# Assignment 1

2025-10-07

**GROUP MEMBERS**

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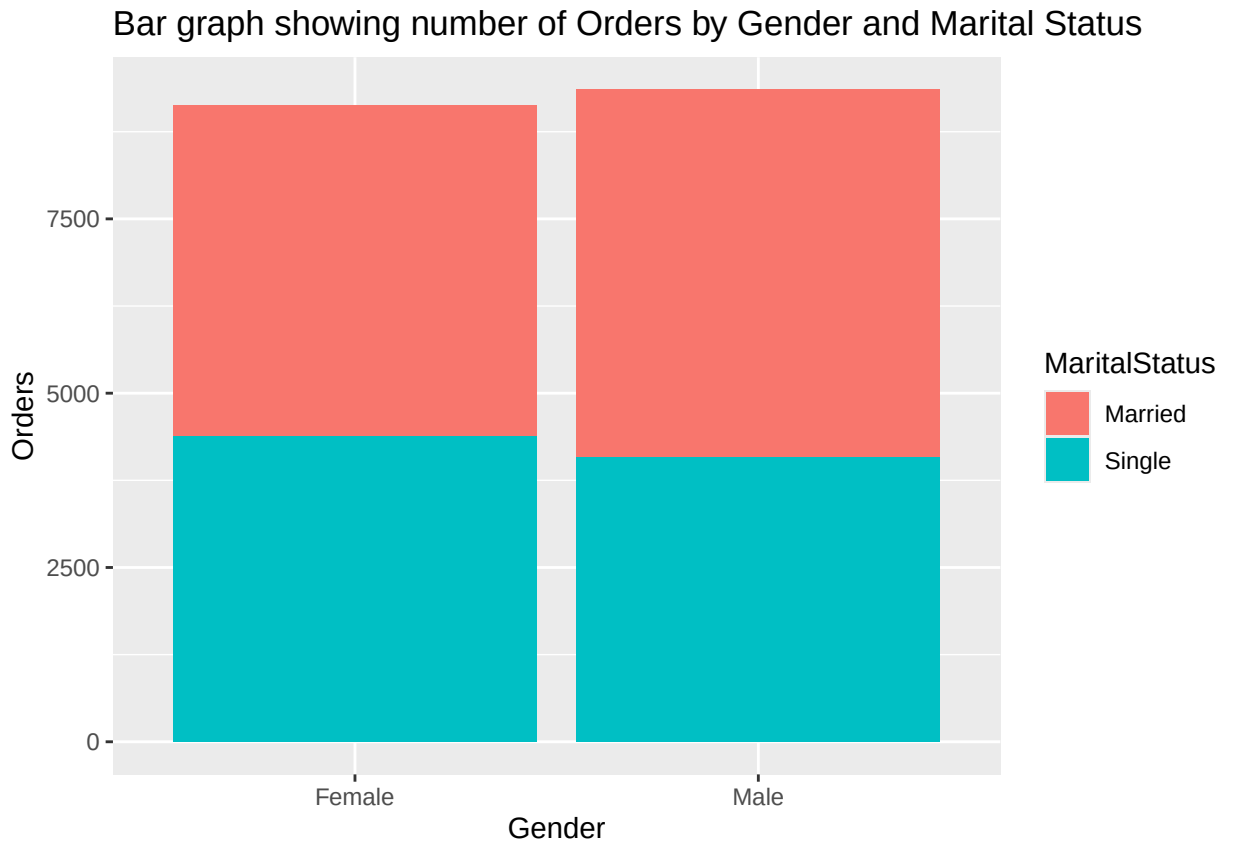
**Importing data and merging required sheets.**

```
path <- 'BA Dataset.xlsx'

sheets <- c('Products', 'Customers', 'Orders')

# Merging vertically
sales <- lapply(sheets, function(s){
  read_excel(path, sheet = s) |>
    mutate(sheet = s, .before = 1)
}) |>
  bind_rows() |>
  mutate(
    Year = year(BirthDate),
    Age = 2025 - Year
  )

sales
```

```
> # A tibble: 79,488 x 47
>    sheet    ProductKey ProductAlternateKey ProductName        ProductSubcategory
>    <chr>         <dbl> <chr>               <chr>              <chr>
>  1 Products          1 AR-5381             Adjustable Race    <NA>
>  2 Products          2 BA-8327             Bearing Ball       <NA>
>  3 Products          3 BE-2349             BB Ball Bearing    <NA>
>  4 Products          4 BE-2908             Headset Ball Bear~ <NA>
>  5 Products          5 BL-2036             Blade              <NA>
>  6 Products          6 CA-5965             LL Crankarm        <NA>
>  7 Products          7 CA-6738             ML Crankarm        <NA>
>  8 Products          8 CA-7457             HL Crankarm        <NA>
>  9 Products          9 CB-2903             Chainring Bolts    <NA>
> 10 Products         10 CN-6137             Chainring Nut      <NA>
> # i 79,478 more rows
> # i 42 more variables: ProductCategoryName <chr>, StandardCost <dbl>,
> #   Color <chr>, ListPrice <dbl>, Size <chr>, SizeRange <chr>, Weight <dbl>,
> #   ProductLine <chr>, Class <chr>, Style <chr>, ModelName <chr>,
> #   Description <chr>, CustomerKey <dbl>, Title <chr>, FirstName <chr>,
> #   LastName <chr>, BirthDate <dttm>, MaritalStatus <chr>, Gender <chr>,
> #   EmailAddress <chr>, YearlyIncome <dbl>, TotalChildren <dbl>, ...
```

