Discovering Feature Flag Interdependencies in Microsoft Office

https://mcschroeder.github.io/#fse2022

Michael Schröder
TU Wien
Vienna, Austria
michael.schroeder@tuwien.ac.at

Katja Kevic
Microsoft
Cambridge, UK
katja.kevic@microsoft.com

Dan Gopstein
Microsoft
New York, USA
dan.gopstein@microsoft.com

Brendan Murphy
Microsoft
Cambridge, UK
brendan.murphy@microsoft.com

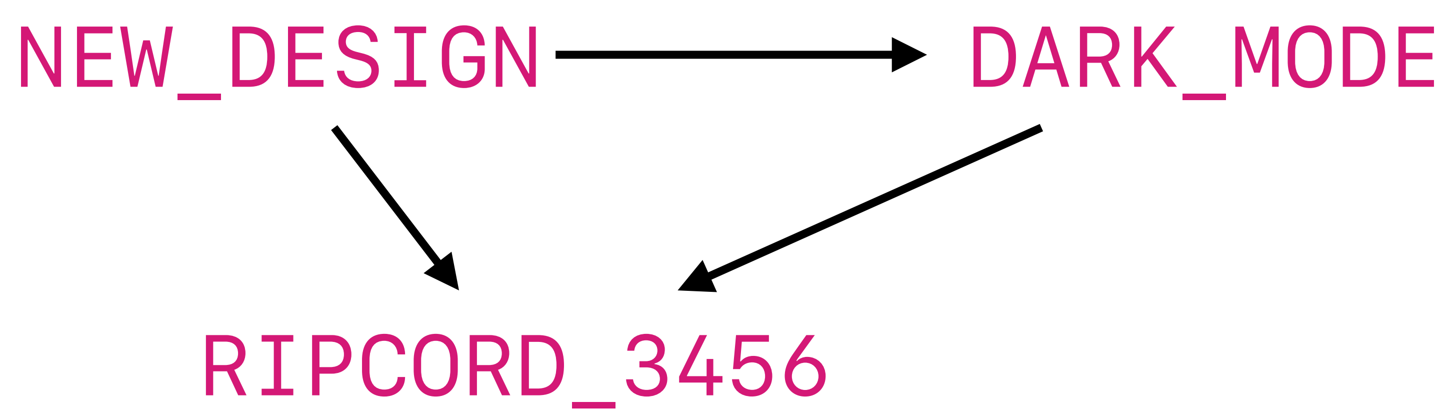
Jennifer Beckmann
Microsoft
Redmond, USA
jennifer.beckmann@microsoft.com

ESEC/FSE 2022, Industry Track
Singapore

Feature Flags

- Design pattern to conditionally enable a code path
  - for running experiments in production (e.g., A/B testing)
  - for rolling out features in a controlled manner
  - for emergency bug mitigation (“e-brakes”)

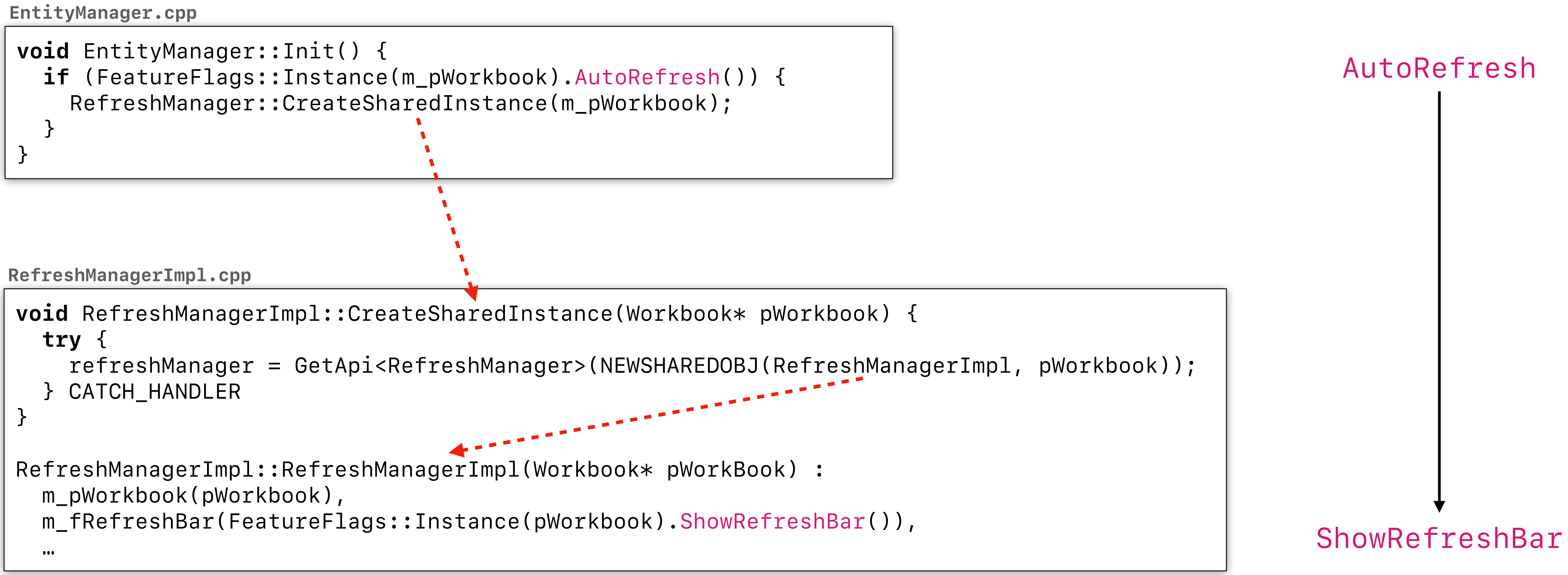
```
if (NEW_DESIGN && DARK_MODE) {
  reduceBrightness();
} else {
  showWhiteBackground();
  if (!RIPCORD_3456) {
    playAnimation();
  }
}
```



- Nesting causes flags to become **interdependent**:
dynamic runtime value of parent flag determines whether child flag is queried

Feature Flags

Example: Indirect relationship spanning multiple files



EntityManager.cpp

```
void EntityManager::Init() {
  if (FeatureFlags::Instance(m_pWorkbook).AutoRefresh()) {
    RefreshManager::CreateSharedInstance(m_pWorkbook);
  }
}
```

RefreshManagerImpl.cpp

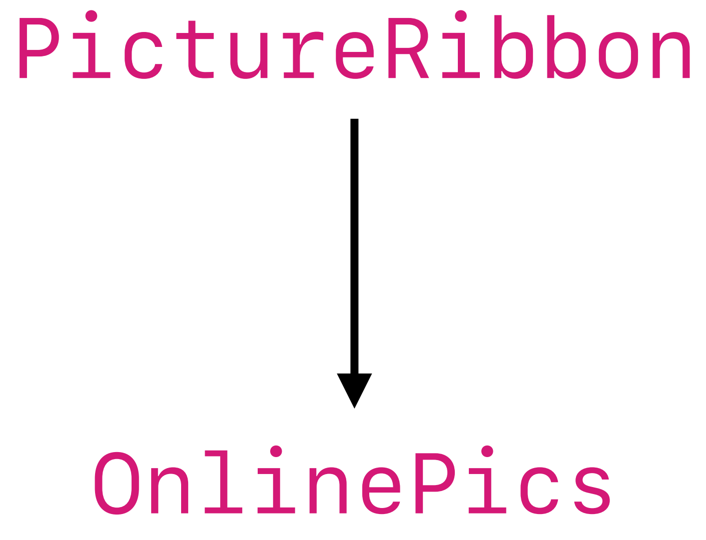
```
void RefreshManagerImpl::CreateSharedInstance(Workbook* pWorkbook) {
  try {
    refreshManager = GetApi<RefreshManager>(NEWSHAREDOBJ(RefreshManagerImpl, pWorkbook));
  } CATCH_HANDLER
}

RefreshManagerImpl::RefreshManagerImpl(Workbook* pWorkBook) :
  m_pWorkbook(pWorkbook),
  m_fRefreshBar(FeatureFlags::Instance(pWorkbook).ShowRefreshBar()),
  …
```

Feature Flags

Example: Relationship in non-code resource file

`Word.xml`

```
<FSDropGallery Id="flyoutInsertPics" FeatureFlag="PictureRibbon">
  <Commands>
    <FSMenuCategory Class="StandardItems">
      <Items>
        <FSExecuteAction Id="insertPicFromFile" />
        <FSExecuteAction Id="insertOnlinePic" FeatureFlag="OnlinePics" />
        <FSExecuteAction Id="clipArtDialog" />
      </Items>
    </FSMenuCategory >
  </Commands>
</FSDropGallery>
```



Feature Flags

- Microsoft Office contains about 12 000 active feature flags
- Unknown interdependencies can be source of serious bugs
- Testing all possible flag combinations is infeasible ($\sim 7.2 \times 10^7$)

Feature Flags

- Microsoft Office contains about 12 000 active feature flags
- Unknown interdependencies can be source of serious bugs
- Testing all possible flag combinations is infeasible (~7.2×10^7)

- Goal: Automatically discover feature flag interdependencies

Feature Flags

- Microsoft Office contains about 12 000 active feature flags
- Unknown interdependencies can be source of serious bugs
- Testing all possible flag combinations is infeasible ($\sim 7.2 \times 10^7$)

- Goal: Automatically discover feature flag interdependencies

- Approach: Probabilistic analysis of feature flag query logs
  - We achieve over 90% precision
  - We are able to recall non-trivial indirect relationships

Query Logs

Any time a feature flag is queried during the run of an application, the query is logged, together with the current value of the flag.

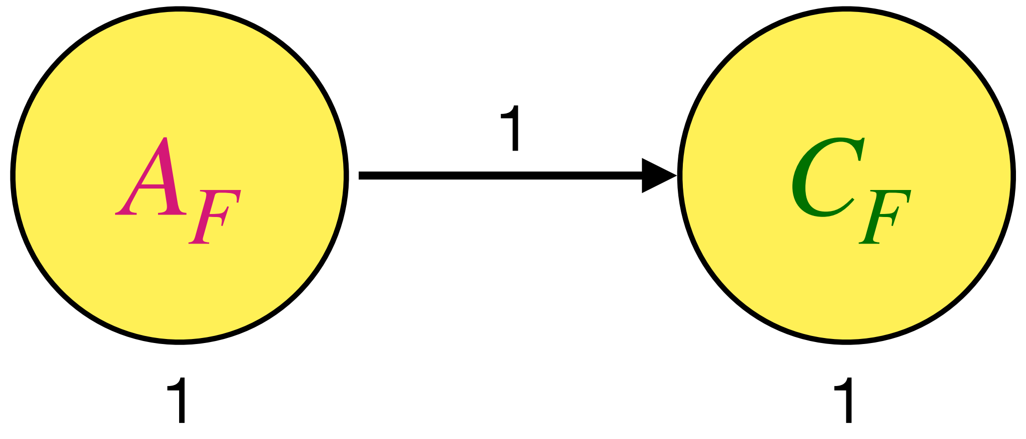
multiple independent runs

Log	Time	Feature	Value
1	14:18:27	A	False
1	14:18:27	C	False
2	09:10:38	B	False
2	09:10:38	C	False
3	23:53:04	A	True
3	23:53:04	B	False
3	23:53:04	C	False

Co-Occurrence Discovery

If two flags co-occur within some time window, they might be related.

