STAT 5650 Statistical Learning and Data Mining 1 Spring 2020

Names: Greg Hoffmann, Kristen Sohm, Michael Huber, Varsha Reddy Mandadi

Submission Date: 04/25/2020

Final Project: Applying Prediction Methods to Hotel Data

210 Points — Due Monday 04/27/2020 (via Canvas by 11:59pm)

Prediction Methods

After working with the data and reviewing the notes from Dr. Cutler on our project proposal we had to edit what methods of prediction we were going to apply against the data. Below is a list of methods that we were able to get to run against our hotel data set.

- Gradient Boosting Machines (GBM)
- Support Vector Machines (SVM)
- Random Forests
- Adaboost
- Classification Trees
- Logistic Regression

Our main objectives were: (1) determine how accurately we can predict hotel booking cancelation using the above methods; (2) determine the most important variables in predicting cancelation; and (3) determine whether the two types of hotel (resort and city) can be treated the same or differently.

Description of the Data

Link to the data: https://www.kaggle.com/jessemostipak/hotel-booking-demand

Hotel Booking Demand

“This data set contains booking information for a city hotel and a resort hotel, and includes information such as when the booking was made, length of stay, the number of adults, children and/or babies, and the number of available parking spaces, among other things. All personally identifying information has been removed from the data.” — Description taken from Kaggle webpage.

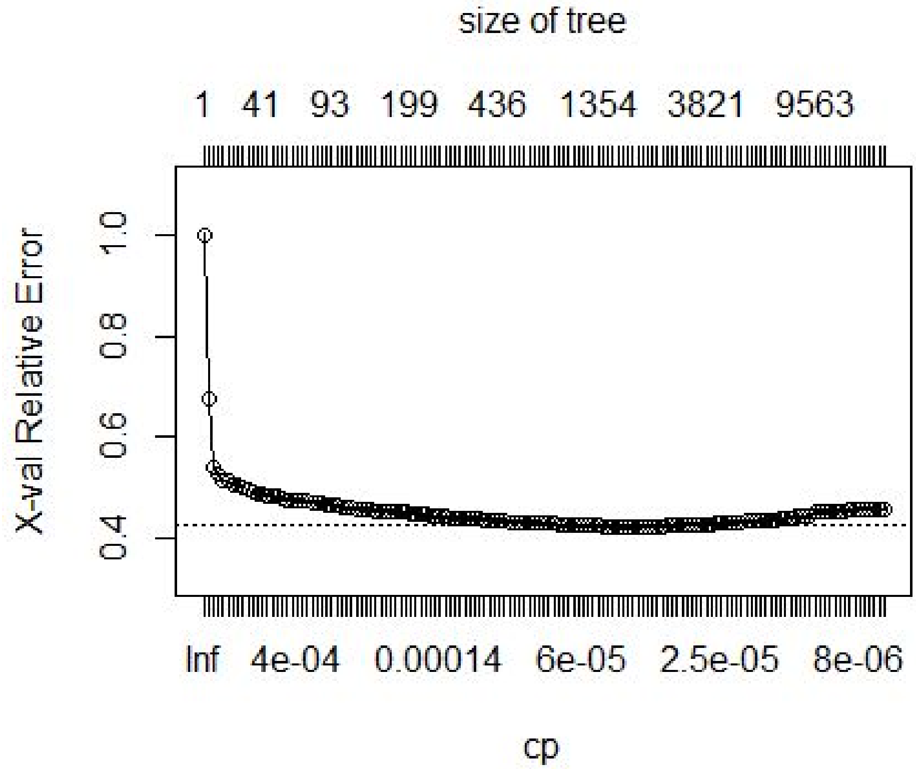
The main response variable for this data set (“Is_canceled”) is coded 0 or 1, where 1 indicates the booking was cancelled. The “Hotel” variable specifies between the resort hotel and the city hotel.

More details:

- Number of columns: 32
- Number of rows: 119391
- Dates covered: 2015-07-01 to 2017-08-31
- Column names (descriptions for the columns can be found on Kaggle):
    - Hotel
    - Is_canceled
    - Lead_time
    - Arrival_date_year
    - Arrival_date_month
    - Arrival_date_week_number
    - Arrival_date_day_of_month
    - Stays_in_weekend_nights
    - Stays_in_week_nights
    - Adults
    - Children
    - Babies
    - Meal
    - Country
    - Market_segment
    - Distribution_channel
    - Is_repeated_guest
    - Previous_cancellations
    - Previous_bookings_not_conceled
    - Reserved_room_type
    - Assigned_room_type
    - Booking_changes
    - Deposit_type
    - Agent
    - Company
    - Days_in_waiting_list
    - Customer_type

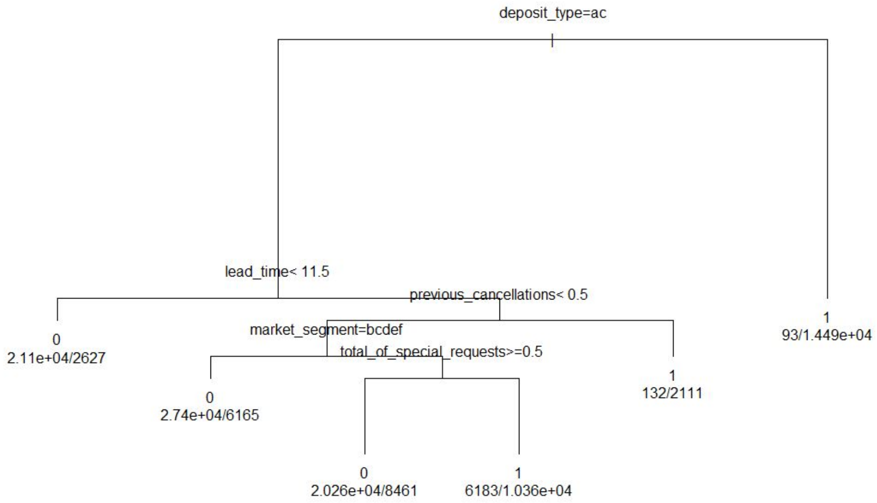
- Adr (average daily rate)
- Required_car_parking_spaces
- Total_ofspecial_requests
- Reservation_status
- reservation_status_date

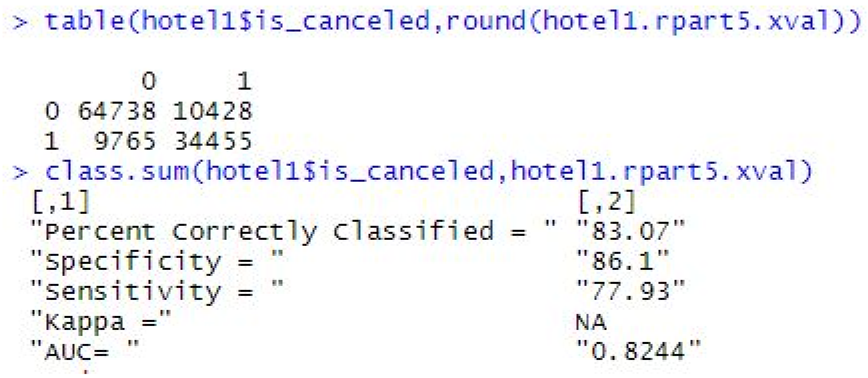
Classification Trees



As the combined data’s cost complexity plot shows, there were just too many tree sizes to choose from, and the tree sizes grew extremely fast. Therefore, we leaned toward interpretability and chose cp values for smaller tree sizes. As the plot also shows, the relative error for the smaller trees is only slightly higher than trees we would have chosen using the 1-SE rule.

Combined data, 5 splits (cp=1.2981e-02)



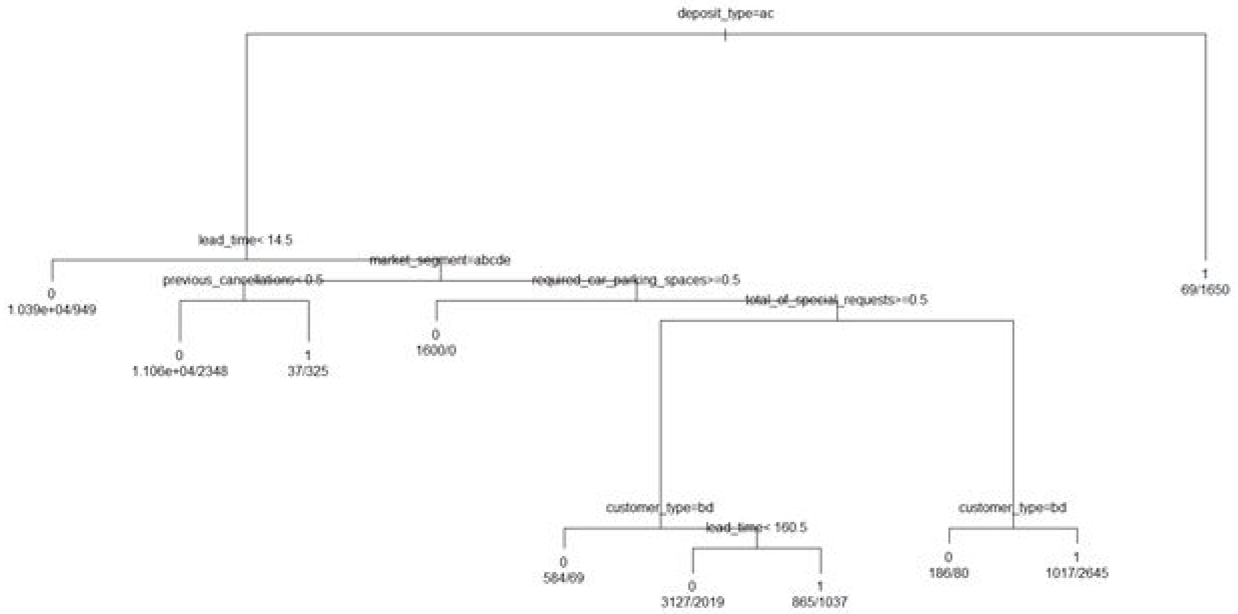


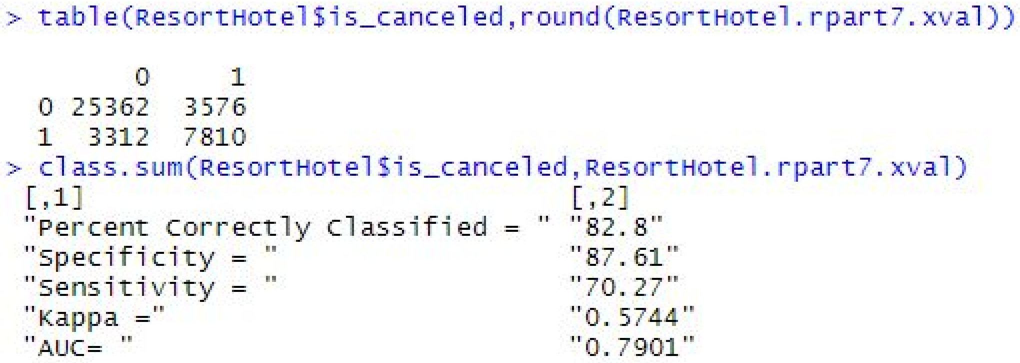
```
> table(hotel1$is_canceled,round(hotel1.rpart5.xval))

        0     1
  0 64738 10428
  1  9765 34455
> class.sum(hotel1$is_canceled,hotel1.rpart5.xval)
 [,1]                                  [,2]
 "Percent Correctly Classified = "  "83.07"
 "Specificity = "                      "86.1"
 "Sensitivity = "                      "77.93"
 "Kappa ="                             NA
 "AUC= "                               "0.8244"
```

- We got fairly high metrics all around for the combined data, even though we chose a tree well above the SE line.
- For the combined data, it appears deposit_type, lead_time, market_segment, and total_of_special_requests were the most important variables.

