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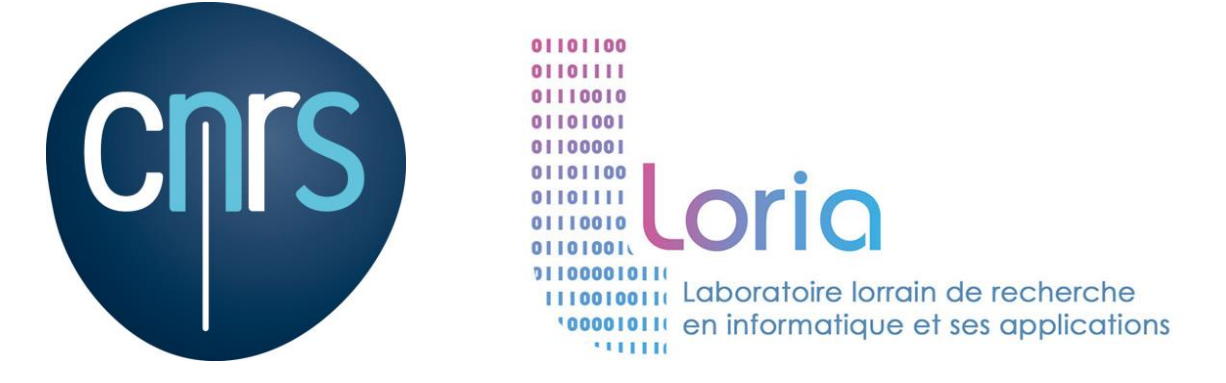
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Sequential pattern mining for analyzing visitor trajectories



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1. Introduction

Hecht Museum is an archaeological museum in Haifa, Israel.

In this work, we present our work on the **grouping** and **mining** of **trajectory** patterns of **visitors** in this museum.

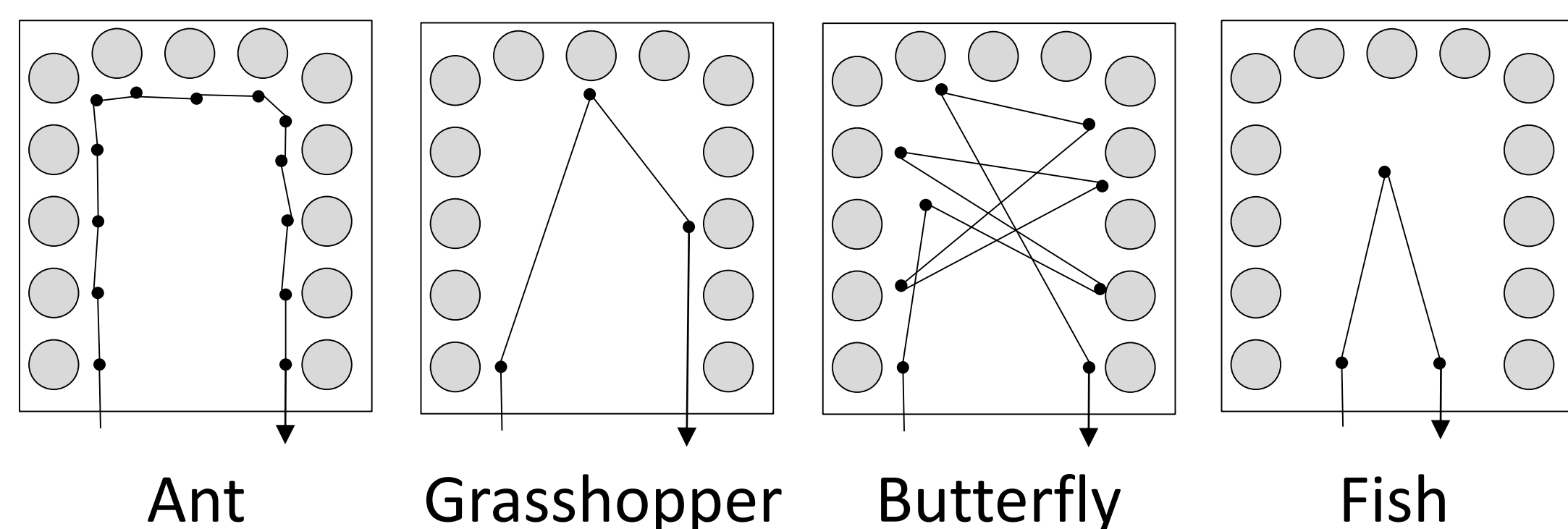
2. Dataset and visitor behaviors

Within the framework of CrossCult project, we are working on a dataset of the trajectories of **254 visitors** in Hecht Museum. Each trajectory contains a **list** of visited **items**. An example is illustrated in the table below.

Table I. An example of one visitor trajectory

Start	Finish	Item	Room
14:10:09	14:11:14	102	1
14:12:45	14:20:19	402	4
14:22:10	14:25:42	407	4

Based on his/her movement, a visitor can be grouped as one of four defined behaviors: ant, grasshopper, butterfly, and fish, as illustrated in the figures below.



