Automatic Detection of Airline Ticket Price and Demand: A review

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***Abstract*—Prediction of airline ticket prices and or demand is very challenging as it depends on various internal and external factors that can dynamically vary within short period of time. Researchers have proposed different types of ticket price/demand prediction models with the aim of either assisting the customer forecast ticket prices or aid the airline to predict the demand. In this paper, we present a review of customer side and airlines side prediction models. Our review analysis shows that models on both sides rely on limited set of features such as historical ticket price data, ticket purchase date and departure date. A combination of external factors such as social media data and search engine query in conjunction with advanced machine learning techniques are not considered.**

Keywords—Ticket Price Prediction, Demand Prediction, Survey, Price Discrimination, Social Media, Deep Learning.

I. INTRODUCTION

The airline industry is considered as one of the most sophisticated industry in using complex pricing strategies. Nowadays, ticket prices can vary dynamically and significantly for the same flight, even for nearby seats [1]-[2]. The last two decades have seen steadily increasing research targeting both customers and airlines. From the customer point of view, determining the minimum price or the best time to buy a ticket is the key issue. The ticket price may be affected by several factors thus may change continuously. To address this, various studies were conducted to support the customer in determining an optimal ticket purchase time (OTPT) and ticket price prediction [3]-[14]. Most of the studies performed on the customer side focus on the problem of predicting OTPT using statistical methods. As noted by [6], predicting the actual ticket price is a more difficult task than predicting an OTPT due to various reasons: absence of enough datasets, external factors influencing ticket prices, dynamic behavior of ticket pricing, competition among airlines, proprietary nature of airlines ticket pricing policies etc. Nevertheless, few studies have attempted to predict actual ticket prices with the work done by the authors in [6]-[7], [11]-[14] as examples.

On the airlines side, the main goal is increasing revenue and maximizing profit. According to [1], airlines utilize various kinds of pricing strategies to determine optimal ticket prices: long-term pricing policies, yield pricing which describes the impact of production conditions on ticket prices, and dynamic pricing which is mainly associated with dynamic adjustment of ticket prices in response to various influencing factors. Long term-pricing policies and yield pricing are associated with internal working of the specific airline and do not help that much in predicting dynamic fluctuations in price. On the other hand, dynamic pricing enables a more optimal forecasting of ticket prices based on vibrant factors such as changes in demand and price discrimination [15]. However, dynamic pricing is challenging as it is highly influenced by various factors including internal factors, external factors, competition among airlines and strategic customers. A diagram illustrating interactions between customers and airlines in determining dynamic pricing is given in Figure 1. Generally, dynamic pricing can be considered as a game between the retailer and consumers where each party tries to maximize its own profit [16]. Therefore, to become profitable in such complex situations, airlines must dynamically adjust ticket prices based on the current demand, the behavior of customers, ticket prices given by competitors in the market and other internal and external factors [16]-[17]. This is known as dynamic pricing.

A significant number of research works have been performed on dynamic pricing which can be classified into two groups: demand prediction [18]-[24] and price discrimination [25]-[28]. Early prediction of the demand along a given route could help an airline company preplan the flights and determine appropriate pricing for the route. Existing demand prediction models generally try to predict passenger demand for a single flight/route and market share of an individual airline. Price discrimination allows an airline company to categorize customers based on their willingness to pay and thus charge them different prices. Customers could be categorized into different groups based on various criteria such as business vs leisure, tourist vs normal traveler, profession etc. Even though there are several studies conducted both customer and airlines side, no attempt has been made to present a literature survey of existing works. Therefore, the main goal of this paper is to present a comprehensive literature review of existing studies.

II. CUSTOMER SIDE MODELS

Even though various ticket pricing strategies are implemented by several airlines and Online Travel agencies (OTA), there are no adequate research papers available discussing this topic. This can be due to two reasons: First, ticket pricing strategies are highly business sensitive and remain proprietary of the owner company [2]. Most airlines do not reveal their ticket pricing strategies because of competition with other airlines. Second, there is lack of publicly available datasets that could enable researchers to conduct their prediction effectively. As a result, researchers are obliged to rely on small datasets that are gathered using Web scrapping programs. Nevertheless, there exist limited works that came up with various techniques for ticket price prediction regardless of the limited resources available [2]-[14]. The studies performed on the customer side can be roughly categorized into two: models that predict OTPT [2]-[5], [8]-[10] and those that try to predict exact value of ticket price [6]-[7], [11]-[14].

