Learning Algorithms for Evaluating Forensic Glass Evidence

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- ISU database of glass fragments can be downloaded from: **www.github.com/CSAFE-ISU/AOAS-2018-glass-manuscript**.
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Partial list of literature cited - I

- Parker and Holford, 1968. *Applied Statistics*
- Curran et al., 1997. *Science and Justice* (I, II, III)
- Curran et al., 2000. *Forensic Interpretation of Glass Evidence*
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- Koons and Buscaglia, 2001. *J of Forensic Sci.*
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Partial list of literature cited - II

- Campbell et al., 2009. *Science and Justice*
- Zadora, 2009. *J of Foren Sci*
- Weis et al., 2011, *J of Anal Atom Spectrometry*
- Hepler et al., 2012. *Foren Sci Int*
- ASTM-E2330-2013, 2013. *ASTM International*
- Trejos et al., 2013, *J of Anal Atom Spectrometry*
- ASTM-E2927-2016, 2016. *ASTM International*
- Park and Carriquiry, 2018. *Annals of Appl Stat*

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Outline

- Setting up the problem
- Data
- Interpretation methods recommended in ASTM-E2330 and ASTM-E2927.
- Approach we propose.
- Comparison of methods.
- Final thoughts.

Some background information

- Glass evidence may arise when a glass object is broken during the commission of a crime.
- Small fragments can transfer to the perpetrator.

Do the fragments on the suspect come from the broken glass object at the scene?

- Two related questions:
  - What is the degree of similarity between fragments on the suspect and the broken glass?
  - Is the degree of similarity *typical* among fragments from the same source?

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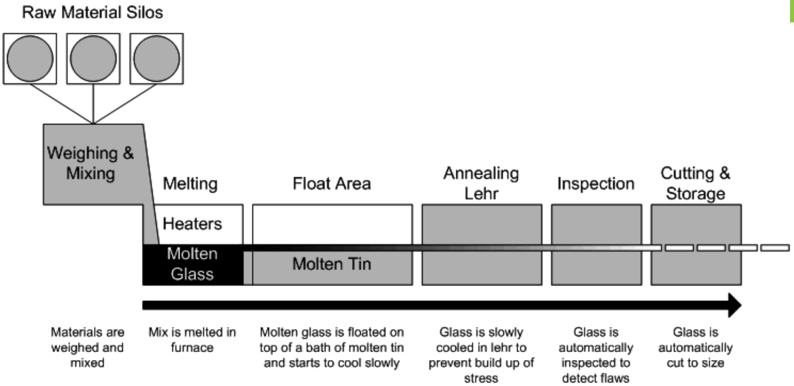
Glass manufacture

- Glass is made by melting together sand, soda ash, dolomite, limestone and sodium sulfate at high temps.
- Manufacturers also add *cullet* (reclycled broken glass) to the mixture.
- Float glass is produced by floating the molten mixture on a bed of liquified tin as it cools down.
- The ribbon of glass is then cut and processed for transportation.

Production of float glass (Tangram Tech)



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Properties of glass

- Physical: color, thickness, coating.
- Optical: refractive index.
- Chemical: concentration of elements in glass.
- **Elemental concentrations** can be measured using different technologies. Here we focus on LA-ICP-MS.
- Typically, 18-20 elements used to characterize glass in forensic applications.

Measurements and datasets

- Focus on the concentration (in ppm) of 18 elements in glass: Li, Na, Mg, Al, K, Ca, Ti, Mn, Fe, Rb, Sr, Zr, Ba, La, Ce, Nd, Hf, Pb.
- Method: LA-ICP-MS (details in github repository for ISU data).
- **BKA database** (Weis et al., 2011):
  - Sixty two samples of float glass with different origin, one fragment per sample, six replicate measurements.
  - One sample from VA, 34 fragments, six replicates. One fragment was measured on 11 consecutive days.

Databases (cont'd)

- **FIU database** (Almirall et al., circa 2002):
  - One hundred twelve samples of architectural float glass, different origin.
  - One fragment per sample, three replicate measurements.
- Fourteen elements in common with Weis et al. database.

