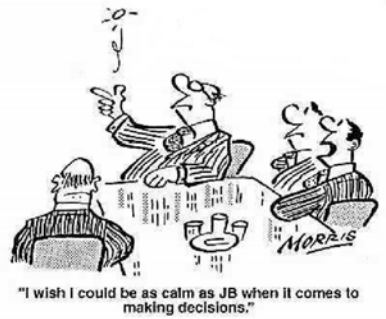
Information theory and databases

Concept of information (through an example)

Information content of data streams, information rate

(Extension: physical entropy and information)

Databases: concept and examples



Concept of information (through an example)

Intuitive concept:

"informare" (Lat.) : „to give form to the mind", or to teach, *instruct somebody*

Thus: „We can only change our minds, when we recieve ***information***."

Or:
„a type of input to an organism or designed device" : Ecology, sensory input
(Smell of food → movement of animal)

Or:
„information is any type of pattern that influences the formation or transformation of other patterns."
(RNA sequence → Protein structure)

Transmitting information – information **coding**

in general

Information **source** — Which event occured from a set of possibilities?

↓ **en**coding — **En**coding: We represent **events** with **NUMBERS**

Transmission **channel**

↓ **de**coding — **De**coding: We reconstruct **events** from **NUMBERS**

Information reciever
destination — (news)

Transmitting information – information **coding**

in general

Information **source**

↓ **en**coding

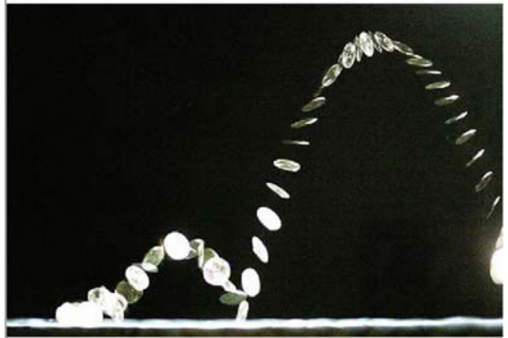
Transmission **channel**

↓ **de**coding

Information reciever
destination

an example

Tossing a dime



Head or Tail?

Transmitting information – information **coding**

in general

Information **source**

↓ **en**coding

Transmission **channel**

↓ **de**coding

Information reciever
destination

an example

Which side is up?

↓ **en**coding — Sides : Head or Tail **into Numbers: 1,0**

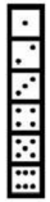
Speech, waves in the air, sms

↓ **de**coding — 1,0 ⟶ head, tail

Decide who wins

Transmitting information – *digital* **coding**

Event		Number	Digital code
	:	1	1
	:	0	0

Event		Number	Digital code
	:	1	001
	:	2	010
	:	3	011
	:	4	100
	:	5	101
	:	6	110

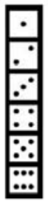
How many **bits** we need?
Bit: **b**inary dig**it**
0 or 1

Transmitting information – *digital* **coding**

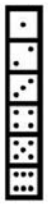
How many **bits** we need?

Bit: **b**inary dig**it**

0 or 1

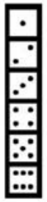
Event		Number	Digital code	Bits needed
	:	1	1	**1**
	:	0	0	
	:	1	001	**3**
	:	2	010	
	:	3	011	
	:	4	100	
	:	5	101	
	:	6	110	

Transmitting information – coding ***efficiency***

Event		Number	Digital code	Bits needed	Maximum number of events
	:	1	1	**1**	**2**
	:	0	0		
	:	1	001	**3**	**8**
	:	2	010		
	:	3	011		
	:	4	100		
	:	5	101		
	:	6	110		
		7	111		
		0	000		

Here we only have 6 events,
but could encode 8 in 3 bits!

Transmitting information – coding ***efficiency***

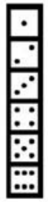
Event		Number	Digital code	Bits needed	Maximum number of events
	:	1	001		
	:	2	010		
	:	3	011	3	8
	:	4	100		
	:	5	101		
	:	6	110		
		7	111		
		0	000		

Here we only have 6 events,
but could encode 8 in 3 bits!

A better encoding:

$\{X_1X_2X_3\}$ group 3 events together
Classic coding
3x3 bits = **9** bits

Transmitting information – coding ***efficiency***

Event		Number	Digital code	Bits needed	Maximum number of events
	:	1	001		
	:	2	010		
	:	3	011	3	8
	:	4	100		
	:	5	101		
	:	6	110		
		7	111		
		0	000		

Here we only have 6 events,
but could encode 8 in 3 bits!

A better encoding:

$\{X_1X_2X_3\}$ group 3 events together : number of possibilities = 6^3 = 216
$256 = 2^8$
Classic coding
3x3 bits = **9** bits → It is possible to encode a group of any 3 events in **8** bits

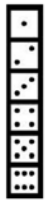
1 bit less!

