A Data-Driven Approach to Model the Generation Process of Bloodstain Patterns

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Background

A challenging task in bloodstain pattern analysis is to evaluate alternative hypotheses regarding the mechanism that produced the pattern. Examples of typical mechanisms:

Impact pattern - *caused by a blunt weapon like hammer or bat, striking the blood source*

Expiration pattern - *Blood were coming out of nose or mouth, e.g., coughing or shouting*

Previous studies [1,2] on the reliability of analysts in determining the causal mechanism of a bloodstain pattern indicated strong context effects.

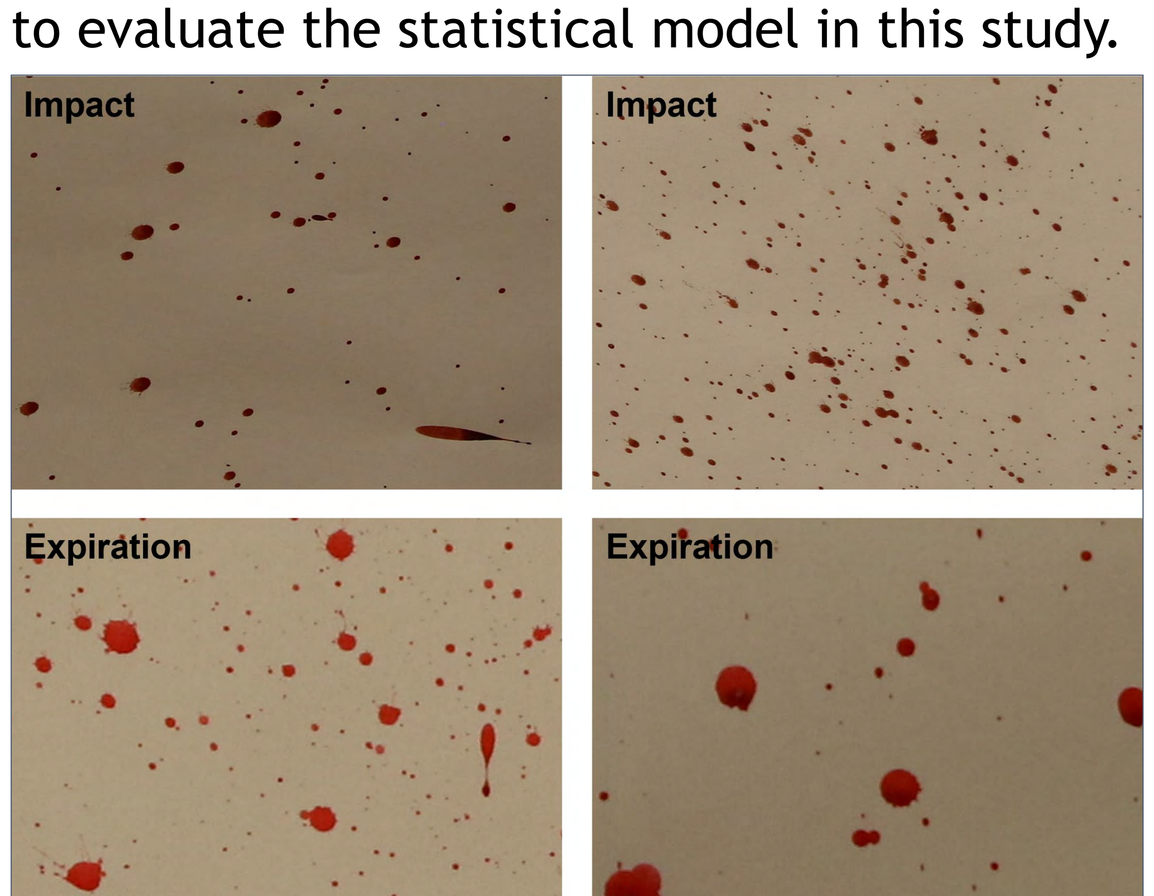
Objectives

We propose a general data-driven framework based on Bayesian nonparametrics to achieve the following goals:

- Model the generation process of bloodstain patterns produced by certain mechanisms
- Evaluate the likelihood ratio as the strength of evidence for assessing two competing hypothetical mechanisms

