

Quantitative Methods to Measure the Risk of Re-identification: Methodology Review

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A Very Simplified View on Risk

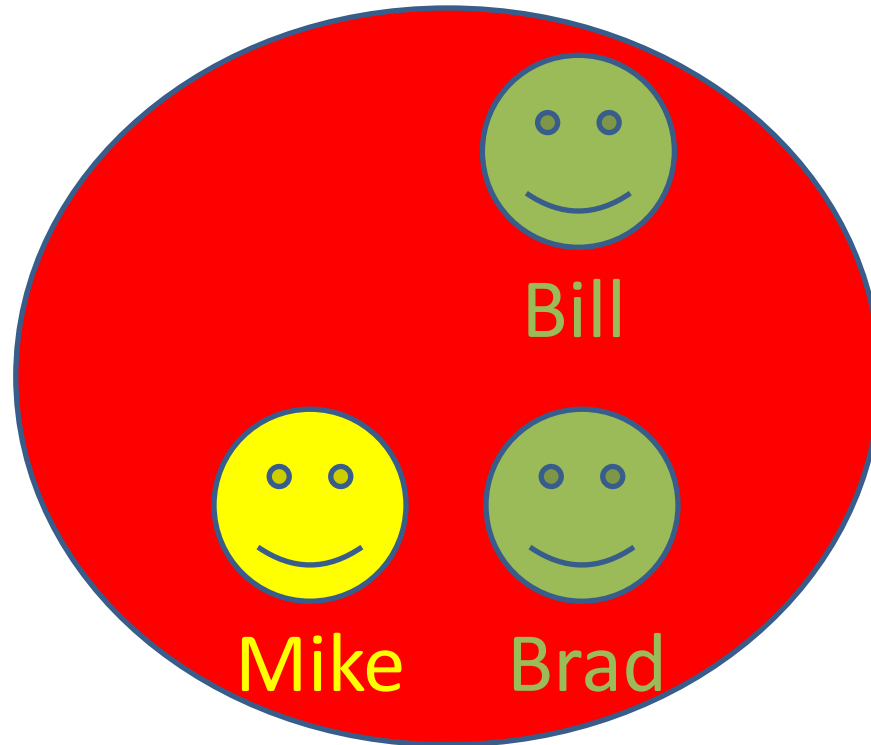
$P(reid) \approx$



- *Distinguishability*
- Replicability
- Availability

