

Structure determination of genomes and genomic domains by satisfaction of spatial restraints

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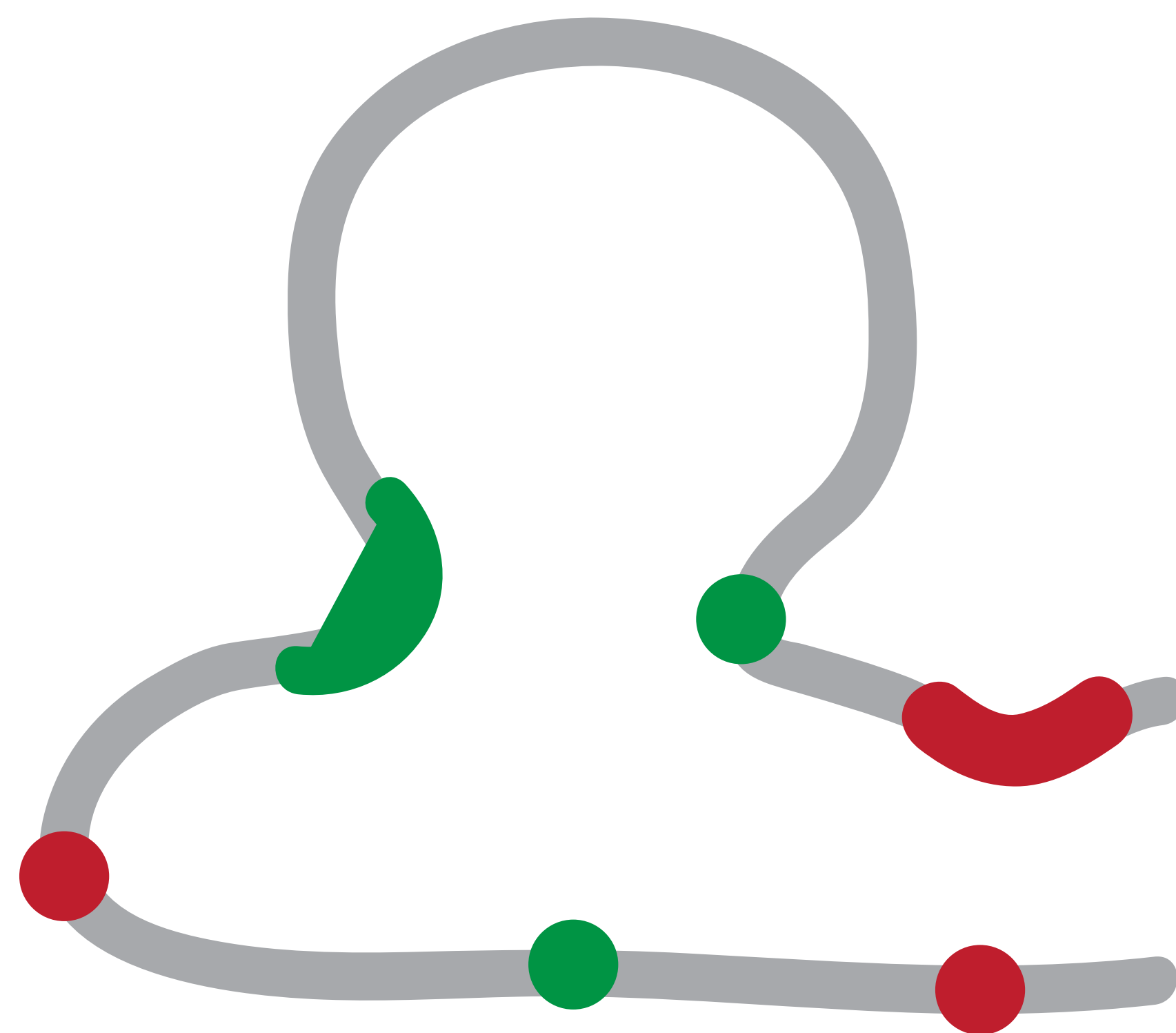
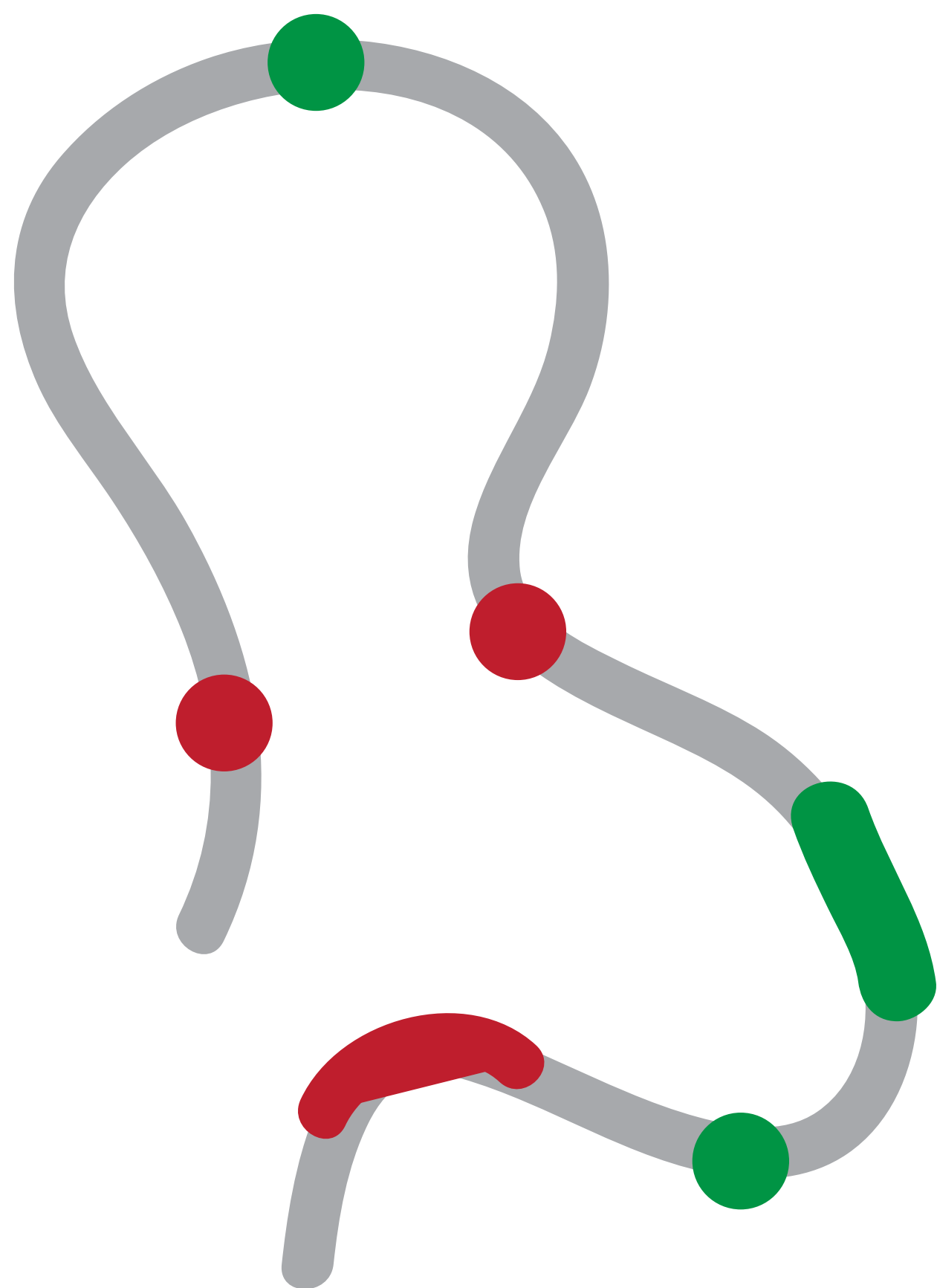
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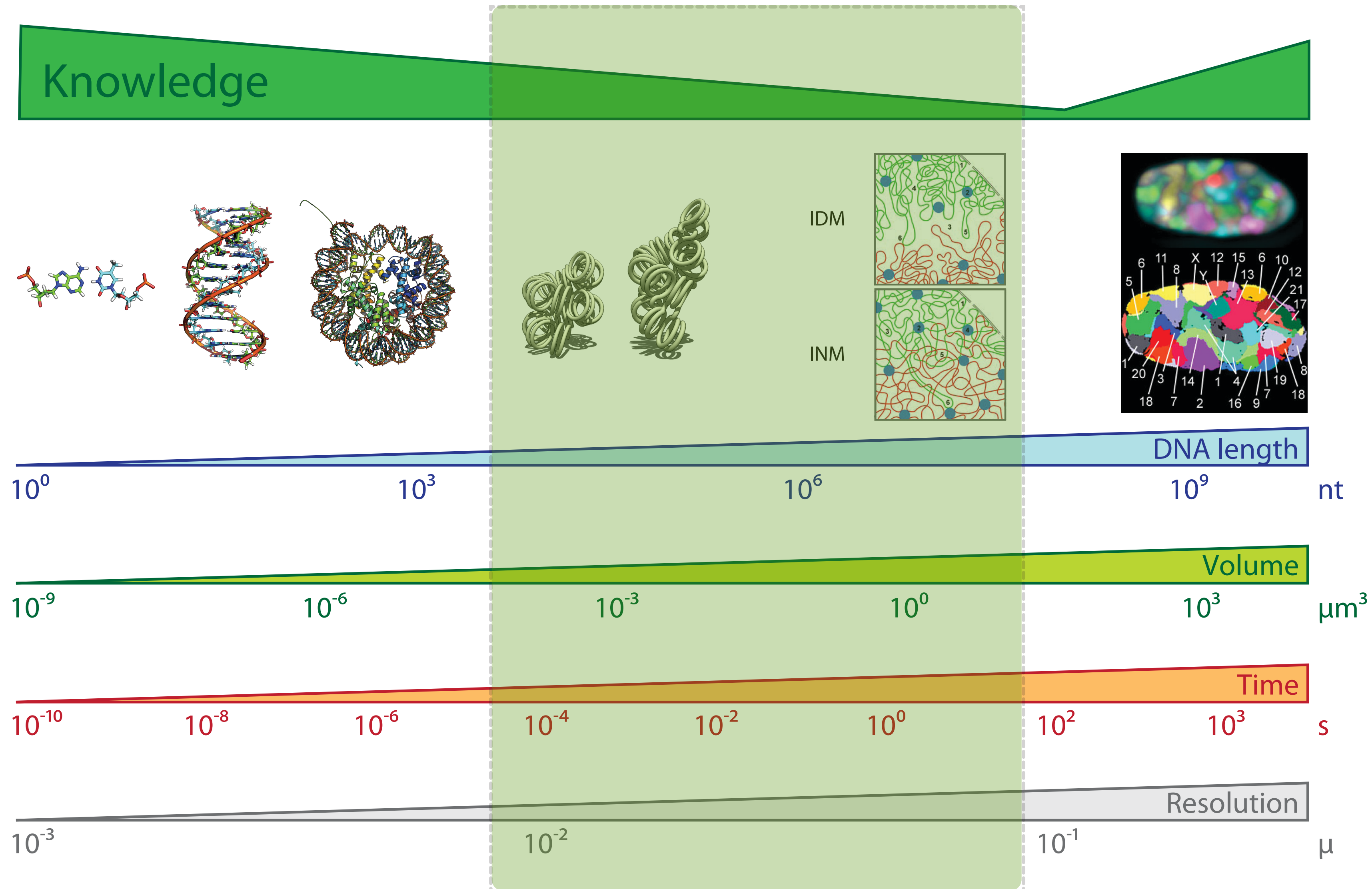
<http://marciuslab.org>
<http://3DGenomes.org>
<http://cnag.crg.eu>

cnag **CRG**  **ICREA**



Resolution Gap

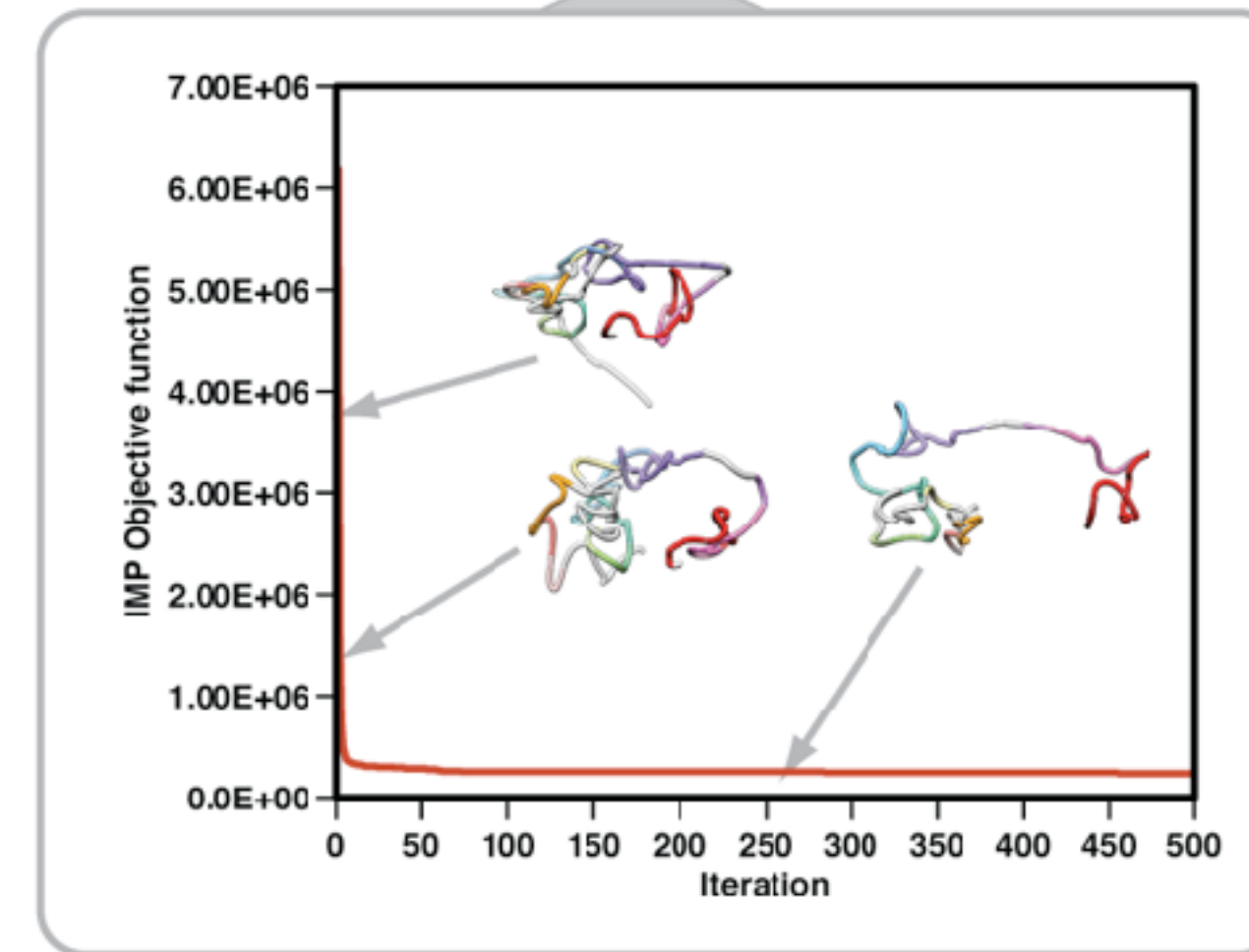
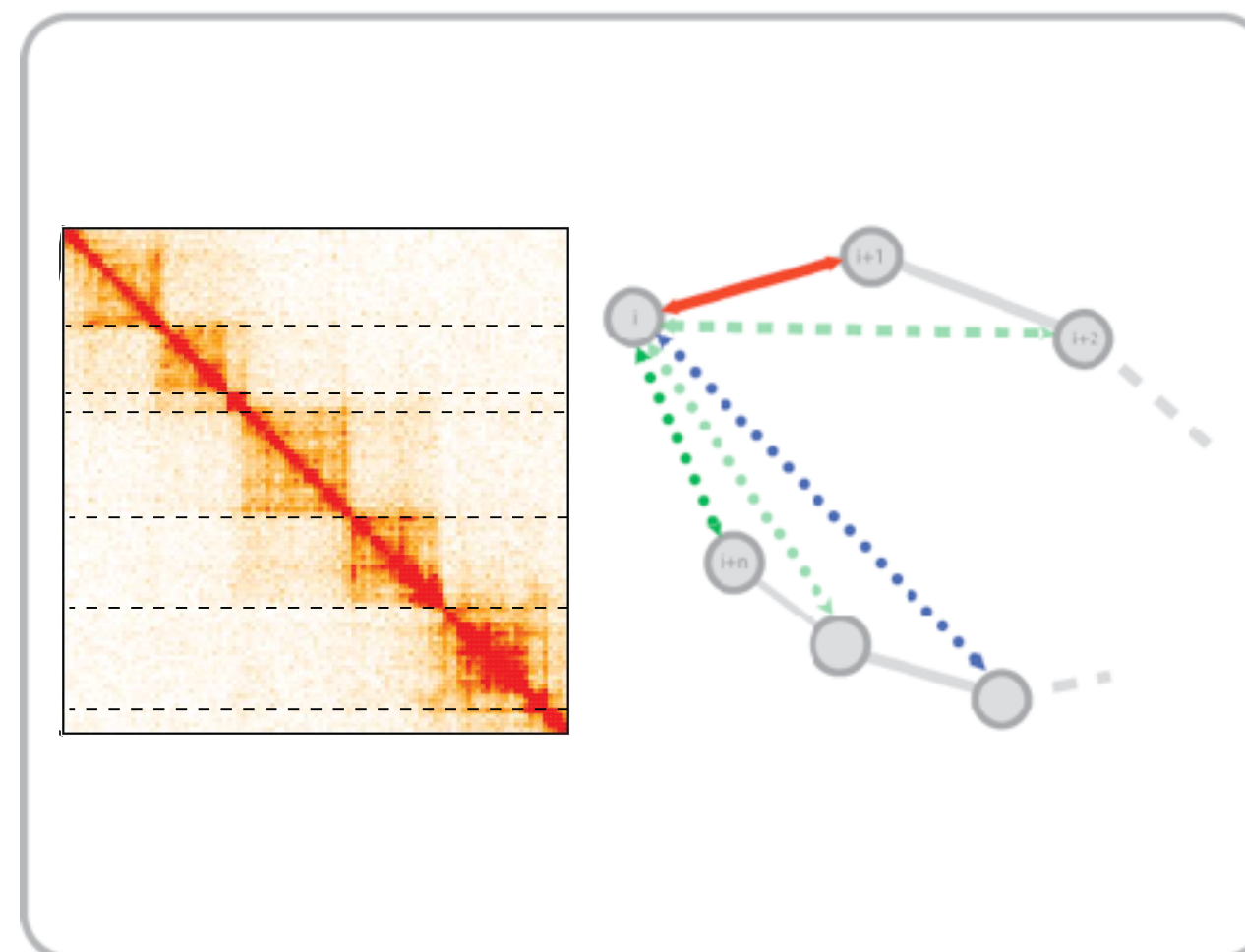
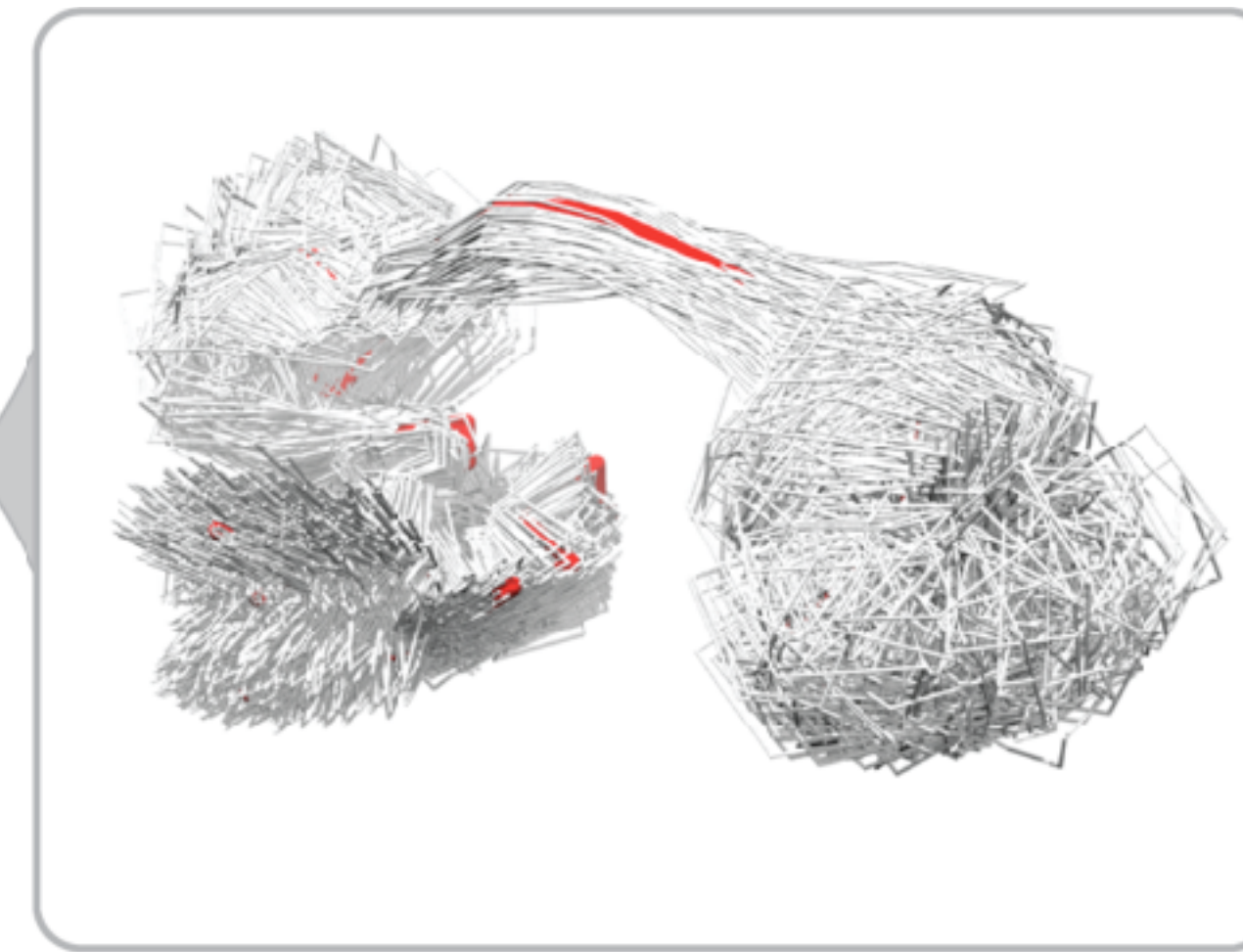
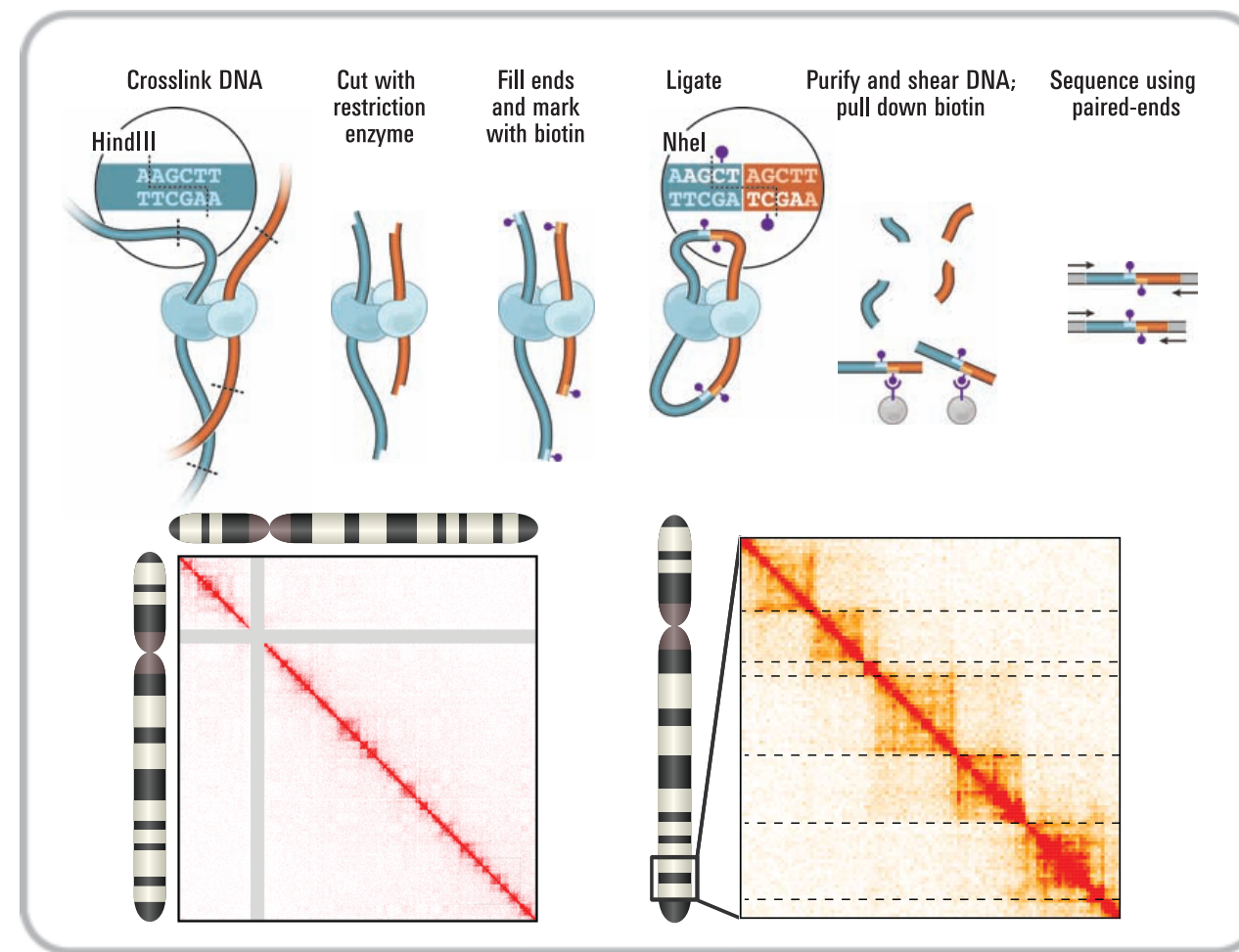
Marti-Renom, M. A. & Mirny, L. A. PLoS Comput Biol 7, e1002125 (2011)



