

Metodologie

(Module 2)

Science IFT3700 data /

IFT6700 Fall 2018 ©

Alain Tapp

Contents

- scientfque method
- Dataset
- Model (parameters)
- Bayesian probability
- Hypothesis testing (P-values)
- statstque recall and Corrélaton
- causal Relaton

**scientific
method**

Clinical Versus Mechanical Prediction: A Meta-Analysis

William M. Grove, David H. Zald, Boyd S. Lebow, Beth E. Snitz, and Chad Nelson
University of Minnesota, Twin Cities Campus

The process of making judgments and decisions requires a method for combining data. To compare the accuracy of clinical and mechanical (formal, statistical) data-combination techniques, we performed a meta-analysis on studies of human health and behavior. On average, mechanical-prediction techniques were about 10% more accurate than clinical predictions. Depending on the specific analysis, mechanical prediction substantially outperformed clinical prediction in 33%–47% of studies examined. Although clinical predictions were often as accurate as mechanical predictions, in only a few studies (6%–16%) were they substantially more accurate. Superiority for mechanical-prediction techniques was consistent, regardless of the judgment task, type of judges, judges' amounts of experience, or the types of data being combined. Clinical predictions performed relatively less well when predictors included clinical interview data. These data indicate that mechanical predictions of human behaviors are equal or superior to clinical prediction methods for a wide range of circumstances.

The axiomatic method

Euclid's Elements

- around 300 BC. AD
- Masterpiece of axiomatic method
- Pythagore's theorem
- Only five Platonic solids



Organum of Aristotle (384 BC. 322 BC. AD)

If I state the following: "**All Men Are Mortal, gold Leon is a man, so Leo is mortal**" no one will find nothing wrong. But if I say "All cats fours, or my dog fours, so my dog is a cat," we retort that I lack of logic! Similarly, if I say, "All men are mortal, gold Leon is deadly, so Leo is a man", my conclusion is not correct because Leo could be an animal (there are not that men die). What difference there-he has different between these sentences? Why only the first can it be considered a valid argument? These statements are syllogisms. Aristotle formalized them precisely in Book III of the *Organum*, which was named *The First Analytics*. It defines syllogism thus: "The syllogism is a reasoning where some things are proven,

Argument

$$2 + 3 = 5$$

for 2, 3 and 5 are the first three primes consécutifs

invalid argument

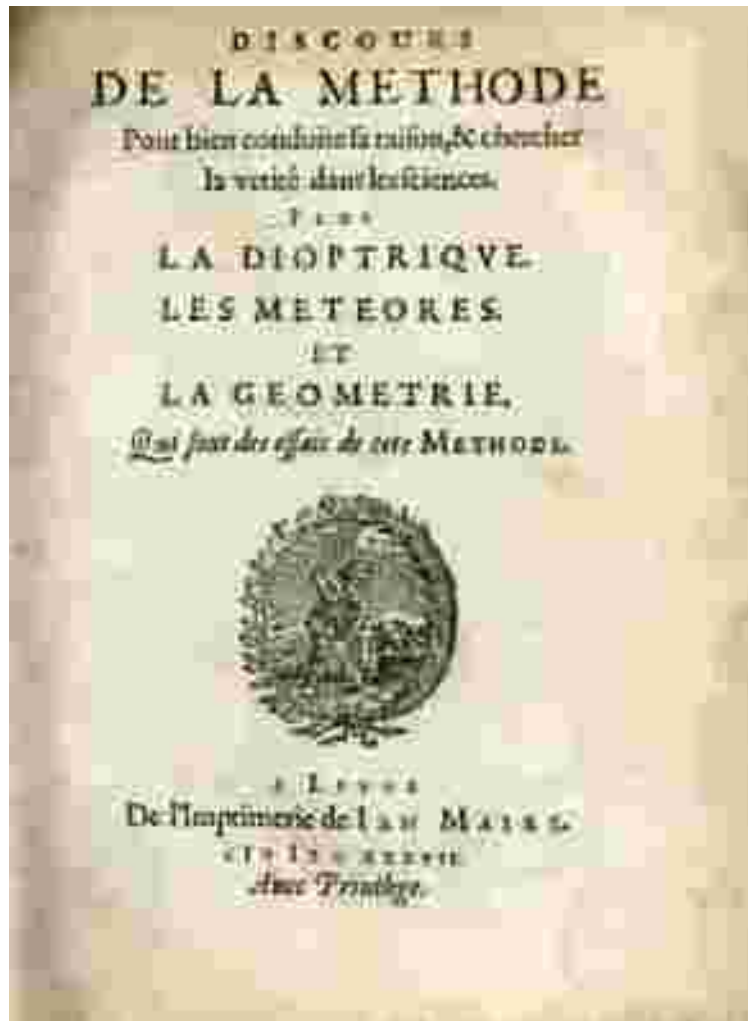
	TRUE	FALSE
VALID	YES	NO
INVALID	YES	YES

Propaganda: show a fool with incorrect proof of non-A to convince A.

Discourse on Method

René Descartes

1637



Discourse on Method

René Descartes

1637

1. Do not accept anything as true as his spirit aura clearly and distinctly treated previously.
2. Divide each difficulty to better address and resolve them.
3. Establish an order of thoughts, starting with the simplest objects to the most complex and diverse, and so retain all and in order.
4. Place all the things reviewed to omit nothing.

Discourse on Method

René Descartes

1637

"Furthermore, I would like them to consider that the great artery and the arterial vein are of composition much harder and firmer than are venous artery and the vena cava; and that these two expand before entering the heart, and there are like two scholarships named Heart earrings, which are composed of flesh like his; and **there is always more heat in the heart than in any other part of the body**, and finally that this heat is able to do that, if he enters a drop of blood in its cavities, it promptly ENFE and expands, and generally do all the liquors, when allowed to fall drop by drop in a vessel which is very hot.

William Harvey, English physician, is famous for the discovery of the blood circulation exposed in his book *De motu cordi* (1628).

"The science is straightforward contre box: much of the literature scientific, Perhaps half, May simply be untrue. Affected by studies with small sample sizes, tiny effects, invalid exploratory analyses, and flagrant conflicts of interest, together with an obsession for Pursuing fashionable trends of dubious importance, science HAS taken a turn Towards Darkness. "

Richard Horton editor of *The Lancet*.

www.thelancet.com Vol 385 April 11, 2015

<http://rsos.royalsocietypublishing.org/content/1/3/100216>

"If you use $p = 0.05$ to suggest That You-have made a discovery, you will be wrong at least 30% of the time. If, as is often the case, experiments are underpowered, you will be wrong MOST of the time. "

David Colquhoun

An investigation of the false discovery rate and the p-values of misinterpretation Published November 19 2010.DOI: 10.1098 / rsos.100216

Why Most Published Research Findings Are False

John P. A. Ioannidis

Summary

There is increasing concern that published research findings are false. The probability that a research finding is true may depend on multiplicity and how the number of tests affects the false discovery rate, and, importantly, the ratio of true to no relationships among the relationships tested. In our framework, a research finding is false if there is no true relationship among the

factors that influence this problem and some corollaries thereof.

Modeling the Framework for False Positive Findings

Several methodologies have pointed out [9-11] that the high rate of nonreplication (lack of confirmation) of research discoveries is a consequence of the convenient, yet ill-founded strategy of claiming conclusive research findings solely on the basis of a single study measured by

is characteristic of the field and can vary a lot depending on whether the field targets highly likely relationships or searches for only once or a few true relationships among thousands and millions of hypotheses that may be postulated. Let us also consider, for computational simplicity, circumscribed fields where either there is only one true relationship (among more than can be hypothesized) or the power is similar to find any of the several selective true relationships. This



Over half of psychology studies fail reproducibility test

Largest replication study to date casts doubt on many published positive results.

[Monica Baker](#)

27 August 2015

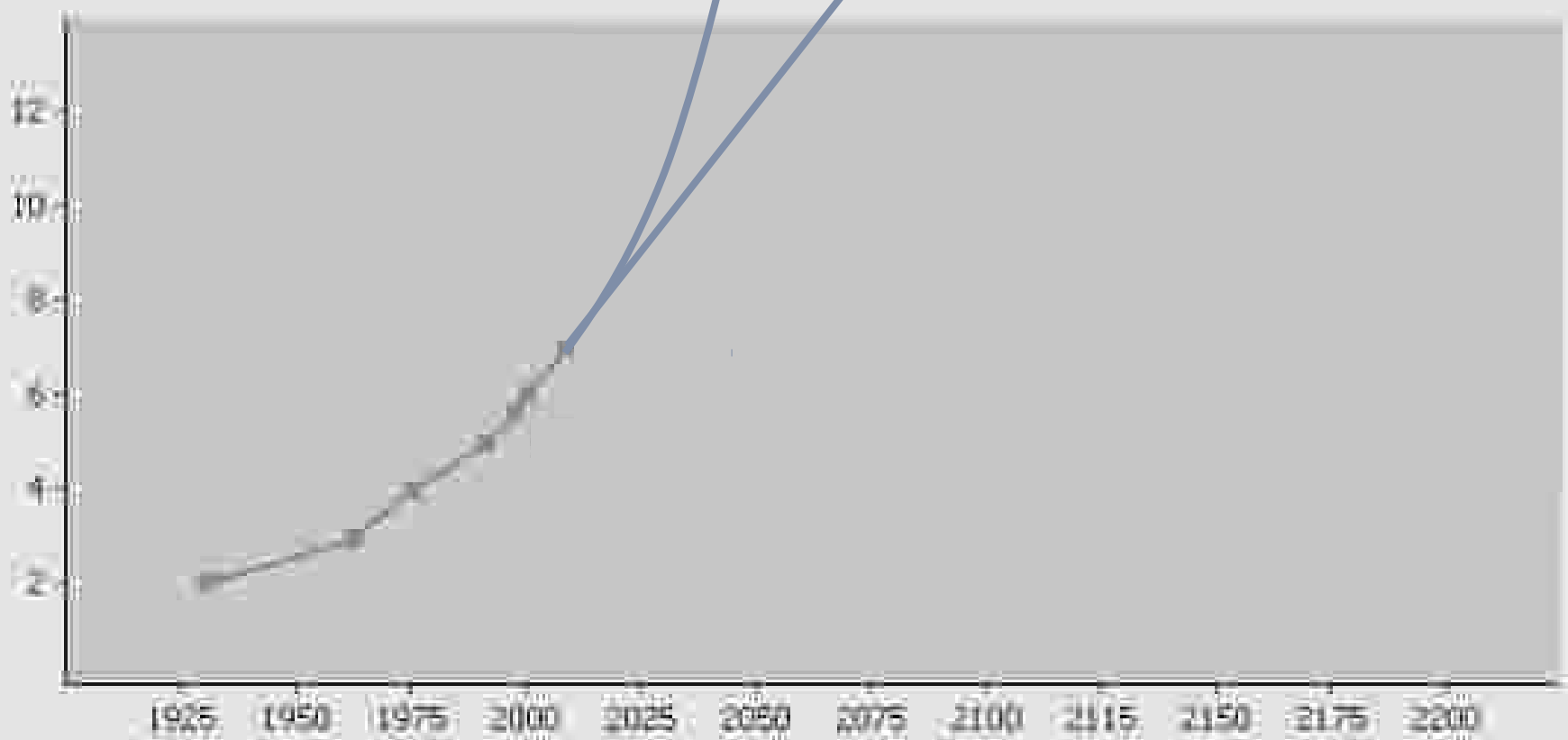
[Rights & Permissions](#)

