Phase 2 - Advanced analytics + EDA

Smart Exploration Problem - Marketing campaign optimization

This Notebook complement phase 1 - initial EDA with aditional information detailed below

- 1. EDA (Exploratory Data Analysis) in more detail
- 2. Build 3 machine learning models and compare the results achieved
- 3. Choose the best model and save it for backup and future use
- 4. Make predictions to give guidences for Ad's priority
- 5. Present the first option for prediction using R and H2O
- 6. Summary and quick review

This Jupyter Notebook is going to be developed using R and H2O (cluster running in CentOS)

In [2]:

```
## Load libraries used in this Notebook
library(data.table)
library(tidyverse)
library(h2o)
```

Connect Notebook to H2O cluster

In [3]:

```
## connect to h2o cluster
h2o.connect('centos')
```

```
 Connection successful!

R is connected to the H2O cluster: 
    H2O cluster uptime:         36 minutes 4 seconds 
    H2O cluster timezone:       America/Sao_Paulo 
    H2O data parsing timezone:  UTC 
    H2O cluster version:        3.26.0.3 
    H2O cluster version age:    3 months and 24 days !!! 
    H2O cluster name:           userds1 
    H2O cluster total nodes:    1 
    H2O cluster total memory:   5.75 GB 
    H2O cluster total cores:    1 
    H2O cluster allowed cores:  1 
    H2O cluster healthy:        TRUE 
    H2O Connection ip:          centos 
    H2O Connection port:        54321 
    H2O Connection proxy:       NA 
    H2O Internal Security:      FALSE 
    H2O API Extensions:         Amazon S3, XGBoost, Algos, AutoML, Core V3, 
Core V4
    R Version:                  R version 3.6.1 (2019-07-05) 

Warning message in h2o.clusterInfo():
"
Your H2O cluster version is too old (3 months and 24 days)!
Please download and install the latest version from http://h2o.ai/download/"
(http://h2o.ai/download/")
```

Remove all objects from H2O cluster

- Clean memory

In [4]:

```
h2o.removeAll()
```

Load the dataset - historical data

In [5]:

```
df <- fread('./data/Historical_Data_Smart_Exploration_Demo_Simulation__CPE.csv')

## Remove columns that is not going to be used and define the target feature
remove_columns <- c('LineItemsID', 'URL', 'spend', 'engagement', 'clicks')
target <- 'CPE'

features <- setdiff(colnames(df), remove_columns)
df <- df[, ..features]

df$xyz_campaign_id <- as.factor(df$xyz_campaign_id)
df$channel <- as.factor(df$channel)
df$channel_ad_id <- as.factor(df$channel_ad_id)
df <- df %>% mutate_if(., is.character, as.factor)

## Filter Spend - CPE > 0
df <- df[df$CPE > 0, ]

## Head the data.frame
head(df)
```

	xyz_campaign_id	channel	channel_ad_id	gender	age	interest	CPE
1	916	1	2	M	45-65+	Interest - 15	0.01
2	916	11	2	M	45-65+	Interest - 16	0.01
4	916	11	1	M	45-65+	Interest - 28	0.01
5	916	1	1	M	45-65+	Interest - 28	0.01
7	916	11	1	M	45-65+	Interest - 15	0.04
8	916	1	1	M	45-65+	Interest - 16	0.01

EDA - Exploratory Data Analysis

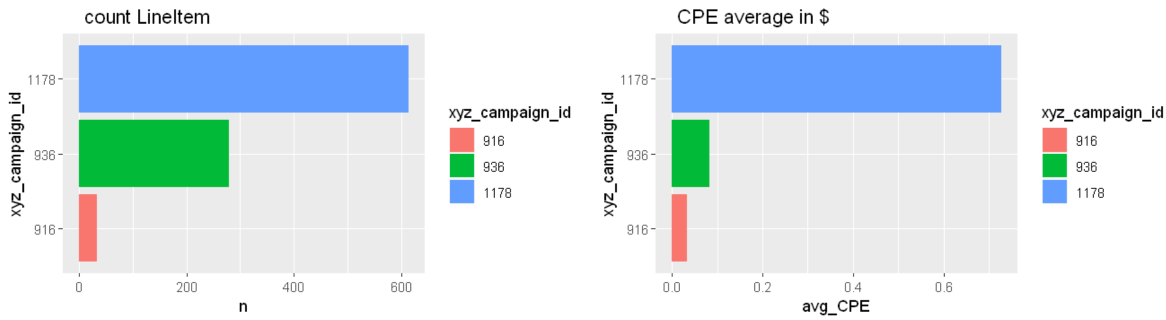
CPE by campaign

- Campaign 1178 was launched many time and have the worse CPE average of $0.72
- Campaign 936 have around 45% ocurrencies compared to campaign 1178 and its CPE average is just $ 0.08 (10% of campaign 1178)
- Campaign 916 do not have many line items launched and have even lower CPE average of $0.03

