Evaluating the Reliability of Randomly Acquired Characteristics (RACs) Identification in Footwear Impression Evidence

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Introduction

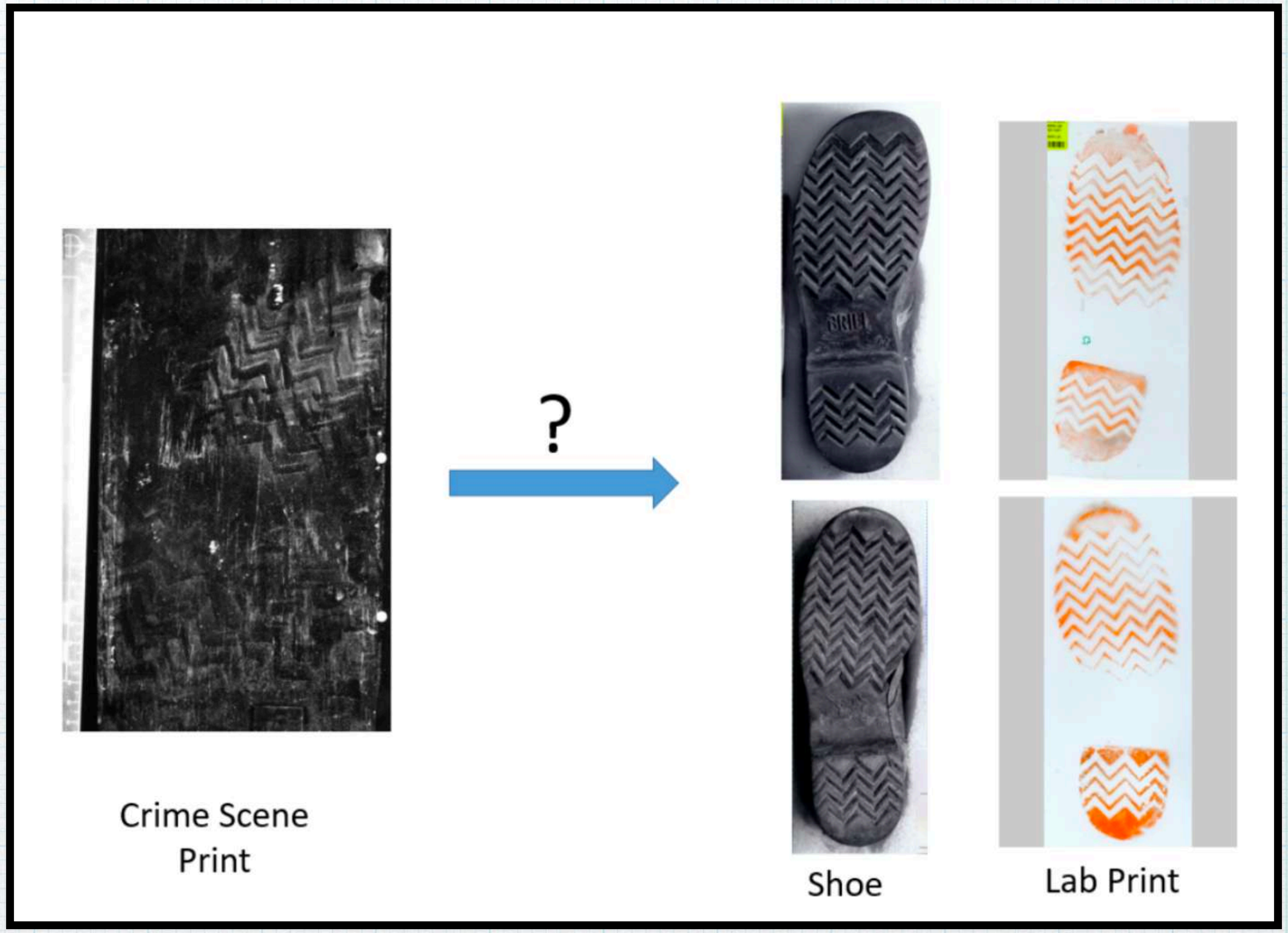
- In this presentation, we will discuss a statistical framework to measure the performance of footwear examiners, with a focus on randomly acquired characteristics (RACs) identification.

Outline of Presentation

- Motivation and Data
- The STAPLE Algorithm
- Hierarchical Framework
- Ongoing/Future Work

Shoe Print Evidence

- Shoe prints may be found at crime scenes and later a suspect's "matching" shoe is found.
- In court, people are interested if the suspect's shoe is the source of the shoe print.
- It can be difficult to identify the source of the shoe print.



