University of Stuttgart
Germany

Quality-Driven Early Stopping for Explorative Cluster Analysis for Big Data

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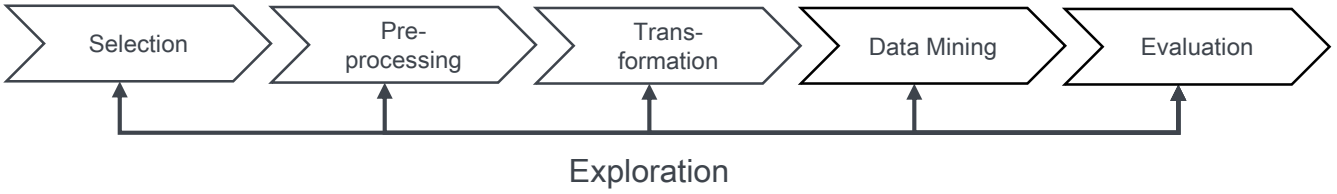
IPVS
University of Stuttgart

Motivation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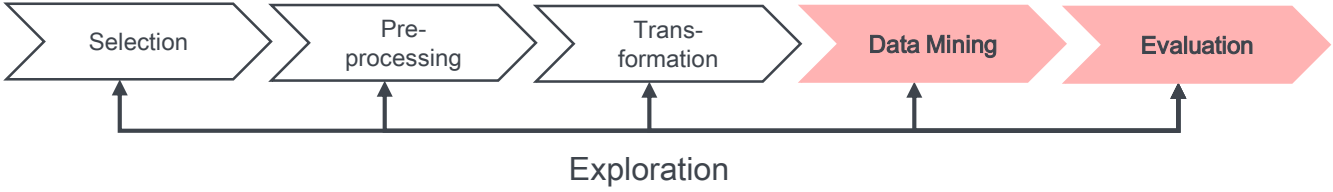
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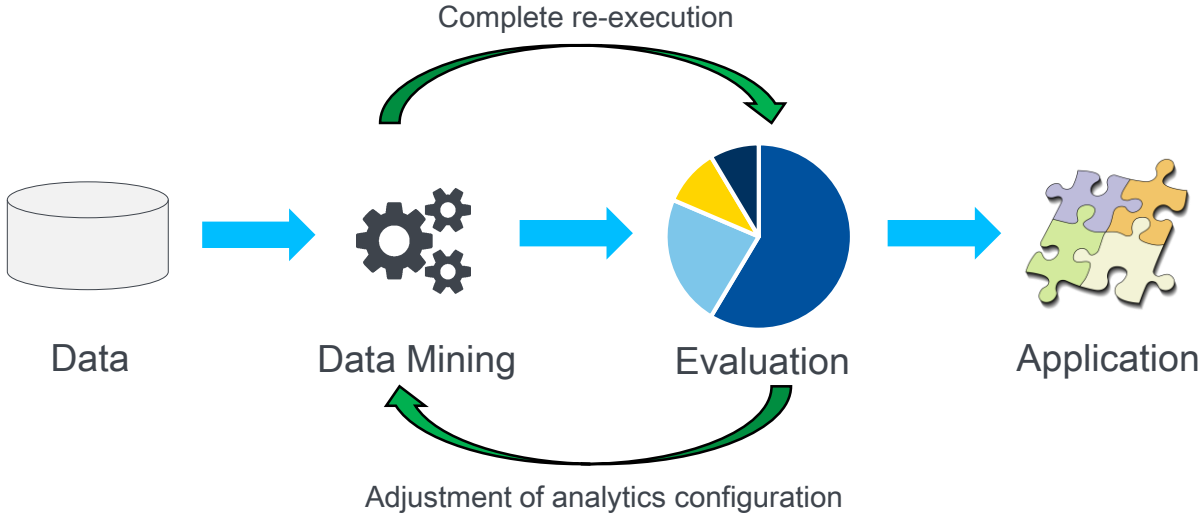
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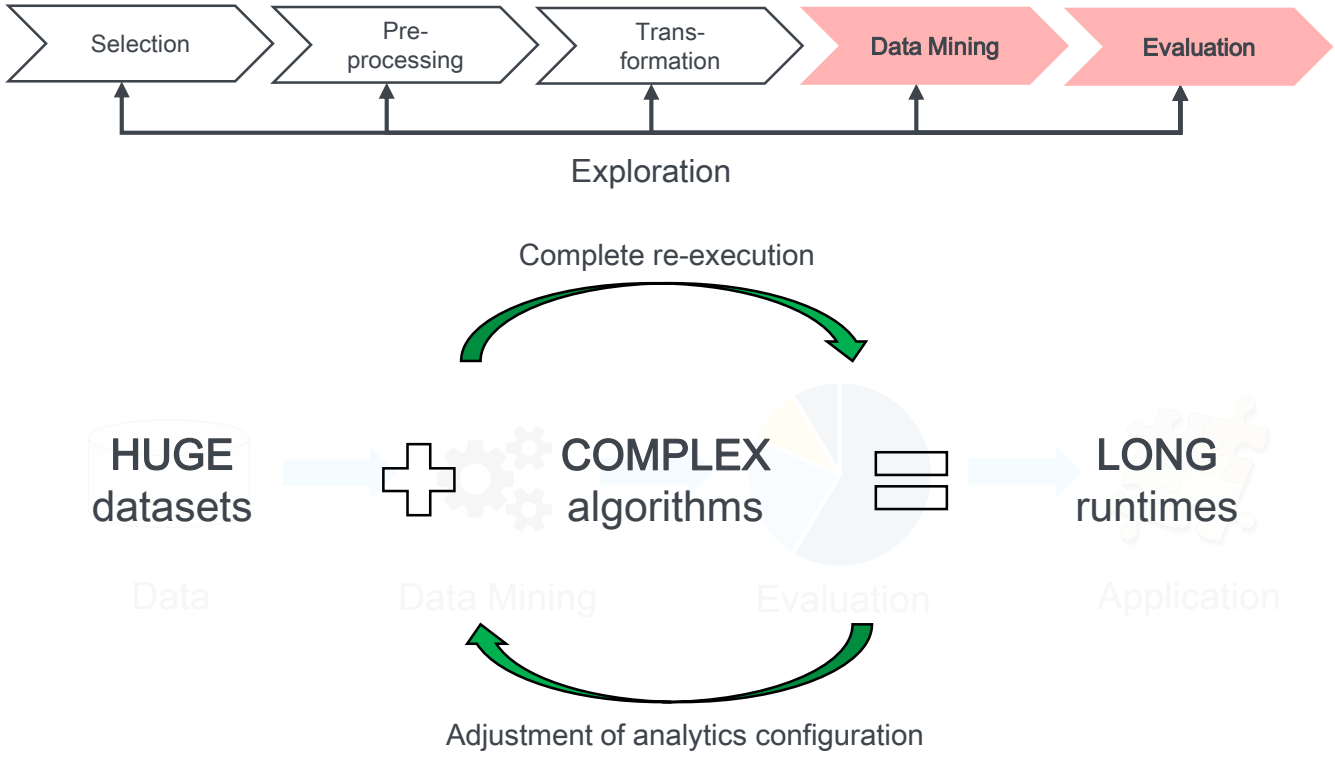
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HUGE datasets
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Partitioning Clustering Algorithms

