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Financial Complaints Text-Mining Analysis

2023-2 Text Mining Team 1

CONTENTS

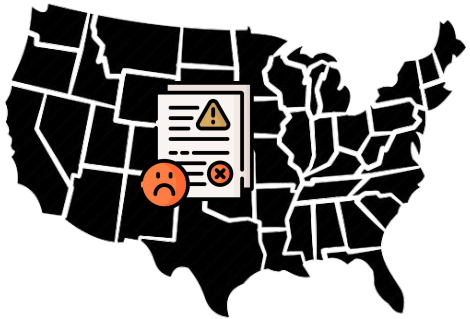
Problem Definition

Banks record 117% increase in customers' complaints

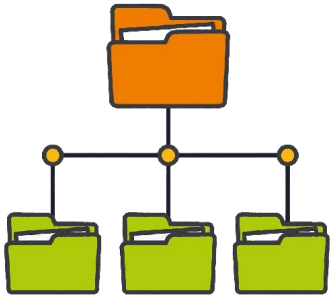
13th October 2023

- Financial companies face a growing volume of customer complaints.
- Prompt and accurate resolution of these complaints is essential.
- However, the increasing number of complaints poses a challenge due to limited company resources.

Project Goal

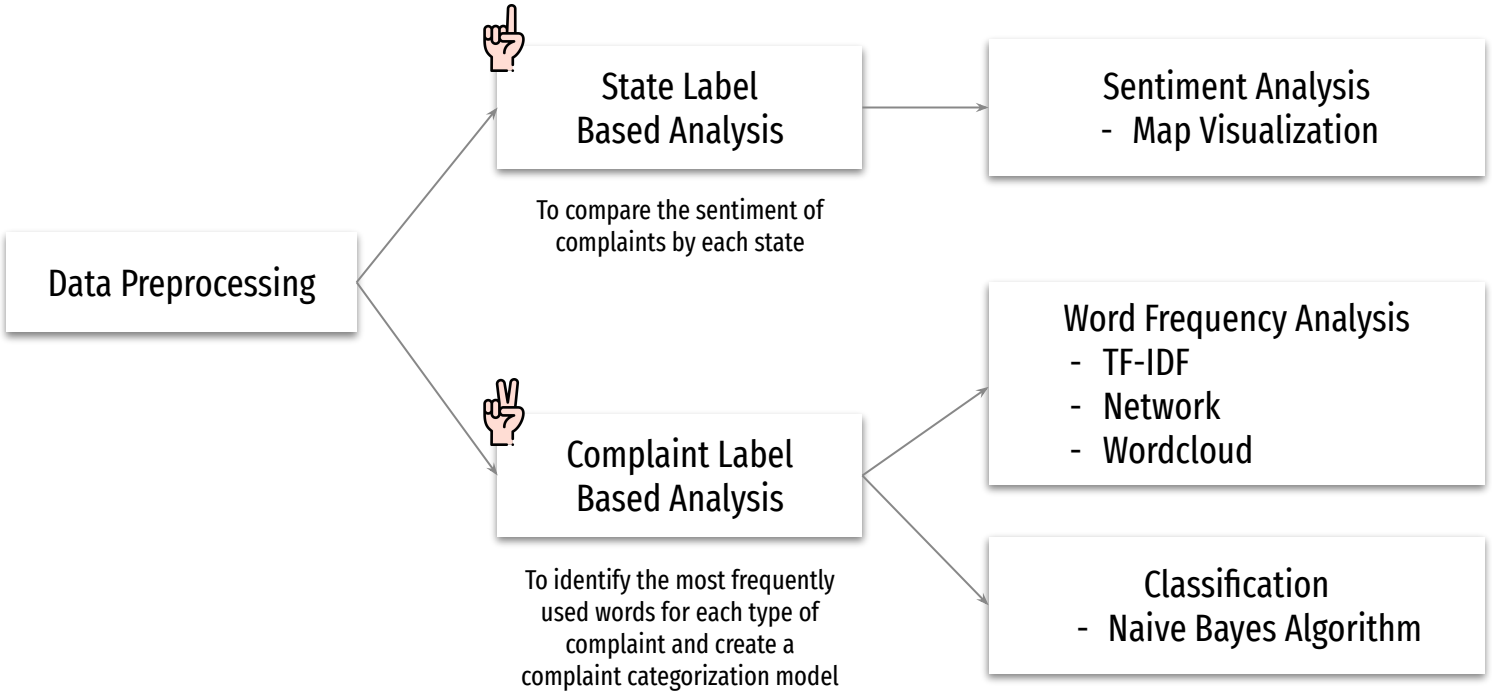


Identify states with the highest complaints and negative sentiments. Understand specific consumer complaints in those states and focus on them for more efficient resolution.



Analyze word frequency by complaint label, create a machine learning model for efficient classification, enabling effective and fast resolution of increasing complaints.

Analysis Overview



Data Source

cfpb Consumer Financial Protection Bureau

Filter results by...

- Date CFPB received the complaint — Show
- Product / sub-product — Show
- Issue / sub-issue — Show
- State — Show
- ZIP code — Show
- Company name — Show
- Did company provide a timely response? — Show

