

# Computational methods and heuristics for zero forcing

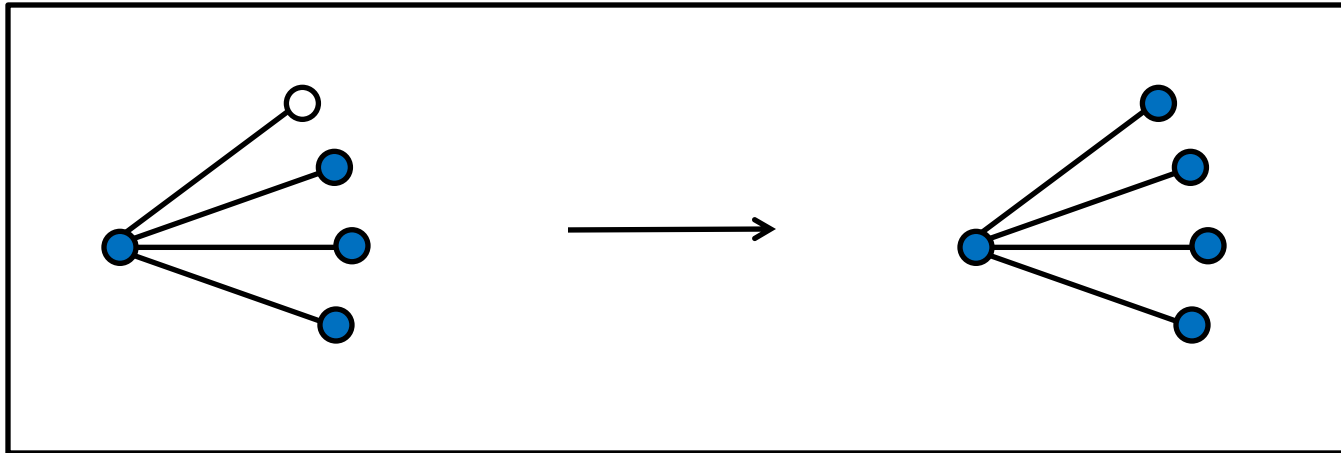
Boris Brimkov

JMM 2021



Slippery Rock University  
Mathematics and Statistics

# Zero forcing



Blue vertex with exactly one white neighbor  
turns that neighbor blue

# Related problems

- Power network monitoring (Haynes et al. 2002)
- Target set selection (Kempe et al. 2003)
- Zero forcing / minimum rank (AIM Group 2008)
- Quantum control (Burgarth et al. 2007)
- Fast mixed network searching (Yang 2013)
- $k$ -forcing (Amos et al. 2015)
- Connected power domination (Brimkov et al. 2018)
- Positive semidefinite zero forcing (Ekstrand et al. 2014)
- Probabilistic zero forcing (Kang & Yi 2012)

# Related problems

- Power network monitoring (Haynes et al. 2002)
- Target set selection (Kempe et al. 2003)
- Zero forcing / minimum rank (AIM Group 2008)
- Quantum control (Burgarth et al. 2007)
- Fast mixed network searching (Yang 2013)
- $k$ -forcing (Amos et al. 2015)
- Connected power domination (Brimkov et al. 2018)
- Positive semidefinite zero forcing (Ekstrand et al. 2014)
- Probabilistic zero forcing (Kang & Yi 2012)

All of these problems are computationally difficult

# Computational methods

- Guess-and-check / brute force (Everyone)
- Dynamic programming (Butler et al. 2014)
- Integer programming and branch-and-bound (Aazami 2010, Ackerman et al. 2010, Ben-Zwi et al. 2011, Mahaei and Hagh 2012, Chiang et al. 2013, Agra et al. 2019)
- **Boolean Satisfiability** (Brimkov et al. 2020)
- **Heuristics** (Agra et al. 2019, Brimkov et al. 2020)

# Dynamic programming

---

## Wavefront Algorithm

---

**Data:** Graph  $G = (V, E)$

**Result:** Zero forcing number of  $G$

$\mathcal{C} \leftarrow \{(\emptyset, 0)\};$

for  $R \in [n]$  do

    for  $(S, r) \in \mathcal{C}$  do

        for  $v \in V$  do

$S' \leftarrow cl(S \cup N[v]);$

$r' \leftarrow r + |\{v\} \setminus S| + \max\{|N(v) \setminus S| - 1, 0\};$

            if  $r' \leq R$  and  $(S', i) \notin \mathcal{C}$  for  $i \leq R$  then

$\mathcal{C} \leftarrow \mathcal{C} \cup \{(S', r')\};$

                if  $S' = V$  then return  $r'$ ;

# Dynamic programming

---

## Wavefront Algorithm

---

**Data:** Graph  $G = (V, E)$

**Result:** Zero forcing number of  $G$

$\mathcal{C} \leftarrow \{(\emptyset, 0)\};$

for  $R \in [n]$  do

    for  $(S, r) \in \mathcal{C}$  do

        for  $v \in V$  do

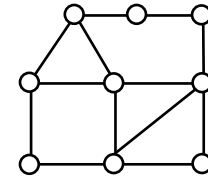
$S' \leftarrow cl(S \cup N[v]);$

$r' \leftarrow r + |\{v\} \setminus S| + \max\{|N(v) \setminus S| - 1, 0\};$

            if  $r' \leq R$  and  $(S', i) \notin \mathcal{C}$  for  $i \leq R$  then

$\mathcal{C} \leftarrow \mathcal{C} \cup \{(S', r')\};$

                if  $S' = V$  then return  $r'$ ;



# Dynamic programming

---

## Wavefront Algorithm

---

**Data:** Graph  $G = (V, E)$

**Result:** Zero forcing number of  $G$

$\mathcal{C} \leftarrow \{(\emptyset, 0)\};$

for  $R \in [n]$  do

    for  $(S, r) \in \mathcal{C}$  do

        for  $v \in V$  do

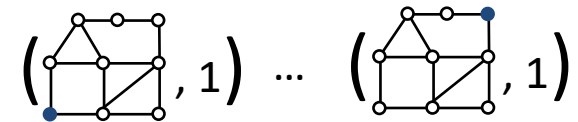
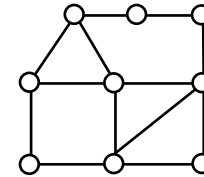
$S' \leftarrow cl(S \cup N[v]);$

$r' \leftarrow r + |\{v\} \setminus S| + \max\{|N(v) \setminus S| - 1, 0\};$

            if  $r' \leq R$  and  $(S', i) \notin \mathcal{C}$  for  $i \leq R$  then

$\mathcal{C} \leftarrow \mathcal{C} \cup \{(S', r')\};$

                if  $S' = V$  then return  $r'$ ;





