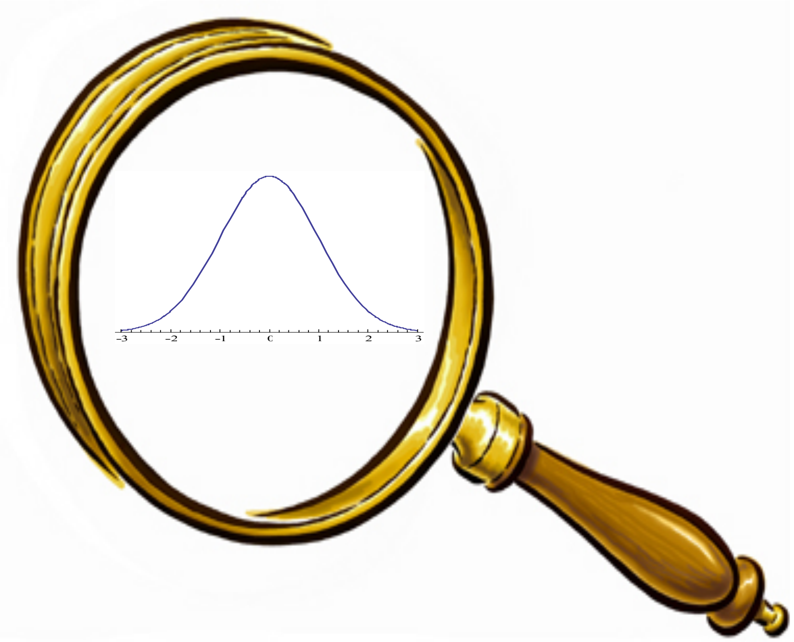
Quantitative Firearms and Toolmark Analysis:

New Developments and Software



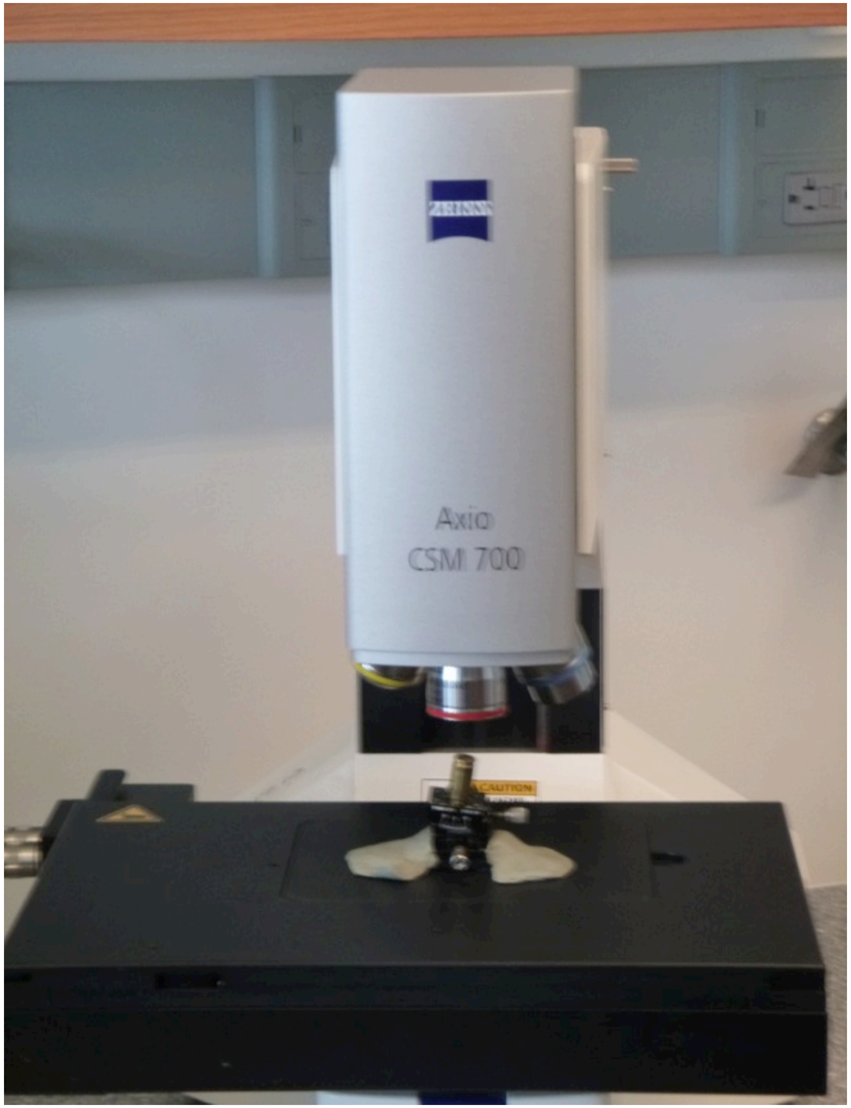
Petraco Group

City University of New York, John Jay College

Outline

- 3D toolmark data, pre-processing and feature extraction: **x3pr**, **feature2**
- The statistics:
  - Identification Error Rates
  - "Match" confidence estimate from Conformal Prediction Theory: **cptID**
  - "Match" probability estimates from Empirical Bayes: **fdrID**
  - "Match" probability estimates from CMS data and Bayesian Networks

