

BUSINESS REPORT ON PREDICTIVE MODELLING PROJECT



- RAHUL SHARMA

<u>Sr. No.</u>	<u>CONTENT</u>	<u>Page no.</u>
A	<u>Problem1:</u>	2-14
1.1	Define the problem and perform exploratory Data Analysis	2-6
1.2	Data Pre-processing	6-8
1.3	Model Building - Linear regression	8-13
1.4	Business Insights & Recommendations	14
B	<u>Problem2:</u>	15-27
2.1	Define the problem and perform exploratory Data Analysis	15-20
2.2	Data Pre-processing	20-21
2.3	Model Building and Compare the Performance of the Models	22-26
2.4	Business Insights & Recommendations	26-27

A Problem1: Comp-active database

The comp-activ database comprises activity measures of computer systems. Data was gathered from a Sun Sparcstation 20/712 with 128 Mbytes of memory, operating in a multi-user university department. Users engaged in diverse tasks, such as internet access, file editing, and CPU-intensive programs.

Being an aspiring data scientist, our aim to establish a linear equation for predicting 'usr' (the percentage of time CPUs operate in user mode). Your goal is to analyze various system attributes to understand their influence on the system's 'usr' mode.

1.1 - Define the problem and perform exploratory Data Analysis

Problem definition - Check shape, Data types, statistical summary - Univariate analysis - Multivariate analysis - Use appropriate visualizations to identify the patterns and insights - Key meaningful observations on individual variables and the relationship between variables.

Problem definition:-

Check shape:- 8192 rows x 22columns

Data types:-

```
Data Types:
lread      int64
lwrite     int64
scall      int64
sread      int64
swrite     int64
fork       float64
exec       float64
rchar      float64
wchar      float64
pgout      float64
ppgout     float64
pgfree     float64
pgscan     float64
atch       float64
pgin       float64
ppgin      float64
pflt       float64
vflt       float64
runqsz     object
freemem    int64
freeswap   int64
usr        int64
dtype: object
```

Statistical Summary:-

```

Statistical Summary:
count      lread      lwrite      scall      sread      swrite \
mean       19.559692    13.106201    2306.318237  210.479980    150.058228
std        53.353799    29.891726    1633.617322  198.980146    160.478980
min         0.000000     0.000000    109.000000     6.000000     7.000000
25%         2.000000     0.000000    1012.000000    86.000000    63.000000
50%         7.000000     1.000000    2051.500000    166.000000    117.000000
75%        20.000000    10.000000    3317.250000    279.000000    185.000000
max       1845.000000  575.000000  12493.000000  5318.000000  5456.000000

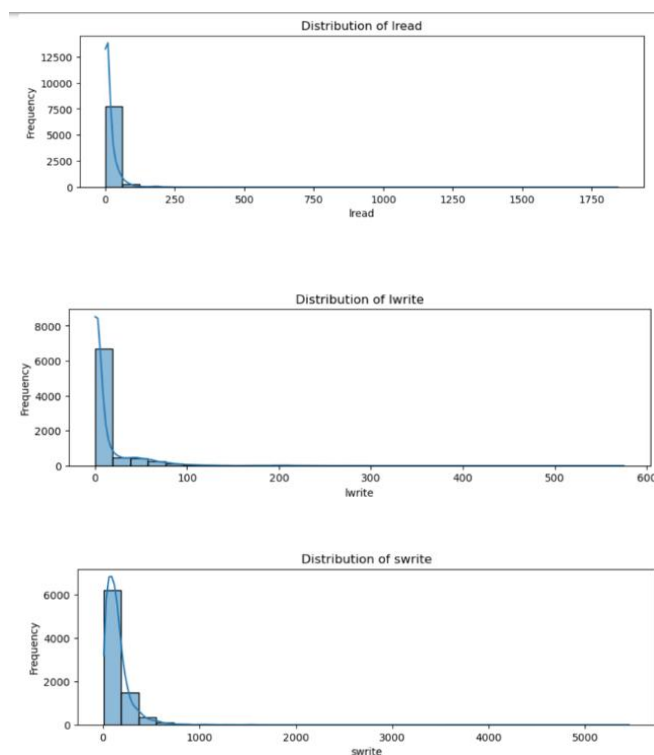
count      fork      exec      rchar      wchar      pgout \
mean       1.884554     2.791998    1.973857e+05  9.590299e+04  2.285317
std        2.479493     5.212456    2.398375e+05  1.408417e+05  5.307038
min         0.000000     0.000000    2.780000e+02  1.498000e+03  0.000000
25%         0.400000     0.200000    3.409150e+04  2.291600e+04  0.000000
50%         0.800000     1.200000    1.254735e+05  4.661900e+04  0.000000
75%         2.200000     2.800000    2.678288e+05  1.061010e+05  2.400000
max        20.120000    59.560000    2.526649e+06  1.801623e+06  81.440000

count      pgfree      pgscan      atch      pgin      ppgin \
mean       11.919712    21.526849    1.127505     8.277960    12.388586
std        32.363520    71.141340    5.708347    13.874978    22.281318
min         0.000000     0.000000     0.000000     0.000000     0.000000
25%         0.000000     0.000000     0.000000     0.600000     0.600000
50%         0.000000     0.000000     0.000000     2.800000     3.800000
75%         5.000000     0.000000     0.600000     9.765000    13.800000
max        523.000000  1237.000000  211.580000  141.200000  292.610000

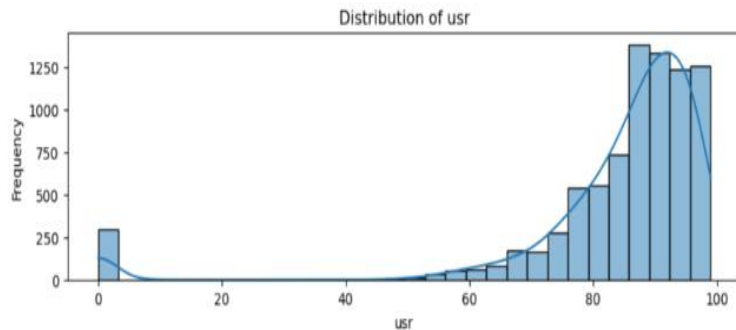
count      pflt      vflt      freemem      freeswap      usr
mean       109.793799  185.315796  1763.456299  1.328126e+06  83.968872
std        114.419221  191.000603  2482.104511  4.220194e+05  18.401905
min         0.000000     0.200000    55.000000    2.000000e+00  0.000000
25%        25.000000    45.400000    231.000000    1.042624e+06  81.000000
50%        63.800000    120.400000    579.000000    1.289290e+06  89.000000
75%       159.600000  251.800000  2002.250000  1.730380e+06  94.000000
max       899.800000  1365.000000  12027.000000  2.243187e+06  99.000000

```

Uni-variate analysis:-

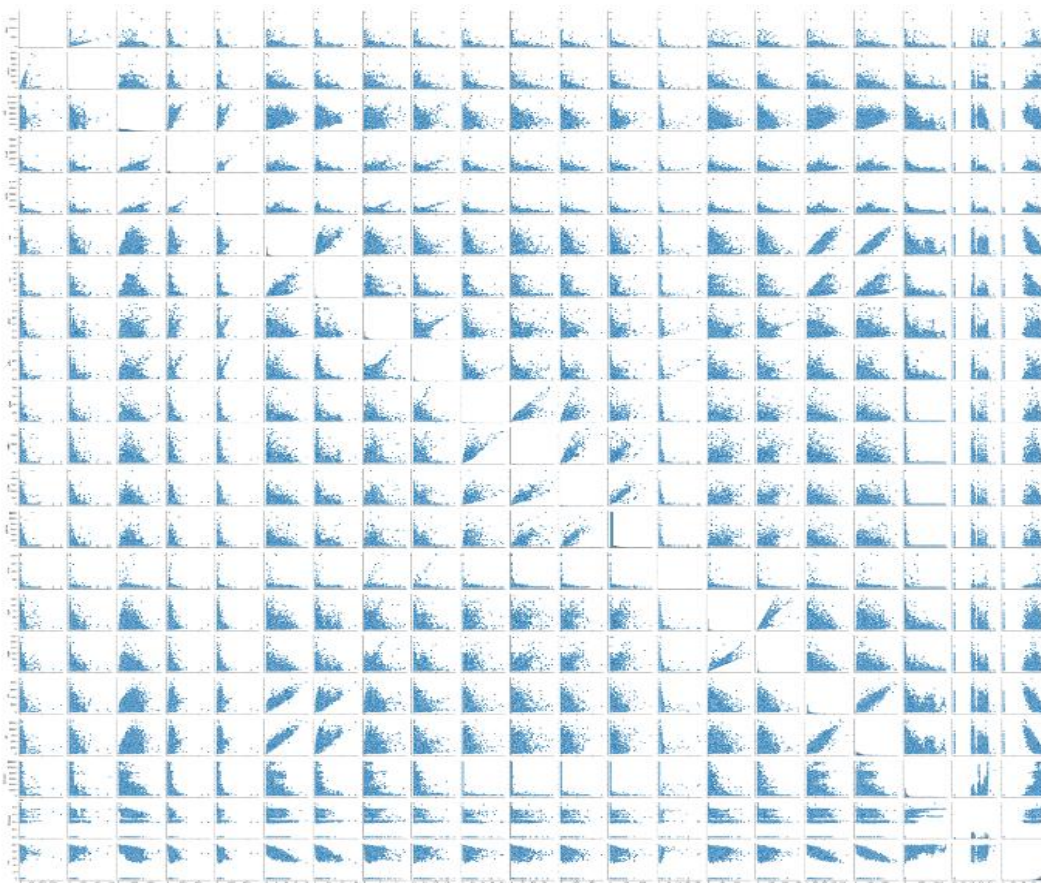


- The transfers per second for both reading and writing are brisk, with the majority occurring at a rapid pace.
- Most transactions are swiftly processed by the system, with a read-write rate that is generally quick, typically under 5%.
- The current situation suggests a relative absence of ongoing activities.



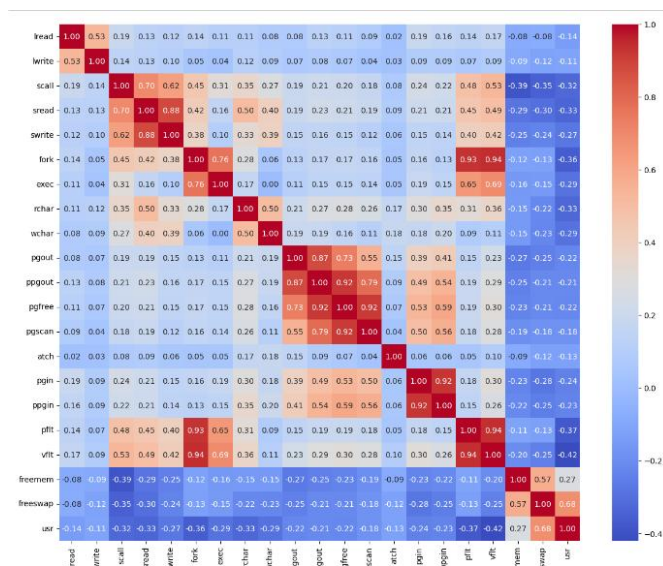
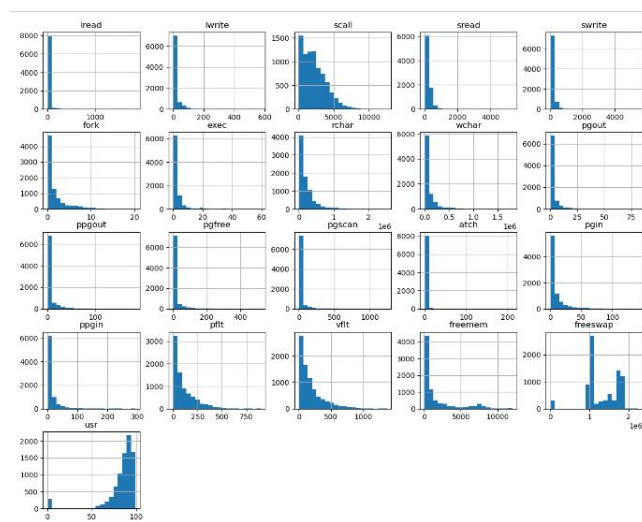
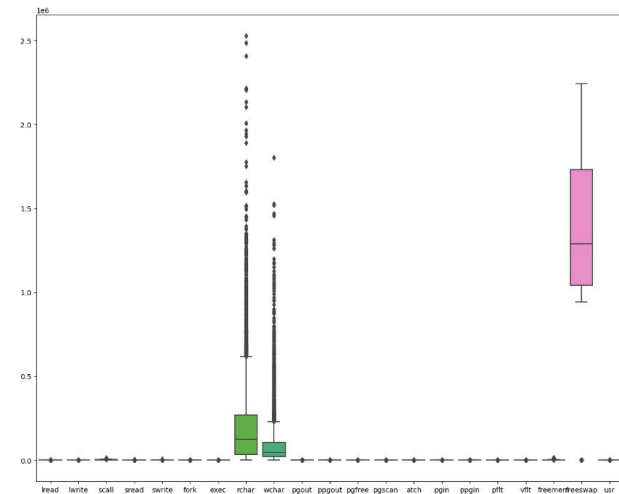
CPU able to run in user mode b/w 80- 99% times & its ideal.

