

From sequences to knowledge, Improving and learning from sequence alignments

Jury:

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Olivier	Gascuel	Examinator
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Luc Bassel – PhD Defense - December 2nd 2022



PR[AI]RIE
PaRis Artificial Intelligence Research InstitutE



PhD context

- 2 **different projects**:
 1. Exploring drug resistance using HIV **MSAs** and ML
 2. Improving long-read **mapping**
- Both linked by **sequence alignment**
- Ignore the chronological **order** for **thematic coherence**

Presentation Outline

1

Introduction

2

Improving
long-read mapping

3

An introduction
to HIV

4

Exploring resistance in
HIV with ML

5

Learning alignment &
Other perspectives

6

Conclusion

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Introduction

Biological sequences

- Sequences are just a **succession of characters**
- Sequences **encode life**
- **Foundation** of bioinformatics and **modern biology**



Introduction

Sequencing

- Sequencing \Leftrightarrow technique for **reading** the biological sequence
- A **read** \Leftrightarrow **approximate subsequence** of the **original** sequence
- Many **technological** advances since **Sanger** in **1977**
- Long Reads: PacBio **2011**, ONT **2014**
- Sequencers make **mistakes**:
 - **Substitutions** $\text{ATG} \rightarrow \text{ACG}$
 - **Indels** $\text{ATG} \rightarrow \text{ATCG}$ $\text{ATG} \rightarrow \text{AG}$

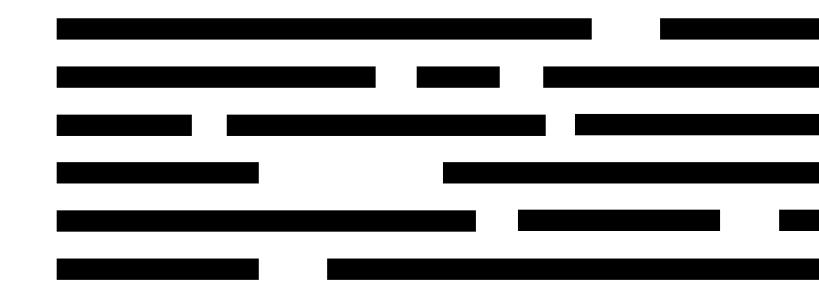
Introduction

Sequence alignment

- Alignment \Leftrightarrow **finding homologies** between sequences
- Alignment \Leftrightarrow **successive operations** to go **from one sequence to another**
- **Hard** problem → Often rely on **heuristics**



pairwise alignment



multiple alignment

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What is read-mapping ?

- Special case of **sequence alignment**
- Finding where a **short subsequence** comes from in a (or several) **long sequence**
- Usually a sequencing **read** is **mapped** to a **reference genome**
- **Fundamental task** in many analyses pipelines

Why long reads ?

A rich information source

Published: 10 November 2014

Resolving the complexity of the human genome using single-molecule sequencing

Mark J. P. Chaisson, John Huddleston, Megan Y. Dennis, Peter H. Sudmant, Maika Malig, Fereydon Hormozdiari, Francesca Antonacci, Urvashi Surti, Richard Sandstrom, Matthew Boitano, Jane M. Landolin, John A. Stamatoyannopoulos, Michael W. Hunkapiller, Jonas Korlach & Evan E. Eichler [✉](#)

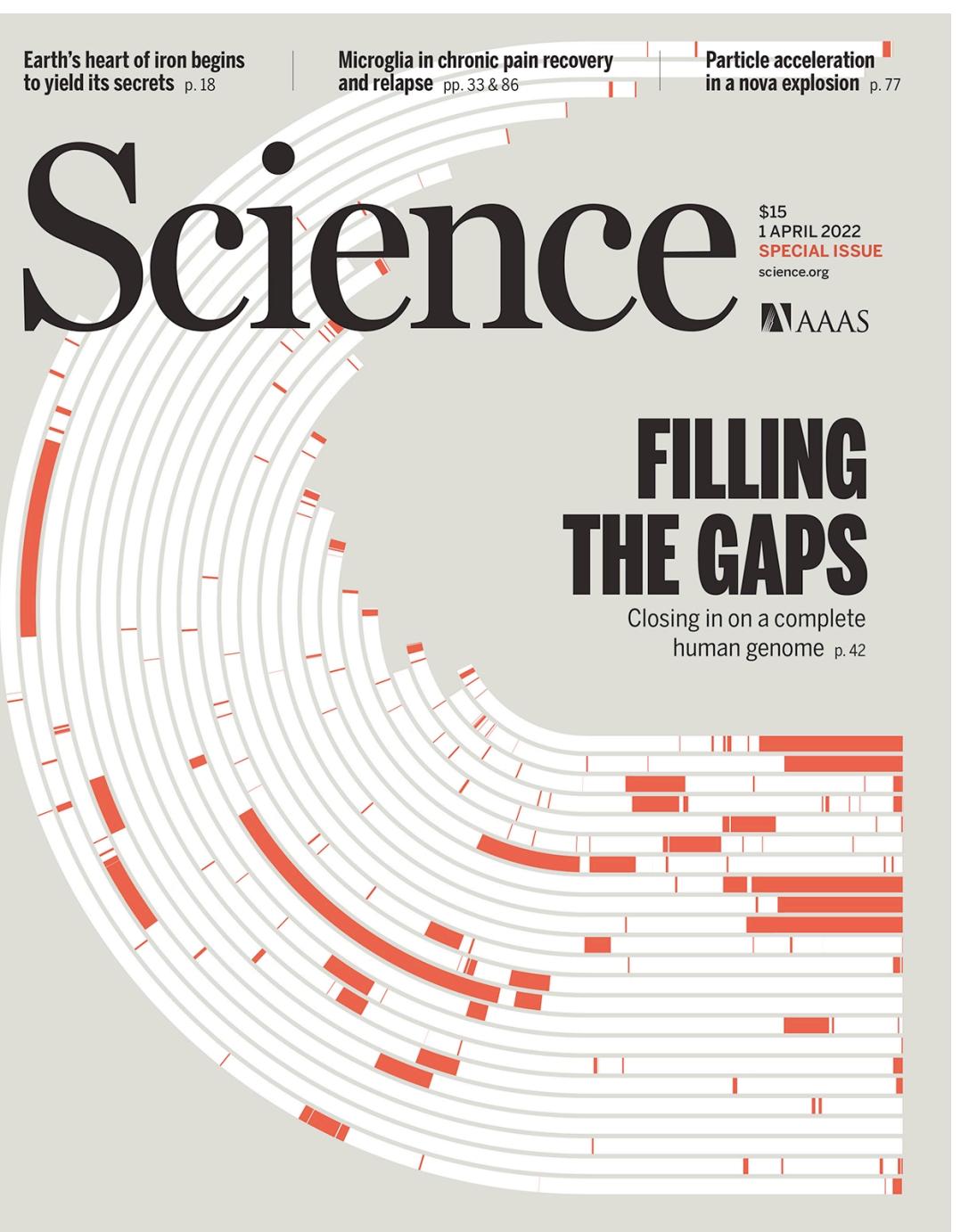
Nature 517, 608–611 (2015) | [Cite this article](#)

37k Accesses | 465 Citations | 257 Altmetric | [Metrics](#)

Long-read sequencing reveals the complex splicing profile of the psychiatric risk gene CACNA1C in human brain

Michael B. Clark, Tomasz Wrzesinski, Aitzane B. Garcia, Nicola A. L. Hall, Joel E. Kleinman, Thomas Hyde, Daniel R. Weinberger, Paul J. Harrison, Wilfried Haerty [✉](#) & Elizabeth M. Tunbridge [✉](#)

Molecular Psychiatry 25, 37–47 (2020) | [Cite this article](#)
9230 Accesses | 59 Citations | 57 Altmetric | [Metrics](#)



Mapping and phasing of structural variation in patient genomes using nanopore sequencing

Mircea Cretu Stancu, Markus J. van Roosmalen, Ivo Renkens, Marleen M. Nieboer, Sjors Middelkamp, Joep de Ligt, Giulia Pregno, Daniela Giachino, Giorgia Mandrile, Jose Espejo Valle-Inclan, Jerome Korzelius, Ewart de Brujin, Edwin Cuppen, Michael E. Talkowski, Tobias Marschall, Jeroen de Ridder & Wigard P. Kloosterman [✉](#)

Nature Communications 8, Article number: 1326 (2017) | [Cite this article](#)

21k Accesses | 176 Citations | 125 Altmetric | [Metrics](#)

Nanopore sequencing and assembly of a human genome with ultra-long reads

Miten Jain, Sergey Koren, Karen H Miga, Josh Quick, Arthur C Rand, Thomas A Sasani, John R Tyson, Andrew D Beggs, Alexander T Dilthey, Ian T Fiddes, Sunir Malla, Hannah Marriott, Tom Nieto, Justin O'Grady, Hugh E Olsen, Brent S Pedersen, Arang Rhee, Holian Richardson, Aaron R Quinlan, Terrance P Snutch, Louise Tee, Benedict Paten, Adam M Phillipi, Jared T Simpson, ... Matthew Loose [✉](#) + Show authors

Nature Biotechnology 36, 338–345 (2018) | [Cite this article](#)

156k Accesses | 853 Citations | 1412 Altmetric | [Metrics](#)

Structural variant calling: the long and the short of it

Medhat Mahmoud, Nastassia Gobet, Diana Ivette Cruz-Dávalos, Ninon Mounier, Christophe Dessimoz [✉](#) & Fritz J. Sedlazeck [✉](#)

Genome Biology 20, Article number: 246 (2019) | [Cite this article](#)

50k Accesses | 156 Citations | 99 Altmetric | [Metrics](#)

Why long reads ?

A high error rate

	Illumina	PacBio	ONT
Length	100 - 200	10,000 - 60,000	12,000 - 2.5 10⁶
Accuracy	99.9 %	85 - 92%	87 - 98%

- Errors **complicate downstream mapping** (*Gusfield, 1997*)
- Long reads plagued by **errors** (*Dohm et al., 2020*):
 - Short **indels**
 - Particularly in **homopolymers**

AAA → AAAAAAA

What is homopolymer compression ?

- HPC **transforms sequences**

HPC(**AAATTGGGCCAAA**) → **ATGCA**

- **Empirically improves** analyses, no guarantee it's the **best**
- Can we **find functions** that **improve** long read **mapping** more than **HPC** ?

A formal definition of HPC

Deriving Mapping-friendly Sequence Reductions (MSR)

- Let us define $\Sigma = \{A, C, G, T\}$ and ε the empty character
- $\forall (x_1, x_2) \in \Sigma^2$

$$g^{HPC}(x_1 \cdot x_2) = \begin{cases} x_2 & \text{if } x_1 \neq x_2 \\ \varepsilon & \text{if } x_1 = x_2 \end{cases}$$

- $HPC(x) \rightarrow$ applying g^{HPC} on a **sliding window** of size 2 **along x** and **concatenating** outputs.
- Different $g = \mathbf{MSR}$

A formal definition of HPC

Deriving Mapping-friendly Sequence Reductions (MSR)

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A A A T G G

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A hand-drawn sequence of DNA bases: A, A, T, G, G. The first 'A' is enclosed in a yellow square. Below the sequence, there is a single red 'A'.

A formal definition of HPC

Deriving Mapping-friendly Sequence Reductions (MSR)

- Let us define $\Sigma = \{A, C, G, T\}$ and ε the empty character

- $\forall (x_1, x_2) \in \Sigma^2$

$$g^{HPC}(x_1 \cdot x_2) = \begin{cases} x_2 & \text{if } x_1 \neq x_2 \\ \varepsilon & \text{if } x_1 = x_2 \end{cases}$$

A A A T G G

A ε

- $HPC(x) \rightarrow$ applying g^{HPC} on a **sliding window** of size 2 **along x** and **concatenating** outputs.
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A | A A | T G G
A ε G ε

A formal definition of HPC

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A A A T G G
A ε ε T

A formal definition of HPC

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- $HPC(x) \rightarrow$ applying g^{HPC} on a **sliding window** of size 2 **along x** and **concatenating** outputs.
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A A A [T G] G
A ε ε T G

A formal definition of HPC

Deriving Mapping-friendly Sequence Reductions (MSR)

- Let us define $\Sigma = \{A, C, G, T\}$ and ε the empty character

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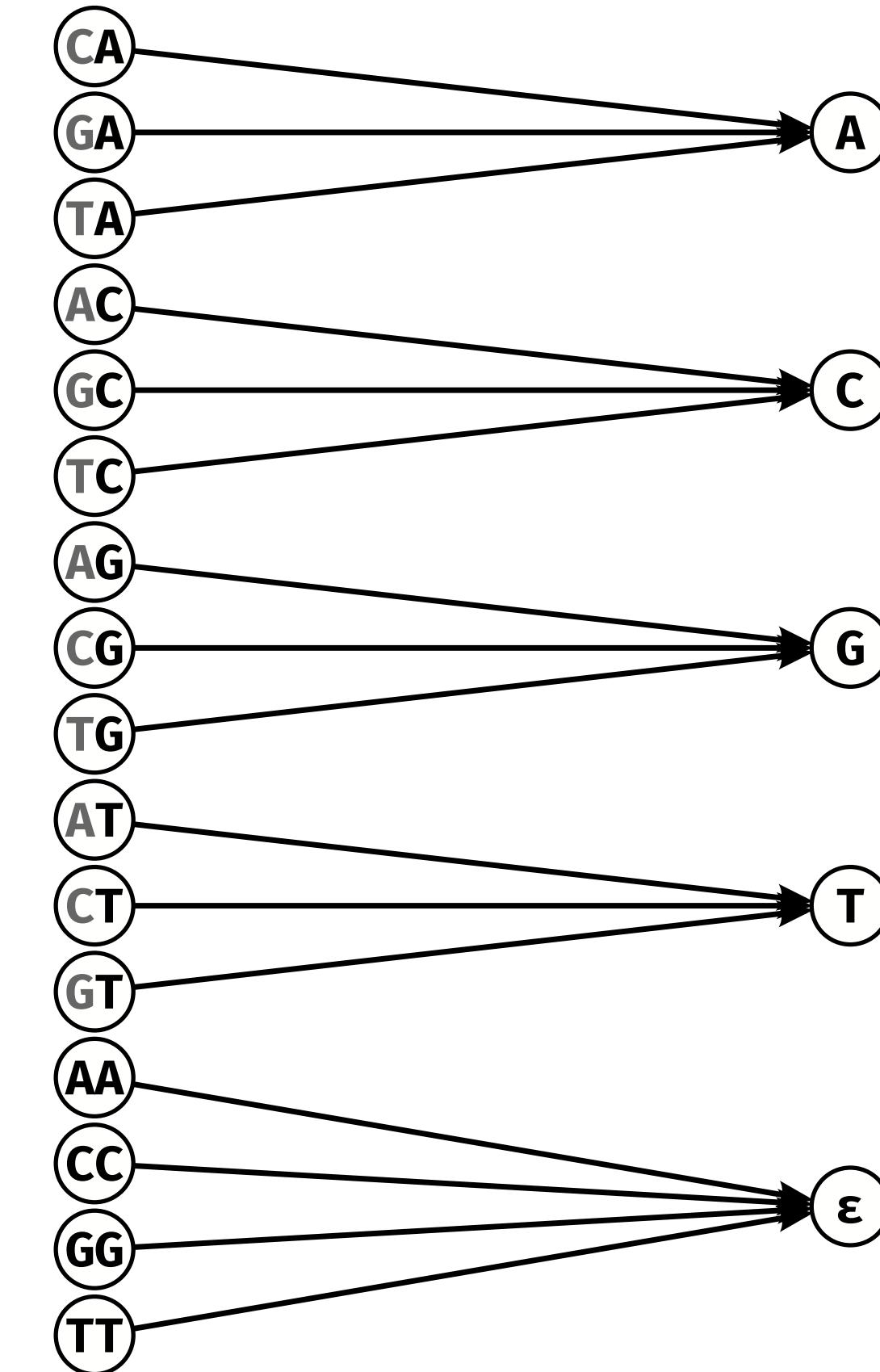
- $HPC(x) \rightarrow$ applying g^{HPC} on a **sliding window** of size 2 **along x** and **concatenating** outputs.
- Different $g = \mathbf{MSR}$

