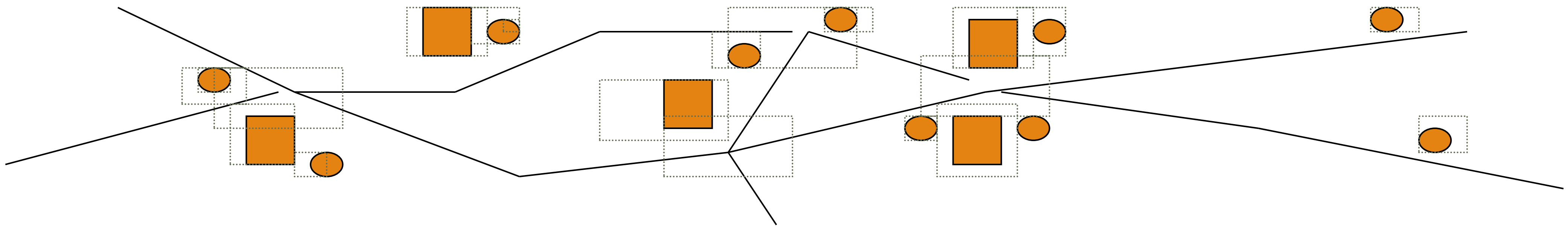
Session 2. Spatiotemporal and Trajectory Pattern Mining

Spatial Patterns and Associations

- Spatial frequent patterns and association rule: $A \Rightarrow B$ [*s%, c%*]
  - A and B are sets of spatial or non-spatial predicates, e.g.,
    - Topological relations: *intersects, overlaps, disjoint,* etc.
    - Spatial orientations: *left_of, west_of, under,* etc.
    - Distance information: *close_to, within_distance,* etc.
  - *s%*: support, and *c%*: confidence of the rule
- Example: Rules likely to be found
  - *is_a(x, large_town) ^ intersect(x, highway) → adjacent_to(x, water) [7%, 85%]*
- Explore *spatial autocorrelation*: Spatial data tends to be highly self-correlated (*nearby things are more related than distant ones)*
  - E.g., neighborhood, temperature

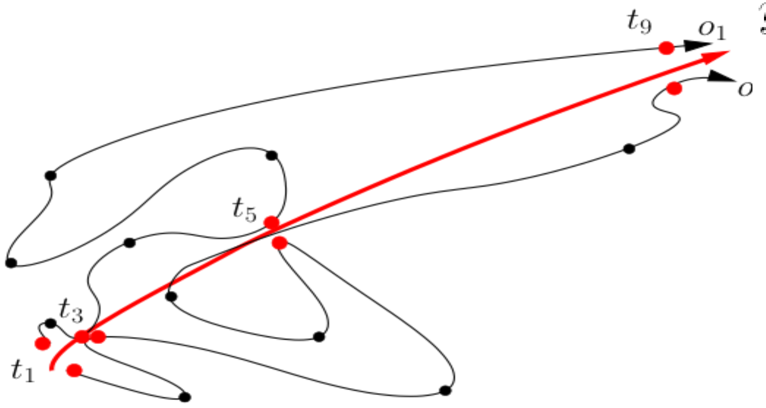
Mining Spatial Associations: Progressive Refinement

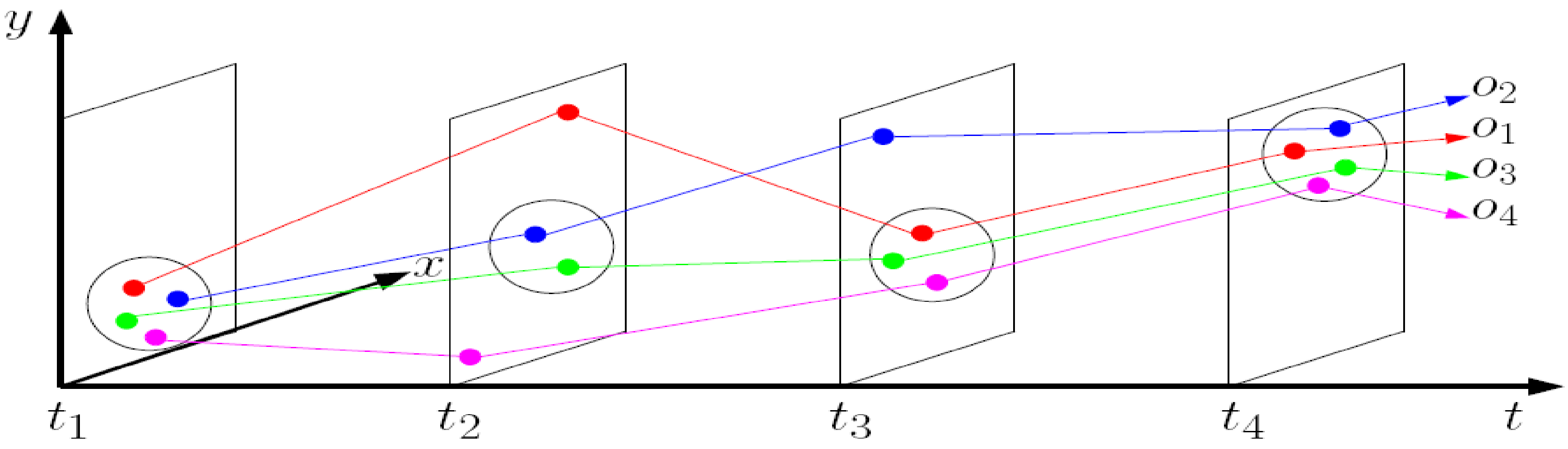
- Hierarchy of spatial relationship:
  - *g_close_to*: *near_by*, *touch*, *intersect*, *contain*, etc.
  - Progressive refinement: First search for rough relationship and then refine it
- Two-step mining of spatial association:
  - Step 1: Rough spatial computation (as a filter)
    - Using MBR (Minimum Bounding Rectangle) or R-tree for rough estimation
  - Step2: Detailed spatial algorithm (as refinement)
    - Apply only to those objects which have passed the rough spatial association test (no less than *min_support*)