In [6]:

```
## CPE BY CAMPAIGN
options(repr.plot.width = 11, repr.plot.height = 3)

## EDA - CPE by Campaign
df_group <- df %>% group_by(xyz_campaign_id) %>% summarise(n = n(), total_CPE = sum(CPE), a

## Average
gg1 <- qplot(data=df_group, x=xyz_campaign_id, y=avg_CPE, geom='col', fill=xyz_campaign_id,
coord_flip()

## Count
gg2 <- qplot(data=df_group, x=xyz_campaign_id, y=n, geom='col', fill=xyz_campaign_id, main=
coord_flip()

gridExtra::grid.arrange(gg2, gg1, nrow = 1)

df_group %>% head()
```

xyz_campaign_id	n	total_CPE	avg_CPE
916	34	1.17	0.03441176
936	280	23.03	0.08225000
1178	613	445.36	0.72652529



Evaluation of top 3 features with higher impact on CPE

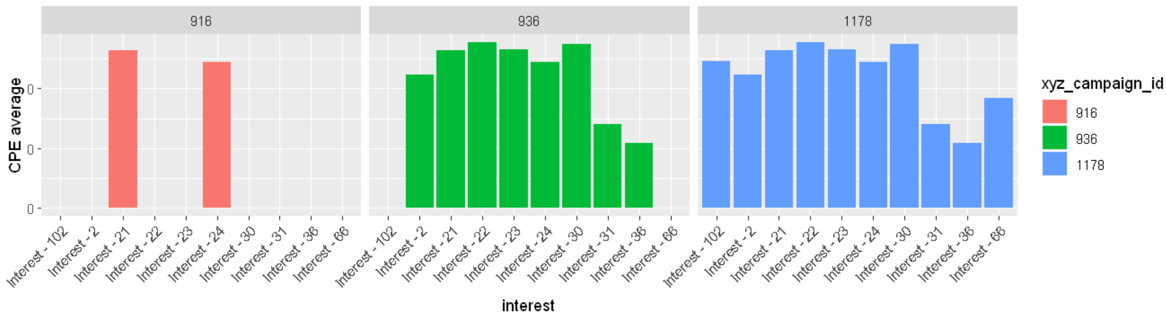
CPE by Interest and campaign

- TOP 10 lower CPE average
- Campaign 918 have much less ocurrence in the data and not all interest are presented
- Interests seems similar between campaigns when presented with lower values to interest 31 and 36

In [7]:

```
df_top10_interest <- df %>% group_by(interest) %>% summarise(n = n(), CPE_mean = mean(CPE))
df_top10_interest_plot <- merge(df_top10_interest, df, by = 'interest')
df_top10_interest_plot %>% group_by(interest, xyz_campaign_id) %>% summarise(CPE_mean = mea
  qplot(data=., x=interest, y= CPE_mean, fill=xyz_campaign_id, facets = ' xyz_campaign_id ~
  scale_y_continuous(name="CPE average", labels = scales::comma)  +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))


df_top10_interest
```

interest	n	CPE_mean
Interest - 36	15	0.1093333
Interest - 31	17	0.1405882
Interest - 66	10	0.1840000
Interest - 2	18	0.2233333
Interest - 24	22	0.2436364
Interest - 102	7	0.2457143
Interest - 21	25	0.2644000
Interest - 23	18	0.2650000
Interest - 30	18	0.2738889
Interest - 22	30	0.2773333



