



Enumerating all Triangulations up to Symmetry

Or: The Power of Order Rightly Used

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Workshop “Geometry meets Combinatorics”

Bielefeld

Agenda

The Problem

Structures for Counting

Structures for Counting Subsets

New Results

Conclusions/Questions

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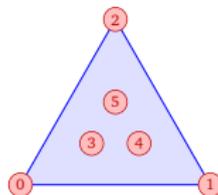
How Many Triangulations Are There?

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Given

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Given A point configuration

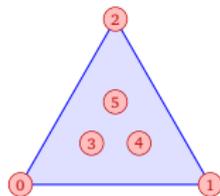


Question 1 **How many** triangulations does it have?

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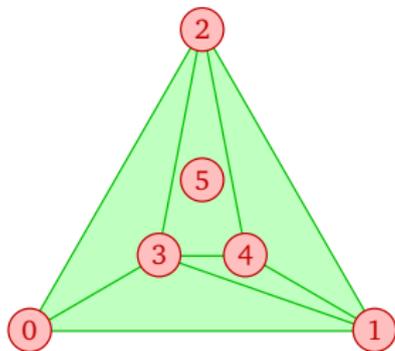
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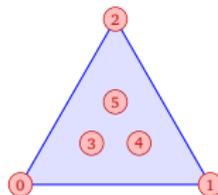


a triangulation

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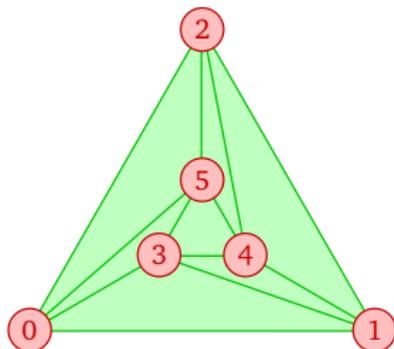
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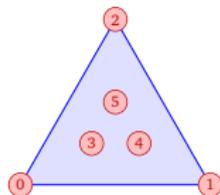


another triangulation

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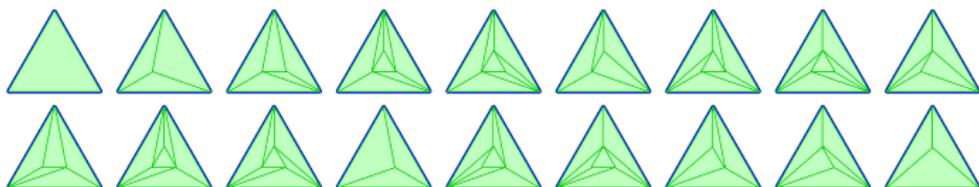
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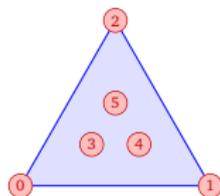
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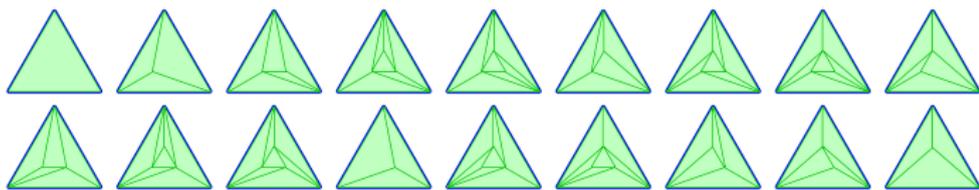
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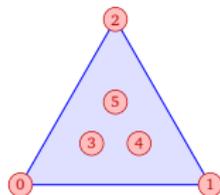


Question 2

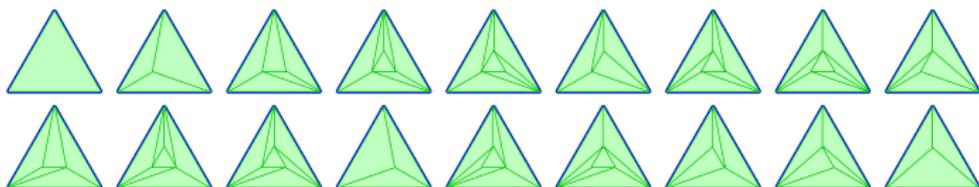
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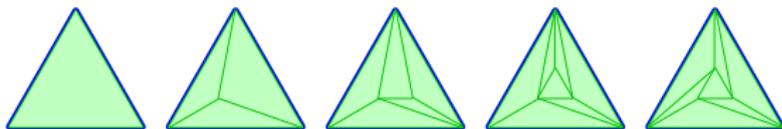
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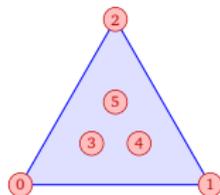


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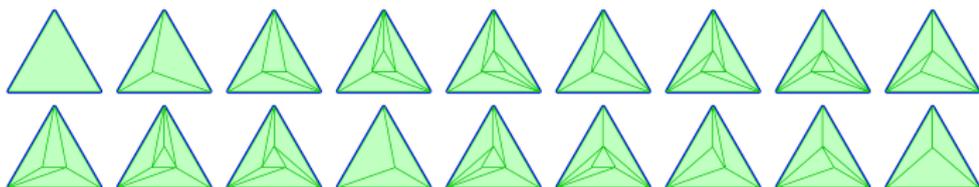


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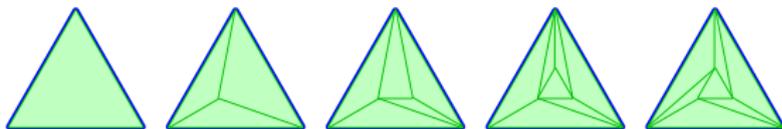
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Question 2 How many triangulations does it have up to symmetry?



This Talk Enumerate them with a computer.

Selected History

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1994

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New:
R. 2022
Parallel symmetric lexicographic subset reverse search
for all triang's
(new C++-code TOPCOM 1.x.x)

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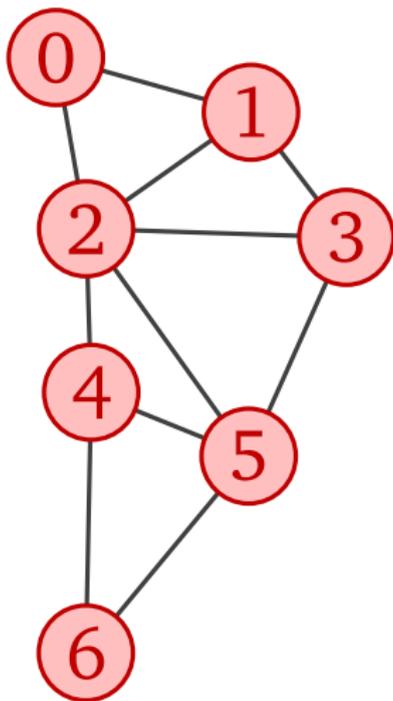
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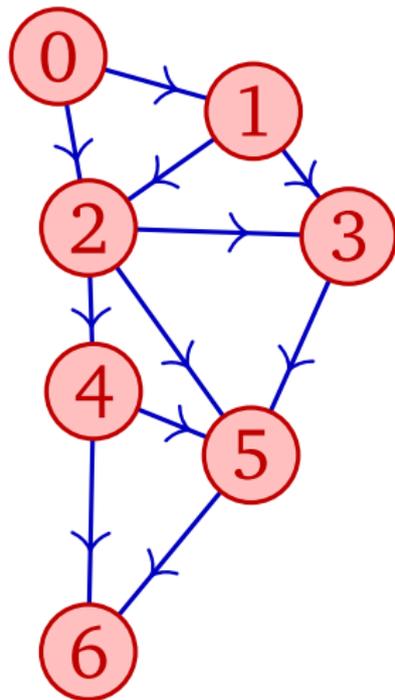
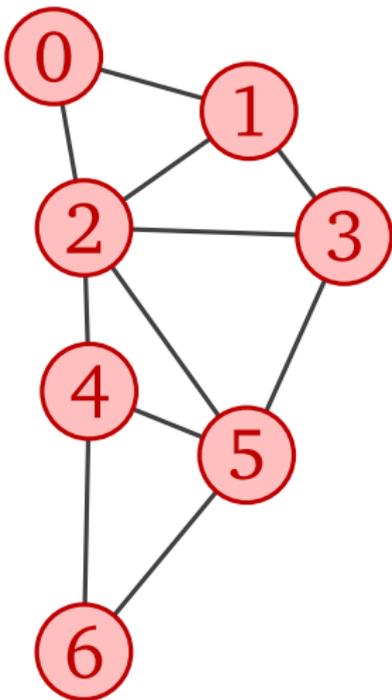
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- ▶ return counter.