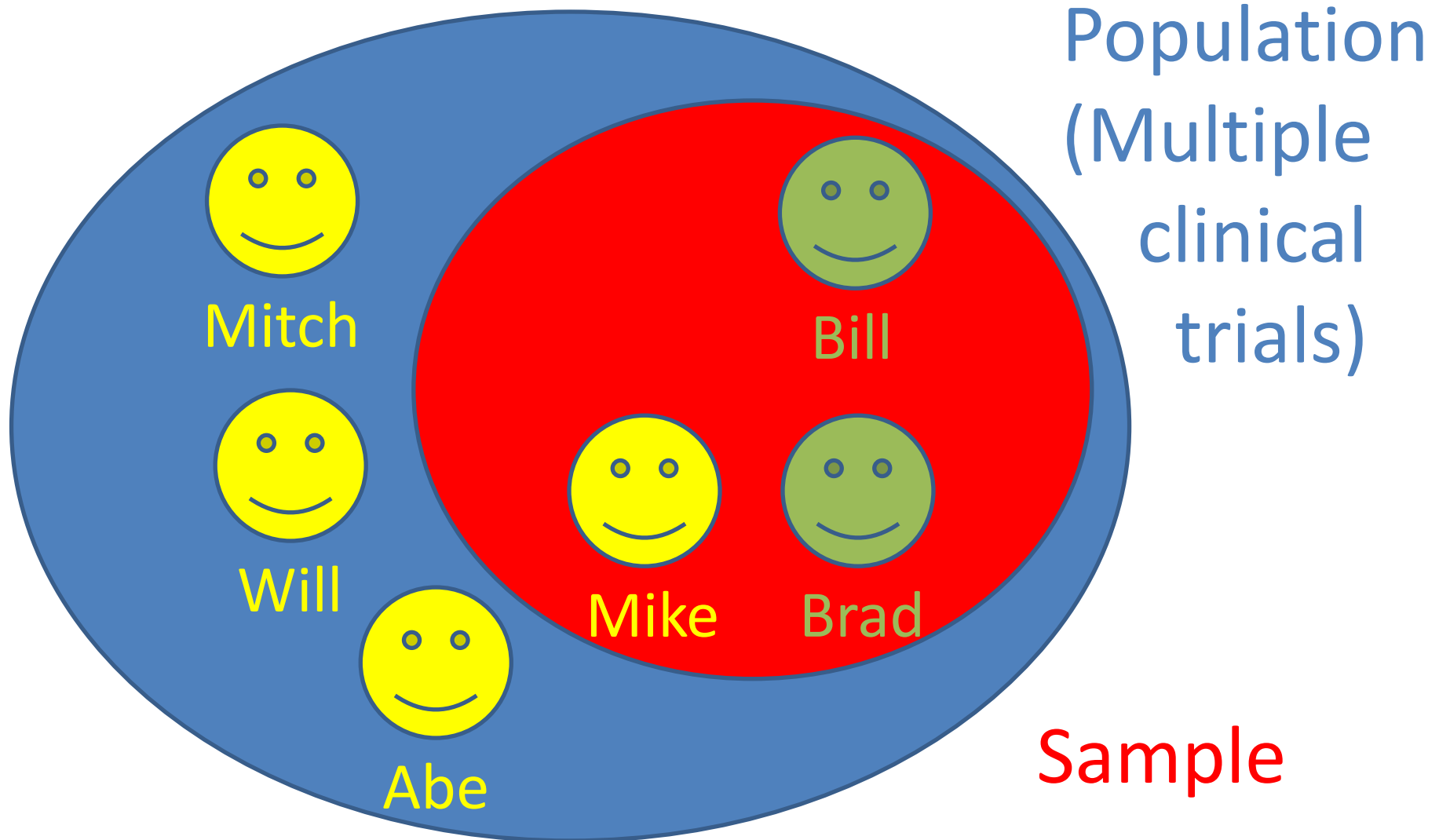
Data

Risk is Contextual

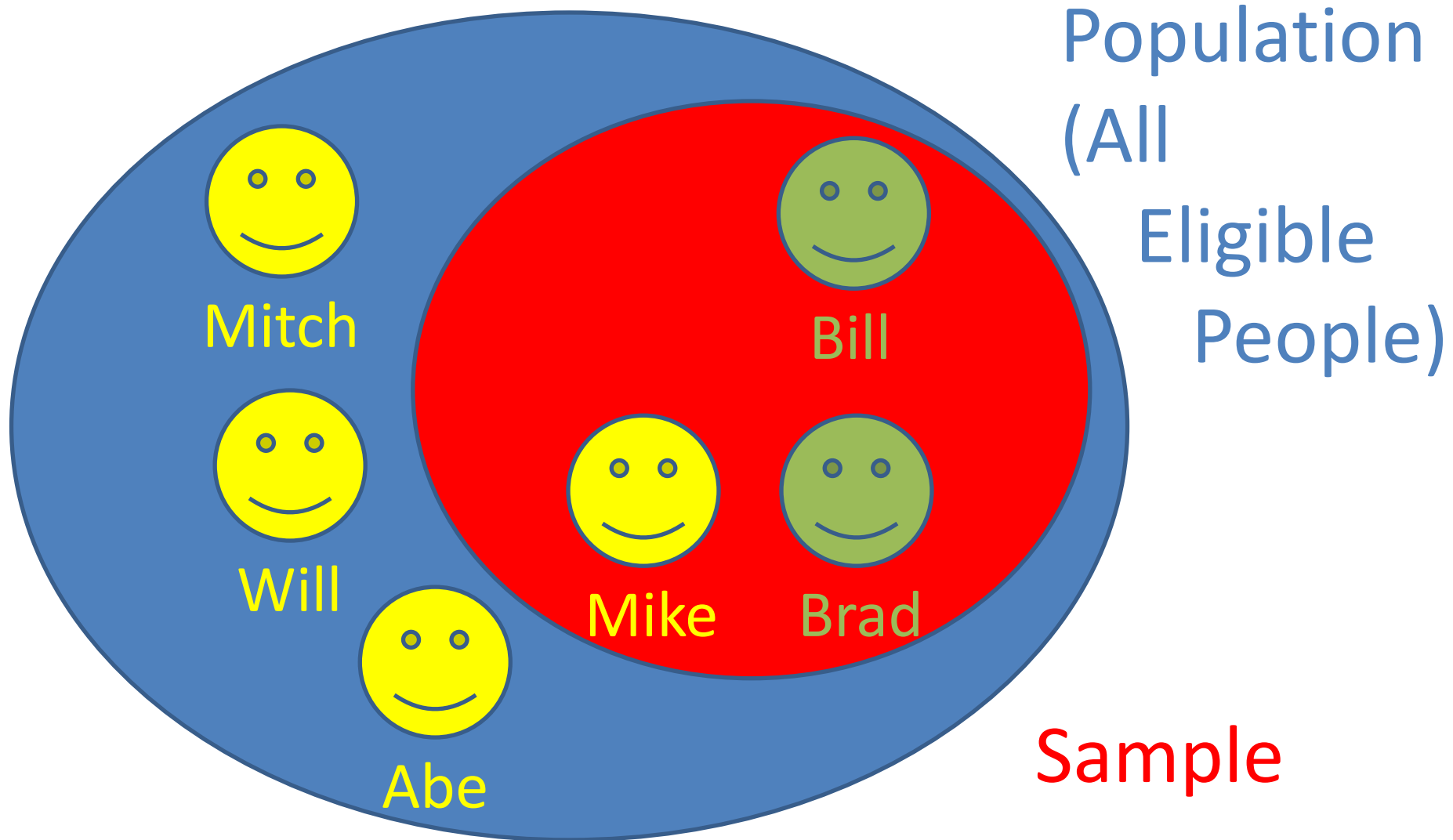


Sample

Risk is Contextual



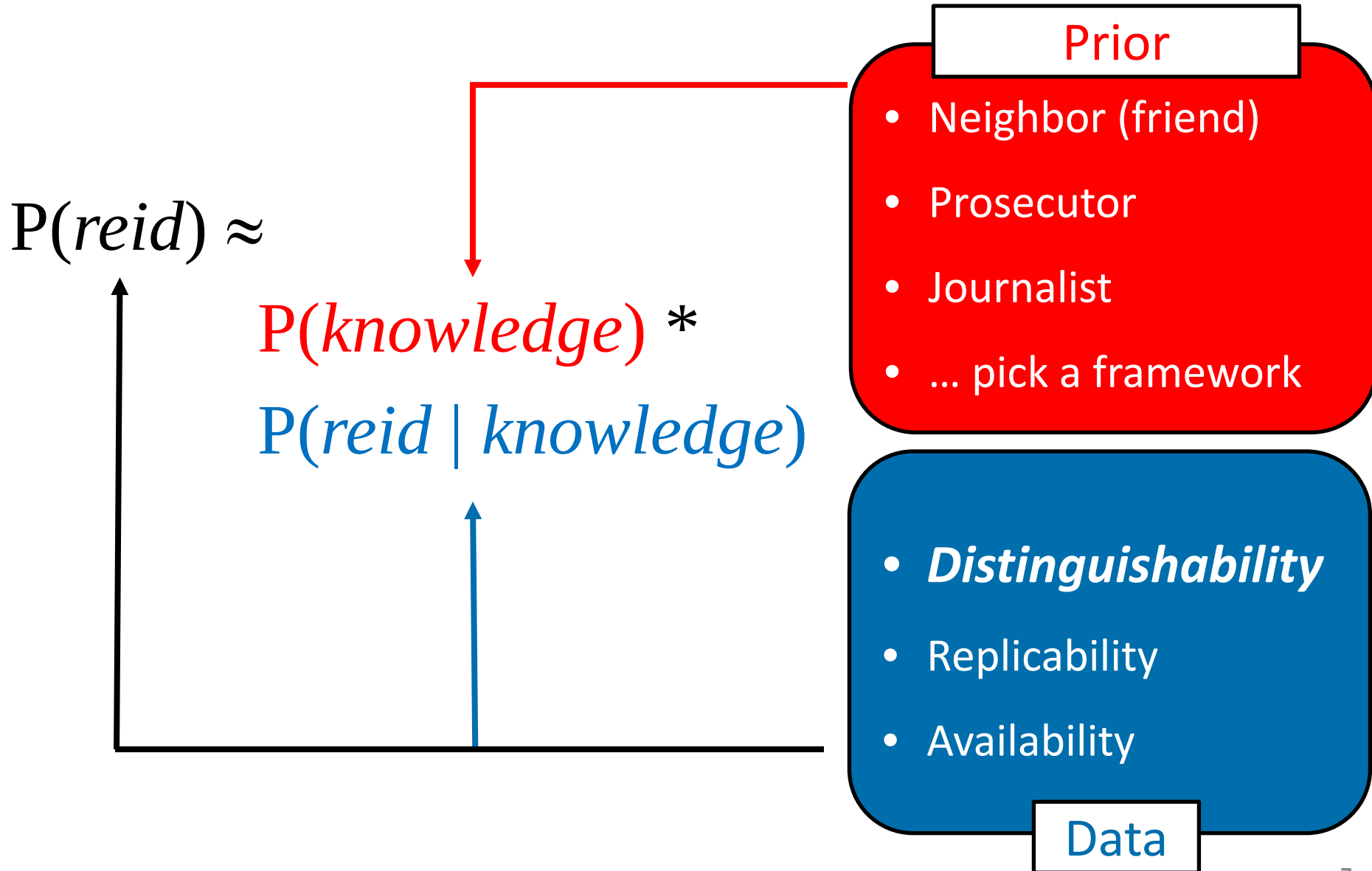
Risk is Contextual



Risk Measures

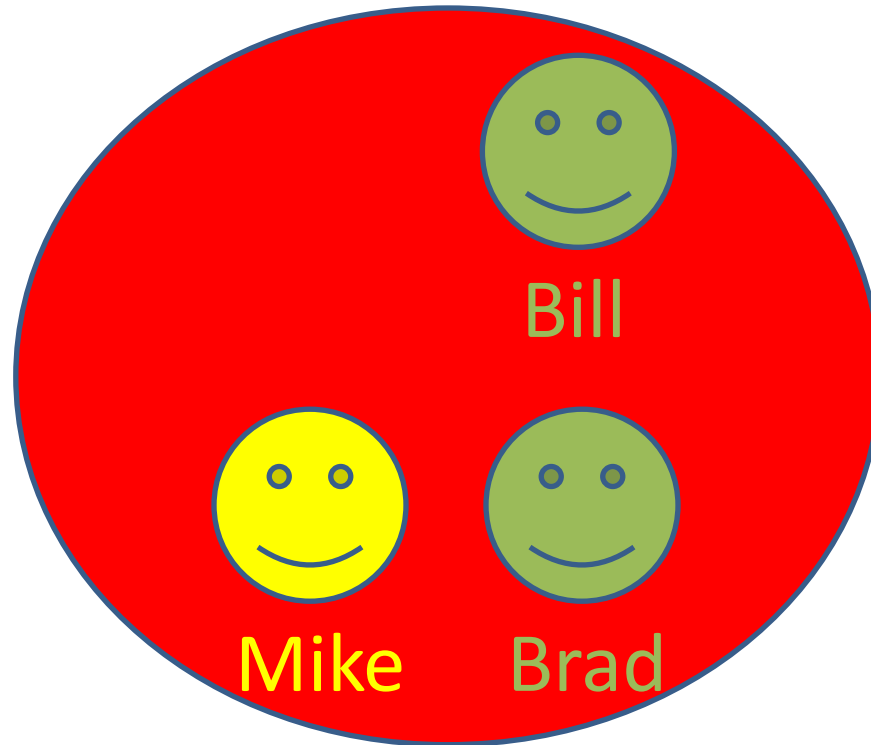
- Worst Case Risk Measures
