Probabilistic Data Linkage: Basic Methods and Applications Lawrence Cook, MStat, PhD **Department of Pediatrics Division of Critical Care** University of Utah



Crash Outcome Data Evaluation System (CODES)

- Initiated in 1992 by the US National Highway Traffic Safety Administration (NHTSA)
- Are safety belts and motorcycle helmets effective at preventing injuries resulting from motor vehicle crashes?



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



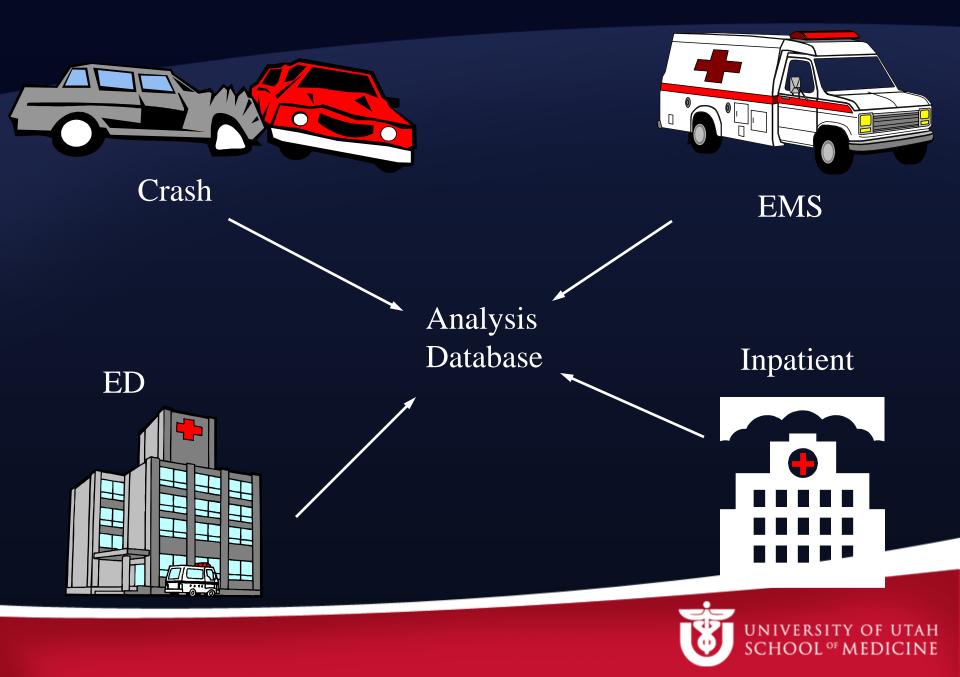
- ICD-9, Procedures, and E Codes
- ED Charges
- No information once admitted to hospital
- No information prior to arrival at ED



Inpatient Database

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





Benefits of Safety Belts

- Odds of being admitted or dying
 -4.3 6.5 times higher if not belted
- Odds of emergency department or worse
 2.8 3.5 times higher if not belted
- Odds of any injury
 - -1.9 4.1 times higher if not belted
- Hospital charges for unbelted
 - 55% increase among hospitalized persons
 - 400% increase among all persons



Probabilistic Linkage

 Probabilistic 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



Record Linkage with Imperfect Data

Crash Record

Mary Smith

F 05/05/45 07/15/10 11:40 Weber US5 Seat=1 Belt=N

Hospital Record

Mary Smith Sanchez F 05/05/44 07/15/10 11:51 Weber Fracture 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.



Mary Smith		15/10 11:47 Weber US5 Seat=1 Belt=N	
Hospital Rec	Probability of true match = 0.0009		
Mary Smith Sa		15/10 11:55 Weber Fracture Mem Hosp	



Mary Smith F 0		Weber US5 Seat=1 Belt=N
Hospital Record	Probability of true match = .0192	
Mary Smith Sanchez F 0		Weber Fracture Mem Hosp



Mary Smith	F 05/05/45 (JS5 Seat=1 Belt=N
Hospital Record		Probability of true match = .0385	
Mary Smith Sanchez	F 05/05/44 (Fracture Mem Hosp



Mary Smith	F 05/05/45 07/15		Seat=1 Belt=N
Hospital Record		Probability of a true match = 0.1429	
Mary Smith Sanchez	F 05/05/44 07/15		re Mem Hosp



Mary Smith	F 05/05/45 07/15/10 11:		3elt=N
Hospital Record		Probability of a true match = 0.9836	
Mary Smith Sanchez	F 05/05/44 07/15/10 11:		Hosp





