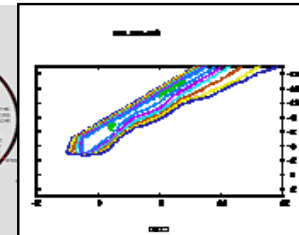
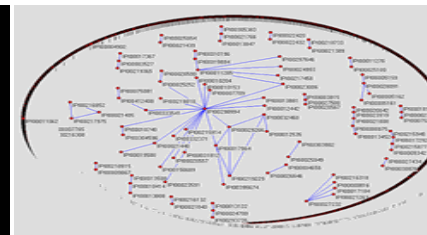
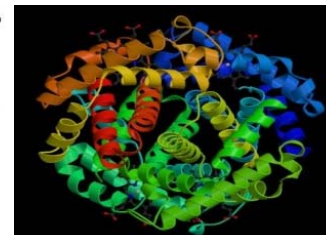
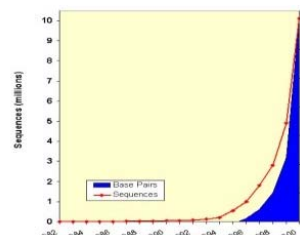


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Outline

- Introduction of Likelihood and Bayesian approach
- Genotyper of MAQ and SNVMix

Likelihood & Bayesian

- Likelihood function
 - a function of the parameters of a statistical model
 - $L(\theta) = P(\text{Data} | \theta)$
- Bayesian approach
 - $P(\theta | \text{Data}) \propto P(\theta) * P(\text{Data} | \theta)$
 - posterior \propto prior * likelihood

A Simple Demostration

- Toss a biased coin, let $\theta = P(\text{Head})$ in one trial
- Probability for seeing HTHH?

$$\begin{aligned} L(\theta) &= P(\text{Data}|\theta) = P(\text{HTHH}|\theta) \\ &= \theta \cdot (1 - \theta) \cdot \theta \cdot \theta = \theta^3(1 - \theta) \end{aligned}$$

Bernoulli distribution

- Probability for seeing 3 Heads in 4 trials?

$$\begin{aligned} L(\theta) &= P(\text{Data}|\theta) = P(3H \text{ in } 4|\theta) \\ &= \binom{4}{3} \theta^3(1 - \theta) \end{aligned}$$

binomial distribution

Models for SNP Calling and Genotyping

- MAQ
 - Li, H., Ruan, J., and Durbin, R. (2008). Mapping short DNA sequencing reads and calling variants using mapping quality scores. *Genome Research* 18, 1851–1858.
- samtools
 - Li, H. (2011). A statistical framework for SNP calling, mutation discovery, association mapping and population genetical parameter estimation from sequencing data. *Bioinformatics* 27, 2987–2993.
- GATK
 - McKenna, A., Hanna, M., Banks, E., Sivachenko, A., Cibulskis, K., Kernytsky, A., Garimella, K., Altshuler, D., Gabriel, S., Daly, M., et al. (2010). The Genome Analysis Toolkit: A MapReduce framework for analyzing next-generation DNA sequencing data. *Genome Research* 20, 1297–1303.
 - DePristo, M.A., Banks, E., Poplin, R., Garimella, K.V., Maguire, J.R., Hartl, C., Philippakis, A.A., del Angel, G., Rivas, M.A., Hanna, M., et al. (2011). A framework for variation discovery and genotyping using next-generation DNA sequencing data. *Nature Genetics* 43, 491–498.
- SNVMix
 - Goya, R., Sun, M.G.F., Morin, R.D., Leung, G., Ha, G., Wiegand, K.C., Senz, J., Crisan, A., Marra, M.A., Hirst, M., et al. (2010). SNVMix: predicting single nucleotide variants from next-generation sequencing of tumors. *Bioinformatics* 26, 730–736.
- ...