RS Example

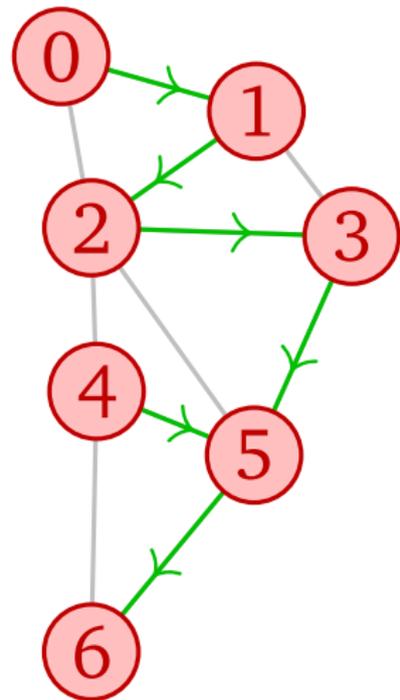
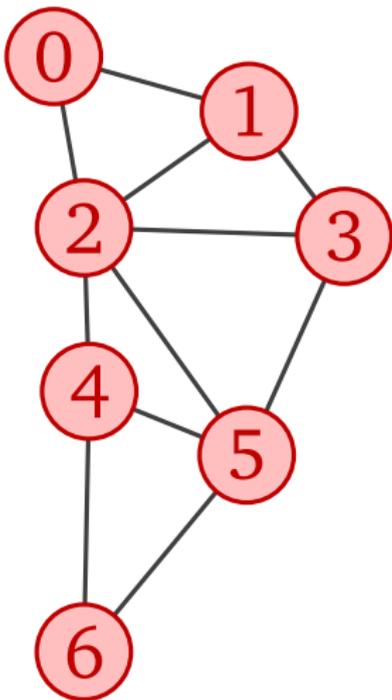
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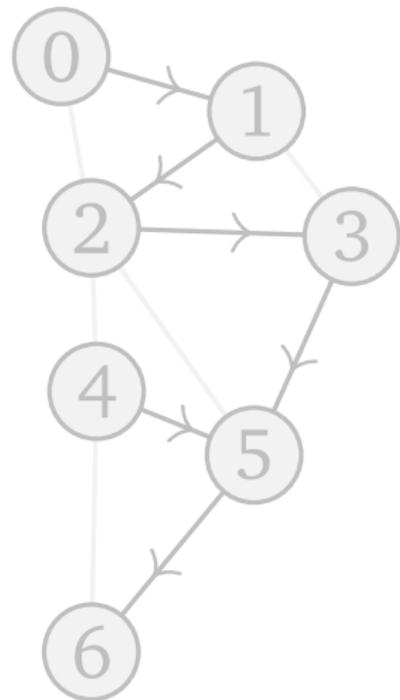
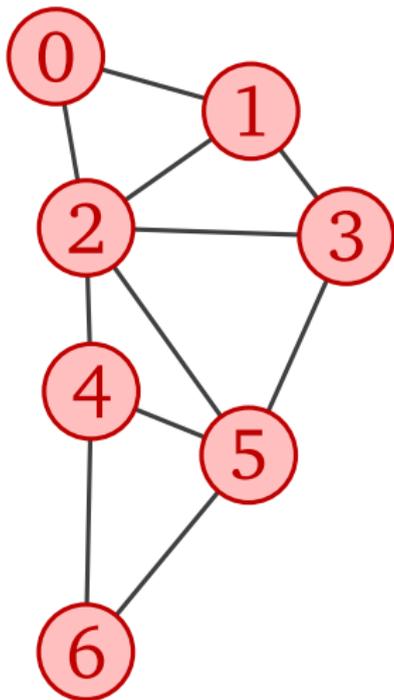
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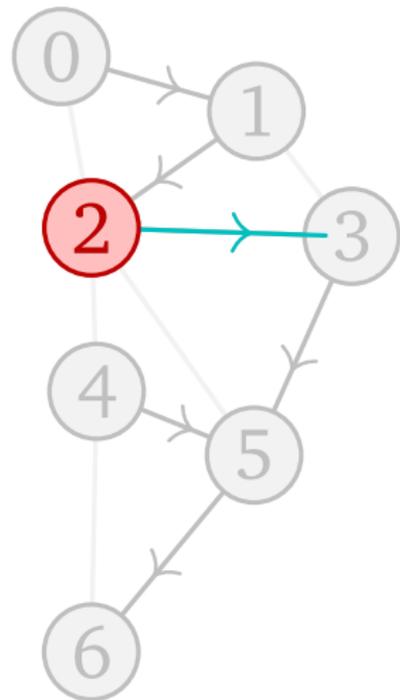
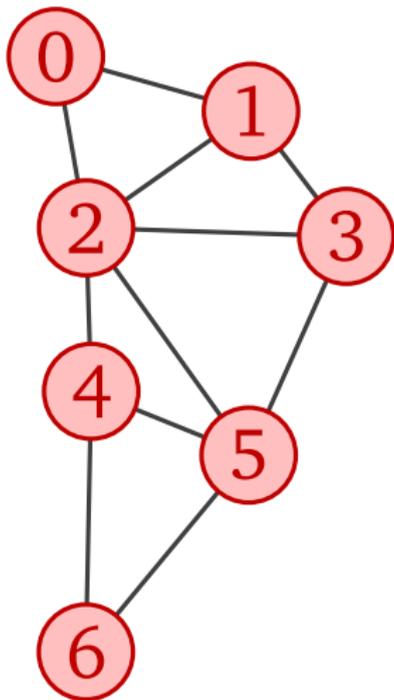
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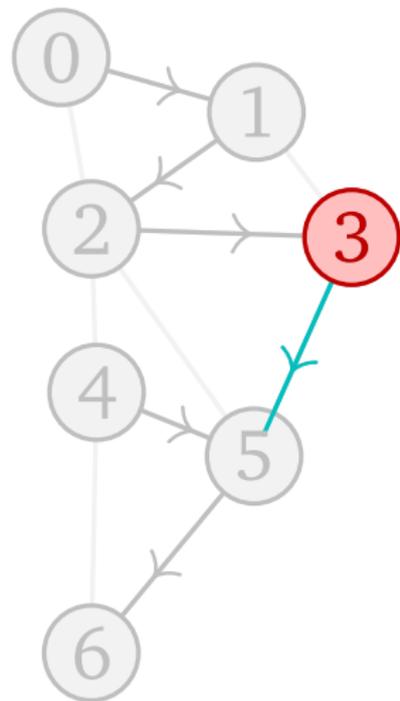
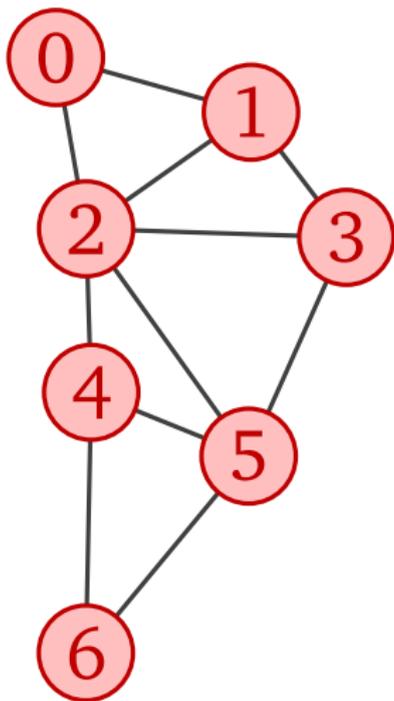
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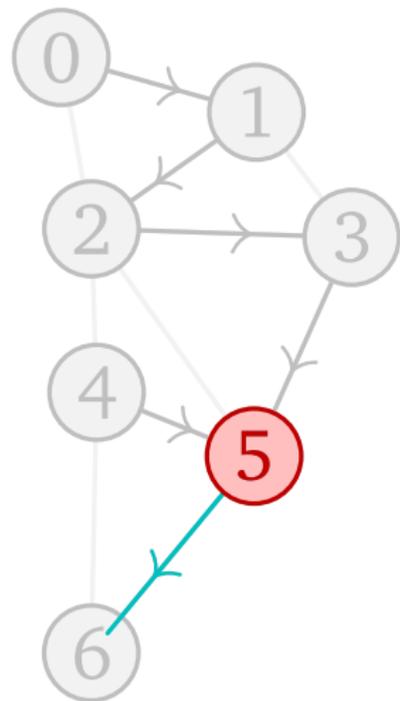
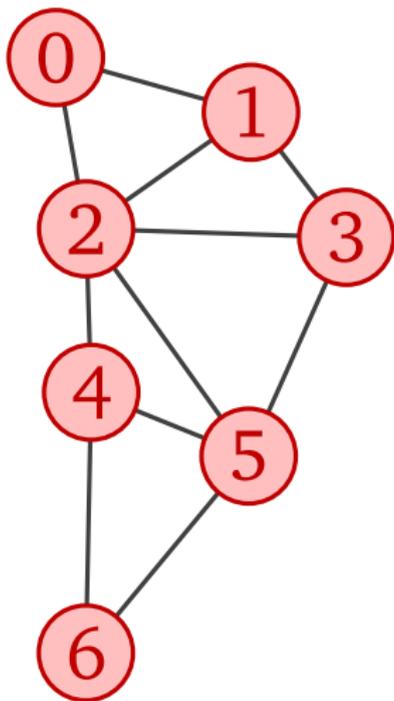
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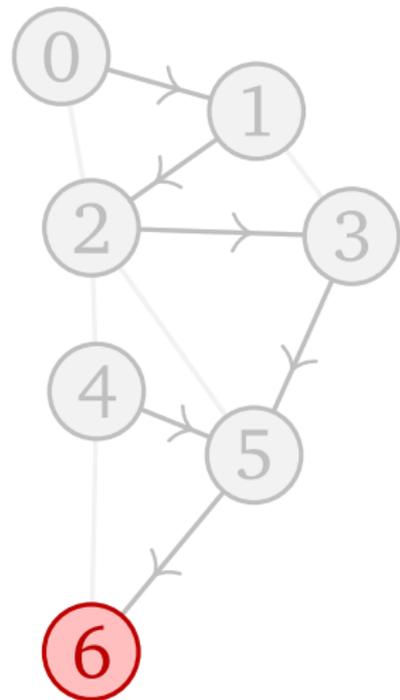
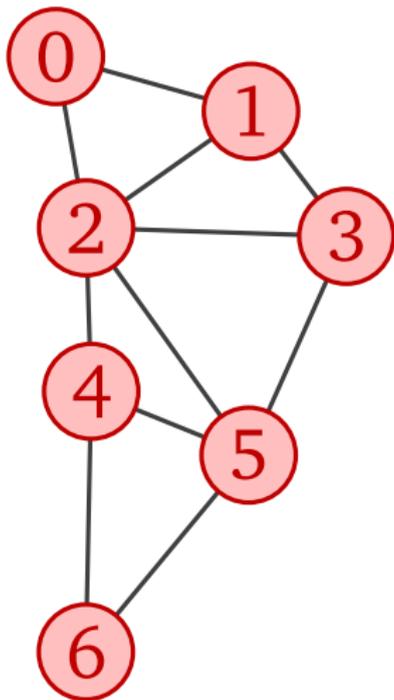
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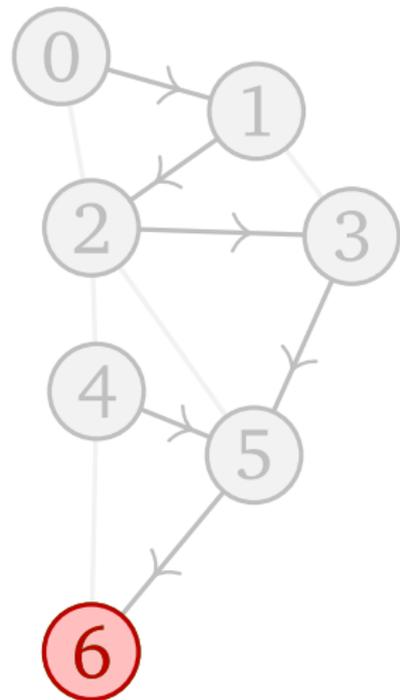
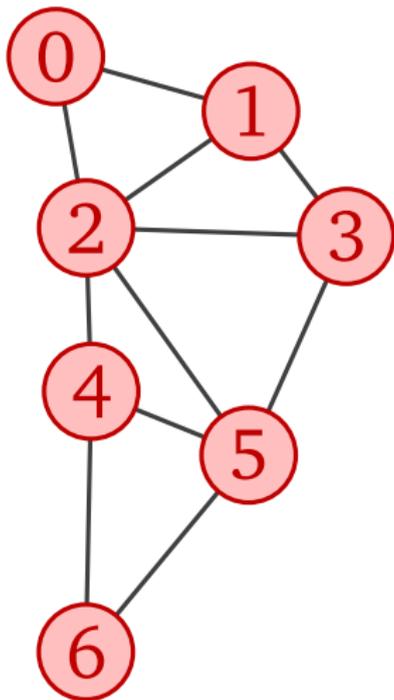
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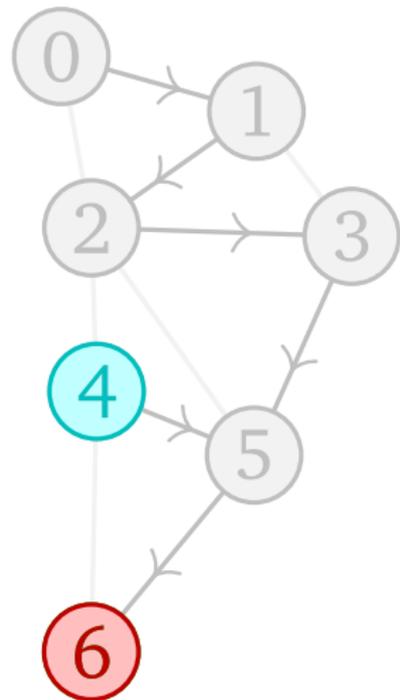
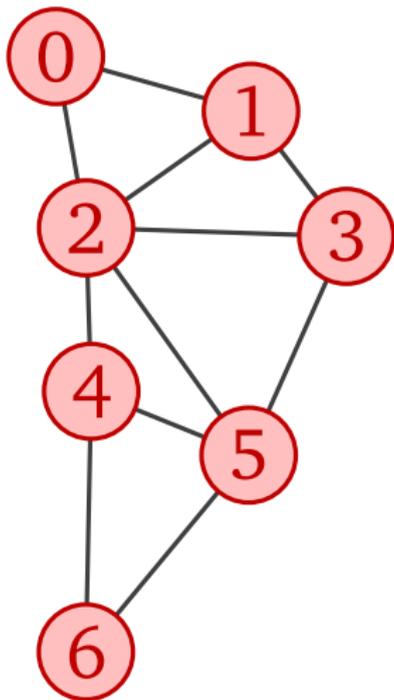
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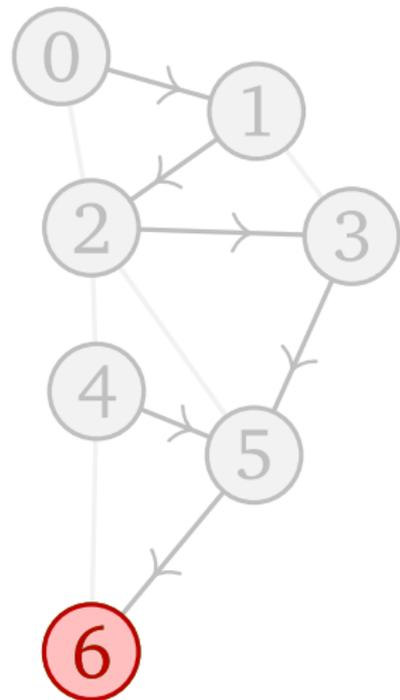
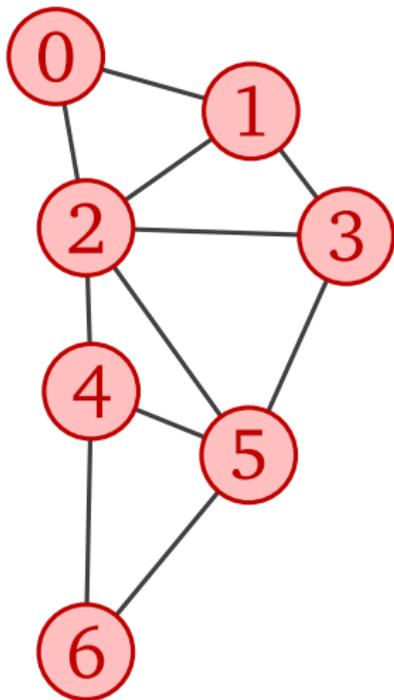
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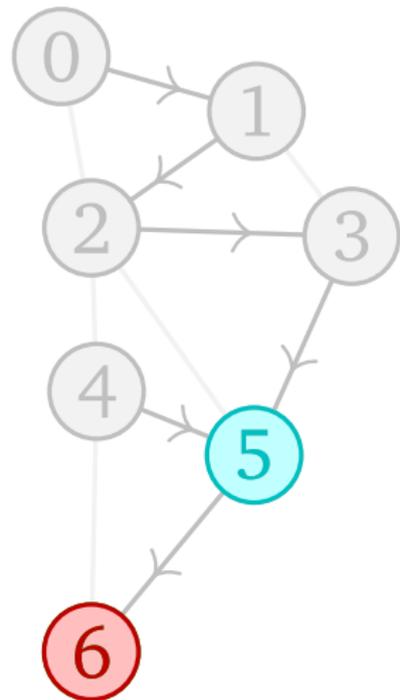
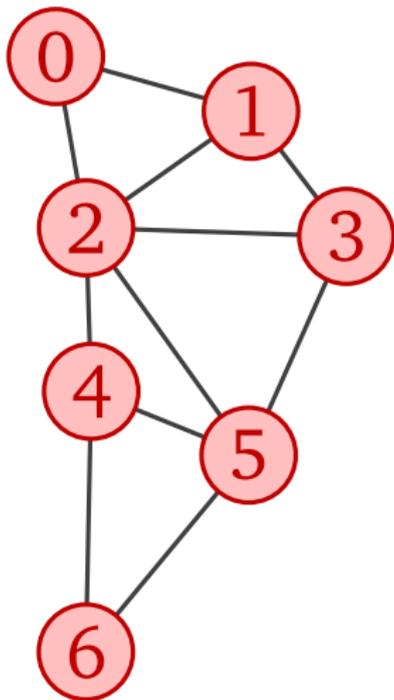