Multivariate analysis:-



- A correlation can be observed between 'vflt,' 'pflt,' and 'fork,' suggesting that an increase in fork calls is associated with a rise in page faults.
- Likewise, there is a strong correlation between the number of page out requests per second and the number of pages paged out per second.

Use appropriate visualizations to identify the patterns and insights:-



- The read system call is the most frequently used call, with an average of 53 calls per second. This is likely because it is used to read data from files and devices.
- The write system call is the second most frequently used call, with an average of 39 calls per second. This is likely because it is used to write data to files and devices.

- The fork system call is the third most frequently used call, with an average of 24 calls per second. This is likely because it is used to create new processes.
- The sread system call is the fourth most frequently used call, with an average of 21 calls per second. This is likely because it is used to read data from sockets.
- The swrite system call is the fifth most frequently used call, with an average of 15 calls per second. This is likely because it is used to write data to sockets.

Key meaningful observations on individual variables and the relationship between variables:-

- Memory Metrics Tango: The amount of available memory (freemem) and its companions are closely connected. When the system needs to use the swap space (a backup memory area), it's like a dance, but a bit more structured.
- I/O, the Lone Wolf: Input and output operations (I/O), represented by sread and swrite, follow their own rhythm. They're less connected to the overall system, moving to their unique beat.
- PFIT Playing Ping-Pong: The page fitting process (pfit) plays a game of ping-pong. It makes fewer mistakes on its own, allowing other processes more freedom to move and operate smoothly.
- CPU, the Independent Actor: The Central Processing Unit (CPU) acts independently. When it executes (exec) or forks, it does so on its own stage, less dependent on other parts of the system.
- System, a Grand Ensemble: The entire system is like a grand ensemble. Many intricate connections exist, and when one metric makes a move (twirls), it affects the entire dance. Everything is interconnected, and each part influences the whole performance.

1.2 Data Pre-processing

Prepare the data for modelling: - Missing Value Treatment (if needed) - Outlier Detection (treat, if needed) - Feature Engineering - Encode the data - Train-test split

Missing Value Treatment (if needed)

```
lread      0
lwrite     0
scall      0
sread      0
swrite     0
fork       0
exec       0
rchar     104
wchar     15
pgout      0
ppgout     0
pgfree     0
pgscan     0
atch       0
pgin       0
ppgin      0
pflt       0
vflt       0
runqsz     0
freemem    0
freeswap   0
usr        0
dtype: int64
```

There are 104 missing values present at rchar & 15 at wchar

AFTER TREATMENT:-

```

lread      0
lwrite     0
scall      0
sread      0
swrite     0
fork       0
exec       0
rchar      0
wchar      0
pgout      0
ppgout     0
pgfree     0
pgscan     0
atch       0
pgin       0
ppgin      0
pflt       0
vflt       0
runqsz     0
freemem    0
freeswap   0
usr        0
dtype: int64

```

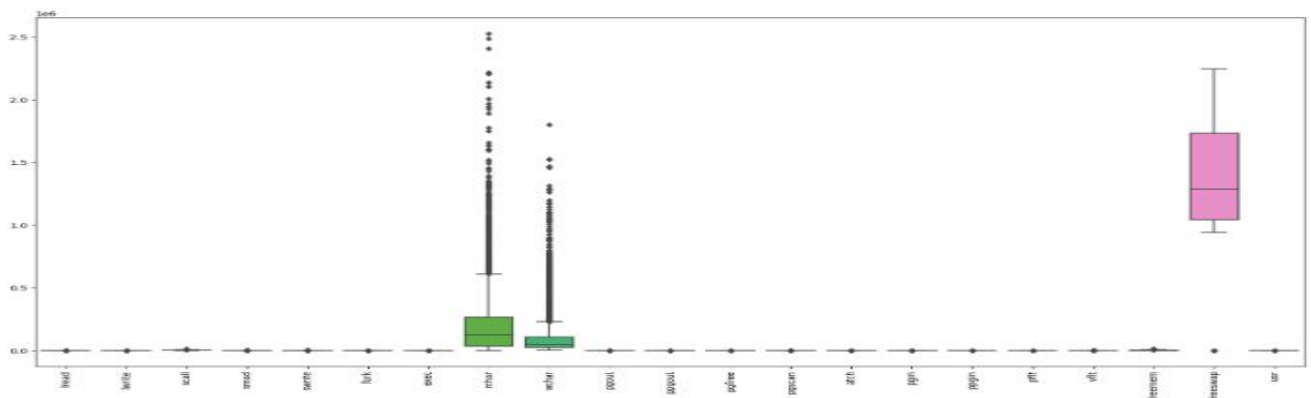
Outlier Detection (treat, if needed):-

```

lread      675
lwrite    2684
scall       0
sread       0
swrite      0
fork       21
exec       21
rchar       0
wchar       0
pgout     4878
ppgout     4878
pgfree     4869
pgscan     6448
atch       4575
pgin       1220
ppgin      1220
pflt        3
vflt        0
runqsz      0
freemem     0
freeswap    0
usr       283
dtype: int64

```

- There are total 31775 outliers present
- All the outliers are treated by adjusting them to the lower and upper bound values calculated by the IQR value.



Feature Engineering:-

- New features - no. of page rate & page requests rate have been added/created with the variables pgin, pgout, ppgin & ppgout.
- Although, these new features has not given any significant output, as the majority of the values are in form of 0 or inf.

Encode the data - Train-test split:-

- After the encoded the data, the data-set has split-ten into training and testing in the 70:30 ratio.
- X_TRAIN 1st 5 rows:-

	const	lread	lwrite	scall	sread	swrite	fork	exec	rchar	\
694	1.0	1	1	1345	223	192	0.6	0.6	198703.0	
5535	1.0	1	1	1429	87	67	0.2	0.2	7163.0	
4244	1.0	1	1	1429	87	67	0.2	0.2	83246.0	
2472	1.0	1	1	1429	87	67	0.2	0.2	96009.0	
7052	1.0	1	1	1429	87	67	0.2	0.2	17132.0	

click to expand output; double click to hide output

	wchar	pgout	ppgout	pgfree	atch	pgin	ppgin	pflt	vflt	\
694	293578.0	0.60	6.20	23.40	2.60	3.80	7.40	28.20	56.60	
5535	24842.0	0.00	0.00	0.00	0.00	1.60	1.60	15.77	30.74	
4244	53705.0	5.39	7.19	7.19	2.79	3.99	4.59	59.88	74.05	
2472	70467.0	0.00	0.00	0.00	0.00	2.80	3.20	129.00	236.80	
7052	12514.0	0.00	0.00	0.00	0.00	0.00	0.00	19.80	23.80	

	freemem	freeswap
694	121	1375446
5535	1476	1021541
4244	82	18
2472	772	993909
7052	4179	1821682

- X_TEST 1ST 5 rows:-

	const	lread	lwrite	scall	sread	swrite	fork	exec	rchar	\
3894	1.0	27	39	1252	53	118	0.2	0.2	26592.0	
4276	1.0	1	0	996	85	55	0.4	0.4	16667.0	
3414	1.0	9	7	1530	247	135	0.4	0.4	14513.0	
4165	1.0	32	4	3243	182	140	5.2	5.6	337517.0	
7385	1.0	16	3	5017	259	249	2.8	1.4	73537.0	

	wchar	pgout	ppgout	pgfree	atch	pgin	ppgin	pflt	vflt	\
3894	54394.0	0.0	0.0	0.0	0.0	0.4	0.6	19.44	20.04	
4276	36431.0	0.0	0.0	0.0	0.0	1.0	1.4	35.53	52.10	
3414	61905.0	13.8	19.2	30.4	10.4	14.8	18.4	26.80	186.20	
4165	94832.0	0.8	1.0	1.0	1.4	4.6	7.0	250.60	420.20	
7385	237547.0	0.0	0.0	0.0	0.0	5.6	5.8	142.80	276.20	

	freemem	freeswap
3894	7762	1875466
4276	2979	1010114
3414	89	11
4165	1300	1535309
7385	2114	988600

1.3 Model Building - Linear Regression

Apply linear Regression using Sklearn - Using Statsmodels Perform checks for significant variables using the appropriate method - Create multiple models and check the performance of Predictions on Train and Test sets using Rsquare, RMSE & Adj Rsquare.

- Standard errors assume that the convenience metrics of the errors is correctly specified.
- The condition number is large, 6.9×10^6 . This might indicate that there are strong multicollinearity or other numerical problems.

OLS Regression Results

Dep. Variable:	usr	R-squared:	0.601
Model:	OLS	Adj. R-squared:	0.600
Method:	Least Squares	F-statistic:	453.9
Date:	Mon, 15 Jan 2024	Prob (F-statistic):	0.00
Time:	17:35:30	Log-Likelihood:	-22102.
No. Observations:	5734	AIC:	4.424e+04
Df Residuals:	5714	BIC:	4.438e+04
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	51.5054	0.736	70.010	0.000	50.063	52.948
lread	-0.0210	0.003	-6.237	0.000	-0.028	-0.014
lwrite	0.0026	0.006	0.401	0.689	-0.010	0.015
scall	0.0005	0.000	3.491	0.000	0.000	0.001
sread	-0.0003	0.002	-0.156	0.876	-0.004	0.003
swrite	-0.0003	0.002	-0.165	0.869	-0.004	0.004
fork	-1.5897	0.258	-6.169	0.000	-2.095	-1.084
exec	-0.0456	0.050	-0.905	0.365	-0.144	0.053
rchar	-5.944e-06	8.72e-07	-6.814	0.000	-7.65e-06	-4.23e-06
wchar	-1.42e-05	1.34e-06	-10.579	0.000	-1.68e-05	-1.16e-05
pgout	-0.1550	0.065	-2.393	0.017	-0.282	-0.028
ppgout	0.0955	0.039	2.471	0.014	0.020	0.171
pgfree	-0.0491	0.014	-3.526	0.000	-0.076	-0.022
atch	-0.0911	0.028	-3.238	0.001	-0.146	-0.036
pgin	0.0669	0.031	2.162	0.031	0.006	0.128
ppgin	-0.0402	0.020	-2.022	0.043	-0.079	-0.001
pflt	-0.0456	0.005	-10.087	0.000	-0.054	-0.037
vflt	0.0221	0.004	6.263	0.000	0.015	0.029
freemem	-0.0014	7.88e-05	-17.347	0.000	-0.002	-0.001
freeswap	3.098e-05	4.76e-07	65.061	0.000	3e-05	3.19e-05

Omnibus:	2007.499	Durbin-Watson:	2.069
Prob(Omnibus):	0.000	Jarque-Bera (JB):	8746.929
Skew:	-1.667	Prob(JB):	0.00
Kurtosis:	8.050	Cond. No.	6.90e+06

- Interpretation of R-squared
- R-squared value can shows 60.1% of the variance in the training set.