Genotyping Model used in MAQ

- Data: a pile of bases, with baseQ
 - k nucleotide b and (n-k) nucleotide b'
 - with error rate $\epsilon_1 \leq \dots \leq \epsilon_k \quad \epsilon_{k+1} \leq \dots \leq \epsilon_n$
- Goal: call genotype $\langle b, b \rangle, \langle b, b' \rangle, \langle b', b' \rangle$
- For $G = \langle b, b' \rangle$, $\Pr\{Data|G = \langle b, b' \rangle\} \approx \frac{1}{2^n} \binom{n}{k}$

Genotyping Model used in MAQ

- For $G=\langle b, b \rangle$,

$$\alpha_{nk} = \Pr\{\text{exactly } k \text{ errors in } n \text{ bases}\}$$

$$\bar{\alpha}_{nk}(\bar{\epsilon}) = \binom{n}{k} \bar{\epsilon}^k (1 - \bar{\epsilon})^{n-k}$$

Genotyping Model used in MAQ

$$\alpha_{nk} = \Pr\{\text{exactly } k \text{ errors in } n \text{ bases}\}$$

$$\beta_{nk} = \begin{cases} \Pr\{\text{more than } k \text{ errors} | \text{more than } k-1 \text{ errors in } n \text{ bases}\} & (k > 0) \\ \Pr\{\text{more than 0 error in } n \text{ bases}\} & (k = 0) \end{cases}$$

$$\alpha_{nk} = (1 - \beta_{nk})\beta_{n(k-1)} \cdots \beta_{n2}\beta_{n1} = (1 - \beta_{nk}) \prod_{i=0}^{k-1} \beta_{ni} \quad \sum_{k=0}^n \alpha_{nk} = 1$$

$$\beta_{nk} = \frac{\sum_{i=k+1}^n \alpha_{ni}}{\sum_{i=k}^n \alpha_{ni}} = \frac{1 - \sum_{i=0}^k \alpha_{ni}}{1 - \sum_{i=0}^{k-1} \alpha_{ni}} \quad \beta_{nn} = 0$$

Genotyping Model used in MAQ

$$\bar{\alpha}_{nk}(\bar{\epsilon}) = \binom{n}{k} \bar{\epsilon}^k (1 - \bar{\epsilon})^{n-k} \quad \bar{\beta}_{nk}(\bar{\epsilon}) = \frac{1 - \sum_{i=0}^k \bar{\alpha}_{ni}}{1 - \sum_{i=0}^{k-1} \bar{\alpha}_{ni}}$$

$$\beta_{nk}(\bar{\epsilon}) = \bar{\beta}_{nk}^{f_k}(\bar{\epsilon}) \quad 0 < f_k \leq 1$$

$$\alpha_{nk}(\bar{\epsilon}) = (1 - \bar{\beta}_{nk}^{f_k}) \prod_{i=0}^{k-1} \bar{\beta}_{ni}^{f_i} = (1 - \bar{\beta}_{nk}^{f_k}) \prod_{i=0}^{k-1} \left(\frac{\bar{\beta}_{ni}}{\bar{\epsilon}} \right)^{f_i} \cdot \bar{\epsilon}^{f_i} = c_{nk}(\bar{\epsilon}) \cdot \prod_{i=0}^{k-1} \bar{\epsilon}^{f_i}$$

$$c_{nk}(\bar{\epsilon}) = (1 - \bar{\beta}_{nk}^{f_k}) \prod_{i=0}^{k-1} \left(\frac{\bar{\beta}_{ni}}{\bar{\epsilon}} \right)^{f_i}$$

