

Design of a diagnosis and follow-up platform for patients with chronic headaches

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Counsellor: ing. Olivier Janssens

Faculty of Engineering and Architecture

Intro

Current process Ghent
University Hospital

Machine learning

Doctor dashboard

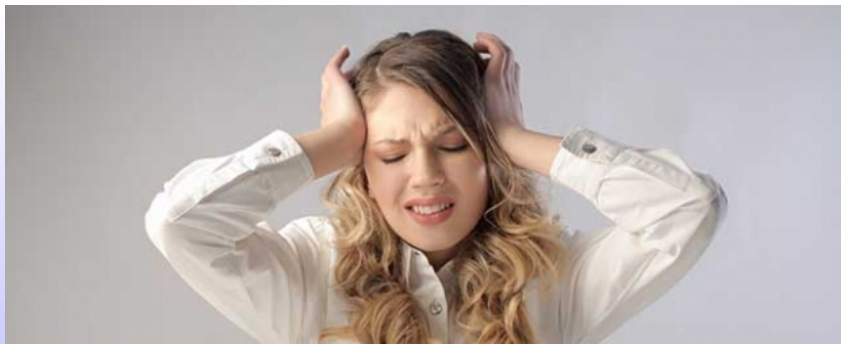
Platform requirements

Conclusion & future work

Mobile application

Backend and data exposure

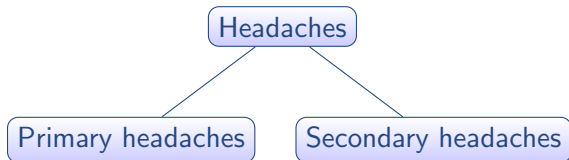
Headaches



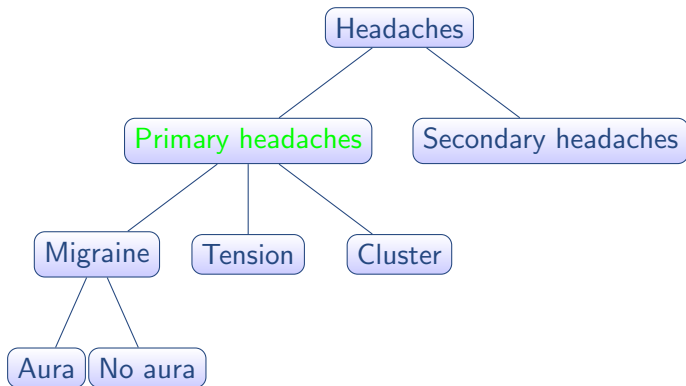
Headaches

Headaches

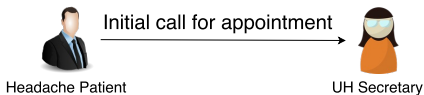
Headaches



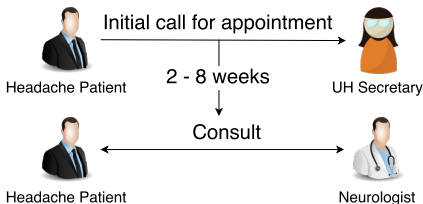
Headaches



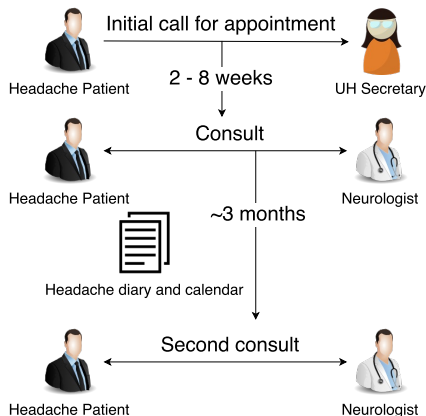
Current process at Ghent UH



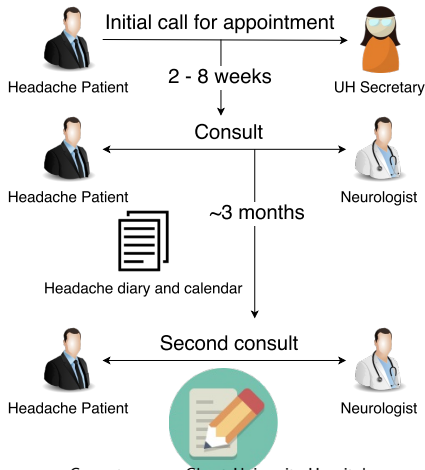
Current process at Ghent UH



Current process at Ghent UH



Current process at Ghent UH



Current process Ghent University Hospital

Current process at Ghent University Hospital is:

- ▶ Not digital
- ▶ cumbersome
- ▶ time consuming

So there is need for a better (digital) alternative! This alternative has to:

- ▶ capture at least the same information as current solution
- ▶ be more efficient
- ▶ support doctors in forming a diagnosis