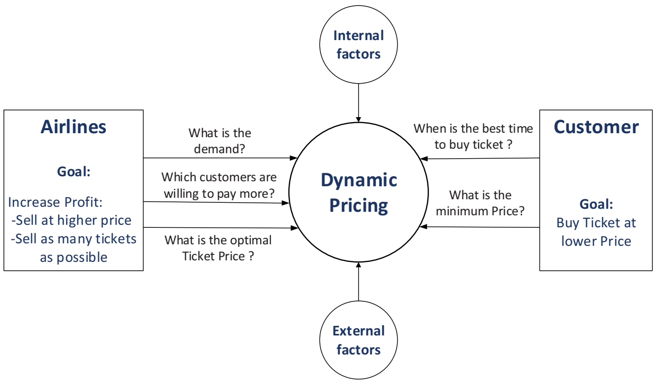

Fig. 1. Dynamic Pricing

A. Optimal Ticket Purchase Timing Prediction

One of the pioneers on OTPT prediction is probably the work done by [2]. The authors proposed a model that advise the user whether to buy a ticket or to wait for a suitable time to buy the ticket. For each query day, the model generates a buy or wait signal based on historical price information. The model uses various data mining techniques such as Rule learning (Ripper), Reinforcement learning (Q-learning), time series methods, and combinations of these to achieve various accuracy levels. The features used by the model include flight number, number of hours until departure, current price, airline and route (origin and destination city). The best accuracy (61.9% as compared to optimal saving) is achieved from the combination of all the techniques used in the study. According to [3], the model proposed by [2] has been implemented in real time for a popular ticket search website known as Bing Travel as “Fare Predictor” tool. A closely related work to that of [2] is also proposed by [3] which predicts OTPT and is in fact inspired by [2]. However, unlike [2], [3] can forecast the optimal purchase time for all available flights across different airlines for a given departure date and route. Two kinds of features were used for the analysis: Deterministic features and aggregated features. Examples of deterministic features include days to departure and quote day of week i.e. the number of different ticket prices available for a given flight on a specific route across different airlines). Aggregated features are features extracted from the historical data such as the minimum price, mean price and number of quotes. Based on experimental analysis for one route with 256 simulated purchases, PLS regression was found to be the best model with 75.3% saving as compared to the optimal one. The same authors also proposed another ticket purchase time optimization model in [4] based on machine learning (ML) techniques. Similar data as that of [3] is utilized but it was collected for 7 routes over 109 days with a total of 23.5 million quotes where each query for a single route gave 1,200 quotes on average. The authors in [5] proposed an OTPT optimizing model based on a special preprocessing step known as marked point processes (MPP), data mining techniques (clustering and classification) and statistical analysis techniques. The MPP pre-processing technique was suggested to convert heterogeneous price series data such as international, national, long and short flights, different providers (low cost and regular) into an interpolated price series trajectory that can be fed to an unsupervised clustering algorithm. The authors claim that the model achieved 55% performance as compared to [2]. The study by [8] suggested a model that predicts the optimal purchase timing based on non-parametric isotonic regression techniques for a specific route, time and airlines. The model determines the maximum number of days users might wait before purchasing ticket without significant price increase and the daily money loss that comes from delaying the purchase. Two types of variables are considered for the prediction: price and date of purchase. The authors claim that the isotonic method is advantageous in that this effect cannot be achieved with other types of regression techniques (e.g. linear regression).

The paper [9] investigated the dependency of ticket price on certain factors and built and compared various types of prediction models that consult the user whether to buy the ticket or wait for some time for a particular flight on a given route and date of departure. The paper has considered five factors including those which have not received much attention from other studies: oil price, number of intermediate stops, number of days before departure, week day of departure and number of competitors on the route. Two different supervised learning approaches have been used to build these models: Regression based modeling and Classification based modeling. The model that was built based on the Naive-Bayes technique was found to be the most accurate. It was tested based on a data that was collected for 2 months and was able to achieve 84% accuracy. Different from the preceding models that perform local (short period e.g. per day) optimal purchase timing prediction based on past static price data, the authors of [10] proposed an optimal purchase decision support system that allows continuous recommendations of the optimal purchase timing for several days before departure date based on real time dynamic price features and multi-step prediction in addition to the historical price data. The summary of OTPT prediction models is given in Table 1.

