Click-through Prediction for Advertising in Twitter Timeline

(Li, et al. 2015)

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Outline

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1. INTRODUCTION

Click-through Prediction

- Goal : Predicting CTR at Twitter
- Learning-to-rank and Online Learning
- Properties of Tweet streams.
  ▷ The stream of Tweets are correspond to her long term interest but do not reflect her current status.
  ▷ Every user has a different timeline which is updated dynamically.
  ▷ Sparse and Unique property .

Outline

2. ADVERTISING IN TWITTER TIMELINE

System overview

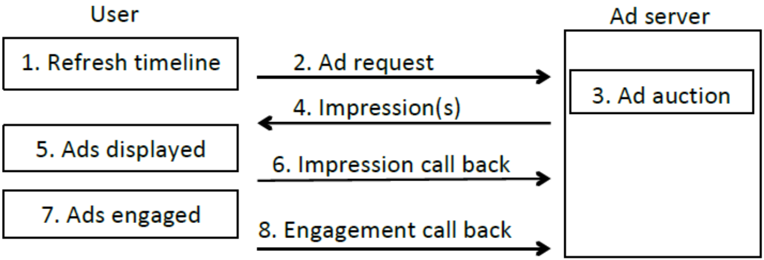

Figure: The process of displaying an ad in Twitter timeline.

- Users could perform a negative engagement with a promoted Tweet by hitting a “dismiss” button.

2. ADVERTISING IN TWITTER TIMELINE

System overview

- An initial set of ad candidates are formed according to the information of the user.
- Auction based on bid price and CTR
- Result : $0 \sim K$ winning ads
- Correct estimation of click probability and good ranking.

Outline

3. METHODS

Pointwise approach : Baseline

- $y \in \{\pm 1\}$: ground-truth binary label
- $\mathbf{x}$: Feature vector from the ad, user, timeline, current session . . .
- Minimizing prediction error
- $\mathbf{D} = \{(y, \mathbf{x})\}$: the set of all instances
- Loss for Pointwise learning

$$L(\mathbf{w}, \mathbf{D}) = \sum_{(y,\mathbf{x}) \in \mathbf{D}} l(y, f(\mathbf{w}, \mathbf{x}))$$

- Loss function for a single instance

$$l(y, f(\mathbf{w}, \mathbf{x})) = log(1 + exp(-yf(\mathbf{w}, \mathbf{x}))) \quad , f(\mathbf{w}, \mathbf{x}) = \mathbf{w}^T \mathbf{x}$$

- Logistic regression with SGD

3. METHODS

Pairwise approach

- Minimizing ranking loss
- Advantage of user's relative ads preference is that we can address the training data sparsity challenge.
- $\mathbf{P} = \{(y_A, \mathbf{x}_A), (y_B, \mathbf{x}_B) \mid y_A \neq y_B\}$: the set of all pairs in the same session.
- Loss for Pairwise learning

$$L(\mathbf{w}, \mathbf{P}) = \sum_{(y_A, \mathbf{x}_A), (y_B, \mathbf{x}_B) \in \mathbf{P}} l(g(y_A - y_b), f(\mathbf{w}, \mathbf{x}_A) - f(\mathbf{w}, \mathbf{x}_B))$$

- Calibration :
  - Preference score $\rightarrow$ [sigmoid function] $\rightarrow$ click probability

3. METHODS

Combined learning

- Online algorithm based on a combined optimization framework

$$\min_{\mathbf{w}}(\alpha L(\mathbf{w}, \mathbf{D}) + (1-\alpha)L(\mathbf{w}, \mathbf{P}))$$

- We can change α by varying the weight w_p of instances formed by a pair of ads.

3. METHODS

Pseudo pairs

- If we fail to obtain enough pairs, model would be biased towards minimizing classification loss.
- We artificially create more pairwise training instances.
  - Across-user grouping (CF), Within-user grouping
- Set of all pseudo-pairs

$$\mathbf{S} = \{((y_A, \mathbf{x}_A, t_A), (y_B, \mathbf{x}_B, t_B) \mid y_A \neq y_B, t_A \neq t_B\}$$

- Loss

$$L(\mathbf{w}, \mathbf{S}) = \sum_{((y_A, \mathbf{x}_A, t_A),(y_B, \mathbf{x}_B, t_B)) \in \mathbf{S}} max(min(log \frac{\mathbf{N}}{|t_A - t_B|}, 1), 0) \cdot l(g(y_A - y_B), f(\mathbf{w}, \mathbf{x}_A) - (\mathbf{w}, \mathbf{x}_B))$$

- Optimization

$$\min_{\mathbf{w}} (\alpha_1 L(\mathbf{w}, \mathbf{D}) + (1 - \alpha_2) L(\mathbf{w}, \mathbf{P}) + (1 - \alpha_1 - \alpha_2) L(\mathbf{w}, \mathbf{S})$$

Outline

4. ONLINE LEARNING INFRASTRUCTURE

Pointwise learning

- Only ads with impression callbacks will be considered as training examples.
- All impressions are always set as negative.
- If ever engagement callback returns, this impression is reset as positive.