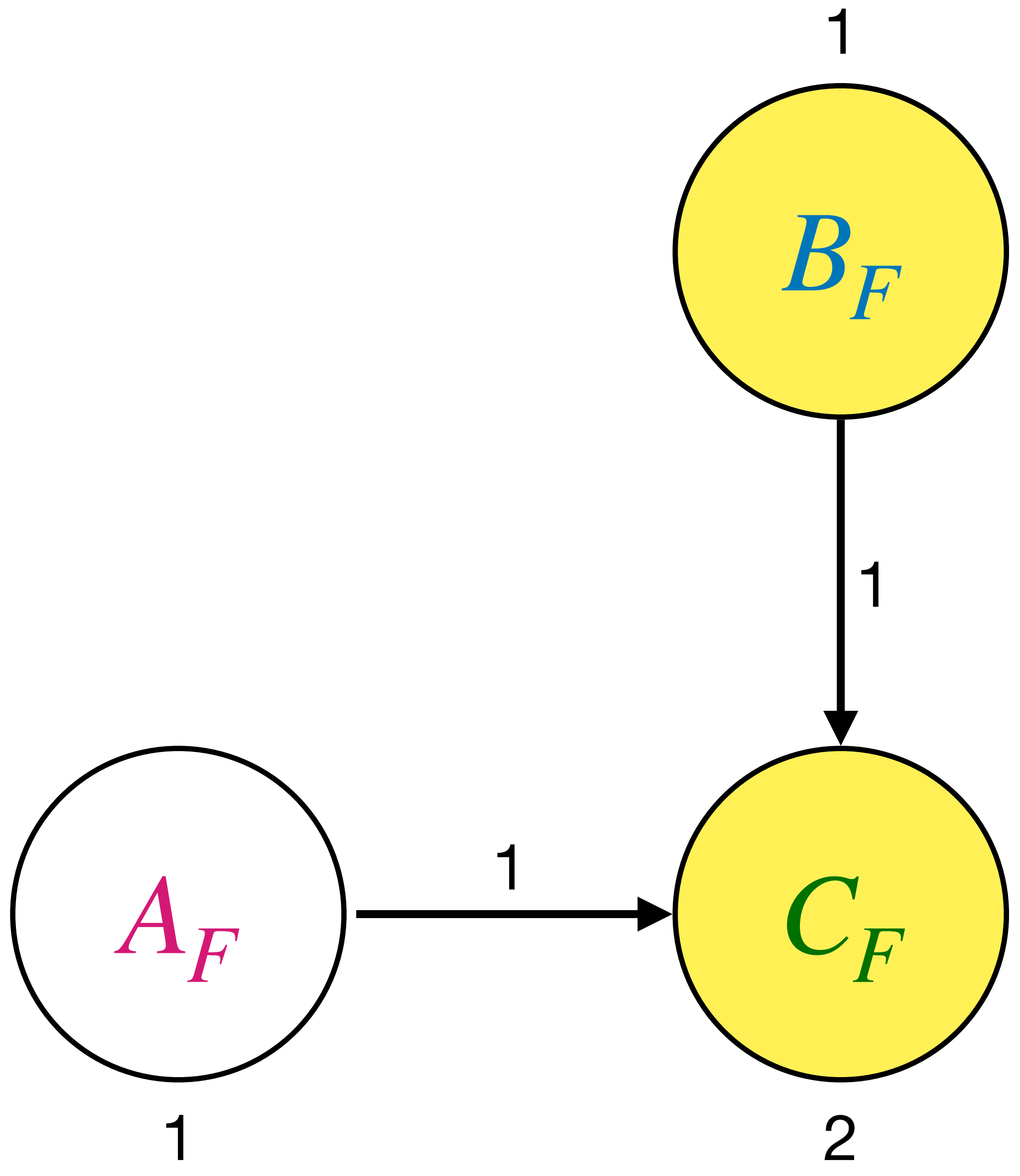
Log	Time	Feature	Value
1	14:18:27	A	False
1	14:18:27	C	False
2	09:10:38	B	False
2	09:10:38	C	False
3	23:53:04	A	True
3	23:53:04	B	False
3	23:53:04	C	False



Co-Occurrence Discovery

If two flags co-occur within some time window, they might be related.

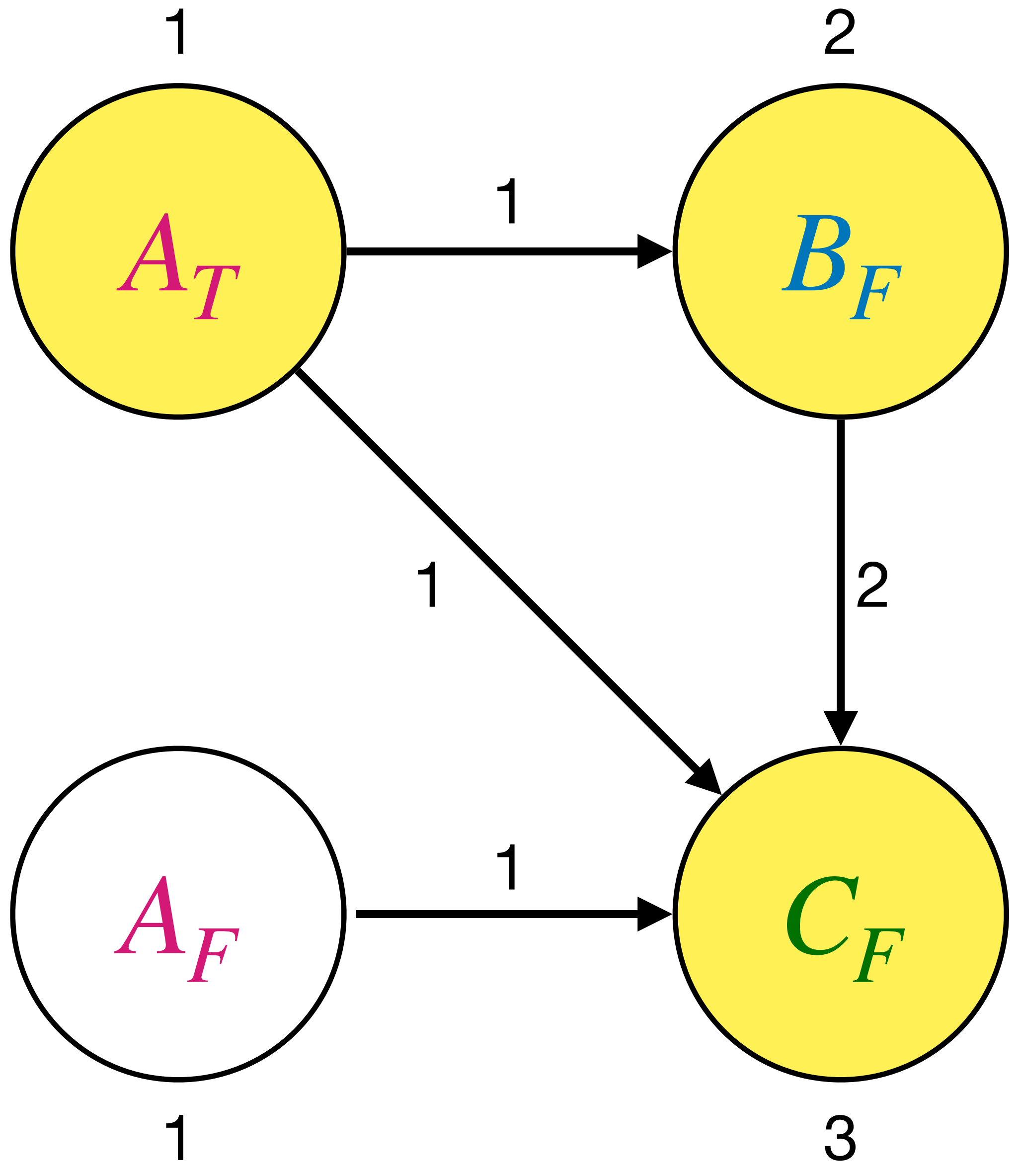
Log	Time	Feature	Value
1	14:18:27	A	False
1	14:18:27	C	False
2	09:10:38	B	False
2	09:10:38	C	False
3	23:53:04	A	True
3	23:53:04	B	False
3	23:53:04	C	False



Co-Occurrence Discovery

If two flags co-occur within some time window, they might be related.

