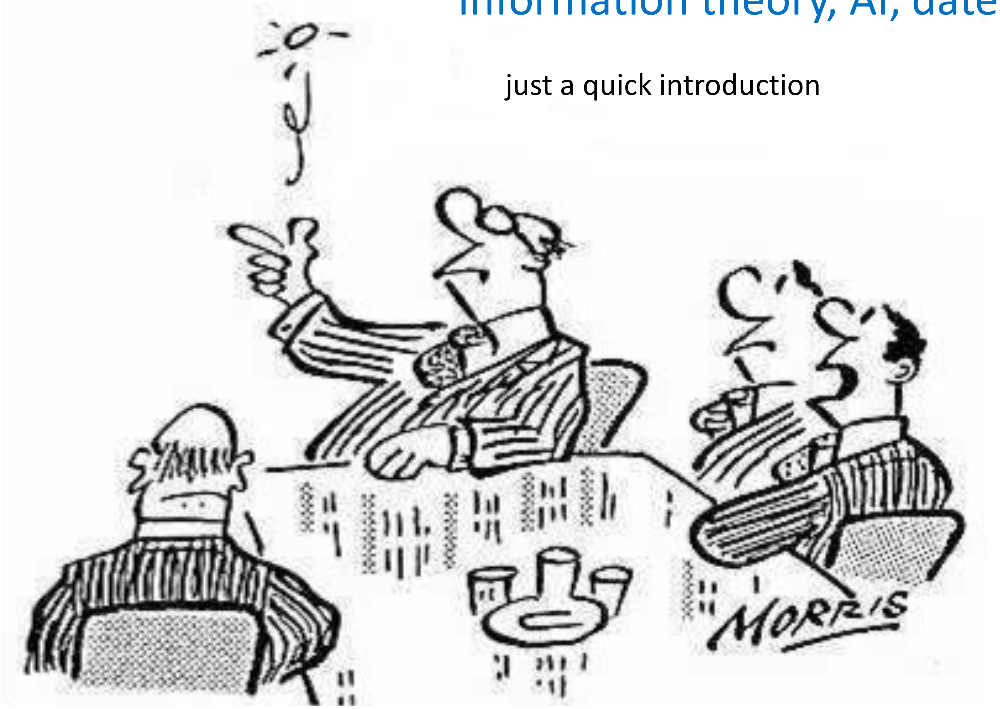
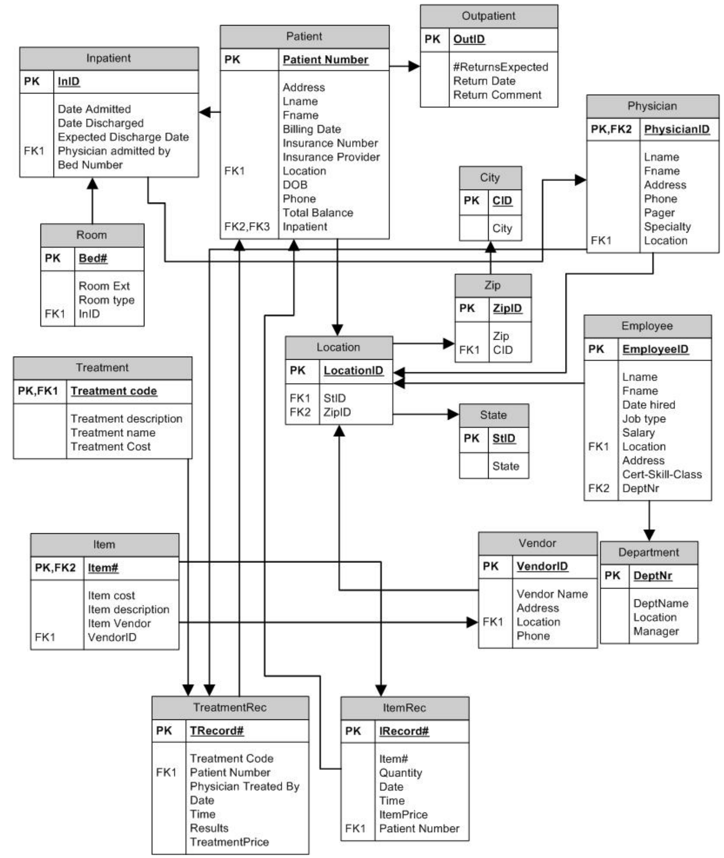
Schay G.

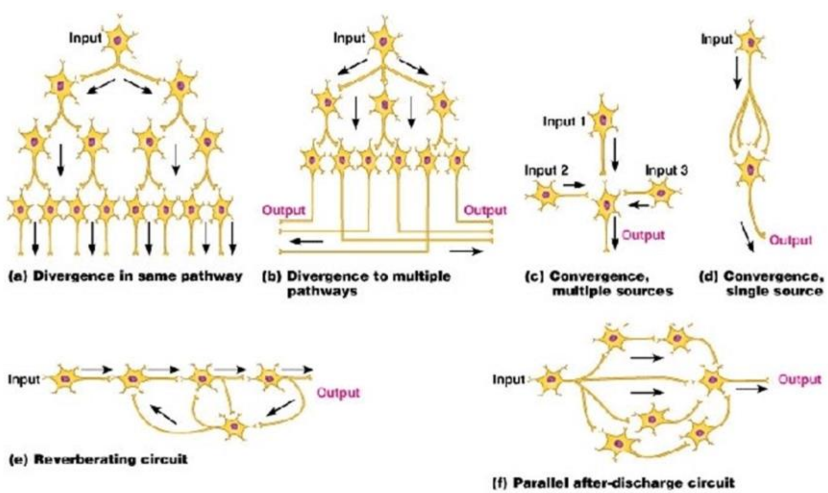
Information theory, AI, datenbases, telemedicine

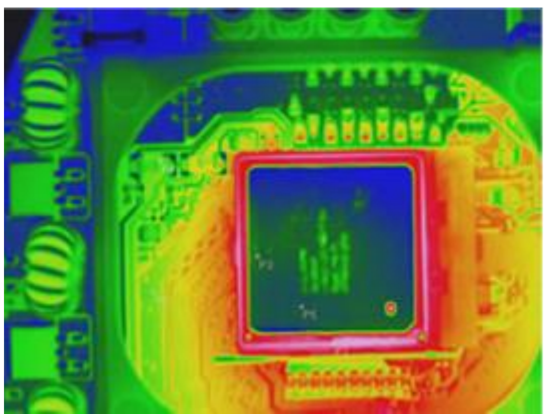
just a quick introduction

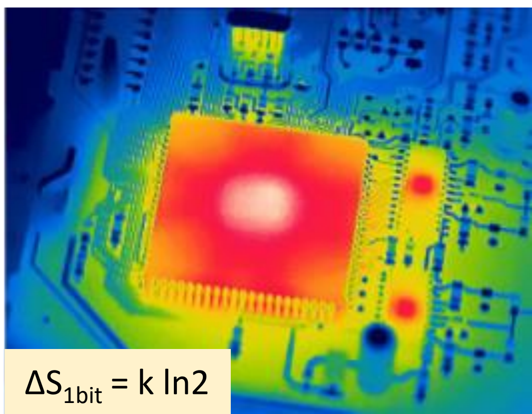


I wish to be as calm as J.B. when it comes to difficult decisions…









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

The concept of information

Intuitíve

"informare" (Lat.) : „form the mind”, teach, instruct somebody

we can only change our mind if we get information

OR:
„any signal or input which generates a response in a machine or living creature”
(e.g. Pavlovian reflex)

OR:
„ such a pattern which influences the formation of other patterns”
(e.g. DNA sequence → protein structure)

“I wish I could be as calm as JB when it comes to making decisions.”

Transmitting information – information **coding**

in general

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

encoding — **En**coding: We represent **events** with **NUMBERS**

Transmission channel

decoding — **De**coding: We reconstruct **events** from **NUMBERS**

Information reciever
destination — (news)

in general

Information **source**

encoding

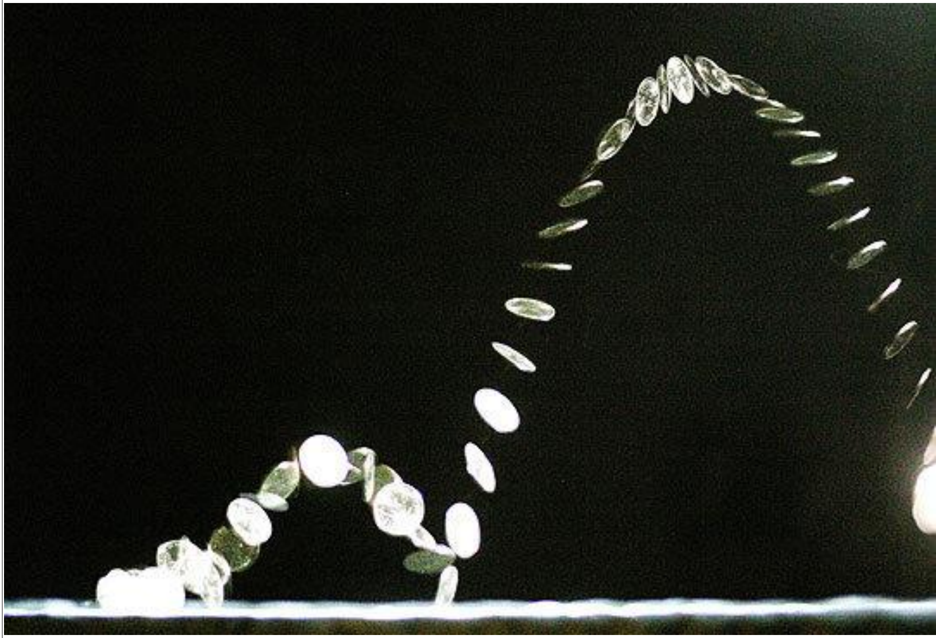
Transmission **channel**

decoding

Information reciever
destination

tossing a dime

head or tail?



