

# Recent Development of Abstract Convex Geometries

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(ETH Zurich)

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## Biased introduction to (abstract) convex geometries

◆ Definition and Examples	(15 min.)
◆ Basic Concepts I	(5 min.)
◆ Classification	(15 min.)
◆ Basic Concepts II	(15 min.)
◆ Others	(5 min.)
◆ Summary	(1 min.)

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## Setup

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## Def.

$\mathcal{L}$  is called a **convex geometry** on  $E$  if  $\mathcal{L}$  satisfies the following conditions.

(1)  $\emptyset \in \mathcal{L}, E \in \mathcal{L}$ .

(2)  $X, Y \in \mathcal{L} \Rightarrow X \cap Y \in \mathcal{L}$ .

(3)  $X \in \mathcal{L} \setminus \{E\} \Rightarrow \exists e \in E \setminus X: X \cup \{e\} \in \mathcal{L}$ .

$X \subseteq E$  is called **convex** if  $X \in \mathcal{L}$ .

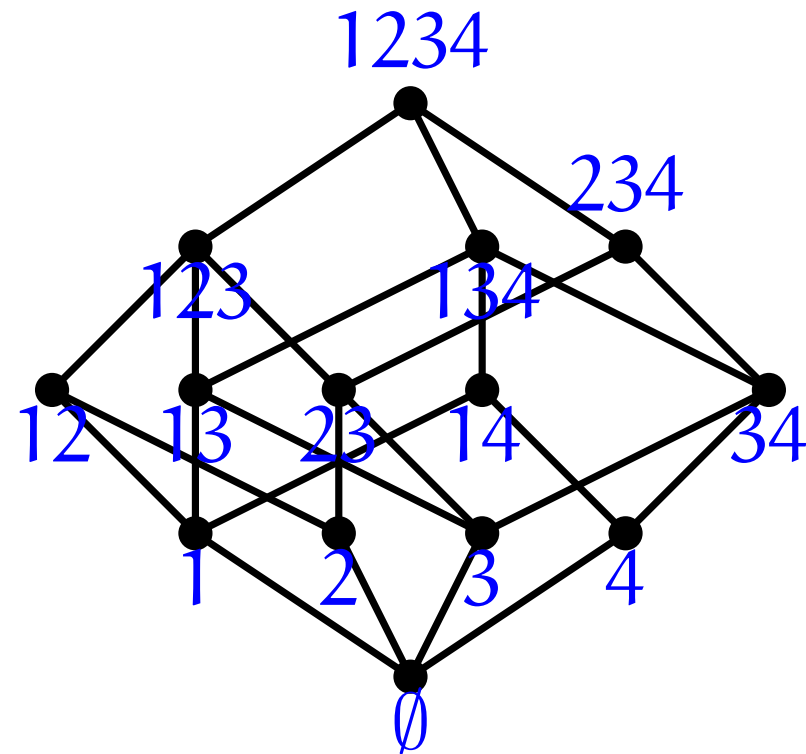
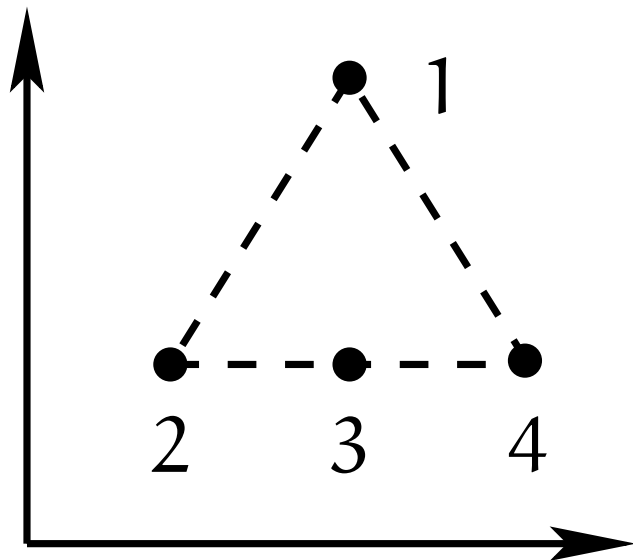
Given

 $\mathcal{P}$  a finite point set in  $\mathbb{R}^d$ 

Def.

 $\mathcal{L}$  the **convex shelling** on  $\mathcal{P}$ :

$$\mathcal{L} = \{X \subseteq \mathcal{P} : \text{conv}(X) \cap \mathcal{P} = X\}$$



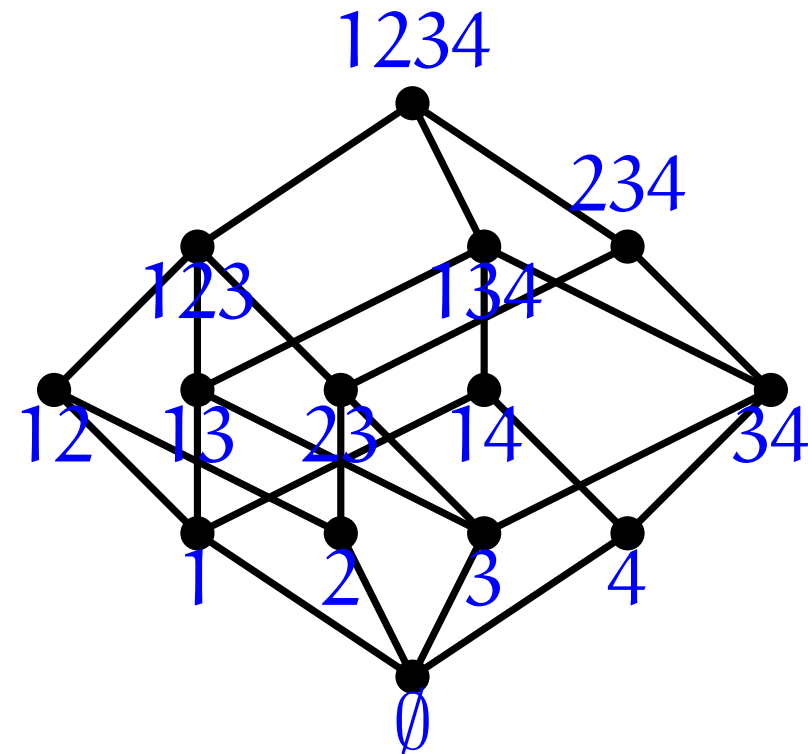
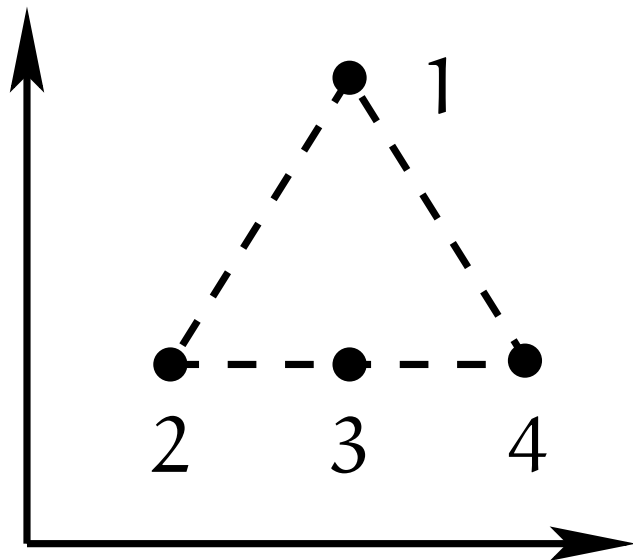
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$$(1) \quad \emptyset \in \mathcal{L}, E \in \mathcal{L}$$

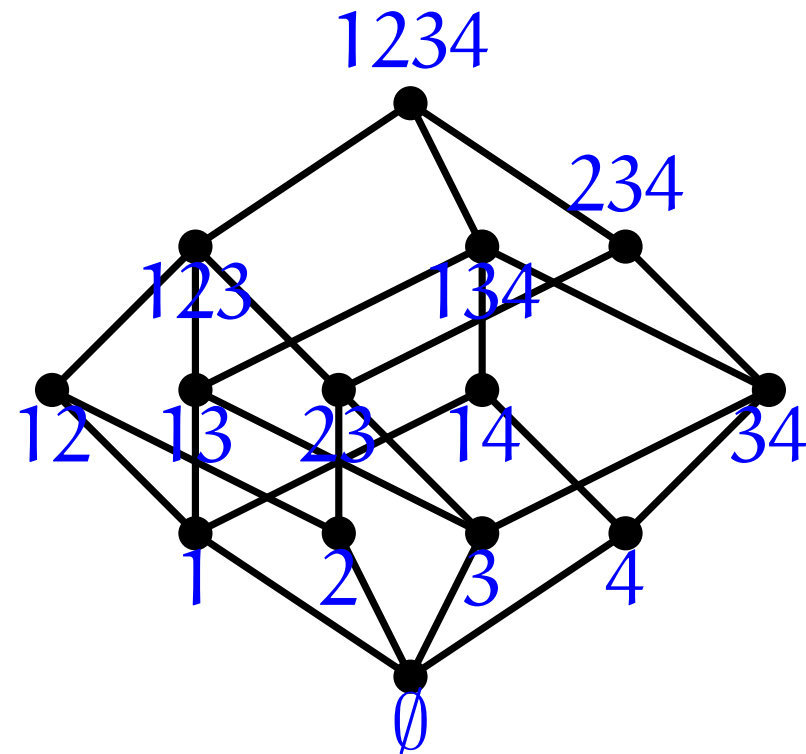
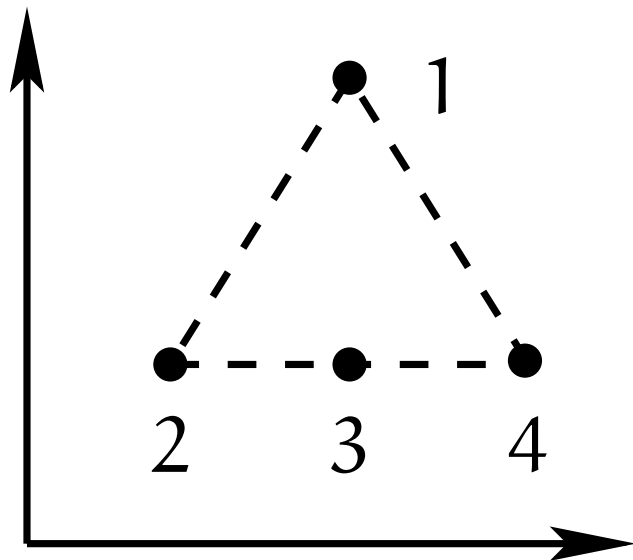
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$$(2) \quad X, Y \in \mathcal{L} \Rightarrow X \cap Y \in \mathcal{L}.$$



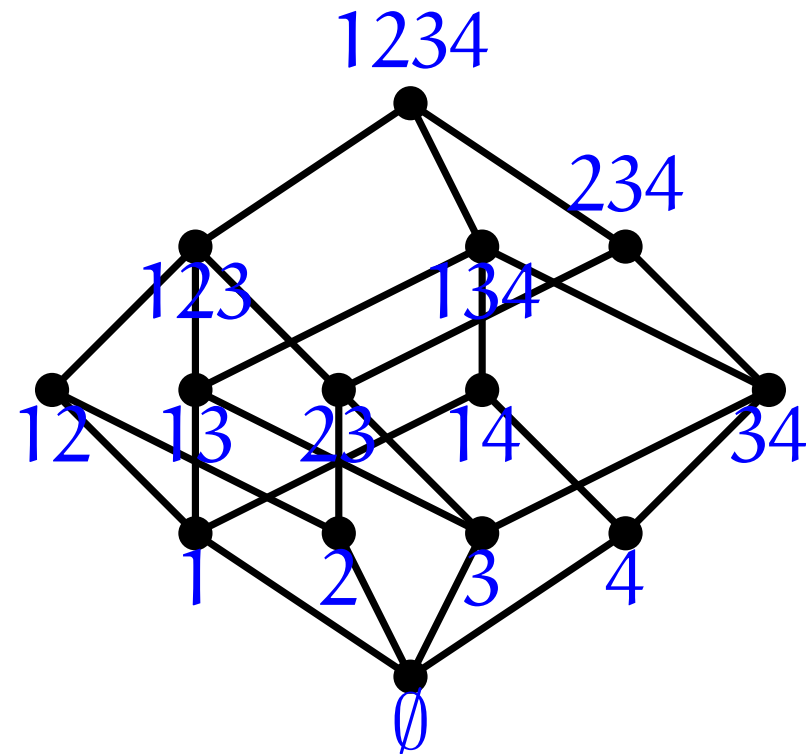
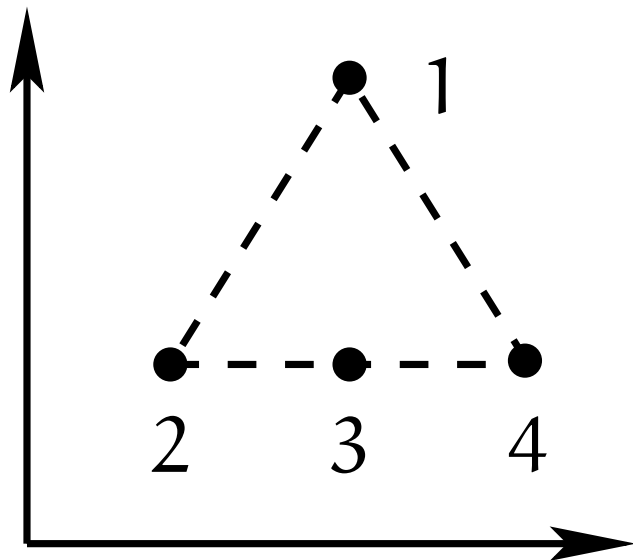
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$$(3) \quad X \in \mathcal{L} \setminus \{E\} \Rightarrow \exists e \in E \setminus X: X \cup \{e\} \in \mathcal{L}.$$

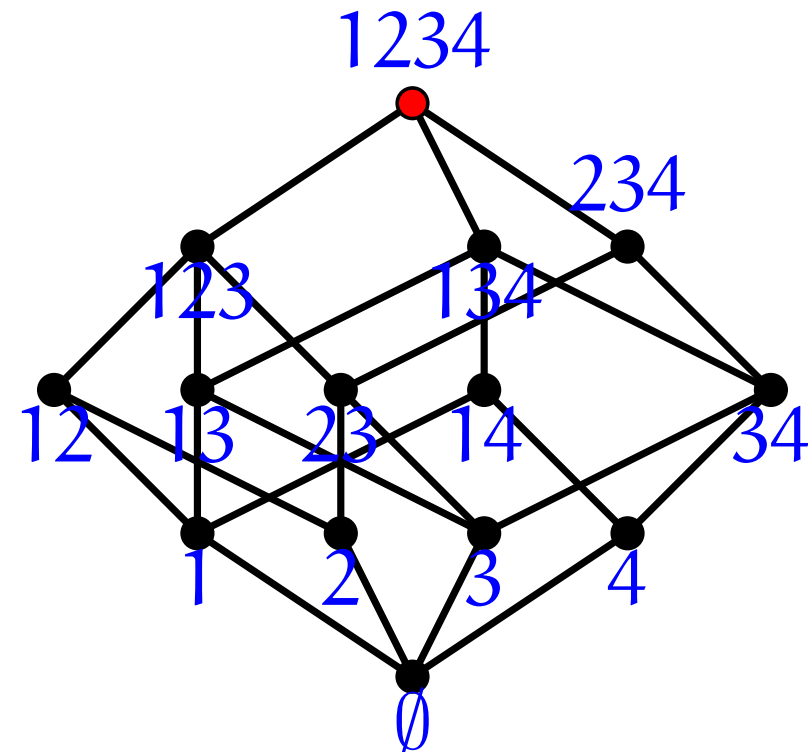
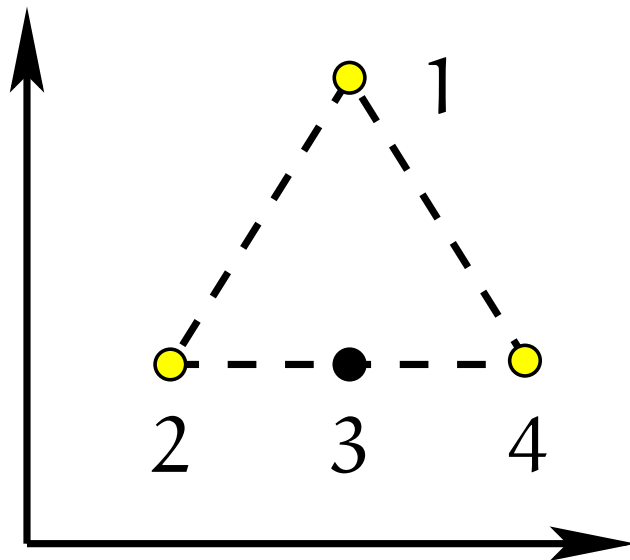
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The extreme points of  $\text{conv}(\{1, 2, 3, 4\}) = \{1, 2, 4\}$

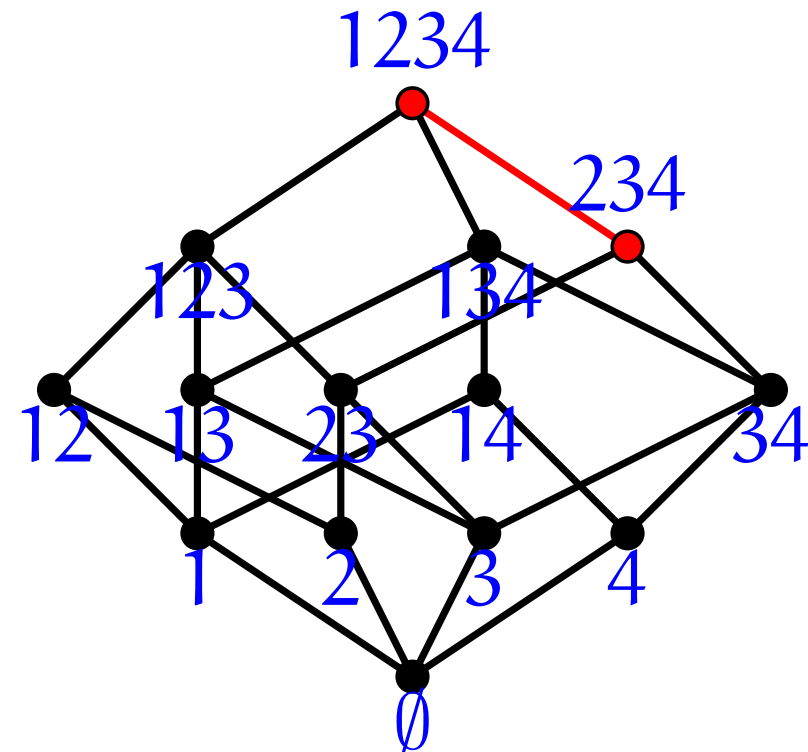
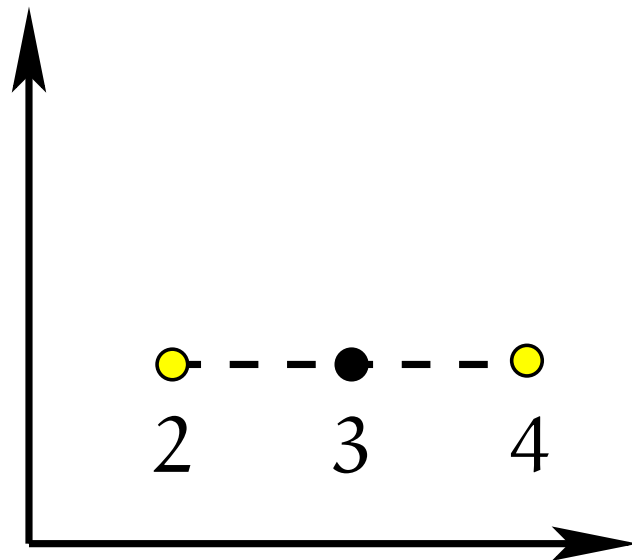
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The extreme points of  $\text{conv}(\{2, 3, 4\}) = \{2, 4\}$

