A decision support system adapted to the constraints and the challenges of decision support in customary medical consultations

Ph.D. Thesis Defense

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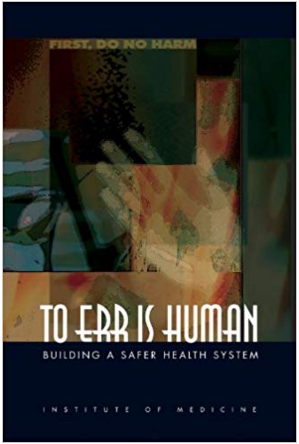
2021, 6th of April

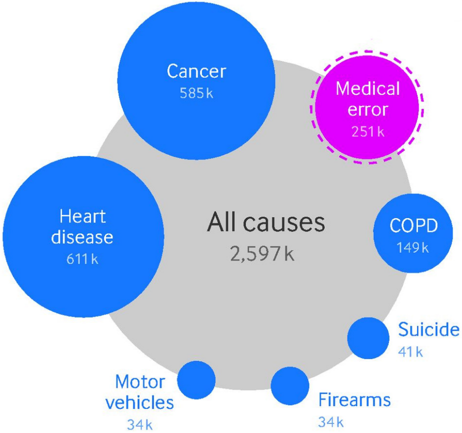
Preventable medical errors are a major cause of death

Between 44k to 98k death in the US in 1997



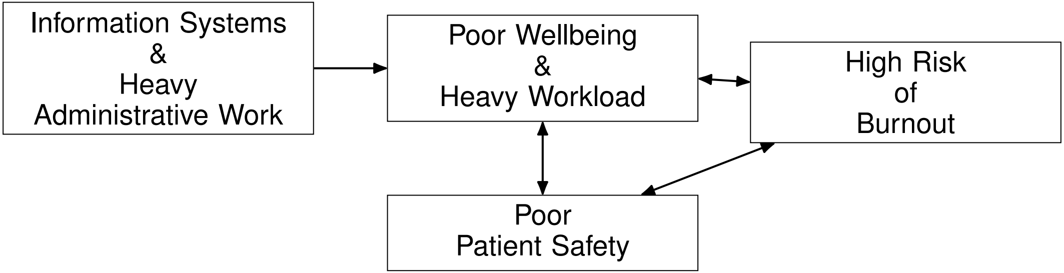
(Donaldson, Corrigan, Kohn, et al. 2000)

The third cause of death in the US in 2013



(Makary and Daniel 2016)

Clinicians' workload is highly correlated with medical errors



(Hall et al. 2016; Tawfik et al. 2018; Bertillot 2016; West, Dyrbye, and Shanafelt 2018)

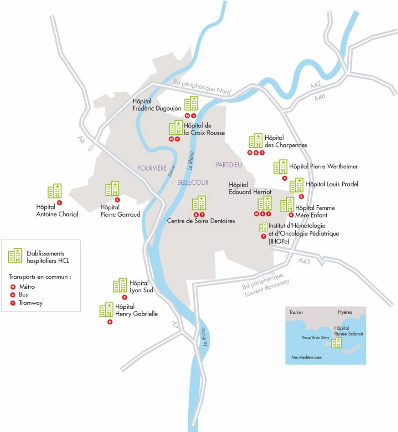
Social demands for reducing clinicians' workload

(Bertillot 2016; Dutheil et al. 2019; El-Hage et al. 2020)

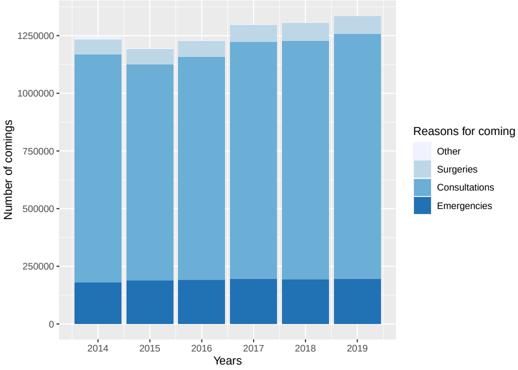
source: https://www.ouest-france.fr/sante/hopital/greve-des-urgences-213-services-touches-la-ministre-reconnait-une-crise-qui-persiste-6467444

The Civil Hospitals of Lyon (HCL)

14 hospitals around Lyon (France)

