Cascaded Machine Learning Model for Efficient Hotel Recommendations from Air Travel Bookings

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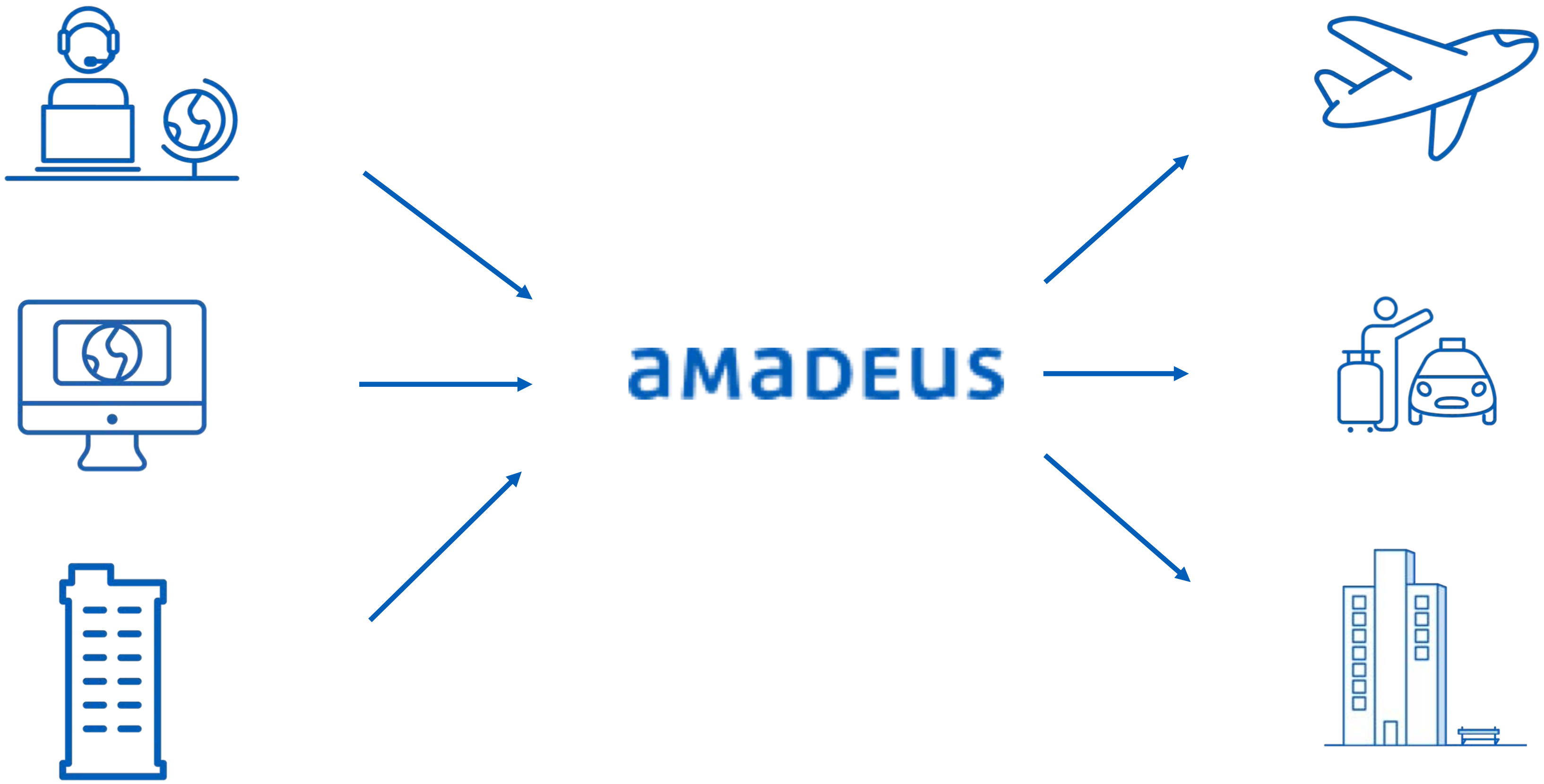
Amadeus and global distribution system



What makes a hotel desirable?

What makes a Hotel desirable?

