Sequential Click Prediction for Sponsored Search with Recurrent Neural Networks

(Zhang, et al. 2017)

Presented by Jiin Seo

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Outline

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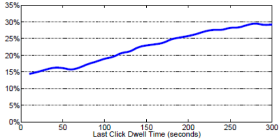
1. Introduction

Sequential Click prediction (Zhang, et al. 2017)

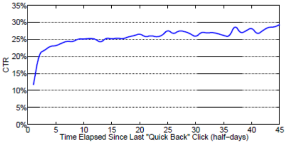
- Goal : Estimating the click-through rate (CTR) of ads with sequential information
- Modeling sequential dependency between user's behaviors
  $\rightarrow$ RNN

Outline

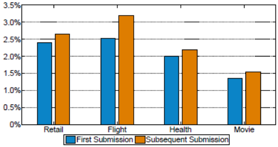
2. Data Analysis on Sequential Dependency



(a) Correlation between last click dwell time and current CTR.



(b) CTR right after a quick back click on the same ad.



(c) CTR on users' first and subsequent submissions of a certain type of query.

Figure: Sequential information

- The model have to learn sequential dependency between user behaviors by itself.

Outline

3. The Proposed Framework

Feature Construction

- Ad features
- User features
- Sequential feature
- We re-organize the input features along with the user dimension.

3. The Proposed Framework

Architecture

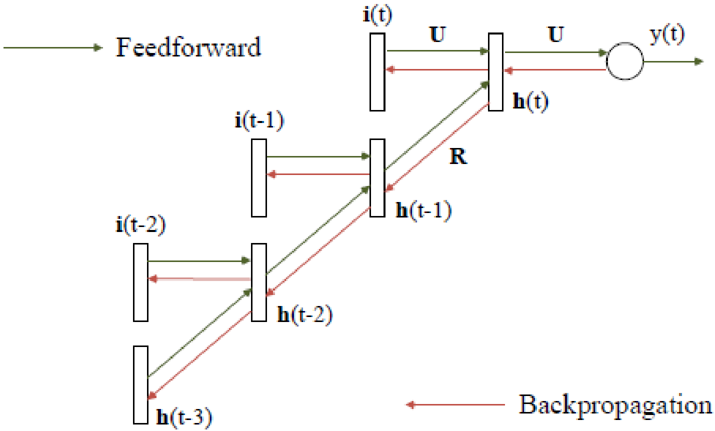


Figure: RNN training process with BPTT algorithm. Unfolding step is set to 3 in this figure.

3. The Proposed Framework

Model

$$
\begin{aligned}
\mathbf{h}(t) &= f(i(t)\mathbf{U}^T + \mathbf{h}(t-1)\mathbf{R}^T), \\
y(t) &= \sigma(\mathbf{h}(t)\mathbf{V}^T)
\end{aligned}
$$

- $\mathbf{R}$: the recurrent connections between $\mathbf{h}(t-1)$ and $\mathbf{h}(t)$,
- $f()$: tanh function , $\sigma()$: sigmoid
- $i(t)$: Features correlated to user's current behavior.
- $\mathbf{h}(t)$: Sequential information of user's previous behaviors.

3. The Proposed Framework

Learning

- Loss (averaged cross entropy)

$$L = \frac{1}{M}\sum_{i=1}^{M}(-y_i log(p_i) - (1 - y_i)log(1 - p_i))$$

- $y_i \in \{0, 1\}$: labeled sample , p_i : the predicted click probability
- Learning Algorithm (Back Propagation Through Time : BPTT)

3. The Proposed Framework

Learning Algorithm(BPTT)

- The gradient of the output layer :

$$e_o(t) = y(t) - l(t)$$

  y(t) : the predicted click prob., l(t) : the binary true label

- The weights($\mathbf{V}$) between the hidden layer($\mathbf{h}(t)$) and output ($y(t)$) :

$$\mathbf{V}(t+1) = \mathbf{V}(t) - \alpha \times e_o(t) \times \mathbf{h}(t)$$

- Gradients of errors :

$$\begin{aligned} e_{\mathbf{h}}(t) &= e_o(t)\mathbf{V} * (\overrightarrow{1} - \mathbf{h}(t) * \mathbf{h}(t)), \\ e_{\mathbf{h}}(t-\tau-1) &= e_{\mathbf{h}}(t-\tau)\mathbf{R} * (\overrightarrow{1} - \mathbf{h}(t-\tau-1) * \mathbf{h}(t-\tau-1)), \\ & \tau \in [0, T) \text{ and } T : \# \text{ of unfolding steps.} \end{aligned}$$

3. The Proposed Framework

Learning Algorithm(BPTT)

- The weight matrix **U** and the recurrent weights **R** :

$$\begin{aligned}
\mathbf{U}(t+1) &= \mathbf{U}(t) - \alpha\left[\sum_{z=0}^{T-1} e_{\mathbf{h}}(t-z)^T i(t-z)\right] \\
\mathbf{R}(t+1) &= \mathbf{R}(t) - \alpha\left[\sum_{z=0}^{T-1} e_{\mathbf{h}}(t-z)^T \mathbf{h}(t-z)\right]
\end{aligned}$$

3. The Proposed Framework

Testing process

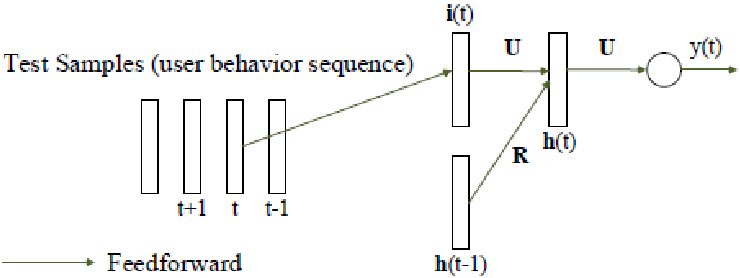


Figure: RNN testing process with sequential input samples.

- We only record the hidden state of the last test sample.

Outline

4. Experiments

Overall performance

- Data : Logs of search engine for 2 weeks (randomly sample a set of users)
- Metric
  - Area Under ROC Curve (AUC)
  - Relative Information Gain (RIG)

Model	AUC	RIG
LR	87.48%	22.30%
NN	88.51%	23.76%
RNN	**88.94%**	**26.16%**

Figure: Overall performance of models

4. Experiments

Performance with History

- RNN model performs the best in all settings
- Long sequences help further improve the accuracy of CTR.

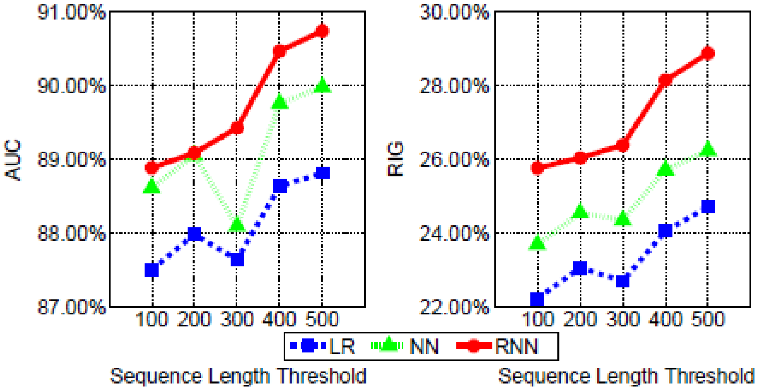


Figure: Performance with Long vs. Short History

4. Experiments

Effect of RNN Unfolding Step

- Unfolding 3 steps is the best.
- The backpropagated error vanishes after 3 steps of unfolding.