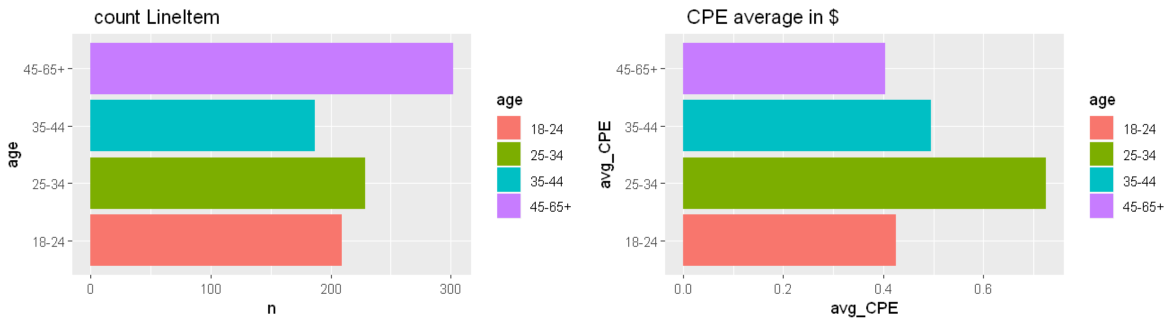
CPE by Age

- All age distribution have CPE average higher than $0.40
- Age between 25-34 have the highest CPE average of $0.72
- Age between 18-24 and 45-65+ have the lowes CPE average and will probably get better margin (in terms of CPE) in current campaign

In [8]:

```
## CPE BY Age
options(repr.plot.width = 11, repr.plot.height = 3)

## EDA - CPE by Campaign
df_group <- df %>% group_by(age) %>% summarise(n = n(), total_CPE = sum(CPE), avg_CPE = mea

## Average
gg1 <- qplot(data=df_group, x=age, y=avg_CPE, geom='col', fill=age
             , main='     CPE average in $', xlab='avg_CPE') + coord_flip()

## Count
gg2 <- qplot(data=df_group, x=age, y=n, geom='col', fill=age, main='     count LineItem') +
coord_flip()

gridExtra::grid.arrange(gg2, gg1, nrow = 1)

df_group %>% head()
```

age	n	total_CPE	avg_CPE
45-65+	302	121.98	0.4039073
18-24	209	88.86	0.4251675
35-44	187	92.69	0.4956684
25-34	229	166.03	0.7250218

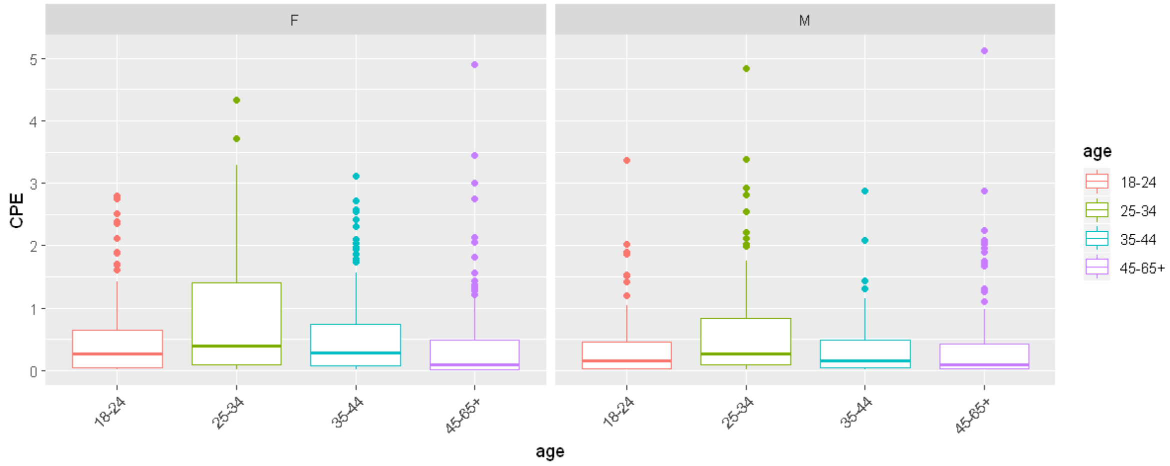


CPE by Age and gender

- age 25-34 (higher distribution) and age 45-65+ (lower distribution) influence the CPE more than others and all have outliers
- Age from 25-34 and gender Female have higher CPE distribution than others and seems to impact even more higher CPE tan Man
- Age 45-65+ contribute for lower CPE for both (man and women)