**Stacked Bar chart of number of orders by Marital Status and Gender**

```
sales |>
  select(MaritalStatus, Gender) |>
  drop_na() |>
  ggplot(aes(x = Gender, fill = MaritalStatus)) +
  geom_bar() +
  labs(
    title = 'Bar graph showing number of Orders by Gender and Marital Status',
    y = 'Orders'
  )
```



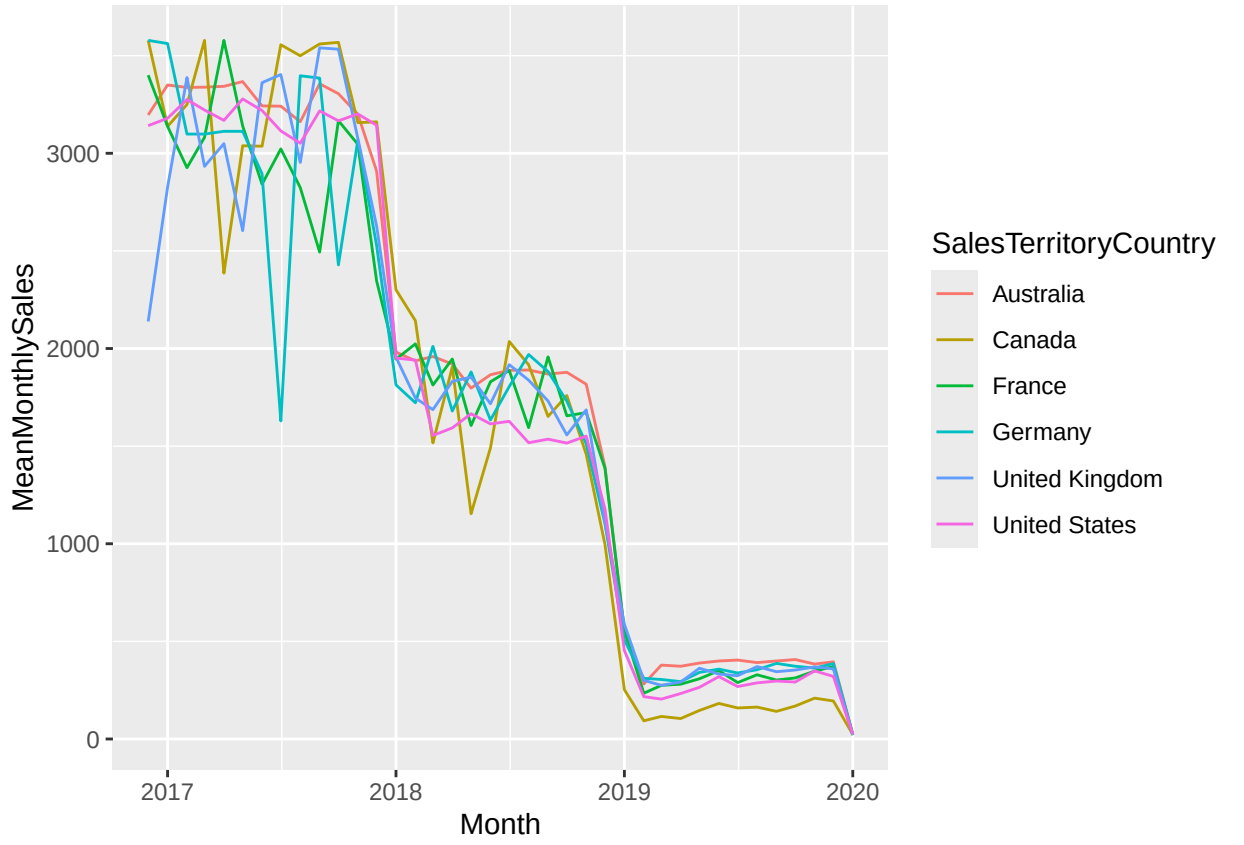

Based on the total length of each bar, we can conclude that the highest number of orders were received from males.

Comparing color segments across gender based on the absolute length of the segments at the baseline, we can conclude that single females had more number of orders than single males.

Also married males had more number of orders compared to married females because the married male's segment baseline was below that of married females and it also close above the segment of married females.

**Grouped line chart of sales amount by order month for each SalesTerritoryCountry**

```
sales |>
  mutate(Date = as.Date(OrderDate), Month = floor_date(OrderDate, 'month')) |>
  group_by(SalesTerritoryCountry, Month) |>
  summarise(MeanMonthlySales = mean(SalesAmount, na.rm = TRUE), .groups = 'drop_last') |>
  ungroup() |>
  drop_na() |>
  ggplot(aes(x = Month, y = MeanMonthlySales, colour = SalesTerritoryCountry,
             group = SalesTerritoryCountry)) +
  geom_line()
```




The line graph shows that the mean monthly sales, at the beginning of year 2017, for the six territory countries was at climax despite United Kingdom having the lowest sales (Below 3000).

There was no clear direction on the trend of sales for every territory country between year 2017 and 2018 except for Germany whose sales spiked lower than others mid 2017 (Below 2000). There was a huge drop on monthly sales for every country across the years, with Canada recording the highest drop on sales, (Below 1500), between late 2017 and mid 2018.

