SA1

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####Univariate Data Analysis Load the dataset and summarize its structure.

```r
library(ggplot2)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

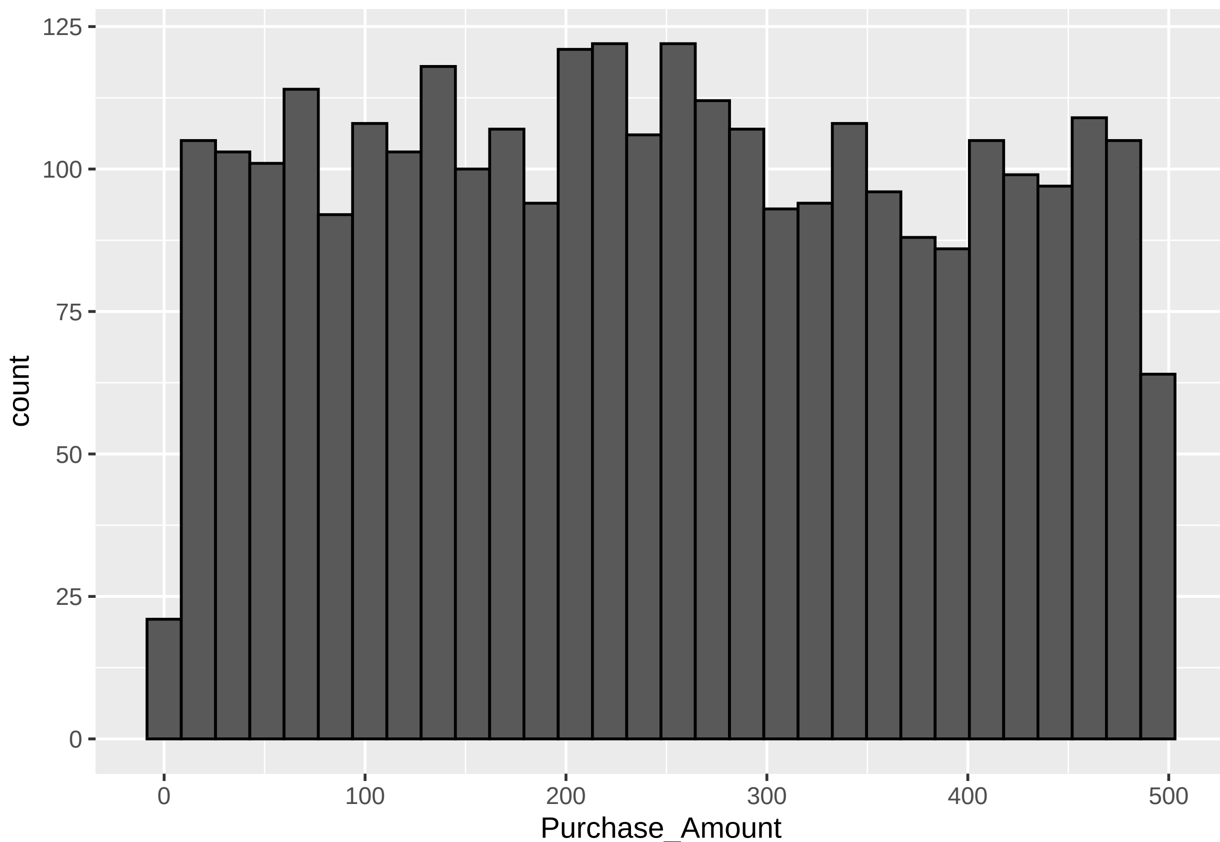
```r
data <- read.csv("D:/FEU/3RD YR 2ND SEM/EDA/EDA_Ecommerce_Assessment.csv")

head(data)
```

```
##   Customer_ID Gender Age Browsing_Time Purchase_Amount Number_of_Items
## 1           1   Male  65         46.55          231.81               6
## 2           2 Female  19         98.80          472.78               8
## 3           3   Male  23         79.48          338.44               1
## 4           4   Male  45         95.75           37.13               7
## 5           5   Male  46         33.36          235.53               3
## 6           6 Female  43         83.39          123.92               9
##   Discount_Applied Total_Transactions       Category Satisfaction_Score
## 1               17                 16       Clothing                  2
## 2               15                 43          Books                  4
## 3               28                 31    Electronics                  1
## 4               43                 27 Home & Kitchen                  5
## 5               10                 33          Books                  3
## 6                5                 29       Clothing                  2
```

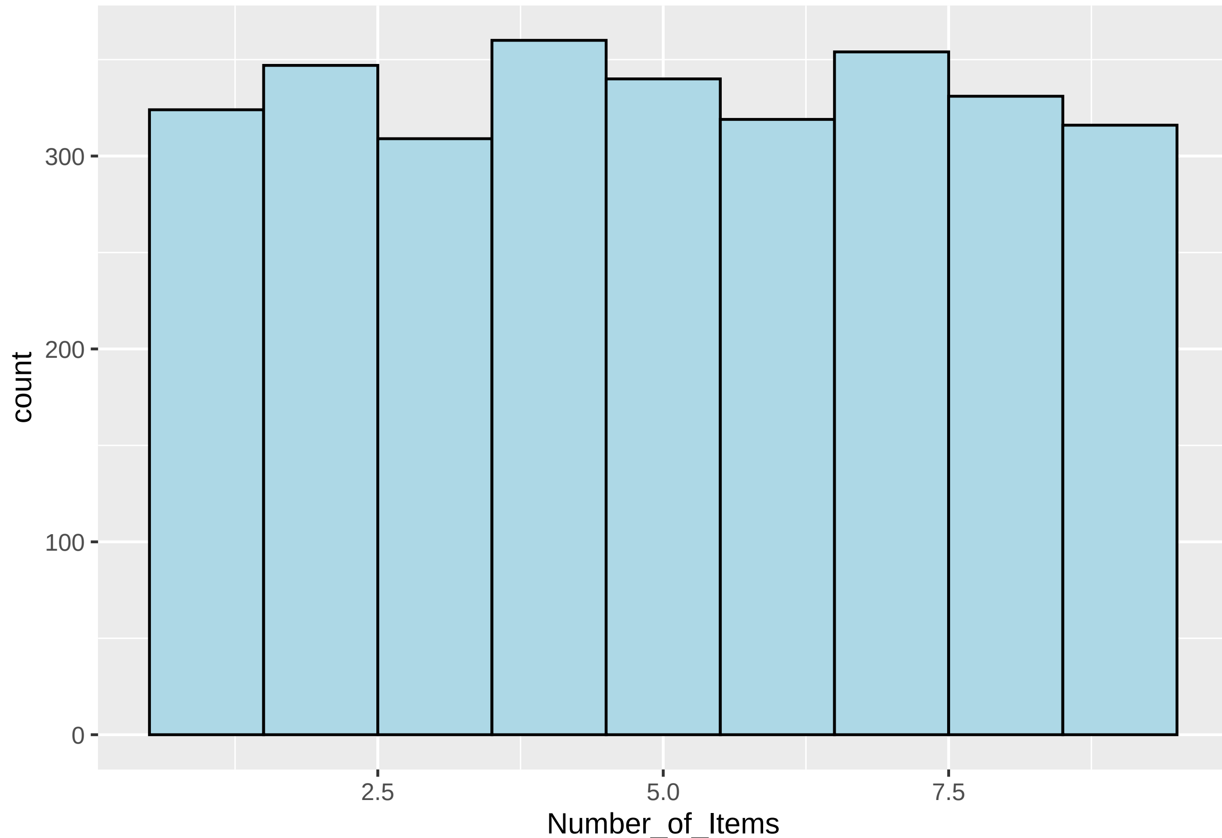
Create histograms and boxplots to visualize the distribution of Purchase_Amount, Number_of_Items, and Satisfaction_Score.

