Statistical models for the generation and interpretation of shoeprint evidence

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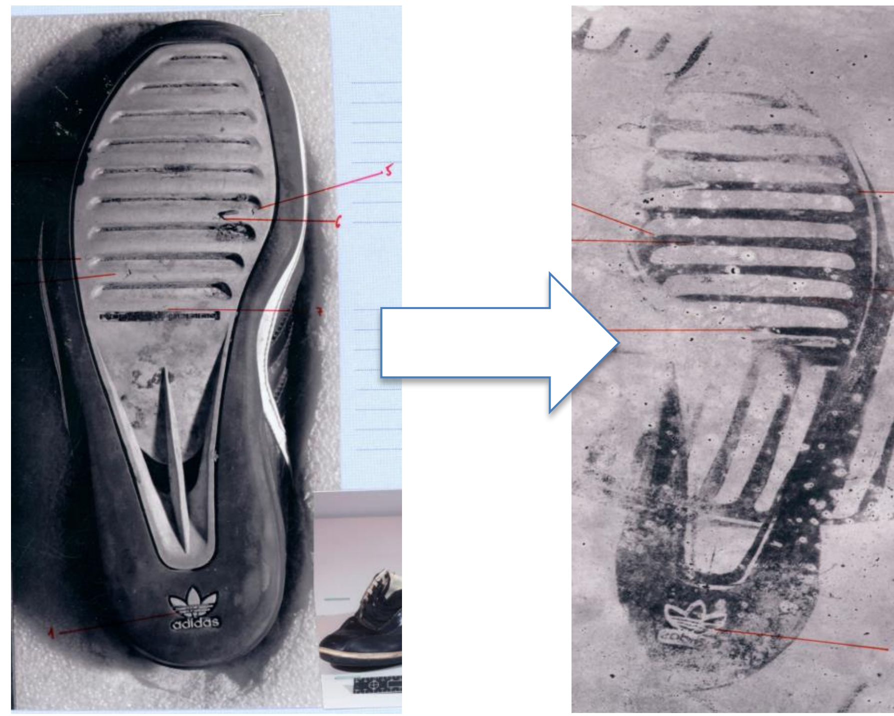
Statistical Reasoning about Footwear Forensics

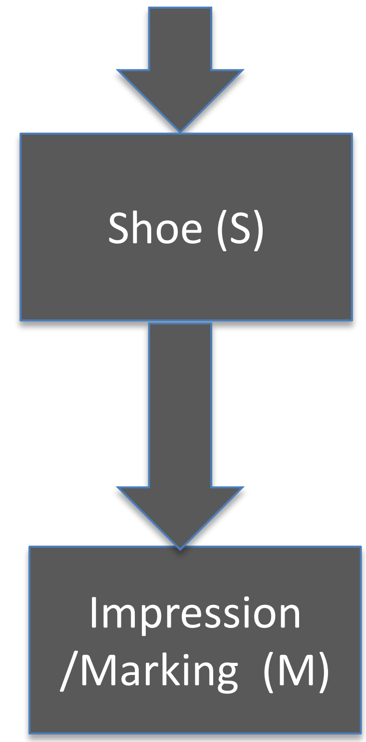
Goal: develop practical statistical models for whether a given shoe is likely to have generated a particular latent print or impression.



Statistical Reasoning about Footwear Forensics

Did shoe S leave mark M?

- Is shoe S capable of generating evidence M?
- Given the circumstances C, could some other shoe S’ have left mark M?
- Were S and/or S’ present at the crime scene?



Uncertainties:

- Process by which a shoe leaves a mark is complex… not every mark left by a given shoe is identical.
- We typically don’t have knowledge of all other possible shoes S’ that might have produced the mark.

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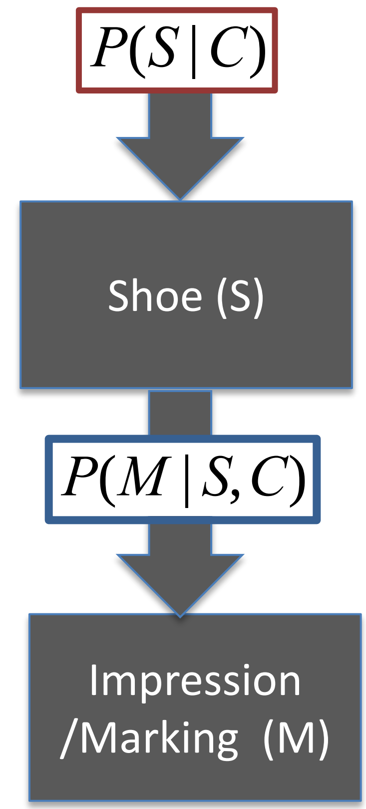
How can we evaluate these competing hypotheses in the presence of uncertainty?



$$LR = \frac{P(M|S,C)P(S|C)}{P(M|S',C)P(S'|C)}$$

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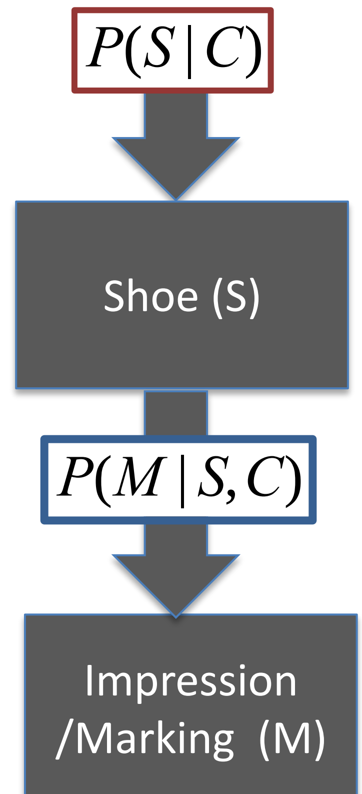
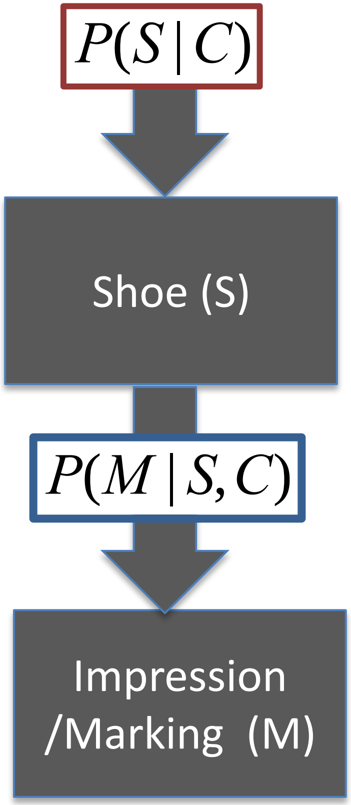


How can we evaluate these competing hypotheses in the presence of uncertainty?

$$LR = \frac{P(M|S,C)P(S|C)}{\sum_{S' \neq S} P(M|S',C)P(S'|C)}$$

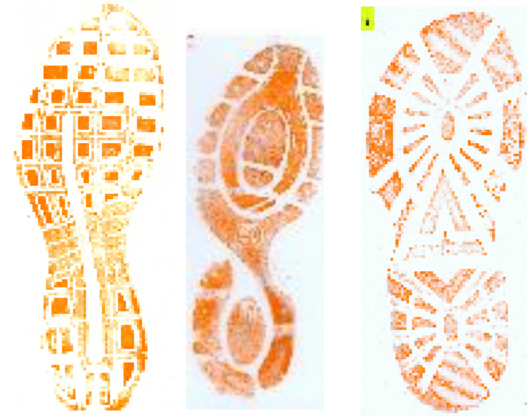
Outline

- Modeling the generation of marks from shoes
- Modeling the distribution of shoes
- Application: evaluating and visualizing reliability of partial matching for class determination