In [9]:

```
options(repr.plot.width = 10, repr.plot.height = 4)
qplot(data=df, x=age, y=CPE, geom='boxplot', color=age, facets = ' gender ~ .') +
  scale_y_continuous(name="CPE", labels = scales::comma)  +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



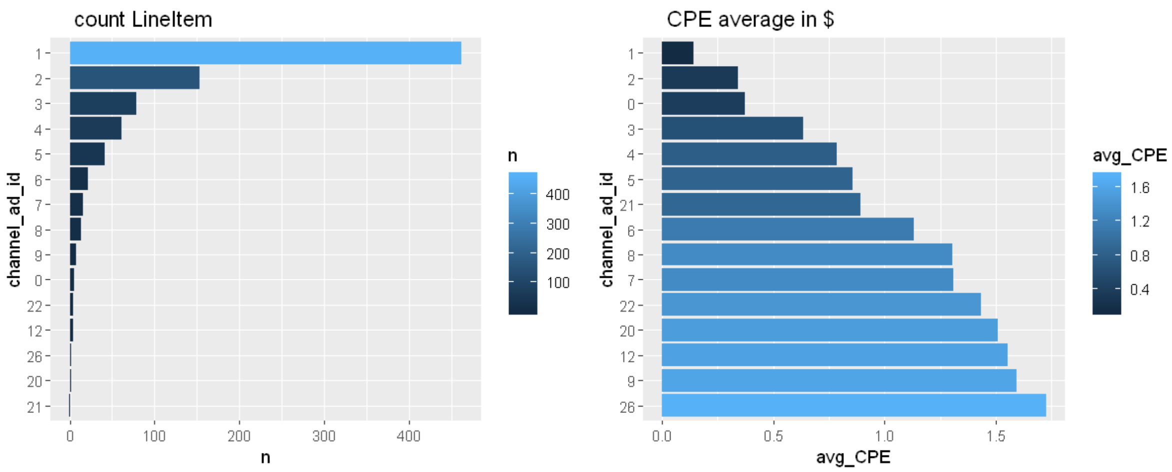
CPE by channel_ad_id

- Channel ad id 2 have the lowest CPE average followed by channel_ad_id 2
- Channel ad id 0 have fewer ocurrencies however also have lower CPE average of $0.37
- All other channel ad id have an CPE average higher than $0.40

In [10]:

```
df_group <- df %>% group_by(channel_ad_id) %>% summarise(n = n(), total_CPE = sum(CPE), avg
    arrange(avg_CPE) %>% head(20)

## Average
gg1 <- qplot(data=df_group[1:15, ], x=reorder(channel_ad_id,-avg_CPE), y=avg_CPE, geom='col
             main='    CPE average in $', xlab='channel_ad_id') + coord_flip()

## Count
gg2 <- qplot(data=df_group[1:15, ], x=reorder(channel_ad_id,n), y=n, geom='col', fill=n,
             main='    count LineItem' , xlab='channel_ad_id') +
  coord_flip()

gridExtra::grid.arrange(gg2, gg1, nrow = 1)

df_group %>% head(10)
```

channel_ad_id	n	total_CPE	avg_CPE
1	462	64.93	0.1405411
2	153	51.99	0.3398039
0	5	1.87	0.3740000
3	78	49.45	0.6339744
4	61	47.85	0.7844262
5	41	35.10	0.8560976
21	1	0.89	0.8900000
6	22	24.93	1.1331818
8	13	16.98	1.3061538
7	16	20.97	1.3106250



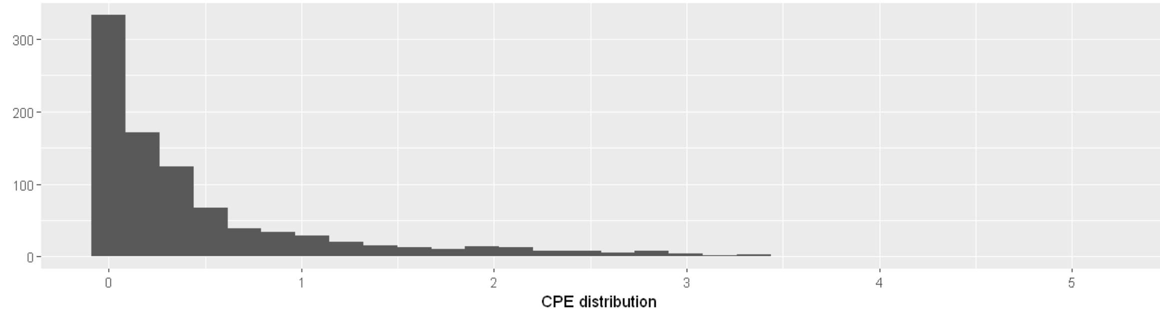
Evalution of CPE distribution

- CPE has skewed distribution and in this type of scenario probably is better to work with CPE in logarithm scale

In [11]:

```
## CPE  distribution
## CPE BY CAMPAIGN
options(repr.plot.width = 11, repr.plot.height = 3)
qplot(df$CPE, xlab = 'CPE distribution ')
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Quick recap until now

- The top 3 influencers of CPE metric are channel ad id, interest and age
- Campaign 936 and 916 have much lower CPE average
- Gender Female with age between 25-34 tends to have higher CPE than others
- Channel ad id (1,2 and 0) have lower CPE average and will probably provide higher margin profit in current campaign
- Ages distribution 45-65+ and 18-25 have lower CPE than others to all genders (male and female)
- Interest 31 and 36 will also provide higher margin profit to the current campaign

Starting point to use AI and Machine Learning to predict CPE (Cost per Engagement)

- After the prediction it is possible to identify and assing priority to respective Line Item
- The metrics R2 (coeficient of determination) and evaluation metrics RMSE / MAE will be used to choose the best machine learning model
- All executions will use cross validation strategy with 5 folds

Preparation of the data to build ml models with h2o

In [12]:

```
## h2o features and target
h2o_features <- setdiff(features, 'CPE')
df$logCPE <- log1p(df$CPE)
target_CPE <- 'CPE'
target_log_CPE <- 'logCPE'
hdf <- as.h2o(df, destination_frame = 'hdf_CPE.hex')
print('H2O features')
h2o_features
```

```
  |======================================================================| 1
00%
[1] "H2O features"
```

'xyz_campaign_id' 'channel' 'channel_ad_id' 'gender' 'age' 'interest'

RF build and performance with default CPE

In [13]:

```
## execution of Random Forest
fit_rf_CPE <- h2o.randomForest(x = h2o_features,
                   y = target_CPE,
                   training_frame = hdf,
                   model_id = 'RF_CPE.model',
                   nfolds = 5,
                   seed = 12345)
h2o.performance(fit_rf_CPE)
```

```
  |======================================================================| 1
00%

H2ORegressionMetrics: drf
** Reported on training data. **
** Metrics reported on Out-Of-Bag training samples **

MSE:  0.2025541
RMSE:  0.4500601
MAE:  0.2534986
RMSLE:  0.2036857
Mean Residual Deviance :  0.2025541
R^2 :  0.629772
```

RF build model and performande with CPE in logarithmic scale

- CPE in logarithmic scale have better results (higher R2 and lower RMSE/MAE) compared with default value
- Use of log_CPE for prediction

  Obs.: to work with default CPE again if necessary, use exponencial function (over logarithmic scale) to get CPE default value again. Example: expm1(log_CPE)

In [14]:

```
## execution of Random Forest
fit_rf_log_CPE <- h2o.randomForest(x = h2o_features,
                   y = target_log_CPE,
                   training_frame = hdf,
                   model_id = 'RF_log_CPE.model',
                   nfolds = 5,
                   seed = 12345)
h2o.performance(fit_rf_log_CPE)
```

```
  |======================================================================| 1
00%

H2ORegressionMetrics: drf
** Reported on training data. **
** Metrics reported on Out-Of-Bag training samples **

MSE:  0.04142841
RMSE:  0.2035397
MAE:  0.1374481
RMSLE:  0.1311561
Mean Residual Deviance :  0.04142841
R^2 :  0.6999998
```

Build and evaluate second machine learning model

GLM - Generalized Linear Model

- One interesting point of GLM using H2O is the automatic creation of One Hot Encoding for categorical features when build the model
- All metrics (R2, RMSE and MAE) are worse with GLM compared to Random Forest as show below

GLM build model and performande with default CPE

In [15]:

```
## execution of GLM - cross validation with 5 folds and CPE
fit_glm_CPE <- h2o.glm(x = h2o_features,
                   y = target_CPE,
                   training_frame = hdf,
                   model_id = 'GLM_CPE.model',
                   nfolds = 5,
                   seed = 12345)
h2o.performance(fit_glm_CPE)
```

```
  |======================================================================| 1
00%

H2ORegressionMetrics: glm
** Reported on training data. **

MSE:  0.2998948
RMSE:  0.5476265
MAE:  0.3338792
RMSLE:  0.2521584
Mean Residual Deviance :  0.2998948
R^2 :  0.4518528
Null Deviance :507.1676
Null D.o.F. :926
Residual Deviance :278.0025
Residual D.o.F. :915
AIC :1540.304
```