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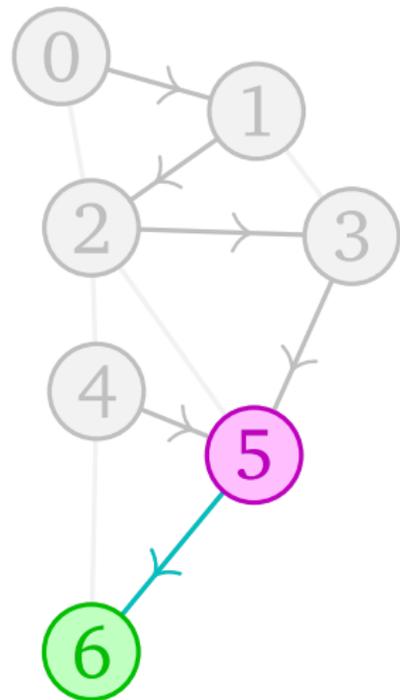
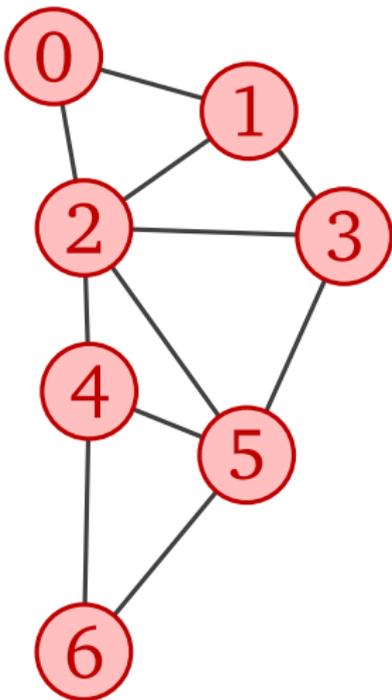
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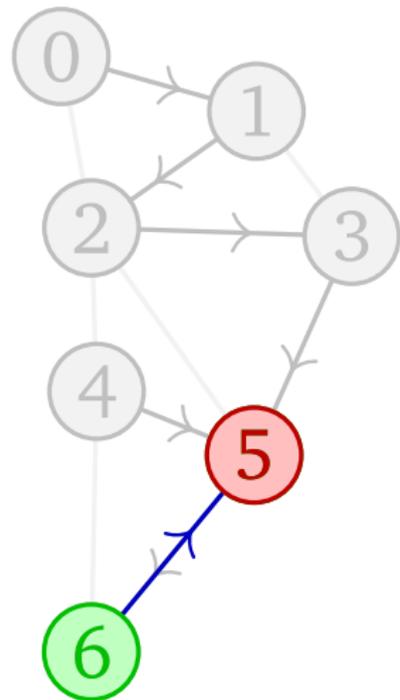
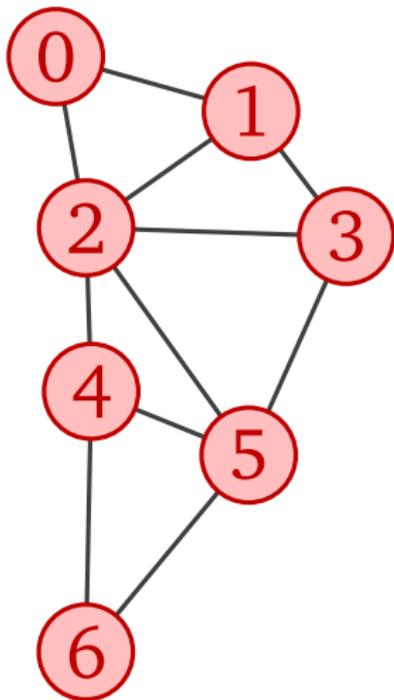
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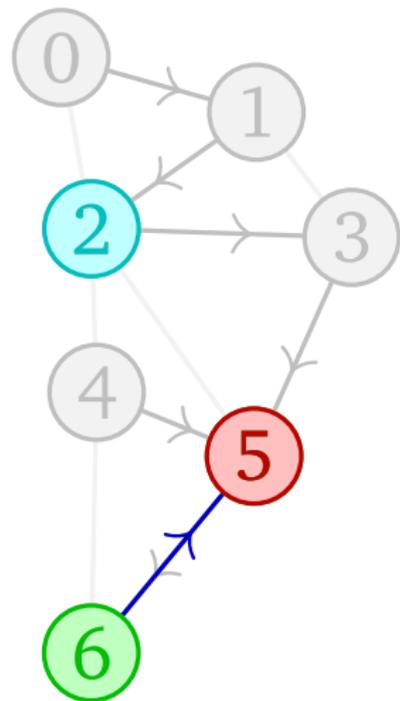
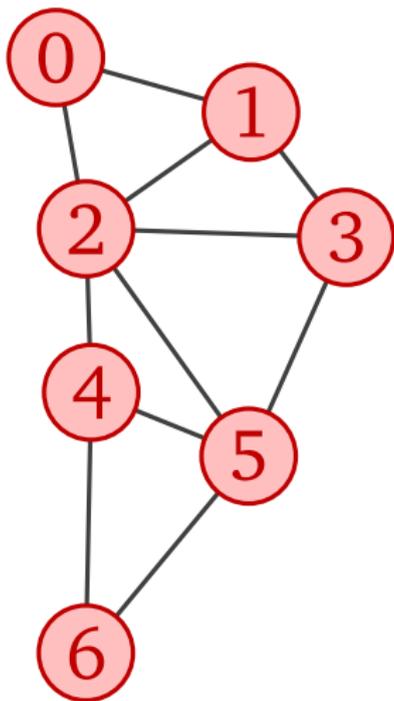
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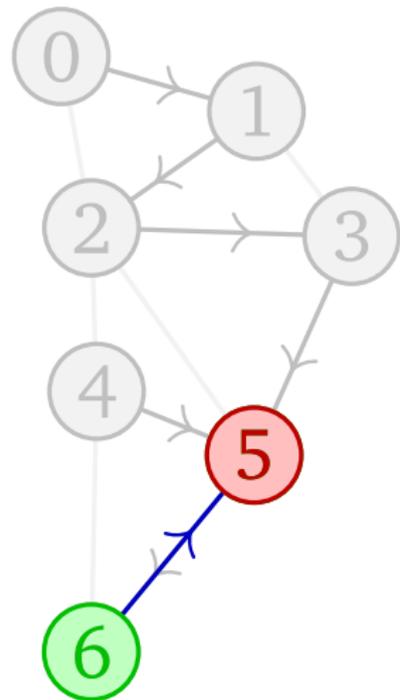
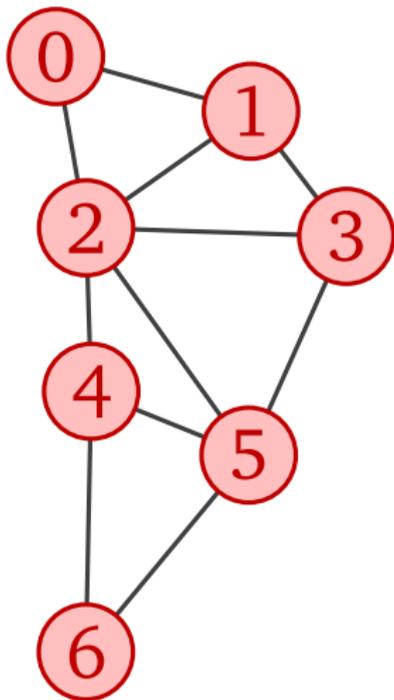
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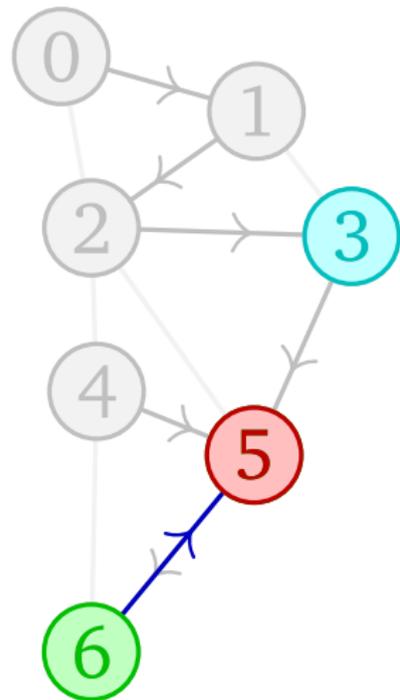
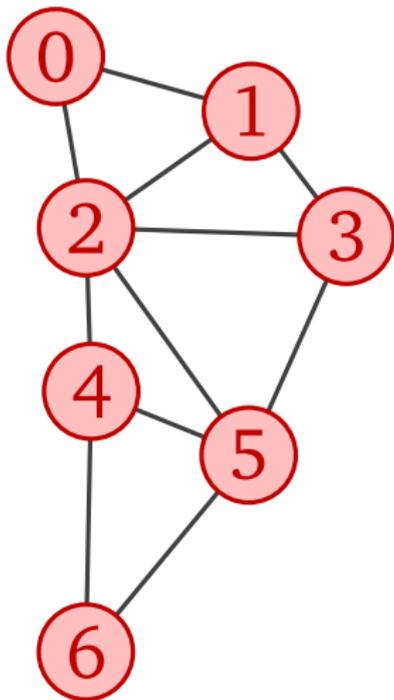
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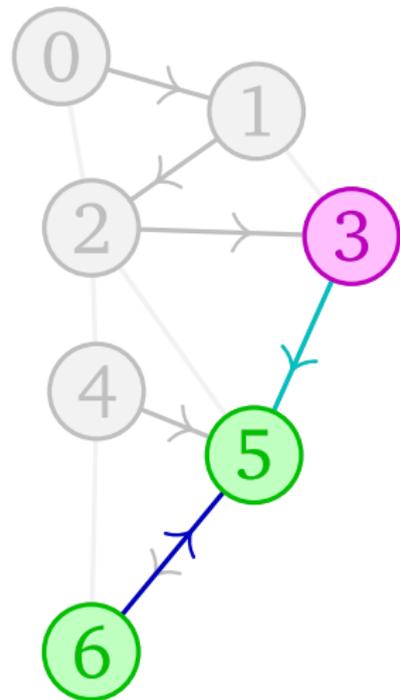
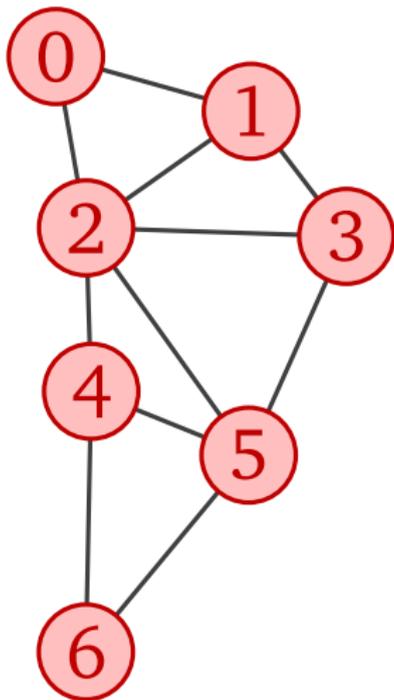
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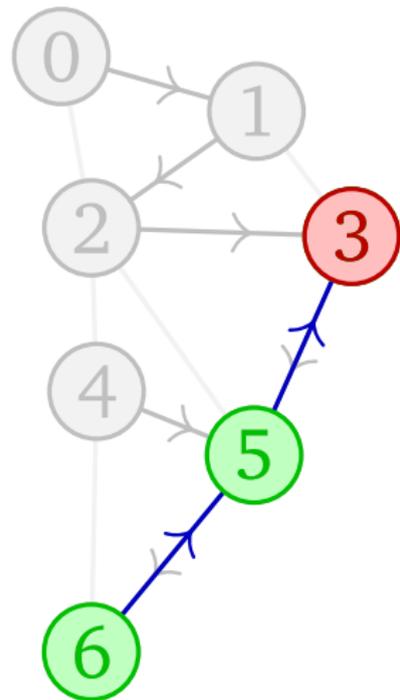
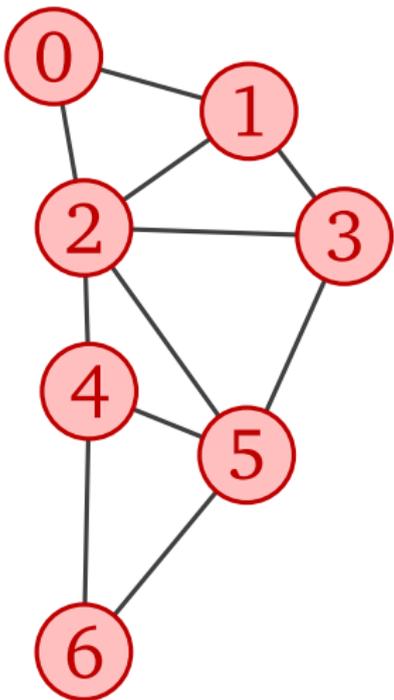
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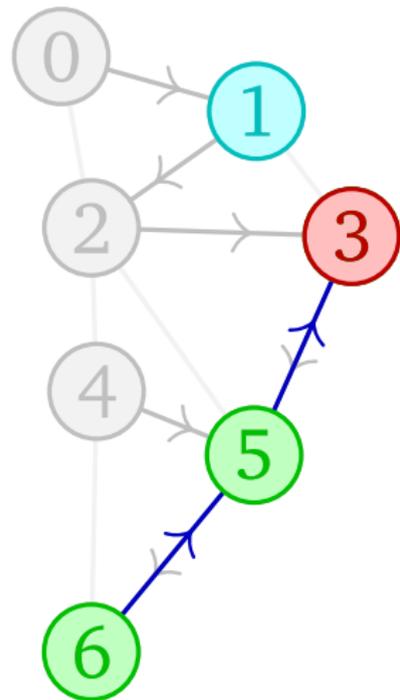
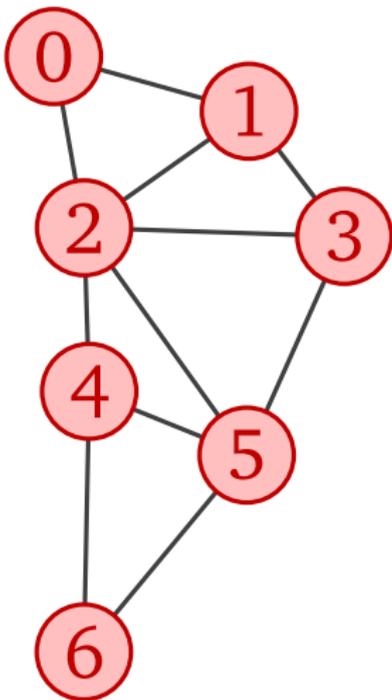
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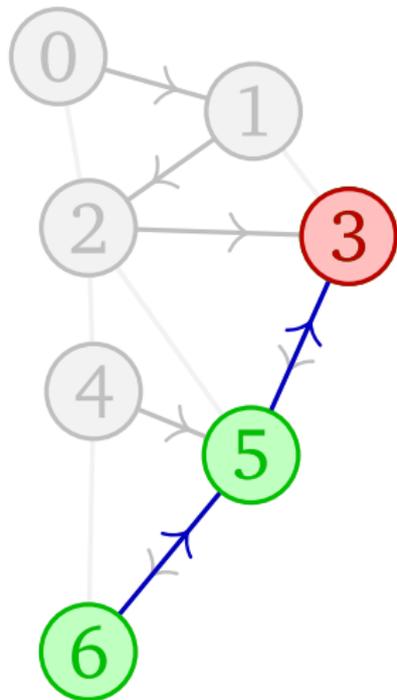
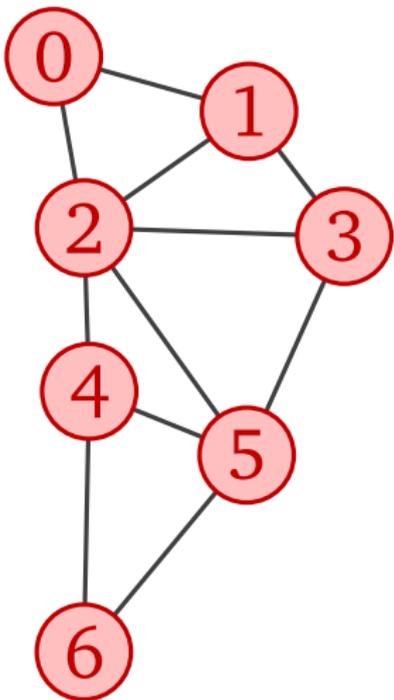
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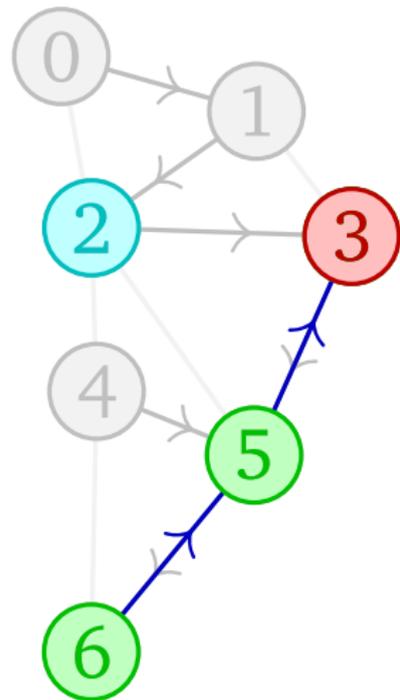
