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Leveraging deep neural networks and semantic similarity measures for medical concept normalisation in user reviews

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Abstract

 Nowadays a new yet powerful tool for drug repurposing and hypothesis generation emerged. Text mining of different domains like scientific libraries or social media has proven to be reliable in that application. One particular task in that area is medical concept normalization, i.e. mapping a disease mention to a concept in a controlled vocabulary, like Unified Medical Language System (UMLS). This task is challenging due to the differences in language of health care professionals and social media users. To bridge this gap, we developed end-to-end architectures based on bidirectional Long Short-Term Memory and Gated Recurrent Units. In addition, we combined an attention mechanism with our model. We have done an exploratory study on hyperparameters of proposed architectures and compared them with the effective baseline for classification based on convolutional neural networks. A qualitative examination of the mentions in user reviews dataset collected from popular online health information platforms as well as quantitative one both show improvements in the semantic representation of health-related expressions in user reviews about drugs.

Keywords

Deep learning, Information extraction, Medical concept mapping, Medical concept normalization, Recurrent neural networks, UMLS

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