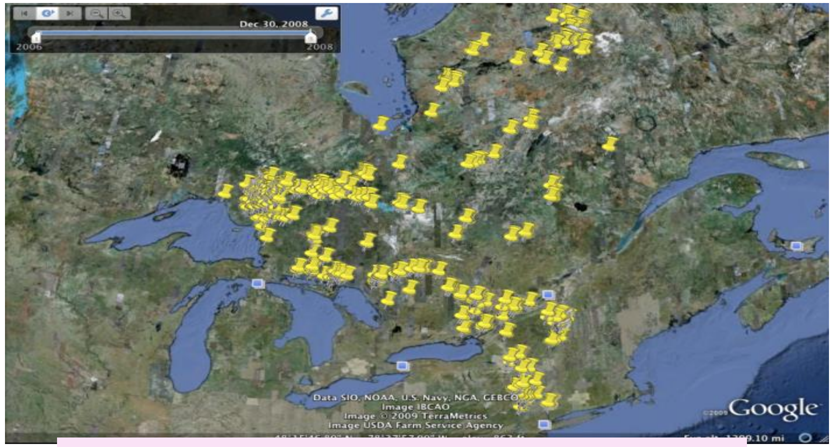
Mining Relative Movement Patterns

- **Flock:** At least *m* entities are within a circular region of ***radius r*** and move in the same direction
- **Convoy:** Uses ***density-based clustering*** at each timestamp; no need to be a rigid circle
- Flock and convoy: Both require *k* consecutive time stamps
- **Swarm:** Moving objects may not be close to each other for all the consecutive time stamps
  - Efficient pattern mining algorithms for uncovering such swarm patterns

