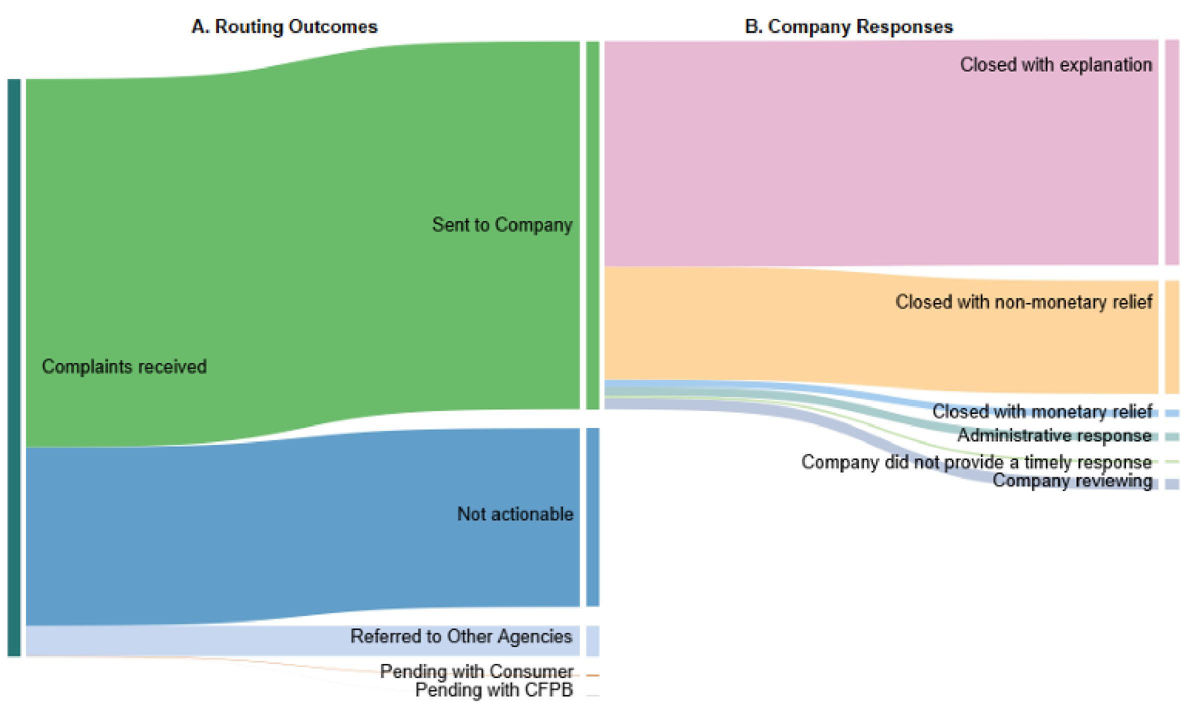
Predicting Company’s Response to Consumer Complaints on Consumer Financial Protection Bureau

Introduction:

CFPB (Consumer Financial Protection Bureau) is a U.S. government agency dedicated to making sure that the consumers are treated fairly by banks, lenders, and other financial institutions. It implements and enforces Federal consumer financial law and ensures that markets for consumer financial products are fair, transparent, and competitive.

As per the annual report for 2022 published by CFPB, Of the approximately 1,287,300 complaints received in 2022, it sent 819,800 (or 64%) to companies for review and response, referred 5% to other regulatory agencies, and found 31% to be not actionable.17 As of February 1, 2023, 0.1% of complaints were pending with the consumer and less than 0.1% were pending with the CFPB.



We here would be looking at the dataset that would contain complaints sent to companies for response.

Data:

The data (555528 rows and 18 columns) has been downloaded from the website of CFPB. This data contains the last six months of complaints received by CFPB, by written, online email and web. It includes information about the type of product and subproduct the customer is complaining about, the issue at hand, customer narrative about the problem, date of receipt of compliant, date the complaint was sent to the company and the response provided by the company. It also says if the company provided a timely response and if there was a monetary settlement by the company. The current would focus on classifying the type of response provided by the company.