```r
plot1<-ggplot()+
      geom_histogram(aes(x=Purchase_Amount), data=data, color = "black")

plot2<-ggplot()+
      geom_histogram(aes(x=Number_of_Items), data=data,bins= 9, color="black", fill="lightblue")

plot3<-ggplot()+
      geom_histogram(aes(x=Satisfaction_Score), data=data, bins=5, color="black", fill="lightpink")

print(plot1)
```

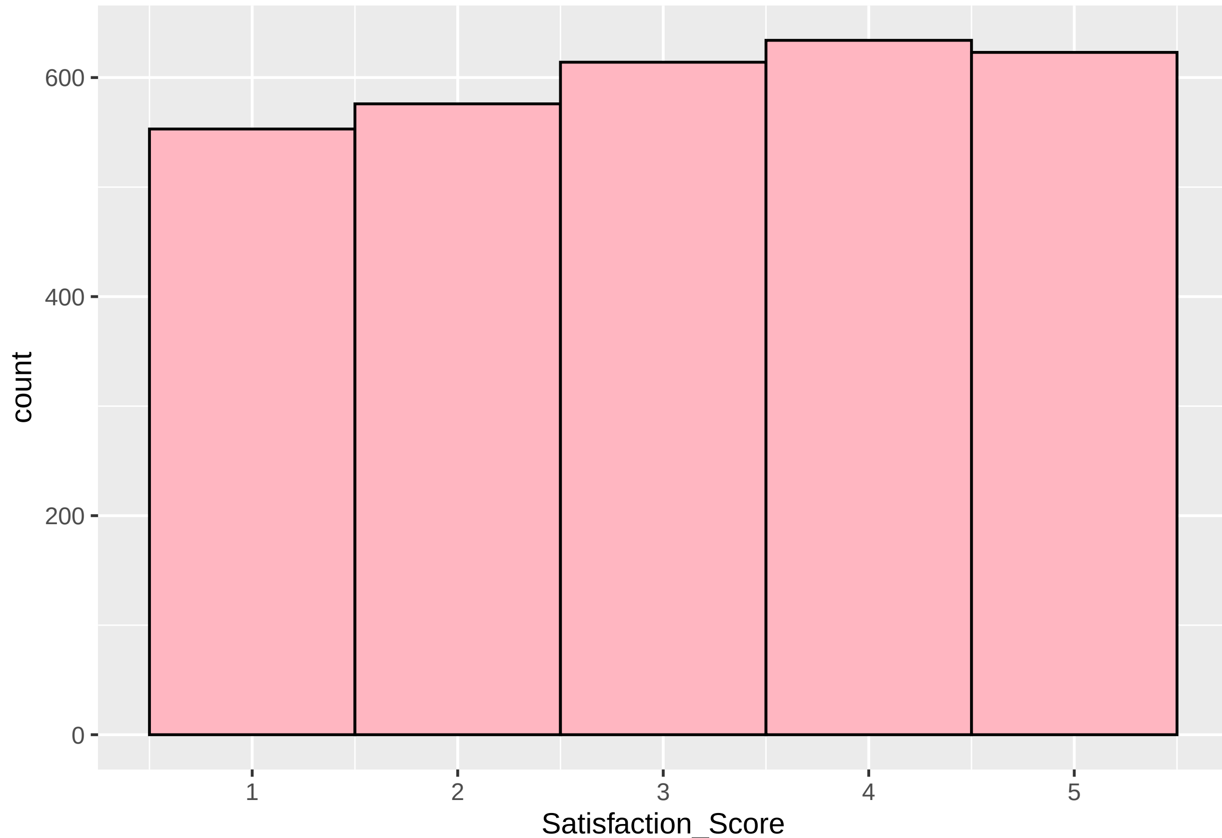
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```




