# ALGORITHMIC CHALLENGES IN RECONSTRUCTING COPY-NUMBER EVOLUTION 

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## Tumours and evolution



- Tumor cells undergo rapid genomic evolutionary changes
- Rearrangements
- Amplifications
- Deletions
- e.g. : breakage-fusion-bridge cycle


$$
\therefore \therefore
$$

## Single cell sequencing

- Assessment of tumor heterogeneity
- Cells within a tumor undergo somatic mutations
=> Different rearrangements, duplications, deletions
=> Difficult to obtain complete genome of every cell
- Copy-numbers are easier to obtain.
- High coverage = expensive \$\$
- Accuracy at low coverage now possible
(Direct libray preparation, 10X Genomics, ...)


## Copy-Number Profile (CNP)



10 copies of segment 1
5 copies of segment 2
0 copies of segment 3
4 copies of segment 4
10 copies of segment 5

## Copy-Number Profile (CNP)

(10, 5, 0, 4, 10)

## Our Solution Features

- Profiles 100 s to 1000 s of cells
- Accurately calls single cell CNV events at 2 Mb resolution
- Detects CNV events down to 100 s of Kb on clusters of cells
- Demonstrated with cell lines, primary cells, fresh and frozen tissue
- Push-button analysis and visualization software



## View the Workflow

Sequence cells from same tumor (single cell sequencing)


Infer copy-number for each segment of interest (for each allele)


Phasing: assign copy-number to allele, get chromosome Copy-Number Profile (CNP)


Reconstruct phylogeny

Sequence cells from same tumor (single cell sequencing)


Infer copy-number for each segment of interest (for each allele)


Phasing: assign copy-number to allele, get chromosome Copy-Number Profile (CNP)


Compare CNPs of each pair of cells => distance matrix

| 0 | 16 | 47 | 72 | 77 | 79 |
| ---: | ---: | ---: | ---: | ---: | ---: |
| 16 | 0 | 37 | 57 | 65 | 66 |
| 47 | 37 | 0 | 40 | 30 | 35 |
| 72 | 57 | 40 | 0 | 31 | 23 |
| 77 | 65 | 30 | 31 | 0 | 10 |
| 79 | 66 | 35 | 23 | 10 | 0 |

Reconstruct phylogeny


$(10,5,0,4,10) \quad(8,6,2,0,8) \quad(1,4,4,4,8)$
(6, 6, 2, 0, 0)
(7, 7, 3, 0, 3)

If we know the Copy-Number Profile (CNP) of each segment of interest in several tumor cells, what can we say about their evolution?

## In this talk

- Comparing integer vectors.
- Comparing genomes an CNPs.
- Comparing integer vectors (with rearrangements).


## In this talk

- Comparing integer vectors.
- We have no idea how!
- Comparing genomes an CNPs.
- We have no idea how!
- Comparing integer vectors (with rearrangements).
- We have no idea how!


## Comparing Copy-Number Profiles

$$
\begin{array}{cc}
\mathbf{u}= & (3,5,3,1,4,2) \\
e_{1}=(2,5,-1) & \downarrow-1 \\
\mathbf{u}_{1}= & (3,4,2,0,3,2) \\
e_{2}=(1,2,-2) & -2 \downarrow \\
\mathbf{u}_{2}= & (1,2,2,0,3,2) \\
e_{3}=(3,6,2) & \downarrow+2 \\
\mathbf{v}= & (1,2,4,0,5,4)
\end{array}
$$

## Why compute distances

- Classic approach 1
- compute $\operatorname{dist}(u, v)$ for each pair $u, v$
- get a distance matrix
- use phylogenetic distance method (e.g. NJ)

|  | $\mathbf{x}$ | $\mathbf{y}$ | $\mathbf{z}$ |
| :---: | :---: | :---: | :---: |
| $\mathbf{x}$ | 5 | 8 | 6 |
| $\mathbf{y}$ |  | 5 | 7 |
| $\mathbf{z}$ |  |  | 2 |



## The story so far

1. Let's use the Euclidean distance (2011)
2. Let's model segmental events on integer vectors (2014)

- Even if minimizing events takes exponential time...
- No actually it takes polynomial time (2017)

