Lecture Notes for

Managing and Mining Multiplayer Online Games

Summer Term 2019

Chapter 7: Spatial Analytics

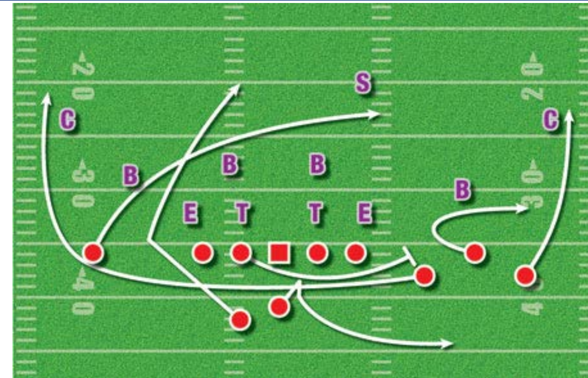
http://www.dbs.ifi.lmu.de/cms/VO_Managing_Massive_Multiplayer_Online_Games

Chapter Overview

- spatial data mining in games
- visual analytics and heat maps
- spatial outliers
- trajectories: representation and similarity
- pattern search on trajectory data

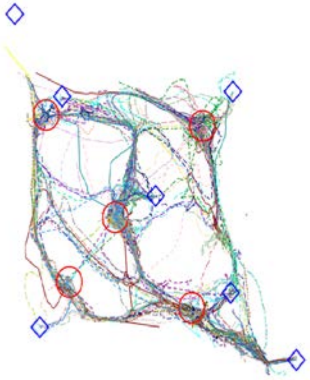
Spatial Data Mining and Games

- many games take place in a virtual 2D-/3D-World
- movement and position is often an important part of game play
- map design is relevant for balancing
- analysis of spatial and spatial-temporal information is referred to as *Spatial Data Mining*



Tasks of Spatial Game Analytics

- find exploitation spots
- extract game moves and movement strategies
- encounter detection (open PVP)
- sub team recognition
- dynamic adjustment of respawn times
- detect bot and multiboxers
- detect movement and teleportation hacks

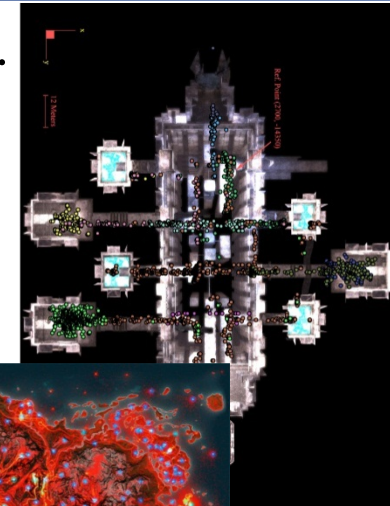


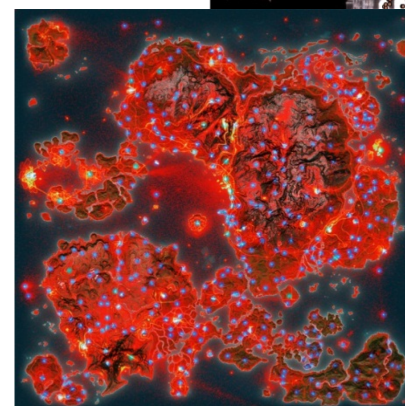
$\Rightarrow$ find specific places (heat-maps, spatial outliers)

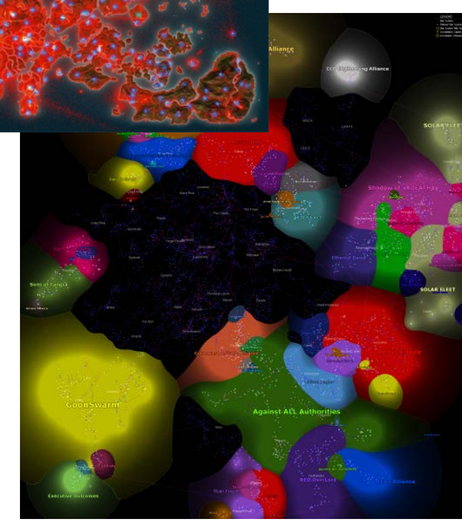
$\Rightarrow$ find movement patterns (trajectory mining)

Spatial Data and Visualization

- spatial data consists of object descriptions and positions. (Example: Marine, 43,56)
- to find special places, object descriptions are aggregated w.r.t. positions (e.g. number of kills at a position, monster's spawn frequency at a place)
- spatial continuity: usually one assumes adjacent positions to behave in a similar fashion.







⇒ presentation of aggregated information in 2D histograms (bin counting)

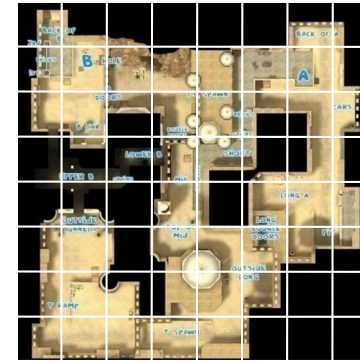
⇒ presentation of spatial continuity with smoothing approach (kernel density estimation)

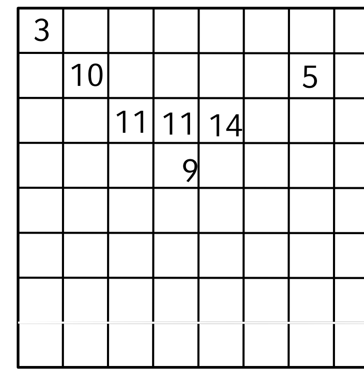
Heat Maps

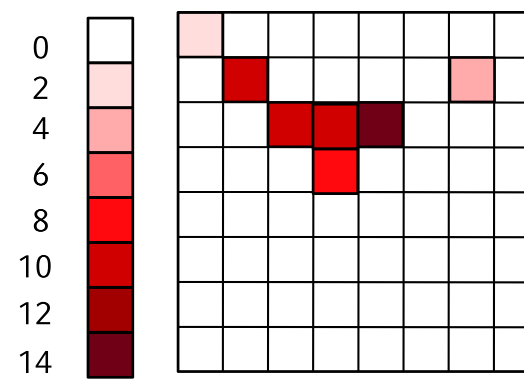
- visualizing the distribution of events on X-,Y-coordinates of a map.
- displaying the distribution as a 2D-Density distribution.
- a bin's height is encoded with it's color.

simple algorithm: Bin Counting

1. place uni-distance Grid overlay on the map
2. for every event
    1. determine grid cell
    2. increase grid cell counter by 1
3. draw the grid and color each cell matching the number within.



