Expedia Hotel Recommendation

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1 Introduction

The objective of **Expedia Hotel Recommendation** is to predict the **hotel cluster** for the user. The hotel clusters are numbered based on many parameters like distance for the city center, amenities like swimming pool, gym etc. They are in the range 1 to 100.

2 Deep Dive into Dataset

2.1 Data Files

The following are the data files provided. They can be accessed from the following *kaggle location* (www.kaggle.com/c/expedia-hotel-recommendations/data).

- **train.csv** - the training dataset
- **test.csv** - the test dataset
- **destinations.csv** - hotel search latent attributes
- **sample_submission.csv** - the sample submission file in the correct format

2.2 Important Fields in the dataset

The following are the important fields which are available in the **training** dataset.

- **date_time** - TimeStamp
- `user location info`
  - **posa_continent** - ID of the continent
  - **user_location_contry** - ID of the country where the customer is located
  - **user_location_region** - ID of the region where the customer is located
  - **user_location_city** - ID of the city where the customer is located
- **orig_destination_distance** - Physical distance between the hotel and customer at the time of search
- `stay information`
  - **srch_ci** - Checkin date
  - **srch_co** - Checkout date
  - **srch_adults_cnt** - Number of adults
  - **srch_childrens_cnt** - Number of childrens
  - **srch_rm_cnt** - Number of rooms requested in the search
- `destination hotel info`
  - **srch_destination_id** - ID of the destination hotel
  - **hotel_continent** - Hotel continent
  - **hotel_country** - Hotel Country
- **is_booking** - 1 if a booking, 0 if a click.
- **cnt** - Number of similar events in the context of same user session.
- **hotel_cluster** - ID of the hotel cluster

Also the **destinations.csv** has the following information.

- **srch_destination_id** - ID of the destination hotel
- **d1-d149** - latent description of search regions

2.3 Format of Submission File

For every user event, we need to predict a space-delimited list of the hotel clusters they booked. we may submit up to 5 predictions for each user event. The file should contain a header and have the following format:

id,hotel_cluster

0,99 3 1 75 20

1,2 50 30 23 9

etc. . .

2.4 Limitations of the Dataset

1. The `user location info` (continent/country/city) and `destination hotel location` (continent/country) are **integer values**. There is no mapping available about the integer values to appripriate cities.
2. The `destination data file` has the information about the hotels in terms of **150 attributes** and they are of **nunerical** value. There is no mapping available for this one as well.

3 Exploring the data

3.1 Sampling the training dataset

The **training** dataset has 37M records with 4GB in size. Because of the huge dataset, we can't load the complete training datset in a normal computer. We need to have a machine with atleast **16GB RAM** size.

However, following are some ways to deal with the big data set for exploration and analysis.

- **sample the training data** - Use CATools package to create a smaller dataset by sampling as below. Note that the sampling will help in the early explorations. But for **final analysis and prediction, we have to run the complete training and test dataset**.

```
# for splitting the training data
library(caTools)

system.time(train_dt <- fread("train.csv", header = TRUE))

#to make it reproducible
set.seed(123)

## specify the column name
split = sample.split(train_dt$hotel_cluster, SplitRatio = 0.75)

new_train_dt = subset(train_dt, split == TRUE)
new_test_dt  = subset(train_dt, split == FALSE)

write.csv(new_train_dt, file = "new_train.csv", row.names = FALSE, quote = FALSE)
write.csv(new_test_dt, file = "new_test.csv", row.names = TRUE, quote = FALSE)
```

- **Use fread()** - The fread() from `data.table` package is faster than the read.csv() function.

Note: For this report, will use sampled training dataset, which has 25 thousand observations.

3.2 Examining the Date info

Let's take a look at the date info in the **training** dataset.

```
train_dt$year <- as.numeric(format(as.Date(train_dt$date_time, "%Y-%m-%d"), "%Y"))
unique(train_dt$year)
```

```
## [1] 2014 2013
```

Examine the records in the **test** data.