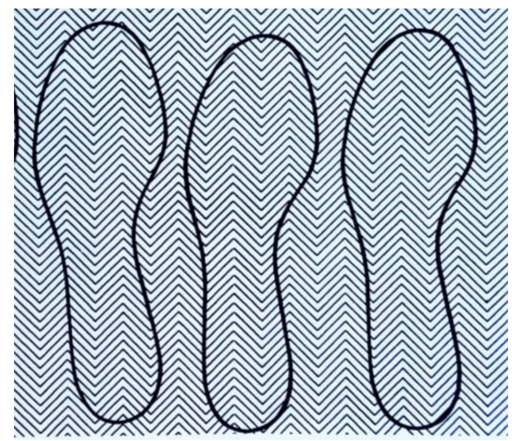


Identifying Characteristics

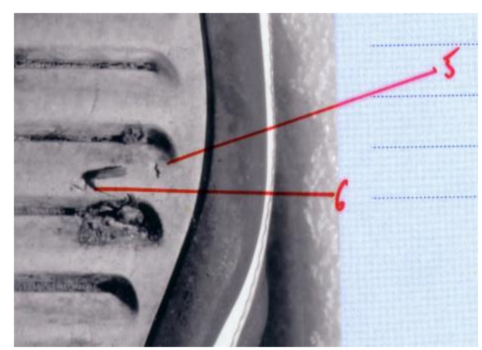
- Class characteristics:
  brand, make, size



- Manufacturing characteristics:
  variation across multiple molds, air bubbles, assembly, …



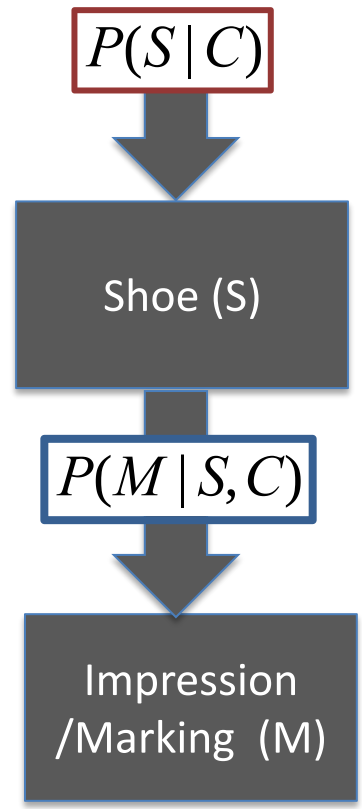
- Acquired characteristics:
  wear patterns, cuts and scratches



Statistical Reasoning about Characteristics

Did shoe S leave mark M?

1. Measure features of observed evidence $\mathbf{F_1(M)}$
2. Measure features of a particular shoe $\mathbf{F_2(S)}$
3. Evaluate if features $\mathbf{F_2(S)}$ are consistent with features of the evidence $\mathbf{F_1(M)}$?



$$P(M \mid S, C) \gg P(F_1(M) \mid F_2(S), C)$$

Measuring Statistics of Characteristics

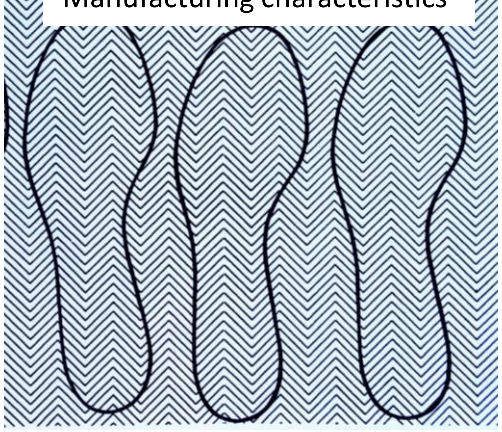
Challenge: Formalize the measurement of identifying characteristics so that statistics can be computed on large quantities of real world data.

Features should correspond closely to forensic investigative practice.

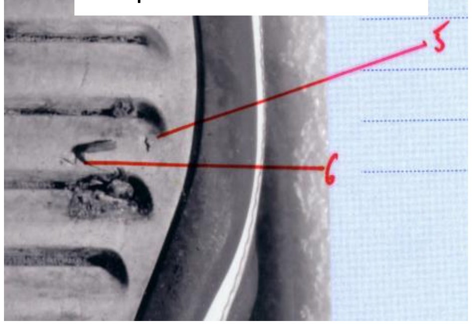
$$F_1(M) \qquad F_2(S)$$

Class characteristics

Manufacturing characteristics

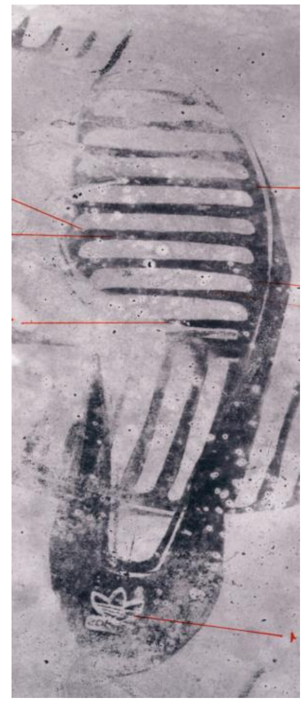


Acquired characteristics

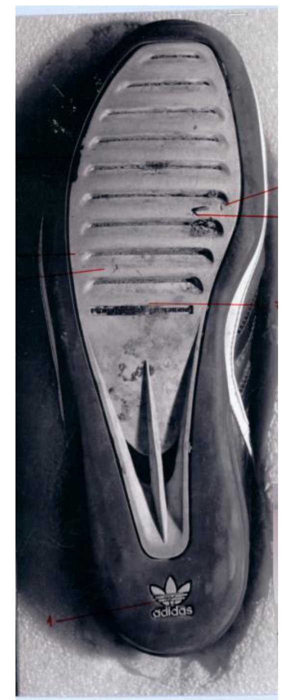


Motivations for 3D acquisition

- To compute $F_2(S)$ we need a digital representation of the shoe
- Characteristics of markings are fundamentally tied to 3D tread shape
  - Contact surface of outsole with hard or soft surfaces
  - Distribution of acquired characteristics (wear patterns, accidentals)
- Methodology and Practice:
  - Assembling datasets for analyzing statistics of tread patterns, evaluating reliability of features
  - Archival documentation of physical evidence



