EMS Data Linkage

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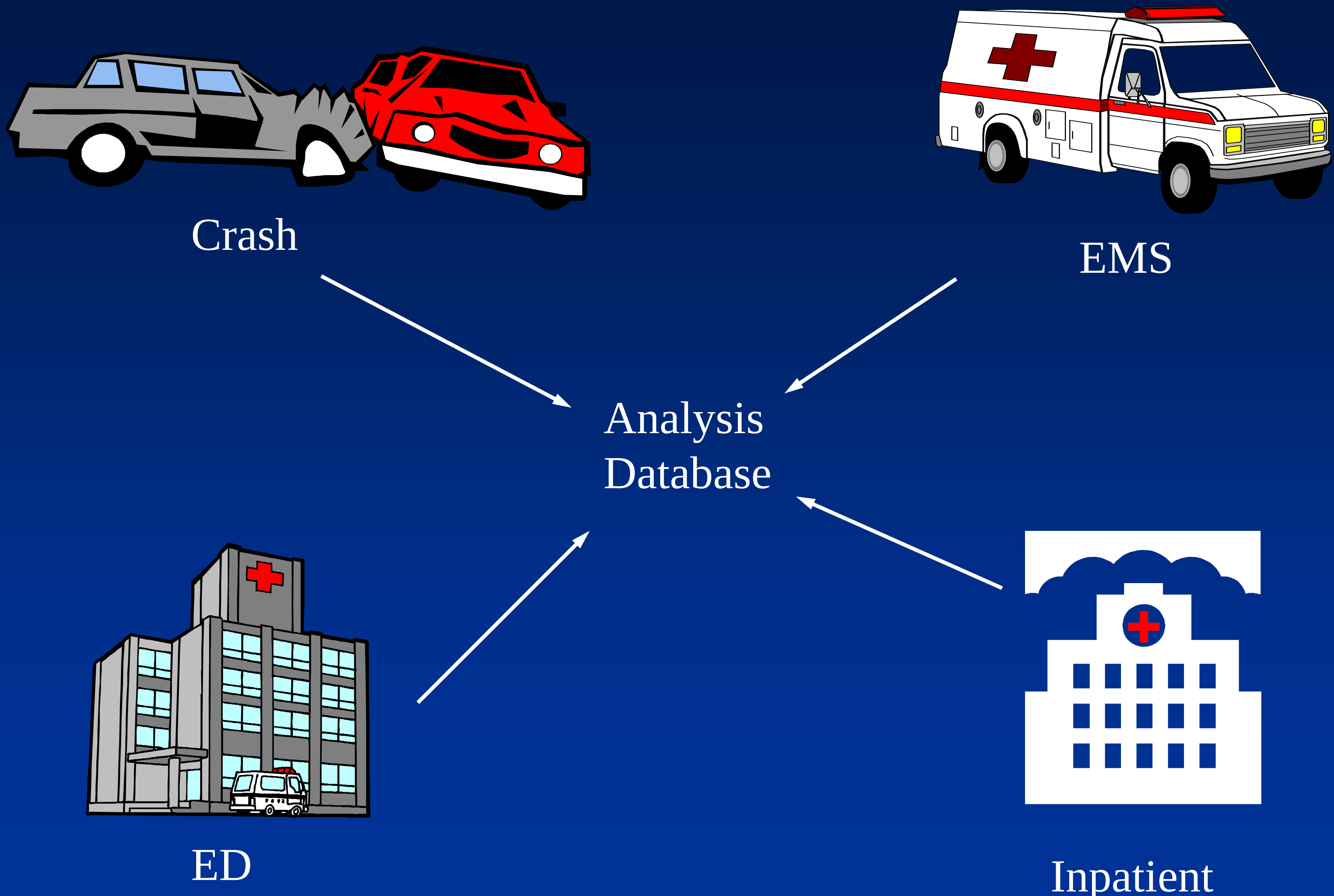
Purpose of Record Linkage

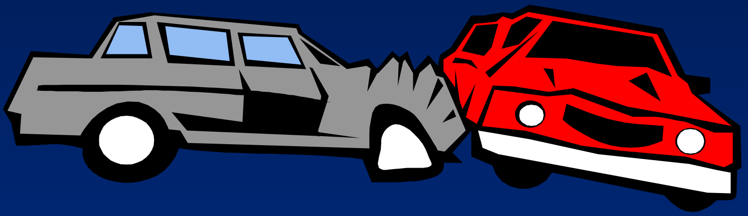
Linkage allows the combination of different databases into one extensive data set for analysis



Crash
EMS
Analysis
Database
ED
Inpatient

Why Combine Multiple Databases?

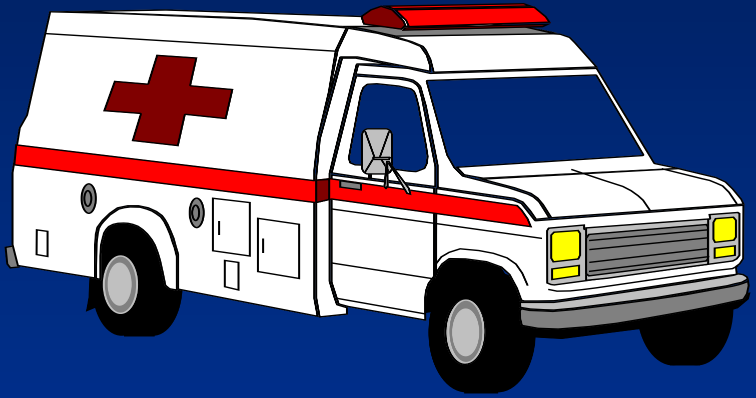
Crash Database



- Crash
  - Date, time, crash type
- Drivers and vehicles
  - Speed, contributing factors, violations
- Occupant
  - Age, gender, seating location, belt usage
- No medical information about occupants

EMS Database

- Patient
- Time
- Scene
- Procedures
- Treatments
- Medications
- No information once dropped off at hospital



ED Database

- Patient
- Time
- ICD-9, Procedures, and E Codes
- ED Charges
- No information once admitted to hospital
- No information prior to arrival at ED

Inpatient Database

- Patient
- Time
- ICD-9, Procedures, and E Codes, ISS
- Hospital Charges
- No information prior to admission to hospital

Why Not Collect Your Own Data?

- Time
- $$$$
- Linkage makes use of existing databases

Types of Record Linkage

- Deterministic
  - Exact matching on a key
  - Linkage scores derived by some predetermined scoring system
  - No consideration on how likely values are to agree by chance
- Probabilistic
  - Linkage scores based on properties of fields being matched
  - Linkage score depends on individual values
  - Probability that two records match

Deterministic Example

- 8 points for agreement on first name
- 6 points for agreement on last name
- 5 points for agreement on date of birth
- 5 points for agreement on event date
- 1 point for agreement on gender
- All records with a score of 16 or higher are matches

Probabilistic Linkage

- Probabilistic record linkage is a method that uses properties of variables common to databases to determine the probability that two records refer to the same person and/or event

Let’s Play 20 Questions

I’m thinking of a person

Probabilistic Linkage Basics

Probabilistic Linkage Theory

Crash Record

Mary Smith F 05/05/45 07/15/96 11:47 Weber US5 Seat=1 Belt=N

Ambulance Record

Mary Smith Sanchez F 05/05/44 07/15/96 11:55 Weber Fracture Mem Hosp

Probabilistic record linkage is a method of using statistical properties of variables common to a pair of records to calculate the probability that the records apply to the same person and event...

Probabilistic Linkage Theory

Mary Smith

Seat=1 Belt=N

Briefly, two statistical properties of each common variable -- **reliability** and **discriminating power** -- determine the **odds ratio** for a true match. The odds ratio is the uniformly most powerful test statistic for discriminating between matched and unmatched record pairs.

Mary Smith Sanc

ure Mem Hosp

Probabilistic Linkage Theory

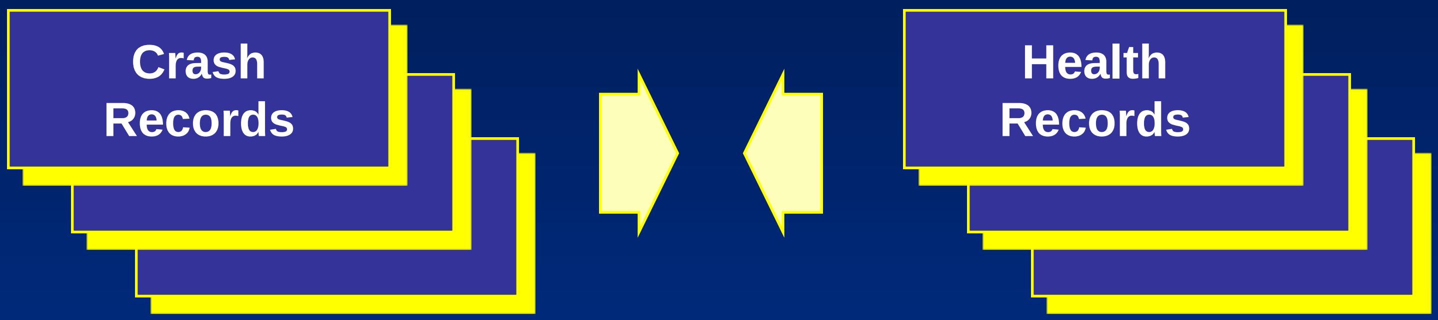
Reliability (m)

Probability that a common variable agrees on a **matched** pair.
Approximately 1 - error rate.

Discriminating Power (u)

Probability that a common variable agrees on an **unmatched** pair.
Approximately the probability of agreeing by chance.

Record Linkage with Imperfect Data



Let us choose a pair of imperfect records and try to decide if they are a match. That is, do they refer to the same individual and event?

Record Linkage with Imperfect Data

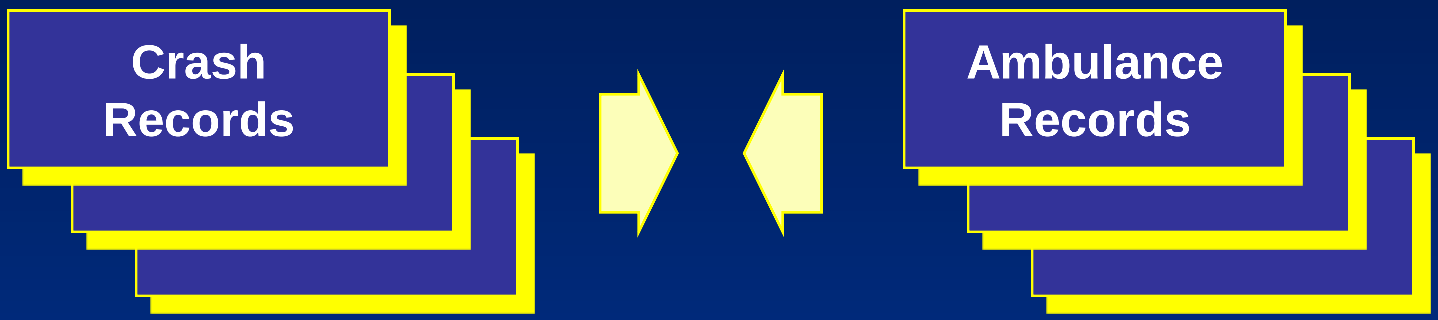
Crash Record

Mary Smith	F	05/05/45	07/15/96 11:40	Weber	US5	Seat=1	Belt=N

Ambulance Record

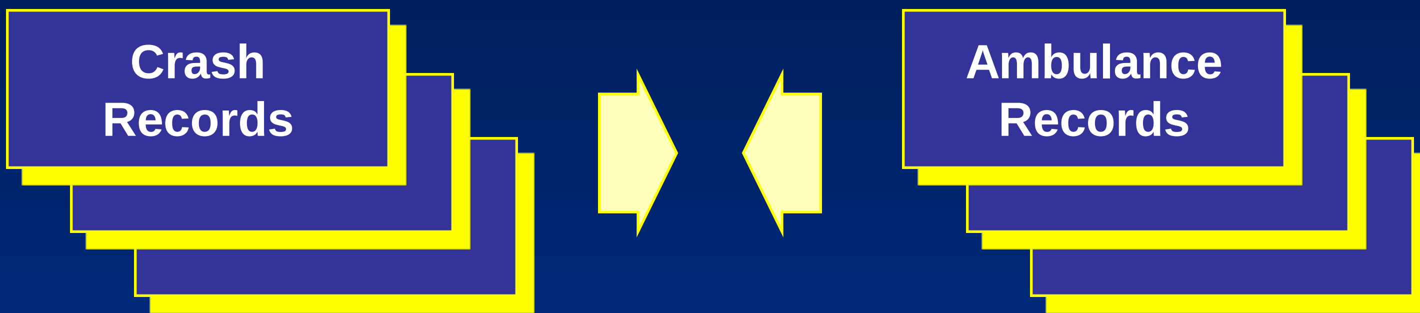
Mary Smith Sanchez	F	05/05/44	07/15/96 11:51	Weber	Fracture	Mem Hosp

Probabilistic Record Linkage



Let's revisit our pair of imperfect records and try to decide if they are a true match by applying the theory of probabilistic linkage.

Probabilistic Record Linkage



If each ambulance record matches to one crash record in a file of 100,000 crashes then the odds for a match at random are

1:99,999

Probabilistic Linkage Theory

Reliability (m)

Probability that a common variable agrees on a **matched** pair. Approximately 1 - error rate.

Discriminating Power (u)

Probability that a common variable agrees on an **unmatched** pair. Approximately the probability of agreeing by chance.

