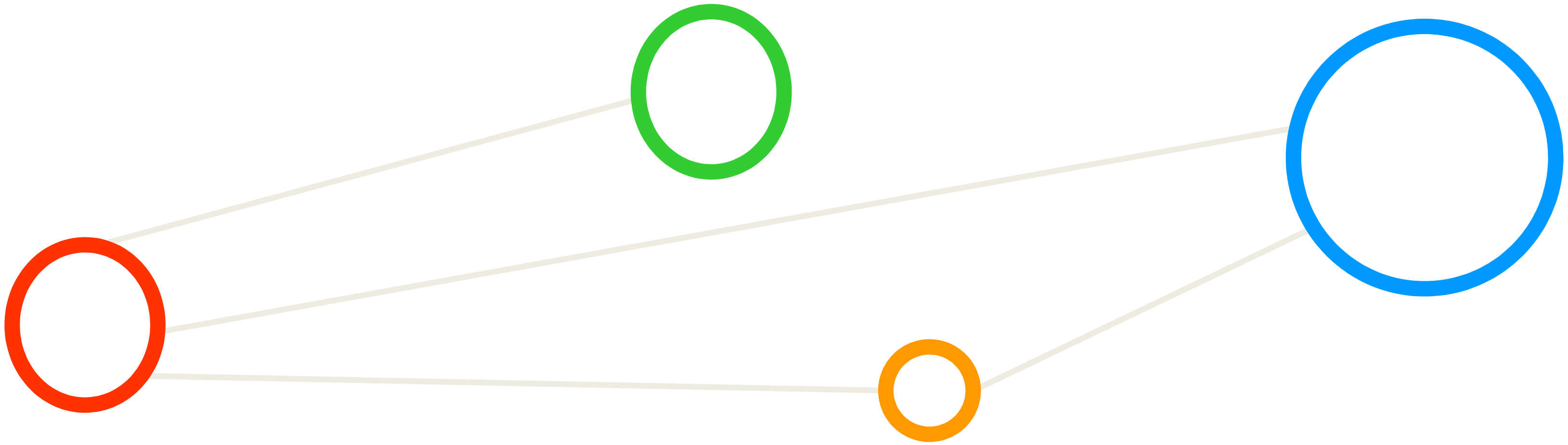
$$\begin{bmatrix} y_1 y_1 x_1^T x_1 & y_1 y_2 x_1^T x_2 & \dots y_1 y_N x_1^T x_N \\ \dots & \dots & \ddots \\ y_N y_1 x_N^T x_1 & y_N y_2 x_N^T x_2 & \dots y_N y_N x_N^T x_N \end{bmatrix}$$

(big data challenge)

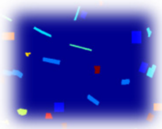
(e.g. all N datasets vs. sampling)

(quadratic coefficients → N x N dense matrix)

Example Analytics Application



Classification of Buildings in Images – (Big) Data

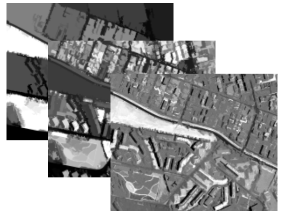


Problem: Multi-Class Classification of buildings from hyper- / multi-spectral images

panchromatic image (972 × 1188 pixels); high resolution; 0.6m

multispectral image with the four bands; low-resolution; 2.4m

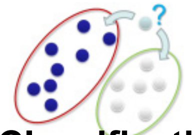
- Classification of buildings from multi-spectral data
  - 1st → Principle Component Analysis (PCA)
  - Classify building classes using image data & ‘attribute filters‘ to increase the accuracy
  - Multi-spectral images can become very large
  - Labelled data with groundtruth data exists



N profiles further improve classification feature vector (area, std deviation, moment of inertia,…)

- **Use parallel Support Vector Machines (SVMs) since it is known as good classification method today**

Classification of Buildings in Images – Toolset (1)



- Performed large survey of parallel SVM implementations (map-reduce)
  - Spark/MLlib (Map-Reduce) *[1] Spark Website*
    → only binary classification, linear SVM
  - Mahout (Map-Reduce) *[2] Mahout Website*
    → no strategy for implementation
  - ParallelSVM on Twister (Iterative Map-Reduce)
    → received beta code per email *[3] Sun Z. & Fox. G et al.*

