Automatic clustering of similar VM to improve the scalability of monitoring and management in IaaS cloud infrastructures

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WEBLab

- **WEBLab: Web Engineering and Benchmarking Lab**
- **Contributing to**
  - DIEF - Department of Engineering "Enzo Ferrari" *(not only automotive)*
  - CRIS - Research center of Security
- **Research interests**
  - Distributed systems
  - Cloud computing
  - Performance / scalability issues
  - Monitoring in distributed systems
  - Security in networked / cloud systems
  - ...

Agenda

- **Background and motivation**
  - IaaS Cloud
  - Reference scenario
  - Traditional approach vs. clustering
  - Impact on monitoring and management
- **Clustering based on metric correlation**
  - Theoretical model(s)
  - Experimental evaluation
- **Clustering based on Bhattacharyya distance**
  - Theoretical model(s)
  - Experimental evaluation
- **Conclusion and future work**

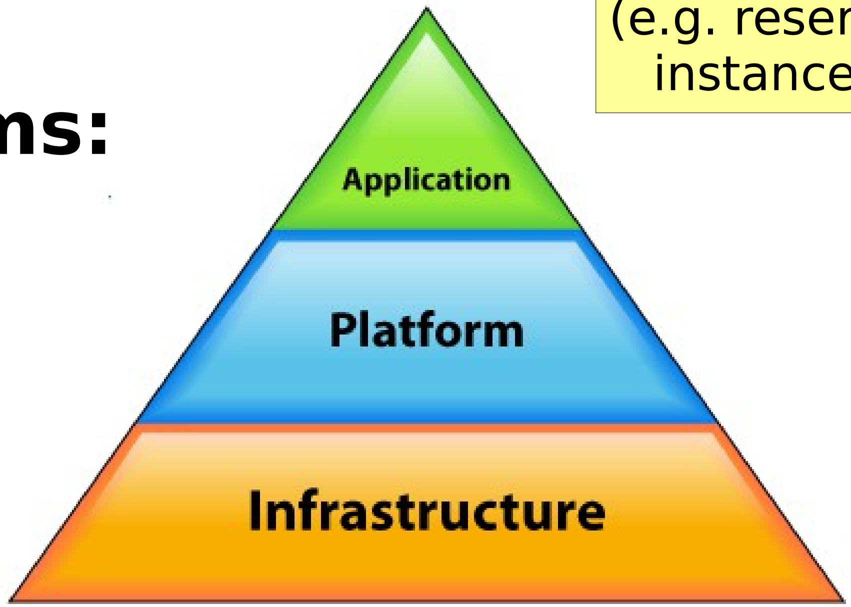
Cloud computing

Cloud computing

- **Cloud computing AKA Utility computing**
- **Access to resources and services:**
  - Multiple customers → same provider
  - Leveraging economies of scale
  - No initial cost (pay per use)
  - Exploit virtualization technologies

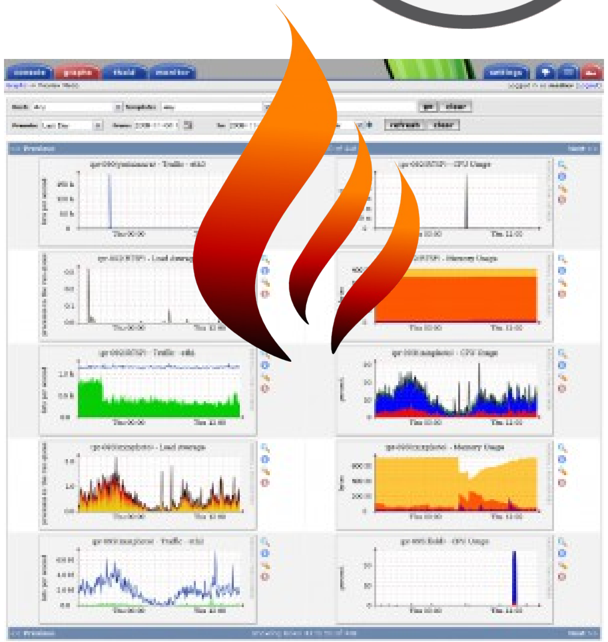
NOTE:
We may still have long-time commitments (e.g. reserved instances)

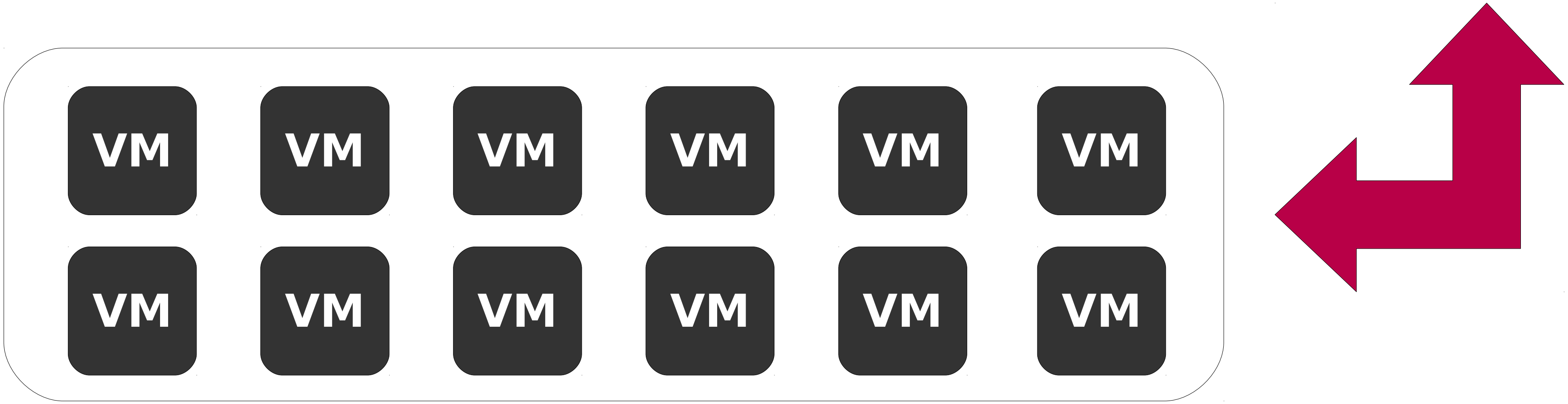
- **Multiple cloud paradigms:**
  - SaaS
  - PaaS
  - **IaaS**



Challenges: monitoring

- **Large data centers (> 10^5 VMs)**
  → huge amount of data
- **Multiple data centers**
  → geographic data exchange
- **VM can be anything**
  → treat VM as black boxes
- **→ Scalability issues**





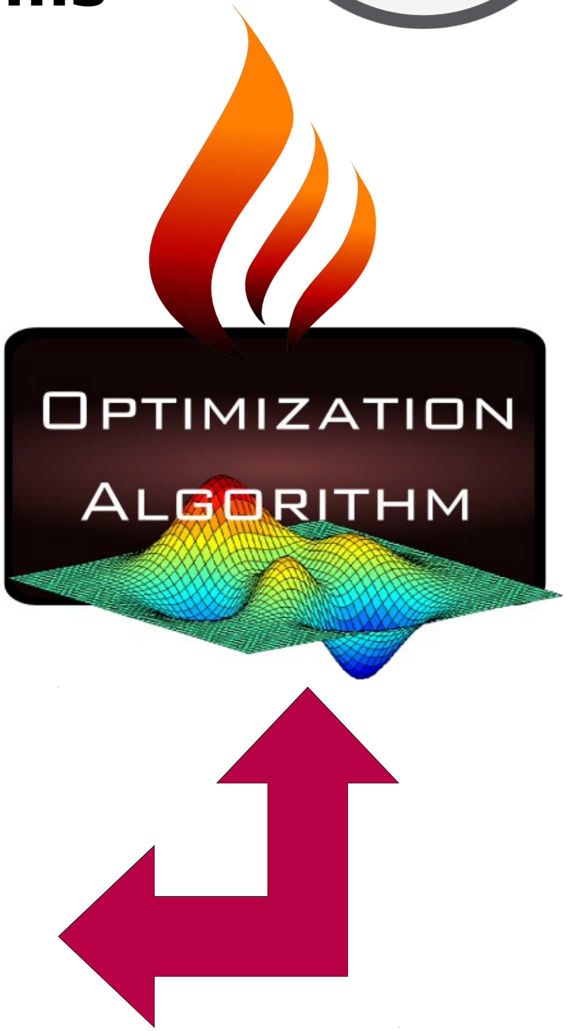
Challenges: monitoring

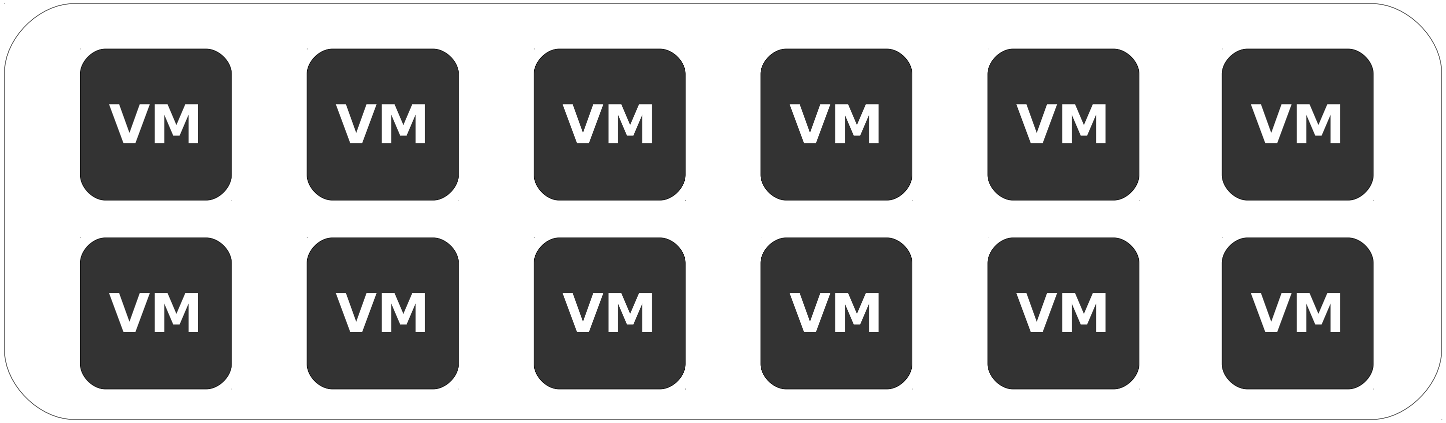
- **Current approach**
  → reduce amount of data in a uniform way:
  - Reduce sampling frequency
  - Reduce number of metrics considered

- **→ Reduced monitoring effectiveness**
  - Less information available to take management decision

Challenges: management

- **Large data centers → large opt. problems**
  - Too many variables
  - Too many bounds
  - Like a *huge* multi-dimensional tetris
- **VM can be anything**
  → treat VM as black boxes
  → difficult search for complementary workloads
- **→ Scalability issues**





Challenges: management

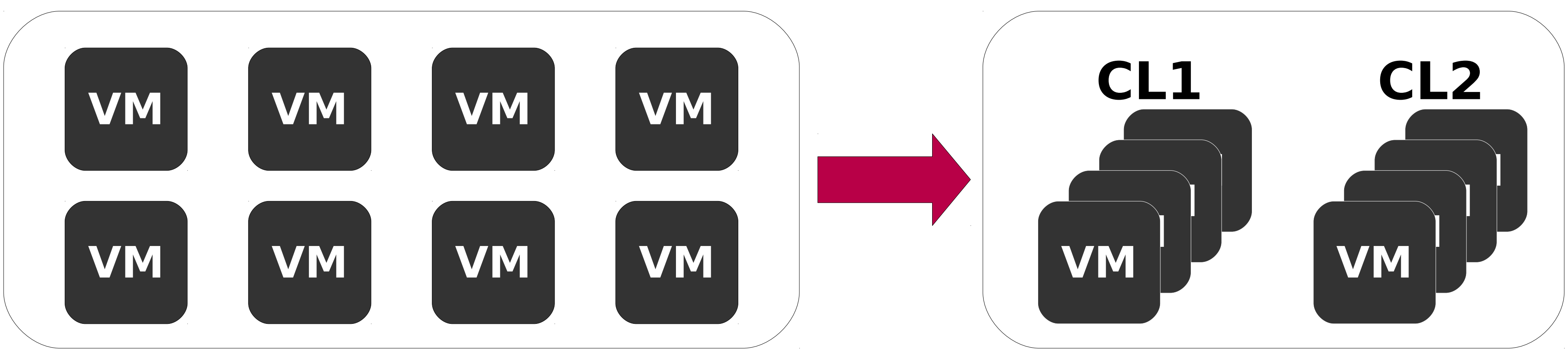
- **Current approach**
  → reduce amount of bounds:
    - Assume VM resource utilization constant over long periods (e.g. day/night)
    - Reduce number of metrics considered
    - Consider only nominal resource utilization

  → rely on hierarchical management

- **→ Reduced management effectiveness**
    - No support for fine grained management
    - Sub-optimal management decisions

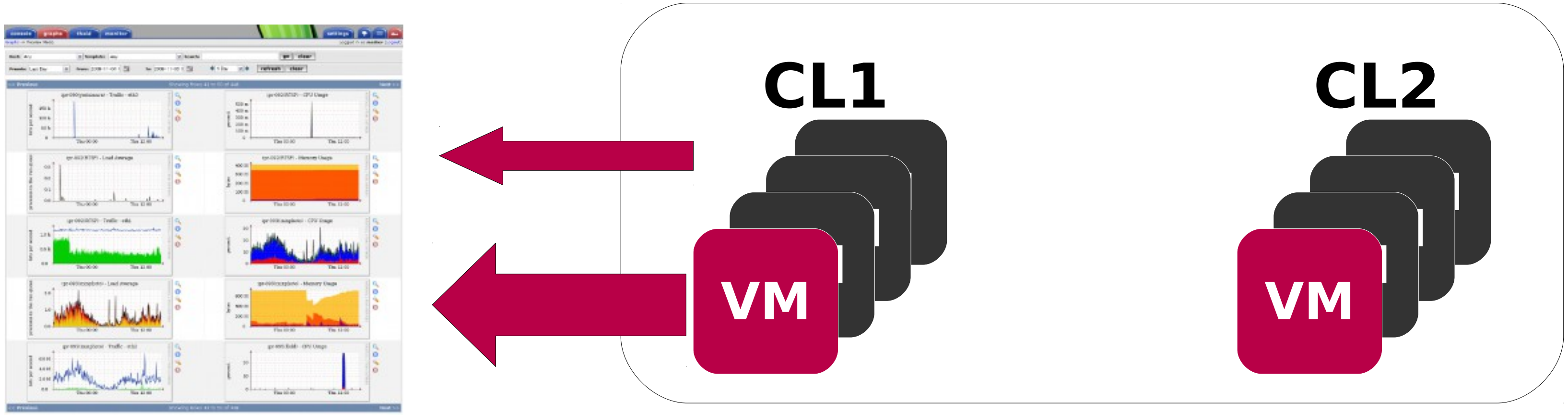
Exploiting VM similarity

- **No information on VM behavior is used to improve scalability**
- **Proposal: <u>automatically</u> cluster VMs with similar behavior**
- **Requirements:**
  - No human intervention
  - No models for VM classes
  - No crystal ball



Improving monitoring scalability

- **Group similar VMs together**
- **Elect a few (e.g., 3) cluster representatives**
  - Support for byzantine failures in representatives
- **Detailed monitoring of cluster representatives**
- **Reduced monitoring of other VMs**



Improving monitoring scalability

- **Numeric example**
- **Every VM as a black box:**

  - 1000 VMs, K metrics,
    1 sample/5 min
  - → 288 10^3 K sample/day
- **With clustering:**

