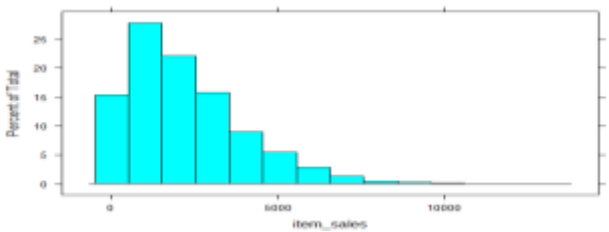
Big Mart Sales – Multi Level Regression Analysis

Relevant Independent variables

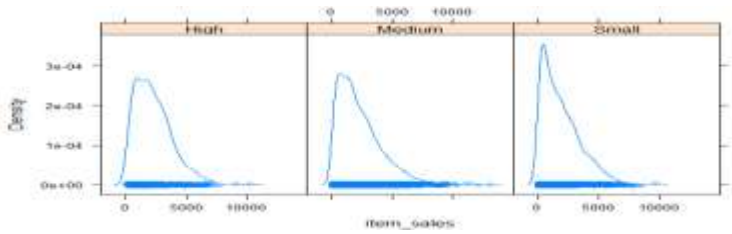
Predictors	Effect	Rationale
Item_Visibility	**+**	Item which has high visibility tend to sale higher as people prefer to buy that item.
Item_Fat_Content	**+/-**	Items with less fat content may sale more as people may prefer to buy less fat content products but it depends on item type and item mrp resulting into both positive or negative effect.
Item_Type	**+/-**	Different types of items such as fruits, vegetables and dairy products are necessities and hence may get sold more than other item types.
Item_Weight	**+/-**	People may prefer light weight items or heavy items based on item types, item visibility and item mrp.
Itemprice_perweight	**+/-**	I have generated one feature which is the ratio of item_price and item_weight. Generally people prefer getting more quantity of items in less price. Also in some cases people like to stick to one brand irrespective of price and weight.
Outlet_size	**+/-**	People may prefer different outlet sizes depending on city type, outlet types.
Outlet_type	**+/-**	Item sales depends on the type of the outlets along with the outlet sizes and item mrp of the respective item types.
Outlet_id	**+/-**	I don't think this variable affect directly to item sales bu I have included this as a random effect to answer question number 3.
City_Type	**+/-**	I don't think this variable affect directly to item sales but I have included this as a random effect to answer question number 2.
Store_years_of_operation	**+/-**	I have generated a new column which represents number of years the store is operating. Considering our dataset is from 2013 I have subtracted each Outlet_Year from 2013. Generally people prefer older stores which they visit frequently. In some cases people like to explore new stores as they tend to give some offers for promotion.

I have not used itemID as we are mostly focusing on outlet and city. Item_price and item_mrp become irrelevant as they have been already used to form new features.

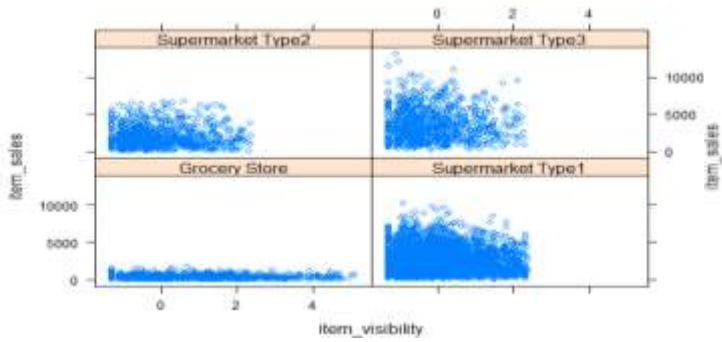
Exploratory Data Analysis.



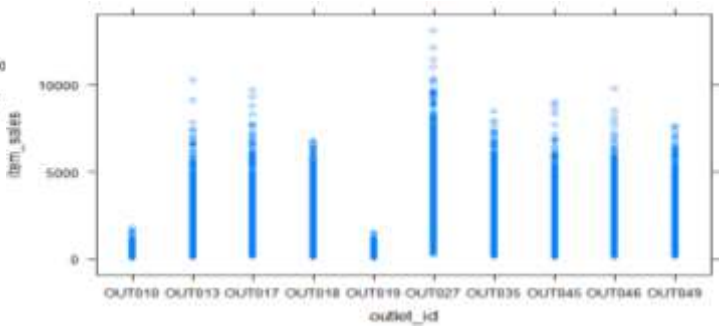
Histogram of Item_Sales



Item_Sales based on Outlet_Size



Item_Sales based on Item visibility and Outlet_types.