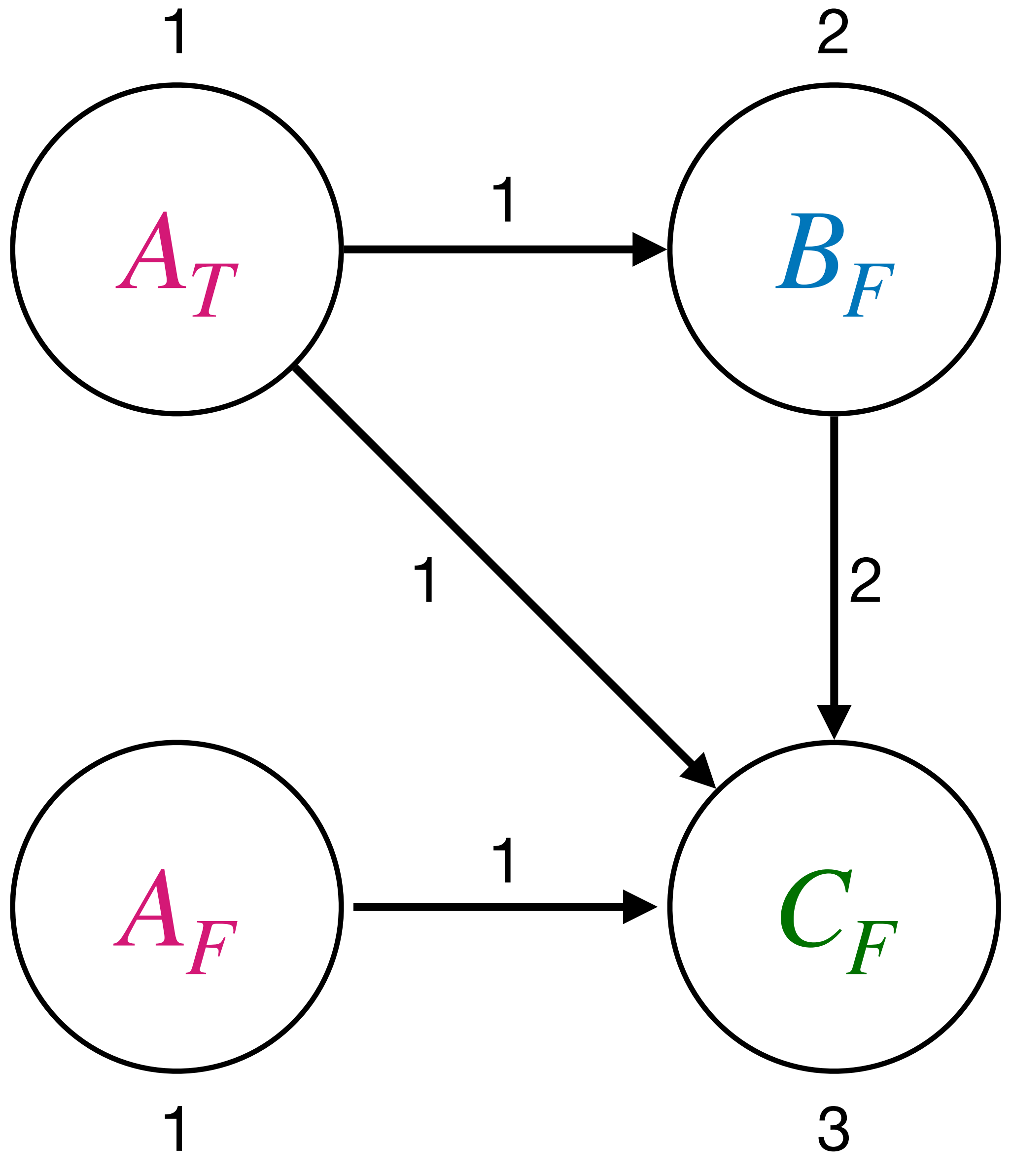
Log	Time	Feature	Value
1	14:18:27	A	False
1	14:18:27	C	False
2	09:10:38	B	False
2	09:10:38	C	False
3	23:53:04	A	True
3	23:53:04	B	False
3	23:53:04	C	False



Co-Occurrence Discovery

If two flags co-occur within some time window, they might be related.

Log	Time	Feature	Value
1	14:18:27	A	False
1	14:18:27	C	False
2	09:10:38	B	False
2	09:10:38	C	False
3	23:53:04	A	True
3	23:53:04	B	False
3	23:53:04	C	False

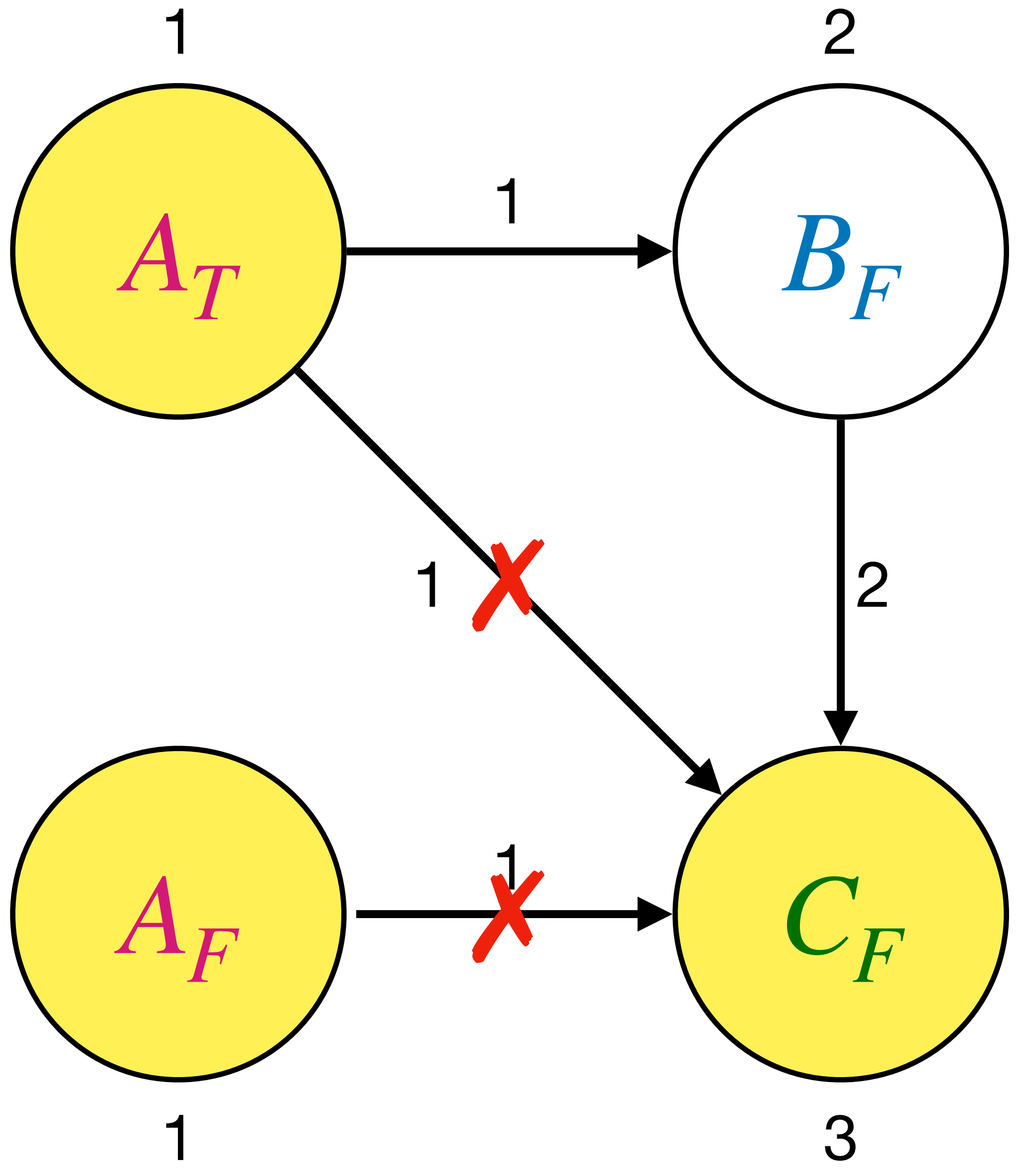


Co-Occurence Graph

Naive Causal Reasoning

Eliminate non-causal relationships.

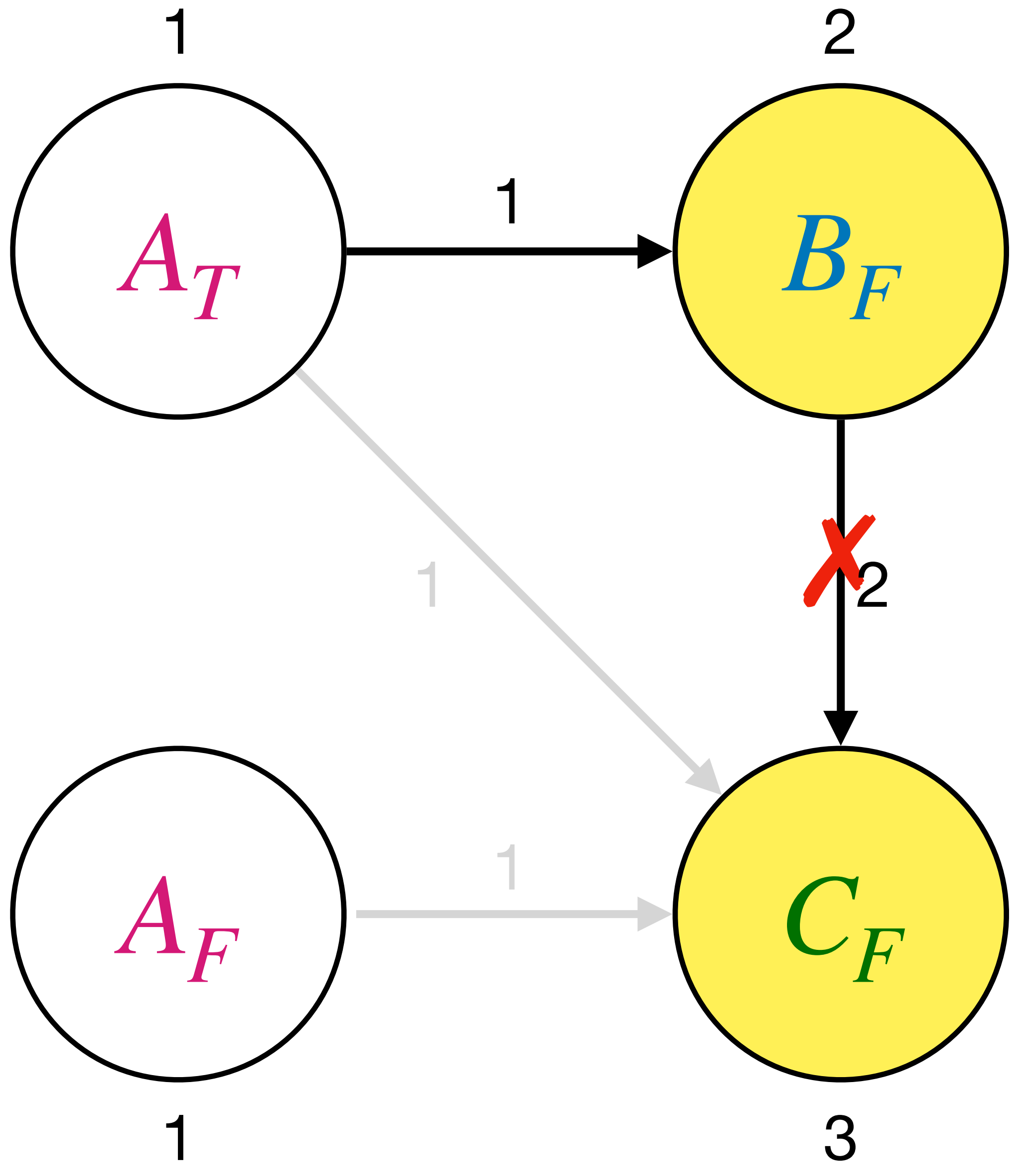
- $A_T \rightarrow C_F$ and $A_F \rightarrow C_F$ therefore $A \nrightarrow C$



Naive Causal Reasoning

Eliminate non-causal relationships.