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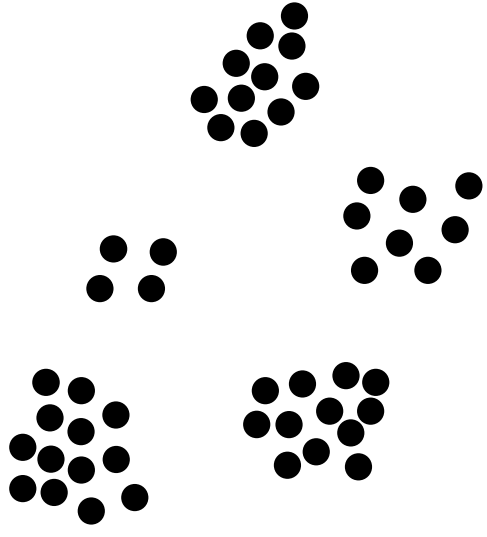

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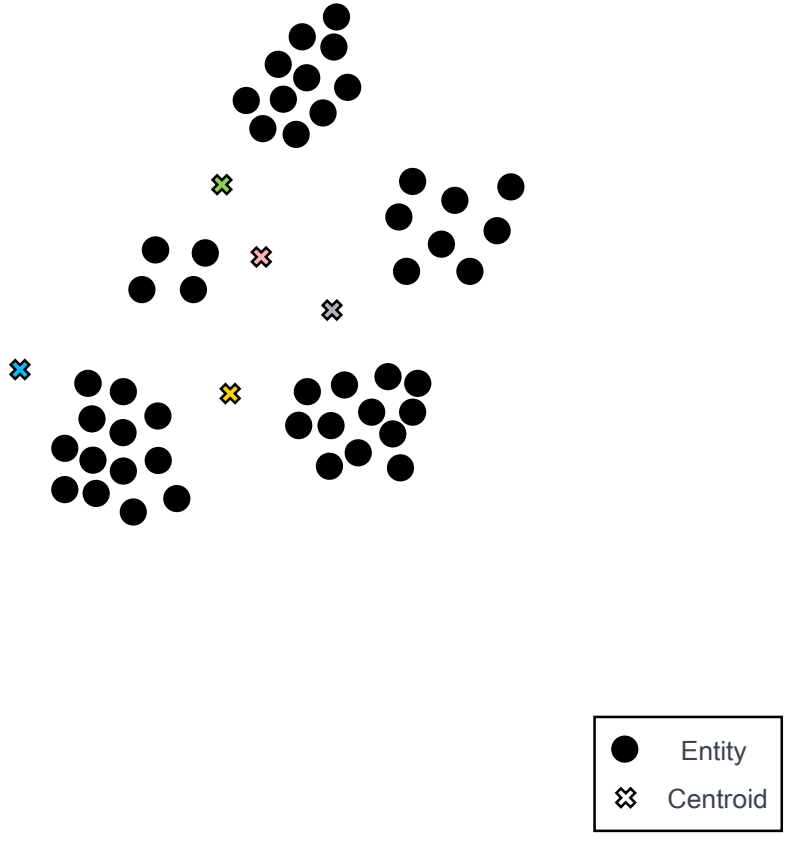

