PM Project - Coded

[F A S N A . P P]
[1 4 - 0 1 - 2 0 2 4]

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Problem - 1

Context

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, you 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.

Data Description :

System measures used:

lread - Reads (transfers per second) between system memory and user memory

lwrite - writes (transfers per second) between system memory and user memory

scall - Number of system calls of all types per second

sread - Number of system read calls per second .

swrite - Number of system write calls per second .

fork - Number of system fork calls per second.

exec - Number of system exec calls per second.

rchar - Number of characters transferred per second by system read calls

wchar - Number of characters transfreed per second by system write calls

pgout - Number of page out requests per second

ppgout - Number of pages, paged out per second

pgfree - Number of pages per second placed on the free list.

pgscan - Number of pages checked if they can be freed per second

atch - Number of page attaches (satisfying a page fault by reclaiming a page in memory) per second

pgin - Number of page-in requests per second

ppgin - Number of pages paged in per second

pflt - Number of page faults caused by protection errors (copy-on-writes).

vflt - Number of page faults caused by address translation .

runqsz - Process run queue size (The number of kernel threads in memory that are waiting for a CPU to run.Typically, this value should be less than 2. Consistently higher values mean that the system might be CPU-bound.)

freemem - Number of memory pages available to user processes

freeswap - Number of disk blocks available for page swapping.

usr - Portion of time (%) that cpus run in user mode

Problem 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.

- importing libaries
- NumPy is a powerful library for numerical operations in Python
- Pandas is a data manipulation library
- Seaborn is a statistical data visualization library based on Matplotlib
- fitting linear regression models and making predictions based on the input features.
- The metrics module in scikit-learn provides various metrics for evaluating the performance of machine learning model.
- Matplotlib is a plotting library in Python
  This import allows you to customize the style of your Matplotlib plots.
- read the data set"compactiv.xlsx"
- print first 5 rows of data set

	lread	lwrite	scall	sread	swrite	fork	exec	rchar	wchar	pgout	...	pgscan	atch	pgin	ppgin	pflt	vflt	runqsz	freemem	freeswap	usr
0	1	0	2147	79	68	0.2	0.2	40671.0	53995.0	0.0	...	0.0	0.0	1.6	2.6	16.00	26.40	CPU_Bound	4670	17309466	95
1	0	0	170	18	21	0.2	0.2	4480	8385.0	0.0	...	0.0	0.0	0.0	0.0	15.63	16.83	Not_CPU_Bound	7278	18690002	97
2	15	3	211	155	111	2.	2.	Na	311	0.	...	0.0	1.	6.	9.	15	22	Not_C	70	10	87

	lread	lwrite	scall	sread	swrite	fork	exec	rchar	wchar	pgout	...	pgscan	atch	pgin	ppgin	pflt	vflt	runqsz	freemem	freeswap	usr
			62	9	9	0	4	N	950.0	0	.		2	0	4	0.20	0.20	PU_Bound	2	2123737	
3	0	0	1600	12	16	0.2	0.2	NaN	8670.0	0.0	...	0.0	0.0	0.2	0.2	15.60	16.80	Not_CPU_Bound	7248	18637044	98
4	5	1	3330	39	38	0.4	0.4	NaN	121185.0	0.0	...	0.0	0.0	1.0	1.2	37.80	47.60	Not_CPU_Bound	633	17602533	90

Table -1-First 5 rows of the dataset

Check shape

check the shape of the data set

(8192, 22)

data set have 8192 rows and 22 columns

Data types

check the data types of te each column of the data set

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8192 entries, 0 to 8191
Data columns (total 22 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   lread     8192 non-null   int64
 1   lwrite    8192 non-null   int64
 2   scall     8192 non-null   int64
 3   sread     8192 non-null   int64
 4   swrite    8192 non-null   int64
 5   fork      8192 non-null   float64
 6   exec      8192 non-null   float64
 7   rchar     8088 non-null   float64
 8   wchar     8177 non-null   float64
 9   pgout     8192 non-null   float64
 10  ppgout    8192 non-null   float64
```