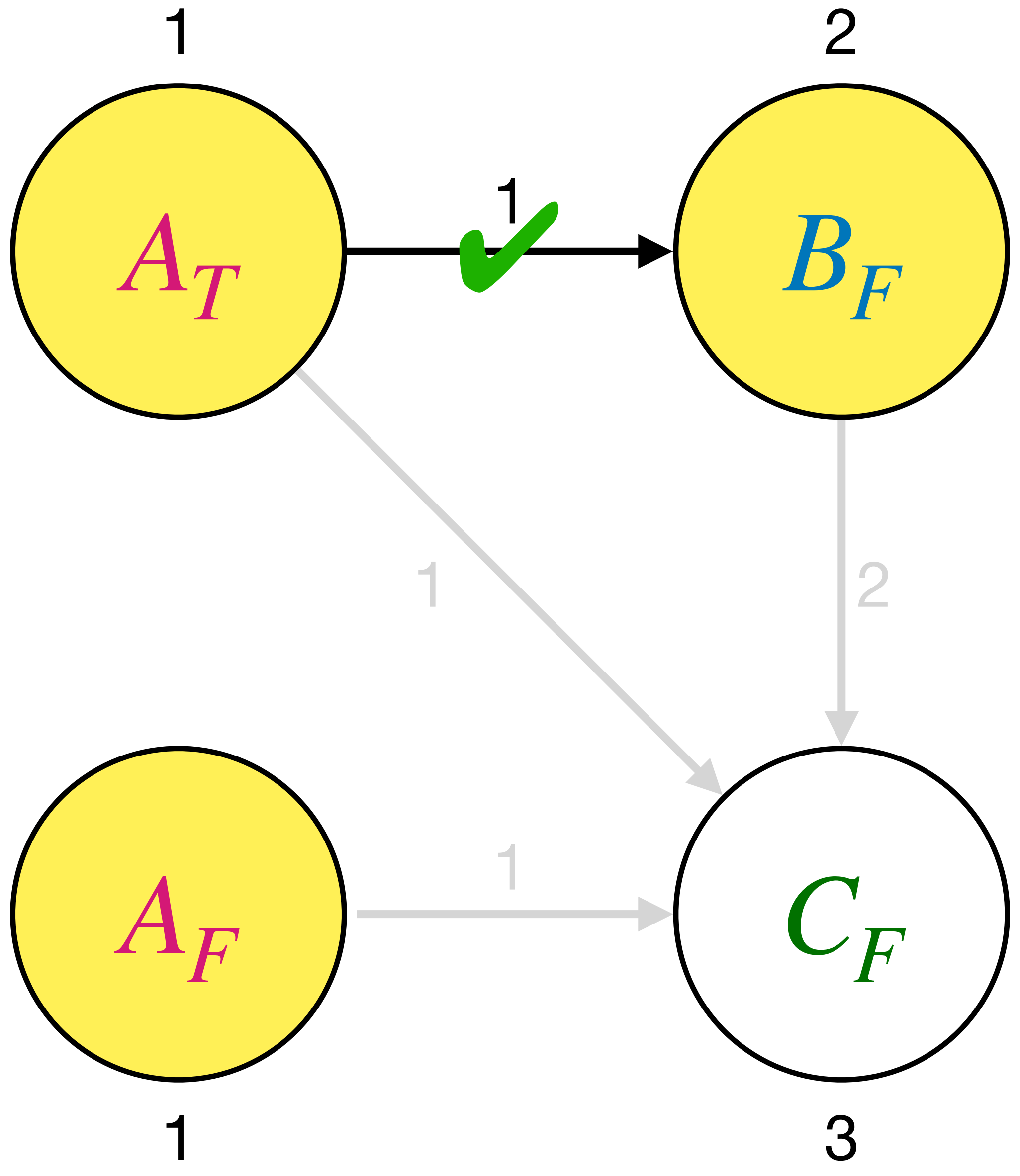
- $A_T \to C_F$ and $A_F \to C_F$ therefore $A \not\to C$
- $B_F \to C_F$ but $B_T \overset{?}{\to} C_F$ therefore $B \not\to C$



Naive Causal Reasoning

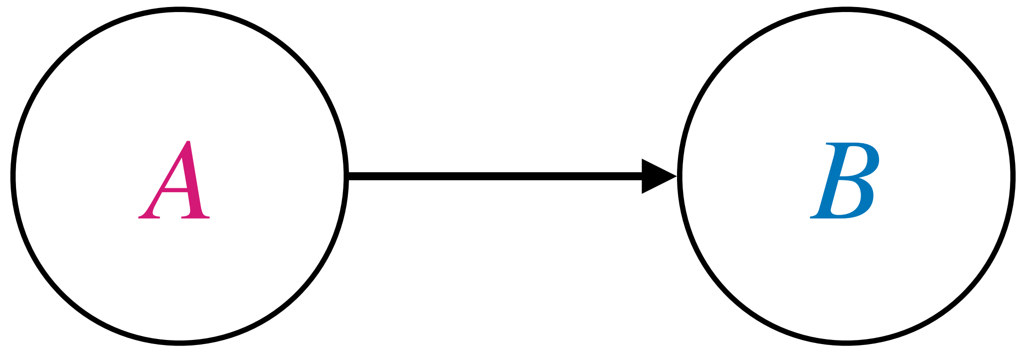
Eliminate non-causal relationships.

- $A_T \rightarrow C_F$ and $A_F \rightarrow C_F$ therefore $A \nrightarrow C$
- $B_F \rightarrow C_F$ but $B_T \overset{?}{\rightarrow} C_F$ therefore $B \nrightarrow C$
- $A_T \rightarrow B_F$ and $A_F \nrightarrow B_F$ therefore $A \rightarrow B$

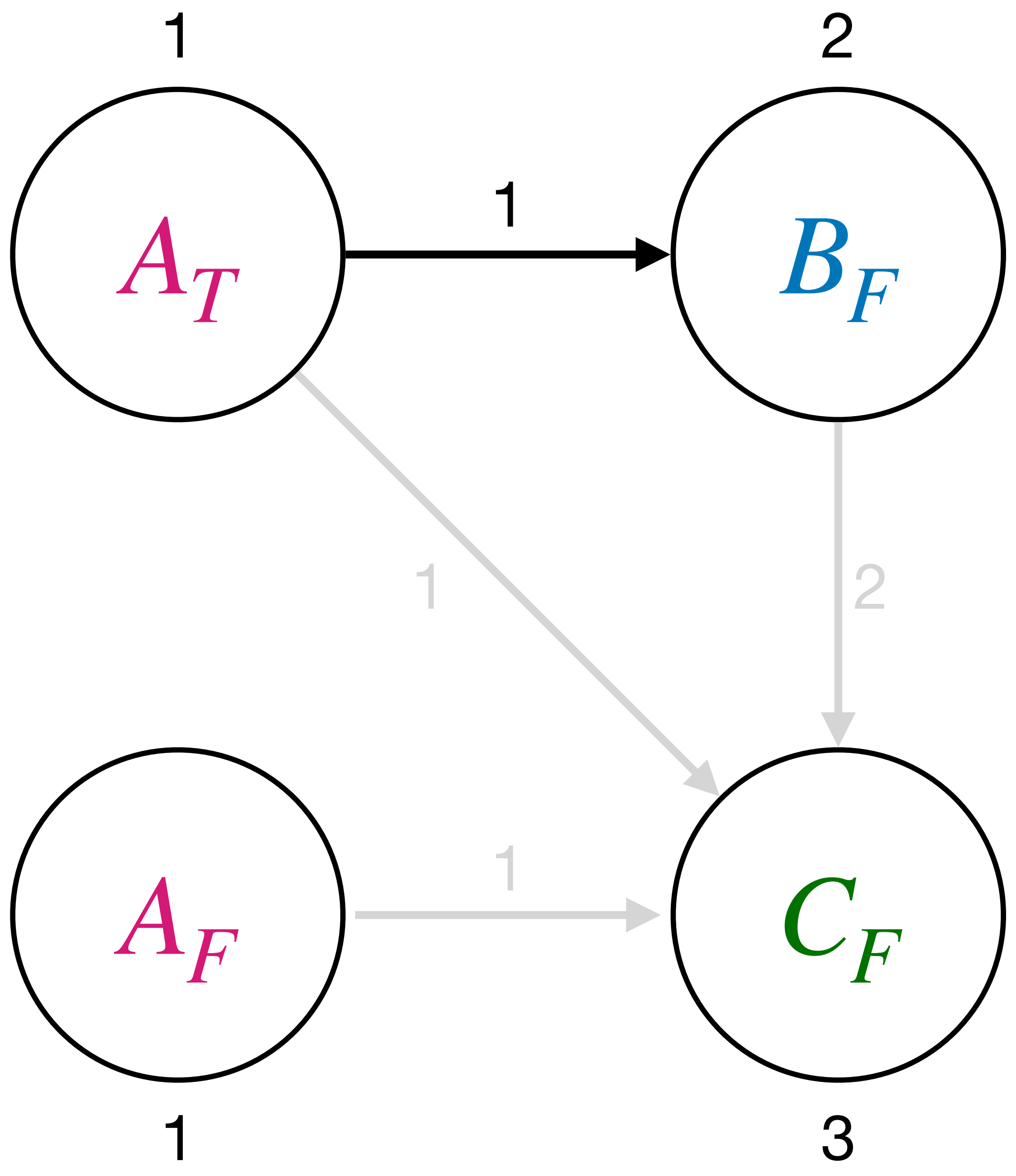


Naive Causal Reasoning

Eliminate non-causal relationships.



