Medica Case Study Report

Catalogue

Executive Summary

The mission of this project is to perform statistical analysis on given data and try to find any possible solution to optimize the process cycle and cross-training. Since we received two versions of data which contain slightly different variables, we are going to identify outliers regarding each dataset.

Our approach is to first clean the data and create dummy variables for further analysis. And we look at the full scope of the dataset and come up with some hypotheses. We decide to take a close look at cycle time and its relationship with other clusters such as claim type, line of business, and processor's name. Cross tabulation is our main approach on dealing with categorical variables with multiple outputs like processor's name.

We visualize our results in histogram and pie-chart and find out those important features to perform further analysis. Our group utilizes logistics regression and multinomial regression to filter independent variables and find out any significant correlations between cycle time and various clusters.

Based on our findings, here are some suggestions we are going to offer:

- Make processors focus more on quality over quantity.
- System should react more efficiently, reducing the delay between system audit and manual audit.
- Spend more resources on training Institutional claims.

Team members Bios

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Background

Medica discovered that people had trouble comprehending American healthcare system. Therefore, the company decided to bring medical claims processing in-house in 2014. However, Medica actually lacked the ability to manage the inventory, resulting in serious backlogs. During this time, not only the costs of employees and claims interest payment increased, but also faced the problem of the abrasion of providers, members, employers as well as employees. Looking closer to the issue, another essential part in this problem is the processing time, which would be affected by medica's claim operation staff and the yearly trend of claims.

Medica eagered to find ways to solve this dilemma, mainly figuring out the reason for backlogs. Addition, setting up an optimal inventory target with the goal of minimizing processing costs. Finally, find a staffing model that can help Medica to allocate work to each employee as well as determine the needs of the hiring and training program.

Scope

Assumptions:

1. There is a relationship between bad claims and touch counts.
2. There is a relationship between bad claims and processors.
3. We made a hypothesis that there exists some relationships between cycle time and each cluster.

Limitations:

- There are two columns of claim type, one includes only professional and institutional. The other one not only includes these two but also contains outpatients and MSHA. We just analyzed the first column of claim type.

And since there is an enormous amount of categorical data in the “Place of Service” cluster, we are not able to analyze it by multiple regression methods. Otherwise, the report we received from the SPSS would be too tough and lengthy to read.

- We do not have access to processor’s information on Individual Family Business (IFB)’s claim. When proving the hypothesis of the relationship between cycle time and processors, we can only test it on Commercial claims.

- For further analysis on bad claims, we would like to know each tiers of claims. For example, if you can split claims levels into different groups, we would be able to identify each processor’s performance more precisely.

- We are unable to know why claims are rejected or denied, so we do not have enough information to explore the cause of denied and rejected claims. We are mainly going to find any relationships in bad claims only.

- Due to the limited resources, when finding who closed the bad claims, we only see the last one who closed the claims. But for adjustment claims, there are multiple touches on claims. It would be better if we are given all processors’ names who touch claims.

- There is also some data that needed further cleaning or further information. Some have blank values, or repeated categories, others like current indication and authentic indication requiring more explanations.

Data Analyzed

We investigated the correlation between cycle time and various clusters of the data. We first tried to clean the data and create variables that are going to be dependent and independent variables such as bad_claims, cycle_time, total_touch_counts in Python. Then we split data into different subsets to investigate the correlations within clusters, for example, Line of Business, Claim Type, Transaction Data, and Place of Service. Then we tried to visualize the bad claims and its causes using cross tabulation. After dealing with data, we utilized SPSS to build regression models and tried to find if there are any relationships between each cluster and cycle time.

