

Reference (1)

Jeff (CHI-HSUAN HO)



Bioinformatics Analyses – Genotyping (GT), APT, CPT

Jeff (CHI-HSUAN HO)

Genotyping Analysis Development and Deployment



Genotyping Procedure Documents for Each Chip

Algorithm	Array Type
BRLMM	Human Mapping 100K Array Human Mapping 500K Array
BRLMM-P	Genome-Wide Human SNP Array 5.0 Rat and Mouse Arrays
Birdseed v1 or Birdseed v2	Genome-Wide Human SNP Array 6.0
Axiom GT1 (BRLMM-P)	Axiom Arrays, including: • Axiom Human Arrays: • Axiom Genome-Wide Human Arrays • Axiom Genome-Wide CEU 1 Array • Axiom Genome-Wide ASI 1 Array • Axiom Genome-Wide YRI 1 Array set • Axiom myDesign Custom Arrays • Axiom Genome-Wide BOS 1 Array

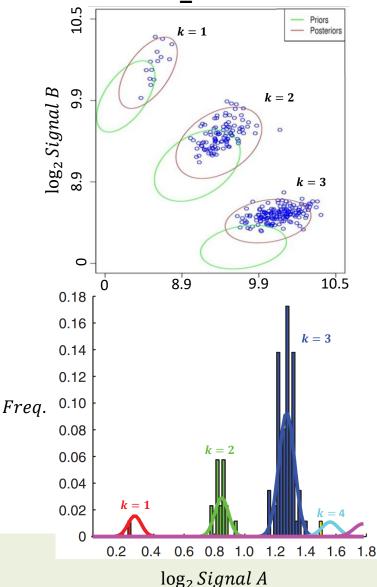
GTC v4.2 P/N 702982 Rev. 3

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Gaussian Mixture Model (GMM)







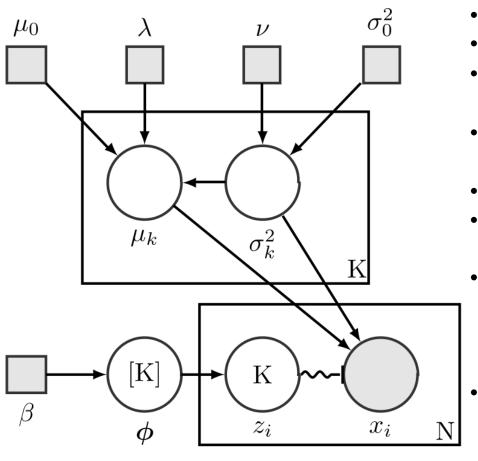
- Bayesian framework clustering model
 - Prior → A guess (e.g. from HapMap)
 - Posterior → A correction of cluster membership
- Applications (Genotyping, CNV analysis):
 - Birdseed (2-D)
 - Brlmm-P (1-D)
 - Canary (1-D)
- Model: $p(\mathbf{x}|\Theta) = \sum_{k=1}^{K} w_k \cdot N(\mathbf{x}|\boldsymbol{\mu}_k, \Sigma_k)$,

where $N(\cdot)$ = Gaussian (Normal) dist., w_k = the k_{th} cluster proportion

- Evaluation (Model-based, Domain knowledge):
 - Bayesian Information Criterion (BIC)
 - Resolution of posterior cluster centroids
 - Model reasonability (e.g. outlier cluster)
 - Similarity between posterior and prior (e.g. w_k , μ_k)
 - Biological insight (e.g. Hardy-Weinberg penalty)

Bayesian Gaussian Mixture Model

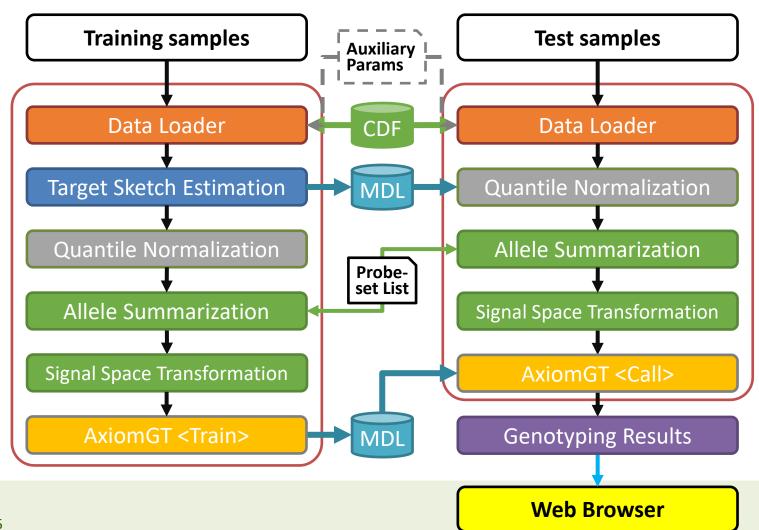




- Model: $\sum_{k=1}^{K} \phi_k N(\mu_k, \sigma_k^2)$
- *K* = Number of mixture components
- σ_k^2 = Variance of component k, $\sigma_k^2 \sim \text{Inverse-Wishart}(\nu, \sigma_0^2)$
- μ_k = Mean of component k, $\mu_k \sim \text{Normal}(\mu_0, \lambda \sigma_k^2)$
- *N* = Number of observations
- z_i = Component (category) of observation i, $z_i \sim \text{Categorical}(\phi), \ z_i \in \{1, 2, ..., k\}$
- $\phi_k =$ Mixture weight, i.e. prior probability of a particular component k, $\phi \sim$ Symmetric-Dirichlet(β), $\sum_k \phi_k = 1$
- $x_i = \text{Observation } i$, $x_i \sim \text{Normal}(\mu_{z_i}, \sigma_{z_i}^2)$



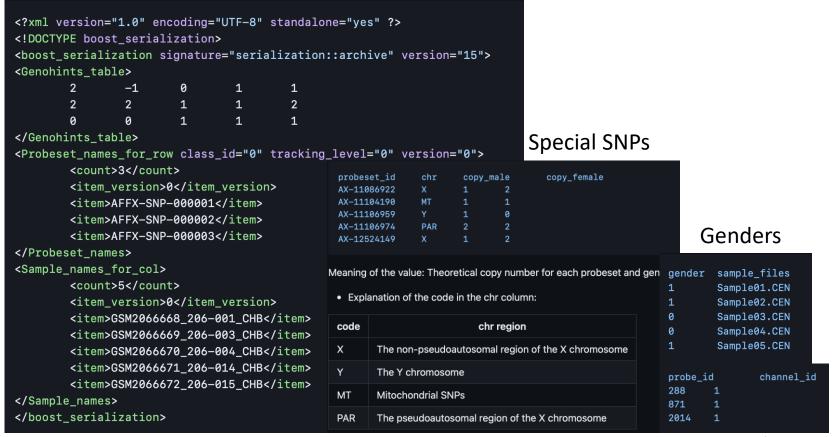
AxiomGT Framework







Genotype



Sex Probes



Genotyping Results

Call Rate

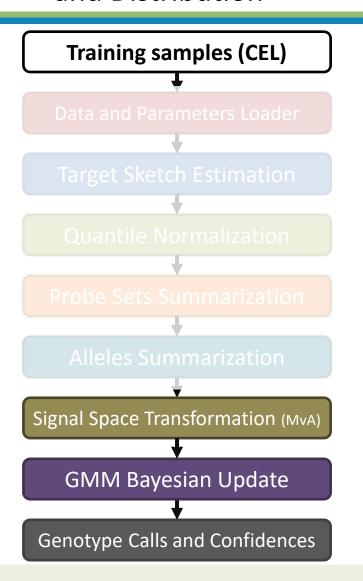
	can nate
call_rate	sample_name
0.994788	GSM2066668_206-001_CHB
0.994555	GSM2066669_206-003_CHB
0.994841	GSM2066670_206-004_CHB
0.995426	GSM2066671_206-014_CHB
0.994742	GSM2066672_206-015_CHB
0.995266	GSM2066673_206-016_CHB
0.994938	GSM2066674_206-018_CHB
0.995377	GSM2066675_206-019_CHB
0.992347	GSM2066676_206-021_CHB
0.967893	GSM2066677_206-023_CHB
0.972985	GSM2066678_206-028_CHB
0.972951	GSM2066679_206-029_CHB
0.973976	GSM2066680_206-030_CHB
0.973856	GSM2066681_206-032_CHB
0.974752	GSM2066682_206-033_CHB
0.972898	GSM2066683_206-034_CHB

