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Big data in hotel revenue management: Exploring cancellation drivers to gain insights into booking cancellation behavior

Abstract

In the hospitality industry, demand forecast accuracy is highly impacted by booking cancellations, which makes demand management decisions difficult and risky. In attempting to minimize losses, hotels tend to implement restrictive cancellation policies and employ overbooking tactics, which in turn reduces the number of bookings and reduces revenue. To tackle the uncertainty arising from booking cancellations, we combined the data from eight hotels' property management systems with data from several sources (weather, holidays, events, social reputation, and online prices/inventory) and machine learning interpretable algorithms to develop booking cancellation prediction models for the hotels. In a real production environment, improvement of the forecast accuracy due to the use of these models could enable hoteliers to decrease the number of cancellations, thus increasing confidence in demand management decisions. Moreover, this work shows that improvement of the demand forecast would allow hoteliers to better understand their net demand, i.e., current demand minus predicted cancellations. Simultaneously, by focusing not only on forecast accuracy but also on its explicability, this work illustrates one other advantage of the application of these types of techniques in forecasting: the interpretation of the predictions of the model. By exposing cancellation drivers, models help hoteliers to better understand booking cancellation patterns and

enable the adjustment of a hotel's cancellation policies and overbooking tactics according to the characteristics of its bookings.

Keywords: big data; forecasting; prediction; machine learning; revenue management

1 Introduction

Revenue management's objective – increasing revenue – is achieved through demand management decisions, i.e., by estimating demand and its characteristics while implementing price and capacity control to “manage” the demand (Talluri & Van Ryzin, 2005, p. 2). Thus, revenue management is concerned with the methodologies and systems required to make decisions regarding demand. Forecast performance is a critical tool for revenue management systems (RMS). Without accurate forecasts, RMS' rate and availability recommendations would probably be highly inaccurate (Talluri & Van Ryzin, 2005; Larry R. Weatherford & Kimes, 2003). In fact, estimation and forecasting is one of the essential steps in the well-known four-step cyclical revenue management process of data collection, estimation and forecasting, optimization, and control (Talluri & Van Ryzin, 2005).

Together with room nights, arrivals, and price sensitivity, booking cancellations are one of the topics of hotel revenue management forecasts (Talluri & Van Ryzin, 2005; Larry R. Weatherford & Kimes, 2003). With cancellations affecting 20% to 60% of the bookings received by hotels (P. H. Liu, 2004; Morales & Wang, 2010), an accurate forecast for booking cancellations is of major importance in determining the hotel net demand, i.e., the demand that remains after deducting predicted cancellations and no-shows (Rajopadhye, Ghalia, Wang, Baker, & Eister, 2001; Talluri & Van Ryzin, 2005). Since bookings usually allow customers to cancel a service with or without penalties prior to its provision, hotels must assume the risk of guaranteeing rooms for customers

who honor their bookings; however, at the same time, hotels must support the cost of having vacant rooms when customers cancel or do not show up (Talluri & Van Ryzin, 2005). To mitigate this risk, hotels implement overbooking and restrictive cancellation policies (Hayes & Miller, 2011; Hwang & Wen, 2009; Ivanov, 2014; Mehrotra & Ruttley, 2006; Smith, Parsa, Bujisic, & van der Rest, 2015; Talluri & Van Ryzin, 2005; Toh & Dekay, 2002). However, both overbooking and restrictive cancellation policies can have a negative effect on hotel performance. On one hand, overbooking can force the hotel to deny service to a customer; this can be a very bad experience for the customer and may result in online complaints and generation of a negative impact in terms of social reputation (Guo, Dong, & Ling, 2016). Of course, another negative effect is the loss that occurs as a result of the hotel's obligation to compensate the customer, including reallocation costs (Noone & Lee, 2011). Additionally, the hotel may also incur loss of future revenue; this is associated with the possibility that dissatisfied customers might not book the same hotel again (Mehrotra & Ruttley, 2006). On the other hand, restrictive cancellation policies, especially policies that require nonrefundable deposits and cancellation deadlines greater than 48 hours, can lead both to a decrease in the number of bookings and to a decrease in revenue due to the associated price discounts (C.-C. Chen, Schwartz, & Vargas, 2011; Park & Jang, 2014; Smith et al., 2015).

To reduce the negative consequences of overbooking and restrictive cancellation policies, forecasted cancellation and no-show rates are used as key inputs in RMS (Morales & Wang, 2010; Talluri & Van Ryzin, 2005). Although the words "forecasting" and "prediction" are considered synonyms and are employed interchangeably (Clements & Hendry, 1998; Matsuo, 2003), scientifically speaking they have different meanings and definitions. While forecasting aims to calculate or predict future events, usually events associated with a time series, prediction

can also be used to reconstruct and explain past outcomes (Lewis-Beck, 2005; Matsuo, 2003). In revenue management, authors such as Talluri & Van Ryzin (2005) employ the term “estimation” as a synonym for prediction – understanding the past to estimate the future. In fact, as acknowledged by Shmueli (2010), resorting to statistical modeling for causal explanation without employing predictive modeling in a way neglects the significance of existing theories and their capacity to uncover novel causal mechanisms. Understanding past behavior and predictive power is fundamental to improving overbooking tactics and cancellation policies (Antonio, Almeida, & Nunes, 2017a; Falk & Vieru, 2018; Morales & Wang, 2010).

In its initial stage, research on booking cancellation forecasting and prediction was mainly related to airlines and relied on a single data source (Iliescu, Garrow, & Parker, 2008; Lemke, Riedel, & Gabrys, 2013; Petraru, 2016). Commonly, time series historical aggregated data or detailed booking data in the Passenger Name Record (PNR) format, a standard created by the airline industry (International Civil Aviation Organization, 2010), were used. However, it is believed that the use of industry-specific data sources such as hotels’ Property Management Systems (PMS), together with weather forecasts, events, and macroeconomic data, may improve forecast accuracy (Chiang, Chen, & Xu, 2007; Ivanov & Zhechev, 2012; McGuire, 2017; Pan & Yang, 2017b; Talluri & Van Ryzin, 2005). As a matter of fact, the use of multiple data sources and different data types (structured and unstructured) is one of the characteristics of “big data” known as “variety”. The other two characteristics are volume and velocity (Günther, Rezazade Mehrizi, Huysman, & Feldberg, 2017; McGuire, 2017; Wang, Yoonjoung Heo, Schwartz, Legohérel, & Specklin, 2015).

Although several authors advocate the development and use of booking cancellation forecast and prediction models to improve demand forecasts in revenue management (C.-C. Chen, 2016;

Hueglin & Vannotti, 2001; Lemke et al., 2013; Morales & Wang, 2010; Talluri & Van Ryzin, 2005), research on this topic is still sparse, particularly for the hotel industry (Benítez-Aurioles, 2018; C.-C. Chen, 2016; Falk & Vieru, 2018). To the best of our knowledge, no study has attempted to improve hotel demand forecasting by employing big data in booking cancellation prediction. The present work will fill this gap by building machine learning models that can be used to predict hotel booking cancellations using large volumes of data from multiple sources. This is aimed to answer the challenges mentioned by Antonio et al. (2017a) and Pan & Yang (2017b) regarding possible performance improvement in demand forecasting, more specifically in the prediction of booking cancellation probability based on the use of big data. In addition, we will confirm the benefits of employing big data in hospitality research forecasting (McGuire, 2017; Pan & Yang, 2017b; Talluri & Van Ryzin, 2005; Wang et al., 2015; Zhang, Shu, Ji, & Wang, 2015). Finally, rather than targeting only forecast accuracy as many big data forecasting studies have done (Hassani & Silva, 2015), we also wish to use the algorithms' interpretability features to explore other advantages of using big data and advanced prediction algorithms to understand whether the variables' predictive power holds for all hotels and to identify the drivers behind the cancellation of bookings, an area that is in need of further research (Falk & Vieru, 2018; Morales & Wang, 2010).

2 Literature review

2.1 Forecast and prediction in revenue management

Forecasting is considered one of the five areas of revenue management problems (the others are pricing, auctions, capacity control, and overbooking) (Chiang et al., 2007). It is not surprising that forecasting is a topic addressed by a large proportion of revenue management publications (Ivanov & Zhechev, 2012). In a survey of the use of forecasting models in revenue management,

Weatherford (2016) found that 83 articles on this subject were published between 1958 and 2016. However, only six of these articles were specific to hotel demand forecasting. Another review of the literature on revenue management in hospitality and tourism reported that of a total of 158 studies published from 2004 to 2013, 10 concerned demand forecasting (Denizci Guillet & Mohammed, 2015). After pricing and customer and distribution channel management, demand forecasting was one of the dominant topics in revenue management research.

Based on Lee (1990), Ivanov & Zhechev (2012) and Larry R. Weatherford & Kimes (2003) classified forecasting methods as historical, advanced booking and combined. Historical methods are based on traditional forecasting methods such as various forms of exponential smoothing (e.g., simple or weighed moving average), time series, or linear regression. Advanced booking methods use the number of reservations on hand to forecast future bookings. These methods are further divided into additive (e.g., classical or advanced pickup), multiplicative (e.g., synthetic booking curve), and other time series. Combined methods, as the name indicates, use a combination of historical and advanced booking methods. Until the year 2000, traditional forecasting methods, which are mostly based on time-series methods and historical time series data, were the only types of methods and data used in revenue management demand forecasting (Pereira, 2016; L. Weatherford, 2016). Technological advances in processing power, big data, and artificial intelligence have facilitated the development of new forecast/prediction methods and of algorithms that make it possible to solve larger and more complex mathematical problems. A few interesting examples demonstrate the potential of big data in the tourism and hospitality fields. For example, Pan & Yang (2017a) used search engine queries, website traffic and weather data to forecast hotel occupancy. Song & Liu (2017) presented a framework for predicting tourism demand. Liu, Teichert, Rossi, Li, & Hu (2017) employed big data to

investigate language-specific drivers of hotel satisfaction. Kahn & Liu (2016) showed how electricity big data could be used to help hotels improve energy efficiency. The same could be said concerning the application of artificial intelligence in the tourism and hospitality fields, particularly with regard to the application of machine learning techniques. These are models that are built using a set of test data and deployed on unknown data. Logistic regression, clustering, decision trees, and neural networks are some of the algorithms classified as machine learning algorithms (McGuire, 2017). Although there is some evidence of the application of machine learning methods and algorithms to solve revenue management problems in travel-related service industries (McGuire, 2017), the topic is still poorly represented in the scientific literature. Most of the isolated examples found in the literature explore the application of neural networks (Freisleben & Gleichmann, 1993; Huang, Chang, & Ho, 2013; Law, 2000; Padhi & Aggarwal, 2011; L. R. Weatherford, Gentry, & Wilamowski, 2003; Zakhary, Gayar, & Ahmed, 2010). Other examples explore the use of algorithms such as decision trees, support vector machine, logistic regression, and Naïve Bayes (Hueglin & Vannotti, 2001; Lawrence, 2003; Morales & Wang, 2010; Neuling, Riedel, & Kalka, 2004).