# Dynamic programming

---

## Wavefront Algorithm

---

**Data:** Graph  $G = (V, E)$

**Result:** Zero forcing number of  $G$

$\mathcal{C} \leftarrow \{(\emptyset, 0)\};$

for  $R \in [n]$  do

    for  $(S, r) \in \mathcal{C}$  do

        for  $v \in V$  do

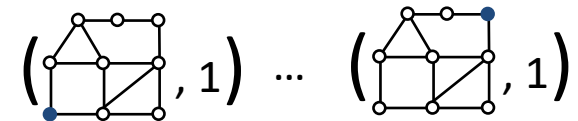
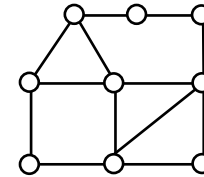
$S' \leftarrow cl(S \cup N[v]);$

$r' \leftarrow r + |\{v\} \setminus S| + \max\{|N(v) \setminus S| - 1, 0\};$

            if  $r' \leq R$  and  $(S', i) \notin \mathcal{C}$  for  $i \leq R$  then

$\mathcal{C} \leftarrow \mathcal{C} \cup \{(S', r')\};$

                if  $S' = V$  then return  $r'$ ;



# Dynamic programming

---

## Wavefront Algorithm

---

**Data:** Graph  $G = (V, E)$

**Result:** Zero forcing number of  $G$

$\mathcal{C} \leftarrow \{(\emptyset, 0)\};$

for  $R \in [n]$  do

    for  $(S, r) \in \mathcal{C}$  do

        for  $v \in V$  do

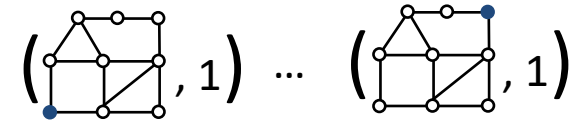
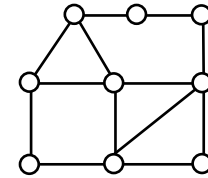
$S' \leftarrow cl(S \cup N[v]);$

$r' \leftarrow r + |\{v\} \setminus S| + \max\{|N(v) \setminus S| - 1, 0\};$

            if  $r' \leq R$  and  $(S', i) \notin \mathcal{C}$  for  $i \leq R$  then

$\mathcal{C} \leftarrow \mathcal{C} \cup \{(S', r')\};$

                if  $S' = V$  then return  $r'$ ;



# IP formulations

## Compact formulation

$$\begin{aligned} \min \quad & \sum_{v \in V} s_v \\ \text{s.t.} \quad & s_v + \sum_{e \in \delta^-(v)} y_e = 1 \quad \forall v \in V \\ & x_u - x_v + (T + 1)y_e \leq T \quad \forall e = (u, v) \in E \\ & x_w - x_v + (T + 1)y_e \leq T \quad \forall e = (u, v) \in E, \forall w \in N(u) \setminus \{v\} \\ & x \in \{0, \dots, T\}^n, s \in \{0, 1\}^n, y \in \{0, 1\}^m \end{aligned}$$

## Noncompact formulation

$$\begin{aligned} \min \quad & \sum_{v \in V} s_v \\ \text{s.t.} \quad & \sum_{v \in B} s_v \geq 1 \quad \forall B \in \mathcal{B} \\ & s \in \{0, 1\}^n \end{aligned}$$

# IP formulations

## Compact formulation

$$\begin{aligned}
 \min \quad & \sum_{v \in V} s_v \\
 \text{s.t.} \quad & s_v + \sum_{e \in \delta^-(v)} y_e = 1 \quad \forall v \in V \\
 & x_u - x_v + (T + 1)y_e \leq T \quad \forall e = (u, v) \in E \\
 & x_w - x_v + (T + 1)y_e \leq T \quad \forall e = (u, v) \in E, \forall w \in N(u) \setminus \{v\} \\
 & x \in \{0, \dots, T\}^n, s \in \{0, 1\}^n, y \in \{0, 1\}^m
 \end{aligned}$$

## Noncompact formulation

$  \begin{aligned}  \min \quad & \sum_{v \in V} s_v \\  \text{s.t.} \quad & \sum_{v \in B} s_v \geq 1 \quad \forall B \in \mathcal{B} \\  & s \in \{0, 1\}^n  \end{aligned}  $	$  \begin{aligned}  \min \quad & \sum_{v \in V} x_v \\  \text{s.t.} \quad & \sum_{v \in V} x_v \geq 1 \\  & x_w - x_v + \sum_{a \in N(w) \setminus \{v\}} x_a \geq 0 \quad \forall (v, w) \text{ with } v \in V, w \in N(v) \\  & x_v = 0 \quad \forall v \in cl(S) \quad x \in \{0, 1\}^n  \end{aligned}  $
--	--

# Boolean SAT formulation

$$\begin{aligned} \min \quad & \sum_{v \in V} (\deg(v)z_v + s_v) \\ \text{s.t.} \quad & \bigwedge_{B \in \mathcal{B}} \left( \bigvee_{v \in B} s_v \vee \bigvee_{v \in T(B)} z_v \right) \wedge \left( \bigvee_{v \in V} z_v \right) \wedge \left( \bigwedge_{\substack{v \in V \\ w \in cl(N[v])}} (\neg s_w \vee \neg z_v) \right) \end{aligned}$$

# Boolean SAT formulation

$$\begin{aligned}
 \min \quad & \sum_{v \in V} (\deg(v)z_v + s_v) \\
 \text{s.t.} \quad & \bigwedge_{B \in \mathcal{B}} \left( \bigvee_{v \in B} s_v \vee \bigvee_{v \in T(B)} z_v \right) \wedge \left( \bigvee_{v \in V} z_v \right) \wedge \left( \bigwedge_{\substack{v \in V \\ w \in cl(N[v])}} (\neg s_w \vee \neg z_v) \right)
 \end{aligned}$$

To generate violated constraints:

$$\begin{aligned}
 \min \quad & \sum_{v \in V} x_v \\
 \text{s.t.} \quad & \bigwedge_{\substack{v \in V \\ w \in N(v)}} \left( x_w \vee \neg x_v \vee \bigvee_{a \in N(w) \setminus \{v\}} x_a \right) \wedge \left( \bigvee_{v \in V} x_v \right) \wedge \left( \bigwedge_{v \in cl(S)} \neg x_v \right)
 \end{aligned}$$

# Alternate constraint generation

---

**Algorithm 1:** Greedy algorithm for finding minimal violated forts

---

```
1 Input: Graph  $G = (V, E)$ , set  $S \subset V$  corresponding to solution of RMP;  
2 Output: Minimal fort  $B$  which violates  $S$ ;  
3  $C \leftarrow cl(S)$ ;  
4 for  $v \in V \setminus C$  do  
5   | if  $cl(C \cup \{v\}) \neq V$  then  
6   |   |  $C \leftarrow C \cup \{v\}$ ;  
7   |   | goto line 4;  
8 return  $B \leftarrow V \setminus C$ 
```