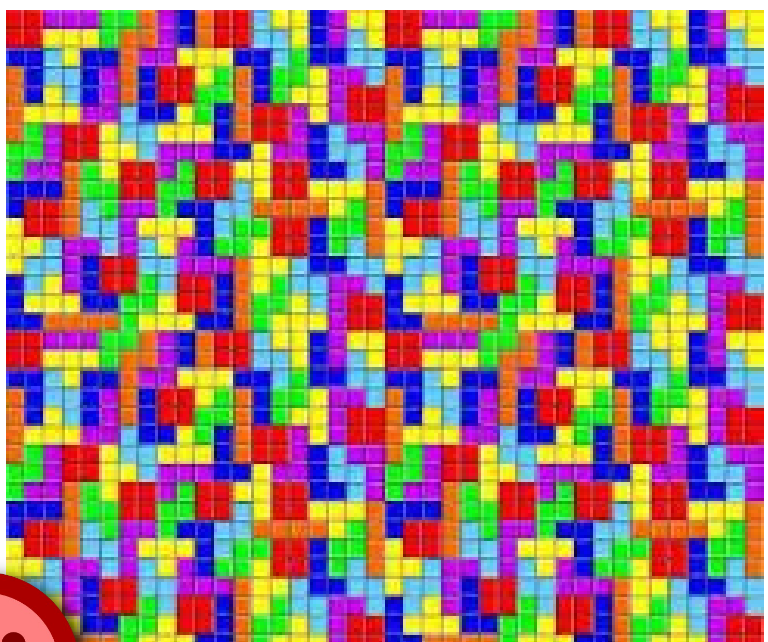
  - 15 clusters, 67 VMs per cluster
  - 3 representative per cluster
    → 45 VMs, K metrics, 1 sample/5 min

  - Non representatives
    → 955 VM, K metrics 1 sample/6 hour
  - → 16,8 10^3 K sample/day
- **Data collected reduced by 17:1**

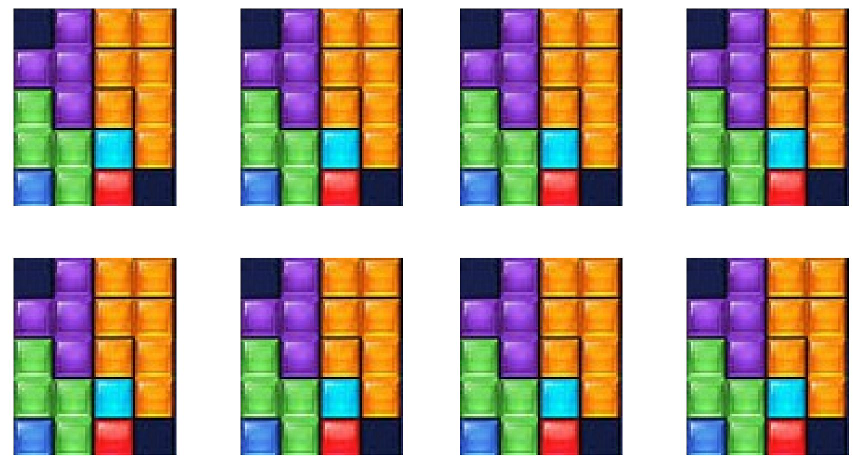
Improving management scalability

- **Server placement and consolidation**
- **Build a small consolidation solution**
- **Replicate solution as a building block**

Global problem



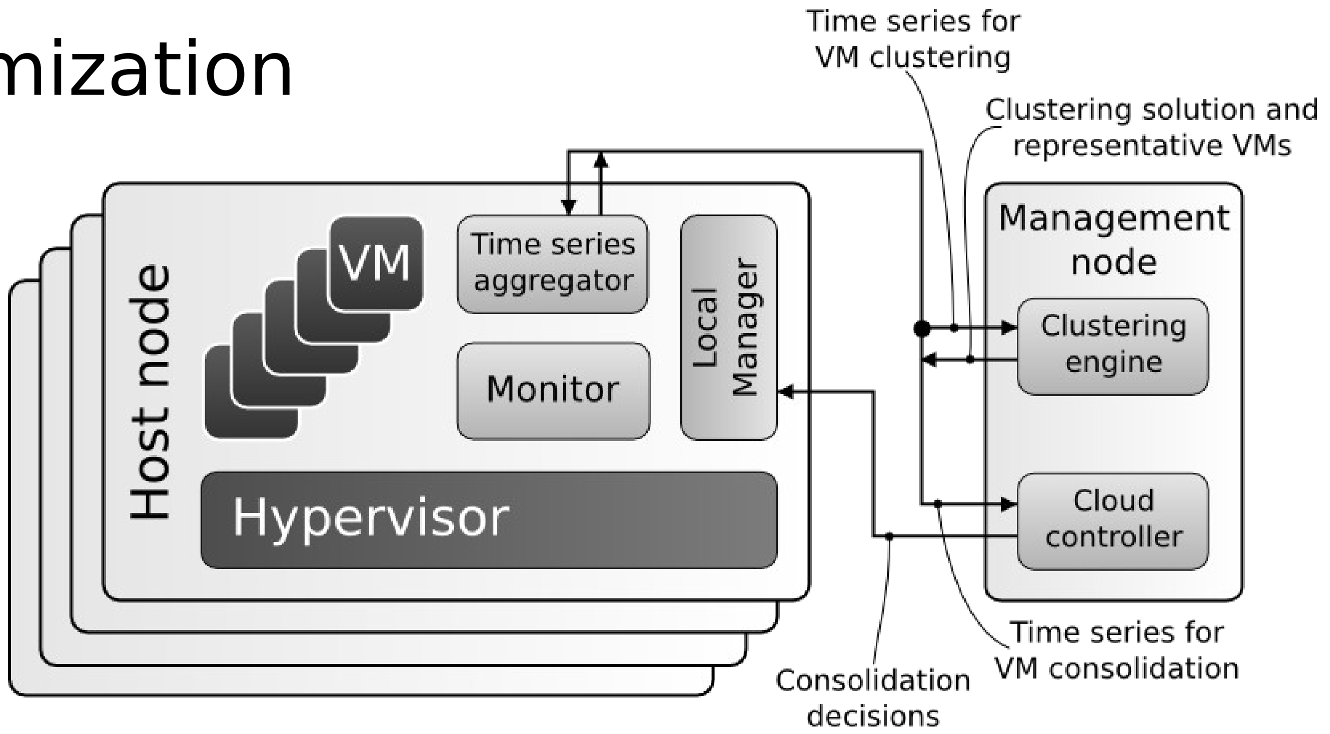
Building block solution



Residual problem solution

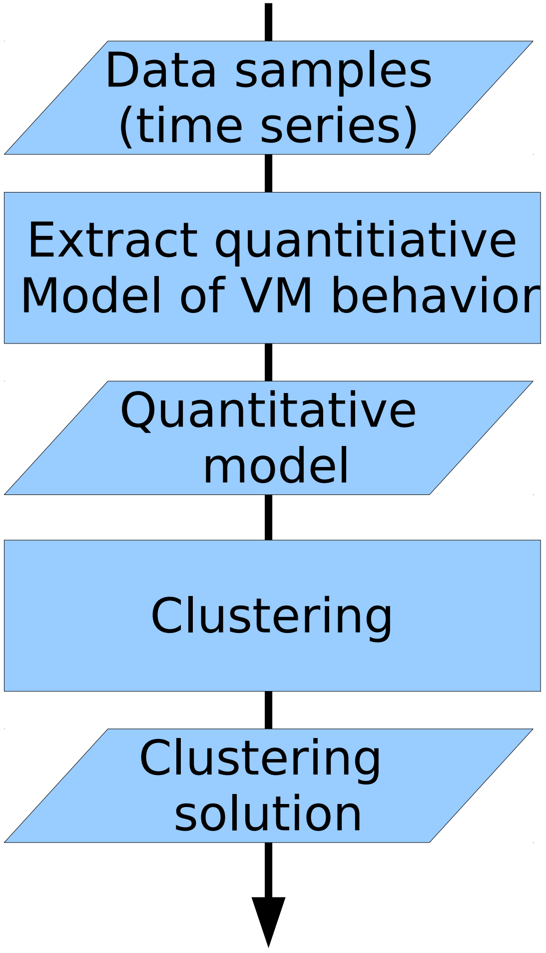
Reference scenario

- **IaaS with long term commitment**
  - Amazon Reserved instances, private cloud
- **Reactive VM relocation**
  - Local manager
- **Periodic global consolidation**
  - Global optimization



Proposed methodology

- **Methodology:**
  - Define quantitative model for VM behavior
  - Cluster similar VM together
- **Elect a few (e.g., 3) cluster representatives**
- **Fine-grained monitoring of cluster representatives**
- **Reduced monitoring applied to other VMs**
  - Reduced number of metrics
  - Lower sampling frequency



Design choices

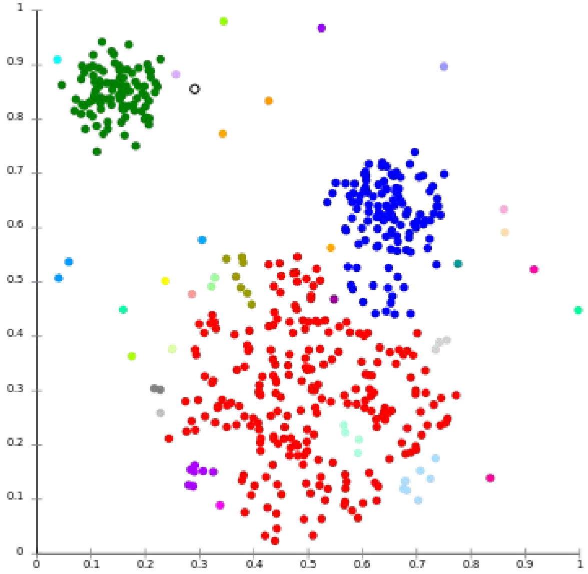
- **How to represent VM behavior?**
- **Use correlation between metrics**
  - Possible enhancement: use PCA
- **Use probability distribution of metrics**
  - Use histograms & Bhattacharyya distance
  - May need to select which information are "useful"
  - Must merge heterogeneous information from multiple metrics
  - May exploit ensemble techniques to provide robust performance
  - Possible enhancement: use histogram smoothing

Design choices

- **How to perform clustering?**

- **Use K-Means**
  - When VM behavior is represented as a feature vector

- **Use spectral clustering**
  - When VM behavior can be used to compute distance/ similarity between VMs



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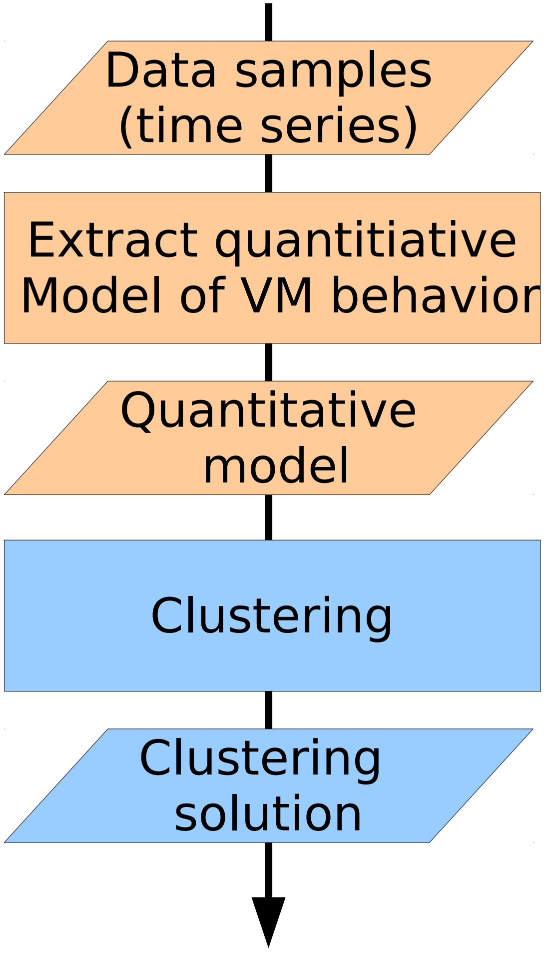
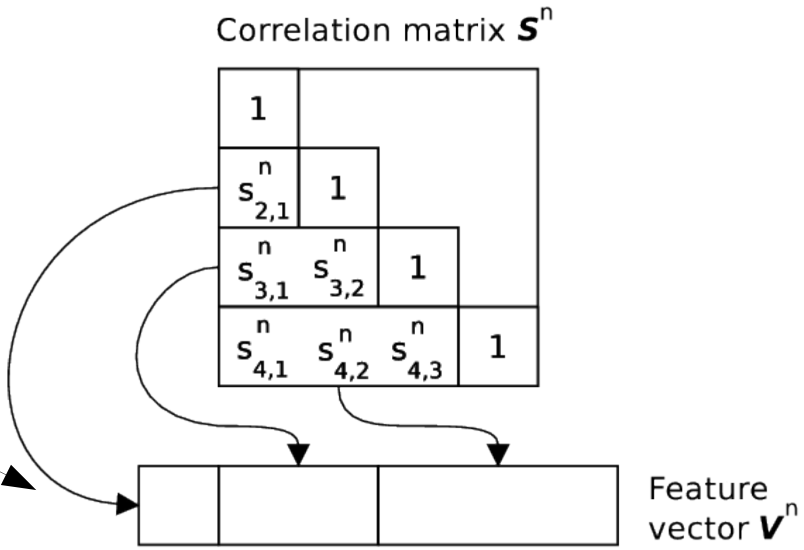
Theoretical model

- **Extraction of a quantitative model of VM behavior**
  - *Input:* time series of metrics describing VM n behavior (X1, ... ,Xm)
  - Compute correlation matrix Sn for each VM n
  - *Output:* feature vectors Vn

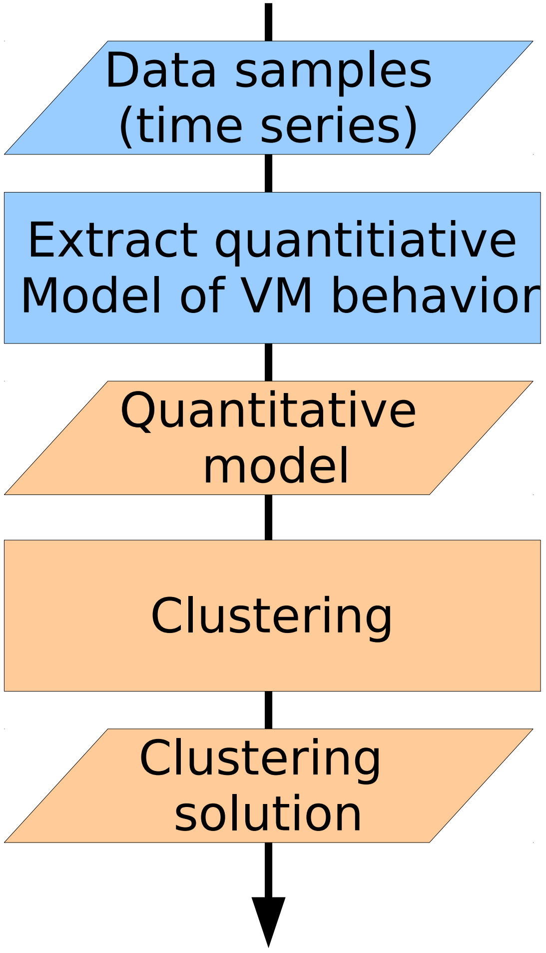


NOTE:
We exploit simmetry in matrix Sn to remove redundant information



Theoretical model

- **Clustering of VMs**
  - *Input:* feature vector Vi
  - Clustering based on k-means algorithm
  - *Output:* clustering solution