In addition to differences in the forecasted/predicted quantities or measures and in the methods employed, forecasts and predictions can be distinguished by level of aggregation (Talluri & Van Ryzin, 2005; L. Weatherford, 2016). Depending on the subject of the forecast and the level of detail offered by the data (the more desegregated the required forecast is, the more detailed the data must be), one of two strategies, either “bottom-up” or “top-down”, is followed (Talluri & Van Ryzin, 2005; Lawrence R Weatherford, Kimes, & Scott, 2001). A “bottom-up” strategy is used when detailed forecasts are required (e.g., occupancy per room type per night). Forecasts can then be combined to obtain global results (e.g., overall occupancy per night). A “top-down”

strategy is used to make global forecasts; the results can then be used to disaggregate the forecasts (e.g., a global forecast of customers per rate category can be used to forecast the length of stay of the customers).

One other characteristic that distinguishes types of forecasts and prediction problems is the type of target variable used. From a machine learning point of view, supervised forecast and prediction problems should be categorized as regression problems when the target variable is continuous and as classification problems when the target variable is categorical (Abbott, 2014; Hastie, Tibshirani, & Friedman, 2001).

2.2 Bookings cancellation forecast and prediction

The literature in bookings cancellation forecast/prediction for travel-related service industries is sparse and relatively recent. Table 1 presents a list of studies that appear to address this topic; all of them were published within the last ten years. Of the 16 publications, 5 use airline data, 4 use railway data, 2 use restaurant data, and 5 use hotel data. Nine of the publications employed detailed booking or ticket data (Table 1). The increasing tendency to employ detailed booking data in forecasting models, particularly the increasing tendency to use data that are in the PNR format rather than time series aggregated data, is related to recent advances in technology and in forecasting algorithms (Morales & Wang, 2010; Petraru, 2016). Some of the publications employ data in the Airlines Reporting Corporation (ARC) format instead of the PNR format. The PNR and ARC formats are both standards from the airline industry; PNR is widely used in demand forecasting, perhaps because of its origin. The main difference between the two is that ARC data are based on the tickets issued, while PNR data are based on bookings.

Costs associated with the storage and processing of detailed booking data have been mitigated by the development of technology in recent years (Petruaru, 2016; Tsai, 2011). The use of detailed booking data instead of aggregated time series historical data not only has the power to improve the accuracy of the forecasts (Hueglin & Vannotti, 2001; Petruaru, 2016) but also permits the development of classification prediction models. Cancellation prediction models are advantageous because they classify the cancellation outcome of each booking and allow an understanding of how each feature³ influences cancellations, i.e., an understanding of cancellation drivers (Morales & Wang, 2010; Petruaru, 2016). Of the identified publications, 10 employed classification algorithms, but only 8 treated the problem as a classification problem (Antonio et al., 2017a; Antonio, Almeida, & Nunes, 2017b, 2017c; Falk & Vieru, 2018; Huang et al., 2013; Iliescu, 2008; Iliescu et al., 2008; Petruaru, 2016). Although Huang et al. (2013) treated the problem as a classification problem, the authors did not pursue the identification of cancellation drivers. The remaining two publications that employed classification algorithms used them to forecast cancellation rates and cancellation deadlines; that is, they treated the problem as a forecasting/regression problem and not as a classification problem (Cirillo, Bastin, & Hetrakul, 2018; Morales & Wang, 2010). The reason for this could lie in the authors' stated belief that "it is hard to imagine that one can predict whether a booking will be canceled or not with high accuracy simply by looking at PNR information" (Morales & Wang, 2010, p. 556). Nevertheless, the results of Antonio et al. (2017a, 2017b, 2017c), Falk & Vieru (2018), and Huang et al. (2013) contradict this. Huang, Chang, and Ho's (2013) back-propagation neural network model for predicting cancellations in restaurants achieved 0.809 in *AUC*, 0.751 in *Accuracy* and 0.389 in *Precision* (information on these machine learning metrics can be found in Appendix B). Using hotel data, Antonio et al. (2017a) obtained an *Accuracy* greater than 0.900, a

Precision greater than 0.806, and an *AUC* greater than 0.935. More recently, Falk & Vieru (2018) obtained an *Accuracy* greater than 0.910. In fact, the latter three publications are the only publications that combine the use of detailed booking data with advanced classification algorithms, a strategy that can be used to implement bottom-up forecasts/predictions. As an example of the booking prediction cancellation problem, one prediction model can generate not only each booking outcome's prediction but also a set of aggregated predictions. By adding up the outcome of bookings predictions for each distribution channel, segment or other aggregation level, it is possible to make predictions at an intermediary level and at a global level. However, only Antonio et al. (2017a, 2017b, 2017c) addressed the possibility of using separate booking cancellation outcome predictions to calculate net demand at different aggregation levels.

<Insert Table 1 here>

2.3 Factors affecting cancellations

As recognized by Jones & Chen (2011), many studies have addressed how customers select hotels and attempted to identify the factors that affect hotel demand. The factors affecting hotel demand can be divided into four categories: hotel, customer, booking and external (Chan & Wong, 2006; Chiang-Ming Chen, Tsai, & Chiu, 2017). Other hotel-related factors include variety of facilities, quality of service (Chan & Wong, 2006), advertisement/brand recognition (Chan & Wong, 2006; J. N. K. Liu & Zhang, 2014), location (Anderson, 2012), and star classification (Masiero & Law, 2015). Customer factors include age group, customer type (e.g., group or transient), market segment (Chan & Wong, 2006; Chiang-Ming Chen et al., 2017; McGuire, 2016), distribution channel (J. N. K. Liu & Zhang, 2014; Masiero & Law, 2015), gender (Chiang-Ming Chen et al., 2017; H. Chen, Phelan, & Jai, 2016), and country of origin (Chiang-Ming Chen et al., 2017). Booking factors include price (Anderson, 2012; Chan &

Wong, 2006; Chiang-Ming Chen et al., 2017; J. N. K. Liu & Zhang, 2014; Lockyer, 2005; Masiero & Law, 2015), length of stay (Chiang-Ming Chen et al., 2017; Masiero & Law, 2015), lead time, party size (Masiero & Law, 2015), time of the year, day of the week, events (McGuire, 2016), and cancellation policy (C.-C. Chen et al., 2011; J. N. K. Liu & Zhang, 2014). External factors include recommendation by a third party (e.g., travel agent, company, or family) (Chan & Wong, 2006), social reputation (Anderson, 2012; Chan & Wong, 2006; J. N. K. Liu & Zhang, 2014; McGuire, 2016), competitors' prices (Enz, Canina, & Lomanno, 2009; McGuire, 2016), special events (McGuire, 2016), weather (C.-M. Chen & Lin, 2014; Day, Chin, Sydnor, & Cherkauer, 2013), and macroeconomic performance (e.g., currency exchange rates) (Ivanov & Zhechev, 2012; Talluri & Van Ryzin, 2005).

Cancellations can occur for reasons that cannot be controlled by the customer, such as changes in plans (e.g., a meeting change), illness, accidents, or weather (C.-C. Chen et al., 2011; Falk & Vieru, 2018). However, cancellations can also occur due to customers' actions, such as finding a hotel that offers a better price (C.-C. Chen et al., 2011), finding a hotel with a better or more desired location (e.g., where a conference is scheduled to take place), finding a hotel with better service/facilities (e.g., one with a better social reputation), or simply deciding to relocate to join friends or relatives in another hotel. However, although some studies mention factors that influence cancellations, few studies have addressed the roles that different factors play in booking cancellation probabilities (Antonio et al., 2017c; Falk & Vieru, 2018; Morales & Wang, 2010).

Like hotel demand and hotel selection, cancellations are affected by diverse factors that are inherent to customers or bookings; these include the timing of the booking, the distribution channel, the origin of the customer (region), the season and duration of the stay, the type of

customer, and the hotel's cancellation policy (C.-C. Chen et al., 2011; P. H. Liu, 2004; McGuire, 2017; Morales & Wang, 2010; Talluri & Van Ryzin, 2005). External factors such as competitors' prices, social reputation, weather and macroeconomic performance may also impact cancellations (C.-C. Chen et al., 2011; Ivanov & Zhechev, 2012; McGuire, 2016, 2017; Talluri & Van Ryzin, 2005). Therefore, bookings cancellation forecast/prediction that uses data representing a large number of these factors is likely to present better performance results. This may help explain the results obtained by Antonio et al. (2017a, 2017b, 2017c), Falk & Vieru, 2018) and Huang et al. (2013) in similar classification problems for different industries. While the latter work employed only 12 features of customer and booking attributes (namely, year, month, day, whether or not the day was a holiday, gender, age, income, educational level, marital status, place of residence, cancellation record, and cumulative number of cancellations) to predict cancellations for a restaurant chain, Antonio et al. (2017a, 2017b, 2017c), Falk & Vieru (2018), and Morales & Wang (2010) used additional features to characterize both the customer and the booking itself. These included features such as room price, booking date, arrival date, length of stay, distribution channel, room category, market segment, distribution channel, and number of guests. Antonio et al. (2017a, 2017b, 2017c) and Morales & Wang (2010) go even further by including a feature with a known predictive power for cancellations, booking cancellation policy (C.-C. Chen, 2016; C.-C. Chen et al., 2011; Talluri & Van Ryzin, 2005). Antonio et al. (2017a, 2017b, 2017c) added another feature, the customer's previous cancellation history, which represents another known cancellation factor (C.-C. Chen, 2016; C.-C. Chen et al., 2011; Talluri & Van Ryzin, 2005). Nevertheless, all of these features were obtained from the same source, the PMS. Although the literature recognizes the benefits that can be obtained by

using data from other sources to predict booking cancellations, none of the studies listed in Table 1 employed features from non-PMS sources.

3 Methodology

Data are considered the lifeblood of a forecasting system (Talluri & Van Ryzin, 2005, p. 412).

Hence, it is not surprising that the data collection and preparation process (collection, integration, and cleansing) forms the core of the present work. In fact, as in any analytical work, data preparation represents a substantial part of the methodology (McGuire, 2017).

The well-known cross-industry standard process model for data mining (CRISP-DM) methodology (Chapman et al., 2000) was employed to build the models used in this study.

CRISP-DM divides the development of predictive models into six phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. An important point in CRISP-DM is that these phases are not necessarily sequential; the construction of a model usually requires several cycles. These development cycles are marked throughout this section by the presentation of intermediate results that justify the methodological choices we made to obtain the final round of results. Subsections 3.1 and 3.2 represent the phases of business and data understanding. Subsection 3.3 describes the phase of data preparation. The modeling phase is described in subsection 3.4, while the evaluation phase is presented in subsection 3.5. The deployment phase is not addressed because it is beyond the scope of this study.

