

SUV Car Sales Performance Report

Contents

Introduction.....	2
Research Question	2
Descriptive Analysis	2
Logistic Regression	4
.....	4
The probability of Total Purchase by Gender (Fisher's exact test).....	5
Probability (Purchasing ratio) by gender "Rows Analysis"	6
Probability (odds ratio for gender) by Purchasing "Column Analysis"	7
The decision.....	8
Conclusion	8
References & dataset	8

Introduction

This report aims to improve sales of SUV cars performance. We will do that by finding the relation between variables, which can help build decisions in many sectors as (Marketing & Advertising, Financial planning). As well as, forecasting the reasons which effect in purchased process.

Giving an overview in predicted age which can buy the cars based on his salary and sex. By the end we can focus on a specific category which help us to increase the sales. We will do that using Fisher's exact test.

In this report, we tried to put hypothesis and determine if the purchased done or not. We analyze dataset using R, SPSS & Power BI to summarize data and use logistic Regression To determine the main factors which effect on our output.

Research Question

We will figure out if there is a relation between Purchased, Age, salary and Gender.

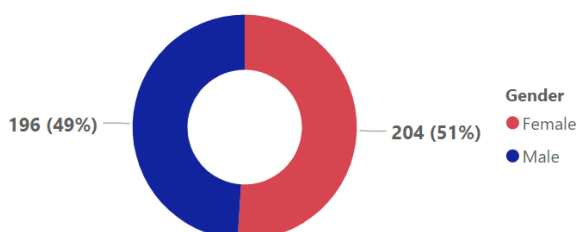
$$\frac{1}{\pi 1 - \pi} = \exp (\beta_0 + B_1 X_1 + B_2 X_2 + B_3 X_3 + B_4 X_4 + \dots + B_k X_k)$$

$$\text{Purchased} = C + [B_1 \times \text{Age} + [B_2 \times \text{salary}] + [B_3 \times \text{Gender (Male)}]$$

Descriptive Analysis

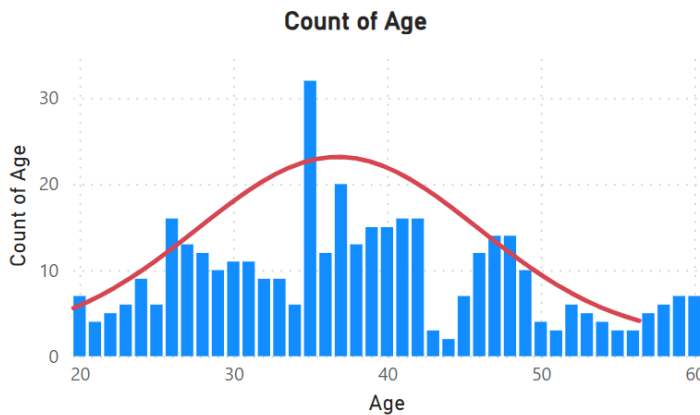
Gender	Count of Gender
Female	204
Male	196
Total	400

Count of Genders

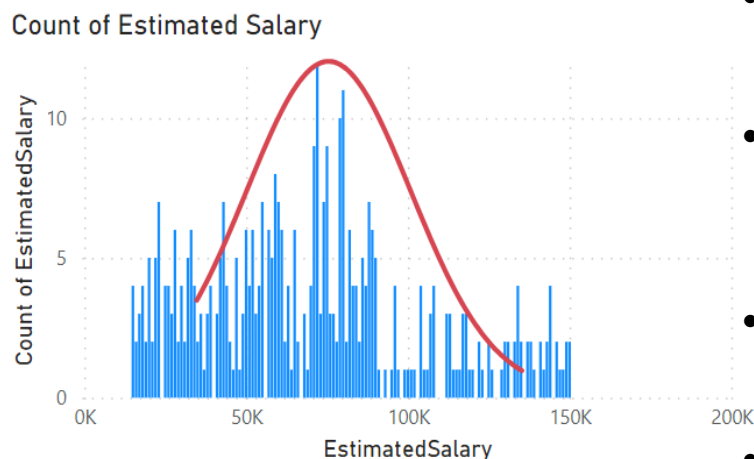


- We took a random sample from sales department which contained of 400 random and unbiased variables.
- We have 204 (51%) females and 196 (49%) males which almost close.

