A Framework for Discovering Co-location Patterns in Data Sets with Extended Spatial Objects

Hui Xiong

Department of Computer Science & Engineering
University of Minnesota - Twin Cities

Overview

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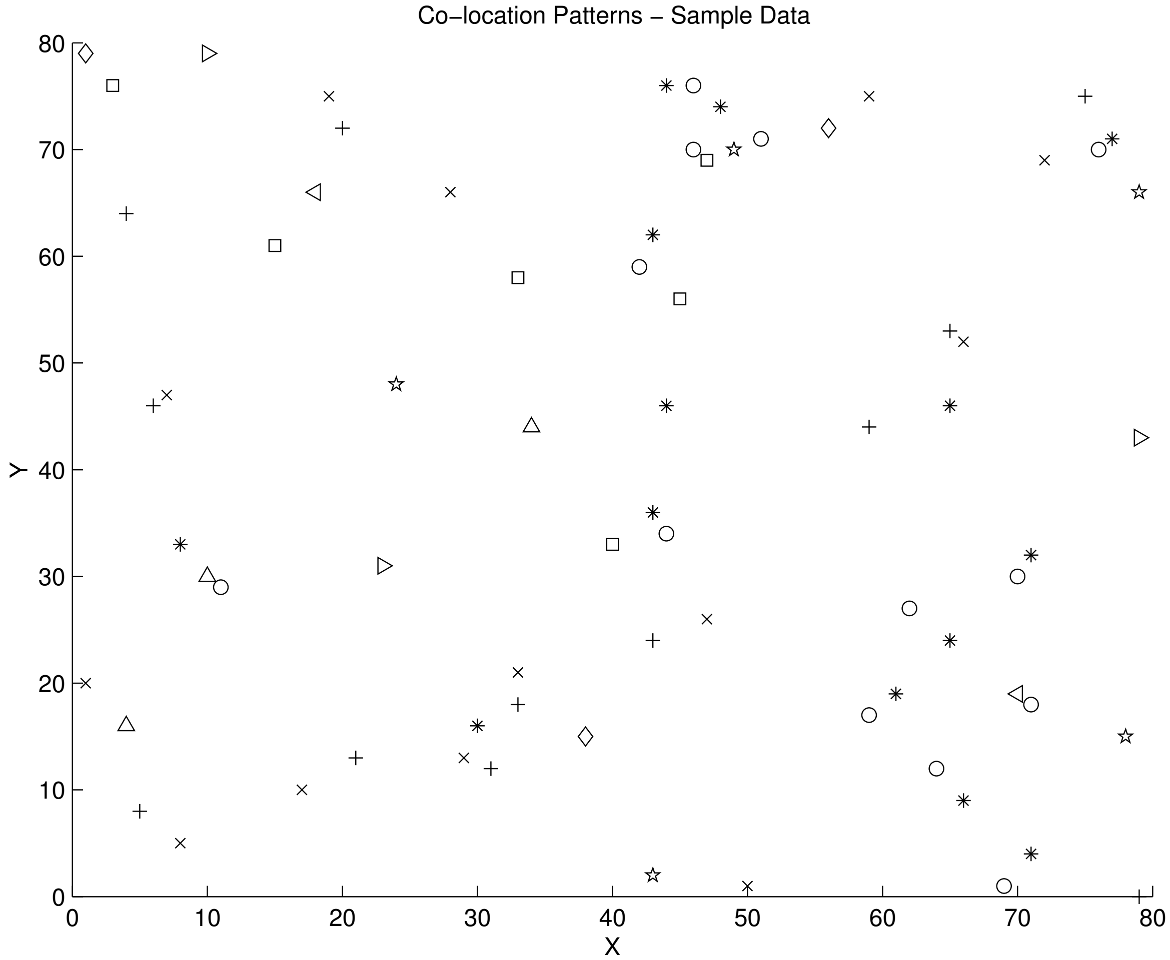
- ◇ Research Motivations

- A Buffer-based Model
- A Filter-and-Refine Co-location Pattern Mining Framework
- Experimental Evaluation
- Conclusions and Future Work