3. Let's weight events by their amplitude (2019)
4. Let's weight events by their length/location (upcoming...)

# nature > letters > article <br> nature <br> International journal of science <br> Letter $\mid$ Published: 13 March 2011 <br> <br> Tumour evolution inferred by single-cell <br> <br> Tumour evolution inferred by single-cell sequencing 

 sequencing}

Nicholas Navin, Jude Kendall, Jennifer Troge, Peter Andrews, Linda Rodgers, Jeanne McIndoo, Kerry
Cook, Asya Stepansky, Dan Levy, Diane Esposito, Lakshmi Muthuswamy, Alex Krasnitz, W. Richard McCombie, James Hicks \& Michael Wigler ${ }^{\text {M }}$

- Sequenced 100 cells from a tumor, reconstructed NJ phylogeny from CNP data.

- In Navin et al. [Nature11] : Euclidean distance
- $\operatorname{dist}(\boldsymbol{u}, \boldsymbol{v})=\sqrt{\sum\left(u_{i_{-}} v i\right)^{2}}$

$(2,5)$

$(5,1)$
dist $=\sqrt{9+16}=5$
- In Navin et al. [Nature11] : Euclidean distance
- $\operatorname{dist}(\boldsymbol{u}, \boldsymbol{v})=\sqrt{\sum\left(u_{i_{-}} v i\right)^{2}}$

$(2,5)$

$(5,1)$

$$
\text { dist }=\sqrt{9+16}=5
$$

- Implicit assumption: positions are independent.

In Schwarz et al. [PlosCB14]: MEDICC model

- Positions should NOT be independent!
- Events can affect segments of genomes


## CNP-2-CNP problem - MEDICC model

- Given: two CNPs $\boldsymbol{u}$ and $\boldsymbol{v}$ (integer vectors)
- Move: alter an interval of $\boldsymbol{u}$ by $+1 /-1$ (a 0 stays a 0 ).

Find: min \# of moves to turn $\boldsymbol{u}$ into $\boldsymbol{v}$

$$
(1,1,1,1,1,1,1)
$$

(1,2,0,0,2,0,2)

## CNP-2-CNP problem - MEDICC model

- Given: two CNPs $\boldsymbol{u}$ and $\boldsymbol{v}$ (integer vectors)
- Move: alter an interval of $\boldsymbol{u}$ by $+1 /-1$ (a 0 stays a 0 ).

Find: min \# of moves to turn $\boldsymbol{u}$ into $\boldsymbol{v}$

$$
\begin{aligned}
& \left(1,1, \frac{1,1,1,1,1)}{\sqrt[\square]{\square}}{ }^{-1}-1\right. \\
& (1,1,0,0,1,1,1) \\
& \frac{\square}{5}-1 \\
& \left(1, \frac{1,0,0,1,0,1)}{\square}+1\right. \\
& (1,2,0,0,2,0,2)
\end{aligned}
$$

## CNP-2-CNP problem - MEDICC model

- In Schwarz \& al [PlosCB14]
- Compute $d(u, v)$ in time $\Omega\left(3^{N}\right), \mathrm{N}=$ max copy-number

$$
\begin{gathered}
(1,1,1,1,1,1,1) \\
(1,1,0,0,1,1,1) \\
\text { ® }^{\square} \\
(1,1,0,0,1,0,1) \\
\underbrace{\square}_{(1,2,0,0,2,0,2)}+1
\end{gathered}
$$

## ZZS algorithm

- In Zeira, Zehavi, Shamir [JCB17]:
- Better algorithms to compute min \# of +1/-1 moves
- Simple DP pseudo-polynomial time algorithm O(nN2)
- More involved $\mathrm{O}(\mathrm{n})$ time algorithm.


## ZZS algorithm

- In Zeira, Zehavi, Shamir [JCB17]:
- Better algorithms to compute min \# of $+1 /-1$ moves
- Simple DP pseudo-polynomial time algorithm $\mathrm{O}\left(\mathrm{nN}^{2}\right)$
- More involved $\mathrm{O}(\mathrm{n})$ time algorithm.
- General idea:
- Show that some optimal solution does all deletions before amplifications.
- Dynamic programming, optimal for every prefix from left to right.
- $M[i, d]=$ optimal for $i$ if $i$-th value is $d$.
$\mathrm{M}[i, d] \leftarrow \min _{0 \leq d^{\prime} \leq N}\left\{\mathrm{M}\left[\operatorname{prev}(i), d^{\prime}\right]+\max \left\{d-d^{\prime}, 0\right\}+\max \left\{a(i, d)-a\left(\operatorname{prev}(i), d^{\prime}\right), 0\right\}\right.$
$\left.+\max \left\{Q_{i}-\max \left\{d, d^{\prime}\right\}, 0\right\}\right\}$.


