

# Aggregate Count Queries in Probabilistic Spatio-Temporal Databases

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# SPOT databases

## **SPOT (Spatial PrObabilistic Temporal) databases**

[Parker, Subrahmanian, Grant. TKDE'07]

- Declarative framework for the representation and processing of probabilistic spatio-temporal databases with uncertain probabilities.

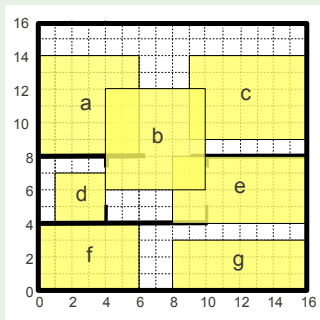
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### Example



A SPOT database:

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Given a region  $r$  and a probability interval  $[\ell, u]$ , find all pairs  $(id, t)$  s.t. object  $id$  is at time  $t$  inside region  $r$  with a probability in  $[\ell, u]$ .
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- **Belief revision** [Grant et al. AIJ'10]:  
Given a SPOT database  $D$  and a new SPOT atom  $A$  (to be added to  $D$ ), if  $D \cup \{A\}$  is inconsistent, then “revise”  $D$  into a new database  $D'$  so that  $D' \cup \{A\}$  is consistent.

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- **Full logic** [Doder, Grant, Ognjanović. J. Log. Comput.'13]:  
More expressive language with with negation, disjunction, and quantifiers.

## **Count Queries** in the SPOT framework:

how many objects are in a certain region at a given time point?

- Syntax and three alternative semantics
  - ▶ *Expected value semantics*
  - ▶ *Extreme values semantics*
  - ▶ *Ranking semantics*
- Properties
- Algorithms
- Complexity



# SPOT databases

## Notation

- $ID$  is the set of all object ids.
- $Space$  is a grid of  $N \times N$  points.
- $T$  is the set of time points.

## Assumptions:

- An object can be in only one location at a time.
- A location may contain more than one object.

# SPOT databases - Syntax

## Definition

A **SPOT atom** is a tuple  $(id, r, t, [\ell, u])$  where

- $id$  is an object id,
- $r$  is a region,
- $t$  is a time point,
- $[\ell, u] \subseteq [0, 1]$  is a probability interval.

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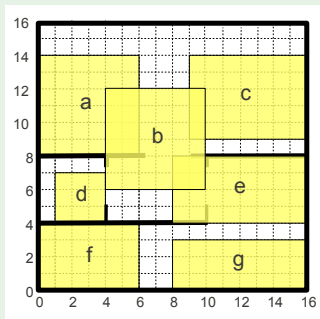
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## Definition

A **SPOT database** is a finite set of SPOT atoms.

# SPOT databases - Syntax

## Example



A SPOT database:

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# SPOT databases - Semantics

## Definition

A **SPOT interpretation** is a function  $I : ID \times Space \times T \rightarrow [0, 1]$  such that for each  $id \in ID$  and  $t \in T$ ,

$$\sum_{p \in Space} I(id, p, t) = 1$$

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A SPOT interpretation  $I$  **satisfies** a SPOT atom  $(id, r, t, [l, u])$  iff

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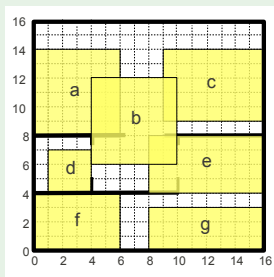
$$\sum_{p \in r} I(id, p, t) \in [\ell, u]$$

## Definition

A SPOT interpretation  $I$  is a **model** for a SPOT database  $D$  iff  $I$  satisfies every SPOT atom in  $D$ .

# SPOT databases - Semantics

## Example



SPOT database  $D$ :

$(id_1, d, 1, [0.9, 1])$

$(id_1, b, 2, [0.6, 1])$

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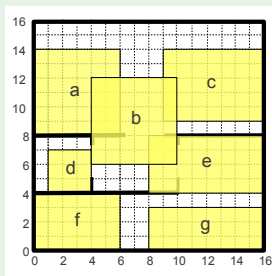
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# SPOT databases - Semantics

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Interpretation  $I$  defined as follows is a model of  $D$

$$I(id_1, (2, 5), 1) = 0.4$$

$$I(id_1, (3, 5), 1) = 0.5$$

$$I(id_1, (10, 6), 1) = 0.1$$

$$I(id_1, (10, 10), 2) = 0.7$$

$$I(id_1, (1, 1), 2) = 0.3$$

$$I(id_2, (7, 8), 1) = 0.7$$

$$I(id_2, (11, 12), 1) = 0.3$$

$$I(id_2, (9, 7), 2) = 0.3$$

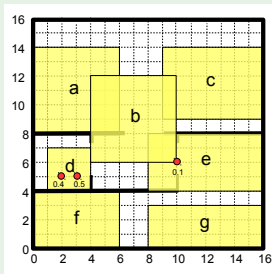
$$I(id_2, (12, 15), 2) = 0.7$$

$I(id, p, t) = 0$  for all triplets  $(id, p, t)$  not mentioned above.

