## Multilevel Models for Estimating the Number of Deaths in Armed Conflict (in Colombia)

#### Shira Mitchell JSM 2014

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# Colombian conflict (1964-present)

From Wikipedia, the free encyclopedia

For other Colombia-related conflicts, see List of wars involving Colombia.



The **Colombian conflict** began approximately in 1964 or 1966 and is an ongoing lowintensity asymmetric war between the Colombian government, drug gangs, paramilitary groups and left-wing guerrillas such as the Revolutionary Armed Forces of Colombia, and the National Liberation Army (ELN), fighting each other to increase their influence in Colombian territory.<sup>[18][19][20][21][22][23][24][25]</sup>

# Casualties and losses

# Army and Police: 4,286 killed, 13,076 injured (since 2002<sup>[6]</sup>)

FARC: 12,981 demobilized (since 2002<sup>[6]</sup>) ELN: 2,789 demobilized (since 2002<sup>[6]</sup>) Since 2002, 34,512 guerrillas captured, 13,197 killed<sup>[6]</sup>

# Data from the Human Rights Data Analysis Group (HRDAG)

NGOs and govt groups provide lists of killings in 1998-2007, Casanare, Colombia: department of Colombia, population 300,000, BP oil pipeline, much corruption and violence.



Goal: Estimate the number of killings in Casanare in years 1998-2007.





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### $n_{k_1k_2} \sim Pois(\mu_{k_1k_2})$ independent

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### $\log(\mu_{k_1k_2}) = \lambda_0 + \lambda_1k_1 + \lambda_2k_2$

# $\Rightarrow \widehat{\mathsf{E}[\mathsf{N}]}_{\mathsf{MLE}} = \frac{\mathsf{n}_{1+}\mathsf{n}_{+1}}{\mathsf{n}_{11}}$

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#### General number of lists

$$\mathbf{k} = (k_1, k_2, ..., k_J)$$
  
for example, if in lists 3, 4, and 6  
= (0, 0, 1, 1, 0, 1)

Independence model:  $log(\mu_k) = \lambda_0 + \lambda_1 k_1 + ... + \lambda_J k_J$ 

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## Data - from HRDAG

#### Matching:

Commission of Jurists			National Police		
Year	Gender	location	Year	Perpetrator	Gender
	:			:	
1998	male	TAMARA		:	
	÷				
				:	
	-		1998	FARC	male

6 lists contain among them 2619 observed killings.

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## Data - from HRDAG

year	IMLM	PN0	VP	CCJ	CIN	CCE
	(govt)	(govt)	(govt)	(NGO)	(NGO)	(NGO)
1998	1	0	0	14	13	3
1999	2	0	0	6	8	2
2000	213	0	5	22	23	0
2001	262	0	2	21	12	0
2002	268	1	0	33	9	0
2003	348	274	2	12	11	0
2004	412	324	295	14	11	1
2005	210	155	138	8	13	16
2006	104	71	26	3	2	15
2007	54	0	33	27	36	35

We're far from the independence model

- Heterogeneity of a person's recordability
- Groups collecting data interact
- Want yearly estimates, but very little data exist in some years
- Groups operating in different but overlapping time periods

Heterogeneity of a person's recordability

 $P_j(\theta) = P(\mathrm{person} \ \mathrm{with} \ \mathrm{recordability} \ \theta \ \mathrm{is} \ \mathrm{recorded} \ \mathrm{on} \ \mathrm{list} \ j)$ 

$$\log\left(\frac{P_{j}(\theta_{govt})}{1 - P_{j}(\theta_{govt})}\right) = \theta_{govt} + \lambda_{j} \text{ for } j \in govts$$
$$\log\left(\frac{P_{j}(\theta_{NGO})}{1 - P_{j}(\theta_{NGO})}\right) = \theta_{NGO} + \lambda_{j} \text{ for } j \in NGOs$$

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Heterogeneity of a person's recordability

Let 
$$(\theta_{NGO}, \theta_{govt}) \sim p(\theta_{NGO}, \theta_{govt})$$
.  
Then

$$\log(\mu_k) = \lambda_0 + \lambda_1 k_1 + \ldots + \lambda_6 k_6 + \gamma(k_+^{NGO}, k_+^{govt})$$

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$$\begin{split} \log(\mu_k) &= \lambda_0 + \lambda_1 k_1 + \ldots + \lambda_6 k_6 + \\ &\sum_{j,j' \in NGOs} \omega_{NGO} k_j k_{j'} + \sum_{j,j' \in \text{govts}} \omega_{\text{govt}} k_j k_{j'} + \sum_{j \in NGOs, j' \in \text{govts}} \omega_{\text{mix}} k_j k_{j'} \end{split}$$

- Heterogeneity of a person's recordability
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$$\begin{split} &\log\left(\mu_{k}^{(t)}\right) = \lambda_{0t} + \lambda_{1,t}k_{1} + ... + \lambda_{6,t}k_{6} + \\ &\sum_{j,j' \in NGOs} \omega_{NGO}k_{j}k_{j'} + \sum_{j,j' \in govts} \omega_{govt}k_{j}k_{j'} + \sum_{j \in NGOs,j' \in govts} \omega_{mix}k_{j}k_{j'} \end{split}$$

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$$\lambda_{j,t} \sim N(\mu_j,\tau^2) \ {\rm for} \ j=1,...,6$$

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#### AR1 Model



- Heterogeneity of a person's recordability
- Groups collecting data interact
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#### Mixture Model

 $\lambda_{j,t} \mid \gamma_{j,t} \sim (1 - \gamma_{j,t}) N(\mu_{\text{inactive}}, \sigma_{\text{inactive}}^2) + \gamma_{j,t} N(\mu_j, \tau^2) \text{ for } j = 1, ..., 6$ 

 $\gamma_{j,t} \sim Bern(p) \,\, \mathrm{independent}$ 

 $p \sim \text{Unif}(0,1)$ 

- Heterogeneity of a person's recordability
- Groups collecting data interact
- Want yearly estimates, but very little data exist in some years

Groups operating in different but overlapping time periods

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Consider inactive lists as missing data [Zwane et al., 2004].

