(Conceptual) Clustering methods for the Semantic Web: issues and applications

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Knowledge Representation and Learning Issues

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Context: The Semantic Web

The *Semantic Web* is a (new) vision of the Web
[T. Berners-Lee at al. @ Scientific American 2001]
Making the Web machine-interoperable
(readable, understandable, . . .)
How:

- adding *meta-data* describing the content of Web resources
- share precise semantics for the meta-data using *ontologies*

Web Ontologies

- An **ontology is** a formal conceptualization of a domain that is *shared* and *reused* across domains, tasks and groups of people
  [A. Gomez Perez et al. 1999]
- *OWL*: standard representation language for web ontologies
  - supported by *Description Logics* (DLs)
  - endowed with by *well-founded semantics*
  - implemented through *reasoning services* (reasoners)

DLs: The Reference Representation

Basics vocabulary: $\langle N_C, N_R, N_I \rangle$

- Primitive *concepts* $N_C = \{C, D, \ldots\}$: subsets of a domain
- Primitive *roles* $N_R = \{R, S, \ldots\}$: binary rels on the domain
- *individual* names $N_I = \{a, b, \ldots\}$ domain objects

Interpretation $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$ where :

- $\Delta^{\mathcal{I}}$: *domain* of the interpretation and
- $\cdot^{\mathcal{I}}$: *interpretation function* assigning *extensions*:
  each concept C with $C^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$ and
  each role R with $R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$
- The **Open World Assumption** made $\Rightarrow$
  different conclusion w.r.t. DB closed-world semantics

DLs: a family of languages

Principal DL concept/role construction operators (a language for each subset)

Name	Syntax	Semantics	
atomic negation	$\neg A$	$A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$	$(A \in N_C)$
full negation	$\neg C$	$C^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$	
concept conj.	$C \sqcap D$	$C^{\mathcal{I}} \cap D^{\mathcal{I}}$	
concept disj.	$C \sqcup D$	$C^{\mathcal{I}} \cup D^{\mathcal{I}}$	
full exist. restr.	$\exists R.C$	$\{a \in \Delta^{\mathcal{I}} \mid \exists b\ (a,b) \in R^{\mathcal{I}} \wedge b \in C^{\mathcal{I}}\}$	
universal restr.	$\forall R.C$	$\{a \in \Delta^{\mathcal{I}} \mid \forall b\ (a,b) \in R^{\mathcal{I}} \rightarrow b \in C^{\mathcal{I}}\}$	
at most restr.	$\leq nR$	$\{a \in \Delta^{\mathcal{I}} \mid \mid \{b \in \Delta^{\mathcal{I}} \mid (a,b) \in R^{\mathcal{I}}\} \mid \leq n$	
at least restr.	$\geq nR$	$\{a \in \Delta^{\mathcal{I}} \mid \mid \{b \in \Delta^{\mathcal{I}} \mid (a,b) \in R^{\mathcal{I}}\} \mid \geq n$	
qual. at most restr.	$\leq nR.C$	$\{a \in \Delta^{\mathcal{I}} \mid \mid \{b \in \Delta^{\mathcal{I}} \mid (a,b) \in R^{\mathcal{I}} \wedge b \in C^{\mathcal{I}}\} \mid \leq n$	
qual. at least restr.	$\geq nR.C$	$\{a \in \Delta^{\mathcal{I}} \mid \mid \{b \in \Delta^{\mathcal{I}} \mid (a,b) \in R^{\mathcal{I}} \wedge b \in C^{\mathcal{I}}\} \mid \geq n$	
one of	$\{a_1, a_2, \ldots a_n\}$	$\{a \in \Delta^{\mathcal{I}} \mid a = a_i, 1 \leq i \leq n\}$	
has value	$\exists R.\{a\}$	$\{b \in \Delta^{\mathcal{I}} \mid (b, a^{\mathcal{I}}) \in R^{\mathcal{I}}\}$	
inverse of	R^-	$\{(a,b) \in \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}} \mid (b,a) \in R^{\mathcal{I}}\}$	

Terminologies as Hierarchies – Subsumption

Concept Subsumption

Given two concept descriptions C and D,

$$D \sqsubseteq C$$

to be read C **subsumes** D (or D *is subsumed by* C) iff for every interpretation $\mathcal{I}$:

$$D^{\mathcal{I}} \subseteq C^{\mathcal{I}}$$

Equivalence: $C \equiv D$ **iff** $C \sqsubseteq D$ and $D \sqsubseteq C$

- It forms *hierarchies* of concepts
- It can be extended to roles

DL Knowledge Base

$\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$

- *TBox* $\mathcal{T}$ is a set of axioms

  $$C \equiv D \text{ (or } C \sqsubseteq D)$$

  where C is a concept name and D is a description
- *ABox* $\mathcal{A}$ contains extensional assertions on concepts or roles

  $$\text{e.g. } C(a) \text{ and } R(a, b)$$

  meaning, resp., that $a^{\mathcal{I}} \in C^{\mathcal{I}}$ and $(a^{\mathcal{I}}, b^{\mathcal{I}}) \in R^{\mathcal{I}}$

Interest in the **models** of $\mathcal{K}$:
interpretations $\mathcal{I}$ that satisfy all axioms/assertions in $\mathcal{K}$

TBox: Example

Primitive concepts:
$N_C = \{\text{Female}, \text{Male}, \text{Human}\}$.
Primitive roles:
$N_R = \{\text{hasChild}, \text{hasParent}, \text{hasGrandParent}, \text{hasUncle}\}$.

