Some thoughts on “Big Data and Marketing Analytics in Gaming: Combining Empirical Models and Field Experimentation” by Nair et al. (2013)

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So what's not to like about this paper?

- Looks at a real problem in an important industry
  - Variants of the problem exist in multiple industries
- Uses many (recent) developments in marketing science to deal with resource allocation in targeted settings
- Uses model based findings to propose a different set of *x*'s for the setting and
- Validates them in the field
  - Hallmark of Misra and Nair!
- Has support of a corporate partner
  - Happens less often than it should

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More what's not to like about this paper..

- Straddles the world of academia and of practice
- Showcases marketing science in the world of Big Data
  - Currently (in my opinion) marketing science is very under-represented
- Casino industry is highly promotion sensitive
  - So very impressive to find 6.7% increase (R$4.57/R$68.07) or $1mm - $ 5 mm incremental return
- Moral of the story – it's all in the data generating process

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The generic sales response model..

$$y_{it} = f\left(x_{it} \middle| \beta_i\right)$$

Unit of aggregation i
(account, store, territory,
customer)

Response Parameters

Inference focuses on conditional model: *y* | *x*

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And the standard solution …

The assumption here is that marginal distribution of *x* ($x_{it}|\theta$) provides no information about the response parameters.

So the likelihood factors as follows

$$\ell(\{\beta_i\},\ \theta) = \prod_{i,t} p(y_{it}|x_{it},\ \beta_i)p(x_{it}|\theta)$$

$$= \prod_{i,t} p(y_{it}|x_{it},\ \beta_i)\prod_{i,t} p(x_{it}|\theta).$$

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But in data-rich settings

- *x* values often set with (partial) knowledge of response parameters
- So model needs to be modified as (Manchanda, Rossi, Chintagunta *JMR* 2004)

$$y_{it} | x_{it}, \beta_i, \text{ and } x_{it} | \beta_i, \tau$$

- This allows us to obtain unbiased parameter estimates
  - In addition, the use of information in *x* about parameters can "sharpen" the estimates

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A different solution here

- Two institutional features (IF) of the data used to address issue
  - Value of corporate partner

- IF 1: The data generating process of x is known (almost perfectly)

- x are a function of past behavior (z) and demographics (d)
  - More important, it turns out that x are not a function of response parameters

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A different solution here (contd.)

- So, given *z* and *d*, each observation (consumer-month) can be assigned to segment *s in a deterministic manner*
  - Assignment does not consider any unobservables so unlike scoring function approach
  - Analysis is *conditional* on consumer belonging to segment *s* at time *t*
  - Allows for within-consumer (time-varying) heterogeneity

- IF 2: Assignment of *x* within segment *s* is *randomly* provided to a subset of consumers in *s*
  - In essence, the response to *x* is estimated in a series of iid draws from within segment *s*

- Thus estimates of the response parameters *for a given segment* are unbiased

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Assumptions and boundary conditions

- Assignment to segment *s* is based (partly) on *z* (past behavior)
  - But past behavior can be a function of responsiveness to promotions (as they affect the propensity to visit, play, spend etc.)
  - So is segment membership completely uncorrelated with response parameters?
    - If not, then response parameters could be biased even within segment e.g., for heavy play segments, promotions are always high (p. 9), leading to spurious correlation between volume of play and promotion
  - Random assignment within segment to conditions of no promotion versus promotion will "unconfound" this
    - Will help if the authors can show these patterns in the data

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Assumptions and boundary conditions

- Response parameters for segment *s* are invariant to who is in segment *s*
  - In other words, if my (*z*, *d*) change and I move from *s*1 to *s*2, then I automatically get assigned *s*2's response parameters
    - Can we get a sense of the movement of individuals across segments?
  - The casino industry actually tries to move you to more active (valuable) segments the more it knows about you
    - So while hope is to change responsiveness, that may or may not happen

- The proportion of consumers assigned to a promotion within a segment needs to be "small"
  - If not, then repetitions are not iid and
  - Effects such as learning etc. can kick in, leading to non-stationary response parameters (within segment)
  - Great if authors could share more data on these proportions

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Assumptions and boundary conditions

- What about strategic behavior?
  - As the authors note, customers form expectations vis-à-vis promotions/ rewards
    - Implication is that promotions need to reach some threshold before response is seen i.e., response curve may be highly non-linear
    - Does the casino company already adjust for that (while the model doesn't)?
    - Probably not an issue in the field experiment as it stays within range of data (and temporal duration of data is short)
- How important is the role of state-dependence?
  - Could manifest itself in satiation, addiction etc. (Narayanan & Manchanda 2012 *QME*), leading to changing promotion response over time
  - Current approach "force-fits" this individual level evolution by moving him/her to "appropriate" segments over time

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Assumptions and boundary conditions

- How much do other context effects matter?
  - Within month variation (weekend, payday etc.), seasonality (Field Experiment in Q3)
  - Competitive promotions
  - Playing alone versus with others (Park & Manchanda 2014, *Marketing Science* forthcoming)
  - ….
  - But at this scale, average effect over segment-month (as reported here) is a good starting point

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Minor quibbles and questions

- Nested Logit structure
  - Does it map to consumer decision making process (even though it's an "as-if" model)?
  - Are promotions seen as discrete choices or as dollar values?
  - Can a consumer really choose from multiple promotions for a given property (and multiple properties) for a given month?
    - Not possible in the field experiment (p. 31)
- Paper notes (p.7, p. 9) that current promotions are based on RFM
  - Is that only across segments or within as well?
  - Great if the authors could show the raw data patterns

