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?

Loading data

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

store %>%
  dim()
```

```
## [1] 372757     23
```

```
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"
```

```
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
```

```
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
```

2017 LOSSES

```
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
```

2018 WORSE OF YEAAR MOY LIFE

```
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.

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

```
store %>%
  group_by(sub_category) %>%
  filter(year == 2017) %>%
  summarise(amt_2017 = sum(quantity)) %>%
  filter(rank(amt_2017) <= 15) %>%
  arrange(amt_2017)
```

```
## # A tibble: 15 x 2
##    sub_category amt_2017
##    <chr>           <dbl>
##  1 Sweet             5
##  2 Masala            9
##  3 Candles          10
##  4 Coffee           14
##  5 Powder           16
##  6 Cut Fruits       18.6
##  7 Condiment        22
##  8 Sweets           24
##  9 spices           26
## 10 Spides           28
## 11 Baking           34
## 12 Papad            39
## 13 Dried Fish       61
## 14 Vinegar          65
## 15 Cereals          66
```

Shows quantity sold for each sub category in the year 2017

```
store %>%
  group_by(sub_category) %>%
  filter(year == 2018) %>%
  summarise(amt_2018 = sum(quantity)) %>%
   filter(rank(amt_2018) <= 15) %>%
  arrange(amt_2018)
```

```
## # A tibble: 15 x 2
##    sub_category amt_2018
##    <chr>           <dbl>
##  1 Balms               4
##  2 Coffee             16
##  3 Health             16
##  4 Papad              20
##  5 Sweet              21
##  6 Vinegar            26
##  7 Condiment          32
##  8 Baking             36
##  9 Spides             36
## 10 Water              36
## 11 Cake               39
## 12 Powder             47
## 13 Cereals            48
## 14 spices             48
## 15 Cut Fruits         55
```

Shows quantity sold for each sub category in the year 2018

```
store %>%
  group_by(sub_category) %>%
  summarise(sub_cc = length(sub_category)) %>%
  arrange(sub_cc)
```

```
## # A tibble: 86 x 2
##    sub_category sub_cc
##    <chr>         <int>
##  1 Balms             4
##  2 Candles           5
##  3 Masala            9
##  4 Sweets           22
##  5 Sweet            25
##  6 Coffee           30
##  7 Condiment        53
##  8 Powder           56
##  9 Papad            58
## 10 Spides           64
## # ... with 76 more rows
```

```
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.
```

FROM OUR ANALYSIS, we 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.

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

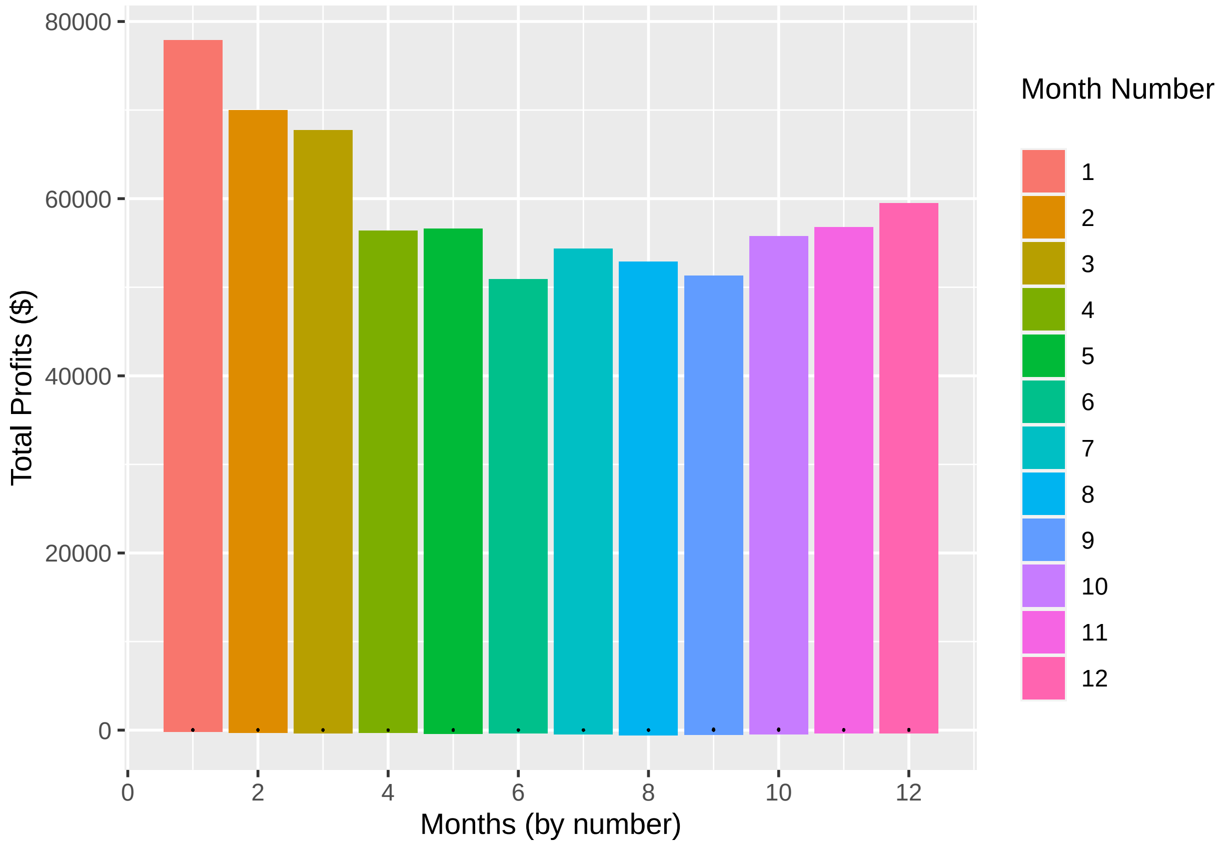
```
## # A tibble: 1 x 3
##   item_name             loss amount
##   <chr>                <dbl>  <dbl>
## 1 Avocado Hass Medium -1116.   1105
```