AAATGG

AεεTGε

MSRs as directed graphs

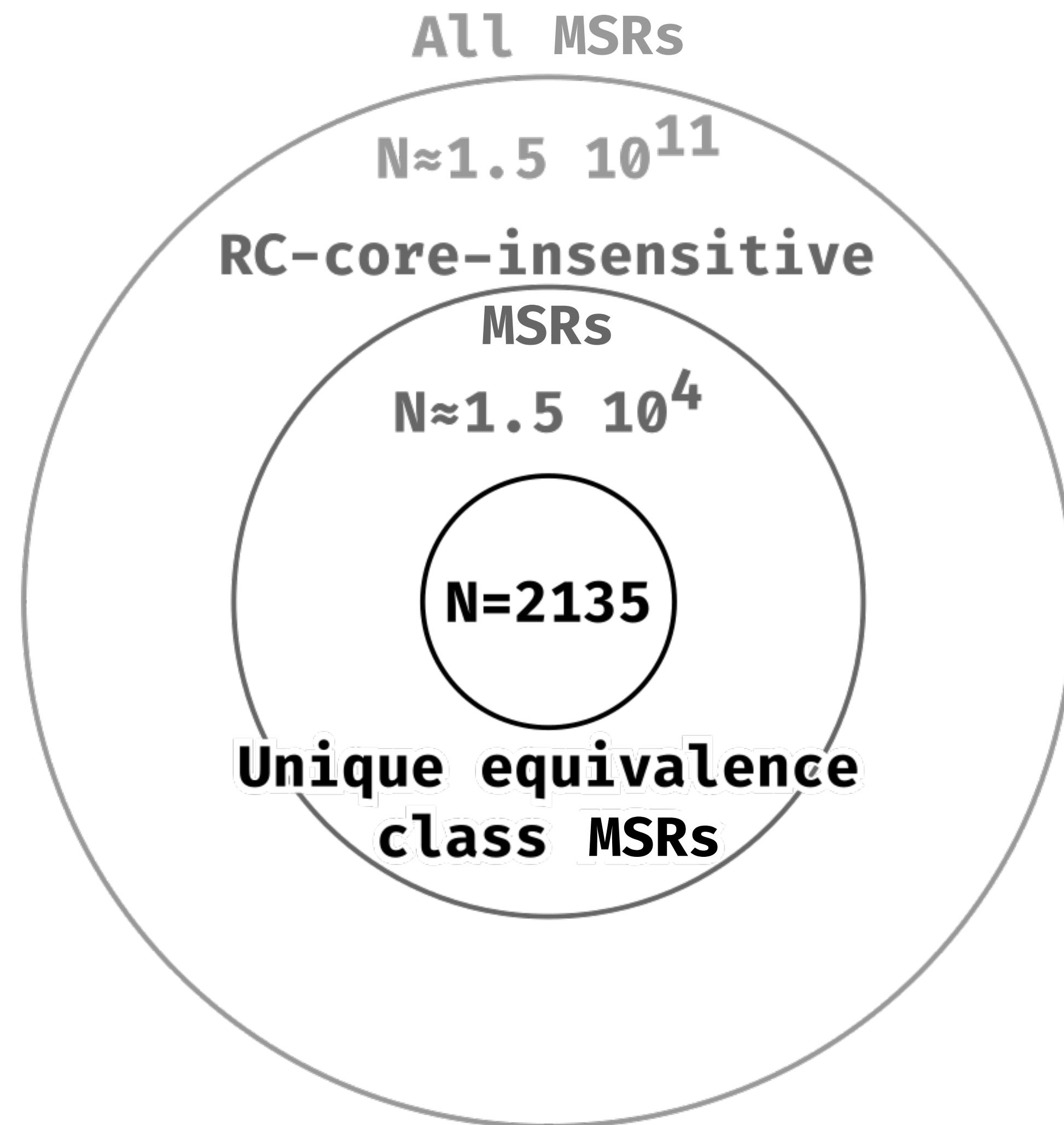
- Each g **function** can be visualised as a **directed graph** defined by a mapping between $|\Sigma^\ell|$ inputs and $|\Sigma| + 1$ outputs
- HPC as a directed graph ($n=16$ inputs $k=5$ outputs)
- There are 5^{16} functions
$$g : \Sigma^2 \rightarrow \Sigma \cup \{\epsilon\}$$
- **Cannot** all be tested



Reducing the search space

- **2 space-reducing strategies:**
 1. MSRs must commute with the **reverse complement** operation
 2. We define **equivalence classes**, based on **RC symmetries**

Reducing the search space



Evaluating MSRs

Datasets

- Simulate ONT reads, with **nanosim**, on 4 references:
 - **Whole human genome**, CHM13hTERT human cell line by the T2T
 - **Whole *Drosophila melanogaster* genome**, Adams *et al.* (2022)
 - **Whole *Escherichia coli* genome**, Blattner *et al.* (1977)
 - **Synthetic human centromeric sequence**, Mikheenko *et al.* (2020) tandemtools mapper test data

Can MSRs **improve mapping** of simulated reads?

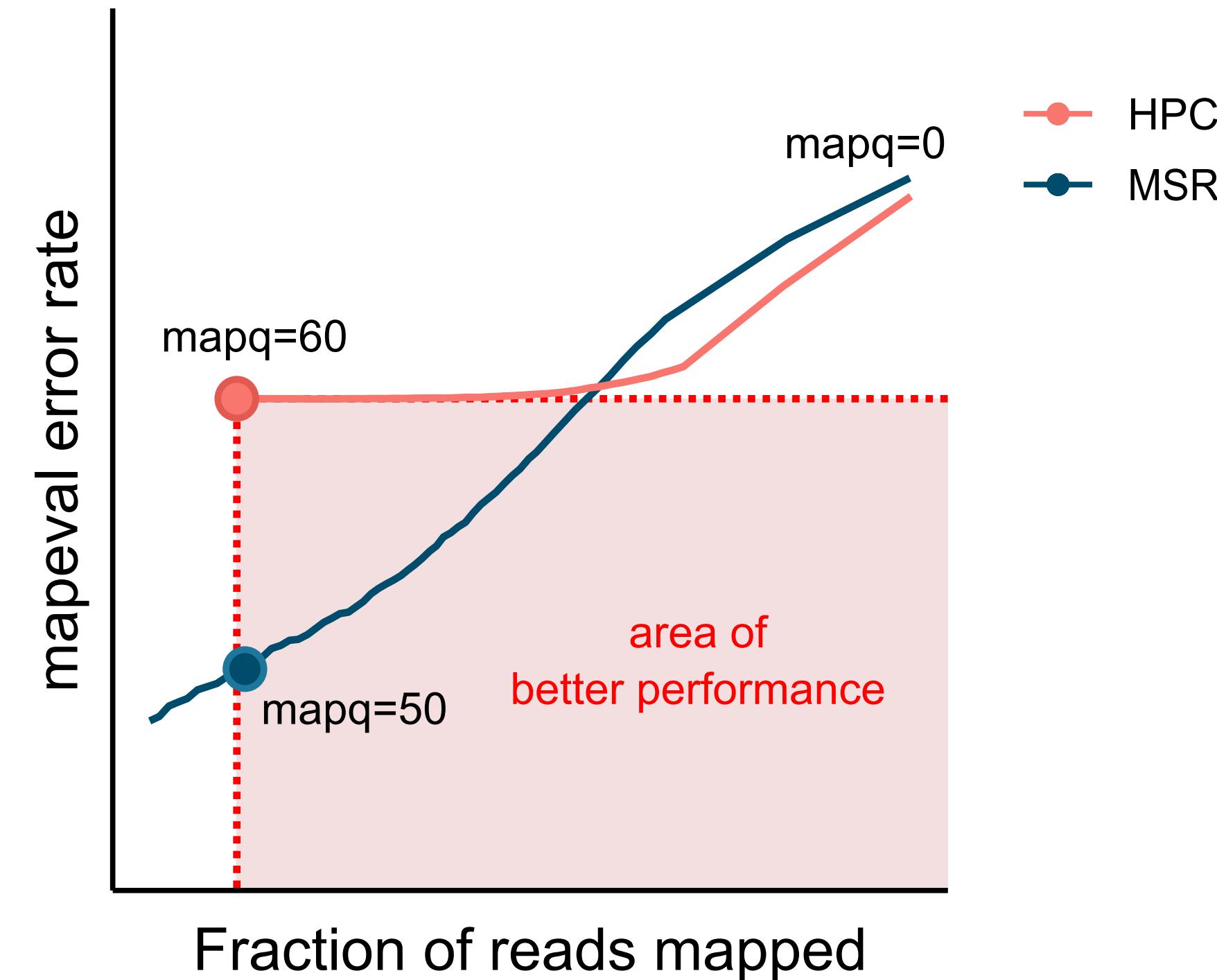
Evaluating MSRs

Evaluation Pipeline

- For **each (MSR, reference) pair** (and no MSR i.e. *raw*):
 1. **Transform** the reference and reads with the MSR
 2. **Map** transformed reads to transformed reference with `minimap2`
 3. **Evaluate** mapping with `paftools mapeval`

