The Hotel Dilemma

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WHAT BROUGHT US HERE TODAY?

RESEARCH QUESTIONS

1. Using data and ML models, can hotel reservation cancellations be predicted?
2. If yes to the above, which models and methods most accurately predict hotel reservation cancellations?

OBJECTIVES

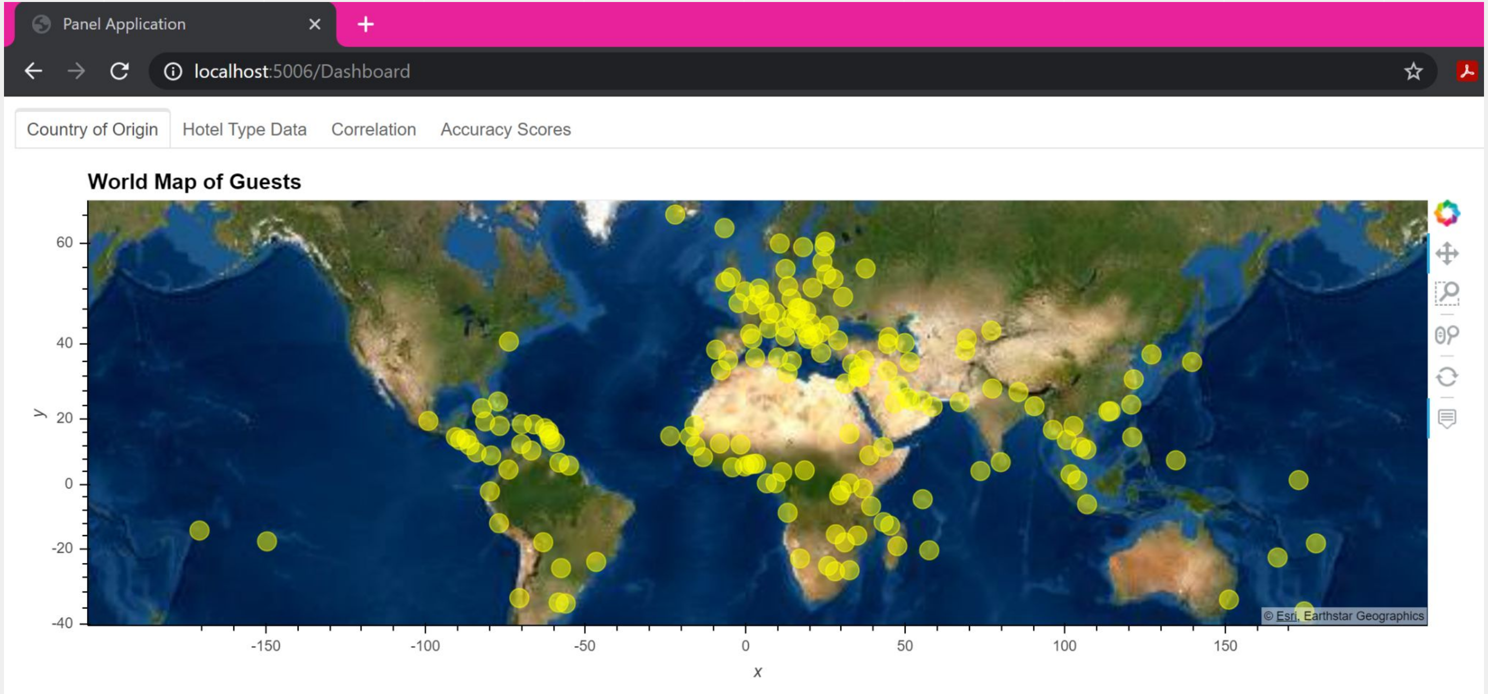
1. Build a ML model that can predict whether a hotel reservation will be cancelled.
2. Analyze and understand data via organization, visualization, and dashboards.