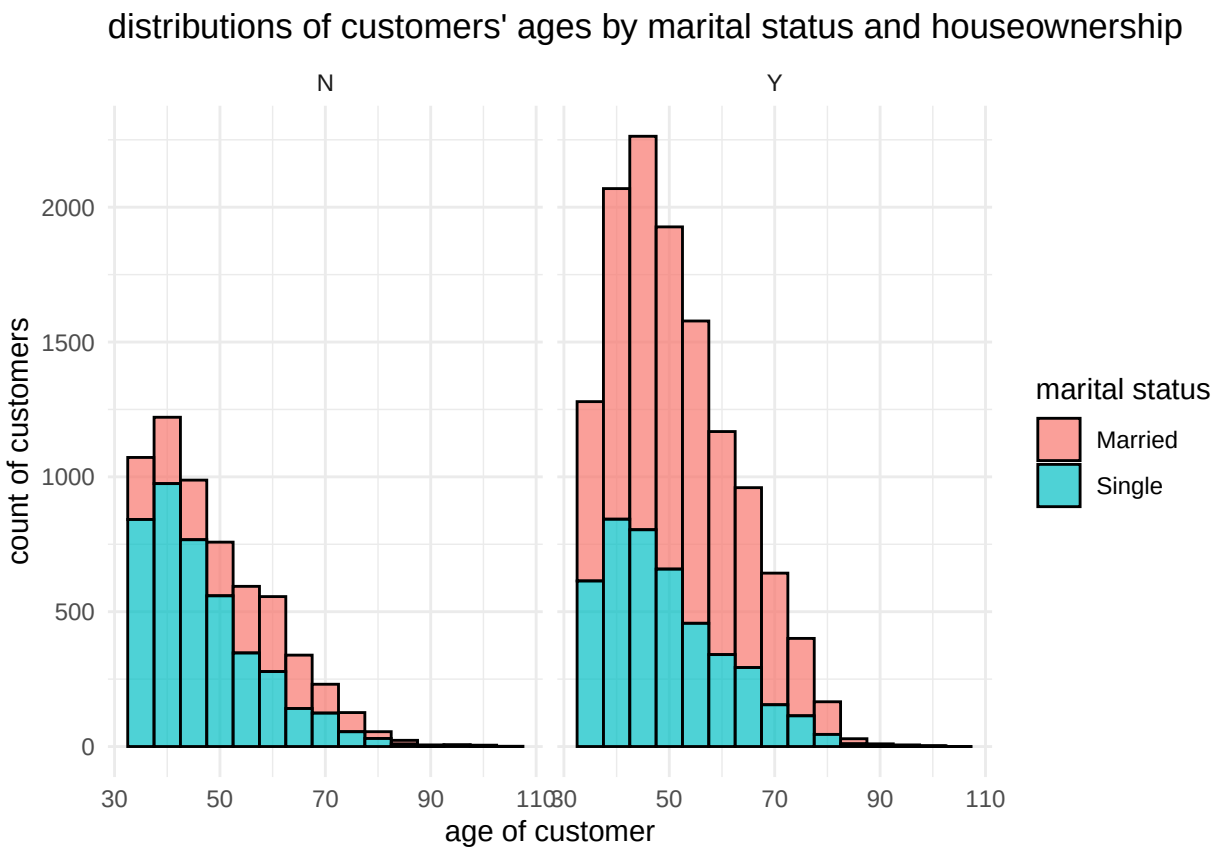
The second phase of monthly sales drop for all the territory countries took place between late 2018 and the beginning of year 2019.

There was no significant growth on sales as the chart was moving horizontally(constant) between 2019 and 2020.

We can conclude that there was a declining mean monthly sales in all the territory countries between year 2017 to 2020.

**Histogram of customers' ages color bars by MaritalStatus and facet wrap by HouseOwnershipFlag**

```
sales |>
  select(Age, MaritalStatus, HouseOwnerFlag) |>
  drop_na() |>
  ggplot(aes(x = Age, fill = MaritalStatus)) +
    geom_histogram(binwidth = 5,color = "black",alpha = 0.7) +
    facet_wrap(~ HouseOwnerFlag) +
    labs(title="distributions of customers' ages by marital status and houseownership",
         x="age of customer",
         y="count of customers",
         fill="marital status") +
    theme_minimal()
```




The panel on the left shows customers who do not own a house.

The majority of these customers are younger, with a peak count in the 30-40 age range and a steady drop from ages 50 to 90.

Within this group, single customers are more prevalent than married customers, especially in the younger age brackets.

The panel on the right shows customers who own a house.

The age distribution for this group is centered on a higher age range, with a peak count between 50 and 60 years old.

In this group, married customers significantly outnumber single customers across all age ranges.

The data suggests a strong positive correlation between age, marital status, and houseownership.

Younger, single customers are more likely to not own a house, while older, married customers are more likely to be homeowners.

