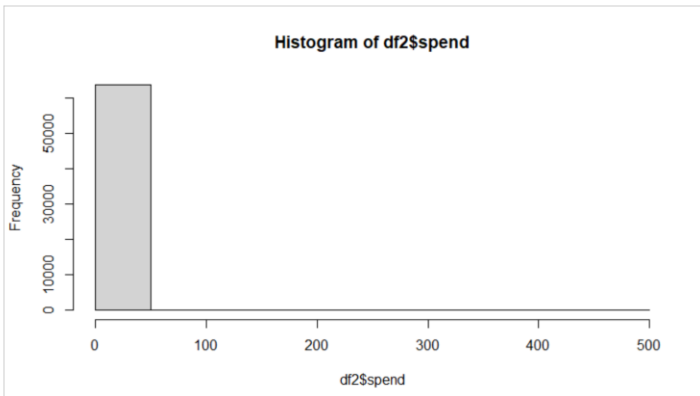
MARKETING CAMPAIGN EFFECTIVENESS A/B TESTING

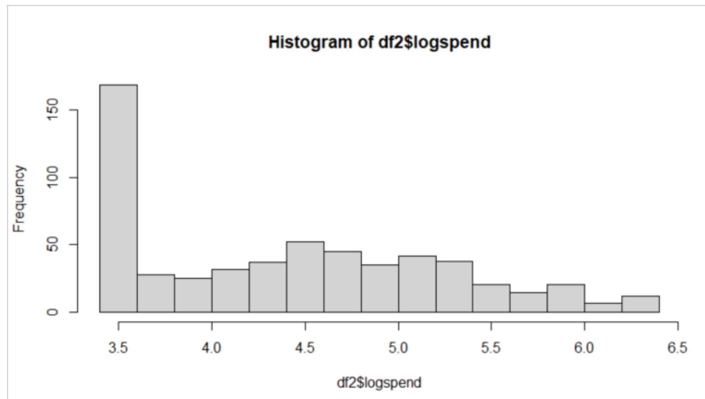
PROBLEM STATEMENT - We have the data of 64000 customers who were chosen post experiment design and sent a marketing campaign. 1/3rd each received a email for either Men's/Women's merchandize vs control group (1/3rd) which received no email. The aim of this project is to utilize metrics such as response rate and conversion rate to analyze the A/B Testing and effectiveness of marketing campaign. Which campaign was successful, by how much and to whom? What can we learn from this campaign and how can we make it better to improve sales?

DATA DISTRIBUTION

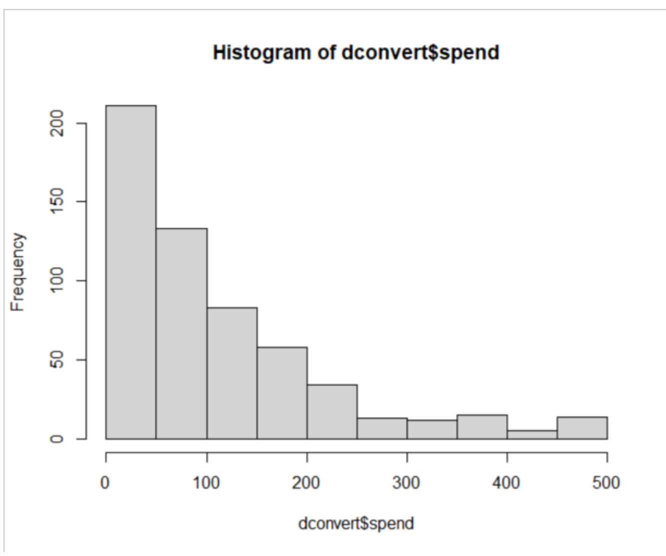
First, let's examine the "spend" variable which shows how much money a customer spent on a purchase.

