EECS 442: Final project

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1 Problem

1.1 Background and problem statement

Businesses, especially large Internet-based ones, often want to analyze customer behavior in order to better serve their customers' interests, and of course to make more money while doing so. One such company is Expedia, a multi-billion dollar travel reservations and booking company. It owns many brands, including (but not limited to) Expedia.com, Hotels.com, trivago, Orbitz, and Travelocity, with the latter three being relatively recent acquisitions. Every year, enormous numbers of people use Expedia-owned sites to search for hotels, flights, and more at various destinations around the world. Recently, Expedia's data division made a sizeable (10.9M rows) dataset available. The dataset covers a subset of search history data for anonymized users of the Expedia.com (US and generic), Expedia.ca (Canada), and Expedia.de (Germany) sites. The dataset is discussed in much more detail in the following section, but a few important details are given here. For example, the two-gigabyte dataset only pertains to hotel searches made from the above three websites over the course of the year 2015. The fields logged include every field present on the Expedia website, as well as information about the hotel, including broad categories describing it. Additionally, a binary field identifying whether the user is using a mobile phone or not is logged, as well as whether or not the user ultimately booked that particular hotel. It is these two fields that shall form the motivating question of this study: to what extent does mobile phone usage cause booking rates?

1.2 Symbol table

In this study, the following symbols will be used. They generally follow those used by Hernan and Robins [1] in their not-quite-published work, *Causal Inference* (the course textbook).

Let	be
A	1 if the user was on a mobile device else 0
Y	1 if the user made a booking else 0
L	a vector of covariates, discussed below
$\vec{l}$	a given row's values for L

2 Data set

2.1 Data source

The dataset used in this report was released by Expedia in early April 2017 for the American Statistical Association's annual Datafest event. It consists of two files, a two-gigabyte file and a hundred-megabyte file.

The larger file covers a subset of search history data for anonymized users of the Expedia.com, Expedia.ca, and Expedia.de sites, as mentioned in the problem definition above. The file is structured as tab-separated values with twenty-seven columns and almost eleven million rows. The columns of this file include: a timestamp (to the nearest minute); which site generated the record; the user's country, region, city, and (if available) the (latitude, longitude) pair and the distance between the user's location and the hotel's location; a user ID number; whether the user accessed the site from a mobile device or otherwise; whether the user was looking for package deals (paying for the hotel and the airfare in the same booking); the ID of a marketing channel; the search parameters (checkin, checkout, number of adults, number of children, number of hotel rooms, and the ID of the destination); the country where the hotel is; whether this viewing of a hotel resulted in a booking; the ID of the hotel; details about the hotel (whether or not it is part of a major chain ("branded"), average star rating by Expedia users on a five-point scale); general "bands" into which the hotel falls (with regard to distance, price, and popularity); and the number of similar events in the user's session. The bands are structured as enumerated types of five values, and have semantic meanings of very low, low, middle, high, and very high.

Unlike the larger file, the smaller file does not contain raw data; rather, it contains Expedia's estimates of how likely users would be to recommend different destinations for different categories of things to do at the different destinations. These values are stored as the base-ten logarithm of the estimated values, which helps compress the wide range of values that the probability can take on. These data are less suited to causal inference than the data present in the larger file and have been ignored for this report.

Finally, it should be noted that bookings ($Y = 1$) are in reality a rare event. To accomodate for this, as well as to obscure their conversion rate, Expedia deliberately included in the dataset a higher percentage of rows where $Y = 1$ than there should be. For example, if one naïvely divides the sum of the full `is-booking` column by the number of rows in that column, one finds that about ten percent of clicks on listings resulted in bookings. This impossibly high value should not be taken literally. Accordingly, any statistical methods relying on the ratio between $Y = 1$ and $Y = 0$ cannot be used, or at least, cannot be used to draw conclusions about Expedia's business.

2.2 Chosen variables

For this report, not all of the columns mentioned above were used. This is due to various reasons. A common reason is that ID numbers are effectively meaningless on their own. The three user location columns (latitude, longitude, and distance) were often null, resulting in their being eliminated from consideration. There are many possible locations, so more granular analyses might violate positivity; to avoid that, location is only used as a binary variable telling whether the country in which the user is located matches tthe hotel's country (1) or not (0). Similarly, there are 365 possible values for both checkin and checkout, but many fewer for their difference, and difference still has semantic meaning. Property details and banding also have few possible values and seem like they might be things that would influence whether or not someone booked a given hotel, given that they describe the hotel itself, as well as whether or not someone would use a phone to view that particular listing (since viewing detailed, high-resolution photographs is easier on larger desktop/laptop monitors than tiny phone screens). The prevalence of the "sync" feature offered by Firefox and Chrome to synchronize the open tabs between one's phone and desktop/laptop is a further argument for people making a concious choice as to which browser to use.