Crime scene mark

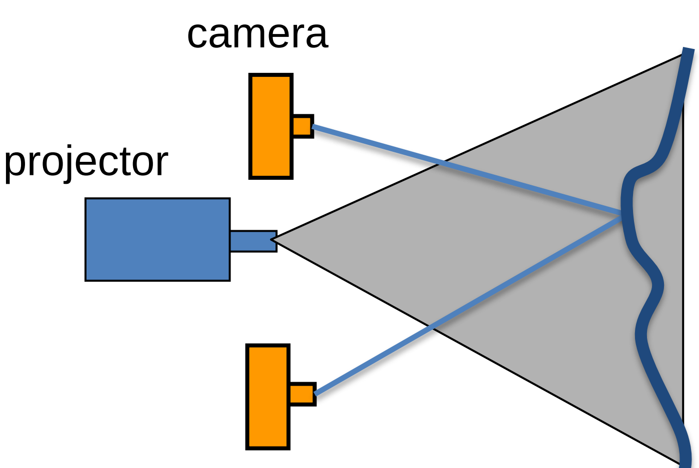


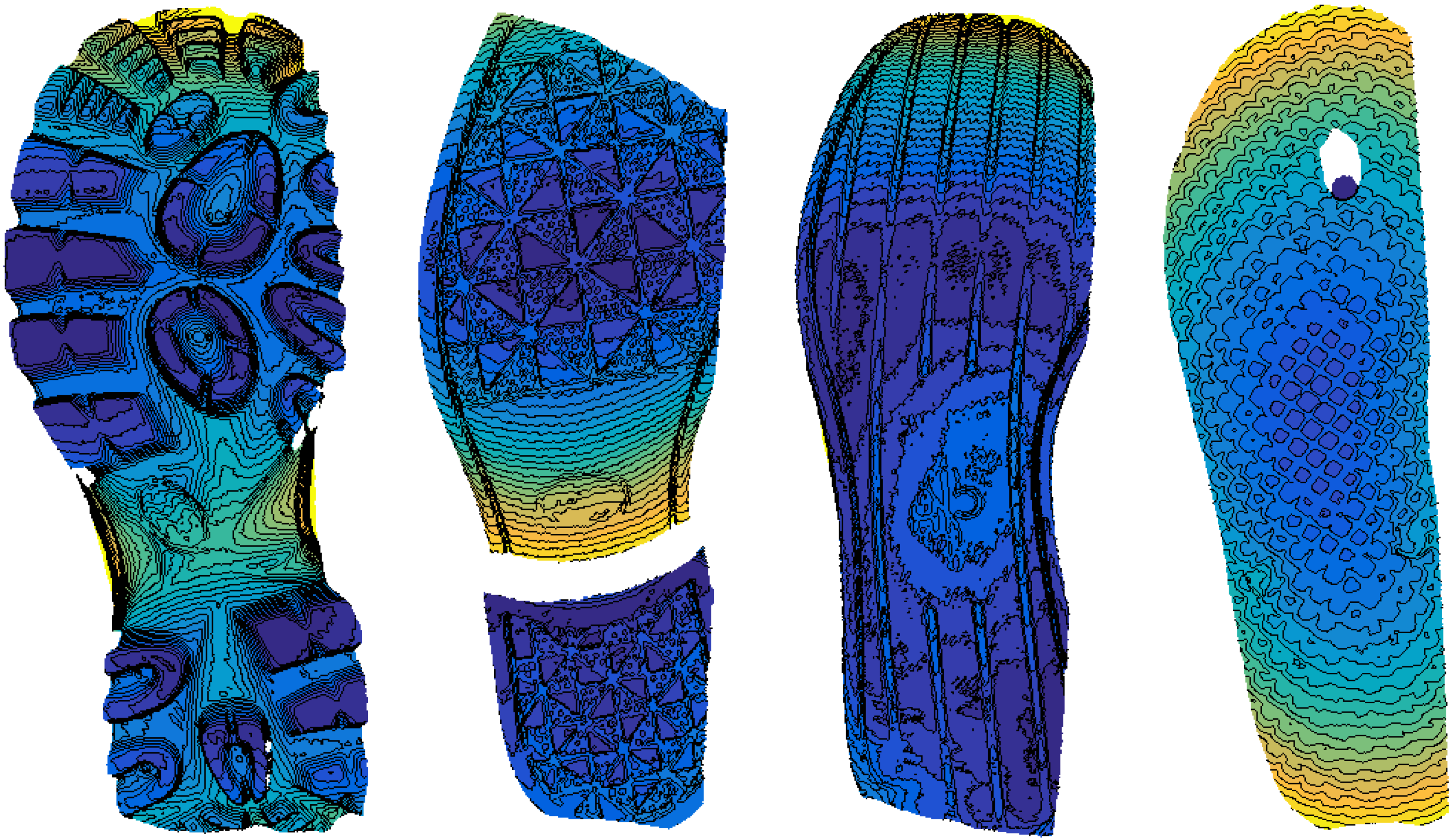
Shoe Photo

Lab Test Impression

2D->3D: Structured-light Scanner

- Stereo triangulation between calibrated camera pair
- Structured illumination aids automatic stereo-correspondence





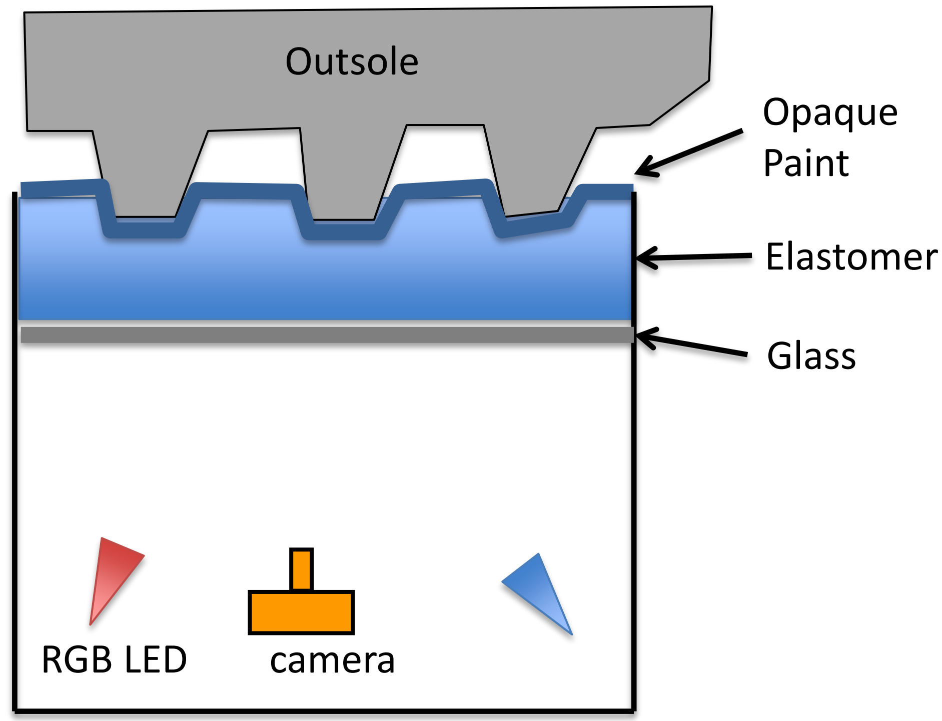
- Resolution limited (missing fine-scale acquired characteristics)
- Doesn't capture shoe shape when it is in contact with surface

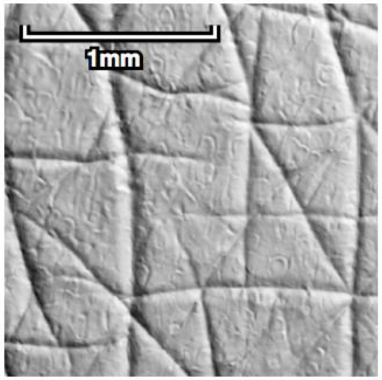
GelSight Sensor

Object is pressed against a conforming elastomeric gel and imaged from below.

Paint on gel surface provides a uniform controlled reflectance.

