Spatial Data Mining

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What is a Spatial Pattern ?

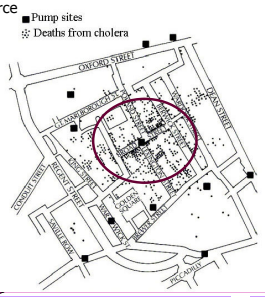
•What is not a pattern?
- Random
- Without definite direction, trend, rule, method
- Accidental - outside regular course of things
- Casual - relatively unimportant

•What is a Pattern?
- A frequent arrangement or regularity
- A rule or law
- A major direction, trend, prediction

Examples of Spatial Patterns

- Historic Example
  - 1855 Asiatic Cholera in London :

A water pump identified as the source

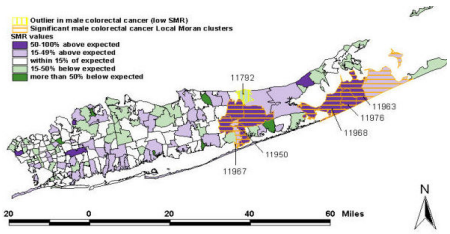


What is Spatial Data Mining?

- Search for **Interesting, useful** and **unexpected** spatial patterns
- **Non-trivial search**
  - Ex. Asiatic cholera : causes - water, food, air, insects, ...; water delivery mechanisms - numerous pumps, rivers, wells, pipes, ...
- **Interesting**
  - **Useful** in certain application domain
  - Ex. Shutting off identified Water pump => saved human life
- **Unexpected**
  - Pattern **is not common knowledge**
  - May provide a new understanding of the world
  - Ex. Connection between Water pump - Cholera

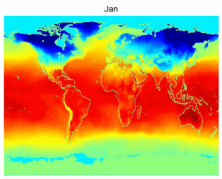
Example of Application Domains

- Questions from Epidemiology (Shekhar 2003)
  - What is the overall pattern of colorectal cancer
  - Is there clustering of high colorectal cancer incidence anywhere in the study area
  - Where is colorectal cancer risk significantly elevated
  - Where are zones of rapid change in colorectal cancer incidence

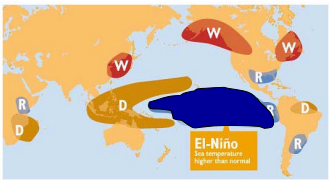


Modern Examples *(Shekhar 2003)*

Unusual warming of Pacific ocean (El Nino) affects weather



Average Monthly Temperature
(Courtesy: NASA, Prof. V. Kumar)



Global Influence of El Nino during the Northern Hemisphere Winter
(D: Dry, W: Warm, R: Rainfall)

What is NOT Spatial Data Mining?

- Simple Querying of Spatial Data
  - Find neighbors of Florianopolis given names and boundaries of all cities
  - Find shortest path from SC to SP
- Uninteresting or obvious patterns in spatial data
  - Heavy rainfall in Florianopolis downtown is correlated with heavy rainfall in downtown São José, given that both cities are less than 20 Kilometers apart
  - Common knowledge: Nearby places have similar rainfall
- Mining of non-spatial data
  - Diaper and beer sales are correlated in evenings

Motivation for Spatial Data Mining

- Answer *Critical* questions:
  - Ex. How is the health of planet Earth?
  - Ex. Characterize or predict effects of human activity on the environment
  - Ex. Predict effect of El Nino on weather and economy
  - ....
- Spatial data is growing too fast to analyze manually
  - Satellite imagery, GPS tracks, sensors on highways, cell phones …

Families of Spatial Patterns

- Common families of spatial patterns
  - Co-location
  - Outliers
  - Classification / Location Prediction
  - Spatial Association Rules
  - Clustering
  - ..
- Other families of spatial patterns may be defined
  - SDM is a growing field, which should accommodate new pattern families

General Overview of Spatial Data Mining Literature

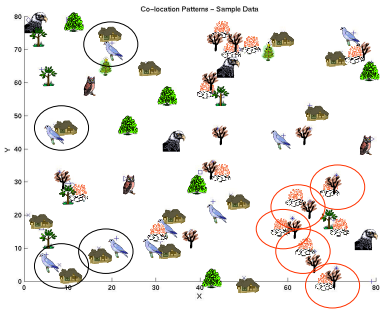
Transaction x Geometry DM

- Quantitative Spatial DM (Geometry-based)
  - Techniques*: Co-location, clustering*
  - Algorithms (SHEKHAR 2001, 2002) (HUANG 2004) (YOO 2005) (ZHANG2004)
    - Distance spatial relationships
    - Most use point spatial representation
    - Not implemented in toolkits
    - Single-granularity
- Qualitative Spatial DM (Transaction-based)
  - Techniques*: Spatial Association Rules, Classification, Clustering, Outlier detection*
  - Algorithms (APPICE 2003) (SHEKHAR, 2001a) (HAN, 2001) (BOGORNY 2006, 2008)
  - DMQL (LU, 1993) (KOPERSKI, 1995) (BIGOLIN 2003) (MALERBA, 2002) (BOGORNY 2008)
  - New operations to compute spatial relationships (ESTER 1997, 2000)
  - Semantic-based data mining (Bogorny 2006, 2007, 2008)
    - Any spatial relationship
    - Any spatial representation
    - Some tools
    - Multiple-Granularity