Probabilistic Record Linkage

Crash Record

Mary Smith		**Weber US5 Seat=1 Belt=N**

First name agrees...

m = 0.90 u = 0.01 ratio = 90**:**1

Ambulance

Mary Smith S		**Weber Fracture Mem Hosp**

Agreement on first name improves the odds for a match:

1**:**99,999 x 90**:**1 = **1:1,111**

Probabilistic Record Linkage

Crash Record

Mary Smith F ... 5 Seat=1 Belt=N

Ambulance Record

Mary Smith Sanchez F ... cture Mem Hosp

Last or middle name agrees with last or middle...

m = 0.90 u = 0.04 ratio = 22:1

Agreement on last name improves the odds for a match:

1:1,111 x 22:1 = **1:51**

Probabilistic Record Linkage

Crash Record

Mary Smith F 05/05/45 Belt=N

Ambulance Record

Mary Smith Sanchez F 05/05/44 em Hosp

Sex agrees...

m = 0.99 u = 0.50 ratio = 2:1

Agreement on sex improves the odds for a match:

1:51 x 2:1 = **1:25**

Probabilistic Record Linkage

Crash Record

Mary Smith F 05/05/45 07/15 ... **=N**

Ambulance Record

Mary Smith Sanchez F 05/05/44 07/15 ... **osp**

Date of Birth
Month agrees...
m = 0.99 u = 0.08 ratio = 12:1
Day agrees...
m = 0.99 u = 0.03 ratio = 30:1
Year disagrees
m = 0.99 u = 0.01 ratio = 1:99

Agreement on birth date improves the odds for a match:

1:25 x 4:1 = **1:6**

Probabilistic Record Linkage

Crash Record

Mary Smith F 05/05/45 07/15/96 11

Ambulance Record

Mary Smith Sanchez F 05/05/44 07/15/96 11

Date of Crash
Month agrees...
m = 0.99 u = 0.08 ratio = 12**:**1
Day agrees...
m = 0.99 u = 0.03 ratio = 30**:**1
Year agrees
m = 1.00 u = 1.00 ratio = 1**:**1

Agreement on crash date improves the odds for a match:

1**:**6 x 360**:**1 = **60:1**

Probabilistic Record Linkage

Crash Record

Ma 15/96 11:47 Weber US5 Seat=1 Belt=N

Time of Crash
Hour agrees...
m = 0.90 u = 0.04 ratio = 23:1
Minute disagrees...
m = 0.50 u = 0.02 ratio = 1:2

Am

Ma 15/96 11:55 Weber Fracture Mem Hosp

Agreement on crash time improves the odds for a match:

60:1 x 12:1 = **1,699:1**

Probabilistic Record Linkage

Crash Record

Mary Sm ... **1:47 Weber US5 Seat=1 Belt=N**

Place of crash agrees...

m = 0.99 u = 0.10 ratio = 10:1

Ambula

Mary Sm ... **1:55 Weber Fracture Mem Hosp**

Agreement on crash location improves the odds for a match:

1,699:1 x 10:1 = **16,990:1**

Probabilistic Record Linkage

Crash Record

Mary Smith	**F**	**05/05/45**	**07/15/96 11:47**	**Weber**	**US5**	**Seat=1**	**Belt=N**

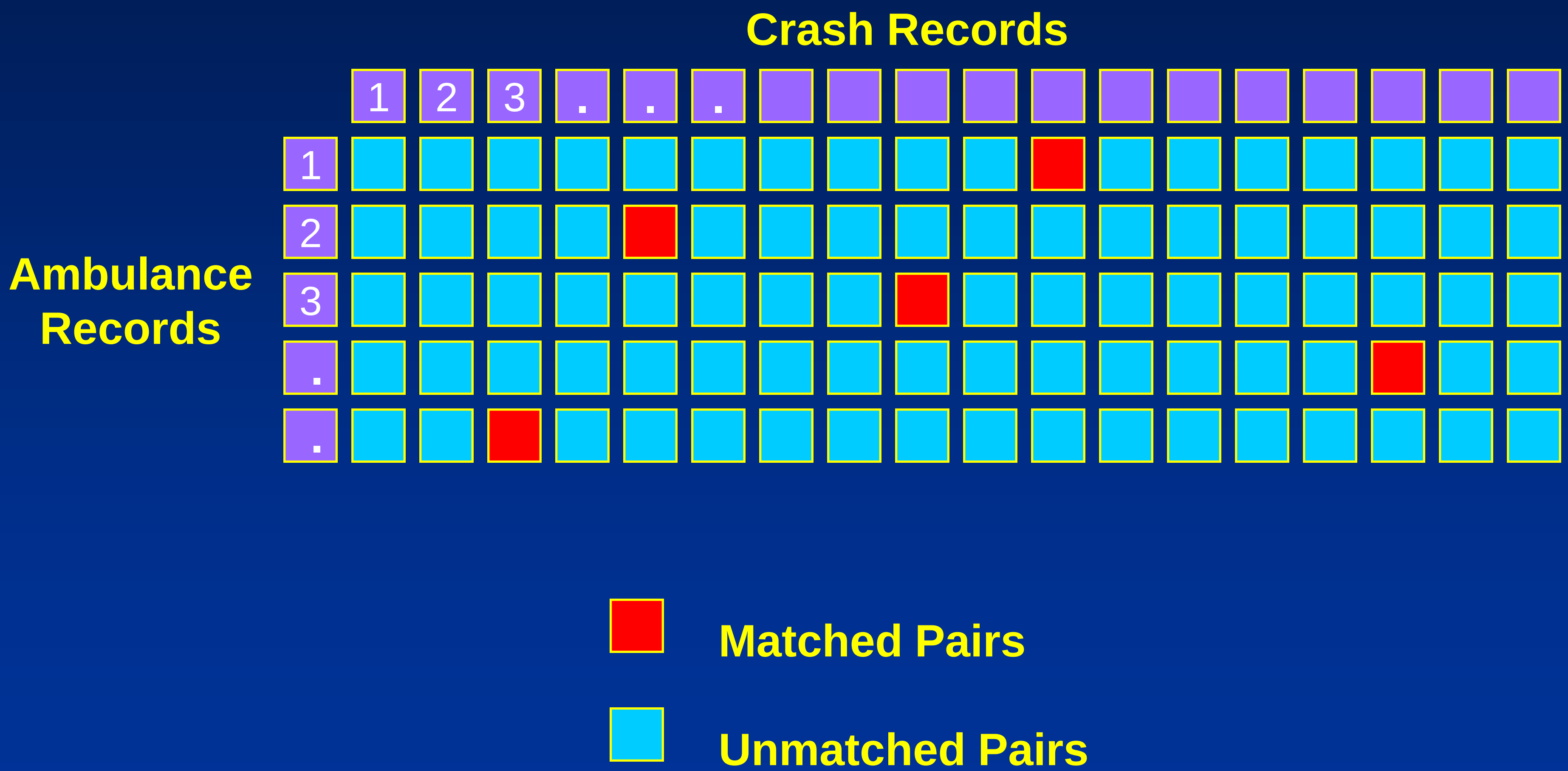
Ambulance Record

Mary Smith Sanchez	**F**	**05/05/44**	**07/15/96 11:55**	**Weber**	**Fracture**	**Mem Hosp**

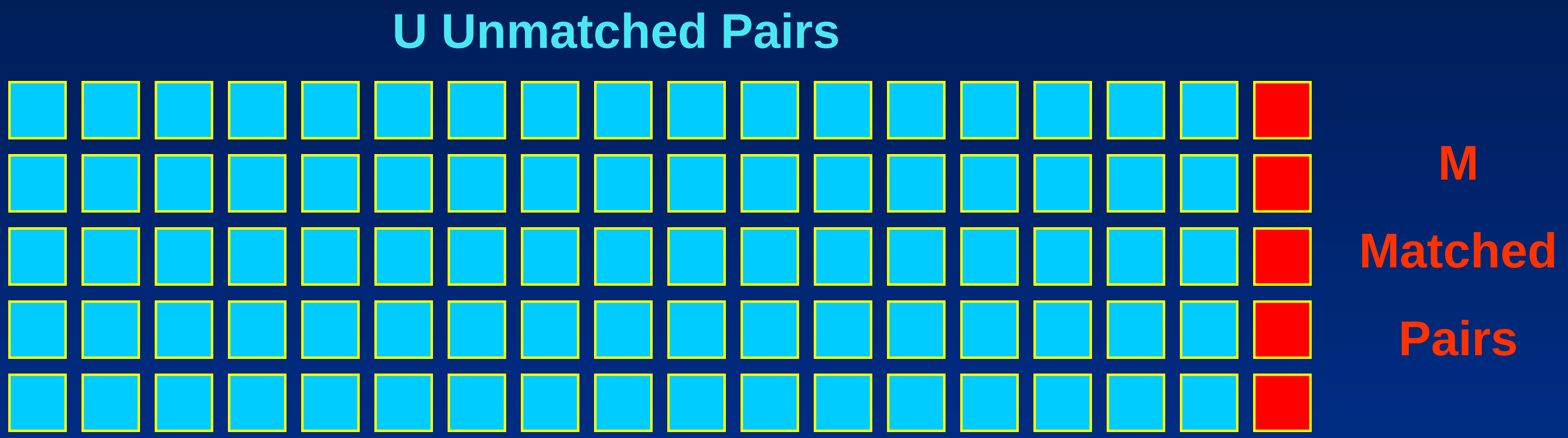
This pair of records has both agreements and disagreements. Our calculations say that the odds are **16,990:1 (p = 0.99994)** that the records refer to the same individual and crash event.

Blocking

Probabilistic Linkage Theory



Probabilistic Linkage Theory

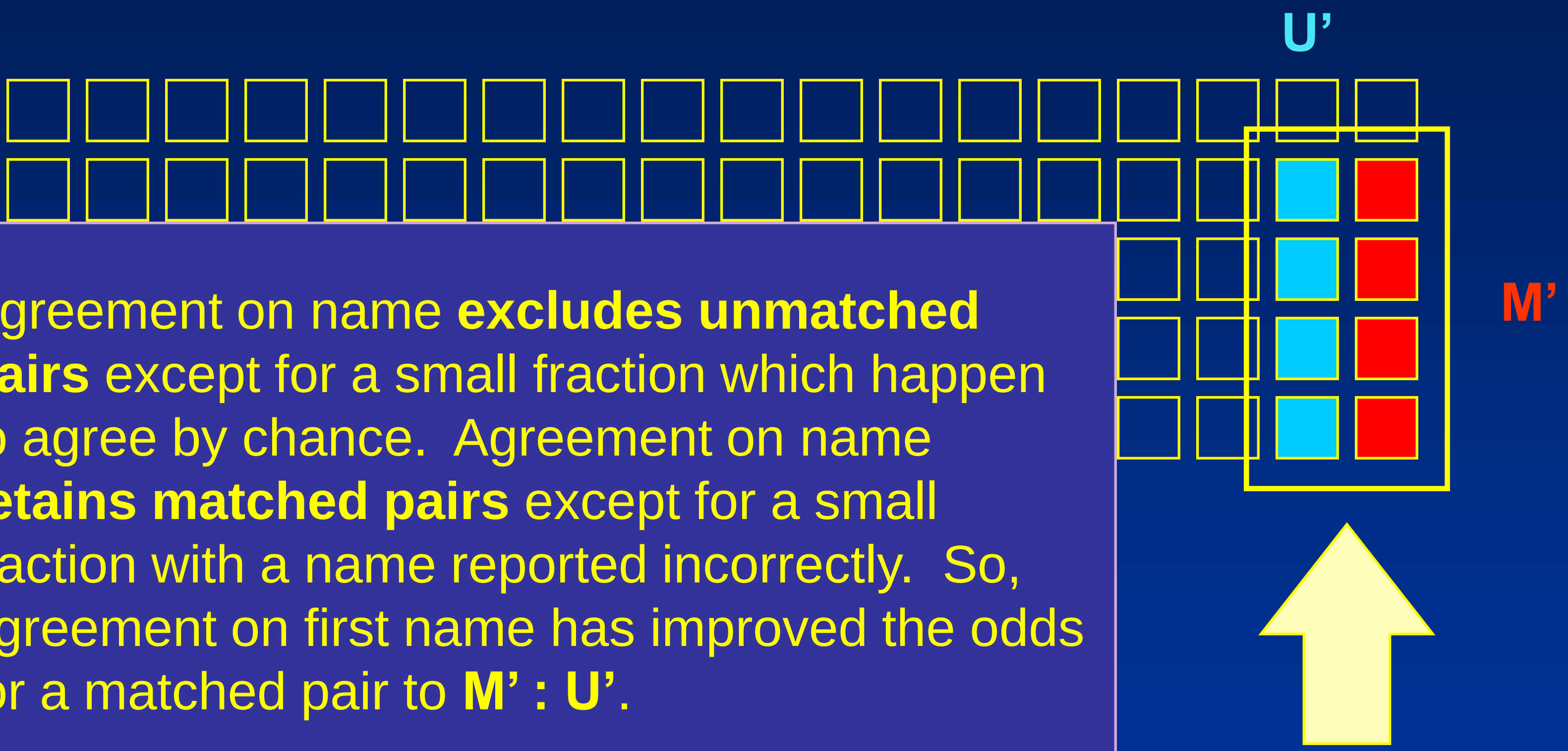


It would be more efficient if there was a way that we could spend more time comparing true matched pairs and less time comparing false pairings.

Probabilistic Linkage Theory

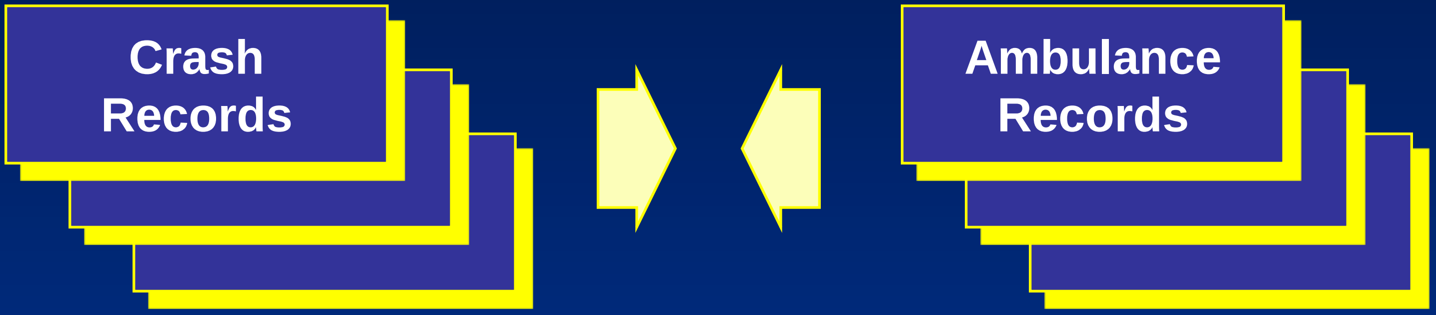
One way might be to limit our attention to those pairs which agree on some common variable, say **first name**.

Probabilistic Linkage Theory



Agreement on name **excludes unmatched pairs** except for a small fraction which happen to agree by chance. Agreement on name **retains matched pairs** except for a small fraction with a name reported incorrectly. So, agreement on first name has improved the odds for a matched pair to **M’ : U’**.

Computational Efficiency

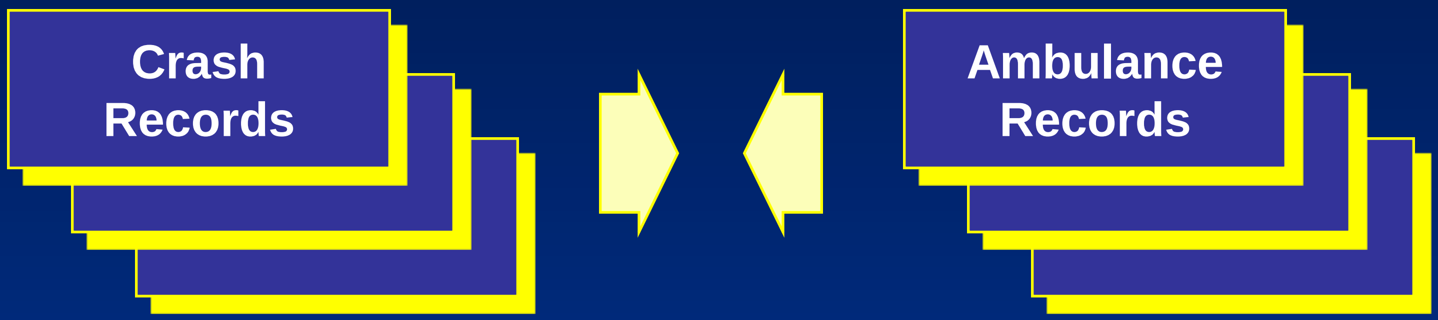


100,000 Records

10,000 Records

In principal, linking **10,000** ambulance records to **100,000** crash records means testing **1,000,000,000** candidate record pairs...

Blocking



100,000 Records **10,000 Records**

In practice, most matched pairs can be found without incurring this excessive computational cost with the technique of **record blocking**. Compare only those record pairs which agree on at least one item.

