

# TODO\*

## TODO

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First sentence. Second sentence. Third sentence. Fourth sentence.

## 1 Introduction

*TODO* today's world, where everything is connected online, cybersecurity is super important. It's all about keeping our digital stuff safe from bad guys who try to steal or mess with it. Cyber threats, like hackers breaking into computer systems or stealing personal information, are becoming more common and tricky to deal with.

This paper is all about diving into the world of cybersecurity to learn about the problems we face, the trends we're seeing, and how we can protect ourselves better. We'll start by looking at some big cyber incidents that have happened recently. By understanding what happened in these incidents, we can figure out how to stop similar attacks in the future.

Then, we'll talk about the new kinds of cyber threats that are popping up all the time. From sneaky tricks like ransomware to people tricking us into giving away our info, we'll explore the different ways bad guys try to break into our digital stuff.

Finally, we'll talk about what we can do to fight back against cyber threats. This includes using smart technology, making rules and policies to keep things safe, and teaching people how to be careful online. By learning more about cyber risks and working together to stay safe, we can make sure our digital world is a lot safer for everyone.

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\*Code and data are available at: [https://github.com/shivankgoel003/DataBreach\\_Ransomware\\_Stats](https://github.com/shivankgoel003/DataBreach_Ransomware_Stats)

## 2 Data

### 2.1 Data Source and Collection:

#### TODO

The study relies on datasets obtained from the provincial open databases of Alberta, accessible through the official website government (2024). Three key datasets were utilized to extract relevant variables for analysis, aiming to uncover the relationship between air quality and mortality rates in Alberta. The analysis begins with the leading causes of death dataset for Alberta, sourced from the provincial open data portal government (2023b). This dataset provides insights into mortality rates associated with various illnesses, facilitating the examination of trends related to respiratory and heart-related illnesses. To explore potential correlations between air quality and mortality rates, the study incorporates the Air Quality Health Index (AQHI) dataset for Alberta, sourced from the provincial open data portal government (2023a). This dataset offers comprehensive information on the AQHI across different municipalities in Alberta over multiple years. Additionally, the study utilizes PM2.5 air pollutant concentration level data sourced from Alberta's official resources Alberta Government (2023). This dataset provides detailed information on the concentration levels of PM2.5 pollutants over several years, offering valuable insights into air quality trends. The following subsections outline the sources, collection methodologies, and data-cleaning procedures implemented to ensure the accuracy and reliability of the datasets used in the analysis. This meticulous approach ensures that the data is prepared for thorough analysis, facilitating the exploration of correlations between air quality indicators and mortality rates in Alberta.

**Leading Causes of Death in Alberta Data:** The disease data is found from the government of Alberta's open data portal, and was last updated on September 22, 2023 and continues to be updated annually. This dataset encompasses mortality data related to the top 30 common causes of death. It reports on types of diseases, causes of death, mortality denoted by total death counts, and ranking for 2000-2022. Due to our focus on respiratory illnesses, in the leading cause of death dataset, we grouped diseases by categories. Our category of focus included filtering on illnesses like acute myocardial infarction, malignant neoplasms of the trachea, bronchus, and lung, other chronic obstructive pulmonary disease, and all other forms of chronic ischemic heart disease. Leading causes of death are measured and ranked by the top 30 most common death causes each specific year. The causes of death are classified based on the International Classification of Diseases 10th Edition.

**AQHI Data:** The second dataset we used is the air quality health index (AQHI) dataset found at the government of Alberta's open data portal. This dataset contains AQHI by municipality for the years 2012-2022 and reports air quality health index, and health risk both quantitatively and qualitatively. To use the AQHI dataset we employed simple data-cleaning practice to maintain descriptive variable names and readability. The data is measured by the percentage of hours for each year at a given air quality level, by municipality. The Air Quality Health Index is calculated based on the relative risks of a combination of common air pollutants that

is known to harm human health. These pollutants are ozone (O<sub>3</sub>) at ground level, particulate matter (PM<sub>2.5</sub>), and nitrogen dioxide (NO<sub>2</sub>). Risks are defined as follows: 1-3 High Quality; 4-6 Moderate Quality; 7-9 Low Quality; 10+ Very Low Quality.

**PM<sub>2.5</sub> Data:** We used the PM<sub>2.5</sub> data set retrieved from Alberta.ca (Government of Alberta) which was last updated in April 2023. It reports on average PM<sub>2.5</sub> concentration levels through the years 2000-2021 using a provincial average, the 10th percentile quantities, and the 90th percentile quantities, with a focus on 8 municipalities Edmonton, Fort McMurray, Grande Prairie, Lethbridge, Medicine Hat, and Red Deer respectively and lastly reports the Canadian Ambient Air Quality Standard (CAAQS) value.

The Alberta Air Zone report Environment and Areas (2021), which is linked to our dataset, provides a detailed explanation of the measurement and processing of the PM<sub>2.5</sub> quantity. Alberta Air Zones divides Alberta into six air zones which are aligned with Alberta's Land-use Framework regional boundaries. Ambient air quality in Alberta is monitored at continuous air monitoring stations located within these air zones. PM<sub>2.5</sub> quantities are taken throughout these stations across Alberta, and they measure the quantities in µg (micrograms per cubic meter of air).

## 2.2 Data Cleaning

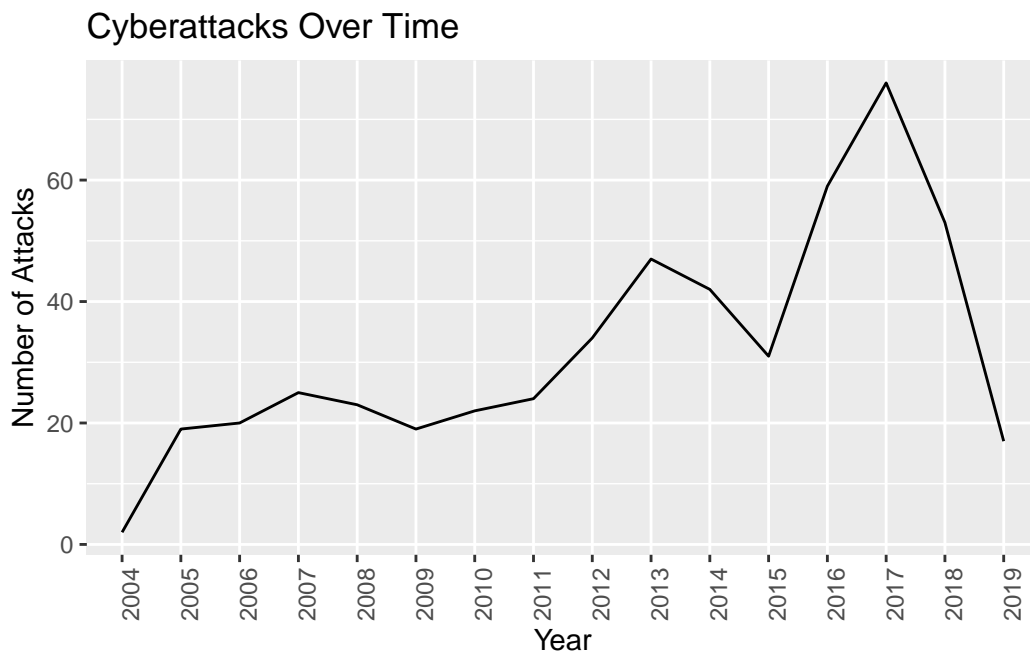
We used R (R Core Team 2023) and Wickham et al. (2019a) for data cleaning and processing, utilizing packages like tidyverse (Wickham et al. 2019b) for data manipulation and janitor (Firke 2023) for cleaning column names. Other packages used includes ggplot2 (Wickham 2016), dplyr (Wickham et al. 2023), readr (Wickham, Hester, and Bryan 2024), tibble (Müller and Wickham 2023), janitor (Firke 2023), reshape2 (Wickham 2007), knitr (Xie 2023), ggbeeswarm (Clarke, Sherrill-Mix, and Dawson 2023), ggrepel (Slowikowski 2024), kableExtra (Zhu 2024), readxl (Wickham and Bryan 2023), MASS (Venables and Ripley 2002), rstanarm (Goodrich et al. 2022), modelsummary (Arel-Bundock 2022) and here (Müller 2020).

The raw air quality data were preprocessed to remove inconsistencies and irrelevant information. Specifically, we filtered the dataset to include observations from the years 2012 to 2021, which are relevant to our analysis. Additionally, we merged this dataset with additional information on peak pollution levels for comprehensive analysis. Similar to the previous datasets, the raw mortality data underwent cleaning procedures to focus on specific causes relevant to our analysis. We filtered the dataset to include observations up to 2021 and merged it with additional information on air quality for correlation analysis. The raw data on AQHI were filtered to include observations from the years 2011 to 2021 for consistency with other datasets. Additionally, the data were aggregated at the municipal level for further analysis.

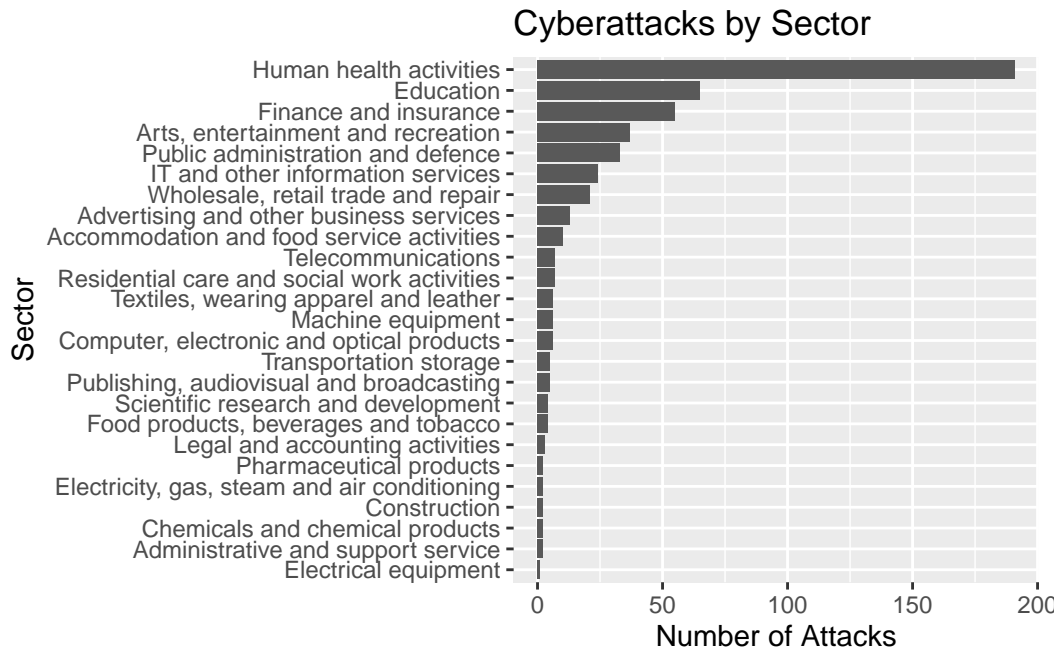
## 2.3 Data Modifications

In this study, we constructed unique datasets by thoughtfully selecting and merging data from the Government of Alberta's open data portal, Alberta.ca, spanning the years 2012 to 2022. Our process involved merging variables from various datasets to create specific datasets tailored for model building and analysis. One such dataset, 'cleaned\_chart\_data,' was created by merging variables such as causes of death, total deaths, provincial average PM2.5 levels, and CAAQS. This dataset was designed to facilitate our analysis of any significant correlations between these variables. A snapshot of this data is referenced in Table X. Additionally, we derived two other datasets, 'merged\_data' and 'merged\_heart\_data,' by merging variables related to heart disease numbers, lung disease numbers, and provincial average PM2.5 values. These datasets were instrumental in examining the impact of PM2.5 on each type of illness, as previously discussed. Overall, our methodology ensured the creation of comprehensive datasets that allowed for a detailed investigation into the relationships between PM2.5 levels and various health outcomes in Alberta.

