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

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- 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



Who – Amalfi Analytics





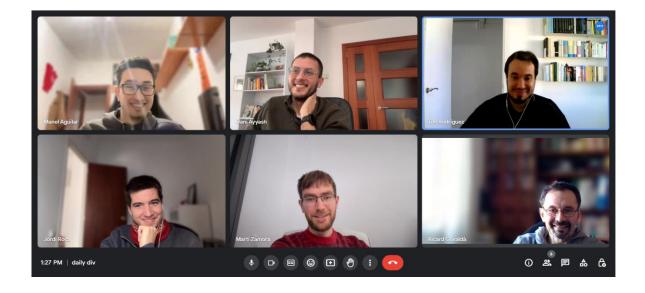
Ricard Gavaldà

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



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



EUROPEAN MUTUAL GROUP



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

Administrative Data: Minimum Basic Dataset

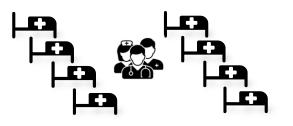


| Patient ID | Sex | Birth year | Zip code | Arrival time | Origin | Discharge time | Discharge status | Diagnostic list | Procedure list |
|------------|-----|---------------|----------|------------------|--------------|------------------|---------------------|-----------------|----------------|
| 31713575 | F | 1964 | 08028 | 01/01/2024 00:03 | Home | 06/01/2024 12:20 | Home | l21.0, F41.0 | 02703ZZ |
| 55556050 | Μ | 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 | Μ | 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





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



Predictive platform

• Support for operational decision making in hospitals

Analytical platform

• Support population health decisions

A predictive platform for hospitals



Predict and match:

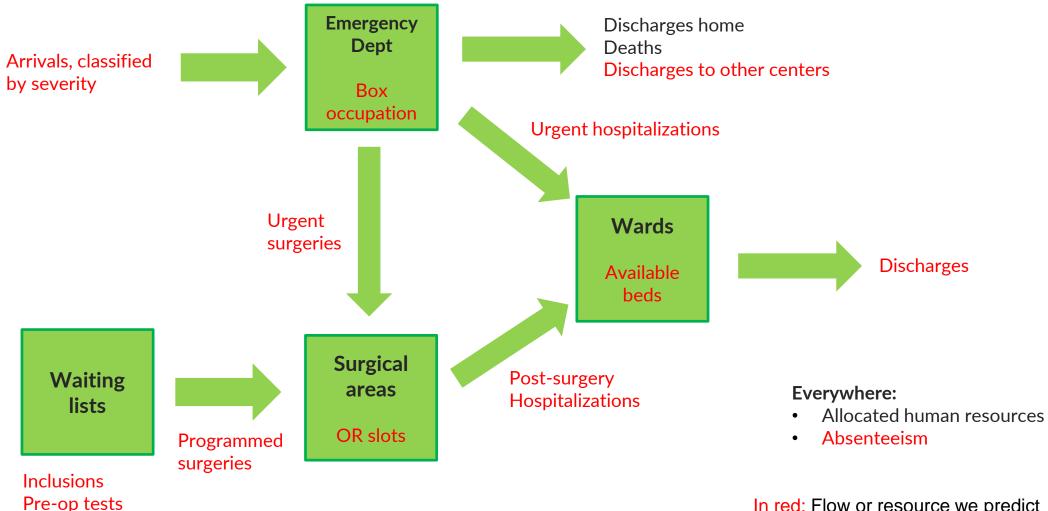
- Activity
- Resources needed
- Resources available

Goal: Anticipate rather than react



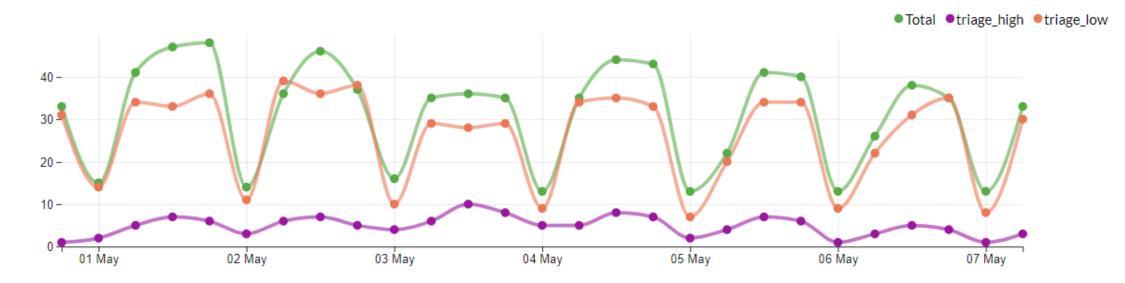
Patient flows and resource demand in hospitals