Filter

BANK OF AMERICA

Most popular Bank

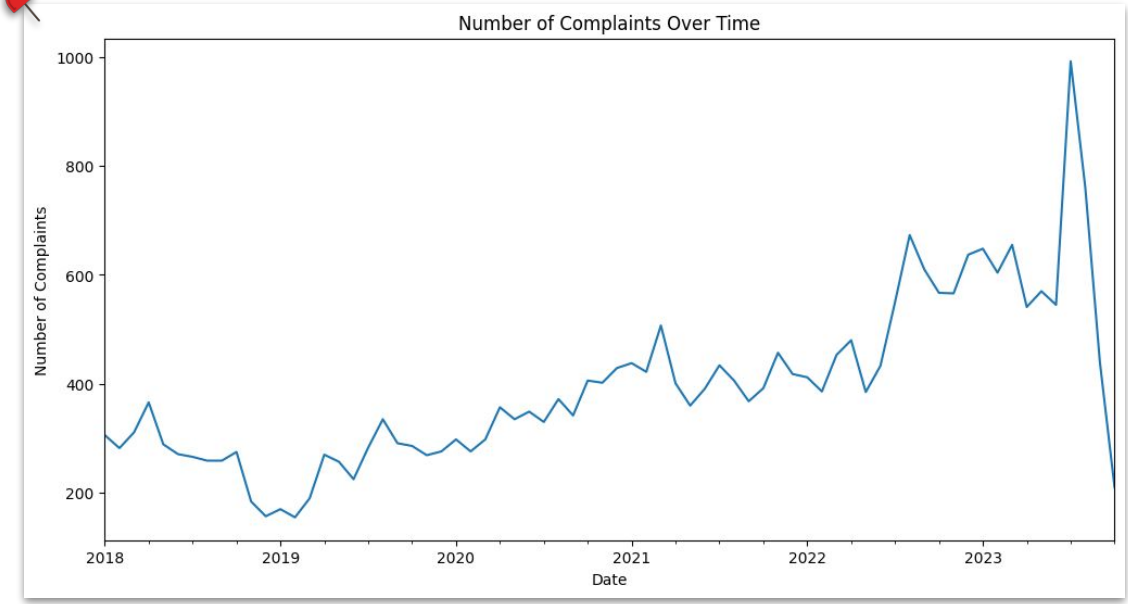
+

2018~2023

Extracted DataFrame

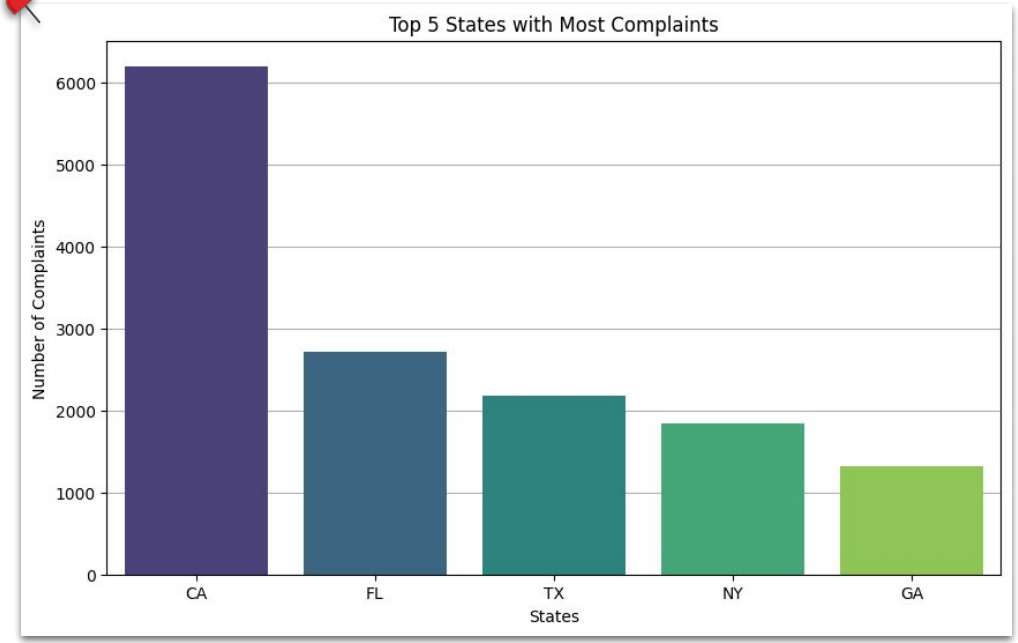
Column-1	Column-2	...	Column-n
		...	
		...	
...	...	...	...
		...	
		...	

Complaints Over Years



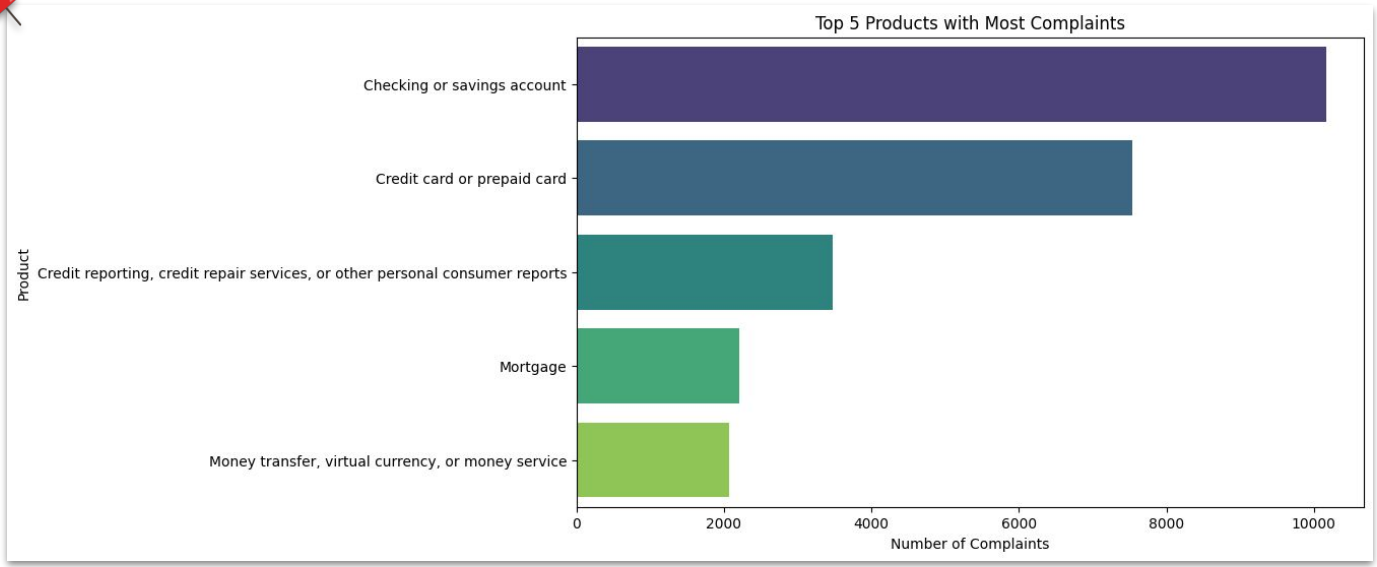
Increase in the number of complaints by year

Top States with Most Complaints



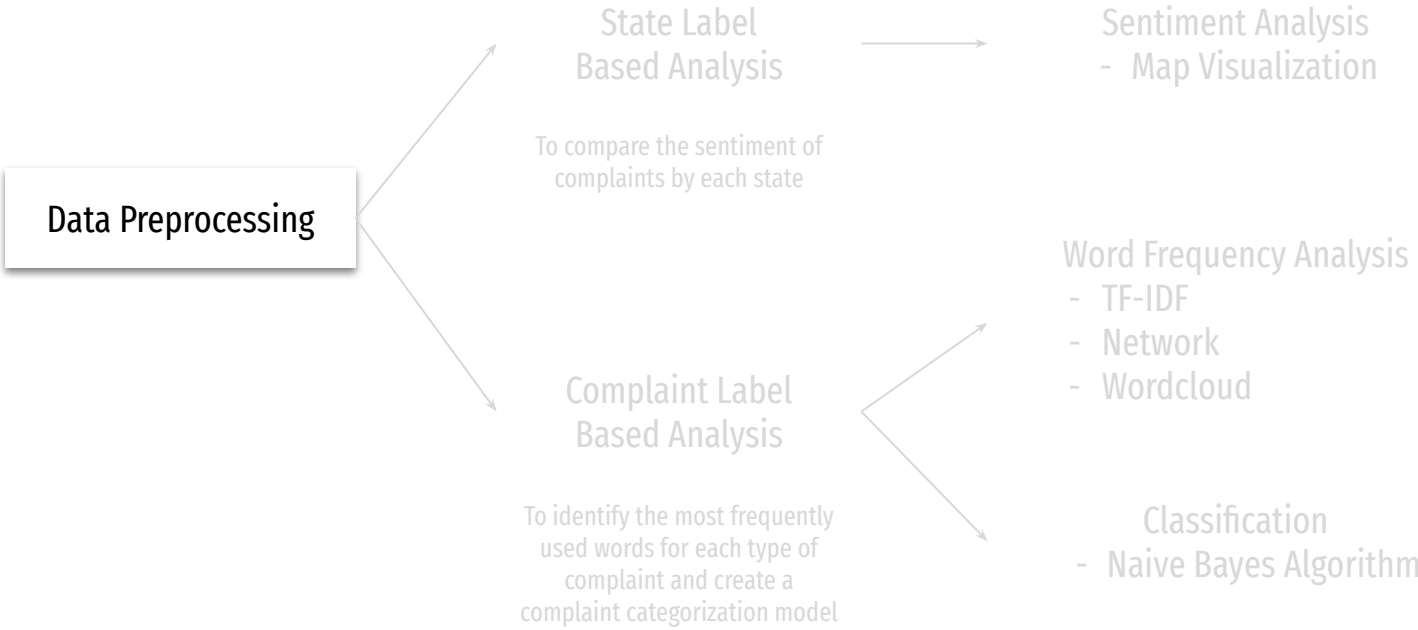
The number of complaints is highest in California, followed by Florida, and Texas.

