Strategy

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CONSTRAINT:

$$\sum_{t=1}^{16} P(type = t) \cdot P(policy\ sold \mid rank = x, type = t) \geq 0.04$$

Note that this is a function of a vector of ranks assigned to the vector of types of people. Here $P(type = t)$ is just the fraction of type t people in the total population.

The objective is harder to formulate without knowledge of costs. Instead of making up data about costs, we will simply require an assigment of rank $x \longleftrightarrow$ type t, given by a vector of ranks for each type $(x_1, \ldots, x_{16})$, such that the highest rank (i.e. the rank which is least expensive) is chosen when possible. We can run through the possible choices of rank for type (there are 5^{16} such choices) but limit it further to only those choices which satisfy the constraint. We will pick the choice of rank for each type by weighting it using the weight function

$$w(x_1, \ldots, x_{16}) = \sum_{t=1}^{16} P(type = t) \cdot \frac{x_t}{5} \cdot \frac{1}{|x_t - x_t^*|}$$

Here x_t is the rank of type t person and x_t^* is the *original* rank of type t person.

OBJECTIVE: We choose ranks $(x_1, \ldots, x_{16})$ such that our constraint probability is ≥ 0.04 and such that the weight function w is maximized. If multiple choices of $(x_1, \ldots, x_{16})$ achieve the maximum of w, pick one randomly.

According to this function, we favor changing the ranks of the most common types of people, we favor setting ranks to 5, and we also favor smaller changes in rank. This is because those in rank 5 will likely cost the least to move up in rank, and changing the ranks of the most common people will be most likely to increase the constraint above 0.04. Favoring smaller changes in rank means we are less likely to greatly increase the cost of advertising.

For each type and rank, we calculate

$$P(\textit{policy sold} \mid \textit{rank} = x,\ \textit{type} = t)$$

by separating it as follows:

$$P(\textit{policy sold} \mid \textit{rank} = x,\ \textit{type} = t) =$$
$$P(\textit{policy sold} \mid \textit{click} = 1,\ \textit{rank} = x,\ \textit{type} = t) \cdot P(\textit{click} = 1 \mid \textit{rank} = x,\ \textit{type} = t)$$

At the moment, Root's current strategy is to assign the rank

$$argmax_{x \in \{1,2,3,4,5\}}(P(\textit{rank} = x \mid \textit{type} = t))$$

over all ranks $x = 1, 2, 3, 4, 5$ to each type of person, t. i.e. each type of person t gets the rank x which is most likely given the *current* data. This corresponds to bidding 10 dollars for each type of person.

We use the best performing algorithms (for EVENTS) at each step. Note that we cannot find the best performing algorithms for PROBABILITIES since we can only compute one probability over the entire data set.

My analysis shows that for predicting the event $(\textit{policy sold} \mid \textit{click} = 1,\ \textit{rank} = x,\ \textit{type} = t)$, the best model is LDA, with accuracy / precision / recall = 61 / 61 / 61.

Similarly, for predicting the event $(\textit{click} = 1 \mid \textit{rank} = x,\ \textit{type} = t)$ the best model is RFC with 73 / 74 / 73.

For predicting the event $(\textit{rank} = x \mid \textit{type} = t)$, the best model is SVC with 42 / 52 / 42.

Then we will compute the probabilities $P(\textit{rank} = x \mid \textit{type} = t)$, $P(\textit{click} = 1 \mid \textit{rank} = x,\ \textit{type} = t)$, and $P(\textit{policy sold} \mid \textit{click} = 1,\ \textit{rank} = x,\ \textit{type} = t)$

using SVC, RFC, and LDA respectively. Then we multiply these together to get $P(policy\ sold \mid rank = x,\ type = t)$ for each type and rank.