The Farmer's Dog

Schwartz

September 6, 2019

1 Lift Analysis

For $Pr(y) = f(t, \text{€}, \$, \text{₿}, \text{₳}, \text{₽}, \%, \text{£})$ experiment from 2014-11-06 to 2014-11-29[1], where

€	int	Employee Count	We expect greater lift for larger counts
$	ord	Size of Account	We expect greater lift for larger sizes; some disagree
		*Also note that:	"Sizes 02-04 should not be included in the experiment."
₿	ord	Brand Support	Might possibly be of interest
₳	cat	Market Source	Might possibly be of interest
₽	cat	Discount Code	Might possibly be of interest
%	int	Discount Percent	We expect more discount to lower lift
£	float	Length of Tenure	Longer lived accounts might perform differently
t	bin	Intervention	$t = 1$ for $\sim$26,500 cases and $t = 0$ for $\sim$28,500 cases
y	bin	Conversion	Tier0 $<$ 2014-11-06 $<$ Tier1

I have

1. constrained the problem (3hrs) [pandas/numpy/datetime/matplotlib]
2. evaluated the experimental design (1hr) [statsmodels.VIF/causalinference]
3. completed model-based EDA (2hrs) [statsmodels.GLM]
4. evaluated complexity requirements (1hr) [sklaern.RandomForestClassifier/GridSearchCV]
5. characterized the evidence afforded by the experiment (5hrs) [PyMC]

   and

6. wrote these notes (4hrs)

$f(t, \text{€}, \$, \text{₿}, \text{₳}, \text{₽}, \%, \text{£})$ is modeled using variable selection priors (selecting differentiating experimental levels) (while providing an automatic multiplicity adjustment) on a second-order experimental design specification with treatment effects estimated hierarchically (with data-driven shrinkage) according to overall and (interactive) main and second-order treatment effects for differentiating experimental levels. Higher order specifications were explored, but insufficiently evidenced for use.

[1] Data frozen on 2014-12-10.

Figure 1: The model hierarchy allows us to select first `beta_mains` and second order `beta_pairs` differentiating experimental levels (as evidenced by the data) with a variable selection priors `ss_mains` and `ss_pairs` (where "ss" references the utilized "spike-and-slab" priors). The additional hierarchy of `p0_mains` and `p0_pairs` provides automatic multiplicity adjustment on variable selection rates. The same `ss_mains` and `ss_pairs` selectors priors simultaneously turn on first `beta_tXmains` and `beta_tXpairs` second order treatment effects estimation within each differentiating experimental level. Information sharing is induced in all estimation parameters through shrinkage on `sigma_*`.

