Informing Maintenance to the U.S. Census Bureau's Master Address File with Statistical Decision Theory

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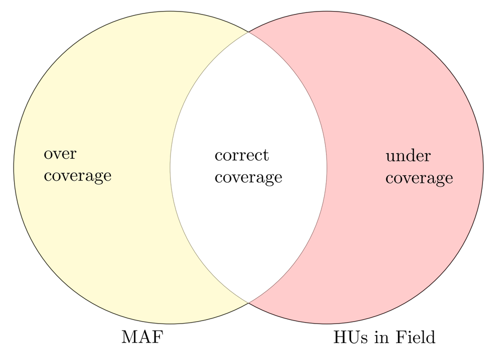
Summary

- The Master Address File (**MAF**) is a database maintained by the Census Bureau of all known housing units.
- The MAF is used to prepare address lists for the decennial census and household surveys (e.g. American Community Survey); it is critical to the Census Bureau's business.
- MAF is regularly updated throughout the decade. Also, a large-scale block listing operation (**2010 Address Canvassing / AdCan**) was carried out before the 2010 Census.
- Census Bureau is now considering alternative strategies to prepare for 2020 Census [6]. The goal is to reduce the cost of updating the MAF without significant loss of coverage.
- Previous work with statistical models used sorted predictions to identify census blocks for closer inspection [2, 3, 7]. This may not capture decision makers' assessment of cost for wasted effort or missed coverage error.
- **Objective:** Explore use of decision theory to assist MAF maintenance. Discrete loss functions are proposed to aid intuition of decision makers.
- Decision maker quantifies: (a) severity of coverage error, and (b) loss due to possible actions under each severity level.
- Even with known "state of nature", optimal decision can vary greatly by decision maker.

Master Address File and Address Canvassing

- To prepare the MAF for the 2010 Decennial Census, the Census Bureau conducted the 2010 AdCan operation. ~111,000 field representatives (FRs) walked ~6 million census blocks in the U.S. and Puerto Rico [5].



- AdCan provided a wealth of data on MAF coverage errors.
  1. A **valid address missing** from the MAF indicated an **undercoverage** error. Address was added to the MAF and an **new add** outcome was recorded.
  2. An **invalid address present** on the MAF indicated an **overcoverage** error. Address was "deleted" from the MAF and a **delete** outcome was recorded.
  3. A **matched add** occurred where an address was already on the MAF, but could not be properly geocoded until located by AdCan.
- Census Bureau initiatives to avoid a large in-field canvassing before 2020 census:
  1. In-office canvassing using aerial imagery review.
  2. Statistical models to help inform a limited field operation.

Review of Decision Theory

- Suppose there are J possible states of nature $\Theta = \{\theta_1, \ldots, \theta_J\}$ and d possible actions $\mathcal{A} = \{a_1, \ldots, a_K\}$.
- Loss function $L(\theta, \delta)$ measures consequence of taking action δ when the state is θ.

	θ_0: No Rain Today	θ_1: It Rains Today
a_0: Leave Umbrella	0	100
a_1: Bring Umbrella	50	20

- θ usually unobservable; inferred through data $\mathcal{D}$, model $p(\mathcal{D} \mid \theta)$, and prior $p(\theta)$.
- For observed data $\mathcal{D}$, take action δ to minimize risk $r(p, \delta) = \mathrm{E}[L(\theta, \delta) \mid \mathcal{D}]$.

Categories of Coverage Error

- Consider the following measure of coverage error for the ith census block,

$$Y_i^* = \frac{\text{NewAdds}_i + \text{MatchedAdds}_i + \text{Deletes}_i}{\text{HU}_i + 1}, \quad i = 1, \ldots, n.$$

- Numerator represents "units of coverage error" and denominator reduces severity for blocks with more preexisting housing units.
- Decision maker defines cutpoints $\gamma_1 < \cdots < \gamma_{J-1}$ to create meaningful categories,

$$\begin{aligned} [\gamma_0 < Y_i^* \leq \gamma_1] &\equiv \text{Least severe coverage error}, \\ &\vdots \\ [\gamma_{J-1} < Y_i^* \leq \gamma_J] &\equiv \text{Most severe coverage error}, \end{aligned}$$

where $\gamma_0 = -\infty$ and $\gamma_J = \infty$ are fixed.

- Let $(Y^*, \boldsymbol{x})$ denote random coverage measurement and fixed covariate for a given block. Let $\mathcal{D} = \{(\text{NewAdds}_i, \text{MatchedAdds}_i, \text{Deletes}_i, \boldsymbol{x}_i) : i = 1, \ldots, n\}$ denote data used to train model.
- Let $\pi_j = \pi_j(\boldsymbol{x}, \boldsymbol{\theta}) = \mathrm{P}_{\boldsymbol{\theta}}(\gamma_{j-1} < Y^* \leq \gamma_j \mid \boldsymbol{x})$ be the probability of category $j = 1, \ldots, J$.
- The exact form of $\boldsymbol{\theta}$ (the "state of nature") is determined by the model. If π_j is not a tractable function of $\boldsymbol{\theta}$ and $\boldsymbol{x}$, can approximate by Monte Carlo.
- We will consider risk functions which depend on $p(\boldsymbol{\theta} \mid \mathcal{D})$ through posterior category probabilities $\mathrm{E}[\pi_j \mid \mathcal{D}]$, $j = 1, \ldots J$.