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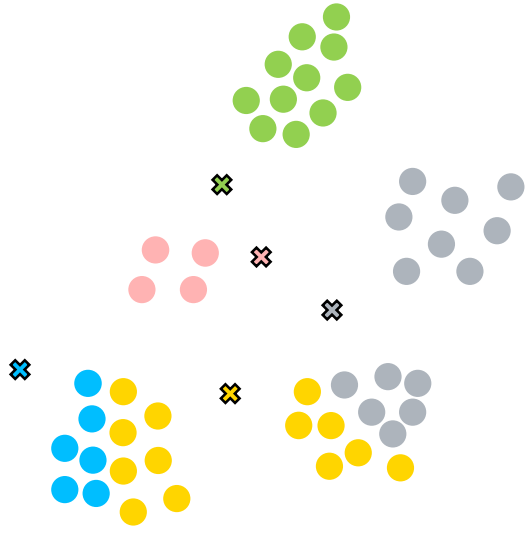

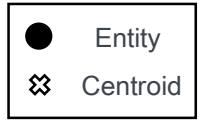

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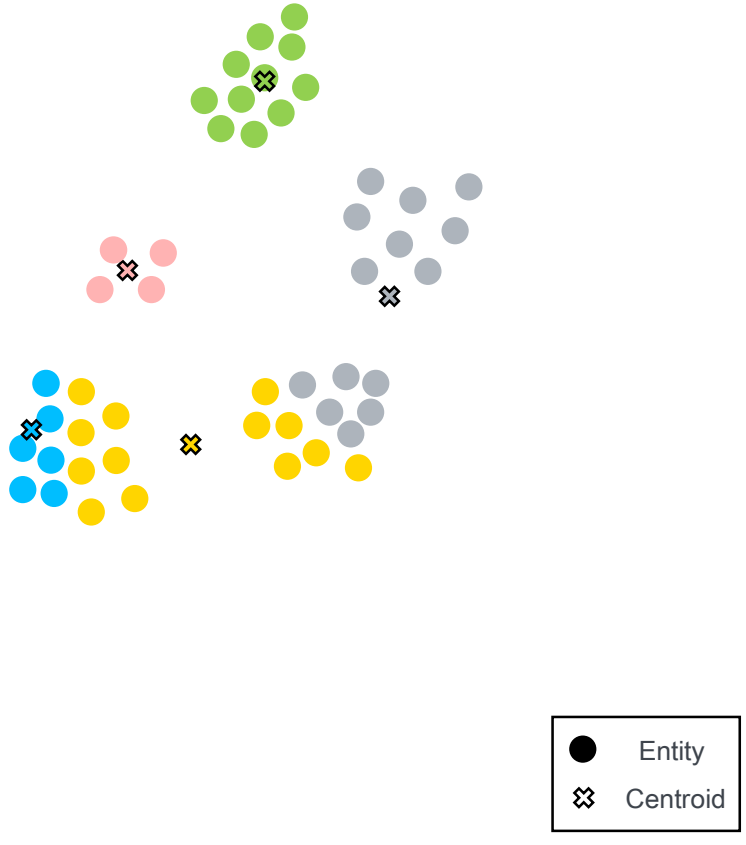