Hybrid Method

Baù, D. & Marti-Renom, M. A. *Methods* 58, 300–306 (2012).

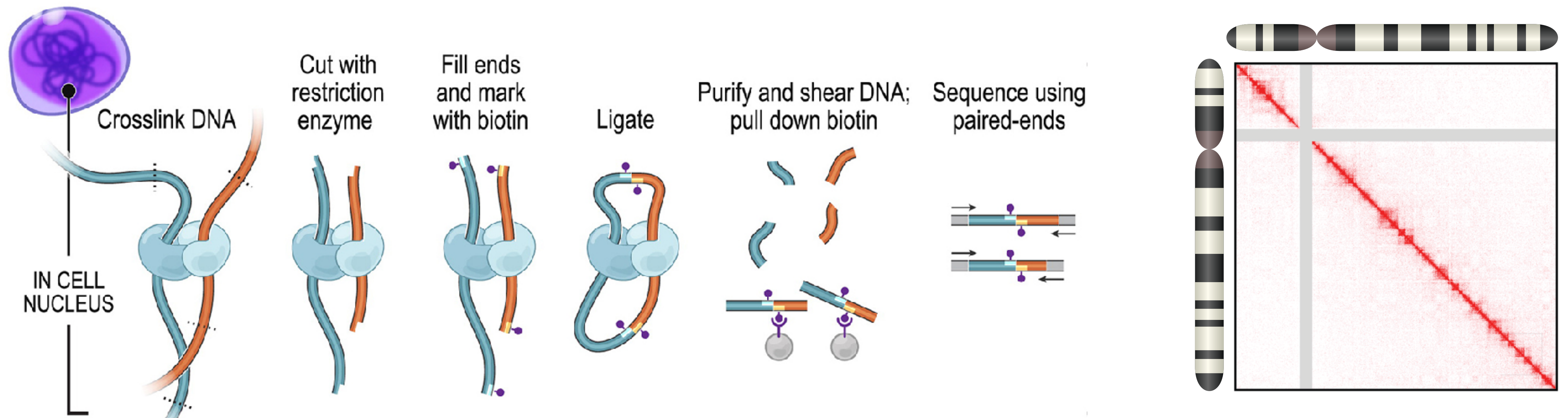
Experiments



Computation

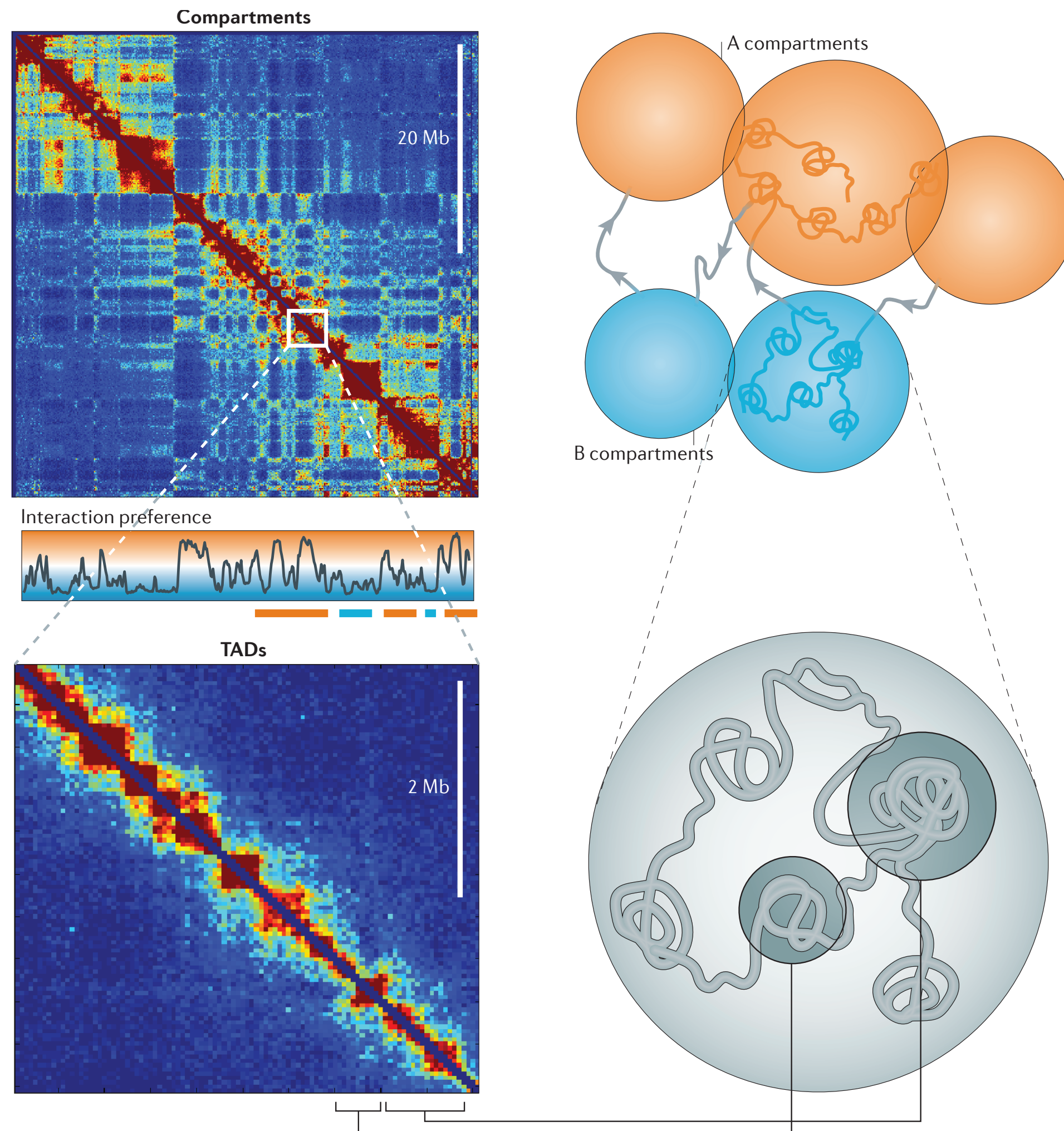
Chromosome Conformation Capture

Dekker, J., Rippe, K., Dekker, M., & Kleckner, N. (2002). *Science*, 295(5558), 1306–1311.
Lieberman-Aiden, E., et al. (2009). *Science*, 326(5950), 289–293.



Higher-order organization

Dekker, J., Marti-Renom, M. A. & Mirny, L. A. Nat Rev Genet 14, 390–403 (2013).

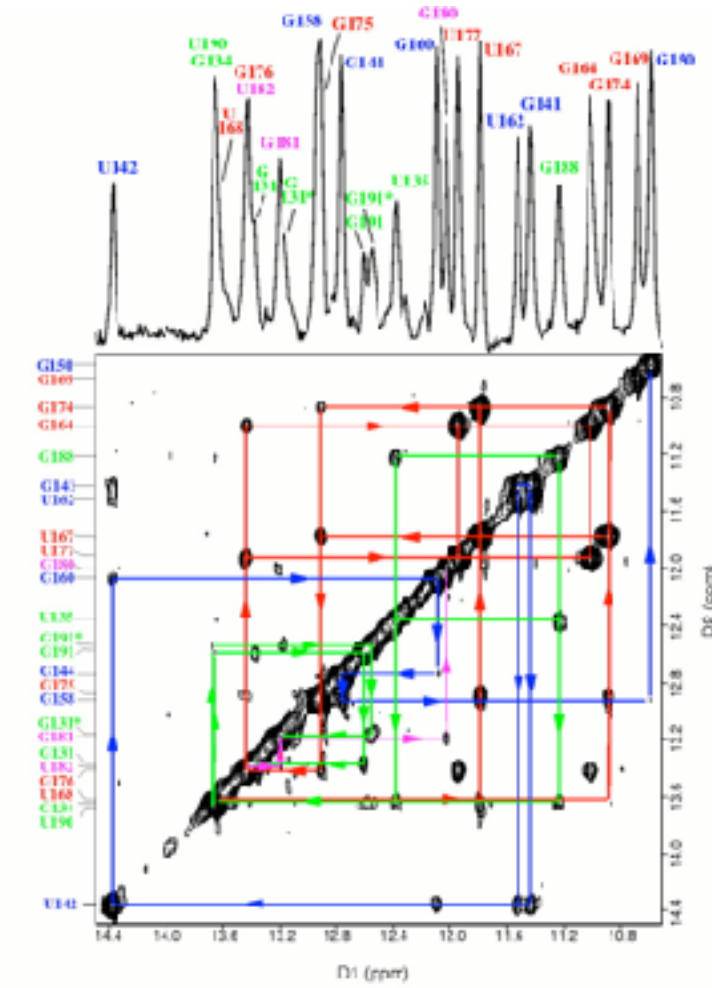
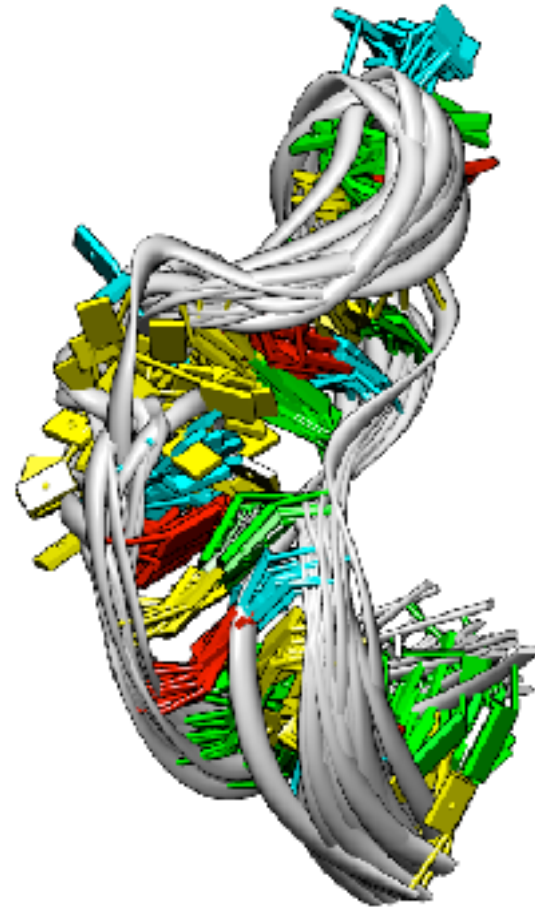


A/B compartments

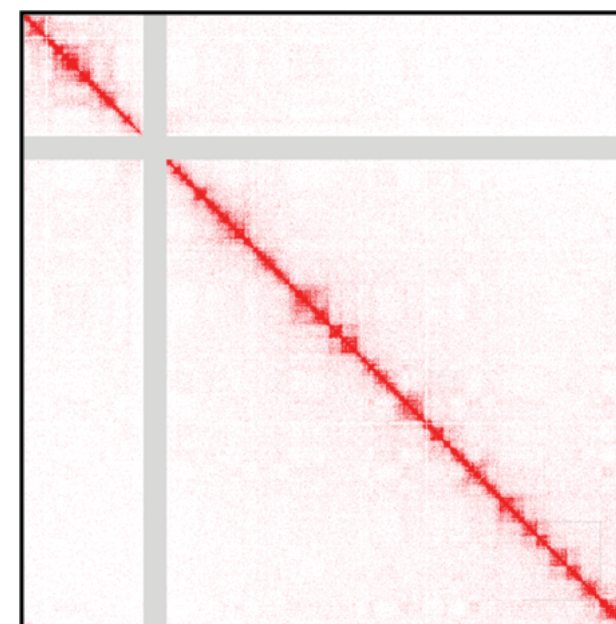
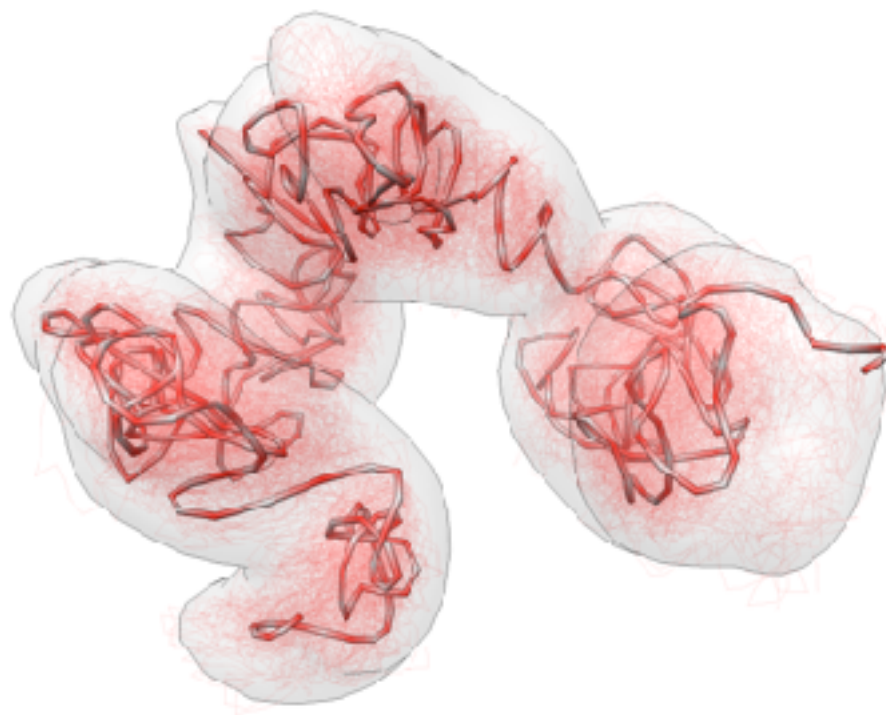
TADs & globules/loops

Restraint-based Modeling

Baù, D. & Marti-Renom, M. A. *Methods* 58, 300–306 (2012).



