Dynamic Pricing Model for a Tourist Attraction
02830 Advanced Project in Digital Media Engineering, DTU

Anna Hálfdánardóttir
s202097

ABSTRACT

In this paper a machine learning approach to dynamic pricing is explored. In collaboration with an Icelandic company in the tourism industry a model is developed that forecasts entry ticket demand fluctuation for their attraction. The factors used in the model are passenger predictions, temporal information (weekday, month, year) and weather information. When the demand has been predicted a pricing strategy is set up accordingly. Finally, different ways of visualizing the model's output are explored.

1 INTRODUCTION

Fluctuation in demand can be a challenge for companies when setting up a pricing strategy. This is certainly the case for the tourism industry in Iceland where demand varies heavily through the year [9]. This project was done in collaboration with an Icelandic company that sells entry tickets to a tourist attraction. Their goal is to smooth out the consumption curve and increase profit from ticket sales.

1.1 Motivation

Today the company sets ticket prices manually for each month. This means that prices are static throughout the whole month. In a market with fluctuating demand a dynamic pricing strategy can increase profit by selling to the right consumer at the right time and for the right price [10]. As a result the pricing process can be partly automated and the prices easily be set to fluctuate between days (or even hours) instead of just months.

While using instinct and preliminary data analysis to set up a dynamic pricing strategy can be beneficial there might be patterns in the demand that a machine learning algorithm identifies that are not clear to the human eye. Combining the two by doing preliminary analysis and incorporating the findings into a model could result in a more accurate prediction in demand.

1.2 Analysis

The aim of this project was to identify a pattern in the demand and predict it ahead of time. This will allow the company to price their entry tickets accordingly. By raising the price on higher demand days and lowering it on lower demand days the consumption can be smoothed over time and hopefully remain close to 100% daily capacity.

With the use of data analysis and machine learning algorithms a dynamic pricing model was developed and validated. Subsequently different visualization of the model output were tested.

1.3 Related Work

Today, many companies in the travel industry use a dynamic pricing strategy. An example of that are the major airlines, who were pioneers in the field [2]. Buying a flight around Christmas is probably going to cost you more than buying one in the middle of May, for example. While this method has mostly been used by big international companies, the same approach can be localized to a smaller scale company in Iceland.

But why is this method not used by all companies? Proven downsides to dynamic pricing include distrust from customers when they see constantly varying prices and the cost of setting up and monitoring a pricing model [5]. The effects of these downsides can be reduced nonetheless and a dynamic pricing strategy, if done well, has been proven to increase profit [10].

2 PROTOTYPE

In this section a prototype of the dynamic pricing model and corresponding user interface will be introduced.

2.1 Machine Learning Model

The goal was to create a model that predicts the popularity of a future day. To do this five different *popularity score categories* were defined. They are 'High', 'Semi-High', 'Average', 'Semi-Low' and 'Low'.

2.1.1 Choice of Model. The model used was a Random Forest Classifier (RFC). An RFC creates a set of decision trees from randomly selected subset of training set. It then aggregates the votes from different decision trees to decide the final class of the test object [7]. The test object here is a given date and the class is a popularity score.

Why use a classifier instead of a regression model? The reason for this is twofold. Firstly, classifying days keeps the number of price points for each product at a sane amount. Secondly, doing the classification afterwards based on a regression model's output was not as successful when tested. That approach had an f1 score of 0.75, compared to the classifier's 0.82 [8].

2.1.2 Data. The historical data used in this project were sales from the company, international passenger counts [1] and weather information obtained from the Icelandic Meteorological Office. The data was cleaned and set up in the following way for each day:

- Feature variables
  - Weekday
  - Month of year (January, February,..)
  - Year
  - Number of passengers (monthly granularity)
  - *Average temperature* (short-time predictions)
  - *Average rainfall* (short-time predictions)
- Target variable
  - Popularity score

The popularity score is calculated from the historical sales data. For each day its percentage of yearly sales is calculated. The days are then split up into yearly sales percentile classes in the ranges:

- 0-10% - Low
- 10-25% - Semi-Low
- 25-75% - Average
- 75-90% - Semi-High
- 90-100% - High

When the classifier has been trained on historical data it can take in future temporal information (weekday, month, year) and passenger predictions and estimate the score of a given day. The passenger predictions used were the ones published by Íslandsbanki [3]. For short-time forecasts the model can also improve its accuracy by using weather predictions.