<u>Resort Hotel Only, 7 splits (cp = 7.7324e-03)</u>

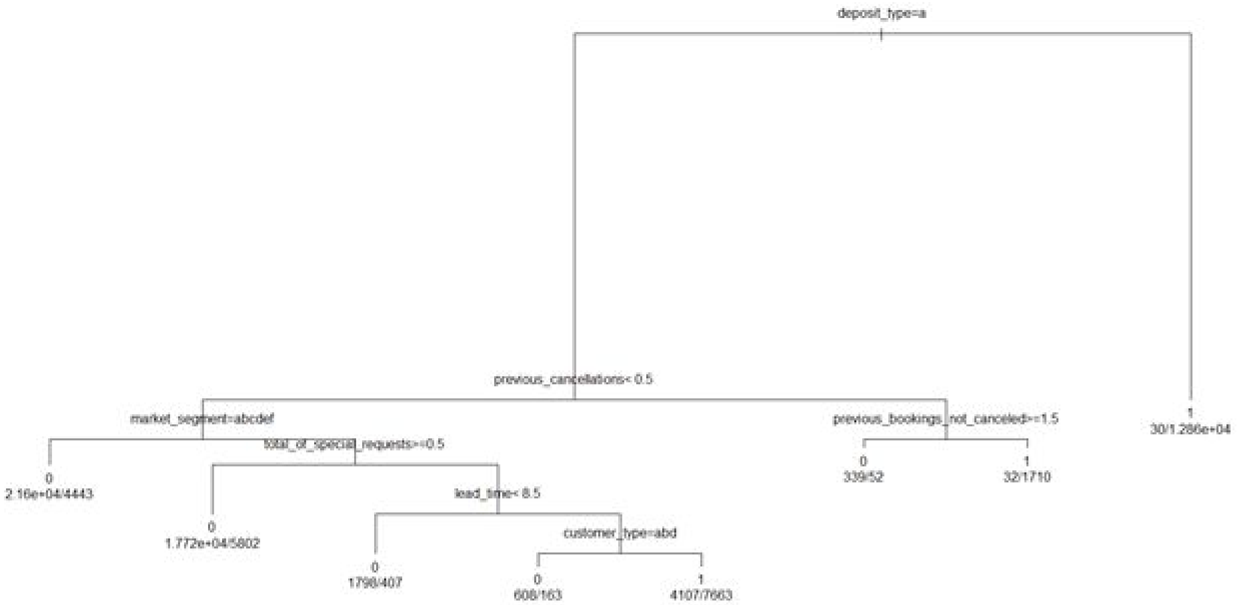


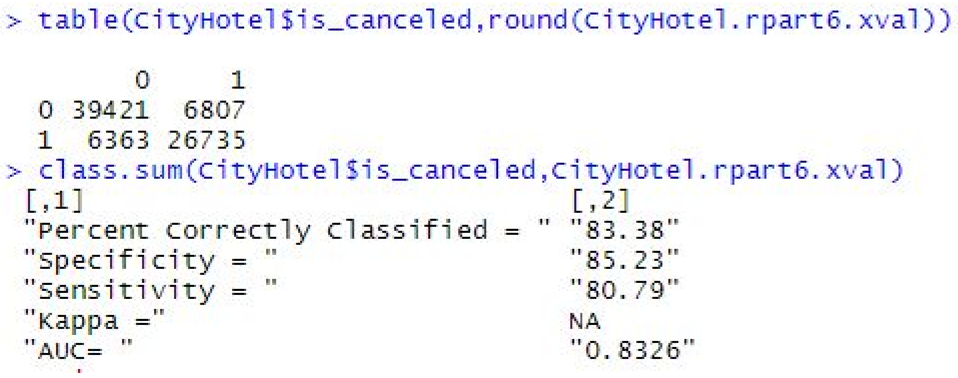

```
> table(ResortHotel$is_canceled,round(ResortHotel.rpart7.xval))

        0     1
  0 25362  3576
  1  3312  7810
> class.sum(ResortHotel$is_canceled,ResortHotel.rpart7.xval)
 [,1]                                [,2]
 "Percent Correctly Classified = " "82.8"
 "Specificity = "                  "87.61"
 "Sensitivity = "                  "70.27"
 "Kappa ="                         "0.5744"
 "AUC= "                           "0.7901"
```

- Our metrics for the resort hotel were almost as good as for the combined data, with slightly lower sensitivity.
- For the resort hotel, it appears deposit_type, lead_time, market_segment, and total_of_special_requests were still important variables, along with customer_type, previous_cancelations, and required_car_parking_spaces.

City Hotel Only, 6 Splits (cp = 8.6712e-03)





```
> table(CityHotel$is_canceled,round(CityHotel.rpart6.xval))

        0     1
  0 39421  6807
  1  6363 26735
> class.sum(CityHotel$is_canceled,CityHotel.rpart6.xval)
 [,1]                              [,2]
 "Percent Correctly Classified = " "83.38"
 "Specificity = "                  "85.23"
 "Sensitivity = "                  "80.79"
 "Kappa ="                         NA
 "AUC= "                           "0.8326"
```

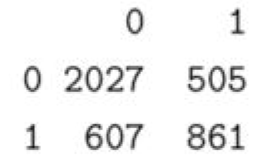
- Our metrics for the city hotel were just slightly better than the combined data’s metrics.
- The city hotel shared all of its important variables with the resort hotel except for required_car_parking_spaces.

Support Vector Machines (SVM)

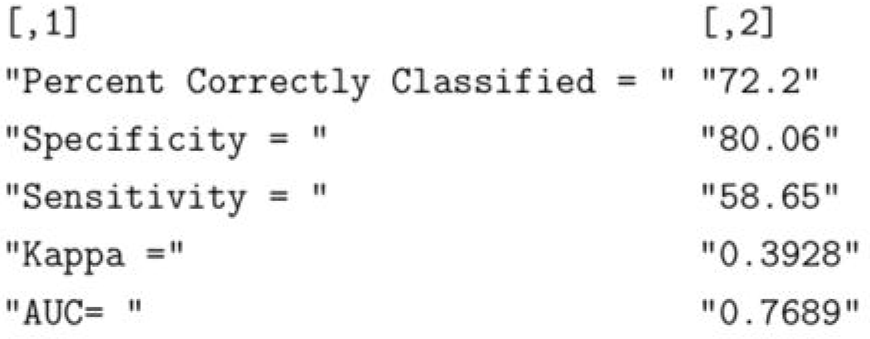
Where our data has over 100,000 rows and many variables to take into consideration, Support Vector Machines would take a very long time to run across all of the data. We did attempt a few different ways of processing all of the data, but even after letting our computers run for over 24 hours they were still processing. When doing some research online we found that other people working in R had to let their systems process for over a week to be able to get results. So instead we took a random sample of 4,000 rows of the data set to see how well SVM's would be able to perform. If possible we would have chosen more rows, but with 4,000 our models were able to complete in a more manageable amount of time.

This does not allow us to compare to the other methods directly but it did give us an idea of how well the model would be able to perform, and given more time and resources we would take the time to run this on a larger sample of the data if not the whole dataset.

Our result from the 4,000 rows is displayed below.



```
     0    1
0 2027  505
1  607  861
```

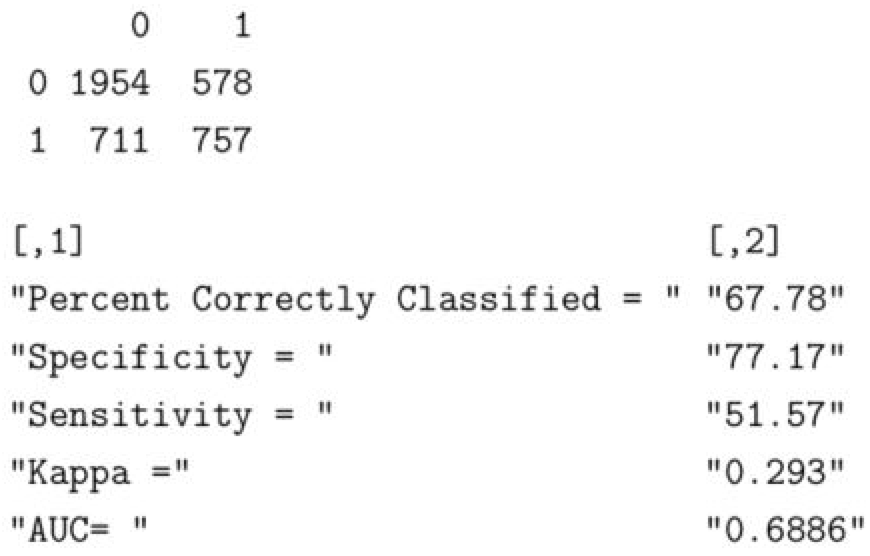


```
[,1]                                [,2]
"Percent Correctly Classified = " "72.2"
"Specificity = "                   "80.06"
"Sensitivity = "                   "58.65"
"Kappa ="                          "0.3928"
"AUC= "                            "0.7689"
```

Gradient Boosting Machines (GBM)

With Gradient Boosting Machines we had the same issues that we had with Support Vector Machines, so we were only able to run it against 4,000 randomly selected rows of the data. So not the best comparison but it will allow us to get an idea of performance.

The only column dropped in this analysis was reservation_status.



```
      0    1
0 1954  578
1  711  757

[,1]                                 [,2]
"Percent Correctly Classified = " "67.78"
"Specificity = "                     "77.17"
"Sensitivity = "                     "51.57"
"Kappa ="                            "0.293"
"AUC= "                              "0.6886"
```

Logistic Regression

We were not able to get the cross validated logistic regression to run in the time we had. So the classification from below is just the basic logistic regression run across the complete population of the data.

Confusion Matrix

```
       0     1
  0 66007  9159
  1 22272 21948
```

```
 [,1]                          [,2]
 "Percent Correctly Classified = "73.67"
 "Specificity = "                 "87.81"
 "Sensitivity = "                 "49.63"
 "Kappa ="                         NA
 "AUC= "                          "0.7942"
```

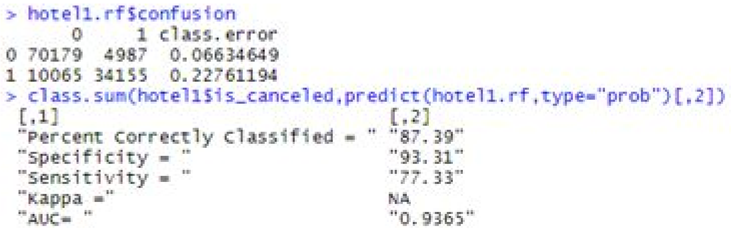
RANDOM FORESTS

We first applied random forests to the original dataset. We dropped the country, agent, company, and reservation_status_date columns because randomForest in R does not handle categorical variables with more than 53 levels. We also dropped reservation_status because it was the same as the is_canceled response variable. Just 4 observations with missing values were dropped as well. We then refit random forests with subsets of the important variables to see the changes in accuracy.