B. Ticket Price Prediction

All the studies discussed in the previous section provided a model that forecast optimal purchase timing for customers. However, predicting real-time flight prices was not considered. Understanding this gap, [6] proposed a model that predicts the lowest price available for a given itinerary. However, the model considers only non-stop flights. The authors in [7] proposed a ticket prediction model based on an empirical data-driven Regression Model. The study by [29] utilized a linear quantile mixed regression model to predict the minimum ticket price that would occur within 60 days before departure. Four variables are considered in the model: price, departure date, observation date, number of days left to departure and feature indicating day of week (weekend or weekday). The data used for the study consists of 2,271 flights with a total of 126,412 records corresponding to a single route collected within 60 days before departure across 6 airlines. The paper [11] compared the performance of eight state of the art regression ML models with respect to predicting airline ticket prices. The

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eight models considered include Multilayer Perceptron (MLP), Generalized Regression Neural Network, Extreme Learning Machine (ELM), Random Forest Regression Tree, Regression Tree, Bagging Regression Tree, Regression SVM (Polynomial and Linear) and Linear Regression (LR). The models were trained based on a dataset consisting of 1,814 flights for a single international route. The results revealed that the "Bagging Regression Tree" model outperforms the other models with accuracy of 87.42%, followed by Random Forest Regression Tree which achieved 85.91%. Similar to [6], an ensemble regression algorithm is proposed by [13] for predicting the lowest price available on a particular route for the days between the purchase date and a given departure date. A summary for the discussed ticket price prediction models is shown in Table 2.

III. AIRLINES SIDE MODELS

Airlines side models represent studies targeting profit gained by airlines and OTAs. Two main categories of researches exist in the literature regarding this. The first group proposes demand prediction models [18]-[24] while the second group focuses on price discrimination [25]-[27].

A. *Demand Prediction*

Among the recent work performed on route demand and market share prediction is the study done by [18]. The authors proposed a data mining technique designed for Maximizing Airline Profits (MAP) through prediction of total route demand and market share of an individual airline.

Table 1. Summary of Optimal Purchase Time Prediction Models

Ref.#	Addressed Problem	Dataset	Features	Computational Techniques Used	Performance Result	Remark
[2]	Predicting OTPT	12,000 ticket price data collected over 41 day	Flight number, number of hours until departure, current price, airline and route	Rule learning ,Reinforcement learning, Time series and combinations of these	61.8% savings as compared to optimal saving.	--Limited data and features - Only 7 days round-trip -No heterogeneous flights
[3]	Predicting OTPT	Data for 3 months 60 days prior to departure date.	Days to departure, Quote day of week, minimum price, mean price, No. of quotes	PLS regression, Decision tree, nu-SVR and Ridge Regression	75.3% saving as compared to optimal saving.	-No heterogeneous flights -Only considers 7 days round-trip
[4]	Predicting OTPT	The same data as above but for 7 routes	Same as above but with the addition of user-guided feature selection	Decision tree (RepTree), PLS regression, RepTree regression, ridge and nu-SVR	69% (compared to the optimal) using PLS regression.	-Does not consider heterogeneous flights -Only 7 days round-trip
[5]	Predicting OTPT	28 days data for 6 routes. Considers round-trips for 3, 7 and 14 days	Departure station, arrival station, departure date, return date, provider, day of week, month and year, and demand	Marked point processes (MPP) for Preprocessing, Clustering, classification and statistical analysis	55% performance as compared to [3].	-No detail performance evaluation steps are presented.
[8]	No. of days to wait before purchasing	2 months daily price extracted 30 days prior to departure	Price and date of purchase	Non-parametric isotonic regression	-	No performance evaluation
[9]	Comparing ML algorithms for OTPT	2 months data	Oil price, No. of stops, No. of days before departure, week day of departure and number of competitors	Regression based modeling and Classification based modeling	84% accuracy using Naive-Bayes technique	
[10]	Optimal purchase decision support	-	Historical price data and real time dynamic price features	-Multi-step prediction model that uses 2 single-step models: Classification & Regression Tree and Moving Average	-	

Table 2. Summary of Ticket Price Prediction Models.