nature
briefing

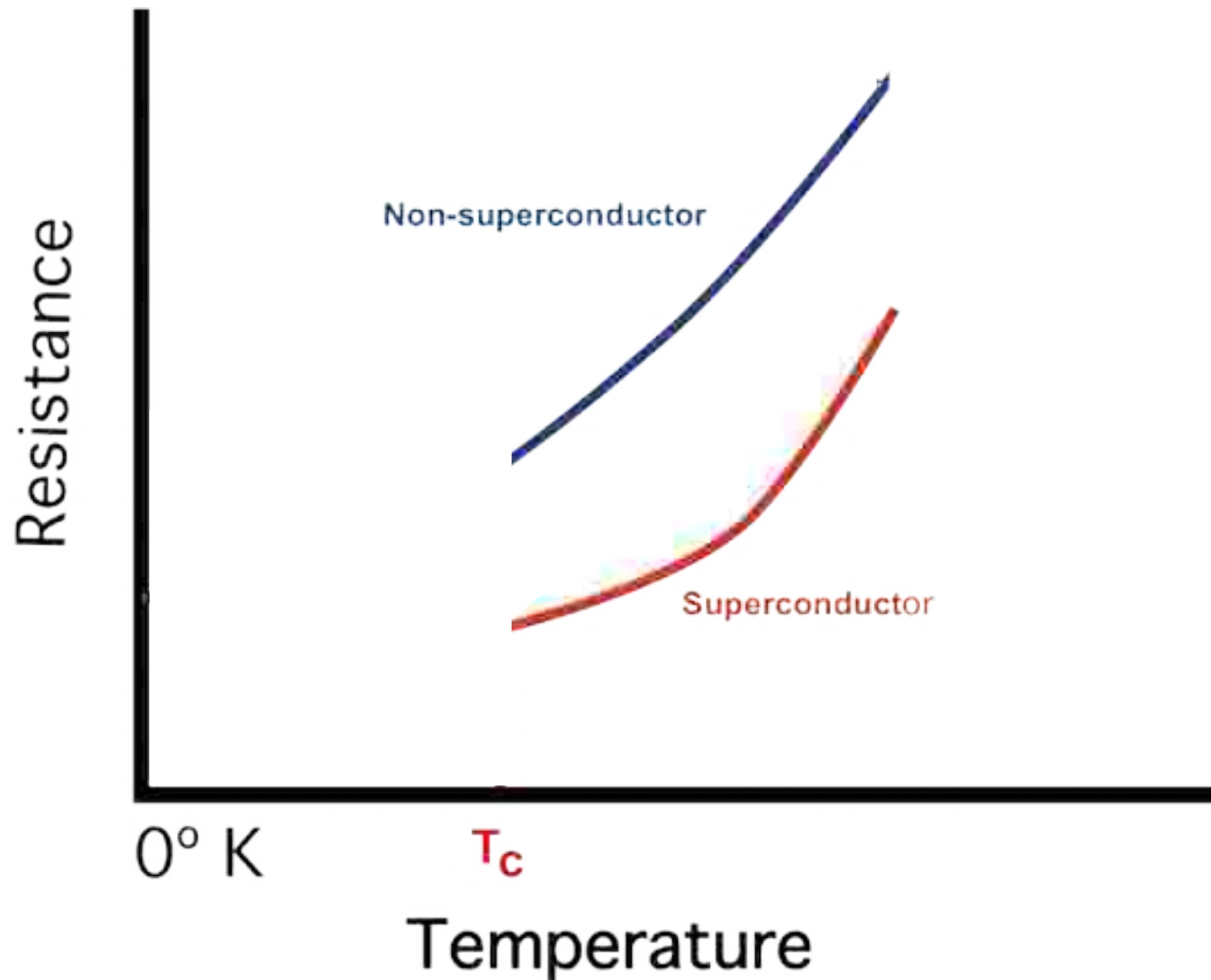


interpolation versus projection

En milliards:



interpolation versus projection



Denying the antecedent

Falsely conclude that A implies B B implies A. Ex. Judging the evidence on the validity of the answer.

The **through retrospectf** (*Hindsight bias*) is a miscalculation cognitf designating the tendency of people to surestmer rétrospectvement that the events could have been antcipés means more foresight or clairvoyance. Ex. Numerous lawsuits against doctors.

Ex. The media ofer a explicaton fellows events without ever being able to predict.

The **Through result** (*Outcome bias*) is an error in Evaluaton the quality of a decision when the result of cete decision is already known. Ex. Justce, murder tentatve vs murder

Decision-making, belief, and behavioral Biases

Ambiguity effect
Anchoring gold focalism
anthropocentric thinking
Anthropomorphism gold personification
Attentional bias
Automaton bias heuristic
Availability Availability
waterfall Backfire effect
Bandwagon effect
Base rate fallacy or base rate neglect
Belief bias
Ben Franklin effect
Berkson's paradox Bias
blind spot Bystander effect
Choice-supportive bias
clustering illusion
Confirmation bias congruence
bias Conjunction fallacy
Conservatism (belief revision)
Continued influence Contrast effect
effect Courtesy bias
Curse of Knowledge
Declinism Decoy effect

Default Denominator effect
effect effect disposition
Distinction bias
Dunning-Kruger effect
Duranton neglect Empathy
Gap Endowment effect
exaggerated expectation
experimenter's gold expectation bias
Focusing Drill effect effect gold Barnum effect
Form function attribution bias Framing effect
Functional fixedness Gambler's fallacy
Hard-easy effect Hindsight Bias Bias Hostile
attribution hot-hand fallacy Hyperbolic
discounting Identifiable victim effect effect
IKEA Illicit transference of control Illusion
Illusion of validity Illusory correlation Illusory
truth effect

Impact Bias Bias information
Insensitivity to sample size
Irrational escalation Law of the
instrument Less-is-better effect
effect Look elsewhere-Loss
aversion Mere exposure effect
Money illusion Moral credential
effect
Negativity bias gold Negativity effect
Neglect of probability Normalcy Bias
Not invented here
Observer-expectancy effect Omission
Bias Bias Optimism Ostrich effect
effect Outcome bias Overconfidence
Pareidolia Pessimism bias Placebo
effect Planning fallacy Post-purchase
rationalization innovation Pro-bias bias
Projection

Pseudocertainty effect
Reactance Reactive
devaluation recency illusion
regressive bias
Restraint Bias Rhyme have
reason effect
Risk compensation / Peltzman effect
Selecton bias Selective perception
Semmelweis Reflex Sexual overperception Bias
/ sexual
Social comparison bias social
desirability bias Status quo bias
Stereotyping Subadditivity effect
Subjective validation Surrogation
Survivorship Bias Time-saving bias
Third-person effect Parkinson's law of
triviality Weber-Fechner law well
traveled road effect Women are
wonderful effect Zero-risk bias
Zero-Sum bias

THE NEW YORK TIMES BESTSELLER

THINKING, FAST AND SLOW



DANIEL
KAHNEMAN

WINNER OF THE NOBEL PRIZE IN ECONOMICS

*"The masterpiece . . . This work of the greatest and most original visionaries of
behavior has the honor and I hope will."* —NICHOLAS LEONARD, *Financial Times*



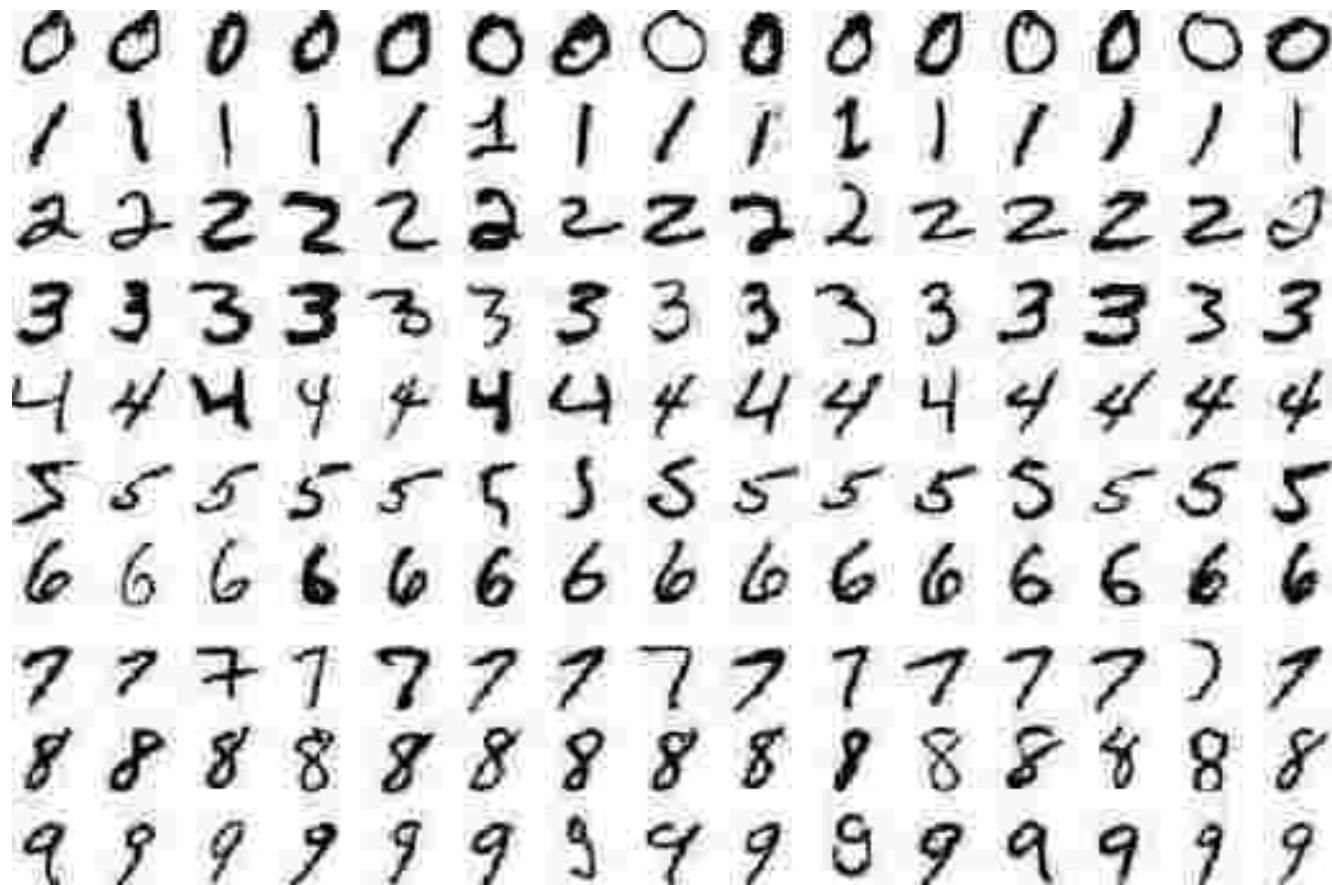
Datasets

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3	6	1	1	1	3	9	5	2	9	4	5	9
4	7	1	2	4	0	2	7	8	3	3	0	0
2	8	3	8	2	4	5	0	3	1	7	7	5
3	9	5	2	1	3	1	3	6	5	7	8	2
6	8	6	8	5	7	8	6	0	2	4	0	2
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8	3	4	4	0	8	8	3	3	1	7	3	5