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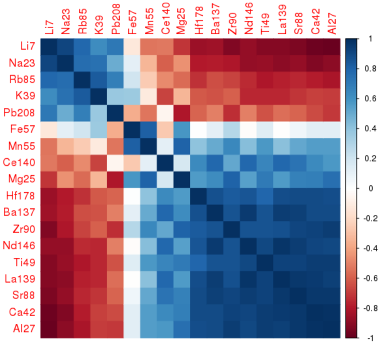
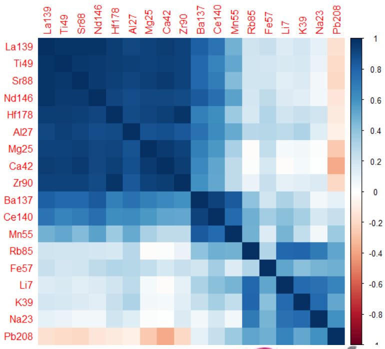
Datasets (cont'd)

- **ISU database** (Park and Carriquiry, 2018):
  - Thirty one samples of architectural float glass from manufacturer A and 17 samples from manufacturer B.
  - Twenty four fragments per sample.
  - Twenty one fragments replicated five times, three fragments replicated 20 times.
- Total: 1,152 fragments, 7,920 measurement vectors.
- Same elements as in BKA analyses.

Some simple statistics





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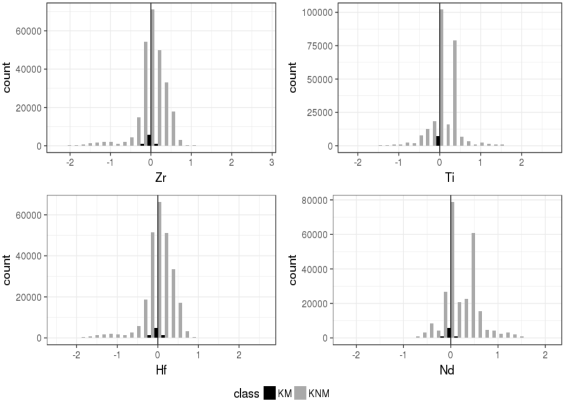
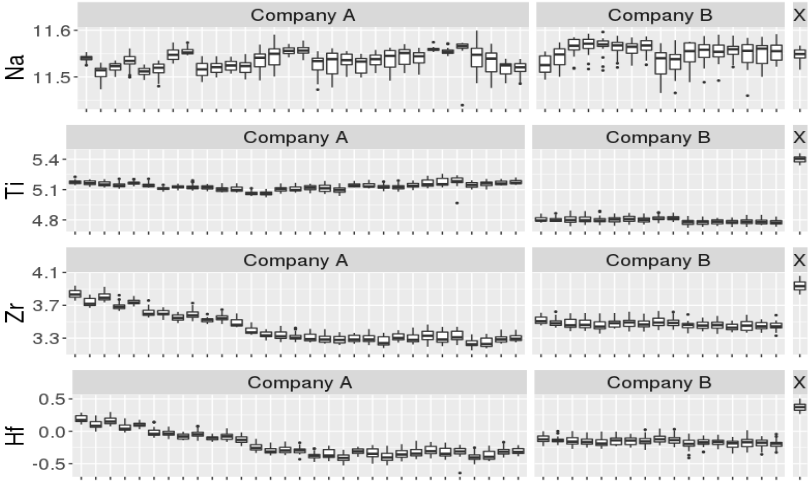
Some simple statistics (cont'd)



Some simple statistics (cont'd)



Analysis and interpretation of data

- Three main types of approaches:
  - **Interval-based, univariate**: Weis et al., 2011, Trejos et al., 2013. Recommended in ASTM-E2330-12 and ASTM-E2927-16.
  - Multivariate, parametric: Parker and Holford (1968), Curran and collaborators (1997, 2000, 2003, 2009...).
  - **Non-parametric, multivariate**: Zadora (2009), Park and Carriquiry (2018).

Interval-based methods

- Proceeding one element at a time, do:
  1. Obtain three replicate measurements from ≥ 3 fragments from K source and fragment from Q sample.
  2. From K fragments, compute mean and SD, and construct interval
$$\text{mean} \pm 4 \times \max(\text{SD}, 0.03\text{mean})$$
- If mean concentrations in Q fall inside the intervals *for all elements*, declare Q to be indistinguishable from the known source.