Biomolecular structure determination
2D-NOESY data



Chromosome structure determination

3C-based data



<http://3DGenomes.org>

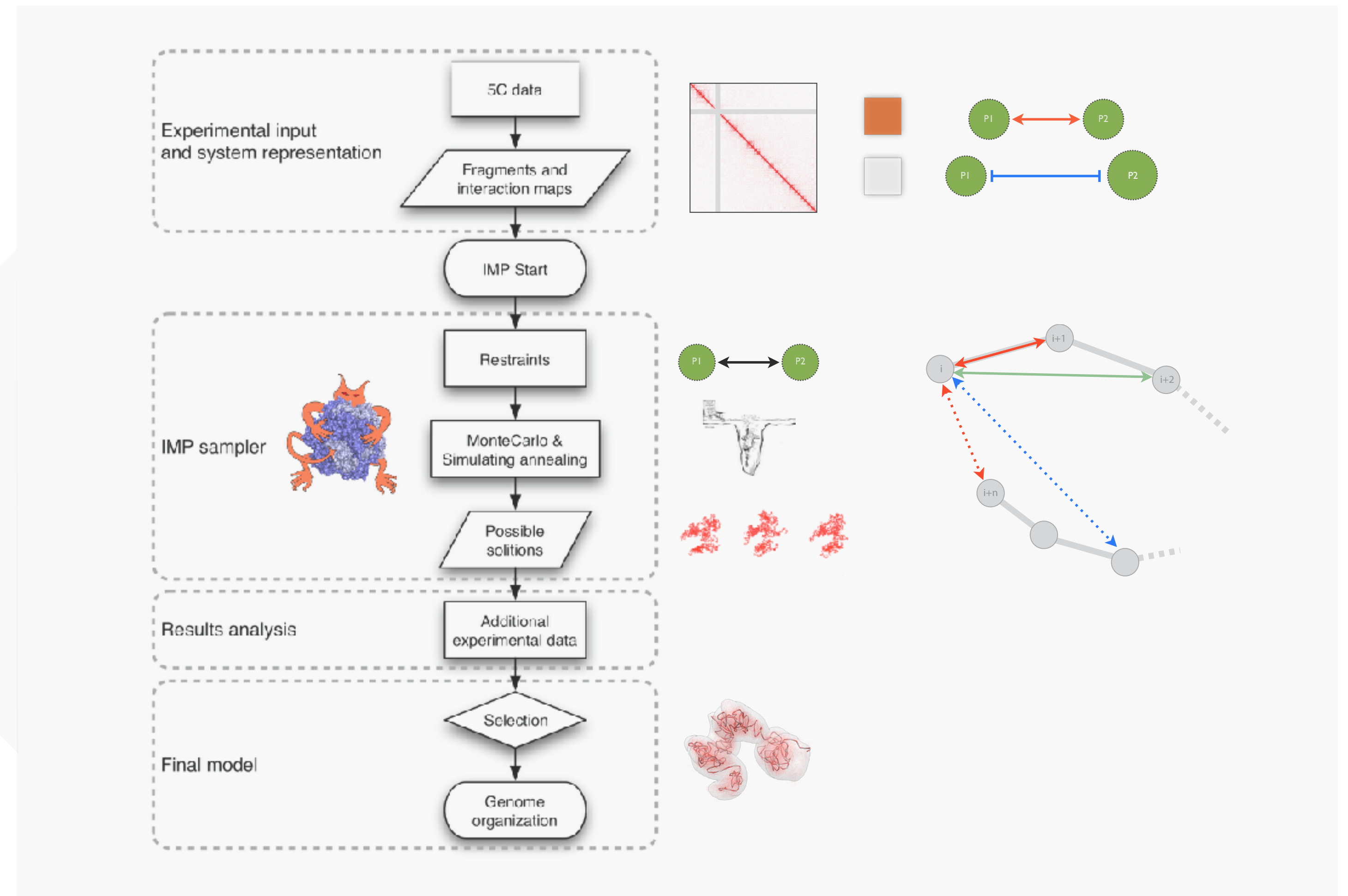
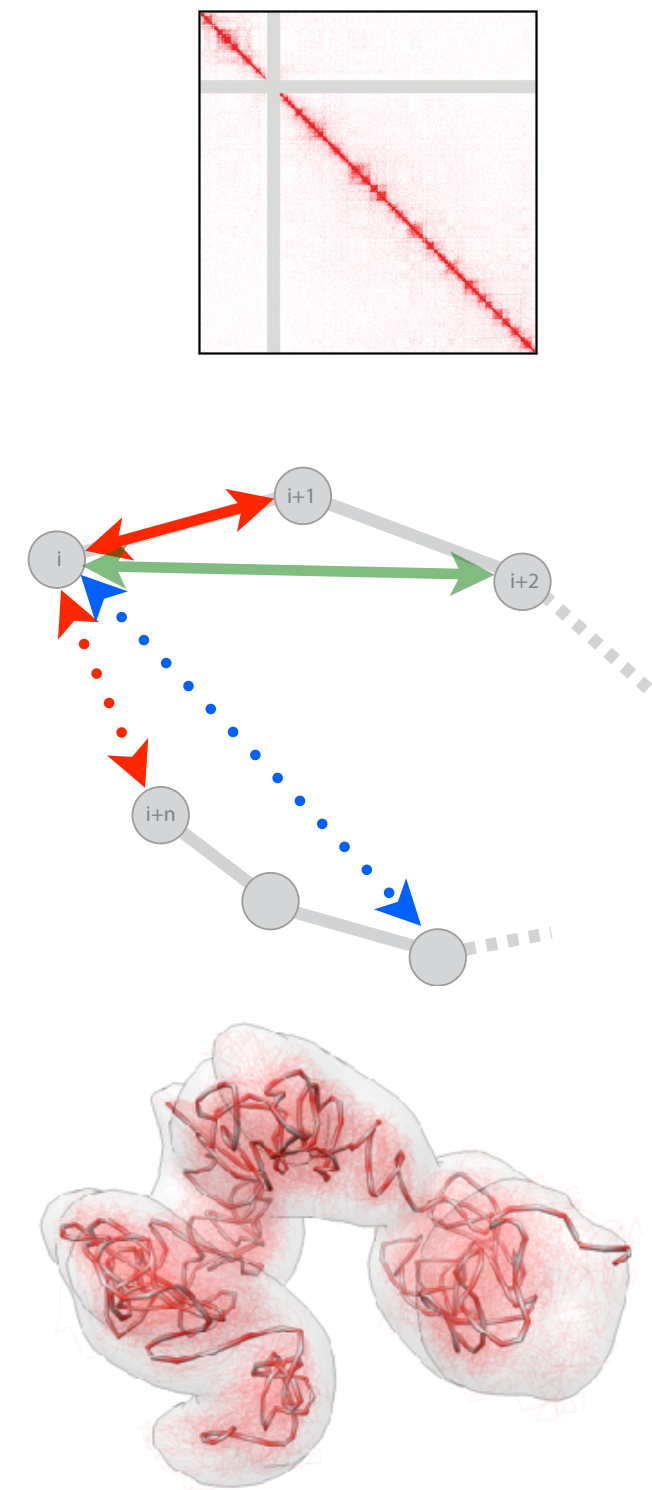


FastQ files to Maps

Map analysis

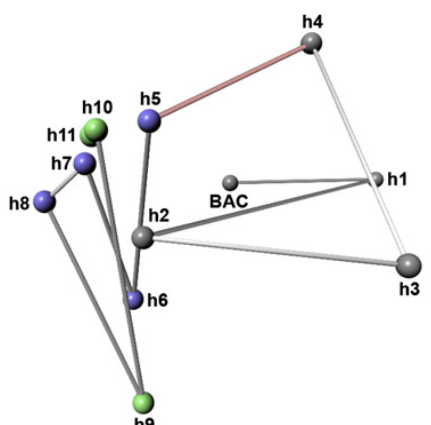
Model building

Model analysis

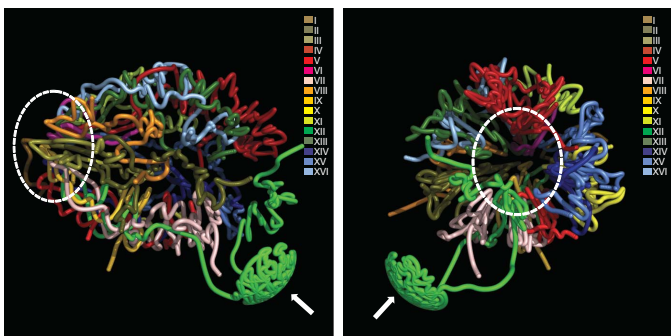


Are the models correct?

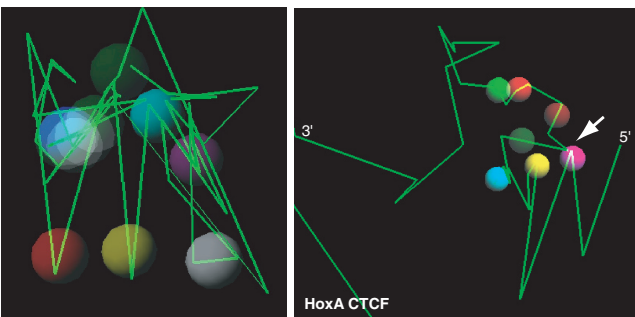
Trussart et al. NAR (2015)



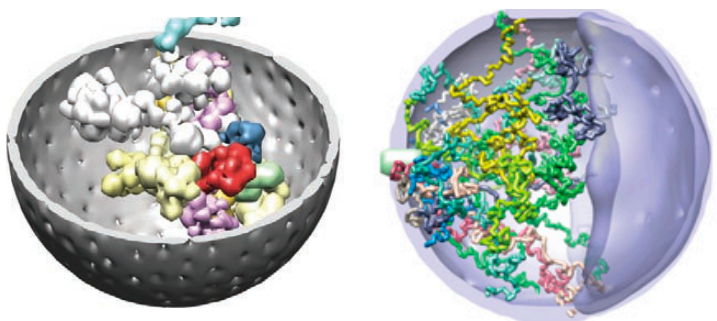
Jhunjunwala (2008) Cell



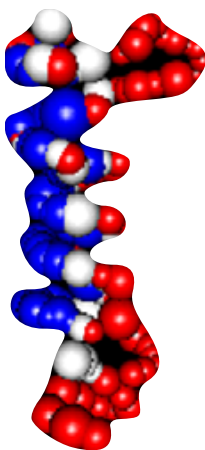
Duan (2010) Nature



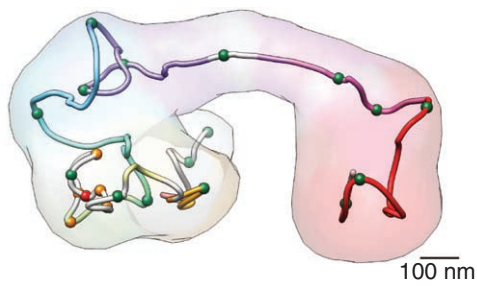
Fraser (2009) Genome Biology
Ferraiuolo (2010) Nucleic Acids Research



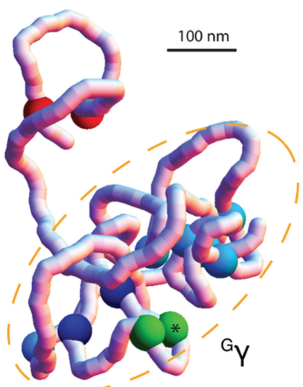
Kalhor (2011) Nature Biotechnology
Tjong (2012) Genome Research



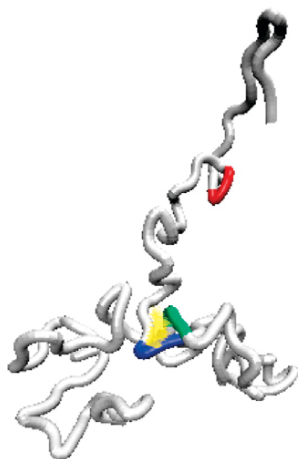
Hu (2013) PLoS Computational Biology



Baù (2011) Nature Structural & Molecular Biology



Junier (2012) Nucleic Acids Research



Giorgetti, (2014) Cell

Nucleic Acids Research Advance Access published March 23, 2015

Nucleic Acids Research, 2015, 1
doi: 10.1093/nar/gkv221

Assessing the limits of restraint-based 3D modeling of genomes and genomic domains

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Received January 16, 2015; Revised February 16, 2015; Accepted February 22, 2015

ABSTRACT

Restraint-based modeling of genomes has been recently explored with the advent of Chromosome Conformation Capture (3C-based) experiments. We previously developed a reconstruction method to resolve the 3D architecture of both prokaryotic and eukaryotic genomes using 3C-based data. These models were congruent with fluorescent imaging validation. However, the limits of such methods have not systematically been assessed. Here we propose the first evaluation of a mean-field restraint-based reconstruction of genomes by considering diverse chromosome architectures and different levels of data noise and structural variability. The results show that: first, current scoring functions for 3D reconstruction correlate with the accuracy of the models; second, reconstructed models are robust to noise but sensitive to structural variability; third, the local structure organization of genomes, such as Topologically Associating Domains, results in more accurate models; fourth, to a certain extent, the models capture the intrinsic structural variability in the input matrices and fifth, the accuracy of the models can be *a priori* predicted by analyzing the properties of the interaction matrices. In summary, our work provides a systematic analysis of the limitations of a mean-field restrain-based method, which could be taken into consideration in further development of methods as well as their applications.

INTRODUCTION

Recent studies of the three-dimensional (3D) conformation of genomes are revealing insights into the organization and the regulation of biological processes, such as gene

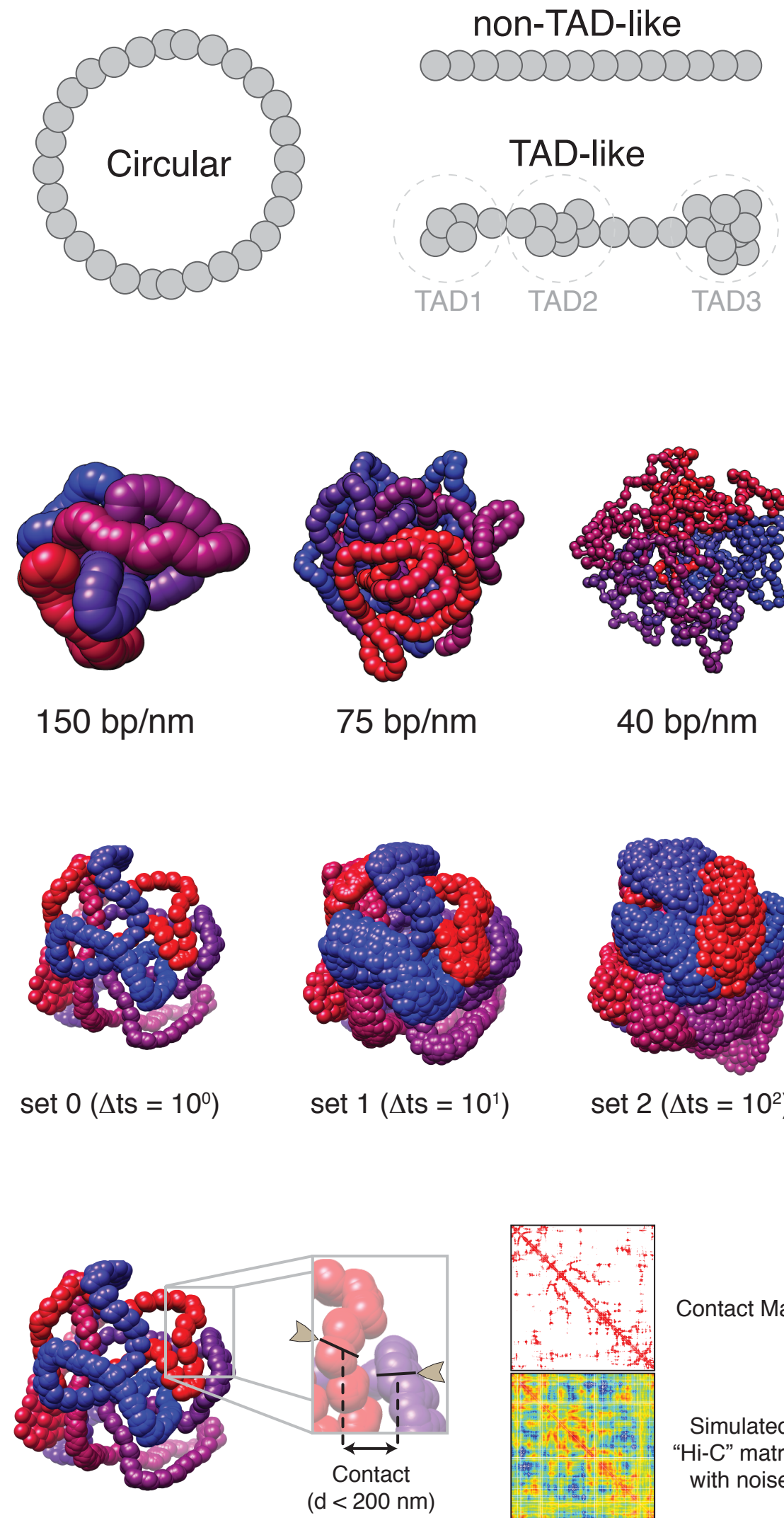
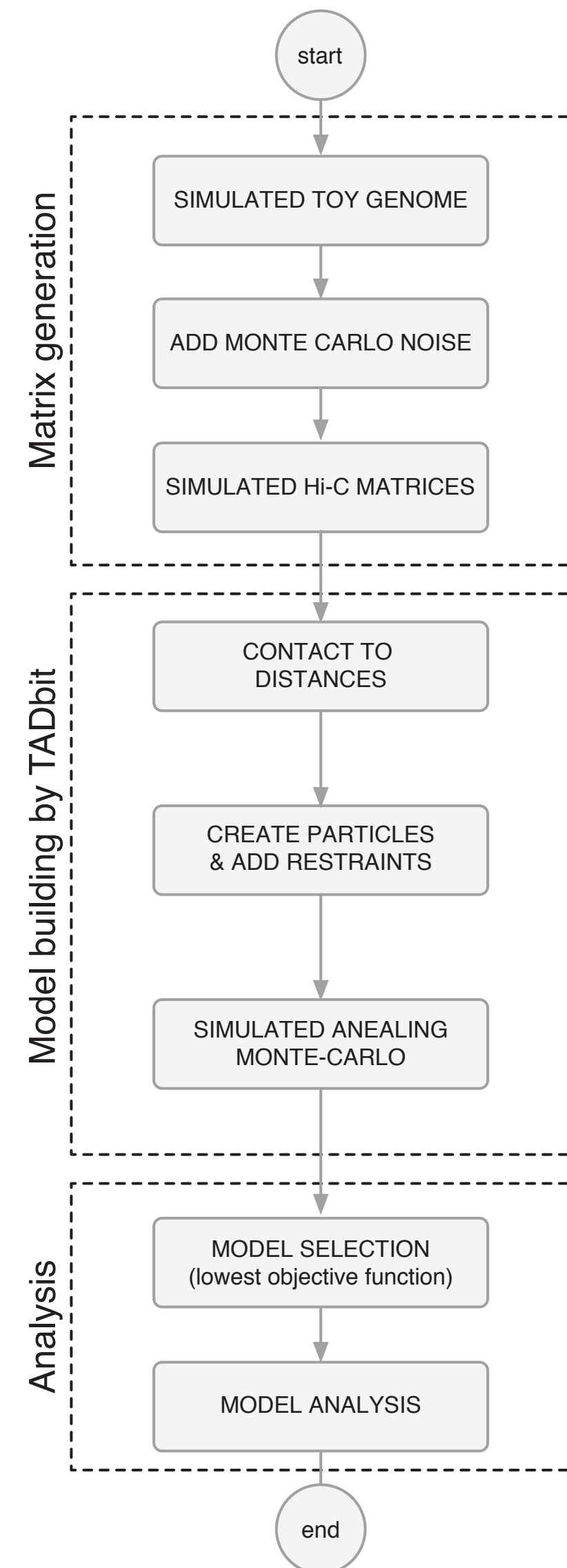
expression regulation and replication (1–6). The advent of the so-called Chromosome Conformation Capture (3C) assays (7), which allowed identifying chromatin-looping interactions between pairs of loci, helped deciphering some of the key elements organizing the genomes. High-throughput derivations of genome-wide 3C-based assays were established with Hi-C technologies (8) for an unbiased identification of chromatin interactions. The resulting genome interaction matrices from Hi-C experiments have been extensively used for computationally analyzing the organization of genomes and genomic domains (5). In particular, a significant number of new approaches for modeling the 3D organization of genomes have recently flourished (9–14). The main goal of such approaches is to provide an accurate 3D representation of the bi-dimensional interaction matrices, which can then be more easily explored to extract biological insights. One type of methods for building 3D models from interaction matrices relies on the existence of a limited number of conformational states in the cell. Such methods are regarded as mean-field approaches and are able to capture, to a certain degree, the structural variability around these mean structures (15).