---

# Runtime comparisons

$G$	$ V $	$Z(G)$	Wavefront	IP Models	Boolean
karate	34	13	329.10	0.16 (M)	<b>0.02</b>
chesapeake	39	14	10.91	35.43 (M)	<b>1.94</b>
dolphins	62	14	2405.56	246.24 (D)	<b>108.59</b>
lesmis	77	40	T	2708.95 (D)	<b>3.74</b>
polbooks	105	N/A	T	{14/27} (D)	{ <b>18/27</b> }
adjnoun	112	N/A	T	{ <b>9/30</b> } (M)	{9/32}
football	115	N/A	T	{ <b>9/38</b> } (M)	{0/40}
jazz	198	N/A	T	{ <b>27/96</b> } (M)	{10/102}
celegansneural	297	N/A	T	{ <b>28/100</b> } (M)	{ <b>15/89</b> }
IEEE 14	14	4	0.01	0.01 (M)	<b>0.001</b>
IEEE 24	24	6	0.07	0.01 (M)	<b>0.004</b>
IEEE 30	30	7	0.82	0.03 (M)	<b>0.010</b>
IEEE 39	39	7	6.69	0.04 (M)	<b>0.019</b>
IEEE 57	57	9	18.76	1.97 (M)	<b>0.282</b>
RTS 96	73	15	T	0.78 (M)	<b>0.641</b>
IEEE 118	118	26	T	734.96 (I)	<b>10.367</b>
IEEE 300	300	N/A	T	{ <b>73/75</b> } (I)	{62/77}



# Runtime comparisons

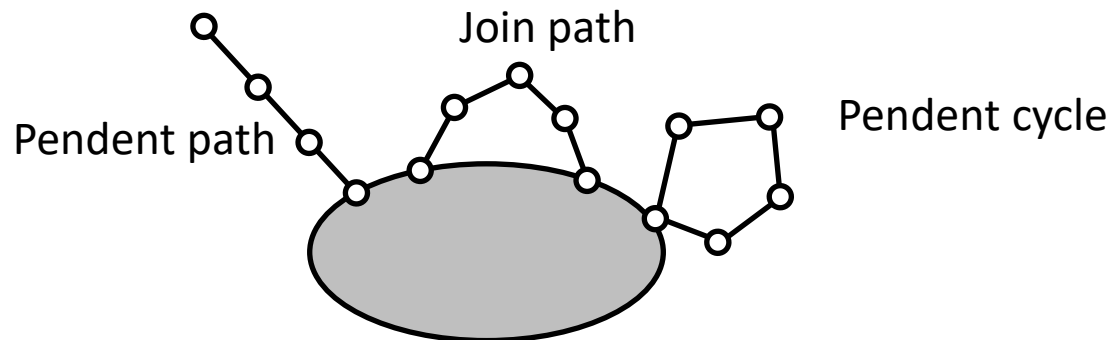
	$ V $	$Z(G)$	Wavefront	IP Models	Boolean
Cubic graphs	10	3	0.01	0.01 (M)	<b>0.000</b>
	20	5	0.02	0.04 (M)	<b>0.009</b>
	30	6	<b>0.13</b>	0.42 (M)	0.142
	40	8	<b>1.95</b>	6.10 (E)	2.624
	50	9	<b>6.69</b>	30.90 (E)	17.527
	60	11	<b>156.83</b>	1363.05 (E)	3138.832
	70	12	<b>370.50</b>	2852.27 (E)	{10.8/12.4}
	80	N/A	<b>1615.85</b>	5341.15 (E)	{10.8/13.8}
	90	N/A	<b>3101.29</b>	{9.4/13.6} (F)	{9.6/14.4}
	100	N/A	T	{ <b>9.6/15.4</b> } (F)	{9.6/15.8}
Avg-cubic	20	5.6	0.10	0.02 (M)	<b>0.003</b>
	40	10.0	796.89	0.63 (M)	<b>0.063</b>
	60	14.4	T	9.24 (I)	<b>0.867</b>
	80	19.4	T	15.45 (I)	<b>7.150</b>
	100	23.4	T	<b>37.23</b> (I)	345.232
	120	30.5	T	<b>109.13</b> (I)	382.478

# Facets of zero forcing polytope

- If a polytope has a large number of facets, it is usually inherently difficult to solve with IP

# Facets of zero forcing polytope

- If a polytope has a large number of facets, it is usually inherently difficult to solve with IP
- There can be  $\Omega(1.3247^{n/3})$  facets defined by forts in pendant paths, join paths, and pendant cycles



# Heuristics

- **Single vertex largest closure:** add a single white vertex to  $Z$ , so that the resulting closure is maximized
- **Neighborhood largest closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the resulting closure is maximized
- **Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized

# Closure based heuristics

---

```
1 Input: Graph  $G = (V, E)$ ;  
2 Output: Zero forcing set  $Z$  of  $G$ ;  
3  $Z \leftarrow \emptyset$ ;  
4  $C \leftarrow \emptyset$ ;  
5 while  $C \neq V$  do  
6    $C^* \leftarrow \emptyset$ ;  
7    $A \leftarrow \emptyset$ ;  
8   for  $v \in V \setminus C$  do  
9      $S \leftarrow C \cup A'(v, C)$ ;  
10    if  $f(cl(S), v, C) > f(C^*, v, C)$  then  
11       $A \leftarrow A'(v, C)$ ;  
12       $C^* \leftarrow cl(S)$ ;  
13   $C \leftarrow C^*$ ;  
14   $Z \leftarrow Z \cup A$ ;  
15  for  $v \in Z$  do  
16    if  $cl(Z \setminus \{v\}) = V$  then  
17       $Z \leftarrow Z \setminus \{v\}$ ;  
18 return  $Z$ 
```