```r
print(plot2)
```

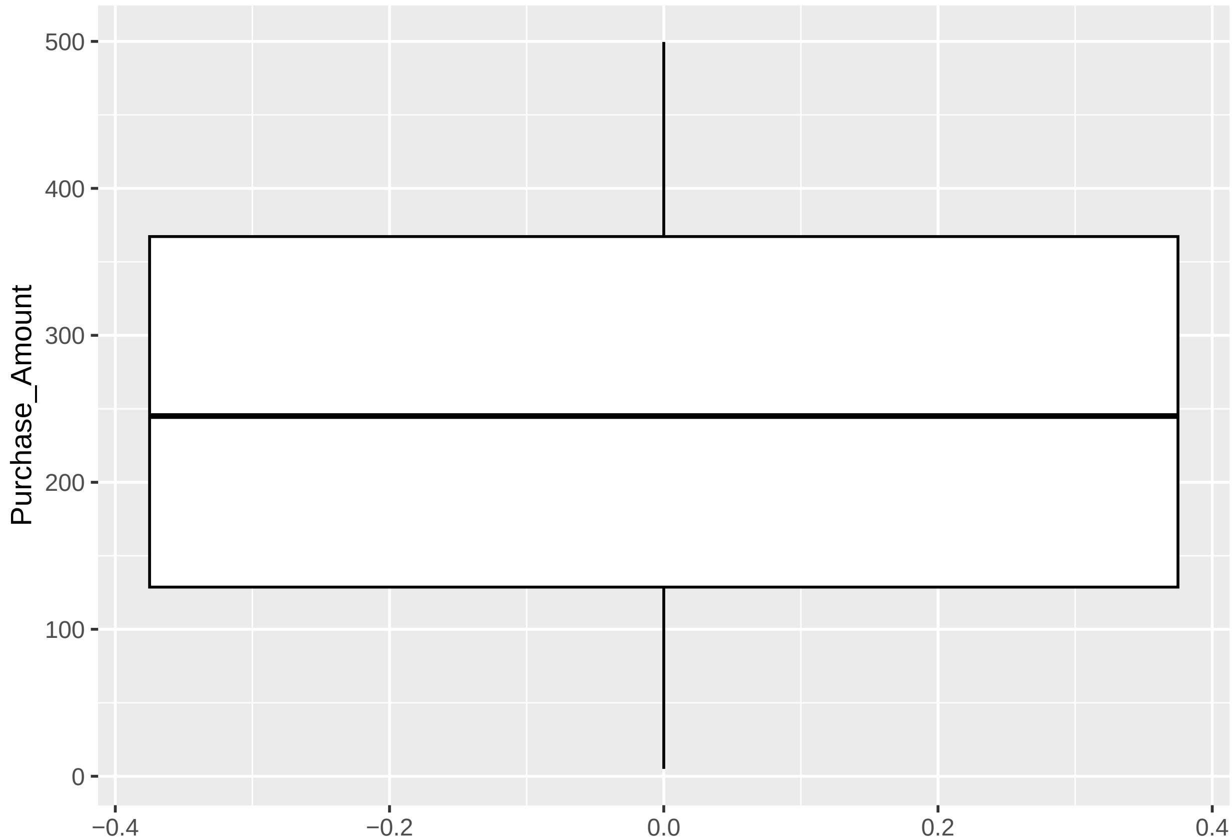



```r
print(plot3)
```

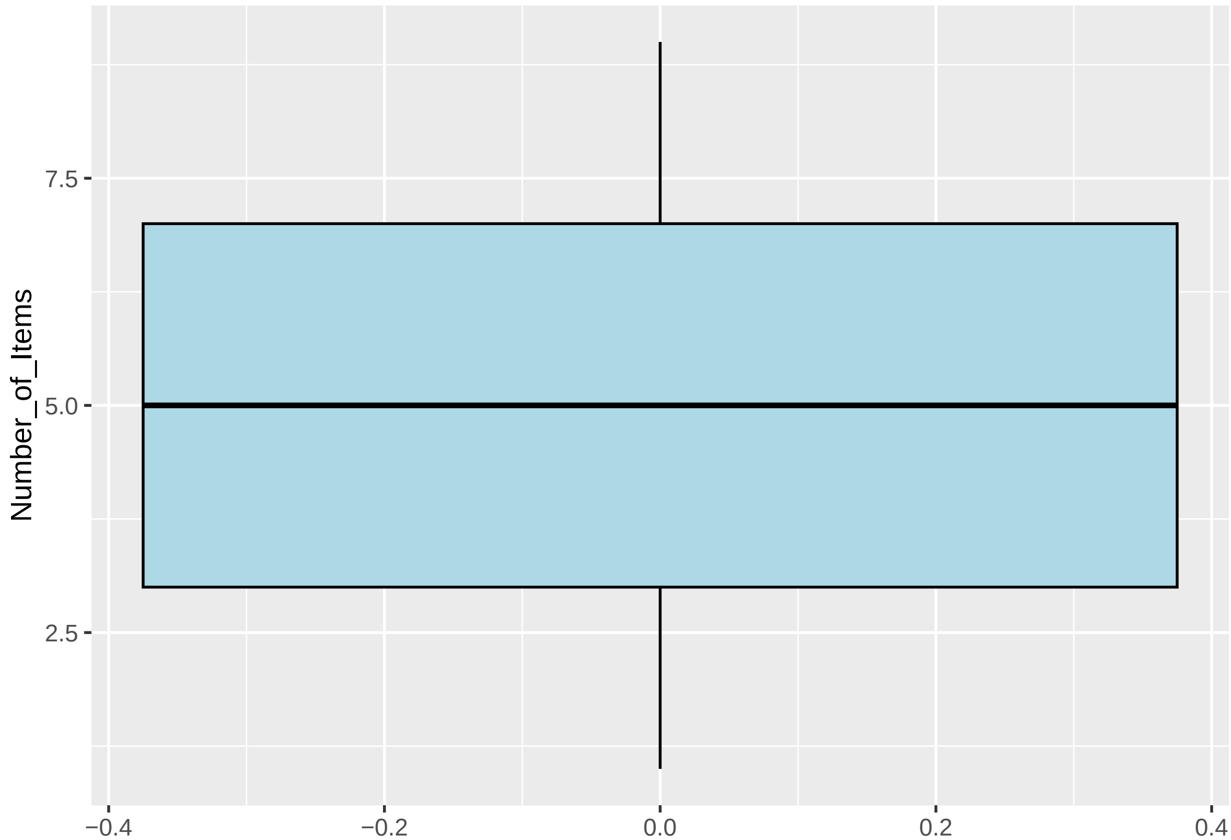


Compute measures of central tendency (mean, median, mode) and spread (variance, standard deviation, IQR) for Purchase_Amount.

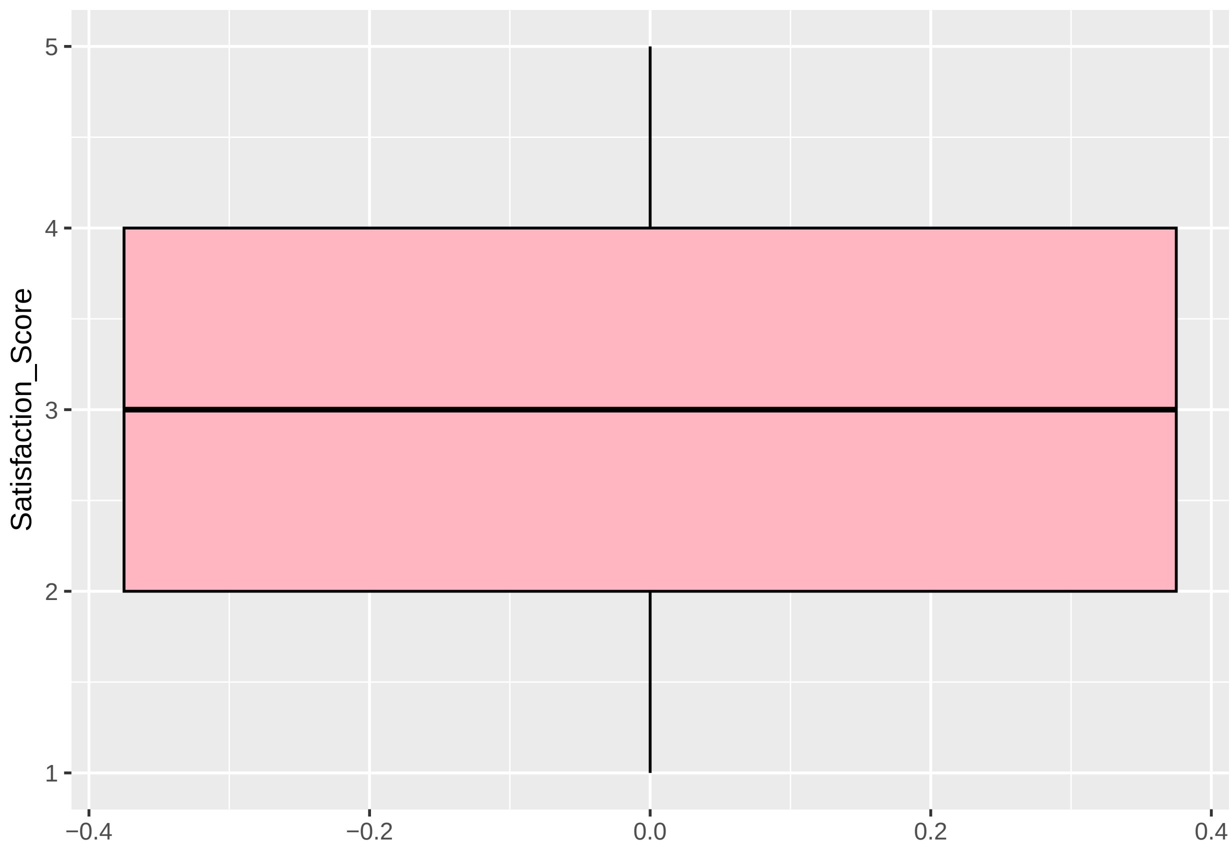
```
plot1 <- ggplot() +
  geom_boxplot(aes(y = Purchase_Amount), data = data, color = "black")

plot2 <- ggplot() +
  geom_boxplot(aes(y = Number_of_Items), data = data, color = "black", fill = "lightblue")

plot3 <- ggplot() +
  geom_boxplot(aes(y = Satisfaction_Score), data = data, color = "black", fill = "lightpink")

print(plot1)
```




```r
print(plot2)
```




```r
print(plot3)
```

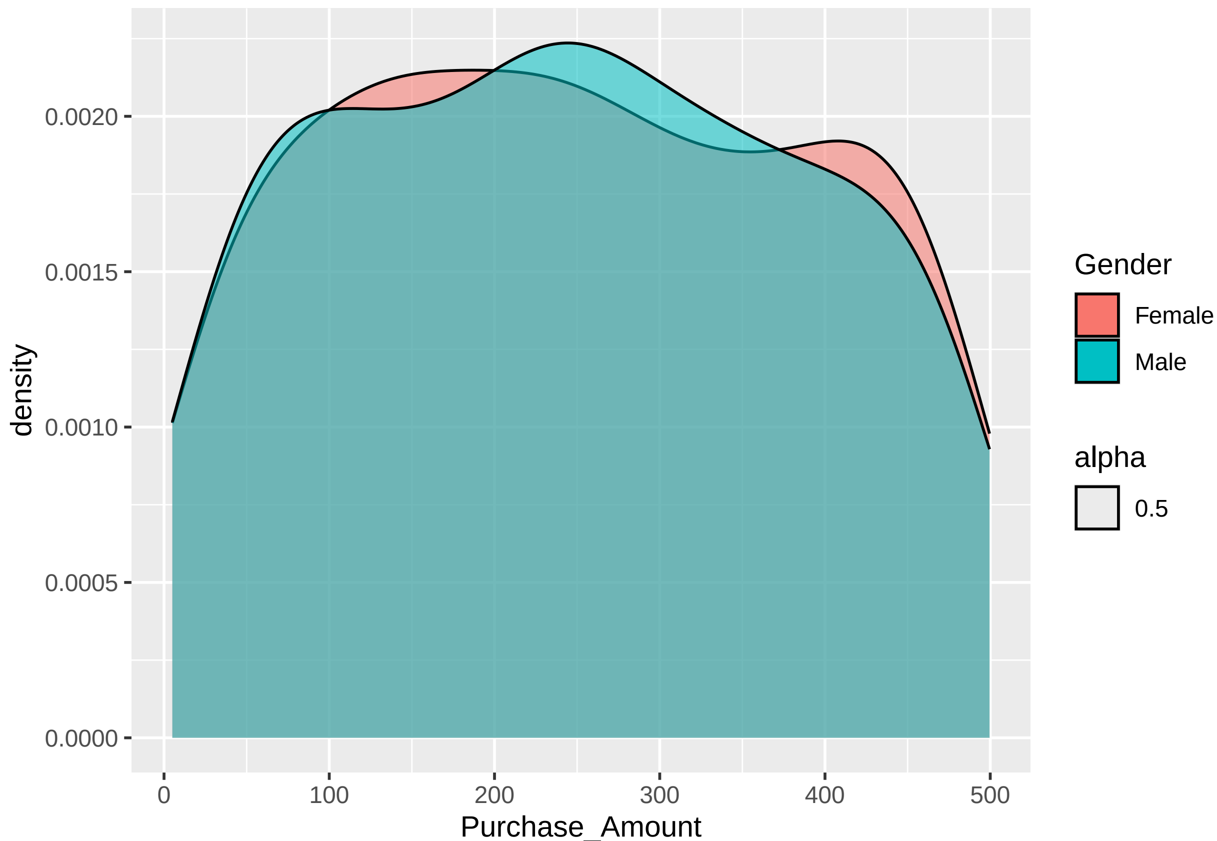



```r
mean_purchase <- mean(data$Purchase_Amount)
median_purchase <- median(data$Purchase_Amount)
mode_purchase <- names(sort(-table(data$Purchase_Amount)))[1]

var_purchase <- var(data$Purchase_Amount)
sd_purchase <- sd(data$Purchase_Amount)
IQR_purchase <- IQR(data$Purchase_Amount)

summary_df <- data.frame(
  Statistic = c("Mean", "Median", "Mode", "Variance", "Standard Deviation", "Interquartile Range"),
  Value = c(mean_purchase, median_purchase, mode_purchase, var_purchase, sd_purchase, IQR_purchase)
)