By dropping multicollinear columns one by one, we observe that some almost remain same And there is quite only 0.001 and 0.002 Downwards difference.

R-squared: 0.601
Adjusted R-squared: 0.60103

On dropping 'ppgout', adj. R-squared almost remains the same.

R-squared: 0.601
Adjusted R-squared: 0.599

On dropping 'pgfree', adj. R-squared decreased by 0.002

R-squared: 0.601
Adjusted R-squared: 0.6

On dropping 'ppgin', adj. R-squared decreased by 0.001

SO ON.....

- There is no effect on adj. R-squared after dropping the 'pggout' column, and it has highest number in value of variance influence factor, so we remove it from the training set.
- Since there is ALSO no effect on adj. R-squared after dropping the 'pgin' column, and it has highest number in value of variance influence factor, so we remove it from the training set.

OLS Regression Results

Dep. Variable:

usr

R-squared:

0.598

Model:

OLS

Adj. R-squared:

0.597

Method:

Least Squares

F-statistic:

531.1

Date:

Mon, 15 Jan 2024

Prob (F-statistic):

0.00

Time:

17:35:31

Log-Likelihood:

-22128.

No. Observations:

5734

AIC:

4.429e+04

Df Residuals:

5717

BIC:

4.440e+04

Df Model:

16

Covariance Type:

nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	52.4355	0.717	73.102	0.000	51.029	53.842
lread	-0.0206	0.003	-6.182	0.000	-0.027	-0.014
lwrite	0.0045	0.006	0.706	0.480	-0.008	0.017
scall	0.0006	0.000	4.440	0.000	0.000	0.001
sread	0.0009	0.002	0.446	0.656	-0.003	0.005
swrite	-0.0030	0.002	-1.440	0.150	-0.007	0.001
exec	-0.2089	0.042	-4.919	0.000	-0.292	-0.126
rchar	-6.121e-06	8.71e-07	-7.025	0.000	-7.83e-06	-4.41e-06
wchar	-1.397e-05	1.35e-06	-10.373	0.000	-1.66e-05	-1.13e-05
pgout	-0.0379	0.043	-0.881	0.378	-0.122	0.046
pgfree	-0.0174	0.008	-2.116	0.034	-0.034	-0.001
atch	-0.0817	0.028	-2.905	0.004	-0.137	-0.027
pggin	0.0073	0.009	0.799	0.424	-0.011	0.025
pflt	-0.0570	0.004	-13.491	0.000	-0.065	-0.049
vflt	0.0115	0.003	3.999	0.000	0.006	0.017
freemem	-0.0014	7.91e-05	-17.247	0.000	-0.002	-0.001
freeswap	3.057e-05	4.72e-07	64.819	0.000	2.96e-05	3.15e-05

Omnibus:

2028.207

Durbin-Watson:

2.066

Prob(Omnibus):

0.000

Jarque-Bera (JB):

9010.669

Skew:

-1.678

Prob(JB):

0.00

Kurtosis:

8.143

Cond. No.

6.68e+06

- As we see, There is little bit effect on adj. R-squared after dropping the 'fork' column.

OLS Regression Results

Dep. Variable:	usr	R-squared:	0.597			
Model:	OLS	Adj. R-squared:	0.596			
Method:	Least Squares	F-statistic:	564.0			
Date:	Mon, 15 Jan 2024	Prob (F-statistic):	0.00			
Time:	17:35:31	Log-Likelihood:	-22136.			
No. Observations:	5734	AIC:	4.430e+04			
Df Residuals:	5718	BIC:	4.441e+04			
Df Model:	15					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	52.9220	0.708	74.767	0.000	51.534	54.310
lread	-0.0204	0.003	-6.134	0.000	-0.027	-0.014
lwrite	0.0053	0.006	0.830	0.407	-0.007	0.018
scall	0.0007	0.000	4.749	0.000	0.000	0.001
sread	0.0012	0.002	0.629	0.529	-0.003	0.005
swrite	-0.0028	0.002	-1.351	0.177	-0.007	0.001
exec	-0.1481	0.040	-3.730	0.000	-0.226	-0.070
rchar	-5.863e-06	8.7e-07	-6.739	0.000	-7.57e-06	-4.16e-06
wchar	-1.461e-05	1.34e-06	-10.913	0.000	-1.72e-05	-1.2e-05
pgout	-0.0476	0.043	-1.107	0.268	-0.132	0.037
pgfree	-0.0112	0.008	-1.380	0.168	-0.027	0.005
atch	-0.0687	0.028	-2.455	0.014	-0.123	-0.014
pggin	0.0115	0.009	1.265	0.206	-0.006	0.029
pflt	-0.0421	0.002	-20.850	0.000	-0.046	-0.038
freemem	-0.0014	7.92e-05	-17.215	0.000	-0.002	-0.001
freeswap	3.022e-05	4.64e-07	65.149	0.000	2.93e-05	3.11e-05
Omnibus:	2077.926	Durbin-Watson:	2.066			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	9404.876			
Skew:	-1.717	Prob(JB):	0.00			
Kurtosis:	8.250	Cond. No.	6.58e+06			

- As we see, There is also little bit effect on adj. R-squared after dropping the 'vflt' column.

OLS Regression Results

Dep. Variable:	usr	R-squared:	0.597
Model:	OLS	Adj. R-squared:	0.596
Method:	Least Squares	F-statistic:	564.0
Date:	Mon, 15 Jan 2024	Prob (F-statistic):	0.00
Time:	17:35:31	Log-Likelihood:	-22136.
No. Observations:	5734	AIC:	4.430e+04
Df Residuals:	5718	BIC:	4.441e+04
Df Model:	15		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	52.9220	0.708	74.767	0.000	51.534	54.310
lread	-0.0204	0.003	-6.134	0.000	-0.027	-0.014
lwrite	0.0053	0.006	0.830	0.407	-0.007	0.018
scall	0.0007	0.000	4.749	0.000	0.000	0.001
sread	0.0012	0.002	0.629	0.529	-0.003	0.005
swrite	-0.0028	0.002	-1.351	0.177	-0.007	0.001
exec	-0.1481	0.040	-3.730	0.000	-0.226	-0.070
rchar	-5.863e-06	8.7e-07	-6.739	0.000	-7.57e-06	-4.16e-06
wchar	-1.461e-05	1.34e-06	-10.913	0.000	-1.72e-05	-1.2e-05
pgout	-0.0476	0.043	-1.107	0.268	-0.132	0.037
pgfree	-0.0112	0.008	-1.380	0.168	-0.027	0.005
atch	-0.00687	0.028	-2.455	0.014	-0.123	-0.014
ppgin	0.0115	0.009	1.265	0.206	-0.006	0.029
pflt	-0.0421	0.002	-20.850	0.000	-0.046	-0.038
freemem	-0.0014	7.92e-05	-17.215	0.000	-0.002	-0.001
freeswap	3.022e-05	4.64e-07	65.149	0.000	2.93e-05	3.11e-05

Omnibus:	2077.926	Durbin-Watson:	2.066
Prob(Omnibus):	0.000	Jarque-Bera (JB):	9404.876
Skew:	-1.717	Prob(JB):	0.00
Kurtosis:	8.250	Cond. No.	6.58e+06

- There is no effect on adj. R-squared after dropping the 'sread', 'lread', 'pgfree' column

OLS Regression Results						
Dep. Variable:	usr	R-squared:	0.594			
Model:	OLS	Adj. R-squared:	0.593			
Method:	Least Squares	F-statistic:	643.7			
Date:	Mon, 15 Jan 2024	Prob (F-statistic):	0.00			
Time:	17:35:31	Log-Likelihood:	-22155.			
No. Observations:	5734	AIC:	4.434e+04			
Df Residuals:	5720	BIC:	4.443e+04			
Df Model:	13					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	53.1584	0.709	75.026	0.000	51.769	54.547
lwrite	-0.0143	0.006	-2.594	0.010	-0.025	-0.003
scall	0.0006	0.000	4.796	0.000	0.000	0.001
swrite	-0.0018	0.001	-1.396	0.163	-0.004	0.001
exec	-0.1575	0.040	-3.963	0.000	-0.235	-0.080
rchar	-5.49e-06	7.99e-07	-6.871	0.000	-7.06e-06	-3.92e-06
wchar	-1.484e-05	1.34e-06	-11.077	0.000	-1.75e-05	-1.22e-05
pgout	-0.0487	0.043	-1.128	0.259	-0.133	0.036
pgfree	-0.0098	0.008	-1.206	0.228	-0.026	0.006
atch	-0.00688	0.028	-2.452	0.014	-0.124	-0.014
ppgin	0.0051	0.009	0.562	0.574	-0.013	0.023
pflt	-0.0424	0.002	-20.988	0.000	-0.046	-0.038
freemem	-0.0014	7.95e-05	-17.171	0.000	-0.002	-0.001
freeswap	3.01e-05	4.64e-07	64.878	0.000	2.92e-05	3.1e-05
Omnibus:	2085.639	Durbin-Watson:	2.065			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	9428.526			
Skew:	-1.725	Prob(JB):	0.00			
Kurtosis:	8.250	Cond. No.	6.57e+06			

- As we see, There is little bit effect on adj. R-squared after dropping the 'pflt' column.

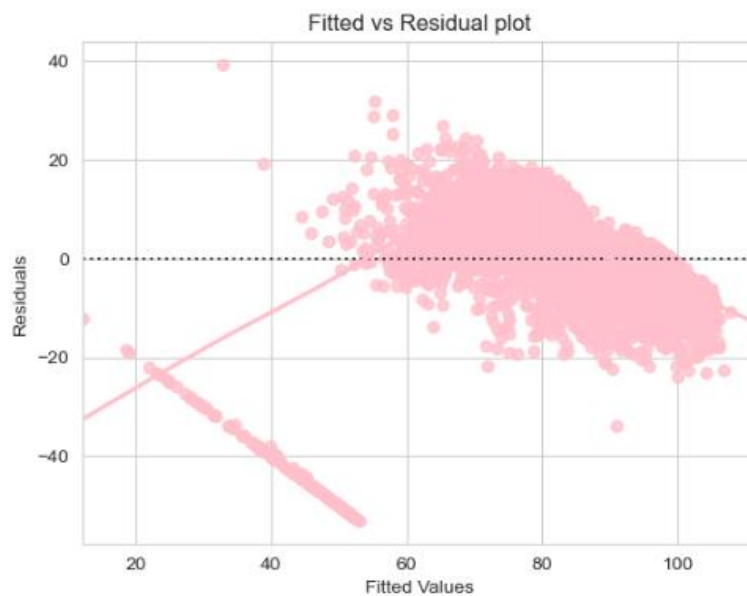
After dropping the features causing strong multicollinearity and the statistically insignificant ones, our model performance hasn't dropped sharply. This shows that these variables did not have much predictive power.