## At Recomb-CG 2019

Same problem, but not restricted to $+1 /-1$.

## At Recomb-CG 2019

Same problem, but not restricted to $+1 /-1$.
A single event could double copy numbers (e.g. WGD).

## CNP-2-CNP problem - extended MEDICC

- Given: two CNPs $\boldsymbol{u}$ and $\boldsymbol{v}$ (integer vectors), cost function $f$
- Move: alter a contiguous interval of $\boldsymbol{u}$ by any amount.
- Find: min \# of moves to turn $\boldsymbol{u}$ into $\boldsymbol{v}$


## CNP-2-CNP problem - extended MEDICC

- Difference vector $\boldsymbol{w}=\boldsymbol{u}-\boldsymbol{v}$
- Intuition: "squish" values of $w$ to 0 .

$$
\mathbf{u}=(3,5,3,1,4,2)
$$

$$
e_{1}=(2,5,-1) \quad \downarrow-1
$$



$$
\mathbf{u}_{1}=(\underline{(3,4}, 2,0,3,2)
$$

$$
e_{2}=(1,2,-2) \quad-2 \downarrow
$$

$$
\begin{array}{rr}
\mathbf{u}_{2}= & (1,2,2,0,3,2) \\
e_{3}=(3,6,2) & \downarrow+2 \\
\mathbf{v}= & (1,2,4,0,5,4)
\end{array}
$$

$$
\mathbf{u}_{\mathbf{2}}-\mathbf{v}: \uparrow \quad 1 \quad|-2| \begin{array}{|c|c|}
\hline-2 & -2 \\
\hline
\end{array}
$$



## Theorem

In the extended MEDICC model, the CNP-2-CNP problem is strongly NP-hard.
(strongly => hard even if the numbers are polynomial in $n$ )

## Positive results

## Theorem

If the CNP's have no 0-positions, there is a linear time factor 2 approximation algorithm for the extended CNP-2CNP problem.

The algorithm
Return the number of flat intervals in the difference vector.

Flat interval = contiguous positions in which difference vector has same value.
Below: 5 flat intervals
Lemma
One moves reduces number of flat intervals by at most 2 $=>\operatorname{dist}_{\text {any }}(\boldsymbol{u}, \boldsymbol{v})$ is at least $1 / 2$ the number of flat intervals.


Flat interval = contiguous positions in which difference vector has same value.
Below: 5 flat intervals
Lemma
One moves reduces number of flat intervals by at most 2 => dist ${ }_{\text {any }}(\boldsymbol{u}, \boldsymbol{v})$ is at least $1 / 2$ the number of flat intervals.
Trivial 2-approx: remove each flat interval one by one.


## Experiments

- If we simulate amplifications and deletions on genomes (and not CNPs), can we reconstruct phylogenies?
$\mathrm{n}=$ number of leaves in random tree (def. $\mathrm{n}=100$ )
I = number of genes per chromosome (def. $\mathrm{I}=100$ )
$\partial=$ prob. of duplication (def. $\partial=0.5$ )
$\left(e_{1}, e_{2}\right)=$ range of \# of events per branch (def. [5..10])
$(p, q)=$ control length of events




## More leaves = easier to predict








More genes $=$ easier to predict

## Extended-extended MEDICC model

- Some events are more likely to affect certain regions of the genome.
- e.g. arm duplications => ends of CNP vector more susceptible to amplification
- Extended model : each interval $[i . . j]$ has its own weight.
- Weights can be inferred from cancer patient data.
- (not published yet, and not my work)


## Comparing Genomes with Copy-Number Profiles


$(2,5,0,4,3)$

## Problems with segmental events on CNPs

- Assumes that order of segments remains fixed.
- Rearrangements change the order.
- Some, drastically.