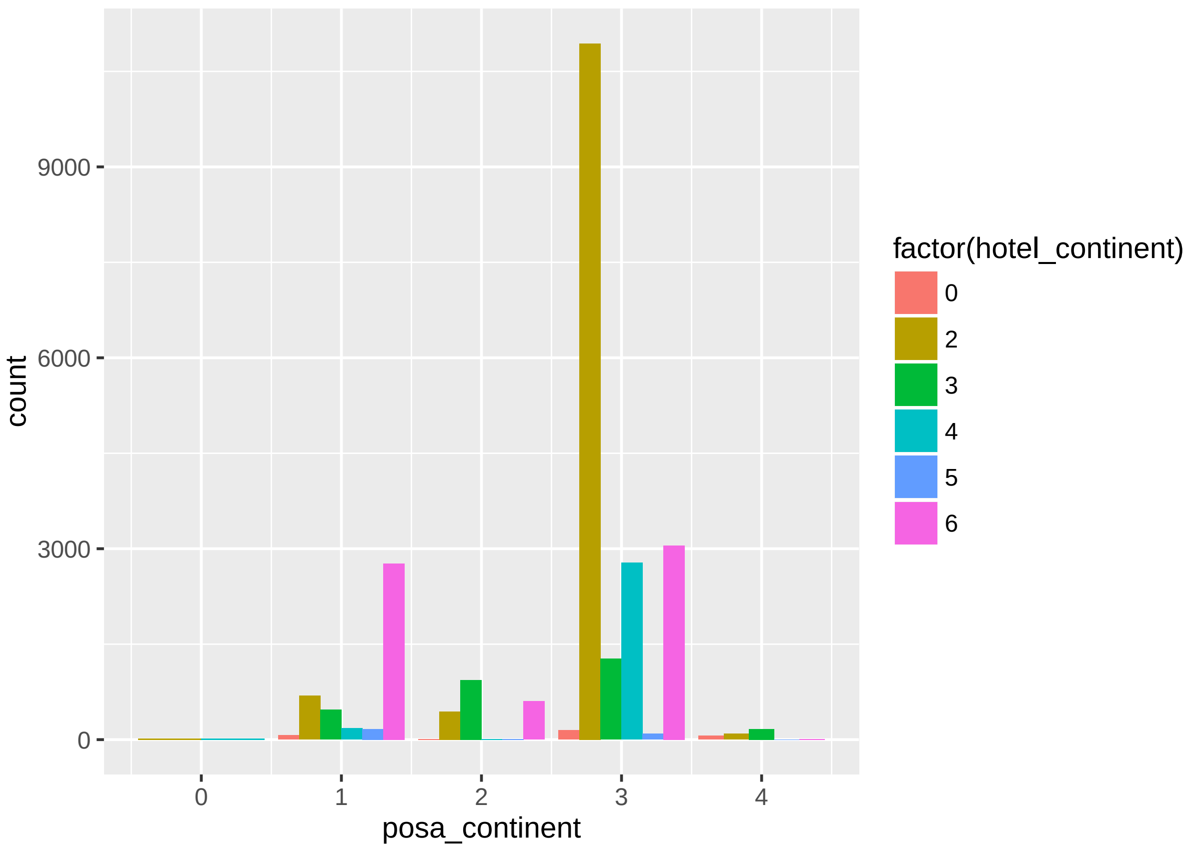
```
test_dt$year <- as.numeric(format(as.Date(test_dt$date_time, "%Y-%m-%d"), "%Y"))
unique(test_dt$year)
```

```
## [1] 2015
```