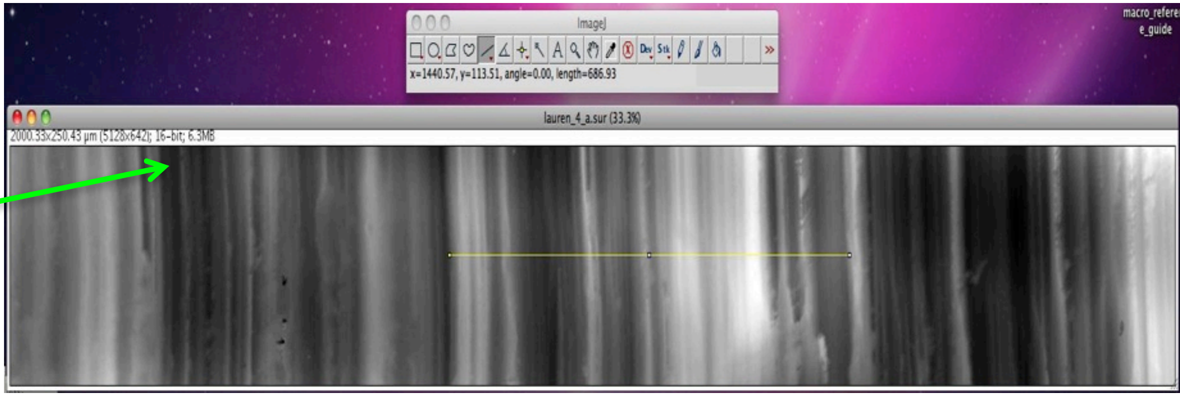
Data Acquisition For Toolmarks



Confocal Microscope

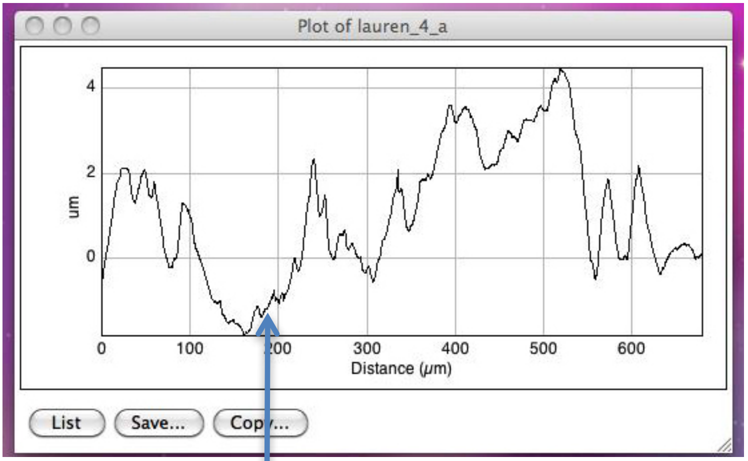
Focus Variation Microscope

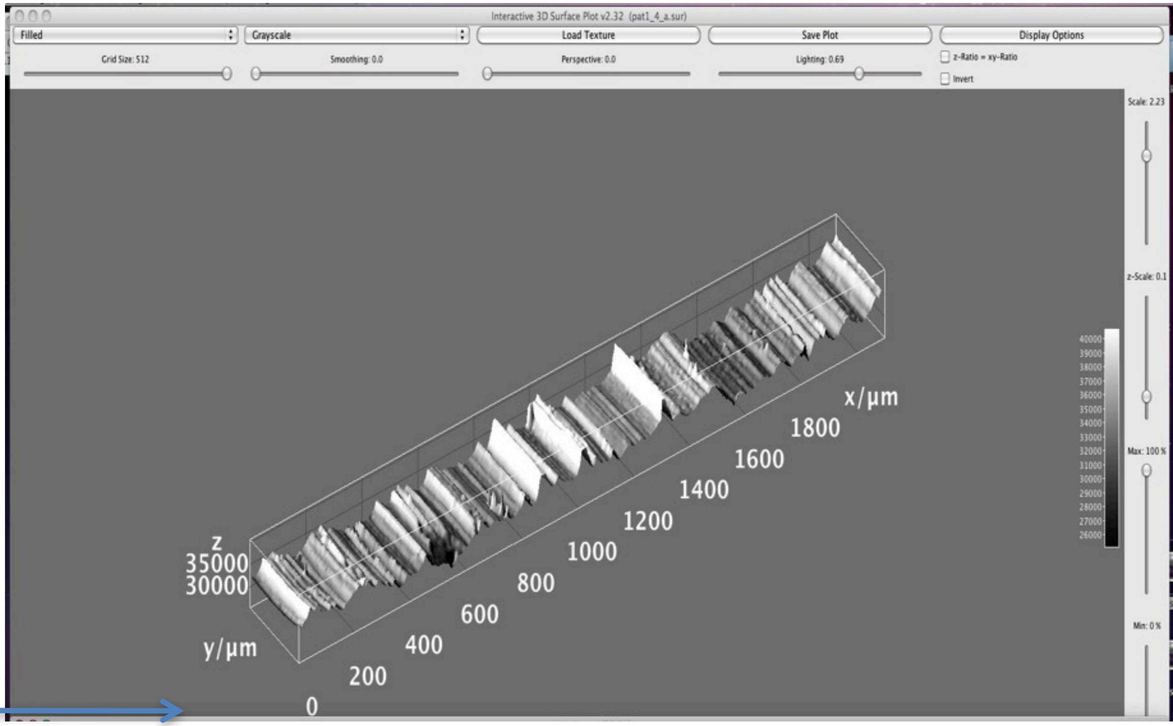
Screwdriver Striation Patterns in Lead



x=1440.57, y=113.51, angle=0.00, length=686.93

2000.33x250.43 µm (5128x642); 16-bit; 6.3MB





Filled

Grayscale

Grid Size: 512

Smoothing: 0.0

Perspective: 0.0

Lighting: 0.69

☐ z-Ratio = xy-Ratio

☐ Invert

Scale: 2.23

z-Scale: 0.1

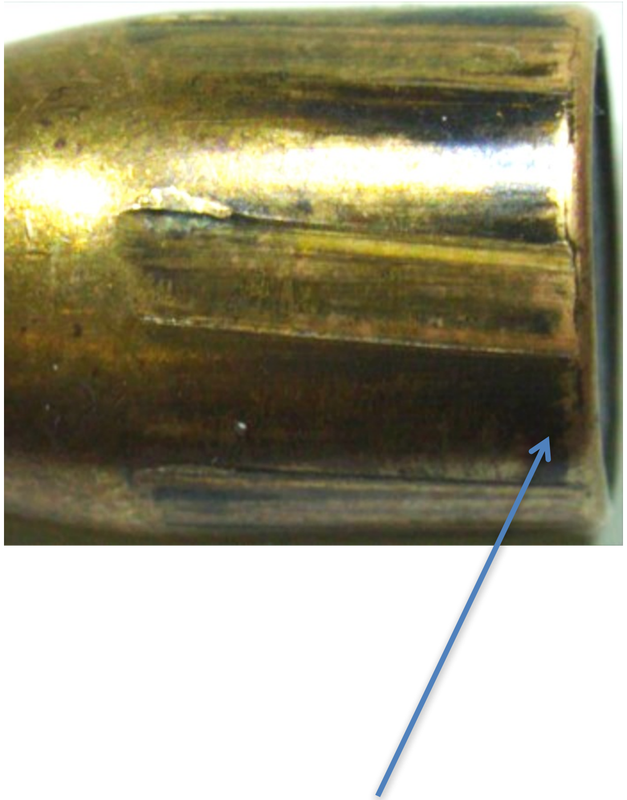
Max: 100 %

Min: 0 %

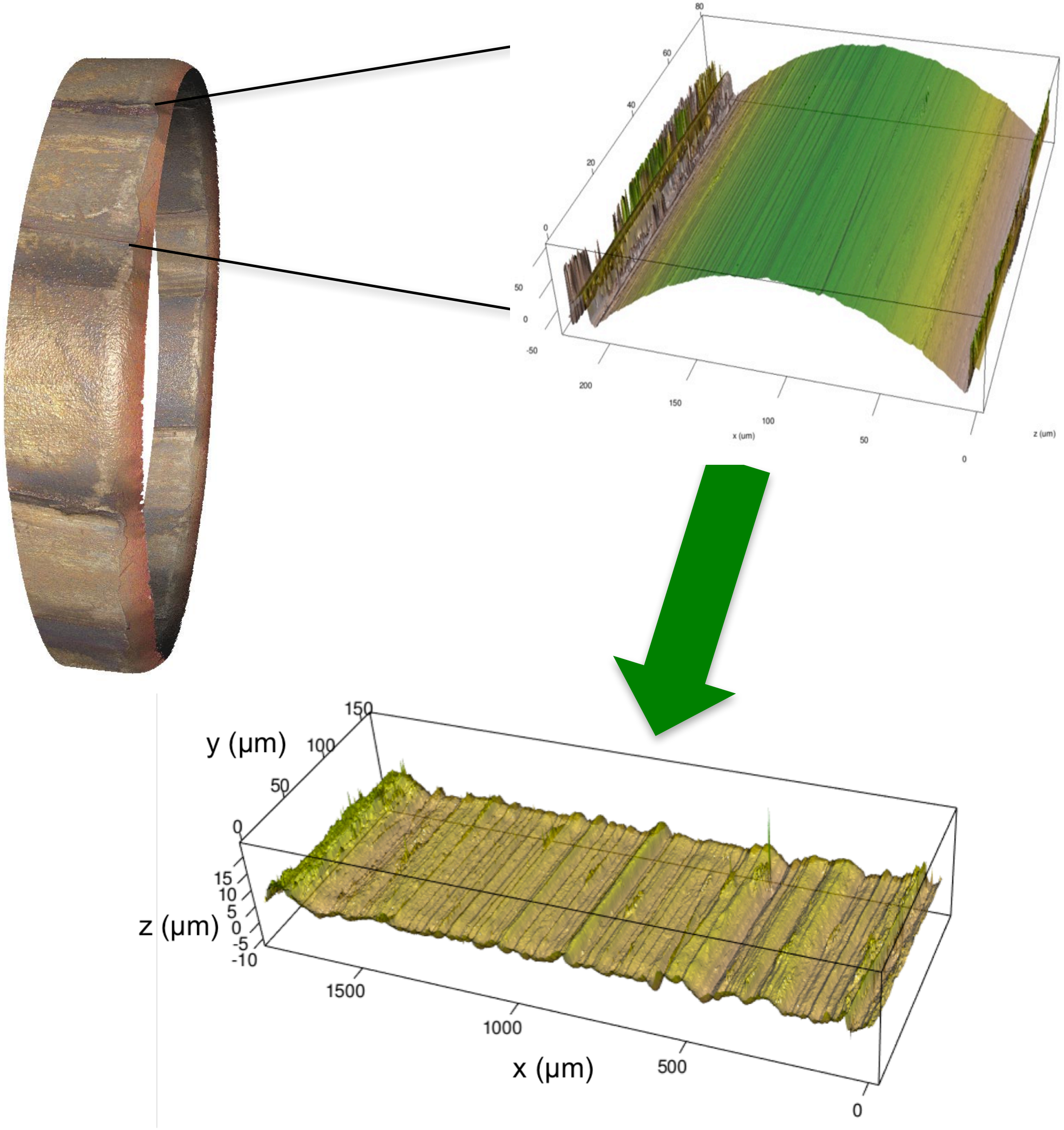
2D profiles

3D surfaces (interactive)

Bullets



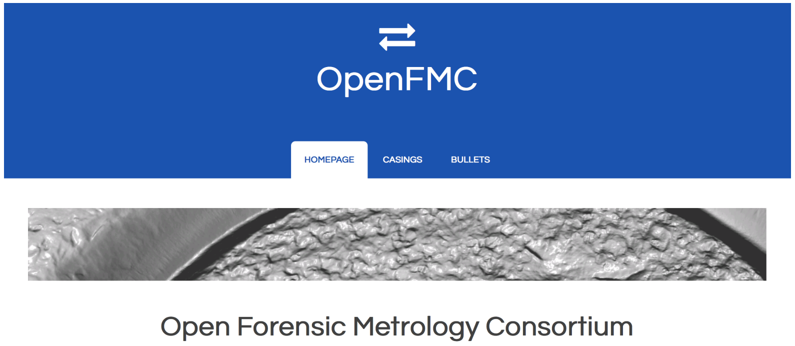
Bullet base, 9mm Ruger Barrel



Toolmark Surface Data

- A growing database[Zheng]:
  - http://www.nist.gov/forensics/ballisticsdb/

- Put in your two cents: OpenFMC[Lillien]
  - http://www.openfmc.org/

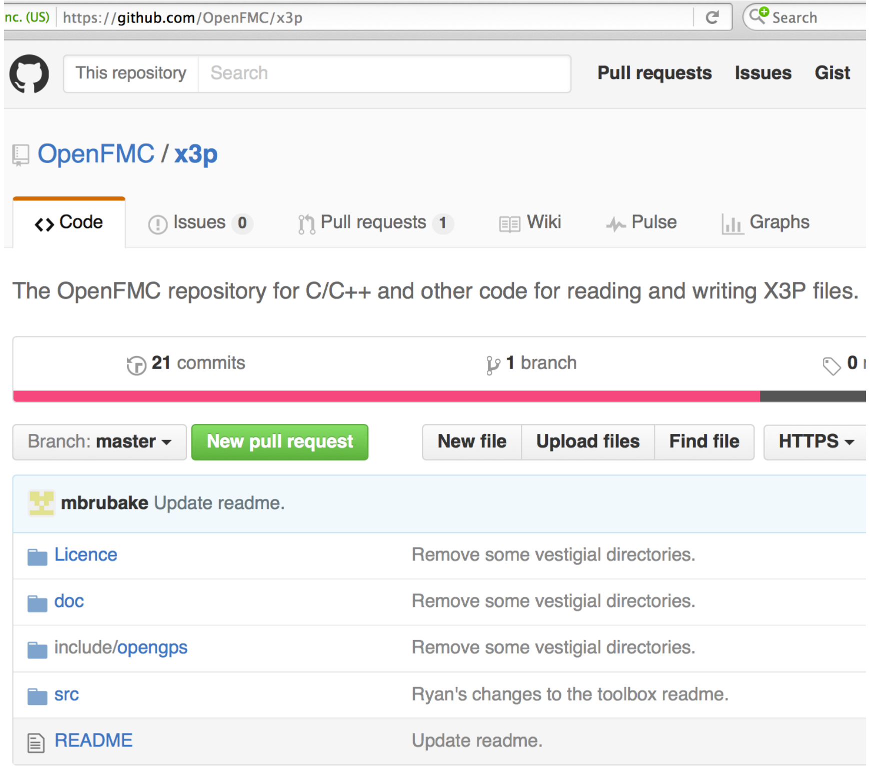


Open Forensic Metrology Consortium

Toolmark Surface Data

- Standardizing file format: .x3p
  - http://www.nist.gov/forensics/ballisticsdb/dataformat.cfm

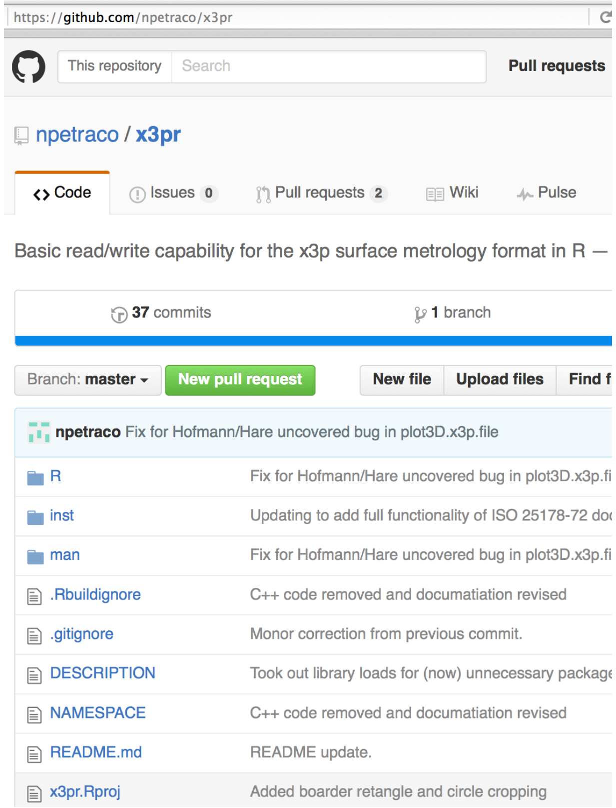
x3p C++/ library, Windows$^{\text{Brubaker}}$ **x3pr**$^{\text{Petraco}}$ for , Any OS



The OpenFMC repository for C/C++ and other code for reading and writing X3P files.

mbrubake Update readme.

Licence	Remove some vestigial directories.
doc	Remove some vestigial directories.
include/opengps	Remove some vestigial directories.
src	Ryan's changes to the toolbox readme.
README	Update readme.



Basic read/write capability for the x3p surface metrology format in R —

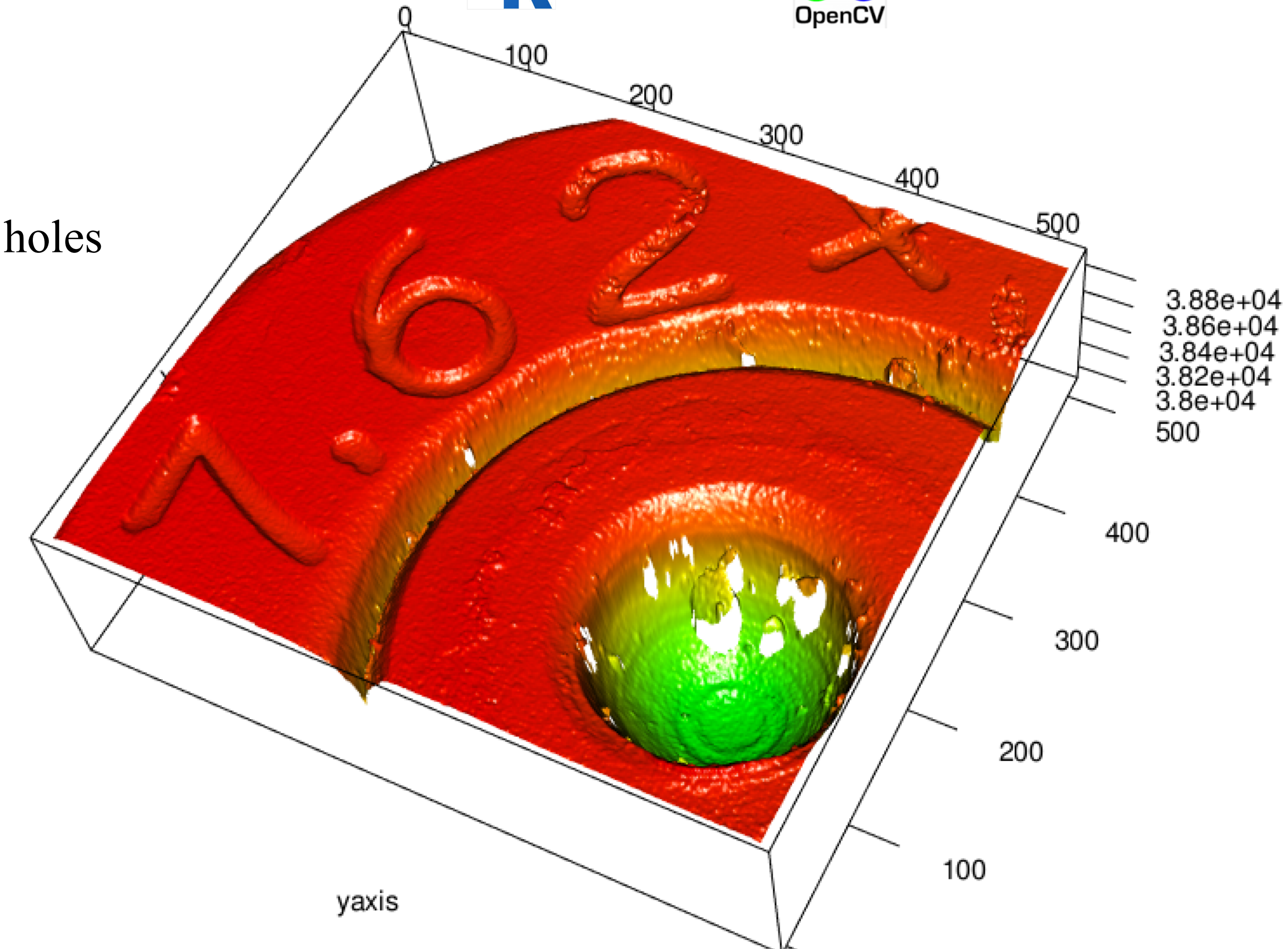
npetraco Fix for Hofmann/Hare uncovered bug in plot3D.x3p.file