Ref.#	Addressed Problem	Dataset	Features	Computational Techniques Used	Performance Result	Remark
[6]	Minimum Ticket Price Prediction	More than 3 months (110 days) data for 5 international routes.	Prices of the same itinerary, prices of recent itineraries before the target day, prices of itineraries with the same day of week and a month.	An ensemble-based learning algorithm Learn++.NSE is modified and used	Mean absolute percentage error (MAPE) of 10.7%	-No flight level prediction - No multi-stop flights included
[7]	Ticket Price per kilometer Prediction	Data collected for 75 and 90 days (local & international flights).	City of departure, destination, ticket purchase date, departure date, ticket options with the price	Regression Model	Not given	-No performance evaluation. -Limited dataset
[29]	Predict the minimum ticket price before departure	2,271 flights with a total of 126,412 records for a single route	Price, departure date, observation date, number of days before departure and day of week (weekend or weekday)	Linear quantile mixed regression model	Performs well for shorter period but is inefficient for longer period	Only way trip and leisure tickets with non-stop flights
[11]	Comparison of regression ML models for ticket price prediction.	A dataset consisting of 1814 flights for a single international route	Departure and arrival time, No. of free luggage, days before departure, No. of stops, holiday, time of day and day of week	Eight regression ML models	Bagging Regression: 87.42%, and Random Forest Regression Tree: 85.91% accuracy	
[13]	Predicting the lowest price available before departure date	Data consisting of 19 different routes and spans three months period (92 days).	Historical ticket prices, a signal indicting whether the departure date is holiday or not and number of days before departure	Ensemble model that uses K-Nearest Neighbors, Random Forest and Bayesian	Improved the MAPE from (7% -12%) to (3.7% - 6%) compared to single model	
[14]	Ticket price prediction	51,000 records of a 7-day round trip non-stop flights from 3 domestic airlines	Airline, flight, price, fare class, purchase date, departure date and time, arrival time and date, No. of stops, departure & arrival airport	A Stacked prediction model based on Random Forest and Multilayer Perceptron model	4.4% and 7.7% better than Random Forest and Multilayer Perceptron as measured by R^2	

They also suggested two algorithms (Bi-level Branch and Bound algorithm and Greedy algorithm) that find the optimum frequency allocation of flights for an individual airline while utilizing the route demand and market share predicted using the proposed prediction model. The model outperforms previous models based on three performance metrics: Pearson Correlation Coefficient (CC), R^2, and Mean Absolute Error (MAE). The Correlation Coefficient was 0.95 for market share and 0.98 for demand as compared to 0.82 and 0.77 for previous models. However, the proposed model has higher time overheads in comparison with previous models because of the additional time for clustering and more advanced regression methods. The same authors above provided the extension of their work in another article [21] where they introduce two new concepts on the basic Frequency-Based Profit Maximization algorithms to capture the conservative nature of airlines in deciding flight frequencies: bounded frequency and long-term profits. The decision of customers to buy a ticket for a given flight and route depends on various factors such as airlines' market share, customer membership (loyalty), and travelers' personal preferences of popular cities for destination and popular airlines for travel etc. [22]. The article proposed a probabilistic framework model that enables to model airline customer travel preferences and to predict personalized airline passenger demand i.e. the destination and the airline an individual customer will choose.

Other studies attempted to predict airline demand based on price elasticity. Price elasticity varies as a function of several factors. For example, it has been found that flights purchased on week days are more inelastic (less price sensitive) than flights purchased on weekends [30]. Similarly, business class flights are more inelastic as compared to leisure class as business customers have less flexibility to change or cancel their travel date [20]. A study by [23] investigated how demand changes with the number of days left before departure and found that the number of active consumers increases closer to departure date and consumers become more price sensitive as time to departure approaches. The article in [24] tried to predict changes in demand through examining the relationship between the purchase timing preferences of airline passengers and their characteristics. However, the data is limited in that it covers only a single route between Taiwan and Singapore and the respondents consist mainly of Taiwanese passengers. The results indicated that heterogeneous demand change patterns are observed for different types of passengers owing to the differences in their preferences of booking time. The summary of Demand Prediction Models is given in Table 3.