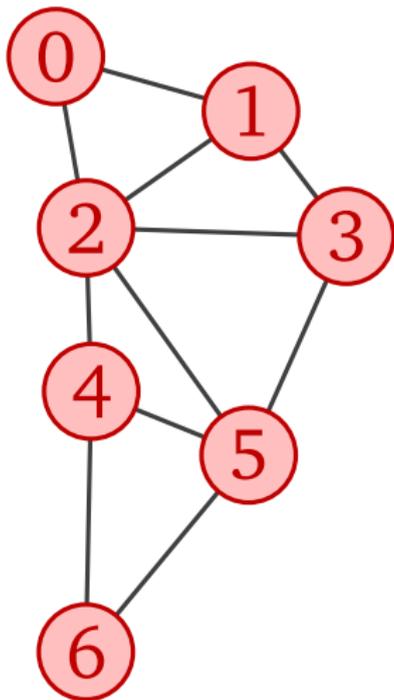
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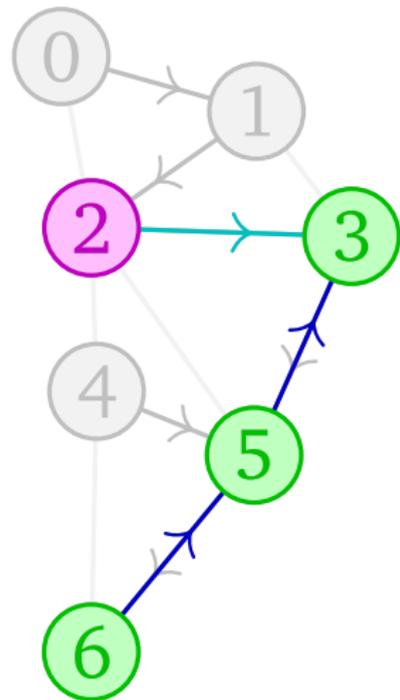
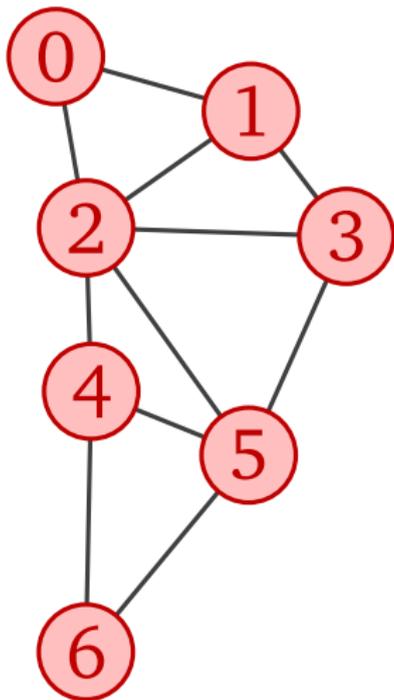
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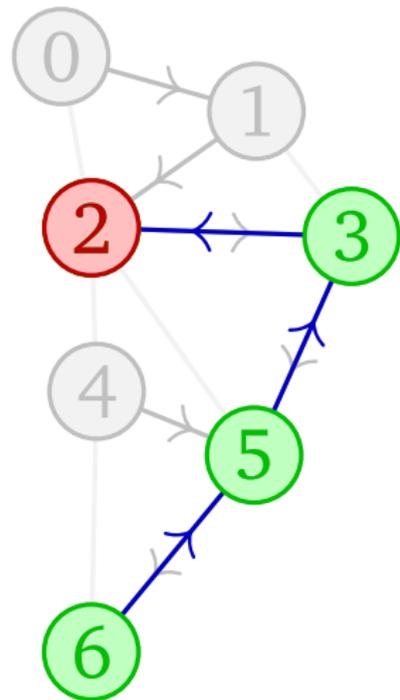
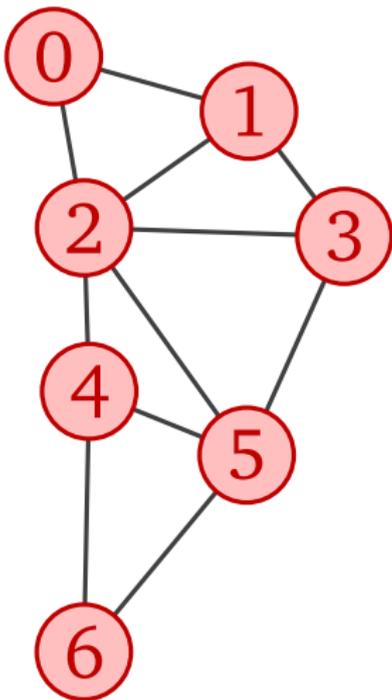
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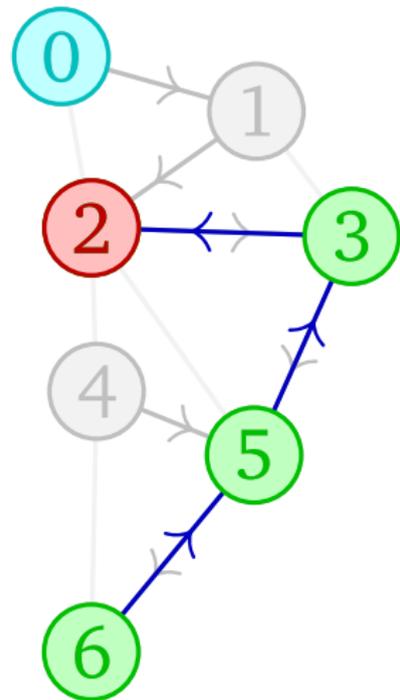
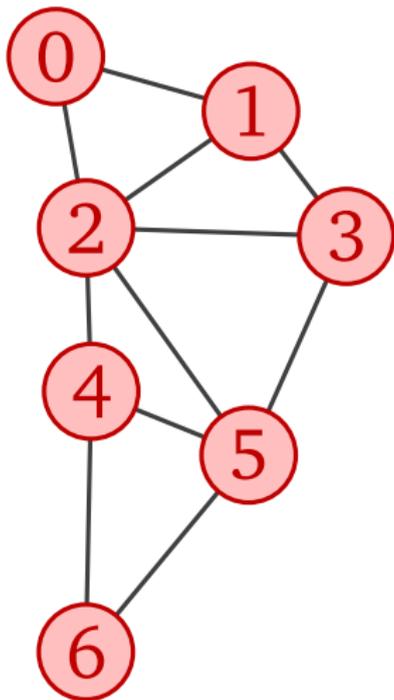
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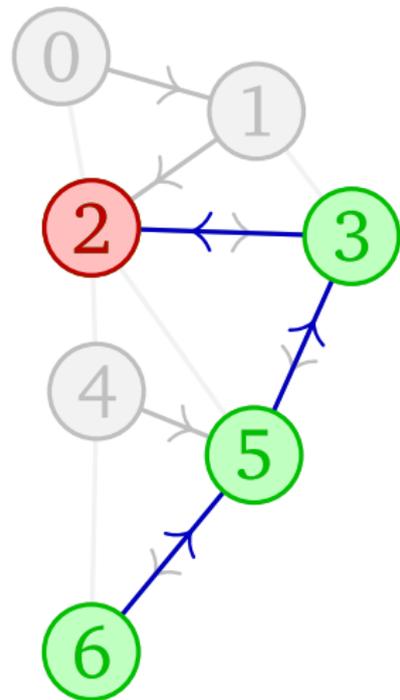
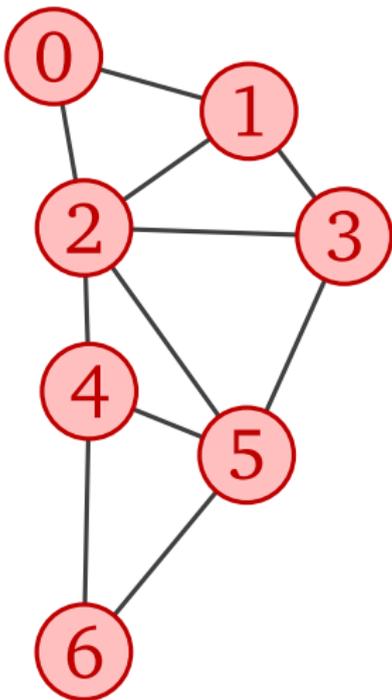
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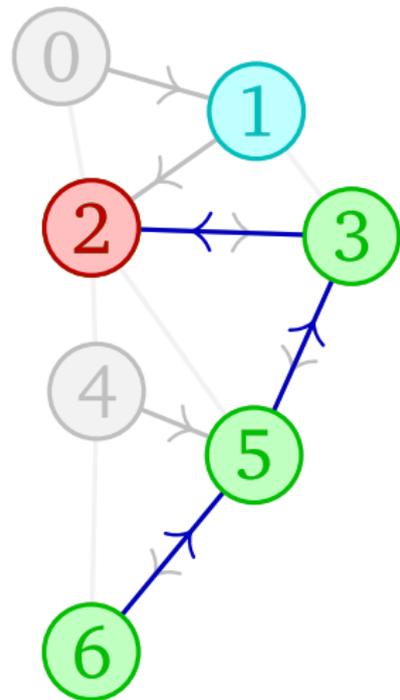
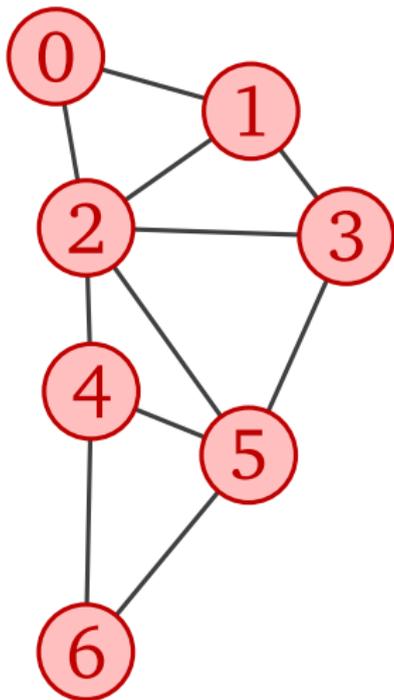
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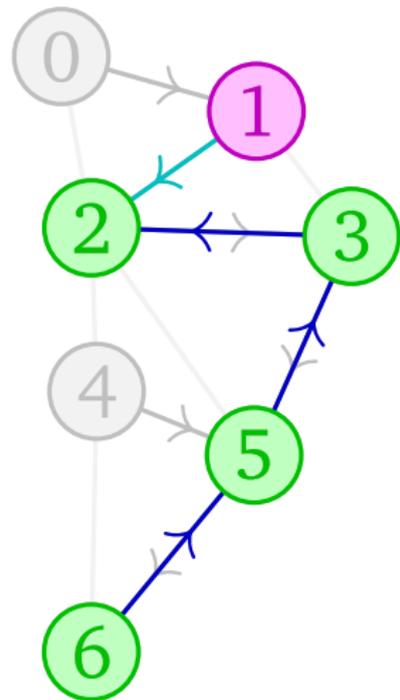
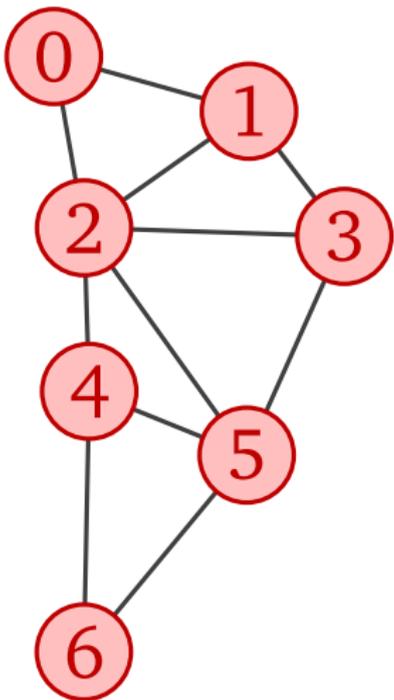
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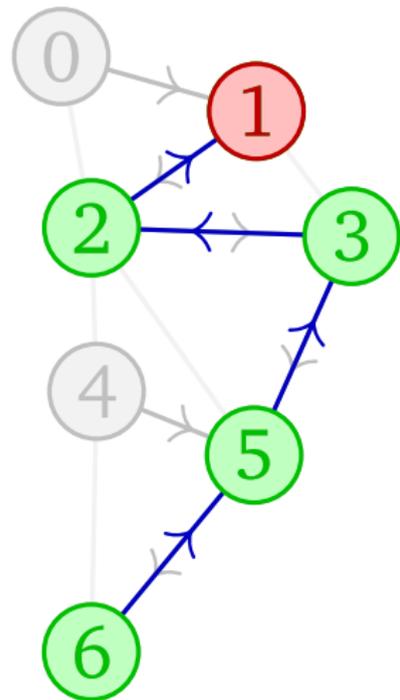
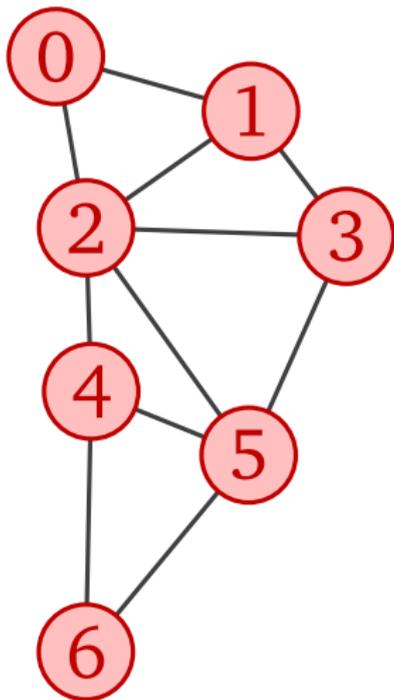
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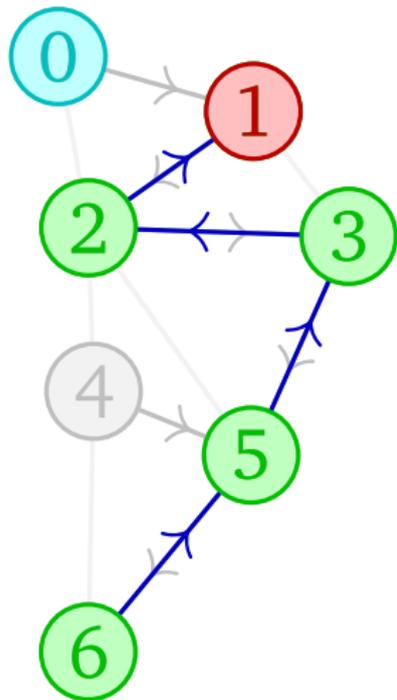
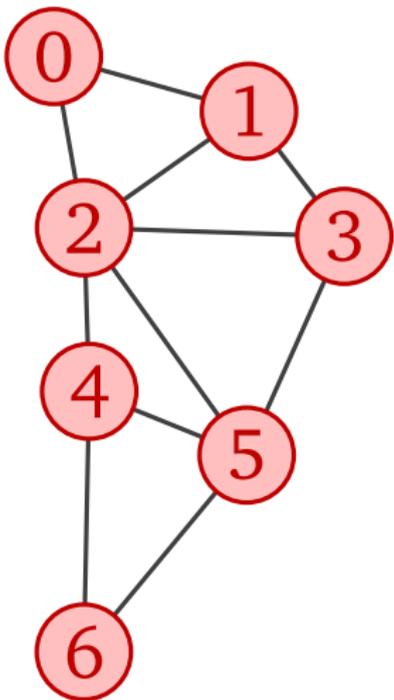
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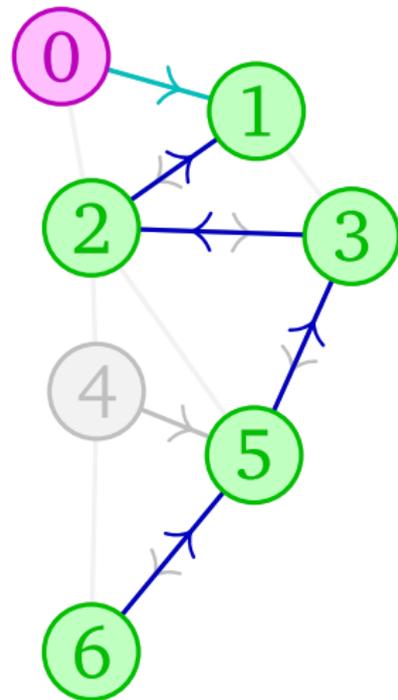
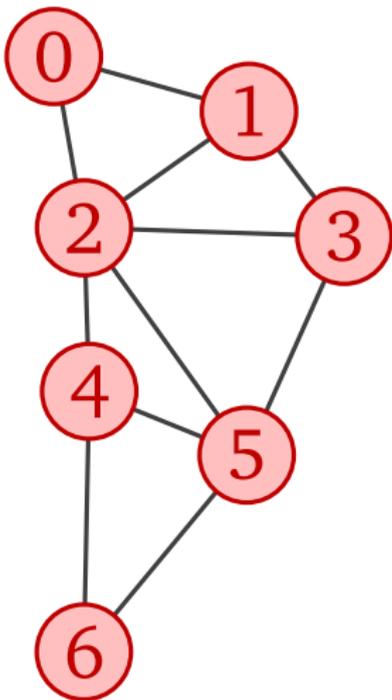
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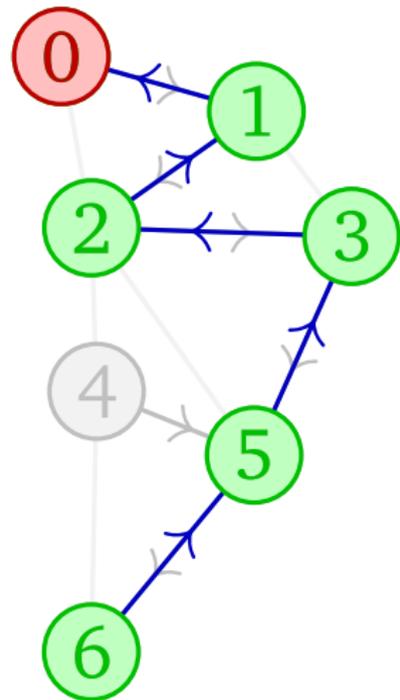