Genotype Inference Report

	b_allele				beset_name		
-2.42229	9.69654	2		FFX-SNP-000001			
-0.213343	10.0077	1		FFX-SNP-000001			В
2.62502 9.22	2009 0	0.	999929 AFFX-	SNP-000001 GSN	12066670 <u>_</u> 206	-004_снв	
-0.312298	9.95922	1	0.99998 AFFX-	SNP-000001 GSN	12066671_206·	-014_снв	
-0.264381	9.80488	1	0.999976 A	FFX-SNP-000001	L GSM2066672	_206-015_сні	В
0.0327307	10.0347	1	0.999982 A	FFX-SNP-000001	L GSM2066673	_206-016_сні	В
-2.92652	9.55797	2	0.999928 A	FFX-SNP-000001	L GSM2066674	_206-018_chi	В
-2.49338	9.65748	2	0.999975 A	FFX-SNP-000001	L GSM2066675	_206-019_сні	В
0.0407013	9.7349	1	0.999969 A	FFX-SNP-000001	L GSM2066676	_206-021_сні	В
-2.94063	9.34759	2	0.999895 A	FFX-SNP-000001	L GSM2066677	_206-023_chi	В
3.0863 9.23	524 0	0.	999049 AFFX-	SNP-000001 GSN	12066678_206·	-028_снв	
2.45937 9.39	49 0	0.	99994 AFFX-SNP-	000001 GSM2066	679_206 ⁻ 029	_CHB	
0.0585673	10.002	1	0.99998 AFFX-	SNP-000001 GSN	12066680_206	-030_снв	
-0.260712	10.2414	1	0.999986 A	FFX-SNP-000001	L GSM2066681	_206-032_chi	В
-0.468117	9.97722	1	0.999958 A	FFX-SNP-000001	L GSM2066682	_206-033_сні	В
-3.29787	9.4166	2	0.996784 A	FFX-SNP-000001	L GSM2066683.	_206-034_сні	В
-0.125064	10.003	1	0.999986 A	FFX-SNP-000001	L GSM2066684.	_206-038_сні	В
-3.08476	9.3733	2	0.999697 A	FFX-SNP-000001	L GSM2066685	_206-040_сні	В
-0.0546291	9.93013	1		FFX-SNP-000001			В
2.82779 9.32	064 0	0.	999878 AFFX-	SNP-000001 GSN	12066687_206·	-043_снв	
-2.80064	9.3799	2		SNP-000001 GSN			
-0.144338	9.56211	1	0.99996 AFFX-	SNP-000001 GSN	12066689_206	-045_снв	
-2.77376	9.40567	2	0.999957 A	FFX-SNP-000001	L GSM2066690 <u>.</u>	_206-048_сні	В
-0.0830618	9.82269	1	0.99998 AFFX-	SNP-000001 GSN	12066691_206	-049_снв	
-0.286435	10.002	1	0.999982 A	FFX-SNP-000001	L GSM2066692	_206-054_сні	В
-0.0575499	9.98275	1	0.999985 A	FFX-SNP-000001	L GSM2066693 _.	_206-056_сні	В
-3.01959	9.36143	2		FFX-SNP-000001			
-2.95238	9.45029	2	0.999904 A	FFX-SNP-000001	L GSM2066695	_211-003_сн	В
-2.94825	9.37206	2	0.999895 A	FFX-SNP-000001	L GSM2066696	_211-006_сні	В
-3.12067	9.36538	2	0.999569 A	FFX-SNP-000001	L GSM2066697	_211-009_сні	В
-3.72513	9.12557	-1	0.123354 A	FFX-SNP-000001	L GSM2066698	_211-010_сні	В

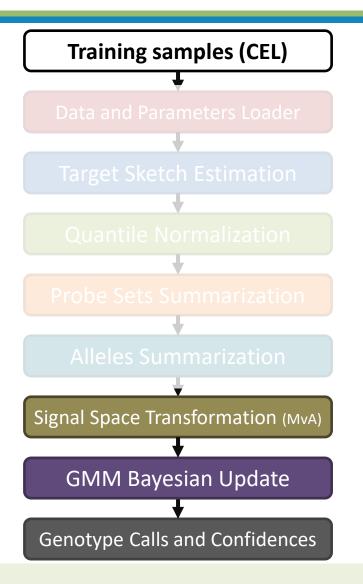
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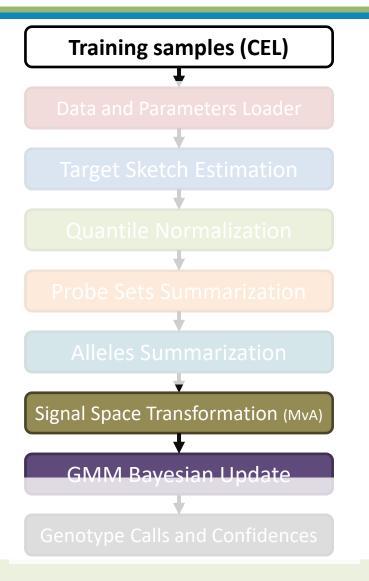
- AxiomGT1 Algo (bayes_label)
 - initialize_bins
 (x -> bins domain)
 - Integratebrlmmoverlabelings (bins domain)
 - labels_two_posterior
 (bins domain)
 - make_two_calls
 (bins domain params results
 -> x calls)





- Sort (x, y) and other related params by x (increasing order).
- O Create bins data (setup_bins $(x \rightarrow bins domain)$) $delta = \frac{Range(x)}{sp. bins + 1}, \quad sp. bins = 100 (default)$
 - Create a new bin and reset collected statistics if
 - 1. When current data point x lies outside current boundary (previous x + delta) \Rightarrow Create new boundary by using current x.
 - 2. sp.bins = 0 (bins is turned off)
 - 3. When data points are fewer than bins.
 - Statistics are collected and computed in the same bin:
 - Data points number
 - 2. $x, x^2, y, y^2, x \cdot y$
 - Penalty from each known genotype and inbreeding status (Only used in supervised mode)





- Compute Quality Score (Posterior Analog) (for each partition)
 - (sp.mix) mixture_penalty
 - (sp.bic) BIC (k*log(N) part)
 - 1D (x) Log likelihood under posterior params
 - 1D (x) Log prior probability of posterior params
 - $\frac{1}{2}$ * Quality Score Correction
 - (sp.CSepPen) Geman-McClure transformed
 FLD penalty for non-well-separated
 clusters cases.
- Compute Relative Probability for (Each Partition)
 & (Each Data Point to Be Each Genotype) under
 Posterior Information.