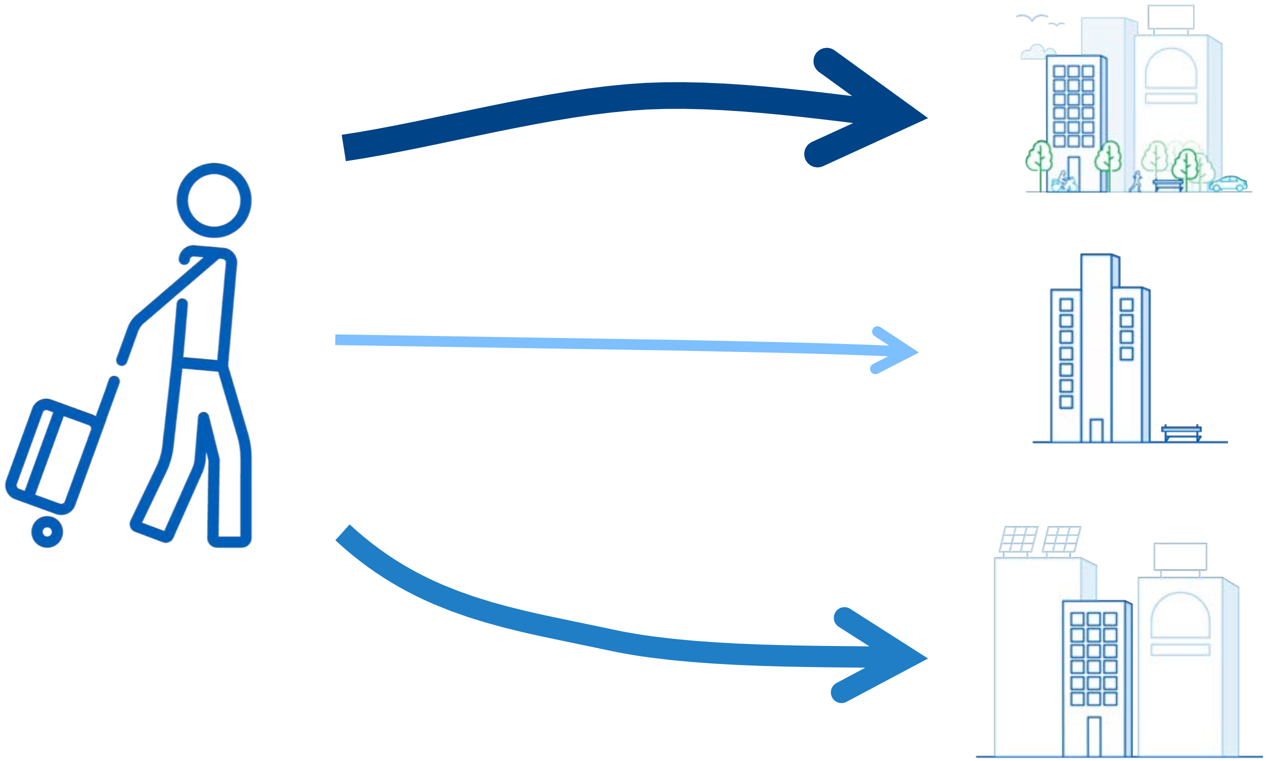
- Price
- Room
- Location
- Ratings
- Reviews
- Services
- Amenities

Different travellers will have different preferences

How to construct a hotel recommender system?

Construct a detailed profile of the traveller based on historical bookings of the traveller.

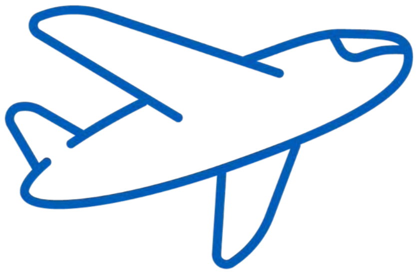
Use this information in a normal content based or collaborative filtering recommender



However, in this context we do not have any historical data about individual travellers.

Estimating hotel conversion from flight booking information

- Origin
- Cabin class
- Airline
- Advance booking



- Price
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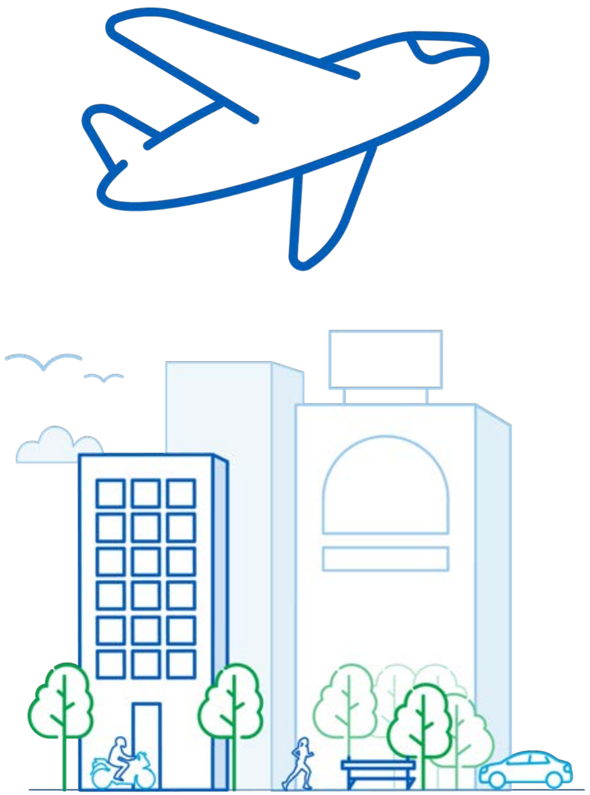
In the absence of traveller history, we can build a machine learning model based on historical data to model the conversion probability of a hotel based on its attributes and the context of a flight booking.