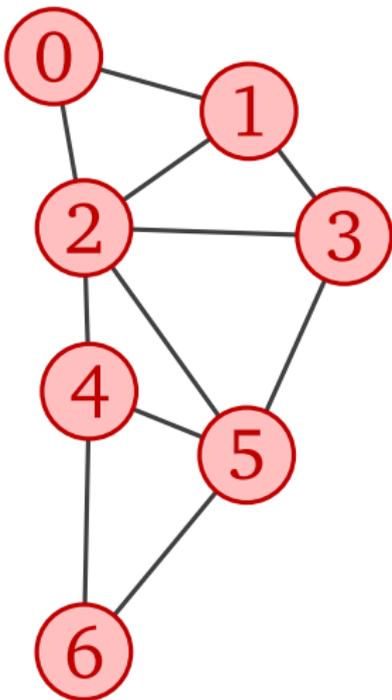
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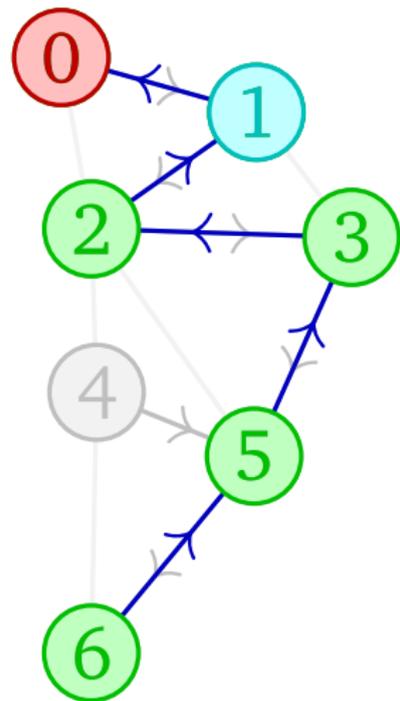
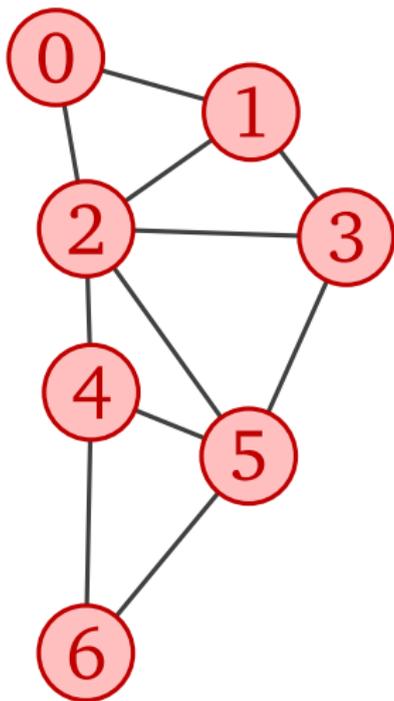
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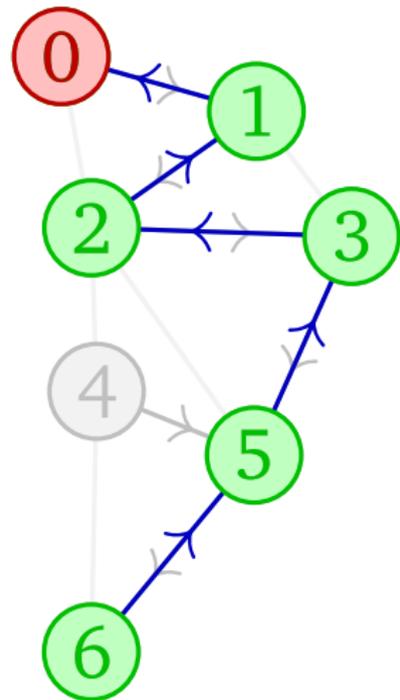
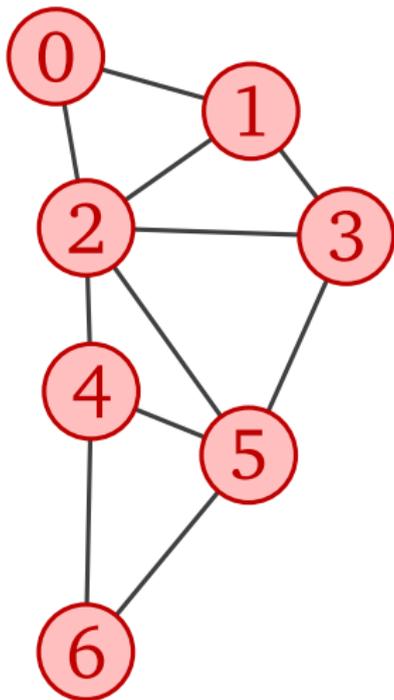
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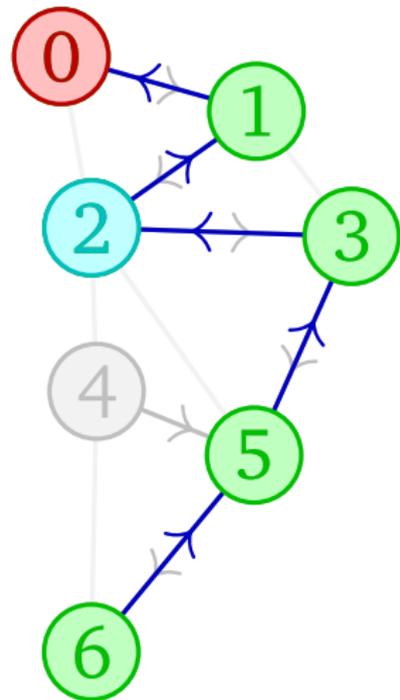
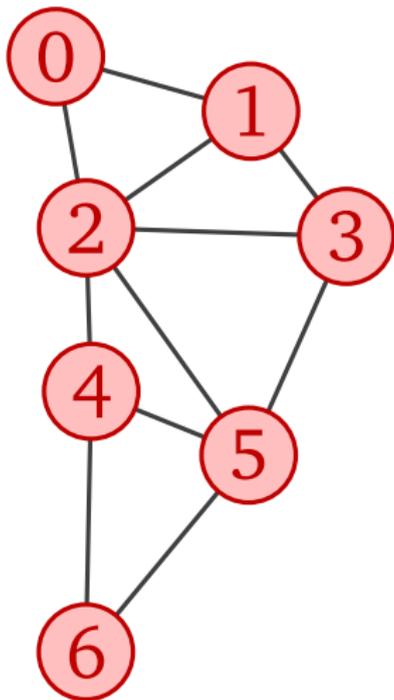
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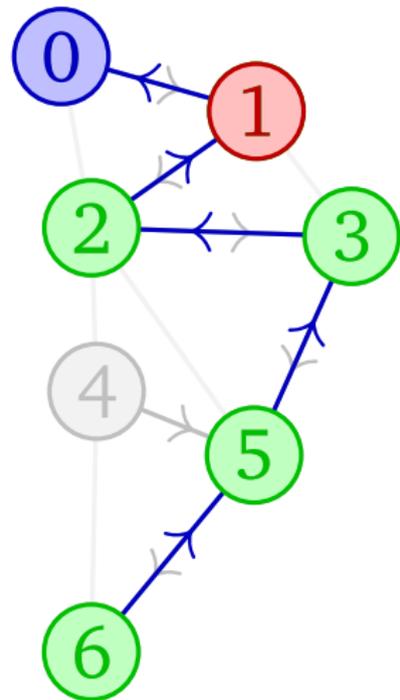
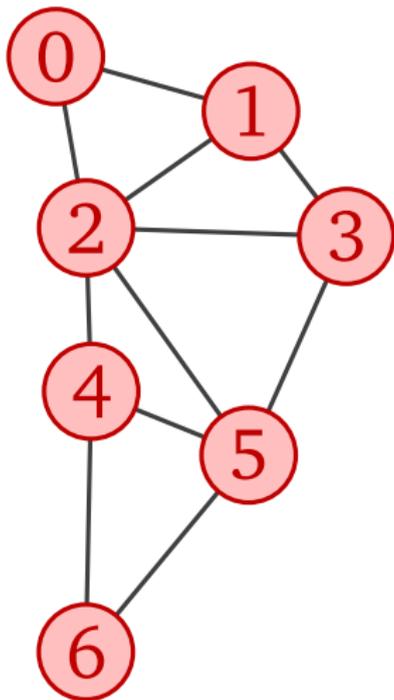
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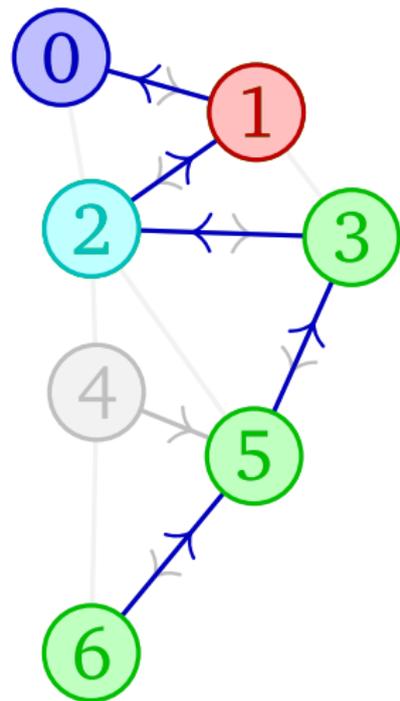
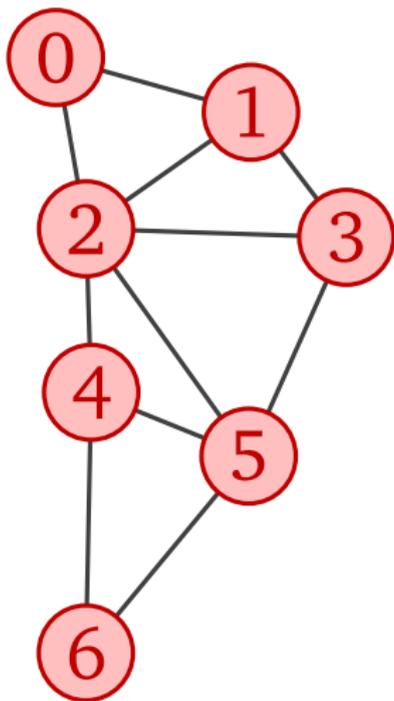
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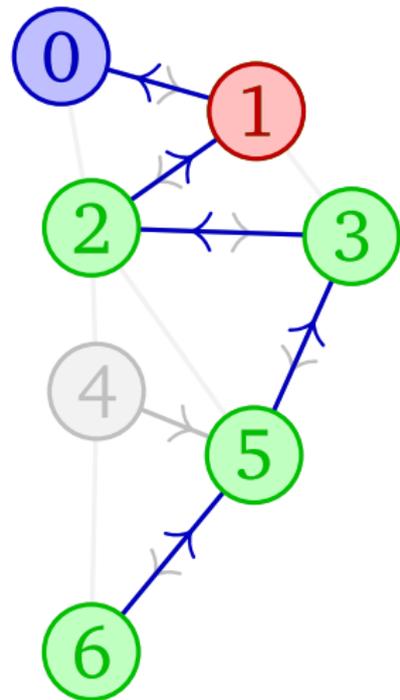
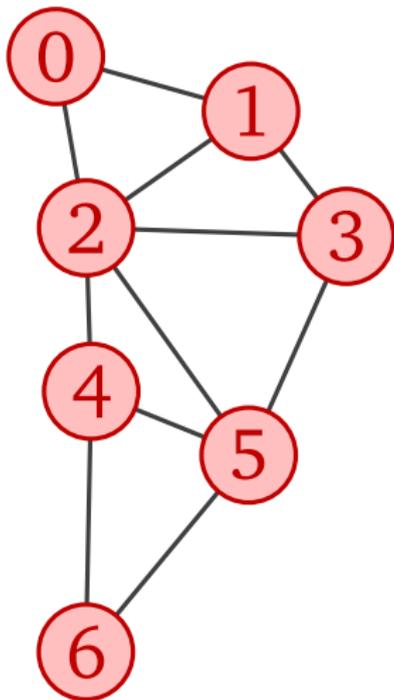
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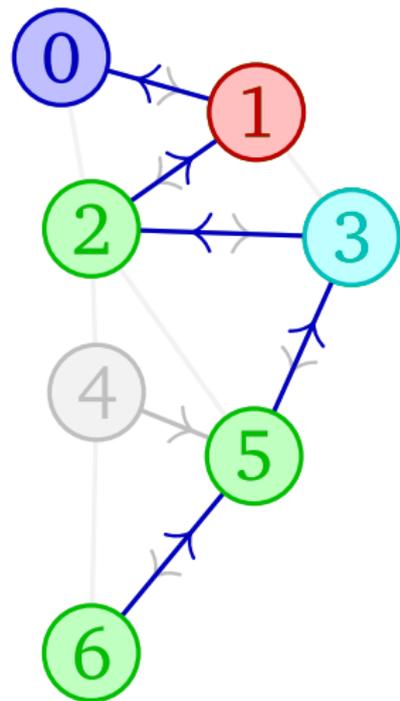
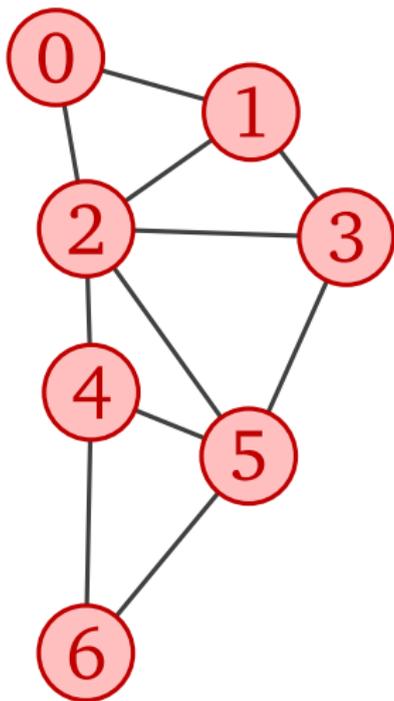
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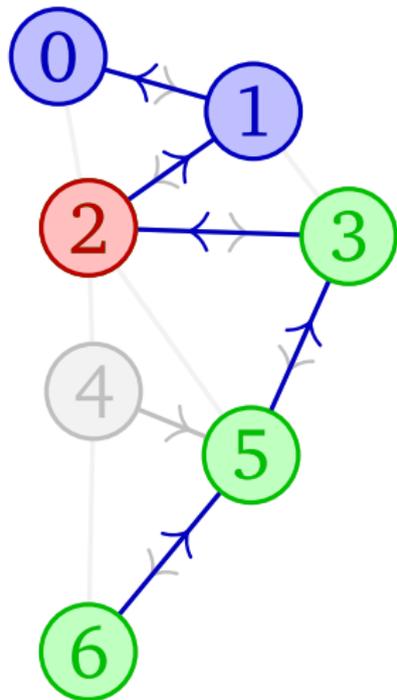
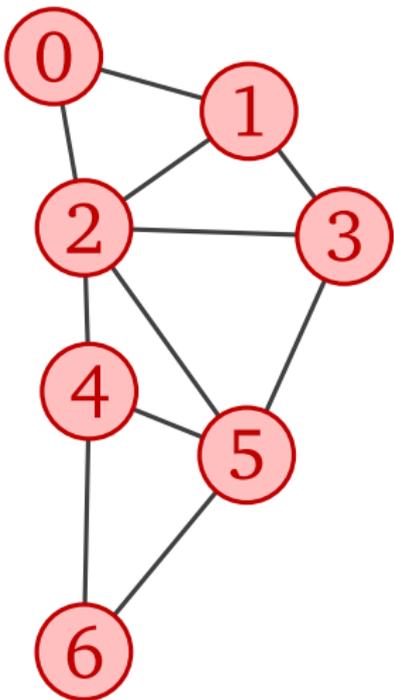
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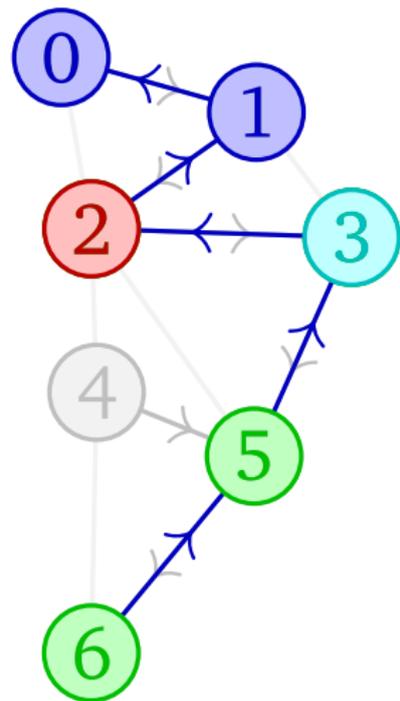
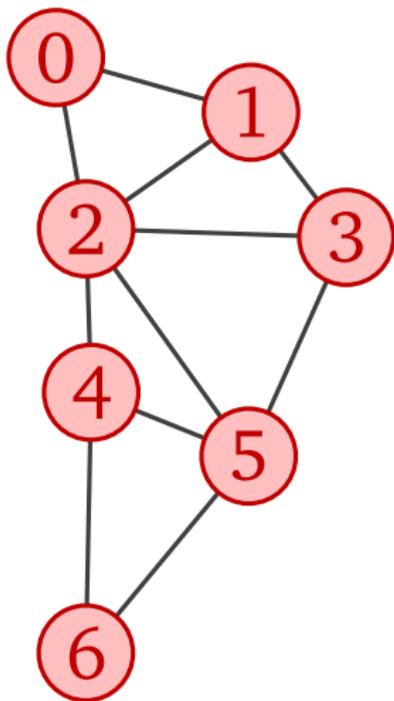
