Cancer stratification and prognosis from mutations using gene networks

Marine Le Morvan Advised by Jean-Philippe Vert & Andrei Zinoyev

CBIO - Mines Paristech, INSERM U900 - Curie institute, Paris, France

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Cancer genomics

- Genome sequencing
- Mutations in cancer
- Towards precision medicine

Cancer stratification and survival prediction from mutation data

A word on my current work

Outline

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- Human DNA is contained into 22 pairs of chromosomes, plus X and Y.
- Each chromosome is a long molecule of DNA.
- A total of 3 billion nucleotides A, T, C, G (Les Misérables V. Hugo $\times 1000$).
- It is estimated that the human genome contains 20000-25000 protein coding genes.

The Human Genome Project



Figure: Covers of Science and Nature in 2001 announcing that the human genome has been sequenced (almost completely) for the first time.

- The Human Genome Project cost 3 billion dollars over the period 1990-2003.
- It was the first *reference* genome for *Homo Sapiens*, assembled from the genomes of a few donors.

Sequencing cost for a whole genome



- Sequencing costs have plummeted since 2007 thanks to the advent of next-generation sequencing.
- In 2019, a whole genome can be sequenced in a day for around 1000\$, and less for whole exome (i.e only genes).





soure: https://strandls.com/what-is-cancer

- The mechanisms that lead to the onset cancer are not fully understood yet.
- The disease is driven by genetic alterations in cancer cells that induce uncontrolled cell proliferation.
- Disease alterations mean point mutations, insertions, deletions, copy number variations, methylation changes, ...









- Single Nucleotide Polymorphism (SNP):
 - $\checkmark\,$ Variation compared to a reference genome in typically > 1% of the population.

Germline mutation:

- $\checkmark\,$ Variation compared to a reference genome in typically <1% of the population.
- Somatic mutation:
 - $\checkmark\,$ Variation compared to one's germline cells. Appears during one's lifetime and is not present in all cells.
 - \checkmark Somatic mutations play an important role in the onset of many cancers.

Driver mutations

- Somatic mutations naturally occur in a lifetime and accumulate with age.
- The number of mutations in protein coding genes widely varies across cancers, from a 10s to 1000s.
- Recent studies have estimated that cancer cells have on average between 1 and 10 driver mutations depending on cancer types.
- A central topic in cancer research: distinguish driver from passenger mutations (Proto-oncogenes and tumor-supressor genes).



Figure: Vogelstein et al., 2013

Matched tumor & normal tissues from more than 11,000 patients, representing 33 cancer types.



- Large scale tumor sequencing efforts from 2006 to 2018.
- Provide in particular somatic mutation data, as well as patients clinical records.

Precision medicine:

• aims at integrating the genetic specificities of an individual with its conventional medical record to adapt treatment, or prevention strategies.

Examples of research questions:

- Patient stratification
- Prediction of survival, relapse, metastasis, drug toxicity, drug resistance, ...



Cancers are usually classified by tissue of origin (breast, lung, ...). However, it slowly evolves towards a classification based on molecular descriptors.

• Within tumor type heterogeneity: example of breast cancer.



Basal-like: PARP inhibitors ERBB2+: HER2-targeted drugs Normal Breast-like Luminal Subtype C Luminal Subtype B: Hormonal manipulation, HER2-targeted drudge CDK inhibitors Luminal Subtype A: Hormonal manipulation, CDK inhibitors

Figure: Breast cancer patient stratification obtained via unsupervised clustering of gene expression profiles. Figure adapted from Perou et al., with treatment information from Jeanne De Lartigue.

• Recent studies have also highlighted shared alterations across cancer types (drug repurposing).

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RESEARCH ARTICLE

NetNorM: Capturing cancer-relevant information in somatic exome mutation data with gene networks for cancer stratification and prognosis

Marine Le Morvan^{1,2,3}, Andrei Zinovyev^{1,2,3}, Jean-Philippe Vert^{1,2,3,4}*

- A new representation of somatic mutation profiles,
- based on gene networks,
- to improve patients stratification and survival prediction.





The raw data:

- Binary mutation profiles where a 1 stands for the presence of one (or more) mutation in a given gene for a given patient
- yield poor survival prediction performances,
- are not well suited for patient stratification.

Challenges:

- High dimension (around $\approx 20,000$ genes).
- Low mutation frequency.
- Patients share few mutations in common.

Somatic mutations



• Observed behaviour:

• Patient stratification:

- Non-negative Matrix factorisation (NMF)
- ✓ Consensus clustering



• Desired behaviour:



Somatic mutations



Gene-gene interaction networks

- An idea is to use protein-protein interaction networks to create an overlap between patients.
- Many types of interactions recorded:
 - ✓ Complexes and physical interactions
 - ✓ Biochemical reactions (phosphorylation, ...)







• Hypothesis: if two mutations in different genes are close on the gene network, they may cause similar downstream effects.

Previous work: Network-based stratification (NBS)



Assumption

Even if two tumors have no mutations in common, the same subnetworks may be affected.

Method

Network smoothing.

