Using Latent Variable Models to Estimate the Prevalence of Sexual Violence in Armed Conflict: An Introduction

Jule Krüger,
Center for Political Studies, University of Michigan

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This tutorial builds on ongoing research with

Ragnhild Nordås

and

Christopher Fariss

Wartime Sexual Violence

- Includes the use of rape and other forms of sexual violence
- Constitutes a severe human rights problem
- Is difficult to observe and document as a practice

A lack of systematic data impedes empirical analysis with regard to extent, spatiotemporal trends, and patterns.

Why Conflict-Related Sexual Violence Is Hard to Measure

- Shame, fear of retaliation, stigma and rejection due to socio-cultural taboos
- Inconsistency in testimony and lack of clear narrative due to trauma-induced memory loss
- Differing conceptualizations and language used to refer to sexual violence events
- Perpetrators' incentives to conceal activity and evade accountability for war crimes
- Blending of state actors and institutions with regard to the perpetration and reporting of these crimes

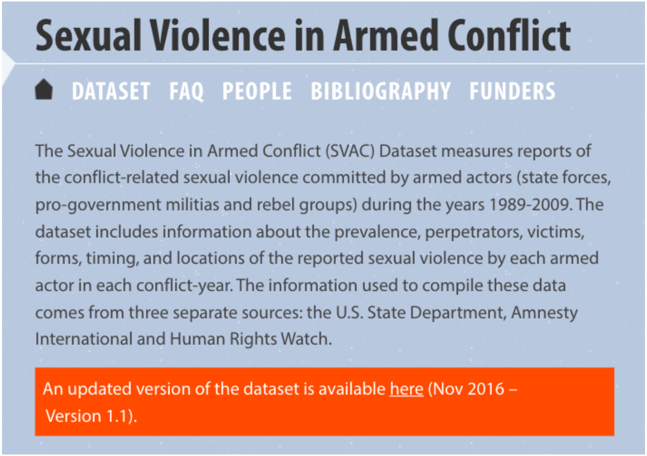
All of these issues vary over space and time.

Why the Observation of Wartime Sexual Violence May Improve over Time

- Increasing international focus
- Changing norms and perceptions of survivors
- Recent challenges to societal taboos
- Growing initiatives to empower survivors to speak out
- Changes in the wording of sexual violence experiences leading to more explicit descriptions
- Growth in documentation efforts paired with improved documentation practices

While these trends vary across space, we will likely see higher reporting rates in some places over time.

How We Currently Measure Wartime Sexual Violence



Sexual Violence in Armed Conflict

DATASET FAQ PEOPLE BIBLIOGRAPHY FUNDERS

The Sexual Violence in Armed Conflict (SVAC) Dataset measures reports of the conflict-related sexual violence committed by armed actors (state forces, pro-government militias and rebel groups) during the years 1989-2009. The dataset includes information about the prevalence, perpetrators, victims, forms, timing, and locations of the reported sexual violence by each armed actor in each conflict-year. The information used to compile these data comes from three separate sources: the U.S. State Department, Amnesty International and Human Rights Watch.

An updated version of the dataset is available here (Nov 2016 – Version 1.1).

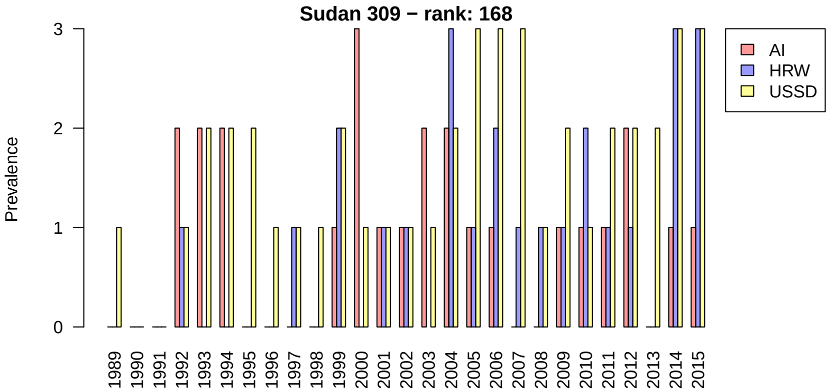
Three ordinal SVAC variables based on human-coded annual human rights reports http://www.sexualviolencedata.org/