Transmitting information – information content

Information content = how many bits do we *minimally* need to encode

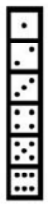
(This also gives the encoding efficiency limit)

Transmitting information – measure of information – example of two dices

Fair	P_i	probability	code example	bits needed	p*(number of bits needed)
	1/6	0,17	000	3	0,5
	1/6	0,17	001	3	0,5
	1/6	0,17	010	3	0,5
	1/6	0,17	011	3	0,5
	1/6	0,17	100	3	0,5
	1/6	0,17	101	3	0,5

Expected number of bits needed: **3** $\mu=\sum(x_i * p_i)$

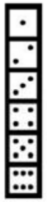
We can encode more efficiently here, for example such:

Loaded dice	P_i	probability	code example	bits needed	p*(number of bits needed)
	1/2	0,5	0	1	0,5
	1/4	0,25	10	2	0,5
	1/8	0,13	110	3	0,38
	1/16	0,06	1110	4	0,25
	1/32	0,03	11110	5	0,16
	1/32	0,03	11111	5	0,16

Expected number of bits needed: **1,94**

Transmitting information – measure of information – example of two dices

Fair



P_i	probability	code example	bits needed	p*(number of bits needed)
1/6	0,17	000	3	0,5
1/6	0,17	001	3	0,5
1/6	0,17	010	3	0,5
1/6	0,17	011	3	0,5
1/6	0,17	100	3	0,5
1/6	0,17	101	3	0,5

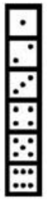
Here we do NOT Expect anything

Maximal uncertainity

Expected number of bits needed: **3**

Gained information is proportional to the number of bits needed

Loaded dice



P_i	probability	code example	bits needed	p*(number of bits needed)
1/2	0,5	0	1	0,5
1/4	0,25	10	2	0,5
1/8	0,13	110	3	0,38
1/16	0,06	1110	4	0,25
1/32	0,03	11110	5	0,16
1/32	0,03	11111	5	0,16

Here we *expect* „one" (most probable) or „two"

On average we **learn less**

Expected number of bits needed: **1,94**

Here the *overall, average* information content is less.

Transmitting information – measure of information

How should be information content **matematically** specified? (Shannon 1948)

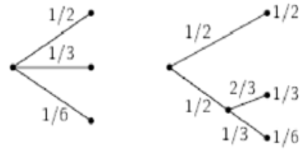
1.: H should be *continuous* in the p_i (small change in p_i → small change in H)

2.: Unlikely events carry a high information content:
H should be in some way inverse proportional to p
If all the p_i are equal, (p_i = 1/n)
then H should be a monotonic increasing function of n.

With equally likely events there is more choice, or uncertainty, when there are more possible events.

3.: Branching Chioces:
If a choice can be broken down into two successive choices,
the original H should be the weighted sum of the individual values of H.

$$H\left(\frac{1}{2},\frac{1}{3},\frac{1}{6}\right)=H\left(\frac{1}{2},\frac{1}{2}\right)+\frac{1}{2}\cdot H\left(\frac{2}{3},\frac{1}{3}\right)$$



Transmitting information – measure of information

Shannon : define measure as: $$H = p\cdot\log_2\left(\frac{1}{p}\right)$$

$\log_2$: 2-base logarithm

Examples:

$\log_2(2) = 1$
$\log_2(4) = 2$
$\log_2(8) = 3$

Transmitting information – measure of information

Shannon $$H = p\cdot\log_2\left(\frac{1}{p}\right)$$ [bit]

If we have multiple events in the set, then it is a sum for every possible event:

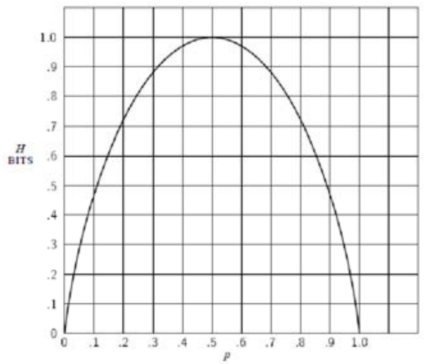
$$H=\sum_i p_i\cdot\log_2\left(\frac{1}{p_i}\right)=\sum_i -p_i\cdot\log_2 p_i$$

other log-bases:
$\log_e$ (ln) : [nat]
$\log_{10}$ (lg) : [ban]

measure of information - entropy

Dime tossing

p q = 1-p



$$H=\sum_i -p_i\cdot\log_2 p_i=-p\cdot\log_2 p-q\cdot\log_2 q=-p\cdot\log_2 p-(1-p)\cdot\log_2(1-p)$$

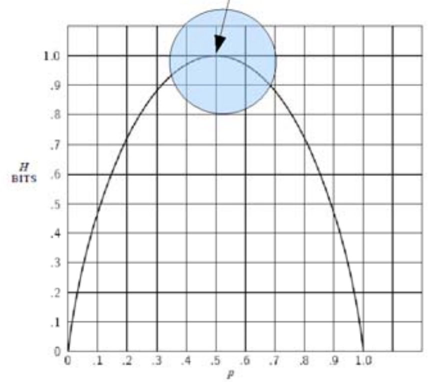
measure of information - entropy

Fair dime: p = ½

no prior expectations equals maximal uncertainity

Dime tossing

p q = 1-p



$$H=\sum_i -p_i\cdot\log_2 p_i=-p\cdot\log_2 p-q\cdot\log_2 q=-p\cdot\log_2 p-(1-p)\cdot\log_2(1-p)$$

