

# Group2-PDF

Shuting Li, Lauren Marie, Zening Ye, Keliang Xu

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## Clean data

We have three data files – strawberries, insecticides, and herbicides-fungicides-other. The first two data files are used as data basis of our project, and the third one is the background information we need in the project.

```
## import original data  
strawb <- read_csv("data/Strawberries.csv")  
pesti <- read_csv("data/Pesticides.csv")
```

### data cleaning about strawb.csv

There may be missing data during data collection process. In this case, we delete the NA conditions to ensure the accuracy of subsequent operations. In addition, the first file – strawberries also contains some unnecessary and repetitive information, which also needs to be preprocessed at this stage. ### drop all NA columns

```
drop_na_info <- function(df){  
  cnames = colnames(df)  
  T = NULL  
  for(i in 1:ncol(df)){T <- c(T, nrow(unique(df[i])))}  
  drop_cols <- cnames[which(T == 1)]  
  return(dplyr::select(df, !all_of(drop_cols)))  
}  
  
strawb1 <- drop_na_info(strawb)  
  
colnames(strawb1)
```

```
## [1] "Program"      "Year"         "Period"       "State"  
## [5] "State ANSI"   "Data Item"    "Domain"       "Domain Category"  
## [9] "Value"        "CV (%)"
```

After dropping NA columns, we get strawb1 with 10 columns.

### Separate ‘Data Item’ into 4 columns

Through the observation of the data, we found that ‘Data Item’ column covers a lot of data we need. There are four types of data in this column and make it messy and long, we need to separate this column into four columns.

```
strawb1 %<>% separate(col = 'Data Item',
                      into = c("Strawberries", "Items", "Discription", "Units"),
                      sep = ",", fill = "right")
```

```
distinct(strawb1, Strawberries)
```

```
## # A tibble: 2 x 1
##   Strawberries
##   <chr>
## 1 STRAWBERRIES
## 2 STRAWBERRIES - YIELD
```

```
distinct(strawb1, Items)
```

```
## # A tibble: 7 x 1
##   Items
##   <chr>
## 1 " ORGANIC - OPERATIONS WITH SALES"
## 2 " ORGANIC - SALES"
## 3 " ORGANIC"
## 4 " MEASURED IN CWT / ACRE"
## 5 " MEASURED IN TONS / ACRE"
## 6 " BEARING - APPLICATIONS"
## 7 " BEARING - TREATED"
```

```
distinct(strawb1, Discription)
```

```
## # A tibble: 12 x 1
##   Discription
##   <chr>
## 1 <NA>
## 2 " MEASURED IN $"
## 3 " MEASURED IN CWT"
## 4 " FRESH MARKET - OPERATIONS WITH SALES"
## 5 " FRESH MARKET - SALES"
## 6 " PROCESSING - OPERATIONS WITH SALES"
## 7 " PROCESSING - SALES"
## 8 " MEASURED IN LB"
## 9 " MEASURED IN LB / ACRE / APPLICATION"
## 10 " MEASURED IN LB / ACRE / YEAR"
## 11 " MEASURED IN NUMBER"
## 12 " MEASURED IN PCT OF AREA BEARING"
```

```
distinct(strawb1, Units)
```

```
## # A tibble: 4 x 1
##   Units
##   <chr>
## 1 <NA>
## 2 " MEASURED IN $"
## 3 " MEASURED IN CWT"
## 4 " AVG"
```

Separate 'Data Item' into "Strawberries", "Items", "Discription", "Units".

## Separate 'Domain' into 2 columns

The same as 'Data Item' column, 'Domain' column also contains two sets of data information.

```
strawb1 %<>% separate(col = Domain, into = c("dname", "type"), sep = ",", fill = "right")
distinct(strawb1, dname)
```

```
## # A tibble: 4 x 1
##   dname
##   <chr>
## 1 ORGANIC STATUS
## 2 TOTAL
## 3 CHEMICAL
## 4 FERTILIZER
```

```
distinct(strawb1, type)
```

```
## # A tibble: 5 x 1
##   type
##   <chr>
## 1 <NA>
## 2 " FUNGICIDE"
## 3 " HERBICIDE"
## 4 " INSECTICIDE"
## 5 " OTHER"
```

Separate 'Domain' into "dname", "type".