```
 11  pgfree    8192 non-null   float64
 12  pgscan    8192 non-null   float64
 13  atch      8192 non-null   float64
 14  pgin      8192 non-null   float64
 15  ppgin     8192 non-null   float64
 16  pflt      8192 non-null   float64
 17  vflt      8192 non-null   float64
 18  runqsz    8192 non-null   object
 19  freemem   8192 non-null   int64
 20  freeswap  8192 non-null   int64
 21  usr       8192 non-null   int64
dtypes: float64(13), int64(8), object(1)
memory usage: 1.4+ MB
```

13 float ,8 int,1 object data types in the data set

statistical summary

statistical summary of the data set

	lread	lwrite	scall	sread	swrite	fork	exec	rchar	wchar	pgout	...	pgfree	pgscan	atch	pgin	ppgin	pflt	vflt	freemem	freeswap	usr
count	8192.000000	8192.000000	8192.000000	8192.000000	8192.000000	8192.000000	8192.000000	8.088000e+03	8.177000e+03	8192.000000	...	8192.000000	8192.000000	8192.000000	8192.000000	8192.000000	8192.000000	8192.000000	8192.000000	8.192000e+03	8192.000000
mean	19.559692	13.106201	2306.318237	210.479980	150.058228	1.884554	2.791998	1.973857e+05	9.590299e+04	2.285317	...	11.919712	21.526849	1.127505	8.277960	12.388586	109.793799	185.315796	1763.456299	1.326812e+06	83.968872
std	53.353799	29.891726	1633.613722	198.980146	160.478980	2.479493	5.212456	2.398375e+05	1.408417e+05	5.307038	...	32.363520	71.141340	5.708347	13.874978	22.281318	114.419221	191.006003	2482.104511	4.220194e+05	18.401905
min	0.000000	0.000000	109.000000	6.000000	7.000000	0.000000	0.000000	2.780000e+02	1.498000e+03	0.000000	...	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.200000	55.000000	2.000000e+00	0.000000
2	2.	0.	10	86	63	0.	0.	3.4	2.2	0.	.	0.	0.	0.	0.	0.	25	45	23	1.04	81.00

	lread	lwrite	scall	sread	swrite	fork	exec	rchar	wchar	pgout	...	pgfree	pgscan	atch	pgin	ppgin	pflt	vflt	freemem	freeswap	usr
5%	000000	000000	12.000000	.000000	.000000	400000	200000	09150e+04	91600e+04	000000	...	000000	000000	000000	600000	600000	.000000	.400000	1.000000	2624e+06	0000
50%	7.000000	1.000000	2051.500000	166.000000	117.000000	0.800000	1.200000	1.254735e+05	4.661900e+04	0.000000	...	0.000000	0.000000	0.000000	2.800000	3.800000	63.800000	120.400000	579.000000	1.28929e+06	89.000000
75%	20.000000	10.000000	3317.250000	279.000000	185.000000	2.200000	2.800000	2.678288e+05	1.061010e+05	2.400000	...	5.000000	0.000000	0.600000	9.765000	13.800000	159.600000	251.800000	2002.250000	1.73038e+06	94.000000
max	1845.000000	575.000000	12493.000000	5318.000000	5456.000000	20.120000	59.560000	2.526649e+06	1.801623e+06	81.440000	...	523.000000	1237.000000	211.580000	141.200000	292.610000	899.800000	1365.000000	12027.000000	2.243187e+06	99.000000

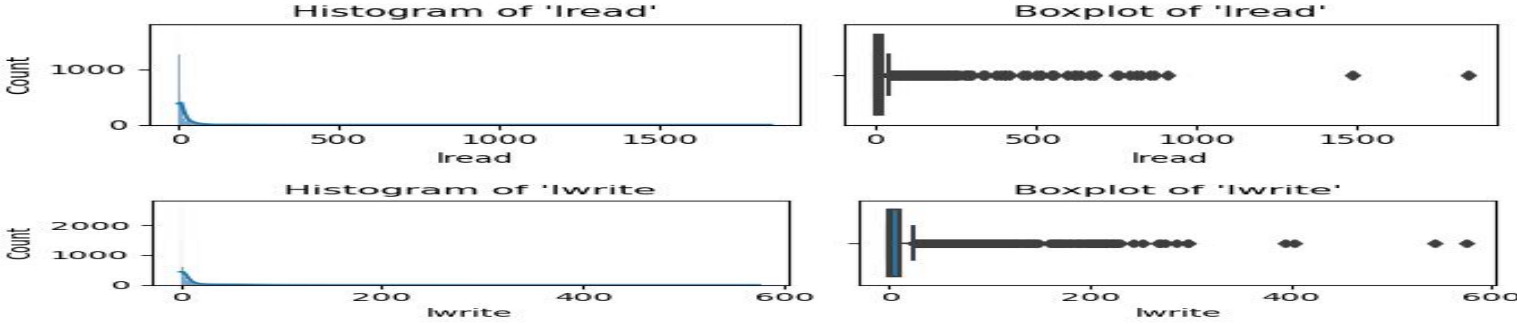
Table-2-statistical summary of the data set

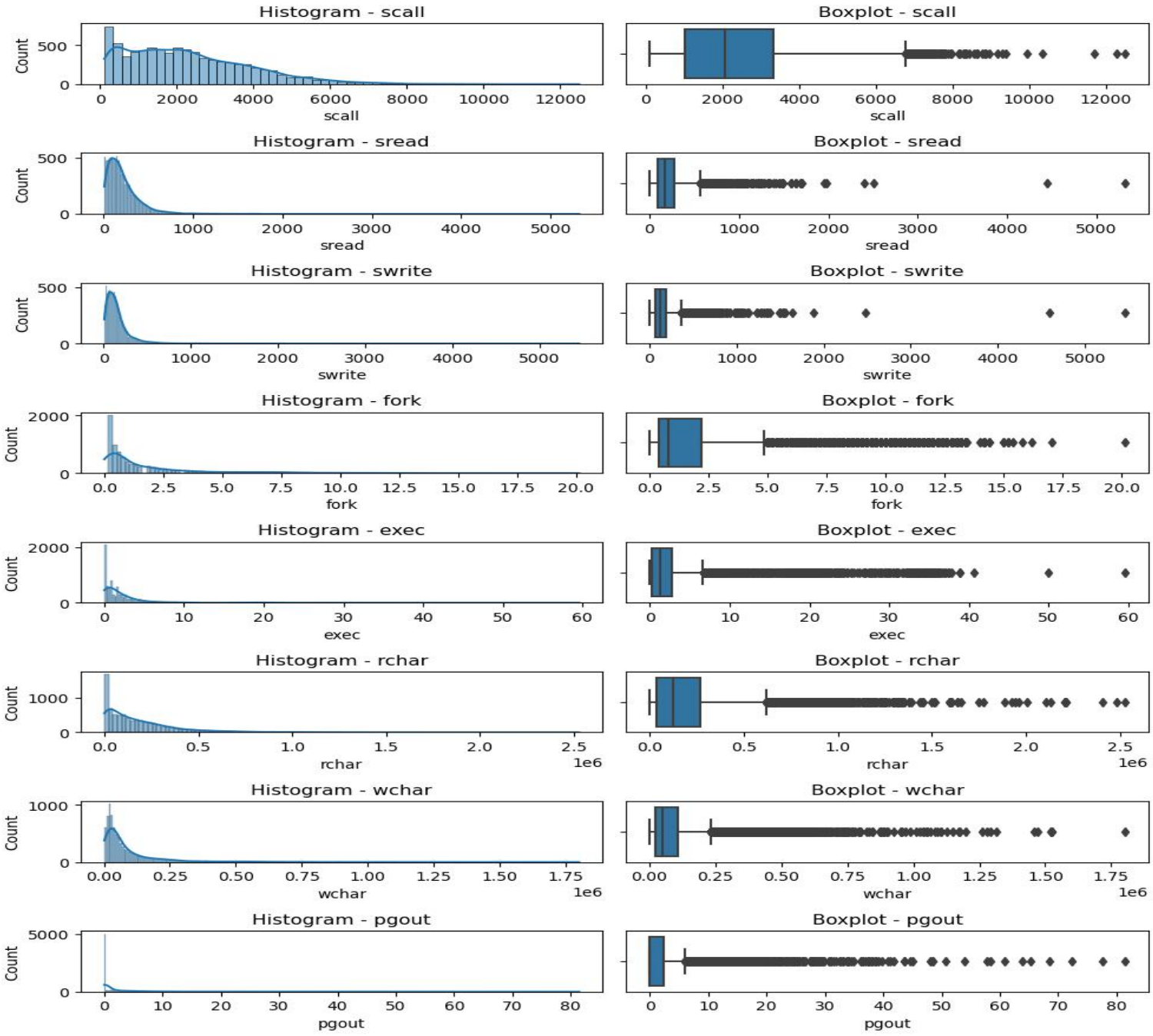
Univariate analysis

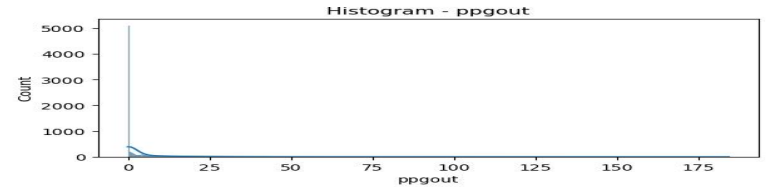
- create new data frame with all numerical variables
- Numerical columns

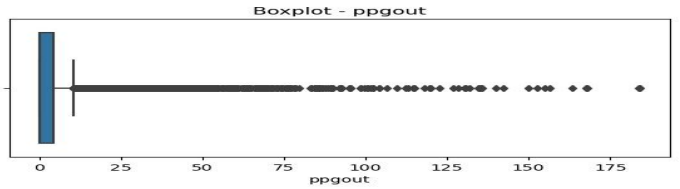
['lread', 'lwrite', 'scall', 'sread', 'swrite', 'fork', 'exec', 'rchar','wchar', 'pgout,'ppgout','pgfree', 'pgscan', 'atch', 'pgin', 'ppgin', 'pflt', 'vflt', 'freemem', 'freeswap', 'usr']

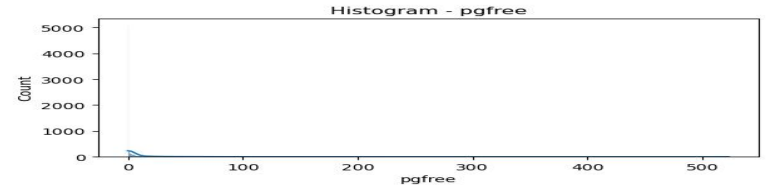
- create data frame with all categorical variable
- create histograms and box plots of numerical variables

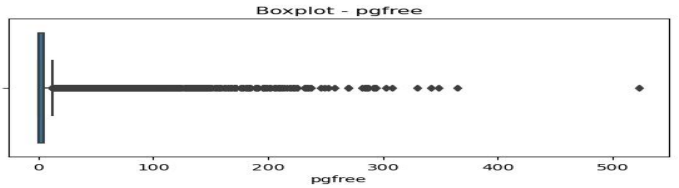


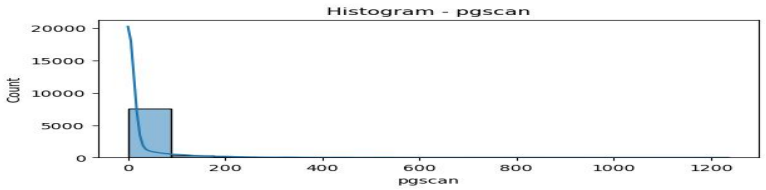

Histogram - scall
Boxplot - scall
Histogram - sread
Boxplot - sread
Histogram - swrite
Boxplot - swrite
Histogram - fork
Boxplot - fork
Histogram - exec
Boxplot - exec
Histogram - rchar
Boxplot - rchar
Histogram - wchar
Boxplot - wchar
Histogram - pgout
Boxplot - pgout
Count
scall
sread
swrite
fork
exec
rchar
wchar
pgout
1e6

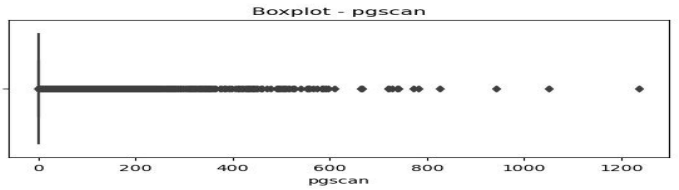

Histogram - ppgout
Count
ppgout

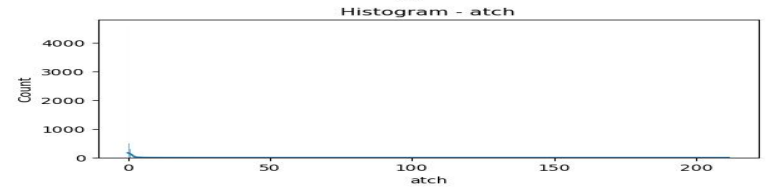

Boxplot - ppgout
ppgout

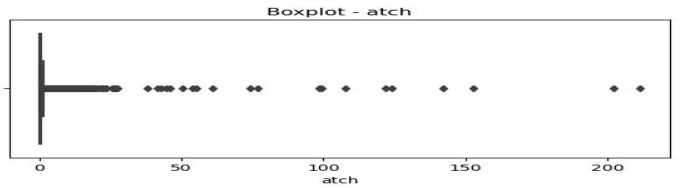

Histogram - pgfree
Count
pgfree

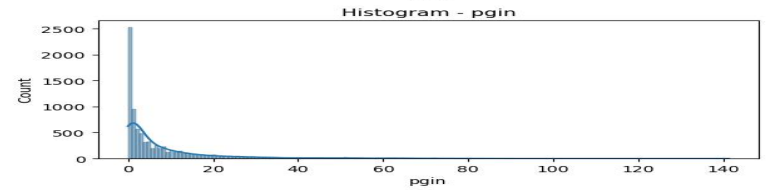

Boxplot - pgfree
pgfree

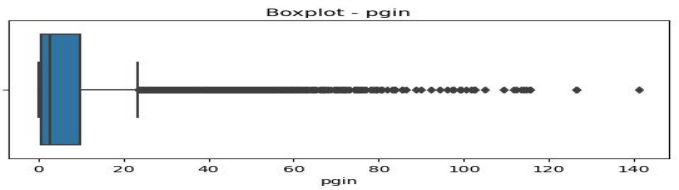

Histogram - pgscan
Count
pgscan

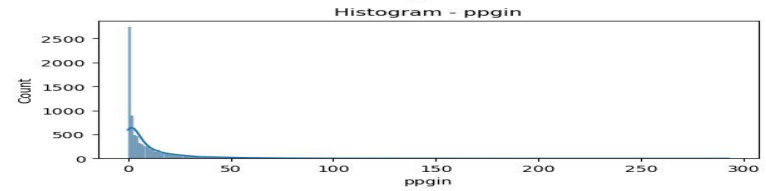

Boxplot - pgscan
pgscan

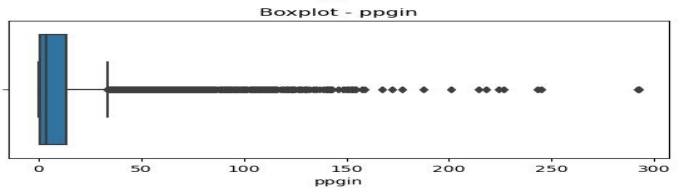

Histogram - atch
Count
atch

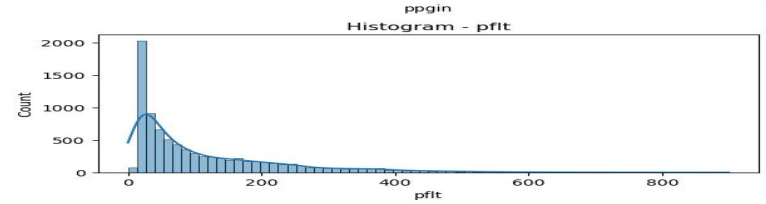

Boxplot - atch
atch

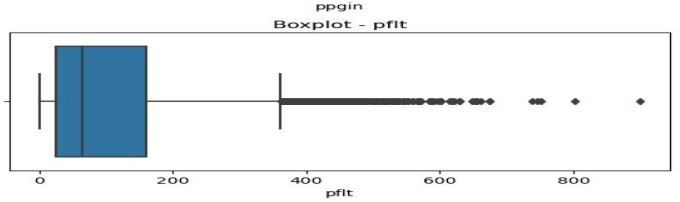

Histogram - pgin
Count
pgin

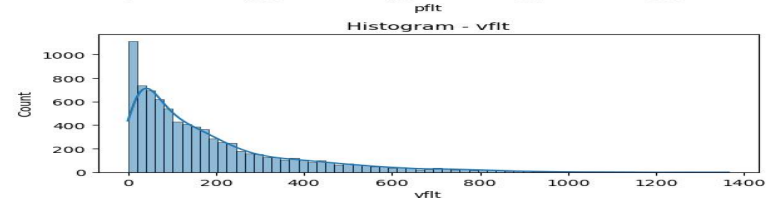

Boxplot - pgin
pgin

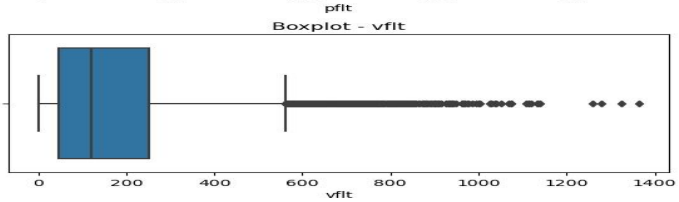

Histogram - ppgin
Count
ppgin

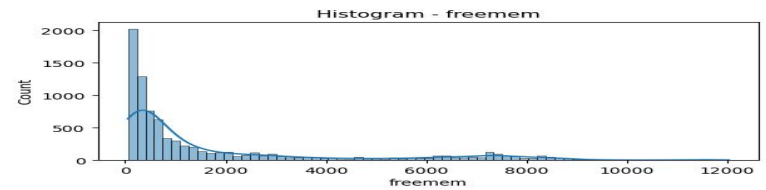

Boxplot - ppgin
ppgin

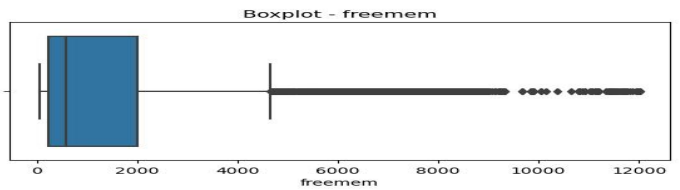

Histogram - pflt
Count
pflt

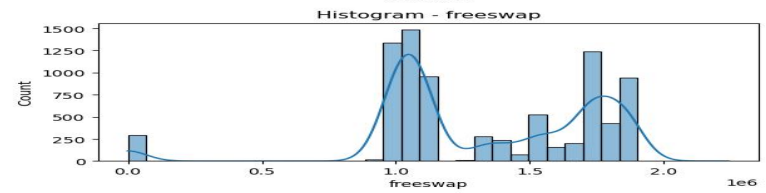

Boxplot - pflt
pflt

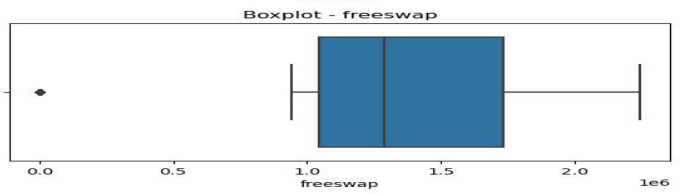

Histogram - vflt
Count
vflt

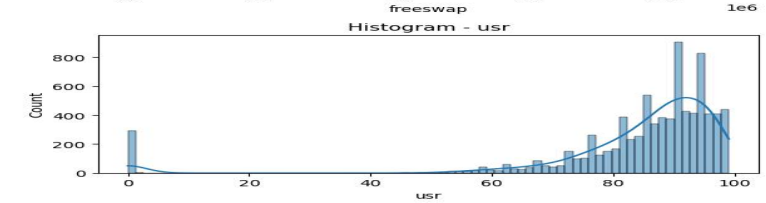

Boxplot - vflt
vflt


Histogram - freemem
Count
freemem


Boxplot - freemem
freemem


Histogram - freeswap
Count
freeswap
1e6


Boxplot - freeswap
freeswap
1e6


Histogram - usr
Count
usr

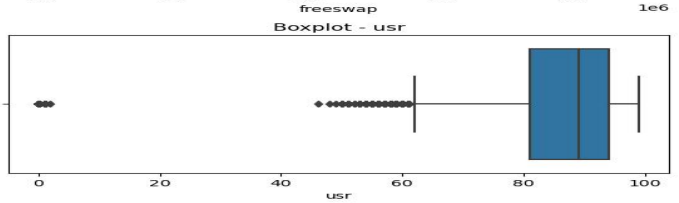

Boxplot - usr
usr

Figure-1-histograms and box plots of numerical variables

- 'lread', 'lwrite', 'scall', 'sread', 'swrite', 'fork', 'exec', 'rchar', 'wchar', 'pgout', 'ppgout', 'pgfree', 'pgscan', 'atch', 'pgin', 'ppgin', 'pflt', 'vflt', 'freemem' these have outliers in higher values.
- 'freeswap','usr' these 2 have outliers in lower values.

uni variate analysis for categorical variable

#count plot of runqsz

Figure-2-count plot of runqsz

Process run queue size is not_cpu_bond(less than 2) more than cpu_bond.

Multivariate analysis

#plot the correlation map

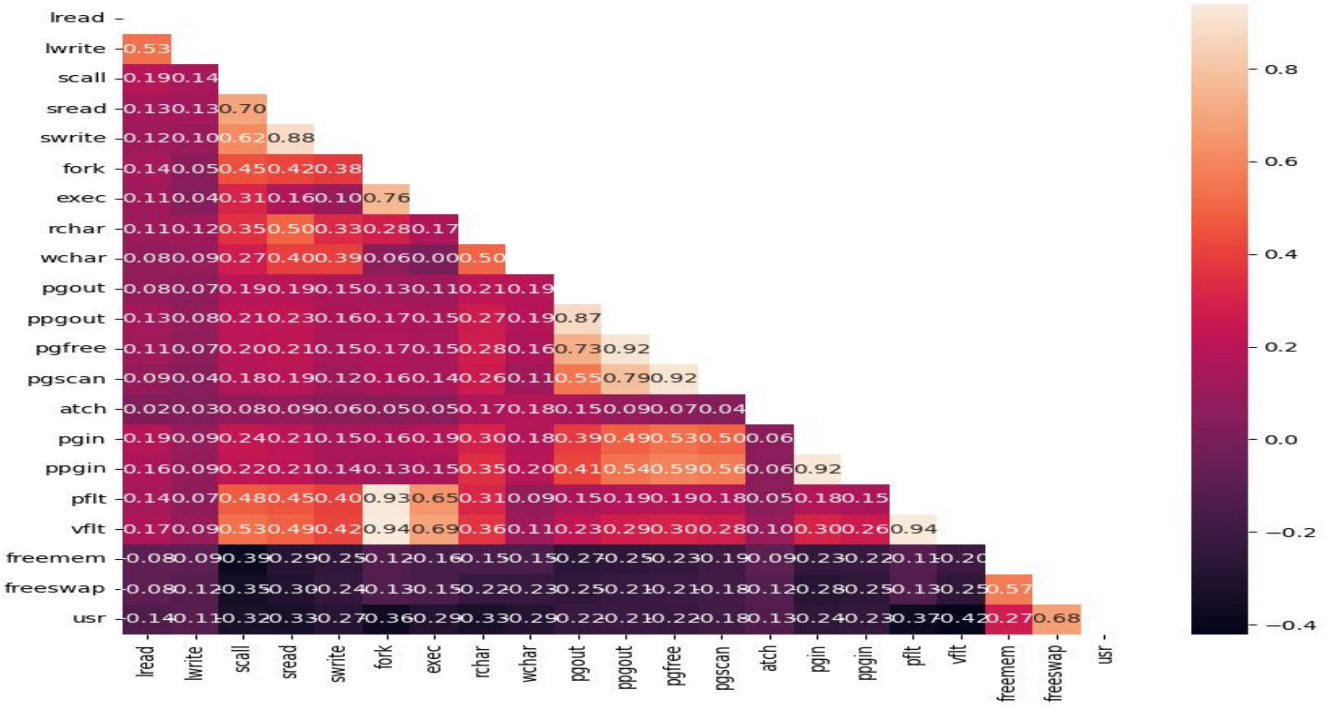


Figure-3-correlation map

- usr is highly correlated between freemem,freeswap.
- usr is negatively correlated between other 'lread', 'lwrite', 'scall', 'sread', 'swrite', 'fork', 'exec', 'rchar', 'wchar', 'pgout', 'ppgout', 'pgfree', 'pgscan', 'atch', 'pgin', 'ppgin', 'pflt', 'vflt'.
- fork is highly correlated between pflt,vflt.

