

Y Chromosomal STR Markers: Assessing Evidential Value

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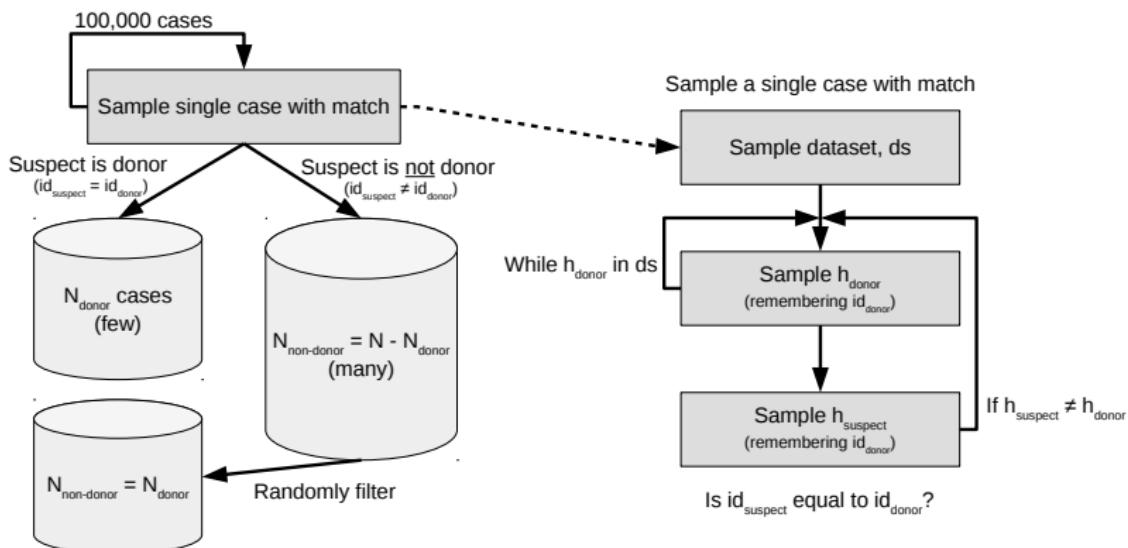
LR and donorship

- ▶ Profile from donor to crime scene stain, h_{donor}
- ▶ Profile from suspect, $h_{\text{suspect}} = h_{\text{donor}}$ (we have a match)
- ▶ Reference database
- ▶ Decision problem: Is the suspect the donor? Answer based on h_{suspect} and reference database
- ▶ Simple case:
 $LR = 1/\text{match probability} = 1/\text{population frequency}$
- ▶ Decision problem tried solved by LR
- ▶ Higher LR , more evidence that the suspect is the donor



Simulate cases with known donor

- ▶ Simulate population (simple) of approx 2,000,000 individuals
 - ▶ FW, 100,000 in 300 generations w/ growth rate 1.01
 - ▶ 7 loci, neutral single-step mutation model ($\mu = 0.003$)





Estimators problem

Database size n :