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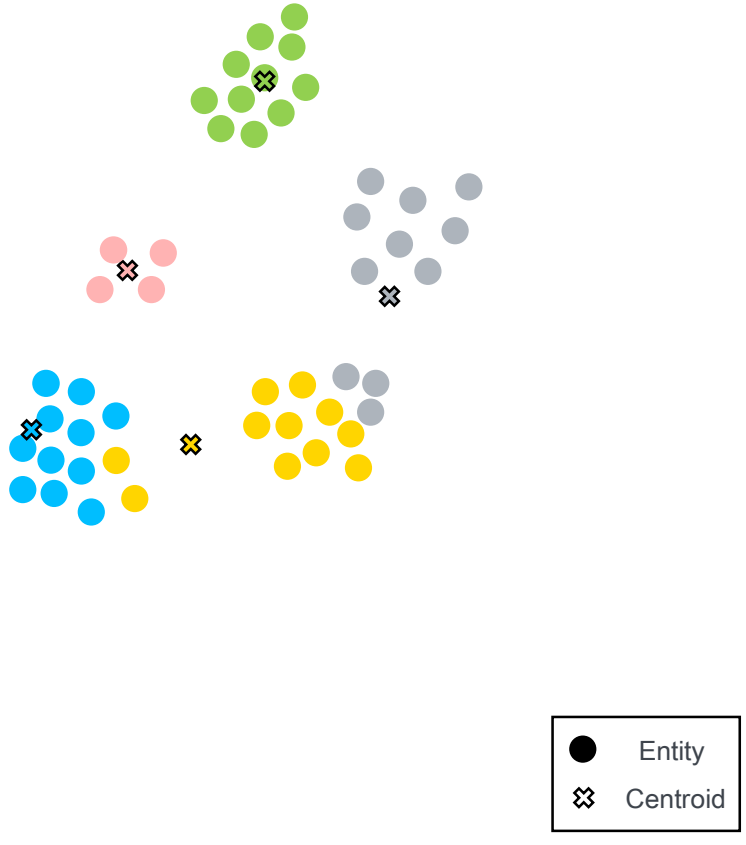

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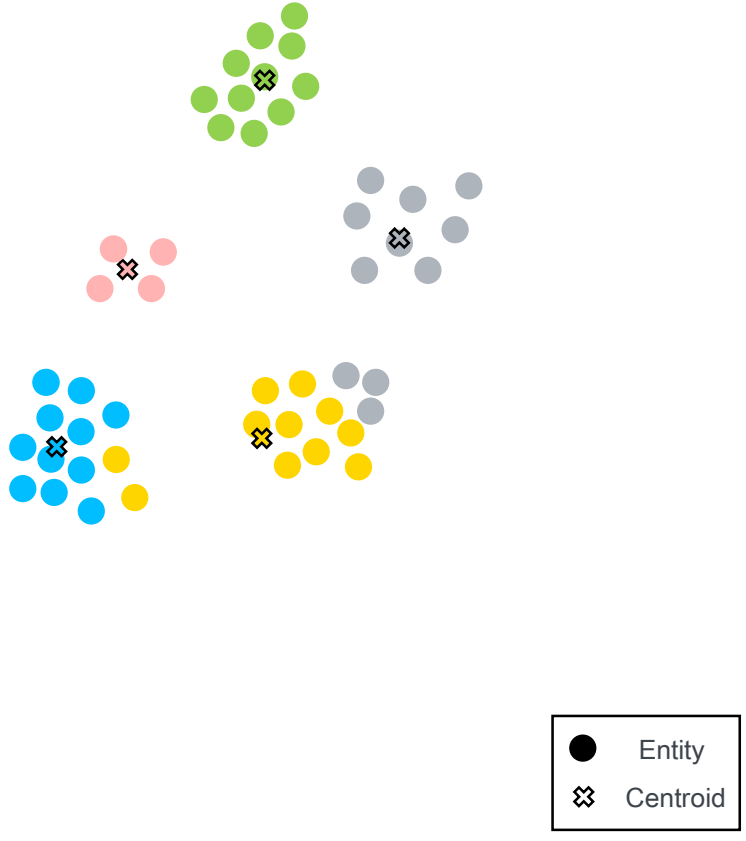

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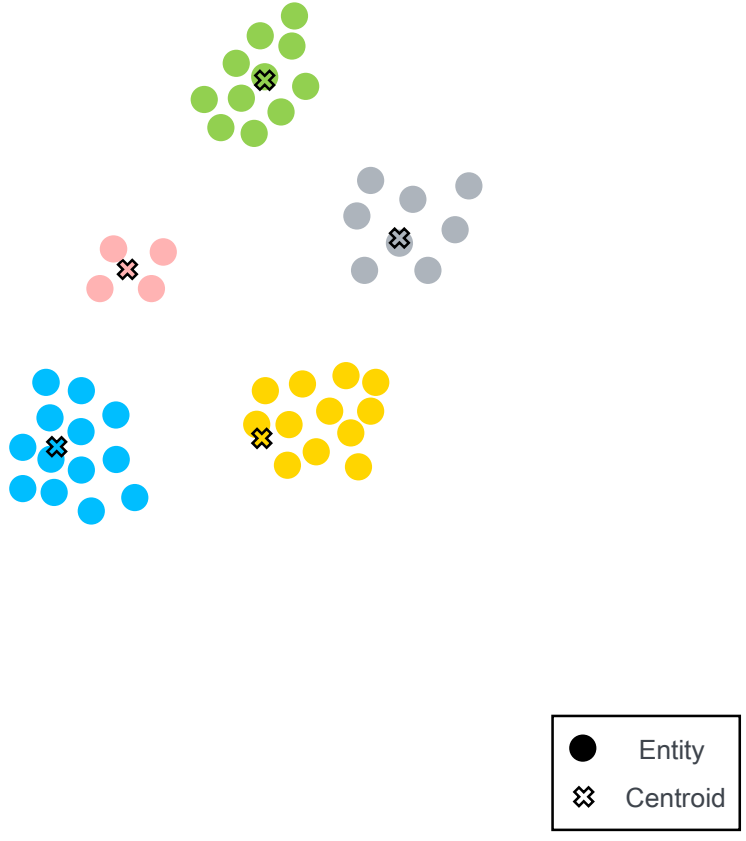

