DATATHON

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Brainstorm

Questions we will be answering

Which items should the store stop selling? Why?

What was the most profitable month in the dataset?

```
library(tidyverse)
library(scales)
library(tinytex)
store <- read_delim("sales_data_2017_2018_for_tableau_with_new_date_columns.csv")


names(store)
```

```
##  [1] "receipt_id"          "date"                "hour"
##  [4] "quarter"             "year"                "month_number"
##  [7] "month_name"          "day_of_week_name"    "week_number"
## [10] "is_weekday"          "is_weekend"          "item_code"
## [13] "item_name"           "main_category"       "sub_category"
## [16] "quantity"            "payment_type"        "unit_buying_price"
## [19] "unit_selling_price"  "unit_price_margin"   "total_buying_price"
## [22] "total_selling_price" "total_profit"
```

These were the variables that we were working with while we attempted to answer the questions.

Profits and Losses of Store

```
store %>%
group_by(main_category) %>%
summarise(main_cc = length(main_category), profit = sum(total_profit)) %>%
  arrange(desc(main_cc))
```

```
## # A tibble: 10 x 3
##    main_category          main_cc  profit
##    <chr>                    <int>   <dbl>
##  1 Fresh Produce           333206 643988.
##  2 Pantry Staples           21514  36457.
```

```
##  3 Snacks                      6870   8324.
##  4 Dairy, Cheese, and Eggs     5783   5068.
##  5 Breads & Bakery             2074   2448.
##  6 Beverages                   1602   2111.
##  7 Bag                          967   1085
##  8 Flowers                      676   5844
##  9 Beverage                      56    157.
## 10 Miscellaneous                  9     24
```

This table shows the the amount of products bought and their profits. This would be organized by having the products be grouped by their main category in the store.

```r
store %>%
  group_by(sub_category) %>%
  filter(total_profit < 0, year == 2017) %>%
  summarise(profit_2017 = sum(total_profit)) %>%
  filter(rank(profit_2017) <= 20) %>%
    arrange(profit_2017)
```

```
## # A tibble: 13 x 2
##    sub_category    profit_2017
##    <chr>                 <dbl>
##  1 Cabbages             -274.
##  2 Pears                -259.
##  3 Bunch Vegies         -155.
##  4 Avocadoes            -147.
##  5 Bananas              -138.
##  6 Asian Vegies         -105.
##  7 Root Vegies           -44.1
##  8 Grapes                -36.0
##  9 Tropical Fruits       -24.9
## 10 Citrus Fruits         -15.3
## 11 Condiments             -5.4
## 12 Deals                  -4.69
## 13 Melons                 -2.73
```

This table organized the data set by the store's sub categories and would show what sub categories were losing the store money and by how much it was losing it by in the year 2017.

```r
store %>%
  group_by(sub_category) %>%
  filter(total_profit < 0, year == 2018) %>%
  summarise(profit_2018 = sum(total_profit)) %>%
  filter(rank(profit_2018) <= 20) %>%
    arrange(profit_2018)
```

```
## # A tibble: 14 x 2
##    sub_category    profit_2018
##    <chr>                 <dbl>
##  1 Cabbages            -1836.
##  2 Avocadoes            -969.
##  3 Asian Vegies         -136.
```

```
##   4 Bunch Vegies        -133
##   5 Bananas             -105.
##   6 Condiments           -34.2
##   7 Citrus Fruits        -25.7
##   8 Tropical Fruits      -21.3
##   9 Deals                -20.8
##  10 Vinegar               -7.74
##  11 Melons                -2.02
##  12 Root Vegies           -1.72
##  13 Apples                -1.24
##  14 Tomatoes              -1
```

This table shows the sub categories that were lsoing the most amount of money and by how much. This would allow us to see what categories need to be revised in order to see where the store is truly losing their money in.

```r
store %>%
  group_by(sub_category) %>%
  filter(year == 2017) %>%
  summarise(amount_2017 = sum(quantity)) %>%
  filter(rank(desc(amount_2017)) <= 15) %>%
    arrange(desc(amount_2017))
```

```
## # A tibble: 15 x 2
##    sub_category  amount_2017
##    <chr>               <dbl>
##  1 Bananas            13912.
##  2 Melons             12507.
##  3 Other Vegies       12361.
##  4 Potatoes           10340.
##  5 Citrus Fruits       8386.
##  6 Apples              8367.
##  7 Bunch Vegies        8177.
##  8 Tomatoes            7343.
##  9 Stonefruits         6870.
## 10 Herbs               5258.
## 11 Pumpkins            5020.
## 12 Cucumbers           4845.
## 13 Grapes              4560.
## 14 Deals               4541
## 15 Lettuces            4459.
```