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## Problems with segmental events on CNPs

- Assumes that order of segments remains fixed.
- Rearrangements change the order.
- Some, drastically.
- Introduce actual rearrangements into the model.


## Genome-to-CNP

- In [Zhu \& al, ACM-BCB 2018]:
- Given the CNP of of a single cell $C$, infer the rearrangements that occurred from a healthy genome to $C$.

Normal human genome

## Genome-to-CNP

- In [Zhu \& al, ACM-BCB 2018]:
- Given the CNP of of a single cell $C$, infer the rearrangements that occurred from a healthy genome to $C$.

Normal human genome

Abnormal CNP
abcdbcefabbc

(2, 5, 0, 4, 3)

## Genome-to-CNP

- In [Zhu \& al, ACM-BCB 2018]:
- Given the CNP of of a single cell $C$, infer the rearrangements that occurred from a healthy genome to $C$.
- Allowed: segmental duplications \& deletions.

Normal human genome

Abnormal CNP
abcdbcefabbc

$(2,5,0,4,3)$

## Genome-to-CNP

- Given: string $S$ and copy-number vector $C$
- Move: segmental duplications and deletions.
- Find: min \# of moves to turn $S$ into any $T$ whose CNP is $C$

Normal human genome

Abnormal CNP
abcdbcefabbc

(2, 5, 0, 4, 3)

## Example

abcd
$(2,4,1,3)$

Need
$2 \times \mathrm{a}$
$4 \times b$
$1 \times c$
$3 \times d$

## Example

## abcd

abcdbcd
Segmental duplication (this one is tandem)
(2, 4, 1, 3)

Need<br>$2 \times \mathrm{a}$<br>$4 \times b$<br>$1 \times c$<br>$3 \times d$

## Example

## abcd

abedbcd
abdbcd
Deletion (this one is not segmental)
(2, 4, 1, 3)

Need<br>$2 \times \mathrm{a}$<br>$4 \times b$<br>$1 \times c$<br>$3 \times d$

## Example

## abcd

abcdbcd
abdbcd
abdbabdbcd
$(2,4,1,3)$

Need
$2 \times \mathrm{a}$
$4 \times b$
$1 \times c$
$3 \times d$

## Example

## abcd

abcdbcd
abdbcd
abdbabdbcd
(2, 4, 1, 3)

Need
$2 \times \mathrm{a}$
$4 \times b$
$1 \times c$
$3 \times d$

## But why?



## But why?

abcdbcefabbc

(10, 5, 0, 4, 10)
$(8,6,2,0,8)$
(1, 4, 4, 4, 8)
$(6,6,2,0,0)$
(7, 7, 3, 0, 3)

## But why?

abcdbcefabbc

$(10,5,0,4,10) \quad(8,6,2,0,8) \quad(1,4,4,4,8)$
(6, 6, 2, 0, 0)

(7, 7, 3, 0, 3)

## But why?



## But why?



## Genome-to-CNP

- The problem is NP-hard [Zhu \& al., 2018]
- Reduction from set-cover: design S and CNP C so that
- each elements = 1 character
- choosing a set = deleting elements
- must delete one occurrence of each element


## Genome-to-CNP

In [Lafond, Zhu \& Zou, CPM, submitted]

## Theorem

The Genome-to-CNP problem (probably) does not admit a constant factor approximation and (probably) is not FPT.

## Genome-to-CNP

## Open problem

Find any practical approach!

## Genome-to-CNP

## Open problem

If initial string $S$ is exemplar, is Genome-to-CNP in P?

Exemplar $=$ no characer occurs more than once.

Could be useful: we may model each chromosome of the healthy genome as exemplar.