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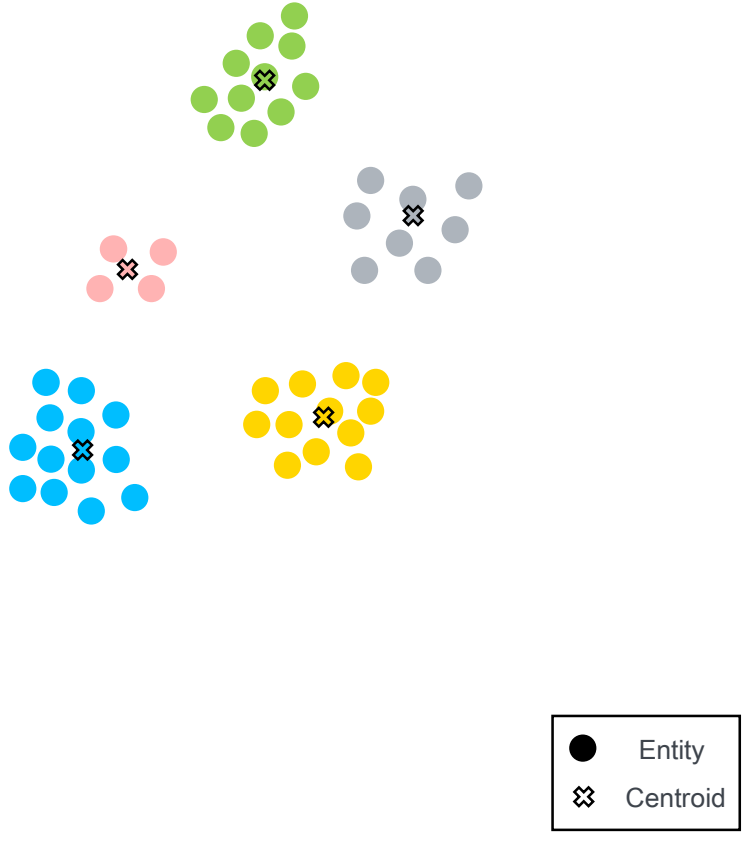

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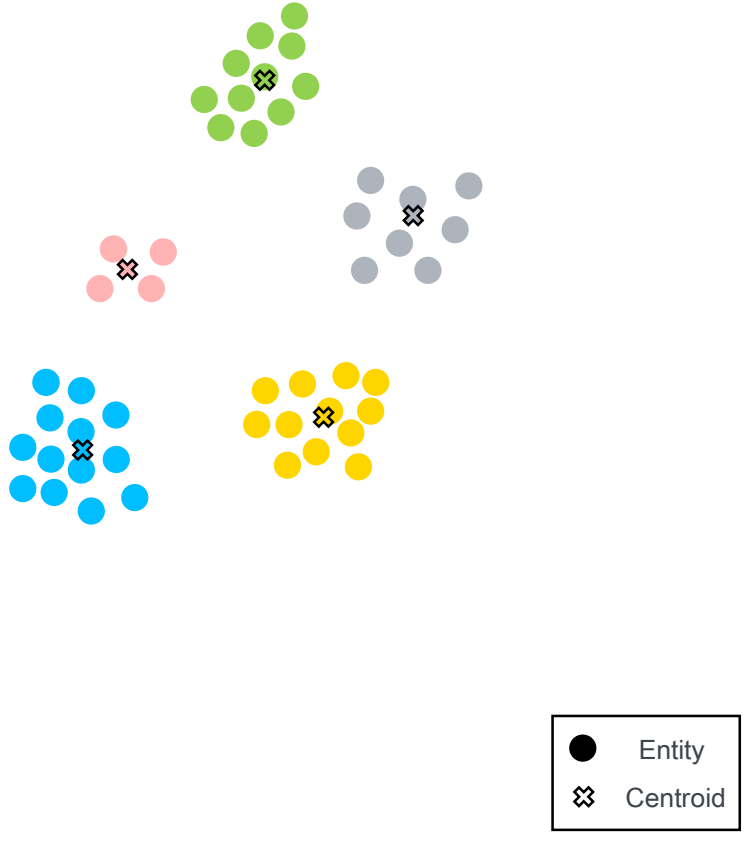

