

# Example 5: Automated computation of process quality indicators



Literature review:

Djaber Babaousmail

Rules implementation and case review:

Aurélien Schaffar

Study design, development of inference machine:

Emmanuel Chazard



# Introduction, definitions



# Quality of care

- Complex definition. Institute of Medicine:
  - *“the degree to which health care services for individuals and populations increase the likelihood of desired outcomes and are consistent with current professional knowledge”*
- Assessment of quality of care = a mandatory step in quality of care improvement
- Three families of quality indicators



# 3 families of quality indicators

- Input indicators (structure): amount of resources consumed
  - *E.g. 2.3 patients per nurse in the intensive care unit*
  - Drawback: do not reflect the outcome on patients' health
- Output indicators (results): results of the process
  - *E.g. 9% of death in the intensive care unit*
  - Drawback: the outcome is mainly in relation with the initial severity of the patients => can hardly be interpreted
- Process indicators: notably adherence to guidelines
  - *E.g. for patients admitted in ICU after emergency repatriation, a screening for multi-resistant bacteria was performed in 72% cases*
  - Close to patients' outcome (# input indicators)
  - Not impacted by the initial severity of the patients, easier to interpret (# output indicators)
  - Immediately enable to identify areas of improvement
  - Improving the processes is commonly described as the best way to improve outcomes



# Qualities expected from quality indicators - Objective

- Qualities defined by the AHRQ:
  - (...)
  - Scientific soundness
    - Reliability
    - Validity
  - Feasibility
    - Explicit specification of numerator and denominator
    - Data availability
- Our objective:
  - to build a set of process indicators for quality of care evaluation in hospitals
  - only indicators published in peer-reviewed journals
  - that could automatically be computed by reusing routinely collected data from hospital EHRs

AHRQ: Agency for Healthcare Research and Quality

EHRs: electronic health records



# Definition of a minimal dataset

## widely available, to compute process indicators?

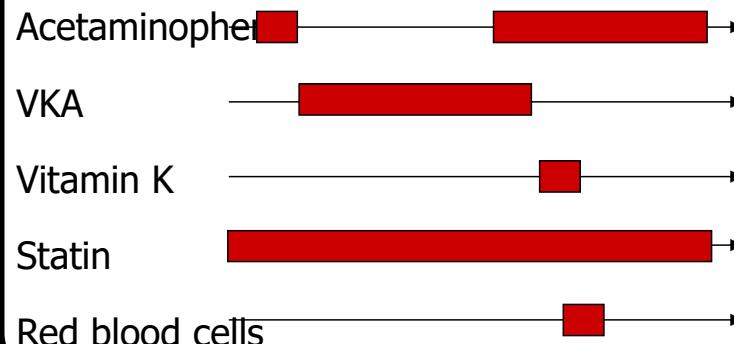
### Administrative data

88 years old woman

### Diagnoses

- I10 Arterial hypertension
- Z8671 Personal history of myocardial ischemia
- I620 Non-traumatic subdural hemorrhage

### Drugs



### Medical procedures

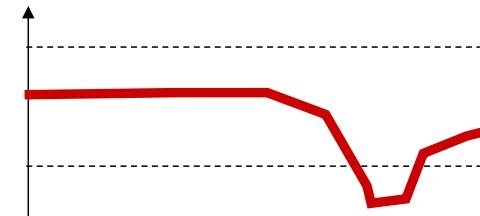
- ABJA002 Drainage of an acute subdural hemorrhage, by craniotomy
- FELF001 Transfusion