Training samples (CEL)

Signal Space Transformation (MvA)

GMM Ravesian Undate

- **Quality Score (Posterior Analog) (for each partition)** 0
 - (sp.mix) mixture penalty

$$-\sum_{g=1}^{3} N_g * \log \left(\frac{\left(N_g + lambda\right)}{\sum_{g} \left(N_g + lambda\right)} \right), \quad lam gd\overline{\overline{a}} \stackrel{1}{=} \{BB\}, 2 (AB), 3 (AA)$$

(sp.bic) BIC (k*log(N) part)

$$c*bic_k*log\left(\sum_{g}N_{g}\right), \quad bic_k=2\Rightarrow mean, var, \quad c=1,2,3$$

- 1D (x) Log likelihood under posterior params
 - $\mathbf{u}_{3x1}' = \left(\mathbf{K}_{0\,3x3}^{-1} + \mathbf{N}_{3x3}'\right)^{-1} * \left(\mathbf{K}_{0\,3x3}^{-1} * \mathbf{u}_{0\,3x1} + \mathbf{N}_{3x3} * \mathbf{m}_{3x1}\right),$

$$\boldsymbol{K}_{0\,3x3}^{-1} = \begin{bmatrix} \frac{k_{10}}{\sigma_{10}^2} & \frac{\sigma_{120}}{\sigma_{10}\sigma_{20}} & \frac{\sigma_{130}}{\sigma_{10}\sigma_{20}} \\ \frac{\sigma_{120}}{\sigma_{10}\sigma_{20}} & \frac{k_{20}}{\sigma_{20}^2} & \frac{\sigma_{230}}{\sigma_{20}\sigma_{30}} \\ \frac{\sigma_{130}}{\sigma_{10}\sigma_{30}} & \frac{\sigma_{230}}{\sigma_{20}\sigma_{30}} & \frac{k_{30}}{\sigma_{30}^2} \end{bmatrix}, \qquad \boldsymbol{N'}_{3x3} = \begin{bmatrix} \frac{N_1}{\sigma_{10}^2} & 0 & 0 \\ 0 & \frac{N_2}{\sigma_{20}^2} & 0 \\ 0 & 0 & \frac{N_3}{\sigma_{30}^2} \end{bmatrix}$$

$$\mathbf{N'}_{3x3} = \begin{bmatrix} \frac{N_1}{\sigma_{10}^2} & 0 & 0\\ 0 & \frac{N_2}{\sigma_{20}^2} & 0\\ 0 & 0 & \frac{N_3}{\sigma_{30}^2} \end{bmatrix}$$

$$\mathbf{u}_{0 \ 3 \times 1} = \begin{bmatrix} \mathbf{u}_{10} \\ \mathbf{u}_{20} \\ \mathbf{u}_{30} \end{bmatrix}, \qquad \mathbf{m}_{3 \times 1} = \begin{bmatrix} \sum_{i} x_{1i} \\ \sum_{i} x_{2i} \\ \sum_{i} x_{3i} \end{bmatrix}, \qquad \mathbf{N}_{3 \times 3} = \begin{bmatrix} \frac{1}{\sigma_{10}^{2}} & 0 & 0 \\ 0 & \frac{1}{\sigma_{20}^{2}} & 0 \\ 0 & 0 & \frac{1}{\sigma_{30}^{2}} \end{bmatrix}$$



Training samples (CEL)

Data and Parameters Loadei

Target Sketch Estimation

Quantile Normalization

Probe Sets Summarization

Alleles Summarization

Signal Space Transformation (MVA)

GMM Bavesian Update

Genotype Calls and Confidences

- Quality Score (Posterior Analog) (for each partition)
 - 1D (x) Log likelihood under posterior params

(sp.hardshell) Isotonic Regression adjustment for cluster centers (separated by at least delta (0.75)). u_{3x1}^{\prime}

$$w_g = N_g + k_{g0},$$
 $g = 1, 2, 3$
 $gamma = delta * \frac{w_1 - w_3}{w_1 + w_2 + w_3}$

$$u'_{3x1} = \begin{bmatrix} u'_1 \\ u'_2 \\ u'_3 \end{bmatrix}, \qquad \begin{aligned} u'_1 &= u'_1 + delta - gamma \\ u'_2 &= u'_2 - gamma \\ u'_3 &= u'_3 - delta - gamma \end{aligned}$$

Pool Adjacent-Violators (PAV) algo.

$$\begin{cases} u'_{g}, u'_{g+1}, & u'_{g} \leq u'_{g+1} \\ u'_{g}, u'_{g+1} = \frac{\sum_{g \in A} w_{g} * u'_{g}}{\sum_{g \in A} w_{g}}, & A = \{g | u'_{g} > u'_{g+1}\}, \end{cases}$$

$$= 1, 2, 3$$

$$\mathbf{u'_{3x1}} = \begin{bmatrix} \mathbf{u'_{1}} \\ \mathbf{u'_{2}} \\ \mathbf{u'_{3}} \end{bmatrix}, \qquad \begin{aligned} \mathbf{u'_{1}} &= \mathbf{u'_{1}} - delta + gamma \\ \mathbf{u'_{2}} &= \mathbf{u'_{2}} + gamma \\ \mathbf{u'_{3}} &= \mathbf{u'_{3}} + delta + gamma \end{aligned}$$





Data and Parameters Loader

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GMM Bayesian Undate

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(sp.hardshell) Isotonic Regression adjustment for cluster centers (separated by at least delta (0.75)). u'_{3v1}

$$\sigma'_{g}^{2} = \frac{v_{g0}*\sigma_{g0}^{2} + \sum_{i} (x_{gi} - \bar{x}_{g})^{2} + \frac{k_{g}*N_{g}}{k_{g} + N_{g}}*(u'_{g} - u_{g0})^{2}}{v_{g0} + N_{g}} \Rightarrow \frac{v_{g0}*\sigma_{g0}^{2} + \sum_{i} x_{gi}^{2} - \sum_{i} x_{gi}*\sum_{i} x_{gi}*\frac{1}{N_{g} + 0.0001} + \frac{k_{g}*N_{g}}{k_{g} + N_{g}}*(u'_{g} - u_{g0})^{2}}{v_{g0} + N_{g}}, \quad g = 1, 2, 3$$

(sp.comvar) Ad-hoc shrinkage for σ'_g^2 of each cluster (controlled by mixing proportion (lambda) (1)).

Adjusted Pooled Variance.

$$\begin{split} & w_{g} = N_{g} + v_{g0}, \quad g = 1, 2, 3 \\ & {\sigma'}_{t}^{2} = \frac{\sum_{g} w_{g} * {\sigma'}_{g}^{2}}{\sum_{g} w_{g}}, \quad t = 1, 2, 3 , \\ & \Rightarrow \frac{(3 - 2 * lambda) * w_{t} * {\sigma'}_{t}^{2} + \sum_{g \neq t} lambda * w_{g} * {\sigma'}_{g}^{2}}{(3 - 2 * lambda) * w_{t} + \sum_{g \neq t} lambda * w_{g}} \end{split}$$



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- Quality Score (Posterior Analog) (for each partition)
 - 1D (x) Log likelihood under posterior params

$$\mathbf{u}'_{3x1} = \left(\mathbf{K}_{0\,3x3}^{-1} + \mathbf{N}'_{3x3}\right)^{-1} * \left(\mathbf{K}_{0\,3x3}^{-1} * \mathbf{u}_{0\,3x1} + \mathbf{N}_{3x3} * \mathbf{m}_{3x1}\right),$$