Estimating hotel conversion from flight booking information



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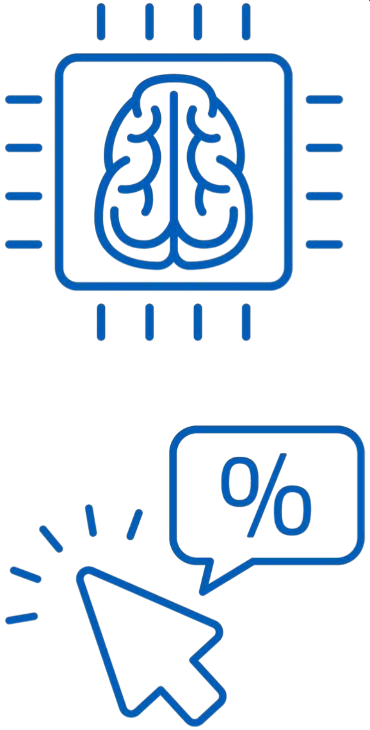
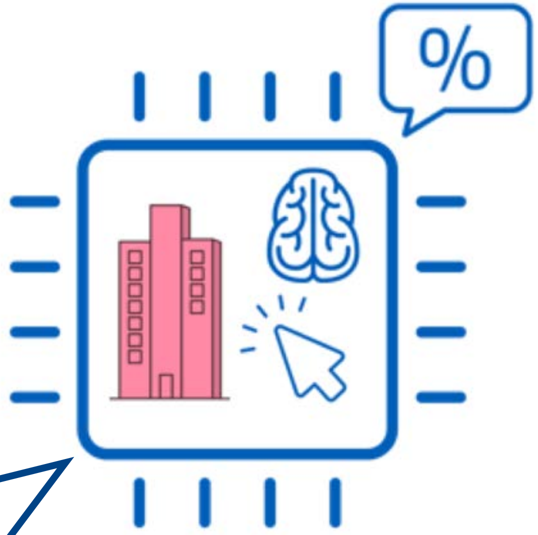
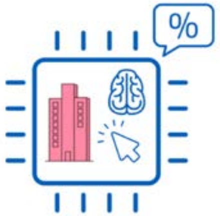




Hotel model

A **machine learning model** based on historical data to model the conversion probability (**click through rate** in this study) of **a hotel** based on its attributes and the context of a flight booking.

Hotel conversion model



Individual hotel dataset:
- 715,952 elements.
- 3,588 clicks
- 0.5% conversion rate

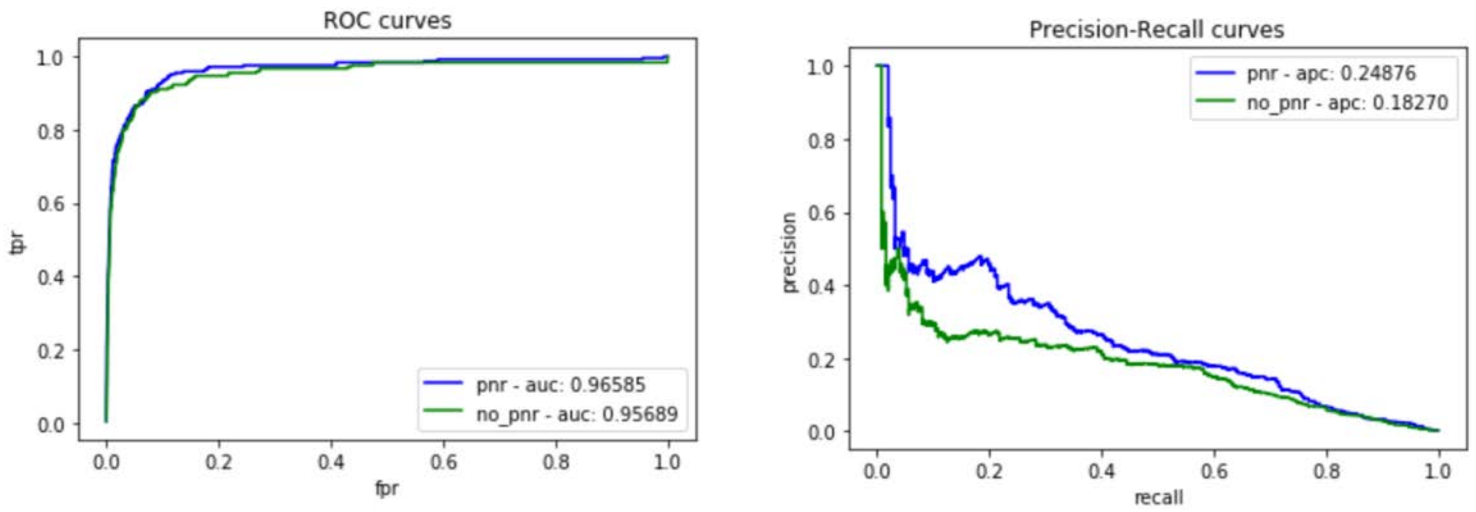


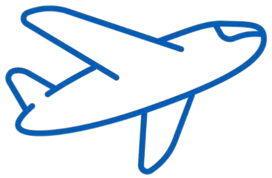
Figure 4.3: Representation of ROC and APR curves for two Random Forest models with and without the PNR data.