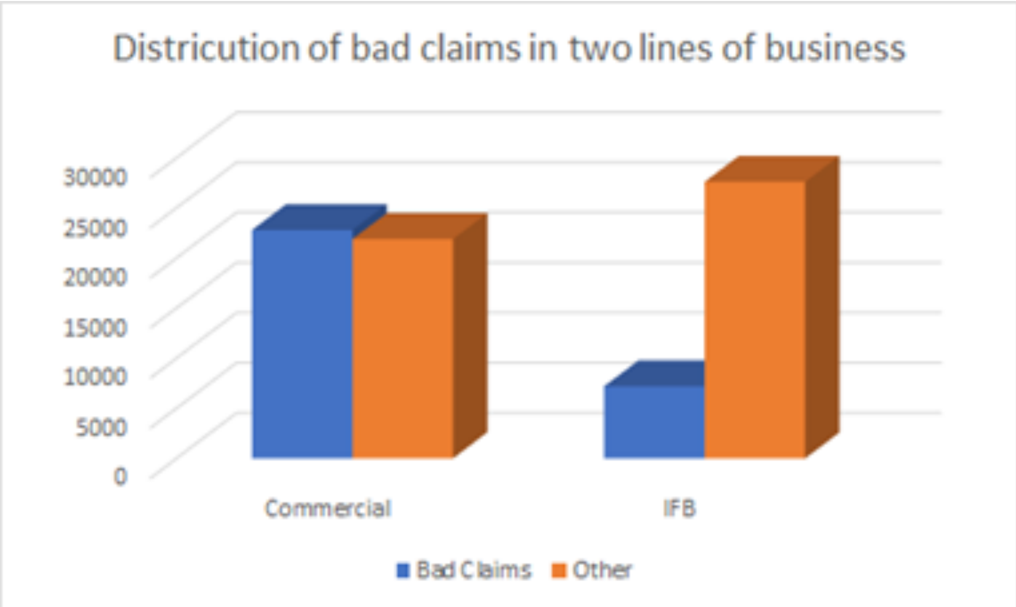
We investigated the correlation between cycle time and various clusters of the data. During the process of analysis, we used data processing softwares to clean the datasets, such as figuring out the outliers, eliminating empty values, and plotting graphs to visualize the data. After dealing with data, we utilized SPSS to build regression models and tried to find if there are any relationships between each cluster and cycle time.

Interpretation of Data

We define the **bad claim** as the claim is processed in the final transaction with more than 30 days of cycle time and have allowed billed more than 0.

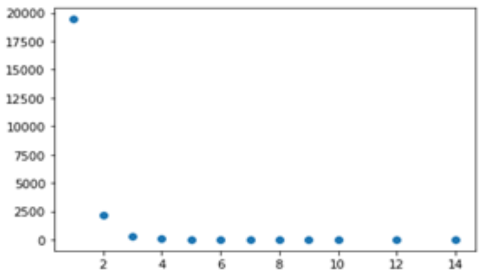
Analysis of touch count:

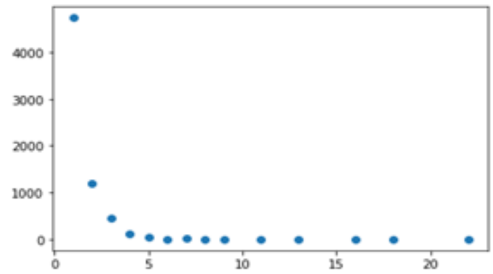
Medica has two lines of business: Commercial and IFB. 51.0% of the commercial claims are bad claims and 20.7% of IFB claims are bad claims.



We try to prove our hypothesis that there is a relationship between bad claims and touch count. To do that, we add up touch counts with the same ID and have two scatter plots shown blows:

Distribution For Bad Commercial Claims   Distribution For Bad IFB Claims



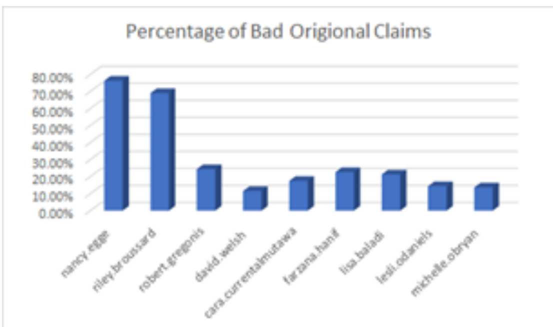


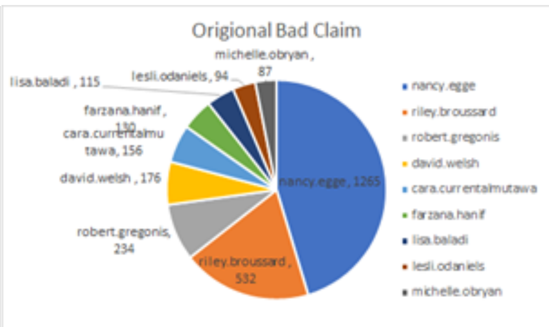
From the two scatter plots shown above, we can see that there are outliers in the bad claims, but it takes very little portion of whole data. Over 95% of bad claims have less or equal to 3 Touch Counts in total indicating that there is not significant relationship between cycle time and touch count.

Analysis of processor's performance

For the two datasets we received, variables are slightly different. We would like to give a deeper analysis on IFB business, but unfortunately, we don't have access to the employer information as well as Workbasket about IFB business. So, we are only going to find the relationship between bad claims and processors in the commercial aspect.

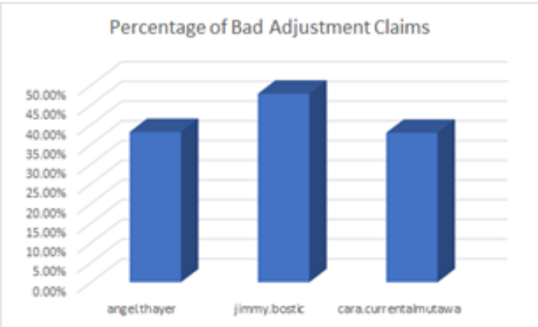
Out of those bad commercial claims, we split it into two parts: original claims and adjustment claims. The original claims are mostly reviewing and repairing, and adjustment claims are mostly dealing with NonWB Item. We listed each employee's percentage of ending with a bad claim.

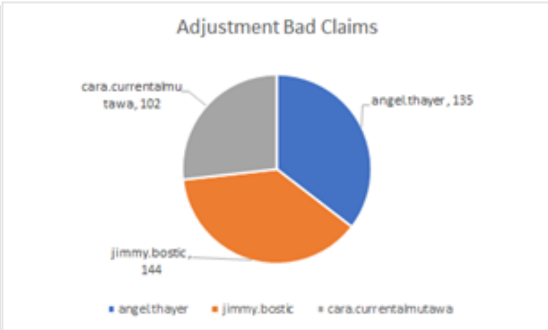




We consider **SA_ClmOpsQAWSUser** is the system bot and hence we don't compare its performance with other processors.

Among bad original claims, two processors have relatively high percentages of closing bad claims: Nancy Egge and Riley Broussard who also process the top 2 total bad claims. Unfortunately, there is not much information explaining the reason for the bad claims. Maybe Nancy and Riley are supervisors who oversee those bad claims, we do not have enough evidence to conclude that their performances are awful.