Top Products with Most Complaints



Checking or savings account is the “Product” with the most complaints

Analysis Overview

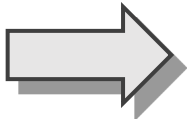


Column Selection

<Original Data>

Date.received
Product
Sub.product
Issue
Sub.issue
Consumer.complaint.narrative
Company.public.response
Company
State
ZIP.code
Tags
Consumer.consent.provided.
Submitted.via
Date.sent.to.company
Company.response.to.consumer
Timely.response.
Consumer.disputed.
Complaint.ID

(27536 * 18)



<Selected Columns>

Date
Label
- Card&Account
- Credit_Managaement
- Loan

Complaint
State

(27536 * 4)

Column Selection

- Credit card or prepaid card
- Credit card
- Prepaid card
- Checking or savings account
- Money transfer, virtual currency, or money service

- Credit reporting, credit repair services, or other personal consumer reports
- Credit reporting or other personal consumer reports
- Debt or credit management
- Debt collection

- Mortgage
- Vehicle loan or lease
- Payday loan, title loan, or personal loan
- Student loan
- Payday loan, title loan, personal loan, or advance loan

Card&Account

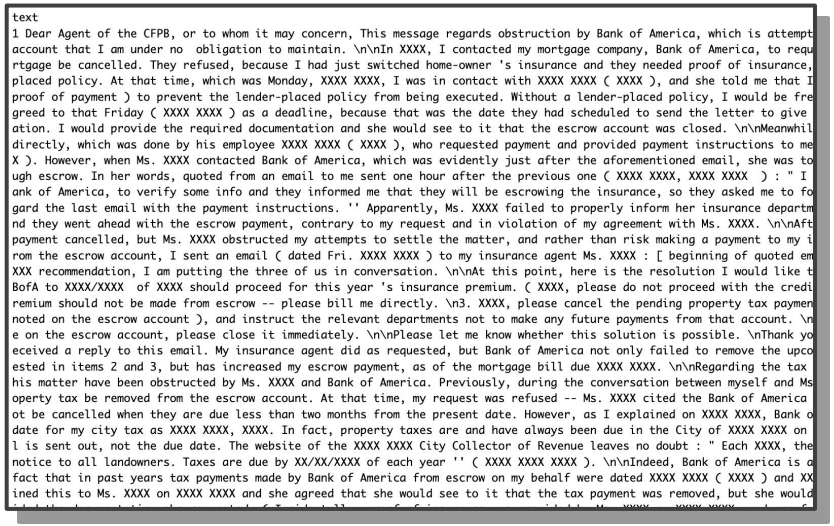
Credit Management

Loan

Preprocessing Steps

DATA PREPROCESSING

Corpus → Text Pre-processing → DTM



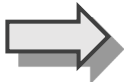
text
1 Dear Agent of the CFPB, or to whom it may concern, This message regards obstruction by Bank of America, which is attempt
account that I am under no obligation to maintain. \n\nIn XXXX, I contacted my mortgage company, Bank of America, to requ
rtgage be cancelled. They refused, because I had just switched home-owner 's insurance and they needed proof of insurance,
placed policy. At that time, which was Monday, XXXX XXXX, I was in contact with XXXX XXXX (XXXX), and she told me that I
proof of payment) to prevent the lender-placed policy from being executed. Without a lender-placed policy, I would be fre
greed to that Friday (XXXX XXXX) as a deadline, because that was the date they had scheduled to send the letter to give
ation. I would provide the required documentation and she would see to it that the escrow account was closed. \n\nMeanwhil
directly, which was done by his employee XXXX XXXX (XXXX), who requested payment and provided payment instructions to me
X). However, when Ms. XXXX contacted Bank of America, which was evidently just after the aforementioned email, she was to
ugh escrow. In her words, quoted from an email to me sent one hour after the previous one (XXXX XXXX, XXXX XXXX) : " I
ank of America, to verify some info and they informed me that they will be escrowing the insurance, so they asked me to fo
gard the last email with the payment instructions. '' Apparently, Ms. XXXX failed to properly inform her insurance departm
nd they went ahead with the escrow payment, contrary to my request and in violation of my agreement with Ms. XXXX. \n\nAft
payment cancelled, but Ms. XXXX obstructed my attempts to settle the matter, and rather than risk making a payment to my i
rom the escrow account, I sent an email (dated Fri. XXXX XXXX) to my insurance agent Ms. XXXX : [beginning of quoted em
XXX recommendation, I am putting the three of us in conversation. \n\nAt this point, here is the resolution I would like t
BofA to XXXX/XXXX of XXXX should proceed for this year 's insurance premium. (XXXX, please do not proceed with the credi
remium should not be made from escrow -- please bill me directly. \n3. XXXX, please cancel the pending property tax paymen
noted on the escrow account), and instruct the relevant departments not to make any future payments from that account. \n
e on the escrow account, please close it immediately. \n\nPlease let me know whether this solution is possible. \nThank yo
eceived a reply to this email. My insurance agent did as requested, but Bank of America not only failed to remove the upco
ested in items 2 and 3, but has increased my escrow payment, as of the mortgage bill due XXXX XXXX. \n\nRegarding the tax
his matter have been obstructed by Ms. XXXX and Bank of America. Previously, during the conversation between myself and Ms
operty tax be removed from the escrow account. At that time, my request was refused -- Ms. XXXX cited the Bank of America
ot be cancelled when they are due less than two months from the present date. However, as I explained on XXXX XXXX, Bank o
date for my city tax as XXXX XXXX, XXXX. In fact, property taxes are and have always been due in the City of XXXX XXXX on
l is sent out, not the due date. The website of the XXXX XXXX City Collector of Revenue leaves no doubt : " Each XXXX, the
notice to all landowners. Taxes are due by XX/XX/XXXX of each year '' (XXXX XXXX XXXX). \n\nIndeed, Bank of America is a
fact that in past years tax payments made by Bank of America from escrow on my behalf were dated XXXX XXXX (XXXX) and XX
ined this to Ms. XXXX on XXXX XXXX and she agreed that she would see to it that the tax payment was removed, but she would

```
> docs # Check the corpus
<<VCorpus>>
Metadata:  corpus specific: 0, document level (indexed): 1
Content:  documents: 27536
```

DATA PREPROCESSING

Corpus → **Text Pre-processing** → DTM

```
> lapply(docs, content)[c(10, 100, 1000)] # Check the content
$`10`
[1] "I have been requesting Bank of America remove PMI from my account for over 5 years. \n\nI w
t the letter stated Bank of America needs a property valuation with a fee of {$100.00}. \n\nI pa
unt of {$100.00}. On XX/XX/2023 I called Bank of America about PMI removal and spoke to someone
To my surprise He advised that regardless of what the original letter statedit was no longer val
0 days. \n\nNo where in that original letter does it state This letter is valid for 30 days. Or
no later than 30 days. \n\nThis is unfair to consumers and should have been disclosed. It appear
once again. \n\nHow much money is Bank of America making by holding these PMI payments for years
nd delays to avoid deleting PMI."

$`100`
[1] "We are in a Hurricane Irma FEMA designated area ( XXXX Florida- XXXX , FL vicinity ). \n\nW
eferred minimum payment grace period on our Bank of America credit card ending in -XXXX. \n\nWe
ent as promised in XX/XX/XXXX until we filed a CFPB complaint in XX/XX/XXXX. Bank of America Irm
elp us resolve the issue for deferred minimum payment. \n\nWhen the deferred minimum payment iss
a, it was done very poorly. \n\nBank of America has been the LEAST helpful to Hurricane Irma vic
e can name a dozen other banks who have been so much more understanding and helpful. Bank of Ame
ccount hurricane fees of {$27.00} on XX/XX/XXXX ; {$38.00} on XX/XX/XXXX ; {$38.00} on XX/XX/XXX
as caused us great emotional distress by reporting to the credit bureaus a late payment notifica
ment until Hurricane Irma. Our local TV station is requesting to do an in-depth expose on the tr
ed Hurricane Irma victims in our area, which has been horrible. \n\nWe should not be charged ri
on XX/XX/XXXX ; {$38.00} on XX/XX/XXXX ; {$38.00} on XX/XX/XXXX nor be subjected to a credit bur
to Hurricane Irma. We feel like Bank of America has no compassion for Hurricane Irma victims, es
category. \n\nXXXX XXXX"

$`1000`
[1] "XXXX  % XXXX check could not be processed by a XXXX  insurance carrier. The Check has the c
ansit & Account number along with Item number encoded. \nOn the first failed attempt BofA valida
ut could not locate an attempt for the item to clear the bank.\n\nAfter XXXX attempts to process
of America, I authorized the transaction using the card as the medium. \n\nIn a followup call, B
by transferring the card based transaction into the promotion. \n\nIn short, this scheme of prov
itutes a bait & switch in an attempt to defraud the customer. \n\nI requested he log a customer
ich he committed to do, but could not ( or would not ) tell me if I would be contracted in respo
ed him that I would make this regulator complaint to be sure the complaint was heard an acted on
```



```
> lapply(docs, content)[c(10, 100, 1000)] # Check the content
$`10`
[1] "request bank america remove pmi account account eligible letter bank america property va
america pmi removal speak pmi department surprise advise original letter statedit valid day o
mer send payment late day unfair consumer disclose process delay money bank america hold pmi
lete pmi"

$`100`
[1] "hurricane irma fema designate florida fl vicinity apply grant defer minimum payment grac
eive payment deferment promise file cfpb complaint bank america irma relief resolve issue def
ent issue correct bank america bank america helpful hurricane irma victim bank institution do
ica charge credit card account hurricane fee additionally bank america emotional distress rep
cation late payment hurricane irma local station request indepth expose treatment bank americ
ble charge ridiculous hurricane fee subject credit bureau late payment notification hurricane
rricane irma victim minority category"

$`1000`
[1] "check process insurance carrier check customary route transit account numb numb encode f
e attempt bank attempt process check supply bank america authorize transaction card medium fo
ansfer card base transaction promotion short scheme provide nonnegotiatble check constitute b
equest log customer complaint commit contract response complaint inform regulator complaint c
```