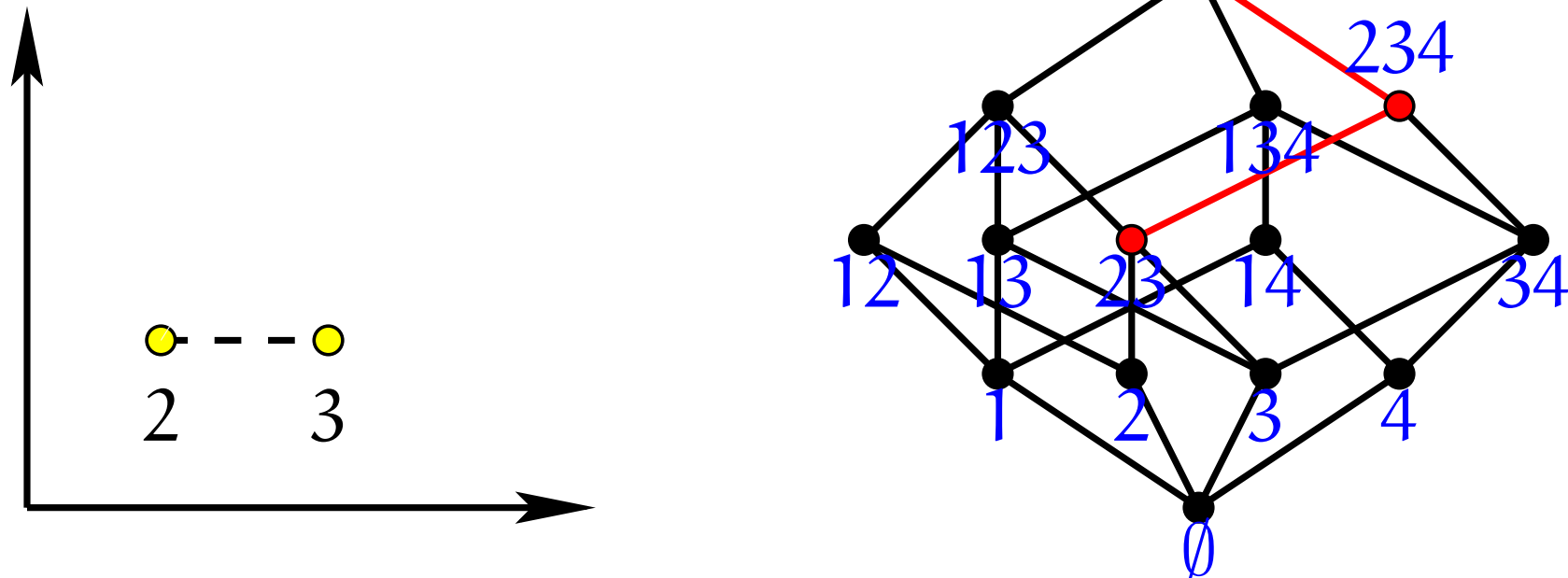
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The extreme points of  $\text{conv}(\{2, 3\}) = \{2, 3\}$

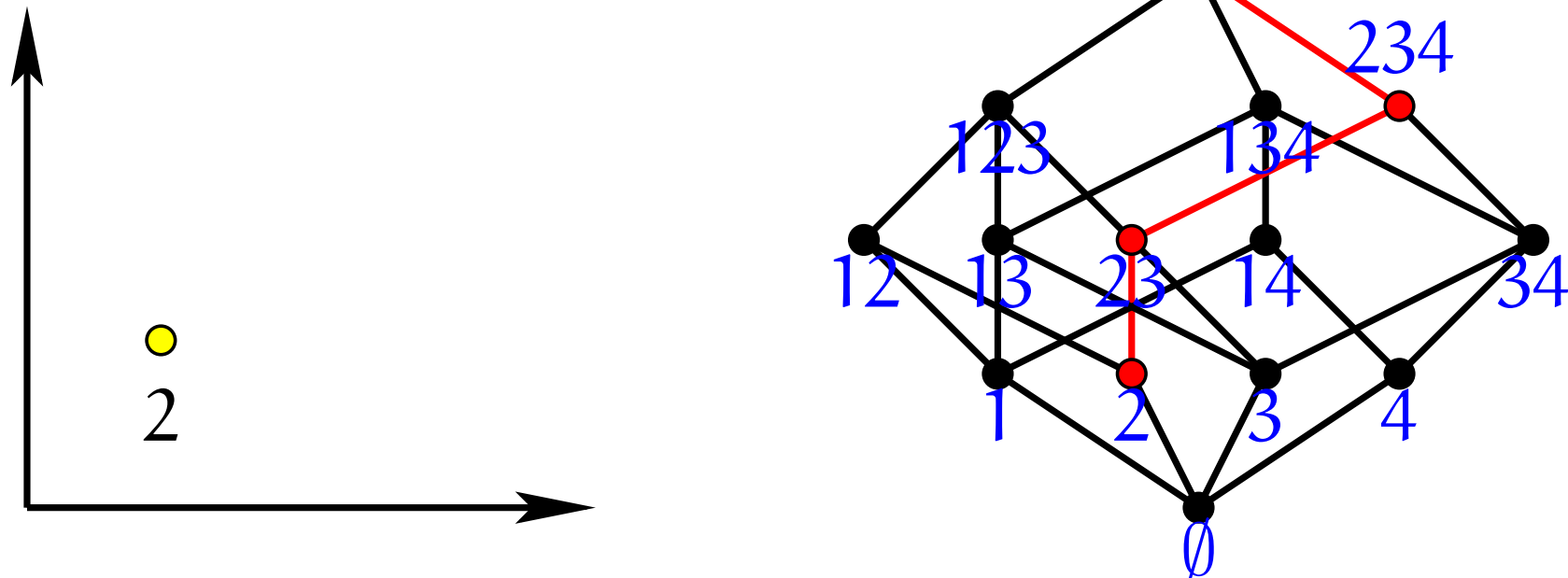
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The extreme points of  $\text{conv}(\{2\}) = \{2\}$

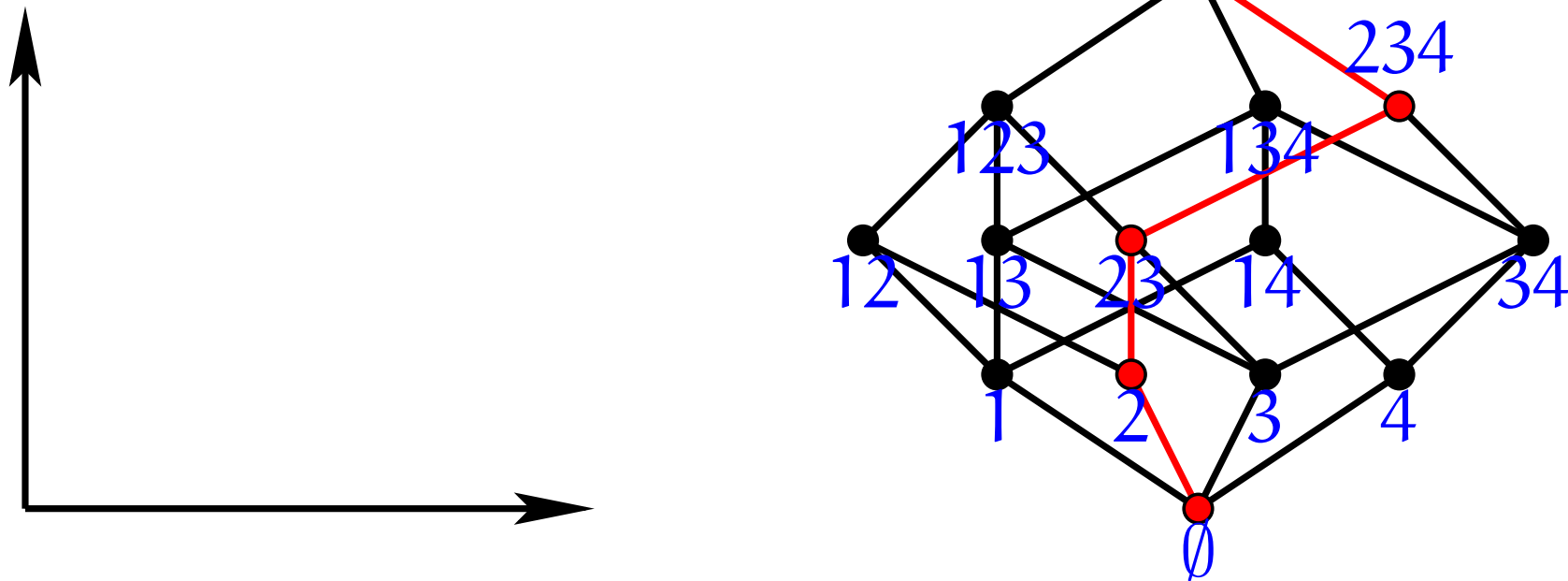
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The extreme points of  $\text{conv}(\emptyset) = \emptyset$

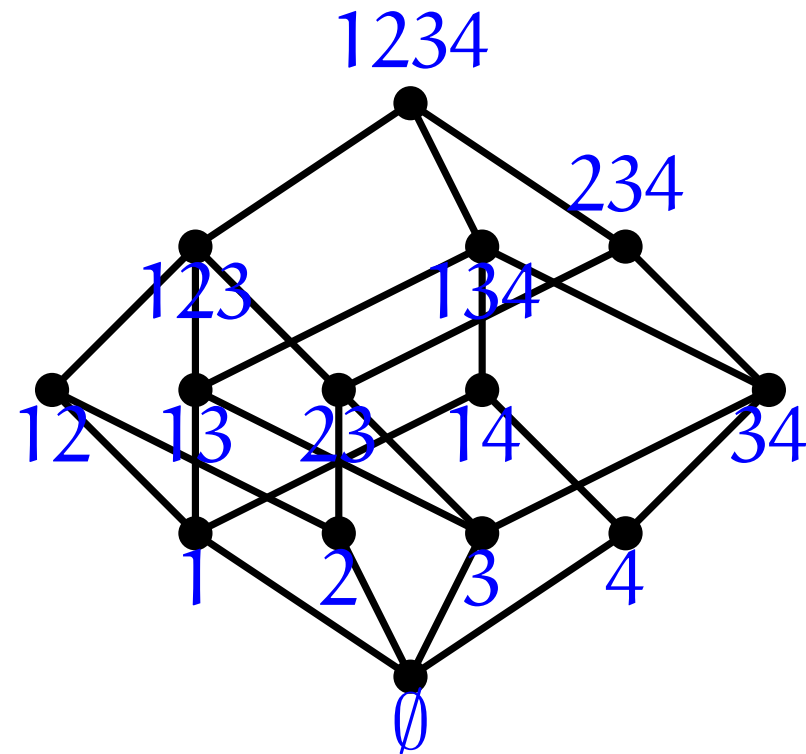
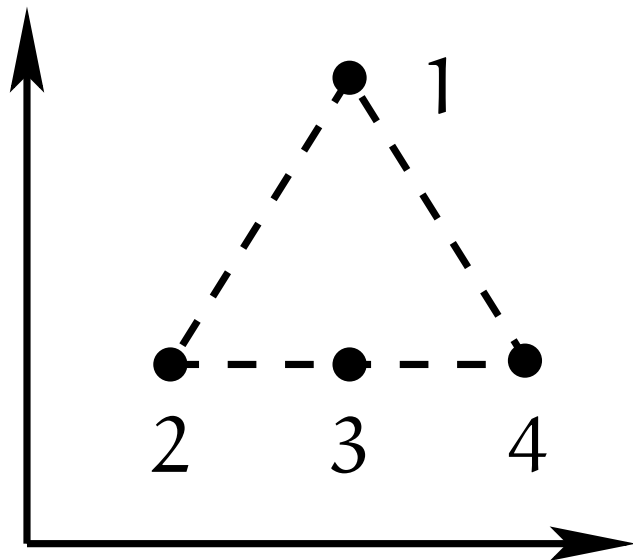
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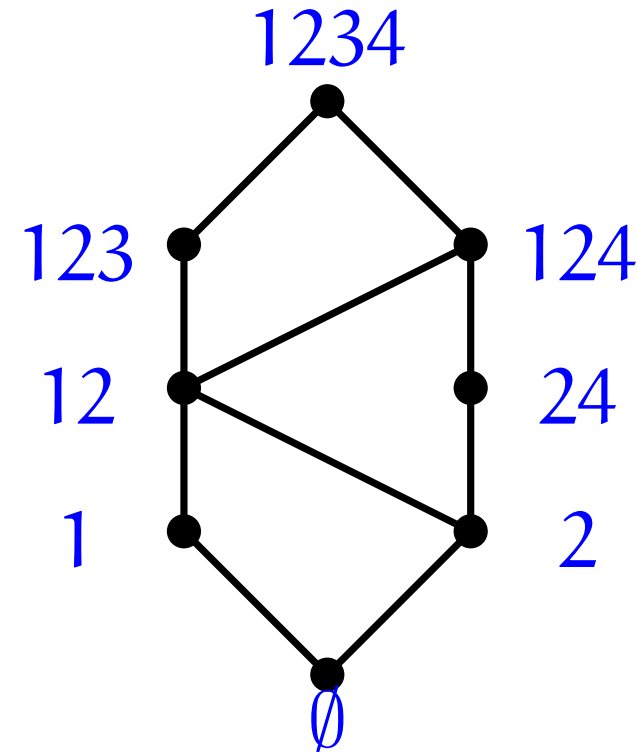
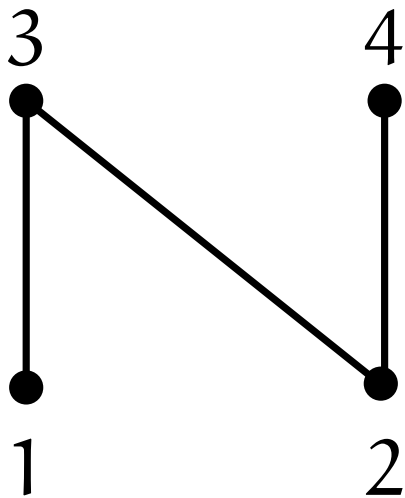
Given

 $P = (E, \leq)$  a partially ordered set

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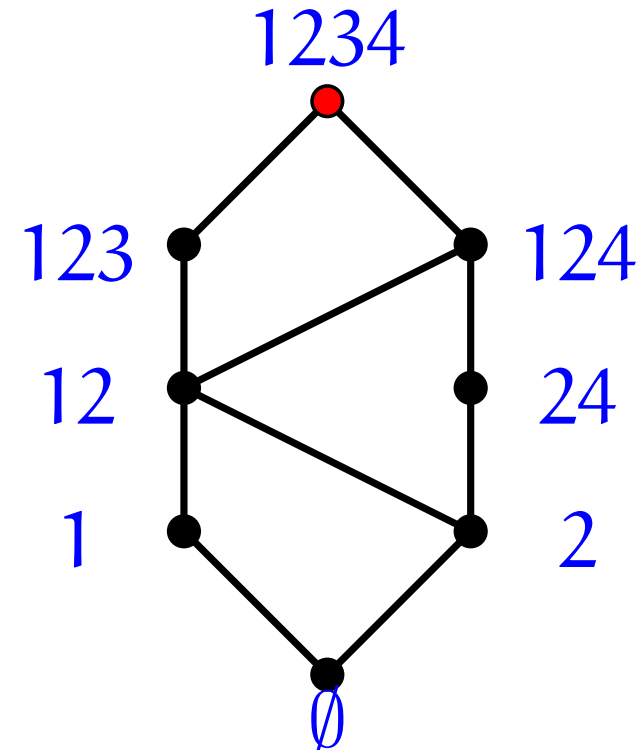
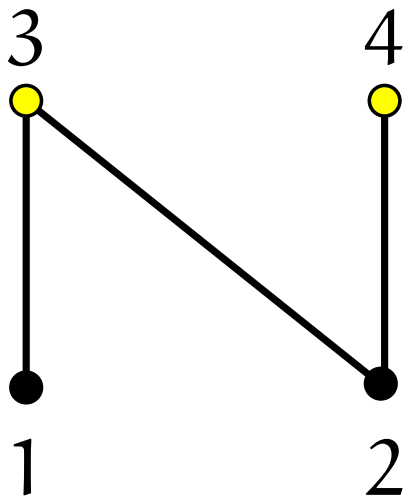
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The maximal elements of  $\{1, 2, 3, 4\} = \{3, 4\}$

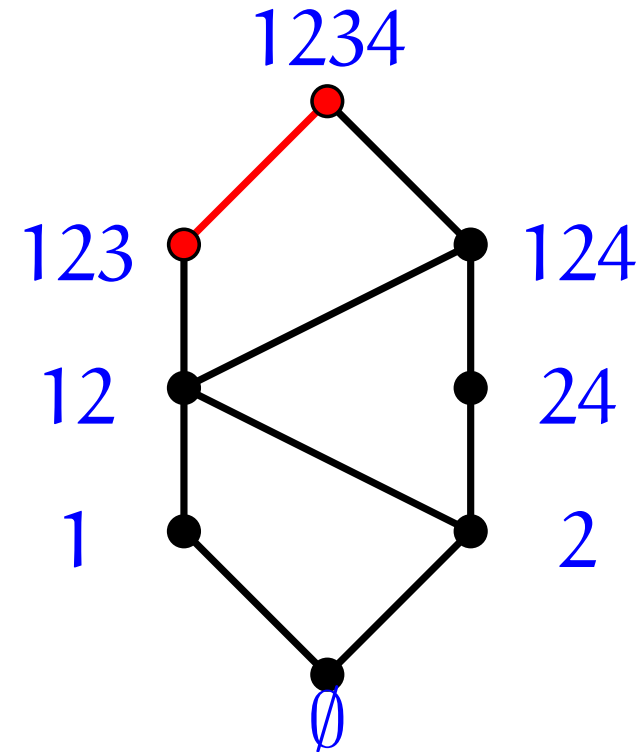
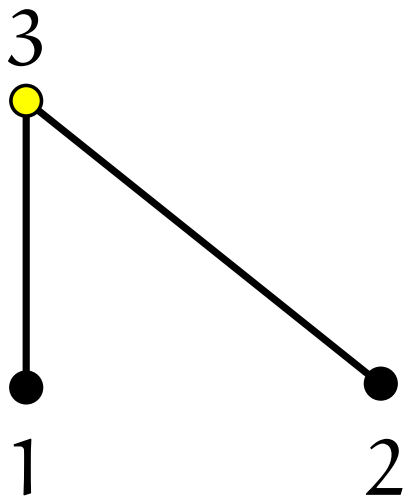
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The maximal elements of  $\{1, 2, 4\} = \{4\}$

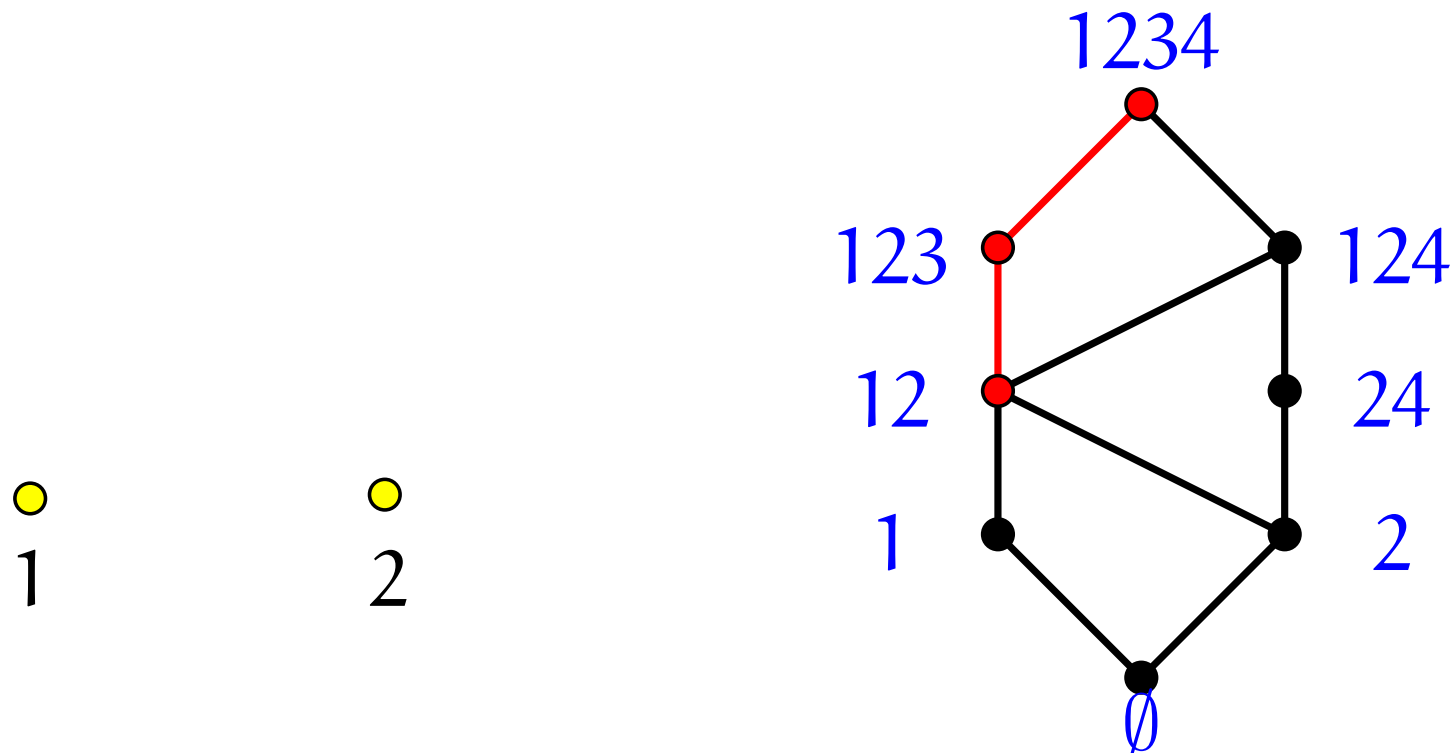
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The maximal elements of  $\{1, 2\} = \{1, 2\}$