Transmitting information – information **coding**

in general

Information **source**

encodin
g

Transmission **channel**

decodin
g

Information reciever
destination

an
example

Which side is up?

1  0

encodin
g

Sides : Head or
Tail
into Numbers: 1,0

Speech, waves in the air, sms

decodin
g

1,0 ⟶ head,
tail 1  0

Decide who
wins

Transmitting information – *digital* **coding**

How many **bits** we need?

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

0 or 1

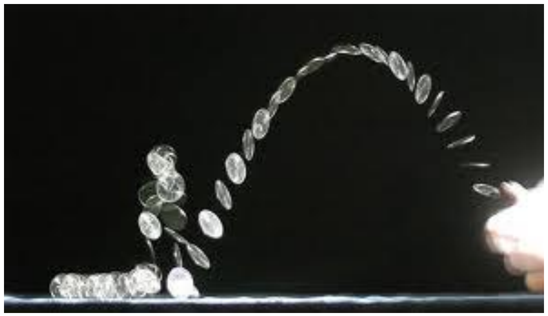
digits: we use them to express numbers, like: $19 = 1*10 + 9*1 = 1*10^1 + 9*10^0$

we are used to the decimal system having a base of 10, but any base is possible.

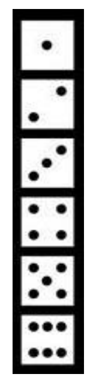
digital: base is 2

example: $101_2 = 1*4+0*2+1*1 = 1*2^2 + 0*2^1 + 1*2^0 = 5_{10}$

Transmitting information – *digital* **coding**



Event		Number	Digital code
	:	1	1
	:	0	0

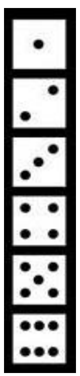


	:	1	001
	:	2	010
	:	3	011
	:	4	100
	:	5	101
	:	6	110

2-base numbers: example: $101_2 = 1*2^2 + 0*2^1 + 1*2^0 = 5$

bit = „binary digit”

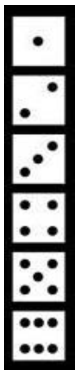
Transmitting information – coding ***efficiency***

Event		Number	Digital code	Bits needed	Maximum number of events
	:	1	1	**1**	**2**
	:	0	0		
	:	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!

extension material

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:

$\{X_1\ X_2\ X_3\}$ group 3 events together : number of possibilities = $6^3 = 216$

Classic coding
3x3 bits = **9** bits

→ 1 bit less!

$256 = 2^8$

It is possible to encode 3 events in **8** bits

This is **2.66** bit/event

extension material

Transmitting information – information content

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

(This also gives the encoding efficiency limit)

How does this connect with intuitive information content?

-I have tossed a dime. Head or Tail?

-It is light traffic this morning

-It will rain tomorrow.

-I have won the lottery!

Transmitting information – information content

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

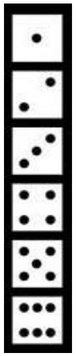
(This also gives the encoding efficiency limit)

How does this connect with intuitive information content?

	p	q	
-I have tossed a dime. Head or Tail?	½	½	No idea
-It is light traffic this morning	¼	¾	
-It will rain tomorrow.	1%	99%	
-I have won the lottery!	1/13,983,816	0.999....	Probably no win

Transmitting information – measure of information

Fair



P	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

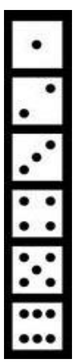
Here we do NOT Expect anything

Maximal uncertainity

Expected number of bits needed: **3** **(2.66)**

Gained information is proportional to the number of bits needed

Loaded



P	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)

On average we **learn less**

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

Here the information content is less.

extension material

Extension Material

Transmitting information – measure of information

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

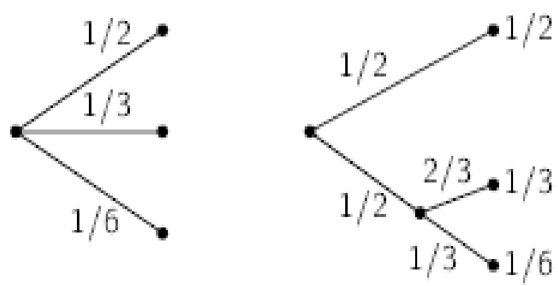
1.: H should be *continuous* in the *p*   (small change in p → small change in H)

2.: Unlikely events carry a high information content:
H should be in some way inverse proportional to p
If all the p are equal, (p = 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

We have a way to define the information content ONLY with the probability, without the need of a specific encoding scheme

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

It is also useful to calculate the information content *of a single event*:

$$I = log_2\left(\frac{1}{p}\right)$$

Thus, the H=p*I is a weighted value of the information content,
the weighting factor is the probability. This will be useful, if the **average** information content is needed.

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

log : 2-base logarithm

Examples:

log (2) = 1
log (4) = 2
log (8) = 3

informational entropy

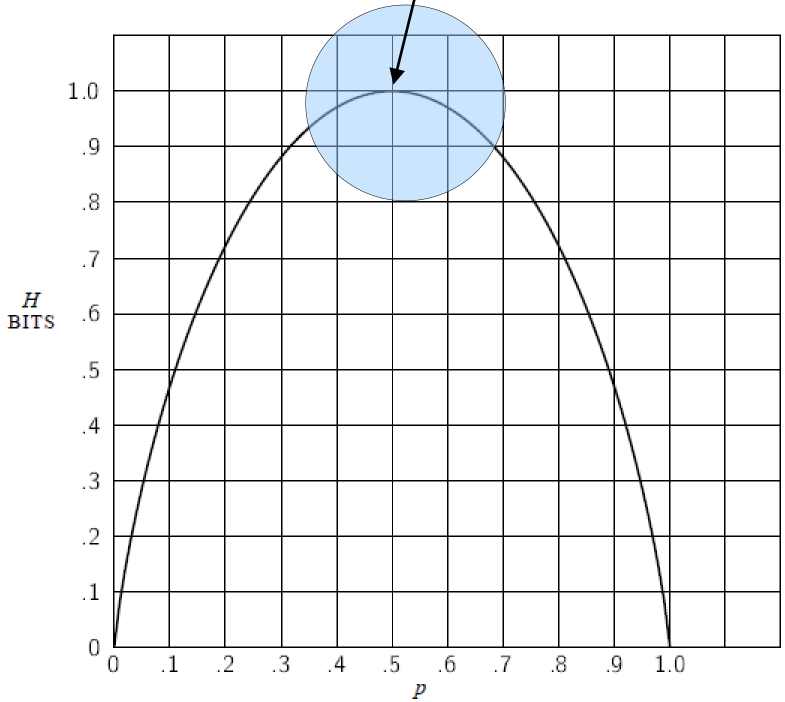
Fair dime: p = ½

no assumptions, maximal uncertainity

head or tail

p

q = 1-p



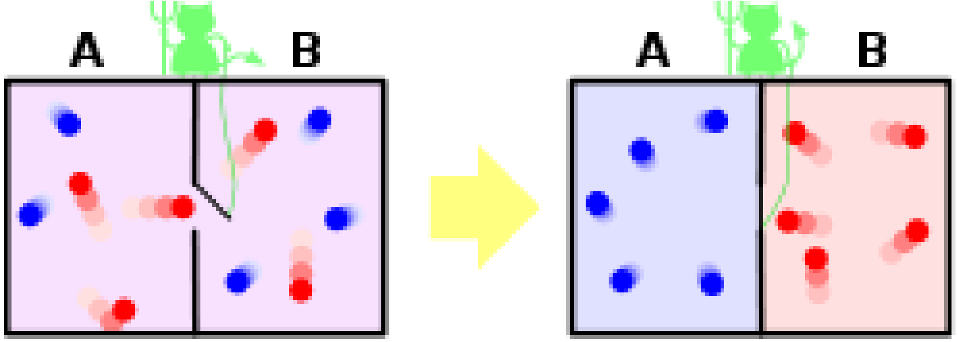
$$H = \sum_i -p_i \cdot log_2 p_i = -p \cdot log_2 p - q \cdot log_2 q = -p \cdot log_2 p - (1-p) \cdot log_2 (1-p)$$

Shannon-entropy: is is maximal if avery event is equally probable
(like the maximum number of microstates)

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 ?