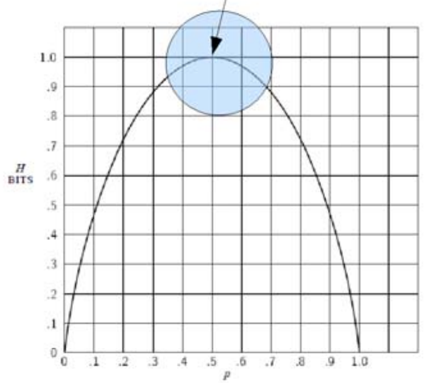
measure of information - entropy

Fair dime: p = ½

no expectations maximal uncertainity

Dime tossing

p q = 1-p



H has another name: **Shannon-entropy**

H has a maximum when we know nothing in advance (all p_i-s are equal, $p_i = 1/n$)

Expected outcomes are maximized: each state is equally probable

⇕

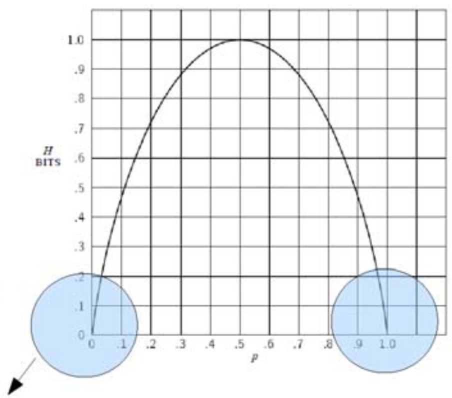
Physical entropy (S) has a maximum if the number of microstates is maximal.

measure of information - entropy

Dime tossing

p q = 1-p

H has another name: **Shannon-entropy**

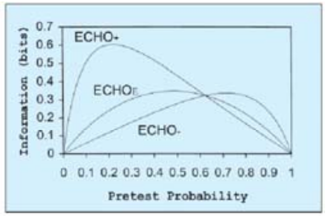


H vanishes ONLY if we are absolutely certain of the outcome: p=0 or p=1

⇕

Physical entropy (S) vanishes ONLY if there is exactly 1 microstate

Examples of usage in medicine



Bayes-theorem based methods:

The amount of information gained by performing a diagnostic test can be quantified by calculating the relative entropy between the posttest and pretest probability distributions

Application:
- Diagnostic tests
- expert systems

a_i: pretest probability
b_i: post test probability

$$D(b\|a) = \sum_{i=1}^{n} b_i \log_2(b_i/a_i)$$

Testing Situation	Pretest Probability of Disease	Test Operating Characteristics: Sensitivity/Specificity	Test Result	Posttest Probability of Disease	Information Gained
Breast cancer screening with mammography	0.01	0.75/0.94	Positive Negative	0.11 0.003	0.25 bits 0.006 bits
Mammography given palpable breast mass	0.2	0.80/0.90	Positive Negative	0.67 0.05	0.74 bits 0.13 bits
Screening for HIV with antibody test	0.001	0.99/0.998	Positive Negative	0.33 0.00001	2.4 bits 0.001 bits
Presence of tonsillar exudate in diagnosing infection with group A streptococci	0.1	0.45/0.84	Positive Negative	0.24 0.07	0.11 bits 0.01 bits
Colon cancer screening by fecal occult blood testing	0.005	0.40/0.90	Positive Negative	0.02 0.003	0.02 bits 0.0005 bits

Databases

Databases store information:

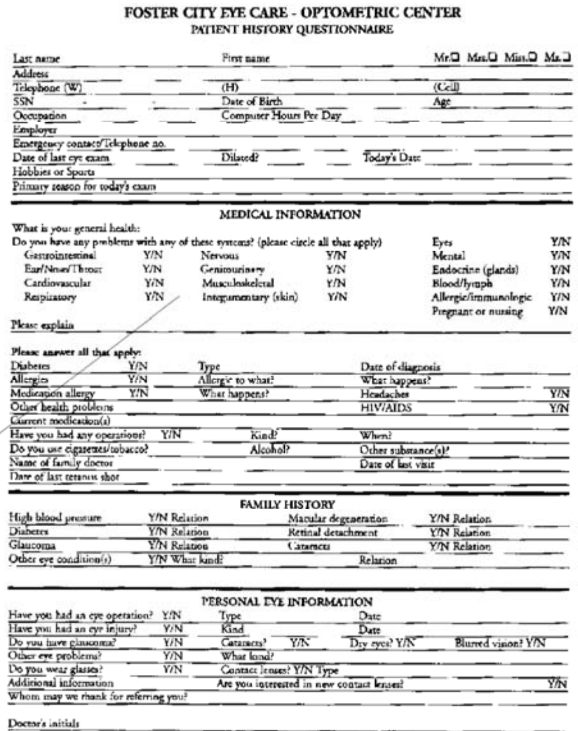
Databases are used for:
storage, structuring and extraction of ***information*** gathered previously.