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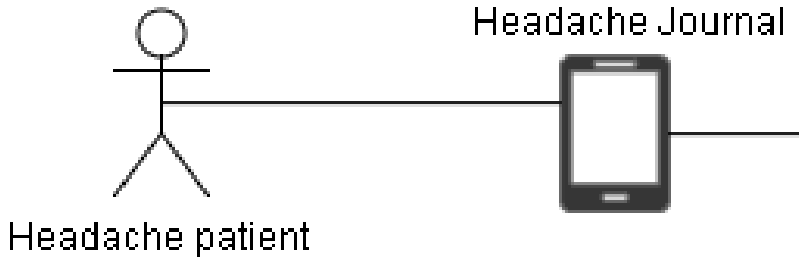
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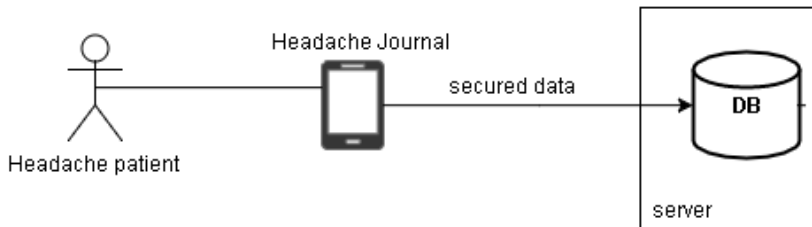
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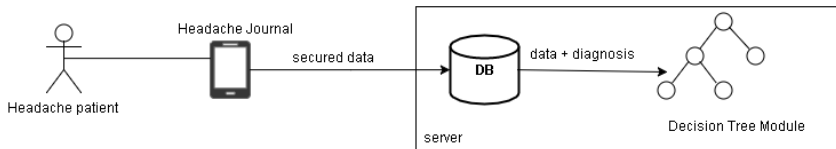
Platform requirements



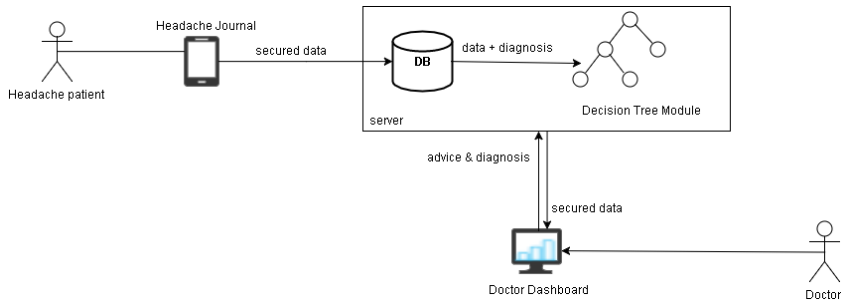
Platform requirements



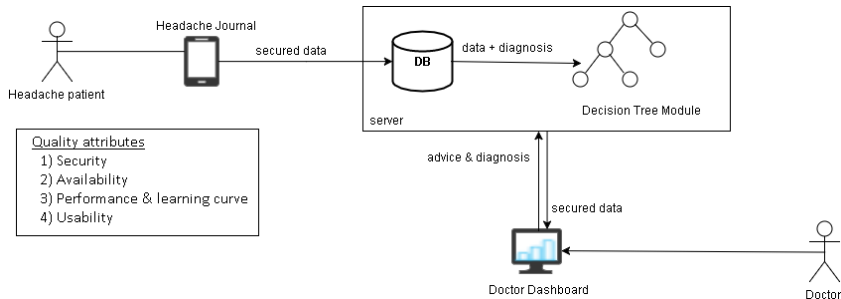
Platform requirements



Platform requirements



Platform requirements



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Platform requirements

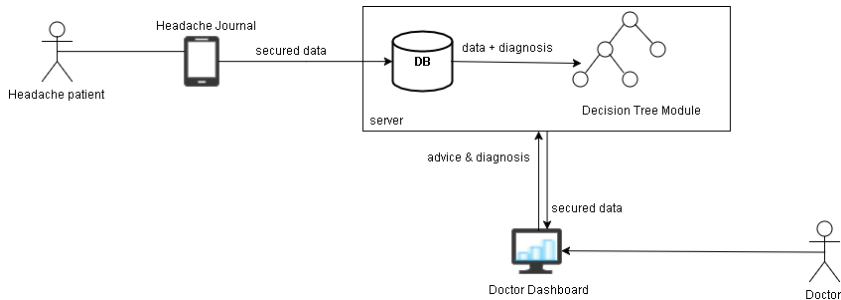
Doctor dashboard

Mobile application
Chronicals

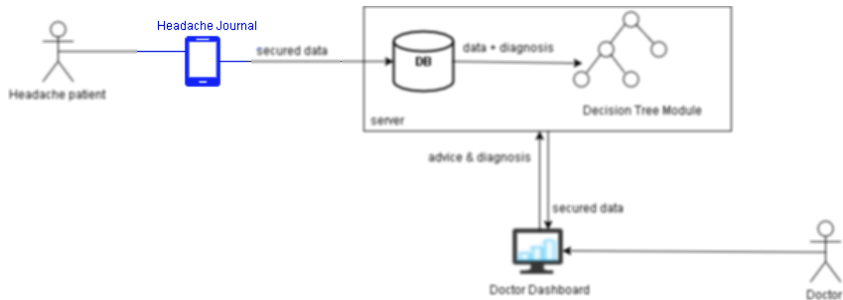
Conclusion & future work

Backend and data exposure

Mobile Application



Mobile Application



Mobile Application

Why create a new application?