Shoe Print Examination Process

Step 1:

Rule out any shoes that do not match the basic characteristics of the suspect shoe (size or tread pattern)

Step 2:

Examine Randomly Acquired Characteristics

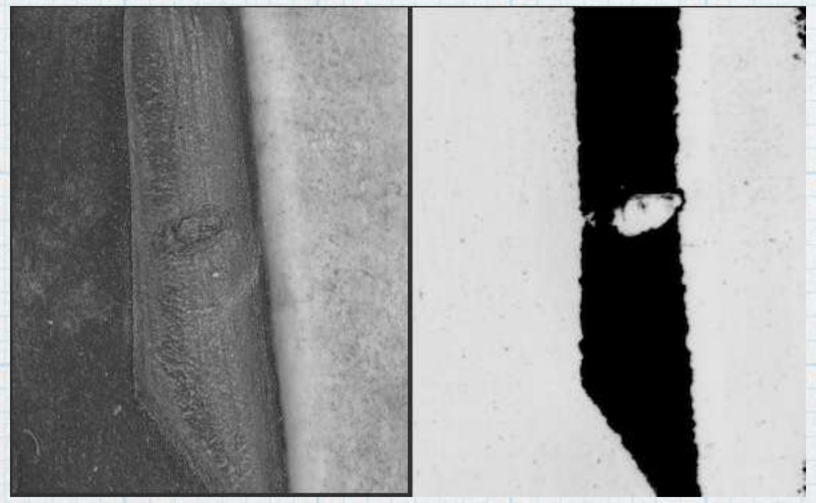
Step 3:

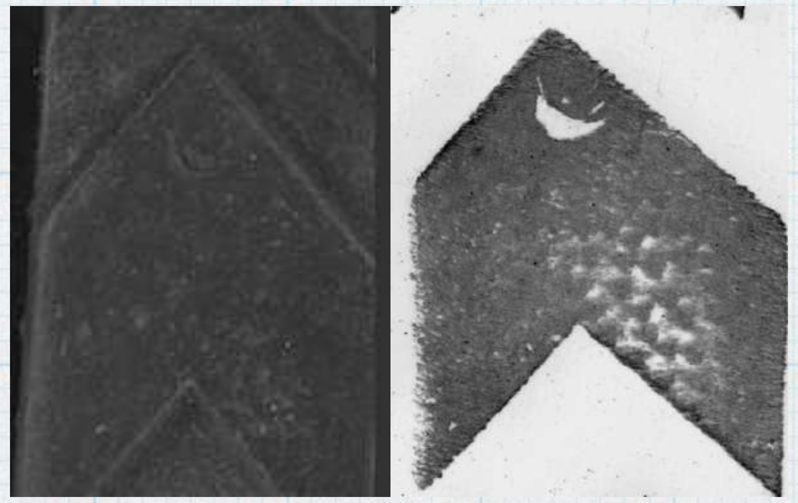
Assess the strength of the evidence regarding the hypothesis that the suspect shoe left the print at the crime scene.

What is a RAC?

- A randomly acquired characteristic is a unique marking, such as a scratch or hole, that forms on the sole of footwear as it is being worn.
- Manufacture defects are not considered RACs.
- RACs are examined in order to better assess the evidence regarding whether or not the suspect shoe left the print at the crime scene.

Examples:





RAC Identification Challenges

1. Examiners need the physical shoe to find RACs on the lab print.
   - Without the physical shoe, differentiating between RACs and shoe pattern could be difficult
2. Some examiners identify RACs that were not identified by other examiners.
3. RACs can change overtime
4. Not all RACs appear on both the crime scene print and the suspects shoe.
   - Some are too small to leave an impression or only a partial print is found.

