A Mechanism for Mining Top Impacted Segments in Web Analytics based on the Variants used for AB Testing

Mubbashir Nazir¹, Umar Mir² and Anuj Yadav³

¹²M.Tech Scholar Department of Computer Science & Information Technology DIT University Dehradun
²Assistant Professor Department of Computer Science & Information Technology DIT University Dehradun

Abstract

In this paper, a new approach for Impact Analysis of AB Testing is presented that aids in mining Top Impacted Behavioral Segments in Web Analytics, based on the variants used for AB Testing. First we propose a method for calculating Segment Exposure Ratio (SER), to determine the user exposure ratio for each segment. Then we calculate the Impact score for each segment based on the experiments and the corresponding versions to which the segments are exposed to, facilitating the discovery of top impacted segments. Finally we calculate the interestingness score of the different variants of an experiment based on the impact score of each segment, providing the interesting patterns if any among the different version of an experiment.

Keywords: AB Testing, Web Analytics, Behavioral Segments, Segment Exposure Ratio (SER), Interestingness, Impact Score, Interesting Patterns.

1. INTRODUCTION

With the advancements in technology and the advent of internet, the domain of business extended to web based initiatives such as E-commerce. For any E-commerce site the success largely depends upon the sales and conversions rates. The design and the usability of the E-commerce site and software substantially contribute to these goals. In order to enhance the design effectiveness of the E-commerce site, users should be exposed to different variants of the site design and each variant should be tested for effectiveness in terms of metrics such as number of hits, conversion rates, landing pages etc. In online marketing such approach is referred to as AB Testing. AB Testing (also termed as Split Testing) is the method of pitting up two variants of a web page against each other to determine which one performs better. It is a method to validate that any new design or change to an element on a webpage is improving the conversion rates before making that change in the site code. In this method the two variants of a web page are exposed to randomly selected sample of users, and the impact of the two variations on key success measures such as conversion, is statistically analyzed.

Testing takes the guesswork out of website optimization and enables the data-backed decisions that shift business conversations from “We Think” to “We Know”. By measuring the impact that changes have on metrics such as purchases, add to cart etc it can be ensured that every change produces the positive results.

Fig 1: Example of AB testing using two design versions (A, B) on randomly distributed visitors

In the Proposed approach we use AB Testing in Web Analytics (a tool that provides objective tracking, collection, measurement, reporting, and analysis of quantitative Internet data to optimize websites and web marketing initiatives [1]) to perform Impact Analysis of segments in order to determine the Top Impacted segments for each of the design variants used, thereby enhancing the design effectiveness of the site and also aid in increasing the sales and conversion rates.

2. AB TESTING FRAMEWORK

A user is exposed to multiple tests, assigned form a pool of running tests. Each test has multiple versions which are mutually exclusive i.e. only one version of a test can be assigned to a user. Each test can ran either exclusively or shared.
Based on the success measures such as conversion rates one of the winning versions are assigned. If there is no winning version then one version from running versions is randomly assigned. Exclusiveness is used to disassociate any biasness induced by the experimentation running.

Creation of experiment involves two steps. One which will create an Experiment Group (or simply experiment) and the other will create a new version by providing the experiment Id. All experiments and versions are induced as first party cookies, thus enabling us to track user behavior with each test the user is exposed to.

- No cookie parameter is passed i.e. user is new
- Inactivity exceeds TTL value of current allotted experiment version
- Currently assigned experiment is paused or closed

Home >> Manage Experiments

![Fig 2: Scenario depicted AB Testing framework](image)

![Fig 3: AB testing result set based on visits, page views, unique clicks, and avgclicks](image)
3. The Proposed Approach

In order to mine the top impacted segments we identified various measures which on processing help in determining the top impacted segments based on AB Testing variants. The measures are listed as below:

- Total user exposure for an experiment (TUE)
- User Exposure per segment for an experiment (USE)
- Segment Exposure Ratio (SER)
- Total user exposure for a version (TUV)
- User exposure per segment for a version (USV)
- Segment Impact Score (SIS)
- Interestingness Score (IS)

![Flow Diagram for Impact Analysis on AB Testing](image)

3.1 Algorithm for calculating Segment Exposure Ratio (SER)

Stage 1: Generate Clickstream

Stage 2: Filter Clickstream by IP and check if segment record is not null

Stage 3: Extract records having unique experiment Id

Stage 4: Calculate total users exposed (TUE) for each unique Experiment as:

\[ TUE = \sum DV \]

Where DV refers to distinct users visiting the site identified by the unique first party cookie and unique experiment Id

Stage 5: Calculate User exposure for each segment (USE) for each unique Experiment as:

\[ USE = \sum DSV \]

Where DSV refers to distinct users visiting the site identified by the unique first party cookie, unique experiment Id and unique segment name.

Stage 6: Calculate Segment Exposure Ratio (SER) as:

\[ SER = \frac{USE}{TUE} \]

SER gives traffic distribution ratio for each behavioral segment with unique experiments

3.2 Algorithm for calculating Segment Impact Score

Stage 1: Generate Clickstream

Stage 2: Filter Clickstream by IP and segment record is not null
Stage 3: Extract records having unique version Id for each AB experiment

Stage 4: Calculate total users exposed for a version (TUV) for each unique Experiment as:

\[ TUV = \sum DVV \]

Where DVV refers to distinct users visiting the site identified by the unique first party cookie, unique experiment Id and unique version Id

Stage 5: Calculate User exposure for each segment (USV) for each version having unique Experiment as:

\[ USV = \sum DSVV \]

Where DSVV refers to distinct users visiting the site identified by the unique first party cookie, unique experiment Id, unique version Id and unique segment name.

Stage 6: Calculate Segment Impact Score (SIS) as:

\[ SIS = \frac{\text{DSVV}}{TUV} \]

Stage 7: Normalize the SIS score for each segment

SIS gives traffic distribution ratio for each behavioral segment exposed to different AB experiment variants. The segment with the highest Impact Score is tagged as the **Top Impacted Segment** exposed to a unique experiment with different variants

### 3.3 Calculating Interestingness Score

Interestingness Score helps in mining the interesting patterns among different versions of a specific AB experiment. Interestingness score is calculated by taking the standard deviation of the Segment Impact Score for each version of a specified experiment. The greater the number of positive standard deviations the more interesting the design patterns are. The interestingness score is calculated as:

\[ IS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (SIR_i - \mu)^2} \]

where \( \mu = \frac{1}{N} \sum_{i=1}^{N} SIR_i \)

Where N is the number of unique version of a specific experiment

![Fig 5: IS, SER, SIS values stored in read-only database (Splout Sql)](image)
4. CONCLUSION
The research presented, will thus provide Impact Analysis of AB experiment variants leading to the discovery of non-trivial, valid, and novel design patterns of E-commerce site that play an important role in driving the growth of an organization. The proposed work has been successfully tested on an E-commerce site Artsya (www.artsya.com) and it was observed that the system performs better, providing programmable actions by performing deeper analysis of the available metrics that can be used as feedback for personalization.

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