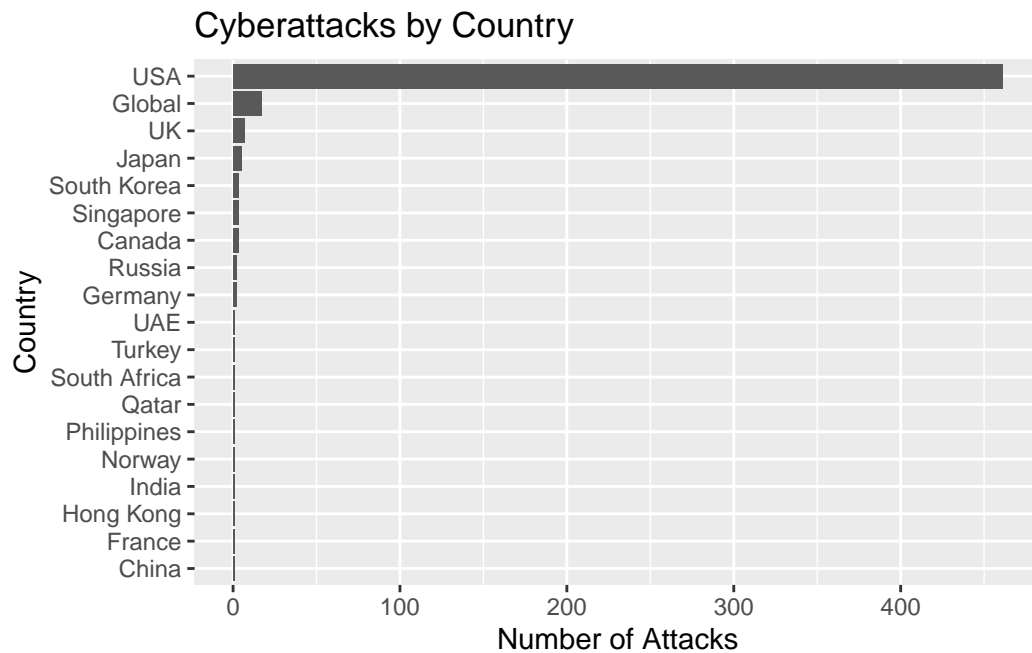
```
breach_data %>%  
  count(year) %>%  
  ggplot(aes(x = as.factor(year), y = n)) + # Convert year to factor to treat it as discrete  
  geom_line(group=1) + # Ensure geom_line treats the data as connected points  
  scale_x_discrete(breaks = levels(as.factor(breach_data$year))) + # Specify breaks at every  
  labs(title = "Cyberattacks Over Time", x = "Year", y = "Number of Attacks") +  
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) # Rotate x labels to fit them all
```



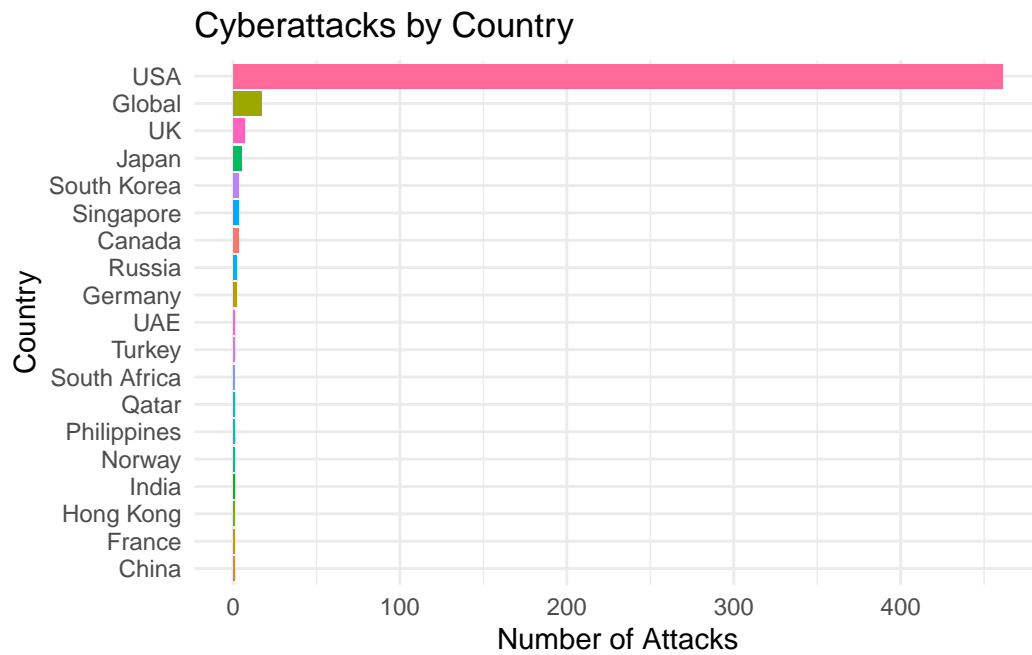
```
breach_data %>%
  count(sector) %>%
  ggplot(aes(x = reorder(sector, n), y = n)) +
  geom_bar(stat = "identity") +
  coord_flip() +
  labs(title = "Cyberattacks by Sector", x = "Sector", y = "Number of Attacks")
```



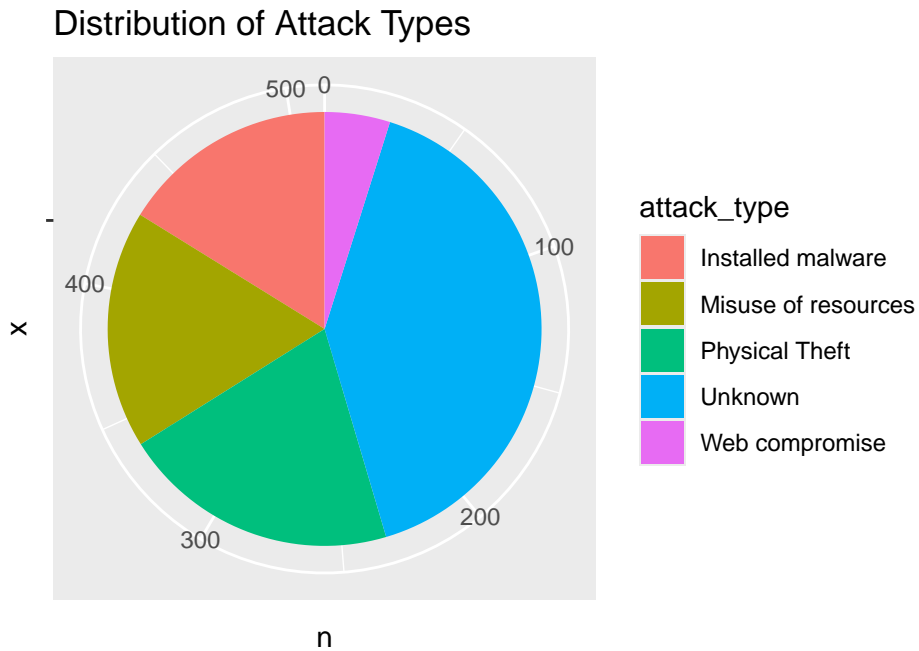
```
breach_data %>%
  count(country) %>%
  ggplot(aes(x = reorder(country, n), y = n)) +
  geom_bar(stat = "identity") +
  coord_flip() +
  labs(title = "Cyberattacks by Country", x = "Country", y = "Number of Attacks")
```



```
breach_data %>%  
  count(country) %>%  
  ggplot(aes(x = reorder(country, n), y = n, fill = country)) +  
  geom_bar(stat = "identity") +  
  coord_flip() +  
  labs(title = "Cyberattacks by Country", x = "Country", y = "Number of Attacks") +  
  theme_minimal() +  
  theme(legend.position = "none") # Hides the legend
```



```
breach_data %>%
  count(attack_type) %>%
  ggplot(aes(x = "", y = n, fill = attack_type)) +
  geom_bar(width = 1, stat = "identity") +
  coord_polar("y") +
  labs(title = "Distribution of Attack Types")
```

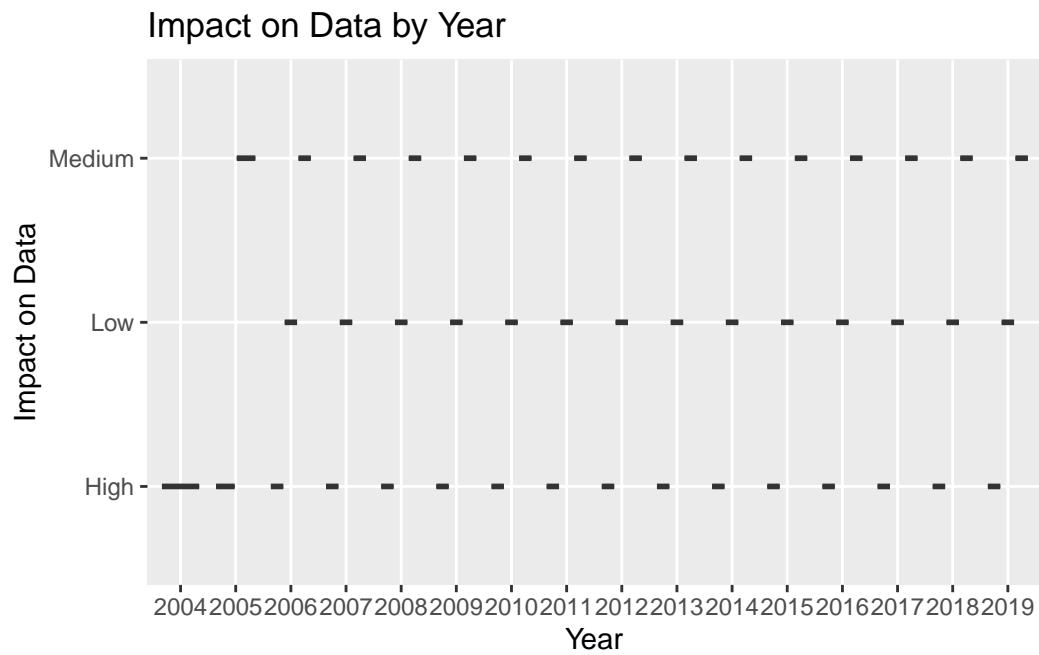


Talk more about it.

