**Probabilistic Genotyping: Considerations for** Implementation

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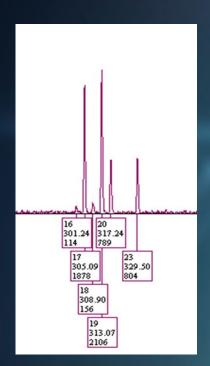
"Probabilistic genotyping refers to the use of biological modeling, statistical theory, computer algorithms, and probability distributions to calculate likelihood ratios (LRs) and/or infer genotypes for the DNA typing results of forensic samples ("forensic DNA typing results")." – SWGDAM Guidelines for the Validation of Probabilistic Genotyping Systems



Two Main Functions of Probabilistic Genotyping (Prob Gen):

- Mixture deconvolution based on data in DNA profile, agnostic to race or ethnicity
- Calculation of the statistical weight of a comparison to a Person of Interest (POI)
  - based on relevant population databases

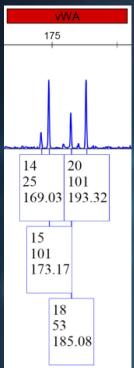
# Evolution of DNA Mixture Interpretation



Analysis Approach		4 allele	
СРІ	17,19; 17,20; 17	7,23; 19,20; 19,23; 20, 20,20; 23,23	23; 17,17; 19,19
RMP		17,19; 20,23	
	17, 19	20, 23	9.3953E-1
	19, 23	17, 20	1.9485E-2
	17, 23	19, 20	1.6781E-2
	19, 20	17, 23	1.0811E-2
	17, 20	19, 23	8.7925E-3
STRmix™	20, 23	17, 19	4.6043E-3



# Evolution of DNA Mixture Interpretation



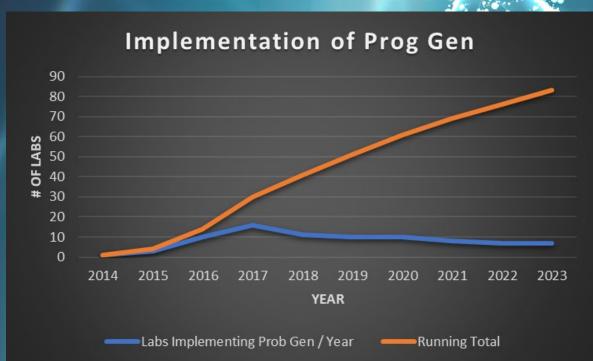
	CPI	
14,15	14,18	14,20
15,18	15,20	18,20
14,14	15,15	18,18
	20,20	

М	odified RIV	IP
14,15	14,18	14,20
15,18	15,20	18,20

		All the second s	
vWA	15, 20	14, 18	4.8320E-1
	18,20	14, 15	1.2234E-1
	15, 18	14, 20	1.0884E-1
	14, 18	15, 20	4.6498E-2
	14, 20	15, 18	4.3751E-2
	14, 15	18, 20	3.9500E-2
	15,20	18, 20	3.2796E-2
	15, 18	20, 20	2.3010E-2
	15, 20	15, 18	2.1751E-2
	15, 20 15, 18	18, 20 20, 20	3.2796E-2 2.3010E-2

The Forensic Community is Moving Toward the Use of Prog

Gen





- Quality Assurance Standards (QAS) for Forensic DNA Testing Laboratories
- ANSI / ASB
- OSAC
- UK Forensic Science Regulator
- DNA Commission of the International Society of Forensic Genetics

# Common Themes of Validation

- Ensure that the software is fit-for-purpose
- Validation performed using the types of evidence samples expected to be encountered in casework (template amounts, mixture ratios, number of contributors, degradation, inhibition, etc.)
- Accuracy
- Precision
- Sensitivity (true contributors, Type I errors)
- Specificity (non-contributors, Type II errors)
- Comparison to previous methods

# Common Themes of Validation

- Validation determines the limits of the conditions where the software is expected to produce reliable results find the breaking points
- The results of the laboratory's validation are used to inform the software use and interpretation protocols

# PCAST Report (2016)

Finding 3: DNA analysis of complex-mixture samples

Foundational validity. PCAST finds that:

(2) Probabilistic genotyping. Objective analysis of complex DNA mixtures with probabilistic genotyping software is relatively new and promising approach. Empirical evidence is required to establish the foundational validity of each such method within specified ranges. At present, published evidence supports the foundational validity of analysis, with some programs, of DNA mixtures of 3 individuals in which the minor contributor constitutes at least 20 percent of the intact DNA in the mixture and in which the DNA amount exceeds the minimum required level for the method. The range in which foundational validity has been established is likely to grow as adequate evidence for more complex mixtures is obtained and published.