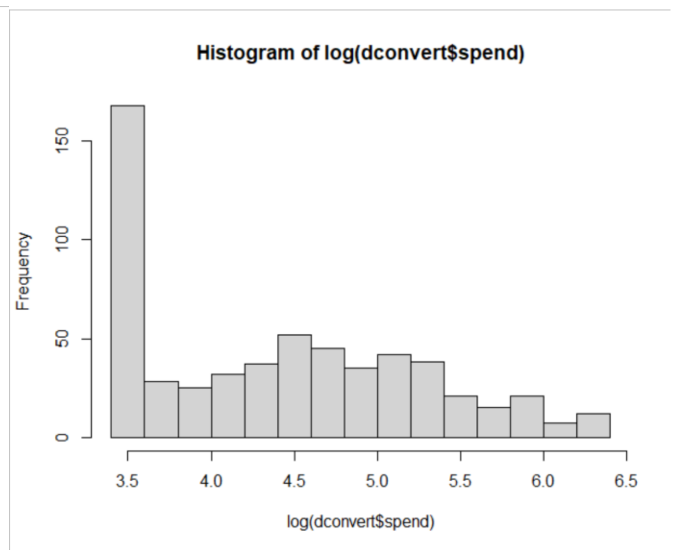
Spend for all users-



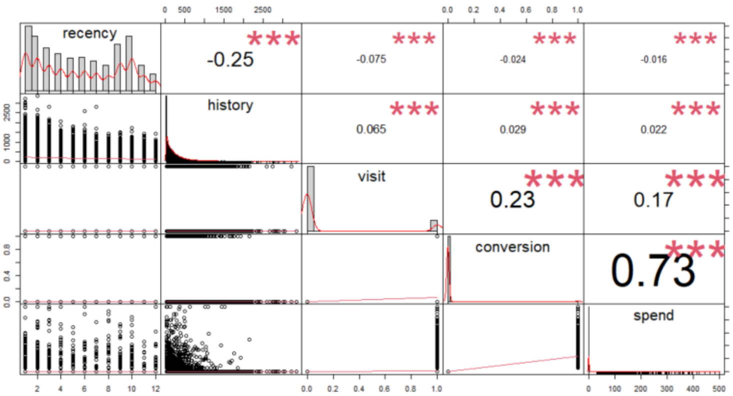


Spend for converted users who made a purchase-

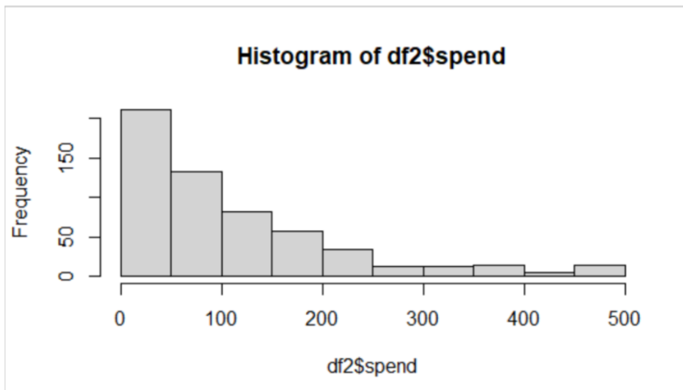




Histogram shows that the variable distribution is not normal. OLS will not work. After performing log transformation, we can see that the data follows Poisson distribution (also has high number of 0's as seen in the histogram). We need to use a Poisson Regression model after ensuring that the assumptions of multicollinearity and independence are met, if not, in order to account for the excess zeroes in the data, we need to use hurdle or zero inflated models which are robust to excess zeroes. Performance Analytics correlation plot for numerical variables below-

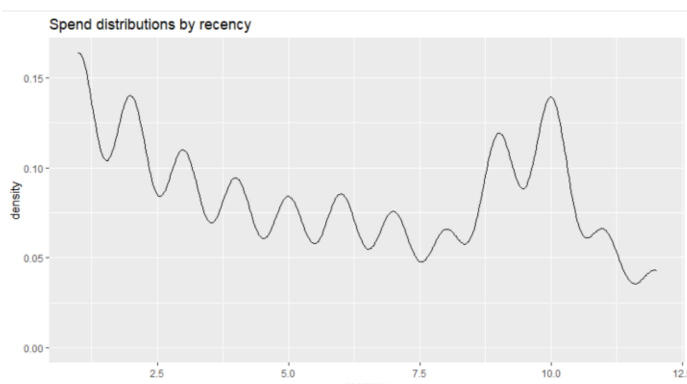


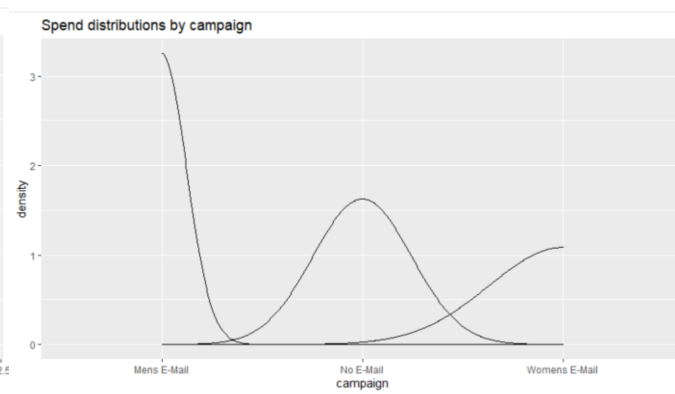
Since we are working with a reduced dataset where conversion=1 because we are testing effectiveness of the campaign for customers who successfully spent post the campaign , the histogram now looks like this for the 578 observations.