Genotyping Model used in MAQ

$$\alpha_{nk}(\epsilon_1, \dots, \epsilon_k; \epsilon_{k+1}, \dots, \epsilon_n) \approx c_{nk}(\bar{\epsilon}) \cdot \prod_{i=0}^{k-1} \epsilon_{i+1}^{f_i}$$

$$\log \bar{\epsilon} = \frac{\sum_{i=0}^{k-1} f_i \log \epsilon_{i+1}}{\sum_{i=0}^{k-1} f_i} \quad \prod_{i=0}^{k-1} \bar{\epsilon}^{f_i} = \prod_{i=0}^{k-1} \epsilon_{i+1}^{f_i}$$

$$f_k = 0.85^k$$

$$\alpha_{nk}(\epsilon_1, \dots, \epsilon_k; \tilde{\epsilon}_1, \dots, \tilde{\epsilon}_k; \epsilon_{k+1}, \dots, \epsilon_n; \tilde{\epsilon}_{k+1}, \dots, \tilde{\epsilon}_n) \approx c_{nk}(\bar{\epsilon}) \prod_{i=0}^{k-1} \epsilon_{i+1}^{f_i} \cdot c_{\bar{n}\bar{k}}(\bar{\tilde{\epsilon}}) \prod_{\bar{i}=0}^{\bar{k}-1} \tilde{\epsilon}_{\bar{i}+1}^{\tilde{f}_{\bar{i}}}$$

Genotyping Model used in MAQ

- For $G=\langle b, b \rangle$,

$$\Pr\{Data|G=\langle b, b \rangle\} = \alpha_{nk}(\epsilon_1, \dots, \epsilon_k; \epsilon_{k+1}, \dots, \epsilon_n)$$

- For $G=\langle b, b' \rangle$,

$$\Pr\{Data|G=\langle b, b' \rangle\} \approx \frac{1}{2^n} \binom{n}{k}$$

- For $G=\langle b', b' \rangle$,

$$\Pr\{Data|G=\langle b', b' \rangle\} = \alpha_{n, n-k}(\epsilon_{k+1}, \dots, \epsilon_n; \epsilon_1, \dots, \epsilon_k)$$

Genotyping Model used in MAQ

$$\Pr\{G|Data\} \propto \Pr\{G\} \cdot \Pr\{Data|G\}$$

- For $G=<b,b>$,

$$\Pr\{G=<b,b>|Data\} =$$

$$\Pr\{G=<b,b>\} \cdot \Pr\{Data|G=<b,b>\}$$

$$\Pr\{G=<b,b>\} \cdot \Pr\{Data|G=<b,b>\} + \Pr\{G=<b,b'>\} \cdot \Pr\{Data|G=<b,b'>\} + \Pr\{G=<b',b'>\} \cdot \Pr\{Data|G=<b',b'>\}$$

- For $G=<b,b'>$,

$$\Pr\{G=<b,b'>|Data\} =$$

$$\Pr\{G=<b,b'>\} \cdot \Pr\{Data|G=<b,b'>\}$$

$$\Pr\{G=<b,b>\} \cdot \Pr\{Data|G=<b,b>\} + \Pr\{G=<b,b'>\} \cdot \Pr\{Data|G=<b,b'>\} + \Pr\{G=<b',b'>\} \cdot \Pr\{Data|G=<b',b'>\}$$