- ▶ n_1 : singletons
- ▶ n_2 : doubletons
- ▶ κ : n_1/n

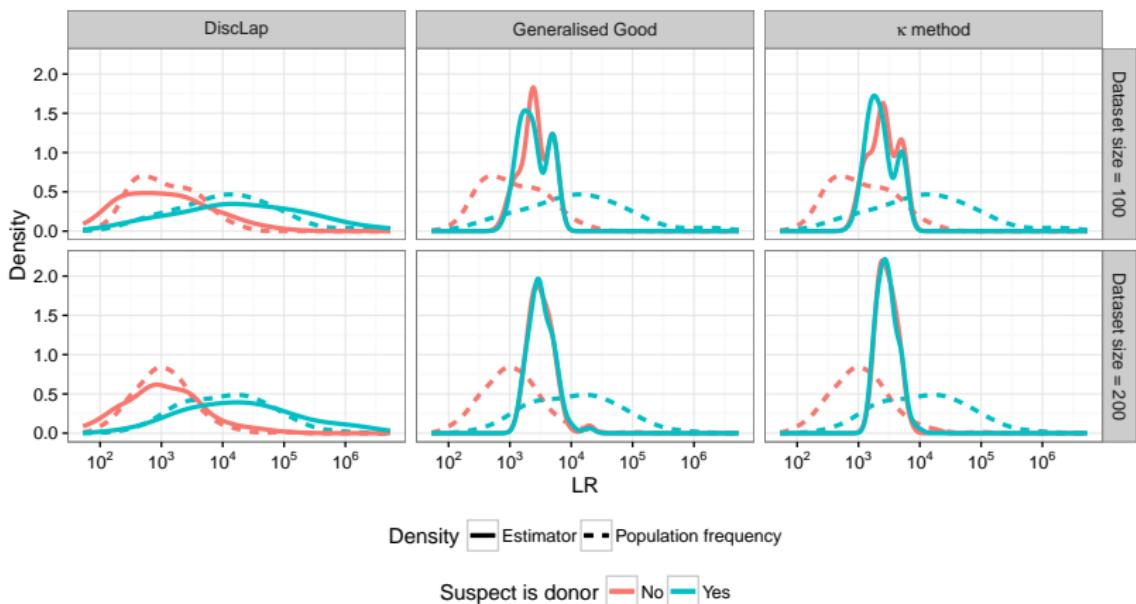
Estimators:

- ▶ Kappa (Brenner, 2010): $LR = n/(1 - \kappa) = n \cdot \frac{n}{n-n_1} > n$
- ▶ Generalised Good (Cereda, 2015): $LR = (n \cdot n_1)/(2 \cdot n_2) = n \cdot \frac{n_1}{2n_2}$
- ▶ Discrete Laplace (Andersen, 2013): Statistical model using genetic information

```
fit <- disclapmix(db, 5L)
LR = 1/predict(fit, h)
```

LR distributions

- Dataset size $n = 100$: $N_{\text{donor}} = N_{\text{non-donor}} = 135$
- Dataset size $n = 200$: $N_{\text{donor}} = N_{\text{non-donor}} = 148$
- [Larger dataset, greater LR , and greater $P(\text{suspect} = \text{donor} \mid \text{match})$ hence more cases where it happens.]

