Professional Development and Research Skills
CMM507 Coursework
Group 2: Plastic Pollution in Oceans

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1 Introduction

1.1 Problem Statement

Plastic pollution is a serious problem in the marine environment where they have major impact on marine and human health. In order to understand the depth of the problem, it is essential to understand the amount and composition of marine litter. This can help in applying various mitigation strategies. This section will include:

- An overview of the marine pollution
- Motivation behind this topic
- Aim and objectives of this report

1.2 Overview

Marine pollution is a major global issue which impacts on environment, economy and human health. Although marine pollution is caused by many different materials, plastics consist of 60-80% of the marine litter. Synthetic organic polymer derived from polymerisation of monomers extracted from oil and gas make up the plastics.[1] [2] The lightweight feature and its durability make it very suitable to make a range of products that we use in our everyday life.[3] [4] These same features have been a major cause of pollution due to overuse and non-managed waste disposal system worldwide with plastic contributing to the 10% of the waste generated worldwide.[3] Due to its buoyancy, plastic debris can be dispersed over long distances and they can persist for a long time. Although, plastic litter has been a major cause of marine pollution for a while, its seriousness has only been realised recently. Jambeck et al.,[5] reported that in 2010 alone, between 4.8 million to 12.7 million metric tons of plastics entered the ocean. Plastics are now everywhere in the marine environment and urgent action is required to mitigate this problem and reduce the harmful impact.[2] [6]

1.3 Motivation

Impact of plastic pollution on marine life have been reviewed extensively. [7] [8] [9] [10] Over 700 marine wildlife species are affected due to entanglement in plastic ropes and materials and in- gestion of plastics in the ocean.[7] Over 340 species of marine animals were found to be entangled. [8] Over time plastic disintegrates into small microplastics which are easily consumed by fish from where they enter the food chain. Plastics have been found in a third of fish caught in the UK which included the popular fishes such as cod, haddock and mackerel (Lusher et al., 2013). Impact of plastic entering the human food chain and the effects are still to be studied. Plastic toxicity and the occurrence of microplastics and nanoplastics in the water supply can also be a direct impact on human health in addition to the contamination in seafood.[6] [11]

Reducing plastic pollution has recently been a global aim. Research in plastic pollution in marine environment has played a big role in reducing it and raising awareness all over the world. In order to understand the plastic pollution in marine environments and its effect in long term, it is essential to keep collecting data on patterns of marine debris around the world. Effective monitoring of plastic debris is very essential in order to reduce the abundance of plastic debris everywhere. In addition, monitoring the type, frequency and the source of the litter is also important for prevention initiative of marine pollution. Most of the monitoring are done by surveys looking at frequencies of beach litter collected by organisations and volunteers.[12] Most abundant litter can be found close to urban areas where beach visitor numbers are higher.[13]

1.4 Objectives

The main objectives of this project are outlined as follows:

- To research marine plastic problems and their impacts
- To find a dataset suitable for this study
- Look at the composition of litter collected
- Summarise the results that were found

2 Research

Our group conducted some literature search in order to identify how researchers have been trying to monitor coastal pollution and find the problems associated with it. Several studies have reported the abundance of plastic as a coastal litter through survey and citizen science. A 12-year dataset on coastal debris pollution in Taiwan using Citizen science also revealed that most debris items found were plastic. [14] 19 categories of debris items were collected during the clean-up events. The five most commonly recorded debris categories were plastic shopping bags, plastic bottle caps, disposable tablewares, fishing equipment, and plastic drinking straws. There have been many other studies around the world regarding littering of the shores. A study in Western Japan and eastern coasts of Russia found out that 55% to 93.4% of items over the Japanese shores were plastic. The second most abundant item was resin pellet, which is a form of plastic too. For the eastern Russian coast plastic items were also the most abundant 55% litter, with plastic fragments being the most abundant within the plastics category. The composition of litter was similar in the two countries, although the concentration of plastics was much higher in Japan. [15] Further on the Asian upper east, hard plastic and Styrofoam were the dominant plastic types on Korean beaches. On average, hard plastic and Styrofoam comprised 32% and 48.5% (by number) of the total debris, respectively.

In an older study over the region of Caribbean the most common types of debris stranded on the Caribbean coast of Panama were plastic and Styrofoam, with plastics being household or consumer related. Styrofoam packing materials were also abundant, and may have come from trans-shipment activities of Colon's Free Zone, as well as from household trash or from offshore (STEPHEN D. GARRITY and SALLY C. LEVINGS, 1993). A recent annual study (2016/2017) on 8 beaches in Tenerife in Canary island also found that plastic was the most abundant litter. They also reported that there were more accumulated plastic debris in remote beaches compared to the beaches near the city indicating that more debris were transported by tides. More long term study is required to look at the changes in the results reported over time. [16]

As one may easily observe there are quite a few variations in terms of how studies over litter accumulation have been conducted. The variation has to do with the time span of the research, the part of the beach from which litter was collected, as well as the categorization of littering. This creates a problem when researchers want to compare different studies. The problem basically amounts to assessing changes in accumulation rates and composition, trends over time and the effectiveness of management systems, a hard task without good monitoring methodologies. Although monitoring of marine litter is currently carried out within a number of countries around the world, the methods of survey and monitoring used tend to be very different, preventing comparisons and harmonization of data across regions or time-scales.

This is why the scientific community has been trying to create some common ground which has led to some initiatives joined by many countries worldwide. One of them and probably the most important one is the International Clean Coast (ICC) program which is a new, long-term approach for cleaner beaches by various activities to increase public awareness. [17] This initiative aimed at a comprehensive litter characterization scheme to be developed that uses both material composition and form. This allows Litter Monitoring Repeated surveys of beaches, sea bed and/or surface waters to determine litter quantities such that information can be compared with baseline data to see if changes occur through time and / or in response to management arrangements.

The ICC uses some specific developed categorizations of coast litter, with the most accepted one being the Clean Coastal Index (CCI) protocol, which is very useful, in terms of simplicity and information provided, allowing comparison between different times and places. The CCI protocol is very different from most others having a focus on operational clean-up of beaches as well. The CCI is suggested as a tool for evaluation of the actual coast cleanliness. It measures plastic debris as a beach cleanliness indicator, in an easy way precluding bias by the assessor. The CCI also proved to be a useful tool for measuring progress and the success of activities to raise awareness among the general public. [18]

A study in Israel followed the CCI protocol and found out that plastic is the most ubiquitous beach litter item. An important contribution of this study has to do with comparing its findings with other Mediterranean beaches showing that plastic might be the dominant pollutant, though non-plastic litter is highly specific to the region and cannot be treated universally. [19] In another study on litter pollution in a region of India, once again the CCI protocol for the categorization of litter was followed. Once again plastic was the main source of litter 45%, with plastic bags topping the index at 33%, followed by food wrappers and then plastic cups. Cigarettes/cigar tips were scarcely found amounting to only 5.5%. [20] The use of the common protocol in these two studies allows for researchers to compare their findings and create common plastic pollution models, even though the two coasts are continents apart.

Another study conducted at the other side of the Mediterranean, in Cadiz, found that plastic bottles/containers were the most frequent items followed by plastic bags. This research points out that surveys are heavily affected by clean-ups performed at beaches. [21] Even though this study reaches to some important conclusions on ways to clean coasts the correct way, it cannot be easily compared, or its conclusions easily applied even with the case of the study in Israel, which is also in the Mediterranean.

We can clearly see that there have been many studies done to monitor marine pollution using various different ways. One of the cost effective and easy method is the use of citizen science where the public can easily record any observations of marine litter. As discussed above, records without proper guidance could be unreliable. The Marine Debris Tracker (MDT) Initiative was started from 2010 in North America. This allowed anyone to record the marine debris observation through a mobile application. The only report using the data from this app is the original report by Tablada in 2018 [22] where data analysis was done on the data of 8 years and mainly focused on North America which also concluded that plastic was the main type of debris that was recorded with cigarettes being the top litter. Given the literature above, our group went on to work with a world-wide coastal littering dataset from the MDT website spanning a timeframe of a decade with an interest to see if its findings match the above: be it if plastic is the most abundant litter, within the plastic categories which are the most important subclasses found and could there be a way to computationally monitor the coastal littering problem. For this we followed the CCI categorization of litter.