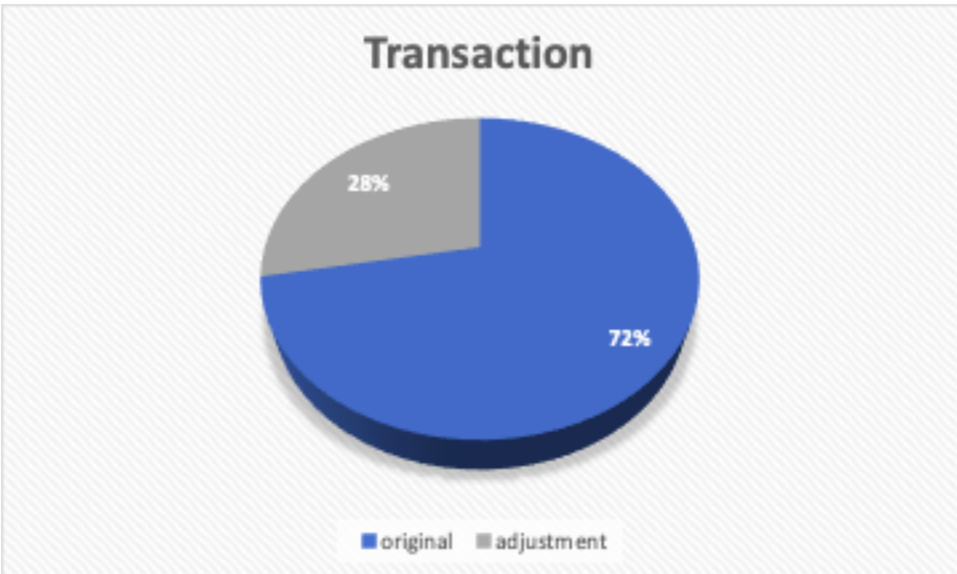


SA_ClmOpsQAWSUser	331
	187
jimmy.bostic	144
angel.thayer	135
cara.currentalmutawa	102

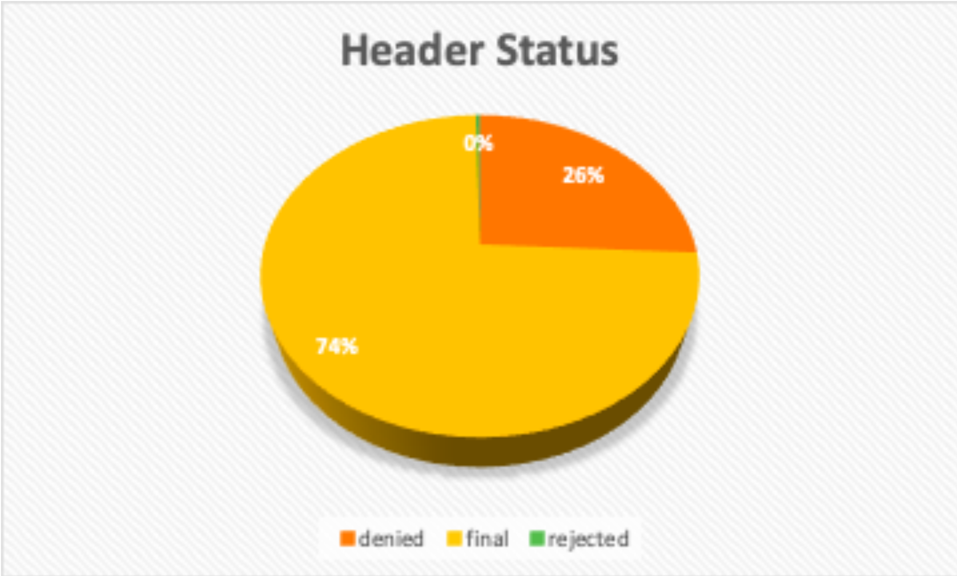
Among adjustment bad claims, three processors are doing equally poorly. All of them have over 40% of closing bad adjustment claims, and their numbers are close. Also, there are 187 missing values which is larger than other three processors' claims. We can conclude that bad adjustment claims are processed by three processors and they have similar performance meaning that there is no significant relationship between processors and bad claims given adjustment claims.