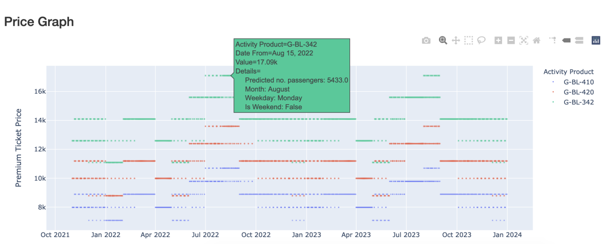
2.1.3 Pricing. After a popularity score has been predicted the price is calculated. Each package type has five price points that are each connected to a single popularity score. They are calculated in the following manner:

$$prices = \{0.8, 0.9, 1.0, 1.1, 1.2\} \cdot basePrice$$

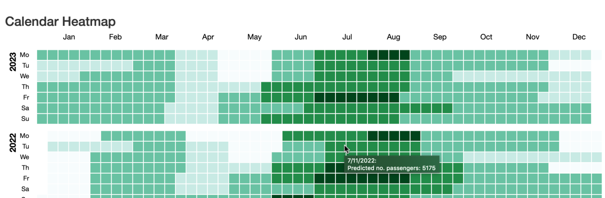
Where the base price for each product is defined by the company.

2.2 Visualization of ML Output

A user interface (UI) was implemented that allows the user to select a date range, one or more package types and visualize the model output over a time period. The user can choose between three different visualizations; a price table, scatter plot and calendar heatmap. The scatter plot shows exact price points for each selected package while the calendar heatmap shows the change in popularity scores over time. Examples from the UI can be seen in Figure 1



(a) Scatter Plot



(b) Calendar Heatmap

Figure 1: Price visualization UI

In both the scatter plot and calendar heatmap additional information on a given day is available upon hovering over a point/square. In the scatter plot the user can see the values of the model's feature variables to get a sense of why the day is given a specific popularity score. In the calendar heatmap the exact date and passenger prediction is available upon hover. This should help the user better understand why, for example, a Monday in May might not be classified the same way as a Monday in August.

3 METHOD

3.1 Model Evaluation

To develop the model an iterative approach was used. At the end of each iteration the model was evaluated by looking at the f1 score and confusion matrix.

3.1.1 Variable Correlation. To decide on what features to use as input to the model it is important to look at their correlation with the target variable (sales).

From Figure 2 it seems that the passenger count and sales have a high positive correlation.

Figure 2: Passenger Count vs. Sales Correlation

The corresponding Pearson's correlation coefficient was calculated and is 0.92. This confirms the assumption. The historical passenger numbers are therefore crucial for the model. This also means that the quality of the model in practice will depend heavily on the use of precise passenger predictions.

A pattern between sales and temporal information can be investigated by looking at categorical plots.

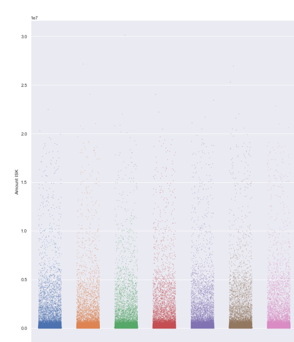


Figure 3: Weekdays and Sales

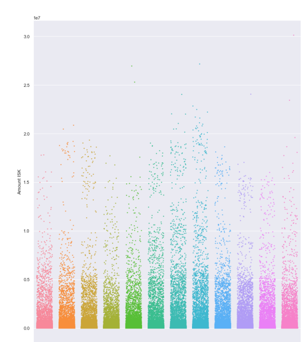


Figure 4: Months and Sales

From Figure 3 it can be seen that there is a some pattern where Tuesdays and Wednesdays seem to be least popular. The pattern is not highly apparent but enough for weekday to be worth including in the model. Figure 4 shows a clear difference in sales between months. Sales rise throughout the summer with a peak in August. There is also a small peak in December and February. Late summer and the Christmas are clearly busy times for obvious reasons like work and school holidays. February is not what one would consider to be a peak tourist month but it seems that time is more popular for travelling to Iceland than Easter, for example. This is an example where solely using intuition might have caused Easter to be evaluated as a high demand period when the data shows otherwise. Month is clearly an important feature for the model.

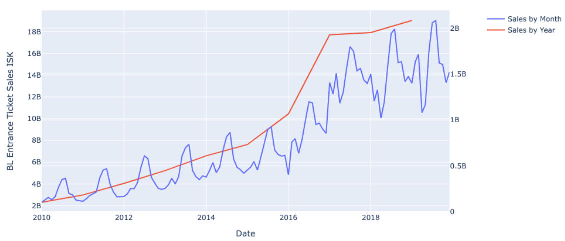


Figure 5: Yearly/Monthly Sales

Figure 5 displays a clear positive trend in sales between years. This is of course partly due to inflation but can also indicate that the company's attraction has grown in popularity. The monthly trend also seems to have changed. After 2016 there is not a single peak each year but multiple ones. Year is clearly an important feature for the model.