3 Methods

3.1 Dataset Description

This paper was conducted using secondary data collection methods only. The authors did not collect or create any new data using primary methods. Data was obtained by downloading from Marine Debris Tracker website (www.marinedebris.engr.uga.edu). It is a citizen science project where individuals or organisation can record the marine debris observations through the mobile application known as Marine Debris Tracker (MDT)(SAMDI, 2010). [22] The users can choose the category from the list provided to record the observations. Observations in the website can be found as different lists as specific users can make their own group to list the records. For this study "Marine Debris Items" was chosen in order to download the data from 2010 to Feb 2020. The dataset was composed by combining the multiple csv files gathered from here into a single set after which the "date" data type was renamed as "Time".
Can we also add to this information of how the data is entered e.g. optional/mandatory fields, free-text or dropdown fields. The use of IDs suggest these are option fields with lookup tables somewhere.

need to mention that we downloaded 2010-2020 but decided to keep only 2012-2019 inclusive and why. This may belong in the cleaning section

Variable	Description	Mandatory
ListID	the ID code for the list	non mandatory
ListName	the name of the list	non mandatory
ItemID	ID code given to the item of debris	non mandatory
ItemName	name we give to item of debris	mandatory
LogID	ID code given to the location of the debris	non mandatory
Quantity	number of pieces of debris in the observation	mandatory?
Error radius	radius around the observation site within the error for reasonable doubt	mandatory
Latitude	coordinates of the location where the observation was made	mandatory
Longitude	coordinates of the location where the observation was made	mandatory
Altitude	coordinates of the location where the observation was made	mandatory
Location	area the observation of debris was made in	non mandatory
Description	description of the area the debris was found in	non mandatory
MaterialID	ID code of the material that the debris was composed of	non mandatory
MaterialDescription	description of material the debris was composed of	mandatory
Time	time of observation	non mandatory

3.2 Dataset Pre-processing

```r
library(tidyverse)
library(purrr)
library(magrittr)
library(treemap)
library(mapdata)
library(viridis)
library(lubridate)
library(imager)
library(xtable)
library(dplyr)


data <- list.files(path = "data/debris/", full.names = TRUE) %>%
  lapply(FUN = read_csv, col_types = "ififiddddcfcif") %>%
  reduce(rbind)
```

```r
# Data wrangling

# replace the column for time as a date data type, renaming it "Time"
data$Time <- data$Timestamp %>%
  parse_datetime(format = "%Y%m%d%H%M%S")
data$Timestamp <- NULL

# MissingValues
data %>% select_if(function(x) any(is.na(x))) %>% colnames()

## [1] "Location"    "Description"

# explicit missing value for the location factor
data$Location <- data$Location %>% fct_explicit_na()

# Remove redundant data
data <- data %>% select(-ListID,-ListName)

# Filter for observations occuring between the years 2012-2019 inclusive
data <- data %>% filter(as.integer(year(Time)) %in% 2012:2019)
```

The following actions were performed on the dataset:
'ListID', 'ListName', 'ItemID' (couldn't delete 'itemid' because it's being used in a chart below) and 'Material ID' were found to be redundant and removed from the dataset as they all have accompanying textual descriptions which are more meaningul.
Nulls found in ItemName and Description.
this means every entry has a material at least? why? could be a required field? that would explain why some entries are rubbish if people are forced to pick a category it is also worth discussing the merits of dropdown entries: standardises input but forces a value where none might be appropriate, or a default it selected?
Stuart: Yes, it is a required field. I checked on the mobile app and you select a item type from different material sections. Note however that there is a material type *Other Items* which contains the items *Other* and *Test Item*. Therefore users are able to categorise an item as other if it is not appropriate for any other option on the list.
also maybe worth looking at: what's the significance of some of these itemIDs where the itemname is blank? It could be an item once that was then deleted or categorised retrospectively. Do a groupby ItemID and see if more than one material or item name turns up.

Unique values for each column: can we present these unique counts as a formatted table? I think it's interesting that 55 unique items can have ~8k descriptions

```r
data %>%
  summarise_all(~length(unique(.))) %>%
  pivot_longer(cols = everything(), names_to = "Column Name", values_to = "Unique Values") %>%
  arrange(desc(`Unique Values`)) %>%
  xtable()
```

	Column Name	Unique Values
1	LogID	349556
2	Time	237066
3	Latitude	144820
4	Altitude	133174
5	Longitude	132316
6	Error Radius	16930
7	Description	7982
8	Location	1352
9	Quantity	494
10	ItemID	55
11	ItemName	55
12	Material ID	8
13	Material Description	8

3.3 Data Quality Issues: Classification

The authors find that there are multiple instances of missclassified items. Where their descriptions appear to not match their material categorisation
Lets see if there are any "ItemNames" associated with more than one "Material Descriptions".

```
data %>% select(`Material Description`, ItemName) %>%
  distinct() %$%
  table(ItemName) %>%
  as_tibble() %>%
  filter(n > 1)

## # A tibble: 1 x 2
##   ItemName          n
##   <chr>         <int>
## 1 Rubber Gloves     2
```

So rubber gloves are associated with two material descriptions, but otherwise a one to many relationship exists between "Material Description" and "ItemName".

```
data %>% select(`Material Description`, ItemName, Quantity) %>%
  filter(ItemName == "Rubber Gloves") %>%
  group_by(`Material Description`) %>%
  summarise(Quantity = sum(Quantity))

## # A tibble: 2 x 2
##   `Material Description` Quantity
##   <fct>                     <dbl>
## 1 PLASTIC                    2092
## 2 RUBBER                       89
```

It seems that most rubber gloves are classified as plastic rather than rubber.

```
data %>% select(`Material Description`, ItemName, Description) %>%
  filter(ItemName == "Rubber Gloves", !is.na(Description))

## # A tibble: 30 x 3
##    `Material Description` ItemName      Description
##    <fct>                  <fct>         <chr>
##  1 PLASTIC                Rubber Gloves thermal
##  2 PLASTIC                Rubber Gloves Near water
##  3 PLASTIC                Rubber Gloves Taste of Omaha Cleanup
##  4 PLASTIC                Rubber Gloves Taste of Omaha Cleanup
##  5 PLASTIC                Rubber Gloves 2 diff kinds
##  6 PLASTIC                Rubber Gloves undefined
##  7 PLASTIC                Rubber Gloves Latex
##  8 PLASTIC                Rubber Gloves Hose
##  9 PLASTIC                Rubber Gloves Cap
## 10 PLASTIC                Rubber Gloves Vial
## # ... with 20 more rows
```

All instances of rubber gloves with non-missing descriptions are categorised as plastic. We also see that the descriptions suggest that the categorisation may be innaccurate: the last two instances here have "Balloon" in the extra descriptions... why aren't they categorised as such? another thing maybe worth looking at: all MATERIALS!=Plastic yet have the term "plastic" in the description. could further expand this to descriptions which have any of the material terms in them, but is not its own material. further explores the point about missclassified data.

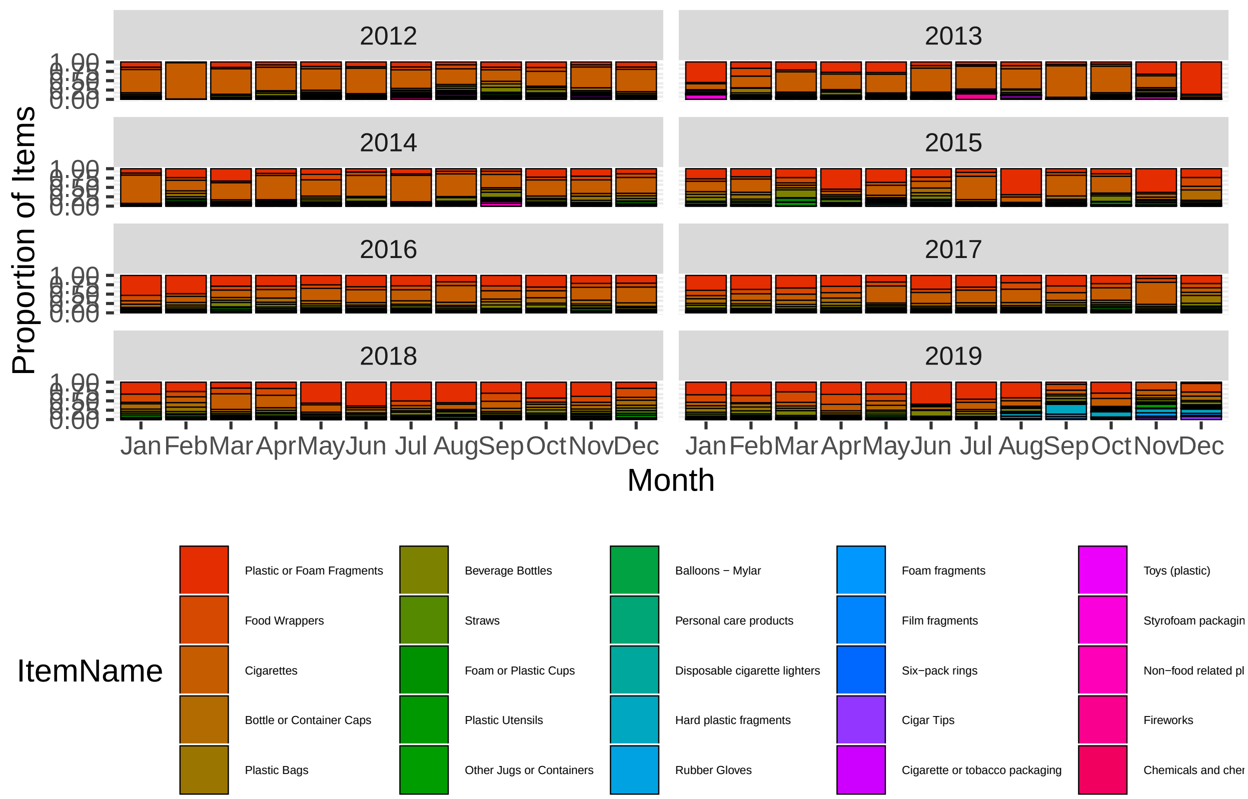
3.4 Recategorisation

After the issues with the dataset that were identified in the section above, it was decided that it would be best to transform the dataset in the following ways:

- reclassified some labels because variation was too high (there were too many labels)
- The values of the missing data were removed.
- It was decided that subsets that were not needed were removed while retaining the necessary subsets.

```
plastic_ordered <- data %>%
  filter(`Material Description` == "PLASTIC") %>%
  select(ItemName, Quantity) %>%
  group_by(ItemName) %>%
  summarise(Total = sum(Quantity)) %>%
  arrange(desc(Total))
```

```r
data %>%
  filter(`Material Description` == "PLASTIC") %>%
  mutate(month = month(Time, label = TRUE),
         year = as.integer(year(Time)),
         ItemName = fct_infreq(ItemName)) %>%
  filter(year > 2010) %>%
  group_by(month, year, ItemName) %>%
  summarise(`Total Quantity` = sum(Quantity)) %>%
  ggplot(aes(x = month, y = `Total Quantity`, fill = ItemName)) +
    geom_col(colour = "black", size = 0.2, position = "fill") +
    facet_wrap(~year, nrow = 4) +
    scale_fill_hue(l=50, c=150) +
    xlab("Month") +
    ylab("Proportion of Items") +
    theme(legend.position="bottom",
          legend.text=element_text(size=4))
```



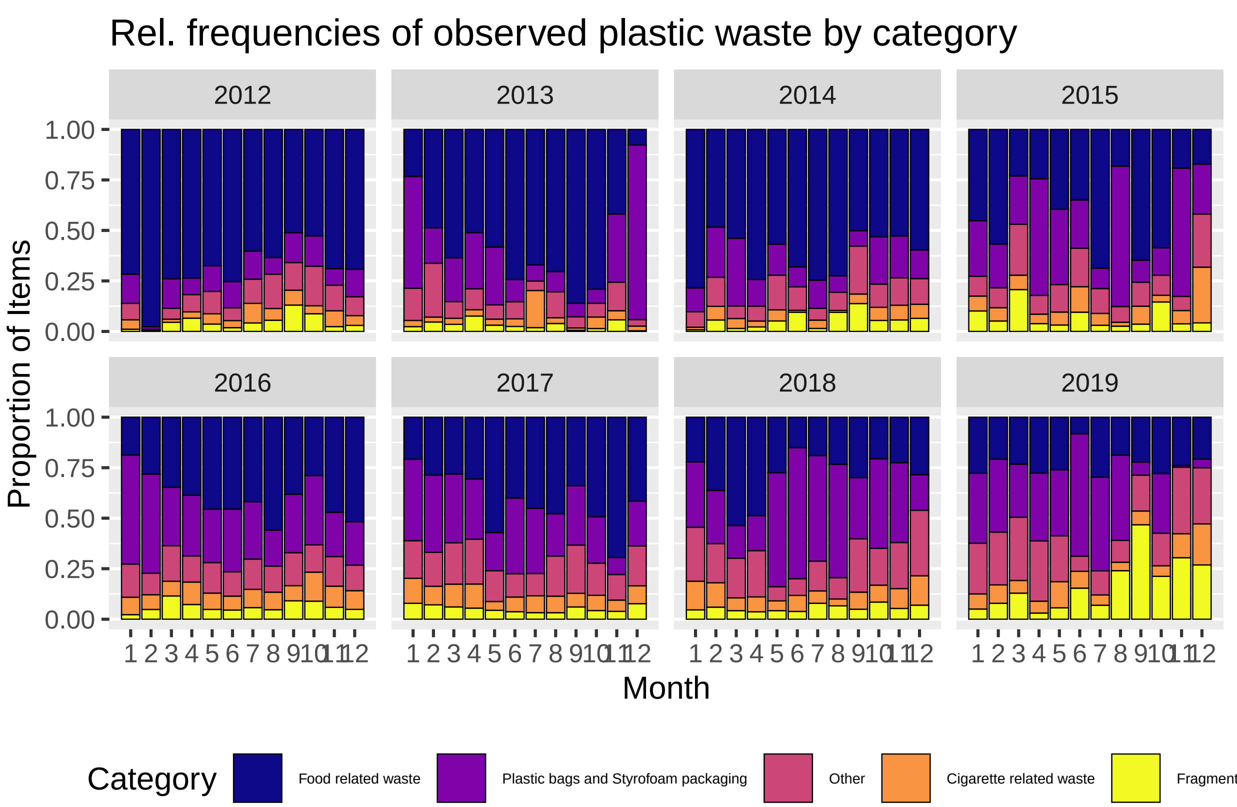

```r
    #scale_fill_viridis_d(option = "magma")

#ggsave("plots/pastic_debris_plot.png", width = 40, height = 20, units = "cm")
```

Figure 1: Debris by categorisation

```r
# all cigarette related waste: 1, 4, 6, 22
# Food related waste: 3, 2,7,9,10, 17, 23, 11
# Non food related waste: 8, 14, 15, 16, 18, 19, 21, 20
```

```r
# Plastic bags and Styrofoam packaging:12, 13
# Fragments: 5, 23, 24,25

recategorise <- function(x){
  out = ""
  if(x %in% c(1,4,6,22)){out = "Cigarette related waste"}
  if(x %in% c(2,3,7,9,10,17,23,11)) out = "Food related waste"
  if(x %in% c(8,14,15,16,18,19,21,20)) out = "Other"
  if(x %in% c(12,13)) out = "Plastic bags and Styrofoam packaging"
  if(x %in% c(5,23,24,25)) out = "Fragments"
  if(out == "") stop(paste("Error in recategorise:", x))
  return(out)
}

plastic_types <- data %>%
  filter(`Material Description` == "PLASTIC") %>%
  select(ItemName, ItemID) %>%
  distinct() %>%
  mutate(label = 1:n()) %>%
  mutate(category = purrr::map(label, recategorise)) %>%
  mutate(category = as_factor(as.character(category))) %>%
  select(ItemID, category)


plastic <- data %>%
  filter(`Material Description` == "PLASTIC") %>%
  full_join(plastic_types, by = "ItemID")

ordered_levels <- plastic %>%
  group_by(category) %>%
  summarise(totObs = sum(Quantity)) %>%
  ungroup() %>%
  arrange(desc(totObs)) %>%
  select(category) %$%
  category
plastic$category <- factor(plastic$category, levels = ordered_levels)
rm(ordered_levels)
```

```
plastic %>%
  mutate(month = month(Time, label = FALSE),
         year = as.integer(year(Time))) %>%
  filter(year > 2010) %>%
  group_by(month, year, category) %>%
  summarise(`Total Quantity` = sum(Quantity)) %>%
  ggplot(aes(x = month, y = `Total Quantity`, fill = category)) +
    geom_col(colour = "black", size = 0.2, position = "fill") +
    facet_wrap(~year, nrow = 2) +
    scale_fill_viridis(discrete = TRUE, option = "plasma") +
    xlab("Month") +
    ylab("Proportion of Items") +
    ggtitle("Rel. frequencies of observed plastic waste by category") +
    scale_x_continuous(breaks = 1:12) +
    theme(panel.grid.major.x = element_blank(),
          panel.grid.minor.x = element_blank(),
          legend.position = "bottom",
          legend.text=element_text(size=5)) +
    guides(fill=guide_legend(title="Category"))
```




```
#ggsave("plots/pastic_debris_plot_recategorised.png", width = 40, height = 20, units = "cm")
```

Figure 2: Recategorisation by year. Colour scale ordered by ranking of total observed quantity.

4 Exploration

Here we describe the things we found...

4.1 Proportion Trends

How pollutant proportions change over time.

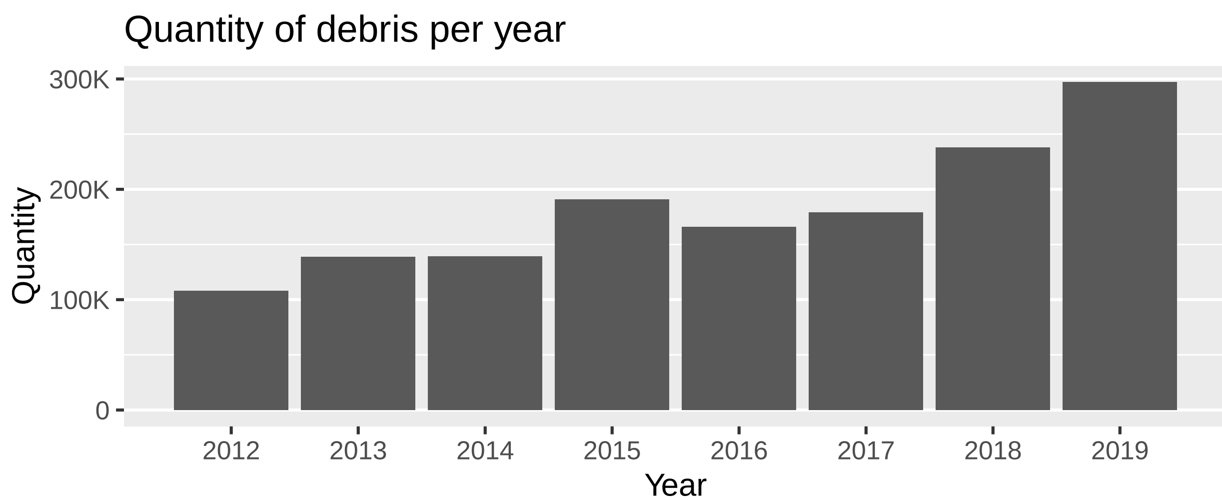
Cigarette butts proportions and raw counts decrease over time: possibly less people smoking, or moving to vaping

General pollution count going down over time?

