STSCI 4780:
Continuous parameter estimation, cont'd

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Plan

Inference with discrete spaces

- **Lec03:** Binary hypothesis space (C, $\overline{C}$), binary data ($+$, $-$)

- **Lec04:** Larger discrete hypothesis space (doors, α_i), discrete data from *multiple* binary outcomes

Inference with continuous spaces

- PDFs vs. PMFs

- Bernoulli trials with *continous* parameter space

- Multinomial distribution: Multiple, discrete outcomes (categorical data)

- Poisson distribution: Inferring rates from count data over intervals

Recap

- PMFs on discrete spaces, PDFs on continuous spaces

- BT holds for PDFs ($d\theta$'s cancel)

- Estimating the outcome probability, α, for binary outcomes

Setup

$\mathcal{C}$ specifies existence of two outcomes, S and F, in each of N cases or trials; for each case or trial, the probability for S is α; for F it is $(1 - \alpha)$

The trial probabilities are *IID* (independent and identically distributed)

$H_i =$ Statements about α, the probability for success on the next trial $\rightarrow$ seek $p(\alpha|D, \mathcal{C})$

Adopt a *flat/uniform prior* as a default expression of initial ignorance about α — two motivations

Posterior (using sequence, binomial, negative binomial data)

$$p(\alpha|D,\mathcal{C}) \;=\; \frac{(N+1)!}{n!(N-n)!}\alpha^n(1-\alpha)^{N-n}$$

A *Beta distribution*.

Beta distribution (in general)

A two-parameter family of distributions for a quantity α in the unit interval $[0, 1]$:

$$p(\alpha|a,b) = \frac{1}{B(a,b)}\alpha^{a-1}(1-\alpha)^{b-1}$$

A PDF over possible 2-outcome PMFs

The beta-binomial conjugate model

Generalize from the flat prior to a $\mathrm{Beta}(\alpha|a, b)$ prior for α

$$
\begin{aligned}
p(\alpha|n, M') &\propto \mathrm{Beta}(\alpha|a, b) \times \mathrm{Binom}(n|\alpha, N) \\
&\propto \alpha^{a-1}(1-\alpha)^{b-1} \times \alpha^{n}(1-\alpha)^{N-n} \\
&\propto \alpha^{n+a-1}(1-\alpha)^{N-n+b-1}
\end{aligned}
$$

$\Rightarrow$ the posterior is $\mathrm{Beta}(\alpha|n + a, N - n + b)$

When the prior and likelihood are such that the posterior is in the same family as the prior, the prior and likelihood are a *conjugate* pair

A Beta prior is a conjugate prior for the Bernoulli process, binomial, and negative binomial sampling distributions

Conjugacy $\rightarrow$ it's easy to chain inferences from multiple experiments

Probability & frequency

Recall $\hat{\alpha} = \frac{n}{N}$, the *relative frequency* of successes;
also $\sigma_\alpha \approx \frac{\sqrt{n}}{N}$ for $N, n \gg 1$

Frequencies arise when modeling repeated trials, or repeated sampling from a population or ensemble.

Finite-sample frequencies are observables

- When available, can be used to *infer* probabilities for next trial
- When unavailable, can be *predicted*

Bayesian/Frequentist relationships

- Relationships between probability and frequency
- Long-run performance of Bayesian procedures in IID settings (no accumulation of information)

Probability & frequency in IID settings

Frequency from probability

Bernoulli's (weak) law of large numbers: In repeated IID trials, given $P(\text{success}|\ldots) = \alpha$, predict

$$\frac{n_{\text{success}}}{N_{\text{total}}} \to \alpha \quad \text{as} \quad N_{\text{total}} \to \infty$$

"Bernoulli's swindle" — B. argued this justified estimating a next-trial probability with a (finite-sample) frequency

Probability from frequency

Bayes's "An Essay Towards Solving a Problem in the Doctrine of Chances" $\rightarrow$ First use of Bayes's theorem:

Probability for success in next trial of IID sequence:

$$\mathbb{E}(\alpha) \to \frac{n_{\text{success}}}{N_{\text{total}}} \quad \text{as} \quad N_{\text{total}} \to \infty$$

If $P(\text{success}|\ldots)$ does not change from sample to sample, it may be estimated using relative frequency data
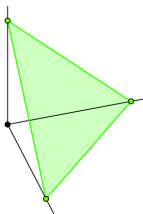
Categorical data

D = Discrete outcomes from N observed trials, $o_1 o_2 o_3 \ldots o_N$:
  Roles of a die: 321344622...
  Customer choices: AAOBBOOO... (*A*pple, *B*anana, *O*range)

$\mathcal{C}$ = Each outcome in one of K categories; parameters $\alpha \equiv \{\alpha_k\}$
such that $P(o_i = k | \alpha, \ldots, \mathcal{C}) = \alpha_k$ (*categorical distribution*)

Constraint: $\sum_k \alpha_k = 1$; equivalently $\alpha_K = 1 - \sum_{k=1}^{K-1} \alpha_k$
I.e., the K-dimensional α must lie on the $(K-1)$-dimensional
standard simplex:

$K = 3$ case

Sequence sampling dist'n/Likelihood function

$$
\begin{aligned}
p(D|\alpha, \mathcal{C}) &= p(o_1 = k_1 | \alpha, \mathcal{C}) \times p(o_2 = k_2 | \alpha, \mathcal{C}) \times \cdots \\
&= \prod_k \alpha_k^{n_k} \\
&\equiv \mathcal{L}(\alpha)
\end{aligned}
$$

The counts (frequencies) are sufficient statistics

Count data sampling dist'n/Likelihood function

Take $D' = \{n_k\}$ (e.g., histogram); then the sampling PMF is a *multinomial dist'n*:

$$
\begin{aligned}
p(D'|\alpha, \mathcal{C}) &= \frac{N!}{\prod_k n_k!} \prod_k \alpha_k^{n_k} \\
&\propto \mathcal{L}(\alpha)
\end{aligned}
$$

The factor $N! / \prod_k n_k!$ counts the number of sequences having the stated numbers of outcomes in each category

Uniform prior

Prior PDF over $(K-1)$-D standard simplex:

$$p(\alpha_1, \ldots, \alpha_{K-1}|\mathcal{C}) = \begin{cases} C & \text{for } 0 \leq \alpha_k \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

with $1/C =$ "volume" of the $(K-1)$-D standard simplex satisfying the normalization constraint (one of the boundaries of the K-D corner simplex in the full α space)

Posterior

Posterior PDF over $(K-1)$-D standard simplex (using either D or D'):

$$p(\alpha_1, \ldots, \alpha_{K-1} | D, \mathcal{C}) \propto$$
$$\begin{cases} \left[\prod_{k=1}^{K-1} \alpha_k^{n_k} \right] \left(1 - \sum_{k=1}^{K-1} \alpha_k \right)^{n_K} & \text{for } 0 \leq \alpha_k \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

This has the form of a *Dirichlet dist'n* (the multivariate generalization of the beta dist'n)

Symmetrical treatment with delta functions

Write a PDF over a $(K-1)$-D standard simplex as a K-D function *constrained* to lie on the $(K-1)$-D simplex:

$$p(\alpha_1, \ldots, \alpha_K | \ldots) =$$
$$p(\alpha_1, \ldots, \alpha_{K-1} | \ldots) \times p(\alpha_K | \alpha_1, \ldots, \alpha_{K-1}, \ldots)$$

where $p(\alpha_K | \alpha_1, \ldots, \alpha_{K-1}, \ldots)$:

- Must set $\alpha_K = 1 - \sum_{k=1}^{K-1} \alpha_k$
- Must be a proper PDF (normalized!)