```
#pair plot
```

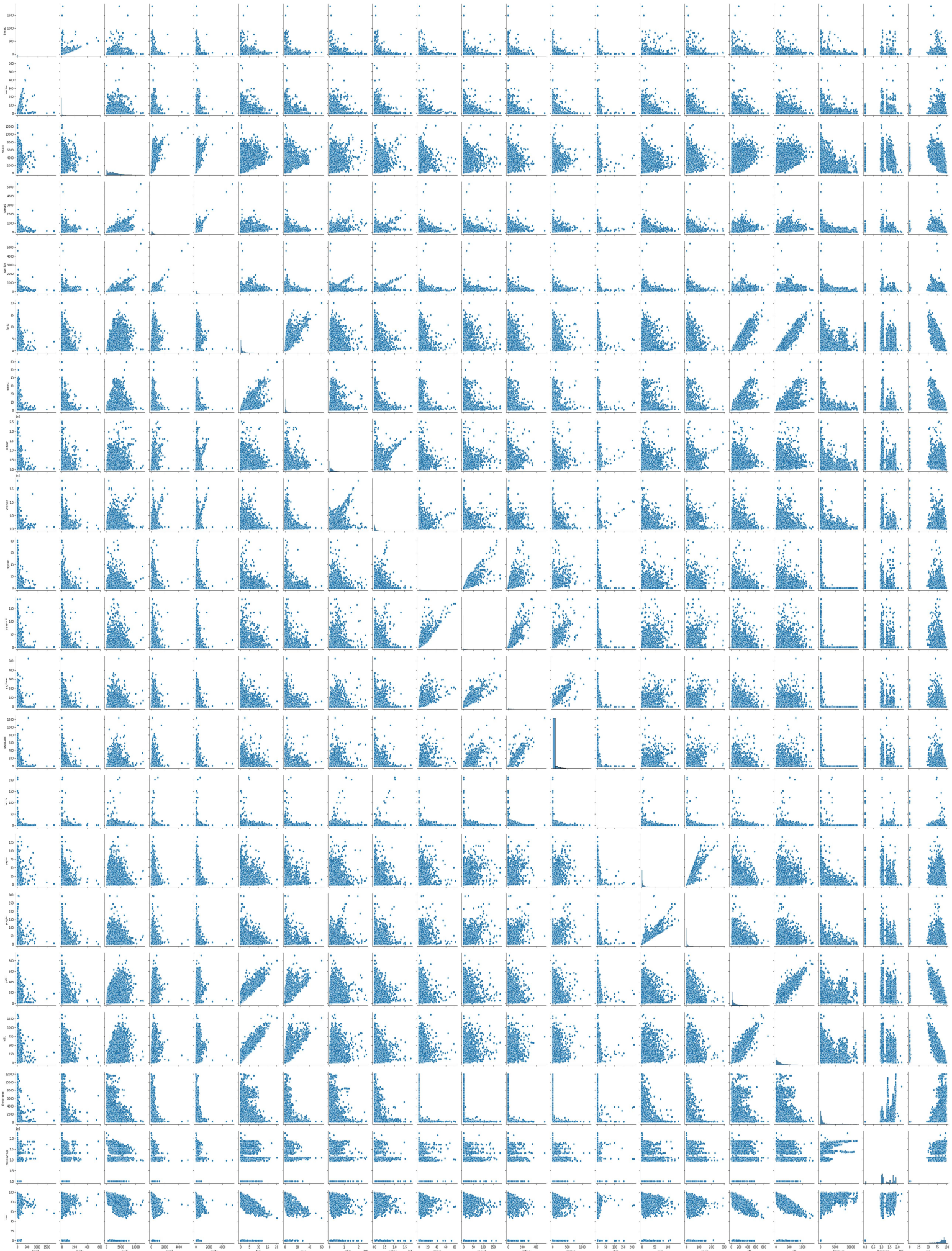

tread
twrite
scall
sread
swrite
fork
exec
rchar
wchar
pgout
pgpgout
pgfree
pgscan
atch
pgin
ppgin
pflt
vflt
freemem
freeswap
usr

Figure-4-pair plot

usr', 'lread', 'lwrite', 'scall', 'sread', 'swrite'this are decreasing when increasing usr .this means the these are inversely propotional to the usr.

Use appropriate visualizations to identify the patterns and insights - Key meaningful observations on individual variables and the relationship between variables

```
#create barplot of usr with runqsz
```

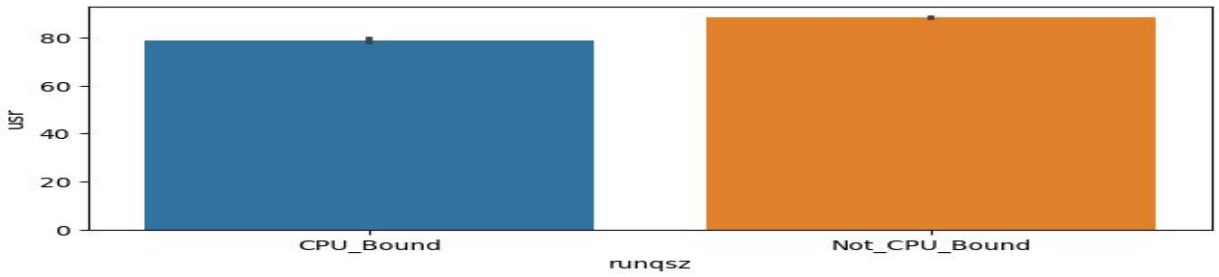


Figure-5- barplot of usr with runqsz

Portion of time (%) that cpus run in user mode is not_cpu_bound is higer than cpu_bond

insights:

Key Meaningful Observations:

1.

Dataset Overview:

2.

- The dataset comprises 8192 rows and 22 columns.
- Data types include 13 float columns, 8 integer columns, and 1 object column.

3.

Outliers:

4.

- Outliers in Higher Values:
  - 'lread', 'lwrite', 'scall', 'sread', 'swrite', 'fork', 'exec', 'rchar', 'wchar', 'pgout', 'ppgout', 'pgfree', 'pgscan', 'atch', 'pgin', 'ppgin', 'pflt', 'vflt', 'freemem'.
- Outliers in Lower Values:
  - 'freeswap', 'usr'.

5.

Process Run Queue Size:

6.

- The process run queue size indicates whether the system is CPU-bound.
- Observed that the process run queue size is not CPU-bound (less than 2), suggesting a system that is not consistently waiting for CPU resources.

7.

Correlations:

8.

- **Positive Correlations:**
  - 'usr' is highly positively correlated with 'freemem' and 'freeswap'.
- **Negative Correlations:**

- 'usr' is negatively correlated with 'lread', 'lwrite', 'scall', 'sread', 'swrite', 'fork', 'exec', 'rchar', 'wchar', 'pgout', 'ppgout', 'pgfree', 'pgscan', 'atch', 'pgin', 'ppgin', 'pflt', 'vflt'.
- 'fork' is highly negatively correlated with 'pflt' and 'vflt'.

9.

Null values and zero values: "rchar","wchar" these columns have null values,this data set have many zero values, percentages for zero values

10.

- pgout --59.545898
- ppgout --59.545898
- pgfree --59.436035
- pgscan --100.000000
- atch --55.847168
- pgin --14.892578
- ppgin --14.892578
- pflt --0.036621
- lread --8.239746
- lwrite --32.763672

Relationship Between Variables:

Memory and User Mode:

- 'usr' is highly correlated with both 'freemem' and 'freeswap', suggesting that the user mode percentage is influenced by the availability of memory resources.

CPU-Bound Observation:

- The portion of time (%) that CPUs run in user mode ('usr') is higher when the system is not CPU-bound. This implies that when the process run queue size is less than 2, the system is not consistently waiting for CPU resources, and 'usr' is higher.

Negative Correlations:

- 'usr' has negative correlations with various system attributes ('lread', 'lwrite', 'scall', 'sread', 'swrite', 'fork', 'exec', 'rchar', 'wchar', 'pgout', 'ppgout', 'pgfree', 'pgscan', 'atch', 'pgin', 'ppgin', 'pflt', 'vflt'). This suggests that as these activities increase, the user mode percentage tends to decrease.
- This negative correlation suggests that when the system is more actively involved in these operations, there is a tendency for a lower portion of time spent in user mode. It implies that high levels of these activities may require more kernel-level processing, leading to a decrease in user mode time.

Fork and Page Faults:

- 'fork' is highly correlated with page faults ('pflt' and 'vflt'), indicating that forking processes may contribute to protection errors and address translation faults.

Outlier Impact:

- 'lread', 'lwrite', 'scall', 'sread', 'swrite', 'fork', 'exec', 'rchar', 'wchar', 'pgout', 'ppgout', 'pgfree', 'pgscan', 'atch', 'pgin', 'ppgin', 'pflt', 'vflt', 'freemem' these have outliers in higher values.
- 'freeswap','usr' these 2 have outliers in lower values.

- Understanding the impact of outliers in higher and lower values on the analysis is crucial. Further investigation or treatment of outliers may be necessary.

Problem 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)

```
# chekcing null values
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 null values in "rchar",15 null values in "wchar" columns.
```

```
➢       # replace null values by its means
➢       "Number of zeros in each column:"
lread        8.239746
lwrite      32.763672
scall        0.000000
sread        0.000000
swrite       0.000000
fork         0.256348
exec         0.256348
rchar        0.000000
wchar        0.000000
```

```
pgout       59.545898
ppgout      59.545898
pgfree      59.436035
pgscan      78.710938
atch        55.847168
pgin        14.892578
ppgin       14.892578
pflt         0.036621
vflt         0.000000
runqsz       0.000000
freemem      0.000000
freeswap     0.000000
usr          3.454590
dtype: float64
```

Outlier Detection (treat, if needed)

```
#checking outliers using boxplot
```

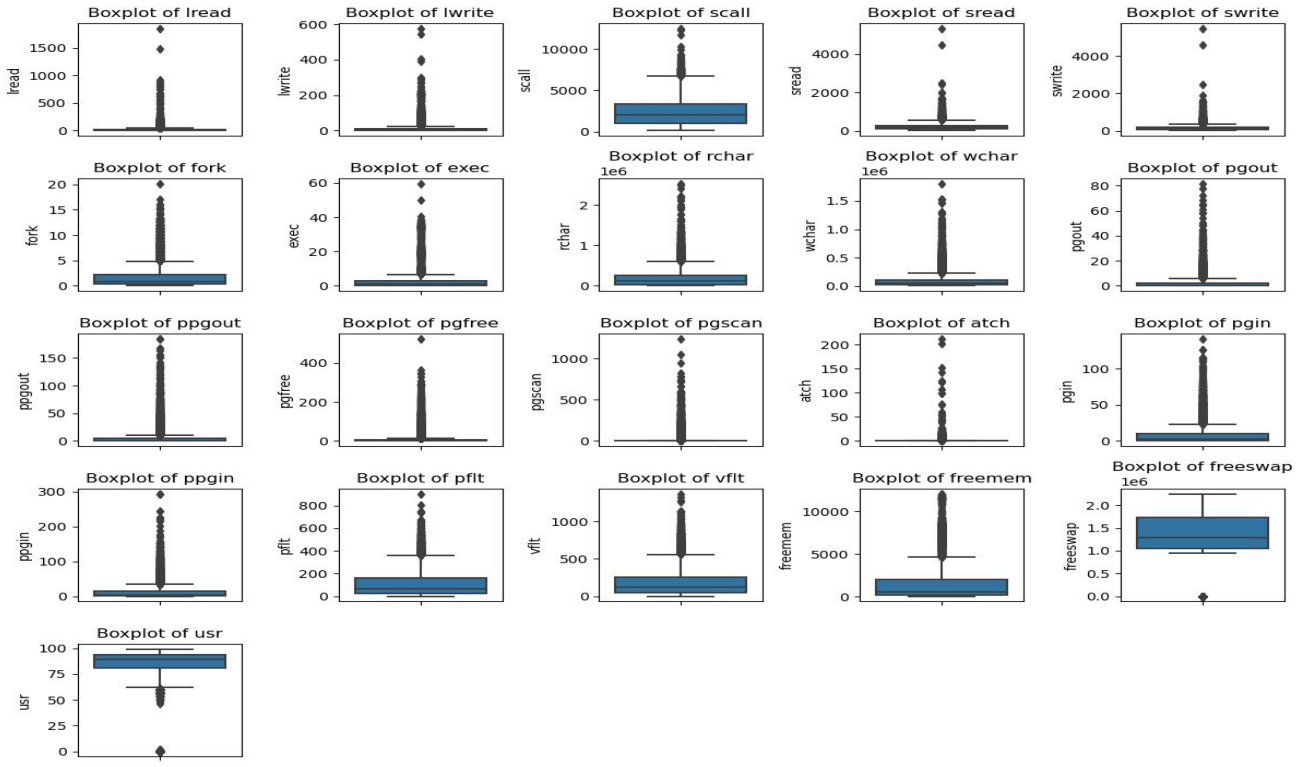


Figure-6-*checking outliers using boxplot*

- 'lread', 'lwrite', 'scall', 'sread', 'swrite', 'fork', 'exec', 'rchar', 'wchar', 'pgout', 'ppgout', 'pgfree', 'pgscan', 'atch', 'pgin', 'ppgin',
- 'pflt', 'vflt', 'freemem' these have outliers in higher values.
  'freeswap','usr' these 2 have outliers in lower values.

❖ remove outliers

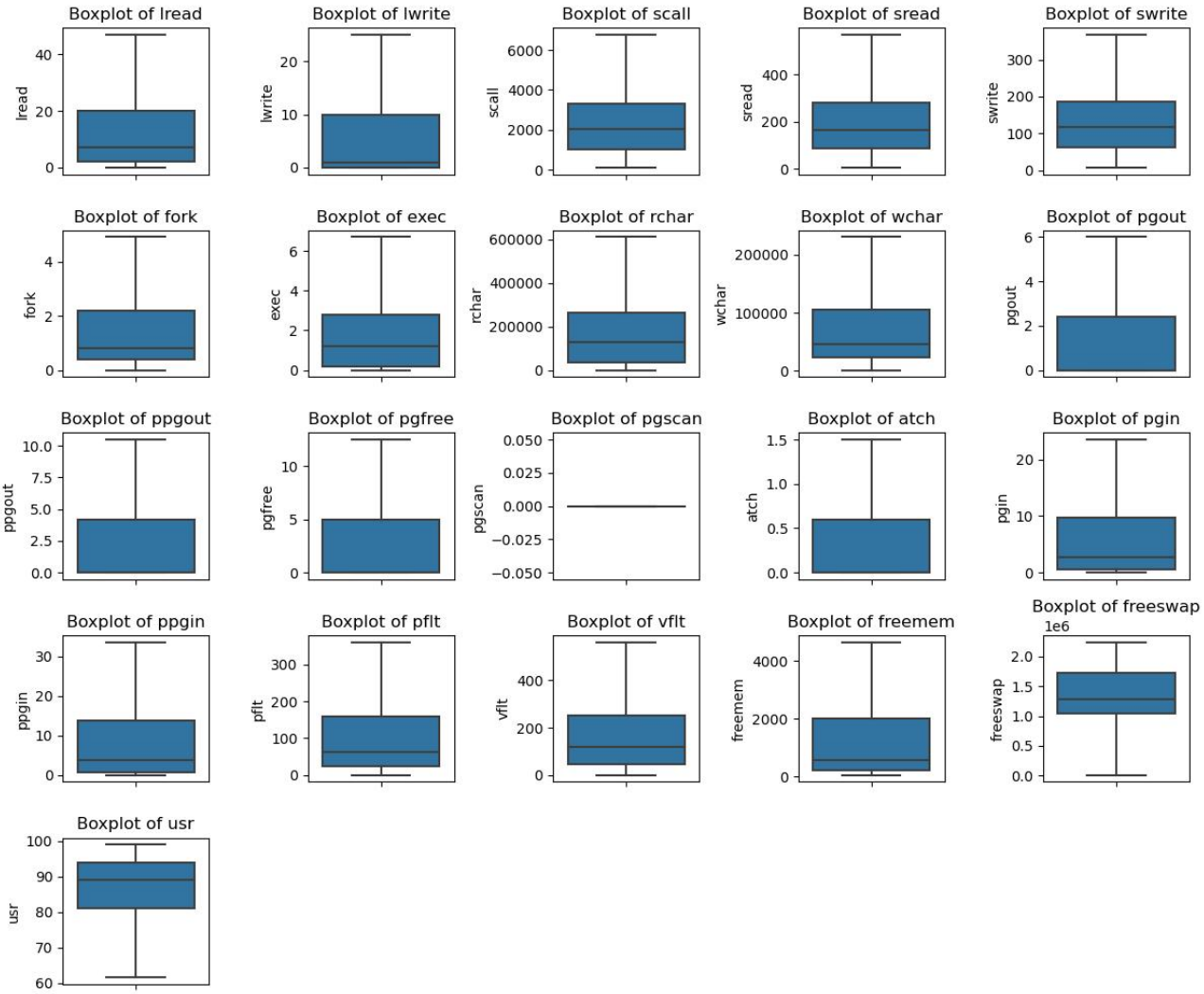


Figure-7-Box plots after treatments

Feature Engineering

Insights

1. Observed null values in 2 fields rchar and wchar.
2. We imputed the null values with mean value of the data set
3. Most of the of the continuous fields had outliers and we have treated them using the IQR approach
4. In this case, it is not necessary to scale the data as, we'll get an equivalent solution whether we apply some kind of linear scaling or not. For example, to find the best parameter values of a linear regression model, there is a closed-form solution, called the Normal Equation. If our implementation makes use of that equation, there is no stepwise optimization process, so feature scaling is not necessary
5. Removing the records with 0 values is not necessity ,as it might not have an impact on the model building.