Old pollutants fall away (cigarette butts) but new ones are introduced

Question: Are observed plastic item proportions time invariant?

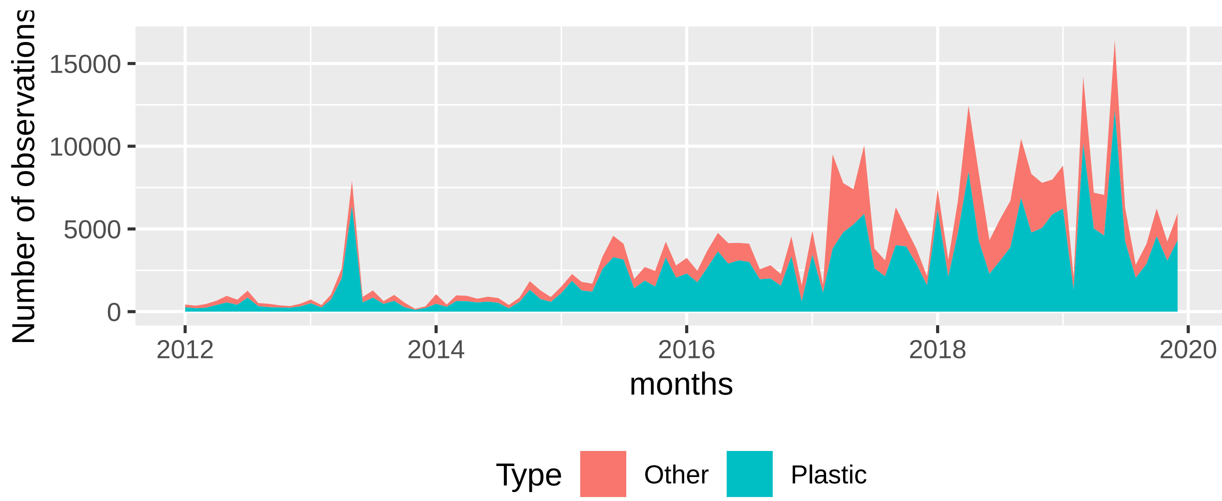
```r
#Linechart quantity of debris per year
data %>%
  mutate(year = year(Time)) %>%
  filter(year > 2010, year < 2020) %>%
  group_by(year) %>%
  summarise(quan = sum(Quantity)) %>%
  ggplot(aes(x = year, y = quan)) +
    geom_col() +
    scale_x_continuous(breaks = 2011:2019) +
    xlab("Year") +
    ylab("Quantity") +
    ggtitle("Quantity of debris per year") +
    theme(panel.grid.major.x = element_blank(),
          panel.grid.minor.x = element_blank()) +
    scale_y_continuous(labels = scales::label_number_si(accuracy = 1))
```




```r
#ggsave("plots/observations.png")
```

Figure 3: Trend of debris observered

```
#Histogram of observations: Total v Plastic
data %>%
  mutate(Type = if_else(`Material Description` == "PLASTIC", "Plastic", "Other"),
         months = floor_date(Time, 'month')) %>%
  group_by(months, Type) %>%
  summarize(`Number of observations` = n()) %>%
  ggplot(aes(x = months, y = `Number of observations`)) +
    geom_area(aes(fill = Type)) +
    theme(legend.position = "bottom")
```




```
  # ggplot() +
  # geom_histogram(aes(x = Time))
```

Figure 4: Observations of plastic debris v all debris

4.2 Distribution of observed debris:

MaterialQuantities

```r
data %>% select(Quantity,Description,`Material Description`) %>%
  group_by(`Material Description`) %>%
  summarise(Quantity = sum(Quantity)) %>%

  ggplot(aes(x = reorder(`Material Description`, Quantity), y = Quantity)) +
    geom_col() +
    ylab("Total recorded quantity") +
    xlab("Material class") +
    coord_flip()
```

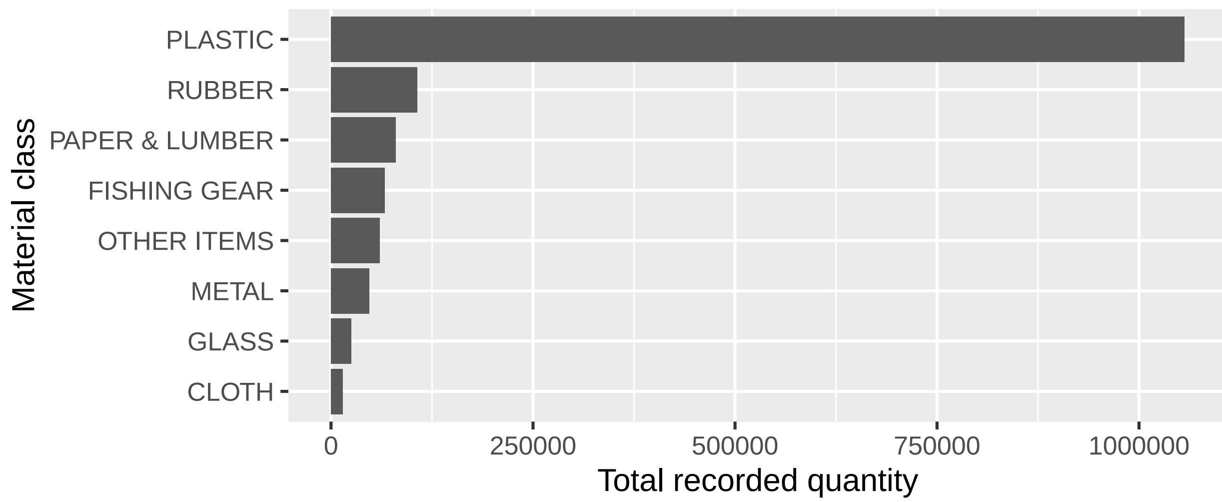
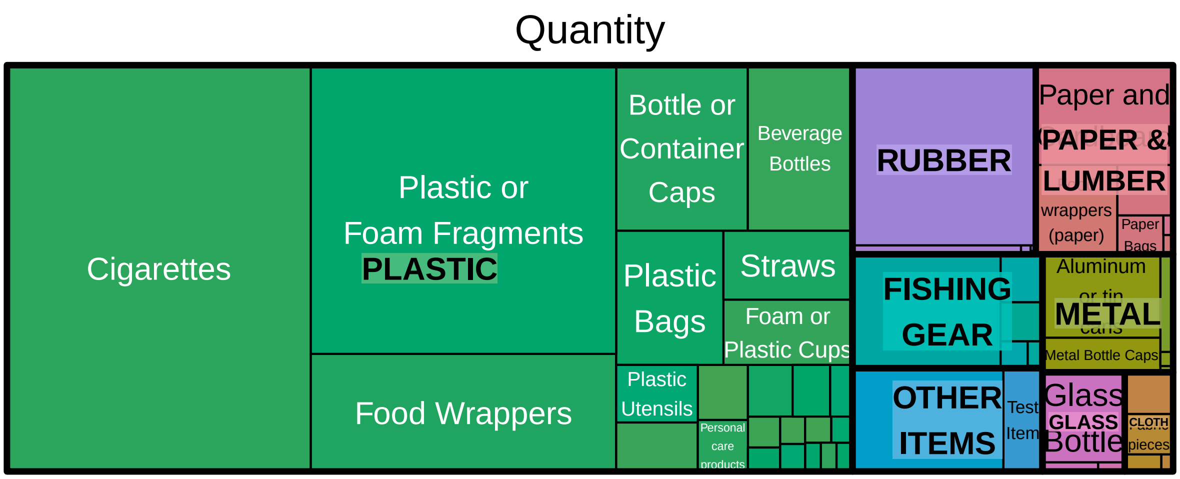


Figure 5: Material Quantities

So the most populated material class is Plastic. Note that this does not necessarily mean that plastic is the largest quantity of debris, just that the individual number of items categorised is largest.
A tree map of material quantities:

```r
#treemap of debris categories
#png("plots/treemap.png")
data %>%
  select(`Material Description`, ItemName, Quantity) %>%
  group_by(`Material Description`, ItemName) %>%
  summarise(Quantity = sum(Quantity)) %>%
  treemap(index = c("Material Description", "ItemName"),
          vSize = "Quantity", draw = TRUE) -> tm
```