Co-Location

Co-location *(Shekhar 2003)*

Answers:

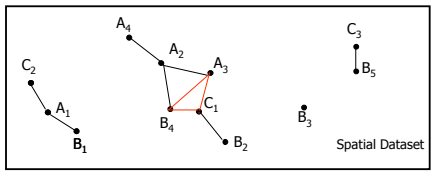


find patterns from the following sample dataset

Co-Location Patterns (Huang 2004, Yoo 2005)

- Input:
  - Spatial dataset
  - Distance threshold
  - Minimum participation index
- Method
  - Find neighbors
  - Find co-location candidates
  - Find frequent co-location sets
  - Extract co-location rules

Co-location Mining

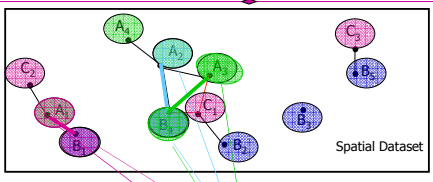


A, B, C: Spatial Feature Types

A1, A2... Spatial Feature Instances

Edges: neighbor

Co-location Mining



Set of Spatial Feature Types {A, B, C}

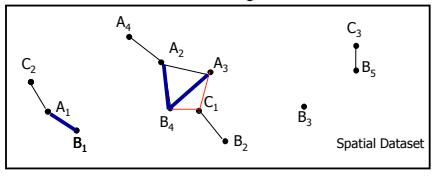
Candidates of size k=1

Candidates of size k=2

A B | A C | B C → Co-location

instances

Co-location Mining



Candidates of size k=1

Candidates of size k=2

A B | A C | B C → Co-location

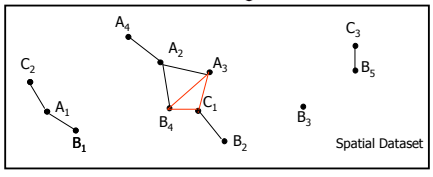
instances

2/4 2/3

3/4 2/5

3/5 2/3 → Participation ratio

Co-location Mining



Candidates of size k=2

A B | A C | B C → Co-location

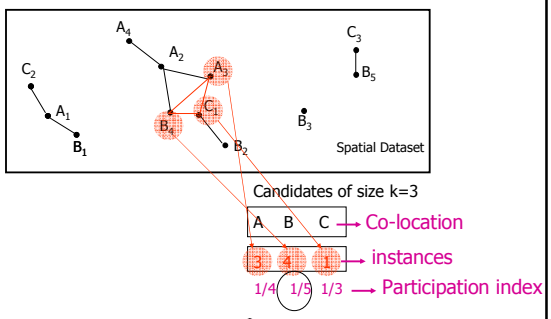
instances

2/4

2/5 3/5

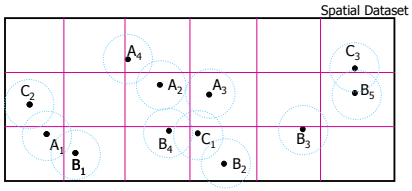
Participation Index (Lowest index) (If participIndex>minPartIndex) → frequent set

Co-location Mining



Co-Location Mining (Zhang 2004)

- Divide the space in cells (with size at least 2d)
- Buffer on each object,
  - object belongs to all cells that the buffer intersects (most 4 cells)
- All objects in a cell should fit in memory (are stored in a bucket)
- For each cell, objects are co-located if they are close



Co-location Example (Shekhar 2003)

Cropland with Roads
Roads with Bridges

Cropland
Roads
Bridges

Outliers?

Outliers

Outliers

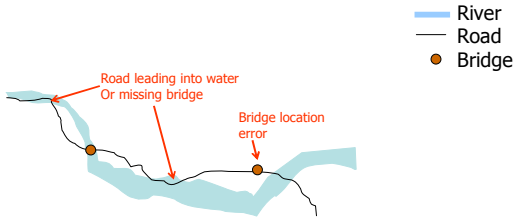
- What is an outlier?
  - Observations inconsistent with the rest of the dataset
- What is a spatial outlier?
  - Observations inconsistent with their neighborhoods
  - A local instability or discontinuity

Outliers (Shekhar 2001, 2003)

- *Global* outliers are observations of data inconsistent with the rest of the data in the database
  - has a number of practical applications in areas such as *credit card fraud, athlete performance analysis, voting irregularity, and severe weather prediction*
- A *spatial* outlier is a spatially referenced object whose non-spatial attribute values are significantly different from those of other spatially referenced objects in its spatial neighborhood.
  - For example, a new house in an old neighborhood is a spatial outlier based on the non-spatial attribute house age
- Tests to detect spatial outliers separate the spatial attributes from the non-spatial attributes.
  - Spatial attributes are used to characterize location, neighborhood, and distance.
  - Non-spatial attributes are used to compare a spatial referenced object to its neighbors.