Databases

Databases store information:

Databases are used for:
storage, structuring and **extraction** of ***information*** gathered previously.

It is hard to ***extract*** or modify information stored on paper


FOSTER CITY EYE CARE - OPTOMETRIC CENTER
PATIENT HISTORY QUESTIONNAIRE

Last name / First name / Mr.☐ Mrs.☐ Miss.☐ Ms.☐
Address
Telephone (W) / (H) / (Cell)
SSN - - / Date of Birth / Age
Occupation / Computer Hours Per Day
Employer
Emergency contact/Telephone no.
Date of last eye exam / Dilated? / Today's Date
Hobbies or Sports
Primary reason for today's exam

MEDICAL INFORMATION
What is your general health:
Do you have any problems with any of these systems? (please circle all that apply)
Gastrointestinal Y/N / Nervous Y/N / Eyes Y/N
Ear/Nose/Throat Y/N / Genitourinary Y/N / Mental Y/N
Cardiovascular Y/N / Musculoskeletal Y/N / Endocrine (glands) Y/N
Respiratory Y/N / Integumentary (skin) Y/N / Blood/lymph Y/N
Allergic/immunologic Y/N
Pregnant or nursing Y/N
Please explain

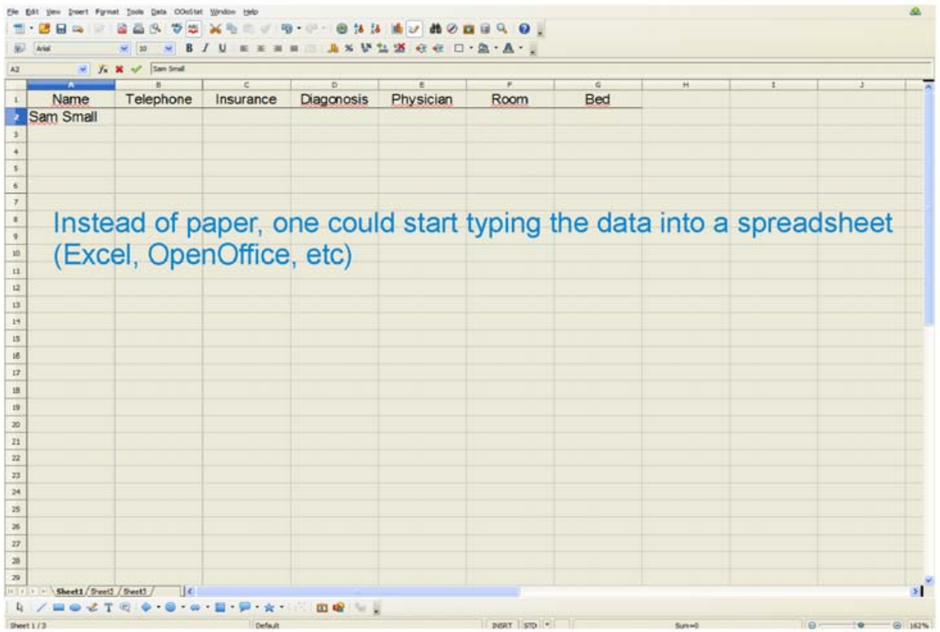
Please answer all that apply:
Diabetes Y/N / Type / Date of diagnosis
Allergies Y/N / Allergic to what? / What happens?
Medication allergy Y/N / What happens? / Headaches Y/N
Other health problems / HIV/AIDS Y/N
Current medication(s)
Have you had any operations? Y/N / Kind? / When?
Do you use cigarettes/tobacco? / Alcohol? / Other substance(s)?
Name of family doctor / Date of last visit
Date of last tetanus shot

FAMILY HISTORY
High blood pressure Y/N Relation / Macular degeneration Y/N Relation
Diabetes Y/N Relation / Retinal detachment Y/N Relation
Glaucoma Y/N Relation / Cataracts Y/N Relation
Other eye condition(s) Y/N What kind? / Relation

PERSONAL EYE INFORMATION
Have you had an eye operation? Y/N / Type / Date
Have you had an eye injury? Y/N / Kind / Date
Do you have glaucoma? Y/N / Cataracts? Y/N / Dry eyes? Y/N / Blurred vision? Y/N
Other eye problems? Y/N / What kind?
Do you wear glasses? Y/N / Contact lenses? Y/N Type
Additional information / Are you interested in new contact lenses? Y/N
Whom may we thank for referring you?

