Proactive Detractor Detection Framework Based on Message-Wise Sentiment Analysis Over Customer Support Interactions

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1. Introduction

We propose a framework relying solely on chat-based customer support (CS) interactions for predicting the recommendation decision of individual users in the scope of the Net Promoter Score (NPS). For our case study, we analyzed a total number of 16.4k users and 48.7k customer support conversations within the financial vertical of a large e-commerce company in Latin America. Consequently, our main contributions and objectives are to use Natural Language Processing (NLP) to assess and predict the recommendation behavior where, in addition to using static sentiment analysis, we exploit the predictive power of each user's sentiment dynamics. Our results show that, with respective feature interpretability, it is possible to predict the likelihood of a user to recommend a product or service, based solely on the message-wise sentiment evolution of their CS conversations in a fully automated way.

2. Detractor Detection Framework Based on Sentiment Analysis

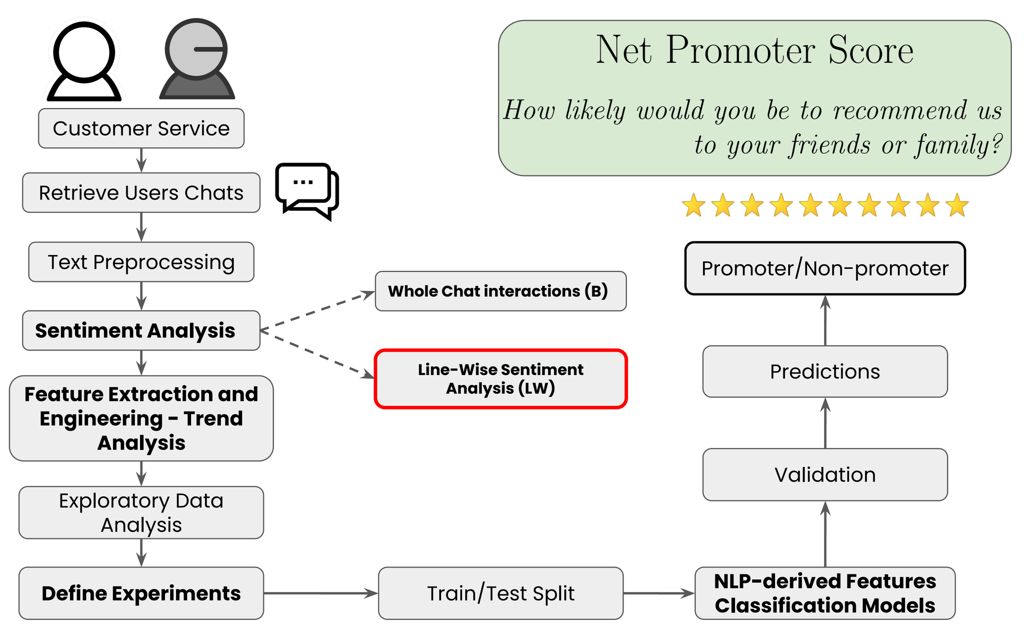


Figure 1: Our proposed framework for proactive *promoter/non-promoter* user detection for any chat-based user interaction.

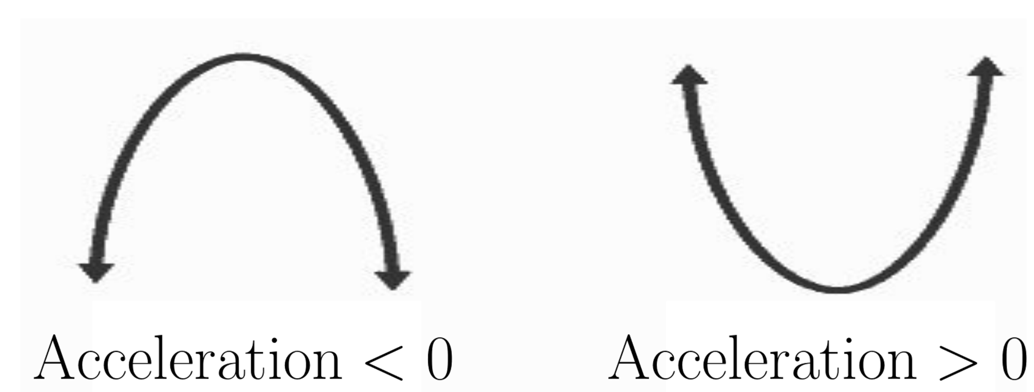
3. Formalization

In order to capture the sentiment evolution of a CS conversation $\hat{c} := (m_1, ...m_n)$ we define the **continuous sentiment curve** as follows:

- The sentiment measure $SS(m_i)$ and probability $P(SS(m_i))$ is computed for each message m_i using BERT.
- We begin considering the vector of message-wise sentiment as $\mathrm{MWS(c)}{:=}(\mathrm{SS}(\mathrm{m}_1), ..., SS(m_n))$
- The continuous curve $cont(\hat{c})$ is constructed using the following step wise vector representation: $\mathrm{cont}(\hat{c}) := (SS(\hat{m}_1) + P(SS(\hat{m}_1))_i$ which can be smoothed computing MA as:
  $\mathrm{MA}_j := \alpha \cdot cont(\hat{c})_j + (1-\alpha) \cdot MA_{j-1}$

We apply a simple linear regression on MA to capture the trend. Then the value slope is used as a feature for our classification model.

Concavity Analysis



4. Line-wise Sentiment Analysis Model

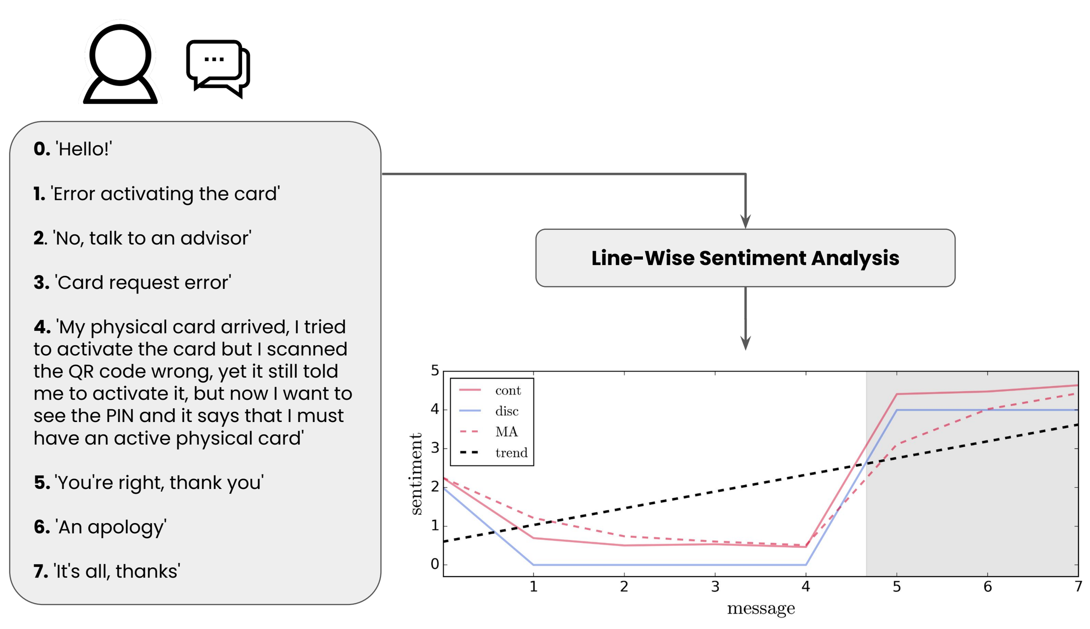


Figure 2: We depict a typical example of user-sent messages in a particular interaction with customer service.

5. Results and Discussion

	XGBoost		
Experiment	**AUC**	**KS**	**Macro F1**
B	0.5513	0.0801	0.54
B + LW	0.6199	0.1843	**0.58**
B + LW{NP}	**0.6455**	**0.2389**	**0.58**

Table 1: XGBoost Classification results in terms of AUC, KS, and Macro F1 score for our three experiments: baseline **(B)**, message-wise sentiment evolution analysis including **(B + LW)**, and ignoring *passive* users **(B+LW{NP})**