Allows for non-destructive, high-resolution recovery of surface shape, even for transparent, soft and reflective objects



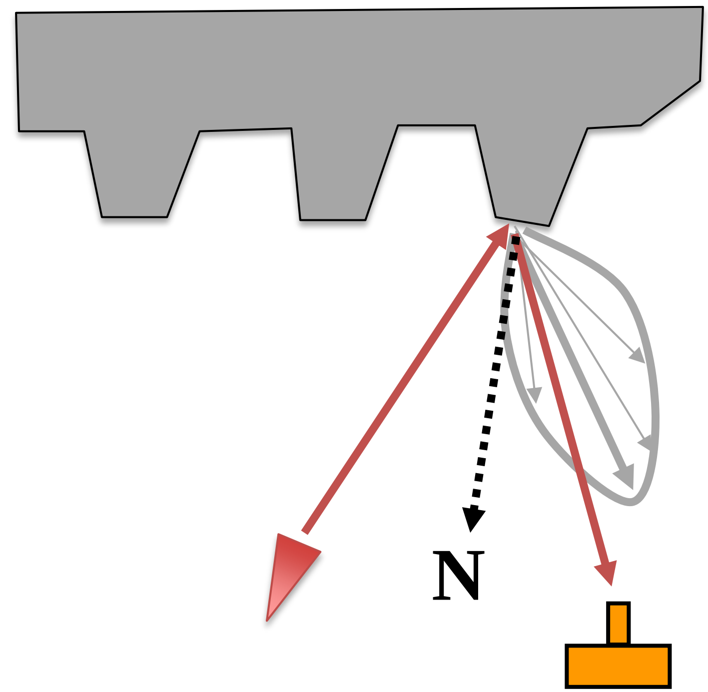


human skin

“Retrographic Sensing for the Measurement of Surface Texture and Shape”, Micah K. Johnson and Edward H. Adelson. CVPR 2009

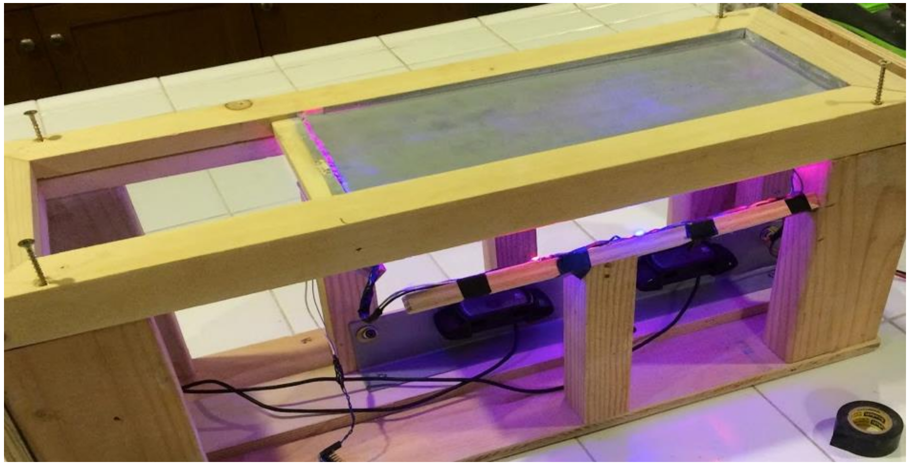
Operating Principle: Shape from Shading

- The intensity of light reflected from a surface depends on the orientation of the surface relative to the light.
  - Use multiple colored light sources to multiplex several intensity measurements into a single color image.
  - Optimize paint reflectance and camera geometry to maximize accuracy
- Shape-from-shading techniques applicable to a wider variety of situations (e.g. images of shoes, crime scene impressions)

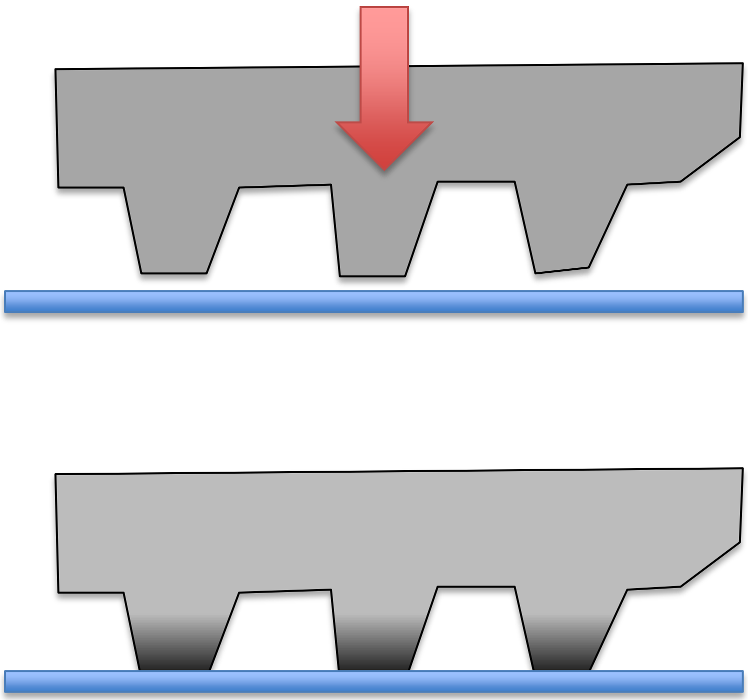


Retrographic Shoe Scanner Prototype

- Sensor surface scaled up to cover whole shoe tread from commodity components.
- Recapitulates impression process.
  - Modulate gel stiffness to simulate interaction with different surfaces
  - In principle high-speed cameras should allow dynamic analysis.. just walk across!

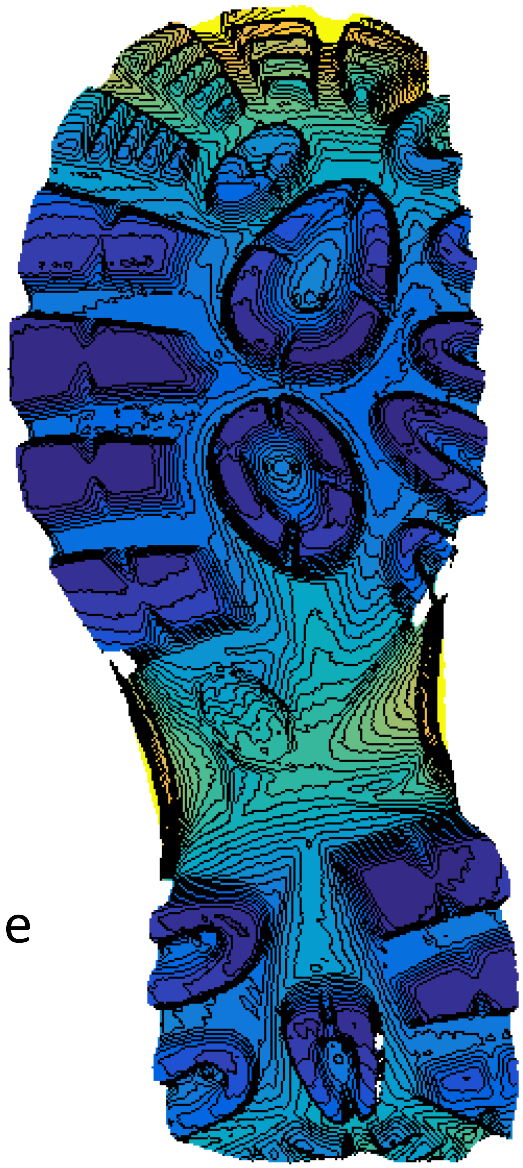


3D-> 2D: A simple generative model for marks



Rigid body simulation to determine contact surface.

Assume small elastic deformation compressing tread ridges.