All the models created for this work were programmed in R (R Core Team, 2016).

3.1 Bookings data

Uncensored real booking data from eight Portuguese hotels were used. Since these are real bookings and data, the hotels wished to remain anonymous, and no personal information about

the customers or hotels is disclosed. The hotels are identified as R1 to R4 (four resort hotels) and C1 to C4 (four city hotels). The datasets were collected directly from the hotels' PMS databases using Structured Query Language (SQL) queries. As described in the following subsection, historical data were not available for the majority of the non-PMS data sources, which meant that extractors had to be built to collect daily data from non-PMS data sources. These extractors ran from January 1st, 2016 to November 20th, 2017. As such, PMS booking data were retrieved for the same period. During this period, the cancellation ratios for these hotels varied from 12.2% to 40.0% (Table 2).

<Insert Table 2 here>

PMS databases contain bookings with a known outcome (“canceled” or “not canceled”) and bookings with an “unknown” outcome, i.e., bookings for future dates. The latter were not extracted because, although these bookings had not been canceled at the moment of extraction, they could still be canceled prior to the guest’s expected arrival date. Therefore, the resulting dataset included only canceled bookings for future dates, making it highly imbalanced but reducing the risk of leakage¹ and incorrect training². Additionally, because predictive modeling makes use of historical data to predict future actions, the timeline of the historical data must be shifted for these data to be effective. In other words, the values of the input features should be obtained from a period prior to the fixation of the target variable (Abbott, 2014). As an example, it is common for bookings to undergo changes and amendments between the time at which they are entered into the hotel PMS and the time at which the guest checks out or cancels the booking. Some of these changes and amendments involve correction of the information that was entered or changes to the service required; they include changes in the length of stay, the number of guests, the type of meals and the addition of special requests or additional services (e.g., spa

treatments). In fact, it is very common for hotels not to record certain details until check-in, including the guest's country of origin, his or her birthdate and other personal information. It is also common for guests to change their booking details at check-in (e.g., to add or remove nights or change the number of persons). Understandably, this situation makes the distributions of some features differ with respect to the cancellation outcome. If the objective of the model is to predict bookings cancellation outcomes for features that are set at the cancellation date or at the check-in date, the values of the input features must reflect this. Therefore, instead of extracting PMS data from the bookings table, the data were extracted from the bookings log table, which stores all changes that have been made in the details of bookings over time. This permitted extraction of the data in the state they were in prior to check-in for all bookings that were not canceled and in the state they were in on the cancellation date for canceled bookings.

The features extracted from the hotels' PMS databases, as well as all other features employed in this work, are described in detail in Appendix A.

3.2 Additional data sources

One of the major difficulties encountered in this study was the selection of other data sources and the choice of methods for incorporating those data. Despite the recognized importance of external factors in cancellations, to date no bookings cancellation forecast/prediction studies have employed data sources other than PMS data. Due to the importance of external factors in hotel demand, we decided to identify and collect data from other sources to make it possible to assess how features from non-PMS data sources contribute to enhancing the prediction of booking cancellations. However, as recognized by McGuire (2017), the identification of data sources proved to be a difficult task. One of the main reasons for this is the bidimensionality of data for hotel demand forecasting; the data include both the date of creation of the booking and

the date on which the room was occupied or the reservation was canceled (Larry R. Weatherford & Kimes, 2003). This requires that data sources present valid data for both dimensions. For example, despite the importance of weather in explaining hotel demand (McGuire, 2017 and Pan & Yang, 2017a), the incorporation of a weather forecast for far-off future dates is nonviable. However, depending on the selected data point, weather forecasts can be used as a feature in a machine learning model. This data point is the arrival date for bookings that are not canceled or the cancellation date for canceled bookings. In this way, the model can use this feature to determine whether or not the weather forecast is related to the booking cancellation outcome. One other essential requirement was the availability of “quality” data, i.e., the data had to be accurate, reliable, unbiased, valid, appropriate, and timely (McGuire, 2017; Rabianski, 2003). Lastly, we required that our data be public and available for general use to enable replication and, eventually, application by other hotels. This meant that access to external data had to be free and that data extraction could be accomplished using the data providers’ Application Programming Interfaces (APIs) or, at least, via web scraping.

Based on the requirements for weather data incorporation, we selected the Weather Underground website (Weather Underground, n.d.). This popular website provides a powerful API that allows the user to obtain current and 10-day forecast weather conditions for almost any location in the world. An automatic application was developed to call this API on a daily basis.

For the collection of information on a country’s national and local holidays, an automated web scraper was developed to extract data. TimeAndDate.com was considered since it is the largest time zone-related website (TimeAndDate.com, n.d.).

For data on special events that were scheduled to occur near the hotel’s location, another automated web scraper was built; on a daily basis, it extracted information from the popular

website Lanyrd.com (Lanyrd.com, n.d.). All of this information was later manually analyzed and used to classify the events into major and minor events. Special events with nationwide recognition were classified as major events, while more local events or events that only attracted a niche market were considered minor events.

Social reputation data were extracted from online reviews available on two of the most popular websites in the area, Booking.com and Tripadvisor.com (European Commission, 2014). This extraction was again performed daily and automatically via custom-built web scrapers. All the collected data were stored in local databases.

Because of the increasing number of customers searching online for the best deals, sometimes even after having already booked their accommodations for a trip (C.-C. Chen et al., 2011), we decided to collect this type of data from Booking.com and use it to study the possible relationship between online prices and cancellations. The rationale for this was to understand whether, during the studied time period, a change in price or availability at a different hotel could lead a customer to cancel a booking. Booking.com was chosen as the source for this type of data; due to its predominance in Europe, it is representative of the influence that online travel agencies (OTA) exert on hotels (HOTREC - Association of Hotels, Restaurants and Cafes and similar establishments of Europe, 2016). In fact, for the studied hotels, OTA's market share ranged from 4.5% to 83.2% (Table 2 and Figure 1), revealing a moderate correlation (0.5255) between the OTA's market share and the cancellation ratio.

<Insert Figure 1 here>

An automatic web scraper extracted these data from Booking.com on a daily basis. In addition to price data, data on the inventory on sale were also extracted. Due to the previously mentioned issue of the two-fold dimensionality associated with time of booking, this data extraction also

required collecting data regarding future dates. Therefore, each day the extractor collected the prices and available quantities of all types of accommodation for each of the following 365 days. This process enabled the creation of features that could be used to study the impact of both online prices and available inventory on booking cancellation outcomes. As in the case of social reputation, data about the hotels' competitors was also extracted. For each studied hotel, this competitive set consisted of five other hotels that were identified by the studied hotel's manager. The data extractors for most of the additional data sources collected data from January 1st, 2016 to November 20th, 2017. Data regarding online prices and inventory on sale were collected from August 1st, 2016 to November 20th, 2017. Overall, more than 1 terabyte of data was collected for this period. As shown in Table 3, the number of observations collected from some sources, such as online prices and inventory, were very high, exceeding 80 million observations. The collected data (raw data) were then prepared and aggregated according to the features developed to represent each source (prepared data). This highly computing-intensive task reduced the number of observations and permitted merging of the resulting features with features obtained from the PMS data.

<Insert Table 3 here>

3.3 Data preparation

Data analysis and summary statistics showed that despite the presence of some abnormalities, overall the data from all sources were of good quality. Except for the weather forecast dataset, none of the datasets presented missing values; the observations represented all bookings and dates, the categorical features were not of high multiplicity for the same meaning, and the data were properly formatted. For numeric/integer features, the abnormalities were essentially outliers that could be explained by the way hotels operate.

Feature selection, particularly feature engineering, can contribute positively to the accuracy of prediction models due to the information gain obtained from the association of multiple input variables (Abbott, 2014; Kuhn & Johnson, 2013). Indeed, authors such as Domingos (2012) consider feature engineering the key factor in the success of machine learning projects. In feature engineering, creativity, intuition, and domain knowledge are as important as technical knowledge.

Based on features that could represent hotel demand/selection and on the features already employed in previous booking cancellation forecast/prediction research, our starting point was the inclusion of the PMS-based features *Adults*, *Babies*, *Children* (Antonio et al., 2017b; Falk & Vieru, 2018), *Agent*, *Company*, *CustomerType*, *DepositType*, *MarketSegment* (Antonio et al., 2017b; Morales & Wang, 2010), *DistributionChannel*, *LeadTime* (Antonio et al., 2017b; Falk & Vieru, 2018; Morales & Wang, 2010), *IsRepeatedGuest*, *PreviousCancellationRatio* (Antonio et al., 2017b; Huang et al., 2013), *BookingChanges*, *DaysInWaitingList*, *Meal*, *StaysInWeekendNights*, *StaysInWeekNights*, *ThirdQuartileDeviationADR*, and *TotalOfSpecialRequests* (Antonio et al., 2017b). Considering that we improved the method used to extract data from the hotels' PMS by extracting the values of the input variables at a time prior to check-in/cancellation, we were able to include additional important PMS-based features to represent the origin of the customer, the season, and the room type (Antonio et al., 2017c; Falk & Vieru, 2018; Morales & Wang, 2010); these features were *Country*, *DayOfYear*, and *ReservedRoomType*. Furthermore, for models optimized for two of the hotels, we even included additional PMS-based features that represented special requests made by customers (*SRDoubleBed*, *SRHighFloor*, *SRQuietRoom*, *SRTtogether*, and *SRTwinBed*) and features that represented services these two hotels offered that other hotels did not (*AssociatedToEvent* and

BookedSPA). The extraction and engineering of other PMS-based features, including features employed in previous research (e.g., gender, rate code), was also tested (Morales & Wang, 2010), but the results did not show any improvement. None of the features proved to have predictive value. One example of these additional features was a feature that was designed to capture the time at which a booking was canceled prior to the guest's expected arrival. The feature was calculated based on the time during which the booking was "alive", that is, the number of days that elapsed between booking and check-in or cancellation, according to the outcome of the booking. One other feature tested with the same purpose was calculated by determining the number of days between the arrival date and the date of the booking outcome (check-in or cancellation). A description of these and all other features employed in the development of the models can be found in Appendix A; it can be observed that, of the 37 features employed, only 12 were created directly from the input variables. The remaining 25 features were engineered from multiple input variables (e.g., *DepositType*) or multiple observations of the same input variables (e.g., *PreviousCancellationRatio*) or were at least based on some type of computational result (e.g., *StaysInWeekendNights*).

The outcome variable *IsCanceled* was directly extracted from the hotels' PMS databases. This categorical variable is assigned a value of 0 for not canceled bookings and a value of 1 for canceled bookings. For the purpose of this research, although no-shows differ from cancellations, no-shows were treated as cancellations because customers do not inform hotels of their check-in failure.

