Evaluating Software Clustering

What is a good software decomposition?

The problem

- How do we know that a particular decomposition of a software system is good?
- What does “good” mean anyway?
- We can compare against a
  - Mental model
  - Benchmark standard
- Can be done either manually or automatically

Manual evaluation

- Have experts evaluate automatic decompositions
- Very time-consuming, impractical
- Also quite subjective
- Need an automatic, objective way of doing it

Automatic evaluation

- Usually measures the similarity of an automatic decomposition A to an authoritative decomposition B (prepared manually)
- Major drawback: Assumes there exists one “correct” decomposition
- Other evaluation approaches are possible, such as measuring the stability or the extremity distribution of a clustering algorithm

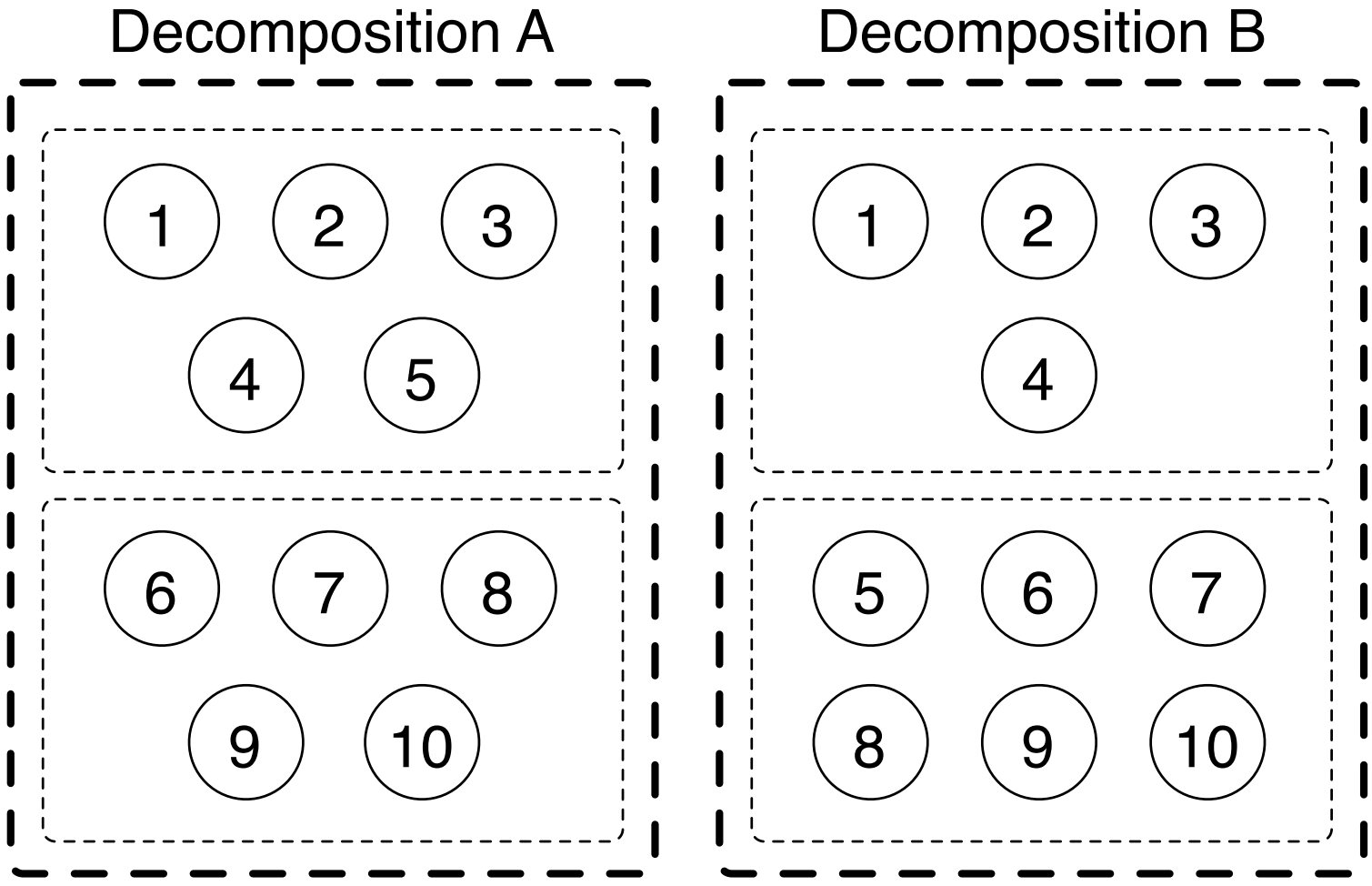
Precision/Recall

- Standard Information Retrieval measures
- Were applied in a software clustering context by Anquetil
- Definitions:
  - Intra pair: A pair of software entities in the same cluster
  - Inter pair: A pair of entities in different clusters