DATA PREPROCESSING

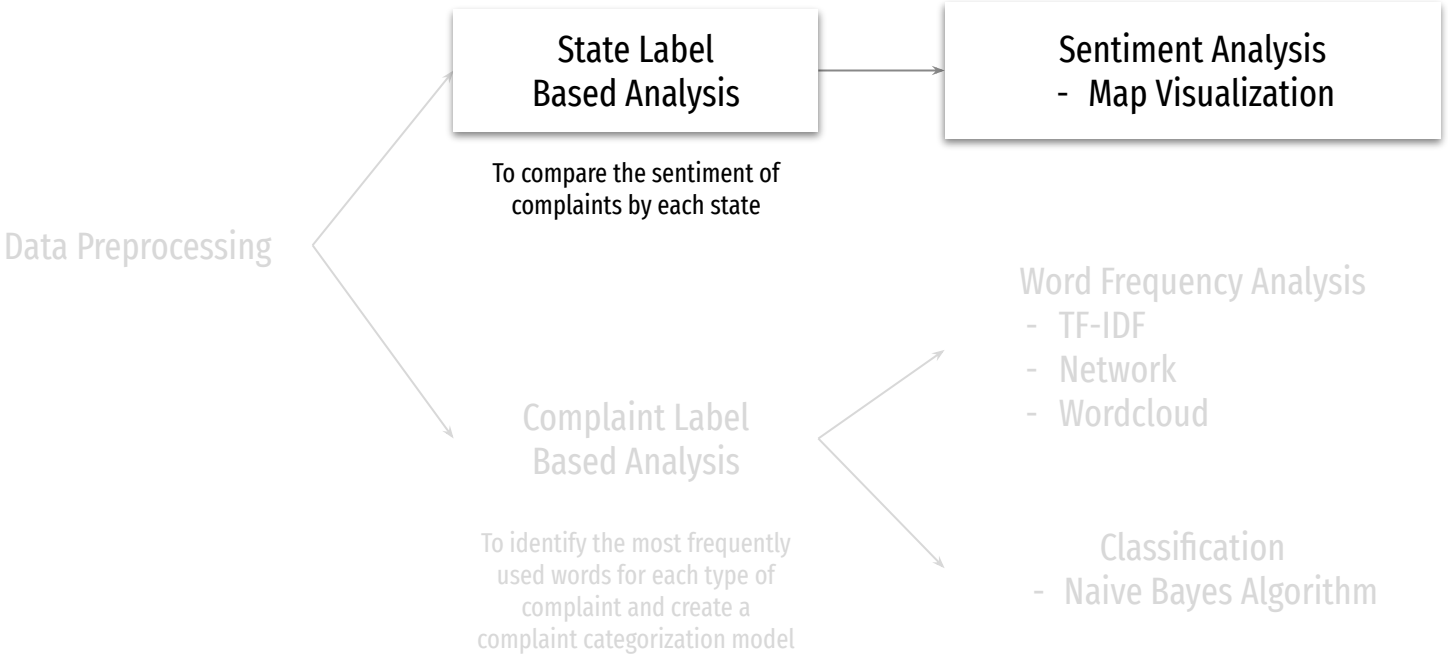
Corpus → Text Pre-processing → DTM

```
> lapply(docs, content)[c(10, 100, 1000)] # Check the content
$`10`
[1] "request bank america remove pmi account account eligible letter bank america property val
america pmi removal speak pmi department surprise advise original letter statedit valid day o
mer send payment late day unfair consumer disclose process delay money bank america hold pmi p
lete pmi"

$`100`
[1] "hurricane irma fema designate florida fl vicinity apply grant defer minimum payment grace
eive payment deferment promise file cfpb complaint bank america irma relief resolve issue defe
ent issue correct bank america bank america helpful hurricane irma victim bank institution doz
ica charge credit card account hurricane fee additionally bank america emotional distress repo
cation late payment hurricane irma local station request indepth expose treatment bank america
ble charge ridiculous hurricane fee subject credit bureau late payment notification hurricane
rricane irma victim minority category"

$`1000`
[1] "check process insurance carrier check customary route transit account numb numb encode fo
e attempt bank attempt process check supply bank america authorize transaction card medium fo
ansfer card base transaction promotion short scheme provide nonnegotiatble check constitute ba
equest log customer complaint commit contract response complaint inform regulator complaint co
```

```
> inspect(dtm) # Check the DTM
<<DocumentTermMatrix (documents: 27536, terms: 703)>>
Non-/sparse entries: 912738/18445070
Sparsity           : 95%
Maximal term length: 14
Weighting          : term frequency (tf)
Sample             :
       Terms
Docs    account america bank card check credit money payment receive report
  10068      35       1    1    0     1     98     0      28       0    116
  10807       8       5   10    0     1      2     4       1       1      1
  13893      30      15   38    0    57      0     1       4      18      5
  15010      35       1    1    0     1     98     0      28       0    116
  20395      19       0    7    0     0     19     1       7       6     75
  21676      11       1    1    1     1     68     0      16       0    102
  24375      14      20   36    1     1      2     4      13       1      4
  26884      23       0    1    0     3     29     1       3       3     73
  5283        6       1    1    0     1     53     0      11       0     82
  5513       15       1    1    0     1     74     0      18       0    109
```

- Limit the word length (3, Inf)
- Lower (0.05%) and upper limits (95%) for the number of documents that appear
- Remove rows with sparsity over 0.99

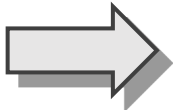
Analysis Overview



Preprocessing Steps

Use sentiment method ‘afinn’

```
> State.affin %>% head()
# A tibble: 6 × 3
  State word       value
  <chr> <chr>      <dbl>
1 AE    fraudulent    -4
2 AE    charges       -2
3 AE    no            -1
4 AE    no            -1
5 AE    restricted    -2
6 AE    dire          -3
```



Sum of each group value

```
> total_State_sum %>% head()
# A tibble: 6 × 2
  State value
  <chr> <dbl>
1 AE      -43
2 AK      -157
3 AL      -190
4 AP       -2
5 AR       -56
6 AZ      -954
```