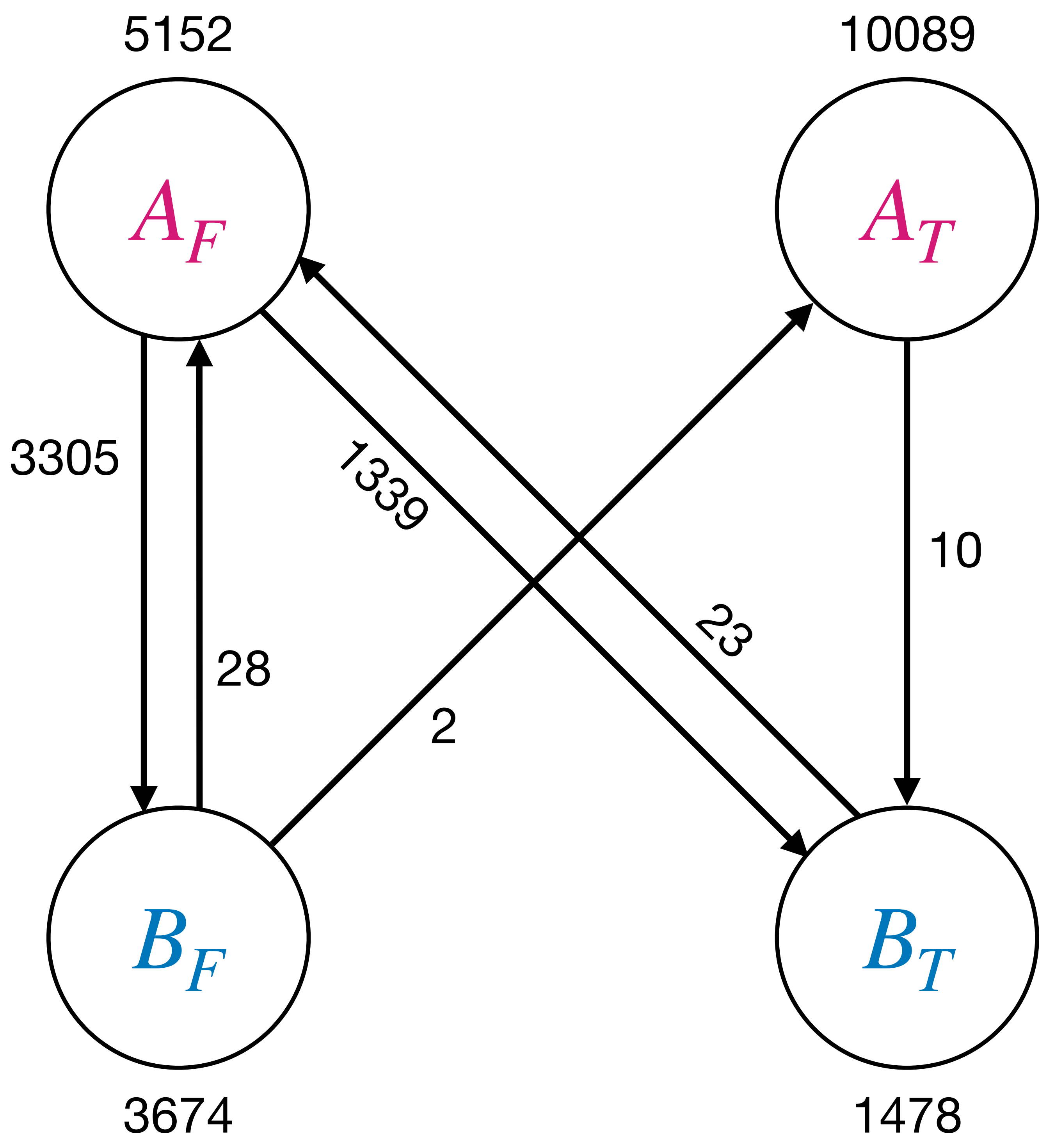
Causal Graph



Meanwhile, in the real world…

- Real data has **noise**
  - Bugs in the logging pipeline
  - Crossed signals (app/version differences)
  - Code drift
  - Coincidences

- We can't eliminate all sources of noise
- We can't use naive reasoning on noisy data
- Which relationships are true and causal?



Noisy real-world co-occurence graph

Causal Reasoning with Probabilities

- How likely is it that B will be queried if A has the value x?

$$P(B \mid A_x) = \frac{P(A_x \cap B)}{P(A_x)} = \frac{\text{co-occurrences of } A_x \text{ with } B}{\text{total occurrences of } A_x}$$

Causal Reasoning with Probabilities

- How likely is it that B will be queried if A has the value x?

$$P(B \mid A_x) = \frac{P(A_x \cap B)}{P(A_x)} = \frac{\text{co-occurrences of } A_x \text{ with } B}{\text{total occurrences of } A_x}$$

- How likely is it that A had the value x if we know that B was queried?

$$P(A_x \mid B) = \frac{P(A_x \cap B)}{P(B)} = \frac{\text{co-occurrences of } A_x \text{ with } B}{\text{total occurrences of } B}$$

Causal Reasoning with Probabilities

What are the expected probabilities of a real causal relationship?

```
if (A) {B}
```

Causal Reasoning with Probabilities

What are the expected probabilities of a real causal relationship?

```
if (A) {B}
```

$$P(B \mid A_T) = 1$$

Causal Reasoning with Probabilities

What are the expected probabilities of a real causal relationship?

```
if (A) {B}
```

$$P(B \mid A_T) = 1$$

$$P(B \mid A_F) = 0$$

Causal Reasoning with Probabilities

What are the expected probabilities of a real causal relationship?

```
if (A) {B}
```

$$P(B \mid A_T) = 1$$

$$P(B \mid A_F) = 0$$

$$P(A_T \mid B) = 1$$

Causal Reasoning with Probabilities

What are the expected probabilities of a real causal relationship?

```
if (A) {B}
```

$$P(B \mid A_T) = 1$$
$$P(B \mid A_F) = 0$$
$$P(A_T \mid B) = 1$$
$$P(A_F \mid B) = 0$$

Causal Reasoning with Probabilities

What are the expected probabilities of a real causal relationship?

```
if (A) {B}

if (A) {X}
if (A && X) {B}
```

other children of A

$$P(B \mid A_T) = 1 - \alpha$$

$$P(B \mid A_F) = 0$$

$$P(A_T \mid B) = 1$$

$$P(A_F \mid B) = 0$$

Causal Reasoning with Probabilities

What are the expected probabilities of a real causal relationship?

```
if (A) {B}

if (A) {X}
if (A && X) {B}

if (X) {B}
if (X || A) {B}
```

$$P(B \mid A_T) = 1 - \alpha$$

other children of A

$$P(B \mid A_F) = 0$$

$$P(A_T \mid B) = 1 - \beta$$

$$P(A_F \mid B) = 0$$

other parents of B

Causal Reasoning with Probabilities

What are the expected probabilities of a real causal relationship?

`if (A) {B}`

$A_T \rightarrow B$

$$P(B \mid A_T) \approx 1$$

$$P(B \mid A_F) \approx 0$$

$$P(A_T \mid B) \approx 1$$

$$P(A_F \mid B) \approx 0$$

Causal Reasoning with Probabilities

What are the expected probabilities of a real causal relationship?

`if (A) {B}`

$A_T \rightarrow B$

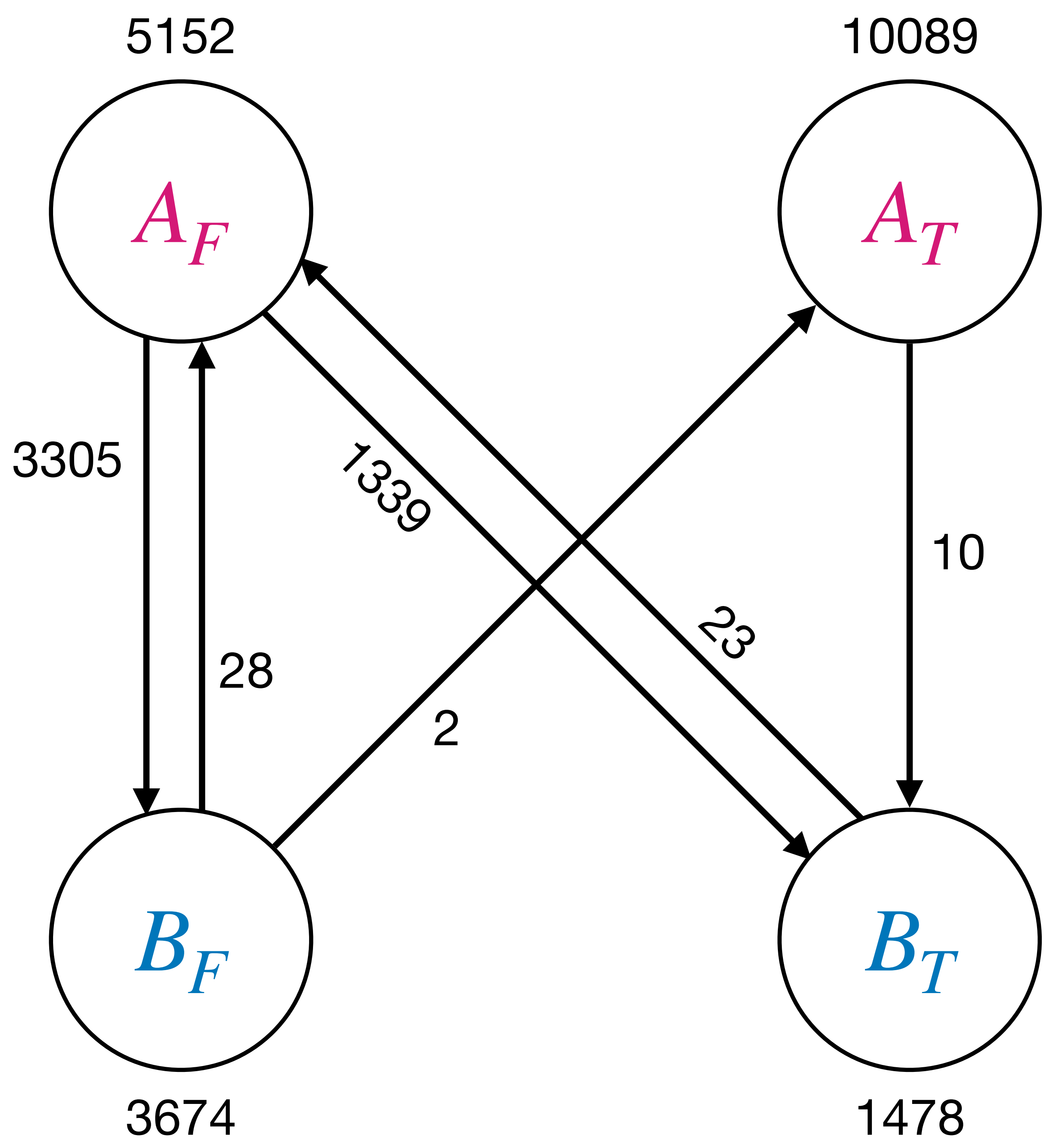
$$P(B \mid A_T) \approx 1$$
$$P(B \mid A_F) \approx 0$$
$$P(A_T \mid B) \approx 1$$
$$P(A_F \mid B) \approx 0$$