While this study is a Multiclass Classification problem and focuses primarily on the last six months of data, the research can be expanded in future to examine the following.

- In-depth study of the patterns in the products.
- Predicting the response using Sentiment analysis.
- A time series prediction of the responses and further classifying the responses.

Data Wrangling:

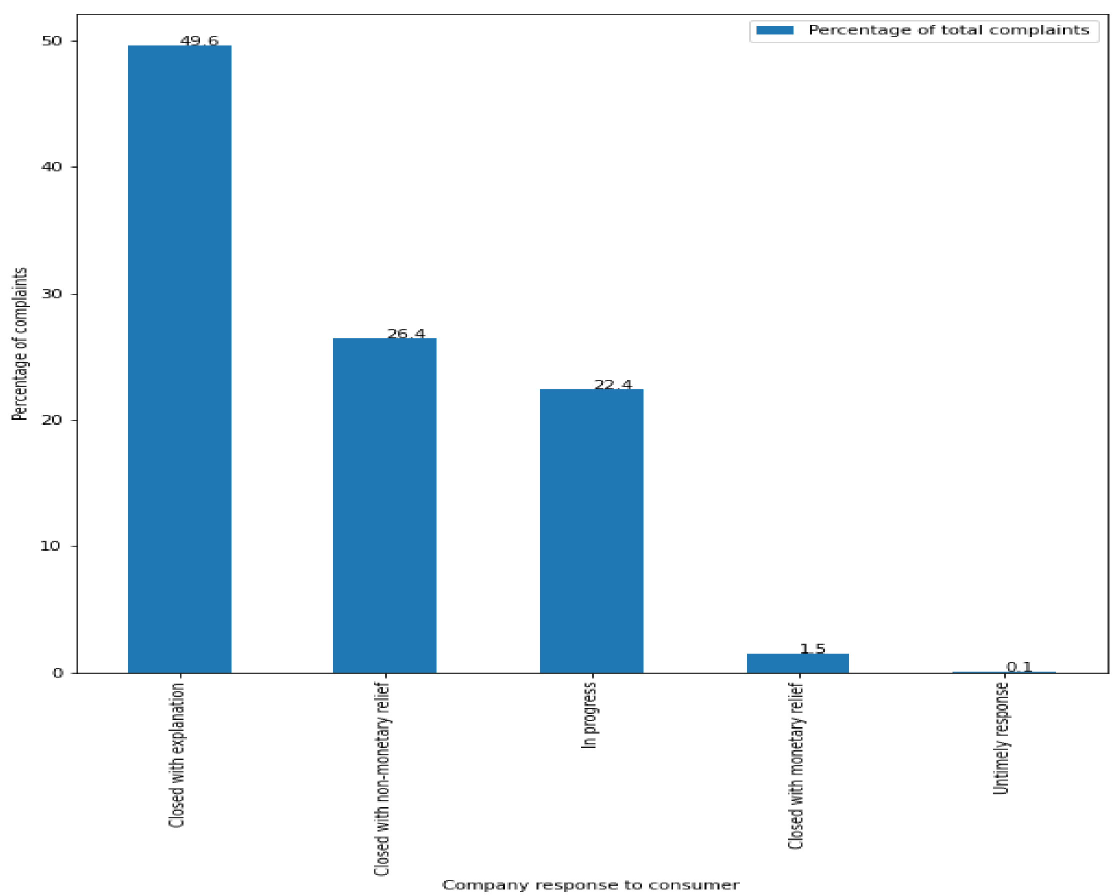
We begin by analyzing the missing values. We notice that all the cases where the feature Consumer Consent is null, it looks like Customer Narrative is also null. Consent refers to the consent of the consumer to share their narrative. The consumer disputed column does not have any entries. The columns that would aid in this study are identified as Date received, Date sent to company, Company response to Consumer and Consumer complaint narrative. We convert the dates to datetime type. We eliminate the column- Consumer Disputed as it has no significant relevance to our current study. However, the dates provided do not indicate the time taken by the company. Time taken by the company to provide a response has been separately captured as a feature – 'Timely response'. This provides scope for elimination of dates in this study.

