Network models of carcinogenesis in colorectal adenocarcinoma and vestibular schwannoma

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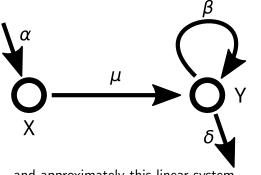
28 March 2022

*(sort of)

Warning

There will be very few equations in this talk!

This network...



corresponds to this stochastic process:...

$$\emptyset \to X, \quad \text{rate } \alpha$$
 $X \to X + Y, \quad \text{rate } \mu X$
 $Y \to Y + Y, \quad \text{rate } \beta Y$
 $Y \to \emptyset, \quad \text{rate } \delta Y$

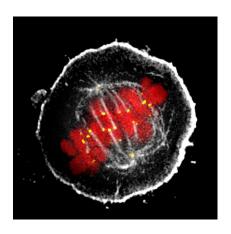
and approximately this linear system...

$$\frac{d}{dt} \begin{pmatrix} E[X] \\ E[Y] \end{pmatrix} = \begin{bmatrix} 0 & 0 \\ \mu & \beta - \delta \end{bmatrix} \cdot \begin{pmatrix} E[X] \\ E[Y] \end{pmatrix} + \begin{pmatrix} \alpha \\ 0 \end{pmatrix}$$

Most of our models are linear, high-dimensional and sparse¹

¹C. Paterson, I. Bozic, H. Clevers, PNAS 2020; 117(34): 20681-20688

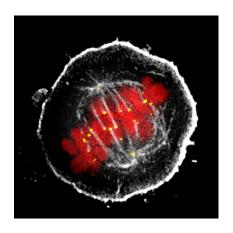
What is cancer?



- Various risk factors
- ► Mutations accumulate
- ► Loss of control of cell growth & death
 - ↓ gets us a benign tumour/neoplasia...
 - ↓ something happens...
- Dedifferentiation, migration...
- ▶ Malignancy = cancer

¹Figure: HeLa cell https://wellcomecollection.org/works/vpgx8zcd

What is cancer?



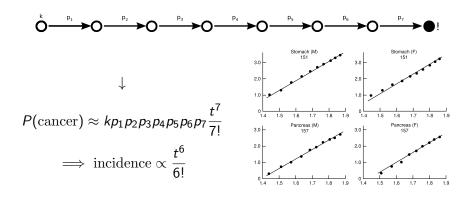
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- Mutations accumulate
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 - ↓ something happens...
- Dedifferentiation, migration...
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Why do we believe this?

¹Figure: HeLa cell https://wellcomecollection.org/works/vpgx8zcd

Multi-stage models

P. Armitage and R. Doll²

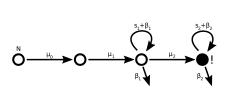


¹P. Armitage and R. Doll, British Journal of Cancer 1954; 8: 1–12

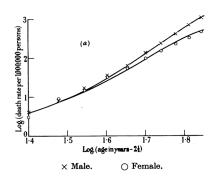
²note that P(t) = 1 - S(t), other authors (e.g. Knudson)

Multi-stage models

2-3 rate limiting steps¹²³



- Add selection s_k
- ▶ Better fit, more plausible μ_k



¹P. Armitage and R. Doll, British Journal of Cancer 1957; 11(2): 161-169

²S. Moolgavkar and G. Luebeck, JNCI 1992; 84(8): 610-618

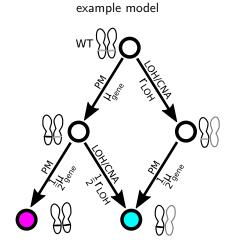
³F. Michor, Y. Iwasa and MA. Nowak, Nature Reviews Cancer 2004; 4:

¹⁹⁷⁻²⁰⁵ doi:10.1038/nrc1295

Network models

- 1. Study **specific genes** and mechanisms of interest
- 2. Fix parameters from sequences and experiments
- 3. Distinguish different orders of events

Predict copy number alterations (etc.)

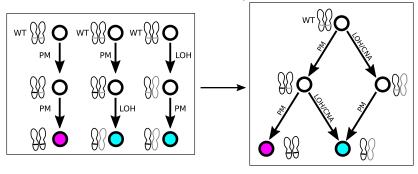


This gets us the incidence of specific karyotypes

Network models

Worked example: tumour suppressor loss-of-function

Two events of interest, 3 possible orders:

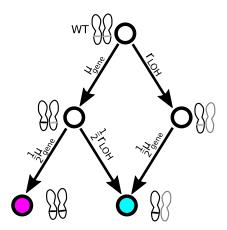




← this order of events is impossible (resulting cells are non-viable)