Due to low conversion rate, PR AUC is a more representative metric. We note that features from the flight context improve this metric from 0.18 to 0.25.

Table 1: Summary of AUC, AP, F_1 and $F_{0.5}$ metrics for the hotel model.

Model	AUC	AP	F1	F0.5
GLM	0.625	0.128	0.247	0.274
NBC	0.819	0.058	0.175	0.159
RF	0.966	**0.249**	**0.320**	**0.334**
GBM	0.953	0.210	0.294	0.288
NN	0.965	0.165	0.245	0.219
STK (all)	0.924	0.182	0.271	0.288
STK (RF + NN)	**0.969**	0.242	0.314	0.284

How to estimate the desirability of a list of hotels?



- Origin
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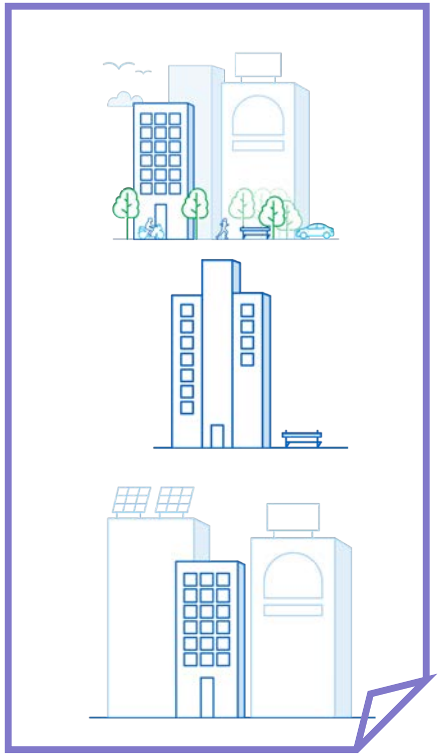
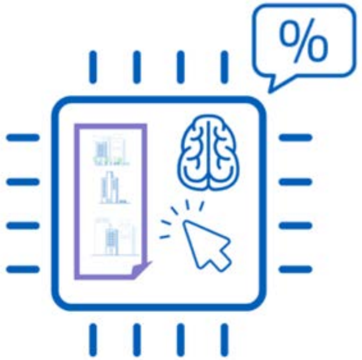


- Aggregates: (min, max, mean, std)
  - Price
  - Ratings



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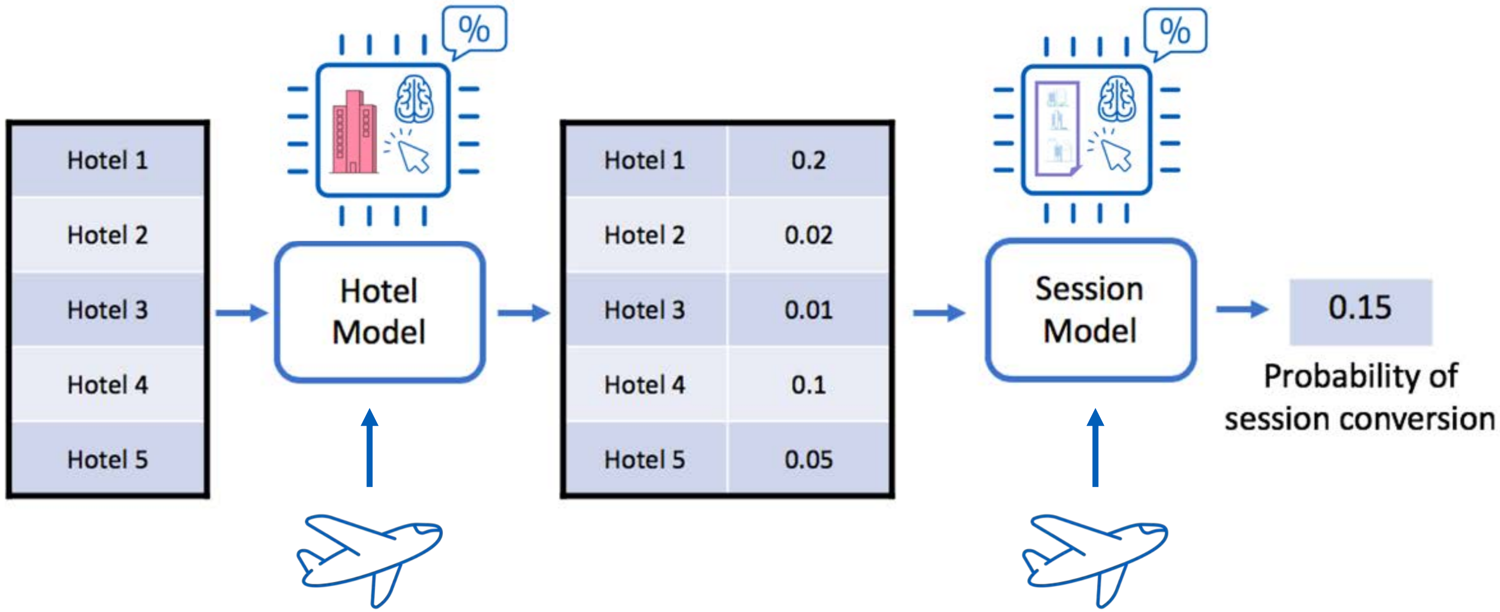
In a click through rate (CTR) based revenue model, the important metric is the CTR of the list of hotels presented, rather than that of the individual hotel. We refer to an algorithm which estimates this probability as the **session model**.