In year t, lists 3 and 4 are inactive.

Treat  $n_{01000}^{(t)}$  as margin  $n_{01++0}^{(t)}$ , and cells  $n_{01000}^{(t)}$ ,  $n_{01010}^{(t)}$ ,  $n_{01100}^{(t)}$ ,  $n_{01110}^{(t)}$  as missing data.

Zeros from missing data (ZM) vs Zeros from sampling (ZS)

	Zeros from missing data (ZM)	Zeros from sampling (ZS)
unpooled main effects (U)	U-ZM	U-ZS
Multilevel model (M)	M- <mark>ZM</mark>	M-ZS AR1-ZS



#### **Casanare Data Results**

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#### Posterior Predictive Checks: M-ZS



### Simulations

Simulate from posterior predictive distribution of M-ZM, M-ZS, and AR1-ZS fit to Casanare data.

Fit all the models.

- Coverage is similar for all models.
- Multilevel models have narrower intervals, and lower bias.

- In many applications, lists concentrate effort in different years, locations, or demographics.
- If these groups are overlapping ⇒ fit joint models, to be able to model more list interactions, and to borrow information across strata.

#### We recommend Multilevel Models

- In years with little data, we might not trust unpooled estimates high variance, likely to get extreme estimates.
- Exchangeability and normality can be assessed via posterior predictive checks, relaxed by expanding the model.
- If we want monthly estimates at municipality-level, less and less data per stratum.
  - Colombia (2003-2011)
  - Syria (2011-2013)

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- F Dominici. Combining contingency tables with missing dimensions. *Biometrics*, 56(2):546–553, 2000.
- A Gelman, A Jakulin, M G Pittau, and Y Su. A weakly informative default prior distribution for logistic and other regression models. *The Annals of Applied Statistics*, 2(4):1360–1383, 2008.
- E N Zwane, K van der Pal-de Bruin, and P G M van der Heijden. The multiple-record systems estimator when registrations refer to different but overlapping populations. *Statistics in Medicine*, 23:2267–2281, 2004.

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$$\begin{array}{c|c} n_{11} & n_{10} & n_{1+} \\ n_{01} & n_{00} & n_{0+} \\ n_{+1} & n_{+0} & n_{++} = N \end{array}$$

 $n_{11}|n_{1+}, n_{+1}, N \sim \text{HGeom}(n_{1+}, N - n_{1+}, n_{+1})$  $\widehat{N}_{\text{MLE}} = \left\lfloor \frac{n_{1+}n_{+1}}{n_{11}} \right\rfloor$ 

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## EM-like algorithm

#### E step:

$$\hat{n}_{01010}^{(t)} = \frac{\sum_{s=1}^{T} \mu_{01010}^{(s)}}{\sum_{s=1}^{T} \left( \mu_{01000}^{(s)} + \mu_{01010}^{(s)} + \mu_{01100}^{(s)} + \mu_{01110}^{(s)} \right)} n_{01++0}^{(t)}.$$

#### M step:

Fit log-linear model to completed data  $\{n_k^{(t)}\}_{k\neq 00000,00010,00100,00110}.$ 

Bayesian version [Dominici, 2000].

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Sensitivity Analysis: Choice of  $\mu_{inactive}$ ,  $\tau^2_{inactive}$ 

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#### Posterior Predictive Checks: AR1-ZS



#### Posterior Predictive Checks: M-ZM



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#### Generate data from M-ZM: Coverage



Generate data from M-ZS: Coverage



#### Generate data from AR1-ZS: Coverage



#### Generate data from M-ZM: Bias



#### Generate data from M-ZS: Bias



#### Generate data from AR1-ZS: Bias



#### Generate data from M-ZM: Interval Width



#### Generate data from M-ZS: Interval Width



#### Generate data from AR1-ZS: Interval Width



#### Continuous Model Expansion

$$\begin{split} &\log\left(\mu_k^{(t)}\right) = \lambda_{0t} + \lambda_{1,t}k_1 + ... + \lambda_{6,t}k_6 + \\ &\sum_{j,j' \in NGOs} \omega_{NGO}k_jk_{j'} + \sum_{j,j' \in govts} \omega_{govt}k_jk_{j'} + \sum_{j \in NGOs,j' \in govts} \omega_{mix}k_jk_{j'} \end{split}$$

 $\boldsymbol{\omega}_{j,j'} \sim N\left(\boldsymbol{\omega}_{NGO}, \sigma_{NGO}^2\right)$ 

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Continuous Model Expansion: 3-way log-linear interactions

- Population heterogeneity ⇒ higher-order interactions.
- Story for list cooperations?

Continuous Model Expansion: 3-way log-linear interactions A Story:



Continuous Model Expansion: 3-way log-linear interactions

- Cauchy priors regularization [Gelman et al., 2008]
- Exchangeable based on NGO/govt

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