Competition

- ▶ Migraine Buddy
- ▶ Headache Diary
- ▶ Pfizer headache journal

Mobile Application

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All good, but:

Mobile Application

Why create a new application?

Competition

- ▶ Migraine Buddy
- ▶ Headache Diary
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All good, but:

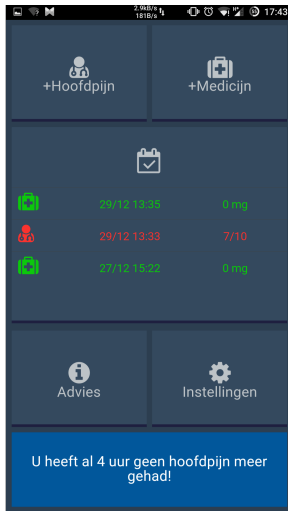
- ▶ none captures all data needed
- ▶ none offers usable data export

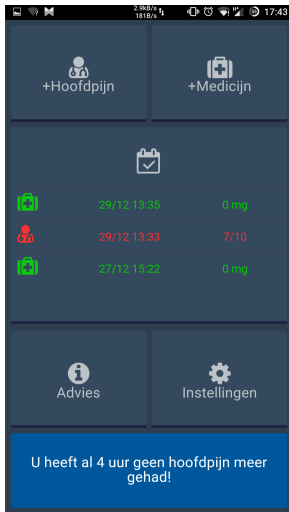
Cross platform vs Native

	Native	Cross-platform
+	+ Native UX	+ 1 language
	+ device-specific features	+ Write once, run everywhere
	+ Better performance	+ Less maintenance
-	- Multiple languages	- Slower (lower performance)
	- Time consuming (development)	- Less device specific features
		- Harder to release online (Play Store/App Store)

Cross platform vs Native

	Native	Cross-platform
+	<ul style="list-style-type: none"> + Native UX + device-specific features + Better performance 	<ul style="list-style-type: none"> + 1 language + Write once, run everywhere + Less maintenance
-	<ul style="list-style-type: none"> - Multiple languages - Time consuming (development) 	<ul style="list-style-type: none"> - Slower (lower performance) - Less device specific features - Harder to release online (Play Store/App Store)





Chronicals



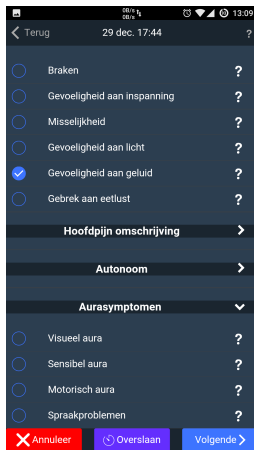
Chronicals



Chronicals

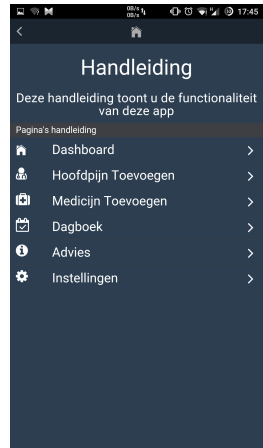
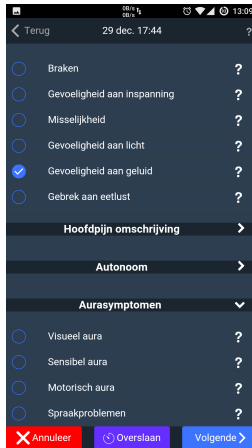
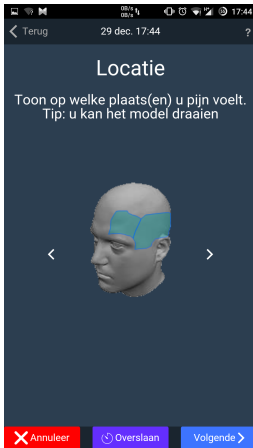


Mobile application



Chronicals

Chronicals



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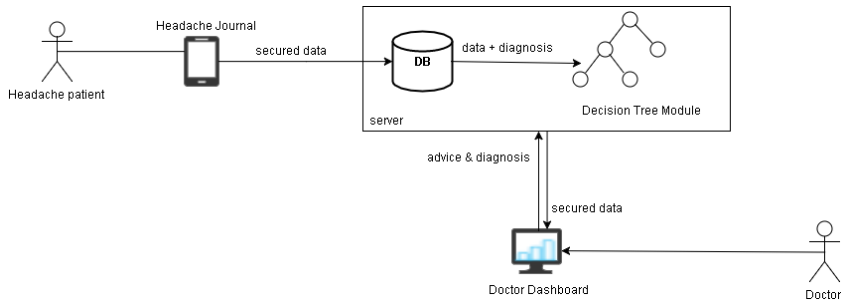
Doctor dashboard