Precision/Recall

- Precision: Percentage of intra pairs in A which are also intra in B
- Recall: Percentage of intra pairs in B also found in A
- A good algorithm should exhibit high values in both measures

Precision / Recall example



Pair 1-5: Intra pair in A but not in B

Precision: 16/20 = 80% Recall: 16/21 = 76.2%

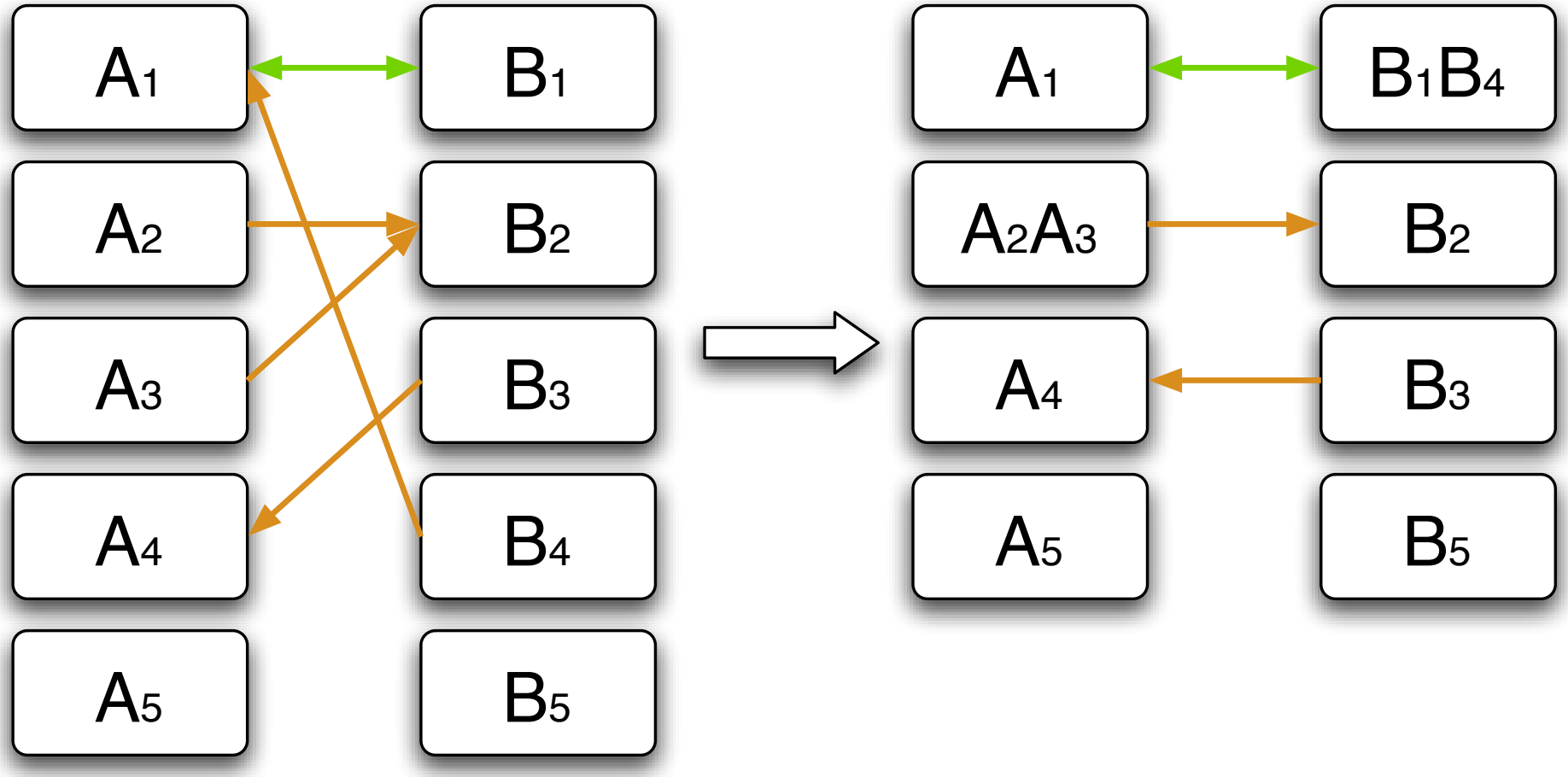
Problems with Precision / Recall

- Sensitive to the size and number of clusters
  - Differences are exaggerated if you have small/many clusters
- Two values makes comparison harder
- The two values are interchangeable if there is no authoritative decomposition

Koschke - Eisenbarth measure (KE)

- Loosely based on Precision/Recall
- Attempts to be less strict
- Definitions:
  - GOOD match: Two clusters (one in A, one in B) with both precision and recall larger than a threshold p (typical value 70%)
  - OK match: Two clusters with only one of the measures larger than p