$\mathcal{T} = \{\ \text{Woman} \equiv \text{Human} \sqcap \text{Female},$
$\text{Man} \equiv \text{Human} \sqcap \text{Male},$
$\text{Parent} \equiv \text{Human} \sqcap \exists \text{hasChild}.\text{Human},$
$\text{Mother} \equiv \text{Woman} \sqcap \text{Parent},$
$\text{Father} \equiv \text{Man} \sqcap \text{Parent},$
$\text{Child} \equiv \text{Human} \sqcap \exists \text{hasParent}.\text{Parent},$
$\text{Grandparent} \equiv \text{Parent} \sqcap \exists \text{hasChild}.(\ \exists\ \text{hasChild}.\text{Human}),$
$\text{Sibling} \equiv \text{Child} \sqcap \exists \text{hasParent}.(\ \exists\ \text{hasChild} \geq 2),$
$\text{Niece} \equiv \text{Human} \sqcap \exists \text{hasGrandParent}.\text{Parent} \sqcup \exists \text{hasUncle}.\text{Uncle},$
$\text{Cousin} \equiv \text{Niece} \sqcap \exists \text{hasUncle}.(\exists\ \text{hasChild}.\text{Human}) \quad \}$

ABox: Example

$\mathcal{A} = \{$Woman(Claudia), Woman(Tiziana), Father(Leonardo), Father(Antonio), Father(AntonioB), Mother(Maria), Mother(Giovanna), Child(Valentina), Sibling(Martina), Sibling(Vito), hasParent(Claudia,Giovanna), hasParent(Leonardo,AntonioB), hasParent(Martina,Maria), hasParent(Giovanna,Antonio), hasParent(Vito,AntonioB), hasParent(Tiziana,Giovanna), hasParent(Tiziana,Leonardo), hasParent(Valentina,Maria), hasParent(Maria,Antonio), hasSibling(Leonardo,Vito), hasSibling(Martina,Valentina), hasSibling(Giovanna,Maria), hasSibling(Vito,Leonardo), hasSibling(Tiziana,Claudia), hasSibling(Valentina,Martina), hasChild(Leonardo,Tiziana), hasChild(Antonio,Giovanna), hasChild(Antonio,Maria), hasChild(Giovanna,Tiziana), hasChild(Giovanna,Claudia), hasChild(AntonioB,Leonardo), hasChild(Maria,Valentina), hasUncle(Martina,Giovanna), hasUncle(Valentina,Giovanna) $\}$

Inference Services

Besides standard inferences
(satisfiability, inconsistency, subsumption checks):

instance checking decide whether an individual is an instance of a concept ($\mathcal{K} \models C(a)$)

retrieval find all individuals beloging to a given concept

least common subsumer find the most specific concept that subsumes two (or more) given concepts

realization find the concepts which an individual belongs to, esp. the most specific one: the *most specific concept* of a w.r.t. $\mathcal{A}$ is $C = \mathsf{MSC}_{\mathcal{A}}(a)$, such that:
1. $\mathcal{K} \models C(a)$ and
2. $C \sqsubseteq D$, $\forall D\ \mathcal{K} \models D(a)$.

Clustering

Clustering discover groupings of domain objects

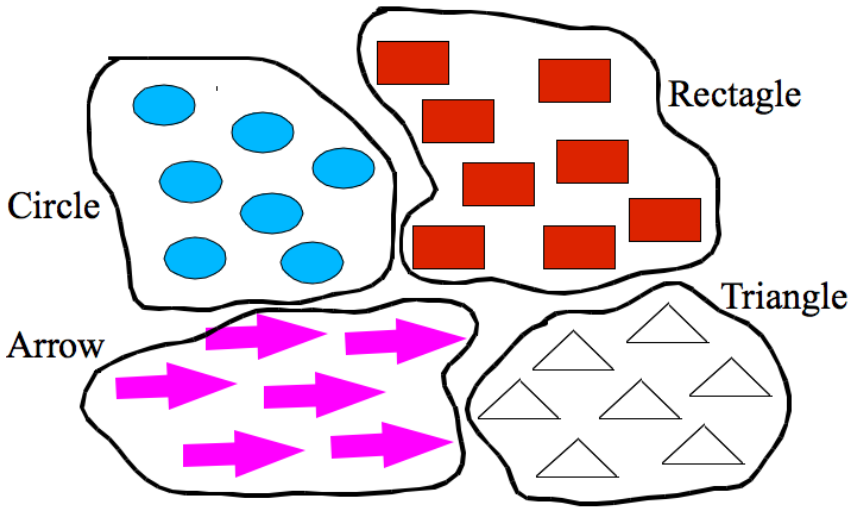
Many methods in the literature,

e.g. optimize both

- intra-cluster *similarity* (*maximize*)
- inter-cluster *similarity* (*minimize*)

Many forms: hierarchical, probabilistic, fuzzy, etc. . . .

Different strategies: partitional, agglomerative



Issues with Multi-Relational Settings

In classical clustering settings:

- Data represented as feature *vectors* in an n-dimensional space
- Similarity can be defined *algebraically* (geometrically)
- The notion of *centroid* as a cluster representative often used

Issues with clustering individuals in knowledge bases:

- Individuals within KBs to be logically manipulated
- *Similarity measure* for DLs required
- An *alternative* cluster *representative* may be necessary, or, even better: a *generalization procedure* for producing intensional cluster descriptions (concepts/predicates)

DL Dissimilarity Measures

- Measures for comparing concepts
  - simple DL, allowing only disjunction [Borgida et al., 05]
  - *structural*/semantic measures for $\mathcal{ALC}$ [d'Amato et al., 05] [d'Amato et al., 06]
  - *structural*/semantic measures for $\mathcal{ALCNR}$ and $\mathcal{ALCHQ}$ [Janowicz, 06] [Janowicz et al., 07]
  - semantic measure for $\mathcal{ALE}(\mathcal{T})$ [d'Amato et al., 07]

