Discovering Spatial Co-location Patterns

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Biography

* Education
  * Ph.D. Candidate, C.S., UMN, Fall 98 - May 03 (expected)
  * B.S., C.S., Beijing University, Fall 93 - Fall 97
* Research Interests
  * Database, Spatial Database, Data Mining, Geographic Information Systems
* Publications
  * Spatial Co-location Patterns
    - S. Shekhar and Y. Huang, Discovering Spatial Co-location Patterns : A Summary of Results, In ***Proc. of 7th Intl Symposium on Spatial and Temporal Databases (SSTD)***, Springer-Verlag, Lecture Notes in Computer Science, LNCS 2121, p.236 ff, July 2001
    - S. Shekhar and Y. Huang, Multi-resolution Co-location Miner: a New Algorithm to Find Co-location Patterns from Spatial Datasets, ***SIAM SDM02 Workshop on Mining Scientific Datasets***, April 2002
    - Y. Huang, H. Xiong, S. Shekhar, and J. Pei, Mining Confident Co-location Rules without A Support Threshold, in ***Proc. of 18th ACM Symposium on Applied Computing (ACM SAC)***, March 2003
    - Y. Huang, S. Shekhar, and H. Xiong, Discovering Co-location Patterns from Spatial Datasets: A General Approach, submitted to ***IEEE Transactions on Knowledge and Data Engineering (TKDE)***

Biography

- ⋆ Vector Map Compression
  - S. Shekhar, Y. Huang, J. Djugash, and C. Zhou, Vector Map Compression: A Clustering Approach, in ***Proc. of 10th ACM Intl. Symposium. on Advances in Geographic Information Systems (ACM-GIS)***, November 2002
  - S. Shekhar, Y. Huang, and J. Djugash, Dictionary Design Algorithms for Vector Map Compression, In ***Proc. of IEEE Data Compression Conference (DCC)***, April 2002
- ⋆ Spatial Time-series Correlation Join
  - P. Zhang, Y. Huang, S. Shekhar, and V. Kumar, Efficient Algorithms for Correlation Join over Spatial Time-series Datasets, to appear in ***Prof. of 7th Pacific-Asia Conference on Knowledge Discovery and Data Mining (PAKDD)***, 2003
- ⋆ Misc - Spatial Data Mining
  - S. Shekhar, Y. Huang, W. Wu, C.T. Lu, and S. Chawla, What's Spatial about Spatial Data Mining: Three Case Studies, book chapter: ***Data Mining for Scientific and Engineering Applications***, R. Grossman, C. Kamath, P. Kegelmeyer, V. Kumar, R. Namburu (eds.), ISBN1-4020-0033-2, Kluwer Academic Publishers, 2001

Overview

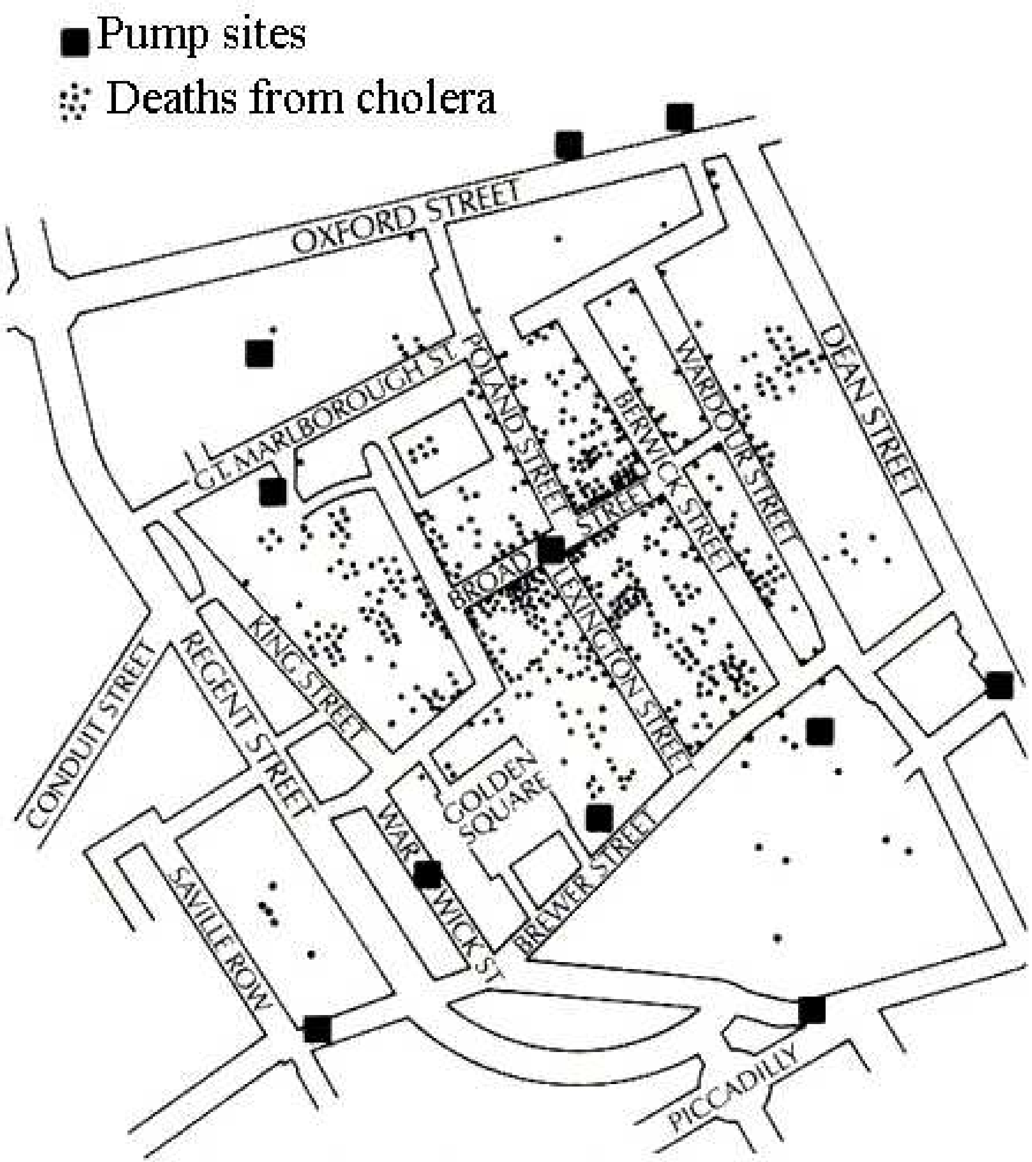
- ⇒ Introduction
- ⋆ Related Work
- ⋆ Event Centric Approach
- ⋆ Co-location Miner Algorithm
- ⋆ Evaluation
- ⋆ Conclusions and Future Work

Spatial data mining (SDM)

- The process of discovering
  - interesting,useful, non-trivial patterns
  - from large spatial datasets
- Spatial patterns
  - Spatial outlier, discontinuities
    - bad traffic sensors on highways (DOT)
  - Location prediction models
    - model to identify habitat of endangered species
  - Spatial clusters
    - crime hot-spots (NIJ), cancer clusters (CDC)
  - Co-location patterns
    - predator-prey species, symbiosis
    - Dental health and fluoride
    - Chromium 6 used by PG&E, health problems in Hinkley CA

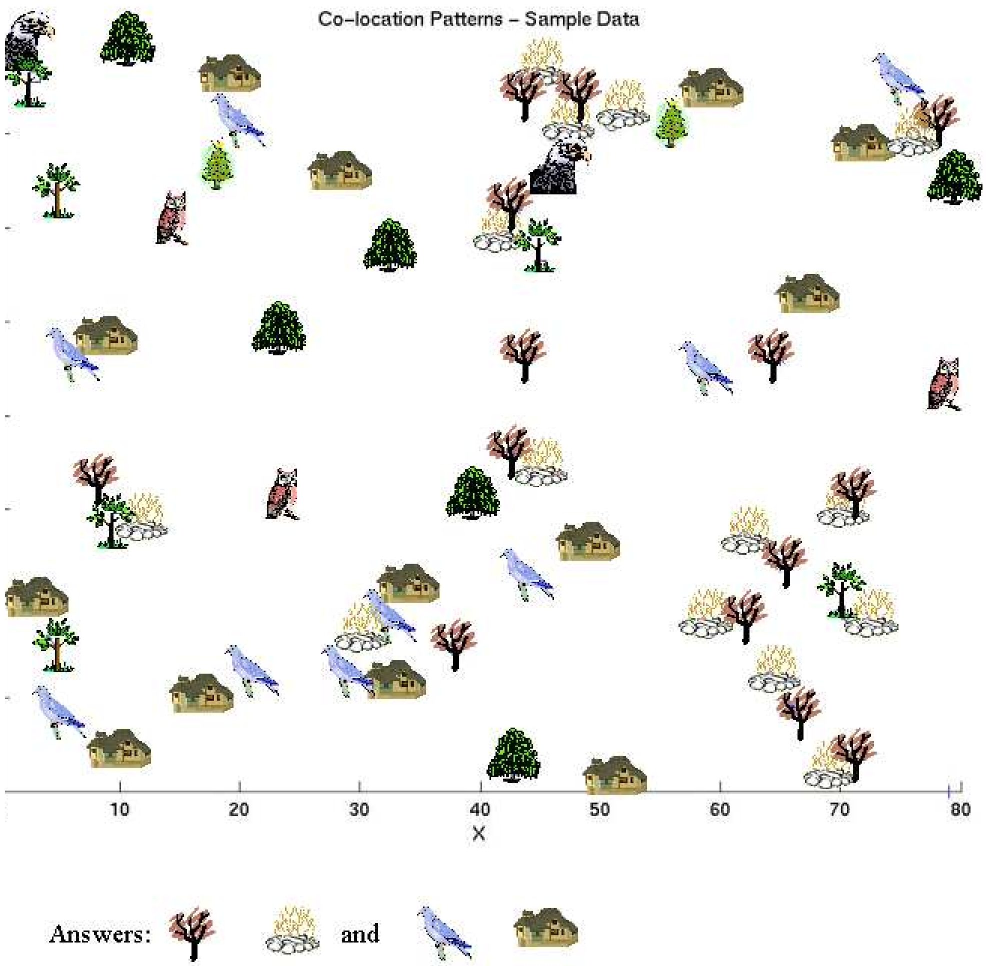
Example Spatial Pattern: Spatial Cluster

