Fatigue-Aware Ad Creative Selection

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Background

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We call this **ad creative**.

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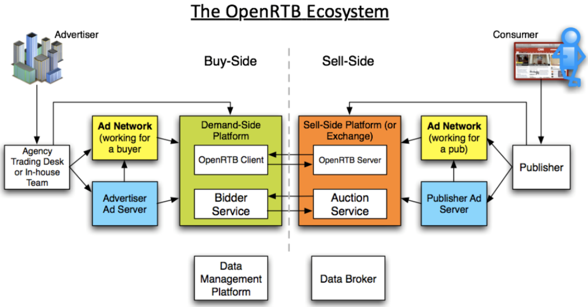
Background

Ad is delivered to consumers through DSP and SSP
DSP makes bids for **auctions** hosted by SSP and select ad creative.
No bidding strategy today. Just consider selection of ad creative.



IAB, `https://www.iab.com`

Motivation

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Figure 2: A set of ad creative candidates

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Usually, there are many candidates.
New ad creatives are continuously added during day.

Figure 2: A set of ad creative candidates

Motivation

DSP needs to determine the best ad creative without enough information
= typical **Bandit problem**.

Thompson sampling is one of bandit algorithms.

- Easy to implement
- Good performance in online ad/rec environment (Chapell&Li, 2011)

Motivation

Thompson sampling

Sample a parameter for each ad creative.

select

$$a_t = \arg\max_{a_t} r(a_t)$$

$r(a_1) \sim B(\alpha(a_1), \beta(a_1))$

$r(a_2) \sim B(\alpha(a_2), \beta(a_2))$

$r(a_3) \sim B(\alpha(a_3), \beta(a_3))$

Motivation

Thompson sampling with **context** x_t

$$\hat{r}_t(a_t) = \quad (\quad _{0} \quad \mathrm{x}_{\mathbf{t}} + \quad (a_t) \quad \mathrm{x}_{\mathbf{t}});$$

where

$$(a_t) \quad N (\quad (a_t); \quad \quad (a_t))$$

select

$$a_t = \arg\max_{a_t} r(a_t)$$

Motivation

Problem with bandit

DSP *randomly* chooses ad creative at first.

Figure 3: Little data = Random

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- DSP *randomly* chooses ad creative at first.
- Once DSP learned enough data, (a_t) become deterministic. Same ad creative is chosen repeatedly.

Figure 4: Enough data = Deterministic

Motivation

Problem with bandit

- DSP *randomly* chooses ad creative at first.
- Once DSP learned enough data, (a_t) become deterministic. Same ad creative is chosen repeatedly.
- Uncomfortable due to boredom, fatigue.

Figure 4: Enough data = Deterministic

Motivation

In **marketing science**, it is widely understood that repeated exposure has two phases.

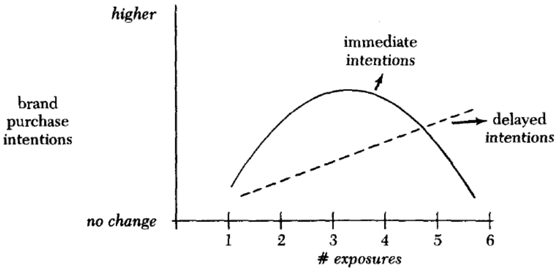

Figure 5: Figure from Pechman and Stewart (1988)

Motivation

Two-factor model assumes repetitive advertising has two effect.

Positive effect: “hello effect”, (Zajonc 1968)

Negative effect: fatigue, boredom, physiological reactance

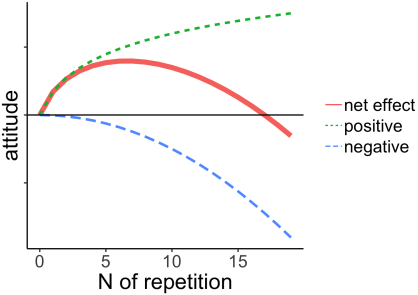

Figure 6: Two factor model

Proposed Method

Fatigue-Aware ad creative selection

Idea: penalize ad creatives with higher fatigue by lowering $r(\hat{a}_t)$

Proposed Method

Good fatigue measure should

- increase with # of exposure to same ad creative
- increase with # of exposure to similar creatives
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We define fatigue measure $_{i,t}(a_t)$ as follows.
Let $s(a_t, a_{t'})$ be **similarity scores** between a_t and $a_{t'}$.
Then, fatigue measure $_{i,t}(a_t)$ is defined as a sum of similarity scores between a_t and past ad exposure $a_{t'}, t' < t$.

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Similarity score is constructed from text and image of ad creatives.

- Vector representations using MobileNetV3 for image and BoW for text.
- cosine similarity for image and text
- weighted average of image similarity and text similarity. Ratio text:image = 3:1.

