Machine Learning for Clinical Management: From the Lab to the Hospital

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relyens
EUROPEAN MUTUAL GROUP
INSURANCE AND RISK MANAGEMENT

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Outline

- Healthcare has a big problem
- Amalfi Analytics and our approach
- Two ML-powered platforms
- From the lab to the hospital
- Wrap-up

The “Silver Tsunami”

22% of Europeans are over 65 today

40% will be over 65 by 2040

Aging, chronic disease 70% of the expense

Healthcare is >10% GDP, >20% public expense in the EU

How to do more with less?

- Reduce the burden of low-value tasks
- **Reduce waste using existing data**

Image: https://www.pexels.com/photo/patient-having-an-online-appointment-with-a-doctor-using-laptop-7195084/

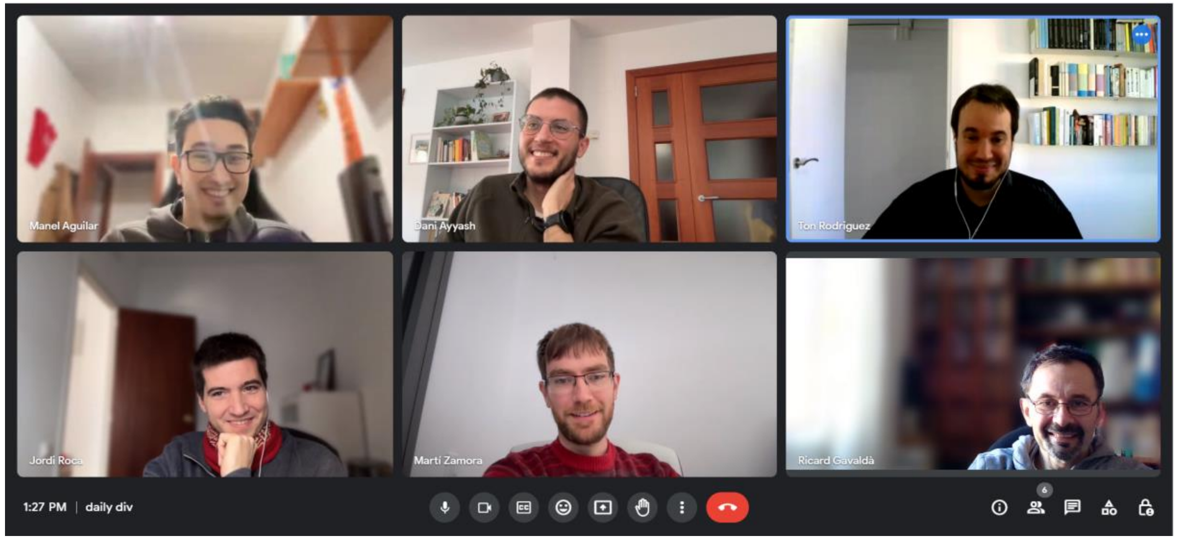
Who – Amalfi Analytics

Ricard Gavaldà

Professor at the Technical University of Catalonia

Dr. Julianna Ribera

30+ years in healthcare management positions



Fantastic technical team:

Martí Zamora (CTO), Ton Rodriguez, Jordi Roca, Manel Aguilar, Dani Ayyash

Past: Laura Aviñó, Idoia Beraza, Konstantin Kutzkov, Jose Munuera

Where we are now

Aug 2024: Present or tested in 25 hospitals

Dec 2023: Acquired by the Relyens group,
the European mutual group specialising
in risk management services for health

The Amalfi way

Administrative healthcare data
+
Machine Learning algorithms
=
Efficiency
Quality of care
Reduced risks
Scalability

Administrative Data: Minimum Basic Dataset

Patient ID	Sex	Birth year	Zip code	Arrival time	Origin	Discharge time	Discharge status	Diagnostic list	Procedure list
31713575	F	1964	08028	01/01/2024 00:03	Home	06/01/2024 12:20	Home	I21.0, F41.0	02703ZZ
55556050	M	1938	42078	01/01/2024 00:25	Other hosp.	03/01/2024 09:15	Death	N39.0, E11.91	0T2BX0Z
81564163	F	1946	08015	01/01/2024 01:06	Other hosp.	25/02/2024 12:00	Other hosp.	N18.4	5A1D70Z
75421493	F	2024	08015	01/01/2024 01:15	Home	05/01/2024 16:00	Home	S06.0X0A	B020ZZZ
55455670	M	1996	43015	01/01/2024 01:46	Primary care	01/01/2024 12:25	Escape	F22, Z86.59	GZ2ZZZZ

Billing = MBD + aggregators such as DRG

Levels in healthcare system management

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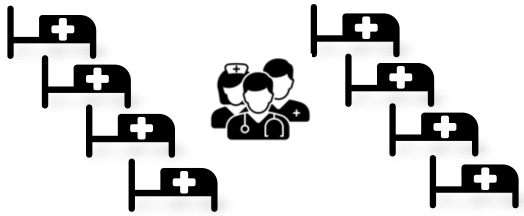
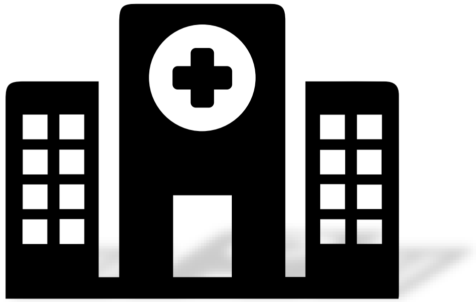