The following five categories could exist in the type of response from the company.

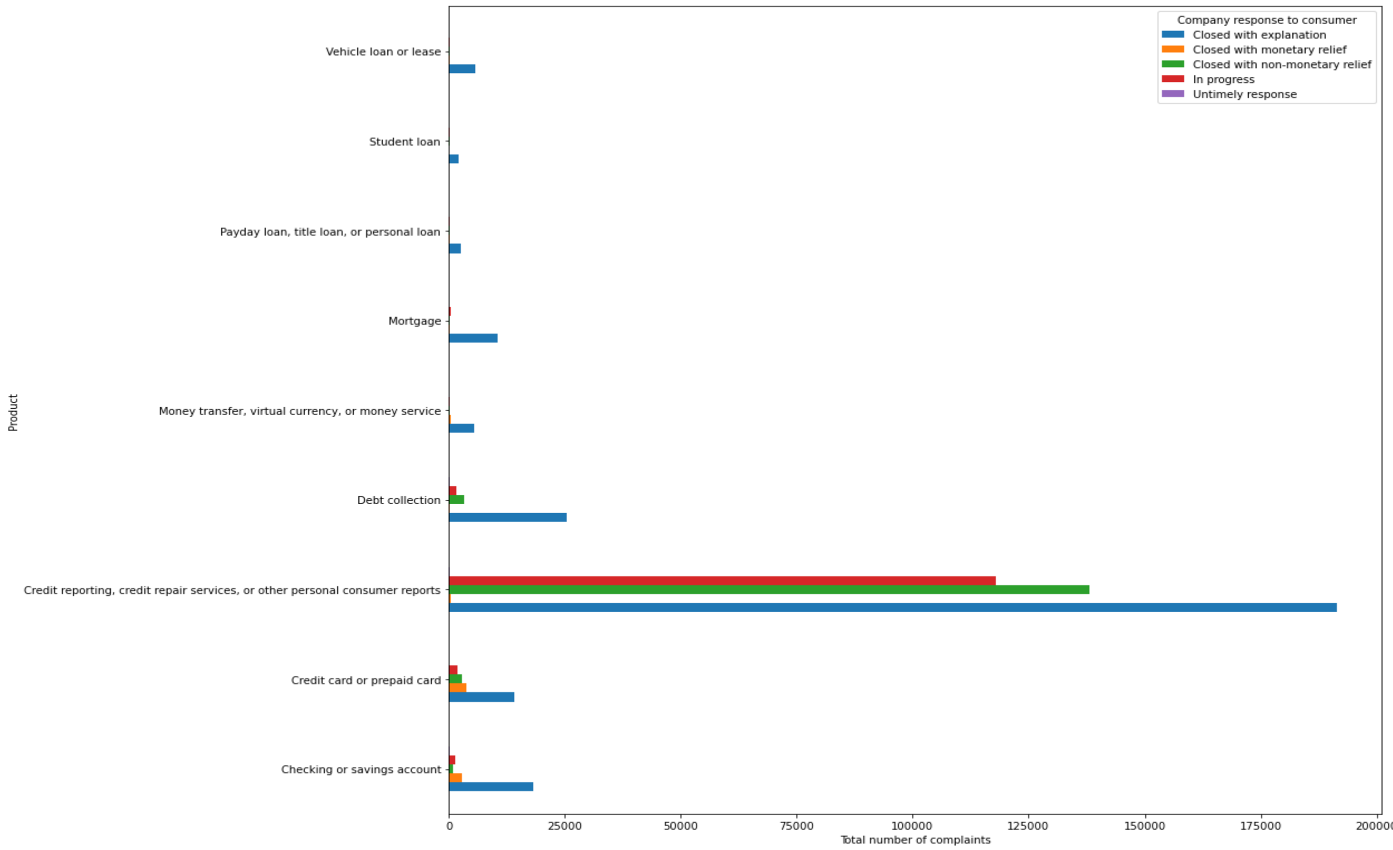
1) Closed with explanation.
2) Closed with non-monetary relief.
3) Closed with monetary relief.
4) In progress
5) Untimely response.