⋆ 1854 cholera epidemic London map



Example Spatial Pattern: Co-locations

- Given:
  - A collection of different types of spatial events
- Illustration



- Find: Co-located subsets of event types

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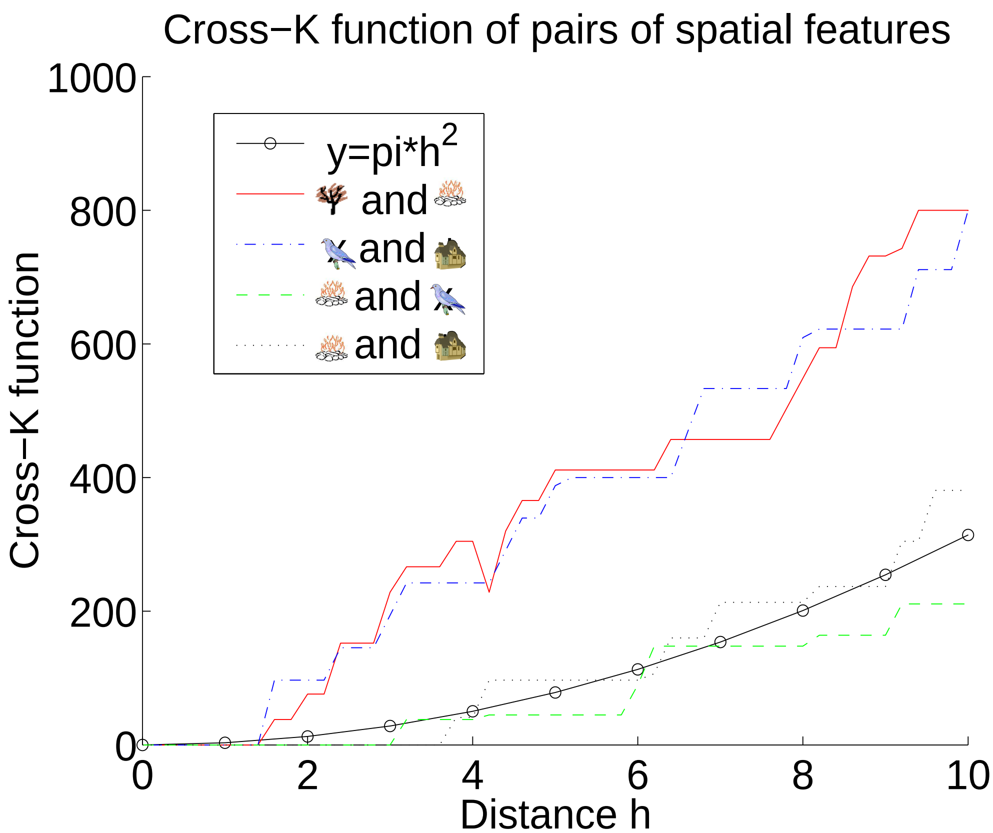
Related Work

- Spatial statistical approach
- Classical data mining association rule approach
  - Reference feature approach
  - Partitioning approach

Related Work: Statistical Approach

- Ripley's K-function:
  - $K_{ij}(h) = \lambda_j^{-1} E$ [number of type j event within distance h of a randomly chosen type i event]
  - Ripley's K-function of some pair of spatial feature types



- Properties:
  - Not well defined for size ≥ 3
  - Expensive Monte Carlo simulation for confidence band

Association Rules - An Analogy

- Association rule e.g. (Diaper in T $\Rightarrow$ Beer in T)

rans.	Items Bought
	{socks,  milk, , beef, egg, ... }
	{ pillow,  , toothbrush, ice-cream, muffin, ... }
	{  ,  , pacifier, formula, blanket, ... }
.	...
	{battery, juice, beef, egg, chicken, ... }

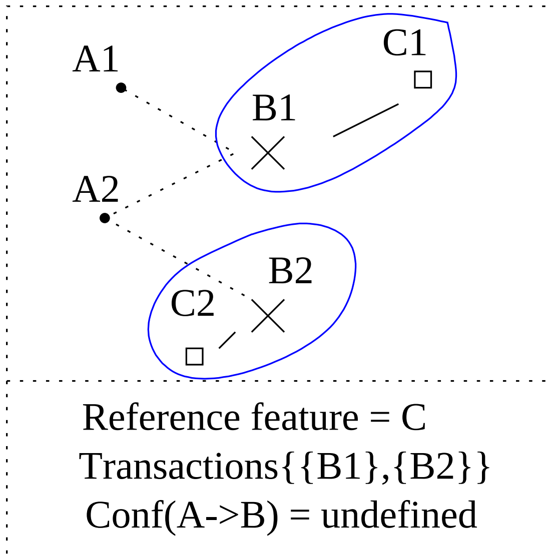
  - Support: probability(Diaper and Beer in T) = 2/5
  - Confidence: probability(Beer in T$|$Diaper in T)= 2/2

- Algorithm Apriori [Agrawal, Srikant, VLDB94]
  - Support based pruning using monotonicity

- Note: **Transaction is a core concept!**

Related Work: Association Rule Approach

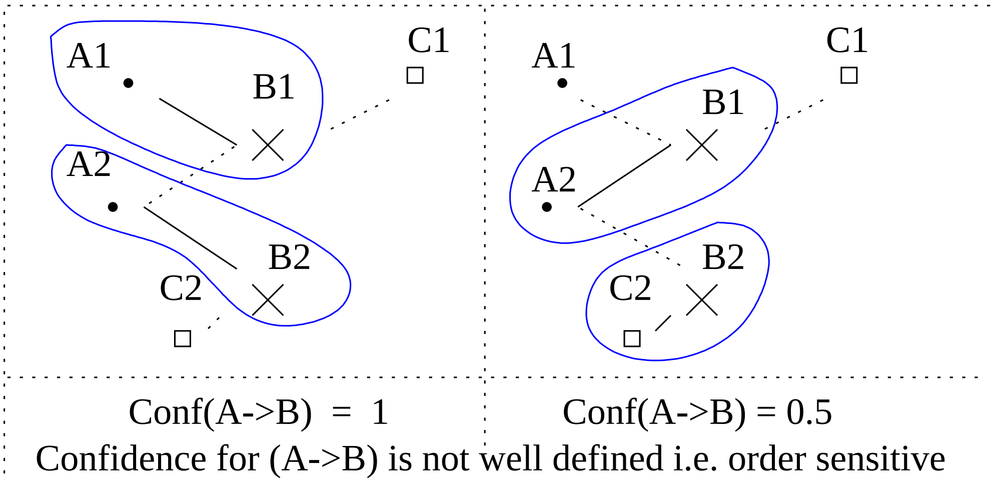
- Reference feature centric model [Koperski, Han, SSD95]



- Properties
  - All relevant co-locations reference to one feature
  - Item types = boolean spatial features
  - Transactions = defined around instances of reference feature
  - Force-fit notion of transaction
- Limitations
  - May under-count support for a pattern, e.g (A,B)
  - May over-counter support
  - Results not comparable with spatial statistical approach

Related Work: Association Rule Approach

* Partitioning approach [Morimoto, SIGKDD01]



* Properties
  * Divide dataset into partitions
  * Item types = boolean spatial features
  * Transactions = partitions
* Limitations
  * Order sensitive transactions
  * Support and confidence are ill-defined

Limitation of Related Work and Our Contributions

- Limitation of Related Work
  - Expensive computation
  - Force-fit transaction on spatial dataset
- Our Contributions
  - Event centric co-location model
    - Robust in face of overlapping neighborhoods
  - Co-location Miner algorithm
    - Computational efficiency
  - High confidence low prevalence co-location patterns
  - Validity of inferences

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Our Approach: Event Centric Model

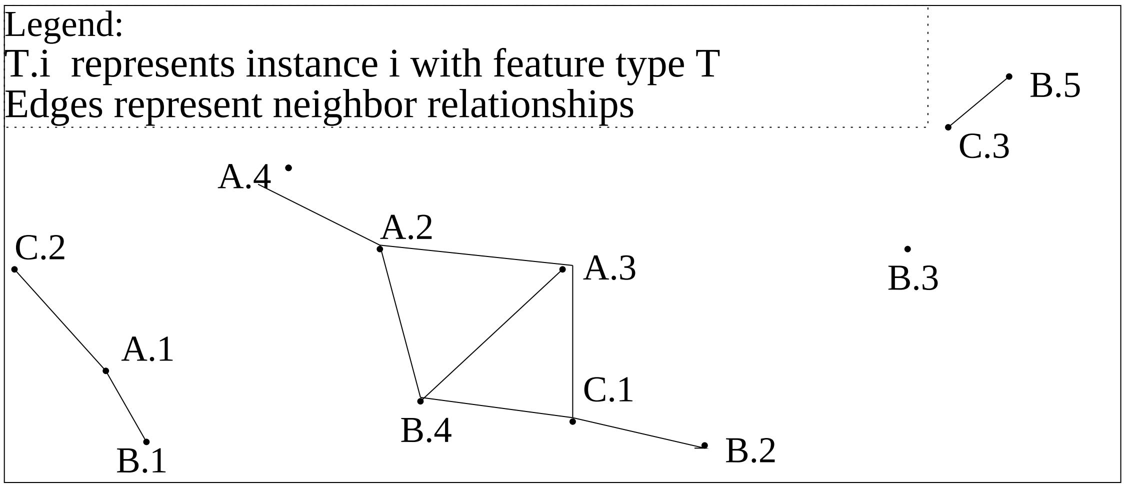
⋆ Association Rules Vs. Co-location Rules

Criteria	Association Rule	Co-location Rule
Underlying Space	Discrete Sets	Continuous Space
Item Types	Product types	Spatial Features(Boolean)
Item Collections	Transactions $\{T_i\}$	**Neighborhoods**
Prevalence ($A \rightarrow B$)	Support: $p(A \cup B \in T_i)$	Participation Index
Conditional Probability ($A \rightarrow B$)	$p(B \in T_i \mid A \in T_i)$	$p(B \in \mathrm{Nbr}(L) \mid A\, at\, L)$

⋆ An example: A happens $\rightarrow$ B happens in A's neighborhood with 100% conditional probability