Cascaded generalisation

We propose to use **cascaded generalisation**, using the probabilities of the hotel model as features to the session model.
Thus, the session model features are the **flight details**, aggregates of the **hotel features** and aggregates of the **individual hotel conversion probabilities**.



Session model performance:

Session based dataset:

- 200285 elements.
- 1061 clicks
- 0.5% conversion rate

Defining the best algorithm is more complicated in this case than for the hotel model. A Stacking model made up of RF and 2 linear methods leads to the best AUC, AP and F1, but GBM achieves the highest F0.5 value.

Table 2: Summary of AUC, AP, F_1 and $F_{0.5}$ metrics for the session model.

Model	AUC	AP	F1	F0.5
GLM	0.822	0.395	0.520	0.538
NBC	0.933	0.342	0.467	0.408
RF	0.971	0.446	0.529	0.508
GBM	0.958	0.383	0.531	**0.542**
NN	0.967	0.433	0.483	0.467
STK (RF + GLM + NBC)	**0.972**	**0.453**	**0.539**	0.529

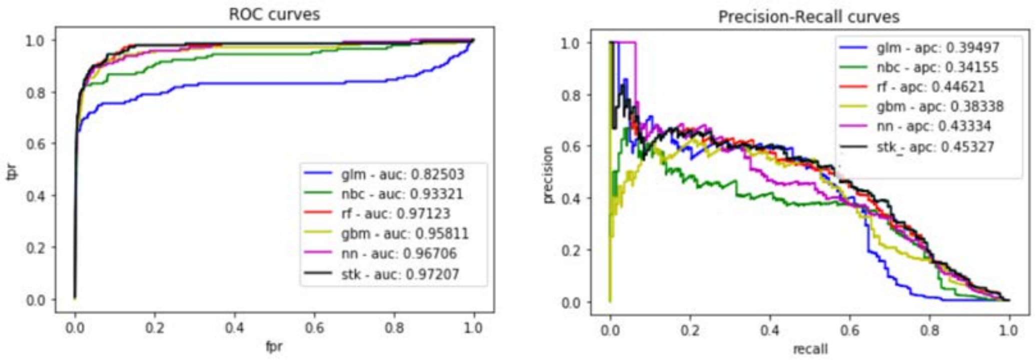
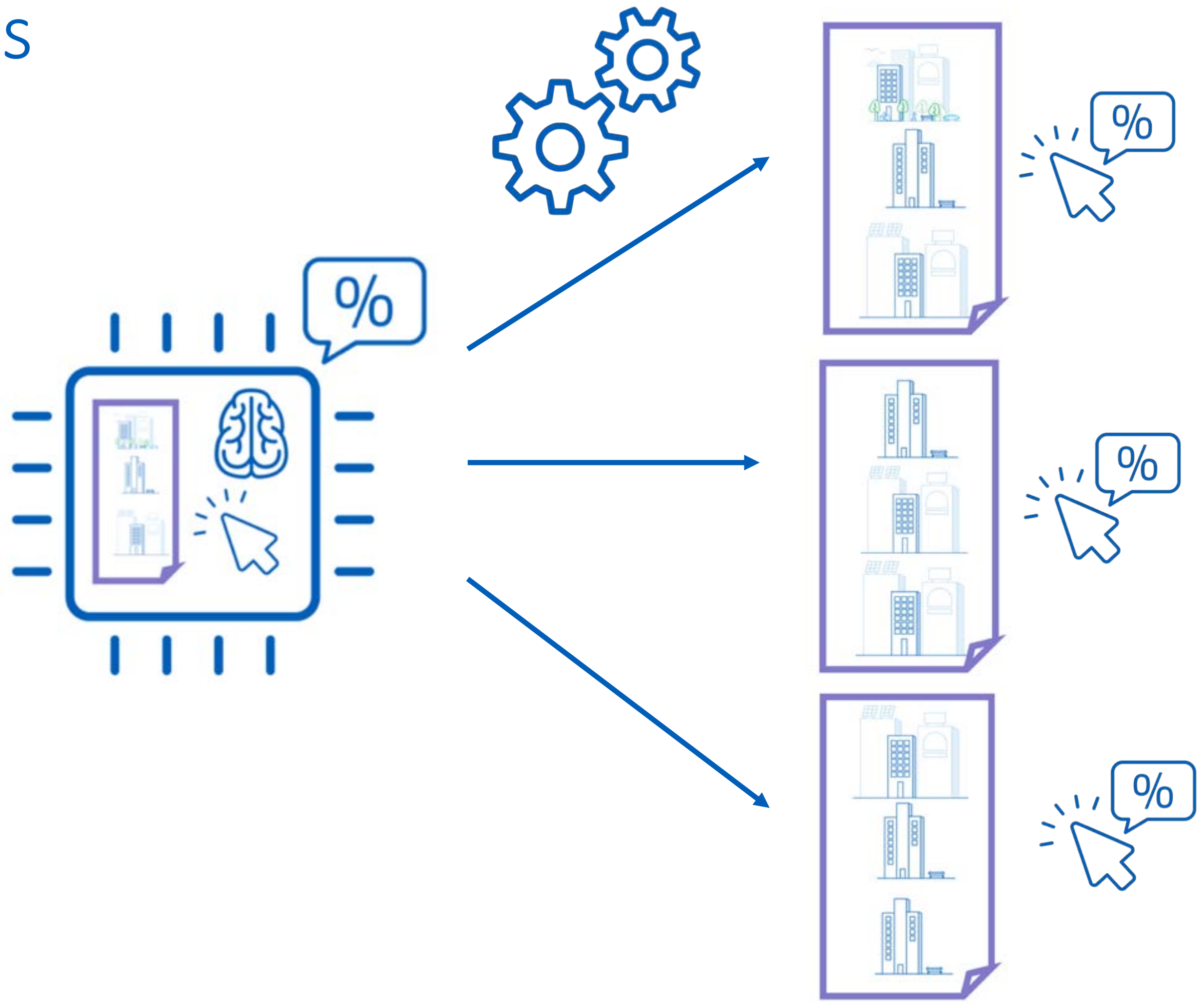