# SPOT databases - Semantics

## Example

object  $id_1$   
at time point 1



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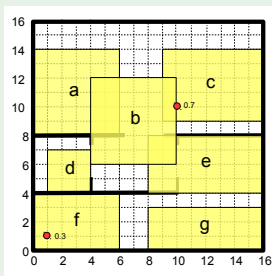
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# SPOT databases - Semantics

## Example

object  $id_1$   
at time point 2



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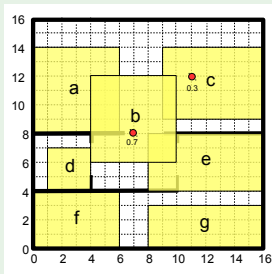
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# SPOT databases - Semantics

## Example

object  $id_2$   
at time point 1



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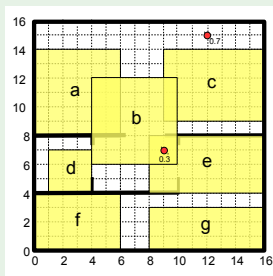
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object  $id_2$   
at time point 2



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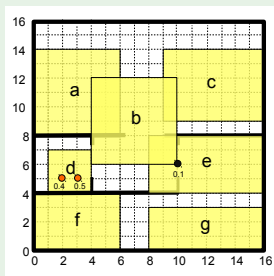
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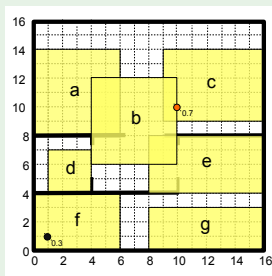
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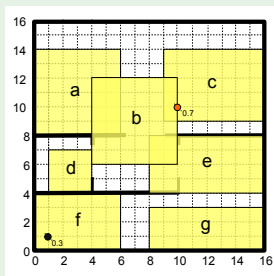
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# Count Queries in SPOT databases - Syntax

## Definition

A **count query** is an expression of the form

$$\text{Count}(r, t)$$

where  $r$  is a region (i.e., a subset of *Space*) and  $t$  is a time point.

Intuitively,  $\text{Count}(r, t)$  asks:  
“How many objects are inside region  $r$  at time  $t$ ?”.

# Count Queries in SPOT databases - **Semantics**

We propose three alternative semantics for interpreting count queries:

- 1 the *expected value semantics*,
- 2 the *extreme values semantics*,
- 3 the *ranking semantics*.

# Expected Value Semantics

Basic idea: Given a count query  $Count(r, t)$  and a SPOT database  $D$ ,

- Define the **expected number of objects** in  $r$  at time  $t$  **w.r.t. to a model  $M$** .
- Take the **minimum and maximum expected number of objects across all models** of  $D$ .

# Expected Value Semantics

Consider a count query  $Count(r, t)$  and a SPOT database  $D$  with  $n$  objects.

## Definition

Let  $M$  be a model for  $D$  and  $X_M$  a random variable representing the number of objects in region  $r$  at time  $t$  according to  $M$ .

The expected number of objects in  $r$  at time  $t$  w.r.t.  $M$  is:

$$Q^{exp}(M) = \mathbb{E}[X_M] = \sum_{i=0}^n i \cdot \Pr(X_M = i)$$

## Definition (Expected value semantics)

The **expected value answer** is  $[c, C]$  where:

$$c = \min_{M \text{ is a model of } D} Q^{exp}(M) \quad \text{and} \quad C = \max_{M \text{ is a model of } D} Q^{exp}(M)$$

# Expected Value Semantics

Consider a count query  $Count(r, t)$  and a SPOT database  $D$ .

## Proposition

*If  $[c, C]$  is the expected value answer, then  $\forall v \in [c, C]$  there exists a model  $M$  of  $D$  s.t.  $Q^{exp}(M) = v$ .*

# Extreme Values Semantics

Basic idea: Given a count query  $Count(r, t)$  and a SPOT database  $D$ , return **the lowest and the highest numbers of objects** that can be inside region  $r$  at time  $t$  (according to the different models of  $D$ ).

# Extreme Values Semantics

Consider a count query  $Count(r, t)$  and a SPOT database  $D$ .