Outliers – Examples *(Shekhar 2003)*

- Map Production
  - Error identification
  - E.g., spatial object violation



Spatial Association Rules

Association Rules (Agrawal 1993)

- Association rule is an implication of form

X → Y (support) (confidence)

Support : #(X∪Y) / #, where # is the number of rows in the dataset
Confidence : suport(X∪Y) / suport(X)

1 Generate frequent itemsets

Tid	Itemset
1	A, C, D, T, W
2	C, D, W
3	A, D, T, W
4	A, C, D, W
5	A, C, D, T, W
6	C, D, T

Set *k*	Frequent itemsets with minsup 50%
k=1	{A}, {C}, {D}, {T}, {W}
k=2	{A,C}, {A,D}, {A,T}, {A,W}, {C,D}, {C,T}, {C,W}, {D,T}, {D,W}, {T,W}
k=3	{A,C,D}, {A,C,W}, {A,D,T}, {A,D,W}, {A,T,W}, {C,D,T}, {C,D,W}, {D,T,W}
k=4	{A,C,D,W}, {A,D,T,W}

Support {AC} = 3/6 (50%)

2 Extract association rules

Confidence A→C = 3/4 (75%)

Association Rules

- Main Problem: Generate hundreds or thousands of rules
- **Frequent Itemsets:** generate all possible frequent itemsets
  - Apriori-like (generate candidates) (Agrawal, 1994)
  - Pattern-growth (without candidate generation) (Han, 2000)
- **Closed frequent itemsets:** generate non-redundant frequent itemsets
  - Apriori-like (generate candidates) (Pasquier, 1999) (Zaki, 2000)
  - Pattern-growth (without candidate generation) (Han, 2001) (Zaki 2002).....

Redundant Rules

A Redundant rule has same support and confidence of another rule generated from the same set of transactions

Frequent Itemsets

Tid	Itemset
1	A, C, D, T, W
2	C, D, W
3	A, D, T, W
4	A, C, D, W
5	A, C, D, T, W
6	C, D, T

TidSet	Frequent itemsets with *minsup* 50%
123456	{D}
12456	{C} {C,D}
12345	{W} {D,W}
1245	{C,W} {C,D,W}
1345	{A} {A,D}, {A,W} {A,D,W}
1356	{T}, {D,T}
145	{A,C}, {A,C,W}, {A,C,D}, {A,C,D,W}
135	{A,T}, {T,W}, {A,D,T}, {A,T,W}, {D,T,W} {A,D,T,W}
156	{C,T},{C,D,T}

A→W (suport= 4/6) (confidence = 4/4)

A→ DW (suport = 4/6) (confidence = 4/4)

25 frequent itemsets / 9 closed frequent itemsets

Spatial *Association Rules*

- Spatial association rule is an implication of the form

X → Y (support)(confidence)

- at least one element in *X* or *Y* is a spatial predicate
  - is_a(island) → **within**(river)
  - ***closeTo(slum)*** → *criminalityRate=High*

Different Spatial Objects are Stored in Different Relations

Street

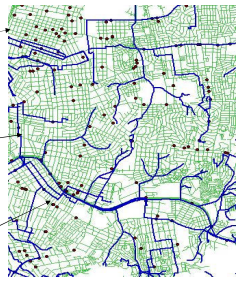
Gid	Name	Shape
1	Ijui	Multiline [(x1,y1),(x2,y2),..]
2	Lavras	Multiline [(x1,y1),(x2,y2),..]

WaterResource

Gid	Name	Shape
1	Jacui	Multiline [(x1,y1),(x2,y2),..]
2	Guaiba	Multiline [(x1,y1),(x2,y2),..]
3	Uruguai	Multiline [(x1,y1),(x2,y2),..]

GasStation

Gid	Name	VolDiesel	VolGas	Shape
1	BR	20000	85000	Point[(x1,y1)]
2	IPF	30000	95000	Point[(x1,y1)]
3	Esso	25000	120000	Point[(x1,y1)]



Most Spatial Association Rule Mining algorithms have a single table/file INPUT format

Different Relations (tables) need to be Spatially Joined

Preprocessed Geographic Data for Transaction-Based Data Mining

Target feature

Tuple (city)	Spatial Predicates							
1	contains(Port)	contains(Hospital)	contains(Street),	contains(Factory)	crosses(Water Body)
2		contains(Hospital)	contains(Street),		crosses(Water Body)
3	contains(Port)		contains(Street),	contains(Factory),	crosses(Water Body)
4	contains(Port)	contains(Hospital)	contains(Street),		crosses(Water Body)
5	contains(Port)	contains(Hospital)	contains(Street),	contains(Factory)	crosses(Water Body)
6		contains(Hospital)	contains(Street),	contains(Factory)	