Item_Sales based on OutletID

1. What type of outlet will return him the best sales: Grocery store or Supermarket Type 1, 2, or 3.

Model:

re3 <- lmer(item_sales~ item_fat_content + item_visibility + itemprice_perweight + store_years_of_operation + outlet_size +(1 | outlet_type), data=master.dataset, REML=FALSE)

I tried various combinations of independent variables and built 3 different models. This model gave me best AIC, Residual Variance, Log Likelihood and Beta Coefficients values, hence I have selected this model as my best model.

```
Random effects:
 Groups      Name        Variance Std.Dev.
 outlet_type (Intercept) 1522986  1234
 Residual                1745926  1321
Number of obs: 8523, groups:  outlet_type, 4

Fixed effects:
                          Estimate Std. Error t value
(Intercept)               2227.643    636.789   3.498
item_fat_contentRegular     35.703     29.999   1.190
item_visibility            -16.068     14.961  -1.074
itemprice_perweight        685.370     14.359  47.730
store_years_of_operation    -3.501      4.701  -0.745
outlet_sizeMedium          -84.848     92.037  -0.922
outlet_sizeSmall            -6.663     77.507  -0.086
```

```
Correlation of Fixed Effects:
            (Intr) itm__R itm_vs itmpr_ str___ otlt_M
itm_ft_cntR -0.016
item_vsblty  0.001 -0.050
itmprc_prwg -0.004 -0.020 -0.001
str_yrs_f_p -0.234  0.000 -0.009  0.025
outlt_szMdm -0.235 -0.002 -0.009  0.015  0.843
otlt_szSmll -0.214 -0.001 -0.013  0.014  0.742  0.898
```

```
    AIC      BIC   logLik deviance df.resid
146733.3 146796.8 -73357.7 146715.3     8514

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.5799 -0.6385 -0.1333  0.4468  6.5921
```

```
> ranef(re3)
$outlet_type
                 (Intercept)
Grocery Store       -1717.9362
Supermarket Type1     142.3013
Supermarket Type2    -180.0143
Supermarket Type3    1755.6492

with conditional variances for "outlet_type"
```

Interpretations and Recommendations.

1) Looking at the random effect coefficients we can infer that **Supermarket Type 3** outlet type has **1755.6492 more sales** than the mean. Hence **Supermarket Type 3** is the best performing outlet type in the data.

2) On the other hand **Grocery store** has **1717.9362 less sales** than the mean which is least among all outlet types hence **Grocery store is least performing** outlet type among all other outlet types.

2. What type of city will return him the best sales: Tier 1, 2 or 3.

Model:

ct3 <- lmer(item_sales~ itemprice_perweight + store_years_of_operation + item_type + outlet_size + item_visibility + (1 | city_type), data=master.dataset, REML=FALSE)

I tried various combinations of independent variables and built 3 different models. This model gave me best AIC, Residual Variance, Log Likelihood and Beta Coefficients values, hence I have selected this model as my best model.

```
Random effects:
 Groups    Name        Variance Std.Dev.
 city_type (Intercept)   63960   252.9
 Residual              2306333  1518.7
Number of obs: 8523, groups:  city_type, 3

Fixed effects:
                                Estimate Std. Error t value
(Intercept)                     1142.830    177.791   6.428
itemprice_perweight              685.721     16.562  41.281
store_years_of_operation          39.561      2.614  15.132
item_typeBreads                  -27.982    113.051  -0.247
item_typeBreakfast               185.747    156.718   0.868
item_typecanned                  133.616     84.408   1.583
item_typeDairy                   227.219     83.342   2.726
item_typeFrozen Foods            109.657     79.106   1.386
item_typeFruits and Vegetables   235.045     73.733   3.188
item_typeHard Drinks             -39.645    119.855  -0.331
item_typeHealth and Hygiene       14.079     89.532   0.157
item_typeHousehold               132.593     78.174   1.696
item_typeMeat                     82.008     84.865   0.970
item_typeOthers                   21.402    131.230   0.163
item_typeseafood                 178.098    199.073   0.895
item_typeSnack Foods             206.586     74.082   2.789
item_typeSoft Drinks             -59.178     93.540  -0.633
item_typeStarchy Foods           371.273    138.384   2.683
outlet_sizeMedium                454.169     64.516   7.040
outlet_sizeSmall                  81.250     75.614   1.075
item_visibility                 -221.443     16.656 -13.295
```

```
     AIC      BIC   logLik deviance df.resid
149118.3 149280.4 -74536.1 149072.3     8500

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.1536 -0.6747 -0.1600  0.5261  6.2469
```

```
> ranef(ct3)
$city_type
       (Intercept)
Tier 1  -289.75251
Tier 2   323.05228
Tier 3   -33.29977

with conditional variances for "city_type"
```

Interpretations and Recommendations.