■ (sp.hardshell) Isotonic Regression adjustment for cluster centers (separated by at least delta (0.75)). u_{3x1}'

$$\sigma'_g^2 = \frac{v_0 * \sigma_{g_0}^2 + \sum_i (x_{gi} - \bar{x}_g)^2 + \frac{k_g * N_g}{k_g + N_g} * (u'_g - u_{g_0})^2}{v_0 + N_g}, \quad g = 1, 2, 3$$

(sp.comvar) Ad-hoc shrinkage for σ'_g^2 of each cluster (controlled by mixing proportion (lambda) (1)).

$$\ell = \log \prod_{g} \prod_{i=1}^{N_g} N(u'_g, \sigma'_g^2) = \sum_{g} \sum_{i=1}^{N_g} \log \left(N(u'_g, \sigma'_g^2) \right) \Rightarrow \\
-\frac{1}{2} \left[\sum_{g} N_g \log (\sigma'_g^2) + \frac{1}{\sigma'_g^2} \left(\sum_{i=1}^{N_g} x_i^2 - 2u'_g \sum_{i=1}^{N_g} x_i + N_g u'_g^2 \right) \right] \\
\Rightarrow -2 * \ell \\
= \sum_{g} N_g \log (\sigma'_g^2) + \frac{1}{\sigma'_g^2} \left(\sum_{i=1}^{N_g} x_i^2 - 2u'_g \sum_{i=1}^{N_g} x_i + N_g u'_g^2 \right)$$



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- Quality Score (Posterior Analog) (for each partition)
 - 1D (x) Log prior probability of posterior params

$$\ell = \log \prod_{g} N\left(u_{g0}, \frac{\sigma_{g0}^{2}}{k_{g0}}\right) = \sum_{g} \log\left(N\left(u_{g0}, \frac{\sigma_{g0}^{2}}{k_{g0}}\right)\right) \Rightarrow$$

$$-\frac{1}{2} \left[\sum_{g} \log\left(\frac{\sigma_{g0}^{2}}{k_{g0}}\right) + \frac{k_{g0}}{\sigma_{g0}^{2}}\left(u_{g}' - u_{g0}\right)^{2}\right]$$

$$\Rightarrow -2 * \ell = \sum_{g} \log\left(\frac{\sigma_{g0}^{2}}{k_{g0}}\right) + \frac{k_{g0}}{\sigma_{g0}^{2}}\left(u_{g}' - u_{g0}\right)^{2}$$

$$\bullet \qquad \ell = \log \prod_g IG(v_0, \sigma_{g0}^2) \Rightarrow -\ell = \sum_g \frac{\sigma_{g0}^2}{{\sigma'}_g^2} + (v_0 + 1) * \log(\sigma'_g^2)$$

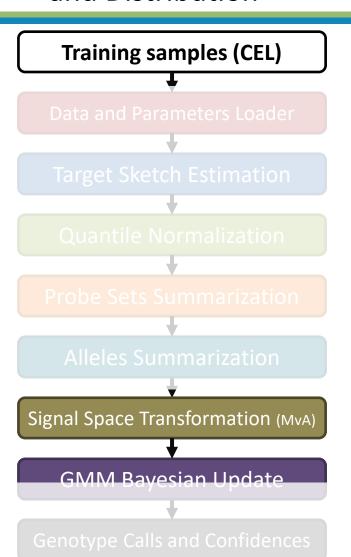
- $-\frac{1}{2}*$ Quality Score
- (sp.CSepPen) Geman-McClure transformed FLD penalty for non-well-separated clusters.

$$-CSepPen * \sum_{i,j,i\neq j} FLD'_{ij}, i,j \in g = \{1,2,3\},\$$

$$FLD'_{ij} = \begin{cases} \frac{FLD_{ij}}{1 + \frac{FLD_{ij}}{CSepThr}} * (N_i + N_j), & other\\ \frac{FLD_{ij}}{1 + \frac{FLD_{ij}}{2 * CSepThr}} * (N_1 + N_3), & i = 1, j = 3 \end{cases}$$

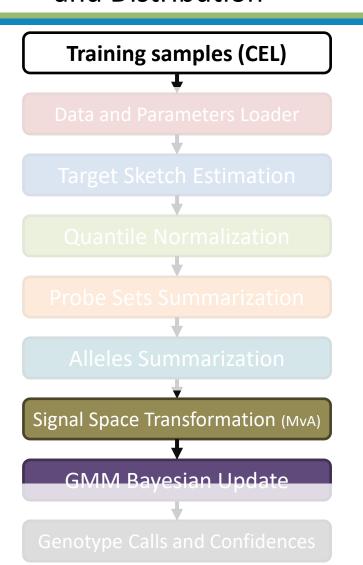
$$FLD_{ij} = FLD_{ji} = \frac{\left(\mathbf{u}_i' - \mathbf{u}_j'\right)^2}{{\sigma'}_i^2 + {\sigma'}_i^2}, \qquad \textit{CSepPen} = 0.1, \qquad \textit{CSepThr} = 4$$





- Relative Probability for Each Partition under Posterior Information.
 - Quality Score $Q_{i,j}$ for partition i,j
 - Relative Probability $q_{i,j} = \frac{\exp(-Q_{i,j})}{\exp(-\min Q_{i,j})} = \exp(\min Q_{i,j} Q_{i,j})$ $= \frac{Posterior\ Probability\ of\ Specified\ Partition\ (i,j)}{Maximal\ Posterior\ Probability}$





Relative Probability for Each Data Point to Be Each Genotype under Posterior Information after dividing $q_{...}$

 $q_{i,j}$

j	0	1	2	3	4	q_i .	$\sum_i q_i$.	$q_{\cdot \cdot} - \sum_{i} q_{i \cdot}$
0	сссс	bccc	bbcc	bbbc	bbbb	q_0 .	$\sum_{i=0}^{0} q_i.$	$\sum_{i=1}^4 q_i.$
1		accc	abcc	abbc	abbb	q_1 .	$\sum_{i=0}^{1} q_i.$	$\sum_{i=2}^4 q_i.$
2			aacc	aabc	aabb	q_2 .	$\sum_{i=0}^2 q_i.$	$\sum_{i=3}^4 q_i.$
3				aaac	aaab	q_3 .	$\sum_{i=0}^3 q_i.$	$\sum_{i=4}^4 q_i.$
4					aaaa	q_4 .		
$q_{\cdot j}$	$q_{\cdot 0}$	$q_{\cdot 1}$	$q_{\cdot 2}$	$q_{\cdot 3}$	$q_{\cdot 4}$	<i>q</i>		
$\sum_j q_{\cdot j}$	$\sum_{j=0}^{0} q_{\cdot j}$	$\sum_{j=0}^{1} q_{\cdot j}$	$\sum_{j=0}^{2} q_{\cdot j}$	$\sum_{j=0}^{3} q_{\cdot j}$				

The relative counts of *Sth* data point being genotype "c" after observing all data.

Let "a" \equiv BB genotype, "b" \equiv AB genotype, "c" \equiv AA genotype.