Doctor's initials

Databases – storing information



Instead of paper, one could start typing the data into a spreadsheet (Excel, OpenOffice, etc)

Databases – storing information

Name	Telephone	Insurance	Diagnosis	Physician	Room	Bed
Sam Small	(763) 865 345	Medicaid	Influenza	Dr. Barkins	37	2
Sara Goldmann	(691) 579 467	Medicare	Ascites	Dr. Magenheim	21	1
Dan Trideman	(691) 556 322	Medicaid	Malaria	Dr. Haydens	17	2
Bill Hardy	(691) 654 321	Medicare	Diabetes	Dr. Haydens	43	1
Bob Mindy	(691) 143 613	Tricare	Not yet known	Dr. Barkins	33	1
Yo Him	(691) 244 567	Medicare	Colitis	Dr. Magenheim	27	3
Kim Suhan	(691) 379 788	Tricare	Pneumonia	Dr. Barkins	37	1

Databases – storing information

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Kim Suhan	(691) 379 788	Tricare	Pneumonia	Dr. Barkins	37	1

Table : ordered set of data (information)

Databases – storing information

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Yo Him	(691) 244 567	Medicare	Colitis	Dr. Magenheim	27	3
Kim Suhan	(691) 379 788	Tricare	Pneumonia	Dr. Barkins	37	1

Record : Information *grouped together*
(one ROW in a Table)

Each row is a selected set of data

Every row has the same structure

Databases – storing information

Name	Telephone	Insurance	Diagnosis	Physician	Room	Bed
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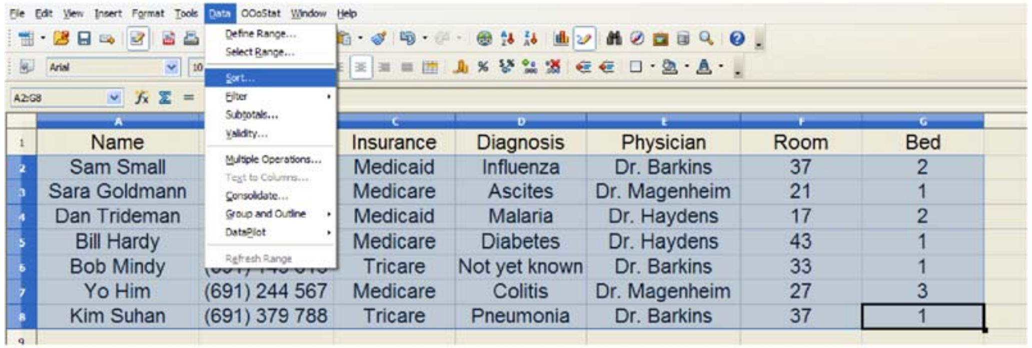
Column: data type

Databases – manipulating information

Sorting data



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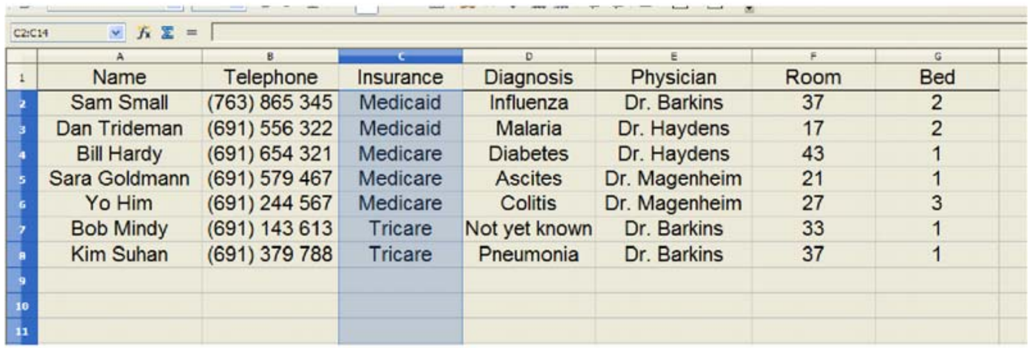
Databases – manipulating information



Name	Telephone	Insurance	Diagnosis	Physician	Room	Bed
Sam Small	(763) 865 345	Medicaid	Influenza	Dr. Barkins	37	2
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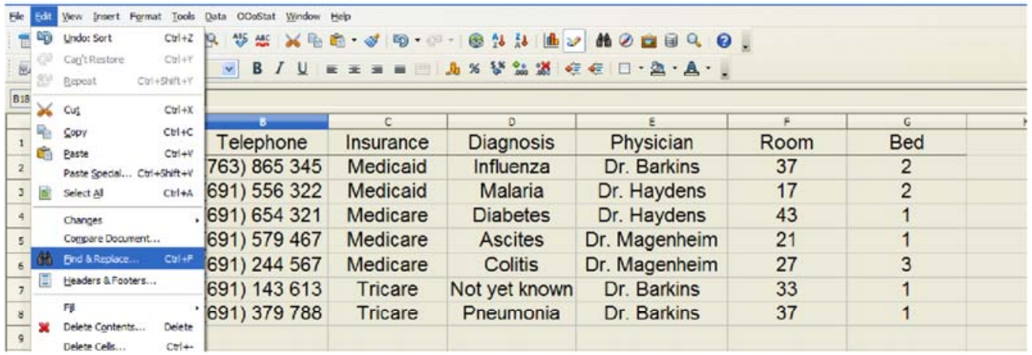
Databases – retrieving information



