Mining Consumer Complaints*

Extended Abstract†

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ABSTRACT

Upon browsing data on us.gov's website, the data file containing millions of data points on credit card, mortgages, and bank loan customer issues immediately caught our eye. Credit cards are plastic, a material so meaningless. That piece of plastic can cause you large sums of money if stolen and headaches if you experience problems. Nowadays, customers are encountering a myriad of problems with their credit cards. The technological advances associated with finances are growing at at a rate that can hardly be kept up with. This causes an overwhelmingly large amount of customer issues from incorrect account balances to identity theft. Since the plastic card is now a part of millions of Americans' everyday lives, we decided to find out what kind of trends can be found between certain companies – some companies have many more reports than others, what the complaint is – balance issues, student debt problems, mortgage issues, credit reporting, and consumer loans.

After discovering the large amount of customer issues, we wanted to find specific trends that correlated with the issues. Taking both the company and the problem, we were able to cluster these problems at their zip codes. By analysing the amount of customer issues along with specific zip codes, we were able to find specific problem areas. We quickly noticed that the problem areas we were seeing correlated very similarly to a population density map. Our most interesting finding occurred at the periphery of large cities – suburbs. Suburbs were a hotspot for mortgage issues, while the city centers showed little clustering of mortgage issues. Student loan issues were spread most widely. We believe this to be a result of the numerous locations of universities in all states and the densest cities not always hosting the largest schools in that state. If more trends can be found using deeper data, competing credit card companies can advertise their problem-free solutions in areas where customers are known to be experiencing issues. This would not only allow competing credit card companies a more efficient way to advertise to its customers, but it would also allow credit card companies to fix specific issues for the customers. This would clearly result in better service all around.

PROBLEM STATEMENT / MOTIVATION

In 2016 alone, The Federal Trade Commission reported 3 million accounts of credit card fraud or identity theft related complaints. If companies can find trends in data and narrow down fraudulent activity, they will be able to find solutions as to why common areas may be targeting users. We strive to find complaints about fraudulent credit or debit card use and link these issues to specific Card Companies as well as finding trends in common zip codes. Fraud most commonly occurs online or over the phone with credit card information stolen.

In 2016, 15.4 million Americans were affected by credit card fraud (Weisbaum, nbcnews.com). The number significantly increases every year and will continue to do so as the card robbers have better technology and strategies at their fingertips. This collection of data will hopefully shed some light on what the common factors are.

Figure 0:

HOW MANY CARDS DOES THE AVERAGE AMERICAN HAVE?

	None	1-2	3-4	5-6	7+	Mean (incl. those with none)	Mean (card owners only)
2014	29%	33%	18%	9%	7%	2.6	3.7
2008	22%	35%	22%	11%	9%	2.9	3.7
2006	20%	35%	23%	11%	8%	2.9	3.6
2004	21%	33%	25%	11%	8%	2.9	3.6
2002	17%	35%	23%	12%	11%	3.3	4
2001	22%	33%	23%	11%	9%	3.1	4

Source: Gallup[2]

Credit card ownership statistics. 2018. Found at https://www.creditcards.com/credit-card-news/ownership-statistics.php.

If trends can be caught in certain areas and logged, data mining can help make conclusions about where threats are posed and how to avoid them. Certain stores, zip codes, card companies, are all evidence that can be tied together and analyzed for results. We hope to find patterns based on the company used, credit card issue, and area that will help consumers and companies alike understand the types of credit card crimes that are common. We believe that by finding trends, patterns, and/or correlations between these certain attributes, it may help credit card companies become more secure, more reliable, and be able to offer the consumer a safer, better, and more secure experience while using their cards. If this is achieved, the overall confidence of the consumer in the credit card company will increase, benefiting both parties.

Figure 0 shows astonishing numbers of how many people in America own credit cards. For our purposes and many companies, this means a lot of potential to have issues. With almost 4 credit cards per person for those that do own them, that's 4 opportunities to go wrong and call up the hosting company.