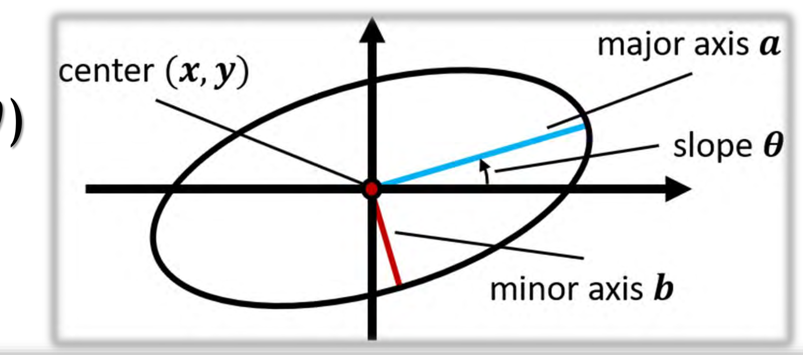
Material

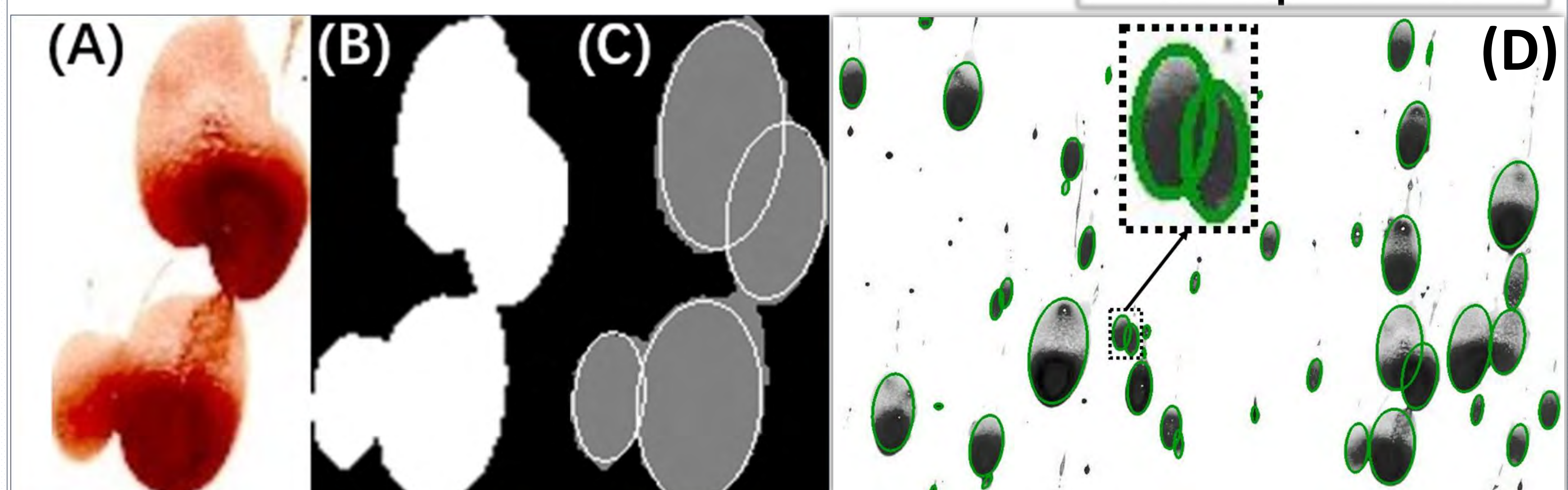
Distinction between patterns caused by impact and expiration can be ambiguous to analysts [2]. We use two groups of images of 172 impact patterns and 112 expiration patterns generated with swine blood in different experimental settings and conditions to evaluate the statistical model in this study.



Ellipse Representation

- Image Preprocessing (A→B): patterns are binarized and smoothed by morphological operations including erosion, dilation and hole-filling
- Ellipse Recognition[3] (B→C): a segmentation algorithm based on elliptical distance transforms of binary image is modified to fit non-elliptical components with multiple ellipses
- Ellipse Representation (D):
  - Each ellipse is characterized by five variables (x, y, a, b, θ)
  - Each stain is approximated by one or more ellipses
  - Each bloodstain pattern consists of multiple stains





Generative Model

Bloodstain patterns p_i can be represented by tables

Pattern 1: Impact

	x	y	a	b	φ
s_1					
s_2					
…	…	…	…	…	…
s_{n_1}					

Pattern 2: Gunshot

	x	y	a	b	φ
s_1					
s_2					
…	…	…	…	…	…
s_{n_2}					

…

Pattern N: cast-off

	x	y	a	b	φ
s_1					
s_2					
…	…	…	…	…	…
s_{n_N}					

where $s_j = (x_j, y_j, a_j, b_j, \theta_j)$ are variables for ellipses j in the pattern. The Generative process of a table can be modeled by a ***Hierarchical Dirichlet Process (HDP)***:

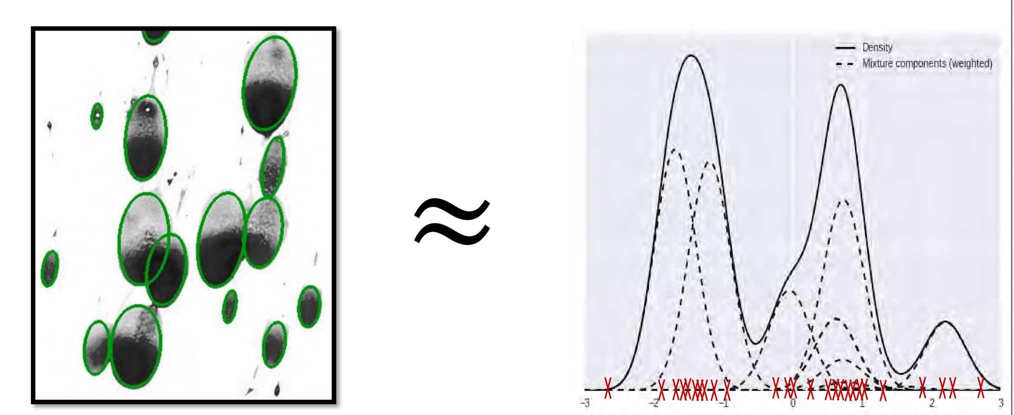
$$p_i(s) \approx \int k(s|\,\phi)dF_i(\phi)$$

$$F_i(\phi) \sim DP(\alpha, G)$$

$$G(\phi) \sim DP(\gamma, H)$$

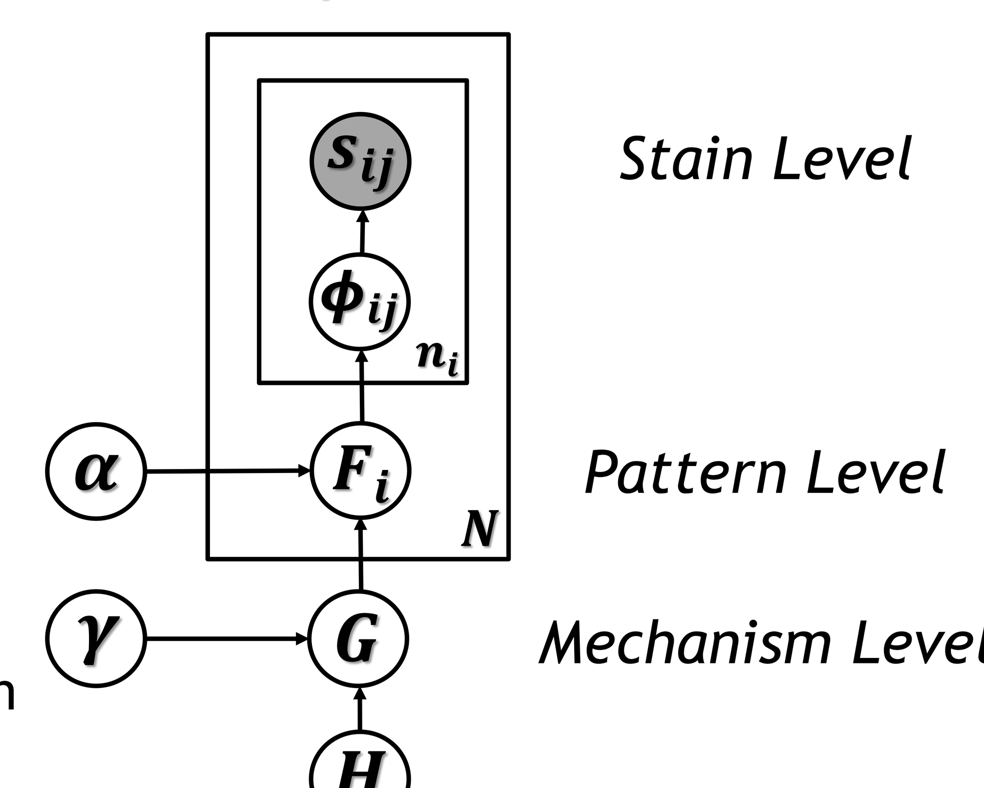
The likelihood of a pattern conditioning on the mechanism can be evaluated through the model.