Scanned Shoe Model

Synthesized Mark

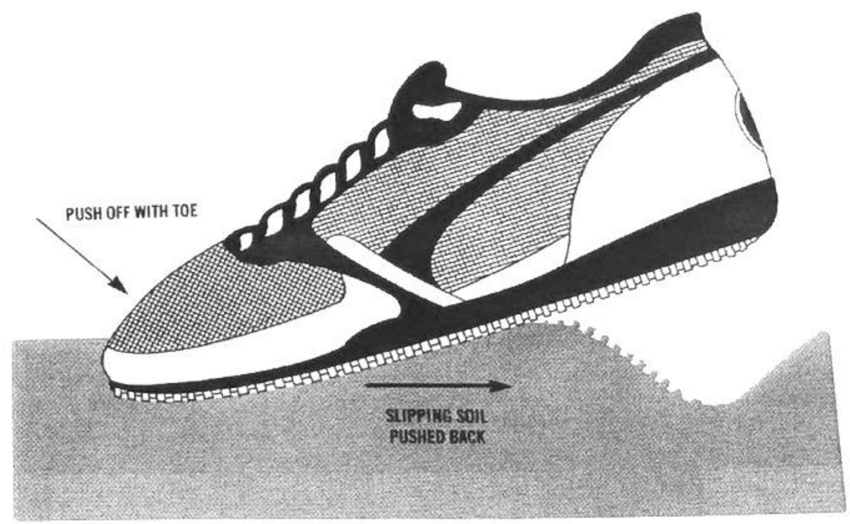
From contact surface to marks and impressions

Statistics of marks on hard surfaces at crime scene depend on:

- modality (paint, dirt, dust, oil, blood)
- circumstances (not all contact points may be “inked”)

Dynamic complexity:

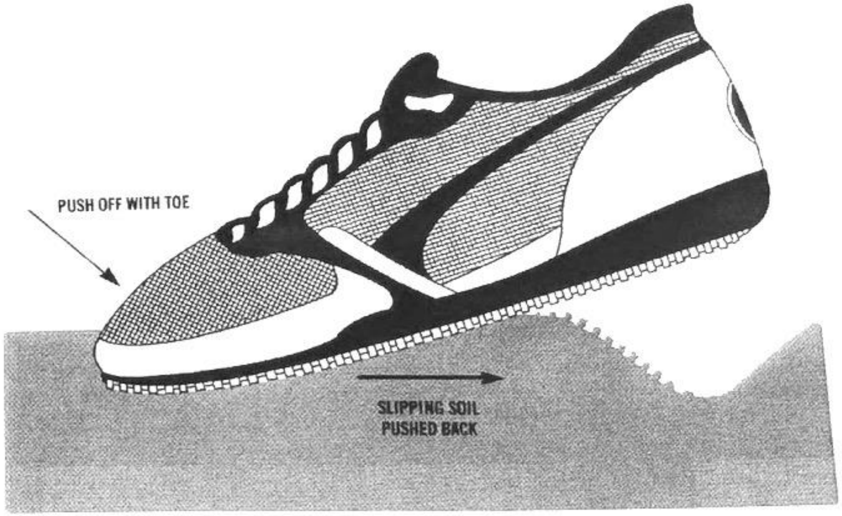
- rolling and slippage of tread against rigid surfaces
- interaction of shoe and gait with non-rigid surfaces



From contact surface to marks and impressions

Generative model doesn't need to be photorealistic to provide useful feature statistics (overall tread pattern, location and shape of acquired features, wear patterns, etc).

$$P(F_1(M) \mid F_2(S), C)$$



Going forward…

We plan to assemble a pilot dataset of scanned 3D shoe treads along with multiple test impressions

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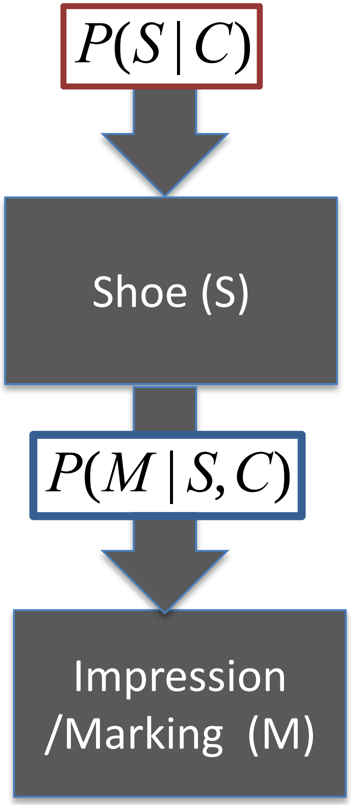


Prior distribution of shoes

Need to understand what alternative shoes S' might have left a mark at a crime scene.

$$P(S \mid C)$$

Challenges:

- Unlike, e.g. fingerprints, we don't have large databases of candidates
- What statistics are relevant to the circumstances?

Based on United States sales figures through April, 1998, of 316,215,000 pairs of men's shoes, the following gives a breakdown of the numbers sold and percentage sold, for each half size in U.S. men's sizes.

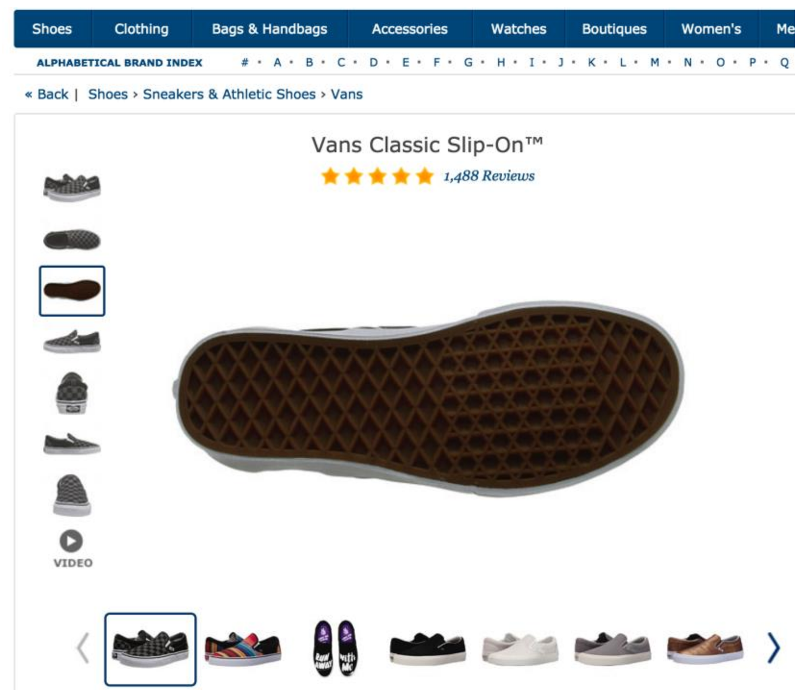
6	4,324,000 / 1.4%	11	39,147,000 / 12.4%
6 ½	2,646,000 / .8%	11 ½	9,504,000 / 3%
7	6,766,000 / 2.1%	12	33,030,000 / 10.4%
7 ½	6,704,000 / 2.1%	12 ½	1,603,000 / .5%
8	17,969,000 / 5.7%	13	19,616,000 / 6.2%
8 ½	20,371,000 / 6.4%	13 ½	415,000 / .1%
9	33,231,000 / 10.5%	14	3,492,000 / 1.1%
9 ½	33,601,000 / 10.6%	15	1,657,000 / .5%
10	43,332,000 / 13.7%	16	363,000 / .1%
10 ½	38,205,000 / 12.1%	17 +	115,000 / <.1%