The two variables that were used from the historic weather data were temperature and rainfall. The were both grouped into six categories each and therefore consist of integer values on the range 1-6. The reasoning for grouping them into categories instead of using exact values is that there probably isn't a difference in attraction based on whether the temperature was 16 or 17 degrees but there might be a difference between a "chilly" and a "warm" day or a "dry" and a "showers" day.

Figure 6: Temperature and Sales

From Figure 6 it can be seen that temperature affects ticket sales. The attraction is mostly located outdoors so this makes sense. The last group contains days where the average temperature was over 15 degrees (high for Iceland) and almost all of the days had relatively high sales. The same was the case for rainfall as can be seen in A. In practice, however, it is not wise to count on weather predictions more than one week ahead. This means that they are only helpful for the model when making short-time predictions. For this reason the model was evaluated in two parts, how well it performs with and without the weather information.

3.1.2 F1 score. There are many ways to evaluate an RFC's quality. In this project f1 score and confusion matrix were used. The f1 score is a better metric than accuracy, which is often used, for this case since accuracy assumes that all classes are equally important. A model that always predicts "Average" will have 50% accuracy but it is nonetheless not very useful. By using the f1 score it is possible to get a score for each of the classes [8]. In this case the 'High' and 'Low' days are the most important ones since these are the days where the company will likely have had trouble with either supplying the demand or with obtaining full capacity. The confusion matrix gives the number of correct and incorrect predictions, summarized with count values and broken down by each class [8].

In order to evaluate a machine learning model's quality it can be useful to "save" part of the historical data for testing and use the rest for training the model. In this project 70% of the data was used for training and 30% was saved for testing.

The two models, with and without weather information (WI), performed in the following way on the test data:

Evaluator	With WI					Without WI				
Confusion Matrix	479	15	16	5	8	399	71	23	15	15
	53	467	36	6	15	125	361	58	9	24
	35	76	377	59	14	47	82	310	98	24
	7	3	28	485	34	21	33	36	402	65
	6	7	18	50	439	10	5	33	91	381
F1 Score	0.82					0.68				

Table 1: Model Evaluation

It is clear that including weather information improves the model. The f1 score is much higher (0.14) and from the confusion matrix it can be seen that it makes fewer wrong predictions for all popularity scores. This means that long-term demand predictions will be less accurate than short-term ones, which is normal. The model can still provide valuable long-term predictions as can be seen from the confusion matrix. 'High' days in the testing set are a total of 520. Out of those 520, 381 were correctly identified. This is an accuracy of 73%. Out of the 139 wrongly predicted 'High' days, 65% of them were predicted as 'Semi-High' days. This means that out of all the 'High' demand days, the model will have set either a 'High' or a 'Semi-High' price for over 90% of them.

3.1.3 Oversampling. When grouping the historical data into popularity score categories there was an imbalance in the data where 50% of the data fell into the 'Average' category, 15+15% into the 'Semi-High/Low' categories and 10+10% into the 'High/Low' ones. To make the model less biased towards the popularity scores that more data was available on *oversampling* was used [6]. This was done by randomly duplicating rows of data for the smaller categories until an equal amount of data was available for all categories.

3.2 Visualization Evaluation

The UI for this project was, like the model, developed in an iterative process. At the start the UI was a simple table. While it contained all of the information available for each data point it was in no way useful for identifying patterns in the popularity score predictions. This is where exploration of different plots started.

3.2.1 A/B Testing. A key tool in evaluating and comparing different visualizations was A/B testing [4]. In total four different visualizations were presented. The first visualization was the table, which can be seen in A The first plot developed was a non-interactive date vs. price scatter plot. The next one was 1a. Lastly, the calendar heatmap shown in 1b was introduced. The results of the A/B testing were the following:

Component	Comments	Final UI?
Table	Liked search and sorting feature. No overview of all data points and therefore hard to explore patterns.	Yes
Basic Scatter	Better overview of prices and able to see some patterns. Weekday patterns for example not identifiable however. Also want to get more information on *why* the model came to predict the given popularity score.	No
Interactive Scatter	Nice to see the passenger prediction in popup. Showing weekdays in the popup also makes it easier to try to see a pattern. Still requires opening all popups.	Yes
Calendar Heatmap	Easier to identify temporal patterns (weekdays, months,..). Liked seeing passenger predictions in popup. Not possible to see exact prices for each product.	Yes

Table 2: A/B Testing Results

It was decided to not include the basic scatter plot. The reason for keeping both the interactive scatter plot and calendar heatmap was that the scatter plot is able to show prices for different products and the calendar heatmap shows temporal patterns better than the scatter plot. The table was included but is more intended for lookup of individual days/products rather than for visualization purposes.