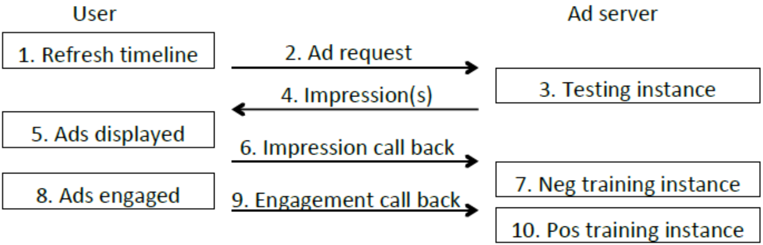

Figure: Online pointwise learning process.

4. ONLINE LEARNING INFRASTRUCTURE

Combined learning

- The positive instance is paired with all negative instances belonging to one session.
- Algorithm : Updated model parameter **w**.

$imp\_map \leftarrow cache.get(req\_id)$
$(y, \mathbf{x}) \leftarrow imp\_map.get(imp\_id)$ // get impression
if $type = impression\_call\_back$ **then**
    $imp\_map.set(imp\_id, (-1, \mathbf{x}))$ // set label to negative
    update $\mathbf{w}$ using $(-1, \mathbf{x})$ by SGD // pointwise learning
else // handle engagement call back
    $imp\_map.set(imp\_id, (+1, \mathbf{x}))$ // set label to positive
    update $\mathbf{w}$ using $(+1, \mathbf{x})$ by SGD // pointwise learning
    $P \leftarrow extract\_pairs(imp\_map, (+1, \mathbf{x}))$
    if $P.length > 0$ **then** // pairwise learning
        for Each pair $((y_A, \mathbf{x}_A), (y_B, \mathbf{x}_B))$ in P **do**
            $\mathbf{x} \leftarrow (\mathbf{x}_A - \mathbf{x}_B)$
            $y \leftarrow g(y_A - y_B)$
            update $\mathbf{w}$ using $(y, \mathbf{x})$ and weight w_p by SGD
        end for
    end if

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5. OFFLINE EXPERIMENT

Metrics

- NRIG (Normalized relative information gain) : To quantify the accuracy of predicted click prob.
- AUC (Area under receiver operator curve) : To measure ranking quality

Procedure

- Tweets from random week of year 2014.
- Features : Ad., User, Ad-user interaction, Context of the stream
- Progressive validation
- All parameters are tuned using the first day's data.

5. OFFLINE EXPERIMENT

Experiment Result

- Overall performance (baseline : Pointwise)

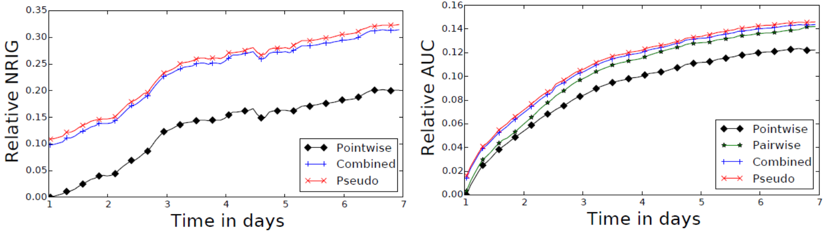
Method	Pairwise	Combined	Pseudo
Relative NRIG (%)	-75.90	$+9.44$	$+10.25$
Relative AUC (%)	$+1.76^{***}$	$+1.91^{***}$	$+2.11^{***}$

Figure: Performance relative to pointwise learning method

5. OFFLINE EXPERIMENT

Experiment Result

- Learning behavior



(a) Relative NRIG (b) Relative AUC

Figure: Learning behavior of one week excluding the first day

Outline

6. ONLINE EXPERIMENT

Metrics

- CTR (click-through rate)
- RPMq (revenue per thousand requests)

Procedure

- Evaluating pointwise learning and combined learning.
- Online A/B tests
- Weaker baseline random-pointwise : baseline

6. ONLINE EXPERIMENT

Experiment Result

- Overall performance

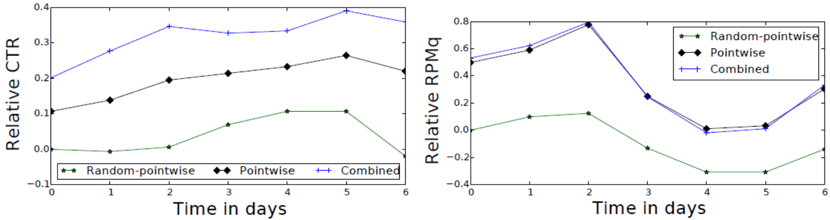
Method	Pointwise	Combined
Relative CTR (%)	+14.59	+26.10(+10.05)
Relative RPMq (%)	+57.20	+57.89(+0.44)

Figure: performance relative to random pointwise

6. ONLINE EXPERIMENT

Experiment Result

- Learning behavior



(a) Relative CTR (b) Relative RPMq

Figure: Learning behavior

- Combined model is showing fewer ads to users, but these ads lead to higher click-throughs.
- User experience is improved when using combined learning.