  All these *hardly scale* to more expressive DLs
- In Ontology Mining need for metrics for individuals
  - measures resort to the MSC approximations (not always available) for lifting individuals to the concept level
  - need for a *language-independent* measure

A Family of Semi-Distance Measures

- **IDEA**: *on a semantic level, similar individuals should behave similarly w.r.t. the same concepts*
- Inspired by **[Sebag 1997]**: individuals compared on the grounds of their behavior w.r.t. a set of *discriminating features*

$$\mathsf{F} = \{F_1, F_2, \ldots, F_m\}$$

i.e. a collection of (primitive or defined) concept descriptions
  - it may be found using stochastic search (GP)
- dependence only on *semantic* aspects related to the individuals

A Family of Semi-Distance Measures – Definition

[Fanizzi et al. @ DL 2007] Given $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$, let $\mathsf{Ind}(\mathcal{A})$ be the set of the individuals in $\mathcal{A}$, $\mathsf{F} = \{F_1, F_2, \ldots, F_m\}$, $p > 0$, and a weight vector $\vec{w}$, the *family of semi-distance functions* $d_p^{\mathsf{F}} : \mathsf{Ind}(\mathcal{A}) \times \mathsf{Ind}(\mathcal{A}) \mapsto [0, 1]$ is defined:

$$\forall a, b \in \mathsf{Ind}(\mathcal{A}) \quad d_p^{\mathsf{F}}(a, b) := \frac{1}{m} \left[\sum_{i=1}^{m} w_i \cdot \mid \pi_i(a) - \pi_i(b) \mid^p \right]^{1/p}$$

where $\forall i \in \{1, \ldots, m\}$ the *projection function* π_i are defined:

$$\forall a \in \mathsf{Ind}(\mathcal{A}) \quad \pi_i(a) = \begin{cases} 1 & \mathcal{K} \models F_i(a) \qquad (F_i(a) \in \mathcal{A}) \\ 0 & \mathcal{K} \models \neg F_i(a) \qquad (\neg F_i(a) \in \mathcal{A}) \\ pr_i & \textit{otherwise} \end{cases}$$

Conceptual Clustering

Performed during a *supervised learning phase*
using the results of the *unsupervised clustering phase*:

Problem Definition:

- *Given*
  - individuals in a cluster C regarded as *positive* examples of the concept to learn;
  - individuals in the others regarded as *negative* examples
  - $\mathcal{K}$ as background knowledge
- *Learn*
  - a definition D in the *DL language of choice* so that
  - the individuals in the target cluster are instances of D while those in the other clusters are not

Conceptual Clustering: Related Works

- **Few** algorithms for Conceptual Clustering (CC) with multi-relational representations [Stepp & Michalski, 86]
- **Fewer** dealing with the SemWeb standard representations
  - KLUSTER [Kietz & Morik, 94]
  - CSKA [Fanizzi et al., 04]
    - Produce a *flat output*
    - *Suffer from noise* in the data
- **Idea:** adopting a CC algorithm that combines
  - a **similarity-based** clustering method $\Rightarrow$ *noise tolerant*
  - a DL concept learning method (YINYANG, DL-LEARNER, DLFOIL)

Clustering Methods and Applications

Claudia d'Amato

ECM: Evolutionary Clustering around Medoid...

[Fanizzi et al. @ Information Systems Journal 2009]

- The notion of *medoid* (drawn from the PAM algorithm) rather than the notion of *centroid* (that is a weighted average of points in a cluster) is introduced
- A *medoid* is the **central element in a group of individuals**

$$m = \text{medoid}(C) = \operatorname*{argmin}_{a \in C} \sum_{j=1}^{n} d_p(a, a_j) \qquad \textit{where } a \neq a_j$$

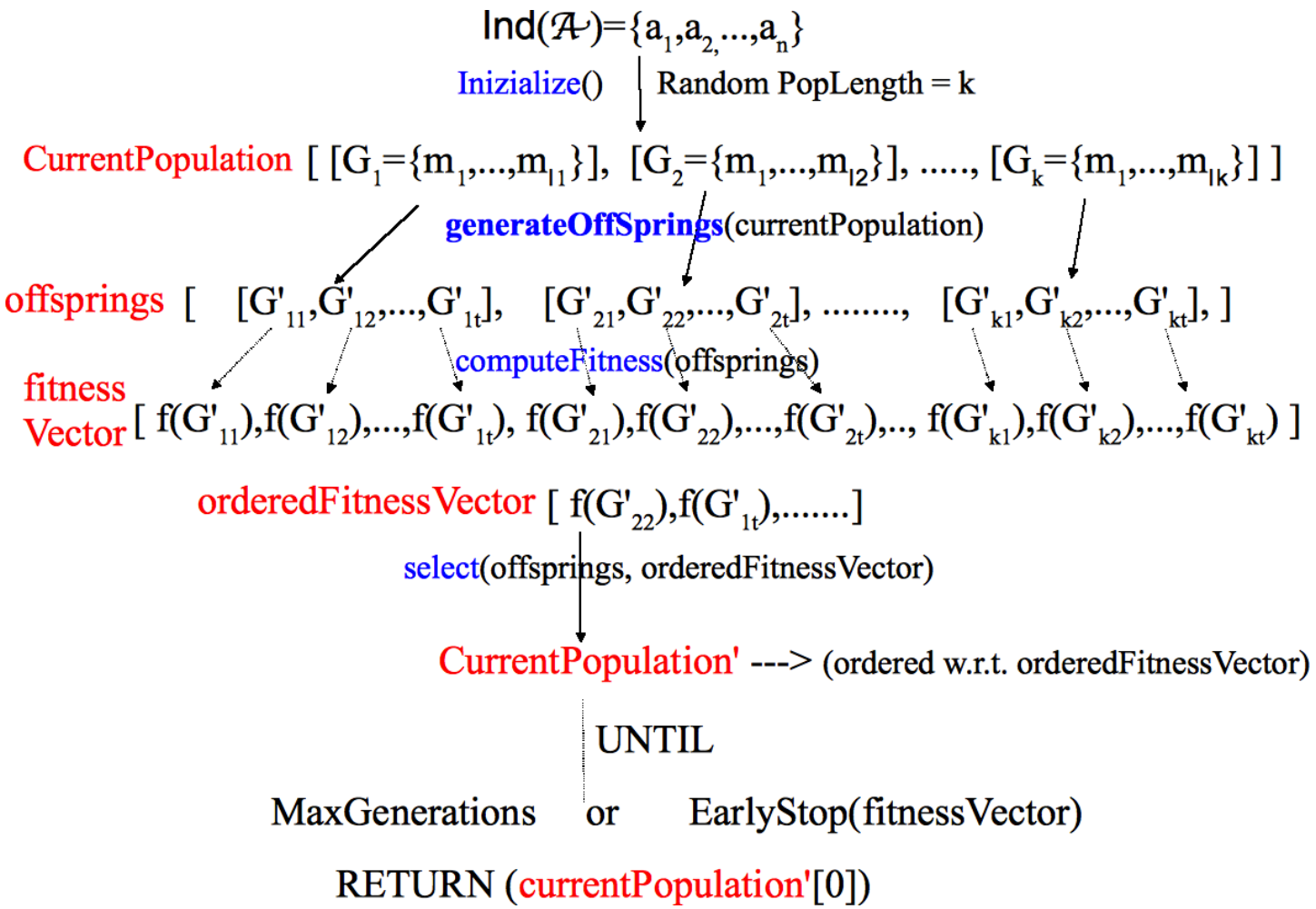
...ECM: Evolutionary Clustering around Medoid