---

**Single vertex largest closure**

$$A'(v, C) = \{v\}$$

$$f(S, v, C) = |S|$$

**Neighborhood largest closure**

$$A'(v, C) = (N[v] \cap (V \setminus C)) \setminus \{u\}$$

for some  $u \in N(v) \cap (V \setminus C)$

$$f(S, v, C) = |S|$$

**Neighborhood scaled closure**

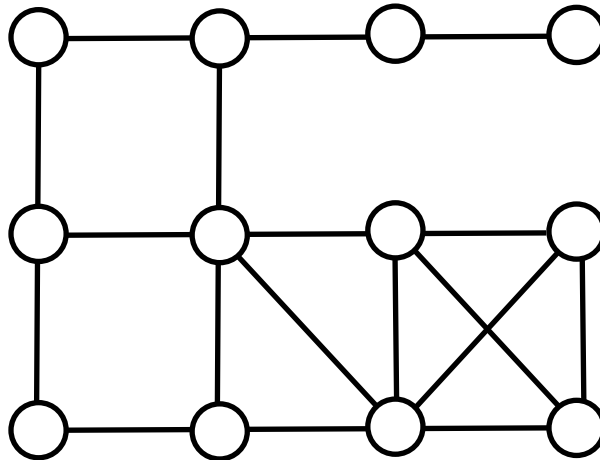
$$A'(v, C) = (N[v] \cap (V \setminus C)) \setminus \{u\}$$

for some  $u \in N(v) \cap (V \setminus C)$

$$f(S, v, C) = (|cl(S)| - |C|) / |A'(v, C)|$$

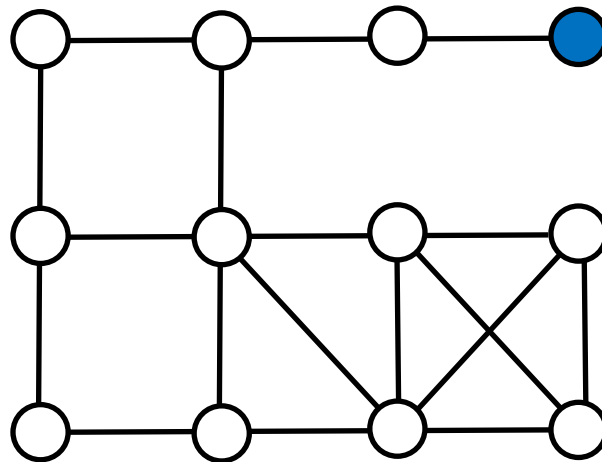
# Heuristics

**Single vertex largest closure:** add a single white vertex to  $Z$ , so that the resulting closure is maximized



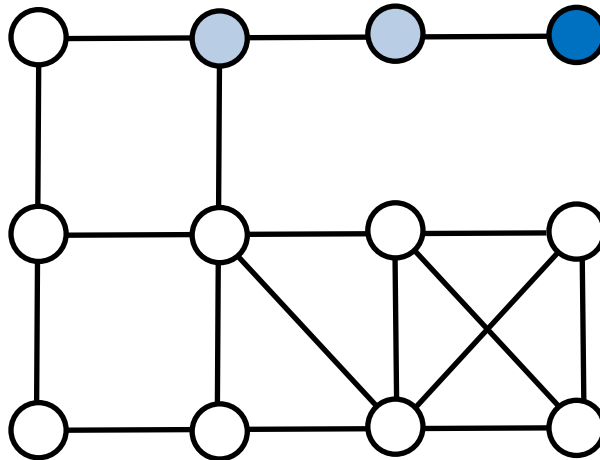
# Heuristics

**Single vertex largest closure:** add a single white vertex to  $Z$ , so that the resulting closure is maximized



# Heuristics

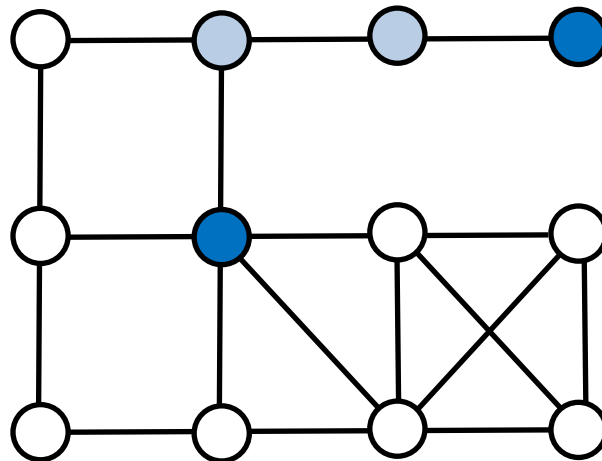
**Single vertex largest closure:** add a single white vertex to  $Z$ , so that the resulting closure is maximized