B. Price Discrimination

Previous research indicates that airlines use various kinds of price discrimination mechanisms to charge customers different prices based on their willingness to pay for travel [25]-[27]. However, these studies are focused on testing a hypothesis to proof the existence of price discrimination and did not propose specific models or techniques for price discrimination. Moreover, mainly day dependent price discrimination was considered. Researches indicate that consumer profiling is performed by airlines for price discrimination based on either direct information sources (e.g. consumer registration) or indirect sources such as cookie files. The paper [28] conducted research to identify what kind of customer information is exploited by airlines to perform customer profiling. Price discrimination increases the revenue of the airlines. On the other hand, it could have negative effect on the consumer welfare of airline customers. A study by [31] developed a model that estimates the demand for airline with the presence of price discrimination and investigated the effect of inter-temporal price discrimination on consumer welfare.

IV. DISCUSSION AND ANALYSIS OF EXISTING WORK

Based on what we have presented, we can infer that ticket price prediction and demand prediction research is at an infancy stage. There is room for improvements in several areas including predicting exact value of ticket prices/demand, address dataset issues, and limitation of features. Most researches conducted in this area do not predict the exact value of a ticket price or the demand. Moreover, the maximum performance achieved so far is 75% which is not always acceptable. Nevertheless, there are few studies which attempted to predict the exact value of ticket prices [6]. However, the used models in these studies suffer from computational overhead as it is computationally more intensive than predicting the optimal purchase time. In demand prediction, the most notable work [18] predicts quarterly route demand but cannot work for short term prediction. The other models in [19]-[20] suggested for demand prediction only estimate the percentage increment or decrement in demand for a flight based on price elasticity. Another important topic that is not yet explored well is related to the development of a price discrimination model. None of the previous studies propose a technique for price discrimination but they rather focus on proving the existence of price discrimination in airlines pricing strategies. Lack of generality is also one of the weaknesses noticed among existing studies. On the other hand, dataset issues, limitation in features and techniques employed are probably the most important issues and need to be discussed in detail. Therefore, we look at each of these in a separate section.

A. Dataset Issues

The lack of benchmarking data is one of the major obstacles for researches in this area. To the best of our knowledge, there is no publicly available datasets that sufficiently satisfies the needs of most of the research to be conducted. The most common public dataset used by many earlier researchers is the one provided by the U.S. Department of Transportation (DB1B). However, this dataset only provides a 10% average of ticket price for different itineraries performed in each quarter for US domestic flights. Moreover, it does not specify the purchase date or departure date which makes it unsuitable for predicting short term and flight level ticket/demand prediction.

B. Features

Proper selection of features that can affect prediction results is an important step towards building good prediction models. In this part, we summarize the set of features used in previous work and suggest additional features that are important for ticket/demand prediction. Table 4 shows the list of most commonly used features by earlier studies.

Table 3. Summary of Demand Prediction Models

Ref .#	Addressed Problem	Dataset	Features	Techniques Used	Performance Result	Remark
[18] [21]	Demand and Market share prediction	10 years (40 quarters) of data for 13 airlines and 700 routes	Ticket price, No of flights, delay time, delay ratio, cancel ratio, average stop and safety, aircraft size, total seat, average price, population income, customer price index (CPI) and Nash equilibrium pricing .	Ensemble Forecasting that uses existing demand and market share prediction models, clustering and game theoretic analysis	CC of 0.95 and 0.98 for market share demand respectively	-The prediction is quarterly -High overhead
[19]	Ticket demand forecasting	3 years customer call, ticket sales and search query	Internal factors (number of customer calls), External factors: Two query key words: "Ticket", "TaobaoTrip" and ticket price	Neural Networks and two types of support regression ($\mathcal{E}$-SVR and v-SVR)	MAPE of 0.0466	Data set is limited
[20]	Demand prediction	A total of 7522 bookings data for 21 dates	Number of advanced bookings, booking day of week, departure day of week and time of day and competitor promotions	Linear regression	Price elasticity of 1.97	-No performance evaluation -Non-stop flights only - 25% missing data
[22]	Predicting airline passenger demand	2-year passenger records with > 50 million flights & 3 million customers	ID number, name, and gender, and flight-related information such as airline, origin and destination airport	Bayesian network to model behavior of customers and a Multiple Factor Travel model to predict Demand	F1-score ≈ 0.33	The performance evaluation is based on the first 5 top-ranked probabilistic predictions
[24]	Predicting changes in Demand	Not specified	User related features (e.g. age, occupation, gender, education level, and income) and flight related data such as ticket price, purpose of travel, airline, purchase date etc.	Trigonometric Function	-	- Only a single route and homogenous passenger data - No detail performance evaluation