Case study

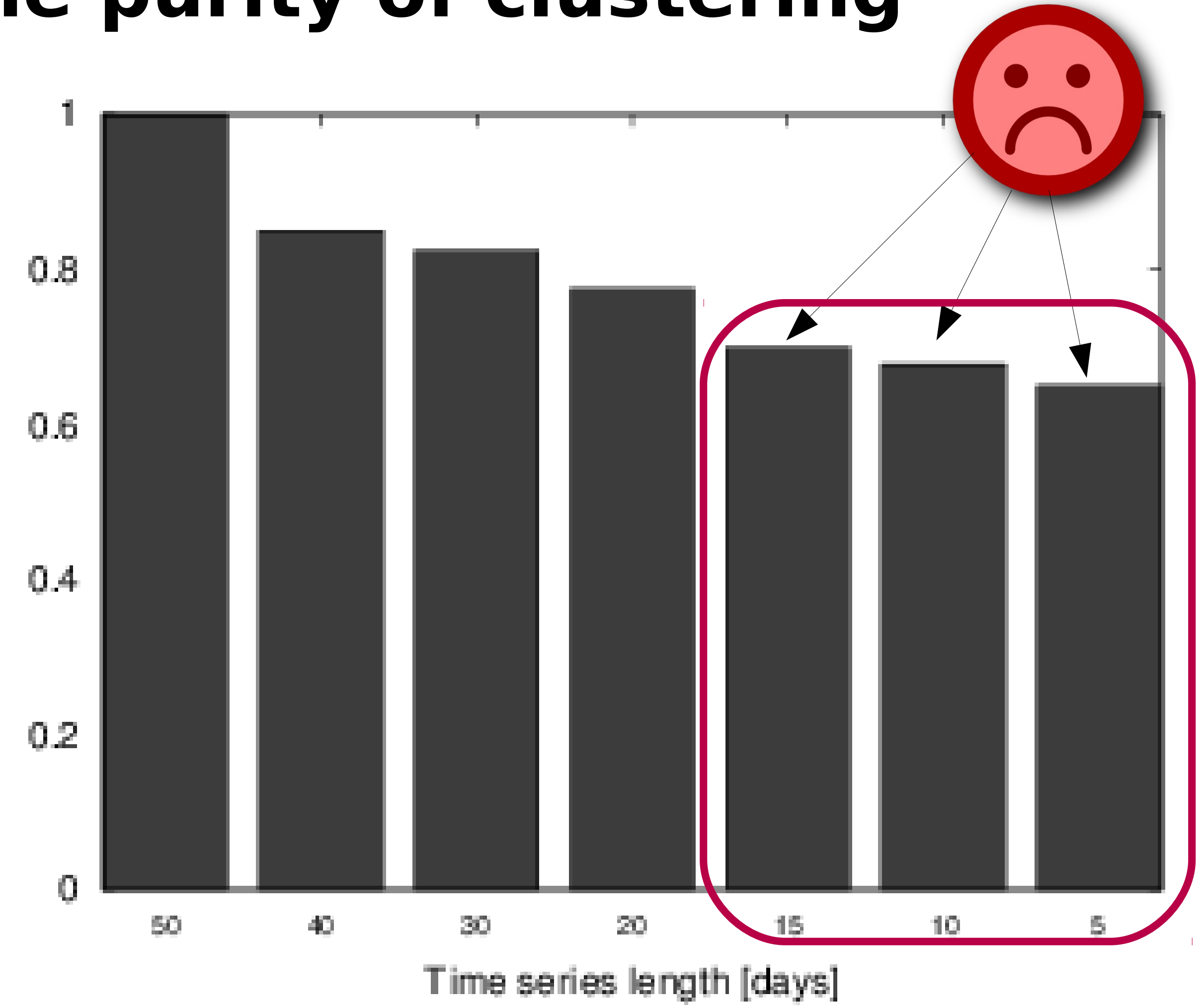
- **Datacenter supporting a e-health Web application**
  - Web server and DBMS
  - 110 VMs
  - 11 metrics for each VM,
  - Sampling frequency: 5 min

- **Goal: separate Web servers and DBMS**
  - Main metric: Purity of clustering
- **Three types of analyses**
  - Impact of time series length
  - Impact of filtering techniques
  - Impact of number of nodes

Impact of time series length

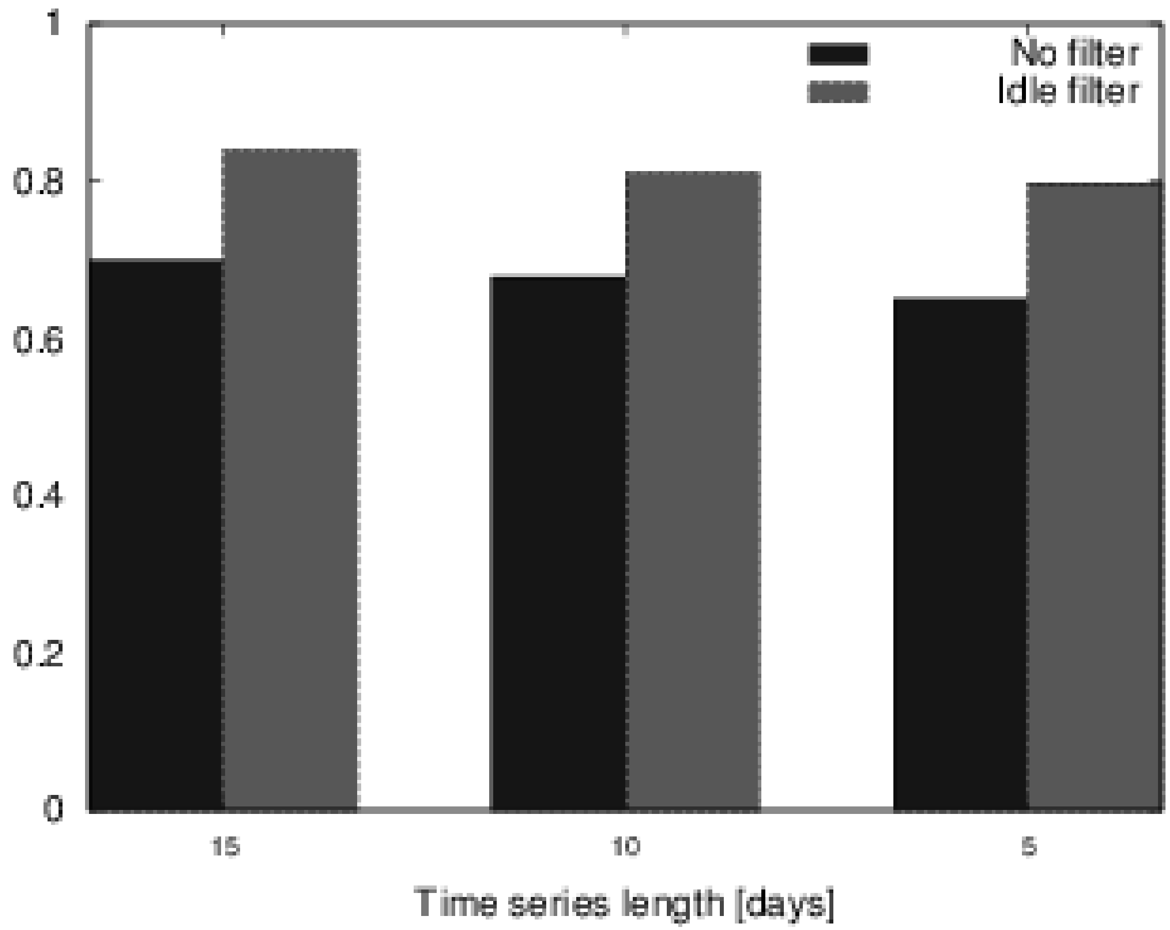
- **Reduction of available data → reduction in the purity of clustering**

- **Purity > 0.7 for time series > 20 dd**



Impact of filtering techniques

- **Application of data filtering:**
  - Remove idle periods in time series
- **Data filtering improves performance**
  - Removal of periods providing limited information
- Purity >0.8 even for 5 days time series



Impact of number of nodes

Number of VMs	Purity	Clustering time [s]
10	1	49.7
30	0.86	59.5
50	0.84	68.6
70	0.84	78.0
90	0.83	88.3
110	0.84	95.3

- **Purity is not adversely affected by # of VM**
  - **Purity ~ 0.85 for [30-110] VMs**

Proposed enhancement

- **The clustering time grows**
  - Linearly with # of VM
  - Quadratically with # of metrics

- **→ Potential scalability issue**

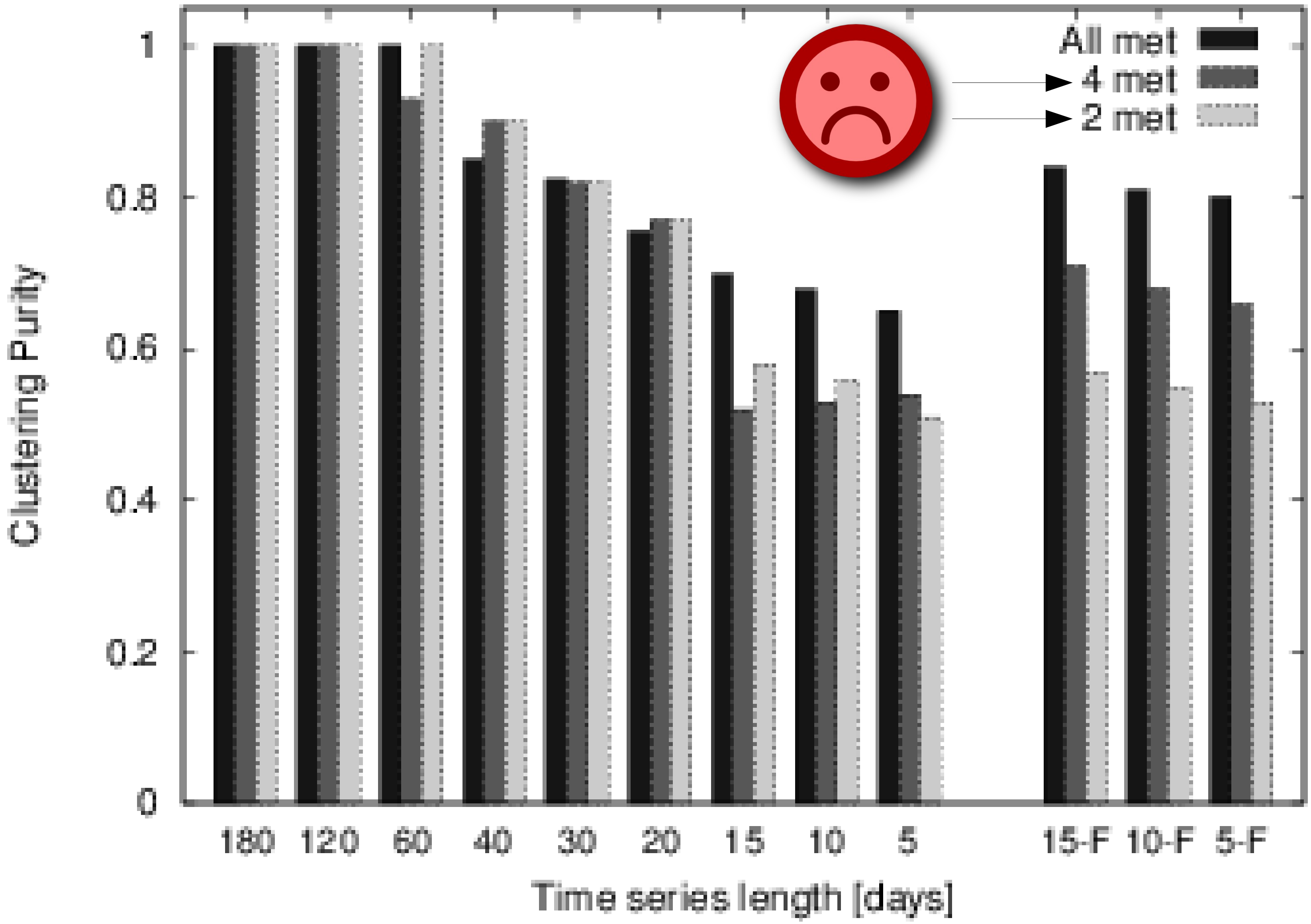
- **Can we reduce the number of metrics?**

- **Can we reduce the quadratic relationship?**

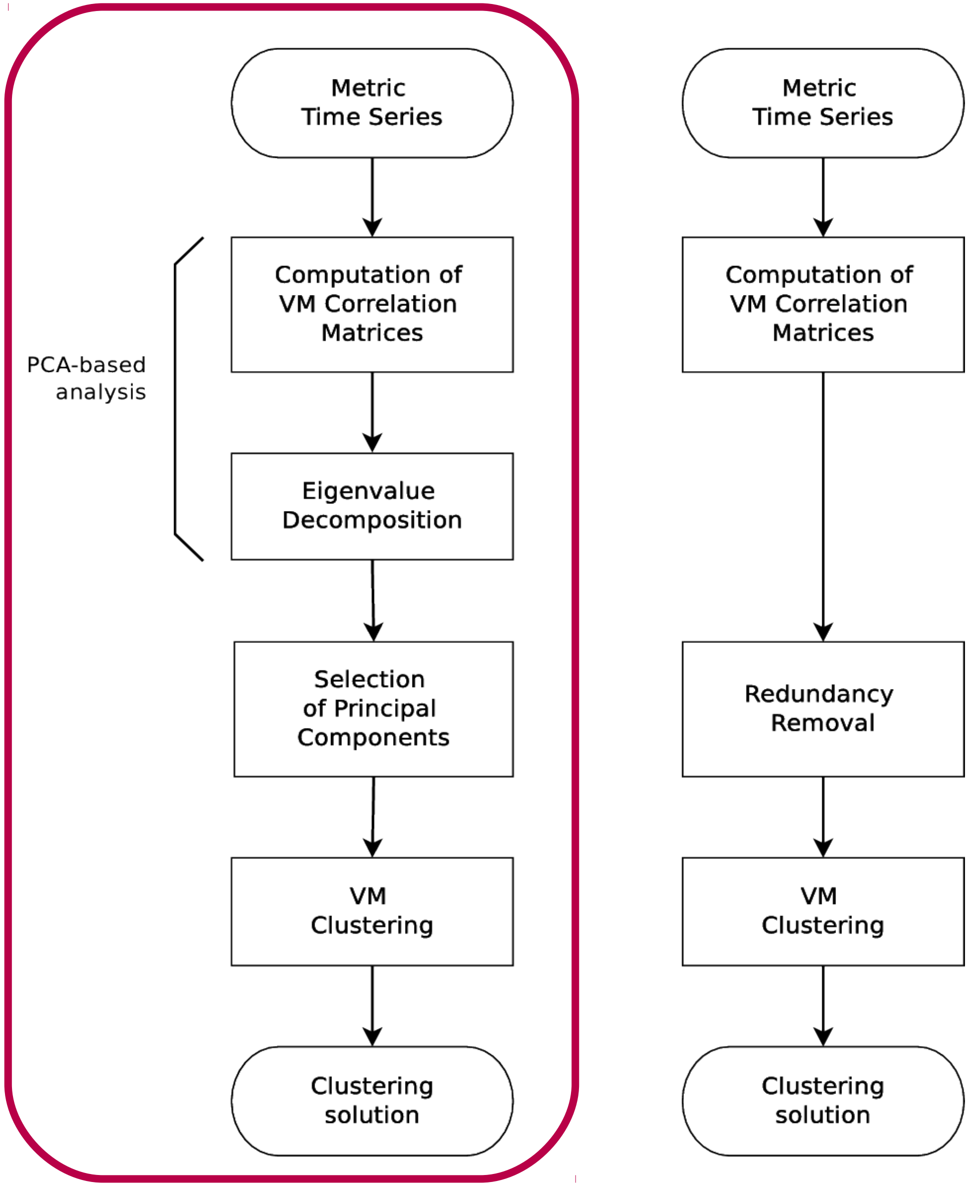
Proposed enhancement

- **The clustering time grows**
  - Linearly with # of VM
  - Quadratically with # of metrics
- **→ Potential scalability issue**
- **Can we reduce the number of metrics?**
  → NO: clustering purity is heavily affected
- **Can we reduce the quadratic relationship?**
  → YES: can exploit PCA techniques

