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Week 8 Summary

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In the article “Time Matters: Sequential Recommendation with Complex Temporal Information”, the authors point out the inefficient usage of temporal information on sequential recommendations. Existing sequential recommendation algorithms mostly focus on the sequences of users’ behaviors while ignoring their temporal patterns. So far, there are some initial efforts on integrating temporal information into sequential recommendations, but they mostly take incomplete or partial temporal information into consideration. To solve this problem, the authors systematically investigate the effects of the temporal information in sequential recommendations, and two typical temporal patterns of user behavior sequences can be recognized which are absolute time pattern and relative time pattern. The absolute time pattern is a point-wise concept, characterizing the absolute timestamp as a unique variable in depicting user-item interactions. Timestamp can provide the context and auxiliary information to determine whether a user is interested in an item, which is useful in revealing periodical behaviors. The relative time pattern is a pair-wise concept, which focuses on the time interval between each pair of user behaviors. Intuitively, such information reflects the influence of the former behavior upon the latter one, and different pairs may exhibit various patterns. Furthermore, it can be divided into two subcategories: Self-relative Time Pattern and Relatedness Relative Time Pattern. According to the above observations, the authors propose a novel neural network framework named Temporal Attentive Sequential recommendation (TASER), which can jointly learn these temporal patterns and user interests for sequential recommendation. For each input sequence, an absolute temporal module that contains a group auto-encoder embedding network is introduced to embed the time sequences. This module enriches the capacity for representing the absolute time, compared with traditional time packetization methods. Together with the absolute temporal module, a relative temporal module injects the relative temporal effects into the relationships between two actions of user behavior sequences in an explicit manner. So, the methodology of TASER consists of four components as follows:

* Absolute Temporal Module: This module is designed to capture the absolute time information. The input of this module includes four components: the sequence of items , the corresponding sequence of time , the target user and the next interaction time . The output is , where . is the embedding layer. Formally, . The granularity of the packetization may vary quite differently, and inappropriate packetization usually results in poor performances. To address this issue, the authors integrate group auto-encoder into this module. The goal of a group auto-encoder is to encode the time embedding into a probability distribution over the set of latent groups of vectors .
* Relative Temporal Module: In this section, the authors deploy the relative temporal attention which can make full use of all the edges associated with relative time to make predictions, and the relationship between each pair of items can be calculated directly. The output of the whole Relative Temporal Module can be formulated as follows:
  + Where
    - And
* Decoder Module: In this section, the authors adopt an alternative bi-linear decoding scheme to compute a similarity score between the representations of the current user and each candidate item, which is formulated as follows: .
* Loss Function: The total loss consists of three terms: the prediction loss , the auto-encoder loss and the temporal loss , which are combined linearly as follows:

For the experiment and result, the authors use two datasets (LastFM and Amazon) and two evaluation metrics (F1-score and NDCG). By comparing to the other 9 baseline, TASER achieves the state-of-the-art performance.