Micro level: Quality and safety

Organize the service

Identify risks

Improve quality of care



Meso level: Efficient resource use

Match resources to needs

Anticipate scenarios

Fulfill contracts with payers

Macro level: Accessibility and equity

Plan for a territory

Coordinate the different health services

(Re)design hospitals & services

Create prevention programs

Two platforms

Predictive platform

- Support for operational decision making in hospitals

Analytical platform

- Support population health decisions

A predictive platform for hospitals

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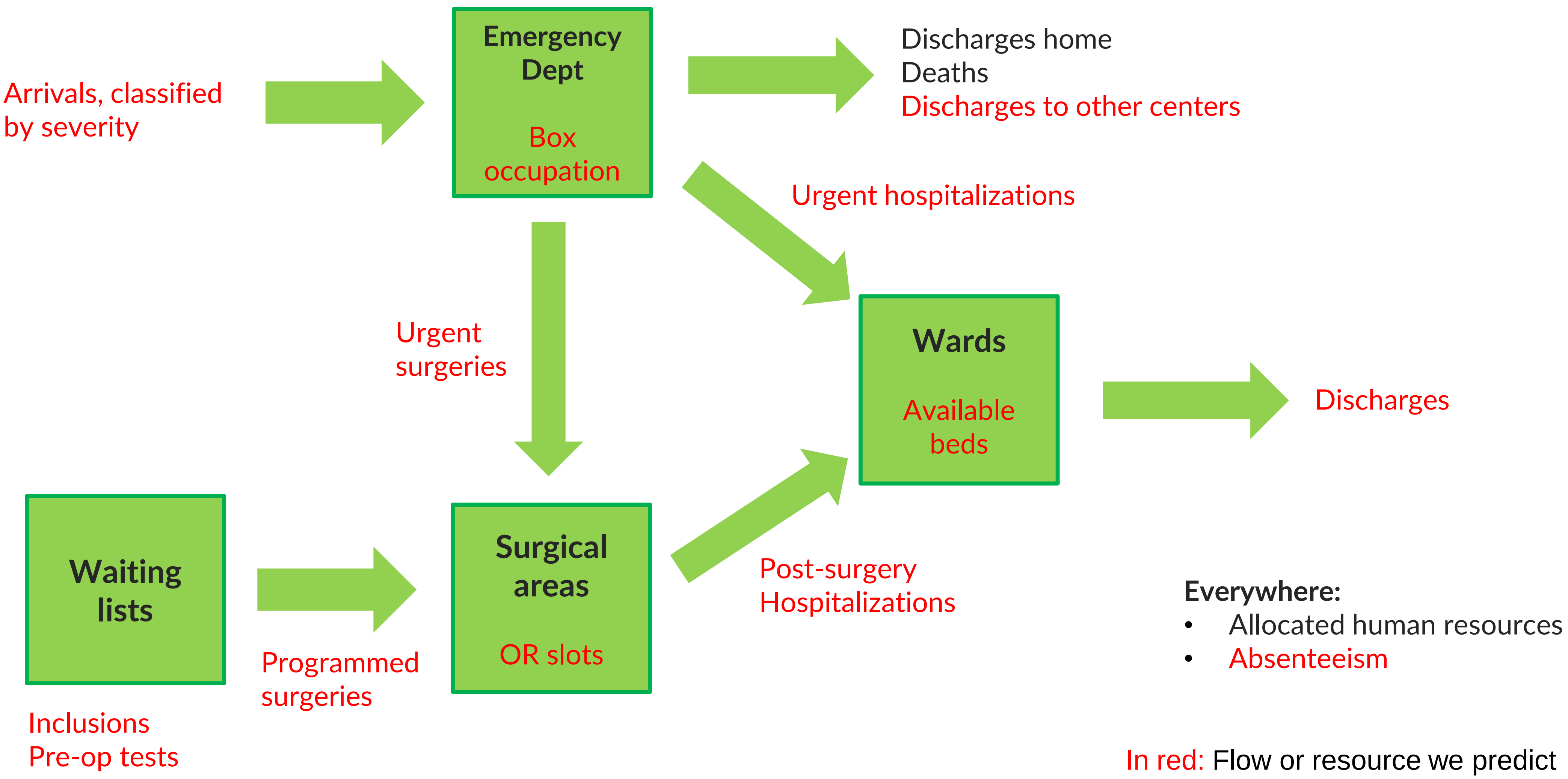
Predict and match:

- Activity
- Resources needed
- Resources available

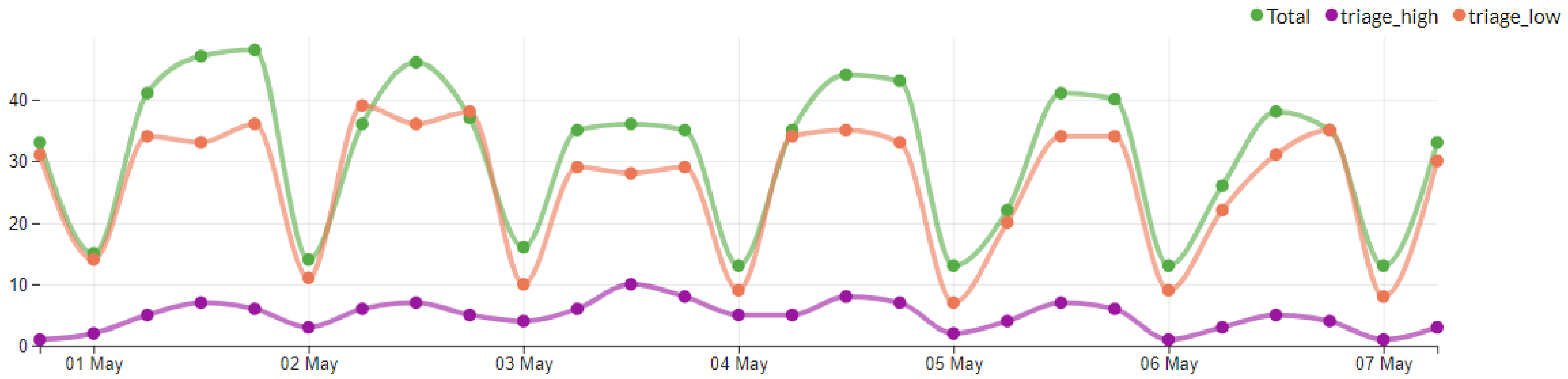
Goal: Anticipate rather than react



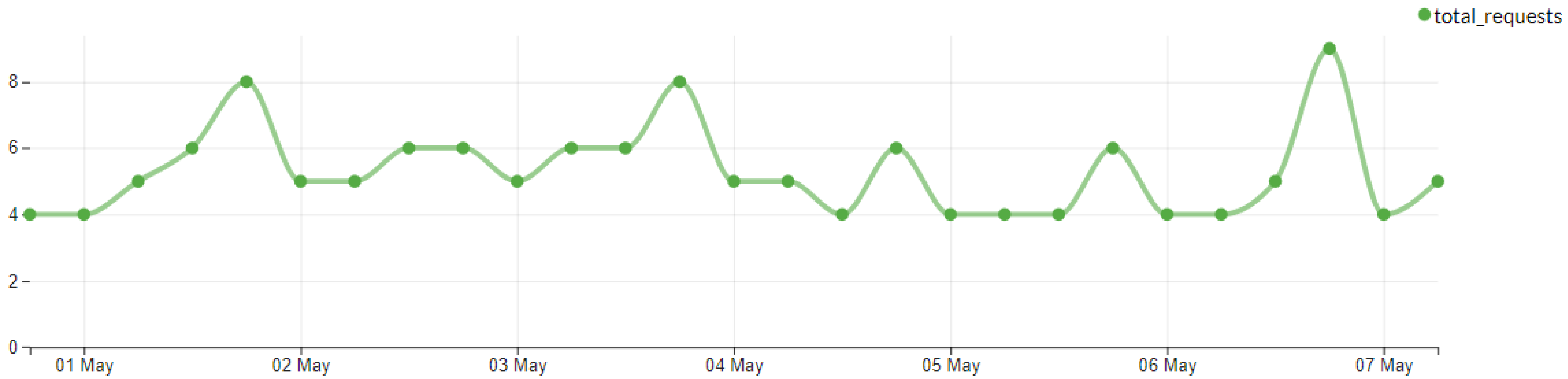

Patient flows and resource demand in hospitals



Weekly influx



Weely hospitalization requests



Technicalities

- Time series prediction
- Drift is the problem
- Mixture of Poisson + person-by-person probability estimation
- Ad-hoc customer metrics

- Ensembled algorithms
- Pool of candidate features
- Prepared for comm faults and data errors
- Ready to add external variables. Cost/benefit

- Infrastructure to continuously train, test & choose best configuration
- Customer specifics addressed via metadata

SOCIÉTÉ • CRISE DE L'HÔPITAL

Urgences : une nuit passée sur un brancard augmente de 40 % le risque de mortalité des pati

Every night spent on a stretcher increases mortality by 40%

Une étu quantifie les cons s populati e une alarme.

https://www.lemonde.fr/societe/article/2023/11/08/urgences-une-nuit-passee-sur-un-brancard-augmente-de-40-le-risque-de-mortalite-des-patients-ages_6199042_3224.html

Human factors and medication errors: a case study

Gluyas H, Morrison P (2014) Human factors and medication errors: a case study.
Nursing Standard. 29, 15, 37-42. Date of submission: August 22 2014; date of acceptance: September 30 2014.

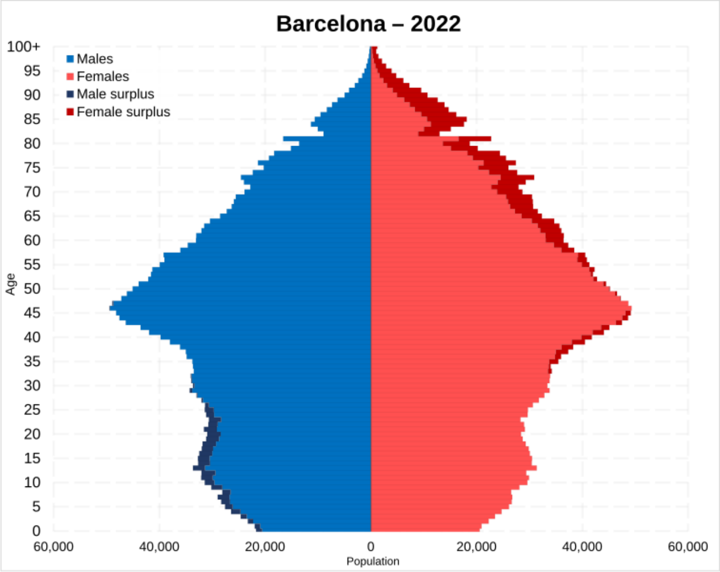
Human beings are error prone. A significant component of human error is flaws inherent in human cognitive processes, which are exacerbated by situations in which the individual making the error is distracted, stressed or overloaded, or does not have sufficient knowledge to undertake an action correctly. The scientific discipline of human factors

