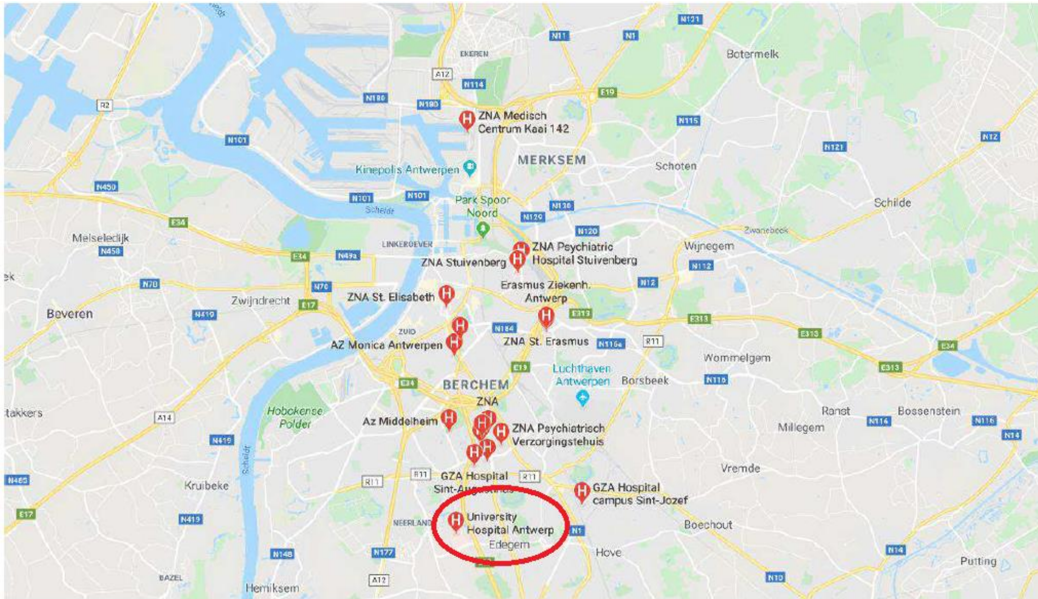
AI
success stories

CIONET Belgium virtual event – 2/06/2020

Case of Antwerp University Hospital

Antwerp University Hospital



Resultaten medisch

30.372
verblijven met overnachting

48.391
daghospitalisaties

18.364
operaties

714.423
raadplegingen en technische verstrekkingen

Resultaten financieel

€ 432.5 miljoen
totale bedrijfsopbrengsten

€ 372.5 miljoen
omzet

€ 14.8 miljoen
resultaat van het boekjaar

Strategy

2020 – the year of creativity – 12 big development areas

Big Data: a UZA data hub will be developed to allow our own datascientist build up knowlegde from our data through machine learning and AI.

AI strategy:

- Integrate game changing commercial AI solutions into our existing application landscape to optimize patient care
- Create our own algoritmes from our own data together with partners to innovate our organization and processes.

Own (success?) stories

1. Early detection of brain injury and Sepsis for neonates

2. Early prediction of ER outcomes

Early detection of brain injury and Sepsis for neonates

Early detection of brain injury and Sepsis for neonates

At Neonatology we care for the ill and premature newborn infants. They are the most fragile human beings. Every detail in the treatment is crucial.

We focus on the pathology of brain injury and sepsis (blood-poisoning) as these are the major mortality threats at the NICU.

Partnership between UZA, UA and Innocense supported by ML6

Early detection of brain injury and Sepsis for neonates

Today, we apply the sick-cure model:

- Exam patient daily at fixed timing
- Tiny “snaphot” of available data
- Initiate treatment when overt signs/alarms of sickness

Tomorrow, we want to apply proactive care through an AI based 24/7 decision support system.

Tomorrow is not there yet!

Early detection of brain injury and Sepsis for neonates

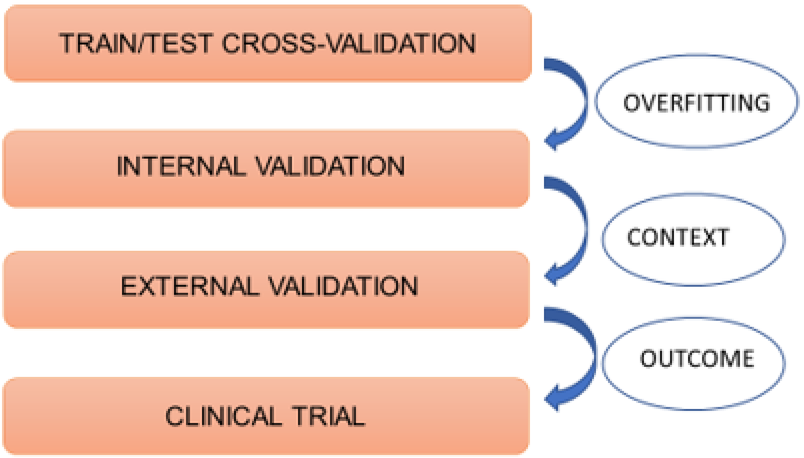
Datasources:

