Targets

- Bioinformatics
- Plus Comp. Bio
- BMC bioinformatics
- Nature Scientific Reports.
- Genome Biology (published MuSE (Fan et al. 2016))
- Nucleic Acids Research published EBCall in 2013

Introduction

Cancer is an evolutionary process, and understanding initiation, progression, and metastasis will require applications of evolutionary theory. One of the major tools in the evolutionary theory toolbox is the allele frequency spectrum. This allele frequency spectrum is constructed from single nucleotide variant calls in the tumor.

If tumors, as evidence suggests (Marc J Williams et al. 2016; Marc J Williams et al. 2018; Bozic, Gerold, and Nowak 2016), evolve essentially neutrally, then even driver mutations can't be expected to rise to high frequency during tumor evolution. As a result, finding mutations important to progression, resistance, and metastasis requires finding lower frequency mutations. Tumor heterogeneity has been associated with prognosis (1-4 in chuang paper) and the evolutionary trajectory helps identify the number of tumor subclones and their selective advantage.

The variant allele frequency spectrum that is currently used most often in cancer is truncated at a level above 5-10% because of difficulties in identifying low frequency variants.

- There are two main tracks in variant calling.
  - Heuristic filters
  - Statistical models of sequencing error
- We focus here on a model of mutation probability, including but not limited to sequencing error.
- Many types of callers, all assume there is no biological preference for mutation at a given site. Any site specific estimates are site specific sequencing/alignment error models(Xu 2018).
- Mutect2, FreeBayes and others are haplotype based callers
- Callers with site specific variant probabilities generate them either from other samples or through deep sequencing (deepSNV,EBCall,LoLoPicker). They are essentially generating a site specific sequencing error model, not a site specific probability of mutation
- Need to think about how the method applies to UMI (barcode) based sequencing, which are mostly deep targeted MuSE is continuous time

markov evolutionary model, still assuming no biological difference in site specific mutation probability(Fan et al. 2016)
- very little attention to the statistical model, either in competition or development
- there is useful biology.....
  - (Temko et al. 2018) links between mutational processes and driver mutations
  - (Van den Eynden and Larsson 2017) mutational signature critical for estimating selection
  - (Kandoth et al. 2013; Alexandrov et al. 2013) Underlying mutational processes generate tumor and tumor type specific mutation signatures
- Rather than using a constant probability for mutation, as other variant callers do, we convert that to an average or expected mutation probability, and compute the probability conditional on context and genome composition
- Poisson models make similar assumptions about the probability of an allele at a site. (Illumina technical note https://www.illumina.com/Documents/products/technotes/technote_so
- we simulate neutral tumor evolution, and assign vafs using a Beta(1,6) distribution
  - if M(f) is proportional to 1/f, then an exponential distribution is implied (Tarabichi et al. 2018; Marc J. Williams et al. 2017)(and the answering note by De, which also has a strong argument about why we need lower frequencies to do evolutionary inference). We choose a beta distribution to draw vafs and tuned to achieve a slightly fatter distribution in the 2-5% range in which we are most interested.
- Need a list of why evolutionary inference on tumors is important. Resistance, virulence(heterogeneity), biology (mutation rate/signature/microenvironment).

Results

MuTect computes the probability of a mutation from reference allele r to base m as a function of base calls b, estimated allele frequencies f, and per base error probabilities e. The probability that a given base is correctly called can be written as

$$P(b_i \mid e_i, r, m, f) = \begin{cases} f\frac{e_{b_i}}{3} + (1-f)(1-e_{b_i}) & b_i = r \\ f(1-e_{b_i}) + (1-f)\frac{e_{b_i}}{3} & b_i = m \\ \frac{e_{b_i}}{3} & otherwise. \end{cases}$$