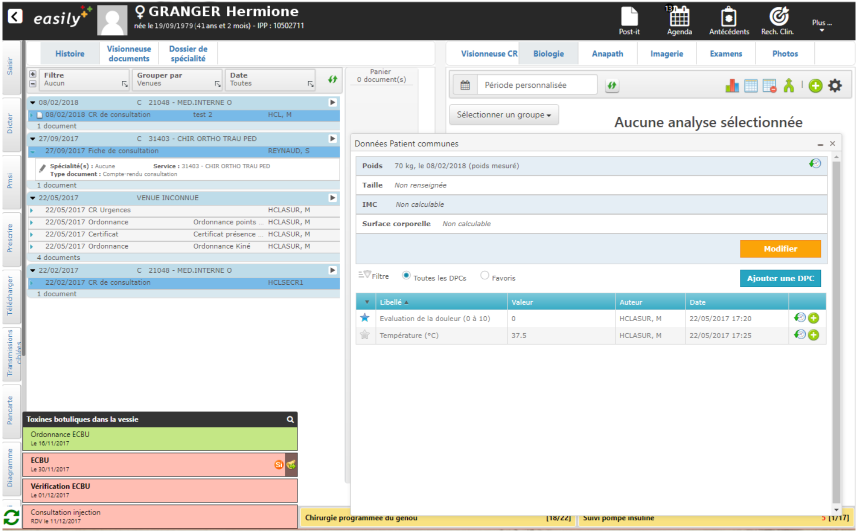


Customary medical consultations, a major part of the HCL's activities

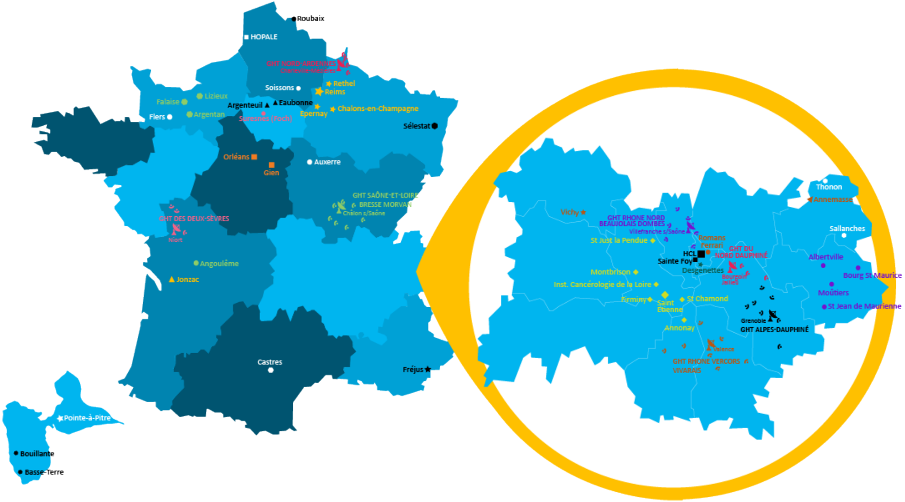


internal sources

User interface of Easily® for medical consultations (with a fictitious patient)



Groups of hospitals currently using Easily® in France (deployed by Hopsis)



internal sources

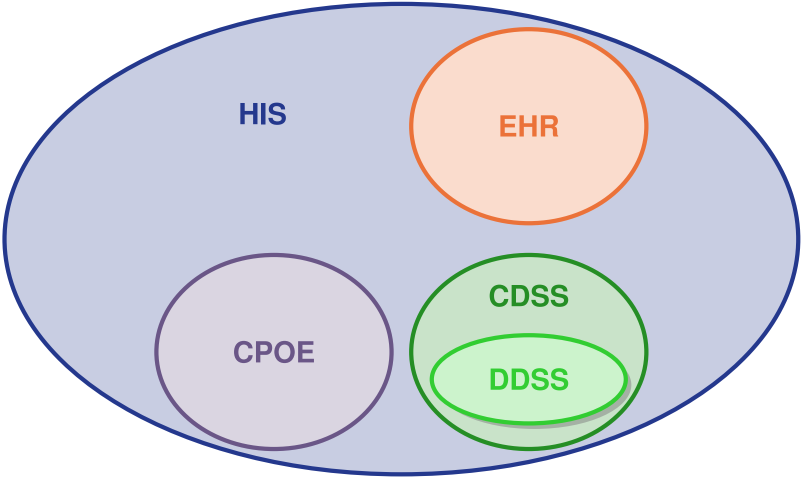
Objective: proposing a decision support system for customary medical consultations

How to support physicians during customary medical consultations?