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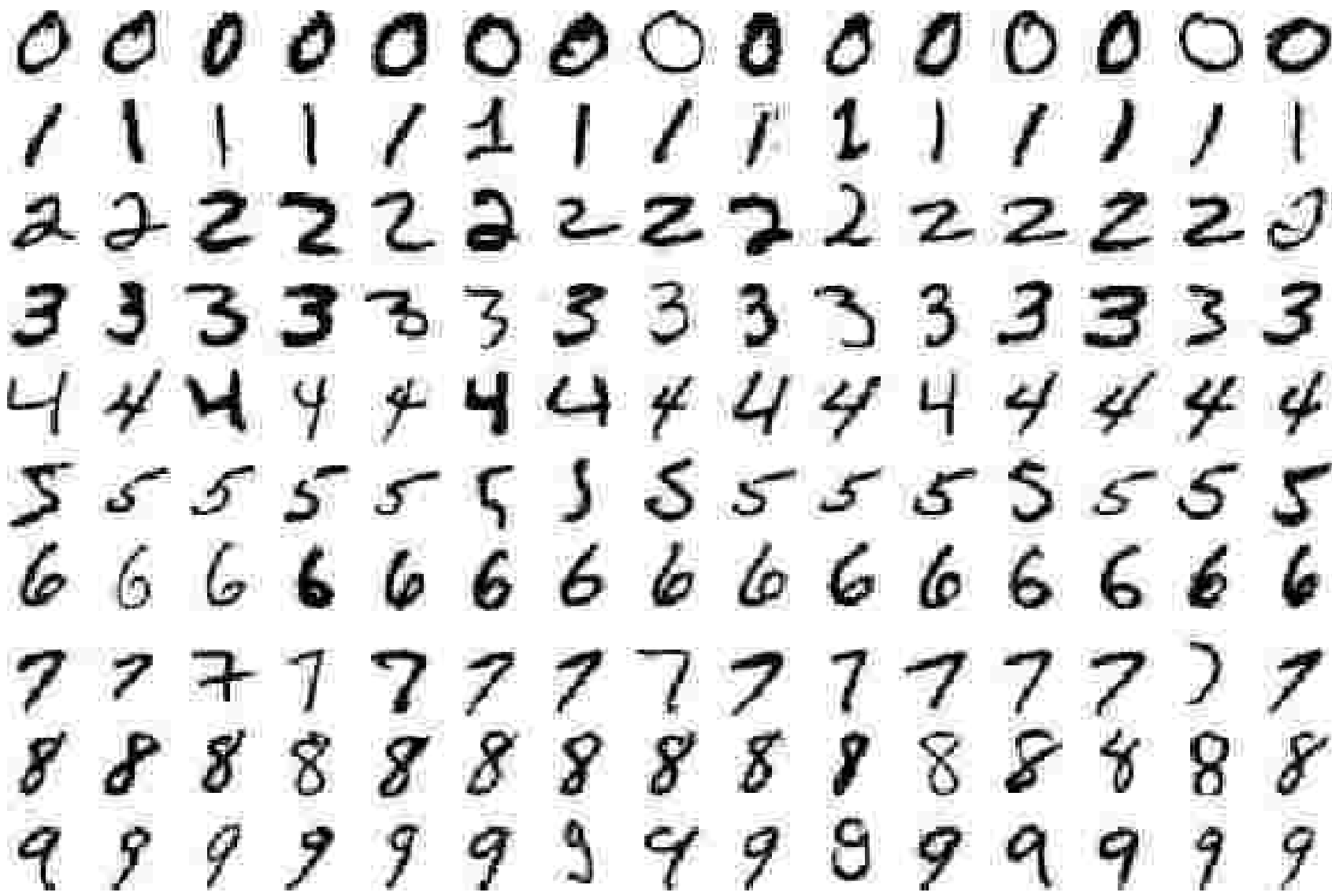
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3 6 1 1 1 3 9 5 2 9 4 5 9 3 9 0 3 6 5 5 7 2 2 7 1 2 8 4 1 7 3 3
4 7 1 2 4 0 2 7 4 3 3 0 0 3 1 9 6 5 2 5 7 2 9 3 0 4 2 0 7 1 1 2
2 8 3 8 2 4 5 0 3 1 7 7 5 7 9 7 1 9 2 1 9 2 9 2 0 4 9 1 4 8 1 8
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6 8 6 8 5 7 8 6 0 2 4 0 2 2 3 1 9 7 5 1 0 8 4 6 2 4 7 9 3 2 9 8
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8 3 4 4 0 8 8 3 3 1 7 3 5 8 6 3 2 6 1 3 6 0 7 2 1 7 1 9 2 8 2 1
1 4 4 6 0 2 9 1 4 7 4 7 3 9 8 8 4 7 1 2 1 2 2 3 2 3 2 3 9 1 7 4
9 0 2 5 1 9 7 8 1 0 4 1 7 9 5 4 2 6 8 1 3 7 5 4 8 1 8 1 3 8 1 2
7 8 5 9 7 9 6 9 6 3 7 4 4 5 8 5 4 7 8 7 8 0 7 6 8 8 7 3 3 1 9 5
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4 4 1 2 9 1 4 6 9 9 3 9 8 4 4 3 1 3 1 8 8 7 9 4 8 8 7 9 7 1 4 5
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3 7 1 3 0 3 4 4 3 8 9 2 3 9 7 1 1 7 0 4 9 6 5 9 1 7 0 2 0 0 4 6

MNIST



70000 examples with good étquete.

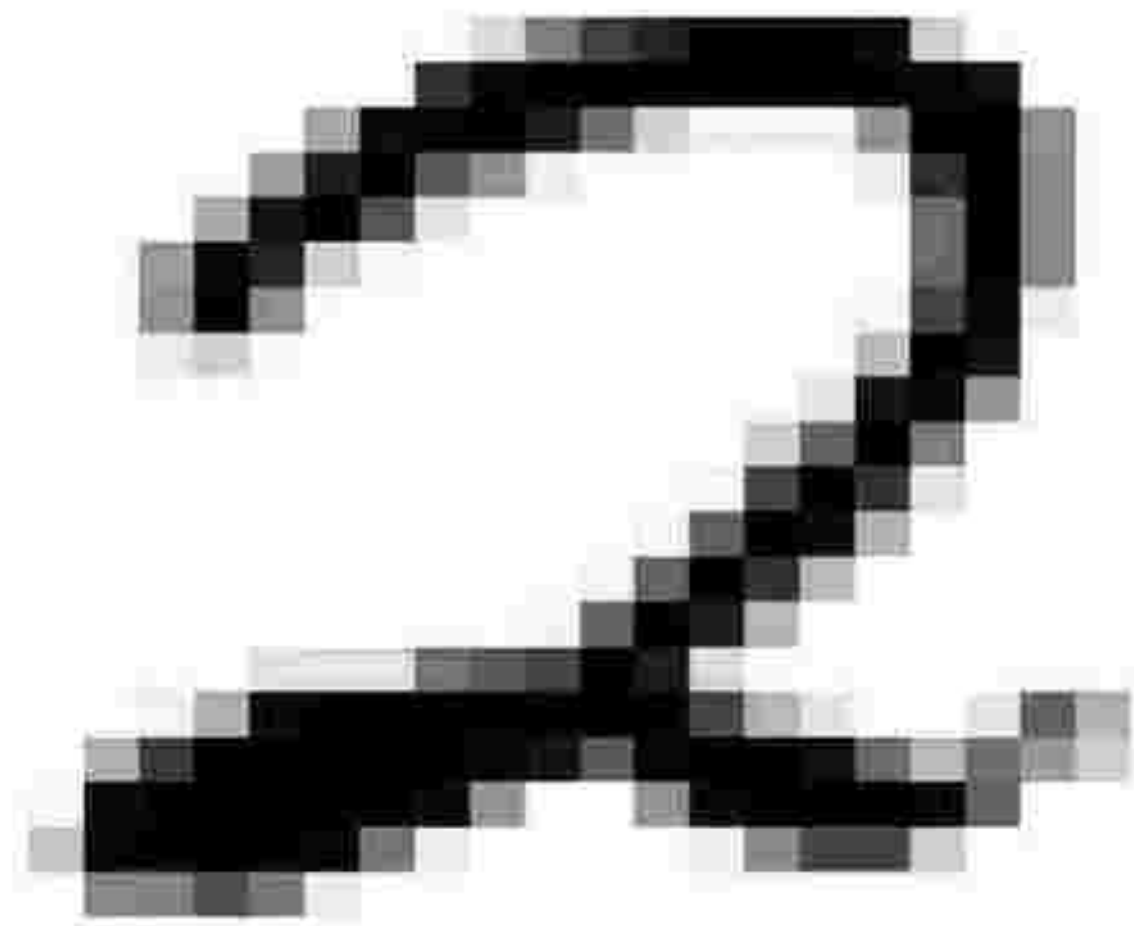
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1=
2=
3=
4=
5=
6=
7=
8=
9=



MNIST CVS

- mnist_train.csv, 60000 x 785, 18KB
- mnist_test.csv, 10000 x 785, 107KB

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28x20,28x25,28x26,28x27,28x28



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0

ADULT

08502 individuals (32261 + 16281) 10

caractéristiques

age, workclass, fnlwgt, educaton, educaton-num, occupaton,
relatonship, race, sex, capital gain, capital loss, hours-per-week,
native-country incomes

[http: //mlr.cs.umass.edu/ml/datasets/Adult](http://mlr.cs.umass.edu/ml/datasets/Adult)

**age, workclass, fnlwgt, educaton, educatonnaum, occupaton, relatonship,
race, sex, capitalngain, capitalnloss, hoursnpernweek, natvencountry,
incomes**

39 State-gov, 77516, Bachelors, 13, Never-married, ADM-clerical, Not-in-family,
White, Male, 2170, 0, 00, United-States, <= 50K

50, Self-emp-not-inc, 83311, Bachelors, 13, Married CIV-spouse,
Exec-managerial, Husband, White, Male, 0, 0, 13, United-States, <= 50K

38, Private, 215606, HS-grad, 9, Divorced, Handlers-cleaners, Not-in-family,
White, Male, 0, 0, 00, United-States, <= 50K

53, Private, 230721, 11th, 7, civ-Married-spouse, Handlers- cleaners,
Husband, Black, Boy, 0, 0, 00, United-States, <= 50K

Adult

age: continuous

workclass: Private, Self-emp-not-inc, Self-emp-Inc, Federal-gov, gov-Local, State-gov, Without-Pay, Never- Worked

fnlwgt: continuous

educaton: Bachelor, Some-college, 11th, HS-grad, Prof-school, Assoc-MDC, Assoc-voc, 9th, 7th, 8th, 12th, Masters, 1st-0th, 10th, Doctorate, 5th-6th, Preschool

educatonnum: continuous.marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent Married-AF-spouse

occupaton: Tech-support, Craf-repair, Other Service, Sales Exec-managerial, Prof-specialty, Handlers- cleaners, machine-op-inspct, Adm-clerical, Farming-fshing, Transport-moving, Priv-house-serv, Protective-serv, Armed Forces,

relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried

race: White, Asian-Pac-Islander Amer-Indian-Eskimo, Other, Black

sex: Female, Male

capitalngain: continuous

capitalnloss: continuous

hoursnpernweek: continuous

natvencountry: United-States, Cambodia, England, Puerto Rico, Canada, Germany, Outlying-US (USVI-Guam- etc.), India, Japan, Greece, South, China, Cuba, Iran, Honduras, the Philippines, Italy, Poland, Jamaica , Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Hait, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El Salvador, Trinidad & Tobago, Peru, Hong, Holand-Netherlands

incomes: > 50K <= 50K

modeling

modeling

- modeling
- Explain
- Simplifier
- Compress
- Reduce
- Schématser
- mapping
- A theory