- Implements a genetic programming learning schema
- Search space made by
  - *Genomes* = strings (list) of **medoids** of variable length
    - Each *gene* stands as a prototypical for a cluster
- *Performs a search in the space of possible clusterings of the individuals, by optimizing a fitness measure* (for a Genome G)

$$\text{FITNESS}(G) = \left(\sqrt{k+1} \sum_{i=1}^{k} \sum_{x \in C_i} d_p(x, m_i) \right)^{-1}$$

- On each generation those strings that are best w.r.t. the fitness function are selected for passing to the next generation.

ECM Algorithm: Main Idea



Running the ECM Algorithm...

medoidVector : ECM(maxGenerations,nGenOffsprings,nSelOffsprings)
output: medoidVector: list of medoids
static: offsprings: vector of generated offsprings, fitnessVector: ordered vector of fitness values, generationNo: generation number

currentPopulation = INITIALIZE() generationNo = 0
repeat
  offsprings = GENERATEOFFSPRINGS(currentPopulation,nGenOffsprings)
  fitnessVector = COMPUTEFITNESS(offsprings)
  currentPopulation = SELECT(offsprings,fitnessVector,nSelOffsprings)
  ++generationNo
until (*generationNo* = *maxGenerations* OR EARLYSTOP(fitnessVector))
return SELECT(currentPopulation,fitnessVector,1) *// fittest genome*

...Running the ECM Algorithm

Evolutionary Operators

offsprings : GENERATEOFFSPRINGS(currentPopulation)

DELETION(G) drop a randomly selected medoid: $G := G \setminus \{m\}, m \in G$

INSERTION(G) select $m \in \mathsf{Ind}(\mathcal{A}) \setminus G$ that is added to G: $G := G \cup \{m\}$

REPLACEMENTWITHNEIGHBOR(G) randomly select $m \in G$ and replace it with $m' \in \mathsf{Ind}(\mathcal{A}) \setminus G$ s.t. $\forall m'' \in \mathsf{Ind}(\mathcal{A}) \setminus G \; d(m, m') \leq d(m, m'')$: $G' := (G \setminus \{m\}) \cup \{m'\}$

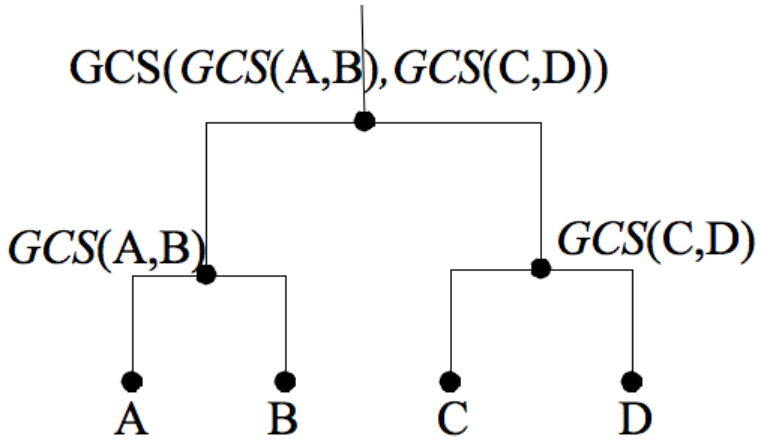
CROSSOVER(G_A, G_B) select subsets $S_A \subset G_A$ and $S_B \subset G_B$ and exchange them between the genomes: $G_A := (G_A \setminus S_A) \cup S_B$ and $G_B := (G_B \setminus S_B) \cup S_A$

ECM Algorithm: Discussion

- **The ECM algorithm** *the optimal number of cluster* reflecting the **data distribution**
  - the algorithm can be easily modified if the number of clusters is known thus reducing the search space
- The ECM algorithm is *grounded on the notion of* **medoid**
- *Medoids* are *more robust* in presence of *outliers* w.r.t. centroids that are weighted average of points in a cluster
  - The medoid is dictated by the location of predominant fraction of points inside a cluster
- An alternative partitional clustering method for DLs inspired to the k-Means algorithm **[Fanizzi et al. @ ESWC 2008]**

