ORIGINAL ARTICLE

Machine Learning for Predicting Patient Wait Times and Appointment Delays

Catherine Curtis, MS[a], Chang Liu, MS[a], Thomas J. Bollerman, MS[a], Oleg S. Pianykh, PhD[a]

Abstract

Being able to accurately predict waiting times and scheduled appointment delays can increase patient satisfaction and enable staff members to more accurately assess and respond to patient flow. In this work, the authors studied the applicability of machine learning models to predict waiting times at a walk-in radiology facility (radiography) and delay times at scheduled radiology facilities (CT, MRI, and ultrasound). In the proposed models, a variety of predictors derived from data available in the radiology information system were used to predict waiting or delay times. Several machine-learning algorithms, such as neural network, random forest, support vector machine, elastic net, multivariate adaptive regression splines, *k*-th nearest neighbor, gradient boosting machine, bagging, classification and regression tree, and linear regression, were evaluated to find the most accurate method. The elastic net model performed best among the 10 proposed models for predicting waiting times or delay times across all four modalities. The most important predictors were also identified.

Key Words: Machine learning, radiology information system, regression, predictive model, operations management, elastic net

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INTRODUCTION

Being able to accurately predict waiting times and scheduled appointment delays can increase patient satisfaction and enable staff members to more accurately assess and respond to patient flow [1,2].

A few studies have already acknowledged the importance of this issue and proposed models attempting to predict waiting time by using a range of statistical methods. For example, linear regression on the basis of the current time and mean wait time of the past three and past five patients seen immediately prior has been suggested [3]. However, limited numbers of predictors often lead to considerable discrepancies between predicted and actual waiting times, as we demonstrate later in this report. Predicting wait time on the basis of patient acuity category, patient queue sizes, and flow rates has been investigated [4] with quantile regression to provide patients with a range of expected values, from the median to the 95th percentile. Range outputs are much more likely to include the true waiting time than a single predicted value. However, the width of the prediction intervals can render them ultimately unhelpful in assuaging patient concerns about lack of waiting time information.

In our previous research, we have already developed predictive models that use current and recent patient waiting line sizes [5]. With our models, we created applications that show estimated waiting times on displays visible in the reception areas in our hospital. One year after the implementation, we conducted a survey to gauge patients' opinions of the waiting time displays over the course of 10 days. Most (82% of those surveyed) liked the displays and wanted to see them expanded to all waiting rooms [2]. We noticed that most patients who were dissatisfied with the displayed waiting times were delayed for longer than predicted, so the need for more accurate models became imminent. We also wanted to predict not only waiting times for the walk-in facilities (our original design) but also delays for the scheduled facilities.

To achieve this goal, we needed more sophisticated and flexible algorithms, and machine learning (ML) was a very logical choice. We also knew that ML could be one

[a]Department of Radiology, Massachusetts General Hospital, Boston, Massachusetts.

Corresponding author and reprints: Oleg S. Pianykh, PhD, Department of Radiology, Massachusetts General Hospital, 25 New Chardon Street, Office #470, Boston, MA 02114; e-mail: opianykh@mgh.harvard.edu.

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of the best practical ways of dealing with the extreme complexity and randomness of wait and delay time patterns. At its core, ML provides a set of tools for efficient data mining and modeling, especially for large and imperfect data sets [6-9]. Models built with ML have the ability to reflect sophisticated trends that are hard to capture with conventional regression approaches. They also can resist noise and abnormal outliers, adapt to changing environments, and run without human supervision. As a result, the ultimate objective of this work was to create a universal model that improves the accuracy of predictions for both walk-in and scheduled-appointment facilities using more advanced ML methods.

METHODS

Data Preparation

This was a retrospective study of patient examinations performed in the Massachusetts General Hospital Department of Radiology between July 2016 and January 2017. We considered examinations of the following modalities: CT, MRI, ultrasound, and radiography. Among the four modalities, only radiography had walk-in examinations; the other modalities had scheduled appointments. Using our radiology information system (RIS) (Epic Radiant, Verona, Wisconsin, USA), we extracted nine principal examination parameters: patient arrival time, examination begin and complete times, time of the first image acquisition, examination code, examination description, scanner name, modality, and division of examination. The scheduled appointment times of CT, MRI, and ultrasound examinations were also recorded. The time of the first image was captured automatically by the imaging modality. Other time stamps were recorded manually in real time by medical staff members using the RIS interface.

Initially, our analysis considered all finalized examinations (Fig. 1, Step 1). A few observations had missing values because of manual data entry errors and were excluded from our analysis (Fig. 1, Step 2). We also discarded units with illogical discrepancies, such as arrival time after first image time (Fig. 1, Step 3). Additionally, many patients had multiple examinations on a given day, so we grouped them and used the earliest arrival and first image times as the definitive arrival and first image times for that visit. Similarly, we assigned the latest completion time as the completion time of that patient's whole visit (Fig. 1, Step 4). The vast majority of removed observations came in this step.

We defined *delay time* as the time between scheduled time and first image time for modalities with appointments, and we defined *wait time* as time elapsed between patient arrival time and the first image time for walk-ins. After computing the delay or wait time for each visit, we found some observations with extreme wait or delay time values. For example, in some cases the date of the appointment was different from the date the examination was performed. To consistently exclude errors such as

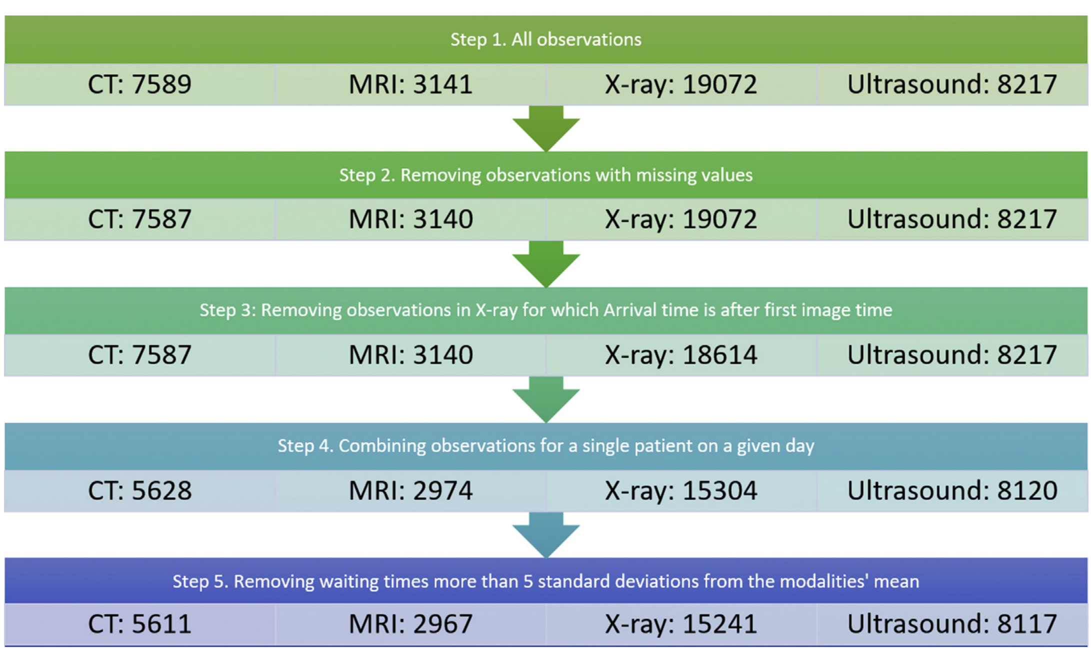

Fig 1. Number of observations in each step of data cleaning.