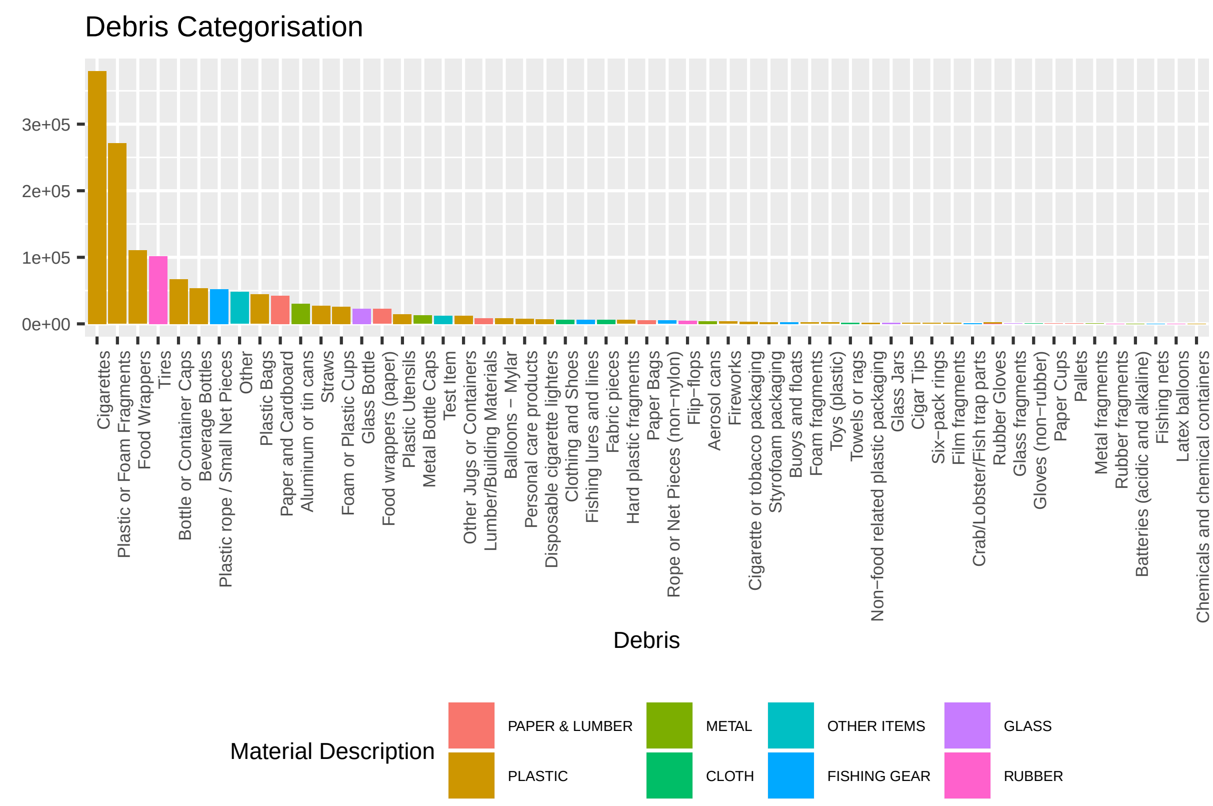



```r
#tm
#dev.off()
#save.image(file = "plots/treemap.png")
```

Figure 6: Debris categorisation

Cigarettes are the most common item recorded as seen in. Perhaps some of the debris is not actually from the sea, but rather from people littering by the coastline? Does debris littered on the coastline end up in the oceans?
This is a great chart, but not the best to support the statement that cigarettes is most popular - a column or bar chart here will be much better (area charts are not as effective as charts you can level-compare), potentially use proportions or data labels to further drive the point that it IS the largest. Treemap suggest moving back into pre-processing section.

```r
#bar of debris categories
data %>%
  select(`Material Description`, ItemName, Quantity) %>%
  group_by(`Material Description`, ItemName) %>%
  summarise(Quantity = sum(Quantity)) %>%
  ggplot(aes(x=reorder(`ItemName`, -Quantity), y=Quantity, fill=`Material Description`)) +
  geom_bar(stat="identity") +
  ggtitle("Debris Categorisation") +
  xlab("Debris") +
  ylab("") +
  #coord_flip() +
  theme(text = element_text(size=8),
        axis.text.x=element_text(angle=90, hjust=1),
        plot.title = element_text(size=10),
        legend.text=element_text(size=5),
        legend.position = "bottom")
```




```r
  #treemap(index = c("Material Description", "ItemName"),
  #         vSize = "Quantity", draw = TRUE) -> tm
```

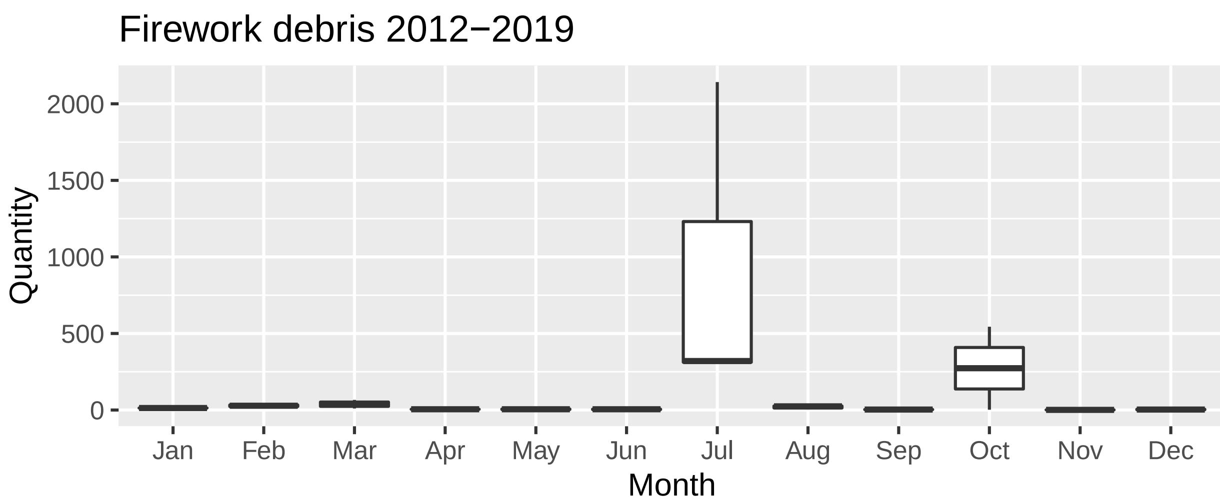
Figure 7: Debris categorisation

maybe make this top 10 or 15 items.

4.3 Event-Driven Pollution

Fireworks found in July and North-America only: possibly 4th July celebrations
4th July and Firework link? (Karen's Idea)

```
#Boxplot of fireworks distribution by month (across all years)
data %>%
  filter(`Material Description` == "PLASTIC",
         ItemName %in% c("Fireworks"),
         year(Time) >= 2012, year(Time) <= 2019) %>%
  mutate(month = month(Time, label = TRUE),
         year = as.integer(year(Time))) %>%
  group_by(month, year) %>%
  summarise(quantity = sum(Quantity)) %>%
  ggplot() +
    geom_boxplot(aes(x = month, y = quantity)) +
    xlab("Month") +
    ylab("Quantity") +
    ggtitle("Firework debris 2012-2019")
```




```
#ggsave("plots/fireworks.png")
```

Figure 8: Boxplot of fireworks distribution by month, across all years

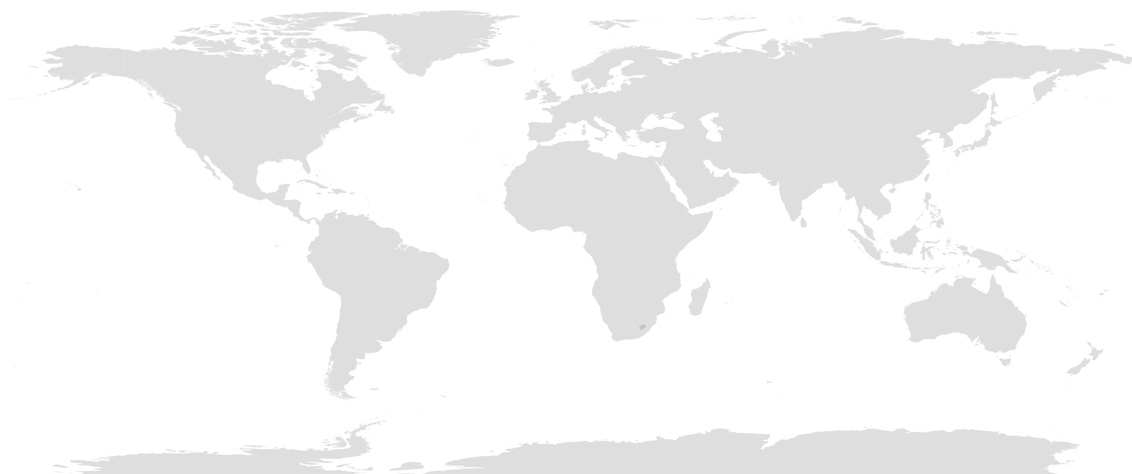
4.4 Location-Driven Pollution

Rubber found in Indoneasia only: possibly a recording bias.