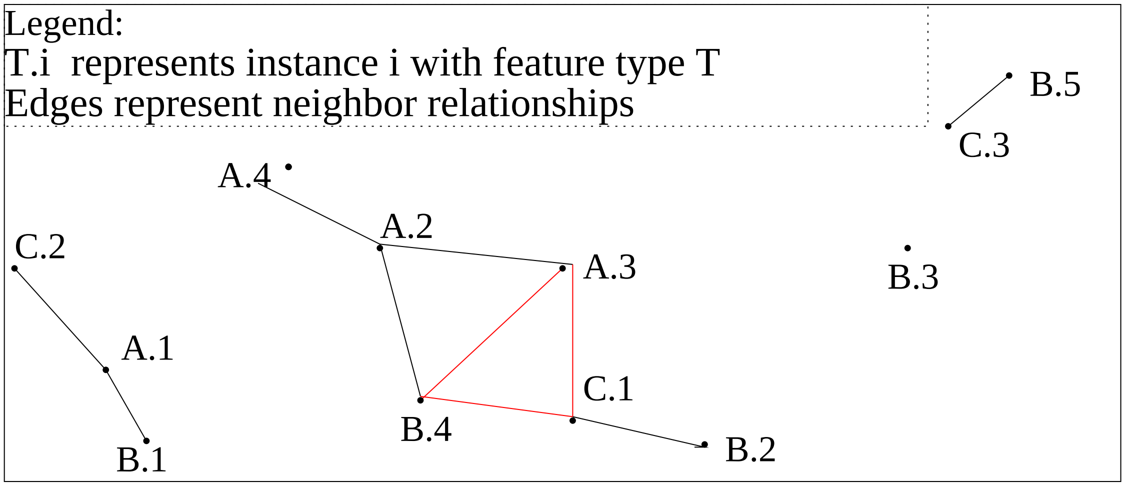
Key Concepts

⋆ Example Dataset



Key Concepts

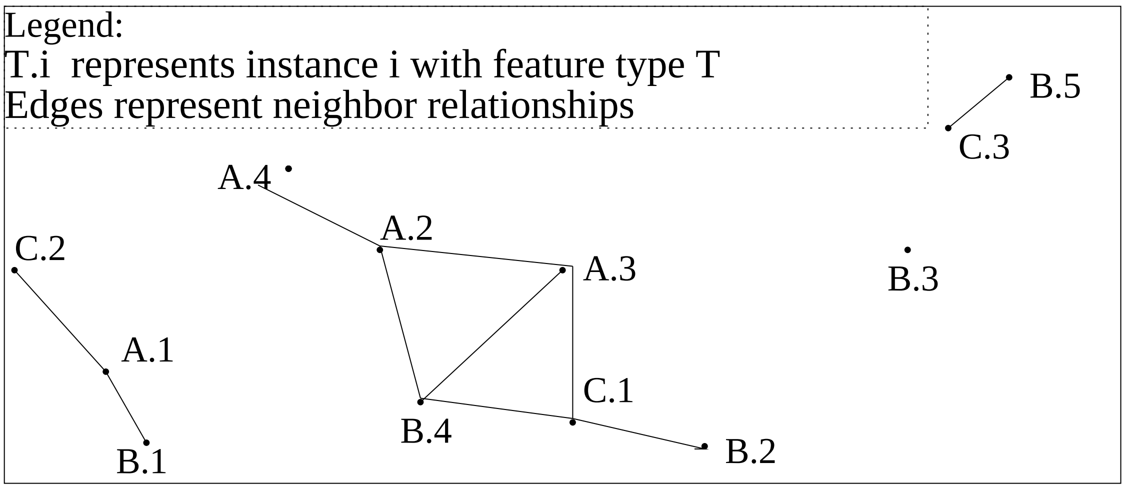
- Example Dataset

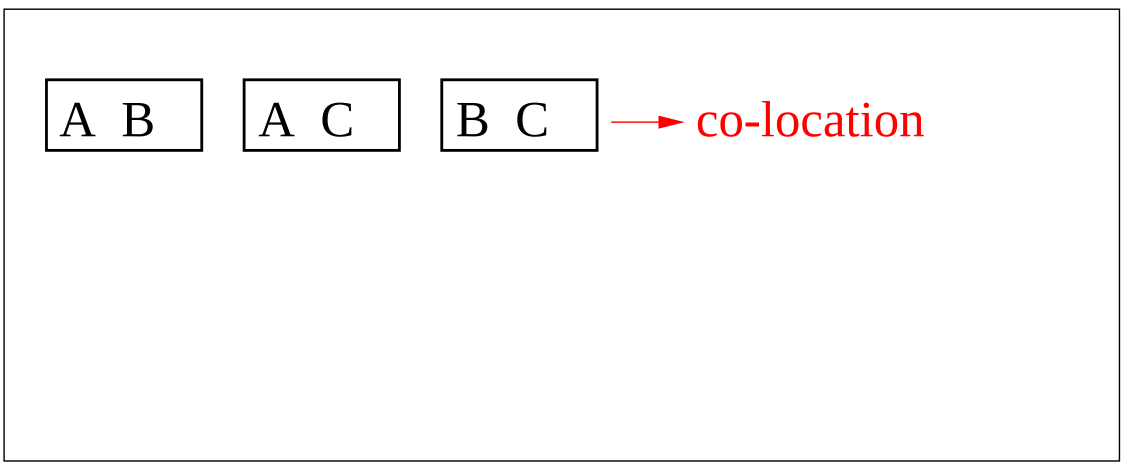


- A **neighborhood:**
  - A clique in a graph of neighbor relation R

Key Concepts

⋆ Example Dataset



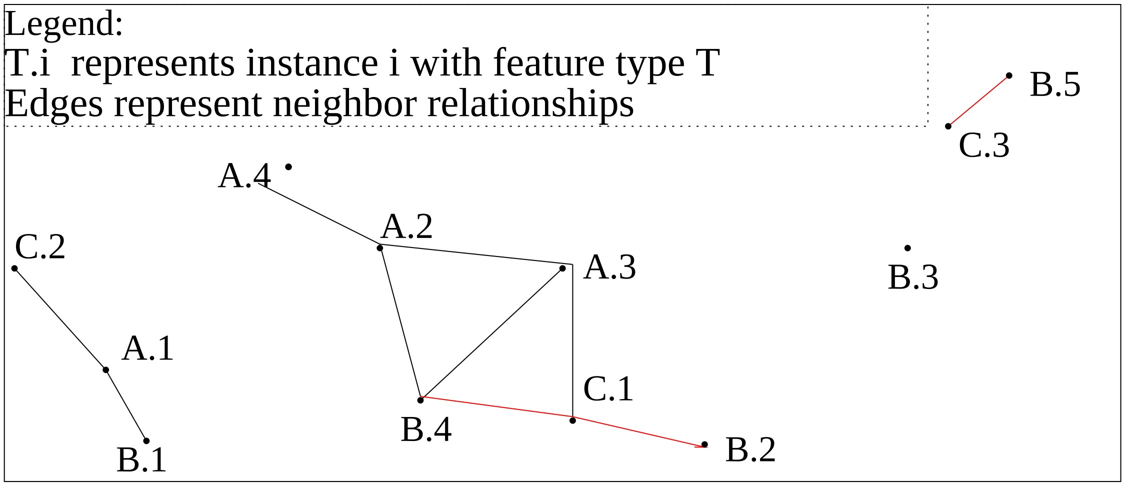


⋆ A **co-location** C:

- ⋆ A subset of boolean spatial features

Key Concepts

⋆ Example Dataset



A	B
1	1
2	4
3	4

A	C
1	2
3	1

B	C
2	1
4	1
5	3

→ co-location

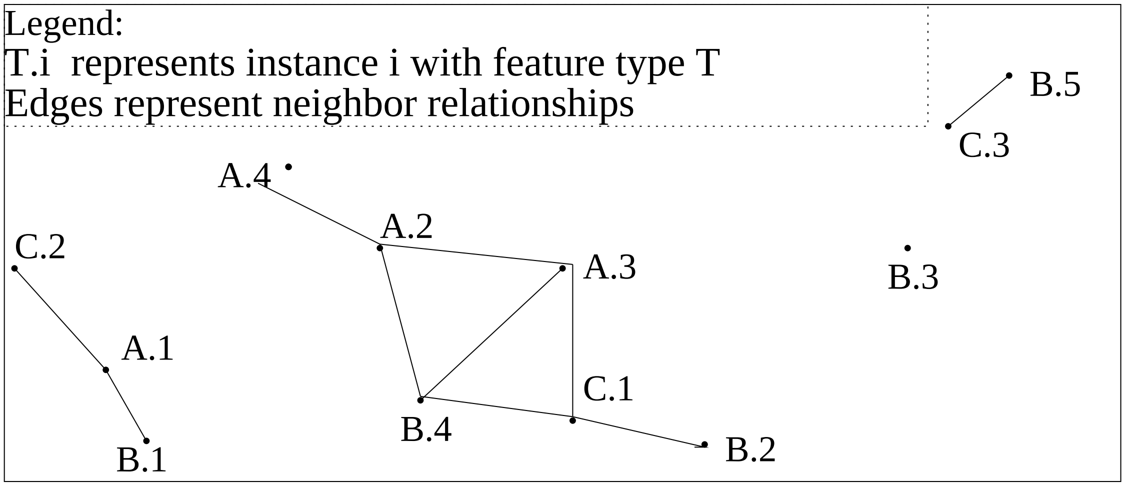
→ row instance

⋆ A **row instance** I of a co-location $C = \{f_1, \ldots, f_k\}$:

- ⋆ $I = \{i_1, \ldots, i_k\}$
- ⋆ i_j: instance of $f_j (\forall j \in 1, \ldots, k)$
- ⋆ I is a neighborhood

