Long-Term RNN: Predicting Hazard Function for Proactive Maintenance of Water Mains

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For the urban water utilities, the cost of maintaining water mains has become the major concern. A recent report indicates that the maintenance cost is over 1.4 billion AU dollar in Australia. The proactive management techniques, especially the proactive maintenance (PM), have become increasingly important with the machine learning advances.

Introduction

- The main kind of approaches to predict the failure events is based on hazard function and survival analysis.
- There are two major obstacles to use survival analysis in PM:
  1. It heavily relies on the assumption of fixed forms of hazard functions.
  2. The loss function of a specific group does not consider the influence of other groups.
- This paper models the prediction by solving the two problems.
  1. The information of all older groups can be used by jointly transferring the information with a non-linear function using RNN.

Groups \ age	1	2	3	4	5	6	7	8
A	0.04	0.02	0.71	0.87	0.57	0.87	0.55	0.79
B	0.70	0.48	0.65	0.23	0.78	0.76	0.16	
C	0.27	0.78	0.61	0.05	0.73	0.60		
D	0.69	0.12	0.55	0.55	0.99			
E	0.87	0.14	0.38	0.61				

Prediction using both auto-regression and information from older Groups $\lambda_E(5)$ $\lambda_E(6)$ $\lambda_E(7)$ $\lambda_E(8)$

  2. A more efficient RNN model, long-term RNN (LT-RNN), is proposed to be directly applied to hazard function prediction in various long-term periods.

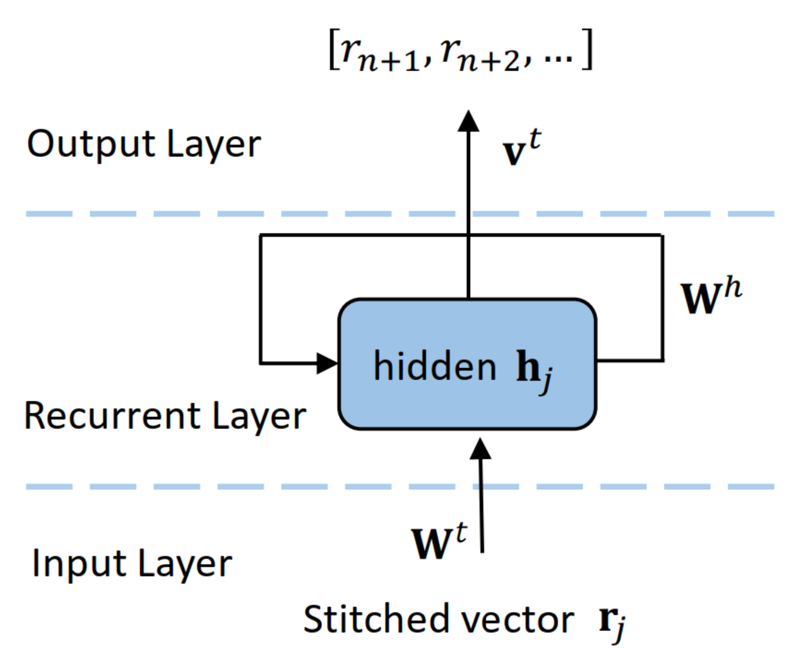
Contribution

1. The model interprets the survival analysis as a nonlinear mapping, which is established by RNNs.
2. The proposed model enables to predict hazard functions in long-term periods.
3. The model is evaluated on a large dataset from an Australian water utility to perform water mains failure prediction for PM. The comprehensive experiments demonstrate the effectiveness and robustness of the proposed method

Problem Definition

- The input data is a set of sequences $C = \{S^1, S^2, \dots\}$
- Each $S^i = \left(\left(t_1^i, r_1^i\right), \left(t_2^i, r_2^i\right), \dots\right)$ is a sequence of pairs $\left(t_j^i, r_j^i\right)$ where r_j^i is the failure rate of group at the aligned time t_j^i
- In PM of water mains
  - S^i : a sequence of observed time for a group of water mains
  - r_j^i : the frequency with which the group fails at the age of t_j^i
- Based on this, this paper aims to build a model which is able to:
  - Let groups with short length leverage the precedent information shared by other groups with long length;
  - Predict multiple failure rates $r_{n+1}^i, r_{n+2}^i, \cdots$ for the group *i* in long-term period given a set of sequences with events that have happened up to time t_n.