Certain classes are found in certain regions only: not because they don't exist elsewhere but because of recording bias focus in those areas

We have locational data, so lets check for any geographical observation bias.

```
world <- map_data("world")
data %>%
  select(Latitude, Longitude, Quantity, Location, `Material Description`) %>%
  ggplot() +
    geom_polygon(data = map_data("world"), aes(x = long, y = lat, group = group), fill = "grey", alpha = 0.5) +
    geom_hex(aes(x = Longitude, y = Latitude), bins = 50) +
    scale_fill_viridis(trans = "log", breaks = c(5, 50, 500, 5000, 50000)) +
    theme_void() +
    guides(fill=guide_legend(title="Observations"))
```



```
#ggsave("plots/map.png", width = 20, height = 10, units = "cm")
```

We need to know how reliable the location data is. I'm going to filter for "united kingdom" in the location field and plot the raw coordinates.

Figure 9: Longitude and Latitude discrepancies

Questions
Distribution of plastic by location.
Are the distributions of plastic fairly constant for the locations with the most observations?

```r
#columnchart of debris locations
topLocations <- data %>%
  group_by(Location) %>%
  summarise(sumQuantity = sum(Quantity)) %>%
  arrange(desc(sumQuantity)) %>%
  top_n(5,sumQuantity)

data %>%
  filter(Location %in% topLocations$Location) %>%
  group_by(Location, `Material Description`) %>%
  summarise(sumQuantity = sum(Quantity)) %>%
  arrange(desc(sumQuantity)) %>%
  ggplot(aes(x = `Material Description`, y = sumQuantity, fill = Location)) +
    geom_col() + theme(legend.position = 'top')
```

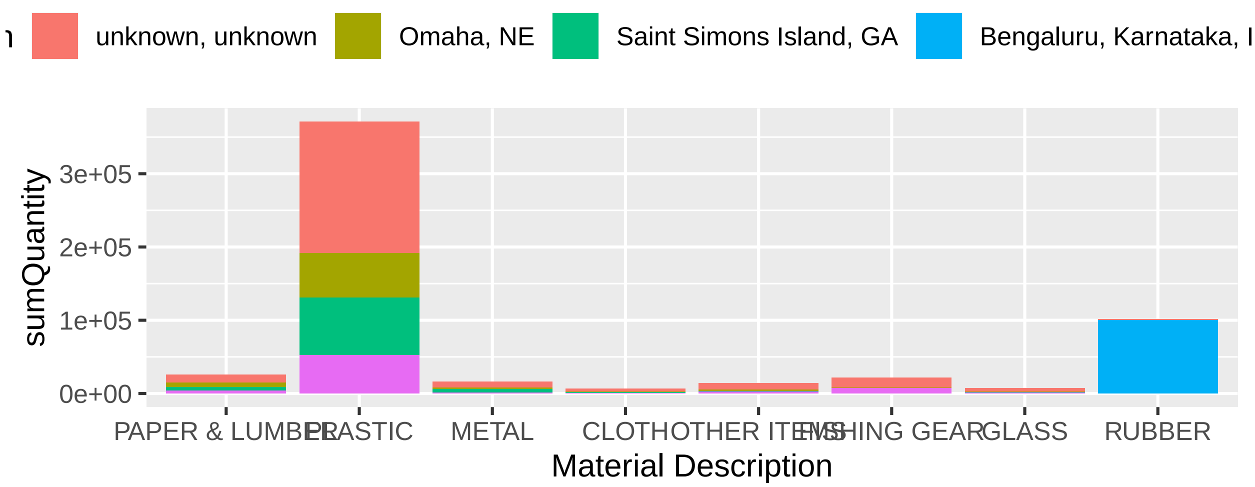


Figure 10: Debris by location

We see that the Location "unknown" has the most plastic... note that this is distinct from "(Missing)", which was our original NA values. Maybe we should merge these.

4.5 Item Pairing

(e.g. are 6-pack beer rings observed at the same time as fireworks?) are we going to explore this one?

5 Predictive Modelling

Given the variability of plastic pollution trends given event-driven and location-driven pollution as explored earlier in this report, the authors of this report built a model to predict the proportion of plastics given Month and Location. This would give more accurate predictions as opposed to a simple linear model accomodating such time factored

5.1 Description of Model

```
plasticN <- plastic %>%
  mutate(month = month(Time, label = FALSE), year = as.integer(year(Time))) %>%
  filter(year > 2010) %>%
  group_by(year, category, month) %>%
  summarise(`Total Quantity` = sum(Quantity))

####


df11N <- plasticN  %>%
  filter(year == 2011) %>%
  group_by(year, month) %>%
  mutate(freq = `Total Quantity` / sum(`Total Quantity`))

df12N <- plasticN  %>%
  filter(year == 2012) %>%
  group_by(year, month) %>%
  mutate(freq = `Total Quantity` / sum(`Total Quantity`))


df13N <- plasticN  %>%
  filter(year == 2013) %>%
  group_by(year, month) %>%
  mutate(freq = `Total Quantity` / sum(`Total Quantity`))


df14N <- plasticN  %>%
  filter(year == 2014) %>%
  group_by(year, month) %>%
  mutate(freq = `Total Quantity` / sum(`Total Quantity`))

df15N <- plasticN  %>%
  filter(year == 2015) %>%
  group_by(year, month) %>%
  mutate(freq = `Total Quantity` / sum(`Total Quantity`))


df16N <- plasticN  %>%
  filter(year == 2016) %>%
  group_by(year, month) %>%
  mutate(freq = `Total Quantity` / sum(`Total Quantity`))



df17N <- plasticN  %>%
  filter(year == 2017) %>%
  group_by(year, month) %>%
  mutate(freq = `Total Quantity` / sum(`Total Quantity`))
```

```r
df18N <- plasticN  %>%
  filter(year == 2018) %>%
  group_by(year, month) %>%
  mutate(freq = `Total Quantity` / sum(`Total Quantity`))

df19N <- plasticN  %>%
  filter(year == 2019) %>%
  group_by(year, month) %>%
  mutate(freq = `Total Quantity` / sum(`Total Quantity`))


dfTotN <- rbind(df11N, df12N, df13N, df14N, df15N, df16N, df17N, df18N, df19N)
```

```r
# plot for observing the data
(time_plotfr2N <- ggplot(dfTotN, aes(x = year, y = freq, color=category, fill = category)) +
  geom_smooth(method="lm", level=0.95) +
  theme_bw() +
  xlab("Years") +
  ylab("relative frequency") +
  ggtitle("portion of plastic") +
  expand_limits(y=0) +
  scale_y_continuous() +
  scale_x_continuous()+
  theme(legend.position="bottom")+
  theme(legend.text = element_text(size=5, face="bold")))
```