Blocking, 1st Initial

Maria Roberts

Martha Sayer

Mary Smith

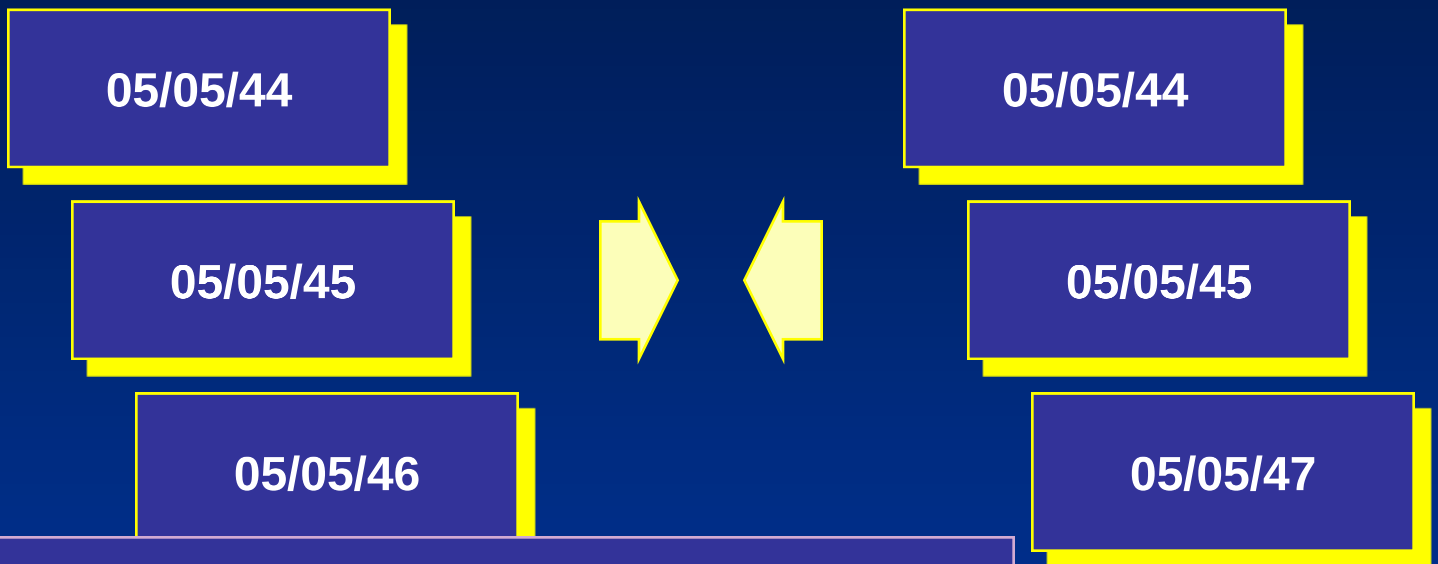
Milo Smith

Mary Sanchez

Mary Thomas

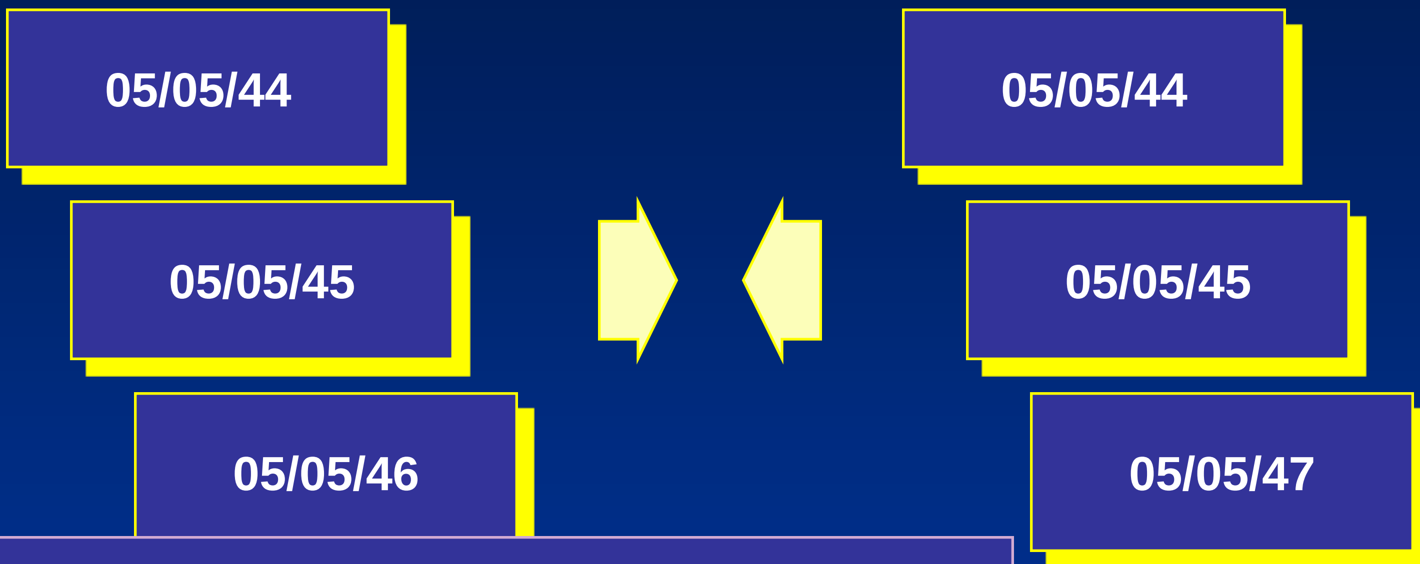
If we compare blocks of records with the same first initial then there are approximately 100,000 / 26 X 10,000 / 26 = 1,479,290 pairs in each block, or **38,461,538** pairs in total. This is only 1/26th of 1,000,000,000 pairs.

Blocking, Birth Date



If we compare blocks of records with the same birthday then there are approximately 100,000 / 365 X 10,000 / 365 = 7,506 pairs in each block, or **2,739,726** pairs in total. This is only 1/365th of 1,000,000,000 pairs.

Blocking, Birth Date



Smaller blocks mean greater computational efficiency. However, getting smaller blocks by forcing more items to be equal has a cost -- some matched pairs will be excluded because they disagree on one of those items.

Blocking

Crash Record

Mary Smith F 05/05/45 07/15/96 11:47 Weber US5 Seat=1 Belt=N

Ambulance Record

Mary Smith Sanchez F 05/05/44 07/15/96 11:55 Weber Fracture Mem Hosp

Since a matched pair might disagree on any particular data item, multiple record blocking passes must be used in order to find all the matches...

Blocking

Crash Record

Mary Smith F 05/05/45 07/15/96 11:47 Weber US5 Seat=1 Belt=N

Ambulance Record

Mary Smith Sanchez F 05/05/44 07/15/96 11:55 Weber Fracture Mem Hosp

For example, first block on birth date, then on crash date, then on first name, then on last name. The only matched pairs that can escape your net are those which disagree on birth date **and** crash date **and** first name **and** last name -- truly rare pairs.

What Do You Need For Probabilistic Linkage

Data Files

- Variables common to both files
- Variable definitions same on each file
- Missing values represented by NULL

Common Linkage Variables

- First and Last Names
- Soundex of Names (Sounds like)
  - Lawrence Cook = L652 C200
  - Laurence Cooke = L652 C200
- Date of Birth and Age
- Incident Date
- Time of Incident
- Location: County, City, Zip, Latitude/Longitude

Are Names Necessary for Probabilistic Linkage?

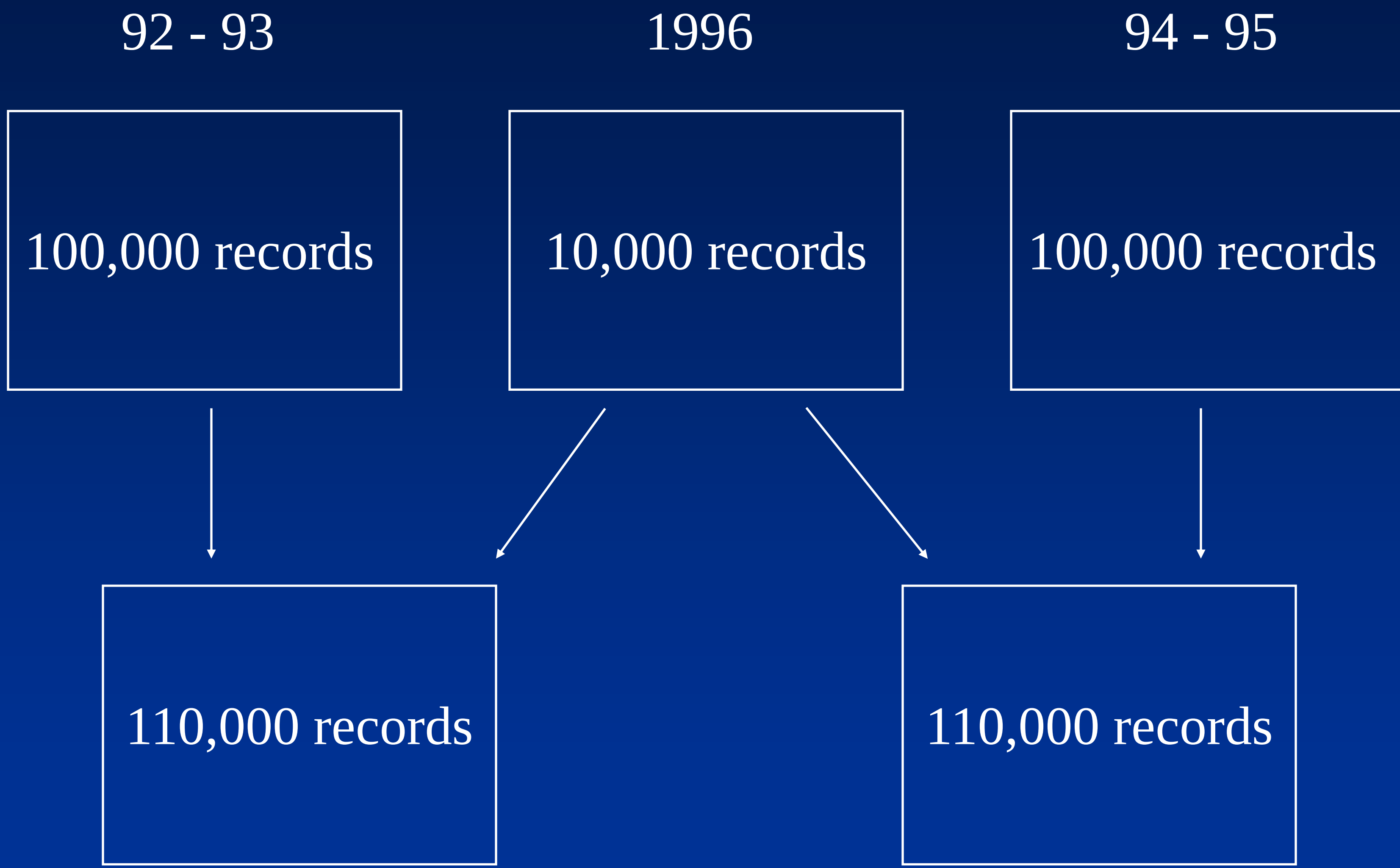
Usefulness of Names

- Name are powerful identifiers
- Confidentiality concerns
- Names may become impossible to obtain in the future

Objective

The objective of our study was to determine the impact of name information on probabilistic record linkage

Crash Data



92 - 93
1996
94 - 95
100,000 records
10,000 records
100,000 records
110,000 records
110,000 records

Simulated Databases

- 2 databases 110,000 records each
- 10,000 records known to be exact matches
- 100,000 records known not to match to any record in the other file

Linking Information

First and Last Name
Date of Birth
Gender

County of Crash
Crash Time
Crash Date

Levels of Name Information

- Full first and last names
- SOUNDEX of first and last names
- First and last initials
- No name information

Levels of Non-Name Information

- All available non-name information
- Remove date of birth (personal)
- Also remove county (location)
- Also remove time (time)

Simulated Key Punch Error Rates

- No errors
- 1%
- 5%
- 10%
- 25%
- Errors could only be valid entries

Linkage Performance Measures

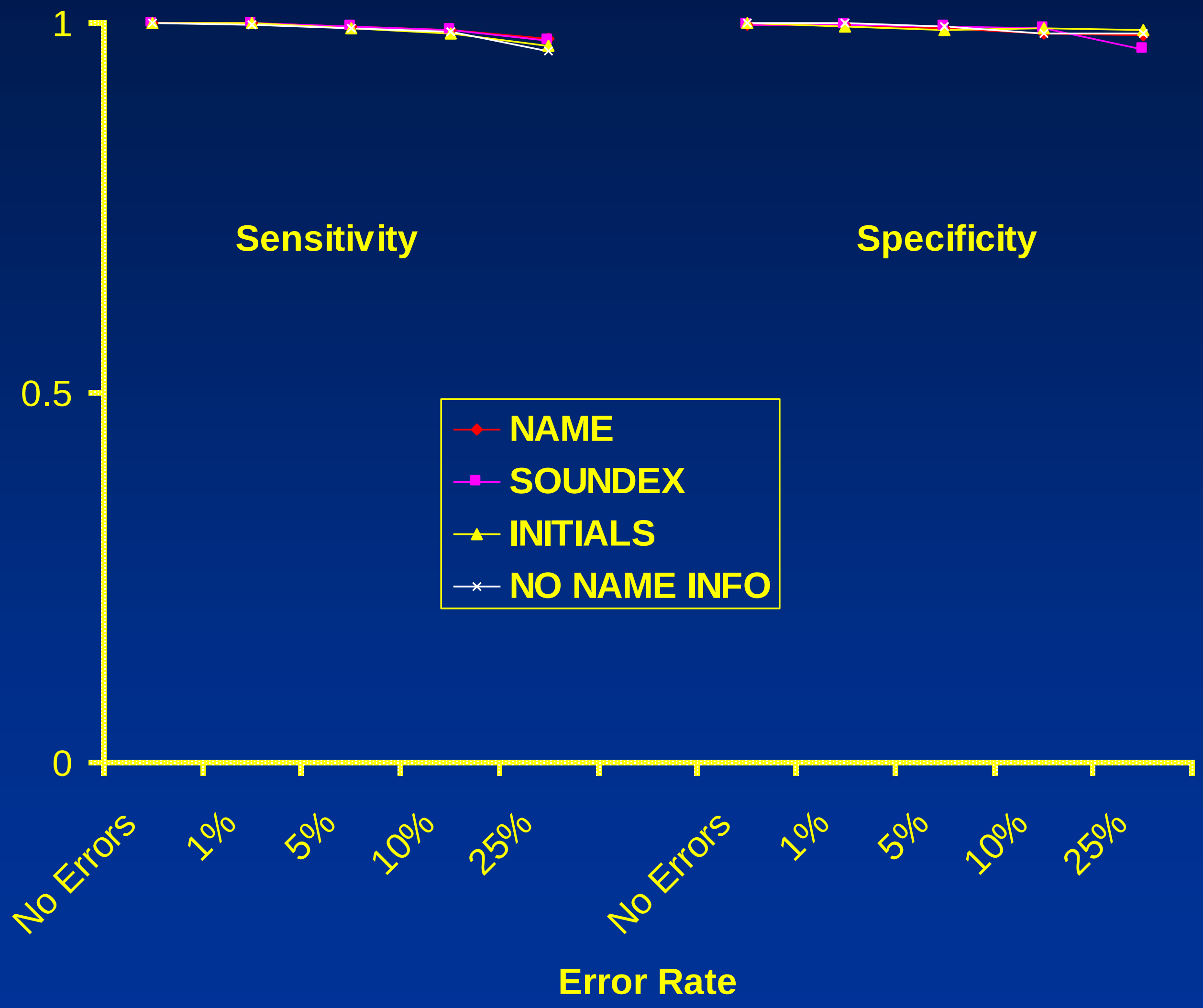
- Sensitivity - Ability to recognize true matches

