An AI Walk from Pharmacokinetics to Marketing

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**INTRODUCTION**

This work is intended for providing a review of real-life practical applications of Artificial Intelligence (AI) methods. We focus on the use of Machine Learning (ML) methods applied to rather real problems than synthetic problems with standard and controlled environment. In particular, we will describe the following problems in next sections:

- Optimization of Erythropoietin (EPO) dosages in anaemic patients undergoing Chronic Renal Failure (CRF).
- Optimization of a recommender system for citizen web portal users.
- Optimization of a marketing campaign.

The choice of these problems is due to their relevance and their heterogeneity. This heterogeneity shows the capabilities and versatility of ML methods to solve real-life problems in very different fields of knowledge. The following methods will be mentioned during this work:

- Artificial Neural Networks (ANNs): Multilayer Perceptron (MLP), Finite Impulse Response (FIR) Neural Network, Elman Network, Self-Organizing Maps (SOMs) and Adaptive Resonance Theory (ART).
- Other clustering algorithms: K-Means, Expectation-Maximization (EM) algorithm, Fuzzy C-Means (FCM), Hierarchical Clustering Algorithms (HCA).
- Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH).
- Support Vector Regression (SVR).
- Collaborative filtering techniques.
- Reinforcement Learning (RL) methods.

**BACKGROUND**

The aim of this communication is to emphasize the capabilities of ML methods to deliver practical and effective solutions in difficult real-world applications. In order to make the work easy to read we focus on each of the three separate domains, namely, Pharmacokinetics (PK), Web Recommender Systems and Marketing.

**Pharmacokinetics**

Clinical decision-making support systems have used Artificial Intelligence (AI) methods since the end of the fifties. Nevertheless, it was only during the nineties that decision support systems were routinely used in clinical practice on a significant scale. In particular, ANNs have been widely used in medical applications the last two decades (Lisboa, 2002). One of the first relevant studies involving ANNs and Therapeutic Drug Monitoring was (Gray, Ash, Jacobi, & Michel, 1991). In this work, an ANN-based drug interaction warning system was developed with a computerized real-time entry medical records system. A reference work in this field is found in (Brier, Zurada, & Aronoff, 1995), in which the capabilities of ANNs and NONMEN are benchmarked.
Focusing on problems that are closer to the real-life application that will be described in next section, there are also a number of recent works involving the use of ML for drug delivery in kidney disease. For instance, a comparison of renal-related adverse drug reactions between rofecoxib and celecoxib, based on the WHO/Uppsala Monitoring Centre safety database, was carried out by (Zhao, Reynolds, Lejkowith, Whelton, & Arellano, 2001). Disproportionality in the association between a particular drug and renal-related adverse drug reactions was evaluated using a Bayesian confidence propagation neural network method. A study of prediction of cyclosporine dosage in patients after kidney transplantation using neural networks and kernel-based methods was carried out in (Camps et al., 2003). In (Gaweda, Jacobs, Brier, & Zurada, 2003), a pharmacodynamic population analysis in CRF patients using ANNs was performed. Such models allow for adjusting the dosing regime. Finally, in (Martín et al., 2003), the use of neural networks was proposed for the optimization of EPO dosage in patients undergoing anaemia connected with CRF.

**Web Recommender Systems**

Recommender systems are widely used in web sites including Google. The main goal of these systems is to recommend objects which a user might be interested in. Two main approaches have been used: content-based and collaborative filtering (Zukerman & Albrecht, 2001), although other kinds of techniques have also been proposed (Burke, 2002).

Collaborative recommenders aggregate ratings of recommendations of objects, find user similarities based on their ratings, and finally provide new recommendations based on inter-user comparisons. Some of the most relevant systems using this technique are GroupLens/NetPerceptions and Recommender. The main advantage of collaborative techniques is that they are independent from any machine-readable representation of the objects, and that they work well for complex objects where subjective judgements are responsible for much of the variation in preferences.

Content-based learning is used when a user’s past behaviour is a reliable indicator of his/her future behaviour. It is particularly suitable for situations in which users tend to exhibit idiosyncratic behaviour. However, this approach requires a system to collect relatively large amounts of data from each user in order to enable the formulation of a statistical model. Examples of systems of this kind are text recommendation systems like the newsgroup filtering system, NewsWeeder, which uses words from its texts as features.

**Marketing**

The latest marketing trends are more concerned about maintaining current customers and optimizing their behaviour than getting new ones. For this reason, relational marketing focuses on what a company must do to achieve this objective. The relationships between a company and its customers follow a sequence of action-response system, where the customers can modify their behaviour in accordance with the marketing actions developed by the company.

The development of a good and individualized policy is not easy because there are many variables to take into account. Applications of this kind can be viewed as a Markov chain problem, in which a company decides what action to take once the customer properties in the current state (time $t$), are known. Reinforcement Learning (RL) can be used to solve this task since previous applications have demonstrated its suitability in this area. In (Sun, 2003), RL was applied to analyse mailing by studying how an action in time $t$ influences actions in following times. In (Abe et al., 2002) and (Pednault, Abe & Zadrozny, 2002), several RL algorithms were benchmarked in mailing problems. In (Abe, 2004), RL was used to optimize cross channel marketing.

**AI CONTRIBUTIONS IN REAL-LIFE APPLICATIONS**

Previous section showed a review of related work. In this section, we will focus on showing authors’ experience in using AI to solve real-life problems. In order to show up the versatility of AI methods, we will focus on particular applications from three different fields of knowledge, the same that were reviewed in previous section.

**Pharmacokinetics**

Although we have also worked with other pharmacokinetic problems, in this work, we focus on maybe the most relevant problem, which is the