## Separate 'Domain Category' into 2 columns

There are a lot of information in 'Domain Category' column that needs attention. Firstly, part of the information is repeated with previous column. Secondly, the information contains many unnecessary symbols such as "(, ", ", ")". The main work of the following program is to isolate a small part of the information needed.

```
strawb1 %<>%
  mutate(Chemicals = `Domain Category`) %>%
  relocate(Chemicals, .after = `Domain Category`)

strawb1 %<>%
  separate(Chemicals, into = c('Title', 'Details'), sep = ":", fill = "right")

distinct(strawb1, Details)
```

```
## # A tibble: 159 x 1
##   Details
##   <chr>
## 1 " (NOP USDA CERTIFIED)"
## 2 <NA>
## 3 " (AZOXYSTROBIN = 128810)"
## 4 " (BACILLUS AMYLOLIQUEFACIENS MBI 600 = 129082)"
```

```
## 5 " (BACILLUS AMYLOLIQUEFACIENS STRAIN D747 = 16482)"
## 6 " (BACILLUS PUMILUS = 6485)"
## 7 " (BACILLUS SUBT. GB03 = 129068)"
## 8 " (BACILLUS SUBTILIS = 6479)"
## 9 " (BLAD = 30006)"
## 10 " (BORAX DECAHYDRATE = 11102)"
## # ... with 149 more rows
```

```
strawb1$Details <- str_replace(strawb1$Details, "\\(", "")
strawb1$Details <- str_replace(strawb1$Details, "\\)", "")

strawb1 %<>%
  separate(Details, into = c('Chemical Name', "Number"), sep = "=", fill = "right")

distinct(strawb1, `Chemical Name`)
```

```
## # A tibble: 159 x 1
##   `Chemical Name`
##   <chr>
## 1 " NOP USDA CERTIFIED"
## 2 <NA>
## 3 " AZOXYSTROBIN "
## 4 " BACILLUS AMYLOLIQUEFACIENS MBI 600 "
## 5 " BACILLUS AMYLOLIQUEFACIENS STRAIN D747 "
## 6 " BACILLUS PUMILUS "
## 7 " BACILLUS SUBT. GB03 "
## 8 " BACILLUS SUBTILIS "
## 9 " BLAD "
## 10 " BORAX DECAHYDRATE "
## # ... with 149 more rows
```

```
distinct(strawb1, Number)
```

```
## # A tibble: 153 x 1
##   Number
##   <chr>
## 1 <NA>
## 2 " 128810"
## 3 " 129082"
## 4 " 16482"
## 5 " 6485"
## 6 " 129068"
## 7 " 6479"
## 8 " 30006"
## 9 " 11102"
## 10 " 128008"
## # ... with 143 more rows
```

```
strawb1$`Chemical Name` <- str_trim(strawb1$`Chemical Name`)
```

Replicate 'Domain.Category' to new variable and separate this new variable into 'Title', 'Details'.

And then clean 'Details' and separate it into 'Chemical Name', "Number". Also capitalize all words in 'Chemical Name'.

## drop useless columns

After the data cleaning step, the data set looks clearly and we start to try data analysis in R. In the analysis, we found that some columns is not needed. So we dropped these useless columns in this step.

```
drops <- c("Strawberries", "Domain Category")
strawb1 <- strawb1[ , !(names(strawb1) %in% drops)]
```

Drop “Strawberries”, “Domain Category”, because it is useless in data analysis.

## data cleaning about pesti.csv

After processing the strawberries file, we begin to deal with pesti.csv. This file has less data, so the data cleaning required is relatively simple. ### drop NA rows in pesti.csv and clean it

```
pesti1 <- pesti %>% rename('Chemical Name' = Pesticide )
pesti1 %<>% filter(!is.na(pesti1))
pesti1$`Chemical Name` <- toupper(pesti1$`Chemical Name`)
```

Drop NA rows in pesti.csv, finally we get pesti1 with 45 rows.

And then rename ‘Pesticide’ to ‘Chemical Name’ and capitalize all words in ‘Chemical Name’.

## Define Human Toxins level

Based on the existing information, we hope to construct a variable to represent human toxin levels.

```
pesti1 <- pesti1 %>% mutate('Human Toxins' = case_when(
  pesti1$Carcinogen == "known" | pesti1$Neurotoxins== "present" | pesti1$`Developmental or Reproductive
  pesti1$Carcinogen == "possible" & pesti1$`Hormone Disruptor`=="suspected" & is.na(pesti1$Neurotoxins)
  pesti1$Carcinogen == "possible" & is.na(pesti1$`Hormone Disruptor`) & is.na(pesti1$Neurotoxins) & is.na(pesti1$Carcinogen) & pesti1$`Hormone Disruptor`=="suspected" & is.na(pesti1$Neurotoxins) & is.na(pesti1$Carcinogen)
  pesti1$Carcinogen == "probable" & is.na(pesti1$`Hormone Disruptor`) & is.na(pesti1$Neurotoxins) & is.na(pesti1$Carcinogen)
  is.na(pesti1$Carcinogen) & pesti1$`Hormone Disruptor`=="suspected" & is.na(pesti1$Neurotoxins) & is.na(pesti1$Carcinogen)
))
```

Use columns ‘carcinogen’, ‘Neurotoxins’, ‘Developmental or Reproductive Toxins’ to define human toxins level.

High toxic for human: carcinogen = known or Neurotoxins = present or Developmental or Reproductive Toxins = present.

Moderate toxic for human: carcinogen = probable/possible and Hormone Disruptor = suspect.

Slight toxic for human: carcinogen= possible/possible or Hormone Disruptor = suspect, only one happens.

## wrangling two datasets

These two data sets use the same chemical name column(pesticide name) as the join key.

```

strawbPesti <- inner_join(strawb1, pesti1, by="Chemical Name")

# Write the dataset into csv.
write_csv(strawbPesti, "strawbPesti.csv")

```

Combine two dataset into strawbPesti.csv by key column ‘Chemical Name’. Only keep rows with known pesticides.