This shows the most bought sub categories in the store. Items that could be dropped would be Asian Veggies since they are not being sold a lot compared to its other sub categories and the store is paying money to import them which is causing loss in profit in that sub category. Something else we can get rid of are condiments since they are also not selling as much as the other categories and their loss in profit has increased more in 2018 than it has in 2017. Therefore, if the store does not get rid of it, then the loss in profit will only increase over the next couple of years.

```r
store %>%
  group_by(sub_category) %>%
  filter(year == 2018) %>%
  summarise(amount_2018 = sum(quantity)) %>%
```

```r
  filter(rank(desc(amount_2018)) <= 15) %>%
    arrange(desc(amount_2018))
```

```
## # A tibble: 15 x 2
##    sub_category  amount_2018
##    <chr>               <dbl>
##  1 Other Vegies       11730.
##  2 Melons             11155.
##  3 Bananas            10540.
##  4 Potatoes            9099.
##  5 Bunch Vegies        8159
##  6 Citrus Fruits       7443.
##  7 Apples              7126.
##  8 Tomatoes            6026.
##  9 Stonefruits         5357.
## 10 Herbs               4951.
## 11 Eggs                4604
## 12 Pumpkins            4185.
## 13 Onions              4041.
## 14 Lettuces            3963.
## 15 Deals               3687
```

This part of the data shows what sub categories customers were buying the most of. This would allow us to see if the sub categories that were losing money were being bought a lot or not. That way we can determine if the products in that sub category are worth selling the store anymore. The data was set to be for 2018.

```r
store %>%
  filter(total_profit < 0)%>%
  filter(sub_category == "Cabbages") %>%
  mutate(loss = sum(total_profit), amount = sum(quantity)) %>%
  select(item_name, loss, amount) %>%
  head(1)
```

```
## # A tibble: 1 x 3
##   item_name        loss amount
##   <chr>           <dbl>  <dbl>
## 1 Cabbage Wombok -2110.   938.
```

By looking at this data, we determined that the store should stop selling Wombok Cabbages because they are the only item that is causing loss in profit. Meanwhile the rest of the cabbages gain profit after each purchase.