We recently developed a mean-field method for modeling 3D structures of genomes and genomic domains based on 3C interaction data (9). Our approach, called TADbit, was developed around the Integrative Modeling Platform (IMP, <http://integrativemodelling.org>), a general framework for restraint-based modeling of 3D bio-molecular structures (16). Briefly, our method uses chromatin interaction frequencies derived from experiments as a proxy of spatial proximity between the ligation products of the 3C libraries. Two fragments of DNA that interact with high frequency are dynamically placed close in space in our models while two fragments that do not interact as often will be kept apart. Our method has been successfully applied to model the structures of genomes and genomic domains in eukaryote and prokaryote organisms (17–19). In all of our studies, the final models were partially validated by assessing their

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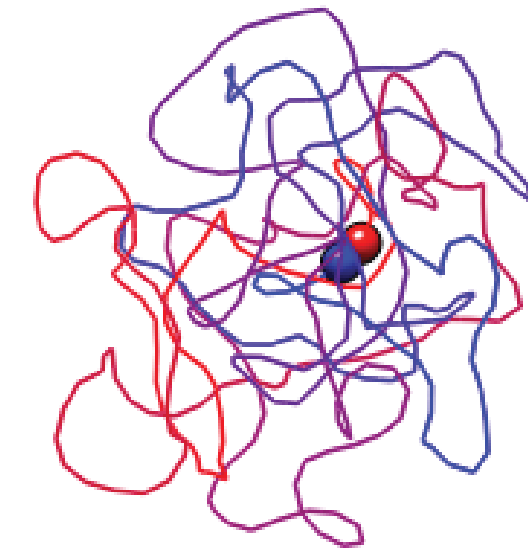
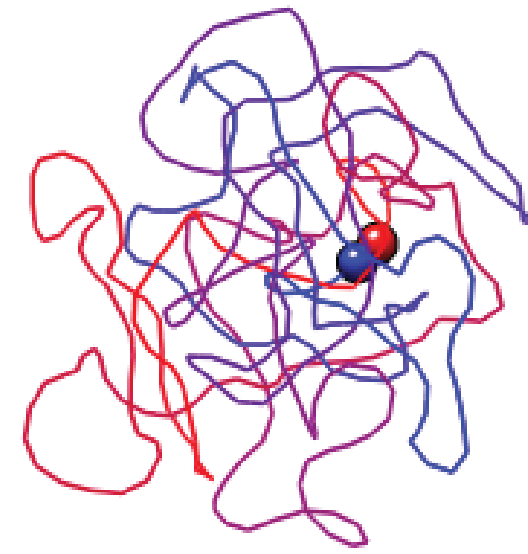
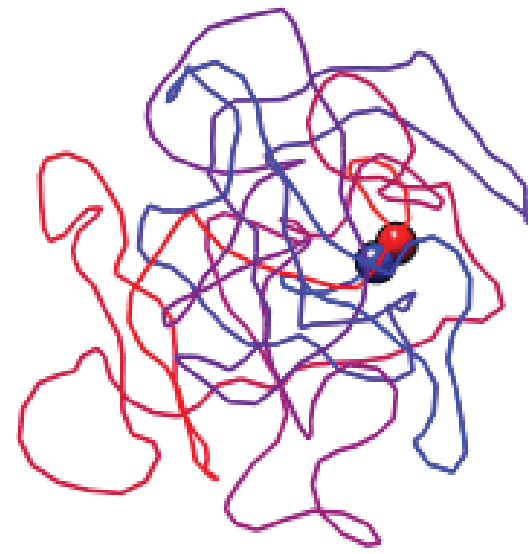
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Toy models

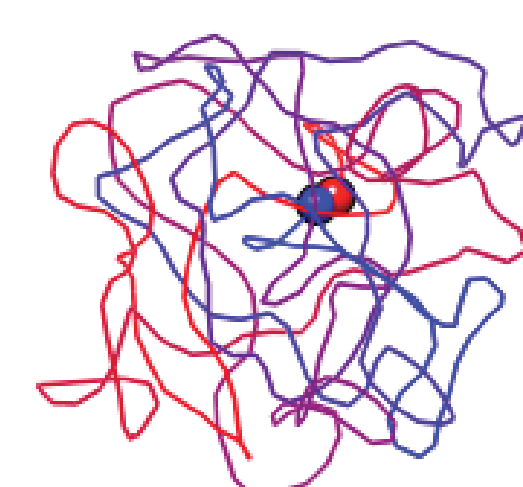
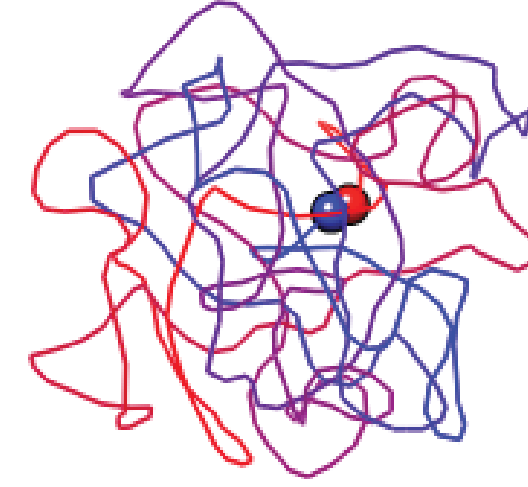
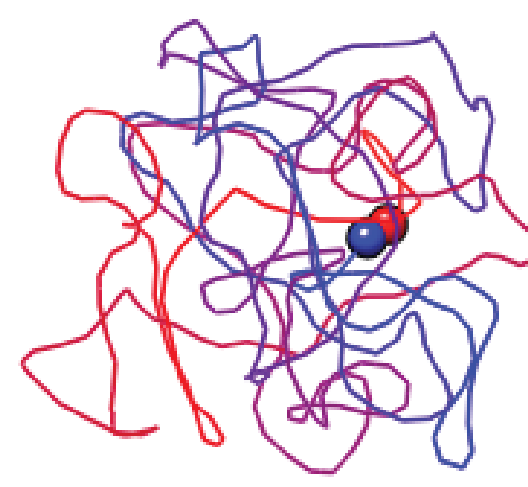
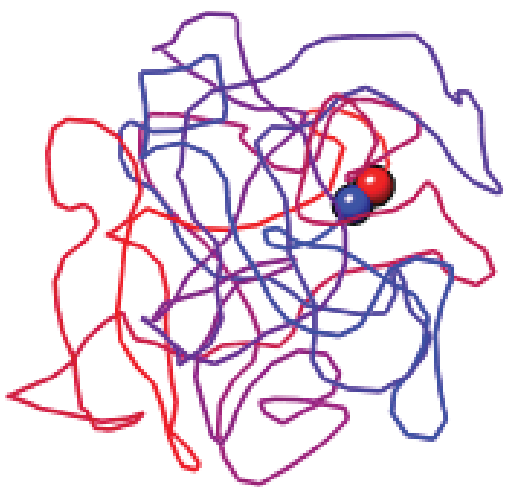
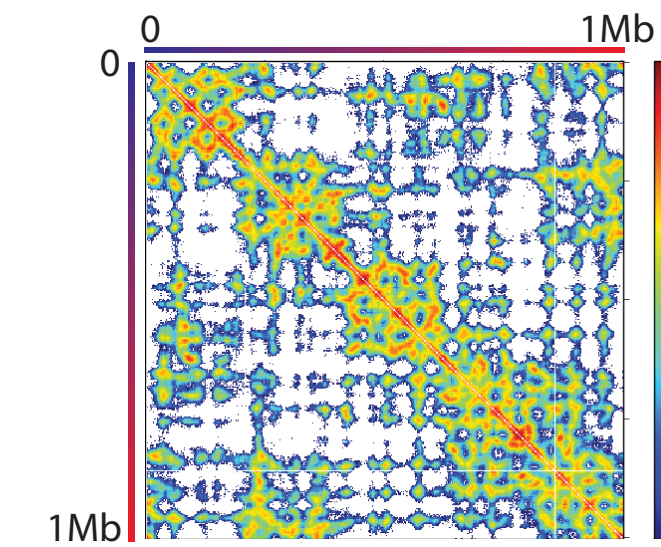


by Ivan Junier

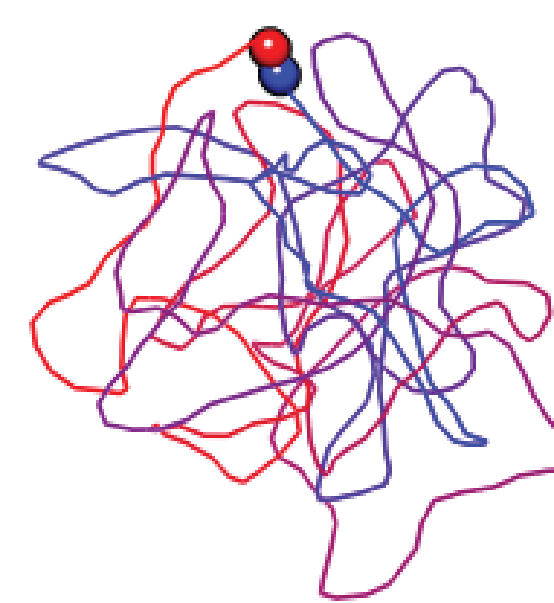
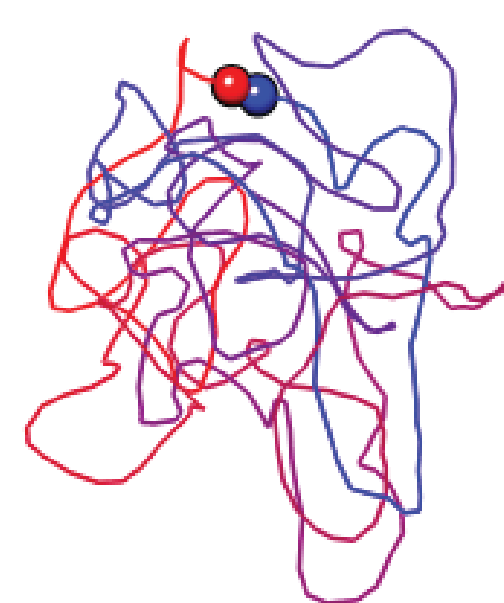
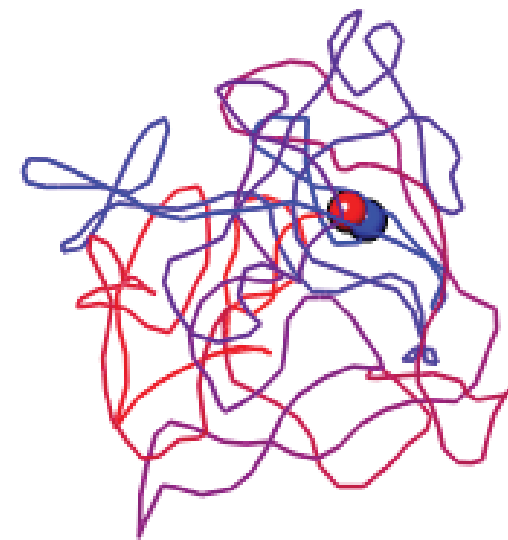
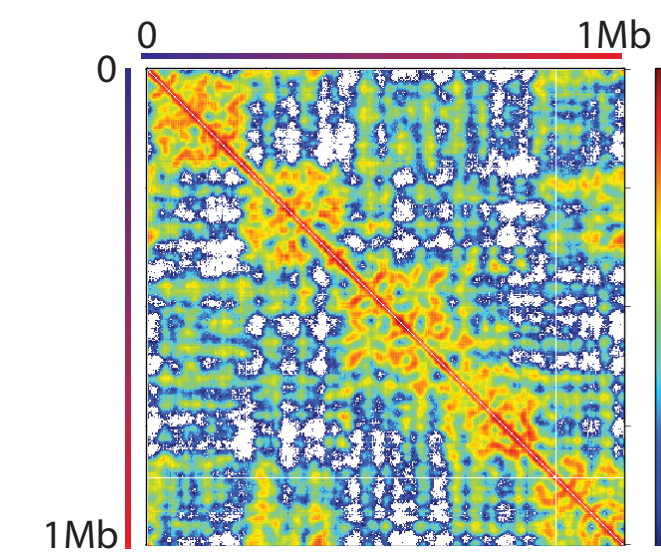
Toy interaction matrices



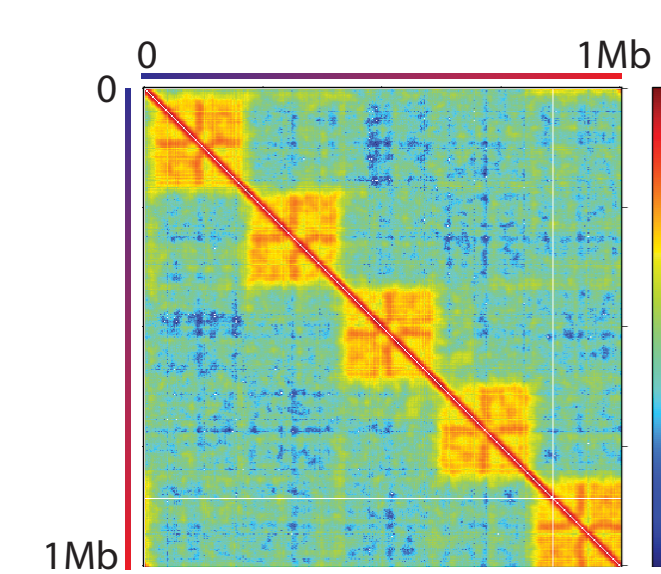
set 0 ($\Delta ts=10^0$)



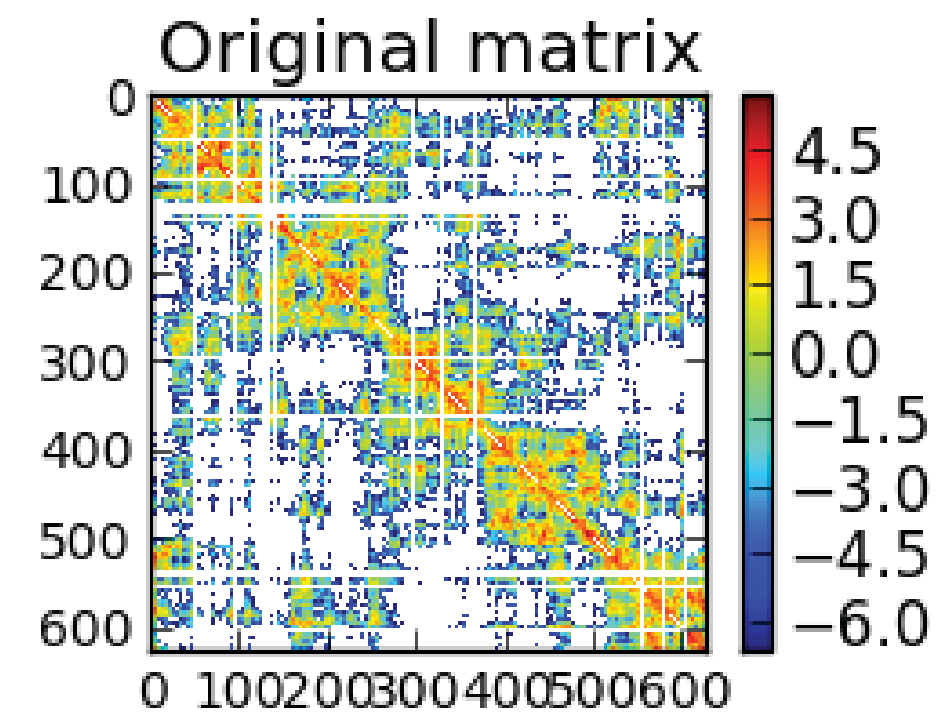
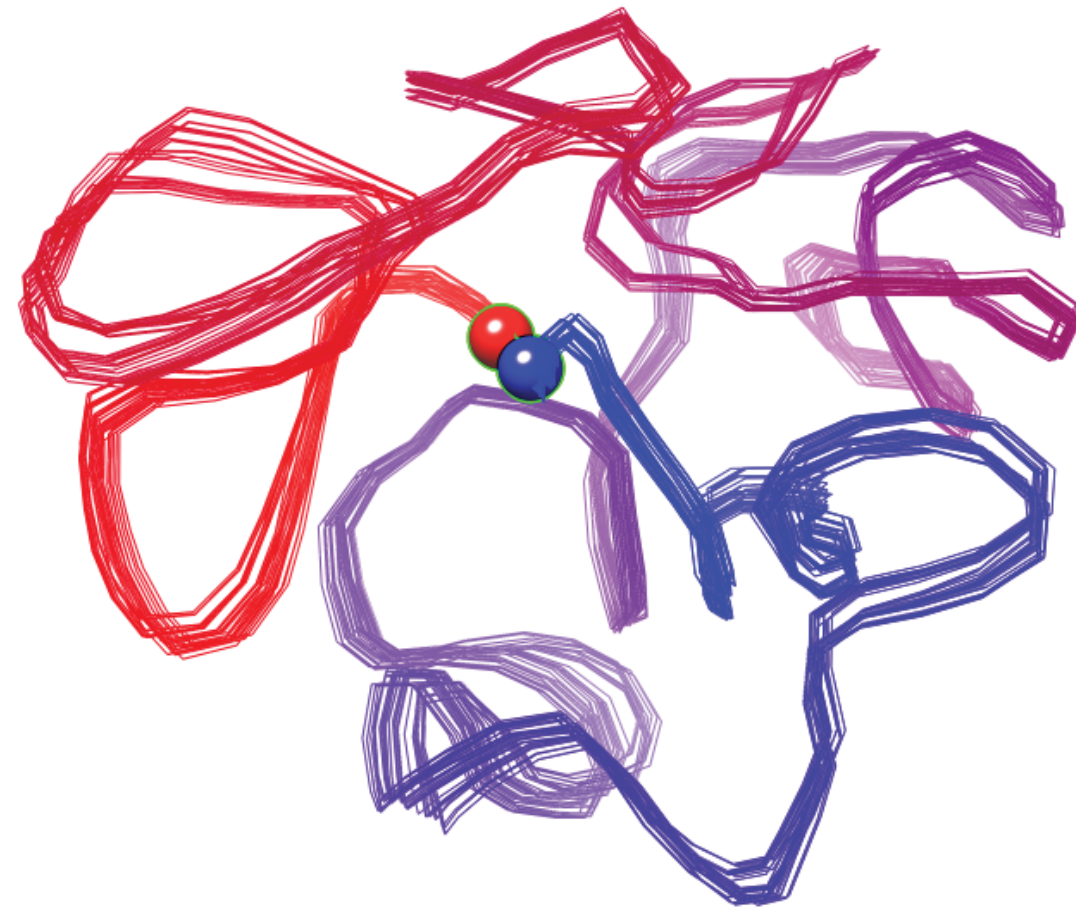
set 4 ($\Delta ts=10^4$)



set 6 ($\Delta ts=10^6$)