Mobile application

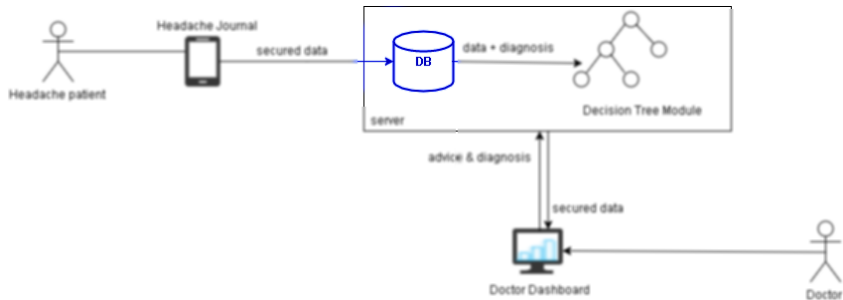
Conclusion & future work

Backend and data exposure

Backend and data exposure



Backend and data exposure

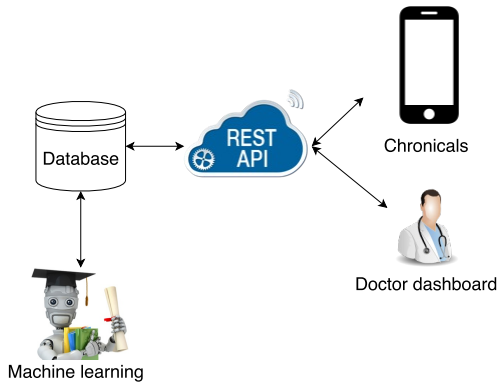


Backend and data exposure

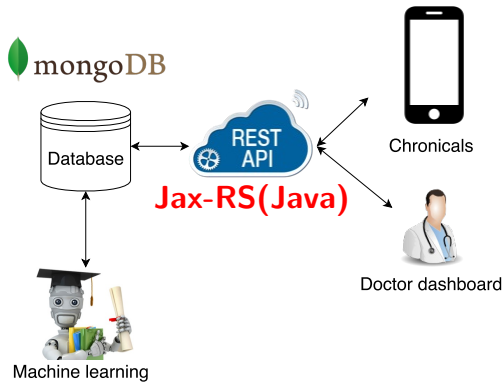
Components

- ▶ Database
- ▶ Connection to App
- ▶ Connection to Doctor Dashboard
- ▶ Connection Machine learning module

System



System



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Platform requirements

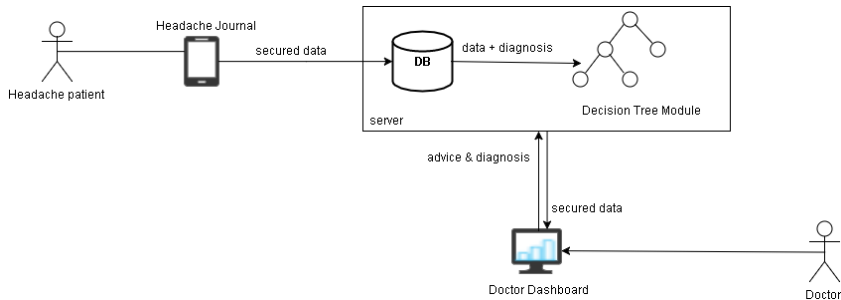
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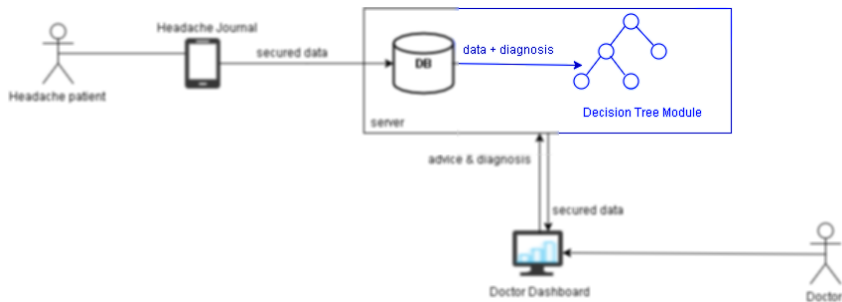
Conclusion & future work

Backend and data exposure

Machine learning



Machine learning



1. Introduction

Why white box models? - Flaws of current approaches

2. Decision tree merging

Merging decision trees in a single, interpretable tree

3. Genetic approach

4. Evaluation

Used datasets - Results - Our headache dataset

Machine Learning

Decision support (\neq decision making) \Rightarrow White box model

Possible models

- ▶ Decision trees
- ▶ Random Forests (Gray box)
- ▶ Bayesian networks

Machine Learning

Decision support (\neq decision making) \Rightarrow White box model

Possible models

- ▶ Decision trees
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Many different DT induction algorithms



C4.5 (C5.0)



CART



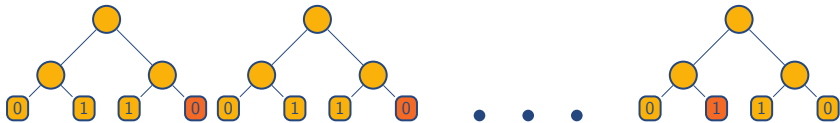
QUEST

...