Relevant features

Spatial Association Rules

- Are computed in 3 main steps:
  - Data preprocessing: compute spatial relationships (spatial joins). Most expensive step
  - Compute frequent itemsets
  - Generate association rules

Transaction Dataset X Preprocessed Spatial Dataset

Transactional Dataset

Transaction	Items
1	milk, bread, butter, cereal
2	milk, bread
3	beer, bread, chocolate
4	cereal, meet, milk
5	milk, beer, nuts, orange, cereal

- rows are transactions
- attributes are items, supposed to be independent

Spatial Dataset

Tuple (city)	Spatial Predicates
1	contains(Port), contains(Hospital), contains(TreatedWaterNet), contains(Factory), crosses(WaterBody)
2	contains(Hospital), contains(TreatedWaterNet), crosses(WaterBody)
3	contains(Port), contains(TreatedWaterNet), contains(Factory), crosses(WaterBody)
4	contains(Hospital), contains(TreatedWaterNet), crosses(
5	contains(Port), contains(Hospital), contains(TreatedWaterNet), contains(Factory), crosses(
6	contains(Hospital), contains(TreatedWaterNet), contains(Factory)

- rows are instances of the target feature type
- attributes are predicates
- spatial predicates are spatial relationships between the target feature type and relevant feature types

Spatial Predicate Computation (Preprocessing)

Given: D, //geographic database

e.g. [river, bridge, city, district, waterBody, island, road, cellularAntenna, gasStation, hospital, school, treatedWaterNetwork, port, industry]

$T = \{t_1, t_2, ..., t_n\}$, // target feature type

e.g. [city]

$S = \{O_1, O_2, ..., O_m\}$, // set of relevant feature types

e.g. [river, road, waterBody, hospital, school, gasStation, industry, port]

R //spatial relationships

e.g. [topological]

Find: a spatial dataset Ψ for mining SAR;

$\boldsymbol{T = \{t_1, t_2, ..., t_n\}}$

$\boldsymbol{S = \{O_1, O_2, ..., O_m\}}$, **where** $O_i = \{o_1, o_2, ..., o_k\}$,

Spatial Join - bottleneck

Some Spatial Association Rule Mining Algorithms

- Koperski 1995
- Spada (Appice 2003)
- Clementini (2003)
- Apriori-KC (Bogorny 2006)
- Max-FGP (Bogorny 2006a)
- ...

- Preprocess geographic data and apply classical DM algorithms

(Koperski 1995)

- In a first step spatial approximations are calculated (distance),
- In a second step, more precise spatial relationships are computed to the result of the first step (touches, contains, crosses, etc)
- Minimum support is used to extract only *frequent spatial relationships*.
- Multiple-granularity approach

Spada (Appice 2003)

- Inductive Logic Programming (ILP) approach
  - compute all spatial relationships in preprocessing steps
    - transform the result into a deductive relational database (set of predicates)
  - Compute frequent itemsets (as in Apriori)
  - Generate association rules
  - Filter association rules with declarative bias *a posteriori*
    - Pattern_constraint (*AtomList, Min_occur*),
    - Example: pattern_constraint (crossesRiver, 5)
- A large amount of background knowledge is required from the data mining user, which has to define all possible frequent patterns to be eliminated.

Semantic-based Spatial Association Rule Mining

Semantic-based SAR Mining - Motivation

- Existing approaches for spatial data mining, in general, do not make use of background knowledge
  - Use *syntactic constraints* for frequent set and rule prunning
  - Only the data is considered, not the schema
- Result
  - Same associations explicitly represented in the schema (database designer) are extracted by SAR mining algoritms
- Bogorny (2006) and Bogorny (2007, 2008) introduced the idea of using ***background knowledge***
  - in data preprocessing, to reduce spatial joins
  - in spatial association rule mining, to eliminate well known patterns

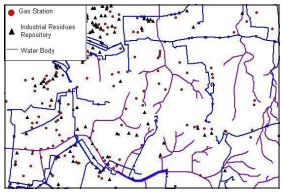
Spatial Relationships

- Mandatory (Spatial constraints) Dependences:
  <island> <inside> <1><1> <Water Body>
- Prohibited:
  <River> <*contains*> <0><0> <Road>
- **Possible**: Normally undefined
  Road *crosses* River

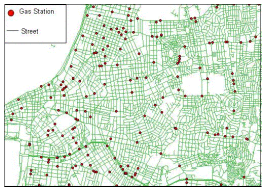
For data mining and knowledge discovery,
only POSSIBLE/PROHIBITED RELATIONSHIPS are interesting!!!!
Mandatory relationships are well known.