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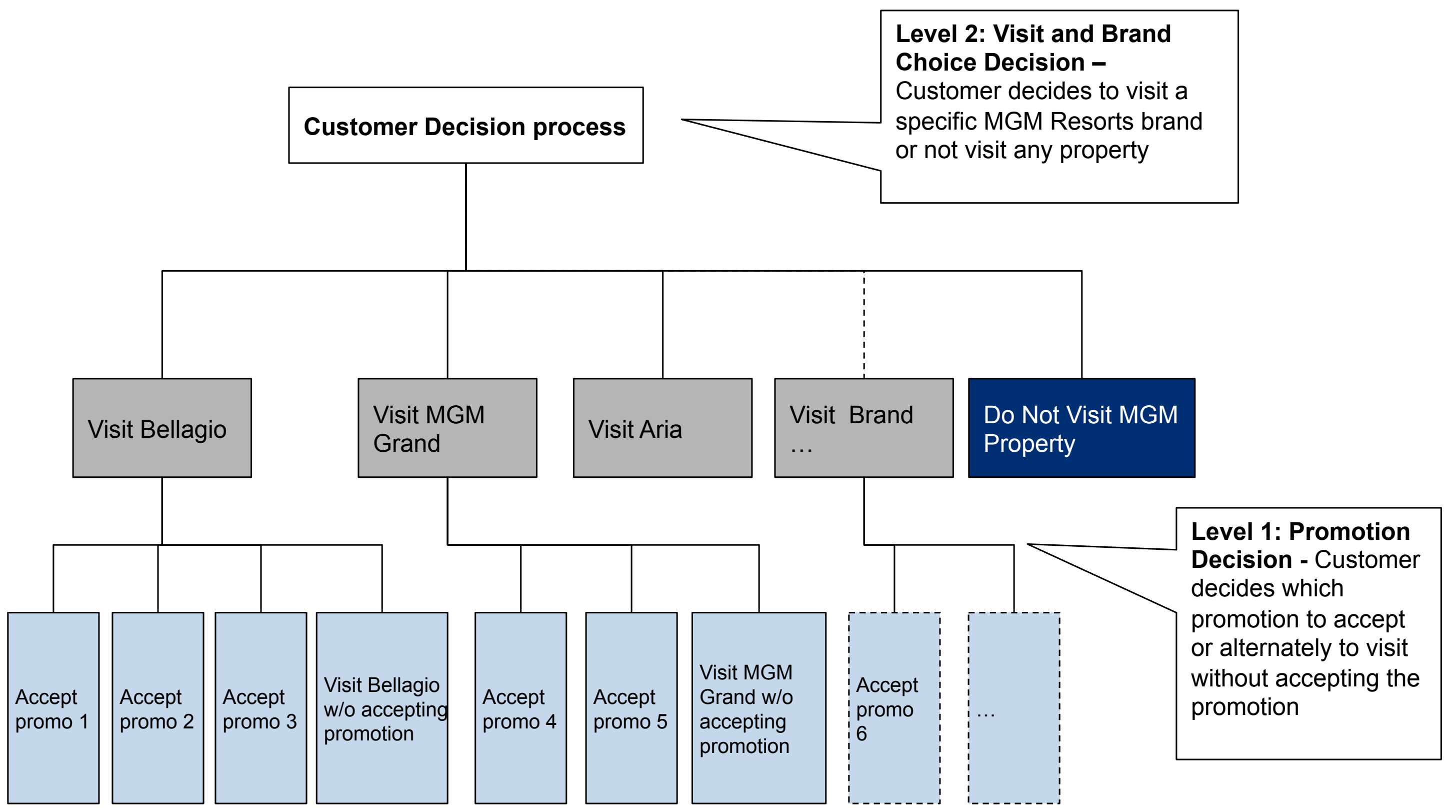
Minor quibbles and questions

Figure 4: Nesting Structure Used in Model Setup



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Minor quibbles and questions

- Is this is really an application of Big Data?
  - Is no. of segments, coefficients etc. what decides Big versus Small data?
    - CPG firms run very large scale models at SKU level
    - Pharma companies run large non-linear models for 1mm+ physicians
    - Targeting here is quite macro
      - Segments in order of 100s – consumers in order of 1,000,000s
  - Caveat: Big Data is like teenage sex
  - Opportunity for authors to take a stand on definition

- How representative is the casino industry?
  - 15-20 year history of very detailed data collection and analytics
  - Random assignment within segments is unusual in most other settings
  - Highly promotion sensitive customer base
  - Is there much more upside with respect to promotion?

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The bigger picture

- Authors conclude the paper with some valuable tips on how to get analytics to work inside the organization
  - Adding to that, in my experience, top management involvement is critical
  - Would also have been nice to get some detail on the cost of data collection & cleaning (authors note that is a very painstaking process), running experiments, data analysis, optimization etc.
    - If the time it takes to do this on a regular basis > decision-making cycle, then need some shortcuts
- The role of structure
  - If objective is prediction (and profit), how much worse off are we running (model free) large scale random experiments (e.g., A/B testing in each segment)?
    - This is especially relevant for digital businesses as cost of experimentation is low
- How do we foster an environment where more academic researchers can engage with companies at this level of rigor and relevance?

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