The cppad_mixed Capture Example and Speed Test

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Introduction

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Program Input

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Program Output

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- Interesting numerical AD method used to avoid overflow.
- Optional constraints.

Data Model

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- \triangleright N_i is the size of the population at location i.
- q_t is the probability of capture at time t.
- ▶ The conditional probability of $y_{i,t}$ given N_i and q_t is

$$\mathbf{p}(y_{i,t}|N_i,q_t) = \left(\begin{array}{c}N_i\\y_{i,t}\end{array}\right)q_t^{y(i,t)}\left(1-q_t\right)^{y(i,t)}$$

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- We use a Poisson distribution to model the probability of N_i given θ

$$\mathbf{p}(N_i|\theta) = \theta_0^{N(i)} \frac{\exp[-\theta_0]}{N_i!}$$

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$$\log[q_t/(1-q_t)] = u_t + \theta_1$$

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$$\log[q_t/(1-q_t)] = u_t + \theta_1$$

▶ The probability of capture at time t given θ and u is

$$q_t(\theta, u) = \mathbf{p}(q_t | \theta, u) = [1 + \exp(-u_t - \theta_1)]^{-1}$$



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$$\mathbf{p}(y_i|N_i,\theta,u) = \prod_{t=0}^{T-1} \begin{pmatrix} N(i) \\ y_{i,t} \end{pmatrix} q_t(\theta,u)^{y(i,t)} \left(1 - q_t(\theta,u)\right)^{y(i,t)}$$

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- ▶ Probability of y_i given θ , u, is modeled using the sum

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$$\prod_{i=0}^{K-1} \left[\sum_{k=0}^{K-1} \theta_0^k \frac{\exp[-\theta_0]}{k!} \prod_{t=0}^{T-1} \binom{k}{y_{i,t}} q_t(\theta, u)^{y(i,t)} (1 - q_t(\theta, u))^{y(i,t)} \right]$$

Program Input

Random Likelihood Function

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The user defined random likelihood for this example is

$$f(\theta, u) = -\log[\mathbf{p}(y|\theta, u)\mathbf{p}(u|\theta)]$$

Other User Defined Functions

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$$\hat{u}(\theta) = \operatorname{argmin} f(\theta, u) \text{ w.r.t. } u$$



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- A is the random constraint matrix.
- ▶ The random constraint function is

$$0 = A\hat{u}(\theta) = \hat{u}_1(\theta) + \cdots + \hat{u}_{T-1}(\theta)$$



random_seed

non-negative integer $\ 0$, match previous

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    random_seed non-negative integer 0 , match previous
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    number_locations positive integer , R 50
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    number_times positive integer , T 10
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max_population
▶ mean_population
                         positive real , \theta_0
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std_logit_probability
                           positive real , \theta_2
                                                  0.5
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•	$number_fixed_samples$	positive integer	1000
•	number_locations	positive integer , R	50
•	number_times	positive integer , ${\it T}$	10
•	$max_population$	positive integer , ${\it K}$	50
>	$mean_population$	positive real , $ heta_0$	5.0
>	$mean_logit_probability$	real , $ heta_1$	-0.5
•	$std_{L}logit_{L}probability$	positive real , $ heta_2$	0.5
•	quasi_fixed	true or false	true

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•	$mean_logit_probability$	real , $ heta_1$	-0.5
•	$std_logit_probability$	positive real , $ heta_2$	0.5
•	quasi_fixed	true or false	true
>	$random_constraint$	true or false	false , true

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•	$number_fixed_samples$	positive integer	1000
•	$number_locations$	positive integer , R	50
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•	mean_population	positive real , $ heta_0$	5.0
•	$mean_logit_probability$	real , $ heta_1$	-0.5
•	$std_{-}logit_{-}probability$	positive real , $ heta_2$	0.5
•	quasi_fixed	true or false	true
•	$random_constraint$	true or false	false , true
•	$trace_optimize_fixed$	true or false	false

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•	$random_constraint$	true or false	false , true
•	$trace_optimize_fixed$	true or false	false