- Vitalsigns: second to second data
- Structured diagnosis reporting
- Structured labtest results

Time series Classification:

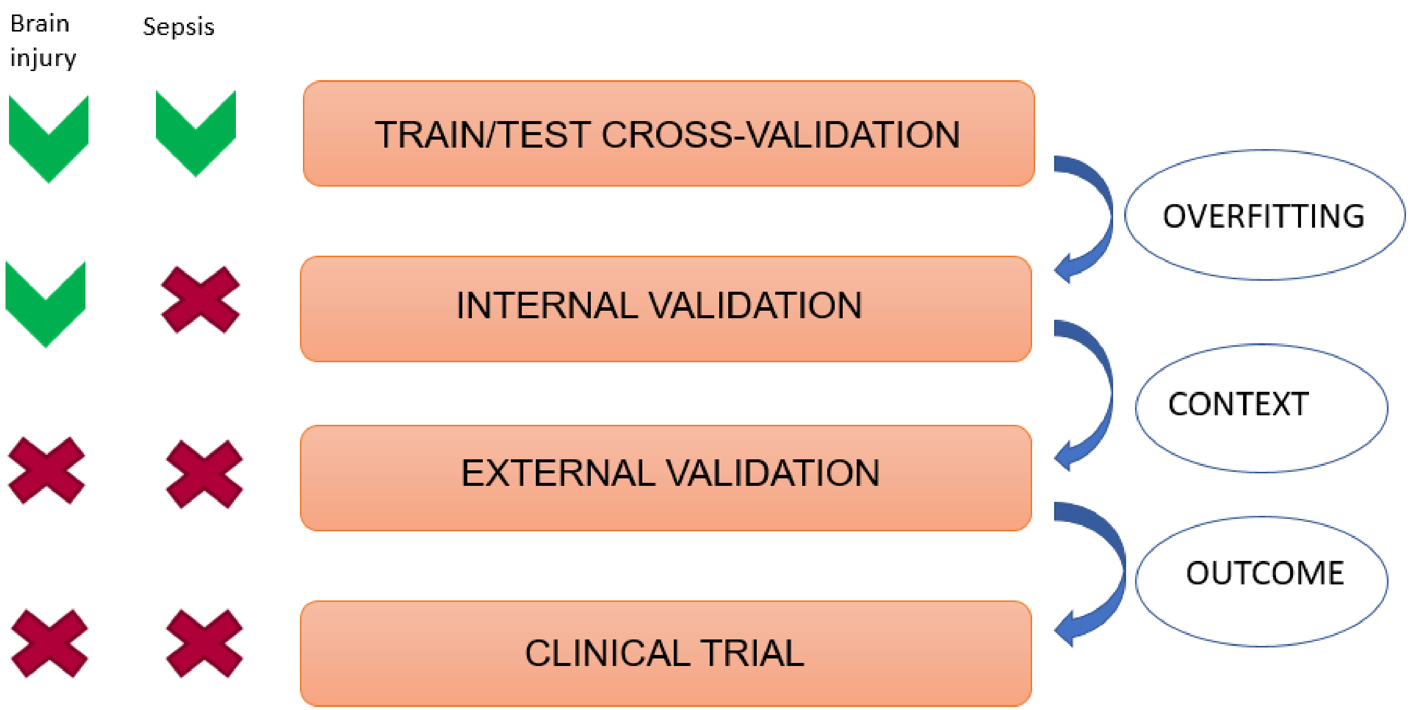
- UZA dataset (10yrs Time series vital signs & annotated)
- Supervised ML algorithms (Patterns in vital signs)
- Continuous prediction (Rolling window perfomance)

Trained classifier: validation cycle



Early detection of brain injury and Sepsis for neonates

VALIDATION TRAJECTORY ML MODELS



Early detection of brain injury and Sepsis for neonates

Architecture of the 24/7 AI based decisionsupport

- On premise solution for realtime decisionsupport
  - Edge device integrated in the UZA application landscape
- Cloud infrastructure for learning and retraining models
  - Piloting the big three (AWS, Google and MS)