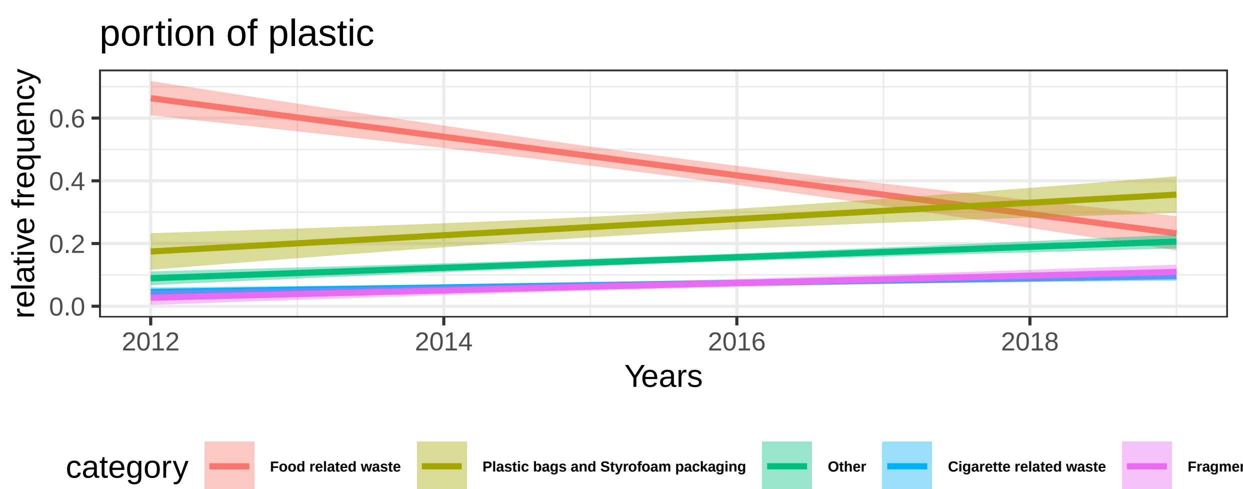


Figure 11: Some sort of caption here

We see here a graphical representation of the relative frequency of the 5 different categories of plastic debris over the years. The hint we are getting here is that ”Cigarette realted waste, ”Food related waste”, ”Fragments” seem to experiance some change, whereas ”Other” and Plastic bags and styrofoam packaging” seem to remain steady. We go on and create a model and test it on untrained data to see if what is the actual case.

```r
#1/4/20
### MODELING with new categorisation


# create train and test set
n <- nrow(dfTotN)  # Number of observations
ntrain <- round(n*0.75)  # 75% for training set
set.seed(314)    # Set seed for reproducible results
tindex <- sample(n, ntrain)   # Create a random index
train_dfTotN <- dfTotN[tindex,]   # Create training set
test_dfTotN <- dfTotN[-tindex,]

# modelling for category "Cigarette related waste"

train_Cigrel <- train_dfTotN %>%
  filter(category=="Cigarette related waste") %>%
  group_by(year)

test_Cigrel <- test_dfTotN %>%
  filter(category=="Cigarette related waste") %>%
  group_by(year)

set.seed(1234)
train_Cigrel.modelN <- lm(freq ~ year, data = train_Cigrel)
summary(train_Cigrel.modelN)

##
## Call:
## lm(formula = freq ~ year, data = train_Cigrel)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.06059 -0.02546 -0.00721  0.01012  0.20490
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -15.866832   4.775446  -3.323  0.00146 **
## year          0.007910   0.002369   3.338  0.00139 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.04331 on 66 degrees of freedom
## Multiple R-squared:  0.1444,Adjusted R-squared:  0.1315
## F-statistic: 11.14 on 1 and 66 DF,  p-value: 0.00139

print("PREDICTION")

## [1] "PREDICTION"

pred_Cigrel <- predict(train_Cigrel.modelN, test_Cigrel)
summary(pred_Cigrel)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.04720 0.06301 0.07092 0.07714 0.09465 0.10256

actuals_predsCigrel <- data.frame(cbind(actuals=test_Cigrel$freq, predicteds=pred_Cigrel))
head(actuals_predsCigrel)

##      actuals predicteds
```

```
## 1 0.05109361 0.04719559
## 2 0.05814490 0.04719559
## 3 0.03971631 0.04719559
## 4 0.03750621 0.05510514
## 5 0.01202405 0.05510514
## 6 0.05699357 0.05510514

correlation_accuracy <- cor(actuals_predsCigrel)
min_max_accuracy <- mean(apply(actuals_predsCigrel, 1, min) / apply(actuals_predsCigrel, 1, max))

mape <- mean(abs((actuals_predsCigrel$predicteds - actuals_predsCigrel$actuals))/actuals_predsCigrel$actuals)

correlation_accuracy

##              actuals predicteds
## actuals    1.0000000  0.5444291
## predicteds 0.5444291  1.0000000

min_max_accuracy

## [1] 0.7259542

mape

## [1] 0.7522119
```

```
# modelling for category "Food related waste"

train_Foodrel <- train_dfTotN %>%
  filter(category=="Food related waste") %>%
  group_by(year)

test_Foodrel <- test_dfTotN %>%
  filter(category=="Food related waste") %>%
  group_by(year)

set.seed(1234)
train_Foodrel.modelN <- lm(freq ~ year, data = train_Foodrel)
summary(train_Foodrel.modelN)

##
## Call:
## lm(formula = freq ~ year, data = train_Foodrel)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.50287 -0.07168 -0.00561  0.10218  0.34829
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 118.166588  15.395217   7.676 5.31e-11 ***
## year         -0.058414   0.007638  -7.647 6.00e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1541 on 74 degrees of freedom
## Multiple R-squared:  0.4414,Adjusted R-squared:  0.4339
## F-statistic: 58.48 on 1 and 74 DF,  p-value: 5.998e-11
```

```r
print("PREDICTION")

## [1] "PREDICTION"

pred_Foodrel <- predict(train_Foodrel.modelN, test_Foodrel)
summary(pred_Foodrel)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.2292  0.3314  0.4921  0.4395  0.5213  0.6381

actuals_predsFoodrel <- data.frame(cbind(actuals=test_Foodrel$freq, predicteds=pred_Foodrel))
head(actuals_predsFoodrel)

##     actuals predicteds
## 1 0.9761681  0.6381043
## 2 0.6351528  0.5796905
## 3 0.5822665  0.5796905
## 4 0.7911040  0.5796905
## 5 0.4837153  0.5212767
## 6 0.5395366  0.5212767

correlation_accuracy <- cor(actuals_predsFoodrel)
min_max_accuracy <- mean(apply(actuals_predsFoodrel, 1, min) / apply(actuals_predsFoodrel, 1, max))
# => 53.73%, min_max accuracy
mape <- mean(abs((actuals_predsFoodrel$predicteds - actuals_predsFoodrel$actuals))/actuals_predsFoodrel$actuals)

correlation_accuracy

##              actuals predicteds
## actuals    1.0000000  0.8537377
## predicteds 0.8537377  1.0000000

min_max_accuracy

## [1] 0.8523448

mape

## [1] 0.1546258

# modelling for category "Other"
train_Other <- train_dfTotN %>%
  filter(category=="Other") %>%
  group_by(year)

test_Other <- test_dfTotN %>%
  filter(category=="Other") %>%
  group_by(year)

set.seed(1234)
train_Other.modelN <- lm(freq ~ year, data = train_Other)
summary(train_Other.modelN)

##
## Call:
## lm(formula = freq ~ year, data = train_Other)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.131735 -0.041328 -0.005655  0.035206  0.134108
```

```
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -33.991092   6.112772  -5.561 4.73e-07 ***
## year          0.016938   0.003033   5.585 4.30e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.06088 on 69 degrees of freedom
## Multiple R-squared:  0.3113,Adjusted R-squared:  0.3013
## F-statistic: 31.19 on 1 and 69 DF,  p-value: 4.296e-07
```

```
print("PREDICTION")
```

```
## [1] "PREDICTION"
```

```
pred_Other <- predict(train_Other.modelN, test_Other)
summary(pred_Other)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.08807 0.12195 0.13889 0.14228 0.17276 0.20664
```

```
actuals_predsOther <- data.frame(cbind(actuals=test_Other$freq, predicteds=pred_Other))
head(actuals_predsOther)
```

```
##      actuals predicteds
## 1 0.05367366 0.08807451
## 2 0.13682008 0.08807451
## 3 0.26636312 0.10501246
## 4 0.10336403 0.10501246
## 5 0.05515197 0.10501246
## 6 0.14156627 0.10501246
```

```
correlation_accuracy <- cor(actuals_predsOther)  # 5.31%
min_max_accuracy <- mean(apply(actuals_predsOther, 1, min) / apply(actuals_predsOther, 1, max))
mape <- mean(abs((actuals_predsOther$predicteds - actuals_predsOther$actuals))/actuals_predsOther$actuals)

correlation_accuracy
```

```
##              actuals predicteds
## actuals    1.0000000  0.4983376
## predicteds 0.4983376  1.0000000
```

```
min_max_accuracy
```

```
## [1] 0.7441029
```

```
mape
```

```
## [1] 0.354683
```

```
# modelling for category "Plastic bags and Styrofoam packaging"
train_Plbag <- train_dfTotN %>%
  filter(category=="Plastic bags and Styrofoam packaging") %>%
  group_by(year)

test_Plbag <- test_dfTotN %>%
  filter(category=="Plastic bags and Styrofoam packaging") %>%
  group_by(year)

set.seed(1234)
train_Plbag.modelN <- lm(freq ~ year, data = train_Plbag)
summary(train_Plbag.modelN)
```

```
##
## Call:
## lm(formula = freq ~ year, data = train_Plbag)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.31838 -0.09726 -0.02112  0.05326  0.66454
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -53.792345  16.802490  -3.201  0.00204 **
## year          0.026822   0.008336   3.217  0.00194 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1608 on 72 degrees of freedom
## Multiple R-squared:  0.1257,Adjusted R-squared:  0.1136
## F-statistic: 10.35 on 1 and 72 DF,  p-value: 0.001939
```

```
print("PREDICTION")
```

```
## [1] "PREDICTION"
```

```
pred_Plbag <- predict(train_Plbag.modelN, test_Plbag)
summary(pred_Plbag)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.1732  0.2000  0.2536  0.2609  0.3341  0.3609
```

```
actuals_predsPlbag <- data.frame(cbind(actuals=test_Plbag$freq, predicteds=pred_Plbag))
head(actuals_predsPlbag)
```

```
##      actuals predicteds
## 1 0.12998318  0.1731621
## 2 0.14728033  0.1731621
## 3 0.08181818  0.1731621
## 4 0.13607595  0.1731621
## 5 0.28635887  0.1999839
## 6 0.06939979  0.1999839
```

```
correlation_accuracy <- cor(actuals_predsPlbag)  # 5.31%
min_max_accuracy <- mean(apply(actuals_predsPlbag, 1, min) / apply(actuals_predsPlbag, 1, max))
mape <- mean(abs((actuals_predsPlbag$predicteds - actuals_predsPlbag$actuals))/actuals_predsPlbag$actuals)

correlation_accuracy
```

```
##              actuals predicteds
## actuals    1.0000000  0.3534861
## predicteds 0.3534861  1.0000000
```

```
min_max_accuracy
```

```
## [1] 0.6623657
```

```
mape
```

```
## [1] 2.273597
```

```r
# modelling for category "Fragments"
train_Frag <- train_dfTotN %>%
  filter(category=="Fragments") %>%
  group_by(year)

test_Frag <- test_dfTotN %>%
  filter(category=="Fragments") %>%
  group_by(year)

set.seed(1234)
train_Frag.modelN <- lm(freq ~ year, data = train_Frag)
summary(train_Frag.modelN)
```

```
##
## Call:
## lm(formula = freq ~ year, data = train_Frag)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.07328 -0.03075 -0.01469  0.01405  0.36377
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -21.074627   6.678746  -3.155  0.00237 **
## year          0.010490   0.003314   3.165  0.00230 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.06143 on 69 degrees of freedom
## Multiple R-squared:  0.1268,Adjusted R-squared:  0.1142
## F-statistic: 10.02 on 1 and 69 DF,  p-value: 0.002305
```

```r
print("PREDICTION")
```

```
## [1] "PREDICTION"
```

```r
pred_Frag <- predict(train_Frag.modelN, test_Frag)
summary(pred_Frag)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.03035 0.05133 0.07231 0.06812 0.09329 0.10378
```

```r
actuals_predsFrag <- data.frame(cbind(actuals=test_Frag$freq, predicteds=pred_Frag))
head(actuals_predsFrag)
```

```
##        actuals predicteds
## 1 0.0006645432 0.03035393
## 2 0.0365704287 0.03035393
## 3 0.0420180954 0.03035393
## 4 0.0553760960 0.03035393
## 5 0.0240641711 0.03035393
## 6 0.0239271782 0.04084348
```

```r
correlation_accuracy <- cor(actuals_predsFrag)  # 5.31%
min_max_accuracy <- mean(apply(actuals_predsFrag, 1, min) / apply(actuals_predsFrag, 1, max))
mape <- mean(abs((actuals_predsFrag$predicteds - actuals_predsFrag$actuals))/actuals_predsFrag$actuals)

correlation_accuracy
```

```
##             actuals predicteds
## actuals    1.0000000  0.4961031
## predicteds 0.4961031  1.0000000

min_max_accuracy

## [1] 0.5303913

mape

## [1] 2.69393
```