DATA VISUALIZATION

Hotels in Portugal - Guests Data

(July 2015 through December 2017)

- Country of origin



Hotels in Portugal - Guests Data

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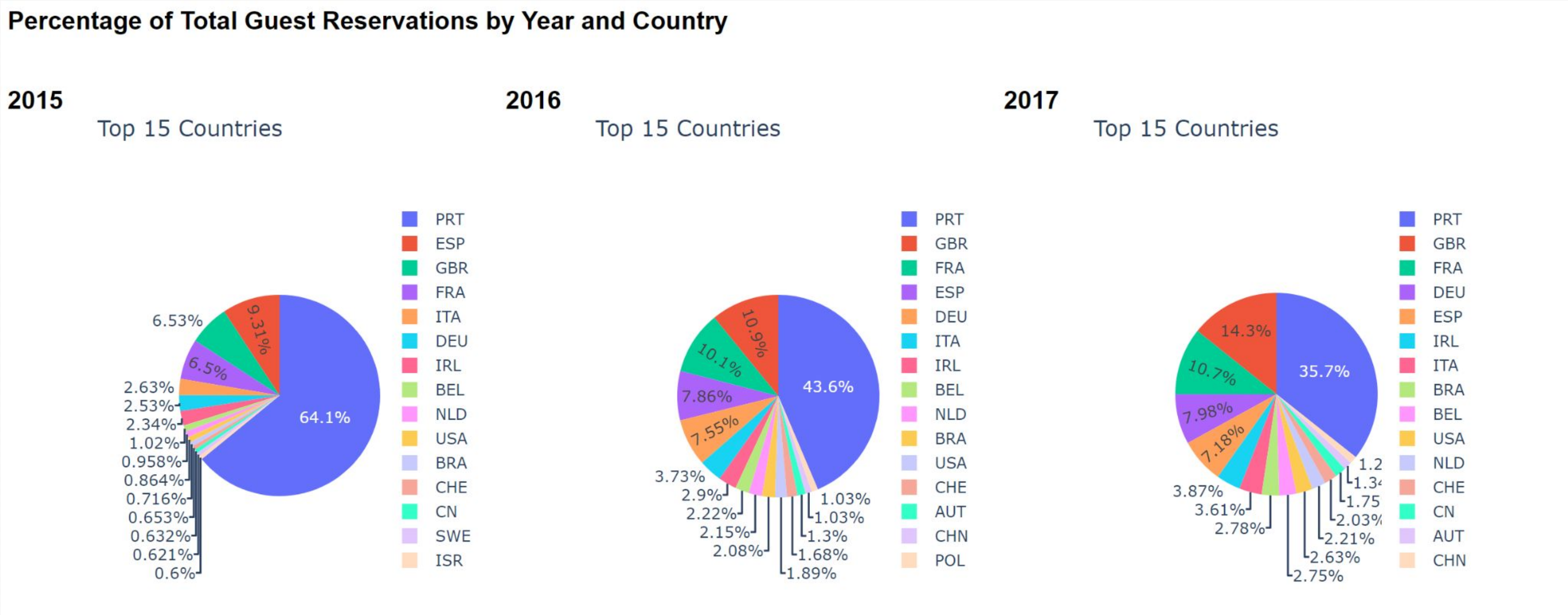
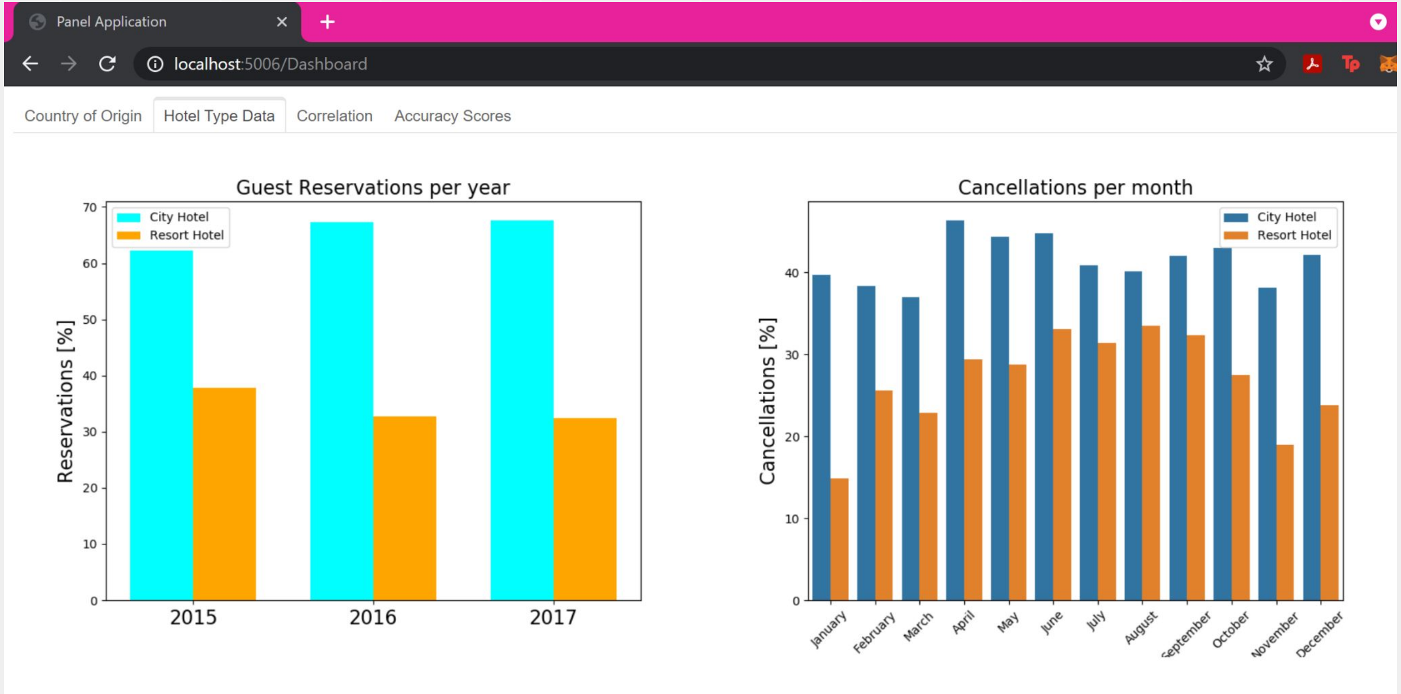