Reducing number of metrics

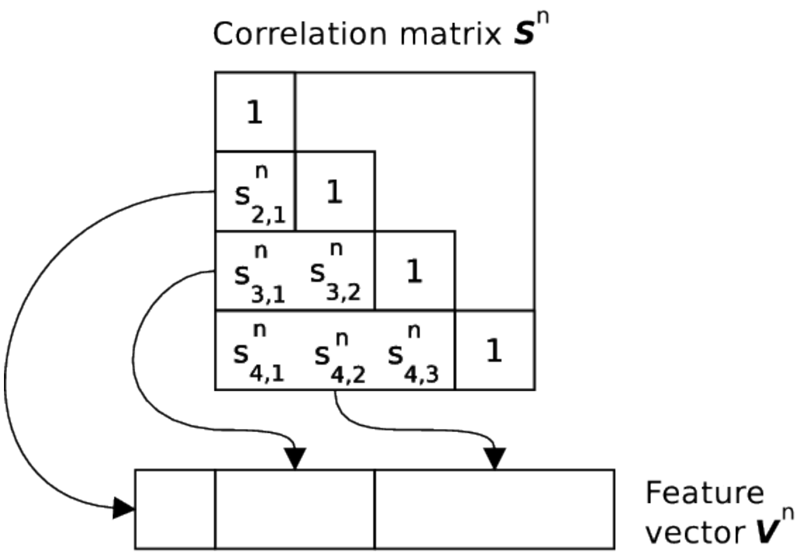


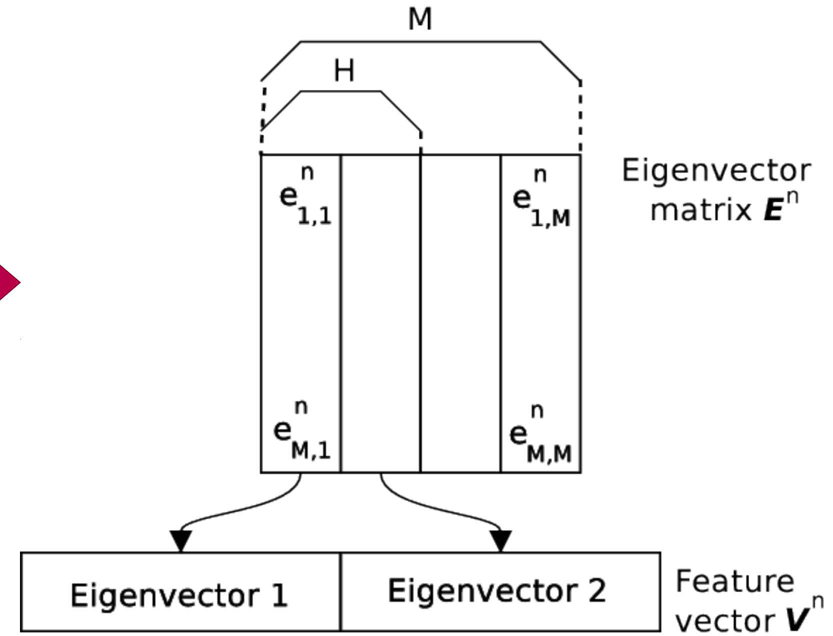
PCA-based technique



PCA-based technique

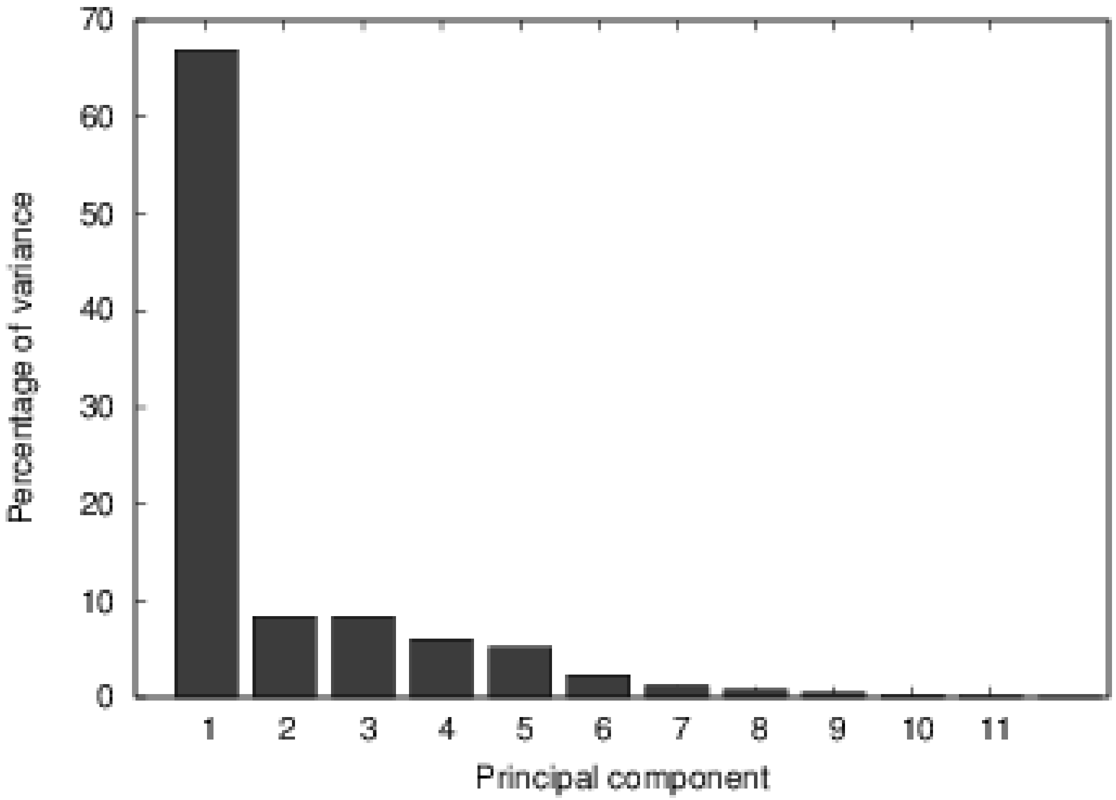
- **Building the feature vector:**



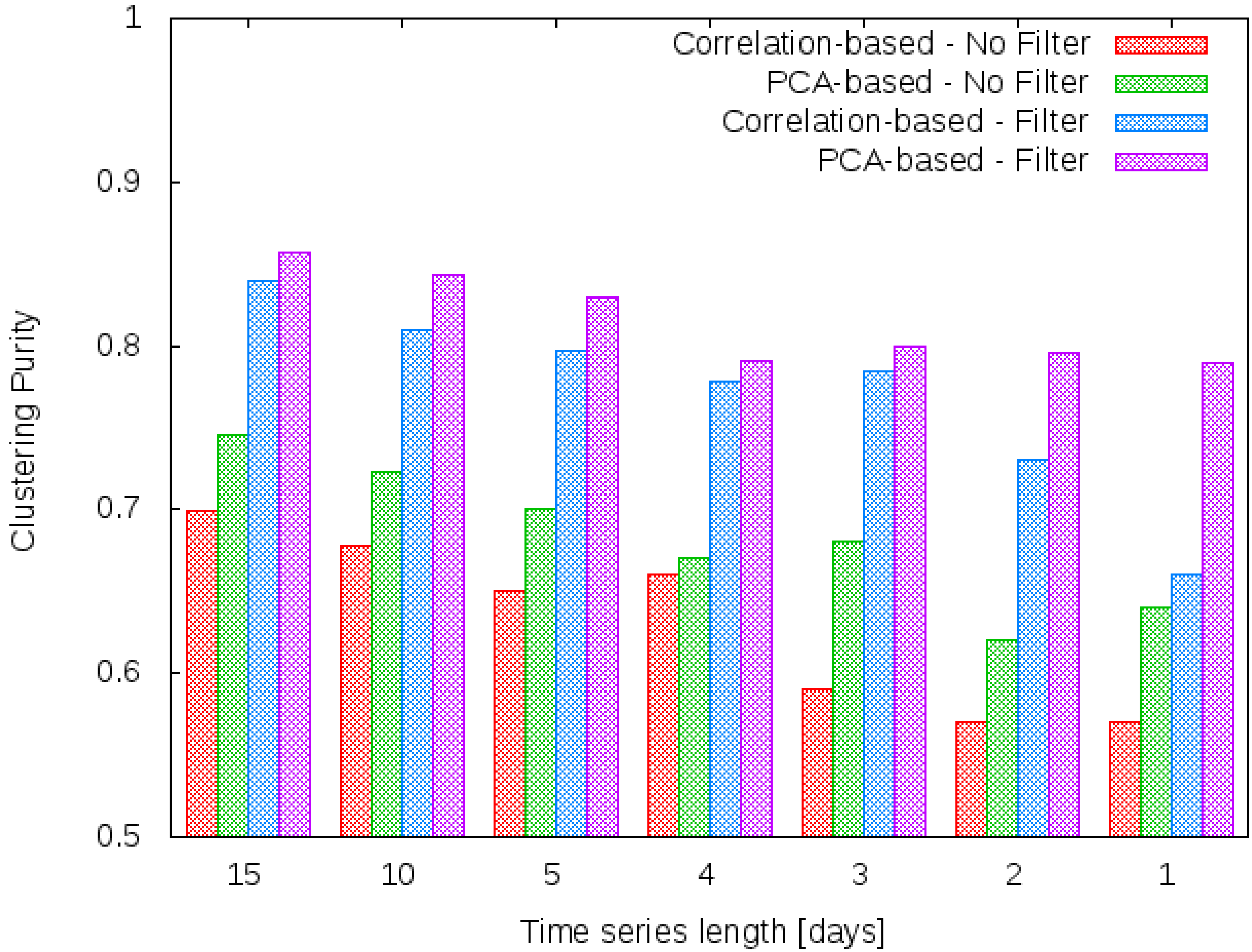


How many principal components?

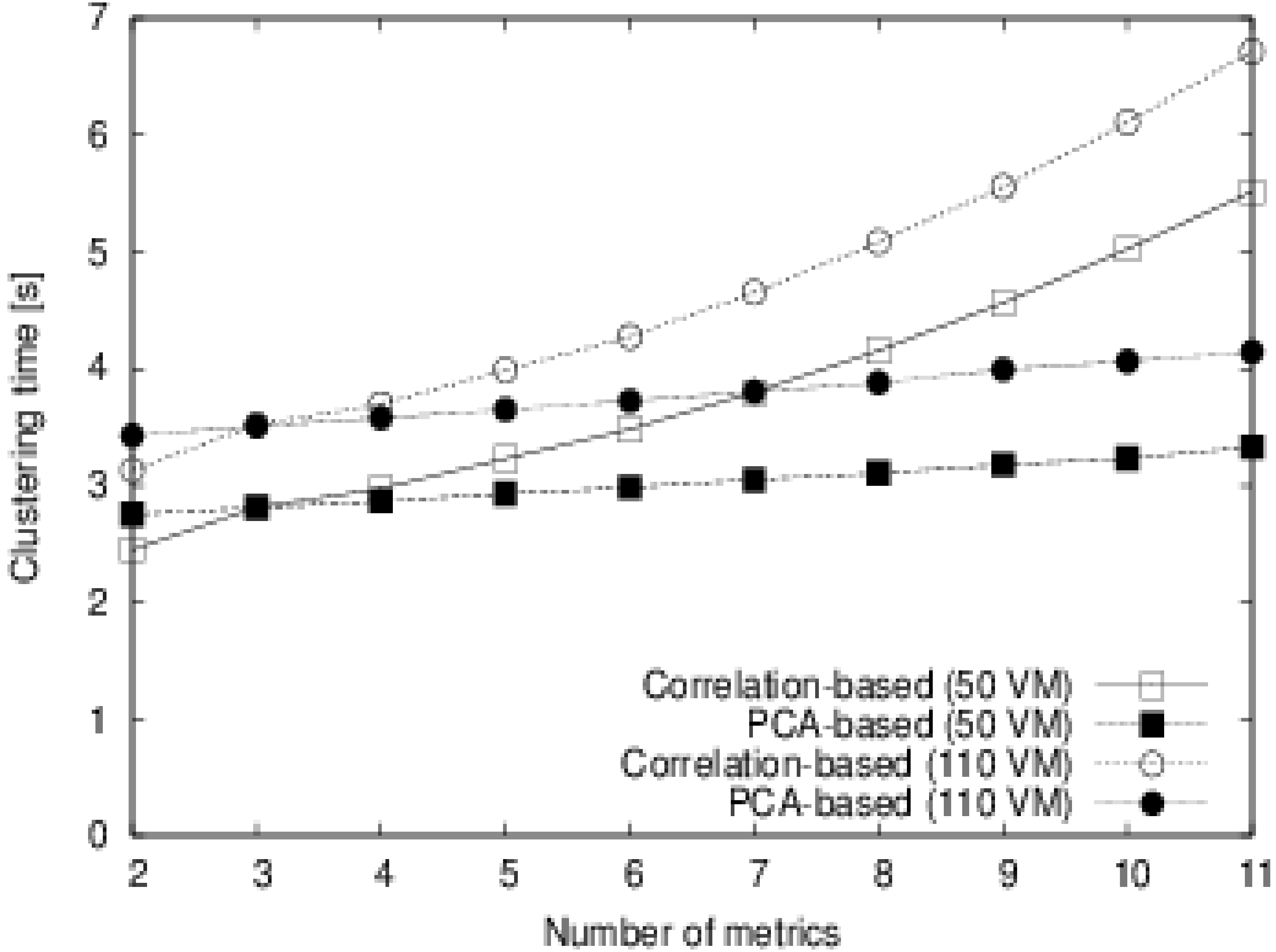
- **Use of Skree plot**
- **1 component captures ~60% of variance**
- **→ good enough for us**