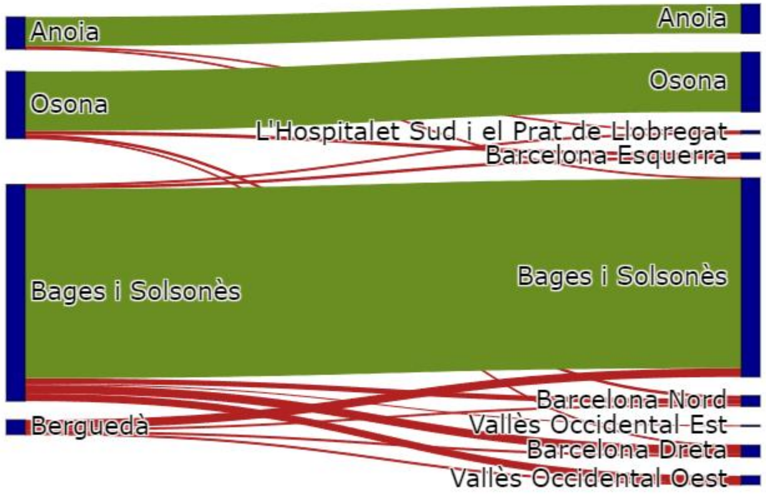
An analytical platform for population health

Activity $\neq$ Needs

Understand how patients are,
not only why they visit

Focus on patients at highest risk

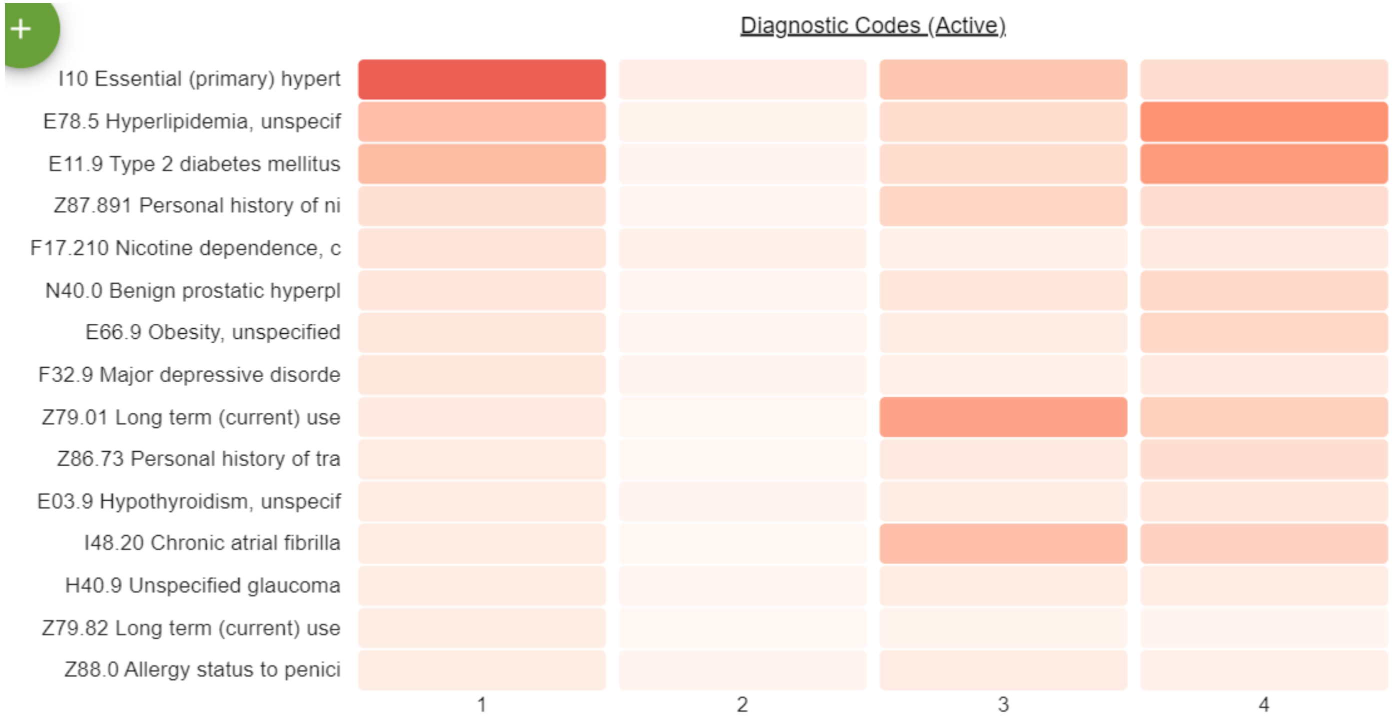




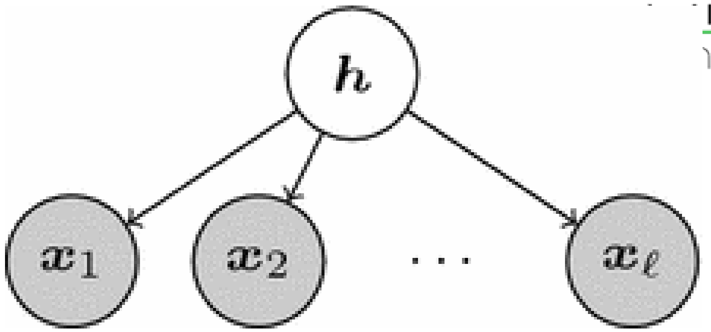
The analytical platform

Exploratory, non-prescriptive tool
4 algorithms:

- Patient clustering
- Association explorer
- Population comparison
- Flow analysis



Model-based clustering



Due to M. Ruffini, UPC PhD thesis (2019)

- Naïve Bayes model: $\Pr(x_i \mid h, x_j) = \Pr(x_i \mid h)$
- Tensor-based decomposition to extract parameters from data

Advantages:

- No curse of dimensionality
- One pass over the data
- (Mostly) deterministic
- Rigorous convergence guarantees
- And it works in practice: finds interesting clusters in real data

Use case:

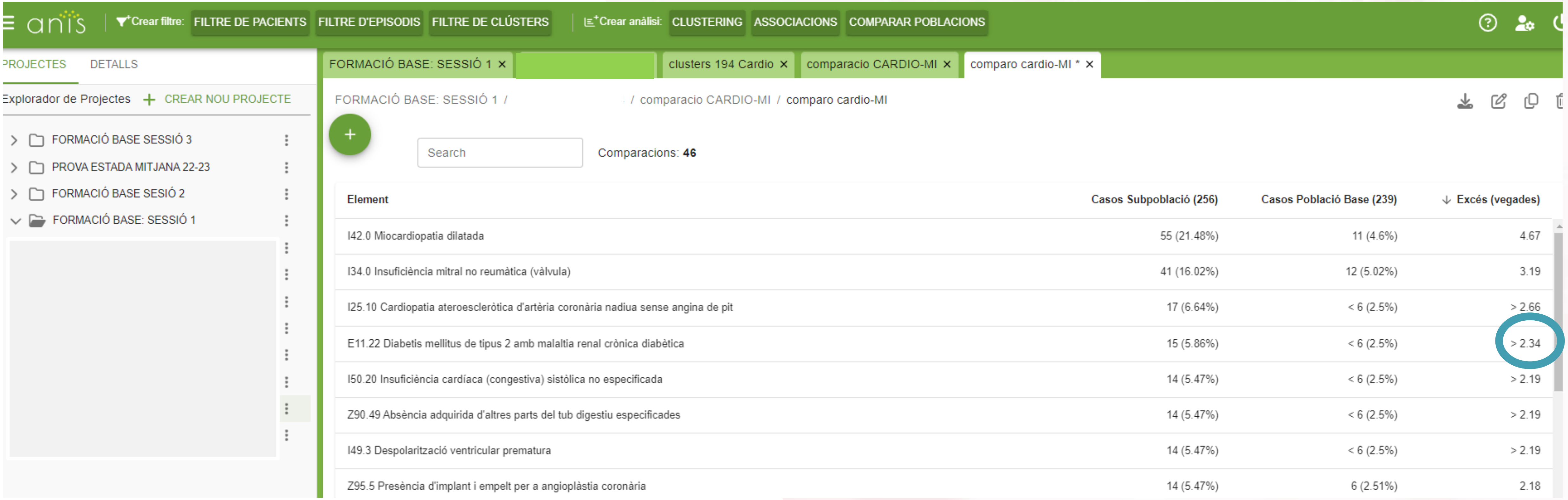
DRG analysis by department

DRG 194, chronic heart failure

Present both in Cardiology and Internal Medicine Department

With different profiles, and different results

Improve protocols for admission to one or the other

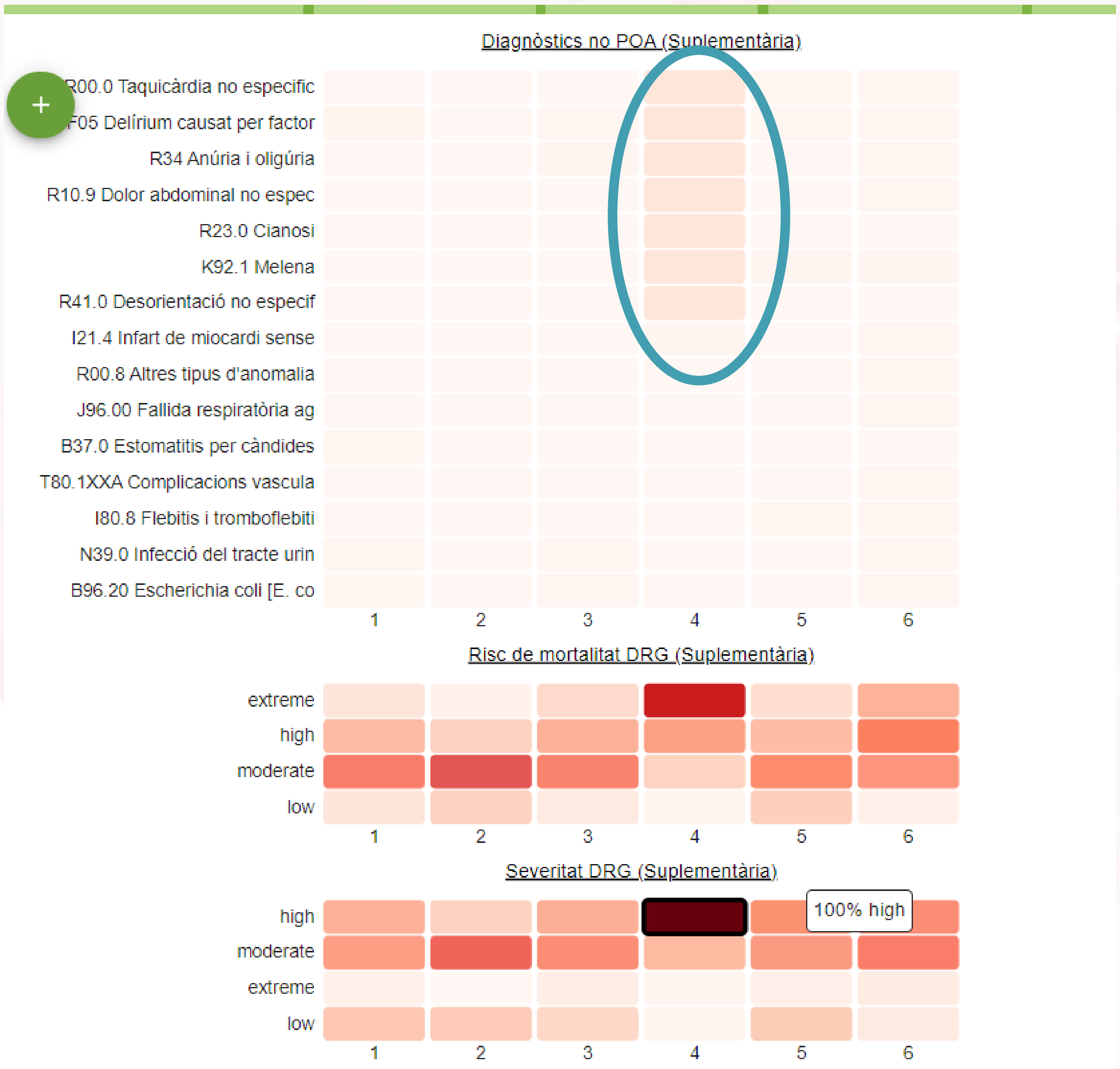