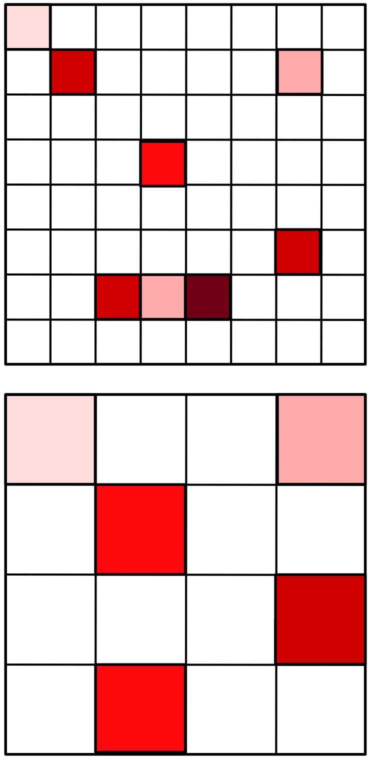




Heat Maps

Problems with bin counting:

- setting grid-size:
  - too small: torn view, few dense areas
  - too big: rough view, few differences
- grid position influences result
- spatial continuity may be hardly discernible



Remedy: smooth curves with kernel density estimation

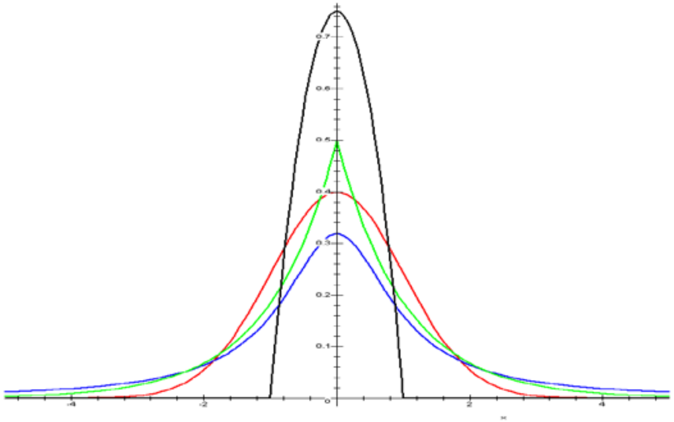
estimate density with the sum of kernel functions

$\Rightarrow$ continuous and smoothed density function

$\Rightarrow$ discretization of data only for drawing

Kernel density estimator

- method to estimate a continuous density function from a sample set *X*.
- consider density *p(t)* as mixture model of *|X|* distributions, all of them distributed with kernel function *K(t)*:
- common kernel functions: $p(x) = \frac{1}{|X|} \sum_{t \in X} K(t-x)$
  - Gauss-kernel : $K(t) = \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{1}{2}t^2\right)}$
  - Cauchy-kernel: $K(t) = \frac{1}{\pi\left(1+t^2\right)}$
  - Picard-kernel : $K(t) = \frac{1}{2} e^{(-|t|)}$
  - Epanechnikow-kernel: $K(t) = \begin{cases} \frac{3}{4}\left(1-t^2\right), & falls \quad t \in [-1;1] \\ 0 & sonst \end{cases}$



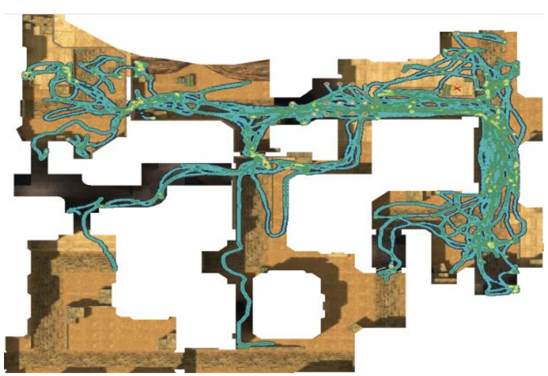
Heatmaps with kernel density estimators

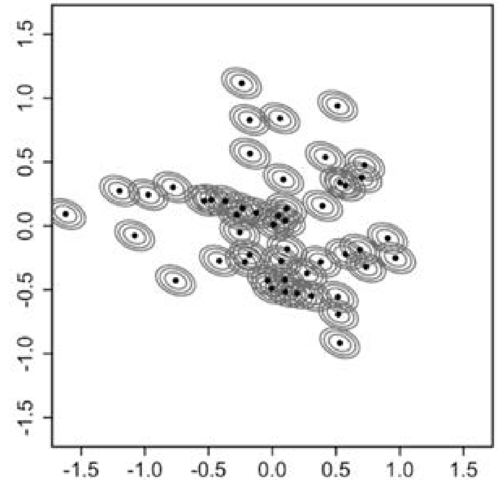
- kernels in *2D*-Space assuming independent dimensions:

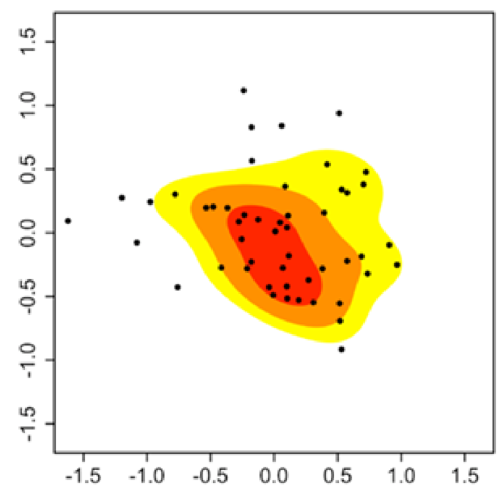
$$p(t) = \left(\frac{1}{|X|} \sum_{x \in X} K(t_1 - x_1) \right) \cdot \left(\frac{1}{|X|} \sum_{x \in X} K(t_2 - x_2) \right)$$

- every bin corresponds to one pixel
- for every pixel *P*, *p(m)* is calculated based on pixel center *m*
- for efficient calculation:

for all points *x*:
    for all pixel *p*:
        for both dimensions:
            increase the value of *p*
            by $K(x-p_m)$ with p_m *center of p*







Spatial Data Mining

- particular data mining methods for spatial objects.
- object *O* consists of a spatial component $p \in IR^2/IR^3$ and an object description $v \in F$. *(F is an arbitrary feature space)*
- special tasks in spatial data mining:
  - **Spatial Outlier Detection**: find places where the feature descriptions significantly varies from the object description of close objects.
    (Example: exploitation spots where you can not be hit.)
  - **Spatial Prediction**: prediction of areas where certain phenomena are more frequent. (Example: calculate the probability of a certain behavior occurring at a certain spot.)
  - **Spatial Clustering**: Clustering using proximity as well as similarities of the feature space to create or differentiate clusters.
    (Example: Are any actions frequently taken at certain areas of the map?)
  - **Spatial Rule Mining:** Derivation of association rules based on frequent spatial patterns. (Example: 80% of cities built within 50 km of another players settlement do not survive until the end of the game.)

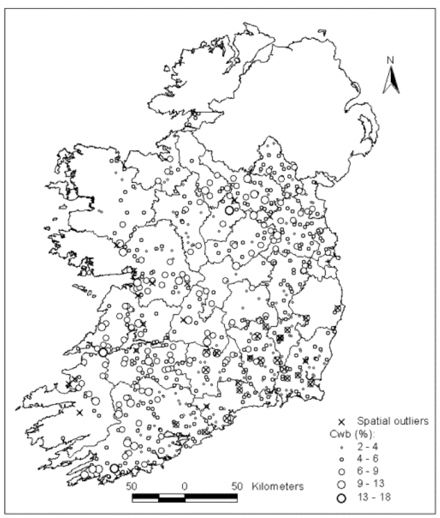
Spatial Outlier Detection

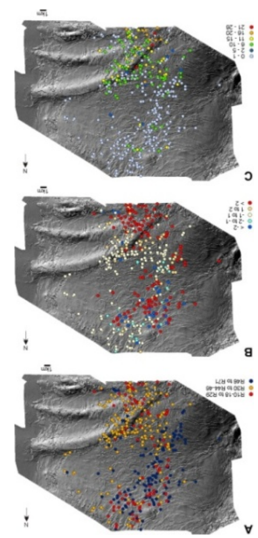
Given: A set DB of spatial objects O = (p,v).

