1 Genotype Likelihoods from Reads

$$\begin{split} L(g=1) &= p(d \mid g=1) \\ &= p(d,g=ra \mid g=1) + p(d,g=rb \mid g=1) + p(d,g=rc \mid g=1) \\ &= \sum_{a} p(d \mid g=ra) \times p(g=ra \mid g=1) \end{split}$$

Here we do not favour any heterozygous genotype, and all have likelihood 1/3. This may be changed to reflect empirical or dbSNP data

$$\begin{split} L(g=1) &= 1/3 \sum_{a} p(d \mid g=ra) \\ &= 1/3 \sum_{a} p(d \mid g=ra, \text{ado}) \times p(\text{ado}) + p(d \mid g=ra, \text{no ado}) (1-p(\text{ado})) \\ p(d \mid g=ra, ado) &= p(d \mid g=ra, dropr) * p(dropr) + p(d \mid g=ra, dropa) * p(dropa) \end{split}$$

Here we assume either allele is equally likely to be dropped in an ado event and p(drop r) = p(drop a) = 0.5. This is unlikely to change.

$$p(d \mid g = ra, ado, drop a) = \prod_{i} p(d_i \mid g = rr)$$

 $p(d \mid g = ra, ado, drop r) = \prod_{i} p(d_i \mid g = aa)$

2 Cell-locus Posterior probabilities

Using Bayes' rule:

$$p(g = k | d) = \frac{p(d | g = k) p(g = k)}{p(d)}$$
$$= \frac{p(d | g = k) \mu^{k} (1 - \mu)^{2 - k}}{p(d)}$$

where k is the mutation rate, a learnable parameter. Note: this parameter may be overestimated if the algorithm finds more mutations, increases the rate prior, and so finds more mutations. There may be no reason for this to converge.

Since p(d) is the same for all values of k at a cell-locus, we do not need to find it and can simply normalise.

3 Probabilistic Hamming distance

The Hamming distance between two sequences s, p both length n is given by

$$\sum_{i}^{n} (1 - \delta_{s_i p_i})$$

where δ_{ab} is the Kronecker delta. Since we have a probabilistic tree, we use a similar metric but weighted by the posterior probabilities of the genotypes at each locus:

$$\sum_{i}^{n} \sum_{(a,b)\in\{0,1\}\times\{0,1\}} (1-\delta_{ab})p(s_{i}p_{i}=ab)$$