### Laboratory results

INR



Hemo-globin



### Free-text reports

Discharge letter

Surgical report



# **Part 1:**

# **Which indicators are apparently implementable?**

## **- Literature review -**

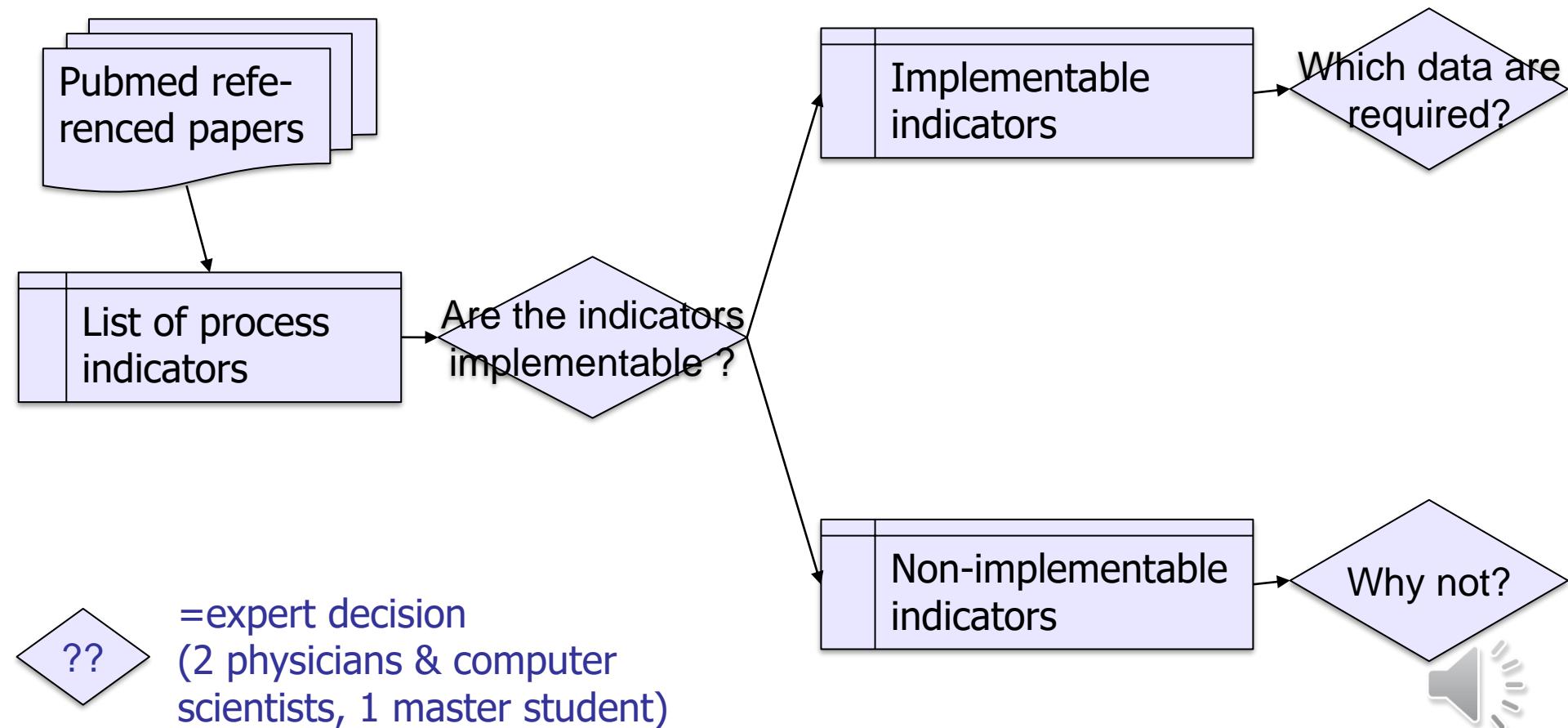


# Systematic literature review

- Source: Pubmed
  - Keywords: “Quality indicator(s)”, “Process indicator(s)”, “Quality of care AND indicator(s)”, “Care quality AND indicator(s)”, “Health care AND indicator(s)”, “Healthcare AND indicator(s)”, “Assessing AND quality of care”
  - Language: En
  - Publication dates: from 01/01/2000 to 12/31/2012
- Full-text retrieval
  - Pubmed Central, Google Scholar, Google
  - Editors' websites (university subscription)
  - Contacting the authors
- Filters: papers describing at least 1 process indicator
- => list of papers, but almost list of indicators



# Classification of the indicators



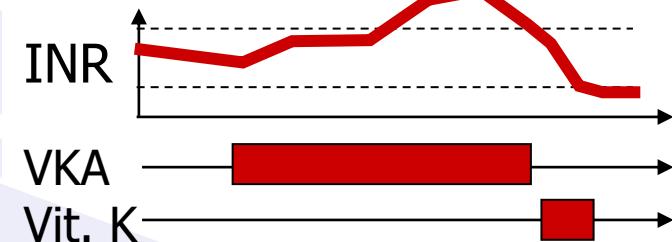
# Are the indicators implementable?

- Definition of a “standard” hospital dataset
  - For each inpatient stay:
    - Basic administrative data
    - Encoded diagnoses\* (ICD10)
    - Encoded procedures (CCAM)
    - Laboratory results
    - Drug administrations (ATC)
    - Free-text reports  
(basic word detection)
    - Patient dependence (ADL)
  - Unique patient identifier  
(different stays of a given patient)
- Outpatient consultations not available

82 years old woman, admit. 2015-02-03

I620 Non-traumatic subdural hemorrhage

ABJA002 Drainage of an acute subdural hemorrhage, by craniotomy

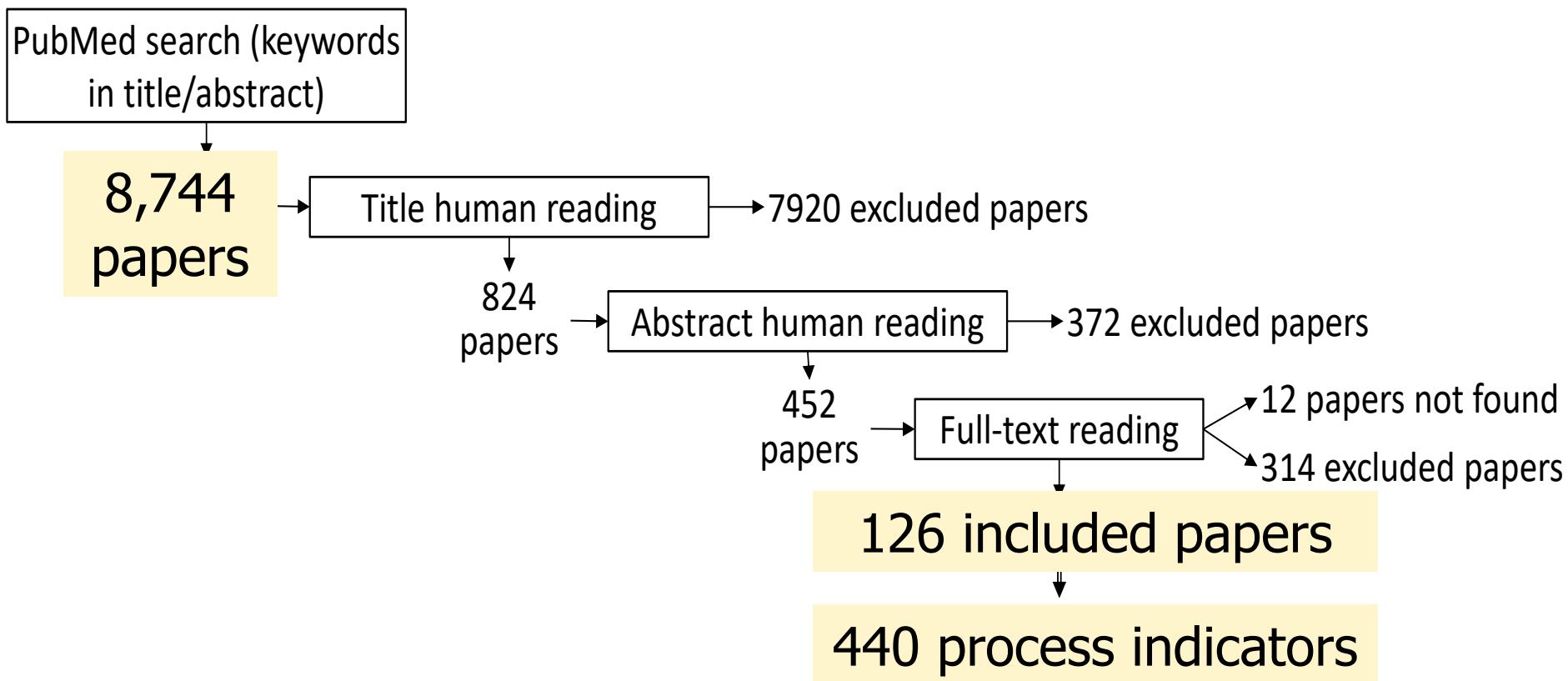


Principal Diagnosis (include site if relevant)  
I50.0 Heart failure - Congestive heart failure. LVF secondary to acute viral myocarditis.  
Admitted with a history of worsening shortness of breath and palpitations on baseline of recent days, developing tachypnoea, tachycardia and new onset of fever. Found to be in AF on ECG, with acute renal failure, hypotension and raised liver enzymes. Urgent echocardiogram showed severely impaired LV function with ejection fraction of 15-20%. Central venous pressure monitoring, patient commenced on 750ml fluid restriction, Digoxin and Amiodarone for management of AF and anticoagulation with Warfarin due to atrial fibrillation. Clinical symptoms gradually improved, with 10kg weight loss through diuresis and shortness of breath much improved. Pulse rate controlled on Digoxin. Amiodarone antiarrhythmic blocker also added which is well tolerated and liver function remains stable. Undiagnosed intra-abdominal bleed in view to DIC cardiovascular however this showed a thrombus in the left atrial appendage. Warfarin was therefore commenced with plan for repeat TOE in 4-5 days. D/C cardioversion. On discharge patient comfortable, mobilising around the ward. Reviewed by heart failure nurse with follow-up.