print(summary_df)
```

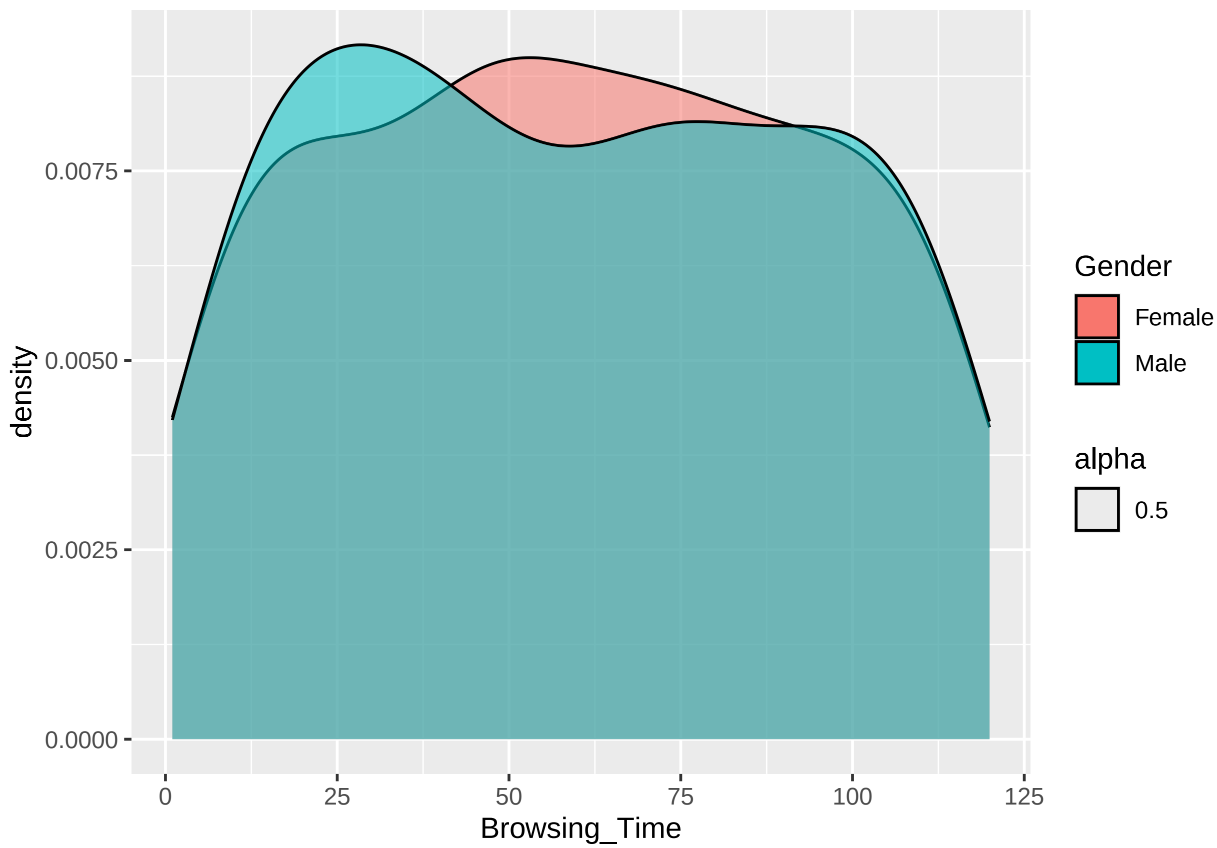
```
##             Statistic            Value
## 1                Mean        247.96254
## 2              Median           245.09
## 3                Mode            29.33
## 4            Variance 19845.9862093515
## 5  Standard Deviation 140.875782905904
## 6 Interquartile Range          238.505
```

Compare the distribution of Browsing_Time and Purchase_Amount across different Gender groups using density plots.

```
ggplot(data=data, aes(x=Purchase_Amount, group=Gender, fill=Gender, alpha=0.5)) +
  geom_density(adjust=1.5)
```




```
ggplot(data=data, aes(x=Browsing_Time, group=Gender, fill=Gender, alpha=0.5)) +
  geom_density(adjust=1.5)
```



Apply a logarithmic or square root transformation on Browsing_Time and evaluate changes in skewness.

```r
library(moments)

data <- data%>%
  mutate(Log_Browsing_Time = log(Browsing_Time + 1))  # +1 to avoid log(0)

skewness_value <- skewness(data$Log_Browsing_Time, na.rm = TRUE)
print(paste("Skewness of Log_Browsing_Time:", skewness_value))
```

```
## [1] "Skewness of Log_Browsing_Time: -1.21898281542323"
```

This is skewed to the left.

Fit a simple linear regression model predicting Purchase_Amount based on Browsing_Time. Interpret the results.

```r
model<-lm(Purchase_Amount~Browsing_Time, data=data)
summary(model)
```

```
##
## Call:
## lm(formula = Purchase_Amount ~ Browsing_Time, data = data)
##
## Residuals:
```

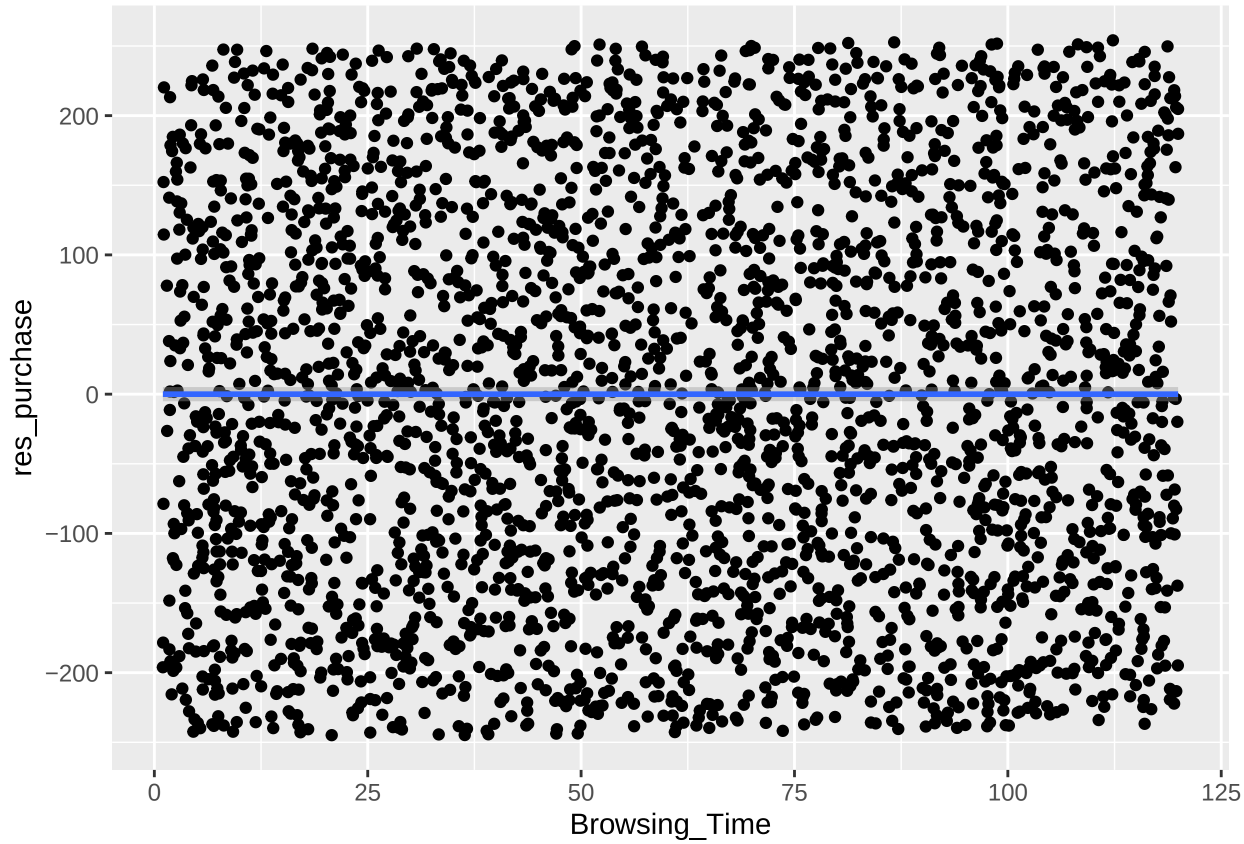
```
##      Min       1Q   Median       3Q      Max
## -244.867 -120.473   -2.946  118.246  254.069
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   252.65596    5.17524  48.820   <2e-16 ***
## Browsing_Time  -0.07839    0.07501  -1.045    0.296
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 140.9 on 2998 degrees of freedom
## Multiple R-squared:  0.0003642,  Adjusted R-squared:  3.075e-05
## F-statistic: 1.092 on 1 and 2998 DF,  p-value: 0.2961
```

There is no strong evidence that browsing time significantly affects purchase amounts ($p > 0.05$). The model suggests that when browsing time is zero, customers spend about ₱253 on average. While browsing time shows some relationship with spending, the connection isn't statistically strong enough in this data to be certain it's not just random variation.

Use ggplot2 (or equivalent) to create scatter plots and regression lines.

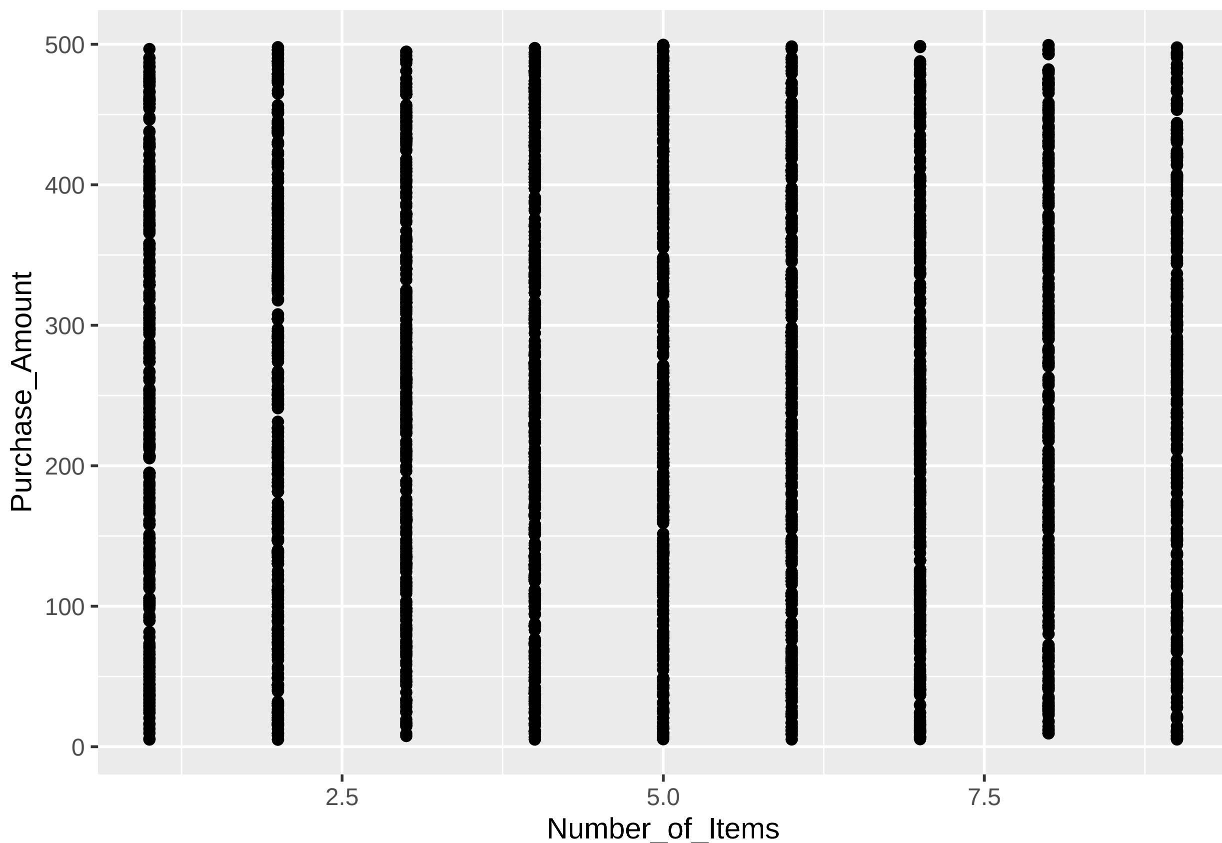
```
res_purchase <- resid(model)
data$res_purch <- res_purchase