## Data Visualization

```
pacman::p_load('ggplot2', 'plotly', "dplyr")
```

clean strawbPesti.csv

```
distinct(strawbPesti, State)
```

```

## # A tibble: 4 x 1
##   State
##   <chr>
## 1 CALIFORNIA
## 2 FLORIDA
## 3 OREGON
## 4 WASHINGTON

```

```

strawbPesti <- arrange(strawbPesti, `Chemical Name`)
#colnames(strawbPesti)
strawbPesti1 <- strawbPesti[,-13]
strawbPesti2 <- strawbPesti1[,c(2,4,7,12,13,20)]
strawbPesti3 <- filter(strawbPesti2, Discription==" MEASURED IN LB")
strawbPesti4 <- filter(strawbPesti3, Value != "(D)")
strawbPesti4$Value <- as.numeric(sub(",", "", strawbPesti4$Value, fixed = TRUE))

strawbPestiAVG <- strawbPesti4 %>%
  group_by(State, `Chemical Name`, `Human Toxins`) %>%
  summarise(Value, Value=mean(Value))

```

Only choose columns we will use: ‘Year’, ‘State’, ‘Discription’, ‘Chemical Name’, ‘Value’, ‘Human Toxins’. Which is dataset “strawbPesti2”.

We can see from strawbPesti2, values are different depend on measured methods for each chemical type in each state, so we can choose one method to go deep, finally we chose “MEASURED IN LB”. Then we get dataset “strawbPesti3”.

Then we drop no meaning rows of value. And change value into numeric variable. Finally we get dataset “strawbPesti4”.

To compare pesticides’ toxin level, we can take average value across 2016-1019. We build dataset “strawbPestiAVG”.

## Questions

How Toxic are the chemicals on strawberries for humans?

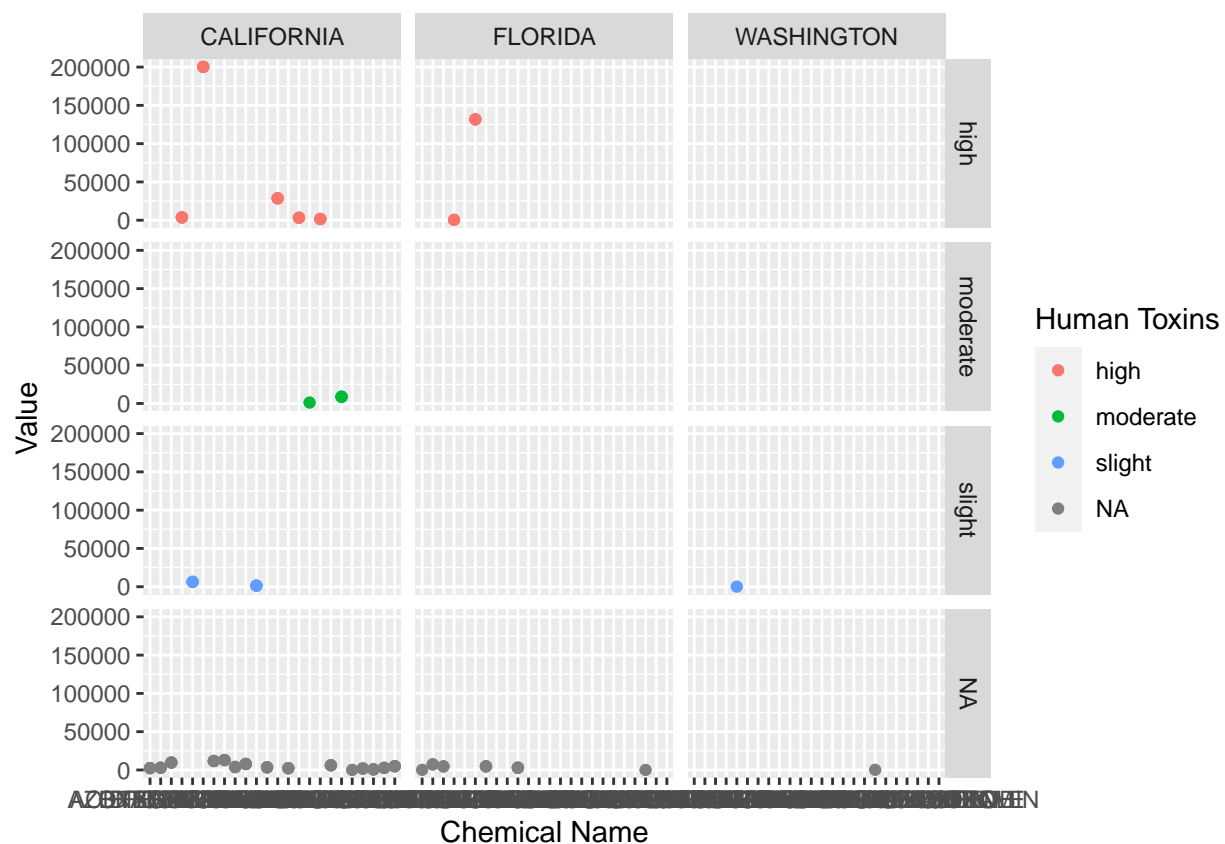
How Toxic are the chemicals on strawberries for bees?

These two issues are what our team members intend to start studying. Because the main content of the pes file is the toxins of pesticides, we began to study the degree of toxins to humans and to bees.