3.3 User's current location and the destination hotel location

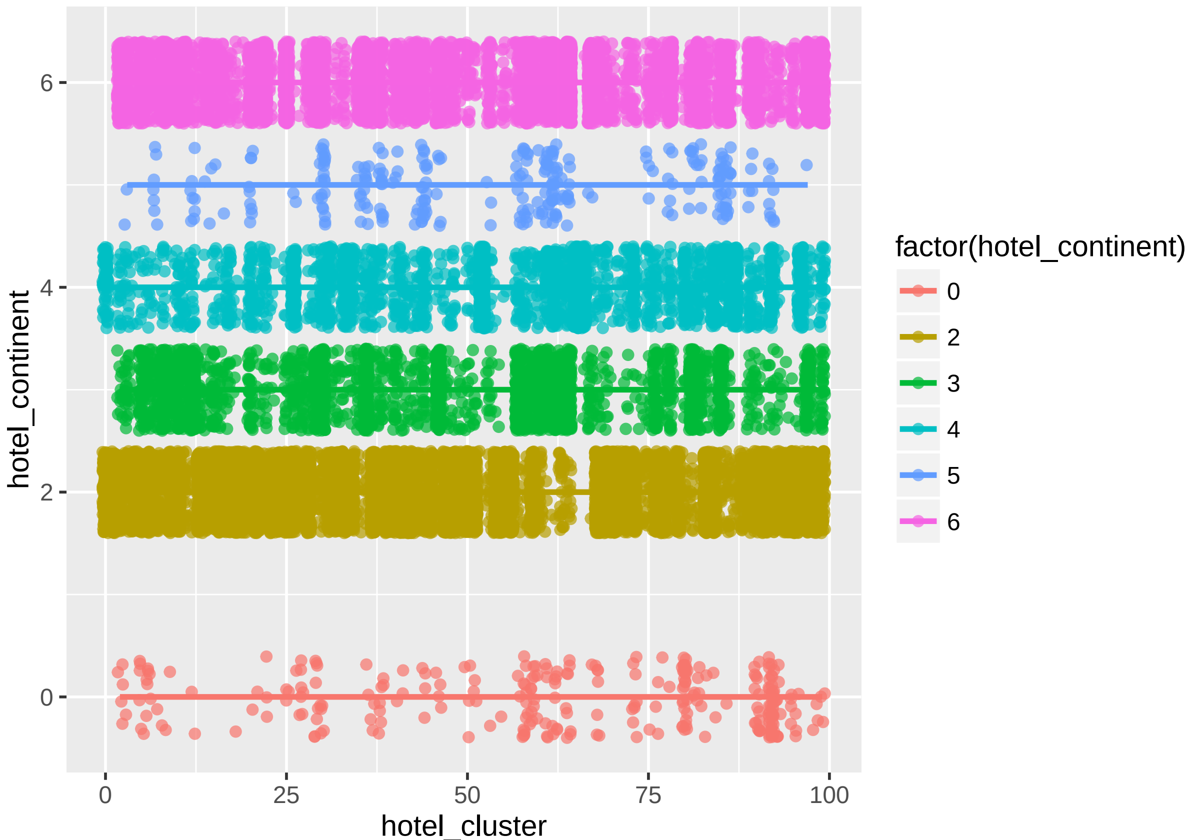
The posa_continent is user current location at the time of booking and the hotel_continent is the desitnation location.

```
ggplot(train_dt, aes(posa_continent, fill = factor(hotel_continent))) + geom_bar(position = "dodge")
```



3.4 Spread of hotel clusters in different continents.

```
ggplot(train_dt,
       aes(x = hotel_cluster, y = hotel_continent, col = factor(hotel_continent))) +       # to avoid o
  geom_jitter(alpha = 0.7) +
      geom_smooth(method = "lm", se = F)
```



4 Approach to solution

4.1 Correlation Info of hotel_cluster with rest of attributes.

```
cor(train_dt$hotel_cluster, train_dt$srch_destination_id)
```

```
## [1] 0.003811001
```

```
cor(train_dt$hotel_cluster, train_dt$posa_continent)
```

```
## [1] 0.0004647611
```

```
cor(train_dt$hotel_cluster, train_dt$user_location_country)
```

```
## [1] -0.0338143
```

```
cor(train_dt$hotel_cluster, train_dt$user_location_region)
```

```
## [1] 0.01410099
```

```r
cor(train_dt$hotel_cluster, train_dt$user_location_city)
```

```
## [1] -0.01355649
```

```r
cor(train_dt$hotel_cluster, train_dt$orig_destination_distance)
```

```
## [1] NA
```

```r
cor(train_dt$hotel_cluster, train_dt$user_id)
```

```
## [1] 0.01577343
```

```r
cor(train_dt$hotel_cluster, train_dt$is_package)
```

```
## [1] 0.05255554
```

```r
#cor(train_dt$hotel_cluster, train_dt$srch_ci)
#cor(train_dt$hotel_cluster, train_dt$srch_co)
cor(train_dt$hotel_cluster, train_dt$srch_adults_cnt)
```

```
## [1] 0.0136383
```

```r
cor(train_dt$hotel_cluster, train_dt$srch_children_cnt)
```

```
## [1] 0.01279837
```

```r
cor(train_dt$hotel_cluster, train_dt$srch_rm_cnt)
```

```
## [1] -0.00102075
```

```r
cor(train_dt$hotel_cluster, train_dt$srch_destination_id)
```

```
## [1] 0.003811001
```

```r
cor(train_dt$hotel_cluster, train_dt$srch_destination_type_id)
```

```
## [1] -0.03006388
```

```r
cor(train_dt$hotel_cluster, train_dt$is_booking)
```

```
## [1] -0.02241071
```

```r
cor(train_dt$hotel_cluster, train_dt$cnt)
```

```
## [1] -0.002306554
```

```r
cor(train_dt$hotel_cluster, train_dt$hotel_continent)
```

```
## [1] 0.004342731
```

```r
cor(train_dt$hotel_cluster, train_dt$hotel_country)
```

```
## [1] -0.003691975
```

```r
cor(train_dt$hotel_cluster, train_dt$hotel_market)
```

```
## [1] 0.01885019
```