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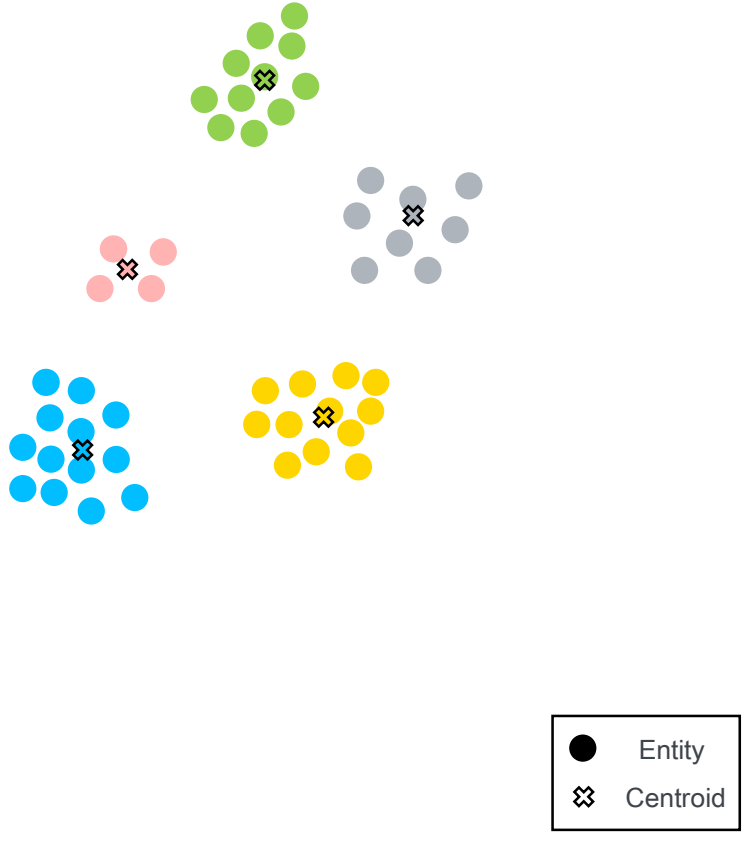

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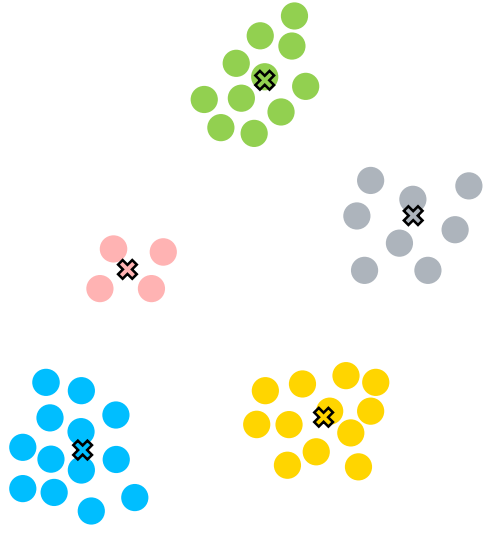