Thesis:

An adapted and acceptable decision support system must respect the know-how of physicians and leave them the responsibility of the decisions taken during consultations, by limiting itself to providing them with pieces of information on their patients which are necessary for their decision-making

Definitions



CDSS:
Clinical Decision Support System

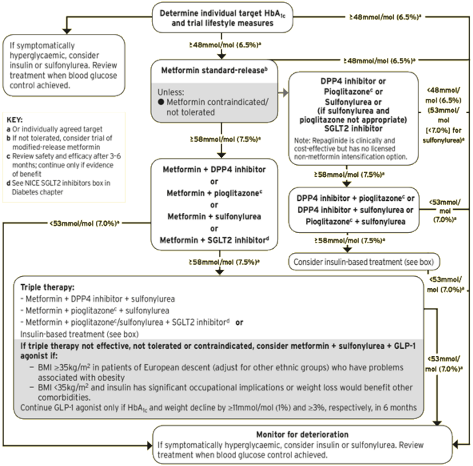
DDSS:
Diagnostic Decision Support System

HIS:
Health Information System

CPOE:
Computer Physician Order Entry

EHR:
Electronic Health Record

Guideline-based DDSSs

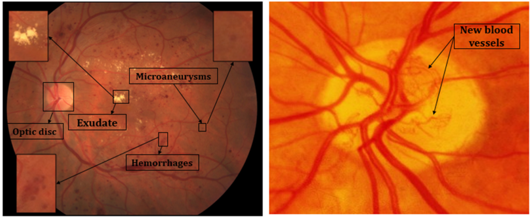


Summary of NICE's guidelines on treatments for type 2 diabetes

source: https://www.mims.co.uk/management-type-2-diabetes-nice-guideline/diabetes/article/891805

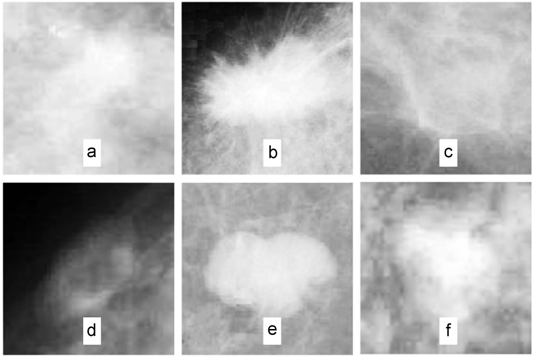
ML-based DDSSs

Identification of ocular diseases



(Asiri et al. 2019)

Detection of breast nodules



(Joo et al. 2004; Miranda and Felipe 2015)

A paradoxical situation for DDSSs

Can improve physicians' diagnostic skills in trials

(Povyakalo et al. 2013; Kirby et al. 2018)

Are overridden or ignored in practice

(Sittig et al. 2006; Onega et al. 2010; Masud, Al-Rei, and Lokker 2019)

Several barriers

A fear to lose diagnostic skills

Wrong recommendations tend not to be detected by physicians (Tsai, Fridsma, and Gatti 2003)

Decrease the diagnostic skills of experienced physicians (Povyakalo et al. 2013)

A lack of agreement

"Black boxes" prompting distrust (Cabitza, Rasoini, and Gensini 2017)

Physicians report a fear to lose control of their decisions (Heeks 2006)

Responsibility issues

If a physician has used a DDSS and DDSS's recommendations have led to a medical error, who is responsible?

Health Institutions?

Physicians?

Engineers?

Nobody?

There is social pressure on the responsibility of physicians using DDSSs
(Itani, Lecron, and Fortemps 2019)

Rationally select an adapted approach to support decision

According to Meinard and Tsoukiàs 2019, several approaches possible:

Conformist

Decisions must **conform** to **irrevocable** “gold-standards”

Objectivist

There are **objective** and **unquestionnable** facts and theories that should determine the decision

Adjustive

Support must **adjust** itself to the **sanctified** capacity for initiative of decision-makers

Identifying the dominant constraint binding decision support is necessary to choose the most relevant approach

The case of decision support for child health in developing countries

(Dalaba et al. 2014; Bessat, Zonon, and D'Acremont 2019; Bernasconi et al. 2019)

- Caregivers are not necessarily well-trained physicians
- Caregivers can ignore the best practices for specific diseases