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

how to approach

```
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.

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

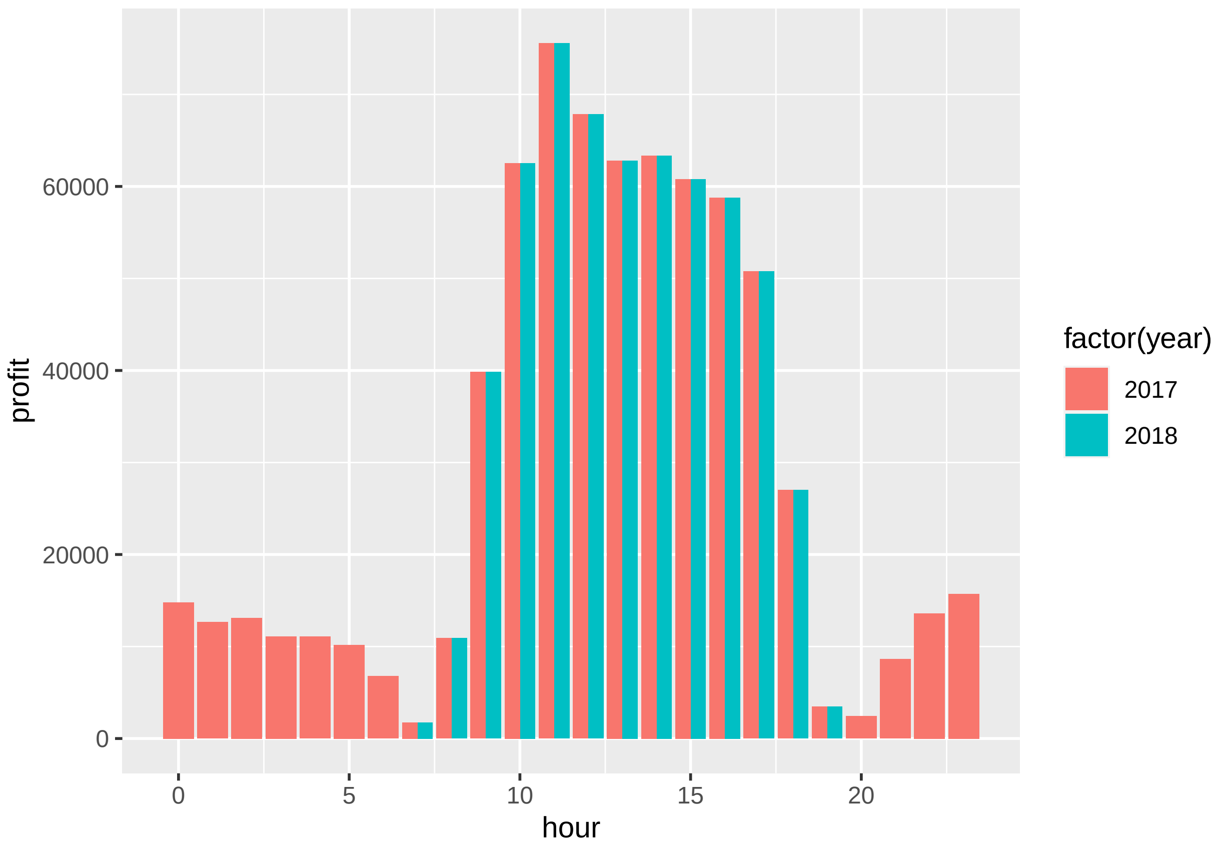
```
## # A tibble: 17,046 x 23
##    receipt_id  date   hour quarter  year month~1 month~2 day_o~3 week_~4 is_we~5
##    <chr>       <chr> <dbl>   <dbl> <dbl>   <dbl> <chr>   <chr>     <dbl>   <dbl>
##  1 e07045cf-0~ 4/9/~    17       2  2018       4 April   Monday       15       1
##  2 32410b44-3~ 4/9/~    17       2  2018       4 April   Monday       15       1
##  3 76577560-3~ 4/7/~    17       2  2018       4 April   Saturd~      14       0
##  4 f60aa4ff-8~ 4/22~    12       2  2017       4 April   Saturd~      16       0
##  5 8cf74f57-4~ 5/27~    11       2  2017       5 May     Saturd~      21       0
##  6 92bf4549-2~ 4/26~     9       2  2017       4 April   Wednes~      17       1
##  7 78878cf1-4~ 4/26~    10       2  2017       4 April   Wednes~      17       1
##  8 b1803785-5~ 5/26~    11       2  2017       5 May     Friday       21       1
##  9 85666ed1-8~ 5/12~    11       2  2018       5 May     Saturd~      19       0
## 10 99bee43e-9~ 4/30~    15       2  2018       4 April   Monday       18       1
## # ... with 17,036 more rows, 13 more variables: 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>,
```

```
## #   and abbreviated variable names 1: month_number, 2: month_name,
## #   3: day_of_week_name, 4: week_number, 5: is_weekday
```

```
  # 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.

```
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 this thing, 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.