VIF values:

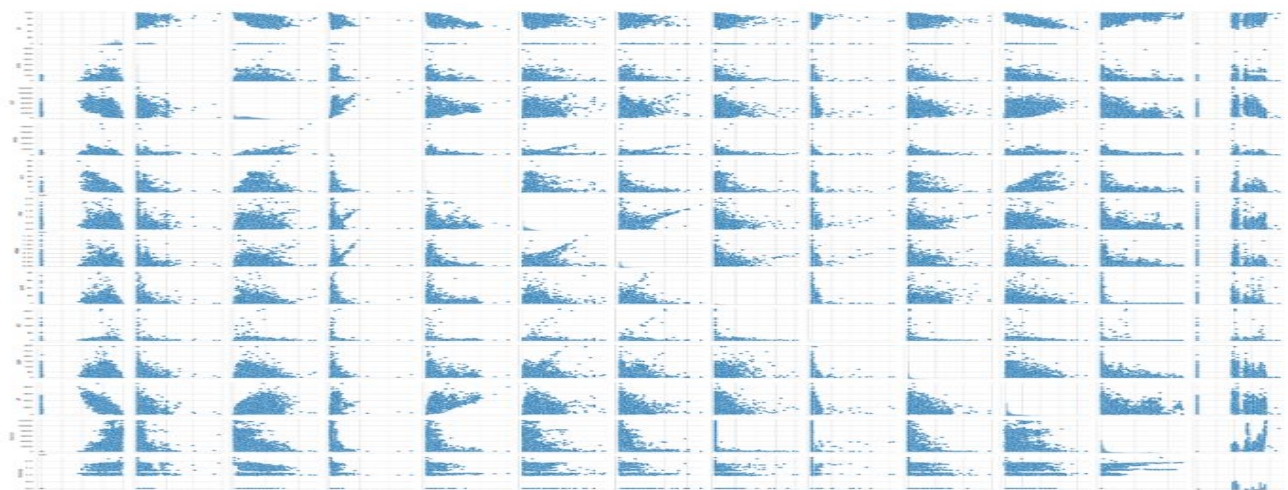
```
const      21.464308
lwrite     1.035666
scall      2.001498
swrite     1.734373
exec       1.150736
rchar      1.546040
wchar      1.474051
pgout      1.303067
atch       1.058744
ppgin      1.358639
freemem    1.628732
freeswap   1.615183
dtype: float64
```

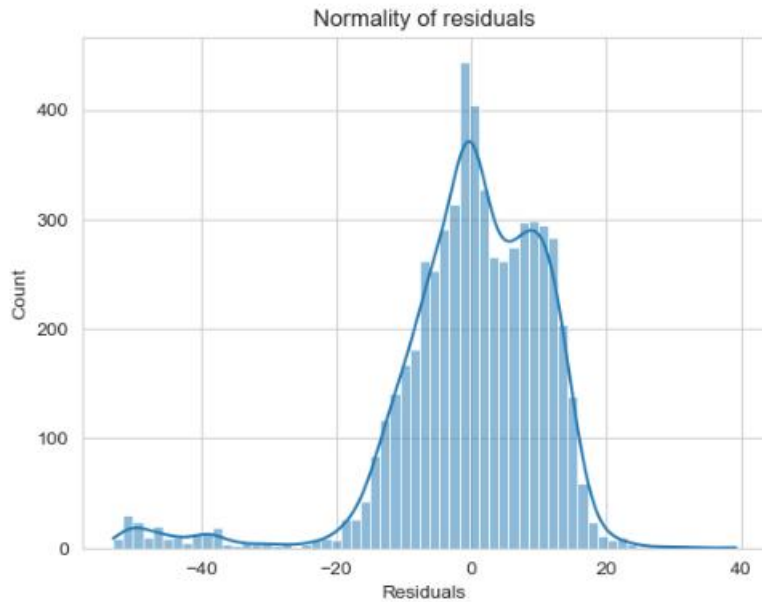
	Actual Values	Fitted Values	Residuals
0	91	87.763486	3.236514
1	94	81.573558	12.426442
2	0	49.452329	-49.452329
3	83	76.852838	6.147162
4	94	100.704003	-6.704003

- **VIF for all features is <3**
- VIF method can be used for identifying important variables & eliminating/removing the ones that may not significant and have high multicollinearity.

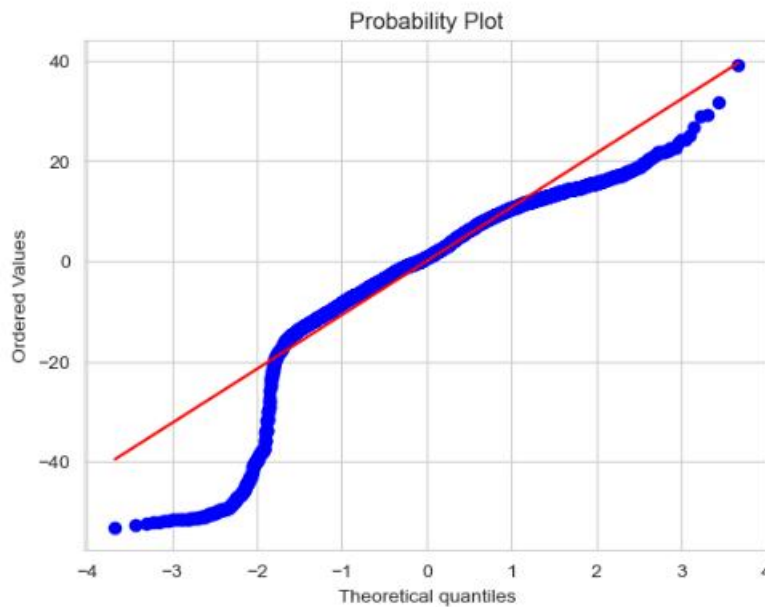


- We observe that the pattern has slightly decreased and that Data points seems to be randomly distributed.





- The QQ plot of residuals can be used to visually check the normality assumptions.
- The normally probability plot of residual should approximately follow a straight line.



- Partially, the points are laying on the straight line in QQ plot.

```
ShapiroResult(statistic=0.870936930179596, pvalue=0.0)
```

If p-value is < 0.05 , the residuals are rejected in shapiro test. but the tested value is greater than 0.05

1.4 Business Insights & Recommendations

Comment on the Linear Regression equation from the final model and impact of relevant variables (atleast 2) as per the equation - Conclude with the key takeaways (actionable insights and recommendations) for the business

```
usr = 53.15841989513942 + -0.014313539866501968 * ( lwrite ) + 0.0006412128351541196 * ( scall ) +
-0.0017623354119870706 * ( swrite ) + -0.15746936975672624 * ( exec ) + -5.489953524181218e-06 * (
rchar ) + -1.483808894410539e-05 * ( wchar ) + -0.04871487082115683 * ( pgout ) + -0.0097722267068
38933 * ( pgfree ) + -0.06880039797948492 * ( atch ) + 0.005072879579547759 * ( ppgin ) + -0.04244
390275143818 * ( pflt ) + -0.001364771082210648 * ( freemem ) + 3.0097946945968897e-05 * ( freeswap
)
```

- RMSE on the train data = 11.5289
- MAE on the train data = 8.1244
- RMSE on the train and test sets are comparable. So, our model may not suffer from over-fitting.
- MAE indicates that our current model able to predict mpg within a mean error of the test data.
- Therefore, we can assume the model "fitres-42" is good for prediction as well as inference purposes.

Key Influence of Process Run Queue Size:

The CPU run-time in user mode shows a significant dependency on the Process run queue size. Understanding and managing the size of the queue for running processes are crucial for optimizing CPU performance.

Sensitivity to CPU Bound Queue Size:

A noteworthy finding is that increasing the CPU bound queue size by just 1 unit leads to a substantial 33.5 times increase in the percentage of time the CPU runs in user mode. This suggests that proper management of CPU-bound tasks in the queue is vital for improving user mode run-time.

Impact of Non-CPU Bound Queue Size:

Similarly, the non-CPU bound queue size has a significant impact, with a 32.7 times increase in CPU run-time in user mode for every 1-unit increase. Balancing and optimizing I/O-bound tasks in the queue are important considerations for overall system performance.

Cumulative Effect of Process Run Queue Size:

When considering both CPU and non-CPU bound queues, the overall impact on the percentage of time the CPU runs in user mode is substantial, approximately 132 times, including the Intercept. This underscores the holistic influence of the process run queue size on CPU behavior.

Constant Impact of Other Features:

The analysis suggests that, while the process run queue size has a substantial impact, the other features considered in the model do not significantly affect CPU run-time. This could guide resource allocation efforts, focusing primarily on optimizing the process run queue size.

B Problem2: Contraceptive Method Data-set

In your role as a statistician at the Republic of Indonesia Ministry of Health, you have been entrusted with a dataset containing information from a Contraceptive Prevalence Survey. This dataset encompasses data from 1473 married females who were either not pregnant or were uncertain of their pregnancy status during the survey.

NOW, we predicting whether these women opt for a contraceptive method of choice. This prediction will be based on a comprehensive analysis of their demographic and socio-economic attributes.

2.1 Define the problem and perform exploratory Data Analysis

Problem definition - Check shape, Data types, statistical summary - Univariate analysis - Multivariate analysis - Use appropriate visualizations to identify the patterns and insights - Key meaningful observations on individual variables and the relationship between variables.

Problem definition:-

Check shape:- 1473 rows x 10columns

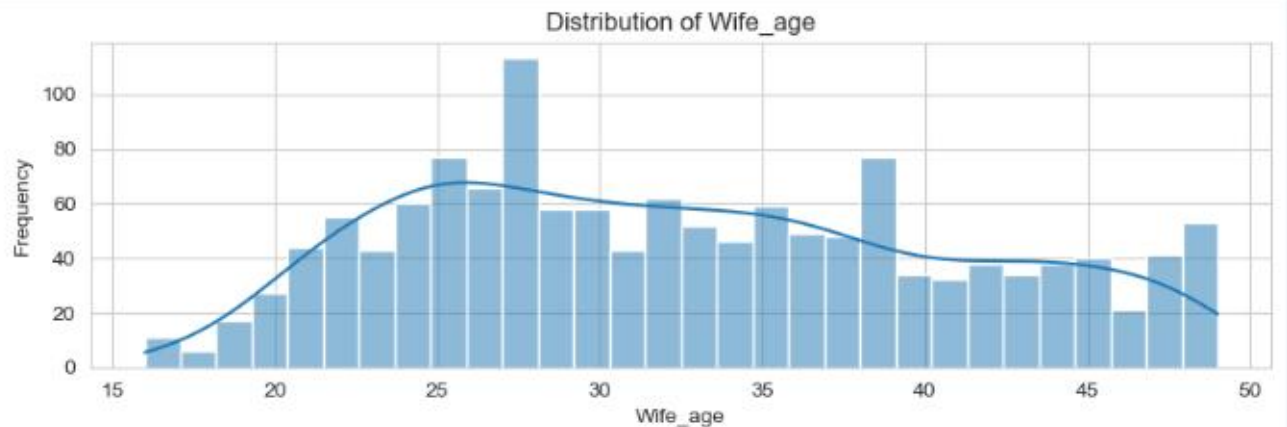
Data types:-

```
Data Types:
Wife_age          float64
Wife_education    object
Husband_education object
No_of_children_born float64
Wife_religion     object
Wife_Working      object
Husband_Occupation int64
Standard_of_living_index object
Media_exposure    object
Contraceptive_method_used object
dtype: object
```

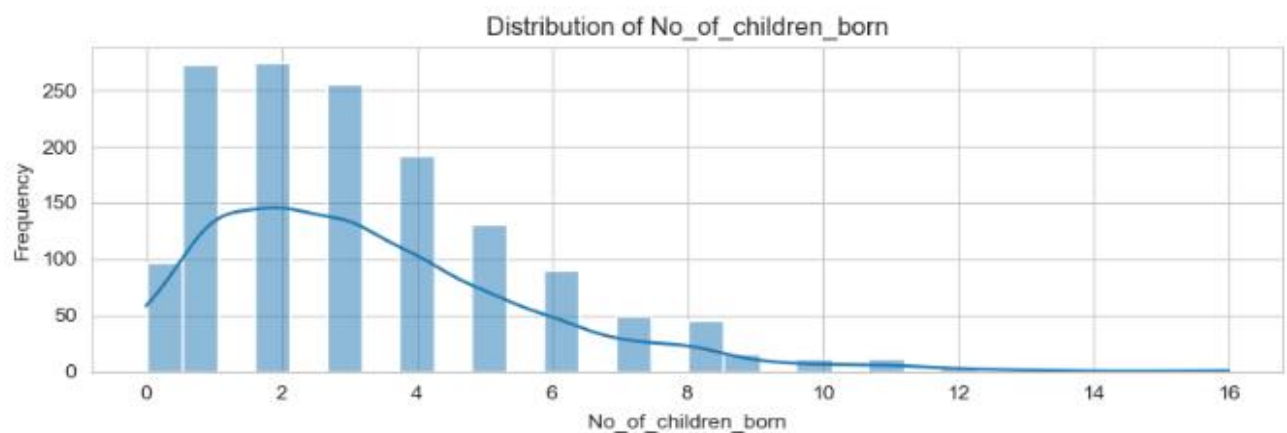
Statistical Summary:-

```
Statistical Summary:
count      Wife_age  No_of_children_born  Husband_Occupation
mean      32.606277      3.254132      2.137814
std        8.274927      2.365212      0.864857
min       16.000000      0.000000      1.000000
25%       26.000000      1.000000      1.000000
50%       32.000000      3.000000      2.000000
75%       39.000000      4.000000      3.000000
max       49.000000     16.000000      4.000000
```