 - **Prosecutor**: Most risky record in the *sample*
 - **Journalist**: Most risky record in the *population*
- Amortized (or Average) Measure
 - **Marketer**: Expected risk of an arbitrary record

A Very Simplified View on Risk



Prosecutor Risk

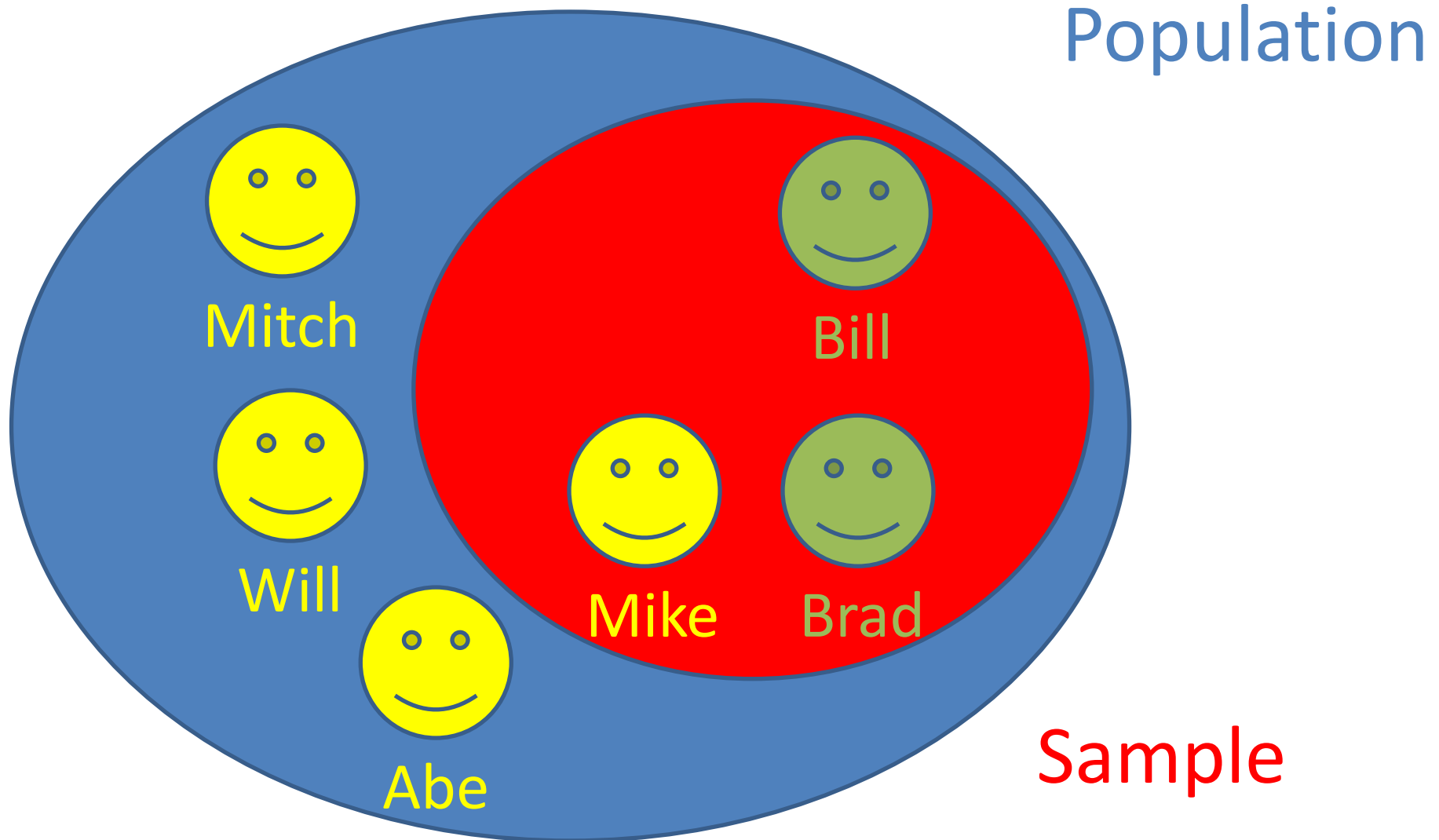
1 (Because of Mike)