Koschke - Eisenbarth metric



$$\frac{\sum_{(a,b)\in \mathrm{GOOD}} \mathrm{overlap}(a,b) + \sum_{(a,b)\in \mathrm{OK}} \mathrm{overlap}(a,b)}{|\mathrm{GOOD}| + |\mathrm{OK}| + |\mathrm{true\ negatives}|}$$

Koschke - Eisenbarth metric

- Does not take edges into account
- In extreme situations (each cluster contains only one element) may provide strange results (similarity of 100%)
- No penalty for joining clusters

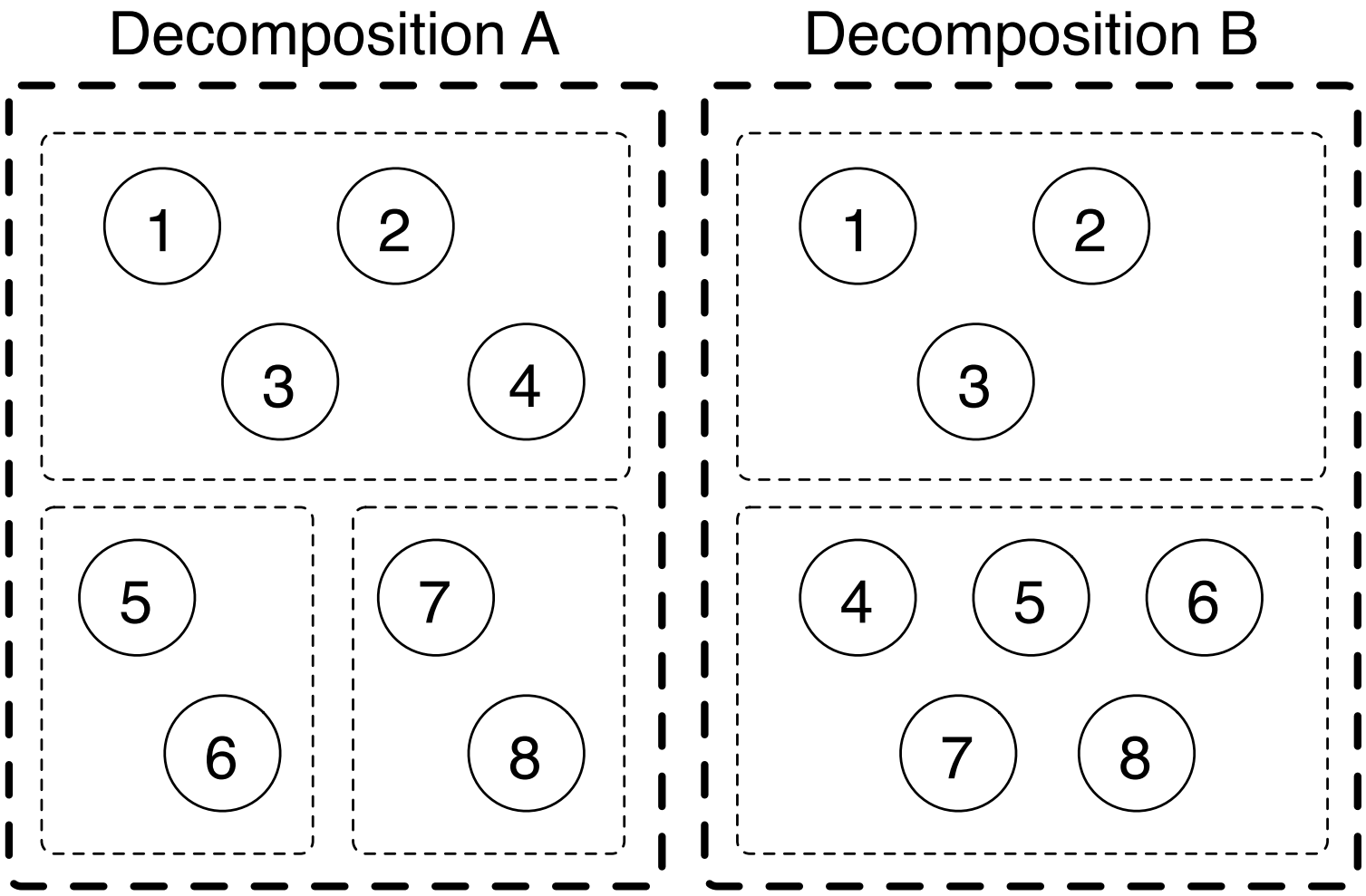
Assignment tool: ke

- Takes two .kos files containing different decompositions of the same set of entities
- Example:
  `ke -cand dec1.kos -ref dec2.kos`
- Produces lots of output. We're interested in the recall rate
- Transform an RSF file with contain facts to the KE format with
  `unitrans input.rsf output.kos`

MoJo distance

- The distance between two different partitions of the same software system is defined as the minimum number of Move and Join operations to transform one to the other
  - Move: Remove an object from a cluster and put it in a different cluster
  - Join: Merge two clusters into one
  - Split: Has to be simulated by Move operations

MoJo example



MoJo(A,B) = 2

MoJo(B,A) = 3

Why only Move and Join?