Introduction & Background



Examples of Co-location Patterns

Domains	Example Features	Example Co-location Patterns
Ecology	Species	(Nile crocodile,Egyptian plover)
Earth science	climate and disturbance events	(wild fire, hot, dry, lightning)
Economics	industry types	(suppliers, producers, consultants)
Epidemiology	disease types and environmental events	(West Nile disease, stagnant water sources, dead birds, mosquitoes)
Location-based service	service type requests	(tow, police, ambulance)
Weather	fronts, precipitation	(cold front, warm front, snow fall)
Transportation	delivery service tracks	(US Postal Service, UPS, newspaper delivery)

Related Works

- Spatial Statistics
  - ◇ Use measures of spatial correlation to characterize the relationship between spatial features
    - * the cross-K function with Monte Carlo simulation
    - * mean nearest neighbor distance
    - * spatial regression model
  - ◇ Computationally expensive
- Data Mining Approaches
  - ◇ A clustering based approach by Estivill-Castro et al.
    - * Features can be completely spatially random or declustered.
    - * Sensitive to the choices of clustering algorithms.
  - ◇ Asssocation-rule based approaches.

Related Works - Cont.

- Asssocation-rule based approaches.
  - Transaction-based approaches.
    - A reference-feature centric model by Koperski et al.
      - Generalizing this paradigm to the case where no reference feature is specified is non-trivial.
      - May yield duplicate counts for many candidate associations.
  - Distance-based approaches.
    - k-neighboring classs sets by Morimoto.
      - the number of instances for each pattern is used as the prevalence measure
    - an event centric model by Shekhar et al.
  - All these approaches are for point spatial features.

Motivation

- Identifying co-location patterns in data sets with extended spatial objects (e.g. polygons and line strings).
  - ◇ Highway often have frontage road nearby in large metropolitan.
  - ◇ $nomandale\ Road \Rightarrow highway\ 100$

Problem Formulation

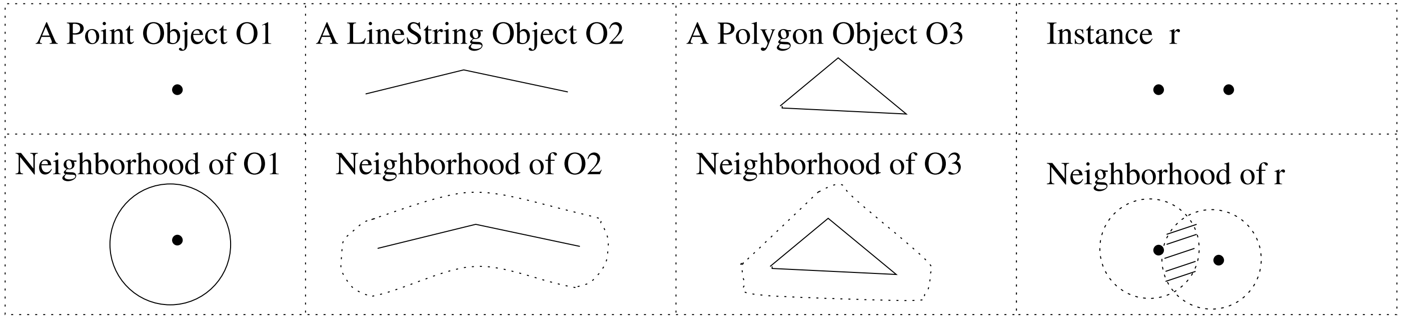
- Given:
  - ◇ A set T of K spatial feature types $T = \{f_1, f_2 \ldots, f_k\}$ and spatial data types can be point as well as other extended spatial objects, such as line strings and polygons.
  - ◇ A set of N instances $P = \{p_1 \ldots p_N\}$, each $p_i \in P$ is a vector $<$instance-id, spatial feature type, location$>$ where spatial feature type $\in T$ and location $\in$ spatial framework S.
  - ◇ A buffer size, a minimum prevalence threshold, a minimum conditional probability threshold.
- Find: Co-location Patterns and Co-location Rules.
- Objective: Computational Efficiency.
- Constraints: Correctness and Completeness.