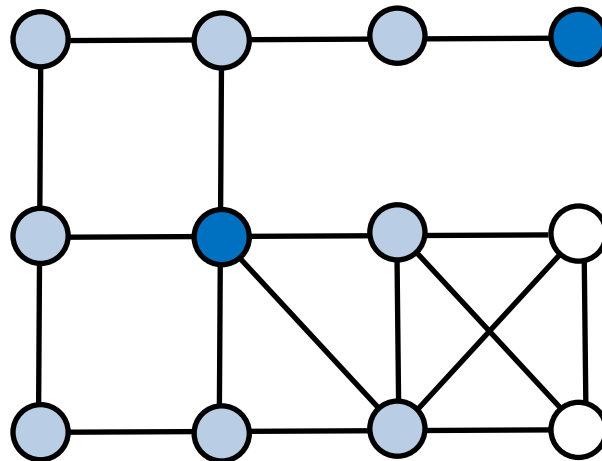
# Heuristics

**Single vertex largest closure:** add a single white vertex to  $Z$ , so that the resulting closure is maximized



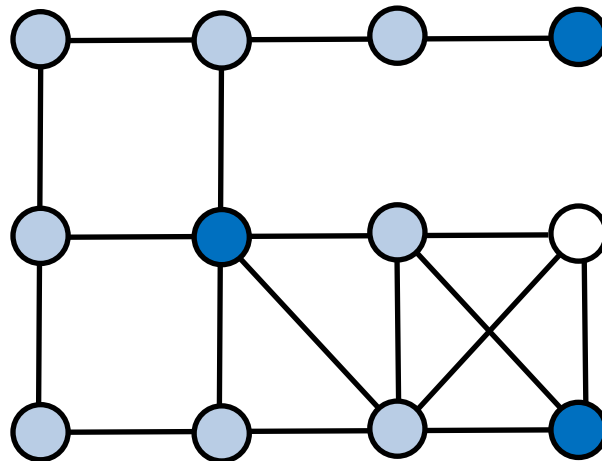
# Heuristics

**Single vertex largest closure:** add a single white vertex to  $Z$ , so that the resulting closure is maximized



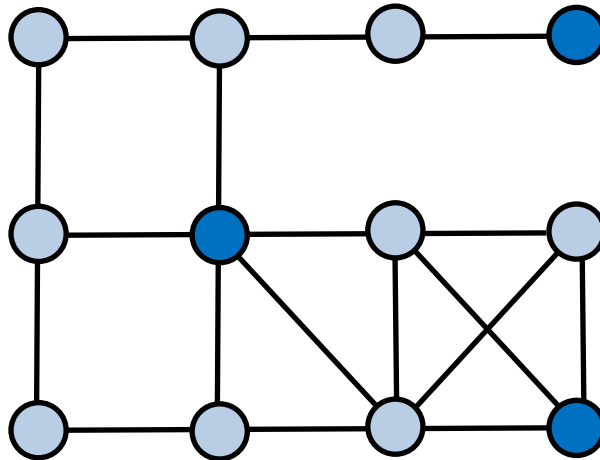
# Heuristics

**Single vertex largest closure:** add a single white vertex to  $Z$ , so that the resulting closure is maximized



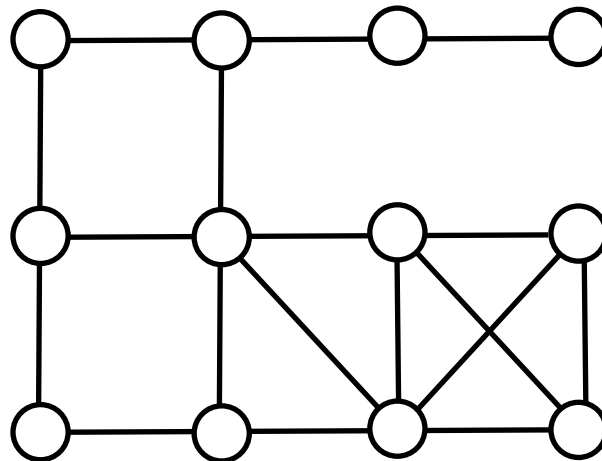
# Heuristics

**Single vertex largest closure:** add a single white vertex to  $Z$ , so that the resulting closure is maximized



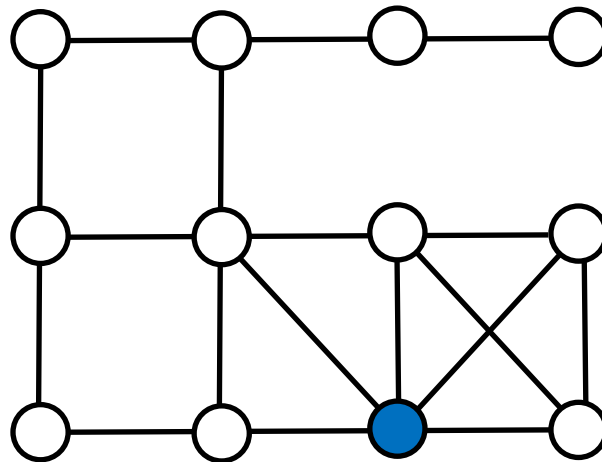
# Heuristics

**Neighborhood largest closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the resulting closure is maximized; take minimal subset



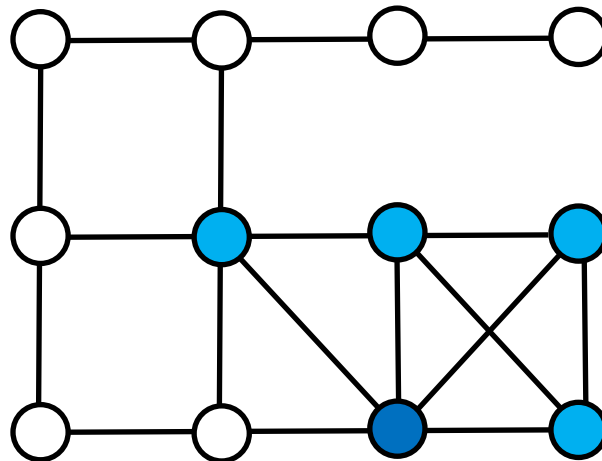
# Heuristics

**Neighborhood largest closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the resulting closure is maximized; take minimal subset



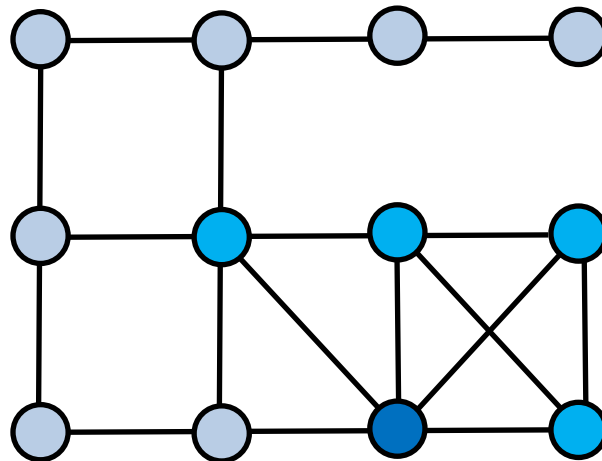
# Heuristics

**Neighborhood largest closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the resulting closure is maximized; take minimal subset



# Heuristics

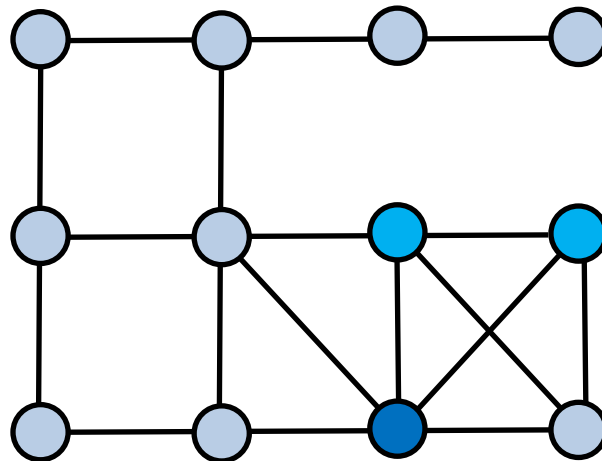
**Neighborhood largest closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the resulting closure is maximized; take minimal subset





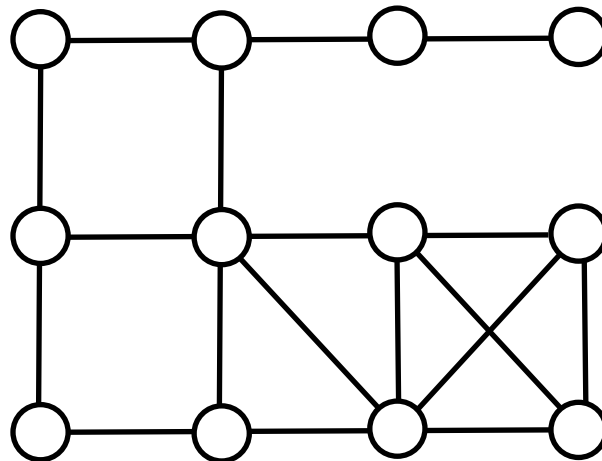
# Heuristics

**Neighborhood largest closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the resulting closure is maximized; take minimal subset



