We propose a new method to detect when users express the intent to leave a service, also known as churn. While previous work solely focuses on social media, we show that this intent can be detected in chatbot conversations as companies increasingly rely on chatbots. To this end, we crowdsource and publish a dataset of churn intent expressions in chatbot interactions in German and English. Moreover, we show that classifiers trained on social media data can detect the same intent in the context of chatbots.

II. METHODOLOGY

A. MODEL ARCHITECTURE

Our churn detection architecture is a text classifier based on cascaded collaborative layers where different feature extractors and aggregators complement each other. More precisely, we employ a combination of a CNN and a bidirectional Gated Recurrent Unit (BiGRU) to make use of both spatial and temporal dependencies in the data. On top of that, an attention mechanism is employed in order to recognize which BiGRU outputs have higher weights of importance. The model architecture is depicted in Figure 1.

B. COMPOUND WORDS

In German, two compound words that share the same root, here "Vetrags", but express two different meanings. For example, "Vetragverlängerung" means extension of contract, whereas "Vertragsverlängerung" means contract extension. The same word may have different meanings depending on its subwords.

III. DATASET

As presented in [1], we use pairs of datasets from two different languages (English and German) with the certainty that churn detection is a universal problem and therefore does not depend on the language. Each pair is composed of a Twitter and a chatbot conversations dataset. Moreover, we use an additional dataset on sentiment analysis in German [2] to assert our results on compound words.

A. ENGLISH TWITTER (ENT)

The dataset is introduced by [3] and composed of English tweets that show mentions of Verizon, AT&T and T-Mobile.

B. GERMAN TWITTER (DE

We crawl all mentions on Twitter of multiple telecom brands that are active in German speaking countries for a period of 6 months. The result is a large Twitter conversations dataset. Moreover, we use an additional dataset on sentiment analysis in German [2] to assert our results on compound words.

C. FROM SOCIAL MEDIA TO CHATBOTS

Twitter, tends to carry specific structures that might prevent our model from detecting churn in chatbot conversations. Therefore, we can remove such patterns from tweets as in:

```
"@B1 I am fed up! Please let me switch to @B2 as soon as possible!"
```

By removing first mention to brand (B1) and twitter patterns such as @, we obtain a chatbot-like entry. As a result, we prove that Twitter content and chatbot conversations are similar.

V. REFERENCES