Figure 4.4: Representation of ROC and APR curves for the different techniques in the session model. The best score for the APR is for the Stacked Ensemble.

Creating an optimal list of hotels

The session model allows us to rate a list of hotels, but can we use the model to generate better candidate lists of hotels?

Typically, we can achieve this by analysing the model to determine the features that influence the model most. This is quite simple for linear models, but more difficult from non-linear models. Furthermore, in highly imbalanced problems, the dominant class may bias the feature importance

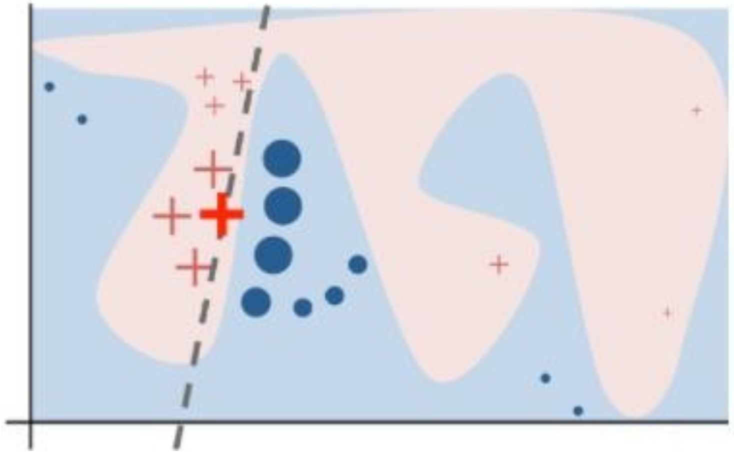


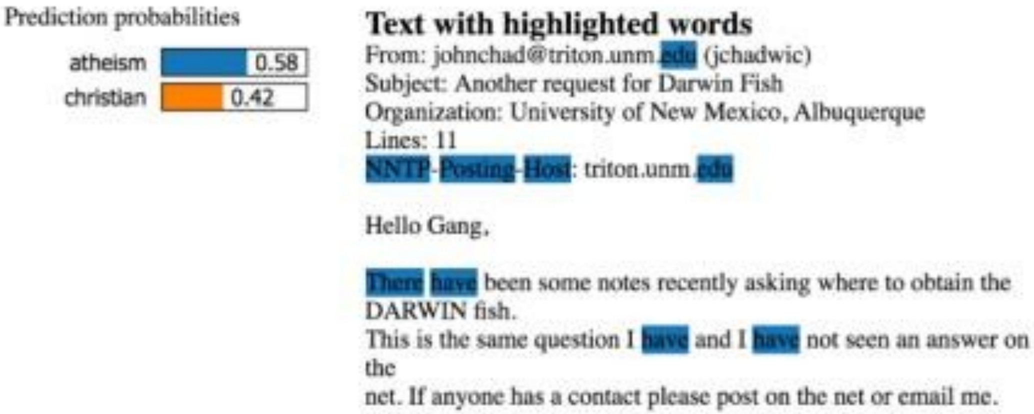
Interpretable AI

Local Interpretable Model-Agnostic Explanations (LIME)

_What? Explains in an **interpretable way** the predictions of **individual observations** of any classifier.