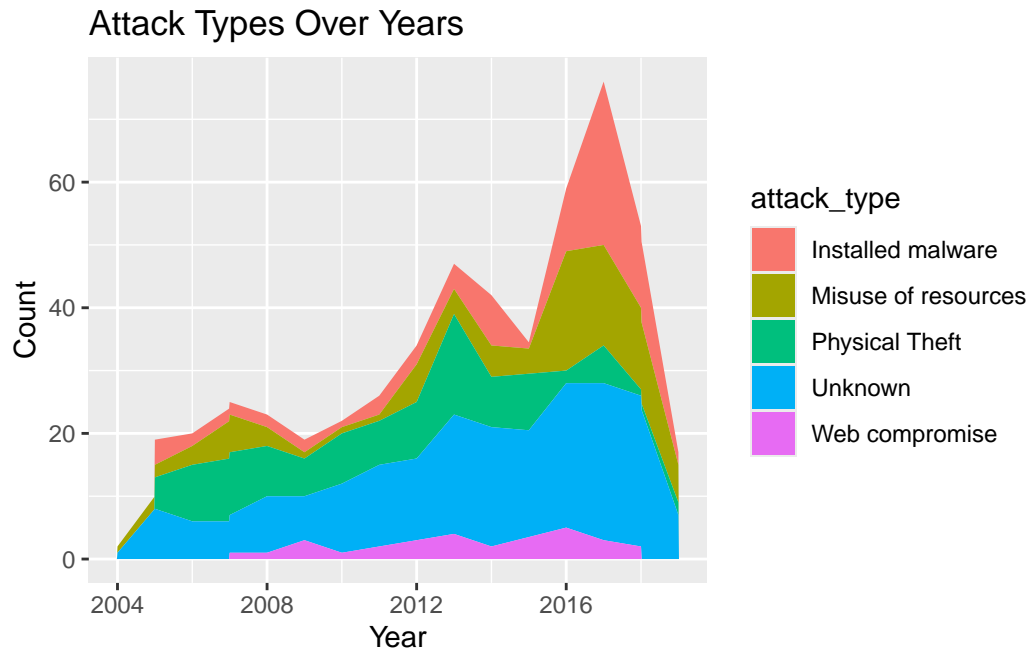
And also planes (?@fig-planes). (You can change the height and width, but don't worry about doing that until you have finished every other aspect of the paper - Quarto will try to make it look nice and the defaults usually work well once you have enough text.)

```
breach_data %>%
  ggplot(aes(x = as.factor(year), y = impact_on_data)) +
  geom_boxplot() +
  labs(title = "Impact on Data by Year", x = "Year", y = "Impact on Data")
```





```
breach_data %>%
  count(year, attack_type) %>%
  ggplot(aes(x = year, y = n, fill = attack_type)) +
  geom_area(position = 'stack') +
  labs(title = "Attack Types Over Years", x = "Year", y = "Count")
```



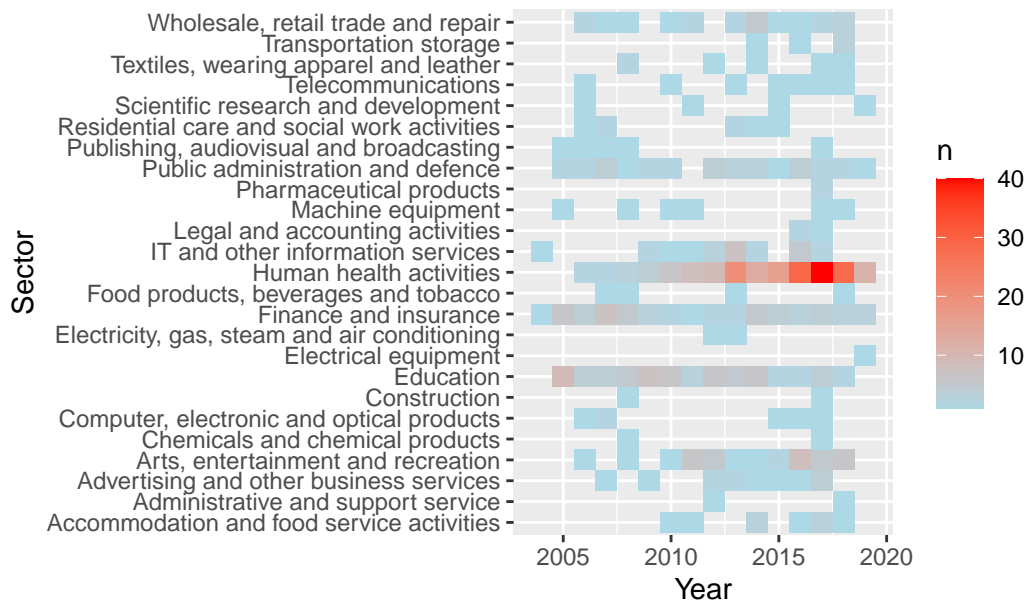
```
library(ggplot2)
library(dplyr)

# Assuming 'overall_nature_of_attack' is your categorical variable indicating the nature/type
# and 'number_of_users_affected' is a numeric variable indicating the number of users impacted

# First, let's calculate summary statistics for each nature of attack

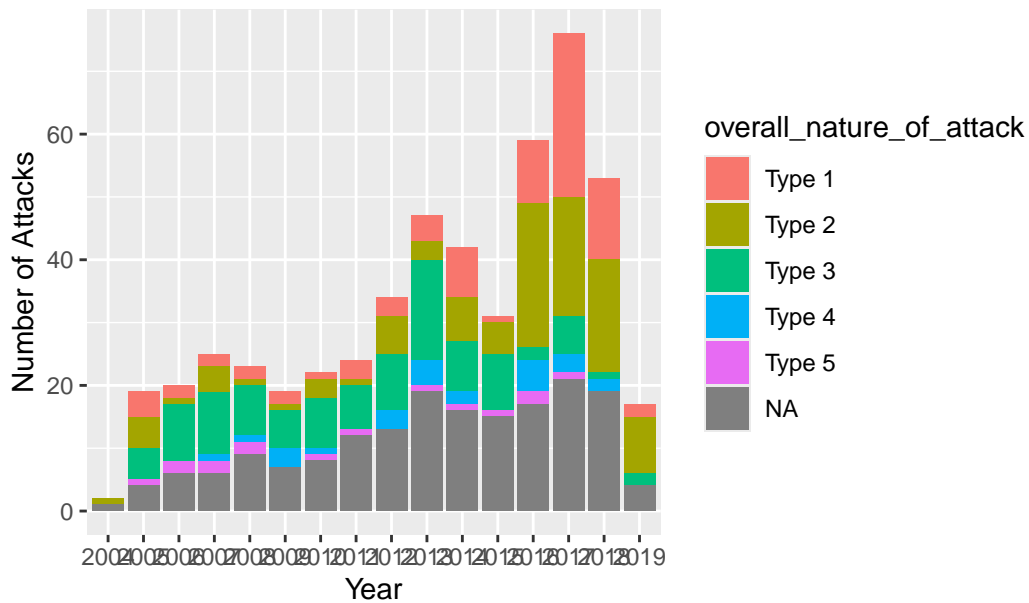
breach_data %>%
  count(year, sector) %>%
  ggplot(aes(x = year, y = sector, fill = n)) +
  geom_tile() +
  scale_fill_gradient(low = "lightblue", high = "red") +
  labs(title = "Heatmap of Cyberattacks per Year and Sector",
       x = "Year",
       y = "Sector")
```

# Heatmap of Cyberattacks per Year



```
breach_data %>%
  count(year, overall_nature_of_attack) %>%
  ggplot(aes(x = as.factor(year), y = n, fill = overall_nature_of_attack)) +
  geom_bar(stat = "identity") +
  labs(title = "Stacked Bar Chart of Attack Types by Year",
       x = "Year",
       y = "Number of Attacks")
```

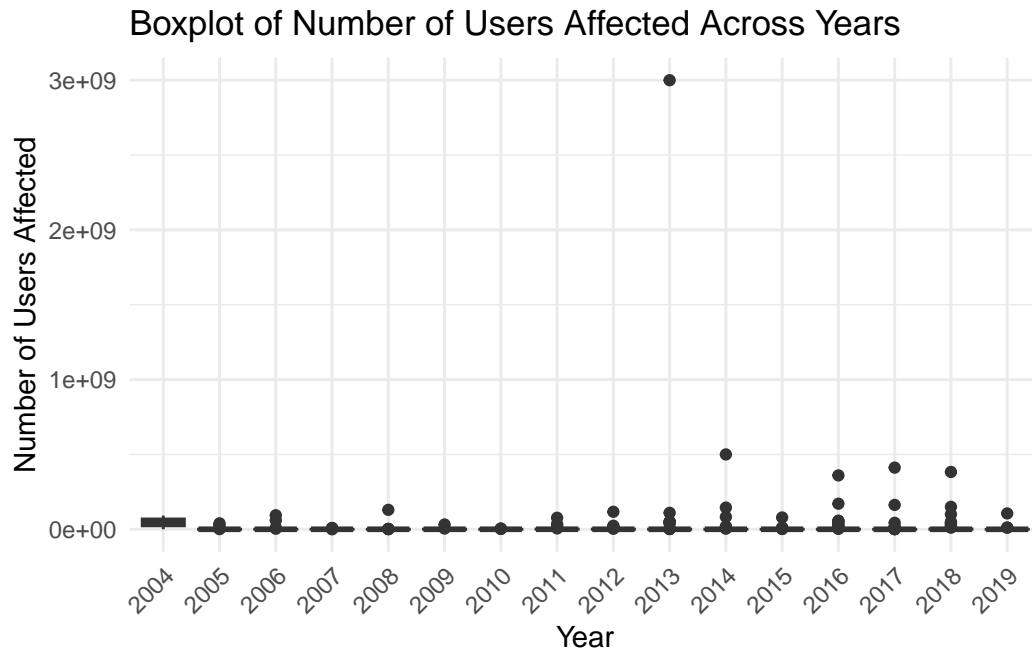
### Stacked Bar Chart of Attack Types by Year



```
library(ggplot2)

ggplot(breach_data, aes(x = as.factor(year), y = number_of_users_affected)) +
  geom_boxplot() +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  labs(title = "Boxplot of Number of Users Affected Across Years",
       x = "Year",
       y = "Number of Users Affected")
```