	N	Range	Minimum	Maximum	Sum	Mean		Std. Deviation	Variance	Skewness	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error
Age	400	42	18	60	15062	37.65	.524	10.483	109.891	.231	.122
EstimatedSalary	400	135000	15000	150000	27897000	69742.50	1704.848	34096.960	1162602701	.495	.122
	400										



- As we can see that the average of ages is 37.65 which mean that our customers center in the medium age between (25 - 44) and maximum is 60 and as we can see that the old people are less interested than the young and because of that we can see a positive skewness (0.231) but it's very small.
- The mode is 35 years old, Which mean that the most age interesting and buying SUV cars is (35 years old)



- The average of salary is 69,742 \$ and that is not mean that we just focus in people who get this salary.
- We had minimum salary which is 15,000\$ and maximum is 150,000 \$.So, it means that all categories between those salary interested in this type of cars.
- Also we have positive skewness (0.495) and the mode is 72,000 \$ (The most salary interested in this type of cars).
- The Standard deviation is very high that's mean the salary is not clustered around the mean we have different types of salaries.

Logistic Regression

Call:

```
glm(formula = new_df$Purchased ~ new_df$Age + new_df$EstimatedSalary +
    new_df$gender, family = "binomial")
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-1.278e+01	1.359e+00	-9.405	< 2e-16	***
new_df\$Age	2.370e-01	2.638e-02	8.984	< 2e-16	***
new_df\$EstimatedSalary	3.644e-05	5.473e-06	6.659	2.77e-11	***
new_df\$gender	3.338e-01	3.052e-01	1.094	0.274	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 521.57 on 399 degrees of freedom
 Residual deviance: 275.84 on 396 degrees of freedom
 AIC: 283.84

Number of Fisher Scoring iterations: 6

- We can see in this model that the function will be

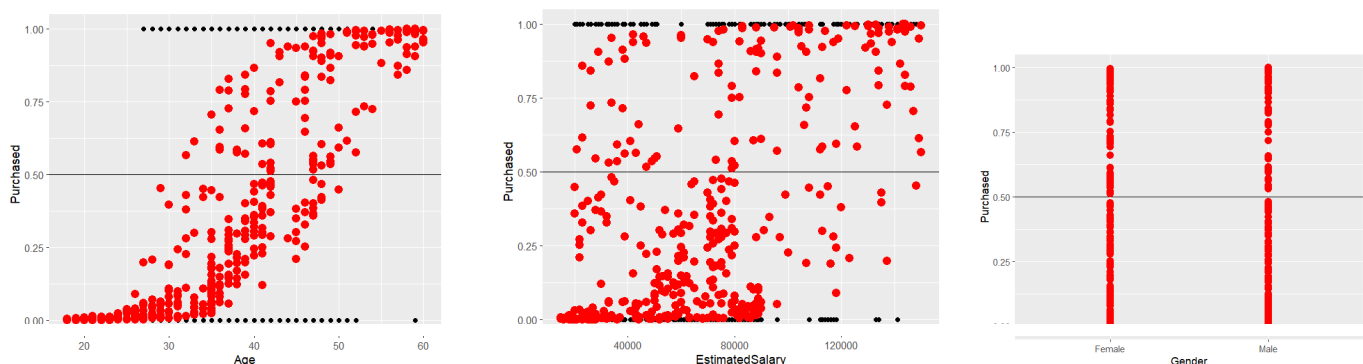
$$\ln(\text{Purchase}) = B_0 + [B_1 \times \text{Age}] + [B_2 \times \text{Salary}] + [B_3 \times \text{Gender}]$$

$$\frac{1}{\pi(1-\pi)} = \exp(-12.7836 + [\text{Age} \times 0.2370] + [\text{Salary} \times 0.00004] + [\text{Gender} \times 0.3338])$$

- From the output, We can see that age and salary are significant in our model. It can effect on the purchase process probability. As well, Gender is not significant and it doesn't effect. So, We can't focus on males and ignore females.

