

# Selecting Multiple Website Elements

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## THE PROBLEM

Select a set of **website elements** to display to a user.

- Adverts on search results.
- Movie suggestions.
- Recommendations on a retail site.

Shop for bikes on Google

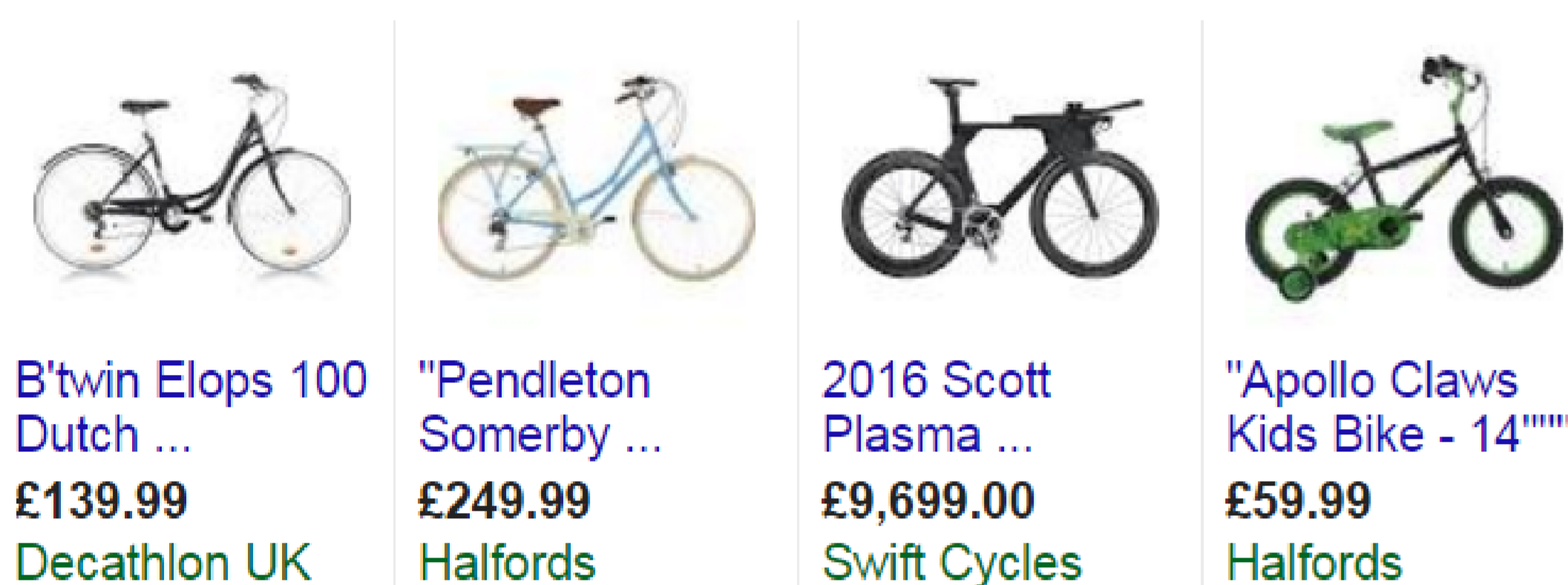


Figure 1: A diverse(!) set of adverts for Google search for “bikes”.

### The objective

Maximise current and future user **clicks** on the elements. Clicks are affected by:

- The quality of the element (initially unknown).
- The relevance of the element to the current user.

### The Main Difficulty

Clicks depend on the **set of elements** not individual elements.

- The set is different from the sum of its parts.
- Combinatorial explosion in possible sets.
- So learn about individual elements but choose sets.

### Diversity

Similar elements in the set creates *redundancy*.

- Consider a set of all action movies or books by one author.
- If one element is not clicked then a similar one is unlikely to be clicked either.
- A diverse set avoids this problem.

**How can this be modelled? How diverse should the set be?**

## MODELLING

The quality of each element must be learnt through observing user feedback (clicks). This is a bandit problem whose arms are the elements. The objective is to maximise expected **click-through rate (CTR)** over time.

### Context and Uncertainty

The **context** is extra information specific to each time that affects the CTR e.g. user information (location, preferences) or search terms entered. This is rarely known exactly:

- A search term has multiple meanings e.g. jaguar or flash.
- A travel based search could be for business or a holiday.
- Movie preferences change when watching alone or with friends.

This is captured by using a **probability distribution as context**.

**This uncertainty induces diversity in solution sets.**

### Click Models

At each time the user is summarised by a latent state  $x \in \{1, 2, \dots, n\}$ . Only its distribution is known. Each arm  $a$  has  $n$  corresponding weights  $w_{a,x} \in [0, 1]$  representing its quality for state  $x$ .

For a single arm the CTR is  $w_{a,x}$ . For a set of arms  $A$  either one or none are clicked. Two possible models for **set CTR** are:

- **Probabilistic Click Model (PCM)**. An independent  $Bern(w_{a,x})$  trial is run for each arm. There is a click if any is a success.
- **Threshold Click Model (TCM)**. Each user has a threshold  $u \sim U(0, 1)$ . There is a click if  $\exists a \in A$  such that  $w_{a,x} > u$ .

The set CTR is then:

$$Pr(\text{Click}) = \begin{cases} 1 - \prod_{a \in A} (1 - w_{a,x}) & \text{for PCM} \\ \int_{u=0}^1 1 - \prod_{a \in A} (1 - \mathbb{1}_{w_{a,x} > u}) du & \text{for TCM.} \end{cases}$$

**Comparison.** PCM is simpler but TCM induces greater diversity. With two identical arms the second arm increases CTR under PCM but not under TCM. This suggests PCM undervalues diversity.

## SOLUTION METHOD

The solution method takes three parts:

- A Bayesian scheme that converges to the true weights with sufficient observations (**updating beliefs**).
- An algorithm that chooses a good arm set when weights are known (**exploitation**).
- A bandit algorithm that learns the weights without neglecting short term rewards (**exploration**).

### Updating Beliefs

The unobserved state  $x$  makes exact updating impractical. A form of **online expectation maximisation** can be used:

1. Obtain  $\tilde{X}$ , the posterior distribution for  $x$  given user action.
2. Sample an  $\tilde{x}$  from  $\tilde{X}$ .
3. Update weight beliefs assuming  $x = \tilde{x}$ .

### Exploitation

The CTR for both PCM and TCM is **submodular**. For these problems a greedy algorithm is known to perform well. Arms are added sequentially, choosing at each step the arm that maximises the increase in expected CTR.

### Exploration

The true weights are not known so instead a proxy  $\tilde{w}$  is used. This is usually some function of the weight beliefs and can be implemented easily by adapting an existing bandit index policy e.g. Thompson Sampling, UCB.

### Acknowledgements

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