Warning: Removed 1 row containing non-finite outside the scale range (`stat\_boxplot()`).



```
breach_data %>%
  filter(year == 2013) %>%
  arrange(desc(number_of_users_affected)) %>%
  head() # This shows the top entries for 2013
```

	year	organisation	critical_industry	organisation_size		level_of_digital_intensity	sector	country
1	2013	Yahoo	Yes	Large		High	IT and other information services	USA
2	2013	Target	No	Large		Medium-High	Wholesale, retail trade and repair	USA
3	2013	Evernote	Yes	Medium		High	IT and other information services	Global
4	2013	Living Social	No	Large		High	Advertising and other business services	USA
5	2013	Scribd	Yes	Medium		High	IT and other information services	USA
6	2013	Adobe	Yes	Large		High	IT and other information services	Global
		cyber_security_role	cyber_security_frameworks	education_and_awareness_policy				
1		Yes	No	No				
2		Yes	No	No				

3	Yes	No	No
4	No	No	No
5	No	No	No
6	No	No	No
policy prevention_detection_and_recovery improper_network_segmentation			
1	Yes	Medium	<NA>
2	Yes	High	Yes
3	Yes	Medium	<NA>
4	Yes	Low	<NA>
5	Yes	Low	<NA>
6	Yes	Low	Yes
inappropriate_remote_access absence_of_encryption detector			
1	<NA>	<NA>	Organisation
2	Yes	Yes	Organisation
3	<NA>	No	Organisation
4	<NA>	Yes	Organisation
5	No	Yes	Organisation
6	<NA>	Yes	Organisation
restructuring_after_attack bribe_ransom_paid			
1	Yes	No	
2	Yes	No	
3	Yes	No	
4	No	No	
5	No	No	
6	Yes	No	
free_identity_or_credit_theft_monitoring additional_disclosure_of_information			
1	Yes	Yes	Yes
2	Yes	Yes	Yes
3	No	No	Yes
4	No	No	Yes
5	No	No	No
6	No	No	No
number_of_users_affected overall_nature_of_attack attack_type attacker			
1	3.0e+09	<NA>	Unknown External
2	1.1e+08	Type 1	Installed malware External
3	5.0e+07	<NA>	Unknown External
4	5.0e+07	<NA>	Unknown External
5	5.0e+07	<NA>	Unknown External
6	3.8e+07	<NA>	Unknown External
attack_vector impact_on_data			
1	<NA>	Low	
2	Vendor vulnerability	High	
3	<NA>	Low	

4	<NA>	Low
5	<NA>	Low
6	Unknown network attack	High
aspect_of_confidentiality_integrity_availability_triad_affected		
1		Confidentiality
2		Confidentiality
3		Confidentiality
4		Confidentiality
5		Confidentiality
6		Confidentiality
individual_s_name_s_leaked_exposed address_es_leaked_exposed		
1	Yes	No
2	Yes	Yes
3	Yes	No
4	Yes	No
5	Yes	No
6	Yes	No
other_personally_identifiable_information_pii_leaked_exposed		
1		Yes
2		Yes
3		Yes
4		Yes
5		Yes
6		Yes
track_1_credit_card_details_leaked_exposed		
1		No
2		Yes
3		No
4		No
5		No
6		Yes
track_2_credit_card_details_leaked_exposed		
1		No
2		<NA>
3		No
4		No
5		No
6		<NA>
social_security_number_tax_number_leaked_exposed		
1		No
2		Yes
3		No
4		No

5		No	
6		No	
	subsequent_fraudulent_use_of_data	investigation	undertook_investigation
1	No	Yes	Yes
2	Yes	Yes	Yes
3	No	No	No
4	No	No	No
5	No	Yes	Yes
6	No	Yes	Yes
	litigation_by_public	penalties_settlement_paid_or_actions_imposed	
1	Yes		Yes
2	Yes		Yes
3	No		No
4	No		No
5	No		No
6	Yes		Yes
	imposed_penalties_or_actions_on_organisation		
1		No	
2		Yes	
3		No	
4		No	
5		No	
6		No	
	fines_issued_by_government_or_relevant_body	settlement_paid	
1		No	Yes
2		Yes	Yes
3		No	No
4		No	No
5		No	No
6		No	Yes
	effect_on_share_price		summary
1	<NA>		Unknown
2	↓ Through vendor access, PoS target		
3	<NA>		Unknown
4	<NA>		Unknown
5	<NA>		Unknown
6	↓ Found a backup server and raided		

```
breach_data %>%
  filter(year == 2014) %>%
  arrange(desc(number_of_users_affected)) %>%
  head() # This shows the top entries for 2013
```



year	organisation	critical_industry	organisation_size
1 2014	Yahoo	Yes	Large
2 2014	eBay	No	Large
3 2014	JP Morgan Chase	Yes	Large
4 2014	Korea Credit Bureau	Yes	Unknown
5 2014	Experian	Yes	Large
6 2014	P.F. Changs	Yes	Large
level_of_digital_intensity	sector		
1	High	IT and other information services	
2	Medium-High	Wholesale, retail trade and repair	
3	High	Finance and insurance	
4	High	Finance and insurance	
5	High	Finance and insurance	
6	Low	Accommodation and food service activities	
country	cyber_security_role	cyber_security_frameworks	
1 USA	Yes	No	
2 Global	No	No	
3 USA	No	No	
4 South Korea	No	No	
5 UK	No	No	
6 USA	No	No	
education_and_awareness_policy	policy	prevention_detection_and_recovery	
1	No	Yes	Low
2	No	Yes	Low
3	No	Yes	Low
4	No	Yes	Low
5	No	Yes	Low
6	No	Yes	Low
improper_network_segmentation	inappropriate_remote_access		
1	Yes	<NA>	
2	Yes	No	
3	Yes	No	
4	Yes	No	
5	<NA>	<NA>	
6	No	No	
absence_of_encryption	detector	restructuring_after_attack	
1	Yes	Organisation	Yes
2	Yes	Organisation	Yes
3	Yes	<NA>	Yes
4	Yes	Public	Yes
5	<NA>	Organisation	<NA>
6	Yes	Federal Agency	<NA>
bribe_ransom_paid	free_identity_or_credit_theft_monitoring		

1	No	Yes
2	No	No
3	No	No
4	No	Yes
5	No	Yes
6	No	Yes
additional_disclosure_of_information number_of_users_affected		
1	Yes	5.00e+08
2	No	1.45e+08
3	Yes	8.30e+07
4	Yes	2.00e+07
5	<NA>	1.50e+07
6	Yes	7.00e+06
overall_nature_of_attack attack_type attacker		
1	Type 2 Misuse of resources	External
2	<NA>	Unknown External
3	Type 2 Misuse of resources	External
4	Type 5 Misuse of resources	Internal
5	<NA>	Unknown External
6	Type 1 Installed malware	External
attack_vector impact_on_data		
1	Social engineering	Low
2	<NA>	High
3	Insufficient authentication validation	Medium
4	Inappropriate use of privilege	High
5	Unknown network attack	Medium
6	Unknown network attack	High
aspect_of_confidentiality_integrity_availability_triad_affected		
1		Confidentiality
2		Confidentiality
3		Confidentiality
4		Confidentiality
5		Confidentiality
6		Confidentiality
individual_s_name_s_leaked_exposed address_es_leaked_exposed		
1	Yes	No
2	Yes	Yes
3	Yes	Yes
4	Yes	No
5	Yes	No
6	Yes	Yes
other_personally_identifiable_information_pii_leaked_exposed		
1		Yes

2			Yes
3			Yes
4			Yes
5			Yes
6			Yes
track_1_credit_card_details_leaked_exposed			
1		No	
2		Yes	
3		No	
4		Yes	
5		No	
6		Yes	
track_2_credit_card_details_leaked_exposed			
1		No	
2		<NA>	
3		No	
4		<NA>	
5		No	
6		<NA>	
social_security_number_tax_number_leaked_exposed			
1		No	
2		No	
3		No	
4		No	
5		Yes	
6		No	
subsequent_fraudulent_use_of_data investigation undertook_investigation			
1	No	Yes	Yes
2	No	Yes	No
3	No	Yes	Yes
4	No	Yes	Yes
5	No	Yes	Yes
6	No	Yes	Yes
litigation_by_public penalties_settlement_paid_or_actions_imposed			
1	Yes		Yes
2	Yes		No
3	No		No
4	No		No
5	No		No
6	Yes		No
imposed_penalties_or_actions_on_organisation			
1		No	
2		No	

3	No	
4	No	
5	No	
6	No	
	fines_issued_by_government_or_relevant_body	settlement_paid
1	No	Yes
2	No	No
3	No	No
4	No	No
5	No	No
6	No	No
	effect_on_share_price	summary
1	<NA>	Spear phishing
2	No change	Unauthorised access but unknown
3	↓ Server was hacked due to lack of proper authentication	
4	<NA>	Contractor took data
5	↓	Unauthorised access but unknown
6	<NA>	Malware installed on PoS

```
# Install and load the scales package
if (!requireNamespace("scales", quietly = TRUE)) {
  install.packages("scales")
}
library(scales)
```

Attaching package: 'scales'

The following object is masked from 'package:purrr':

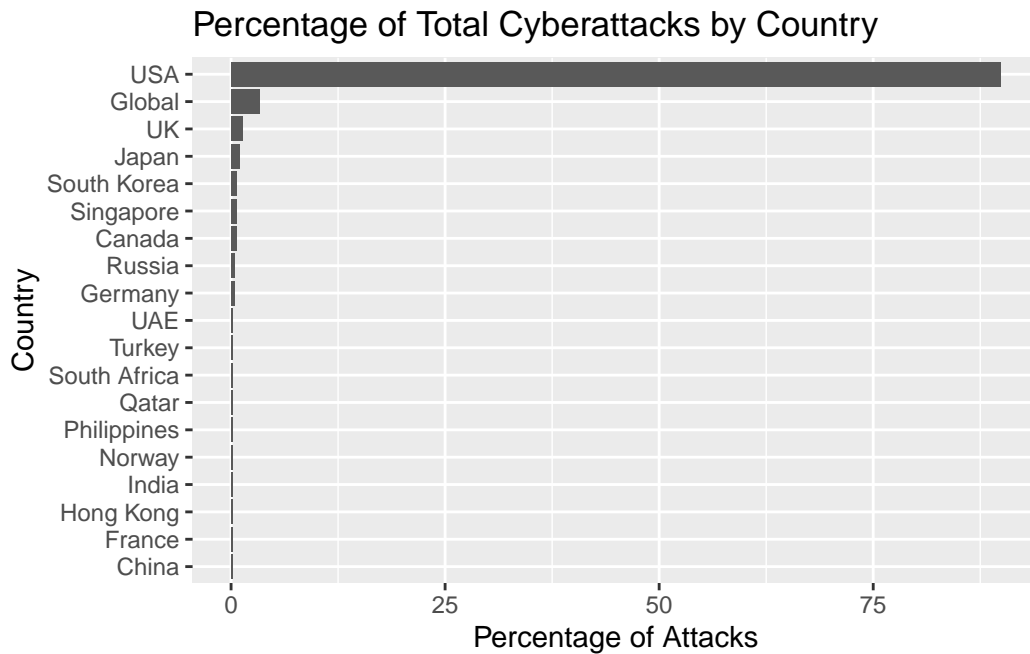
discard

The following object is masked from 'package:readr':