### show all states chemical usage value

Compared with other states, California has more data, so there are more samples with vlue as high, while Washington state has less data. It can be seen from the figure that the pesticides that are more harmful to humans are mainly distributed in California and Florida.

```
ggplot(strawbPestiAVG) +  
  geom_point(aes( x= `Chemical Name`, y= Value,col=`Human Toxins`)) +  
  facet_grid(`Human Toxins`~State)
```



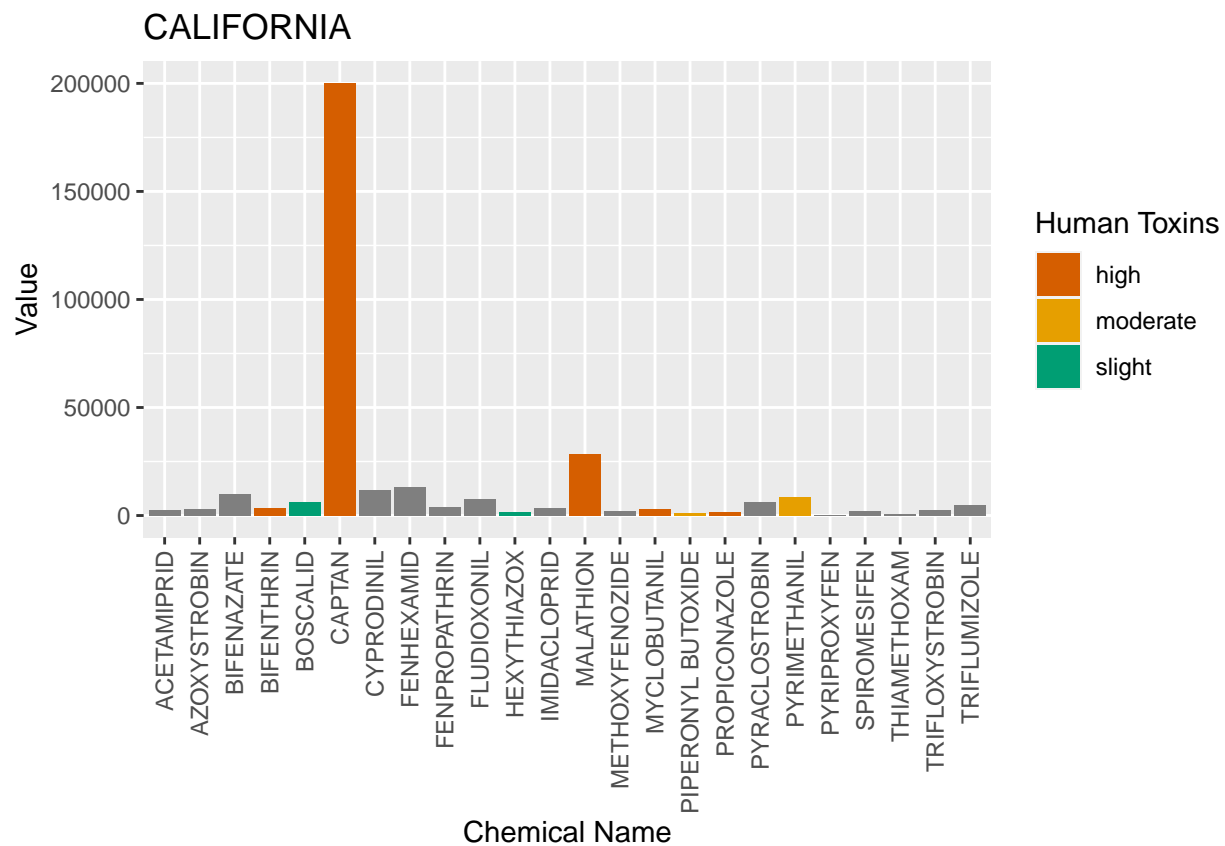
### Chemical usage in different states

Take California as an example, and list the data graph and plot.

```
## choose input by yourself
pestiToxin <- function(state1){
  data <- filter(strawbPestiAVG,State==state1)
  bar <- ggplot(data)+
    geom_bar(mapping = aes(x=`Chemical Name`,y=Value,fill=`Human Toxins`), position = "dodge",stat = "identity")+
    scale_fill_manual(values = c("high" = "#D55E00", "moderate"="#E69F00", "slight"="#009E73"))+