R	Fix for Hofmann/Hare uncovered bug in plot3D.x3p.fi
inst	Updating to add full functionality of ISO 25178-72 do
man	Fix for Hofmann/Hare uncovered bug in plot3D.x3p.fi
.Rbuildignore	C++ code removed and documatiation revised
.gitignore	Monor correction from previous commit.
DESCRIPTION	Took out library loads for (now) unnecessary package
NAMESPACE	C++ code removed and documatiation revised
README.md	README update.
x3pr.Rproj	Added boarder retangle and circle cropping

Pre-processing Surface Data

- 3D tool mark data usually needs (a lot of…) preprocessing
  - We use a combination of R and **C++**/ OpenCV (via **Rcpp**$^{\text{Edd}}$) = **feature2**$^{\text{Petraco}}$

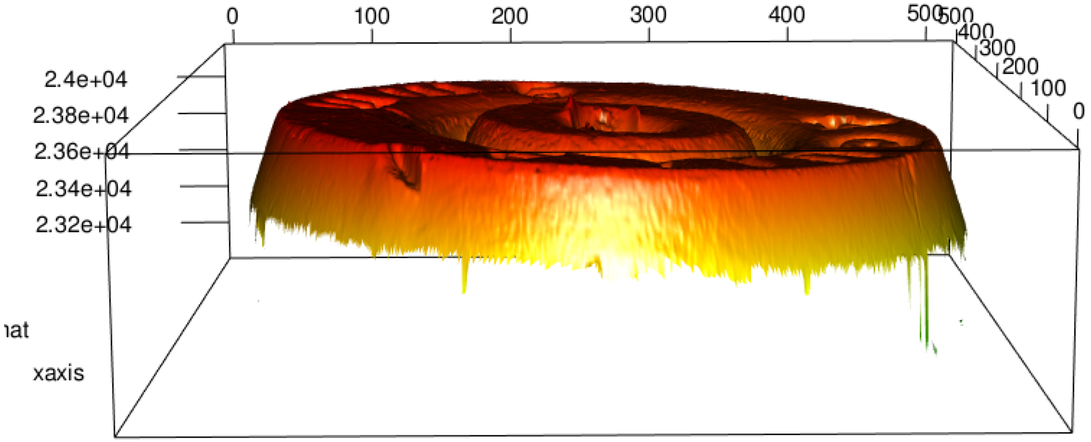
Possibly fill holes



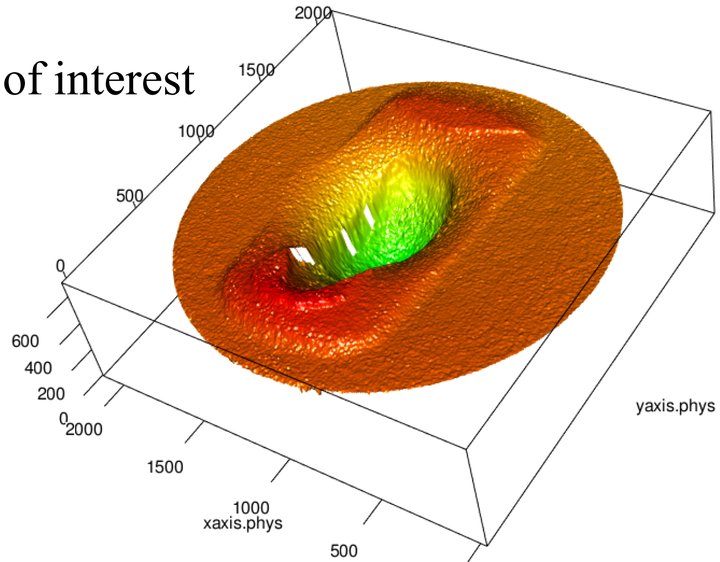
Preprocessing Surface Data

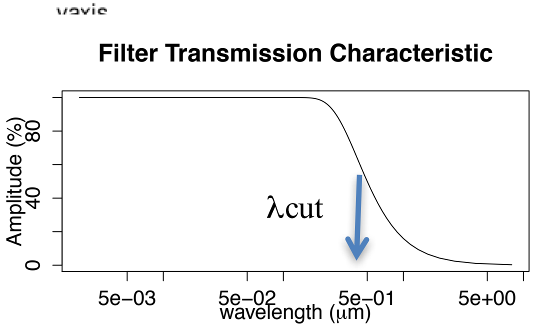
- 3D tool mark data usually needs (a lot of…) preprocessing
  - In **feature2**:

Possibly remove "long range" behavior (leveling, form removal)



Crop out areas of interest





Bandpass filters via:

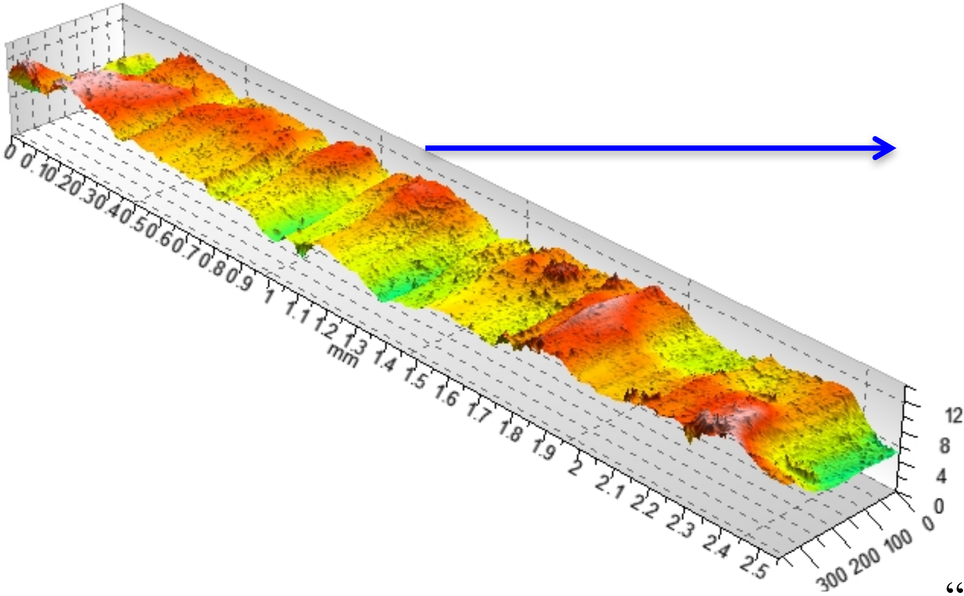
waveslim[Whitcher]

OpenCV

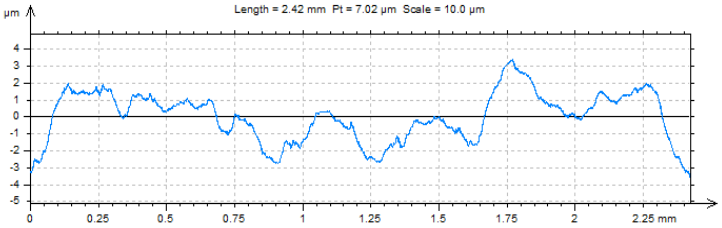
Good Features are the Key!

- We need a tool mark feature set that is:
  - Large in number
  - (possibly) transnationally invariant
  - (possibly) rotationally invariant
  - Mostly statistically independent
  - DISCRIMINATORY!

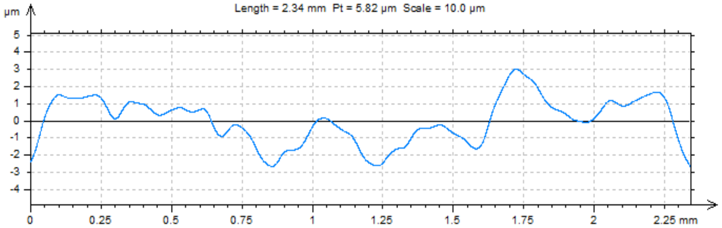
Toolmark Features



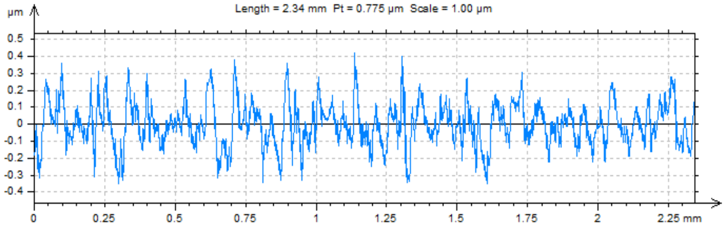
Mean total profile:



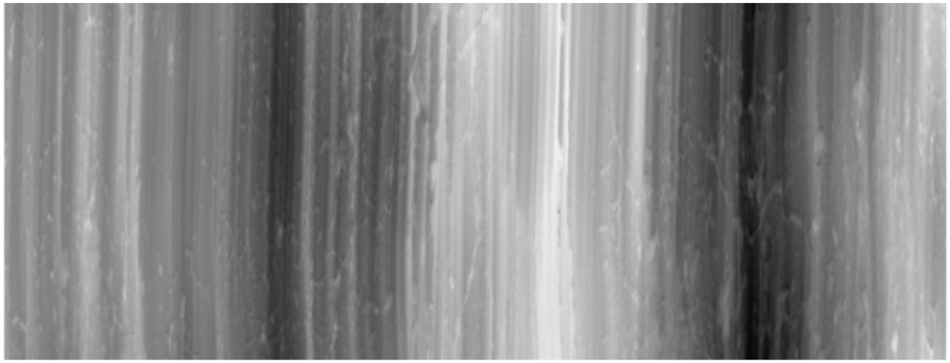
Mean “waviness” profile:

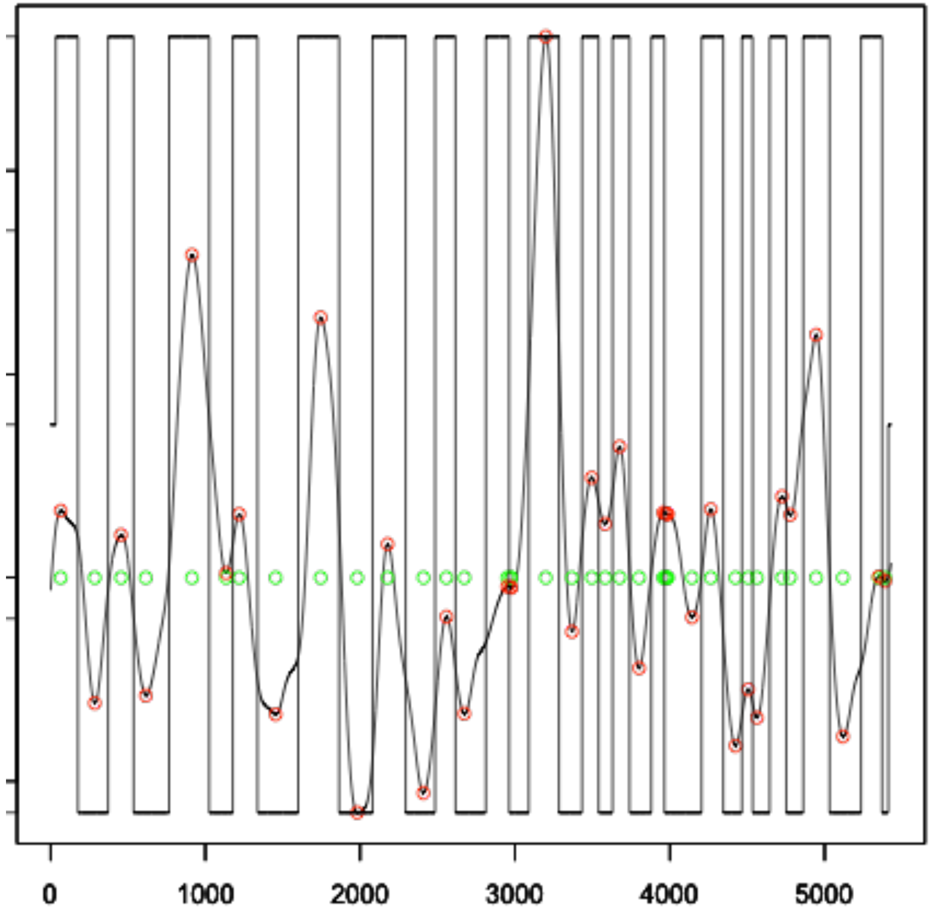


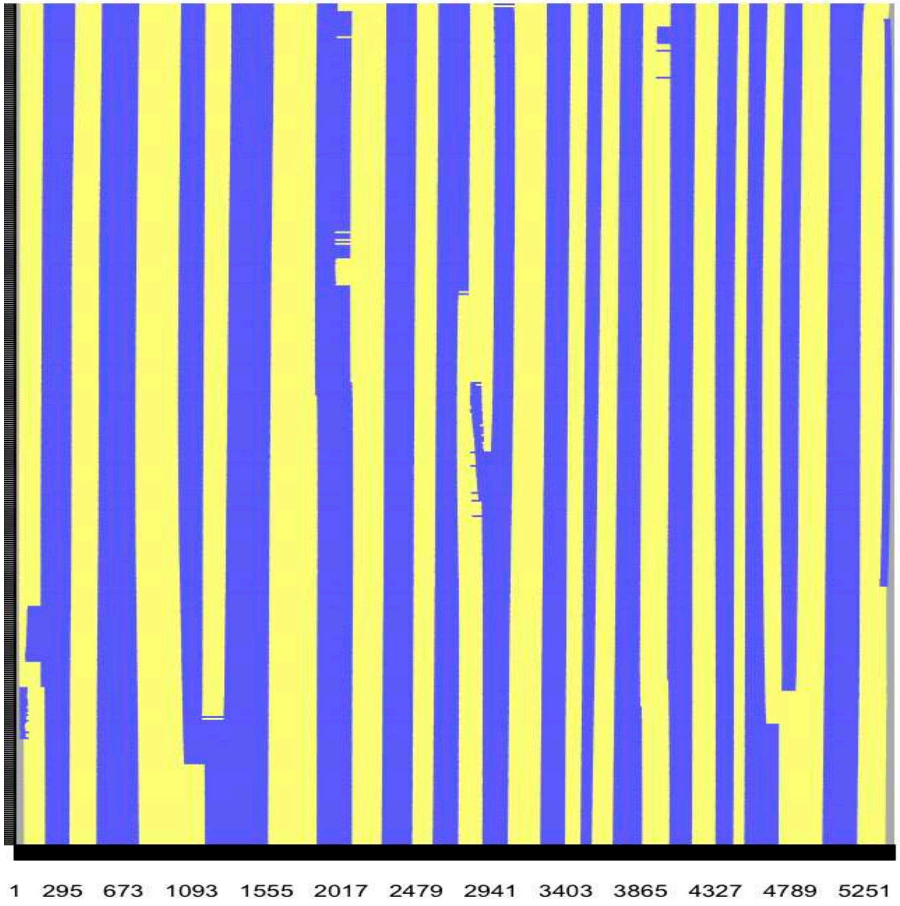
Mean “roughness” profile:



Aperture primer shear on a 9mm cartridge case fired from the a Glock 19



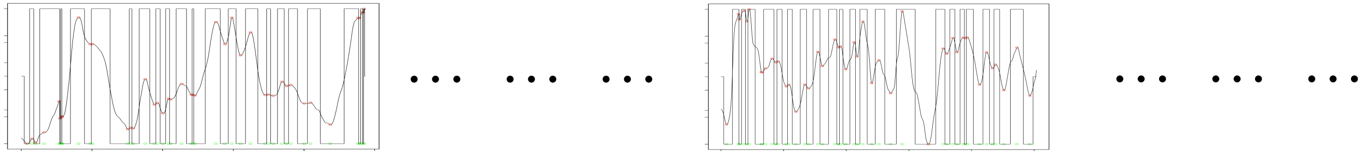

0
1000
2000
3000
4000
5000


1
295
673
1093
1555
2017
2479
2941
3403
3865
4327
4789
5251

FAST-Consecutive Matching Striae (CMS)-Space

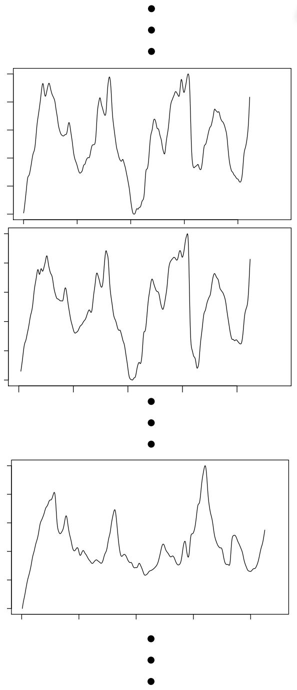
Biasotti-Murdock dictionary: “Closest Match Ref Set”

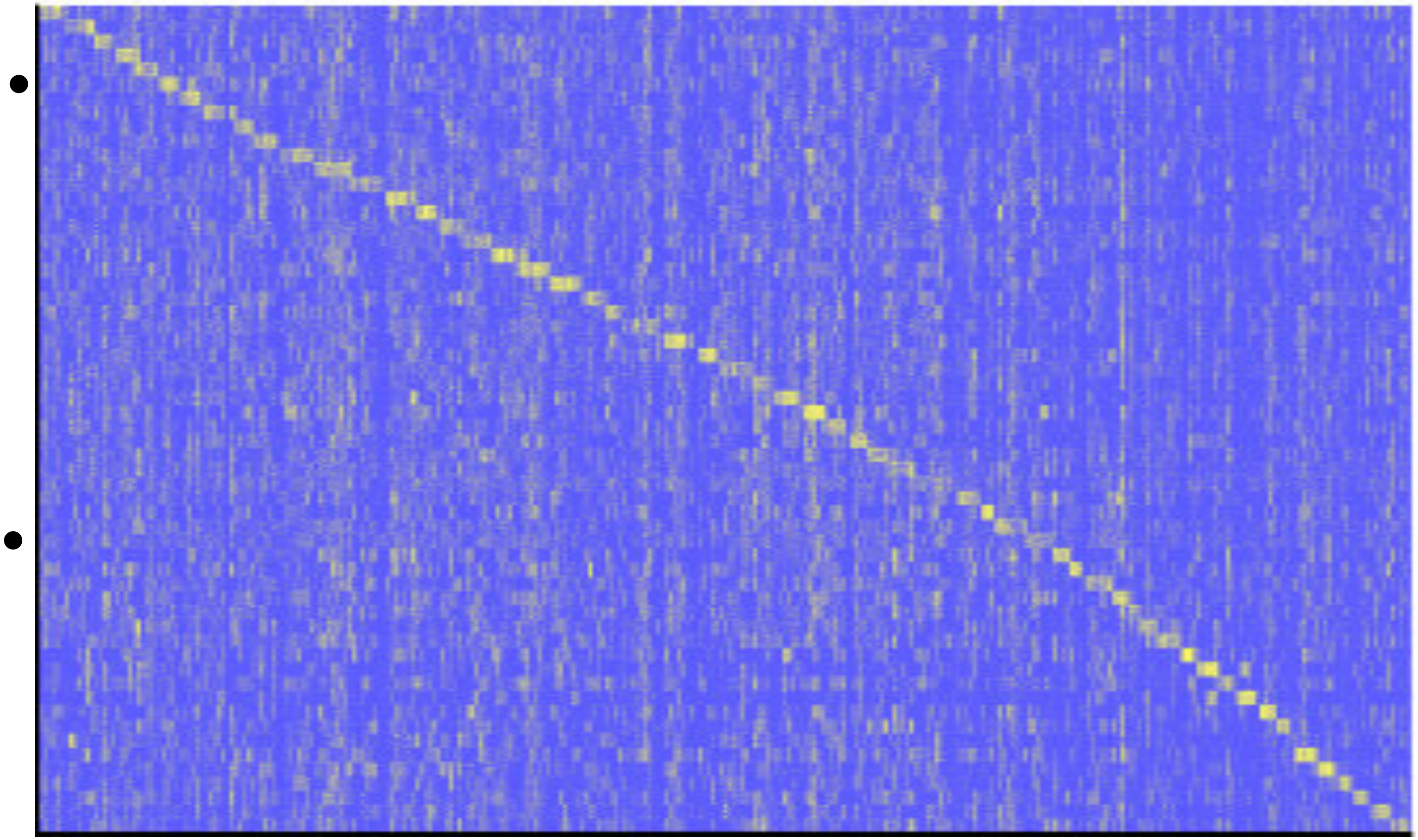
Rcpp and **parallel**$^{\text{R-core}}$ packages are great for quick and easy speedups



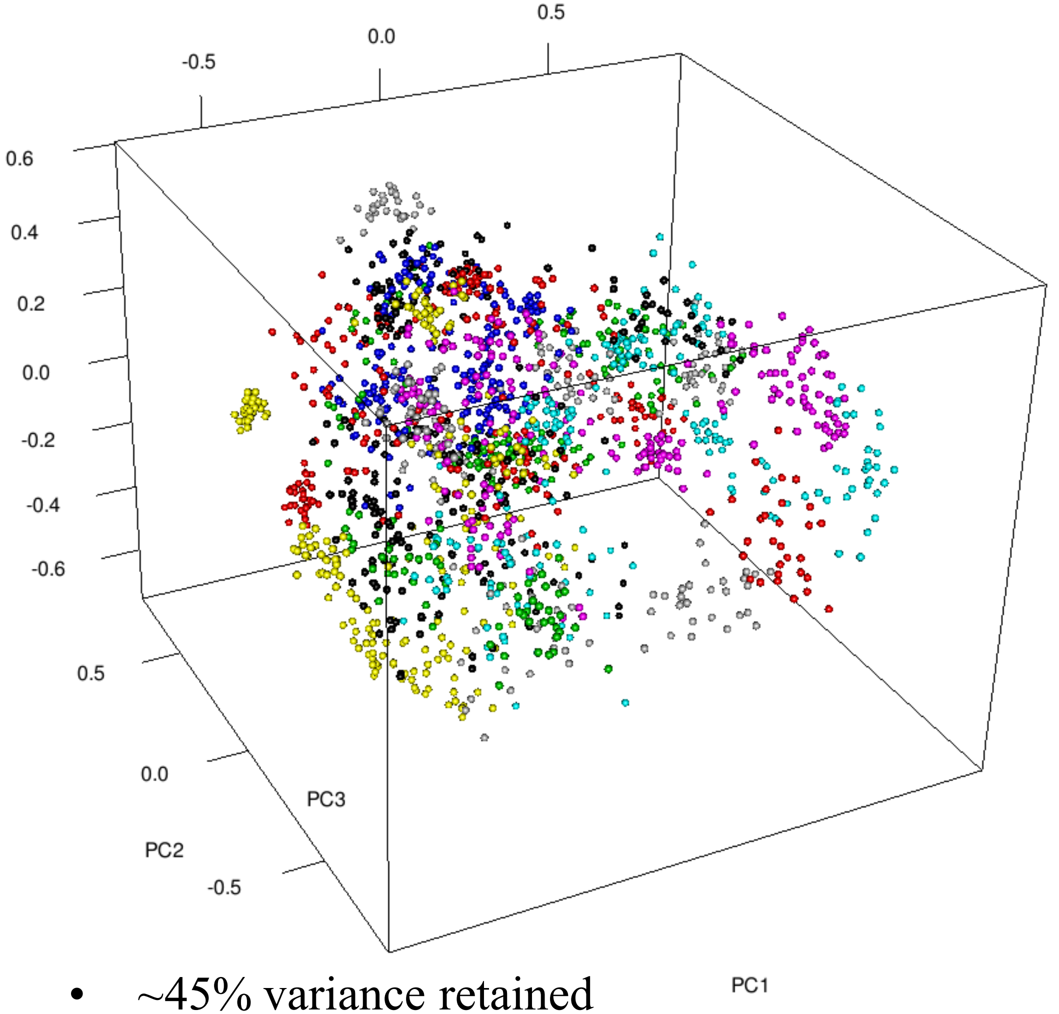
… … … … … …

Database/queries





- 3D PCA of 1740 real and simulated mean profiles of striation patterns from 58 screwdrivers:



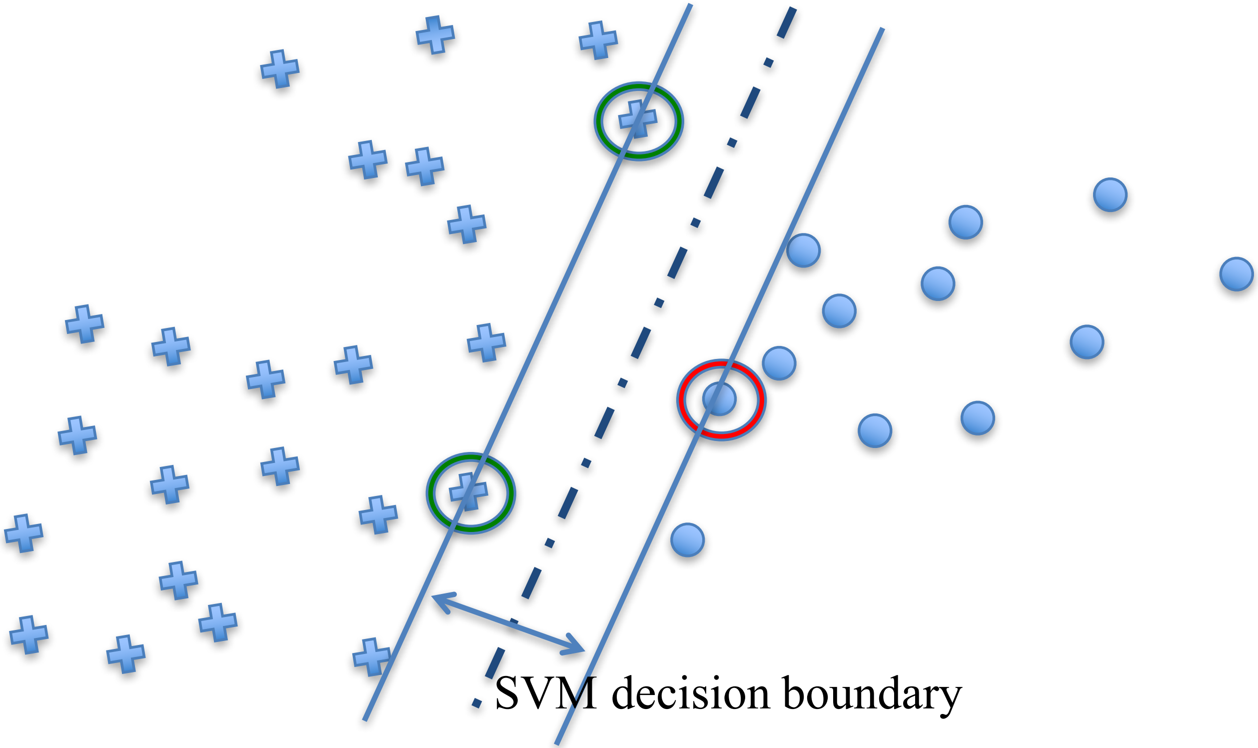
- How many PCs should we use to represent the data??
    - No unique answer

- FIRST we ***need an algorithm to I.D. a toolmark*** to a tool

- ~45% variance retained

Support Vector Machines

- Support Vector Machines (SVM) determine efficient association rules
  - ***<u>In the absence of specific knowledge of probability densities</u>***

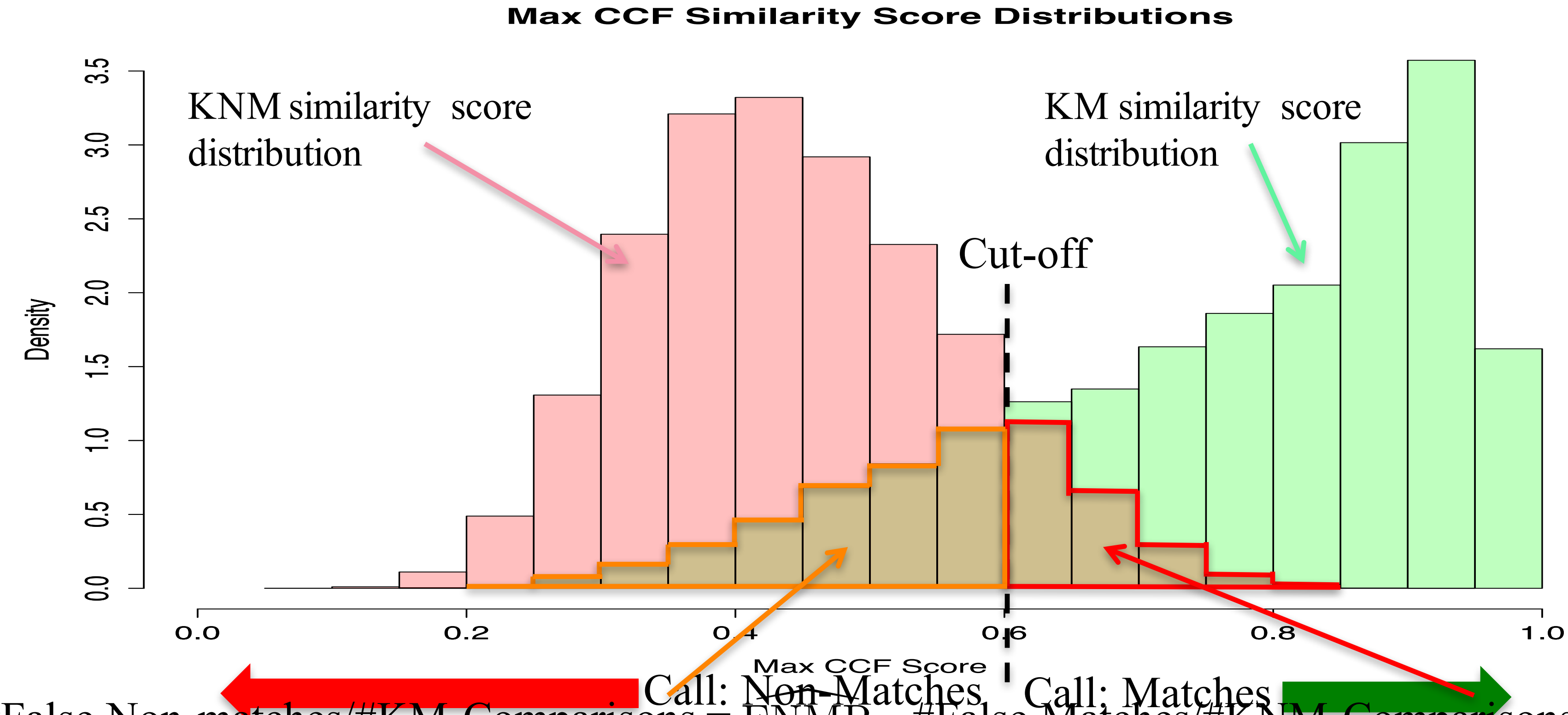


Error Rate Estimation: Machine Learning

- **Cross-Validation**: hold-out chunks of data set for testing
  - Known since 1940s
  - Most common: **Hold-one-out**
- **Bootstrap**: Randomly selection of observed data (with replacement)
  - Known since the 1970s
  - Can yield ***confidence intervals around error rate estimate***
- **The Best**: Small training set, BIG test set

Error Rate Estimation: Pair-Wise Comparisons

- **Univariate** approaches compute estimates of similarity score distributions for **Known Matches** (KM) and **Known Non-Matches** (KNM)



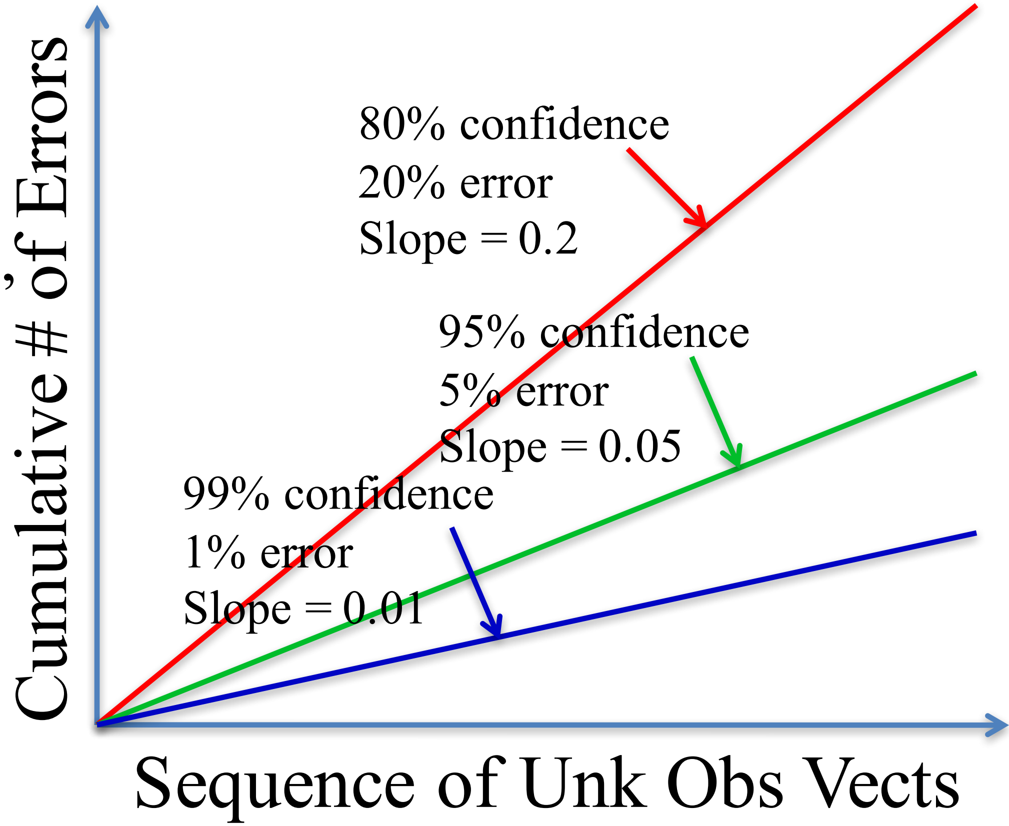
#False Non-matches/#KM-Comparisons = FNMR #False Matches/#KNM-Comparisons = $\widehat{\text{FMR}}$

$\widehat{\text{Error Rate}}$ = (#False Non-matches + #False Matches)/#Comparisons

How good of a “match” is it?