Evaluating MSRs

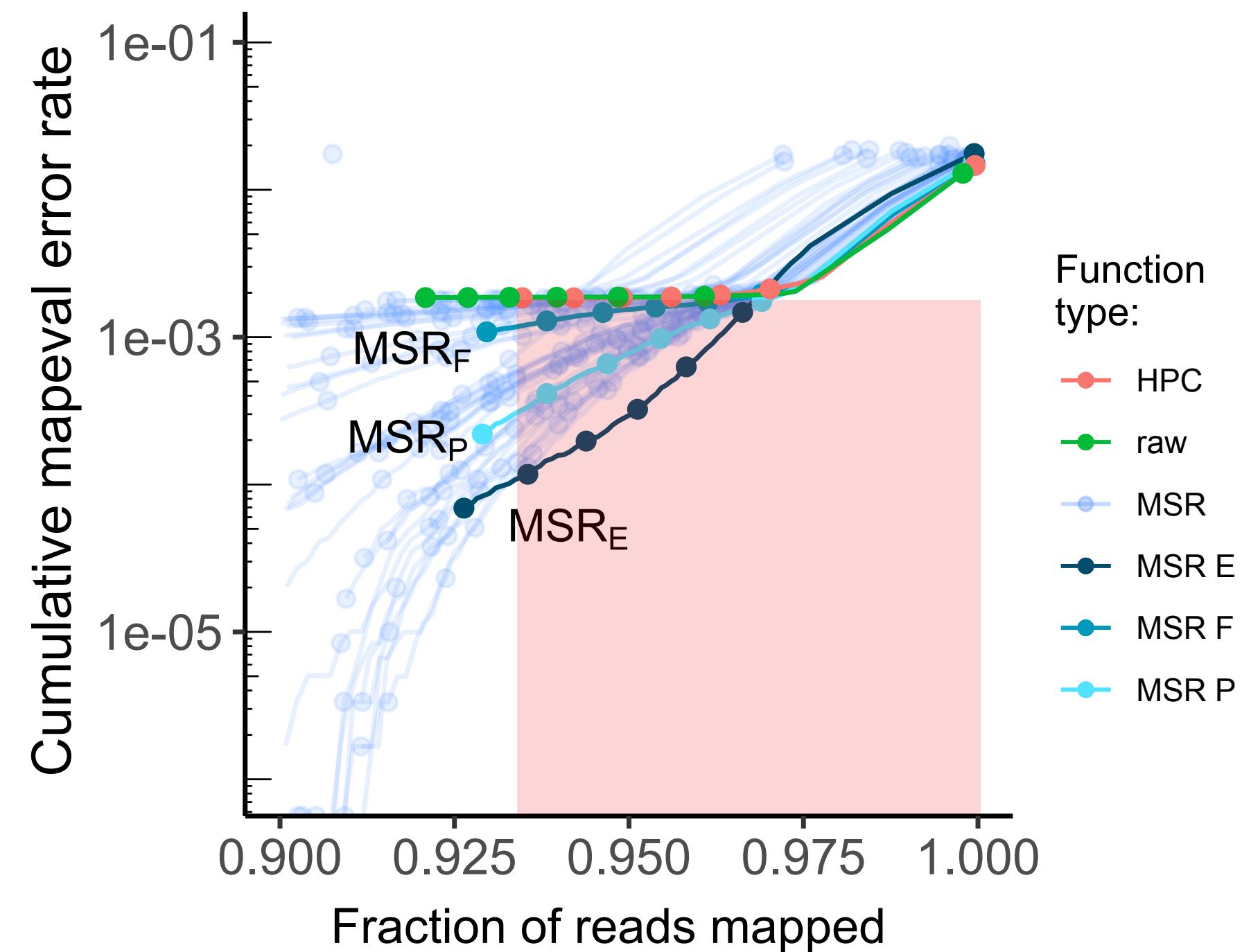
Comparing to HPC



We compare **MSRs** to **HPC** at **mapq 60**

Results

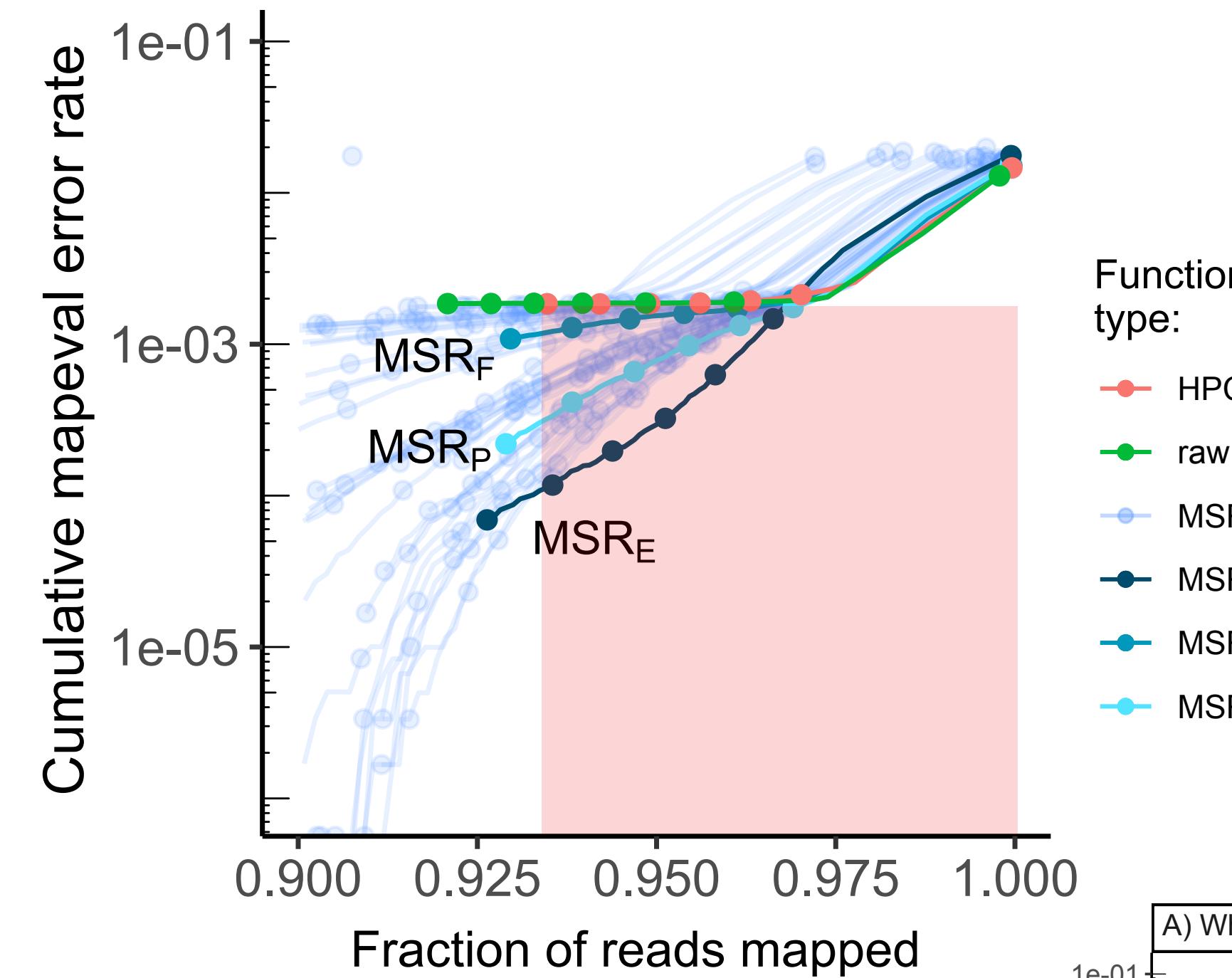
Across whole human genome



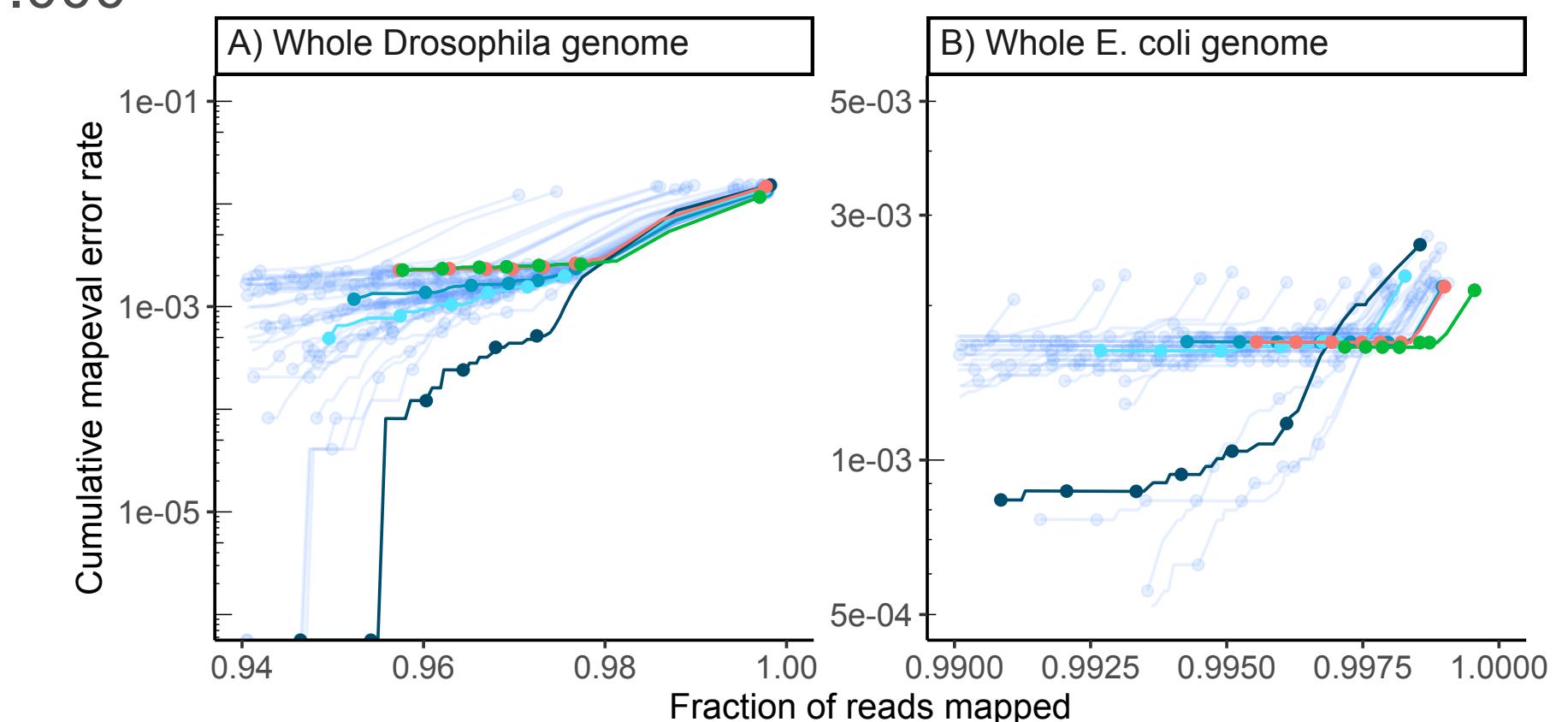
Many MSRs are **better** than HPC60

Results

Across whole human genome

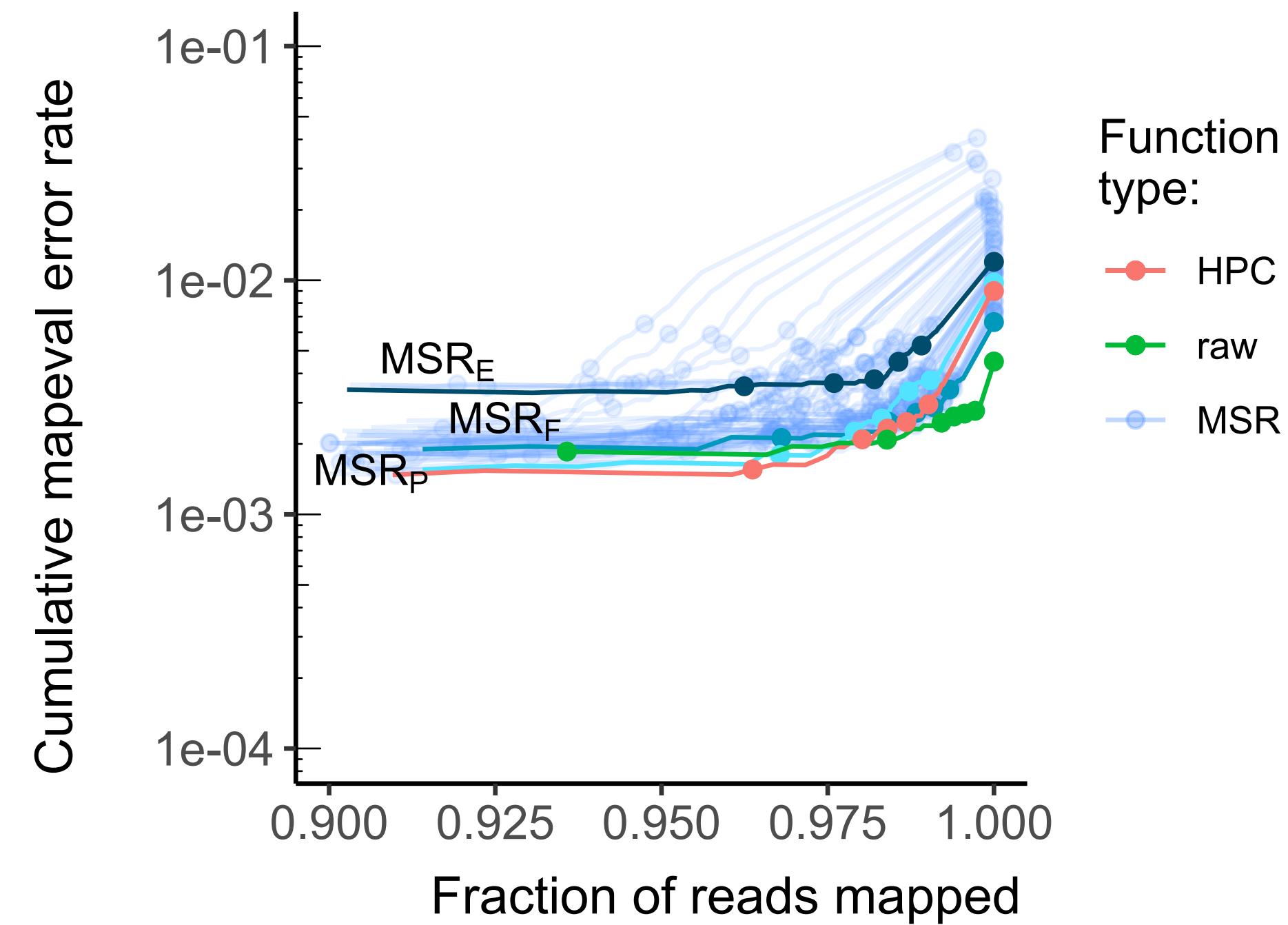


Many MSRs are **better** than HPC60



Results

Centromeric sequence



Mapping to **centromeres** is hard,
best not to apply any function

Take home message

- Some **MSRs** are better than HPC
- In some cases, the **mapping error rate** goes from 10^{-3} to 10^{-6}
- **MSRs** are **easy to implement** in existing aligners,
i.e. cheap performance gains

iScience



Volume 25, Issue 11, 18 November 2022, 105305

Article

Mapping-friendly sequence reductions: Going beyond homopolymer compression

Luc Blassel^{1, 2}✉, Paul Medvedev^{3, 4, 5}, Rayan Chikhi^{1, 6}✉

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<https://doi.org/10.1016/j.isci.2022.105305>

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Perspectives

- MSRs work on simulated data → How do we evaluate on **real datasets** ?
(fraction of mapped reads, mismatch rate, ...)
- Explore **higher-order MSRs** ($N(3) \approx 3 \cdot 10^{21}$ and $N(4) \approx 10^{85}$):
 - **Reduce** the search space
 - **Explore** search space **better**:
 - Define objective function and **optimise**
 - **“Learn”** MSRs

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What is HIV ?

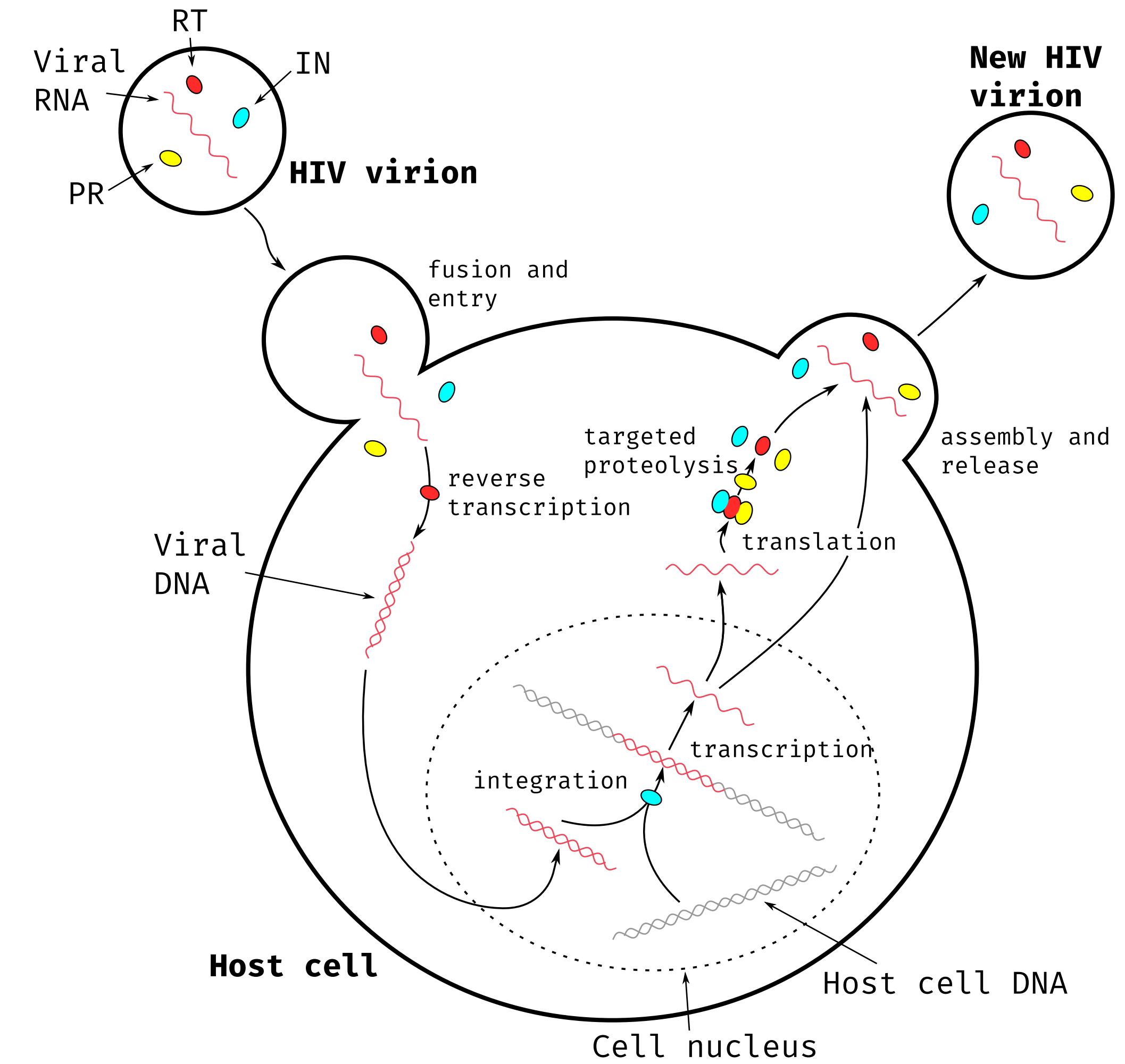
- Human **Immunodeficiency** Virus, discovered in **1983**
- Transmission: **sexual** contact, **blood**
- **40M** total deaths, **650k** in **2021**
- **40M** living with HIV in **2021**
- **Global health problem**



UNAIDS Global AIDS Update 2022 report cover

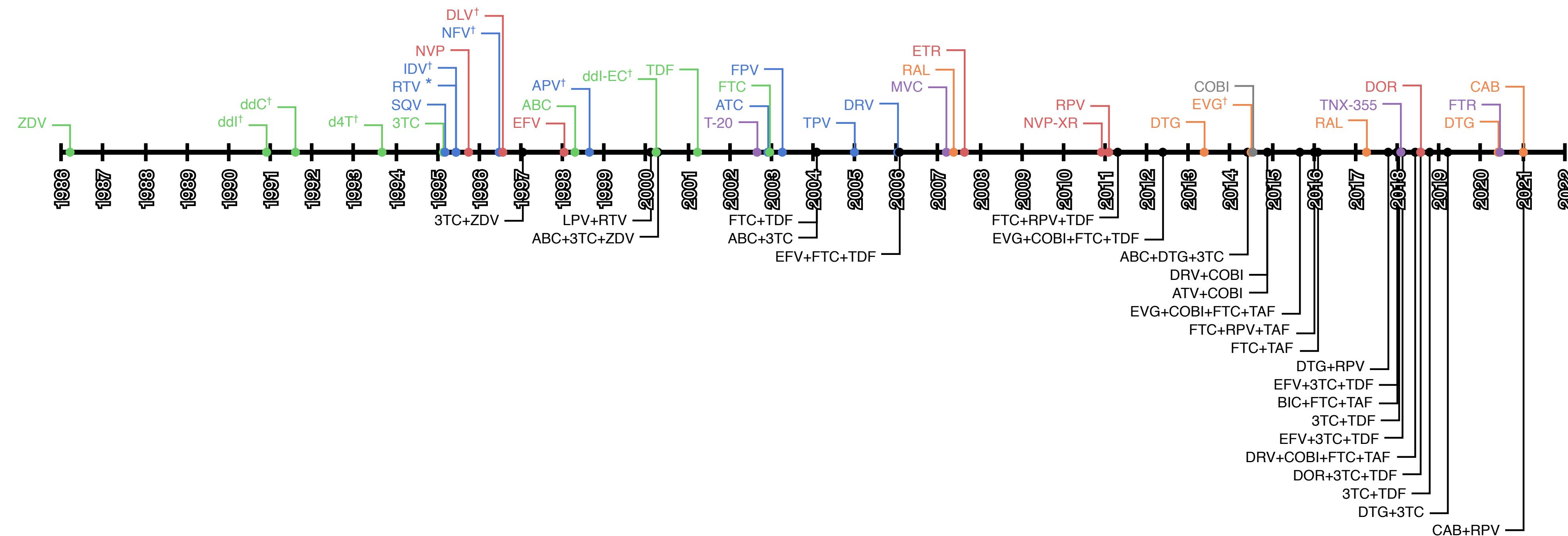
How does HIV work ?