A Buffer-based Model

Definition 1 Buffer is a zone of specified distance around spatial objects. The boundary of the buffer is the isoline of equal distance to the edge of the objects.

- Motivation
  - ◇ Objects in space frequently have sort of impact on the objects and areas around them
    - * freeways create "noise pollution" that can be heard blocks away.
    - * factories emit fumes that can affect people for miles around.

A Buffer-based Model



Definition 2 $N(p)$, the size-d Euclidean neighborhood of a point location p, is a circle of side d with p as its center.

Definition 3 $N(o)$, the size-d neighborhood of an extended spatial object (e.g. polygon, line-string), is defined by the buffer operation.

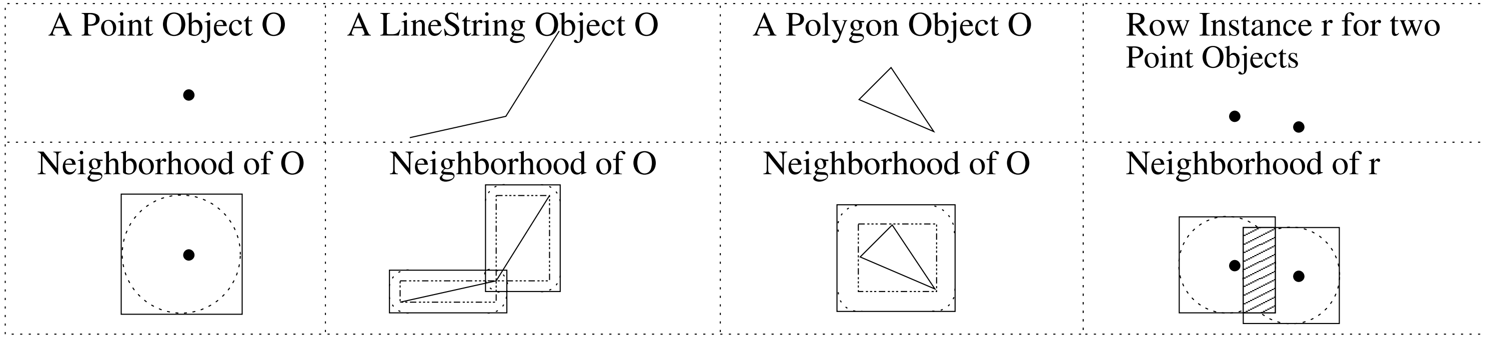
A Buffer-based Model - Cont.

Definition 4 The **coverage ratio** $Pr(f_1 f_2 \ldots f_k)$ for a co-location $C = \{f_1, \ldots, f_k\}$ is $\frac{N(f_1 f_2 \ldots f_k)}{The\,total\,area\,of\,the\,plane}$, where $N(f_1 f_2 \ldots f_k)$ is the Euclidean neighborhood of the co-location C.

Definition 5 The **conditional probability** $Pr(C_2|C_1)$ of a co-location rule $C_1 \to C_2$ is the probability of finding the neighborhood of C_2 in the neighborhood of C_1. It can be computed as $\frac{N(C_1 \cup C_2)}{N(C_1)}$ using the neighborhoods of co-locations C_1 and $C_1 \cup C_2$.

Lemma 1 The coverage ratio for co-location patterns is monotonically non-increasing with the size of the co-location pattern increasing.

A Coarse-Level Co-location Pattern Mining Framework



Definition 6 $BN(o)$, the bounding neighborhood of a spatial object is defined as MBBR(Buffer(MOBR(Spatial Object O), d)), where MOBR is the minimum object bounding box, Buffer is the buffer operation with a buffer size as d, and MBBR is the minimum buffer bounding box.

Definition 7 The Euclidean bounding neighborhood $BN(f_j)$ of a spatial feature f_j is the union of $BN(i_l)$ for every instance i_l of the spatial feature f_j.