Use case:
Risk of complications

DRG 194, chronic heart failure

Identify groups at higher risk of in-hospital complications

Focus the prevention actions



Use case:
Length-of-stay analysis

For the 10 DRG with largest length-of-stay deviations:

- Explain and characterize length of stay

Potential savings of hundreds of bed days

anis — Crear filtre: FILTRE DE PACIENTS | FILTRE D'EPISODIS | FILTRE DE CLÚSTERS — Crear anàlisi: CLUSTERING | ASSOCIACIONS | COMPARAR POBLACIONS

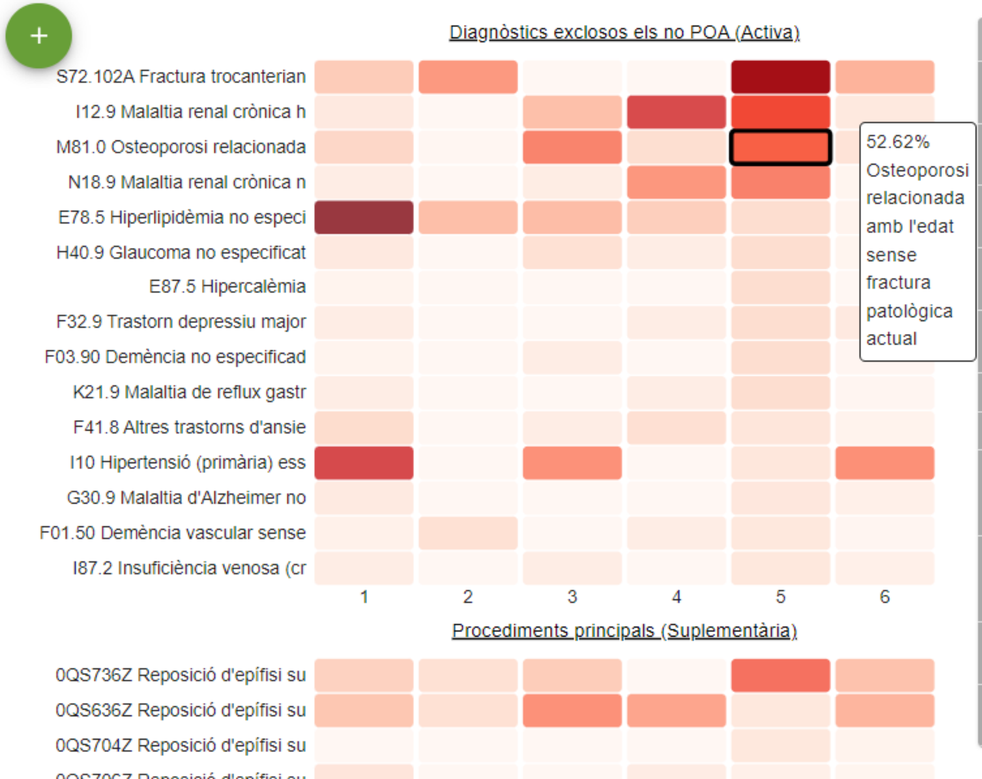
PROJECTES | DETALLS

Explorador de Projectes + CREAR NOU PROJECTE

FORMACIÓ BASE SESSIÓ 3

FORMACIÓ BASE: SESSIÓ 1 × | × | clusters 194 Cardio × | comparacio CARDIO-MI × | comparo cardio-MI × | FORMACIÓ BASE SESIÓ 2 × | analisi IC × | clusters 194 × | FORMACIÓ BASI