A Two Decision Problem to Aid In-Office Canvassing

- Census Bureau is considering aerial imagery and other in-office alternatives to a full scale canvassing operation.
- Using past data on MAF coverage errors, statistical models could help by triggering high-risk census blocks for closer review. With sufficiently good predictors, it may be possible to capture errors not detectable by other in-office approaches.
- Consider $J = 5$ categories of coverage error for each block,

$$\{\text{None}, \text{Lo}, \text{Med}, \text{Hi}, \text{Severe}\}, \text{ with cutpoints } \gamma_1 = 1, \gamma_2 = 4, \gamma_3 = 10, \gamma_4 = 20.$$

- For a given census block, there are two possible actions: **do trigger** the block for review (a_1) and **do not trigger** the block for review (a_0).
- Consider the linear loss function

$$L(\boldsymbol{\theta}, \delta) = \begin{cases} \boldsymbol{c}_0^T \boldsymbol{\pi} = c_{01}\pi_1 + \cdots + c_{0J}\pi_J, & \text{if } \delta = a_0 \\ \boldsymbol{c}_1^T \boldsymbol{\pi} = c_{11}\pi_1 + \cdots + c_{1J}\pi_J, & \text{if } \delta = a_1. \end{cases}$$

based on positive costs $\boldsymbol{c}_0 = (c_{01}, \ldots, c_{0J})$ and $\boldsymbol{c}_1 = (c_{11}, \ldots, c_{1J})$.

- Decision maker determines $\boldsymbol{c}_0$ and $\boldsymbol{c}_1$ before making any actual decisions.
  1. Order the $2J$ outcomes $\langle a_k, \theta_j \rangle$ from least to most desirable.
  2. Solicit loss values for ordered outcomes using algorithm from [1, Ch. 2].
  3. Let c_{kj} be the loss associated with outcome $\langle a_k, \theta_j \rangle$.
- Notice that we always want $c_{01} \leq \cdots \leq c_{0J}$ and $c_{11} \geq \cdots \geq c_{1J}$.
- Using posterior distribution $p(\boldsymbol{\theta} \mid \mathcal{D})$, the posterior risk is

$$r(p, \delta) = \begin{cases} \boldsymbol{c}_0^T \, \mathrm{E}[\boldsymbol{\pi} \mid \mathcal{D}], & \text{if } \delta = a_0 \\ \boldsymbol{c}_1^T \, \mathrm{E}[\boldsymbol{\pi} \mid \mathcal{D}], & \text{if } \delta = a_1. \end{cases}$$

- Optimal decision is a_0 if $(\boldsymbol{c}_0 - \boldsymbol{c}_1)^T \, \mathrm{E}[\boldsymbol{\pi} \mid \mathcal{D}] \leq 0$, and a_1 otherwise.