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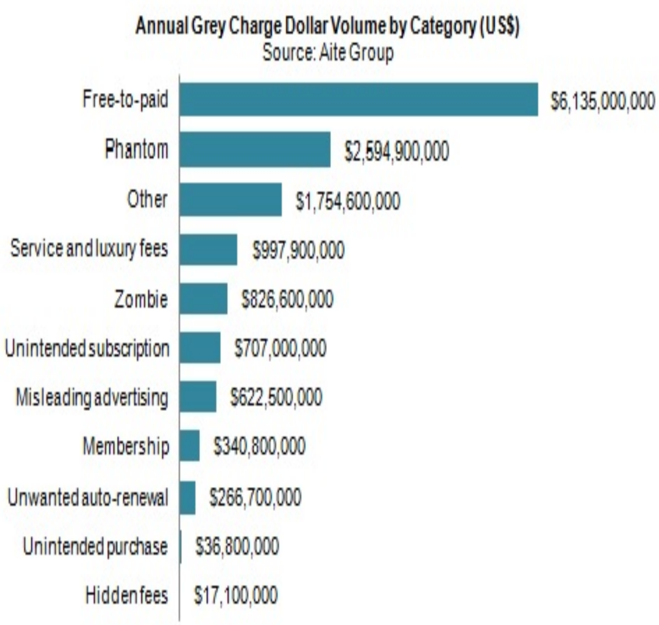
Gonzalez-Garcia, Jamie. igure 0: Credit card ownership statistics. 2018. Found at https://www.creditcards.com/credit-card-news/ownership-statistics.php.

1 LITERATURE SURVEY

Data in Action - Combatting Fraud: One company uses big-data analytics to find grey charges on user's credit cards and debit cards by drawing upon billing dispute data from the web, banks, and the CFPB's open consumer complaint database. 'Grey' charges are defined as lingering charges that a user previously signed up for a subscription or renewal service and may not be aware of the charge on their credit or debit card. While grey charges are not illegal, the user may not remember or have completely understood the terms presented and the charges can be misleading. Data.gov provides the highlight of a non-specific company combating grey charges using our same database, but the specifics of their analysis have not been released yet. Therefore, their research and techniques will not influence our Data Mining much, but it is important to note that work in this field is being conducted.

Figure 1:



The Economic Impact of Grey Charges on Debit and Credit Card Issuers. 2012. Found at https://aitegroup.com/report/economic-impact-grey-charges-debit-and-credit-card-issuers

Figure 1 clearly shows the Volume of Grey charges occurring in a single year – the front runner being free-to-paid subscriptions customers likely forget about. There is a fine line between fraud and grey charges and the described study works to understand the difference.

2 PROPOSED WORK

2.1 What Needed for Data Collection

It was fairly easy to collect our data. The Financial Services Consumer Complaint Database has been collecting this data for a long time and had a large data set that we were able to access and download. Since the data came from a .gov website, it was organized and formatted well and had plenty of data points. We also knew that since the data was collected by a government, then it was likely highly reputable and reliable. However, since it was such a large database, we knew that it would be more susceptible to error and empty data points, and would therefore not be perfect and would need cleaned up, a prediction which proved to be true.

2.2 Preprocessing

In order for our data to be usable, it will be necessary to clean up the large number of data points we have. Our data was organized well and due to it being collected from a good source, was formatted nicely. Inconsistent quotations will need to be synchronized and made consistent throughout the data set. There are many cases of empty cells, inconsistent formatting on cells, and partial zip codes. By getting rid of incomplete entries or making them zeros or empty strings, we should be able to make our data consistent, considering the data is in an excel type format. There are also several attributes that don't serve our purpose for the intent of this project that will also be removed.