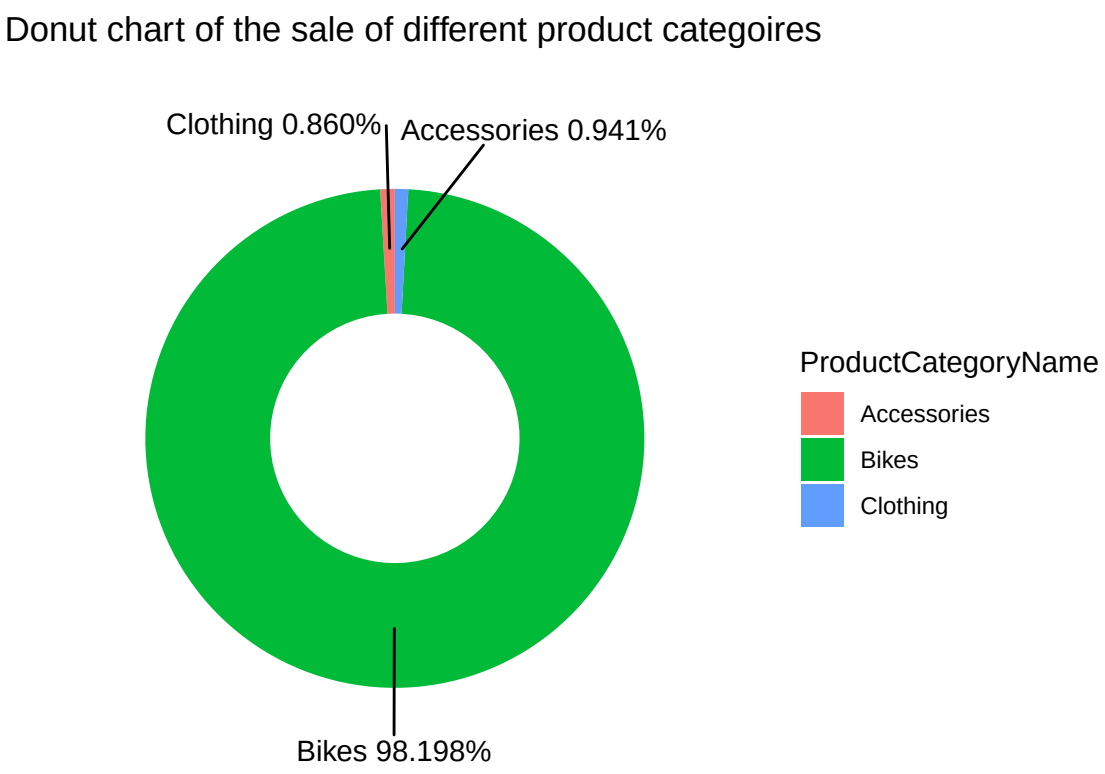
### Donut chart of ProductCategoryName vs SalesAmount

*Importing and merging dataset in required format*

```
# Performing left join merge style
products <- read_excel(path, sheet = "Products")
orders <- read_excel(path, sheet = "Orders")

Category_Sales <- orders |>
  left_join(products, by = c("ProductStandardCost" = "StandardCost")) |>
  select(ProductStandardCost, ProductCategoryName, SalesAmount)

Category_Sales
```

```
> # A tibble: 174,882 x 3
>    ProductStandardCost ProductCategoryName SalesAmount
>                  <dbl> <chr>                      <dbl>
>  1                2171. Bikes                      3578.
>  2                2171. Bikes                      3578.
>  3                2171. Bikes                      3578.
>  4                2171. Bikes                      3578.
>  5                2171. Bikes                      3578.
>  6                1912. Bikes                      3400.
>  7                1912. Bikes                      3400.
>  8                1912. Bikes                      3400.
>  9                1912. Bikes                      3400.
> 10                1912. Bikes                      3400.
> # i 174,872 more rows
```

```r
Category_Sales |>
  group_by(ProductCategoryName) |>
  summarise(Sales = sum(SalesAmount)) |>
  mutate(
    Fraction = Sales / sum(Sales),
    Label = paste0(ProductCategoryName, " ", scales::percent(Fraction))
  ) |>
  ggplot(aes(x = 2, y = Fraction, fill = ProductCategoryName)) +
  geom_bar(stat = "identity", width = 1) +
  coord_polar("y") +
  theme_void() +
  geom_text_repel(aes(label = Label, y = cumsum(Fraction) - Fraction / 2),
                  nudge_x = 1, show.legend = FALSE, size = 4) +
  xlim(c(0.5, 3)) +
  guides(fill = guide_legend(title = "ProductCategoryName")) +
  labs(title = 'Donut chart of the sale of different product categoires',
       caption = 'There were no sales of the components category')
```