Let's import the data into R and take a look at it:

```
$: cd ~/git/SVAC-LVM-tutorial/import
$: open -a Rstudio src/import-check-data-main.R
```

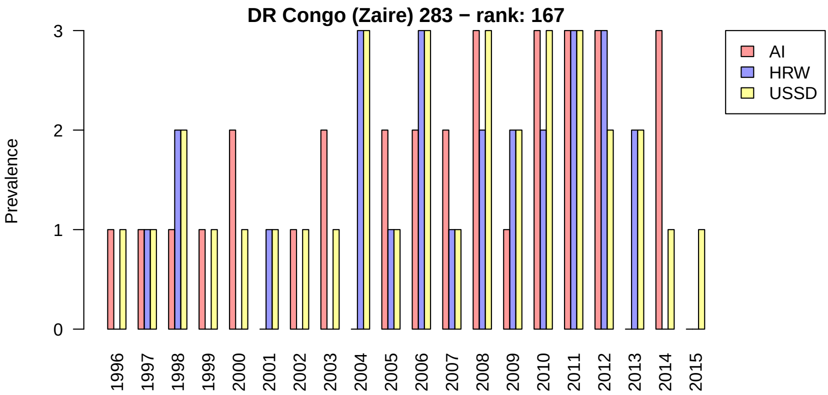
In this tutorial, we will only look at reported SVAC with respect to state forces ('GOV').

SVAC Provides Three Indicators that Report Prevalence of Wartime Sexual Violence: Sudan



Reported level of engagement in wartime sexual violence by state forces in Sudan according to three sources static

Another Case: DRC



Reported level of engagement in wartime sexual violence by state forces in DRC according to three sources static

Let's make some more barplots of reported state behavior for other armed conflict cases:

```
$: cd ../visualize
$: open -a Rstudio
   src/barplot-sources-by-conflict.R
```

For Every Conflict-Year, We Have Three Sources Reporting on SVAC Prevalence

- For many years, the three prevalence measures diverge (e.g., Sudan 2006, DRC 1998)
- In other years, the three sources seem to agree (e.g., Sudan 2001-2, DRC 2011)
- In a considerable number of years (when looking at the entire dataset), the three sources do not report any SV (e.g., Sudan 1990-1)

How do we deal with converging/diverging information across the three sources? Shall we average across them, or should we choose the most common/lowest/highest level?

What If, for a Given Conflict-Year, We Understand

- True SVAC prevalence as a *latent trait* that can't be observed directly but estimated using observed outcomes
- Available human rights reports as imperfect measures of the latent level due to observational challenges
- Human-coded SVAC variables as imperfect measures of human rights reports due to perceptual coding error
- Information convergence/divergence across sources as a measure of certainty regarding SVAC prevalence

The logic of latent variable models (LVM) follows precisely this conceptual approach to measurement.

The Added Value of Latent Variable Models

- Leverage information from multiple sources
- Provide probabilistic estimates of a latent trait, SVAC in our case
- Express our uncertainty regarding the estimates of the latent trait through credible intervals
- Compute the estimated latent trait at the interval-level (instead of ordinal), which simplifies subsequent analysis
- Enable direct probabilistic comparisons across conflict-years and cases

Parametrizing a LVM to Estimate SVAC, I

(Cf. Schnakenberg and Fariss (2014:7-10) for details.)

We assume that the observed human rights reports for each conflict-year are functions of a unidimensional latent variable θ that represents the level of SVAC.

For each conflict-year observation, we index conflicts with i and years with t.

For each model, we have three ordinal indicators J with levels 0 (no reports), 1 (some), 2 (several/many), and 3 (massive).

Parametrizing a LVM to Estimate SVAC, II

The observed values of each indicator (or, "item") are denoted as y_{itj} for a given conflict-year and assumed to depend on θ_{it}.

Using these observed values, our goal is to estimate θ_{it}, i.e., the latent SVAC prevalence in conflict i in year t.

For each item (i.e., indicator), we estimate an "item discrimination" parameter β_j and a set of $K_j - 1$ difficulty cut-points $(\alpha_{jk})_{k=1}^{k_j}$. (We will plot these cut-points later on.)

Parametrizing a LVM to Estimate SVAC, III

There is also an error term ε_{itj} for each item, which in our case represents observational challenges and coding errors.