For the features that were added based on other data sources, the selection criterion was the possible impact the feature might have on booking cancellations. These features were the culmination of hundreds of iterations and experiments that were conducted with the purpose of

understanding which features were likely to contribute to improving the models. For example, it is known that precipitation should be considered over temperature when pondering the impact of weather (Day et al., 2013). Therefore, we constructed the feature

AvgQuantityOfPrecipitationInMM, which was based on the average forecasted quantity of precipitation during each booking's period of stay at the outcome date (*StatusDate* - the cancellation date for canceled bookings) or the arrival date for not canceled bookings.

CompSetSocialReputationDifference, which was crafted to include the impact of hotels' social reputations, was designed to reflect the fact that a customer might cancel a booking in one hotel in favor of a similar hotel with a better reputation. Since Booking.com and Tripadvisor.com use different rating scales, we employed one of the most commonly used normalization formulas

(Abbott, 2014), the min-max formula, to normalize the ratings. The hotel daily ratings for each of the sources were normalized over the range 1-100 using $x' = \frac{(x - \min(x))}{(\max(x) - \min(x))} \times 100$. We also

took into account that Booking.com ratings actually range from 2.5 to 10 and not from 1 to 10 (Mellinas, María-Dolores, & García, 2016). The normalized ratings of the two sources were then averaged to obtain one overall daily rating for the hotel in question. Next, the number of hotels from the competitive set with better average ratings in relation to the hotel's booking was added to obtain the final feature value. The rating employed was the rating at the time of each booking's outcome date.

We created two features to reflect the possibility that a customer might cancel a booking in favor of a similar hotel with a better price: *RatioADRbyCompsetMedianDifference* and

HotelsWithRoomsAvailable. While the first feature attempts to depict the relationship of each booking price to the hotel's competitive set's median average price, the second is designed to reflect demand by revealing how many hotels in the competitive set still have rooms available.

After retrieving the booking *StatusDate*, we fetched the cheapest price offered by each competitor for each night of the booking's stay for a similar accommodation (i.e., accommodating the same number of people and providing the same type of meal package). These prices were used to calculate the median price of the competitive set per day. The median was chosen over the mean because it is less sensitive to outliers. Next, the average price for each booking's period of stay was calculated using the daily calculated median price. Finally, the ratio between each booking's average daily rate (ADR) and the average median price for the competitive set was calculated. The rationale was to understand at what point competitor's prices could influence a customer's decision to cancel a booking.

The feature *HotelsWithRoomsAvailable* was calculated by counting the number of hotels in the competitive set that had accommodations available during the entire booking's stay.

To reflect the number of holidays that a booking coincided with, we created the feature *nHolidays*. The rationale behind this feature was that a customer who planned to travel or be on vacation during a holiday would probably be less likely to cancel than someone who was not traveling on a holiday. Initially, the plan was to count these holidays according to the country of origin of the customer. However, due to the previously identified problem with the country variable, we opted to count the number of holidays at the hotel's location, considering that most customers come from Portugal or nearby countries and thus share many public holidays.

To reflect the possibility that special events such as conferences, sports events and concerts might generate more demand and therefore influence customers not to cancel, we created two other features: *RatioMajorEventsNights* and *RatioMinorEventsNights*. These features were obtained by dividing the total number of days of each booking's stay by the number of days on

which major or minor events, respectively, were scheduled during that period. The characteristics and engineering details of all of these features are described in Appendix A. After merging the data from the different sources into a unique dataset, we processed all features for missing values and cardinality. For the former, we employed the R package “MissForest” (Stekhoven, 2013), in which a random forest machine learning algorithm is used to train a model on observed values to predict the missing values. To process cardinality in categorical features, we employed the R package “vtreat” (Mount & Zumel, 2017). In fact, features with a high degree of cardinality can make model training slow and overfit the data (Abbott, 2014). Models that overfit do not generalize well (Hastie et al., 2001). To avoid this, we encoded all levels of categorical features with a minimum frequency of 0.02 into an indicator column (one-hot encoding⁴). However, so as not to lose information about the less frequent levels, a new numeric feature was built for each categorical feature. This feature’s value represents the Bayesian change in the logit-odds from the mean distribution conditioned on the observed value of the original feature. Vtreat adds a suffix to the feature name according to the type of feature: “_clean” for numeric features, “_catB” for features that represent a Bayesian change of categorical features, and “_lev_x.<level name>” for indicator features for categorical levels with a frequency greater than 0.02.

3.4 Model development

Most high-performance machine learning techniques are fundamentally black boxes that generate highly complex predictive equations (Kuhn & Johnson, 2013). Nonetheless, the outputs of some techniques, such as those that are based on decision trees, are easier for humans to understand (Abbott, 2014; Hastie et al., 2001; Kuhn & Johnson, 2013). Decision tree-based

techniques also have the advantage of automatically incorporating the treatment of outliers, handle missing data well, are not affected by feature skewness, inherently detect feature interactions, are nonparametric (making no distribution assumptions about features and the outcome variable) and have a built-in feature selection mechanism (Abbott, 2014; Kuhn & Johnson, 2013). However, decision tree techniques also have weaknesses, including non-adaptability to slight changes in the data and failure to generalize well. To overcome these weaknesses, some approaches employ ensemble methods, which, by combining multiple trees into one model, tend to have better performance (Hastie et al., 2001; Kuhn & Johnson, 2013). We decided to employ the award-winning ensemble tree-based machine learning algorithm XGBoost (T. Chen & Guestrin, 2016), which is a gradient boosting-based algorithm. Gradient boosting algorithms are usually faster than other methods in training models and allow the user to understand the importance of each feature and its contribution to the prediction of the outcome (Hastie et al., 2001). XGBoost, one of the fastest and best machine learning algorithms available today (T. Chen & Guestrin, 2014/2018), is capable of addressing both regression and classification problems and was designed to facilitate the understanding of the predictive power of the features employed in the models built with it. Therefore, XGBoost is the ideal algorithm for building “bottom-up” cancellation prediction models – models that can be used to make predictions at the booking level but whose results can also be used to make aggregated predictions. Because data for the same period were not available from all data sources, we made the decision to build different models using datasets that differed in terms of features and numbers of observations. The first model, Model 1, which used exclusively PMS features, encompassed arrivals from January 1st, 2016 to November 20th, 2017. A second model, Model 2, which also used PMS features, used arrivals from August 1st, 2016 to November 20th, 2017. The

objective was to understand whether reduction in the number of observations had a severe impact on the model's performance. The third model, Model 3, included features from all sources (PMS, weather, social reputation, holidays, special events, and online prices/available inventory) and used observations from the same period as in the second model so that we could determine whether the inclusion of features from additional sources improved the results. Lastly, we decided to build an optimized model (Model 4) for hotels R1 and C1 because these hotels shared characteristics that permitted the creation of some additional features; the observations for Model 4 were from the same time window as those for Models 2 and 3. The intention was to understand whether models that included features specifically tailored to each hotel's characteristics and operations would provide better results than models built with "generic" features.

Comparing to previously published research, XGBoost use per se was not the major innovation introduced in the modeling. The novelty was the combination of XGBoost with the way in which data were extracted from the PMS and other sources and how datasets were split for training with XGBoost. Because we had a data-rich situation, we employed the approach recommended by Hastie et al. (2001) of splitting the datasets into three parts: a training set for fitting the model, a validation set for assessing the prediction error, and a test set (hold-out) for assessing the generalization error. There is no specific rule for defining the quantity of observations or for determining which observations are included in each set; this depends on the characteristics of the data, such as size and structure (Hastie et al., 2001; Kuhn & Johnson, 2013). Furthermore, time is not irrelevant. For example, the more cancellations a customer has made in the past, the higher is the customer's likelihood of canceling. This can be considered a temporal data problem; thus, data for the test set should be chosen from a period that is not "known" by the training and validation sets (Abbott, 2014; Hastie et al., 2001). The *StatusDate* was selected as

the date to use for splitting in the creation of the test set. Thus, all bookings that were canceled or checked in after August 31st, 2017 formed the test set. Since hotel operations are not static, new travel operators emerge while others disappear, patterns in prices and booking antecedence change, customers' preferences change over time, and the distribution of input features changes in relation to the outcome label; these changes contribute to what is known as "concept drift" (Gama, Medas, Castillo, & Rodrigues, 2004; Webb, Hyde, Cao, Nguyen, & Petitjean, 2016). To capture changes in behavioral data over time, we followed Antonio et al. (2017b) by dividing the remaining data into training and validation sets using the "convenience splitting" approach (Reitermanová, 2010). The remaining observations were ordered by arrival date and subdivided into month/year blocks. To preserve the features distribution of the outcome, we performed stratified splitting of each of these blocks, placing 75% in the training set and the remaining 25% in the validation set.

3.5 Evaluation

In this section, we present and discuss our results using the common machine learning metrics *Accuracy*, *Precision*, and *Area Under the Curve (AUC)*. *Accuracy* is a description of systematic error. In this context, it is calculated by dividing the number of bookings whose outcomes were correctly predicted by the total number of bookings. *Precision* is considered a description of random error; it is calculated by dividing the number of bookings that were predicted as "likely to cancel" and were actually canceled by the total number of bookings that were predicted as "likely to cancel". *AUC* can be described as a measure of how well a model distinguishes between classes; in this case, the classes are "canceled" and "not canceled". These and other associated metrics are described in more detail in Appendix B.

One of the first observations about the modeling results (Table 4) is that they differed not only for different models but also within hotels when the same type of model was employed.

<Insert Table 4 here>

Models 1 and 2 used only PMS data, but Model 2 was fed with data from a shorter period.

However, in general, Model 2 showed better results than Model 1. The latter was better in only three cases, namely, for hotels R1, R4, and C3. In the validation set for R1, the *Accuracy* of Model 2 was 0.8232, whereas that of Model 1 was 0.8431. For *Precision*, we obtained 0.6934 for Model 2 and 0.7542 for Model 1. The *AUC* results were 0.8892 for Model 2 and 0.9051 for Model 1. The test set results for R1 were similar. In terms of *Accuracy*, the value was 0.8381 for Model 2 and 0.8409 for Model 1. The *Precision* of Model 2 was 0.4568 and that of Model 1 was 0.4607. The *AUC* for Model 2 was 0.8180, whereas that for Model 1 was 0.8293. The results were similar for R4 and C3. However, for these two hotels, the results diverged in some sets. For example, in R4 the *Accuracy* on the test set in Model 2 (0.8687) was slightly superior to that in Model 1 (0.8659), but the inverse was true for the validation set. There, *Accuracy* in Model 1 was 0.8582, while in Model 2 it was 0.8438. For the remaining hotels, most metrics presented better results both for the validation and test sets when Model 2 was used. These differences show that the use of more data does not always produce better predictive models (Abbott, 2014). Furthermore, as recognized by McGuire (2016), the use of more data from the same source might not result in better-performing models. This is particularly true if the data do not have a significant causal relationship with the outcome, if the data lack quality, or if the data do not change significantly over time.