Now consider two models for the data. Model M_0 in which there are no variants at a site, and M_f^m where allele m is present at allele fraction f. Assuming reads are independent the likelihood of the model given the data is

$$\mathcal{L}(M_f^m) = P(\{b_i\} \mid \{e_{b_i}\}, r, m, f) = \prod_{i=1}^{d} P(b_i \mid e_{b_i}, r, m, f)$$

and the probability of M_f^m can be written

$$P(m, f \mid \{b_i\}, \{e_{b_i}\}, r) = \mathcal{L}(M_f^m) \frac{P(m, f)}{P(\{b_i\} \mid \{e_{b_i}\}, r)}.$$

Because we are ultimately going to evaluate the odds in favor of M_f^m given the data, it is useful to note that we can write this probability in terms of the model M_0

$$1 - P(m, f \mid \{b_i\}, \{e_i\}, r) = \mathcal{L}(M_0) \frac{1 - P(m, f)}{P(\{b_i\} \mid \{e_{b_i}\}, r)}.$$

Taking the log of the ratio of the two previous equations gives the log odds in favor of M_f^m, and some cancellation yields the following expression

$$LOD_T(m, f) = \log_{10} \left(\frac{\mathcal{L}(M_f^m) P(m, f)}{\mathcal{L}(M_0^m)(1 - P(m, f))} \right).$$

We can construct a classifier for variants by selecting an odds threshold δ_T and labeling variants satisfying the condition

$$LOD_T(m, f) = \log_{10} \left(\frac{\mathcal{L}(M_f^m) P(m, f)}{\mathcal{L}(M_0^m)(1 - P(m, f))} \right) \geq \log_{10} \delta_T$$

as true variants, and rejecting them otherwise. Note that the expression for $LOD_T(m, f)$ can be further factorized as the sum of the log-likelihood ratio of the two models and the log odds of the prior for M_f^m. Current variant callers calculate this prior by assuming the allele and its frequency are independent, and that $f \sim \mathrm{U}(0, 1)$, so that $P(f) = 1$. If all substitutions are equally likely, then $P(m) = \mu/3$ where $\mu = 3 \times 10^{-6}$, the estimated per-base mutation rate in tumors. Given these assumptions the log prior odds is a constant, and the classifier can be re-written as

$$LOD_T(m, f) = \log_{10} \left(\frac{\mathcal{L}(M_f^m)}{\mathcal{L}(M_0^m)} \right) \geq \log_{10} \delta_T - \log_{10} \left(\frac{P(m)}{1 - P(m)} \right) \geq \theta_T.$$

If $\delta_T = 2$, i.e the odds in favor of M_f^m is 2, then $\theta_T = 6.3$, and this is the threshold implemented in MuTect 1.

The conditional probability that a mutation to allele m will occur given a specific genomic context C, $P(m \mid C)$ can be computed from the empirical data in Figure **??**, but $P(M \mid C)$ can not be. Using Bayes rule we can rewrite$P(m \mid C)$ as

$$P(m \mid C) = P(C \mid m)\frac{P(m)}{P(C)}.$$

Now $P(C \mid m)$ is the mutation spectrum of the tumor. The new expression for the log odds is

$$LOD_T(m, f) = \log_{10}\left(\frac{\mathcal{L}(M_f^m)P(m \mid C)}{\mathcal{L}(M_0^m)(1 - P(m \mid C))}\right).$$

Sensitivity in real data We examined two real tumor datasets in which variants had been validated by deep targeted resequencing (M. Griffith et al. 2015; Shi et al. 2018). M. Griffith et al. (2015) performed whole genome sequencing of an acute myeloid leukemia to a depth of ~312X, called variants with seven different variant callers and validated over 200,000 variants by targeted re-sequencing to a depth of ~1000X. This led to a platinum set of variant calls containg 1,343 SNVs. We obtained BAM files from this experiment and called variants using MuTect 1.1.7, then compared the sensitivity of the calls between MuTect and our method (Figure 1A). At any relevant threshold our method is slightly more sensitive than MuTect. MuTect is unable to recover 100% of the calls due to hueristic filtering and other differences between MuTect and the other variant callers used.