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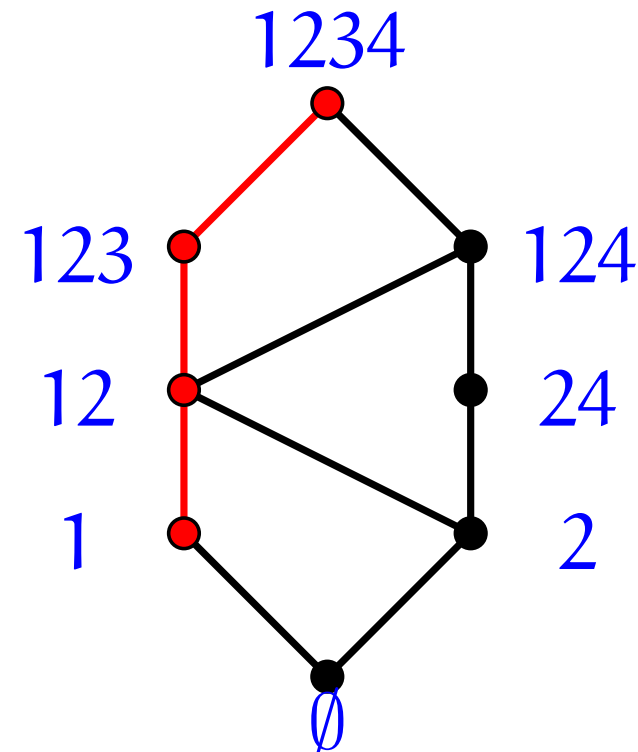
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The maximal elements of  $\{1\} = \{1\}$

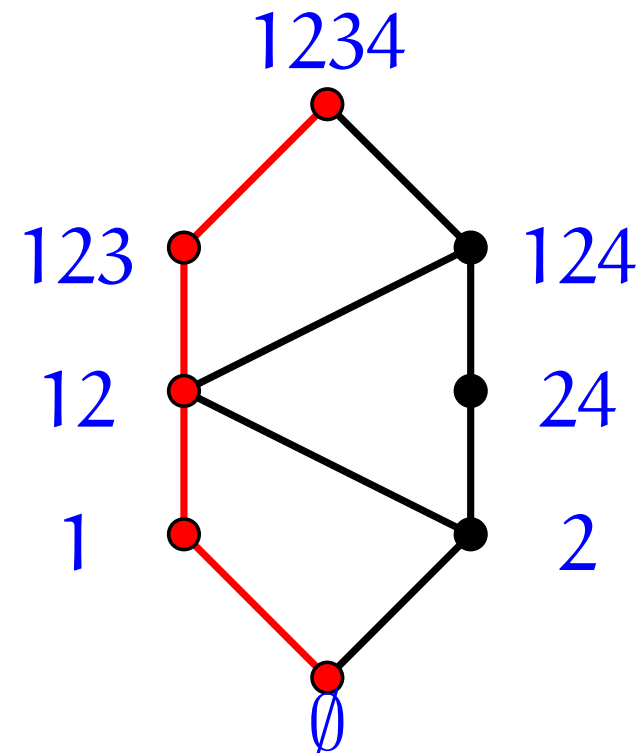
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The maximal elements of  $\emptyset = \emptyset$

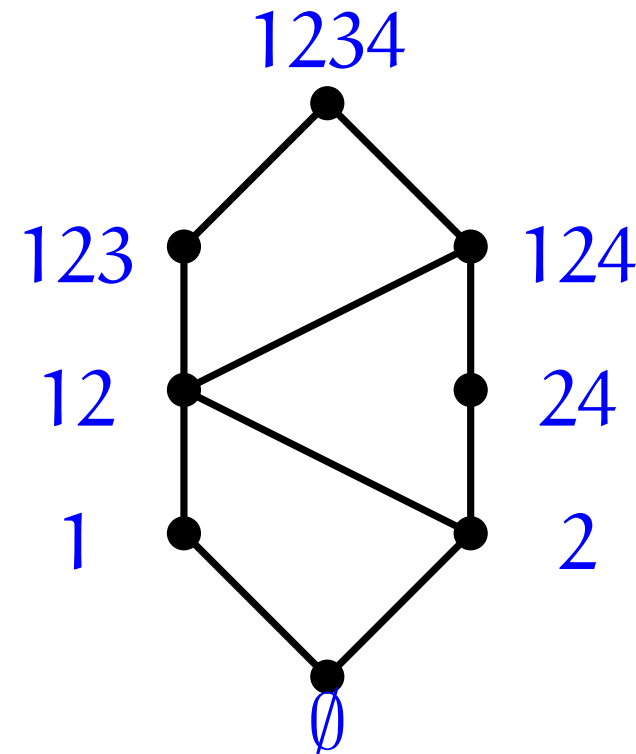
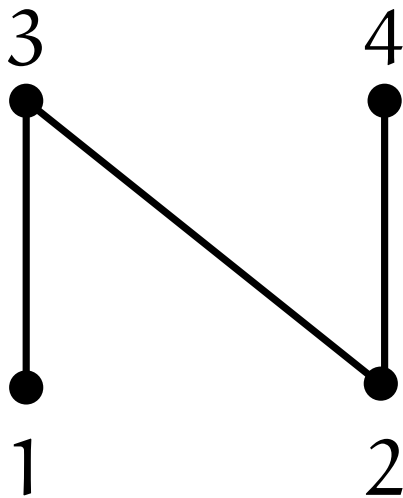
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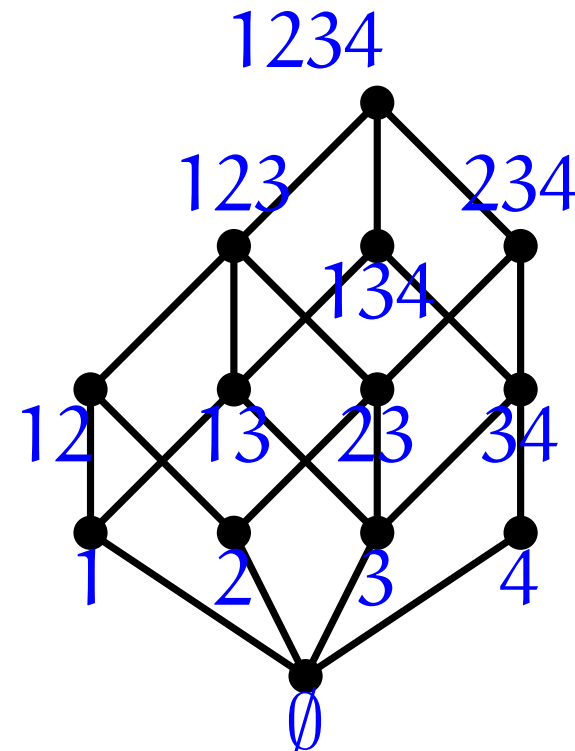
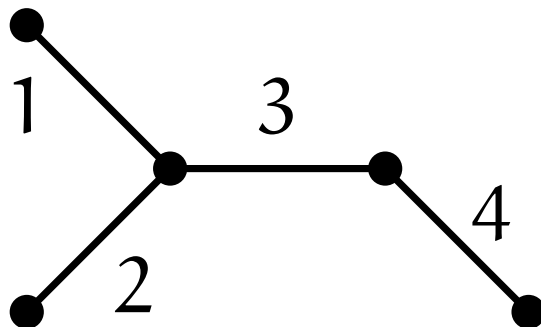
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Given

 $T = (V, E)$  a tree

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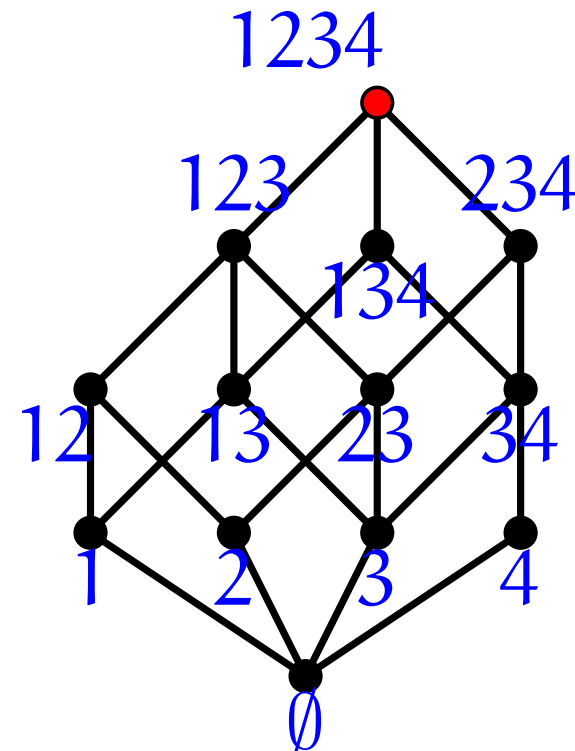
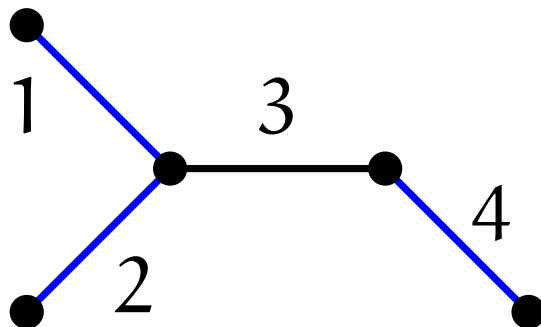
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(Remove an edge incident to a leaf one by one)

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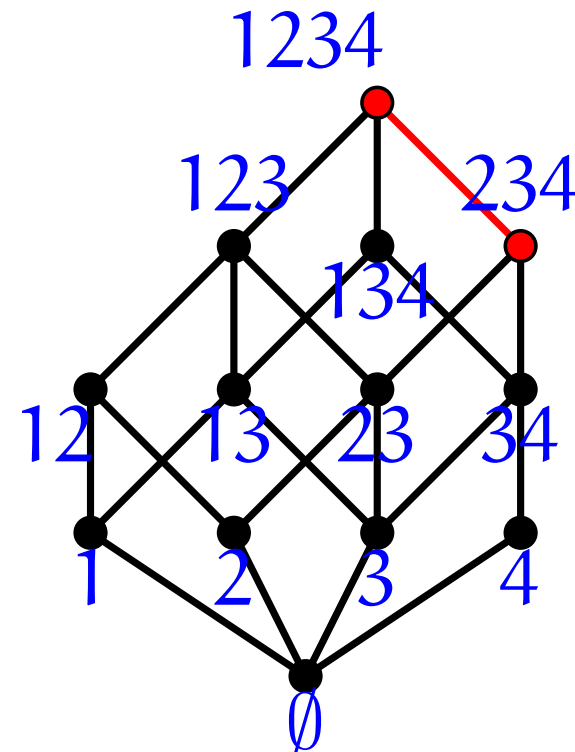
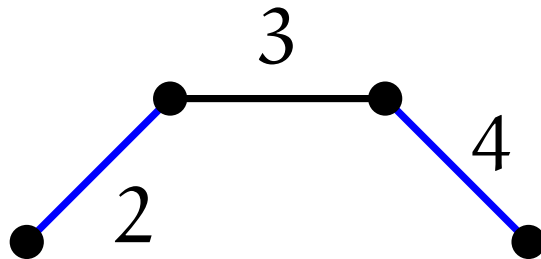
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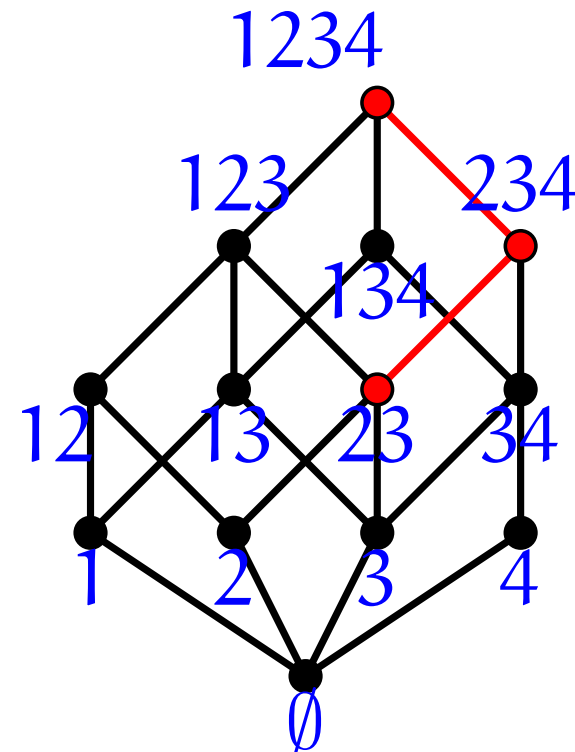
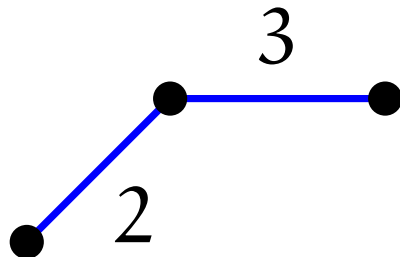
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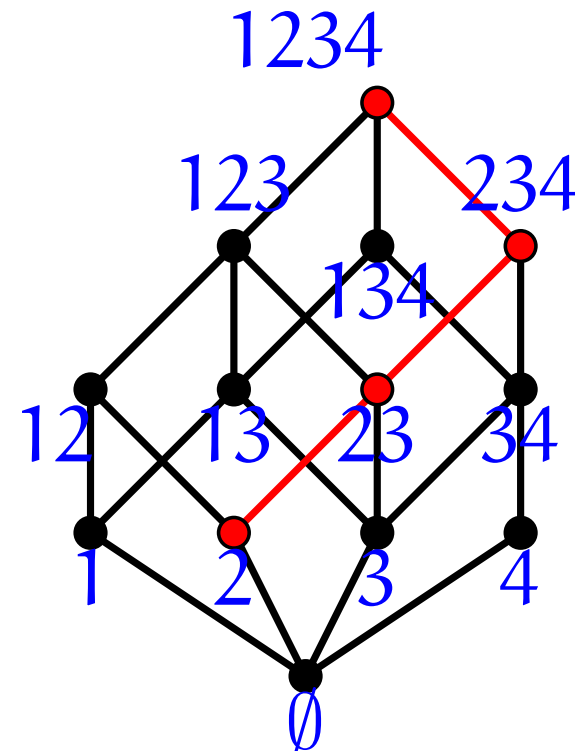
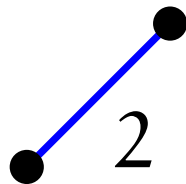
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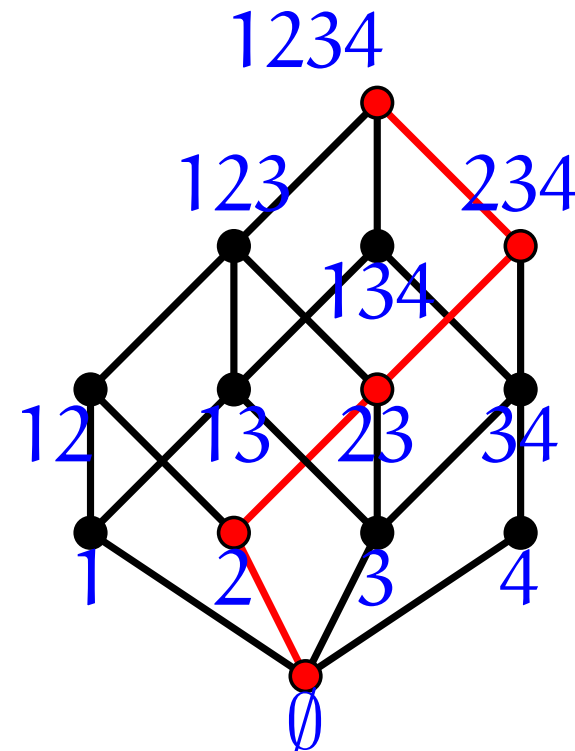
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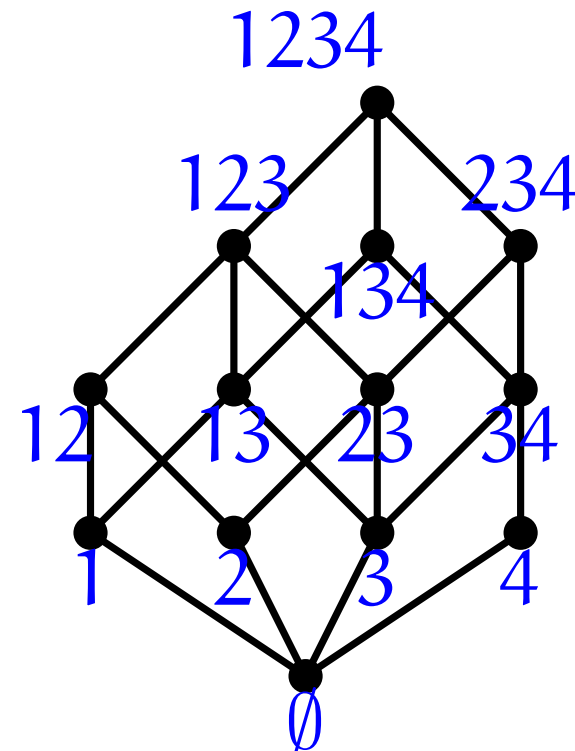
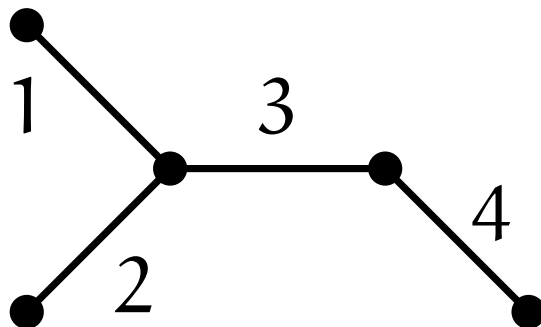
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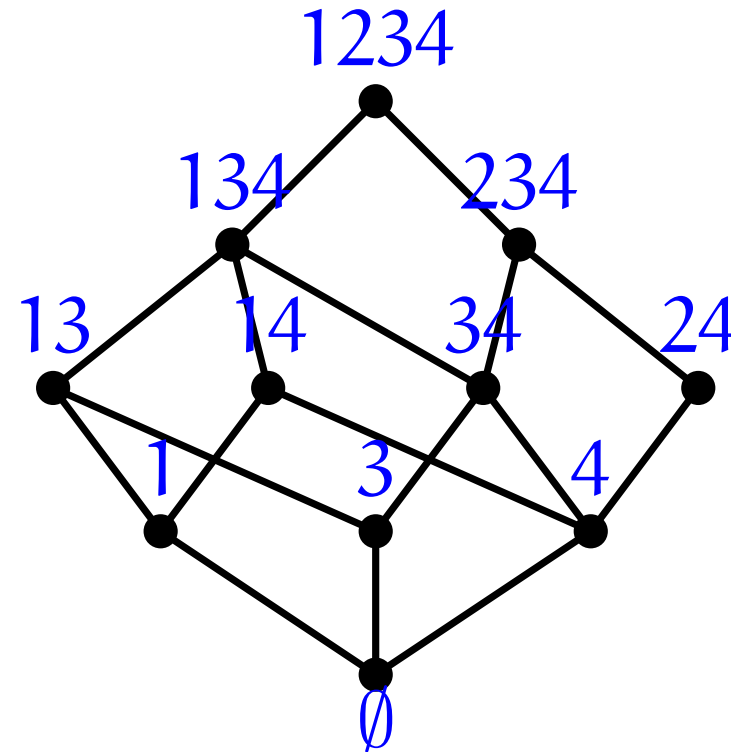
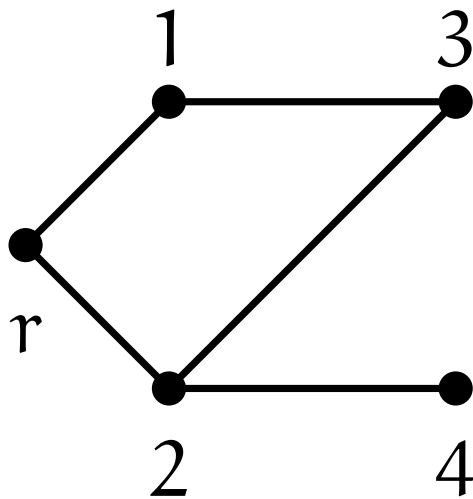
Given

 $G = (V \cup \{r\}, E)$  a graph,  $r$  a root

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(Consider the search on a graph)