ggplot(data=data, aes(x=Browsing_Time, y=res_purchase)) +
  geom_point()+
  geom_smooth()
```

```
## `geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```



Bivariate Data Analysis Create scatter plots to explore the relationship between Purchase_Amount and Number_of_Items.

```
ggplot(data=data, aes(x=Number_of_Items, y=Purchase_Amount)) +
  geom_point()
```

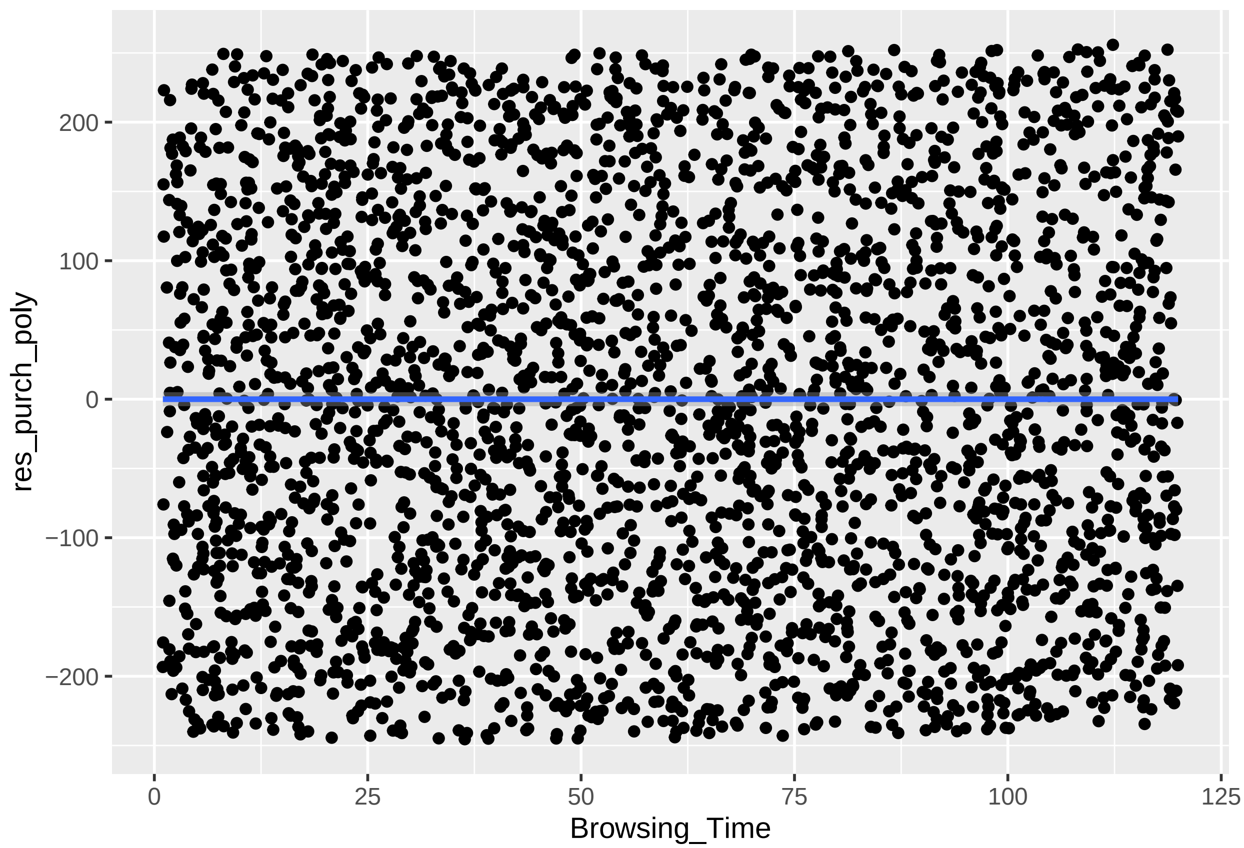


Purchase_Amount is varying from 0-500. This indicates that there are products that have higher value than others and since Purchase_Amount vary across all points, there are no clear relationship between Number_of_Items and Purchase_Amount.

Fit a polynomial regression model for Purchase_Amount and Browsing_Time and compare it with a simple linear model.