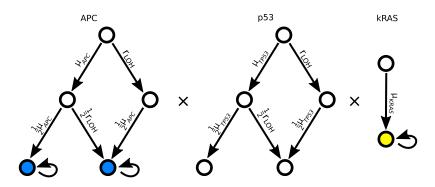
Network models

Worked example: tumour suppressor loss-of-function



Assign rates to events:

- ▶ Get μ_{gene} from $n_{gene} \times u \times b$
- ► To get *n*_{gene}, count possible nonsense mutations
- Fix r_{LOH} by looking at relative frequency of LOH

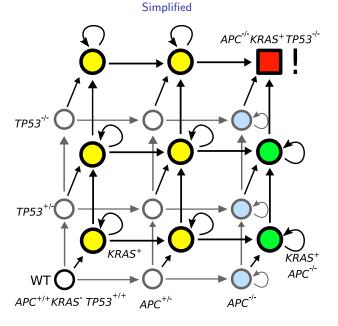


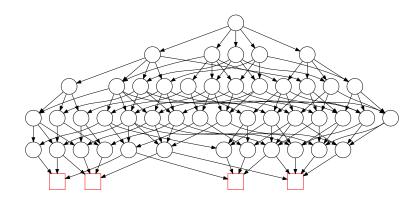
- ► APC-p53-kRAS combo accounts for about 15% of incidence
- ► 5-year survival about 60% (any stage)

¹Fearon et al. TODO

¹M. S. Lawrence et al., Nature 2014; 505: 495-501

²Office for National Statistics, England 2019

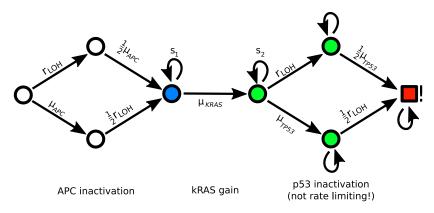




each end node is a different copy number profile

e.g.
$$(-17p, -5q)$$
, etc

¹C. Paterson, I. Bozic, H. Clevers, PNAS 2020; 117(34): 20681-20688 (supp. material)



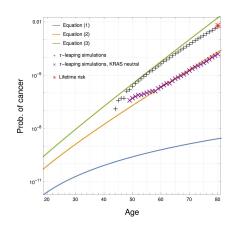
$$P(t) \sim te^{s_2 t}$$

- ▶ The 4 most likely paths account for 50% of the risk
- Consistent with classic model²

¹C. Paterson, I. Bozic, H. Clevers, PNAS 2020; 117(34): 20681-20688

²Kinzler and Vogelstein 1990

Successful ab initio model



- Gets proportion of incidence right – with no fitting!
- ► Can constrain APC/KRAS epistasis ($s_2 < 0.31/yr$)
- ► Timing of *p53* inactivation: must be *late*²
- Compatible with 3-hit models, similar curve: p53 not rate limiting
- Conditional path probabilities P(X_i) encode fitnesses

¹C. Paterson, I. Bozic, H. Clevers, PNAS 2020; 117(34): 20681-20688

²(relative to the others)

Science is very hard

- 1. model only accounts for 15% of lifetime risk^{1,2}
- often malignant on discovery: difficult to constrain timing³ or effect of drivers
- 3. 5 hits, 50 nodes, 120 edges, 270 paths, strong selection: complicated
- 4. approximations inaccurate when probabilities large

¹M. S. Lawrence et al., Nature 2014; 505: 495-501

²C. Paterson, I. Bozic, H. Clevers, PNAS 2020; 117(34): 20681-20688

³(relative to malignant transformation)

common and malignant = difficult to study

¹https://commons.wikimedia.org/wiki/File:Sun_(Earth_POV).jpg

Why study vestibular schwannoma?

Sometimes rare events make more interesting science possible

- 1. genomic subtypes better characterised: *NF2/Merlin* altered in 85-100% of cases^{1,2}, *TP53* in $\approx 0\%$
- 2. usually benign = **easier to study timing!** (of drivers, malignant transformation...)
- 3. only 3 hits, weak selection (almost neutral)
- 4. probabilities low: approximations v. accurate **because it's** rare

¹ML Carlson et al., Otology & Neurotology: 2018;39(9):860 - 871

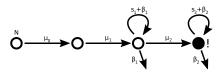
²AL Håvik et al., Journal of Neurosurgery JNS. 2017;128(3):911 – 922.