Motivation for Understanding the Reliability of RAC Identification

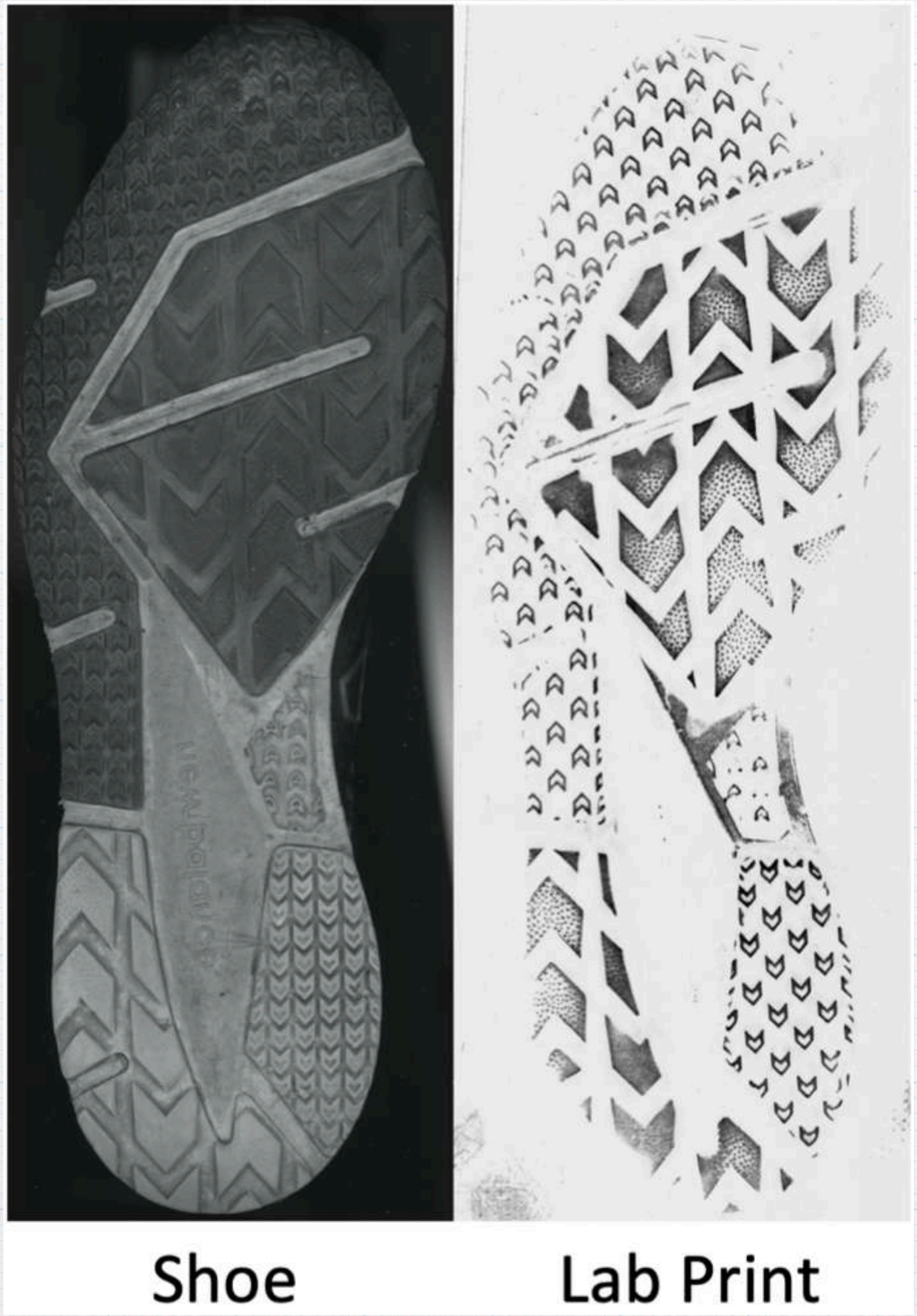
- Forensic evidence, in general, requires a strong scientific foundation to be a trusted source of evidence in investigation and legal proceedings (NRC 2009, PCAST 2016)

