MULTIBRAND GEOGRAPHICAL EXPERIMENTS AND ANALYSIS

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MULTIBRAND GEOGRAPHICAL EXPERIMENTS AND ANALYSIS

Entities expend significant resources to advertise or market their services or products to potential customers. Advertisements can be provided to potential customers via online advertisement infrastructure, including, for example, by a content selection server for display on a web page or other application executed or provided by a computing device. However, it may be challenging to measure the causal impact advertising can have on sales for a brand or product.

The proposed technique solves this by measuring the causal impact of advertising on sales by establishing and executing randomized experiments, and analyzing the data collected from the experiments. The randomized experiment can include raising or lowering an advertising budget by an amount for a subset of computing devices, such as computing devices in a given geographical area. Unfortunately, there may be insufficient impression inventory to sustain a large budget increase, or doing so might distort from usual practice. The technique can address this by simultaneously experimenting on more than one product or brand. By pooling data from multiple brands (e.g., toothpaste, shampoo, diapers, etc.) or multiple geographic regions, the technique can establish a combined experiment large enough to accurately estimate the average return on investment in advertising over the set of brands. Furthermore, using statistical pooling, such as Bayesian methods or empirical Bayesian methods (e.g., Stein shrinkage), data from one brand can be used to improve the accuracy of an estimated impact for another brand.

Figure 1 illustrates a system 1 that includes a data processing system 5 to perform the technique. The system 1 can include or interact with one or more computing devices 2, one or more content providers 3, and one or more content publishers 4 via a network 10. The data processing system 5 can include an experiment generation component 6, a data collection component 7, an impact analysis component 8, and a data repository 9. The data processing system 5, experiment generation component 6, data collection component 7, impact analysis component 8, computing device 2, content provider 3, and content publisher 4 can include one or more servers, processors, computing devices, memory, logic arrays, circuitry, software or hardware modules, logic elements, or digital logic blocks configured to facilitate socially sharing content items.
Computing device 2 can include, for example, mobile computing devices, mobile telecommunications devices, smartphones, personal digital assistants, laptop computers, notebooks, tablet computers, smart watches, or wearable devices. The computing device 2 can include a display such as a liquid crystal display, light emitting diode (LED) based display, organic light emitting diode based display, bitmap display, pixel display, electronic ink display, or other display configured to visually output content including text, characters, strings, symbols, images, or multimedia content provided by a data processing system 5. The computing device 2 can include an input interface designed and constructed to receive input from a user. Input interfaces can include or provide, for example, touch input, keyboard, mouse, motion, sensor, location sensor, touchpad, trackpad, or a scroll wheel. The location sensor can provide location information or facilitate determining a location of the computing device. The location sensor can determine the location of the ordering device using one or more techniques such as global positioning system, WIFI triangulation, IP address, Bluetooth, or cellular tower triangulation. The location information can be used to facilitate selecting content items. The network 10 can include one or more of any type of computer network such as the Internet, cellular network, WIFI network, WiMAX network, mesh network, Bluetooth, near field communication, satellite network, or other data network that facilitates communications between the data processing system 5 and computing device 2.

A content provider 3 can refer to, or include, an advertiser or other provider of content items, such as online documents, blogs, media or advertisements. The content provider 3 can establish an advertisement campaign with advertisements and advertisement selection criteria, such as keywords and geographic location. The content provider 3 can further establish a budget or spend amount for the advertisement campaign. The content publisher 4 can refer to or include a web site operator, such as an entity that operates a web page. The web site operator or content publisher 4 can include at least one web page server that communicates with the network 10 to make the web page available to the computing device 2.

The experiment generation component 6 can establish an experiment for one or more brands using one or more experiment parameters. The experiment can include running one or more advertisement campaigns with varying parameters. For example, the experiment generation component 6 can determine or implement a strategy for varying advertising spending.
The experiment generation component 6 can identify one or more brands and one or more geographic regions in which to provide advertisements for the one or more brands. The experiment generation component 6 can identify, for a given content provider 3, brands and geographic locations. For example, the experiment generation component 6 can identify the following six brands: toothpaste, soap, shampoo, sunscreen, baby powder, hairspray; and the following six geographic locations: Los Angeles, Washington DC, Chicago, Boston, Miami, Austin.