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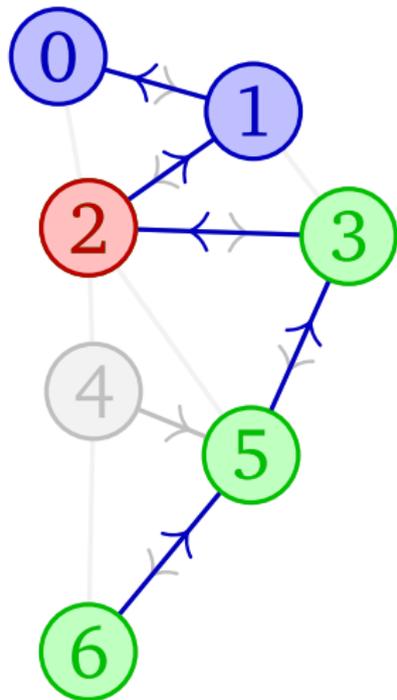
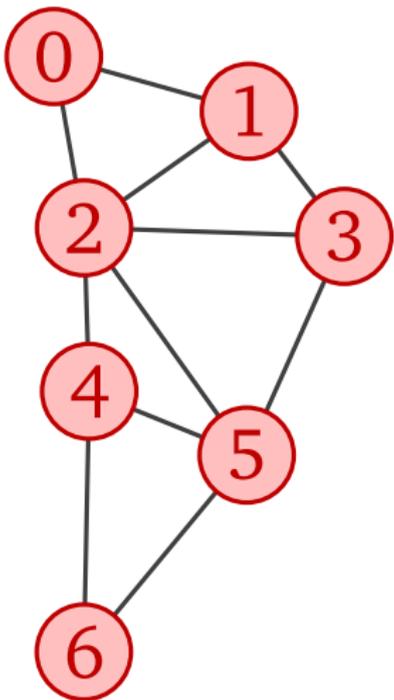
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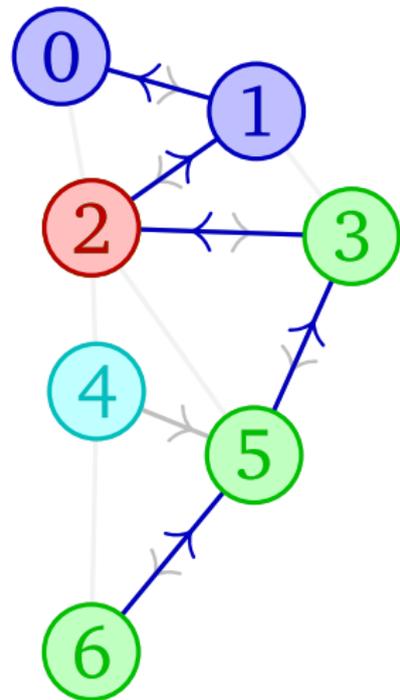
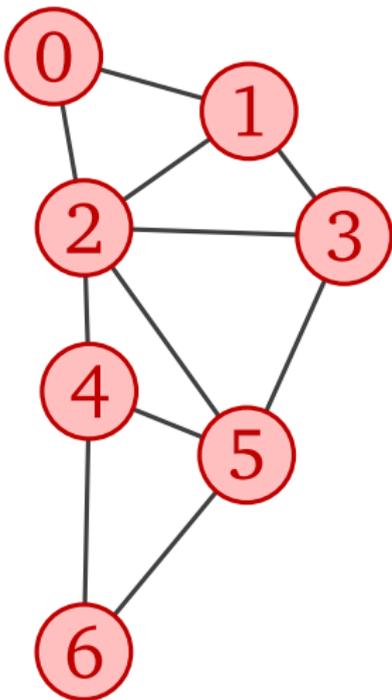
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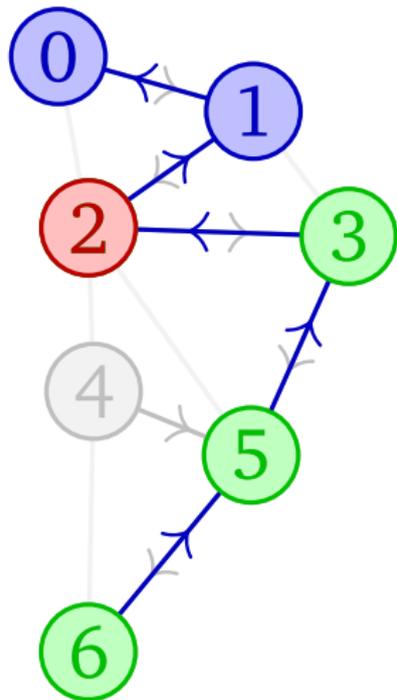
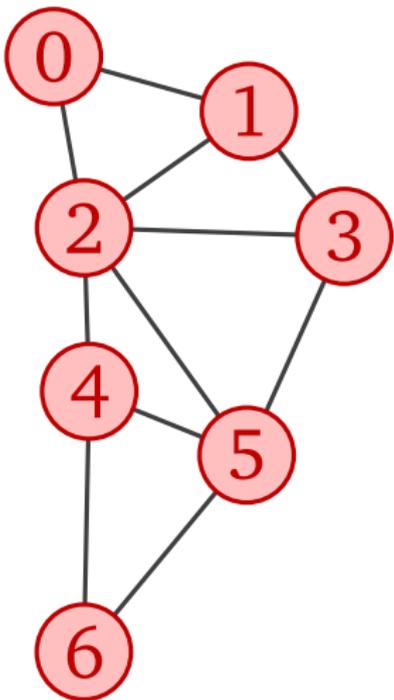
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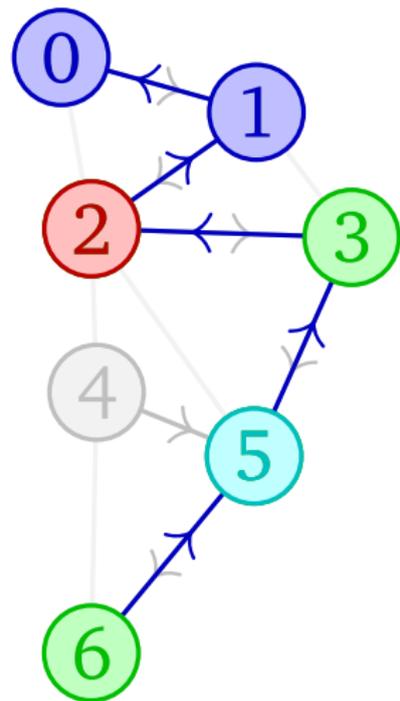
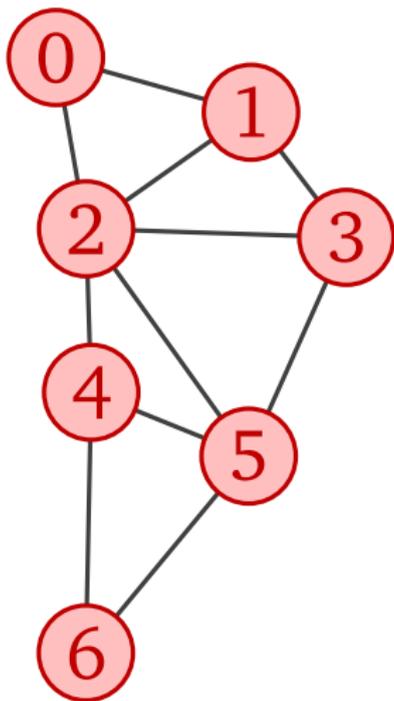
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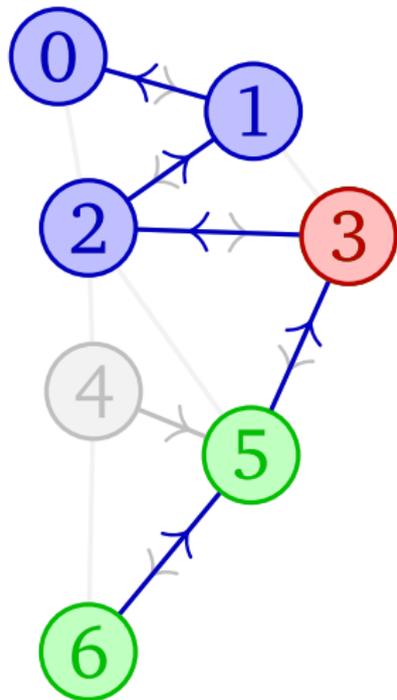
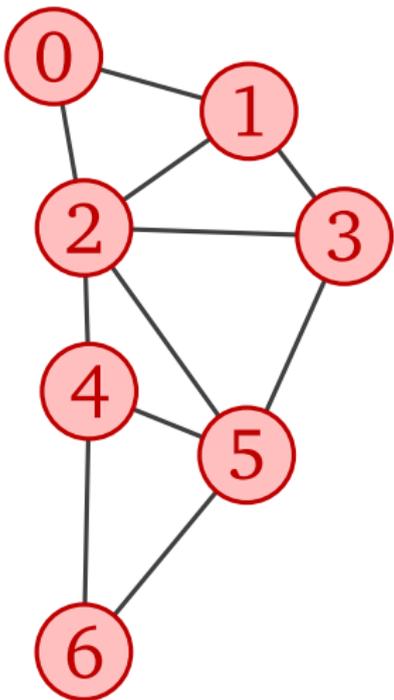
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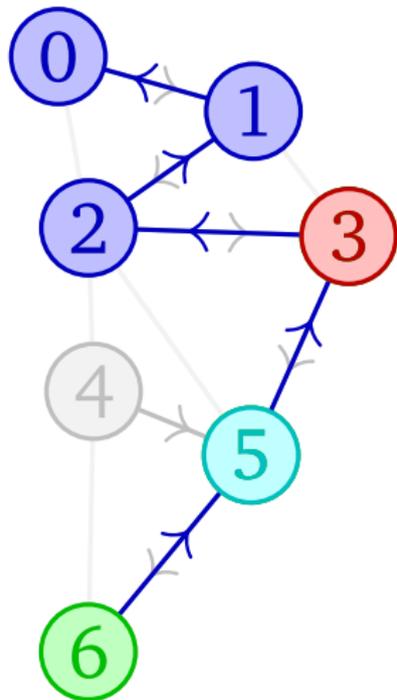
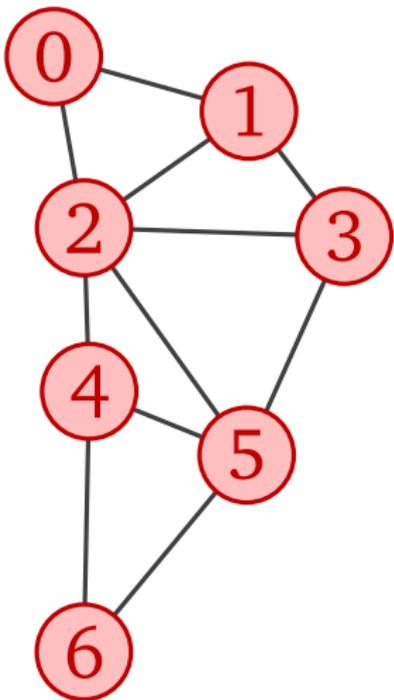
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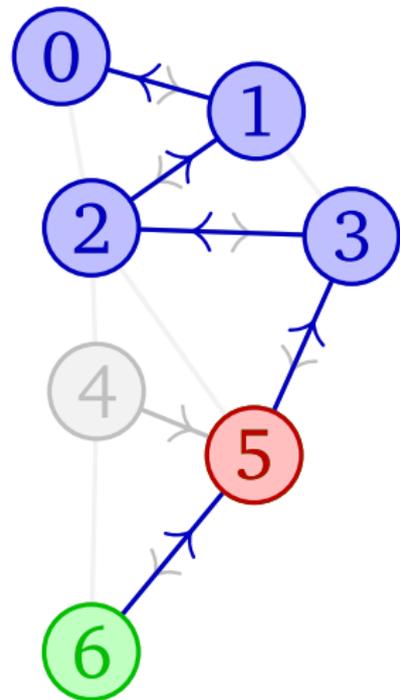
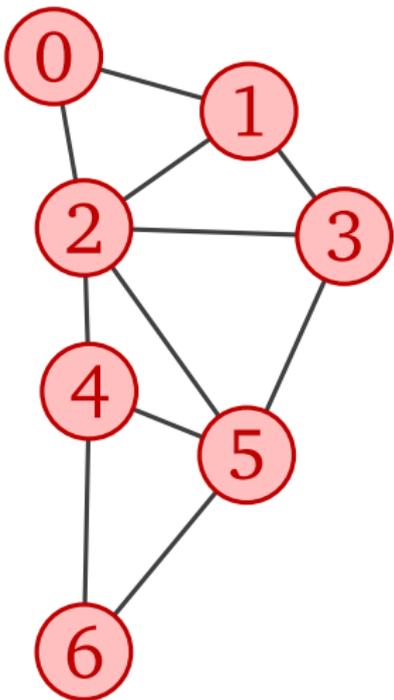
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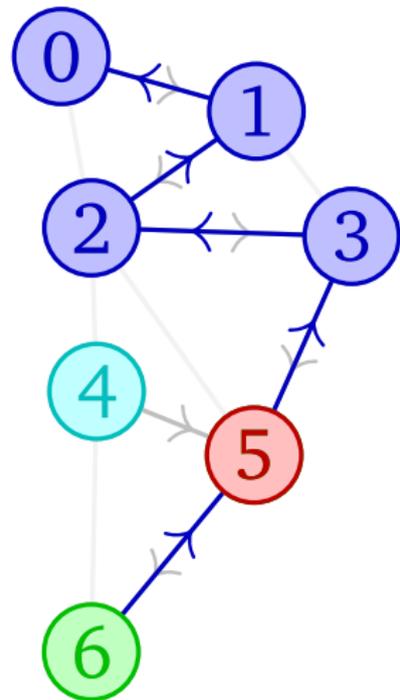
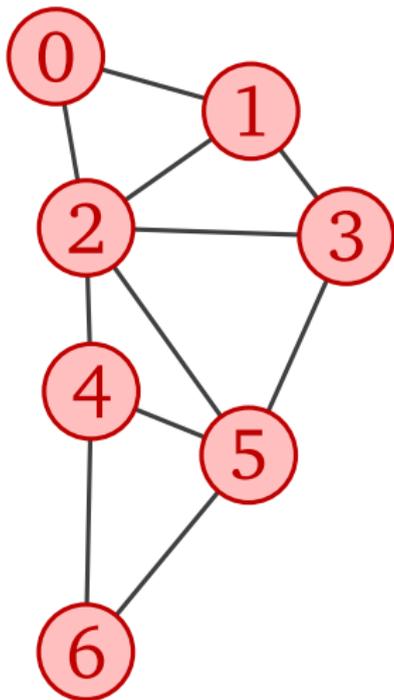
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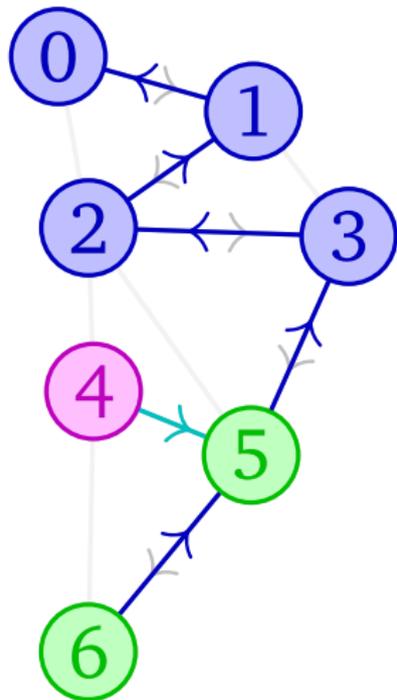
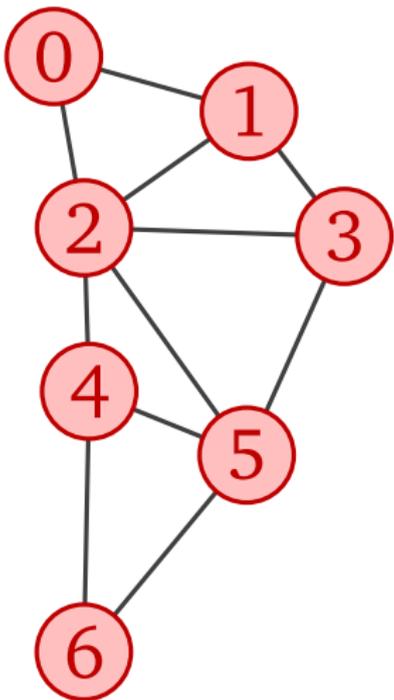
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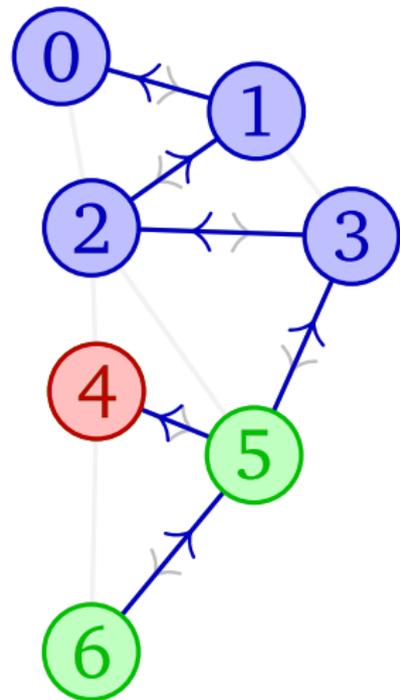
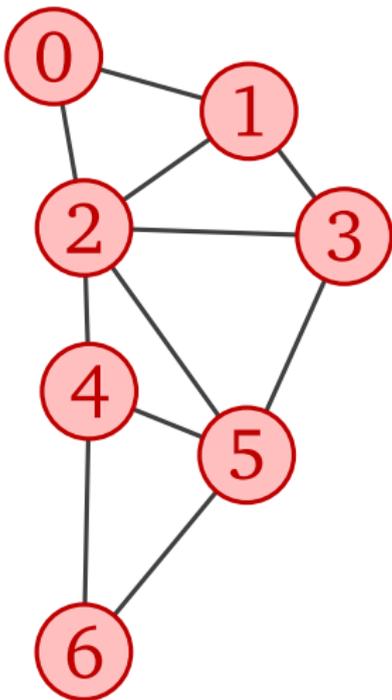
