



Identification of the mutational signatures active in individual tumors

Rosario Michael Piro

Freie Universität Berlin Charité–Universitätsmedizin Berlin German Cancer Consortium (DKTK)

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#### Outline



#### **Background**

Mutational processes and mutational signatures De-novo inference of mutational signatures

#### Mutational signatures in individual tumors

Alexandrov signatures

Shiraishi signatures: decompTumor2Sig

#### Results

**Evaluation** 

Decomposition of tumor genomes into signatures

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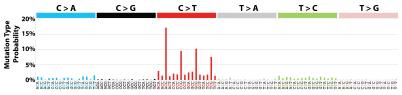
# Mutational processes and somatic mutations

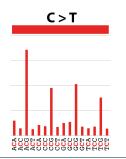
- Somatic mutations of individual tumors are caused by different mutational processes
- Mutational processes can significantly vary between tumors
  - between different cancer types
  - between individual tumors of the same cancer type
- ► The sequence context of mutated bases is important!
- Examples
  - Lung cancers of tobacco smokers have a highly increased number of cytosine>adenine (C>A) transversions
  - Spontaneous deamination of 5-methylcytosine (age-related) causes cytosine>thymine (C>T) transitions in the context of CpGs
  - See, for example, Alexandrov and Stratton, Curr Opin Genet Dev 24:52–60, 2014
- Mutational processes can be represented by means of "mutational signatures"
  - Reflect the frequencies of base changes within their sequence context



First published concept/notion of mutational signatures:

"Full" model (Alexandrov et al, Nature 500:415-421, 2013)

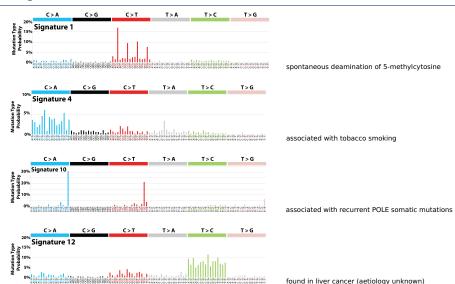




- ► Full dependency between mutated and adjacent bases
- For 3-base sequence contexts: 6 x 4 x 4 = 96 parameters
- Can be described by a vector of 96 probabilities (i.e., sum is 1)

# https://cancer.sanger.ac.uk/cosmic/ signatures

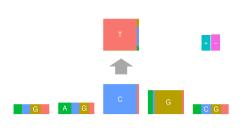






Alternative concept/notion of mutational signatures:

"Independent" model (Shiraishi et al, PLoS Genet 11:e1005657, 2015)



Nucleotide	change	(central	base)	

C>A	C>G	C>T	T>A	T>C	T>G
0.004	0.006	0.928	0.009	0.038	0.015

Flanking base	es			
Position	A	С	G	T
-2	0.237	0.228	0.293	0.242
-1	0.362	0.220	0.279	0.139
+1	0.131	0.053	0.764	0.052
+2	0.232	0.277	0.277	0.214

Transcription s	strand		
plus strand	minus	strand	
0.493	0.	507	

- Mutated base and adjacent bases as independent features
- For 5-base sequence contexts + transcriptional direction: 6+4 x 4+2 = 24 parameters
- ► Can be described by a table



(The following describes Alexandrov signatures; same for Shiraishi)

- ► The somatic mutations of a tumor are caused by multiple mutational processed. → We observe an overlap of multiple mutational signatures!
- ▶ Basic idea: the 96 mutation frequencies observed in tumor genome  $\vec{g}$  can be described as the weighted sum of N signature vectors  $\vec{s}_k$ :

$$ec{g} = \sum_{k=1}^N w_k ec{s}_k \qquad ext{with} \qquad \sum_{k=1}^N w_k = 1, w_k \geq 0$$

► For a set of G tumor genomes we have:

$$G = S \times W$$

- ► **G** is the 96 × G-matrix of observed mutation frequencies in the tumors;
- **S** is the  $96 \times N$ -matrix containing all signatures (one per column); and
- ► **W** is the *N* × *G*-matrix of weights (also called "exposures" or "contributions") of the signatures in the single tumors

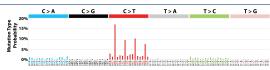
#### How are mutational signatures derived?

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$$\textbf{G} = \textbf{S} \times \textbf{W}$$

- ► **G** is the 96 × *G*-matrix of observed mutation frequencies in the tumors;
- ► **S** is the 96 × *N*-matrix containing all signatures (one per column); and
- ▶ **W** is the *N* × *G*-matrix of weights (also called "exposures" or "contributions") of the signatures in the single tumors
- Derive S and W at the same time!
  - Non-negative matrix factorization (Alexandrov et al, Cell Reports 3:246–259, 2013)
  - Principal component analysis (Gehring et al, Bioinformatics 31:3673–3675, 2015)
- Requires a large set of tumors!
- What if you what to determine which mutational processes contributed to the mutation load of a single tumor???
   (E.g., in a clinical setting)

# Alexandrov signatures in a single tumor



▶ Remember: the 96 mutation frequencies observed in *one* tumor genome  $\vec{g}$  can be described as weighted sum of N signatures  $\vec{s}_k$ :