    labs(title = state1)+
    theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
  bar2 <- ggplot(data)+
    geom_bar(mapping = aes(x=`Chemical Name`,y=Value,fill=`Human Toxins`), position = "dodge",stat = "identity")+
    scale_fill_manual(values = c("high" = "#D55E00", "moderate"="#E69F00", "slight"="#009E73"))+
    labs(title = state1)
  list(bar, bar2+coord_polar())
}

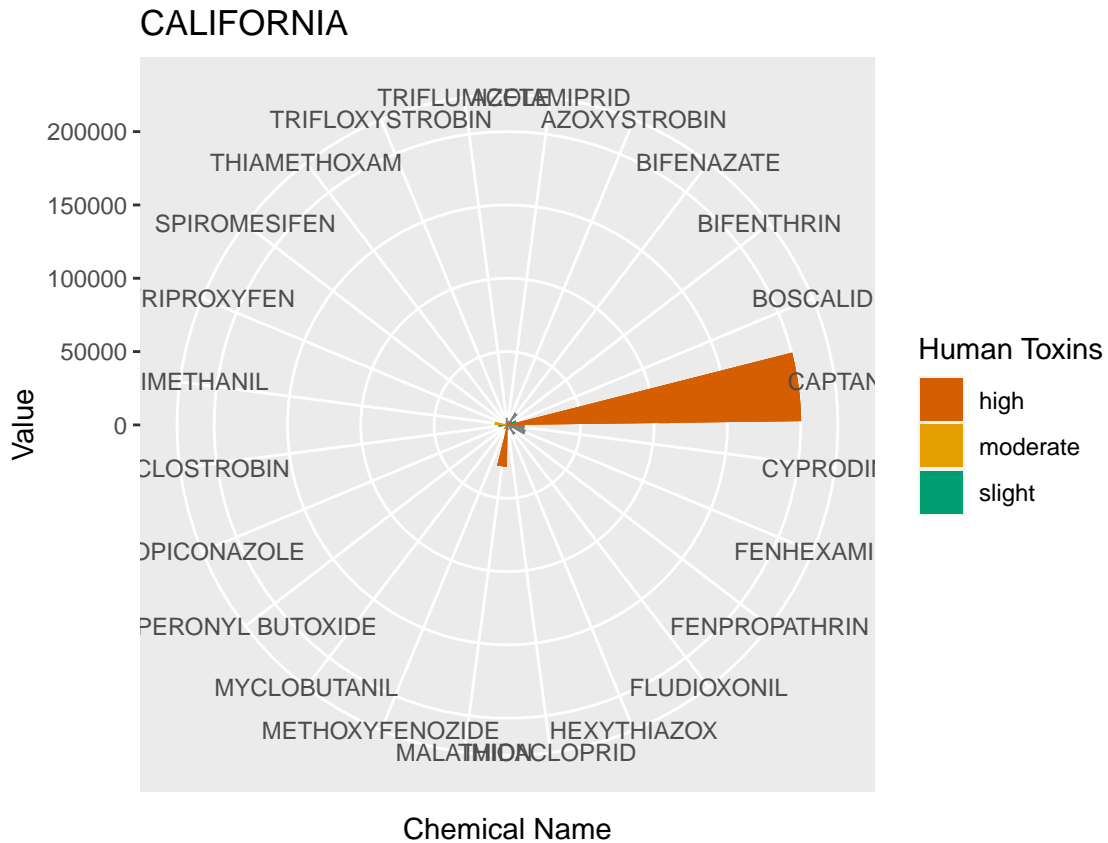
pestiToxin("CALIFORNIA")
```

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



```
##
## [[2]]
```



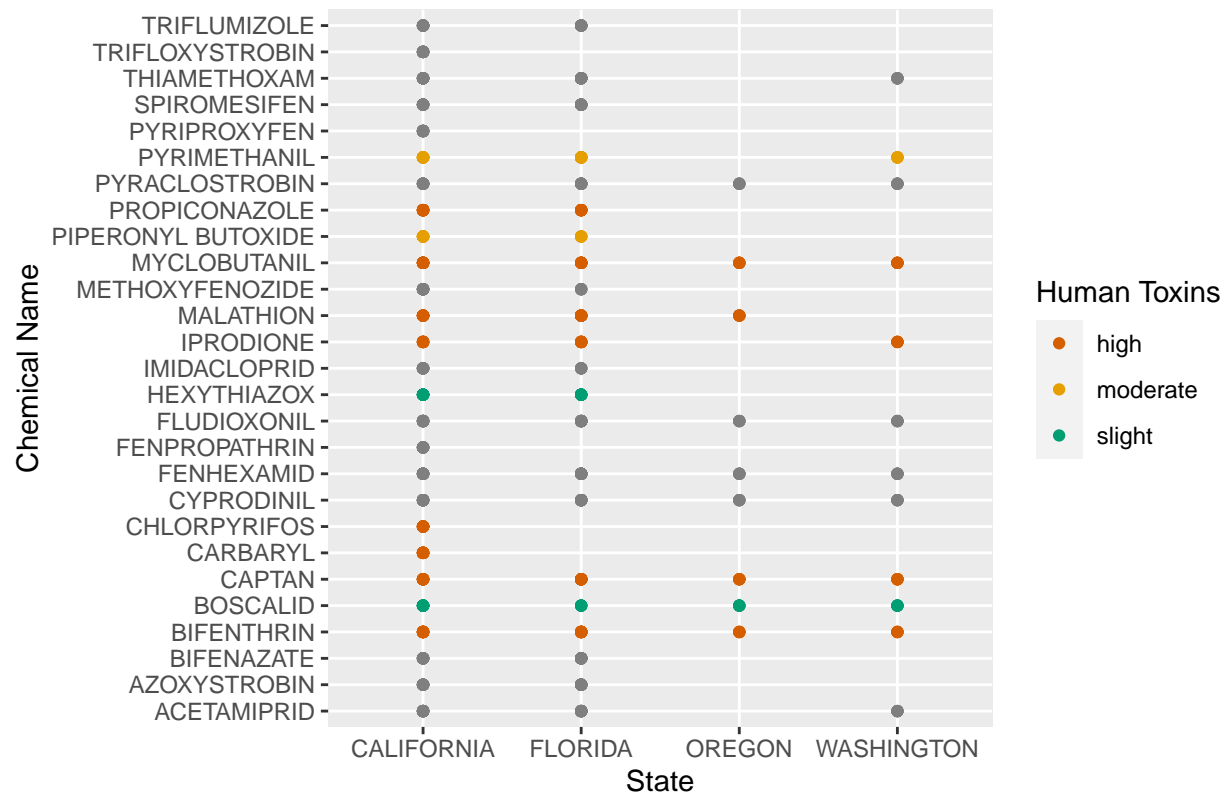


## How Toxic are the chemicals on strawberries for humans?

Then let's look at more specific issues. According to the colors shown in the pictures, the hazards of various chemicals can be seen.

```
Plot <- ggplot(strawbPesti) + geom_point(aes (x= State, y= `Chemical Name`, color= `Human Toxins`)) + 1
#colors used are from the color blind palette
Plot
```