The experiment generation component 6 can determine or establish parameters for the experiment. Parameters can include, for example, a baseline time interval, an experimental time interval, an increase in advertisement spend, and a decrease in advertisement spend. The baseline time interval can be less than, equal to, or greater than the experimental time interval. The baseline time interval can be 1 week, 2 weeks, 4 weeks, 6 weeks, 8 weeks or other time interval. The experimental time interval can be 1 week, 2 weeks, 4 weeks, 6 weeks, 8 weeks or other time interval.

The experiment generation component 6 can establish an experiment that includes providing advertisements for each brand in one or more geographic locations in accordance with an established parameter. Advertisements for each identified brand can be provided in each identified geographic region at a control or nominal level for a predetermined time interval. Each brand can be advertised at an increased level in half of the geographic regions and at a decreased or a nominal level in the other half. Similarly each geographic region can be the site of increased advertising for half of the brands and decreased or nominal advertising for the other half of the brands.

The experiment generation component 6 can establish the baseline time interval (e.g., 8 weeks). During the baseline time interval, the data processing system 5 can deliver advertisements at a baseline or nominal level. The baseline or nominal level can be set by a content provider 3, or determined based by the experiment generation component 6 based on an advertisement budget or spend allocated for the advertisement or content campaign.

The experiment generation component 6 can establish a follow-up period, or experimental time interval (e.g., 4 weeks) during which the level of advertisement is varied in some or all of the geographic regions. The experiment generation component 6 can increase the
advertisement delivery for each brand in half of the geographic locations, and decrease the advertisement delivery for each brand in the other half of the geographic locations. The experiment generation component 6 can establish the varying amounts of advertisement delivery by adjusting the spend or budget for the advertisement campaign for the brand in each geographic location. The experiment generation component 6 can vary the budget such that the overall budget (e.g., budget per week) for the brand remains the same as the budget (e.g., budget per week) for the brand established during the baseline time interval. Thus, the experiment generation component 6 can increase the budget for a brand in half the cities, and decrease the budget in some or all of the other half of the cities to offset the increase.

The geographic regions in which the advertisement level is increased can be referred to as the “treatment” geographic locations. The second group of geographic regions in which the advertisement level is decreased or remains the same can be referred to as the “control” geographic regions. The experiment generation component 6 can randomly or pseudo-randomly assign geographic regions as treatment geographic regions or control geographic regions. The experiment generation component 6 can use a function, algorithm, or other technique to assign geographic regions as treatment geographic regions or control geographic regions. Assigning geographic regions to treatment versus control can facilitate the impact analysis component 8 identifying differences in, for example, sales that can be given a causal interpretation.

The experiment generation component 6 can establish the experiment such that the geographic regions are in the treatment group for approximately half of the brands, and are in the control group for approximately the other half of the brands. The experiment generation component 6 can assign the geographic regions such that two geographic regions would not be in the treatment group for the exact same set of brands. Further, the experiment generation component 6 can assign the geographic regions such that a geographic region is not the control every time another geographic region was the treatment. The experiment generation component 6 can establish the experiment to have a near equal allocation for pairs of cities to the four categories: treatment-treatment, treatment-control, control-treatment and control-control. Similarly and simultaneously the experiment generation component 6 establishes such a near equal allocation for pairs of brands. The experiment generation component 6 can choose an experiment so the average allocation (e.g., the root mean squared correlation over pairs of cities
or brands) satisfies a threshold. The experiment generation component 6 can establish the experiment such that no two brands get the treatment in the exact same set of geographic regions. Thus, the experiment generation component 6 can use an algorithm or technique to put each brand in the treatment group for exactly half of the geographic regions, and then approximately balance the treatment versus control distribution for pairs of geographic regions and for pairs of brands. The experiment generation component 6 can be configured with a randomized algorithm. The randomized algorithm can be one that can be used for sampling tables of numbers with given row and columns sums.

Table 1 illustrates the experimental/second time interval after the baseline time interval.