- **Parallel implementations based on Map-Reduce are emerging but stabilility needs to be improved**

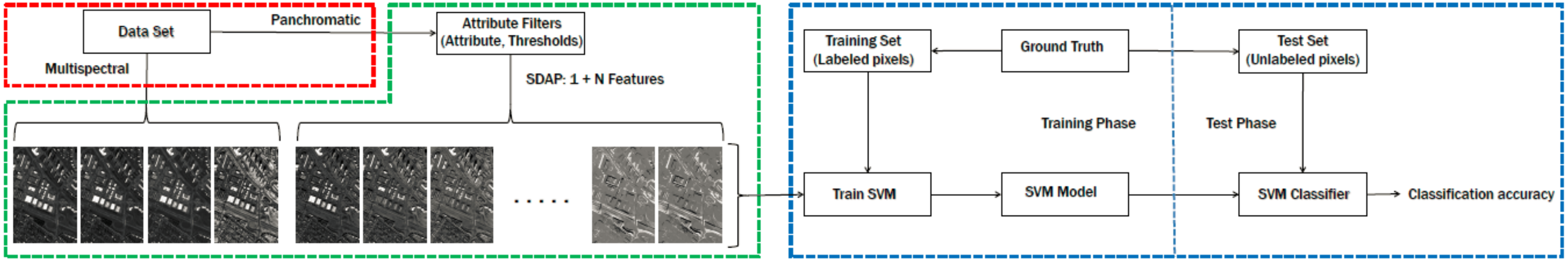
Classification of Buildings in Images – Toolset (2)

Classification++

- Performed large survey of parallel SVM implementations (MPI & GPGPUs)
  - piSVM
    → Open source code, scalability limits
    [4] piSVM Website
  - pSVM
    → Open source code, beta quality
    [5] pSVM Website
  - GPULibSVM,
    → Open source code, beta quality
    [8] GPU LibSVM

- **Parallel implementations based on MPI + GPGPUs are openly available, but show scalability limits**

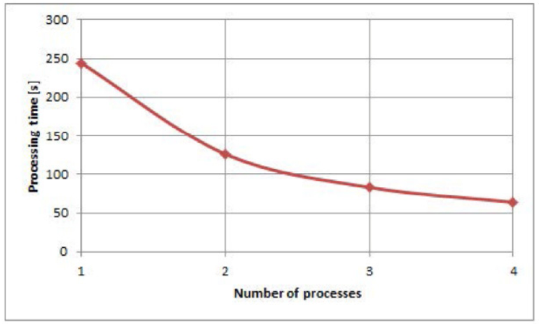
Building Classification in Images – Some Results



- Serial Matlab scripts used before
  - Not scalable to big data sets → parallelization

[6] G. Cavallaro & M. Riedel et al., 2014

- E.g. piSVM
  - Speed-up, but also shows limits



Reproducable Findings:

B2SHARE Store and Share Research Data

Data is publicly available

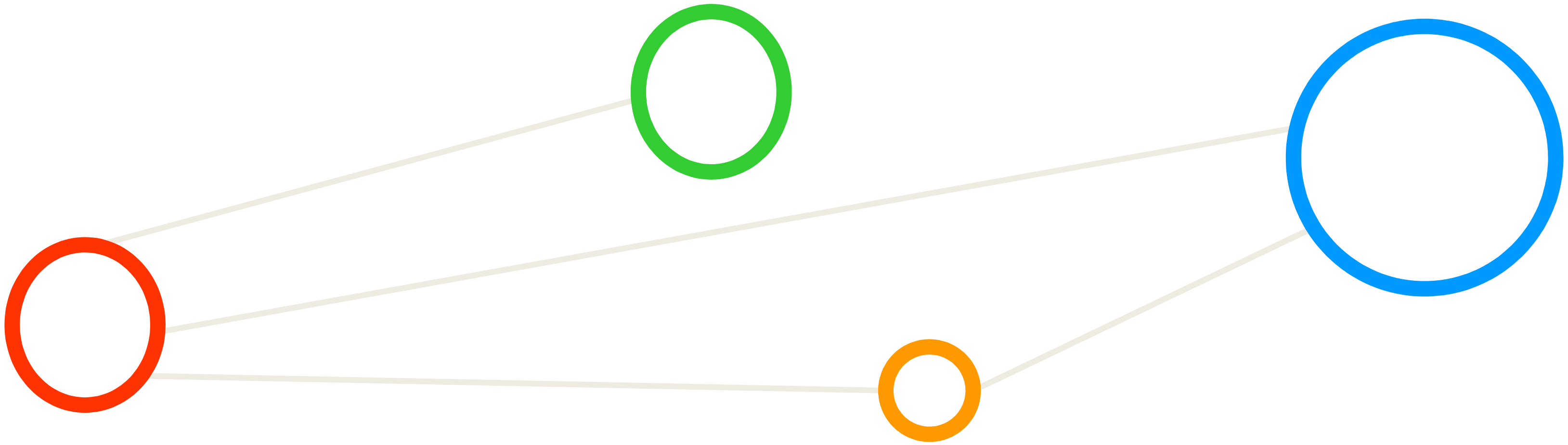
[9] Rome Dataset

Code is publicly available

[4] piSVM Website

- **Take away message from applications: Mostly multi-class SVMs used in science & engineering**

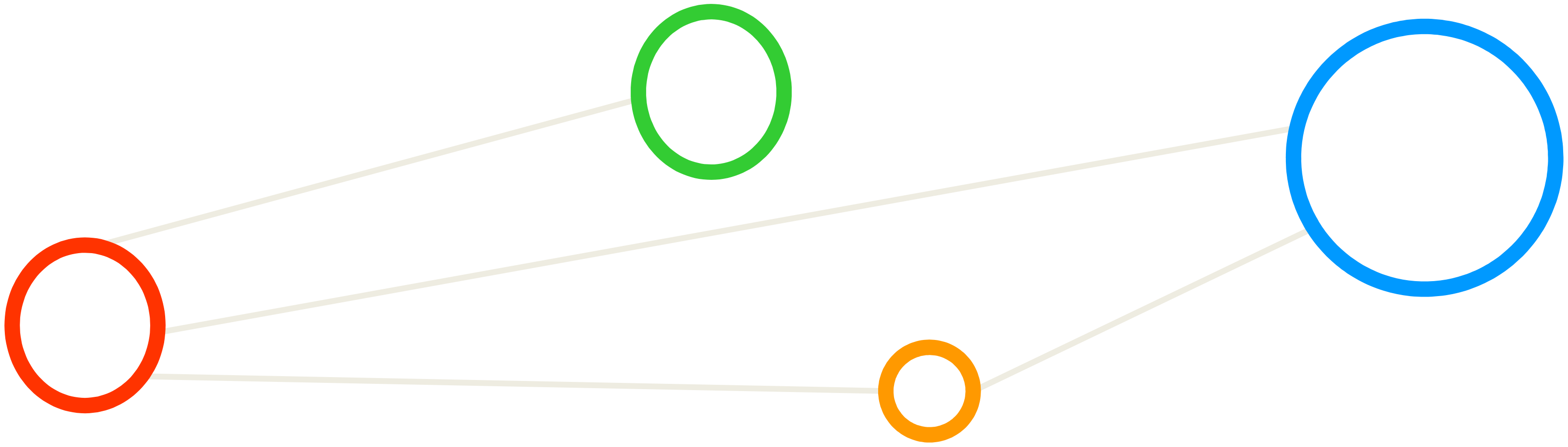
Conclusions



Conclusions

- Big Data Analytics
  - Requires smart parallel data analytics methods
  - Enables high productivity (big) data processing
  - Apply (existing) or research parallel methods
- Methods Reviewed & Applied
  - CRISP-DM guides well the systematic analytics
  - Availability of parallel implementations of analytic algorithms rare, simple, or non existent
  - SVM: Map-Reduce less stable, MPI / GPGPUs ok

References



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[5] Online: https://code.google.com/p/psvm/

[6] G. Cavallaro and M. Riedel, 'Smart Data Analytics Methods for Remote Sensing Applications', 35th Canadian Symposium on Remote Sensing (IGARSS), 2014, Quebec, Canada, to appear

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[10] Research Data Alliance, Big Data Analytics IG,
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Talk available at:

www.morrisriedel.de/talks

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