Sample

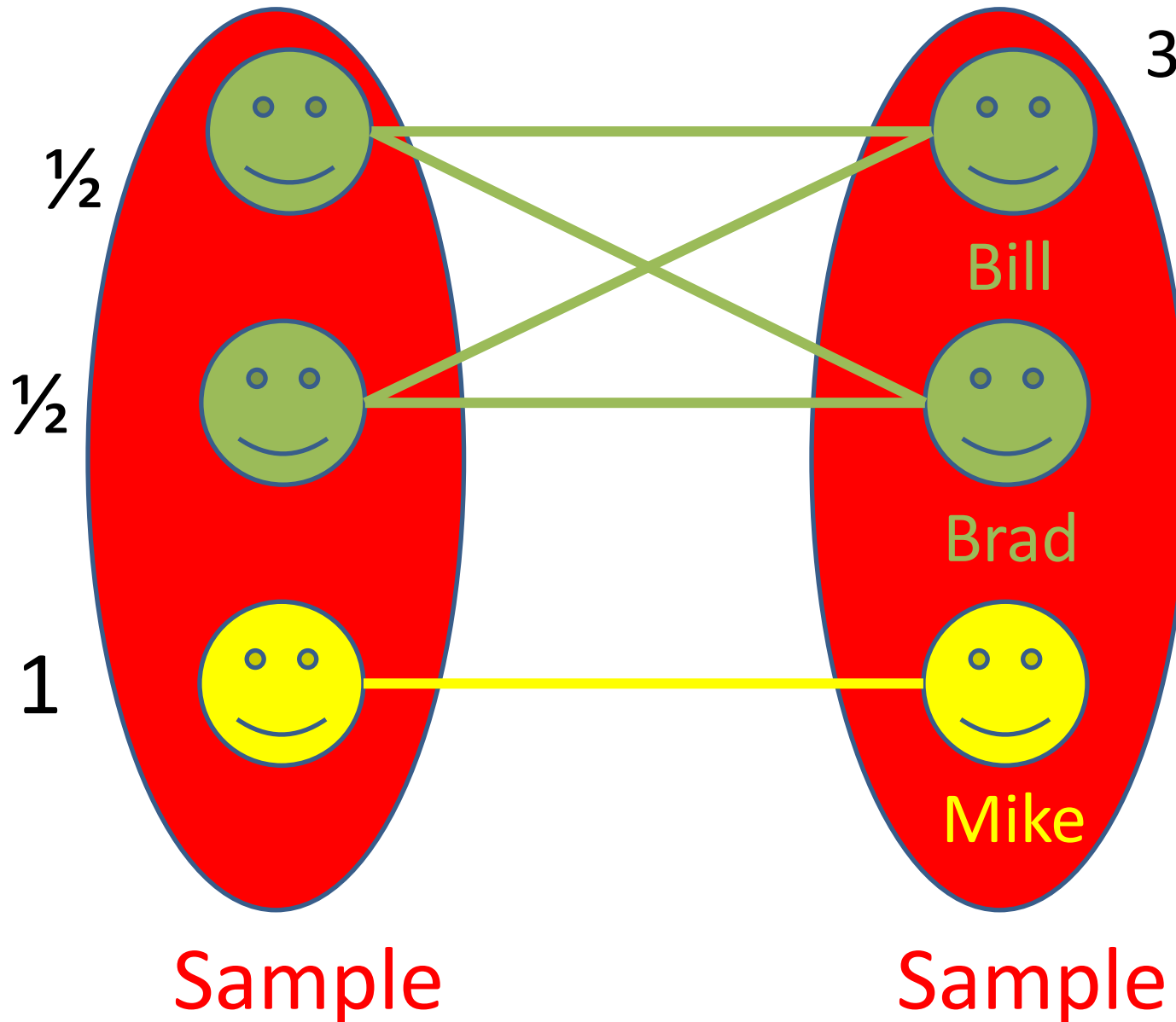
Journalist Risk

$\frac{1}{2} = 0.5$ (Because of Bill & Brad)