Performance evaluation



Performance evaluation



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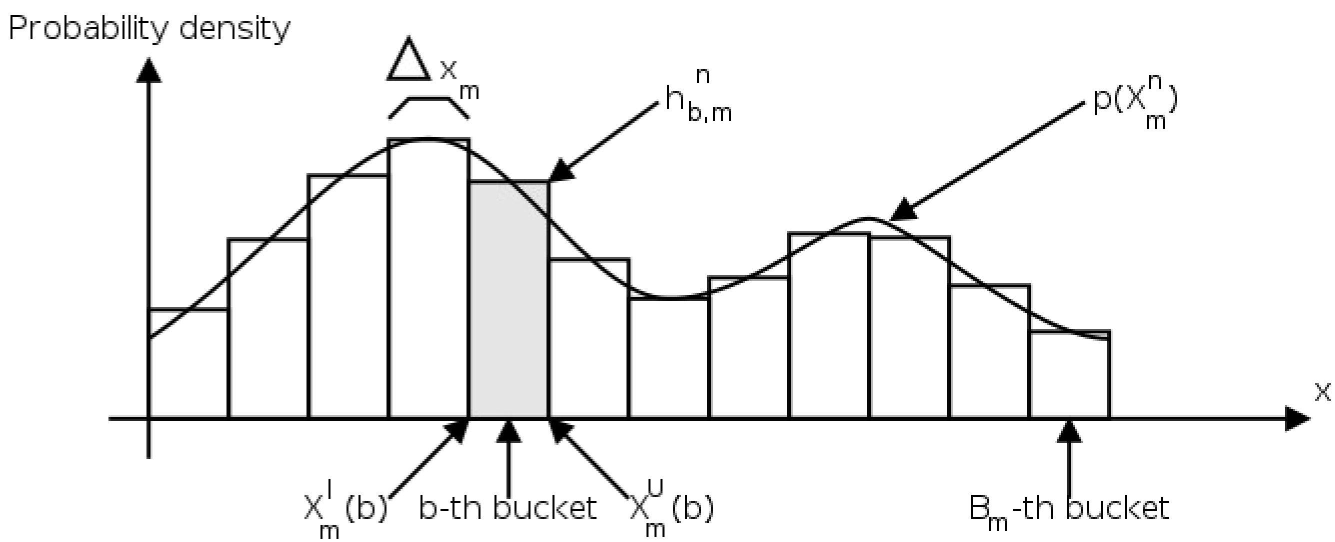
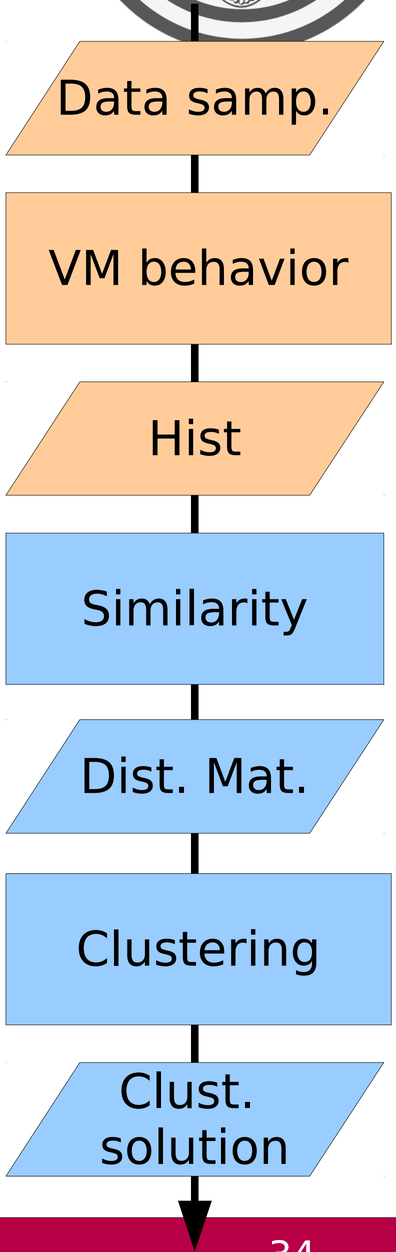
Modeling VM behavior

- **Model based on probability distribution of resource usage**
  - Multiple resources considered (metrics)
- **Histogram for every metric, every VM**
  - Normalized histogram (∑h=1)
  - B: number of buckets (critical)

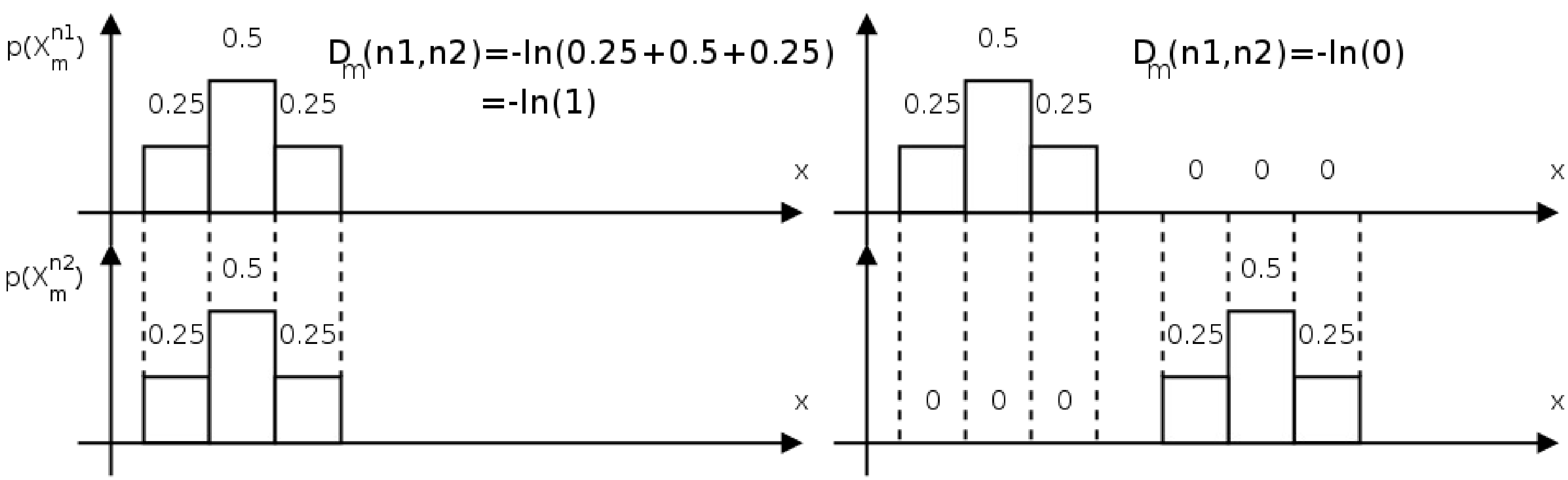


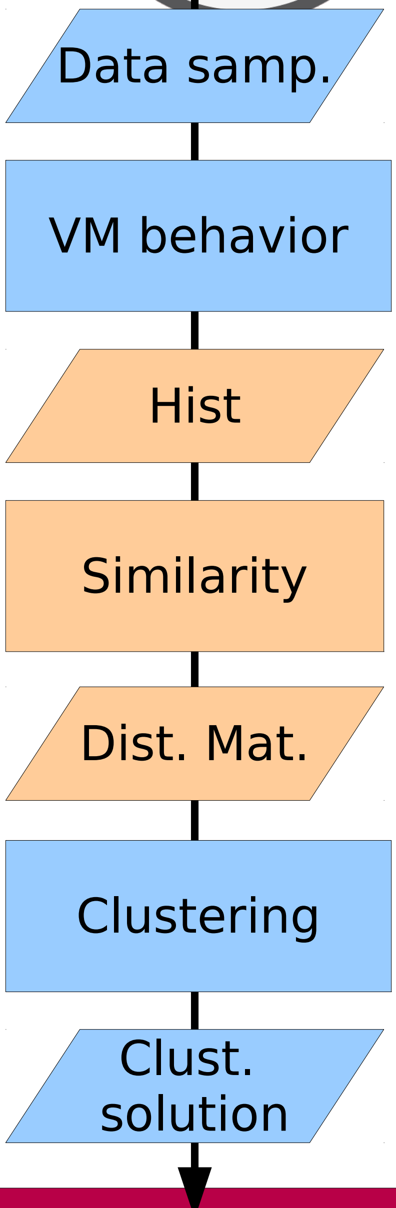


Defining VM similarity

- **Use of Bhattacharyya distance**
  - Determine distance matrix for each couple of VMs, each metric

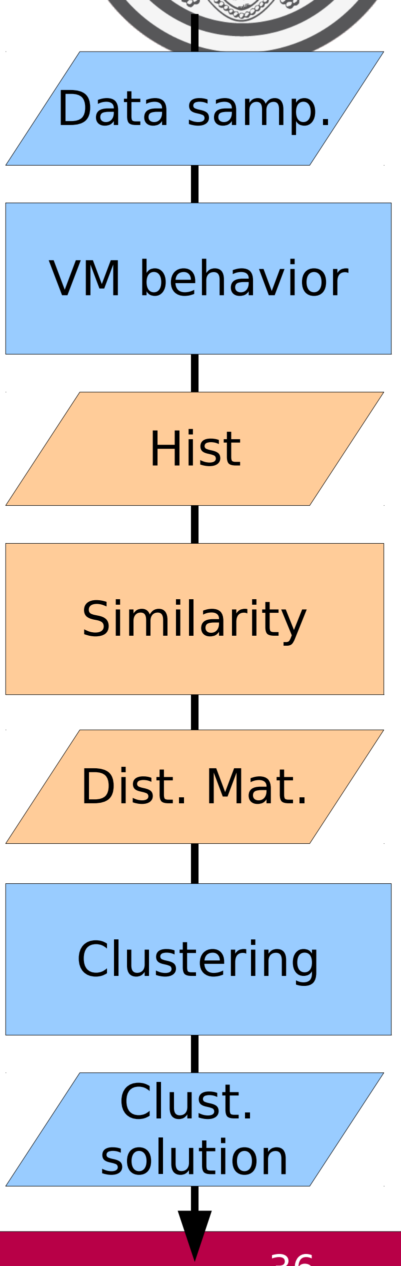
$$D_m(n1,n2) = -\ln\left(\sum_i \sqrt{h_{n1,i} \cdot h_{n2,i}}\right)$$





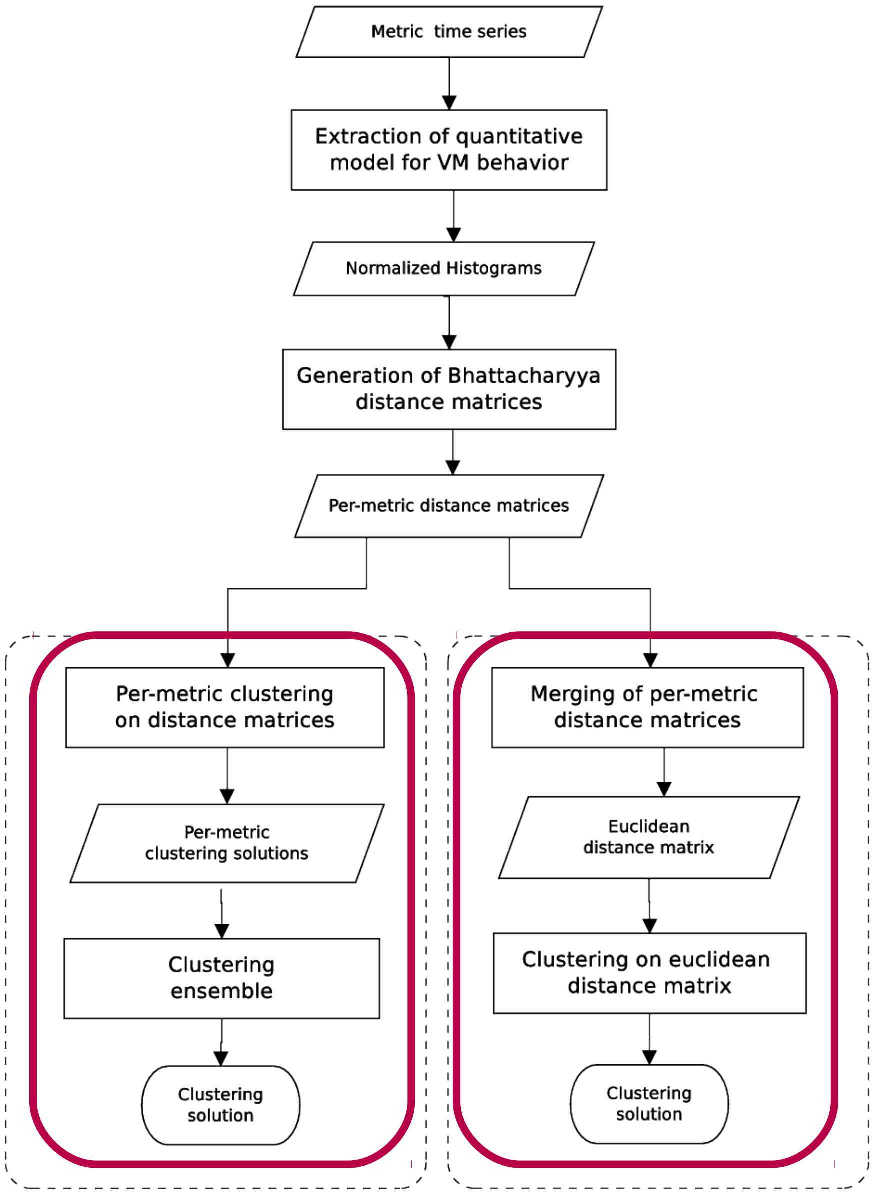
Merging multi-metric information

- **For each metric we have a different distance information**
- **How to merge the contribution of each metric?**
- **Two solutions:**
  - Euclidean distance merging
  - Solve separate clustering problems and merge clustering solutions (clustering ensemble)



Merging multi-metric information

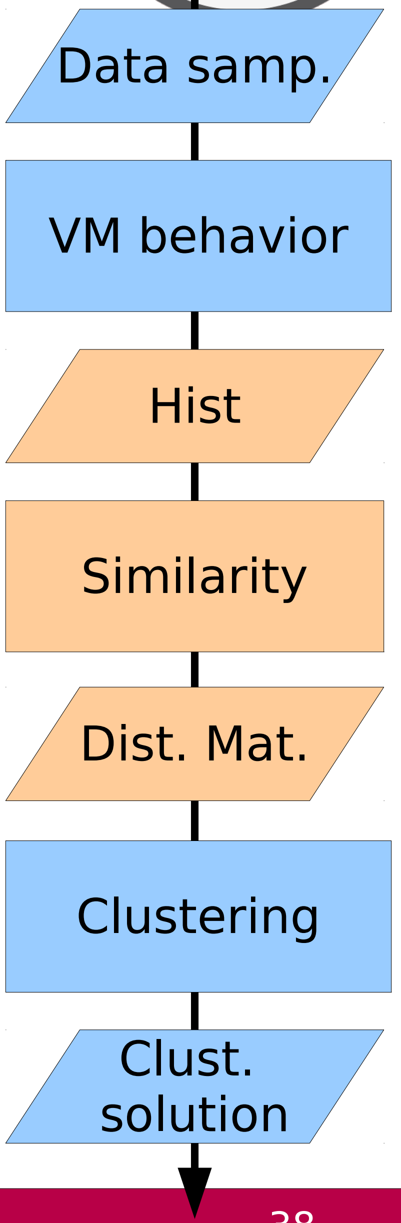
Clustering ensemble



Euclidean Distance merging

Euclidean distance merging

- **For each VMs n1, n2**
- $$D(n_1, n_2) = \sqrt{\sum D_m(n_1, n_2)^2 \cdot a_m}$$
- **Open problems:**
  - Is it correct to consider every metric together?
  - Is there a way to select the *right* metrics?

