## Simultaneous Embeddability of Two Partitions

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## Introduction

## Partitions

definition: partition of a finite universe $U$

- $\mathcal{P}=\left\{B_{1}, \ldots, B_{n}\right\}$ collection of subsets ("blocks") of $U$
- every $u \in U$ contained in exactly one $B \in \mathcal{P}$



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## occurrence of partitions

- induced by parameter of a dataset
- multiple independent parameters possible
- result of a clustering algorithm
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How can we compare two partitions?

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Related Work

- numeric measures of similarity for two partitions [Wagner \& Wagner 2007]
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- Venn- and Euler diagrams and hypergraph / set visualization [Chow 2007, Mäkinen 1990, Kaufmann et al. 2009]
- the more general case, not restricted to pairs of partitions


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## our contribution

- classification of simultaneous embeddings of two partitions


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definition: embedding of a collection of subsets of $U$ embedding $\Gamma$ of $\mathcal{S} \subseteq 2^{U}$ maps

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- $S \in \mathcal{S} \rightarrow \Gamma(S) \subset \mathbb{R}^{2}$ such that
- $\Gamma(S)$ is simple, bounded, and closed region
- $\Gamma(u) \in \Gamma(S) \Leftrightarrow u \in S$
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two partitions $\mathcal{P}_{1}$ and $\mathcal{P}_{2}$
- (simultaneous) embedding := embedding of $\mathcal{P}_{1} \cup \mathcal{P}_{2}$


## Embeddability Classes

Overview

examples of simultaneous embeddings of two partitions

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examples of simultaneous embeddings of two partitions

How to classify a "good" embedding?

## Embeddability Classes

Weak Embeddability
definition: weak embedding no two block regions of the same partition intersect

non-weak embedding

weak embedding

## Embeddability Classes

Weak Embeddability

theorem
Any two partitions on any point set have a weak embedding.

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weak embedding + each connected component of the intersection of two block regions contains at least one element

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- only because $\left(U, \mathcal{P}_{1} \cup \mathcal{P}_{2}\right)$ is 2-regular hypergraph
- equivalent to existence of planar support ( $\rightarrow$ later) [Kaufmann et al. 2009]


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theorem
$\left\{\mathcal{P}_{1}, \mathcal{P}_{2}\right\}$ strongly embeddable
$\Leftrightarrow$
$\left(U, \mathcal{P}_{1} \cup \mathcal{P}_{2}\right)$ has planar support


## Embeddability Classes

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## Embeddability Classes

Hierarchy of Embeddability


## theorem <br> The hierarchy is strict.


weak embedding

strong embedding

full embedding

## Complexity results

NP-completeness of Strong Embeddability
definition: support of a hypergraph [Kaufmann et al. 2009]

- $H=(U, \mathcal{S})$ is hypergraph with $\mathcal{S} \subseteq 2^{U}$
- support: graph $G=(U, E)$ on $U$
- induced subgraph $G[S]$ for every hyperedge $S \in \mathcal{S}$ connected


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theorem (reminder)
$\left\{\mathcal{P}_{1}, \mathcal{P}_{2}\right\}$ strongly embeddable $\Leftrightarrow$
$\left(U, \mathcal{P}_{1} \cup \mathcal{P}_{2}\right)$ has planar support


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$\Rightarrow$ implies NP-completeness of deciding vertex planarity for 2 -regular hypergraphs

## Complexity results <br> NP-completeness of Strong Embeddability

theorem
Deciding strong embeddability is NP-complete.
sketch of proof
show that finding a planar support is NP-complete

- membership in NP
- guess support graph
- check planarity and support-property in polynomial time
- NP-hardness
- reduction from Planar-Monotone-3-Sat
- inspired by more general proof from [Buchin et al. 2010]


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3-SAT formula with planar monotone rectilinear representation (MRR)

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\begin{aligned}
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& C_{2}=\left(x_{2} \vee x_{3} \vee x_{5}\right) \\
& C_{3}=\left(x_{3} \vee x_{4} \vee x_{5}\right) \\
& C_{4}=\left(x_{1} \vee x_{1} \vee x_{2}\right) \\
& \\
& C_{5}=\left(\overline{x_{2}} \vee \overline{x_{3}} \vee \overline{x_{4}}\right) \\
& C_{6}=\left(\overline{x_{2}} \vee \overline{x_{4}} \vee \overline{x_{6}}\right) \\
& C_{7}=\left(\overline{x_{1}} \vee \overline{x_{2}} \vee \overline{x_{6}}\right)
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& C_{7}=\left(\overline{x_{1}} \vee \overline{x_{2}} \vee \overline{x_{6}}\right)
\end{aligned}
$$

- NP-complete problem [de Berg \& Khosravi 2010]

Complexity results<br>NP-completeness of Strong Embeddability

given an MRR $\Phi$

- fix clusters on a grid to follow structure of $\Phi$
- inspired by the proof in [Chaplick et al. 2012]


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## Thank you!

Results and Extensions

## future work

- more than two partitions
- algorithms for visually appealing embeddings
- respect an underlying graph structure

weak embedding
$\Rightarrow$ exists always

strong embedding
$\Rightarrow$ NP-complete

full embedding
$\Rightarrow$ check in lin. time