Table 4. Summary of Features Used by Previous Studies

Feature	OTPT	Ticket Price Prediction	Demand Prediction	Price Discrimination	Papers Using the Feature
Flight Number, Route	✓				[2]
Number of Days before departure	✓			✓	[2], [3], [35], [25], [26]
Quote Day of Week	✓			✓	[3], [5]
Ticket Price history (minimum, maximum, mean, average and nash equilibrium)	✓	✓	✓	✓	[2], [3], [35], [7], [18], [19], [25], [26]
Airline	✓				[2], [5]
Number of Quotes per day	✓				[3], [35]
Departure & Arrival Station, Return Date, Departure Day of Month & Year	✓				[5]
Departure Date	✓	✓			[5], [7]
Departure Day of Week	✓		✓	✓	[5], [20], [25]
Demand (e.g. recent demand history)	✓			✓	[5], [25]
Prices of (the same itinerary, recent itineraries before target date, itineraries with the same day of week and with the same day of month)		✓			[6]
Departure City, Destination City, Purchase Date		✓			[7]
Airline delay, cancel ratio, average stop and safety, capacity, Population income, Customer price index (CPI), No. of flights			✓		[18]
Number of Customer Calls, Search Engine Query			✓		[19]
No of Advance bookings, Departure time, Competitor Promotions			✓		[20]
Purchase day of week			✓	✓	[20], [25], [26]
Purchase deadline, travel restriction or duration of stay			✓		[25]

C. Techniques

A wide range of modeling techniques have been applied for ticket price/demand prediction. To summarize, we can classify the techniques employed so far into three categories: Simple hypothesis testing and regression techniques, various kinds of ML techniques, and ensemble learning.

V. Future Directions

One of the future directions that has great potential to improve the ticket price and demand prediction is to use the latest and advanced ML techniques (i.e. deep learning) in conjunction with valuable social media-based data. We can think of various useful features from social media that can possibly forecast airlines passenger demand and or ticket prices. For example, sentiment analysis of different twitter hash tags could convey the presence of some event at a flight origin/destination city that improves the prediction of ticket price/demand. This kind of feature extraction might involve searching for special keywords or group of terms, determining the number of times they appear, understanding the location and the date, their context etc. Recently, deep learning techniques have revolutionized many areas of computer science including computer vision leading to dramatic performance improvements on a variety of traditional problems. Within deep learning, convolutional neural networks (CNNs) [32] have received much attention recently and has been widely adopted by the computer vision community. To the best of our knowledge, pre-trained word embedding and CNNs are yet to be explored for airline ticket price/demand prediction especially when considering external factors. As ticket price and demand prediction is a supervised learning problem, CNN can be used to classify data extracted from social media into popular destinations, future events, etc. Other than CNNs, Recurrent Neural Networks (RNNs) [33] analyze the text data word by word where the semantics of previously seen text is stored in the hidden layer. This hidden layer is of fixed size. Different to CNNs that are hierarchical, RNNs are sequential architectures and are shown to provide promising results on document-level sentiment classification [34]. Existing features such as current price, days to departure, quote day of week, departure airport, departure date, return date, provider, etc. can be combined with features extracted from various sources including news media, search engines and social media. Suitable text analytics tools can be used to extract relevant information related to public feelings about a particular airline (sentiment analysis), popular destinations, events, environmental conditions, natural disasters, etc.

VI. CONCLUSIONS

In this paper, we presented a survey of ticket and demand prediction models. We classified existing models into customer side and airline side models based on their designed goals. We then discussed the strengths and weaknesses of existing work. Our analysis result showed that this research area has not been greatly explored and that there exist several aspects which need to be thoroughly investigated including: performance issues, dataset issues, usage of dynamic external features such as social media data and search engine query. Therefore, we suggested a deep learning and social media data-based prediction model as one promising approach.

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