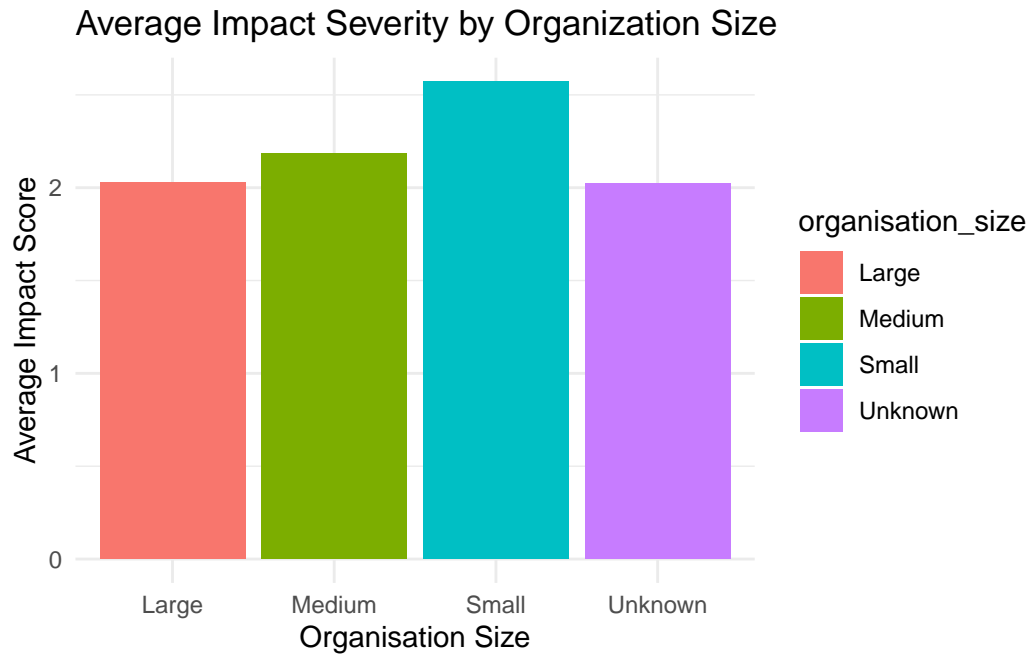
col\_factor

```
breach_data %>%
  count(country) %>%
  mutate(percentage = n / sum(n) * 100) %>%
  ggplot(aes(x = reorder(country, percentage), y = percentage)) +
  geom_bar(stat = "identity") +
```

```
coord_flip() +
labs(title = "Percentage of Total Cyberattacks by Country",
     x = "Country",
     y = "Percentage of Attacks")
```



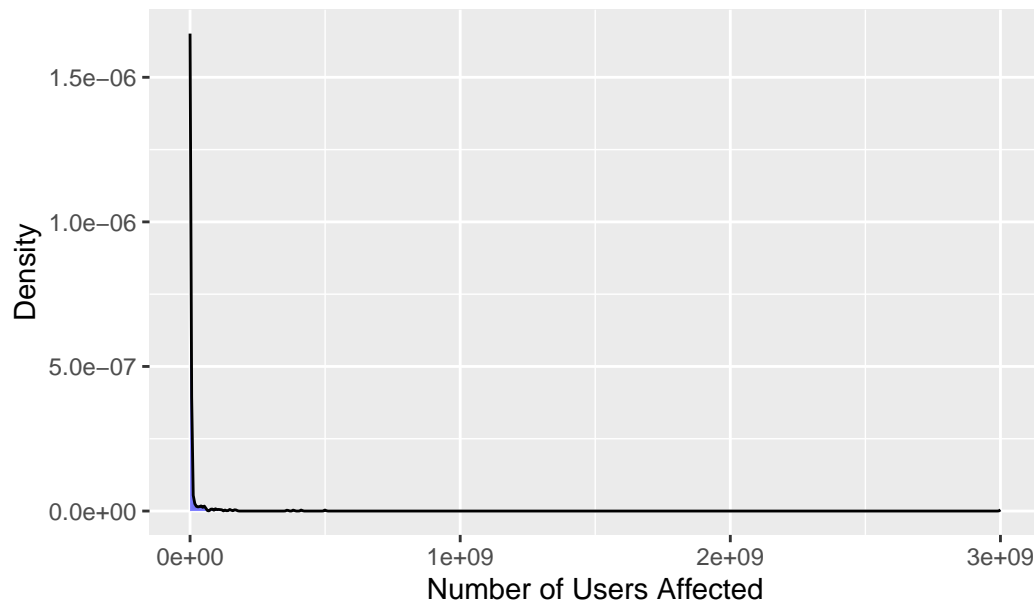
```
breach_data %>%
  mutate(impact_score = case_when(
    impact_on_data == "Low" ~ 1,
    impact_on_data == "Medium" ~ 2,
    impact_on_data == "High" ~ 3,
    TRUE ~ NA_real_
  )) %>%
  group_by(organisation_size) %>%
  summarize(average_impact = mean(impact_score, na.rm = TRUE)) %>%
  ggplot(aes(x = organisation_size, y = average_impact, fill = organisation_size)) +
  geom_col() +
  labs(title = "Average Impact Severity by Organization Size",
       x = "Organisation Size",
       y = "Average Impact Score") +
  theme_minimal()
```



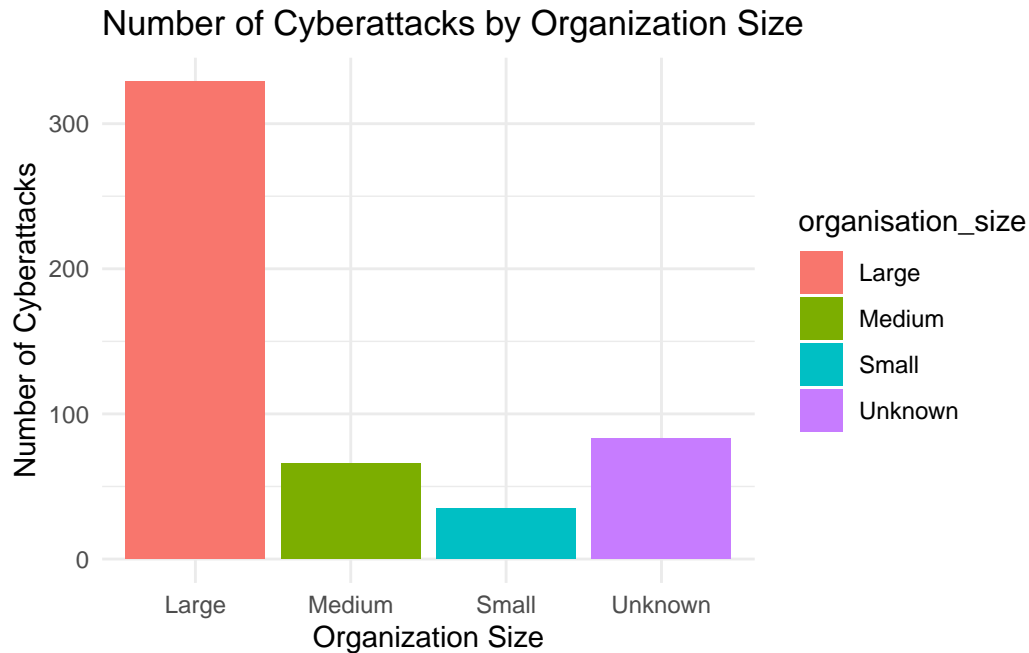
```
ggplot(breach_data, aes(x = number_of_users_affected)) +  
  geom_density(fill = "blue", alpha = 0.5) +  
  labs(title = "Density Plot of Number of Users Affected by Cyberattacks",  
        x = "Number of Users Affected",  
        y = "Density")
```

Warning: Removed 1 row containing non-finite outside the scale range  
(`stat\_density()`).

Density Plot of Number of Users Affected by Cyberattacks



```
ggplot(breach_data, aes(x = organisation_size, fill = organisation_size)) +  
  geom_bar() +  
  labs(title = "Number of Cyberattacks by Organization Size",  
        x = "Organization Size",  
        y = "Number of Cyberattacks") +  
  theme_minimal()
```



```
library(modelsummary)
```

Version 2.0.0 of `modelsummary`, to be released soon, will introduce a breaking change: The default table-drawing package will be `tinytable` instead of `kableExtra`. All currently supported table-drawing packages will continue to be supported for the foreseeable future, including `kableExtra`, `gt`, `huxtable`, `flextable`, and `DT`.

You can always call the `config_modelsummary()` function to change the default table-drawing package in persistent fashion. To try `tinytable` now:

```
config_modelsummary(factory_default = 'tinytable')
```

To set the default back to `kableExtra`:

```
config_modelsummary(factory_default = 'kableExtra')
```

```
logistic_model <- readRDS(file = here::here("models/restructuring_model.rds"))  
modelsummary(list("Logistic Regression" = logistic_model))
```



Warning:

``modelsummary`` uses the ``performance`` package to extract goodness-of-fit statistics from models of this class. You can specify the statistics you wish to compute by supplying a ``metrics`` argument to ``modelsummary``, which will then push it forward to ``performance``. Acceptable values are: "all", "common", "none", or a character vector of metrics names. For example: ``modelsummary(mod, metrics = c("RMSE", "R2"))`` Note that some metrics are computationally expensive. See ``?performance::performance`` for details.