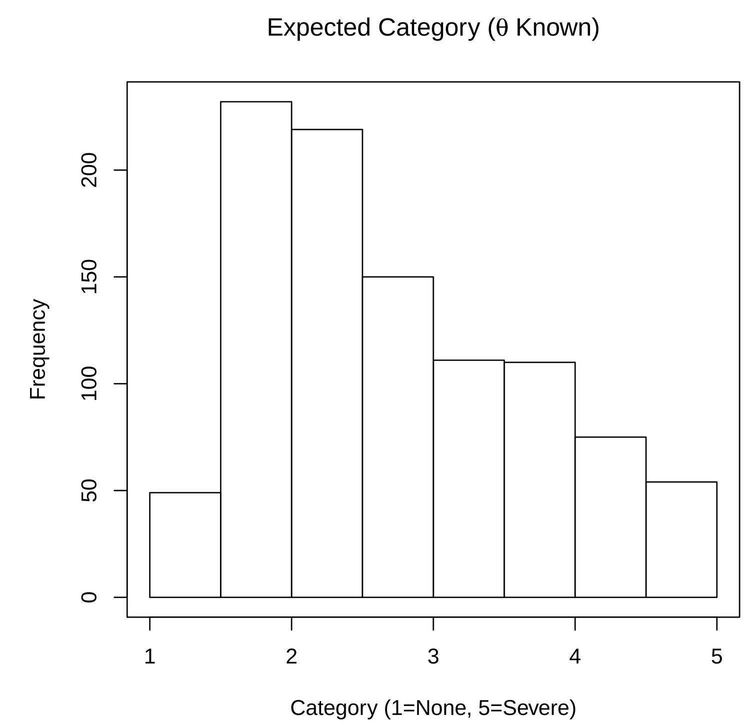
Simulation

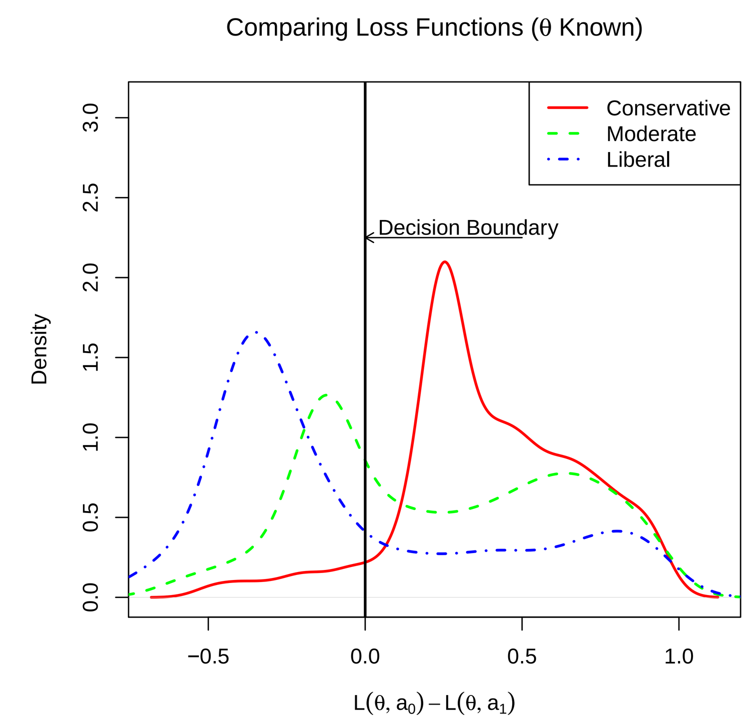
Compare several decision makers in the following scenario. Assume $\boldsymbol{\theta} = (\boldsymbol{\beta}^A, \boldsymbol{\beta}^M, \boldsymbol{\beta}^D, \tau_A^2, \tau_M^2, \tau_D^2)$ is known for now (i.e. a no-data problem).

$$\begin{aligned} &x_i \overset{\text{iid}}{\sim} \mathrm{U}(0, 8), \quad \text{HU}_i \overset{\text{iid}}{\sim} \text{NegBin}(\mu, \kappa), \quad \text{for } i = 1, \ldots, n = 1000, \\ &\text{NewAdds}_i \overset{\text{ind}}{\sim} \text{Poisson}\left(\exp(\beta_0^A + \beta_1^A x_i + \beta_2^A \log(\text{HU}_i + 1) + e_i^A)\right), \\ &\text{MatchedAdds}_i \overset{\text{ind}}{\sim} \text{Poisson}\left(\exp(\beta_0^M + \beta_1^M x_i + \beta_2^M \log(\text{HU}_i + 1) + e_i^M)\right), \\ &\text{Deletes}_i \overset{\text{ind}}{\sim} \text{Binomial}\left(\text{HU}_i, \text{logit}^{-1}(\beta_0^D + \beta_1^D x_i + e_i^D)\right), \\ &e_i^A \overset{\text{iid}}{\sim} \mathrm{N}(0, \tau_A^2), \quad e_i^R \overset{\text{iid}}{\sim} \mathrm{N}(0, \tau_M^2), \quad e_i^D \overset{\text{iid}}{\sim} \mathrm{N}(0, \tau_D^2). \end{aligned}$$

Utility functions (rank for each outcome is shown in parentheses).

"Conservative"	None	Low	Med	Hi	Severe
a_0	1 (9)	0.375 (4)	0.25 (3)	0.125 (2)	0 (1)
a_1	0.5 (5)	0.625 (6)	0.75 (7)	0.875 (8)	1 (9)
"Moderate"	None	Low	Med	Hi	Severe
a_0	1 (9)	0.625 (6)	0.25 (3)	0.125 (2)	0 (1)
a_1	0.375 (4)	0.5 (5)	0.75 (7)	0.875 (8)	1 (9)
"Liberal"	None	Low	Med	Hi	Severe
a_0	1 (9)	0.75 (7)	0.875 (8)	0.125 (2)	0 (1)
a_1	0.25 (3)	0.375 (4)	0.5 (5)	0.625 (6)	1 (9)





Number of blocks triggered for review: Conservative (927), Moderate (609), Liberal (255).

Conclusions and Next Steps

- Even when θ is fully known, "optimal" result may vary greatly by decision maker.
- Investigate integrating decision framework with actual data, models, and operations.
- Incorporate model uncertainty into loss functions, to avoid too many triggers.
- Problem of selecting blocks for a limited in-field canvasssing before 2020 census.

References

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