Standardization

```
> total_State_sum %>% head()
# A tibble: 6 × 4
  State value count   pro
  <chr> <dbl> <int> <dbl>
1 AE      -43     6 -7.17
2 AK     -157    14 -11.2
3 AL     -190    34 -5.59
4 AP       -2     2 -1
5 AR      -56    31 -1.81
6 AZ     -954   174 -5.48
```

Sentiment Score of a State

Complaint Count of a State

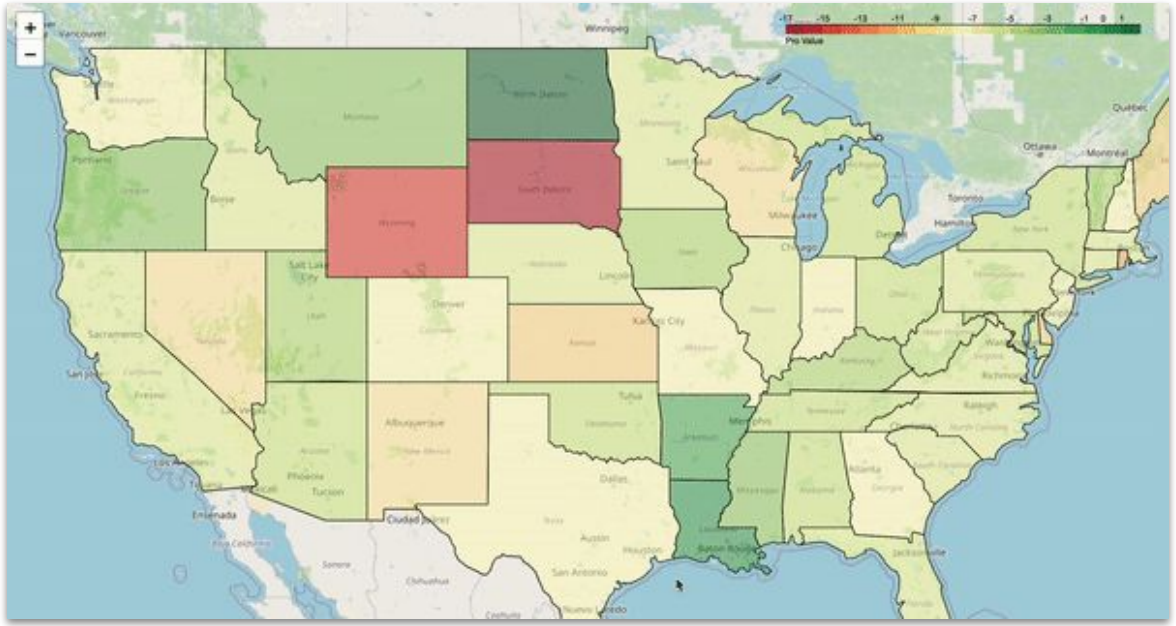
To standardize the varying counts across states,
we create a column named 'pro' by dividing the value by the count.

Complaint Visualization

Top 5 States by Number of Complaints

1. California
2. Florida
3. Texas
4. New York
5. Georgia

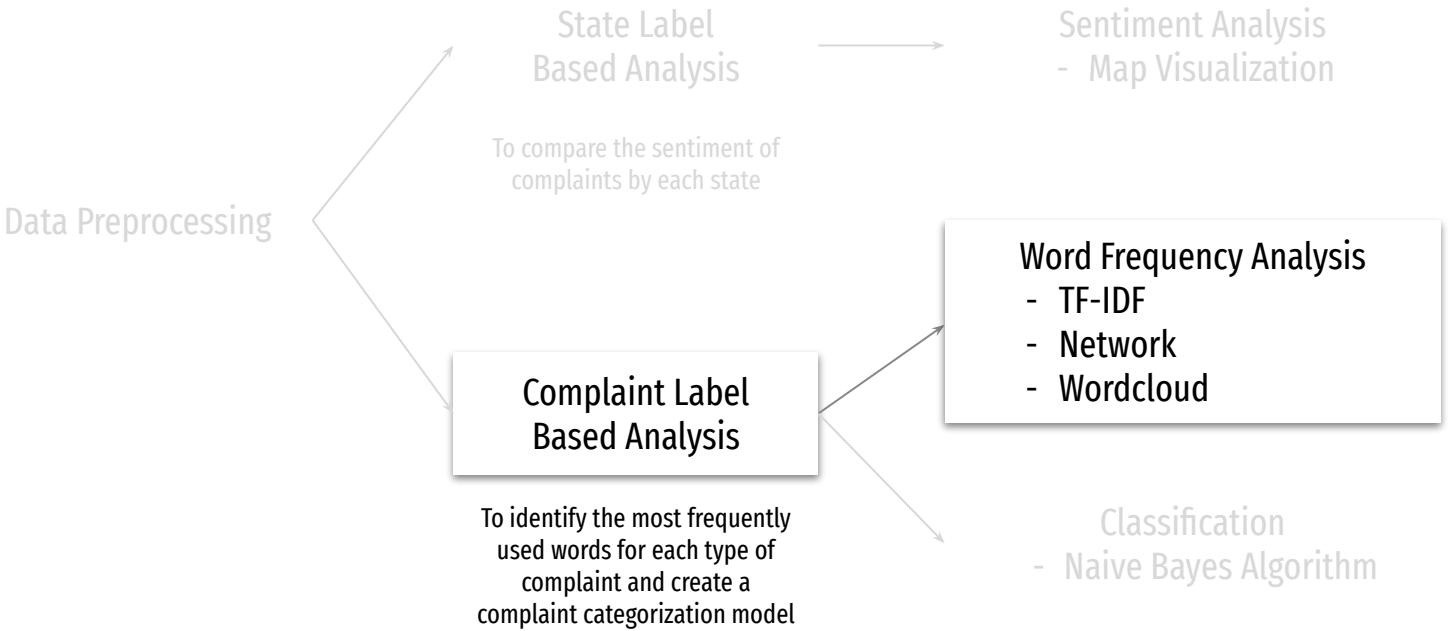
Sentiment Visualization



Top 5 States by Negative Sentiments

1. South Dakota
2. Hawaii
3. Wyoming
4. Alaska
5. Rhode Island

Analysis Overview



Top 5 TF-IDF words

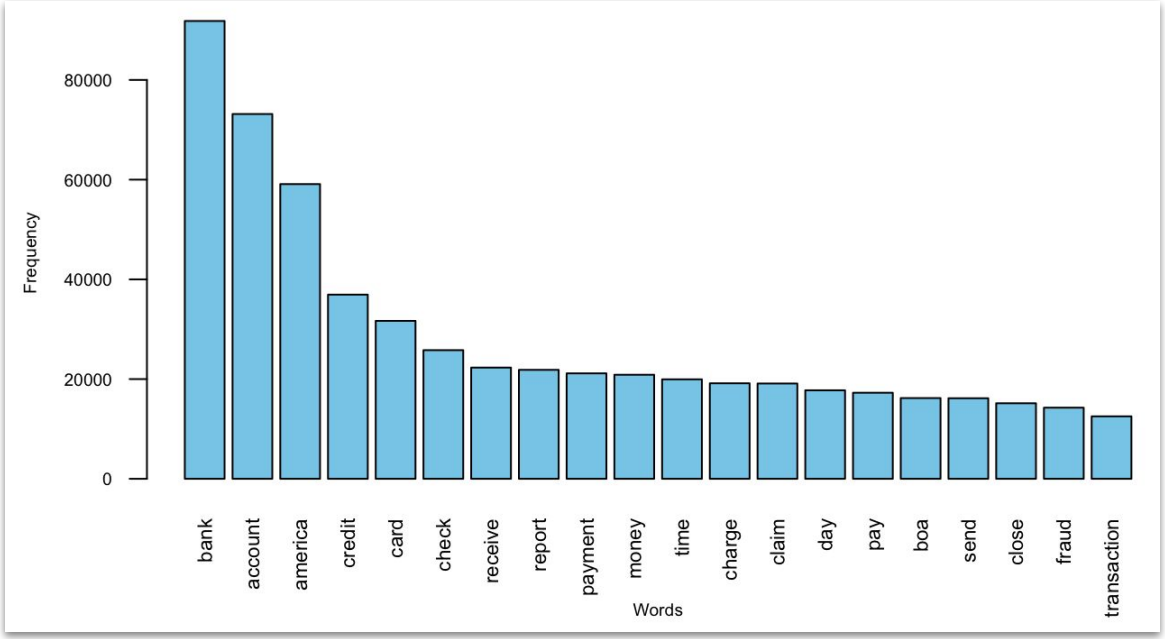
```
> comp.table %>% arrange(desc(TF)) %>% head(10)
   doc     term    TF TF_IDF W_TF_IDF
1    1     bank 72151      0        0
2    1  account 59281      0        0
3    1  america 44265      0        0
4    1     card 28405      0        0
5    1    check 23326      0        0
6    1   credit 23046      0        0
7    1    money 18978      0        0
8    1    claim 17623      0        0
9    1  receive 17414      0        0
10   1   charge 17022      0        0
```

```
> comp.table %>% arrange(desc(TF_IDF)) %>% head(10)
   doc         term  TF    TF_IDF W_TF_IDF
1    3          pmi 218 345.5218    0.001
2    1 merchandise 371 217.0211    0.000
3    1       flight 349 204.1519    0.000
4    1    fraudster 306 178.9985    0.000
5    1         chip 276 161.4497    0.000
6    1        puppy  94 148.9865    0.000
7    1    cellphone  81 128.3820    0.000
8    1     harmless  81 128.3820    0.000
9    1   mastercard 198 115.8226    0.000
10   1    redeposit  64 101.4376    0.000
```