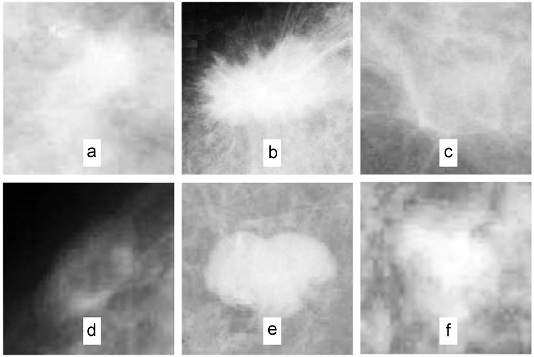
$\Downarrow$

Main constraint:
Clinical decisions must **conform** to guidelines of health authorities to minimize medical errors
(Reider 2016)

$\Downarrow$

A **conformist** support, such as Guideline-based DDSS, is relevant

The case of decision support for the detection of nodules by radiologists



(Joo et al. 2004; Miranda and Felipe 2015)

- ML algorithms outperforming physicians capacity for image analysis
- Large amount of cases available

⇓

Main constraint:
There are tools based on **objective** facts and theories that should be used to optimize nodules detection
(Yanase and Triantaphyllou 2019)

⇓

An **objectivist** support, such as ML-based DDSS, is relevant

The case of decision support for customary medical consultations

1. Physicians are competent to conduct customary consultations
2. Their responsibility is highly engaged
3. They want to stay in charge of their decision processes

$\Longrightarrow$

Main constraint:

Decisions depend on physicians' idiosyncrasies, expertise, and capacity for initiative

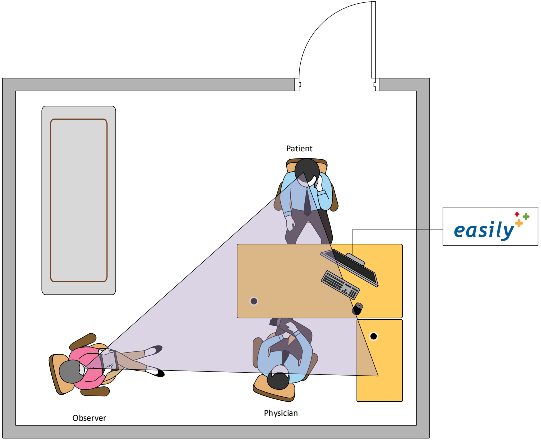
Must adjust decision support to physicians' needs and preferences
and not interfering with their capacity for initiative

Our positionning

An **adjustive** approach can rationally and legitimately be selected to support customary medical consultations

It implies that the needs of physicians should be analyzed

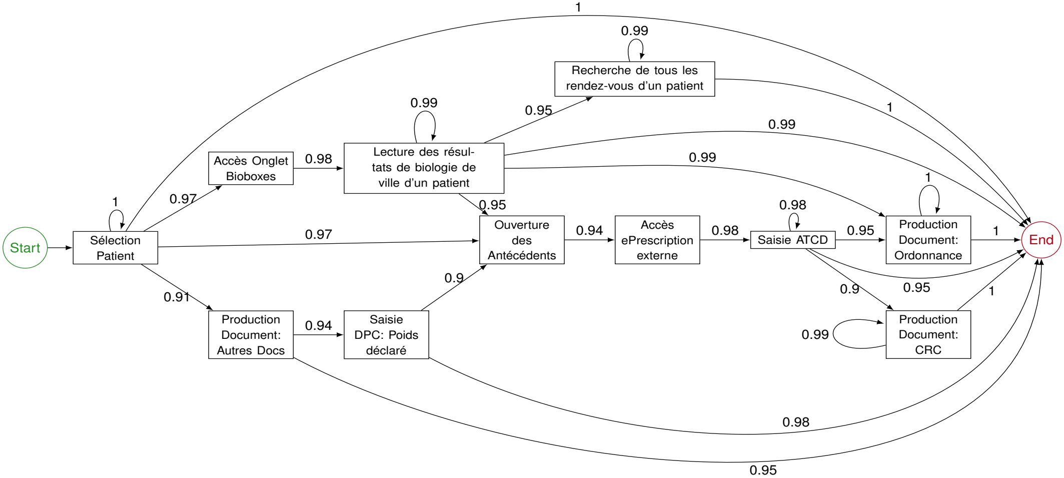
Field observations (17 consultations by 2 physicians)