Figure 2

Original:

Date receive	Product	Sub-product	Issue	Sub-issue	Consumer cc	Company pu	Company	State
3/12/14	Mortgage	Other mortg	Loan modification,collection,foreclosure				M&T BANK C	MI
10/1/16	Credit reporting		Incorrect inf	Account stat	I have outdat	Company ha	TRANSUNION	AL
10/17/16	Consumer Lc	Vehicle loan	Managing the loan or leas		I purchased a new car on X		CITIZENS FIN	PA
6/8/14	Credit card		Bankruptcy				AMERICAN E	ID
9/13/14	Debt collecti	Credit card	Communicat	Frequent or repeated calls			CITIBANK, N.	VA
11/13/13	Mortgage	Conventiona	Loan servicing, payments, escrow account				U.S. BANCOF	MN
6/15/15	Credit reporting		Credit report	Inadequate h	An account on my	Company ch	Experian Infc	VA
11/13/15	Mortgage	Other mortg	Loan modification,collection,foreclosur			Company be	Aldridge Pite	CA
10/21/14	Mortgage	Conventiona	Loan modification,collection,foreclosure				OCWEN LOA	FL
4/14/17	Mortgage	Other mortg	Loan modification,collection,foreclosur			Company be	Shellpoint Pa	CA
3/30/12	Student loan	Non-federal	Repaying your loan				Student Loar	MN
2/3/16	Debt collecti	Other (i.e. ph	Disclosure ve	Not given en	This company refuses to p		The CBE Grou	TX
1/7/15	Credit reporting		Incorrect inf	Account status			Experian Infc	NV
3/15/13	Credit card		Closing/Cancelling account				FIRST NATIOI	NY
7/18/16	Credit reporting		Incorrect inf	Account status			EQUIFAX, IN(	FL
2/17/16	Debt collecti	Credit card	Improper coi	Talked to a tl	This	Company ha	SQUARETWC	NE
11/7/14	Mortgage	Conventiona	Loan modification,collection,foreclosure				U.S. BANCOF	MT
4/17/15	Mortgage	FHA mortgag	Application, originator, mortgage broker				WELLS FARG	ME
3/9/16	Credit reporting		Incorrect inf	Information is not mine		Company ha	Experian Infc	CA
2/4/15	Debt collecti	Mortgage	Cont'd atten	Debt was paid			PHH Mortga	CA
3/17/17	Bank accoun	Checking acc	Making/receiving payments, sending m			Company be	UNITED SERV	WI
3/8/12	Mortgage	Other mortg	Loan servicing, payments, escrow account				Ditech Finan	CA
3/27/13	Mortgage	Conventiona	Loan servicing, payments, escrow account				NATIONSTAF	WA
2/25/14	Debt collecti	Other (i.e. ph	Cont'd atten	Debt is not mine			Navient Solu	RI
11/18/16	Mortgage	Conventiona	Settlement process and cc		Started the refinance of h		AMERICAN N	NJ
7/16/15	Mortgage	Conventiona	Application, originator, m		In XXXX, I and my ex-husb		HSBC NORTH	IL
11/3/15	Debt collecti	Medical	Disclosure ve	Right to dispute notice no		Company ch	Revenue Rec	FL
8/9/16	Credit reporting		Credit report	Problem with	I have disputed several ac		EQUIFAX, IN(	MS

Figure 3

Pre-processed:

Date receive	Product	Sub-product	Issue	Sub-issue	Consumer cc	Company pu	Company	State
3/12/14	Mortgage	Other mortg	Loan modific	empty	empty	empty	M&T BANK C	MI
10/1/16	Credit report	empty	Incorrect inf	Account stat	I have outdat	Company ha	TRANSUNION	AL
10/17/16	Consumer Lc	Vehicle loan	Managing th	empty	I purchased a	empty	CITIZENS FIN	PA
6/8/14	Credit card	empty	Bankruptcy	empty	empty	empty	AMERICAN E	ID
9/13/14	Debt collecti	Credit card	Communicat	Frequent or r	empty	empty	CITIBANK, N.	VA
11/13/13	Mortgage	Conventiona	Loan servicin	empty	empty	empty	U.S. BANCOF	MN
6/16/15	Debt collecti	Medical	Improper coi	Contacted er	empty	Company be	California Ac	CA
6/15/15	Credit report	empty	Credit report	Inadequate h	An account	Company ch	Experian Infc	VA
11/13/15	Mortgage	Other mortg	Loan modific	empty	empty	Company be	Aldridge Pite	CA
10/21/14	Mortgage	Conventiona	Loan modific	empty	empty	empty	OCWEN LOA	FL
4/14/17	Mortgage	Other mortg	Loan modific	empty	empty	Company be	Shellpoint Pa	CA
3/30/12	Student loan	Non-federal	Repaying you	empty	empty	empty	Student Loar	MN
2/3/16	Debt collecti	Other (i.e. ph	Disclosure ve	Not given en	This compan	empty	The CBE Grou	TX
1/7/15	Credit report	empty	Incorrect inf	Account stat	empty	empty	Experian Infc	NV
3/15/13	Credit card	empty	Closing/Canc	empty	empty	empty	FIRST NATIOI	NY
7/18/16	Credit report	empty	Incorrect inf	Account stat	empty	empty	EQUIFAX, IN(	FL
2/17/16	Debt collecti	Credit card	Improper coi	Talked to a tl	This	Company ha	SQUARETWC	NE
11/7/14	Mortgage	Conventiona	Loan modific	empty	empty	empty	U.S. BANCOF	MT
4/17/15	Mortgage	FHA mortgag	Application,	empty	empty	empty	WELLS FARG	ME
3/9/16	Credit report	empty	Incorrect inf	Information i	empty	Company ha	Experian Infc	CA
2/4/15	Debt collecti	Mortgage	Cont'd atten	Debt was pai	empty	empty	PHH Mortga	CA
3/17/17	Bank accoun	Checking acc	Making/rece	empty	empty	Company be	UNITED SERV	WI
3/8/12	Mortgage	Other mortg	Loan servicin	empty	empty	empty	Ditech Finan	CA
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2/25/14	Debt collecti	Other (i.e. ph	Cont'd atten	Debt is not m	empty	empty	Navient Solu	RI
11/18/16	Mortgage	Conventiona	Settlement p	empty	Started the r	empty	AMERICAN N	NJ
7/16/15	Mortgage	Conventiona	Application,	empty	In XXXX, I an	empty	HSBC NORTH	IL

2.3 How Mining Consumer Complaints is Different from Previous Work

For what we would like to do, we will not be looking at the types of charges that were made on the credit cards. We will be looking at the complaint, how the complaint was handled, the credit card company used, etc., without going into depth on purchases made with the credit cards. We wanted to avoid the purchases and financial part of the data, and focus on the customer service response from the customer complaint.

3 DATA SET

We are using the Financial Services Consumer Complaint Database found at: https://www.data.gov/consumer/. Currently downloaded on Cary's Mac (469 MB). Within the data set there are 18 attributes to include: 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, and Complaint ID. These attributes and data accumulate to over 17 million data points.

Some of the attributes are not completely necessary for our project's use. For instance, "consumer complaint narrative", "tags", and "company public response" were all too frequently blank to be useful. In this event, we decided to go ahead and delete those.

4 EVALUATION METHODS

Our results were mostly evaluated visually. We continued to learn that our results are about as complex as we want to make them. Narrowing our solutions down to zip codes and what kind of issues customers are having in those zip codes simplified our evaluation.

Evaluation mostly took place in the form of graphs and analyzing "what can this graph tell us." It was extremely useful once we were able to visualize how the data looked in relation to other attributes. For example, once we graphed the customer issues in relation to the zip code of the consumer, we were able to see where the issues were coming from and the concentration of the issues around certain areas within the United States. This helped us visualize where the hot spots of consumer complaints were coming from and what that meant depending on the issue that was more common within that area. Additionally, we were able to learn equally as much from issues we didn't find concentrated around urban areas or areas of high population density. For example, student loan issues were an issue that seemed to be equally spread around and across the United States.