A Coarse-Level Co-location Pattern Mining Framework - Cont.

Definition 8 The Euclidean bounding neighborhood $BN(f_1 f_2 \dots f_k)$ for a coarse-level co-location pattern $CC = \{f_1, \dots, f_k\}$ is the intersection of $BN(f_i)$ for every spatial feature f_i in CC.

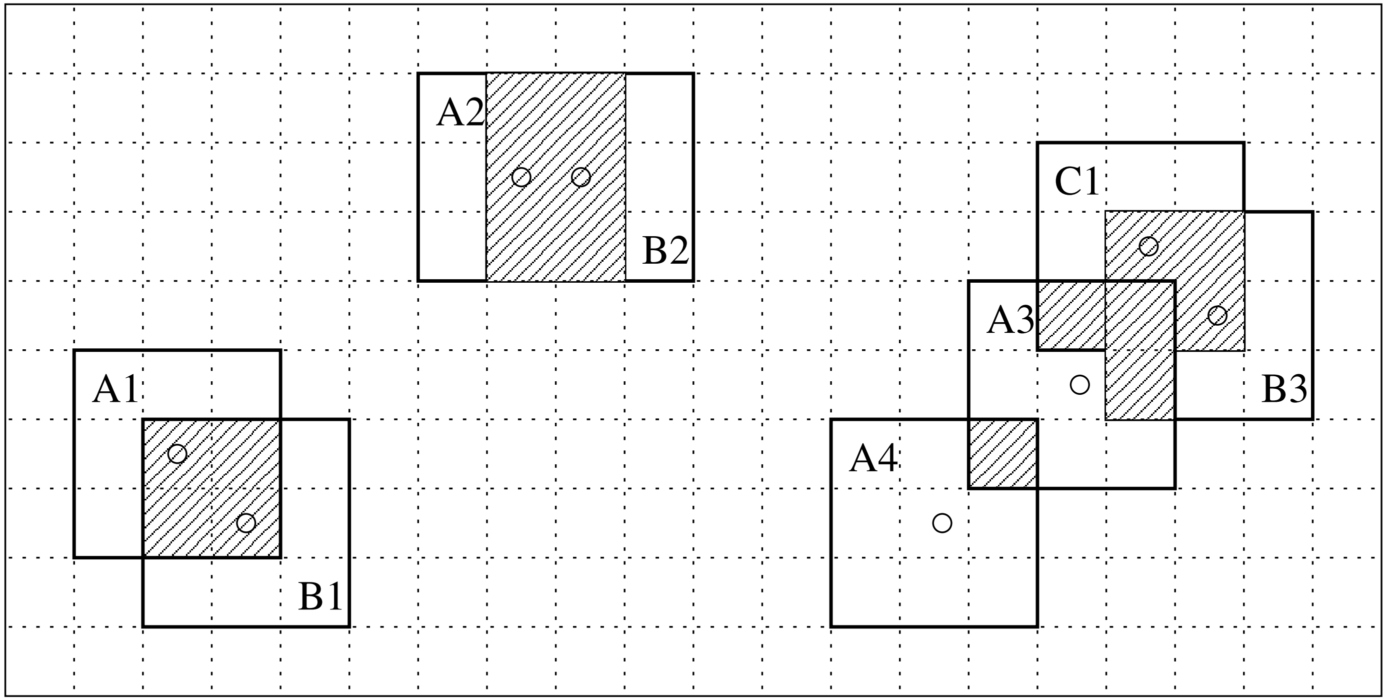
Definition 9 The **coarse-level coverage ratio** $CPr(f_1 f_2 \dots f_k)$ for a coarse-level co-location pattern $CC = \{f_1, \dots, f_k\}$ is $\frac{BN(f_1 f_2 \dots f_k)}{The\, total\, area\, of\, the\, plane}$, where $BN(f_1 f_2 \dots f_k)$ is the Euclidean bounding neighborhood of the coarse-level co-location pattern CC.

A Coarse-Level Co-location Pattern Mining Framework - Cont.