1-D Illustration



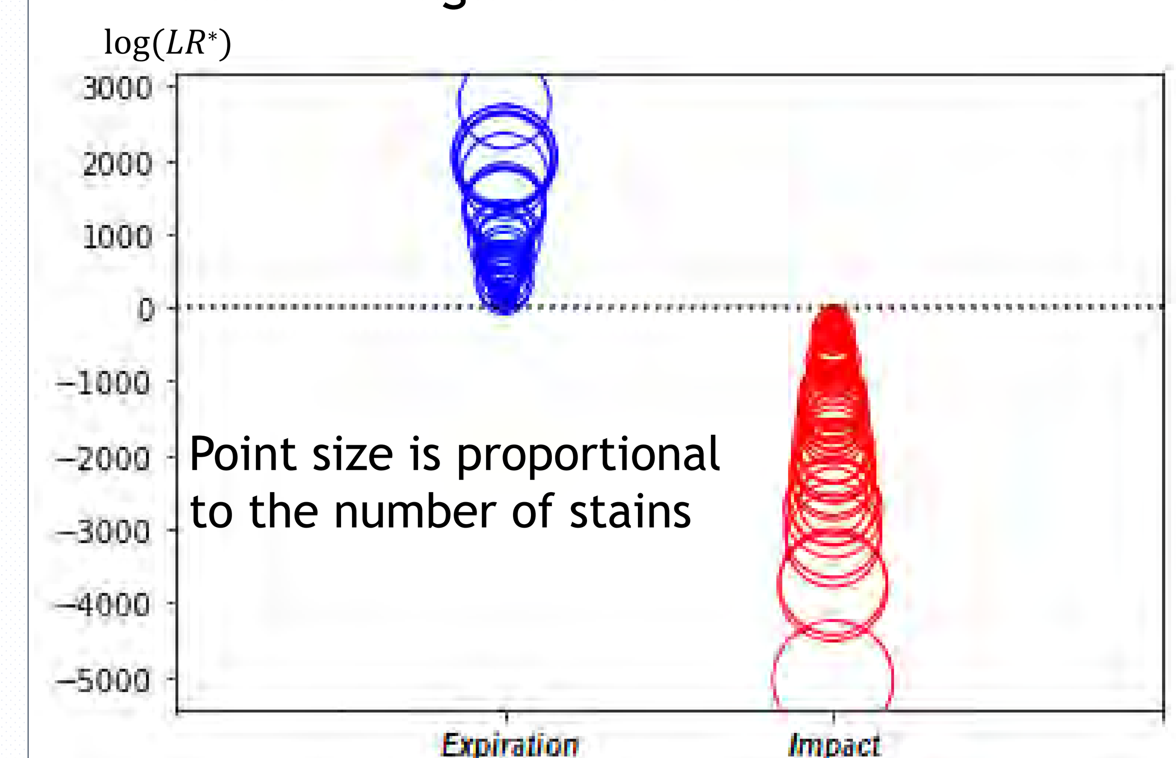
Ellipse Representation ≈ Probability Distribution

Graphical Model of HDP



Experiments

- 60% of both impact patterns and expiration patterns are used to separately train the two models of corresponding mechanisms
- The remaining patterns are evaluated by both models and acquires two likelihoods
- The likelihood ratio measures the degree to which the evidence supports one mechanism against the other



$^*LR = \mathrm{Prob}(p|\mathrm{Expiratioin}) / \mathrm{Prob}(p|\mathrm{Impact})$

Conclusions

- The generative model relies on the ellipse representation of bloodstain patterns
- All test patterns being correctly identified regarding their likelihood ratio indicates potential of the likelihood ratio approach
- Extreme values of likelihood ratio suggest further calibration of the model is needed

Reference

1. National Research Council et al. Strengthening forensic science in the United States: a path forward. National Academies Press, 2009
2. R Austin Hicklin et al. Accuracy and reproducibility of conclusions by forensic bloodstain pattern analysts. Forensic Science International, page 110856, 2021.
3. Tong Zou et al. Recognition of overlapping elliptical objects in a binary image. Pattern Analysis and Applications, pages 1-14, 2021.

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