## How Toxic are the chemicals on strawberries for humans?

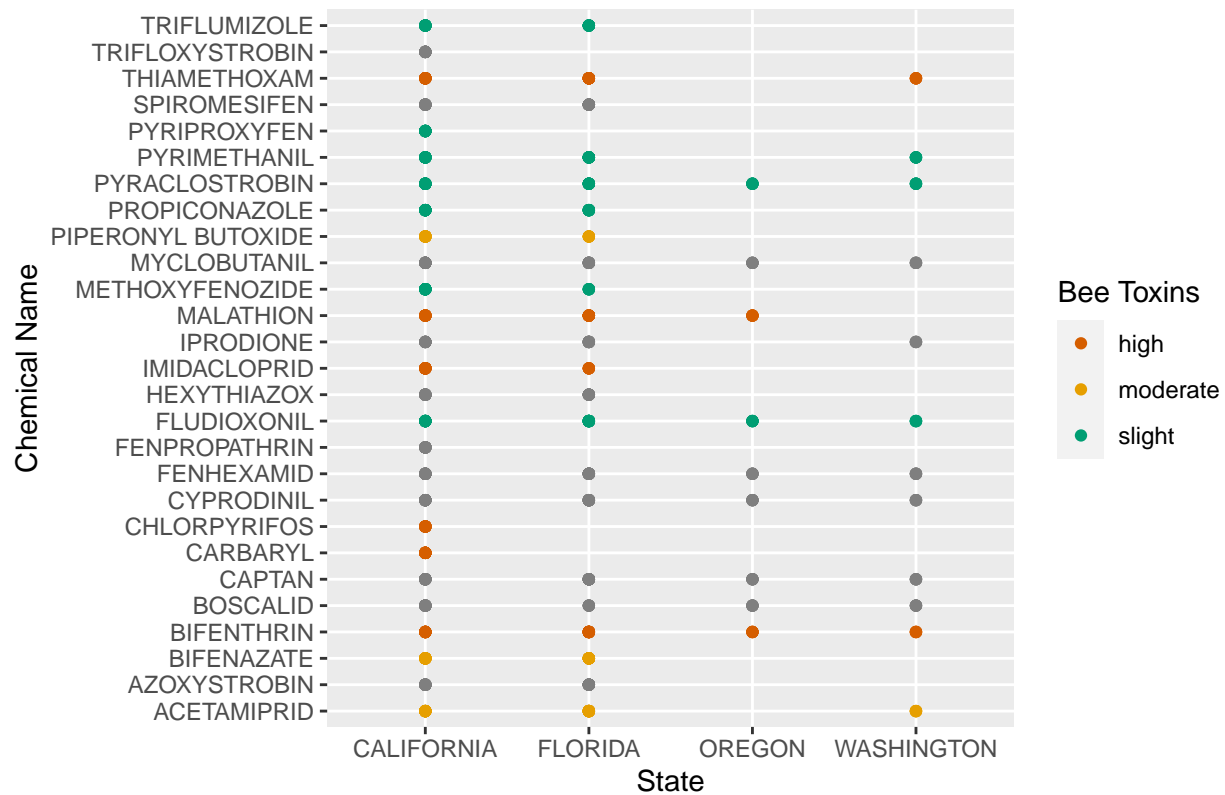


*#add a note about how we determined human toxins*

## How Toxic are the chemicals on strawberries for bees?

```
Plot1 <- ggplot(strawbPesti) + geom_point(aes (x= State, y= `Chemical Name`, color= `Bee Toxins`)) + labs(
Plot1
```