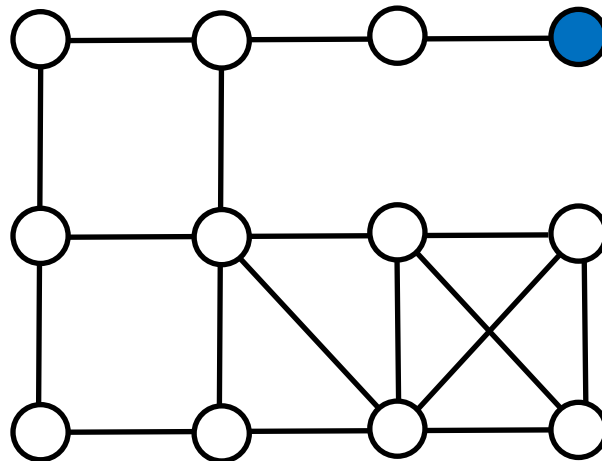
# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



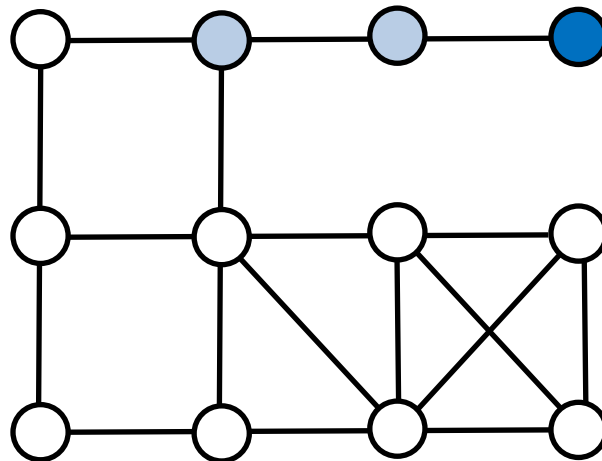
# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



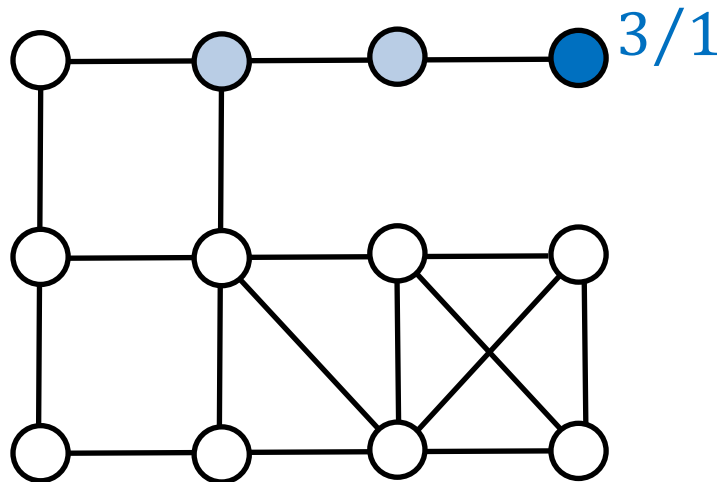
# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



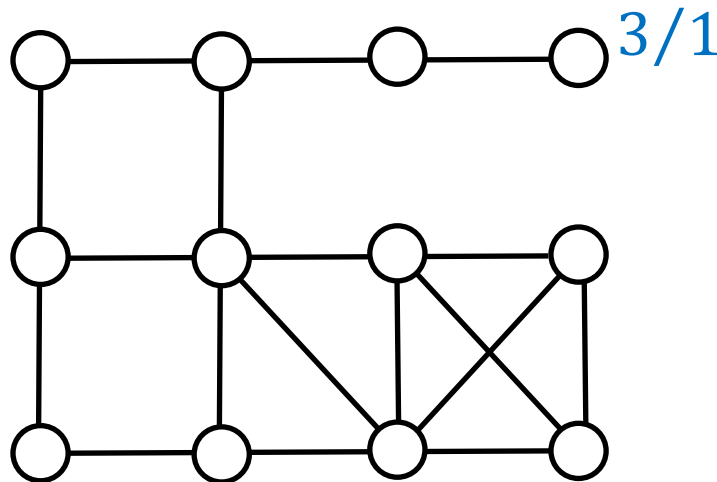
# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



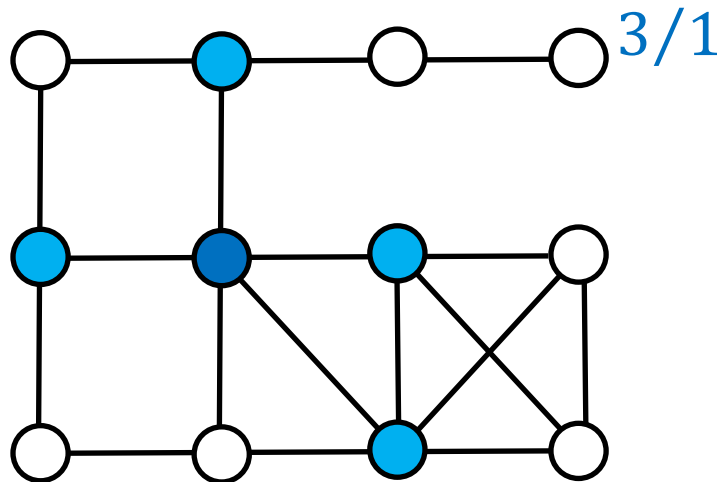
# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



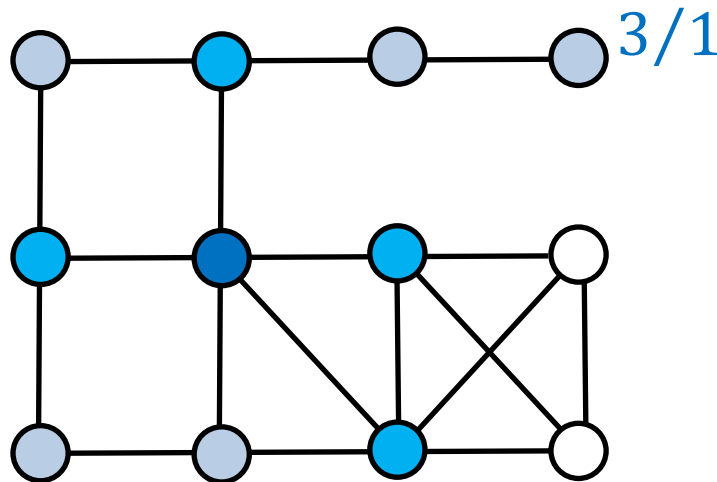
# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