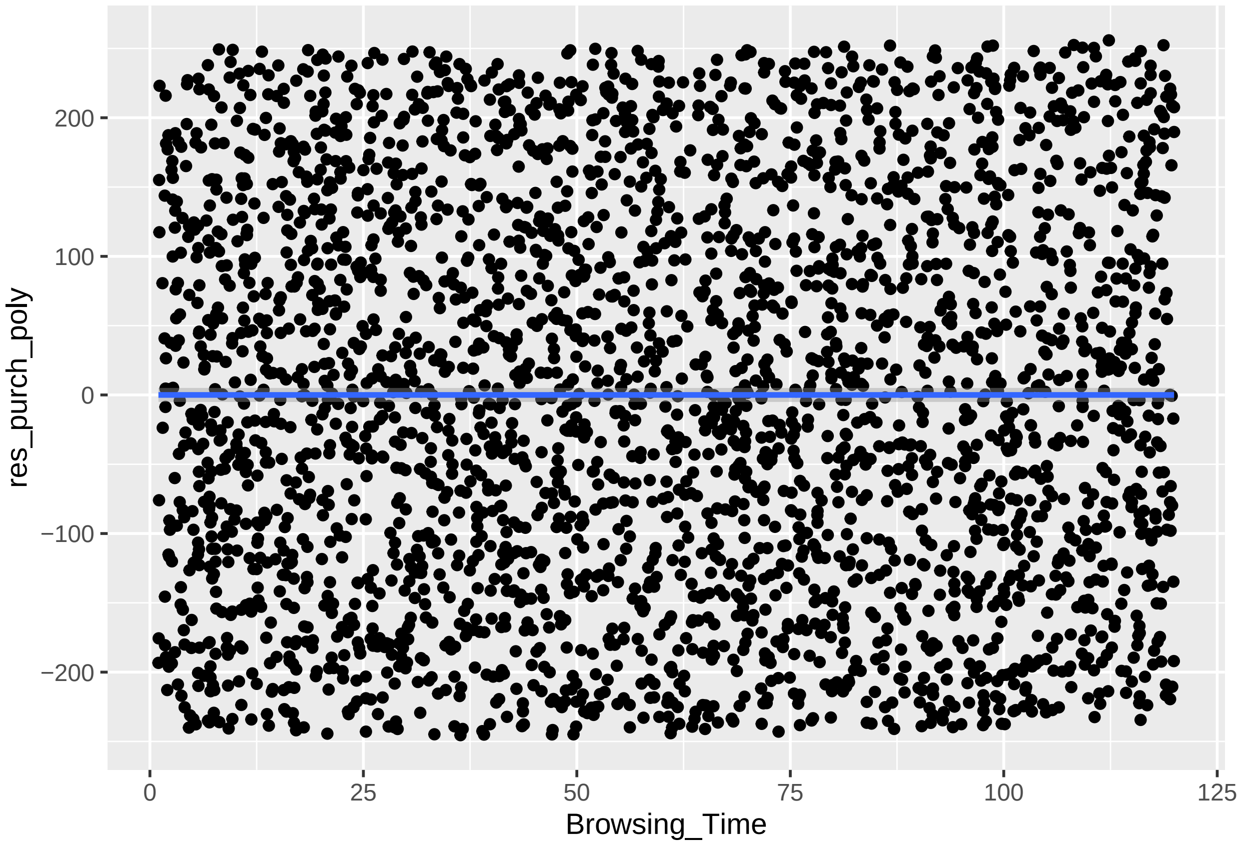
```
model<-lm(Purchase_Amount~poly(Browsing_Time, 2), data=data)

res_purch_poly <- resid(model)
data$res_purch_poly <- res_purch_poly

p1<-ggplot(data=data, aes(x=Browsing_Time, y=res_purch_poly)) +
      geom_point()+
      geom_smooth()

p2<-ggplot(data=data, aes(x=Browsing_Time, y=res_purch_poly)) +
      geom_point()+
      geom_smooth()

p1
```

```
## `geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```




```
p2
```

```
## `geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```

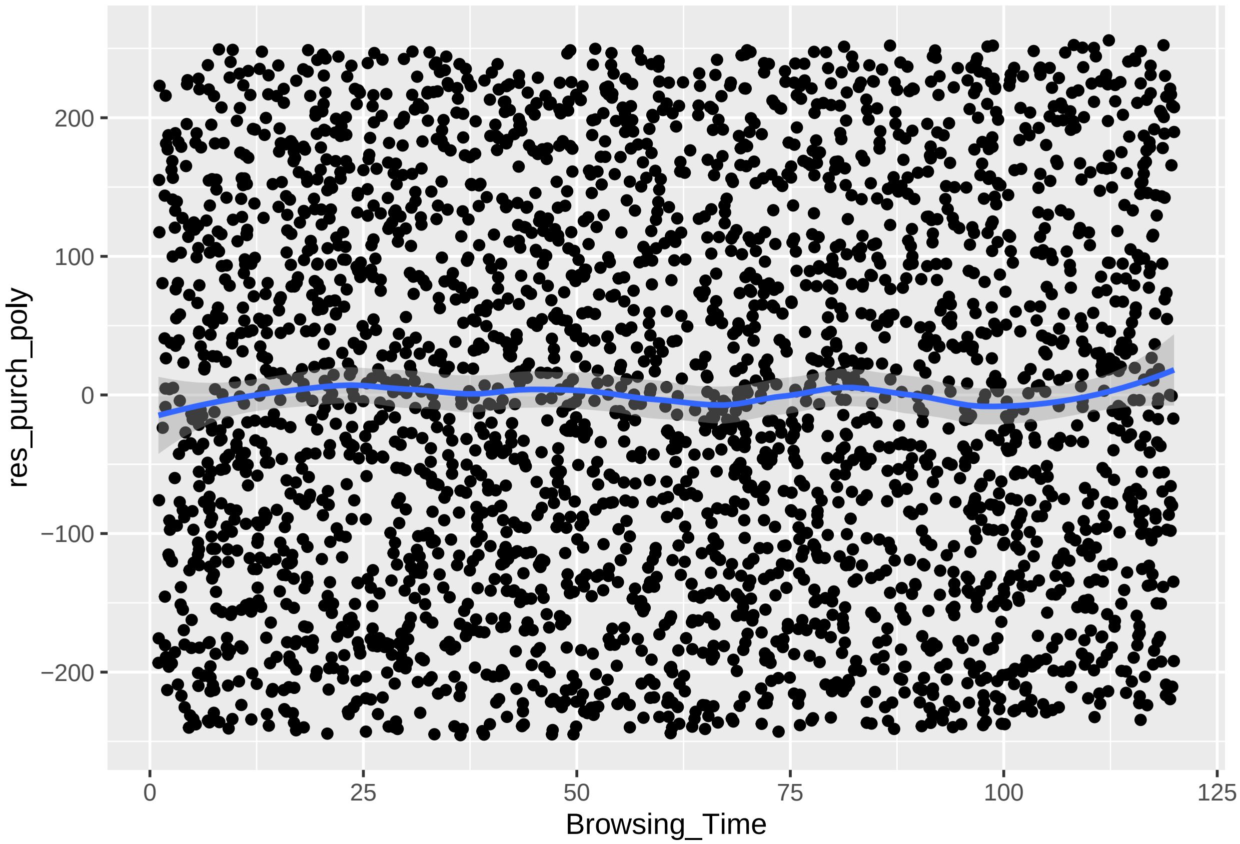


There are no difference between the two even if you look very closely.

Apply LOESS (Locally Estimated Scatterplot Smoothing) to Purchase_Amount vs. Browsing_Time and visualize the results.

```
ggplot(data=data, aes(x=Browsing_Time, y=res_purch_poly)) +
  geom_point()+
  geom_smooth(method="loess", span=0.4, se=TRUE)
```

```
## `geom_smooth()` using formula = 'y ~ x'
```



LOESS (blue squiggly line) has a few fluctuations throughout the map, but there is still no strong relationship between the two.

Compare robust regression methods (Huber or Tukey regression) with ordinary least squares (OLS).

```r
library(MASS)
```

```
##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select
```

```r
huber_model <- rlm(Purchase_Amount ~ Browsing_Time, data = data, psi = psi.huber)
summary(huber_model)
```

```
##
## Call: rlm(formula = Purchase_Amount ~ Browsing_Time, data = data, psi = psi.huber)
## Residuals:
##      Min       1Q   Median       3Q      Max
## -244.818 -120.331   -2.848  118.291  254.289
##
## Coefficients:
##             Value    Std. Error t value
## (Intercept) 252.6462   5.3363    47.3448
```

```
## Browsing_Time  -0.0803   0.0773    -1.0378
##
## Residual standard error: 176.9 on 2998 degrees of freedom
```