Searched: Objects that are unusual for their neighborhood.

General procedure:

1. Determine neighborhood *N* for every object *O*.
   (e.g *N* consists of k closest neighbors of *O*).
2. Compare the feature description of *O.v* with the distribution of feature descriptions in *N*.

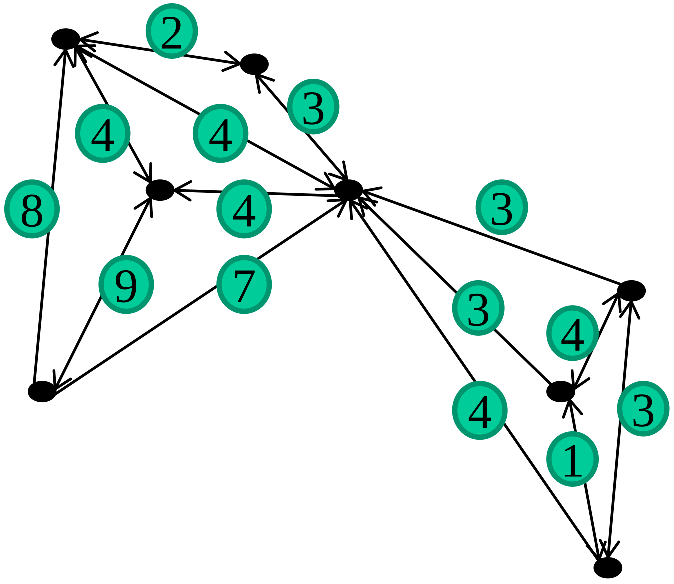




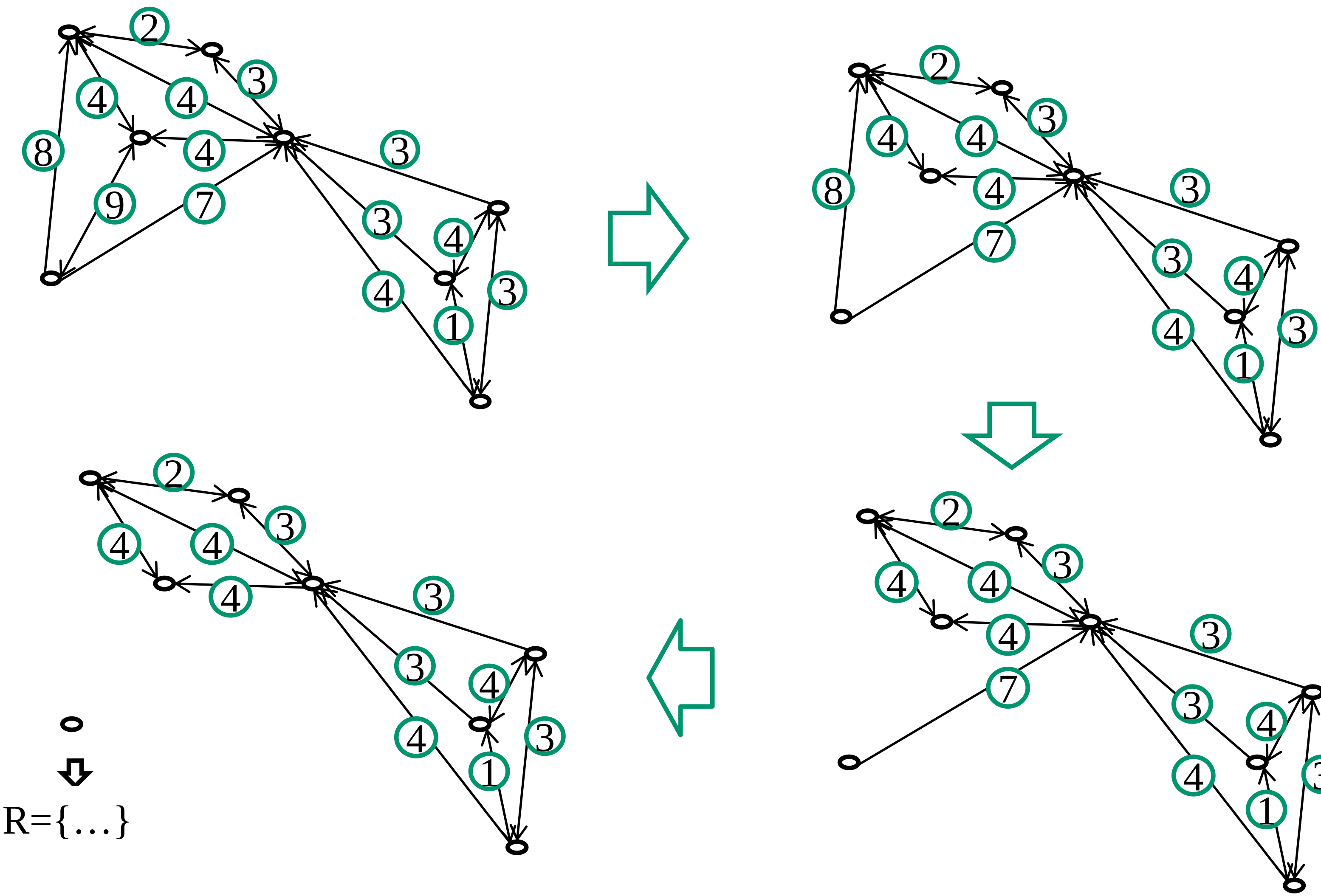
Spatial Outlier Detection

Point Outlier Detection (POD):

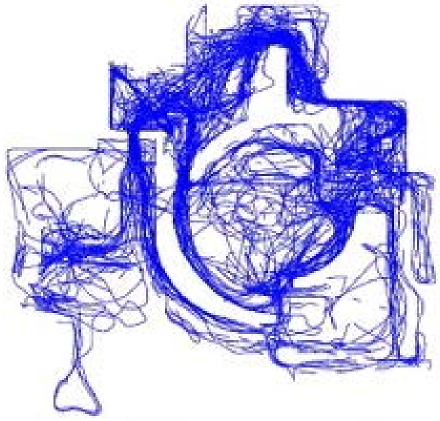
1. set up a nearest neighbor graph G(DB,E) for spatial positions.
   $E := \{(o_i,o_j) \mid o_i,o_j \in DB \wedge o_j \in NN_k(o_i)\}$
   weighting function:
   $w(o_i,o_j) = || o_i.v - o_j.v ||$
2. sort E by $w(o_i,o_j)$ *in d*escending order
3. while $|R| < m$
   (m outliers not found yet)
   1. remove the edge (o_i,o_j) with max. weight $w(o_i,o_j)$
   2. if o_i is isolated, insert o_i into the result R