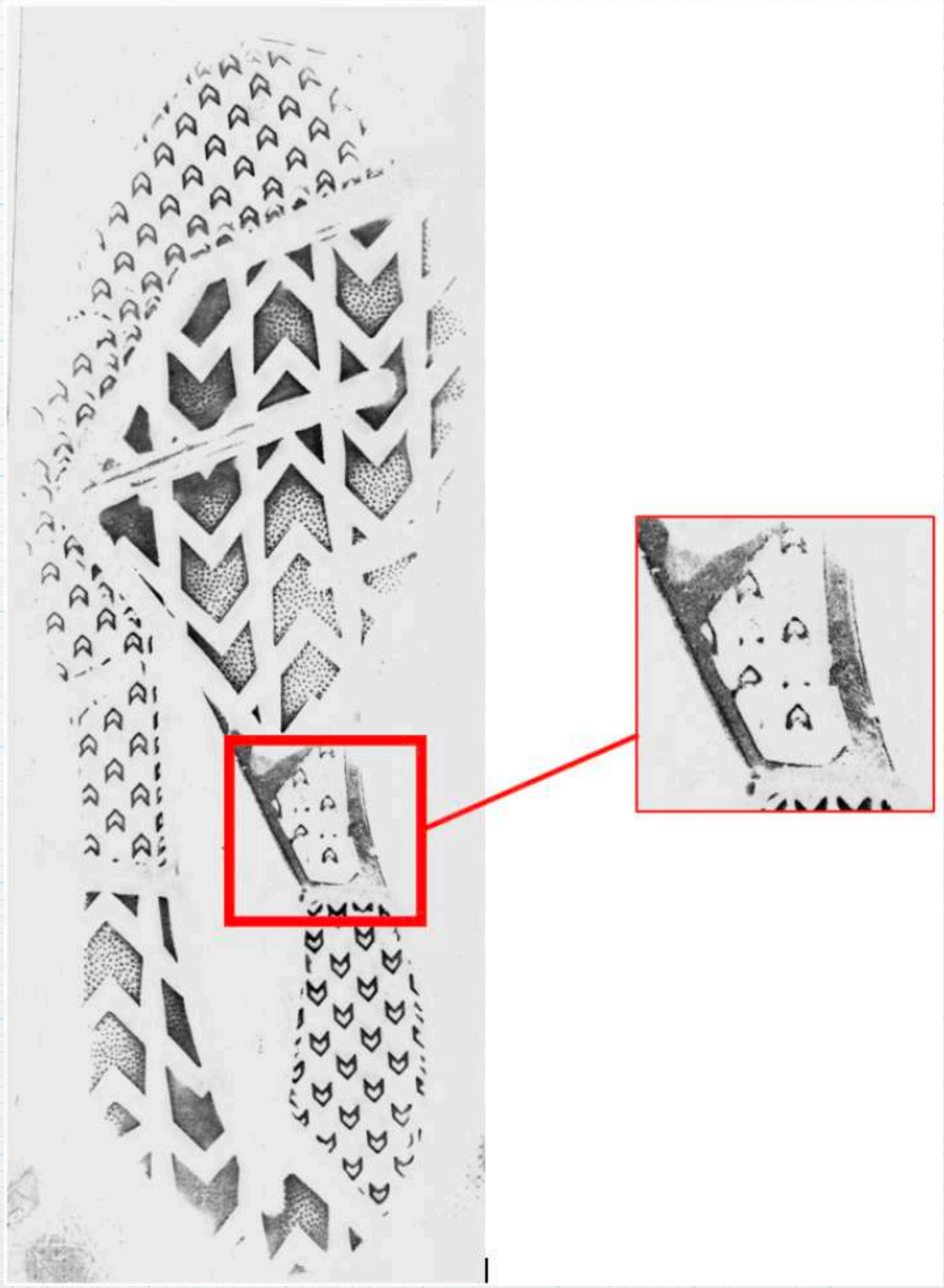
- Research on examiner reliability and performance is mainly focused on the examiner's ability to match the suspected shoe print to the source (the final decision) and not on RAC identification (Hammer et al. 2013, Richetelli et al. 2020).