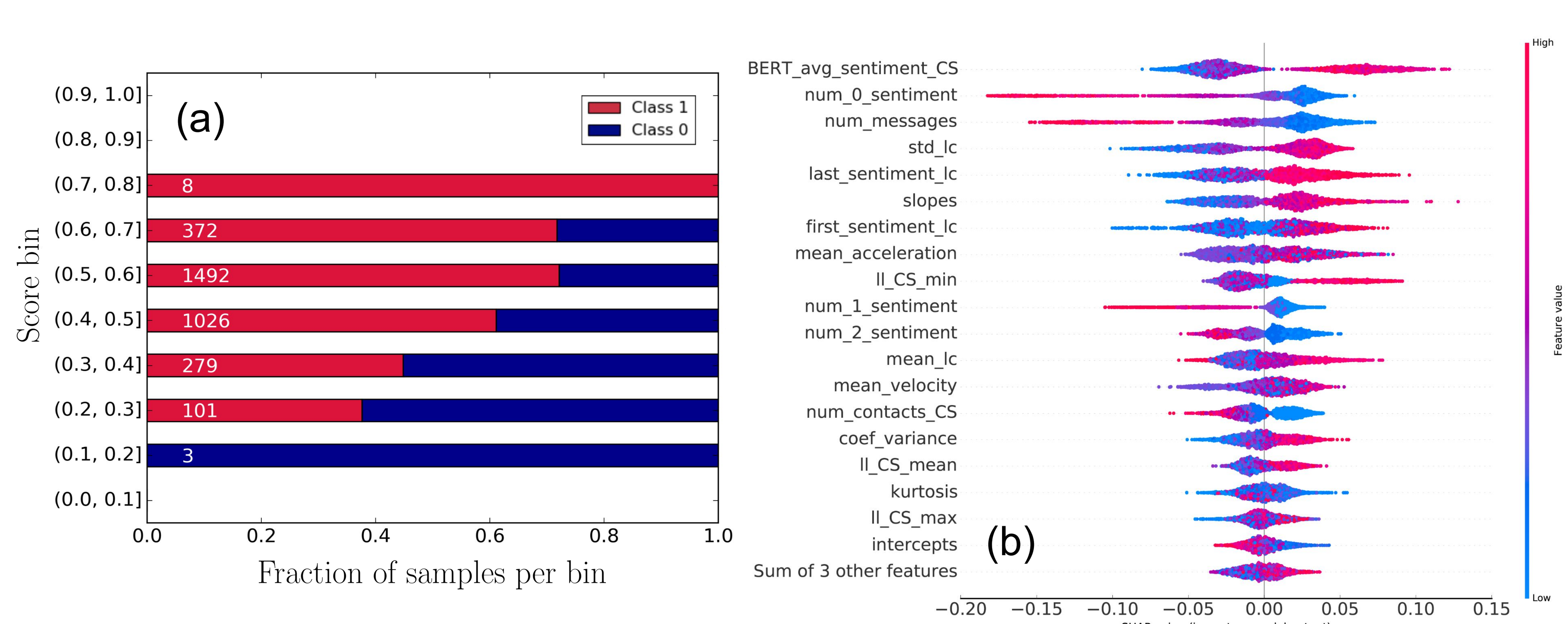
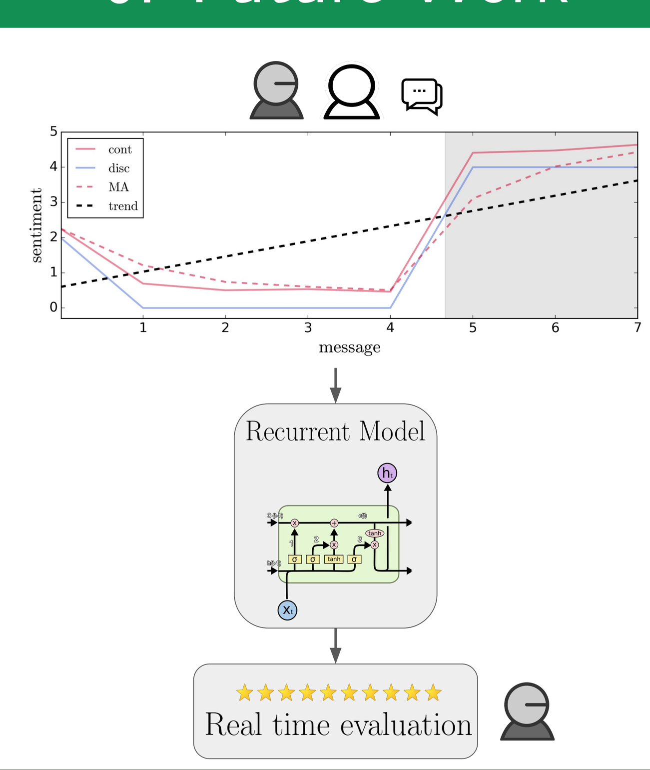


Figure 3: Results for the **(B + LW)** experiment: (a) Relative distribution of number of samples belonging to each respective class. The score represents the $P(promoter)$. (b) SHapley Additive exPlanations (SHAP) values for individual features of the line-wise sentiment analysis.

6. Future Work



7. Conclusions

Our results show that it is possible to predict the recommendation decision of users based on dynamic sentiment classification of chat-based data sources employing transformer-based methods. Results show substantially superior performance gains of about 10-14% obtained when considering a sentiment evolution analysis versus a purely aggregated, review-based, sentiment classification.

Selected References

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[3] S. Chatterjee: *Explaining customer ratings and recommendations by combining qualitative and quantitative user generated contents*. Decision Support Systems, vol. 119, pp. 14–22, 4 (2019).