Exploratory Data Analysis:

We see that monetary relief is an extremely small share of the total responses by Companies.

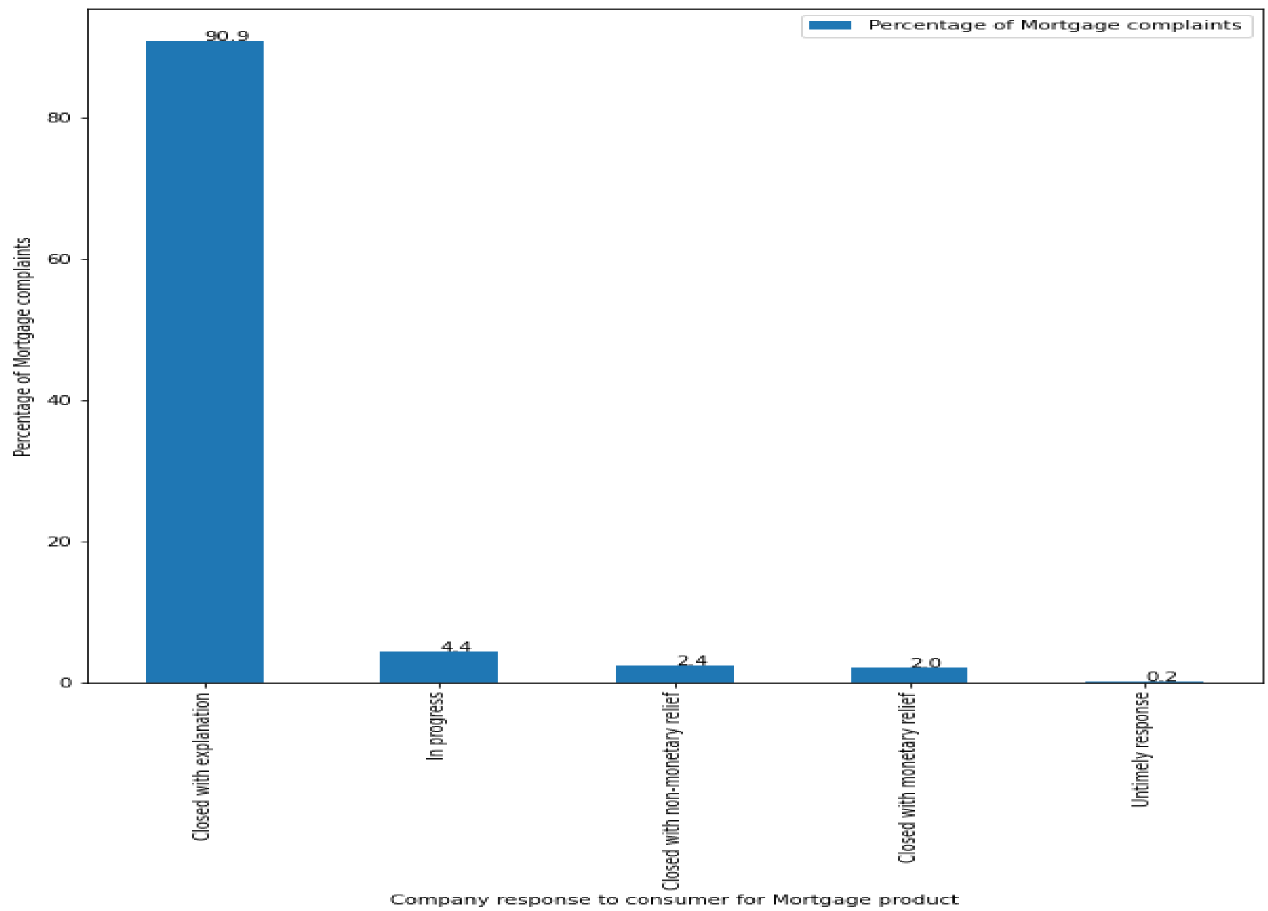


Most companies respond with explanation. What kind of responses receive non-monetary relief? and which products are mostly closed with monetary relief?