PROVA ESTADA MITJANA 22-23 / 2023 / 308 REPARA FX FEMUR / 308 reparacio fxf



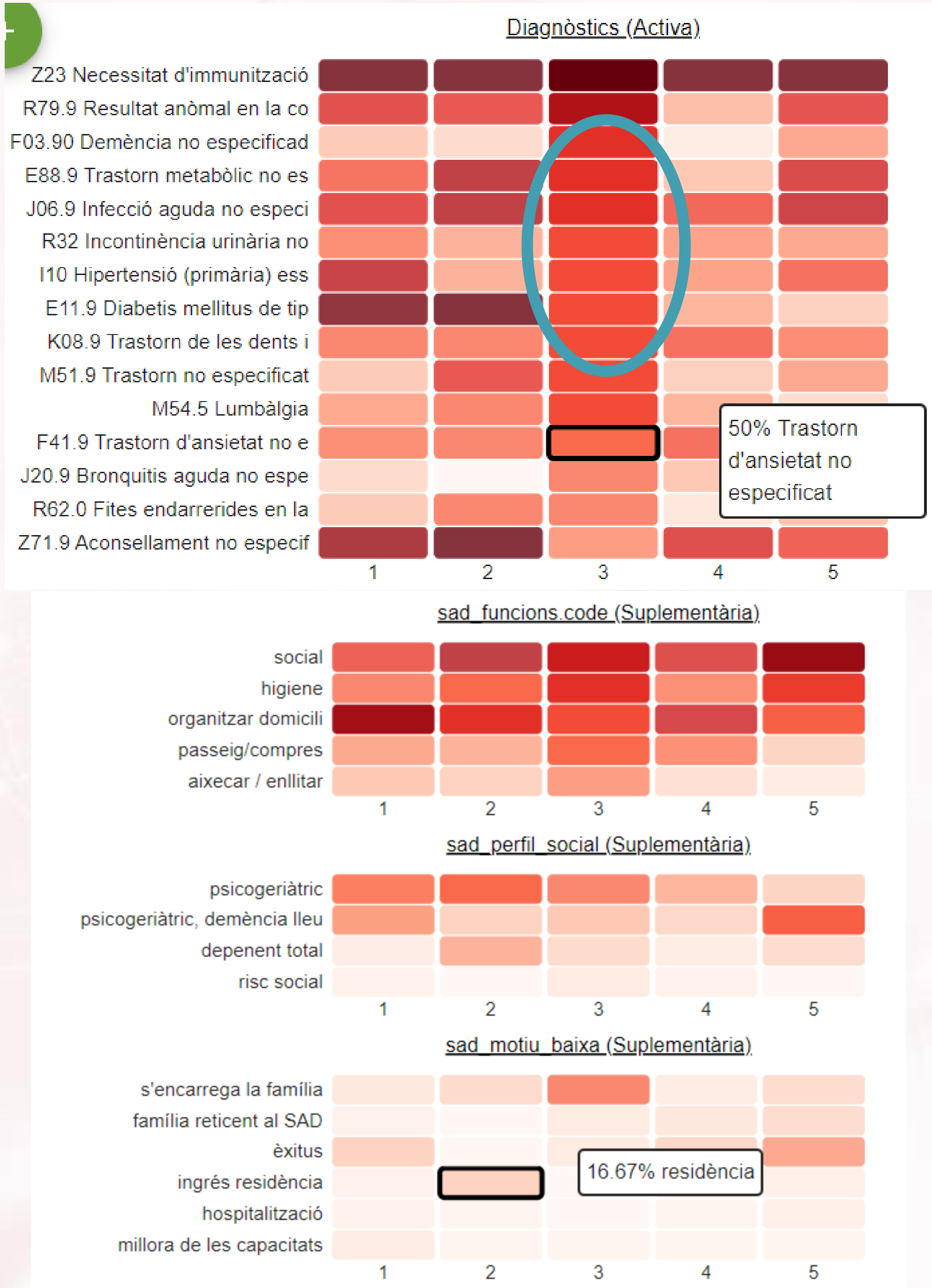
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Pacients (% del total)	43 (22.2%)	7 (3.6%)	14 (7.2%)	13 (6.7%)	19 (9.8%)	98 (50.5%)
Episodis (% del total)	44 (22.6%)	7 (3.6%)	14 (7.2%)	13 (6.7%)	19 (9.7%)	98 (50.3%)
Sexe (Dona, Home)	32 (74.4%), 11 (25.6%)	3 (42.9%), 4 (57.1%)	12 (85.7%), 2 (14.3%)	8 (61.5%), 5 (38.5%)	14 (73.7%), 5 (26.3%)	61 (62.2%), 37 (37.8%)
Mitjana d'edat (Dona, Home)	85.8 (86, 85.3)	83.7 (80.3, 86.2)	83.9 (83.7, 85.5)	77.6 (88, 61)	84.2 (86.7, 77)	75.9 (83.6, 63.4)
Estada mitjana (dies)	10.2	12.4	12.4	9.7	10.6	9.6
Èxitus	0 (0%)	0 (0%)	0 (0%)	1 (7.7%)	2 (10.5%)	3 (3.1%)
Derivacions	26 (60.5%)	5 (71.4%)	10 (71.4%)	6 (46.2%)	[illegible]	39 (39.8%)
Readmissions urgents a 7 dies	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Readmissions urgents a 30 dies	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Episodis amb diags. no POA	24 (54.5%)	5 (71.4%)	10 (71.4%)	7 (53.8%)	14 (73.7%)	48 (49%)
Mitjana de pes de GRD	1.3	1.5	1.4	1.3	1.5	1.3