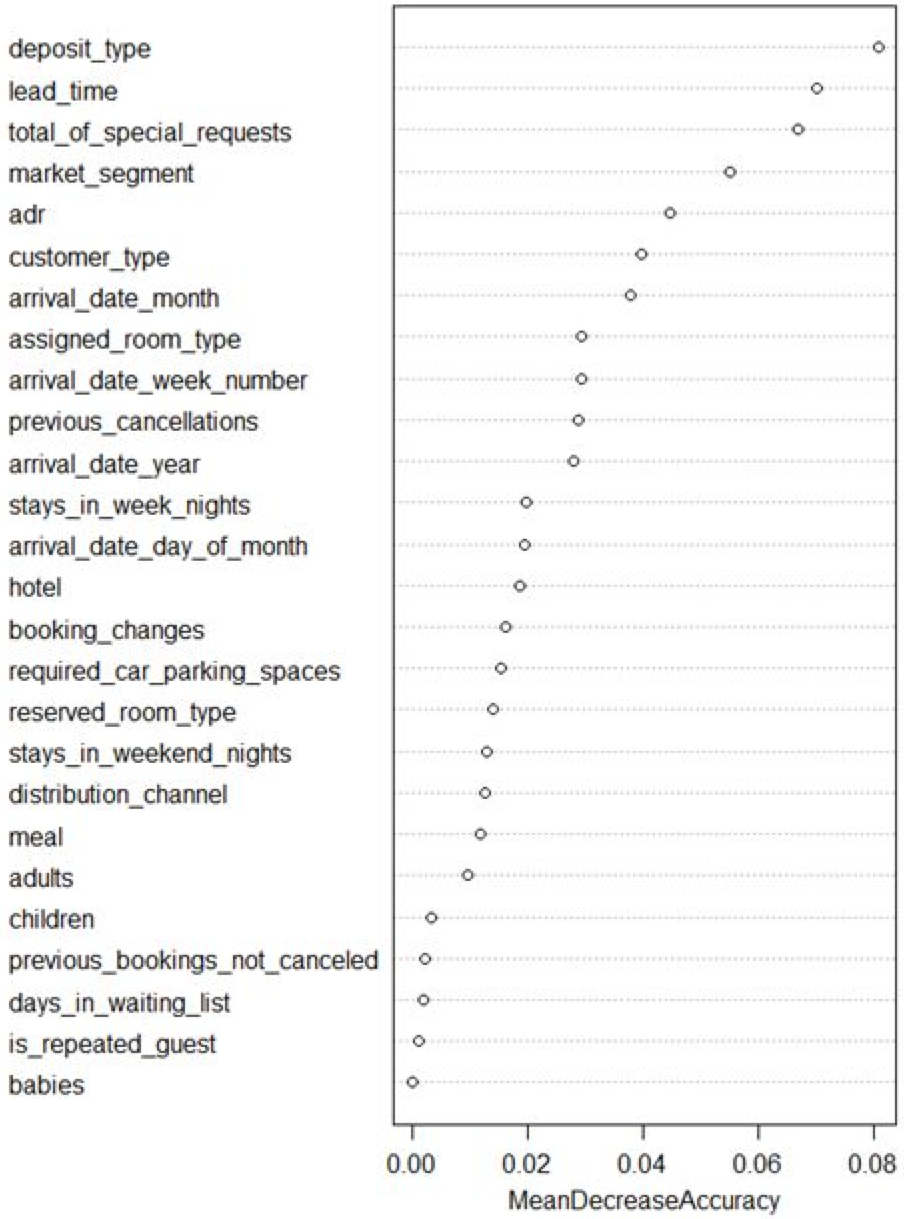
After analyzing the combined data, we applied random forests to the two hotel types separately to discover their differences. We also produced some two-way frequency tables to examine important variables for the combined and separated datasets. This was another good way to find differences between the resort hotel and the city hotel.

Finally, we applied random forests using hotel type as the response variable (as in the Nest data homework) to identify where misclassifications were occurring.

<u>Combined data random forests result:</u>

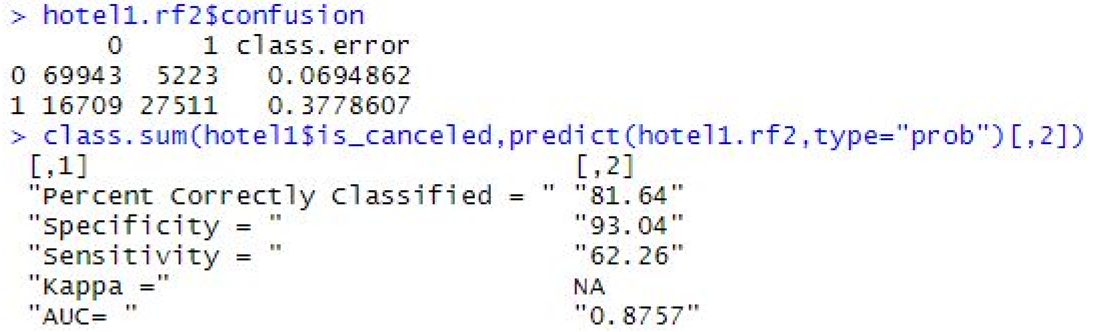


```
> hotel1.rf$confusion
      0     1 class.error
0 70179  4987  0.06634649
1 10065 34155  0.22761194
> class.sum(hotel1$is_canceled,predict(hotel1.rf,type="prob")[,2])
 [,1]                              [,2]
 "Percent Correctly Classified = " "87.39"
 "Specificity = "                  "93.31"
 "Sensitivity = "                  "77.33"
 "Kappa ="                         NA
 "AUC= "                           "0.9365"
```



The overall accuracy for random forests is very good, but we have less than ideal sensitivity. We chose to refit random forests using the top 7 variables, and then using the top 4 variables.

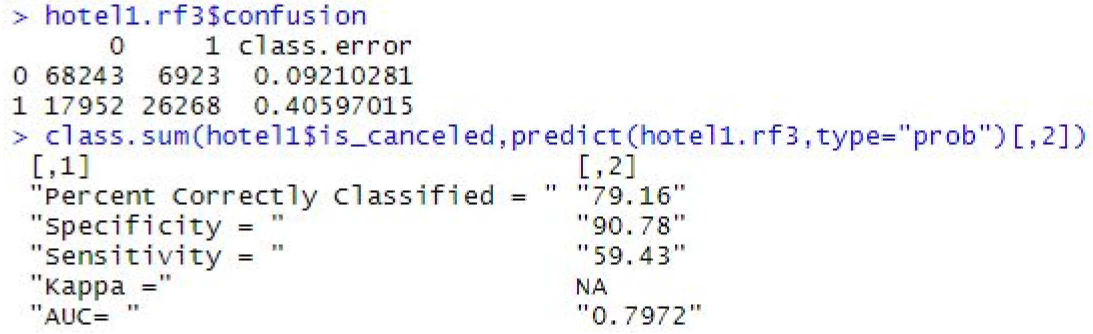
7-variable model:



```
> hotel1.rf2$confusion
      0     1 class.error
0 69943  5223   0.0694862
1 16709 27511   0.3778607
> class.sum(hotel1$is_canceled,predict(hotel1.rf2,type="prob")[,2])
  [,1]                               [,2]
  "Percent Correctly Classified = " "81.64"
  "Specificity = "                   "93.04"
  "Sensitivity = "                   "62.26"
  "Kappa ="                          NA
  "AUC= "                            "0.8757"
```

The overall accuracy decreased by about 6 percentage points, and the sensitivity decreased drastically.

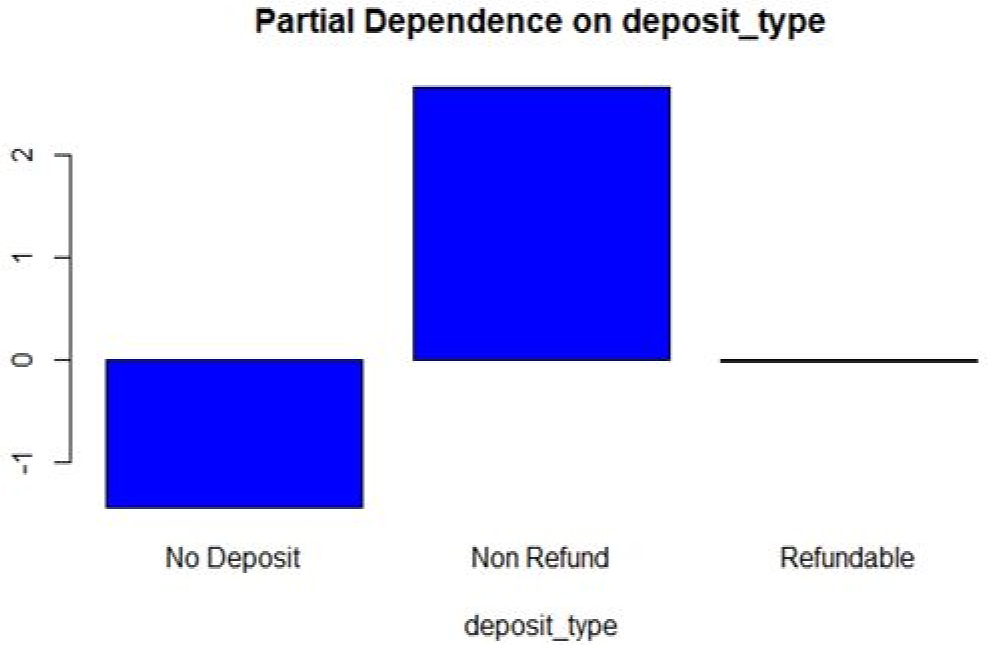
4-variable model:



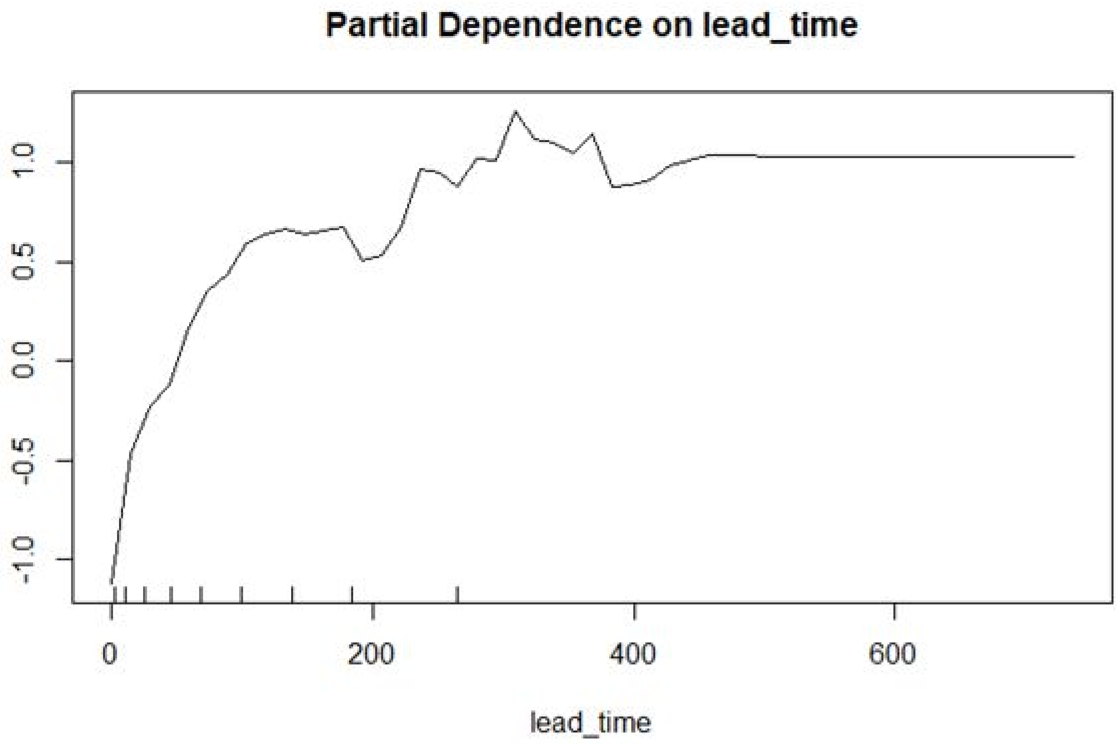
```
> hotel1.rf3$confusion
      0     1 class.error
0 68243  6923  0.09210281
1 17952 26268  0.40597015
> class.sum(hotel1$is_canceled,predict(hotel1.rf3,type="prob")[,2])
  [,1]                               [,2]
  "Percent Correctly Classified = " "79.16"
  "Specificity = "                   "90.78"
  "Sensitivity = "                   "59.43"
  "Kappa ="                          NA
  "AUC= "                            "0.7972"
```

Each metric decreased further by a few percentage points.