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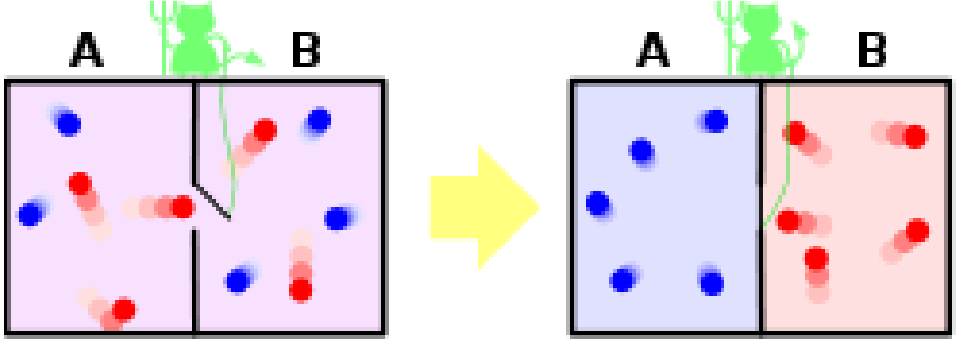


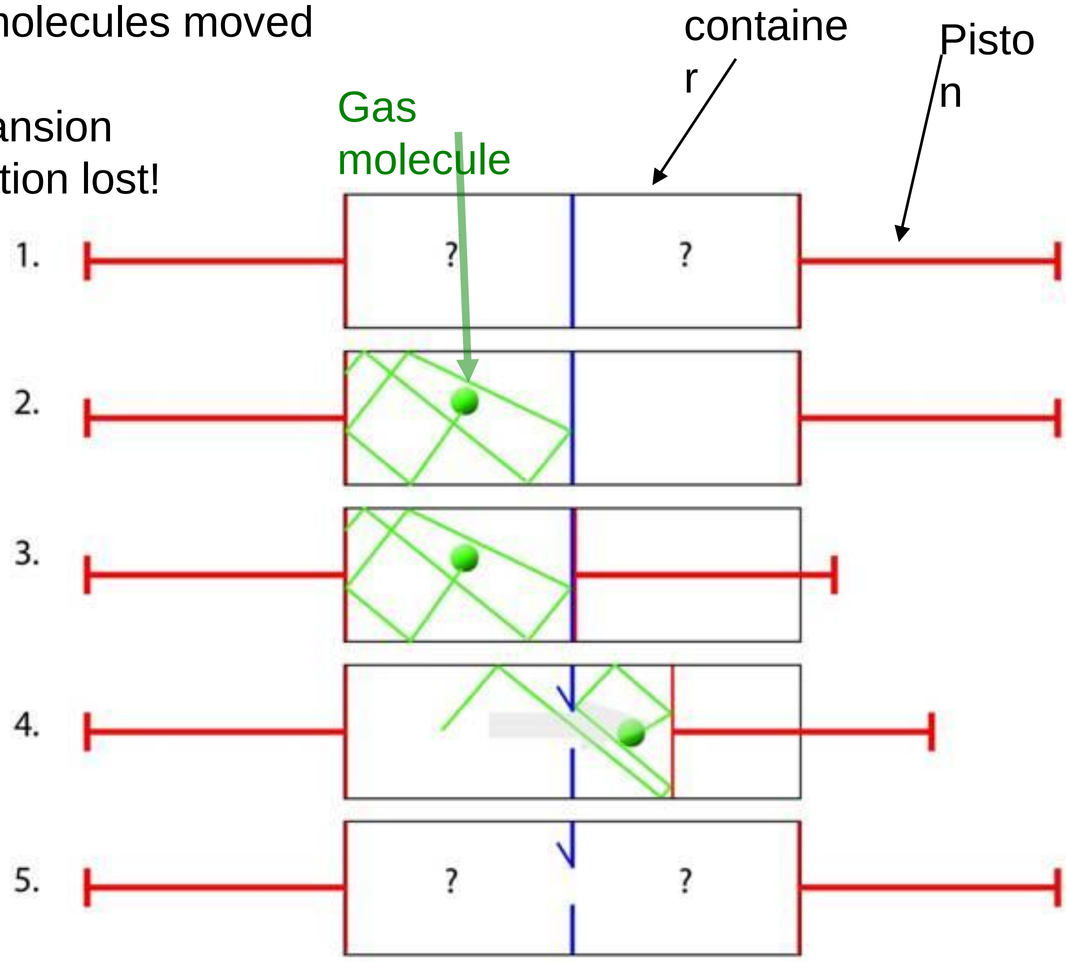
Temperature of A decreses, B increases → Violation of Law II.
?

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

Extension Material

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:

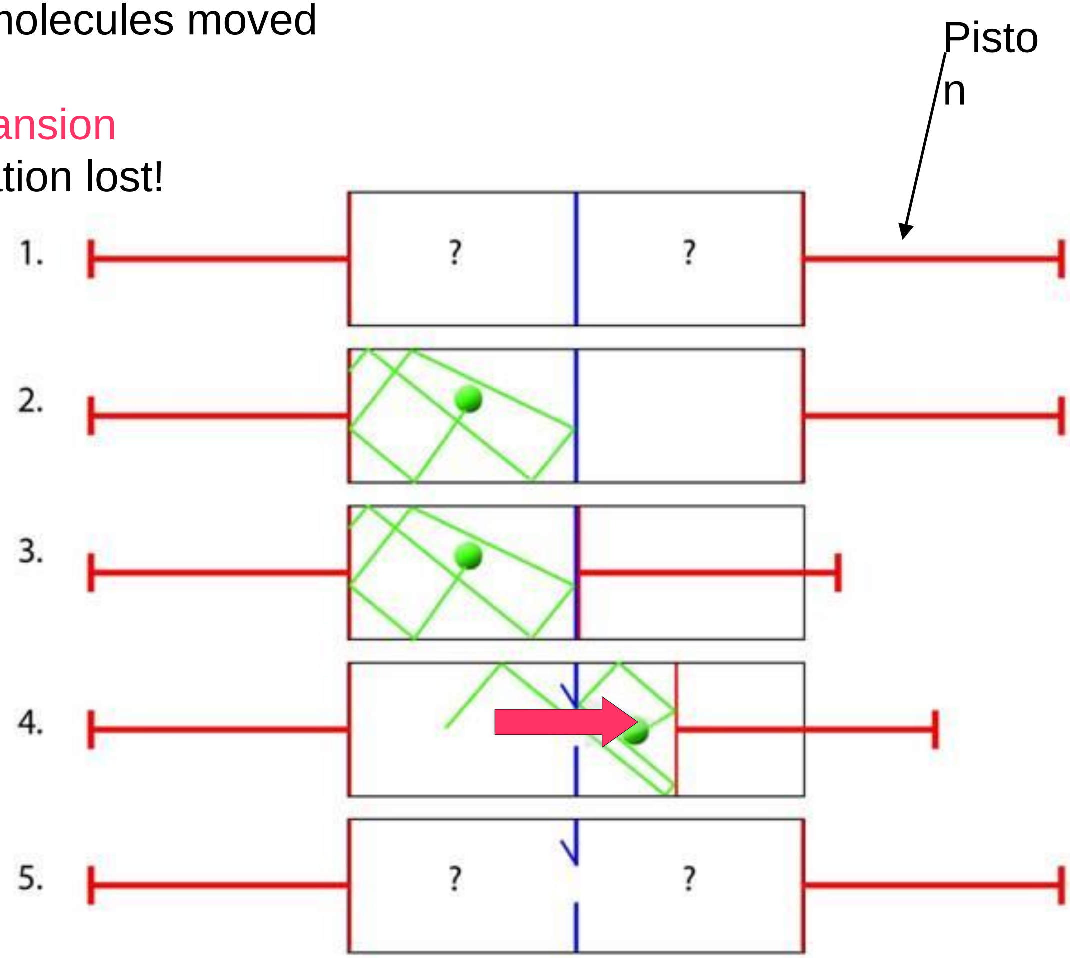
N=1

V /V = 2

Hence

W = kT ln(2)

Work is produced here!



