

## Software Clustering

Decomposing a large software system into meaningful subsystems

# Understanding the Structure of Programs is Difficult

- Developers create sophisticated applications that are complex and involve a large number of interconnected components.
- **Result:** Program understanding is difficult
- **Goal:** Use automated techniques to help developers understand the structure of software systems.

# Common Problems

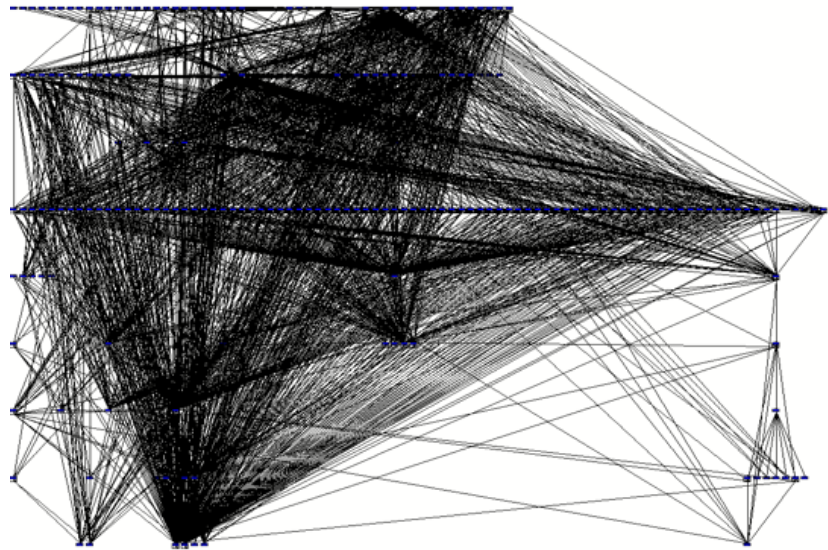
- Creating a good mental model of the structure of a complex system.
- Keeping a mental model consistent with changes that occur as the system evolves.
- These problems are exacerbated by:
  - Non-existent or inconsistent design documentation
  - High rate of turnover among IT professionals
- **Assumption:** Understanding the structure of a software system is valuable for maintainers.

- **Automatic:** Use software clustering techniques to decompose the structure of software systems into meaningful subsystems.
  - Subsystems help developers navigate through the numerous software components and their interconnections.
- **Manual:** Use notations such as UML to specify the software structure.

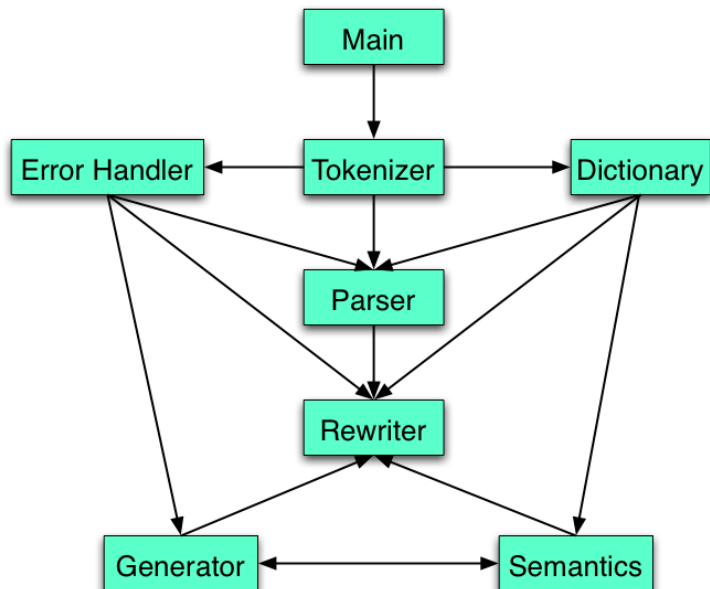
## Why is clustering useful?

- Helps new developers create a mental model of the software structure.
- Especially useful in the absence of experts or accurate design documentation.
- Helps developers understand the structure of legacy software.
- Enables developers to compare the documented structure with the automatically created (actual) structure.

## Example (before)



## Example (after)



# Software Clustering Challenges

- There are many ways to partition a set of entities into clusters.
- How do we create efficient algorithms to find partitions that are representative of a system's structure?
- How do we distinguish between **good** and **bad** partitions?