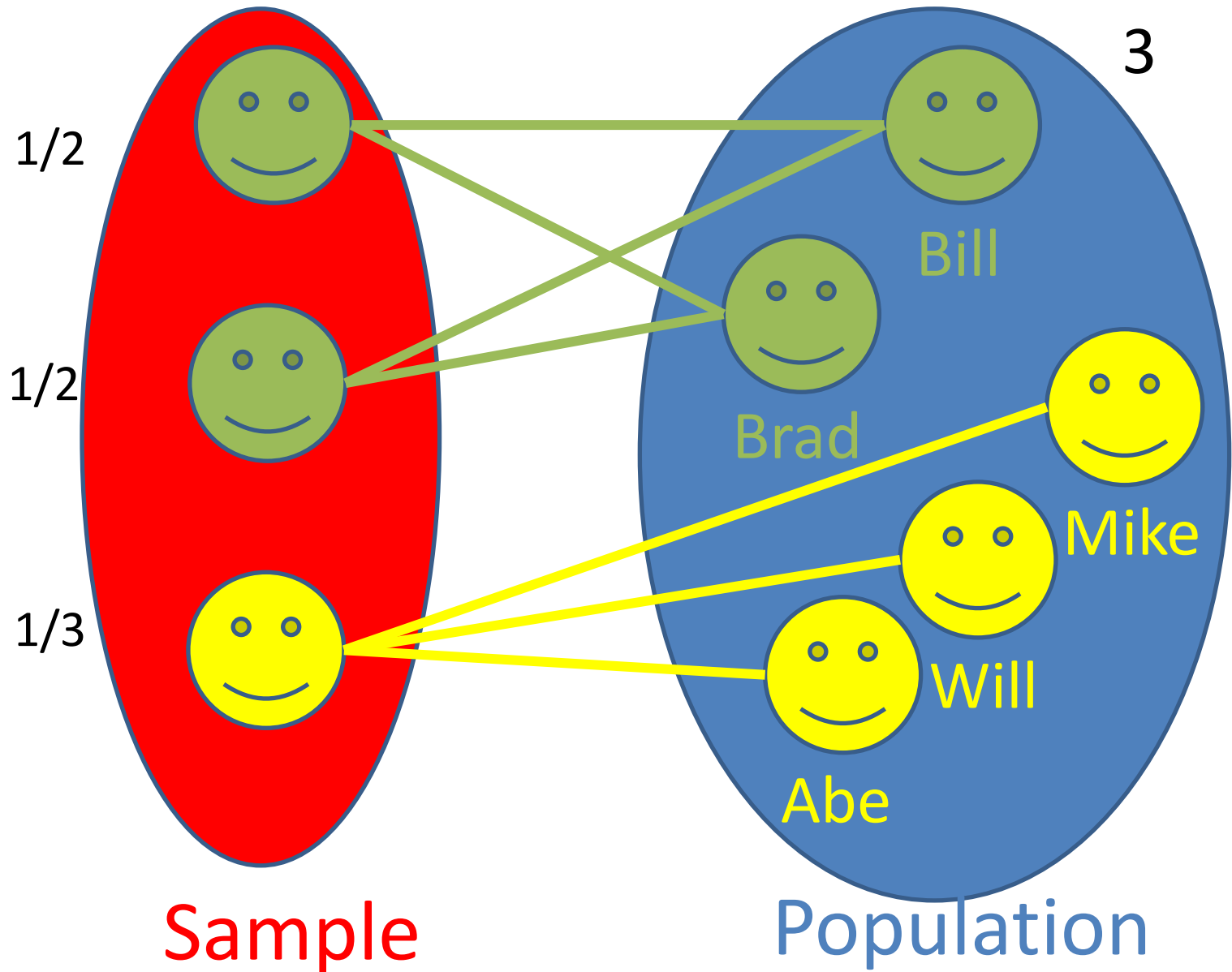
Marketer Risk (Sample)

$$\frac{\frac{1}{2} + \frac{1}{2} + 1}{3} = \frac{2}{3}$$

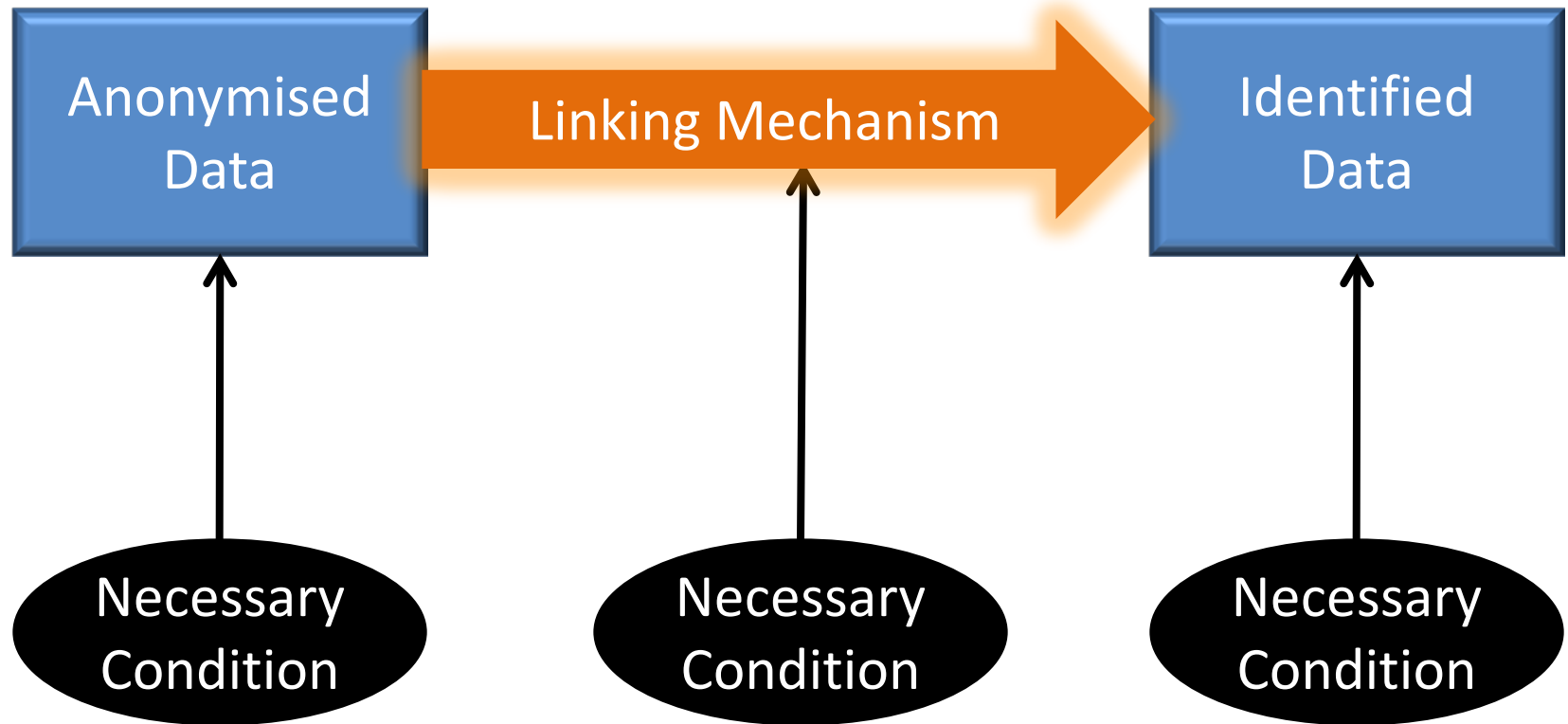


Marketer Risk (Population)