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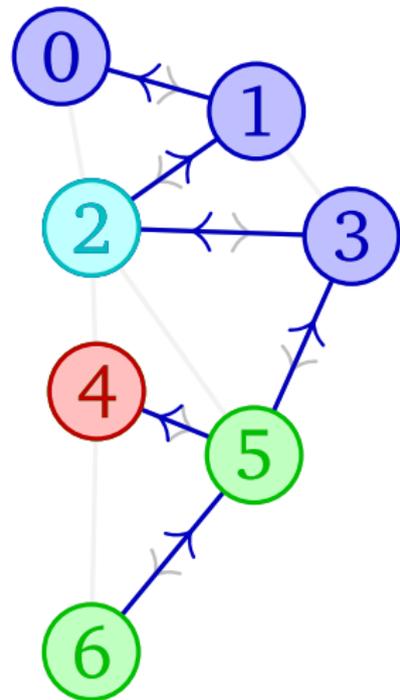
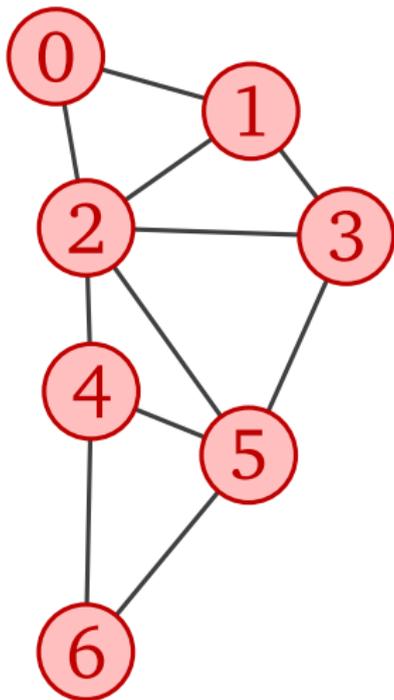
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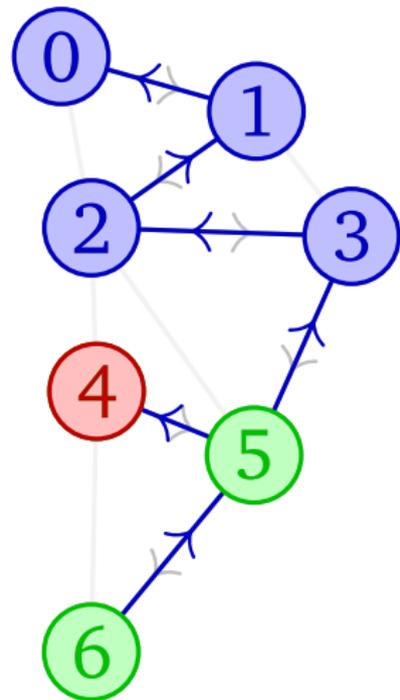
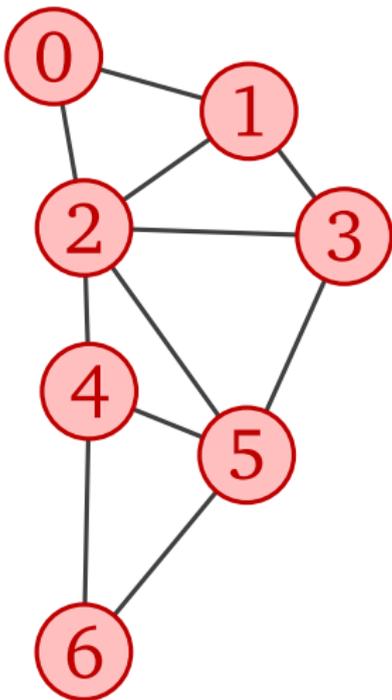
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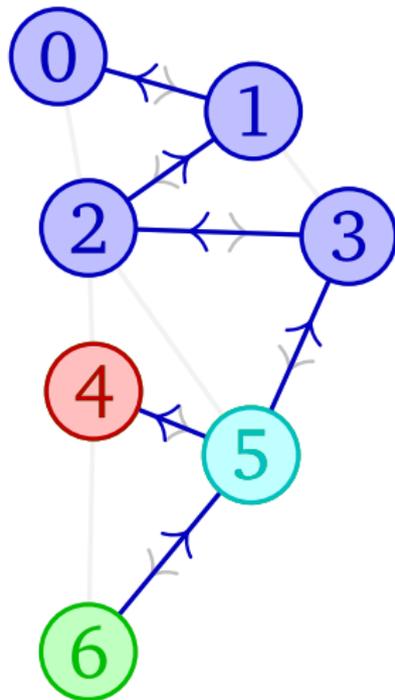
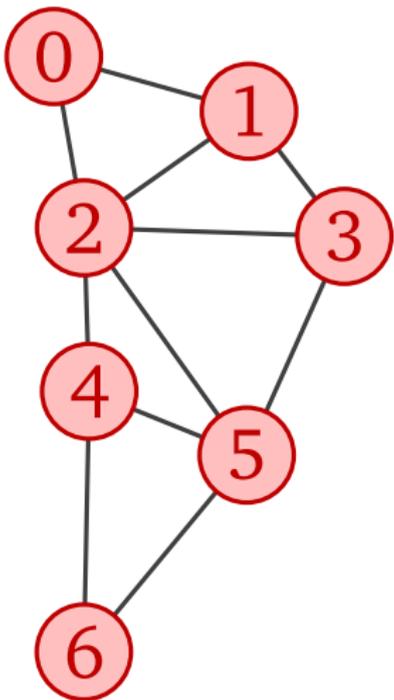
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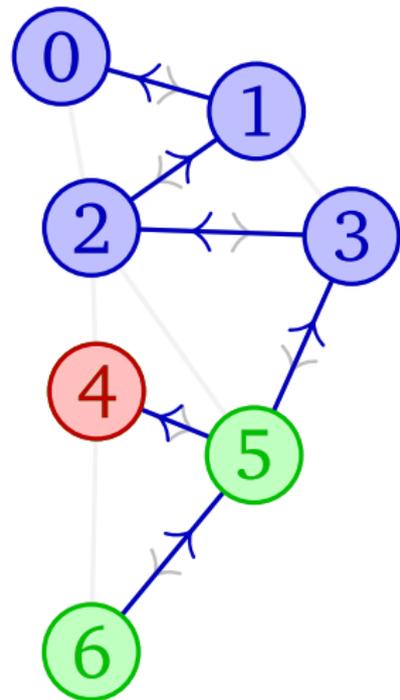
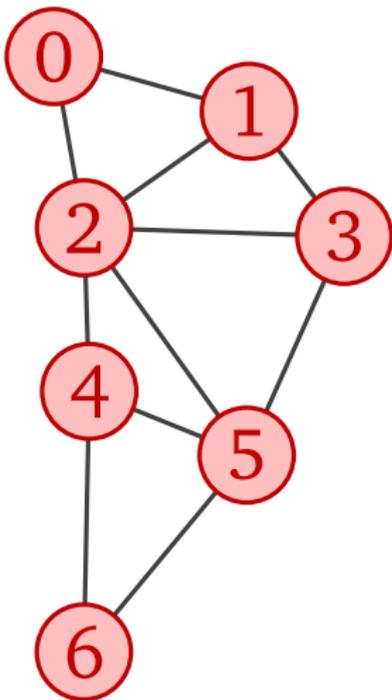
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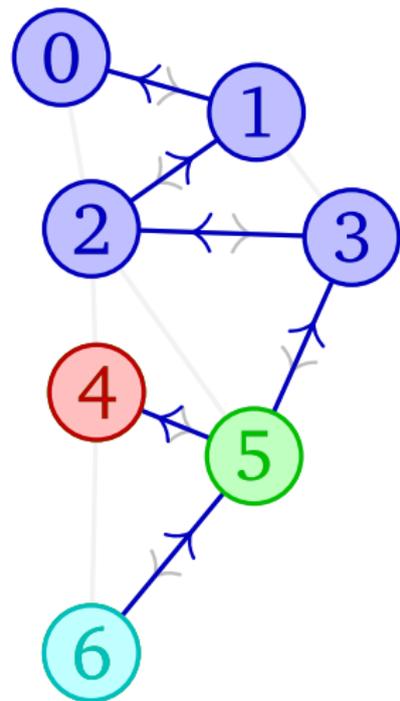
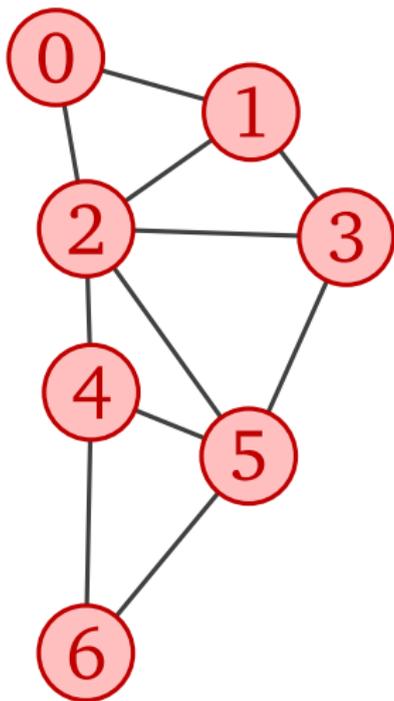
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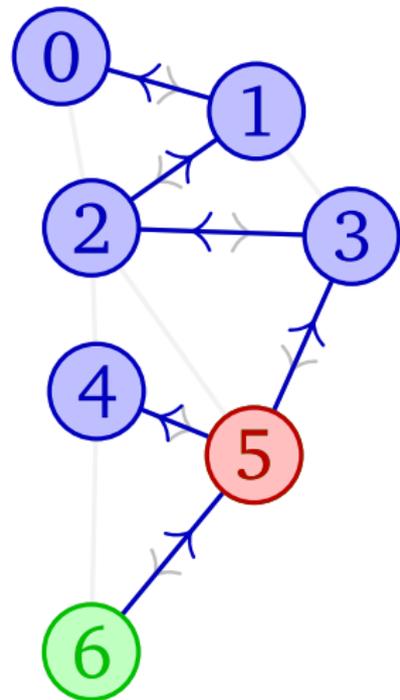
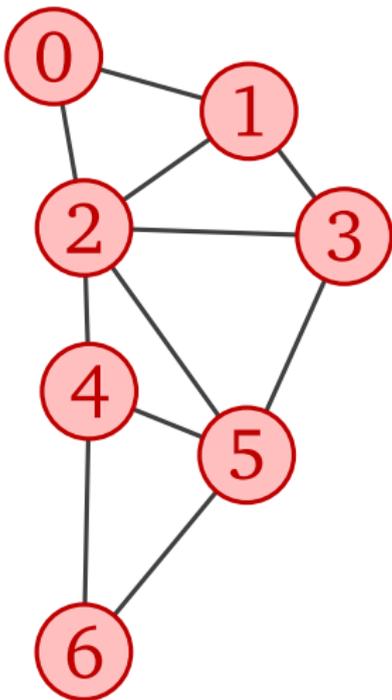
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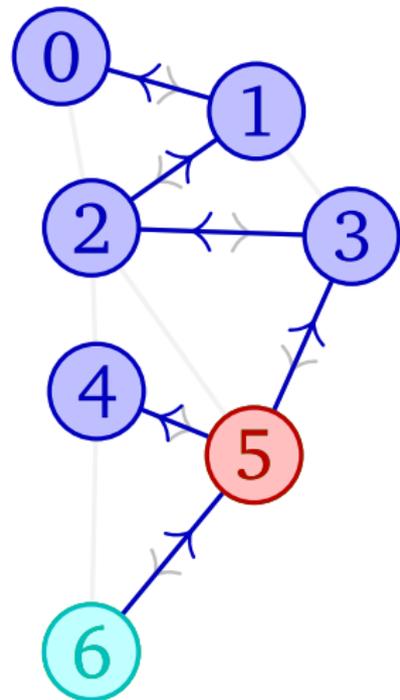
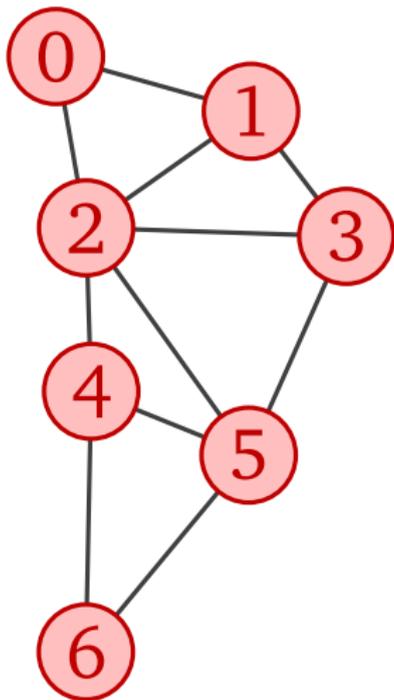
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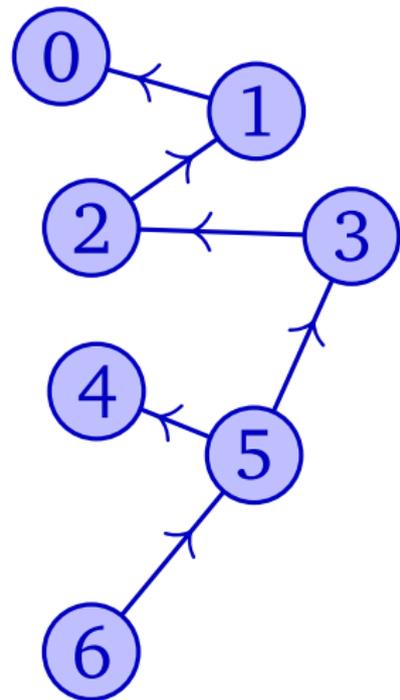
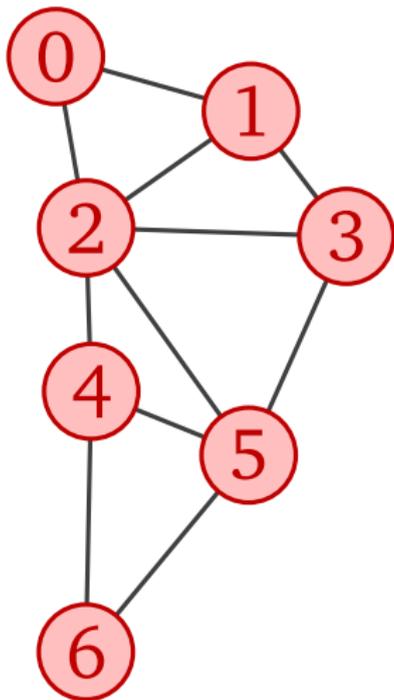
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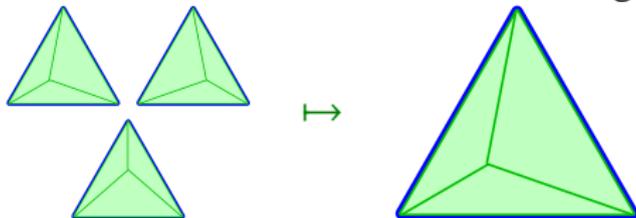
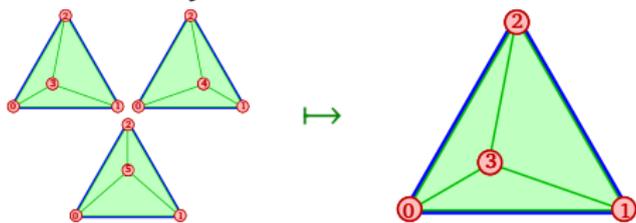
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Reverse Search on Orbits