## How Hard is this Problem?

- The number of partitions of  $n$  objects into  $k$  clusters is:

$$S_{n,k} = \frac{1}{k!} \sum_{j=0}^k (-1)^{k-j} \binom{k}{j} j^n$$

- The number of ways to partition a set of  $n$  objects is:  $B_n = \sum_{k=1}^n S_{n,k}$
- This function grows exponentially with respect to  $n$ . Some values:

1	5	10	15	20
1	52	115,975	1,382,958,545	51,724,158,235,372

## Some solutions

- Enumerating every possible partition of the software structure graph is not practical.
- Heuristics can be used to reduce the number of partitions:
  - Searching algorithms
  - Knowledge about the source code
    - Names, directory structure, designer input
  - Remove entities that provide little structural value
    - Libraries, omnipresent nodes
- Result is sub-optimal, but often adequate.

- Clustering Procedures/Functions into Modules
- Clustering Modules/Classes into Subsystems
- Evaluating clustering algorithms
  - Measuring distance between partitions
  - Algorithm stability

# Clustering Techniques

- There are many different clustering techniques, but they all need to consider:
  - **Representation:** The entities and relationships to be clustered
  - **Similarity:** What determines the degree of similarity between the software entities
  - **Algorithms:** Algorithms that use the similarity measurement to make clustering decisions

- There are many choices based on the desired granularity of recovered system design
  - Entities may be variables/procedures or modules/classes.
  - What types of relationships will be considered?
  - Will the relationships be weighted?

- Similarity measurements are used to determine the degree of similarity between a pair of entities
- Different types:
  - **Association coefficients:** Based on common features that exist (or do not exist) between a pair of entities
    - Most common type of similarity measurement
  - **Distance measures:** Measure of the degree of dissimilarity between entities.

# Similarity Measurements

- Assume that every entity is expressed in terms of binary features, TRUE denoting the existence of a feature.
- We can then define:
  - **a**: Number of common features in entity *i* and entity *j*
  - **b**: Number of features unique to entity *i*
  - **c**: Number of features unique to entity *j*
  - **d**: Number of features absent in both entity *i* and entity *j*

# Association Coefficients

- Association co-efficients can be defined based on these values:

Simple Matching coefficient  $\frac{a+d}{a+b+c+d}$

Jaccard coefficient  $\frac{a}{a+b+c}$

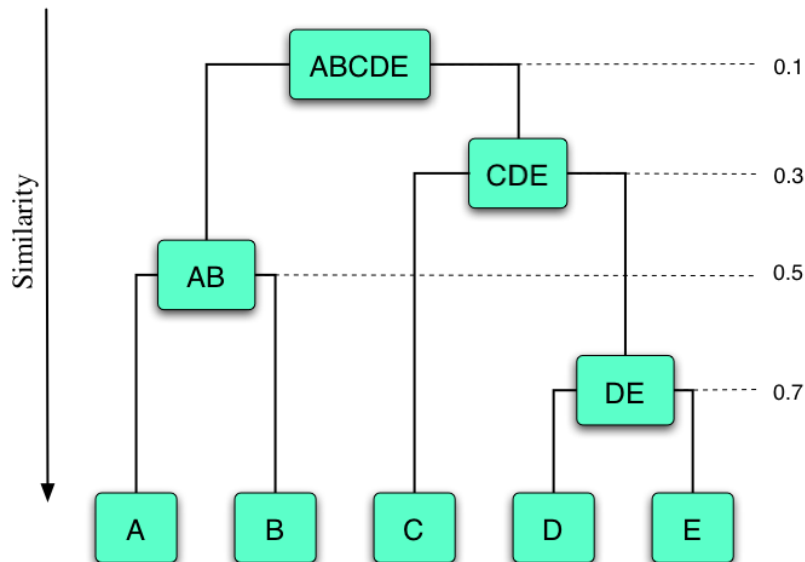
Sorensen coefficient  $\frac{2a}{2a+b+c}$



# Agglomerative hierarchical algorithm

- Start by creating one cluster for each object
- Join the two most similar objects into one cluster
- Continue joining the two most similar objects/clusters until everything is in one cluster
- What you get is a dendrogram...