GLM build model and performande with CPE in logarithmic scale

In [16]:

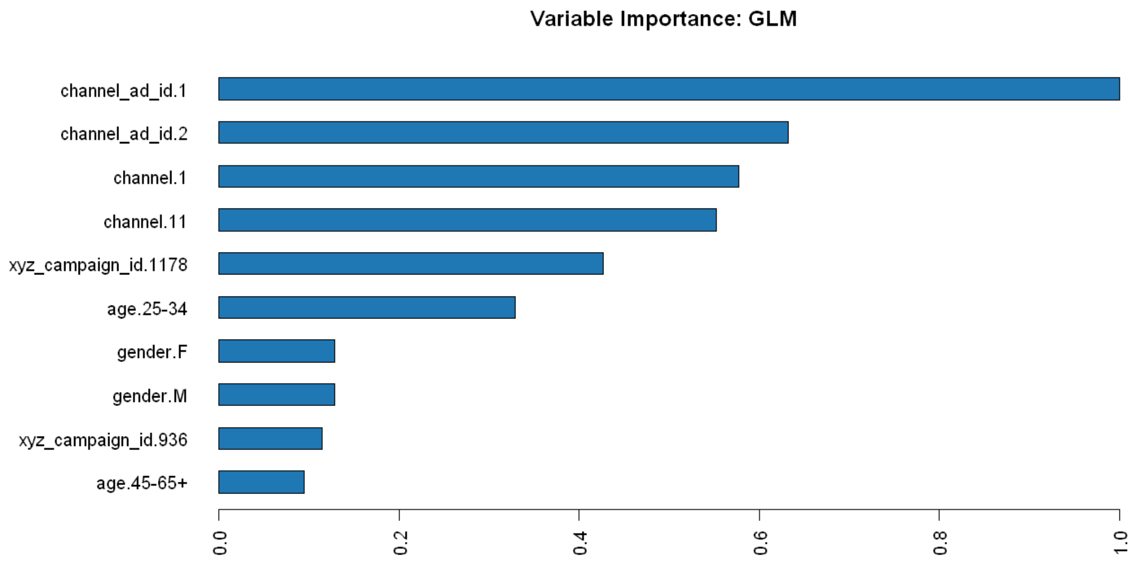
```
## execution of GLM - cross validation with 5 folds and log of CPE (skewed distribution)
fit_glm_log_CPE <- h2o.glm(x = h2o_features,
                   y = target_log_CPE,
                   training_frame = hdf,
                   model_id = 'GLM_log_CPE.model',
                   nfolds = 5,
                   seed = 12345)
h2o.performance(fit_glm_log_CPE)
```

```
  |======================================================================| 1
00%

H2ORegressionMetrics: glm
** Reported on training data. **

MSE:  0.06176227
RMSE:  0.2485202
MAE:  0.1748241
RMSLE:  0.1576422
Mean Residual Deviance :  0.06176227
R^2 :  0.552754
Null Deviance :128.0137
Null D.o.F. :926
Residual Deviance :57.25363
Residual D.o.F. :916
AIC :73.51525
```

Feature importance - GLM

In [17]:

```
options(repr.plot.width = 11, repr.plot.height = 6)
h2o.varimp_plot(fit_glm_CPE)
```



GLM results

- The GLM algorithm shows the coeficient of determination (R2) worse than Random Forest
- The RMSE and MAE are lower when working with CPE in logarithm scale (skewed distribution) as expected
- Channel_ad_id.1 e channel_ad_id.2 have higher influence in the CPE (confirmation of explanation above)
- Campaign 1178 has big negative impact on CPE
- All others features/characterist of data were already explained the influence over CPE (positive and negative) and again presented above in the chart
  age.25-34
  gender.F
  gender.M
  campaign 936
  age.45-65+
- Interesting point to evaluate are channel 1 and channel 11 with higher influence also in CPE and presented below