- Given the importance of RACs in this process, it is important to explore the reliability of examiners on this task.

Data

Shoe Prints - Our Data





Data

- Data was taken from a pilot study conducted by CSAFE and the Israel National Police Division of Identification and Forensic Science.

- 20 shoes (10 Pairs), all of the same brand and model, worn by police officers.

- Marked by 4 different students that received some training.

Data

- This data is valuable because it includes:
  - Repeated examinations (same examiner examining the same impression twice).
  - Reproduced examinations (different examiners examine the same impressions).
  - Examinations of the same shoes with different amounts of wear (45 days, 90 Days, 135 Days, and180 Days of wear).
- But the data is limited, there are only a few examinations of each of the above types.

Variables for Each RAC

- Location on normalized shoe print (x and y coordinate of the center of gravity in 2D space)
- Type of RAC (7 categories)
- Estimated Area of RAC (in pixels)
- Orientation Angle of RAC

The STAPLE Algorithm

Simultaneous Truth And Performance Level Estimation

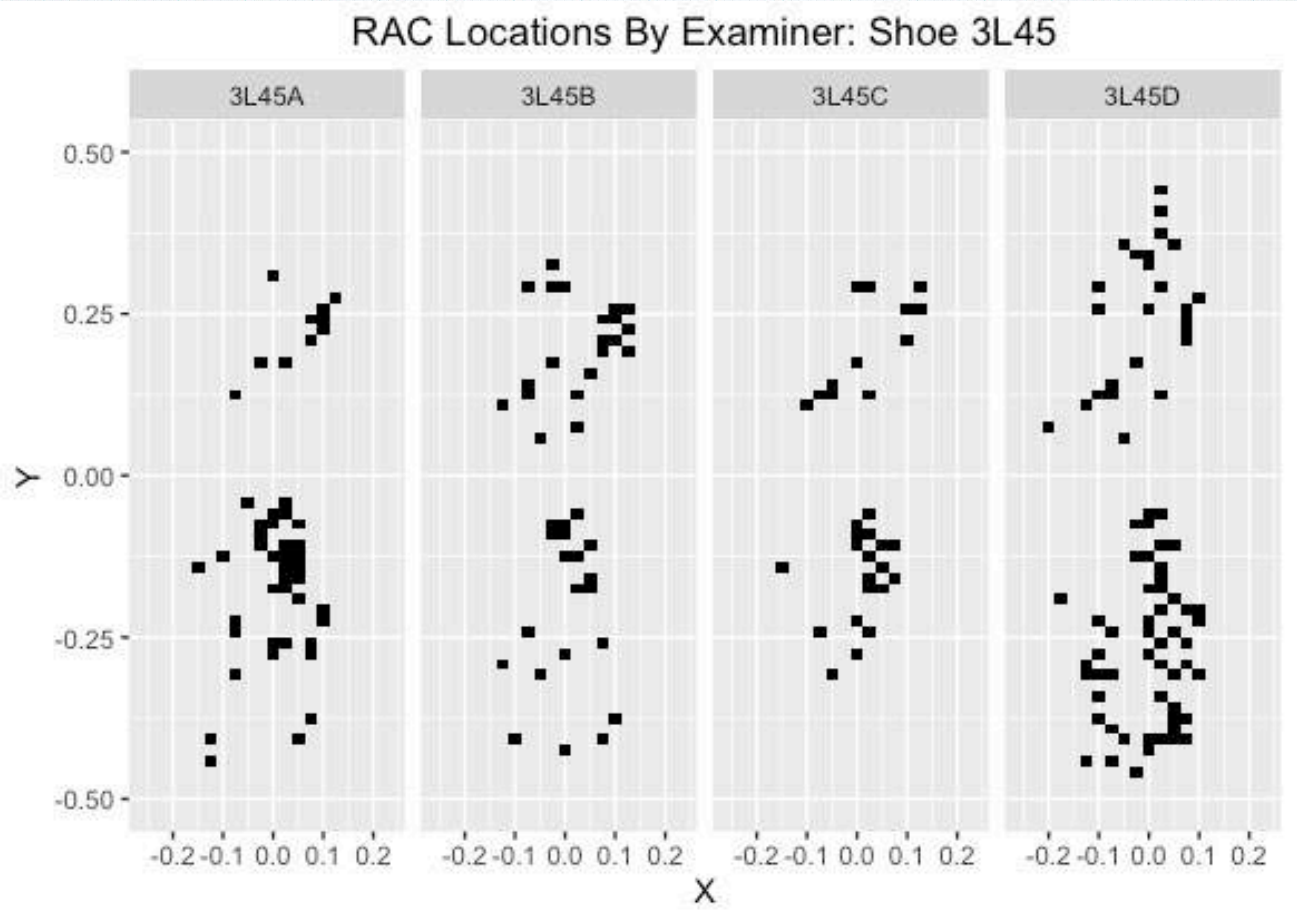
- The STAPLE algorithm (Warfield et al. 2004) is an Expectation-Maximization (EM) algorithm for estimating the unknown ground truth and examiner performance parameters in image analysis.

- Developed for brain imaging.

- Relies on having the same image examined by multiple examiners.

Data Preprocessing

- In order to implement the STAPLE algorithm, the data is transformed into binary data.
- This is done by placing a grid over the shoe and using the location of the RACs to determine presence/absence of a RAC in each grid cell.


RAC Locations By Examiner: Shoe 3L45
3L45A
3L45B
3L45C
3L45D
0.50
0.25
0.00
-0.25
-0.50
Y
-0.2 -0.1 0.0 0.1 0.2
X

Empirical RAC Prevalence By Examiner

Shoe\Examiner	A	B	C	D	Naive Estimate*
1L45	NA	0.056	0.055	0.025	0.110
1R45	NA	0.034	0.036	0.042	0.075
2L45	0.014	0.017	NA	NA	0.028
2R45	0.009	0.008	NA	NA	0.015
3L45	0.039	0.034	0.026	0.064	0.103
3R45	0.037	0.038	0.038	0.078	0.118
4L45	NA	0.028	0.022	NA	0.043
4R45	NA	0.009	0.010	NA	0.017
5L45	NA	0.026	0.013	0.028	0.053
5R45	NA	0.003	0.010	0.020	0.033
7L45	0.015	0.018	0.028	0.020	0.064
7R45	0.027	0.014	0.029	0.019	0.064
9R45	NA	0.012	NA	0.014	0.024
10L45	NA	0.026	0.024	0.042	0.077
10R45	NA	0.010	0.008	0.022	0.037

* All cells with a RAC by any examiner divided by the number of cells (1200).

Notation

N: number of cells in the grid ($n \times m$)

J: number of examiners

D_{ij}: binary presence/absence of RACs in cell i $(i = 1 : N)$ as determined by locations marked by examiner j $(j = 1 : J)$

$\mathbf{D}$: the $N \times J$ matrix of observed data

Ground Truth Parameters:

T_i: true binary presence/absence of RACs in cell i $(i = 1 : N)$

$\mathbf{T}$: The length N vector of true presence/absence of RACs

π: Prevalence of RACs on the Shoe

Performance Parameters:

p_j: Sensitivity of examiner j

q_j: Specificity of examiner j

$\overrightarrow{p}, \overrightarrow{q}$: J length vectors of sensitivity and specificity