- HIV is a **Retrovirus**
- Genetic **information** contained in **RNA**
- Key **proteins**:
 - Reverse Transcriptase **RT**
 - Integrase **IN**
 - Protease **PR**



How do we treat HIV ?

- Antiretroviral Therapy (**ART**)
- Most drugs target **RT**, **IN** or **PR** → **RTI**, **INI** or **PI**



What are DRMs ?

- **Resistance** arises in **response** to treatment **pressure**
- Drug resistance mutations (**DRMs**) have been found for **every drug**
- To **mitigate DRM** effects:
 - Treatment **switching**
 - **Combination** therapy

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Why study DRMs ?

- In **lower-income** countries, **access** to treatment is **not easy**
- In **higher-income** countries, **transmission to and within treatment-naive** populations
- DRMs **limit treatment options at population level**

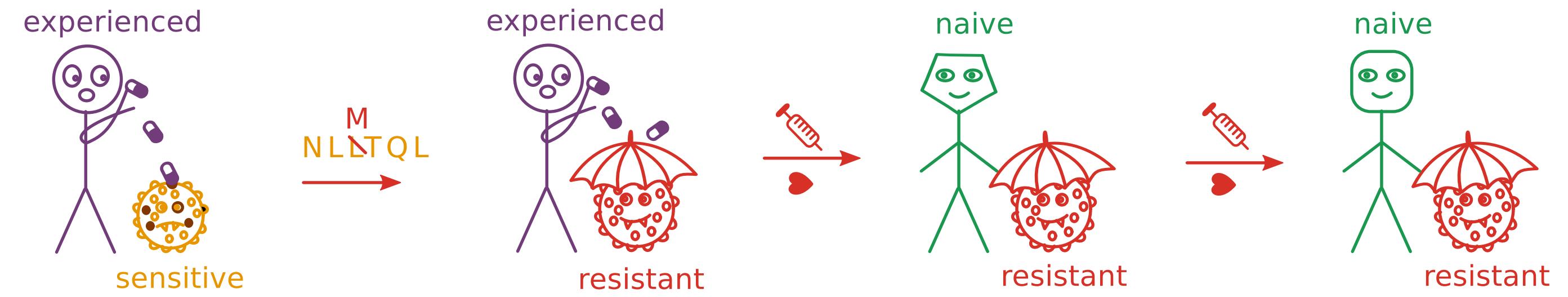
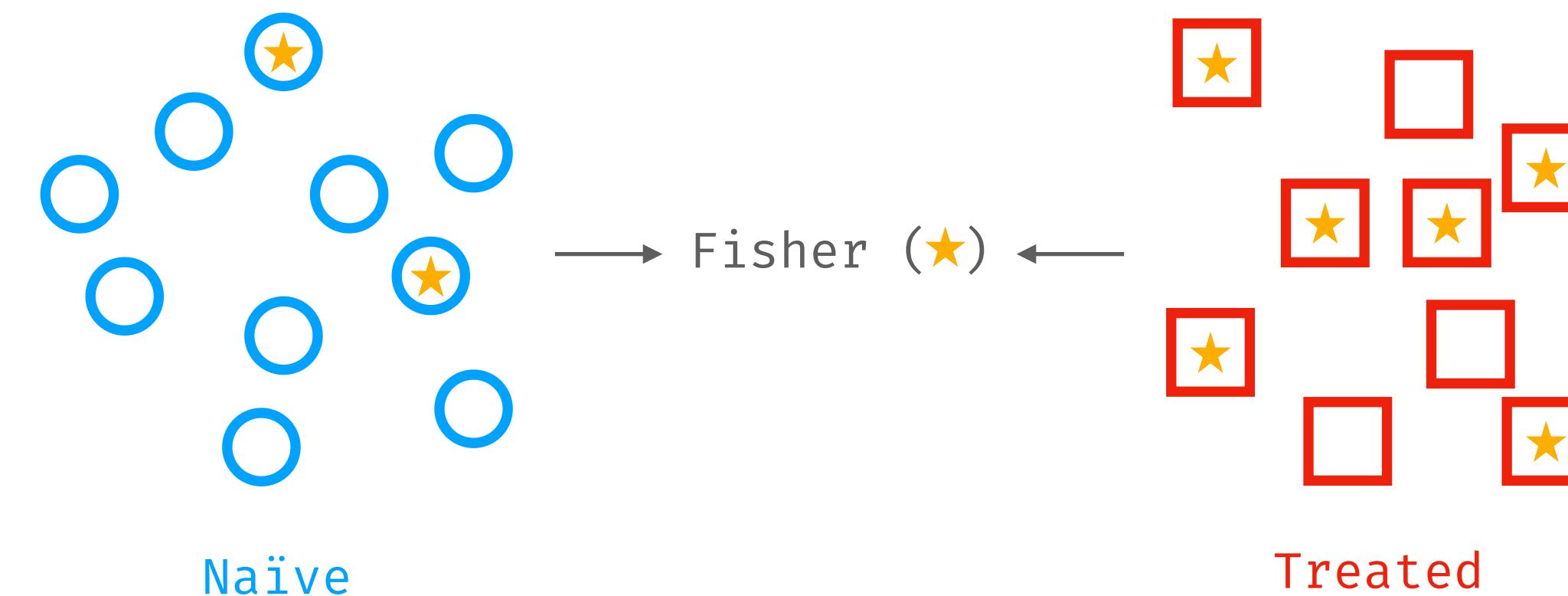


Fig A. Zhukova

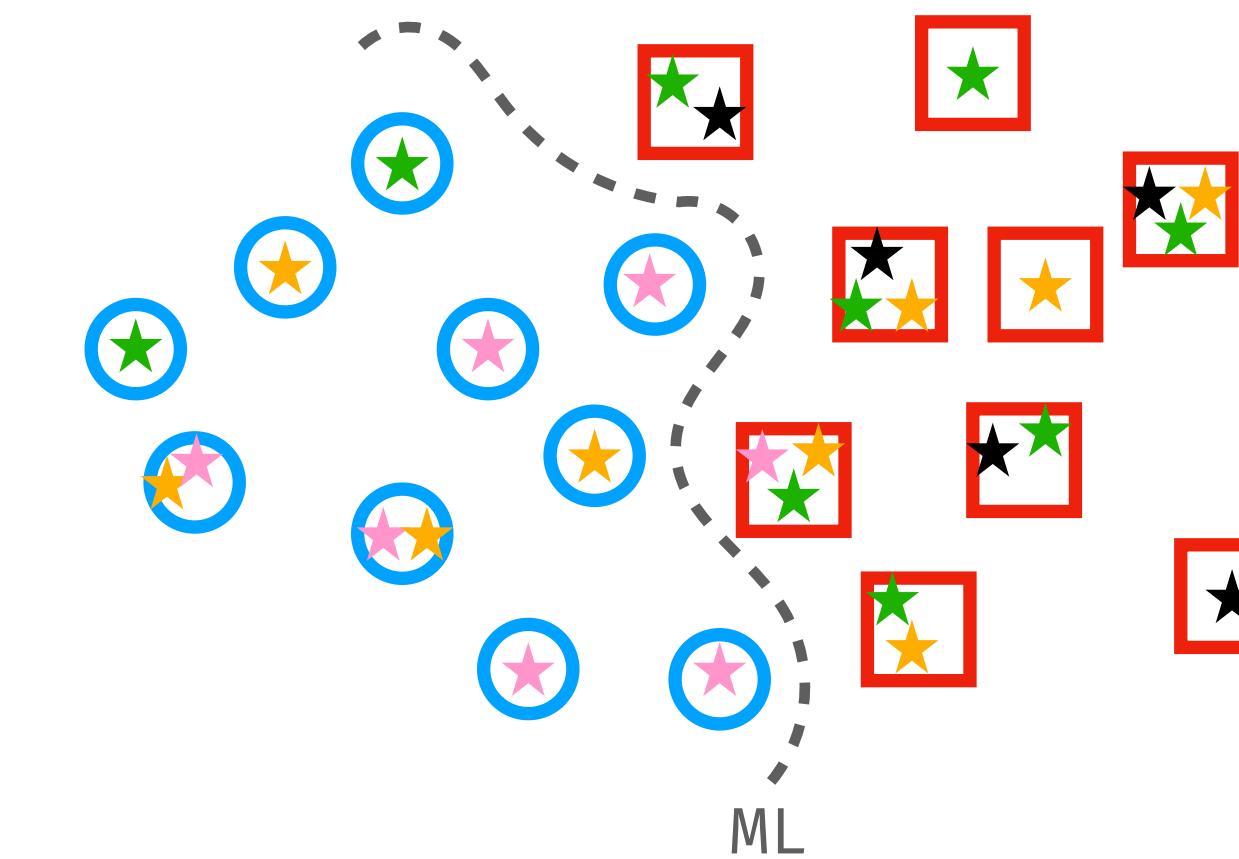
How do we find DRMs ?

- **Test statistical association** to treatment for **each mutation**
- **Multiple testing** correction → usually **decrease** in statistical **power**
- **Epistasis** and **groups** of mutations **worsen** problem



Using machine learning to find DRMs

- **Encode each mutation as binary feature**
- Train model to **discriminate experienced from naive** sequences
- **Important model features** might be **DRMs**
- **Treatment status** is a **proxy**



What models do we use ?

- **Random Forest**, can capture complex interaction between features
- **LASSO Logistic Regression**, class-specific weights & feature selection
- **Naive Bayes**, simple and statistical interpretation
- All classifiers are **easy to train** and **easy to interpret**

What do we learn from ?

- **UK Drug Resistance Database:**
 - **55,000 RT sequences**
 - Subtypes **B 68% & C 32%**
 - Naive **75%** & Experienced **25%**
- **African dataset:**
 - **4,000 RT sequences**
 - **24 subtypes**
 - Naive **58%** & Experienced **42%**

Confounding factors

- **Unbalanced** classes in **training** data
 - Use **adapted** performance **metrics**
- **Sequences** are evolutionarily **related** (*i.e. not independent*)
 - **Separate subtypes** during **training & testing**
- **Known DRMs** have very **strong signal**
 - **Remove** known DRM **signal**

Removing known signal DRM features

	181V	181K	182D	182F	184V	184E	187K
Seq	1	0	0	0	0	0	0
Seq 2	0	0	1	0	0	0	0
Seq 3	0	0	0	0	1	0	0
Seq 4	0	1	0	0	0	1	1
Seq 5	0	0	0	1	0	0	0

Known Known

Removing known signal DRM features

	181V	181K	182D	182F	184V	184E	187K
Seq	1	0	0	0	0	0	0
Seq 2	0	0	1	0	0	0	0
Seq 3	0	0	0	0	1	0	0
Seq 4	0	1	0	0	0	1	1
Seq 5	0	0	0	1	0	0	0

Known Known

Removing known signal

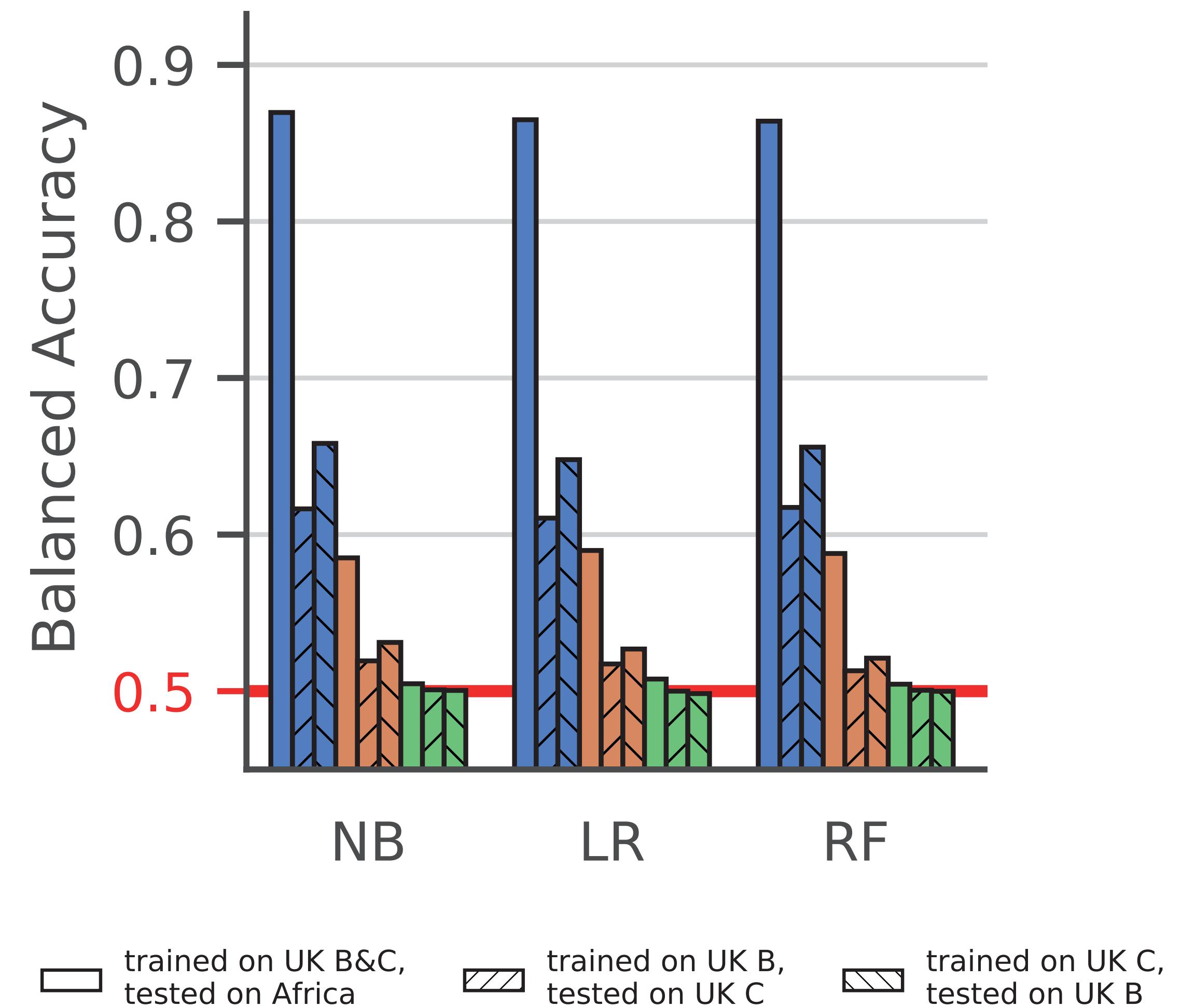
DRM features & DRM sequences

	181V	181K	182D	182F	184V	184E	187K
Seq 1	1	0	0	0	0	0	0
Seq 2	0	0	1	0	0	0	0
Seq 3	0	0	0	0	1	0	0
Seq 4	0	1	0	0	0	1	1
Seq 5	0	0	0	1	0	0	0