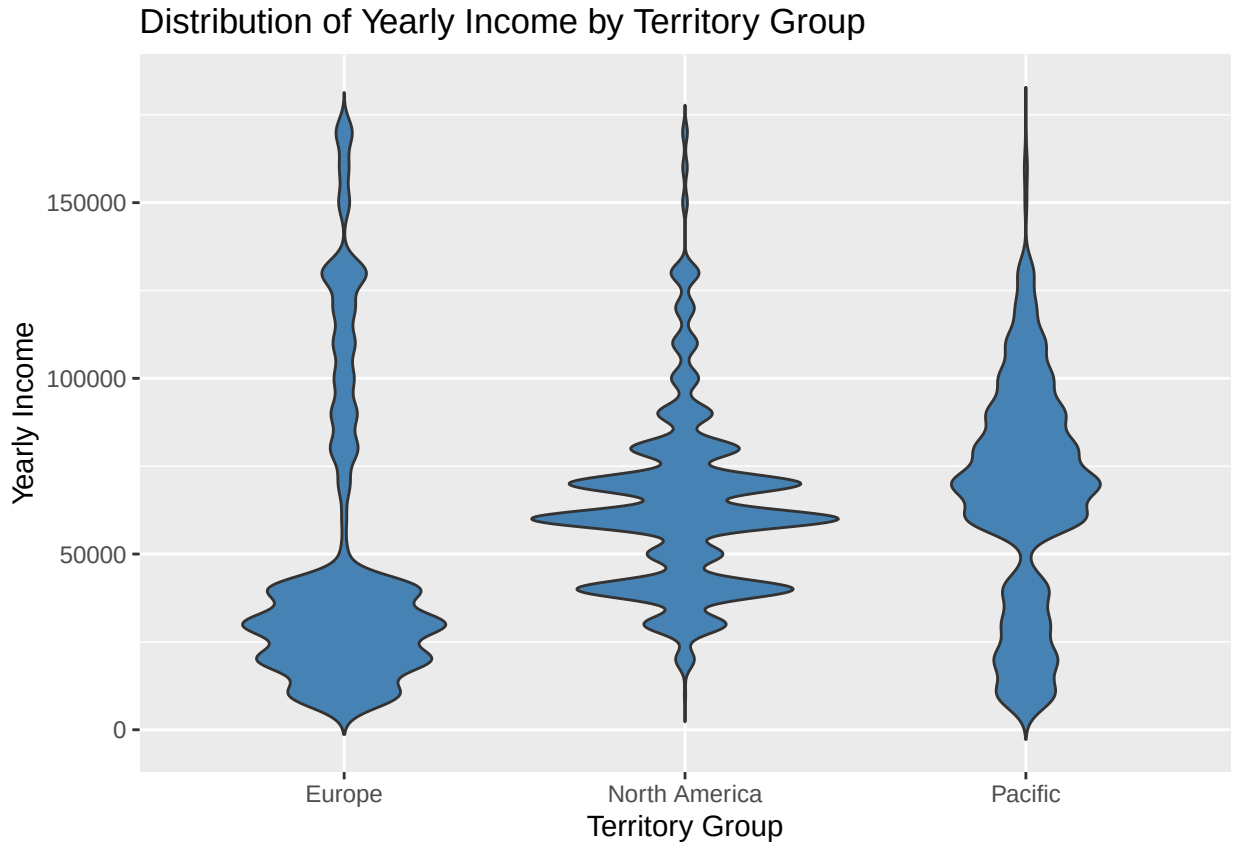

The chart shows that Bikes make up the vast majority of sales, accounting for 98.198% of the total.

The other categories, accessories-0.941% and clothing-0.860%, represent a much smaller fraction of sales.

The caption states that there was an additional Product Category called components. These had no sales at all and were therefore excluded from the graph.

**Violin plot of YearlyIncome vs SalesTerritoryGroup**

```
Customers <- read_excel(path, sheet = 'Customers')

Territory_income <- inner_join(Customers, orders, by = 'CustomerKey') |>
  select(SalesTerritoryGroup, YearlyIncome)

ggplot(Territory_income, aes(x = SalesTerritoryGroup, y = YearlyIncome,
                             fill = SalesTerritoryGroup)) +
  geom_violin(trim =FALSE, fill='steelblue')+
  labs(
    title = "Distribution of Yearly Income by Territory Group",
    x = "Territory Group",
    y = "Yearly Income"
  ) +
  scale_fill_brewer()
```




- **Europe**

Majority of people here earn below 50000 as shown by the big bulge below this range.

There are a few but significant number of people here earning a yearly income of around 125,000.

There's also few but still sizeable high earners, who have a yearly income of more than 150,000

The distribution appears a bit skewed to the right since most earners are in the lower proportions.