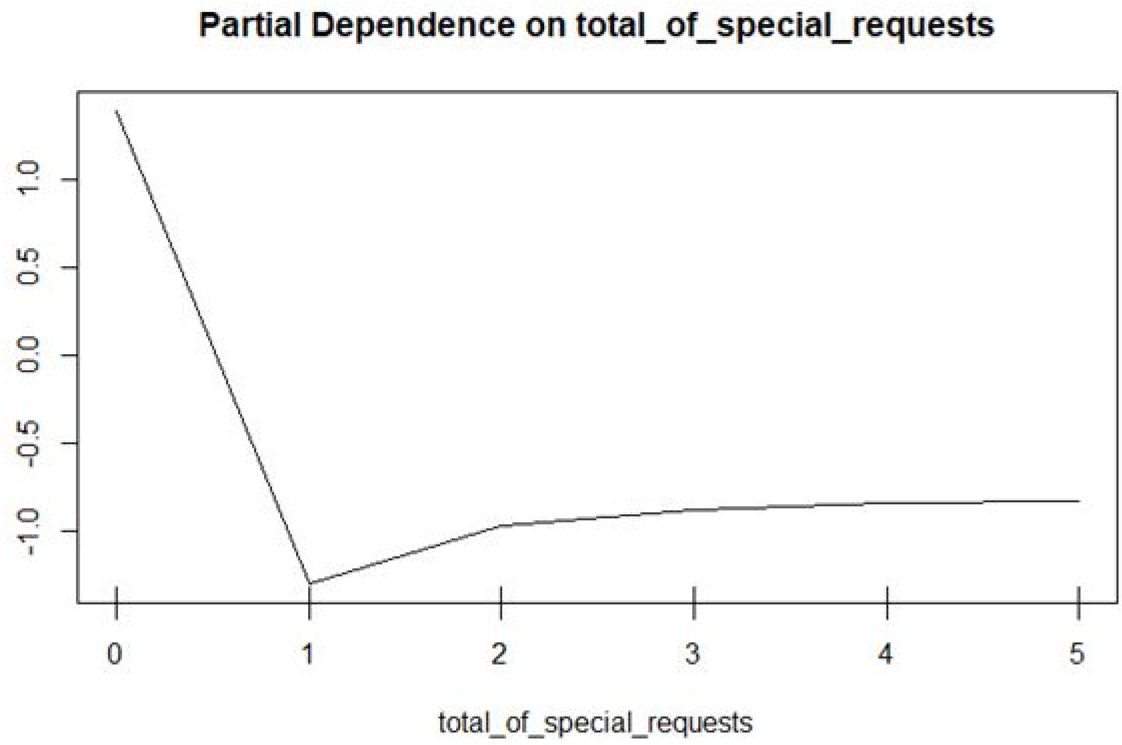
Partial Dependence Plots for Combined Data (Top 8 Variables, and Hotel):



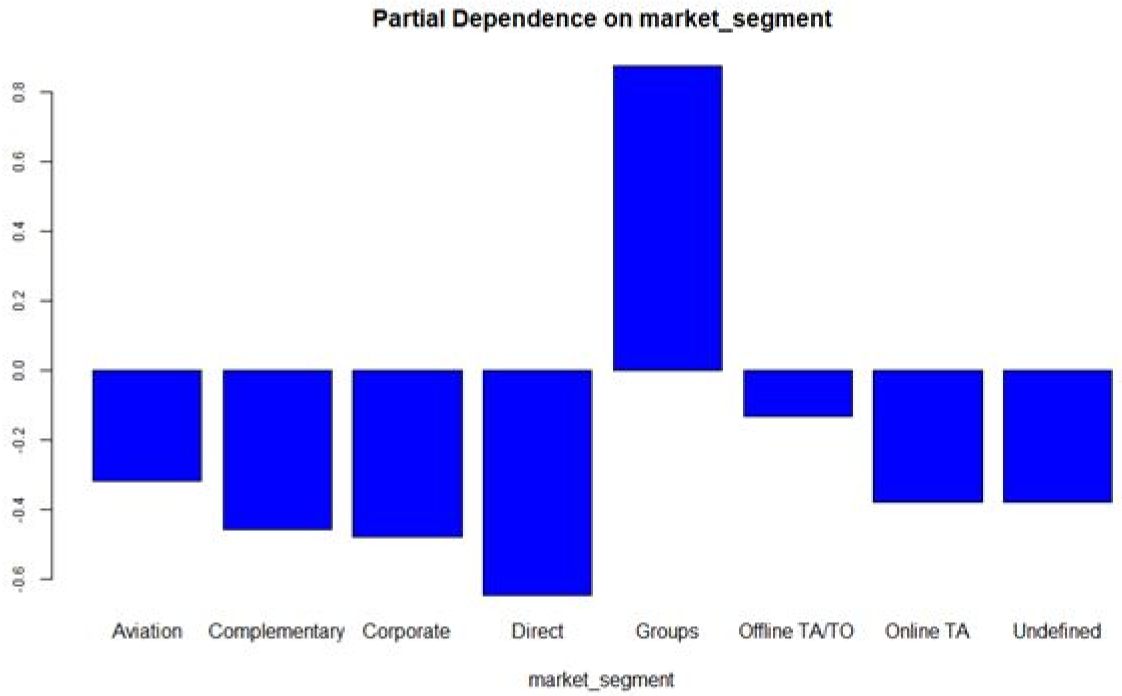
Bookings were much more likely to be cancelled if deposit_type was Non Refund (Non Refund indicates a deposit was made in the value of the total stay cost).



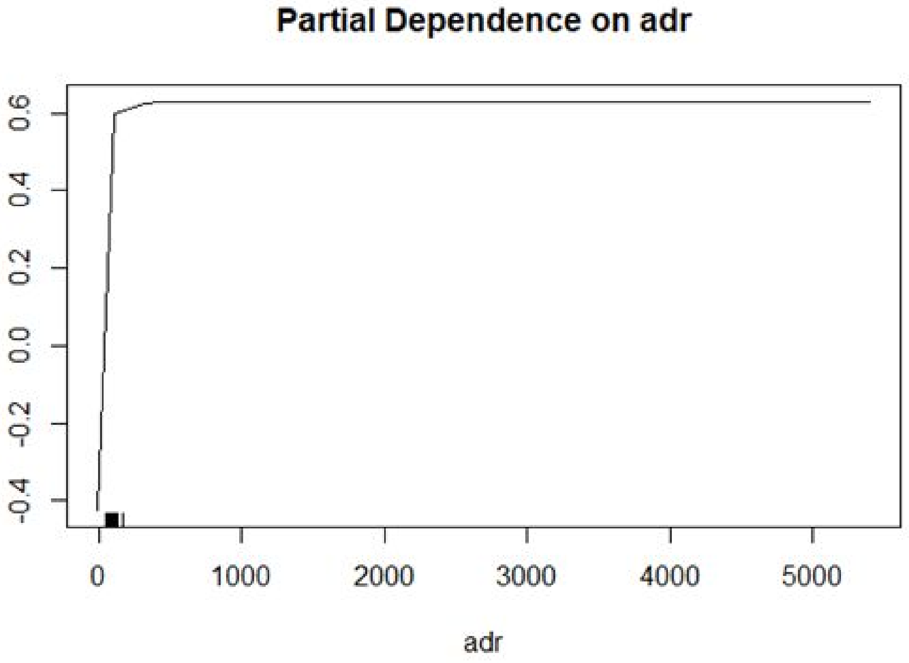
Cancellation was more likely for higher lead times between reservation and arrival. The likelihood changes most between about 0 and 100 days.



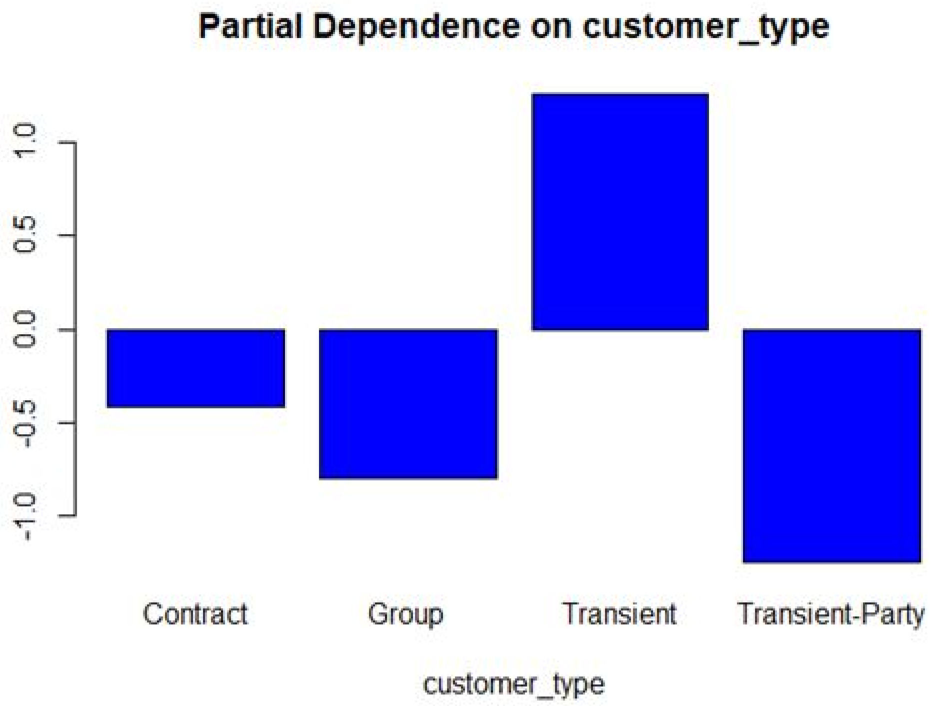
Cancellation dropped drastically where at least one special request was made.



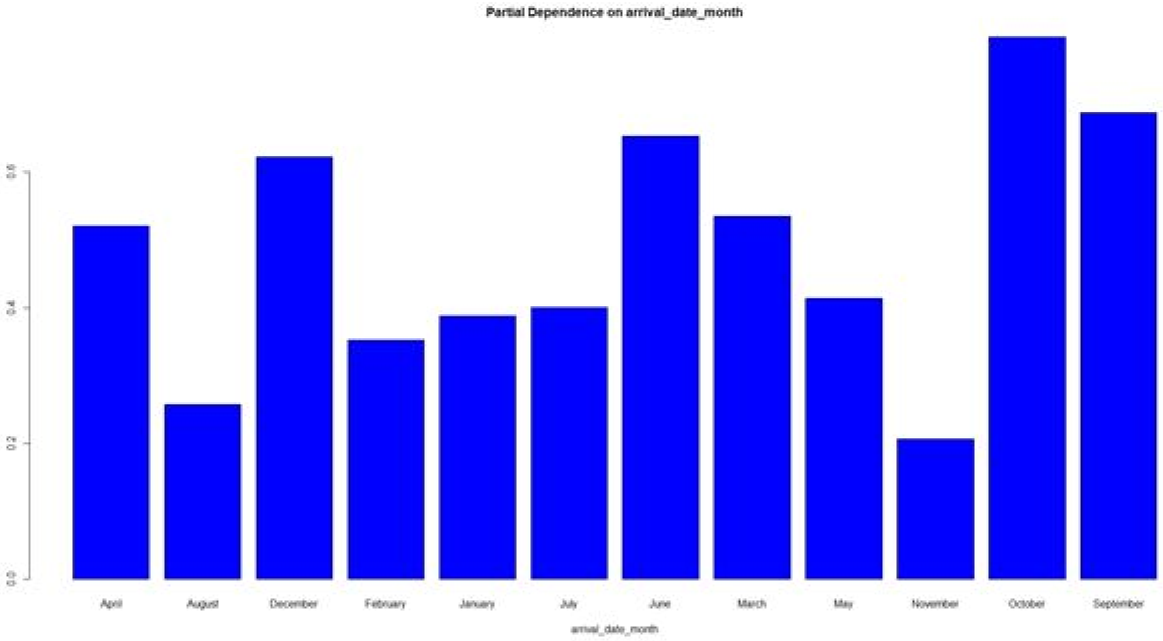
Groups were much more likely to cancel than any other market segment.