<table>
<thead>
<tr>
<th>Brand / Geo</th>
<th>Los Angeles</th>
<th>Washington D.C.</th>
<th>Chicago</th>
<th>Boston</th>
<th>Miami</th>
<th>Austin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Toothpaste</td>
<td>T</td>
<td>T</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>T</td>
</tr>
<tr>
<td>Soap</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>T</td>
<td>T</td>
<td>T</td>
</tr>
<tr>
<td>Shampoo</td>
<td>T</td>
<td>T</td>
<td>C</td>
<td>T</td>
<td>C</td>
<td>C</td>
</tr>
<tr>
<td>Sunscreen</td>
<td>T</td>
<td>C</td>
<td>T</td>
<td>C</td>
<td>T</td>
<td>C</td>
</tr>
<tr>
<td>Baby powder</td>
<td>C</td>
<td>T</td>
<td>T</td>
<td>C</td>
<td>T</td>
<td>C</td>
</tr>
<tr>
<td>Hairspray</td>
<td>C</td>
<td>C</td>
<td>T</td>
<td>T</td>
<td>C</td>
<td>T</td>
</tr>
</tbody>
</table>

Table 1: Varying Advertisement Spend for each brand and geographic

The experiment generation component 6 can establish the parameters during the experimental time interval such that every brand is advertised in every location, and some of the brands in each location are advertised at a treatment level (e.g., an increased advertisement spend, budget, or delivery), and some of the brands are advertised at a control level (e.g., decreased or nominal advertisement spend, budget, or delivery). The experiment generation component 6 can establish the experiment with some variability such that the same brands are not low and high in the same cities. In some cases, the geographic randomization can be independent for each brand.

The data processing system 5 can include a data collection component 7 that monitors the advertisement campaign and collects data related to the performance of the advertisement campaign. The data processing system 5 can receive, obtain, or otherwise identify data for each
brand and each geographic region of the experiment. The data processing system 6 can receive or identify the data during the baseline time interval or the experimental time interval.

The data collection component 7 can provide an interface configured to receive the performance data. Performance data can include impression records. Performance data can include information about clicks, selections, or conversions related to the content item or advertisement. Performance data can further include return on investment. In some cases, the content provider 3 can provide sales information or sales data to the data processing system 5. In some cases, the data processing system 5 can determine the sales data if, for example, the content item is for a product or service provided via the data processing system 5 (e.g., via an online marketplace provided or administered by the data processing system 5, or a transaction processing system established, provided, or administered by the data processing system 5).

The data processing system 5 can include an impact analysis component 8 that analyzes the obtained performance data to determine an impact on sales of a product or service due to advertising. The impact analysis component 8 can determine the impact for a given brand to estimate or predict the performance of another brand. For example, an impact determined using data for five brands can be used to predict a performance of a sixth brand in the experiment.

For example, the impact analysis component 8 can be configured with a regression technique that estimates an impact of advertising for each brand. For example, the linear regression model can include advertising as the predictive variable with sales for a brand as the dependent variable. The data processing system 5 can provide an improved estimate of impact on sales due to advertising by adjusting or shrinking the estimated return on advertising investment for each brand towards an estimate of the overall average return of all the brands. Content providers 3 can use this information to set spending levels for an ad campaign.

The impact analysis component 8 can be further configured with a statistical tool, such as Bayesian analysis or empirical Bayes analysis, that allows the data processing system 5 to generate an improved estimate of the impact on sales for a brand due to advertising. The impact analysis component 8 can use the Stein shrinkage technique to improve the estimate for one brand by pooling or using data from one or more other brands. Although it may seem counter-intuitive to use data from other potentially unrelated brands to improve the estimate of a brand, the estimate may be improved because good or bad 'luck' for each brand's numbers can be
countered by pulling them all towards their common mean. If the true effects for brands are roughly similar, then very large efficiency gains are possible from this pooling. The Stein effect for pooling towards the common mean can be observed or established mathematically when there are four or more brands. When there are four or more brands in the experiment, pooling can increase statistical efficiency or accuracy even if the brands are unrelated or different. Even though the technique may make some assumptions about normal distributions, the central limit theorem ordinarily makes the per-brand estimates nearly normal, and the Stein effect can be observed in non-normal settings too.