# Dendrogram example



## Cut height

- By choosing to “cut” the dendrogram at a particular height, we can create a partition of the set of objects, e.g. a cut height of 0.45 in the previous example would give us 3 clusters
- Finding an appropriate cut height is a tough problem
- Heuristics, such as the number of clusters, are usually employed

- How to determine the similarity between two already formed clusters (or an object and a cluster)
- Many possibilities
  - Minimum of all pair-wise similarities
  - Maximum of all pair-wise similarities
  - Weighted or unweighted averages

## Assignment tool: aa

- The aa tool allows to run any version of the agglomerative algorithms described before
- **Example:** `aa input.mbd contain.rsf -c0.4 -s1 -a2`
  - Cluster the objects in `input.mbd` using a cut-height of 0.4, the Simple Matching Coefficient, and the Weighted Average Algorithm
- The `.mbd` stands for “market basket data”. You can transform from RSF to MBD with:  
`unitrans input.rsf output.mbd`

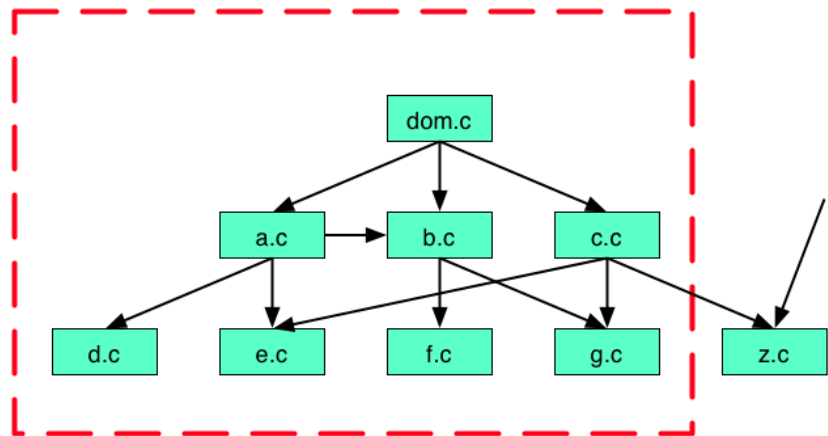
## Pattern-based software clustering

- Manual decompositions of large pieces of software often contain certain types of subsystems
- A software clustering algorithm that creates clusters based on these patterns would have a better chance of creating a decomposition that can help system comprehension
- These clusters can also have better names (based on the pattern they were derived from) as well as a more manageable number of contents

# The ACDC algorithm

- A skeleton of the decomposition is created based on the identified patterns
- Entities not clustered this way are assigned to the cluster that they exhibit the largest connectivity to
- Experiments with large systems have shown that the skeleton usually contains at least half the system entities

## Example pattern: Subgraph Dominator





## Assignment tool: acdc

- The acdc tool is an implementation of this algorithm

- Example:

```
acdc input.rsf output.rsf -125
```

- Cluster the objects in `input.rsf` with a maximum size of 25 for the Subgraph Dominator pattern

# Optimization-based Clustering

- If one can express the desired properties of a clustering as a formula, then the problem of clustering is reduced to that of finding the decomposition that optimizes the value of the formula
- A typical goal is to maximize cohesion and minimize coupling

- Bunch attempts to maximize the value of the MQ function

$$MQ = \begin{cases} \frac{\sum_{i=1}^k A_i}{k} - \frac{\sum_{i,j=1}^k E_{i,j}}{\frac{k(k-1)}{2}} & k > 1 \\ A_1 & k = 1 \end{cases}$$

where  $A_i = \frac{\mu_i}{N_i^2}$  and  $E_{i,j} = \begin{cases} 0 & i = j \\ \frac{\epsilon_{i,j}}{2N_i N_j} & i \neq j \end{cases}$

$N_i$ : the number of entities in cluster  $i$

$\mu_i$ : the number of intra-edges in cluster  $i$

$\epsilon_{i,j}$ : the number of inter-edges between clusters  $i$  and  $j$

- Finding the optimal clustering based on this formula is impractical
  - Exhaustive search is not recommended for more than 15 entities
- Bunch employs hill climbing and genetic algorithms to find approximate solutions

## Assignment tool: bunch

- Bunch is an interactive tool written in Java
- Input is in a format that is exactly like RSF except that the first token is missing, i.e. only one type of relationship is assumed
- Output is in a format called SIL that can be translated to RSF (see webpage)

- The literature contains many more ideas for clustering algorithms
- Data mining techniques as well as mathematical tools such as concept analysis have been used for clustering purposes
- Using naming or ownership information has also been shown to improve clustering results