### Al at the Webscale Project Results

Bas Bootsma & Fenno Vermeij

Radboud University Nijmegen

30th June 2015

## Approach

- Epsilon-greedy Good baseline
- Gibbs-sampling Too computationally expensive
- Thompson-sampling

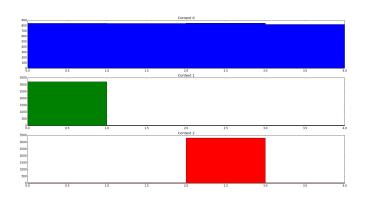


#### Model

$$r = \beta_0 + \beta_{x_1}c_1 + \ldots + \beta_{x_k}c_k + \beta_{y_1}a_1 + \ldots + \beta_{y_l}a_l + \beta_{z_1}c_1a_1 + \ldots + \beta_{z_m}c_ka_l$$

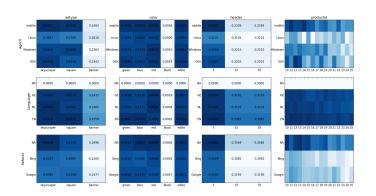
- Reward for update: use price · effect instead of effect
- Price: Maximize polynomial:  $\beta_0 + \beta_1 \cdot p + \beta_2 \cdot p^2$  instead of bucketing: [1, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50]

# Visualization of policy



• Pre-defined distribution for 3 context parameters, and 4 arms

## Visualization of context vs. proposal



ullet Every possible combination of proposal parameters, except  $\mathit{price} = 1$ 

- Multivariate Gaussian speedup: using Cholesky transformation
- Use 5000 random interactions to give model 'warm star before doing actual predictions
- Add features for user ID: average price user paid previously, and whether the user actually bought anything

- Multivariate Gaussian speedup: using Cholesky transformation
- Use 5000 random interactions to give model 'warm start' before doing actual predictions
- Add features for user ID: average price user paid previously, and whether the user actually bought anything

- Multivariate Gaussian speedup: using Cholesky transformation
- Use 5000 random interactions to give model 'warm start before doing actual predictions
- Add features for user ID: average price user paid previously, and whether the user actually bought anything

- Multivariate Gaussian speedup: using Cholesky transformation
- Use 5000 random interactions to give model 'warm start' before doing actual predictions
- Add features for user ID: average price user paid previously, and whether the user actually bought anything

#### Results

• Average reward: 16.75

Standard deviation: 5.07

• Time taken:  $\sim$ 01:25h per run

• Any questions?

