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.

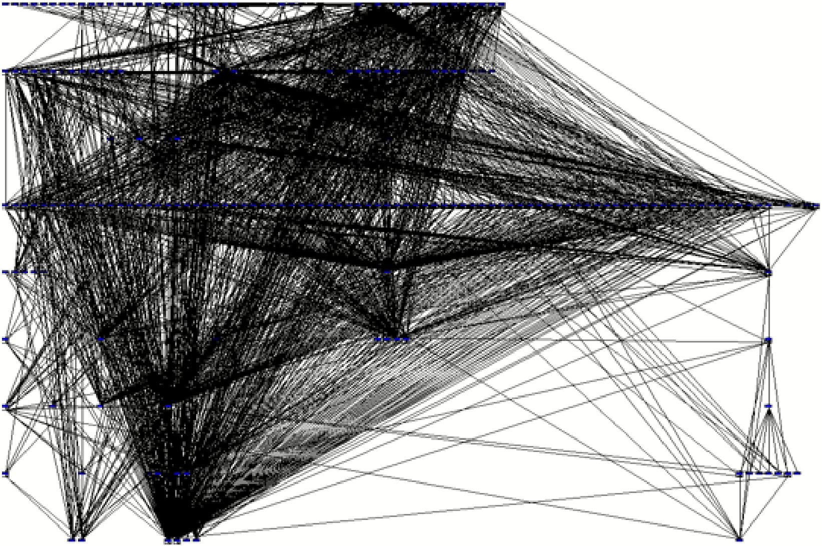
Solutions

- **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.

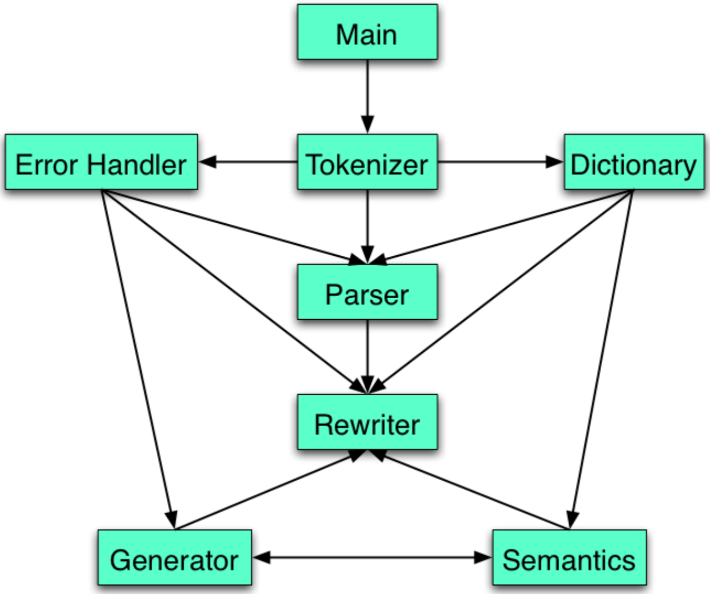
Why is clustering useful?

- 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.

Software Clustering Research

- 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

Representation

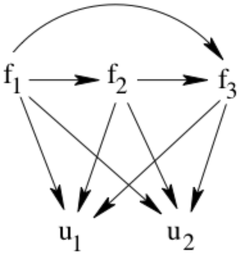
- There are many choices based on the desired granularity of recovered system design
  - Entities may be variables/procedures or modules/classes.
  - What types of relationships will be considered?
  - Will the relationships be weighted?

Similarity

- 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, 1 denoting the existence of a feature, 0 its absence.



	$\mathbf{f_1}$	$\mathbf{f_2}$	$\mathbf{f_3}$	$\mathbf{u_1}$	$\mathbf{u_2}$
f_1	0	1	1	1	1
f_2	1	0	1	1	1
f_3	1	1	0	1	1
u_1	1	1	1	0	0
u_2	1	1	1	0	0

Similarity Measurements

- We can also include information about who developed what file, and where each file is located

	$\mathbf{f_1}$	$\mathbf{f_2}$	$\mathbf{f_3}$	$\mathbf{u_1}$	$\mathbf{u_2}$	**Alice**	**Bob**	$\mathbf{p_1}$	$\mathbf{p_2}$	$\mathbf{p_3}$
f_1	0	1	1	1	1	1	0	0	1	0
f_2	1	0	1	1	1	0	1	1	0	0
f_3	1	1	0	1	1	0	1	0	1	0
u_1	1	1	1	0	0	1	0	0	0	1
u_2	1	1	1	0	0	0	1	0	0	1

For two entities i and j, we can define...