6. Results

Patterns	Count
(1, 1, 1)	33
(1, 7)	13
(1, 1)	66

Patterns	Count
(1, 3)	38
(3, 1)	9
(4, 7)	31
(7, 4)	11

Visitors	Patterns	Cluster	Behavior
70, 107, 121, 133, 201, 202	(1, 1, 402)	A	ant
103, 165, 188	(701, 707)	B	ant
4, 8, 32	(101, 102, 101)	C	ant/butterfly
46, 47	(101, 602)	D	grasshopper
89, 163	(602, 203)	D	grasshopper
71, 79	(701, 504)	D	grasshopper
97, 98	(701, 406)	D	grasshopper
		E	fish

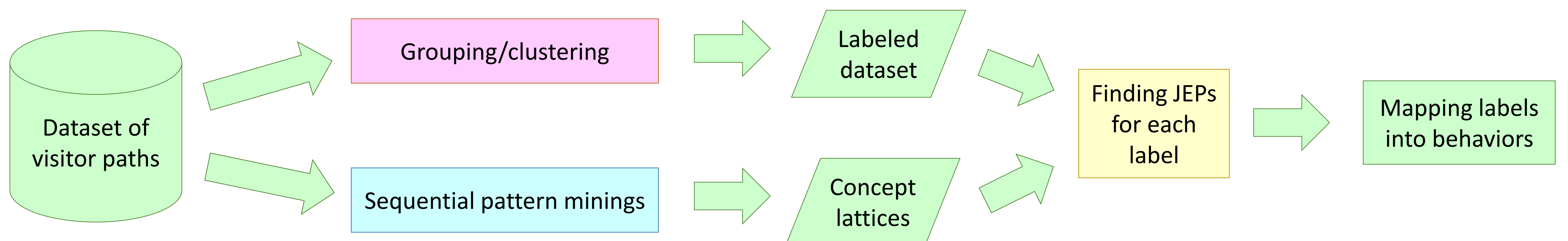
7. Conclusion

Our results highlight some **interesting patterns** that may define visitor **behaviors**. This can help museum researchers to analyze and evaluate the placement of items and the visiting styles. Furthermore, these patterns can be analyzed to build a **recommendation system** for future visitors.

8. References

- [1] E. Egho et al., 2015, On measuring similarity for sequences of itemsets. *Data Mining and Knowledge Discovery* 29(3), 732–764.
- [2] A. Buzmakov et al., 2016, On mining complex sequential data by means of FCA and pattern structures. *International Journal of General Systems* 45(2), 135–159.
- [3] V. Codocedo et al., 2017, A proposition for sequence mining using pattern structures. *Proceedings of ICFA*, 106–121.

3. Workflow



4. Clustering

Each trajectory is modeled as a **sequence of items**.

The trajectory in Table I becomes:
 (102, 402, 407)

Distance between any two sequences is measured by simACS [1].

5. Sequential pattern mining

We apply two algorithms to obtain two lattices:

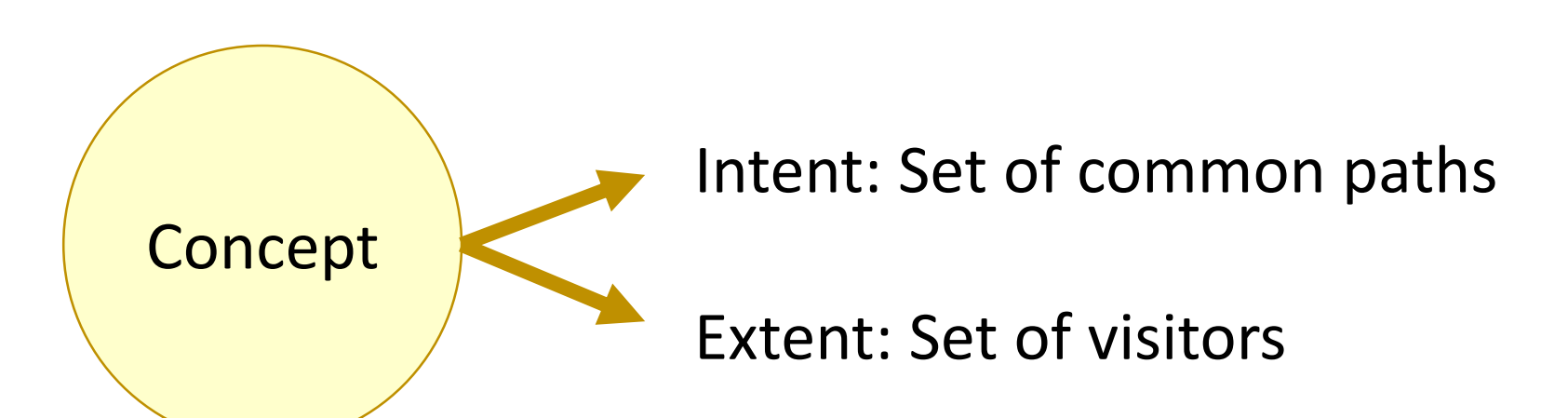
- MFCS (mining frequent **contiguous** sequences) [2]

(102, 202, 301, 402) → (102, 202, 301)

- MRGS (mining rare **general** sequences) [3]

(102, 202, 301, 402) → (102, 202, 402)

6. Jumping emerging pattern (JEP)



From the two lattices, there are some concepts whose **extent** contains visitors from the **same label**. The **intent** of such concepts is a JEP.