Model

Complete Data: $(\mathbf{D}, \mathbf{T})$

Observed Data: $(\mathbf{D})$

$$T_i \sim Bernoulli(\pi)$$

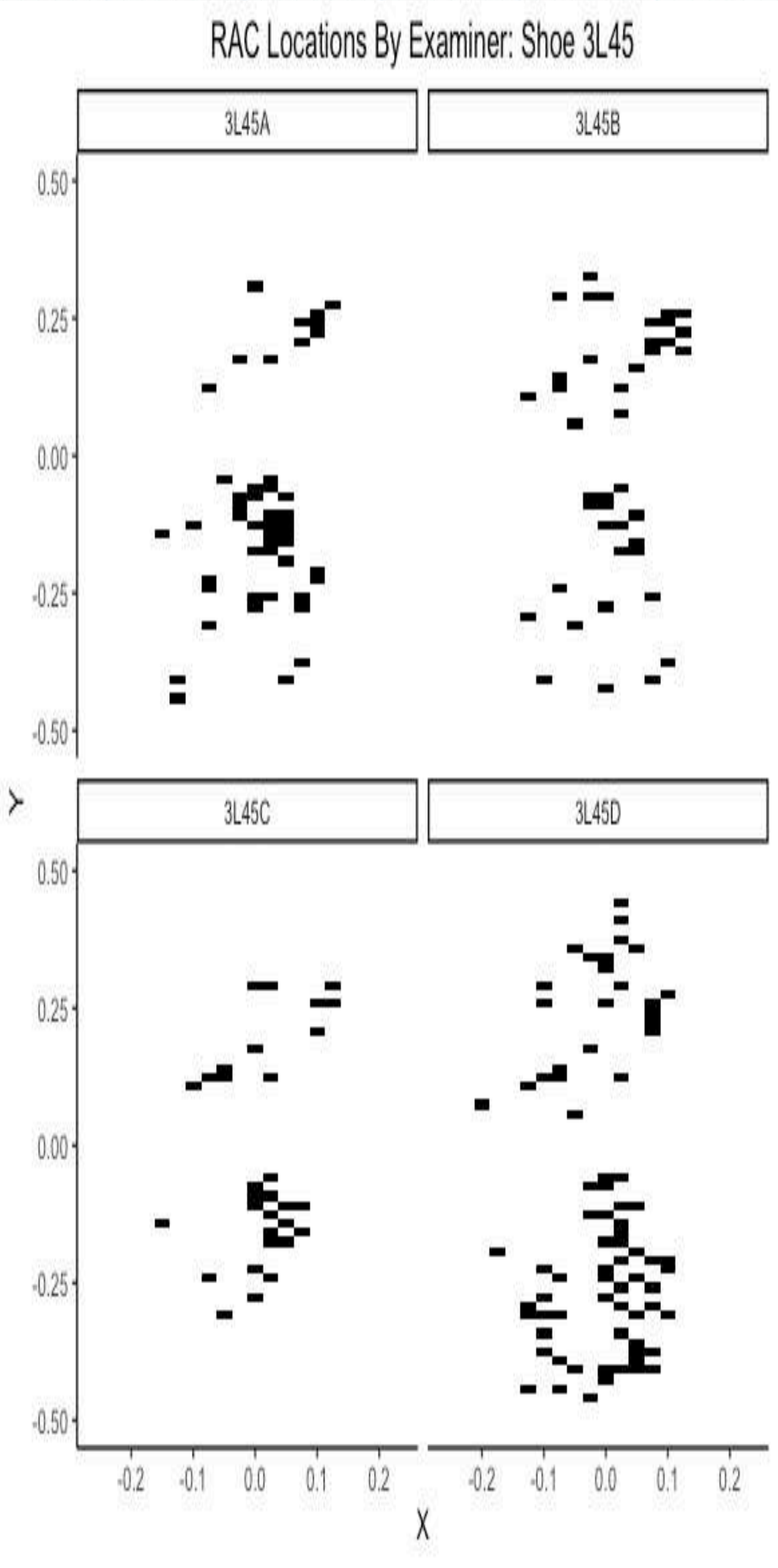
$$p_j = P(D_{ij} = 1 \,|\, T_i = 1).$$

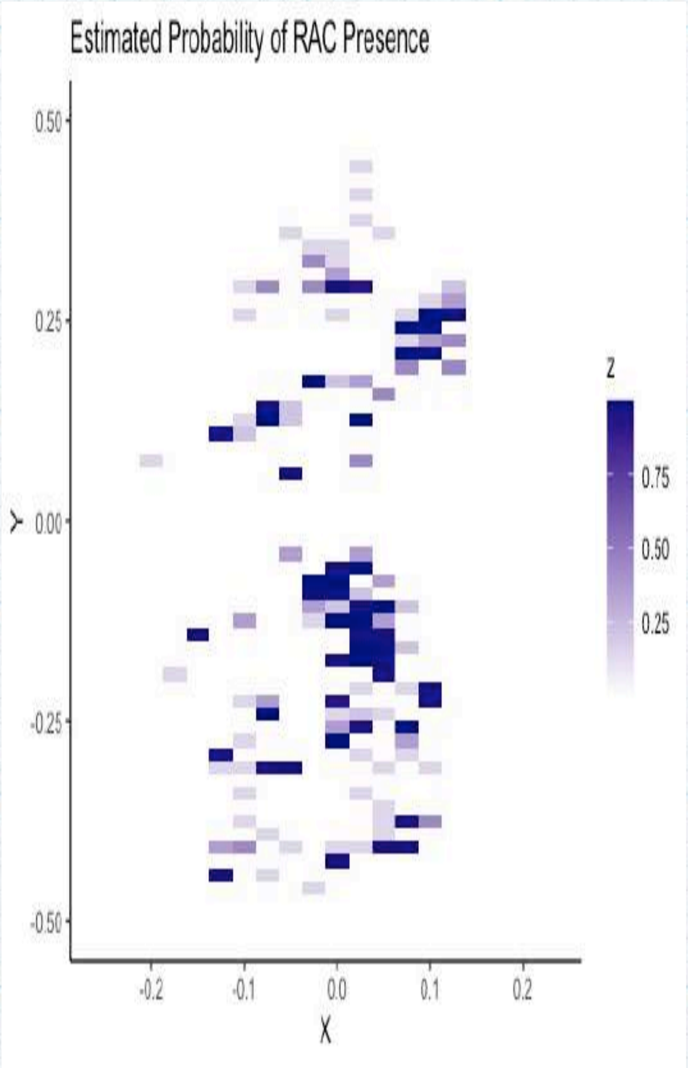
$$q_j = P(D_{ij} = 0 \,|\, T_i = 0).$$

(Observed Data) $D_{ij} \,|\, T_i = t_i, p_j, q_j \sim Bernoulli(p_j^{t_i}(1 - q_j)^{(1-t_i)}).$

An EM algorithm is used to find the maximum likelihood estimates of the parameters.

Example - Shoe 3L45





	Estimates	Lower Bound 95% CI	Upper Bound 95% CI
π	0.0574	0.0344	0.0804
p_A	0.5438	0.3705	0.7172
p_B	0.5010	0.3389	0.6810
p_C	0.3312	0.1900	0.4724
p_D	0.5829	0.4107	0.7552
q_A	0.9916	0.9833	0.9998