Conformal Prediction$^{\text{Vovk}}$

- Can give a judge or jury an easy to understand measure of reliability of classification result
  - *Confidence* on a scale of 0%-100%
  - *Testable claim*: Long run I.D. error-rate should be the chosen significance level
- This is an orthodox “frequentist” approach
  - Roots in Algorithmic Information Theory
- Data should be IID but that’s it



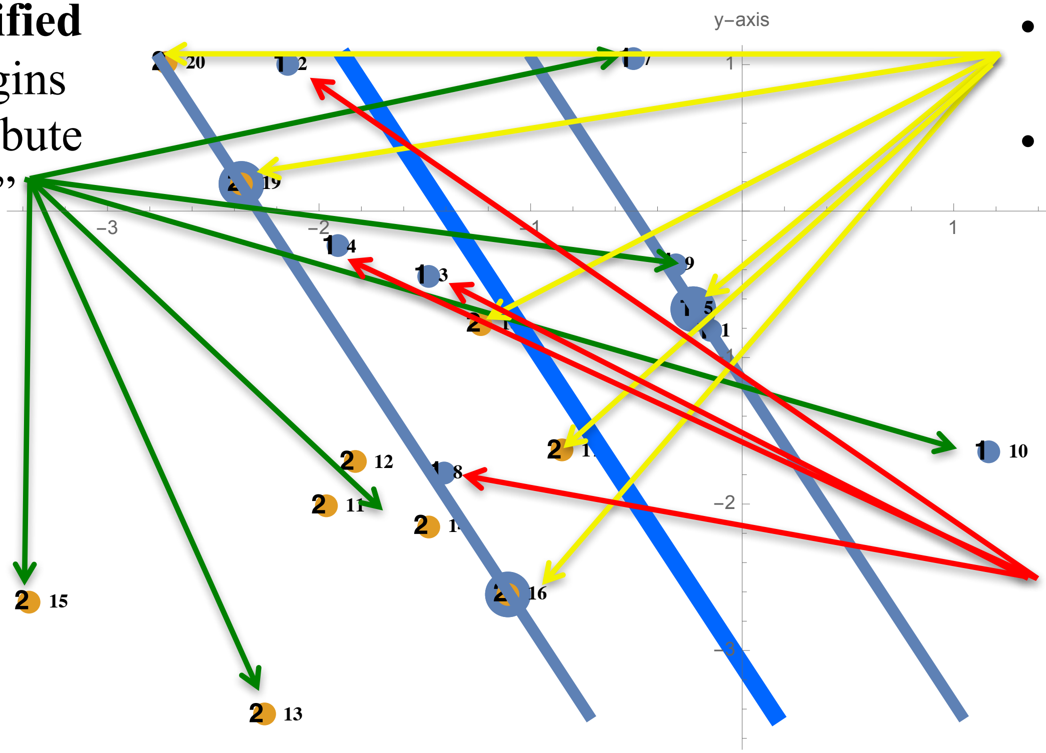
How Conformal Prediction works for us

- Given a "bag" of obs with known identities and one obs of unknown identity[Vovk]
  - Estimate how "wrong" labelings are for each observation with a **non-conformity** score ("wrong-iness")
  - For us, one-vs-one SVMs: $t_i = \frac{1}{k-1}\sum_{j=1}^{k(k-1)/2}\lambda_{i,j}$

$\underline{\lambda = 0}$

- **Correctly classified** and behind margins
- Shouldn't contribute to "wrong-iness"

Intuition:



$\underline{0 < \lambda < C}$

- Correctly classified but **SVs or marginal**
- Should contribute something to "wrong-iness"

$\underline{\lambda = C}$

- **Wrong**
- Should contribute most "wrong-iness"

How Conformal Prediction works for us

- Given a “bag” of obs with known identities and one obs of unknown identity[Vovk]
  - Looking at the “wrong-iness” for all the known observations in the bag:
    - Ask: Does labeling-*i* for the unknown have an unusual amount of “wrong-iness”??:

Given “wrong-iness” for labeling-*i* of unknown, number of obs with at least as much “wrongi-ness”

$$p_{\text{possible-ID}_i} = \frac{\#\left\{ j \in \{1,2,\ldots,n\} : t_j^{\text{possible-ID}_i} \geq t_{\text{test-pattern}}^{\text{possible-ID}_i} \right\}}{n} \qquad i \in \{1,2,\ldots,k \text{ I.D.s}\}$$

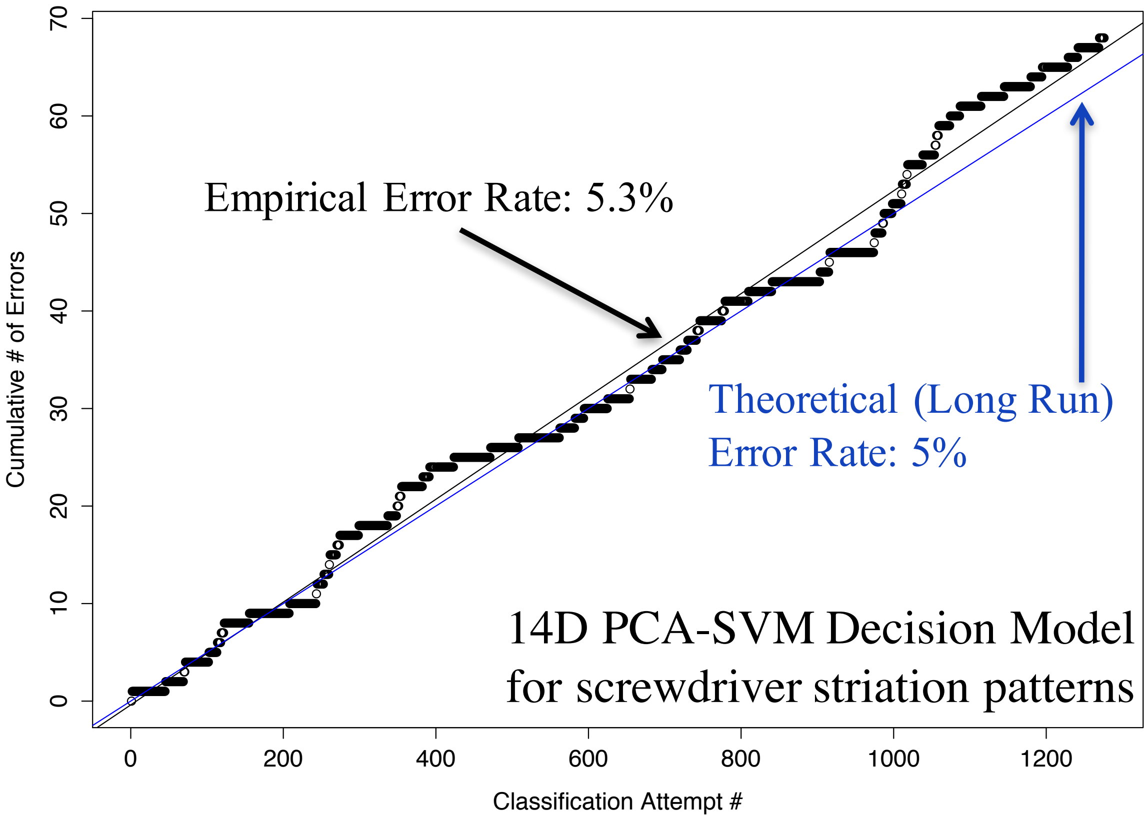
- If not:
  - $p_{\text{possible-ID}_i} \geq$ chosen level of significance α
  - Put ID_i in the $(1 - \alpha)$*100% confidence interval: $\Gamma^{1-\alpha}$

$$\text{ID}_i \in \Gamma^{1-\alpha} \quad \text{if } p_{\text{ID}_i} \geq \alpha$$

Conformal Prediction

- For 95%-CPT (PCA-SVM) confidence intervals will not contain the correct I.D. 5% of the time *in the long run*
  - *Straight-forward validation/explanation picture for court*

cptID$^{\text{Petraco}}$ for R
Coming soon…



95% CPT Cumulative Errors: On–line Mode

Empirical Error Rate: 5.3%

Theoretical (Long Run)
Error Rate: 5%

14D PCA-SVM Decision Model
for screwdriver striation patterns

How good of a "match" is it?

Efron Empirical Bayes

- An I.D. is output for each questioned tool mark
  - This is a computer "match"
- What's the **probability the tool is truly the source of the tool mark**?

- Similar problem in genomics for detecting disease from microarray data
  - They use *data* **and** *Bayes' theorem* to get an estimate

Empirical Bayes

- From Bayes' Theorem we can get[Efron]:

Estimated probability of not a true "match" given the algorithms' output z-score associated with its "match" →

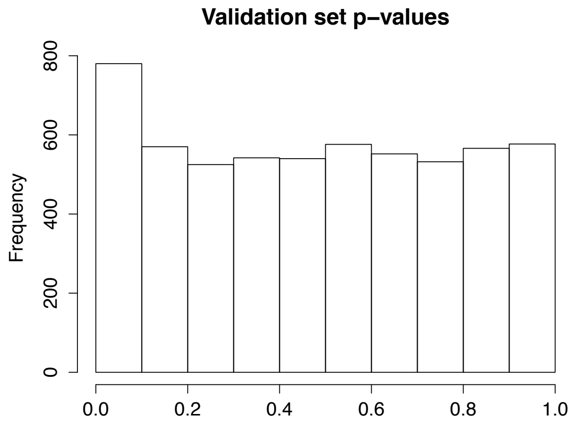
$$\hat{\Pr}\left(S^- \mid z\right) = \frac{\hat{p}\left(z \mid S^-\right)}{\hat{f}\left(z\right)} \hat{\Pr}\left(S^-\right)$$

Names: **Posterior error probability (PEP)**[Kall]
Local false discovery rate (lfdr)[Efron]

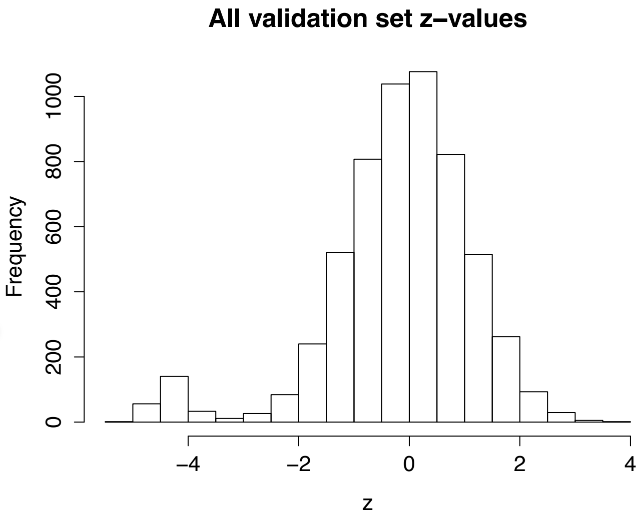
- Suggested interpretation for casework:

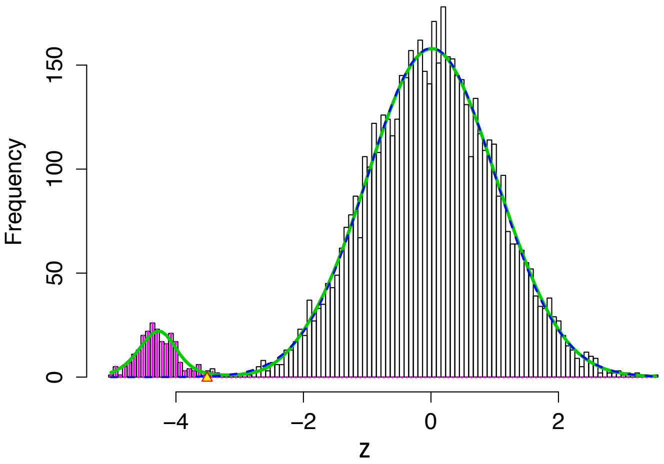
$1 - \hat{\Pr}\left(S^- \mid z\right)$ = Estimated "***believability***" that the specific tool produced the tool mark

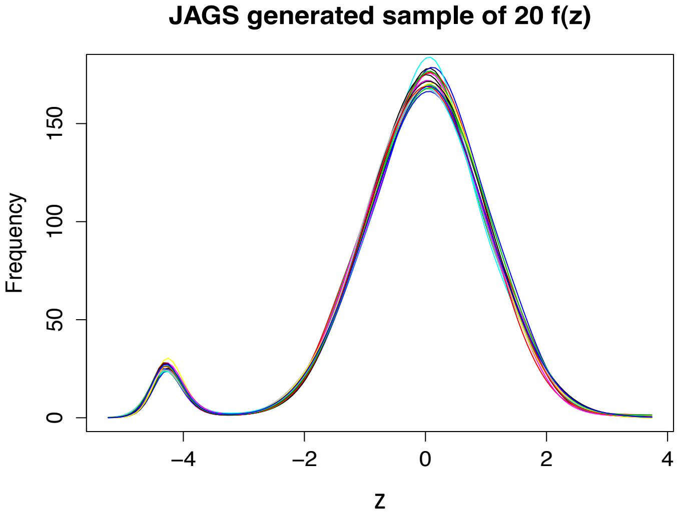
Fit local-fdr models


Validation set p–values

$\Phi^{-1}(p\text{-values})$


All validation set z–values




JAGS generated sample of 20 f(z)