Mary Smith) 11:47 Weber US5 Seat=1 Belt=N
Hospital Record	Probability of a true match = 0.9817	
Mary Smith Sanch) 11:55 Weber Fracture Mem Hosp



Mary Smith	F		Weber US5 Seat=1 Belt=N
Hospital Record		Probability of a true match = 0.9999	
Mary Smith Sanchez	F		Weber Fracture Mem Hosp



Crash Record

Mary Smith

F 05/05/45 07/15/10 11:47 Weber US5 Seat=1 Belt=N

Hospital Record

Mary Smith Sanchez F 05/05/44 07/15/10 11:55 Weber Fracture Mem Hosp

This pair of records has both agreements and disagreements. Our calculations say that the odds are p = 0.9999 that the records refer to the same individual and crash event.



Research Studies



Impact of Passengers on Crash Outcomes of Teenage Drivers?

> Motor Vehicle Crash Hospital Discharge Vital Records



Risk of Hospitalization or Death to the Teenage Driver

	Teens	Adults
	Odds Ratio	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)
\geq 2 passenger vs. \leq 1	1.6 (1.2,2.1)	1.2 (1.1,1.4)
\geq 3 passenger vs. \leq 2	1.7 (1.2,2.4)	1.1 (1.0,1.3)
\geq 4 passenger vs. \leq 3	1.9 (1.2,3.2)	1.3 (1.1,1.7)
\geq 5 passenger vs. \leq 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?

Student Injury Reports Emergency Department Hospital Discharge



Shop Class Injuries

One-year ED

- 167 in class injuries
- 45 seen at ED
- 1/2 were saw related
- Open wounds, 64%
- Fractures, 9%
- 2 amputations
- \$16,571 ED charges

Five-years Inpatient

• 1,008

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



Repeat Patients to the Emergency Department

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 (> 5 visits) in year remained serial users the next year



Defining Serious Injuries for Motor Vehicle Crashes



Crash View of Injuries

- KABCO
 - K or killed within 30 days of the crash date
 - A or incapacitating injury
 - B or non-incapacitating injury
 - C or possible injury
 - O or no injury
- Assigned by investigating officer at the crash scene



Serious Injury Rates

- Serious = K or A injuries
- Can serious injury rates be measured similarly across states or over time?
- Case study Utah
 - Complete redesign of crash report in 2006
 - New definitions for KABCO



Utah KABCO

Pre 2006

• K – Fatal

- **Post 2006**
- K Fatal

- A Broken bones & bleeding
- B Bruises & abrasions
- A Incapacitating injury
- B Non-incapacitating injury

- C Possible injury
- O No injury

- C Possible injury
- O No injury

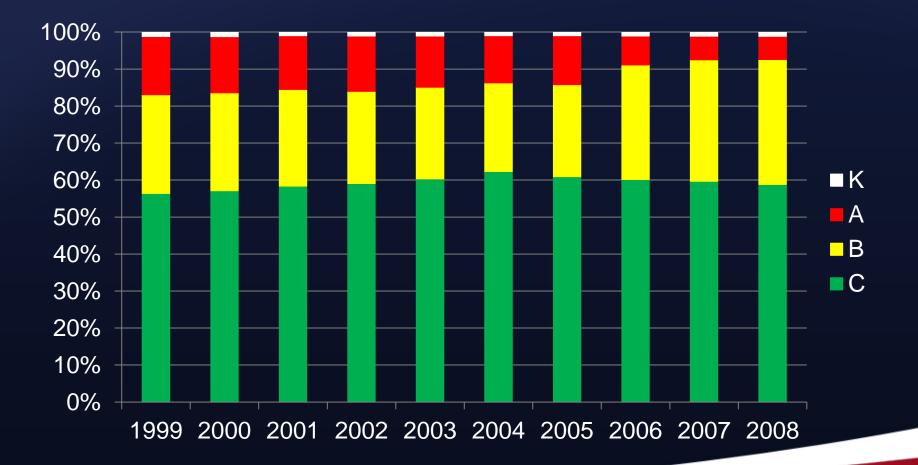


Methods

- Remove all non-injured occupants
- Compare distribution of K, A, B, C injuries before and after crash report change
- Will there be a difference?



Utah KABCO Data





Can Hospital Files be Used to Measure Serious Injury Rates?