High TF does not guarantee high TF-IDF

```
> top_terms_df # Print the result (Top 5 TF-IDF words in each document)
                    Doc_id       Term1    Term2           Term3       Term4       Term5
Card&Account             1 merchandise   flight       fraudster        chip       puppy
Credit_management        2  subscriber antedate creditreporting permissible furnishers
Loan                     3         pmi      ltv            haf  recontrust      recast
```

Top 20 Words



Top 5 Words by Word Frequency

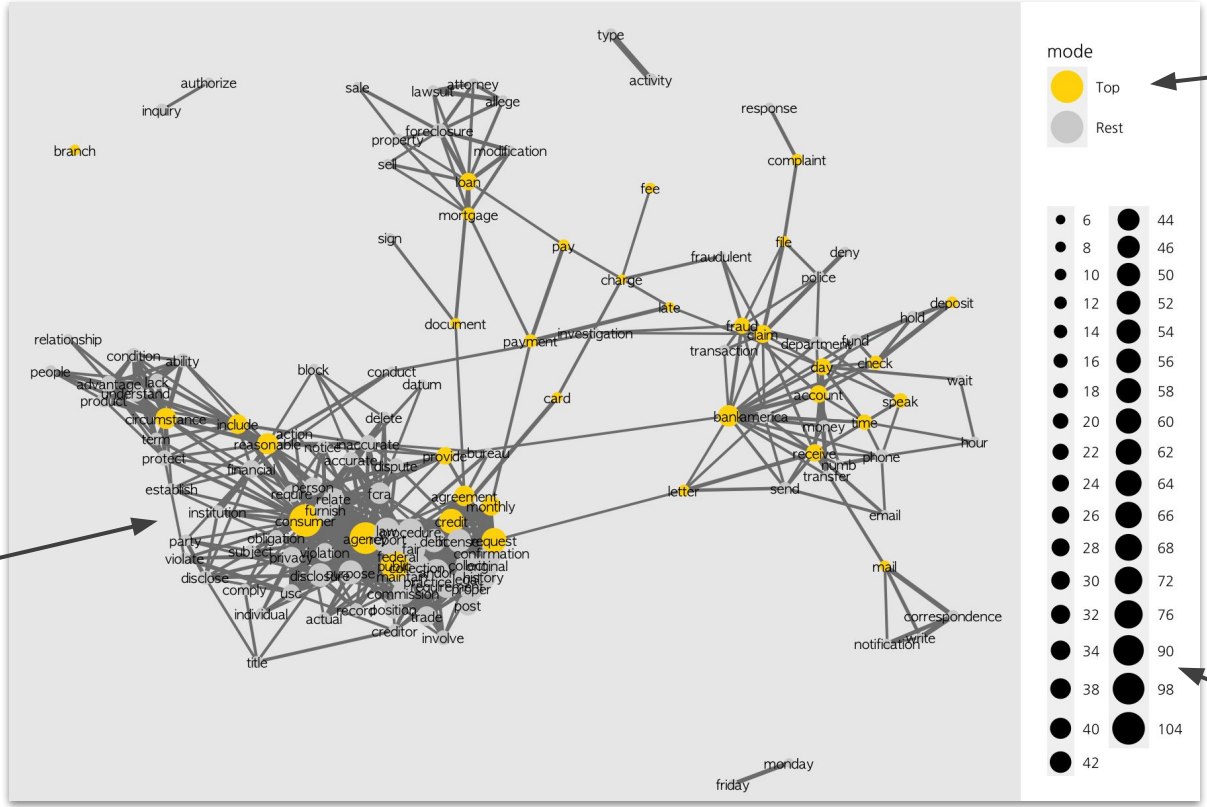
1. bank
2. account
3. america
4. credit
5. card

Correlation of High Frequency Words with Other Words

```
> findAssocs(dtm, c("bank", "account", "america", "credit", "card"), 0.25) # Check the high frequency words with correlation
$bank
      fraud     receive       money        time       check    customer         day  department        send       claim
       0.35        0.34        0.33        0.33        0.30        0.30        0.30        0.30        0.30        0.28
       fund       issue       phone    transfer     contact        numb      letter     provide transaction
       0.27        0.27        0.27        0.27        0.26        0.26        0.25        0.25        0.25

$account
     close      check      fraud       numb   transfer      money     access        day       fund       time department
      0.38       0.32       0.30       0.30       0.30       0.29       0.28       0.27       0.27       0.27       0.26

$america
receive   fraud  letter    send    time   claim
   0.32    0.28    0.26    0.26    0.26    0.25

$credit
      report         fair   collection        andor       agency      history  requirement    procedure       public
        0.56         0.49         0.44         0.42         0.41         0.41         0.39         0.38         0.38
    practice       proper        score        legal      request      federal      collect     consumer       bureau
        0.36         0.36         0.36         0.35         0.34         0.33         0.32         0.32         0.31
        debt     maintain     original      dispute          law      license confirmation      purpose   commission
        0.30         0.30         0.30         0.29         0.29         0.29         0.27         0.27         0.26
    creditor
        0.26

$card
   debit   charge activate
    0.34     0.30     0.28
```