Well Known Geographic Dependences

Non-obvious spatial relationships

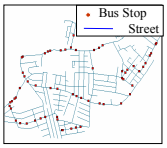


Well known dependences



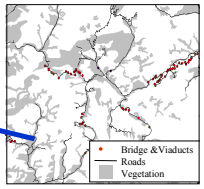
Is_a(gasStation) → intersects(street) (100%)

Well Known relationships X Association Rules

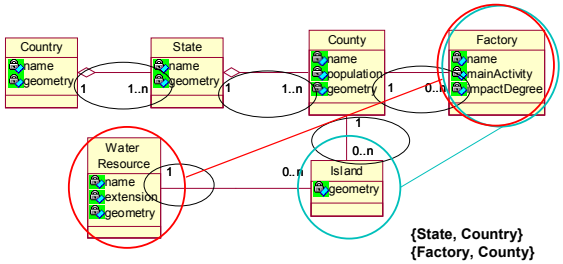


intersects(busStop) → intersects(Street) (100%)

Contains(viaduct) → contains(road) (100%)

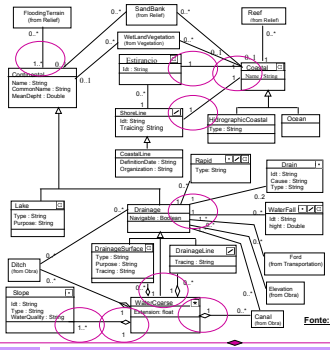


Well Known Associations – Conceptual Schemas



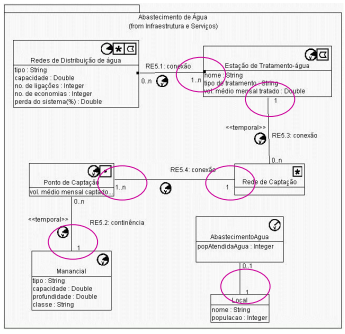
{State, Country}
{Factory, County}
{Island, WaterBody}
....

Well Known Associations – Conceptual Schemas

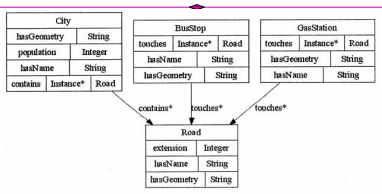


Fonte: 1ª Divisão de Levantamento do Exército Brasileiro

Well Known Associations – Conceptual Schemas



Well Known Associations – Geo-Ontologies




```
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  <rdfs:subClassOf>
    <owl:Restriction>
      <owl:minCardinality rdf:datatype="&int;" >1</owl:minCardinality>
      <owl:onProperty>
        <owl:ObjectProperty rdf:about="#touches"/>
      </owl:onProperty>
      <owl:valuesFrom rdf:resource="#Road"/>
    </owl:Restriction>
  </rdfs:subClassOf>
  <rdfs:subClassOf rdf:resource="http://www.w3.org/2002/07/owl#Thing"/>
</owl:Class>
```


Well known dependences X Spatial Association Rules (SAR)

- Well knonw dependences affect the 3 main steps in the process of mining SAR:
  - Spatial predicate computation: compute unnecessary relationships
  - Frequent set generation: generate frequent itemsets with well known patterns
  - Association rule extraction: produce a high number of rules with well known dependences

How do Well Known Dependences appear in SAR Mining?

Problem I - Geographic Dependences between the Target Feature and Relevant Features

Dependence = City and Street → contains(Hospital) → contains(Street)

Tuple (city)	Spatial Predicates		
1	contains(Port), contains(Hospital),	contains(Street),	contains(Factory), crosses(Water Body)
2	contains(Hospital),	contains(Street),	crosses(Water Body)
3	contains(Port),	contains(Street),	contains(Factory), crosses(Water Body)
4	contains(Port), contains(Hospital),	contains(Street),	crosses(Water Body)
5	contains(Port), contains(Hospital),	contains(Street),	contains(Factory), crosses(Water Body)
6	contains(Hospital),	contains(Street),	contains(Factory)

Minconf=70%

100% de support

Min Sup %	Total FrequentSets/ Rules	Rules with Dependence / Rules without Dependence	FrequentSets with dependence / FrequentSets without dependence
20	31 / 180	130 / 50	16 / 15
50	25 / 96	72 / 24	13 / 12

Problem II - Dependences among Relevant Feature Types

Dependence = {Port, WaterBody}

Tuple (city)	Spatial Predicates		
1	contains(Port),	contains(Hospital), contains(Street), contains(Factory)	crosses(Water Body)
2	contains(Hospital),	contains(Street),	crosses(Water Body)
3	contains(Port),	contains(Street), contains(Factory)	crosses(Water Body)
4	contains(Port),	contains(Hospital), contains(Street),	crosses(Water Body)
5	contains(Port),	contains(Hospital), contains(Street), contains(Factory)	crosses(Water Body)
6	contains(Hospital), contains(Street), contains(Factory)		

Minsup=50%

25 frequent sets (6 contain the dependence)

9 closed frequent sets (3 have the dependence)

contains(Port) → crosses(WaterBody)

Problem III - Redundant Frequent Itemsets

- For MinSup 50% we have:
  - 25 frequent sets
  - 9 closed frequent sets (3 contain the dependence)
  - 16 redundant frequent sets