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Training samples (CEL)

Data and Parameters Loader

Target Sketch Estimation

Quantile Normalization

Probe Sets Summarization

Alleles Summarization

Signal Space Transformation (MVA)

GMM Bavesian Update

Genotype Calls and Confidences

- Relative Probability for Each Data Point to Be Each Genotype under Posterior Information.
 - The relative probability for the S_{th} data point being AA genotype: $\frac{\sum_{j=0}^{S} q_{\cdot j}}{q}$
 - The relative probability for the S_{th} data point being BB genotype: $1-\frac{\sum_{i=0}^{S}q_{i\cdot}}{a}$
 - The relative probability for the S_{th} data point being AB genotype: $1-\left(1-\frac{\sum_{i=0}^S q_{i\cdot}}{q_{\cdot\cdot}}\right)-\frac{\sum_{j=0}^S q_{\cdot j}}{q_{\cdot\cdot}}=\frac{\sum_{i=0}^S q_{i\cdot}-\sum_{j=0}^S q_{\cdot j}}{q_{\cdot\cdot}}$



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GMM Bayesian Update

Genotype Calls and Confidences

 Update 2D Data model parameters with soft assignment of each data bin

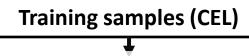
-
$$u'_{6x1} = (K_{0\,6x6}^{-1} + N'_{6x6})^{-1} * (K_{0\,6x6}^{-1} * u_{0\,6x1} + m_{6x1}),$$

$$- \qquad K_{0\,6x6}^{-1} = \begin{bmatrix} k_{10} & \mathbf{0} & \sigma_{xx120} & \mathbf{0} & \sigma_{xx130} & \mathbf{0} \\ \mathbf{0} & k_{10} & \mathbf{0} & \sigma_{yy120} & \mathbf{0} & \sigma_{yy130} \\ \sigma_{xx120} & \mathbf{0} & k_{20} & \mathbf{0} & \sigma_{xx230} & \mathbf{0} \\ \mathbf{0} & \sigma_{yy120} & \mathbf{0} & k_{20} & \mathbf{0} & \sigma_{yy230} \\ \sigma_{xx130} & \mathbf{0} & \sigma_{xx230} & \mathbf{0} & k_{30} & \mathbf{0} \\ \mathbf{0} & \sigma_{yy130} & \mathbf{0} & \sigma_{yy230} & \mathbf{0} & k_{30} \end{bmatrix},$$

$$- \qquad \textit{N}_{6 \times 6} = \begin{bmatrix} \sum_{i} p_{1i} & \mathbf{0} & & \dots & & \mathbf{0} \\ \mathbf{0} & \sum_{i} p_{1i} & & & & & \vdots \\ & & & \sum_{i} p_{2i} & & & \vdots \\ \vdots & & & & \sum_{i} p_{2i} & & & \\ \mathbf{0} & & & \dots & \mathbf{0} & \sum_{i} p_{31} \end{bmatrix}$$

$$- \qquad \mathbf{u_{0 \ 6x1}} = \begin{bmatrix} \mathbf{u_{x10}} \\ \mathbf{u_{y10}} \\ \mathbf{u_{x20}} \\ \mathbf{u_{x30}} \\ \mathbf{u_{y30}} \end{bmatrix}, \qquad \mathbf{m_{6x1}} = \begin{bmatrix} \sum_{i} x_{1i} \\ \sum_{i} y_{1i} \\ \sum_{i} x_{2i} \\ \sum_{i} y_{2i} \\ \sum_{i} x_{3i} \\ \sum_{i} y_{2i} \\ \sum_{i} y_{2i} \end{bmatrix}$$





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Alleles Summarization

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GMM Bayesian Update

Genotype Calls and Confidences

O Update 2D Data model parameters with soft assignment of each data bin

-
$$u'_{6x1} = (K_{06x6}^{-1} + N'_{6x6})^{-1} * (K_{06x6}^{-1} * u_{06x1} + m_{6x1}),$$

$$- k'_g = k_{g0} + \sum_i p_{gi}$$
, $g = 1, 2, 3$

- (sp.hardshell) Isotonic Regression adjustment for cluster centers (separated by at least sp.shellbarrier (delta, 0.75)). $u_{x\,3x1}'$

$$\begin{aligned} w_g &= k_g', & g &= 1, 2, 3 \\ gamma &= delta * \frac{w_1 - w_3}{w_1 + w_2 + w_3} \\ u_{x \, 3x1}' &= \begin{bmatrix} u_{x1}' \\ u_{x2}' \\ u_{x3}' \end{bmatrix}, & u_{x1}' &= u_{x1}' + delta - gamma \\ u_{x2}' &= u_{x2}' - gamma \\ u_{x3}' &= u_{x3}' - delta - gamma \end{aligned}$$

Pool Adjacent-Violators (PAV) algo.

$$\begin{cases} u'_{xg}, u'_{xg+1}, & u'_{xg} \leq u'_{xg+1} \\ u'_{xg}, u'_{xg+1} = \frac{\sum_{g \in A} w_g * u'_{xg}}{\sum_{g \in A} w_g}, & A = \{g | u'_{xg} > u'_{xg+1}\}' \\ g = 1, 2, 3 & \\ \left[u'_{x1}\right] & u'_{x1} = u'_{x1} - delta + gamma \end{cases}$$

$$g = 1, 2, 3$$

$$u'_{3x1} = \begin{bmatrix} u'_{x1} \\ u'_{x2} \\ u'_{x3} \end{bmatrix}, \quad u'_{x1} = u'_{x1} - delta + gamma$$

$$u'_{x2} = u'_{x2} + gamma$$

$$u'_{x3} = u'_{x3} + delta + gamma$$



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-
$$u'_{6x1} = (K_{0 6x6}^{-1} + N'_{6x6})^{-1} * (K_{0 6x6}^{-1} * u_{0 6x1} + m_{6x1}),$$

$$- k'_g = k_{g0} + \sum_i p_{gi}, \quad g = 1, 2, 3$$

- (sp.hardshell) Isotonic Regression adjustment for cluster centers (separated by at least sp.shellbarrier (delta, 0.75)). $u'_{r,3x1}$

-
$$v'_g = v_{g0} + \sum_i p_{gi}$$
, $g = 1, 2, 3$

$$- \sigma'_{xxg}^{2} \Rightarrow \frac{v_{g0} * \sigma_{xxg0}^{2} + \left(\sum_{i} v_{gi} x_{gi}^{2} - \sum_{i} v_{gi} x_{gi} * \sum_{i} v_{gi} x_{gi}\right) * \frac{1}{\sum_{i} v_{gi} + 0.001} + \frac{k_{g0} * \sum_{i} v_{gi}}{k_{g0} + \sum_{i} v_{gi}} * \left(u'_{xg} - u_{xg0}\right)^{2}}{v'_{g}}$$

$$- \qquad \sigma'_{yyg}^{2} \Rightarrow \frac{v_{g0} * \sigma_{yyg0}^{2} + \left(\sum_{i} p_{gi} y_{gi}^{2} - \sum_{i} p_{gi} y_{gi} * \sum_{i} p_{gi} y_{gi}\right) * \frac{1}{\sum_{i} p_{gi} + 0.001} + \frac{k_{g0} * \sum_{i} p_{gi}}{k_{g0} + \sum_{i} p_{gi}} * \left(u'_{yg} - u_{yg0}\right)^{2}}{v'_{g}}$$

$$- \sigma_{xyg}^{\prime 2} \Rightarrow \frac{v_{g0} * \sigma_{xyg0}^{2} + \left(\sum_{i} p_{gi} x y_{gi} - \sum_{i} p_{gi} x_{gi} * \sum_{i} p_{gi} y_{gi}\right) * \frac{1}{\sum_{i} p_{gi} + 0.001} + \frac{k_{g0} * \sum_{i} p_{gi}}{k_{g0} + \sum_{i} p_{gi}} * \left(\mathbf{u}_{yg}^{\prime} - \mathbf{u}_{yg0}\right) * \left(\mathbf{u}_{xg}^{\prime} - \mathbf{u}_{xg0}\right)}{v_{g}^{\prime}}$$

Ad-hoc shrinkage for $\sigma'^2_{\cdot\cdot\cdot g}$ of each cluster (controlled by mixing proportion (lambda) (1)).