We assume that the error terms are independently drawn from a logistic distribution.

The distribution of the error terms determines the likelihood of our model.

Estimating a Latent Variable Model

Following our parametrization, we can derive a probability distribution for a given response to item j.

A likelihood function for β, α and θ given the data enables estimation of our unobserved parameters.

If you are interested in the math underlying Bayesian ordinal item-response theory, please refer to Schnakenberg and Fariss (2014: 7-8) for a start.

For time constraints, we will limit our tutorial to LVM implementation in R.

Let's Run Some LVMs!

```
$: cd ../estimate
$: open -a Rstudio src/estimate-static-SVAC.R
```

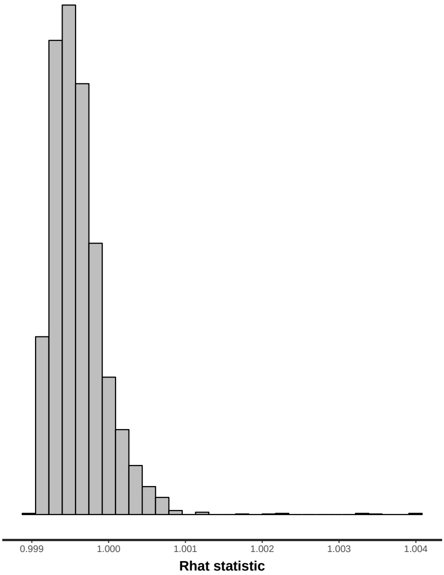
Checking Model Convergence

We can check whether our model converged successfully by plotting the Rhat statistic.

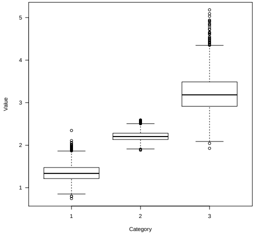
If the Rhat values remain below 1.1, we conclude model convergence has occurred.

If the values are above 1.1, we would rerun the model with a higher number of iterations until we reach convergence.

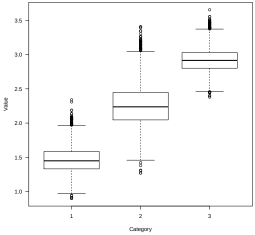
An Rhat Plot for the Static LVM



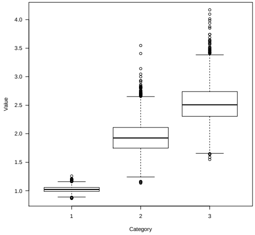
Plotting the α Difficulty Cut-Points



(a) AI



(b) HRW

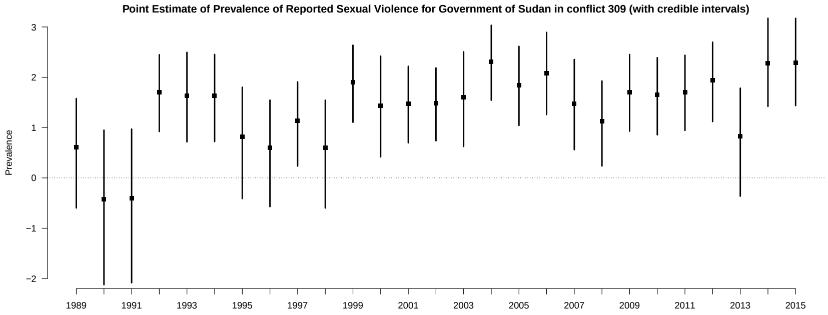


(c) USSD

Visualizing Our θ Estimates

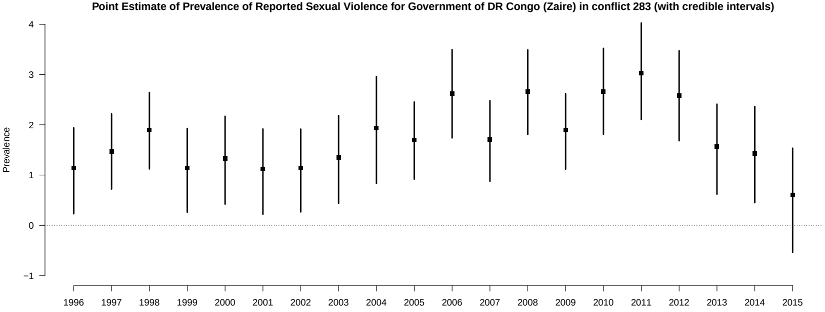
```
$: cd ../visualize
$: open -a Rstudio
   src/plot-LVM-estimates-by-conflict.R
```