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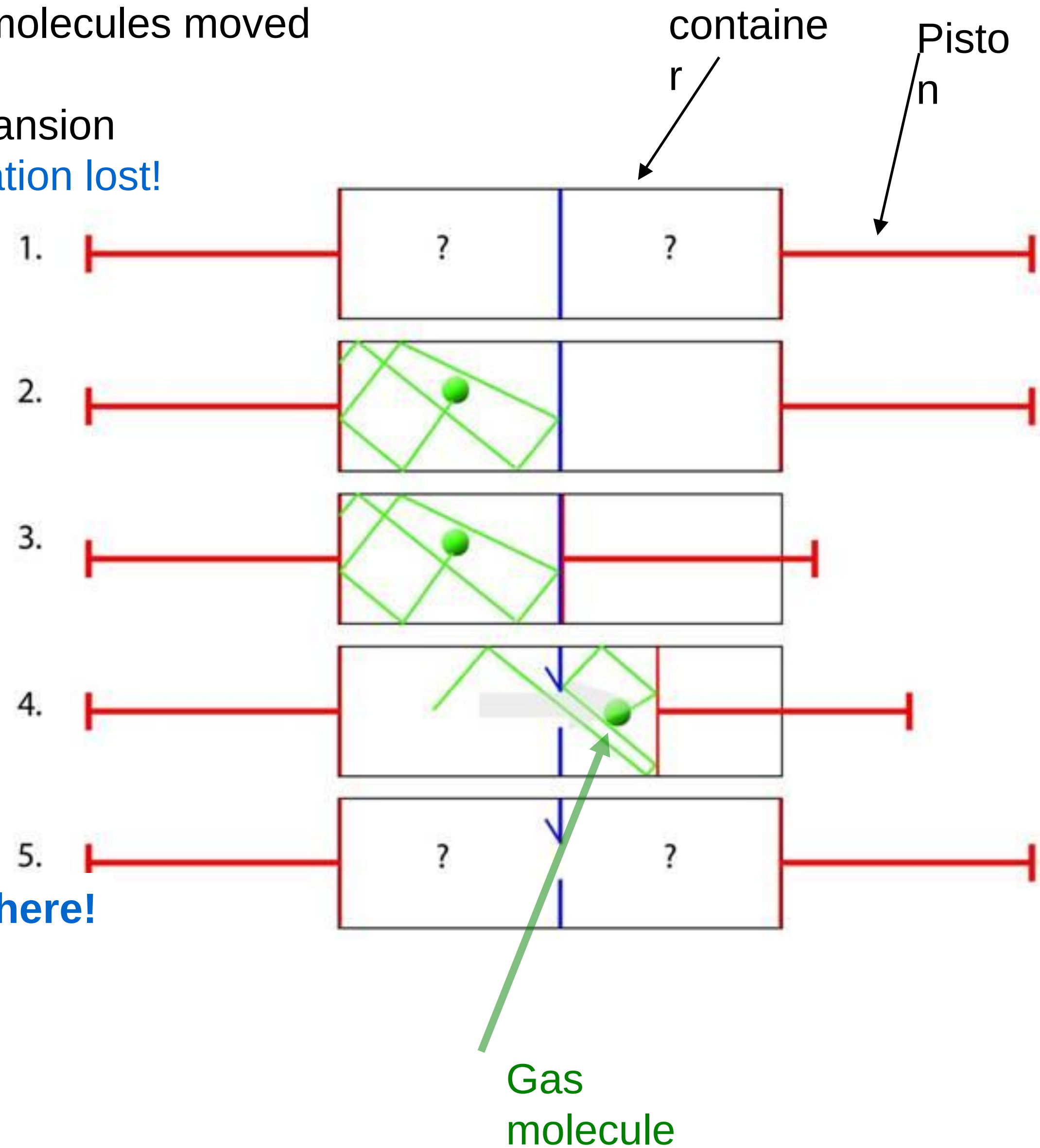
N=1
V /V = 2

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 $W = T\Delta S$

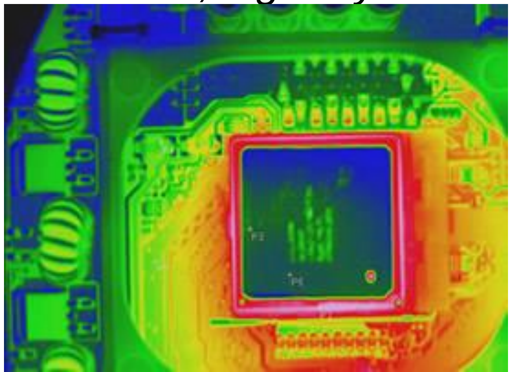
$$W \qquad\qquad = W$$

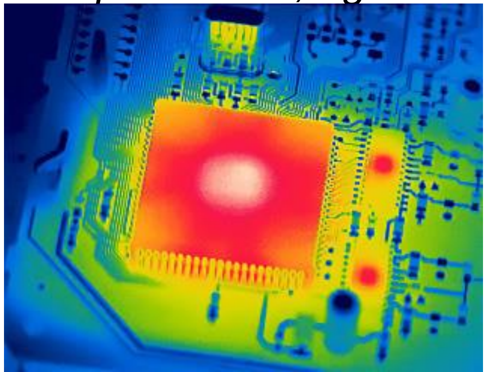
$$T\Delta S \quad = kT \ln 2$$

$$\Delta S \quad = k \ln 2$$

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

(Landauer 1971, logically irreversible processes, eg. AND-gate)





Databases

Databases store information:

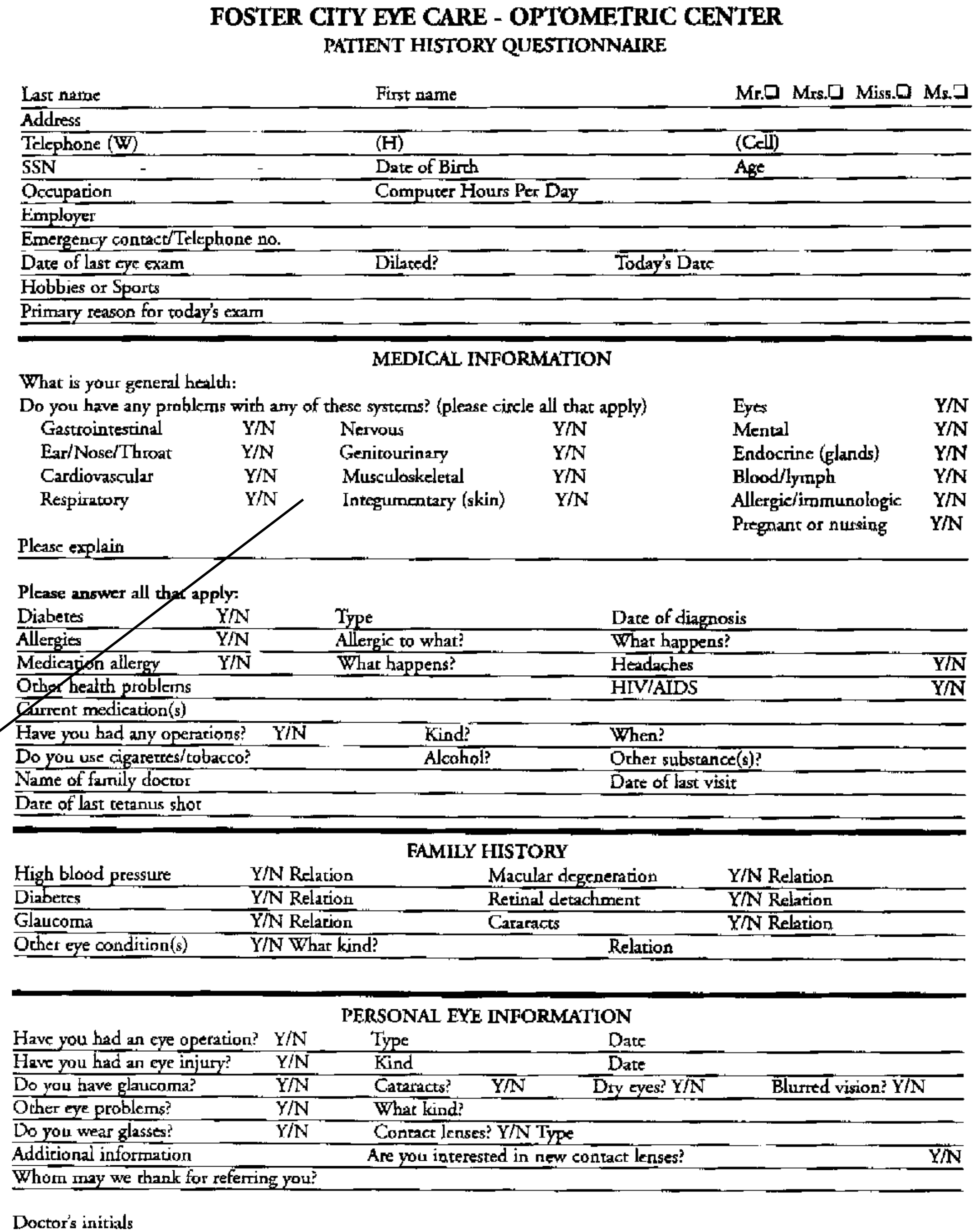
Databases are used for:
storage, structuring and extraction of ***information*** gathered previously.

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?