  # correct matches identified / 10,000

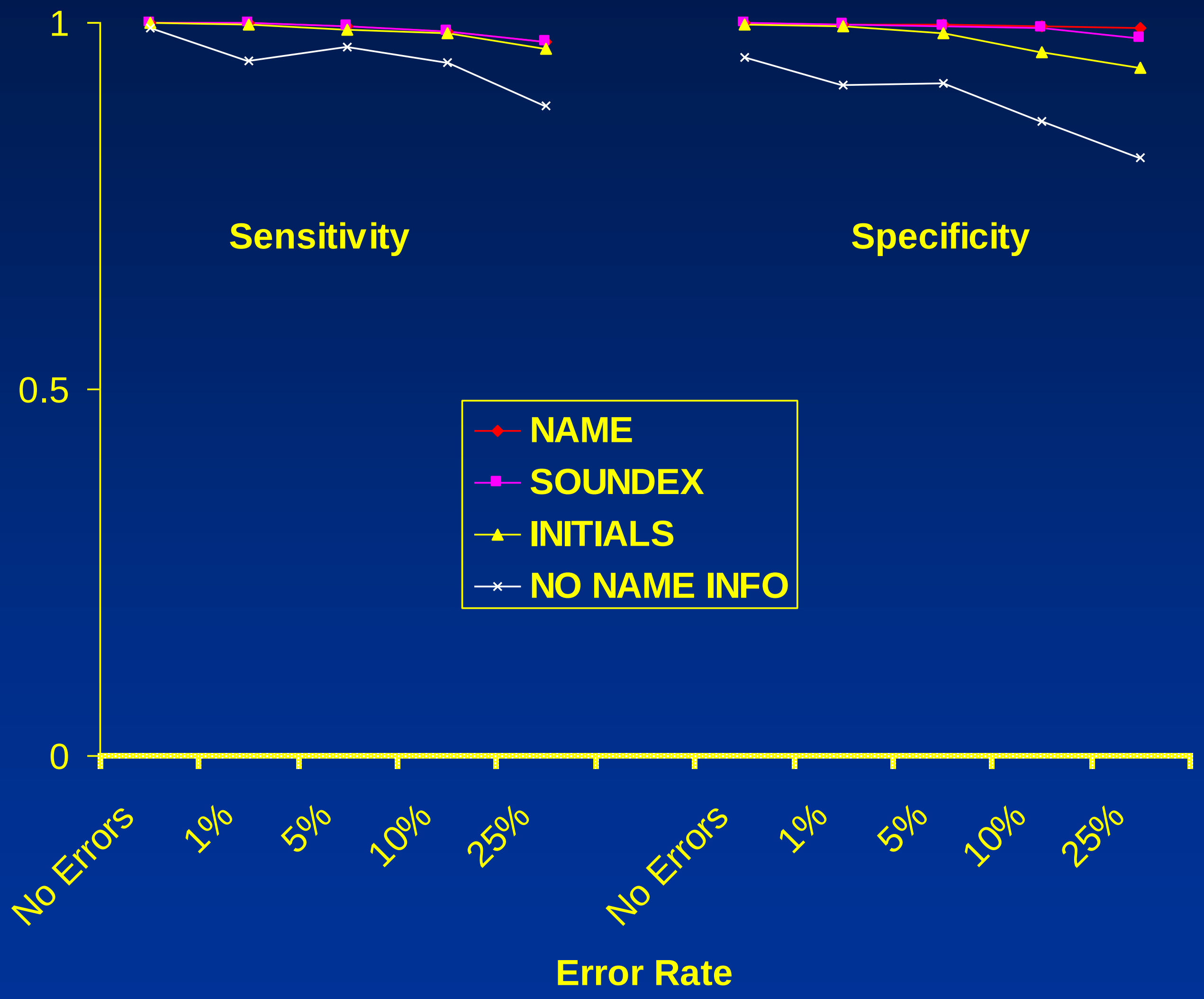
- Specificity - Ability to recognize incorrect matches

  1 - # incorrect matches / total matches

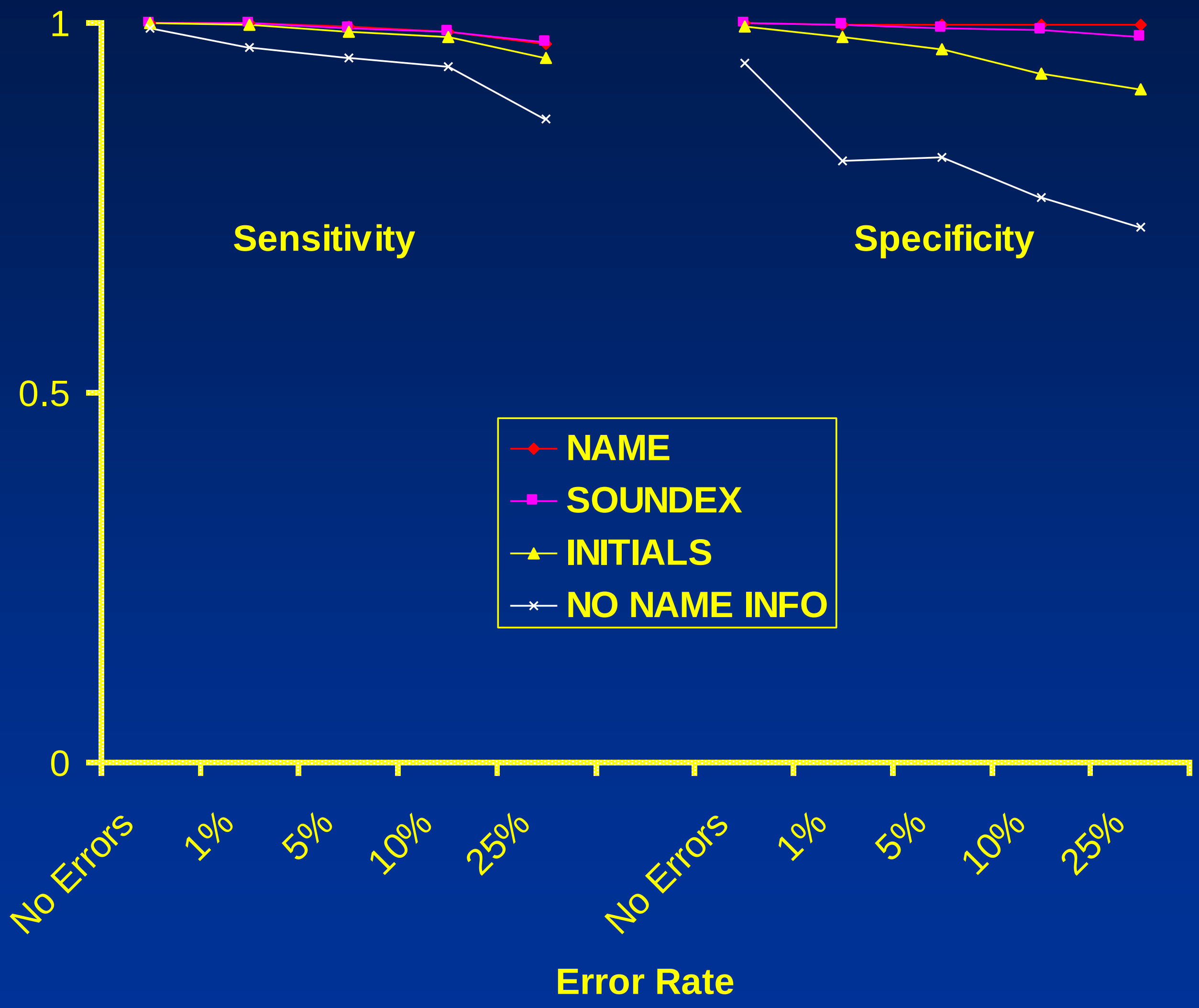
DOB, Gender, County, Time, Incident Date



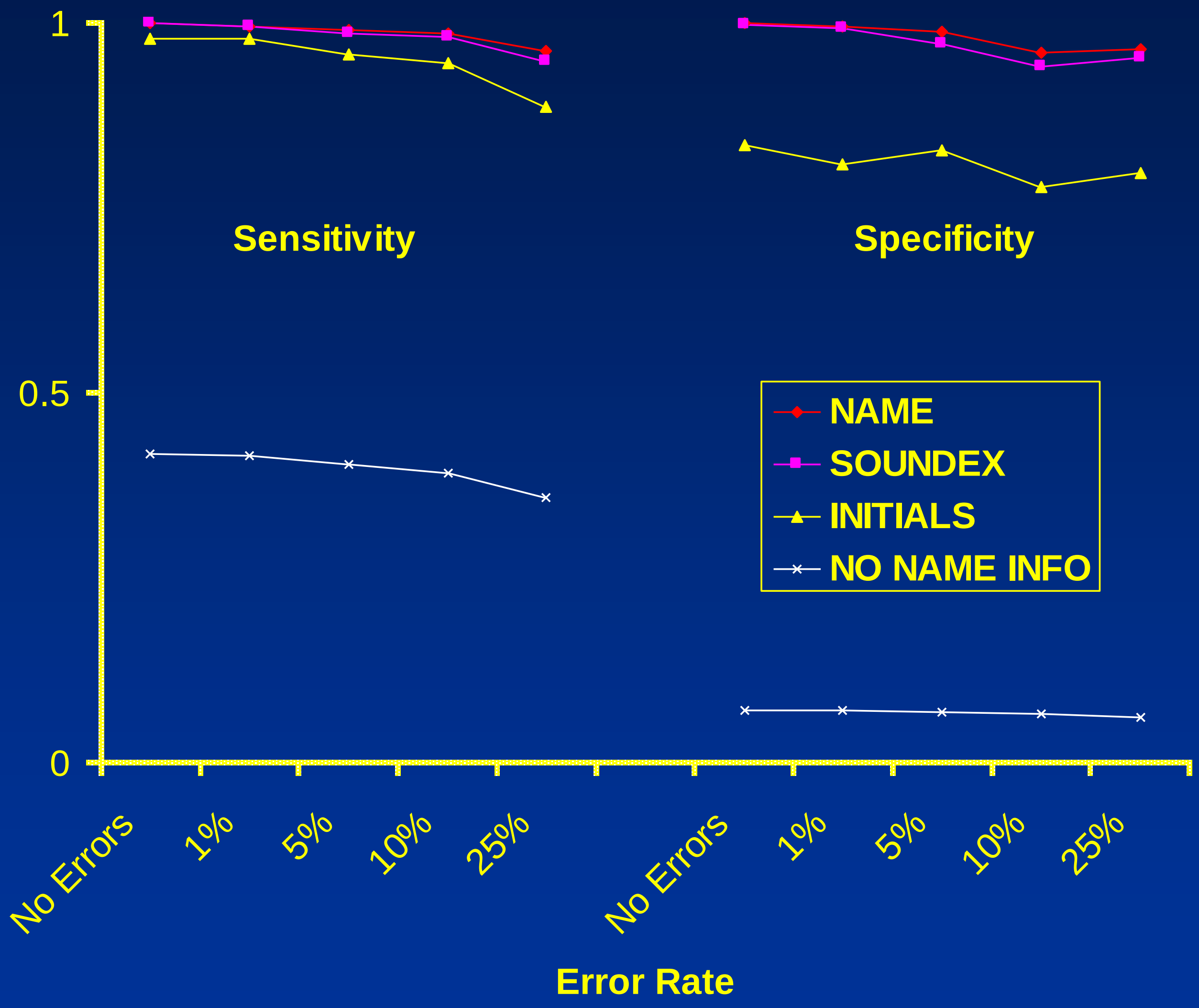
DOB, Age, Gender, County, Time, Incident Date



DOB, Age, Gender, County, Time, Incident Date



DOB, Age, Gender, County, Time, Incident Date



Summary

- Lack of name information had no effect on linkages when all available non-name information was present.
- Performance declines when non-name information is removed.
  - Linkages using names and SOUNDEX were less affected
  - Linkages using initials and no name information most affected
- Performance declines with increasing error rates.

Conclusions

- Identifiers are needed for probabilistic linkage
- Is name information necessary?
  - If many non-name identifiers are available then name information may not be needed
  - If few non-name identifiers are available then name information becomes crucial

Calculating Match Weights

Match Probabilities: M and U

Reliability (m)

Probability that a common variable agrees on a **matched** pair. Approximately 1 - error rate.

Discriminating Power (u)

Probability that a common variable agrees on an **unmatched** pair. Approximately probability of agreeing by chance.

Agreement Probabilities

m_i = probability the i^{th} field agrees given that the two records match
(1 - probability of a miscode)

$(1 - m_i)$ = probability the i^{th} field disagrees given that two records match
(probability of a miscode)

Programmer supplies m probabilities

Disagreement Probabilities

u_i = probability the ith field agrees by chance

$(1 - u_i)$ = probability the ith field disagrees by chance

Computer calculates u probabilities.

$$u = \frac{\#\text{ of times a value occurs}}{\#\text{ of records}}$$

The odds of an event A

$$\text{Odds} = \frac{P(A)}{P(A^c)} = \frac{P(A)}{1 - P(A)}$$

A tiny bit of algebra shows

$$P(A) = \frac{\text{Odds}}{1 + \text{Odds}}$$

Match Weights

Given the i^{th} field agrees between two records, then the odds that the two records are a match are

$$(m_i/u_i)$$

Fellegi and Sunter proved this was the most powerful test

Match Weights

Given the i^{th} field agrees between two records, then the odds that the two records are a match is

Given the i^{th} field disagrees between two records, then the odds of a match are:

$$(1-m_i)/(1-u_i)$$

Fellegi and Sunter proved this was the most powerful test

Example: Gender

Gender has two levels: Male, Female

$m_i = 90\% = 0.9$ $(1 - m_i) = 0.1$

$u_i = 50\% = 0.5$ $(1 - u_i) = 0.5$

If two records agree on gender then

odds of a match = $m_i/u_i = 0.9/0.5 = 1.8$

If two records disagree on gender then

odds = $(1-m_i)/(1-u_i) = (1-.9)/(1-.5) = .1/.5 = .2$

Example: SSN

$m_i = 0.9$ $1-m_i = 0.1$

$u_i = (10)^{-9}$ $1-u_i = 1$

given agreement then

odds of a match = $.9/(10)^{-9} = 900{,}000{,}000$

given disagreement then

odds of a match = $.1/1 = .1$

Match Weight = $\log_2$(odds)

Gender agrees: Weight = $\log_2(1.8) = 0.85$

Gender disagrees: Weight = $\log_2(0.2) = -2.32$

SSN agrees: Weight = $\log_2(9X10^9) = 29.7$

SSN disagrees: Weight = $\log_2(0.1) = -3.32$

Example: Gender and SSN

Assume matching variables are independent!

Probability of agreeing on gender and SSN is P(Gender) X P(SSN)

Odds work the same way.