Program Output

actual_seed

1466520673 , 1466520673

- actual_seed
- initialize_bytes

- 1466520673, 1466520673
- 27,728,078 , 27,728,078

actual_seed

1466520673 , 1466520673

initialize_bytes

27,728,078 , 27,728,078

initialize_seconds

0.244 , 0.259

▶ actual_seed 1466520673 , 1466520673

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optimize_fixed_seconds5.49 , 2.96

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▶ initialize_bytes 27,728,078 , 27,728,078

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optimize_fixed_seconds
5.49, 2.96

optimize_random_seconds 0.077 , 0.101

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▶ initialize_bytes 27,728,078 , 27,728,078

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optimize_random_seconds 0.077 , 0.101

▶ information_mat_seconds 1.24 , 1.21

•	actual_seed	1466520673 , 1466520673
•	initialize_bytes	27,728,078 , 27,728,078
•	initialize_seconds	0.244 , 0.259
•	$optimize_fixed_seconds$	5.49 , 2.96
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•	$information_mat_seconds$	1.24 , 1.21
•	sample_fixed_seconds	0.024 , 0.041

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•	$optimize_fixed_seconds$	5.49 , 2.96
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•	$information_mat_seconds$	1.24 , 1.21
•	sample_fixed_seconds	0.024 , 0.041

sum_random_effects

-0.0698 , 1.33227e-15

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mean_population_estimate

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mean_logit_probability_estimate -0.607 , -0.494

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    mean_population_estimate 5.84 , 5.35
    mean_logit_probability_estimate -0.607 , -0.494
    std_logit_probability_estimate 0.583 , 0.667
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    sum_random_effects -0.0698 , 1.33227e-15
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    mean_logit_probability_estimate -0.607 , -0.494
    std_logit_probability_estimate 0.583 , 0.667
    mean_population_std 0.579 , 0.492
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sum_random_effects	-0.0698 , 1.33227e-15
mean_population_estimate	5.84 , 5.35
$\qquad \qquad \blacksquare \ \ mean_logit_probability_estimate$	-0.607 , -0.494
std_logit_probability_estimate	0.583 , 0.667
mean_population_std	0.579 , 0.492
mean_logit_probability_std	0.23, 0.092

sum_random_effects	-0.0698 , 1.33227e-15
mean_population_estimate	5.84 , 5.35
$\textcolor{red}{\blacktriangleright} \ \ mean_logit_probability_estimate$	-0.607 , -0.494
std_logit_probability_estimate	0.583 , 0.667
mean_population_std	0.579 , 0.492
mean_logit_probability_std	0.23 , 0.092
std_logit_probability_std	0.142 , 0.161

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mean_population_ratio	1.45 , 0.702
mean_logit_probability_ratio	-0.464 , 0.07

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mean_logit_probability_ratio	-0.464 , 0.07
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optimize_fixed_seconds_avg
5.59 , 2.71

optimize_fixed_seconds_avgmean_population_error_avg5.59 , 2.710.41 , 0.37

•	optimize_fixed_seconds_avg	5.59 , 2.71
•	mean_population_error_avg	0.41 , 0.37
>	mean_population_std_avg	0.52 , 0.49

```
    optimize_fixed_seconds_avg
    mean_population_error_avg
    mean_population_std_avg
    mean_logit_probability_error_avg
    0.52 , 0.49
    mean_logit_probability_error_avg
    0.18 , 0.10
```

	optimize_fixed_seconds_avg	5.59 , 2.71
•	mean_population_error_avg	0.41 , 0.37
•	mean_population_std_avg	0.52 , 0.49
•	$mean_logit_probability_error_avg$	0.18 , 0.10
•	mean_logit_probability_std_avg	0.21 , 0.09

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•	mean_population_error_avg	0.41 , 0.37
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•	mean_logit_probability_std_avg	0.21 , 0.09
>	std_logit_probability_error_avg	0.13 , 0.13

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mean_logit_probability_error_avg	0.18 , 0.10
mean_logit_probability_std_avg	0.21 , 0.09
std_logit_probability_error_avg	0.13 , 0.13
std_logit_probability_std_avg	0.12 , 0.12

optimize_fixed_seconds_avg	5.59 , 2.71
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std_logit_probability_error_avg	0.13 , 0.13
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