- Examine an injury severity measure based on hospital information
- Consider non-linked occupants as uninjured
- Maximum Abbreviated Injury Scale (MAIS)

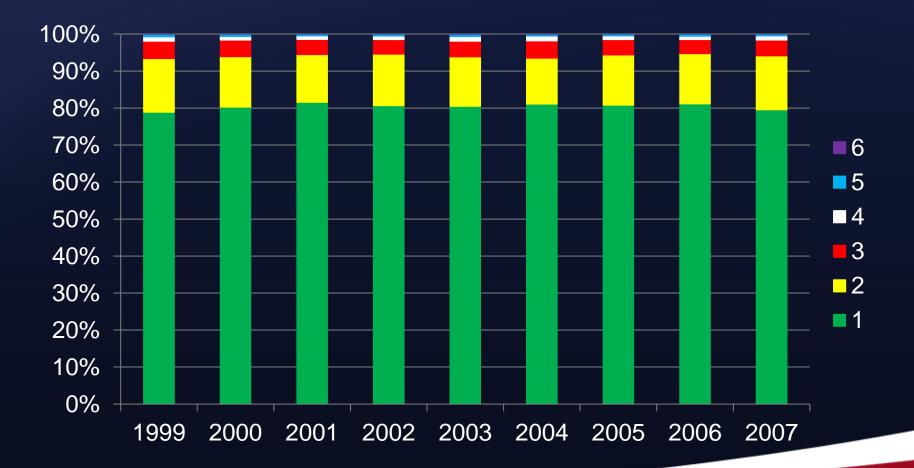


Severe Injury – Medical Record

- MAIS
 - -1 Minor
 - 2 Moderate
 - 3 Serious
 - -4-Severe
 - 5 Critical
 - 6 Not survivable
- Derived from ICD-9 codes using ICDMap90



Utah MAIS Data





Summary

- Does wording on crash report matter?
 KABCO distribution appears to change
 MAIS remained more consistent
- Extend study to multiple states



Multi-State Analysis



Comparing Serious Injury Rates Across US States

- States determine the reporting criteria for motor vehicle crashes
 - Monetary
 - Injury
- States also control
 - Design and format of crash report
 - Definitions of fields on crash report



Crash Severity of Injury

State A

- K Fatal
- A Incapacitated
- B Visible Injury
- C Momentary unconsciousness/ Complaint of pain

- State B
- K Fatal
- A Life Threatening
- B Serious
- C Complaint of Pain

• O – No injury

• O – No injury

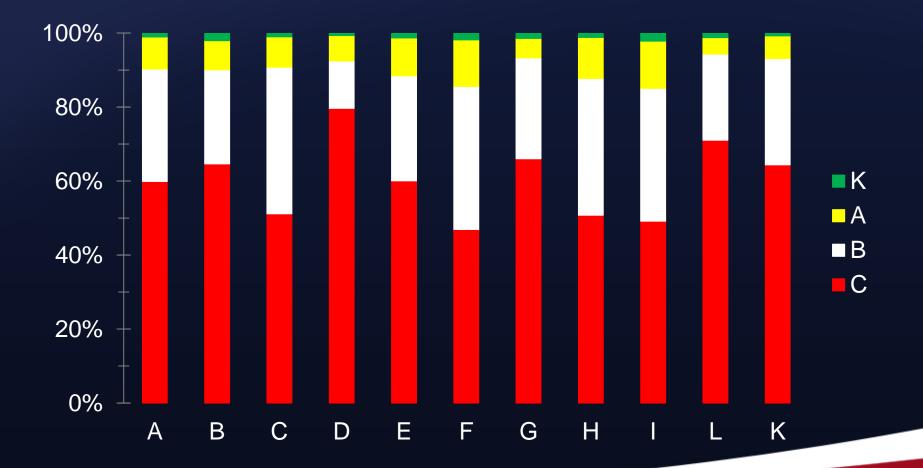


Methods

- Collected data from 11 states from crash years 2005 to 2008
- Remove all non-injured occupants
- Compare distribution of K, A, B, C injuries