$\text{Odds}_{\text{gender and SSN}} = \text{Odds}_{\text{gender}} * \text{Odds}_{\text{SSN}}$

Example: Gender and SSN

$\log_2(\text{Odds}_{gender} * \text{Odds}_{SSN})$

$= \log_2(\text{Odds}_{gender}) + \log_2(\text{Odds}_{SSN})$

$= w_{gender} + w_{SSN}$

SSN's agree and Gender agree = 29.7 + 0.85

SSN's agree and Gender doesn't = 29.7 + -2.32

SSN's disagree and Gender same = -3.32 + 0.85

SSN's and Gender disagree = -3.32 + -2.32

Match Weights in Practice

- A separate weight is calculated for each value of a variable
- M probability doesn't depend on observed value
- U probabilities are assigned based on observed frequencies
  - Frequent values have large u probabilities
  - Rare values have small u probabilities

Match Weights in Practice

- Remember w ~ m/u

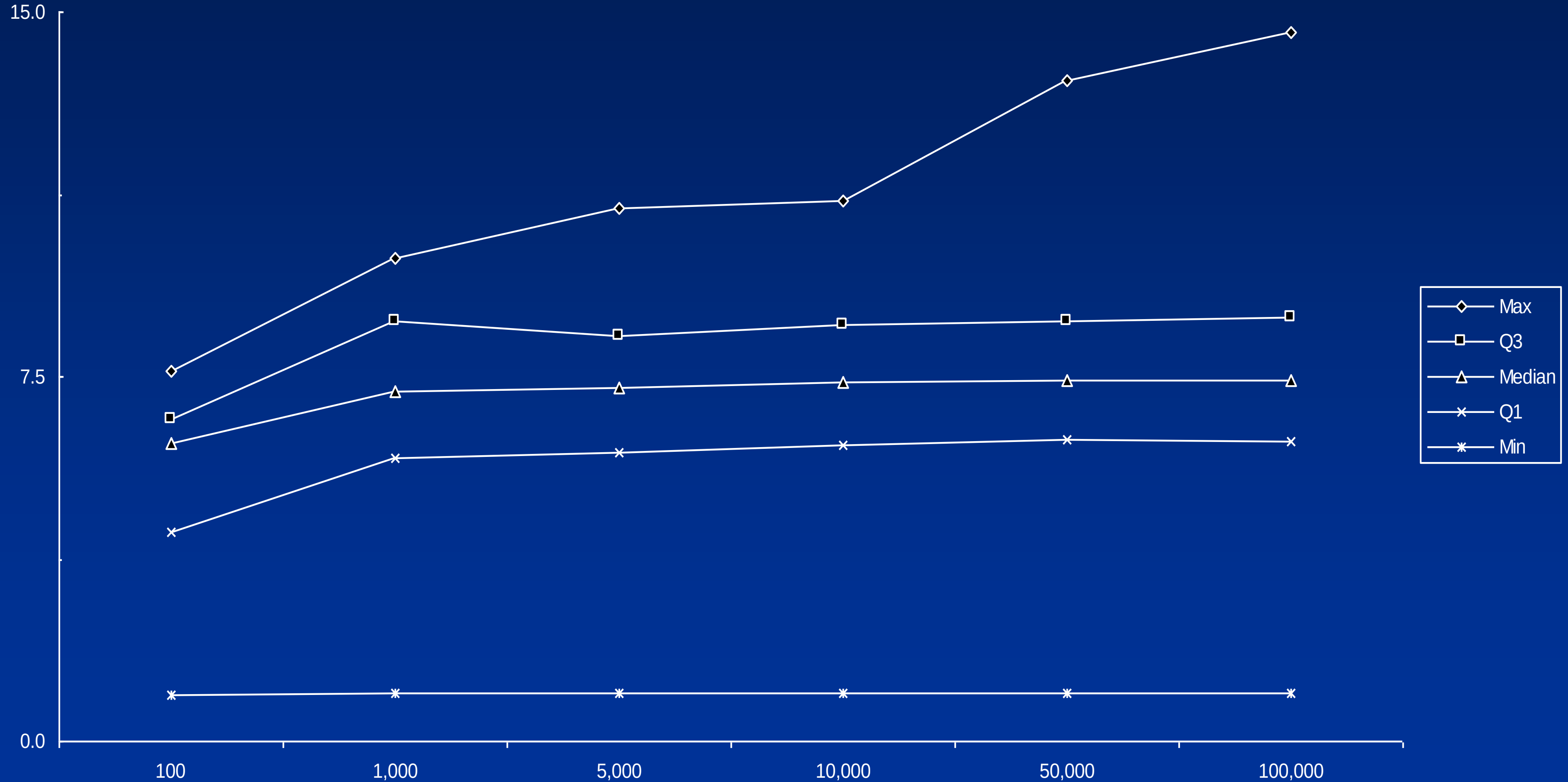
=> as u increases, weight decreases

  - Common values have low weights

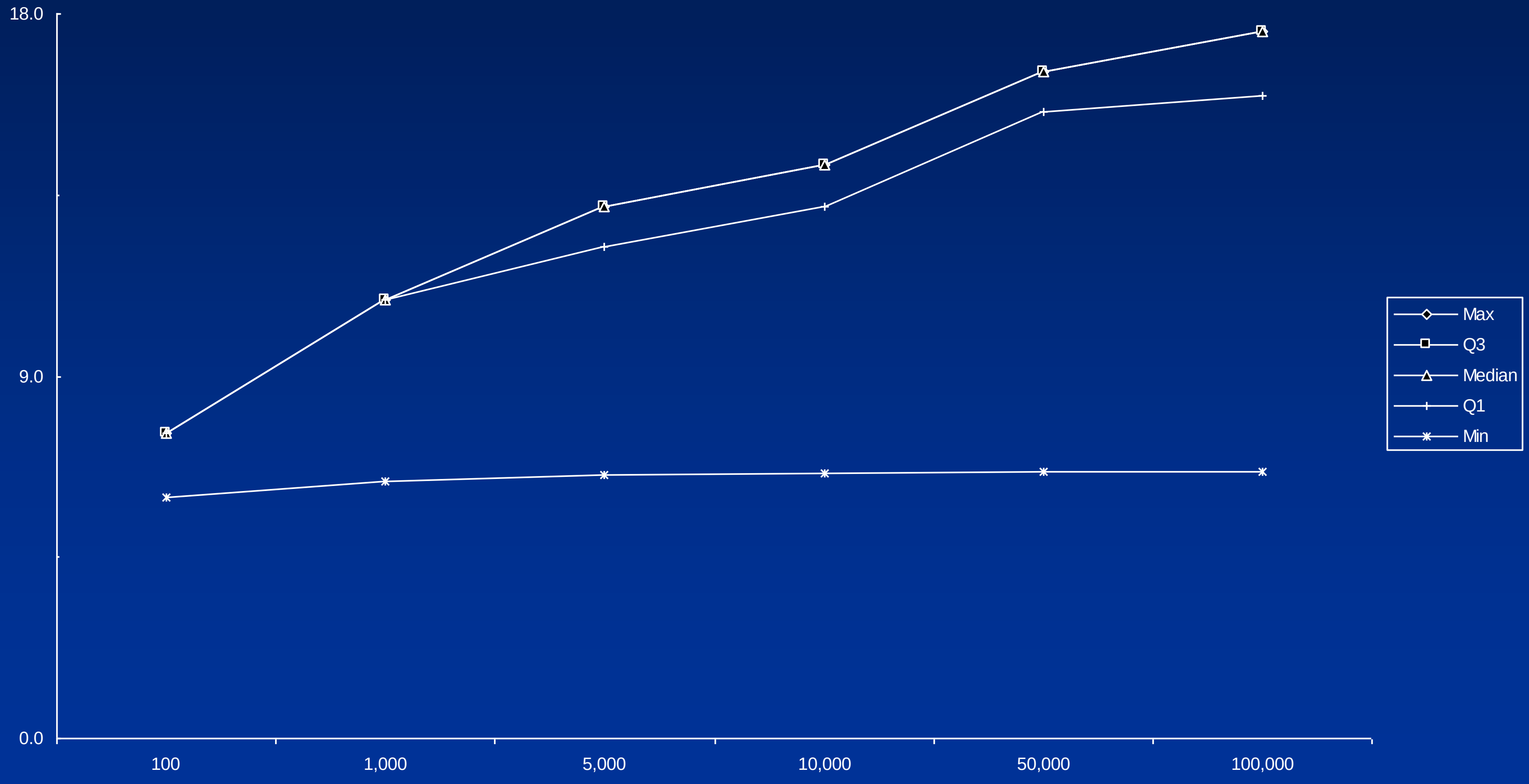
=> as u decreases, weight increases

  - Rare values have high weights

Match Weights for County by File Size



Match Weights for Last Name by File Size.



Choosing Cutoff Weights

Graph vs. Math

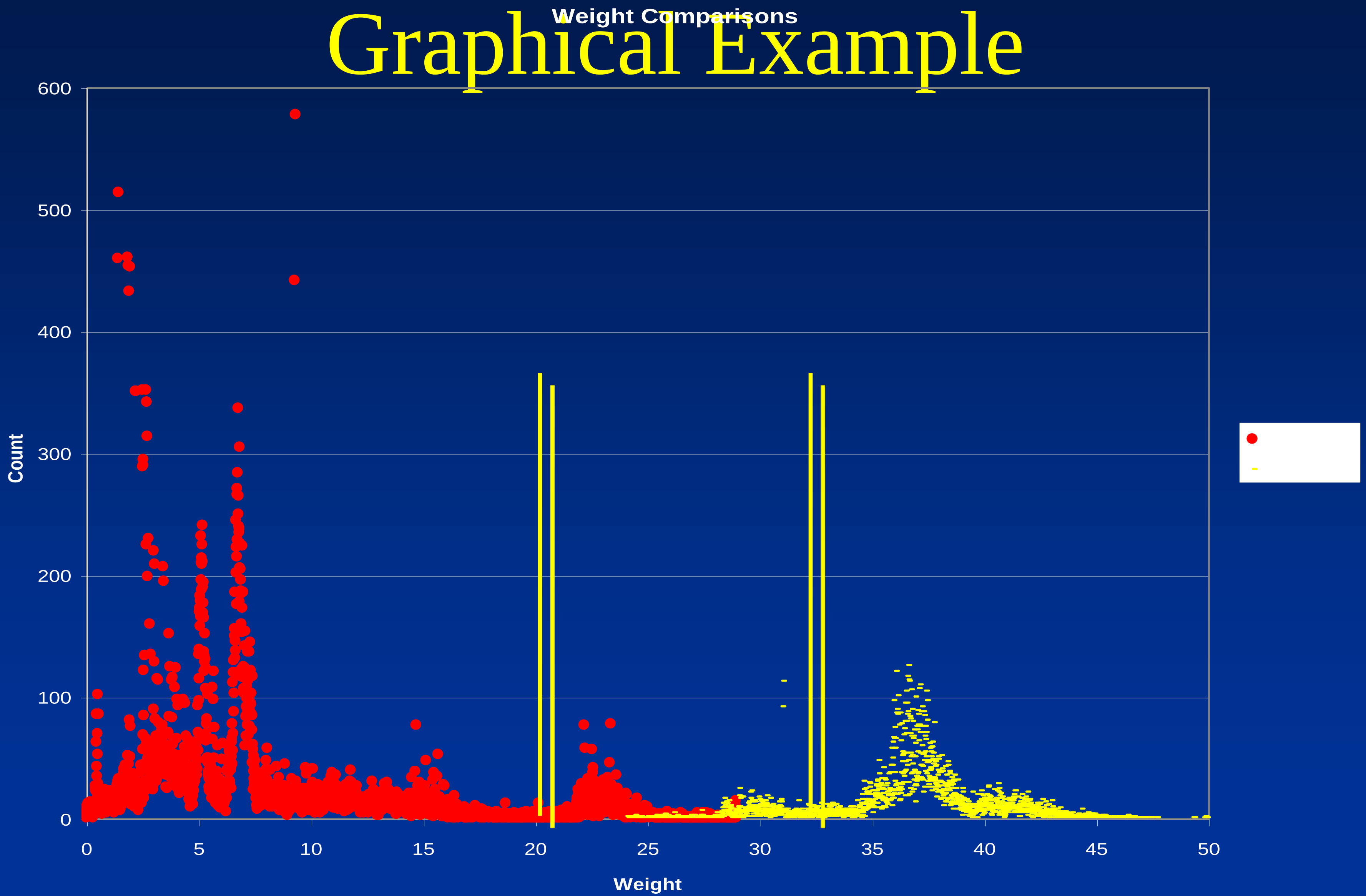
Cutoff Weights

- Traditionally, choose two cutoff weights
- Choose one such that every pair above the cutoff is a match
- Choose the second such that every pair below the cutoff is not a match
- Any record between two cutoffs is manually reviewed

Graphical Method

- Make a graph of all match weights
- Hope to see a small clump of pairs at high weights
  - First cutoff
- Hope to see a large clump of pairs at lower weights
  - Second cutoff
- Some overlap that needs to be reviewed

Graphical Example



Cutoff Points

- Formula for determining cutoff point for accepting/rejecting match pairs
- Depends on
  - File sizes
  - Expected number of matches
  - Desired probability of a correct match

Cutoff Point Formula

A = Size of file A

B = Size of file B

E = expected # of matches

p = minimum acceptable probability of a true match

$$\text{cutoff} = \log_2 \left(\frac{\frac{p}{1-p}}{\frac{E}{A \text{x} B - E}} \right)$$

Cutoff Point Formula

Decreasing expected pairs (E)

=> higher cutoff

Increasing probability (p)

=> higher cutoff

Increasing file sizes (A & B)

=> higher cutoff

$$\text{cutoff} = \log_2 \left(\frac{\frac{p}{1-p}}{\frac{E}{AxB - E}} \right)$$

Choosing Cutoff Points

- Calculate weight for high probability (0.9)
- Calculate weight for low probability (0.5)
- Review everything in between
- For example
  - High weight is 13.13
  - Low weight is 9.96
- Traditionally, we have chosen the same high and low weight (no review)

Linkage Feasibility Test

- Calculate the cutoff point based on the formula
- Calculate the minimum weight associated with each variable available for linkage
- Compare the sum of the weights to the cutoff point
- If sum is less than cutoff then results may be suspect

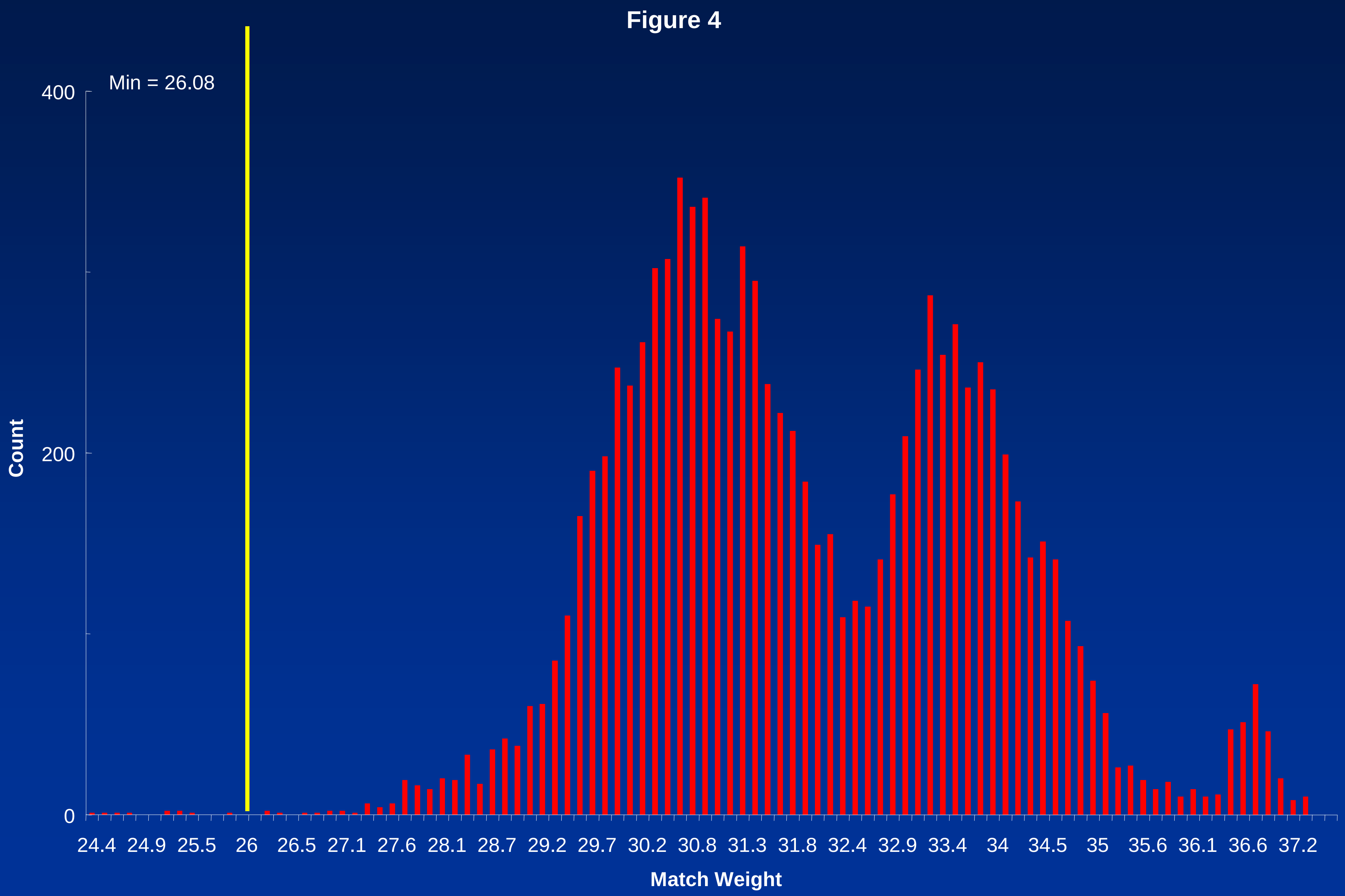


Figure 4
Min = 26.08
Count
400
200
0
24.4
24.9
25.5
26
26.5
27.1
27.6
28.1
28.7
29.2
29.7
30.2
30.8
31.3
31.8
32.4
32.9
33.4
34
34.5
35
35.6
36.1
36.6
37.2
Match Weight

