Display Advertising Optimization by Quantum Annealing Processor

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Overview

1. Introduction
2. Our approach
3. Experiments
4. Summary
1. Introduction

• What is Display Advertising?
  – Advertisements appearing on websites

• Main purpose
  – Deliver general advertisements and brand messages
Behind the Scenes

Publisher → SSP

SSP: Supply-Side Platform

DSP: Demand-Side Platform

RTB: Real Time Bidding
Behind the Scenes

Publisher

Impression

SSP: Supply-Side Platform

DSP: Demand-Side Platform

RTB: Real Time Bidding

1.0$ → RTB

0.9$ → Advertiser

0.7$
Behind the Scenes

Publisher

SSP

Winner!

1.0$

RTB

0.9$

0.7$

DSP

Advertiser

SSP: Supply-Side Platform
DSP: Demand-Side Platform
RTB: Real Time Bidding
Behind the Scenes

Publisher

SSP: Supply-Side Platform
DSP: Demand-Side Platform
RTB: Real Time Bidding
Business Model

• Advertiser pays a publisher when the ad is clicked

• Performance Indicator
  – Click Through Rate (CTR)
  – Cost Per Impression (CPI)
  – Cost Per Click (CPC) ...etc
CTR Prediction with Machine-Learning (Click-through-rate)

- Machine-Learning (ML) tech is often used for CTR prediction
- ML has succeeded in this field

<table>
<thead>
<tr>
<th>Click</th>
<th>F1</th>
<th>F2</th>
<th>F3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>M</td>
<td>01</td>
<td>2.13</td>
</tr>
<tr>
<td>0</td>
<td>F</td>
<td>07</td>
<td>2.12</td>
</tr>
<tr>
<td>0</td>
<td>F</td>
<td>23</td>
<td>4.2</td>
</tr>
<tr>
<td>?</td>
<td>F</td>
<td>99</td>
<td>1.2</td>
</tr>
</tbody>
</table>
Budget Pacing

• **Budget pacing** is also important

• Control of budget pacing helps advertisers to…
  – Reach a wider range of audience
  – Avoid a premature campaign stop / overspending
Budget Pacing

• Two lines of strategies
  – Bid modification
  – Probabilistic throttling

• We propose a different way based on a bipartite graph and inspired by financial theory

• Our research strengthens existing research rather than replacing it
Our Approach: Model and Formulation

• Display advertising is represented by the edge-weighted bipartite matching problem
• Edge weight = CTR (in our research)

CTR: Click Through Rate
Our Approach: Model and Formulation

- Control the variation rate of CTR
- Find a matching with
  - High CTR
  - Low variation of CTR
Our Approach: Model and Formulation

- Objective Function as QUBO

\[
\arg \max_x \left\{ \mathbb{E} \left[ w^T \right] x - \alpha x^T W x - \beta (P x - 1)^2 \right\}
\]

- Maximize CTR
- Low variation
- Constraint

- \( N_a, N_c \): Size of each vertex
- \( x \in \{0, 1\}^{N_a \times N_c} \): Decision variable
- \( w : \Omega \rightarrow \mathbb{R}^{N_a \times N_c} \): Weights vector (CTR, CVR etc) for each edge
- \( W \in \mathbb{R}^{(N_a \times N_c)^2} \): Covariance matrix of \( w \)
- \( P \): Matrix which expresses a restriction
- \( 1 \): Vector with all elements as one
- \( \alpha, \beta \in \mathbb{R} \): Control parameters
Experiments with Real World Data

• Setup
  – Data: our Display Ad campaign data
  – Combination: 14-advertisement campaign and 24 user (cluster)
  – CTR and its variation are estimated by historical data
    • Sample average and variance-covariance matrix
Experiments with Real World Data

• Use quantum annealing processor, D-Wave 2X

• Some techniques for optimization
  – Pruned edges with less impact
  – Reduce the solution space by clustering users
Experiments with Real World Data

- Correlation between edges (CTR correlation)
Performance Measure

Consolidated Table (CTR)

Edge

<table>
<thead>
<tr>
<th>AD1 x User1</th>
<th>AD2 x User1</th>
<th>AD3 x User1</th>
<th>AD1 x User2</th>
<th>AD2 x User2</th>
</tr>
</thead>
</table>

1: Estimate parameters
2: Optimize by D-Wave

Time (Hour)

Actual CTR
Performance Measure

Edge
AD1 x User1
AD2 x User1
AD3 x User1
AD1 x User2
AD2 x User2

CTR Matrix

1: Estimate parameters
2: Optimize by D-Wave

Actual CTR

Time (Hour)

18
Experiments with Real World Data

• Hourly performance of each strategy
• Greedy method: Choose maximum CTR edge for each user

CTR

- QA
- Greedy
Experiments with Real World Data

- Quantum annealing (QA) finds a better solution than the greedy method
  - Almost same CTR level
  - Low variation of CTR

Performance

CTR

Low volatility (≈30% reduced)
4. Summary

• Budget pacing is important for display advertising
• Formulate the problem as QUBO
• Use D-Wave 2X to solve budget pacing control optimization problem
• Quantum annealing finds a better solution than the greedy method.
Thank you for listening
Memo
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