Calculate fatigue for each creative

Figure 7: Similarity matrix

Figure 8: Calculation of fatigue

Proposed Method

Finally just add quadratic function of fatigue ${}_{i;t}(a_t)$ to the linear predictor

$$\hat{r}_{i;t}(a_t) = \ (\ {}_0 \ \boldsymbol{x_t} + \ (a_t) \ \boldsymbol{x_t} + b_1 \ {}_{i;t}(a_t) + b_2 \ {}_{i;t}(a_t)^2):$$

b_1 and b_2 take any value.

- $b_1 > 0$ and $b_2 < 0$: inverse-U
- $b_1 < 0$ and $b_2 < 0$: keep decreasing
- $b_1 > 0$ and $b_2 > 0$: keep increasing
- $b_1 < 0$ and $b_2 > 0$: U-shape

Proposed Method

Estimation:

- L2-regularized logistic regression
- Get mean of weight vector $_0$ for $\mathbf{0}$, (a_t) for (a_t), and b_1, b_2 with SGD
- Get variance-covariance matrix for weight vector (a_t) from negative log-likelihood + L2 term by taking 2nd order derivative of them

Summary of the algorithm

for $t = 1, \dots, T$ **do**

  for each $a_t \in \mathcal{A}_t$, Sample $(a_t) \sim N(\ (a_t), \ (a_t))$ and Calculate $\hat{r}_t(a_t)$

  Select $a = \arg\max_{a \in \mathcal{A}_t} \hat{r}_t(a)$

  Observe $r_t \in \{0, 1\}$

  if t is the last impression of the day **then**

    Update $N(\ (a_t), \ (a_t)), b_1, b_2$ for all the a_ts on data from previous day

  end if

end for

Proposed Method

One additional ingredient is "forced exploration".
Each time t, if the DSP finds unknown ad creative a' in candidate set $|A_{i,t}|$, then it assigns very high $\hat{r}(a')_t$ at the probability of $1/|A_{i,t}|$.

Implementation

Implementation in the real production environment is challenging because,

- RTB is very latency-sensitive. No time for complex calculation.
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Tricks:

- Calc. similarity score offline
- Cache user's ad exposure on memory & Capping # of user-ad logs
- Remove logs 24+ hours before

Experiment

Offline evaluation is very difficult for this setting. Replay method needs exact matching of path.

Online A/B testing

- Fatigue-Aware algo (FA) vs. Contextual Bandit-based algo. w/o fatigue (Baseline) vs. Random algo (Random)
- Split users into three groups.
- FA and Baseline learns logs from each group.

Environment

Three advertising campaigns for mobile game titles

3 million impressions in total

5-21 creatives per campaign

One week.

Hyper-parameters are shared. Tuned for Baseline.

Results

Overall results show FA outperforms the others.

Alg.	Imp.	norm'd CTR	norm'd CVR	Post-Click CVR	Post-Imp CVR
FA	1,097,261	**1.08**	**1.12**	1.04	**1.09**
Baseline	1,081,393	1.04	1.10	**1.05**	1.04
Rand	1,087,931	1.00	1.00	1.00	1.00

Table 1: $P < 0{:}1 :^{*}; P < 0{:}05 :^{**}; P < 0{:}01 :^{***}$

Results

Breakdown reveals heterogeneity in campaigns.

	Campaigns		
Alg	A	B	C
FA	**1.21**	**1.04**	**1.32**
Baseline	0.95	1.03	1.11
Rand	1.00	1.00	1.00

Table 2: CTR by campaign.

Post-experiment Analysis

The fatigue is actually reduced for FA.

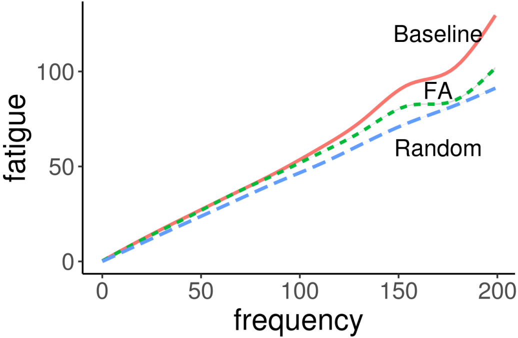
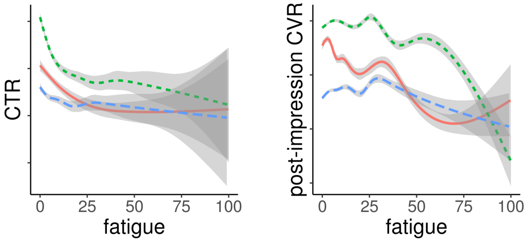


Figure 9: The relationship between the number of ad exposures in past 24 hours for each user (frequency) and the level of fatigue. Loess.

Post-experiment Analysis

CTR decreases with fatigue while CVR peak at around 30.

- People click by curiosity.
- Attitude increases with repetition.



Summary

We propose fatigue-aware ad creative selection algorithm that explicitly consider user's fatigue when selecting ad creative.

Online experiment shows superiority of the method.

Post-experiment analysis shows the method worked as expected. There are different relationship of click-fatigue and conversion-fatigue.

Final Remark

Thank you for listening!