Goal: Quality-Driven Early Stopping Criterion

Entity
Centroid

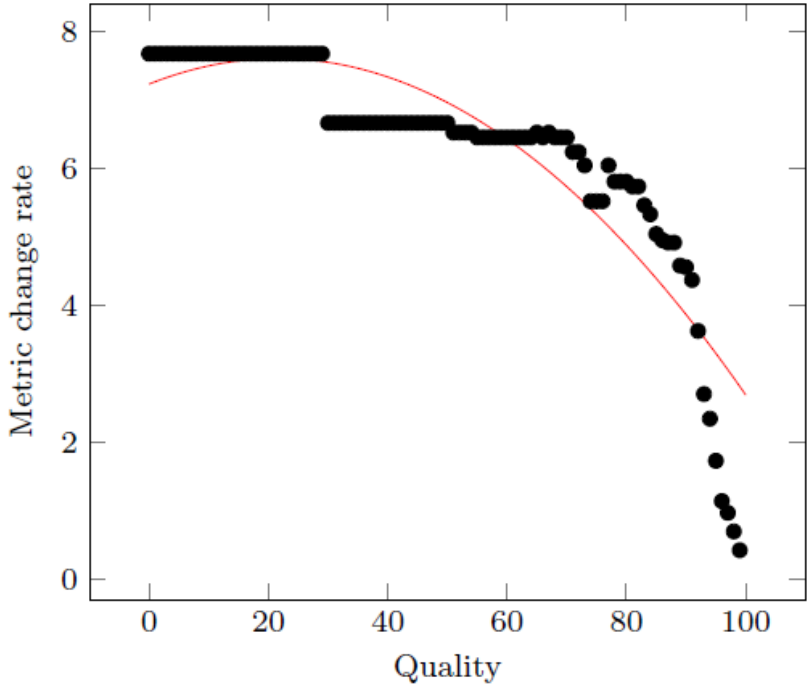
Metrics

Metric	Abbreviation	Formula	Normalized
Separation	SEP	$\sum_{i=1}^{k} \sum_{j=1}^{k} dist(z_i, z_j)$	✗
Compactness	COM	$\sum_{i=1}^{k} \sum_{d_m \in Z_i} dist(z_i, d_m)$	✗
Sum of squared errors	SSE	$\sum_{i=1}^{k} \sum_{d_m \in Z_i} dist(z_i, d_m)^2$	✗
Dunn Index	DUI	$\frac{\min(SEP(z_i, z_j))}{\max(COM(Z_i))} \mid \forall z_i, z_j \in Z, z_i \neq z_j$	✗
Coggins-Jain Index	CJI	$\min\left(\frac{SEP(z_i, z_j)}{COM(Z_i)}\right) \mid \forall z_i, z_j \in Z, z_i \neq z_j$	✗
Davies-Bouldin Index	DBI	$\frac{1}{k} \sum_{i=1}^{k} \max_{j \neq i} \left(\frac{\frac{1}{\lvert Z_i \rvert} COM(Z_i) + \frac{1}{\lvert Z_j \rvert} COM(Z_j)}{SEP(z_i, z_j)}\right)$	✗
Silhouette coefficient	SIC	$avg\left(\frac{b(d_m) - a(d_m)}{\max(a(d_m), b(d_m))} \mid \forall d_m \in D\right)$	✓

$b(d_m) = min_{z_i \neq z_j}\{avg\{dist(d_m, d_l) \mid d_m \neq d_l, d_l \in Z_j\}\}$
$a(d_m) = avg\{dist(d_m, d_l) \mid d_m \neq d_l; d_m, d_l \in Z_i\}$

Correlation Analysis

Metric value and Quality



Our Approach

Quality-Driven Early Stopping

10 Data sets

Training

5 Data sets

Application

5 Data sets

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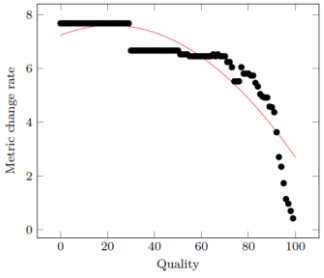
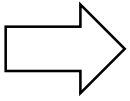




if corresponding metric value is met

Track metrics per iteration

Create regression curve per metric

Apply convergence criterion on unseen data

Evaluation

Metric Performance

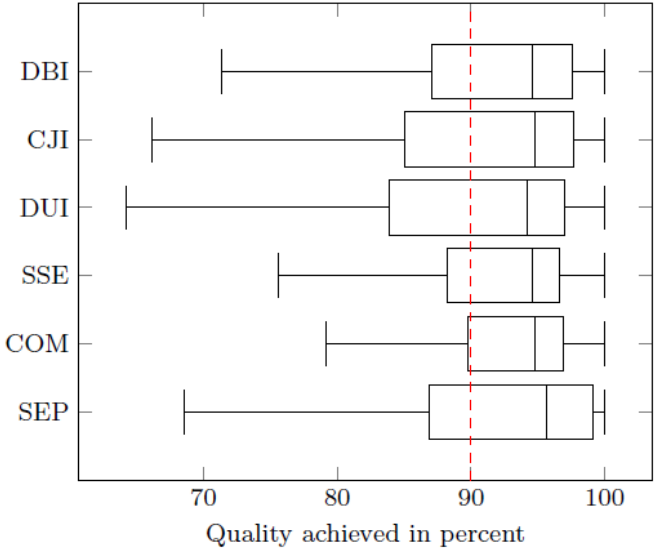


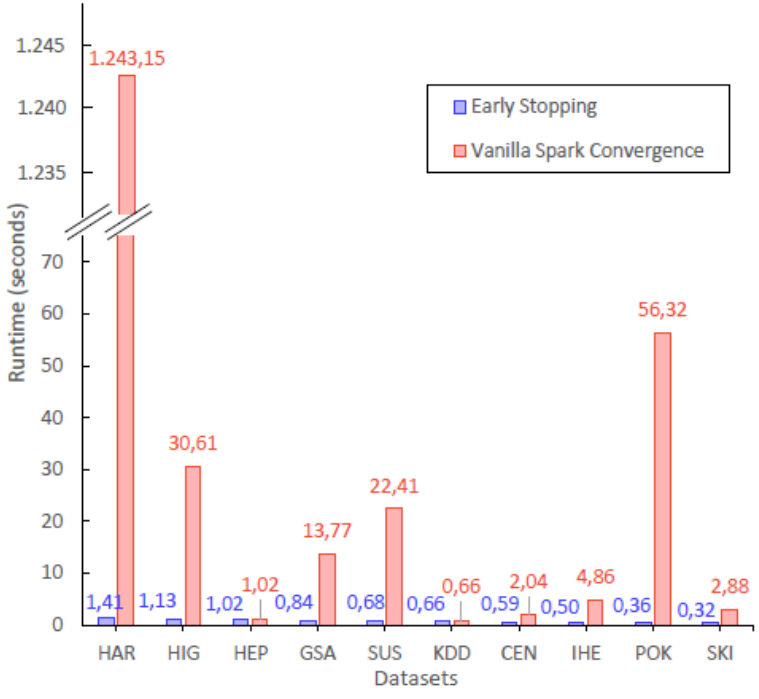
Fig. 2: Lower quartile, median and upper quartile per metric when demanding a quality of 90 %.