Shi et al. (2018) performed multi-region sequencing of 6 breast tumors to evaluate the effects of variant calling and sequencing depth on estimates of tumor heterogeneity, validating 1,385 somatic SNVs. As with the leukemia we obtained BAM files for this experiment and compared our method to raw MuTect calls (Figure 1B). We again find that our method is more sensitive than MuTect across the full range of relevant thresholds.

What does one star do?

A) AML31 platinum SNV calls (M. Griffith et al. 2015). B) Validated SNV in 6 breast cancers(Shi et al. 2018).

Sensitivity and specificity in simulated data

In order to describe the operating characteristics of our score as a classifier compared to MuTect, we simulated six tumors (see methods), three 100X whole genomes and three 500X whole exomes, with three differnent mutation spectra(methods). In WES simulations the relatively smaller number of variants, and consequent lower number of very low frequency variants, causes the methods to perform similarly, but our method is slightly more sensitive and has slightly

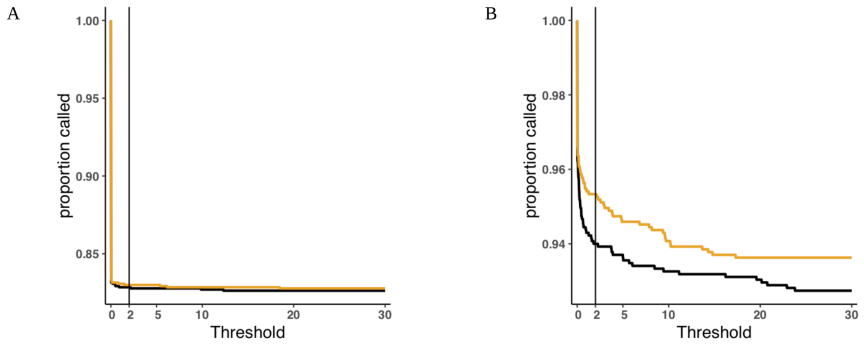

Figure 1: Sensitivity in real tumors

higher AUROC than raw MuTect scores. The large number of mutations present and at low frequency in whole genome simulations provide a clearer demonstration of the benefits of the method. The portion of the ROC curve for our method is substantially higher than the curve for MuTect, and the MuTect curve is essentially linear, is due to the effect of the prior. The prior is lowering scores of false positive mutations and raising the scores of true positives in this region. (This is super inelegant{bkm}).

A-C) Whole exome simulation. D-F) Whole genome simulation.

Convergence of the prior to simulated target distributions.

In both whole genome (Figure 3) and whole exome (supplement) simulations, the estimated mutation spectrum is very close to the simulated spectrum. The conditional probability of mutation at a given site averaged over all sites is 3e-6 (the $P(m) = \mu$ used by MuTect; important that this is averaged over every site in the genome. The probability here includes estimates of the context content of the genome $P(m \mid C) = P(C \mid m) * P(m)/P(C)$), but our method overweights some contexts and underweights others in line with the data generating distribution. (I think I need an exome too. I have the B figure, but need to generate the C figure{bkm}) Supplementary figures for other target distributions? Or a different type of figure than we have here? Or something else? We get what we would expect with other simulated spectra. The prior is as sharp or diffuse as the data generating process.

Prior probability of mutation estimated from high confidence calls. A) The simulated mutation spectrum (1,7,11). B) The maximum likelihood estimate of the data generating distribution (Dirichlet). C) The conditional probability of mutation at a site given its genomic