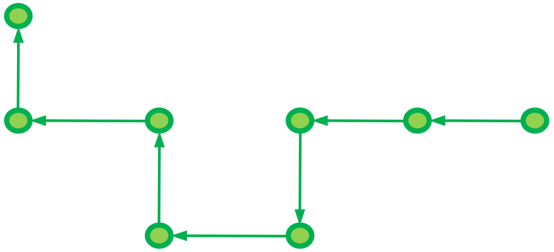
Example POD



Trajectories



- trajectories describe a movement through space (time series of spatial positions)
- **spatial trajectory**: $Q=(x_1, \ldots, x_l) \in IR^2 \times \ldots \times IR^2$ is known as spatial trajectory of length l over IR^2.
- **spatial-temporal trajectory**: Let T be a domain to present time, then $Q=((x_1, t_1),.., (x_l, t_l)) \in (IR^2 \times T) \times .. \times (IR^2 \times T)$ is a spatial-temporal trajectory of length l over IR^2.
- alternatively trajectories can be described relatively to a starting position.
- movement is continuous: to get a continuous path, the movement between two positions is assumed to be linear and to be traversed with constant speed.



go , go, turn left, go, turn right, go, turn right, go, turn left, go, turn right, go

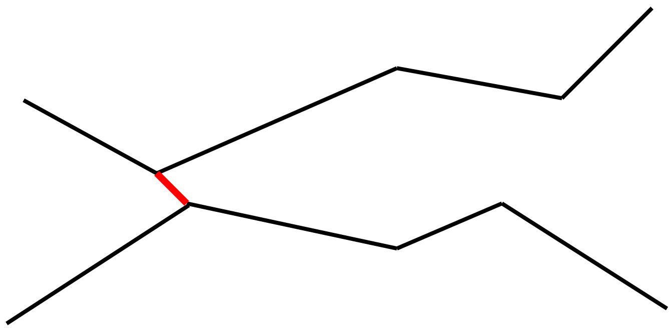
Distance Measure for Trajectories

- **point to trajectory**: Given $p \in IR^2$ and trajectory $Q=((x_1,t_1), \ldots, (x_l,t_l))$:
$$D(p,Q) = \min_{(x,t)\in Q} d(p,x)$$

- **trajectory to trajectory**: Given $Q=((x_1,t_1), \ldots, (x_l,t_l))$ and $P= ((y_1,t'_1), \ldots, (y_l,t'_l))$:

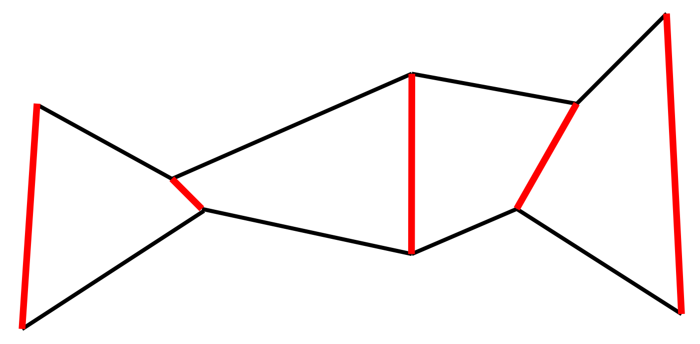
  Closest Pair Distance:

$$CPD(Q,P) = \min_{(x_i,t_i)\in Q,(y_j,t'_j)\in Q} d(x_i,y_j)$$



  Sum-of-Pairs:

$$SPD(Q,P) = \sum_{i=1}^{n} d(x_i,y_i)$$



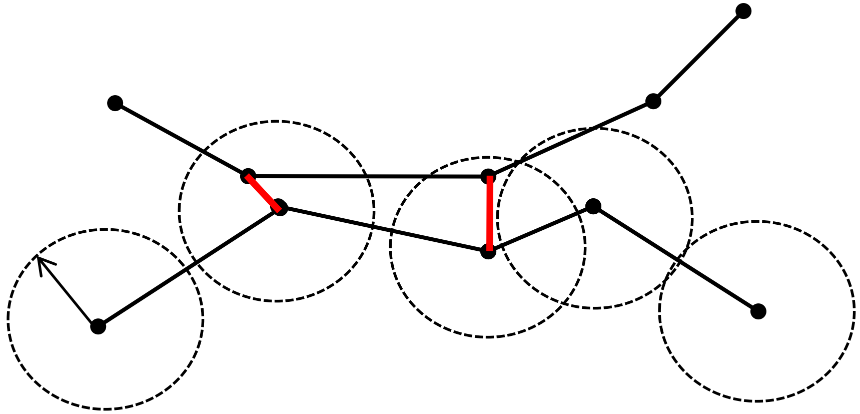
Distance Measures for Trajectories

- for different lengths: DTW (See Chapter 8)

  but: DTW is susceptible to outliers.
- longest common sub-sequence (similarity measure!)
  LCSS (Longest Common Sub-Sequence):

$$LCSS(Q,P)=\begin{cases} 0,\ falls\quad n=0 \vee m=0 \\ 1+LCSS(\mathrm{Rest}(Q),\mathrm{Rest}(P)),\ falls\quad d(Head(Q),Head(P)) \le \varepsilon \wedge |n-m| < \delta \\ \max(LCSS(\mathrm{Rest}(Q),P),LCSS(Q,\mathrm{Rest}(P)),sonst \end{cases}$$

- ε : threshold for position matching, δ max. shift
- calculation by recursion



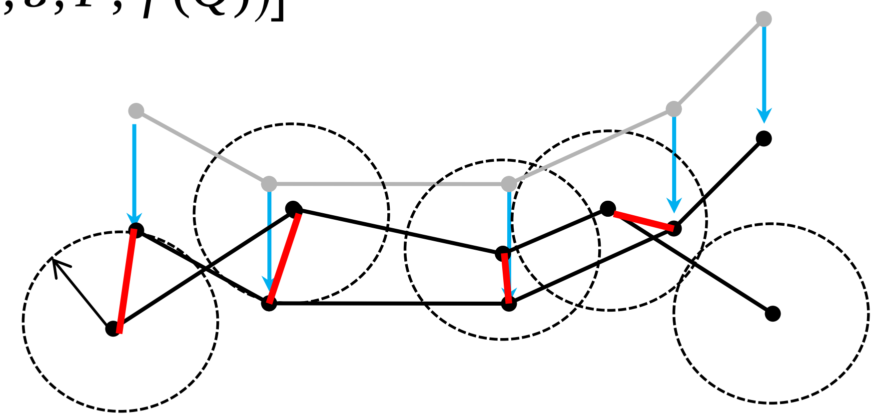
LCSS Similarity

- LCSS(P,Q) only counts the length of the longest commons sub-sequence up to now, but is not normalized yet:

$$S1(\delta, \varepsilon, P, Q) = \frac{LCSS(P,Q)}{\min(|P|, |Q|)}$$

- similarity does not yet take the translation of trajectories into account
(translation: Shifting all positions by a fixed vector):
Let *F* be the set of all translations and *f(Q)* *F* one translation:

$$S2(\delta, \varepsilon, P, Q) = \max_{f \in F}\left[S1(\delta, \varepsilon, P, f(Q))\right]$$



Compressing trajectories

characteristics of trajectories in games:

- high resolution (ca. 20-30 points/s)
- no measuring errors for positions
- velocity gradation is usually steady and movement is often linear.

problems: resolution is often too high and redundant

- extremely high memory requirement
- comparisons become very expensive
  (e.g., all DTW based measures are square)

approach: reduce waypoints

⇒ compression by omitting waypoints

⇒ good methods minimize approximation errors

Douglas-Peucker Algorithm

Given: A trajectory $Q=((x_1,t_1), \ldots, (x_l,t_l))$ of l length.