```
#copy the numerical frame to knew data frame
#add object colum to new data frame
#print first 5 rows of new data frame
```

	lread	lwrite	scall	sread	swrite	fork	exec	rchar	wchar	pgout	...	pgscan	atch	pgin	ppgin	pflt	vflt	freemem	freeswap	usr	runqsz
0	1.0	0.0	2147.0	79.0	68.0	0.2	0.2	40671.000000	53995.0	0.0	...	0.0	0.0	1.6	2.6	16.00	26.40	4659.125	1730946.0	95.0	CPU_Bound
1	0.0	0.0	170.0	18.0	21.0	0.2	0.2	448.000000	8385.0	0.0	...	0.0	0.0	0.0	0.0	15.63	16.83	4659.125	1869002.0	97.0	Not_CPU_Bound
2	15.0	3.0	2162.0	159.0	119.0	2.0	2.4	197385.728363	31950.0	0.0	...	0.0	1.2	6.0	9.4	150.20	220.20	702.000	1021237.0	87.0	Not_CPU_Bound
3	0.0	0.0	160.0	12.0	16.0	0.2	0.2	197385.728363	8670.0	0.0	...	0.0	0.0	0.2	0.2	15.60	16.80	4659.125	1863704.0	98.0	Not_CPU_Bound
4	5.0	1.0	330.0	39.0	38.0	0.4	0.4	197385.728363	12185.0	0.0	...	0.0	0.0	1.0	1.2	37.80	47.60	633.000	1760253.0	90.0	Not_CPU_Bound

Encode the data

```
#encode data
```

	lread	lwrite	scall	sread	swrite	fork	exec	rchar	wchar	pgout	...	pgscan	atch	pgin	ppgin	pflt	vflt	freemem	freeswap	usr	runqsz_Not_CPU_Bound
0	1.0	0.0	2147.0	79.0	68.0	0.2	0.2	40671.000000	53995.0	0.0	...	0.0	0.0	1.6	2.6	16.00	26.40	4659.125	1730946.0	95.0	0
1	0.0	0.0	170.0	18.0	21.0	0.2	0.2	448.000000	8385.0	0.0	...	0.0	0.0	0.0	0.0	15.63	16.83	4659.125	1869002.0	97.0	1
2	1	3.	21	1	11	2	2	19738	31	0	.	0.	1	6	9	15	22	702	1021237	87	1

	lread	lwrite	scall	sread	swrite	fork	exec	rchar	wchar	pgout	...	pgscan	atch	pgin	ppgin	pflt	vflt	freemem	freeswap	usr	runqsz_Not_CPU_Bound
	5.0	0	62.0	59.0	9.0	.0	.4	5.728363	9500.0	.0	..	0	.2	.0	.4	0.20	0.20	.000	.0	.0	
3	0.0	0.0	160.0	12.0	16.0	0.2	0.2	19738 5.728363	8670.0	0.0	...	0.0	0.0	0.2	0.2	15.60	16.80	4659.125	1863704.0	98.0	1
4	5.0	1.0	330.0	39.0	38.0	0.4	0.4	19738 5.728363	12185.0	0.0	...	0.0	0.0	1.0	1.2	37.80	47.60	633.000	1760253.0	90.0	1

Table-3-encoded data frame

#drop the "pgscan" column from new data frame because all values are zero in new dataframe

Train-test split

 # Copy target into the y dataframe.
 # Copy all the predictor variables into X dataframe
 # Split X and y into training and test set in 70:30 ratio

Problem 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.

linear Regression using Sklearn

 # Initialize and fit the linear regression model
 # Make predictions on the test set and train data
 # Assuming 'model' is your trained linear regression model
 # Create a Data Frame with column names and corresponding coefficients
 # Print or use the coefficients Data Frame as needed

	Column	Coefficient
0	lread	-0.063410
1	lwrite	0.048018
2	scall	-0.000664
3	sread	0.000339
4	swrite	-0.005460
5	fork	0.029633
6	exec	-0.321063
7	rchar	-0.000005
8	wchar	-0.000005
9	pgout	-0.366852
10	ppgout	-0.078609
11	pgfree	0.085258
12	atch	0.630438

13 pgin 0.019754
14 ppgin -0.067154
15 pflt -0.033592
16 vflt -0.005465
17 freemem -0.000458
18 freeswap 0.000009
19 runqsz_Not_CPU_Bound 1.613737
#intercept of model
Intercept: 84.13143842096483
#mean squared error of test and train data
mean squared error(MSE) On training data: 19.5277083787279
mean squared error(MSE) On testing data: 21.64966602459875
 # Calculate root mean squared error of train data
Root Mean Squared Error of train data: 4.419016675543094
Root Mean Squared Error of test data: 4.652920160995539
 # R-squared value on the training set
R-squared on the training set: 0.7961565330395103
R-squared on the test set: 0.7676695029858773
#adjacent r values for test ,train data
adjecent r value for training: 0.7954429203422917
adjecent r value for test: 0.7657628103554783

- Linear Regression model accuracy of training data: 0.7961565330395103, so 80% of the variation in the user is explained by the predictors in the model for the training set.
- Linear Regression model accuracy of testing data: 0.7676695029858773, so 78% of the variation in the user is explained by the predictors in the model for the test.

Linear Regression Using Stats models

#apply linear regression and fit

OLS Regression Results

Dep. Variable:	usr	R-squared:	0.796
Model:	OLS	Adj. R-squared:	0.795
Method:	Least Squares	F-statistic:	1116.
Date:	Thu, 11 Jan 2024	Prob (F-statistic):	0.00
Time:	09:09:26	Log-Likelihood:	-16656.
No. Observations:	5734	AIC:	3.335e+04
Df Residuals:	5713	BIC:	3.349e+04
Df Model:	20		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	84.1314	0.316	266.122	0.000	83.512	84.751
lread	-0.0634	0.009	-7.064	0.000	-0.081	-0.046
lwrite	0.0480	0.013	3.660	0.000	0.022	0.074
scall	-0.0007	6.28e-05	-10.576	0.000	-0.001	-0.001
sread	0.0003	0.001	0.336	0.737	-0.002	0.002
swrite	-0.0055	0.001	-3.805	0.000	-0.008	-0.003
fork	0.0296	0.132	0.225	0.822	-0.229	0.288

```
exec                -0.3211      0.052     -6.219      0.000      -0.422      -0.220
rchar            -5.212e-06   4.87e-07    -10.696      0.000   -6.17e-06   -4.26e-06
wchar            -5.346e-06   1.03e-06     -5.179      0.000   -7.37e-06   -3.32e-06
pgout               -0.3669      0.090     -4.077      0.000      -0.543      -0.190
ppgout              -0.0786      0.079     -0.999      0.318      -0.233       0.076
pgfree               0.0853      0.048      1.786      0.074      -0.008       0.179
atch                 0.6304      0.143      4.414      0.000       0.350       0.910
pgin                 0.0198      0.028      0.695      0.487      -0.036       0.076
ppgin               -0.0672      0.020     -3.406      0.001      -0.106      -0.029
pflt                -0.0336      0.002    -16.954      0.000      -0.037      -0.030
vflt                -0.0055      0.001     -3.831      0.000      -0.008      -0.003
freemem             -0.0005   5.07e-05     -9.022      0.000      -0.001      -0.000
freeswap          8.829e-06    1.9e-07     46.463      0.000    8.46e-06     9.2e-06
runqsz_Not_CPU_Bound     1.6137      0.126     12.807      0.000       1.367       1.861
==============================================================================
Omnibus:                     1102.551   Durbin-Watson:                   2.016
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2367.549
Skew:                          -1.118   Prob(JB):                         0.00
Kurtosis:                       5.216   Cond. No.                     7.74e+06
==============================================================================
```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
[2] The condition number is large, 7.74e+06. This might indicate that there
are
strong multi col-linearity or other numerical problems.

```
# Root Mean Squared Error (RMSE) for training set
# R-squared and Adjusted R-squared for training set
Training RMSE: 4.419016675543094
Training R-squared: 0.7961565330395103
Training Adjusted R-squared: 0.7954429203422917
# Root Mean Squared Error (RMSE) for test set
# R-squared and Adjusted R-squared for test set
Test RMSE: 4.652920160995539
Test R-squared: 0.7676695029858773
Test Adjusted R-squared: 0.7657628103554783
# let's check the VIF of the predictors
VIF values:
lread                9.504596
lwrite               6.548395
scall                8.826526
sread               18.169718
swrite              16.767689
fork                25.002523
exec                 6.092313
rchar                4.361875
wchar                3.344787
pgout               16.004026
```

```
ppgout                40.799885
pgfree                22.974096
atch                  2.736070
pgin                  23.072561
ppgin                 23.162737
pflt                  24.685476
vflt                  33.872228
freemem               3.406754
freeswap              7.114274
runqsz_Not_CPU_Bound  2.155858
dtype: float64
```

AS few predictors have VIF values > 5 therefore there is some multicolinearity in the data We remove those predictors with multicolinarity due to which there is least impact on the adjusted R2

- Variance Inflation Factor (VIF) is one of the methods to check if independent variables havecorrelation between them. If they are correlated, then it is not ideal for linear regression models asthey inflate the standard errors which in turn affects the regression parameters. As a result, theregression model becomes non-reliable and lacks interpretability.
- General rule of thumb: If VIF values are equal to 1, then that means there is no multicollinearity. IfVIF values are equal to 5 or exceedingly more than 5, then there is moderate multicollinearity. If VIF is10 or more, then that means there is high collinearity.
- From the above I can conclude that variables have moderate correlation.

```
#drop "ppgout" for check
```
R-squared: 0.96508
Adjusted R-squared: 0.964964
```
#check diffence between Adjusted rvalues of orginal and after droping "ppgout"
0.795-0.965
```
-0.16999999999999993
```
#drop "vflt" for check
```
R-squared: 0.964999
Adjusted R-squared: 0.964882
```
#drop "fork" for check
```
R-squared: 0.9648555
Adjusted R-squared: 0.964739
```
#drop "pflt" for check
```
R-squared: 0.9647796
Adjusted R-squared: 0.964662
#drop "pgin" for check
R-squared: 0.9651407
Adjusted R-squared: 0.965025
droping high vIF variables ,we get very high effect on the adjusted R we can't choose to drop it .

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

The model equation will be as follows:

usr =
84.13143842098094 + -0.06340997319302627 * (lread) + 0.04801838613981681 * (lwrite) + -0.0006643523374678602 * (scall) + 0.00033858757891686887 * (sread) + -0.0054598818143035965 * (swrite) + 0.02963299570810818 * (fork) + -0.3210632504853652 * (exec) + -5.21187915604 4134e-06 * (rchar) + -5.346335455375872e-06 * (wchar) + -0.3668522981361845 * (pgout) + -0.0786092007452569 * (ppgout) + 0.08525820125748329 * (pgfree) + 0.6304380351235959 * (atch) + 0.019753855912710894 * (pgin) + -0.06715372112650217 * (ppgin) + -0.033591989662575365 * (pflt) + -0.005464921751521254 * (vflt) + -0.00045766140080 71696 * (freemem) + 8.82932042043399e-06 * (freeswap) 1.6137372384501392 * (runqsz_Not_CPU_Bound)

Observations

- 1 unit increase in the lwrite lead to a 0.04 times increase in the usr.
- 1 unit increase in the fork lead to a 0.03 times increase in the usr.
- if run que size is not CPU bonded for a property it increses the usr by a factor of 1.61.

Insights

System Call Efficiency:

The 'scall' variable has a negative coefficient, indicating that a higher number of system calls per second is associated with lower 'usr' values. To improve overall system performance, focus on optimizing and reducing unnecessary system calls.

Memory Management Impact:

Memory-related variables such as 'lwrite,' 'pgfree,' and 'freeswap' have significant coefficients. Efficient memory management is crucial for enhancing 'usr' values, and efforts should be directed toward minimizing page faults and optimizing memory usage.

CPU-Bound Processes:

The 'runqsz_Not_CPU_Bound' variable has a positive coefficient, Optimize CPU-Bound Processes Since the runqsz_Not_CPU_Bound variable is related to CPU-bound processes, optimizing these processes can lead to a reduction in the run queue size, positively impacting usr. Implement efficient task scheduling and resource allocation strategies to minimize CPU-bound situations.

Disk I/O Operations:

Variables related to disk I/O operations ('pgout' and 'ppgout') also impact 'usr.' Optimization of these operations, such as reducing the number of page out requests and pages paged out per second, can positively influence 'usr.'

Execution Calls and CPU Usage:

The 'exec' variable has a notable negative coefficient, indicating that a higher number of system exec calls per second is associated with lower 'usr' values. Streamlining and optimizing execution calls can lead to improved CPU usage efficiency.

Data Transfer Efficiency:

'swrite' and 'wchar' variables have negative coefficients, suggesting that optimizing write calls and character transfers between system write calls can positively impact 'usr' by reducing system delays.

Page Attachments and Page-In Requests:

'atch' and 'pgin' variables have positive coefficients, highlighting the importance of efficiently managing page attachments and page-in requests for better 'usr' values.

Model Confidence:

The overall model has a high R-squared value (0.796), indicating that a significant proportion of the variability in 'usr' can be explained by the selected system measures. However, it's crucial to monitor and validate the model's performance over time.

Business Recommendations

Optimize System Executions:

Given the significant impact of the 'exec' variable on 'usr,' focus on optimizing and streamlining system executions. Work with the IT team to identify and minimize unnecessary system exec calls, potentially through code optimization or system configuration changes.

Efficient Memory Operations:

Improve the efficiency of memory operations, as indicated by positive coefficients for 'lwrite,' 'sread,' 'fork,' 'pgfree,' 'atch,' and 'pgin.' Consider optimizing data transfer and memory management processes to reduce latency and enhance overall system performance.

Reduce Unnecessary System Calls:

Negative coefficients for 'lread,' 'scall,' 'swrite,' 'rchar,' 'wchar,' 'pgout,' 'ppgout,' 'pflt,' 'vflt,' 'freemem,' and 'freeswap' suggest that decreasing unnecessary system calls and optimizing resource usage can positively impact 'usr.' Review and eliminate redundant or inefficient system calls.

Memory Optimization:

Optimize memory usage and reduce page faults ('pflt') and address translation errors ('vflt'). Efficient memory management can lead to a reduction in interruptions, improving the overall performance of the CPUs.

Optimize CPU-Bound Processes:

Since the runqsz_Not_CPU_Bound variable is related to CPU-bound processes, optimizing these processes can lead to a reduction in the run queue size, positively impacting usr. Implement efficient task scheduling and resource allocation strategies to minimize CPU-bound situations.

Collaboration with IT Teams:

Foster collaboration between business stakeholders and IT teams to implement and test optimizations. Regular communication and knowledge exchange between these teams are essential for aligning technical improvements with business objectives.

Training and Skill Development:

Invest in training and skill development for IT teams to stay updated on the latest technologies and best practices in system performance optimization. Ensuring that the team has the right skills is crucial for implementing effective solutions.

Problem - 2

Objective

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.

Your task involves 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.

Data Description

1. Wife's age (numerical)

2. Wife's education (categorical) 1=uneducated, 2, 3, 4=tertiary
3. Husband's education (categorical) 1=uneducated, 2, 3, 4=tertiary
4. Number of children ever born (numerical)
5. Wife's religion (binary) Non-Scientology, Scientology
6. Wife's now working? (binary) Yes, No
7. Husband's occupation (categorical) 1, 2, 3, 4(random)
8. Standard-of-living index (categorical) 1=verlow, 2, 3, 4=high
9. Media exposure (binary) Good, Not good
10. Contraceptive method used (class attribute) No,Yes

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