Telephone	Insurance	Diagnosis	Physician	Room	Bed
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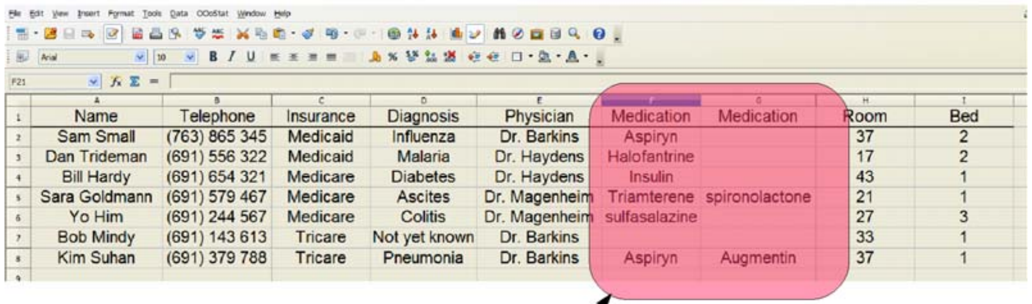
691) 556 322	Medicaid	Malaria	Dr. Haydens	17	2
691) 654 321	Medicare	Diabetes	Dr. Haydens	43	1
691) 579 467	Medicare	Ascites	Dr. Magenheim	21	1
691) 244 567	Medicare	Colitis	Dr. Magenheim	27	3
691) 143 613	Tricare	Not yet known	Dr. Barkins	33	1
691) 379 788	Tricare	Pneumonia	Dr. Barkins	37	1

Databases – problems with simple methods



Name	Telephone	Insurance	Diagnosis	Physician	Medication	Medication	Room	Bed
Sam Small	(763) 865 345	Medicaid	Influenza	Dr. Barkins	Aspiryn		37	2
Dan Trideman	(691) 556 322	Medicaid	Malaria	Dr. Haydens	Halofantrine		17	2
Bill Hardy	(691) 654 321	Medicare	Diabetes	Dr. Haydens	Insulin		43	1
Sara Goldmann	(691) 579 467	Medicare	Ascites	Dr. Magenheim	Triamterene	spironolactone	21	1
Yo Him	(691) 244 567	Medicare	Colitis	Dr. Magenheim	sulfasalazine		27	3
Bob Mindy	(691) 143 613	Tricare	Not yet known	Dr. Barkins			33	1
Kim Suhan	(691) 379 788	Tricare	Pneumonia	Dr. Barkins	Aspiryn	Augmentin	37	1

Records do not have the same size

Waste of space
Adding new data types tedious
Inconsistency : is a field empty by error?

Databases – problems with simple methods

Name	Telephone	Insurance	Diagnosis	Physician	Medication	Medication	Room	Bed
Sam Small	(763) 865 345	Medicaid	Influenza	Dr. Barkins	Aspiryn		37	2
Dan Trideman	(691) 556 322	Medicaid	Malaria	Dr. Haydens	Halofantrine		17	2
Bill Hardy	(691) 654 321	Medicare	Diabetes	Dr. Haydens	Insulin		43	1
Sara Goldmann	(691) 579 467	Medicare	Ascites	Dr. Magenheim	Triamterene	spironolactone	21	1
Yo Him	(691) 244 567	Medicare	Colitis	Dr. Magenheim	sulfasalazine		27	3
Bob Mindy	(691) 143 613	Tricare	Not yet known	Dr. Barkins			33	1
Kim Suhan	(691) 379 788	Tricare	Pneumonia	Dr. Barpins	Aspiryn	Augmentin	37	1

Entering the same data multiple times:

Typos
Redundancy
Later change almost impossible – too many items
...

Databases – SQL

Relational database:
we store data together with a logic.
Data types have logical connections.
Every data is stored only once,
but can be used multiple times.

Information Retrieval — P. BAXENDALE, Editor

A Relational Model of Data for Large Shared Data Banks

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Future users of large data banks must be protected from having to know how the data is organized in the machine (the internal representation). A prompting service which supplies such information is not a satisfactory solution. Activities of users at terminals and most application programs should remain unaffected when the internal representation of data is changed and even when some aspects of the external representation are changed. Changes in data representation will often be needed as a result of changes in query, update, and report traffic and natural growth in the types of stored information.

Existing noninferential, formatted data systems provide users with tree-structured files or slightly more general network models of the data. In Section 1, inadequacies of these models are discussed. A model based on *n*-ary relations, a normal form for data base relations, and the concept of a universal data sublanguage are introduced. In Section 2, certain operations on relations (other than logical inference) are discussed and applied to the problems of redundancy and consistency in the user's model.

KEY WORDS AND PHRASES: data bank, data base, data structure, data organization, hierarchies of data, networks of data, relations, derivability, redundancy, consistency, composition, join, retrieval language, predicate calculus, security, data integrity
CR CATEGORIES: 3.70, 3.73, 3.75, 4.20, 4.22, 4.29

1. Relational Model and Normal Form

1.1. Introduction

This paper is concerned with the application of elementary relation theory to systems which provide shared access to large banks of formatted data. Except for a paper by Childs [1], the principal application of relations to data systems has been to deductive question-answering systems. Levein and Maron [2] provide numerous references to work in this area.