\* Without date



# Systematic literature review

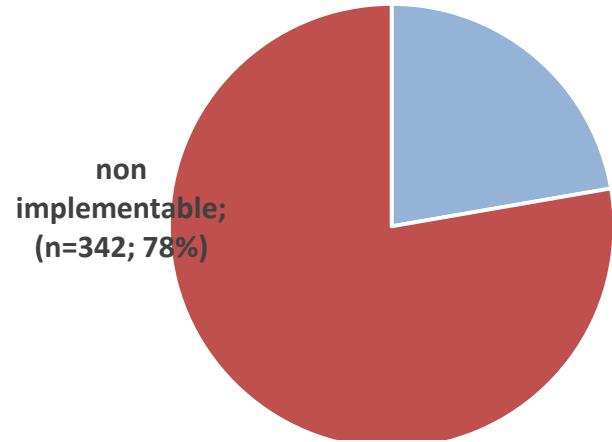


# Classification of the indicators

Specialty	Domains	Total number of indic.	Implementable indic.
Cardiology	Angina, myocardial infarction	24	18
Endocrinology	Diabetes	13	7
Gastroentero & Hepatology	Cirrhosis	5	4
Geriatrics	Arthrosis, general, surgery	105	18
Neurology	Dementia, Parkinson disease, stroke, T.I.A.	25	7
Obstetrics	Pregnancy monitoring	2	0
Oncology	Colon and rectum, esophagus, general, liver, lung, pancreas, prostate, skin, testicles	124	25
Pediatrics	Sickle cell	38	6
Psychiatry	General	9	0
Pulmonology	Asthma, chronic obstructive pulmonary disease	13	4
Rheumatology, internal med.	Lupus, rheumatoid arthritis, sclerosis	77	8
Traumatology	General	5	1
<b>TOTAL</b>		<b>440</b>	<b>98</b>



# 78% of non-implementable indicators



e.g. "This exam must be performed before the surgical procedure" (possibly before admission)

e.g. "the urinary function should be assessed"

e.g. "control the temperature"

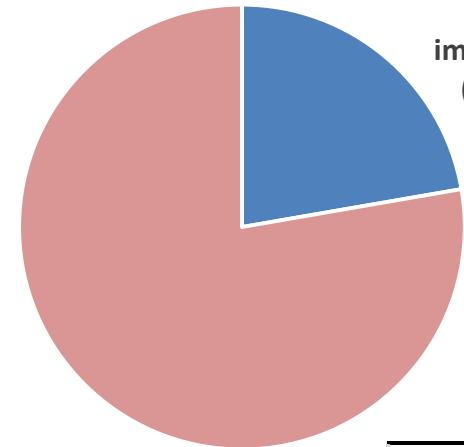
e.g. "the patient should be informed that..."

## Not implementable because

	Number	Proportion
Missing outpatient data	209	61.1%
Missing structured data	147	43.0%
Missing unstructured data	90	26.3%
Information given to the patient	29	8.5%



# 22% of implementable indicators



Required data	Number	Proportion
Diagnoses (without date)	97	99.0%
Drug prescriptions (with date)	58	59.2%
Medical procedures (with date)	47	48.0%
Basic administrative data	29	29.6%
Laboratory results (with date)	20	20.4%
Free-text documents with basic keyword research	19	19.4%
Ability to link the patient's previous stays	11	11.2%
Dependence scale	3	3.1%



# Summary

- 126 selected papers, 440 process indicators, 98 (22%) could be computed fully automatically by reusing EHR data
- 61% of non-implementable indicators require a linkage with outpatient data
- Next step:
  - Implement indicators as a precise algorithm
  - Strong interpretation choices...
  - Validation of the indicators
  - Goal: avoiding over-alerting in detecting uncompliant cases
- Final objective:
  - Automated fast computation of indicators
  - Complete history, even in case the indicators are modified
  - Data mining to discover risk factors of low guideline adherence



## Part 2:

# Is it possible to automatically compute process indicators?

**- proof of concept -**



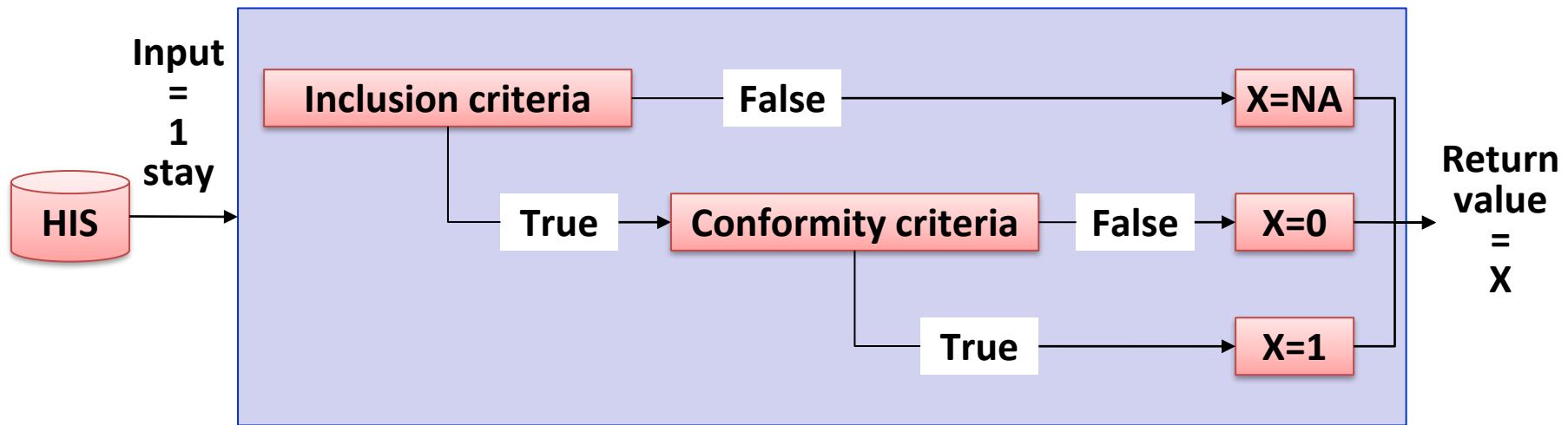
# Material

- Inpatient stays
  - 15,000 randomly-selected and de-identified inpatient hospital stays, from a French community hospital (ICD10, CCAM, ATC, local names for laboratory results)
- Process indicators
  - 9 process indicators defined in free-text:
  - Example 1: *“If an elderly patient is undergoing surgery, then creatinine clearance should be estimated.”*