In total we see that time is statistically significant in the change of proportions of certain categories of plastic waste: ”cigarette related waste”, ”food related waste”, ”fragments”. This is not the case for the ”Other” and ”Plastic bags and Styrofoam packaging” . Some plastic waste categories are time variant while others aren’t and this has to do a lot with sampling techniques and one-sidedness of datasets. It does not mean that the datasets are wrong it just shows even more that what we have talked about over many group meetings regarding the dataset being biased one way or the other is clearly backed by statistical evidence within this dataset and by referencial evidence too.”
”Paper: Spatial and Temporal Patterns of Stranded Intertidal Marine Debris: Is There a Picture of Global Change?”

```r
plastic_category <-(c("cigarette related waste", "food related waste","Fragments", "Other","Plastic bags and Styrof
slope_scores <- c(-0.05512,0.030425, 0.030950,-0.002428,-0.001151)
slope_interpretation <-c("downward", "upward", "upward", "relatively steady", "relatively steady")
p_value<-c("<0.05","<0.05","<0.05", ">0.05",">0.05")
corr_accuracy<-c(0.62, 0.35,0.48, 0.27,0.38)
min_max_Acc<-c(0.67,0.72,0.67, 0.65 ,0.67)
MAPE_scores<-c(0.99,0.91,0.54, 0.89, 0.43)
score_table <- data.frame(plastic_category, p_value,slope_scores, slope_interpretation, corr_accuracy,min_max_Acc,
```

On metrics used: $Pr(>|t|)$ is the p-value, defined as the probability of observing any value equal or larger than t if H0 is true. The larger the t statistic, the smaller the p-value. Generally, we use 0.05 as the cutoff for significance. When p-values are smaller than 0.05, we reject H0 that there’s no difference between the means and conclude that a significant difference does exist. If the p-value is larger than 0.05, we cannot conclude that a significant difference exists. P-value¡0.05 means that there is statistical significance in the results presented. If p-value¿0.05 we can not conclude on the statistical significance.
Correlation accuracy: A simple correlation between the actuals and predicted values can be used as a form of accuracy measure. A higher correlation accuracy implies that the actuals and predicted values have similar directional movement, i.e. when the actuals values increase the predicted values also increase and vice-versa.
MinMax Accuracy: MinMax tells you how far the model’s prediction is off. For a perfect model, this measure is 1.0. The lower the measure, the worse the model, based on out-of-sample performance. min_max_accuracy
MAPE: The mean absolute percentage error (MAPE) is a statistical measure of how accurate a forecast system is. It measures this accuracy as a percentage, and can be calculated as the average absolute percent error for each time period minus actual values divided by actual values. eg a MAPE value of 0.99 states that our model’s predictions are, on average, 0.99% off from actual value.
On values of metrics used: MinMax Accuracy is generally above 65% but never exceeds 72% for all cases, which means that the model does a moderate job in predicting accurately the relative frequency of each category over time. The correlation accuracy is not that good which implies that the predicted values do not always follow the true values observed. The best value is for the model predicting on ”cigarette related waste”. MAPE scores are pretty good for all models showing that no model’s predictions are on average more than 1% off from actual value.

5.2 Model Evaluation

5.3 Model Results

6 Discussion

It was noted that the main system for reporting debris was used by large scale clobes. This means that data is not a continuous and even flow so during events such as international beach cleanup day there may be more data in the respective month. Since these events aim mostly to cleanup after big social events extra effort might have been made to retrive entertainment based debris such as fireworks, food packaging and six pack rings.The decrease in cigarette waste was observed to be in corelation with a decreesing smoking rate.

7 Conclusion and Future Work

Our hypothesis stands/does not stand. The hypothesis H1 stands. This is no evident as to a change in the percentage of marine debris being plastic in origin that can be observed in results such as in figure 4. Future work might involve continuing to study corelations similar to the fireworks/july corelation.

8 Project Management

8.1 Facilities

Group 2 communicated using a dedicated Slack Channel, Github repository and weekly 1 hour meetings before the wednesday lab. All project documents used and the final report can be accessed from the *Public Github Repository* obviously we need to mention the whole covid-19 thing and how we worked around it.

8.2 Project Progress

```
require(openxlsx);
require(readxl)
library(stringr);library(data.table)
library(XLConnect)
library(xtable)

# Sheets names
fileName <- 'data/meetings.xlsx'
sheets <- readxl::excel_sheets(fileName)
#length(sheets)
# Read 1st sheet (you shouldn't have more than one sheet for this task)
# read sheet into dataframe, and rbind
dfs <- readWorksheet(loadWorkbook("data/meetings.xlsx"),sheet=1)
dfs$Date <-as.character(dfs$Date)
print(xtable(dfs,
                    caption = "Record of Team Meetings",
                    label = "tab:one",
                    table.placement = "",
                    # align changes subject to number of columns
                    align = "lllp{8cm}lllll"),include.rownames=FALSE,
                    caption.placement = "top")
```

Table 1: Record of Team Meetings

No	Date	Topic	Alex	Georgios	Karen	Roshi	Stuart
1.00	2020-02-05	Group Formation: set up communication channel in Slack and GitHub repository	yes	yes	yes	yes	yes
2.00	2020-02-11	Agreed topic of ”Plastic Pollution”, distributed research activity for week	yes	yes	yes	yes	yes
3.00	2020-02-18	Presented inividuals’ research findings and discussed hypothesis	yes	yes	yes	yes	yes
4.00	2020-02-25	Decided on final dataset to use and hypothesis of ”proportion of marine plastics pollution does not change over time”	yes	yes	yes	yes	yes
5.00	2020-03-04	Presentation draft agreed	yes	yes	yes	yes	yes
6.00	2020-03-10	Distributed section writing activity for week	yes	yes	yes	yes	yes
7.00	2020-03-17						
8.00	2020-03-24						
9.00	2020-03-31						
10.00	2020-04-07						
11.00	2020-04-14						
12.00	2020-04-21						

8.3 Peer-assessment

```r
require(openxlsx);
require(readxl)
library(stringr);library(data.table)
library(XLConnect)
library(xtable)

# Sheets names
fileName <- 'data/peers.xlsx'
sheets <- readxl::excel_sheets(fileName)
#length(sheets)
# Read 1st sheet (you shouldn't have more than one sheet for this task)
# read sheet into dataframe, and rbind
dfs <- readWorksheet(loadWorkbook("data/peers.xlsx"),sheet=1)

# convert fields into chars
dfs[, ] <- lapply(dfs[, ], as.character)

print(xtable(dfs,
                    caption = "Peer Assessment out of 100",
                    label = "tab:two",
                    table.placement = "",
                    # align changes subject to number of columns
                    align = "lllllll"),include.rownames=FALSE,
                    caption.placement = "top")
```

Table 2: Peer Assessment out of 100

Peer.Review	Alex	Georgios	Karen	Roshi	Stuart
Alex	100	100	100	100	100
Georgios	100	100	100	100	100
Karen	100	100	100	100	100
Roshi	100	100	100	100	100
Stuart	100	100	100	100	100

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