- For $G=<b',b'>$,

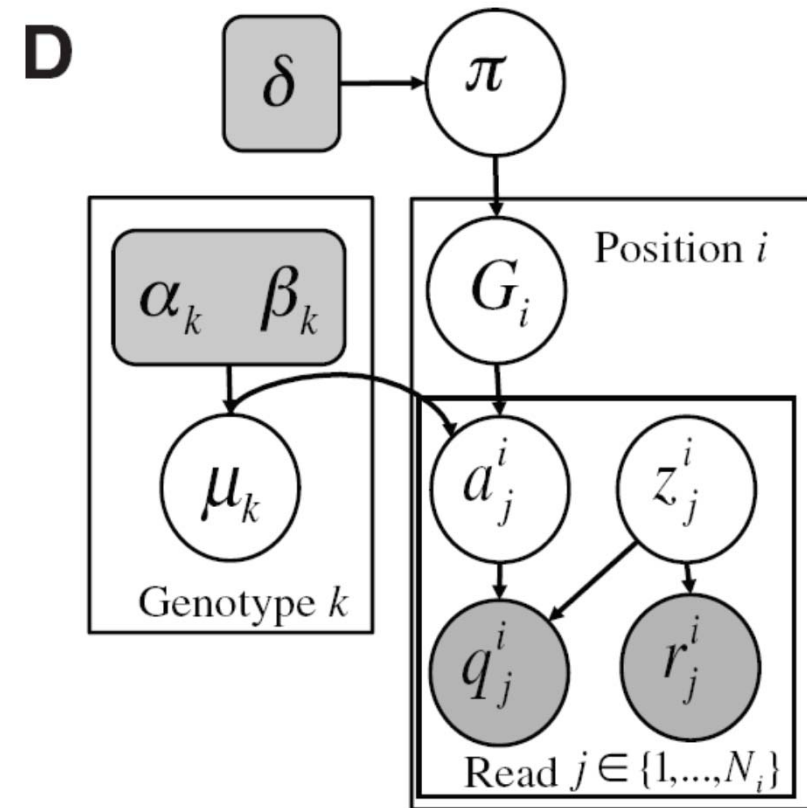
$$\Pr\{G=<b',b'>|Data\} =$$

$$\Pr\{G=<b',b'>\} \cdot \Pr\{Data|G=<b',b'>\}$$

$$\Pr\{G=<b,b>\} \cdot \Pr\{Data|G=<b,b>\} + \Pr\{G=<b,b'>\} \cdot \Pr\{Data|G=<b,b'>\} + \Pr\{G=<b',b'>\} \cdot \Pr\{Data|G=<b',b'>\}$$

Genotyping Model used in SNVMix

- Probabilistic Graphical Model
 - position i , read j , genotype k
 - G_i : genotype
 - a_j^i : match reference allele or not?
 - q_j^i : prob. of correct base calling
 - z_j^i : alignment correct or not?
 - r_j^i : prob. of correct mapping
 - μ_k : parameter of binomial for genotype k



SNVMix2 model

Goya, R., et al. (2010). SNVMix: predicting single nucleotide variants from next-generation sequencing of tumors. *Bioinformatics* 26, 730–736.