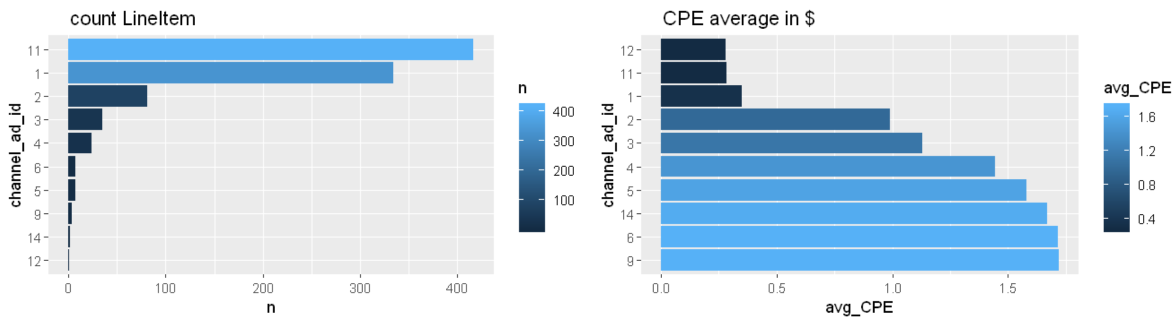
Top 10 channel with lowest CPE average

- channel 12 has only one ocurrency and so without influence in CPE average
- channel 1 and 11 have lower CPE average than others and below of $0.40
- all other channel have the CPE average higher than $0.99

In [18]:

```
## CPE BY CHANNEL
options(repr.plot.width = 11, repr.plot.height = 3)

df_group <- df %>% group_by(channel) %>% summarise(n = n(), total_CPE = sum(CPE), avg_CPE =
  arrange(avg_CPE) %>% head(10)

## Average
gg1 <- qplot(data=df_group[1:10, ], x=reorder(channel,-avg_CPE), y=avg_CPE, geom='col', fil
             main='     CPE average in $', xlab='channel_ad_id') + coord_flip()

## Count
gg2 <- qplot(data=df_group[1:10, ], x=reorder(channel,n), y=n, geom='col', fill=n,
             main='     count LineItem' , xlab='channel_ad_id') +
  coord_flip()

gridExtra::grid.arrange(gg2, gg1, nrow = 1)

df_group %>% head(10)
```

channel	n	total_CPE	avg_CPE
12	1	0.28	0.2800000
11	417	117.99	0.2829496
1	334	117.27	0.3511078
2	81	80.18	0.9898765
3	35	39.53	1.1294286
4	24	34.71	1.4462500
5	7	11.06	1.5800000
14	2	3.34	1.6700000
6	7	12.02	1.7171429
9	3	5.16	1.7200000



GBM (Gradient Boosting Machine) - build and performance

- GBM has the best results compared to Random Forest and GLM
- GBM achieved
  R^2 : 0.92
  RMSE: 0.10
  MAE: 0.07

GBM build model and performande with CPE in logarithmic scale

In [19]:

```
## execution of GBM
fit_gbm_log_CPE <- h2o.gbm(x = h2o_features,
                   y = target_log_CPE,
                   training_frame = hdf,
                   model_id = 'GBM_log_CPE.model',
                   nfolds = 5,
                   seed = 12345)
h2o.performance(fit_gbm_log_CPE)
```

```
  |======================================================================| 1
00%

H2ORegressionMetrics: gbm
** Reported on training data. **

MSE:  0.01096274
RMSE:  0.1047031
MAE:  0.07048631
RMSLE:  0.07453724
Mean Residual Deviance :  0.01096274
R^2 :  0.9206143
```

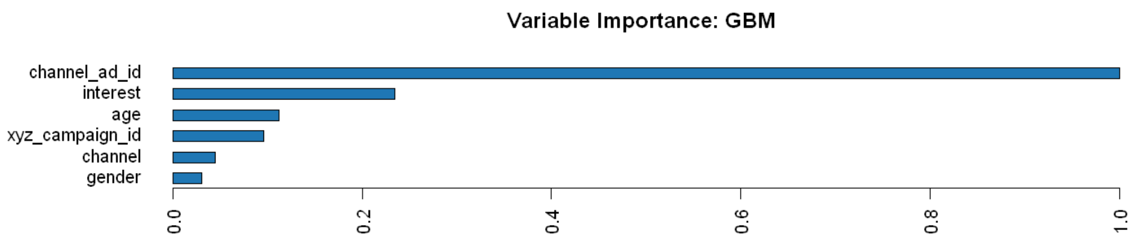
Plot feature importance - GBM

The 3 most important features that impact CPE in this historical data are exactly the same of Random Forest:

- channel_ad_id
- interest and
- age

In [20]:

```
h2o.varimp_plot(fit_gbm_log_CPE)
```



Considerations about machine learning model performance and possible improvements