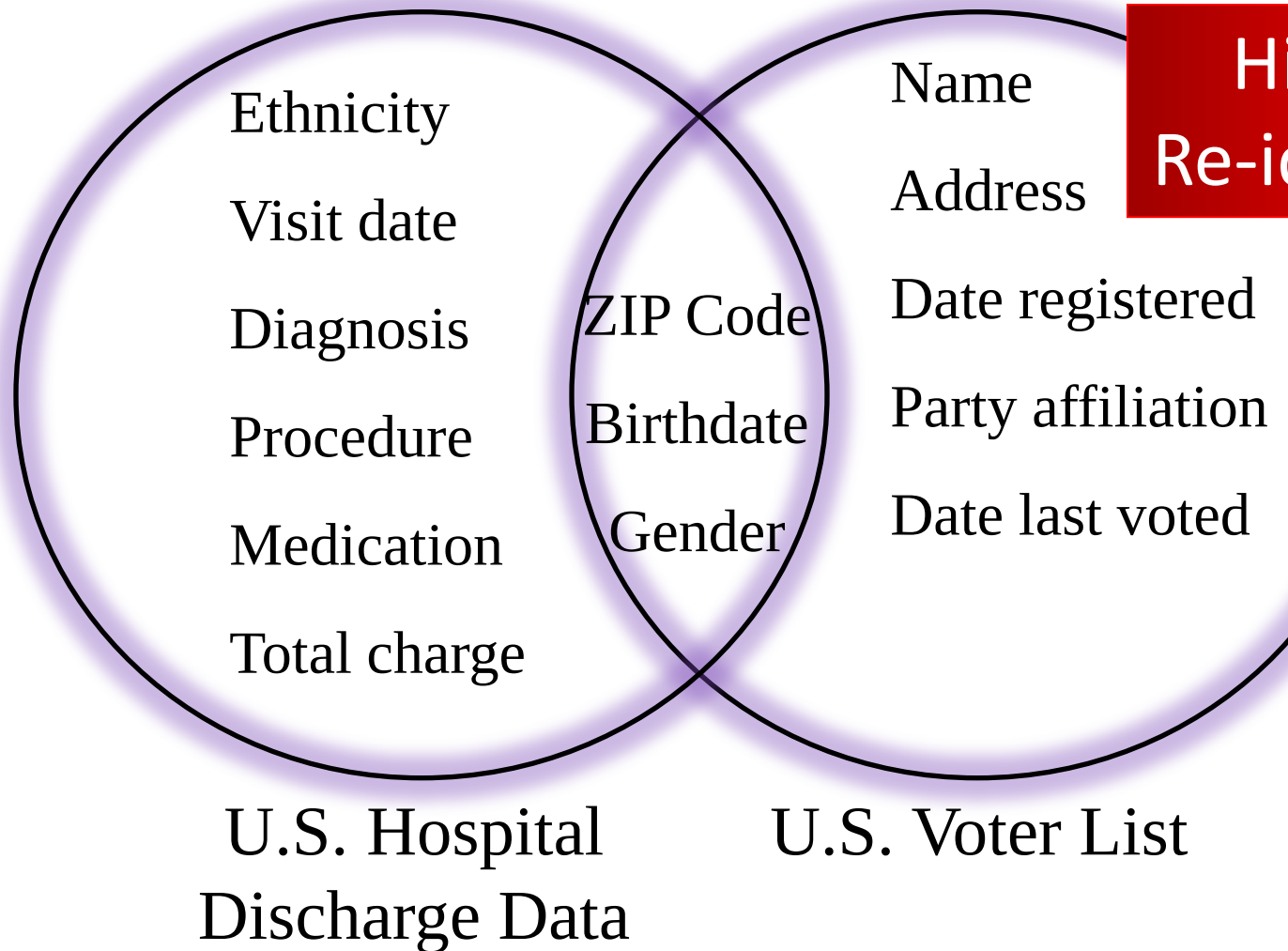
$$\frac{.5 + .5 + .33}{3} = .44$$



Central Dogma of Re-identification



A Famous Linkage Attack



**High Profile
Re-identification**



But availability of Demographics Varies...

	IL	MN	TN	WA	WI
WHO	Registered Political Committees (ANYONE – In Person)	MN Voters	Anyone	Anyone	Anyone
Format	Disk	Disk	Disk	Disk	Disk
Cost	\$500	\$46; “use ONLY for elections, political activities, or law enforcement”	\$2500	\$30	\$12,500
Name	●	●	●	●	●
Address	●	●	●	●	●
Date of Birth	●	○	●	●	
Sex	●		●	●	
Race			●		
Phone Number	●	●			

Adversaries are Not All Knowing

- Research subject demographics
 - Unique (potential)
 - Replicable
 - Available
- Series of drug doses administered
 - Unique (potential)
 - Not replicable
 - Not available

Adversaries are Not All Knowing

(Assume knowledge between x and y features)

Feature	Observation
Date of Birth	1/1/1970
Gender	Male
Race	White
Country	France
Death	Yes
Occupation	Teacher
Married	Yes