Clusters of the data:

1. Transaction data: Original, Adjustment

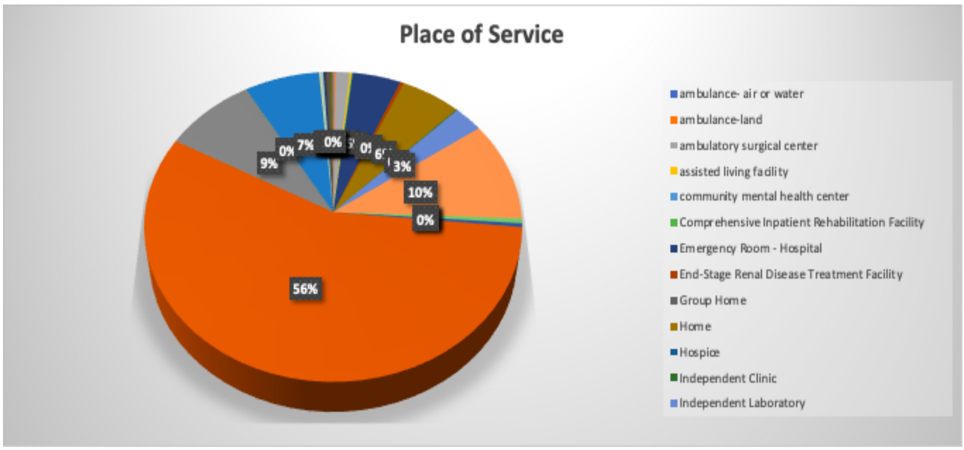


2. Claim Header status: Denied, Final, Rejected



3. Claim type: Professional, Institutional

4. Place of Service: Home, office, Other places



- Correlation between bad claim and Claim Type:

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	CLAIM_TYPE_CD_DESC (1)	.262	.024	122.229	1	.000	1.300	1.241	1.361
	Constant	-.532	.008	4781.848	1	.000	.588		

a. Variable(s) entered on step 1: CLAIM_TYPE_CD_DESC.

Categorical Variables Codings

		Frequency	Parameter coding (1)
CLAIM_TYPE_CD_DESC	Institut	8106	1.000
	Professi	72589	.000

Dependent Variable Encoding

Original Value	Internal Value
False	0
True	1

Based on the report we got from SPSS, we can see that p-value is smaller than 0.05, which indicates that we can reject the null hypothesis which is supposing that there isn't any relationship between bad claim and claim type. In addition, the confidence interval doesn't include 1, which also approved that there is a kind of correlation between these two variables. Since the Exp(B) is 1.3, we can conclude that the odds ratio of Institutional claim type of being bad claims is about 1.3 times of the odds ratio of professional claim type of being bad claims. In a word, institutional claim type is more likely to be a bad claim.

Correlation between Transaction code and bad claim

Categorical Variables Codings

		Frequency	Parameter coding (1)
TRANSACTION_CD_DESC	Adjustme	22532	1.000
	Original	58163	.000

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	TRANSACTION_CD_DESC(1)	-.160	.016	95.147	1	.000	.853	.826	.880
	Constant	-.461	.009	2927.710	1	.000	.631		

a. Variable(s) entered on step 1: TRANSACTION_CD_DESC.

From this report, we can find that p-value is also smaller than 0.05, which means that there exists a sort of relationship between bad claim and transaction code. The confidence interval doesn't contain 1, which approved our hypothesis as well. 0.853 exponential value of B indicates that the odds ratio of a claim with adjustment transaction code being a bad claim is 0.853 times the odds ratio of a claim with original transaction code being a bad claim.

Correlation of bad claims and other factors

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	cycle_time	-.014	.000	6107.349	1	.000	.986	.986	.986
	CURRENT_INDC(1)	.329	.029	127.576	1	.000	1.389	1.312	1.471
	SVC_TYPE_CD			159.366	4	.000			
	SVC_TYPE_CD(1)	.172	.183	.880	1	.348	1.188	.829	1.701
	SVC_TYPE_CD(2)	.361	.197	3.378	1	.066	1.435	.976	2.110
	SVC_TYPE_CD(3)	.178	.031	33.822	1	.000	1.195	1.125	1.269
	SVC_TYPE_CD(4)	-.588	.073	65.775	1	.000	.555	.482	.640
	LINE_OF_BUSINESS			4350.216	2	.000			
	LINE_OF_BUSINESS(1)	-.616	.070	76.545	1	.000	.540	.470	.620
	LINE_OF_BUSINESS(2)	-1.187	.018	4343.913	1	.000	.305	.295	.316
	Constant	1.798	.033	3038.314	1	.000	6.038		

a. Variable(s) entered on step 1: cycle_time, CURRENT_INDC, SVC_TYPE_CD, LINE_OF_BUSINESS.