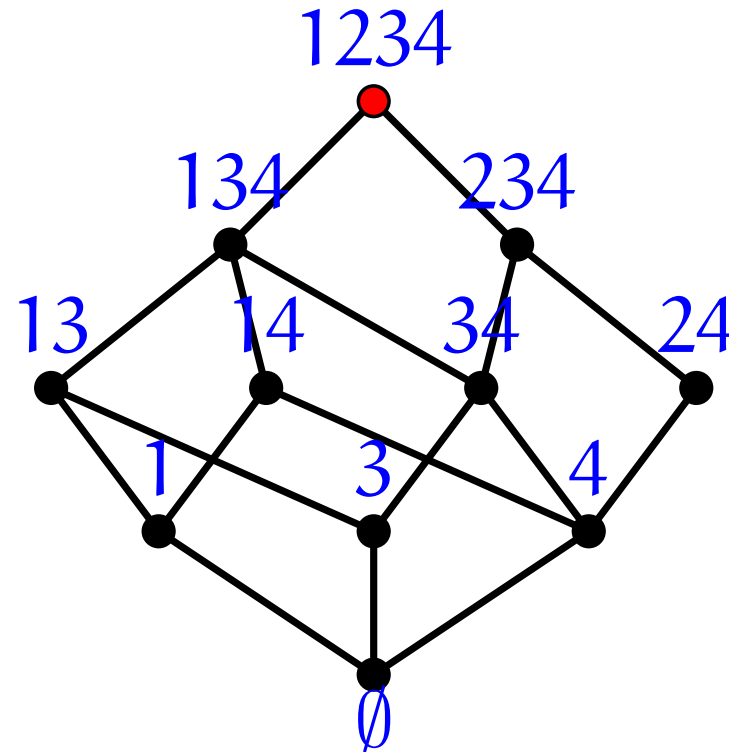
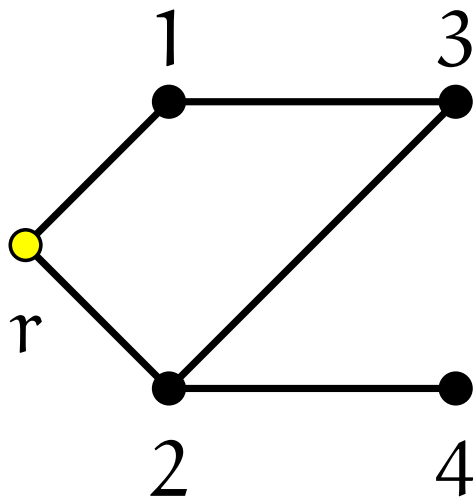
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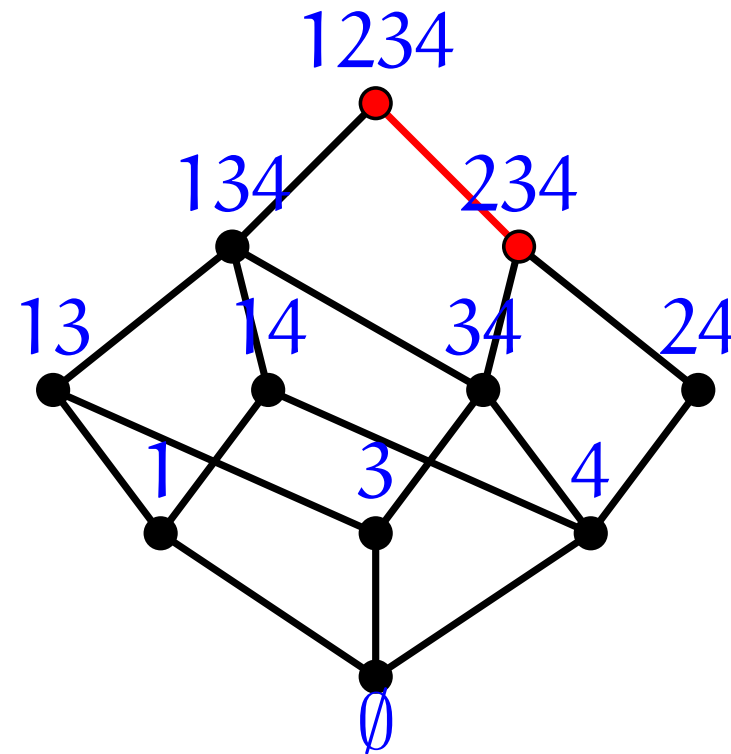
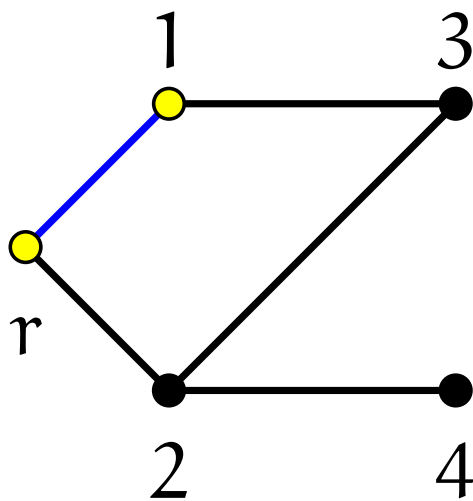
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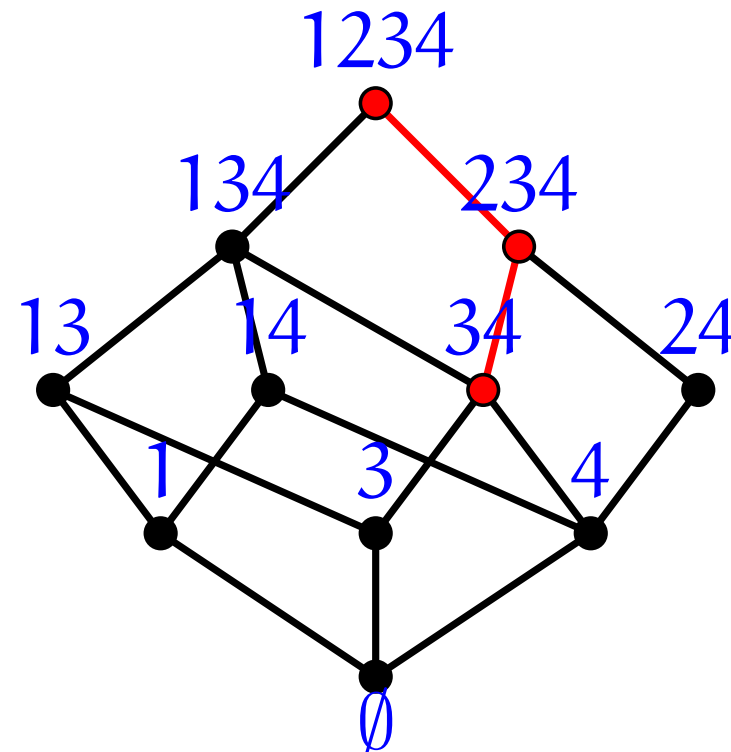
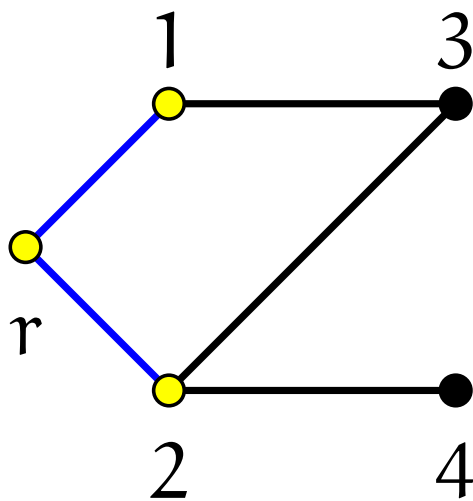
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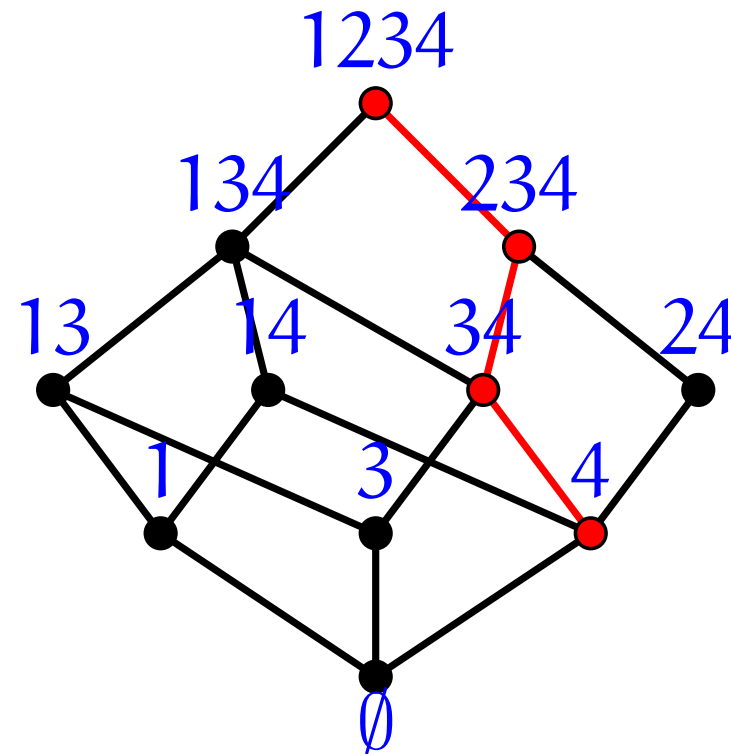
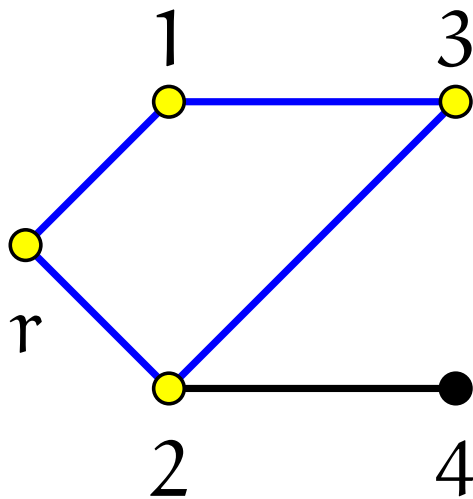
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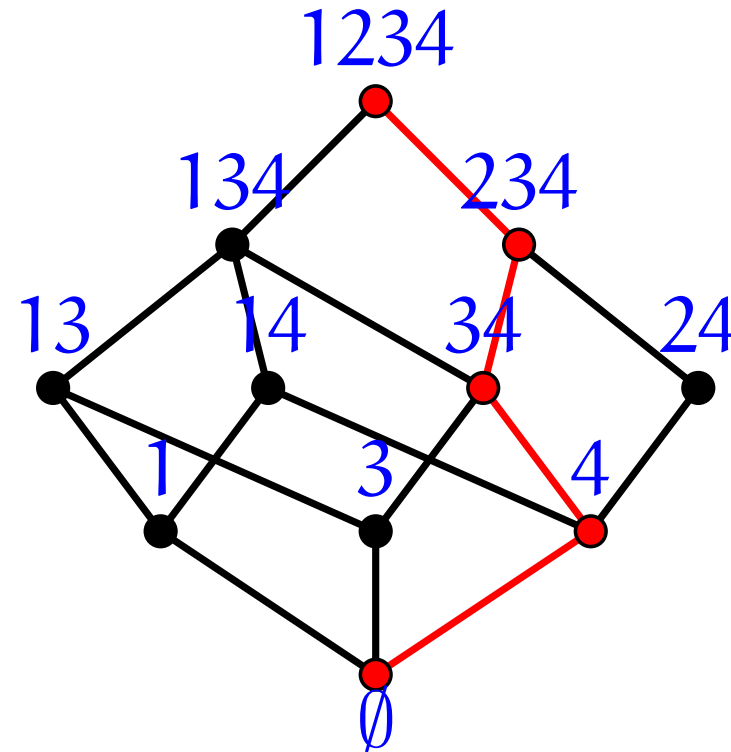
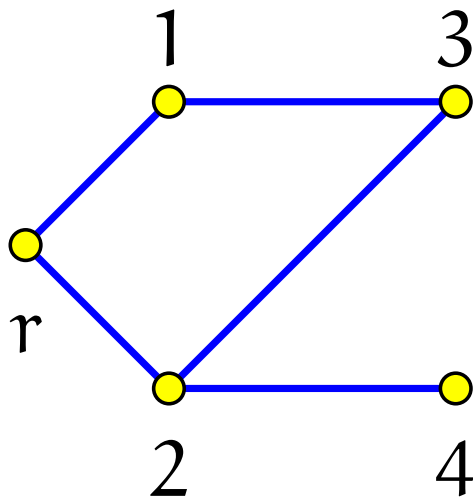
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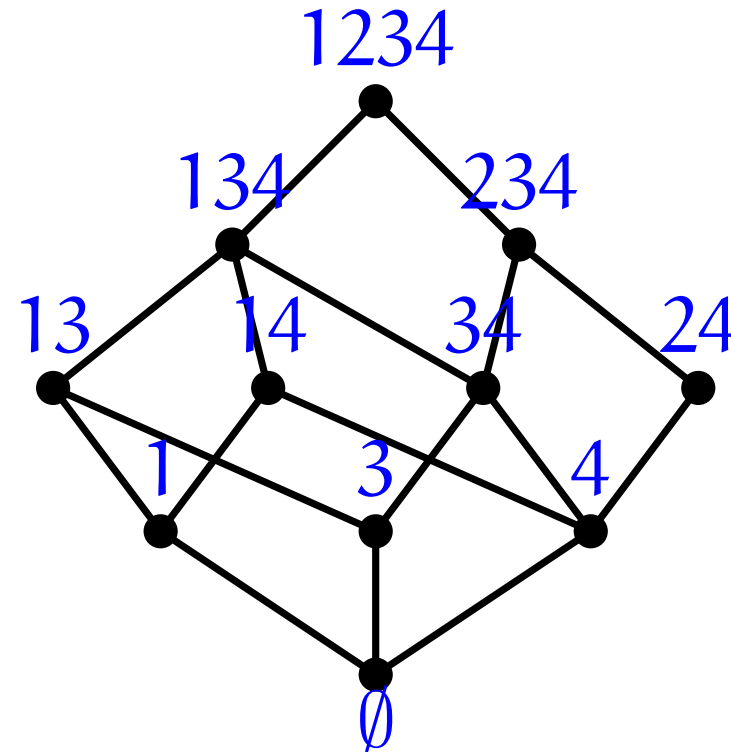
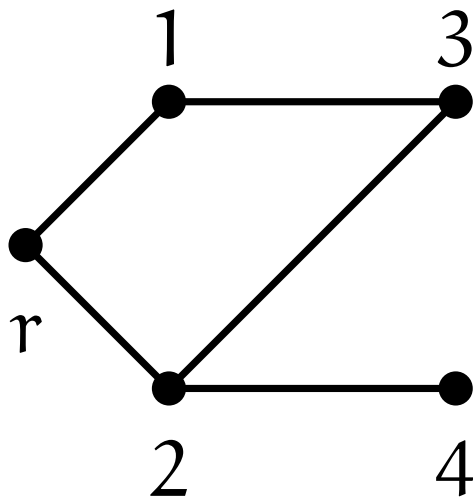
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(Consider the search on a graph)

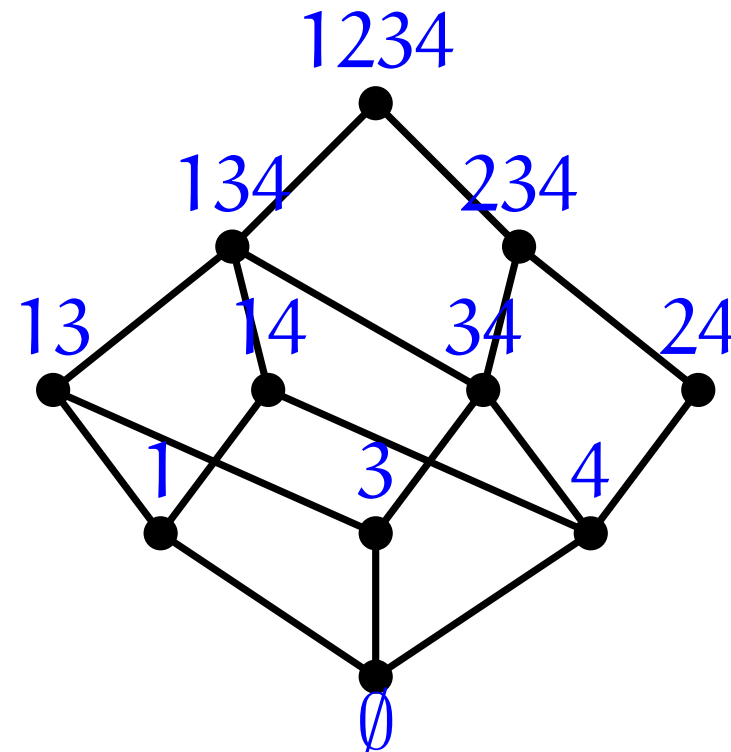
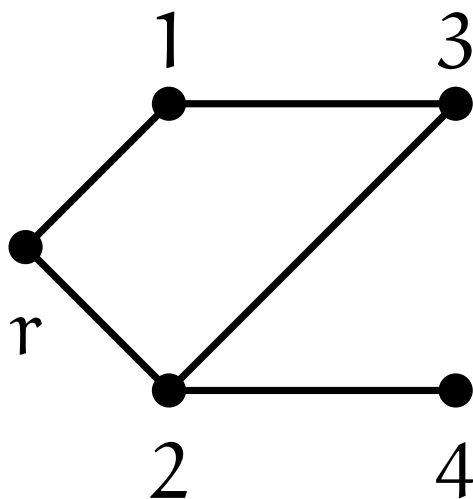
Given

 $G = (V \cup \{r\}, E)$  a graph,  $r$  a root

Def.

 $\mathcal{L}$  the **graph search** on  $G$ :

$$\mathcal{L} = \{V \setminus X : \forall v \in X \exists \text{ an } (r, v)\text{-path in } G[X \cup \{r\}]\}$$



Rem. undirected/directed graph, point/line-search

## There are many other examples...

### ◆ From graphs

- The family of connected subgraphs in a block graph (Jamison-Waldner '81)
- The family of monophonically convex sets in a chordal graph (Farber & Jamison '86)
- The family of geodesically convex sets in a Ptolemaic graph (Farber & Jamison '86)
- The family of  $m^3$ -convex sets in an HDDA-free graph (Dragan, Nicolai & Branstädt '99)

### ◆ From partially ordered sets

- The family of order convex sets in a poset
- The family of  $k$ -antichains in a poset (Greene & Kleitman '76)
- The family of subsemilattices in a semilattice (Jamison-Waldner '78)

### ◆ From geometry

- Lower convex shelling on a finite point set
- Convex shelling on an acyclic oriented matroid (Edelman '82)

### ◆ From matroids

- Line-search in a matroid (Goecke, Korte & Lovász '89)

and more!

- ◆ Understanding “Convexity”  
in an axiomatized combinatorial setting
- ◆ Counterpart of matroids
- ◆ Equivalent to antimatroids (and others)
- ◆ Mathematical social science, mathematical psychology
- ◆ AND/OR networks, scheduling, project planning
- ◆ Directed hypergraphs
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- ◆ Lattice theory...

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## Biased introduction to (abstract) convex geometries

- ◆ Definition and Examples (15 min.)
- ◆ **Basic Concepts I** (5 min.)
- ◆ Classification (15 min.)
- ◆ Basic Concepts II (15 min.)
- ◆ Others (5 min.)
- ◆ Summary (1 min.)

**Setup** $\mathcal{L}$  a convex geometry on  $E$ **Obs.** $\mathcal{L}$  forms a lattice with  $\subseteq$ .The maximum element  $= E$ .The minimum element  $= \emptyset$ .The meet of  $X, Y \in \mathcal{L}$   $= X \cap Y \in \mathcal{L}$  (by **(2)**).



Setup

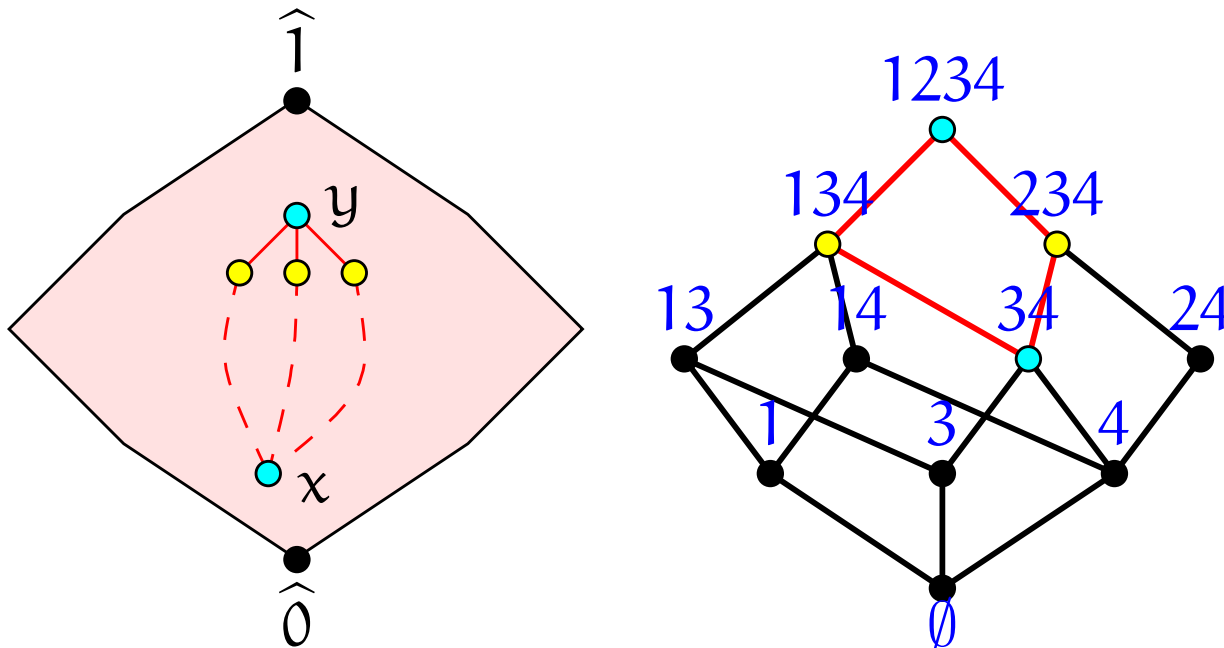
 $\mathcal{L}$  a convex geometry on  $E$ 

Obs.