Hotels in Portugal - Guests Data

(July 2015 through December 2017)

City Hotel vs. Resort Hotel



Data Cleaning & Preparation

Data: The Source?

- Data from an article written by Nuno Antonio, Ana Almeida, and Luis Nunes, for Data in Brief, Volume 22, February 2019 (ScienceDirect Journal)
- Data was downloaded and cleaned by Thomas mock and Antoine Bichat on February 11th, 2020 (we had to conduct additional cleaning)
- Original source unknown, appears to be extracted from a site such as Expedia


ELSEVIER

Data in Brief

Volume 22, February 2019, Pages 41-49

Journal Data in Brief

Data Article

Hotel booking demand datasets

Nuno Antonio [a, b], Ana de Almeida [a, c, d], Luis Nunes [a, b, d]

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The Basics

- 31 Columns (or “features”)
- 119,391 Rows, each an instance of a hotel reservation (very robust)
- Looks at bookings data between July 2015 and August 2017
- All data is from Portugal, and includes both a city hotel and a resort hotel
- Example of feature descriptions in the academic text:

Variable	Type	Description	Source/Engineering
ADR	Numeric	Average Daily Rate as defined by [5]	BO, BL and TR / Calculated by dividing the sum of all lodging transactions by the total number of staying nights
Adults	Integer	Number of adults	BO and BL
Agent	Categorical	ID of the travel agency that made the booking[a]	BO and BL
ArrivalDateDayOfMonth	Integer	Day of the month of the arrival date	BO and BL