### Validation

- PubMed search "Probabilistic Genotyping" > 800 publications listed
- Every US laboratory that has implemented some form of Prob Gen has performed an internal validation (> 80)
- Difficult to publish validations because they are not considered novel by the journals



Contents lists available at ScienceDirect

Forensic Science International: Genetics



journal homepage; www.elsevier.com/locate/fsigen

Research paper

#### Internal validation of STRmix™ - A multi laboratory response to PCAST



Jo-Anne Bright<sup>a,\*</sup>, Rebecca Richards<sup>a</sup>, Maarten Kruijver<sup>a</sup>, Hannah Kelly<sup>a</sup>, Catherine McGovern<sup>a</sup>, Alan Magee<sup>b</sup>, Andrew McWhorter<sup>c</sup>, Anne Ciecko<sup>d</sup>, Brian Peck<sup>c</sup>, Chase Baumgartner<sup>c</sup>, Christina Buettner<sup>s</sup>, Scott McWilliams<sup>s</sup>, Claire McKenna<sup>b</sup>, Colin Gallacher<sup>l</sup>, Ben Mallinder<sup>l</sup>, Darren Wright<sup>l</sup>, Deven Johnson<sup>k</sup>, Dorothy Catella<sup>l</sup>, Eugene Lien<sup>m</sup>, Craig O'Connor<sup>m</sup>, George Duncan<sup>a</sup>, Jason Bundy<sup>o</sup>, Jillian Echard<sup>p</sup>, John Lowe<sup>d</sup>, Joshua Stewart<sup>r</sup>, Kathleen Corrado<sup>s</sup>, Sheila Gentile<sup>s</sup>, Marla Kaplan<sup>i</sup>, Michelle Hassler<sup>u</sup>, Naomi McDonald<sup>s</sup>, Paul Hulme<sup>w</sup>, Rachel H. Oefelein<sup>s</sup>, Shawn Montpetit<sup>y</sup>, Melissa Strong<sup>y</sup>, Sarah Nöël<sup>s</sup>, Simon Malsom<sup>A</sup>, Steven Myers<sup>B</sup>, Susan Welti<sup>c</sup>, Tamyra Moretti<sup>b</sup>, Teresa McMahon<sup>E</sup>, Thomas Grill<sup>F</sup>, Tim Kalafut<sup>G</sup>, MaryMargaret Greer-Ritzheimer<sup>H</sup>, Vickie Beamer<sup>I</sup>, Duncan A. Taylor<sup>J,K</sup>, John S. Buckleton<sup>a,L</sup>



## Calibration:

- Logical expectations
- Turing expectations
- Hannig et al.
- Ramos and Gonzalez-Rodriguez

#### Are reported likelihood ratios well calibrated?

Jan Hannig<sup>a,c,\*</sup>, Sarah Riman<sup>b</sup>, Hari Iyer<sup>a</sup>, Peter M. Vallone<sup>b</sup>

Forensic population genetics - original research

Testing likelihood ratios produced from complex DNA profiles

Duncan Taylor <sup>a,b,\*</sup>, John Buckleton <sup>c</sup>, Ian Evett <sup>d</sup>

## Applying calibration to LRs produced by a DNA interpretation software

Jo-Anne Bright<sup>a</sup>, M. Jones Dukes<sup>b</sup>, S. N. Pugh<sup>c</sup>, I. W. Evett<sup>d</sup> and J. S. Buckleton<sup>a</sup>

<sup>a</sup>Institute of Environmental Science and Research Limited, Auckland, New Zealand; <sup>b</sup>QIAGEN LLC, Germantown, MD, USA; <sup>c</sup>Palo Cedro, CA, USA; <sup>d</sup>Principal Forensic Services Ltd., Bromley, UK

#### Calibration of STRmix LRs following the method of Hannig et al.

John Buckleton<sup>1,2</sup>, Maarten Kruijver<sup>2</sup>, James Curran<sup>1</sup>, and Jo-Anne Bright<sup>2</sup>