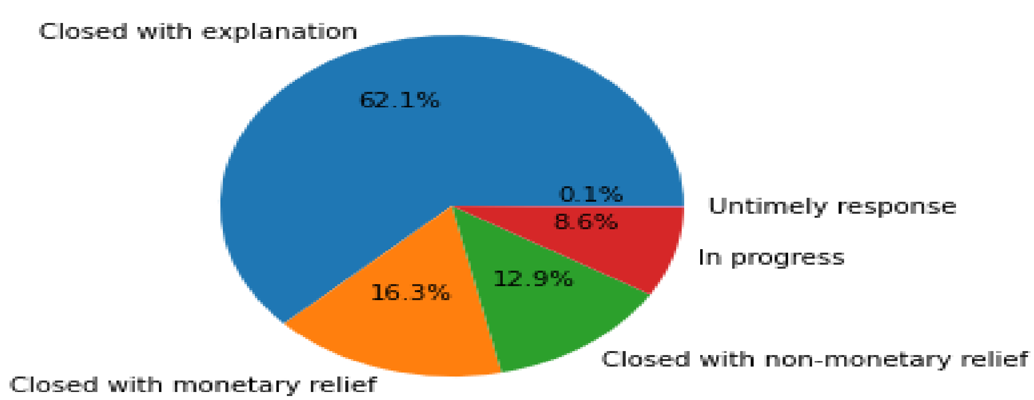


We see considerable cases of closure with monetary relief in Credit Card/ Prepaid card and Chequing/ Savings account based complaints. We analyze each of the product lines separately.

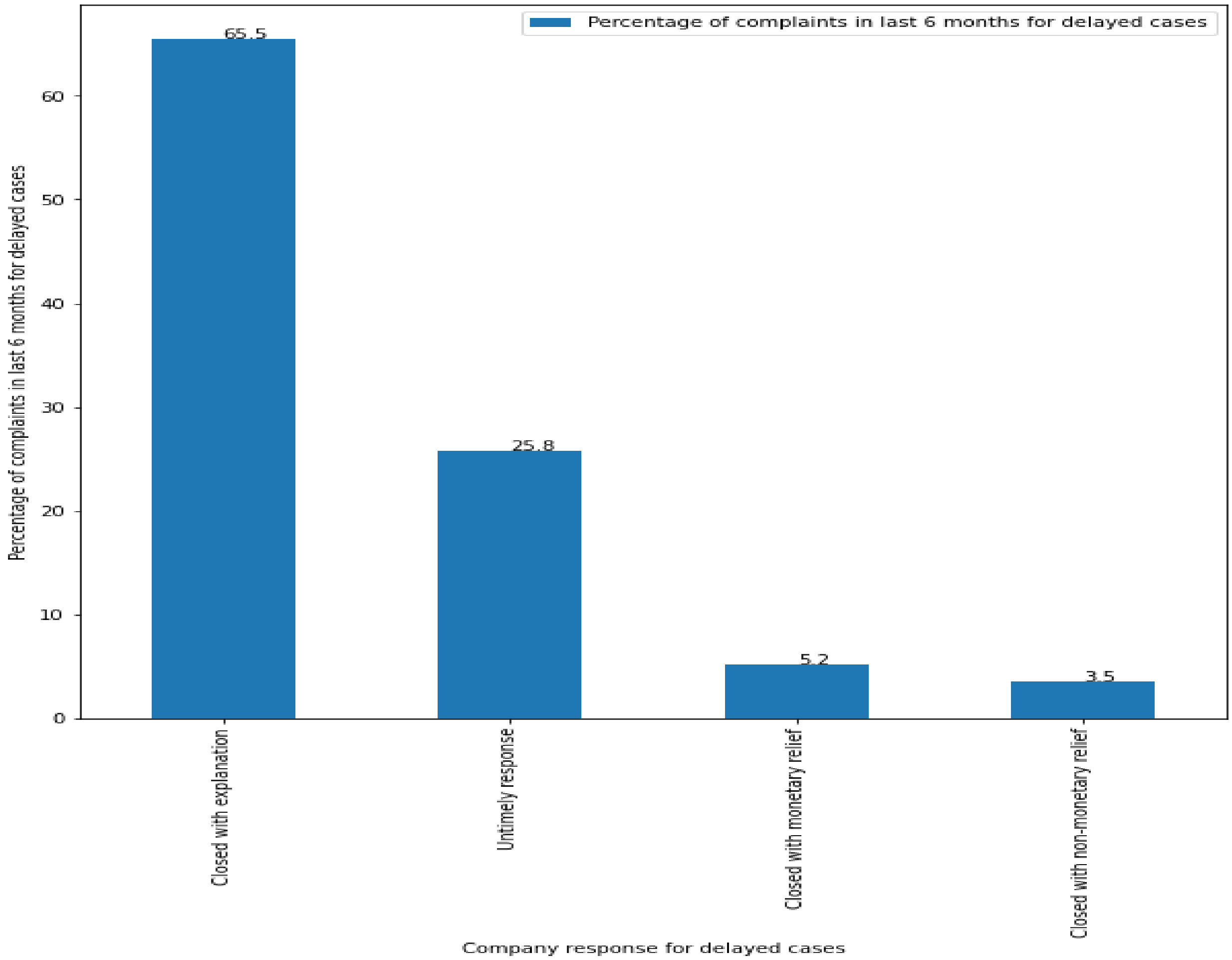
With Mortgage product line, we see that most complaints have been addressed with explanation. Monetary relief payments are higher overall and Non-monetary and in-progress cases are smaller in Mortgage category.