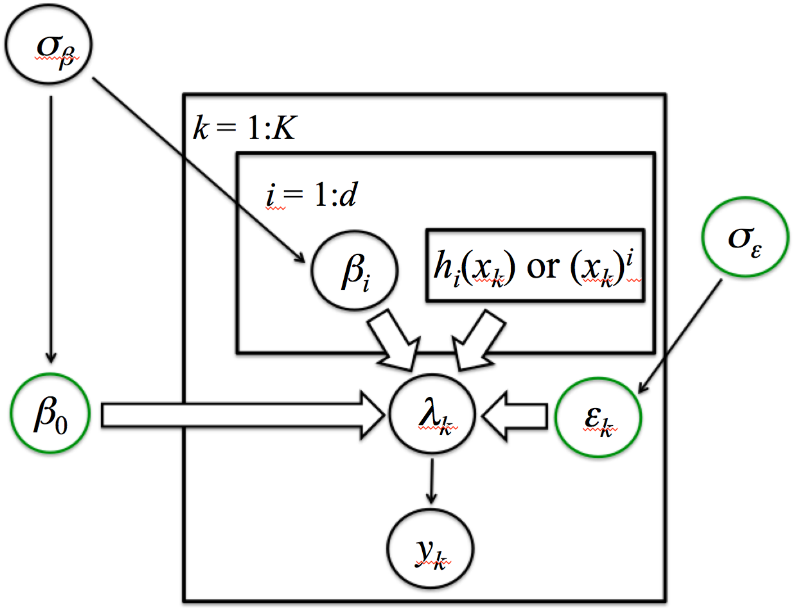
Use locfdr[locfdr]
Fit classic Poisson regression for f(z)

Use modified locfdr/JAGS[JAGS,Plummer] or Stan[Stan]
Fit Bayesian hierarchical Poisson regressions

Bayesian Hierarchical Poisson Regression Details

- To run the Bayesian Estimation we use **JAGS**$^{\text{Plummer}}$ or **Stan**$^{\text{Gelman}}$:

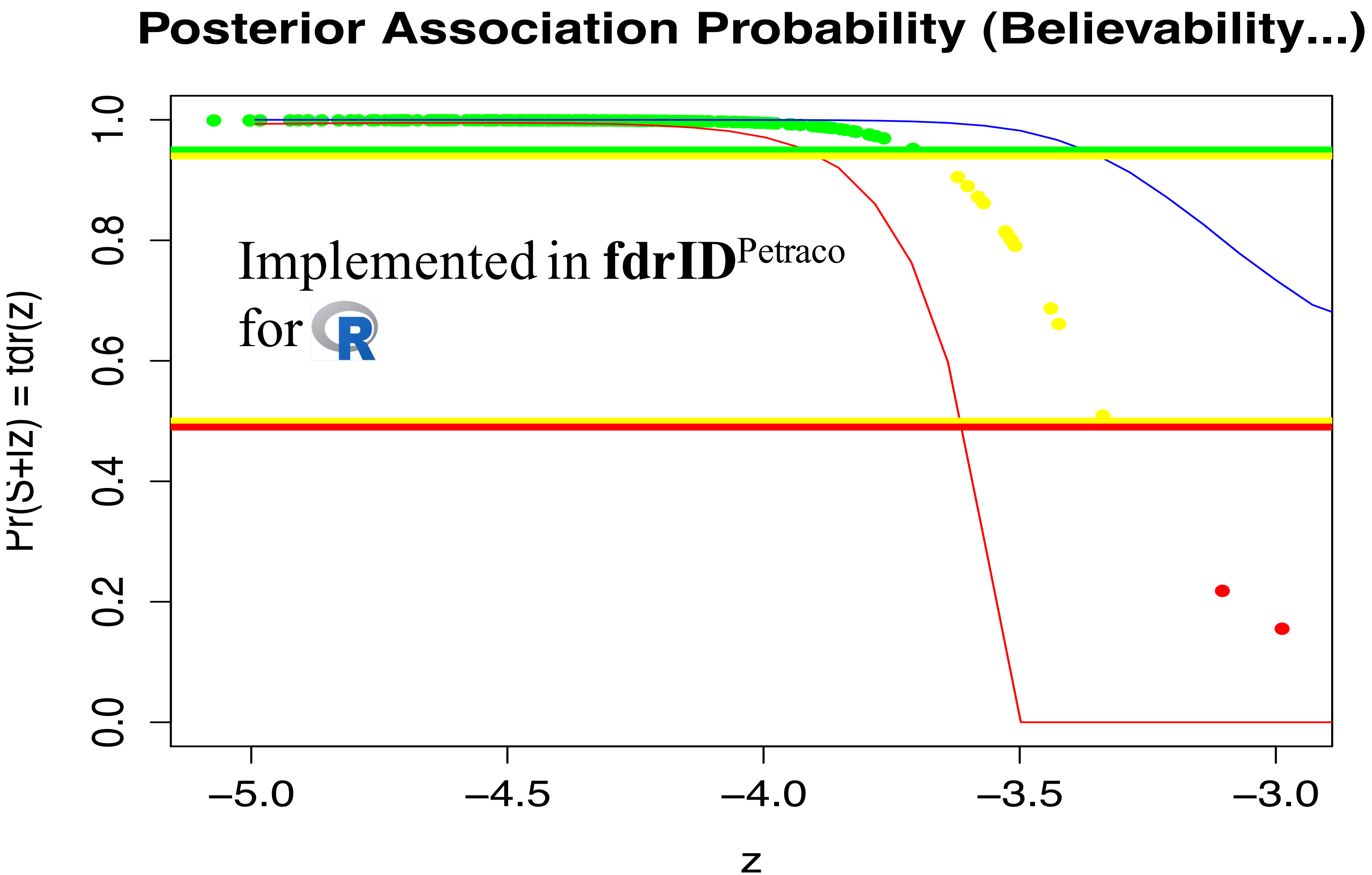
DAG for the Poisson Regression



$$\begin{aligned}
\sigma_\beta &\sim \mathrm{Uniform}(0, 100) \\
\sigma_\epsilon &\sim \mathrm{Uniform}(0, 100) \\
\beta_0 &\sim \mathrm{Normal}(0, \sigma_\beta) \\
\epsilon_i &\sim \mathrm{Normal}(0, \sigma_\epsilon) \\
\beta_j &\sim \mathrm{Normal}(0, \sigma_\beta)
\end{aligned}$$

Suggested by Gelman

A Bayesian Hierarchical Model: Believability Curve

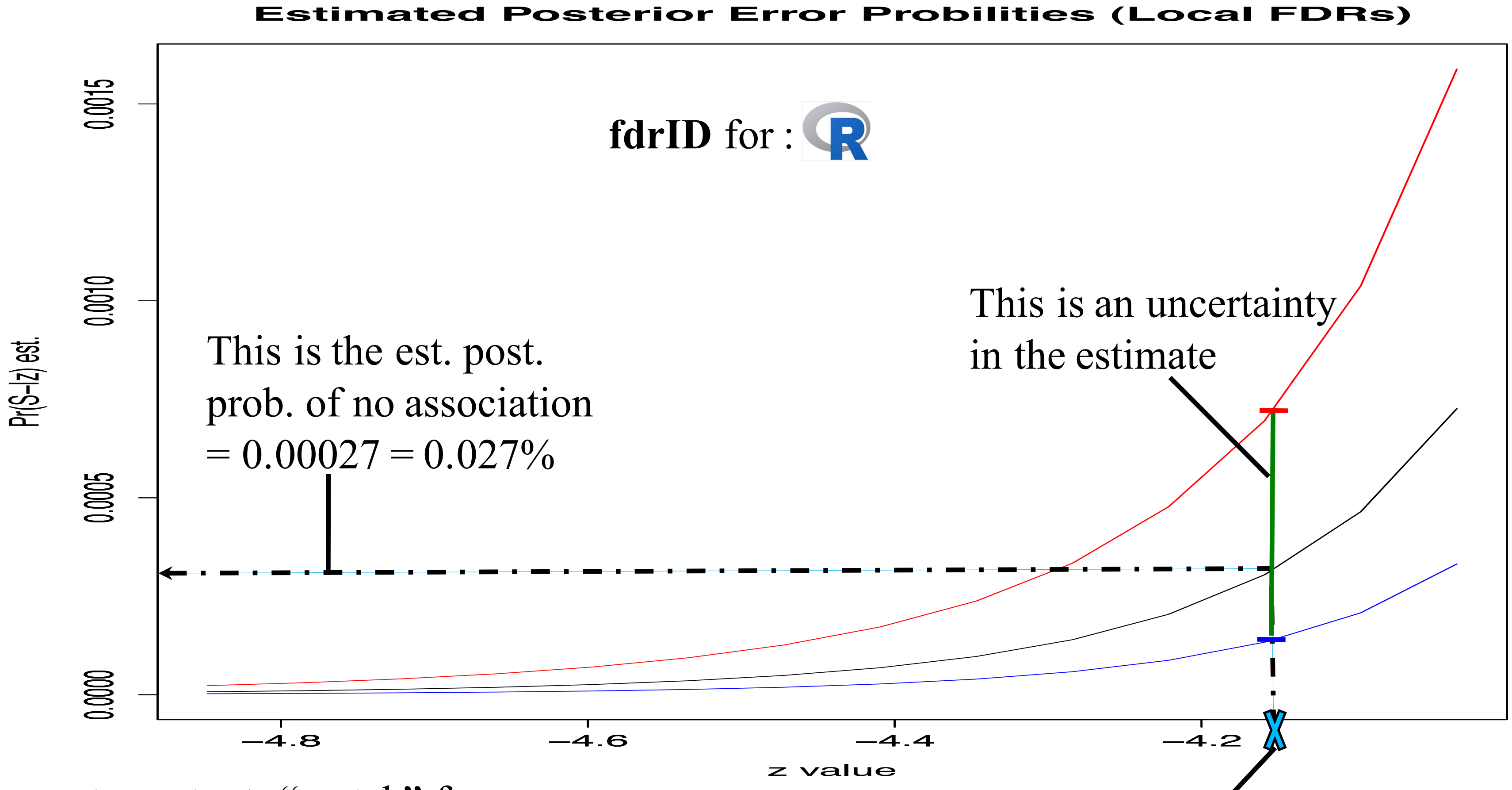


Implemented in **fdrID**$^{\text{Petraco}}$
for R

JAGS MCMC Bayesian over-dispersed Poisson with intercept, on test set

Empirical Bayes'

- Model's use with crime scene "unknowns":