```
> round(exp(model$coefficients), 5)
      (Intercept)      new_df$Age new_df$EstimatedSalary      new_df$gender
      0.00000      1.26740      1.00004      1.39632
```

- Increasing Age by 1 year correspond to increasing odds of the purchased process by 0.26 %. Also increasing Salary by 1 \$ causes increasing the probability of purchasing by 0.00004 %
- Gender is not significant so males for example doesn't effect in the purchase process.

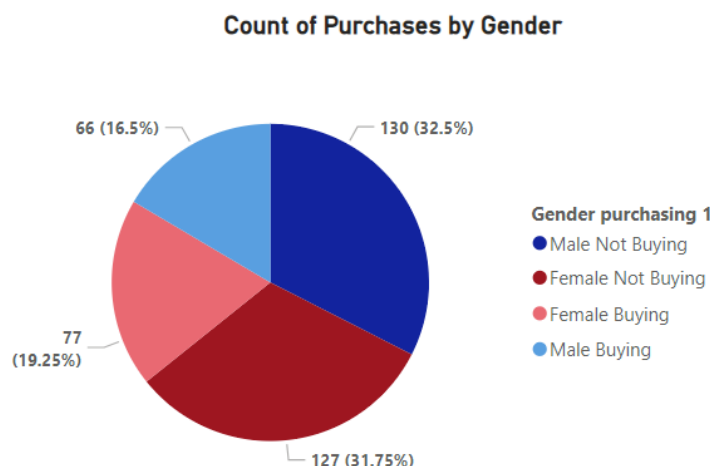
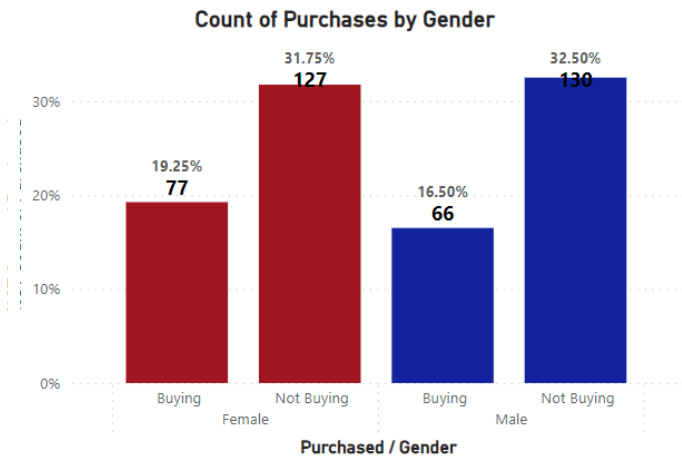


- As we can see in figure 1, the probability of purchased for ages which are higher than 30 is higher than whose age is 20 years. So, We should focus on this age.
- On the other side , all salaries has the probability to purchasing. So, We should focus on all salaries.
- For gender we can't predict by the logistic regression so we will try another method.

The probability of Total Purchase by Gender (Fisher's exact test)

- In this part , we want to determine whether there is a statistically significant association between Gender and Purchasing process.
- We will use Fisher's exact test to see if there is association between Gender and Purchases

Gender	0	1	Total	Gender	Buying	Not Buying	Total
Female	127	77	204	Female	19.25%	31.75%	51.00%
Male	130	66	196	Male	16.50%	32.50%	49.00%
Total	257	143	400	Total	35.75%	64.25%	100.00%



- As we can see the total number of Purchasing from male are 66 out of 196 males which represent 16.50% from total purchasing.
- Compared to females 77 out of 204 which represent 19.25% of total purchasing.
- We can see that females have higher percentage of purchasing SUV cars than males but still we can not say that there's a relation between gender and Purchasing.
- But we can say that females prefer SUV cars than males.

Probability (Purchasing ratio) by gender “Rows Analysis”

```
$data
  purchase
gender not Buy buy Total
Male   130   66  196
Female 127   77  204
Total  257  143  400

$measure
risk ratio with 95% C.I.
gender estimate lower upper
Male   1.000000    NA    NA
Female 1.120915 0.8608868 1.459484

$sp.value
two-sided
gender midp.exact fisher.exact chi.square
Male   NA        NA        NA
Female 0.3983004  0.4057912 0.3956648

$correction
[1] FALSE

attr(,"method")
[1] "Unconditional MLE & normal approximation (Wald) CI"
```

```

  purchase
gender    0      p0  1      p1 riskratio lower upper p.value
Female 127 0.6225490 77 0.3774510 1.0000000    NA    NA    NA
Male   130 0.6632653 66 0.3367347 0.8921283 0.6851737 1.161593 0.4057912

$measure
[1] "wald"

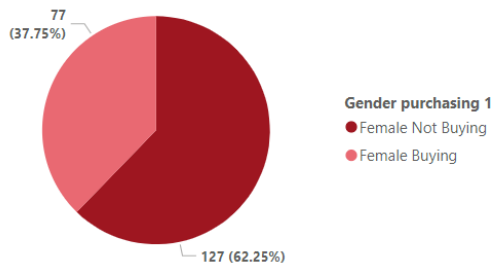
$conf.level
[1] 0.95

$spvalue
[1] "fisher.exact"
```

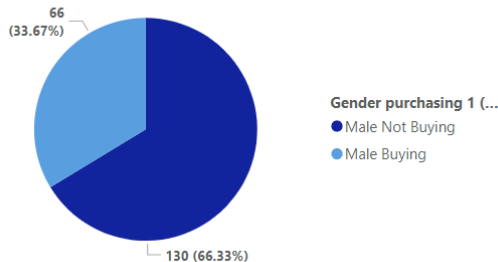
Count Purchasing / Total by Gender

Gender	0	1	Total	Gender	Buying	Not Buying	Total
Female	127	77	204	Female	37.75%	62.25%	100.00%
Male	130	66	196	Male	33.67%	66.33%	100.00%
Total	257	143	400	Total	35.75%	64.25%	100.00%

Count of Purchases by Gender



Count of Purchases by Gender



- From this data we have the probability of purchasing among Males and females

For example:

- We have 37.7% of females buying SUV cars compared to females which not buying 62.25%.
- On the other hand , 33.67% from males buying SUV cars and 66.33% not buying.

- From this output, We can say that females are 1.12 times higher interested and preferred purchasing SUV cars than males.

- Males are 0.107 times lower interested in SUV Cars than females.

- The percentage of males who buys SUV cars (33.67%) is lower than females (37.75 %). Beside that, Male has higher percentage for not buying (66.33%) compared to females (62.25%) .

Probability (odds ratio for gender) by Purchasing "Column Analysis"