```
#read the the data set
#print first 5 rows
```

	Wife_age	Wife_education	Husband_education	No_of_children_born	Wife_religion	Wife_Working	Husband_Occupation	Standard_of_living_index	Media_exposure	Contraceptive_method_used
0	24.0	Primary	Secondary	3.0	Scientology	No	2	High	Exposed	No
1	45.0	Uneducated	Secondary	10.0	Scientology	No	3	Very High	Exposed	No
2	43.0	Primary	Secondary	7.0	Scientology	No	3	Very High	Exposed	No
3	42.0	Secondary	Primary	9.0	Scientology	No	3	High	Exposed	No
4	36.0	Secondary	Secondary	8.0	Scientology	No	3	Low	Exposed	No

Table-4-first 5 rows of the data set

```
#check shape
```

(1473, 10)

data set has 1473 rows and 10 columns

```
#Data types
```

Data columns (total 10 columns):

#	Column	Non-Null Count	Dtype
0	Wife_age	1402 non-null	float64
1	Wife_ education	1473 non-null	object
2	Husband_education	1473 non-null	object
3	No_of_children_born	1452 non-null	float64
4	Wife_religion	1473 non-null	object
5	Wife_Working	1473 non-null	object
6	Husband_Occupation	1473 non-null	int64
7	Standard_of_living_index	1473 non-null	object

```
 8   Media_exposure            1473 non-null   object
 9   Contraceptive_method_used  1473 non-null   object
dtypes: float64(2), int64(1), object(7)
memory usage: 115.2+ KB
```

- data set has 7 object,1 int,2 float type data types
- wife_age , No_of_children_born columns have null values

 # statistical summary -

	Wife_age	No_of_children_born	Husband_Occupation
count	1402.000000	1452.000000	1473.000000
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

Table-5-statistical summary

#check the duplicate values

80

data set has 80 rows are duplicated values.

#drop the duplicated values

#Check the shape of data set

(1393, 10)

#value counts of categorical variables.

```
WIFE_ EDUCATION :  4
Uneducated    150
Primary       330
Secondary     398
Tertiary      515
Name: Wife_ education, dtype: int64

HUSBAND_EDUCATION :  4
Uneducated     44
Primary       175
Secondary     347
Tertiary      827
Name: Husband_education,

WIFE_RELIGION :  2
Non-Scientology     207
Scientology        1186
Name: Wife_religion, dtype: int64