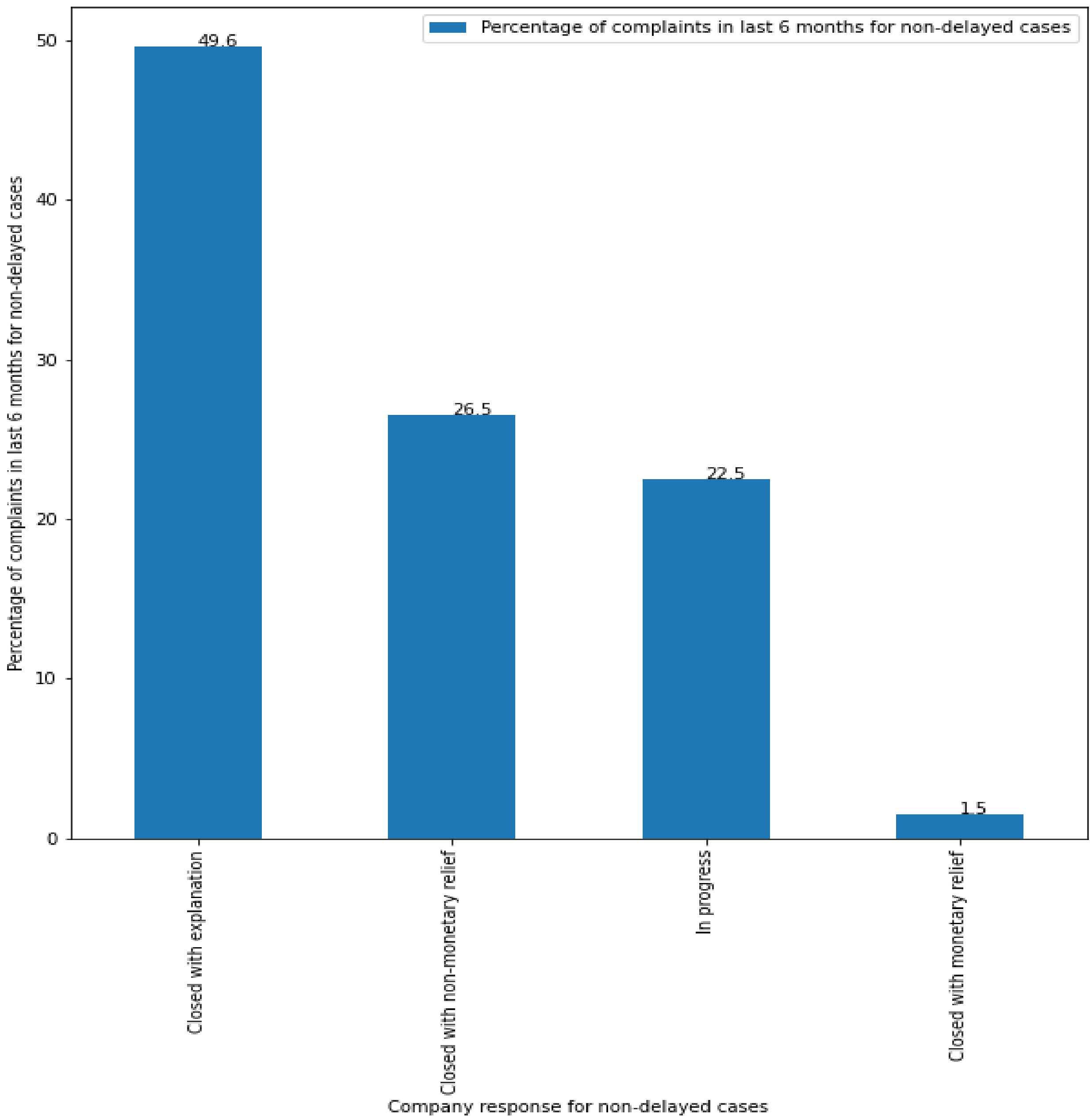


Clearly the monetary relief and non-monetary relief responses occupy a larger piece of the pie than the previous product category. So we see less cases of closed with explanation in Card complaints.It also is the highest when it comes to monetary relief cases.



After product wise analysis, we check how responses have compared with timeliness.





Delayed cases there were more monetary relief responses and higher explanation responses too. This could mean that companies when delay a response may have to compensate with monetary relief or vice versa. This leads us to investigate the potential effect of sentiments in the narratives on causing a delay or seeking a monetary response relief.

Preprocessing and Training:

We check the unique values in the features - Company, Sub-Issue and Zip code. Due to high cardinality, the columns may not help the model even if they were encoded. These features would be essential to a study examining the company influence or a detailed analysis of the issue at hand on the type of response. Similarly, since we have state information, a zip code level information would not be required in the current study. However here, we could limit the study to other columns with moderate cardinality and proceed with encoding.

We conduct a text analysis of the customer narratives to check on the most common words that are used. The target variable is selected as the Company response to the customer. We split into train and test sets with a 70: 30 ratios.

Our train set consists of Product, subproduct, issue company public response (if any), State, submitted via, Timely response(yes/no) and consumer consent provide? (yes/no).

