

# Assignment 5

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## 1. Fitting a Mixture Model to Estimate Probabilities and Mean Number of Events

Parameters to estimate are:

p\_w: probability that a person is a whale

pzero\_0: probability that a person is a non-purchaser, given that a person is not a whale, when group 0

pzero\_1: probability that a person is a non-purchaser, given that a person is not a whale, when group 1

mu\_0: mean number of events for casual purchaser, when group 0

mu\_1: mean number of events for casual purchaser, when group 1

mu\_w\_diff: mean number of events for whale – mu\_0

Priors are set as:

p\_w ~ invlogit( N( logit( 0.005, tau=1) ) )

pzero\_0 ~ invlogit( N( logit(0.85, tau=1) ) )

pzero\_1 ~ invlogit( N( logit(0.85, tau=1) ) )

mu\_0 ~ HN( tau=1)

mu\_1 ~ HN( tau=1)

mu\_w\_diff ~ HN( tau=0.01)

For group i, a mixture model is fit using

$X_i \sim \text{Mixture}([f_w, f_n], [p_w, 1-p_w])$

$f_w \sim \text{Poisson}(\mu_0 + \mu_w\_diff)$  : distribution for whales

$f_n \sim \text{ZeroInflatedPoisson}(\psi=1-pzero\_i, \mu=\mu\_i)$  : distribution for non-whales

Results from Pymc are summarized in the following table.

	mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_hat
<b>mu_0</b>	4.305	0.076	4.163	4.443	0.001	0.001	5114.0	3296.0	1.0
<b>mu_w_diff</b>	59.088	1.611	56.139	62.172	0.021	0.015	5830.0	3105.0	1.0
<b>mu_1</b>	3.044	0.071	2.911	3.174	0.001	0.001	5551.0	3062.0	1.0
<b>p_w</b>	0.002	0.000	0.002	0.003	0.000	0.000	6417.0	3325.0	1.0
<b>pzero_0</b>	0.845	0.005	0.835	0.855	0.000	0.000	5792.0	3178.0	1.0
<b>pzero_1</b>	0.855	0.005	0.845	0.864	0.000	0.000	5572.0	3196.0	1.0

## 2. Deciding Price to Minimize Expected Loss

If the price is \$3.99 (group 0), then the expected revenue per user is

$$\begin{aligned} \text{rev\_0} &= 3.99 * \text{expected purchases} \\ &= 3.99 * (p\_w * (\mu\_0 + \mu\_w\_diff) + (1 - p\_w) * (1 - pzero\_0) * \mu\_0) \end{aligned}$$

Similarly, the expected revenue per user when the price is \$4.99 is

$$\text{rev\_1} = 4.99 * (p\_w * (\mu\_0 + \mu\_w\_diff) + (1 - p\_w) * (1 - pzero\_1) * \mu\_1)$$

For each sample in the posterior, we can calculate values for both  $\text{rev\_0}$  and  $\text{rev\_1}$ . In each sample, decision 0's loss will be 0 if  $\text{rev\_0} \geq \text{rev\_1}$ , and  $\text{rev\_1} - \text{rev\_0}$  if  $\text{rev\_0} < \text{rev\_1}$ . Decision 1's loss will be 0 if  $\text{rev\_0} \leq \text{rev\_1}$ , and  $\text{rev\_0} - \text{rev\_1}$  if  $\text{rev\_0} > \text{rev\_1}$ .

Finally, to calculate the expected loss per user for each decision, we simply compute the mean of losses over the posterior samples.

The result is:

```
3  
4 print(f"Expected Loss per person when price is $3.99: ${loss_0:.4f}")  
5 print(f"Expected Loss per person when price is $4.99: ${loss_1:.4f}")
```

```
Expected Loss per person when price is $3.99: $0.0011
```

```
Expected Loss per person when price is $4.99: $0.2896
```

Therefore we decide to price our in-app feature at \$3.99 so that expected loss is minimized.