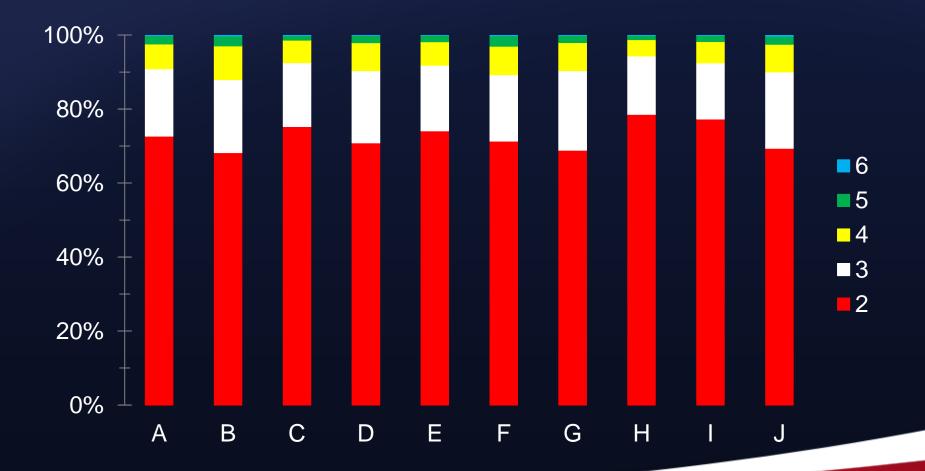
KABCO by State





TAH

MAIS by State





UTAH

Summary

- A lot of variation between severity of injury coding on state crash reports
- Using MAIS helps to smooth the injury distribution
- More research needed



More Linkage Studies

- Crash to birth certificates
- Crash to bankruptcy
- Poison control to hospital and death
- EMS to hospital, trauma, and death
- Endotracheal intubation outcomes



What Do You Need For Probabilistic Linkage



Data Files

- Data use agreements
- Institutional Review Board (IRB) Approvals
- Memoranda of understanding
- Variables common to both files



Linkage Variables

- Many levels
- Observations spread throughout levels
- Reasonable accuracy
- Mix of person and event information
- 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?



Name Dilema

- Name are powerful identifiers
- Confidentiality concerns
- Names may not be collected in database
- Simulation study to determine effect of name information on linkage projects

- We know the answers



Linkage Performance Measures

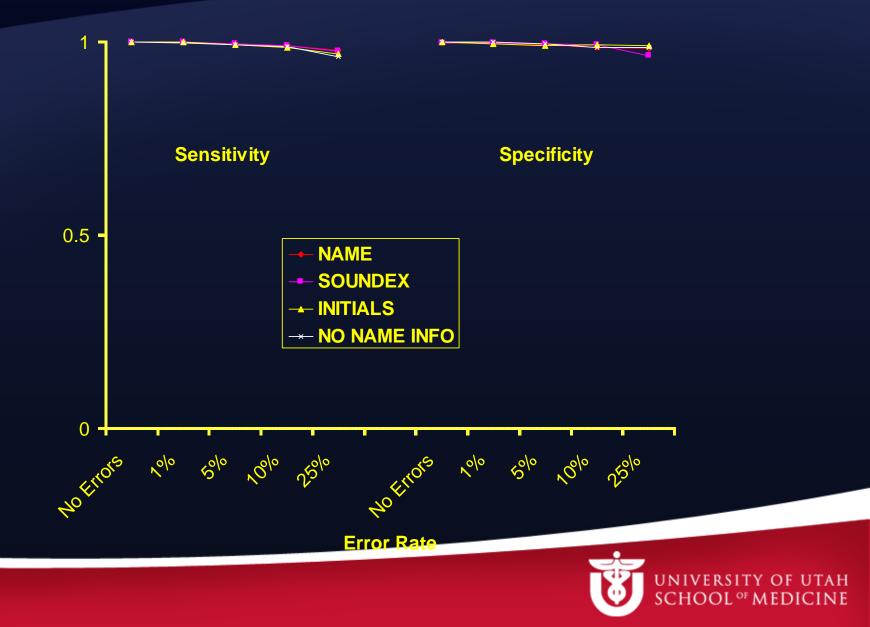
 Sensitivity - Ability to recognize true matches