- Two clusters can be joined in only one way. One cluster can be split in two in an exponential number of ways
- Joining two clusters only means that we performed more detailed clustering than required
- Splitting is effectively assigned a weight equal to the cardinality of the smaller of the two resulting clusters

Computing MoJo distance

- MoJo distance can be computed in polynomial time
- Worst case complexity is $O(n^3)$ but with real data it is no worse than $O(n \log n)$

Assignment tool: mojo

- Takes two .rsf files containing different decompositions of the same set of entities
- Example: `mojo dec1.rsf dec2.rsf`
- Output: `383`
- If the two decompositions do not refer to the same set of entities, only the intersection of the two sets is considered.

MoJoFM Effectiveness Metric

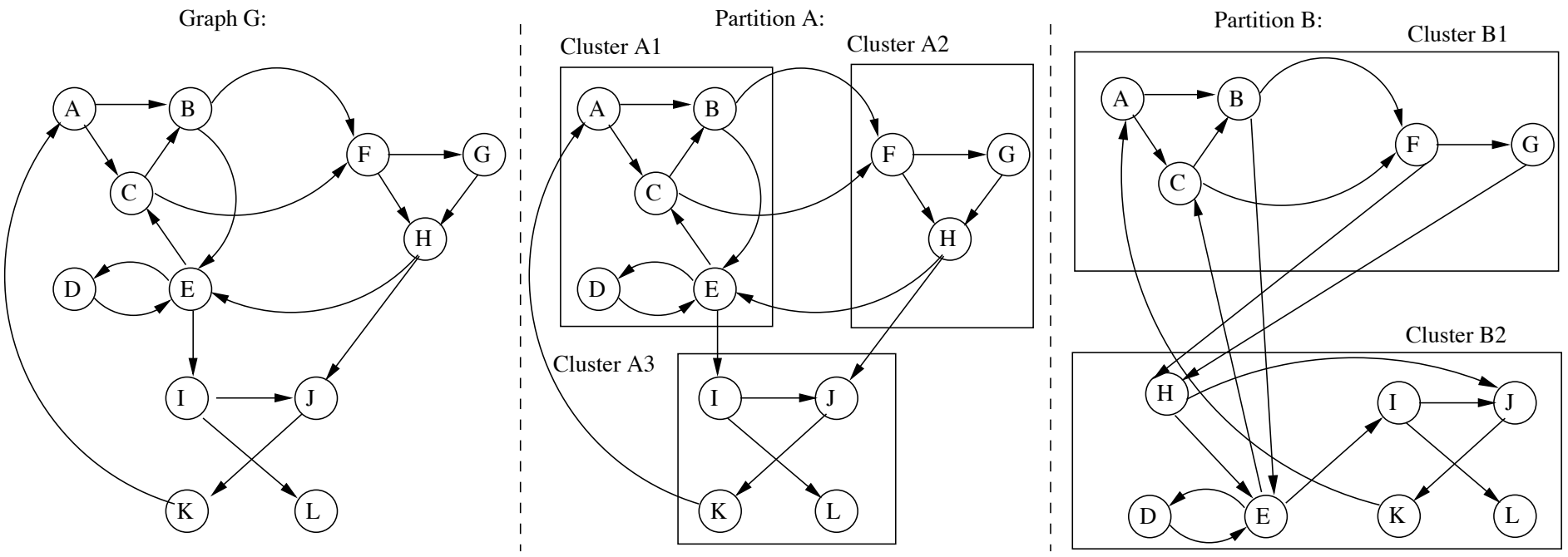
$$MoJoFM(A) = (1 - \frac{MoJo(A, B)}{max_{\forall c}(MoJo(C, B))}) \times 100\%$$

- The denominator is the maximum possible MoJo distance to decomposition B
  - Can be computed by construction

EdgeSim

- Other measures do not consider edges
- Edges might convey important information
- EdgeSim penalizes clustering algorithms for changing the edge types