Known Known

Results

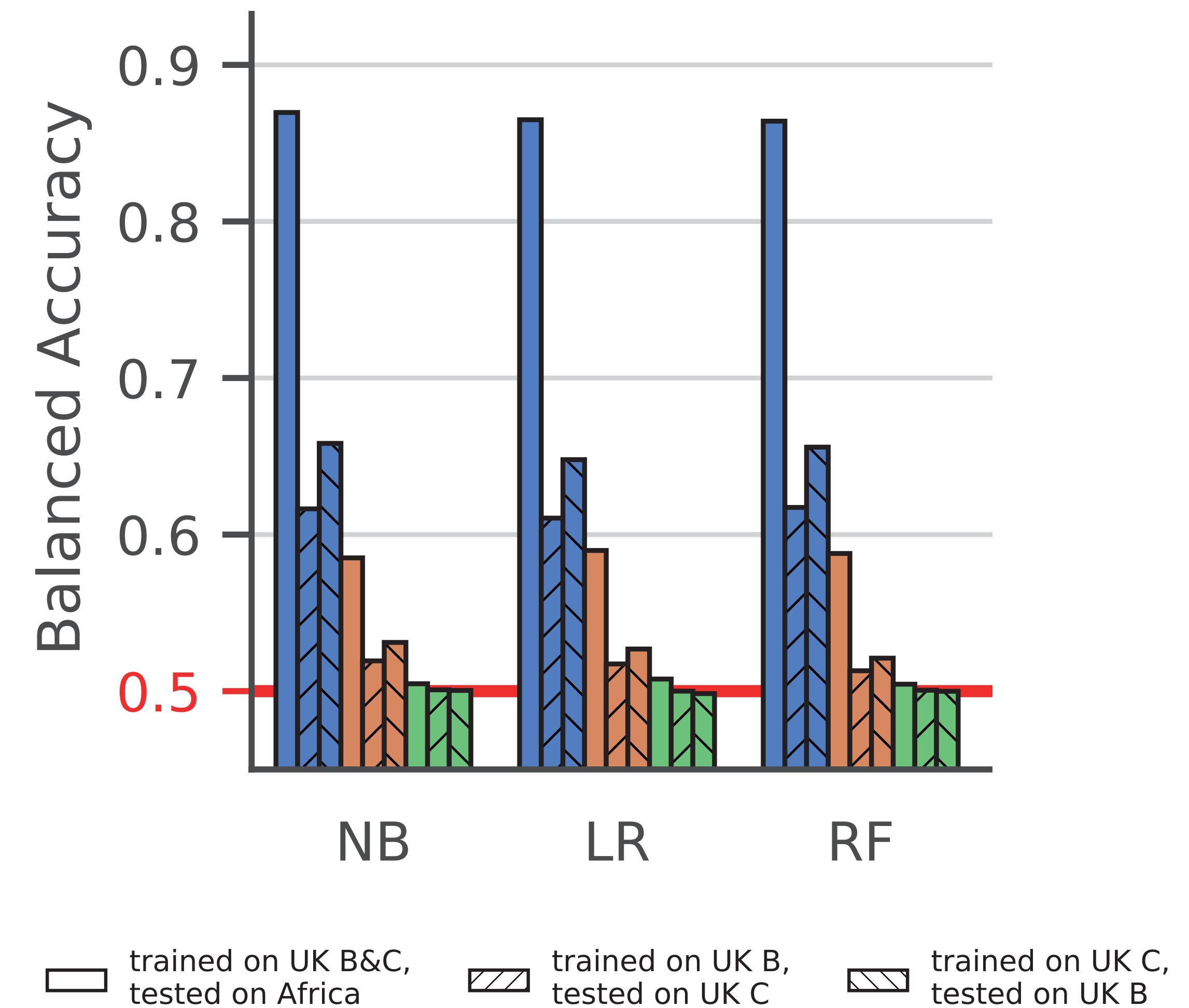
Classifier performance



Results

Classifier performance

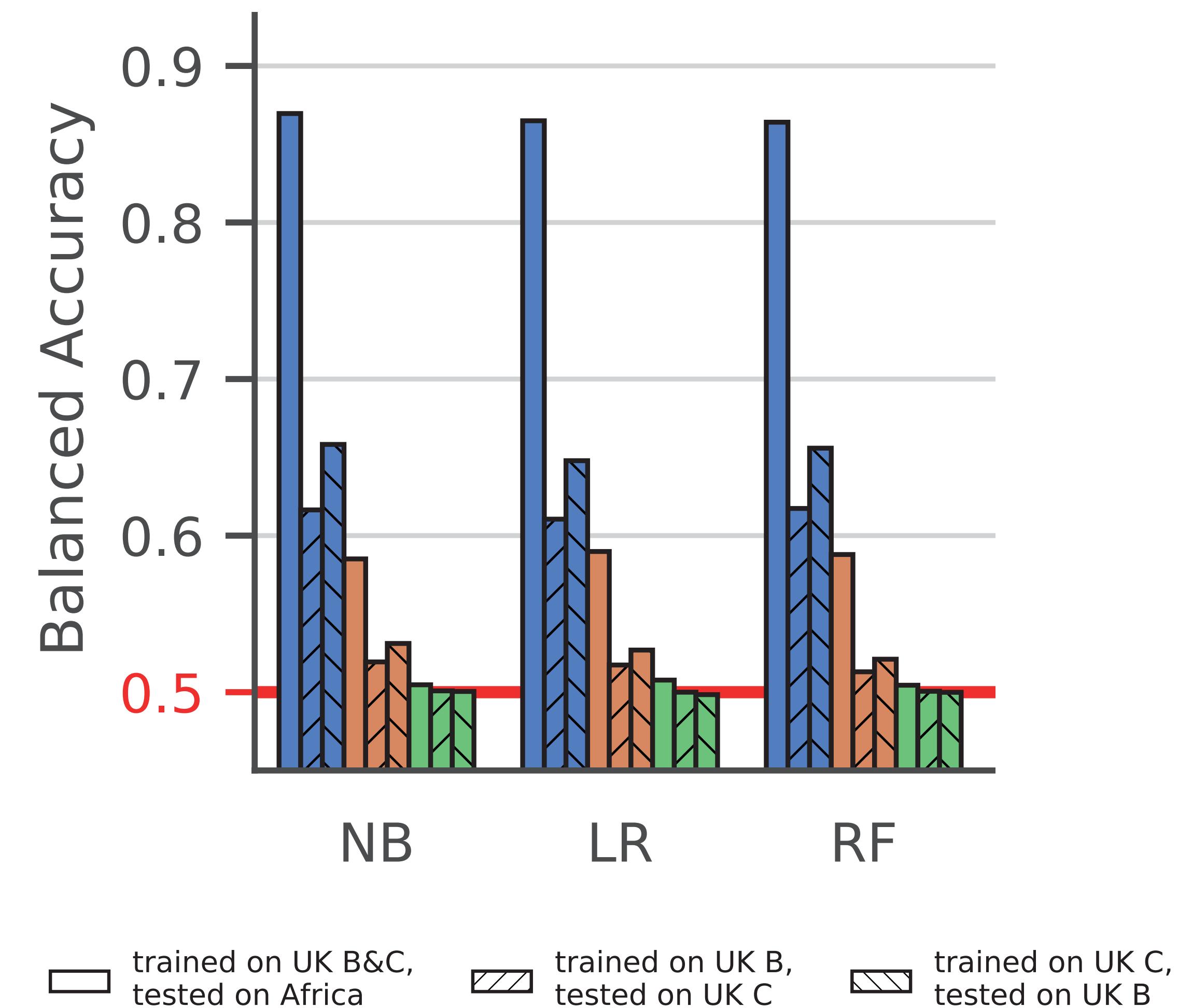
- High accuracy with all signal



Results

Classifier performance

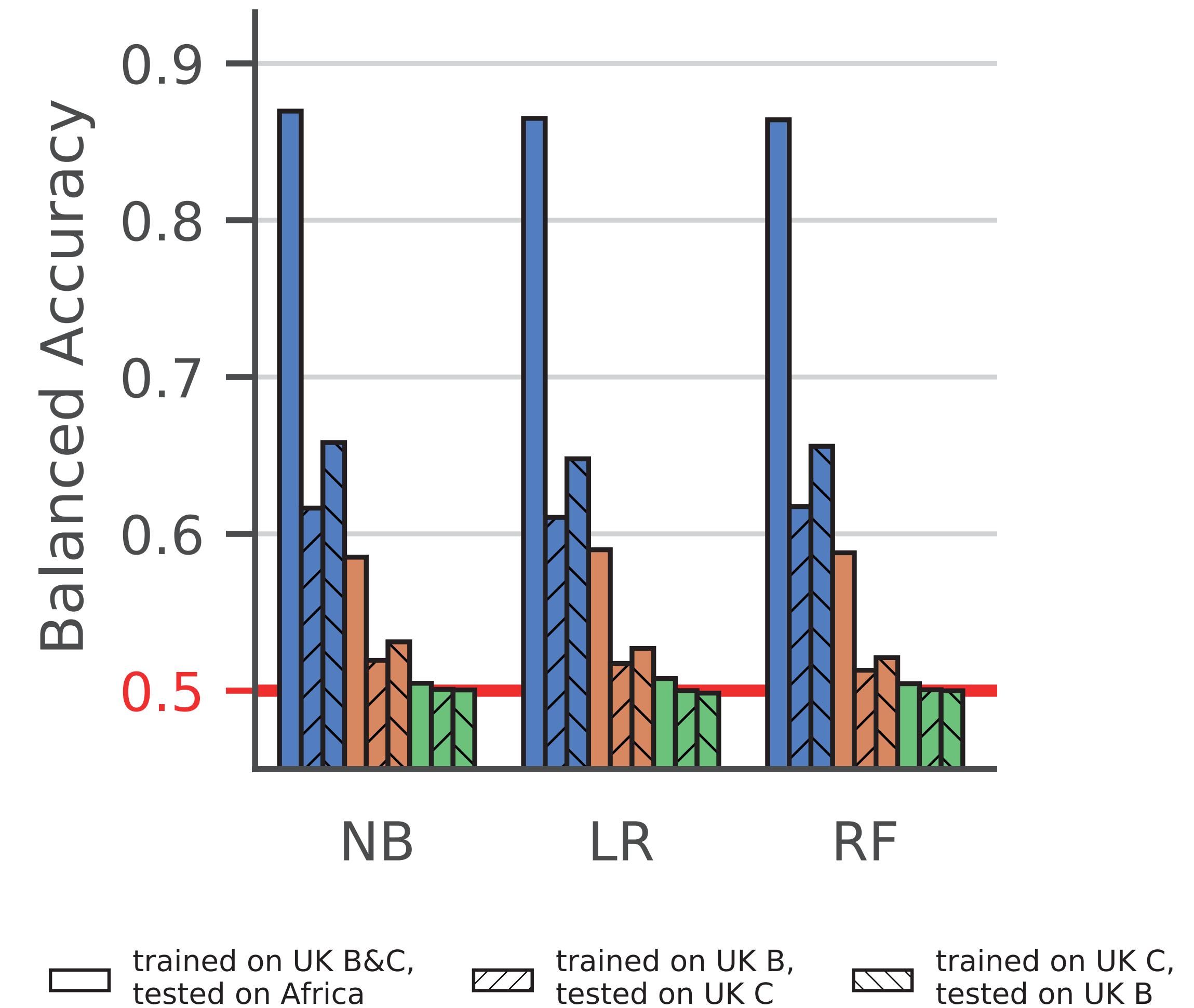
- **High accuracy** with all signal
- **Significantly better** than random when **removing DRM features**



Results

Classifier performance

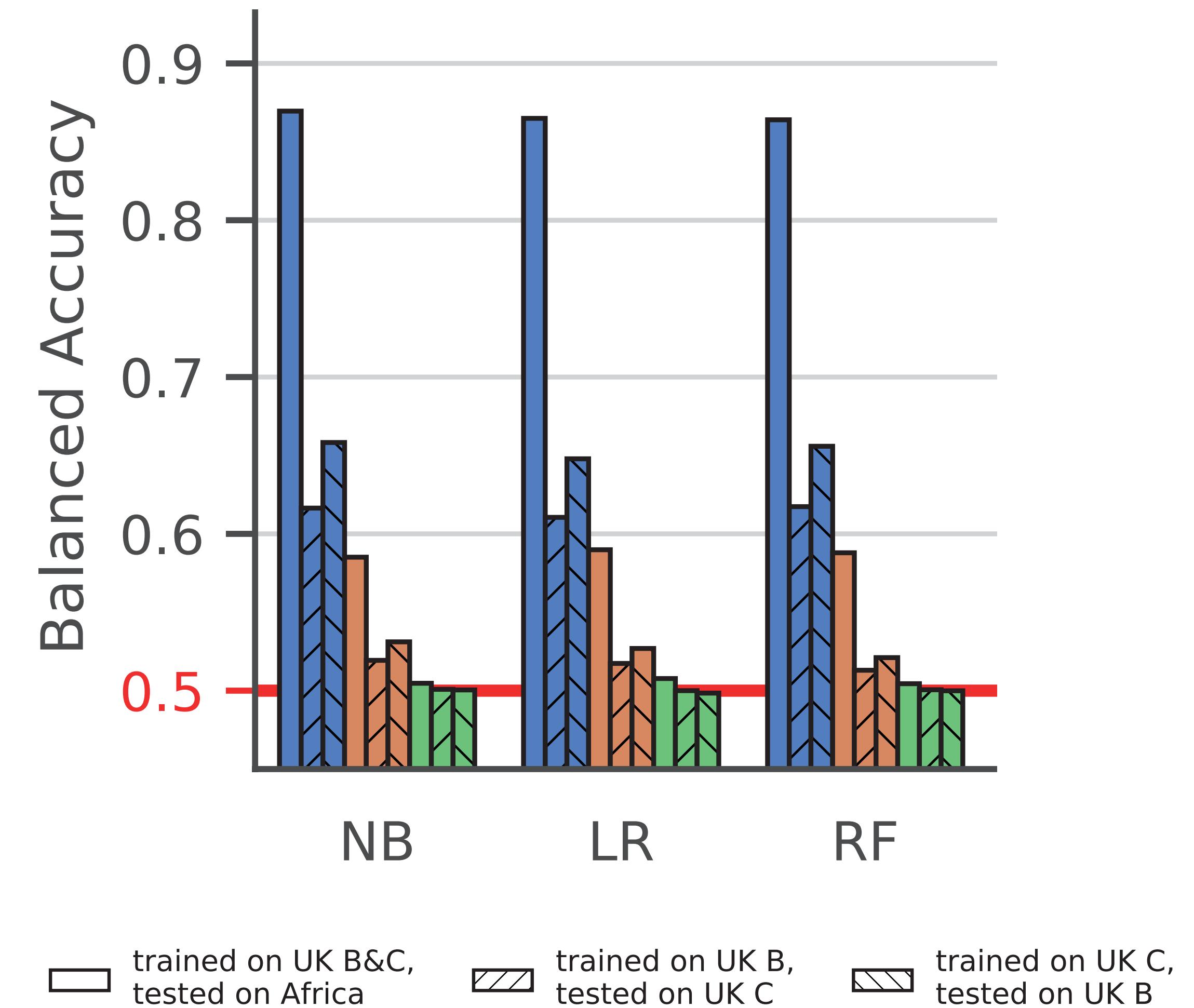
- **High accuracy** with all signal
- **Significantly better** than random when **removing DRM features**
- **No signal left** when also **removing DRM sequences**



Results

Classifier performance

- **High accuracy** with all signal
- **Significantly better** than random when **removing DRM features**
- **No signal left** when also **removing DRM sequences**
- **Probably** means that **all** primary **DRMs** are known



Results

Finding new DRMs

- We studied the **most important features**:
 - Across different **training settings**
 - Across different **classifiers**
- We identified **6 potential DRMs**:

L228R E203K D218E L228H I135L H208Y

- These **potential DRMs** are most likely **accessory mutations**

Results

New ?