Reconstructing toy models



chr40_TAD

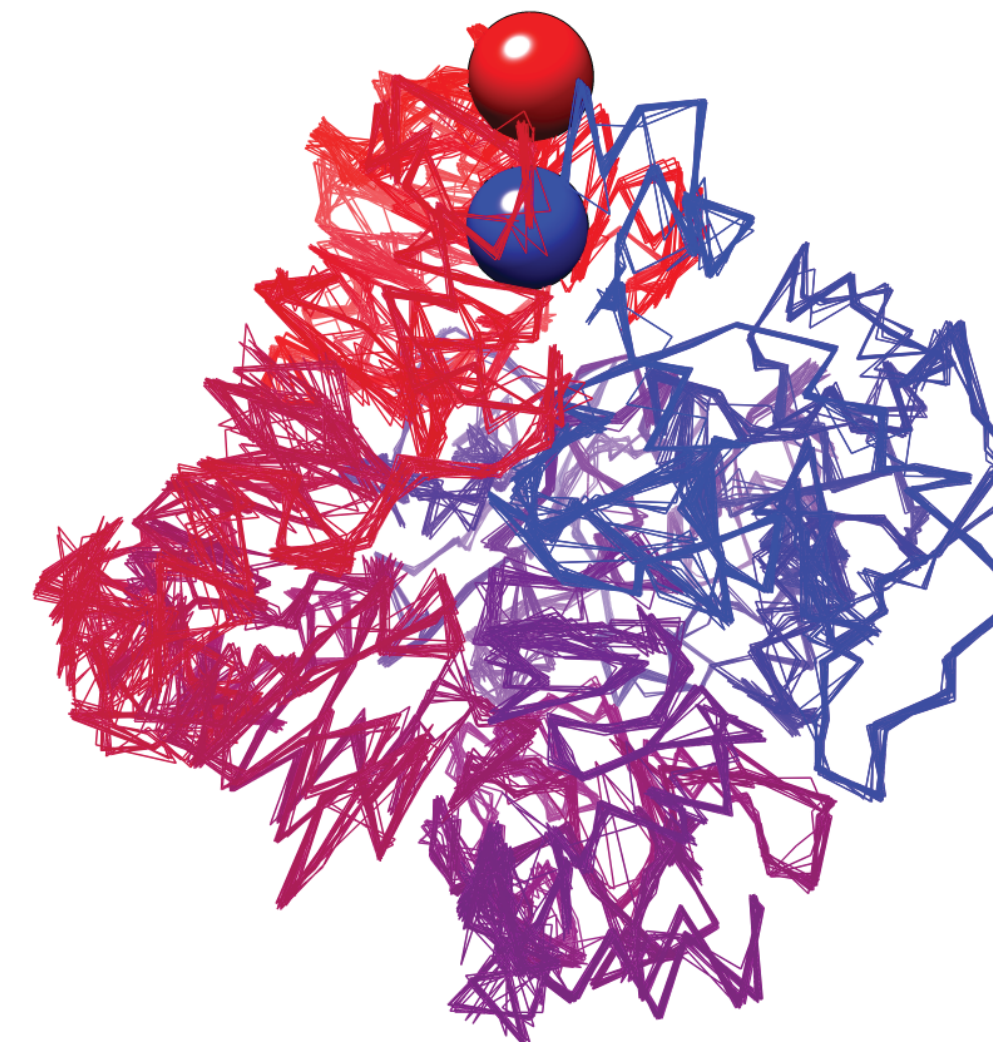
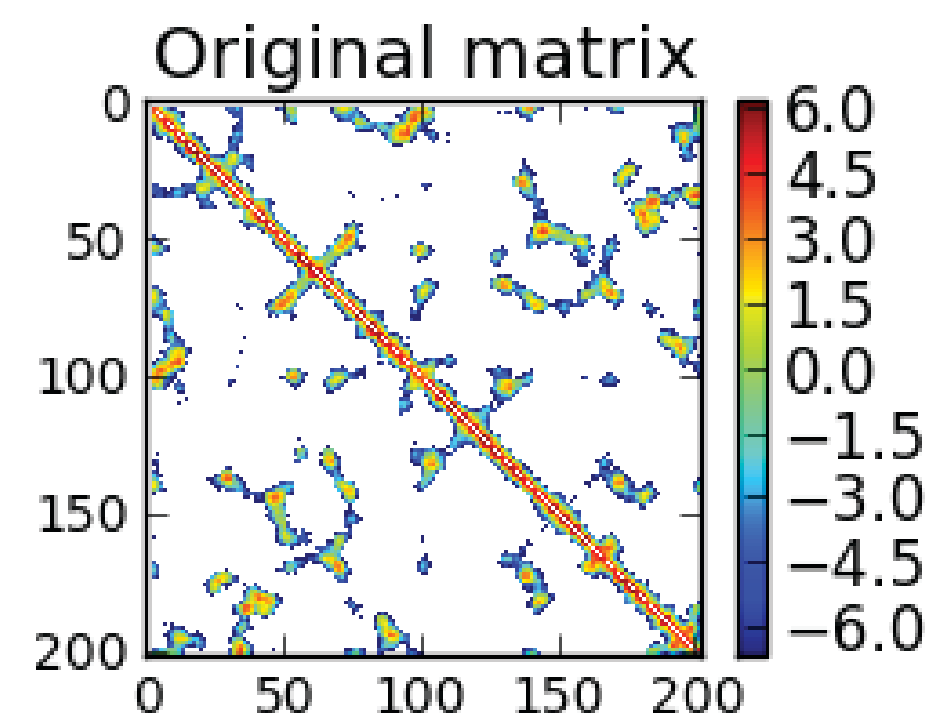
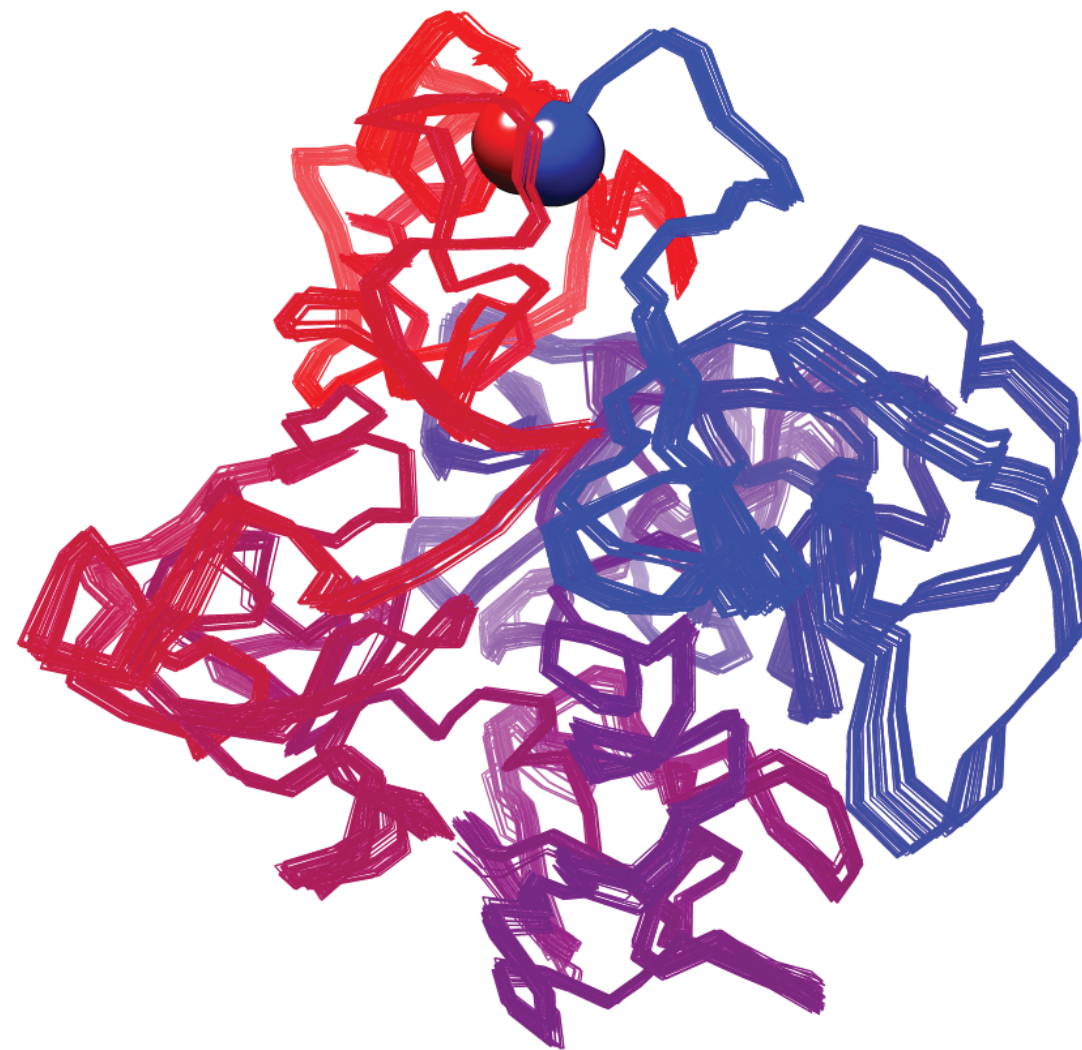
$\alpha=100$

$\Delta t_s=10$

TADbit-SCC: 0.91

$\langle d_{\text{RMSD}} \rangle$: 32.7 nm

$\langle d_{\text{SCC}} \rangle$: 0.94



chr150_TAD

$\alpha=50$

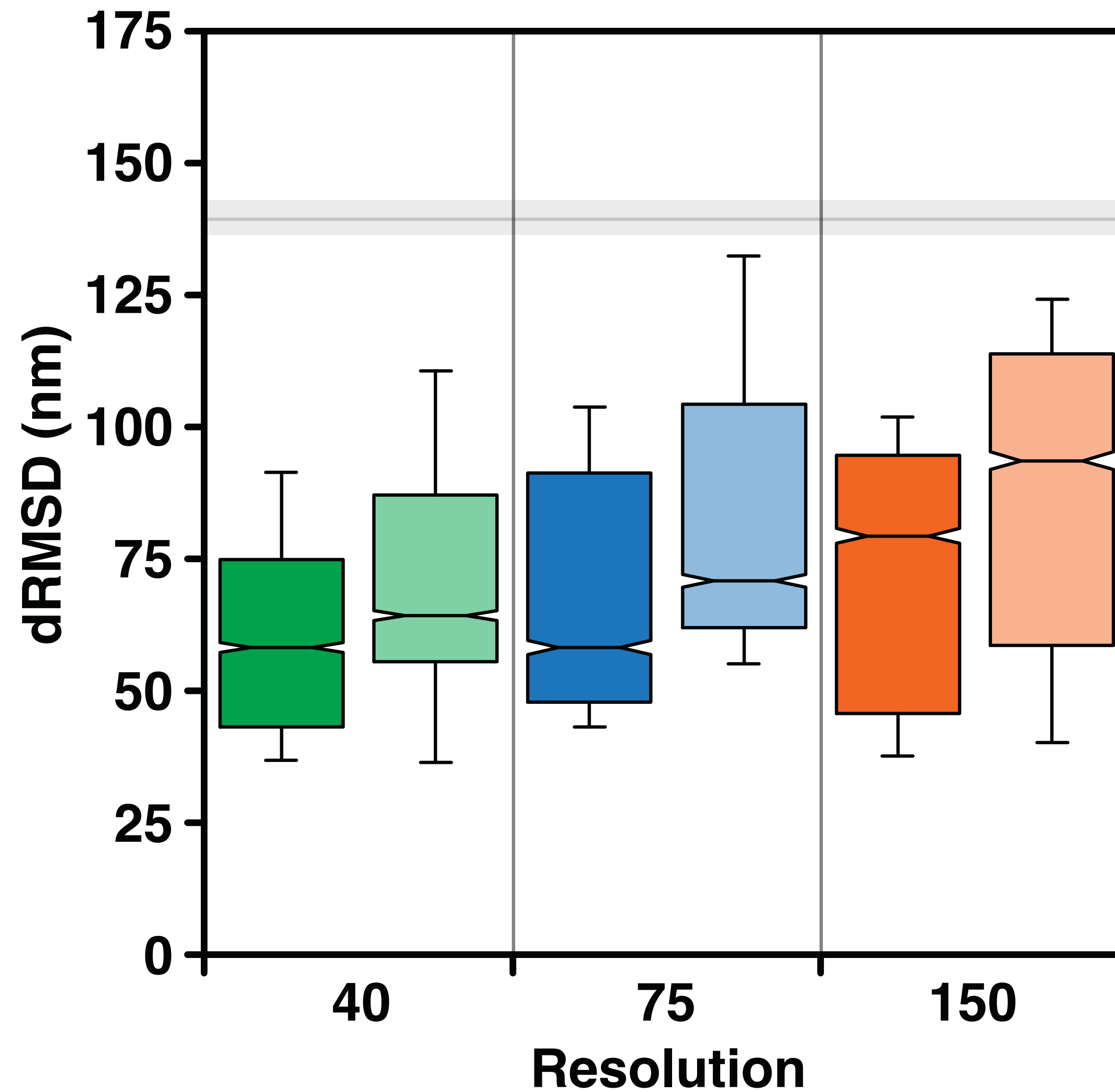
$\Delta t_s=1$

TADbit-SCC: 0.82

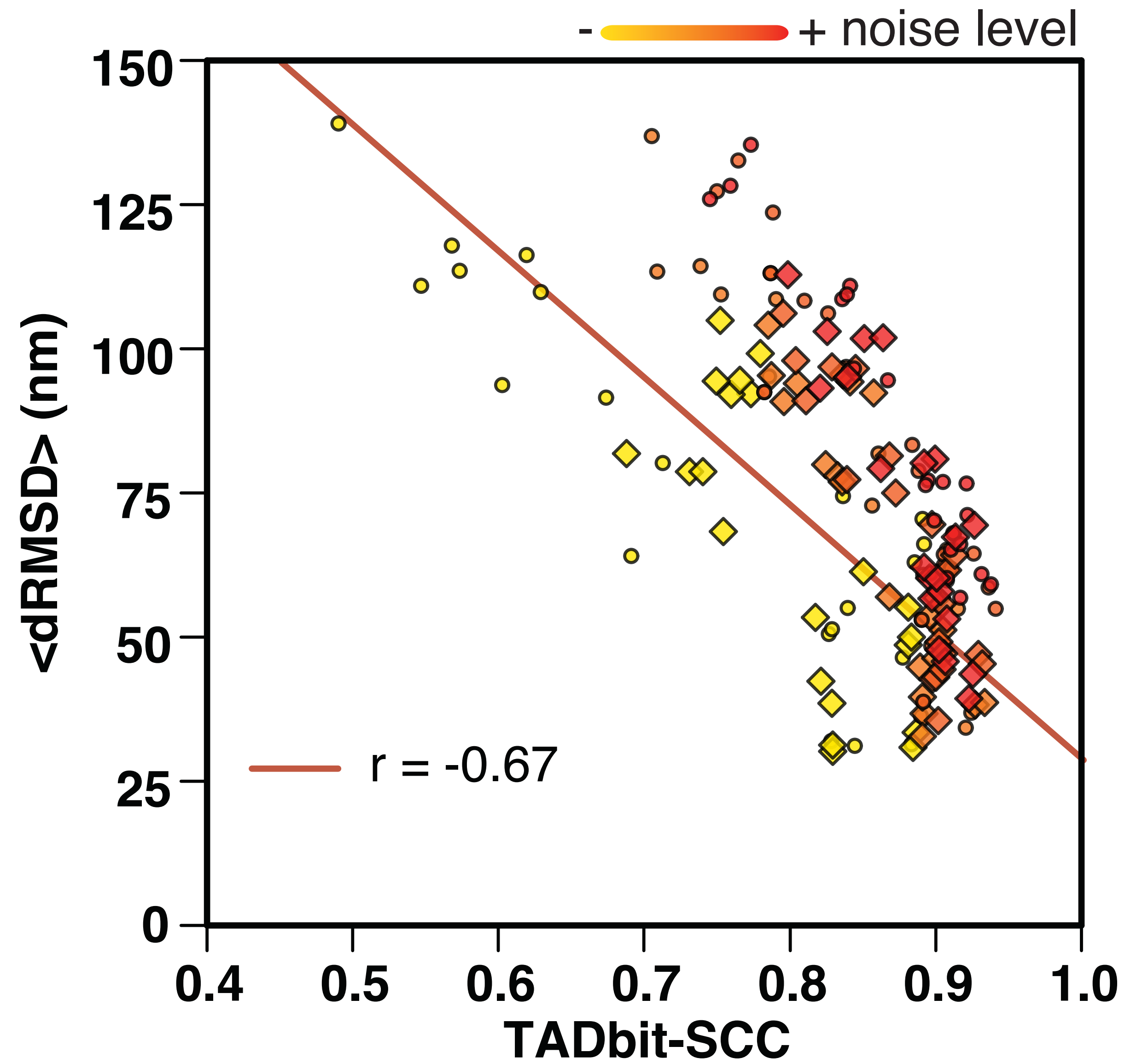
$\langle d_{\text{RMSD}} \rangle$: 45.4 nm

$\langle d_{\text{SCC}} \rangle$: 0.86

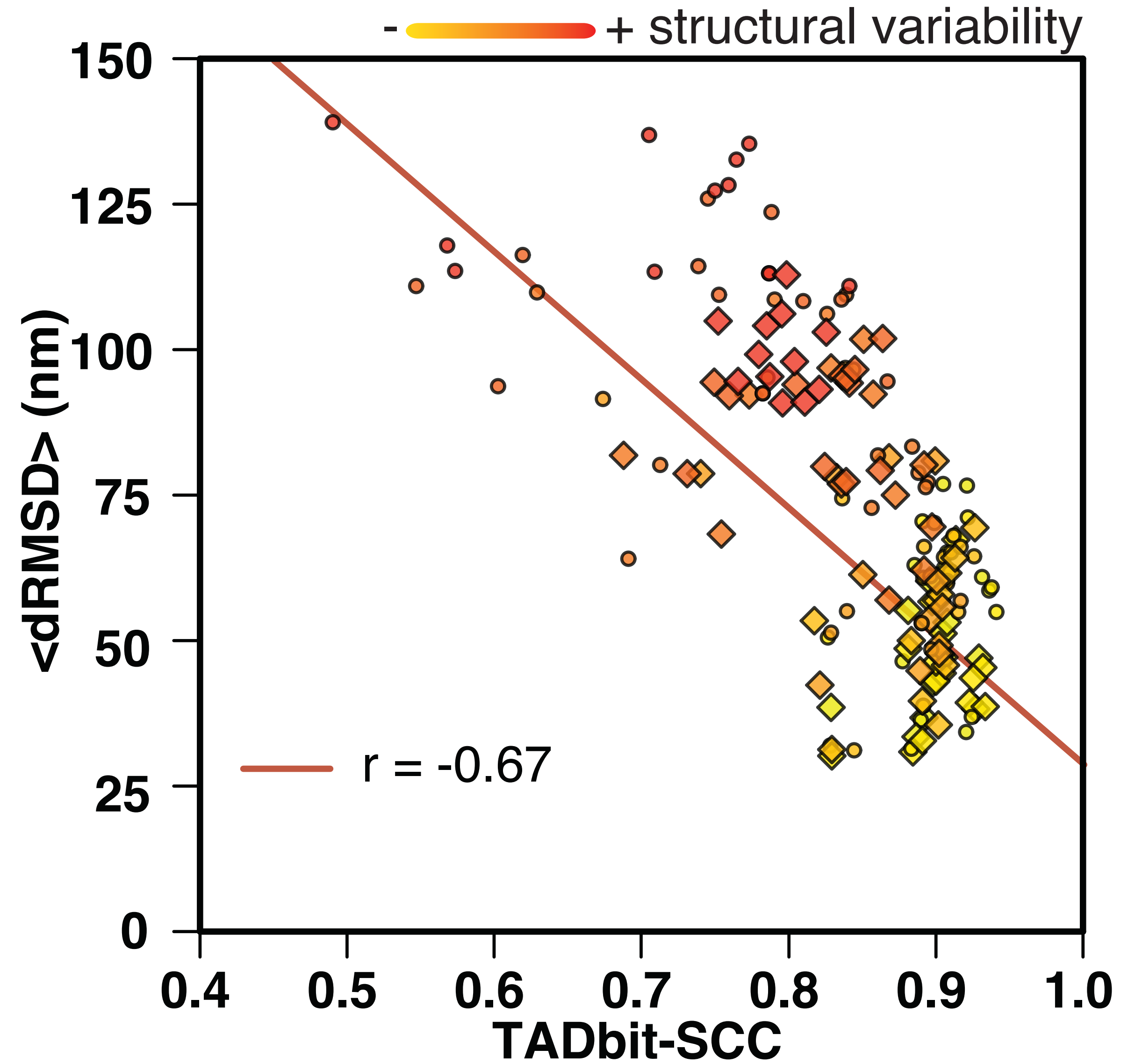
TADs & higher-res are "good"