The *Dirac delta function*, $\delta(x)$, can accomplish this

Delta function development, whiteboards 1 & 2

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Whiteboard 1:

| Delta functions | Try to devise a "PDF" that sets $X = 0$; $\delta(x)$
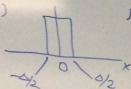
$\rho_\Delta(x) = \begin{cases} 1/\Delta & x \in [-\Delta/2, \Delta/2] \\ 0 & \text{for } x < -\Delta/2, > \Delta/2 \end{cases}$ $[P] = \frac{1}{[x]}$ ✓

$\int_{-\infty}^{\infty} dx\, \rho_\Delta(x) = 1 = \int_{-\Delta/2}^{\Delta/2} dx\, C = C\Delta = 1$

C in Δ

Whiteboard 2:

Functional = map from functions to real numbers

Small Δ: $f(x) = f(0) + x f'(0) + \dots$ Taylor exp.

$I_\Delta[f] = \int_{-\infty}^{\infty} dx\, \rho_\Delta(x)\, f(x) \overset{=}{\underset{\text{small }\Delta}{}} \frac{1}{\Delta} \int_{-\Delta/2}^{\Delta/2} dx\, [f_0 + x f_0'] = \left(f_0 x + \frac{x^2}{2} f_0' \right) \Big|_{-\Delta/2}^{\Delta/2}$

$= \frac{1}{\Delta}\left(f_0 \Delta + f_0'\left(\frac{\Delta^2}{8} - \frac{\Delta^2}{8} \right) \right) = f_0 = f(0)$
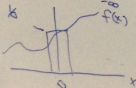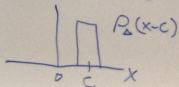
$$\int_{-\infty}^{\infty} dx\, p_\Delta(x) = 1 = \int_{-\Delta/2}^{\Delta/2} dx\, C = C\Delta = 1$$

Define "Dirac δ func" $\delta(x) = \lim_{\Delta \to 0} p_\Delta(x)$ use only in integrals!

"∞ @ 0, vanishes elsewhere"

i.e $\lim_{\Delta \to 0} \int dx\, p_\Delta(x)\, x \cdots$ To set $x = C \to \delta(x-C)$

Functional analysis

δ is a "distribution"

$p_\Delta(x-c)$

Normalization constant

Generalized beta integral:

$$\int_0^\infty d\alpha_1 \cdots \int_0^\infty d\alpha_K \; \alpha_1^{\kappa_1-1} \cdots \alpha_K^{\kappa_K-1} \delta\left(a - \sum_k \alpha_k\right) =$$
$$\frac{\Gamma(\kappa_1)\cdots\Gamma(\kappa_K)}{\Gamma(\kappa_0)} \; a^{\kappa_0-1}$$

with $\kappa_0 \equiv \sum_{k=1}^K \kappa_k$

With $a = 1$ this is also known as the *multinomial beta function*

$$\Rightarrow p(\alpha|D,\mathcal{C}) = \frac{(N+K-1)!}{n_1! \cdots n_K!}\left[\prod_k \alpha_k^{n_k}\right] \delta\left(1 - \sum_k \alpha_k\right)$$

For $K = 2$ we recover beta posterior from Bernoulli/binomial cases

Marginal PDF for one category

Consider $K = 3$, but suppose we are interested only in α_1:

$$
\begin{aligned}
p(\alpha_1|D,\mathcal{C}) &= \int d\alpha_2 \int d\alpha_3 \; p(\alpha|D,\mathcal{C}) \\
&= C\alpha_1^{n_1} \int d\alpha_2 \int d\alpha_3 \; \alpha_2^{n_2}\alpha_3^{n_3} \\
&\quad \times \delta\left[(1-\alpha_1) - (\alpha_2 + \alpha_3)\right] \\
&= C'\alpha_1^{n_1}(1-\alpha_1)^{n_2+n_3+1}; \quad \text{note } n_2 + n_3 = N - n_1
\end{aligned}
$$

The marginal for a single category is a beta PDF, almost as if the data from the other categories were pooled—*but not quite*.