Use case:
Rationalize home care

Coordinate use of different healthcare mechanisms + social care

Design better personalized plans
Identify premature dropout

Cluster 3, with a pattern of dementia, anxiety and breathing problems, has the highest dropout rate in less than 6 months, at 25%. It also has the most hours by home healthcare, and few by the social team, so coordination needs to be improved



Geppetto – LLM to improve UX

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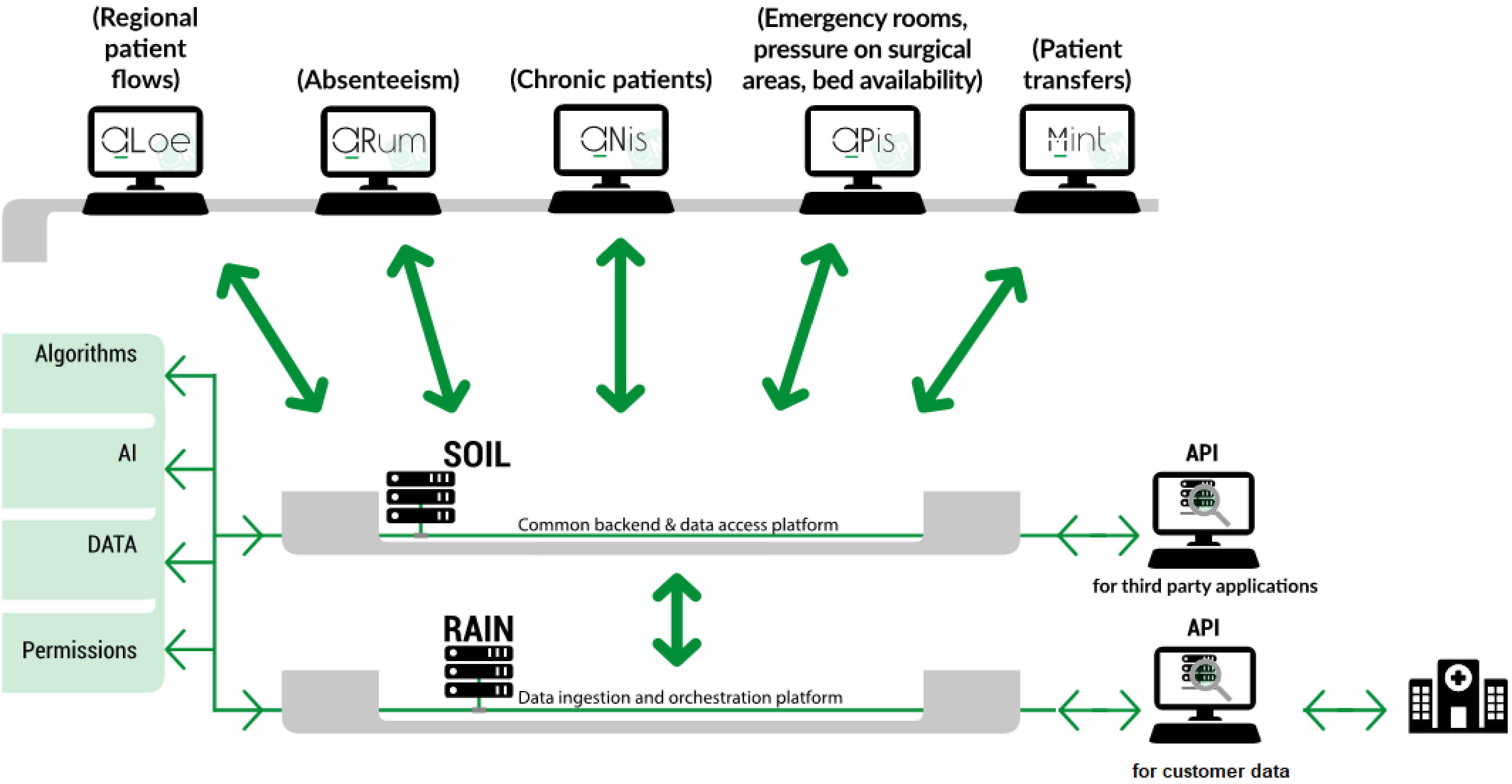
"Give me all patients over 35yo that have arrived for childbirth during 2023 or later, and that have been diagnosed as diabetics at least once"

```
age: ≥36
and
episodes:
   admission:
      time: ≥2023-01-01T00:00:00+01:00
   and
   diagnoses:
      code: ^O80.*
and
episodes:
   diagnoses:
      code: ^E10.*|^E11.*|^E12.*|^E13.*|^E14.*
```

Patient Filter: Patients aged 36 or older with a history of admission starting from January 1, 2023, and a diagnosis code that starts with "O80" (indicating a single spontaneous delivery). Additionally, these patients have a history of diagnoses where the code matches "E10", "E11", "E12", "E13", or "E14" (indicating various types of diabetes mellitus).

Architecture



From the lab to the hospital

Very small team for everything we need to do

No hard distinction data scientist / software engineer / devops
Everybody knows about everything (to some extent)

Pair programming, rotating pairs
Tests before code
An alert for each error in production
Once a task has been performed 3 times manually, it should be automatized

Everything customer-specific in metadata - possible to outsource non-core tasks
“Technical team size should be O(1)” - independent of number of customers

Wrap-up

Management problems as the easy way-in for AI in health

- Deploy in days, not months
- Avoid the silo problem
- Fewer ethical & regulatory concerns
- Result visible soon
- Make users' lives easier
- Fast adoption

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