Preliminary results

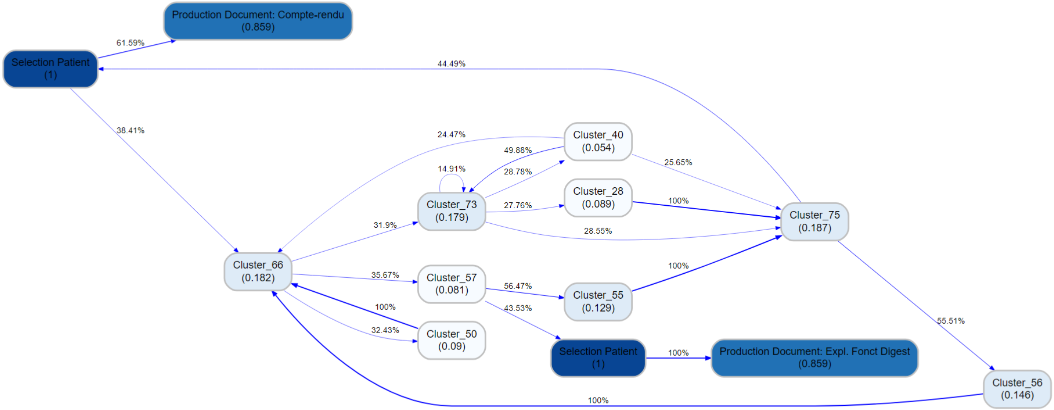
- Two kinds of actions performed by physicians:
  1. Searching for pieces of information concerning the patient
  2. Producing an order (ex. drug prescription)
- Action [1] occurs more frequently than action [2]
- Consultations end by the production of a summary document

Process Mining (3439 consultations by 75 physicians) - Heuristic Miner



* **Bioboxes:** Biology Module | **DPC:** Commun Data | **Antécédents (ATCD):** Medical Background | **CRC:** Consultation Report

Process Mining (3439 consultations by 75 physicians) - Fuzzy Miner

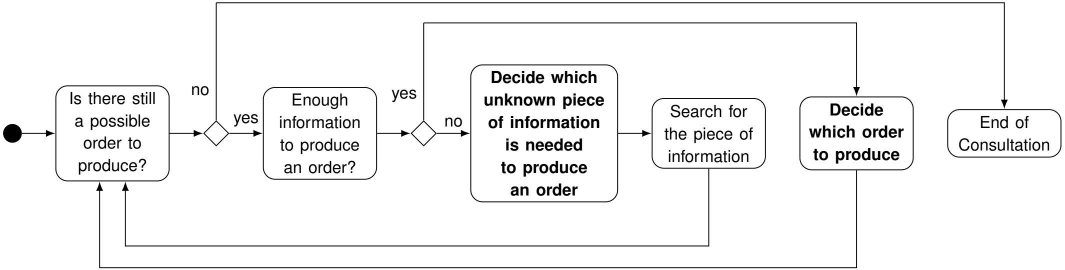


Analyses reproducible at: https://git.lamsade.fr/a_richard/consultation-process-analysis

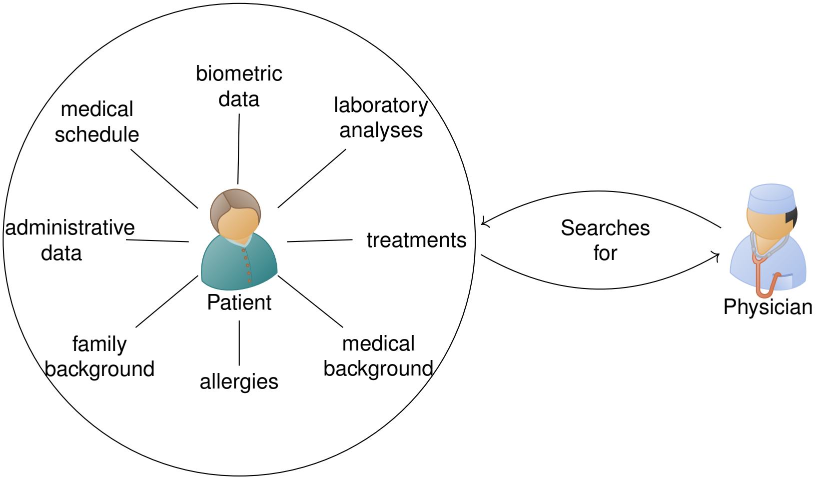
Formalizing specific consultations

T_c	$\mathcal{X}$							$\mathcal{A}$
	Sex	Age	BMI	Disease	HDL	LDL	TG	
t_0	♂	55	$\emptyset$	HChol	$\emptyset$	$\emptyset$	$\emptyset$	Search for HDL
t_1	♂	55	$\emptyset$	HChol	1.1	$\emptyset$	$\emptyset$	Search for LDL
t_2	♂	55	$\emptyset$	HChol	1.1	5.53	$\emptyset$	Search for TG
t_3	♂	55	$\emptyset$	HChol	1.1	5.53	1.98	Prescribe Ezetrol
t_4	♂	55	$\emptyset$	HChol	1.1	5.53	1.98	Search for BMI
t_5	♂	55	24.43	HChol	1.1	5.53	1.98	End of Consultation