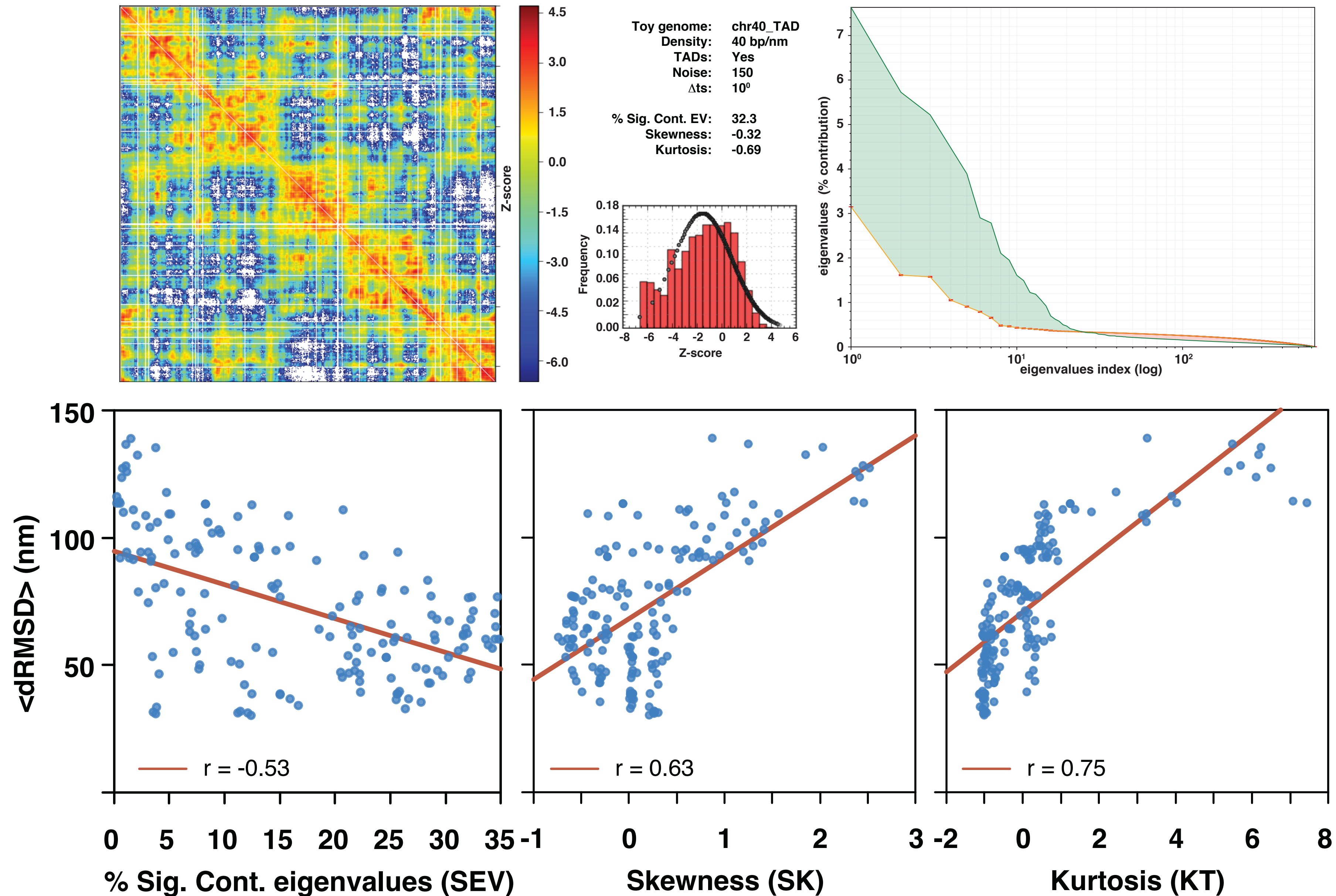
Noise is "OK"



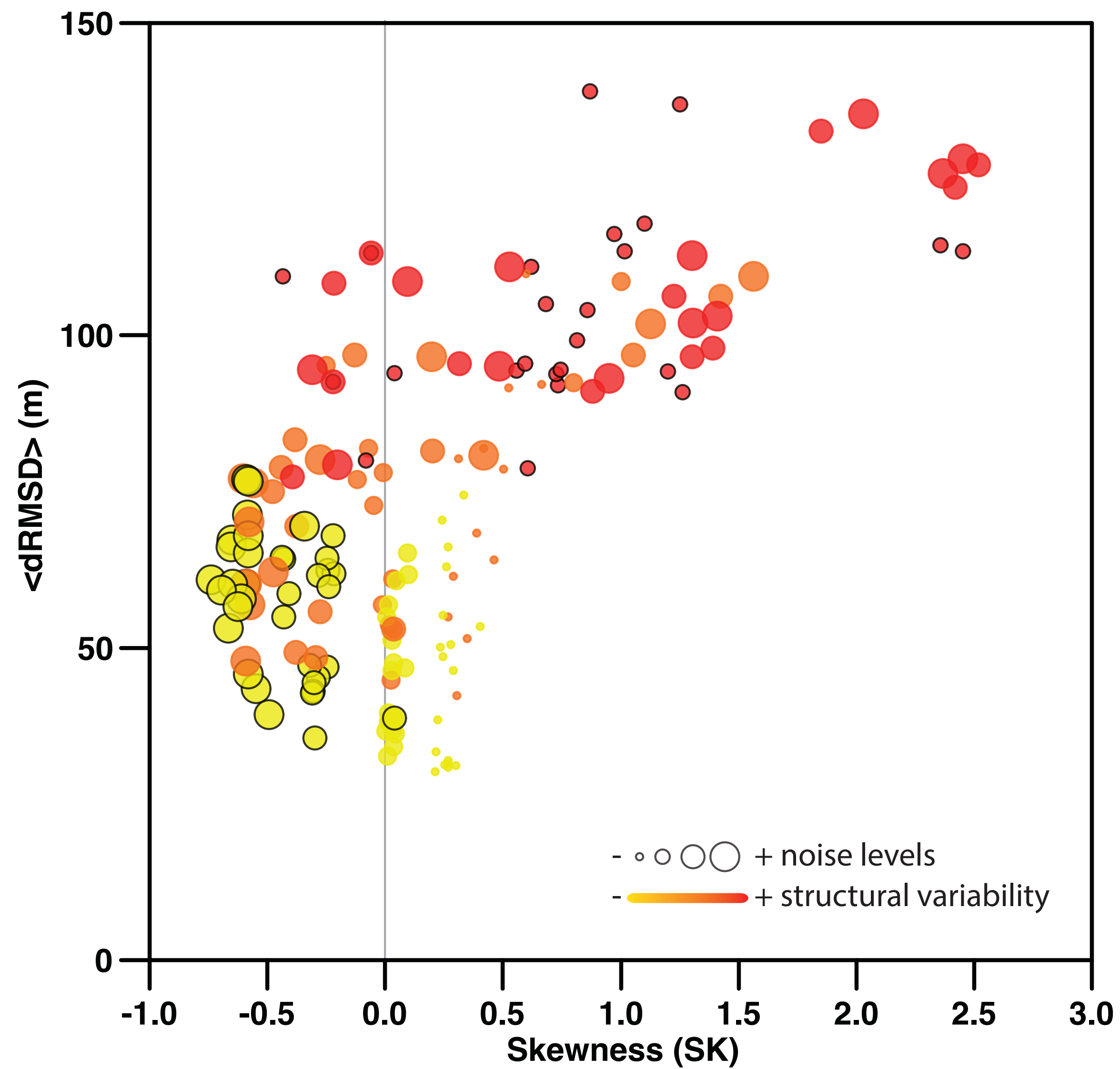
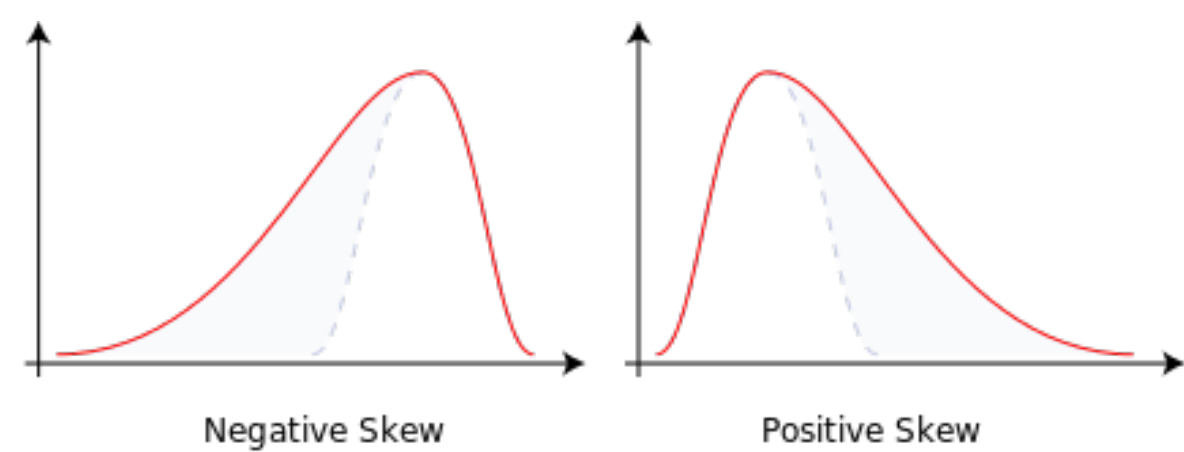
Structural variability is "NOT OK"



Can we predict the accuracy of the models?

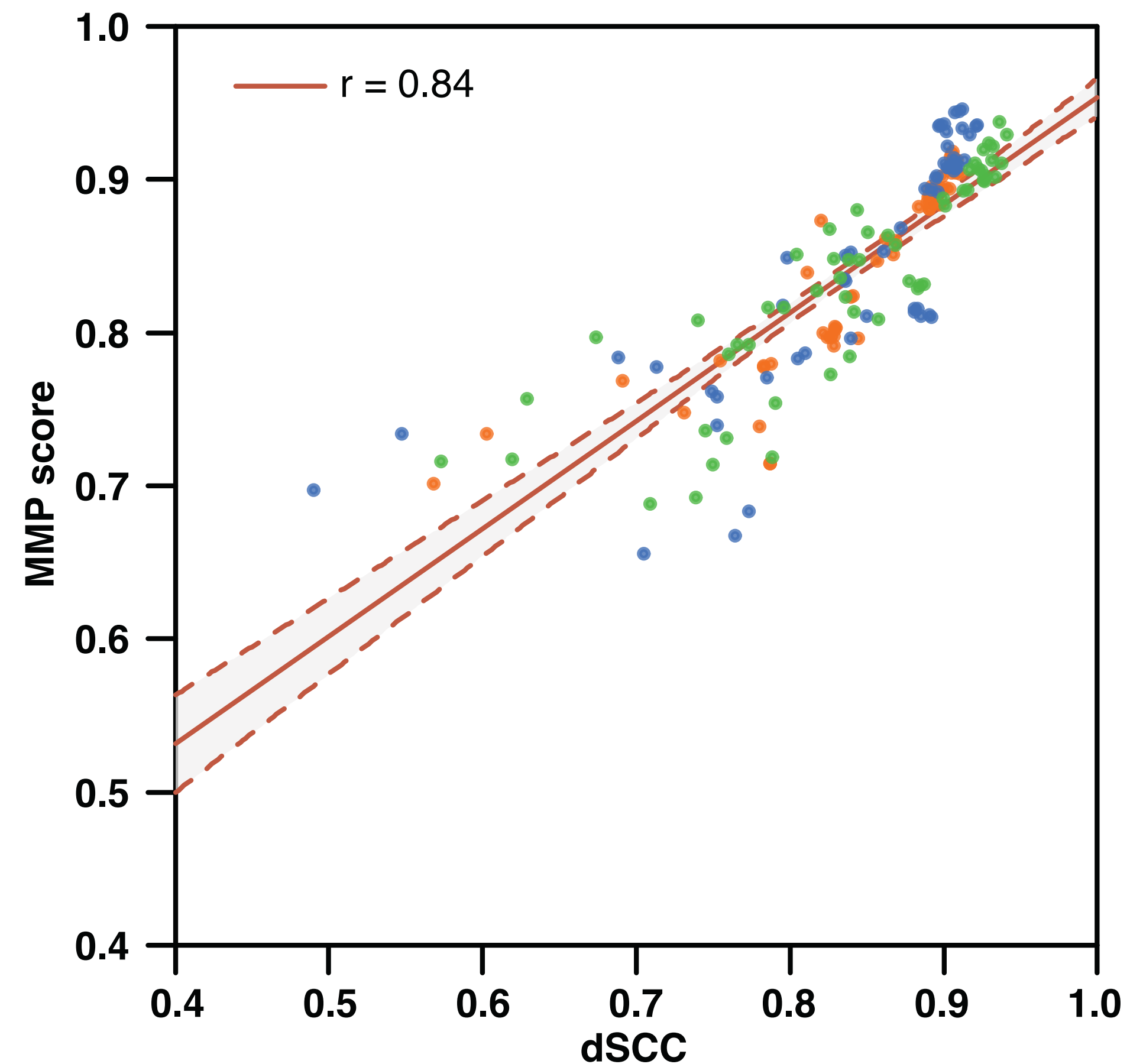


Skewness "side effect"



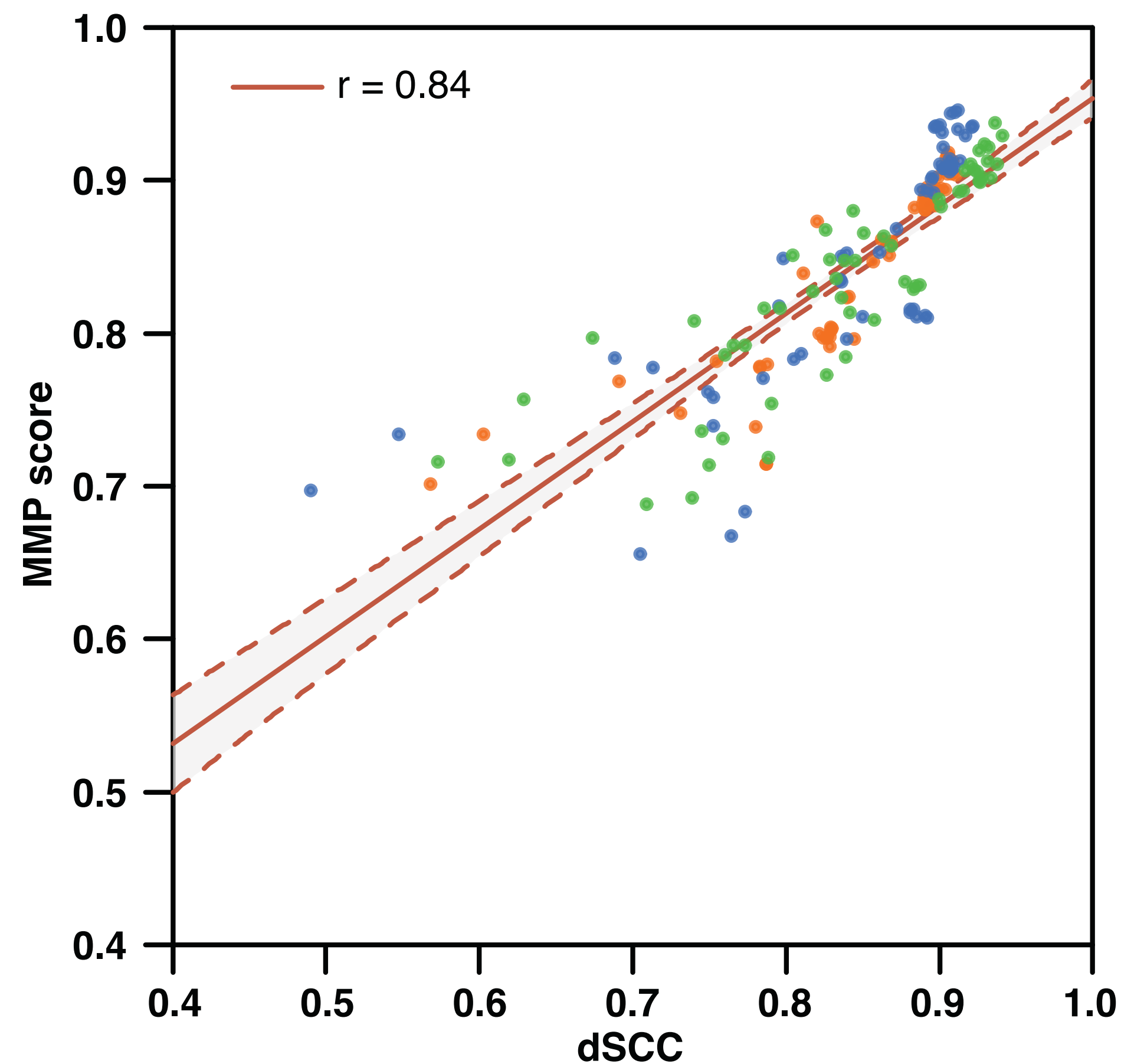
Can we predict the accuracy of the models?

$$\text{MMP} = -0.0002 * \text{Size} + 0.0335 * \text{SK} - 0.0229 * \text{KU} + 0.0069 * \text{SEV} + 0.8126$$

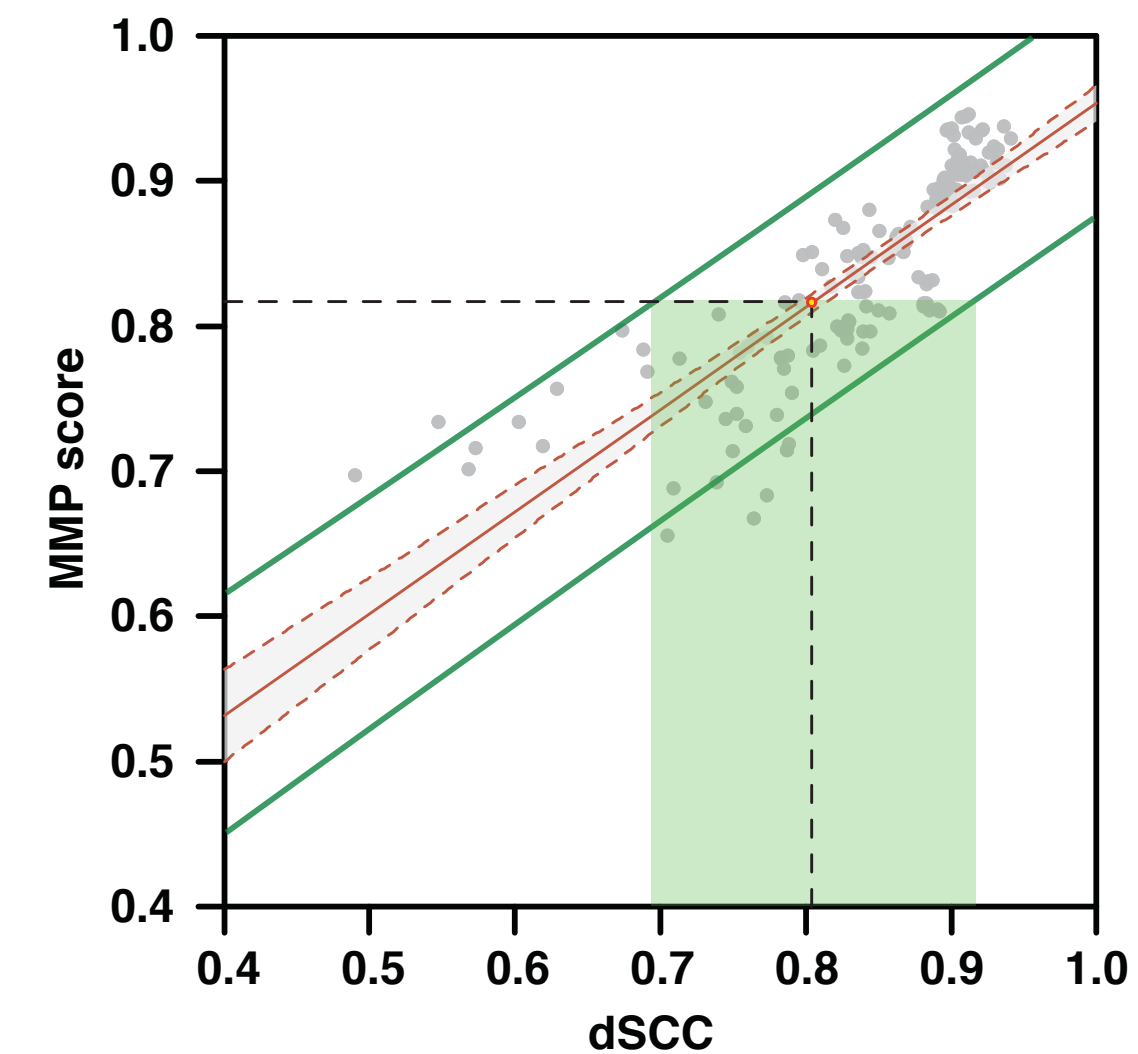
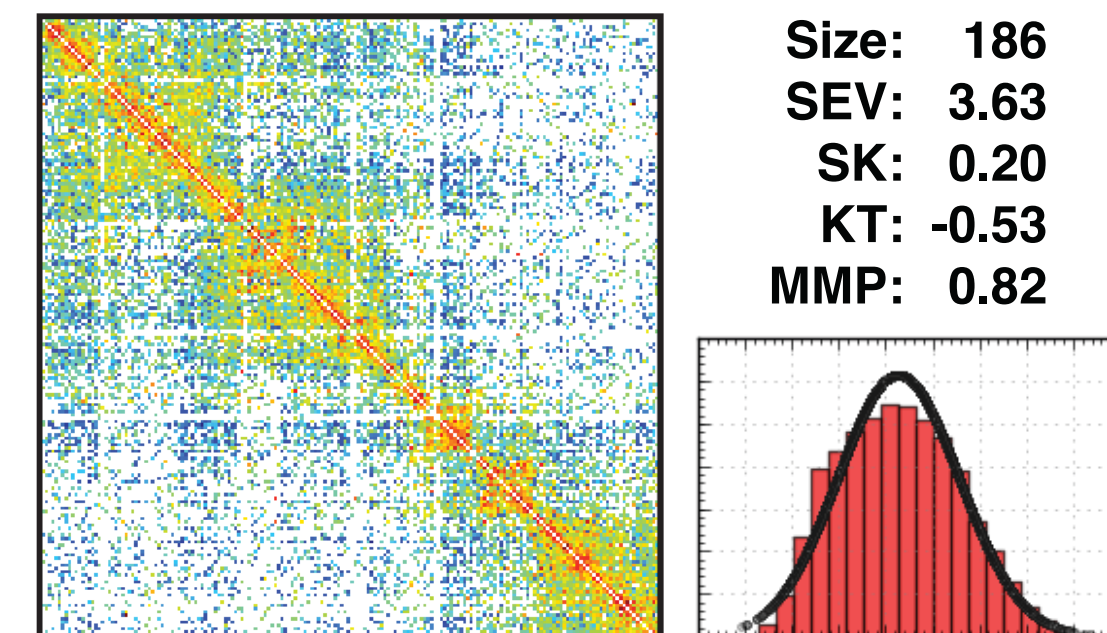


