# Literature Summary

Gajananan et al. (2018) developed a model to extract sentiment polarity changes from sequences of support tickets issued over a period and they utilized machine learning to predict the subscription renewal by the customer. The goal of this study is to categorize the sentiment polarity changes extracted from sequences of support tickets, in combination with other ticket history data, by learning a feature representation that subsequently can be passed to a standard binary classifier to predict subscription renewal. In this work, the authors relied on representation learning to automatically understand the sentiment features with characteristics, such as being able to a) encode the temporality associated to the sequence of tickets b) be treated as a vector of continuous values. In addition, this research study was to seek the impact of learned representations of sentiment polarity changes extracted from sequences of support tickets, in combination with other feature families, on the performance of cloud-based service subscription renewal prediction. The dataset used in this research contained around 90,000 associated support tickets. Some features derived from the tickets combined with other handcrafted features relating to ticket data, was passed through a classifier which estimated the likelihood of service subscription renewal by the customer. A total seven case features were derived from the ticket data. The IBM Watson cloud platform was utilized, and the natural processing language API was used to extract the sentiments (Gajananan et al., 2018).

White and Rege (2020) performed sentiment analysis using tools on the google cloud platform. The experiment was conducted utilizing two services available on the Google Cloud Platform (GCP) for performing sentiment analysis, which are Natural Language API and Auto-ML Natural Language. Comparisons were made between these two services. The dataset used in this experiment consists of 1.5 million labeled comments which was retrieved from the Kaggle website. 1,675,189 comments were labeled as positive sentiments, while 104,796 were labeled as negative comments. Python scripting language was used in the pre-processing and removal of duplicate comments. When performing sentiment analysis using Natural language API on GCP, the authors created a project on google cloud platform, then they enabled the google Natural Language API. They created a service account on the platform to bill them for whatever service they would be utilizing. A private key was provided to the authors as a JSON file to enable the virtual python development environment. Finally, the authors execute the commands for sentiment analysis using the python development environment. The results obtained when using natural language API were represented in a confusion matrix and an ROC Curve. The overall accuracy of the prediction was only 57%. When utilizing Auto-ML natural language, the author labeled the data as “TRAIN”, “VALIDATION”, and “TEST”. The Auto-ML service will automatically train a model using the training and validation data. After the training is complete, the service uses the testing data to determine the true quality of the sentiment analysis and makes various quality metrics available on the GCP console (White & Rege, 2020).

Qaisi and Aljarah (2016) performed sentiment analysis using the following cloud service providers namely, Amazon and Microsoft Azure to analyze their customers opinions and reviews. To do that, two datasets are extracted which are consisting of tweets that had either organizations names or cloud names. In this experiment, two datasets were created from the twitter API. Navies Bayes classifier was the algorithm used to train the dataset. Results were analyzed and explained in terms of polarity and emotions classifications, this was to prove the impact of sentiment analysis to support organizations decisions. The total number of tweets extract for each dataset was 1500tweets. After analysis, results show from the emotions classification that, Microsoft Azure has 65% positive tweets compared to 45% positive tweets for Amazon. Amazon has 50% negative polarity compared to 25% negative polarity for Microsoft Azure. Word cloud representation was used to identify the most frequent words in each emotions category(Qaisi & Aljarah, 2016).

Alkalbani, Ghamry, Hussain, and Hussain (2016) proposed a research study which was to investigate consumers experience of using SaaS services. In other to establish this, the authors applied sentiment analysis and classification using NLP and ML on the Blue Pages Reviews dataset (BPR) that was generated by crawling SaaS consumers reviews from different web portals. Alkalbani et al. (2016) extracted 4000 online reviews and they utilized sentiment analysis to identify the polarity of each review, that is, whether the sentiment being expressed is positive, negative, or neutral. This research also develops a model for predicting the sentiment of Software as a Service consumers’ reviews using a supervised learning machine called a support vector machine (SVM). The application of both Natural Language Processing (NLP) and Machine Learning(ML) was achieved by using Rapid Miner environment and a SaaS application called Semantria, developed by Lexalytics. The most important step of this research was the pre-processing of the text. To accomplish this task the authors made use of Text Processing Plug-in Rapid Miner to perform this task, this tool was called “Process Document from Data”. They made use of SVMs with three different approaches to word vectors, namely Binary Occurrence, Term Frequency and Term Frequency-inverse document frequency (TF-IDF). The sentiment results show that 62% of the reviews were positive which indicated that more consumers were satisfied with SaaS services. The results of the prediction accuracy of the SVM-based Binary Occurrence approach (3-fold cross-validation testing) was 92.30%, which indicated better performance in determining sentiment compared to the other approaches (Term Occurrences, TFIDF) (Alkalbani et al., 2016).

Alkalbani, A. M., Ghamry, A. M., Hussain, F. K., & Hussain, O. K. (2016). *Sentiment analysis and classification for software as a service reviews.* Paper presented at the 2016 IEEE 30th international conference on advanced information networking and applications (AINA).

Gajananan, K., Loyola, P., Katsuno, Y., Munawar, A., Trent, S., & Satoh, F. (2018). *Modeling sentiment polarity in support ticket data for predicting cloud service subscription renewal.* Paper presented at the 2018 IEEE International Conference on Services Computing (SCC).

Qaisi, L. M., & Aljarah, I. (2016). *A twitter sentiment analysis for cloud providers: a case study of Azure vs. AWS.* Paper presented at the 2016 7th International Conference on Computer Science and Information Technology (CSIT).

White, T. E., & Rege, M. (2020). Sentiment Analysis on Google Cloud Platform. *Issues Inf. Syst, 21*, 221-228.