A generic model of physicians' decision processes



The core process of customary medical consultations



Our positionning

Physicians mainly need:

Pieces of information on their patients

Not guidelines

Not recommendations

$\Longrightarrow$

Constraints:

Possibly available in Easily® database, but

⋮

it's time-consuming to get them

Objective: anticipating and providing pieces of information needed by physicians

How to know which pieces of information are needed by physicians?

Hypothesis:

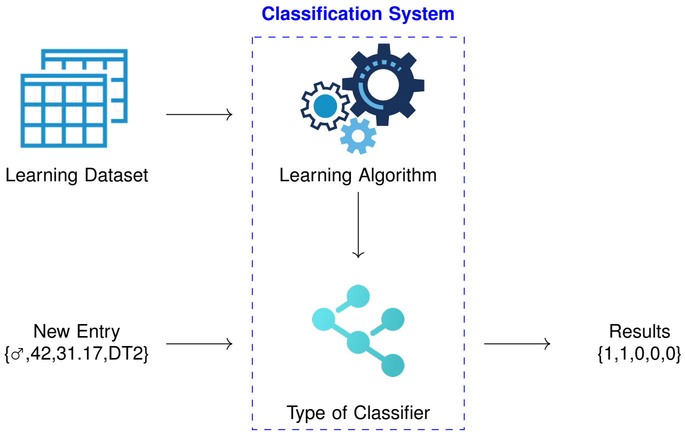
Physicians are competent and do not look randomly at data on patients, so we can learn their needs based on their activities

From specific consultations to a multi-label dataset

T_c	$\mathcal{X}$							$\mathcal{A}$
	Sex	Age	BMI	Disease	HDL	LDL	TG	
t_0	♂	55	$\emptyset$24.43	HChol	$\emptyset$	$\emptyset$	$\emptyset$	Search for HDL
t_1	♂	55	$\emptyset$24.43	HChol	1.1	$\emptyset$	$\emptyset$	Search for LDL
t_2	♂	55	$\emptyset$24.43	HChol	1.1	5.53	$\emptyset$	Search for TG
t_3	♂	55	$\emptyset$24.43	HChol	1.1	5.53	1.98	Prescribe Ezetrol
t_4	♂	55	$\emptyset$24.43	HChol	1.1	5.53	1.98	Search for BMI
t_5	♂	55	24.43	HChol	1.1	5.53	1.98	End of Consultation

$\mathcal{X}$: pieces of information known on patients				$\mathcal{Y}$: pieces of information on patients needed by physicians					
Sex	Age	BMI	Disease	HbA1c	Blood Sugar	HDL	LDL	Creatinine	Microalbumin
♂	55	24.43	HChol	0	0	1	1	0	0

Learning which pieces of information are needed



Looking for “transparent” systems

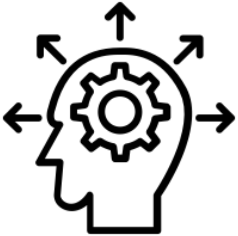
- To improve acceptability (Sinha and Swearingen 2002, Holzinger et al. 2017)
- To decrease workload (Bertillot 2016, West, Dyrbye, and Shanafelt 2018)

"Transparency" requirements

Understandable

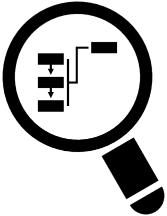
Must be based on notions already known to physicians (Montavon, Samek, and Müller 2018)

Interpretable



Must ensure that physicians reach conclusions without bias (Spagnolli et al. 2017)

Retraceable



Must allow tracing back algorithm's actions (Hedbom 2008)

Revisable

Must take into account feedback from physicians (Zarsky 2013)

Selection of a “transparent” classification system

	Not at all	*Not really*	*Partially*	*Totally*
Understandable System?	○	☆	◇ △	□
Interpretable Classifier?	○	☆	◇	△ □
Interpretable Algorithm?	○	☆	◇ △	□
Retracable System?		◇	○ ☆	△ □
Revisable Classifier?	○	☆	◇ □	△

- ○ **BP-MLL** (Zhang and Zhou 2006)
- ◇ **ML-kNN** (Zhang and Zhou 2007)
- □ **Naive Bayes** (John and Langley 1995)
- △ **C4.5** (Quinlan 1993) **RIPPER** (Cohen 1995)
- ☆ **SMO** (Keerthi et al. 2001)

A Naive Bayes variation for multi-label classification

Probability of B occurring given evidence A has already occurred

Probability of A occurring

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

Probability of A occurring given evidence B has already occurred

Probability of B occurring

Why Naive Bayes?