This warning appears once per session.

```
breach_data <- breach_data %>% mutate(row_id = row_number())

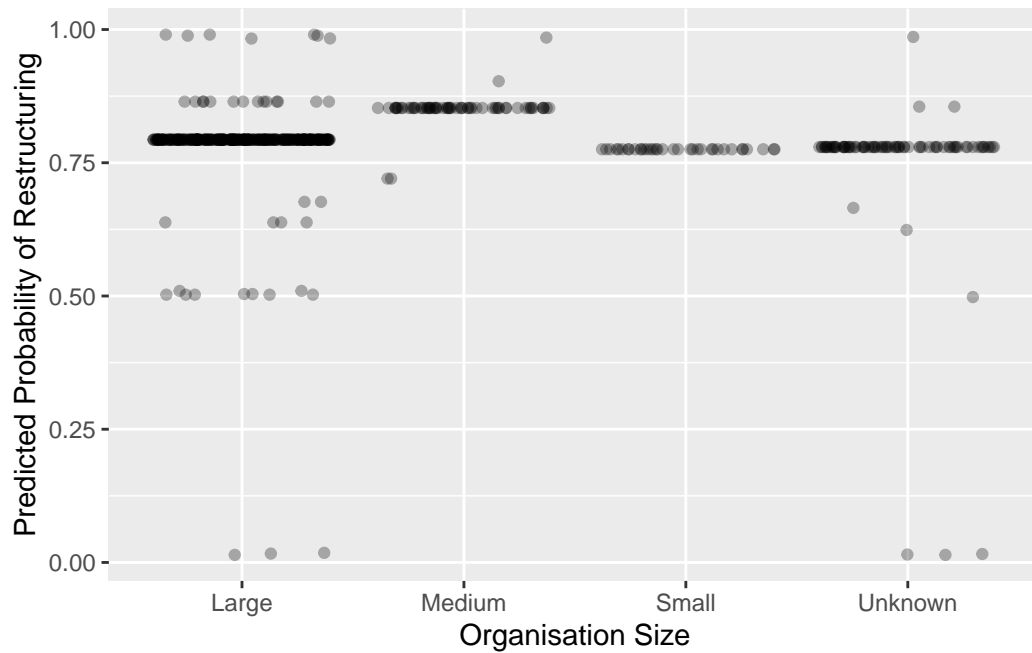
# Adjust factors in your data to match the model's training data
breach_data <- breach_data %>%
  mutate(country = factor(country, levels = levels(logistic_model$model$country)))

# Generate predictions
breach_predictions <- predict(logistic_model, newdata = breach_data, type = "response")

# Combine the predictions with the original data
breach_data <- breach_data %>% mutate(predicted_prob = breach_predictions)

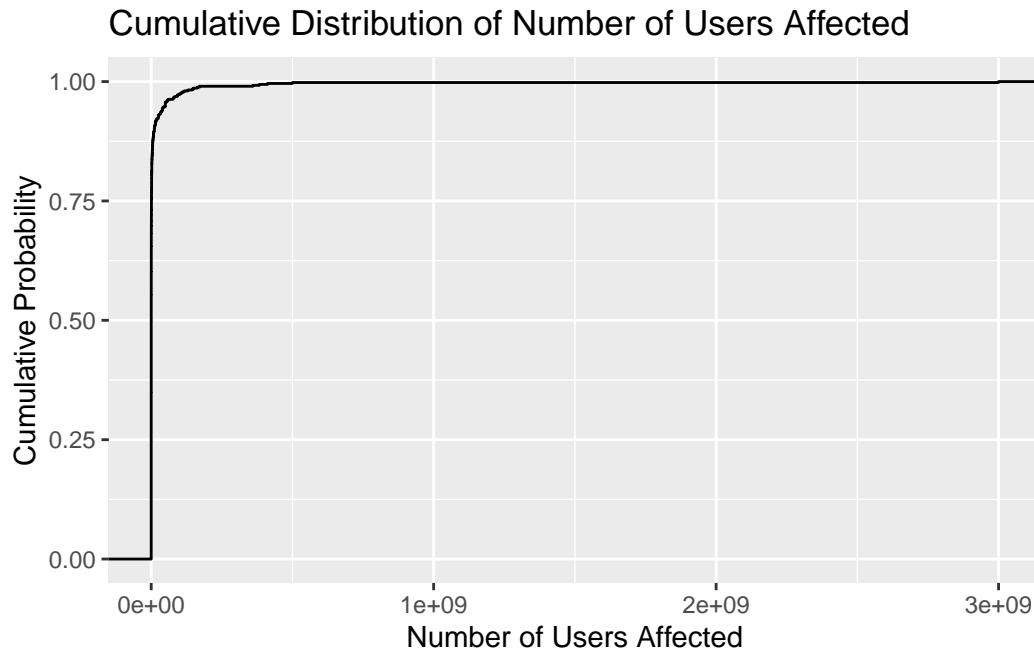
# Scatter plot with jitter
ggplot(breach_data, aes(x = organisation_size, y = predicted_prob)) +
  geom_jitter(alpha = 0.3) +
  labs(x = "Organisation Size", y = "Predicted Probability of Restructuring")
```

Logistic Regression	
(Intercept)	0.950
organisation_sizeMedium	0.437
organisation_sizeSmall	−0.076
organisation_sizeUnknown	−0.073
countryChina	33.477
countryFrance	−35.649
countryGermany	22.523
countryGlobal	1.069
countryHong Kong	32.456
countryIndia	−36.446
countryJapan	−0.987
countryNorway	−35.822
countryPhilippines	−35.592
countryQatar	−34.998
countryRussia	−0.999
countrySingapore	19.070
countrySouth Africa	34.073
countrySouth Korea	−0.897
countryTurkey	−36.347
countryUAE	34.251
countryUK	−0.348
countryUSA	0.394
Num.Obs.	417
R2	0.093
Log.Lik.	−203.054
ELPD	−221.7
ELPD s.e.	12.5
LOOIC	443.5
LOOIC s.e.	25.0
WAIC	434.9
RMSE	0.40

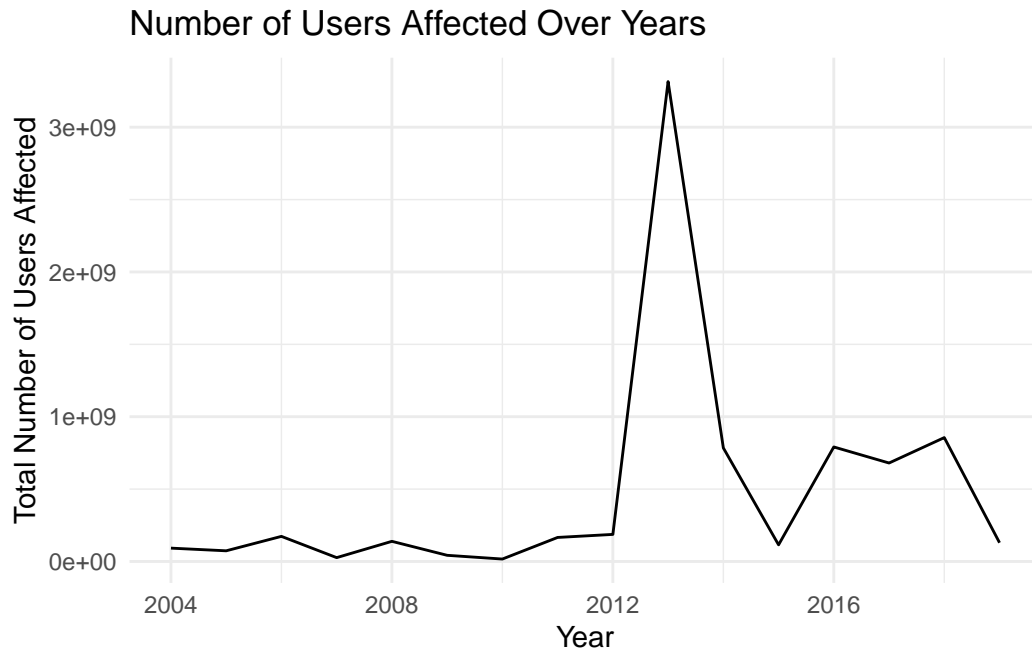


```
ggplot(breach_data, aes(x = number_of_users_affected)) +
  stat_ecdf(geom = "step") +
  labs(title = "Cumulative Distribution of Number of Users Affected",
        x = "Number of Users Affected",
        y = "Cumulative Probability")
```

Warning: Removed 1 row containing non-finite outside the scale range (`stat\_ecdf()`).

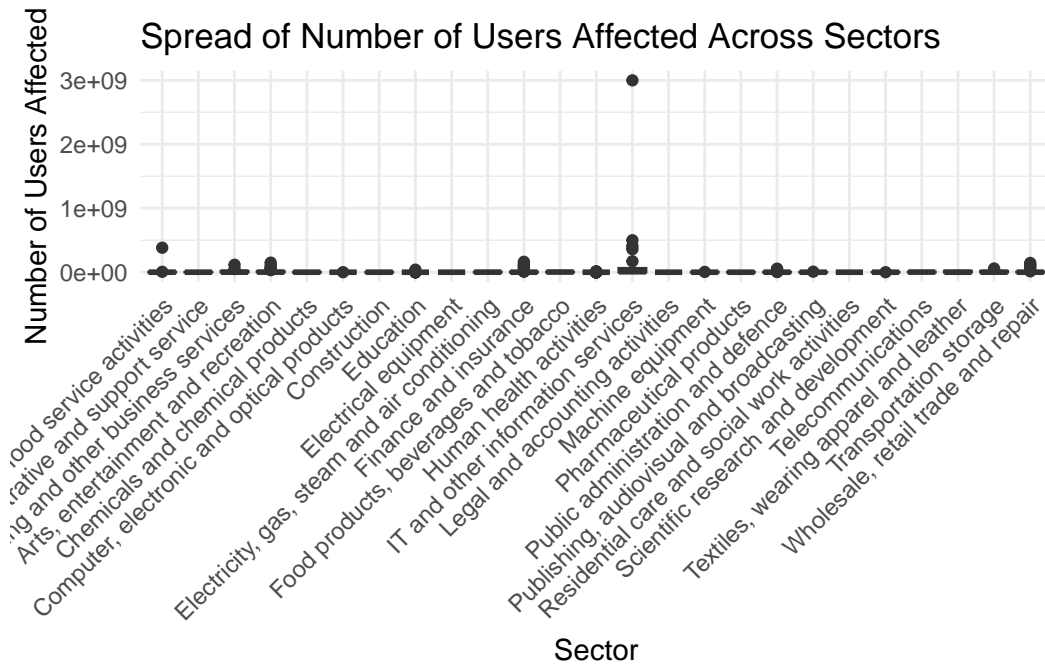


```
breach_data %>%  
  group_by(year) %>%  
  summarize(total_users_affected = sum(number_of_users_affected, na.rm = TRUE)) %>%  
  ggplot(aes(x = year, y = total_users_affected)) +  
  geom_line() +  
  labs(title = "Number of Users Affected Over Years",  
        x = "Year",  
        y = "Total Number of Users Affected") +  
  theme_minimal()
```



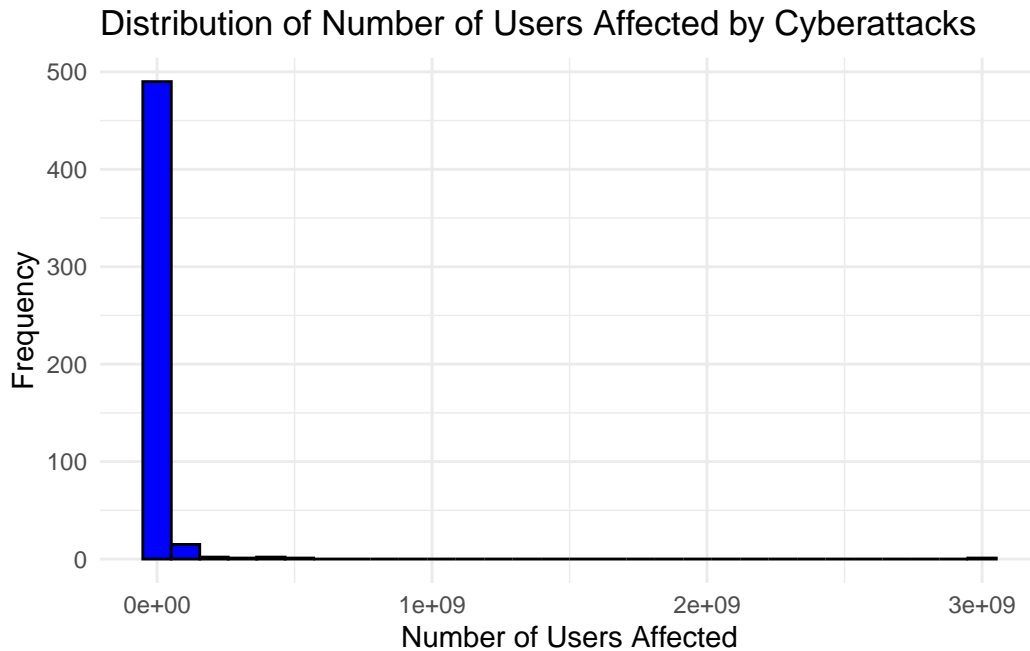
```
breach_data %>%  
  ggplot(aes(x = sector, y = number_of_users_affected)) +  
  geom_boxplot() +  
  labs(title = "Spread of Number of Users Affected Across Sectors",  
        x = "Sector",  
        y = "Number of Users Affected") +  
  theme_minimal() +  
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

Warning: Removed 1 row containing non-finite outside the scale range  
(`stat\_boxplot()`).