A Note of Caution

- Make sure you have controlled for
  - Dependencies (day of week and time of day)
  - False precision (using tolerances)
    - Date comparisons should have 365 outcomes
    - If you give a tolerance of the day before and day after there are only 365/3, 122 outcomes
    - Treating times as continuous when the majority are segmented into 15 minute intervals
  - Have the correct m probability
    - Most linkage programs have defaults (m = 0.01)
  - Have used every piece of information available

Low Probability Matches

Imputed Links

Nagging Questions

- What if you can’t reach the necessary cutoff point
  - Too few expected matches
  - Files are too large / not enough identifiers
  - Very stingy about what is a true match
- What if you set the cutoff to correspond to a probability of 0.9 and a matched pair reaches a probability of 0.89?
- If you only keep the “best” pairs are you biasing your linkage and results?

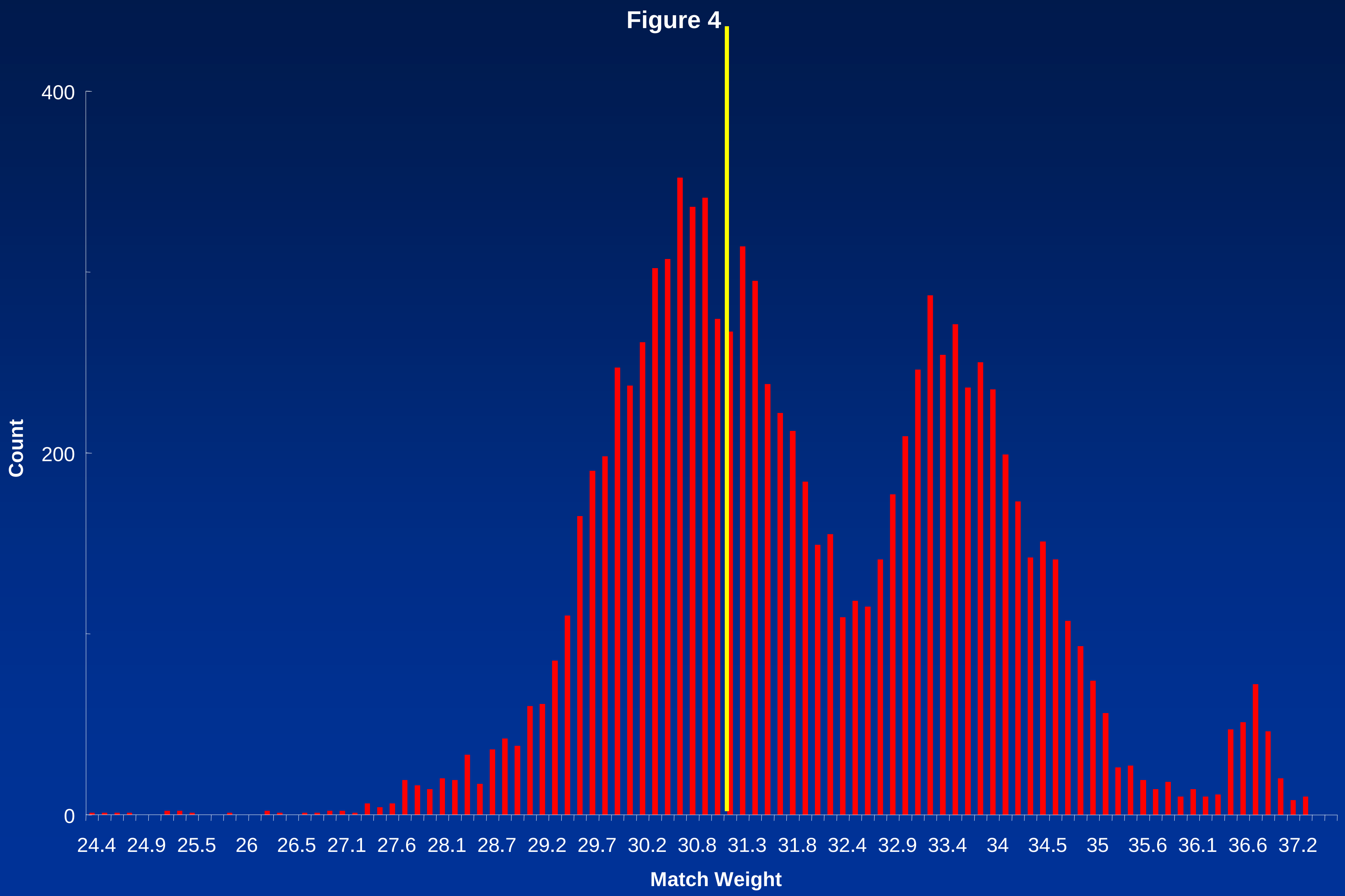
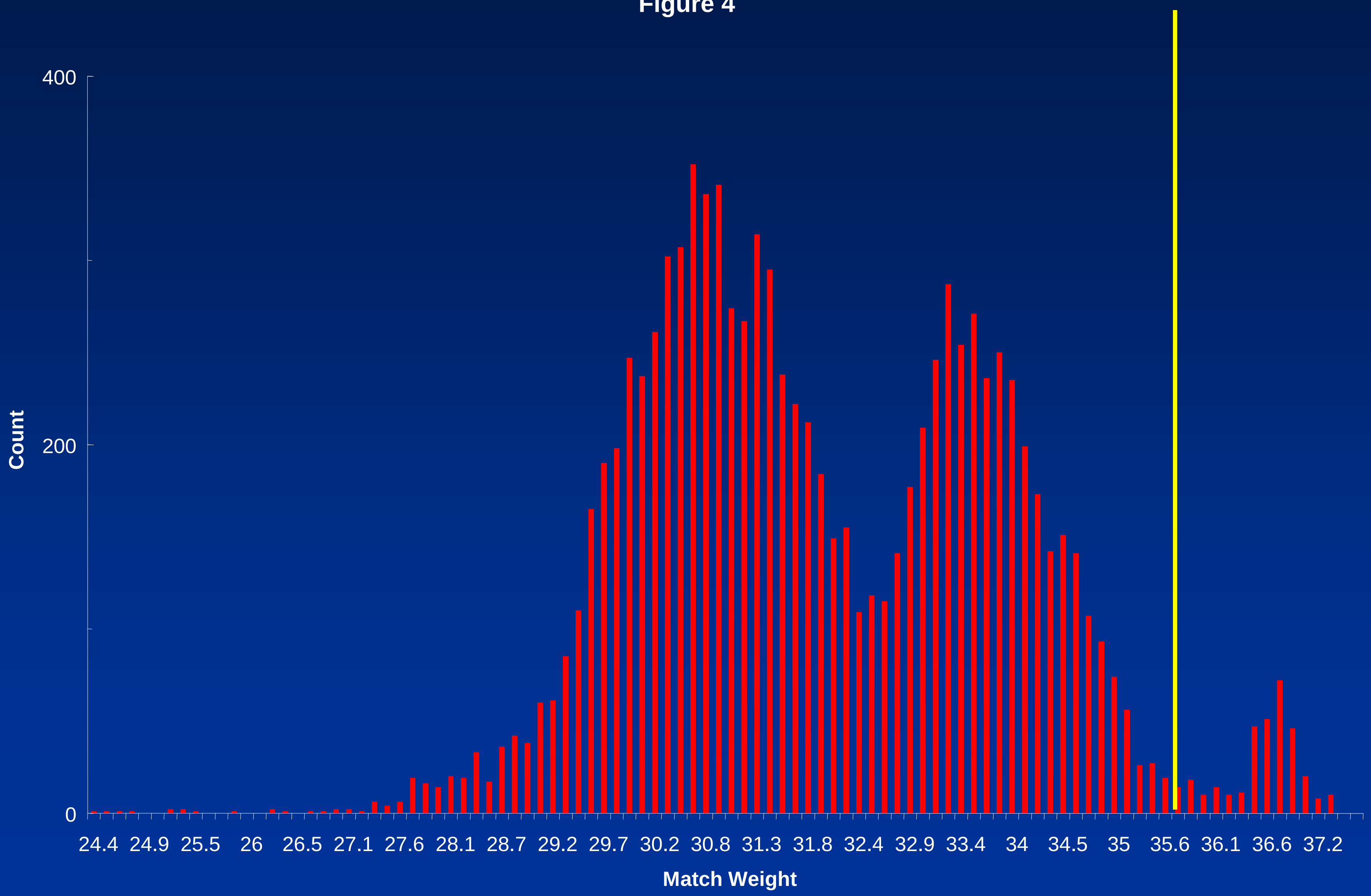


Figure 4
400
200
0
Count
24.4
24.9
25.5
26
26.5
27.1
27.6
28.1
28.7
29.2
29.7
30.2
30.8
31.3
31.8
32.4
32.9
33.4
34
34.5
35
35.6
36.1
36.6
37.2
Match Weight

Figure 4



400
200
0
Count
24.4
24.9
25.5
26
26.5
27.1
27.6
28.1
28.7
29.2
29.7
30.2
30.8
31.3
31.8
32.4
32.9
33.4
34
34.5
35
35.6
36.1
36.6
37.2
Match Weight

Linkage Imputation

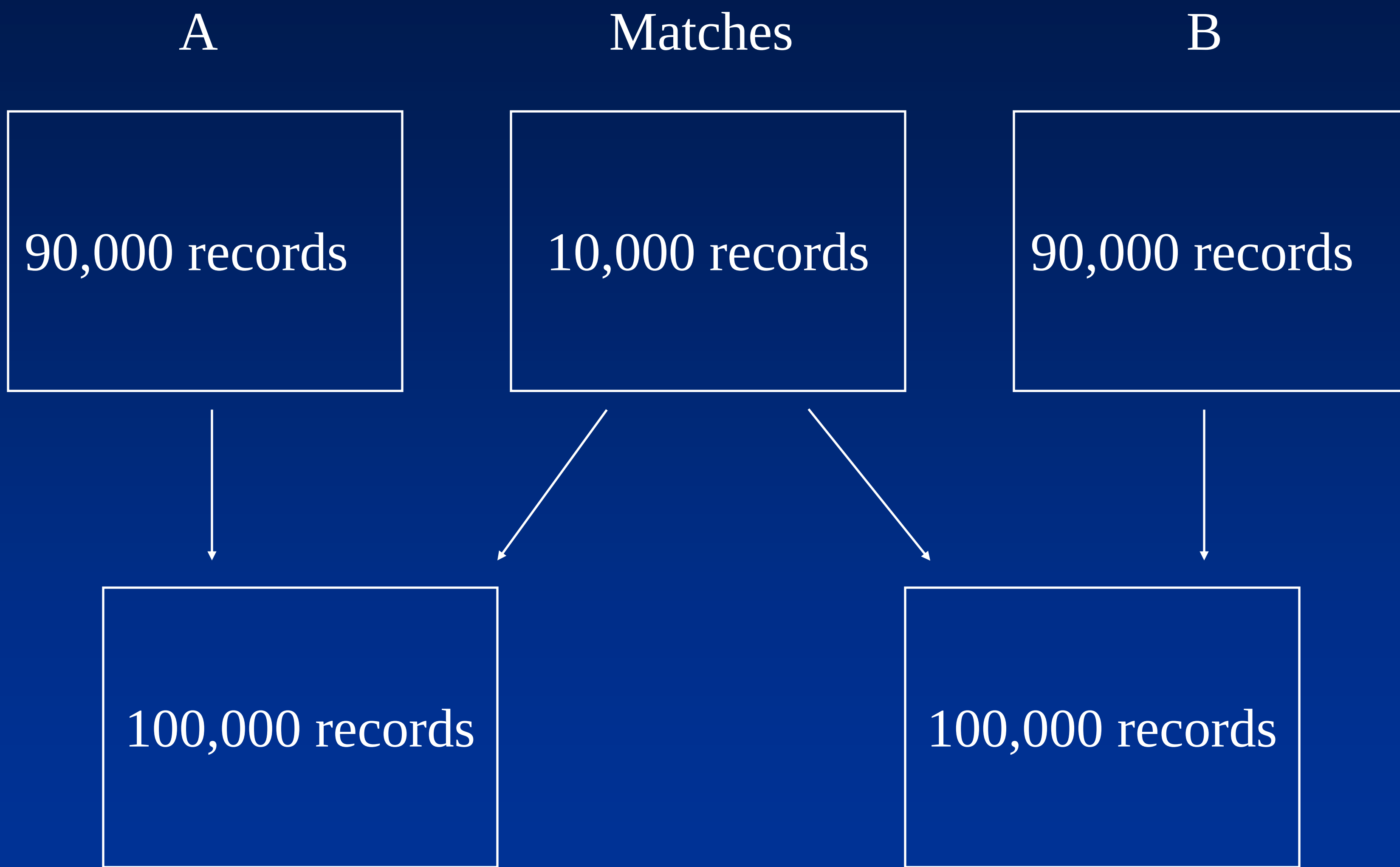
- It has been suggested that statistical imputation might allow you to analyze the impact of these lower weight pairs
- Algorithm for incorporating imputation
  - Don't set a cutoff weight (take all pairs)
  - Take a probability sample of all matched pairs
    - weighted by probability of being a true pair
  - Take several probability samples (5 – 10)
  - Conduct analysis on each imputed sample separately
  - Use developed methods to combine results

Simulation Study

Purpose

- Determine if restricting matches to those with probabilities of 0.9 or higher can lead to biased distributions of linkage variables

Databases


A
Matches
B
90,000 records
10,000 records
90,000 records
100,000 records
100,000 records

Levels of Linkage Variables

A	B	C
Name	Date of Birth	Age
Date of Birth	Date of Event	Date of Event
Date of Event	Gender	Time of Event
Time of Event	County	Gender
Gender		County
County		

Linkages

- Linkage algorithms were developed for each of the three combinations of variables
- Results of each linkage
  - High probability set
    - All matches greater than 0.9
  - Five imputed sets
    - Probability samples from entire distribution of matches