Key Concepts

⋆ Example Dataset



t4

A	B
1	1
2	4
3	4

t5

A	C
1	2
3	1

t6

B	C
2	1
4	1
5	3

table Id

co-location

row instance

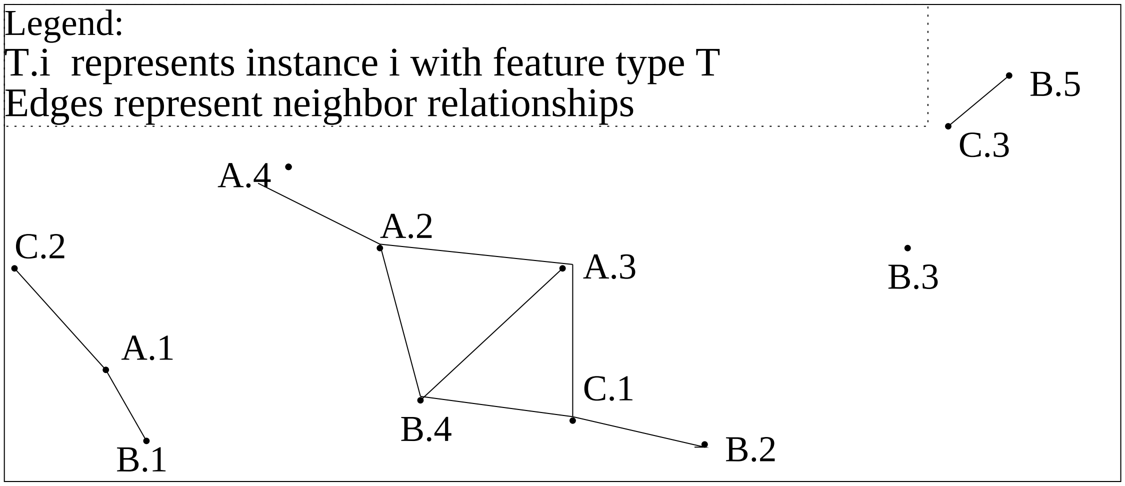
table instance

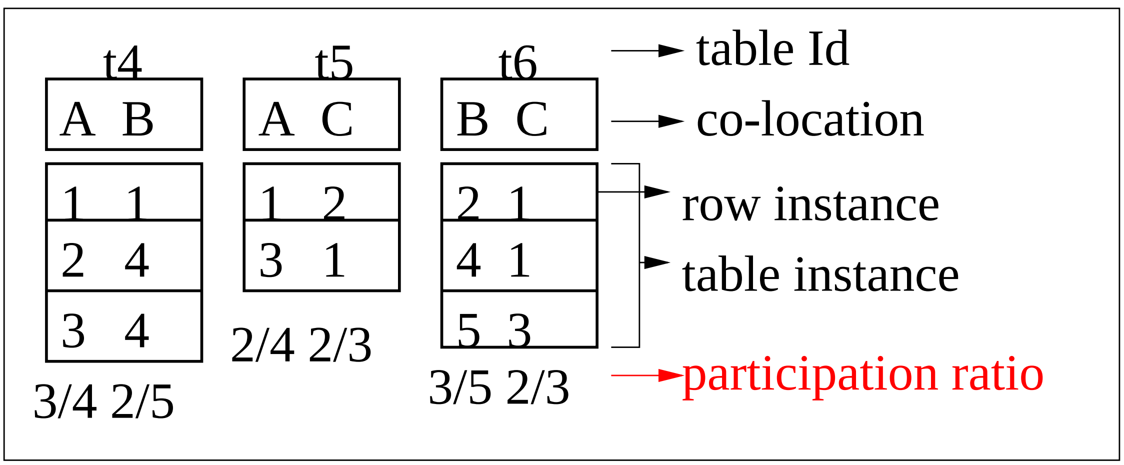
⋆ **Table instance**(co-location $C = \{f_1, \ldots, f_k\}$):

- ⋆ Collection of all its row instances
- ⋆ Spatial join interpretation

Key Concepts

* Example Dataset

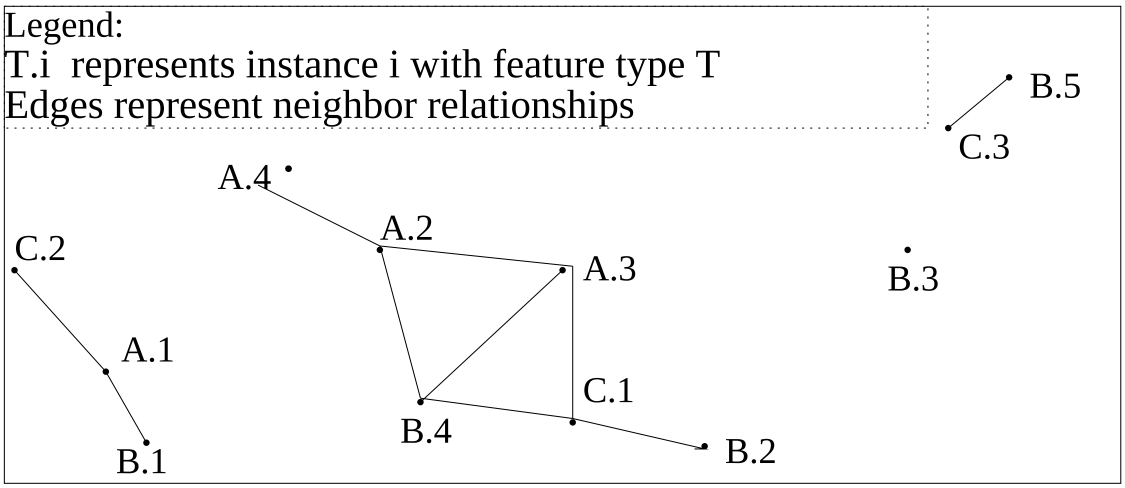


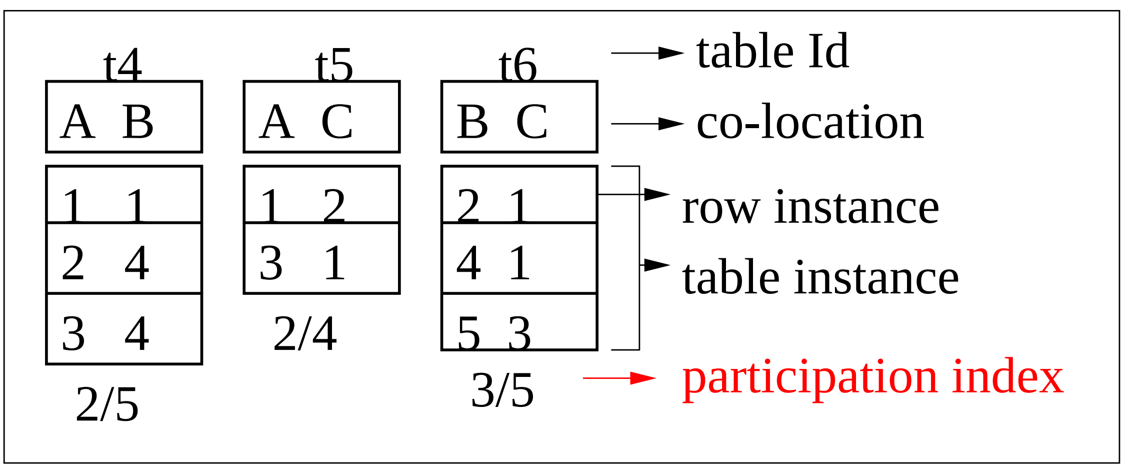


* **Participation ratio**
  * $pr(C, f_i) = |\pi_{f_i} table\, instance(C)| / |instances(f_i)|$
  * $C = \{f_1, f_2, \ldots, f_k\}$
  * Co-location strength of a spatial feature in a pattern

Key Concepts

- Example Dataset





- The **participation index**
  - $pi(C) = min_{i=1}^{k} pr(C, f_i)$
  - Co-location strength of a pattern

Key Concepts

* A **neighborhood:**
  * A clique in a graph of neighbor relation R
* A **co-location** C:
  * A subset of boolean spatial features
* A **row instance** I of a co-location $C = \{f_1, \ldots, f_k\}$:
  * $I = \{i_1, \ldots, i_k\}$
  * i_j: instance of $f_j (\forall j \in 1, \ldots, k)$
  * I is a neighborhood
* **Table instance**(co-location $C = \{f_1, \ldots, f_k\}$):
  * Collection of all its row instances
  * Spatial join interpretation

Key Concepts

- **Participation ratio (PR)**
  - $pr(C, f_i) = |\pi_{f_i} table\,instance(C)| / |instances(f_i)|$
  - $C = \{f_1, f_2, \ldots, f_k\}$
- **Participation index (PI)**
  - $pi(C) = min_{i=1}^{k} pr(C, f_i)$
- **Lemma 1** [Monotonicity] Participation ratio and participation index are monotonically decreasing with respect to co-location size
  - Proof:
    - An instance of A participates in $\{A, B, \ldots\}$, it must participate in $\{A, B\}$
    - PR is monotonic
    - PI is the minimal of PR, monotonic too
- A **co-location rule** $C_1 \rightarrow C_2(p, cp)$:
  - C_1 and C_2 are co-locations
  - p = prevalence measure, e.g. participation index
  - cp = Pr[$C_2 \in$ N(L) | C_1 @ L]= $\frac{|(\pi_{C_1}(table\,instance\,of\ (C_1 \cup C_2))|}{|instance\,of\,C_1|}$
    - π is a projection operation

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Problem Formulation

- Given:
  - K Boolean spatial feature types
  - Instances <id, feature type t , location l >
  - A neighbor relation R over locations
  - Prev_threshold and cp_threshold
- Find:
  - Co-location rules with prevalence > prev_threshold and conditional probability > cp_threshold
- Objectives:
  - Efficiency
- Constraints:
  - Correctness
    - Every co-location found has prevalence > prev_threshold and conditional probability > cp_threshold
  - Completeness
    - Find all the co-locations with prevalence > prev_threshold and conditional probability > cp_threshold
  - Monotonic prevalence measure
  - Event centric model

Revisit related work in light of problem formulation

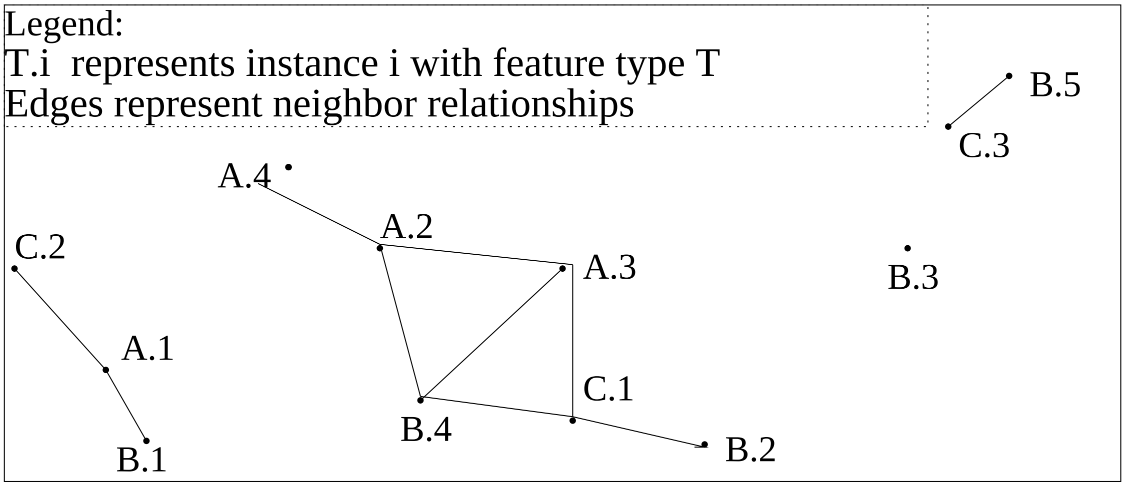
	Correct	Complete	Efficient
K function	Y	Y	N
Reference feature centric	N	N	Y
Partitioning	N	N	Y
Event centric	Y	Y	Y