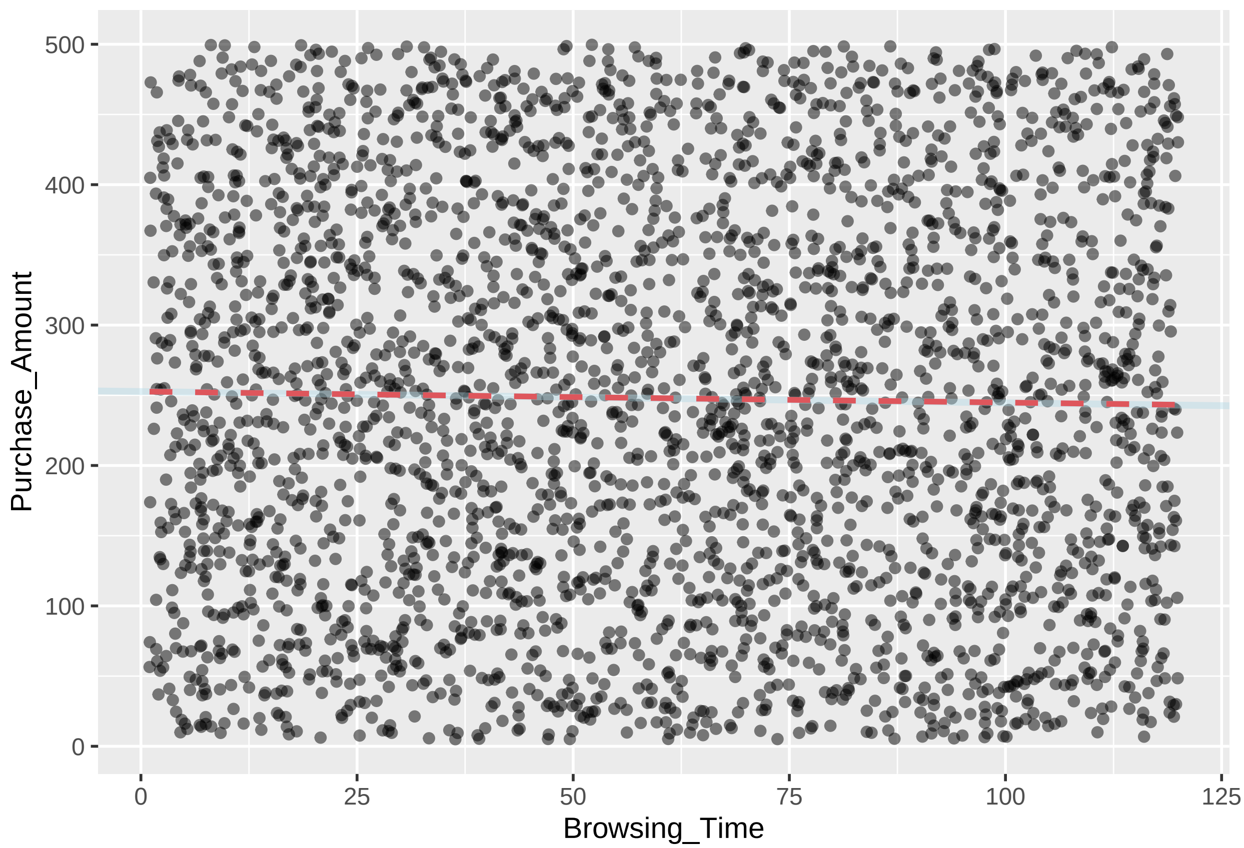
```r
ols_model <- lm(Purchase_Amount ~ Browsing_Time, data =data)
summary(ols_model)
```

```
##
## Call:
## lm(formula = Purchase_Amount ~ Browsing_Time, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -244.867 -120.473   -2.946  118.246  254.069
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   252.65596    5.17524  48.820   <2e-16 ***
## Browsing_Time  -0.07839    0.07501  -1.045    0.296
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 140.9 on 2998 degrees of freedom
## Multiple R-squared:  0.0003642,  Adjusted R-squared:  3.075e-05
## F-statistic: 1.092 on 1 and 2998 DF,  p-value: 0.2961
```

```r
ggplot(data, aes(x = Browsing_Time, y = Purchase_Amount)) +
  geom_point(alpha = 0.5, color = "black") +
  geom_smooth(method = "lm", color = "red", se = FALSE, linetype = "dashed") +
  geom_abline(slope = coef(huber_model)[2], intercept = coef(huber_model)[1], color = "lightblue", size
```

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

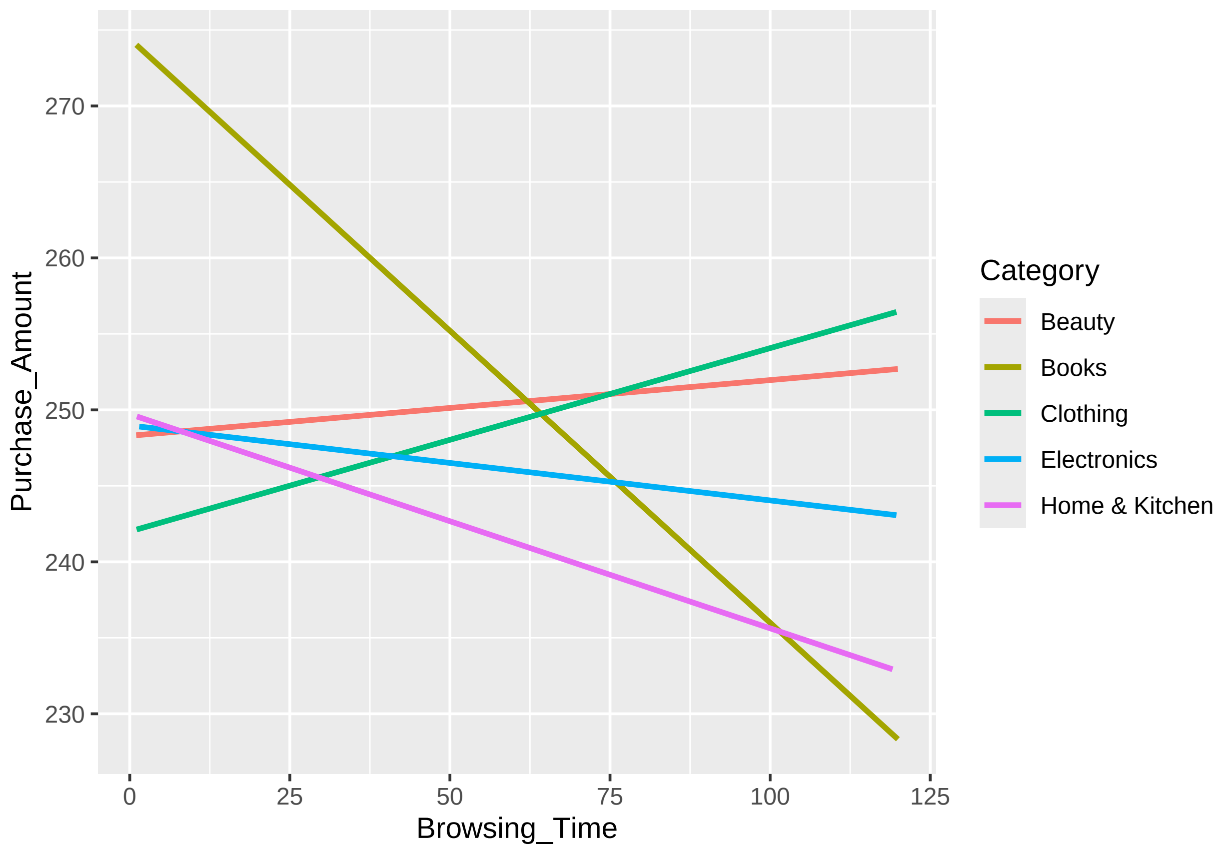


Looking at the summary they have minor differences to each other but in the graph they traverse the same line and are almost the same, with minimal differences.