_How? By learning an interpretable model locally around the prediction.



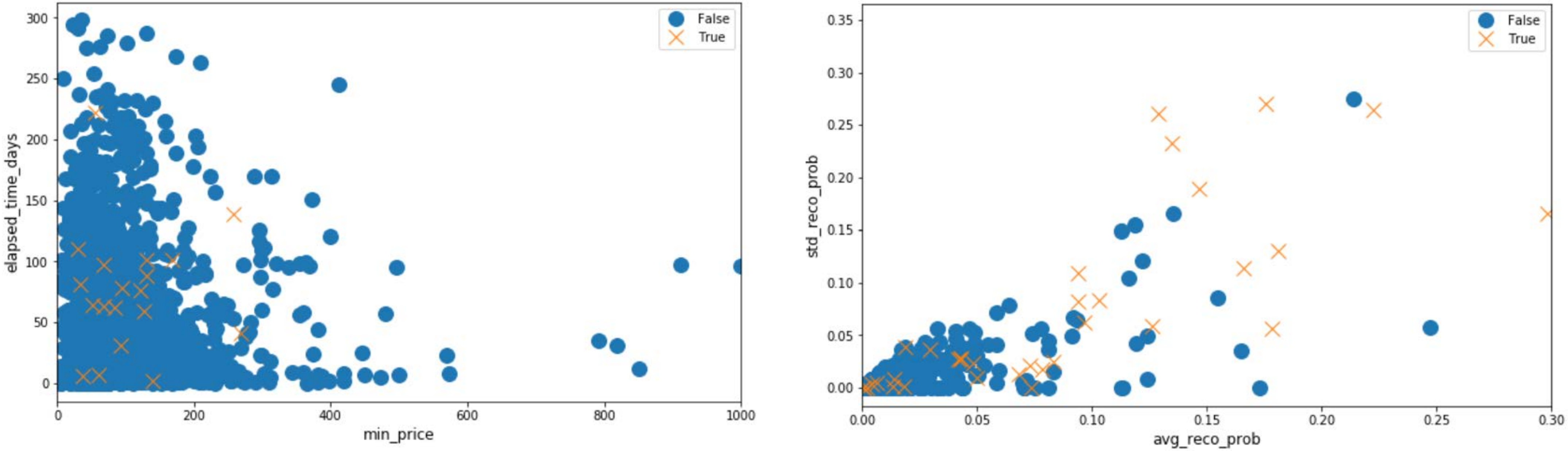


Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. Why should I trust you?: Explaining the predictions of any classifier. SIGKDD (2016)