## Definition (Extreme values semantics)

The **extreme values answer** is  $[z, Z]$  where:

$$z = \min_{M \text{ is a model of } D} |\{id \mid M(id, r, t) = 1\}|$$

$$Z = \max_{M \text{ is a model of } D} |\{id \mid M(id, r, t) \neq 0\}|$$

# Extreme Values Semantics

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## Proposition

*If  $[c, C]$  is the expected value answer and  $[z, Z]$  is the extreme value answer, then  $z \leq c \leq C \leq Z$ .*



# Ranking Semantics

Basic idea: Given a count query  $Count(r, t)$  and a SPOT database  $D$  with  $n$  objects, return a set of pairs

$$\begin{aligned} &\langle 0, [\ell_0, u_0] \rangle \\ &\langle 1, [\ell_1, u_1] \rangle \\ &\langle 2, [\ell_2, u_2] \rangle \\ &\langle 3, [\ell_3, u_3] \rangle \\ &\quad \vdots \\ &\langle n, [\ell_n, u_n] \rangle \end{aligned}$$

where  $[\ell_i, u_i]$  is a probability interval for exactly  $i$  objects being in region  $r$  at time  $t$ .

## Ranking Semantics

We assume independence of events involving the locations of different objects.

Consider a count query  $Count(r, t)$  and a SPOT database  $D$  with  $n$  objects.

### Definition

$$Prob^{min}(r, t, i) = \min_{M \text{ is a model of } D} Prob_M(r, t, i) \quad \text{for } 0 \leq i \leq n$$

$$Prob^{max}(r, t, i) = \max_{M \text{ is a model of } D} Prob_M(r, t, i) \quad \text{for } 0 \leq i \leq n$$

where  $Prob_M(r, t, i)$  is the probability of having exactly  $i$  objects in  $r$  at time  $t$  w.r.t. model  $M$ , i.e.,

$$\sum_{\substack{S \text{ is a set of ids} \\ \text{and } |S| = i}} \left( \prod_{id \in S} M(id, r, t) \cdot \prod_{id \in \{\text{all ids}\} \setminus S} (1 - M(id, r, t)) \right)$$

## Ranking Semantics

Consider a count query  $Count(r, t)$  and a SPOT database  $D$  with  $n$  objects.

### Definition

The **ranking answer** is

$\langle 0, [\ell_0, u_0] \rangle$  where  $\ell_0 = Prob^{min}(r, t, 0)$  and  $u_0 = Prob^{max}(r, t, 0)$

$\langle 1, [\ell_1, u_1] \rangle$  where  $\ell_1 = Prob^{min}(r, t, 1)$  and  $u_1 = Prob^{max}(r, t, 1)$

$\vdots$

$\langle n, [\ell_n, u_n] \rangle$  where  $\ell_n = Prob^{min}(r, t, n)$  and  $u_n = Prob^{max}(r, t, n)$

## Ranking Semantics

Consider a count query  $Count(r, t)$  and a SPOT database  $D$  with  $n$  objects.

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$\vdots$

$\langle n, [\ell_n, u_n] \rangle$  where  $\ell_n = Prob^{min}(r, t, n)$  and  $u_n = Prob^{max}(r, t, n)$

### Proposition

For a **simple** SPOT database (i.e., with a single model)

- The expected answer is  $[\sum_{i=0}^n i \cdot \ell_i, \sum_{i=0}^n i \cdot u_i]$
- The extreme answer is  $[\min\{i \mid 0 \leq i \leq n \wedge \ell_i = 1\}, \max\{i \mid 0 \leq i \leq n \wedge \ell_i \neq 0\}]$

# Algorithms

- ① Algorithm to compute the expected value semantics
  - ▶ It leverages a linear program derived from the SPOT database
  - ▶ Polynomial time
- ② Algorithm to compute the extreme values semantics
  - ▶ It leverages a linear program derived from the SPOT database
  - ▶ Polynomial time
- ③ Algorithm to compute the ranking semantics
  - ▶ Exponential time algorithm
  - ▶ Polynomial time algorithm for *simple* SPOT database (i.e., admitting a single model)

## Definition

Given a SPOT database  $D$ , an object  $id$ , and a time point  $t$ ,  $LC(D, id, t)$  is the linear program consisting of the following linear constraints:

$$l \leq \sum_{p \in r} v_p \leq u \quad \text{for each } (id, r, t, [l, u]) \in D$$

$$v_p \geq 0 \quad \text{for each location } p \in Space$$

$$\sum_{p \in Space} v_p = 1$$

# Computing expected value semantics

Consider a count query  $Count(r, t)$  and a SPOT database  $D$  with  $n$  objects.