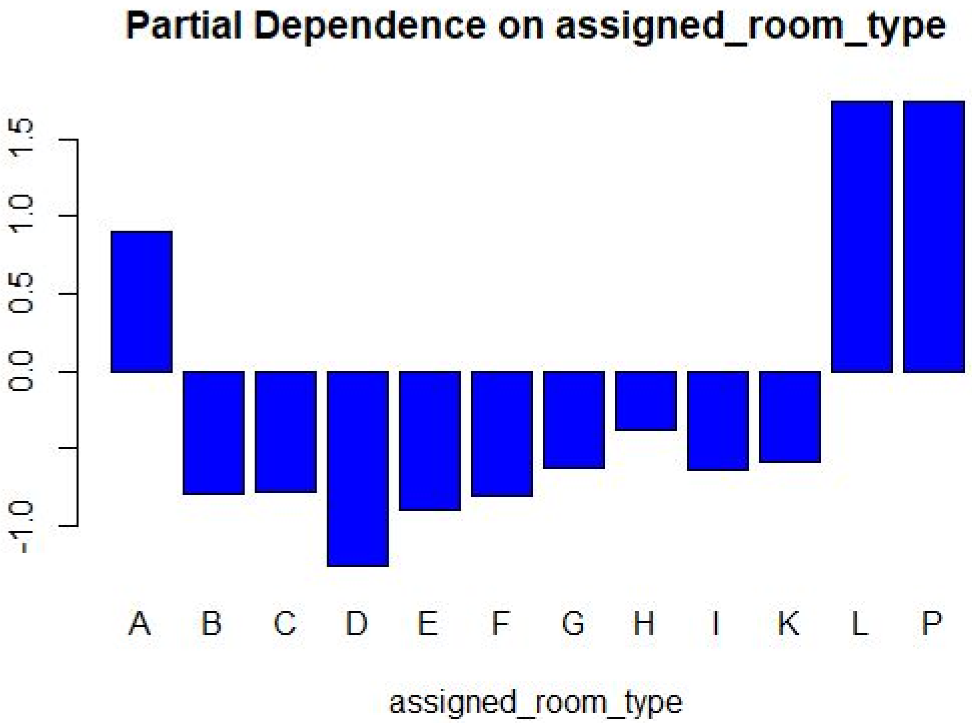
Cancellation was much more likely beyond an average daily rate of about 100 to 200.



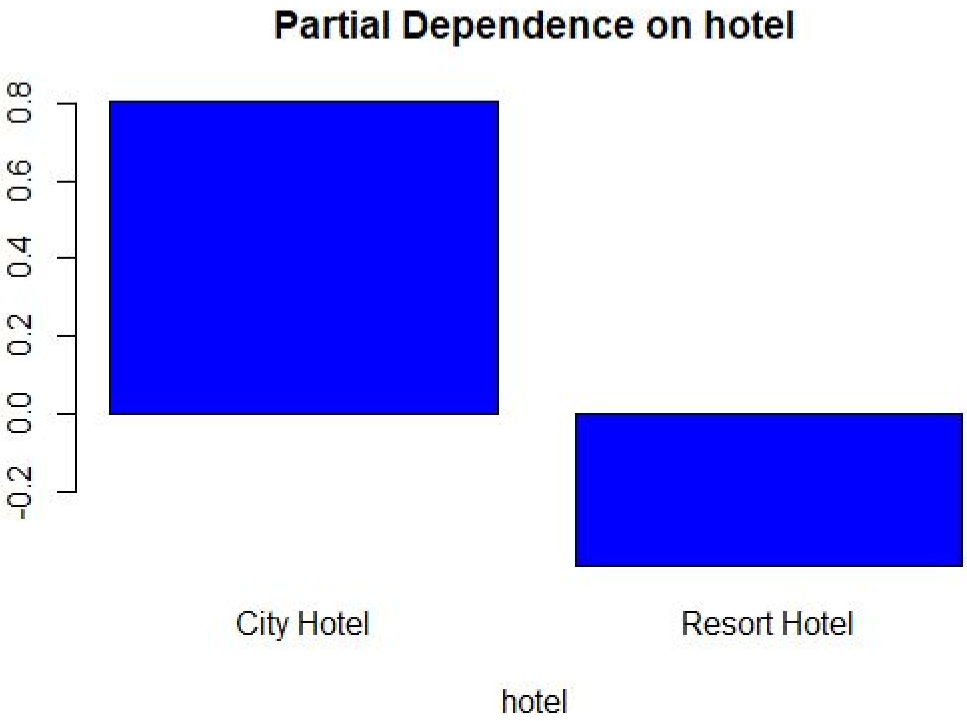
Transient customers were more likely to cancel – this was also shown in classification trees.



For the combined data, cancellations were more likely in October.



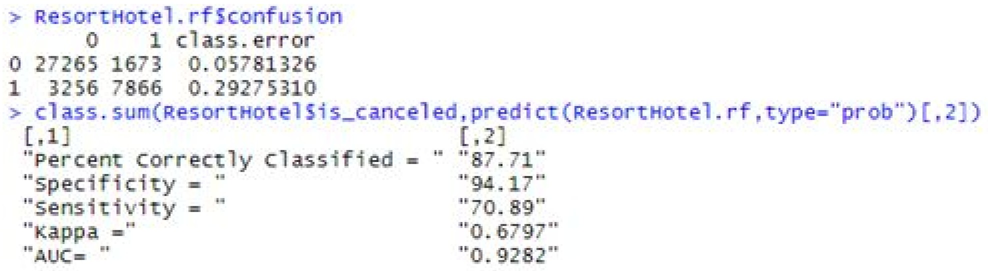
Room type A was more likely to be cancelled, and there were very few observations with room types L and P, which were all cancelled.



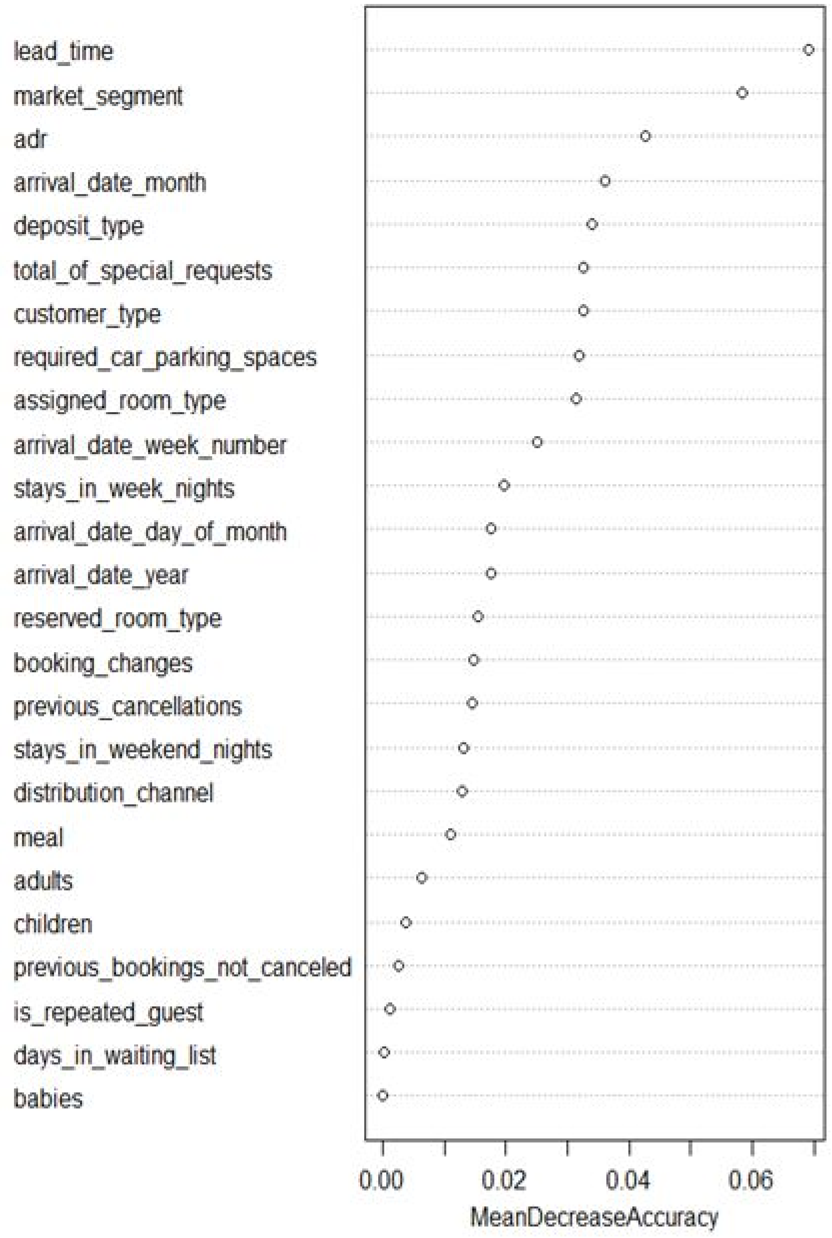
The city hotel had a higher cancellation rate than the resort hotel.

Separate Hotel Types Random Forests Results:

Resort hotel random forests result:

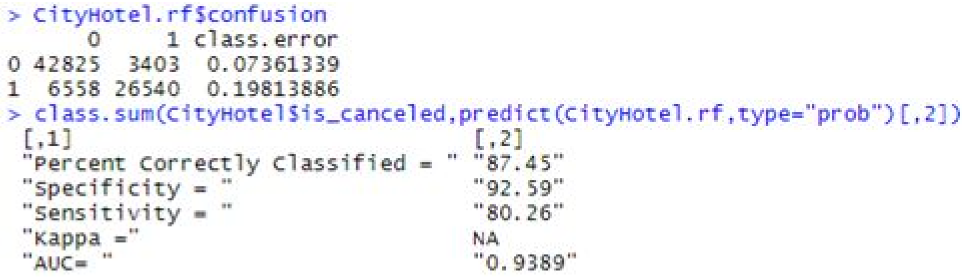


```
> ResortHotel.rf$confusion
      0    1 class.error
0 27265 1673  0.05781326
1  3256 7866  0.29275310
> class.sum(ResortHotel$is_canceled,predict(ResortHotel.rf,type="prob")[,2])
 [,1]                              [,2]
 "Percent Correctly Classified = " "87.71"
 "Specificity = "                  "94.17"
 "Sensitivity = "                  "70.89"
 "Kappa ="                         "0.6797"
 "AUC= "                           "0.9282"
```

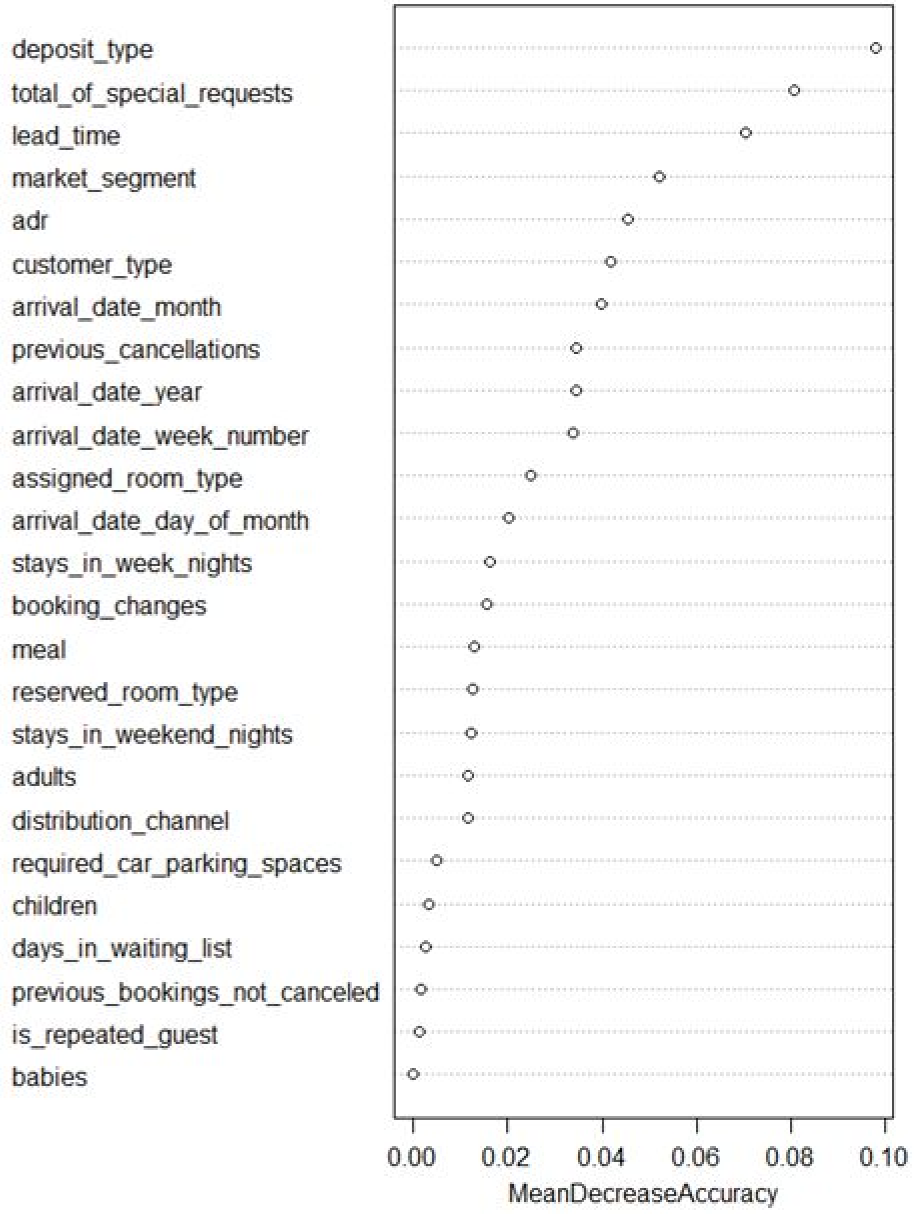


Random forests on the resort hotel had the highest overall accuracy and specificity, but lower sensitivity. The important variables shifted around a lot, with lead_time now at the top and deposit_type fifth. This suggests the resort hotel is different from the city hotel.