- **North America**

Most individuals cluster between yearly incomes of 25,000 and 100,000 since the bulges are compressed in

this ranges.

The biggest bulge is between 50,000 and 75,000. Most people lie here

Few earn above 100,000 and fewer still earn below 25,000

The distribution appears fairly symmetric

**Pacific**

Most people earn around 60,000 yearly.

A sizeable population here earns below 50000

There's a small number of very high earners

The overall spread is wide showing a wide range of incomes from individuals here

The distribution has some bit of skewness to the right. Since most earners are lower than 60,000. However, there's a significant number of people earning more than this.

*Though most earn below 50,000, income inequality is high in Europe as there are clusters in higher income ranges. Higher variability is evident here.*

*Yearly Income in North America looks more normal as it's centered around 50,000 with few earners in the extreme ranges*

*The Pacific shows generally lower incomes though not as much as in Europe, but still one of the highest variability among income ranges*

### Heatmap of Total sales by SalesTerritoryCountry and EnglishEducation

*Importing and merging data set in required format*

```
Country_Education_sales <- inner_join(Customers, orders, by = 'CustomerKey') |>
  select(SalesTerritoryCountry, EnglishEducation, SalesAmount)

Country_Education_sales
```

```
> # A tibble: 60,398 x 3
>    SalesTerritoryCountry EnglishEducation SalesAmount
>    <chr>                 <chr>                  <dbl>
>  1 Australia             Bachelors             3400.
>  2 Australia             Bachelors             2320.
>  3 Australia             Bachelors               22.0
>  4 Australia             Bachelors             2384.
>  5 Australia             Bachelors               29.0
>  6 Australia             Bachelors                4.99
>  7 Australia             Bachelors               35.0
>  8 Australia             Bachelors               54.0
>  9 Australia             Bachelors             3375.
> 10 Australia             Bachelors             2320.
> # i 60,388 more rows
```