Searched: Q' with | Q' |<< l and approximation error smaller than δ .

Algorithm:

DP(Q, δ)

Q' = $((x_1,t_1), (x_l,t_l))$

FOR ALL (x_i,t_i) *in Q*

IF $Error(x_i, Q') > \delta$ THEN

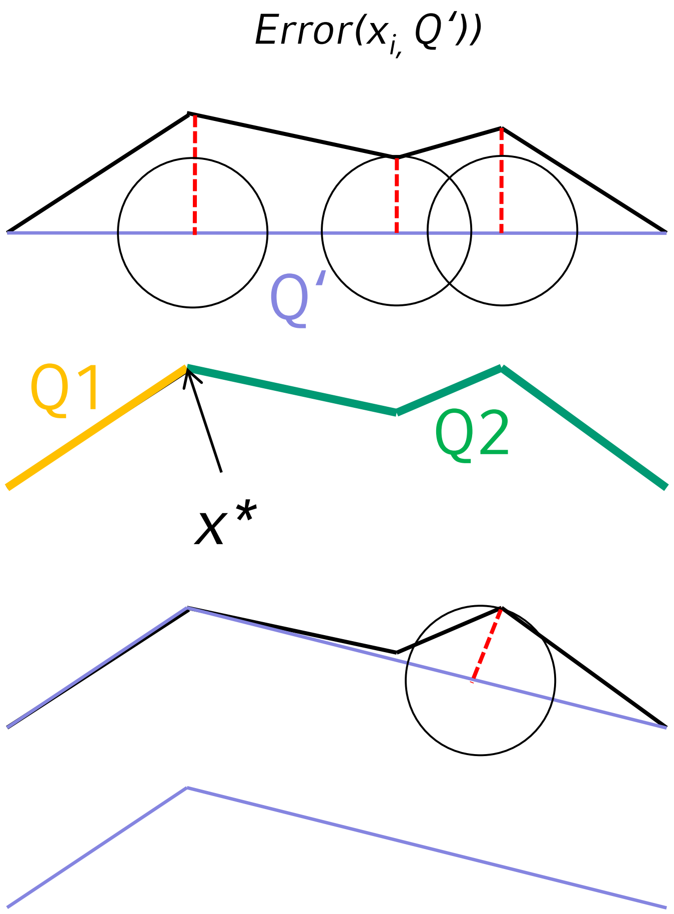
determine x^* with max($Error(x_i, Q')$)

$(Q1,Q2) = split(Q,x^*)$

RETURN $DP(Q1, \delta)$ $DP(Q2, \delta)$

ENDFOR

RETURN Q'



Compressing with Speed and Direction

- Consider last 2 waypoints q_{i-2}, q_{i-1} and calculate movement direction $d_i = \frac{q_{i-2} - q_{i-1}}{\|q_{i-2} - q_{i-1}\|}$ and speed $v_i = \frac{\|q_{i-2} - q_{i-1}\|}{t_{i-2} - t_{i-1}}$

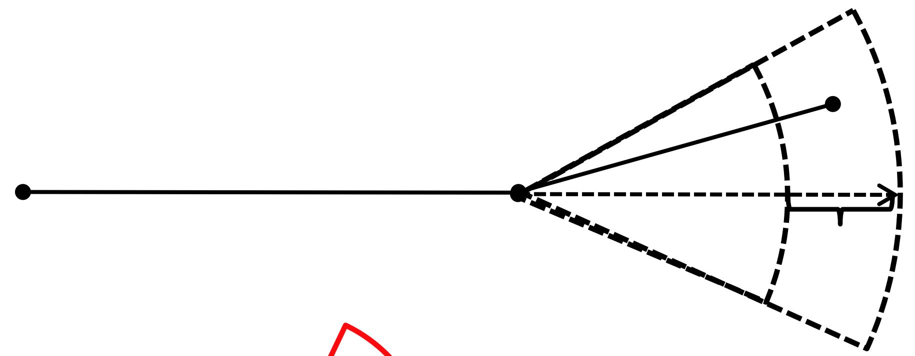
- extrapolate next waypoint $q_{i-1} + d_i\, v_i(t_{i+1} - t_i)$ and test:

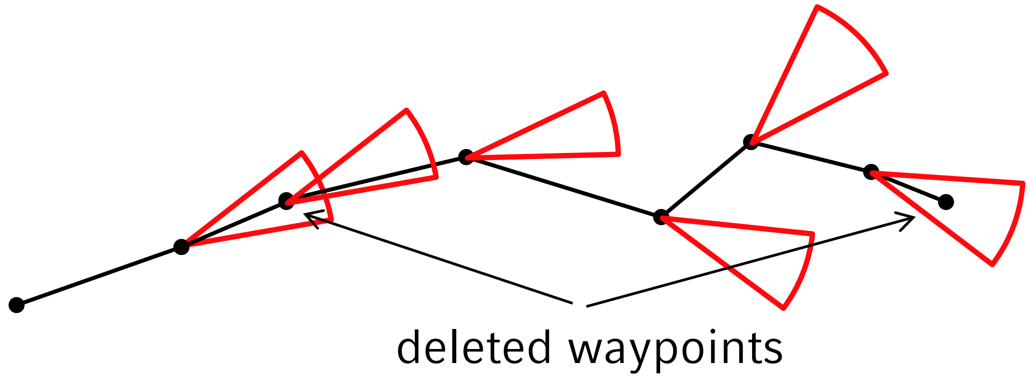
  If $|v_i(t_i - t_{i-1}) - (q_i - q_{i-1})|$ and $\frac{\langle d_i, q_i - q_{i-1} \rangle}{\|d_i\| \cdot \|q_i - q_{i-1}\|} \leq \alpha$

  delete q_i

  else

  go to $i+1$





Pattern Search in Trajectories

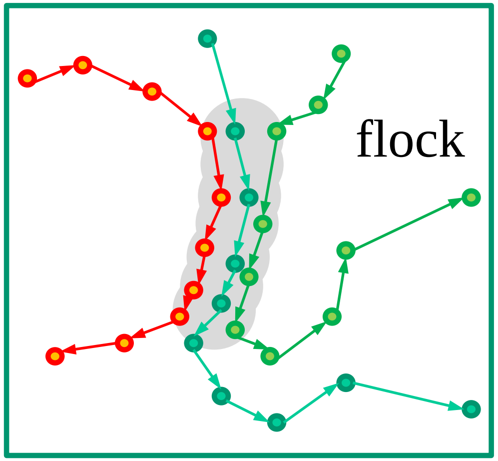
- like other objects, trajectories can be analyzed with distance based data mining (z.B. OPTICs) and corresponding distance measures (LCSS).
- but resulting patterns consist of globally similar trajectories
- many interesting trajectory patterns are based on small parts of trajectories
- interesting patterns usually have spatial constraints