Our Process

- Import CSV
- Check nulls and assign values if needed
- Check data types (address non-integer types)
- Utilize labelencoder on “object” data types
- Run a correlation matrix
- Delete unneeded features
- Final data set for modelling ⇒

```
Data columns (total 29 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   hotel                           119390 non-null  int64
 1   is_canceled                     119390 non-null  int64
 2   lead_time                       119390 non-null  int64
 3   arrival_date_year               119390 non-null  int64
 4   arrival_date_month              119390 non-null  int64
 5   arrival_date_week_number        119390 non-null  int64
 6   arrival_date_day_of_month       119390 non-null  int64
 7   stays_in_weekend_nights         119390 non-null  int64
 8   stays_in_week_nights            119390 non-null  int64
 9   adults                          119390 non-null  int64
 10  children                        119390 non-null  int64
 11  babies                          119390 non-null  int64
 12  meal                            119390 non-null  int64
 13  country                         119390 non-null  int64
 14  market_segment                  119390 non-null  int64
 15  distribution_channel            119390 non-null  int64
 16  is_repeated_guest               119390 non-null  int64
 17  previous_cancellations          119390 non-null  int64
 18  previous_bookings_not_canceled  119390 non-null  int64
 19  reserved_room_type              119390 non-null  int64
 20  assigned_room_type              119390 non-null  int64
 21  booking_changes                 119390 non-null  int64
 22  deposit_type                    119390 non-null  int64
 23  agent                           119390 non-null  int64
 24  days_in_waiting_list            119390 non-null  int64
 25  customer_type                   119390 non-null  int64
 26  adr                             119390 non-null  int64
 27  required_car_parking_spaces     119390 non-null  int64
 28  total_of_special_requests       119390 non-null  int64
dtypes: int64(29)
```

Preprocessing & Model Preparation

- X = independent variables, or our "features"
- y = dependent variable, or our "was the reservation cancelled?" variable (75k cancelled to 44k not cancelled observations)
- Split into training & testing segments, and scaled
- Tested 5 models:
  - BalancedRandomForest; LogisticRegression; EasyEnsemble
  - Applied naive random oversampling and SMOTEENN to BalancedRandomForest

```
# Define X (indpendent) and y (dependent) values for modelling, here we s
X = hotel.drop(columns="is_canceled")
y = hotel["is_canceled"]
```

```
# Check target counts: canceled (1) or not (0)
y.value_counts()
```

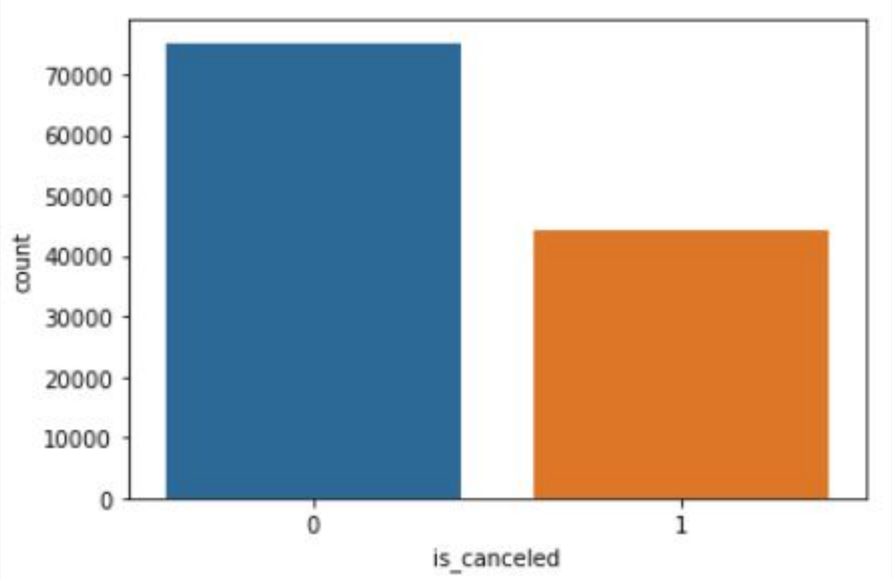
```
0    75166
1    44224
Name: is_canceled, dtype: int64
```

```
# Split the X and y into X_train, X_test, y_train, y_test
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)

# Create the StandardScaler instance, then scale the X data
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

# Fit the Standard Scaler with the training data
X_scaler = scaler.fit(X_train)

# Scale the training and testing data
X_train_scaled = X_scaler.transform(X_train)
X_test_scaled = X_scaler.transform(X_test)
```