We conducted a logistic model to find the relationship between bad claims and other factors, through the test we know that bad claims are possibly related to some of the important variables, like service type, line of business, current indication and cycle time. According to the outcome, we can conclude that with the increase of cycle time, the odds of being a bad claim would decrease nearly 1.1 times. When current indication shows value, the odds of bad claims would increase 1.4 times compared to no value. For service type, only type 3 and type 4 (inpatient type and professional type) are significant. It shows that, compared to type 5, the odds of bad claims would increase 1.1 times when the claim is inpatient type and decrease about 2 times when the claim is professional type. Line of business is also significant. Line of business 2 represents commercial type claim, therefore, the odds of bad claims would decrease 3.3 times when it is a commercial type compared to other types. Because the variables of line of business have some blank value, it would be hard to interpret the effect of individual type of claims and commercial type of claims alone. So, we use additional analysis to find out.

Correlation of bad claims and other factors split by line of business

Variables in the Equation[a]

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[b]	cycle_time	-.023	.000	5011.499	1	.000	.977	.976	.978
	CURRENT_INDC(1)	-.195	.047	16.981	1	.000	.823	.750	.903
	SVC_TYPE_CD			446.831	4	.000			
	SVC_TYPE_CD(1)	.852	.227	14.081	1	.000	2.345	1.502	3.660
	SVC_TYPE_CD(2)	.651	.456	2.039	1	.153	1.917	.785	4.686
	SVC_TYPE_CD(3)	.564	.046	153.526	1	.000	1.758	1.608	1.922
	SVC_TYPE_CD(4)	-.981	.094	109.719	1	.000	.375	.312	.451
	Constant	1.940	.045	1885.817	1	.000	6.957		

a. LINE_OF_BUSINESS = Individual Family Business (IFB)

b. Variable(s) entered on step 1: cycle_time, CURRENT_INDC, SVC_TYPE_CD.

To see the effect of line of business better, we use split to do the analysis under the separation of different kinds of claims. However, under the effect of commercial claims, most of the variables are not significant and the goodness of fit of the model is not ideal, therefore, we can only see when the claim is an individual family business, and it has a similar effect as the unsplit one.

Conclusion

We have found that the SA_ClmOpsQAWSUser closes over 800 bad claims meaning that there is either someone processes the claim and lets the system close the claim or the system itself takes too long to close the claim. Either way, the company should make the system run more efficiently and reduce the delay time between system audit and processor.

The other suggestion would be trying to assign claims to processors that are capable of doing these. Sometimes it is invertible either because it is missing information, or it takes longer to audit the claim. Try to train the processor to not chase for quantity but quality instead.

For adjustment claims, there is around 50% chance that it is going to be bad claims. So, we need more workforce processing the adjustment claims as it showed before, only three processors are doing claims, they might need some help. Or the company needs to avoid multiple touches just like the previous suggestion.

Based on the analysis above, we can conclude that the probability of being a bad claim can be influenced by different clusters. In the cluster of claim type, institutional claim is more likely to be a bad claim compared to the professional claim. And in the cluster of transaction code, a claim with original transaction code is more likely to be assessed as a bad claim. Therefore, we suggest that the company needs to concentrate more on training employees' ability to deal with the institutional claim. Furthermore, bad claims have relationships with other variables, such as service type, line of business and so on. Due to the limitation of the length of the report, we cannot illustrate each one of them here. Perhaps they will come with the following detailed report.