This is the est. post. prob. of no association = 0.00027 = 0.027%

This is an uncertainty in the estimate

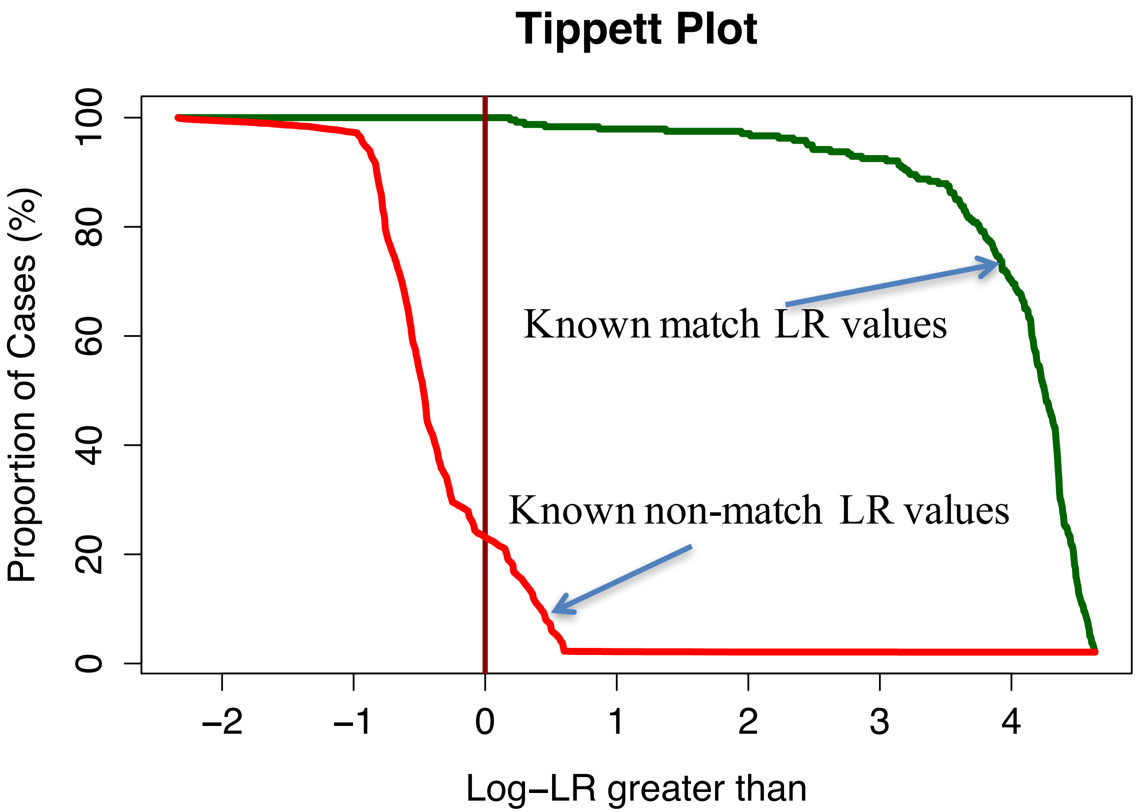
Computer outputs "match" for:

unknown crime scene toolmarks-with knowns from "Bob the burglar" tools

Likelihood Ratios from Empirical Bayes

- Using the fit posteriors and priors we can obtain the likelihood ratios

$$\widehat{\mathrm{LR}}(z) = \frac{\hat{\Pr}(H_p|E)}{\hat{\Pr}(H_d|E)} \Bigg/ \frac{\hat{\Pr}(H_p)}{\hat{\Pr}(H_d)} = \frac{\widehat{\mathrm{tdr}}(z)\ \hat{\pi}_0}{\widehat{\mathrm{fdr}}(z)\ 1-\hat{\pi}_0}$$



Known match LR values

Known non-match LR values

Bayesian Match Probabilities from CMS

- 2007 Neel and Wells study[Neel, Wevers, Buckleton]:
  - Count the number of each type of CMS run for KM and KNM comparisons
    - A CMS type is its run length:
      - 4X means 4 matching adjacent lines in a comparison of two striation patterns

914 KM comparisons

Number observed	CMS run lengths: 2X	3X	4X	…
0	508	612	694	…
1	186	172	135	…
2	109	59	43	…
3	39	29	19	…
4	21	15	16	…
5	10	9	2	…
6	4	9	1	…
7	10	6	3	…
8	14	2	0	…
>8	13	1	1	…

1411 KNM comparisons

Number observed	CMS run lengths: 2X	3X	4X	…
0	771	1239	1357	…
1	298	124	47	…
2	143	35	4	…
3	84	10	2	…
4	46	2	1	…
5	21	1	0	…
6	13	0	0	…
7	14	0	0	…
8	6	0	0	…
>8	15	0	0	…

Model each column of counts as arising from a multinomial distribution with Dirichlet prior

Bayesian Match Probabilities from CMS

- Updated CMS run length probabilities:

KM comparisons

Number observed	CMS run lengths: 2X	3X	4X	…
0	0.550	0.663	0.752	…
1	0.202	0.187	0.147	…
2	0.119	0.065	0.047	…
3	0.043	0.032	0.022	…
4	0.024	0.018	0.019	…
5	0.012	0.011	0.003	…
6	0.005	0.011	0.002	…
7	0.012	0.008	0.004	…
8	0.016	0.003	0.001	…
>8	0.015	0.002	0.002	…

KNM comparisons

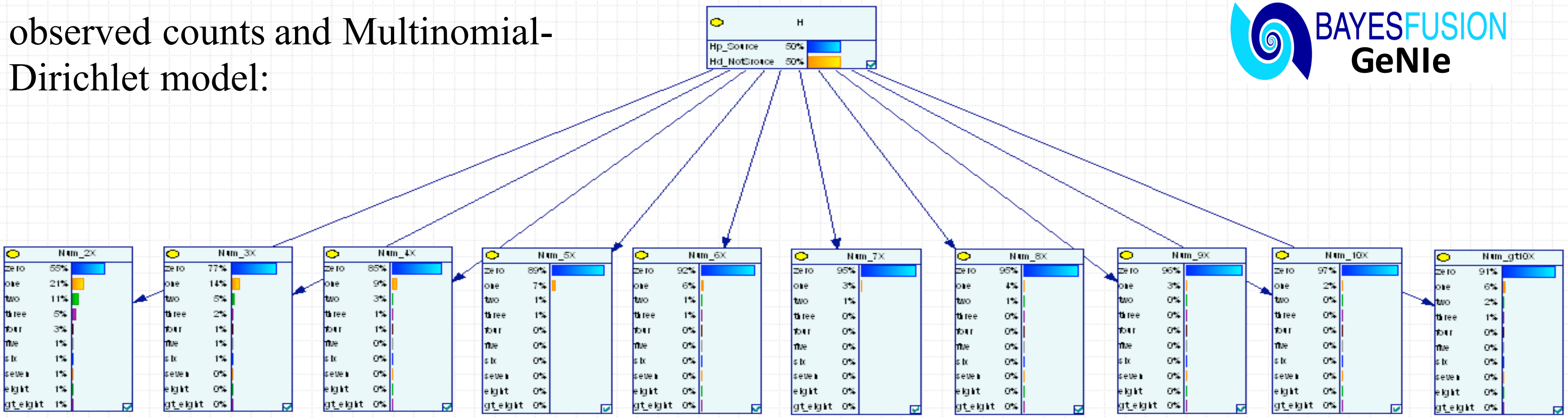
Number observed	CMS run lengths: 2X	3X	4X	…
0	0.5440	0.8726	0.9556	…
1	0.2099	0.0880	0.0338	…
2	0.1010	0.0254	0.0035	…
3	0.0598	0.0078	0.0021	…
4	0.0332	0.0021	0.0014	…
5	0.0155	0.0014	0.0007	…
6	0.0099	0.0007	0.0007	…
7	0.0105	0.0007	0.0007	…
8	0.0049	0.0006	0.0007	…
>8	0.0113	0.0007	0.0007	…

- So what can we use these for??
  - Lot’s of stuff, but we put them into a **Bayesian network**:
    - BN model for *Match/Non-match probabilities* given observed numbers of CMS runs

Bayesian Networks

"Prior" network based on Neel and Wells observed counts and Multinomial-Dirichlet model:

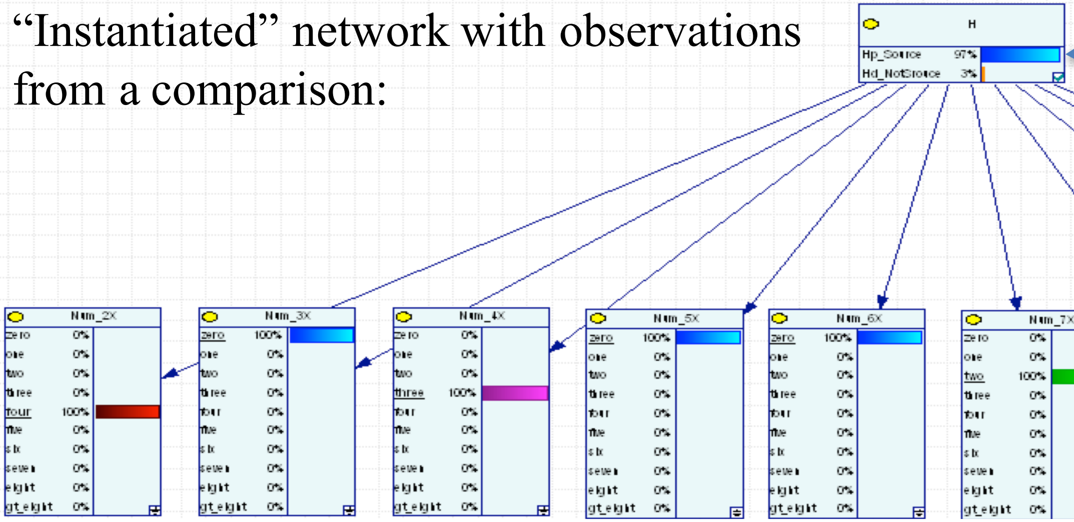
BAYESFUSION GeNIe



H	
Hp_Source	50%
Hd_NotSrouce	50%

	Num_2X	Num_3X	Num_4X	Num_5X	Num_6X	Num_7X	Num_8X	Num_9X	Num_10X	Num_gt10X
zero	55%	77%	85%	89%	92%	95%	95%	96%	97%	91%
one	21%	14%	9%	7%	6%	3%	4%	3%	2%	6%
two	11%	5%	3%	1%	1%	1%	1%	0%	0%	2%
three	5%	2%	1%	1%	1%	0%	0%	0%	0%	1%
four	3%	1%	1%	0%	0%	0%	0%	0%	0%	0%
five	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%
six	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%
seven	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%
eight	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%
gt_eight	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%

"Instantiated" network with observations from a comparison:



H	
Hp_Source	97%
Hd_NotSrouce	3%

	Num_2X	Num_3X	Num_4X	Num_5X	Num_6X	Num_7X	Num_8X	Num_9X	Num_10X	Num_gt10X
zero	0%	100%	0%	100%	100%	0%	100%	100%	100%	100%
one	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
two	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%
three	0%	0%	100%	0%	0%	0%	0%	0%	0%	0%
four	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%
five	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
six	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
seven	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
eight	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
gt_eight	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Estimate of the "match" probability which can be turned into an LR if so desired

Future Directions

- **Clean up:** cptID, feature2, fdrID
- **GUI modules** for common toolmark comparison tasks/calculations using 3D microscope data
- **2D features** for toolmark impressions
- **Parallel/GPU/FPGA** implementation of computationally intensive routines e.g. ALMA Correlator for astronomy data
  - Especially for retrieving “relevant pop/best match” reference sets
- **Uncertainty for Bayesian Networks**
  - Models, parameters…

References

Zheng: http://www.nist.gov/forensics/ballisticsdb/

Lillien:

- http://www.openfmc.org/
- http://www.cadreforensics.com/

Brubaker: https://github.com/OpenFMC/x3p

Petraco:

- https://github.com/npetraco/x3pr
- https://github.com/npetraco/feature2
- https://github.com/npetraco/cptID
- https://github.com/npetraco/fdrID

Edd:

- https://cran.r-project.org/web/packages/Rcpp/index.html
- http://dirk.eddelbuettel.com/code/rcpp.html

OpenCV: http://opencv.org/

Whitcher: https://cran.r-project.org/web/packages/waveslim/index.html

R-Core: https://www.r-project.org/

Vovk: http://www.alrw.net/

Efron:

- Efron, B. “Large-Scale Inference: Empirical Bayes Methods for Estimation, Testing, and Prediction”, Cambridge, 2013.

References

locfdr: https://cran.r-project.org/web/packages/locfdr/index.html

JAGS:

- http://mcmc-jags.sourceforge.net/
- https://cran.r-project.org/web/packages/rjags/index.html

Stan:

- http://mc-stan.org/
- https://cran.r-project.org/web/packages/rstan/index.html

Neel:

- Neel, M and Wells M. "A Comprehensive Analysis of Striated Toolmark Examinations. Part 1: Comparing Known Matches to Known Non-Matches", AFTE J 39(3):176-198 2007.

Wevers:

- Wevers, G, Michael Neel, M and Buckleton, J. "A Comprehensive Statistical Analysis of Striated Tool Mark Examinations Part 2: Comparing Known Matches and Known Non-Matches using Likelihood Ratios", AFTE J 43(2):1-9 2011.

Buckleton:

- Buckleton J, Nichols R, Triggs C and Wevers G. "An Exploratory Bayesian Model for Firearm and Tool Mark Interpretation", AFTE J 37(4):352-359 2005.

BayesFusion: http://www.bayesfusion.com/

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