## How Toxic are the chemicals on strawberries for bees?

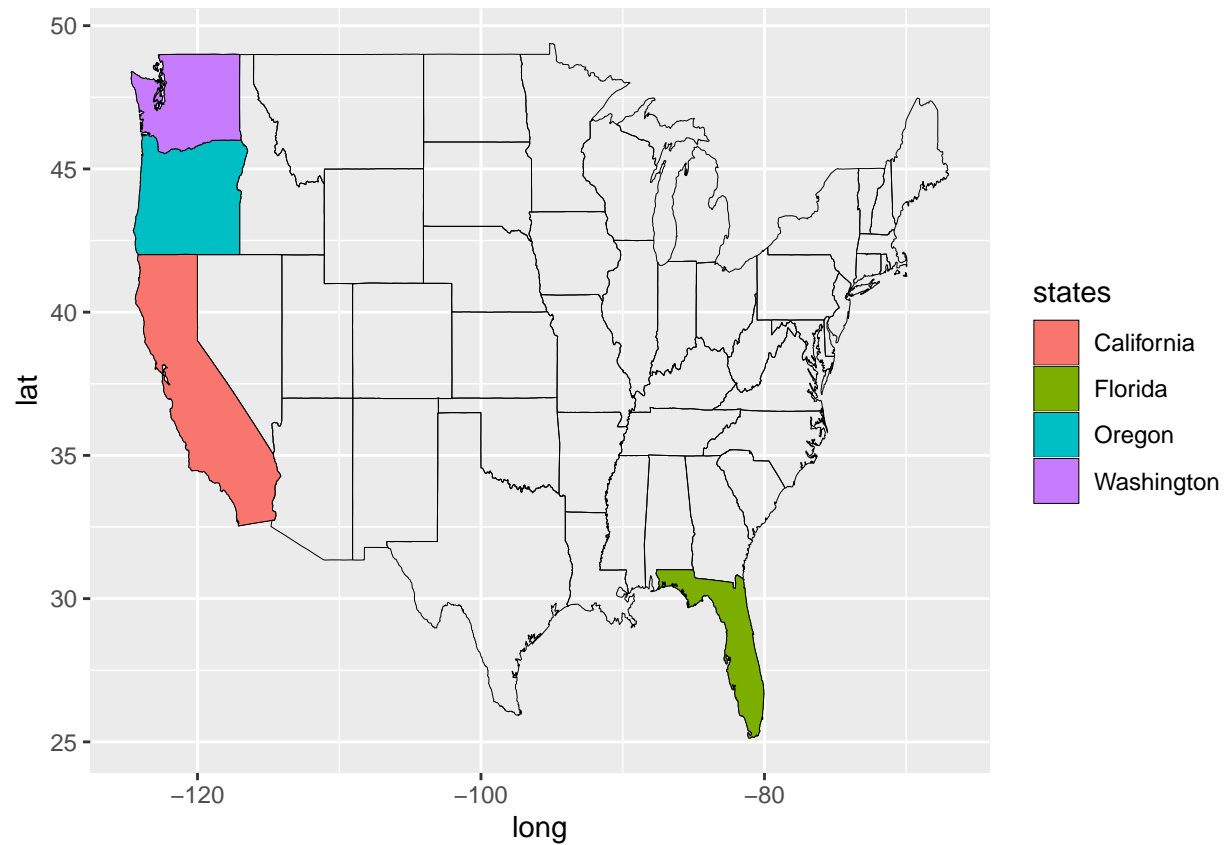


## Map of states in USA

There are only four states used in data sets, which are shown in colors on the map of the United States.

```
usamap<-function(){
  usa_map <- map_data("state")
  states<-c("California","Florida","Oregon","Washington")
  region<-tolower(states)
  tmp<-data.frame(cbind(states,region))
  gg <- ggplot()
  gg <- gg + geom_map(data=usa_map, map=usa_map,
    aes(long, lat, map_id=region),
    color="black", size=0.15, fill=NA)
  gg <- gg + geom_map(data=tmp, map=usa_map,
    aes(fill=states, map_id=region),
    color="black", size=0.15)
  gg
}
```

usamap()