5 TOOLS

We used Python and tools and libraries within such as mathplotlib, pandas, numpy, etc. Python and mathplotlib were used to create graphs and representations of our data that were helpful in visualizing our data and in seeing patters and connections within out data set. Pandas was used primarily for cleaning the data and filling in or deleting null entries. Pandas was also used to normalize the data, making it more consistent throughout. Also, we hoped to get familiar with WEKA in order to take advantage of its evaluation tools, however we found that that didn't seem necessary because we were able to get a good understanding of our data through the tools listed above, and WEKA proved more difficult for us to understand and effectively utilize than we had previously thought.

6 MILESTONES

Our milestones were originally spaced out fairly evenly throughout the semester in order to give us time to work on each milestone. However, the dates set for our milestones were essentially thrown out, as certain milestones took much longer than anticipated and others took less time. The milestones were helpful in giving us a checklist of things we needed to complete and needed to get done in order to complete our project and data analysis.

6.1 Milestones Completed

- All data cleaned up and groomed – 19 March.

Cleaning took a very long time with millions of data points. We decided to fill the empty cells with a null value since deleting said columns or averaging would skew the data too much. Below in the "Results so far" category is a side-by-side comparison of what the empty cells look like with an "empty" filling them.

- Simple scatter plots and data correlation – 2 April.

This milestone took us longer to complete due to the unexpected effort for cleaning.

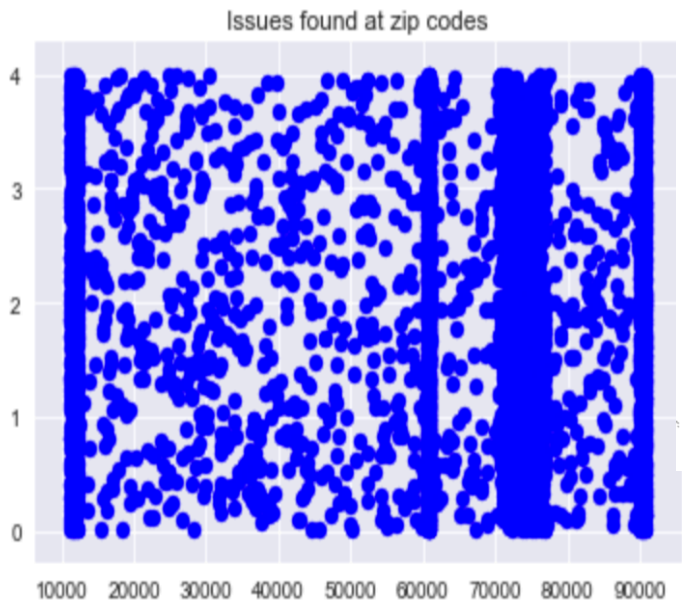
- Using methods such as clustering and sequential patterns based on previous findings – 13 April.

We ended up using mostly clustering in our analysis as we found that this was a great way to visualize our data and let us see how out data was connected in ways we might not have seen before.

- Analysis of all results – 19 April.
- Refactoring – 23 April.
- Final analysis and conclusion – 26 April.

RESULTS SO FAR

Figure 4:



The above scatter plot compares issues vs. zip codes. In order to produce a scatter plot we could not use string names as an axis. Therefore, the numbers on the y-axis correlate to: 0 as bank issues, 1 as mortgage, 2 as debt collection, 3 as student loans, and 4 as general. This graph does not include all zip codes. We specifically wanted to try out some ranges and the results are obvious. The distinct columns that you see are heavily populated cities. The column right about 10000 contains New York and surrounding zip codes. This is our second most dense area. The column right about 60000 is the Chicago/Illinois area. The very thick column right about 75000 is mostly Texas but also includes states such as Colorado and New Mexico because their zip codes are packed so tightly together. Finally, the last column and the right is Los Angeles, CA and the tight circle around them. These zip code areas can be seen in the map below.

Figure 5:

Code Zones

//www.unitedstateszipcodes.org/images/zip-codes/zip-codes.png

Producing these types of scatter plot let us visually confirm the heat maps of the united states.

We’ve done a lot of data cleaning, filling empty cells with "empty" to allow for uniformity. This will make it easier once we finish out analysis and apply our code to the data.