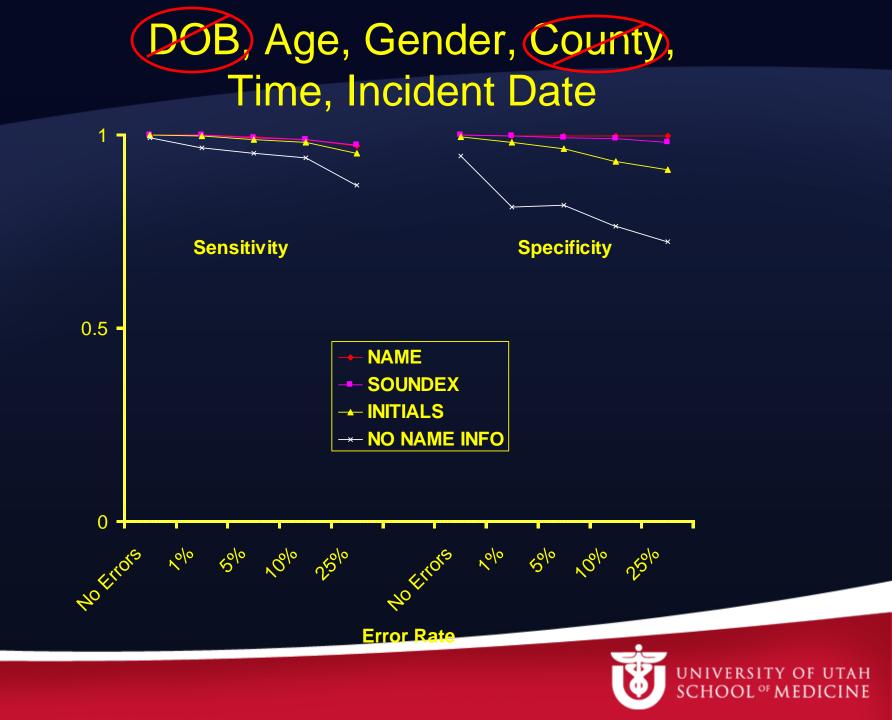
% of true matches identified

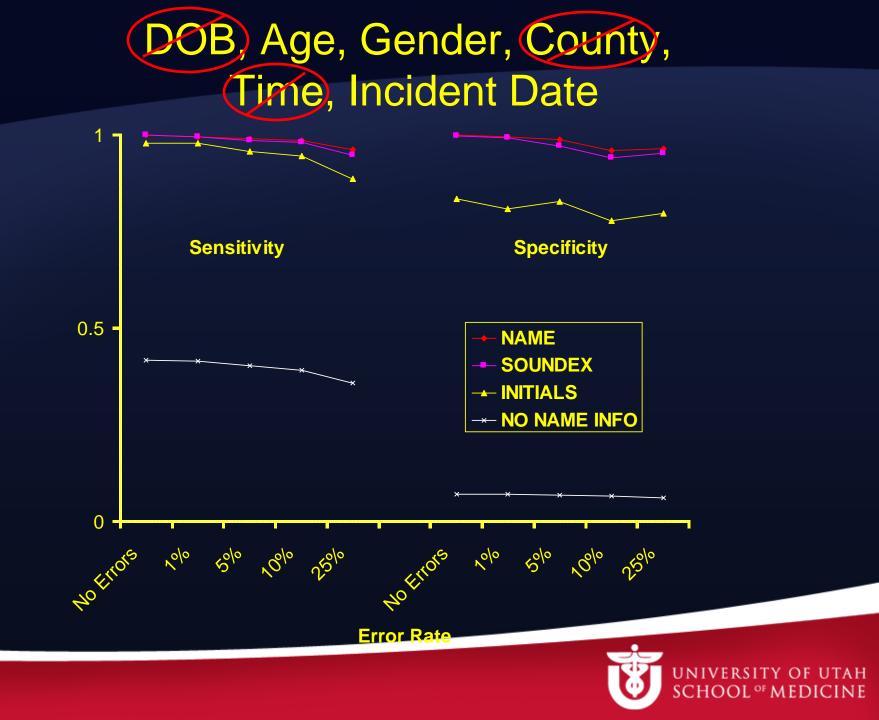
- Specificity Ability to recognize incorrect matches
 - 1 false positive rate



DOB, Gender, County, Time, Incident Date







Summary

- 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
- Linkage feasibility test
 - Cook LJ, Olson LM, Dean JM. (2001). Probabilistic record linkage: relationships between file sizes, identifiers and match weights. *Methods Inf Med*, *40*(3), 196-203.



Other Linkage Considerations

- Confidentiality concerns
 - IRBs & data sharing/use agreements
 - Separate tables of identifiers
- Databases
 - Missingness and accuracy of matching fields
 - Timeliness
- Analysis



Probabilistic Linkage Software

- LinkSolv
- Link Plus (CDC)
- Link King
- RecordLinkage (R)
- FRIL
- FEBRL
- Write your own
 - Handbook of Record Linkage Methods for Health and Statistical Studies, Howard Newcombe



Software Checklist

- Size of databases
- Add custom variable types and comparisons
- Unduplication / self match
- Link more than two files
- Training and documentation



Questions?

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