Long-Term Recurrent Neural Network



(b) Structure of LT-RNN.

- **Input Layer**
  For the timing input t_j, the associated stitched vector $\mathbf{r}_j$ is projected into a latent space by the weight matrix $\mathbf{W}^t$
- **Recurrent Layer**
  The hidden vector is updated by using activation function
  $$\mathbf{h}_j = \max(\mathbf{W}^t\mathbf{r}_j + \mathbf{W}^h\mathbf{h}_{j-1} + \mathbf{b}_h, 0)$$
- **Output Layer**
  The estimated hazard function can be formulated by
  $$\lambda(t) = \exp\left(\mathbf{v}^{t\mathrm{T}} \cdot \mathbf{h}_j + w^t(t - t_j) + b^t\right)$$

Case Study

- **Task**: predict the long-term hazard function for each group (water mains are grouped by laid year).

Table 1: Statistics of each group

Group	Training set (2000-2010) Count	Length	Ave. FR	Testing set (2011-2015) Count	Length	Ave. FR
1966	1413	300	38.42	684	135	40.92
1967	1211	259	29.62	603	134	32.44
1968	1468	308	31.62	692	145	32.79
1969	1182	240	30.26	532	101	29.96
1970	1050	207	25.69	491	100	26.43
1971	834	158	24.65	385	77	25.03
1972	848	190	21.13	407	98	22.31
1973	753	145	20.78	357	73	21.67
1974	552	112	21.75	275	68	23.84
1975	752	181	24.04	341	89	23.99

- **Experimental Results**
- predictive performance consistently outperforms other methods among all groups

Performance comparison

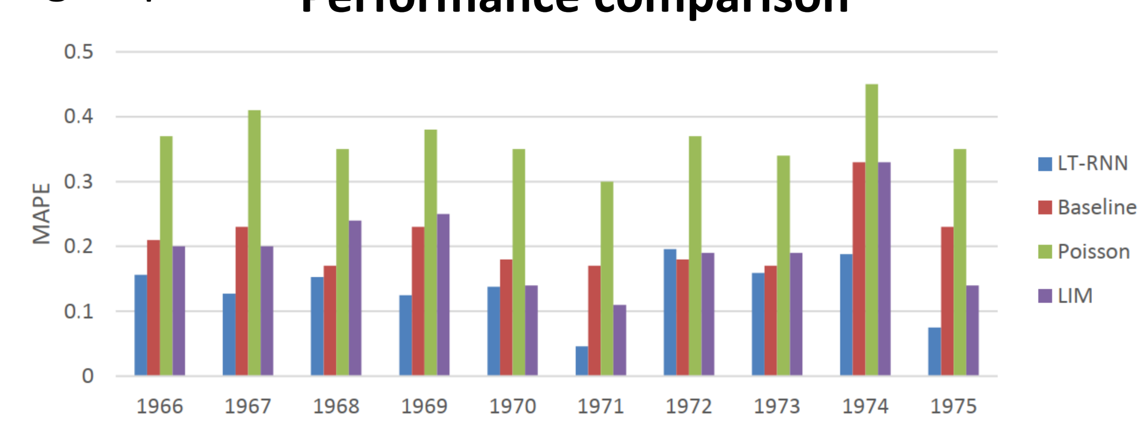


Figure 3: Comparison with different methods.

- The proposed method is robust to different long-term periods

Performance for various long-term periods

Table 2: MAPE of predicting failure rate for $m = 1 \ldots 5$.

Group	$m=1$	$m=2$	$m=3$	$m=4$	$m=5$
1966	0.206	0.167	0.176	0.167	0.156
1967	0.127	0.127	0.126	0.127	0.127
1968	0.116	0.134	0.137	0.132	0.153
1969	0.122	0.132	0.138	0.134	0.125
1970	0.162	0.143	0.121	0.115	0.138
1971	0.100	0.086	0.057	0.042	0.046
1972	0.198	0.167	0.175	0.192	0.196
1973	0.159	0.158	0.157	0.208	0.159
1974	0.188	0.203	0.218	0.203	0.188
1975	0.067	0.046	0.049	0.052	0.075
Overall	0.145	0.136	0.135	0.137	0.136

FOR FURTHER INFORMATION
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