Adjusted Pooled Variance.

$$\begin{split} w_g &= v_{g0} + \sum_i p_{gi}, \quad g = 1,2,3 \\ \sigma'^2_{xxt} &= \frac{\sum_g w_g * \sigma'^2_{xxg}}{\sum_g w_g} \;, \quad \sigma'^2_{yyt} = \frac{\sum_g w_g * \sigma'^2_{yyg}}{\sum_g w_g}, \quad t = 1,2,3 \;, \\ &\Rightarrow \frac{(3-2*lambda)*w_t * \sigma'^2_t + \sum_{g \neq t} lambda * w_g * \sigma'^2_g}{(3-2*lambda)*w_t + \sum_{g \neq t} lambda * w_g} \\ \sigma'^2_{xyt} &= \left(\sigma'_{xxt} * \sigma'_{yyt}\right) * \frac{\sigma'_{xyg}}{\sigma'_{xxg} * \sigma'_{yyg}}, \quad t = 1,2,3 \;, \; g = t, \text{means before shrinkage adjustment.} \end{split}$$



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-
$$\mathbf{u}'_{6x1} = \left(\mathbf{K}_{\mathbf{0} \ 6x6}^{-1} + \mathbf{N'}_{6x6}\right)^{-1} * \left(\mathbf{K}_{\mathbf{0} \ 6x6}^{-1} * \mathbf{u}_{\mathbf{0} \ 6x1} + \mathbf{m}_{\mathbf{6x1}}\right),$$

$$-k'_g = k_{g0} + \sum_i p_{gi}, \quad g = 1, 2, 3$$

- (sp.hardshell) Isotonic Regression adjustment for cluster centers (separated by at least sp.shellbarrier (delta, 0.75)). $u_{x\,3x1}'$

$$v'_g = v_{g0} + \sum_i p_{gi}, \quad g = 1, 2, 3$$

$$- \sigma'_{xxg}^2$$
, σ'_{yyg}^2 , σ'_{xyg}^2 , $g = 1, 2, 3$

- Ad-hoc shrinkage for $\sigma'^2_{\cdot\cdot\cdot g}$ of each cluster (controlled by mixing proportion (lambda) (1)).

$$- \qquad \sigma'_{xx12} = \sigma_{xx120}, \qquad \sigma'_{xx13} = \sigma_{xx130}, \qquad \sigma'_{xx23} = \sigma_{xx230}$$

$$\sigma'_{yy12} = \sigma_{yy120}, \qquad \sigma'_{yy13} = \sigma_{yy130}, \qquad \sigma'_{yy23} = \sigma_{yy230}$$





Data and Parameters Loadei

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o (sp.mix, freqflag) compute the frequency of each cluster (AA, AB, BB)

$$- f_t = \frac{k'_t}{\sum_g k'_g}, t = 1, 2, 3$$

$$\Rightarrow log f_t = log k'_t - log(\sum_g k'_g)$$

$$\Rightarrow -log f_t = -log k'_t + log(\sum_g k'_g)$$

o For each point, compute the the probability that a data point X (x, y) belongs to each genotype.

$$- \qquad p(X \in t|X) = \frac{p(X \in t, X)}{p(X)} = \frac{p(X \in t)p(X|X \in t)}{ocean + \sum_{g} p(X \in g)p(X|X \in g)} =$$

$$\frac{f_{t} \cdot BVN\left(X \middle| \mathbf{u}_{t}', \left(1 + \frac{inflatePRA}{k_{t}'}\right) \cdot \boldsymbol{\sigma}_{t}'\right)}{ocean + \sum_{g} f_{g} \cdot BVN\left(X \middle| \mathbf{u}_{g}', \left(1 + \frac{inflatePRA}{k_{g}'}\right) \cdot \boldsymbol{\sigma}_{g}'\right)'}$$

$$inflatePRA = 0 (default), ocean = 0.00001 (default)$$

$$- log p(X \in t) p(X|X \in t) = log(p(X \in t)) + log(p(X|X \in t))$$

- If copynumber=1,
$$p(X \in AB)p(X|X \in AB) = 0$$



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o (sp.mix, freqflag) compute the frequency of each cluster (AA, AB, BB)

$$- f_t = \frac{k_t'}{\sum_g k_g'}, t = 1, 2, 3$$

o For each point, compute the the probability that a data point X (x, y) belongs to each genotype.

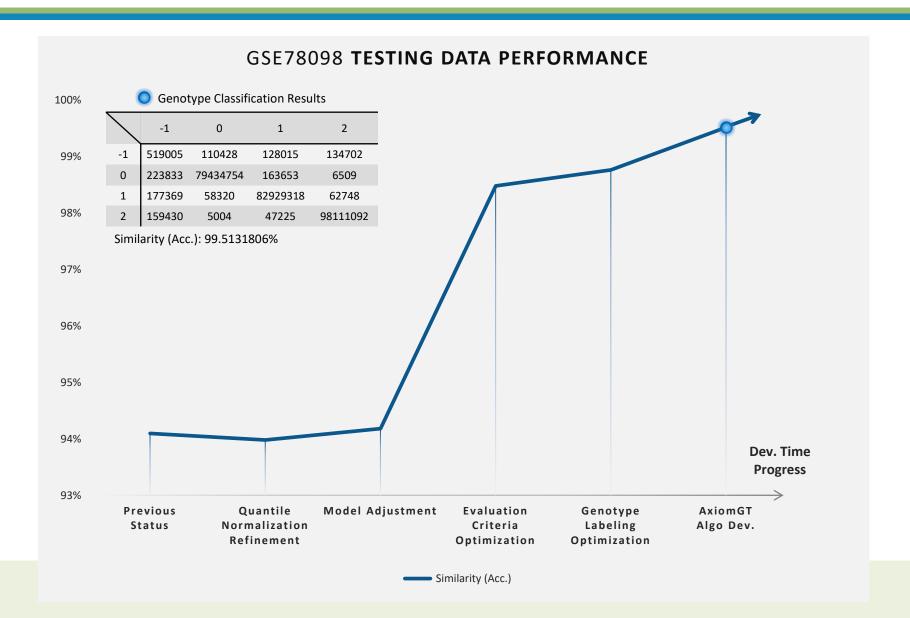
$$- p(X \in t|X) = \frac{p(X \in t, X)}{p(X)} = \frac{p(X \in t)p(X|X \in t)}{ocean + \sum_{g} p(X \in g)p(X|X \in g)}, t = 1, 2, 3$$

- For each point, make a call.
 - $\qquad \hat{t} = \operatorname*{argmax} p(X \in t|X)$
 - confidence = $1 p(X \in \hat{t}|X)$
 - No call: If confidence > MS, MS = 0.15 (default) @ getGTypeCall()