PLOS COMPUTATIONAL BIOLOGY

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RESEARCH ARTICLE

HIV-1 Subtype B Protease and Reverse Transcriptase Amino Acid Covariation

Soo-Yon Rhee, Tommy F Liu, Susan P Holmes, Robert W Shafer

Published: May 11, 2007 • <https://doi.org/10.1371/journal.pcbi.0030087>

JOURNAL OF
MEDICAL VIROLOGY

Research Article | Free Access

Impact of unreported HIV-1 reverse transcriptase mutations on phenotypic resistance to nucleoside and non-nucleoside inhibitors

A. Saracino, L. Monno, L. Scudeller, D.C. Cibelli, A. Tartaglia, G. Punzi, C. Torti, S. Lo Caputo, F. Mazzotta, G. Scotto, G. Carosi, G. Angarano

First published: 18 November 2005 | <https://doi.org/10.1002/jmv.20500> | Citations: 25

American Society for Microbiology
Journal of Virology
Volume 74, Issue 22, 15 November 2000, Pages 10269-10273
<https://doi.org/10.1128/JVI.74.22.10269-10273.2000>

Vaccines and Antiviral Agents

Reduced Susceptibility of Human Immunodeficiency Virus Type 1 (HIV-1) from Patients with Primary HIV Infection to Nonnucleoside Reverse Transcriptase Inhibitors Is Associated with Variation at Novel Amino Acid Sites

Andrew J. Leigh Brown ^{1,*}, Heather M. Precious ¹, Jeannette M. Whitcomb ², Joseph K. Wong ³, Marlynne Quigg ¹, Wei Huang ², Eric S. Daar ⁴, Richard T. D'Aquila ⁵, Philip H. Keiser ⁶, Elizabeth Connick ⁷, Nicholas S. Hellmann ², Christos J. Petropoulos ², Douglas D. Richman ³, and Susan J. Little ³

Emergence of the H208Y mutation in the reverse transcriptase (RT) of HIV-1 in association with nucleoside RT inhibitor therapy

G. Nebbia, Caroline A. Sabin, D. T. Dunn,

Anna Maria Geretti on behalf of the UK Collaborative Group on HIV Drug Resistance and the UK Collaborative HIV Cohort (CHIC) Study Group

Journal of Antimicrobial Chemotherapy, Volume 59, Issue 5, May 2007, Pages 1013–1016, <https://doi.org/10.1093/jac/dkm067>

Published: 13 March 2007 Article history ▾

Improved Interpretation of Genotypic Changes in the HIV-1 Reverse Transcriptase Coding Region That Determine the Virological Response to Didanosine

Andrea De Luca , Simona Di Giambenedetto, Maria Paola Trotta, Manuela Colafogli, Mattia Prosperi, Lidia Ruiz, John Baxter, Philippe Clevenbergh, Roberto Cauda, Carlo-Federico Perno ... [Show more](#)

The Journal of Infectious Diseases, Volume 196, Issue 11, 1 December 2007, Pages 1645–1653, <https://doi.org/10.1086/522231>

Published: 01 December 2007 Article history ▾

Antiviral Therapy 11:693–699

Impact of HIV-1 reverse transcriptase polymorphism at codons 211 and 228 on virological response to didanosine

Anne-Genevieve Marcellin ^{1,*}, Philippe Flandre ², Andre Furco ³, Marc Wirden ¹, Jean-Michel Molina ² and Vincent Calvez ¹ on behalf of the AI454-176 Jaguar Study Team [†]

Reverse transcriptase mutations 118I, 208Y, and 215Y cause HIV-1 hypersusceptibility to non-nucleoside reverse transcriptase inhibitors

Clark, Shauna A^a; Shulman, Nancy S^b; Bosch, Ronald J^c; Mellors, John W^a

[Author Information](#)

AIDS: April 24, 2006 - Volume 20 - Issue 7 - p 981-984

doi: 10.1097/01.aids.0000222069.14878.44

Take home message

- We found 6 new potential DRMs
- Most likely accessory mutations
- All primary resistance mutations are probably known

PLOS COMPUTATIONAL BIOLOGY

OPEN ACCESS PEER-REVIEWED

RESEARCH ARTICLE

Using machine learning and big data to explore the drug resistance landscape in HIV

Luc Bassel , Anna Tostevin, Christian Julian Villabona-Arenas, Martine Peeters, Stéphane Hué, Olivier Gascuel ,
On behalf of the UK HIV Drug Resistance Database 

Version 2

Published: August 26, 2021 • <https://doi.org/10.1371/journal.pcbi.1008873>

Perspectives

- **Experimental confirmation of DRMs**
- **Search for complex epistasis with more refined models**
 - Deep Learning → black box
 - Neural Network interpretation is an active field
- **Fine-grained knowledge with more metadata**

Presentation Outline

1

Introduction

2

Improving
long-read mapping

3

An introduction
to HIV

4

Exploring resistance in
HIV with ML

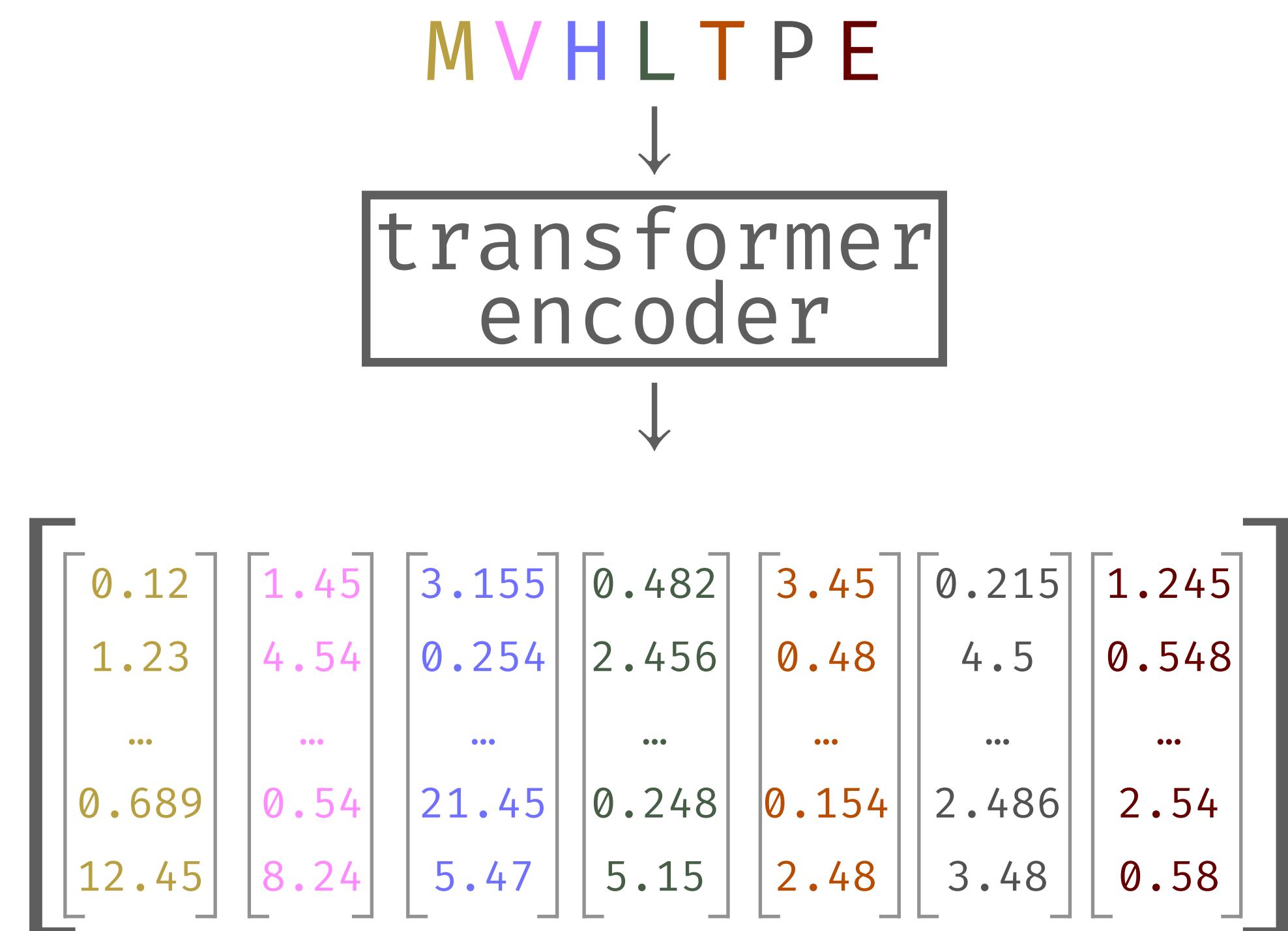
5

Learning alignment &
Other perspectives

6

Conclusion

Transformers and their embeddings

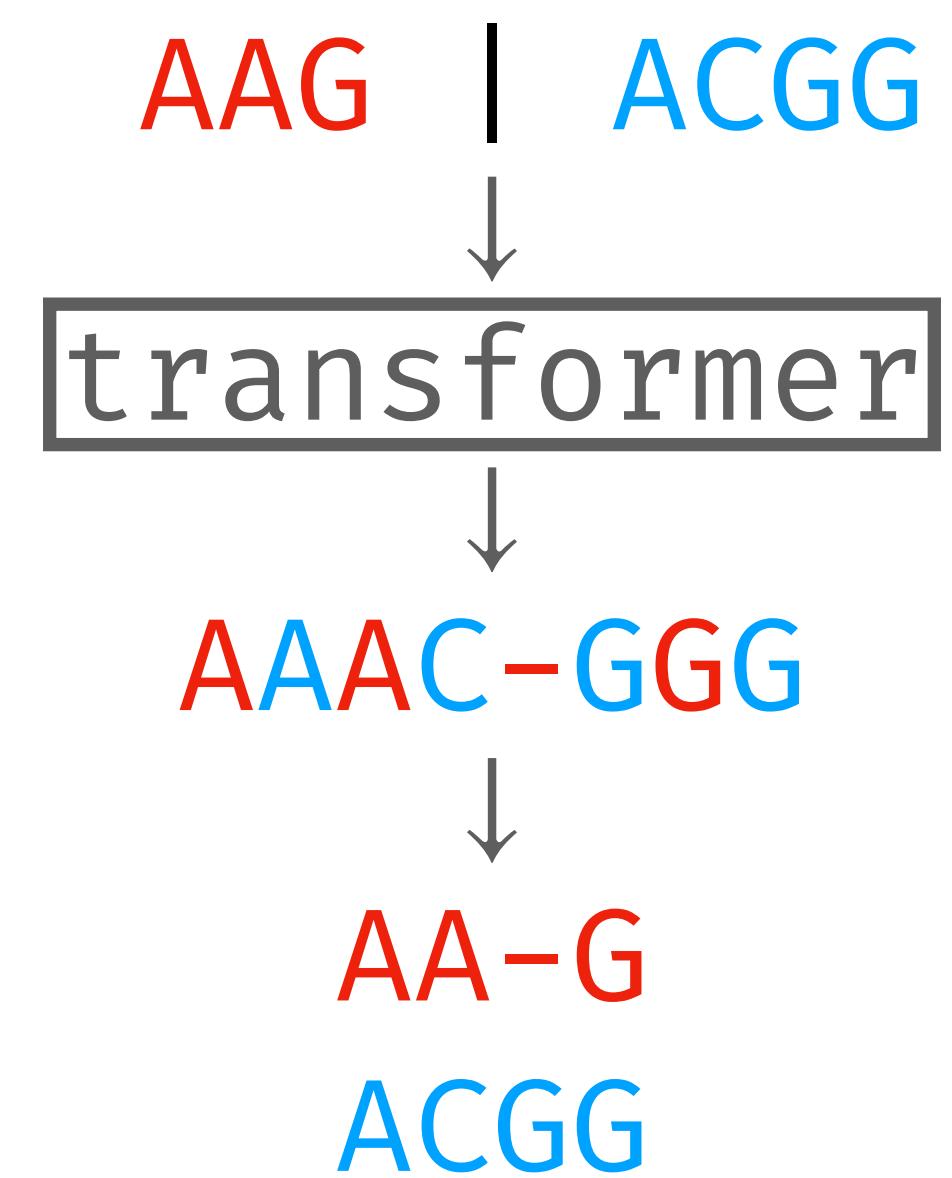


Using embeddings for alignments

- With embedding we can **learn** custom **parameters** for sequence **alignment**
- **DEDAL** **learns** a custom **substitution** matrix, for aligning 2 sequences
- **Better** pairwise **alignments** on **remote homologs** than standard methods

Alignment as a translation task

- Translate “**Unaligned language**” to “**aligned language**”



Caveats

- Main **problem** is **scaling** up
- **Self-attention** mechanism is very **memory hungry**
 - Approximations
 - Other mechanisms
- **Inference** time can be long

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Conclusion

Conclusion

- **Improving sequence alignments:**
 - We **improve** long-read **mapping**
 - **Better** than Homopolymer compression
 - Centromeres are **hard**
 - **Learning** sequence alignment is an exciting **perspective**
- **Learn** from sequence **alignments:**
 - Searching for **resistance** in HIV
 ⇒ sequence **classification**
 - Found potential **new resistance mutations**
 - Primary **resistance mutations are known**

Scientific output

First Author

iScience

Volume 25, Issue 11, 18 November 2022, 105305

Article

Mapping-friendly sequence reductions: Going beyond homopolymer compression

Luc Bassel ^{1, 2, 8}, Paul Medvedev ^{3, 4, 5}, Rayan Chikhi ^{1, 6}  

Show more 

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<https://doi.org/10.1016/j.isci.2022.105305>

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RESEARCH ARTICLE

Using machine learning and big data to explore the drug resistance landscape in HIV

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On behalf of the UK HIV Drug Resistance Database 

Version 2 Published: August 26, 2021 • <https://doi.org/10.1371/journal.pcbi.1008873>

Co-first Author

Current Opinion in Virology

Volume 51, December 2021, Pages 56-64

Drug resistance mutations in HIV: new bioinformatics approaches and challenges

Luc Bassel ^{1, 2, 8}, Anna Zhukova ^{1, 3, 8}, Christian J Villabona-Arenas ^{4, 5}, Katherine E Atkins ^{4, 5, 6}, Stéphane Hué ^{4, 5}, Olivier Gascuel ⁷ 

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<https://doi.org/10.1016/j.coviro.2021.09.009>

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Middle Author

Comptes Rendus Biologies

2021, 344, n° 1, p. 57-75 <https://doi.org/10.5802/crbiol.129>

SARS-CoV2 and the many facets of the Covid19 pandemic / *Le SARS-CoV2 et les multiples facettes de la pandémie Covid19*

Origin, evolution and global spread of SARS-CoV-2
Origine, évolution et propagation mondiale du SARS-CoV-2

Anna Zhukova ^{a, b, c}, Luc Bassel ^{a, b}, Frédéric Lemoine ^{a, b, c}, Marie Morel ^{a, b}, Jakub Voznica ^{a, b} and Olivier Gascuel ^{a, b} 

JOURNAL ARTICLE

COVID-Align: accurate online alignment of hCoV-19 genomes using a profile HMM  

Frédéric Lemoine   Luc Bassel, Jakub Voznica, Olivier Gascuel 

Bioinformatics, Volume 37, Issue 12, 15 June 2021, Pages 1761–1762, <https://doi.org/10.1093/bioinformatics/btaa871>

Published: 12 October 2020 Article history 

Thank you all!