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c ESR, Private Bag 92021, Auckland 1142, New Zealand

d Principal Forensic Services Ltd., London, UK

# **DNA Analyst Training:**

- Basic DNA interpretation and mixture interpretation
- Expected variation in DNA profiles (stochastic effects, stutter, peak height balance, degradation, inhibition, etc.)
- · Manual deconvolution of mixtures is critical
- Underlying principles of Prob Gen software used
- Limits of the software used based on the validation

D8S11789	Alleles Present	RFU			Potent	tial Gen	otype Cor	mbinatio	ons		
	11		П	1 allele		3 a	lleles			4 alleles	
1	12		1		11	11	y 12	13			
	13		1		12	12	11	13			
			1		13	13	11	12			
	Total RFU =			2 alleles	11	12	y 11	13			
					12	13	11	13			
Possible co	mplete loss	N	1		11	12	12	13			
of gen	otype?	IN	Ш		11	Х	12	13			
					12	Х	11	13			
1					13	X	11	12			
							ļ				
										1	
											Possible
											Contributir
			т								Genotype

Poss				Caucasiar	1	Afric	an Americ	can	- 1	Hispanic	
Geno	types		f(Allele 1)	f(Allele 2)	RMP	f(Allele 1)	f(Allele 2)	RMP	f(Allele 1)	f(Allele 2)	RMP
11	11	AA	0.059		0.004	0.036		0.002	0.062		0.004
11	12	AB	0.059	0.145	0.017	0.036	0.108	0.008	0.062	0.121	0.015
11	13	AC	0.059	0.339	0.040	0.036	0.222	0.016	0.062	0.325	0.040
		AD	0	0		0	0		0	0	
		AX	0			0			0		
		BB	0			0			0		
12	13	BC	0.145	0.339	0.099	0.108	0.222	0.048	0.121	0.325	0.078
		BD	0	0		0	0		0	0	
		BX	0			0			0		
		CC	0			0			0		
		CD	0	0		0	0		0	0	
		CX	0			0			0		
		RMP:			0.160			0.074			0.138

# **DNA Analyst Training:**

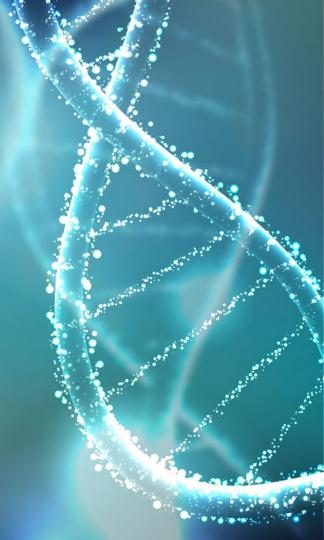
 Background training then allows the analyst to evaluate the Prob Gen results to ensure they meet logical expectations – not a "black box"

CONTRIBUTORS	1	2	
Template (rfu)	660	178	
Mixture Proportion	79%	21%	
Degradation starts at 89bp			
Degradation linear approximation (rfu/bp)	0.666	0.196	
Degradation exponential curve	1.1280E-3	1.2466E-3	
DOST RUDN-IN SUMMARY			
POST BURN-IN SUMMARY	2.502.150	Association	- Lin C 41
Total iterations	2,563,156	Acceptance rate	1 in 6.41
Total iterations Effective sample size	7,169.35	Acceptance rate log(likelihood)	1 in 6.41 32
Total iterations		·	
Total iterations Effective sample size	7,169.35	·	
Total iterations Effective sample size Gelman-Rubin convergence diagnostic	7,169.35 1.06	log(likelihood)	32



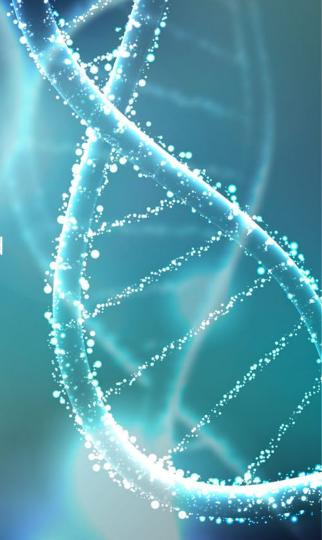
## Benefits:

- Better use of the genetic data in the DNA profile
  - Increased discrimination results in higher exclusion of non-contributors
- Reduced subjectivity during interpretation
- Greater consistency over time within the laboratory and between analysts within the laboratory



## Weaknesses:

- Conveying the meaning of an LR to a lay person
- Interpretation and review are more complicated and time-consuming
- Validation of software is very time consuming and labor-intensive (6 months to 1 year or more)



# THANK YOU