# Implementation of the process indicators

- Direct implementation of each indicator as a function, returning X
- Conformity rate = mean(X)



- During the implementation: getting a good precision, decreasing the over-alerting by:
  - relaxing the conformity criteria
  - tightening the inclusion criteria



# Evaluation of each process indicator

- Rate of normal stays, among included stays  
Automated computation:  
 $\text{conformity} = (a+b+c)/(a+b+c+d+e+f) = \text{mean}(X)$
- Precision of the detection of “abnormal” stays  
Expert review (45 stays per indicator):  
 $\text{precision} = e/(d+e+f) = \#(X=0 \cap Y=0)/\#(X=0)$

$Y=\text{Expert advice}$

		Compliant	Not compliant	Excluded
		a	b	c
X= Auto- mated output	Compliant	a	b	c
	Not compliant	d	e	f
Excluded		g	h	i





# Indicator #01: creatinine clearance dosage

*If an elderly patient is undergoing surgery, then creatinine clearance should be estimated.*

- Inclusion criteria
  - **age≥75 & surgical stay & emergency admission**
  - *impossible to screen ambulatory laboratory exams in case of pre-planned admission => only emergency admissions are analyzed*
- Conformity criteria
  - **creatinine clearance or creatinine dosage before surgery**
  - *we assumed some physicians were able to compute the creatinine clearance by hand from the creatinine dosage*
- Results
  - n=238
  - conformity=86.6% [81.6; 90.7]
  - precision=86.7% [59.5; 98.3]

Some dosages could be absent from databases but cited in the discharge letter.





# Indicator #02: confusion

If an elderly patient is undergoing surgery, and has a new diagnosis of delirium, then an evaluation should be undertaken for: infection, electrolyte abnormalities, hypoxia, uncontrolled pain, urinary retention or fecal impaction, use of sedative-hypnotic drugs.

- Inclusion criteria
  - **age≥75 & surgical stay & ICD code (F05\* | R410\*)**
  - *impossible to analyze the date of the diagnoses*
- Conformity criteria
  - **postoperative dosage of Na+ & K+ & Creat. & Uremia & Glycemia**
  - *impossible to automatically detect whether the physicians had searched for other clinical factors or drugs administrations.*
- Results
  - n=8
  - conformity=75 % [34.9; 96.8]
  - precision=0%

Capillary blood glucose had been measured from patient bedside but not traced in the databases. In 2 cases there was a post-operative confusion without ICD10 code.



# Indicator #03: beta blockers

If an elderly patient is undergoing surgery and takes a beta blocker as an outpatient, then beta blocker therapy should be continued postoperatively.

- Inclusion criteria
  - **age $\geq$ 75 & surgical stay & ATC code C07\* at d0 or d1 & no death**
  - *Unavailable outpatient treatment. Contraindications could not be traced using ICD10 codes. Dead patients were excluded.*
- Conformity criteria
  - **ATC code C07\* administered from d2 to day prior discharge**
- Results
  - n=18
  - conformity=27.8% [9.7; 53.5]
  - precision=46.2% [19.2; 74.9]

ATC codes missing in the database, but drugs described in the discharge letters.





# Indicator #04: intravenous antibiotic prophylaxis (onset)

If an elderly patient is undergoing surgery, then intravenous antibiotic prophylaxis should be started within 1h of skin incision.

- Inclusion criteria
  - age $\geq$ 75 & surgical stay & no ICD code of (bacterial infection, unprecise infection, or open fracture)
  - We excluded cases where an oral antibiotic treatment was already indicated
- Conformity criteria
  - **intravenous administration of antibiotic the day of surgery**
- Results
  - n=607
  - conformity=2.4% [1.5; 4.2]
  - precision=93.3% [68.1; 99.8]

All false positives:  
absence of ICD10 codes  
despite an active infection,  
for which the oral antibiotic  
treatment was appropriate



# Indicator #05: intravenous antibiotic prophylaxis (continuation)

If an elderly patient is undergoing surgery, intravenous antibiotic prophylaxis should be discontinued within 24h after surgery (48h for cardiac surgery).

- Inclusion criteria
  - **age $\geq$ 75 & surgical stay & no ICD code of (bacterial infection, unprecise infection, or open fracture)**
  - We excluded cases where an oral antibiotic treatment was already indicated
- Conformity criteria
  - **no ATC code J01\* at d3 of surgery**
  - The type of surgery was not taken into account, and a permissive delay was used.
- Results
  - n=607
  - conformity=2.3% [1.3; 3.9]
  - precision=93.3% [68.1; 99.8]

All false positives:  
absence of ICD10 codes  
despite an active infection,  
for which the oral antibiotic  
treatment was appropriate



# Indicator #06: deep venous thrombosis prevention

If an elderly patient is undergoing surgery, then deep venous thrombosis prophylaxis should be provided (unfractionated or low molecular weight heparin) or document why not appropriate. For cancer or previous thromboembolism, mechanical prophylaxis should be added.

- Inclusion criteria
  - **age $\geq$ 75 & surgical stay & CCAM code of (major surgery of lower limbs | major digestive surgery) & no ICD10 code of heparin contra-indication**
  - *It was not possible to trace mechanical prophylaxis. Therefore we traced heparin administration, only for high risk surgeries. We searched for contra-indication.*
- Conformity criteria
  - **ATC code B01AB\***
  - *The type of surgery was not taken into account, and a permissive delay was used.*
- Results
  - n=314
  - conformity=70.0% [65.6; 76.0]
  - precision=53.3% [26.6; 78.7]

False positives mainly due to the inclusion of non-surgical inpatient stays



# Indicator #07: anemia treatment

If an elderly patient is undergoing surgery, and has anemia, then the following should be set up prior to surgery: iron, vitamin C, erythropoietin, blood transfusion if hemoglobin < 7 g/dl.

- Inclusion criteria
  - **age $\geq$ 75 & surgical stay & hemoglobin value $<$ 10**
  - *The threshold was not specified. The severity of anemia is handled in indicator #08.*
- Conformity criteria
  - **ATC code B03A\*/B05AX01 | ICD10 code Z5130 | transfusion**
- Results
  - n=217
  - conformity=60.4% [53.5; 66.9]
  - precision=86.7% [59.5; 98.3]

False positives due to the absence of administered drugs from the databases.