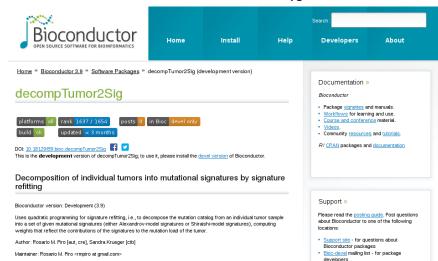
$$\vec{g} = \sum_{k=1}^{N} w_k \vec{s}_k$$
 with  $\sum_{k=1}^{N} w_k = 1, w_k \ge 0$ 

- ▶ Given:  $\vec{g}$  (observed mutations),  $\vec{s}_k$  (signatures)
- ► Goal: "Signature refitting"

  Compute weights  $w_k$  which minimize the error terms  $(\epsilon_k)$ !
  - → most likely contributions to the mutational load of the tumor!
- ► Tool: deconstructSigs (Rosenthal et al, Genome Biol 17:31, 2016)
  - ▶ R package; constructs a solution by iteratively adding single mutational signatures to minimize the sum-squared error between  $\vec{g}$  and  $\sum_{k=1}^{N} (w_k \vec{s}_k)$



# decompTumor 2549.



# Quadratic programming approach

(Following Lynch, F1000Research 5:1253, 2016)

We want  $\mathbf{S}\vec{w} \approx \vec{g}$ , so we can solve the following (because  $\vec{\epsilon} = \vec{g} - \mathbf{S}\vec{w}$ )

#### Problem

minimize 
$$(\vec{g} - \mathbf{S}\vec{w})^T (\vec{g} - \mathbf{S}\vec{w})$$
  
subject to  $\sum_{s=1}^k w_s = 1, w_s \ge 0$ 

Since  $\vec{g}^T \vec{g}$  is constant and  $(\mathbf{S}\vec{w})^T \vec{g} = \vec{g}^T \mathbf{S}\vec{w}$ , we can simplify the problem:

minimize 
$$-\vec{g}^T \mathbf{S} \vec{w} + \frac{1}{2} \vec{w}^T \mathbf{S}^T \mathbf{S} \vec{w}$$
 subject to  $\sum_{s=1}^k w_s = 1, w_s \ge 0$ 

- Classical quadratic programming problem!
- ► Can be easily solved using the R package quadprog

# Accuracy of signature contributions/weights

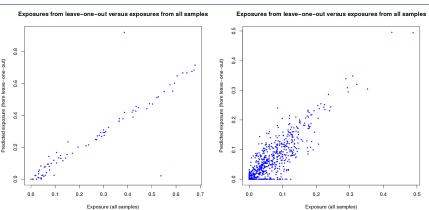
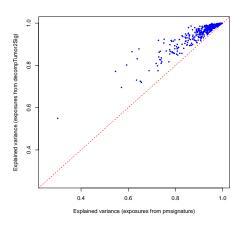


Figure 2: Comparison of contributions/weights ("exposures") predicted for individual tumors (decompTumor2Sig; y-axis) and collectively computed (pmsignature; x-axis). Left: leave-one-out test on 21 breast cancers (r = 0.923). Right: test set of 44 out of 435 tumors (r = 0.807).

Median weight differences ( $|w_k - w'_{\nu}|$ ): (A) 0.018 and (B) 0.019





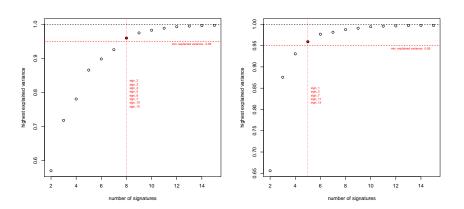
- Signature refitting better explains the observed variance of a tumor's mutation frequencies
- Explained variance R<sup>2</sup> defined as:

$$R^2 = 1 - \frac{\mathrm{Var}(g - \hat{g})}{\mathrm{Var}(g)} = 1 - \frac{\sum_{i=1}^{p} (g_i - \hat{g}_i)^2}{\sum_{i=1}^{p} (g_i - g_i^*)^2}$$

where g is the observed,  $g^*$  a uniform, "flat" tumor genome, and  $\hat{g}$  the genome predicted by the computed weights (hence  $g - \hat{g}$  is the error).

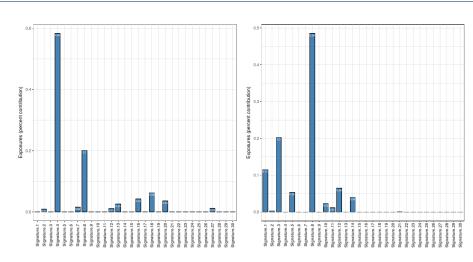
 Much less parameters to be estimated ...

# Subsets of signatures explain tumor genomes



In many cases >95% of the variance in a tumor's mutation frequencies is determined by a subset of signatures.

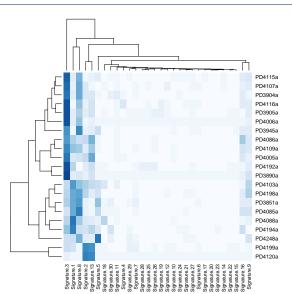
### Decomposition of example tumors



Contributions to lung adenocarcinoma (left) and medulloblastoma (right)







Contributions to 21 breast cancer genomes (data: Nik-Zainal et al., Cell, 2012)

#### Signature 3:

associated with failure of DNA double-strand break-repair (germline and somatic mutations in BRCA1 and BRCA2)

#### Signature 1:

spontaneous deamination of 5-methylcytosine (age-related)

#### Signatures 2 & 13:

attributed to activity of APOBEC family members

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### Questions?