Lemma 2 The coarse-level coverage ratio for coarse-level co-location patterns is monotonically non-increasing with the size of the coarse-level co-location pattern increasing.

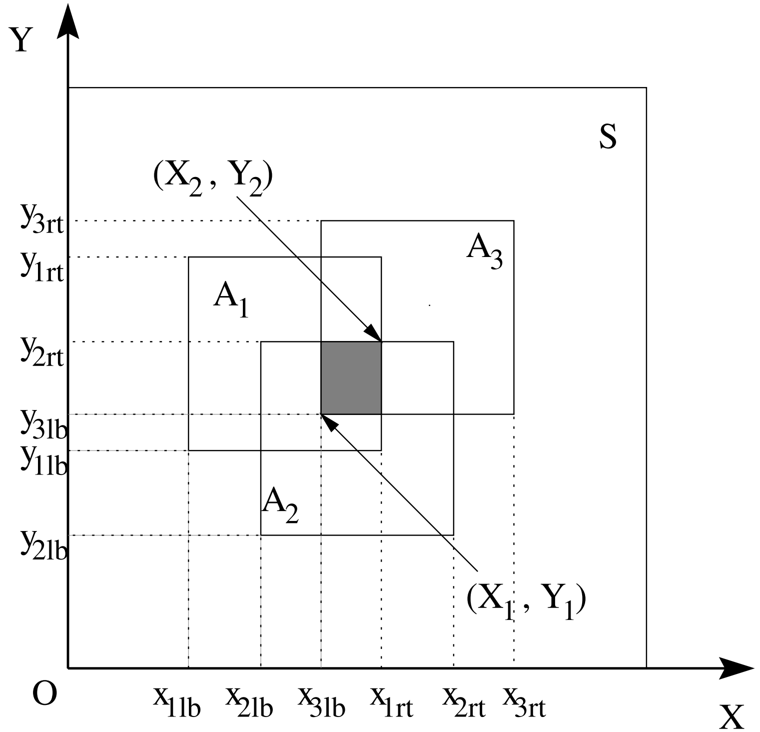
Lemma 3 For any spatial feasure set $F = \{f_1, f_2, \ldots, f_k\}$, the coarse-level coverage ratio CPr(F) is larger than or equal to the coverage ratio Pr(F).

A Coarse-Level Co-location Pattern Mining Framework - Cont.



- $CPr(A) = \frac{BN(A)}{The\, total\, area\, of\, the\, plane} = \frac{35}{200} = 0.175$
- $CPr(AB) = \frac{BN(AB)}{The\, total\, area\, of\, the\, plane} = \frac{12}{200} = 0.06.$

Geometric Challenges and Solutions



Lemma 3 For any n spatial events $A_1, \ldots, A_n$,

$$\bigcup_{i=1}^{n} BN(A_i) = \sum_{i=1}^{n} BN(A_i) - \sum_{i<j} BN(A_iA_j) + \sum_{i<j<k} BN(A_iA_jA_k) - \sum_{i<j<k<l} BN(A_iA_jA_kA_l) + \ldots + (-1)^{n+1} BN(A_1A_2\ldots A_n). \qquad (1)$$

Geometric Challenges and Solutions - Cont.

Theorem 2 Given any n spatial events $A_1,\ A_2,\ \ldots,A_n$ and the corresponding bounding neighborhoods $((x_{1lb}, y_{1lb}), (x_{1rt},\ y_{1rt}))$, $((x_{2lb}, y_{2lb}), (x_{2rt}, y_{2rt}))$, ..., $((x_{nlb}, y_{nlb}), (x_{nrt}, y_{nrt}))$, where the bounding neighborhood of the event A_i, $1 \leq i \leq n$, is represented by the left bottom point $(x_{ilb},\ y_{ilb})$ and the right top point $(x_{irt},\ y_{irt})$, if the bounding neighborhoods of these n spatial events have the common intersection area, then this intersection area can be computed by Equation 2.