→ **Which tree is the most beautiful?**

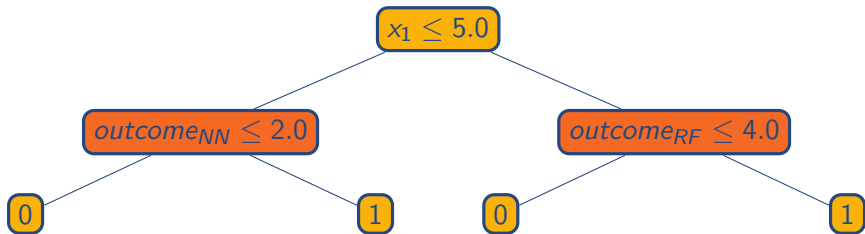
Current ensembles lack interpretability

Boosting, bagging, random forests, etc. require majority voting (classification) or mean calculation (regression) to obtain prediction



Current ensembles lack interpretability

The final decision tree obtained by **stacking** contains uninterpretable internal nodes



An ensemble technique WITH interpretability

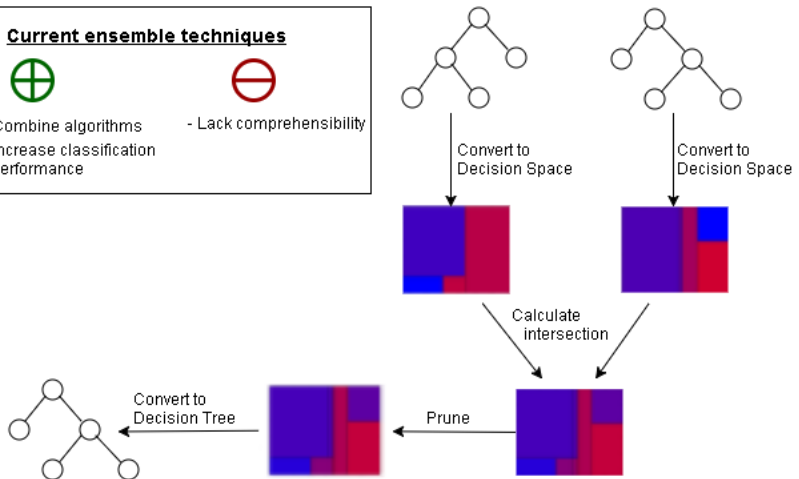
Current ensemble techniques



- Combine algorithms
- Increase classification performance



- Lack comprehensibility

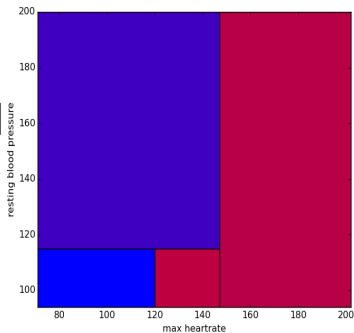
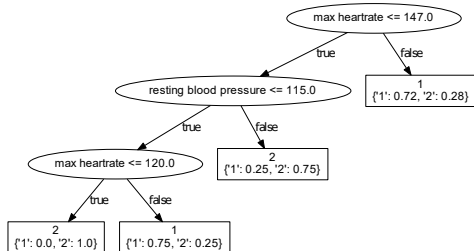


Decision tree \rightarrow decision space

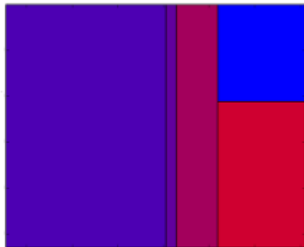
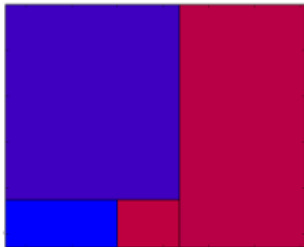
Converting decision trees to decision spaces

We can define a one-to-one mapping between a decision tree and a set of k -dimensional hyperplanes ($k = \text{\#features}$), called **decision space**. Each node in the decision tree corresponds to a hyperplane in the decision space.