- **a**: Number of features present in both entities
- **b**: Number of features unique to entity i
- **c**: Number of features unique to entity j
- **d**: Number of features absent in both entities

Association Coefficients

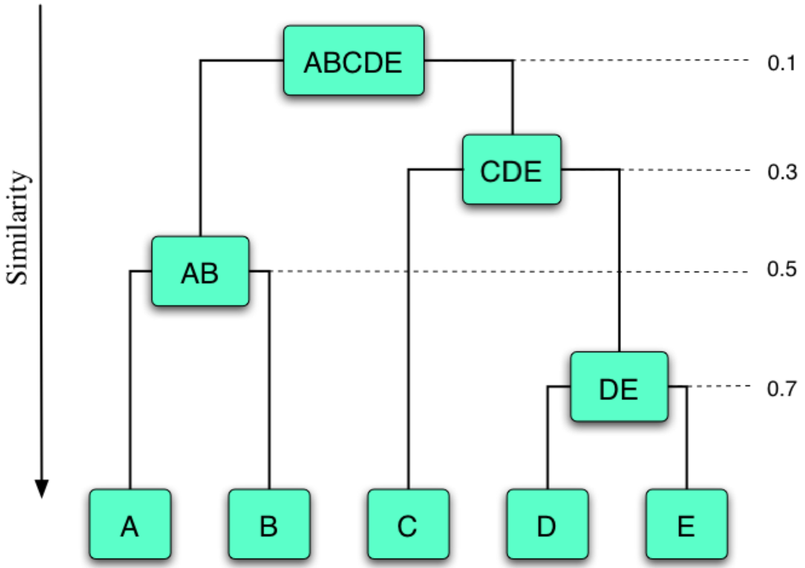
- Association co-efficients can be defined based on these values:

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

Update rule

- 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
- It requires input in "market basket data" form. You can transform from RSF to MBD with:
  `unitrans input.rsf output.mbd`

input.rsf

```
call f1 f2
call f1 f3
call f2 f3
call f1 u1
call f1 u2
call f2 u1
call f2 u2
call f3 u1
call f3 u2
```

output.mbd

```
f1 f2 f3 u1 u2
f2 f1 f3 u1 u2
f3 f1 f2 u1 u2
u1 f1 f2 f3
u2 f1 f2 f3
```

Assignment tool: aa

- 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
- Output:

```
contain ss5 u1
contain ss5 u2
contain ss3 f3
contain ss3 f1
contain ss3 f2
```

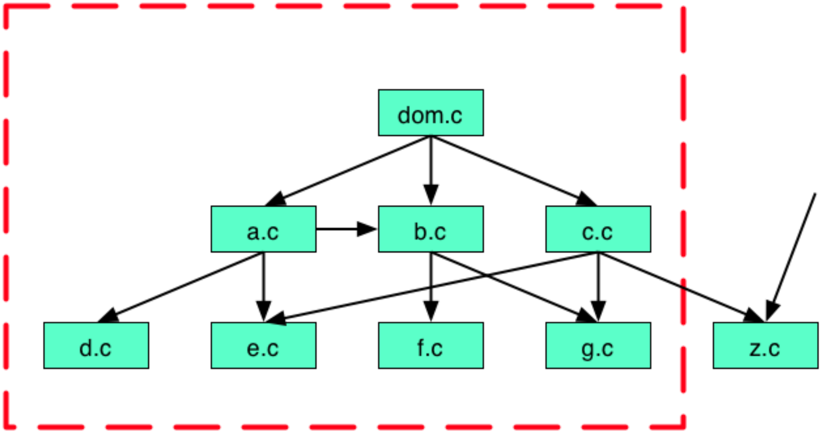
Pattern-based software clustering

- 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 -l25`
  - 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

- 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 $E_{i,j} = \begin{cases} 0 & i = j \\ \frac{\epsilon_{i,j}}{2N_iN_j} & i \neq j \end{cases}$

N_i: the number of entities in cluster i

μ_i: the number of intra-edges in cluster i

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

Bunch

- 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)

Other ideas

- 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