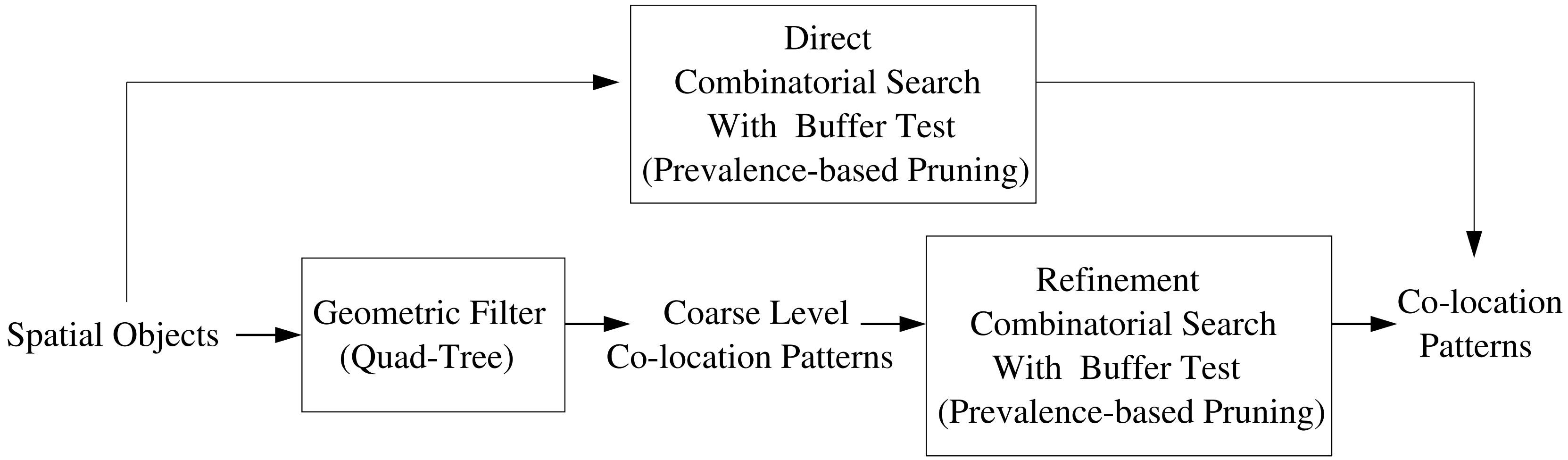
$$BN(A_1A_2\ldots A_n) = (X_2 - X_1) * (Y_2 - Y_1) \tag{2}$$

where

$$X_2 = min\{x_{1rt},\ x_{2rt},\ \ldots, x_{nrt}\},$$
$$X_1 = max\{x_{1lb},\ x_{2lb},\ \ldots, x_{nlb}\},$$
$$Y_2 = min\{y_{1rt},\ \ y_{2rt},\ \ldots,\ y_{nrt}\},$$
$$Y_1 = max\{y_{1lb},\ \ y_{2lb},\ \ldots,\ y_{nlb}\}.$$