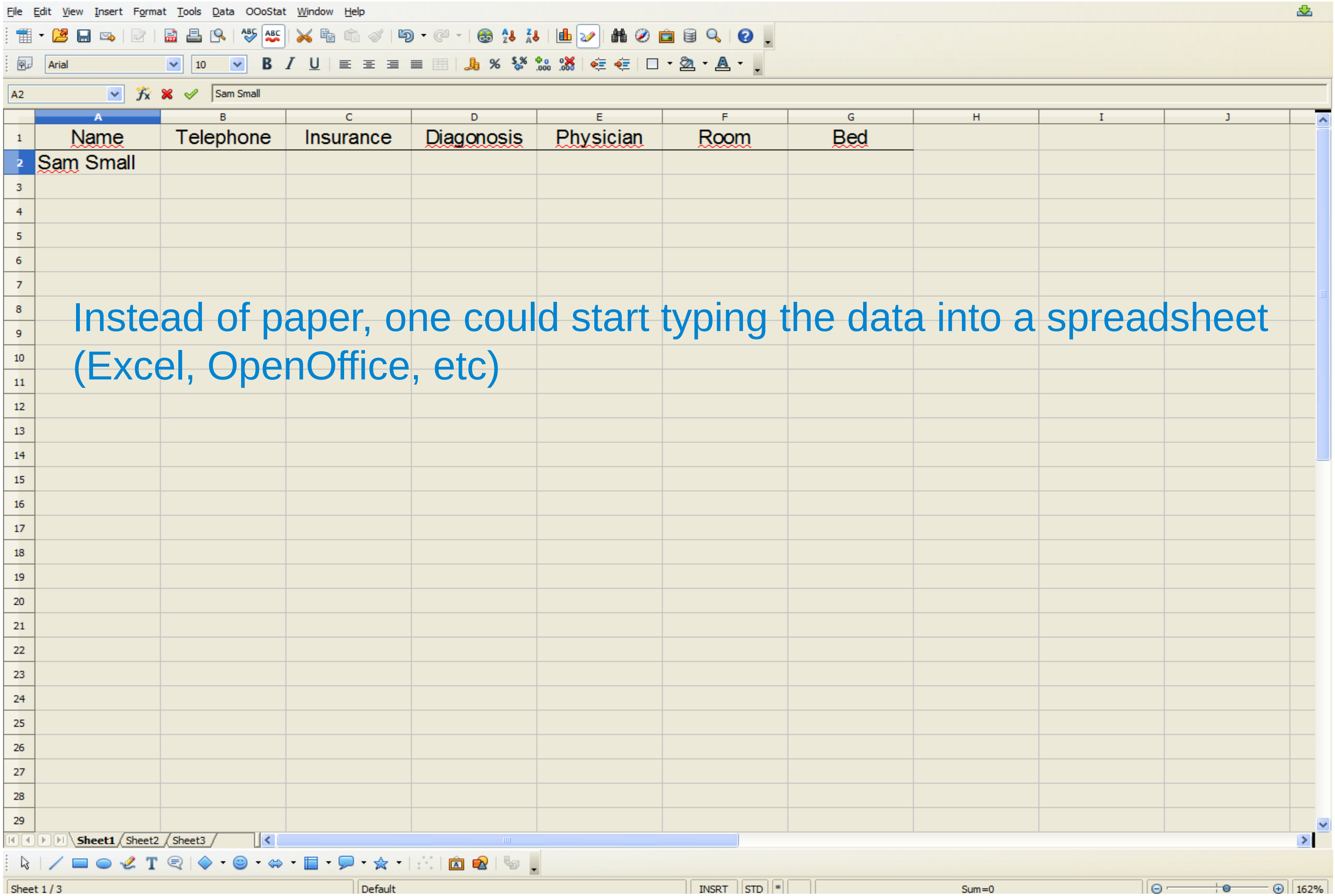
Do you wear glasses? Y/N Contact lenses? Y/N Type

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

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Table : ordered set of data (information)

Databases – storing information

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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

	A	B	C	D	E	F	G
1	Name	Telephone	Insurance	Diagnosis	Physician	Room	Bed
2	Sam Small	(763) 865 345	Medicaid	Influenza	Dr. Barkins	37	2
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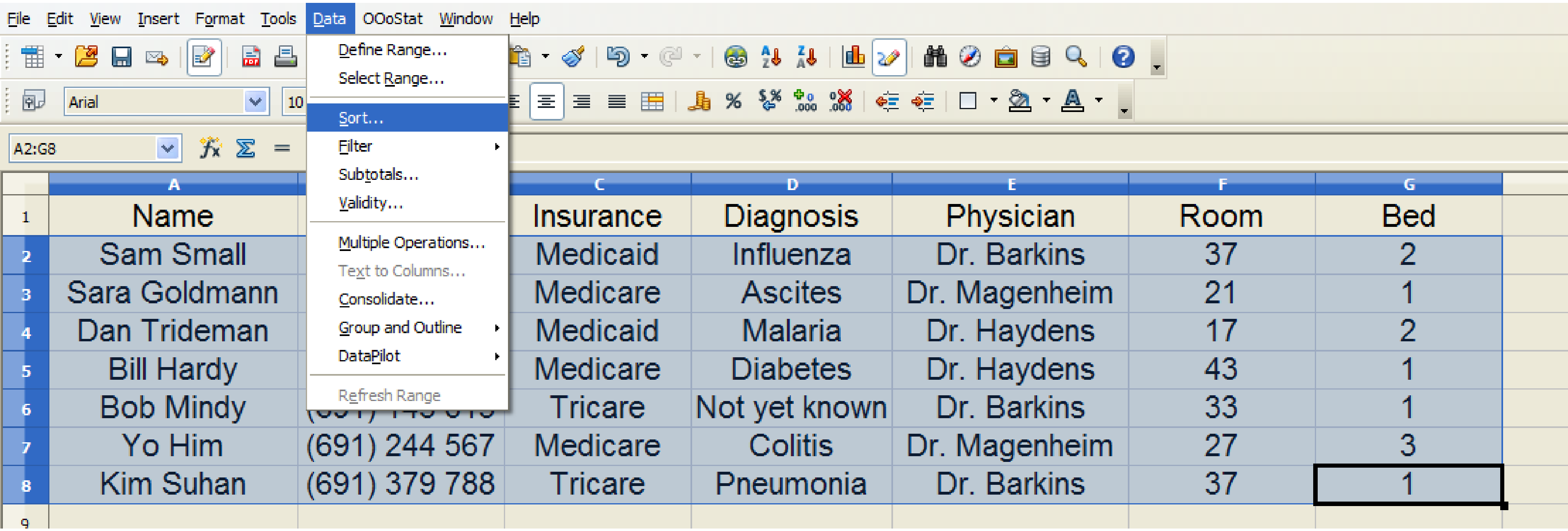
6	Bob Mindy	(691) 143 613	Tricare	Not yet known	Dr. Barkins	33	1
7	Yo Him	(691) 244 567	Medicare	Colitis	Dr. Magenheim	27	3
8	Kim Suhan	(691) 379 788	Tricare	Pneumonia	Dr. Barkins	37	1

Column: data type

Databases – manipulating information

Sorting data



Databases – manipulating information

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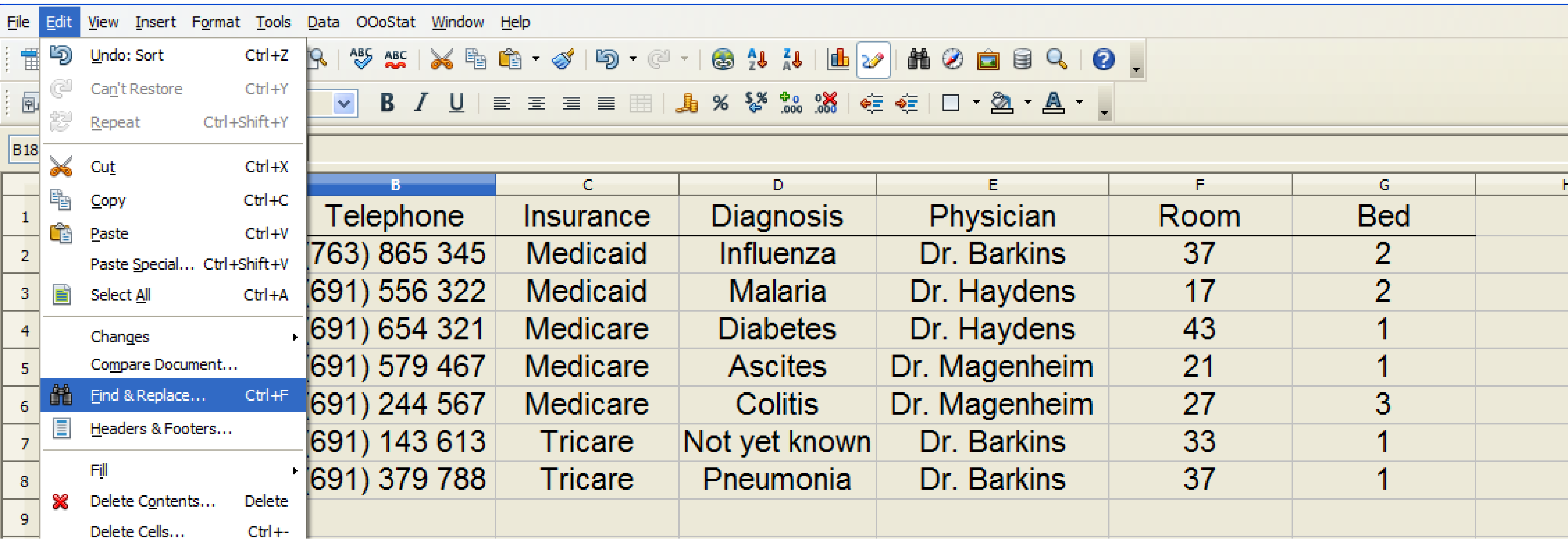
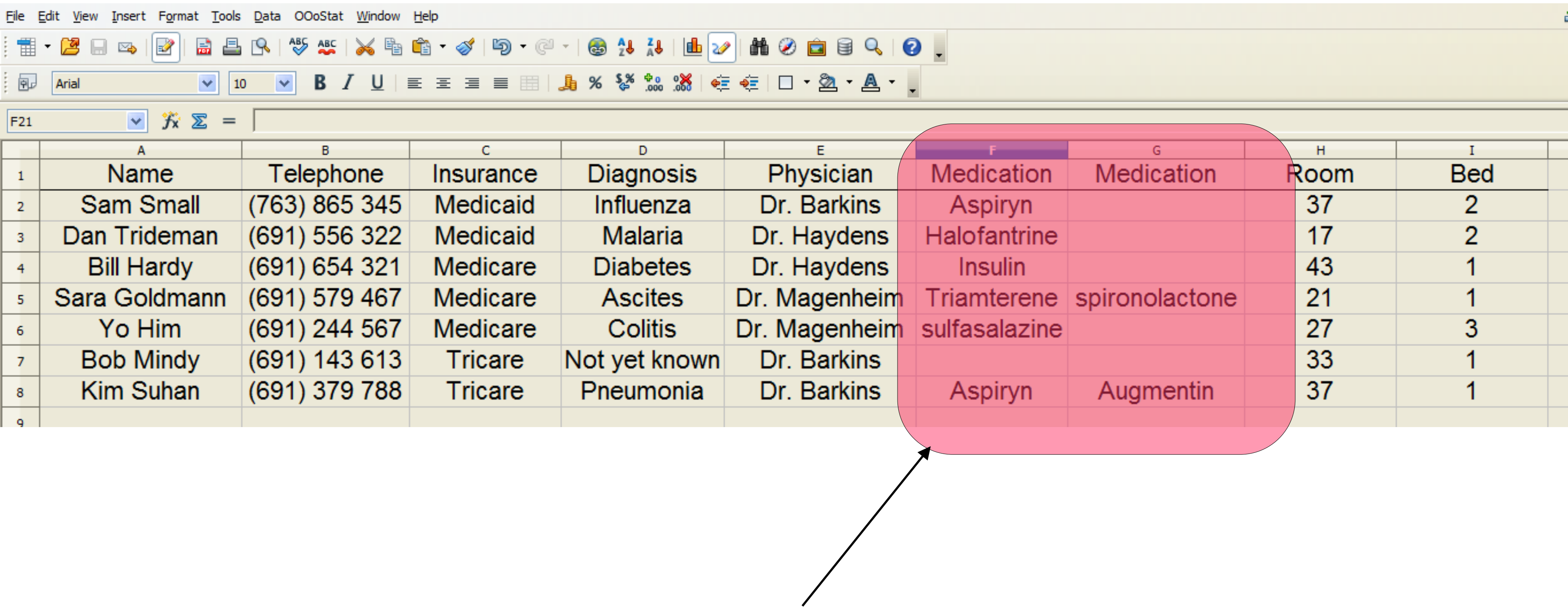
Databases – retrieving information