Co-location Miner Algorithm: Basic Idea

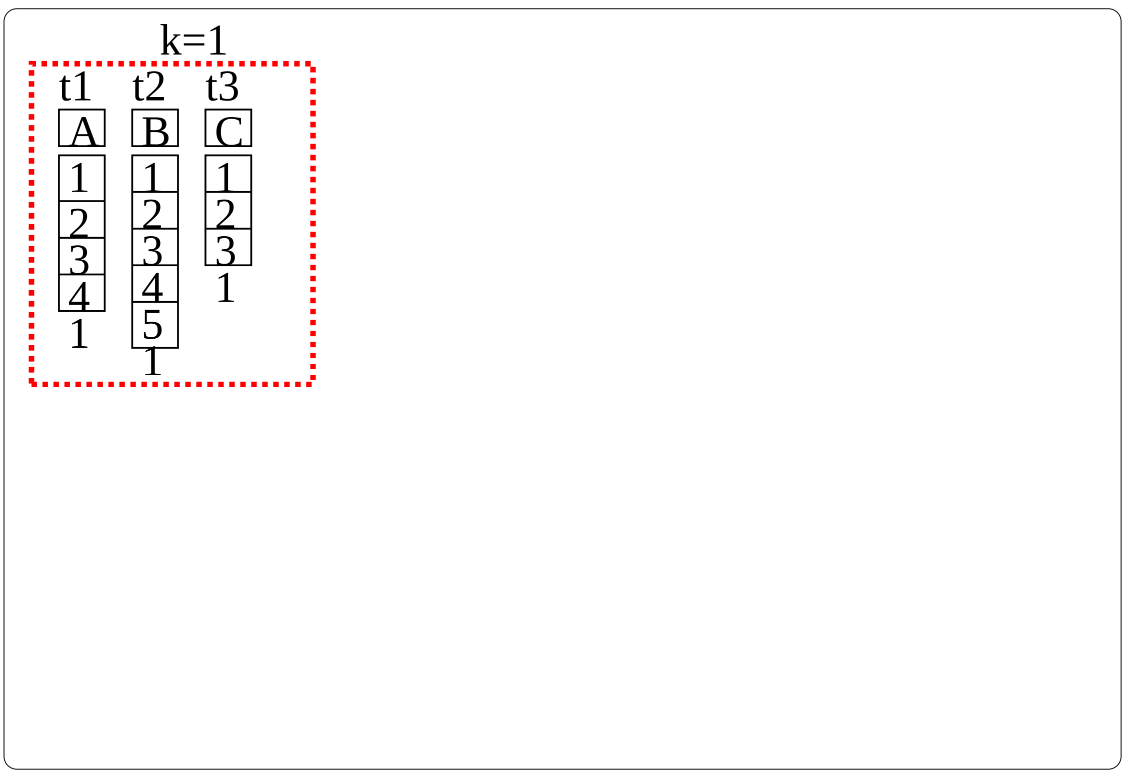
- Initialization
- **for** k in $(2, 3, \ldots, K-1)$ **and** prev. co-location found **do**
  - 1.Generate size k candidate co-locations
  - 2.Multi-resolution or other filtering methods
  - 3.Generate table instances
  - 4.Calculate prevalence and select prevalent co-locations
  - 5.Generate co-location rules of size k
- **end**
- Note: Step 3 not needed in mining association rules
  - because item collections (i.e. transactions) are given