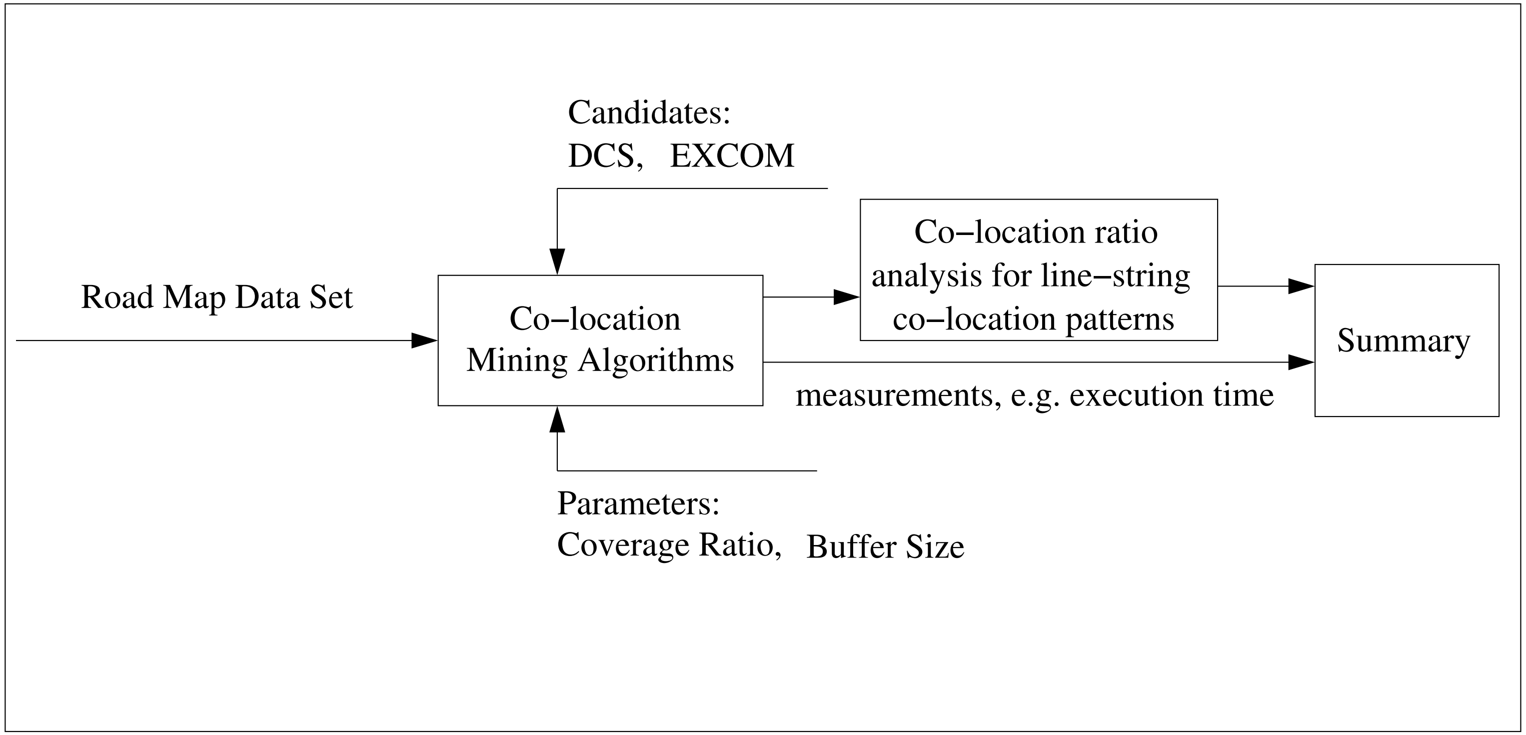
Algorithm Design

- DCS: A Direct Combinatorial Search Algorithm.
- EXCOM: An Extended Co-location Mining Algorithm.