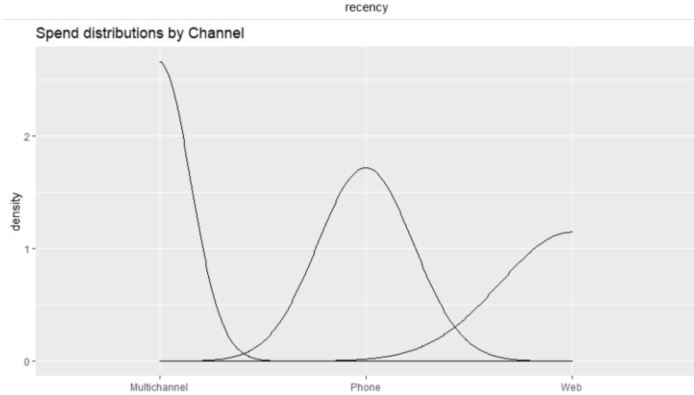


EDA and Data Inspection

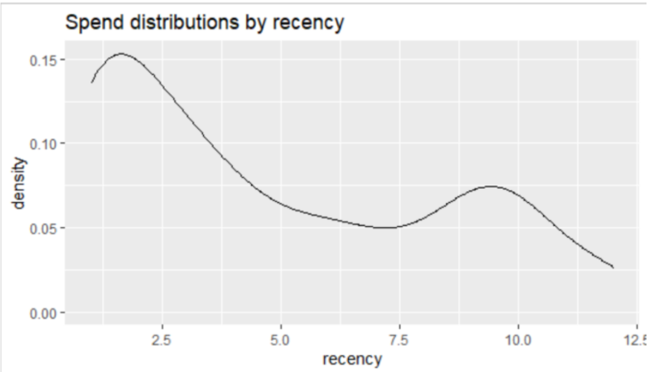
For all customers-

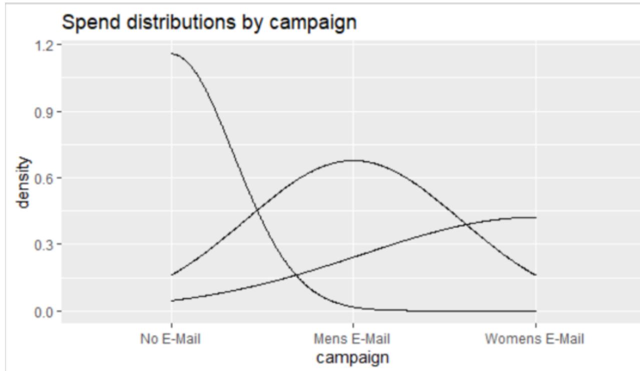


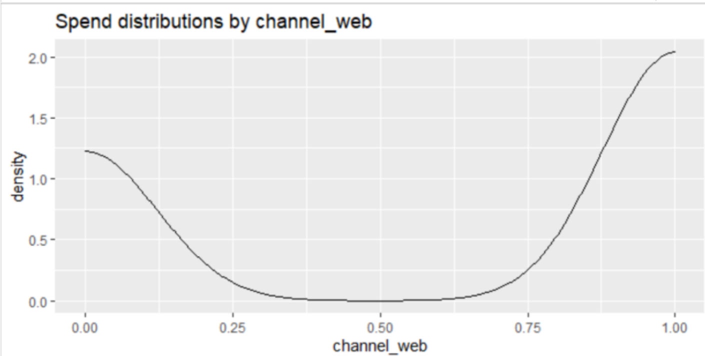


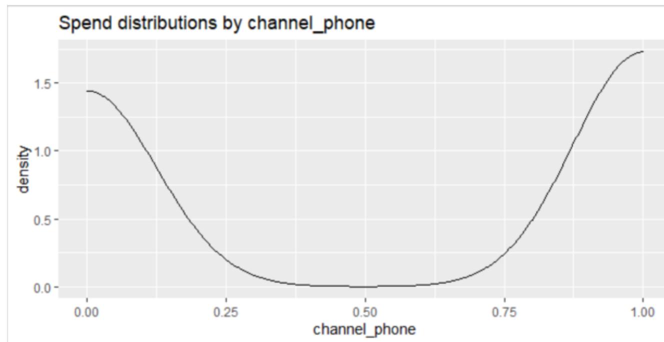


For only the converted customers (Only 10,000 out of 64,000 customers visited the website)-









Basic Inferences-

Upon some basic EDA, we can see that customers who purchased recently tend to spend more whereas for channels of phone and web, we see a lot of similarity in the distribution. Campaign type has a stark difference in effect between mens. vs womens. purchases which we can find out through our analysis.