Algorithm Trace

⋆ Running Example



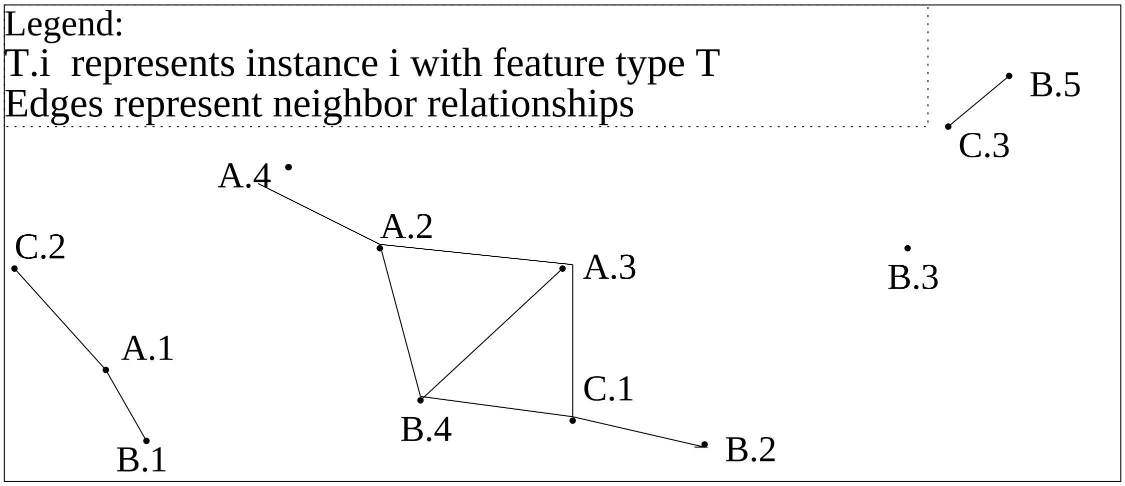
⋆ Running Example



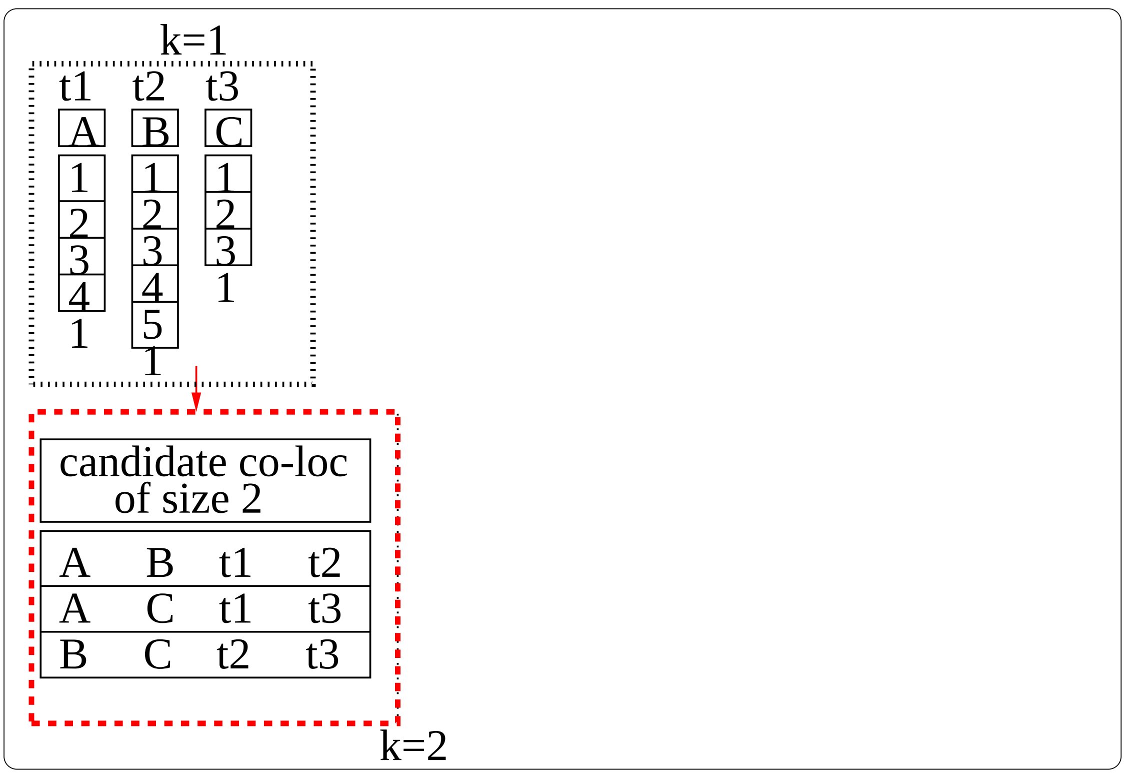
⋆ Initialization

Algorithm Trace

- Running Example



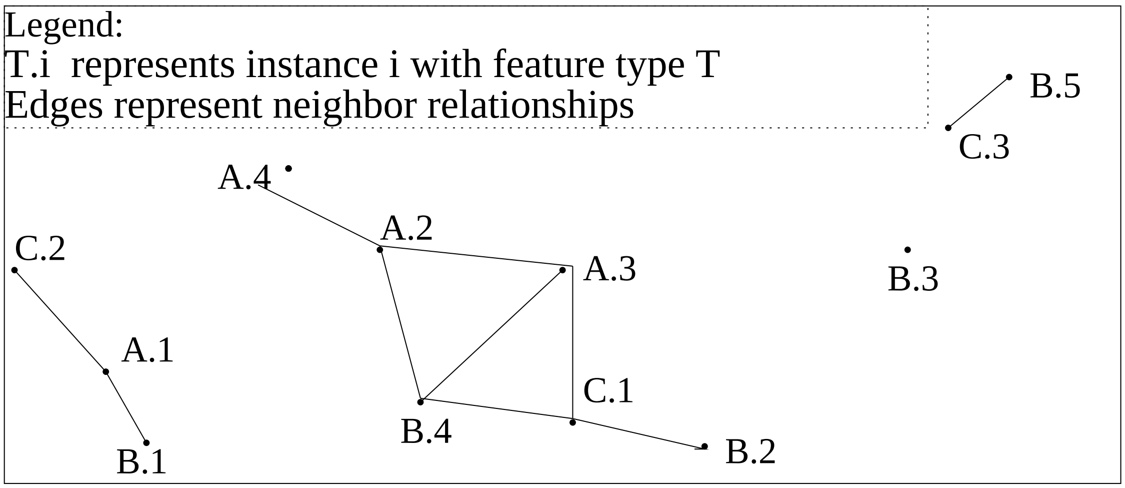
- Running Example



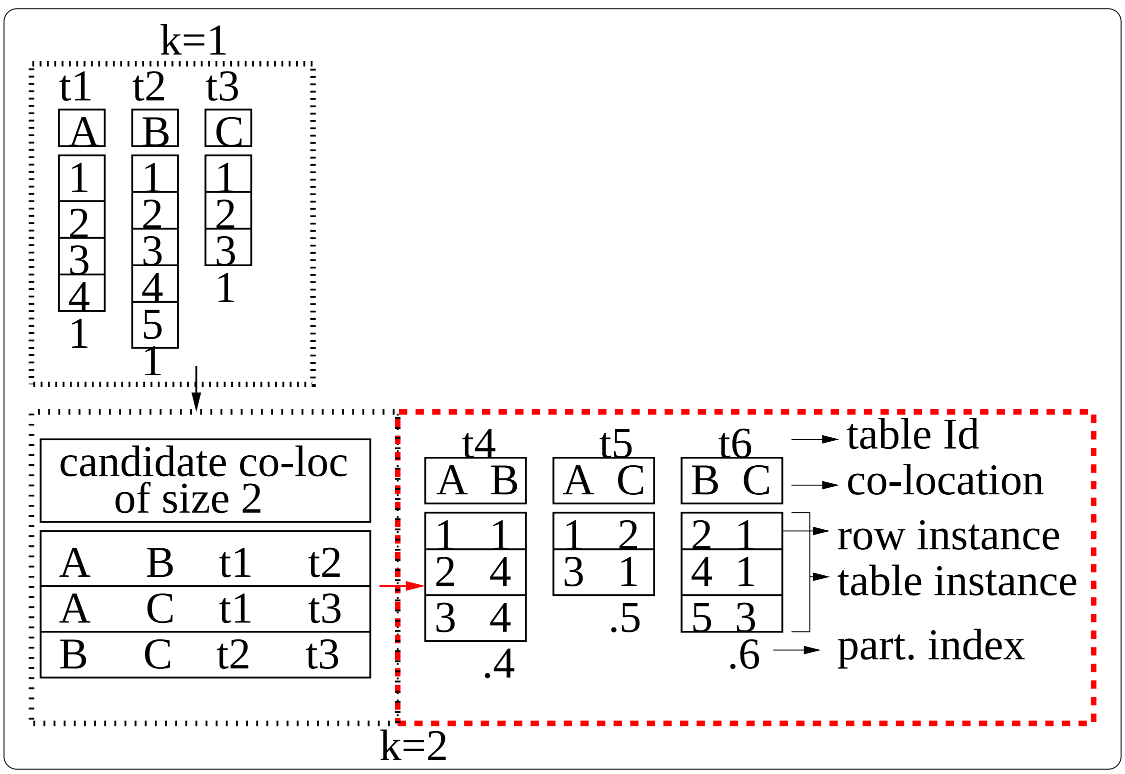
- $k = 2$, generate size 2 candidate co-locations (step 1)

Algorithm Trace

⋆ Running Example



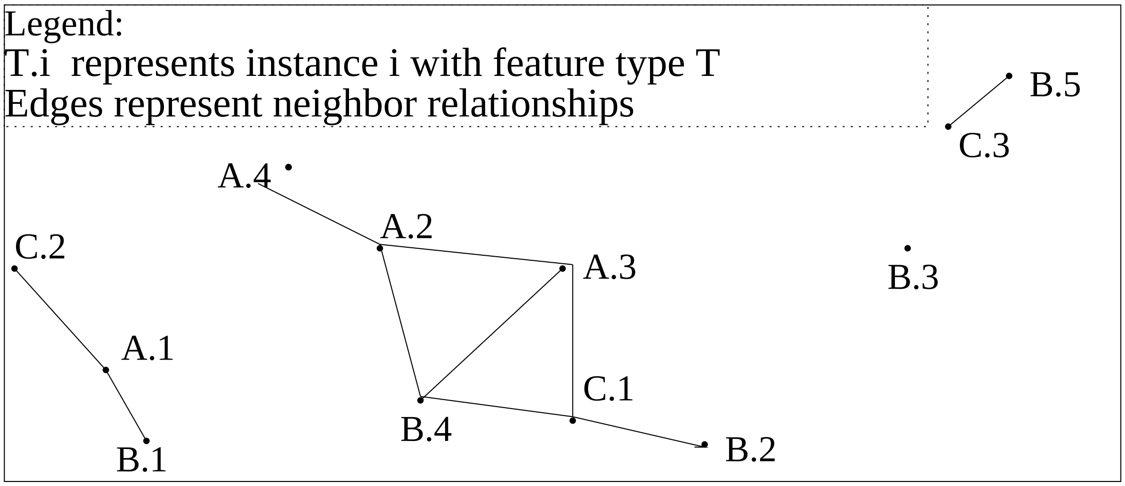
⋆ Running Example



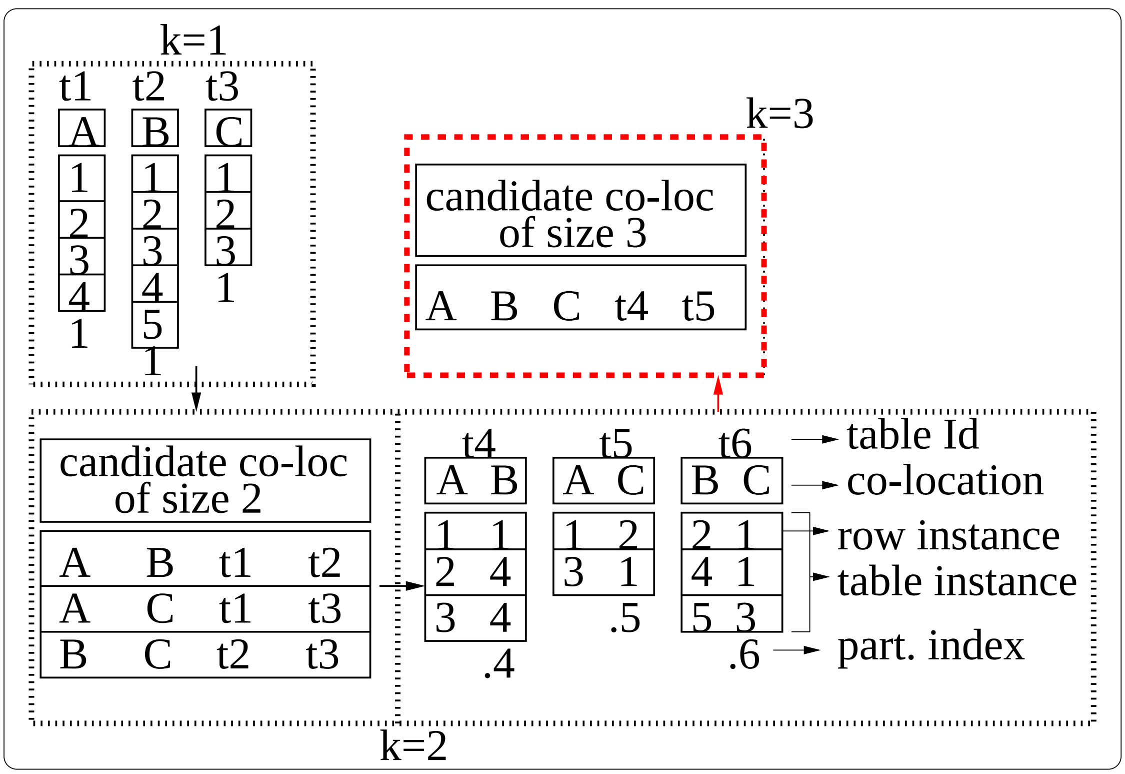
⋆ $k = 2$, generate size 2 table instances ... (steps 3,4,5)

Algorithm Trace

⋆ Running Example



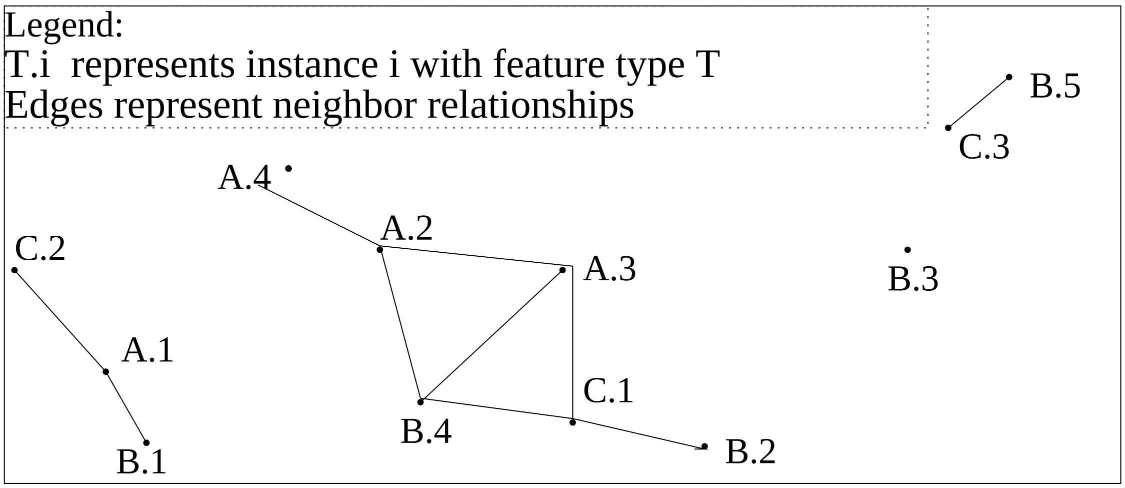
⋆ Running Example



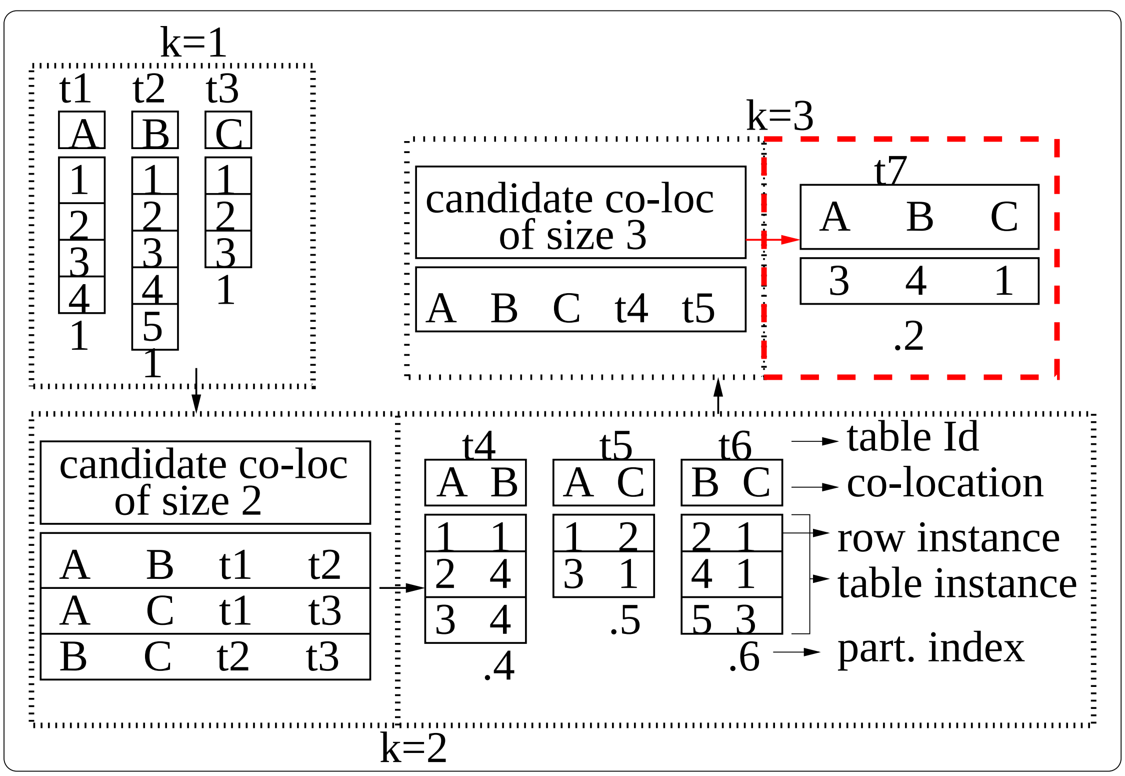
⋆ $k = 3$, generate size 3 candidate co-locations (step 1)