# Heuristics

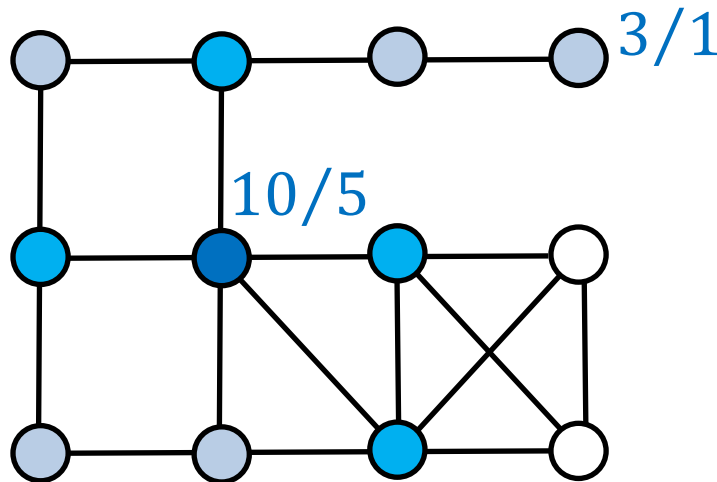
**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized





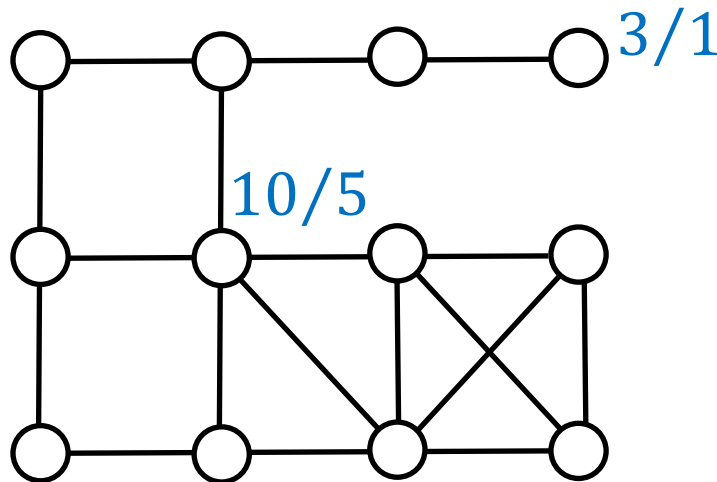
# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



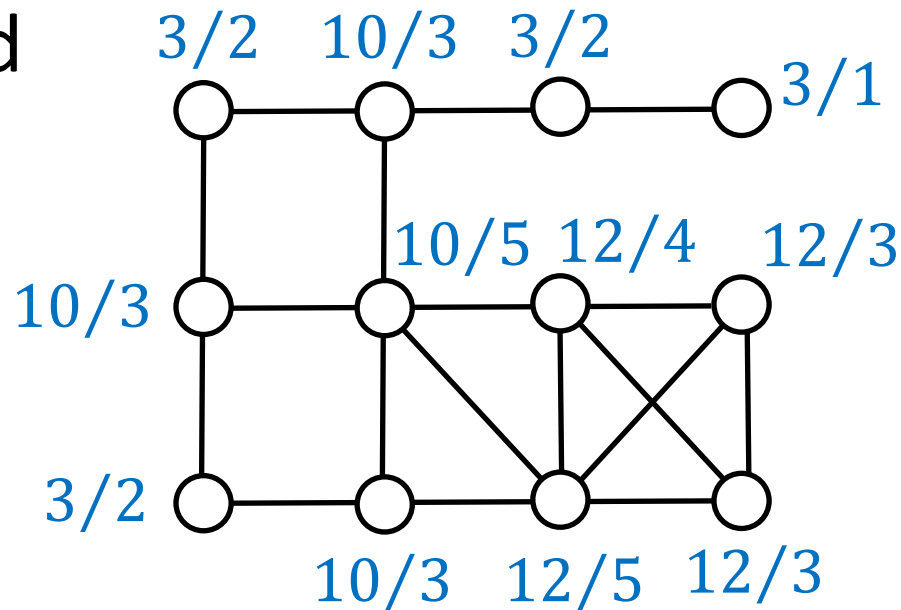
# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



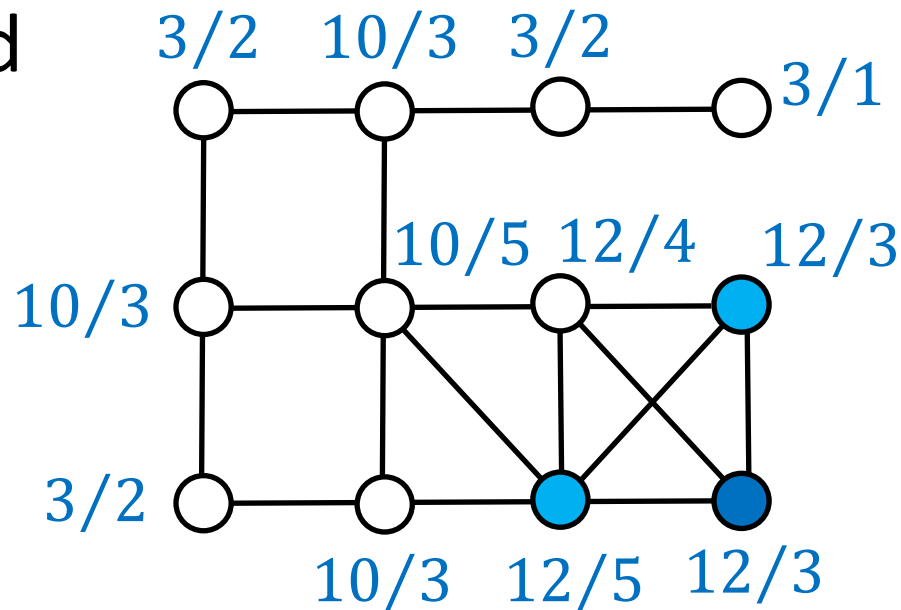
# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



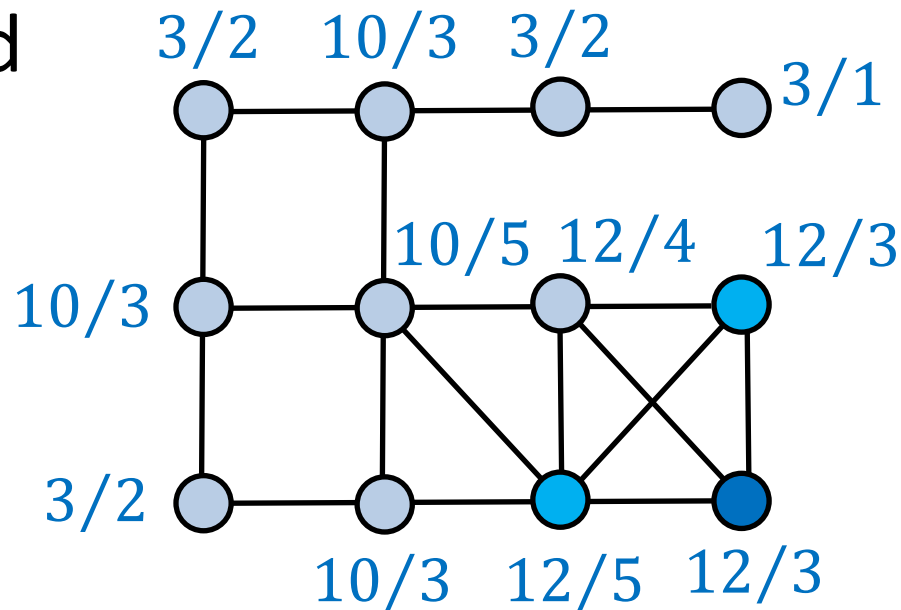
# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