Linkage Performance Measures

- Sensitivity - Ability to recognize true matches

  # correct matches identified / 10,000

- Specificity - Ability to recognize incorrect matches

  1 - # incorrect matches / total matches

High Probability Results

	A	B	C
Min. Prob.	0.999	0.153	0.024
# Matches	10,032	4,333	2,470
Specificity	0.999	0.916	0.913
Sensitivity	0.999	0.397	0.226

Imputed Sets Results

	A	B	C
Min. Prob.	0.999	0.153	0.024
Avg. # Matches	10,032	10,776	11,835
Specificity	0.998	0.775	0.616
Sensitivity	0.991	0.719	0.536

Choices

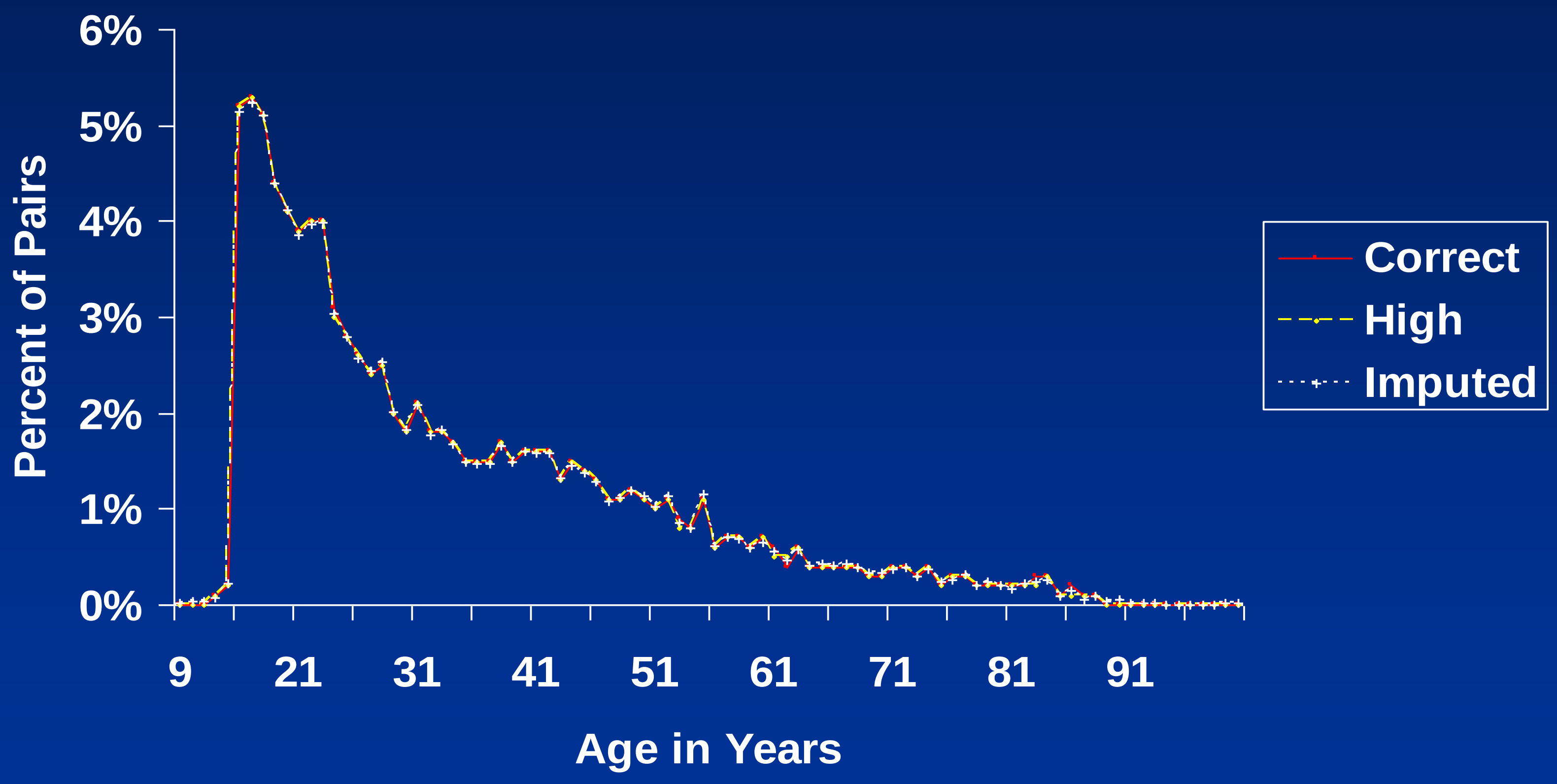
- Very few matches but very good
- Lots of matches but adding a lot of noise

What's happening to the linkage variables?

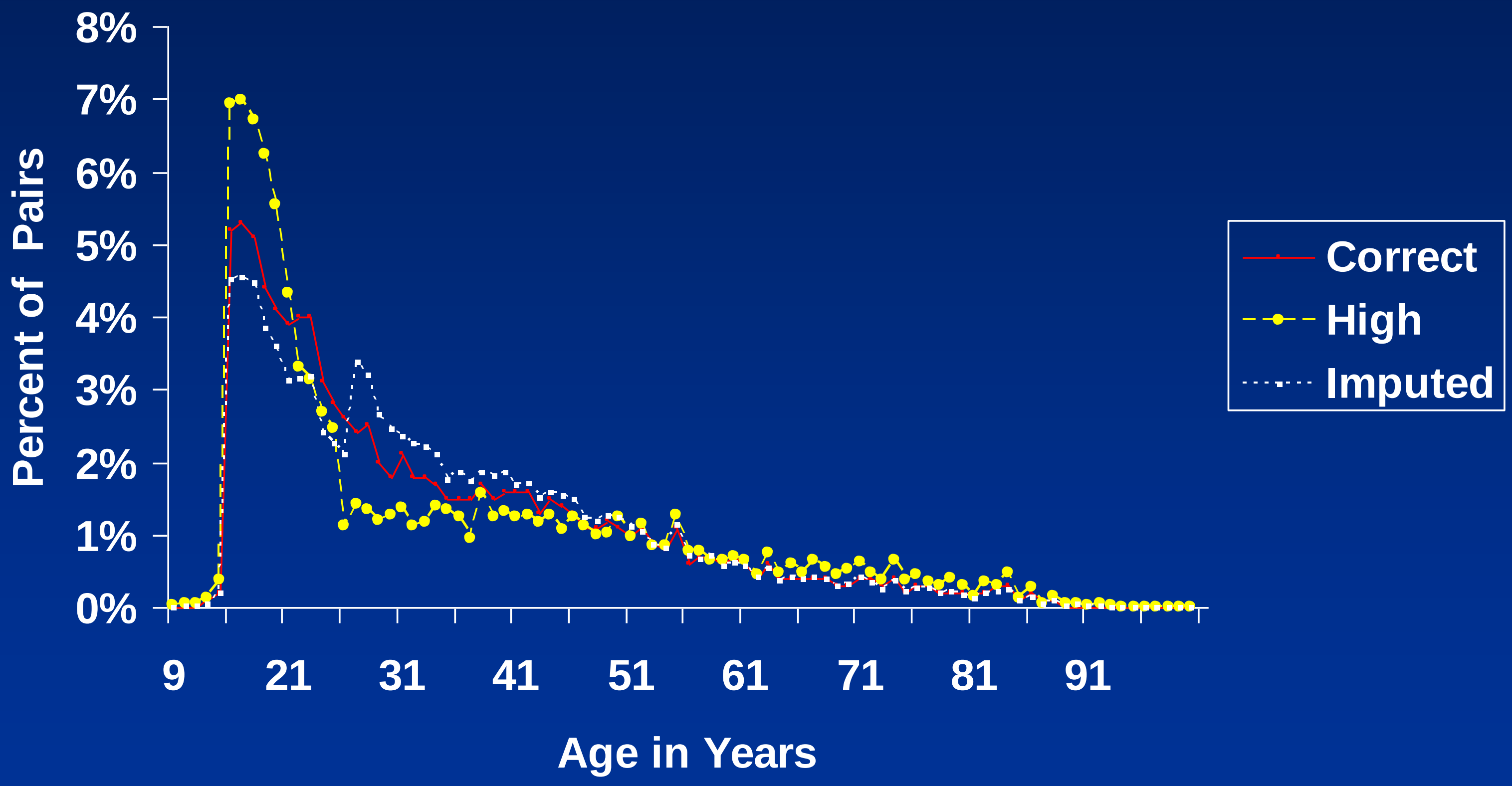
- Look at the distributions for high probability vs. imputed sets
  - Age – continuous variable
  - County – discrete variable