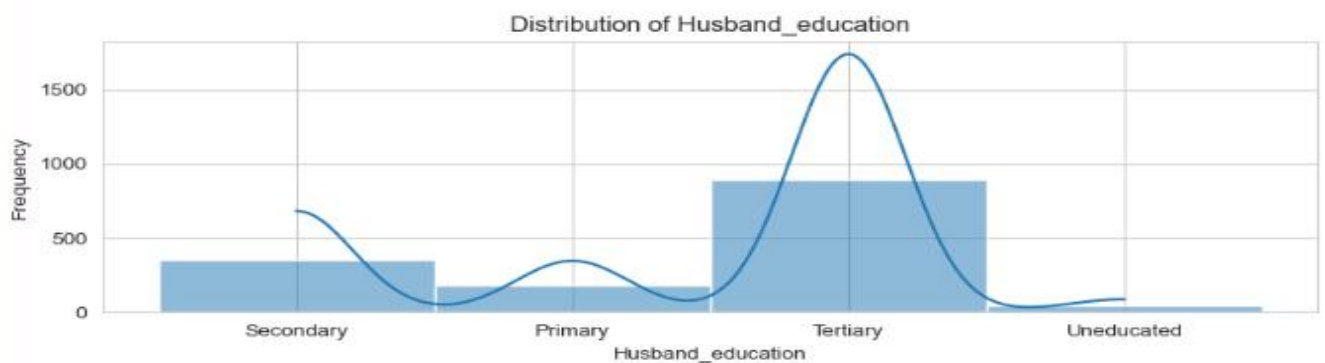
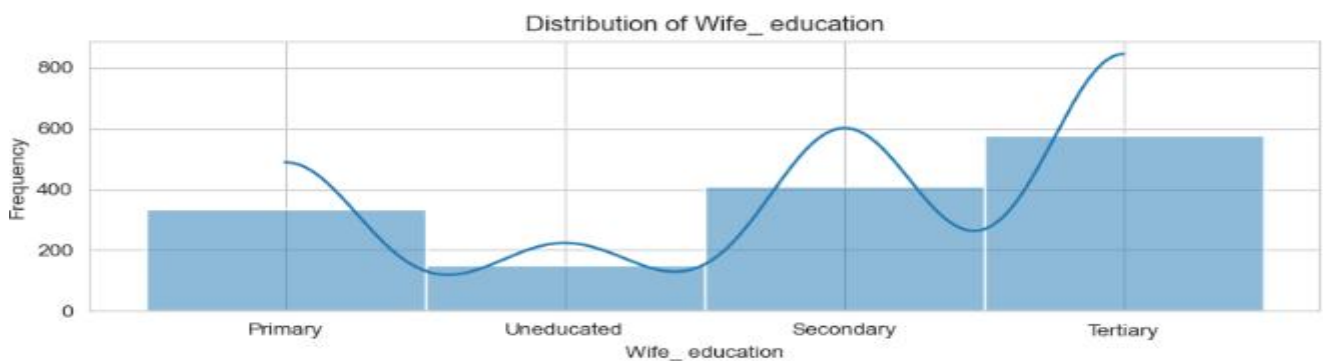

- **Uni-variate analysis:-**



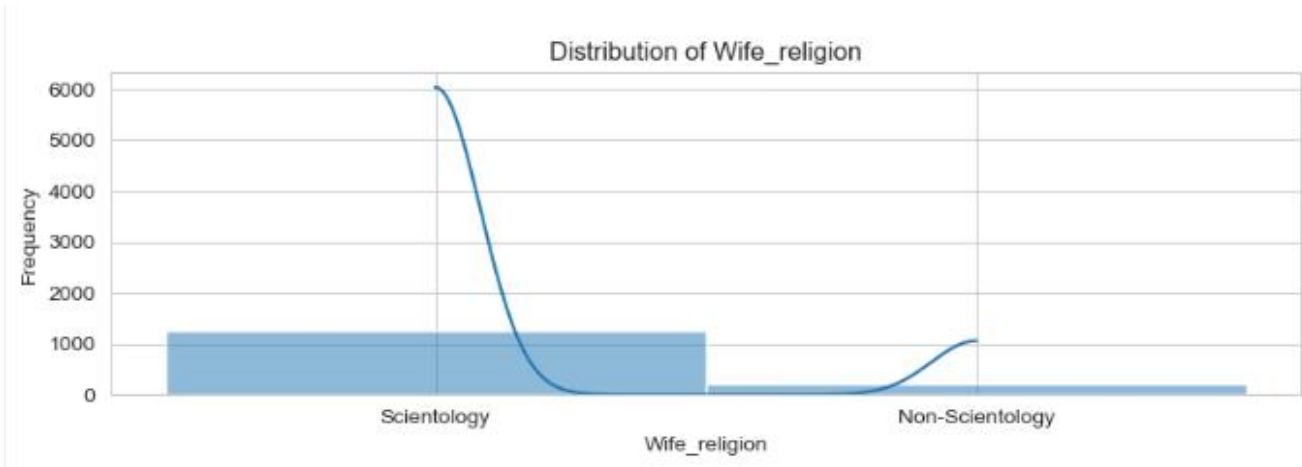
- The age of the wives B\W 17 - 49 years, where mostly they are in 28's and mid 20s - early 50s.



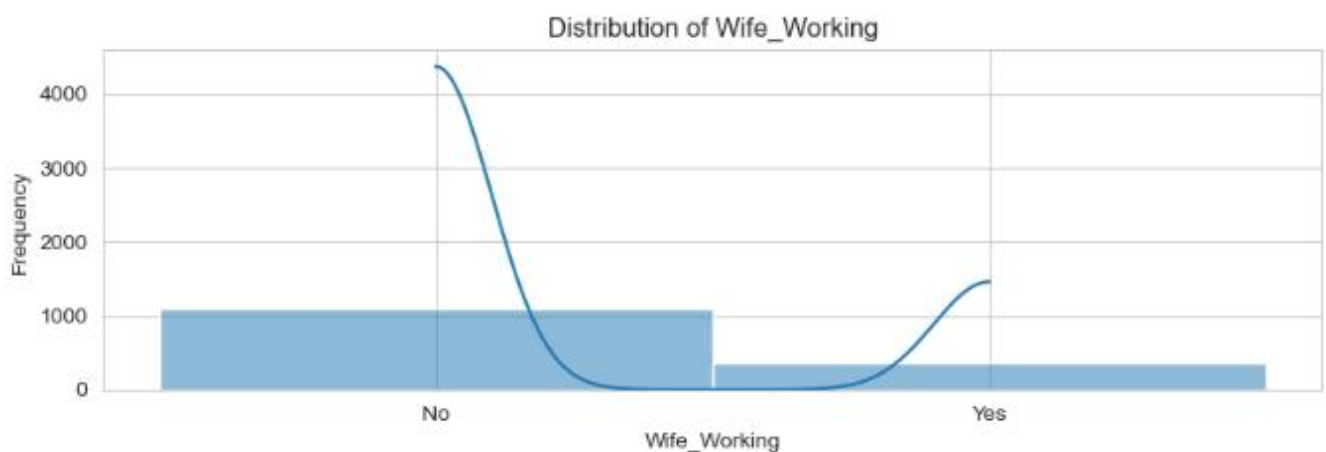
- Majority of the people have 1 or 2 children but a few people have more than 15 children as well.



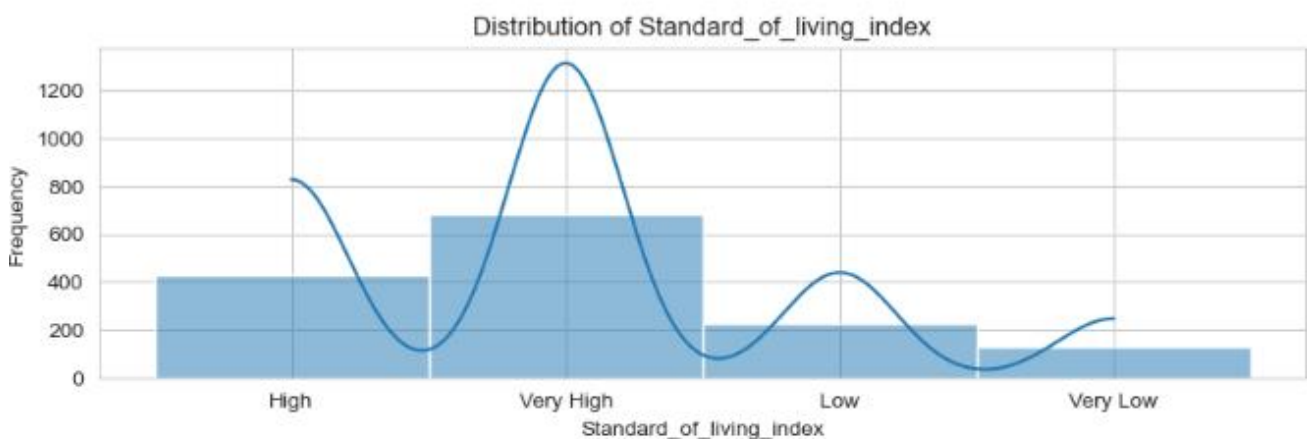
- Wives who have done their secondary and Tertiary education have used contraceptive methods more as compared to the others.
- Wives who are not educated or only completed Primary education are not to use any contraceptive methods.
- Commonly same thing find on the Husband's education.
- Fewer Husbands are uneducated as compared to the wives.



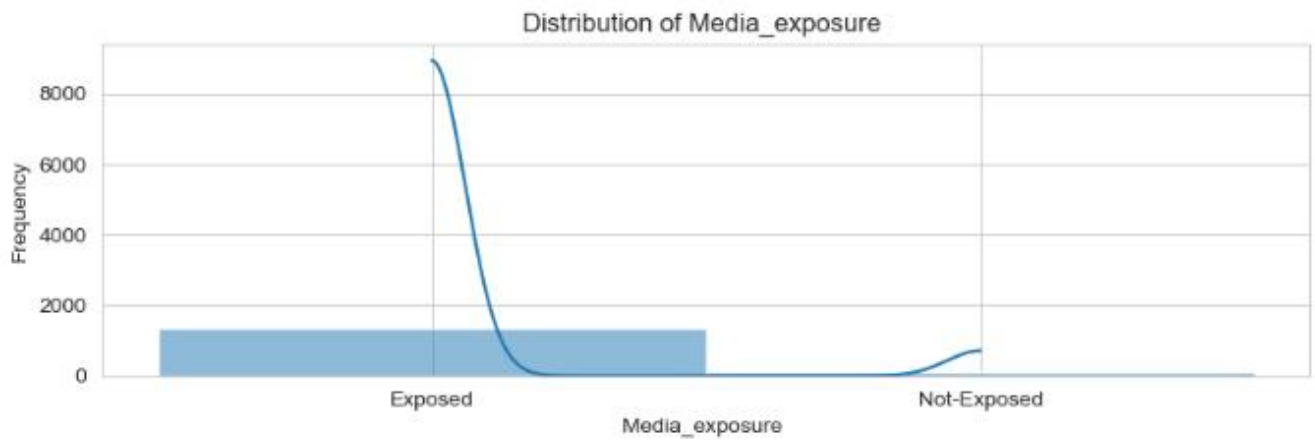
- Scientology is playing wider role in wife region.