Dependence {A,W}

Dataset

Tid (city)	Predicate Set
1	A, C, D,T, W
2	C, D, W
3	A, D, T, W
4	A, C, D, W
5	A, C, D, T, W
6	C, D, T

c) predicates

A = contains(Port)
C = contains(Hospital)
W = crosses(WaterBody)
D = contains(Street)
T = contains(Factory)

TidSet	Frequent sets L (MinSup=50%)
123456	{D}
12456	{C}, {C,D}
12345	{W}, {D,W}
1245	{C,W}, {C,D,W}
1345	{A}, {A,D}, {A,W}, {A,D,W}
1356	{T}, {D,T}
145	{A,C}, {A,C,W}, {A,C,D}, {A,C,D,W}
135	{A,T}, {T,W}, {A,D,T}, {A,T,W}, {D,T,W}, {A,D,T,W}
156	{C,T}, {C,D,T}

9 closed frequent itemsets

Pruning Methods using Background Knowledge

Frequent Set Pruning (Apriori-KC) (Bogorny, 2006a)

{Island,water}

Given: Φ, // set of knowledge constraints
Ψ, // *dataset generated with spatial_predicate_extraction*

minsup, // minimum support
L_1 = {large 1-predicate sets};
For (k = 2; L_{k-1} != ∅; k++) do begin
C_k = apriori_gen(L_{k-1}); // Generates new candidates
If (k=2)
// remove pairs with dependences
(step 1) Delete from C_2 all pairs with a dependence in Φ;

Forall rows w ∈ Ψ do begin
C_w = subset(C_k, w); // Candidates contained in w
Forall candidates c ∈ C_w do
c.count++;
End;
L_k = {c ∈ C_k | c.count ≥ minsup};
End;
Answer = $\cup_k L_k$

Max-FGP (Bogorny 2006c)

Given: *L; // frequent sets without dependences (Apriori-KC)*
Ψ; // dataset generated with spatial_predicate_extraction

Find: Maximal M

```
// find maximal generalized predicate sets
M = L;
For ( k = 2; Mk != ∅; k++ ) do  begin
    For ( j = k+1;  Mj!=0;  j++ ) do  begin
        If  (tidSet (Mk) = tidSet (Mj))
                If (Mk ⊂ Mj)   // Mj is more general than Mk
                        Delete Mk from M;
   End;
End;
Answer = M;
```


Summary

- Well known dependences exist in several non-spatial application domains
  - Biology/Bioinformatics
    - Pregnant → Female (confidence=100%)
    - Breast_cancer → Female (confidence 100%)
    - ...
- Almost no data mining approaches consider background knowledge or domain knowledge

Spatial Classification

Classification

- Given a set of instances, the role of classification is to discover the classes of the instances
- Spatial objects may be characterized (classified) by different types of information (Koperski 1998):
  - non-spatial attributes (e.g. population);
  - spatially related attributes with non-spatial values (e.g. *total population living within 100 meters from cellular antennas);*
  - spatial predicates (e.g. *closeTo_beach);*

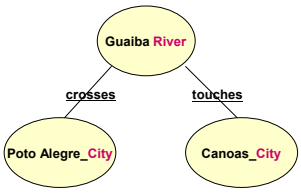
Ester (1997, 2001)

- Proposed a graph-based approach for spatial neighbourhood computation
- Idea is to integrate data mining into database systems, with new database primitives for the computation of spatial relationships
- and explicitly represent spatial relationships that are normally implicit in spatial databases

Ester (1997, 2001)

- A neighborhood graph for a relation "neighbor" in a geographic database is a graph G(N,E), where
  - *N* are nodes
  - *E* are edges
- Each node *N* is an object in the database connected via some *edge* to another node if the neighbor holds.
- Two objects are neighbors if any spatial relationship (topological, distance or order) holds

Ester (1997, 2001)

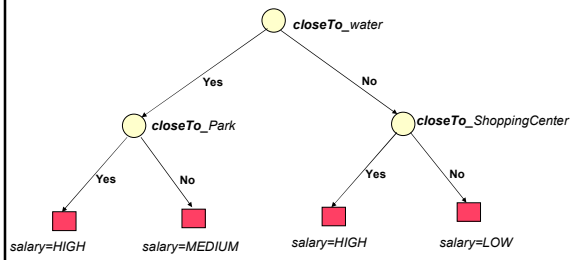


Ester (1997, 2001)

- Operations
  - ***Get_nGraph(db, rel)***: computes all relationships
  - ***Get_neighborhood(graph, o, pred)***: retrieves all objects *o* directly connected via some edge in the *graph* satisfying a condition in *pred*
  - ***Create_nPaths (objects, graph, pred, i):*** *creates a set of all paths from one object following the edges of the neighborhood graph with length<i*
    - the influence of neighboring objects and their attributes decreases with increasing distance
    - the length of the relevant neighborhood paths are limited by an input parameter *max-length*.

