Al for Patient Support:



Predictive Model of Medication Non-Adherence

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Abstract

Adherence in medicine is a measure of how well a patient follows his treatment. Not following the medication plan is actually a major issue as it was underlined in the World Health Organization's reports^{*}. They point out that, in developed countries, only about **50% of patients with chronic diseases correctly follow their treatments**. This severely compromises the efficiency of long-term therapy and increases the cost of health services.

The SNIIRAM Database

. The SNIIRAM Database: records of real reimbursement data from the French health system. As it covers 98.8% of the French population (66M persons), it is possibly the world's **largest** continuous homogeneous claims database with **no biais**.

. The database includes demographic data; health care encounters such as physician or paramedical visits, medicines, medical devices, and lab tests (without results); chronic medical conditions (ICD10 codes); hospitalisations with ICD10 codes for primary, linked and associated diagnoses, date and duration, procedures, diagnostic-related groups, and cost coding; date but currently not cause of death.

This poster reports our work on **modeling patient drug consumption** in breast cancer treatments. We compare different approaches to study patient's paths: one drug-phase centered and one patient centered. Different machine-learning solutions are compared to predict medication non-adherence. They show the ability of the AI to estimate a risk score of a patient's nonadherence and thus improve support throughout their care path.

*: http://www.who.int/chp/knowledge/publications/adherence_full_report.pdf

Phase analysis

. Raw data are processed to phase that allows the reconstruction of the patient's care paths.



. Focus on **women's breast cancer**:

our cohort is composed of 50% of women, diagnosed with breast cancer, having purchased Tamoxifen between 2013 and 2015. . Raw data are processed to phase that allows the reconstruction of the patient's care paths.

Drug transaction analysis

. A **patient-centered approach** focused on all transactions carried out by a patient: every purchase in a pharmacy, every hospitalization,... Solutions using Recurrent Neural Networks (RNN) are explored to use **temporal information** to improve our predictions, especially LSTM (Hochreiter and Schmidhuber [1997]) and GRU (Cho et al. [2014]).

. **Kaplan-Meier Estimator**: (or product-limit estimator) probability of surviving in a given length of time while considering time in many small intervals.

. Hazard function can be derivated from Kaplan-Meier estimator: Roughly characterizes the « **instantaneous probability** » of a drug drop-out at time t

. Cox regression: estimates the **effect of each characteristic** to the study phenomena as an Hazard Ratio (HR)

(HR = 1: no effect; HR < 1: reduction in hazard; HR > 1: increase in hazard)



Variable	HR
CMU-C	1.47
ACS	1.52
Time since ALD status	1.08
Number of medical consultation	0.99
Psychiatric illness	1.19
Recent hospitalization for malignant	0.68
neoplasms of breast	
Previous treatment: Tamoxifen	2.49
Previous treatment: radiotherapy	0.49
Previous treatment: chemotherapy	0.42

. Insight of Cox regression into Kaplan-Meier estimator: Use of information about the patient to compute more accurate survival



. We always obtain a score that allows targeting efficiently a patient with an AUC of 0.82. The CAP curve indicates that, within the first 20% of the surveyed population ranked from the highest to the lowest risk estimated, our models **target 66% of illegitimate stops** of all transactions. This is three times as effective than the current random model currently used by the French Health Services to target patients at risk. This validates our hypothesis that last transactions convey information to detect an illegitimate stop. As French Health Services have a limited number of hours to call patients for support, our model could **double** their efficiency and could be used to **trigger** an SMS based system to contact and motivate a high-risk patient.

<u>Conclusion</u>

functions



. Test of machine-learning algorithms (Logistic regression, Decision tree, gradient boosting, MLP) obtain a 0.7 AUC when predicting an **illegitimate stop after 3/6/12 months** in a phase

. The results obtained with simple models on indirect observations from SNIIRAM (reimbursement data) prove the feasibility to estimate the risk of an illegitimate drug drop-out. . First results are validated with feedbacks from oncologists and medical researchers.

.Our approaches also aim to be coherent with patients' care-paths: we show that we could notify caregivers of the potential risk of a drug drop-out at specific moments of the treatment. This allows to provide a more efficient support at appropriate times while avoiding stress resulting from too frequent unnecessary contacts and limiting the waste of resources for low-risk patients.