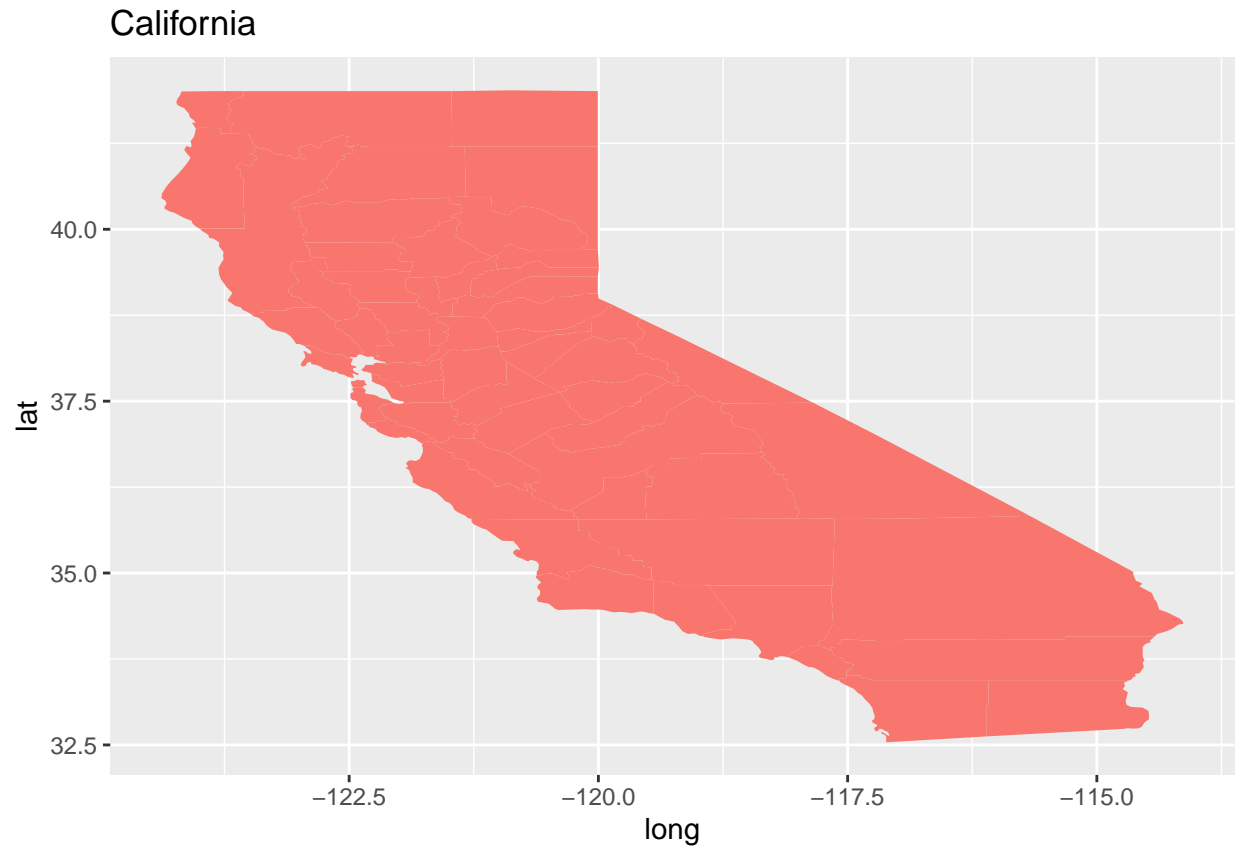


## Map of selected states

Take California as an example, we use a custom function to display a map of California.

```
map<-function(statename){
  m<-map_data("county",statename)

  p<-ggplot(data=m,
            mapping=aes(x=long,y=lat,group=group,fill=region))
  p+geom_polygon()+guides(fill=FALSE)+ggtitle(statename)
}
map("California")
```



## Shiny

Shiny is an R package that makes it easy to build interactive web apps straight from R.

In the shiny we made, click the button in the upper left corner to switch to view the data table, data icon, and map. In the data table, you can select the required data according to the state, year, and type. This interactive shiny file provides visual data content. Bring a more convenient and in-depth experience to those who view the data.

```
knitr::include_graphics("shinypic.png")
```

http://127.0.0.1:7020 [Open in Browser](#) [Publish](#)

Strawberry Data System Visualization Map

Please Select the State:  Year:  Type:

Show 10 entries Search:

Program	Year	Period	State	State ANSI	Items	Description	Units	dname	type	Title	Chemical Name	Number	Value	CV (%)	Carcinogen	Hormone Disruptor	Neurotoxins	Developmental or Reproductive Toxins	Bee Toxins	Human Toxins
SURVEY	2019	YEAR	CALIFORNIA	6	BEARING - APPLICATIONS	MEASURED IN LB		CHEMICAL	INSECTICIDE	CHEMICAL INSECTICIDE	ACETAMIPRID	99050	2,800						moderate	
SURVEY	2019	YEAR	CALIFORNIA	6	BEARING - APPLICATIONS	MEASURED IN LB / ACRE / APPLICATION	AVG	CHEMICAL	INSECTICIDE	CHEMICAL INSECTICIDE	ACETAMIPRID	99050	0.126						moderate	
SURVEY	2019	YEAR	CALIFORNIA	6	BEARING - APPLICATIONS	MEASURED IN LB / ACRE / YEAR	AVG	CHEMICAL	INSECTICIDE	CHEMICAL INSECTICIDE	ACETAMIPRID	99050	0.182						moderate	
SURVEY	2019	YEAR	CALIFORNIA	6	BEARING - APPLICATIONS	MEASURED IN NUMBER	AVG	CHEMICAL	INSECTICIDE	CHEMICAL INSECTICIDE	ACETAMIPRID	99050	1.4						moderate	
SURVEY	2019	YEAR	CALIFORNIA	6	BEARING - TREATED	MEASURED IN PCT OF AREA BEARING	AVG	CHEMICAL	INSECTICIDE	CHEMICAL INSECTICIDE	ACETAMIPRID	99050	42						moderate	
SURVEY	2019	YEAR	FLORIDA	12	BEARING - APPLICATIONS	MEASURED IN LB		CHEMICAL	INSECTICIDE	CHEMICAL INSECTICIDE	ACETAMIPRID	99050	200						moderate	
SURVEY	2019	YEAR	FLORIDA	12	BEARING - APPLICATIONS	MEASURED IN LB / ACRE / APPLICATION	AVG	CHEMICAL	INSECTICIDE	CHEMICAL INSECTICIDE	ACETAMIPRID	99050	0.099						moderate	
SURVEY	2019	YEAR	FLORIDA	12	BEARING - APPLICATIONS	MEASURED IN LB / ACRE / YEAR	AVG	CHEMICAL	INSECTICIDE	CHEMICAL INSECTICIDE	ACETAMIPRID	99050	0.127						moderate	
SURVEY	2019	YEAR	FLORIDA	12	BEARING - APPLICATIONS	MEASURED IN NUMBER	AVG	CHEMICAL	INSECTICIDE	CHEMICAL INSECTICIDE	ACETAMIPRID	99050	1.3						moderate	
SURVEY	2019	YEAR	FLORIDA	12	BEARING - TREATED	MEASURED IN PCT OF AREA BEARING	AVG	CHEMICAL	INSECTICIDE	CHEMICAL INSECTICIDE	ACETAMIPRID	99050	13						moderate	

Program Year Period State State ANSI Items Description Units dname type Title Chemical Na Number Value CV (%) Carcinogen Hormone D Neurotoxins Developmental or Bee Toxi Human To

Showing 1 to 10 of 765 entries

Previous 1 2 3 4 5 ... 77 Next



Figure 1: A shiny App.