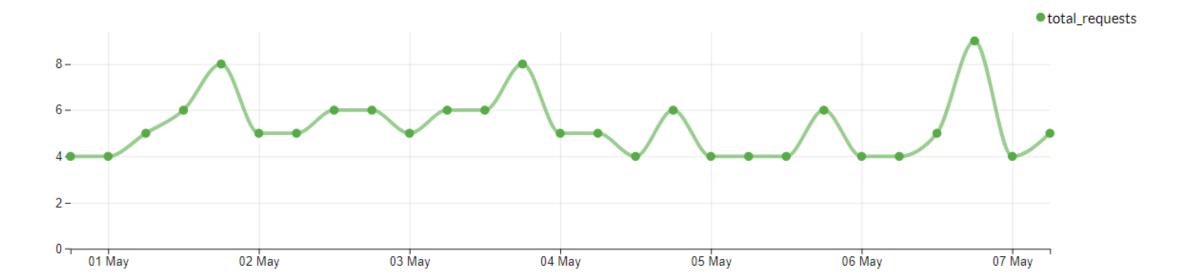


In red: Flow or resource we predict

Weekly influx



Weely hospitalization requests

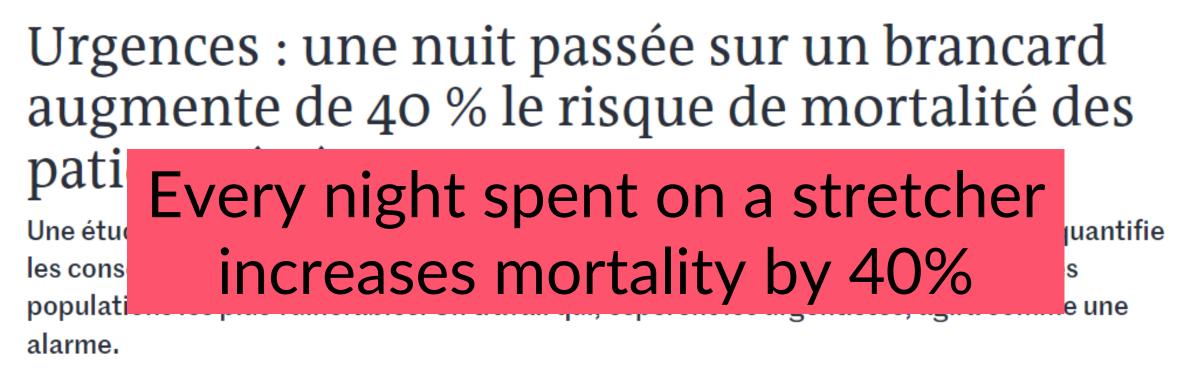


Technicalities



- 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



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.

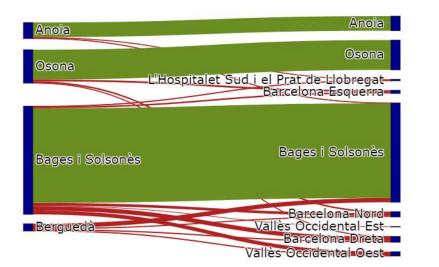
Human beings are error prone. A significant component of human error is flaws inherent in human cognitive processes, which are exacerbated by situations in which the individual making the error is distracted, stressed or overloaded, or does not have sufficient knowledge to undertake an action correctly.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

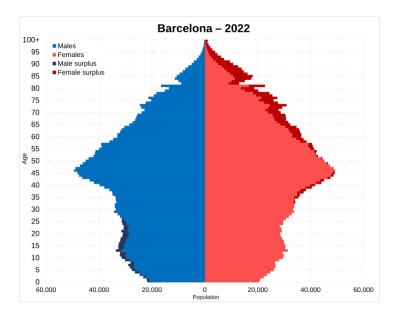
An analytical platform for population health

Activity \neq Needs

Understand how patients <u>are</u>, not only why they <u>visit</u>

Focus on patients at highest risk









The analytical platform



Exploratory, non-prescriptive tool 4 algorithms:

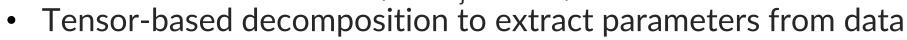
- Patient clustering
- Association explorer
- Population comparison
- Flow analysis

| + | | <u>Diagnostic Co</u> | <u>odes (Active)</u> | |
|--------------------------------|---|----------------------|----------------------|---|
| I10 Essential (primary) hypert | | | | |
| E78.5 Hyperlipidemia, unspecif | | | | |
| E11.9 Type 2 diabetes mellitus | | | | |
| Z87.891 Personal history of ni | | | | |
| F17.210 Nicotine dependence, c | | | | |
| N40.0 Benign prostatic hyperpl | | | | |
| E66.9 Obesity, unspecified | | | | |
| F32.9 Major depressive disorde | | | | |
| Z79.01 Long term (current) use | | | | |
| Z86.73 Personal history of tra | | | | |
| E03.9 Hypothyroidism, unspecif | | | | |
| 148.20 Chronic atrial fibrilla | | | | |
| H40.9 Unspecified glaucoma | | | | |
| Z79.82 Long term (current) use | | | | |
| Z88.0 Allergy status to penici | | | | |
| | 1 | 2 | 3 | 4 |

Model-based clustering

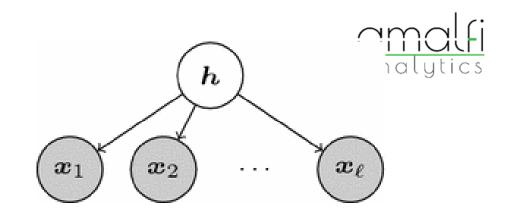
Due to M. Ruffini, UPC PhD thesis (2019)

• Naïve Bayes model: $Pr(x_i | h, x_j) = Pr(x_i | h)$



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

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analytics

With different profiles, and different results

Improve protocols for admission to one or the other

| | 6 FILTRE D'EPISODIS FILTRE DE CLÚSTERS | E ⁺ Crear anàlisi: CLUSTERING ASSOCIACIONS COMPARAR POBLACIONS | | | 3 🏞 🤇 |
|--|--|---|-------------------------|---------------------------|-------------------|
| PROJECTES DETALLS | FORMACIÓ BASE: SESSIÓ 1 × | clusters 194 Cardio × comparacio CARDIO-MI × comparo | cardio-MI * × | | |
| Explorador de Projectes + CREAR NOU PROJECTE | FORMACIÓ BASE: SESSIÓ 1 / | Comparacions: 46 | | | 🛓 Ľ () |
| > D FORMACIÓ BASE SESIÓ 2 | Element | | Casos Subpoblació (256) | Casos Població Base (239) | ↓ Excés (vegades) |
| V 🕞 FORMACIÓ BASE: SESSIÓ 1 | 142.0 Miocardiopatia dilatada | | 55 (21.48%) | 11 (4.6%) | 4.67 |
| | 134.0 Insuficiència mitral no reumàtica (vàlvu | la) | 41 (16.02%) | 12 (5.02%) | 3.19 |
| : | 125.10 Cardiopatia ateroescleròtica d'artèria | coronària nadiua sense angina de pit | 17 (6.64%) | < 6 (2.5%) | > 2.66 |
| | E11.22 Diabetis mellitus de tipus 2 amb mal | altia renal crònica diabètica | 15 (5.86%) | < 6 (2.5%) | > 2.34 |
| | I50.20 Insuficiència cardíaca (congestiva) si | stòlica no especificada | 14 (5.47%) | < 6 (2.5%) | > 2.19 |
| : | Z90.49 Absència adquirida d'altres parts del | tub digestiu especificades | 14 (5.47%) | < 6 (2.5%) | > 2.19 |
| | 149.3 Despolarització ventricular prematura | | 14 (5.47%) | < 6 (2.5%) | > 2.19 |
| | Z95.5 Presència d'implant i empelt per a ang | jioplàstia coronària | 14 (5.47%) | 6 (2.51%) | 2.18 |

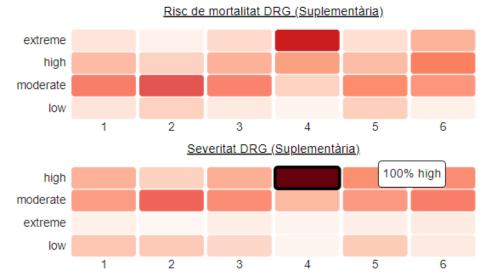
Use case: **Risk of complications**

DRG 194, chronic heart failure

Identify groups at higher risk of in-hospital complications

Focus the prevention actions

Diagnòstics no POA (Suplementària) R00.0 Taquicàrdia no especific 05 Delírium causat per factor R34 Anúria i oligúria R10.9 Dolor abdominal no espec R23.0 Cianosi K92.1 Melena R41.0 Desorientació no especif 121.4 Infart de miocardi sense R00.8 Altres tipus d'anomalia J96.00 Fallida respiratòria ag B37.0 Estomatitis per càndides T80.1XXA Complicacions vascula 180.8 Flebitis i tromboflebiti N39.0 Infecció del tracte urin B96.20 Escherichia coli [E. co 2