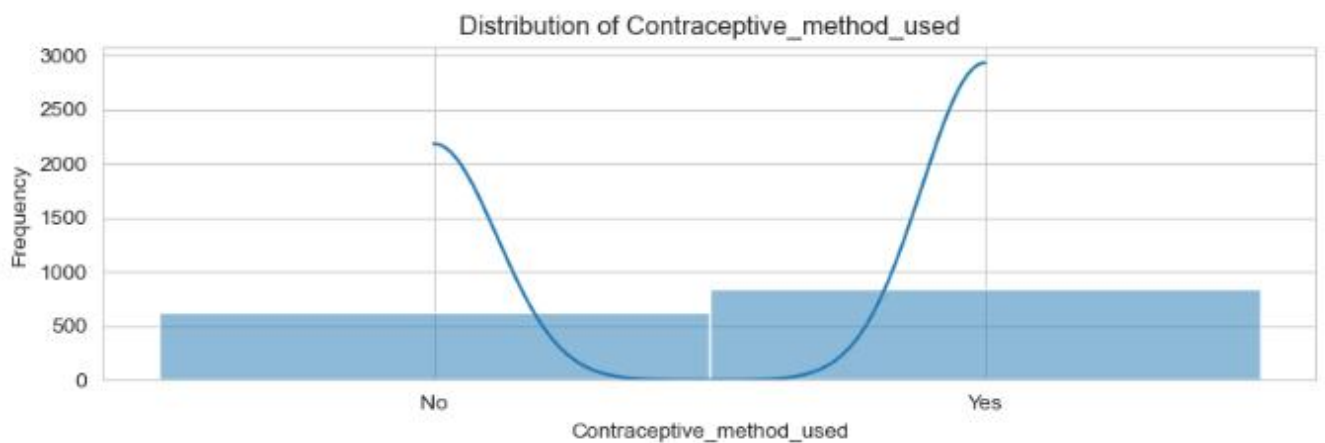
- Mostly Wives are not in working professional.



- Mostly people are belonging the areas where the standard of living is Very High and High.
- Nearly less than 250 people are belonging with Low and Very low standard of living index.

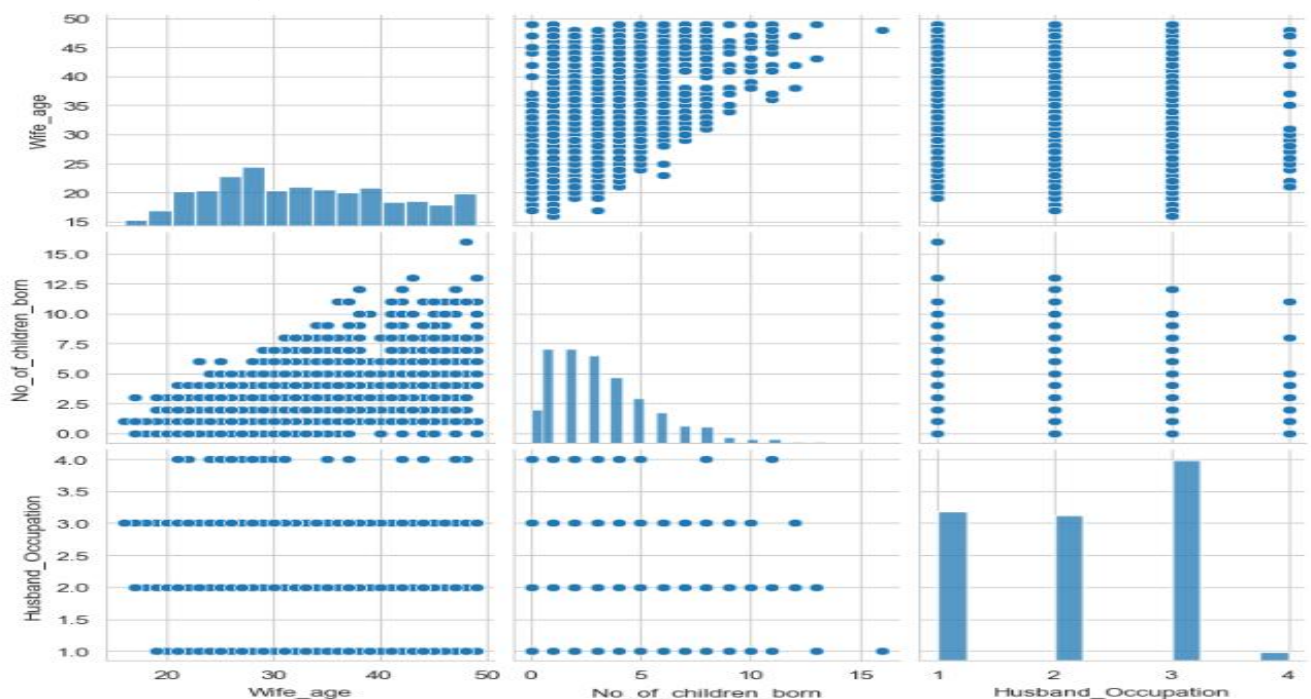


- Distribution of media exposure is quite better, its more than 1000.



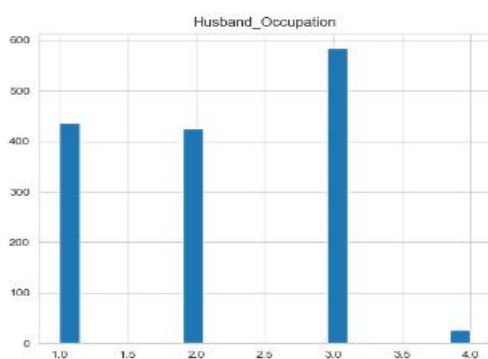
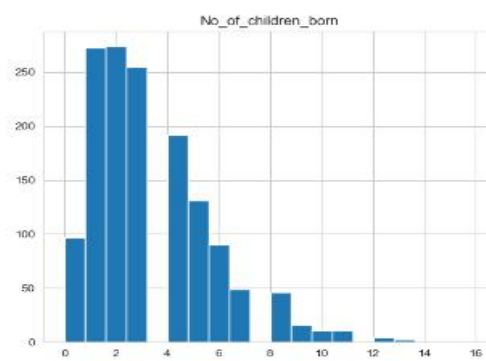
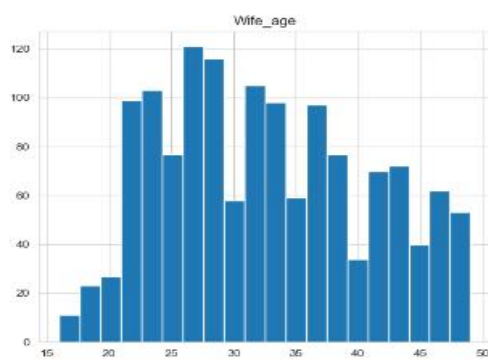
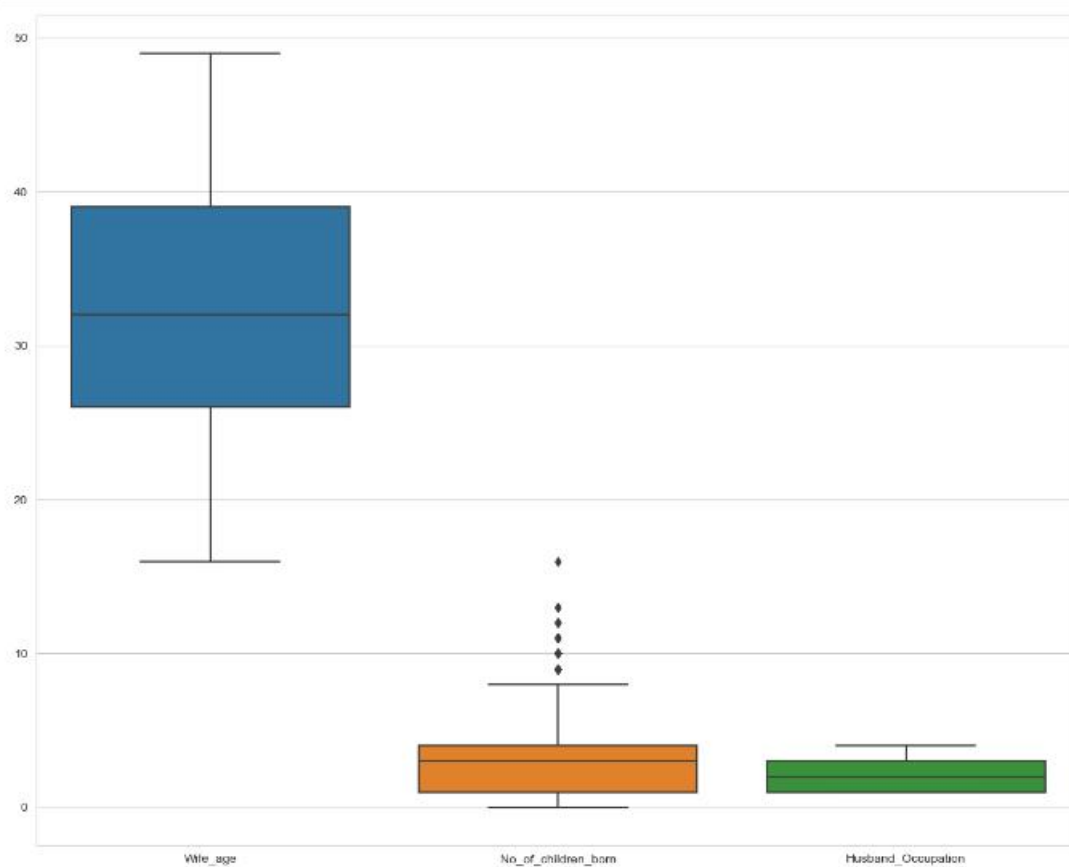
- As we already knew that, the mostly wives have used a contraceptive method, however there is a good proportional as well who have not used any.

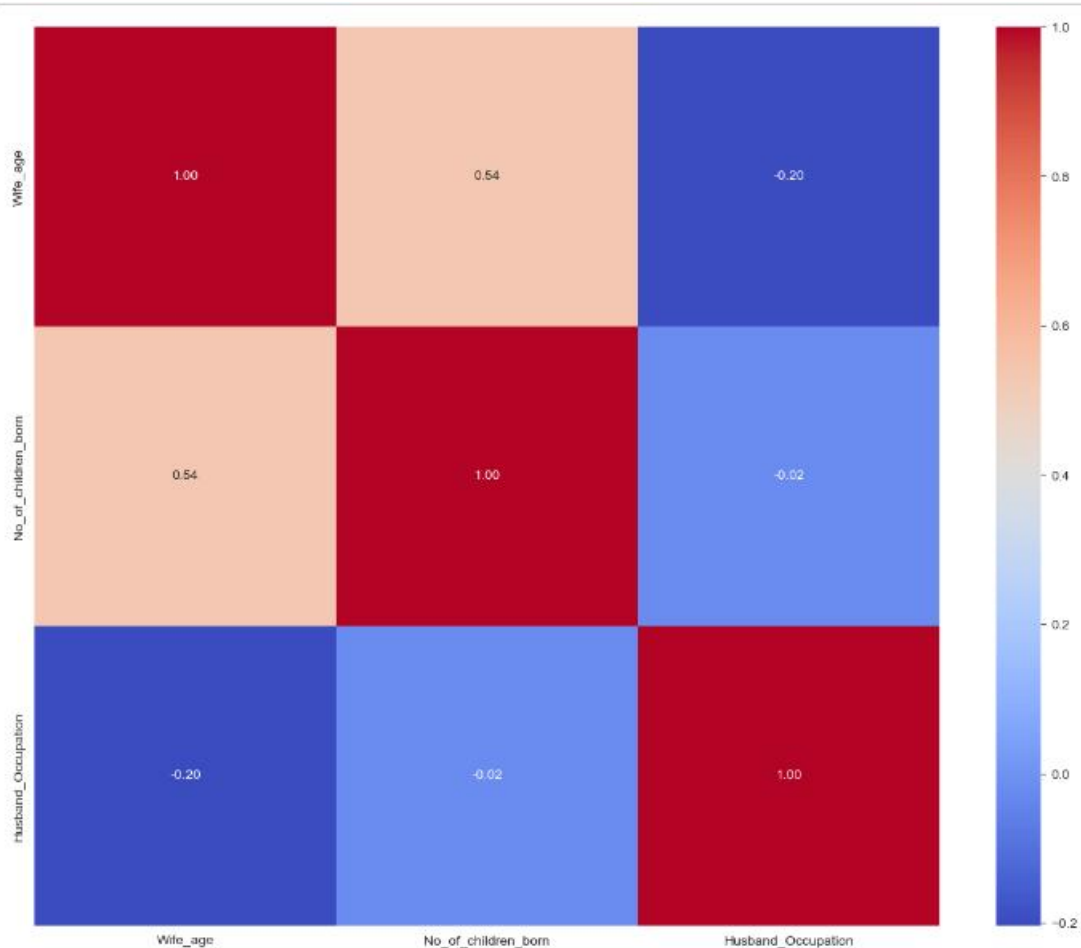
Multivariate analysis:-



- This plot does not identify any major trend/correlation between the variables.
- Very Few of the variables are available in the pair-plot, they don't have the classes of well separated. They will not be a good predictors.