The impact analysis component 8 can use a Stein shrinkage technique to provide an improved estimate of advertisement effectiveness. For example, the data processing system 5 can determine the return on investment for each brand in each geographic region. The data processing system 5 can determine the return on investment as a multiplier of return on investment determined based on a comparison of the return on investment during the experimental time period and the return on investment during the baseline time period. For example, the multiplier can be determined by dividing the return on investment for a brand in a treatment geographic region during the experimental time period with the return on investment for the same brand in the same geographic region during the baseline time period. The multiplier can be determined by dividing the return on investment for a brand in a treatment geographic region or control geographic region during the experimental time period with the return on investment for the same brand in the same geographic region during the baseline time period. The data processing system 5 can determine an average return on investment for a brand across all geographic regions. The data processing system can determine an average return on investment across all brands for each geographic region. The data processing system 5 can determine a common value for the return on investment, and adjust outlier return on investments so they are closer to the common value. For example, if there are 20 brands, and one brand had a 20-times return on investment and the average return on investment was 10-times, then the data processing system 5 can adjust or lower the 20-times return on investment to 15-times return on investment, which is closer to the common value. The data processing system 5 can adjust the return on investment for one or more brands based on a statistical analysis of the return on investment of all brands to generate a more accurate return on investment for each brand (e.g., an
average return on investment for each brand across all geographic regions; or an average return on investment for all brands for each geographic region).

Thus, by experimenting on multiple brands, the data processing system 5 can identify geographic regions in which advertising is more effective than the national average. In such geographic regions, the effects of advertising are consistently stronger for numerous brands, perhaps all of them. A consistent trend over many brands is a may be a stronger signal, as compared to a trend over a single brand. Since some geographic regions may be relatively unaffected by advertising, a content provider 3 can use this data to adjust or modify advertisement spend in certain geographic regions with greater return on investment.

The data processing system 5 can pool unrelated brands together using this technique to estimate causal effects more effectively than can be done with single brand experiments. The data processing system 5 can use data with richer patterns as compared to single-brand experiment to generate improved statistical models or estimates for advertisement effectiveness by brand, as well as advertisement effectiveness by geographic region.

FIG. 2 illustrates an example of a method 20 for determining the impact of advertisement on sales or return on investment. The method 20 can be implemented by system 1. At step 21, the system can establish experiment parameters. At step 22, the system can execute the experiment with the established parameters. At step 23, the system can collect data from the experiment. At step 24, the system can process the collected data. At step 25, the system can generate a report using the processed data that provides an estimate of return on investment for one or more brands.

The system can establish experiment parameters at step 21. The experiment parameters can include brands, number of brands, geographic regions, a baseline time interval, an experimental time interval, treatment groups, control groups, or advertisement spend for each geographic region. In some cases, a content provider can provide one or more of the experiment parameters. In some cases, the system can use predetermined experimental parameters. In some cases, the system can use a function, algorithm, or other technique to determine one or more of the experimental parameters.

At step 22, the system can execute the experiment with the established parameters. Executing the experiment can include selecting advertisements or content items in accordance
with the established parameters for delivery to computing devices located in the selected geographic regions. The advertisements can be selected in response to requests for content items for display on computing devices in the corresponding geographic region. The system can use an advertisement selection process that uses content selection criteria, budget, bids or other parameters or criteria to select a content item to provide to a computing device.

At step 23, the system can collect data from the experiment. The system can collect data from the computing device, content provider, online merchant, physical establishment, or other entity. The data can include information about or related to a conversion, selection of the content item, sale of goods or services, price of the sale, or return on investment.

At step 24, the system can process the collected data to determine a return on investment for each brand in each geographic region during the time interval. The return on investment can refer to the incremental dollars (or other currency) received divided by the incremental dollars spent on advertising. The system can compare an average return on investment for each brand across all geographic regions during the experimental time period with the average return on investment for each brand across all geographic regions during the baseline time period. The system can compare an average return on investment for each geographic region across all brands during the experimental time period with the average return on investment for each geographic region across all brands during the baseline time period.

At step 25, the system can generate a report using the processed data that provides an estimate of return on investment for one or more brands. The report can provide an estimate of the impact advertising can have on return on investment for a brand or a geographic region using performance data from one or more other brands or one or more other geographic regions.