Can we predict the accuracy of the models?

$$\text{MMP} = -0.0002 * \text{Size} + 0.0335 * \text{SK} - 0.0229 * \text{KU} + 0.0069 * \text{SEV} + 0.8126$$



Human Chr1:120,640,000-128,040,000



Higher-res is “good”

put your \$\$ in sequencing

Noise is “OK”

no need to worry much

Structural variability is “NOT OK”

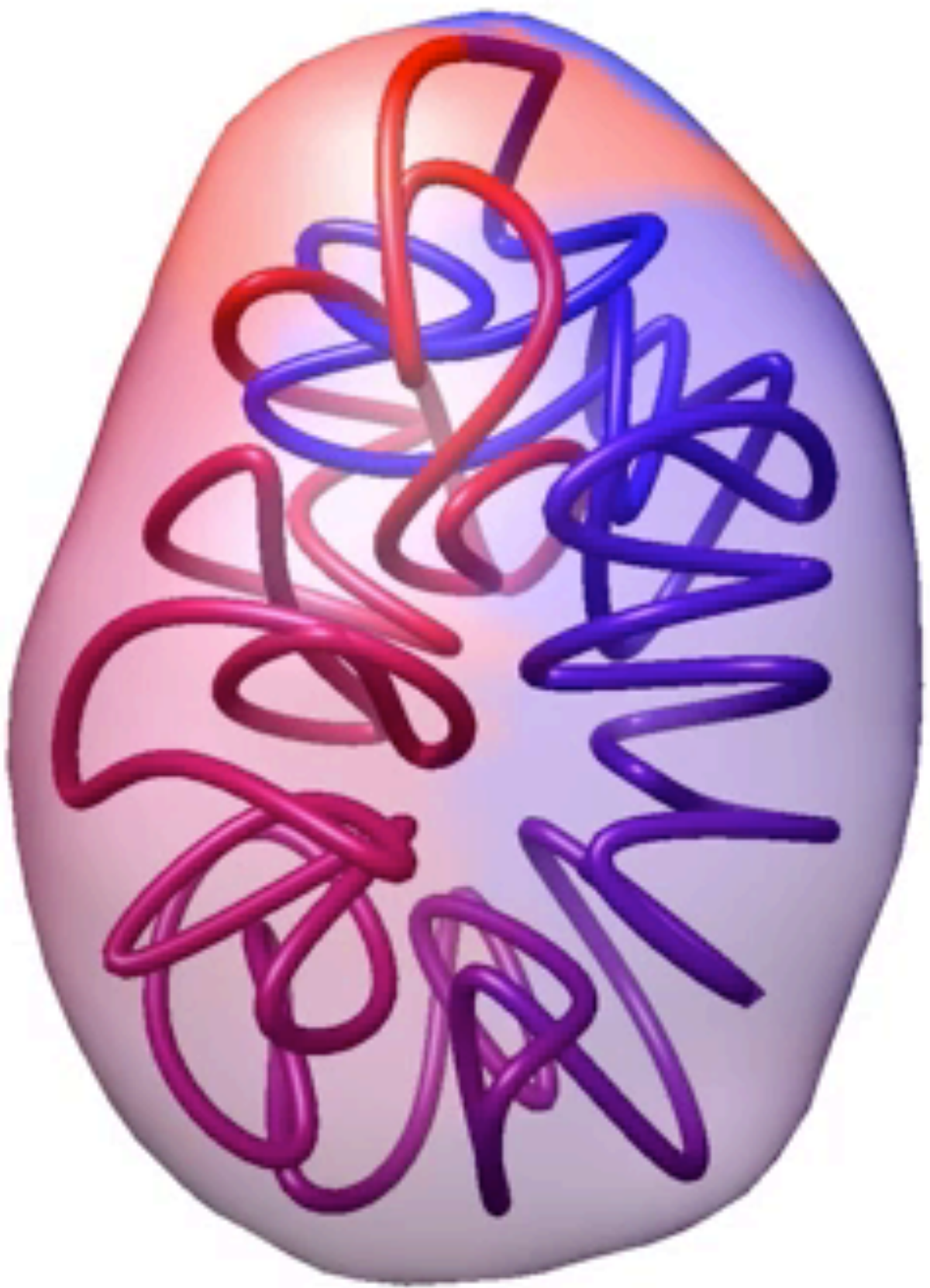
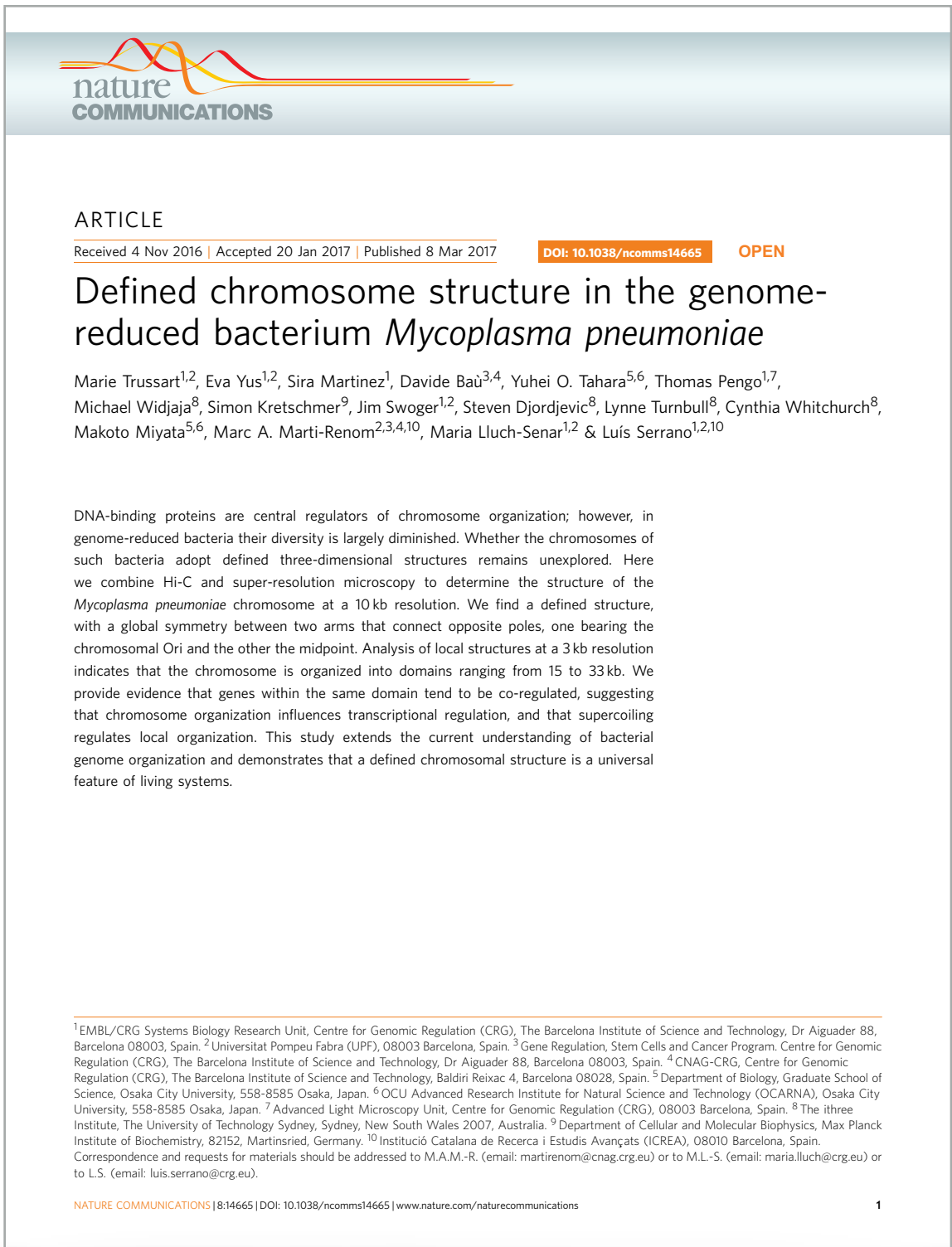
homogenize your cell population!

...but we can differentiate between noise and structural variability

and we can a priori predict the accuracy of the models

Defined chromosome structure in the genome-reduced bacterium *Mycoplasma pneumoniae*

Trussart et al. Nature Communications (2017) 8 14665



Mycoplasma is a small genome with few structural factors

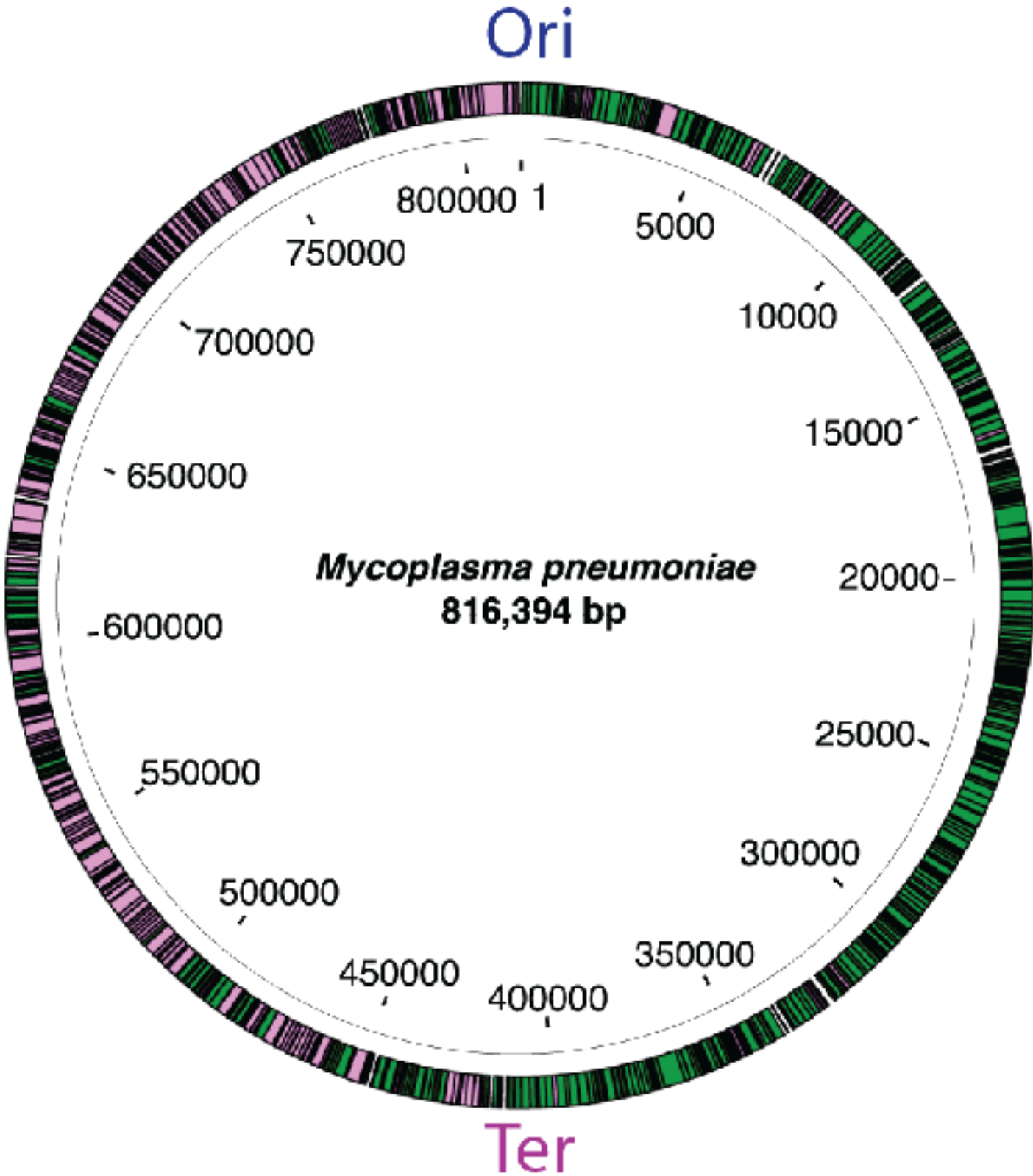
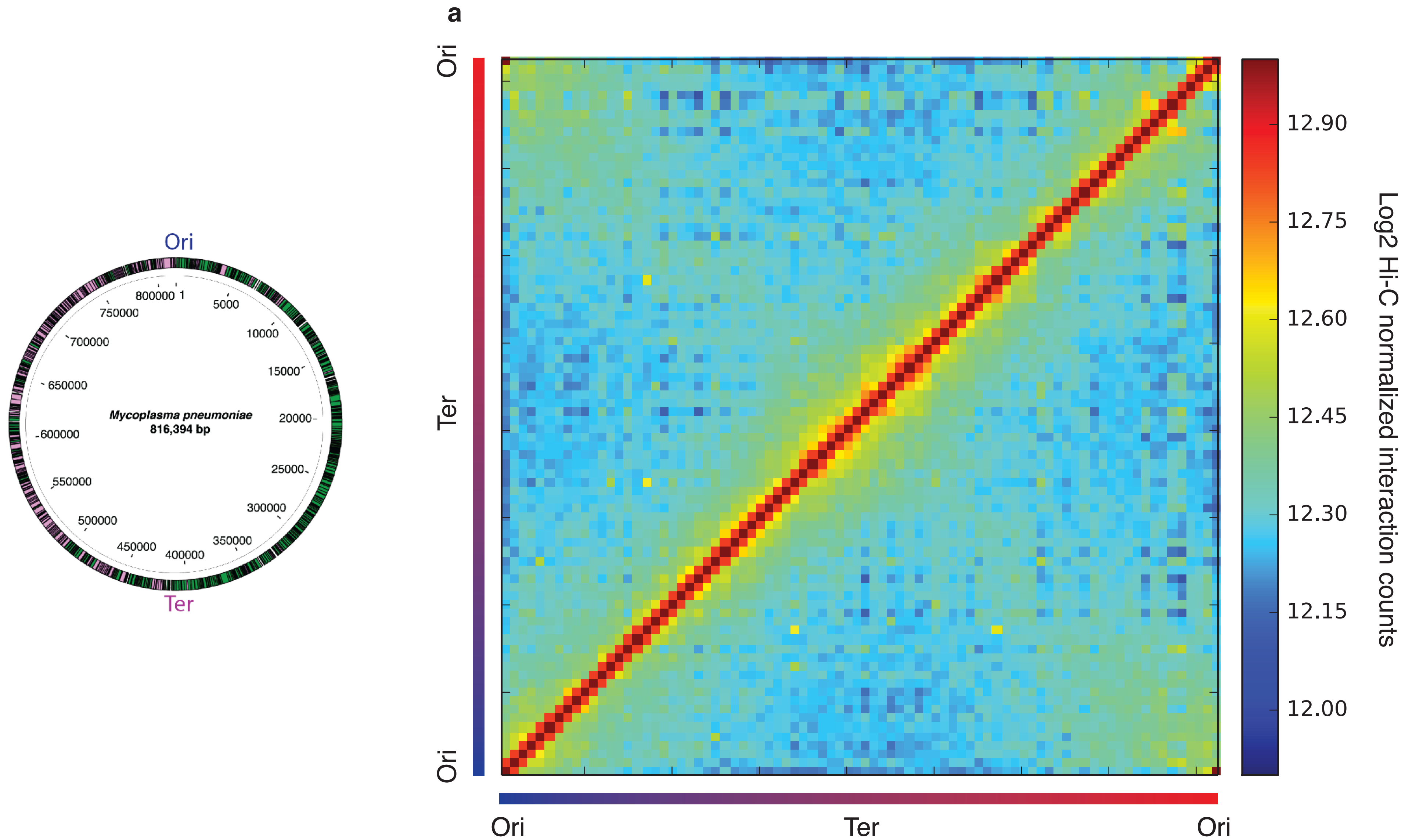