Use appropriate visualizations to identify the patterns and insights:-





- Strong positive correlation shows b/w wife's age and husband's occupation.
- Strong negative correlation shows b/w number of children born and wife's age.
- Based on the above heat-map, it shows that couples where the wife was younger tended to have more children than couples where the wife was older. There are also a few with have much higher number of children born.

2.2 Data Pre-processing

Prepare the data for modelling: - Missing value Treatment (if needed) - Outlier Detection(treat, if needed)
- Feature Engineering (if needed) - Encode the data - Train-test split

Prepare the data for modelling: -

Missing value Treatment (if needed)

```
Wife_age          71
Wife_education    0
Husband_education 0
No_of_children_born 21
Wife_religion     0
Wife_Working      0
Husband_Occupation 0
Standard_of_living_index 0
Media_exposure    0
Contraceptive_method_used 0
dtype: int64
```

- There are 71 missing values are present in "wife_age" and 21 in "no_of_children_born". So now we treat the missing values.

AFTER TREATMENT:

```

Wife_age           0
Wife_education     0
Husband_education  0
No_of_children_born 0
Wife_religion      0
Wife_Working       0
Husband_Occupation 0
Standard_of_living_index 0
Media_exposure     0
Contraceptive_method_used 0
dtype: int64

```

Outlier Detection(treat, if needed)

```

Wife_age           0
Wife_education     0
Husband_education  0
No_of_children_born 97
Wife_religion      0
Wife_Working       0
Husband_Occupation 0
Standard_of_living_index 0
Media_exposure     0
Contraceptive_method_used 0
dtype: int64

```

- 97 Outliers are present. So, it has to treat the outliers.
- Now 'Husband_Occupation' has been also changed to Object data type as it is a categorical variable.
- There are 85 duplicate which can be dropped from the dataset.

Encode the data - Train-test split

- Data has string & categorical variables, these variables must be encoded so that the Machine Learning model understands the data.
- In the targeted variable, "No" is switched to 0 and "Yes" is switched to 1.
- Likewise, other no.'s are given to the values in variables Wife_education, Husband_education & Standard_of_living_index.
- After this, dummy encoding used to encode the data for the rest of the columns.
- After the encoded the data, the data-set has split-ting into training and testing in the 70:30 ratio.

Accuracy = 0.7152

```

X_train shape: (1178, 9)
X_test shape: (295, 9)
y_train shape: (1178,)
y_test shape: (295,)

```

2.3 Model Building and Compare the Performance of the Models:-

Build a Logistic Regression model - Build a Linear Discriminant Analysis model - Build a CART model - Prune the CART model by finding the best hyper parameters using Grid Search - Check the performance of the models across train and test set using different metrics - Compare the performance of all the models built and choose the best one with proper rationale

Build a Logistic Regression model:-

Accuracy: 0.6746

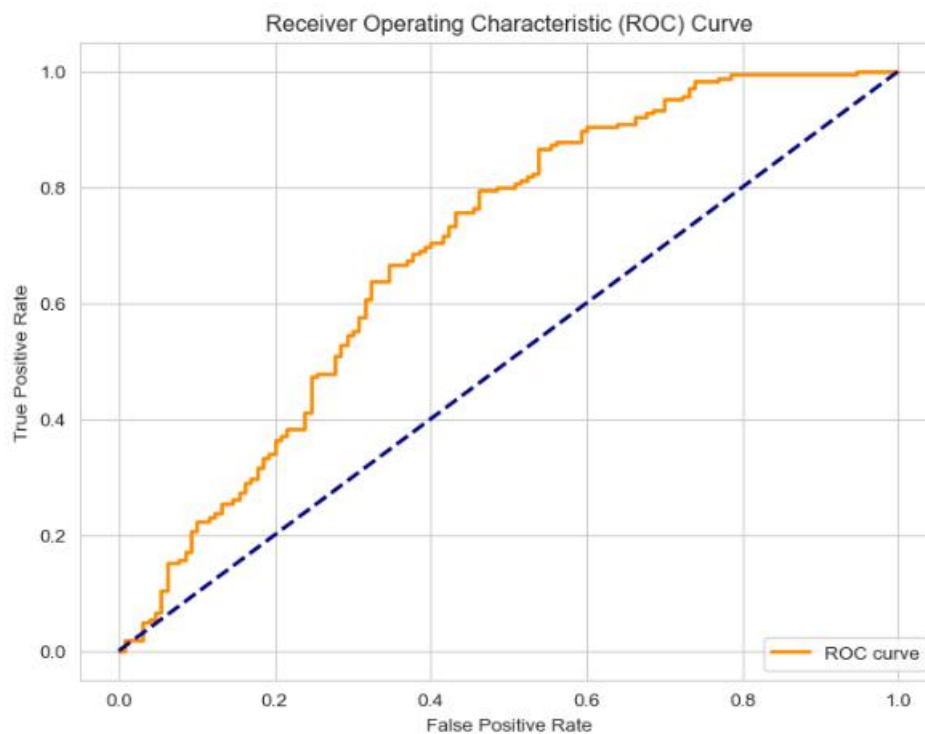
Confusion Matrix:

```
[[ 54  76]
 [ 20 145]]
```

Classification Report:

	precision	recall	f1-score	support
0	0.73	0.42	0.53	130
1	0.66	0.88	0.75	165
accuracy			0.67	295
macro avg	0.69	0.65	0.64	295
weighted avg	0.69	0.67	0.65	295

ROC AUC Score: 0.6943



Build a Linear Discriminant Analysis model:-

Accuracy: 0.6746

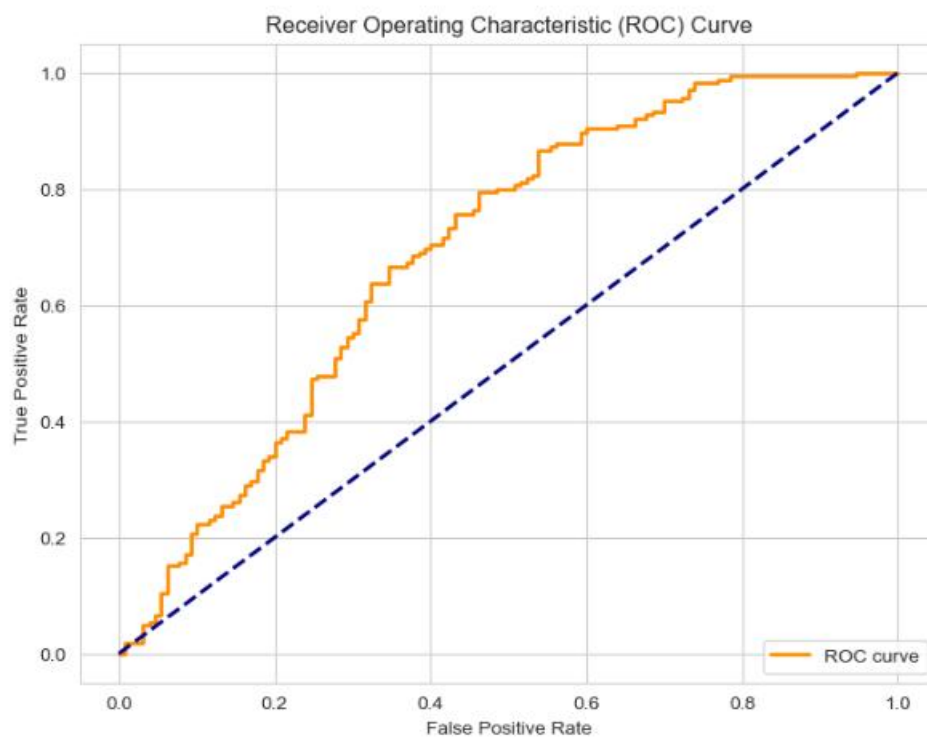
Confusion Matrix:

```
[[ 53  77]
 [ 19 146]]
```

Classification Report:

	precision	recall	f1-score	support
0	0.73	0.42	0.53	130
1	0.66	0.88	0.75	165
accuracy			0.67	295
macro avg	0.69	0.65	0.64	295
weighted avg	0.69	0.67	0.65	295

ROC AUC Score: 0.6943



Build a CART model:-

Accuracy: 0.6610

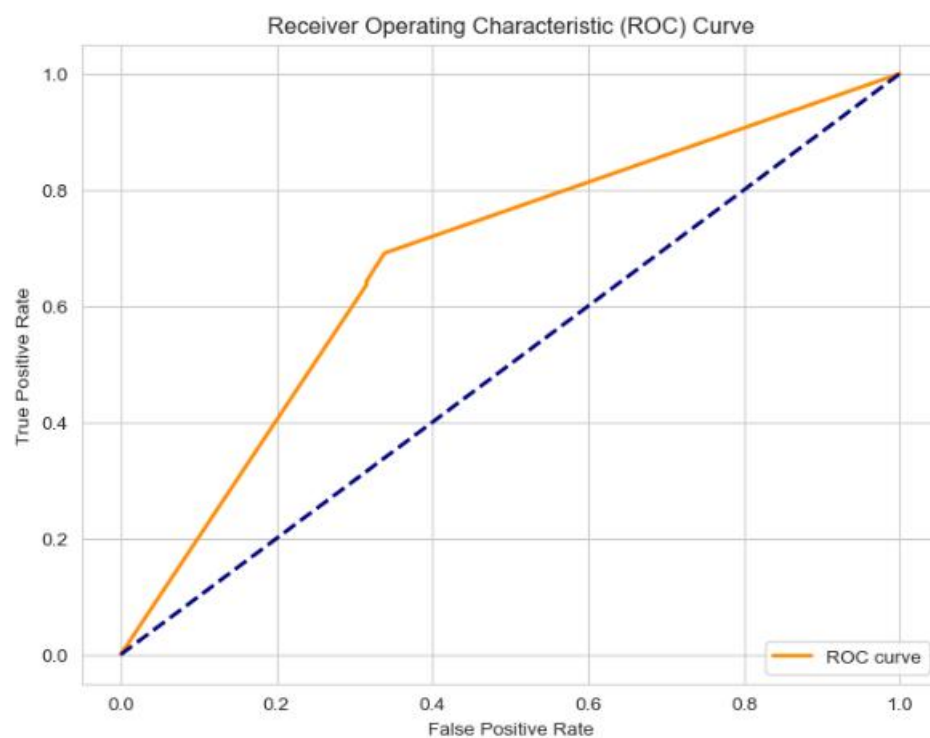
Confusion Matrix:

```
[[ 89  41]
 [ 59 106]]
```