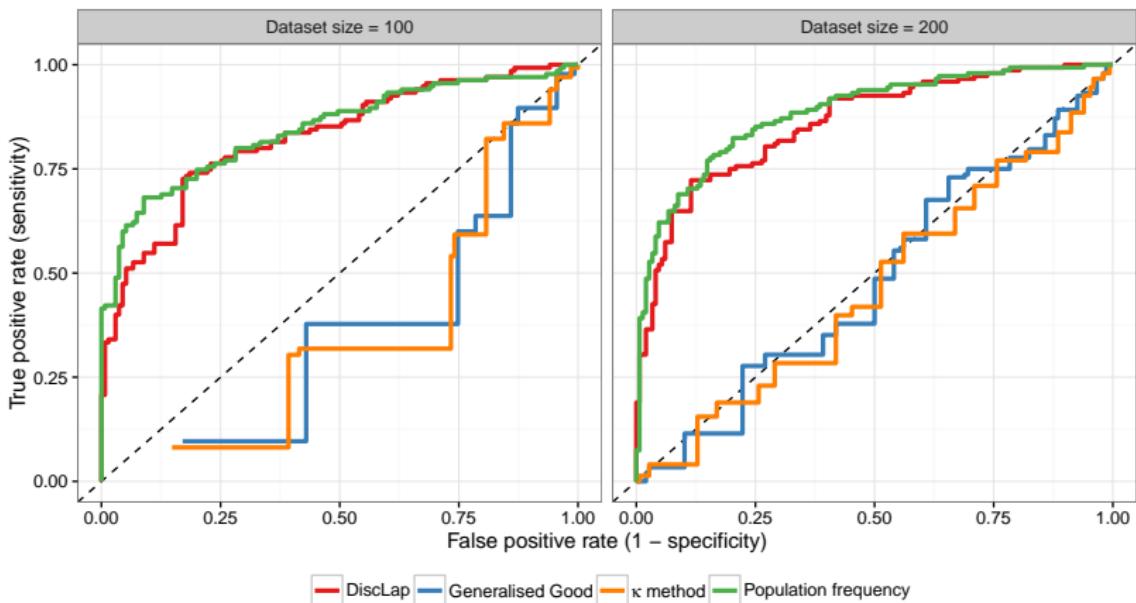




ROC curve of decision problem

- ▶ $LR_{\text{case}} \geq LR_{\text{threshold}}$: Suspect is donor
- ▶ $LR_{\text{case}} < LR_{\text{threshold}}$: Suspect is not donor

For all possible $LR_{\text{threshold}}$'s:





Best LR threshold

Dataset size 200

$$LR_{\text{threshold}} = \operatorname{argmax}_t (\text{sensitivity}(t) + \text{specificity}(t))$$

$$LR_{\text{threshold}}(r) = \operatorname{argmax}_t (\text{sensitivity}(t) + r \cdot \text{specificity}(t))$$

Dataset size 200:

Estimator	r	$LR_{\text{threshold}}(r)$	TP	TN	FP	FN	FPR	FNR
DiscLap	1	3,440	107	131	17	41	0.11	0.28
Generalised Good	1	2,630	107	52	96	41	0.65	0.28
Kappa	1	2,550	88	65	83	60	0.56	0.41
Population frequency	1	2,220	122	118	30	26	0.20	0.18
DiscLap	50	113,650	28	148	0	120	0.00	0.81
Generalised Good	50	20,570	0	148	0	148	0.00	1.00
Kappa	50	20,570	0	148	0	148	0.00	1.00
Population frequency	50	104,770	11	148	0	137	0.00	0.93



Discussion

Validation of estimators:

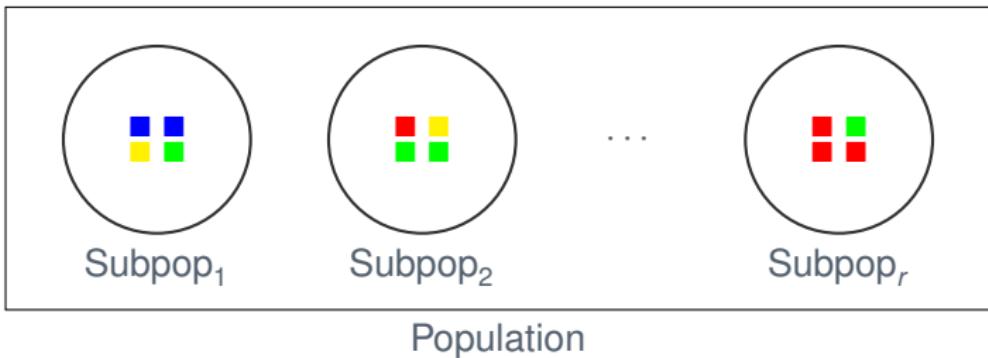
- ▶ Fisher-Wright population too simple
- ▶ Single-step mutation model too simple
- ▶ More realistic reference population simulation schemes agreed upon by community

Discrete Laplace workings in progress:

- ▶ Working on quantifying statistical error of estimate
- ▶ C++ library for faster estimation
- ▶ `'fit <- disclapmix(db)'` (more automatic and user-friendly; maybe using several number of clusters, e.g. a weighted average of 3-5 best)



Population substructure



Coloured squares represent haplotypes.

Random man (donor) and suspect belong to same subpopulation:
Expected to share a haplotype more often than a random database sample from the whole population would represent.

θ (theta) correction seeks to quantify this.



Match probability

H_d : 'A random man – that originate from the same subpopulation as the suspect – left the Y-chromosome DNA in the crime stain.'