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Interval-based methods (cont'd)

- Good attributes of standard interval-based method:
  - Easy to implement.
  - Does not depend on external, reference population data.
- Limitations:
  - Relies only on case work measurements, so does not address **significance of similarity between K and Q**.
  - Statistically inefficient: ignores dependencies among elements.
  - Probability that K and Q are deemed indistinguishable *increases* with noise in the measurements.

Interval-based methods (cont'd)

- The interval based method can be expressed as a score:

$$S_{ASTM\,i} \text{ for element }_i = \left|\frac{\text{mean in K} - \text{mean in Q}}{\max(\text{SD}, 0.03\text{mean})}\right|.$$

  And $S_{ASTM} = \max(S_{ASTM})_i$.
- **Decision rule: if $S_{ASTM} \leq 4$, samples are indistinguishable**.
- Weis et al. (2011) version: Use a fixed *relative standard deviation* (FRSD) computed from 90 mean concentrations of element obtained from DGG 1.
- If FRSD < 0.03mean $\longrightarrow$ FRSD $= 0.03$mean.

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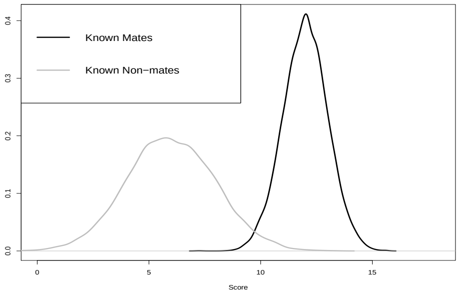
Supervised learning algorithms- General idea

- Develop a score that quantifies the similarity between two fragments of glass.
- Use the score to compare all possible pairs of fragments from a large and "representative" sample of glass fragments.



Learning algorithms - General idea (cont'd)

- **IF** (big if) the "training data" are extensive and representative and **IF** the distribution of scores is different for known mates and known non-mates, **THEN** the practitioner working on a case would:
    1. Compute the similarity score for her pair of known and question fragments. Answers the question: *How similar are these two fragments?*
    2. Compare the value of the score to the reference score distributions. Answers the question: *Is the value typical if my samples have a common source or is it alike scores observed when fragments have a different source?*

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Learning algorithms – Pros

- Advantages:
  - Quantifies the degree of similarity between two fragments.
  - Enables calculation of *probative value of the evidence*.
  - Permits calculation of "error rates".
  - Once trained, algorithm can be used to compare any pair of fragments as long as they are of the same type as the fragments in the training data.
  - Statistically more appealing – exploits dependencies across elemental concentrations.

Learning algorithms – Cons

- Limitations:
  - Performance of algorithm is **critically dependent** on training data.
  - Black box type of approach.
  - Selection of reference population of non-mated pairs requires some thought.
  - Algorithm needs to be re-trained as new population measurements become available.

Learning algorithms – How

- Given pairs of fragments for which we know "ground truth", the algorithm learns which combinations of *feature values* are associated with pairs of fragments that are known mates and known non-mates.
- Presented with a new pair (not in the training dataset), the algorithm determines whether the corresponding feature values suggest whether they are mates or not.

Learning algorithms – Features

- *Features* are measurements determined by us because we believe that they can help us classify fragments into mates/non-mates.
- We defined 18 features as follows:
  - For each fragment, take logs of all concentrations and average over replicates to get 18 mean concentrations.
  - Compute the differences of 18 means for two fragments. These differences are the features we use to classify pairs of fragments as mated or non-mated.

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Learning algorithms – Which

- There are many different supervised learning algorithms: logistic regression, support vector machines, random forests, Bayesian classification and regression trees,....
- We present results obtained using random forests. BART results were similar. (Breiman, 2001; Chipman et al., 2010).
- RFs are not difficult to implement but one must be mindful of:
  - Imbalances in the training data.
  - Independence (or close to) of units in training and testing datasets.

Implementation of RF

- Training and validation dataset: 28 panes from companies A and B produced on different dates plus the 62 panes from different sources from BKA data.
  - 7,705 pairs of mated fragments and 260,573 pairs of non-mated fragments.
- Testing dataset: 20 panes from companies A and B produced on different dates plus the pane from BKA with multiple fragments analyzed.
  - 5,590 mated fragments and over 123,805 non-mated pairs.
- Down-sampling of majority class and 10-fold validation.
- We report only Out-Of-Bag errors.