The DL-Link Algorithm

- Modified average-link algorithm
- *Clusters are always made by a single concept description given by the GCS of the child nodes* (Instead of Euclidean average)
- **Output:** *DL-Tree* where actual *elements to cluster are in the leaf nodes*, *inner nodes* are *intentional descriptions of the child nodes*



Running DL-Link

[d'Amato et al. @ IJSC 2010]

DL-LINK(**S**)
input $\mathbf{S} = \{R_1, \ldots, R_n\}$ the set of available concept descriptions;
output *DL-Tree*: dendrogram of the clustering process

Let $\mathcal{C} = \{C_1, \ldots, C_n\}$ be the set of initial clusters obtained by considering each R_i in a single cluster C_i;
DL-Tree $= \{C_1, \ldots, C_n\}$; $n := |\mathcal{C}|$;
while $n \neq 1$ **do**
  for $i, j := 1$ **to** n
    Compute the similarity values $s_{ij}(C_i, C_j)$;
  Compute $(C_h, C_k) = \text{argmax}_{i,j} s_{ij}$
  Create $C_m = GCS(C_h, C_k)$ the intensional descr. of the new cluster;
  Set C_m as parent node of C_h and C_k in *DL-Tree*;
  Insert C_m in $\mathcal{C}$ and remove C_h and C_k from $\mathcal{C}$;
  $n := |\mathcal{C}|$;
return *DL-Tree*;

DL-Link: Discussion

- The GCS is an approximation of the LCS of ALE(T) concept descriptions **[Baader et al. 2004]**
- Because of the use of the GCS, DL-Link clusters $\mathcal{ALE}(\mathcal{T})$ concept descriptions referring to an $\mathcal{ALC}$ TBox.
- *Individuals can be clustered* by preliminarily computing the **MSC for each of them**
- Alternative hierarchical clustering methods for DL representations **[Fanizzi et al. @ IJSWIS 2008; Fanizzi et al. @ Information Systems Journal 2009]**

Conceptual Clustering Step

How to learn concept definitions?

- For DLs that allow for (approximations of) the msc and lcs, (e.g. $\mathcal{ALC}$ or $\mathcal{ALE}$):
  - given a cluster C_j,
    - $\forall a_i \in C_j$ compute $M_i := msc(a_i)$ w.r.t. the ABox $\mathcal{A}$
    - let $MSCs_j := \{M_i | a_i \in \text{node}_j\}$
  - C_j *intensional description* $lcs(MSCs_j)$
- Alternatively
  - other algorithms for learning concept descriptions expressed in DLs may be employed (**[Fanizzi et al.'08] [Iannone et al.'07] [Lehmann and Hitzler'07] [Fanizzi et al.'10]**)

Clustering Methods for Automated Concept Drift and Novelty Detection: Motivations

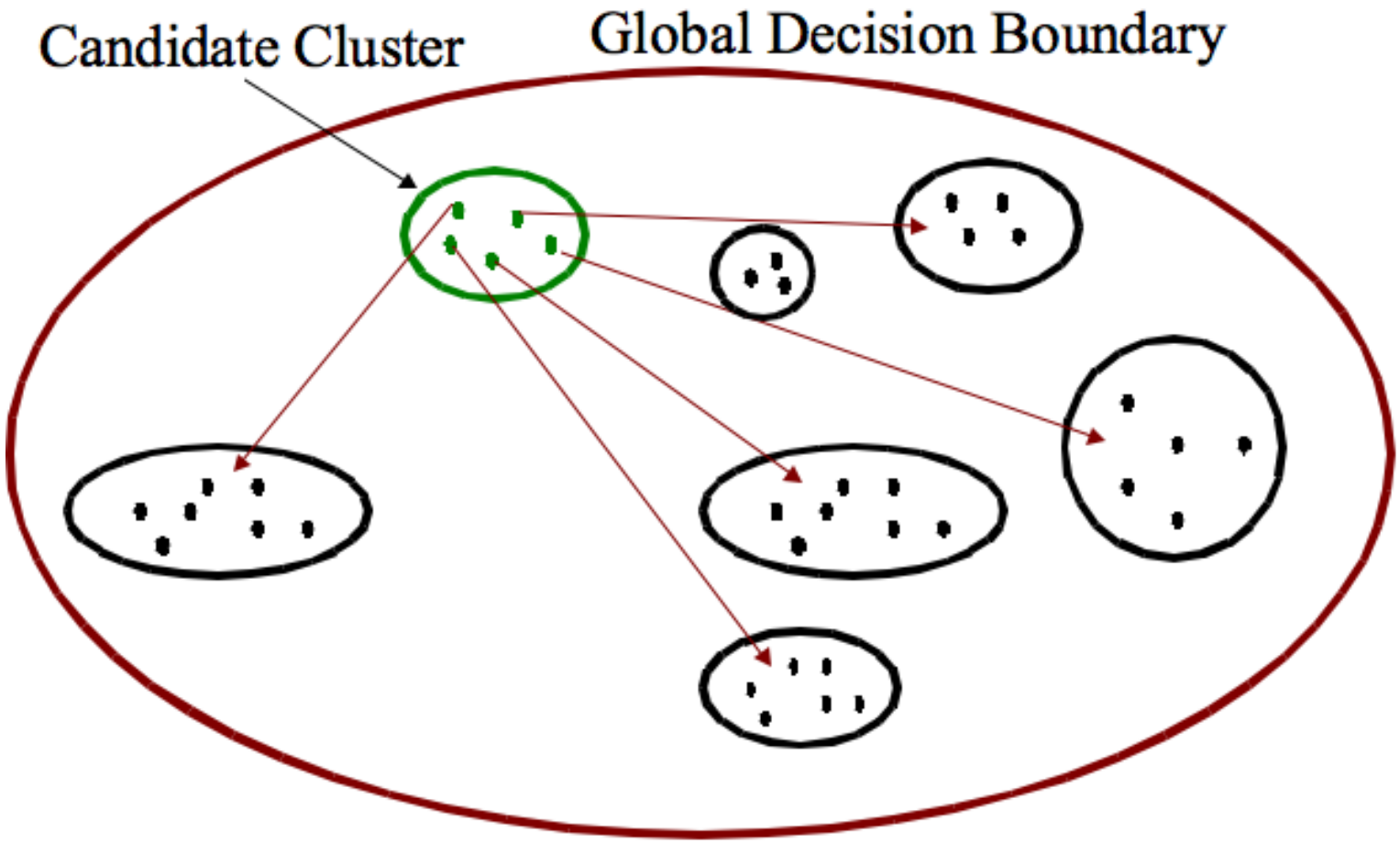
- In the real life, knowledge is generally changing over the time
  - *New instances are asserted*
  - New concepts are defined
- Clustering methods can be used for automatically:
  - learning novel concept definitions which are emerging from assertional knowledge **(Novelty Detection)**
  - for detecting concepts that are evolving, for instance because their intentional definitions do not entirely describe their extensions **(Concept drift)**