- ▶ Reference database from this subpopulation exists
 - ▶ Subpopulation is now the population
 - ▶ Use this reference database and no θ correction!
- ▶ Reference database from population containing subpopulation (as well as other subpopulations, and structure unknown):
 - ▶ One approach (the Balding-Nichols model):
$$P(E \mid H_d) \stackrel{BN}{=} \theta + (1 - \theta)p_h$$
 - ▶ θ (theta) ($0 \leq \theta \leq 1$)
 - ▶ Population parameter (related to how much haplotype frequencies vary in different subpopulations)
 - ▶ Most simple model – many extensions possible
 - ▶ p_h : Population frequency of h ($0 \leq p_h \leq 1$)



Match probability

Note, that

$$P(E | H_d) \stackrel{BN}{=} \theta + (1 - \theta)p_h \geq \theta$$

and

$$P(E | H_d) \stackrel{BN}{=} \theta + (1 - \theta)p_h \geq p_h$$

- ▶ If p_h is really small compared to θ : $\theta + (1 - \theta)p_h \approx \theta$
- ▶ If p_h is really large compared to θ : $\theta + (1 - \theta)p_h \approx p_h$

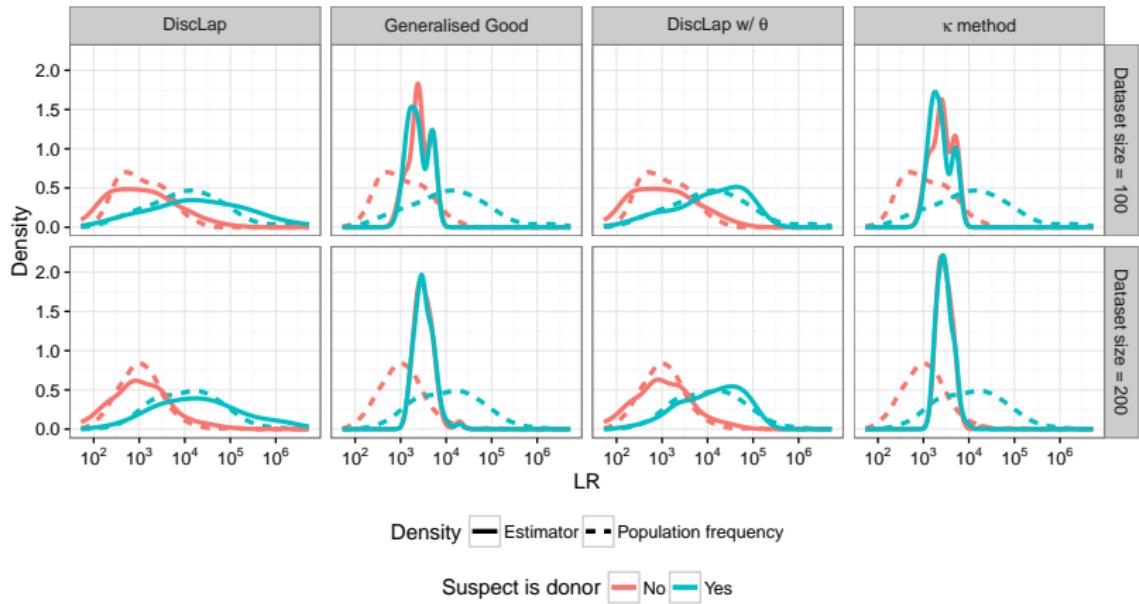
	$p_h = 1/100,000 = 0.00001$	$p_h = 1/100 = 0.01$
$\theta = 0.001$	$P(E H_d) = 0.0010099$	$P(E H_d) = 0.01099$
$\theta = 0.003$	$P(E H_d) = 0.0030099$	$P(E H_d) = 0.01297$



Best LR threshold

Dataset size 200

$$\theta = 0.00001 = 10^{-5} = 1/10^5$$





Best LR threshold

Dataset size 200

$$\theta = 0.00001 = 10^{-5} = 1/10^5$$

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Thank you for your attention

(Slides soon available at <http://people.math.aau.dk/~mikl/>)