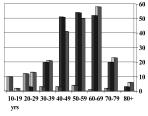
¹https://apod.nasa.gov/apod/ap211209.html

Vestibular schwannoma

3-event model



- Fitness suspiciously low, $s \approx 0.005/\text{yr}^{-1}$
- Suggests nearly-neutral 3-hit model ³





Gareth Evans 2005²

¹R. Woods et al. Genetic Epidemiology (2003)24: 265–272

²DGR. Evans et al. Otology & Neurotology (2005)26:93-97

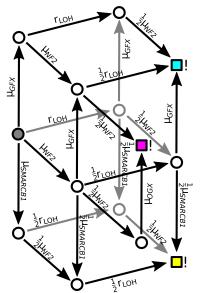
³C Paterson, I Bozic, MJ Smith, X Hoad, DGR Evans, https://doi.org/10.1101/2021.10.03.457528

Our model for sporadic VS

- ► Include *NF2*, *SMARCB1* and (simplified) linkage
- Add hypothetical oncogene GFX

Risk of each subtype looks like

$$P(\square) \propto \frac{t^3}{3!}$$



¹C Paterson, I Bozic, MJ Smith, X Hoad, DGR Evans, https://doi.org/10.1101/2021.10.03.457528

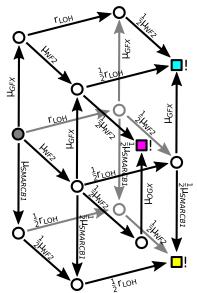
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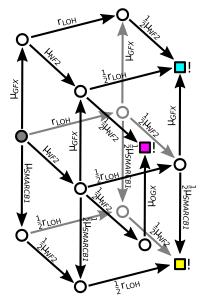
$$P(\square) \propto \frac{t^3}{3!}$$

$$P(\square) \approx N_{WT} \mu_{GFX} r_{LOH} \frac{1}{2} \mu_{NF2} \frac{t^3}{3!} \times 6$$



¹C Paterson, I Bozic, MJ Smith, X Hoad, DGR Evans, https://doi.org/10.1101/2021.10.03.457528

Our model for sporadic VS



- ightharpoonup + \square = have LOH on 22q
- ► frequency of LOH = $f_{LOH} = (\square + \square)/(\square + \square + \square)$
- $ightharpoonup = SMARCB1^{-/-}$
- ▶ frequency of SMARCB1^{-/-}
 = f_{SMARCB1}

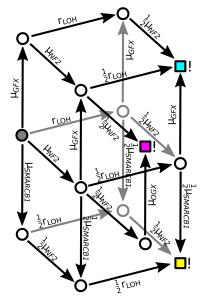
$$= \square/(\square + \square + \square)$$

Can use these to fix parameters!

Our model for sporadic VS

- ▶ Don't use ab initio point estimates for u, r_{LOH}, n_{GFX} this time...
- ► Instead use

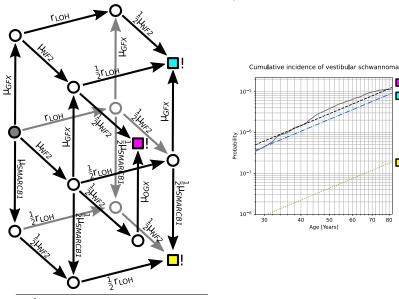
$$P(t) = \square + \square + \square$$
,
 $f_{LOH} = \square + \square$, and
 $f_{SMARCB1} = \square$ to fix
the parameters!



Our model for sporadic VS

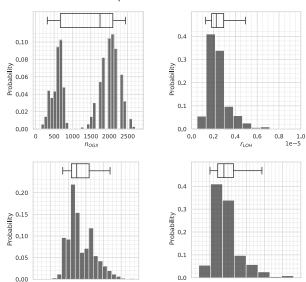
+ 🔲 + 🛄

+ 🔲



 $^{^{1}\}text{C Paterson, I Bozic, MJ Smith, X Hoad, DGR Evans, } \text{https://doi.org/} 10.1101/2021.10.03.457528}$

New parameter estimates



0 1.2 1e-9

0.2 0.4 0.6

и

0.0

0.0 0.5 1.0

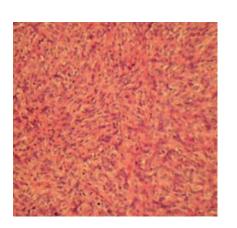
1e-7

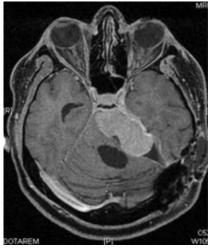
 $p_{LOH}(22q)$

Malignant transformation in vestibular schwannoma

Very rare, very bad

- ightharpoonup Risk pprox 0.1% of VS cases
- ▶ 5-year survival $\approx 12 20\%$





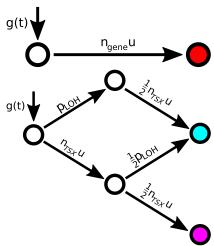
²AK Demetriades et al. Skull Base (2010)20:381–387.

Malignant schwannoma: two models

Timing and identity of drivers

Oncogene activation:

TSX inactivation:

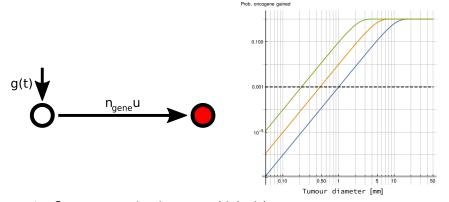


Malignant VS is extremely rare!