modeling

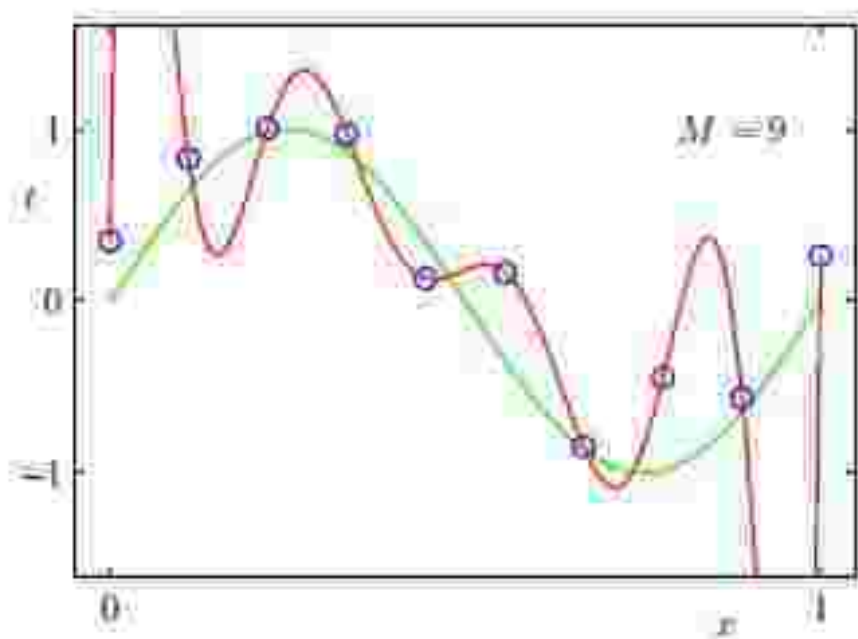
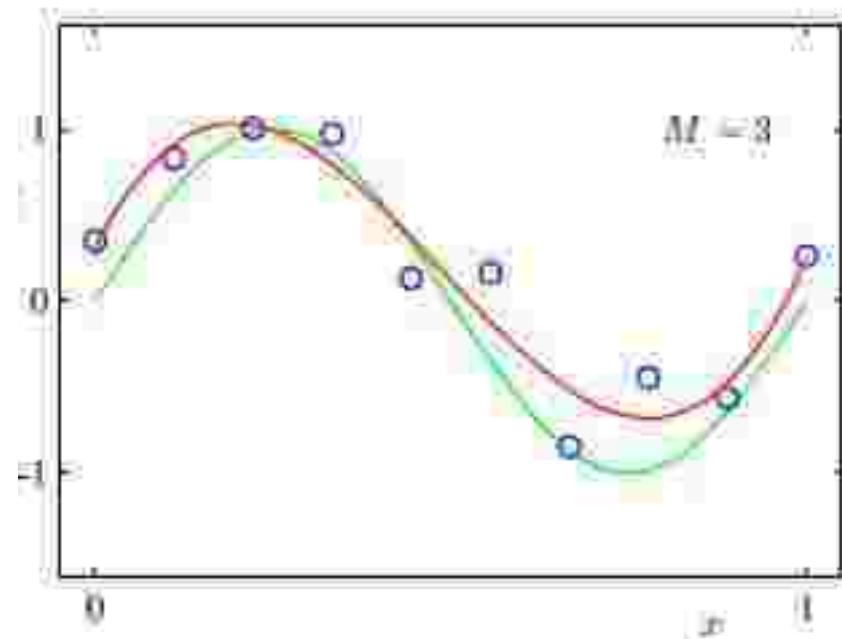
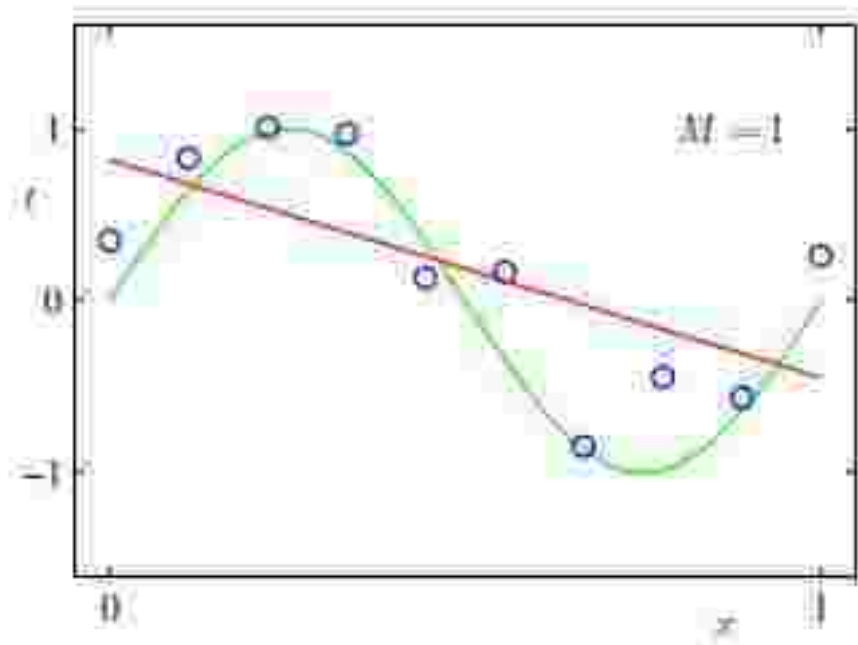
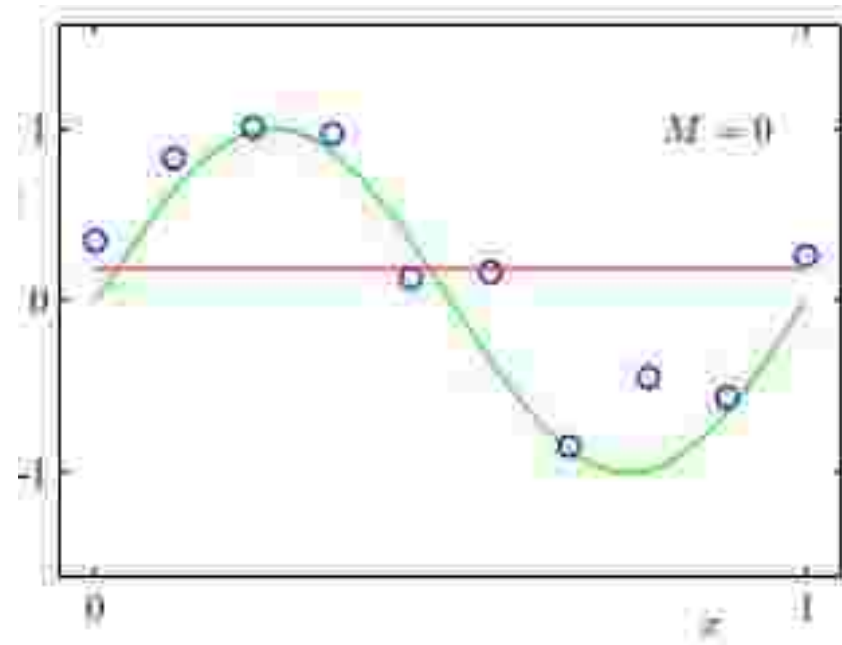
Given: a Characteristic table (dataset)

Model: pressing a formal relation between caractéristiques

Cost: the price paid if utilise model rather than the observed values.

Choice of model

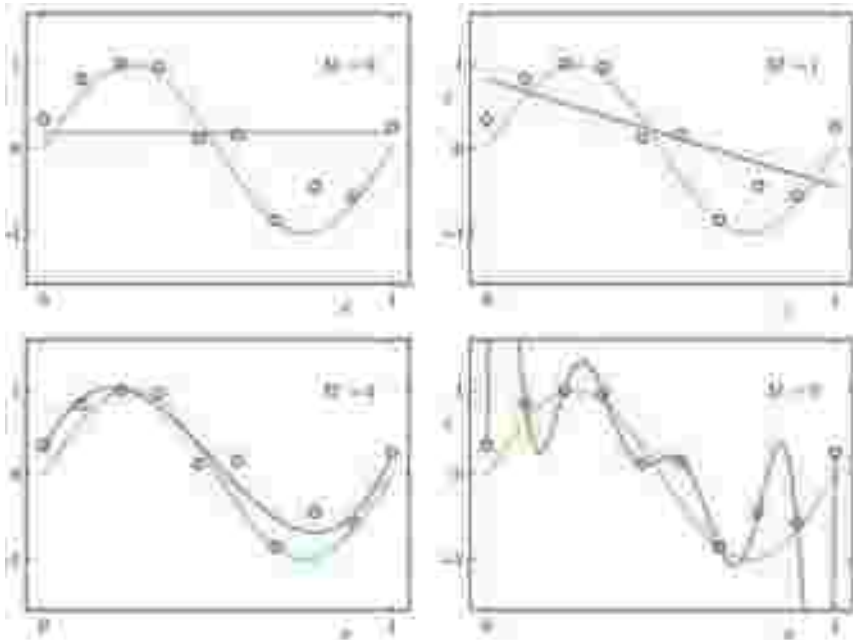
- **Family:** choose
- **hyperparameter:** selected or learned
- **Settings:** learned



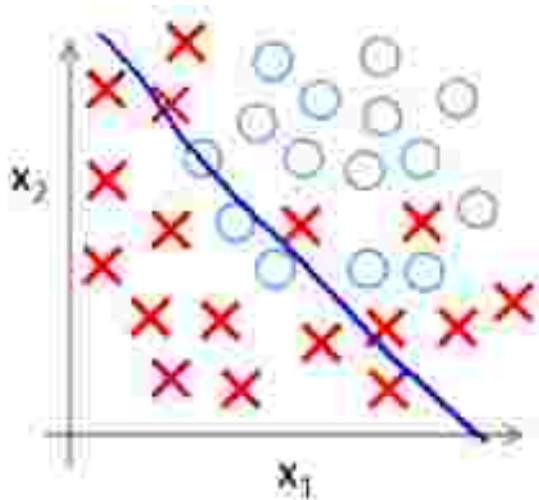
polynomial regression

Family: polynomial

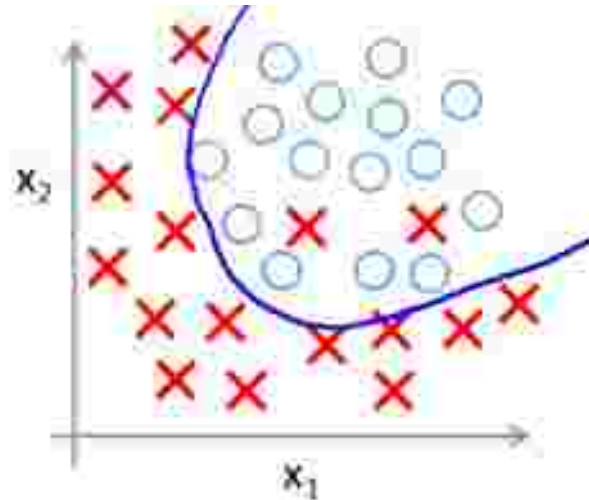
Hyperparameter: Settings degree polynomial: Coefficient
polynomial (degree + 1) cost: Minimizing squared error



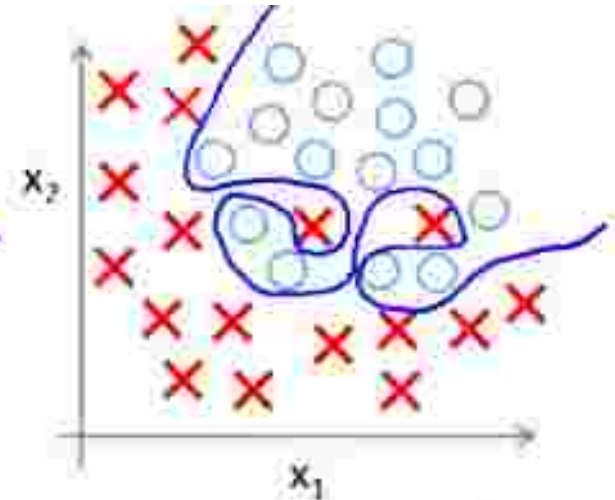
Overtraining?