[Bodziak, Footwear Impression Evidence, 2000]

Mining the Internet for Tread Patterns

Shoe outsole image dataset (UCI-SHOD)

- Images collected from *zappos* and *onlineshoes*
  - 30,374 shoes
  - 74,016 images
- Shoes appearing on both sites
  - 3,549 shoes
  - 20,449 images



UCI SHOD – Inter-class variability

UCI-SHOD -- Intra-class Variations

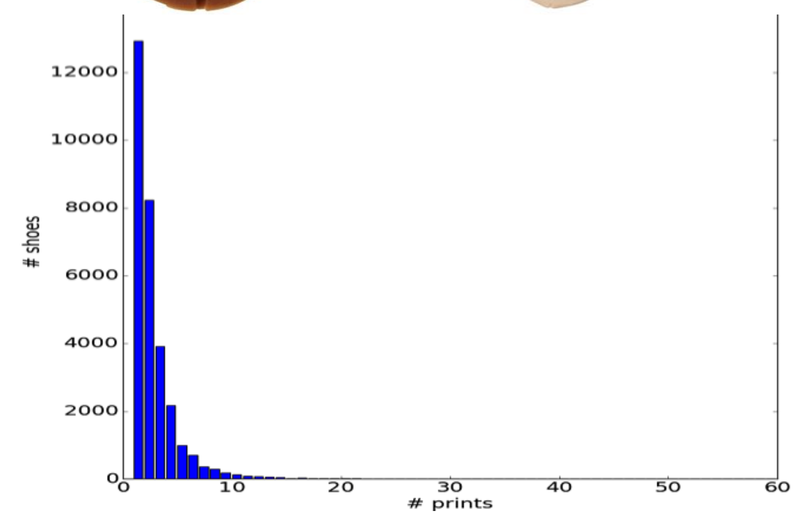
Limitations

Provides a proxy for understanding the diversity of tread features related to class characteristics

- Tread images ≠ Shoes

- Statistics do not reflect practical investigative circumstances
  - Need some additional data

- Relatively few examples of most shoe designs



#images per shoe type

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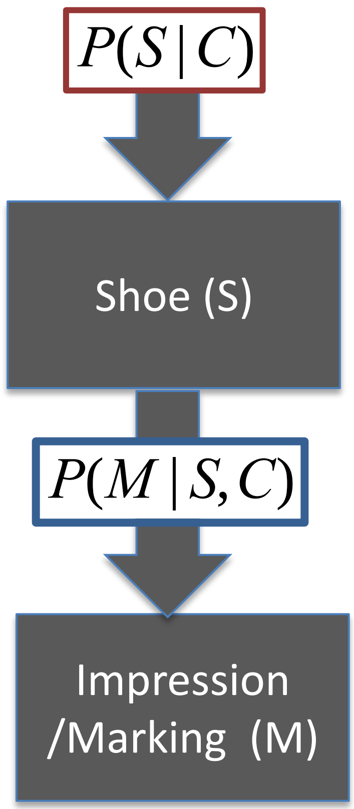


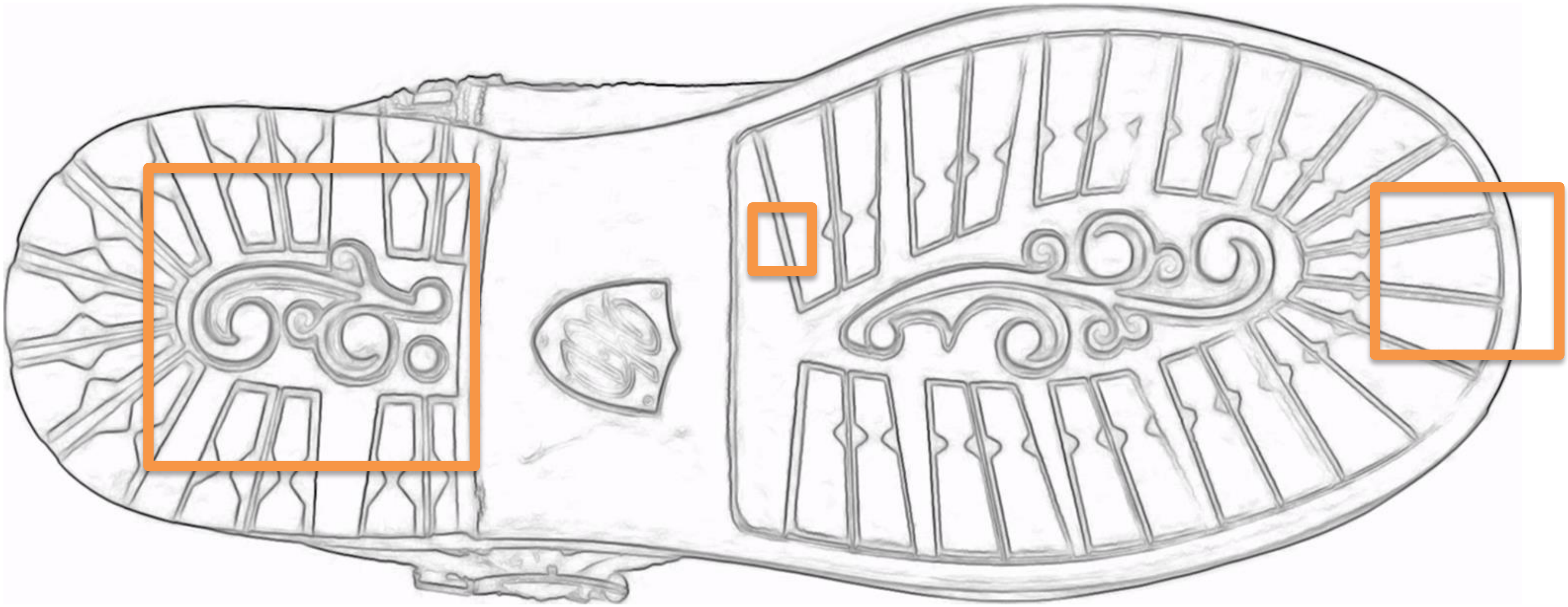
Impressions and prints are typically incomplete

Empirical analysis of reliability of partial prints in class identification

Q: How much tread pattern do you need to see to reliably determine shoe class?

A: Depends on amount of context and empirical diversity of tread patterns “in the wild”.

Identification from local patches



1. Some patches are more distinctive than others
2. Features in different locations do not contribute independently to overall match probability