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Use case: Length-of-stay analysis

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

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analytics

• Explain and characterize length of stay

Potential savings of hundreds of bed days

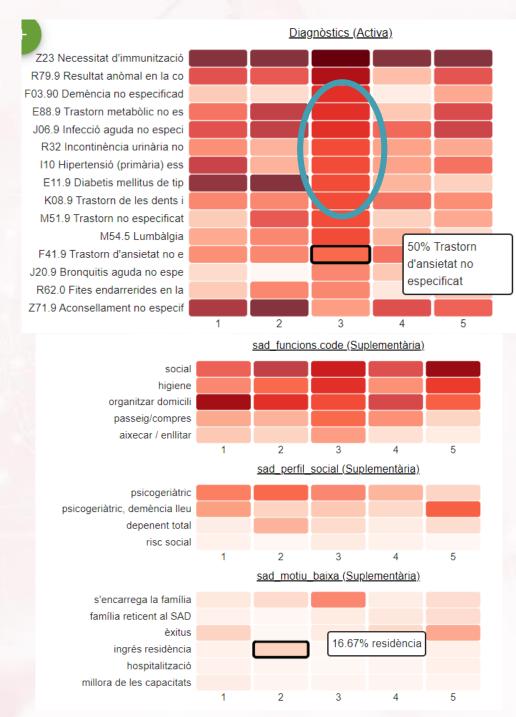
| ■ CINIS ▼ ⁺ Crear filtre: FILTRE DE PACIENTS F | ILTRE D'EPISODIS FILTRE DE CLÚSTERS | E ⁺ Crear | anàlisi: CLUSTE | RING ASSOC | CIACIONS C | OMPARAR POBLA | CIONS | | | | | | 2 |
|---|-------------------------------------|--|-----------------|---------------|------------|----------------------------|-------------------------------|---------------------------|-------------------------|-------------|---------------------------|--------------------------|-----------|
| ROJECTES DETALLS | FORMACIÓ BASE: SESSIÓ 1 × | | × clusters | 194 Cardio 🗙 | compara | cio CARDIO-MI × | comparo caro | io-MI × F | ORMACIÓ BASE | SESIÓ 2 × | analisi IC × | clusters 194 × | FORMACI |
| xplorador de Projectes + CREAR NOU PROJECTE | PROVA ESTADA MITJANA 22-23 / 202 | 23 / 308 REPA | RA FX FEMUR | / 308 reparac | io fxf | | | | | | | * | C P |
| V 🗁 FORMACIÓ BASE SESSIÓ 3 | + | Diagnòstics exclosos els no POA (Activa) | | | | | | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | Cluster 5 | Cluster 6 |
| | S72.102A Fractura trocanterian | | | | | | Pacients (% | 43 (22.2%) | 7 (3.6%) | 14 (7.2%) | 13 (6.7%) | 19 (9.8%) | 98 (50.5% |
| | 112.9 Malaltia renal crònica h | | | | | | del total) | 45 (22.270) | 7 (3.070) | 14 (1.270) | 13 (0.770) | 13 (3.076) | 50 (50.57 |
| | M81.0 Osteoporosi relacionada | | | | | 52.62% | Episodis (% del total) | 44 (22.6%) | 7 (3.6%) | 14 (7.2%) | 13 (6.7%) | 19 (9.7%) | 98 (50.3% |
| | N18.9 Malaltia renal crònica n | | | | | Osteoporosi relacionada | • | 22 (74 40/) | 2 (42 0%) 4 | 12 (85.7%), | 0.(01.50()).5 | 44 (72 70/) | 61 (62.2 |
| | E78.5 Hiperlipidèmia no especi | | | | | amb l'edat | Sexe (Dona, Home) | 32 (74.4%), 11 (25.6%) | 3 (42.9%), 4 (57.1%) | 2 (14.3%) | , 8 (61.5%), 5 (38.5%) | 14 (73.7%), 5 (26.3%) | 37 (37.8 |
| | H40.9 Glaucoma no especificat | | | | | sense | Mitjana d'edat | 85.8 (86, | 83.7 (80.3, | 83.9 (83.7, | 77.6 (88, 61 | 84.2 (86.7, | 75.9 (83 |
| | E87.5 Hipercalèmia | | | | | fractura patològica | (Dona, Home) | 85.3) | 86.2) | 85.5) | 11.0 (00, 01) | , 77) | 63.4) |
| | F32.9 Trastorn depressiu major | | | | | actual | Estada mitjana (dies) | 10.2 | 12.4 | 12.4 | 9.7 | 10.6 | 9.6 |
| | F03.90 Demència no especificad | | | | | | Èxitus | 0 (09() | 0 (09() | 0 (09/) | 4 (7 70/) | 2 (40 5%) | 2 (2 40/ |
| | K21.9 Malaltia de reflux gastr | | | | | | | 0 (0%) | 0 (0%) | 0 (0%) | 1 (7.7%) | 2 (10.5%) | 3 (3.1% |
| | F41.8 Altres trastorns d'ansie | | | | | | Derivacions | 26 (60.5%) | 5 (71.4%) | 10 (71.4%) | 6 (46.2%) |) | 39 (39. |
| | 110 Hipertensió (primària) ess | | | | | | Readmissions urgents a 7 | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) |
| | G30.9 Malaltia d'Alzheimer no | | | | | | dies | 0 (0 /0) | 0 (070) | 0 (070) | 0 (070) | 0 (070) | 0 (070) |
| | F01.50 Demència vascular sense | | | | | | Readmissions | | | | | | |
| | 187.2 Insuficiència venosa (cr | 1 2 | 3 | 4 | 5 | 6 | urgents a 30 dies | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) |
| | | Procediments principals (Suplementària) | | | | | | | | | | | |
| | 0QS736Z Reposició d'epífisi su | | | | | | Episodis amb diags. no POA | 24 (54.5%) | 5 (71.4%) | 10 (71.4%) | 7 (53.8%) | 14 (73.7%) | 48 (49% |
| | 0QS636Z Reposició d'epífisi su | | | | | | Mitjana de | 1.3 | 1.5 | 1.4 | 12 | 1.5 | 1.3 |
| | 0QS704Z Reposició d'epífisi su | | | | | | pes de GRD | 1.0 | 1.5 | 1.4 | 1.3 | 1.0 | 1.0 |
| | | | | | | | | | | | | | |