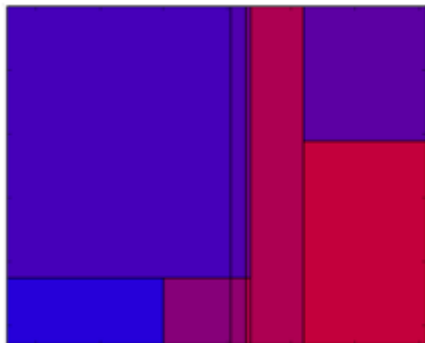
Decision tree → decision space



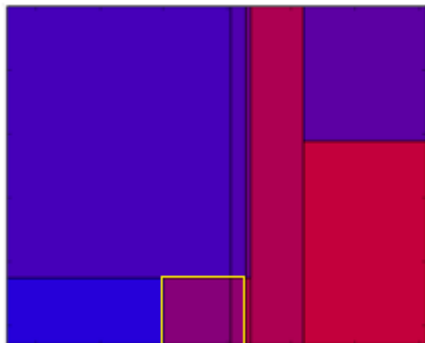
Merging decision spaces

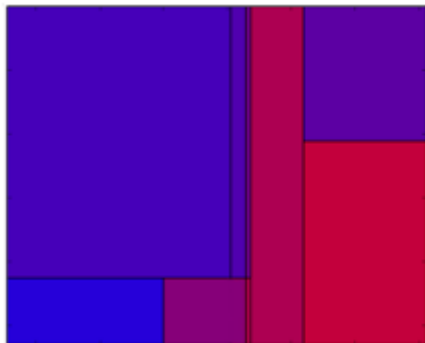


Merging decision spaces



Pruning decision spaces



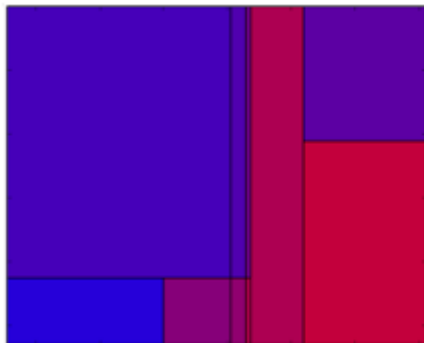


Decision space \rightarrow decision tree

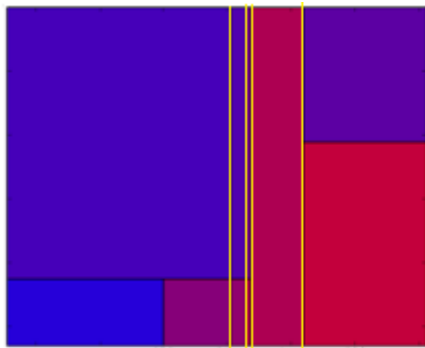
Converting decision spaces to decision trees

One-to-one mapping from decision tree to space is gone because the order is lost during conversion from DT to DS. Therefore, a **heuristic** approach must be taken, identifying **hyperplane candidates** and calculating a metric to choose the 'best' plane.

Decision space \rightarrow decision tree



Decision space \rightarrow decision tree



Decision space \rightarrow decision tree

Finding 'best' candidate hyperplane

Apply metric function to each plane, these include:

- ▶ information gain and Gini
- ▶ pick plane from most correlated feature
- ▶ pick plane that divide space in two most equal subspaces
- ▶ combination

RECAP

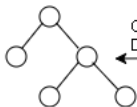
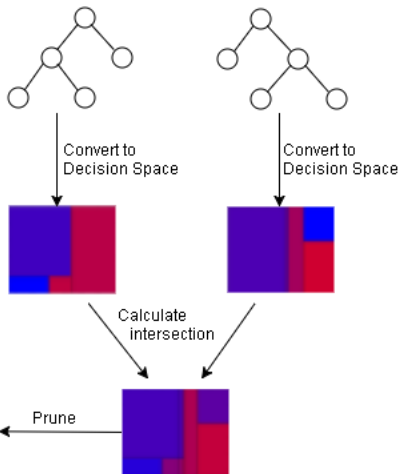
Current ensemble techniques



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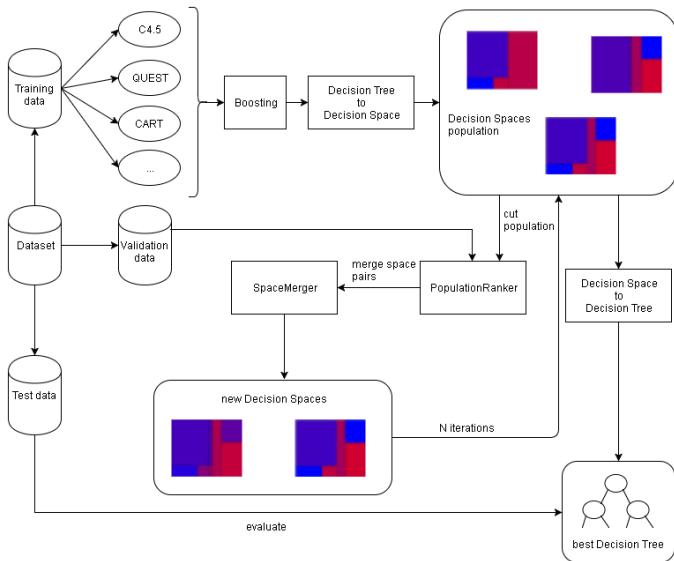


Convert to
Decision Tree

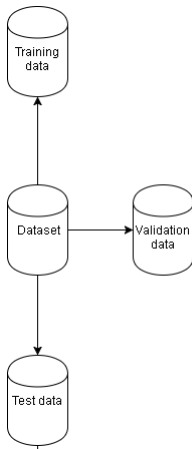
But which decision trees to merge?