Automated Concept Drift and Novelty Detection

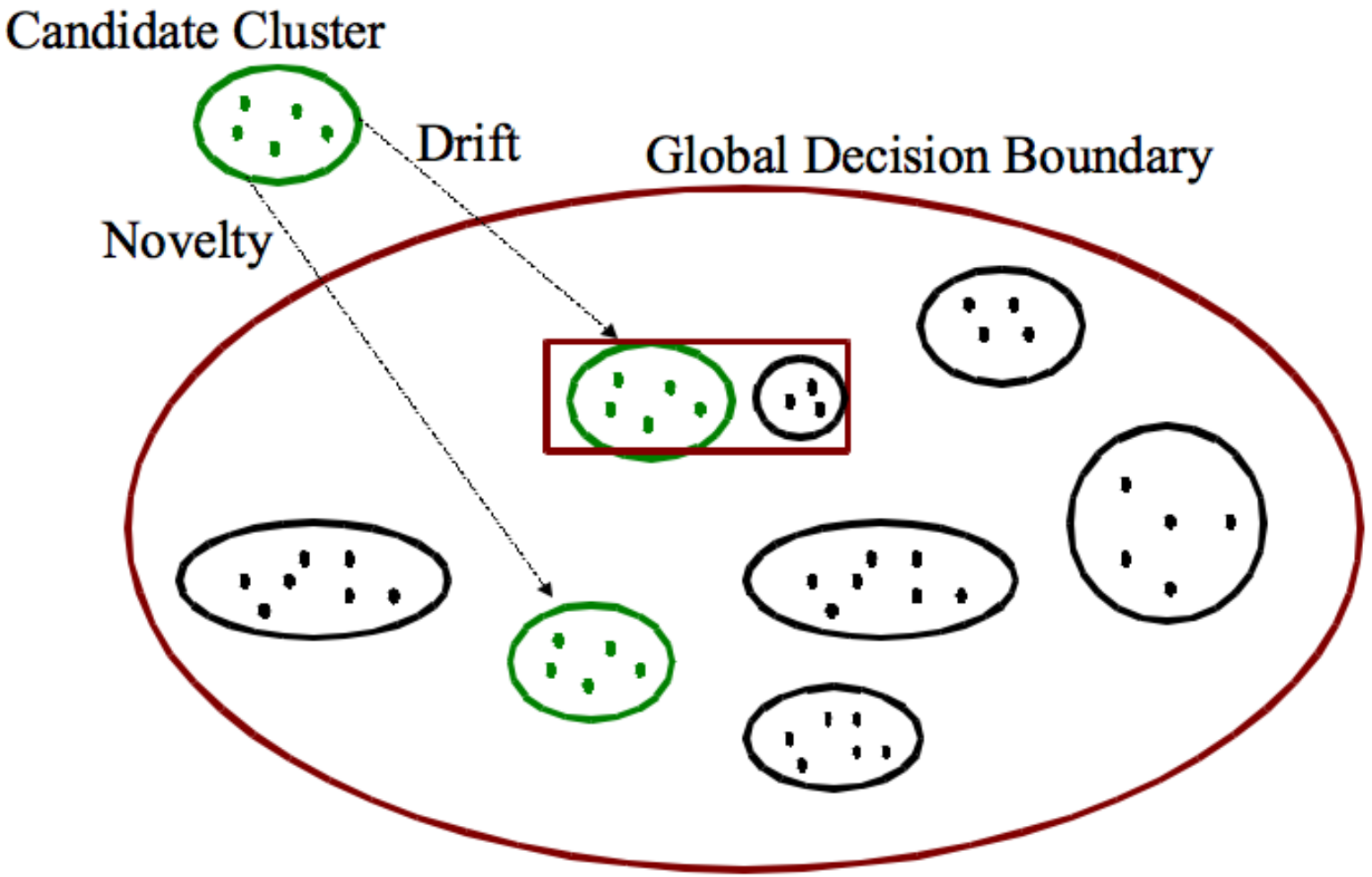
[Fanizzi et al. @ Information Systems Journal 2009]

1. All individuals of the KB of reference are clustered
2. When *new annotated individuals are made available* they have to be integrated in the clustering model
3. **Adopted Approach:** The new instances are considered to be a *candidate* cluster
   - An *evaluation* of it is performed in order to assess its nature