 $^{^{1}\}mathsf{C}\ \mathsf{Paterson}, \ \mathsf{I}\ \mathsf{Bozic}, \ \mathsf{MJ}\ \mathsf{Smith}, \ \mathsf{X}\ \mathsf{Hoad}, \ \mathsf{DGR}\ \mathsf{Evans}, \ \mathsf{https:}//\mathsf{doi.org}/10.1101/2021.10.03.457528$

Malignant schwannoma: first model

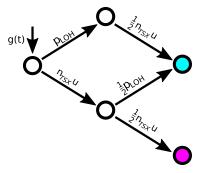
Oncogene activation

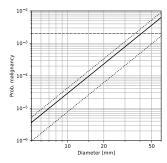


- ▶ Oncogene activation ⇒ high risk
- ▶ But it's a rare outcome
- So it's probably not caused by oncogene activation

Malignant schwannoma: second model

Tumour suppressor *TSX* inactivation

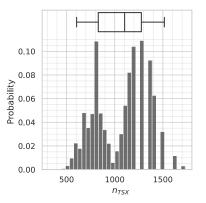




- ightharpoonup TSX inactivation \implies low risk
- \triangleright Can also estimate n_{TSX} that's consistent with incidence

Who is *TSX*?

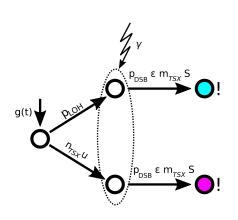
Parameter estimates for n_{TSX}



Probably multiple (10?) distinct tumour suppressors

i.e. not (just) TP53: $n_{TP53} = 73$

Radiation

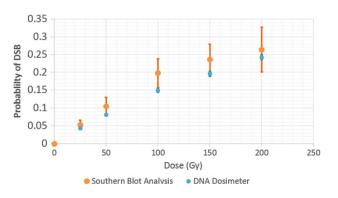


3 dose-dependent effects:

- ▶ DSB induction $p_{DSB}(D)$
- ▶ DSB misrepair $\varepsilon(D)$
- ightharpoonup cell survival S(D)
- + m_{TSX} num. sensitive sites on TSX

DSB induction model

Prob. DSB on a single b.p.



$$p_{DSB} \approx kD$$
, $k = 3.9 \times 10^{-7}/\text{Gy/bp}$

¹M. Obeidat et al., Med. Phys. 45 (7), July 2018

DSB misrepair

- ▶ Should be dose dependent $\varepsilon(D)$...
- ▶ Should also be dose-*rate* dependent $\varepsilon(D, \dot{D})$...
- ▶ But when D and \dot{D} very high can use

$$\varepsilon \approx 50\%$$

i.e. upper bound²

²K Rothkamm et al., Cancer Research (2001) 61(10):3886–3893

Why do we care about *TSX* anyway?

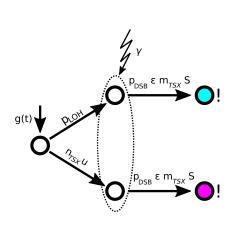
Why do we care about *TSX* anyway?

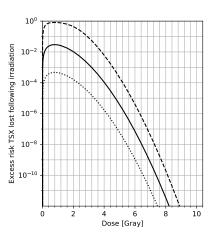
Need to know how many indel sites m_{TSX} result in loss of function:

This is predicted by n_{TSX} :

 $m_{TSX} \approx 0.42 n_{TSX}$

Radiation





Uncontroversial conclusions, but...

- ▶ Model is missing mechanisms (what is ε ? multiple genes?)
- Multifocality and familial NF2?
- ► Margin clearance & recurrence?

What experiments could constrain these?

Main outputs

- 1. Better estimates of event rates in Schwann cells
- 2. Can constrain timing of "TSX" (resp. for malignancy)
- 3. Can constrain size of GFX and TSX
- 4. Radiotherapy probably OK (w. caveats + huge error bars)

Main outputs

but...

- 1. Uncertainties still large
- 2. Identity of TSX unknown
- 3. Constraints weak: GFX and TSX probably multiple genes
- 4. Don't know about NF2

To do list

Next gen sequencing...

- ▶ Sporadic VS to constrain $f_{SMARCB1}$: n > 300
- CNA/NGS in MPNST (rare!): n > 30

but also...

- ▶ Better models!!! CNA/VAF models, machine learning, optimal clustering, $\mu_{C>T}$ etc.
- SEER data too?
- Multiple genes GFX and TSX?
- Haploinsufficiency, selection?

Lots to do!

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In order of appearance...

- Ivana Božić
- Hans Clevers
- ► Gareth Evans
- Xanthe Hoad
- Miriam Smith