Algorithm Trace

⋆ Running Example



⋆ Running Example



⋆ $k = 3$, generate size 3 table instances .. (steps 3,4,5)

Some Details of Co-location Miner

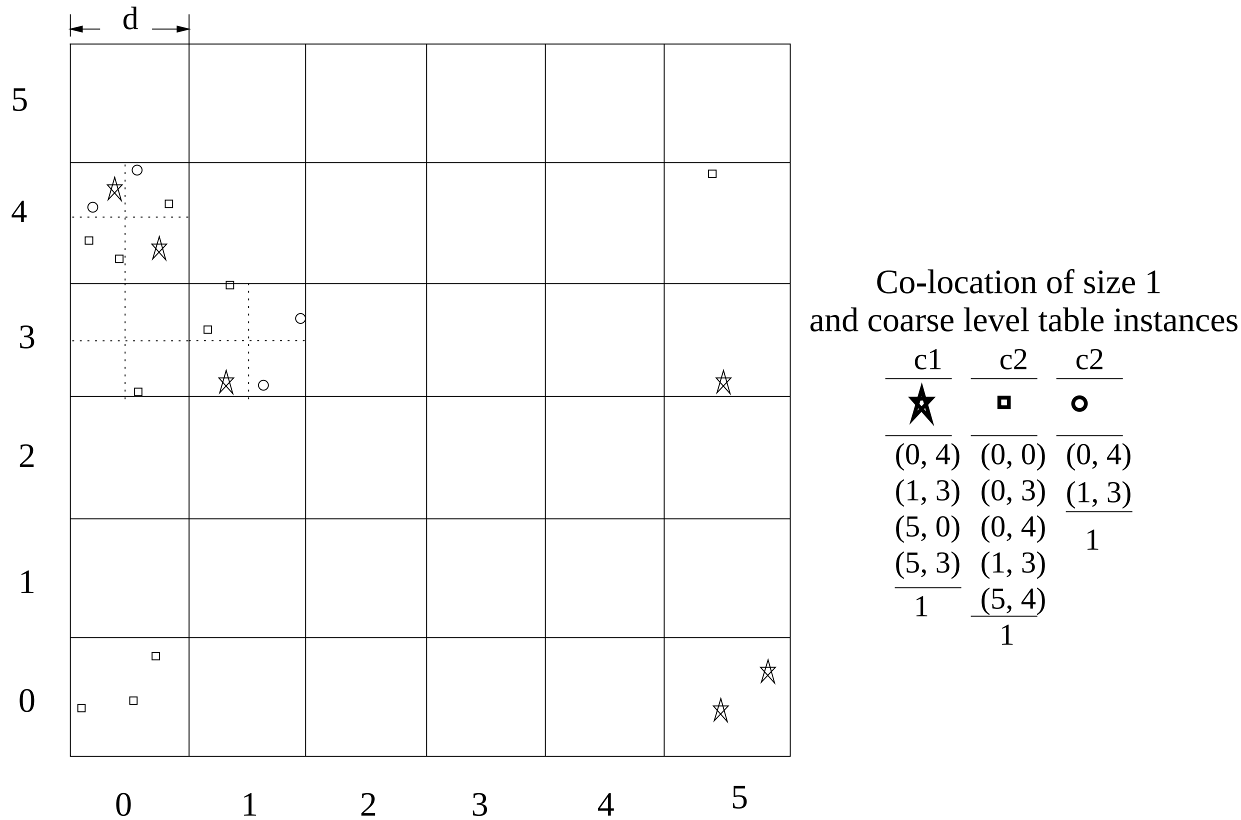
- Generate candidate co-locations
  - Similar to that in association rule mining
- Participation indexes calculation
  - Bitmap index based
  - One scan of table instances in current iteration
- Co-location rule generation
  - Conditional probability of co-location rule $C_1 \rightarrow C_2$
    - $\frac{|(\pi_{C_1}(table\, instance\, of\ (C_1 \cup C_2))|}{|instance\, of\, C_1|}$
  - Bitmaps or other data structures
  - Similar strategies for prevalence based pruning

Performance Tuning

- An optional filter
  - Multi-resolution filter
  - Hierarchical structure, e.g. grid files and R-tree
  - Reuse bitmaps in the previous iteration
- Join strategies for generating table instances
  - Geometric: plane sweep, space partition, and tree matching
  - Combinatorial
  - Hybrid

A Multi-resolution Filter

- Illustration:



- Process
  - Summarize data at a coarse resolution
  - Generate coarse level table instances
  - Calculate over-estimated participation index
  - Eliminates a co-location if its over-estimated index falls below user give threshold

Join Strategies

- Geometric
  - In practice use filter and refine
  - Minimum bounding rectangle
  - then exact geometry and predicates are considered
- Combinatorial
  - Sort-merge join strategy
    - Match the first k-1 instances
    - Efficient since instances of co-locations are sorted already
  - then check if the last two instances are neighbors
- Hybrid
  - Choose the more promising of the
    - spatial and combinatorial approaches
    - in each iteration

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Analytical Evaluation: Correctness and Completeness

- Definition:
  - Completeness:
    Find all rules with prevalence > prev_threshold and conditional probability > cp_threshold
  - Correctness:
    Any rules found have prevalence > prev_threshold and conditional probability > cp_threshold
- Lemma
  - Co-location Miner is complete and correct
- Proof Sketch
  - Participation index is monotonic in size of co-location
  - Any subset of a prevalent co-location is prevalent
  - Table join will not miss any row instance

Analytical Evaluation: Ascertaining the Quality of the Inferences

- $pi(A, B)$ is an upper bound on $\frac{\hat{K_{AB}}(h)}{W}$
  - $\hat{K_{AB}}(h)$ is the estimation of the $K(A, B)$
  - W is the total area defined by distance $\leq h$
- Table instance $t(A, B)$ of a binary co-location (A, B)
  - has enough information to compute $\hat{K_{AB}}(h)$
  - for $h = d$
  - $\frac{\hat{K}_{AB}(h)}{W} = \frac{1}{|A|} \cdot \frac{|t(A,B)|}{|B|}$

Analytical Evaluation: Choice of Join Strategies

- Geometric
  - keep information of nearby regions
  - Lack spatial feature type level pruning
- Combinatorial
  - benefits from spatial feature type level pruning
  - do not keep spatial proximity information
- Hybrid: integrate the best features of the two join strategies

Analytical Evaluation: When to Use Additional Filtering

- Running time ratio without/with filtering:

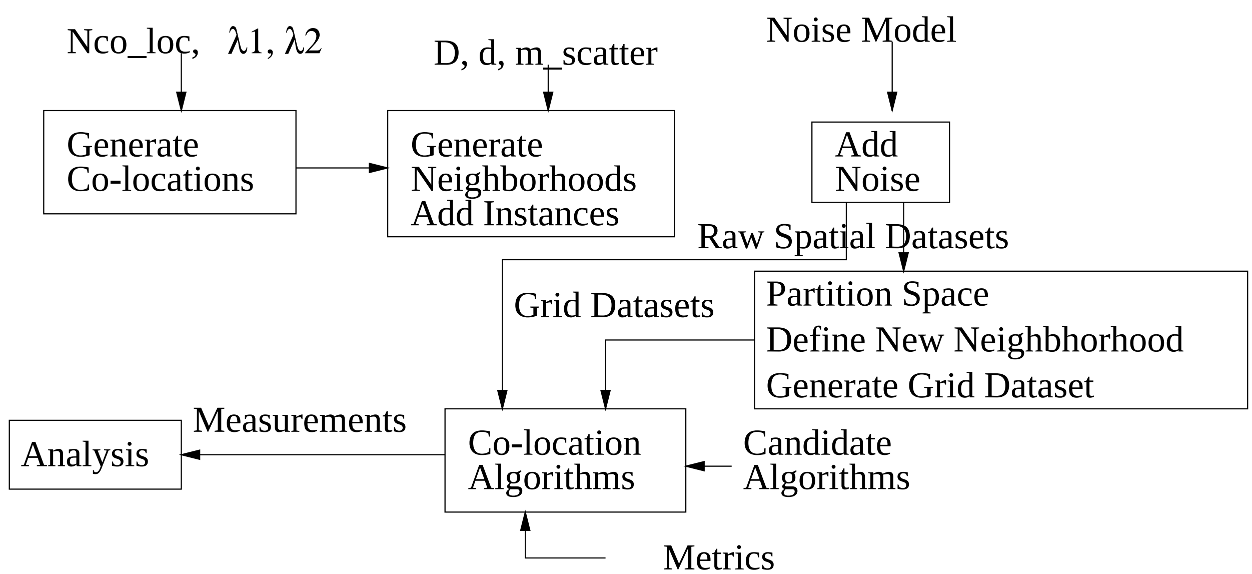
$$\begin{aligned}\frac{t_{filter}(k)}{t(k)} &\approx \frac{|C_{k+1}| \times T_{grid}(k) + |C'_{k+1}| \times T_{orig}(k)}{|C_{k+1}| \times T_{orig}(k)} \\ &= \frac{T_{grid}(k)}{T_{orig}(k)} + \frac{|C'_{k+1}|}{|C_{k+1}|}\end{aligned} \quad (1)$$

  - C_{k+1}: number of size k+1 candidates before filtering
  - C'_{k+1}: number of size k+1 candidates after filtering
  - $T_{grid}(k)$: average time for a coarse level table instance
  - $T_{orig}(k)$: average time for a fine level table instance