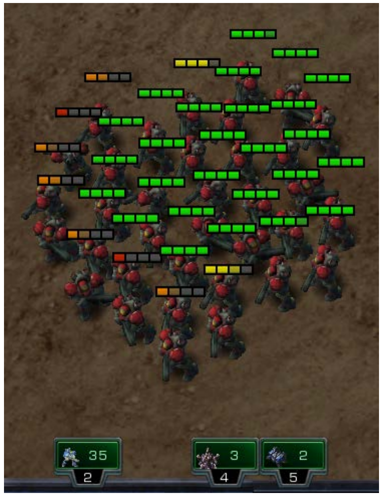
=> special pattern search methods for trajectories

Continuous Flocks

Idea: Find objects that share a path
for a certain time interval.

Example: subteams in games, convoys,…





Definition: Continuous *(m,k,r)-Flock*

Let *DB* be a set of trajectories of length *l*, a Flock within the time interval $I=[t_i,t_j]$ where $j-i+1 \geq k$ consists of at least *m* objects, so that a disc with radius *r*, enclosing all *m* objects, exists in *I*.

Remark: Calculating the flock with the longest duration and the flock with the largest subset are NP-hard problems.

=> solutions are complex or only approximate

Flocks with discrete Time

Definition: *discrete (m,k,r)-Flock*

Let *DB* be a set of trajectories of *l* length, a Flock in $I=[t_i,t_j]$ with $j-i+1 \geq k$ consists of at least *m* objects, so that a disc with radius *r*, enclosing all *m* objects, exists for each discrete time t_l where $i \leq l \leq j$.

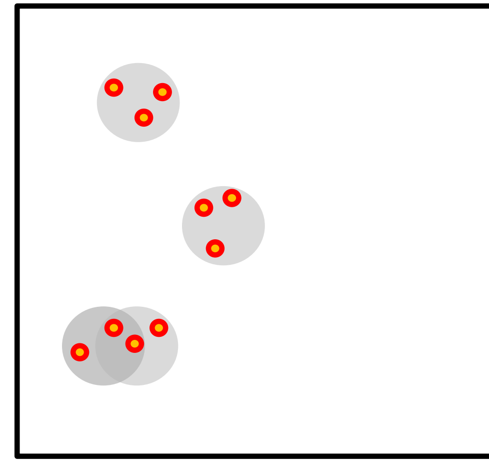
- **Lemma**: If objects move with constant speed and on a direct line between waypoints, discrete and continuous flocks are equivalent.
- **Advantage**: Turning a continuous problem into a discrete one.
  But: Complexity remains unchanged and comes from the combination of possible subsets.

  The possible number of flocks with *m* elements is: $\binom{|DB|}{m} \cdot (l-k+1)$

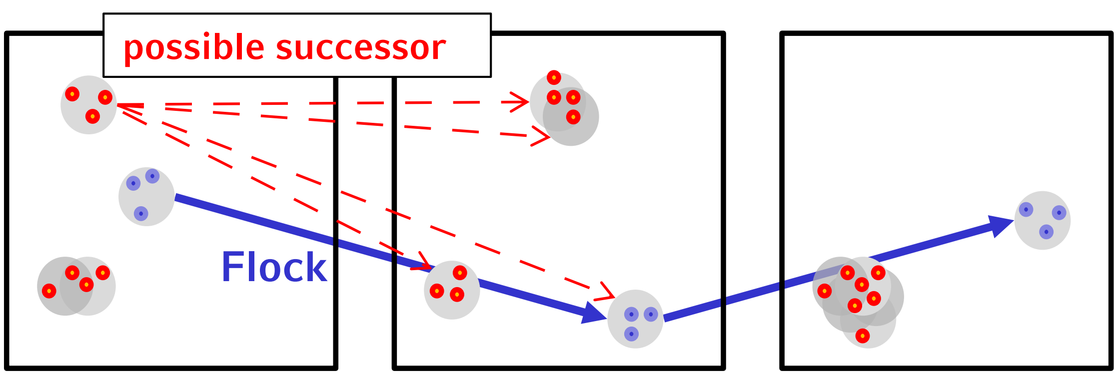
Searching for Flocks

algorithm encompasses 2 subtasks:

1. Find all discs of radius *r*, containing at least *m* points for time t_i.
   - => sequence of subsets of DB
   - => one trajectory may be part of several subsets.



2. Find sequence $(S(t_i), \ldots, S(t_j))$ of discs $S(t_l)$ for the points in time t_l with $i \leq l \leq j$ for which the following condition holds: $\left| \bigcap_{i \leq l \leq j} S(t_l) \right| \geq m$



Find all Discs for the Point in Time t

Discs(t_i)

build grid index I for DB_i

FOR ALL non-empty cells gx $\in$ I **DO**

  Pr = gx

  Ps= NeighborCells(gx)

  IF $|Ps| \geq m$ **THEN**

   FOR EACH *pr* $\in$ *Pr* **DO**

    H=Range(pr,2r)

    FOR *each pj* $\in$ H **DO**

     IF *not computed {pr,pj }* **THEN**

      compute disks {c1,c2} from {pr,pj }

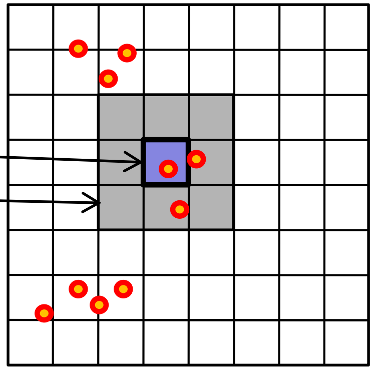
      FOR EACH *disk ck* $\in$ *{c1,c2}* **DO**

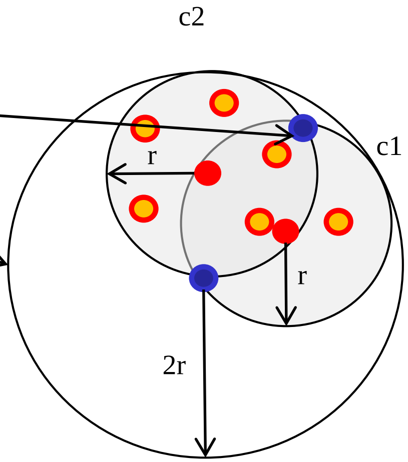
       $c = ck \cap H$

       IF $|c| \geq m$ **THEN**

        C.add(c)

RETURN *C*





Finding (m,k,r)-Flocks

Continuous Refinement Evaluation (CRE)

CRE(DB,k)