WIFE_WORKING :  2
Yes     350
```

No 1043
Name: Wife_Working, dtype: int64

STANDARD_OF_LIVING_INDEX : 4
Very Low 129
Low 227
High 419
Very High 618
Name: Standard_of_living_index, dtype: int64

MEDIA_EXPOSURE : 2
Not-Exposed 109
Exposed 1284
Name: Media_exposure , dtype: int64

CONTRACEPTIVE_METHOD_USED : 2
No 614
Yes 779
Name: Contraceptive_method_used, dtype: int64

Univariate analysis

 # create data frame with numerical columns
#create data frame with categorical columns
create histograms and boxplots of numerical variables

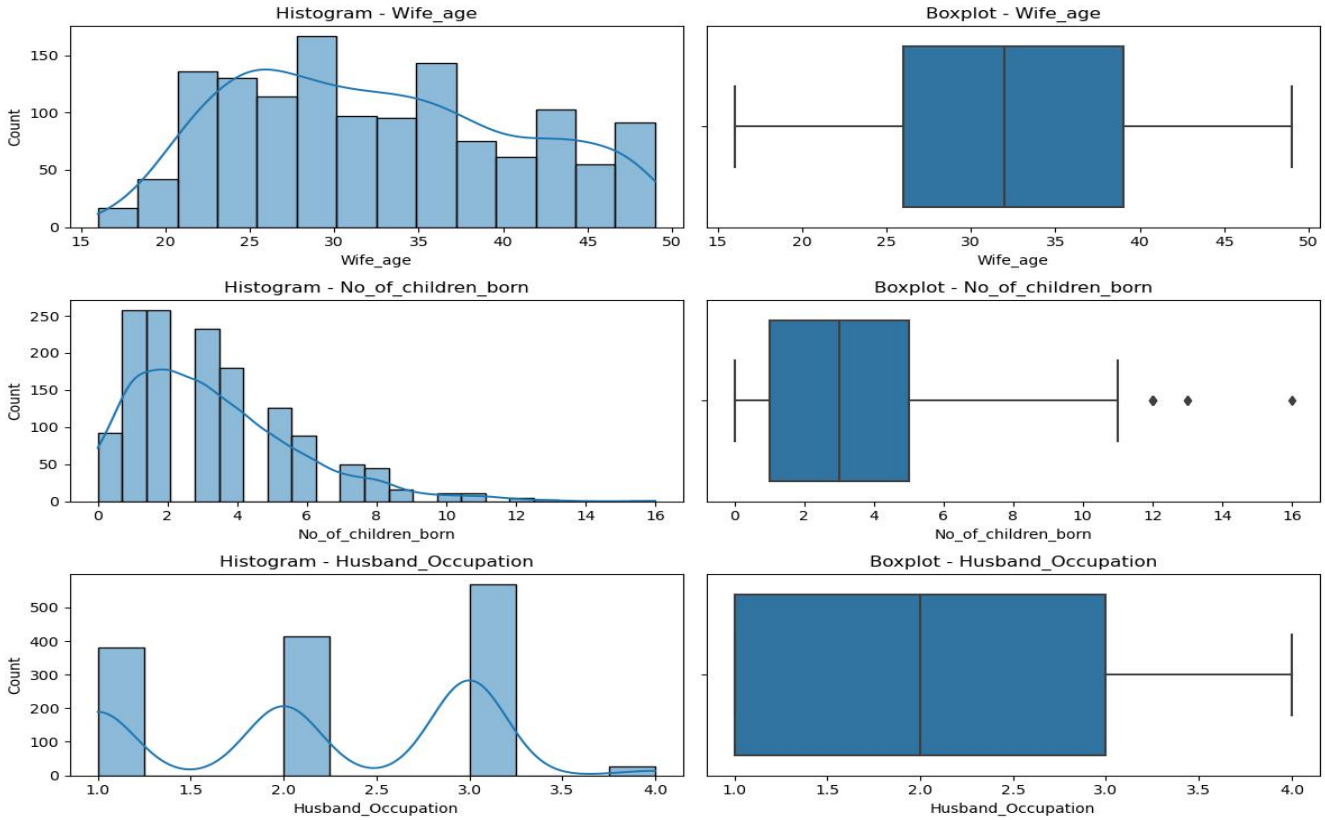
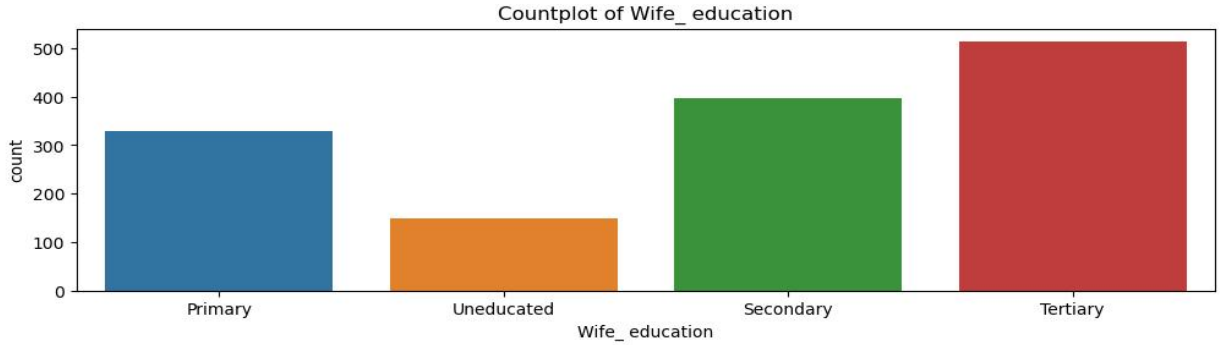
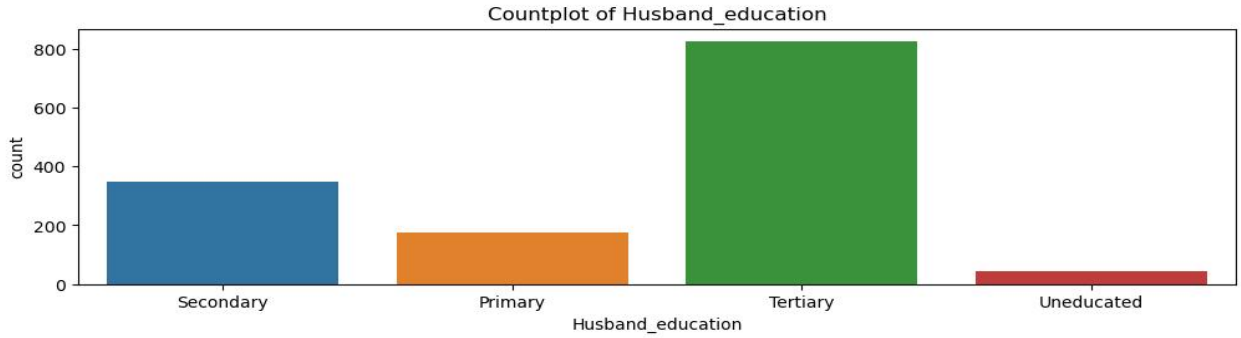


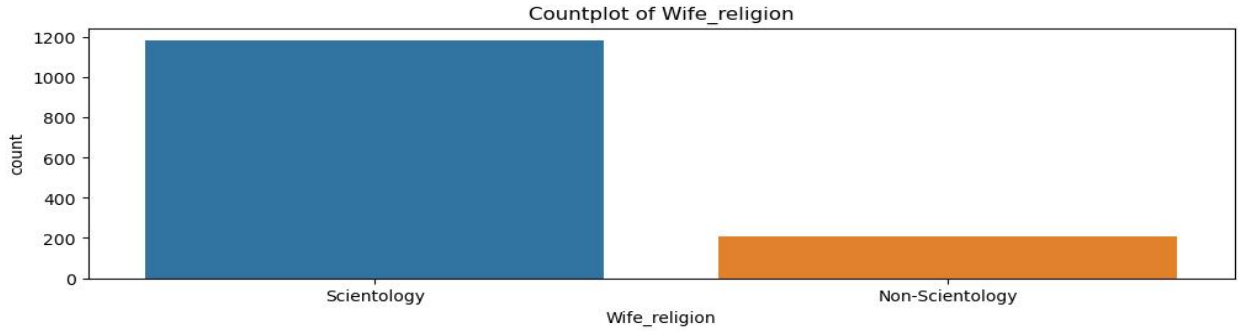
Figure-8- *create histograms and boxplots of numerical variables*

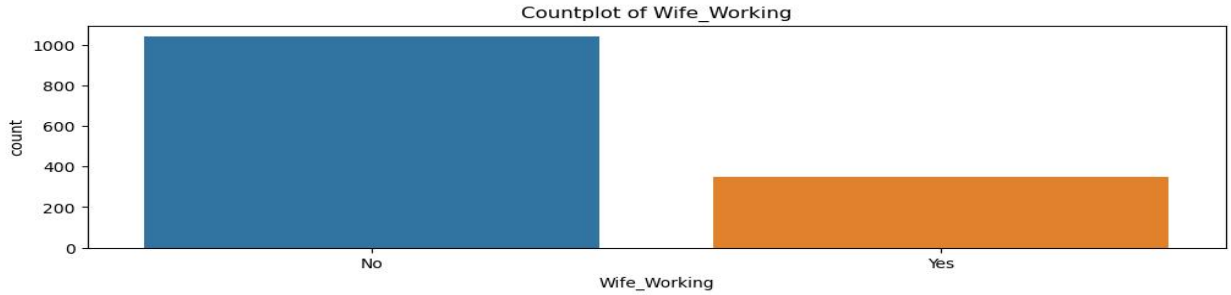
- ✧ range of wife age in between 16 to 49
- ✧ 50% of no.of children born is 5
- ✧ maximum of husband occupation is 4.

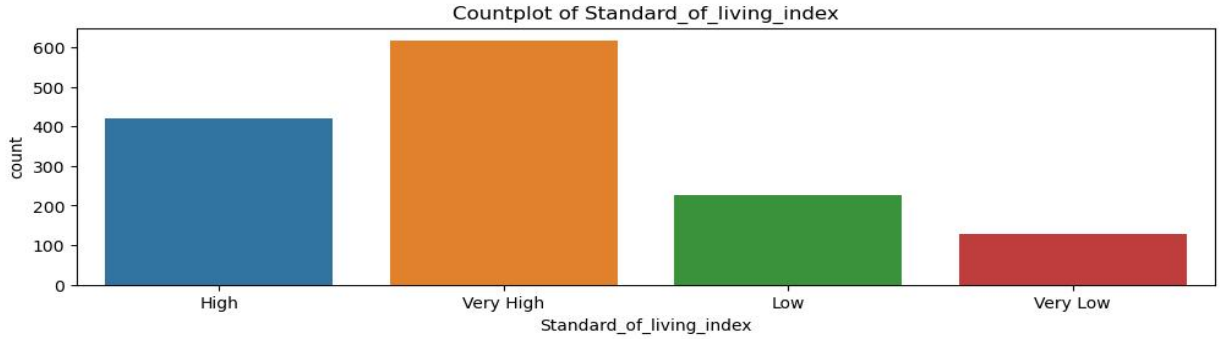
#Countplots of categorical variable


Countplot of Wife_ education
count
0
100
200
300
400
500
Primary
Uneducated
Secondary
Tertiary
Wife_ education


Countplot of Husband_education
count
0
200
400
600
800
Secondary
Primary
Tertiary
Uneducated
Husband_education


Countplot of Wife_religion
count
0
200
400
600
800
1000
1200
Scientology
Non-Scientology
Wife_religion


Countplot of Wife_Working
count
0
200
400
600
800
1000
No
Yes
Wife_Working


Countplot of Standard_of_living_index
count
0
100
200
300
400
500
600
High
Very High
Low
Very Low
Standard_of_living_index

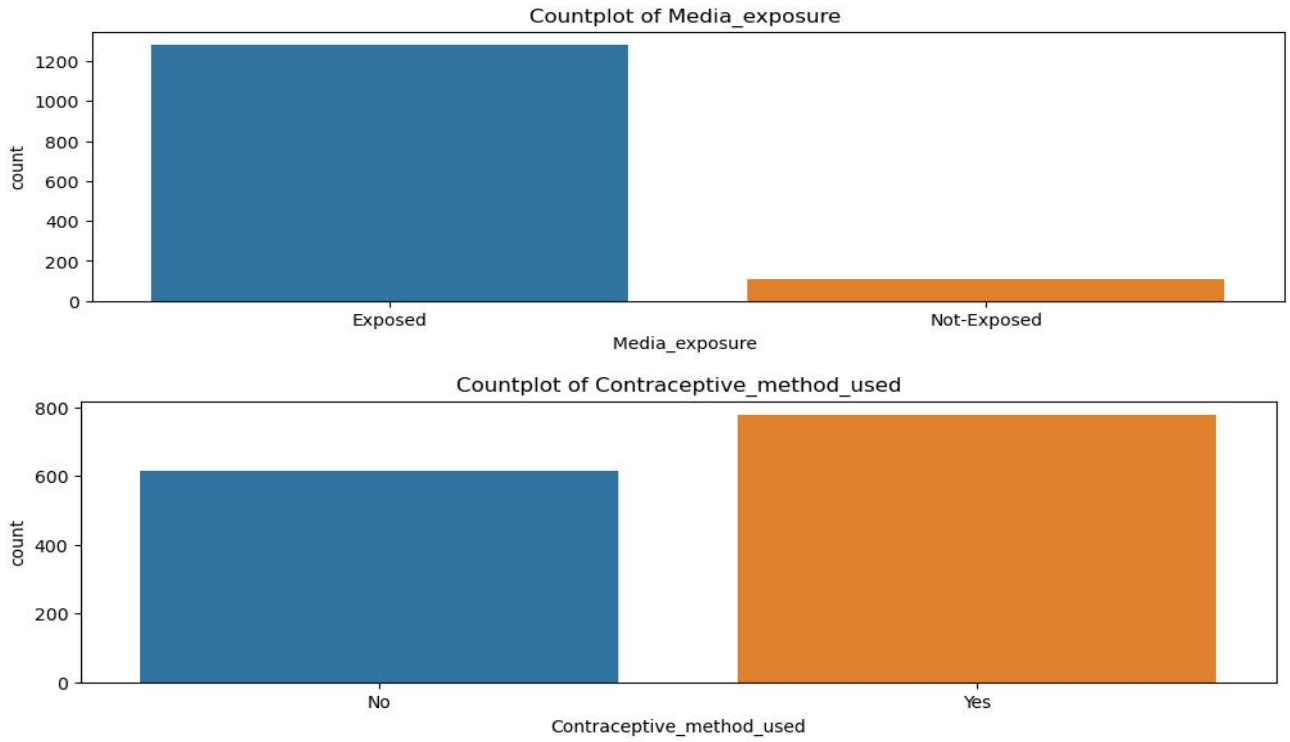


Figure-9-*Countplots of categorical variable*

- tertionary education is high for both wife,s and husband's education.
- both are have smallest amount uneducated persons.
- uneducated persons are high in wifes than husbands
- scientology is high for wife's religion.
- wifes are not working
- highest persons standard living index is "very high" category.
- more persons are media exposure.
- more persons used the contraceptive method.

multivariate analysis

#correlation heat map.

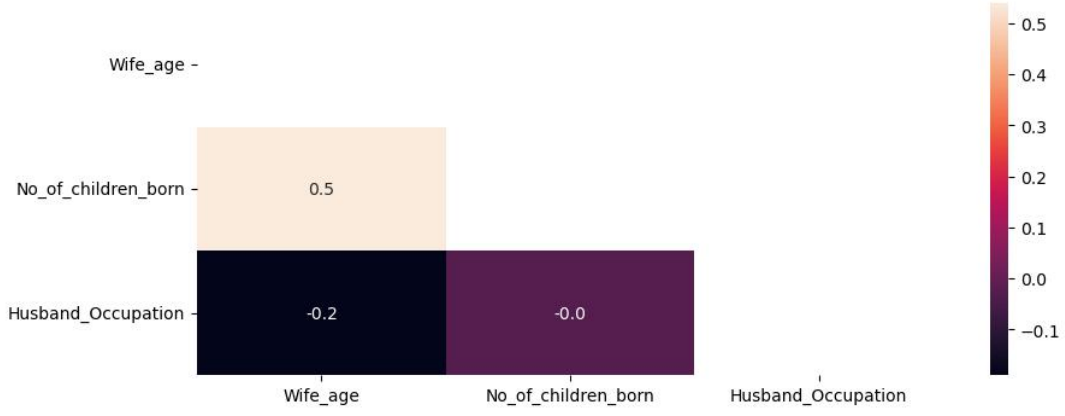


Figure-10-*correlation heat map.*

- wife,s age and husband occupation are higly negatively correlated.
- no.of children born and husband occupation are negatively correlated.
- no.of children born and wife age are positively correlated.

#pair plot of numerical variables

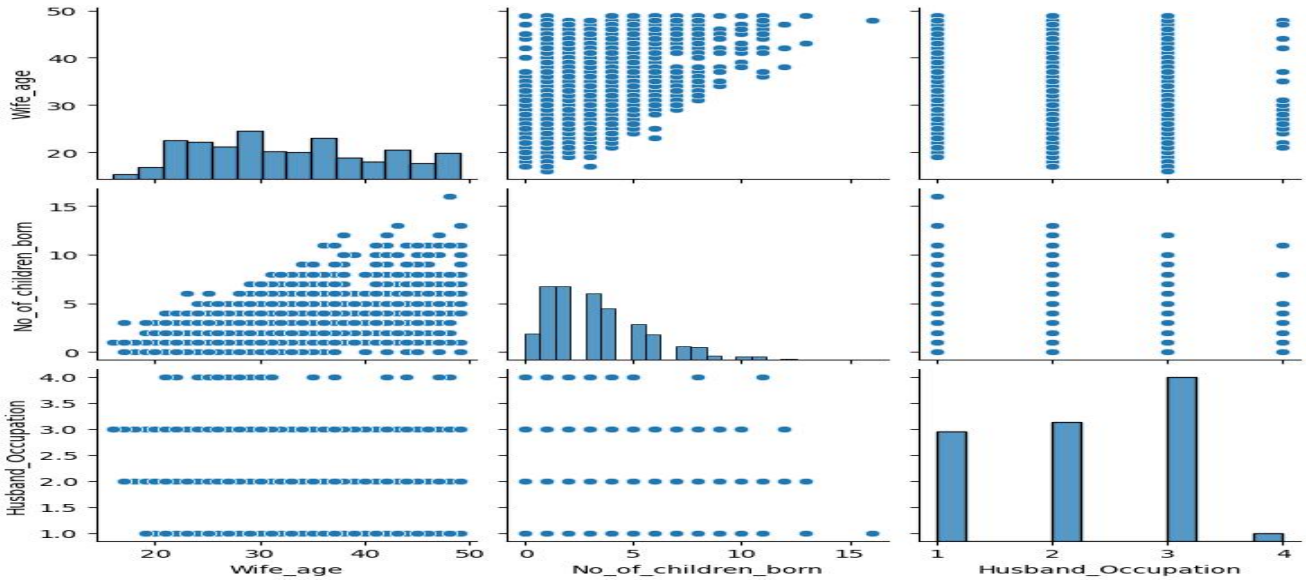


Figure-11-pair plot of numerical variables

#barplot of "Contraceptive_method_used" with "No_of_children_born"

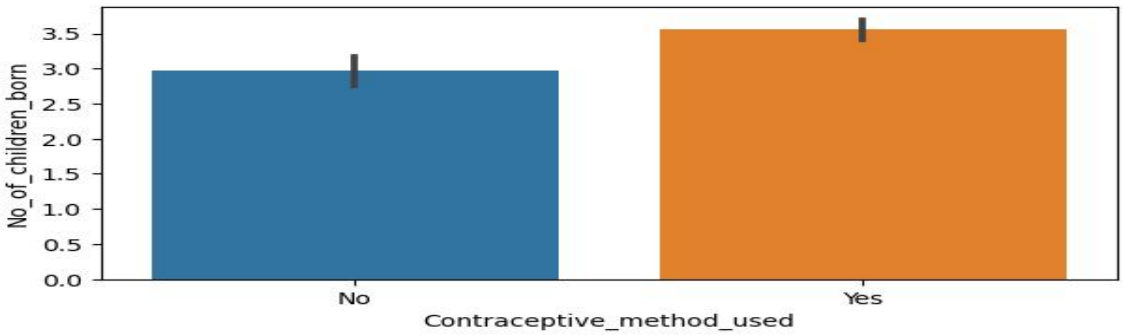


Figure-12-*barplot of "Contraceptive_method_used" with "No_of_children_born"*

couples have a high number of children, who are more used to contraceptive methods

#barplot of "Contraceptive_method_used" with "wife working"

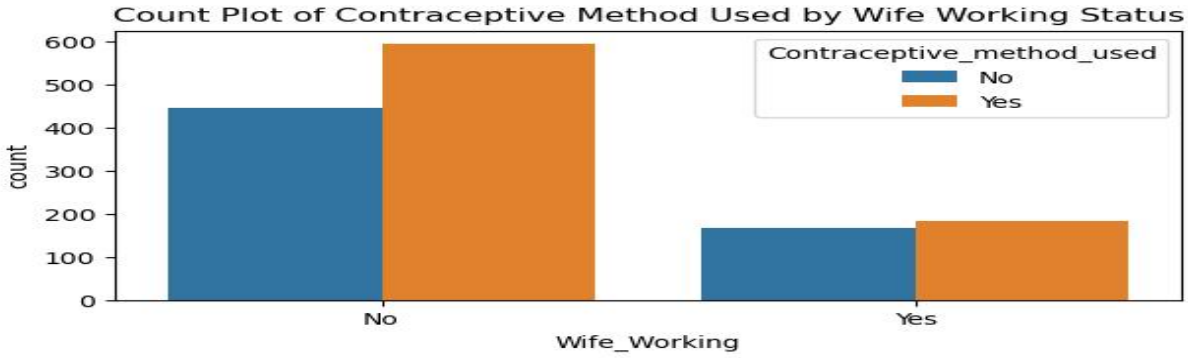


Figure-13-*barplot of "Contraceptive_method_used" with "wife working"*

- wife's not working couples are more using contraceptive method than wife's working couples.
- taking working wife's couples whose use contraceptive method

#Count Plot of Contraceptive Method Used by Wife age Status

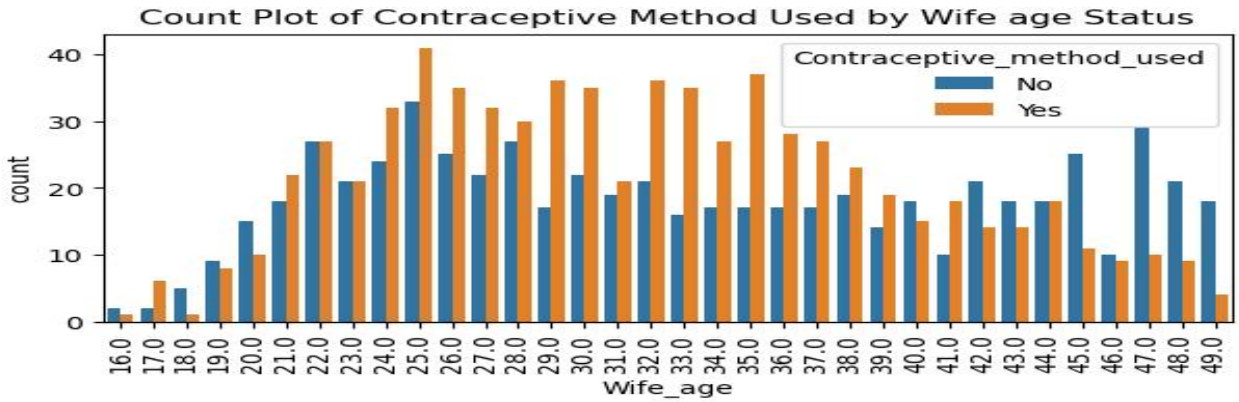


Figure-14-*Count Plot of Contraceptive Method Used by Wife age Status*

- wife's age 25 couples who are most using contraceptive method.
- wife's age 42 to 49 couples who are more not using contraceptive method.

 # Count Plot of Contraceptive Method Used by husband occupation Status')

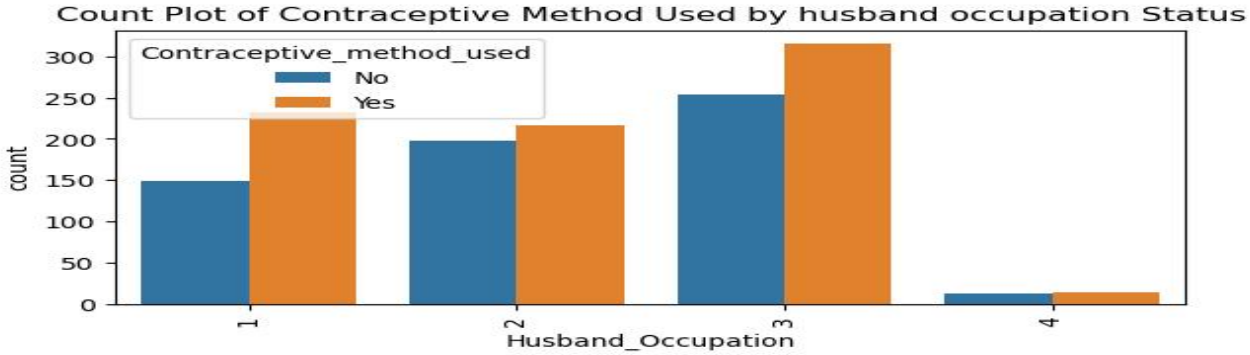


Figure-15-Count Plot of Contraceptive Method Used by husband occupation Status')

- 3 husband occupation couples are more using contraceptive method.
- 4 husband occupation couples are less using contraceptive method.

#Count Plot of Contraceptive Method Used by Standard_of_living_index Status'

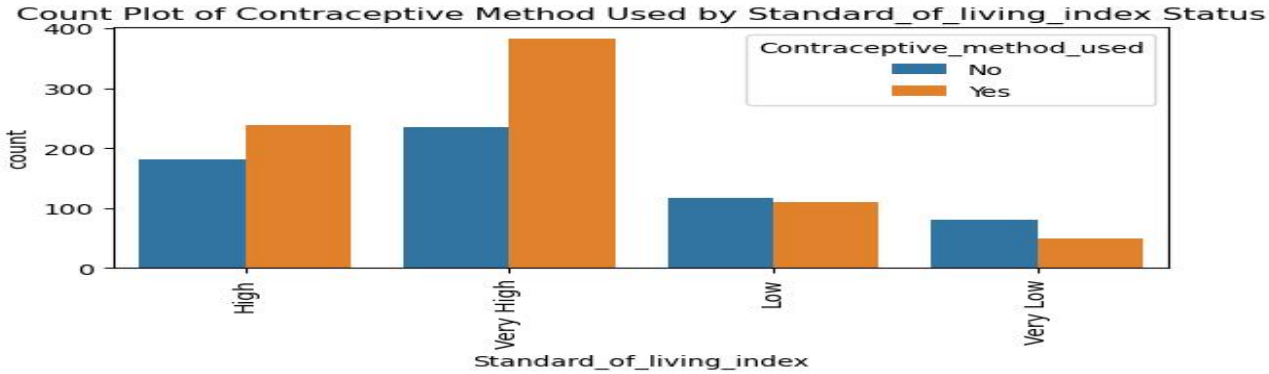


Figure-16-*Count Plot of Contraceptive Method Used by Standard_of_living_index Status'*

"very high"standard of living index couples are most using contraceptive method.

Use appropriate visualizations to identify the patterns and insights - Key meaningful observations on individual variables and the relationship between variables

Insights

The dataset contains 1473 rows and 10 columns.
Data types include 7 object (likely categorical), 1 int, and 2 float.
wife_age , No_of_children_born columns have null values
There are 80 rows with duplicated values.

Tertiary education is high for both wives and husbands.
Uneducated persons are more common among wives than husbands.
Scientology is the predominant religion among wives.
Most wives are not working.
The highest standard of living index is in the "very high" category.
A significant number of persons have media exposure.
A considerable number of persons use contraceptive methods.
Couples with a "very high" standard of living index are more likely to use contraceptives.
Wife's age and husband's occupation are highly negatively correlated.
Number of children born and husband's occupation are negatively correlated.
Number of children born and wife's age are positively correlated.
Couples with working wives are more likely to use contraceptive methods.
Couples with wives aged 25 are most likely to use contraceptive methods.
Couples with wives aged 42 to 49 are more likely not to use contraceptive methods.
Couples with specific husband occupations (3 and 4) are more likely to use or not use contraceptive methods.

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

Ans:::