Evaluating the Candidate Cluster: Main Idea 1/2



Evaluating the Candidate Cluster: Main Idea 2/2



Evaluating the Candidate Cluster

- Given the initial clustering model, a *global boundary* is computed for it
  - $\forall C_i \in$ Model, *decision boundary cluster* $= max_{a_j \in C_i} d(a_j, m_i)$ (or the average)
  - The average of the decision boundary clusters w.r.t. all clusters represent the *decision boundary model or global boundary* $d_{overall}$
- The decision boundary for the candidate cluster CandCluster is computed $d_{candidate}$
- if $d_{candidate} \leq d_{ovevrall}$ then CandCluster is a *normal* cluster
  - *integrate* :
    $\forall a_i \in$ CandCluster $a_i \rightarrow C_j$ $s.t.$ $d(a_i, m_j) = min_{m_j} d(a_i, m_j)$
- else CandCluster is a **Valid Candidate** for *Concept Drift* or *Novelty Detection*

Evaluating Concept Drift and Novelty Detection

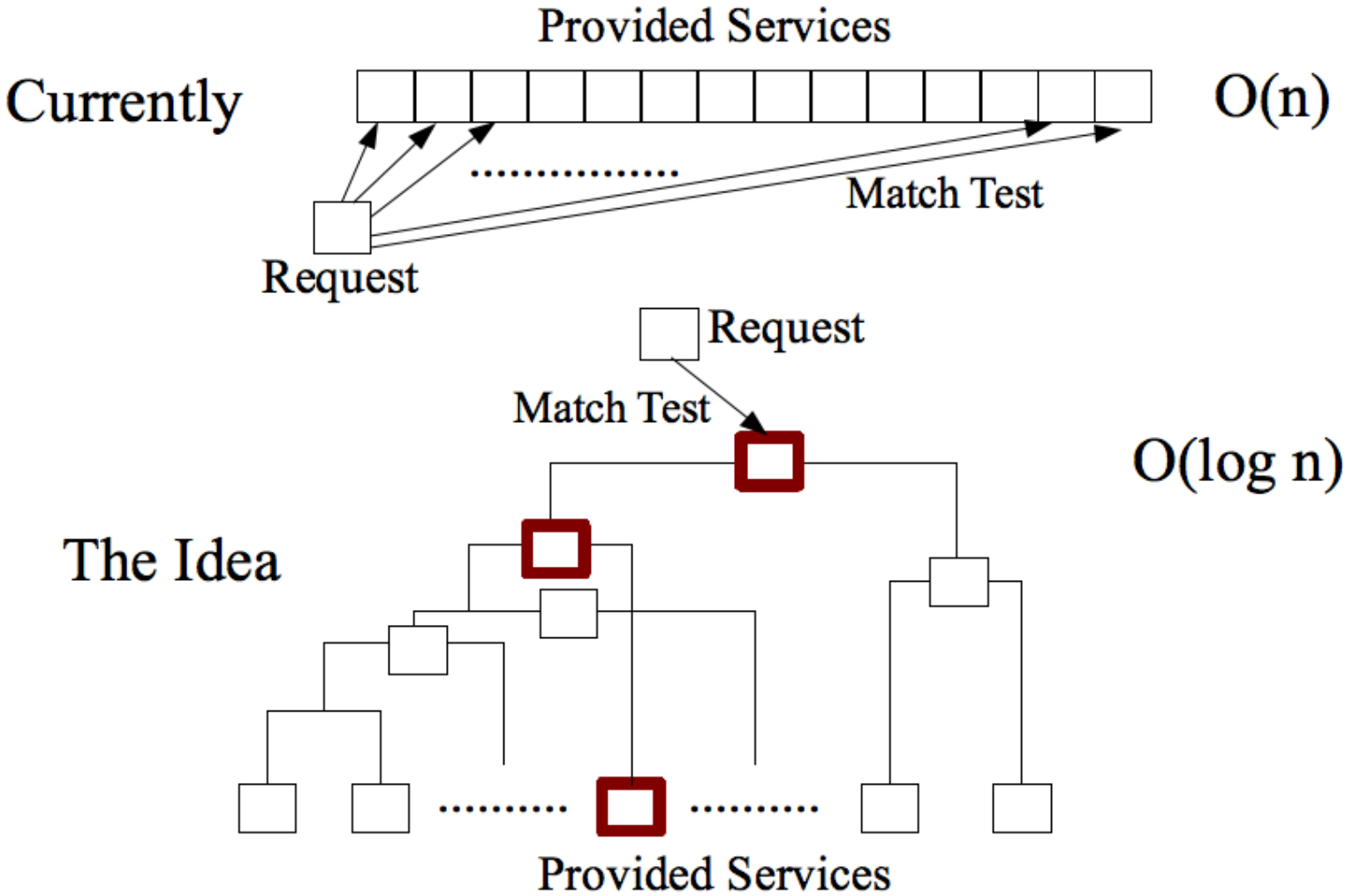
- The *Global Cluster Medoid* is computed
  $\overline{m} := \mathrm{medoid}(\{m_j \mid C_j \in \mathsf{Model}\})$
- $d_{\max} := \max_{m_j \in \mathsf{Model}} d(\overline{m}, m_j)$
- if $d(\overline{m}, m_{CC}) \leq d_{\max}$ the CandCluster is a *Concept Drift*
  - CandCluster is **Merged** with the most similar cluster $C_j \in \mathsf{Model}$
- if $d(\overline{m}, m_{CC}) \geq d_{\max}$ the CandCluster is a *Novel Concept*
  - CandCluster is **added** to the model
    - in case of a hierarchical approach the cluster is added at the level j where the most similar cluster is found

Efficient Resource Retrieval: Motivation 1

- Resource Retrieval is performed:
  - by matching a request **R** with each provided resource description, in order to detect relevant ones
  - **Example:** "*finding the low cost companies that fly from Bari to Cologne?*"
    - **the query is expressed as a concept description**

- *Problem:* inefficient approach with growing number of available resources
- *Solution:* similarly to databases, *exploiting* a *tree-based index* for *DL resource specifications* to improve the retrieval efficiency

Overall Idea



Efficient Resource Retrieval: Motivation 2...