 $\mathcal{L}$  forms a lattice with  $\subseteq$ .

Def.

A lattice  $L$  is **meet-distributive**  $\Leftrightarrow$   
 for every  $x, y \in L$  such that  $x$  is the meet of  
 elements  $y$  covers,  $[x, y]$  is Boolean



Setup

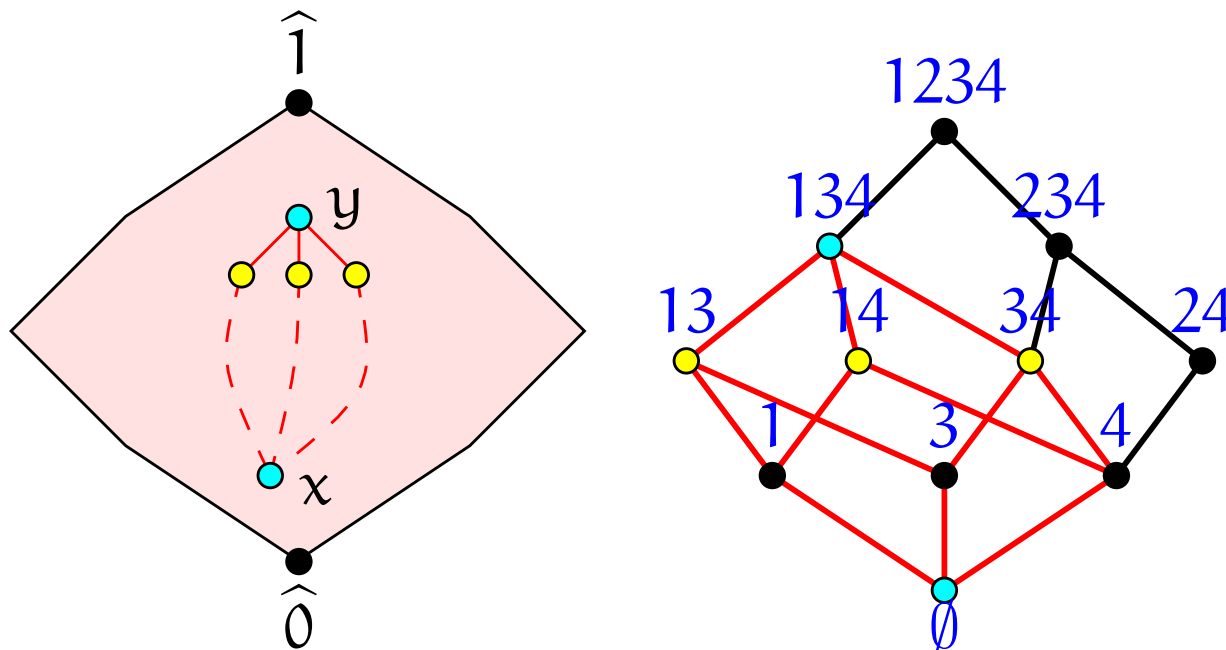
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**Obs.** $\mathcal{L}$  is meet-distributive.

Setup

 $\mathcal{L}$  a convex geometry on  $E$ 

Obs.

 $\mathcal{L}$  forms a lattice with  $\subseteq$ .

Def.

A lattice  $L$  is **meet-distributive**  $\Leftrightarrow$   
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Obs.

 $\mathcal{L}$  is meet-distributive.

Thm.

(Edelman '80)

$\forall$  **finite meet-distributive lattice  $L$**   
 $\exists$  **a convex geometry  $\mathcal{L}$  on  $E$  s.t.  $L \cong \mathcal{L}$ .**

Convex geometries  $\equiv$  Meet-distributive lattices

**Corresp.**

Set systems

≡

Lattices

**Thm.**

(Edelman '80)

Convex geometries ≡

Meet-distributive

**Corresp.**

Set systems

≡

Lattices

**Thm.**

(Edelman '80)

Convex geometries ≡

Meet-distributive

**Thm.**

(Birkhoff '33)

Poset shellings ≡

Distributive

Corresp.

Set systems

 $\equiv$ 

Lattices

Thm.

(Edelman '80)

Convex geometries  $\equiv$ 

Meet-distributive

Thm.

(Birkhoff '33)

Poset shellings  $\equiv$ 

Distributive

Thm.

(Birkhoff '35; Whitney '35)

Matroids  $\equiv$ 

Geometric

Corresp.

Set systems

 $\equiv$ 

Lattices

Thm.

(Edelman '80)

Convex geometries  $\equiv$ 

Meet-distributive

Thm.

(Birkhoff '33)

Poset shellings  $\equiv$ 

Distributive

Thm.

(Birkhoff '35; Whitney '35)

Matroids  $\equiv$ 

Geometric

Thm.

(Campbell '43; Birkhoff &amp; Frink '48)

Closure spaces  $\equiv$ 

General



Corresp.

Set systems

 $\equiv$ 

Lattices

Thm.

(Edelman '80)

Convex geometries  $\equiv$ 

Meet-distributive

Thm.

(Birkhoff '33) [characterization of poset shellings]

Poset shellings  $\equiv$ 

Distributive

Thm.

(Birkhoff '35; Whitney '35)

Matroids  $\equiv$ 

Geometric

Thm.

(Campbell '43; Birkhoff &amp; Frink '48)

Closure spaces  $\equiv$ 

General

## Biased introduction to (abstract) convex geometries

- ◆ Definition and Examples (15 min.)
- ◆ Basic Concepts I (5 min.)
- ◆ **Classification** (15 min.)
- ◆ Basic Concepts II (15 min.)
- ◆ Others (5 min.)
- ◆ Summary (1 min.)

**Aim**

$\mathcal{L}$  a convex geometry

To find:  $\mathcal{L}$  belongs to a certain class



$\mathcal{L}$  satisfies a certain property

**Aim**

$\mathcal{L}$  a convex geometry

To find:  $\mathcal{L}$  belongs to a certain class



$\mathcal{L}$  satisfies a certain property

Certain classes??: in this talk

- ◆ convex shellings of finite point sets
- ◆ poset shellings
- ◆ tree shellings
- ◆ graph searches

Certain properties??: in this talk

- ◆ forbidden minors

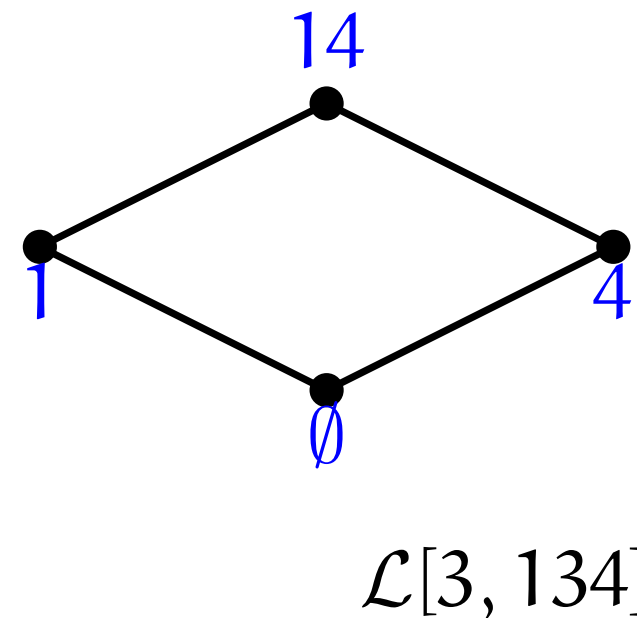
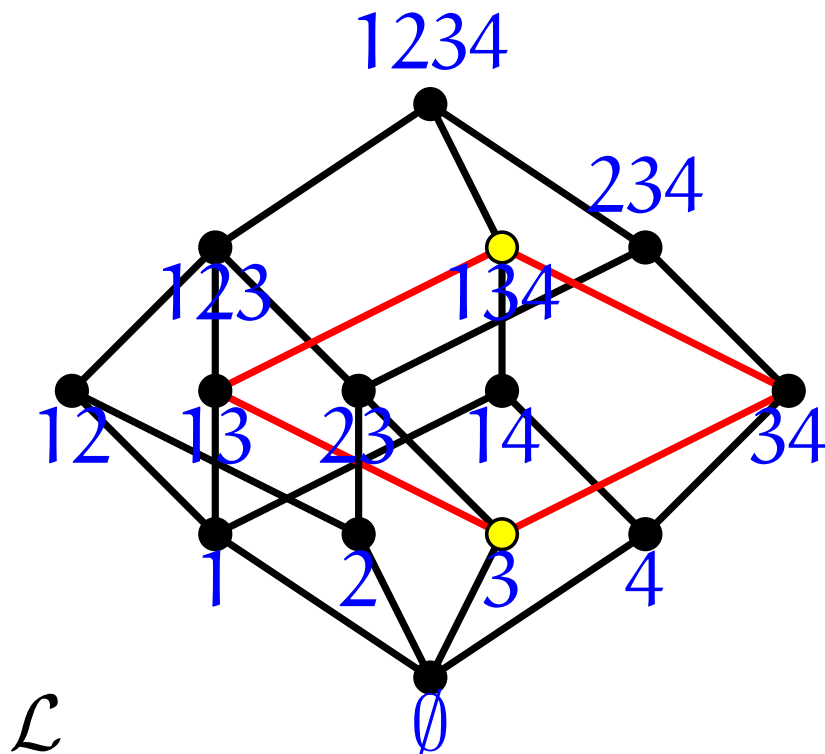
Setup

$\mathcal{L}$  a convex geometry on  $E$ ,  $A, B \in \mathcal{L}$ ,  $A \subseteq B$

Def.

The **minor** of  $\mathcal{L}$  w.r.t.  $(A, B)$  is defined by

$$\mathcal{L}[A, B] = \{X \setminus A : X \in \mathcal{L}, A \subseteq X \subseteq B\}.$$



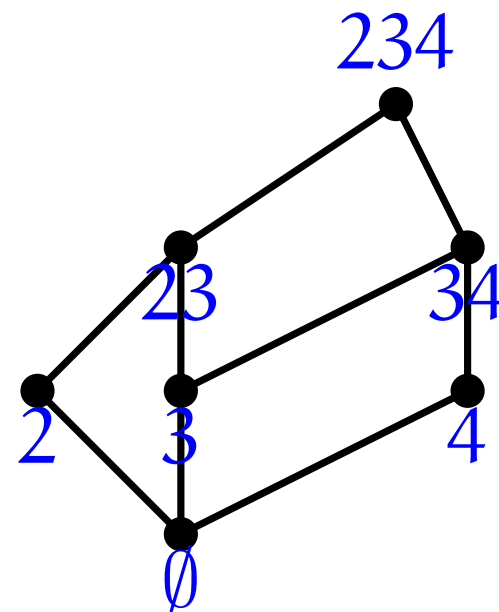
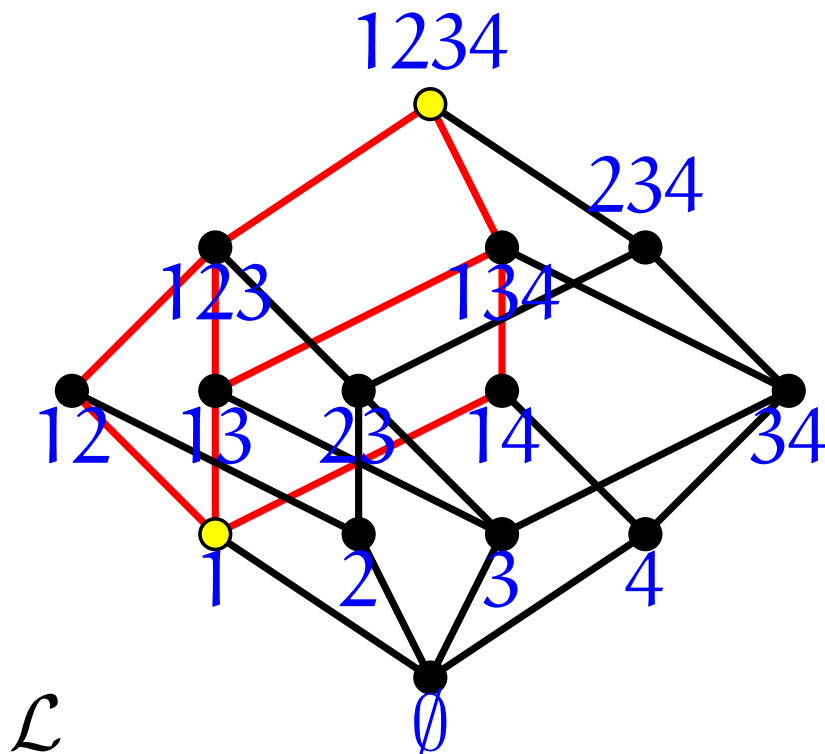
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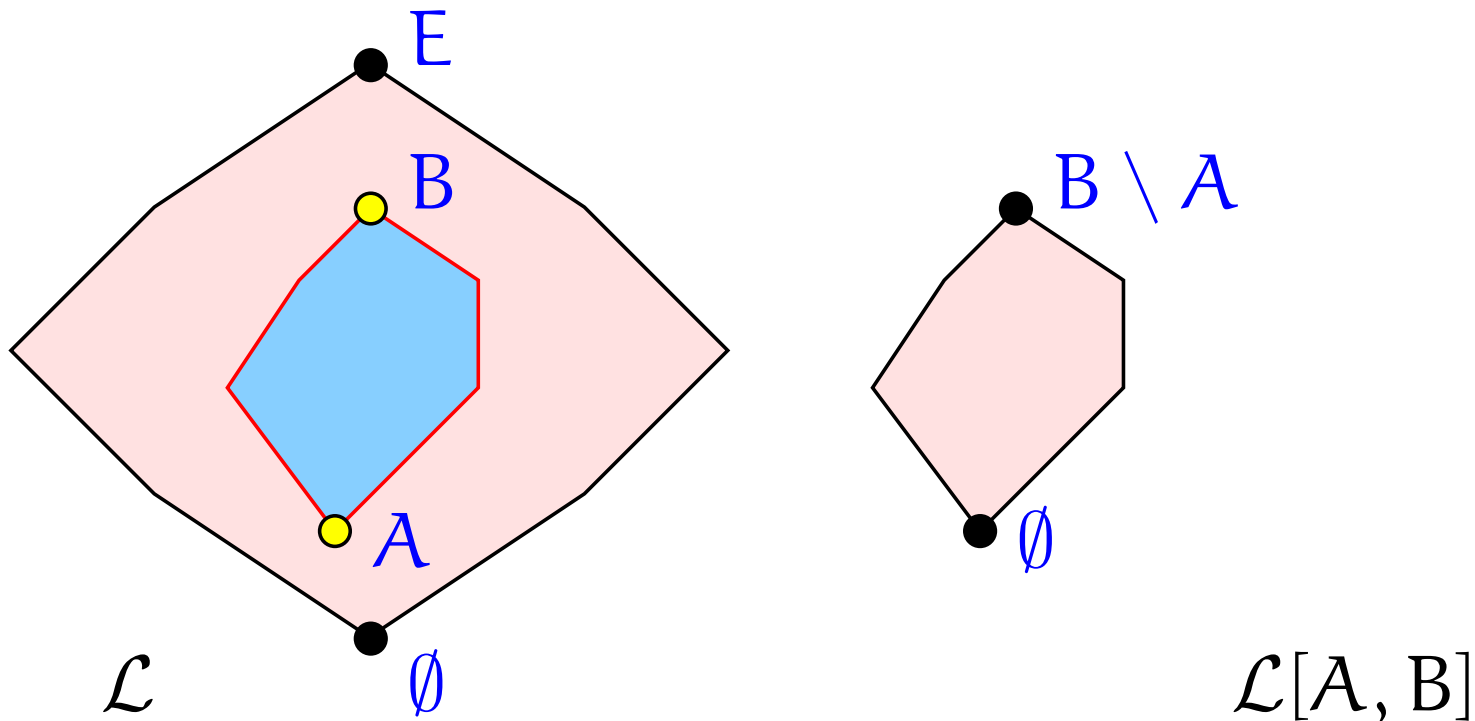


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The **minor** of  $\mathcal{L}$  w.r.t.  $(A, B)$  is defined by  
 $\mathcal{L}[A, B] = \{X \setminus A : X \in \mathcal{L}, A \subseteq X \subseteq B\}$ .



Rem.

A minor is also a convex geometry.

## Classes closed under taking minors

- ◆ Poset shellings
- ◆ Graph searches
  - directed/point
  - undirected/point
  - directed/line
  - undirected/line

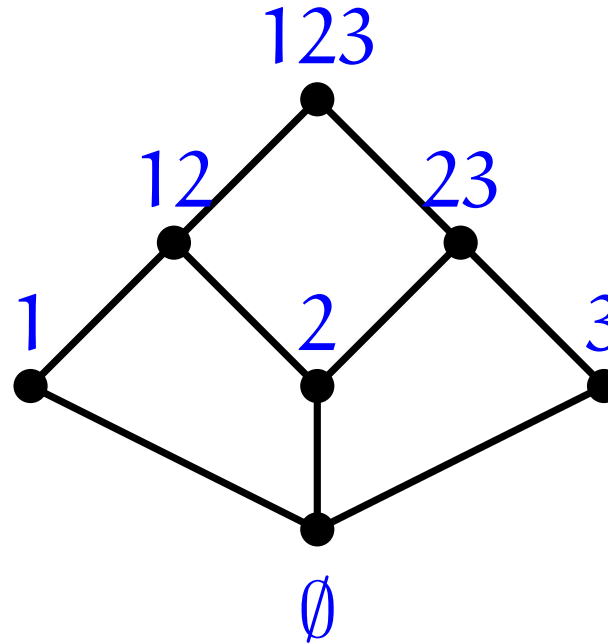
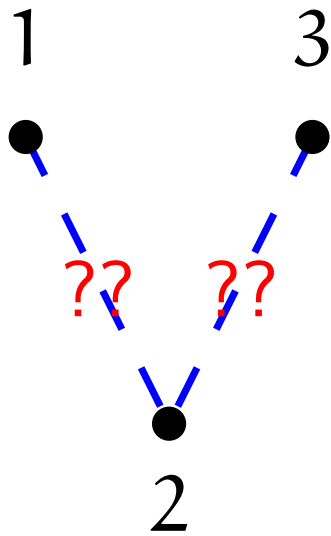
## Classes not closed under taking minors

- ◆ Convex shellings of finite point sets
- ◆ Tree shellings



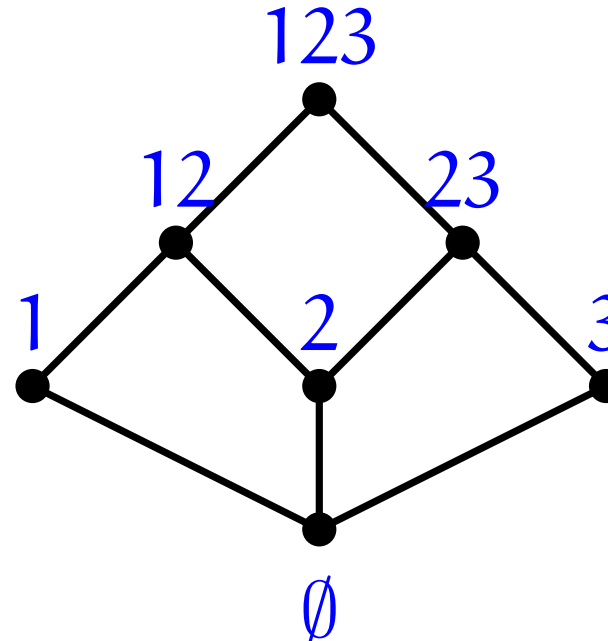
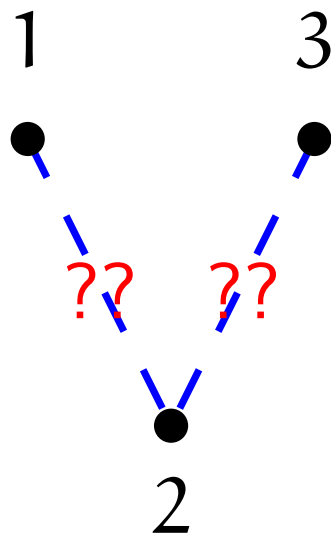
**Obs.**

This is not a poset shelling.



Obs.

This is not a poset shelling.