Trivariate/Hypervariate Data Analysis Explore interaction effects between Browsing_Time and Category on Purchase_Amount using interaction plots.

```
ggplot(data, aes(x = Browsing_Time, y = Purchase_Amount, color = Category)) +
  geom_smooth(method = "lm", se = FALSE)
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

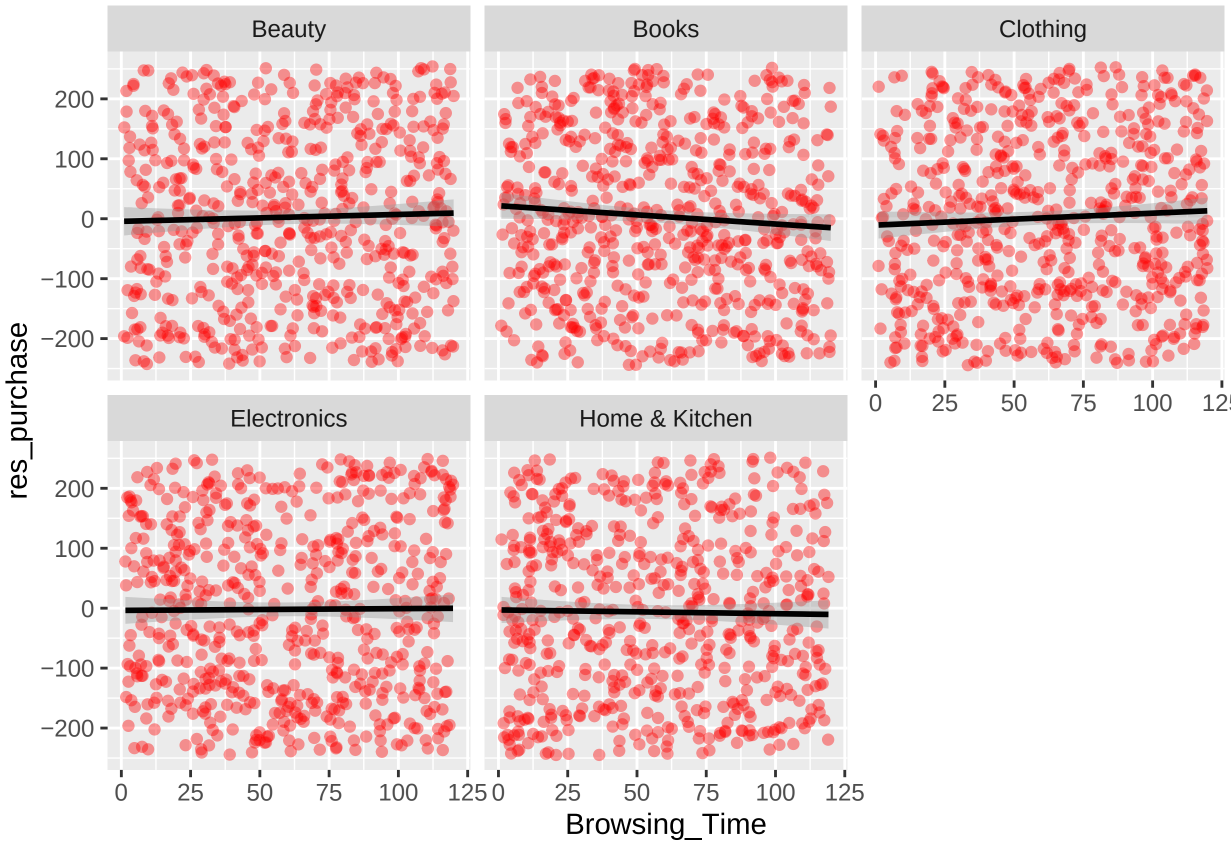


We can see that there are different interactions between purchase amount and browsing time and that there are categories like books and home & kitchen that have a negative relationship (intersecting point below) and positive relationships with clothing and beauty (intersecting point above).

Create coplots of Purchase_Amount against Browsing_Time for different levels of Category.

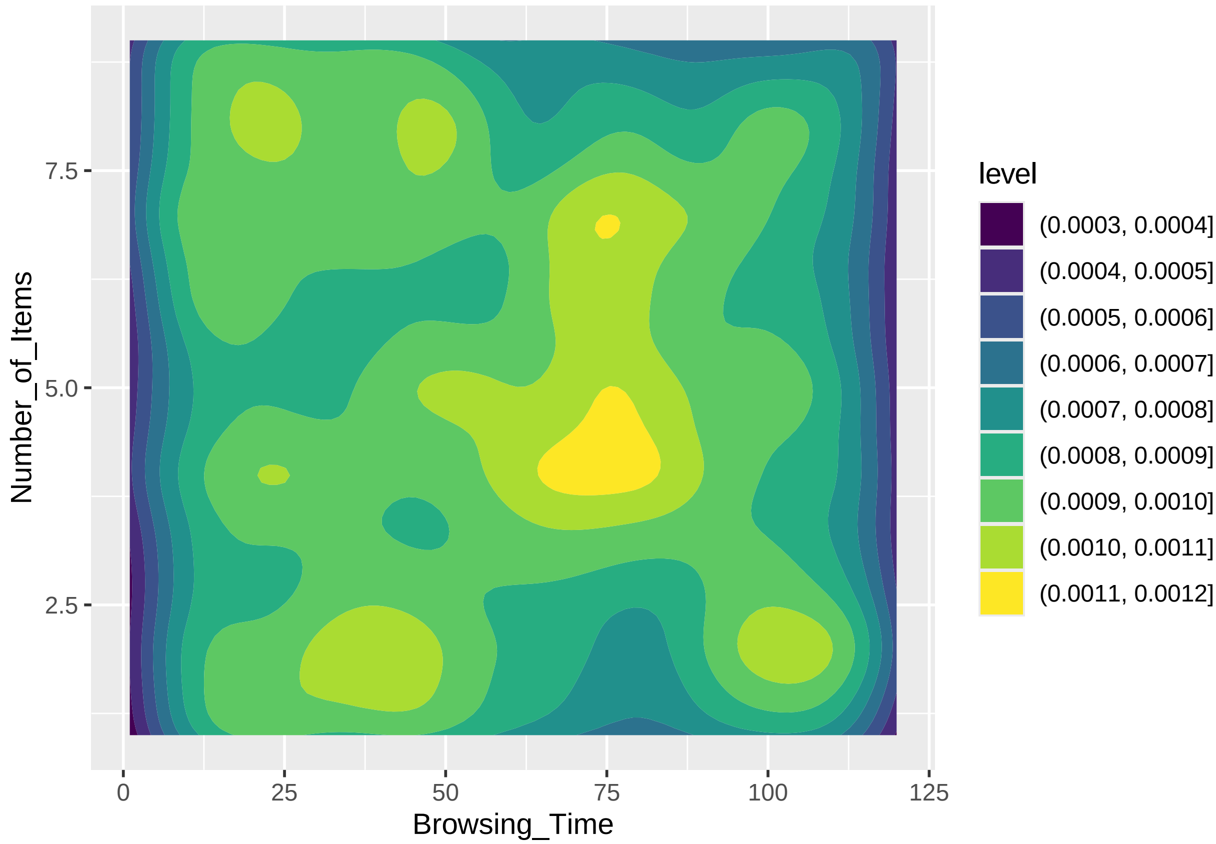
```
ggplot(data, aes(x = Browsing_Time, y = res_purchase)) +
  geom_point(alpha = 0.4, color = "red") +
  geom_smooth(method = "lm", se = TRUE, color = "black") +
  facet_wrap(~ Category)
```

```
## `geom_smooth()` using formula = 'y ~ x'
```




```r
ggplot(data, aes(x = Browsing_Time, y = Number_of_Items, z = Purchase_Amount)) +
  geom_density_2d_filled()
```

```
## Warning: The following aesthetics were dropped during statistical transformation: z.
## i This can happen when ggplot fails to infer the correct grouping structure in
##   the data.
## i Did you forget to specify a ‘group‘ aesthetic or to convert a numerical
##   variable into a factor?
```



There are higher densities on the yellow region as seen in the legend to the right and most common behaviours in terms of browsing time and number of items.

Perform multiple regression with Purchase_Amount as the dependent variable and Browsing_Time, Number_of_Items, and Satisfaction_Score as predictors. Perform model selection and assess variable importance.

```
model_multi<-lm(Purchase_Amount~Browsing_Time+Number_of_Items+Satisfaction_Score ,data=data)
summary(model_multi)
```

```
##
## Call:
## lm(formula = Purchase_Amount ~ Browsing_Time + Number_of_Items +
##     Satisfaction_Score, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -250.668 -120.856   -2.846  118.899  255.664
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        261.34993    9.24929  28.256   <2e-16 ***
## Browsing_Time       -0.07954    0.07504  -1.060    0.289
## Number_of_Items     -0.78321    1.00497  -0.779    0.436
## Satisfaction_Score  -1.53871    1.83444  -0.839    0.402
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 140.9 on 2996 degrees of freedom
## Multiple R-squared:  0.0007932,  Adjusted R-squared:  -0.0002073
## F-statistic: 0.7928 on 3 and 2996 DF,  p-value: 0.4978
```

```r
stepwise<-step(model_multi, direction="both")
```

```
## Start:  AIC=29691.89
## Purchase_Amount ~ Browsing_Time + Number_of_Items + Satisfaction_Score
##
##                      Df Sum of Sq      RSS   AIC
## - Number_of_Items     1     12056 59482958 29691
## - Satisfaction_Score  1     13966 59484867 29691
## - Browsing_Time       1     22299 59493201 29691
## <none>                            59470902 29692
##
## Step:  AIC=29690.5
## Purchase_Amount ~ Browsing_Time + Satisfaction_Score
##
##                      Df Sum of Sq      RSS   AIC
## - Satisfaction_Score  1     13479 59496437 29689
## - Browsing_Time       1     21541 59504498 29690
## <none>                            59482958 29691
## + Number_of_Items     1     12056 59470902 29692
##
## Step:  AIC=29689.18
## Purchase_Amount ~ Browsing_Time
##
##                      Df Sum of Sq      RSS   AIC
## - Browsing_Time       1     21676 59518113 29688
## <none>                            59496437 29689
## + Satisfaction_Score  1     13479 59482958 29691
## + Number_of_Items     1     11569 59484867 29691
##
## Step:  AIC=29688.27
## Purchase_Amount ~ 1
##
##                      Df Sum of Sq      RSS   AIC
## <none>                            59518113 29688
## + Browsing_Time       1     21676 59496437 29689
## + Satisfaction_Score  1     13614 59504498 29690
## + Number_of_Items     1     10822 59507290 29690
```

```r
summary(stepwise)
```

```
##
## Call:
## lm(formula = Purchase_Amount ~ 1, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -242.933 -119.268   -2.873  119.237  251.647
##
```

```
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  247.963      2.572   96.41   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 140.9 on 2999 degrees of freedom
```

We can say that it removed all the predictors leaving behind Purchase_Amount alone using the stepwise model,indicating that the 3 predictors did not have significance value in explaining Purchase_Amount.