Correlation ≥ 0.25

Network Analysis

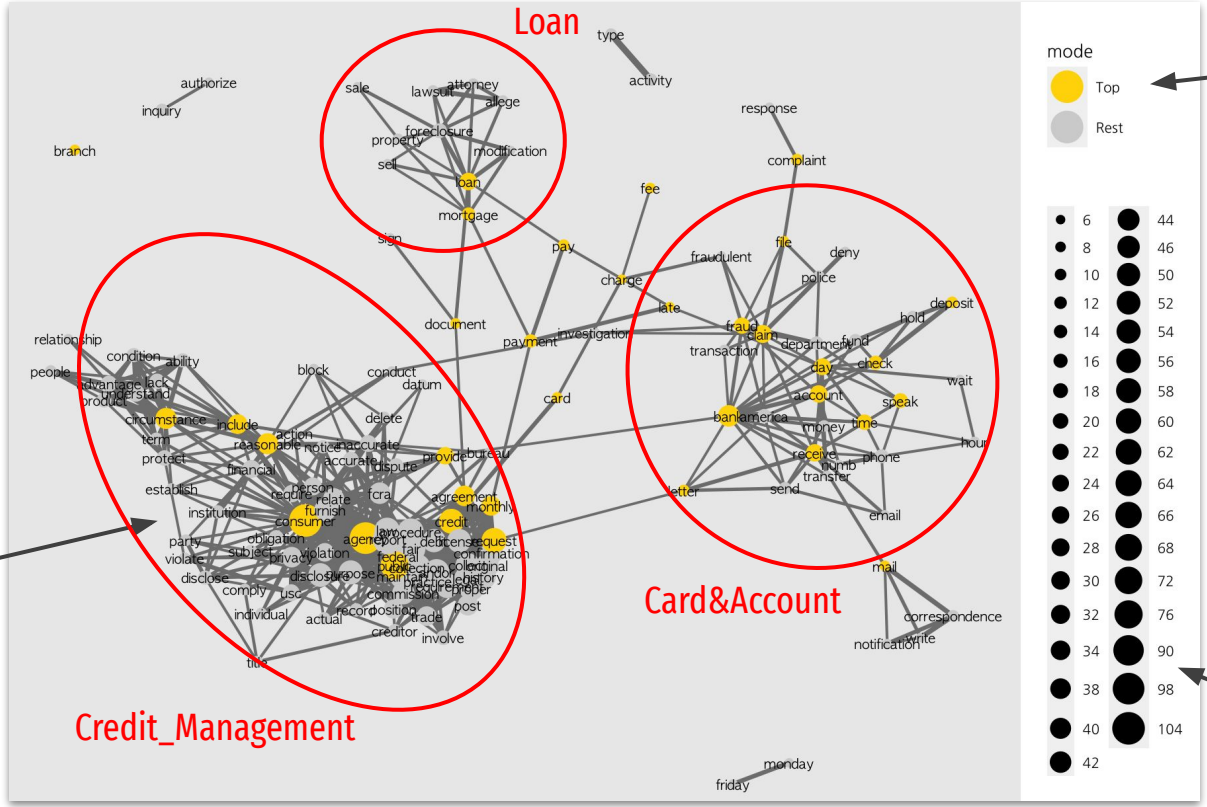


Betweenness
Top 5%

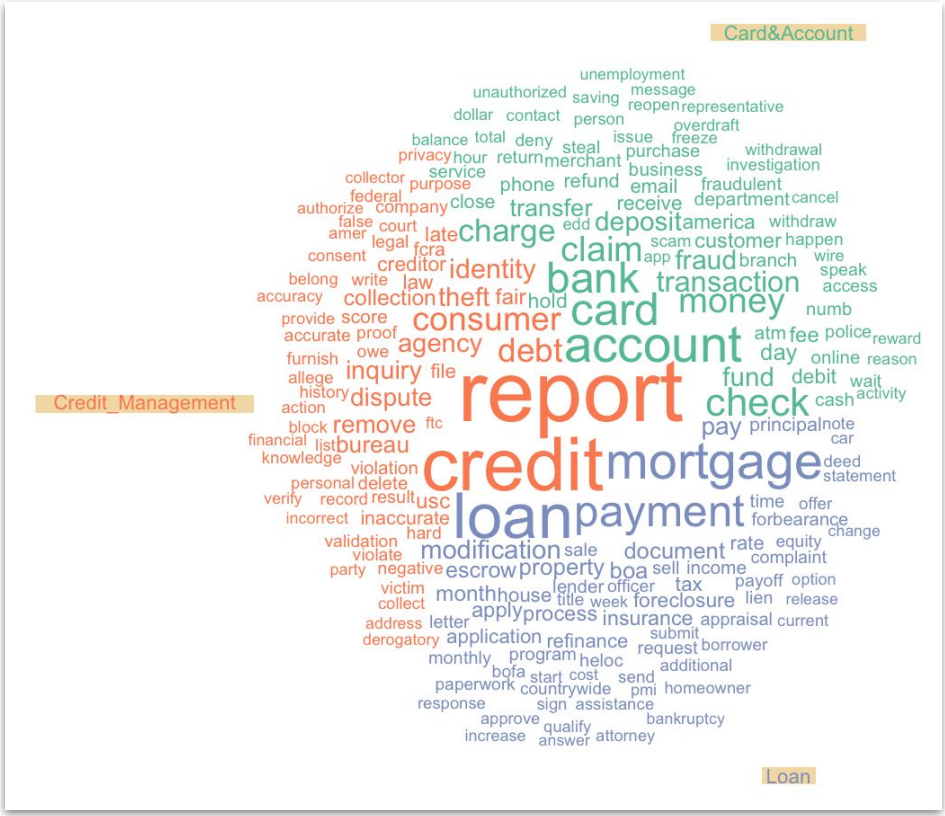
Closeness

Degree

Network Analysis



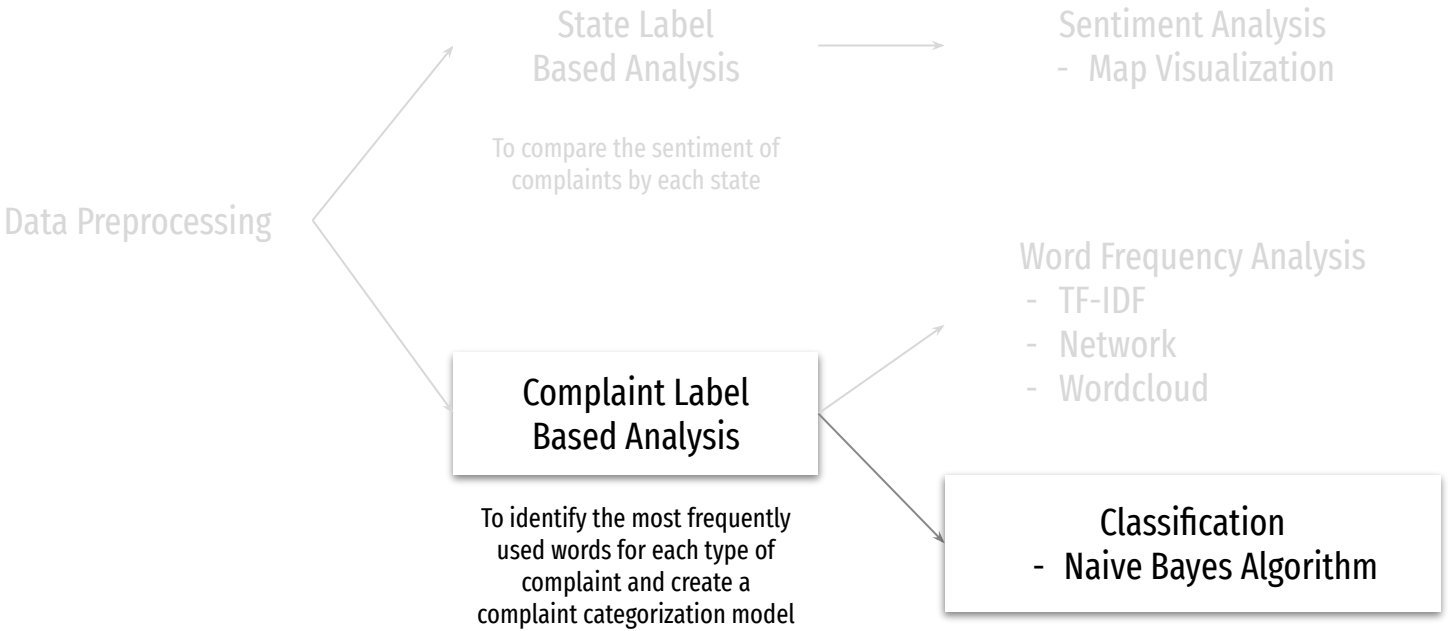
Comparison Wordcloud



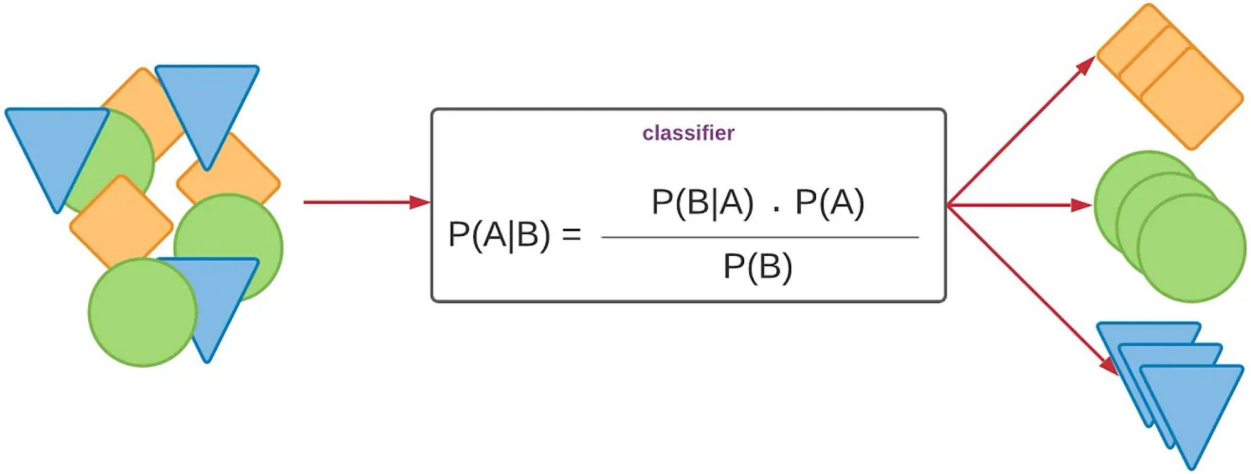

```
> comparision.label[, 1:10] # Displaying a subset of the matrix wher
                   aaa abandon abide ability abnormal abovementioned
Card&Account        56      37    60     387       20             12
Credit_Management   23       8    31     139        1              5
Loan                 0      15    12      70        0              0
```

```
set.seed(123)
# Create a comparison cloud by transposing the matrix
# Rows become words, columns become categories
comparison.cloud(t(comparision.label),
                 # Title size
                 title.size = 0.7,
                 # Color palette from Set2 with 3 colors
                 colors = brewer.pal(3, "Set2"),
                 # Title color palette
                 title.colors = brewer.pal(3, "Set2"),
                 # Random order False
                 random.order=FALSE,
                 # Title background color
                 title.bg.colors = "wheat",
                 # Rotation percentage (0 for horizontal)
                 rot.per = 0,
                 # Scale for word sizes
                 scale = c(3, 0.5),
                 # Maximum number of words
                 max.words = 200)
```

Analysis Overview



Naive Bayes Classification



Naive Bayes classification algorithm is a probabilistic machine learning method based on Bayes' theorem, assuming independence between features, and is particularly effective for text classification tasks.

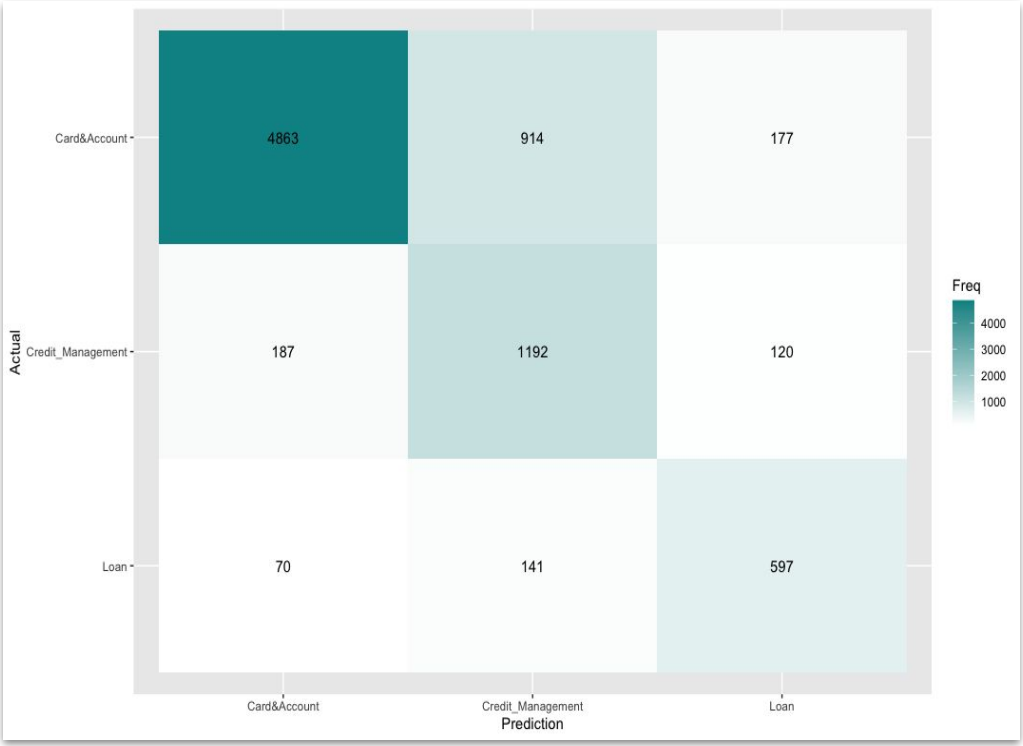
Train & Test Set Split

Train and test set well reflect the proportions of the entire dataset.

```
> table(y.train) # Number of labels in train data
y.train