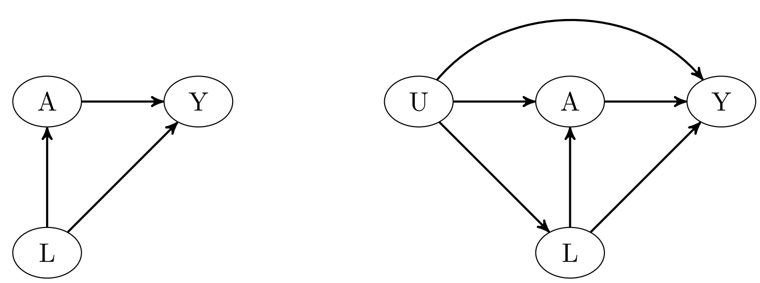
When doing causal inference, it is quite helpful for several key properties to hold. An important one is conditional exchangeability: within each value for L, the expected couterfactual outcome Y^a should (theoretically) be independent of the value of A. This can be expressed as

$$E[Y^a|A=1, L=l] = E[Y^a|A=0, L=l]$$

for binary A. If Y^a is binary, as it is for this report, then the expected values simplify to probabilities. Outside of controlled clinical trials, this value is hard to guarantee, but is thought to be at least plausible for this observational dataset due to the prevalence of browser sync features. Another important property is positivity, where every potential value of the vector L should have a nonzero (*i.e.*, positive) number of occurences. Despite the attempts to reduce the likelihood that positivity will be violated (implemented via selecting which variables to use), several of the columns being used correlate with each other, and might result in a hole. For example, two of the values of L correspond to historical price and star rating. It seems doubtful that there will be many, if any, values with high prices and low star ratings, and vice versa. Nevertheless, the enormous size of the dataset helps guard against positivity losses, so this selection of L variables should be suitable. One more important property for causal inference is that of well-defined interventions for the variable A. Since the vast majority of people do not interfere with their browsers' user agents, and since user agents are unambiguous, this likely holds for the dataset as well.

2.3 Causal graph

To make dependencies explicit, we here give the causal graph that is assumed for this report (left). It is a relatively common confounding graph, with the L variables influencing both mobile usage and booking rates.



In reality, the graph on the right (where U represents unmeasured values) is more likely. It is also likely that there are more U-like values, each pointing to a subset of the available nodes. The difficulty of working with such an ambiguous graph is what leads to the decision to use the graph on the left.

3 Analysis

The code for this report was written in Python with Pandas and the causalinference package (available via pip).

Due to computational limitations, instead of using the full eleven-million rows for computation, only a random subset was used. This subset was drawn with replacement from the full set of rows and contains ten thousand rows.

For this report, we restrict the analysis to the US site and ignore the others, in order to limit the modification of the effect caused by the different users of the different sites. As described above, we only use eleven columns from the initial dataset, and assume that they suffice to give conditional exchangeability, as unlikely as that may be. We use this to compute the following: general summary statistics (as a baseline/reference against which to compare the more advanced techniques that follow); an ordinary linear least-squares estimate (to find the average treatment effect for each of the treated and the controls); propensity scores (including a few quadratic terms where $L_i \times L_j$), which are used for future analyses; stratification by those propensity scores; and finally an estimate (using matching) of the effect of mobile phone usage on booking.

3.1 Summary statistics

As mentioned above, these were only computed to serve as reference, and to show whether controlling for L (as the next subsections do) made a difference. These statistics include the mean and standard deviation of each of the treated and controls, as well as of each element of L, also split by treatment.

3.2 Least-squares

In an attempt to improve upon the results of the summary statistics above, a linear least-square model was fit to the sampled data. While this does not make complete sense for all eleven members of L, it does for most of them.

For example, on the Expedia website, several search fields (including the number of adults, children, and rooms) are pre-filled, and are filled with low values. Any value greater than these defaults suggests that someone manually changed them, thus making that person more likely to want to actually book a room instead of just looking at what is available. The Expedia mobile site does not make this any harder or easier than the normal website does, so the impact there should be minimal.

As another example, star ratings are integers between zero and five, inclusive. A rating of zero means that no data are available. Since better-rated hotels are more likely to attract lookers and bookers than low-ranking (or unranked) hotels, this also makes sense to be linear.