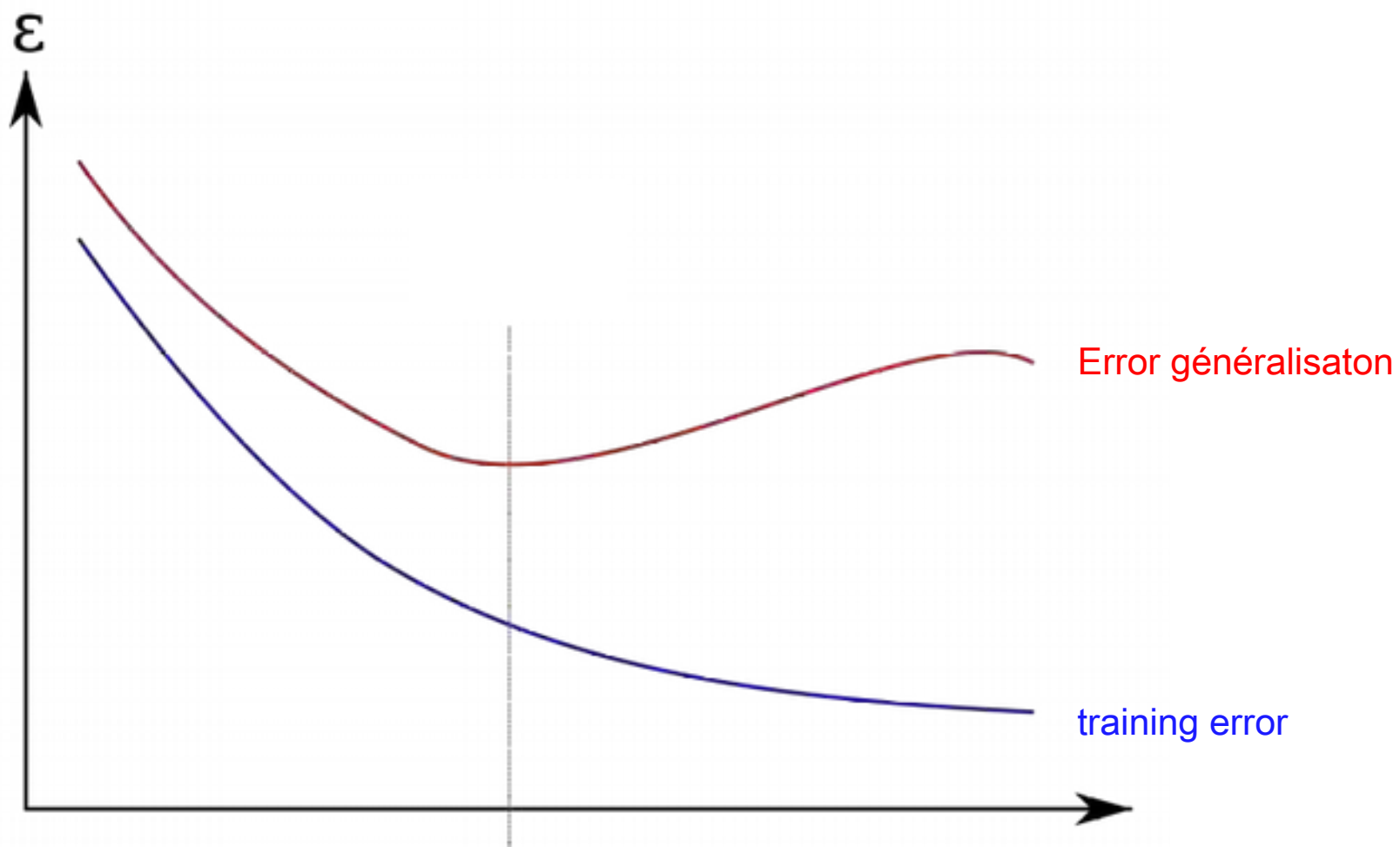
Deputy apprentissage



good généralisaton



Surapprentissage



100%

Examples

85%

15%



Apprentissage

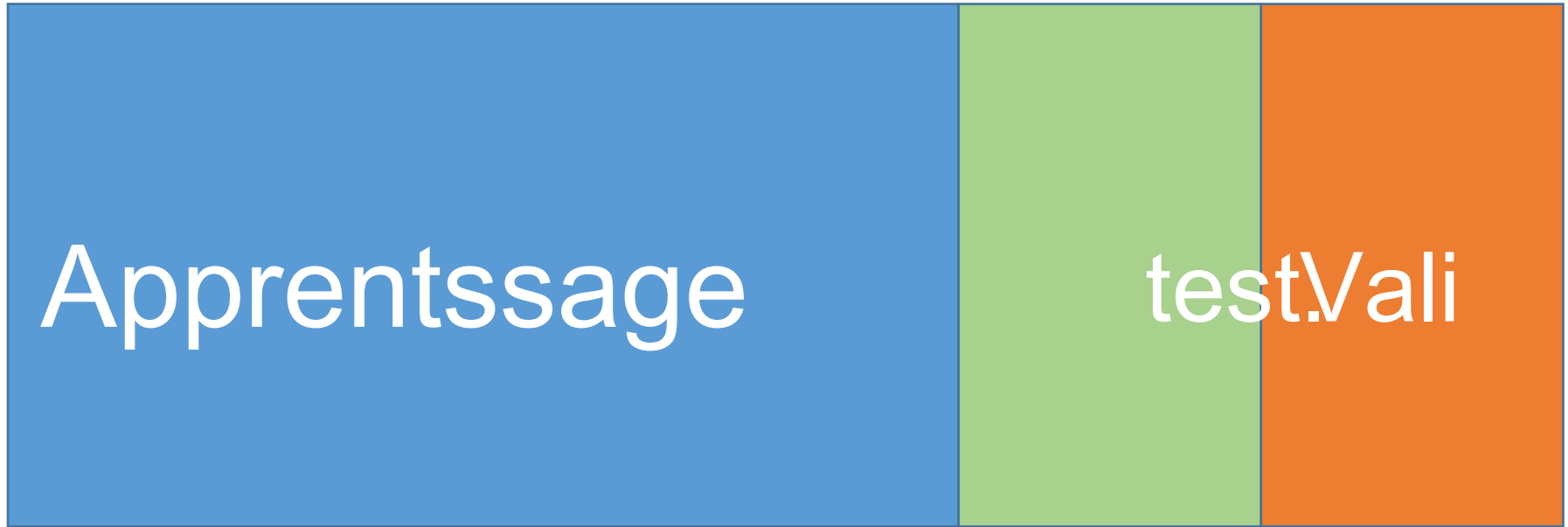
Test

It is learned settings then tested with fresh data.

70%

15%

15%



the parameters and hyper parameters is learned then tested with fresh data.

The hyper parameters are learned Fonction all validation.

Settings and hyper parameters

The apprentissage is an algorithmic mechanism permettant get good parameters for our model.

The **ability of a model** refers to its ability to mémorisation.

- Capacity
- Number of parameters
- Complexity

The training time refers to the time when we voluntarily decided, at a optimisation, terminate the progression of the algorithm to avoid over apprentissage. By **régularisation** of references has potentiellement harmful stress has optimisation, but may have an impact on the généralisation.

The Bayesian approach

Probability

Definition events form a universe Ω

Axiom 1

For any event A dans Ω

$$0 \leq P(A) \leq 1$$

Axiom 2

$$P(\Omega) = 1$$

Axiom 3

Any two events Family disjoint (incompatible)

$$P(A_1 \cup A_2 \cup \dots) = \sum_i P(A_i)$$

Theorem

Théorème

$$P(\emptyset) = 0$$

unsolicited Medical Test

Amyotrophic lateral sclerosis

valid test 95%

False Positive feedback ratio and false négatf

We test you by mistake.

The test is Positive feedback ratio.

Worried?



- valid test was 95% (False Positive feedback ratio and false négatif)
- Population 10 million.
- Prevalence in population 1/100 000.

If one tests the entire population, only 0.019% of positive results are in fact carrier.

	Total	Sick	Healthy
Total	10000000	100	9999900
Positive feedback ratio	500095	95	099995
Négatif	9099905	5	9099905

A Positive feedback ratio test indicates augmentation a factor of 20 risk (the test is wrong again on 20) is significant, but we must not neglect the basic rate.

Bayes Theorem

$P(C)$ = Probabilité de la Classe a priori.
= Probability of Class prior. = Probability of

Observation prior.
 $P(O)$ = Probabilité de l'Observation a priori.

$P(O|C)$ = La vraisemblance de l'Observation étant donné la Classe.
= The likelihood of Observation given the class.

$P(C|O)$ = Probabilité conditionnelle de la Classe étant donné l'Observation.
= Probability of Class conditionnelle given the Observation.

$$P(C|O) = \frac{P(O|C)P(C)}{P(O)}$$

The Bayesian approach

$P(C)$ = Probabilité de la Classe a priori. (1/100 000)

$P(O)$ = Probabilité de l'Observation a priori. ($P(\text{patient}) * 95\% + P(\text{healthy}) * 5\%$)

$P(O|C)$ = la probabilité de l'Observation étant donné la Classe. (95%)

$P(C|O)$ = Probabilité conditionnelle de la Classe étant donné l'Observation.

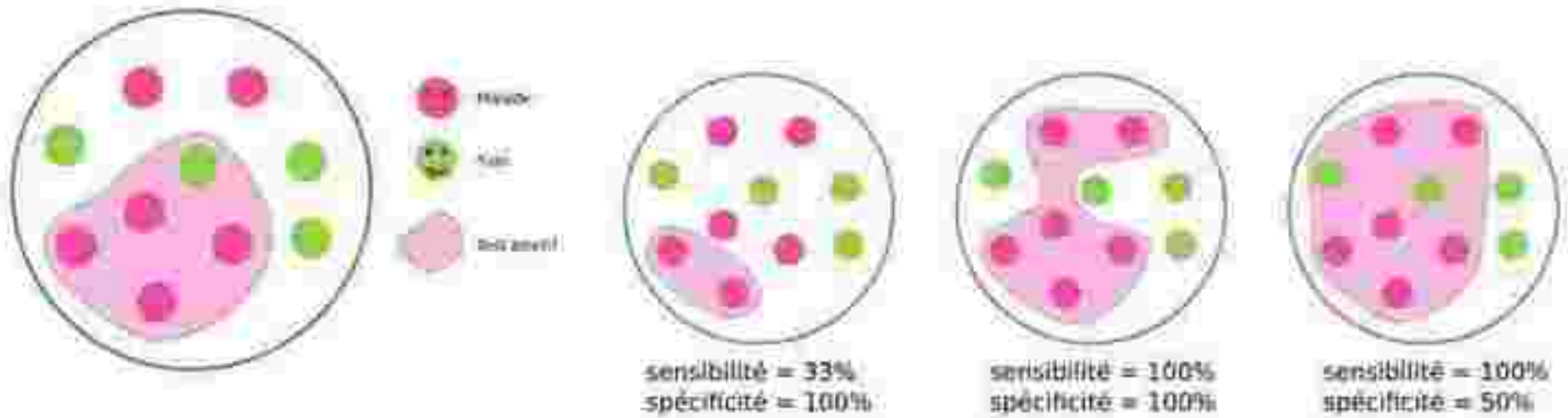
$$P(C|O) = \frac{P(O|C)P(C)}{P(O)}$$

$$P(C|O) = \frac{\frac{19}{20} * \frac{1}{100000}}{\frac{1}{100000} * \frac{19}{20} + \frac{99999}{100000} * \frac{1}{20}}$$

$$P(C|O) = 0.0001899658$$



Example



Prévalence = 10% of sick

$$P(M|P) = \frac{P(P|M)P(M)}{P(P)}$$

$$P(S|N) = \frac{P(N|S)P(S)}{P(N)}$$

$$100\% = \frac{0.33 + 0.1}{0.1 + 0.33 + 0.9 + 0}$$

$$96\% = \frac{1.0 + 0.9}{0.1 + 0.33 + 0.9 + 1.0}$$

100%

100%

$$14\% = \frac{0.75 + 0.1}{0.1 + 1.0 + 0.9 + 0.5}$$

$$100\% = \frac{0.5 + 0.9}{0.1 + 0.0 + 0.9 + 0.5}$$

The problem of induction

All crows are black?