City hotel random forests result:



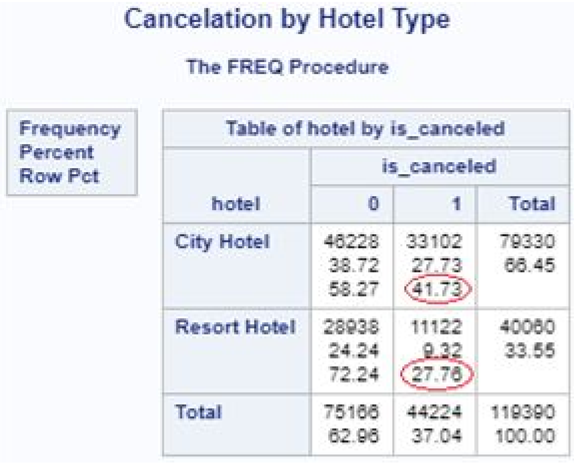
```
> CityHotel.rf$confusion
      0     1 class.error
0 42825  3403  0.07361339
1  6558 26540  0.19813886
> class.sum(CityHotel$is_canceled,predict(CityHotel.rf,type="prob")[,2])
 [,1]                               [,2]
 "Percent Correctly Classified = " "87.45"
 "Specificity = "                   "92.59"
 "Sensitivity = "                   "80.26"
 "Kappa ="                          NA
 "AUC= "                            "0.9389"
```



We got slightly higher accuracy and sensitivity with the city hotel, and the most important variables stayed relatively the same as the combined data.

<u>Frequency Tables for Important Variables</u>

Cancelation by hotel type:



Cancelation by Hotel Type

The FREQ Procedure

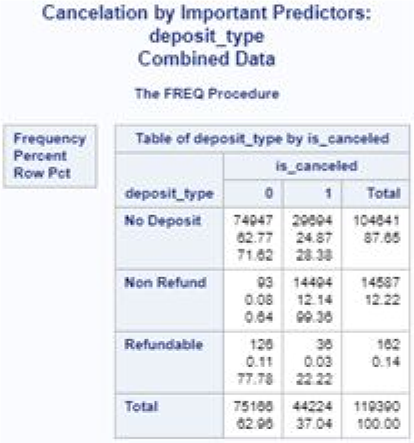
Frequency
Percent
Row Pct

Table of hotel by is_canceled

	is_canceled		
hotel	0	1	Total
City Hotel	46228 38.72 58.27	33102 27.73 41.73	79330 66.45
Resort Hotel	28938 24.24 72.24	11122 9.32 27.76	40060 33.55
Total	75166 62.96	44224 37.04	119390 100.00

The two hotels had very different overall cancellation rates (27.76% versus 41.73%), which is good evidence for treating them separately.

Deposit_type:



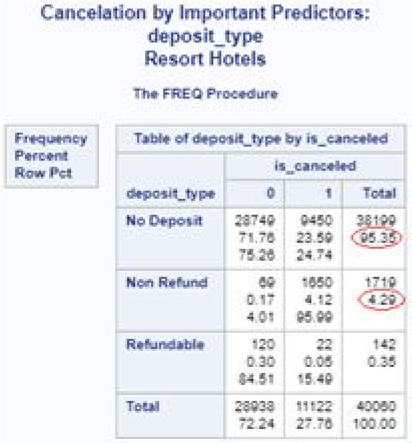
Cancelation by Important Predictors:
deposit_type
Combined Data

The FREQ Procedure

Frequency
Percent
Row Pct

Table of deposit_type by is_canceled

	is_canceled		
deposit_type	0	1	Total
No Deposit	74947 62.77 71.62	29694 24.87 28.38	104641 87.65
Non Refund	93 0.08 0.64	14494 12.14 99.36	14587 12.22
Refundable	126 0.11 77.78	36 0.03 22.22	162 0.14
Total	75166 62.96	44224 37.04	119390 100.00



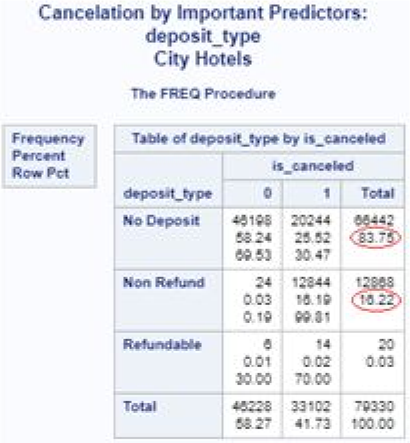
Cancelation by Important Predictors:
deposit_type
Resort Hotels

The FREQ Procedure

Frequency
Percent
Row Pct

Table of deposit_type by is_canceled

	is_canceled		
deposit_type	0	1	Total
No Deposit	28749 71.76 75.26	9450 23.59 24.74	38199 95.35
Non Refund	69 0.17 4.01	1650 4.12 95.99	1719 4.29
Refundable	120 0.30 84.51	22 0.05 15.49	142 0.35
Total	28938 72.24	11122 27.76	40060 100.00



Cancelation by Important Predictors:
deposit_type
City Hotels

The FREQ Procedure

Frequency
Percent
Row Pct

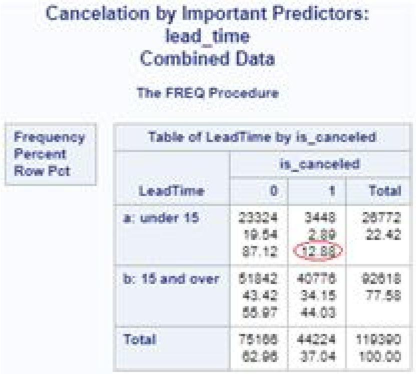
Table of deposit_type by is_canceled

	is_canceled		
deposit_type	0	1	Total
No Deposit	46198 58.24 69.53	20244 25.52 30.47	66442 83.75
Non Refund	24 0.03 0.19	12844 16.19 99.81	12868 16.22
Refundable	6 0.01 30.00	14 0.02 70.00	20 0.03
Total	46228 58.27	33102 41.73	79330 100.00

- In all three cases, the Non Refund deposit type had extremely high cancellation rates. This was surprising because Non Refund indicates a deposit was made in the value of the total stay cost. One explanation may be that only 4.29% of resort hotel bookings were Non Refund, and only 16.22% of city hotel bookings were Non Refund, so it was a less typical option.

- This also highlights a difference between the resort hotel and the city hotel. As shown in the variable importance plots, deposit_type is less important for the resort hotel because over 95% of resort bookings were No Deposit, and slightly less Non Refund bookings were canceled.

lead_time:



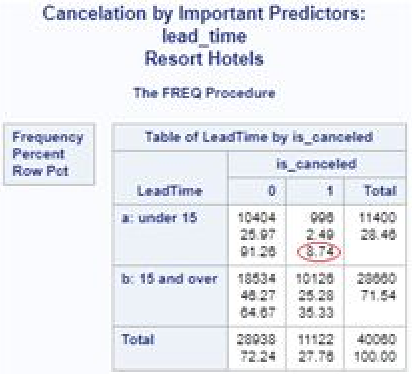
Cancelation by Important Predictors:
lead_time
Combined Data

The FREQ Procedure

Frequency
Percent
Row Pct

Table of LeadTime by is_canceled

	is_canceled		
LeadTime	0	1	Total
a: under 15	23324 19.54 87.12	3448 2.89 12.88	26772 22.42
b: 15 and over	51842 43.42 55.97	40776 34.15 44.03	92618 77.58
Total	75166 62.96	44224 37.04	119390 100.00



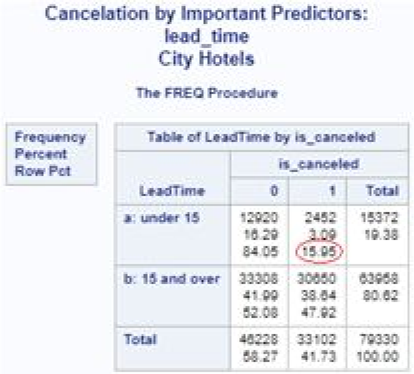
Cancelation by Important Predictors:
lead_time
Resort Hotels

The FREQ Procedure

Frequency
Percent
Row Pct

Table of LeadTime by is_canceled

	is_canceled		
LeadTime	0	1	Total
a: under 15	10404 25.97 91.26	996 2.49 8.74	11400 28.46
b: 15 and over	18534 46.27 64.67	10126 25.28 35.33	28660 71.54
Total	28938 72.24	11122 27.76	40060 100.00



Cancelation by Important Predictors:
lead_time
City Hotels

The FREQ Procedure

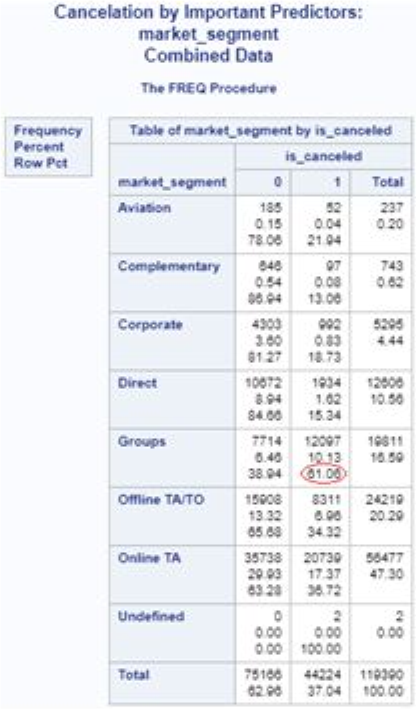
Frequency
Percent
Row Pct

Table of LeadTime by is_canceled

	is_canceled		
LeadTime	0	1	Total
a: under 15	12920 16.29 84.05	2452 3.09 15.95	15372 19.38
b: 15 and over	33308 41.99 52.08	30650 38.64 47.92	63958 80.62
Total	46228 58.27	33102 41.73	79330 100.00

In all three cases, cancelation rates were much lower when reservations were made less than 15 days before arrival. The grouping cutoff of 15 days is based on the lead_time split from the Resort Hotel classification tree. The variable importance plot above also shows lead_time as the resort hotel's most important variable.

market_segment:



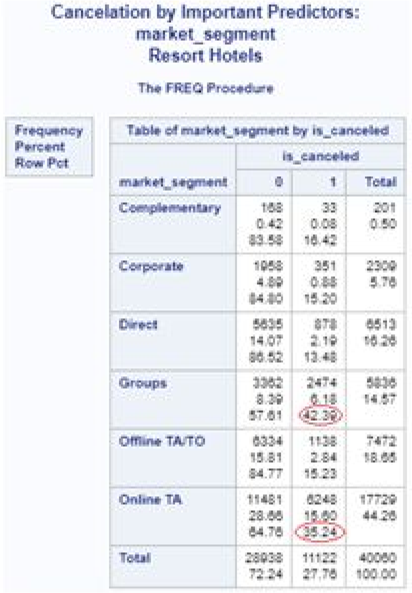
Cancelation by Important Predictors:
market_segment
Combined Data