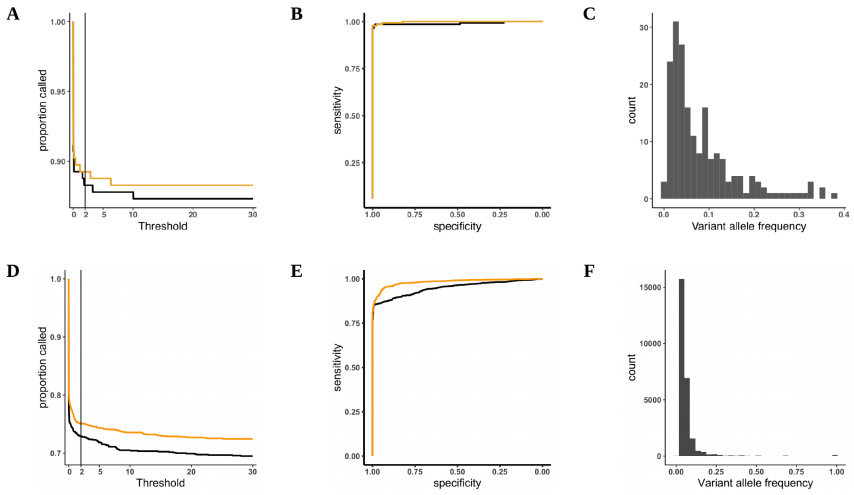

Figure 2: Sensitivity in simulated tumors

context (bar at 3e-6, the global estimate of mutation rate)

Discussion

LOL

Methods

100X whole genome and 500X whole exome for each of three signatures

1,7,11 UV (Very concentrated at C>T) 1,4,5 Tobacco (Slight concentation at C>A and C>T) 1,3,5 Breast (diffuse)

All vafs will be from the beta(1,6) which is a fat exponential

Notice that the average in Figure 3 (3e-6) is hard to rationalize. Has to do with the full probability including the global proportion of each context in the genome. So some of the wierdness is due to GC content and so forth. # Figures

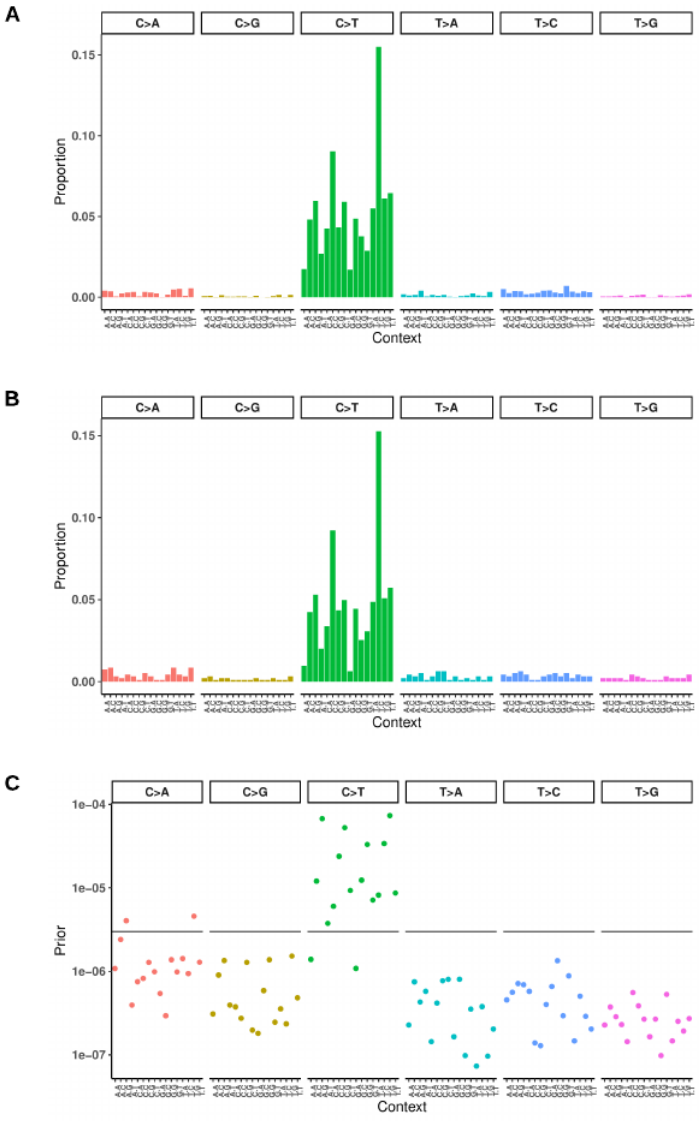

Figure 3: Sensitivity in simulated tumors

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