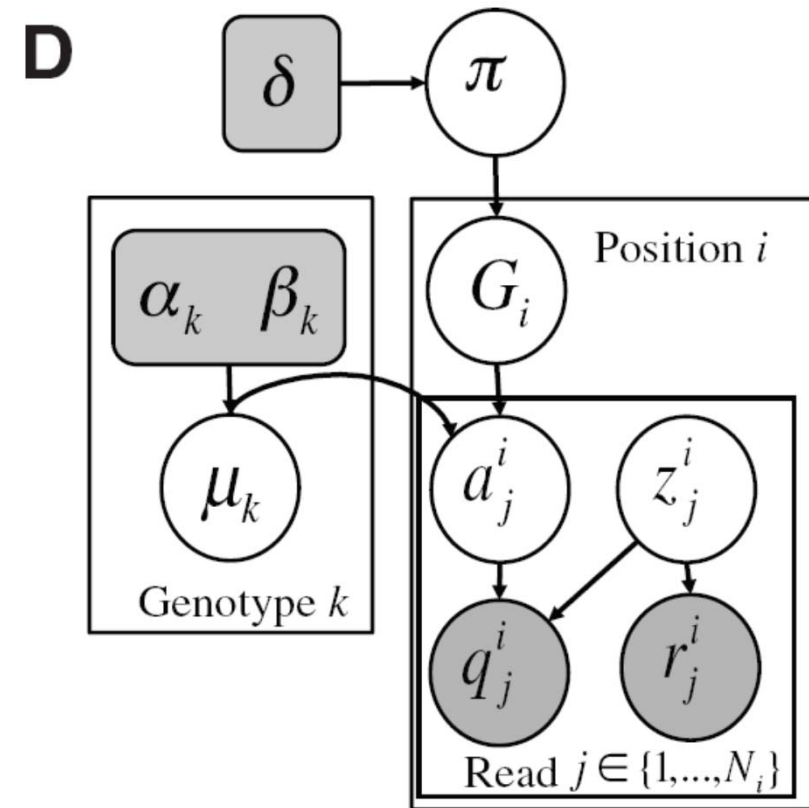
Genotyping Model used in SNVMix

$$p(G_i|\pi) = \text{Multinomial}(G_i|\pi, 1)$$

$$p(\pi|\delta) = \text{Dirichlet}(\pi|\delta)$$

$$p(a_j^i|G_i = k, \mu_k) = \text{Bernoulli}(a_j^i|\mu_k)$$

$$p(\mu_k|\alpha_k, \beta_k) = \text{Gamma}(\mu_k|\alpha_k, \beta_k)$$



SNVMix2 model

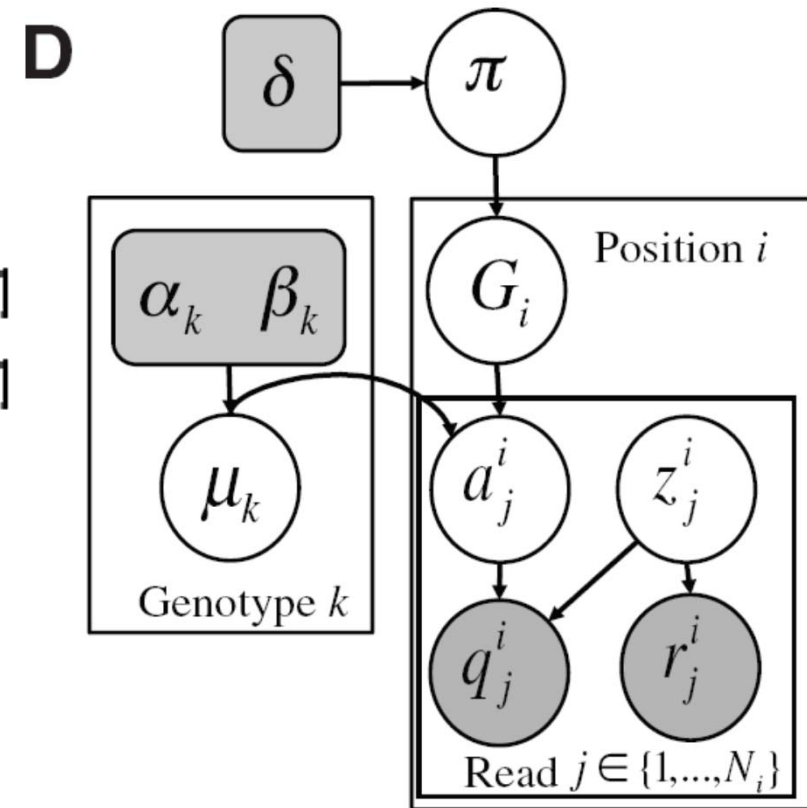
Goya, R., et al. (2010). SNVMix: predicting single nucleotide variants from next-generation sequencing of tumors. *Bioinformatics* 26, 730–736.

Genotyping Model used in SNVMix

$$p(z_j^i) = \text{Bernoulli}(z_j^i | 0.5)$$

$$p(q_j^i | a_j^i, z_j^i) = \begin{cases} q_j^i & \text{if } a_j^i = 1, z_j^i = 1 \\ 1 - q_j^i & \text{if } a_j^i = 0, z_j^i = 1 \\ 0.5 & \text{if } z_j^i = 0 \end{cases}$$

$$p(r_j^i | z_j^i) = \begin{cases} r_j^i & \text{if } z_j^i = 1 \\ 1 - r_j^i & \text{if } z_j^i = 0 \end{cases}$$



SNVMix2 model

Goya, R., et al. (2010). SNVMix: predicting single nucleotide variants from next-generation sequencing of tumors. *Bioinformatics* 26, 730–736.

Thank you for your attention



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