Figure 6:

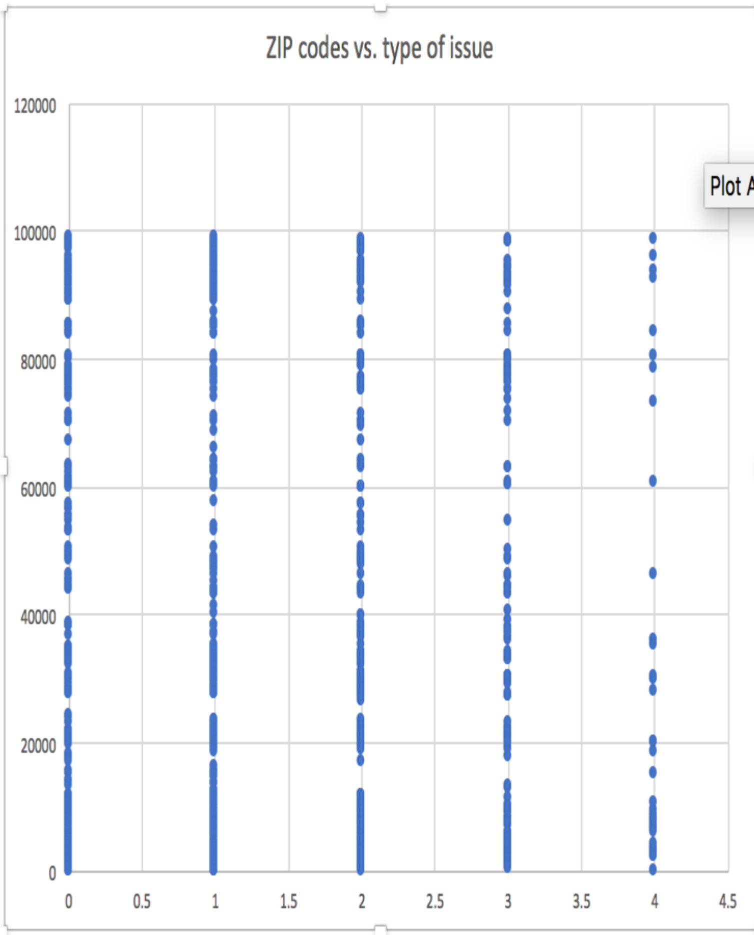


Figure 6 plot is a different technique used in figure 4. Instead, by changing the zip codes to the y-axis and the type of issue to the x-axis, we can instead see the volume of *issues* as opposed to volume at zip codes. We found this useful because there is still density at certain zip codes on the left but we can clearly conclude that, 1 Mortgages, is our biggest issue among credit card users.

This is a condensed sample size from the millions of data points for a cleaner visual.

MAIN TECHNIQUES USED

The main technique we used was clustering. We ed out trying to cluster using multiple attributes, found that to be too noisy and messy, making it ossible to extrapolate and conclusion off of the ts. We then decided to cluster using much fewer butes, just zip code and the issue reported.

results were mostly evaluated visually. We inued to learn that our results are about as plex as we want to make them. Narrowing our ions down to zip codes and what kind of issues omers are having in those zip codes simplified our uation.

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Figure 7:

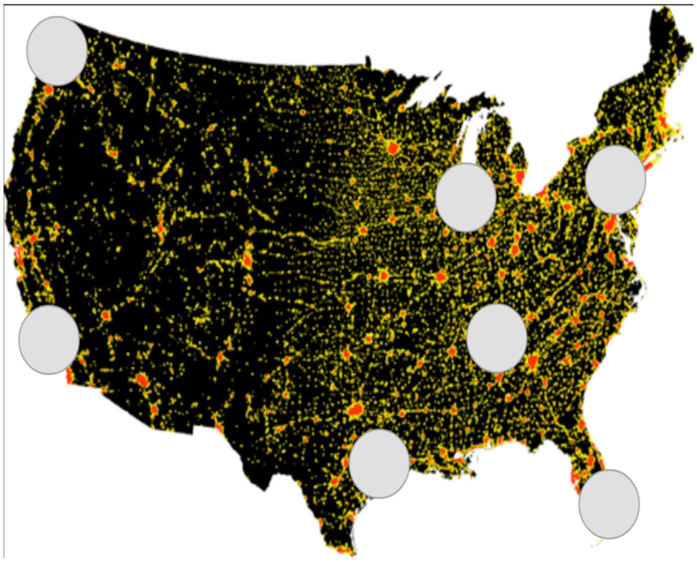

Figure 7 acts as a visualization for clustering around dense areas. The circles are found on Seattle, Los Angeles, Chicago, Austin, Miami, New York, and Nashville.

The clustering methods resulted in the exact solution we expected since it was not a very complex mining technique on limited attributes.

KEY RESULTS

Working with a data set of 14 million data points proved difficult, yet far from impossible. Following the clustering of our data, the main thing we noticed was that the issues reported by the consumers were mostly coming from densely populated areas, i.e. urban areas and cities. This made sense to us, since cities and urban areas provide more opportunities for credit card use than a rural area would. This also makes sense since cites will have the higher populations and therefore more people using credit cards or taking out mortgages**,** which means that there will be more issues with these products. The only thing that seemed to be a little surprising were which cities had a higher number of issues. The greater Nashville area was a city that had a number of issues similar to larger cities like Los Angeles, Austin, and New York City.

We also noticed that one issue seemed to be exclusive to the urban/suburban area, and that issue was mortgage or FHA mortgage issues like loan modifications. This made sense since suburban areas are where most people go to start a family, and therefore purchase a house. Within cities however, the number of mortgage issues was much lower. We believe this to be because within cities, many people choose to rent over purchasing a home or apartment.

One product and issue that did not appear to be tied to a geographical area was student loans. Student loans appeared to be evenly distributed across the United States. Colleges and universities are spread out fairly evenly across the United States, with a slight concentration around larger cities.

Unfortunately, we found that most results were pretty noisy. If we were to do this again we would like to take the time to use more intelligent data mining software than go through the headache of using simple tools like excel or pandas to plot hundreds of thousands of data. The data inside of the spreadsheet is really valuable and if used correctly could show some very unique trends.

APPLICATIONS

Credit card fraud is a huge issue facing America and credit card companies need to do everything in their power to stop it, or at the very least, make it much more difficult to do, and be able to detect it, and prevent it from getting worse when it is detected. It is pretty evident from our results that credit card companies can do more to protect urban consumers more. Large companies that have a large number of urban clientele should vastly increase their security and fraud detection. Making this a priority and successfully implementing better security will increase credibility and trust in the company. An increase in trust benefits both parties, as consumers have a better user experience and can trust in using their cards without the risk of fraud or theft, and companies benefit from an increase in customers because they are more trustworthy.

Small companies can benefit from the results of our research by strategically locating themselves. Since smaller businesses likely don't have the money or resources to increase their fraud protection algorithms and software, it would be beneficial for them to locate themselves in areas with lower fraud issues. Less urban areas have less issues, and therefore are better places to start out a small company.

We just barely scraped the tip of the iceberg looking at zip codes vs. issue. A lot can be done with this data, however. There is an attribute "tags" that briefly describes each customer who called or mailed in an issue. Classifying customers bring demographic to a whole new level along with zip code and type of issue. There is also a customer ID attribute. There are customers who call more than once and that attribute can be pitted against the issues they are having, where they are from, and if one company is likely to have two or more issues per person. What would those averages look like?

Another interesting feature to look at would be how many cards each person has. Even if the cards aren't all from the same company, they could consider a question along the lines of "does having more credit cards lead to more issues, or even someone who is more likely to call in their issues?"

We completely overlooked the date attribute as well. Date is always a useful correlation tool because statistically credit card usage has increased over time. With this increase in overall usage it would be beneficial to see what kind of issues are increasing along the way. Or what states are having more issues than before.

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