Recurrent Point Processes for Dynamic Review Models

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Abstract
Recent progress in recommender system research has shown the importance of including temporal representations to improve interpretability and performance. Here, we incorporate temporal representations in continuous time via recurrent point process for a dynamical model of reviews. Our goal is to characterize how changes in perception, user interest and seasonal effects affect review text.

Introduction
Costumer reviews provide a rich and natural source of unstructured data which can be leveraged to improve interactive and conversational recommender system performance (Liu et al. 2019). Reviews are effectively a form of recommendation. Although causal and temporal relations have been known to improve the performance of recommender systems (Wu et al. 2017), recent natural language process (NLP) methodologies for rating and reviews (Zheng, Noroozi, and Yu 2017) lack behind at incorporating temporal structure in language representations. In the present work, we exploit recurrent neural network (RNN) models for point process and include neural representations of text to characterize costumer reviews. Our goal is to capture the changes in taste and importance of items during time, and how such changes reflect on the text produced by the different users.

The reviews research have sought to characterize usefulness and generation of reviews (Fan et al. 2019; Novgorodov et al. 2019) and provide better representations for rating prediction (Esmaeili et al. 2019). The need to interact with costumers have lead to question answering solutions (Chen et al. 2019; Yu and Lam 2018). Deep neural networks models for rating predictions use embedding representations as well as convolutions neural networks (Catherine and Cohen 2017). Dynamic models of text however have shown more success from the bayesian perspective within topic models (Rudolph and Blei 2018; Wang, Blei, and Heckerman 2012). Self exciting point processes have allow for clustering of document streams (Du et al. 2015; He et al. 2015). Different from these works, we focus on the temporal aspects of the text for each review.

Recall Point Review Model (RPRM)
Consider an item \(a\) (e.g. a business, service or movie) and assume that, since its opening to the public, it has received a collection of \(N_a\) reviews \(r^a\) \(= \{x^a_j, t^a_j\}_{j=1}^{N_a}\), where \(t^a_j\) labels the creation time of review \(x^a_j\) and \(x^a_j = (w^a_1, ..., w^a_M)\) corresponds to its text1. Such a collection of reviews effectively defines a point process in time. Our main idea is to model these point processes as RNNs in continuous time and use their hidden representations, which encode the non-linear relations between text and timing of past reviews, to predict how the reviews’ text of a given item changes with time. The model thus consists of two components: a point process model which leverages the information encoded in the review text and a dynamic neural text model.

We start by transforming the text of each review into a bag of words (BoW) representation \(X_j \in \mathbb{R}^V\), where \(V\) is the vocabulary size (Hinton and Salakhutdinov 2009).

Recurrent Point Process (RPP): Let us consider a point process with compact support \(S \subset \mathbb{R}\). Formally, we write the likelihood of a new arrival (i.e. a new review) \(r_{j+1}\) as an inhomogeneous Poisson process between reviews, conditioned on the history \(H_j \equiv \{r_1, ..., r_j\}\)2 (Daley and Vere-
Concerned here, the conditional likelihood function reads

\[ f^*(t) = \lambda^*(t) \exp \left\{ \int_{t_j}^t \lambda^*(t') dt' \right\}, \]

(1)

where \( \lambda^* \) is (locally) integrable and is known as the intensity function of the point process. Following (Mei and Eisner 2017), (Du et al. 2016a), we define the functional dependence of the intensity function to be given by a RNN with hidden state \( h_j \in \mathbb{R}^d \), where an exponential function guarantees that the intensity is non-negative

\[ \lambda^*(t) = \exp \left\{ \mathbf{v}^t \cdot h_j + u^t \left( t - t_j \right) + b^t \right\}. \]

(2)

Here the vector \( \mathbf{v}^t \in \mathbb{R}^d \) and the scalars \( u^t \) and \( b^t \) are trainable variables. The update equation for the hidden variables of the recurrent network can be written as a general nonlinear function

\[ h_j = f_\theta(t_j, X_j, h_{j-1}), \]

(3)

where \( t_j \) and \( X_j \) label the creation time and the text’s BoW representation of review \( r_j \), respectively, and \( \theta \) denotes the network’s parameters. We thus use the BoW representation of the review text as marks in the recurrent marked temporal point process (Du et al. 2016b). Inserting Eq. (2) into Eq. (1) and integrating over time immediately yields the likelihood \( f^* \) as a function of \( h_j \).