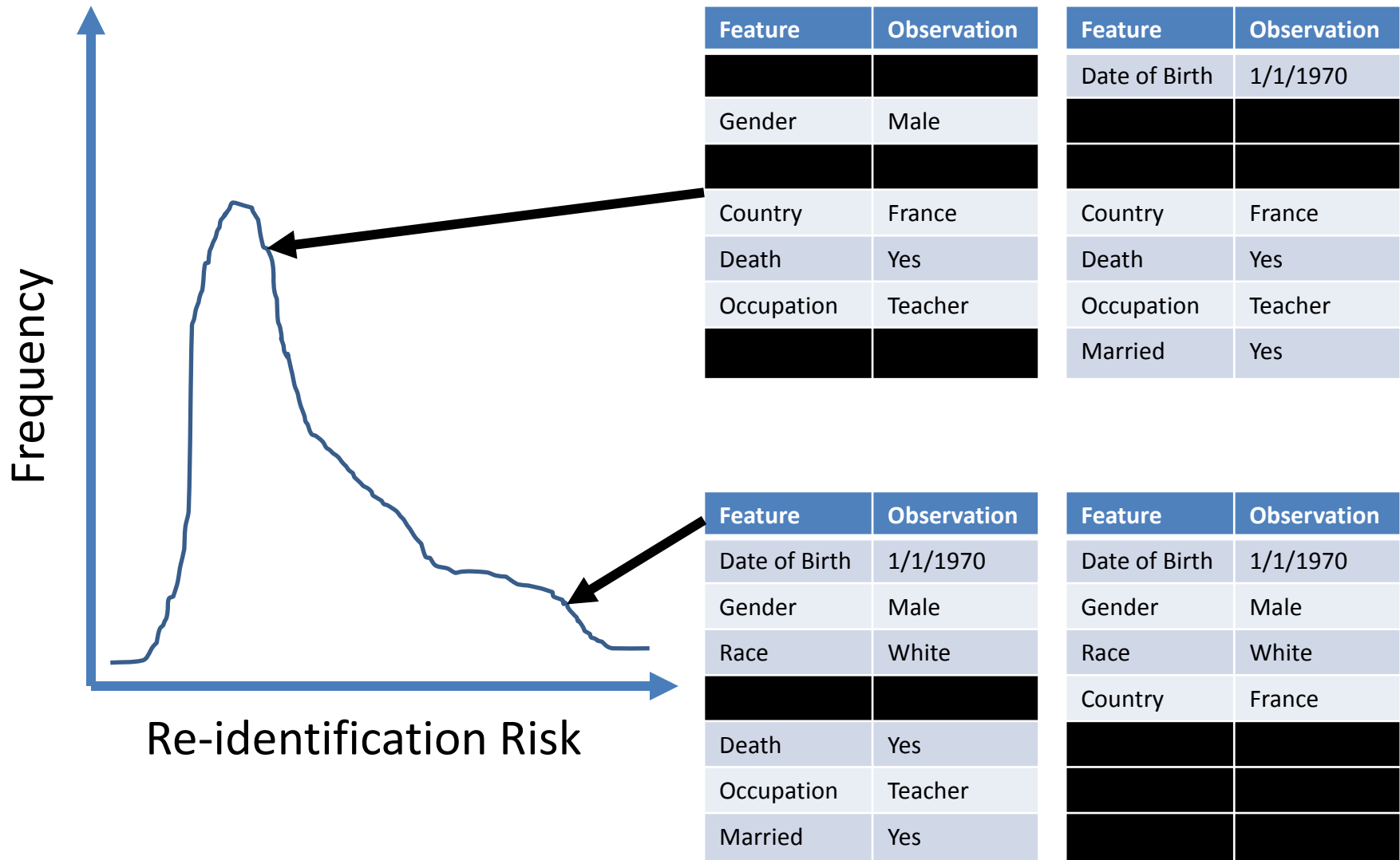
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... Which Means No Single Risk Score



You May Not See Everything

- Field structured databases – you can issue exact queries!
- Semi-structured reports and narratives – you must rely on a mix of
 - Artificial intelligence
 - Human review
 - Sampling
- Problem has become a bit more tricky because leaks can now include *explicitly identifying* values

A Natural Language Setting

Original PHI

Smith, 61 yo ...
daughter, Lynn, to ...
oncologist Dr. White ...
5/13/10 to consider ...
SWOG protocol 1811, ...
was randomized 5/10 ...
to call Mr. Smith on ...
PLAN: Dr White and I ...

- Create a Gold Standard Dataset
 - Ask X humans to read and label a selection of records
 - Ensure concordance between human annotations (e.g., via a Cohen's Kappa)
- Apply (manual or automated) identifier detection strategy
- Compute performance in terms of:
 - (R)ecall – rate at which real identifier instances were detected
 - (P)recision – rate at which claimed identifiers are in fact real
 - F-measure – weighted average of R and P

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was randomized 5/10 ...
to call Mr. Smith on ...
PLAN:Dr White and I ...

****Redacted PHI & Leaked PHI**

****pt_name<A>**, ****age<60s>** yo ...
daughter, Lynn, to ...
oncologist Dr. ****MD_name<C>** ...
****date<5/28/10>** to consider ...
SWOG protocol ****other_id**, ...
was randomized 5/10 ...
to call Mr. ****pt_name<A>** on ...
PLAN:Dr White and I ...

- A leak is not necessarily a re-identification

- Need to assess the potential given the leak rates

- Can assess on a per research subject level (if labels are person specific)

P(date of birth leak, date of death leak)

$$\approx P(\text{date of birth leak}) * P(\text{date of death leak})$$

- Alternatively, may assume each feature leaks at random

Hiding in Plain Sight (Carrell et al, 2013)

- Must be careful – this is a relatively new technique
- Also evidence to suggest a computer may mimic the initial detection strategy... and redact the fakes situated in a pattern (Li et al, 2016)

Original PHI

Smith, 61 yo ...
daughter, Lynn, to ...
oncologist Dr. White ...
5/13/10 to consider ...
SWOG protocol 1811, ...
was randomized 5/10 ...
to call Mr. Smith on ...
PLAN:Dr White and I ...

****Redacted PHI & Leaked PHI**

****pt_name<A>**, ****age<60s>** yo ...
daughter, Lynn, to ...
oncologist Dr. ****MD_name<C>** ...
****date<5/28/10>** to consider ...
SWOG protocol ****other_id**, ...
was randomized 5/10 ...
to call Mr. ****pt_name<A>** on ...
PLAN:Dr White and I ...

Surrogate PHI & Hidden PHI

Jones, a 64 yo ...
daughter, Lynn, for ...
oncologist Dr. Howe ...
5/28/10 to consider ...
SWOG protocol 1798, ...
was randomized 5/10 ...
to call Mr. Jones on ...
PLAN:Dr White and I ...

- In this case, we would need two risk measures
 - Human recognition risk
 - Computer-assisted recognition risk
- Recent approach to prevent this problem, but comes at a massive loss in precision (Li et al, 2017)

If Time Permits...

If Not...