Age

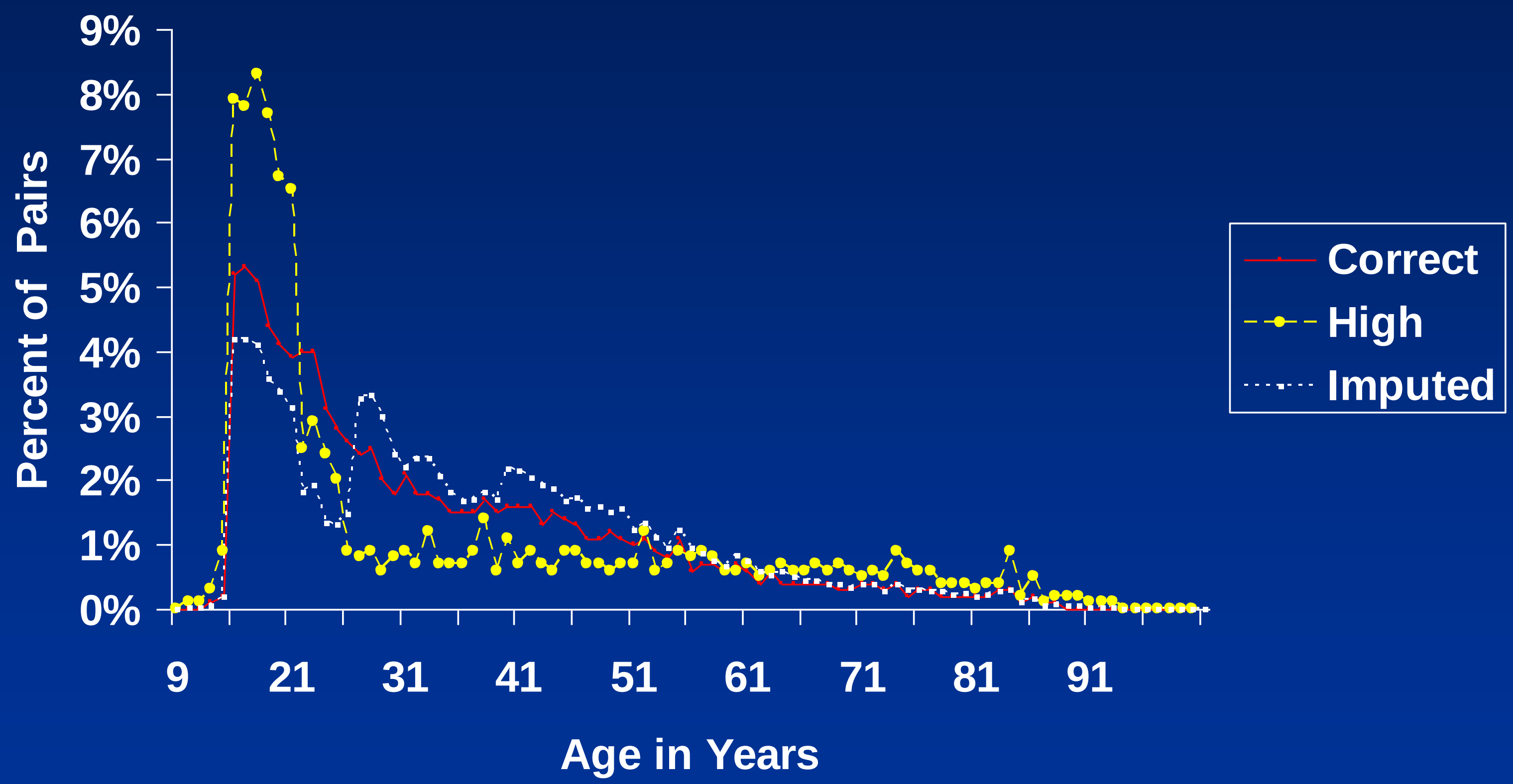
Age Distribution for Linkage A



Age Distribution For Linkage B

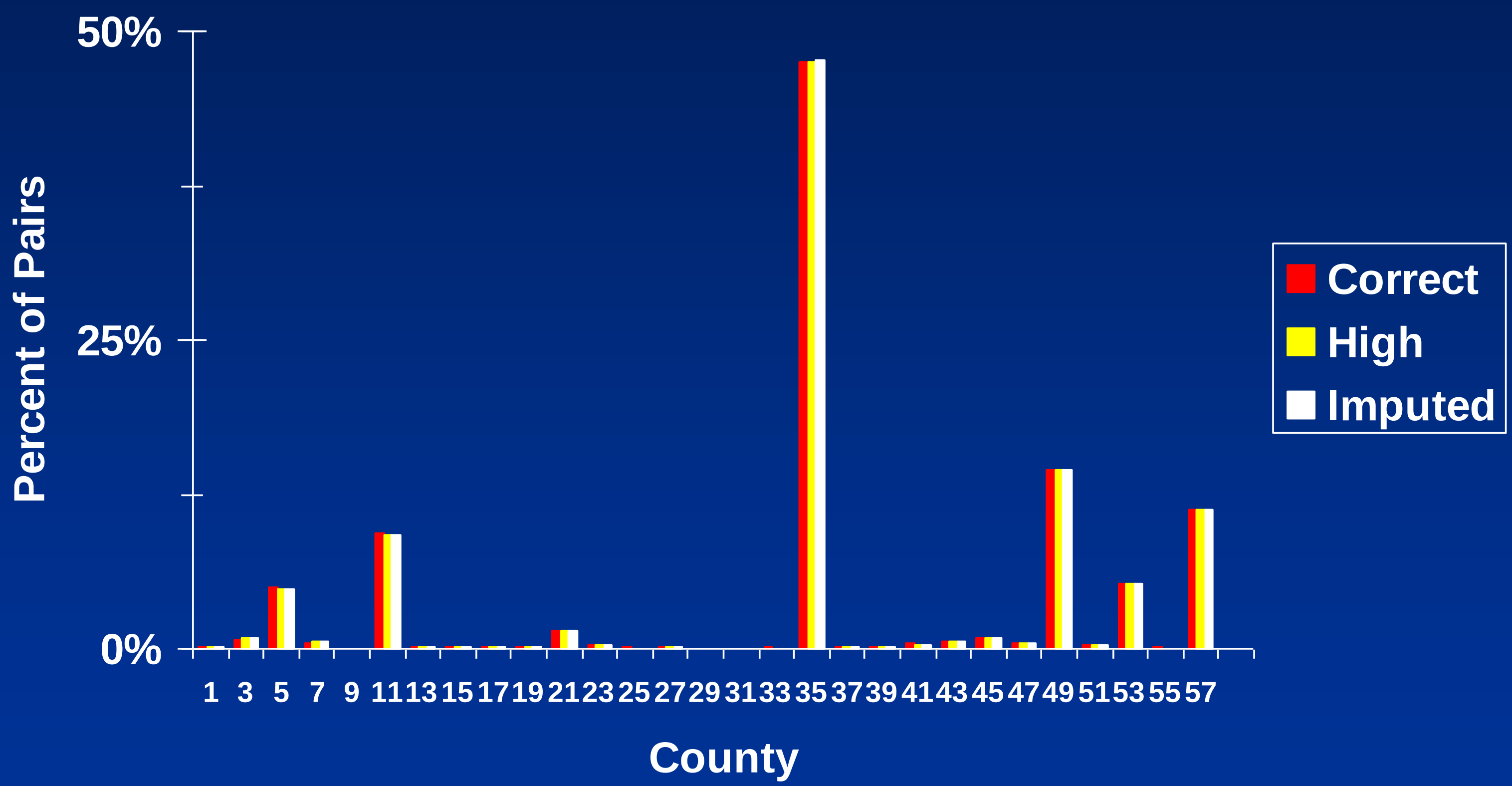


Age Distribution For Linkage C

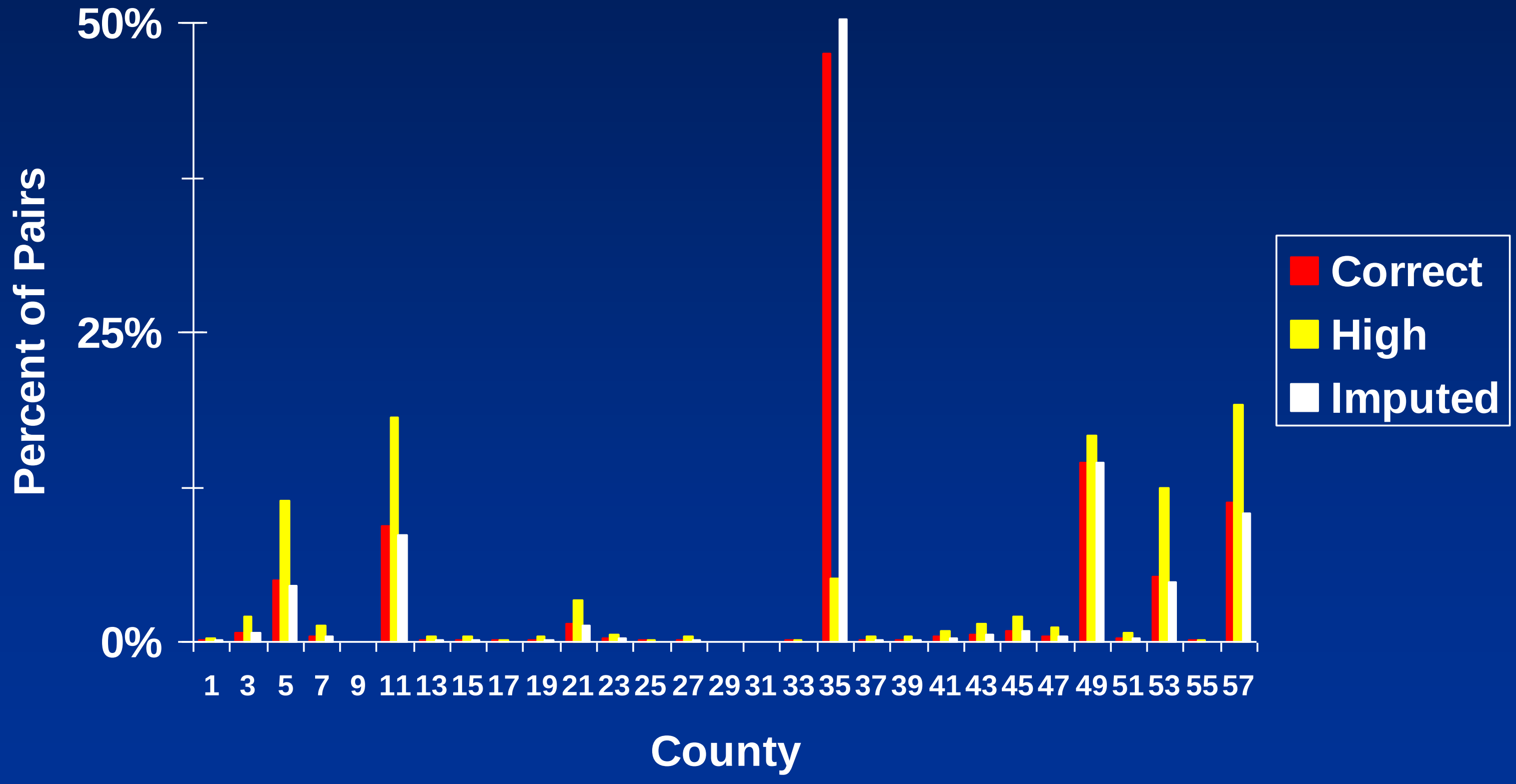


County

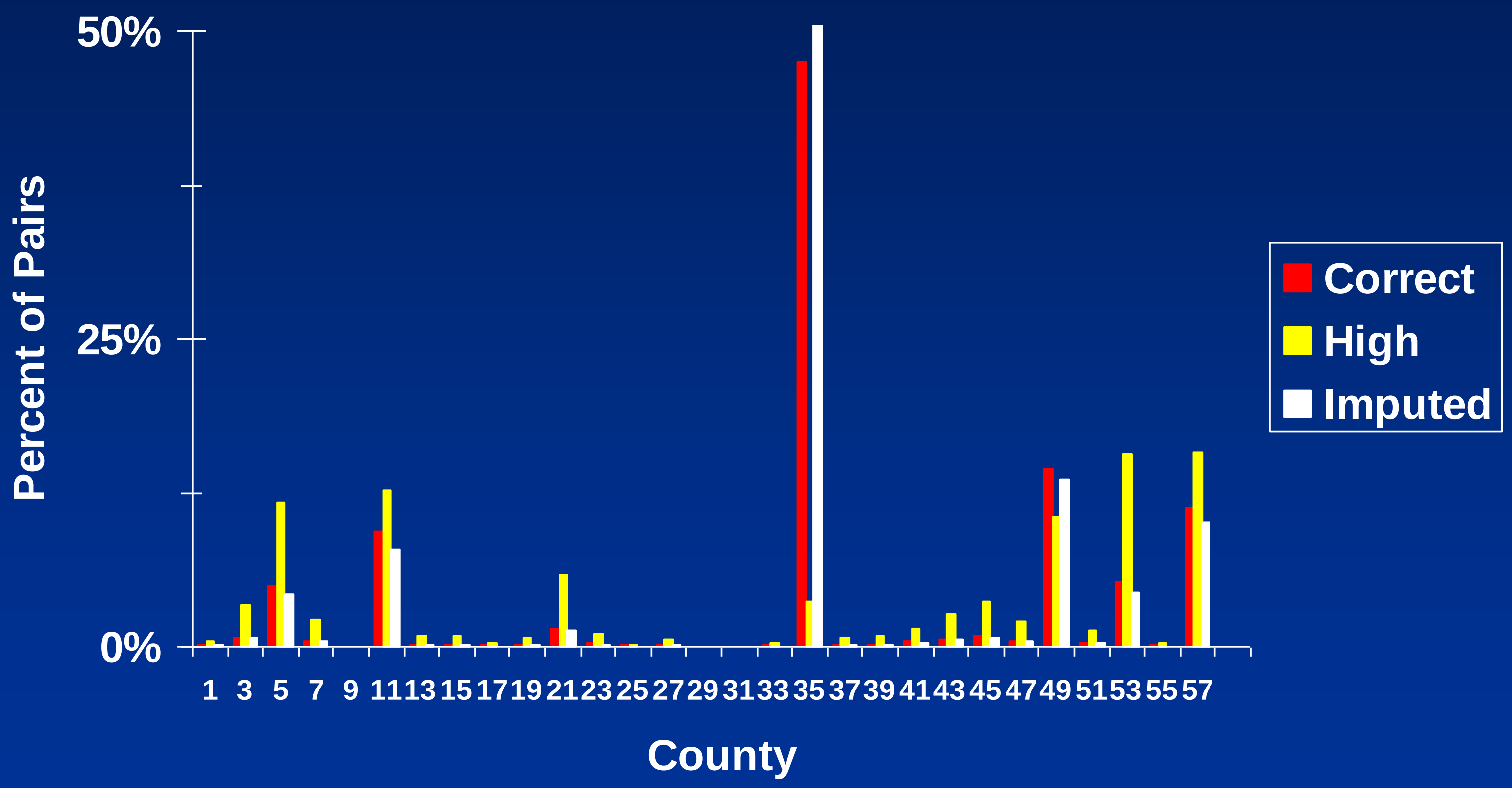
County Distribution for Linkage A



County Distribution for Linkage B



County Distribution for Linkage C



Conclusions

- If you have enough information then imputation does not add anything
- If you have sparse information
  - Imputed sets appear to preserve distributional features better than high probability matches
  - Specificity does decline (false matches)
  - May be good for population studies not tracking individuals

Future Research

- Determine how imputed sets vs. high probability matches impact outcomes analysis

Research Studies

Probabilistic Linkage of Computerized Ambulance and Inpatient Hospital Discharge Records: A Potential Tool for Evaluation of Emergency Medical Services

Results

- Three years of EMS and inpatient records
- Highest linkage rates for dispatch codes of breathing problems and chest pain
- Inpatient mortality was 6.8%
- Median length of stay 3 days
- Median hospital charges were $6,620
  - $286,737,067 total hospital charges

Repeat Patients to the Emergency Department in a Statewide Database

Probabilistic unduplication of three-years of emergency department data

Findings

- 1.37 million visits by 780,000 patients
- Repeat and frequent users account for 1/3 of patients by 2/3 of visits
- Patients attending five or more EDs were more likely to not have insurance
- 1/3 of serial users ($\geq$ 5 visits) in year remained serial users the next year

Analysis of Out of Hospital Endotracheal Intubation

Databases

- Statewide registry of ednotracheal intubations
- EMS
- Hospital discharge
- Death certificates

Results

- 23% of patients experienced at least one ETI error
- Of linked cases – 27% survived discharge
- ETI errors not associated with death
- ETI errors associated with pneumonitis
- Survival associated with rescuer experience for cardiac arrest patients

Software

Software

- SAS
  - Link King/Link Plus/Link Pro
- Access
  - CODES 2000 / LinkSolv
- Other
  - FEBRL/Integrity/home grown
- Pricing
  - Free to $$$$$

Questions?

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Crash Examples

How do Crash Outcomes for Older Drivers Compare to Crash Outcomes for Younger Drivers?

Link Motor Vehicle Crash and Hospital Discharge

Older Drivers

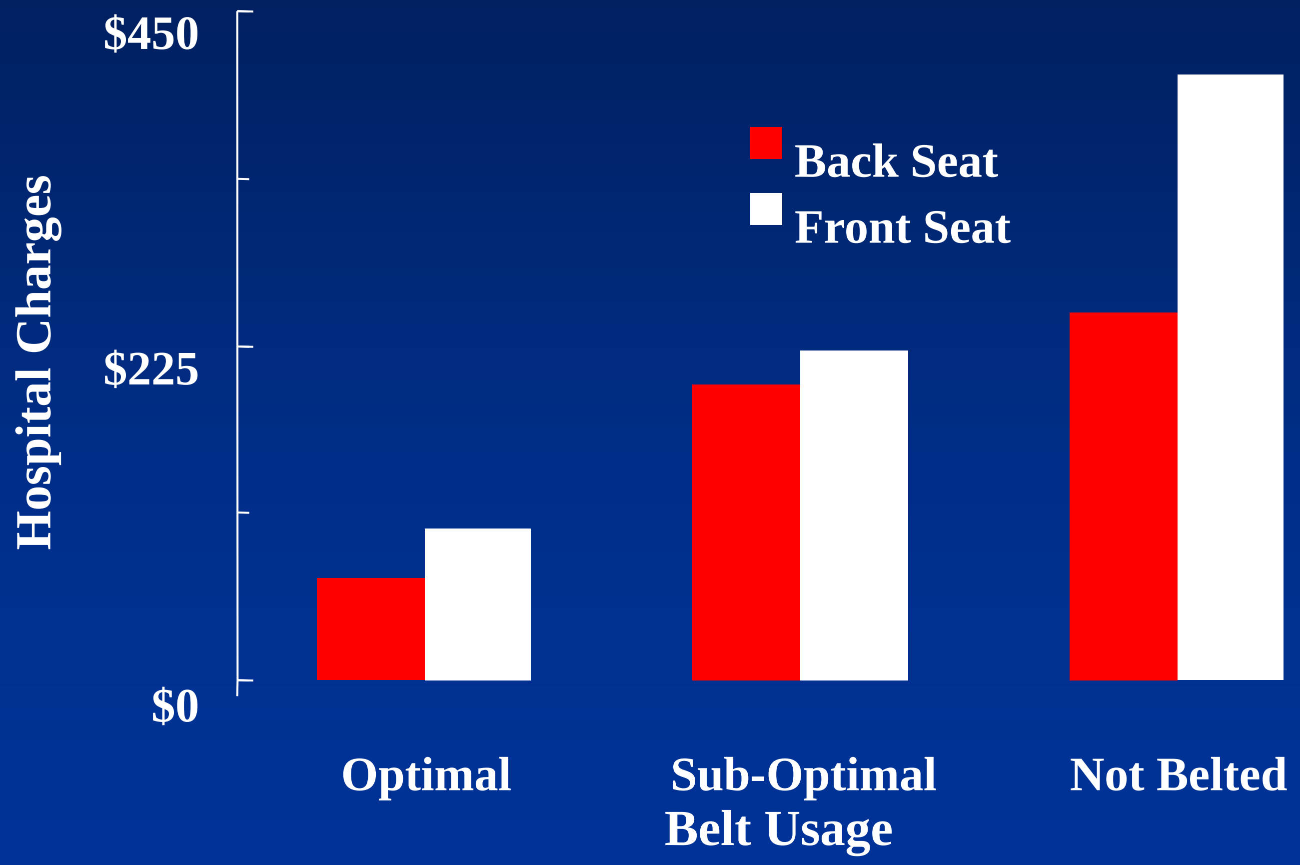
- 2.5 times more likely to be admitted to the hospital after a crash than younger drivers
- Have the same belt usage rate as younger drivers
  - However 68% of older drivers hospitalized were belted
- Are belts providing protection for the elderly?

What is the Medical Impact for a Child in the Front Seat Compared to a Child in the Back Seat?

Link Motor Vehicle Crash and

Hospital Discharge

Charges by Seating Location and Belt Use



What is the Impact of Passengers on Crash Outcomes of Teenage Drivers?

Link Motor Vehicle Crash and Hospital Discharge

Risk of Hospitalization or Death to the Teenage Driver

	Teens Odds Ratio	Adults Odds Ratio
Any passenger vs. alone	1.7 (1.4,2.2)	1.3 (1.2,1.4)
1 passenger vs. alone	1.6 (1.3,2.1)	1.3 (1.1,1.4)
≥ 2 passenger vs. ≤ 1	1.6 (1.2,2.1)	1.2 (1.1,1.4)
≥ 3 passenger vs. ≤ 2	1.7 (1.2,2.4)	1.1 (1.0,1.3)
≥ 4 passenger vs. ≤ 3	1.9 (1.2,3.2)	1.3 (1.1,1.7)
≥ 5 passenger vs. ≤ 4	2.5 (1.1,5.6)	1.8 (1.3,2.6)

What types and how many injuries will occur in shop class over a one year period?

Link Student Injury (92 – 96),

Emergency Department (96),

Inpatient Databases (92 – 96)

Shop Class Injuries

ED 1996

- 167 in class injuries
- 45 seen at ED
- ½ were saw related
- $16,571 ED charges
- Open wounds, 64%
- Fractures, 9%
- 2 amputations

Inpatient 1992 -1996

- 1,008
- 7 admitted
- 6 table saw related
- $26,767 hospital charges
- 3 amputations
- 2 open wound with tendon damage