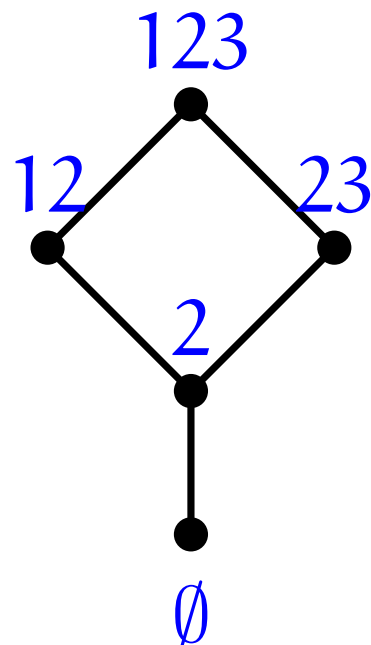
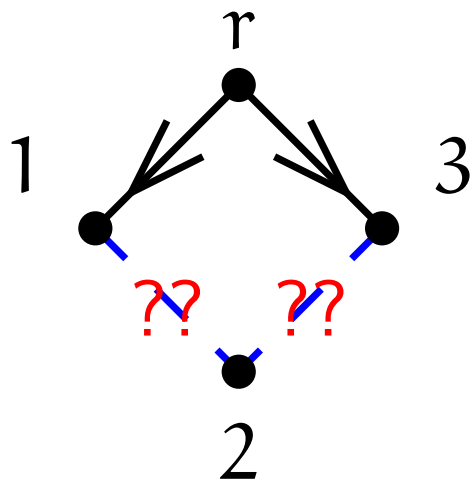
Thm.

(Nakamura '03)

 $\mathcal{L}$  is a poset shelling $\mathcal{L}$  contains no minor isomorphic to the one above.

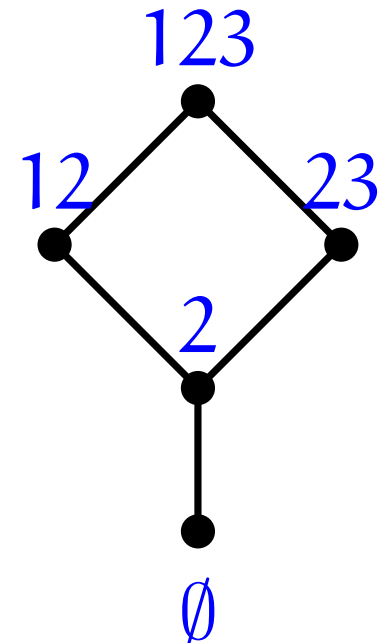
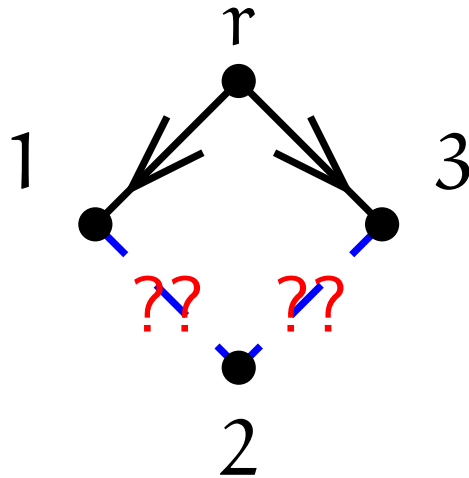
**Obs.**

This is not a digraph point-search.



Obs.

This is not a digraph point-search.



Thm.

(Nakamura '03)

 $\mathcal{L}$  is a digraph point-search $\mathcal{L}$  contains no minor isomorphic to the one above.

- ◆ Poset shellings (Nakamura '03)
- ◆ Graph searches
  - directed/point (Nakamura '03)
  - undirected/point (Nakamura '03)
  - directed/line (Okamoto & Nakamura '03)
  - undirected/line (OPEN)

Open problem

Forbidden-minor characterization of  
undirected graph line-searches

## Classes closed under taking minors

- ◆ Poset shellings
- ◆ Graph searches
  - directed/point
  - undirected/point
  - directed/line
  - undirected/line

## Classes not closed under taking minors

- ◆ Convex shellings of finite point sets
- ◆ Tree shellings

## Classes closed under taking minors

- ◆◆ Poset shellings
- ◆◆ Graph searches
  - directed/point
  - undirected/point
  - directed/line
  - undirected/line
- ◆◆ Minors of convex shellings of finite point sets
- ◆◆ Minors of tree shellings

## Classes not closed under taking minors

- ◆◆ Convex shellings of finite point sets
- ◆◆ Tree shellings

**Thm**

(Kashiwabara, Nakamura &amp; Okamoto '03)

 $\mathcal{L}$  is a minor of a convex shelling $\mathcal{L}$  is a convex geometry.



**Thm**

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 $\mathcal{L}$  is a minor of a convex shelling $\mathcal{L}$  is a convex geometry.

In other words,

Every convex geometry is  
a minor of a convex shelling.

More precisely speaking, ...

**Thm**

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For any convex geometry  $\mathcal{L}$ ,  
there exists a finite point set  $\mathcal{P} = \mathcal{P}(\mathcal{L}) \subseteq \mathbb{R}^d$   
for some  $d = d(\mathcal{L})$

Thm

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 there exists a finite point set  $\mathcal{P} = \mathcal{P}(\mathcal{L}) \subseteq \mathbb{R}^d$   
 for some  $d = d(\mathcal{L})$   
 such that  $\mathcal{L} \cong \mathcal{L}'[A, B]$ ,  
 where  $\mathcal{L}'$  is the convex shelling on  $\mathcal{P}$  and  
 $A, B \in \mathcal{L}'$ ,  $A \subseteq B$ .

Thm

(Kashiwabara, Nakamura &amp; Okamoto '03)

$\forall \mathcal{L} \exists \mathcal{P} = \mathcal{P}(\mathcal{L}) \subseteq \mathbb{R}^d$ , for some  $d = d(\mathcal{L})$ ,  
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 where  $\mathcal{L}'$  is the conv shelling on  $\mathcal{P}$   
 $A, B \in \mathcal{L}'$ ,  $A \subseteq B$ .

Open problem

What is  $\min d(\mathcal{L})$ ?

What's known: let  $\mathcal{L}$  be on an  $n$ -element set

$$\blacklozenge \quad \forall \mathcal{L}: \min d(\mathcal{L}) \leq n - 1$$

$$\blacklozenge \quad \exists \mathcal{L}: \min d(\mathcal{L}) \geq n - 2$$

Thm

(Kashiwabara, Nakamura &amp; Okamoto '03)

$\forall \mathcal{L} \exists \mathcal{P} = \mathcal{P}(\mathcal{L}) \subseteq \mathbb{R}^d$ , for some  $d = d(\mathcal{L})$ ,  
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Open problem

What is  $\min |\mathcal{P}(\mathcal{L})|$ ?

What's known: let  $\mathcal{L}$  be on an  $n$ -element set

$$\blacklozenge \quad \forall \mathcal{L}: n \leq \min |\mathcal{P}(\mathcal{L})| \leq n + |\mathcal{C}(\mathcal{L})|$$

( $\mathcal{C}(\mathcal{L})$  the circuits of  $\mathcal{L}$ , ... defined later)

- ◆ Poset shellings (Nakamura '03)
- ◆ Graph searches
  - directed/point (Nakamura '03)
  - undirected/point (Nakamura '03)
  - directed/line (Okamoto & Nakamura '03)
  - undirected/line (OPEN)
- ◆ Minors of convex shellings (Kashiwabara, Nakamura & Okamoto '03)
- ◆ Minors of tree shellings (OPEN)

Open problem

Forbidden-minor characterization of  
minors of tree shellings

## Setup

Given a convex geometry  $\mathcal{L}$  as the oracle

$$X \longrightarrow \boxed{\text{Oracle}} \longrightarrow \begin{cases} \text{"Yes"} & \text{if } X \in \mathcal{L} \\ \text{"No"} & \text{if } X \notin \mathcal{L} \end{cases}$$

Measure: # of oracle calls

## Thm.

(Enright '01)

- (1) There is a poly-time algorithm to recognize a poset shelling.
- (2) There is no poly-time algorithm to recognize a graph search (directed/point).
- (3) There is no poly-time algorithm to recognize a graph search (undirected/point).



## Biased introduction to (abstract) convex geometries

- ◆ Definition and Examples (15 min.)
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- ◆ **Basic Concepts II** (15 min.)
- ◆ Others (5 min.)
- ◆ Summary (1 min.)

## Framework

Convex geometries

Matroids

---

Convex sets

Flats

Closure

Closure

Extreme points

isthmus

Independent sets

Independent sets

Circuits

Circuits

⋮

⋮

**Setup** $\mathcal{L} \subseteq 2^E$  a convex geometry on  $E$ **Def.**

The **closure operator** of  $\mathcal{L}$  is  
a mapping  $\tau_{\mathcal{L}} : 2^E \rightarrow 2^E$  defined as

$$\tau_{\mathcal{L}}(A) = \bigcap \{X \in \mathcal{L} : A \subseteq X\}$$

= **smallest convex set containing  $A$ .**

**Analogy** $X \subseteq \mathbb{R}^d$  $\text{conv}(X)$  = smallest convex set containing  $X$ .**Obs.** $A \subseteq \tau_{\mathcal{L}}(A)$  for all  $A \subseteq E$

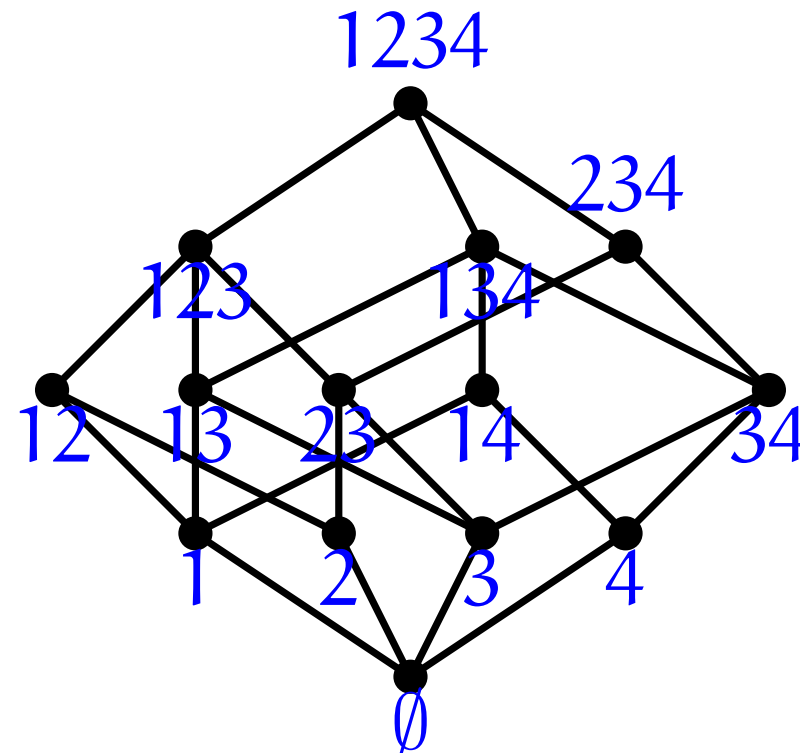
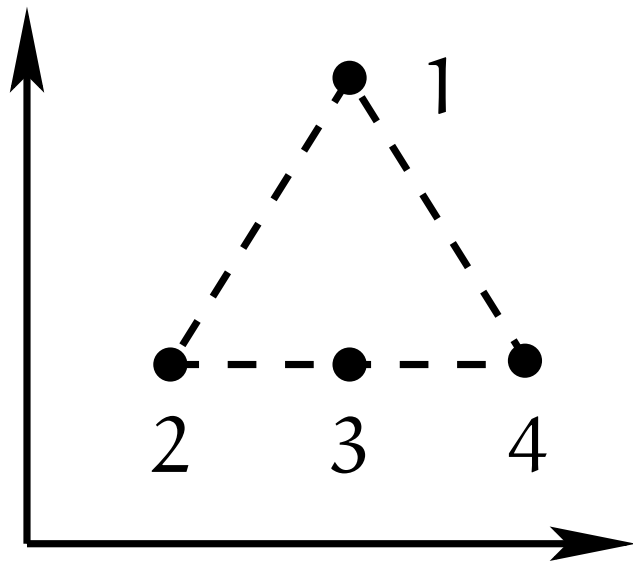
**Def.** $\tau_{\mathcal{L}}(A) = \text{smallest convex set containing } A.$

Def.

 $\tau_{\mathcal{L}}(A) = \text{smallest convex set containing } A.$ 

E.g.

$$\mathcal{L} = \{X \subseteq \mathcal{P} : \text{conv}(X) \cap \mathcal{P} = X\}$$



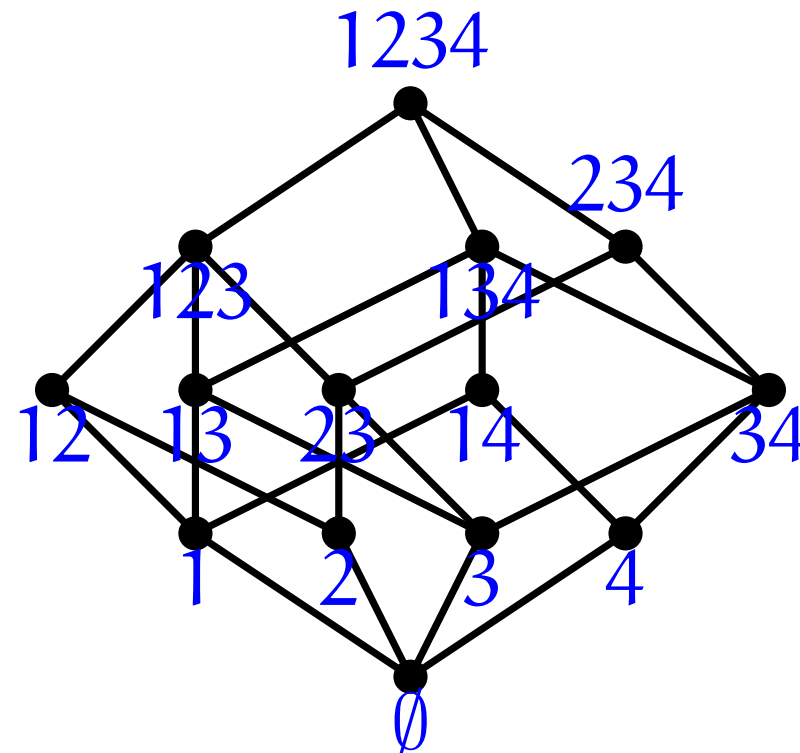
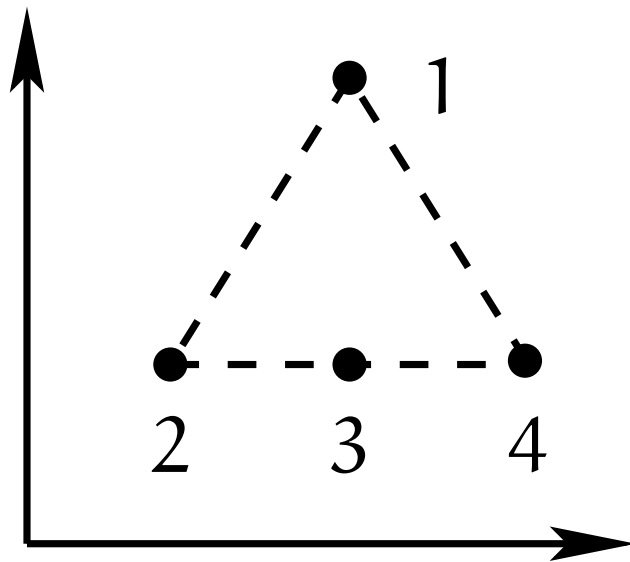
$$\tau_{\mathcal{L}}(\{2, 4\}) = ??$$

Def.

 $\tau_{\mathcal{L}}(A) = \text{smallest convex set containing } A.$ 

E.g.

$$\mathcal{L} = \{X \subseteq \mathcal{P} : \text{conv}(X) \cap \mathcal{P} = X\}$$



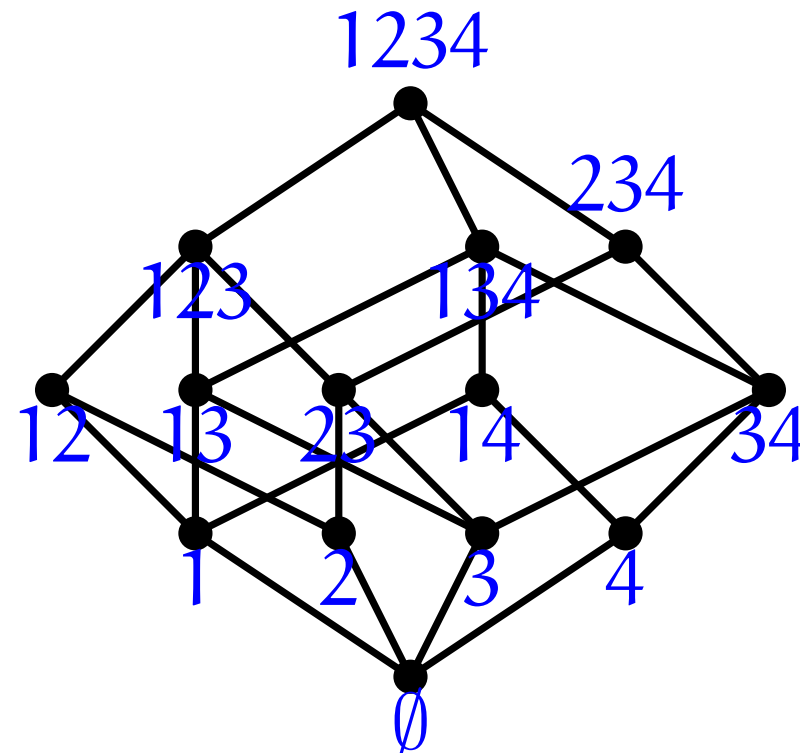
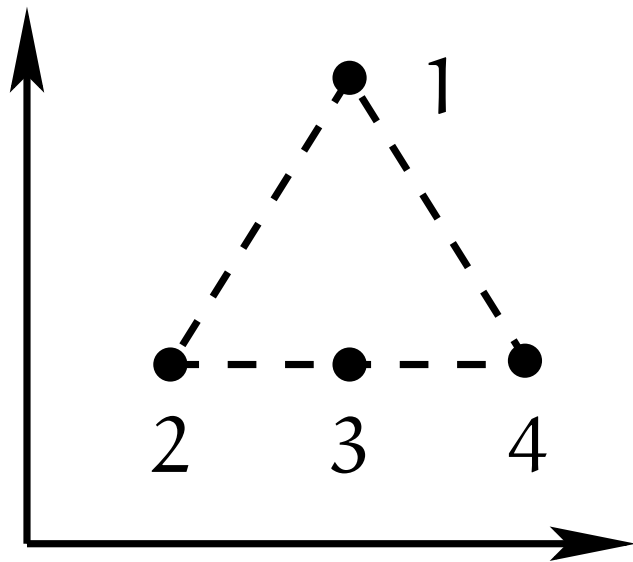
$$\tau_{\mathcal{L}}(\{2, 4\}) = \{2, 3, 4\}.$$

Def.

 $\tau_{\mathcal{L}}(A) = \text{smallest convex set containing } A.$ 

E.g.

$$\mathcal{L} = \{X \subseteq \mathcal{P} : \text{conv}(X) \cap \mathcal{P} = X\}$$



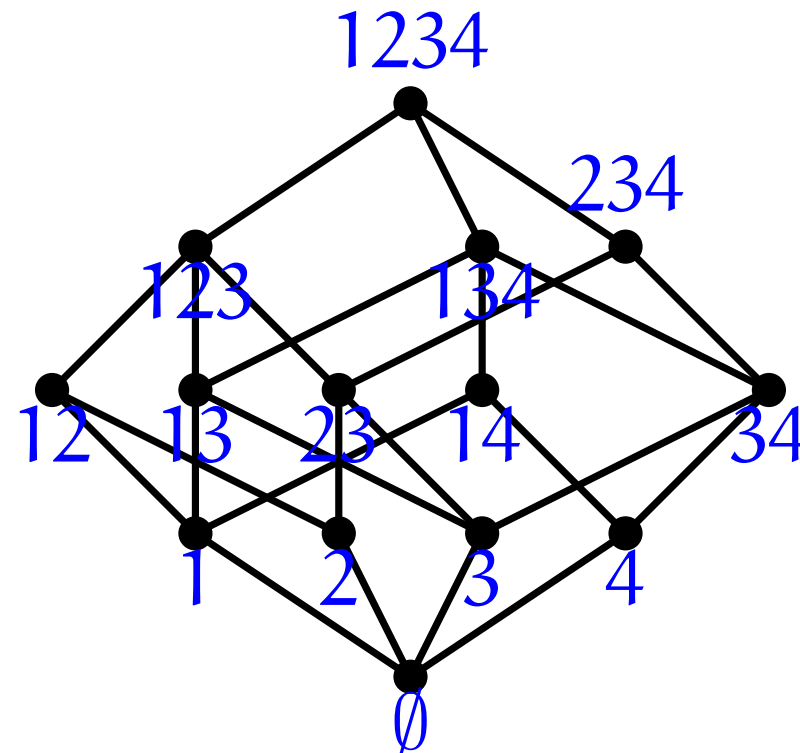
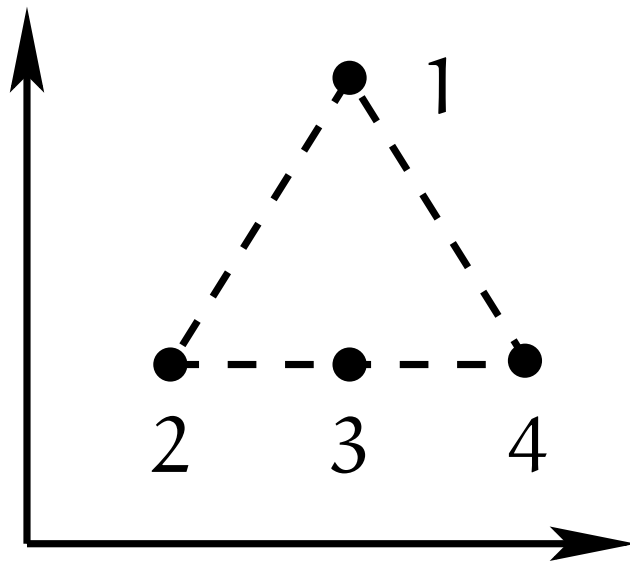
$$\tau_{\mathcal{L}}(\{1, 3\}) = \{1, 3\}.$$

Def.