EdgeSim

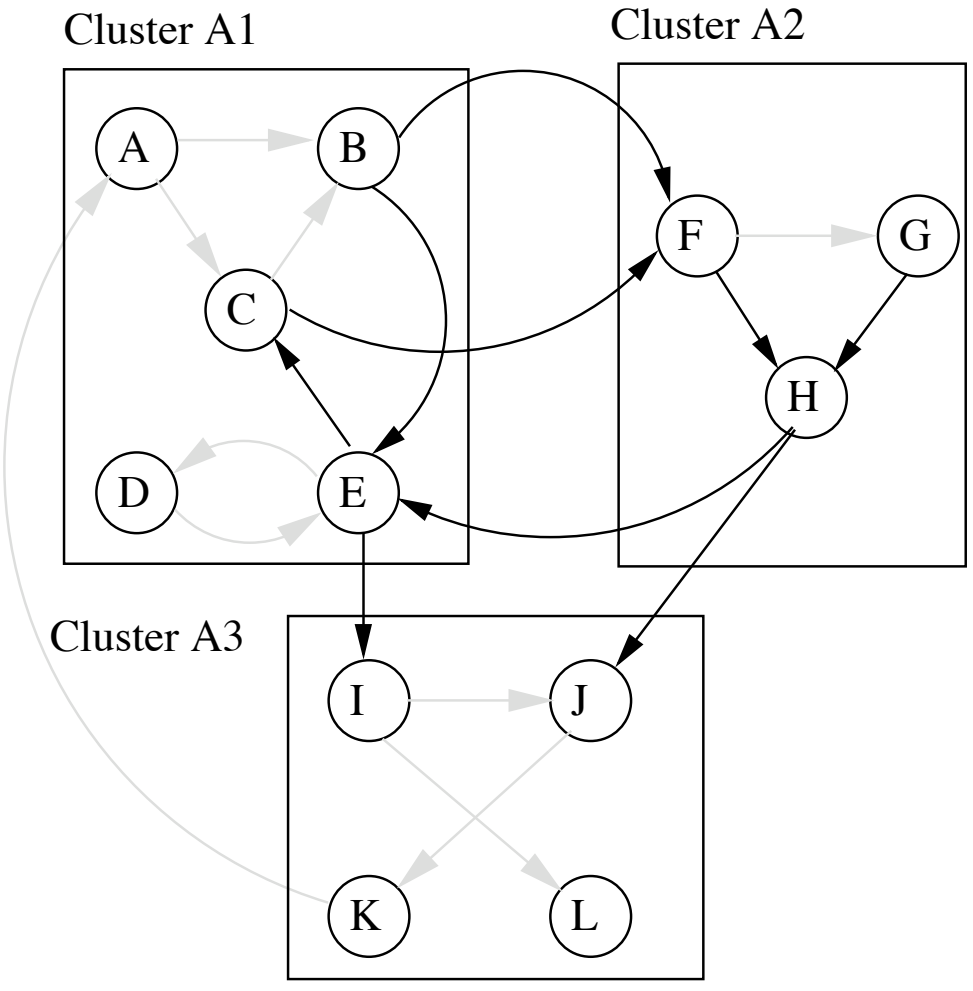


Inter-edge: Edge between clusters

Intra-edge: Edge within a cluster

Y: set of edges that are of the same type in both A and B

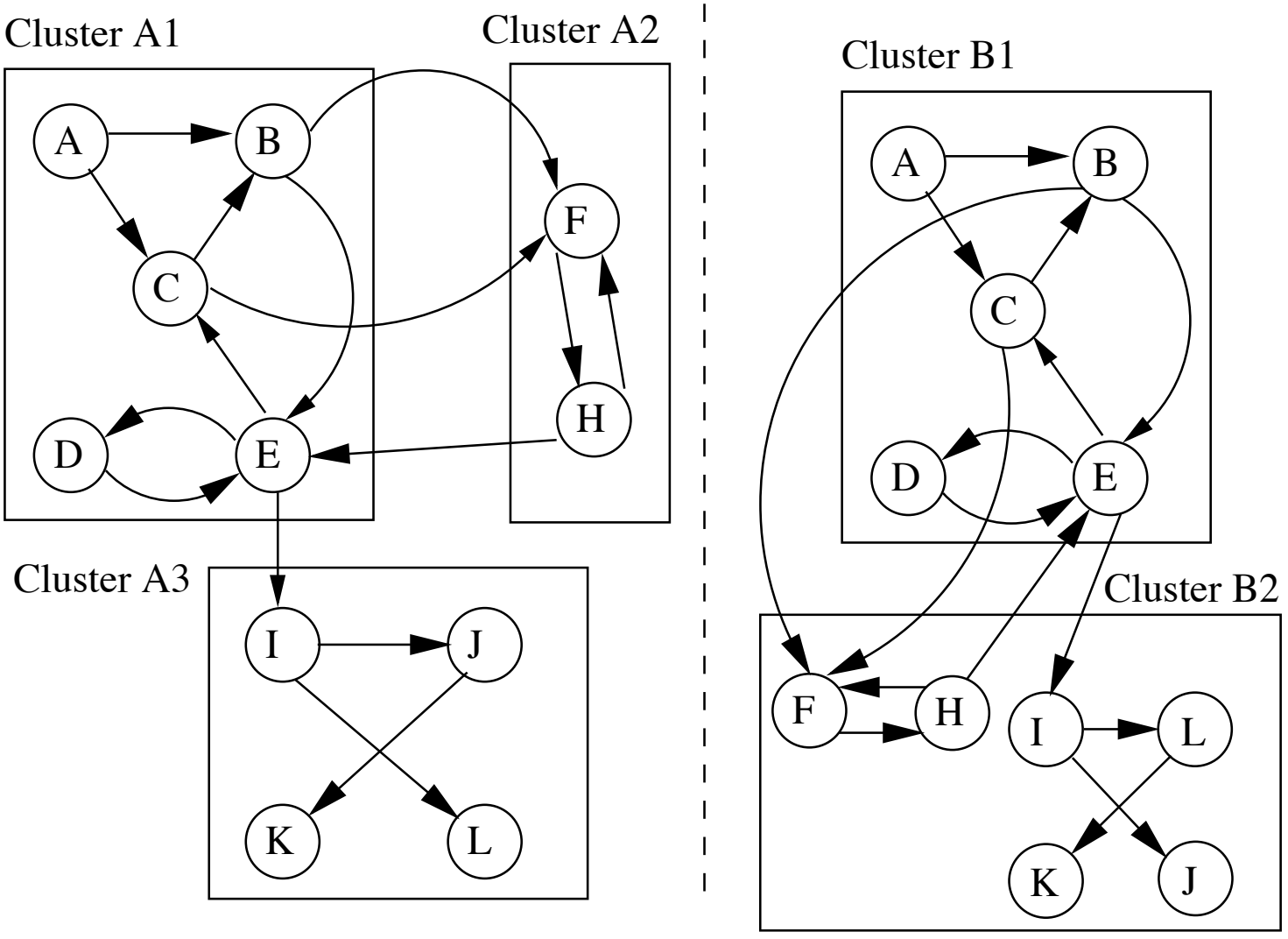
EdgeSim example



$$\text{EdgeSim}(A,B) = \frac{weight(Y)}{weight(E)} \times 100\%$$

In this example, EdgeSim(A,B) = 52.6%