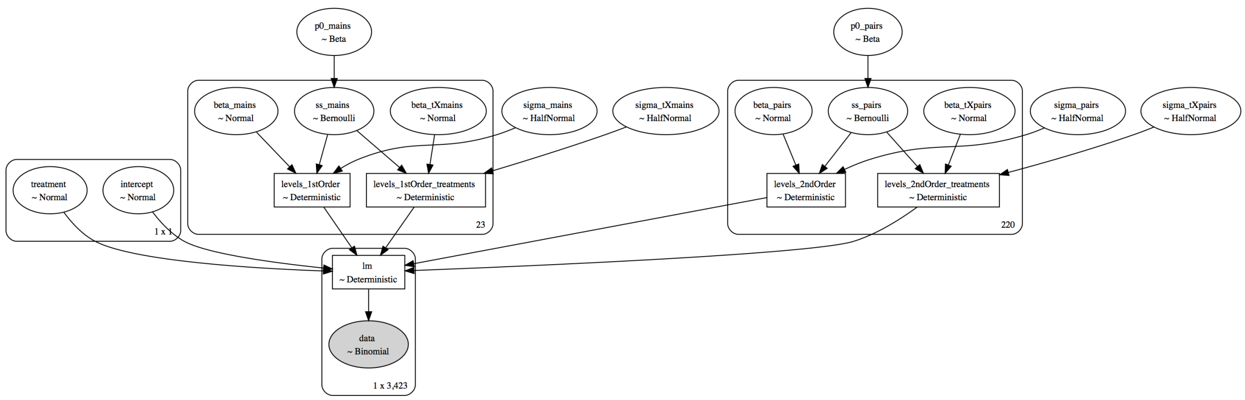
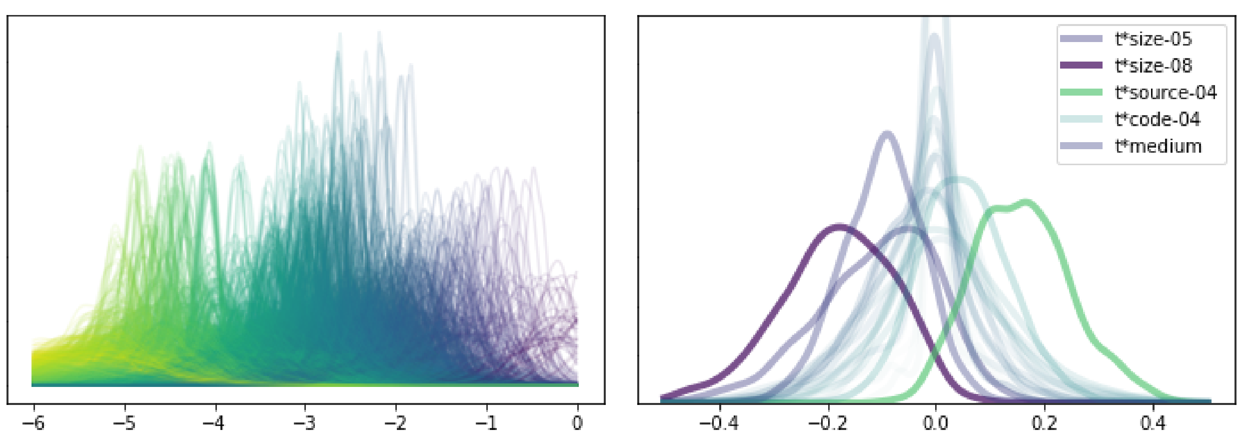


Figure 2: [Left Panel:] This model identifies differentiating experimental levels as evidence by the data (up to a second-order attribution model, and with an intrinsic multiplicity adjustment); and, [Right Panel:] estimates idiosyncratic intervention effects within each differentiating level. All such estimations are hierarchically shrunk towards coarser, lower-order contributing components effects.

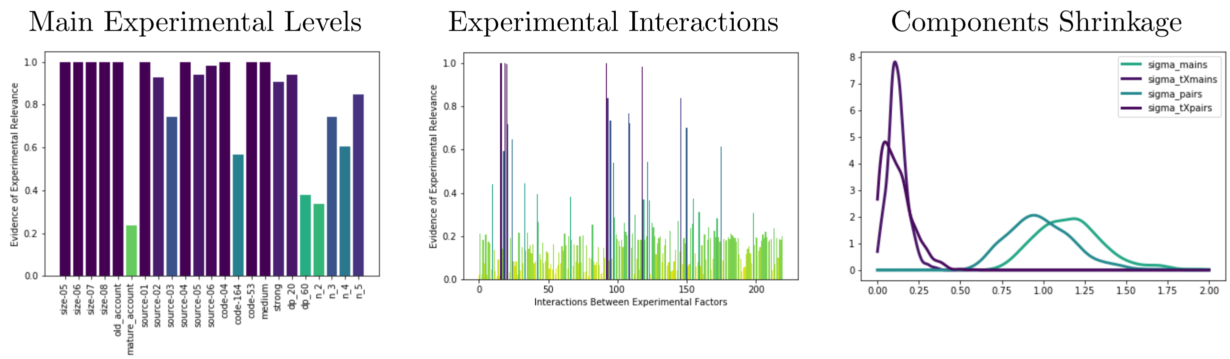


Experimental Level Conversion Log-Odds
(Background Conversion Rates)

Experimental Level Multiplicative Lift
(Observed Intervention Effects)

The singularly compelling positive influence of treatment intervention was a identified within market source ₳=*source-4* and has a 70% Bayesian Credible lift interval of (0.34%, 37.52%). Conversion on the whole, however, varies quite a bit with account sizes \$≠*size-01* strongly outperforming \$=*size-01*. Similar positive effects were seen for old accounts £=*old* discount codes ₽=*code-53*, with the latter seeing a further synergistic boost from ₽×₳ =*code-53*×*source-4*. Other factors appeared to be inconsequential, or negatively impactful, and while some second-order treatment effects hinted at possible relevance, none were deemed sufficiently evidenced in the final analysis.