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
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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

	A	B	C	D	E	F	G	H	I
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8	Kim Suhan	(691) 379 788	Tricare	Pneumonia	Dr. Barpins	Aspiryn	Augmentin	37	1
9									

Entering the same data multiple times:

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

Databases – SQL

A relational database stores each key (information) ONCE, and it stores the connections between objects.

The database models the logic of the data set.

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 non-inferential 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.

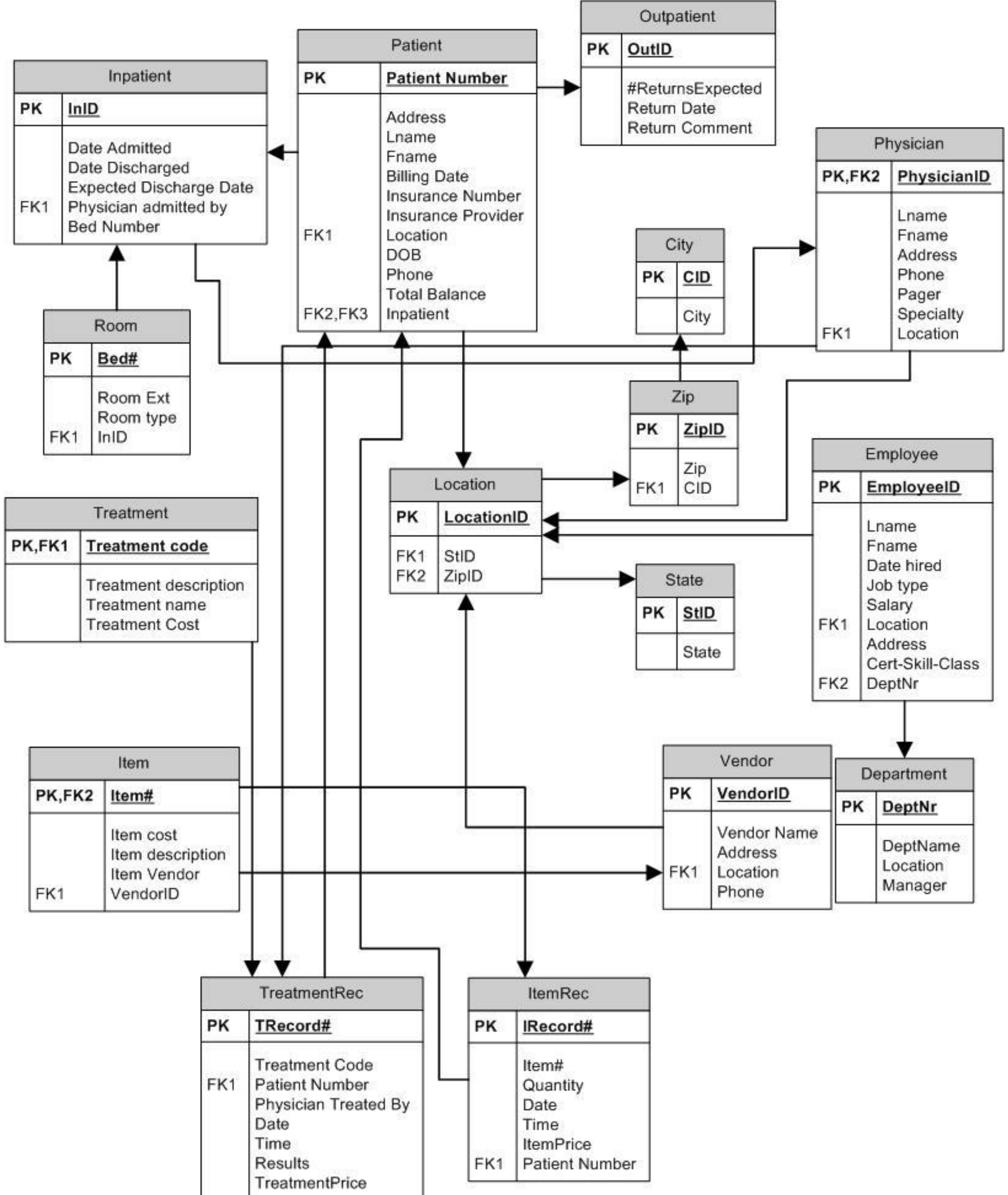
1.2. Data Dependencies in Present Systems

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

Extension Material

Databases



Medical application

information gained by diagnostics

expert systems

genetic databases

Proteomics
Lipidomics
…-omics

personalized medicine

a : pretest prob.
b : post test prob.

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

relative entropy

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

do NOT memorize formula! they are here to see what the software calculates in the background

Kullback–Leibler divergence

$$D_{KL}(P|Q) = \sum_i p_i \cdot log\left(\frac{p_i}{q_i}\right)$$

$$D_{KL}(P|Q) = \int_{-\infty}^{+\infty} p(x) \cdot log\left(\frac{p(x)}{q(x)}\right) dx$$

it connects to the Shannon entropy

$$H = \log(N) - D_{KL}(p(x)|PE_N)$$

our posterior distribution

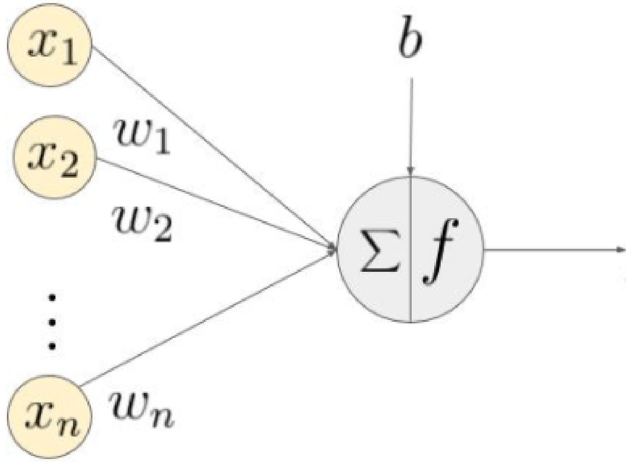
PE_N : N element equal distr.
(least informative prior)

This tells **how much we learn!**

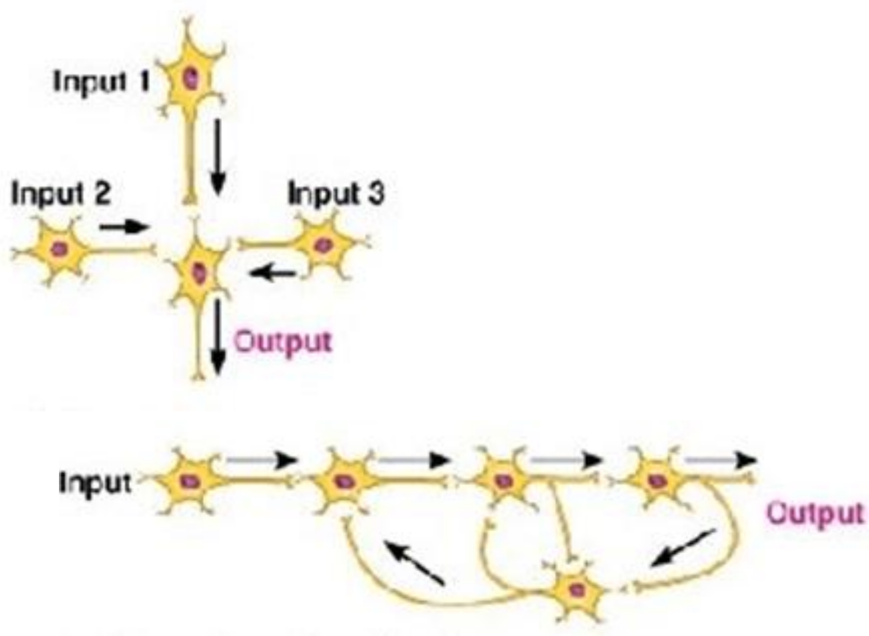
more knowledge means less uncertainity by the given amount of bits.