Feature importance and explainable AI

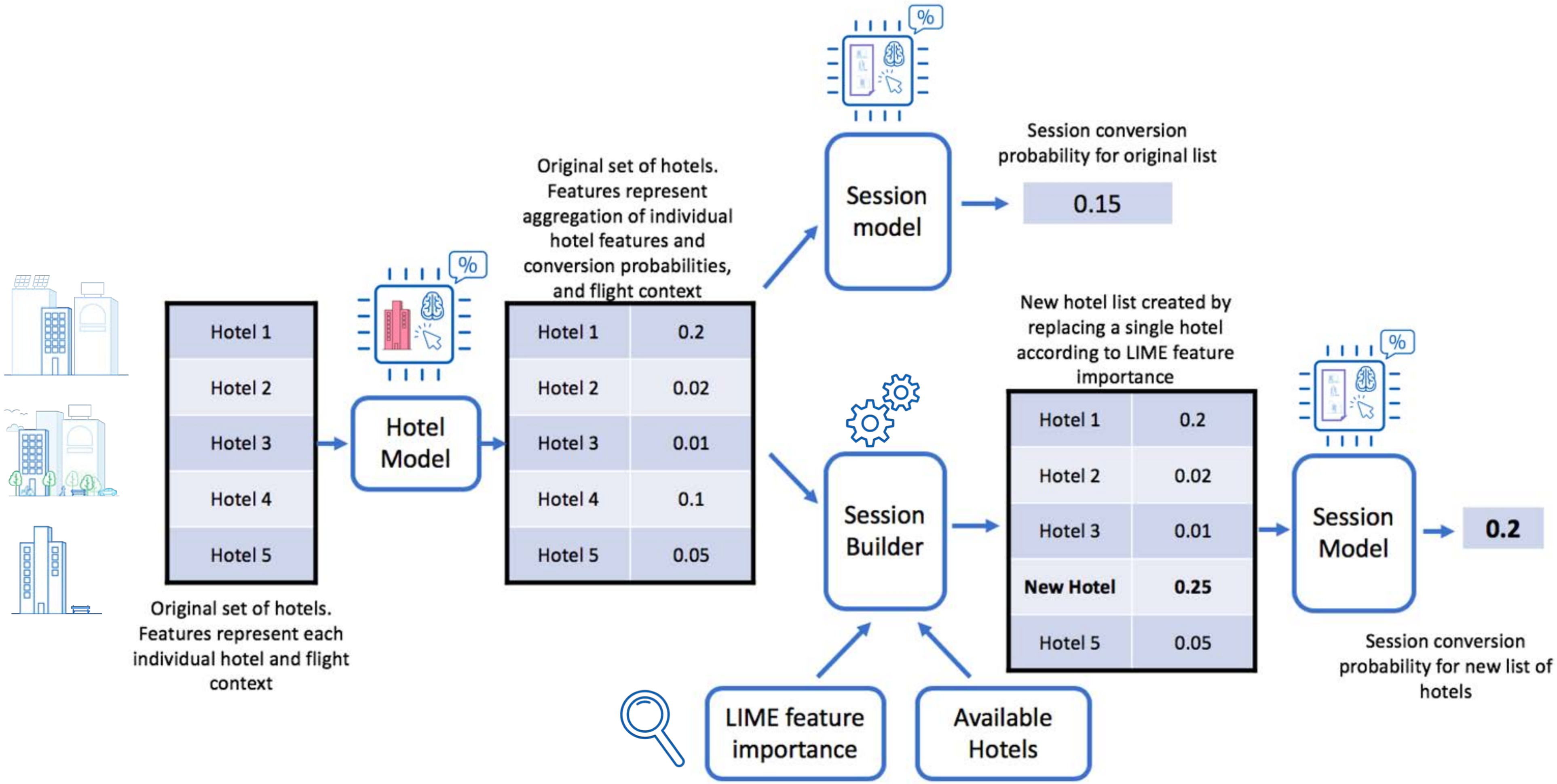
- Feature importance methods allow for understanding of the features that most impact the decision. However in non-linear models it is difficult to use this ranking of features directly, and in highly imbalanced problems (such as CTR problems), the unclicked samples might bias the feature importance.

- Explainable AI models however, allow us to determine the feature importance for a specific instance.



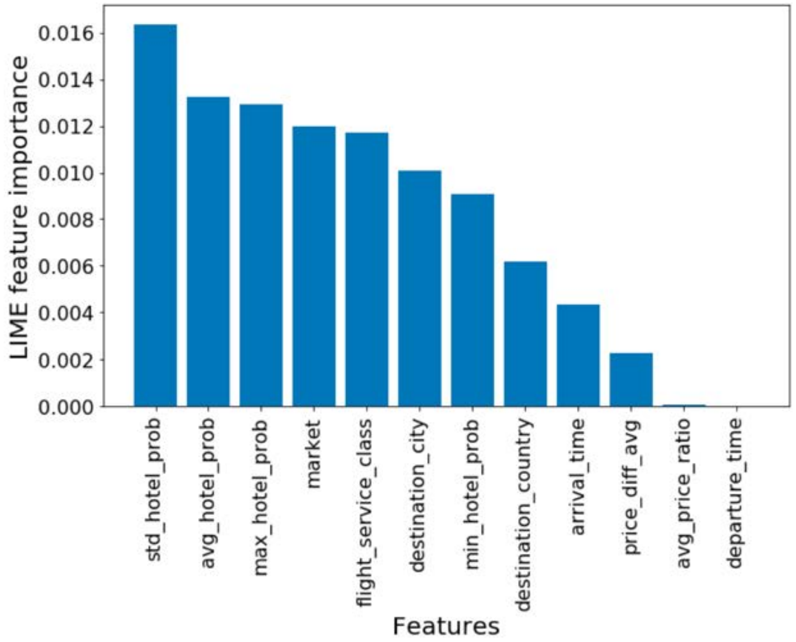
Session builder concept

The aim of the session builder is to increase the conversion probability by proposing optimal lists of hotels.



Session builder in practice

- In practice, the session builder was implemented using an aggregated LIME feature importance over the positive sessions (sessions with clicks).
- The LIME feature importance rates aggregates from the hotel model most highly.
- The following heuristic was used to construct new hotel lists:
  1. Remove the hotel with the closest conversion probability to the mean (to influence the standard deviation)
  2. Replace with a new hotel with the highest conversion probability (to influence the average, max and standard deviation of the list)



	Nice	Barcelona	Complete
Base Conversion	0.0019	0	0.0005
Conversion LIME	0.0207	0.0089	0.0019
Conversion brute	0.0338	0.0125	0.0026
Processing time LIME	23s	23s	4h48m
Processing time brute	314s	496s	13h36m

Thank you

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