In contrast, the problems treated here are those of data independence—the independence of application programs and terminal activities from growth in data types and changes in data representation—and certain kinds of data inconsistency which are expected to become troublesome even in nondeductive systems.

The relational view (or model) of data described in Section 1 appears to be superior in several respects to the graph or network model [3, 4] presently in vogue for noninferential systems. It provides a means of describing data with its natural structure only—that is, without superimposing any additional structure for machine representation purposes. Accordingly, it provides a basis for a high level data language which will yield maximal independence between programs on the one hand and machine representation and organization of data on the other.

A further advantage of the relational view is that it forms a sound basis for treating derivability, redundancy, and consistency of relations—these are discussed in Section 2. The network model, on the other hand, has spawned a number of confusions, not the least of which is mistaking the derivation of connections for the derivation of relations (see remarks in Section 2 on the "connection trap").

Finally, the relational view permits a clearer evaluation of the scope and logical limitations of present formatted data systems, and also the relative merits (from a logical standpoint) of competing representations of data within a single system. Examples of this clearer perspective are cited in various parts of this paper. Implementations of systems to support the relational model are not discussed.

1.2. Data Dependencies in Present Systems

The provision of data description tables in recently developed information systems represents a major advance toward the goal of data independence [5, 6, 7]. Such tables facilitate changing certain characteristics of the data representation stored in a data bank. However, the variety of data representation characteristics which can be changed *without logically impairing some application programs* is still quite limited. Further, the model of data with which users interact is still cluttered with representational properties, particularly in regard to the representation of collections of data (as opposed to individual items). Three of the principal kinds of data dependencies which still need to be removed are: ordering dependence, indexing dependence, and access path dependence. In some systems these dependencies are not clearly separable from one another.

1.2.1. *Ordering Dependence.* Elements of data in a data bank may be stored in a variety of ways, some involving no concern for ordering, some permitting each element to participate in one ordering only, others permitting each element to participate in several orderings. Let us consider those existing systems which either require or permit data elements to be stored in at least one total ordering which is closely associated with the hardware-determined ordering of addresses. For example, the records of a file concerning parts might be stored in ascending order by part serial number. Such systems normally permit application programs to assume that the order of presentation of records from such a file is identical to (or is a subordering of) the

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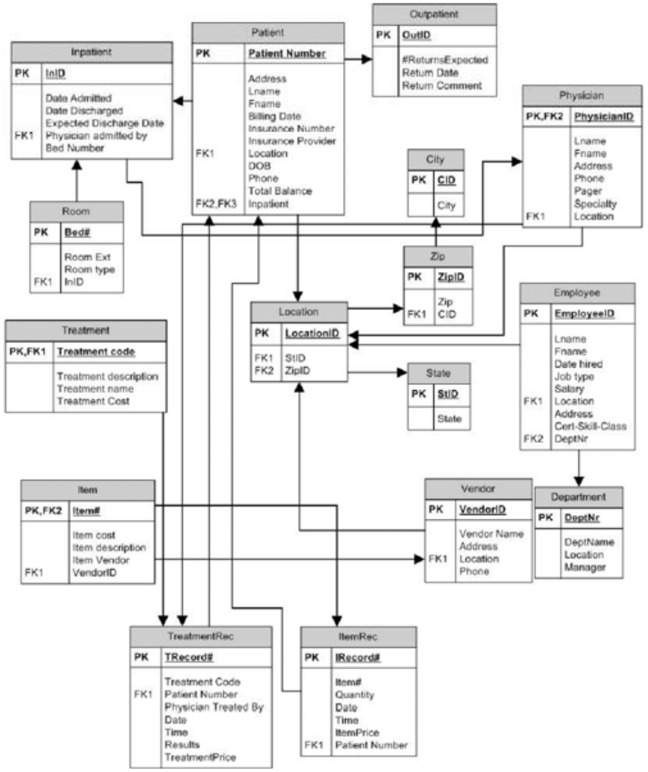
Databases

clinical example:
part of a relational database:
each record has its own KEY.

Two types of keys:
Primary Key (PK)
Foreign Key (FK)

FK-s join the tables together,
and enable re-use of data.

The structure of the database
(layout/content of tables)
represents the logic behind
the workflow for which the
database is being designed.



Extension material:

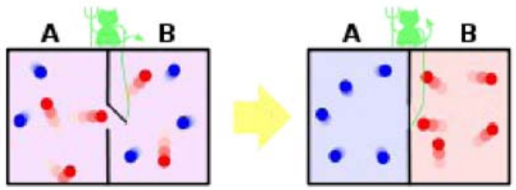
information entropy and physical entropy

(these last few slides are for those who whish to have a starting point for understanding why the term „entropy" is appropriate also for information, and what it has to do with the concept of entropy in physics. It may be a good idea to re-read this part after you study entropy in physics...)