Setting up the comparison

- Focus on results from both interval-based methods and RF, using only the 5,590 + 123,805 fragments in the test dataset.
- To implement Trejos et al. (2013) and Weis et al. (2011) approaches we:
  - Selected a Q fragment at random. Averaged concentrations over five reps.
  - Selected three K fragments at random from either the same or a different pane as Q. Averaged concentrations over 15 reps.
  - Computed S_{ASTM} (as recommended in ASTM-E2927 and ASTM-E2330) and as modified in Weis et al. (2011).
  - Counted how many pairs of fragments were correctly classified.

Setting up the comparison (cont'd)

- For each fragment Q, we randomly selected 30 comparison sets, for a total of 15,300 comparisons of known mates and 150,060 comparisons of known non-mates.

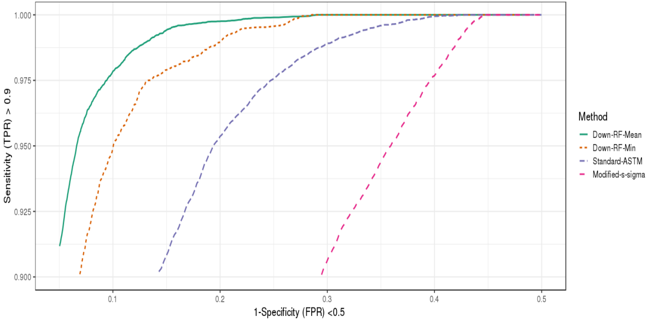
Two possibilities for the RF

- In the RF, we make pairwise comparisons.
- With three fragments (or more) from K, we can construct pairs in different ways:
  - Combine three K fragments into an “average” fragment (akin to ASTM approach).
  - Compute three similarity scores and pick one.
- Thresholds:
  - Interval-based methods: pair is mated if score is less than 4.
  - For RF, classify pair as mated if RF score is larger than 0.5.

Results

Model	AUC	EER	Opt. Threshold	FPR	FNR
RF-Mean	0.984	0.061	0.590	0.076	0.037
RF-Min	0.975	0.080	0.330	0.101	0.049
ASTM	0.954	0.122	3.300	0.142	0.0984
Weis et al.	0.899	0.204	12.961	0.298	0.096

ROC curves



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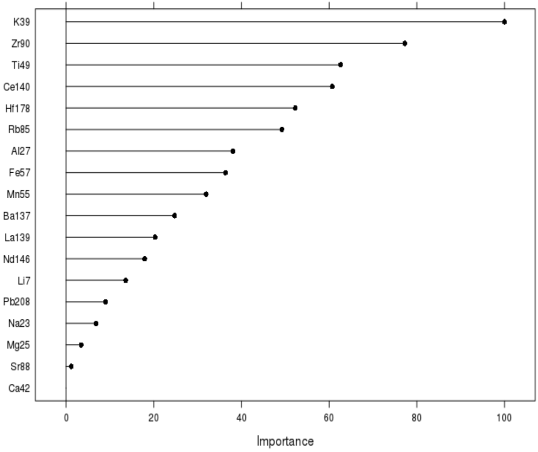
Feature importance



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When methods disagree...

Method	False Negatives	False Positives
Standard ASTM	92	7635
Random Forest	9	2299

Elements driving false positives: K (28%), Li (19%), Zr (14%), Ba (9%), Ti (7%).