FOR EACH point in time t_i **DO**

  L: Trajectories in time interval t_{i-k} to t_i

  $C^1 = Disks(L[t_{i-k}])$ // all containing trajectories in L at t_{i-k}

  $F = \{\}$ // results flocks

  FOR EACH $c1 \in C^1$ **DO** // for each start disc

    L'[1] = trajectories in c1

    $F^1 = c1,\ F^t = \{\}$

    FOR $t = 2$ *to* k **DO** // for the next k-1 times

      $C^t = Disks(L'[t])$

      $F^t = \{\}$

      FOR EACH $c \in C^t$ **DO** // for all disc at time t

        FOR EACH $f \in F^{t-1}$ **DO** // for currently valid flocks

          IF $|c \cap f| \geq m$ **THEN**

            $F^t = F^t \cup \{c \cap f\}$ // extend the flock by one point in time

      IF $|F^t| = 0$ **THEN**

        BREAK

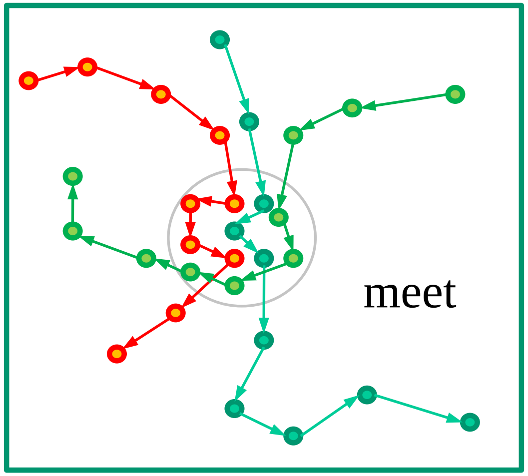
    $F = F \cup F^t$

  RETURN F

Meets (Encounter)

Idea: Find objects that stay together in an area for a certain time.

Examples: Encounter, Combat.



Definition: (m,k,r)-Meet

Let *DB* be a set of trajectories of length l, a meet within the time interval $I=[t_i,t_j]$ with $j-i+1 \geq k$ consists of at least *m* objects, so that for every point in time $t_i \in I$ all *m* objects lie within a disc of radius *r* and center point M.

Remarks: Calculating meets is easier than calculating flocks because for two consecutive points in time only the discs positions, not their trajectories, must be analyzed.

Encounter Detection

Idea: To find out where a team succeeded /failed and find the decisive moments in a game.

- in Dota2 defeating enemy heroes grants the biggest advantage in gold/XP
- find situations where this was possible or succeeded => Encounters

Encounter characteristics

- encounters represent only a portion of the game
- encounters can happen simultaneously
- often only sub teams are involved in encounters

Defining Encounters

Idea: Fights happen when opponents can influence each other.

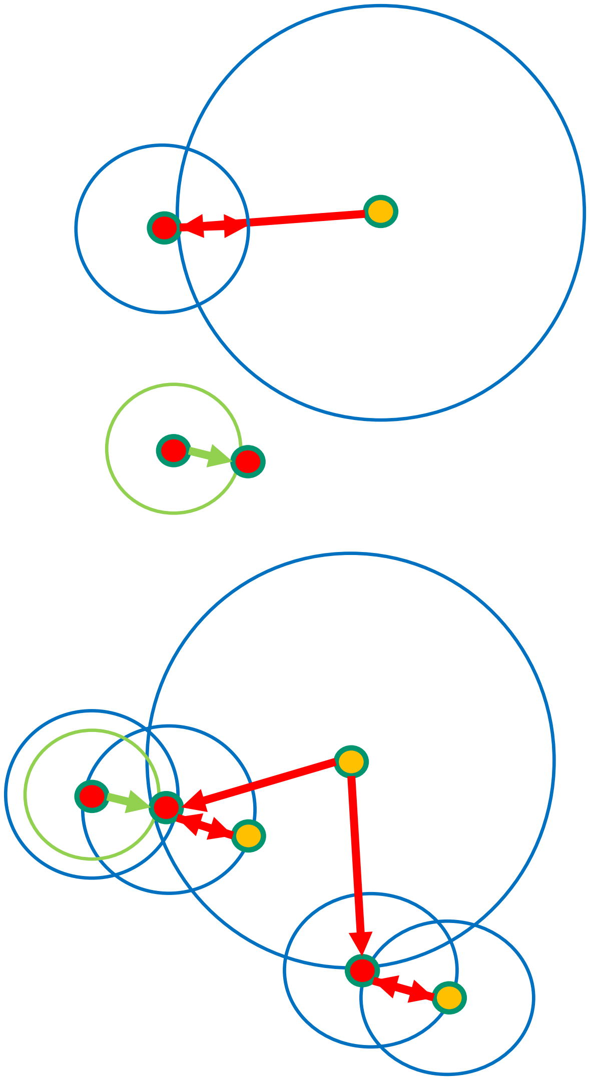
- opponents have to be in fighting range
- each hero unit might have an individual attack range
- heroes can support (e.g. heal) a friendly unit

Which kind of information is necessary?

- Spatial position and unit type for each controlled hero unit
- Attack and support ranges for all units types

Encounter Situations

- ***Combat link***: 2 hero units from different teams A and B. Either A can attack B or vice versa
- ***Support lin***k: 2 hero units from the same team A and B. Either A can support B or vice versa
- Each hero type has individual ***attack and support ranges*** (Ranges are mean values plus to standard deviations)
- ***Component Graph***: Connected Graph build by Combat/support Links



Encounter Situations

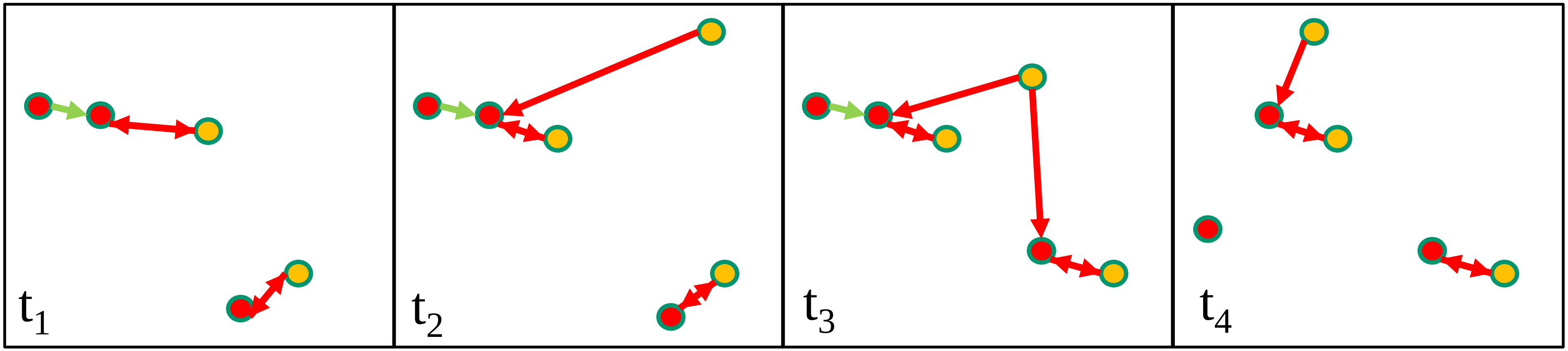
Formally…

Definition: Combat Component

- *units U and the union $E_d = CL \cup SL$ of combat links CL and support links SL* between the units in U.
- $E_u = \{(u_i, u_j) | (u_i, u_j) \in E_d \vee (u_j, u_i) \in E_d\}$
- situation graph $G(U, E_u)$.
- combat component C: connected subgraph $G(\bar{U}, \bar{E})$ of $G(U, E_u)$ where $\bar{U} \subseteq U, \bar{E} \subseteq \bar{U} \times \bar{U}$
  and $\forall u_1, u_l \in \bar{U}: \exists (u_1, u_2, .. u_l)$
  where $i \in \{1, .., l\}: (u_i, u_{i+1}) \in \bar{E}$
  and $\exists u_i, u_j \in \bar{U}: u_1.team \neq u_2.team$.

