

Complaint Narrative Summarization

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Main Purpose

• Users: Workers who process complaint narratives

 Benefit: Summarization can help them grasp important information and consequently improve processing efficiency



Two Approaches

- Text Summarization
- -Extract important sentence in narratives

- Sub-issue Prediction
- -Sub-issue can be blank
- -Sub-issue variable gives detailed summary of problems than issue variable



Text Summarization

• Algorithm:

- -Assume frequent word is important
- -Calculate word frequency in narratives (except for stop words and punctuation)
- -Extract sentence containing frequent terms

• Benefit:

- -Achieve summarization without other input
- -No black box

Disadvantage:

- -Wrong assumption
- -Extraction miss important information



Sub-issue Prediction

Model:

- -Logit Model
- -SVM model
- -Pre-trained word embeddings model
- -LSTM model

• Benefit:

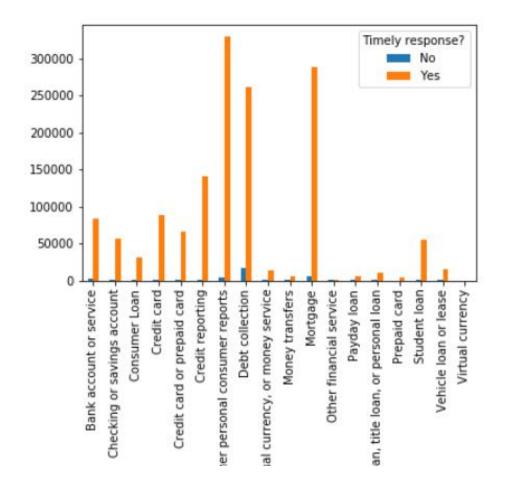
- -Advanced method
- -Sub issue returns summary instead of extraction

• Disadvantage:

- -Need additional input data (sub-issue variable)
- -Too many sub-issue as dependent variable: Take subset of narratives with similar product/issue

Sub-issue Prediction - Dataset

Overview of data with narratives



Focus on

- Products of loan
- -Payday loan, title loan, or personal loan
- -Credit reporting, credit repair services, or other personal consumer reports
- -Payday loan
- Issue: Incorrect information on your report
- Total 75799 narratives

Sub-issue Prediction-Model performance

 Logit model 		precision	recall	f1-score	support
	Information belongs to someone else	0.76	0.77	0.77	1939
	Account status incorrect	0.80	0.78	0.79	1935
	Account information incorrect	0.84	0.83	0.84	1851
	Personal information incorrect	0.96	0.97	0.97	1965
	Old information reappears or never goes away	0.94	0.92	0.93	1978
	Public record information inaccurate	0.96	0.97	0.97	1906
	Information is missing that should be on the report	0.95	0.97	0.96	2019
	accuracy			0.89	13593
	macro avg	0.89	0.89	0.89	13593
 SVM model 	weighted avg	0.89	0.89	0.89	13593
		precision	recall	f1-score	support
	Information belongs to someone else	0.84	0.85	0.84	1939
	Account status incorrect	0.87	0.84	0.86	1935
	Account information incorrect	0.87	0.83	0.85	1851
	Personal information incorrect	0.97	0.99	0.98	1965
	Old information reappears or never goes away	0.95	0.95	0.95	1978
	Public record information inaccurate	0.97	0.98	0.97	1906
	Information is missing that should be on the report	0.97	0.98	0.97	2019
	accuracy			0.92	13593
	macro avg	0.92	0.92	0.92	13593
	weighted avg	0.92	0.92	0.92	13593

Sub-issue Prediction-Model performance

 Pre-trained word embeddings model 	precision	recall	f1-score	support
Information belongs to someone else	0.46	0.01	0.02	1070
Account status incorrect	0.62	0.18	0.28	1107
Account information incorrect	0.94	0.46	0.62	2444
Personal information incorrect	0.06	0.85	0.11	135
Old information reappears or never goes away	0.36	0.34	0.35	321
Public record information inaccurate	0.75	0.67	0.71	323
Information is missing that should be on the report	0.82	0.45	0.58	263
micro avg	0.45	0.34	0.39	5663
macro avg	0.57	0.42	0.38	5663
weighted avg	0.72	0.34	0.42	5663
• LSTM model	0.34	0.34	0.34	5663
	precision	recall	f1-score	support
Information belongs to someone else	0.76	0.17	0.28	1070
Account status incorrect	0.64	0.41	0.50	1107
Account information incorrect	0.91	0.69	0.79	2444
Personal information incorrect	0.28	0.47	0.35	135
Old information reappears or never goes away	0.48	0.48	0.48	321
Public record information inaccurate	0.70	0.82	0.76	323
Information is missing that should be on the report	0.61	0.70	0.65	263
micro avg	0.74	0.53	0.62	5663
macro avg	0.63	0.54	0.54	5663
weighted avg	0.76	0.53	0.60	5663
samples avg	0.53	0.53	0.53	5663



Thank You~