## Comparing Integer Vectors (with rearrangements)


(2, 5, 0, 4, 3)

$(3,6,2,1,3)$

- Interval events may give rise to impossible scenarios.

$$
\begin{aligned}
& \text { (1, 1, 1, 1, 1, 1, 1) } \\
& \text { 凸 -1 } \\
& \text { (1,1,0,0,1,1,1) } \\
& \text { ■ -1 } \\
& \text { (1,1,0,0,1,0,1) } \\
& \text { ■ +1 } \\
& \text { (1,2,0,0,2,0,2) }
\end{aligned}
$$

- Interval events may give rise to impossible scenarios.
- Compare CNPs, but require the existence of actual genomes + rearrangements.

$$
\begin{aligned}
& (1,1,1,1,1,1,1) \\
& \text { (1, 1,0,0, 1, } 1,1 \text { ) } \\
& \text { 凸 - } \\
& \text { (1, 1,0,0, 1,0,1) } \\
& \square+1 \\
& \text { (1,2,0,0,2,0,2) }
\end{aligned}
$$

## Consistent CNP-2-CNP problem

- Given: two CNPs $\boldsymbol{u}$ and $v$
- Move: segmental duplications and deletions (on genomes).
- Find:
- a genome $G_{1}$ whose CNP is $\boldsymbol{u}$;
- a genome $G_{2}$ whose CNP is $v$;
- such that \# of dups/deletions from $G_{1}$ to $G_{2}$ is minimum.


## Consistent CNP-2-CNP problem

(1, 2, 2, 2)
(3, 0, 3, 6)

Go from any genome with
$1 \times \mathrm{a}$
$2 \times b$
$2 \times c$
$2 \times d$
to any genome
with
$3 \times \mathrm{a}$
$0 \times b$
$3 \times c$
$6 \times d$

## Consistent CNP-2-CNP problem

(1, 2, 2, 2)
addccbb
(3, 0, 3, 6)

## Go from any genome with <br> $1 \times \mathrm{a}$ <br> $2 \times b$ <br> $2 \times c$ <br> 2 xd

to any genome
with
$3 \times \mathrm{a}$
$0 \times b$
$3 \times c$
$6 \times d$

## Consistent CNP-2-CNP problem

(1, 2, 2, 2)
addccbb
addcc
(1, 0, 2, 2)
(3, 0, 3, 6)

## Go from any genome with <br> $1 \times \mathrm{a}$ <br> $2 \times b$ <br> $2 \times c$ <br> $2 \times d$

to any genome
with
$3 \times \mathrm{a}$
$0 \times b$
$3 \times c$
$6 \times d$

## Consistent CNP-2-CNP problem

(1, 2, 2, 2)
$a d d c c b b$
addcc
(1, 0, 2, 2)
addcaddcc
(2, 0, 3, 4)
(3, 0, 3, 6)

Go from any genome with
$1 \times \mathrm{a}$
$2 \times b$
$2 \times c$
$2 \times d$
to any genome
with
$3 \times \mathrm{a}$
$0 \times b$
$3 \times c$
$6 \times d$

## Consistent CNP-2-CNP problem

(1, 2, 2, 2)
$a d d c c b b$
addcc
(1, 0, 2, 2)
addcaddcc
(2, 0, 3, 4)
add addcaddcc
(3, 0, 3, 6)

Go from any genome with
$1 \times \mathrm{a}$
$2 \times b$
$2 \times c$
$2 \times d$
to any genome
with
$3 \times \mathrm{a}$
$0 \times b$
$3 \times c$
$6 \times d$

## Consistent CNP-2-CNP problem

## Open problem

Any question you can think of about this problem!

- Very interesting theoretical problem.
- In practice...
- Some optimal solution always has 0 or 1 deletion (we think)
- Gives rise to ridiculous genomes
- e.g. aaaaaabbbbbbbcccccdddd
- More useful formulation: global inference of genomes on a phylogeny


## Phylogenetic CNP problem

- Given: phylogeny $T$ with CNPs at leaves, human genome at root
- Find: a genome assignment at each node of $T$ such that:
- each genome at a leaf has correct CNP;
- sum of rearrangements at branches is minimum.


$$
(10,5,0,4,10) \quad(8,6,2,0,8) \quad(8,6,2,0,8)
$$

## Phylogenetic CNP problem

- Given: phylogeny $T$ with CNPs at leaves, human genome at root
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## Conclusion

- Copy-number profiles carry useful information on tumor heterogeneity.
- Easier to obtain than whole genomes.


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- Copy-number profiles carry useful information on tumor heterogeneity.
- Easier to obtain than whole genomes.
- We are not exploiting this information at its full potential!


## Conclusion

-What this line of research needs:

- Better models
- Better problem formulations
- Better algorithms
- Better access to real data!!!