EdgeSim counterexample



EdgeMoJo philosophy

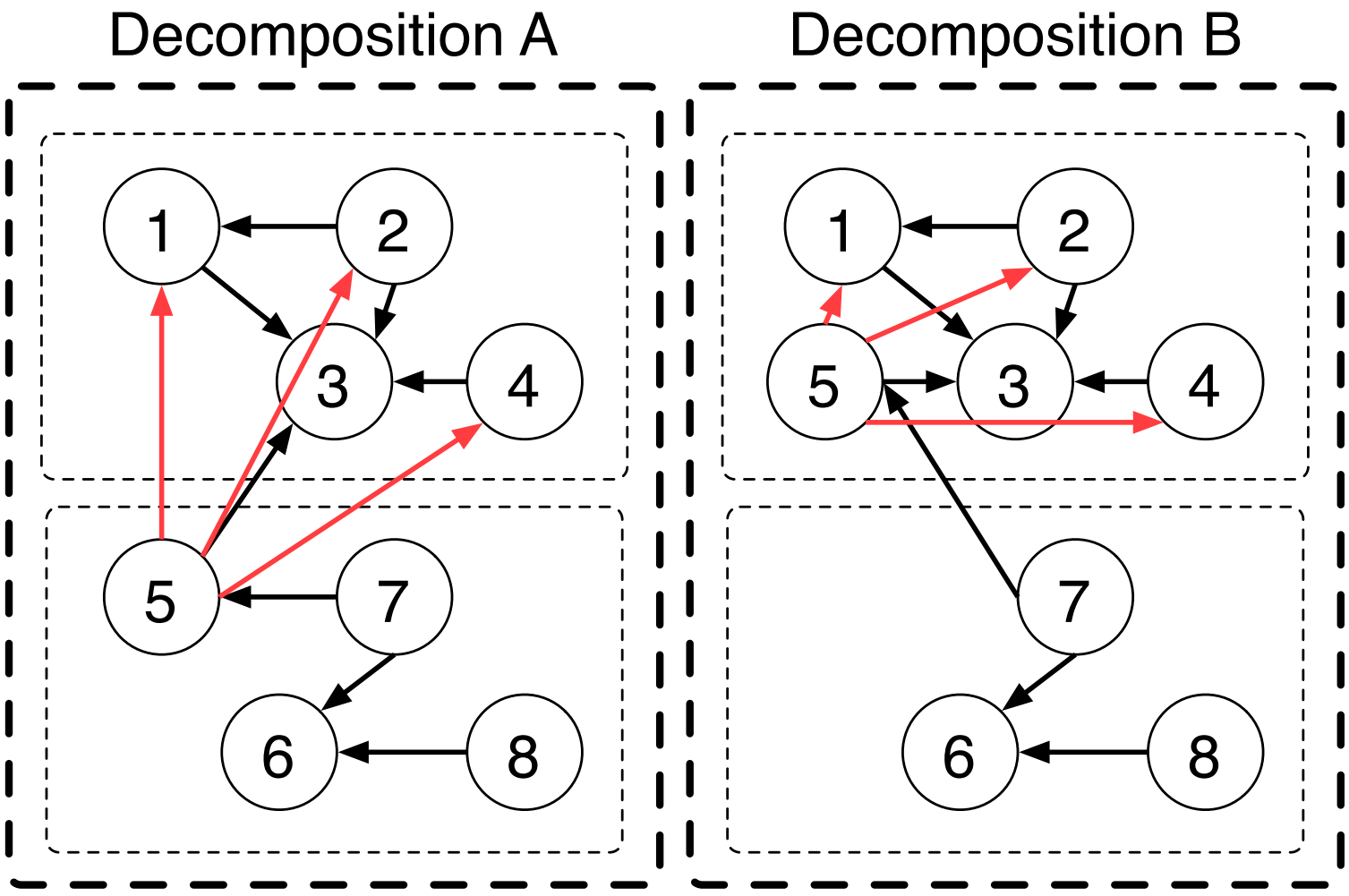
- A similarity measure cannot make assumptions as to what cluster a particular object should belong to
- Dissimilarity between decompositions should increase if the misplacement of an object results in the misplacement of a large number of edges