The induction (philosophy) is the rule that generalizes from a number of examples inf has all the elements. This is one of the most problematic concepts in philosophy.

For us the solution is simple, consider a set of elements inf, uniform échantillonnage and applying Bayes.





Raven paradox and induction

Black Raven paradox

The paradox of Hempel was proposed by the German logician Carl Gustav Hempel in the 1900s to illustrate that the logic inductive could violate intuition. All A are B

All non-B are not A

Each object (not crow) that is not black confirmed ceteris paribus hypothesis.



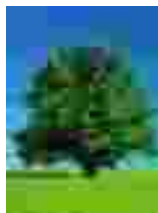
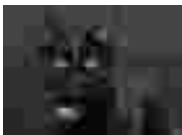
3 despicable **crows**

- Black Crow
- **raven nonnnoir**



11 items **non-black**

- **non-black raven**
- Other non-black



hypothesis test

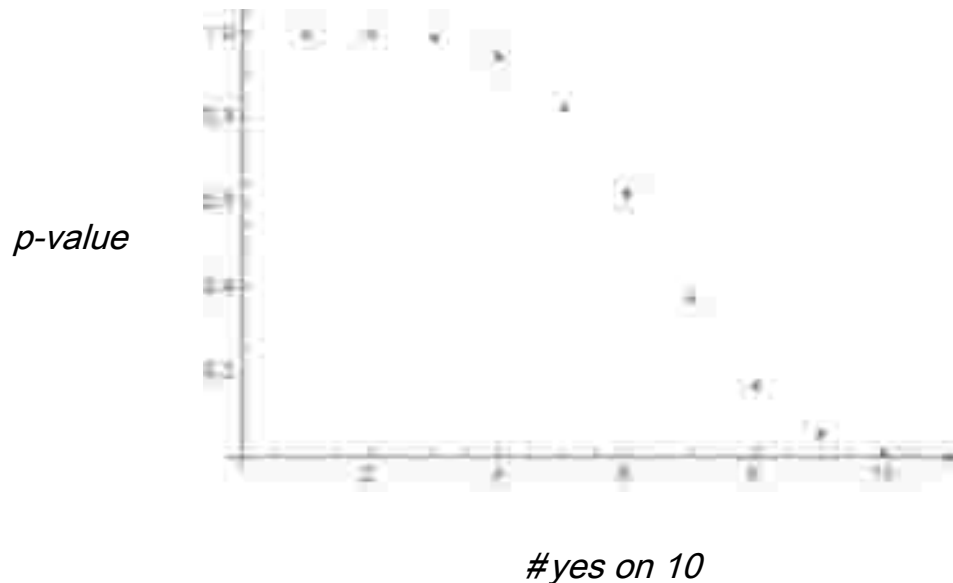
hypothesis test

Hypothesis: confirm what we want to show

Null hypothesis: no confirmation statistic In a test, the p-value (*p-value*) is the probability that a given statistic model under the null hypothesis of obtaining the same value or a value more extreme than observed.

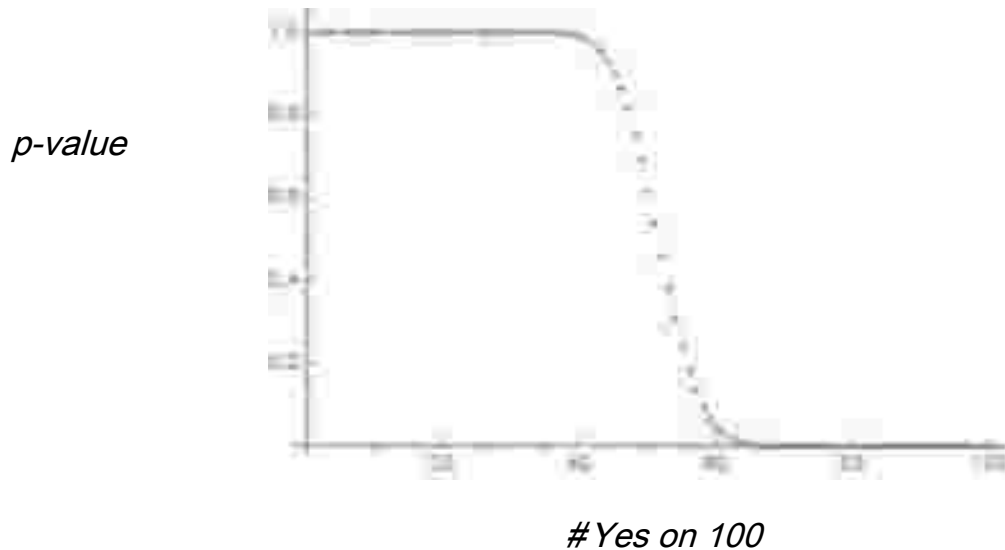
Referendum

- Population 10 million
- Experience Échantillon 10 (random uniform, honest and perfect)
- Hypothesis: population favors
- P value = 0.05 (5%)
- We observe 8 yes and 2 no
- It rejected! (P-value, 0.171875, 17%)



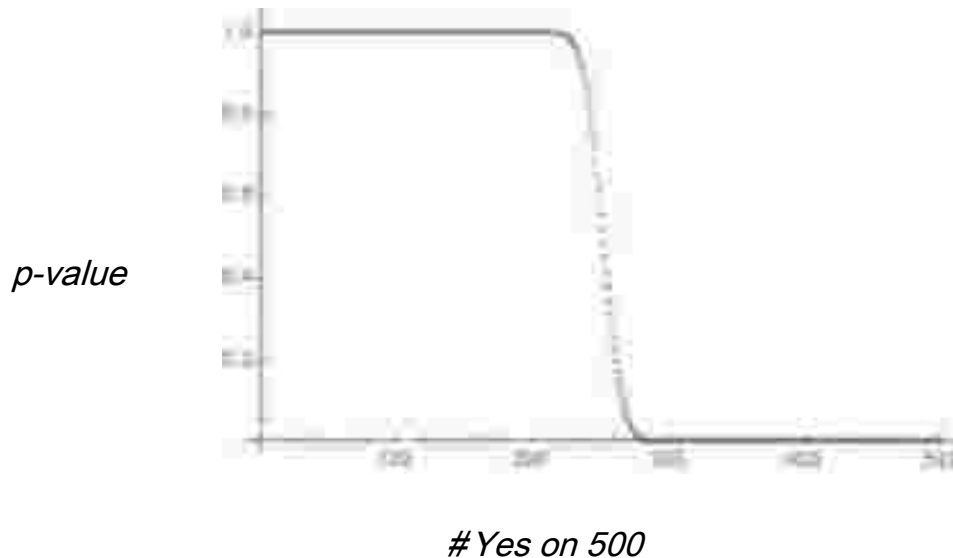
Referendum

- Population 10 million
- Experience Échantillon 100 (random uniform, honest and perfect)
- Hypothesis: population favors
- We observe 58 yes and 02 no
- It rejected! ($P = 10\%$)



Referendum

- Population 10 million
- Experience Échantillon 500 (random uniform, honest and perfect)
- Hypothesis: population favors
- P value = 0.05 (5%)
- 270 yes we observe, not 230
- We accept. (P-value 0.009)



Polls

3%, 19 times out of 20 ... yes, but

- Échantillon not uniform at all.
- How to ask the question has a very big impact.
- Assumes that answering the phone an unknown causes even reaction the confidentiality urn
- People do not know what they did and they do.

correlation and causation

statistical Reminder

the data

$$X = \{x_1, x_2, \dots, x_n\} \in \mathbb{R}^n$$
$$Y = \{y_1, y_2, \dots, y_n\} \in \mathbb{R}^n$$

The average

$$\mu_X = E(X) = \frac{1}{n} \sum_{i=1}^n x_i$$

The standard deviation

$$\sigma_X = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \mu)^2}$$

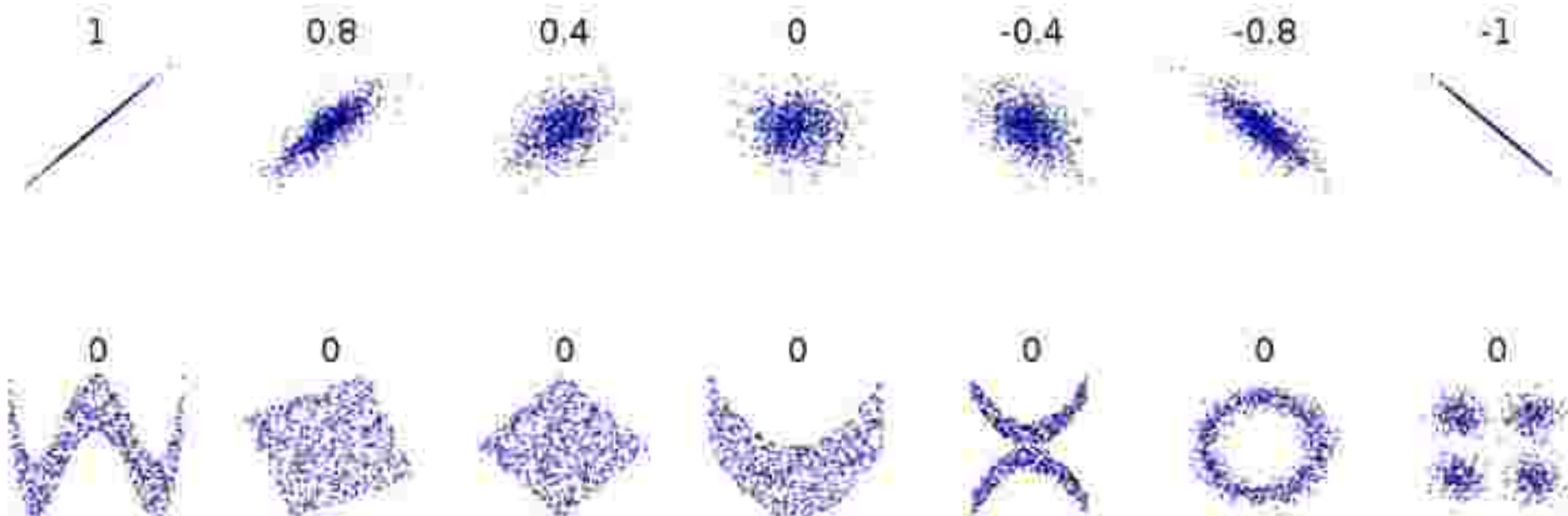
Coefcient of corrélaton

$$r_{X,Y} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \mu_X)(y_i - \mu_Y)}{\sigma_X \sigma_Y}$$