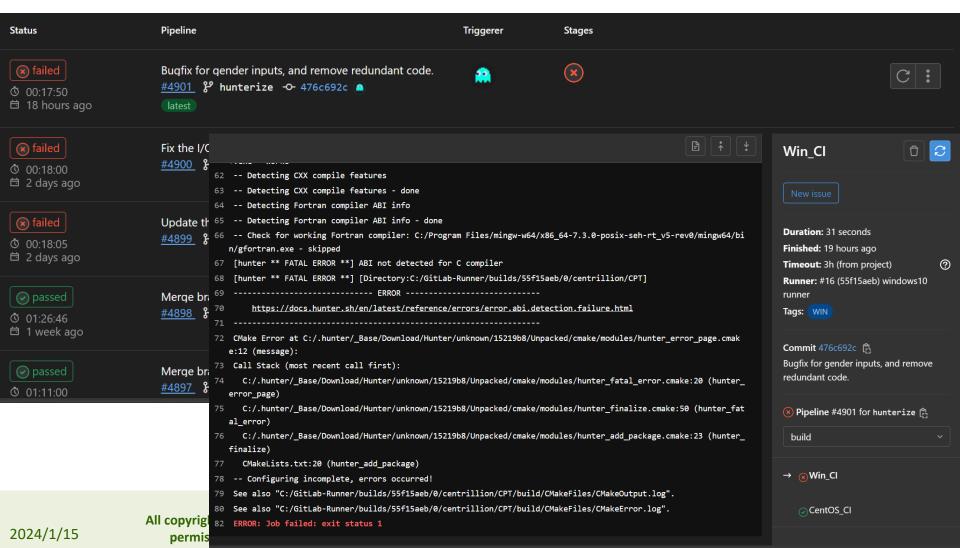
- Evaluation Data: GSE78098
 - Platform: GPL21480 (Axiom GW Hu-CHB SNP)
 - Focus on Chinese (Asian) people.
 - 420 human samples
 - 639653 Probe sets
 - Preprocessing and filter by DQC < 0.82
 - All 419 samples are picked.
- Evaluation Data: Dog Banff
 - Platform: B1C (Banff)
 - 187 dog samples
 - 48283 Probe sets
 - Preprocessing for channel name, vcf allele definition, and change the coordinate system for the Y axis of the heatmap.
 - QC filter by NP probes performance (e.g. NP call rate, NP call slope).
 - 155 dog samples are finally picked and used to build genotyping models.
- O Manual, Reports & Results: Project-CPT/CPT.wiki/AxiomGT.md at main · jeff665547/Project-CPT (github.com)







Bugfix for the CI/CD error when deployment and distribution.





Successful deployment and distribution.

Status	Pipeline	Triggerer	Stages	
passed☼ 01:33:52і 15 hours ago	Bugfix for gender inputs, and remove redundant code. #4901	A		:
passedØ 01:30:03⊟ 14 hours ago	Fix the I/O bug for the MvA Transformation. #4900 & hunterize -O- 99c7889d	A	⊘	:
✓ passedØ 01:30:22☐ 12 hours ago	Update the logging system. #4899 % hunterize -O- 882600dc	A		:
✓ passedØ 01:26:46☐ 1 week ago	Merge branch 'APT_AxiomGT1' into hunterize #4898	A		:
	Merge branch 'APT_AxiomGT1' into hunterize #4897	A		:



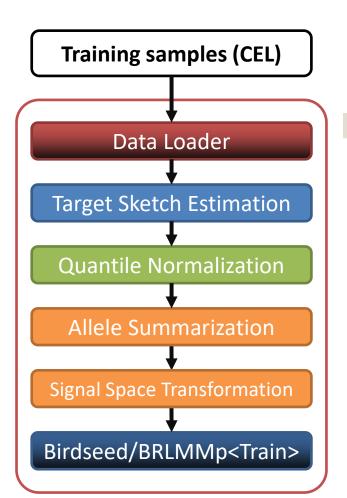
Other Genotyping Models Research and Development

Jeff (CHI-HSUAN HO)

Progress Report and Future Work



Birdseed Framework



TECHNICAL REPORTS

genetics

Integrated genotype calling and association analysis of SNPs, common copy number polymorphisms and rare CNVs

Joshua M Korn^{1–5,10}, Finny G Kuruvilla^{1,4–6,10}, Steven A McCarroll^{1,4,5}, Alec Wysoker¹, James Nemesh¹, Simon Cawley⁷, Earl Hubbell⁷, Jim Veitch⁷, Patrick J Collins⁷, Katayoon Darvishi⁸, Charles Lee⁸, Marcia M Nizzari¹, Stacey B Gabriel¹, Shaun Purcell^{1,5}, Mark J Daly^{1,5,9} & David Altshuler^{1,4,5,9}



Birdseed: K-means training model

 $Model_0$: Gaussian Mixture Model - GMM with K-Means centroid (Existing Model)

 $Model_1$: Non-prbabilistic Model

$$BIC = \frac{1}{\sigma^2} \sum_{i=1}^{K} \sum_{j=1}^{N_j} min \|X_i - \widehat{\mu}_j\|^2 + Kd \cdot \ln(N), \qquad \widehat{\mu}_j = \frac{\sum_{i=1}^{N_j} X_i}{N_j}$$

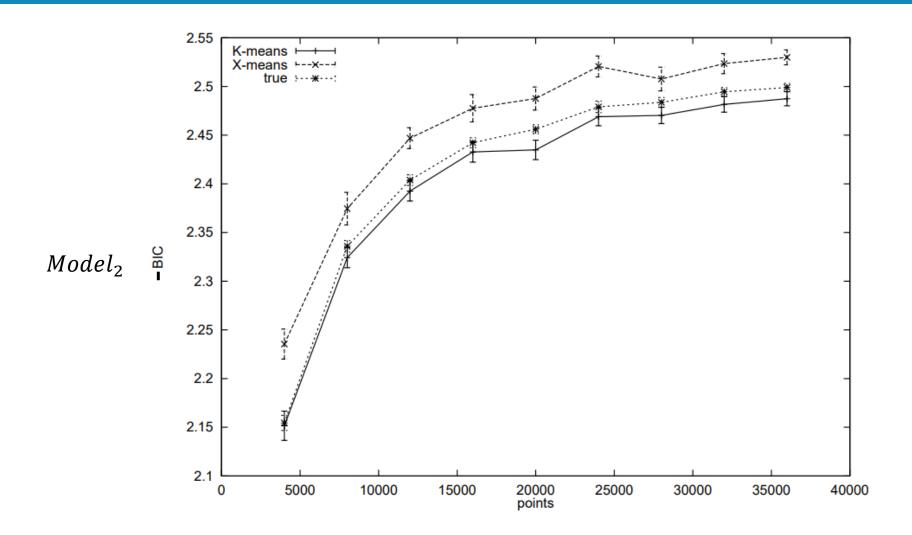
$$Model_2: f(x_i) = \pi_{ij} N(\boldsymbol{\mu}_j, \sigma^2 \cdot \boldsymbol{I}_d)$$

$$BIC = -2\sum_{j=1}^{K} N_{j} \ln(N_{j}) + 2N \ln(N) + dN \ln(2\pi\hat{\sigma}^{2}) + dN + \ln(N) \cdot K(d+1),$$

$$\sum_{j=1}^{K} N_{j} \ln(N_{j}) + 2N \ln(N) + dN \ln(2\pi\hat{\sigma}^{2}) + dN + \ln(N) \cdot K(d+1),$$

where
$$\hat{\sigma}^2 = \frac{1}{dN} \sum_{i=1}^K \sum_{j=1}^{N_j} \|\boldsymbol{X}_i - \widehat{\boldsymbol{\mu}}_j\|^2$$
, $\widehat{\boldsymbol{\mu}}_j = \frac{\sum_{i=1}^{N_j} \boldsymbol{X}_i}{N_j}$