EdgeMoJo calculation

- Apply MoJo and obtain a series of Move and Join operations
- Perform all Join operations
- The cost of each Move operations increases from 1 to

$$m(o) = 1 + \frac{|(W(o, A_{new}) - W(o, A_{old})|}{W(o, A_{new}) + W(o, A_{old})}$$

EdgeMoJo example



$$m(5) = 1 + \frac{|4-1|}{4+1} = 1.6$$

EdgeMoJo in practice

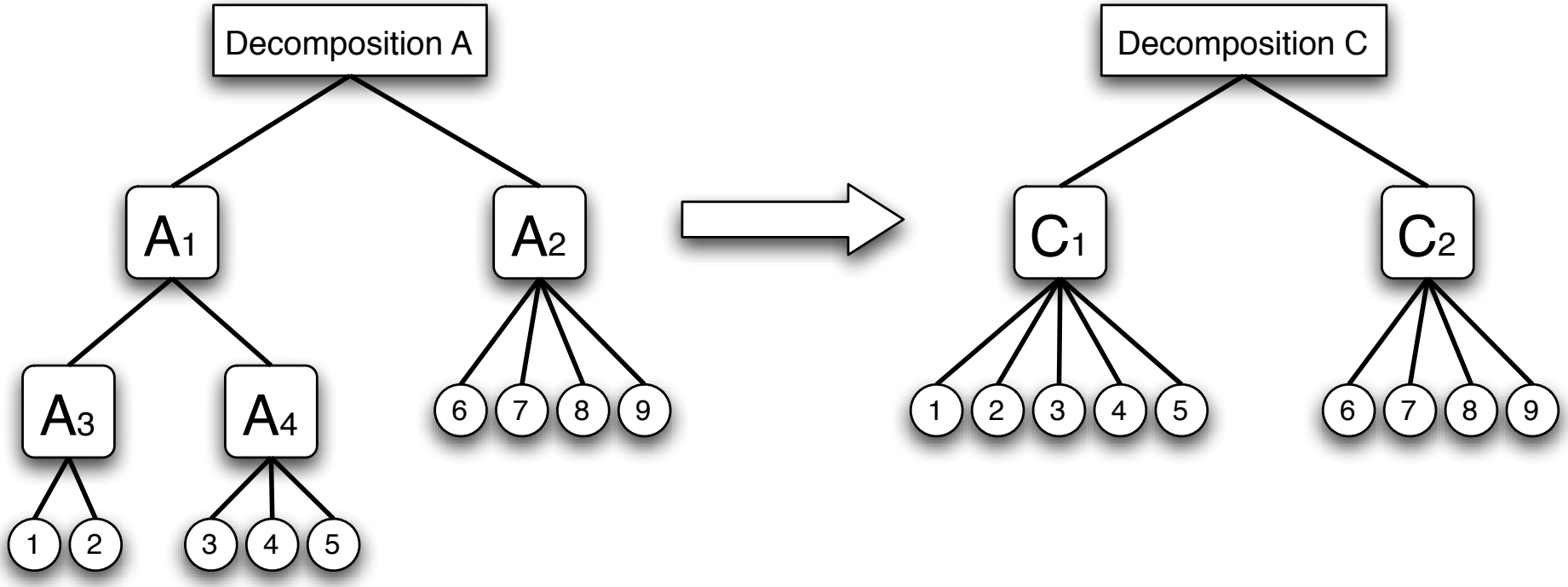
- Experiments with real and synthetic data indicated that EdgeMoJo distance is usually MoJo distance multiplied by a constant factor
- The usefulness of edges in measuring similarity between partitions is still an open question

What about nested decompositions?