Many different algorithms → Trying all combinations takes time

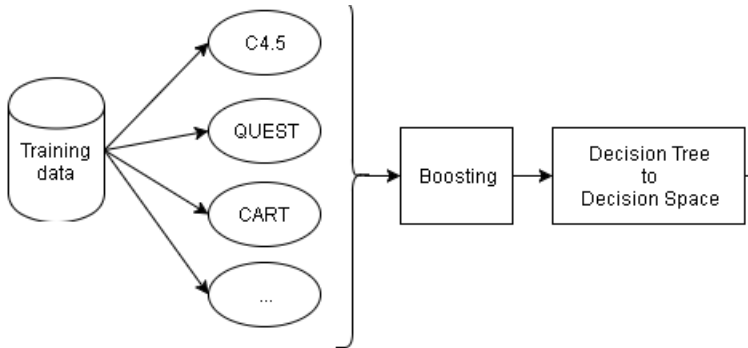
→ Genetic algorithms to the rescue!



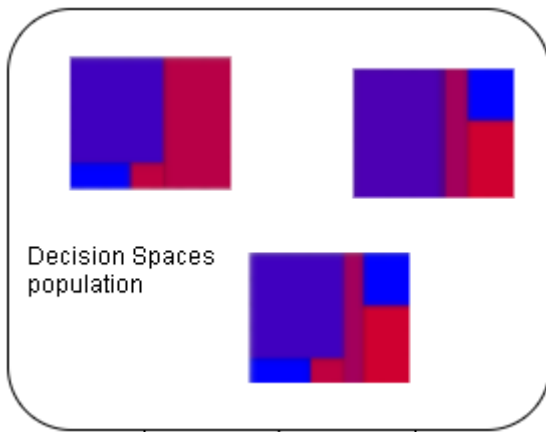
Splitting the data



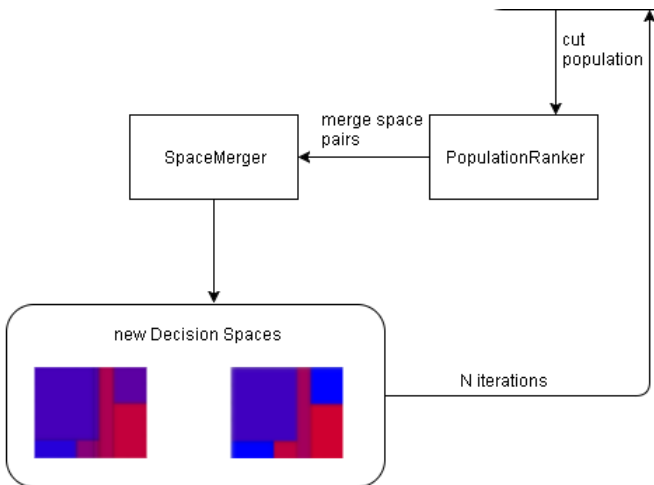
Generate different decision trees



Generate different decision trees



Genetic merging

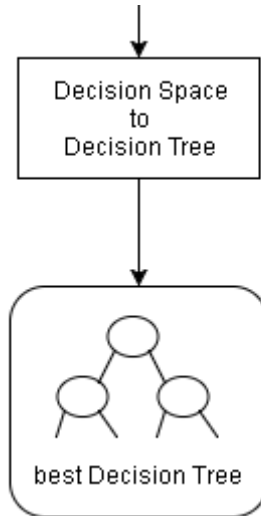


PopulationRanker

Fitness function

A high accuracy is the most important property of a decision tree, followed by its' size (\rightarrow comprehensibility). Genetic algorithms are well suited for **multi-objective optimization**.