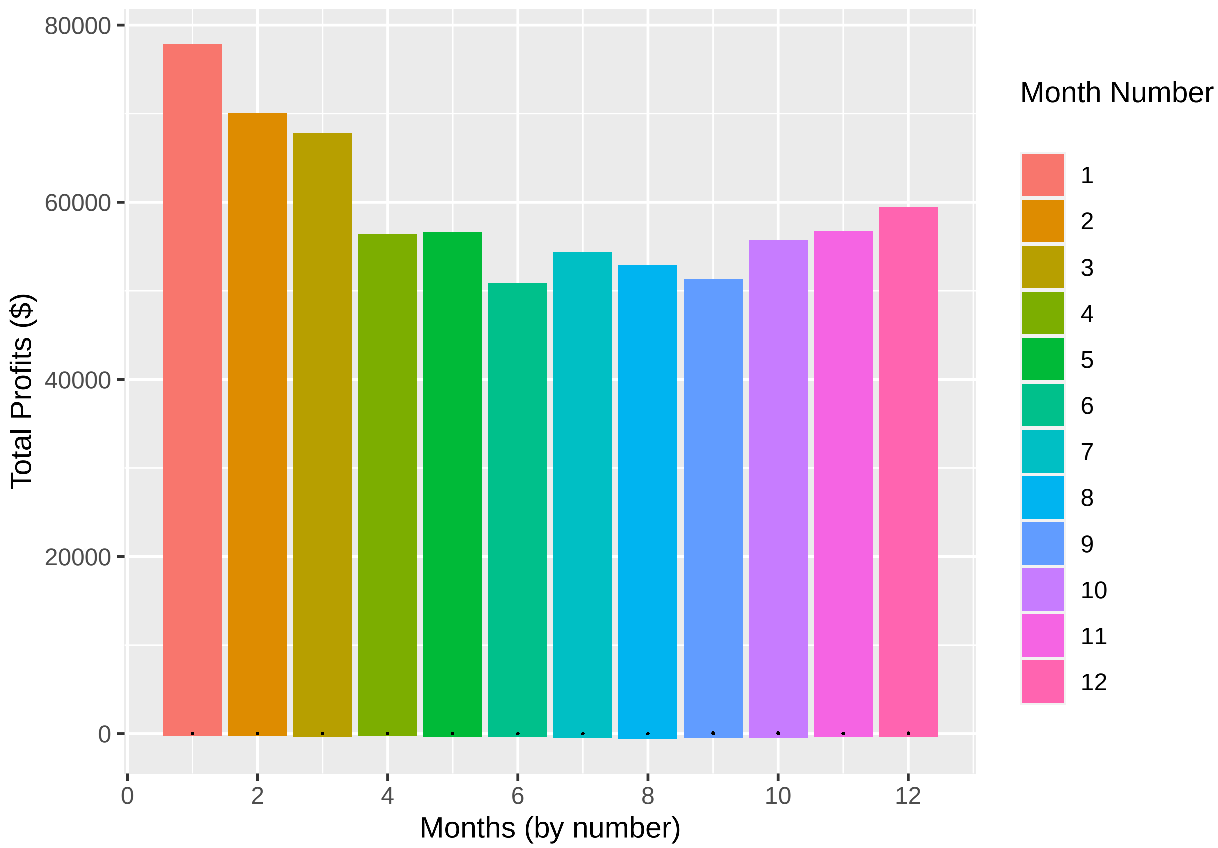
```r
store %>%
  filter(total_profit < 0) %>%
  filter(sub_category == "Avocadoes") %>%
  mutate(loss = sum(total_profit), amount = sum(quantity)) %>%
  select(item_name, loss, amount) %>%
  head(1)
```

```
## # A tibble: 1 x 3
##   item_name             loss amount
##   <chr>                <dbl>  <dbl>
## 1 Avocado Hass Medium -1116.   1105
```

Another item that the store could get rid of would be Avocado Hass Medium since the are the item that loses the second most amount of profit and it is not sold as much as the rest of the avocadoes.

Finding the most profitable month by sales

```
store %>%
  ggplot(aes(month_number, total_profit, fill = factor(month_number)))+
  geom_col()+
  geom_line()+
  scale_x_continuous(breaks = pretty_breaks())+
  labs(x = "Months (by number)",
       y = "Total Profits ($)",
       fill = "Month Number\n")
```



Australia has opposite seasons from us, therefore whenever we have our winter season, they have summer. The peak amount of sales for the store occur when Australia is in its summer season.THese months are towards the beginning and end of the year.

```
store %>%
  filter(sub_category == "Apples") %>%
  # filter(total_profit > 0) %>%
  arrange(total_profit)
```