Ester (1997, 2001)

Class is a non-spatial attribute = *salary*
Class values: high, medium, low



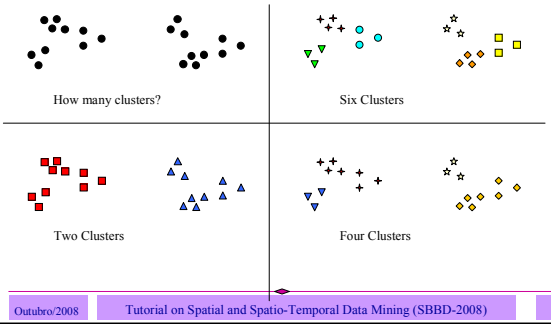
Clustering

Clustering (cluster analysis)

- Clustering is a process of partitioning a set of data into a set of groups called *clusters*
- A cluster is a set of data (objects) with
  - similar characteristics
  - that can be collectively treated as one group
- Clustering is an unsupervised method
  - no predefined classes

Clustering Analysis (Kumar 2005)

Different ways of clustering the same set of points



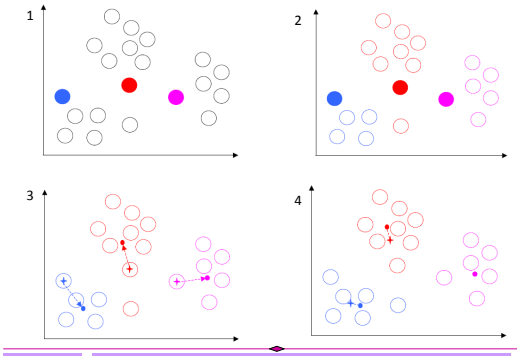
Main Clustering Approaches

- Partitioning
  - A division of data objects into non-overlapping subsets (clusters) such that *each object* is in exactly one subset
- Hierarchical
  - A set of nested clusters organized as a hierarchical tree
- Density-based
  - Find clusters based on density of regions
- Grid-based
  - Find clusters based on the number of points in each cell

K-means

- Partitional clustering approach
- Each cluster is associated with a centroid
- Each point is assigned to the cluster with the closest centroid
- A drawback of the k-means is that the number of clusters *k* is an input parameter.

K-means



K-medoid methods

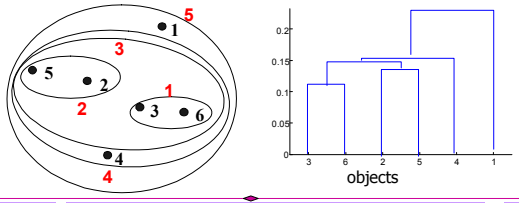
Instead of ***means***, use representative objects called ***medoids***

- *PAM* (Partitioning Around Medoids, 1987) - starts from an initial set of medoids and iteratively replaces one of the medoids by one of the non-medoids if it improves the total distance of the resulting clustering
- *CLARA* (Clustering Large Applications, 1990) – It draws *multiple samples* of the data set, applies *PAM* on each sample, and gives the best clustering as the output
- *CLARANS* (NG 2002) - is an improved *k*-medoid method

Hierarchical Clustering

Two main types: Agglomerative and Divisive

- Agglomerative
  - Start with all objects as individual clusters
  - At each step, merge the two most similar clusters
  - Until rests one cluster (or k clusters)



Hierarchical Clustering

- Divisive
  - Start with one cluster (with all objects)
  - At each step, split a cluster in two
  - Until each cluster contains only one object (or k clusters)

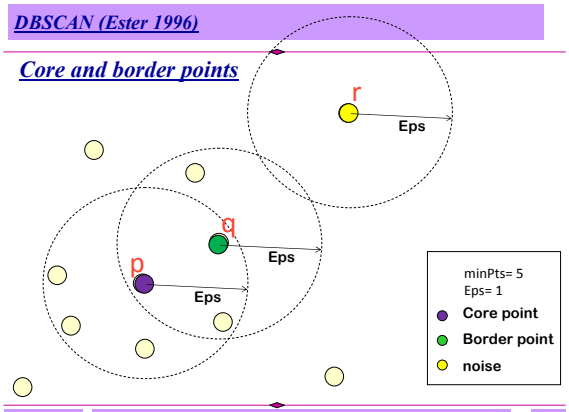
Similarity can be euclidean distance or any other measure

DBSCAN (Ester 1996)

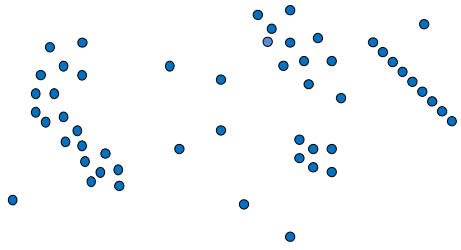
- DBSCAN is a density-based algorithm
  - Density = number of points within a specified radius (*Eps*)
  - A point is a core point if it has more than a specified number of points (*MinPts*) within *Eps*
  - A border point has less than *MinPts* within *Eps*, but it is in the neighborhood of a core point
  - A noise point is any point that is not a core point or a border point.