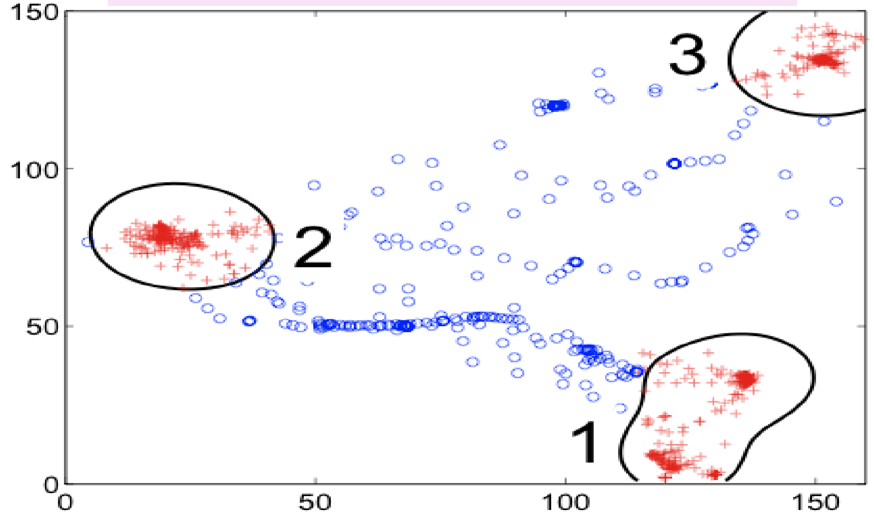


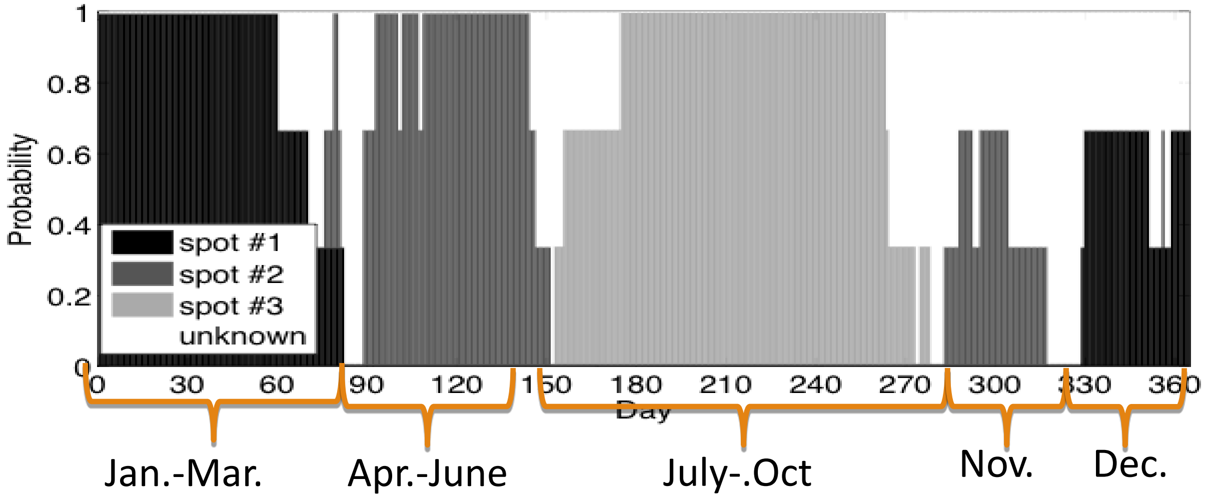


Mining Periodic Patterns with Sparse Data



3-yr Bird migration data: very sparse

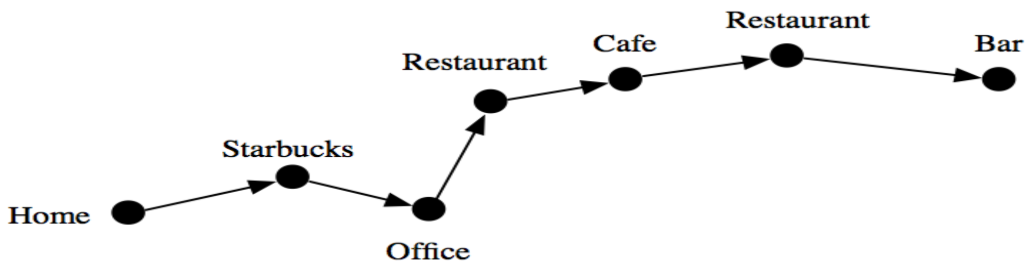


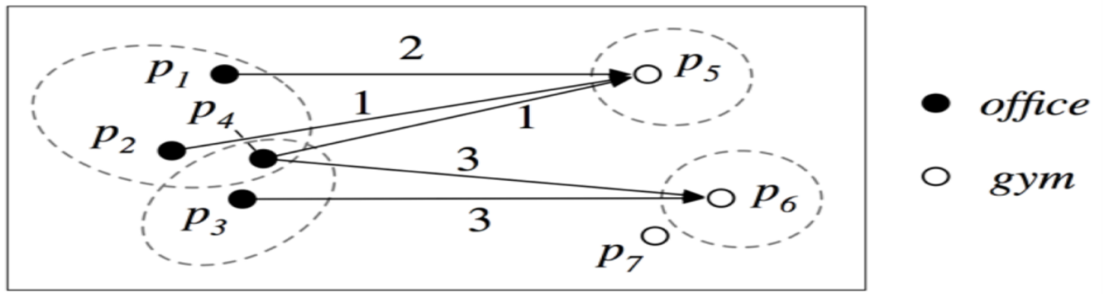


- **Detecting periods**: Cluster to find reference "points" and then detect multiple interleaved periods by Fourier Transform and auto-correlation
- **Summarizing periodic patterns:** By clustering and pattern discovery

Semantic Trajectory Pattern Mining

- Semantic trajectory: Trajectory carries semantics (e.g., category)





- Meaningful sequential patterns: 3 constraints: (i) semantic consistency; (ii) spatial compactness; and (iii) temporal continuity
- Method: A two-step approach
  - 1: Mining coarse patterns that satisfy the semantic and temporal constraints (e.g., office → gym)
    - First, mine semantically meaningful patterns (e.g., categories)
    - Then, detect dense and compact clusters in the high-dimensional space
  - 2: Splitting coarse patterns into fine-grained ones to meet the spatial constraint (e.g., people working in which office tend to go to which gym)

Recommended Readings on Spatiotemporal and Trajectory Pattern Mining

- Y. Huang, S. Shekhar, H. Xiong, Discovering colocation patterns from spatial data sets: A general approach, IEEE Trans. on Knowledge and Data Engineering, 16(12), 2004
- K. Koperski, J. Han, "Discovery of Spatial Association Rules in Geographic Information Databases", SSD'95
- Z. Li, B. Ding, J. Han, R. Kays, "Swarm: Mining Relaxed Temporal Moving Object Clusters", VLDB'10
- Z. Li, B. Ding, J. Han, Roland Kays, Peter Nye, "Mining Periodic Behaviors for Moving Objects", KDD'10
- C. Zhang, J. Han, L. Shou, J. Lu, T. La Porta, "Splitter: Mining Fine-Grained Sequential Patterns in Semantic Trajectories", VLDB'14
- Y. Zheng and X. Zhou, Computing with Spatial Trajectories, Springer, 2011