## Theorem

*The expected value answer  $[c, C]$  can be computed as*

$$c = \sum_{id=1}^n \left( \text{minimize } \sum_{p \in r} v_p \text{ subject to } LC(D, id, t) \right)$$

$$C = \sum_{id=1}^n \left( \text{maximize } \sum_{p \in r} v_p \text{ subject to } LC(D, id, t) \right)$$

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## Corollary

*The expected value answer can be computed in time  $O(n \cdot (|Space| \cdot |D|)^3)$ .*



# Computing extreme value semantics

Consider a count query  $Count(r, t)$  and a SPOT database  $D$  with  $n$  objects.

## Theorem

*The extreme value answer  $[z, Z]$  can be computed as*

$$z = |\{id \text{ appears in } D \text{ and } (\mathbf{minimize} \sum_{p \in r} v_p \text{ subject to } LC(D, id, t)) = 1\}|$$
$$Z = |\{id \text{ appears in } D \text{ and } (\mathbf{maximize} \sum_{p \in r} v_p \text{ subject to } LC(D, id, t)) \neq 0\}|$$

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## Corollary

*The extreme value answer can be computed in time  $O(n \cdot (|Space| \cdot |D|)^3)$ .*

# Computing ranking semantics

## Proposition

The ranking answer  $\langle 0, [\ell_0, u_0] \rangle, \dots, \langle n, [\ell_n, u_n] \rangle$  can be computed as

$\ell_i =$  **minimize**

$$\sum_{\substack{S \text{ is a set of ids} \\ \text{and } |S| = i}} \left( \prod_{id \in S} \sum_{p \in r} v_p^{id} \cdot \prod_{id \in \{\text{all ids}\} \setminus S} (1 - \sum_{p \in r} v_p^{id}) \right)$$

**subject to**

$$LC(D, id_1, t) \cup \dots \cup LC(D, id_n, t)$$

$u_i =$  **maximize**

$$\sum_{\substack{S \text{ is a set of ids} \\ \text{and } |S| = i}} \left( \prod_{id \in S} \sum_{p \in r} v_p^{id} \cdot \prod_{id \in \{\text{all ids}\} \setminus S} (1 - \sum_{p \in r} v_p^{id}) \right)$$

**subject to**

$$LC(D, id_1, t) \cup \dots \cup LC(D, id_n, t)$$

## Computing ranking semantics

For **simple** SPOT databases (i.e., with one single model) we have a polynomial-time dynamic programming algorithm.

### Definition

$$Prob_M(r, t, 0, j) = \prod_{k=1}^j (1 - M(id_k, r, t)) \quad 1 \leq j \leq n$$

$$Prob_M(r, t, j, j) = \prod_{k=1}^j M(id_k, r, t) \quad 1 \leq j \leq n$$

$$Prob_M(r, t, i, j) = M(id_j, r, t) \cdot Prob_M(r, t, i-1, j-1) + (1 - M(id_j, r, t)) \cdot Prob_M(r, t, i, j-1) \quad 2 \leq j \leq n, 1 \leq i \leq j-1$$

# Computing ranking semantics

For **simple** SPOT databases (i.e., with one single model) we have a polynomial-time dynamic programming algorithm.

## Definition

$$\begin{aligned} \text{Prob}_M(r, t, 0, j) &= \prod_{k=1}^j (1 - M(id_k, r, t)) & 1 \leq j \leq n \\ \text{Prob}_M(r, t, j, j) &= \prod_{k=1}^j M(id_k, r, t) & 1 \leq j \leq n \\ \text{Prob}_M(r, t, i, j) &= M(id_j, r, t) \cdot \text{Prob}_M(r, t, i-1, j-1) + \\ & (1 - M(id_j, r, t)) \cdot \text{Prob}_M(r, t, i, j-1) & 2 \leq j \leq n, 1 \leq i \leq j-1 \end{aligned}$$

## Theorem

The ranking answer  $\langle 0, [\ell_0, u_0] \rangle, \dots, \langle n, [\ell_n, u_n] \rangle$  can be computed as

$$\ell_i = u_i = \text{Prob}_M(r, t, i, n)$$

for simple SPOT databases.

# Computing ranking semantics

## Corollary

*The ranking answer can be computed in time  $O(n \cdot (|Space| \cdot |D|)^3)$ .*

# Conclusion

## Count queries in the SPOT framework

- Three alternative semantics
  - 1 Expected value semantics
  - 2 Extreme values semantics
  - 3 Ranking semantics
- Properties, Algorithms, Complexity

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## Count queries in the SPOT framework

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  - 1 Expected value semantics
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## Future work

- No independence assumption for the ranking semantics
- Count queries over time intervals
- Other kinds of count queries



THANKS!  
QUESTIONS?