```
breach_data %>%
  ggplot(aes(x = number_of_users_affected)) +
  geom_histogram(bins = 30, fill = "blue", color = "black") +
  labs(title = "Distribution of Number of Users Affected by Cyberattacks",
       x = "Number of Users Affected",
       y = "Frequency") +
  theme_minimal()
```

Warning: Removed 1 row containing non-finite outside the scale range (`stat\_bin()`).



```
breach_data %>%
  filter(year == 2013) %>%
  summarise(
    median_users = median(number_of_users_affected, na.rm = TRUE),
    iqr_users = IQR(number_of_users_affected, na.rm = TRUE),
    upper_bound = median_users + 1.5 * iqr_users
  )
```

```
      median_users iqr_users upper_bound
1         56000    765688    1204532
```

```
breach_data %>% filter(year == 2019)
```

	year	organisation	critical_industry
1	2019	Blue Cross Blue Shield of Massachusetts	Yes
2	2019	Capital One	Yes
3	2019	Centerstone Insurance Financial Services	No
4	2019	Critical Care, Pulmonary Sleep Associates, PLLP	Yes
5	2019	Dr. DeLuca Dr. Marciano & Associates, P.C.	Yes
6	2019	EyeSouth Partners	Yes
7	2019	Integrated Regional Laboratories, LLC	No
8	2019	Las Colinas Orthopedic Surgery & Sports Medicine, PA	Yes

9	2019		Maffi Clinics	Yes
10	2019		Memorial Hospital at Gulfport	Yes
11	2019		Mitsubishi Electric	Yes
12	2019		Pasquotank-Camden Emergency Medical Service	Yes
13	2019		Providence Health Plan	Yes
14	2019		Quest Diagnostics	Yes
15	2019		Singapore Ministry of Health - HIV	Yes
16	2019		Union Labor Life Insurance Company	No
17	2019		Verity Health System of California, Inc.	Yes
organisation_size level_of_digital_intensity				
1		Large	Low-Medium	
2		Large	High	
3		Medium	High	
4		Medium	Low-Medium	
5		Small	Low-Medium	
6		Medium	Low-Medium	
7		Large	High	
8		Small	Low-Medium	
9		Small	Low-Medium	
10		Large	Low-Medium	
11		Large	Medium-High	
12		Medium	Low-Medium	
13		Large	Low-Medium	
14		Large	Low-Medium	
15		Large	Medium-High	
16		Large	High	
17		Large	Low-Medium	
sector country cyber_security_role				
1		Human health activities	USA	Yes
2		Finance and insurance	USA	Yes
3		Finance and insurance	USA	No
4		Human health activities	USA	No
5		Human health activities	USA	No
6		Human health activities	USA	Yes
7	Scientific	research and development	USA	No
8		Human health activities	USA	No
9		Human health activities	USA	No
10		Human health activities	USA	No
11		Electrical equipment	Japan	Yes
12		Human health activities	USA	No
13		Human health activities	USA	No
14		Human health activities	USA	No
15	Public	administration and defence	Singapore	No



16	Finance and insurance	USA	No
17	Human health activities	USA	No
	cyber_security_frameworks	education_and_awareness_policy	policy
1	No	No	Yes
2	No	No	Yes
3	No	No	Yes
4	No	No	No
5	No	No	Yes
6	No	No	Yes
7	No	No	Yes
8	No	No	Yes
9	No	No	Yes
10	No	No	Yes
11	No	No	Yes
12	No	No	No
13	No	No	Yes
14	No	No	Yes
15	No	No	Yes
16	No	No	Yes
17	No	No	Yes
	prevention_detection_and_recovery	improper_network_segmentation	
1	Medium		<NA>
2	Low		Yes
3	Low		Yes
4	Medium		<NA>
5	High		Yes
6	Medium		No
7	Medium		No
8	Low		No
9	Low		Yes
10	Low		Yes
11	Low		Yes
12	Low		Yes
13	Low		No
14	Low		Yes
15	Low		No
16	Medium		<NA>
17	Medium		No
	inappropriate_remote_access	absence_of_encryption	detector
1	<NA>	<NA>	Organisation
2	<NA>	<NA>	Federal Agency
3	No	Yes	Organisation
4	No	<NA>	Organisation

5	Yes	Yes	Organisation
6	No	No	Organisation
7	No	Yes	Organisation
8	No	Yes	Organisation
9	No	Yes	Organisation
10	No	Yes	Organisation
11	<NA>	Yes	Organisation
12	No	Yes	Organisation
13	No	Yes	Organisation
14	No	Yes	Organisation
15	No	Yes	<NA>
16	<NA>	<NA>	Organisation
17	No	Yes	Organisation
restructuring_after_attack_bribe_ransom_paid			
1	Yes	No	
2	Yes	No	
3	Yes	No	
4	Yes	No	
5	Yes	No	
6	Yes	No	
7	Yes	No	
8	<NA>	No	
9	Yes	No	
10	No	No	
11	No	No	
12	Yes	No	
13	<NA>	No	
14	Yes	No	
15	Yes	No	
16	Yes	No	
17	Yes	No	
free_identity_or_credit_theft_monitoring			
1		Yes	
2		Yes	
3		Yes	
4		No	
5		Yes	
6		<NA>	
7		No	
8		<NA>	
9		No	
10		Yes	
11		<NA>	

12	Yes	
13	<NA>	
14	Yes	
15	<NA>	
16	Yes	
17	Yes	
	additional_disclosure_of_information	number_of_users_affected
1	Yes	11000000
2	Yes	106000000
3	Yes	111589
4	No	23300
5	Yes	23578
6	<NA>	24113
7	<NA>	29644
8	<NA>	76000
9	Yes	10465
10	<NA>	30000
11	<NA>	8000
12	<NA>	40000
13	<NA>	122000
14	Yes	12000000
15	Yes	14200
16	No	87400
17	Yes	14894
	overall_nature_of_attack	attack_type attacker
1	<NA>	Unknown External
2	<NA>	Unknown External
3	Type 2 Misuse of resources	External
4	Type 2 Misuse of resources	External
5	Type 1 Installed malware	External
6	Type 2 Misuse of resources	External
7	Type 2 Misuse of resources	External
8	Type 3 Physical Theft	External
9	Type 1 Installed malware	External
10	Type 2 Misuse of resources	External
11	<NA>	Unknown External
12	<NA>	Unknown External
13	Type 2	Unknown External
14	Type 2 Misuse of resources	External
15	Type 3 Physical Theft	Internal
16	Type 2	Unknown External
17	Type 2	Unknown External
	attack_vector	impact_on_data

1	Unknown network attack	Medium
2	Unknown network attack	High
3	Social engineering	High
4	<NA>	High
5	<NA>	High
6	Social engineering	Medium
7	Vendor vulnerability	Medium
8	Physical device	Medium
9	<NA>	High
10	Social engineering	Medium
11	<NA>	Medium
12	<NA>	Medium
13	Vendor vulnerability	Medium
14	Vendor vulnerability	Low
15	Inappropriate use of privilege	Medium
16	Social engineering	Medium
17	Social engineering	Medium
aspect_of_confidentiality_integrity_availability_triad_affected		
1		Confidentiality
2		Confidentiality
3		Confidentiality
4		Confidentiality
5		Availability
6		Confidentiality
7		Confidentiality
8		Confidentiality
9		Availability
10		Confidentiality
11		Confidentiality
12		Confidentiality
13		Confidentiality
14		Confidentiality
15		Confidentiality
16		Confidentiality
17		Confidentiality
individual_s_name_s_leaked_exposed address_es_leaked_exposed		
1	Yes	Yes
2	Yes	Yes
3	Yes	Yes
4	Yes	Yes
5	Yes	Yes
6	Yes	Yes
7	Yes	Yes

8	Yes	Yes
9	Yes	Yes
10	Yes	Yes
11	Yes	<NA>
12	Yes	Yes
13	Yes	Yes
14	Yes	No
15	Yes	Yes
16	Yes	Yes
17	Yes	Yes
other_personally_identifiable_information_pii_leaked_exposed		
1		Yes
2		Yes
3		Yes
4		Yes
5		Yes
6		Yes
7		Yes
8		Yes
9		Yes
10		Yes
11		Yes
12		Yes
13		Yes
14		Yes
15		Yes
16		Yes
17		Yes
track_1_credit_card_details_leaked_exposed		
1	No	
2	Yes	
3	Yes	
4	No	
5	No	
6	No	
7	No	
8	No	
9	No	
10	No	
11	No	
12	No	
13	No	
14	No	

15	No		
16	No		
17	No		
track_2_credit_card_details_leaked_exposed			
1	No		
2	<NA>		
3	<NA>		
4	No		
5	No		
6	No		
7	No		
8	No		
9	No		
10	No		
11	No		
12	No		
13	No		
14	No		
15	No		
16	No		
17	No		
social_security_number_tax_number_leaked_exposed			
1	Yes		
2	Yes		
3	Yes		
4	Yes		
5	Yes		
6	Yes		
7	Yes		
8	Yes		
9	Yes		
10	Yes		
11	Yes		
12	Yes		
13	Yes		
14	No		
15	No		
16	Yes		
17	Yes		
subsequent_fraudulent_use_of_data investigation undertook_investigation			
1	No	No	No
2	No	Yes	Yes
3	No	Yes	Yes

4		Yes	Yes	Yes
5		No	Yes	Yes
6		No	No	No
7		No	No	No
8		No	No	No
9		No	Yes	Yes
10		No	No	No
11		<NA>	No	No
12		No	No	No
13		No	Yes	Yes
14		No	Yes	No
15		No	Yes	Yes
16		No	No	No
17		No	No	No

litigation\_by\_public penalties\_settlement\_paid\_or\_actions\_imposed

1	No	No
2	No	No
3	No	No
4	No	No
5	No	No
6	No	No
7	No	No
8	No	No
9	No	No
10	No	No
11	No	No
12	No	No
13	No	No
14	Yes	Yes
15	Yes	Yes
16	No	No
17	No	No

imposed\_penalties\_or\_actions\_on\_organisation

1	No
2	No
3	No
4	No
5	No
6	No
7	No
8	No
9	No
10	No

11		No	
12		No	
13		No	
14		No	
15		Yes	
16		No	
17		No	
	fines_issued_by_government_or_relevant_body	settlement_paid	
1		No	No
2		No	No
3		No	No
4		No	No
5		No	No
6		No	No
7		No	No
8		No	No
9		No	No
10		No	No
11		No	No
12		No	No
13		No	No
14		No	Yes
15		No	No
16		No	No
17		No	No
	effect_on_share_price		summary row_id
1	<NA>		Unknown 46
2	No change		Unauthorised access 61
3	<NA>		Email phishing scam 72
4	<NA>		Phishing attack 106
5	<NA>		Ransomware 124
6	<NA>		Unauthorised access to employee email 146
7	<NA>		American Medical Collection Agency data breach 201
8	<NA>		Hard drive stolen 219
9	<NA>		Ransomware 234
10	<NA>		Phishing attack 246
11	<NA>		Unknown 256
12	<NA>		Unauthorised access but unknown 312
13	<NA>		Dominon National was hacked 327
14	<NA>		AMCA vulnerability 335
15	<NA>		Individual gained access through doctor 377
16	<NA>		Phishing attack 441
17	<NA>		Phishing attack 482



	predicted_prob
1	0.7932777
2	0.7932777
3	0.8527533
4	0.8527533
5	0.7752741
6	0.8527533
7	0.7932777
8	0.7752741
9	0.7752741
10	0.7932777
11	0.5024668
12	0.8527533
13	0.7932777
14	0.7932777
15	0.9904011
16	0.7932777
17	0.7932777