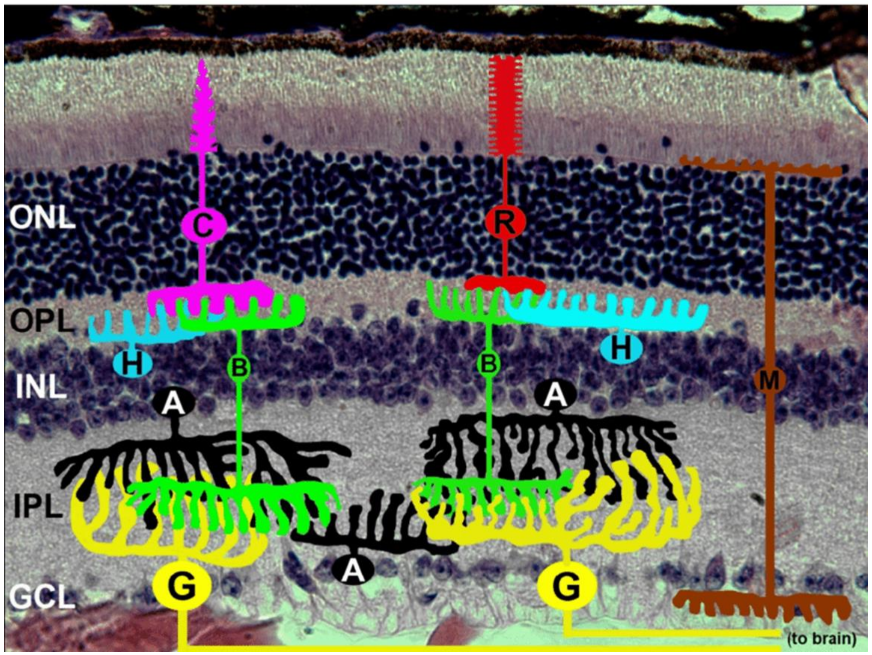
Artificial neuron -> we copy the biology as good as we can

(a good design is worth re-use ☺)

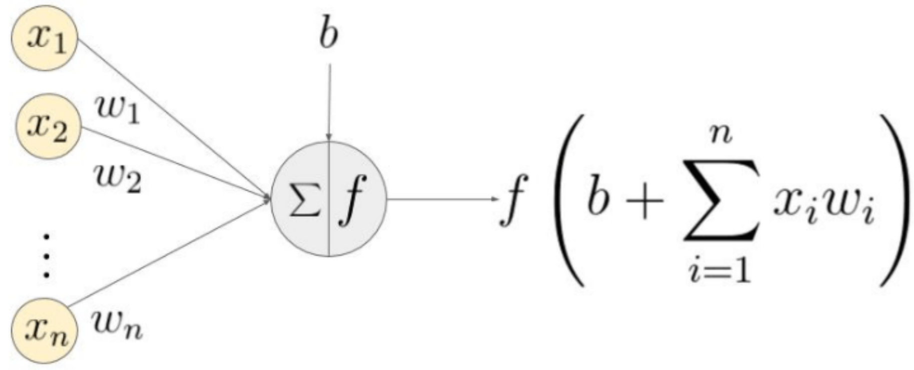


$$f\left(b + \sum_{i=1}^{n} x_i w_i\right)$$



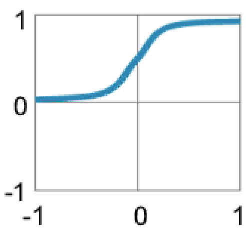


Activation functions



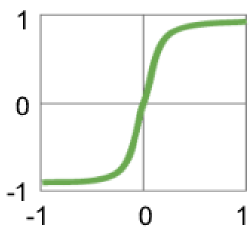
Traditional Non-Linear Activation Functions

Sigmoid



y=1/(1+e⁻ˣ)

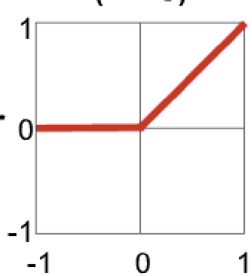
Hyperbolic Tangent



y=(eˣ-e⁻ˣ)/(eˣ+e⁻ˣ)

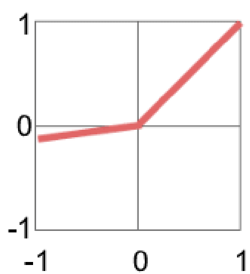
Modern Non-Linear Activation Functions

Rectified Linear Unit (ReLU)



y=max(0,x)

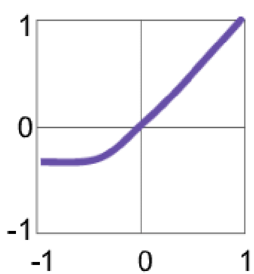
Leaky ReLU



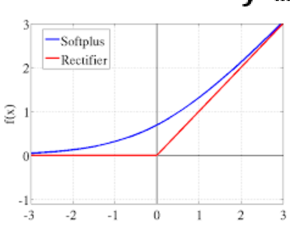
y=max(αx,x)

α = small const. (e.g. 0.1)