q_B	0.9948	0.9878	1.0000
q_C	0.9928	0.9867	0.9989
q_D	0.9674	0.9551	0.9797

Limitations of STAPLE

- Analyzes each shoe separately.
  - Examiners can appear to perform well on some shoes and poorly on others.
  - Performance on one shoe should be related to performance on others.
- Makes strong assumptions about the relationship between the cells on the grid (independence).
- Only incorporating location information (not type, size of RAC).

Multi-Shoe Extension

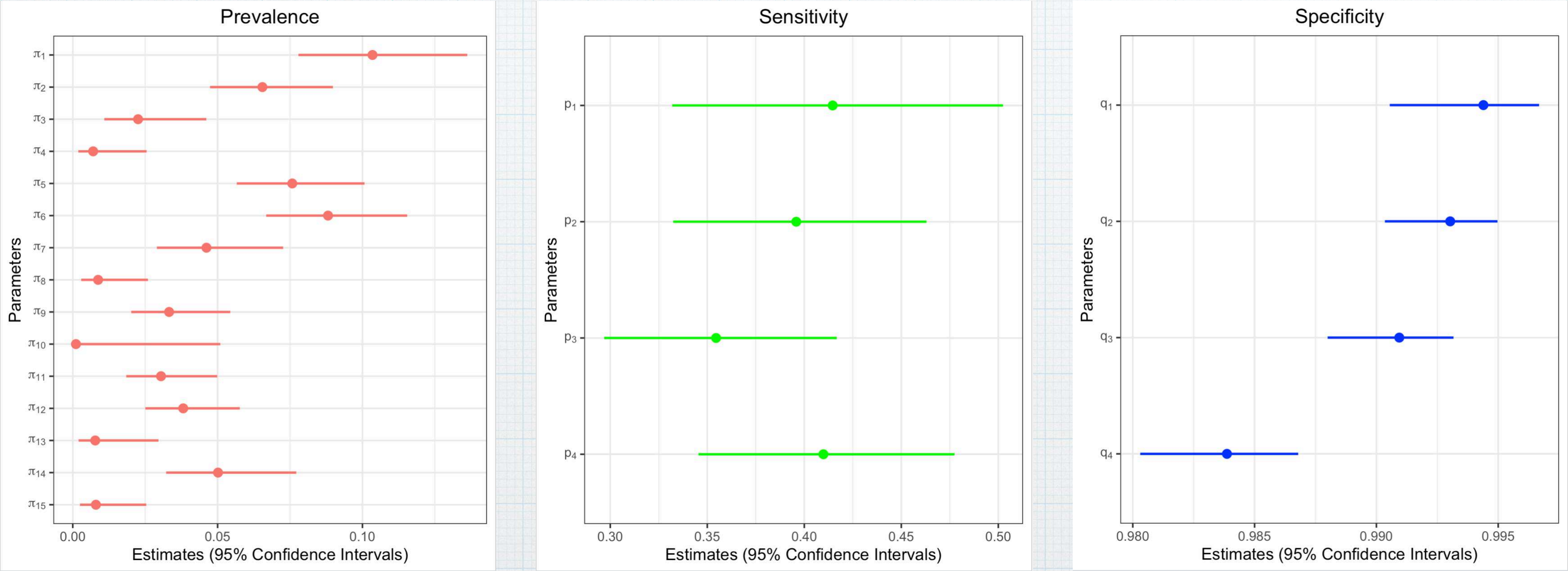
- We incorporate information from images of multiple shoes at the same time. This is accomplished by following the same process as outlined above with theses changes:

1. We assume shoes are independent.

2. This allows us to “average” over the shoes.

Note: Not every examiner has to examine every shoe.

Results: Multi-Shoe Extension



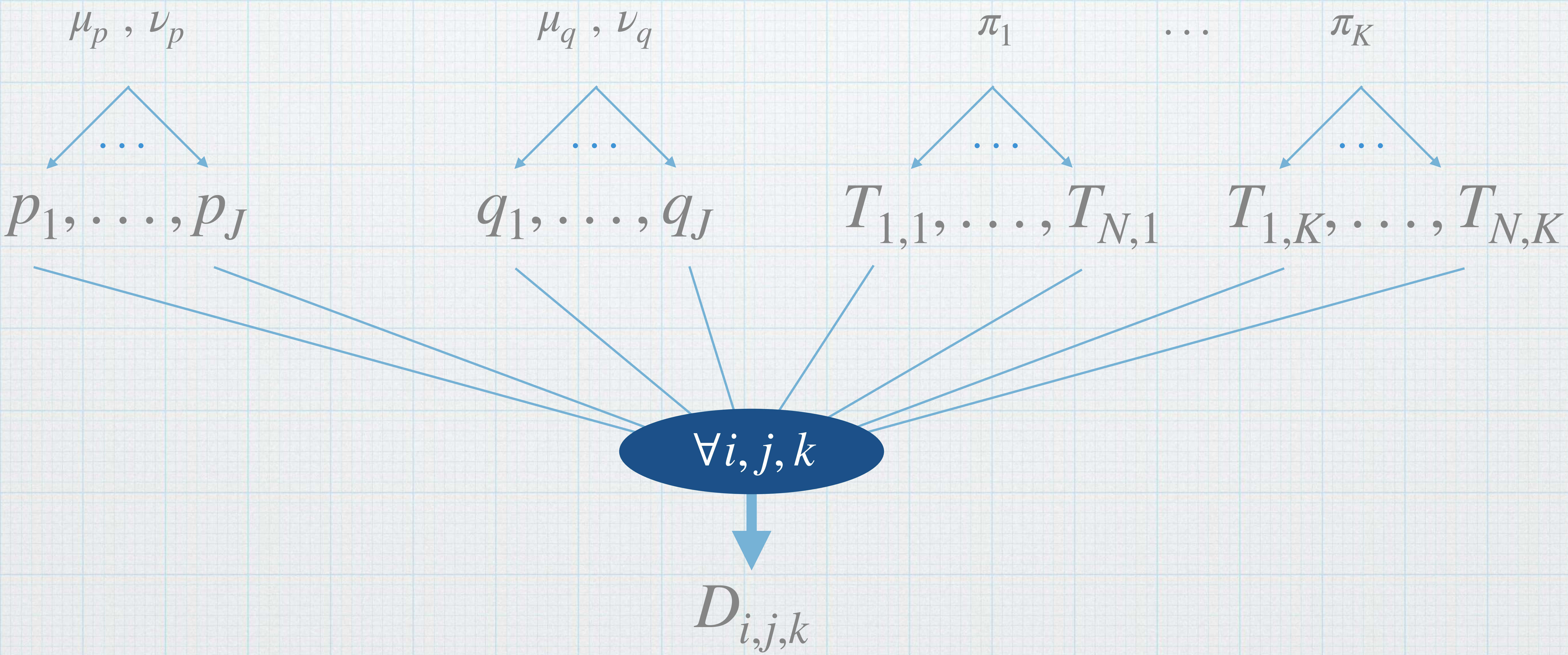
Limitations of this Extension

- Each examiner has a single specificity and sensitivity that applies to all shoes but we know that there is variation in the difficulty associated with impressions.

- The examiners have similar training, so it may make sense to model the performance parameters of examiners jointly.

Hierarchical Framework

The following model is analogous to STAPLE with the addition of a population structure on the performance parameters:



Ongoing/Future Work

1. Fully Bayesian analysis of the hierarchical STAPLE algorithm.

    - Provides the necessary framework to expand model and understand population performance.

2. Autoregressive Model for RAC locations (Spatial Dependence).

3. Clustering Examiners based on performance.

Thank you

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