 $\tau_{\mathcal{L}}(A) = \text{smallest convex set containing } A.$ 

E.g.

$$\mathcal{L} = \{X \subseteq \mathcal{P} : \text{conv}(X) \cap \mathcal{P} = X\}$$



$$\tau_{\mathcal{L}}(\{1, 2, 4\}) = \{1, 2, 3, 4\}.$$

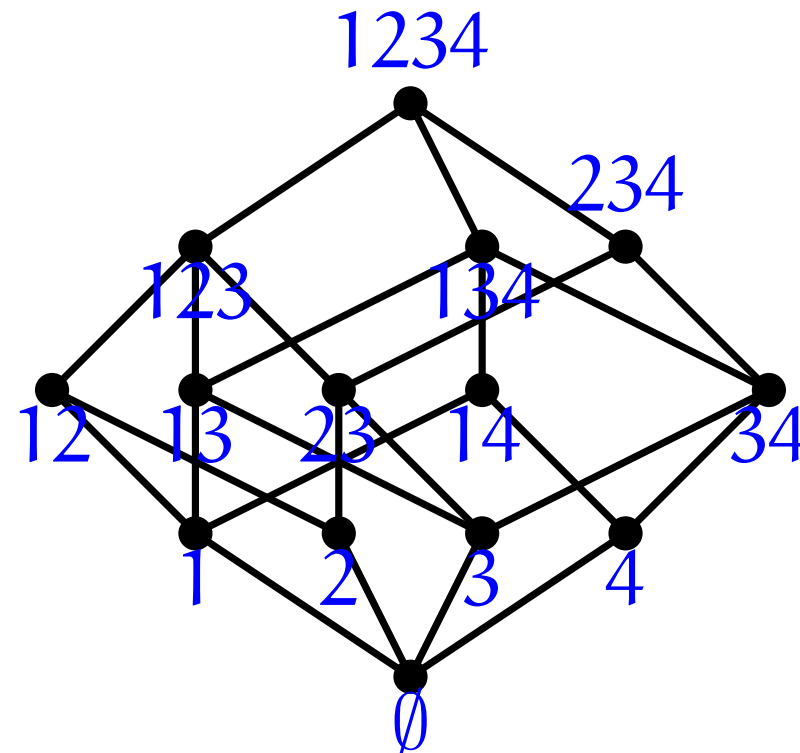
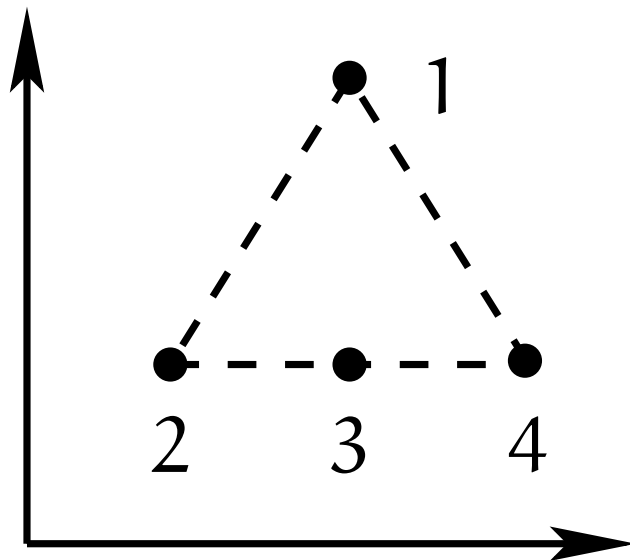


Def.

 $\tau_{\mathcal{L}}(A) = \text{smallest convex set containing } A.$ 

E.g.

$$\mathcal{L} = \{X \subseteq \mathcal{P} : \text{conv}(X) \cap \mathcal{P} = X\}$$



Rem

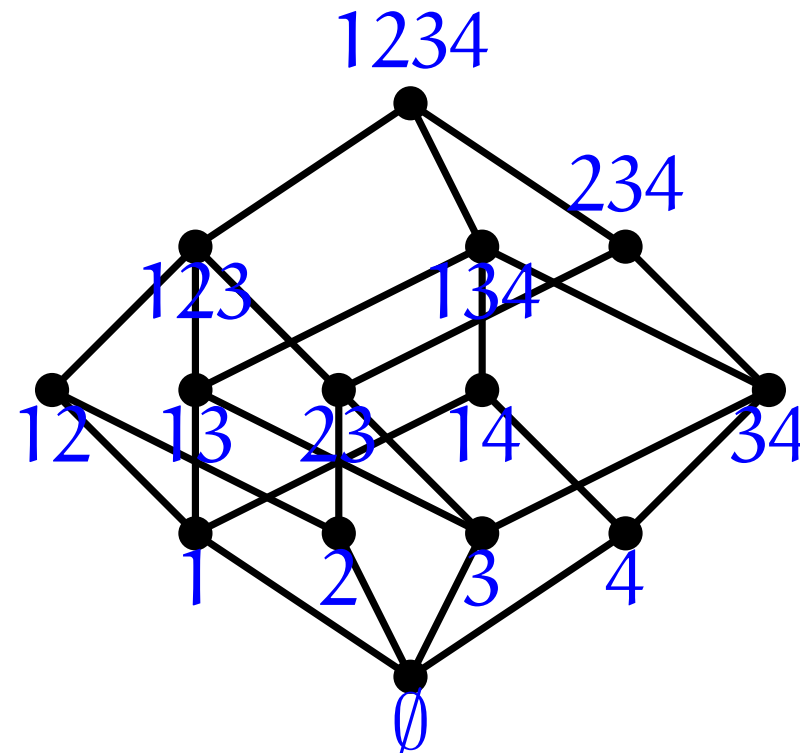
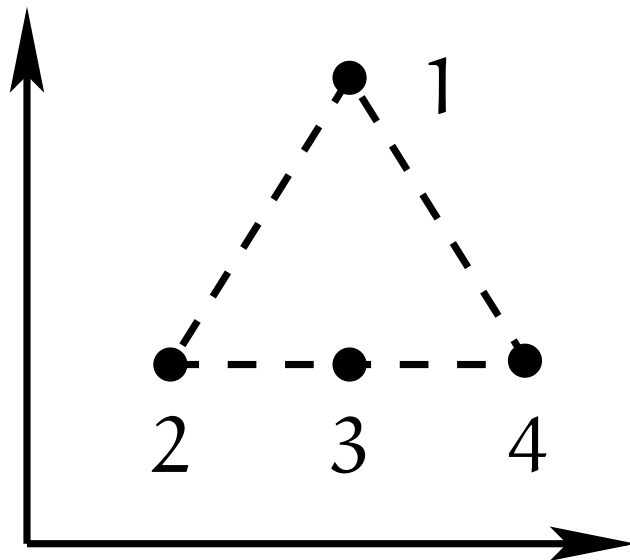
$$\mathcal{L} = \{X \subseteq E : X = \tau_{\mathcal{L}}(X)\} \quad (\text{in general}).$$

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Rem

Characterizations of convex geometries  
by closure operators

(Edelman & Jamison '85)

Setup

 $\tau : 2^E \rightarrow 2^E$  a map

Thm

(Edelman &amp; Jamison '85)

 $\tau$  is the closure operator of some convex geometry

(1)  $\tau(\emptyset) = \emptyset$ .

(2)  $A \subseteq \tau(A)$  for all  $A \subseteq E$

(3)  $A \subseteq B \subseteq E \Rightarrow \tau(A) \subseteq \tau(B)$ .

(4)  $\tau(\tau(A)) = \tau(A)$  for all  $A \subseteq E$ .

(5)  $A \subseteq E$ ,  $e, f \notin \tau(A)$ ,  $e \neq f$ ,  
 $e \in \tau(A \cup \{f\}) \Rightarrow f \notin \tau(A \cup \{e\})$ .

Setup

 $\tau : 2^E \rightarrow 2^E$  a map

Cf.

 $\tau$  is the closure operator of some matroid

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Setup

$\mathcal{L} \subseteq 2^E$  a convex geometry on  $E$

Def.

The **extreme point operator** of  $\mathcal{L}$  is a mapping  $\text{ex}_{\mathcal{L}} : 2^E \rightarrow 2^E$  defined as

$$\text{ex}_{\mathcal{L}}(A) = \{e \in A : e \notin \tau_{\mathcal{L}}(A \setminus \{e\})\}.$$

Analogy

$X \subseteq \mathbb{R}^d$  a convex polyhedron (pointed)  
 $\text{vert}(X)$  = the set of vertices of  $X$ .

Obs.

$\text{ex}_{\mathcal{L}}(A) \subseteq A$  for all  $A \subseteq E$

Def.

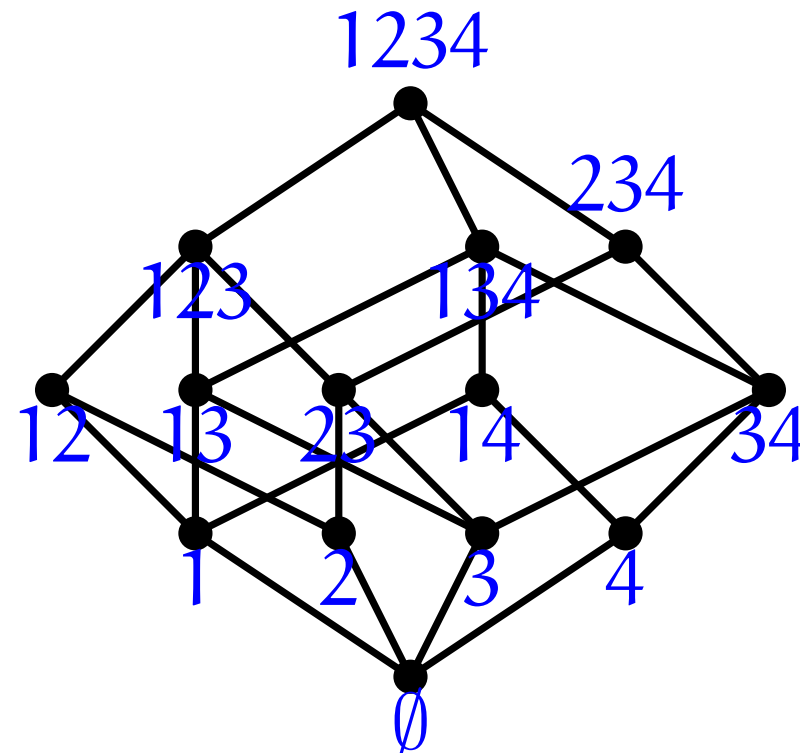
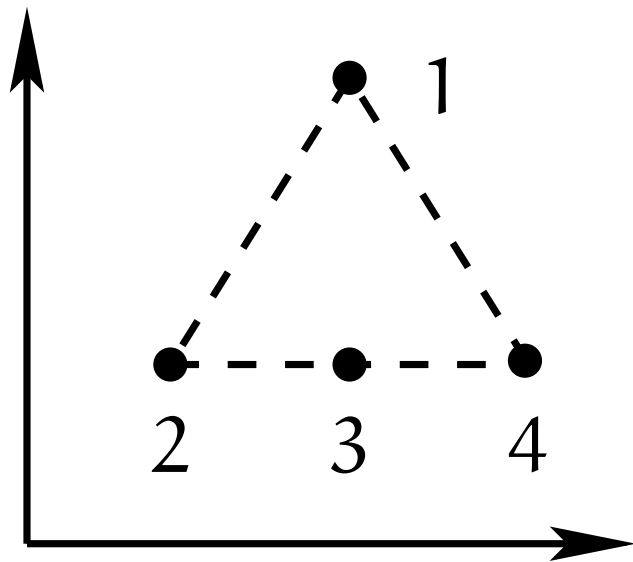
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$$\text{ex}_{\mathcal{L}}(\mathbf{A}) = \{e \in \mathbf{A} : e \notin \tau_{\mathcal{L}}(\mathbf{A} \setminus \{e\})\}.$$

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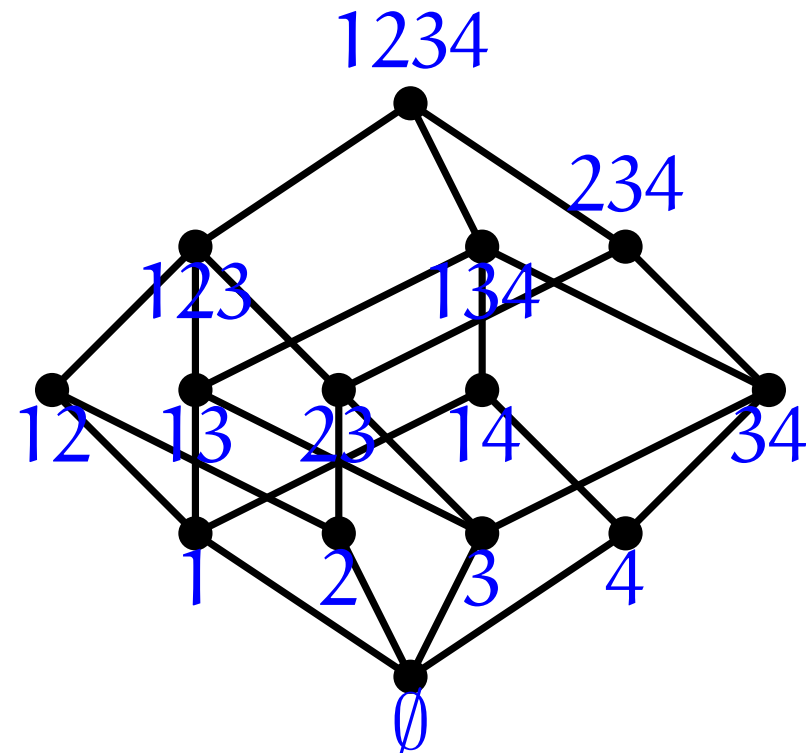
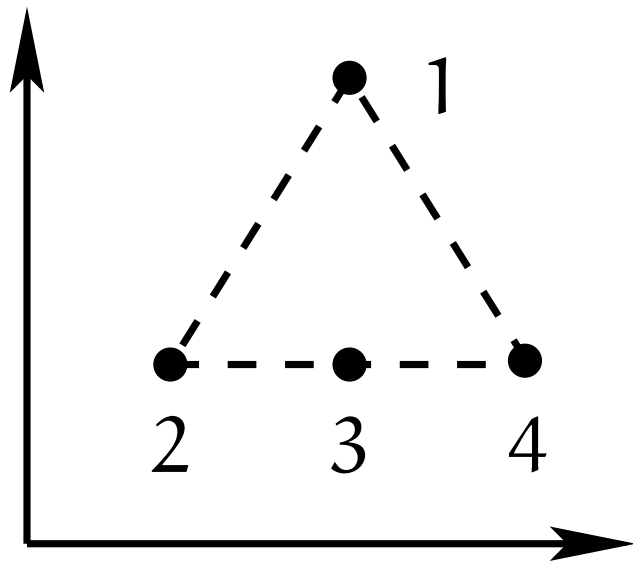
$$\text{ex}_{\mathcal{L}}(\{1, 2, 3, 4\}) = ??$$

Def.

$$\text{ex}_{\mathcal{L}}(\mathbf{A}) = \{e \in \mathbf{A} : e \notin \tau_{\mathcal{L}}(\mathbf{A} \setminus \{e\})\}.$$

E.g.

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$$\text{ex}_{\mathcal{L}}(\{1, 2, 3, 4\}) = \{1, 2, 4\}$$

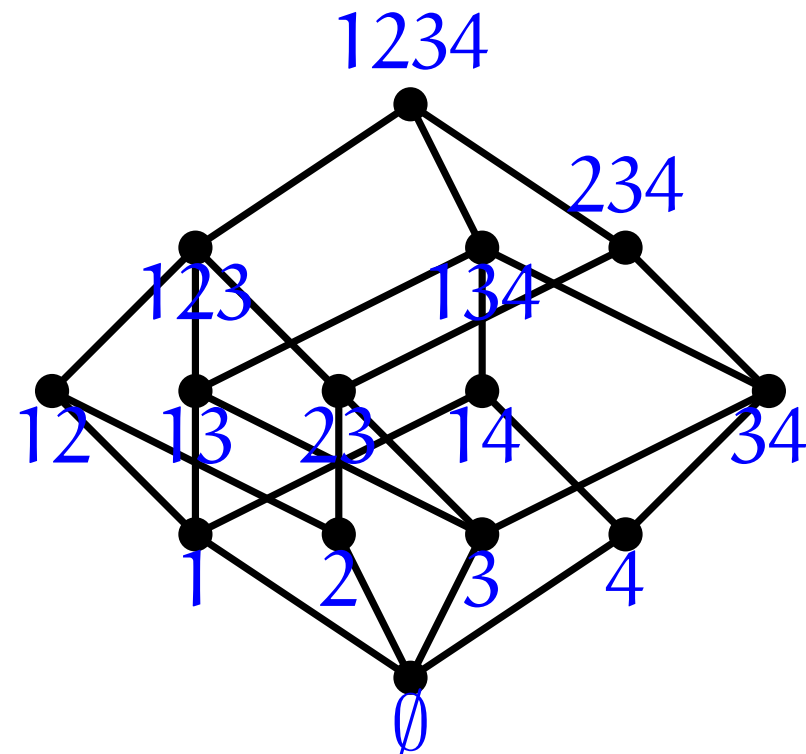
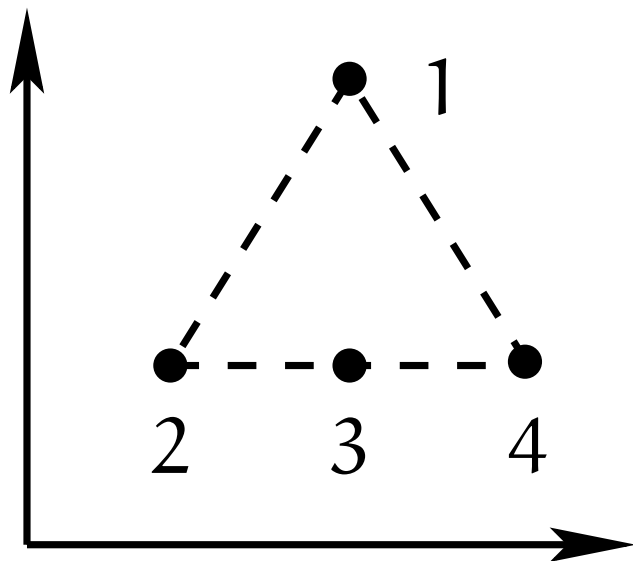


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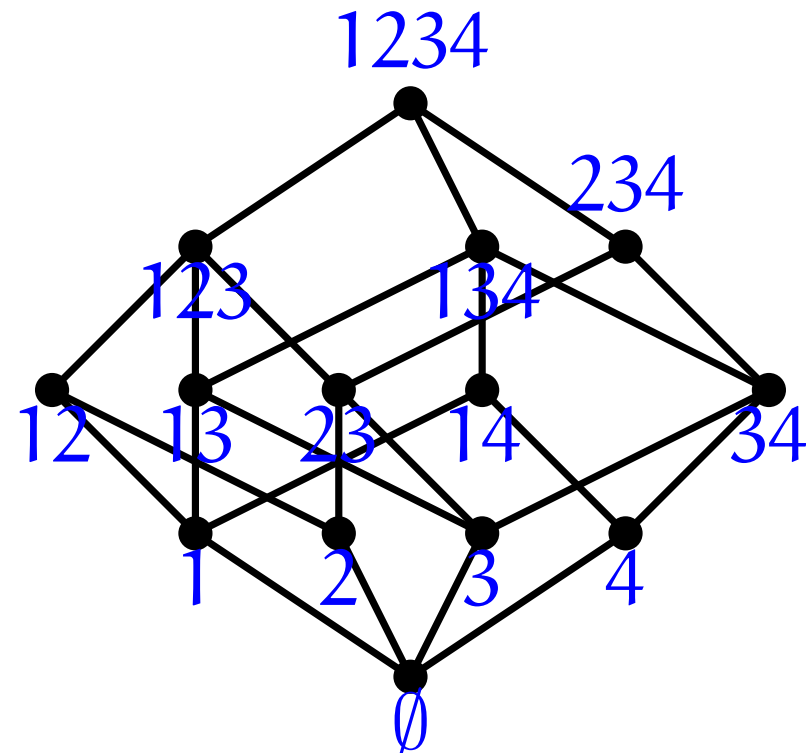
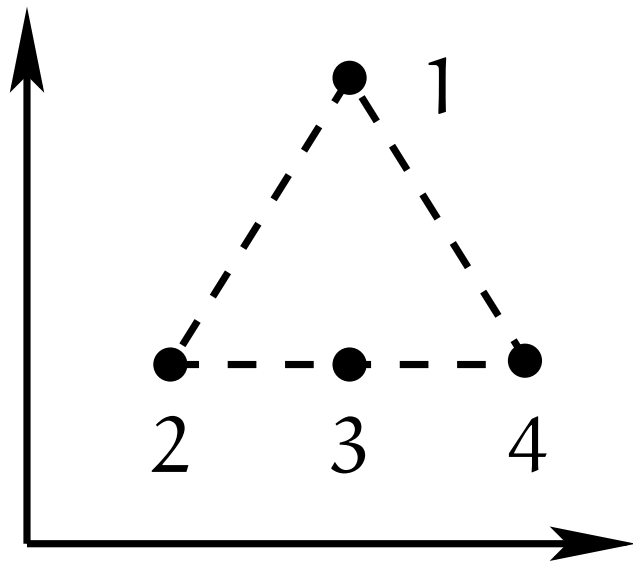
$$\text{ex}_{\mathcal{L}}(\{2, 4\}) = \{2, 4\}.$$

Def.