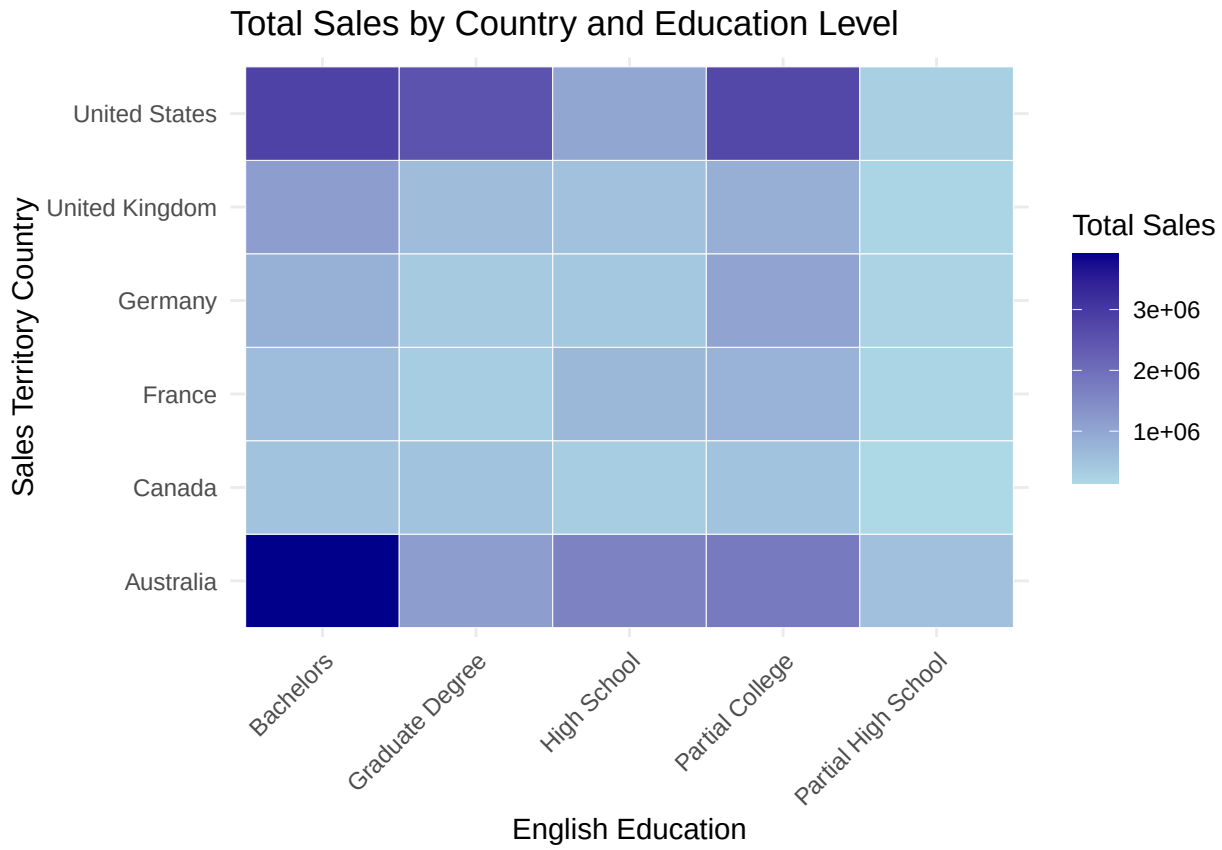
```
# Grouping Data
heatmap_data <- Country_Education_sales |>
  group_by(SalesTerritoryCountry, EnglishEducation) |>
  summarise(TotalSales = sum(SalesAmount, na.rm = TRUE), .groups = 'drop_last')

heatmap_data
```

```
> # A tibble: 30 x 3
> # Groups:   SalesTerritoryCountry [6]
>    SalesTerritoryCountry EnglishEducation    TotalSales
>    <chr>                 <chr>                    <dbl>
>  1 Australia             Bachelors             3922229.
>  2 Australia             Graduate Degree       1147062.
>  3 Australia             High School           1643721.
>  4 Australia             Partial College       1797196.
>  5 Australia             Partial High School    550791.
>  6 Canada                Bachelors              503163.
>  7 Canada                Graduate Degree        499428.
>  8 Canada                High School            329951.
>  9 Canada                Partial College        499950.
> 10 Canada                Partial High School    145354.
> # i 20 more rows
```

```r
# Reshaping into matrix format necessary for heat map
heatmap_data |>
  pivot_wider(
    names_from = EnglishEducation,
    values_from = TotalSales
  )
```

```
> # A tibble: 6 x 6
> # Groups:   SalesTerritoryCountry [6]
>   SalesTerritoryCountry Bachelors `Graduate Degree` `High School`
>   <chr>                     <dbl>             <dbl>         <dbl>
> 1 Australia              3922229.          1147062.      1643721.
> 2 Canada                  503163.           499428.       329951.
> 3 France                  629162.           330788.       687521.
> 4 Germany                 840331.           362447.       424100.
> 5 United Kingdom         1167132.           603455.       544942.