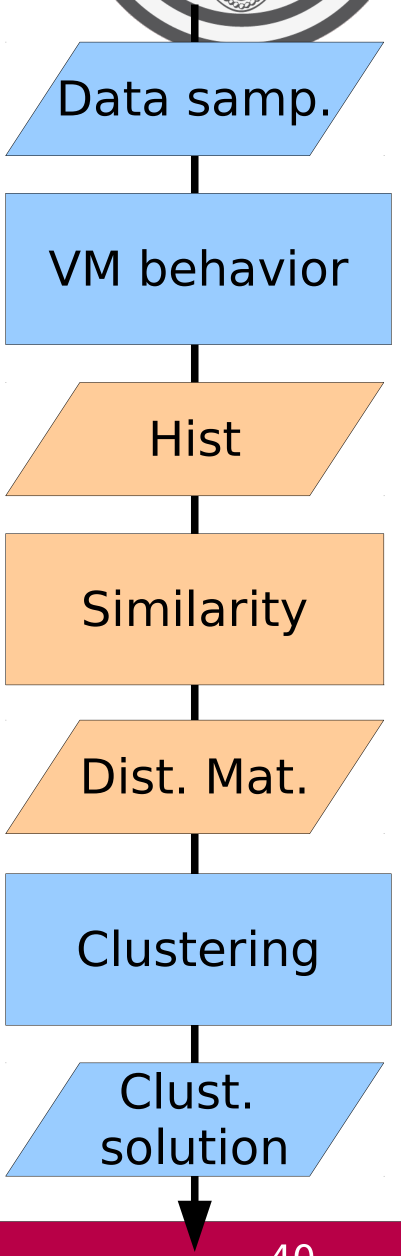


Choosing the right metrics

- **With** **euclidean merging** **multiple metrics determine the final distance matrix**
- **Not every metric provide significant information**
- **Proposal to identify relevant metrics**
  - Consider auto-correlation: ACF decreasing rapidly → random variations
  - Consider Coefficient of Variation:
    CF » 1 → spiky and noisy behavior
    CF « 1 → little information provided
- **→ Merge information from metrics with**
  - ACF decreasing slowly
  - CF ~ 1

Clustering ensemble

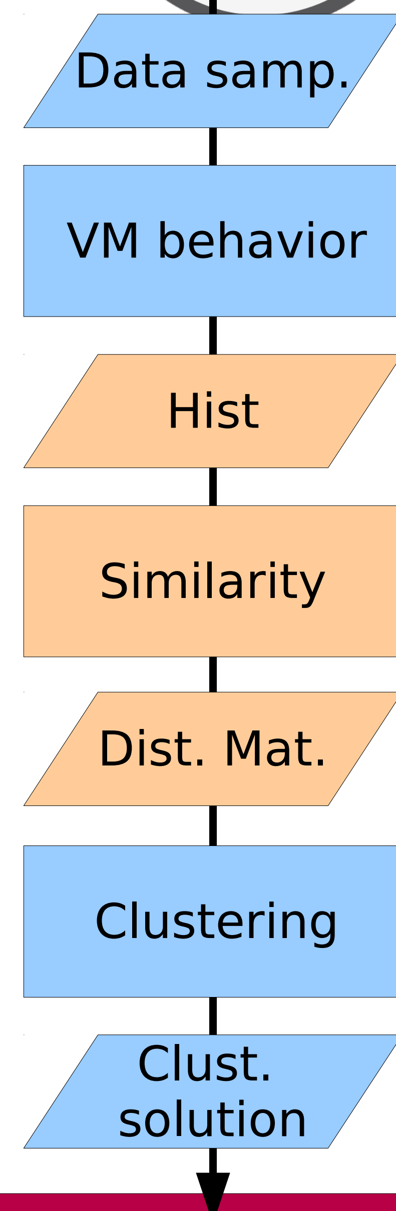
- **Two-step process**
- **For every metric m**
  - Compute Bhattacharyya distance matrix
  - Compute clustering solution
- **Compute co-occurence matrix A**
  - For each couple of VMs compute number of times they are in the same cluster
- **Clustering using matrix A as affinity**
- **OK to consider every metric?**
  - Quorum-based approach ensures good robustness of results



Clustering ensemble: example

Clustering solutions	Metric 1	Metric 2	Metric 3
VM1	CL1	CL2	CL2
VM2	CL1	CL2	CL1
VM3	CL2	CL1	CL1
VM4	CL2	CL1	CL1

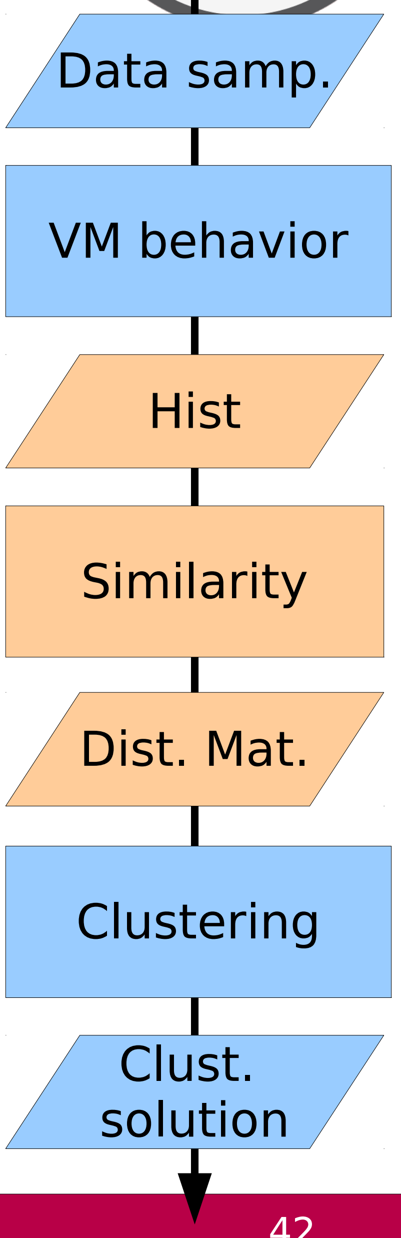
A	VM1	VM2	VM3	VM4
VM1	3	2	0	0
VM2	2	3	1	1
VM3	0	1	3	3
VM4	0	1	3	3



Clustering ensemble: example

Clustering solutions	Metric 1	Metric 2	Metric 3
VM1	CL1	CL2	CL2
VM2	CL1	CL2	CL1
VM3	CL2	CL1	CL1
VM4	CL2	CL1	CL1

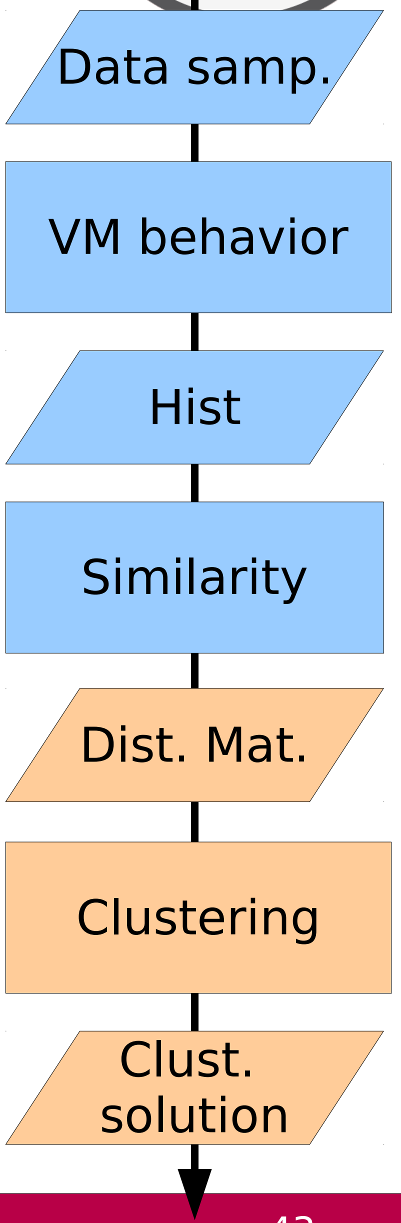
A	VM1	VM2	VM3	VM4
VM1	3	2	0	0
VM2	2	3	1	1
VM3	0	1	3	3
VM4	0	1	3	3



Clustering algorithm

- **Use of spectral clustering algorithm**
  - Input: Square, symmetric distance/affinity matrix
  - Output: Cluster ID for every VM

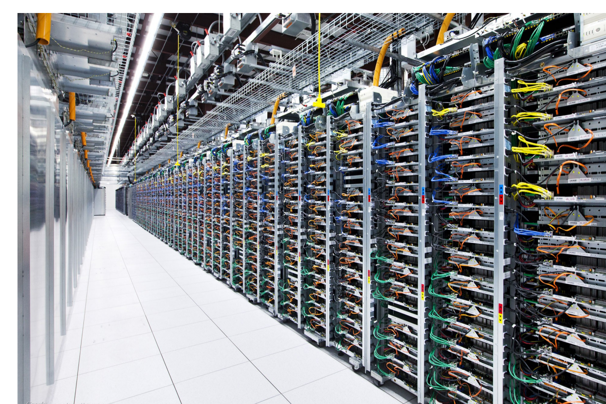
- **Additional feature:**
  - Number of clusters can be automatically determined through spectral gap analysis



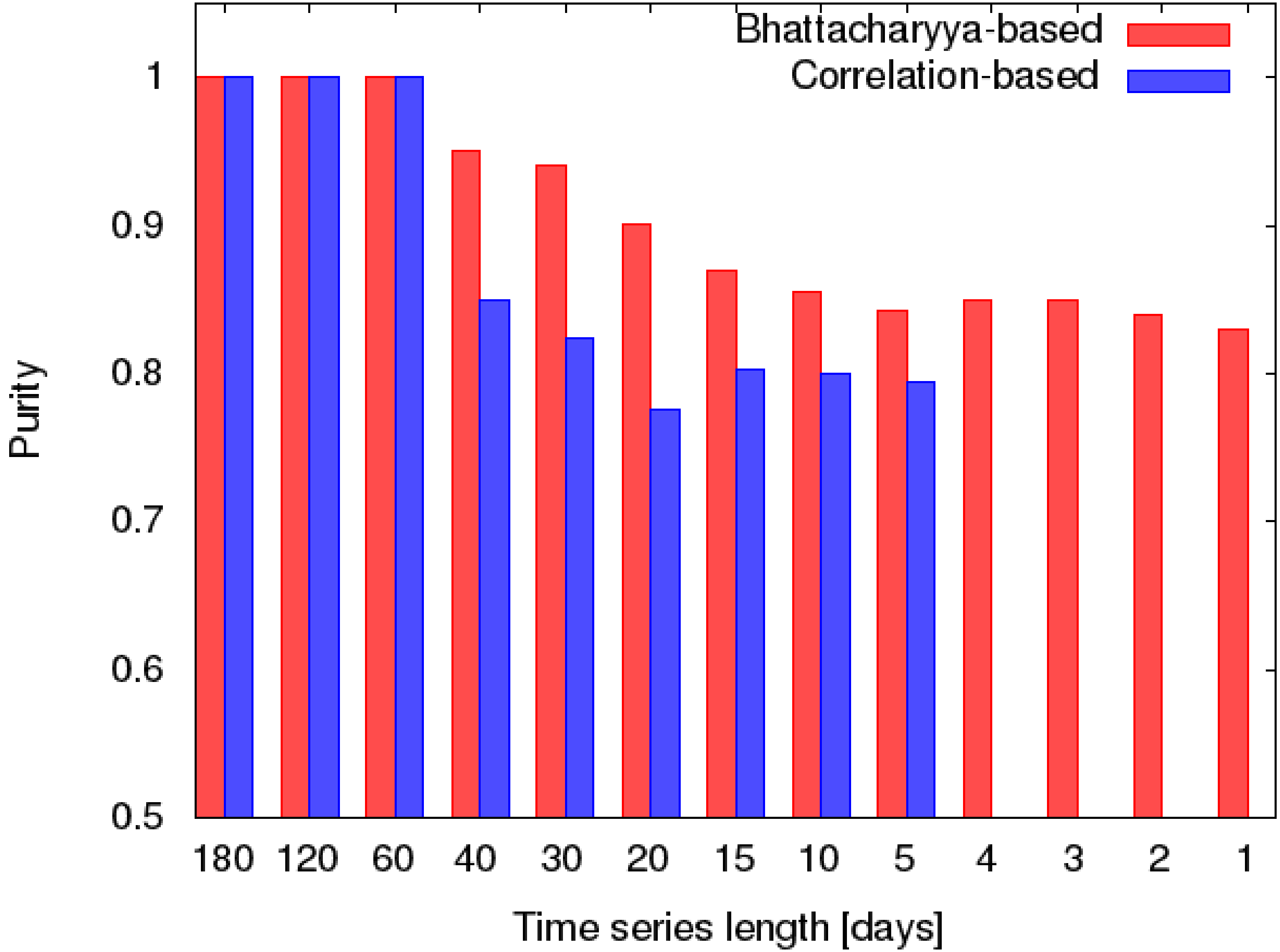
Case study

- **IaaS cloud supporting e-health**
  - Web server and DBMS
  - 110 VMs
  - 10 metrics for each VM,
  - Sampling frequency: 5 min
  - Euclidean merging of metrics

- **Goal: separate Web servers and DBMS**
  - Main metric: Purity of clustering
- **Three types of analyses**
  - Impact of time series length
  - Impact of metric selection
  - Impact of histogram charact.