Information entropy and physical entropy

„ in an isolated system, entropy never decreases." Second Law of Thermodynamics

The Maxwell demon

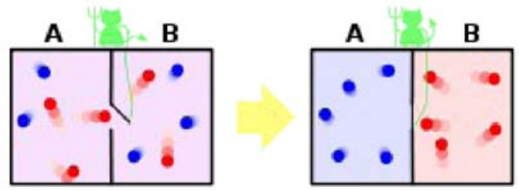


Temperature of A decreses, B increases → Violation of the Second Law ?

Information entropy and physical entropy

„ in an isolated system, entropy never decreases." Second Law of Thermodynamics

The Maxwell demon

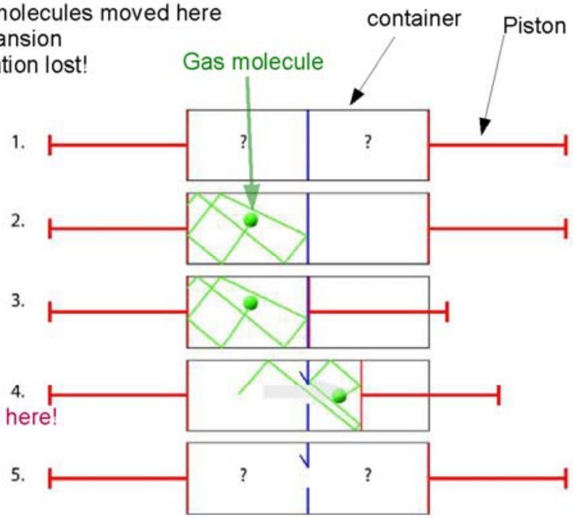


Temperature of A decreses, B increases → Violation of Law II. ?

Solution: NO, since the demon interacts with the system, it must be considered.
The demon acquires ***information***, and this changes it's state!

Information entropy and physical entropy

1. : molecule's position unknown
2. : measure position, information = 1 bit
3. : move appropriate piston, no molecules moved here
4. : release door : isothermal expansion
5. : door opened, position information lost!



Work is produced here!

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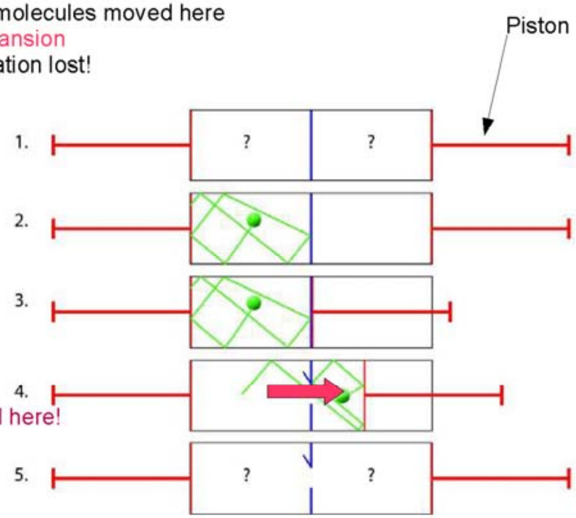
Isothermal expansion:

$$W_{A\to B} = NkT \ln\left(\frac{V_A}{V_B}\right)$$

In this case:
$N=1$
$V_A/V_B = 2$

Hence

$W = kT \ln(2)$ Work is produced here!



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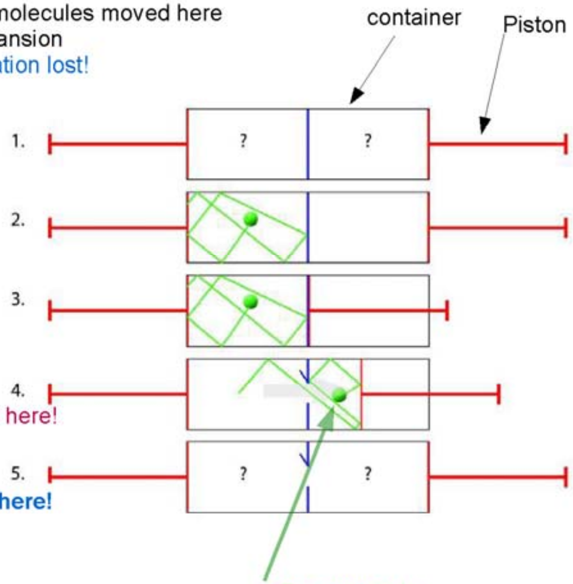
Hence

$W = kT\ln(2)$ Work is produced here!

Information is lost here!



Information entropy and physical entropy

Leo Szilárd:

From Law II. taking into account that $W = T\Delta S$

$$W_{\text{produced by piston}} = W_{\text{loss of information}}$$

$$T\Delta S_{inf} = kT\ln 2$$

$$\Delta S_{1bit} = k\ln 2$$

Ereasing 1 bit of information increases physical entropy by *k·ln2*

(Landauer 1971, logically irreversible processes, eg. AND-gate produce entropy → heating of circuits!)