- All measures we discussed so far assume a flat decomposition
  - No nested clusters
- Clustering algorithms typically create nested decompositions
- One needs to flatten decompositions to use these measures

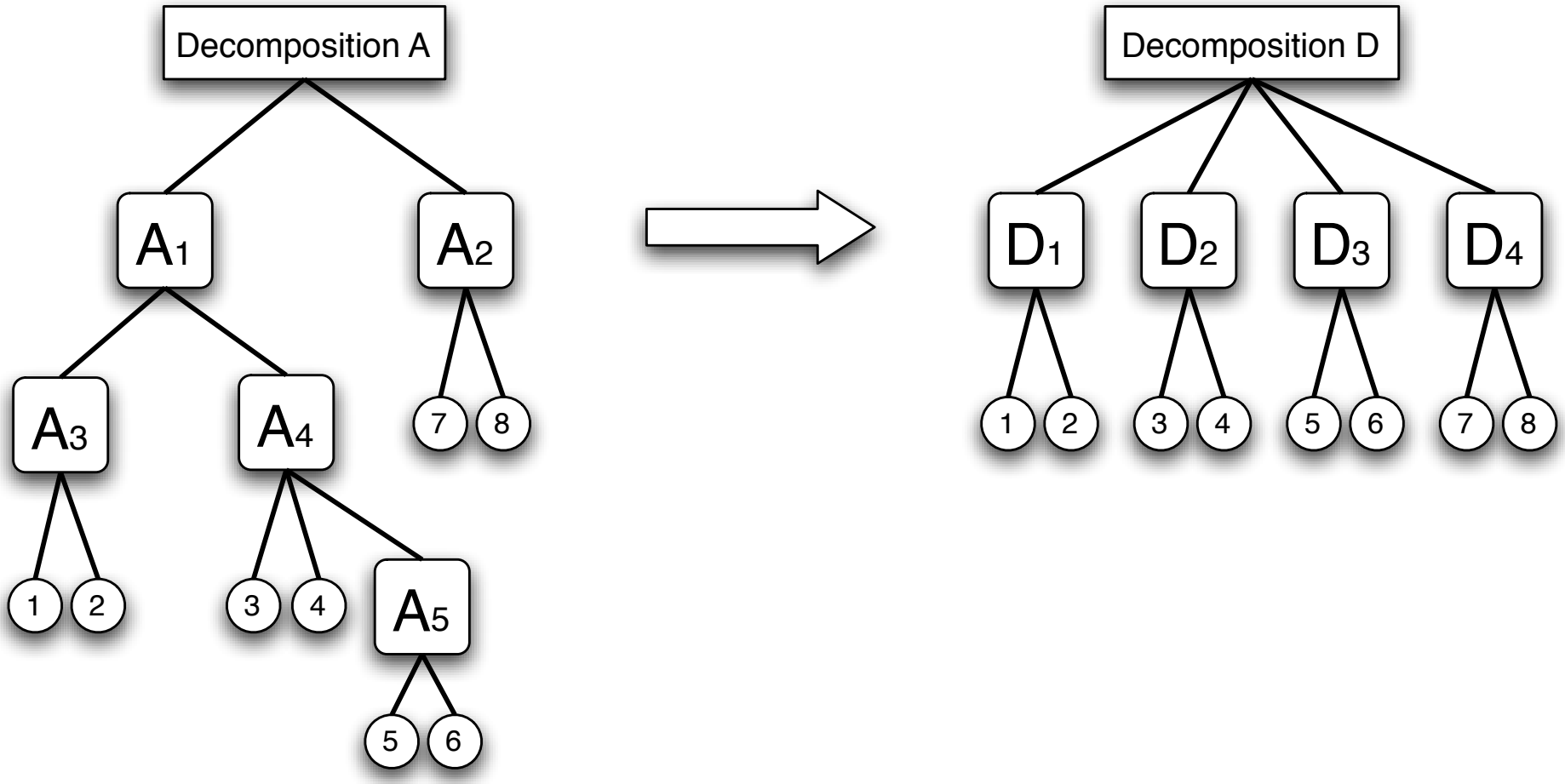
Creating compact flat decompositions

- All objects are re-assigned to the first level cluster they are transitively contained in



Creating detailed flat decompositions

- All clusters are re-assigned to the root



The END framework

- Each decomposition is transformed into a sequence of decompositions
- One for each level in the containment tree
- Compute the value of a flat evaluation measure M at each level
- Obtain a vector of values S_{M_i}

The END framework

- Compute the combined similarity/distance S as

$$\sqrt{\sum (w_i {S_{M_i}}^2)}$$

  where $\sum w_i = 1$

- Weights need to be assigned to each level

A different solution: UpMoJo

- An extension of MoJo distance that includes an Up operation as well
  - Moves an object one level higher in the containment tree
- A series of Up operations ensures that the top level of the containment tree contains the same set of objects
- MoJo rearranges the top level
- The process repeats for each subtree of the top level