Early prediction of ER outcomes

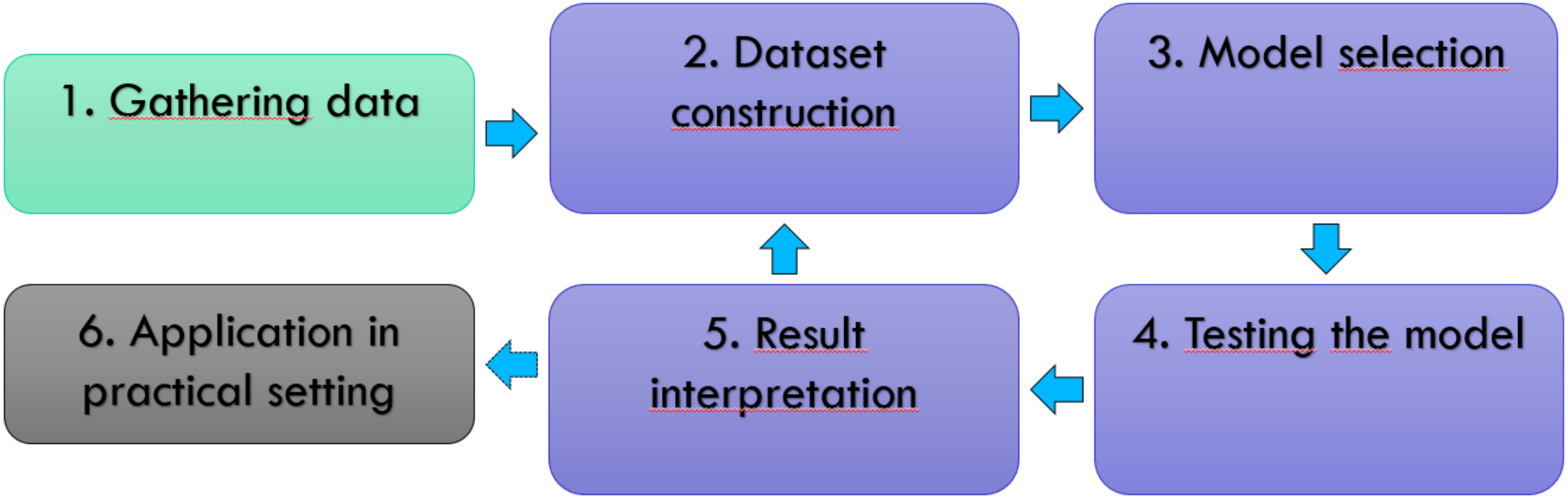
Early prediction of ER outcomes

At the Emergency Department, we care for all the urgent and critical cases. Speed and accuracy are of the essence. Alignment with rest of hospital is a necessity.

When a patient is admitted into the ER, we would like to know if the patient needs to remain in the hospital, the duration of that stay, and the specialism in which the patient will be admitted.

Early prediction of ER outcomes

Model development overview



Early prediction of ER outcomes

Gathering the data:

- Translating the outcome definition to tangible, measured data sources.
- Overview of available sources
  - Availability scope: has data been consistently recorded over the entire period?
- Determining time and sample scope for dataset
  - Which population do we select? Is historical population representative for current patients?

Early prediction of ER outcomes

Data construction:

- Determining an appropriate data model
  - Prediction over time windows, with an iteratively larger window
- Data source representation
  - Feature density, reliability, availability
- Feasibility check of data model when applied in practice
  - Can I represent a currently active patient in the same way?

Early prediction of ER outcomes

Model selection:

- Dataset variants
  - Multiple combinations of input sources to assess complementarity
- Appropriate machine learning model
  - Considering dataset type and size
  - Start with a simple model, with as little assumptions a priori
  - Interpretability of how the chosen model makes predictions
- Additional techniques
  - (Automated) feature selection
  - (Training) sample selection for training

Early prediction of ER outcomes

Current pipeline:

- Multi-class prediction
  - Each source represented as a list of features (with meta-features), with a cutoff in timeframes.
- Multiple machine learning algorithms tested
  - Random Forests (RF)
  - Multi-layer perceptron (deep learning)
  - XGBoost (extreme gradient boosting trees)
- Algorithm selection based on robustness for sparse, large feature matrix

Early prediction of ER outcomes

Testing the model:

- Measuring the performance with metrics
  - Find all patients transferred to the ICU?
  - All predictions for ICU transfer need to be correct?
  - Determined by application in practice!
- Testing environment
  - Strict separation between samples where we train with and samples we test with.
  - Multiple iterations to reduce possibility of ‘lucky’ results

Early prediction of ER outcomes

Result interpretation:

- Evaluating how well your model fits the data
  - Graphical representation
  - Comparing several models
  - Looking into features that the model picked up
- Rinse and repeat
  - Bad results show corrections needed in dataset, selected model, ..