The FREQ Procedure

Frequency
Percent
Row Pct

Table of market_segment by is_canceled

	is_canceled		
market_segment	0	1	Total
Aviation	185 0.15 78.06	52 0.04 21.94	237 0.20
Complementary	646 0.54 86.94	97 0.08 13.06	743 0.62
Corporate	4303 3.60 81.27	992 0.83 18.73	5295 4.44
Direct	10672 8.94 84.66	1934 1.62 15.34	12606 10.56
Groups	7714 6.46 38.94	12097 10.13 61.06	19811 16.59
Offline TA/TO	15908 13.32 65.68	8311 6.96 34.32	24219 20.29
Online TA	35738 29.93 63.28	20739 17.37 36.72	56477 47.30
Undefined	0 0.00 0.00	2 0.00 100.00	2 0.00
Total	75166 62.96	44224 37.04	119390 100.00



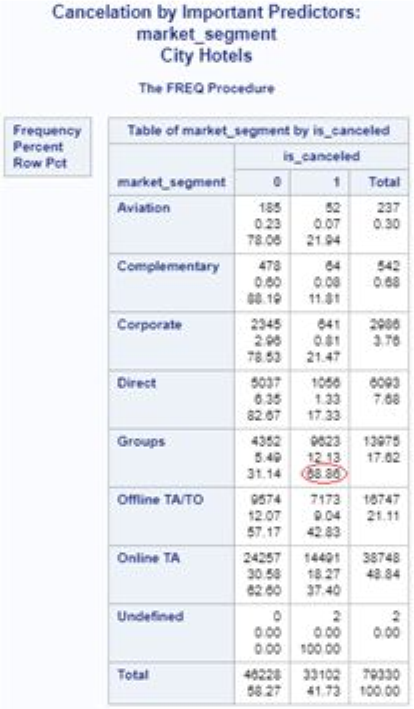
Cancelation by Important Predictors:
market_segment
Resort Hotels

The FREQ Procedure

Frequency
Percent
Row Pct

Table of market_segment by is_canceled

	is_canceled		
market_segment	0	1	Total
Complementary	168 0.42 83.58	33 0.08 16.42	201 0.50
Corporate	1958 4.89 84.80	351 0.88 15.20	2309 5.76
Direct	5635 14.07 86.52	878 2.19 13.48	6513 16.26
Groups	3362 8.39 57.61	2474 6.18 42.39	5836 14.57
Offline TA/TO	6334 15.81 84.77	1138 2.84 15.23	7472 18.65
Online TA	11481 28.66 64.76	6248 15.60 35.24	17729 44.26
Total	28938 72.24	11122 27.76	40060 100.00



Cancelation by Important Predictors:
market_segment
City Hotels

The FREQ Procedure

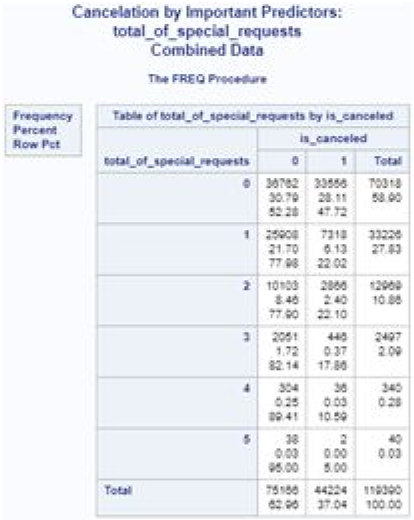
Frequency
Percent
Row Pct

Table of market_segment by is_canceled

	is_canceled		
market_segment	0	1	Total
Aviation	185 0.23 78.06	52 0.07 21.94	237 0.30
Complementary	478 0.60 88.19	64 0.08 11.81	542 0.68
Corporate	2345 2.96 78.53	641 0.81 21.47	2986 3.76
Direct	5037 6.35 82.67	1056 1.33 17.33	6093 7.68
Groups	4352 5.49 31.14	9623 12.13 68.86	13975 17.62
Offline TA/TO	9574 12.07 57.17	7173 9.04 42.83	16747 21.11
Online TA	24257 30.58 62.60	14491 18.27 37.40	38748 48.84
Undefined	0 0.00 0.00	2 0.00 100.00	2 0.00
Total	46228 58.27	33102 41.73	79330 100.00

In all three cases, Groups had the highest cancellation rates. For the resort hotel, the ‘Online TA’ segment had a higher than average cancelation rate as well.

total_of_special_requests:



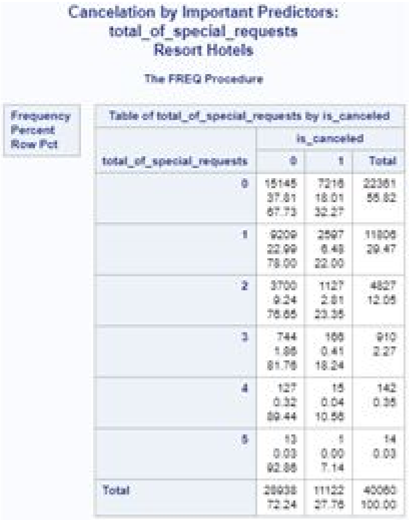
Cancelation by Important Predictors:
total_of_special_requests
Combined Data

The FREQ Procedure

Frequency
Percent
Row Pct

Table of total_of_special_requests by is_canceled

	is_canceled		
total_of_special_requests	0	1	Total
0	36762 30.79 52.28	33556 28.11 47.72	70318 58.90
1	25908 21.70 77.98	7318 6.13 22.02	33226 27.83
2	10103 8.46 77.90	2866 2.40 22.10	12969 10.86
3	2051 1.72 82.14	446 0.37 17.86	2497 2.09
4	304 0.25 89.41	36 0.03 10.59	340 0.28
5	38 0.03 95.00	2 0.00 5.00	40 0.03
Total	75166 62.96	44224 37.04	119390 100.00



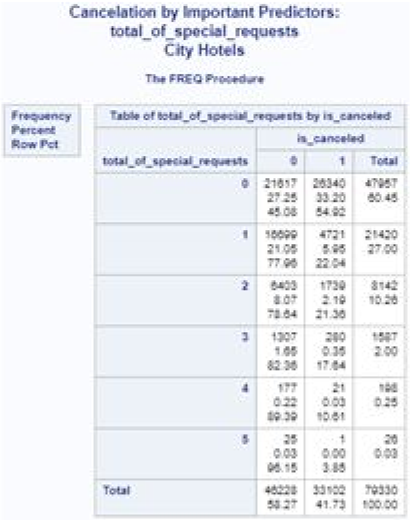
Cancelation by Important Predictors:
total_of_special_requests
Resort Hotels

The FREQ Procedure

Frequency
Percent
Row Pct

Table of total_of_special_requests by is_canceled

	is_canceled		
total_of_special_requests	0	1	Total
0	15145 37.81 67.73	7216 18.01 32.27	22361 55.82
1	9209 22.99 78.00	2597 6.48 22.00	11806 29.47
2	3700 9.24 76.65	1127 2.81 23.35	4827 12.05
3	744 1.86 81.76	166 0.41 18.24	910 2.27
4	127 0.32 89.44	15 0.04 10.56	142 0.35
5	13 0.03 92.86	1 0.00 7.14	14 0.03
Total	28938 72.24	11122 27.76	40060 100.00



Cancelation by Important Predictors:
total_of_special_requests
City Hotels

The FREQ Procedure

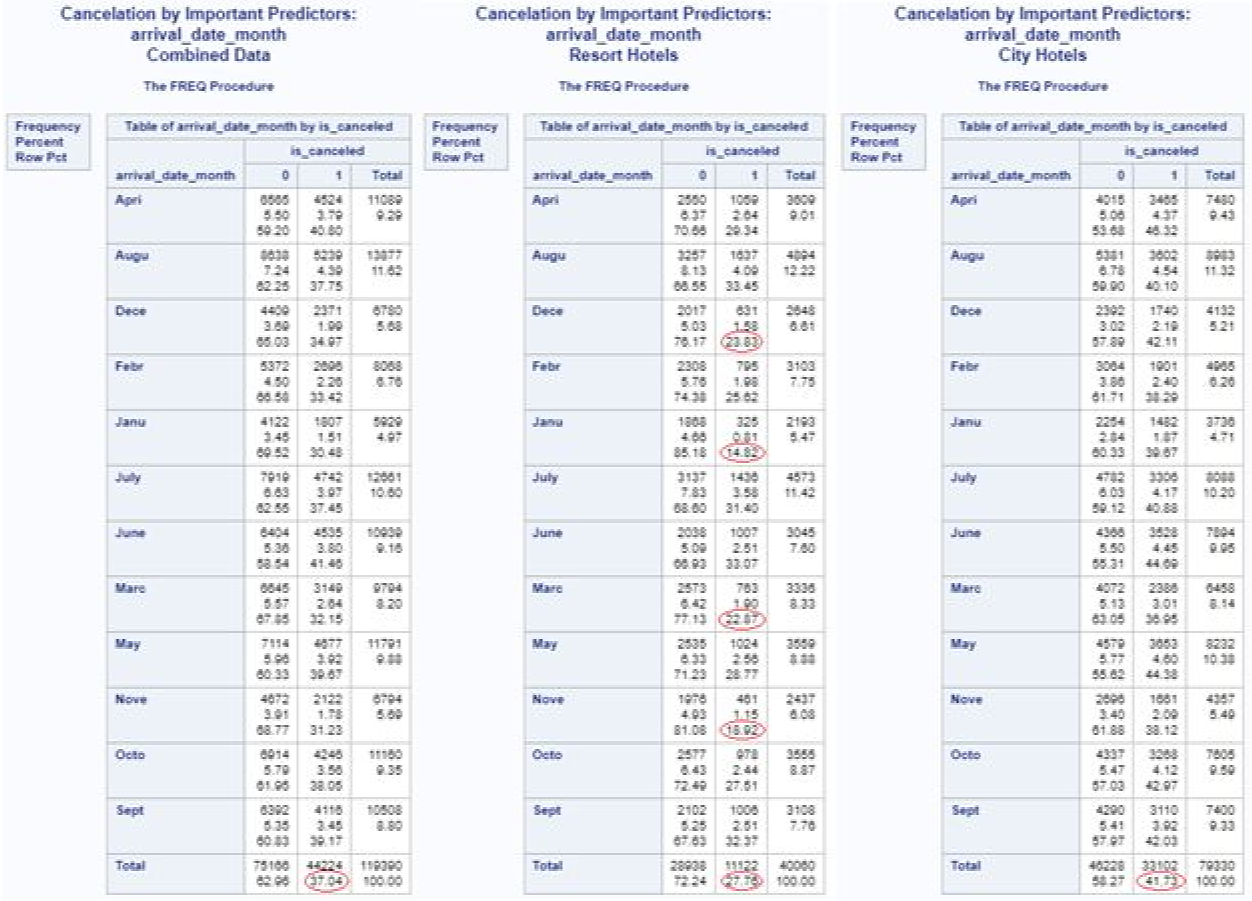
Frequency
Percent
Row Pct

Table of total_of_special_requests by is_canceled

	is_canceled		
total_of_special_requests	0	1	Total
0	21617 27.25 45.08	26340 33.20 54.92	47957 60.45
1	16699 21.05 77.96	4721 5.95 22.04	21420 27.00
2	6403 8.07 78.64	1739 2.19 21.36	8142 10.26
3	1307 1.65 82.36	280 0.35 17.64	1587 2.00
4	177 0.22 89.39	21 0.03 10.61	198 0.25
5	25 0.03 96.15	1 0.00 3.85	26 0.03
Total	46228 58.27	33102 41.73	79330 100.00

Cancellation decreased as special requests increased for the combined data as well as for the separate hotel types.