`if (!A) {B}`

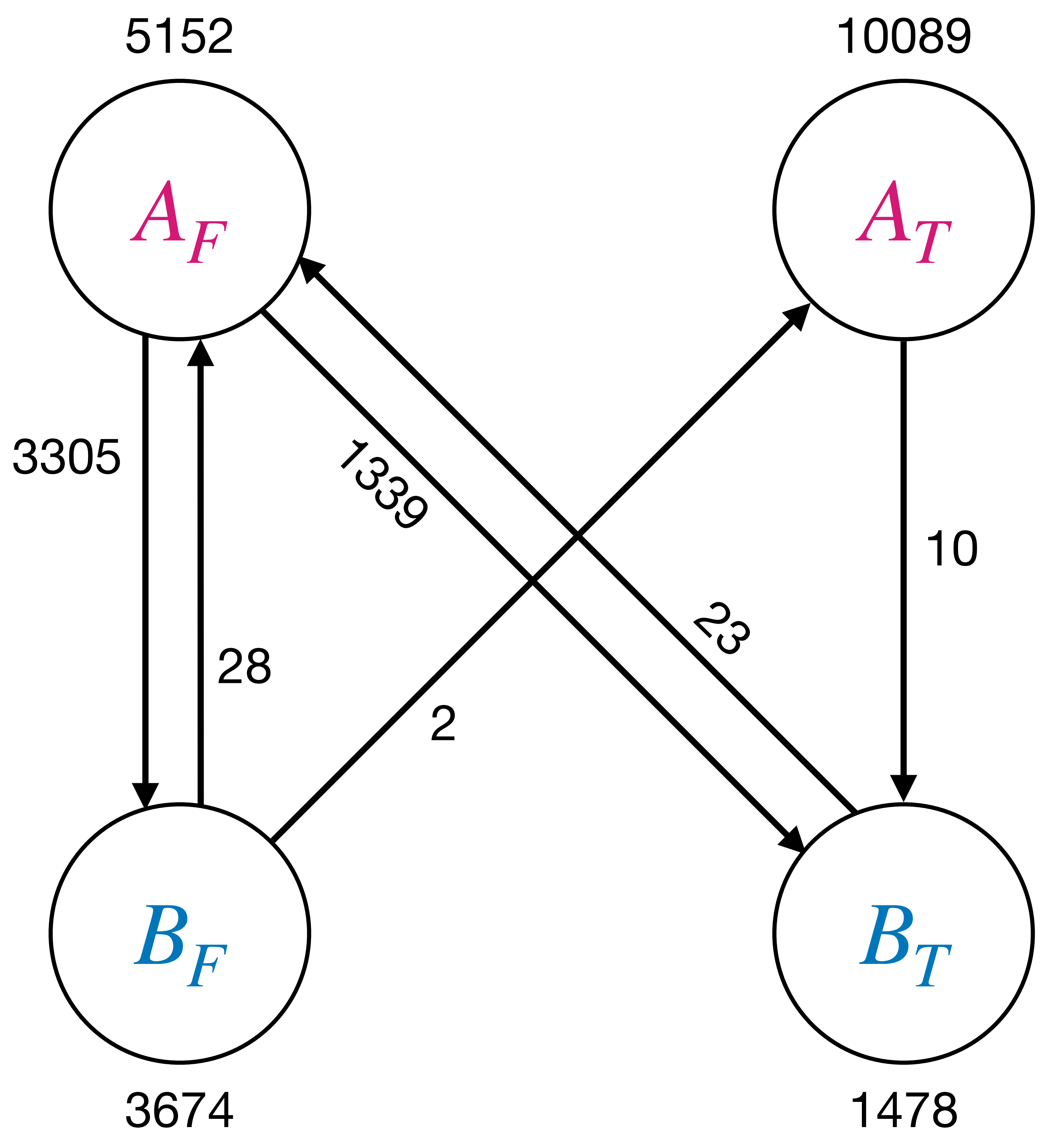
$A_F \rightarrow B$

$$P(B \mid A_T) \approx 0$$
$$P(B \mid A_F) \approx 1$$
$$P(A_T \mid B) \approx 0$$
$$P(A_F \mid B) \approx 1$$

Causal Reasoning with Probabilities



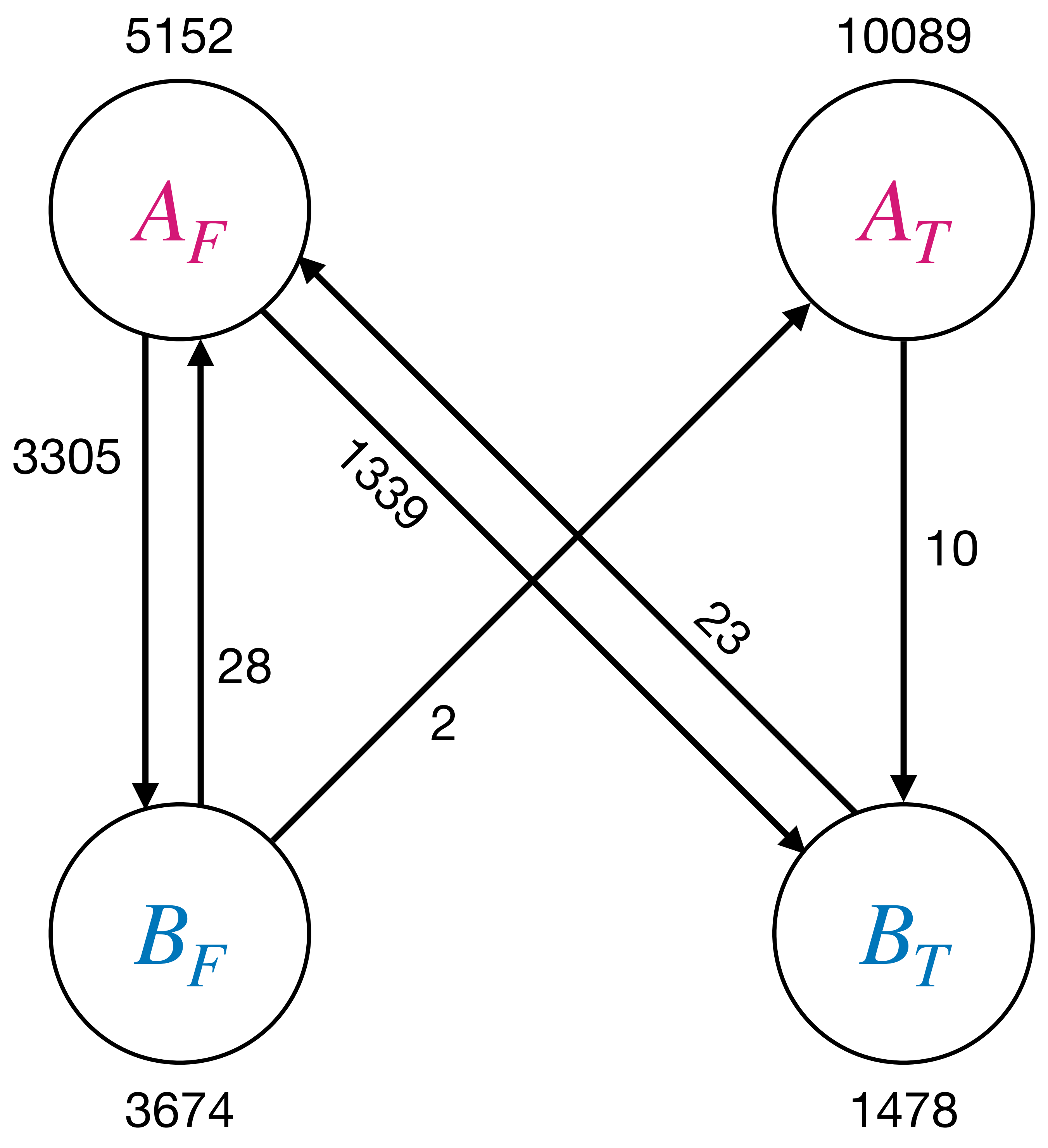
Causal Reasoning with Probabilities



$$P(B \mid A_T) = 10/10089$$
$$P(B \mid A_F) = (3305 + 1339)/5152$$
$$P(A_T \mid B) = 10/(3674 + 1478)$$
$$P(A_F \mid B) = (3305 + 1339)/(3674 + 1478)$$

$$P(A \mid B_T) = 23/1478$$
$$P(A \mid B_F) = (28 + 2)/3674$$
$$P(B_T \mid A) = 23/(5152 + 10089)$$
$$P(B_F \mid A) = (28 + 2)/(5152 + 10089)$$

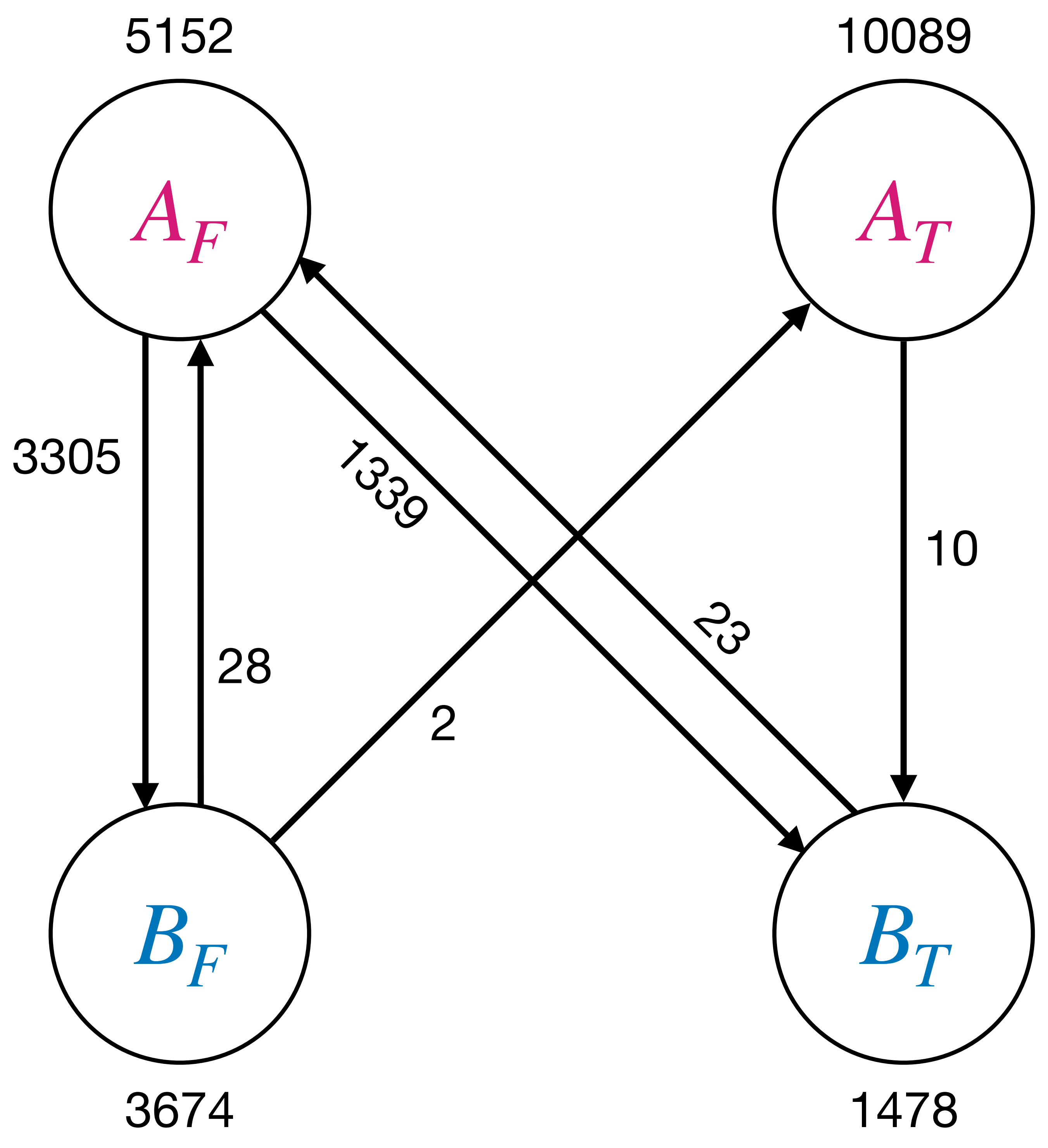
Causal Reasoning with Probabilities



$$P(B \mid A_T) \approx 0.00$$
$$P(B \mid A_F) \approx 0.90$$
$$P(A_T \mid B) \approx 0.00$$
$$P(A_F \mid B) \approx 0.90$$