	Runtime (ms)			
Metric	MIN	MEDIAN	MAX	Averaged Overhead per Iteration
SEP	7.90e−05	2.99e−03	1.14	2.80e−08 %
COM	0.38	82.46	370.46	4.04e−04 %
SSE	0.38	84.16	825.51	4.06e−04 %
DUI	0.39	84.50	347.74	4.04e−04 %
CJI	0.38	84.81	562.14	4.05e−04 %
DBI	0.38	82.55	556.54	4.07e−04 %

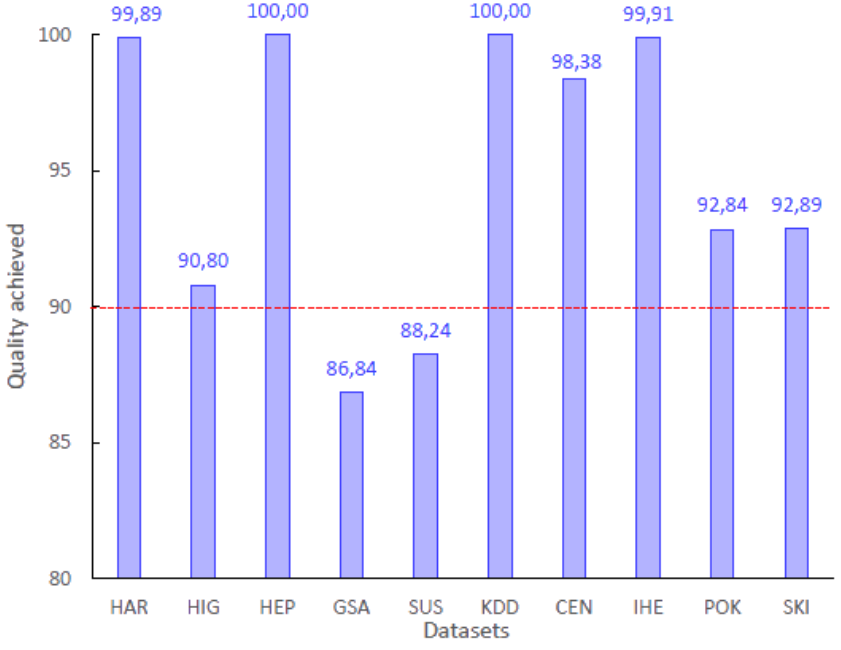
Table 4: Comparison of calculation time per metric throughout all iterations on the provided datasets.

Evaluation

Performance on Spark



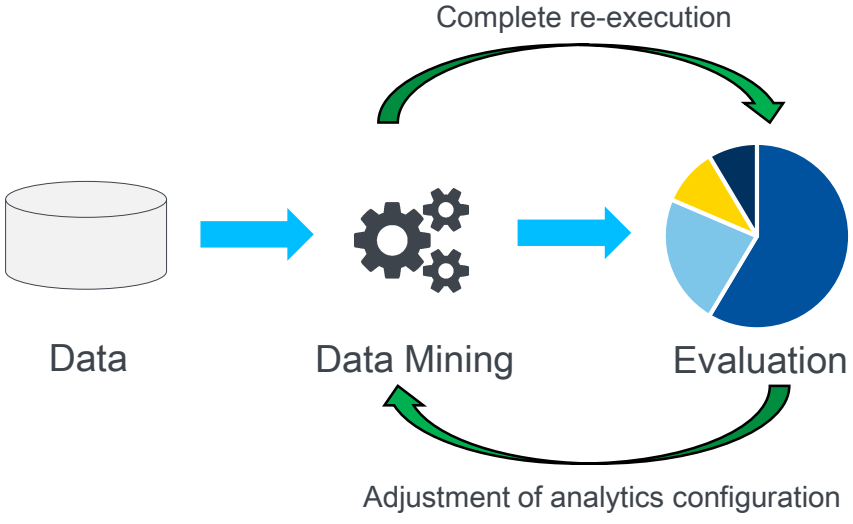
(a) Runtime comparison



(b) Quality reached when early stopping

Fig. 3: Comparison of vanilla Spark implementation of K-Means|| and early stopping when the change rate of SEP is below $-6.30e{-}02$, i.e., a quality of 90 % is demanded. Median values over 10 runs per dataset are depicted.

Conclusion & Outlook



- Considerable time savings (factor up to **800**!)
- Achieving qualitative demands regularly
- Spark Implementation available at: https://github.com/manuelfritz/EarlyStoppingKmeans

→ By how much can we accelerate the **whole** exploration process until a solid solution is achieved?

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Thank you!

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