Features for matching partial prints

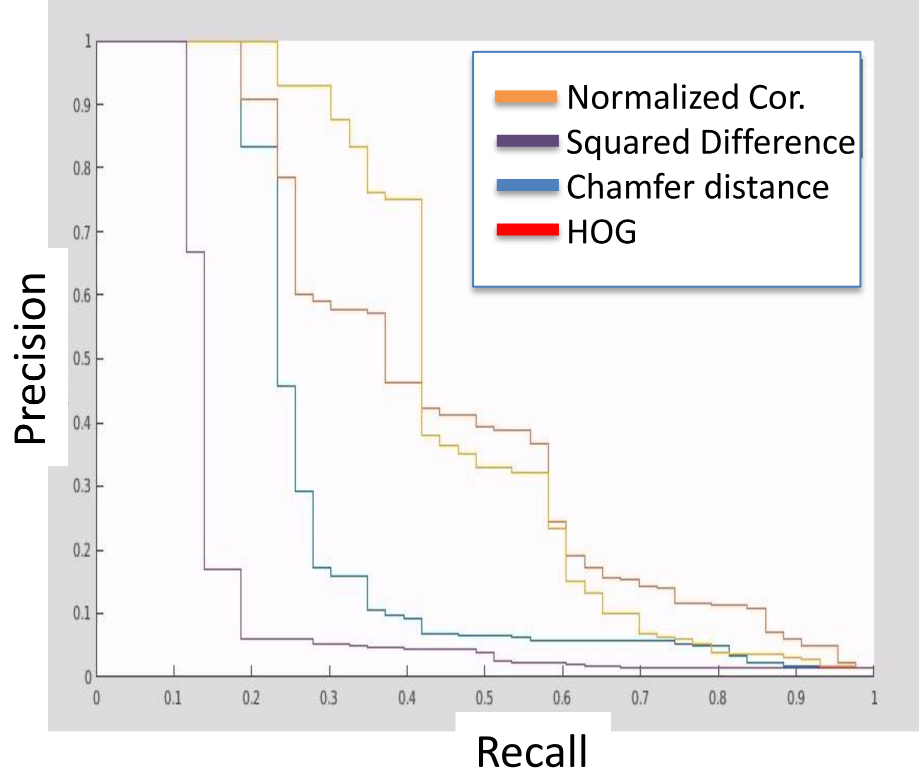
What features should we compute from a marking to measure class characteristics? **$F_1(M)$**

Implement automated image feature extractors (normalized correlation, edge matching, histograms of oriented gradients, deep neural nets)

Evaluate based on class retrieval accuracy:

- UCI-SHOD tread images

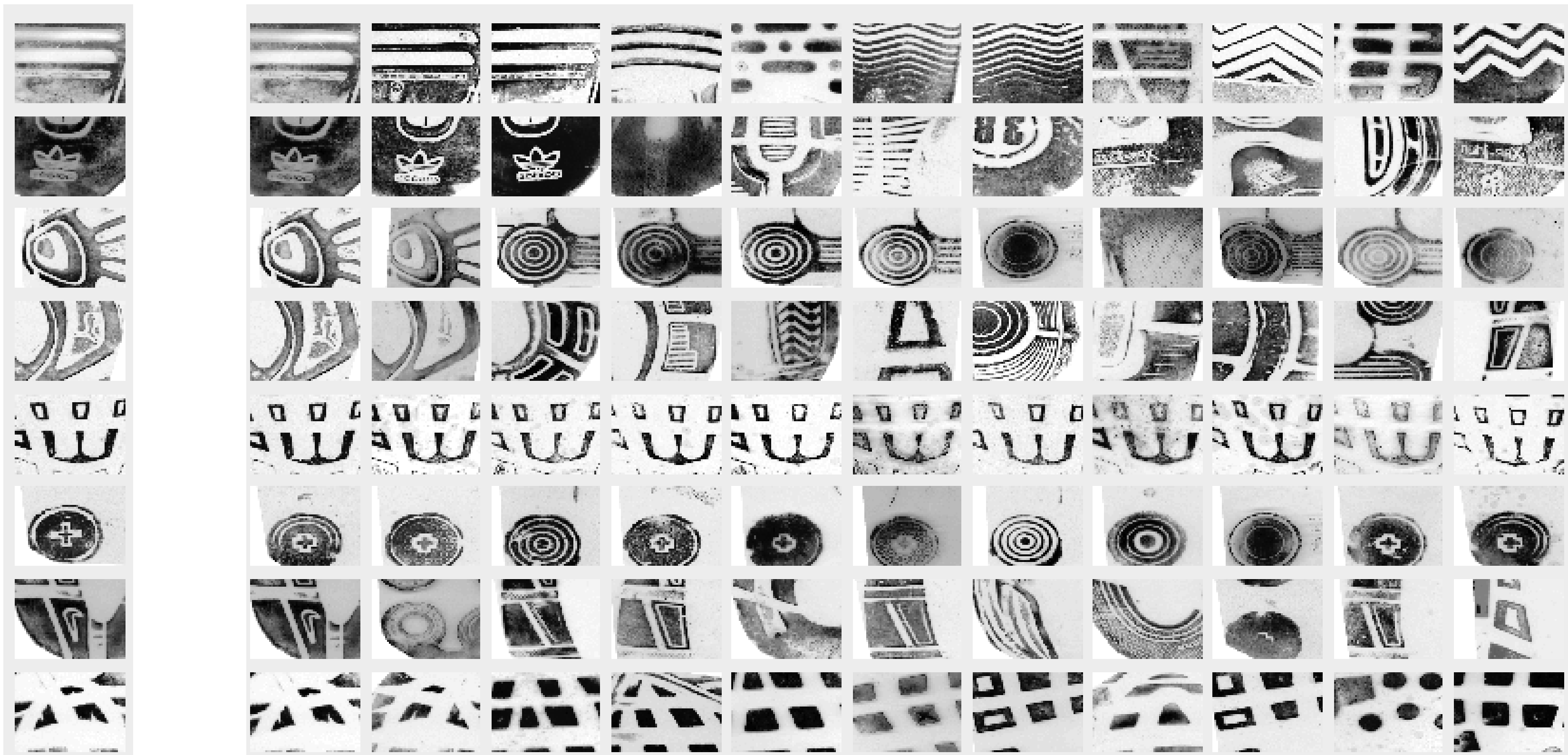
- Shoe test impressions collected by Weisner, et al.