For the $K = 3$ case, there's an $N - n_1{+}1$ exponent, instead of the $N - n_1$ we might expect from pooling the data. This hints at a problem with the uniform prior we adopted; see Lab04 and Assignment03.

Dirichlet distributions

A family of "PDFs for PMFs," i.e., densities over possible categorical or multinomial distributions:

$$\mathrm{Dir}(\alpha|\kappa_1, \ldots, \kappa_K) = \frac{\Gamma(\kappa_0)}{\Gamma(\kappa_1)\cdots\Gamma(\kappa_K)} \left[\prod_{k=1}^{K} \alpha_k^{\kappa_k - 1}\right] \delta\left(1 - \sum_{k=1}^{K} \alpha_k\right)$$

with $\kappa_0 = \sum_k \kappa_k$; the κ_k are *concentration parameters*

Mode: $\hat{\alpha}_k = \frac{\kappa_k - 1}{\kappa_0 - K}$ for $k = 1 \ldots K$

Marginal means: $\mathbb{E}(\alpha_k) = \frac{\kappa_k}{\kappa_0}$

Marginal variances: $\mathrm{Var}(\alpha_k) = \frac{\kappa_i(\kappa_0 - \kappa_i)}{\kappa_0^2(\kappa_0 + 1)}$

All covariances *negative* (necessarily!)

Special case: *Symmetric Dirichlet* with $\kappa_i = \kappa$

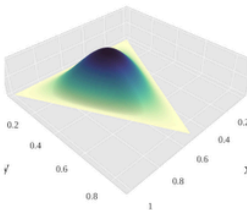Dirichlet distribution priors are *conjugate priors* for categorical and multinomial likelihood functions
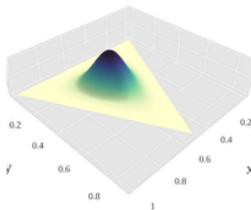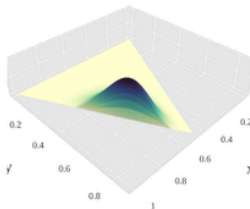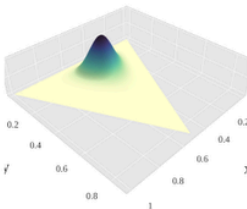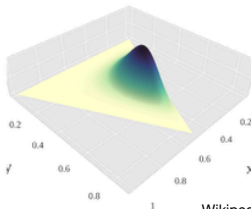
Simplex/ternary plots
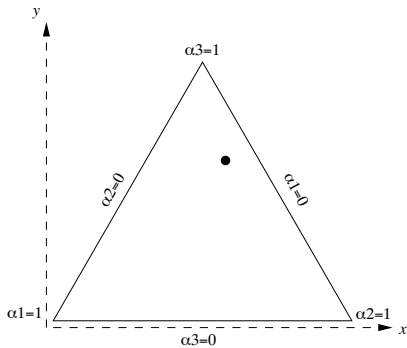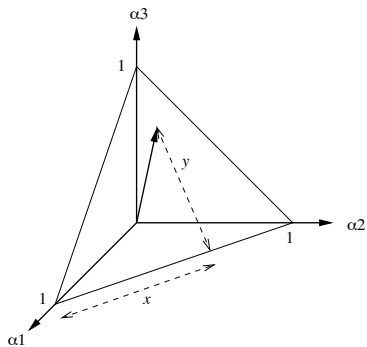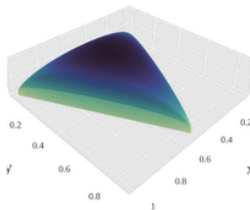
(1.3, 1.3, 1.3)   (3,3,3)   (7,7,7)

(2,6,11)   (14, 9, 5)   (6,2,6)

Wikipedia