6 CONCLUSION

In this paper, we have designed a novel healthcare service by developing an intelligent treatment engine, which can provide a patient with next-period prescriptions automatically and individually in real time. In order to cope with the complexity of medical practice and EMR data due to sequences having different lengths and record frequencies with multiple types of inter-correlations, a new LSTM learning framework has been proposed, so as to construct sequential hidden states for each medical sequences, model their connections with links between hidden neurons, and incorporate static factors with dynamic hidden states. In doing so, three multi-faceted LSTM models have been developed with fully connected, directional, and decomposed internal connections, respectively. Finally, experimental results validated the effectiveness of the proposed models. Particularly, the decomposed heterogeneous LSTM achieved the highest ROC-AUC on all 12 datasets and the highest PR-AUC on 11 out of the 12 datasets. Furthermore, future research will be undertaking from both theoretical and practical perspectives. Theoretically, we will explore how to further improve the performance of the heterogeneous LSTM models by introducing ontology of medicines or knowledge graph of laboratory indicators. In practice, we will apply the treatment engine in real-world applications and compare its results with that of doctors.

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