Modeling and Conclusion:

We apply three classification models – Logistic Regression, Decision Trees, and Random Forest. We apply cross validation with Grid search on the models.

However, it is to be noted that in this multi class classification, the focus is on predicting a monetary relief response more accurately. Imagine a consumer is provided a response of monetary relief based on the prediction, but it turns to be otherwise. This would only make the consumer more unhappy.

Hence the following are two types of critical errors that we must look out for: Error 1: Actual is a monetary relief but the model predicted Explanation or non-monetary relief Error 2: Actual is explanation, non-monetary, In-progress or Untimely and the model predicted it as Monetary relief. Error 2 is severe than Error 1 as this could impact consumers trust on the CFPB.

Let us evaluate each model with respect to the total accuracy score and the two errors.

Model	Accuracy	Error-I	Error-II	Total Error
Logis Reg	0.783606	2291	163	2454
Dec Tree-I	0.779500	2085	1005	3090
Dec Tree-II	0.784700	2393	0	2393
RF-I	0.782420	2106	541	2647
RF-II	0.774700	2394	0	2394

The cross validated result is mentioned as II in each case.

Clearly, the second model of Decision Tree has no error two and scores better accuracy as well. The best params obtained by cross-validation is.

```
{'criterion': 'gini',
 'max_depth': 5,
 'min_samples_leaf': 1,
 'min_samples_split': 3})
```

So now we have developed a model to predict the type of response from the other parameters of the complaint.