PREDICTOR TABLE

EFFECT ON SPEND	PREDICTOR VARIABLE	RATIONALE
"+/-"	recency	Customers who purchased recently are expected to do so again whereas customers who purchased a long time ago, could still be lured tobuy products with good promotions.
"+/-"	history	A customer's spending capacity and budget will influence their future "spend" value.
"+/-"	mens, womens	It is natural to expect that a customer who purchased products of type X is likely to purchase type X again, with an increased probability due to promotions.
"+/-"	zipcode	Included to understand the customer purchase behaviors in urban/rural/suburban settings.
"+/-"	newcustomer	New customers are given more attractive promotions and discounts to lure them in and may tend to buy with a high probability.
"+/-"	channel_phone	Type of promo is necessary to understand effectiveness and impact.
"+/-"	channel_web	Type of promo is necessary to understand effectiveness and impact.
"+/-"	campaign	Type of Campaign is necessary to understand effectiveness and impact.
	EXCLUDED VARIABLES	
NONE	historysegment	Included through history, derived from it and correlated.

NONE	visit	Since we are trying to find the effect of the campaign on customers who made a purchase, which is counted through conversion, we can exclude the visit variable.
NONE	channel	included through channel_phone and channel_web
NONE	conversion	Our analysis is to find success of campaign, for which we only need succesfully converted customer which is included through a df filter, so we can drop this variable.

MODELS

```
m3 <- hurdle(spend ~ campaign*mens + campaign*womens + campaign*newcustomer +
        campaign*history + recency + zipcode + campaign*channelphone +
        campaign*channelweb | visit + conversion,
        data=d, link="logit", dist="negbin")

m4 <- zeroinfl(spend ~ campaign*mens + campaign*womens + campaign*newcustomer +
        campaign*history + recency + zipcode + campaign*channelphone +
        campaign*channelweb | visit + conversion,
        data=d, link="logit", dist="negbin")

#m5 has no interactions and is used for comparison
m5 <- hurdle(spend ~ campaign + history + recency + mens + womens + zipcode +
        newcustomer + channelphone + channelweb | visit + conversion,
        data=d, link="logit", dist="negbin")
```

We learnt from the GLM Negative Binomial model that it suffers from Overdispersion. In order to overcome this, we can use hurdle and zero-inflated models for analysis as they robust to dispersion and also account for the excess zeroes in the dataset since only 10K/64k customers visited the website. For the logit function, we can use visit+ conversion since those are the main variables in the data which separate the 10K customers from the rest.

	Dependent variable:		
	spend		
	hurdle	zero-inflated count data	hurdle
	(1)	(2)	(3)
campaignMen	-0.096 (0.374)	-0.095	0.003 (0.089)
campaignWomen	0.491 (0.418)	0.491	0.104 (0.096)
mens	0.493** (0.238)	0.492	0.137 (0.102)
womens	0.209 (0.232)	0.208	-0.128 (0.101)
newcustomer	-0.249 (0.184)	-0.248	-0.005 (0.074)
history	-0.00005 (0.0002)	-0.00005	0.00004 (0.0001)
recency	-0.004 (0.010)	-0.004	-0.008 (0.010)
zipcodeRural	-0.118 (0.096)	-0.118	-0.090 (0.095)
zipcodeSurburban	0.038 (0.076)	0.038	0.049 (0.076)
channelphone	-0.326 (0.234)	-0.325	-0.090 (0.104)
channelweb	-0.303 (0.230)	-0.302	-0.072 (0.105)
campaignMen:mens	-0.293 (0.279)	-0.292	
campaignWomen:mens	-0.751** (0.311)	-0.750	
campaignMen:womens	-0.168 (0.273)	-0.167	
campaignWomen:womens	-0.845*** (0.304)	-0.843	
campaignMen:newcustomer	0.322 (0.214)	0.321	
campaignWomen:newcustomer	0.289 (0.224)	0.288	
campaignMen:history	0.0001 (0.0003)	0.0001	
campaignWomen:history	0.0001 (0.0003)	0.0001	
campaignMen:channelphone	0.188 (0.278)	0.187	
campaignWomen:channelphone	0.389 (0.297)	0.388	
campaignMen:channelweb	0.228 (0.276)	0.227	
campaignWomen:channelweb	0.317 (0.296)	0.316	
Constant	4.797*** (0.324)	4.798	4.862*** (0.178)
Observations	64,000	64,000	64,000
Log Likelihood	-3,285.681	-3,286.305	-3,292.655
Note:			*p<0.1; **p<0.05; ***p<0.01