Diffusion process. Each mutation profile (row of the mutation matrix) is smoothed independently.



Hofree2013Network



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Quantile normalisation (QN)

The *i*th smallest value of all samples (patients) is set to the median of all *i*th smallest values across samples.

Son-Negative matrix factorisation (NMF).

- Quantile normalisation:
 - \checkmark has no obvious biological motivation.
 - \checkmark it modifies the smoothed mutation profiles so that the interpretation in terms of shared mutated subnetworks is not so straightforward after QN.
 - $\checkmark~$ QN is crucial for NBS to work
- We propose NetNorM a new representation of mutation profiles:
 - ✓ inspired from the crucial role of QN in NBS,
 - $\checkmark\,$ and try to identify and predictive signals created.
- We compare the different representations of mutations (raw binary, NBS, NetNorM) for two tasks:
 - ✓ survival prediction,
 - ✓ patient stratification.

Raw binary mutation matrix



Gene-gene interaction network

NetNorM replaces $x \in \{0,1\}^{p}$ by a representation with more information shared between

samples $\phi(\mathbf{x}) \in \mathcal{H}$ where $\mathcal{H} = \left\{ \mathbf{x} \in \{0, 1\}^p : \sum_{i=1}^p \mathbf{x}_i = k \right\}$ and relies on a gene network to remove/add mutations. k is a parameter chosen by cross-validation.

Overview of NetNorM - 2/2

Toy example with k = 4: (in reality, k is around of few 10s to a few 100s)

Add mutations to patients with fewer than *k* mutations.



Q Remove mutations from patients with more than *k* mutations.



Large-scale efforts to collect exome somatic mutation profiles

Data used in this study:

- 3,378 samples with survival information (somatic mutations in exomes - silent mutations removed)
- from 8 cancer types
- downloaded from TCGA and cBioPortal.



✓ X: mutation matrix

✓ y: months of survival since diagnosis

 $\checkmark \delta$: censoring status (1: deceased, 0: alive)

Cancer type	Patients	Genes
LUAD (Lung adenocarcinoma)	430	20 596
SKCM (Skin cutaneous melanoma)	307	$17 \ 461$
GBM (Glioblastoma multiform)	265	14 748
BRCA (Breast invasive carcinoma)	945	16 806
KIRC (Kidney renal clear cell carcinoma)	411	10 608
HNSC (Head & Neck squam. cell carcinoma)	388	$17\ 022$
LUSC (Lung squamous cell carcinoma)	169	13 589
OV (Ovarian serous cystadenocarcinoma)	363	$10 \ 192$

Comparison of survival prediction performances



- ✓ We assume y = Xw
- ✓ Sparse survival SVM [VanBelle]
- $\checkmark \ \ 4\times 5\text{-fold} \\ \text{cross-validation}$
- ✓ Gene network: Pathway Commons.

Genes frequently selected in survival prediction models



Genes selected at least 10 times out of 20 folds



Mutations in KHDRBS1 are almost only proxy mutations.

Using mutations and clinical data together

- ✓ Models are learned on mutations and clinical data separately and subsequently averaged.
- ✓ Clinical data alone outperforms mutation data alone.
- ✓ There is information in mutation data, as captured by NetNorM, that allows to improve on clinical data alone.



- Unsupervised patient stratification:
 - \checkmark With NMF + consensus clustering.
 - $\checkmark~$ Number of clusters tested vary from 2 to 6.
 - $\checkmark\,$ The logrank test (case > 2 subgroups) tests whether or not there is at least one subgroup whose survival distribution is different from the others.



- Somatic mutation profiles are challenging because:
 - ✓ Low mutation frequency.
 - $\checkmark\,$ Few shared mutations among patients.
 - \checkmark Large variability in the total number of mutations.
- Network smoothing/local averaging sometimes helps
 - \checkmark but with current methods, looking at direct neighbours is good enough.
- Normalising for the total number of mutations is important
 - \checkmark with NSQN or NetNorM.
 - ✓ NetNorM creates a signal related to local and global mutational burden.

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Supervised learning with missing values

Missing values are ubiquitous in various fields/experiments: electronic health records, polls, sensor data, ...





Most off-the-shelf machine learning models cannot be applied with missing values.

What can be done:

- Complete-case analysis?
- imputation prior to learning?

Figure: Traumabase clinical health records.

• Setting:

• Linear regression model of the complete data X:

$$Y = \sum_{j=1}^d \beta_j X_j$$

• We aim to find a predictor \hat{f}_n which minimizes the least squares loss:

$$\hat{f}_n \in \operatorname*{argmin}_{f \in \mathcal{F}} \sum_{i=1}^n \left(Y_i - f(Z_i)\right)^2$$

where Z is the incomplete data.

- We show that the best possible regression function (Bayes predictor):
 - is not linear, and characterize its form.
 - can be computed by a linear regression model on an expanded feature set, or approximated with a single layer perception.

- We are always interested in applying the newly developed methodology to real datasets (for now Traumabase electronic health records, probably paleoclimatology dataset).
- Don't hesitate to contact us if you are faced with missing data problems!

Thank you for your attention!