# Indicator #08: anemia transfusion

If an elderly patient is undergoing surgery, unless otherwise contraindicated or refused by the patient, then he/she should receive blood transfusion at the following hemoglobin/hematocrit threshold: 8/24 (man), 7/21 (woman).

- Inclusion criteria
  - **age≥75 & surgical stay & ((man & (hemoglobin<8 | hematocrit<24)) | (woman & (hemoglobin<7 | hematocrit<21)))**
- Conformity criteria
  - **ATC code B05AX01 | ICD10 code Z5130 | CCAM transfusion**
- Results
  - n=19
  - conformity=73.7% [48.8; 90.9]
  - precision=60.0% [14.7; 94.7]

False positives due to the absence of transfusion encoding



# Indicator #09: postoperative fever

If an elderly patient is undergoing surgery and has a new fever, the following should be performed: urinalysis and urine culture, wound examination, blood cultures of central venous line or catheter, chest radiograph, blood culture.

- Inclusion criteria
  - **age $\geq$ 75 & surgical stay & ICD10 code (R50\* | R65\*)**
  - Note that if the etiology of a fever is found, then it is encoded and the fever is not encoded.
- Conformity criteria
  - **CCAM code of chest radiograph**
  - Clinical exams and some laboratory exams were not available
- Results
  - n=4
  - conformity=75% [19.4; 99.4]
  - precision=0.0%

The inflammatory syndrome was most often present before the surgery (no precise date).



# All the indicators

#	Topic	n	Conformity	Confidence
1	creatinine clearance dosage	238	86.6%	86.7%
2	confusion	8	75.0%	0.0%
3	Beta-blockers	18	27.8%	46.2%
4	intravenous antibiotic prophylaxis (onset)	607	2.4%	93.3%
5	oral antibiotic prophylaxis (continuation)	607	2.3%	93.3%
6	deep venous thrombosis prevention	314	70.0%	53.3%
7	anemia treatment	217	60.4%	86.7%
8	anemia transfusion	19	73.7%	60.0%
9	postoperative fever	4	75.0%	0.0%



# Summary

- Automated computation of process quality indicators:
  - Often feasible (22.3% of indicators in the review)
  - Quickly identify threatening situations
  - Type 1 artificial intelligence (rules written by experts)
- Main problems:
  - Properly handled *a priori*:
    - Need for medical interpretation, requiring special skills in medicine, medical information sciences, and algorithmics
    - Avoiding over-alerting (algorithmic interpretation)
  - Not handled:
    - Data quality: missing codes => solution = free-text analysis
  - Not a problem:
    - Absence of rule management system
    - Absence of ontology
- Evaluation of the precision
  - Mandatory to make this approach acceptable by physicians
  - To be performed in each setting: quality failures are probably hospital-dependent



## Part 3:

# How to use data mining (decision trees) to improve computation of quality indicators?



# Exemple d'indicateur qualité

- Indicateur
  - Règle : une hyperkaliémie doit être recontrôlée le lendemain
  - Dénominateur : séjours avec hyperkaliémie
  - Numérateur : séjours avec hyperkaliémie et recontrôle le lendemain
  - Cas déviants = dénominateur  $\cap$  (numérateur) :  
parmi les hyperkaliémies, celles sans recontrôle le lendemain
- Revue des cas déviants
  - But = découvrir les facteurs qui, parmi les séjours contrôlés (dénominateur) prédisent la déviance (non appartenance au numérateur)
  - « bonne raison » de dévier : le patient est transféré entre-temps, ou dialysé  
*→ il faut ajuster l'indicateur (restreindre le dénominateur)*
  - « mauvaise raison » de dévier : l'hyperkaliémie survient un dimanche  
*→ l'indicateur est alors justifié*



# Définition du data mining

- = fouille statistique de données
- « *Mise en évidence de connaissances jusqu'alors inconnues dans des bases de données de grande dimension, à l'aide de méthodes dérivées des statistiques, de la gestion de données et de l'intelligence artificielle* »
- Grande dimension (big data) :
  - Beaucoup de lignes (patients)
  - Beaucoup de colonnes (variables)
  - Beaucoup de cardinalité (tables et relations)



# Méthodes de data mining

- Data mining non supervisé :
  - recherche de motifs et associations
  - ex : règles d'associations (problème du « panier de la ménagère »)
- Data mining supervisé :
  - Objectifs :
    - Rétrospectif : expliquer une variable Y (à expliquer) par les autres variables Xi (explicatives)
    - Prospectif : prédire la valeur inconnue de cette variable Y par les autres variables Xi
  - Ex : **arbres de décision**

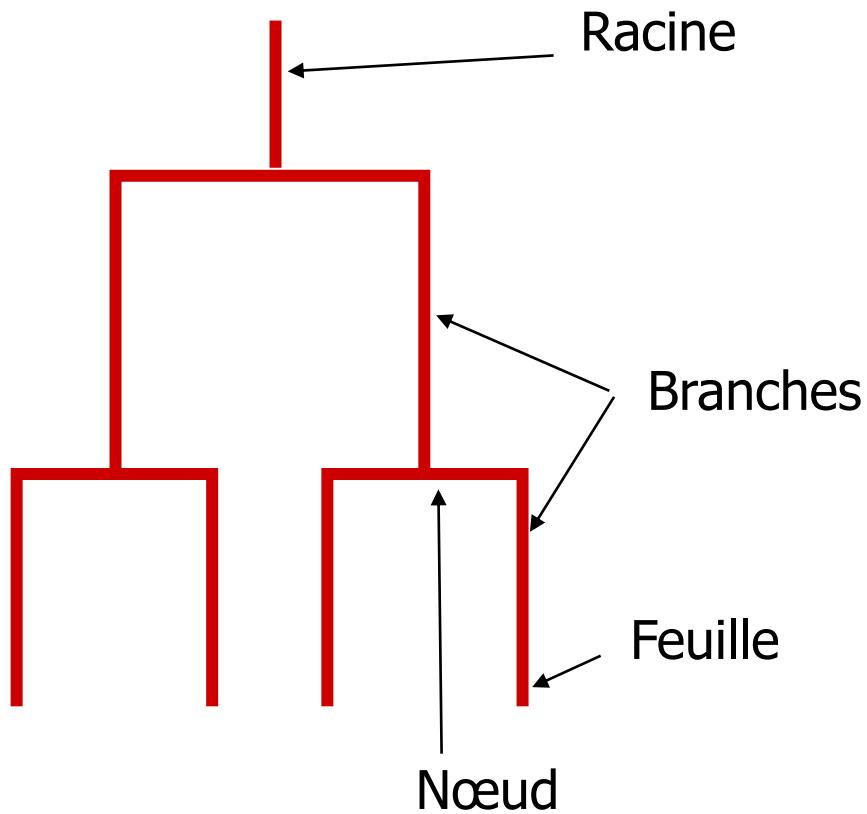


# Les arbres de décision

- Méthode de data mining supervisé, produit des règles
- Variable à expliquer Y :
  - Binaire : arbres de classification (dans cet exemple)
  - Qualitative : arbres de classification
  - Quantitative : arbres de régression
  - Quantitative (nombre d'événements) : arbres de Poisson
  - Censurée : arbres de survie
- Variables explicatives  $X_i$  :
  - Tous les types de variables :
    - Binaires
    - Qualitatives (l'arbre peut proposer des regroupements)
    - Quantitatives (l'arbre propose un seuil)
  - Peut mélanger ces types dans un même arbre