4 RESULTS AND DISCUSSION

It is interesting to see how well the model performs with relatively few features. The input features used were temporal information and passenger counts (and weather information) that gave an f1 score of 0.68 (0.82). Both the passenger count and weather information parameters depend on predictions in practice. This means that the quality of the model will depend heavily on precise predictions of these values. Passenger predictions are published by a number of companies in Iceland and therefore should be easy to access. Examples are the ones made by ISAVIA and Islandsbanki [3]. Weather predictions, as stated before, are not too accurate more than a week ahead in time and will therefore not be of much use except for in short-term predictions.

While increasing profits is great one must keep in mind that a dynamic pricing strategy does not only impose positive effects. Let's look back at the possible drawbacks of using a dynamic pricing strategy introduced earlier. The former one was possible distrust from customers caused by constantly changing prices. This has been taken into consideration and was the main driver behind having only five price points for each product type instead of making the model predict continuous prices with infinite possible values. The second point was the cost of creating and monitoring a pricing model. By using machine learning instead of intuition and manual methods much of the work can be automated. There would however still be some preliminary analysis and monitoring to do.

5 FUTURE WORK

The input variables are still quite few. In order to improve the quality of the model a suitable next step would be to explore other factors that might influence the demand for a given day. Examples of these factors could be consumer price index, currency rates and competitor prices.

Another thing that has yet to be considered are price changes when capacity reaches a certain point. Each day might have a set *base price* but the price of tickets could increase as more are sold. This is also a method used by the airline companies [2].

6 CONCLUSIONS

The goal of this project was to create a model that would help the company set up a dynamic pricing strategy for their tickets. By making the model predict the popularity score of a given day ahead in time the company can use that information to set a corresponding price point for each product. The model can not predict the popularity score of any given day with 100% accuracy but it is fairly precise and should help the company capitalize on the majority of the high demand days by increasing the prices. In a similar fashion the company can reduce the price on lower demand days in order to smooth out the consumption curve and decrease the amount of days where the demand exceeds the supply.

REFERENCES

[1] Ferdamalastofa. 2021. *FERÐAMENN UM KEFLAVÍKURFLUGVÖLL*. Retrieved November 29, 2021 from https://www.ferdamalastofa.is/is/tolur-og-utgafur/fjoldi-ferdamanna/talningar-ferdamalastofu-i-flugstod-leifs-eirikssonar

[2] Chris Gibbs, Daniel Guttentag, Ulrike Gretzel, Lan Yao, and Jym Morton. 2018. Use of dynamic pricing strategies by Airbnb hosts. *International Journal of Contemporary Hospitality Management* (2018).

[3] Islandsbanki. 2021. *Erlendum ferðamönnum fjölgar loks eftir faraldurinn*. Retrieved November 29, 2021 from https://www.islandsbanki.is/is/frett/erlendum-ferdamonnum-loks-farid-ad-fjolga-eftir-faraldurinn

[4] Rochelle King, Elizabeth F Churchill, and Caitlin Tan. 2017. *Designing with data: Improving the user experience with A/B testing.* " O'Reilly Media, Inc.".

[5] Fei Lee and Kent B Monroe. 2008. Dynamic pricing on the internet: A price framing approach. *ACR North American Advances* (2008).

[6] Roweida Mohammed, Jumanah Rawashdeh, and Malak Abdullah. 2020. Machine learning with oversampling and undersampling techniques: overview study and experimental results. In *2020 11th International Conference on Information and Communication Systems (ICICS)*. IEEE, 243–248.

[7] Mahesh Pal. 2005. Random forest classifier for remote sensing classification. *International journal of remote sensing* 26, 1 (2005), 217–222.

[8] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research* 12 (2011), 2825–2830.

[9] Sveinbjörg Rut Pétursdóttir. [n.d.]. *Ferðaþjónusta utan háannatíma*. Ph.D. Dissertation.

[10] Amirreza Rohani and Mohsen Nazari. 2012. Impact of dynamic pricing strategies on consumer behavior. *Journal of Management Research* 4, 4 (2012), 143–159.

A APPENDIX: GRAPHS

Figure 7: Rainfall vs. Sales Correlation

Price Table

Show 10 entries

Search:

Activity Product	Value	Date From	Date To	Details
G-BL-342	12590	2021-11-01	2021-11-02	Predicted no. passengers: 1333.0 Month: November Weekday: Monday Is Weekend: False
G-BL-342	12590	2021-11-02	2021-11-03	Predicted no. passengers: 1333.0 Month: November Weekday: Tuesday Is Weekend: False
G-BL-342	11090	2021-11-03	2021-11-04	Predicted no. passengers: 1333.0 Month: November Weekday: Wednesday Is Weekend: False

Figure 8: UI - Table