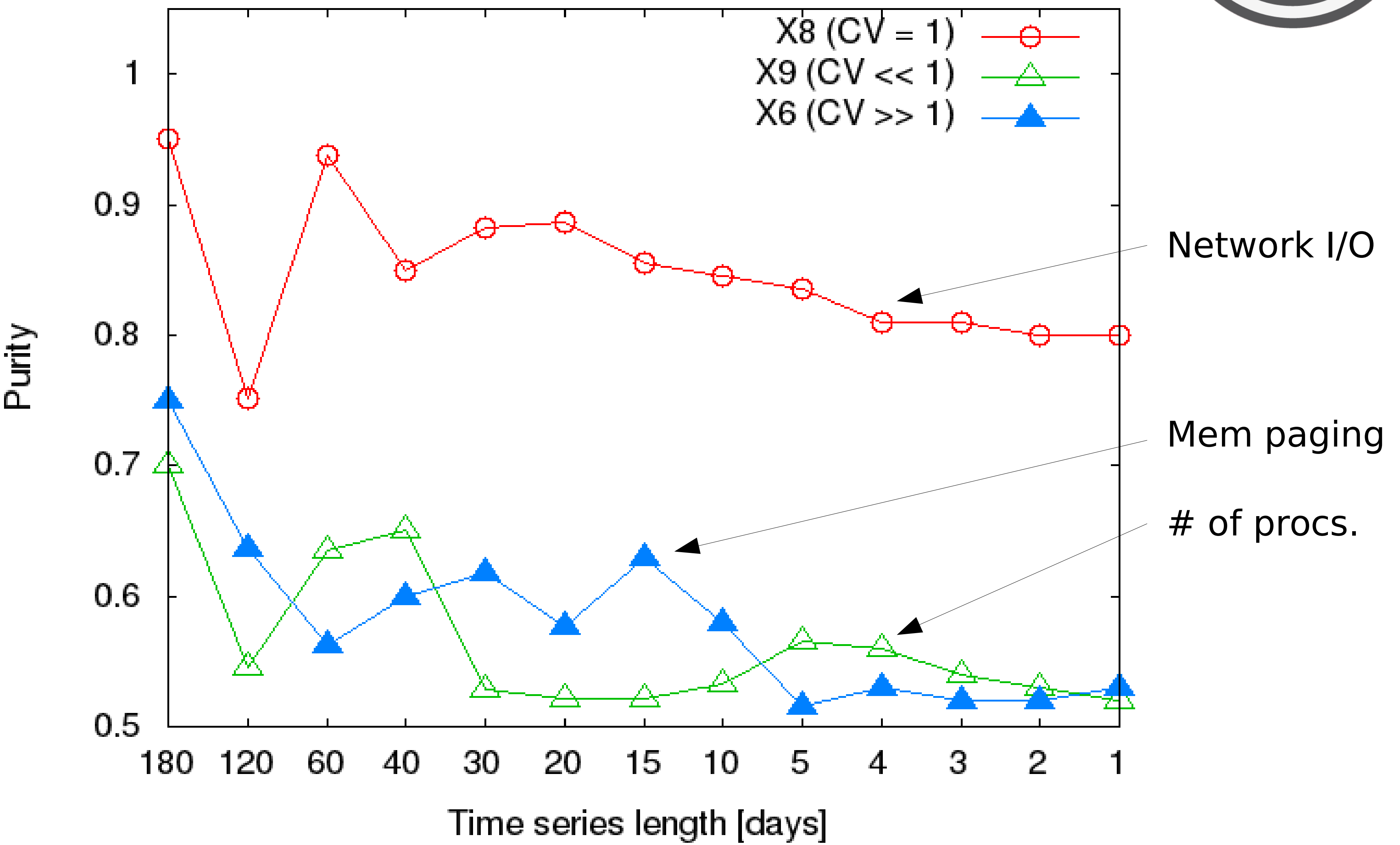


Impact of time series length

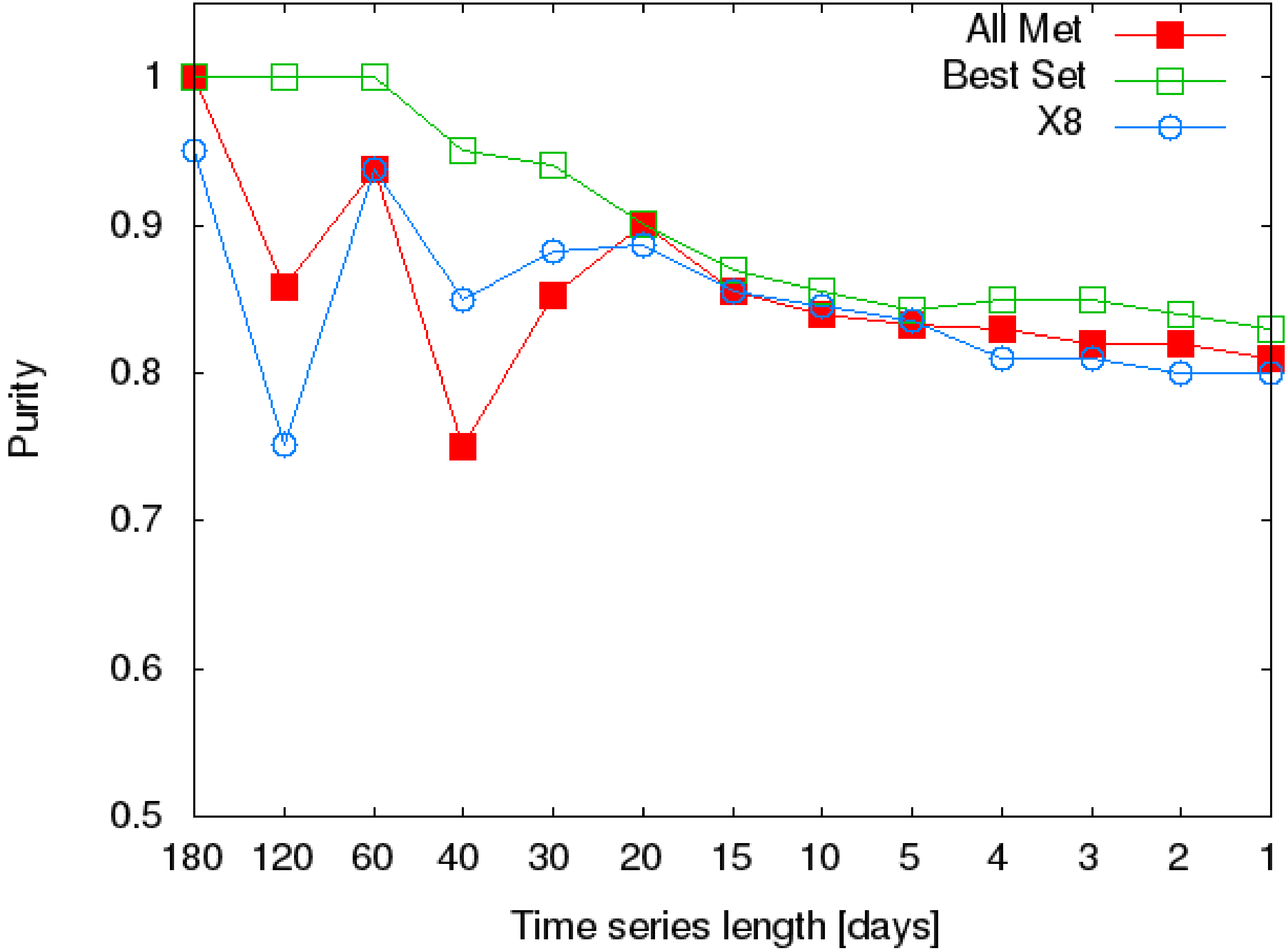


NOTE:
We consider Euclidean distance merging

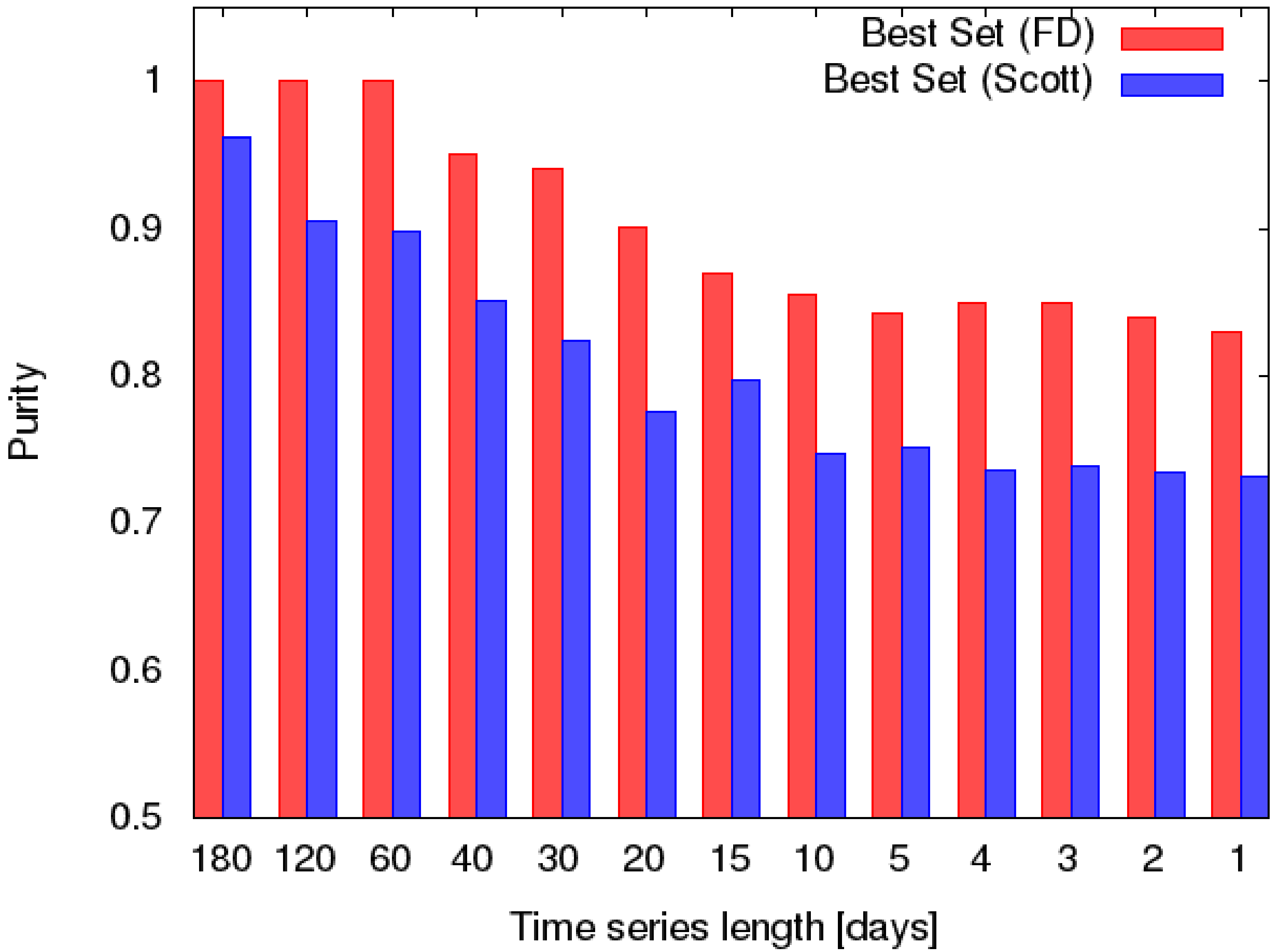
Impact of metric selection



Impact of metric selection

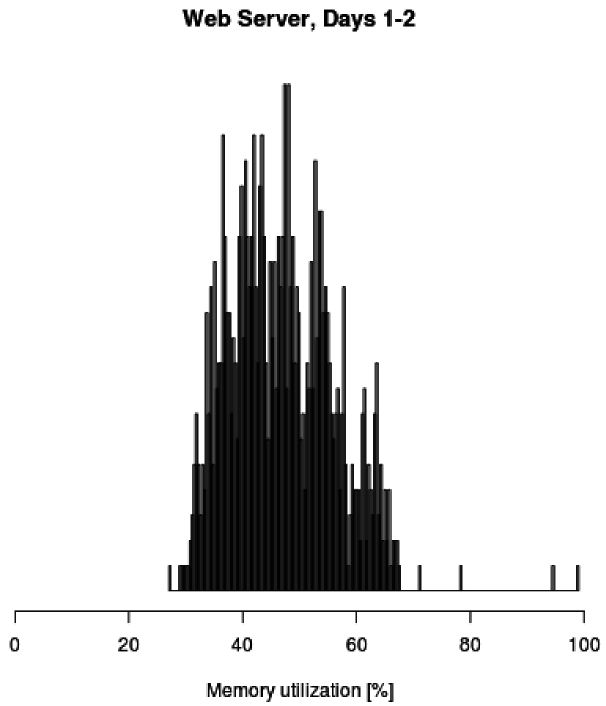


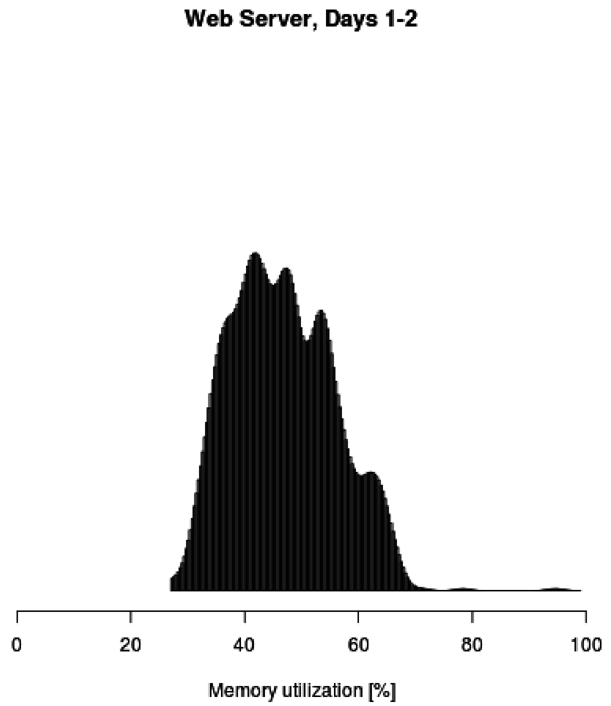
Impact of histogram characteristics



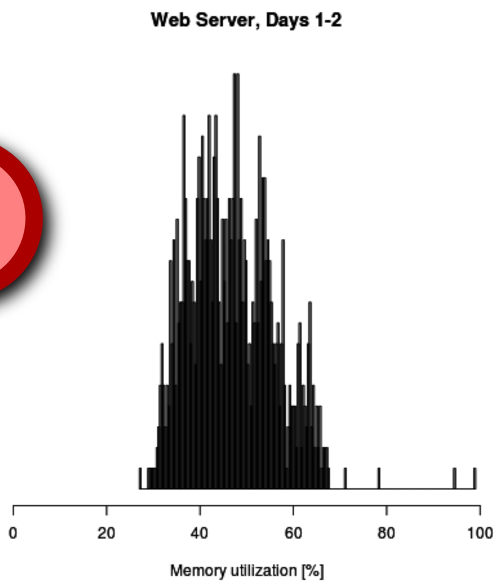
Histogram smoothing

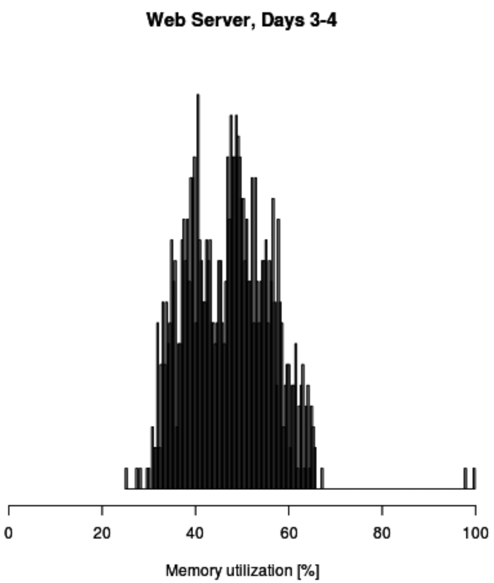
- **Bhattacharyya distance affected by quantization errors in histograms → sensitivity to histogram characteristics**
- **Proposal: gaussian smoothing of histograms before computing Bhattacharyya distance**