Canonical
Representatives

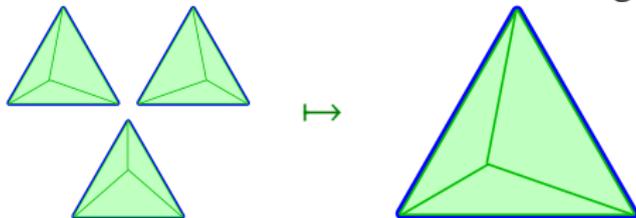
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Function “ G -Orbits \rightarrow Elements”, e.g.,RS-Consistent
Choiceorbit \mapsto objective-minimal sink in orbit, e.g.,

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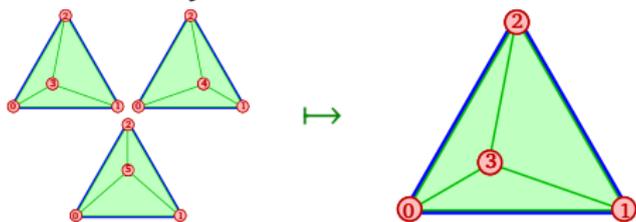
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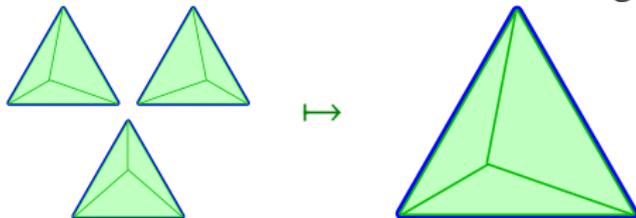
Pivoting Orbits

new pivot := canonical representative \circ old pivot.

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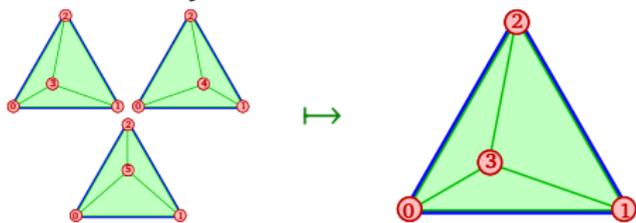
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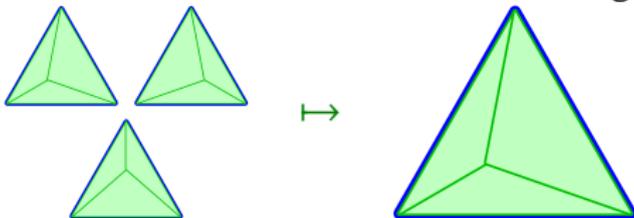
Result

Can enumerate orbits by RS on orbits [Imai et al. 2002].

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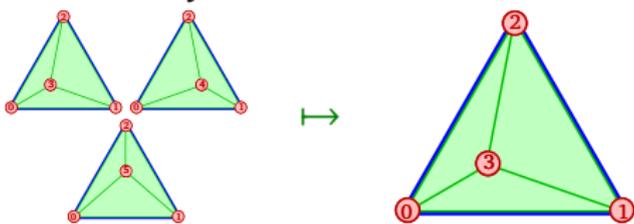
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Bottleneck

Compute canonical representatives.

Agenda

The Problem

Structures for Counting

Structures for Counting Subsets

New Results

Conclusions/Questions

Representation of Objects as Subsets

Observation

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Many objects have a representation as subsets S of $\{1, \dots, n\}$.

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Build objects by **lex-extension**.

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- ▶ there may be dead-ends w.r.t. lex-extension
- ▶ containment in an object may be difficult to tell early

Generic Algorithm: Symmetric LSRS

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Observation

Subset S lex-min in its orbit
 $\implies S \setminus \max S$ lex-min in its orbit.

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Observation

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 $\implies S \setminus \max S$ lex-min in its orbit.

Punch Line

canonical = lex-min \implies canonicals connected

Generic Algorithm: Symmetric LSRS

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(symLSRS) [equivalent: Pech & Reichard 2009]:

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$\rightarrow \text{symLSRS}(\emptyset)$ lex-enumerates all orbit-lex-min objects

Agenda

The Problem

Structures for Counting

Structures for Counting Subsets

New Results

Conclusions/Questions

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Local Data

Store with each subset its **critical-element table**:

$$\text{crit}_S: \begin{cases} G & \rightarrow \{1, \dots, n\} \cup \{\infty\}, \\ \pi & \mapsto \min(S \Delta \pi(S)). \end{cases}$$

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A symmetry π lex-decreases a subset S



$$\text{crit}_S(\pi) \in \pi(S).$$

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\rightsquigarrow roughly $\frac{1}{n}$ of the cases (amortized)

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Convention

All $s \in \{1, \dots, n_s\}$ and $f \in \{1, \dots, n_f\}$
are called simplices and facets, resp.

All $T \subseteq \{1, \dots, n_s\}$ with pairwise proper intersections
are called partial triangulations.

Is a Subset Not Lex-Extendable?

Extendability Check

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[Ruppert & Seidel 1992]:

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Each interior facet must be covered by additional simplices to complete a triangulation.

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Global Data

Preprocess for each simplex s

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Observation

A partial triangulation T is **not** lex-extendable



there is $\{f \in \mathcal{F}(T)\}$ not contained in any $\{s \in \mathcal{A}(T)\}$.

Ingredient II: Lex-pruning/Lex-Breaking

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Theorem

A partial triangulation T with free interior facets $\mathcal{F}(T)$ and properly intersecting greater simplices $\mathcal{A}(T)$ is **not** lex-extendable to a triangulation

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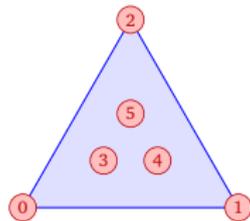
Gain

One integer comparison instead of many subset tests.

Effectivity

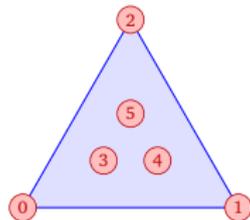
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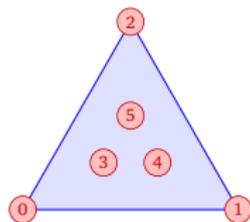


No Pruning



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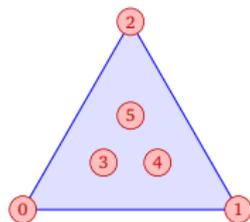


Full Pruning



Effectivity

Comparison (with lex-breaking):



No Pruning



Full Pruning



Lex Pruning



Computational Results for Triangulations

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[Jordan & Joswig & Kastner 2018]

Point Conf.	# Triang's	# Orbits	CPU time [hh:mm:ss]
$[0, 1]^4$	92,487,256	247,451	00:01:56
$3D_3$ (reg./full/output)	22,201,684,367	925,148,763	96:00:00

MPTOPCOM
Flip-Based
CPU Times
(16/40 Threads)

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[R. 2022]

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$3D_3$ (output)	22,201,684,367	925,148,763	01:05:11
$3D_3$ (count)	22,201,684,367	925,148,763	00:21:02
$3D_3$ (regular)	21,861,522,799	910,974,879	20:21:53
$3D_3$ (full)	511,052,427	21,302,400	00:01:01
$3D_3$ (unimod.)	346,903,379	14,459,488	00:00:39
Dodecahedron	1,533,079,037,570	12,775,757,027	11:11:48
Pyritohedron	32,734,029,351,118	1,363,918,758,719	692:30:04
$\Delta_5 \times \Delta_3$	442,472,050,753,920	25,606,173,722	1313:57:17 (M1Max8t)

MPTOPCOM
Flip-Based
CPU Times
(16/40 Threads)

TOPCOM 1.0.8
Subset-Based
CPU Times
(16 Threads)

Bonus Track I

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For Raman

Triangulations with only simplices of min. vol.
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- ▶ $\Delta(6, 1, 4)$ has more than 249,295,320 (347,613 classes)

Bonus Track I

For Raman

Triangulations with only simplices of min. vol.
of generalized hypersimplices [Manecke et al. 2020]:

- ▶ $\Delta(5, 1, 3)$ has 27,780 (250 classes)
- ▶ $\Delta(5, 1, 4)$ has 5 (1 class)
- ▶ $\Delta(6, 1, 3)$ has more than 245,074,320 (340,381 classes)
- ▶ $\Delta(6, 1, 4)$ has more than 249,295,320 (347,613 classes)
- ▶ $\Delta(6, 2, 4)$ has more than 7,248,961,080 (10,068,279 classes)

Bonus Track II

Other Results

Bonus Track II

Enumeration of (co-)circuits (different lex-min check):

Bonus Track II

Other Results



Enumeration of (co-)circuits (different lex-min check):

$[0, 1]^8$ has

38,636,185,528,212,416 circuits in 3,858,105,362 classes
(CPU: 163:37:00)

(asked by Lisa Lamberti and Komei Fukuda)

Bonus Track II

Other Results

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- ▶ $[0, 1]^9$ has
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(CPU: 13:30:12)
(extends [Aichholzer & Aurnhammer 1996])

Bonus Track II

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Sideline

Necessary conditions for lex-extendability

Bonus Track II

Other Results

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- ▶ Necessary conditions for lex-extendability
found for cocircuits

Bonus Track II

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Sideline

Necessary conditions for lex-extendability

- ▶ found for cocircuits
- ▶ but not so far for circuits.

Agenda

The Problem

Structures for Counting

Structures for Counting Subsets

New Results

Conclusions/Questions

Conclusions/Questions

Conclusions

Conclusions/Questions

Enumeration of orbits of triangulations accelerated by
“Geometry meets Combinatorics”:

Conclusions/Questions

Conclusions

Enumeration of orbits of triangulations accelerated by
“**Geometry meets Combinatorics**”:

- ▶ **critical-element tables** for lex-min check

Conclusions/Questions

Conclusions

Enumeration of orbits of triangulations accelerated by
“**Geometry meets Combinatorics**”:

- ▶ **critical-element tables** for lex-min check
- ▶ **minimal-element comparison** for lex-extendability check

Conclusions/Questions

Conclusions

Enumeration of orbits of triangulations accelerated by
“**Geometry meets Combinatorics**”:

- ▶ **critical-element tables** for lex-min check
- ▶ **minimal-element comparison** for lex-extendability check

Questions

Potential further research:

Conclusions/Questions

Conclusions

Enumeration of orbits of triangulations accelerated by
“Geometry meets Combinatorics”:

- ▶ **critical-element tables** for lex-min check
- ▶ **minimal-element comparison** for lex-extendability check

Questions

Potential further research:

- ▶ Investigate the complexity of **symLSRS**.

Conclusions/Questions

Conclusions

Enumeration of orbits of triangulations accelerated by
“**Geometry meets Combinatorics**”:

- ▶ **critical-element tables** for lex-min check
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Questions

Potential further research:

- ▶ Investigate the complexity of **symLSRS**.
- ▶ Apply **symLSRS** to **more examples**.

Conclusions/Questions

Conclusions

Enumeration of orbits of triangulations accelerated by
“Geometry meets Combinatorics”:

- ▶ **critical-element tables** for lex-min check
- ▶ **minimal-element comparison** for lex-extendability check

Questions

Potential further research:

- ▶ Investigate the complexity of **symLSRS**.
- ▶ Apply **symLSRS** to **more examples**.
- ▶ Represent **flip-graph** exploration in terms of **subsets**.