Gascuel O.



Lemoine F.



Morel M.



Voznica J.



Zhukova A.



Bernardini-Ridel M.



Andreace F.



Chikhi R.



Denti L.



Duitama-Gonzales C.



Dufresne Y.



Lemane T.



Vicedomini R.



Medvedev P.



Carcano A.



Holtz A.



Cadet-Diaby F.

Pasteur:

- Didier Mazel
- Jerome Bourret

Friends:

- Balzac
- EGSH
- AgroParisTech

Family (of course)

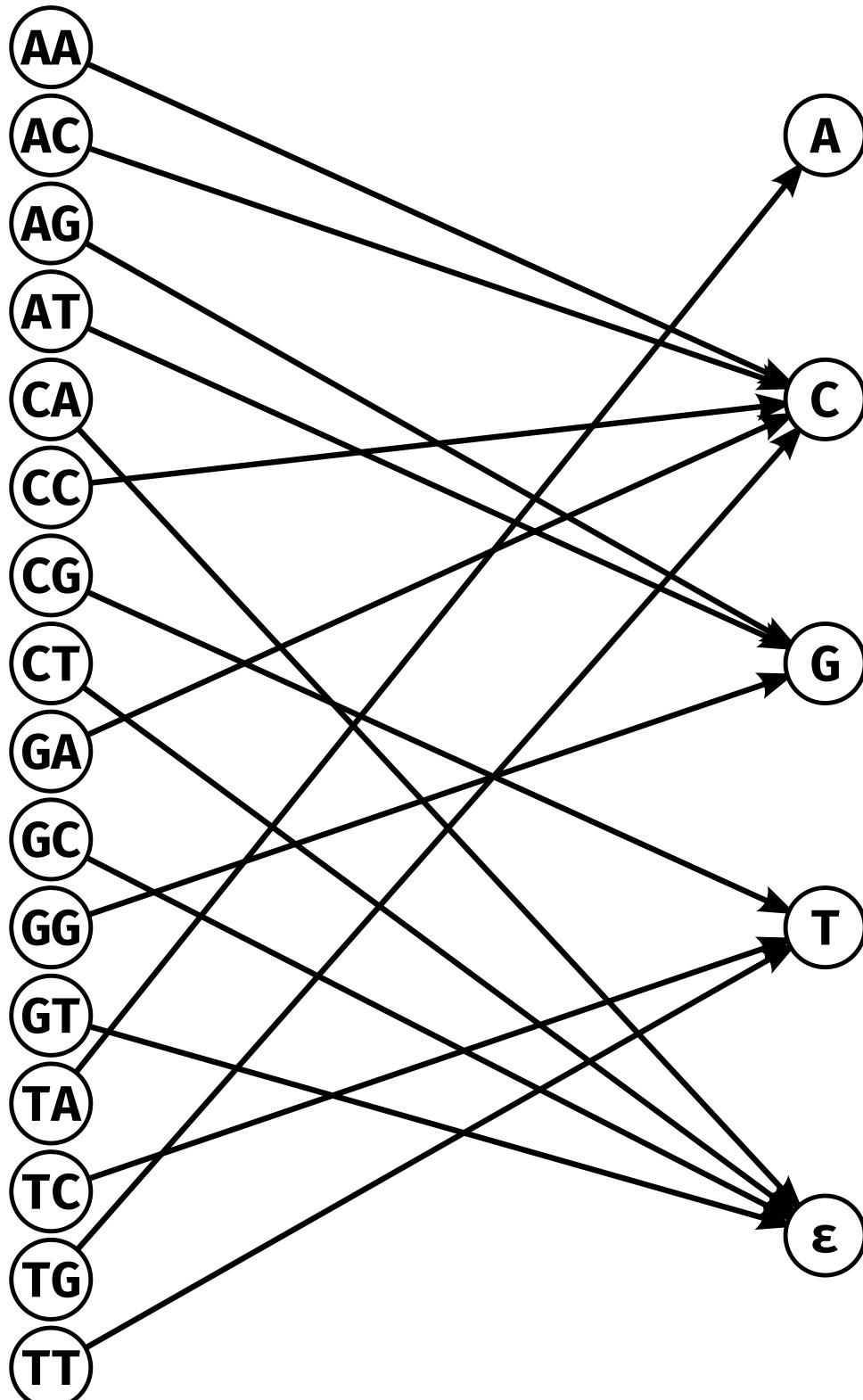
In memory of:

- Pierre Bassel
- John F. Murray

Reducing the search space

Reverse complements

Random SSR f_r ✗



$$x = TAAGTTGA$$

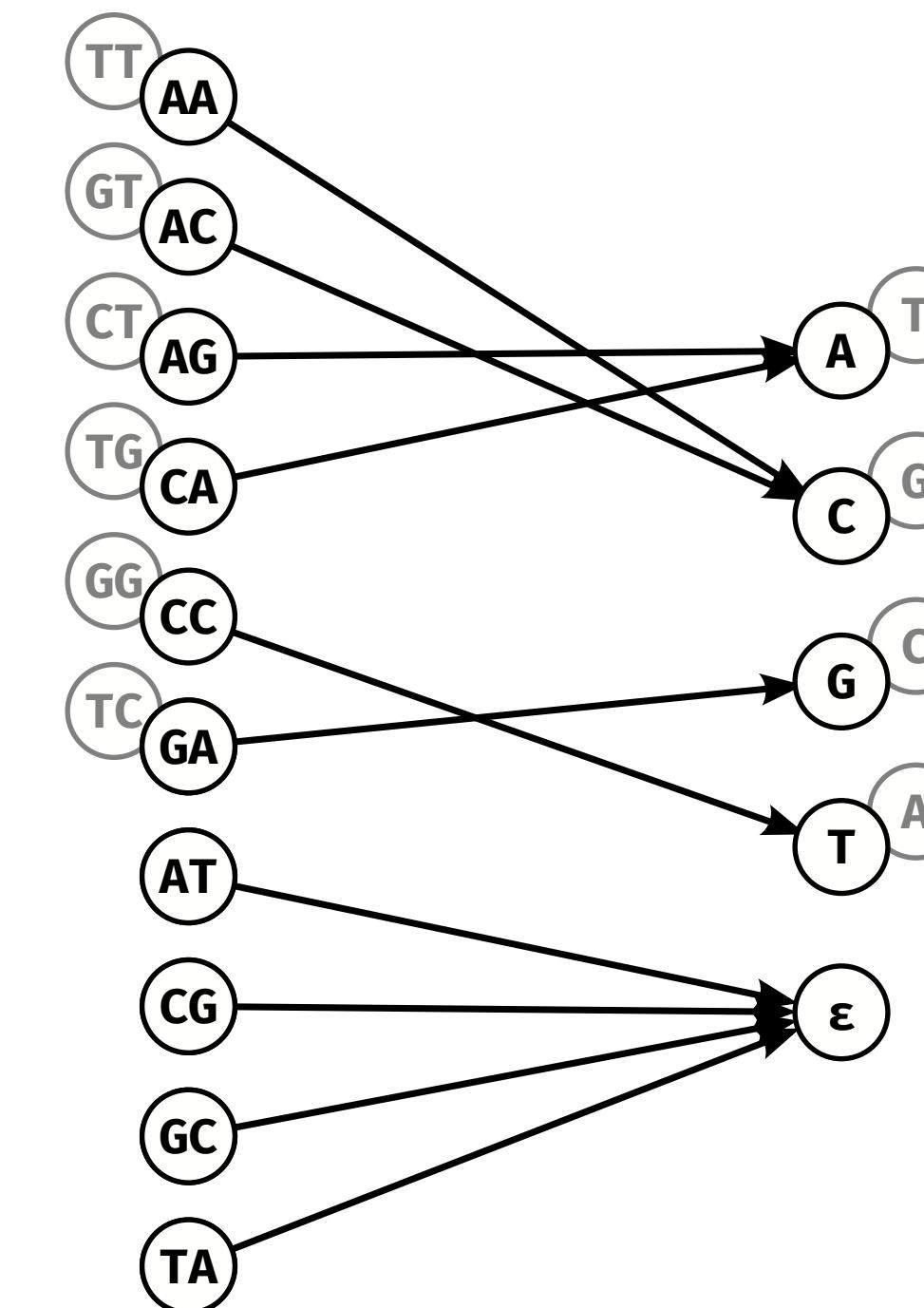
$$f_r(x) = TACGTCC$$

$$RC(x) = TCAACTTA$$

$$f_r(RC(x)) = TTCCTA$$

$$RC(f_r(x)) = GGACGTA$$

RC-core-insensitive SSR f ✓



$$x = TAAGTTGA$$

$$f(x) = TCAGGTG$$

$$RC(x) = TCAACTTA$$

$$f(RC(x)) = TCACCTG$$

$$RC(f(x)) = CACCTGA$$

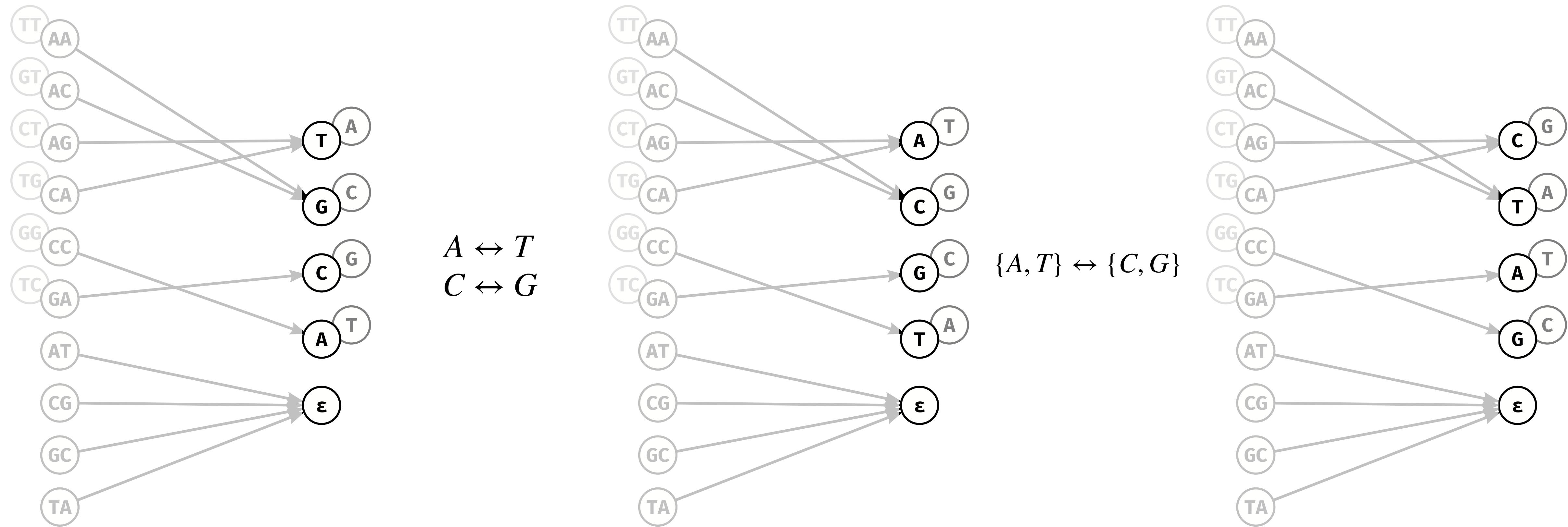
Reducing the search space

Equivalence classes

- Reverse complement **symmetries**:
 - $A \Leftrightarrow T$ and $G \Leftrightarrow C$
 - $\{A, T\}_{pair} \Leftrightarrow \{G, C\}_{pair}$
- We can define **equivalence classes** from them

Reducing the search space

Equivalence classes



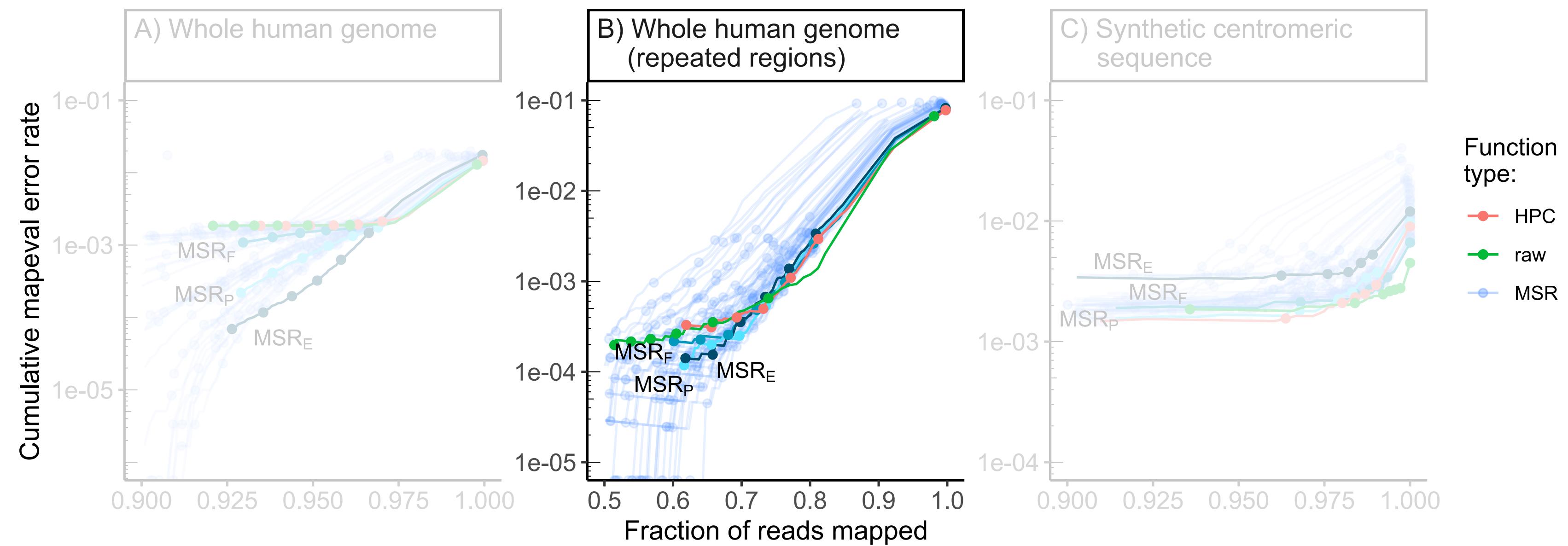
Evaluating MSRs

Evaluation Pipeline

- Mapping quality (**mapq**) is a measure of how confident the aligner is in its read placement. 0 (worse) \leq mapq ≤ 60 (best)
- **mapeval** gives results for **mapq thresholds**
i.e. sets of mapped reads with $\text{mapq} \geq$ than a given value
- **mapeval** reports for each threshold:
 - **Number of reads** mapped
 - Mapping **error rate**