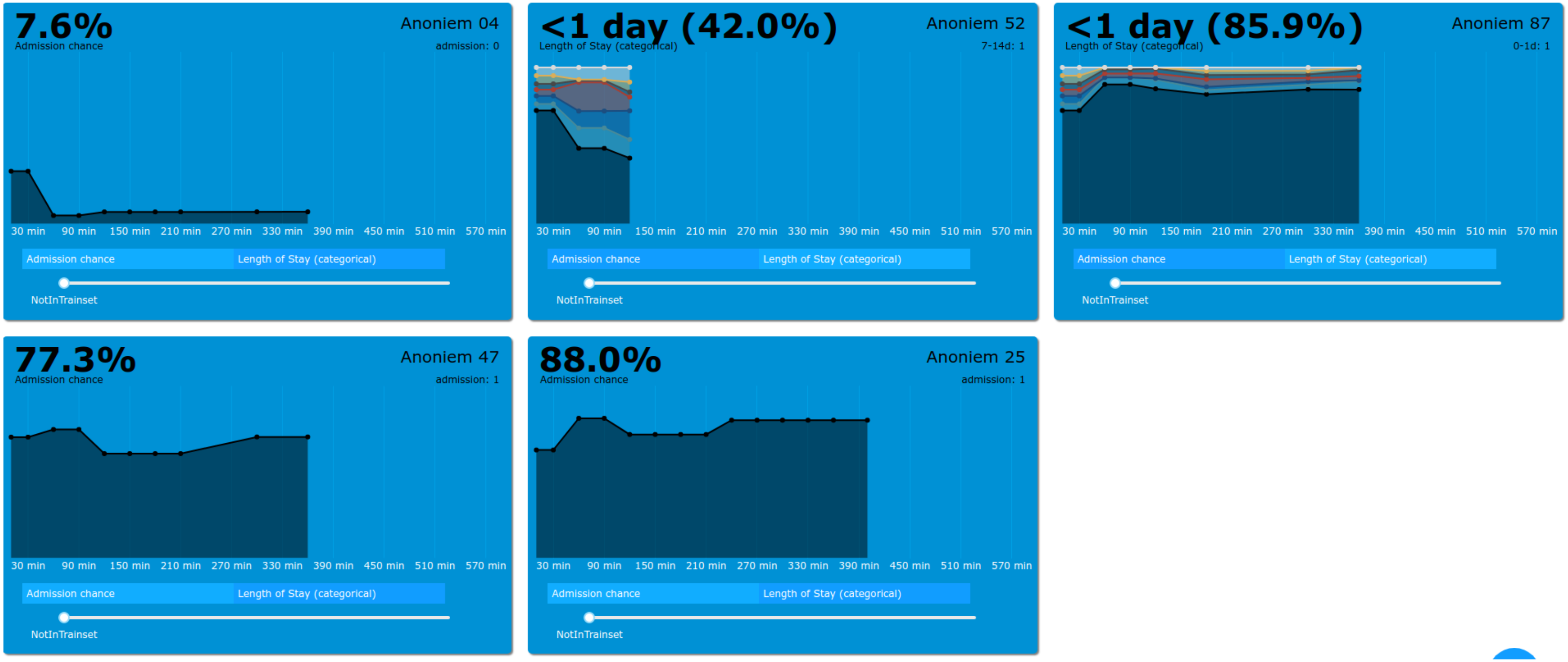
Early prediction of ER outcomes

Actual results:

- Length of stay is correctly predicted for 76,4% of the patients after 60 minutes (77,5% after 360 minutes).
- Type of stay is correctly predicted for 84,7% of the patients after 60 minutes (89,6% after 360 minutes).
- The specialties after a patient's ER visit can be determined with an micro-averaged F-measure of 37,3% after 60 minutes (44,7% after 360 minutes).
- The specific specialties that are being predicted vary widely in score: Cardiology, ICU, and obstretics can be predicted with a certainty of over 60% after 360 minutes.

Early prediction of ER outcomes

Hummingbird



Conclusions

Conclusion

- Big data vs. Relevant data
- Huge effort to prepare datasets for training. Domain knowledge is key.
- Choice of model is crucial. Experience in machine learning is necessity
- Normalising data into dataleaks/warehouses to ensure continuous machine learning development is possible.
- Datascientist are crucial… but hard to find!