Birdseed: K-means training model

$$Model_3$$
: $ANOVA$: $X_{it} = \mu_{it} + E_{it}$, $\mu \in \mathbb{R}^{nxd}$, $E \in \mathbb{R}^{nxd}$, $E_{it} \sim iid \ N(0, \sigma^2)$, $i = 1, 2, ..., N$, $t = 1, 2, ..., d$

$$BIC = Nd \cdot \ln \left(\sum_{j=1}^K \sum_{i=1}^{N_j} \left\| \boldsymbol{X}_i - \widehat{\boldsymbol{\mu}}_j \right\|^2 \right) + Nd \left(1 + \ln \left(\frac{2\pi}{Nd} \right) \right)$$

$$+ \ln(Nd) \cdot \left[Kd + \frac{1}{\tilde{\sigma}} \sum_{j=1}^{K'} \sum_{i=1}^{\widetilde{N}_j} \sum_{t=1}^d \sum_{l \neq c(i)} \phi \left(\frac{\boldsymbol{X}_{i,t} + \delta_l^{i,t} - \widetilde{\boldsymbol{\mu}}_{i,t}}{\tilde{\sigma}} \right) \cdot \lim_{\gamma \neq \delta_l^{i,t}} \mathcal{M} \left(\boldsymbol{X} + \gamma \boldsymbol{e}_{i,t} \right)_{i,t} \right],$$

$$where \ \tilde{\sigma}^2 = \frac{1}{dN} \sum_{j=1}^{K'} \sum_{i=1}^{\widetilde{N}_j} \left\| \boldsymbol{X}_i - \widetilde{\boldsymbol{\mu}}_i \right\|^2, \quad \widetilde{\boldsymbol{\mu}} = \mathcal{M}(\boldsymbol{X}; K') \text{ for some } K' > K,$$

$$\phi(\cdot) \text{ is the pdf of Normal (Gaussian) distribution,}$$

$$\lim_{\gamma \neq \delta_l^{i,t}} \mathcal{M} \left(\boldsymbol{X} + \gamma \boldsymbol{e}_{i,t} \right)_{i,t} = (-1)^{I \left\{ \delta_l^{i,t} > 0 \right\}} \left(\hat{\mu}_{c(i),t} - \frac{N_l}{N_l + 1} \hat{\mu}_{l,t} - \frac{\boldsymbol{X}_{i,t}}{N_l + 1} + \delta_l^{i,t} \left(\frac{N_l + 1 - N_c(i)}{(N_l + 1) \cdot N_c(i)} \right) \right),$$

$$c(i) = argmin_{l \in \{1,2,\dots,K\}} \| \boldsymbol{X}_i - \widehat{\boldsymbol{\mu}}_l \|^2,$$

$$\left(1 - \left(\frac{N_{c(i)} - 1}{N_{c(i)}} \right)^2 \right) \delta_l^{i,t^2} + 2 \cdot \left(\left(\boldsymbol{X}_{i,t} - \hat{\mu}_{l,t} \right) - \left(\boldsymbol{X}_{i,t} - \hat{\mu}_{c(i),t} \right) \cdot \left(\frac{N_{c(i)} - 1}{N_{c(i)}} \right) \right) \delta_l^{i,t} + \left(\boldsymbol{X}_{i,t} - \hat{\mu}_{l,t} \right)^2 - \left(\boldsymbol{X}_{i,t} - \hat{\mu}_{c(i),t} \right)^2 = 0$$









Degrees of freedom and model selection for k-means clustering

Check for updates

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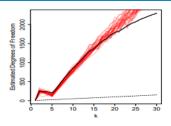
Keywords: Clustering k-means Model selection Cluster number determination Degrees of freedom Bayesian Information Criterion

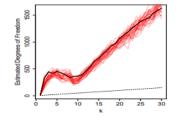
Penalised likelihood

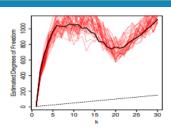
ABSTRACT

A thorough investigation into the model degrees of freedom in k-means clustering is conducted. An extension of Stein's lemma is used to obtain an expression for the effective degrees of freedom in the k-means model. Approximating the degrees of freedom in practice requires simplifications of this expression, however empirical studies evine the appropriateness of the proposed approach. The practical relevance of this new degrees of freedom formulation for k-means is demonstrated through model selection using the Bayesian Information Criterion. The reliability of this method is then validated through experiments on simulated data as well as on a large collection of publicly available benchmark data sets from diverse application areas. Comparisons with popular existing techniques indicate that this approach is extremely competitive for selecting high quality.

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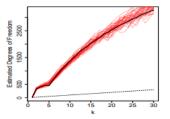


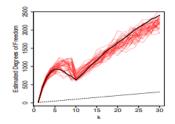


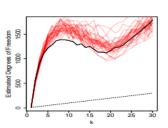
(a) 5 clusters in 5 dimensions

(b) 10 clusters in 5 dimensions

(c) 20 clusters in 5 dimensions



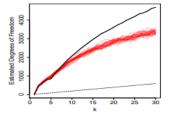


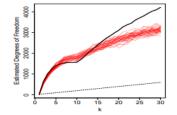


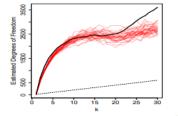
(d) 5 clusters in 10 dimensions

(e) 10 clusters in 10 dimensions

(f) 20 clusters in 10 dimensions









Birdseed: K-means training model

 $Model_0$: Equal weight Before scale: 94.1908%

 $Model_0$: But differnet weight Before scale

- Default (trim BIC, trim Fan): 84.6841% with very highly lose - classified rate.

 $Model_0$: But differnet weight Before scale – no trim BIC: 90.8778%

 $Model_0$: But different weight Before scale – no trim Fan: 0%

 $Model_1$: Before scale

- Default (trim BIC, trim Fan): 98.3863% with very highly lose - classified rate.

 $Model_1$: Before scale - no trim BIC: 98.6603% \rightarrow 98.7585% (BIC under all data)

 $Model_1$: Before scale — no trim Fan: 98.4763%

 $Model_1$: After scale: 94.3179%

```
1 - -2 -1 0 1 2 cen
2 -2 0 0 0 0 0
3 -1 0 0 68556 134030 87256
4 0 0 0 18744020 278090 4160
5 1 0 0 99968 19637894 134212
6 2 0 0 1485 255610 23149219
7 affy
```

0.987585

Centrillion Confider



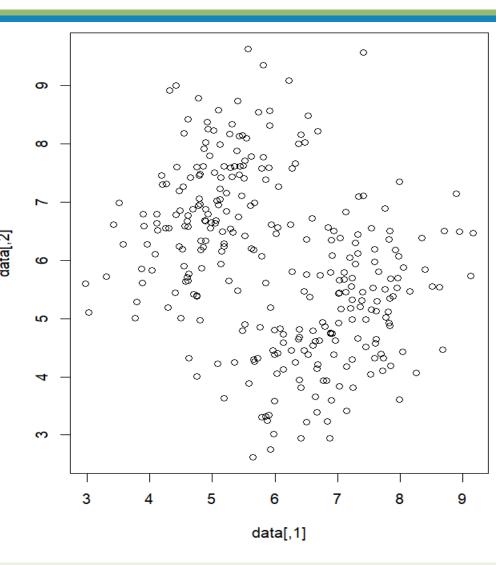
Simulation

sol\$k: Model₃

sol k_1 : Model₁: Before scale $\frac{N}{p}$

> print(sol\$k)
[1] 2
> print(sol\$k_)
[1] 3

Ans: k=2





Simulation

sol\$k: Model₃

sol k_1 : Model₁: Before scale $\frac{n}{n}$

> print(sol\$k)
[1] 3
> print(sol\$k_)
[1] 3

Ans: k=3