Results

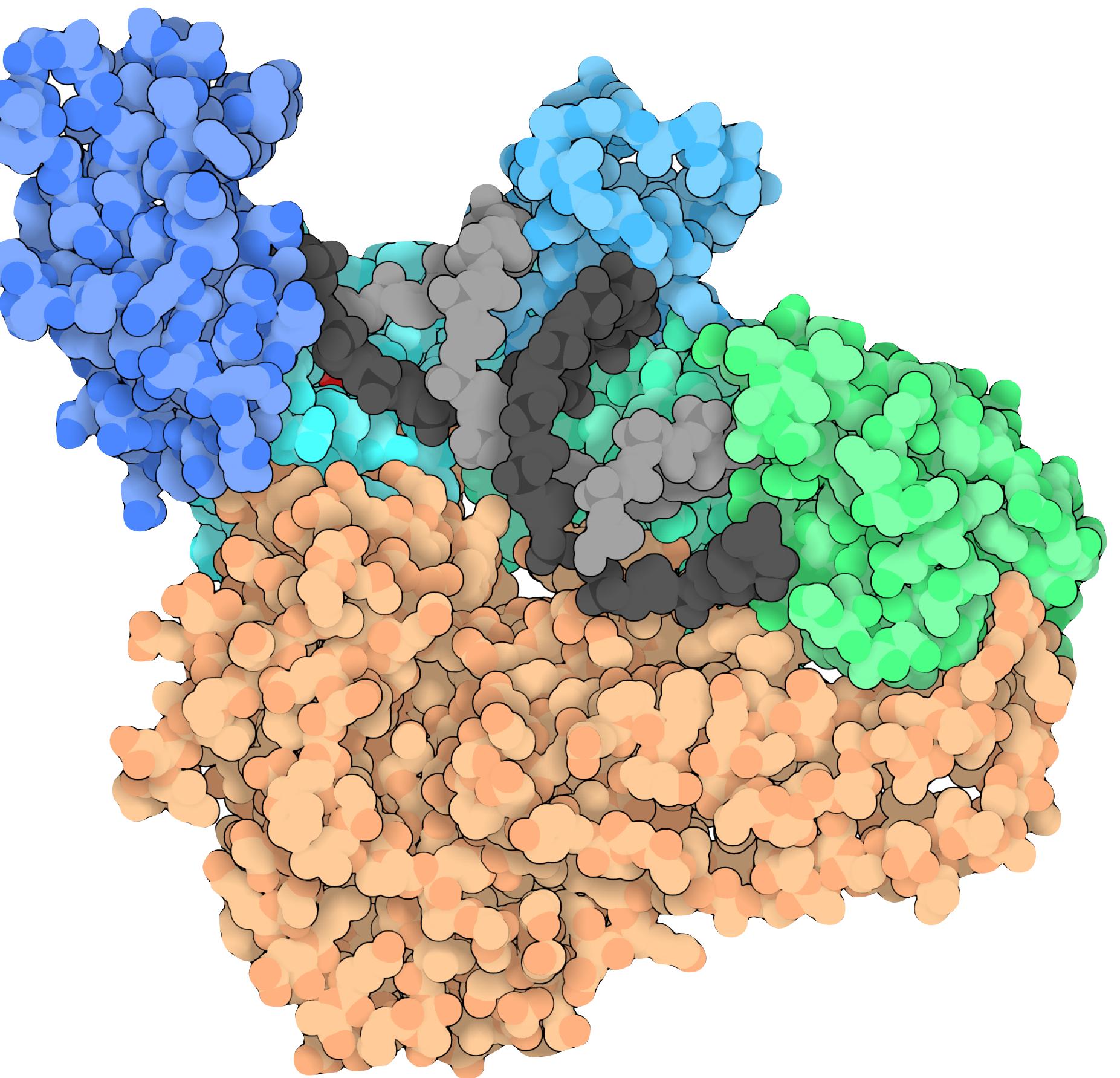
Repeated regions of the genome



MSRs are still **better** than HPC60
but performance **gap is smaller**

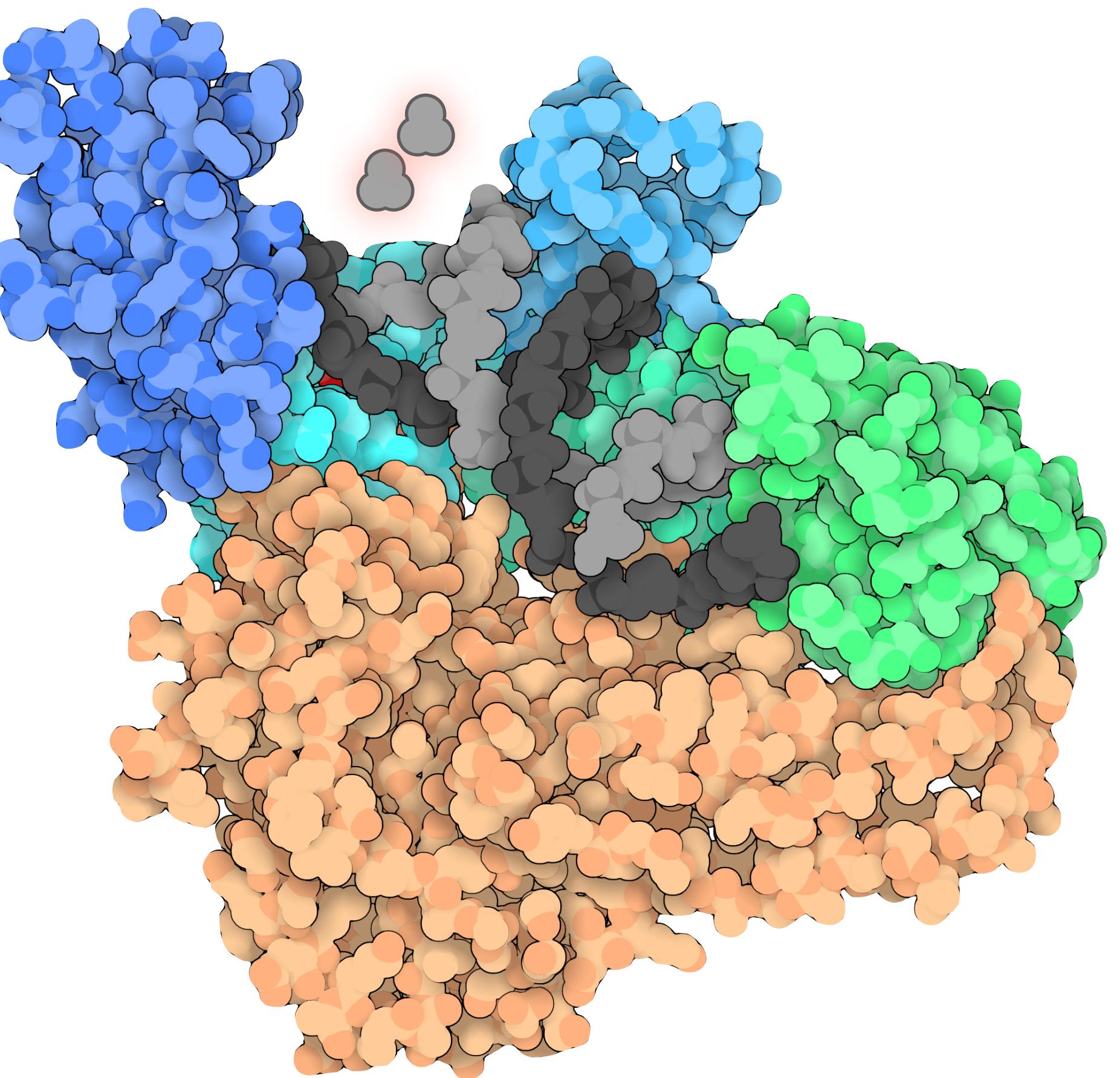
What are DRMs ?

- **Resistance** arises in **response** to treatment pressure
- Drug resistance mutations (**DRMs**) have been found for **every drug**
- **DRMs** often incur a **fitness cost**
- To **mitigate DRM** effects:
 - Treatment **switching**
 - **Combination** therapy



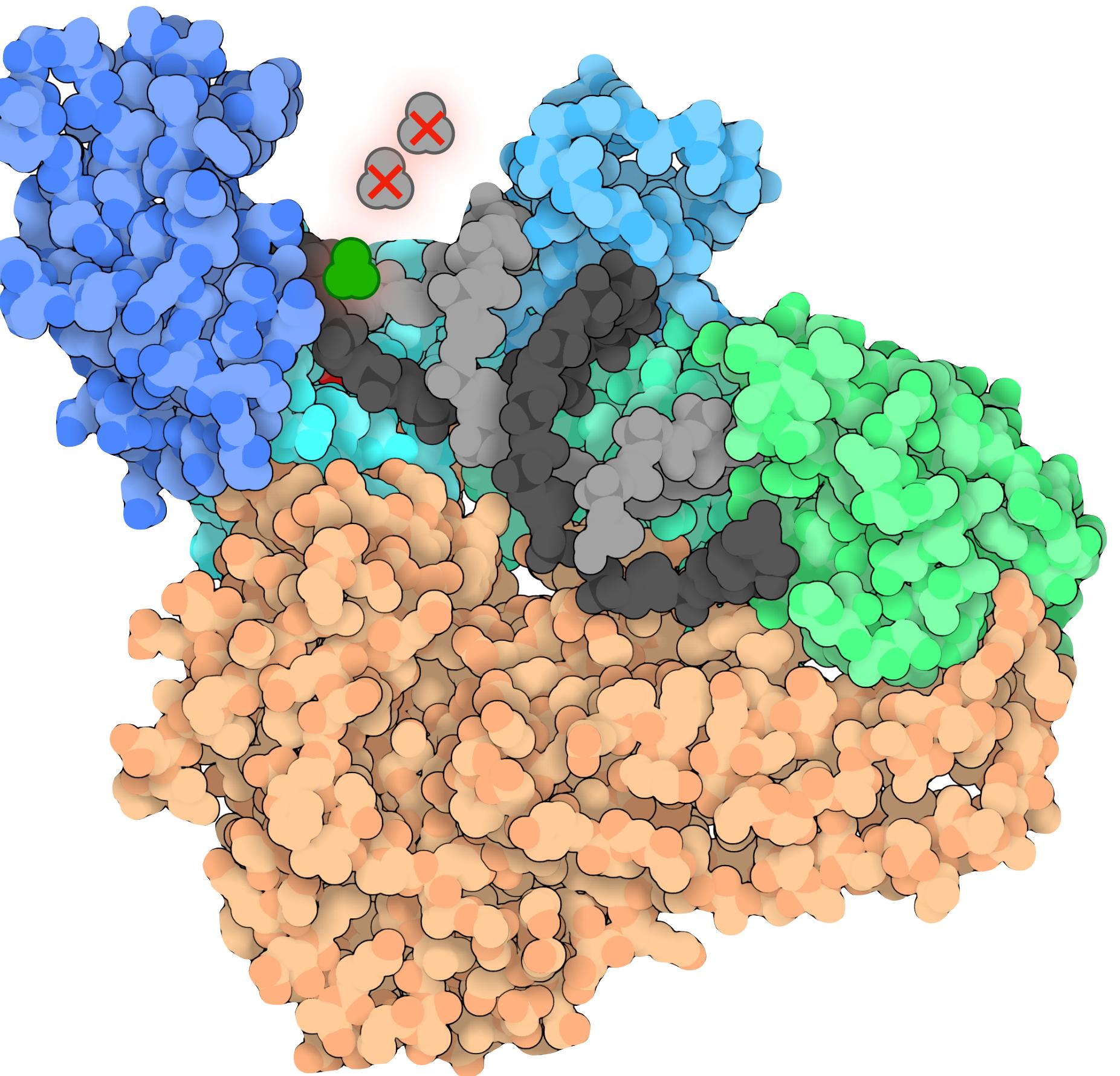
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What are DRMs ?

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Preparing our data

Encoding scheme

180 185

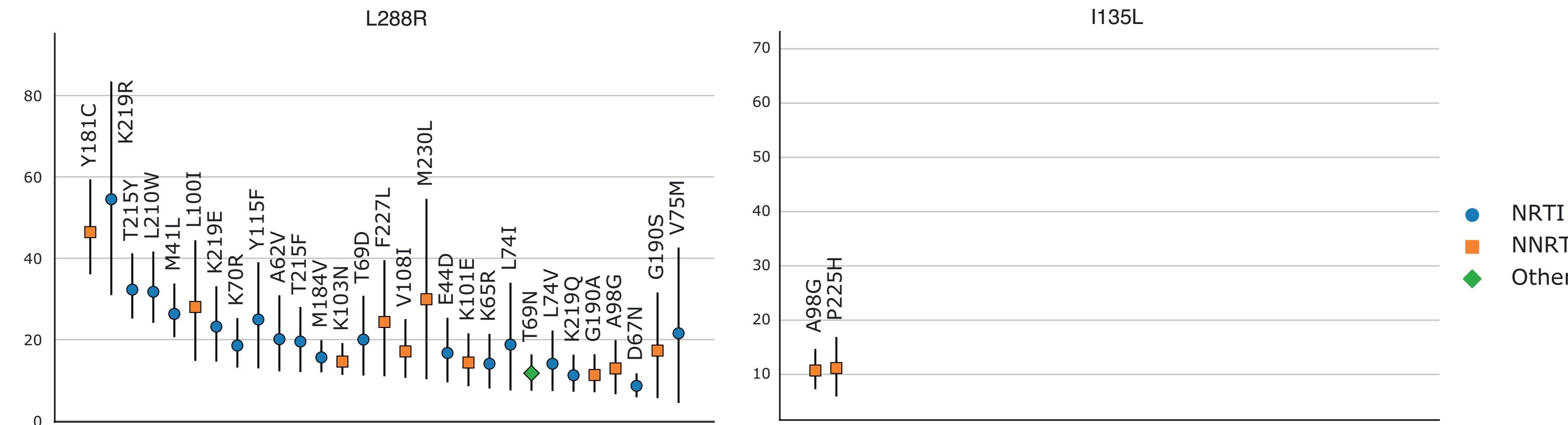
Seq 1	... I VQYMDDL...
Seq 2	...IY D YMDDL...
Seq 3	...IYQ Y VDDL...
Seq 4	...I K Q Y E DD K ...
Seq 5	...IY F YMDDL...

	181V	181K	182D	182F	184V	184E	187K
Seq 1	1	0	0	0	0	0	0
Seq 2	0	0	1	0	0	0	0
Seq 3	0	0	0	0	1	0	0
Seq 4	0	1	0	0	0	1	1
Seq 5	0	0	0	1	0	0	0

Results

Did we find accessory RAMs ?

- **Relative risk between new RAMs and known DRMs**
→ Overrepresentation of RAMs in sequences with DRMs



Results

Structural argument

- **L228R** close to **active site** and **NNIBP**
- **I135L** close to **NNIBP** entrance
- NNIBP → NNRTI
- Active site → NRTI