Correlation Coefficient

$$r_{X,Y} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \mu_X)(y_i - \mu_Y)}{\sigma_X \sigma_Y}$$

$$-1 \leq r_{X,Y} \leq 1$$





POUMONS SAINS



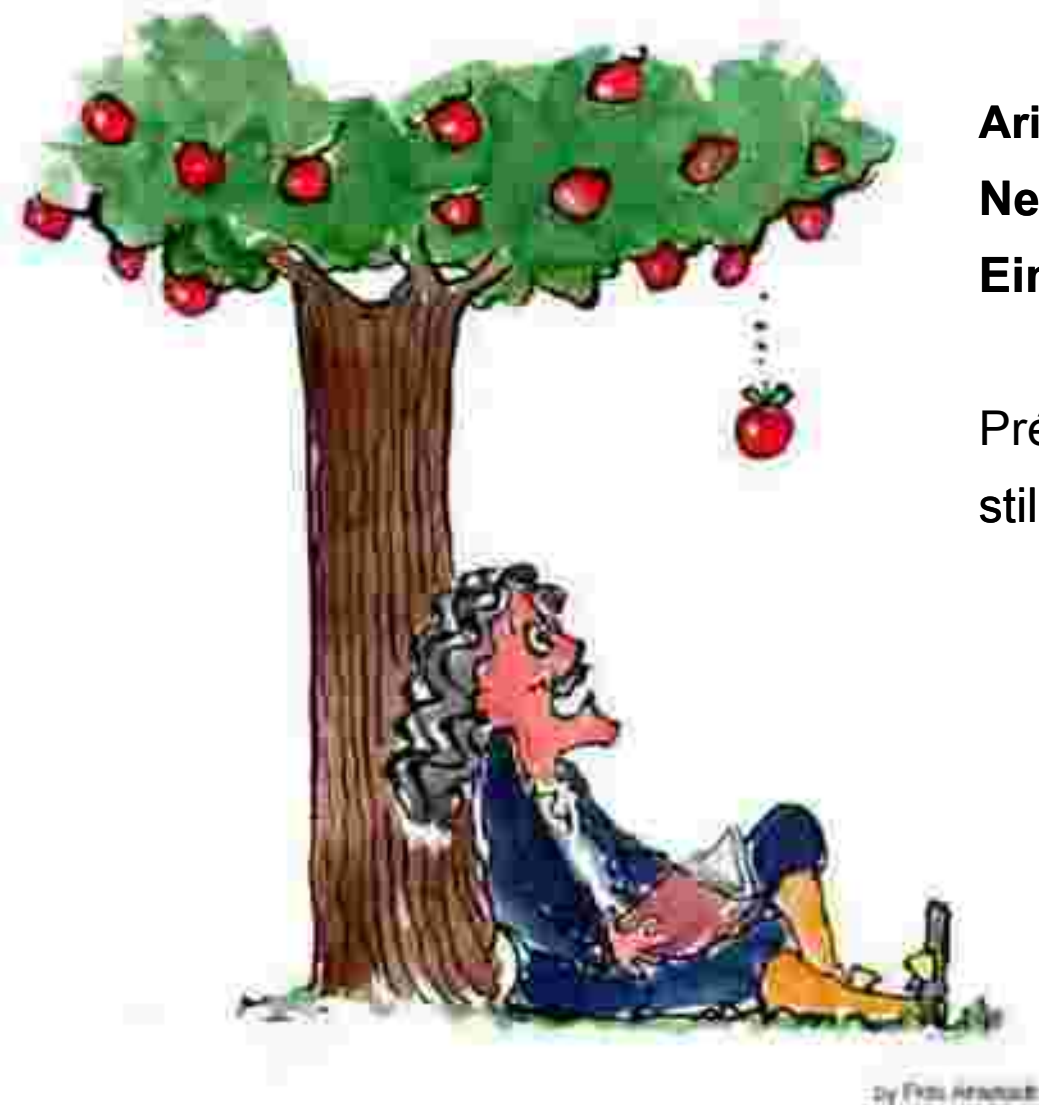
POUMONS TABAGIQUES

**FUMER PROVOQUE
LE CANCER DU POUMON**

Aristotle

"If so everything moved is necessarily moved by something [...] there must be a first mover that is not moved by anything [...] In effect, it is impossible that the series of engines that are themselves moved by something else go to infinity, since in infinite series there is nothing that is first





Aristotle: The nature of the apple.

Newton: gravitationnelle Force

Einstein: Curvature of space

Prédiction quality is improving, but we still have not established **the cause**.

What is the cause of his fall?



What is the cause of his fall?

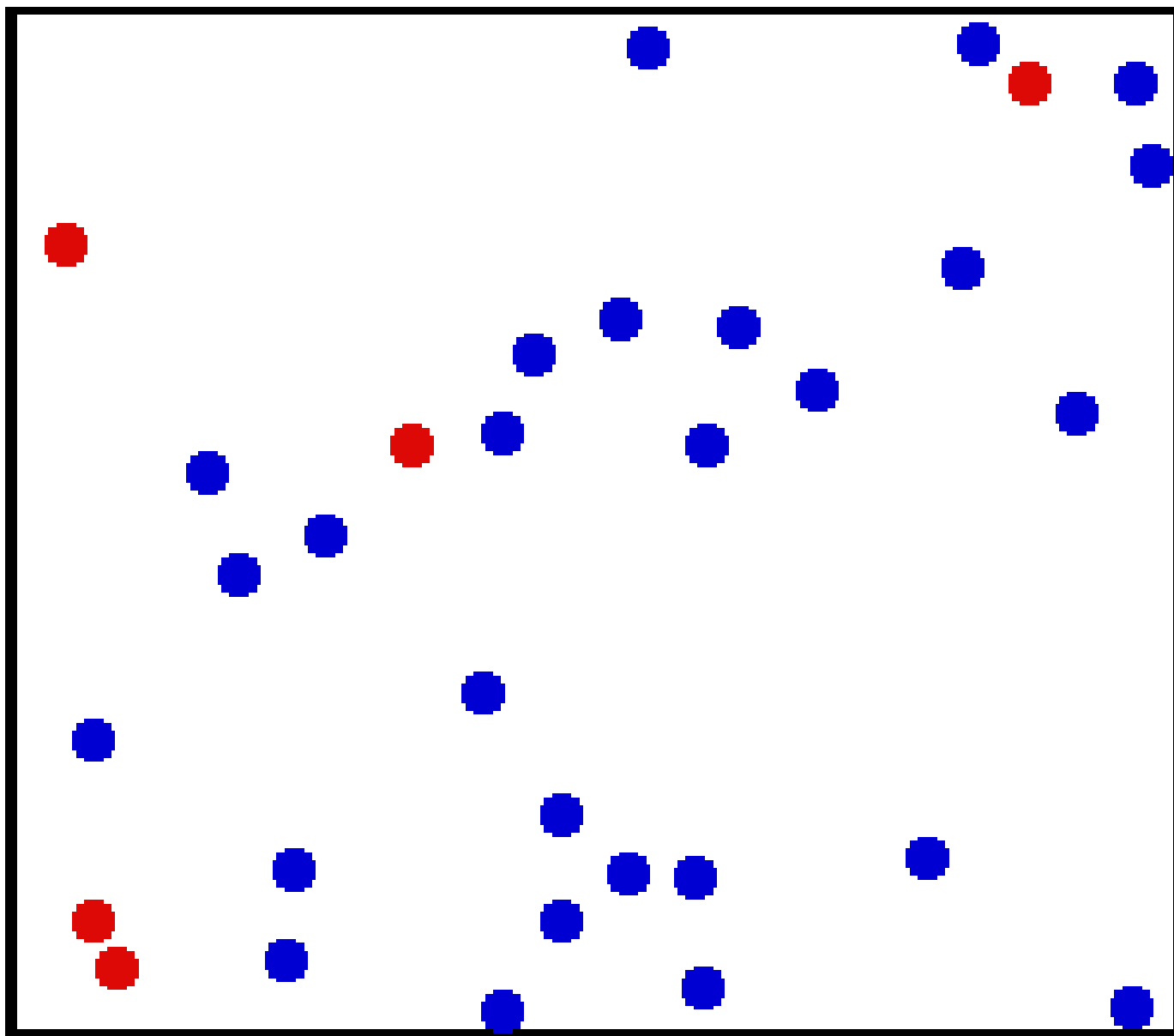


The butterfly effect



What is the butterfly effect? It's a **theory** that a butterfly's wings in Brazil can eventually **provoke**

a storm in Texas. According to the expression coined by meteorologist Edward Lorenz, he sought to **MODIFY** so infamously a parameter in a weather model for the latter is gradually amplified and causes long-term, colossal change.



Free will

Experimental science

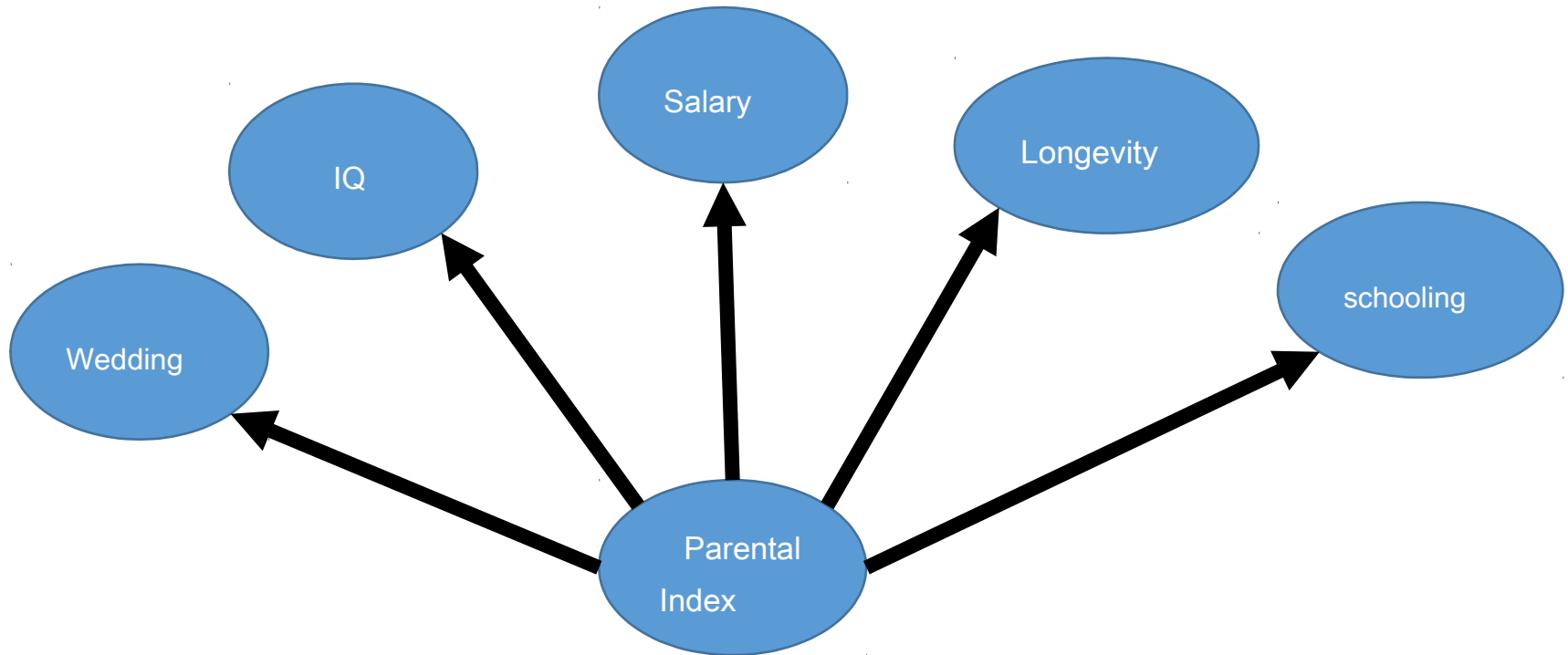
- We **chooses** X and **observed** Y.
- If X had been diferent then Y would also have been diferent

AT is a **cause** B if anyone could change A B to try to avoid and what to produce.