DBSCAN (Ester 1996)

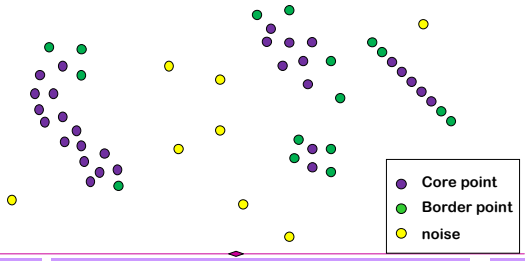
Core and border points



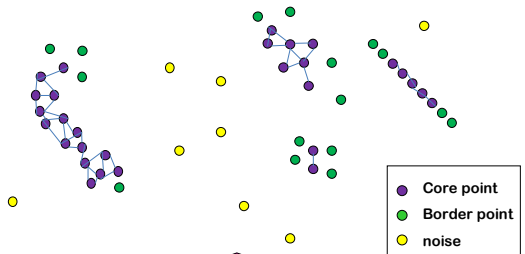
DBSCAN example



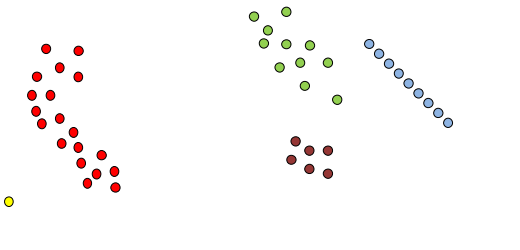
Identifying core, border and noise points



Computing distance



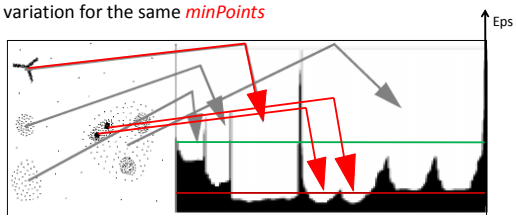
Final Clusters



OPTICS - Ordering Points to Identify the Clustering Structure (Ankerst 1999)

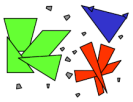
Produces a special order of the database with respect to its density-based clustering structure

EPS variation for the same *minPoints*



GDBSCAN (Generalized DBSCAN) (Sander 1998)

- Generalized version of DBSCAN
- Clusters are formed based on spatial or non-spatial attributes
- Any spatial relationshiop is used to compute neighbors, and spatial objects may have any representation
  - *NPred* : "neighbor",
  - *wCard*: cardinality>=MinCard, (generalizes the condition *NEps(o)>= MinPts)*
  - *MinWeight(N)*: *aggr* (non-spatial values) >= *threshold OR MinPts*
  - *ExampleI:* NPred: distance <= *Eps*, *wCard*: sum of areas, *MinWeight* : >= *MinPts*
  - *ExampleII:* *NPred*: "*intersects*" or "*touches*", *MinWeight(N)*: sum of areas >= *MinArea,*



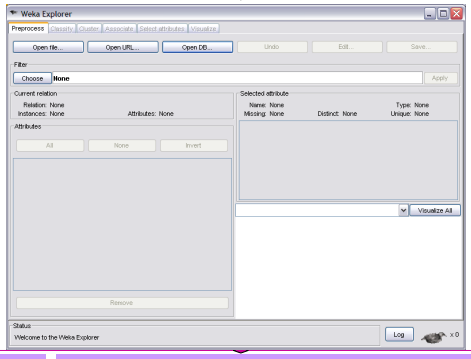
GDBSCAN (Generalized DBSCAN) (Sander 1998)

- Example I: Two cities can be close if they have similar non-spatial attributes
- Using non-spatial attributes as a weight for objects one can "induce" different densities, even if the objects are equally distributed in the space of the spatial attributes.

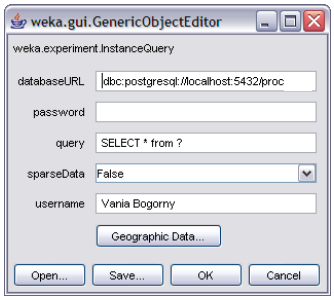
Tools

- GeoMiner (Han 1997)
- INGENS (Malerba 2001)
- Ares (Appice 2005)
- Weka-GDPM (Bogorny 2006d)

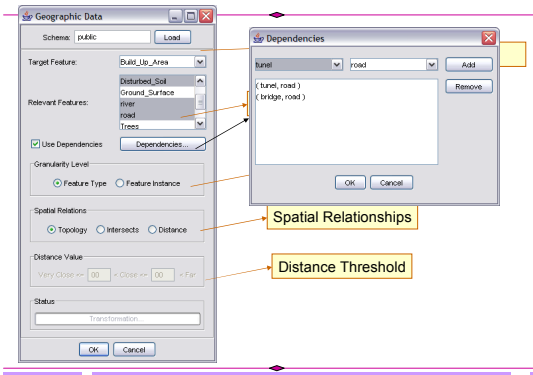
Weka GUI Explorer (Frank 2005)



Weka-GDPM



Weka-GDPM



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