arrival_date_month:



Cancelation by Important Predictors:
arrival_date_month
Combined Data

The FREQ Procedure

Frequency
Percent
Row Pct

Table of arrival_date_month by is_canceled

arrival_date_month	is_canceled 0	 1	 Total
Apri	6565 5.50 59.20	4524 3.79 40.80	11089 9.29
Augu	8638 7.24 62.25	5239 4.39 37.75	13877 11.62
Dece	4409 3.69 65.03	2371 1.99 34.97	6780 5.68
Febr	5372 4.50 66.58	2696 2.26 33.42	8068 6.76
Janu	4122 3.45 69.52	1807 1.51 30.48	5929 4.97
July	7919 6.63 62.55	4742 3.97 37.45	12661 10.60
June	6404 5.36 58.54	4535 3.80 41.46	10939 9.16
Marc	6645 5.57 67.85	3149 2.64 32.15	9794 8.20
May	7114 5.96 60.33	4677 3.92 39.67	11791 9.88
Nove	4672 3.91 68.77	2122 1.78 31.23	6794 5.69
Octo	6914 5.79 61.95	4246 3.56 38.05	11160 9.35
Sept	6392 5.35 60.83	4116 3.45 39.17	10508 8.80
Total	75166 62.96	44224 37.04	119390 100.00

Cancelation by Important Predictors:
arrival_date_month
Resort Hotels

The FREQ Procedure

Frequency
Percent
Row Pct

Table of arrival_date_month by is_canceled

arrival_date_month	is_canceled 0	 1	 Total
Apri	2550 6.37 70.66	1059 2.64 29.34	3609 9.01
Augu	3257 8.13 66.55	1637 4.09 33.45	4894 12.22
Dece	2017 5.03 76.17	631 1.58 23.83	2648 6.61
Febr	2308 5.76 74.38	795 1.98 25.62	3103 7.75
Janu	1868 4.66 85.18	325 0.81 14.82	2193 5.47
July	3137 7.83 68.60	1436 3.58 31.40	4573 11.42
June	2038 5.09 66.93	1007 2.51 33.07	3045 7.60
Marc	2573 6.42 77.13	763 1.90 22.87	3336 8.33
May	2535 6.33 71.23	1024 2.56 28.77	3559 8.88
Nove	1976 4.93 81.08	461 1.15 18.92	2437 6.08
Octo	2577 6.43 72.49	978 2.44 27.51	3555 8.87
Sept	2102 5.25 67.63	1006 2.51 32.37	3108 7.76
Total	28938 72.24	11122 27.76	40060 100.00

Cancelation by Important Predictors:
arrival_date_month
City Hotels

The FREQ Procedure

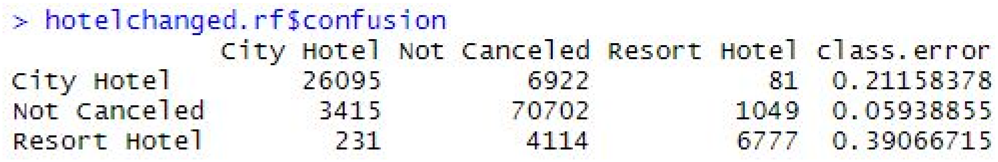
Frequency
Percent
Row Pct

Table of arrival_date_month by is_canceled

arrival_date_month	is_canceled 0	 1	 Total
Apri	4015 5.06 53.68	3465 4.37 46.32	7480 9.43
Augu	5381 6.78 59.90	3602 4.54 40.10	8983 11.32
Dece	2392 3.02 57.89	1740 2.19 42.11	4132 5.21
Febr	3064 3.86 61.71	1901 2.40 38.29	4965 6.26
Janu	2254 2.84 60.33	1482 1.87 39.67	3736 4.71
July	4782 6.03 59.12	3306 4.17 40.88	8088 10.20
June	4366 5.50 55.31	3528 4.45 44.69	7894 9.95
Marc	4072 5.13 63.05	2386 3.01 36.95	6458 8.14
May	4579 5.77 55.62	3653 4.60 44.38	8232 10.38
Nove	2696 3.40 61.88	1661 2.09 38.12	4357 5.49
Octo	4337 5.47 57.03	3268 4.12 42.97	7605 9.59
Sept	4290 5.41 57.97	3110 3.92 42.03	7400 9.33
Total	46228 58.27	33102 41.73	79330 100.00

For the resort hotel, November, December, January, and March had significantly lower cancelation rates than the average of 27.76%. The combined data and the city hotels had less variation in monthly cancelation rates, so it is harder to predict the best times of year for them. This agrees with the variable importance plot for resort hotels, which shows arrival_date_month as more important.

Out-of-Bag Confusion matrix for random forests with HOTEL as response:



```
> hotelchanged.rf$confusion
             City Hotel Not Canceled Resort Hotel class.error
City Hotel        26095         6922           81  0.21158378
Not Canceled       3415        70702         1049  0.05938855
Resort Hotel        231         4114         6777  0.39066715
```

- Most of the misclassifications were the two hotels being confused for Not Canceled. The hotels were not confused for each other very often. This is further reason to treat the resort hotel and the city hotel differently.

- This confusion matrix also shows the lower sensitivity and higher specificity we had with our other random forests fits.

Random Forests Conclusions:

Random Forests gave us very good predictive accuracy for is_canceled compared to the other methods. It identified deposit_type, lead_time, total_of_special_requests, and market_segment among the most important variables for prediction cancelation.

Our reduced models had decreased accuracy, but the 7-variable model was not bad apart from the decreased sensitivity.

The resort hotel is different from the city hotel because:

1. It had a much lower overall cancellation proportion.

2. It had different proportions of deposit types.

3. lead_time was a better cancellation predictor for the resort hotel.

4. It had more variation in cancellation rates by month, which made arrival_date_month a better cancellation predictor.

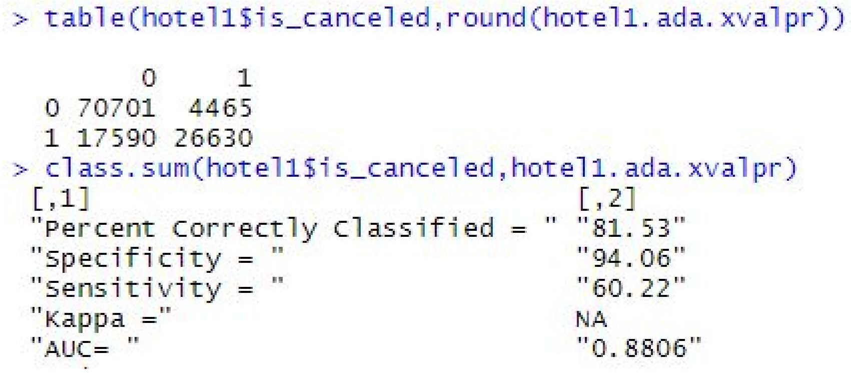
In each case examined, the Groups market segment had the highest cancellation rate.

In each case examined, more special requests resulted in less cancellation.

ADABOOST:

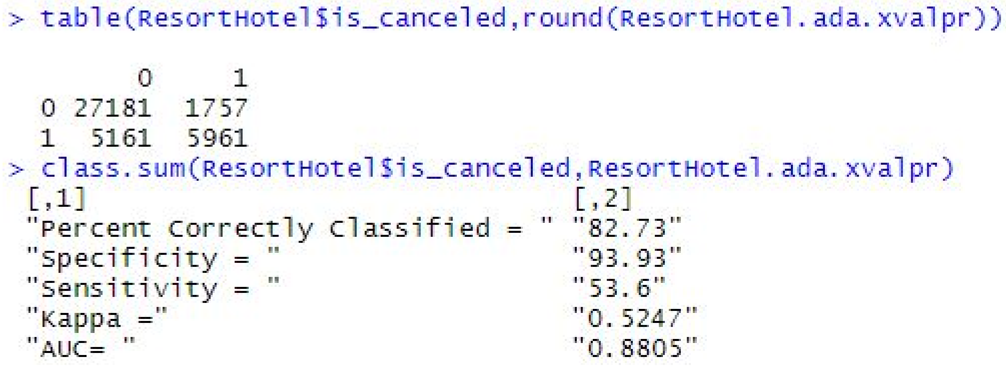
We used adaboost to analyze the combined data along with the two separate hotel types, keeping the same variables as we did for random forests.

Combined data adaboost result:



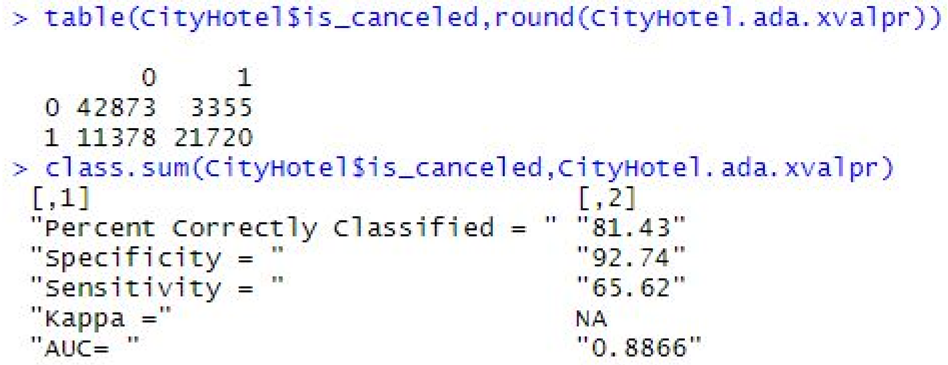
```
> table(hotel1$is_canceled,round(hotel1.ada.xvalpr))
   
        0     1
  0 70701  4465
  1 17590 26630
> class.sum(hotel1$is_canceled,hotel1.ada.xvalpr)
 [,1]                                [,2]    
 "Percent Correctly Classified = " "81.53" 
 "Specificity = "                    "94.06" 
 "Sensitivity = "                    "60.22" 
 "Kappa ="                           NA      
 "AUC= "                             "0.8806"
```

Resort hotel adaboost result:



```
> table(ResortHotel$is_canceled,round(ResortHotel.ada.xvalpr))
   
        0     1
  0 27181  1757
  1  5161  5961
> class.sum(ResortHotel$is_canceled,ResortHotel.ada.xvalpr)
 [,1]                                [,2]    
 "Percent Correctly Classified = " "82.73" 
 "Specificity = "                    "93.93" 
 "Sensitivity = "                    "53.6"  
 "Kappa ="                           "0.5247"
 "AUC= "                             "0.8805"
```

City hotel adaboost result:



```
> table(CityHotel$is_canceled,round(CityHotel.ada.xvalpr))
   
        0     1
  0 42873  3355
  1 11378 21720
> class.sum(CityHotel$is_canceled,CityHotel.ada.xvalpr)
 [,1]                                [,2]    
 "Percent Correctly Classified = " "81.43" 
 "Specificity = "                    "92.74" 
 "Sensitivity = "                    "65.62" 
 "Kappa ="                           NA      
 "AUC= "                             "0.8866"
```

Adaboost Conclusion:

Adaboost gave similar results for each of our three cases, and it was slightly less accurate than random forests.

Comparison of All Methods

Working with this data set did not go as smoothly as we expected. So for some methods such as Random Forests we were able to do a more in depth analysis of the data. While in other areas we were not able to run models across the full population of the data, or we were unable to tune the data or we were only able to do basic prediction on the data and not perform cross validation. So we don't feel that we can do a direct comparison of all the methods and say that in this instance one was better than the other. So that we have some type of comparison we are going to list all of the accuracy scores below for all the predictions we did to predict the variable is_canceled and state which has the highest accuracy even though it may not be the best method for classification of this data.

- Combined data Adaboost: Accuracy = 81.53%
- Combined data Random Forests: Accuracy = 87.39%
- Combined data Gradient Boosting Machine(GBM): Accuracy = 67.78%
- Combined data Support Vector Machines(SVM): Accuracy = 72.2%
- Combined data Logistic Regression: Accuracy = 73.67%
- Combined data Classification Trees: Accuracy = 83.07%

All in all random forests performed best in predicting the variable is_cancelled.