Static Estimates of the Latent Prevalence of Wartime Sexual Violence: Sudan



Estimated level of engagement in wartime sexual violence by state forces in Sudan obs dynamic

Static Estimates: DRC



Estimated level of engagement in wartime sexual violence by state forces in DRC obs dynamic

The Local Independence Assumption in a Static Model

Item-Response Theory requires us to assume local independence in LVMs:

(1) local indepedence of different indicators within the same conflict-year,
(2) local independence of indicators across conflicts within years,
(3) local independence of indicators across years within countries.

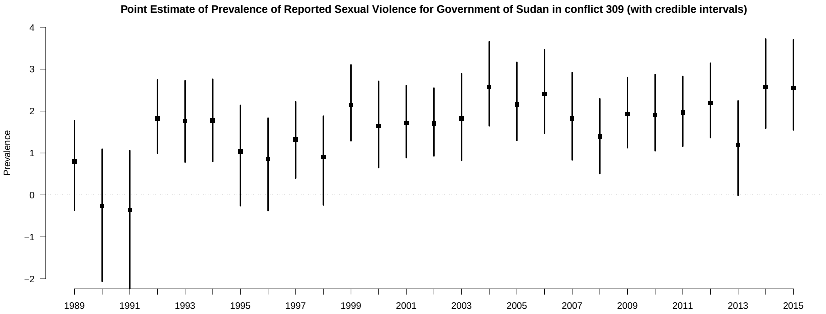
Relaxing the (3) Local Independence Assumption in a Dynamic Model

We relax the (3) local independence assumption to estimate a dynamic model.

- Empirical conflict research shows that the level of political violence in a given year often depends on the level of political violence in the previous year.
- It is similarly plausible that observational challenges are time-dependent in this way.

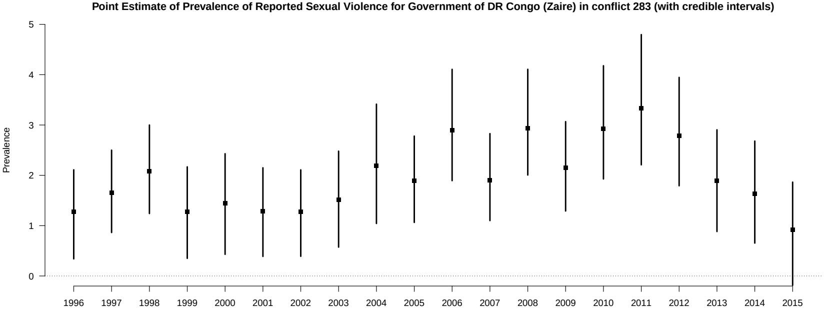
In a dynamic model, we specify hierarchical priors for each θ_{it} that allow the estimated latent level of wartime sexual violence in a given conflict-year to depend on that conflict's value in the previous year.

Dynamic Estimates of the Latent Prevalence of Wartime Sexual Violence: Sudan



Estimated level of engagement in wartime sexual violence by state forces in Sudan static

Dynamic Estimates: DRC



Estimated level of engagement in wartime sexual violence by state forces in DRC static

Current State of this Research Project

- Our goal is to develop a LVM approach for measuring wartime sexual violence.
- Currently, our main concern are the many conflict-years with zero observations, i.e., no reports of sexual violence.
    - Did observational challenges impede our registration of sexual-violence conflict events?
    - Or, was there truly no conflict-related use of sexual violence?

Planned Next Steps

- Include more indicators of wartime sexual violence
- Include measures of "openness"/observability, such as freedom of press, local civil society, total number of sexual violence related news reports, etc.
- Measure the level of event/actor/location (dis)agreement across human rights reports using text analysis
- Explore the use of Bayesian Model Averaging to account for possible list dependence
- Conduct case studies to better understand data-generating processes and finetune models (e.g., Kashmir, Kosovo, ?)

Thank you!

Email me if you have questions or suggestions.