```
breach_data %>%
  filter(year == 2019)%>%
  summarise(
    median_users = median(number_of_users_affected, na.rm = TRUE),
    iqr_users = IQR(number_of_users_affected, na.rm = TRUE),
    upper_bound = median_users + 1.5 * iqr_users
  )
```

	median_users	iqr_users	upper_bound
1	30000	88289	162433.5

```
breach_data$year <- as.numeric(as.character(breach_data$year))

# Now proceed with your data manipulation
breach_data_summary <- breach_data %>%
  mutate(country = fct_collapse(country,
                                "Other" = setdiff(unique(country),
                                                    c("USA", "Australia", "Canada", "Global",
                                                      "India", "Japan", "South Korea", "UK", "USA")),
  group_by(year, country) %>%
  summarize(frequency = n(), .groups = 'drop')

# Separating the data by country for ease of plotting
country_data <- breach_data_summary %>%
```

```

  filter(country != "USA")

usa_data <- breach_data_summary %>%
  filter(country == "USA") %>%
  arrange(year)

# Ensure year is numeric for the line plot
breach_data_summary$year <- as.numeric(as.character(breach_data_summary$year))

# Recalculate max frequencies if necessary
max_usa_freq <- max(usa_data$frequency, na.rm = TRUE)
max_other_freq <- max(country_data$frequency, na.rm = TRUE)

# Determine scale factor for secondary axis
scale_factor <- max_other_freq / max_usa_freq
breach_data_summary$year <- as.numeric(as.character(breach_data_summary$year))
breach_data_summary <- breach_data_summary %>% filter(!is.na(year))

# Plot
# Define a color palette
formal_palette <- c("Australia" = "#4878D0", "Canada" = "#6ACC65", "Global" = "#D65F5F",
  "Japan" = "#B47CC7", "UK" = "#C4AD66", "Other" = "#77BEDB")

# Plot
gg <- ggplot() +
  # Add bars for all countries except USA
  geom_bar(data = country_data, aes(x = year, y = frequency, fill = country), stat = "identity") +
  # Add line for USA
  geom_line(data = usa_data, aes(x = year, y = frequency * scale_factor, group = 1), color = "red") +
  # Define the primary y-axis with the secondary axis for the USA
  scale_y_continuous(
    name = "Frequency of Cyber Attacks (Other Countries)",
    limits = c(0, max_other_freq * 1.1), # Set limits for better control, slightly above max
    sec.axis = sec_axis(~ . / scale_factor, name = "Frequency of USA Cyber Attacks", labels = "Frequency of USA Cyber Attacks") +
  ) +
  # Set breaks for the x-axis to unique years
  scale_x_continuous(breaks = sort(unique(breach_data_summary$year))) +
  # Apply the formal color palette
  scale_fill_manual(values = formal_palette) +
  labs(title = "Overview of Cyber Attacks by Year and Country",
    subtitle = "Bar plots for countries; line plot for USA") +
  theme_minimal() +

```

```

theme(axis.text.x = element_text(angle = 90, hjust = 1), # Rotate x-axis labels
      legend.position = "bottom", # Adjust the position of the legend
      plot.title = element_text(hjust = 0.5), # Center the plot title
      plot.subtitle = element_text(hjust = 0.5)) # Center the plot subtitle

```

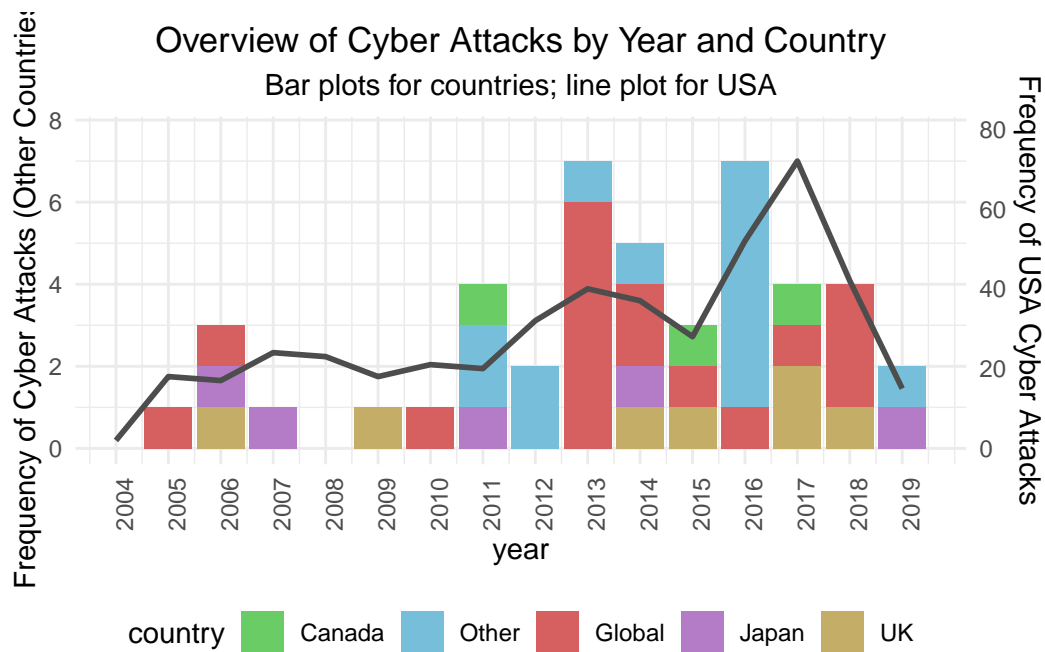
Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.  
 i Please use `linewidth` instead.

```

# Print the plot
print(gg)

```

Warning: Removed 1 row containing missing values or values outside the scale range  
 (`geom\_bar()`).



## References

- Alberta Government. 2023. “Air Indicators – Fine Particulate Matter.” <https://www.alberta.ca/air-indicators-fine-particulate-matter>.
- Arel-Bundock, Vincent. 2022. “modelssummary: Data and Model Summaries in R.” *Journal of Statistical Software* 103 (1): 1–23. <https://doi.org/10.18637/jss.v103.i01>.
- Clarke, Erik, Scott Sherrill-Mix, and Charlotte Dawson. 2023. *Ggbeeswarm: Categorical Scatter (Violin Point) Plots*. <https://github.com/eclarke/ggbeeswarm>.
- Environment, Ministry of, and Protected Areas. 2021. “Status of Air Quality in Alberta.” <https://open.alberta.ca/dataset/9b00aab3-c37d-4080-854e-5f329c621b92/resource/057c65ac-7837-49bb-9528-38c2611540c4/download/epa-alberta-air-zones-report-2019-2021.pdf>.
- Firke, Sam. 2023. *Janitor: Simple Tools for Examining and Cleaning Dirty Data*. <https://github.com/sfirke/janitor>.
- Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2022. “Rstanarm: Bayesian Applied Regression Modeling via Stan.” <https://mc-stan.org/rstanarm/>.
- government, Alberta. 2023a. “Air Quality Index by Municipality.” <https://open.alberta.ca/opendata/air-quality-index-by-municipality#detailed>.
- . 2023b. “Leading Causes of Death.” <https://open.alberta.ca/opendata/leading-causes-of-death>.
- . 2024. “Alberta.” <https://www.alberta.ca/>.
- Müller, Kirill. 2020. *Here: A Simpler Way to Find Your Files*. <https://here.r-lib.org/>.
- Müller, Kirill, and Hadley Wickham. 2023. *Tibble: Simple Data Frames*. <https://tibble.tidyverse.org/>.
- R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.
- Slowikowski, Kamil. 2024. *Ggrepel: Automatically Position Non-Overlapping Text Labels with 'ggplot2'*. <https://ggrepel.slowkow.com/>.
- Venables, W. N., and B. D. Ripley. 2002. *Modern Applied Statistics with s*. Fourth. New York: Springer. <https://www.stats.ox.ac.uk/pub/MASS4/>.
- Wickham, Hadley. 2007. “Reshaping Data with the reshape Package.” *Journal of Statistical Software* 21 (12): 1–20. <http://www.jstatsoft.org/v21/i12/>.
- . 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. <https://ggplot2.tidyverse.org>.
- Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D’Agostino McGowan, Romain François, Garrett Golemund, et al. 2019b. “Welcome to the tidyverse.” *Journal of Open Source Software* 4 (43): 1686. <https://doi.org/10.21105/joss.01686>.
- , et al. 2019a. “Welcome to the tidyverse.” *Journal of Open Source Software* 4 (43): 1686. <https://doi.org/10.21105/joss.01686>.
- Wickham, Hadley, and Jennifer Bryan. 2023. *Readxl: Read Excel Files*. <https://CRAN.R-project.org/package=readxl>.
- Wickham, Hadley, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023. *Dplyr: A Grammar of Data Manipulation*. <https://dplyr.tidyverse.org>.

- Wickham, Hadley, Jim Hester, and Jennifer Bryan. 2024. *Readr: Read Rectangular Text Data*. <https://readr.tidyverse.org>.
- Xie, Yihui. 2023. *Knitr: A General-Purpose Package for Dynamic Report Generation in r*. <https://yihui.org/knitr/>.
- Zhu, Hao. 2024. *kableExtra: Construct Complex Table with 'Kable' and Pipe Syntax*. <https://CRAN.R-project.org/package=kableExtra>.