```
$data
  purchase
gender not Buy buy Total
Male   130   66  196
Female 127   77  204
Total  257  143  400

$measure
odds ratio with 95% C.I.
gender estimate lower upper
Male   1.000000    NA    NA
Female 1.194226 0.7927509 1.79902

$measure
[1] "wald"

$conf.level
[1] 0.95

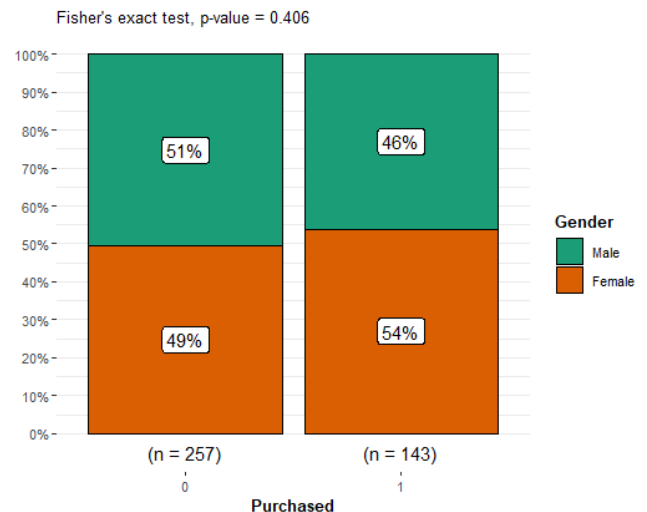
$measure
[1] "fisher.exact"

$measure
two-sided
gender midp.exact fisher.exact chi.square
Male   NA        NA        NA
Female 0.3983004  0.4057912  0.3956648

$correction
[1] FALSE

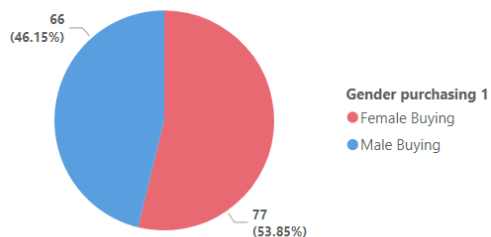
attr("method")
[1] "Unconditional MLE & normal approximation (wald) CI"
>
```

Gender	0	1	Total	Gender	Buying	Not Buying	Total
Female	127	77	204	Female	53.85%	49.42%	51.00%
Male	130	66	196	Male	46.15%	50.58%	49.00%
Total	257	143	400	Total	100.00%	100.00%	100.00%

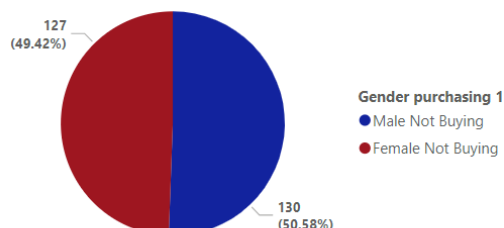


Count Purchasing / Total by Purchasing

Count of Purchases by Gender



Count of Purchases by Gender



- There is no association between gender and Purchasing.
- As we see the distribution in Purchasing with Gender is almost closed.
- By column analysis we can see that the percentage of buying from females is 53.85% compared to males 46.15 %.
- On the other hand, The percentage of not buying from females is 49.42% compared to males which is 50.58%.
- From this output we can say that females are 1.19 times more odds to buying SUV cars than males.

The decision

- Finally, we can take the decision from outputs by focusing on females gender on our advertisements. we can increase the investment in advertisement for females by 20% than males.
- We should also focus on people whose age between 25 and 40 years specifically 35 years.
- The most interested are whose salary are medium between 23,000\$ and 88,000\$ but we should try to attract more whose salary are higher than 88,000 \$.
- There is no association between Gender and Purchasing.

Conclusion

According to the result of our tests and summary, We should be more care about some variables which by that can help in improving SUV cars sales. Also we have to be careful for our advertisements for gender, salaries category and age.

References & dataset

- 1- "SUV data for logistic algorithm" , Retrieved from the link <https://www.kaggle.com/datasets/kadamsuraj/suv-data-for-logistic-algorithm/data> .