Similarly, the results obtained using Model 3 show that the introduction of additional features from other data sources did not produce better results for any of the hotels. For hotels C1, C2,

and C4, Model 3 was beaten in every metric for both the validation and the test sets. However, almost all metrics for the Model 3 test set showed improved results over those of Model 2 for hotels R1, R2, R3, R4, and C3. Nevertheless, this was not matched in the validation set, where the improvement did not occur homogeneously for all the metrics.

On the other hand, the results obtained with Model 4 clearly show that inclusion of features specific to each hotel's characteristics and operations imparts substantial performance improvement. Compared with the Model 3 test set results for R1, *Accuracy* increased by more than 3 percentage points, *Precision* increased by more than 10 percentage points, and *AUC* increased by more than 3 percentage points. For C1, both *Accuracy* and *AUC* increased by more than 3 percentage points, while *Precision* increased by more than 2 percentage points.

From a general point of view, the overall statistics (Table 4) show some of the global results that were obtained. All metrics presented good results in terms of prediction performance using the validation set. *Accuracy* ranged from 0.7775 to 0.8928, *Precision* ranged from 0.5724 to 0.8033, and *AUC* ranged from 0.7864 (a value that is usually considered to indicate a fair-to-good model result) to 0.9307 (a value that indicates an excellent model result). In terms of the generalization performance, i.e., the models' predictive capability using independent test sets (Hastie et al., 2001), the mean and median results show that the results for most hotels were good.

Nevertheless, this was not the case for hotels R2, R3, and R4, particularly with respect to *Precision* and *AUC*. These three hotels also presented the lowest cancellation ratios. This might indicate that, for hotels with low cancellation ratios, additional data or different features should be added to improve the capture of cancellation patterns; alternatively, it might simply be very difficult to predict cancellations for such hotels, perhaps because cancellations have no patterns other than the consumers' own limitations.

Another important consideration arising from the results is the Pearson correlation values between *Accuracy* and the hotels' OTA share and between *Accuracy* and the hotels' cancellation ratios for the Model 3 test set. The correlation between Model 3's *Accuracy* and the OTA share in hotels can be considered moderate to strong (-0.5894). The correlation between Model 3's *Accuracy* and the hotels' cancellation ratio can also be considered strong (-0.6282); the results suggest the existence of a negative association between *Accuracy* and both the hotels' OTA share and the hotels' cancellation ratio. When the OTA share and the cancellation ratio decreased, *Accuracy* increased, and vice versa. Since there was also a moderate positive correlation between OTA share and cancellation ratio, it is suggested that the higher the hotel's OTA market share is, the higher the cancellation ratio will be and the more difficult it will be to accurately predict cancellations.

One of the powerful characteristics of XGBoost is its ability to generate measures of each feature's contribution to the whole model; these measures include *Gain*, *Cover* and *Frequency*. *Gain* measures the improvement in accuracy contributed by a feature to the tree branches on its own. *Cover* measures the relative number of observations for the feature. *Frequency* (also known as *Importance*) is a simpler measure that is calculated by counting the number of times a feature is used in all generated trees. A feature with *Frequency* 0 (zero) was not used in the model. The *Frequency* in Model 3 shows which features were used in each hotel's model version (Table 5). As is common in predictive modeling, not all features had substantial influence on the prediction of the outcome (Hastie et al., 2001). Of the 29 features, only 13 to 15 were used, depending on the hotel. Also interesting is the fact that all the features used originated from the PMS. Features from the other data sources were not used. As previously mentioned, for some hotels the inclusion of features from other data sources resulted in minimal performance improvements that

were not due to the information gain brought to the models by the features but were instead due to the way in which the XGBoost algorithm works. As with other ensemble decision tree-based algorithms, XGBoost controls overfitting to the training data so that it can generalize better with unseen data. This control is achieved by using parameters that allow tuning of the model's complexity (the simpler the model, the less likely it will be to overfit) and parameters that add randomness to make the training more robust to noise. These parameters include definition of the subsample of observations to be used in each tree and definition of the subsample of features to use in each tree and at each tree level. Thus, although introducing features from other data sources may not have added information, it made some of the models more robust to noise.

<Insert Table 5 here>

The analysis of the top 15 most important features per hotel, based on the *Frequency/Importance* measure calculated by XGBoost, is depicted in Figure 2. It is possible to verify that there are differences between the hotels in terms of the number of clusters and in the number of features in each of these clusters as well as in the degree of importance of the features by cluster and by hotel; this is because XGBoost uses one-dimensional clustering to determine the grouping of features in terms of importance. However, some of the features had similar importance for all hotels. *Leadtime* was the most important feature for six of the hotels and the second most important feature for the remaining two hotels (R1 and C1). In hotel R1, a feature that represents bookings from a specific level (240) of the *Agent* categorical feature had the highest importance. In C1, the most important feature was the level "No deposit" jointly with the level "Nonrefundable" of the categorical feature *DepositType*. *Country* was also one of the most important features for all hotels except R3, for which it ranked fourth. For the other hotels, *Country* was usually in second or third place. Another feature of high importance for all hotels

was *BookingChanges*. One other interesting point that Figure 2 highlights is that the feature *StaysInWeekNights* was more important for cancellation prediction than the feature *StaysInWeekendNights* except in the case of hotel C4, for which the results were not distinguishable.

<Insert Figure 2 here>

By identifying the features that are most important in predicting the outcome of a booking, we can narrow down the cancellation drivers. A smaller number of dimensions can make it easier to study the data and uncover hidden patterns. For example, Figure 3 presents a “tableplot”, a powerful technique for the visualization of big data that permits exploration and analysis of large multivariate datasets (Tennekes & de Jonge, 2017). The most important predictive features for hotel C2 using Model 3’s dataset are represented. The plot is composed of 100 bins (lines), and each line is composed of 245 observations. For categorical features, individual colors represent the distribution of a category level in each bin of observations. For numeric features, the bars show the range between the mean value plus the standard deviation and the mean value minus the standard deviation. The plot also includes a line that indicates the mean of each line’s observations. Using such a plot, it is possible to verify at a glance patterns in the distribution of the different features in relation to the outcome label, which is shown in column A. The *IsCanceled* feature shows that cancellations for hotel C2 reach a value of approximately 36% of all bookings, and this is corroborated by the data in Table 2. The first noticeable pattern is that average *LeadTime* tends to be higher in canceled bookings. However, other patterns are also apparent; Portugal presented the following: (1) a higher number of bookings (*Country* feature); (2) the lowest average number of amendments to bookings (*BookingChanges*); (3) a higher average number of adults per booking; (4) a higher percentage of “Nonrefundable” bookings

(*DepositType*); (5) a higher number of stays over weekends (*StaysAtWeekendNights*); (6) a higher number of “Groups” and lowest number of “Leisure” customers (*MarketSegment*); and (7) more canceled bookings for room type “A” than for other room types (*ReservedRoomType*). These patterns, which were identified using a visualization tool, require more in-depth analysis. However, the analysis presented here provides a starting point for understanding the reasons behind cancellations and developing measures to prevent them or at least to better estimate them. As an example, through analysis of the “Nonrefundable” (*DepositType*) canceled bookings in some Asiatic countries (*Country*) and from certain distribution channels (*DistributionChannel* and *Agent*), it is possible to understand why so many “Nonrefundable” bookings are canceled. These bookings are usually made through OTA using false or invalid credit card details. These bookings are issued as support for requests for visas to enter the country (a hotel booking is mandatory for applying for a Portuguese entry visa). After failing to charge the customer’s credit card, the hotel identifies these bookings as “fake” and contacts the customer; however, during the time required to verify these bookings, they contribute negatively to demand forecast and demand management decisions.

<Insert Figure 3 here>

4 Discussion

4.1 Theoretical implications

The results of this study have several important implications for research on booking cancellation prediction. First, as some forecast/prediction studies have recently shown (Antonio et al., 2017b, 2017a, 2017c; Falk & Vieru, 2018; Huang et al., 2013) and contrary to the position previously advocated by Morales & Wang (2010), it has now been confirmed that using advanced machine learning algorithms it is possible to predict each booking’s likelihood of

cancellation. This also confirms that classification prediction models that use detailed booking data, in comparison to regression models and models that use historical data, are much more effective in the development of comprehensive models. Classification prediction models can be used to create “bottom-up” forecasts (Talluri & Van Ryzin, 2005) that can be used to make predictions at a very detailed level (per booking) as well as to predict net demand at global or aggregated levels such as market segment, distribution channel, and travel agency, among others. Second, previous studies that employed machine learning algorithms draw conclusions from prediction error results obtained from validation sets built with data from the same period of the training data (Antonio et al., 2017a, 2017c, 2017c; Huang et al., 2013). By creating a test set consisting of bookings from a period that was not included in the training and validation sets, we demonstrated that models that produce good results with known data do not always generalize well. Therefore, future research should assess results based on data obtained from a period following the period from which the data used in the training and validation sets were obtained. Third, we showed that for booking cancellation prediction problems, booking data should include booking details prior to the cancellation outcome (arrival or cancellation date). In particular, the details of noncancelled bookings should be those obtained by the hotel prior to the arrival date, not those updated at check-in or during the guest’s stay. As such, data should be extracted from PMS database log tables and not directly from PMS database bookings tables. If this is not done, the input features may not reflect the proper distribution in relation to the target variable (*IsCancelled*), thereby leaking the cancellation outcome of the bookings and resulting in weaker prediction models. The importance of extracting data prior to the outcome date is emphasized by the predictive power of the feature *BookingChanges*. The results clearly show that the number of changes/amendments associated with a booking is an important cancellation

indicator. Fourth, demand and cancellations can differ by hotel, customer, or booking or due to external factors. Instead of building models that are generally applicable to the hotels under study, as was done in earlier studies (Falk & Vieru, 2018; Huang et al., 2013; Morales & Wang, 2010), we followed the approach proposed by Antonio et al. (2017a, 2017c, 2017c) and built a specific model for each hotel. This allowed us to confirm previous studies' findings, namely, that factors such as lead time, country, length of stay, market segment and distribution channel are of high importance in predicting cancellations for any hotel (Falk & Vieru, 2018; Morales & Wang, 2010) but that this importance can vary for different hotels. Since we employed data from two different types of hotels with different characteristics, different types of customers and different distribution strategies, it is expected that the cancellation patterns would differ for different hotels. This contributes to the existence of differences among the features' importance rankings at different hotels. Fifth, despite the suggested potential benefits of big data application in hotel revenue management forecasting (McGuire, 2017; Pan & Yang, 2017b; Talluri & Van Ryzin, 2005; Wang et al., 2015; Zhang et al., 2015), no evidence of such benefits was found for booking cancellation prediction. The models' performance did not improve substantially with the inclusion of features from other sources, and none of the features from non-PMS data sources showed predictive importance. These findings are consistent with the findings of Falk & Vieru (2018), which indicated that special events and customer confidence indicators do not explain cancellation patterns. Nonetheless, this study revealed which non-PMS data sources can be used in hotel revenue management forecasting problems and how data can be collected from non-PMS data sources. Lastly, although classical statistical methods are effective in demonstrating the explanatory power of features, explanatory power does not always imply predictive power (Domingos, 2012; Shmueli & Koppius, 2011). As shown, prediction models such as XGBoost

that make use of big data and advanced machine learning algorithms that allow a certain level of interpretability are relevant to understanding features' true predictive power. This highlights how big data and machine learning-based models could be employed to understand and explain a variety of business prediction problems as well as to create more accurate forecasting models.