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



"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.* | × Q 3 | |
|--|---|-------|--|
|--|---|-------|--|

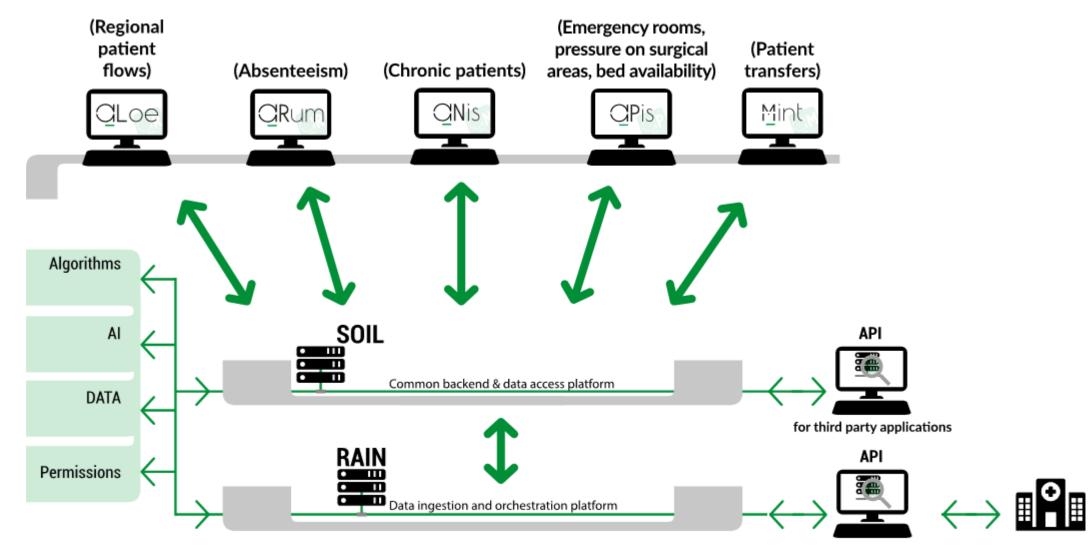
Patients aged 36 or older with a history of admission starting from January 1, 2023, and a diagnosis code that Patient starts with "O80" (indicating a single spontaneous delivery). Additionally, these patients have a history of Filter: diagnoses where the code matches "E10", "E11", "E12", "E13", or "E14"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

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Architecture





for customer data



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 <u>metadata</u> - possible to outsource non-core tasks "Technical team size should be O(1)" - independent of number of customers



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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