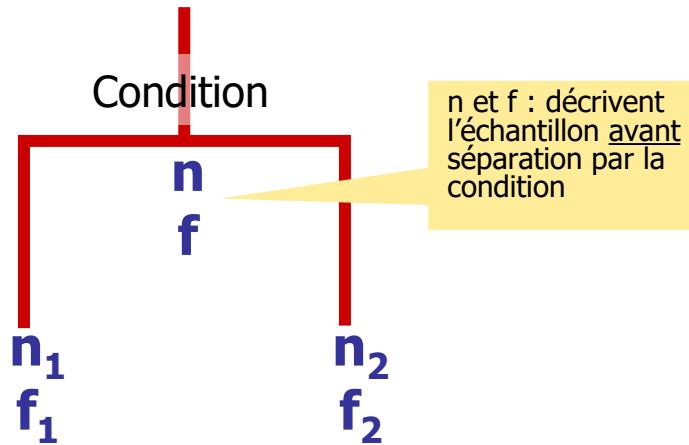


# Arbres de classification binaires



Unité de base : le nœud sépare une branche en deux branches à l'aide d'une condition. Ces deux branches : une avec  $f$  augmentée, l'autre avec  $f$  diminuée.

Sens de lecture

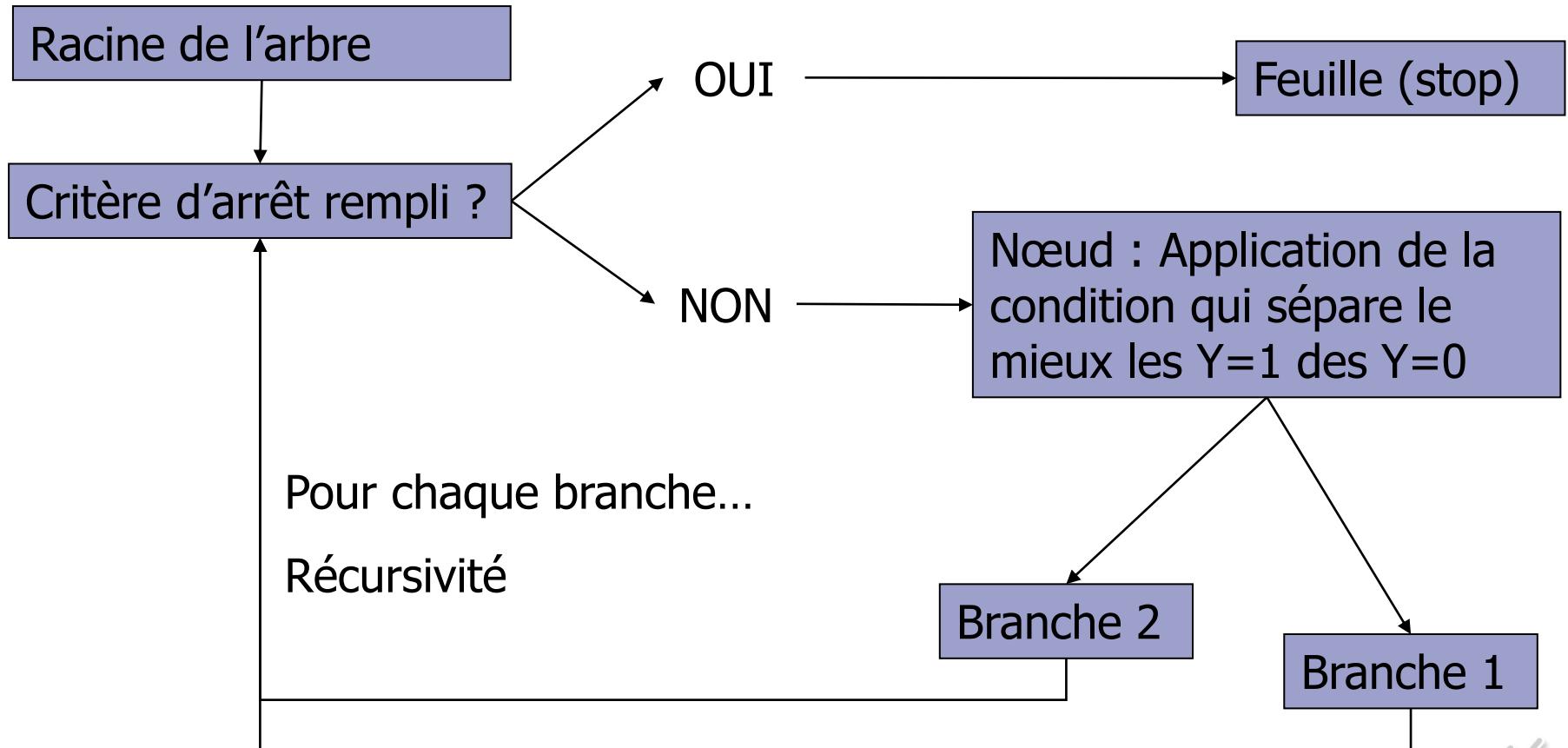


$$n = n_1 + n_2$$
$$f = (n_1/n).f_1 + (n_2/n).f_2$$

Objectif :  $f_1 << f << f_2$



# Arbres de classification binaires



# Approche par l'exemple

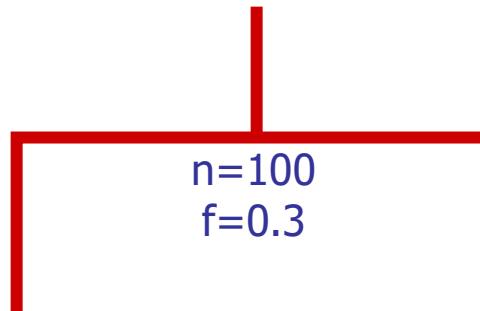
- Echantillon
  - tous les séjours avec une hyperkaliémie
  - N=100
- Variable à expliquer Y binaire :
  - $Y=1$  si séjour déviant (pas de mesure le lendemain)
  - $Y=0$  si séjour normal (avec mesure le lendemain)
  - $f=P(Y)=0.3$
- Variables à expliquer  $X_i$  toutes binaires :
  - $X_1$  = patient transféré {0;1}
  - $X_2$  = l'hyperkaliémie est mesurée un dimanche {0;1}
  - $X_3$  = patient insuffisant rénal {0;1}
  - $X_4$  = patient diabétique {0;1}
  - ...
  - $X_{987} (\dots)$  {0;1}