Latest Development

- Methods presented model data sharer and adversary separately
- New approaches use game theory to consider their interactions (Wan et al 2015)
- Game theory requires robust estimates of many parameters, such as
 - benefit the sharer gets in providing data
 - benefit the attacker gets in re-identifying the data

Stackelberg Game

Sharing Strategy 1
<i>Utility 1</i>
<i>Risk ???</i>

Strategies:

- Generalize Age
- Suppress Dates
- ...
- Perturb Geography

Publisher

Attack Strategy A
<i>Utility A</i>
<i>Risk A</i>

Attack Strategy B
<i>Utility B</i>
<i>Risk B</i>

⋮

Attack Strategy C
<i>Utility C</i>
<i>Risk C</i>

Recipient

Stackelberg Game

Sharing Strategy 1
<i>Utility 1</i>
<i>Risk ???</i>

Attack Strategy A
<i>Utility A</i>
<i>Risk A</i>

Attack Strategy B
<i>Utility B</i>
<i>Risk B</i>

**Recipient's
Best Strategy**

⋮

Attack Strategy C
<i>Utility C</i>
<i>Risk C</i>

Publisher

Recipient

Stackelberg Game

Sharing Strategy 1
<i>Utility 1</i>
<i>Risk B</i>

Attack Strategy A
<i>Utility A</i>
<i>Risk A</i>

Attack Strategy B
<i>Utility B</i>
<i>Risk B</i>

Attack Strategy C
<i>Utility C</i>
<i>Risk C</i>

Recipient's
Best Strategy

Publisher

Recipient

Stackelberg Game

Sharing Strategy 1
<i>Utility 1</i>
<i>Risk B</i>

Sharing Strategy 2
<i>Utility 2</i>
<i>Risk ???</i>

Publisher

Attack Strategy A
<i>Utility A</i>
<i>Risk A</i>

Attack Strategy B
<i>Utility B</i>
<i>Risk B</i>

⋮

Attack Strategy C
<i>Utility C</i>
<i>Risk C</i>

Recipient

Stackelberg Game

Sharing Strategy 1
<i>Utility 1</i>
<i>Risk B</i>

Sharing Strategy 2
<i>Utility 2</i>
<i>Risk A</i>

**Recipient's
Best Strategy**

Attack Strategy A
<i>Utility A</i>
<i>Risk A</i>

Attack Strategy B
<i>Utility B</i>
<i>Risk B</i>

⋮

Attack Strategy C
<i>Utility C</i>
<i>Risk C</i>

Publisher

Recipient

Stackelberg Game

Sharing Strategy 1
<i>Utility 1</i>
<i>Risk B</i>

Sharing Strategy 2
<i>Utility 2</i>
<i>Risk A</i>

⋮

Sharing Strategy Z
<i>Utility Z</i>
<i>Risk Z</i>

Publisher

Stackelberg Game

Sharing Strategy 1
<i>Utility 1</i>
<i>Risk B</i>

Sharing Strategy 2
<i>Utility 2</i>
<i>Risk A</i>

⋮

Sharing Strategy Z
<i>Utility Z</i>
<i>Risk Z</i>

Publisher

Choose strategy that maximizes overall benefit

Optimizes the Risk-Utility tradeoff

Demographic Case Study

- ~30,000 Census records
- Average Payoff Per Record
- \$1200: Benefit per record
- \$300: Cost per violation
- \$4: Access cost per record



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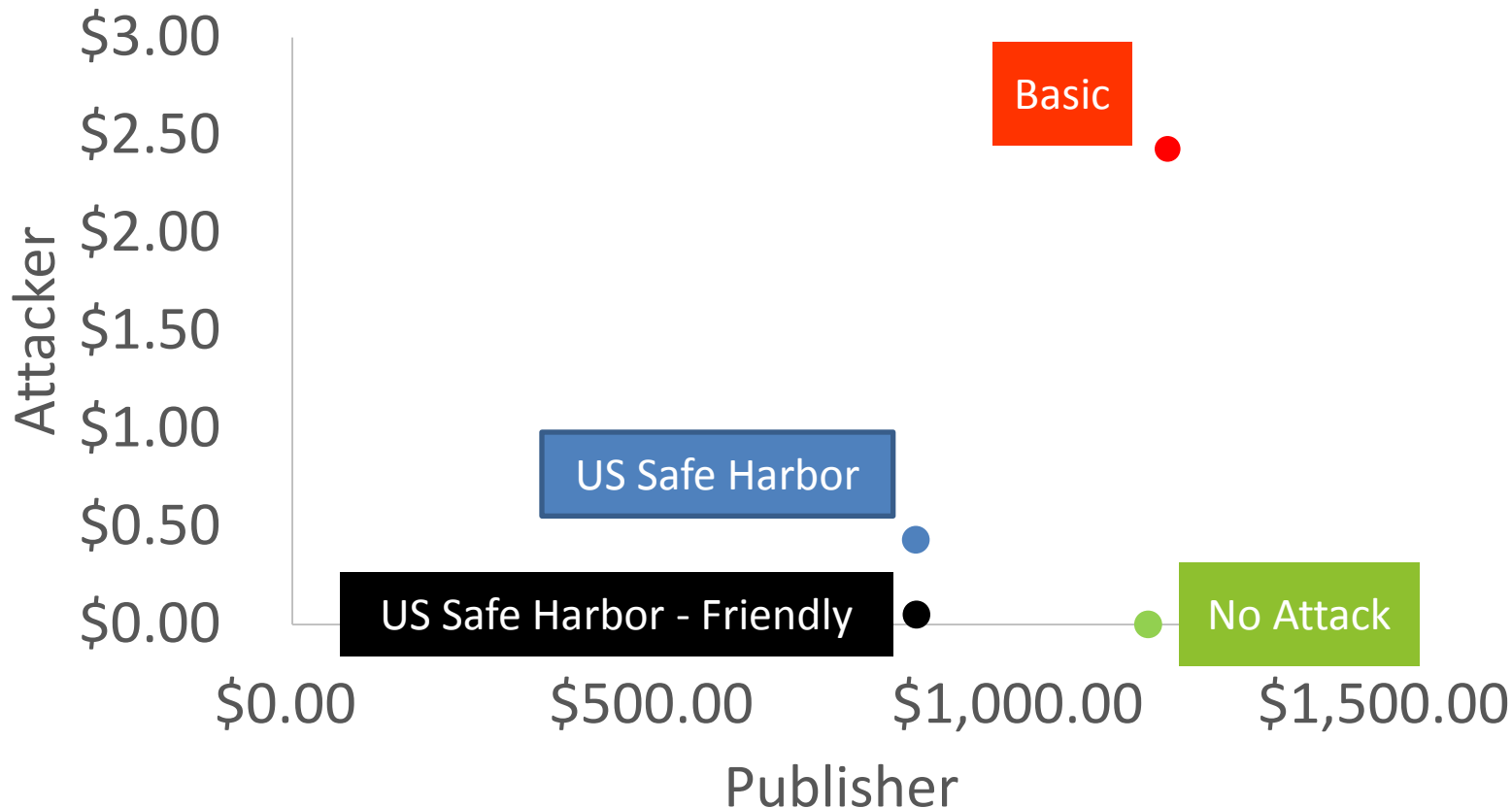
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Some Relevant References

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