# Heuristics

**Neighborhood scaled closure:** add a single white vertex and all-but-one of its white neighbors to  $Z$ , so that the *ratio* of the resulting closure to the number of vertices added is maximized



# Heuristic results

$G$	$ V $	$Z(G)$	Single Node Largest Closure		Neighborhood Largest Closure		Neighborhood Scaled Closure		
			$Z_h$	time	$Z_h$	time	$Z_h$	time	
IEEE 14	14	4	<b>4</b>	0.000	5	0.000	5	0.000	✓
IEEE 24	24	6	<b>7</b>	0.001	<b>6</b>	0.000	<b>6</b>	0.000	✓
IEEE 30	30	7	<b>7</b>	0.000	9	0.000	<b>7</b>	0.000	✓
IEEE 39	39	7	9	0.003	<b>8</b>	0.001	<b>8</b>	0.001	✓
IEEE 57	57	9	<b>10</b>	0.007	<b>10</b>	0.002	11	0.003	✓
RTS 96	73	15	17	0.019	17	0.008	<b>16</b>	0.006	✓
IEEE 118	118	26	<b>27</b>	0.048	32	0.017	28	0.029	✓
karate	34	13	<b>13</b>	0.003	14	0.001	14	0.002	✓
chesapeake	39	14	<b>15</b>	0.007	<b>15</b>	0.002	<b>15</b>	0.002	✓
dolphins	62	14	<b>17</b>	0.015	19	0.003	<b>17</b>	0.004	✗
lesmis	77	40	<b>41</b>	0.040	<b>41</b>	0.008	<b>41</b>	0.026	✓

# Heuristic results

$G$	$ V $	$Z(G)$	Single Node Largest Closure		Neighborhood Largest Closure		Neighborhood Scaled Closure		
			$Z_h$	time	$Z_h$	time	$Z_h$	time	
WS(10,.3)	20	12.0	<b>12.2</b>	0.000	<b>12.2</b>	0.000	<b>12.2</b>	0.000	✓
	30	15.4	16.2	0.002	16.8	0.000	<b>16.0</b>	0.000	✓
	40	18.0	18.4	0.004	18.4	0.001	<b>18.2</b>	0.001	✓
	50	21.8	<b>22.0</b>	0.009	24.0	0.002	23.6	0.002	✓
	60	24.6	<b>24.8</b>	0.015	25.6	0.003	25.8	0.003	✓
	70	27.4	28.8	0.025	<b>28.4</b>	0.005	<b>28.4</b>	0.004	✓
	80	31.2	<b>32.6</b>	0.036	33.8	0.008	33.2	0.007	✗
WS(5,.3)	10	4.4	4.8	0.000	<b>4.6</b>	0.000	<b>4.6</b>	0.000	✓
	20	6.2	<b>6.2</b>	0.000	6.4	0.000	6.4	0.000	✓
	30	7.0	8.0	0.001	<b>7.4</b>	0.000	7.6	0.000	✓
	40	9.4	10.2	0.002	10.6	0.000	<b>9.6</b>	0.000	✓
	50	10.8	<b>11.6</b>	0.005	12.2	0.002	<b>11.6</b>	0.002	✓
	60	11.6	13.6	0.008	14.0	0.002	<b>13.2</b>	0.002	✗
	70	14.0	15.0	0.016	16.2	0.003	<b>14.8</b>	0.004	✓
	80	14.8	<b>16.8</b>	0.015	18.2	0.005	17.2	0.006	✗

# Heuristic results

$G$	$ V $	$Z(G)$	Single Node Largest Closure		Neighborhood Largest Closure		Neighborhood Scaled Closure		
			$Z_h$	time	$Z_h$	time	$Z_h$	time	
Cubic	10	3.8	<b>3.8</b>	0.000	<b>3.8</b>	0.000	<b>3.8</b>	0.000	✓
	20	5.2	5.4	0.000	<b>5.2</b>	0.000	<b>5.2</b>	0.000	✓
	30	6.6	7.4	0.001	7.2	0.000	<b>7.0</b>	0.000	✓
	40	8.8	9.8	0.003	9.6	0.001	<b>9.2</b>	0.001	✓
	50	9.2	10.4	0.005	<b>9.4</b>	0.001	9.6	0.001	✓
	60	11.4	12.4	0.008	12.0	0.003	<b>11.8</b>	0.003	✓
	70	12.0	<b>12.6</b>	0.008	13.2	0.004	12.8	0.004	✓



- Compared different methods for computing  $Z(G)$
- Each has its pros and cons

- Compared different methods for computing  $Z(G)$
- Each has its pros and cons
- Presented heuristics for  $Z(G)$ 
  - Can speed up exact models
  - Very fast and usually pretty accurate
  - Can be adapted to other graph infection problems

- Compared different methods for computing  $Z(G)$
- Each has its pros and cons
- Presented heuristics for  $Z(G)$ 
  - Can speed up exact models
  - Very fast and usually pretty accurate
  - Can be adapted to other graph infection problems
- Future work: develop timestep-based SAT model, derive performance guarantees for heuristics

- Compared different methods for computing  $Z(G)$
- Each has its pros and cons
- Presented heuristics for  $Z(G)$ 
  - Can speed up exact models
  - Very fast and usually pretty accurate
  - Can be adapted to other graph infection problems
- Future work: develop timestep-based SAT model, derive performance guarantees for heuristics

- 
- B. Brimkov, I. V. Hicks, D. J. Mikesell. Improved computational approaches and heuristics for zero forcing *INFORMS Journal on Computing* (2020).
  - B. Brimkov, C.C. Fast, I.V. Hicks. Computational approaches for zero forcing and related problems. *European Journal of Operational Research* (2019).

- Compared different methods for computing  $Z(G)$
- Each has its pros and cons
- Presented heuristics for  $Z(G)$ 
  - Can speed up exact models
  - Very fast and usually pretty accurate
  - Can be adapted to other graph infection problems
- Future work: develop timestep-based SAT model, derive performance guarantees for heuristics

- 
- B. Brimkov, I. V. Hicks, D. J. Mikesell. Improved computational approaches and heuristics for zero forcing *INFORMS Journal on Computing* (2020).
  - B. Brimkov, C.C. Fast, I.V. Hicks. Computational approaches for zero forcing and related problems. *European Journal of Operational Research* (2019).
- 

THANK YOU