Retrieval of matching patches

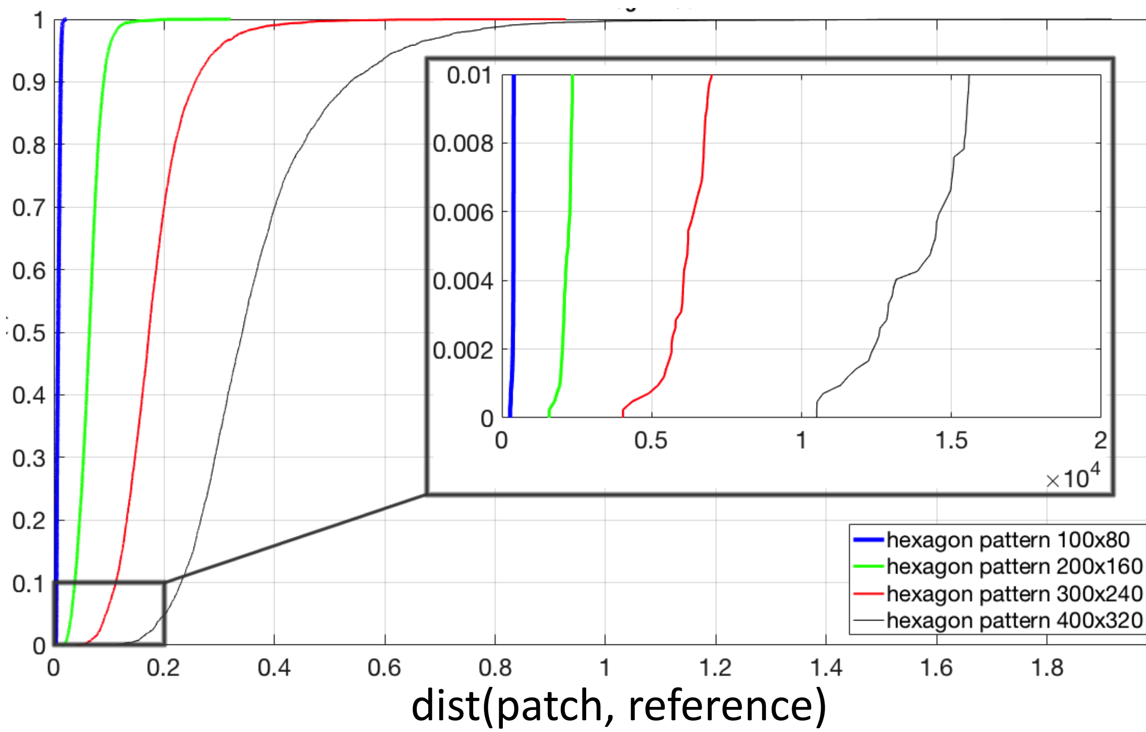
Query patches

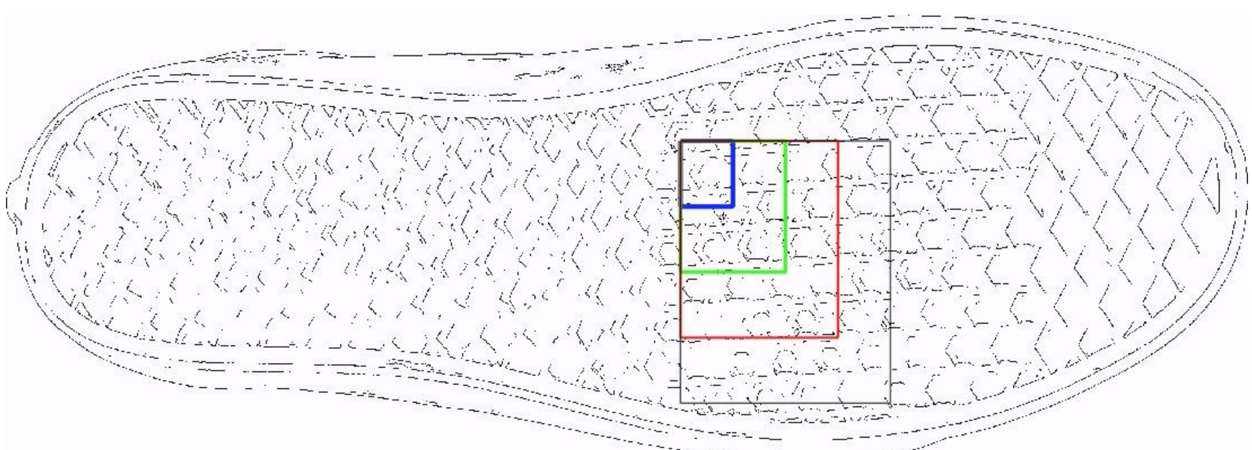
Retrieval results (lineup)



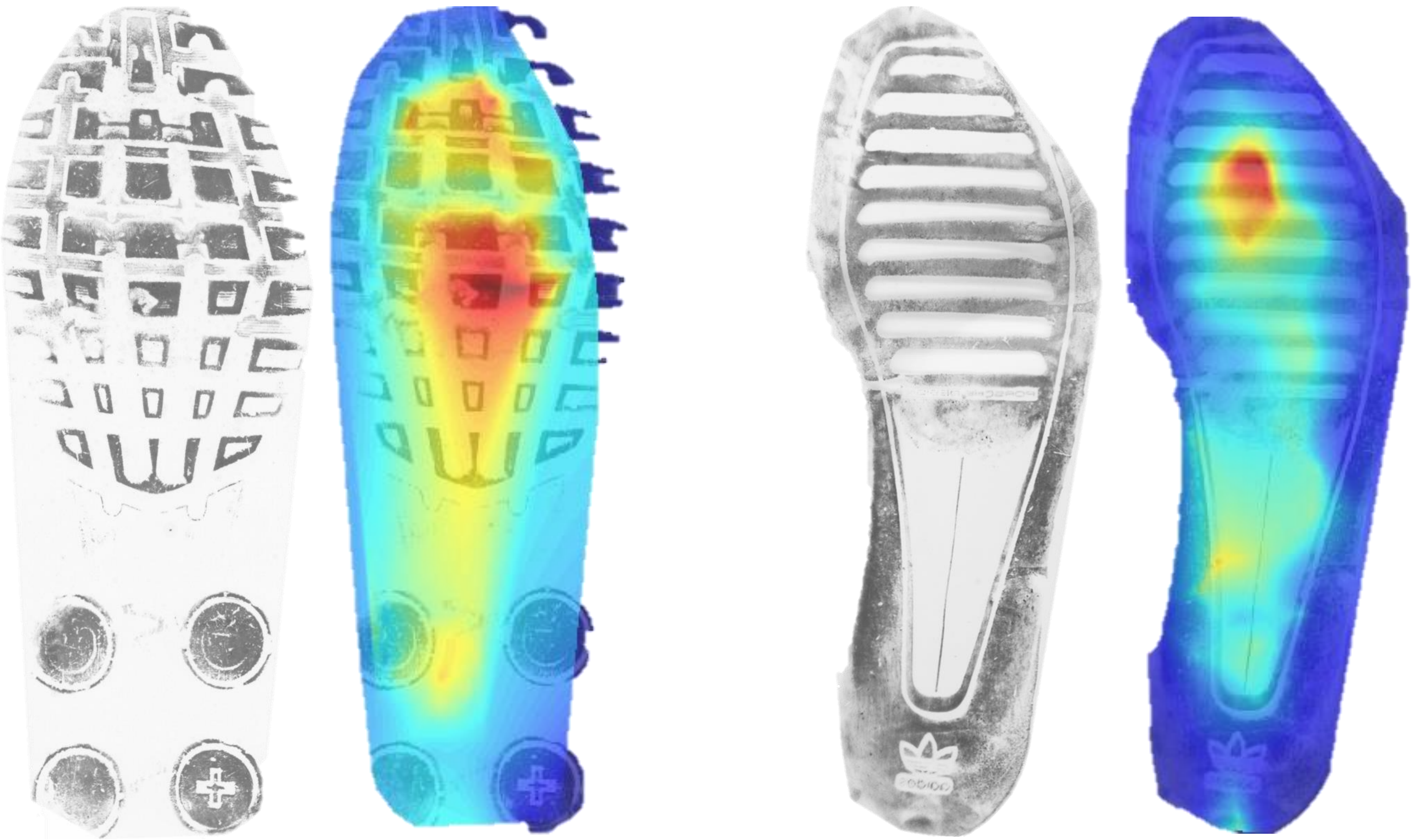
Larger patches are more distinctive

% reference shoes with
dist(patch,ref) < t





Visualizing local distinctiveness



distance within same class / distance to other classes

Conclusion

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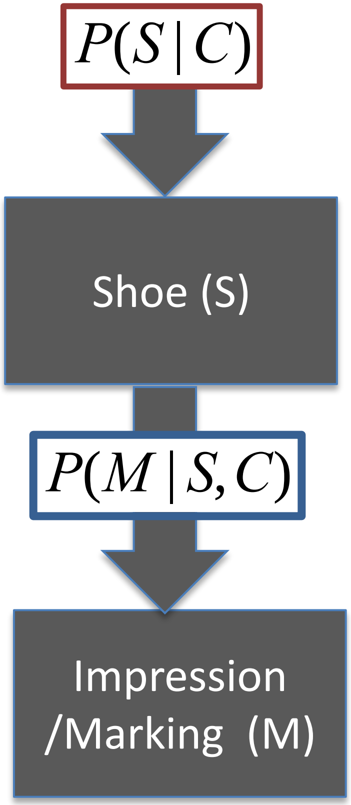

"If you cannot measure it, you cannot improve it"
--Lord Kelvin

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