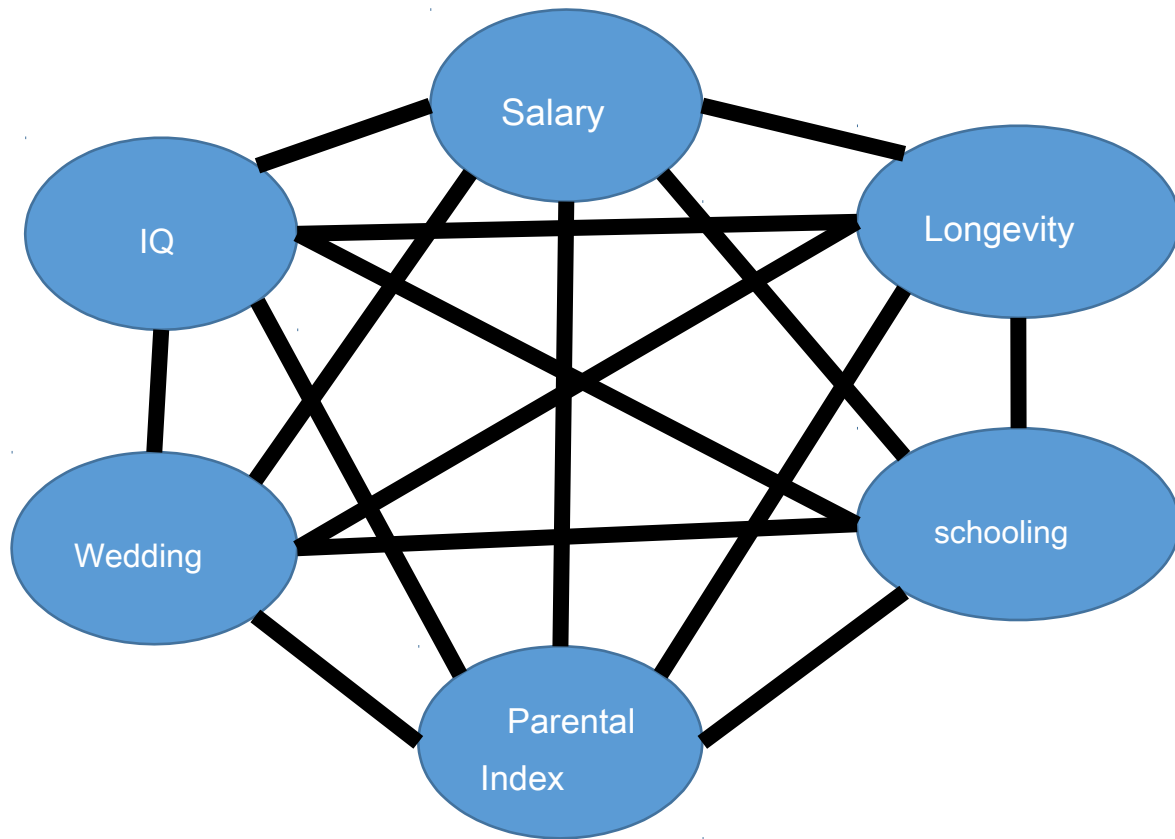
Cete défniton requires free will as a first hypothesis.

Ask freewill assumption provides a ratonnelle Attude is in that key responsibility, good and justce.

parental Index

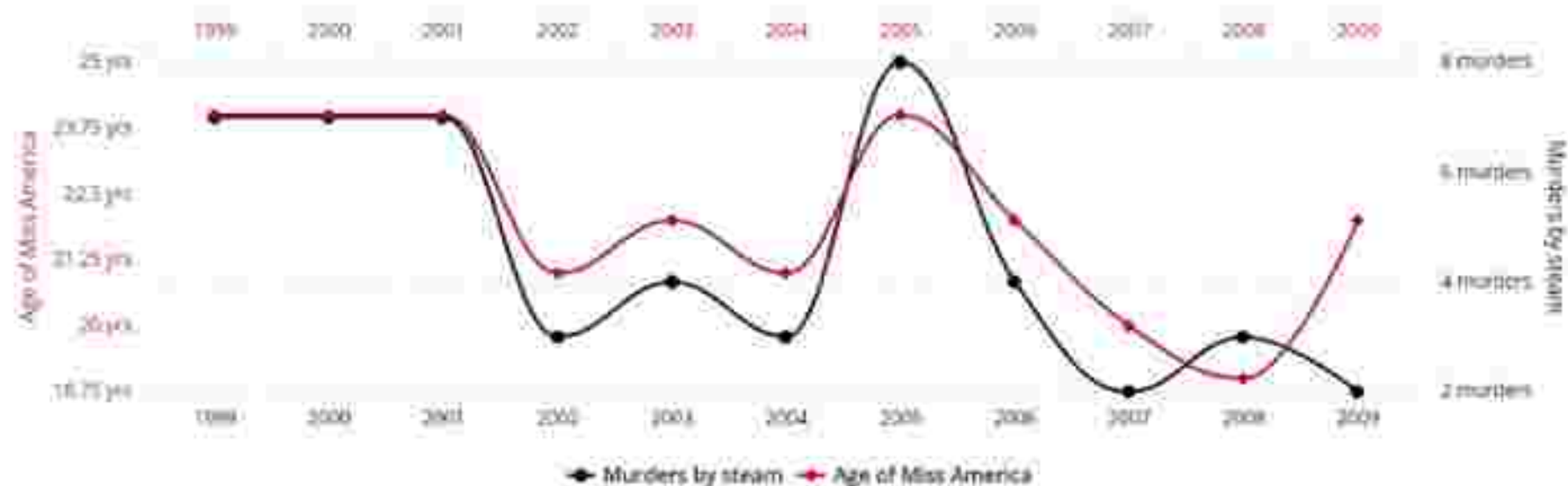


30 links but 5 causes!



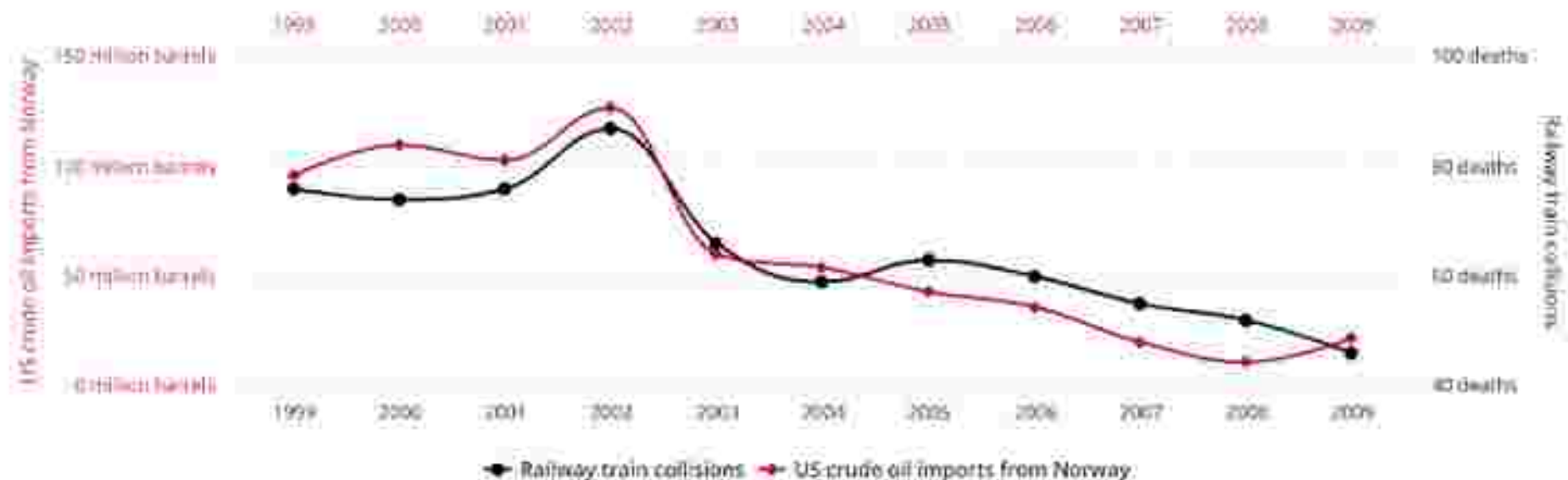
Age of Miss America
correlates with
Murders by steam, hot vapours and hot objects

Correlation: 87.81% ($p=0.000277$)



US crude oil imports from Norway correlates with Drivers killed in collision with railway train

Correlation: 95.431% ($r=0.954509$)



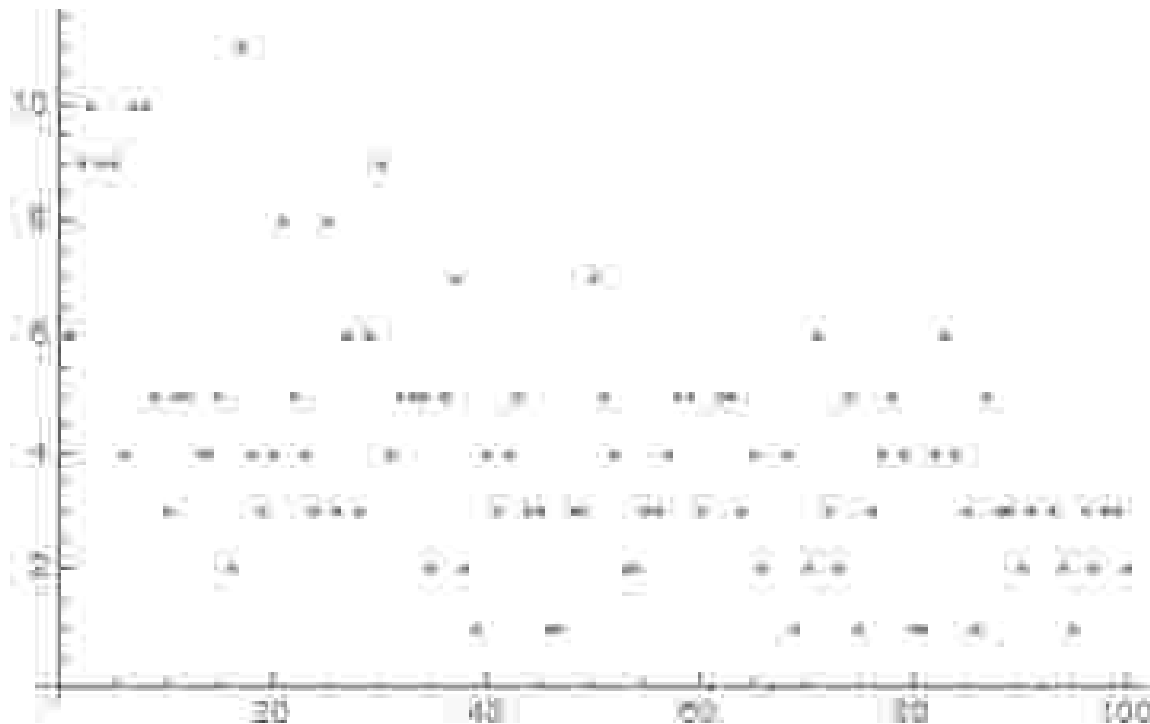
Source: <http://www.eia.doe.gov>

Spurious correlations

<http://tylervigen.com/spurious-correlations>

Warning!

Number of days the record heat is batu per year if we compile the data for 50 years, assuming that the temperature is normally distributed and **the mean is fixed.**



Warning!

If a researcher is studying the impact of coffee on cognition Function of 0 following variables.

- Man and woman
- Child, adolescent, adult and old
- Effect short term and long term
- Affects IQ, creativity or emotional intelligence.

There is a 99% chance to discover a negative Positive feedback ratio or impact on a subgroup even if we replace the coffee with water.