     Card&Account Credit_Management              Loan
            14002               3455              1818
> table(y.test) # Number of labels in test data
y.test
     Card&Account Credit_Management              Loan
             5995               1451               815
```

```
> prop.table(table(complaint$type)) # Entire dataset

     Card&Account Credit_Management              Loan
       0.72621296        0.17816676        0.09562028
> prop.table(table(y.train)) # Train dataset
y.train
     Card&Account Credit_Management              Loan
       0.72643320        0.17924773        0.09431907
> prop.table(table(y.test)) # Test dataset
y.test
     Card&Account Credit_Management              Loan
       0.72569907        0.17564460        0.09865634
```

Accuracy of the Model



$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

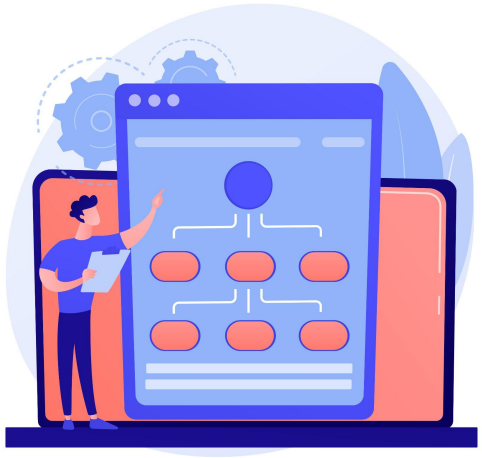
$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

```
> evaluate_model(y.test, complaint.nb.pred)
Accuracy: 0.81
Precision: 0.53
Recall: 0.8
F1 Score: 0.64
```

CONCLUSION



State-Label Based Complaint Analysis

- California had the highest complaint volume.
- South Dakota exhibited the most severe dissatisfaction based on sentiment analysis.
- Identifying high-complaint states helps allocate resources strategically.

Complaint-Label Based Analysis & Classification

- Word frequency analysis unveiled prevalent complaint-related words and correlations between other words.
- The classification model streamlines complaint categorization for swift issue resolution.
- Efficiently managing consumer complaints is anticipated through these insights.

REFERENCES

- Text Mining Lecture Slides
- [Problem Definition]
  https://punchng.com/banks-record-117-increase-in-customers-complaints/
- [Network]
  https://bookdown.org/yuaye_kt/RTIPS/Texnetword-2.html#%EB%84%A4%ED%8A%B8%EC%9B%8C%ED%81%AC-%EA%B0%9D%EC%B2%B4-%EC%B6%94%EC%B6%9C

THANK YOU