Classification Report:

	precision	recall	f1-score	support
0	0.60	0.68	0.64	130
1	0.72	0.64	0.68	165
accuracy			0.66	295
macro avg	0.66	0.66	0.66	295
weighted avg	0.67	0.66	0.66	295

ROC AUC Score: 0.6750



Prune the CART model by finding the best hyper parameters using Grid Search:-

Best Hyperparameters: {'max_depth': 7, 'max_features': 'sqrt', 'min_samples_leaf': 2, 'min_samples_split': 2}

Accuracy with Best Hyperparameters: 0.6847

Check the performance of the models across train and test set using different metrics:-

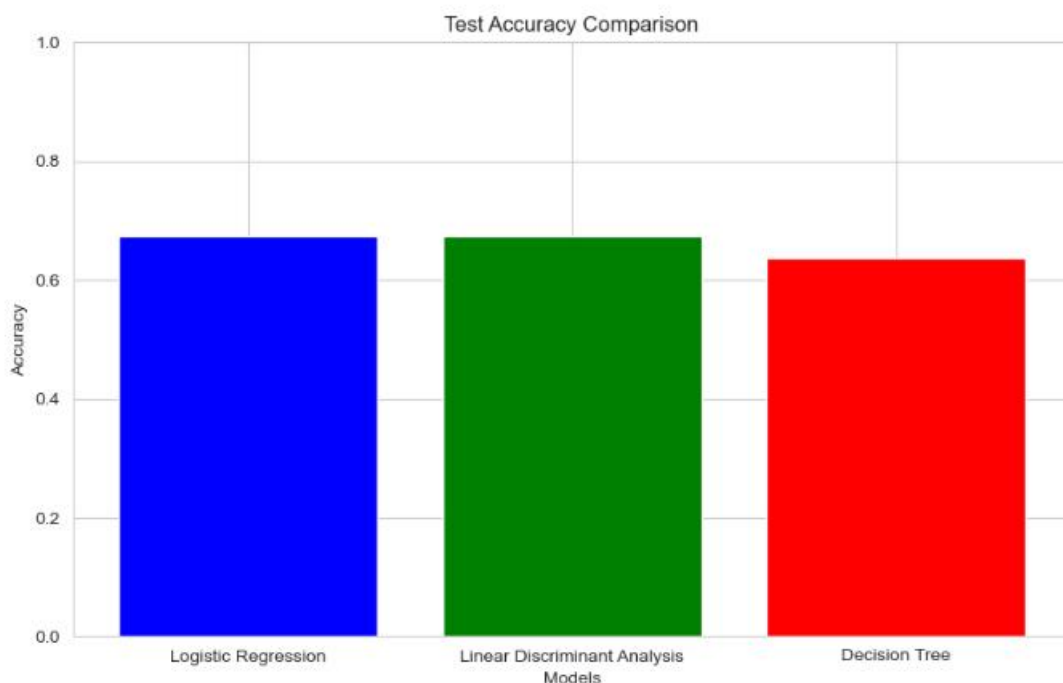
Logistic Regression:
 Train Accuracy: 0.6511035653650254
 Test Accuracy: 0.6745762711864407
 Train Precision: 0.6547344110854504
 Test Precision: 0.6561085972850679
 Train Recall: 0.8350515463917526
 Test Recall: 0.8787878787878788
 Train F1 Score: 0.7339805825242719
 Test F1 Score: 0.7512953367875648
 Train AUC-ROC: 0.6633030420192373
 Test AUC-ROC: 0.6922144522144522

Linear Discriminant Analysis:
 Train Accuracy: 0.6536502546689303
 Test Accuracy: 0.6745762711864407
 Train Precision: 0.6548571428571428
 Test Precision: 0.6547085201793722
 Train Recall: 0.8438880706921944
 Test Recall: 0.8848484848484849
 Train F1 Score: 0.7374517374517374
 Test F1 Score: 0.752577319587629
 Train AUC-ROC: 0.6633030420192373
 Test AUC-ROC: 0.6922144522144522

Decision Tree:
 Train Accuracy: 0.9770797962648556
 Test Accuracy: 0.6440677966101694
 Train Precision: 0.9909638554216867
 Test Precision: 0.6923076923076923
 Train Recall: 0.9690721649484536
 Test Recall: 0.6545454545454545
 Train F1 Score: 0.9798957557706628
 Test F1 Score: 0.6728971962616823
 Train AUC-ROC: 0.6633030420192373
 Test AUC-ROC: 0.6922144522144522

Compare the performance of all the models built and choose the best one with proper rationale:-

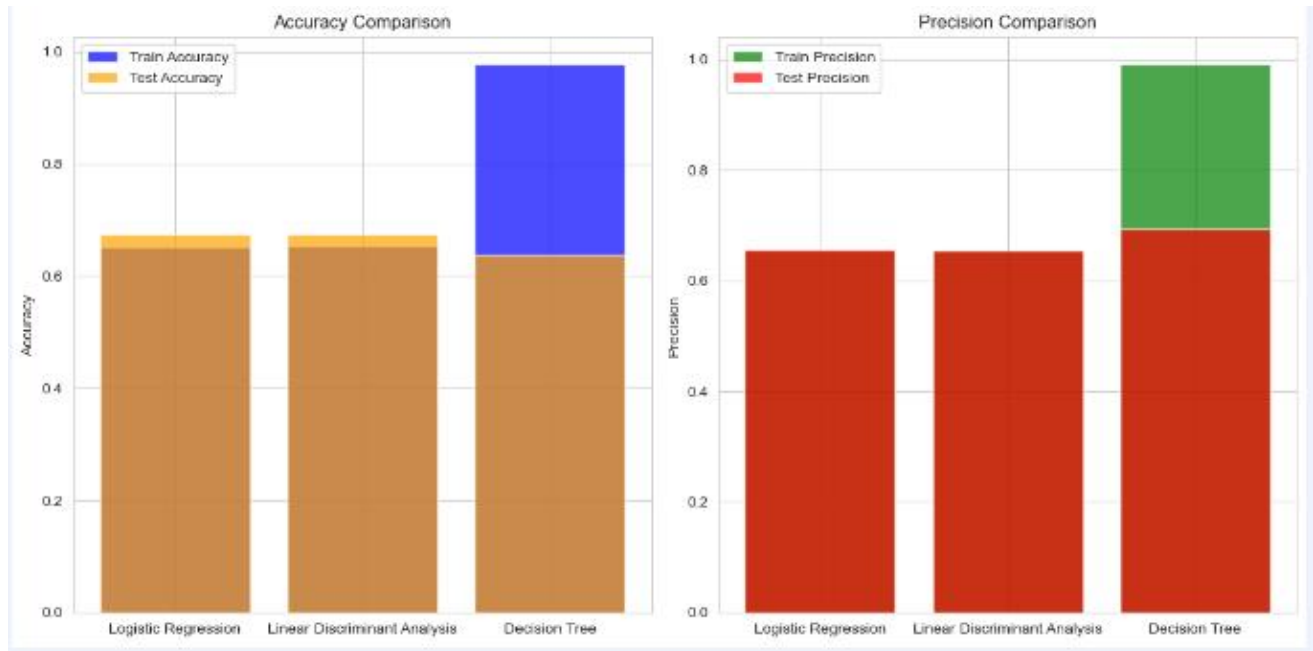
Accuracy score of all the models are above 65% for both test and train data.



- Accuracy: Logistic Regression and Linear Discriminant Analysis have similar test accuracy, but Logistic Regression has a slightly higher accuracy.
- Precision and Recall: Linear Discriminant Analysis has a higher test recall, indicating its ability to correctly identify positive cases. However, Logistic Regression also performs well.
- F1 Score: Linear Discriminant Analysis has a higher F1 score on the test set.

- **AUC-ROC:** Logistic Regression and Linear Discriminant Analysis have the same AUC-ROC on the test set.

Considering the overall performance across these metrics, Linear Discriminant Analysis seems to be a good choice. It strikes a balance between precision and recall, making it suitable for cases where both false positives and false negatives are important.



- **Performance Superiority of CART Model:** The text suggests that the CART model has outperformed all other models considered in the evaluation. The evaluation criterion used is accuracy, where the CART model achieves an accuracy value of 68%, indicating its effectiveness in predicting both classes of interest.
- **Accuracy and Recall Metrics:** The CART model not only achieves a high accuracy value but also demonstrates strong performance in terms of recall. Recall, measuring the ability to correctly identify true positives, is highlighted as a key metric. The CART model and the LDA model both show high recall values, but the slightly higher accuracy of the CART model favors its consideration for prediction.
- **Area Under the Curve (AUC) Analysis:** The AUC, a common metric used in evaluating the performance of classification models, is mentioned. While the AUC values of 82% for the train data and 72% for the test data are acknowledged as not being the best, they still surpass the performance of other models considered. This indicates that the CART model exhibits good discriminative ability.
- **Recommendation for Prediction:** The text concludes that, based on the observed performance metrics, the CART model is suitable for making predictions on unseen data. The combination of high accuracy, recall, and competitive AUC values supports the recommendation to use the CART model in practical predictions.
- **Consideration for Unseen Data:** The statement emphasizes the robustness of the CART model by suggesting that it can be confidently used for making predictions on any unseen data fed to the model. This is a crucial aspect, indicating the generalization capability of the model beyond the training and evaluation data.

2.4 Business Insights & Recommendations:-

- **Wife's Education and Number of Children Born:** Both the Logistic Regression and CART models highlight the importance of the wife's education and the number of children born as key features. These features are identified as significant factors in determining whether women will use contraceptive methods. The emphasis on these variables suggests that they play a crucial role in influencing the decision-making process.
- **Husband's Education:** The text mentions that both models indicate the importance of the husband's education. The suggestion is that, in real-life scenarios, the husband's education

level can have an impact on the wife's decision to use contraceptive methods. This implies a social or contextual influence where the husband's education is considered a relevant factor in the decision-making process.

- **Importance of Features:** The repeated emphasis on the importance of specific features, such as the education levels of both the wife and husband, as well as the number of children born, underscores their significance in predicting contraceptive usage. These features are likely strong predictors in the models, contributing significantly to their predictive performance.
- **Real-World Relevance:** The mention that the importance of husband's education "makes sense" implies a real-world applicability and relevance of the identified features. It suggests that the models are aligning with common societal expectations or patterns where education levels, both of the wife and husband, can influence decisions related to family planning and contraceptive use.
- **Standard of Living Influence:** The statement suggests that women from areas with high and very high standards of living are more likely to use contraceptive methods. This could be indicative of socio-economic factors playing a role in family planning decisions.
- **Age and Education Level:** Women between the ages of 25 to 35 with a good education level are identified as more likely to use contraceptives. This aligns with the understanding that education and age can impact family planning decisions.
- **Husband's Education:** The education level of the husband is highlighted as a significant factor influencing whether the wife will use contraceptive methods. This reinforces the notion that spousal education levels can be interconnected with family planning decisions.
- **Understanding Non-Parental Contraceptive Users:** Expressing the need to understand the viewpoint of women who do not have any children but are still using contraceptives is an important consideration. It suggests the importance of exploring the motivations and circumstances surrounding this demographic.
- **Role of Media Exposure:** The statement recognizes the key role of media exposure in family planning decisions. This underscores the influence of media in shaping perceptions and awareness regarding contraceptive methods.
- **Health Ministry Outreach:** Suggesting that the Republic of Indonesia Ministry of Health can reach out to women who do not use contraceptives for education and awareness indicates a proactive approach to address potential gaps in knowledge or accessibility.
- **Analysis of Education Levels 8, 10, 11, & 12:** Noting that wives with education levels 8, 10, 11, and 12 do not use contraceptives raises a specific area of interest. Further investigation into the reasons behind this pattern could provide valuable insights into cultural, social, or individual factors influencing contraceptive decisions.