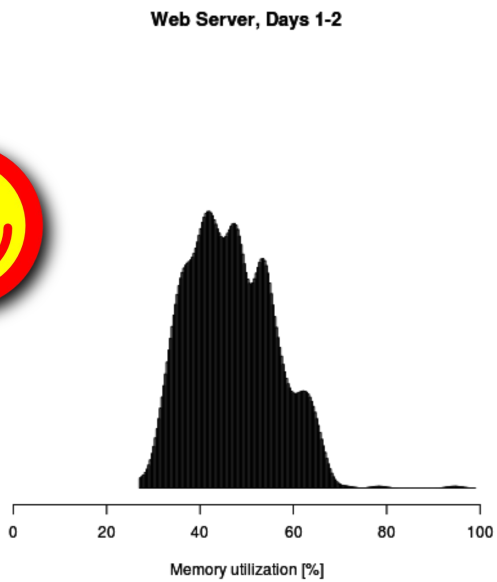


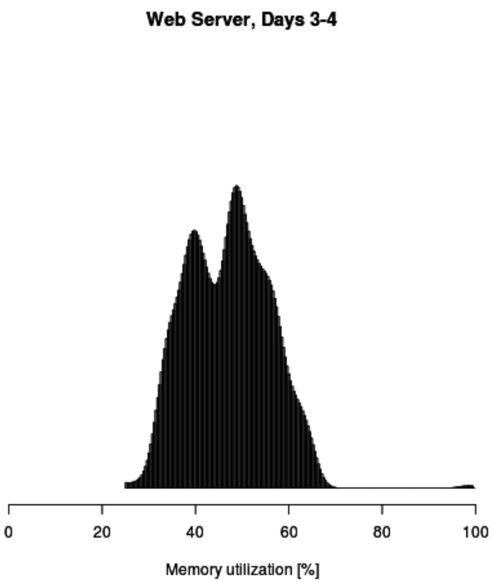
Histogram smoothing





No smoothing:
Bhattacharyya distance
0.496

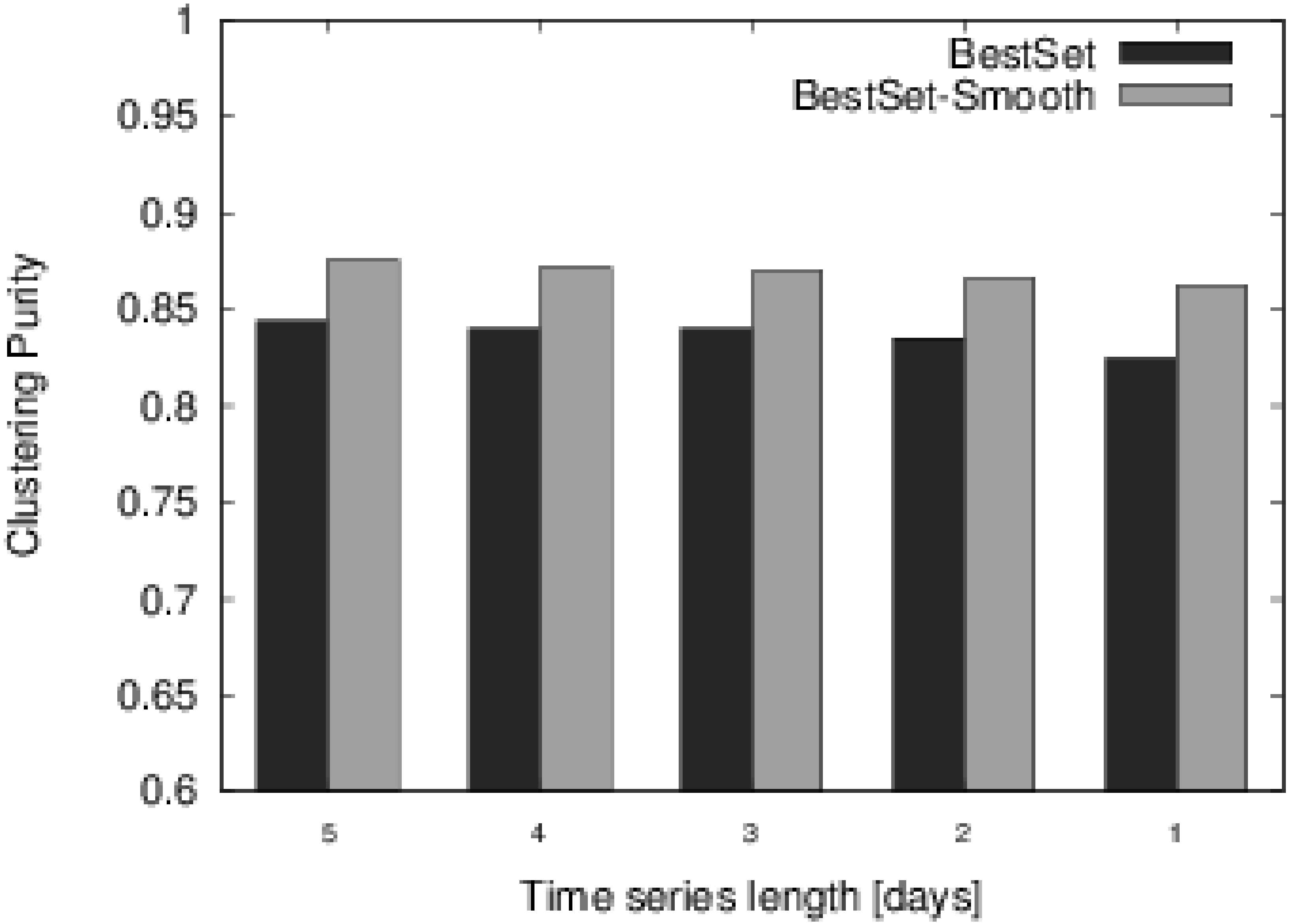




Smoothing:
Bhattacharyya distance
0.297

Reduction by 40%

Effect of histogram smoothing

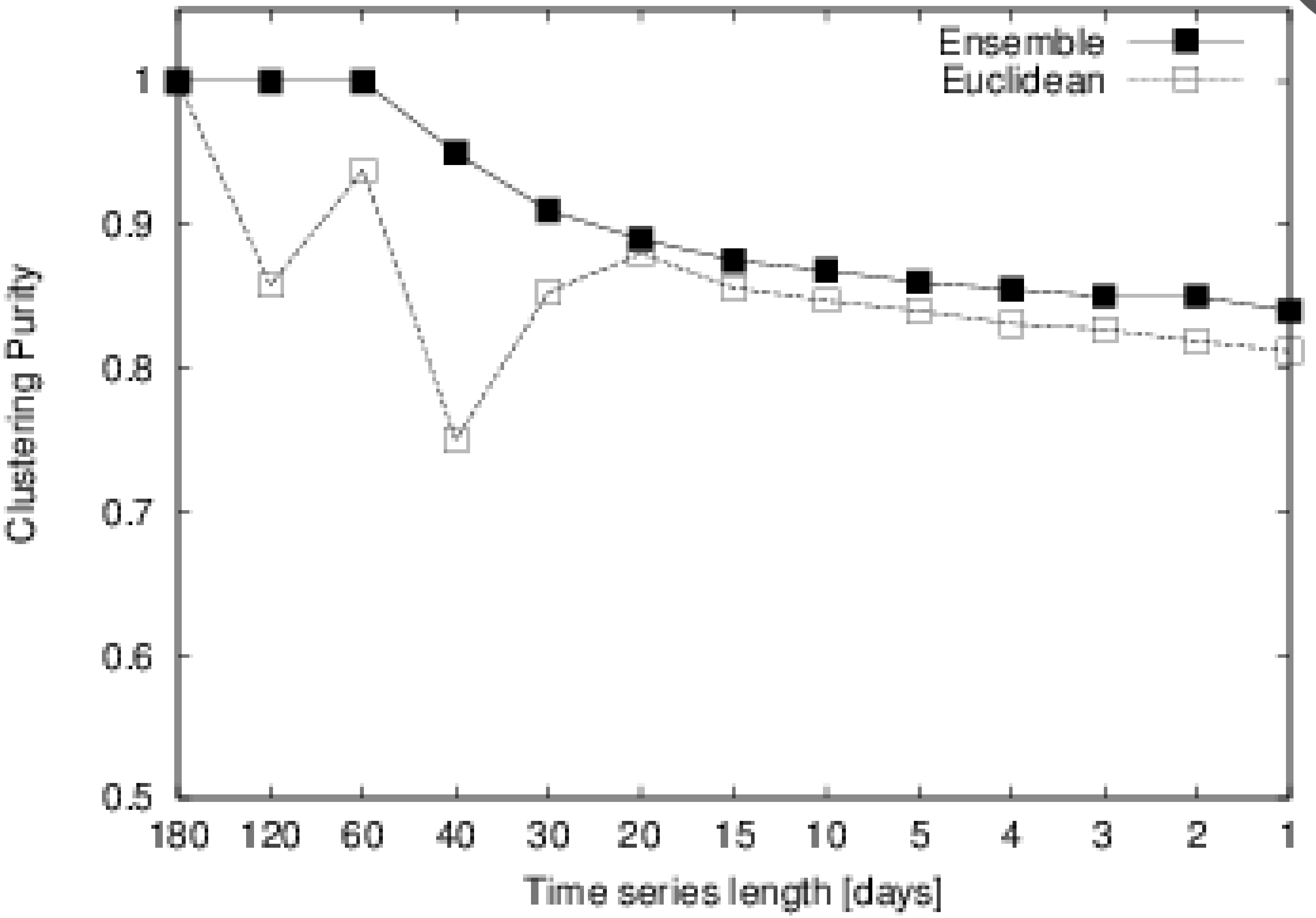


Clustering Ensemble

- **Overall goal:**
  - Reduce sensitivity to histogram characteristics (number of histogram bkts)
  - No need to select significant metrics
  - No smoothing required

- **Potential drawback**
  - Higher computational cost

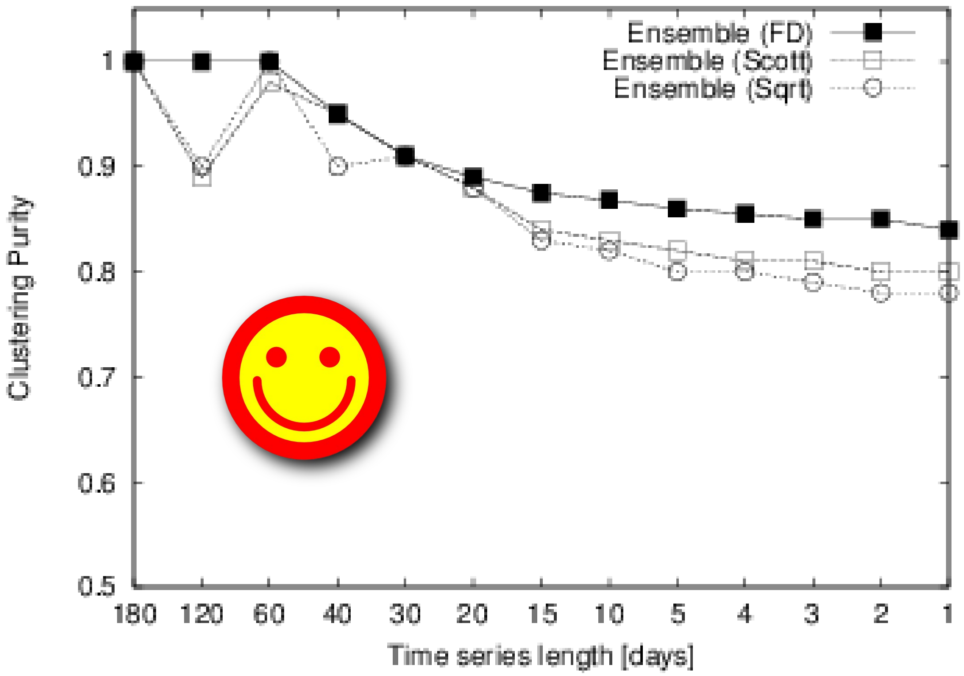
Clustering Ensemble



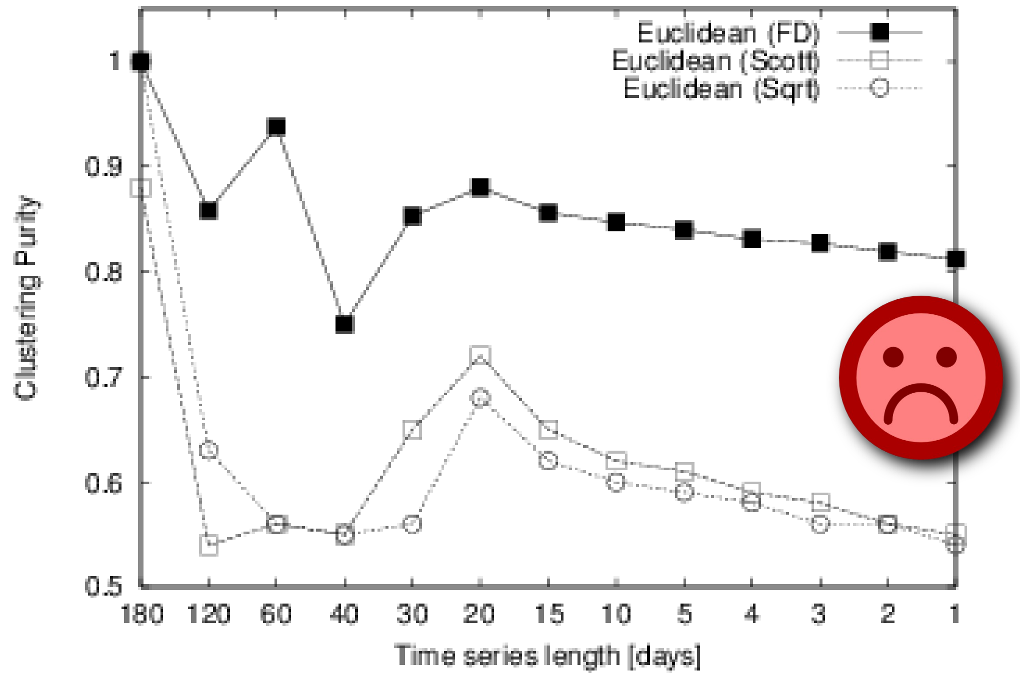
Clustering Ensemble

- **Major stability improvement**
- **Almost insensitive to histogram number of buckets**

Clustering ensemble

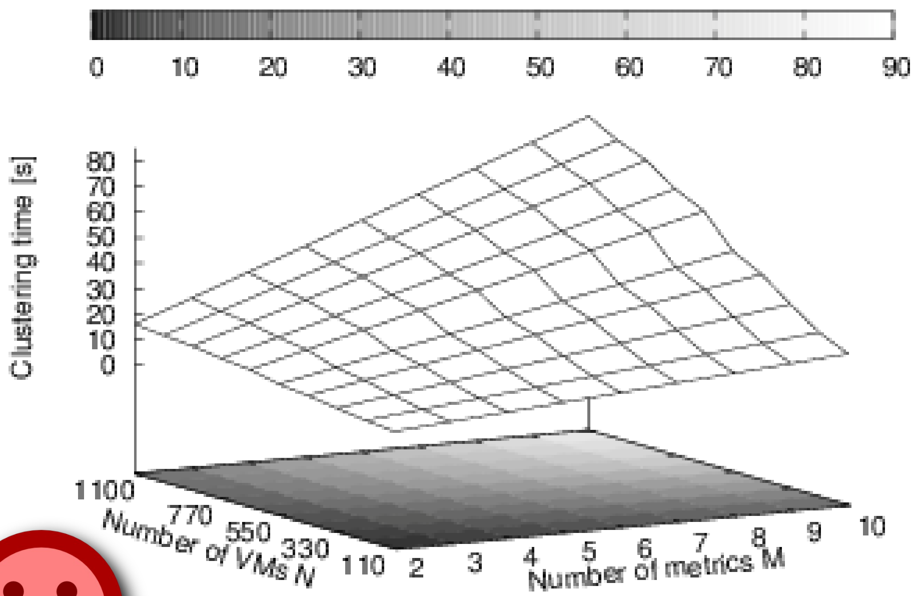


Euclidean merging

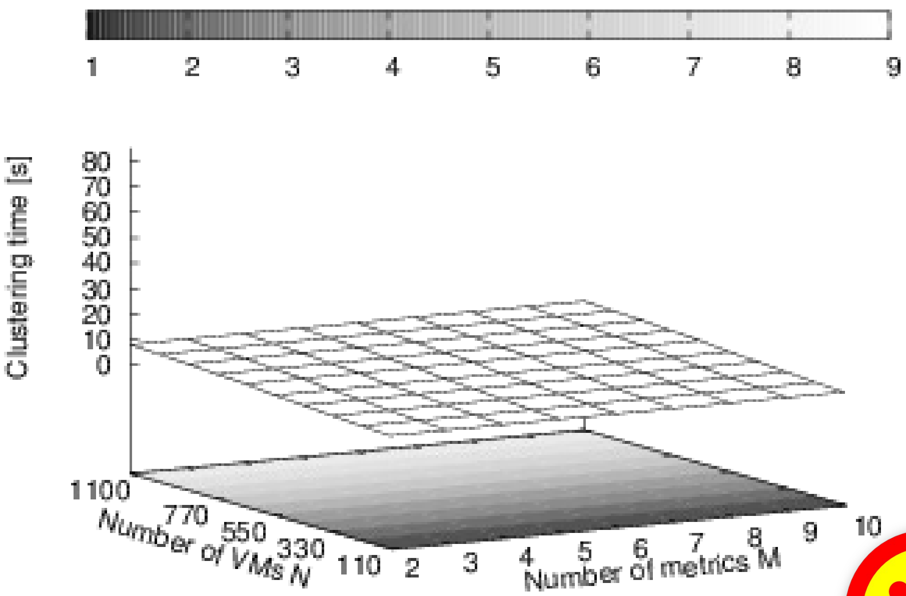


Clustering Ensemble

- **Significant performance penalty:**
- **1 clustering for each metric**
- **Typically uses more metric than euclidean merging**



Clustering ensemble



Euclidean merging

Agenda

- **Background and motivation**
  - IaaS Cloud
  - Reference scenario
  - Traditional approach vs. clustering
  - Impact on monitoring and management
- **Clustering based on metric correlation**
  - Theoretical model(s)
  - Experimental evaluation
- **Clustering based on Bhattacharyya distance**
  - Theoretical model(s)
  - Experimental evaluation
- **Conclusion and future work**

Conclusion and future work

- **Scalability in IaaS cloud systems**
  → open issue
- **Proposal an analysis of mutiple methodologies to improve scalability through clustering of similar VMs**
    - **Representing VM behavior using correlation**
    - Reduction of correlation data with PCA
    - **Representing VM behavior with histograms**
    - Euclidean merging of distances
    - Metric selection
    - Histogram smoothing
    - Clustering ensemble

Conclusion and future work

- **Experimental results are encouraging**
  - Can achieve high clustering purity
  - Can provide accurate clustering even with very short time series
  - Can provide stable results
  - Time for clustering is acceptable

- **This is not a crystal ball**
  - But may be a useful tool to improve monitoring and management of cloud data centers

Conclusion and future work

- **Future research directions:**

- **Evaluate different models for VM behavior**

- **Application of clustering to improve scalability of data center management**

References

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- Claudia Canali, Riccardo Lancellotti, **"Exploiting Ensemble Techniques for Automatic Clustering of Virtual Machine Clustering in Cloud Systems"**, to appear on Automated Software Engineering
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Automatic clustering of similar VM to improve the scalability of monitoring and management in IaaS cloud infrastructures

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