4.2 Linear Model

```r
model = lm(hotel_cluster ~ srch_destination_id + srch_destination_type_id + is_booking + cnt + orig_des
summary(model)
```

```
##
## Call:
## lm(formula = hotel_cluster ~ srch_destination_id + srch_destination_type_id +
##     is_booking + cnt + orig_destination_distance + user_location_country +
##     user_location_region + is_mobile + is_package + hotel_continent +
##     hotel_country + hotel_market, data = train_dt)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -55.424 -24.706  -0.099  23.181  56.510
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                5.066e+01  1.067e+00  47.496  < 2e-16 ***
## srch_destination_id        3.104e-05  2.385e-05   1.302 0.193029
## srch_destination_type_id  -3.446e-01  1.201e-01  -2.870 0.004104 **
## is_booking                -3.015e+00  8.361e-01  -3.606 0.000312 ***
## cnt                       -2.526e-01  2.030e-01  -1.244 0.213385
## orig_destination_distance  9.926e-05  1.270e-04   0.782 0.434327
## user_location_country     -2.748e-02  5.336e-03  -5.151 2.63e-07 ***
## user_location_region       2.158e-03  1.983e-03   1.088 0.276570
## is_mobile                 -2.471e-01  7.117e-01  -0.347 0.728487
## is_package                 3.029e+00  5.665e-01   5.347 9.09e-08 ***
## hotel_continent            5.806e-01  1.771e-01   3.278 0.001048 **
## hotel_country             -9.066e-04  5.071e-03  -0.179 0.858109
## hotel_market              -2.199e-04  4.948e-04  -0.445 0.656679
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 28.68 on 15298 degrees of freedom
##   (9688 observations deleted due to missingness)
## Multiple R-squared:  0.007947,   Adjusted R-squared:  0.007169
## F-statistic: 10.21 on 12 and 15298 DF,  p-value: < 2.2e-16
```

```r
#to avoid multi colinearity, try different model
model2 = lm(hotel_cluster ~ srch_destination_id + cnt + orig_destination_distance + user_location_regio
summary(model2)
```

```
##
## Call:
## lm(formula = hotel_cluster ~ srch_destination_id + cnt + orig_destination_distance +
##     user_location_region + hotel_country + hotel_market, data = train_dt)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -52.470 -24.783   0.041  22.469  49.411
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                5.018e+01  8.613e-01  58.258  < 2e-16 ***
## srch_destination_id       -8.595e-06  2.142e-05  -0.401  0.68818
## cnt                       -4.868e-02  2.012e-01  -0.242  0.80879
## orig_destination_distance  3.087e-04  1.158e-04   2.666  0.00769 **
## user_location_region       6.423e-04  1.964e-03   0.327  0.74367
## hotel_country             -1.542e-03  4.864e-03  -0.317  0.75115
## hotel_market              -3.658e-04  4.948e-04  -0.739  0.45974
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 28.78 on 15304 degrees of freedom
##   (9688 observations deleted due to missingness)
## Multiple R-squared:  0.0005773,  Adjusted R-squared:  0.0001855
## F-statistic: 1.473 on 6 and 15304 DF,  p-value: 0.1828
```

4.3 Non Linear Model

```r
library(rpart)
frmla = hotel_cluster ~ srch_destination_id + user_location_region + orig_destination_distance
ctrl = rpart.control(minSplit=5, minbucket = 50)

expediaTreeModel = rpart(frmla, data = train_dt, method = "class", control=ctrl )

# get the cp - complexity factor
printcp(expediaTreeModel)
```

```
##
## Classification tree:
## rpart(formula = frmla, data = train_dt, method = "class", control = ctrl)
##
## Variables actually used in tree construction:
## character(0)
##
## Root node error: 24341/24999 = 0.97368
##
## n= 24999
```

```
##
##          CP nsplit rel error xerror xstd
## 1 0.0091204      0         1      0    0
```

```
#summary(expediaTreeModel)
```

4.4 Data Analysis approach

From the linear model results, the R-squared value is negligible. So, the dependent variables are correlating well. Using CART (Classification and Regression Tree) - the non linear model also illustrates that the dependent variables are not correlating well for this problem. These basic Machine Learning algorithms are not much of help for this problem.

Another approach would be to try more advanced Machine Learning algorithms like random forest, XgBoost etc, which is outside the scope of this workshop. Also, we need better machine with **16 to 32 GB** size.

Alternatively, we can follow the below heuristics / rules to identify the hotel cluster.

4.4.1 Identify the often used hotel cluster for a destination

4.4.2 Predict based on destination distance

5 Future Exploration and Study