1) Looking at the random effect coefficients we can infer that **City Type Tier 2 has highest item sales of approximately 323.05 higher than the mean.**

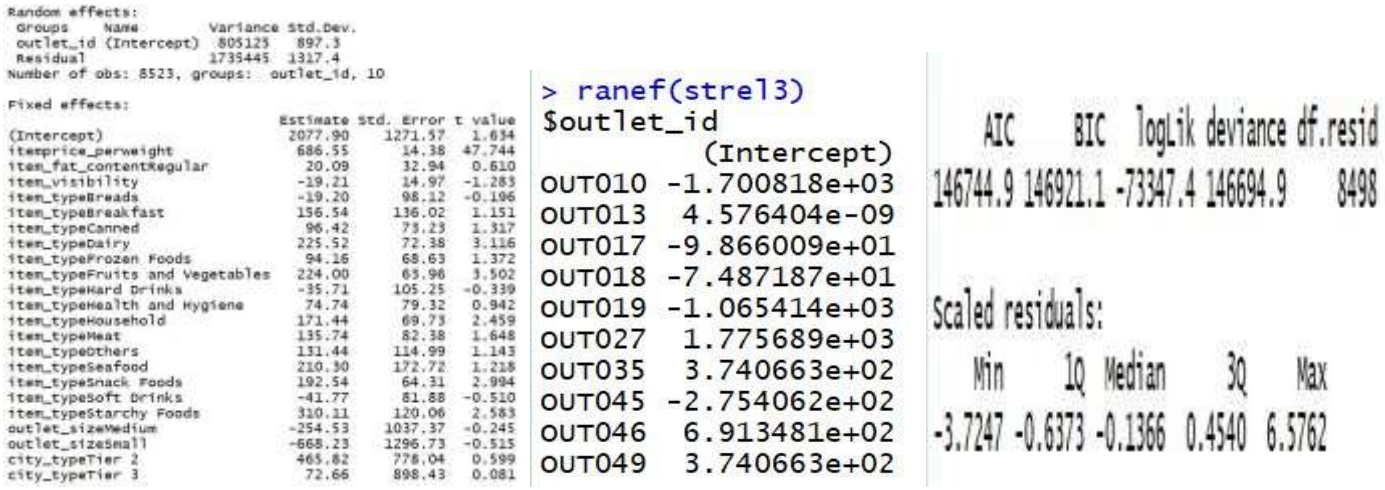
2) On the other hand **City Type Tier 1 has lowest item sales of approximately 289.75 lower than the mean.**

3. What are the top 3 highest performing and lowest performing stores in the sample.

Model

strel3 <- lmer(item_sales~ itemprice_perweight + item_fat_content + item_visibility + item_type + outlet_size + city_type + (1 | outlet_id), data=master.dataset, REML=FALSE)

I tried various combinations of independent variables and built 3 different models. This model gave me best AIC, Residual Variance, Log Likelihood and Beta Coefficients values, hence I have selected this model as my best model.



```
Random effects:
 Groups     Name        Variance Std.Dev.
 outlet_id (Intercept)  805125   897.3
 Residual              1735445  1317.4
Number of obs: 8523, groups:  outlet_id, 10

Fixed effects:
                            Estimate Std. Error t value
(Intercept)                 2077.90    1271.57   1.634
itemprice_perweight          686.55      14.38  47.744
item_fat_contentRegular       20.09      32.94   0.610
item_visibility              -19.21      14.97  -1.283
item_typeBreads              -19.20      98.12  -0.196
item_typeBreakfast           156.54     136.02   1.151
item_typeCanned               96.42      73.23   1.317
item_typeDairy               225.52      72.38   3.116
item_typeFrozen Foods         94.16      68.63   1.372
item_typeFruits and Vegetables 224.00    63.96   3.502
item_typeHard Drinks         -35.71     105.25  -0.339
item_typeHealth and Hygiene   74.74      79.32   0.942
item_typeHousehold           171.44      69.73   2.459
item_typeMeat                135.74      82.38   1.648
item_typeOthers              131.44     114.99   1.143
item_typeSeafood             210.30     172.72   1.218
item_typeSnack Foods         192.54      64.31   2.994
item_typeSoft Drinks         -41.77      81.88  -0.510
item_typeStarchy Foods       310.11     120.06   2.583
outlet_sizeMedium           -254.53    1037.37  -0.245
outlet_sizeSmall            -668.23    1296.73  -0.515
city_typeTier 2              465.82     778.04   0.599
city_typeTier 3               72.66     898.43   0.081
```

```
> ranef(strel3)
$outlet_id
       (Intercept)
OUT010 -1.700818e+03
OUT013  4.576404e-09
OUT017 -9.866009e+01
OUT018 -7.487187e+01
OUT019 -1.065414e+03
OUT027  1.775689e+03
OUT035  3.740663e+02
OUT045 -2.754062e+02
OUT046  6.913481e+02
OUT049  3.740663e+02
```

```
    AIC      BIC   logLik deviance df.resid
146744.9 146921.1 -73347.4 146694.9     8498

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.7247 -0.6373 -0.1366  0.4540  6.5762
```

Interpretations and Recommendations.

1. Looking at the random effect coefficients we can infer that Outlets **OUT027, OUT046, OUT035** are top 3 performing outlets with sales **1775.68, 691.34 and 374.06** more than the mean of the random effect variable.

2. Outlets **OUTO10, OUT019, OUTO45** are least performing outlets with sales **1700.83, 1065.414 and 275.4** less than the mean of the random effect variable.