# Approche par l'exemple

Première itération : nous cherchons la condition qui séparera le mieux les  $Y=1$  (à droite) et les  $Y=0$  (à gauche)

- Echantillon :  $n=100$ ,  $f=0.3$
- Variable à expliquer  $Y$  : séjour déviant ou non {0;1}
- Variables à expliquer  $X_i$  :
  - $X_1$  = patient transféré {0;1}
  - $X_2$  = dimanche {0;1}
  - $X_3$  = insuffisant rénal {0;1}
  - $X_4$  = diabétique {0;1}
  - ...



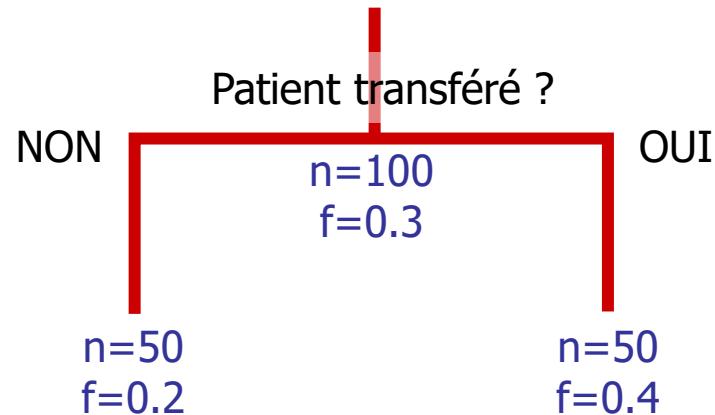
Variable	$p$ du Chi <sup>2</sup> vs Y
$X_1$	1E-04
$X_3$	1E-01
$X_2$	0.15
$X_4$	0.5
...	...



# Approche par l'exemple

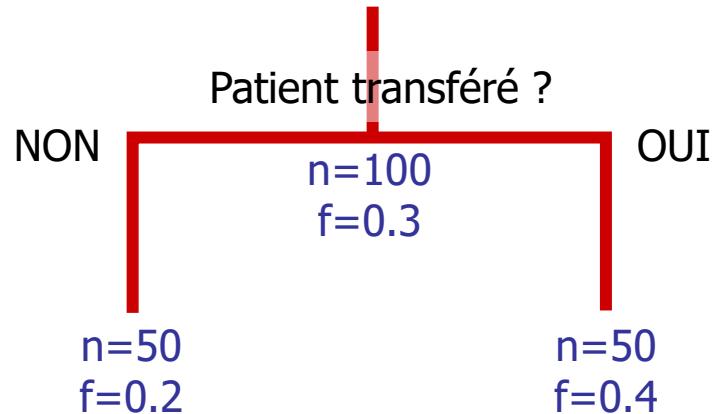
On choisit  $X_1$ , qui est la plus fortement associée à Y.

- Echantillon : n=100, f=0.3
- Variable à expliquer Y : séjour déviant ou non {0;1}
- Variables à expliquer  $X_i$  :
  - $X_1$  = patient transféré {0;1}
  - $X_2$  = dimanche {0;1}
  - $X_3$  = insuffisant rénal {0;1}
  - $X_4$  = diabétique {0;1}
  - ...



# Approche par l'exemple

Itération maintenant sur la branche de droite.



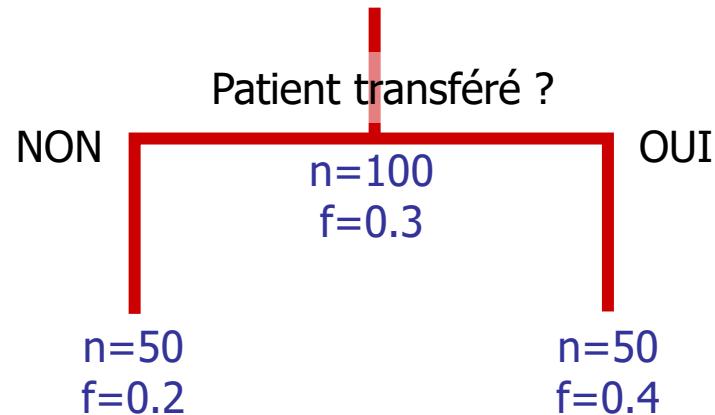
- Echantillon :  $n=100$ ,  $f=0.3$
- Variable à expliquer  $Y$  : séjour déviant ou non {0;1}
- Variables à expliquer  $X_i$  :
  - $X_1$  = patient transféré {0;1}
  - $X_2$  = dimanche {0;1}
  - $X_3$  = insuffisant rénal {0;1}
  - $X_4$  = diabétique {0;1}
  - ...

Variable	P du Chi <sup>2</sup> vs Y
$X_3$	0.21
$X_2$	0.35
$X_4$	0.60
...	...



# Approche par l'exemple

Itération maintenant sur  
la branche de gauche



- Echantillon :  $n=100$ ,  $f=0.3$
- Variable à expliquer  $Y$  : séjour déviant ou non {0;1}
- Variables à expliquer  $X_i$  :
  - $X_1$  = patient transféré {0;1}
  - $X_2$  = dimanche {0;1}
  - $X_3$  = insuffisant rénal {0;1}
  - $X_4$  = diabétique {0;1}
  - ...

Variable	P du Chi <sup>2</sup> vs Y
$X_2$	1E-02
$X_3$	0.36
$X_4$	0.70
...	...