4.2 Managerial implications

This study has important managerial implications. Equipped with cancellation prediction models that can be used to estimate booking cancellation outcomes with high accuracy, hotels, prior to the expected arrival date, can contact customers who have been identified as having a high likelihood of canceling and take action to try to prevent these customers from canceling their bookings. Cancellation predictions could be used as inputs in revenue management systems to improve the systems' accuracy and thereby enhance inventory allocation and pricing recommendations. As a complement to RMS's recommendations or even in the absence of an RMS, revenue managers can use the models' global or aggregated net demand forecasts to make better informed demand-management decisions (e.g., how many rooms to oversell for specific dates or even whether to accept a late walk-in because the system predicts that some of the bookings that are due to arrive will cancel or not show on that day).

Comprehending which features are the best descriptors for cancellation allows hoteliers to rethink their cancellation policies in different ways. Since a large fraction of hotel distribution is now made online, it seems reasonable to take advantage of and encourage the application of dynamic cancellation policies (at least in online channels directly controlled by the hotel/chain). Instead of favoring the application of restrictive cancellation policies, why not foster the application of cancellation policies that vary according to the lead time, country of origin, or other factors with predictive importance? Cancellation penalties could be dynamically calculated

according to the probability of booking cancellation. In this way, the risk of alienating a customer who is not a “deal-seeking” customer through a rigid or high-fee cancellation policy is mitigated while the prerogative of presenting rigid or high-fee cancellation policies to “deal-seeking” customers is maintained.

The fact that the inclusion of data from multiple sources did not produce significant performance improvements, as shown by the finding that features from non-PMS sources had no predictive importance for any of the models, suggests that caution should be used with respect to big data investments. As explored by Pan & Yang (2017a), these results also raise the question of whether the use of big data in hospitality is justifiable. A low performance impact does not always justify the costs associated with collecting, storing and processing data, the time required to process large volumes of data or the time spent in data preparation and modeling. Therefore, the application of big data requires thoughtful study of the associated costs and benefits.

5 Conclusion

The present study confirms that it is indeed possible to construct machine learning models that can predict hotel booking cancellations with high accuracy. Concurrently, it shows that the best models are attained by including features that capture each hotel’s characteristics and operation environment.

Although the models that presented better results (Models 3 and 4) did not surpass the results obtained in previous research (Antonio et al., 2017a), these models were robust. This robustness can be seen in the results of the test set, which unlike previous studies in this field, did not intersect the training set. Additionally, because the processed PMS data did not contain the current values of the variables but only the values prior to check-in/cancellation, we were able to use features that had never before been used. Thanks to these contributions, the new models were

less likely to capture noise in the data and could thus generalize better than previously built models.

The identification and comprehension of the importance of features regarding booking cancellations requires that hotels obtain quality data to better support decisions. Without quality data, models similar to the ones presented here could not be built or, at least, could not achieve such good results. Sometimes a lack of quality results from the human side of data collection; errors may occur at the time of input into various data systems, such as with the classification of a booking market segment. This task is often performed by a human operator. If the hotel/brand does not have clear rules on how bookings should be classified, this is left to the operator's discretion, which results in a worthless classification. Another example is that of the time gap between the booking's delivery to the hotel and the time at which the booking is entered into the system. Although many bookings are automatically entered into the hotel's PMS via various electronic interfaces, depending on the hotel/chain, some bookings are still entered manually. If operators do not enter bookings into the PMS on the day of their delivery or do not enter the correct delivery date at the creation of the booking, one of the most important features in terms of cancellation prediction, *LeadTime* quality, will be negatively influenced.

Despite the enormous potential of big data for the hotel industry, the results presented here show that significant performance improvements were only achieved by the addition of features that characterize a hotel's specific operations (Model 4). The inclusion of more observations or features from non-PMS data sources did not result in significant performance improvement.

The new models not only allow hotels to intervene prior to check-in and to act to prevent cancellations but also allow them to determine the true demand. In addition, by showing what drives cancellations, the models allow hoteliers to adjust their overbooking tactics and

cancellation policies appropriately. Hence, hotels could present less restrictive policies to customers who are predicted to be unlikely to cancel and more restrictive policies to customers who are predicted to be more likely to cancel. The application of less restrictive cancellation policies has the potential to increase the number of bookings and thereby increase revenue, to increase the number of bookings by avoiding the indiscriminate application of restrictive policies and to increase revenue by decreasing the number of bookings with restrictive cancellation policies and thereby reducing the need to offer discounted prices. Additionally, if overbooking is employed more selectively, hotels could decrease their losses related to reallocation costs and immediate and future revenue from walk-out customers.

Finally, the presented results highlight the importance that machine learning can have in hospitality management, particularly in the area of revenue management. Estimation and forecasting are essential processes in revenue management, and machine learning can help managers improve their results by providing superior accuracy in a more timely way and above all in a more pragmatic way that is not highly dependent on personal estimations or speculations.

5.1 Limitations and future work

As is true for most work involving machine learning, the new models' product is a very complex prediction equation. This complexity does not allow the models to be depicted. Nevertheless, other researchers can follow the steps described here to replicate the models.

Although we have shown that our models achieved good results using time periods that were not included in the training data, the models were not deployed in a production environment because this was beyond the scope of the present work. Experiments in a production environment have already been conducted for two hotels, and good results were obtained, although only PMS data were employed. Nevertheless, future work on the subject should assess the reliability of the

models over time by testing these models using multiple data sources in a production environment.

Although inclusion of data from multiple sources has been advocated as a way to improve forecasting performance (McGuire, 2017; Pan & Yang, 2017b; Talluri & Van Ryzin, 2005; Wang et al., 2015; Zhang et al., 2015), the results obtained in this study do not fully support that claim. There are several possible reasons for this. One possible reason is the short time span of the data employed. Model 1 employed data obtained over a period of almost 23 months, and Models 2, 3, and 4 used data from a shorter period, 18 months. By not capturing a minimum of 3 to 4 years' worth of data, it is plausible that cancellation patterns or changes in distribution related to seasonality were not fully apprehended by the models. The lack of relevance in terms of booking cancellations of the data sources employed or the lack of predictive importance of the engineered features may also have influenced the results. Consequently, future work should explore the use of additional features and additional data sources or should engineer different features from the same data sources. For example, although we tested the predictive importance of all booking features employed in previous research, we were constrained by the variables that were stored in the PMS database. Other PMS may store different variables that might have higher predictive importance.

Features engineered from the hotels' competitive sets' social reputation and online prices/inventory did not show any predictive importance, i.e., better social rating or better prices of competitors did not influence cancellations. This raises the question of the effectiveness of using competitive sets. Are today's competitive sets helpful in the hospitality industry? For some types of travelers, this may be questionable. For someone deciding whether to book holidays in Portugal, Spain, or Cyprus and making multiple hotel reservations in these countries, a hotel's

competitors will be hotels outside of its set of competitors. A similar consideration applies to someone who is deciding whether to book a weekend break in Lisbon, Barcelona, or London. Therefore, demand forecast research should consider the use of other data sources such as on-the-books sales data or demand forecast data for competing regions or destinations. However, these data may be difficult to obtain. To overcome this, heuristics could be created from other data sources such as airport passenger traffic forecasts or cruise departures and arrivals. These data sources should be used to complement the hotel's competitive set data.

Since we demonstrated that it is possible to understand the importance of each feature in terms of cancellation and showed that this importance differs for different hotels, future research could explore this knowledge and use it to develop models that can be used to dynamically determine cancellation policies. These models could be applied on hotel/brand websites to adjust the cancellation policy according to the details of each booking search and according to the cancellation probability. A/B testing could be used to assess how customers react to these dynamic cancellation policies.

Appendixes

Appendix A – Features description

Feature	Type	Data source	Models	Description
Adults	N, I	P	1-4	Number of adults
Agent	C, I	P	1-4	ID of agency (if booked through an agency). The levels differ by hotel as each hotel has a list of agencies it works with.
AssociatedToEvent	C, E	P	4	Binary value indicating whether the booking was associated with an event held at the hotel (e.g., meeting or wedding) (0: no; 1: yes)
AvgQuantityOfPrecipitationInMM	N, E	W, P	1-4	Average quantity of precipitation forecasted. This value was calculated by summing the milliliters of precipitation forecast for the days of the stay and dividing that by the number of days of the stay for which there was a weather forecast. The values of the forecast were accounted according to the booking cancellation outcome. For bookings that were not canceled, the arrival date was considered. For canceled bookings, the cancellation date was considered
Babies	N, I	P	1-4	Number of babies
BookingChanges	N, E	P	1-4	Heuristic created by summing the number of booking changes (amendments) prior to arrival that could indicate cancellation intentions (arrival or departure dates, number of persons, type of meals, ADR, or reserved room type). Each variable change is counted as one change. For example, if the arrival date and number of persons were changed in a single operation, that would be counted as two changes
BookedSPA	C, E	P	4	Binary value indicating whether an SPA service was booked prior to the guest's arrival (0: no; 1: yes)
Children	N, I	P	1-4	Number of children
Company	C, I	P	1-4	ID of company/corporation (if an account was associated with it). The levels differ by hotel as each hotel has a list of companies it works with.
CompSetSocialReputationDifference	N, E	R	1-4	Number of hotels in the competition set that had a better rating booking outcome date (arrival or cancellation date according to the outcome). This feature value is obtained by summing the number of hotels from the competitive set that, at the booking outcome date, had better