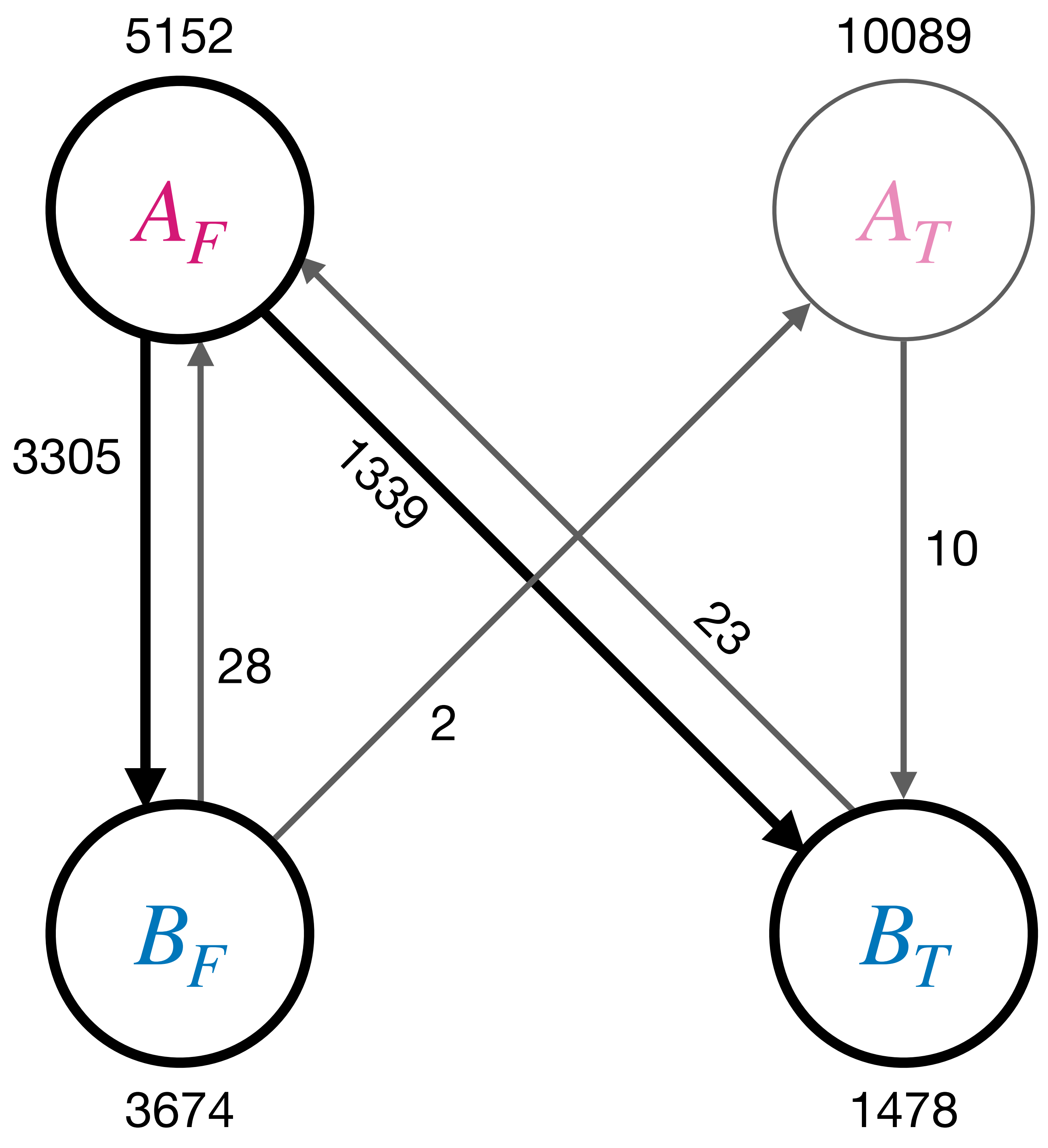
$$P(A \mid B_T) \approx 0.02$$
$$P(A \mid B_F) \approx 0.01$$
$$P(B_T \mid A) \approx 0.00$$
$$P(B_F \mid A) \approx 0.00$$

Causal Reasoning with Probabilities



	$A_T \to B$	$A_F \to B$
$P(B \mid A_T) \approx 0.00$	1	0
$P(B \mid A_F) \approx 0.90$	0	1
$P(A_T \mid B) \approx 0.00$	1	0
$P(A_F \mid B) \approx 0.90$	0	1
$P(A \mid B_T) \approx 0.02$	1	0
$P(A \mid B_F) \approx 0.01$	0	1
$P(B_T \mid A) \approx 0.00$	1	0
$P(B_F \mid A) \approx 0.00$	0	1
	$B_T \to A$	$B_F \to A$

Causal Reasoning with Probabilities



	$A_T \to B$	$A_F \to B$
$P(B \mid A_T) \approx 0.00$	1	0
$P(B \mid A_F) \approx 0.90$	0	1
$P(A_T \mid B) \approx 0.00$	1	0
$P(A_F \mid B) \approx 0.90$	0	1
$P(A \mid B_T) \approx 0.02$	1	0
$P(A \mid B_F) \approx 0.01$	0	1
$P(B_T \mid A) \approx 0.00$	1	0
$P(B_F \mid A) \approx 0.00$	0	1
	$B_T \to A$	$B_F \to A$

Causal Reasoning with Probabilities

- Assuming A is a feature flag with k possible values and A occurs before B
- For each possible $A_i \rightarrow B$ we can compute an error value

$$E_i = \frac{1}{k+2}\left(\left(1 - \frac{A_iB}{A_i}\right) + \sum_{j \neq i}^{k} \frac{A_jB}{A_j} + \left(1 - \frac{A_iB}{B}\right) + \sum_{j \neq i}^{k} \frac{A_jB}{B}\right)$$

Causal Reasoning with Probabilities

- Assuming A is a feature flag with k possible values and A occurs before B
- For each possible $A_i \to B$ we can compute an error value

$$E_i = \frac{1}{k+2}\left(\left(1 - \frac{A_iB}{A_i}\right) + \sum_{j\neq i}^{k} \frac{A_jB}{A_j} + \left(1 - \frac{A_iB}{B}\right) + \sum_{j\neq i}^{k} \frac{A_jB}{B}\right)$$

- $E = \min E_i$ is the overall error for $A \to B$

Causal Reasoning with Probabilities

- Assuming A is a feature flag with k possible values and A occurs before B
- For each possible $A_i \rightarrow B$ we can compute an error value

$$E_i = \frac{1}{k+2}\left(\left(1 - \frac{A_iB}{A_i}\right) + \sum_{j \neq i}^{k} \frac{A_jB}{A_j} + \left(1 - \frac{A_iB}{B}\right) + \sum_{j \neq i}^{k} \frac{A_jB}{B}\right)$$

- $E = \min E_i$ is the overall error for $A \rightarrow B$
- $N = \min\left(A_1, \ldots, A_k, B\right)$ is our confidence in E

Causal Reasoning with Probabilities

- Assuming A is a feature flag with k possible values and A occurs before B
- For each possible $A_i \rightarrow B$ we can compute an error value

$$E_i = \frac{1}{k+2}\left(\left(1 - \frac{A_iB}{A_i}\right) + \sum_{j \neq i}^{k} \frac{A_jB}{A_j} + \left(1 - \frac{A_iB}{B}\right) + \sum_{j \neq i}^{k} \frac{A_jB}{B}\right)$$

- $E = \min E_i$ is the overall error for $A \rightarrow B$
- $N = \min\left(A_1, \ldots, A_k, B\right)$ is our confidence in E

empirically
determined
thresholds

$$\boxed{A \rightarrow B \quad \text{if } k \geq 2 \text{ and } E \leq \hat{E} \text{ and } N \geq \hat{N}}$$

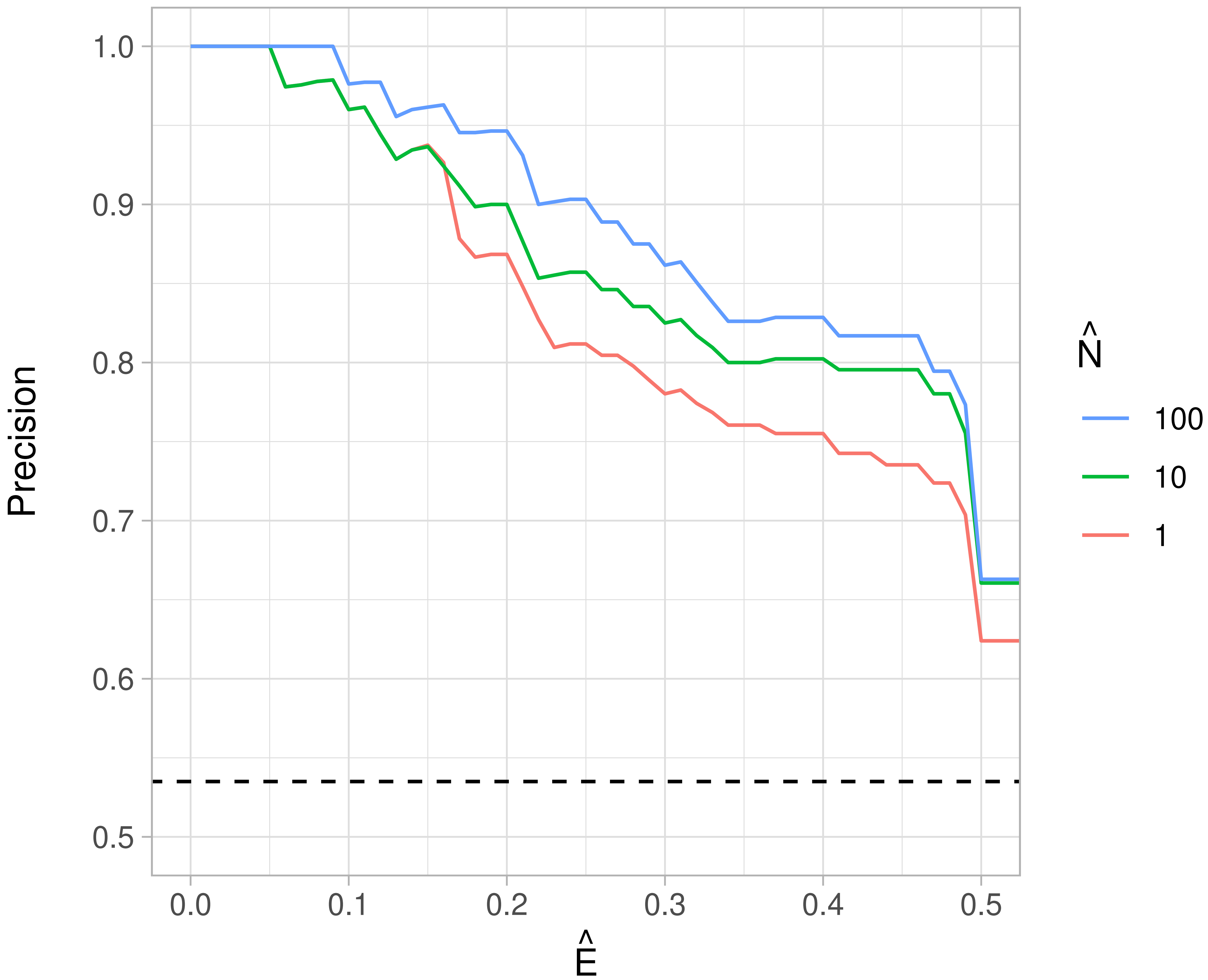
Evaluation

More in the paper!