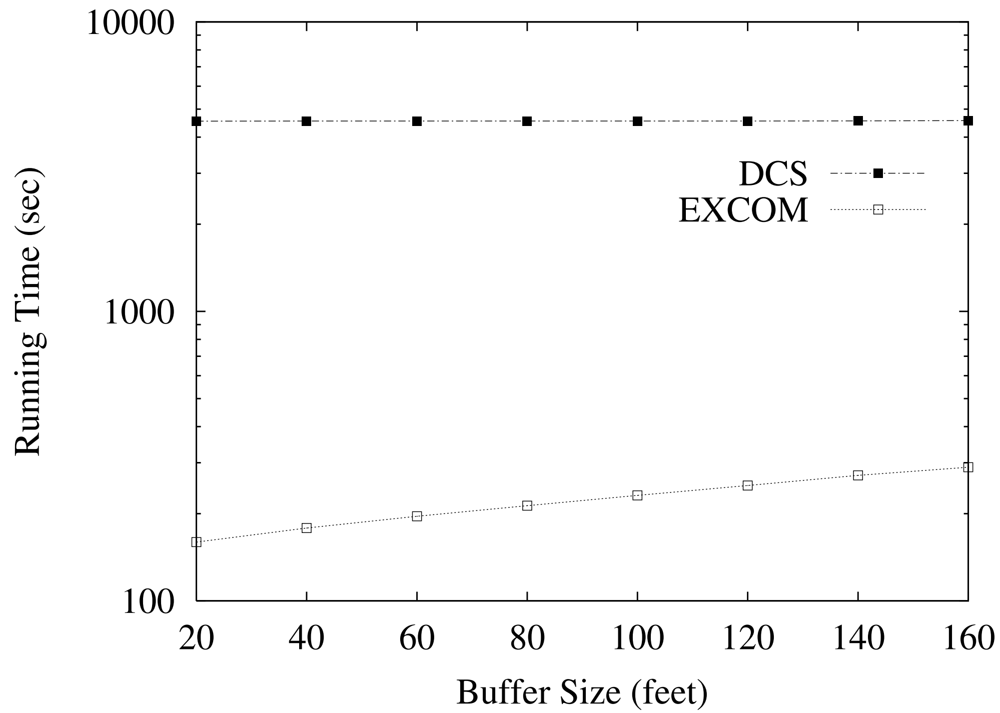


Experimental Setup

- Experimental Data Set: MN/DOT base map.
- Experimental Design



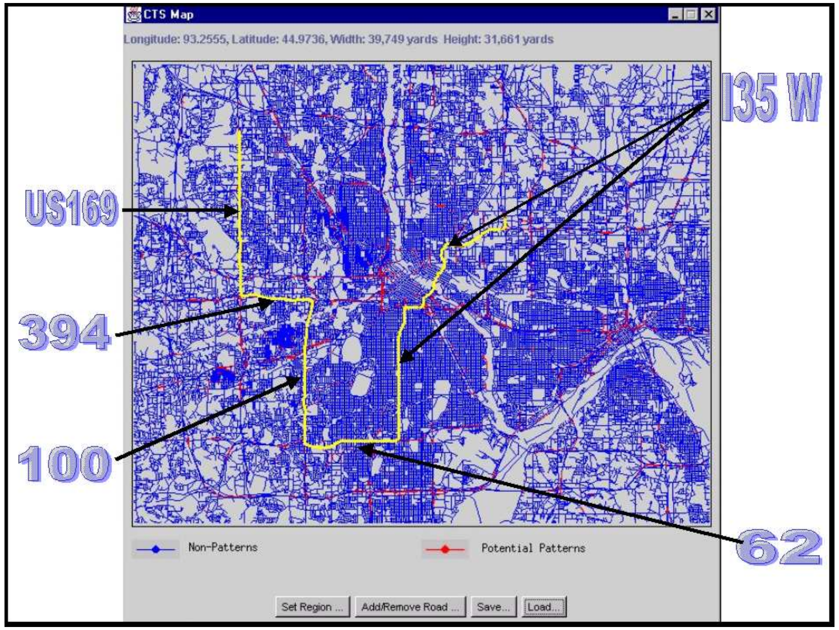
The Filtering Effect of the Geometric Component



- The geometric filter can speed up the prevalence-based pruning approach by a fact of 30 - 40.

Line-String Co-location Patterns for Test Route Selection

- Evaluate the positional accuracy of digital roadmap databases.



- Co-located roads are the most challenging test sites for evaluating the ability of global positioning systems (GPS) systems to identify correct roads from a digital roadmap.

Contributions

- Generalize the concept of co-location patterns to extended spatial objects, e.g. polygons and line-strings.
- Propose a novel buffer-based model for mining co-location pattern. This model has three advantages over the event centric model and is transaction-free.
- Propose a geometric filter-and-refine co-location mining framework.
- Experiment evaluation with a real data set shows that the geometric filter-and-refine approach can speed up the prevalence-based pruning approach by a fact of 30 to 40.
- The application of applying line-string co-location patterns for selecting test routes has been provided to show the usefulness of co-location patterns.

Conclusions and Future Work

- Extending the notion of co-location pattern
  - de-colocation pattern
  - co-incidence pattern
- Applications of Co-location Pattern