Understandable:
basic probability theories are well-known by physicians

Interpretable:
the learning algorithm of Naive Bayes is simple to explain

Retraceable:
the probabilities used can be traced back

Revisable:
physicians’ feedbacks can be used to update probabilities

Naive Bayes classification process

$\mathcal{X}$		$\mathcal{Y}$	
Age	Disease	HbA1c	HDL
42	DT2	1	0
52	HChol	0	1
24	DT1	1	0
67	HChol	1	1

Learning Dataset

Naive Bayes Learning Algorithm

New Patient X:
{42,DT2}

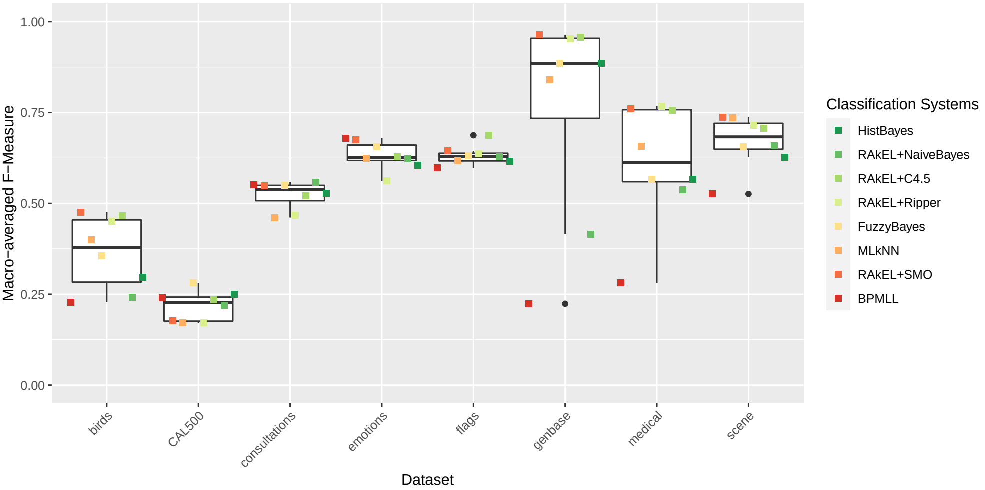
$$
\begin{aligned}
P(\text{HbA1c} &= 0) = 0.25 \\
P(\text{HbA1c} &= 1) = 0.75 \\
P(\text{HDL} &= 0) = 0.5 \\
P(\text{HDL} &= 1) = 0.5 \\
P(\text{Age} < 38.3 \mid \text{HbA1c} &= 1) = 0.33 \\
P(\text{Age} < 38.3 \mid \text{HDL} &= 0) = 0.33 \\
P(\text{Disease} = \text{DT2} \mid \text{HDL} &= 0) = 0.5 \\
&\vdots
\end{aligned}
$$

Results:

$P(\text{HbA1c} = 1 \mid X) = 0.99$

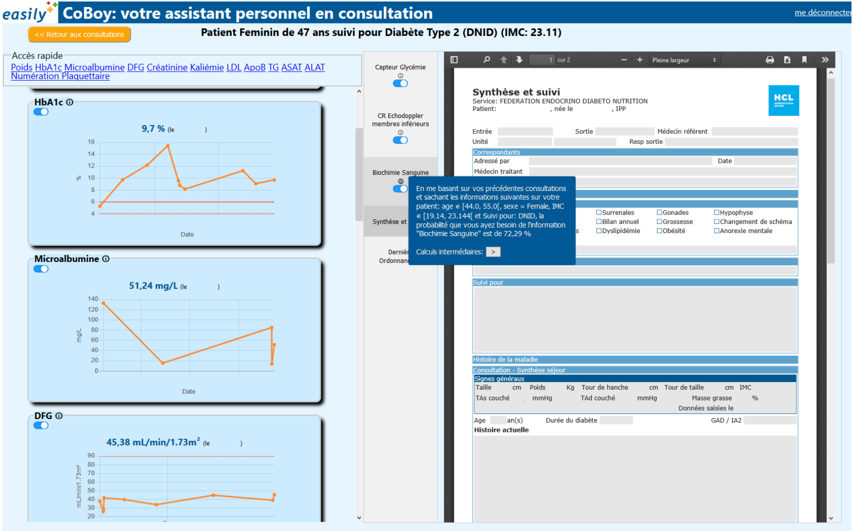
$P(\text{HDL} = 1 \mid X) = 0.000004$

High “transparency” doesn’t mean low performance



reproducible at: `https://git.lamsade.fr/a_richard/transparent-performances`

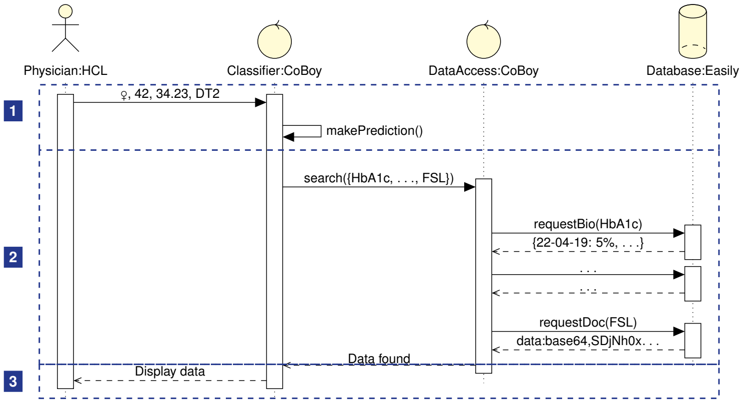
The current user interface of CoBoy (with fictitious data)



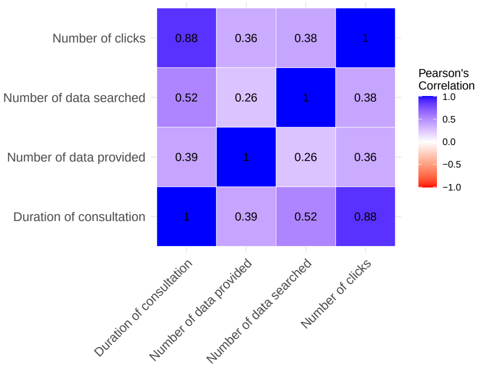
The process of the decision support system

Main phases

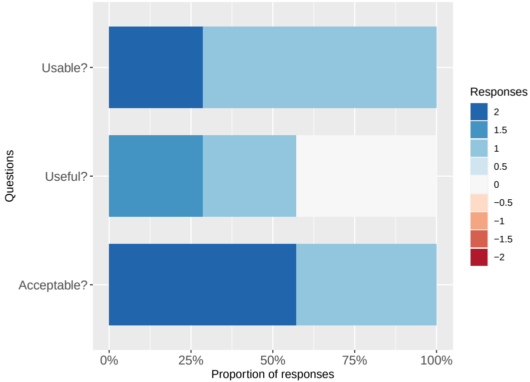
1. Anticipating pieces of information needed by physicians
   1. Rules defined by physicians
   2. Naive Bayes classifier
2. Searching for raw data for each piece of information
3. Displaying raw data collected for each piece of information



Clinical trials (49 consultations by 7 physicians)



Correlation matrix between each criterion observed during clinical trials of CoBoy



Distribution of answers to the satisfaction questionnaire

Thesis

An adapted and acceptable decision support system must respect the know-how of physicians and leave them the responsibility of the decisions taken during consultations, by limiting itself to providing them with pieces of information on their patients which are necessary for their decision-making

Contributions

A critical analysis of clinical decision support systems
(Richard et al. 2020b)

Modelization of physicians' decision processes during medical consultations
(Richard et al. 2018)

Proposal of operational criteria to assess the "transparency" of multi-label classification systems
(Richard et al. 2020a)

Development of a virtual assistant dedicated to supporting physicians' decisions during day-to-day medical consultations
(work in progress: Richard et al. 2021)

Perspectives

Improving

the proposed system and deploying it into other hospital departments

Rethinking

the role of information systems in clinical decision processes

Investigating

the adjustive approach in domains where decision-makers' responsibility is highly engaged

Thank you for your attention

Synthesis

Context	Current DDSSs	Decision Process	Virtual Assistant	Perspectives
▶ medical errors ▶ physicians' workload ▶ supporting consultations	▶ theoritically beneficial ▶ not accepted ▶ responsibility issues	▶ searching for patient data ▶ time-costing	▶ transparency ▶ learning ▶ anticipating ▶ well accepted	▶ improving ▶ rethinking ▶ exploring

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