**Dynamic Neural Text Model:** To model the text component of reviews we assume the words in review \( r_{j+1} \) are generated independently, conditioned on \( h_j \), the temporal representation of the RPP above. Specifically, we follow (Miao, Yu, and Blunsom 2016) and write the conditional probability of generating the \( i \)th word \( w_{j+1}^i \) of the \((j+1)\)th review as

\[ p_\theta(w_{j+1}^i|h_j) = \frac{\exp \left\{ -z(w_{j+1}^i, h_j) \right\}}{\sum_{v=1}^{V} \exp \left\{ -z(w_{j+1}^v, h_j) \right\}}, \]

(4)

\[ z(w_{j+1}^i, h_j) = -h_j^T \mathbf{R} w_{j+1}^i - b w_{j+1}^i, \]

(5)

where \( \mathbf{R} \in \mathbb{R}^{d \times V} \) and \( b \in \mathbb{R}^V \) are trainable parameters, and \( w_{j+1}^i \) is the one-hot representation of the word at position \( i \).

The complete log-likelihood of the RPRM model can then be written as

\[ \mathcal{L} = \sum_{a=1}^{N} \sum_{j=1}^{N_a} \left( \log f^*(\delta_{j+1}^a| h_j) + \log P(X_{j+1}^a|h_j) \right), \]

(6)

where \( \delta_{j+1}^a = t_{j+1}^a - t_j^a \) denotes the inter-review time for item \( a \) and \( P(X_{j+1}^a|h_j) \) is a multinomial distribution over word probabilities (Eq. (4)) and counts.

**Baseline model:** In order to test our model we define LSTM-BoW, which models the inter-review time \( \delta_{j+1} \) as the mean of an exponential distribution with parameter \( \lambda_\phi(h_j^p) \), and the probability over words \( p(w_{j+1}^i|h_j^p) \) as \( \text{softmax}(g_\phi(h_j^p)) \). The functions \( \lambda_\phi \) and \( g_\phi \) are given by neural networks with parameters \( \phi \), and \( h_j^p = f_\phi(t_j, X_j, h_{j-1}) \) is the hidden state of an LSTM network (Hochreiter and Schmidhuber 1997). We also consider additional LSTM and RPP models which only take \( t_j \) as input, as to check whether the BoW representation \( X_j \) helps in the prediction of the inter-review times.

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Table 1: Model performance on RMSE, \( R^2 \) and predictive perplexity.

| Model       | RMSE   | \( R^2 \) | Pred. Perplexity |
|-------------|--------|-----------|-----------------|
| LSTM        | 96.8813| 0.1788    | -               |
| RPP         | 96.3794| 0.1873    | -               |
| LSTM-BoW    | 95.3414| 0.2046    | 519.90          |
| RPRM        | 92.3850| 0.2533    | 511.32          |

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**Experiments and Results**

We test our models on the Yelp19 dataset\(^1\). Specifically we take all reviews for businesses that are labeled with the shopping parent category from 01 Jan 2016 to 30 Nov 2018. The creation time of a review is defined as the difference in days between the original timestamp and 01 Jan 2016. Next, we group reviews by business. All businesses with less than 5 reviews are removed. The text from each review is converted into a BoW vector of size 2000 (Hinton and Salakhutdinov 2009). The result from the preprocessing is a dataset that has in total 262193 reviews, 27185 businesses, 174122 users, 1910299 sentences and 13209813 words. On average we have 9.6 reviews per business with standard deviation of 22.8. Each review has on average 7.2 sentences and 50.2 words, with 5.9 and 46.14 standard deviation respectively.

In the experiments, we randomly split each dataset into two parts: training set (80%) and test set (20%). We use grid search for hyper-parameters finding.

We trained all models on maximum likelihood and use two evaluation metrics: Root-mean-squared error (RMSE) on the inter-review times and predictive perplexity on the review text. The latter is defined as \( \mathcal{PP} = \exp \left\{ -\frac{1}{T} \sum_{j=1}^{T} \frac{1}{|H_j|} \sum_{i \in H_j} \log p(w_j^i|h_{j+1}) \right\} \) (Wang, Blei, and Heckerman 2012), where \( M_j \) is the number of words in review \( r_j \) and \( |H_j| \) is the number of reviews at time \( t_j \). Our results are presented in Table 1 and show that the best model in both metrics is the Recurrent Point Review Model. Note also that the models that leverage the information encoded in the text (through \( X_j \)) show improvement of the RMSE (with respect to the inter-review time) over the models which do not see \( X_j \).

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**Conclusion and Future Work**

In this work we incorporate a bag of word language model as the marks of a recurrent temporal point process. This creates a model which characterize temporal and causal representation for text, allowing for a richer representation for customers reviews. We show that this improves predictive performance for the time of the reviews, as well as opening the door for text prediction. We will extend this methodology for rating prediction as well as more complex models of text.

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\(^1\)https://www.yelp.com/dataset

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