```
#check null values
Wife_age                  67
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
```

- wife_age has 67 , No_of_children_born has 21 null values

```
# replace null values by its means
#its change to the d_num data frame
# check null value after null value treatment
#check outliers
```

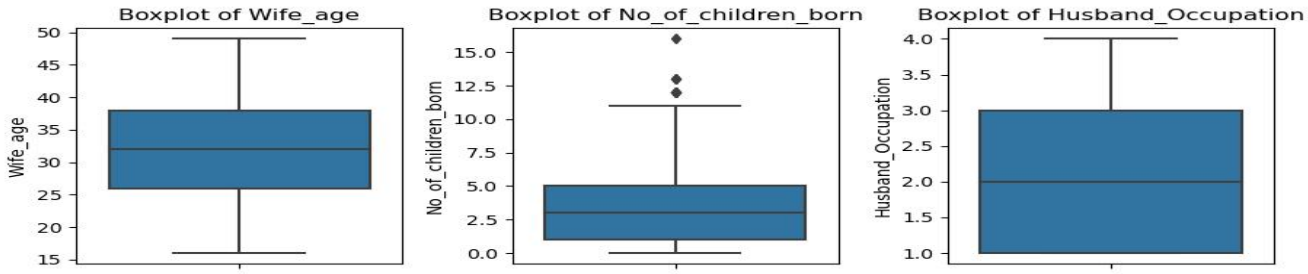


Figure- 17-*check outliers*

outliers present in higher values of "No_of_children_born".

#remove outliers

#boxplot of "No_of_children_born"after treatment

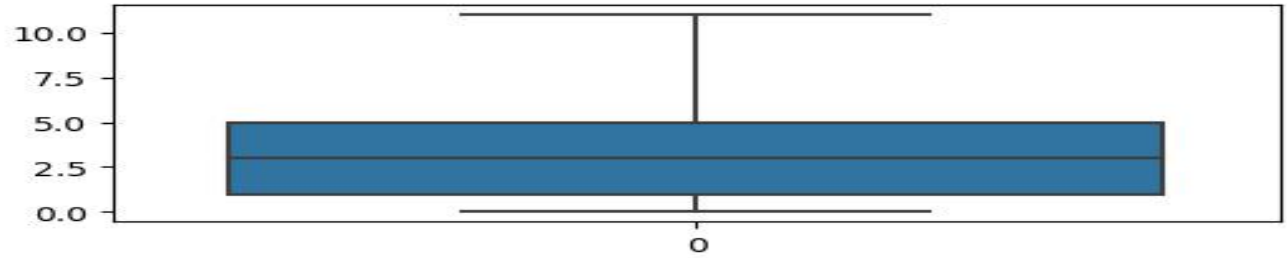


Figure-18-*boxplot of "No_of_children_born"after treatment*

Feature Engineering (if needed)

#create new data frame with both numerical and categorical variables.

#data types of data frames

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1393 entries, 0 to 1472
Data columns (total 10 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Wife_age                1393 non-null   float64
 1   No_of_children_born     1393 non-null   float64
 2   Husband_Occupation      1393 non-null   int64
 3   Wife_ education          1393 non-null   object
 4   Husband_education       1393 non-null   object
 5   Wife_religion           1393 non-null   object
 6   Wife_Working            1393 non-null   object
 7   Standard_of_living_index  1393 non-null   object
 8   Media_exposure          1393 non-null   object
 9   Contraceptive_method_used  1393 non-null   object
dtypes: float64(2), int64(1), object(7)
memory usage: 152.0+ KB
```

#first 5 rows of new data frame.

	Wife_age	No_of_children_born	Husband_Occupation	Wife_education	Husband_education	Wife_religion	Wife_Working	Standard_of_living_index	Media_exposure	Contraceptive_method_used
0	24.0	3.0	2	Primary	Secondary	Scientology	No	High	Exposed	No

	Wife_age	No_of_children_born	Husband_Occupation	Wife_education	Husband_education	Wife_religion	Wife_Working	Standard_of_living_index	Media_exposure	Contraceptive_method_used
1	45.0	10.0	3	Uneducated	Secondary	Scientology	No	Very High	Exposed	No
2	43.0	7.0	3	Primary	Secondary	Scientology	No	Very High	Exposed	No
3	42.0	9.0	3	Secondary	Primary	Scientology	No	High	Exposed	No
4	36.0	8.0	3	Secondary	Secondary	Scientology	No	Low	Exposed	No

Table-5-first 5 rows of new data frame.

Encode the data

```
#Data Types of new data frame
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1393 entries, 0 to 1472
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Wife_age               1393 non-null   float64
 1   No_of_children_born    1393 non-null   float64
 2   Husband_Occupation     1393 non-null   int64
 3   Wife_ education        1393 non-null   object
 4   Husband_education      1393 non-null   object
 5   Wife_religion          1393 non-null   object
 6   Wife_Working           1393 non-null   object
 7   Standard_of_living_index  1393 non-null   object
 8   Media_exposure         1393 non-null   object
 9   Contraceptive_method_used  1393 non-null   object
dtypes: float64(2), int64(1), object(7)
memory usage: 152.0+ KB
#value counts of "Contraceptive_method_used"
Yes    779
No     614
#in "Contraceptive_method_used" column,yes replace by 1,no replace by 0.
1    779
0    614
#encoding data
```

	Wife_age	No_of_children_born	Husband_Occupation	Contraceptive_method_used	Wife_education_Secondary	Wife_education_Tertiary	Wife_education_Uneducated	Husband_education_Secondary	Husband_education_Tertiary	Husband_education_Uneducated	Wife_religion_Scientology	Wife_Working_Yes	Standard_of_living_index_Low	Standard_of_living_index_Very High	Standard_of_living_index_Very Low	Media_exposure_Not-Exposed
0	24.0	3.0	2	0	0	0	0	1	0	0	1	0	0	0	0	0
1	45.0	10.0	3	0	0	0	1	1	0	0	1	0	0	1	0	0
2	43.0	7.0	3	0	0	0	0	1	0	0	1	0	0	1	0	0
3	42.0	9.0	3	0	1	0	0	0	0	0	1	0	0	0	0	0
4	36.0	8.0	3	0	1	0	0	1	0	0	1	0	1	0	0	0

Table-6-encoded data

```
#columns of data frame
Index(['Wife_age', 'No_of_children_born', 'Husband_Occupation',
       'Contraceptive_method_used', 'Wife_ education_Secondary',
       'Wife_ education_Tertiary', 'Wife_ education_Uneducated',
       'Husband_education_Secondary', 'Husband_education_Tertiary',
       'Husband_education_Uneducated', 'Wife_religion_Scientology',
       'Wife_Working_Yes', 'Standard_of_living_index_Low',
       'Standard_of_living_index_Very High',
       'Standard_of_living_index_Very Low', 'Media_exposure _Not-Exposed'],
      dtype='object')
#shape of data data frame
(1393, 16)
```

Train-test split

```
# Copy target into the y dataframe.
# Copy all the predictor variables into X dataframe
#Train-test split
```

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 hyperparameters using GridSearch - 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
# Build Linear Discriminant Analysis model
# Build CART model
```

Applying GridSearchCV for Logistic Regression

```
#Applying GridSearchCV for Logistic Regression
grid={'penalty':['l2','none'],
    'solver':['sag','lbfgs'],
    'tol':[0.0001,0.00001]}
#print best parameters and best estimator
```

{'penalty': 'l2', 'solver': 'sag', 'tol': 0.0001}

LogisticRegression(max_iter=10000, n_jobs=2, solver='sag')

```
# assigning the best estimator from a grid search
# Evaluate models on the train set
# Evaluate models on the test set
```

logistic model

```
#classification report of logistic model train data
```

	precision	recall	f1-score	support
0	0.63	0.52	0.57	192
1	0.65	0.75	0.69	226
accuracy			0.64	418
macro avg	0.64	0.63	0.63	418
weighted avg	0.64	0.64	0.64	418

```
#classification report of logistic model test data
```

	precision	recall	f1-score	support
0	0.64	0.53	0.58	422
1	0.68	0.78	0.73	553
accuracy			0.67	975
macro avg	0.66	0.65	0.65	975
weighted avg	0.67	0.67	0.66	975

```
## Confusion matrix on the training data
array([[ 99,  93],
    [ 57, 169]], dtype=int64)
|## Confusion matrix on the test data
array([[222, 200],
    [123, 430]], dtype=int64)
# calculate AUC of train
```

 # plot the roc curve for the model of train

AUC:0.695

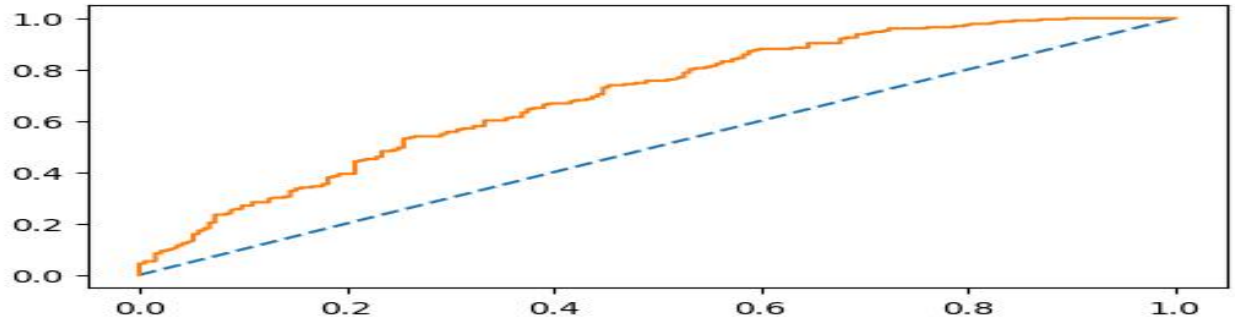


Figure-19-roc curve for the model of train

calculate AUC of test

 # roc curve of test

AUC: 0.699

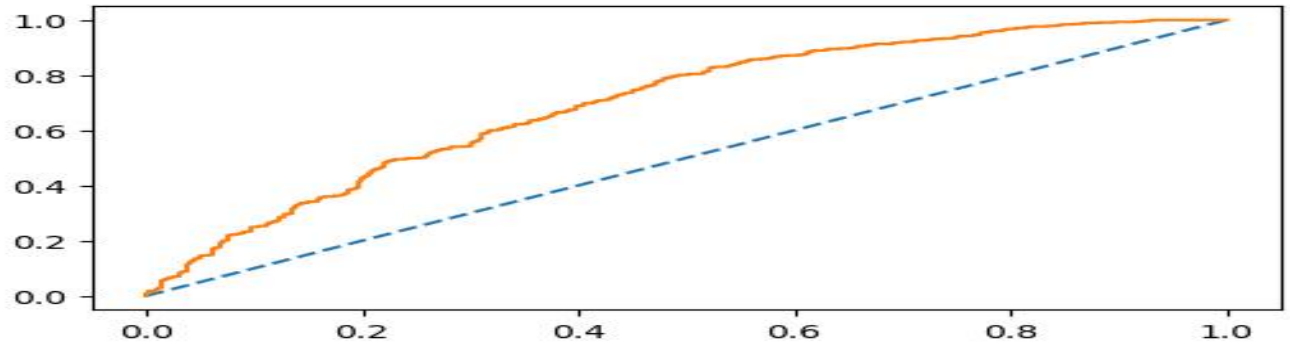


Figure-20-roc curve of test

Insights:

logistic regresson:The logstic model's precision is slightly higher for class 1(contraceptive method used) compared to class 0 in both train and test data.

- Recall is higher for class 1, indicating that the model is better at capturing instances where contraceptive methods are used.
- F1-Score provides a balance between precision and recall for each class.
- The overall accuracy of the train logistic model is 64%, suggesting a moderate level of predictive performance.
- Precision-Recall Trade-off:In the test data, precision and recall for both classes have increased. This suggests that the model is performing slightly better on the test set.
- F1-Score:F1-scores for both classes have increased in the test data, indicating a better balance between precision and recall.
- Accuracy:The model's accuracy has improved slightly on the test data, reaching 67%, compared to 64% on the training data.
- Overall Model Performance:The model generalizes reasonably well from the training set to the test set, with improvements in precision, recall, and F1-score. Class Imbalance:The class imbalance is consistent between the training and test sets, with class 1 having higher support than class 0.
- Comparative Performance:The model appears to generalize well, as indicated by the similar macro and weighted averages for precision, recall, and F1-score between the training and test sets.

- Areas for Consideration:While the model is showing improvement on the test set, consider further refinement, parameter tuning, or exploration of additional features for enhanced performance.

Linear Discriminant Analysis model

#classification report of Linear Discriminant Analysis model train data

	precision	recall	f1-score	support
0	0.63	0.50	0.56	192
1	0.64	0.75	0.69	226
accuracy			0.64	418
macro avg	0.64	0.63	0.62	418
weighted avg	0.64	0.64	0.63	418

#classification report of#classification report of Linear Discriminant Analysis model train data model test data

	precision	recall	f1-score	support
0	0.63	0.52	0.57	422
1	0.68	0.77	0.72	553
accuracy			0.66	975
macro avg	0.66	0.65	0.65	975
weighted avg	0.66	0.66	0.66	975

 # calculate AUC of train

AUC:0.696

 # calculate AUC of test

AUC:0.695

#confusion matrix of Linear Discriminant Analysis model train data

```
array([[ 96,  96],
       [ 56, 170]], dtype=int64)
```

#confusion matrix of Linear Discriminant Analysis model test data

```
array([[219, 203],
       [126, 427]], dtype=int64)
```

- Overall accuracy increased from 0.64 in the train data to 0.66 in the test data.The overall accuracy improved on the test data, indicating that the model generalizes well to new, unseen instances.
- class 1 is more better than class 0.
- the model's performance on the test data is slightly better than on the train data. The improvements in precision, recall, and F1-score for both classes, as well as the increase in overall accuracy, suggest that the model generalizes well and performs effectively on new, unseen data.

CART model

#classification_report of CART model train data

	precision	recall	f1-score	support
0	0.97	1.00	0.99	192
1	1.00	0.98	0.99	226