- Precision
  - 90% at $\hat{E} = 0.25$ and $\hat{N} = 100$
  - 66% at $\hat{E} = 0.50$ and $\hat{N} = 100$

due to co-occurrence discovery

- Recall
  - no *a priori* ground truth
  - indicators of non-trivial recall



Interdependency Patterns

More in the paper!

- Can we identify re-occuring relationship patterns?
- Potential indicators of coupling/complexity
- Future Work

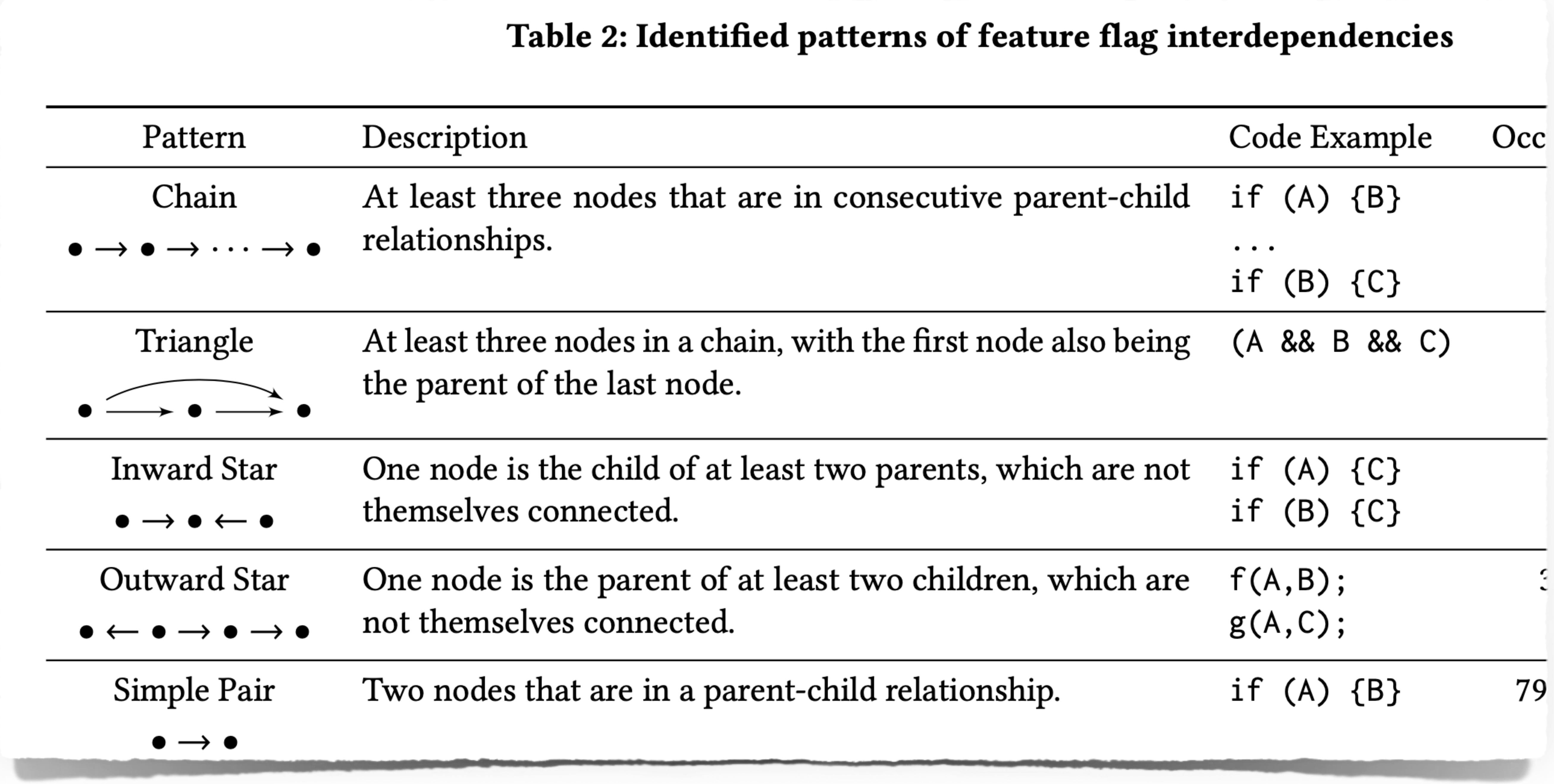
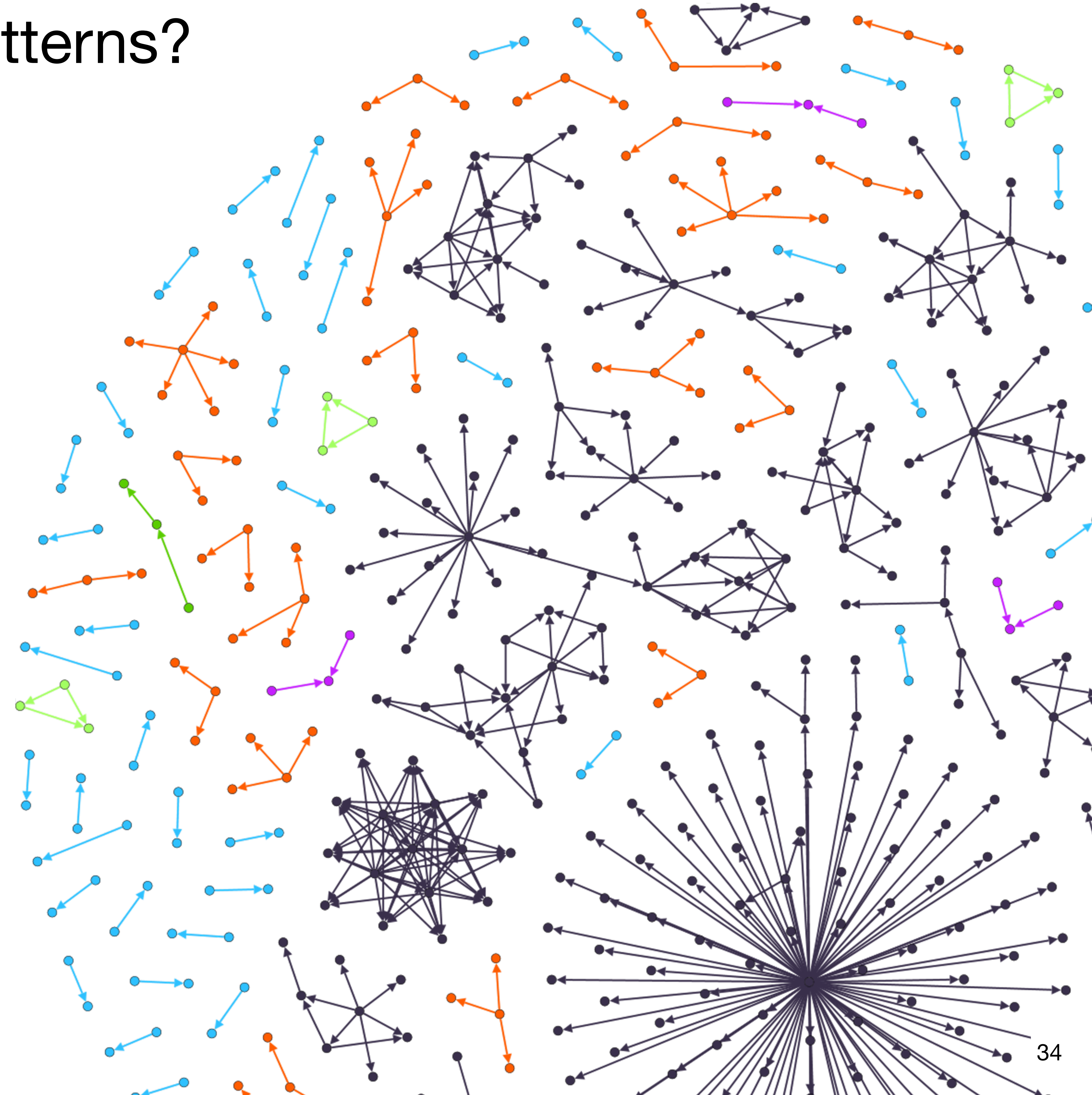


Table 2: Identified patterns of feature flag interdependencies

Pattern	Description	Code Example	Occ

Chain
• → • → ··· → •
	At least three nodes that are in consecutive parent-child relationships.	`if (A) {B}`
		`...`
		`if (B) {C}`	

Triangle • ⟶ • ⟶ •	At least three nodes in a chain, with the first node also being the parent of the last node.	`(A && B && C)`	
Inward Star • → • ← •	One node is the child of at least two parents, which are not themselves connected.	`if (A) {C}` `if (B) {C}`	
Outward Star • ← • → • → •	One node is the parent of at least two children, which are not themselves connected.	`f(A,B);` `g(A,C);`	3
Simple Pair • → •	Two nodes that are in a parent-child relationship.	`if (A) {B}`	79



Discovering Feature Flag Interdependencies in Microsoft Office

https://mcschroeder.github.io/#fse2022

Michael Schröder
TU Wien
Vienna, Austria
michael.schroeder@tuwien.ac.at

Katja Kevic
Microsoft
Cambridge, UK
katja.kevic@microsoft.com

Dan Gopstein
Microsoft
New York, USA
dan.gopstein@microsoft.com

Brendan Murphy
Microsoft
Cambridge, UK
brendan.murphy@microsoft.com

Jennifer Beckmann
Microsoft
Redmond, USA
jennifer.beckmann@microsoft.com

ESEC/FSE 2022, Industry Track
Singapore

Microsoft

TU WIEN Informatics