- Choice of filtering is affected by
  - Filtering ratio
  - Dataset clustering level

Performance Evaluation

- Experiment goals
  - How do join strategies affect the performance?
  - When to use additional filtering?
- Experiment Design



- Setup
  - Sun Ultra 10 work station
  - with a 440 MHz CPU
  - 128 Mbytes memory
  - running the SunOS 5.7 operating system

Performance Evaluation

⋆ Parameters

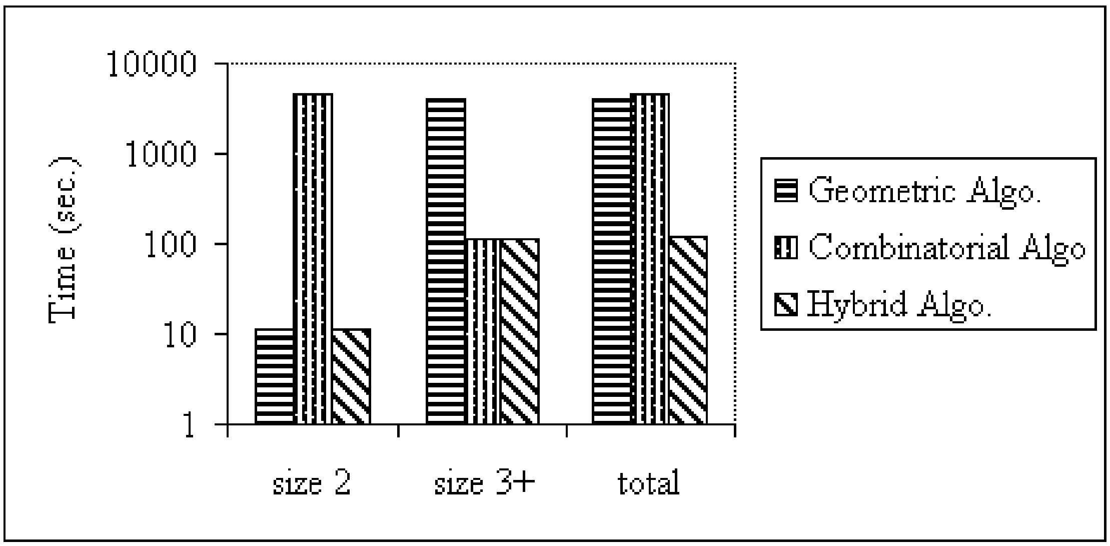
Parameter	Definition	C
N_{co_loc}	The number of core co-locations	5
λ_1	The parameter of the Poisson distribution to define the size of the core co-locations	5
λ_2	The parameter of the Poisson distribution to define the size of the table instance of each co-location when $m_{clump} = 1$	50
$D_1 \times D_2$	The size of the spatial framework	$10^6 \times 10^6$
d	The size of the square to define a co-location	10
r_{noise_f}	The ratio the of number of noise features over the number of features involved in generating the maximal co-location s	.5
r_{noise_n}	The number of noise instances	50,000
$m_{overlap}$	The number of co-location generated by appending one more spatial feature for each core co-location	1
m_{clump}	The number of instances generated for each spatial feature in a neighborhood for a co-location	1

⋆ Report results on a representative dataset C

- ⋆ Variable parameters of dataset C are reported for each experiment

Performance Evaluation

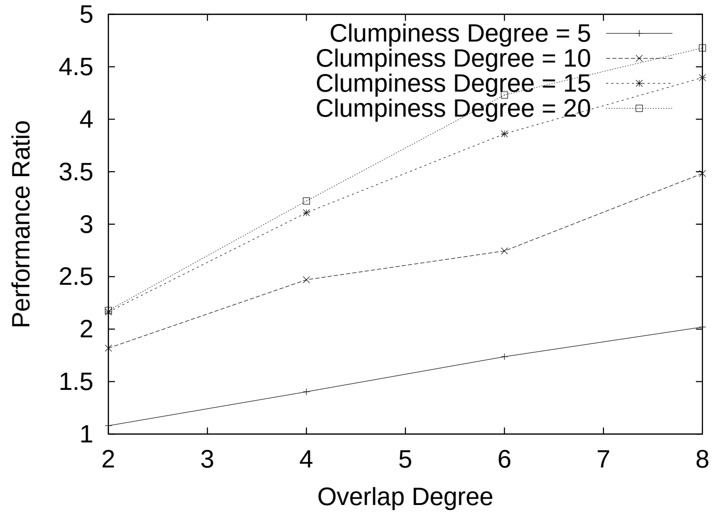
- Relative performance of geometric, combinatorial, and hybrid join strategies
  - Prevalence threshold set to 0.9
- Result



  - Geometric: faster to generate co-locations of size 2
  - Combinatorial: faster (magnitude of 2) to generate co-locations of size 3+
  - Hybrid: combine geometric and combinatorial

Performance Evaluation

- ⋆ Effect of multi-resolution filtering
- ⋆ Variable parameter:$m_{overlap}$ from 2 to 8
- ⋆ Result:

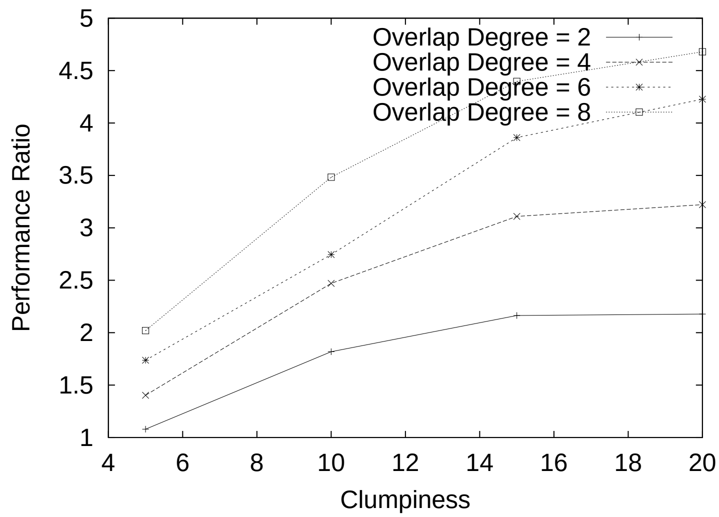


- ⋆ Multi-resolution filtering is effective especially when overlapping degree is high
- ⋆ Algebraic explanation:

$$\frac{t_{filter}(k)}{t(k)} \approx \frac{T_{grid}(k)}{T_{orig}(k)} + \frac{|\mathbf{C'_{k+1}}|}{|\mathbf{C_{k+1}}|} \tag{2}$$

Performance Evaluation

- ⋆ Effect of multi-resolution filtering
- ⋆ Variable parameter:m_{clump} from 5 to 20
- ⋆ Result:

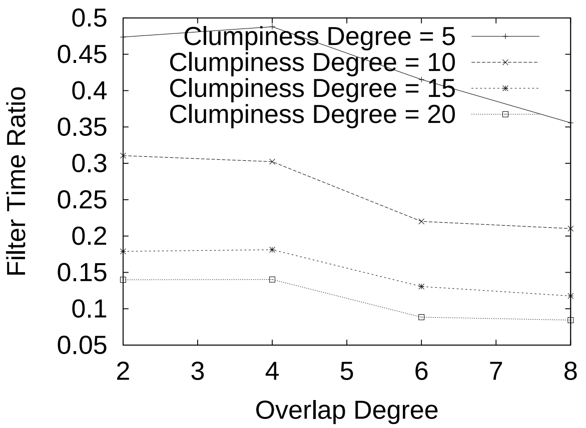


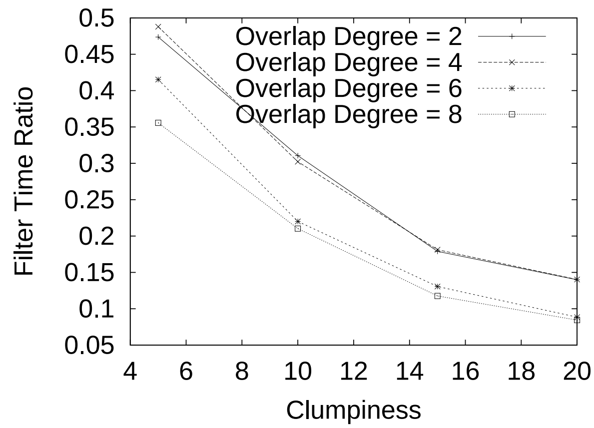
  - ⋆ Multi-resolution filtering is effective especially when dataset is clustered
  - ⋆ Algebraic explanation:

$$\frac{t_{filter}(k)}{t(k)} \approx \frac{\mathbf{T_{grid}(k)}}{\mathbf{T_{orig}(k)}} + \frac{|C'_{k+1}|}{|C_{k+1}|} \tag{3}$$

Performance Evaluation

⋆ Effect of multi-resolution pruning: filter time ratio





⋆ Filter time ratio

- ⋆ Filter time is 10% to 50% of the total running time

Overview

- ⋆ Introduction
- ⋆ Related Work
- ⋆ Event Centric Approach
- ⋆ Co-location Miner Algorithm
- ⋆ Evaluation
- ⇒ Conclusions and Future Work

Conclusions and Future Work

- Our contributions described today
  - Event centric co-location model
    - Robust in face of overlapping neighborhoods
  - Co-location Miner algorithm
    - Computational efficiency
    - Correctness and completeness with various performance tuning
  - Validity of inferences
- Other contributions in my thesis
  - High-confidence Low-prevalence (HCLP) Patterns
    - Prevalence base pruning: hard to retain HCLP patterns
    - Proposed a measure to retain such patterns
    - Proved a week monotonicity of the proposed measure
    - Designed an algorithm using the week monotonicity
  - May find pattern
    - chromium 6 $\rightarrow$ lung disease, breast cancer in spatial proximity

Future Work

- Co-location patterns involving lines and polygons
- Temporal co-incidence mining
  - No natural concept of transactions over temporal datasets
  - Arbitrary windowing may not be desirable
- Spatio-temporal dataset

Future Work in a Longer Term

- ⋆ Environmental Biology
  - ⋆ Jane Goodall's Chimpanzee behavior dataset analysis
- ⋆ Emergency Evacuation Planing
  - ⋆ Heuristic approaches
- ⋆ Scientific Data Management
  - ⋆ EOS by NASA collecting terabyte of information each day
  - ⋆ Spatial and temporal in nature
- ⋆ Moving Object Databases/Location Based Services
  - ⋆ Data mining: location based recommendation
  - ⋆ Database systems
    - support millions of triggers
    - answer proximity queries
    - keep trajectories of moving objects

Thanks!