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E.g.

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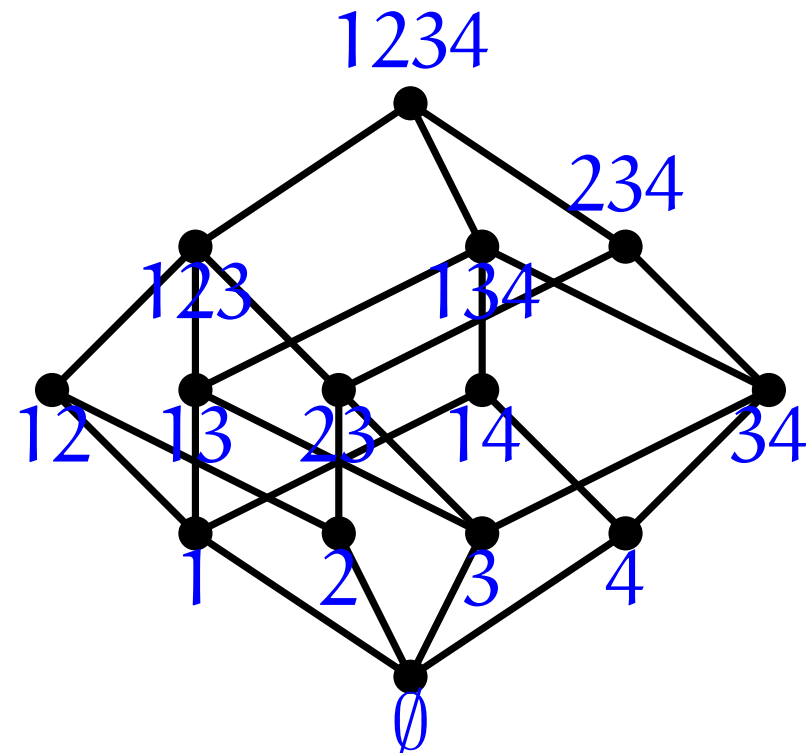
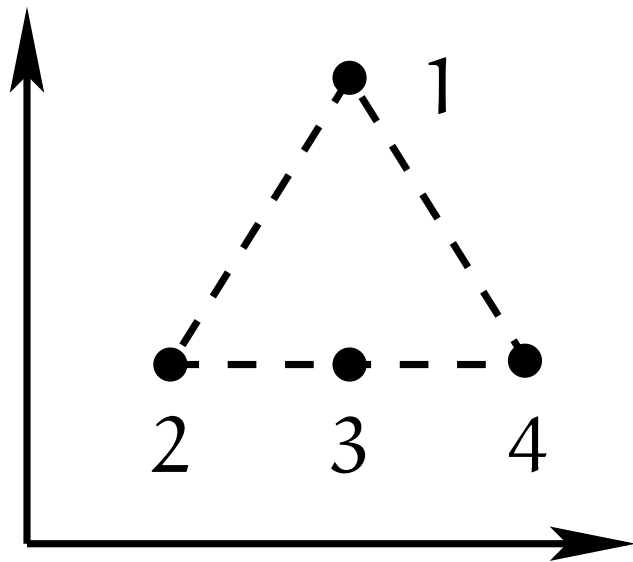
$$\text{ex}_{\mathcal{L}}(\{1\}) = \{1\}$$

Def.

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Rem

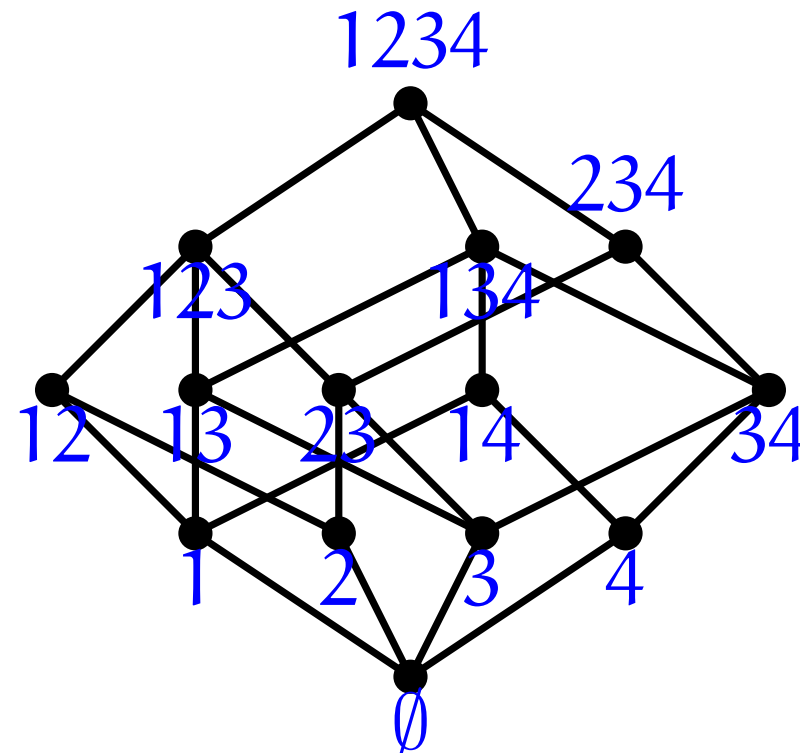
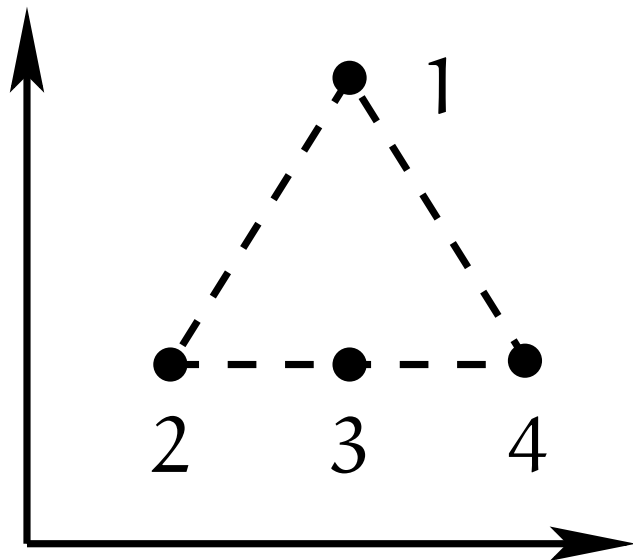
$$\mathcal{L} = \{X \subseteq E : e \in \text{ex}_{\mathcal{L}}(X \setminus \{e\}) \forall e \in E \setminus X\}.$$

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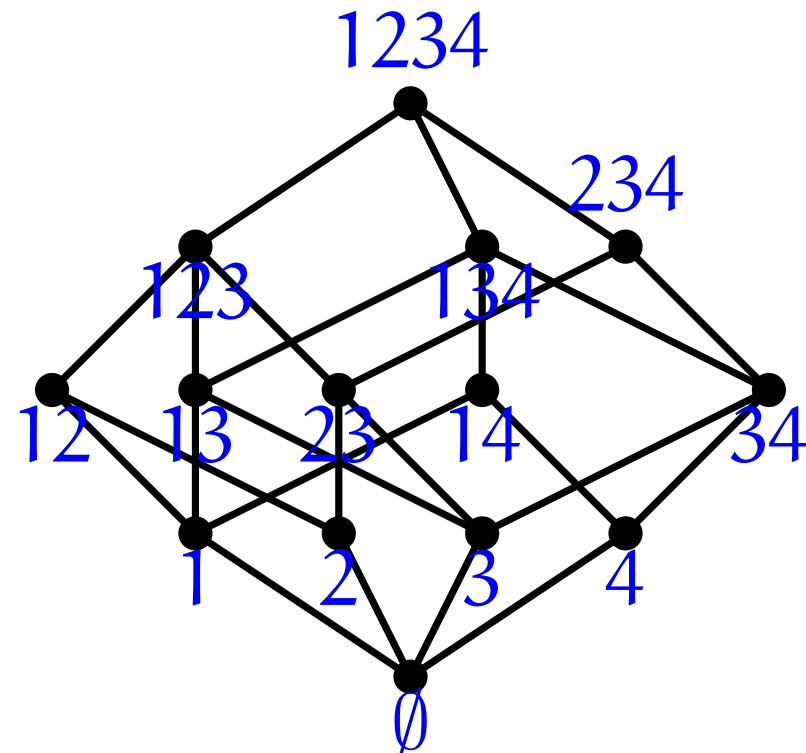
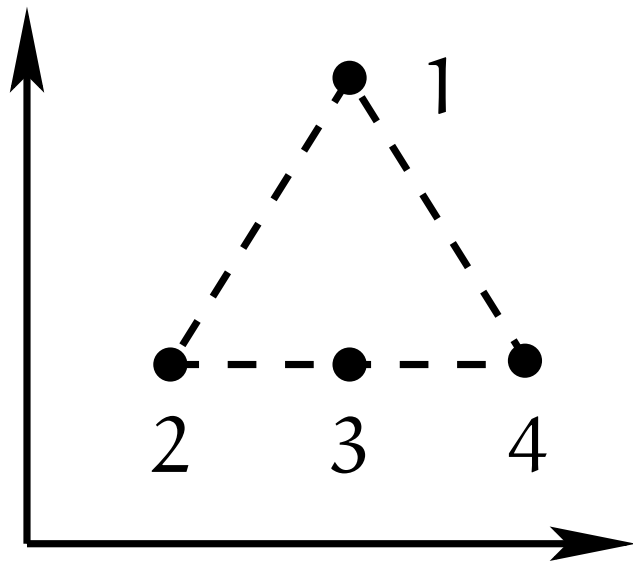
Characterizations of convex geometries by  
 extreme point operators (Koshevoy '99, Ando '02)

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Rem

Characterizations of matroids by  
extreme point operators

(Ando '02)

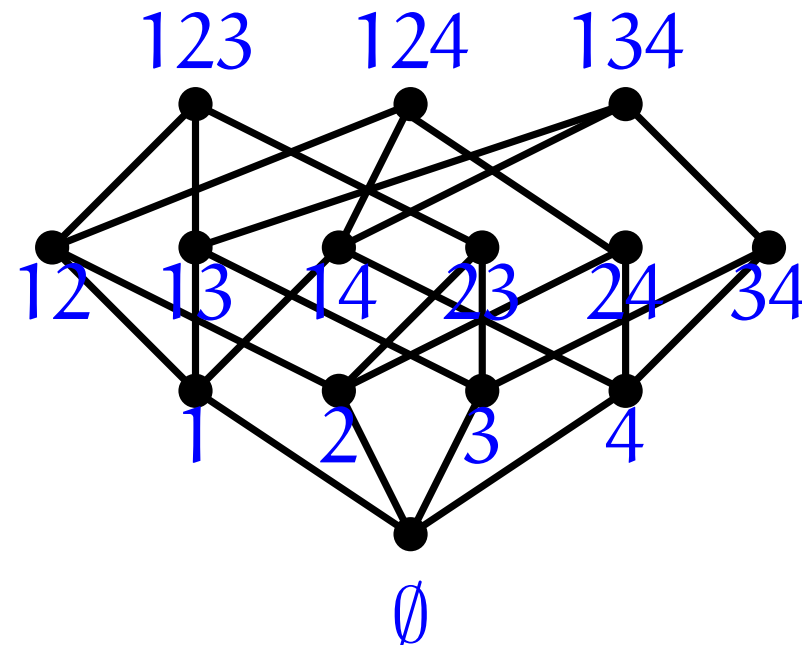
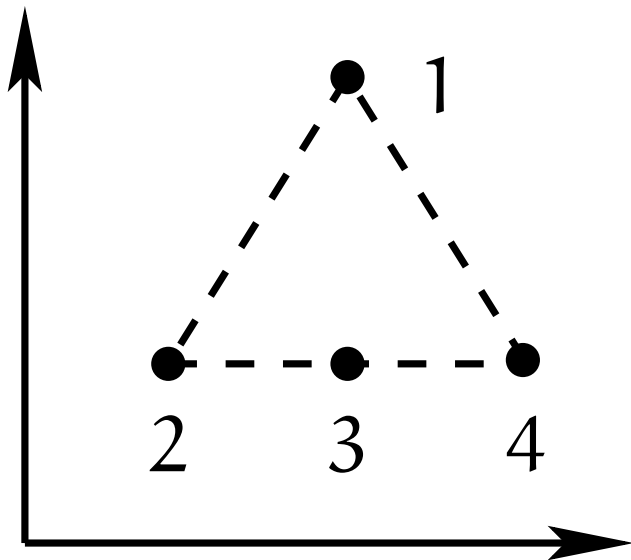
Setup

 $\mathcal{L} \subseteq 2^E$  a convex geometry on  $E$ 

Def.

 A set  $I \subseteq E$  is **independent** in  $\mathcal{L}$  if  $\text{ex}_{\mathcal{L}}(I) = I$ .

E.g.

 $\mathcal{L} = \{X \subseteq \mathcal{P} : \text{conv}(X) \cap \mathcal{P} = X\}$ 
 $\text{ex}_{\mathcal{L}}(A) =$  the set of extreme points of  $\text{conv}(A)$ 


**Def.** $\text{Ind}(\mathcal{L}) =$  the family of independent sets in  $\mathcal{L}$ **Lem.** $I \subseteq J, J \in \text{Ind}(\mathcal{L}) \Rightarrow I \in \text{Ind}(\mathcal{L})$

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characterization of the family

of independent sets in a convex geometry



Def.

$\text{Ind}(\mathcal{L}) =$  the family of independent sets in  $\mathcal{L}$

Lem.

$I \subseteq J, J \in \text{Ind}(\mathcal{L}) \Rightarrow I \in \text{Ind}(\mathcal{L})$

Open problem

characterization of the family

of independent sets in a convex geometry

Cf.

$\mathcal{M}$  a matroid

$\text{Ind}(\mathcal{M})$  is the family of independent sets in  $\mathcal{M}$



(1)  $I \subseteq J, J \in \text{Ind}(\mathcal{M}) \Rightarrow I \in \text{Ind}(\mathcal{M})$ .

(2)  $I_1, I_2 \in \text{Ind}(\mathcal{M}), |I_1| > |I_2|$   
 $\Rightarrow \exists e \in I_1 \setminus I_2: I_2 \cup \{e\} \in \text{Ind}(\mathcal{M})$ .

Setup

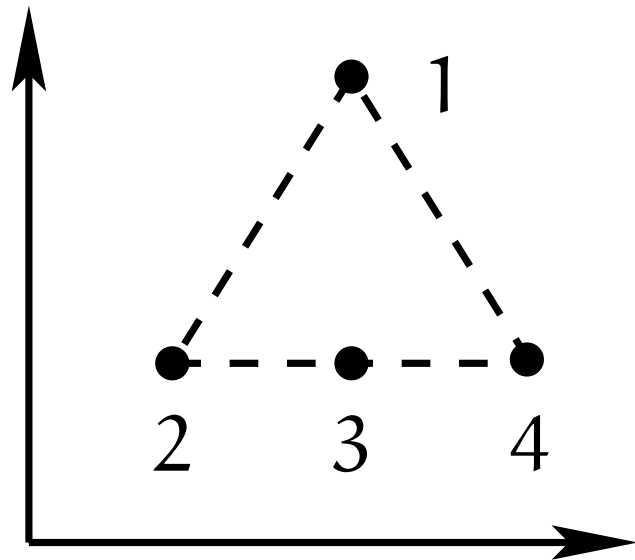
$\mathcal{L} \subseteq 2^E$  a convex geometry on  $E$

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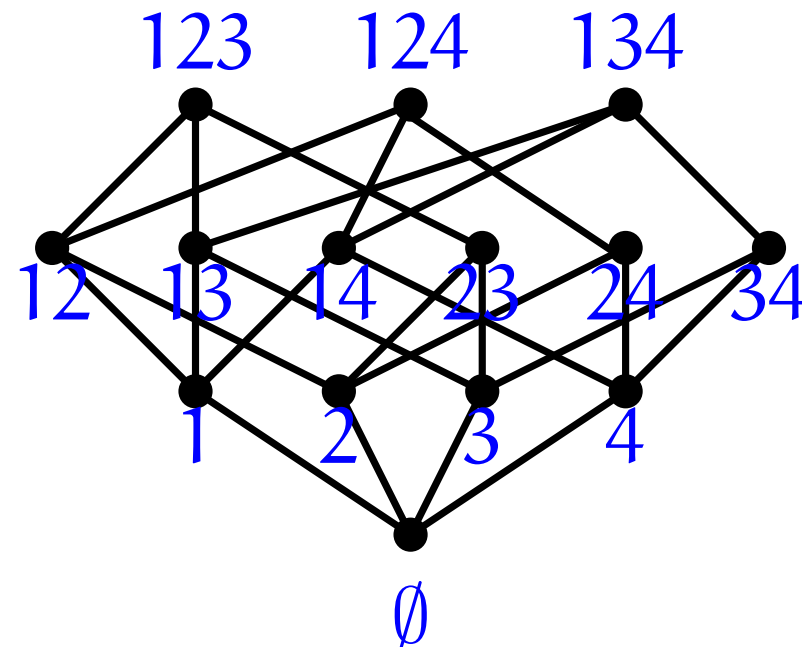
A **circuit** of  $\mathcal{L}$  is a minimal dependent set.

E.g.

$\mathcal{L} = \{X \subseteq \mathcal{P} : \text{conv}(X) \cap \mathcal{P} = X\}$



$\mathcal{C}(\mathcal{L}) = \{234\}$ .



**Def.**

A **circuit** of  $\mathcal{L}$  is a minimal dependent set.

$\mathcal{C}(\mathcal{L}) =$  the family of circuits of  $\mathcal{L}$

**Rem**

Characterization of convex geometries  
by the family of circuits (Dietrich '87)

## Biased introduction to (abstract) convex geometries

- ◆ Definition and Examples (15 min.)
- ◆ Basic Concepts I (5 min.)
- ◆ Classification (15 min.)
- ◆ Basic Concepts II (15 min.)
- ◆ **Others** (5 min.)
- ◆ Summary (1 min.)

- ◆ Goecke '86
  - Linear optimization on convex geometries is NP-hard.
- ◆ Boyd & Faigle '90
  - Greedy algorithm for bottleneck optimization  
(Generalization of Lawler '73)
  - Algorithmic characterization of convex geometries
- ◆ Nakamura '00, Kempner & Levit '03
  - Further study on algor char of convex geometries
- ◆ Kashiwabara & Okamoto '03
  - Submodular-type optimization for convex geometries
  - Introduction of “c-submodular functions”  
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## Cooperative games

Every set of players can form a coalition

## Cooperative games on convex geometries (Bilbao)

A member in a convex geometry can only be a coalition  
(based on Faigle & Kern '92)

- ◆ Power indices (Edelman '97, Bilbao, Jiménez & López '98)
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## ◆ Background

- Gray code for the linear extensions of a poset  
⇒ an efficient enumeration!!
- Linear extensions of a poset  
= Removing sequences in a poset shelling

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## Biased introduction to abstract convex geometries

### Summary

Theory of convex geometries

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- ◆ appears in many guises (by different names).

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- ◆ is looking forward to your contributions.

Thank you very much.

Slides will be obtained from

<http://www.inf.ethz.ch/personal/okamotoy/>

or by email to

[okamotoy@inf.ethz.ch](mailto:okamotoy@inf.ethz.ch)