Feature	Type	Data source	Models	Description
				social reputation rating (normalized aggregated rating) than the tested hotel.
Country	C, I	P	1-4	Country ISO 3166 alpha-3 identification of the main booking holder
CustomerType	C, E	P	1-4	Type of customer (group, contract, transient, or transient-party); the last category is a heuristic built when the booking is transient but is fully or partially paid in conjunction with other bookings (e.g., small groups such as families who require more than one room)
DayOfYear	N, E	P	1-4	Number representing the sequential day of the year. For example, January 1 st is 1, and February 1 st is 32.
DaysInWaitingList	N, I	P	1-4	Number of days the booking was on a waiting list prior to confirmed availability and confirmation as a booking
DepositType	C, E	P	1-4	Since hotels had different cancellation and deposit policies, a heuristic was developed to define the deposit type (nonrefundable, refundable, no deposit): payment made in full before the arrival date was considered a “nonrefundable” deposit, and partial payment before arrival was considered a “refundable” deposit; otherwise it was considered as “no deposit”.
DistributionChannel	C, I	P	1-4	Distribution channel used to make the booking (e.g., OTA, Direct, Travel Operator). The levels differ by hotel, as each hotel works with different distribution channels.
HotelsWithRoomsAvailable	N, E	O	1-4	Number of competitors that have inventory available for the period of the booking stay with the same type of meal package and that could accommodate the same number of adults. Inventory availability is obtained by checking the availability for all nights of the stay (lookup date) of all hotels in the competitive set, on the arrival or cancellation date according to the cancellation outcome (observation date)
IsRepeatedGuest	C, E	P	1-4	Binary value indicating whether the booking holder, at the time of booking creation, was a repeat guest at the hotel (0: no; 1: yes); created by comparing the time of booking with the guest profile creation record
LeadTime	N, E	P	1-4	Number of days prior to arrival that the hotel received the booking (usually, the date when the booking was entered in the PMS)

Feature	Type	Data source	Models	Description
MarketSegment	C, I	P	1-4	Market segment in which the booking was classified. The levels differ by hotel, as each hotel works with different market segments
Meal	C, I	P	1-4	ID of meal the guest requested. The levels differ by hotel as each hotel works with different types of meals.
nHolidays	N, E	H, P	1-4	Number of local holidays that are due to occur during the booking stay (including the check-out date)
PreviousCancellationRatio	N, E	P	1-4	Ratio calculated by dividing the guest's number of previous cancellations by the guest's previous number of bookings at the hotel (as of the booking creation date)
RatioADRbyCompsetMedianDifference	N, E	O, P	1-4	Ratio calculated by dividing the booking ADR by the average of the median price at the competitor hotels for the cheapest room each competitor had available that included the same type of meal package and could accommodate the number of adults in the booking. Competitors' prices are obtained on the arrival or cancellation date according to the cancellation outcome. In other words, the competitor's median prices for each stay night (lookup date) at the booking outcome date (observation date) are summed and divided by the number of nights to obtain a competitor's set average median price. A ratio is then calculated by dividing the booking ADR by the competitor's set median average price. The objective of this feature is to understand whether the competitors are offering a better or worse price and the amplitude of the difference.
RatioMajorEventsNights	N, E	S, P	1-4	Ratio calculated by dividing the total number of major special events that are expected to occur during the stay by the total number of nights of the booking
RatioMinorEventsNights	N, E	S, P	1-4	Ratio calculated by dividing the total number of minor special events that are expected to occur during the stay by the total number of nights of the booking
RequiredCarParkingSpaces	N, I	P	4	Number of car parking spaces required by the guest
ReservedRoomType	C, I	P	1-4	Room type requested by the guest
SRDoubleBed	C, E	P	4	Binary value indicating whether the guest, prior to arrival, asked specifically for a double bed (0: no; 1: yes)
SRHighFloor	C, E	P	4	Binary value indicating whether the guest, prior to arrival, asked specifically for a room on a high floor (0: no; 1: yes)

Feature	Type	Data source	Models	Description
SRQuietRoom	C, E	P	4	Binary value indicating whether the guest, prior to arrival asked specifically for a quiet room (0: no; 1: yes)
SRTogether	C, E	P	4	Binary value indicating whether the guest, prior to arrival, asked specifically to be placed in a room close to another booking (0: no; 1: yes)
SRTwinBed	C, E	P	4	Binary value indicating whether the guest, prior to arrival, asked specifically for a twin bed (0: no; 1: yes)
StaysInWeekendNights	N, E	P	1-4	How many nights of the total stay were on weekends (Saturday and Sunday)
StaysInWeekNights	N, E	P	1-4	How many nights of the total stay were on weekdays (Monday through Friday)
ThirdQuartileDeviationADR	N, E	P	1-4	Ratio calculated by dividing the booking ADR by the third quartile value of all bookings for the same distribution channel and the same reserved room type in the same expected week/year of arrival. The objective of this feature is to understand whether the price of the booking is much higher than that of other similar bookings.
TotalOfSpecialRequests	N, E	P	1-4	Number of special requests made (e.g., fruit basket, sea view, etc.)

Legend:

- Type:
 - C – Categorical
 - E – Engineered
 - I – Input
 - N – Numeric
- Data source:
 - H – Holiday calendar
 - O – Online prices/inventory
 - P – PMS
 - R – Social media reputation
 - S – Special events calendar
 - W – Weather

Appendix B – Machine learning metrics

Accuracy (Acc.): Measure of outcome correctness; it measures the proportion of true results

among the total number of predictions. The formula is as follows: $Acc. = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FP + \sum FN}$.

Area Under the Curve (AUC): Measure of success calculated from the area under the plot of true positive rate (TPR) against false positive rate (FPR).

False Negative (FN): The outcome prediction was negative, but the actual value was positive (e.g., the booking was predicted as likely not to cancel, but it was canceled).

False Positive (FP): The outcome prediction was positive, but the actual value was negative (e.g., the booking was predicted as likely to cancel, but it was not canceled).

False Positive Rate (FPR or Fall-out): Measures the probability of a positive prediction result and the actual value being negative (e.g., the probability of a booking being predicted as likely to cancel and effectively did not cancel). The formula is as follows: $FPR = \frac{\sum FP}{\sum FP + \sum TN}$.

Precision (Pre.): Measures the proportion of correct positive predictions. The formula is as follows: $Pre. = \frac{\sum TP}{\sum TP + \sum FP}$.

True Negative (TN): The outcome prediction was negative, and so was the actual value (e.g., the booking was predicted as likely not to cancel and was not canceled).

True Positive (TP): The outcome prediction was positive, and so was the actual value (e.g., the booking was predicted as likely to cancel and was canceled).

True Positive Rate (TPR or Sensitivity): Measures the probability of a positive prediction result and the actual value being positive (e.g., the probability of a booking being identified as likely to cancel and being canceled). The formula is as follows: $TPR = \frac{\sum TP}{\sum TP + \sum FN}$.

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Notes

¹ “Leakage” is the term employed to describe information in the training data that make models produce unrealistically good predictions. Usually, leakage is associated with the use of information from outside the time frame (Abbott, 2014).

² In Machine Learning, “training” is the term employed to describe the process that modelers conduct to mathematically establish the relationship between the predictors and the outcome (Kuhn & Johnson, 2013).

³ The term “feature” in Machine Learning is similar to the term “independent variable” in traditional statistics. “Feature” is used over “variable” because variables are often replaced by a computational result from one or more input variables.

⁴ “One-hot encoding” or the creation of “dummy variables” is a technique employed in data preparation for numeric representation of categorical data. This technique involves the replacement of the categorical feature by as many features as the number of distinct category levels (Abbott, 2014). For example, if the categorical feature “RoomType” included 3 categories (standard, deluxe and suite), this feature would be removed and replaced by 3 new features, one for each level. A binary value of 0 or 1 would then be assigned to each of these features according to the original category level of the observation. For example, if “RoomType” for a particular booking was “standard”, then the new “standard” feature will be assigned a value of 1, and a value of 0 would be assigned to the features “deluxe” and “suite”.

Tables and Figures

Table 1. Publications on summary bookings cancellation forecast/prediction (ordered by publication year)

Author (Year)	Methods type	Problem type and algorithms	Data and industries
Iliescu et al. (2008)	Advanced booking	Prediction/classification. Discrete time proportional odds	Ticketing data from Airline Reporting Corporation (ARC). Airline industry
Iliescu (2008)	Advanced booking	Prediction/classification. Discrete time proportional odds	Ticketing data from Airline Reporting Corporation (ARC). Airline industry
Lemke, Riedel, & Gabrys (2009)	Advanced booking	Forecasting/regression. Combination of single exponential smoothing, Brown's exponential smoothing and a regression approach	Weekly aggregated booking data from Lufthansa Systems Berlin GmbH. Airline industry
Morales & Wang, (2010)	Advanced booking	Forecasting/classification (for cancellation rate calculation). Average cancellation rate, seasonally averaged rate, logistic regression, C4.4 decision tree, minimum squared expected error tree, random forest, support vector machine and kernel logistic regression	Hotel chain bookings in PNR format. Hotel industry
Tsai (2011)	Combination	Forecasting/regression. Combination of various statistical algorithms	Aggregated railway booking data. Railway industry
Lemke et al. (2013)	Advanced booking	Forecasting/regression. Combination of various statistical algorithms and genetic algorithms	Weekly aggregated booking data from Lufthansa Systems Berlin GmbH. Airline industry
Azadeh, Labib, & Savard (2013)	Historical	Forecasting/classification (for cancellation rate calculation). Multilayer perceptron neural network.	Historical aggregated data of railway operator. Railway industry
Azadeh (2013)	Historical	Forecasting/classification (for cancellation rate cancellation). Multilayer perceptron neural network	Historical aggregated data of railway operator. Railway industry
Huang et al. (2013)	Advanced booking	Forecasting/classification. Back propagation neural network and general regression neural network	Restaurant booking data from a western chain in Taiwan. Restaurant industry
Petraru (2016)	Historical	Forecasting and prediction/regression and classification. Five different time series algorithms	Airline simulated data. Airline industry.
Antonio et al. (2017c)	Advanced booking	Prediction/classification. Nine different classification algorithms	Hotel detailed booking data. Hotel industry

Author (Year)	Methods type	Problem type and algorithms	Data and industries
Antonio et al. (2017a)	Advanced booking	Prediction/classification. Five different classification algorithms	Hotel detailed booking data. Hotel industry
Antonio et al. (2017b)	Advanced booking	Prediction/classification. XGBoost algorithm	Hotel detailed booking data. Hotel industry
Tse & Poon (2017)	Historical	Forecasting/regression. Maximum-likelihood estimation	Daily aggregated booking data from restaurant. Restaurant industry
Cirillo et al. (2018)	Advanced booking	Forecasting/classification. Dynamic discrete choice model	Intercity detailed ticket railway data. Railway industry
Falk & Vieru (2018)	Advanced booking	Prediction/classification. Probit model	Hotel chain detailed booking data. Hotel industry

Table 2. Hotels' bookings summary

	R1	R2	R3	R4	C1	C2	C3	C4
Uncanceled bookings	17 572	4 757	4 781	5 285	31 575	15 648	7 576	13 526
Canceled bookings	6 144	1 114	662	1 176	21 049	8 883	2 758	4 639
Cancellation ratio	25.9%	19.0%	12.2%	18.2%	40.0%	36.2%	26.7%	25.5%
OTA's share	47.8%	4.5%	5.4%	19.5%	55.0%	34.6%	83.2%	81.2%