- These 3 machine learning models (Random Forest, GLM and GBM) could provide even better accuracy with hyper parameter tuning and Feature Engineering for example

Example to export model using command line

Info: Save/export the GBM (best perfomance) model for deployment

In [21]:

```
## Export model with command Line
gbmmodel_Path <- h2o.saveModel(fit_gbm_log_CPE, 'GBM_MODEL')
gbmmodel_Path
```

'/home/userds1/H2O_JAR/GBM_MODEL/GBM_log_CPE.model'

Prediction and deployment

The model that achieve the best result was GBM - Gradient Boosting Machine

The code below present one option do run the model with current campaing data and assing priority to each line item ID

Rules applied for prediction and assign priority to Line Item ID

- 1. Save the model for future use and backup
- 2. Load the model again for prediction
- 3. Load newdata and apply same and apply the same rules during the model building (training done with cross-validation)
- 4. Run the prediction with current campaign data to get CPE prediction
- 5. Convert CPE from logaritmic scale default CPE value
- 6. Assing prioritty to each line item. This rule was implemented in 3 steps as shown below
  6.1: filter all Line Item ID with engagement higher than specific threshold (>= xxxx)
  6.2: sort the new data based on lowest CPE to highest CPE
  6.3: apply the rank from lowest CPE to highers CPE

In [22]:

```
### CODE SAMPLE TO SAVE THE MODEL, PREDICT with NEW DATA AND ASSIGN PRIORITY TO Line Item I

## this demo data used engagement = xxx and for a real scenario choose engagement higher th

# # Code to predict and assing priority ------------------------------------
#
# getwd()
#
# ## Save the model for backup and future use
# gbmmodel_Path <- h2o.saveModel(fit_gbm_log_CPE, 'GBM_MODEL')
#
# ## To load the model again to make prediction just use
# fit_gbm_log_CPE <- h2o.loadModel(gbmmodel_Path)
#
# ## All metrics results still available for later evaluation for example
# h2o.performance(fit_gbm_log_CPE)
#
# ## Load newdata
# newdata <- fread('../data/CURRENT_CAMPAIGN_Smart_Exploration.csv')
# head(newdata)
#
# ## Apply same rules used to buil the model
# newdata$xyz_campaign_id <- as.factor(newdata$xyz_campaign_id)
# newdata$channel <- as.factor(newdata$channel)
# newdata$channel_ad_id <- as.factor(newdata$channel_ad_id)
# newdata <- newdata %>% mutate_if(., is.character, as.factor)
# summary(newdata)
#
# ## Make Predictions using H2O
# h2o_newdata <- as.h2o(newdata, destination_frame = 'current_campaign')
# predict_log_CPE <- h2o.predict(fit_gbm_log_CPE, newdata=h2o_newdata )
#
# ## Convert the Prediction to CPE default value and assing to each line item
# log_CPE <- as.data.frame(predict_log_CPE)
# newdata$CPE <- exp(df_predict_log_CPE$predict - 1)
# summary(newdata$CPE)
#
#
# ## Example of rule that could be used to assing priority
# ##### 1. Filter current data with engagements higher than xxxx
# ##### 2. Rank Line Item ID with lower CPE or lower than CPE average for example
#
# ## code to filter engagement higher than specific threshold
# newdata %>% filter(engagement >= 'xxx')
#
# ## code to assing rank priority based on lower CPE
# newdata <- newdata %>% arrange(CPE)
# newdata$Rank <- rownames(newdata)
# head(newdata)
#
# # final code --------------------------------------------------------------
```

Summary and considerations

The top 3 influencers of CPE metric are channel ad id, interest and age

- Campaign 936 and 916 have much lower CPE average
- Gender Female with age between 25-34 tends to have higher CPE than others
- Channel ad id (1,2 and 0) have lower CPE average and will probably provide higher margin profit in current campaign
- Ages distribution 45-65+ and 18-25 have lower CPE than others to all genders (male and female)
- Interest 31 and 36 will also provide higher margin profit in current campaign

The machine learning model GBM achieved the best results compared to Random Forest and GLM

GBM performance metrics

- R^2 : 0.92
- RMSE: 0.10
- MAE: 0.07

Deployment considerations

- The GBM model build and already saved could be deployed to be used as a batch process (current campaign data) with predictions presented above and also as a java application or microservices architecture for online prediction for specific use cases for example

The next and last notebook (Phase 3 - Deployment) will provide more information related to the deployment and predictions

In [ ]:

```

```