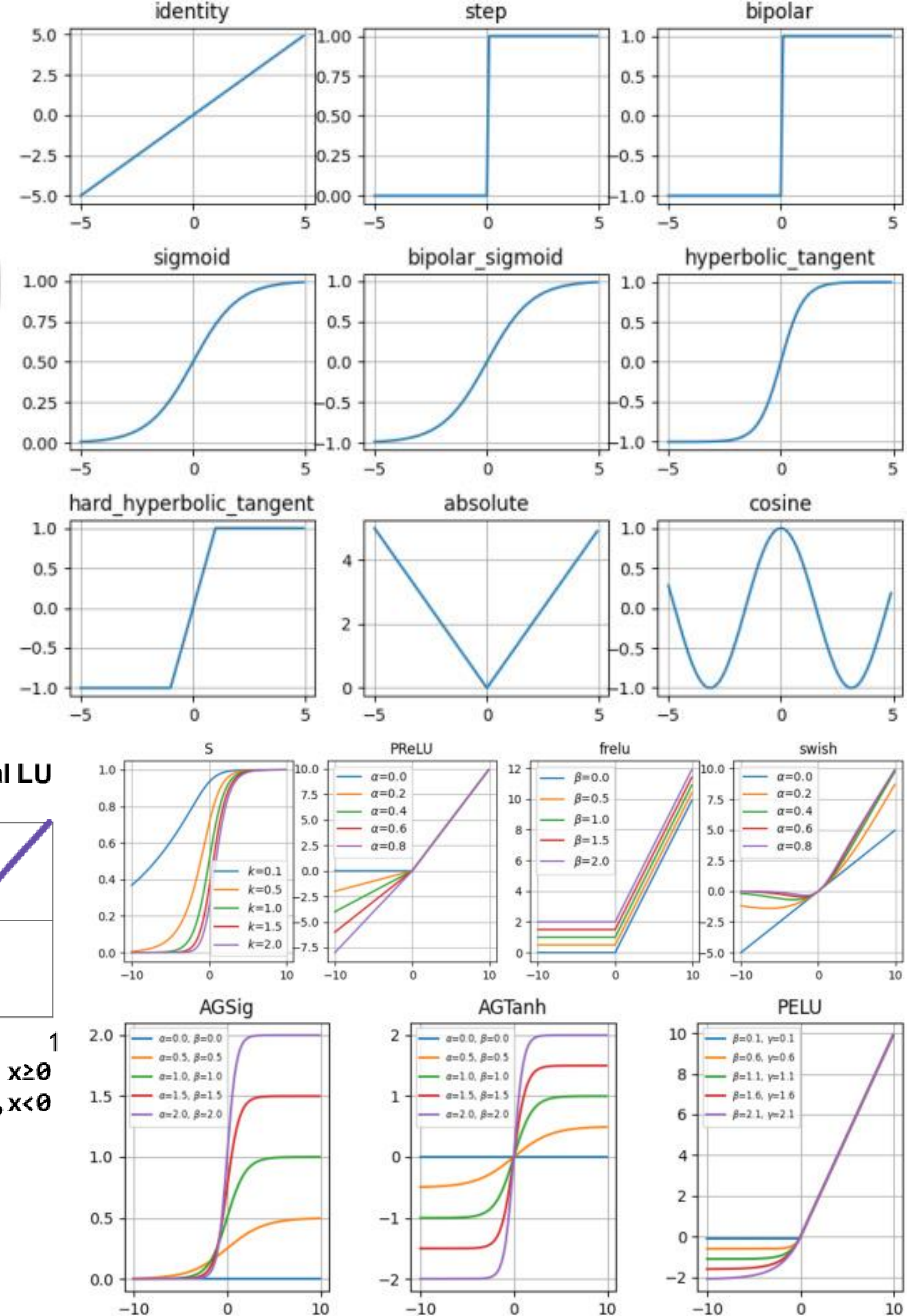
Exponential LU



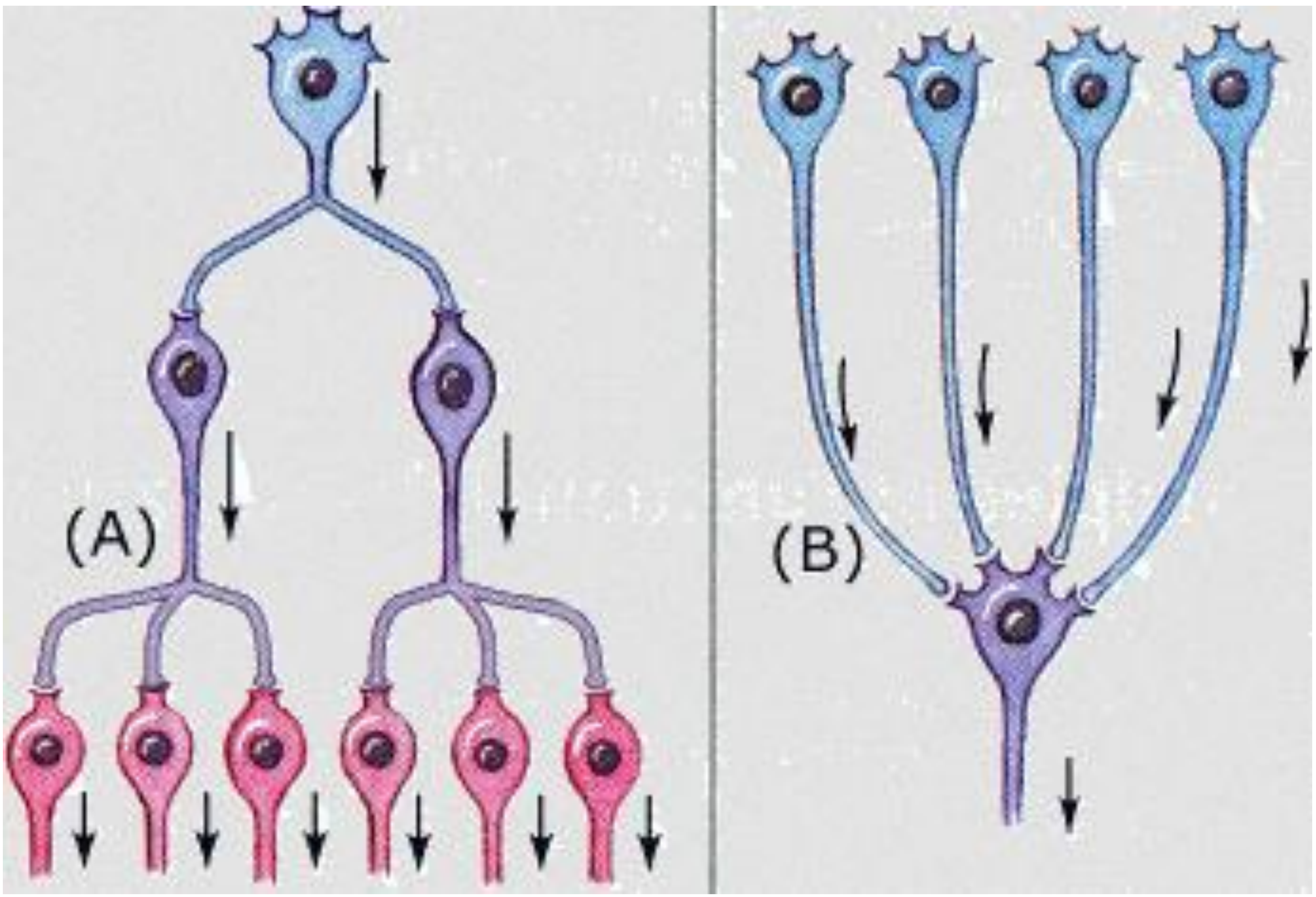
$y=\begin{cases} x, & x\geq 0 \\ \alpha(e^x-1), & x<0 \end{cases}$



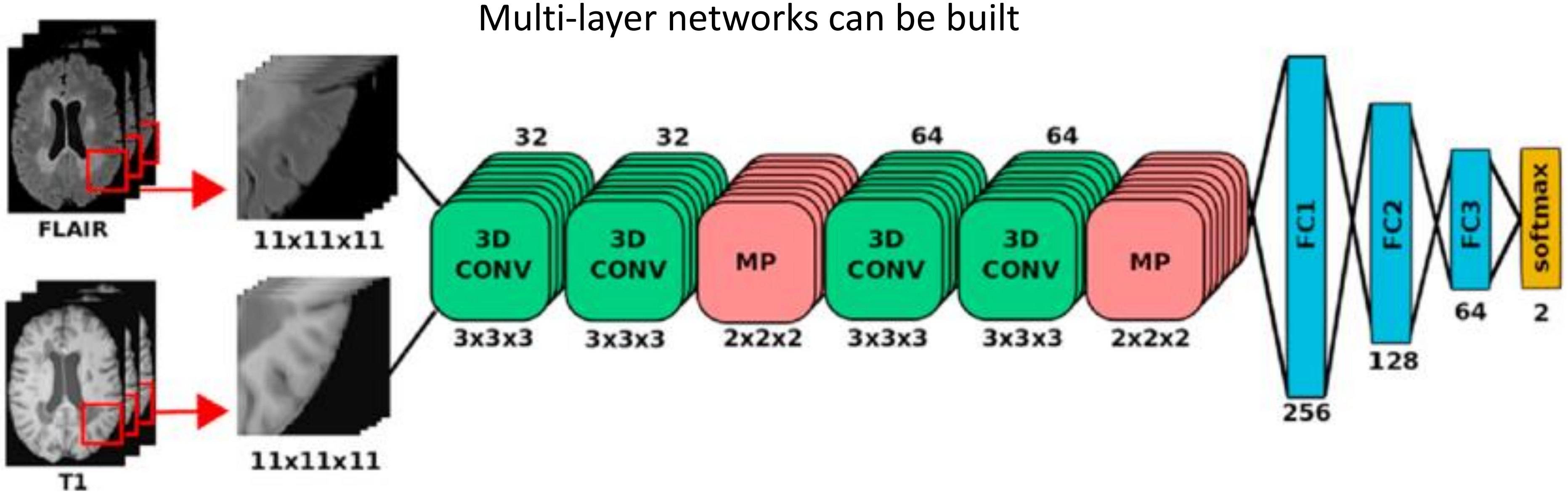
Softplus: $y=\ln(1+e^x)$



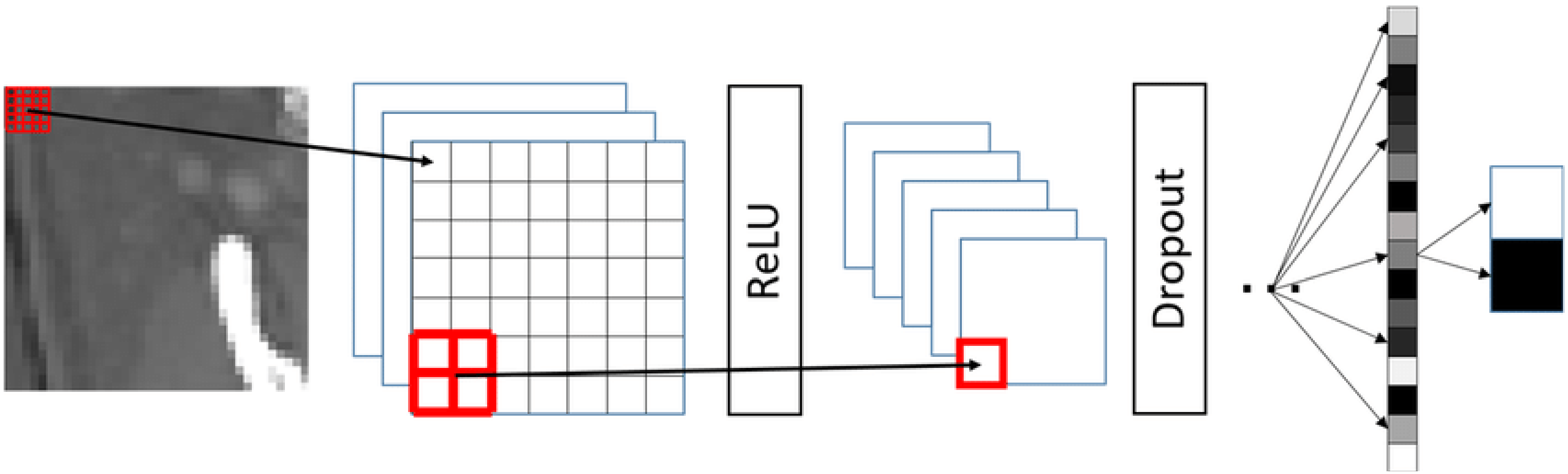
Convergence and divergence



Multi-layer networks can be built



Valverde, Sergi & Salem, Mostafa & Cabezas, Mariano & Pareto, Deborah & Vilanova, Joan C & Ramió-Torrentà, Lluís & Rovira, Alex & Salvi, Joaquim & Oliver, Arnau & Llado, Xavier. (2018). One-shot domain adaptation in multiple sclerosis lesion segmentation using convolutional neural networks. NeuroImage: Clinical. 21. 101638. 10.1016/j.nicl.2018.101638.



input convolution layer (max) pooling classificator

Ibragimov, Bulat & Xing, Lei. (2016). Segmentation of organs-at-risks in head and neck CT images using convolutional neural networks. Medical Physics. 44. 10.1002/mp.12045.