Defining Encounters

- Component Graphs describe an Encounter at tick *t*
- An encounter usually lasts multiple consecutive ticks
- Hero Units can join encounters
- Hero Units might be defeated or leave
- Encounters can split
- Encounters can join



Defining Encounters

Formally…

Definition: Successor

Given a set of components $CS_t = \{ C_{1,t}, \ldots, C_{l,t} \}$ describing encounter E at tick t. Let τ be a timeout threshold. A component $C_{t+\Delta t}$ is a successor of CS_t denoted as $CS_t \rightarrow C_{t+\Delta t}$ if the following conditions hold:

- $\Delta t \leq \tau$
- $\exists u_1, u_2 \in C_{t+\Delta t} : \exists C_{i,t} \in CS_t : u_1 \in C_{i,t} \wedge C_{j,t} \in CS_t : u_2 \in C_{j,t} \wedge u_1.team \neq u_2.team$

Defining Encounters

Formally….

Definition: Encounter

An encounter is a sequence *(CS_0,.., $CS_{,l}$)* of lists of components CS_i where the following condition holds:
$\forall C_{i,t} \in CS_t\colon CS_{t-1} \rightarrow C_{i,t}$ with $t \in \{1,..,l\}$.

Encounter Detection

What is the input data ?

- hero type (combat range, support range), team
- time series of position updates (one at a time)

Algorithm:

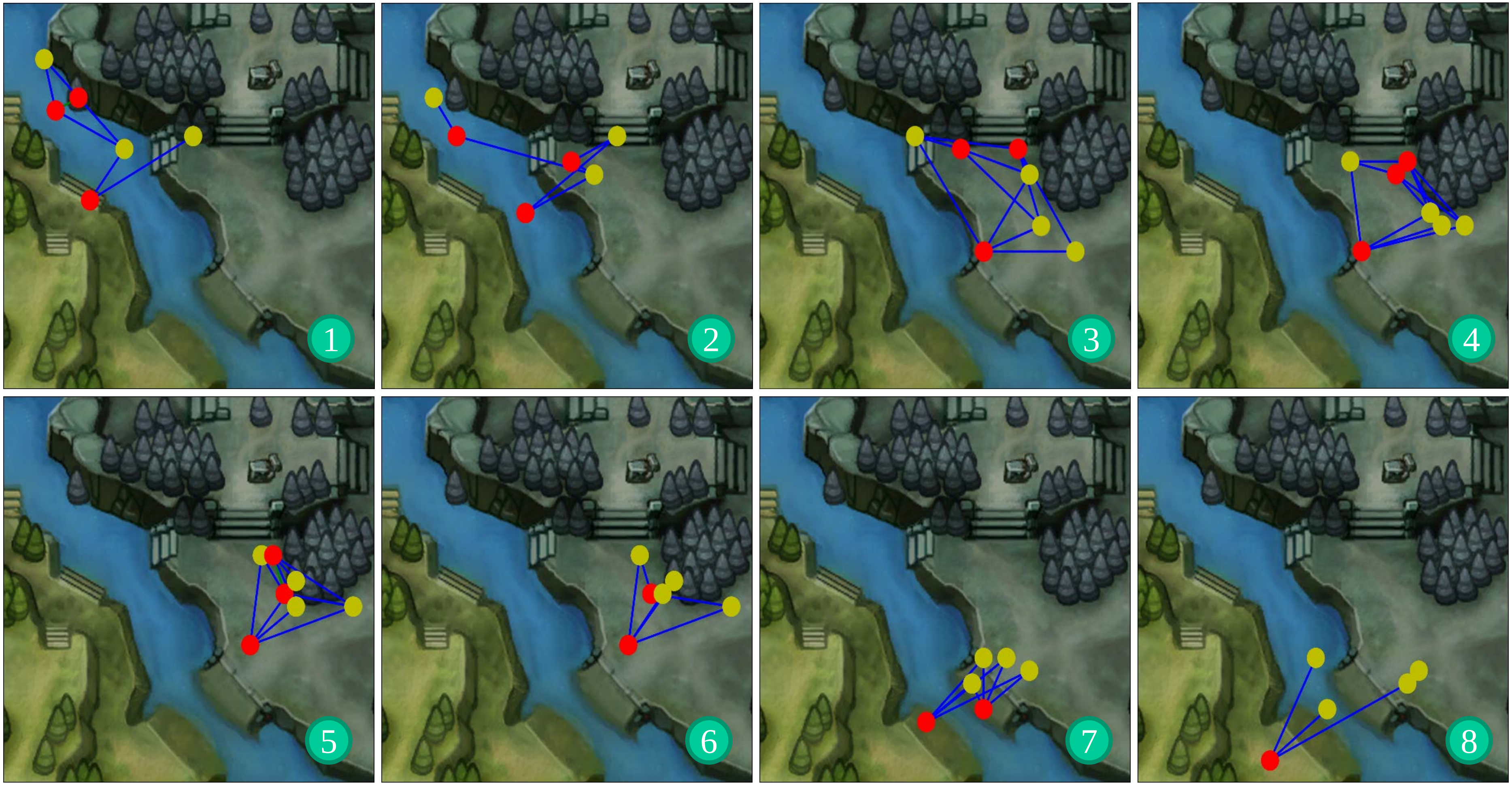
- initialize hero information
- stream over position updates and update distances
- for each player movement process the impact to the current component graphs
- keep lists of open encounters
- move encounters to a closed set if they time out

The Algorithm

```
Encounter Detection (position_stream)
While position_stream.hasNext():
       component = build_component(unit,distance_table)
    If component is combat component:
       compute predecessors(component, open_encounters)
       If predecessors.size() == 0:
         open_encounters.add(new Encounter(component)
       If predecessors.size() == 1:
         predecessors.get(1).update(component)
       If predecessors.size() >1:
         open_encounters.join(predecessors,component)
       For encounter in open_encouters:
         If encounter has timeout:
              move encounter from open_encounter to closed_encounters
For encounter in open_encouters:
        move encounter from open_encounter to closed_encounters
return closed_encounters
```

An Example Encounter

An Example Encounter (Detailed View)



Learning Goals

- use cases for spatial game analytics
- heat maps with bin counting and kernel density estimation
- tasks of spatial data mining
- spatial outlier detection with POD
- trajectories, relative and absolute trajectories
- comparing trajectories (LCSS)
- compressing trajectories
- pattern search in trajectories
  - definition of flocks
  - calculation of flocks
  - definition of meets
  - encounter detection

Literature

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