Final iteration



Evaluating our algorithm

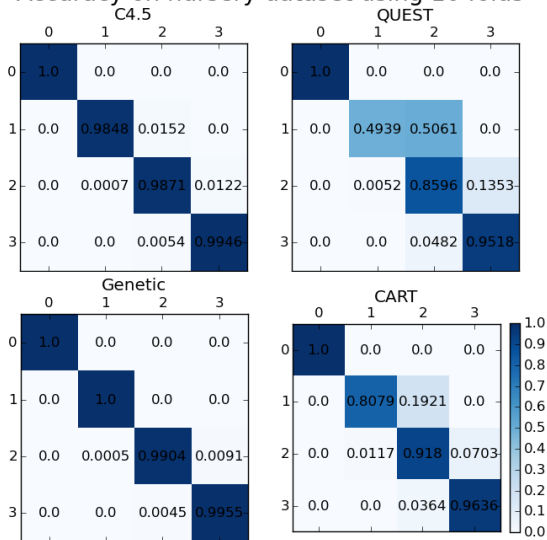
5 datasets from UCI

optimal parameters, feature selection when needed and k-fold CV

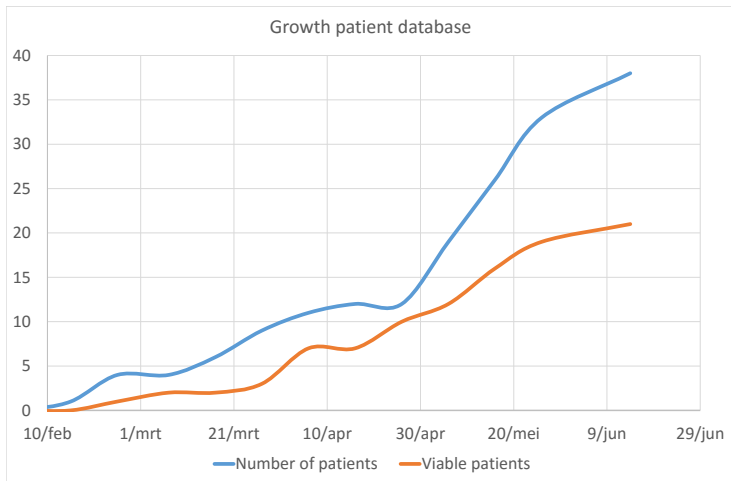
Name	#Samples	#Disc	#Cont	#Class	Imbalance rate
Heart	270	7	6	2	0.058
Car	1728	6	0	4	0.225
Iris	150	0	4	3	0
Shuttle	14500	0	9	7	0.18308
Nursery	12960	8	0	5	0.1498

Dataset	Folds	C4.5	CART	QUEST	Genetic
Heart disease	5	<u>0.8067</u>	0.7844	0.7844	<u>0.8067</u>
	10	<u>0.8104</u>	0.7732	0.7881	0.7993
Iris	3	0.9533	0.9467	0.9467	<u>0.96</u>
	5	0.9467	0.9333	0.9467	<u>0.9533</u>
Cars	3	<u>0.9722</u>	0.9693	0.9229	0.9693
	5	0.9711	0.9682	0.9241	<u>0.9786</u>
	10	0.9756	0.9751	0.9265	<u>0.9803</u>
Shuttle	3	0.9987	0.9983	0.9964	<u>0.9988</u>
	5	0.9986	0.9981	0.9962	<u>0.9988</u>
	10	0.9990	0.9987	0.9941	<u>0.9992</u>
Nursery	3	0.9890	0.9431	0.9147	<u>0.9914</u>
	5	0.9918	0.9498	0.9251	<u>0.9958</u>
	10	0.9937	0.9568	0.9259	<u>0.9954</u>

Accuracy on nursery dataset using 10 folds



Headache dataset



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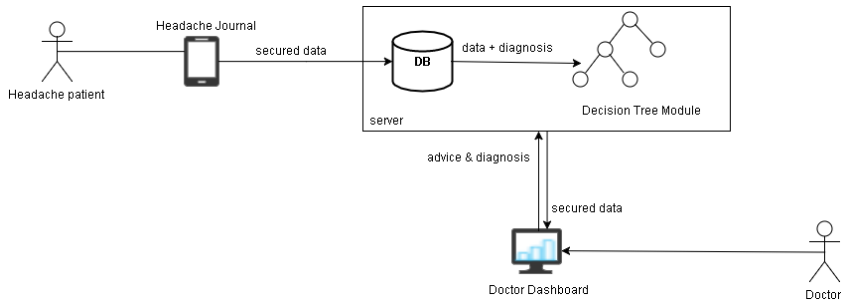
Doctor dashboard

Mobile application

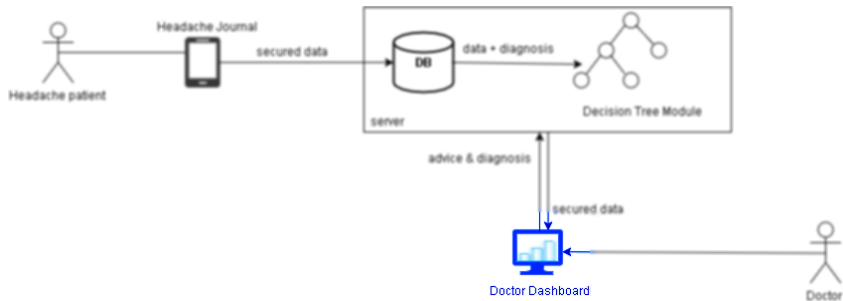
Conclusion & future work

Backend and data exposure

Doctor dashboard



Doctor dashboard



Doctor Dashboard

- ▶ Web application in order for the doctors to access the data exposed by our REST API
- ▶ Preferably in the form of visualizations, which allow to process a lot of data in a small amount of time
- ▶ Developed by Maarten Vanden Berghe

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Conclusion

The current process in the UH of Ghent can be completely digitized:

- ▶ Collect information using a mobile application
 - More efficient than paper calendars
- ▶ Present the data through a web application
 - Visualizations allow to process a lot of information quickly

This leads to an increased efficiency and reduced frequency of consults, resulting in lower health care costs.

Conclusion

A new ensemble technique was developed and tested on very varying datasets:

- ▶ increases classification performance
- ▶ preserves excellent interpretability in contrast to current ones
→ Can easily be visualized

When a higher number of headache patients are registered in our system, the resulting decision tree can be used to support physicians in forming a diagnosis

Future work

- ▶ Develop native applications for iOS and Android to enhance look-&-feel
- ▶ Re-evaluate our machine learning models on a larger headache dataset
- ▶ Implement more induction algorithms and ensemble techniques to create a more diverse initial population
- ▶ Experiment with other selection techniques and fitness functions
- ▶ Optimize the heuristic approach to convert decision spaces to decision trees

Thank you for your attention!

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