> 6 United States          2838125.          2517379.      1007791.
> # i 2 more variables: `Partial College` <dbl>, `Partial High School` <dbl>
```

```r
# Creating Heatmap
heatmap_data |>
  ggplot(aes(x = EnglishEducation, y = SalesTerritoryCountry, fill = TotalSales)) +
  geom_tile(color = "white") +
  scale_fill_gradient(low = "lightblue", high = "darkblue") +
  labs(title = "Total Sales by Country and Education Level",
       x = "English Education",
       y = "Sales Territory Country",
       fill = "Total Sales") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```




**According to country**

- *Australia*

The highest sales overall are to Customers in Australia who have a Bachelors. They take up this ranking both across every country and across every education group.

An increase in total sales here generally corresponds to an increase in the level of English Education. Evidence of some positive correlation

- *United States*

Majority of customers here have high levels of education. As seen by dark shades in the Bachelors, Graduates and Partial College education levels

- *United Kingdom, Germany, France and Canada*

Total sales to customers in these countries are low as seen by the lighter shades.

The least total sales are from Customers in Canada

**According to Education Level**

Customers with the Partial High school level of English Education have the least total sales across every country. This is closely followed by the High school and Graduate levels.

Those with the High school level closely follow as a group with generally low sales across countries.

Those with Partial College education and a Bachelors correspond to generally higher total sales.