In contrast, hotel characteristics (the aforementioned "bands" estimated by Expedia) are more of a mixed bag. While popularity trivially is associated with looking and booking (by definition), distance may not be as useful; an increase in distance is not expected to increase nor decrease looking and booking rates, nor to influence whether a user would choose to view it via a phone or via a desktop/laptop web browser. However, since a flat line (expected) is still a line, it was included anyways.

3.3 Propensity scores

Due to the high dimensionality of L, as well as the diversity of entries that it contains, any direct usage would likely violate positivity in some fashion. While the eleven columns were chosen to lessen this likelihood, there are still thousands of distinct possible values for any given row's $\vec{l}$, so a scalar mapping such as what propensity scores provide is viable, useful, and what was ultimately used.

3.4 Stratification

The propensity values from the previous subsection are used here for separation into strata. Values below about 10% or above about 90% were discarded to avoid outliers. Most propensity scores were fairly low ($< 30\%$), with a few high ones, so bins of equal size were not used. Rather, an adaptive method is used that recursively halves the sample until doing so stops providing significantly useful information.

3.5 Matching

Separately from the computation of the stratification and propensity scores, a matching procedure was used. Matching was chosen because it should help avoid the misleadingly-overrepresented rows where $Y = 1$ (where people made bookings). Each row where $A = 1$ (mobile pageview) was matched with the desktop pageview ($A = 0$) whose $\vec{l}$ was closest to it, where "closest" here means minimizing the Euclidean distance (L_2 norm). This way, rows with identical $\vec{l}$ values are matched, and rows with similar-but-not-identical values can still be kept. There were more desktop pageviews than mobile pageviews, so the leftover desktop data were not used for matching. Matching also ensures positivity, further increasing its usefulness for high-dimensional L.

4 Results

In general, this was a null result. Users of Expedia.com are about as likely to book a hotel when viewing hotel listings from their phones as they are when viewing those same listings from their desktops and laptops. Below are the results of each test.

4.1 Summary statistics

Naïvely, there was no meaningful difference between the means of the mobile viewers and of the desktop viewers, at only 1.3% (8.9% of desktop users booked versus 7.6% of mobile users). Among the means of each element of L, the largest difference was for the same-country-or-not column, whose normalized difference was 36% (mobile users tended to choose the same country more often), followed by the duration column, whose normalized difference was -20% (desktop users tended to pick slightly longer stays). Again, these values do not adjust for L, and should be treated as background. Incidentally, the minute difference in the booking rates is what prompted the selection of A and Y for this report.

4.2 Least-squares

Here, the results were also underwhelming. The difference between the ATC (desktop users) and ATT (mobile users) was minimal, with 95% confidence intervals that mostly overlapped — over half of each interval fit inside the other. Thus, the conclusion at the head of this section is supported.

4.3 Propensity scores and stratification

The results of the stratification can be seen below. The propensities were chosen based on likelihood ratios, and include both linear and quadratic ($L_i \times L_j$, where i, j were not always different) terms. Computing the same ATC and ATT for each stratum resulted in the same conclusion as above: even when controlling for the confounding effect of L, phone usage does not tell us much (if anything) about likelihood of booking. Thus, the conclusion at the head of this section is supported.

	Propensity Score		Sample Size		Avg. Propensity		Outcome
Stratum	Min.	Max.	Desktop	Mobile	Desktop	Mobile	Raw-diff
1	0.087	0.107	295	21	0.098	0.100	-0.037
2	0.107	0.119	270	43	0.113	0.113	-0.084
3	0.119	0.135	541	84	0.127	0.128	-0.060
4	0.135	0.156	1059	194	0.146	0.147	-0.031
5	0.156	0.225	2017	419	0.185	0.185	-0.012
6	0.225	0.276	936	302	0.253	0.254	-0.010
7	0.277	0.299	893	393	0.290	0.290	-0.052
8	0.300	0.318	834	351	0.310	0.310	0.004
9	0.318	0.904	791	440	0.337	0.339	0.011

4.4 Matching

As with the other tests, matching also revealed minimal differences. The average effects in mobile users and in desktop users were -0.019 and -0.012, respectively, and the standard deviation of both was 0.011. While this makes the causal booking ratio look high, the difference is not, just like in the case of least-squares. Thus, the conclusion at the head of this section is supported.

References

[1] Miguel A Hernan and James M Robins. *Causal inference*. CRC Boca Raton, FL: 2010.