```
   accuracy                         0.99       418
  macro avg       0.99      0.99      0.99       418
weighted avg       0.99      0.99      0.99       418
```

```
#classification_report of CART model test data
              precision    recall  f1-score   support

           0       0.54      0.60      0.57       422
           1       0.67      0.61      0.64       553

    accuracy                           0.61       975
   macro avg       0.60      0.61      0.60       975
weighted avg       0.61      0.61      0.61       975
```

```
# calculate AUC of train
AUC:1.000
# calculate AUC of test
AUC:0.611
##confusion matrix of CART model train data
array([[192,   0],
       [  5, 221]], dtype=int64)
##confusion matrix of CART model test data
array([[253, 169],
       [214, 339]], dtype=int64)
```

- Insights:

Precision and Recall Drop: Precision and recall for both classes are notably lower in the test data compared to the training data. This suggests that the model is not generalizing well to unseen examples, leading to more false positives and false negatives.

Class Imbalance Impact: The support values in the test data are larger than in the training data, indicating a different distribution. Class 1 has more instances, which might be impacting the model's performance differently than in the training data.

Overall Lower Performance: The lower accuracy, macro-average F1-score, and weighted-average F1-score on the test data indicate a decrease in overall model performance when applied to new, unseen samples.

Potential Overfitting: The high performance on the training data (0.99 accuracy and F1-scores) suggests the possibility of overfitting. The model might have learned the training data too well, capturing noise or specific patterns that do not generalize to the test data.

Adjustment Needed: Considering the disparities between the training and test data metrics, it might be beneficial to reevaluate the model, potentially adjusting hyper parameters, using more diverse training data, or employing regularization techniques to enhance generalization.

In summary, the model shows signs of overfitting and struggles to generalize well to the test data. Further model tuning and investigation into the data distribution differences could lead to improvements.

Prune the CART model

#classification_report of Prune the CART model train data

	precision	recall	f1-score	support
0	0.63	0.52	0.57	192
1	0.65	0.75	0.69	226
accuracy			0.64	418
macro avg	0.64	0.63	0.63	418
weighted avg	0.64	0.64	0.64	418

#classification_report of Prune the CART model test data

	precision	recall	f1-score	support
0	0.64	0.52	0.57	422
1	0.68	0.77	0.72	553
accuracy			0.66	975
macro avg	0.66	0.65	0.65	975
weighted avg	0.66	0.66	0.66	975

 # calculate AUC of train

AUC:0.696

 # calculate AUC of test

AUC:0.698

#confusion matrix of pruned CART model train data

```
array([[ 99,  93],
       [ 57, 169]], dtype=int64)
```

#confusion matrix of pruned CART model test data

```
array([[221, 201],
       [127, 426]], dtype=int64)
```

- Insights:

Accuracy Improvement: The accuracy on the test data (66%) is slightly higher than that on the train data (64%). This suggests that the model generalizes well to unseen data.

Class-Specific Metrics: In both train and test data, class 1 (positive class) generally has higher precision, recall, and F1-score compared to class 0 (negative class). This indicates that the model performs better on identifying instances of class 1.

Consistency: The macro and weighted averages for precision, recall, and F1-score are relatively consistent between the train and test data, indicating that the model's performance is similar across the two datasets.

Overfitting Consideration: The small difference in performance metrics between train and test data suggests that overfitting might not be a significant issue. The model seems to generalize reasonably well to unseen data.

Room for Improvement: While the model is performing decently, there is room for improvement, especially in terms of precision and recall for class 0.

Inferences of logistics model:

Class 0 (Contraceptive Method Not Used):

- Precision: 64% Among the instances predicted as not using contraceptive methods, 64% are correctly classified.
- Recall: 53% Out of all instances where couples are not using contraceptive methods, the model correctly identifies 53%.
- F1-Score: 58% The F1-Score, a balance between precision and recall, is 58% for couples not using contraceptive methods.

Class 1 (Contraceptive Method Used):

- Precision: 68% Among the instances predicted as using contraceptive methods, 68% are correctly classified.
- Recall: 78% Out of all instances where couples are using contraceptive methods, the model correctly identifies 78%.
- F1-Score: 73% The F1-Score, a balance between precision and recall, is 73% for couples using contraceptive methods.

Accuracy: 67%

The overall accuracy of the model across both classes is 67%, indicating the proportion of correctly predicted instances.
Accuracy, AUC, Precision and Recall for test data is almost inline with training data. This proves no overfitting or underfitting has happened, and overall the model is a good model for classification.

Inferences of Linear Discriminant Analysis model:

Class 0 (Contraceptive Method Not Used):

Precision: 63% Among the instances predicted as not using contraceptive methods, 63% are correctly classified.

Recall: 52%

Out of all instances where couples are not using contraceptive methods, the model correctly identifies 52%.

F1-Score: 57%

The F1-Score, a balance between precision and recall, is 57% for couples not using contraceptive methods. Class 1 (Contraceptive Method Used):

Precision: 68%

Among the instances predicted as using contraceptive methods, 68% are correctly classified.

Recall: 77%

Out of all instances where couples are using contraceptive methods, the model correctly identifies 77%.

F1-Score: 72%

The F1-Score, a balance between precision and recall, is 72% for couples using contraceptive methods. Overall Model Performance:

Accuracy: 66%

The overall accuracy of the model across both classes is 66%, indicating the proportion of correctly predicted instances.

- Accuracy, AUC, Precision and Recall for test data is almost inline with training data. This proves no overfitting or underfitting has happened, and overall the model is a good model for classification
- The model shows a better performance in predicting couples using contraceptive methods (Class 1) compared to those not using (Class 0).
- For Class 1, the model has a higher precision and recall, indicating a better ability to identify instances where contraceptive methods are used.
- For Class 0, precision is moderate, but recall is relatively lower, suggesting room for improvement in identifying instances where contraceptive methods are not used.

Inferences of CART model model:

Class 0 (Contraceptive Method Not Used):

- Precision: 54% Among the instances predicted as not using contraceptive methods, 54% are correctly classified.
- Recall: 60% Out of all instances where couples are not using contraceptive methods, the model correctly identifies 60%.
- F1-Score: 57% The F1-Score, a balance between precision and recall, is 57% for couples not using contraceptive methods.

Class 1 (Contraceptive Method Used):

- Precision: 67% Among the instances predicted as using contraceptive methods, 67% are correctly classified.
- Recall: 61% Out of all instances where couples are using contraceptive methods, the model correctly identifies 61%.
- F1-Score: 64% The F1-Score, a balance between precision and recall, is 64% for couples using contraceptive methods.
- Overall Model Performance:

Accuracy: 61%

The overall accuracy of the model across both classes is 61%, indicating the proportion of correctly predicted instances.
Insights:

- Precision and Recall Drop: Precision and recall for both classes are notably lower in the test data compared to the training data. This

suggests that the model is not generalizing well to unseen examples, leading to more false positives and false negatives.

- The high performance on the training data (0.99 accuracy and F1-scores) suggests the possibility of overfitting. The model might have learned the training data too well, capturing noise or specific patterns that do not generalize to the test data.
- the model shows signs of overfitting and struggles to generalize well to the test data. Further model tuning and investigation into the data distribution differences could lead to improvements.

Inferences of Prune the CART model:

Class 1 (Contraceptive Method Used):

- Precision: 68% Among the instances predicted as using contraceptive methods, 68% are correctly classified.
- Recall: 77% Out of all instances where couples are using contraceptive methods, the model correctly identifies 77%.
- F1-Score: 72% The F1-Score, a balance between precision and recall, is 72% for couples using contraceptive methods.
- Overall Model Performance:

Accuracy: 66%

The overall accuracy of the model across both classes is 66%, indicating the proportion of correctly predicted instances.

- Summary: The model demonstrates a balanced performance between Class 0 and Class 1, with a slightly higher F1-Score for Class 1. For Class 0, recall is relatively lower, suggesting room for improvement in identifying instances where contraceptive methods are not used. For Class 1, precision is relatively higher, indicating a better ability to identify instances where contraceptive methods are used.
- Accuracy, AUC, Precision and Recall for test data is almost inline with training data. This proves no overfitting or underfitting has happened, and overall the model is a good model for classification.

Comparison and Selection:

Logistic Regression vs. LDA:

Both models show similar performance metrics, with Logistic Regression having a slightly higher accuracy.

Logistic Regression vs. CART:

Logistic Regression outperforms CART in terms of accuracy and F1-Score for both classes.

Logistic Regression vs. Pruned CART:

Both models have similar performance in terms of accuracy and F1-Score for Class 1, but Logistic Regression has better precision and recall for Class 0.

Best Model: Logistic Regression

Logistic Regression appears to be the better-performing model overall, demonstrating higher accuracy and balanced precision and recall for both classes.

Rationale:

- Logistic Regression provides a good balance between precision and recall for both classes.
- It shows consistent performance across accuracy, precision, recall, and F1-Score on both training and test data.
- The model has no signs of overfitting or underfitting, as evidenced by similar metrics on the training and test datasets.
- In summary, based on the provided metrics and comparison, the Logistic Regression model seems to be the most suitable for the given classification task.

2-4 Business Insights & Recommendations

- Comment on the importance of features based on the best model - Conclude with the key takeaways (actionable insights and recommendations) for the business

Answers:

importance of features based on the best model

- Logistic Regression appears to be the better-performing model overall, demonstrating higher accuracy and balanced precision and recall for both classes.
- Logistic Regression provides a good balance between precision and recall for both classes.
- It shows consistent performance across accuracy, precision, recall, and F1-Score on both training and test data.
- The model has no signs of overfitting or underfitting, as evidenced by similar metrics on the training and test datasets.
- In summary, based on the provided metrics and comparison, the Logistic Regression model seems to be the most suitable for the given classification task.

Actionable Insights:

Logistic Regression appears to be the better-performing model overall, demonstrating higher accuracy and balanced precision and recall for both classes. Logistic Regression provides a good balance between precision and recall for both classes. It shows consistent performance across accuracy, precision, recall, and F1-Score on both training and test data. The model has no signs of overfitting or underfitting, as evidenced by similar metrics on the training and test datasets. In summary, based on the provided metrics and comparison, the Logistic Regression model seems to be the most suitable for the given classification task.

- Precision and Recall Analysis: Precision for Class 1 (Contraceptive Method Used):

The model has a precision of 68%, indicating that 68% of the couples predicted to be using contraceptive methods are correctly classified. This is valuable for targeted interventions as it minimizes false positives. Recall for Class 1:

The recall for Class 1 is 78%, suggesting that the model correctly identifies 78% of the couples who are actually using contraceptive methods. This is crucial for ensuring that couples in need of contraceptive support are appropriately identified.

- Importance of Features: Identify Key Features:

Explore the coefficients of the Logistic Regression model to identify the features contributing significantly to the prediction of contraceptive use. Positive and Negative Impact:

Understand whether specific features have a positive or negative impact on the likelihood of contraceptive use. This insight can guide targeted interventions.

- Logistic Regression as the Best Model: Model Trustworthiness:

The Logistic Regression model outperforms other models, demonstrating higher accuracy, precision, and recall. The model's consistency across training and test data indicates its reliability. Interpretability:

Logistic Regression provides a clear interpretation of feature importance, making it suitable for understanding the factors influencing contraceptive use.

Key Observations:

Educational and Religious Factors:

- Tertiary education is high for both wives and husbands.
- Uneducated persons are more common among wives.
- Scientology is the predominant religion among wives.

Employment and Standard of Living:

- Most wives are not working.
- The highest standard of living index is in the "very high" category.

Contraceptive Usage:

- A considerable number of persons use contraceptive methods.
- Couples with a "very high" standard of living index are more likely to use contraceptives.
- Couples with working wives are more likely to use contraceptive methods.

Demographic Correlations:

- Wife's age and husband's occupation are highly negatively correlated.
- Number of children born and husband's occupation are negatively correlated.
- Number of children born and wife's age are positively correlated.

Age and Contraceptive Usage:

- Couples with wives aged 25 are most likely to use contraceptive methods.
- Couples with wives aged 42 to 49 are more likely not to use contraceptive methods.

Occupational Influence:

- Couples with specific husband occupations (3 and 4) are more likely to use or not use contraceptive methods.

Actionable Insights:

- Targeted Educational Programs: Develop educational programs targeting wives with lower education levels to increase awareness of contraceptive methods.
- Religious and Cultural Sensitivity: Consider the predominant religion (Scientology) among wives when designing family planning campaigns, ensuring cultural sensitivity.
- Workforce Engagement: Encourage and support workforce engagement for wives, as couples with working wives are more likely to use contraceptive methods.
- Tailored Age-Based Interventions: Tailor family planning interventions based on age groups. For example, focus on promoting contraceptive methods among couples with wives aged 25.
- Occupational Guidance: Provide targeted guidance for couples with specific husband occupations (3 and 4) regarding contraceptive choices.
- Continuous Monitoring: Continuously monitor demographic and cultural shifts to adapt family planning strategies accordingly.

Model Comparison Insights:

- Logistic Regression Superiority: Logistic Regression outperforms both CART and Pruned CART in terms of accuracy and F1-Score for both classes.
- Precision and Recall Balance: Logistic Regression exhibits a better balance between precision and recall for both classes, making it a suitable model for the classification task.
- Consistent Performance: Logistic Regression shows consistent performance across training and test datasets, indicating its reliability and generalizability.

Business Recommendations:

- Invest in Education: Invest in educational programs to empower women with knowledge about family planning, particularly among those with lower education levels.
- Promote Workplace Inclusion: Encourage workplace inclusion for women to positively impact contraceptive use, as observed in couples with working wives.
- Culturally Tailored Campaigns: Develop culturally tailored family planning campaigns that consider religious and cultural nuances.
- Age-Stratified Interventions: Implement age-stratified interventions to address the varying contraceptive needs across different age groups.

- Occupational Guidance Services: Offer guidance services for couples with specific husband occupations, addressing their unique family planning considerations.
- Regular Assessments: Regularly assess and update family planning strategies based on evolving demographic trends and societal changes.
- Targeted Outreach Programs: Precision-Driven Interventions: Leverage the precision of 68% to implement targeted outreach programs for couples who are predicted to be using contraceptive methods. This helps ensure efficient allocation of resources.
- Feature-Informed Interventions: Focus on Influential Features: Utilize the insights from influential features to tailor interventions. Features with a higher impact on contraceptive use can guide the development of targeted educational campaigns or support services.
- Collaboration with Healthcare Providers: Healthcare Provider Partnerships: Collaborate with healthcare providers to enhance family planning services. The model's predictions can inform providers about potential contraceptive needs, allowing for proactive counseling.
- Continuous Monitoring: Regular Model Monitoring: Implement a system for continuous monitoring of the model's performance. Periodically reassess the model's accuracy and update it as needed to reflect changes in the population.
- Community Engagement: Community Workshops and Education: Conduct community workshops and educational campaigns based on the identified influential features. This can empower communities with information about family planning and contraceptive methods.
- Key Takeaways: The Logistic Regression model offers a reliable tool for predicting contraceptive use. Precision and recall metrics provide insights into the model's ability to identify couples using contraceptive methods accurately. Targeted interventions informed by influential features can improve the effectiveness of family planning programs.