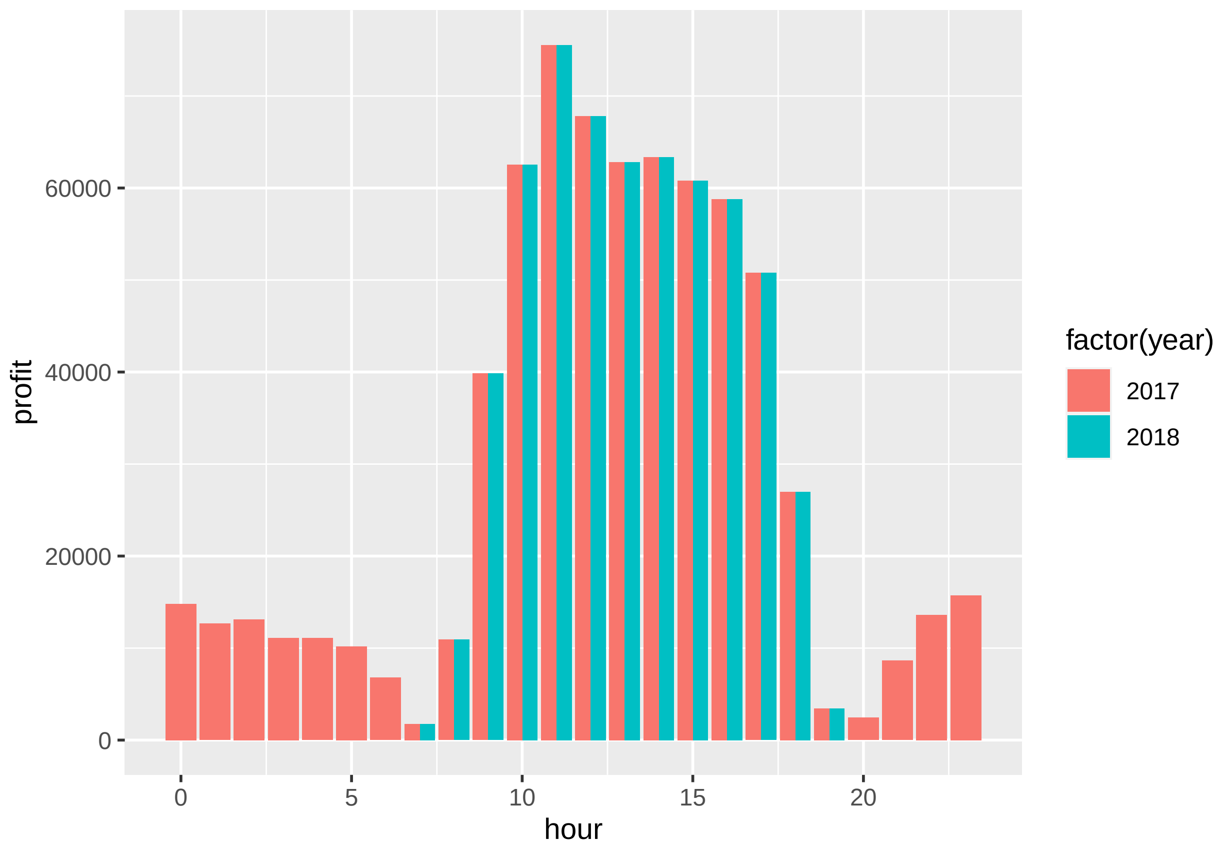
```
## # A tibble: 17,046 x 23
```

```
##    receipt_id date   hour quarter  year month_number month_name day_of_week_name
##    <chr>      <chr> <dbl>   <dbl> <dbl>        <dbl> <chr>      <chr>
##  1 e07045cf-~ 4/9/~    17       2  2018            4 April      Monday
##  2 32410b44-~ 4/9/~    17       2  2018            4 April      Monday
##  3 76577560-~ 4/7/~    17       2  2018            4 April      Saturday
##  4 f60aa4ff-~ 4/22~    12       2  2017            4 April      Saturday
##  5 8cf74f57-~ 5/27~    11       2  2017            5 May        Saturday
##  6 92bf4549-~ 4/26~     9       2  2017            4 April      Wednesday
##  7 78878cf1-~ 4/26~    10       2  2017            4 April      Wednesday
##  8 b1803785-~ 5/26~    11       2  2017            5 May        Friday
##  9 85666ed1-~ 5/12~    11       2  2018            5 May        Saturday
## 10 99bee43e-~ 4/30~    15       2  2018            4 April      Monday
## # i 17,036 more rows
## # i 15 more variables: week_number <dbl>, is_weekday <dbl>, is_weekend <dbl>,
## #   item_code <dbl>, item_name <chr>, main_category <chr>, sub_category <chr>,
## #   quantity <dbl>, payment_type <chr>, unit_buying_price <dbl>,
## #   unit_selling_price <dbl>, unit_price_margin <dbl>,
## #   total_buying_price <dbl>, total_selling_price <dbl>, total_profit <dbl>
```

```
  # summarise(apple_profit = mean(total_profit))
```

Another item that the store should get rid of is Apple Granny Smith 1kg bags because they barely make any sales and are the only apple product that is making the store lose money. The stores sells a lot of apples.

```
store %>%
  group_by(hour) %>%
  mutate(profit = sum(total_profit)) %>%
  ggplot(aes(hour, profit, fill = factor(year)))+
  geom_col(position = "dodge")+
  scale_x_continuous(breaks = pretty_breaks())
```



According to the data, the total profits for the hour in 2017 match the total profits for 2018. However, since 2017 was run 24/7 they generate the greater profit then 2018 because they are not missing out on the money. The only change they can make to improve there margain for profits would be to change the prices on what they are selling, increase costs for customers to buy.