Example: "*finding the low cost companies that fly from Bari to Cologne?*"

- **the query is expressed as a concept description**
- **resources are retrieved** by performing *concept retrieval*

- *Concept retrieval* is performed by executing *instance checking* for each individual in the ontology
- for DL with qualified existential restriction (as the one supporting OWL-DL), *instance checking suffers from an additional source of complexity* which do not show up other inference services such as *concept subsumption*.

...Efficient Resource Retrieval: Motivation 2

Solution: *decrease the complexity of semantic retrieval by using concept subsumption rather than instance checking*

1. compute, for each resource, its **most specific concept** (MSC)
2. *semantic retrieval* : **checking** for each MSC, if **subsumption** between the query concept and the *MSC* holds

- *For a large number of resources*, the naive approach of matching the query w.r.t. each specification becomes *highly inefficient*.
- **Solution:** similarly to databases, *exploiting* a *tree-based index* for *DL resource specifications*

Tree-based index: desired characteristics

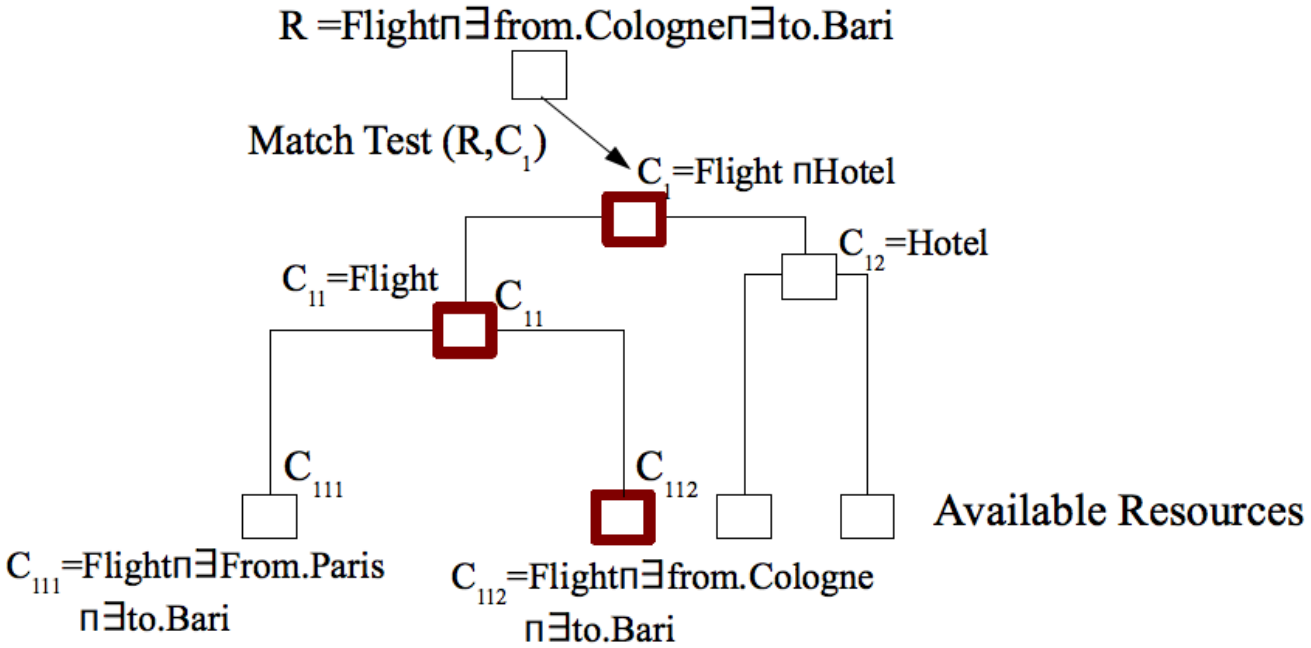
[d'Amato et al. @ IJSC 2010]

- Each leaf node contains a provided resource description
- Each inner node is a generalization of its children nodes
- Nodes at the same level have to be (possibly) disjoint

The DL-Tree obtained as output of the DL-Link algorithm can be exploited

Service Retrieval Exploiting Clustered Service Descriptions

- Checks for subsumption of an available resource description w.r.t the request



- Once the concepts representing the retrieved resource descriptions are found, their instances (namely the actual resources) are collected to assess, via *instance checking* which of them are also instances of the request

Automatic Ontology Refinement: Motivations

[d'Amato et al. @ SWJ 2010]

- Manual ontology refinement is a complex task, particularly for large ontologies.
- Conceptual clustering methods could be adopted to (semi-)automatize this task

Strategy:

1. Given a KB, individuals are clustered
2. A Description for each cluster is learnt
3. The new concepts are merged with the existing ontology by exploiting the subsuption relation
4. In this way the ontology is refined/enriched introducing a fine granularity level in the concept descriptions

Conclusions

Presented:

- issues in applying conceptual clustering methods to the standard SW representation
- some proposals for solving these problems
- exploitation of clustering methods for:
  - Automatically detecting concept drift and new emerging concept in an ontology
  - Improve the efficiency of the resuorce retrieval task
  - Automatically enriching/refining existing (and potentially large) ontologies

Ongoing work with Dr. A. Ławrinowicz:

- Clustering query answers for reducing the information overload

The End

The end!

Questions?

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