Model 5 passes multicollinearity test & Independence test.

```
> vif(m5)
                GVIF Df GVIF^(1/(2*Df))
campaign    5.117314  2        1.504044
history     2.656226  1        1.629793
recency     7.196000  1        2.682536
mens        5.201364  1        2.280650
womens      5.646536  1        2.376244
zipcode     2.674161  2        1.278783
newcustomer 2.174551  1        1.474636
channelphone 5.292357  1       2.300512
channelweb  6.085430  1        2.466866
```

```
> dwtest(m5)

        Durbin-Watson test

data:  m5
DW = 2.006, p-value = 0.7757
```

EQUATION FOR CALCULATIONS

log(spend) = 4.80 – 0.10*campaignMen + 0.49*campaignWomen + 0.49*mens +0.21*womens - 0.25*newcustomer - 0.33*channelphone – 0.30*channelweb – 0.12*zipcodeRural + 0.04*zipcodeSurburban – 0.29*campaignMen:mens – 0.75*campaignWomen:mens – 0.17*campaignMen:womens – 0.85*campaignWomen:womens + 0.32*campaignMen:newcustomer + 0.29*campaignWomen:newcustomer + 0.19*campaignMen:channelphone + 0.39*campaignWomen:channelphone + 0.23*campaignMen:channelweb + 0.32*campaignWomen:channelweb

INTERPRETATIONS and RECOMMENDATIONS to COMPANY

Interpretations through zero inflated model through the marginal effects of dy/dx from the equation, we can draw the below interpretations.

How did the campaigns work compared to control group and which promotions worked better?

- When all other metrics are constant, men's campaign underperformed women's campaign by 0.49-(-0.10) = 0.59 i.e., 59%.
- Men's campaign performed worse than no campaign by -0.10 i.e., 10%.

Whom should our company target these promotions to? New customers (last 12 months) or old ones?

dy/dx =d(spend)/d(newcustomer) = -0.25 + 0.32*campaignMen + 0.29*campaignWomen

This shows that the new customers have a -25% effect compared to old customers in the no campaign group. New customers who got the men's campaign had a &% increase in customer spend compared to no campaign whereas those who received women's campaign had 4% increase in customer spend.

Should promotions target customers with higher or lower spend history?

History has a very low coefficient of -0.00005 which means it has negligible effect, can be ignored.

For which channel did promotions work better, web or phone?

dy/dx =d(spend)/d(channelphone) = -0.33 + 0.19*campaignMen + 0.39*campaignWomen
dy/dx = d(spend)/d(channelweb) = -0.30 + 0.23*campaignMen + 0.32*campaignWomen

Without any campaign being sent, both phone and web channel worked poorly (-33% and -30%).

Men's campaign increased customer phone spend by 19% and web spend by 23%, while women's campaign increased phone spend by 39% and web spend by 32%, still indicating that the overall percentage spend is not in positive percentages for the Men's campaign whereas for the women's campaign it is at +6% for phone and +2% for web channel.
Hence, women's campaign definitely improved customer spend over no campaign. Men's campaign reduced deficit spend compared to no campaign, but still resulted in negative spend.

Will promotion work better if men's campaign is sent to those who purchased men's merchandise before and women's campaign is sent to those who purchased women's merchandise before?

dy/dx =d(spend)/d(mens) = 0.49 – 0.29*campaignMen - 0.75*campaignWomen
dy/dx =d(spend)/d(womens) = 0.21 – 0.17*campaignMen – 0.85*campaignWomen

Men's campaign sent to customers who bought men's products last year had 29% less effect on spend relative to no campaign, while men's campaign sent to customers who bought women's product last year had a -17% effect.
However, women's campaign sent to customers who bought women's products last year had a -85% effect relative to no campaign, while women's campaign sent to men's products had a -75% effect.
Hence, these campaigns seem to have the best effects if directed at new customers rather than to customers who bought products over the last year. In particular, the women's campaign had significantly worse effect than men's campaign, probably owing to the fact that purchases are not strictly gender specific.