Figure 1. OTA share vs cancellation ratio

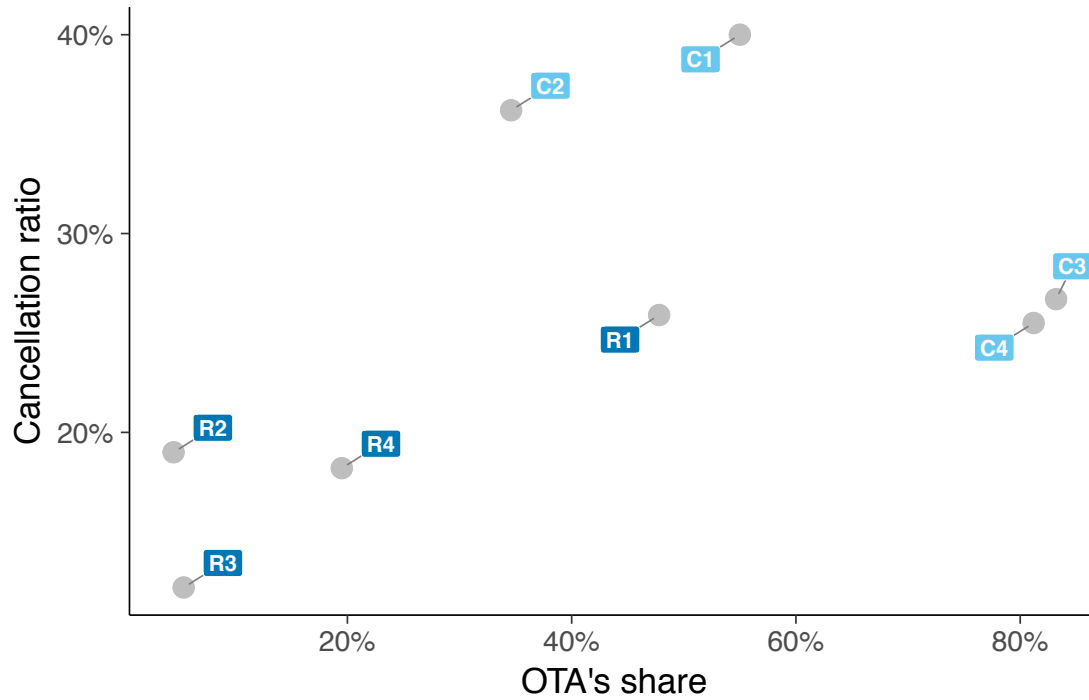


Table 3. Summary of additional data sources observations

Dataset	Observations (raw)	Observations (prepared)
Booking.com online reviews	54 357	6 426
Tripadvisor.com online reviews	54 555	
Booking.com prices and inventory availability	89 839 826	4 676 625
Events	3 956	154
Holidays	14 789	34
Weather forecast	14 250	14 020

Table 4. Models' performance metrics

Hotel	Model	Training set			Validation set			Test set		
		Acc.	Pre.	AUC	Acc.	Pre.	AUC	Acc.	Pre.	AUC
R1	1	0.8492	0.7650	0.9175	0.8431	0.7542	0.9061	0.8409	0.4607	0.8293
	2	0.8471	0.7428	0.9185	0.8232	0.6934	0.8892	0.8381	0.4568	0.8180
	3	0.8459	0.7444	0.9142	0.8229	0.6992	0.8876	0.8434	0.4719	0.8256
	4	0.8846	0.7985	0.9530	0.8563	0.7473	0.9305	0.8736	0.5711	0.8773
R2	1	0.8621	0.7234	0.8954	0.8274	0.5782	0.8035	0.7837	0.2297	0.6513
	2	0.8967	0.7875	0.9375	0.8297	0.6066	0.8192	0.7808	0.2655	0.7020
	3	0.8707	0.7576	0.9203	0.8155	0.5724	0.7864	0.7941	0.2982	0.6935
R3	1	0.8929	0.8629	0.9131	0.8738	0.6162	0.7947	0.9348	0.1818	0.6986

FEATURE	R1	R2	R3	R4	C1	C2	C3	C4
ReservedRoomType	X	X	X	X	X	X	X	X
StaysInWeekendNights	X	X	X	X	X	X	X	X
StaysInWeekNights	X	X	X	X	X	X	X	X
ThirdQuantileDeviationADR								
TotalOfSpecialRequests								
29 Features (without features for specific categorical levels)	15	14	15	15	15	15	13	15

Figure 2. Top 15 features of importance for each hotel (Model 3)

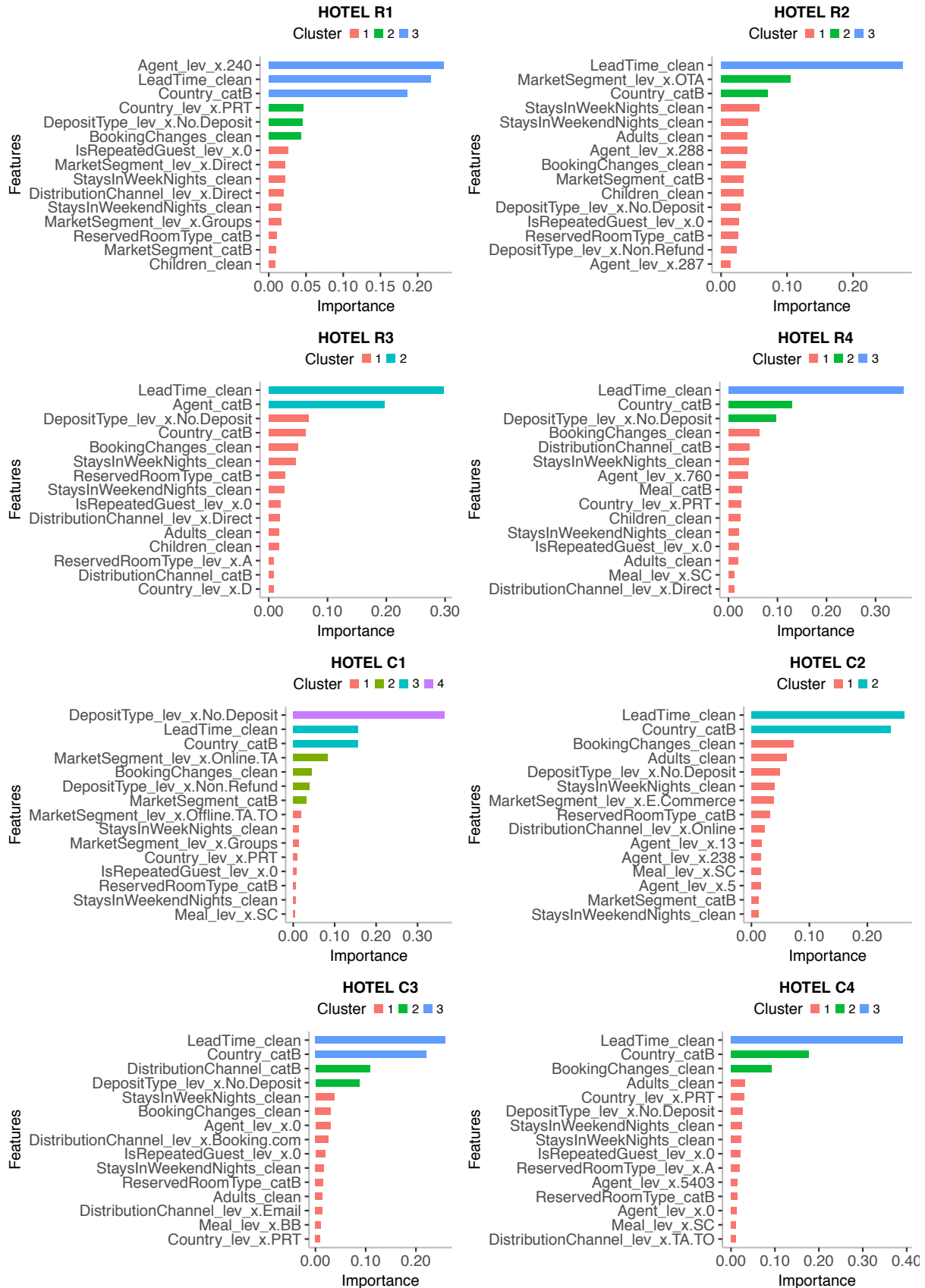
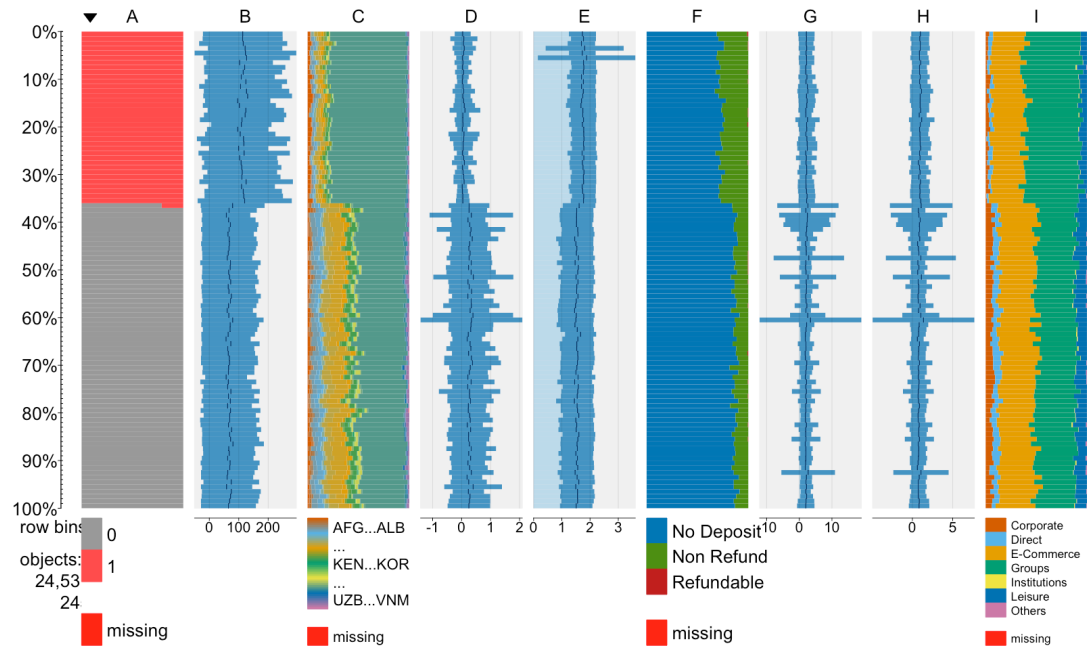


Figure 3. Visualization of top predictive features (Hotel C2 - Model 3 dataset)



Legend for columns: A - *IsCanceled*, B - *LeadTime*, C - *Country*, D - *BookingChanges*, E - *Adults*, F - *DepositType*, G - *StaysInWeekNights*, H - *StaysInWeekendNights*, I - *MarketSegment*.