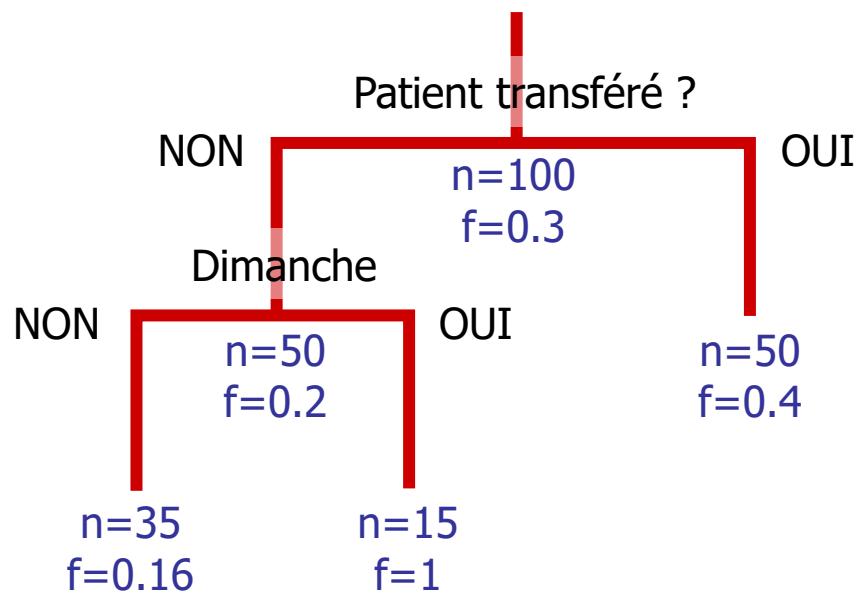


# Approche par l'exemple

On choisit  $X_2$ .

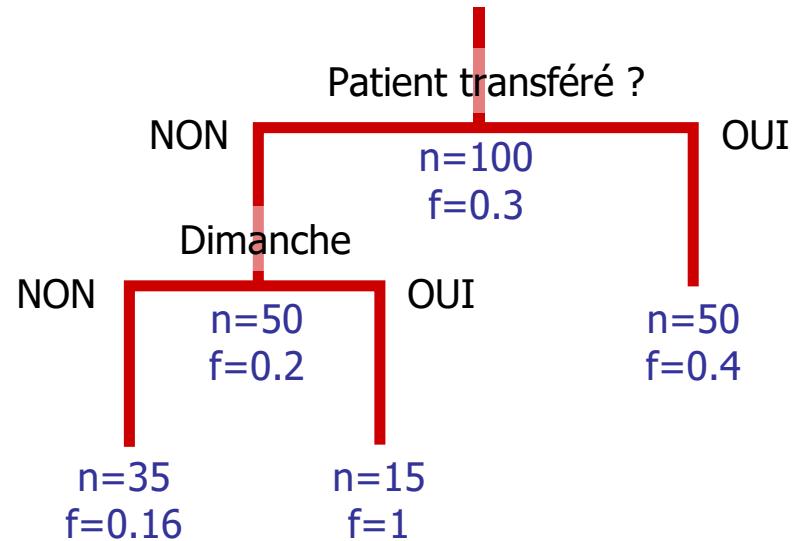
Peut-on encore continuer ?

- Echantillon :  $n=100$ ,  $f=0.3$
- Variable à expliquer  $Y$  : séjour déviant ou non {0;1}
- Variables à expliquer  $X_i$  :
  - $X_1$  = patient transféré {0;1}
  - $X_2$  = dimanche {0;1}
  - $X_3$  = insuffisant rénal {0;1}
  - $X_4$  = diabétique {0;1}
  - ...



# Approche par l'exemple

Arbre à 3 feuilles => 3 règles de classification.  
De droite à gauche :

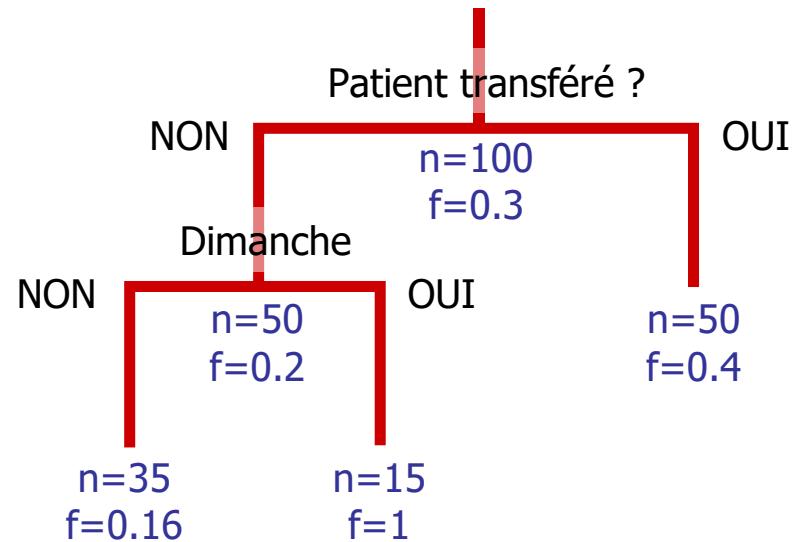


- Racine (tous les séjours) :  $P(Y)=0.3$
- Patient transféré  $\rightarrow P(Y)=0.4$
- Patient non transféré ET mesure le dimanche  $\rightarrow P(Y)=1$
- Patient non transféré ET mesure autres jours  $\rightarrow P(Y)=0.16$



# Approche par l'exemple

- Retour au cas pratique
- Dans ce cas, quelle utilisation peut-on faire des connaissances mises en évidence ?



# Epilogue sur la méthode

- Arbres de décision :
  - En soi, une méthode de *data mining* supervisé parmi d'autres
  - Aussi utilisable comme détecteur d'interactions avant une régression
- Méthode CHAID :
  - Utilisée dans cet exemple, la plus ancienne
  - Chi-squared Automatic Interaction Detector
  - Prédit un Y binaire, avec des  $X_i$  de tous types
- Critère de choix des nœuds dans CHAID :
  - le nœud s'appuie sur la variable  $X_i$  la plus fortement associée à Y par un test du Chi<sup>2</sup> (p valeur la plus faible, ou presque...)
- Critères d'arrêt dans CHAID : au cours de la pousse de l'arbre
  - Branche « pure » :  $f=0$  ou  $f=1$
  - OU Toutes les variables  $X_i$  sont constantes dans la branche
  - OU Aucun Chi<sup>2</sup> significatif
- → Il existe plusieurs autres méthodes d'arbres de décision



# Epilogue sur la méthode

- Avantages des arbres de décision :
  - Construction facile, paramétrable
  - Natures variées de  $Y$
  - Natures variées de  $X_i$ , utilisables en même temps
  - Fonctionne en grande dimension (nombreuses lignes, nombreuses colonnes) sans difficulté
  - Arbre facile à lire, règles faciles à utiliser
  - Règles : systèmes de règles non redondants
- Inconvénients des arbres de décision :
  - Risque de sur-ajustement (associations fortuites)
  - Instabilité des arbres
    - mais prédiction peu altérée
    - solution = *random forest trees*
  - Moins performants que d'autres méthodes
  - Règles utiles à la prédiction mais pas forcément théoriquement valides (ex : variables explicatives corrélées entre elles)



# Tank you for your attention!

[emmanuel@chazard.org](mailto:emmanuel@chazard.org)