ML Model Evaluation

Feature Importance

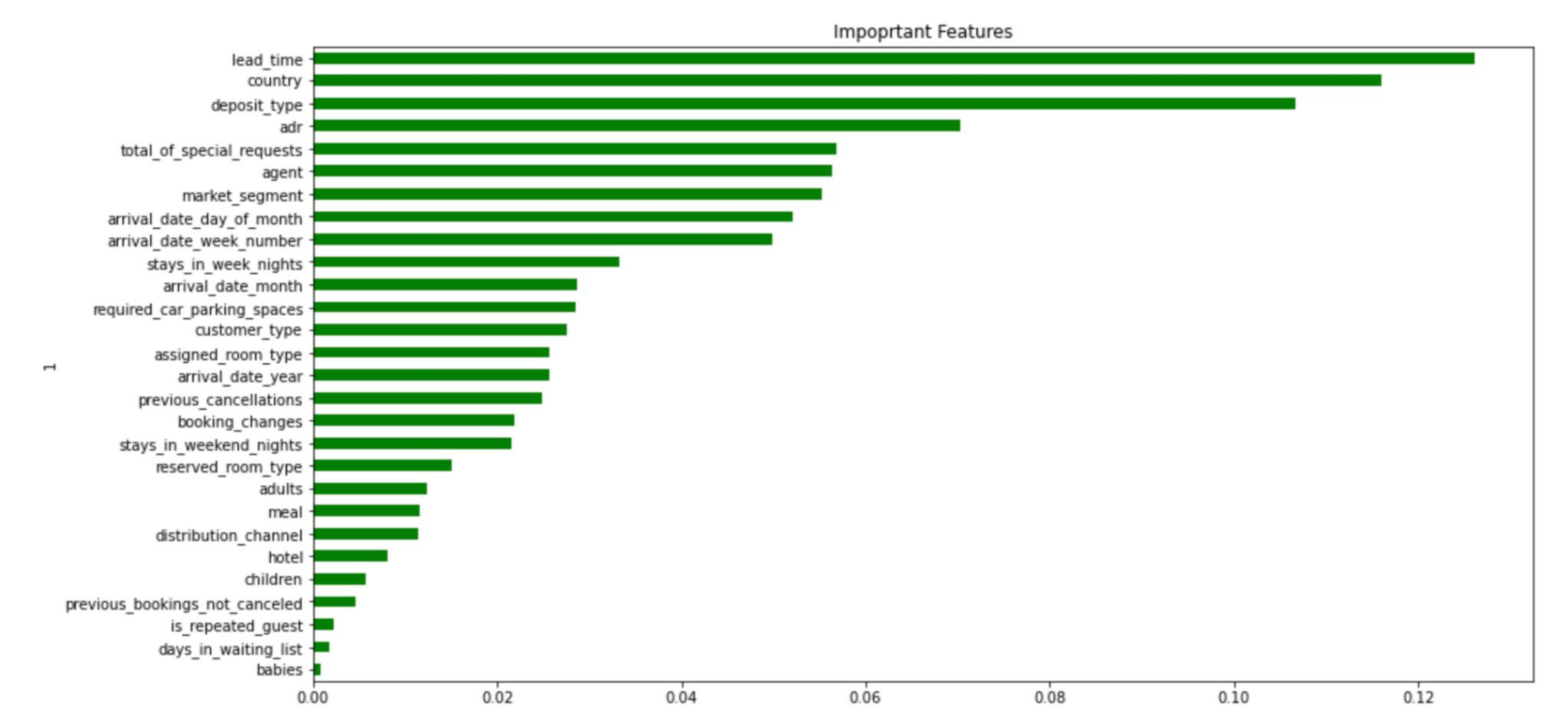
- Reservation canceled (1) or not (0)
- Data is imbalance hence ensemble learning models were chosen



Model Outcomes

ML Model	Accuracy Score	Avg Precision Score	Avg Recall Score
Balanced Random Forest Classifier	0.89	0.89	0.89
Logistic Regression	0.80	0.80	0.80
Easy Ensemble Classifier	0.82	0.83	0.83
Naive Random Oversampler + BRF	0.88	0.89	0.89
SMOTEENN Oversampler + BRF	0.90	0.91	0.90

Feature Importance



Summary

- Customers made more city hotel reservations between 2015-2017 than resort hotels.
- Lead time, country of origin, average daily rate and no deposit/non-refundable were the top features if a booking will be canceled or not.
- SMOTEENN applied to BalancedRandomForest had the best ML model outcomes to predict hotel reservation cancelations.
    - Aid in data driven decisions to plan supply + demand and personnel coverage as needed.

THANKS!

Any questions?