Figure 3: [Left Panel:] The model allows us to select experimental levels with differentiating conversion rates; [Center Panel:] as well as higher order interactions between experimental factors exhibiting further synergistic differentiation properties. As seen here, even first order interactions between primary experimental factors show very little evidence of influence under the current experimental regime (and second order interactions between experimental factors showed even less evidence and have thus ben excluded from modeling). [Right Panel:] All effect estimates (both due to experimental factors as well as treatments) were addressed hierarchically, allowing idiosyncratic behavior to shrink back towards lower level, coarse constituent components. For example, a discount code by brand support ₽×Ƀ interaction shrinks back towards the lower order components ₽+Ƀ which in turn are each shrunk back towards the global intercept. Of particular note is the increased shrinkage of treatment effects (relative to variation attributable to experimental factor) indicating generally decreased evidence of intervention efficacy relative to the other experimental characters.



The net result of this modeling effort is automatic parsimonious modeling of experimental factors and treatment effects therein. Model component decisions deserving further evaluation especially include (a) the shared application of variable selection priors to differentiating experimental levels as well as treatment effects therein (which may optimistically bias treatment estimation), and (b) the application of shrinkage methodology (which may overly regularize parameter estimation).

2 Time to Conversion Analysis (4 hrs)

Using a similar data suite to the above, we add the following

Æ	bool	All[data]Exists	Only 6,797 of 58,905 rows have all data present
₶^{1}	float	New Predictor	Duration of time (in months) for tier0 to tier1 conversion
₶^{2}	float	New Outcome	Duration of time (in months) for tier1 to tier2 conversion (if at all)

and perform a basic Kaplan Meier survival analysis, the bottom line of which is there is a window from two to four weeks after conversion from tier0 to tier2 in which further conversion into tier2 is *extremely* likely, and after which further conversion into tier2 becomes *increasingly* LESS likely.

Of the interventions explored, only discount code ₽=*code-04* positively associates with tier2 conversion. Market source ₳=*source-06* and ₳=*source-03* also appear to positively associate with tier2 conversion. Also of note is that all account sizes $≠*size-08* increasingly (counting down) perform much better than $=*size-08*. Finally, longer (tier0 to tier1 conversion times) ₶^{1} positively associates with tier2 conversion. Other factors appear inconsequential, or negatively impactful.

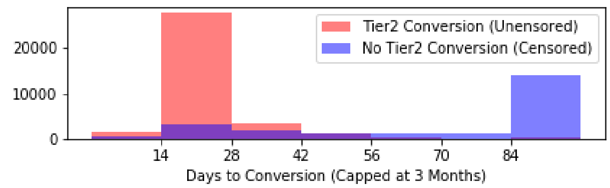


Figure 4: Conversions to Tier2 quickly follow after Tier1 conversions. Chances for conversion to Tier2 remain strong up to two months after Tier1 conversion; prospects thereafter greatly diminish.

Logs

The analysis logs of this work – Schwartz_FarmersDog1.ipynp and Schwartz_FarmersDog2.ipynp – are available at which are only privately viewable with user name `pointOfive-visitor` and password `987-abc`. I can remove the notebooks from my github account upon your request, though I would appreciate it if you're comfortable with my retaining the copies as is behind the password wall. The code itself can be run using `jupyter notebook <filename>.ipynp` (and "shift-entering" done the cells) after installing a python environment (such as anaconda) and the preambled python packages (with `pip install <package>`; though the latest pymc version must be installed via `pip install git+https://github.com/pymc-devs/pymc3@master`).