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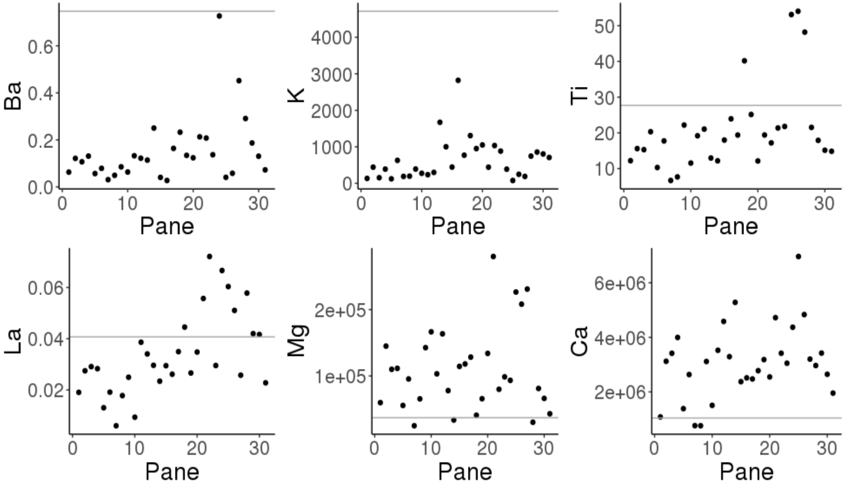
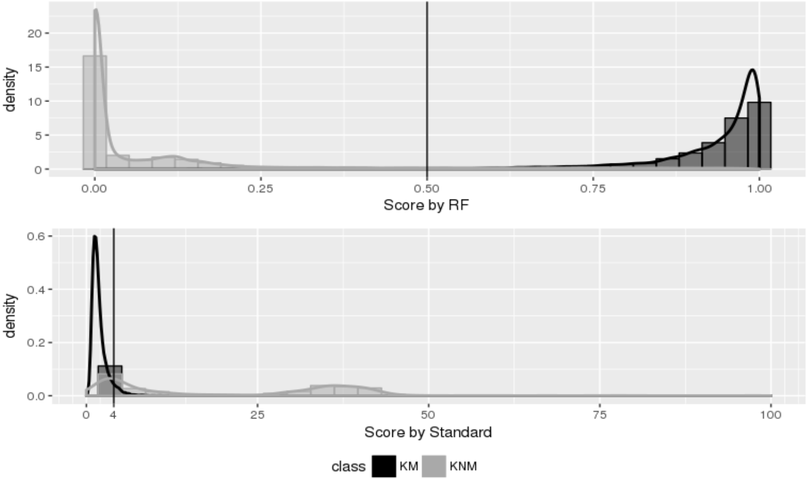
Within and between pane variances

- In these data, interval-based methods produce a high proportion of FPs (falsely declaring that two fragments are mates).
- This occurs because for some elements, the within-pane variance in concentration is *larger* than the between-pane variance.
- When this occurs, intervals get larger.

Within and between variances (cont'd)



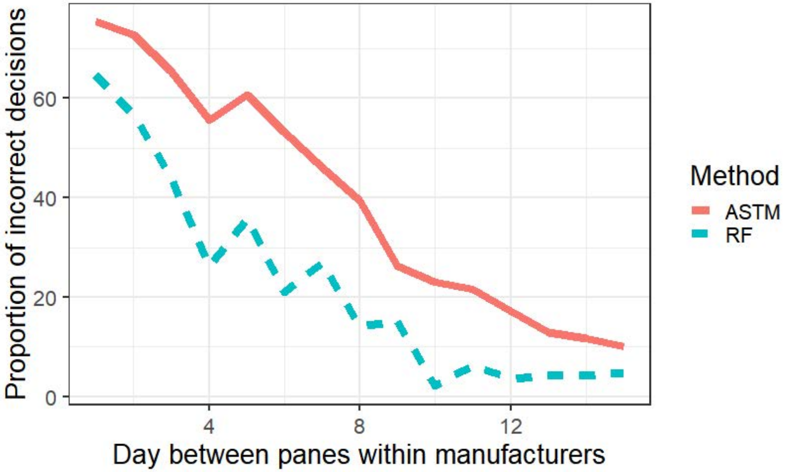
Distributions of scores



Increasing number of K fragments

	Standard 4 - σ			
Error	3 controls	6 controls	9 controls	12 controls
FNR	0.0559	0.0176	0.0067	0.0042
FPR	0.1866	0.1948	0.2017	0.2043
	Modified 4 - σ			
Error	3 controls	6 controls	9 controls	12 controls
FNR	0.4482	0.4303	0.4184	0.4203
FPR	0.0628	0.0646	0.0662	0.0674

Effect of manufacture date



Some final thoughts

- It is possible to do better than the current standards.
- Little progress will occur unless more data become PUBLICLY available. **Not sharing data impedes progress.**
- From a statistical viewpoint, glass problem is similar to bullet lead problem:
  - What do we mean by "same source"?
  - Is it possible to draw conclusions beyond "cannot exclude"?
- Interpretation sections in ASTM standards seem to be premature and can be misleading for lay persons such as jurors.

THANKS

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