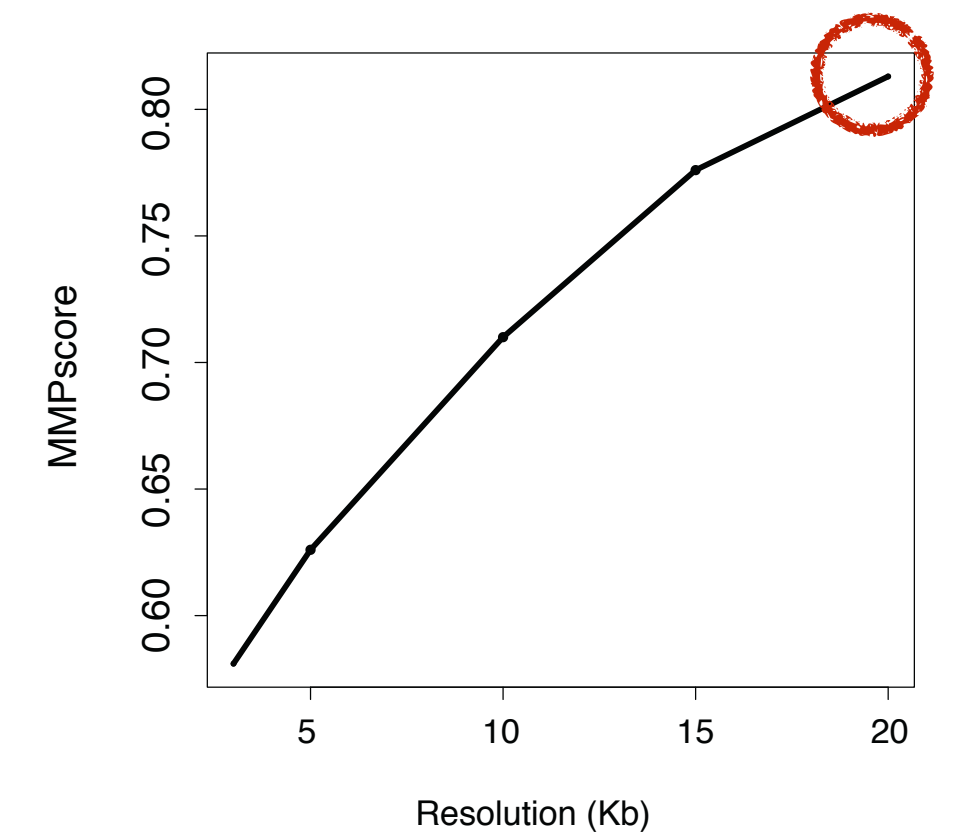
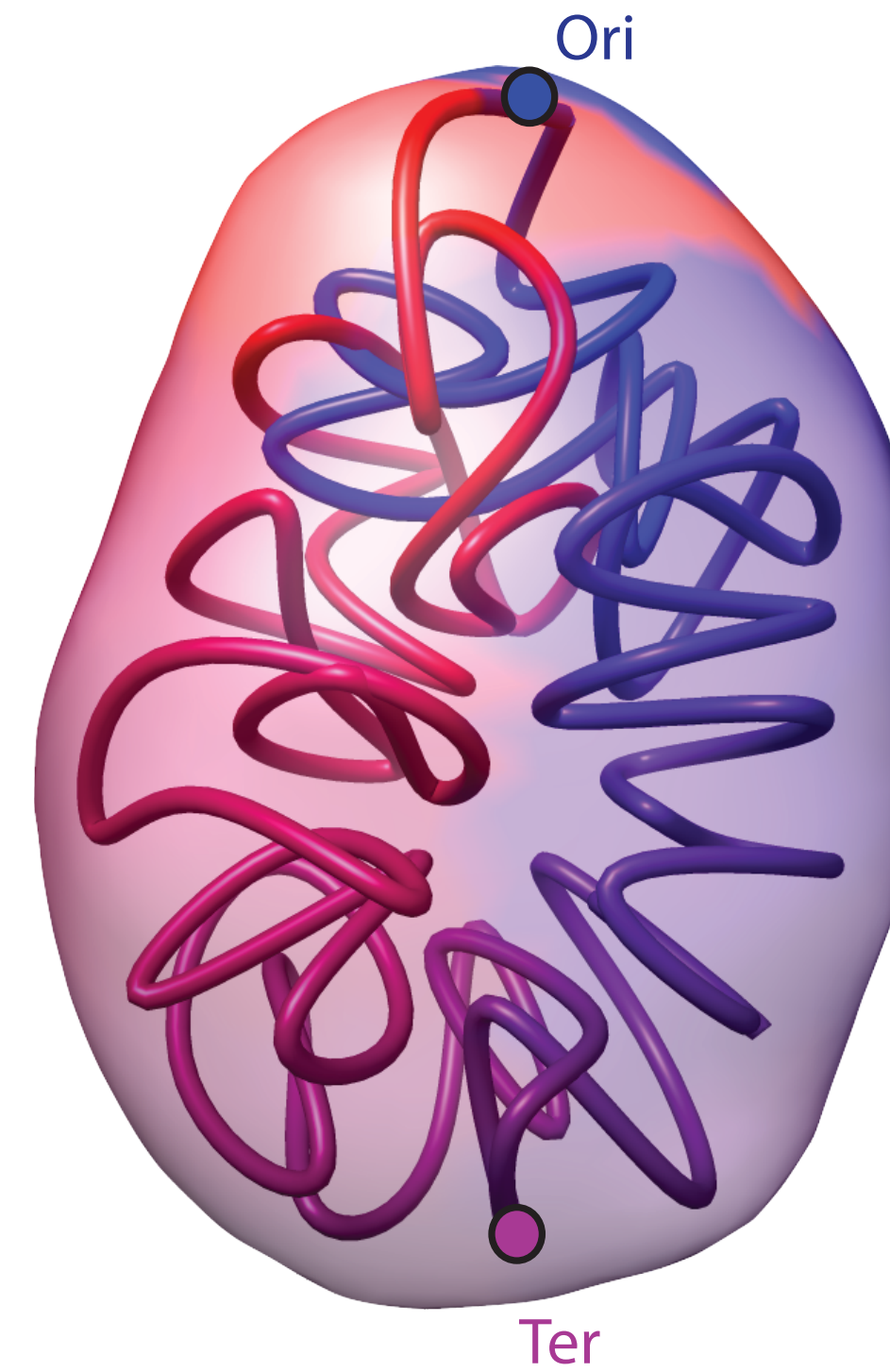
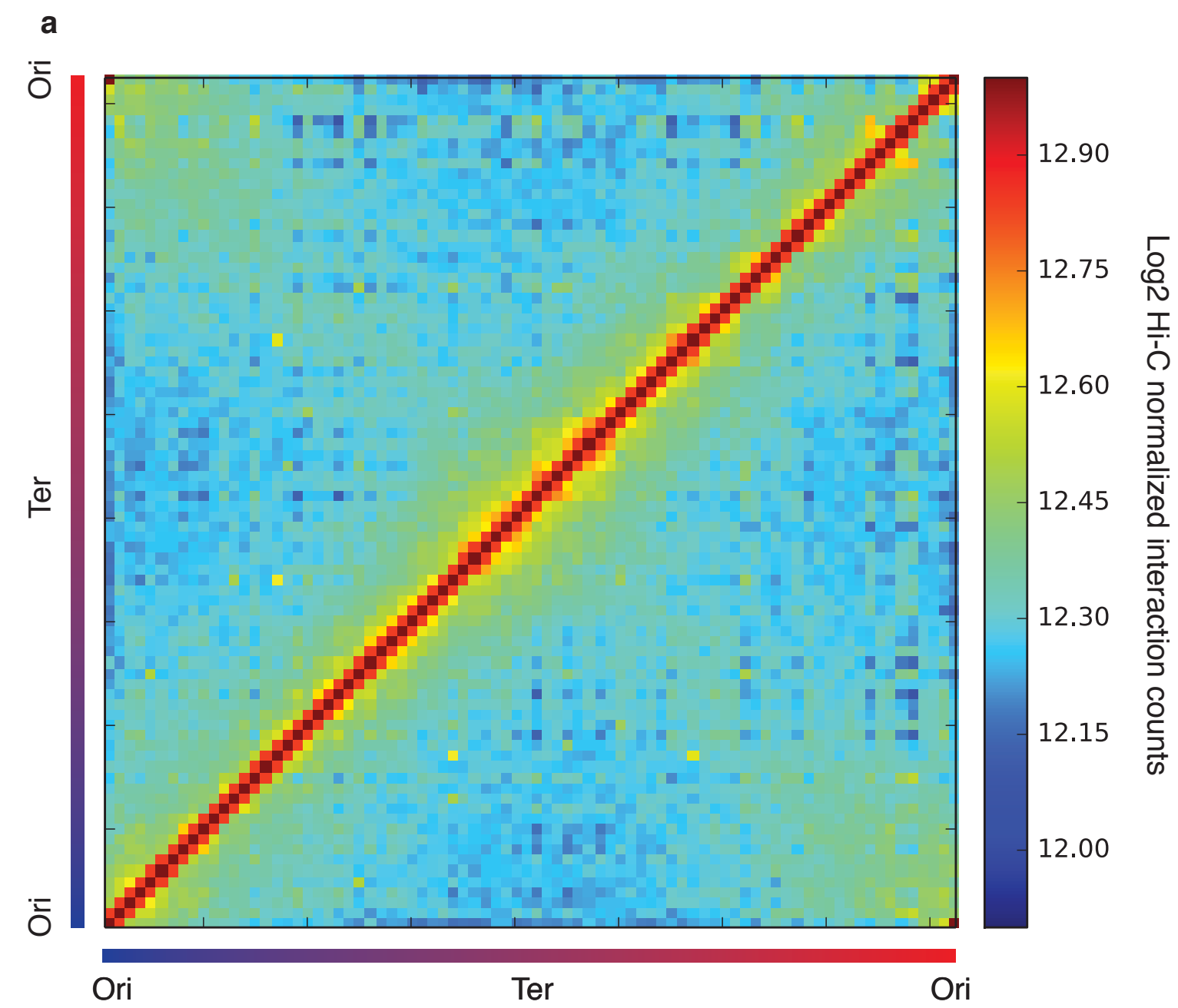
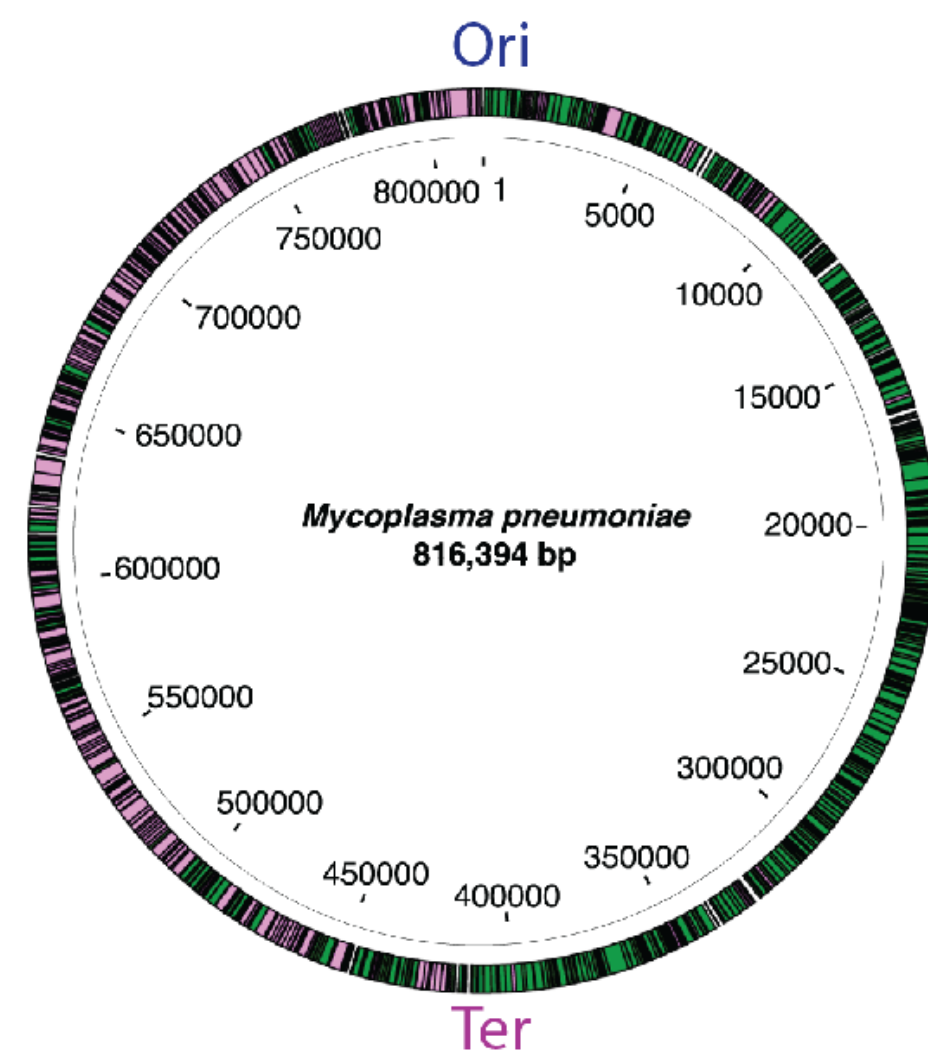
Table 1 List of assigned transcription factors, sigma factors and structural proteins and essentiality with three distinct categories: essential (E), non -essential (NE) and fitness (F).			
Gene number	Gene name	Protein name	Essentiality ⁴⁴
MPN002	cbpA	Curved DNA-binding protein CbpA	F
MPN003	gyrB	DNA gyrase subunit B	E
MPN004	gyrA	DNA gyrase subunit A	E
MPN122	parB	DNA topoisomerase 4 subunit B	E
MPN123	parC	DNA topoisomerase 4 subunit A	E
MPN124	hrcA	Heat-inducible transcription repressor hrcA	E
MPN229	ssbA	SSB-binding ssDNA	E
MPN239	gntR	Probable HTH-type transcriptional regulator gntR	E
MPN241	whiA	Transcription factor with WhiA C-terminal domain	F
MPN266	spxA	Transcriptional regulator Spx	E
MPN275	ybaB	DNA-binding protein, YbaB/ EbfC family	F
MPN294	araC	AraC-like transcriptional regulator	NE
MPN332	lon	ATP-dependent protease La (EC 3.4.21.53)	E
MPN352	sigA	RNA polymerase sigma factor rpoD (Sigma-A) (EC 2.7.7.6)	E
MPN424	ylxM	Putative helix-turn-helix protein, YlxM/ p13-like protein	NE
MPN426	smc	SMC family, chromosome/ DNA binding/ protecting functions	E
MPN478	yrbC	YebC family protein (transcription factor of the tetR family)	E
MPN529	ihf	Histone-like bacterial DNA-binding protein	F
MPN554	ssbB	Putative single-stranded DNA-binding protein	E
MPN572	pepA	Probable cytosol aminopeptidase (EC 3.4.11.1) (leucine aminopeptidase) (LAP) (leucyl aminopeptidase)	E
MPN608	phoU	Transcriptional regulator involved in phosphate transport system	E
MPN626	mpn626	Alternative sigma factor	NE
MPN686	dnaA	Chromosomal replication initiator protein dnaA	E

E, essential; F, fitness; LAP, leucine aminopeptidase; NE, non-essential; ssDNA, single-stranded DNA ⁴⁴.

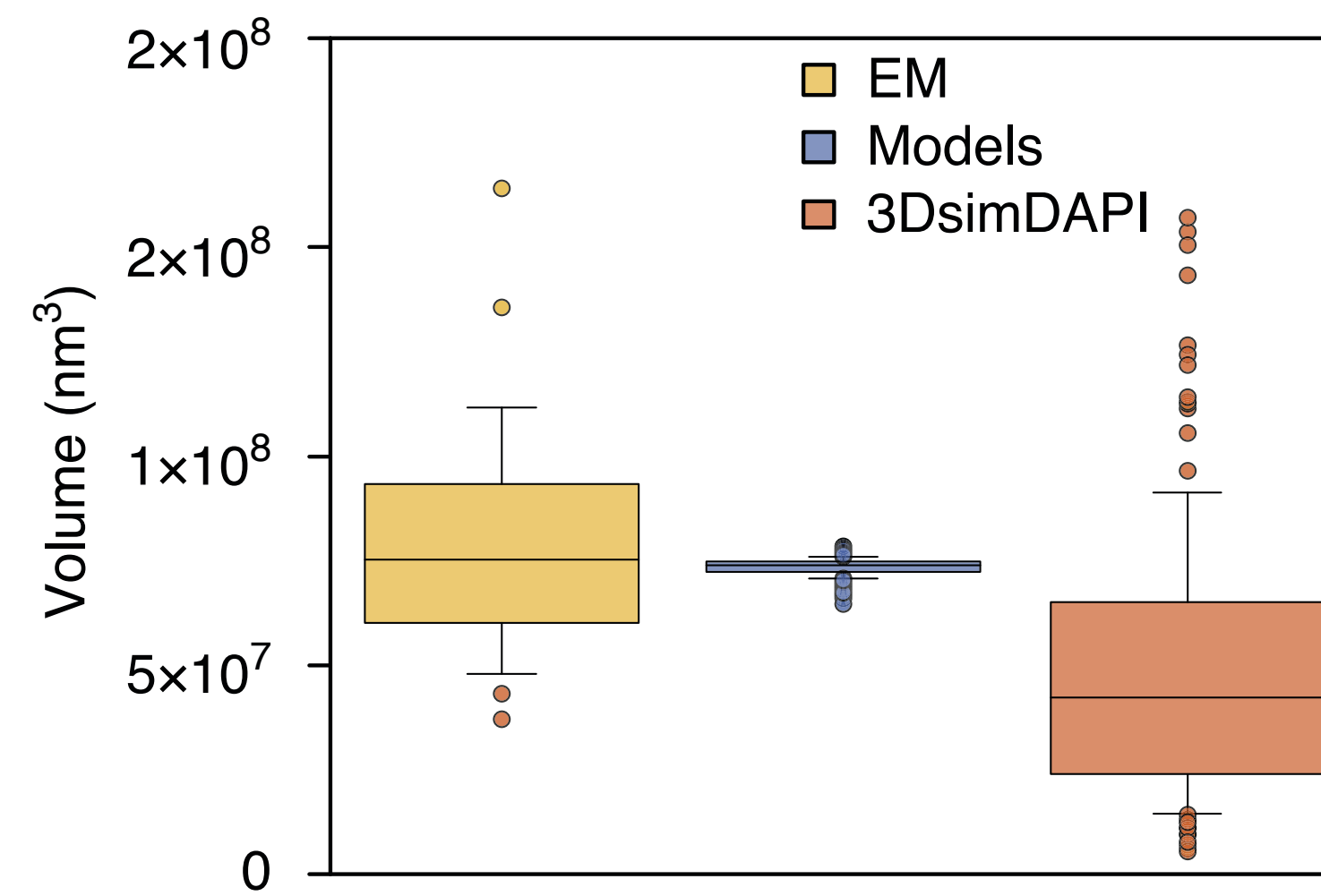
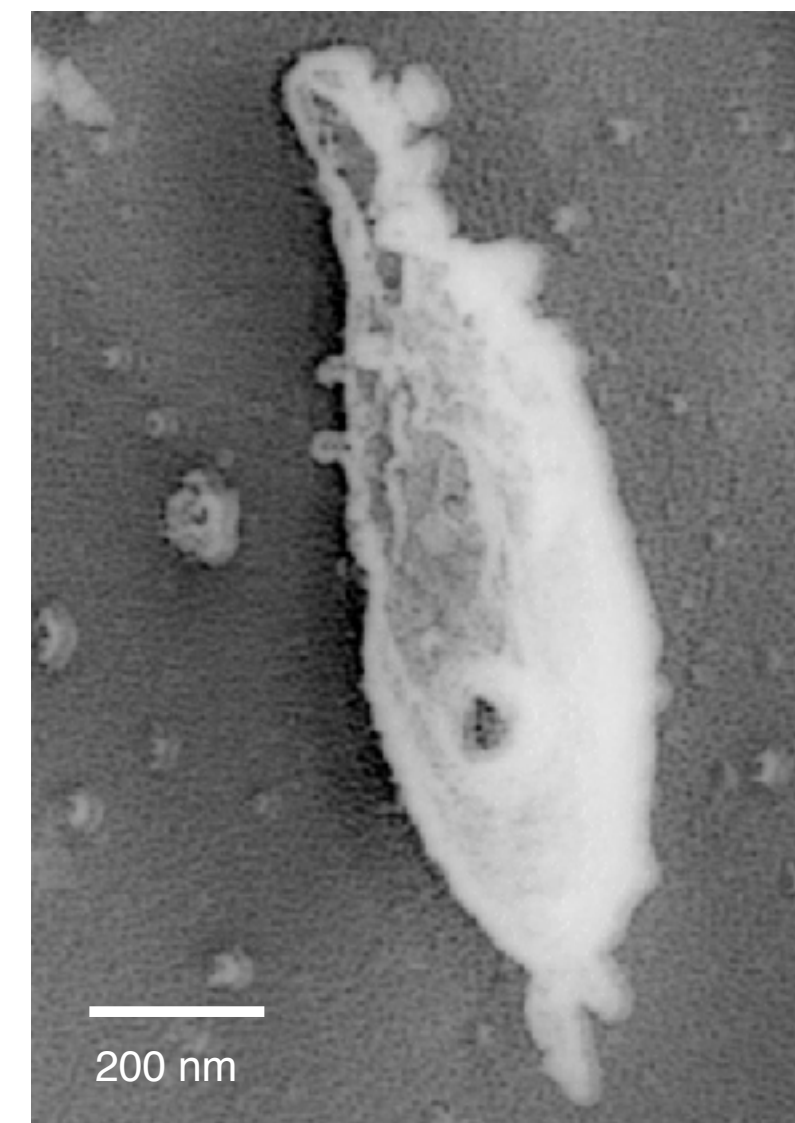
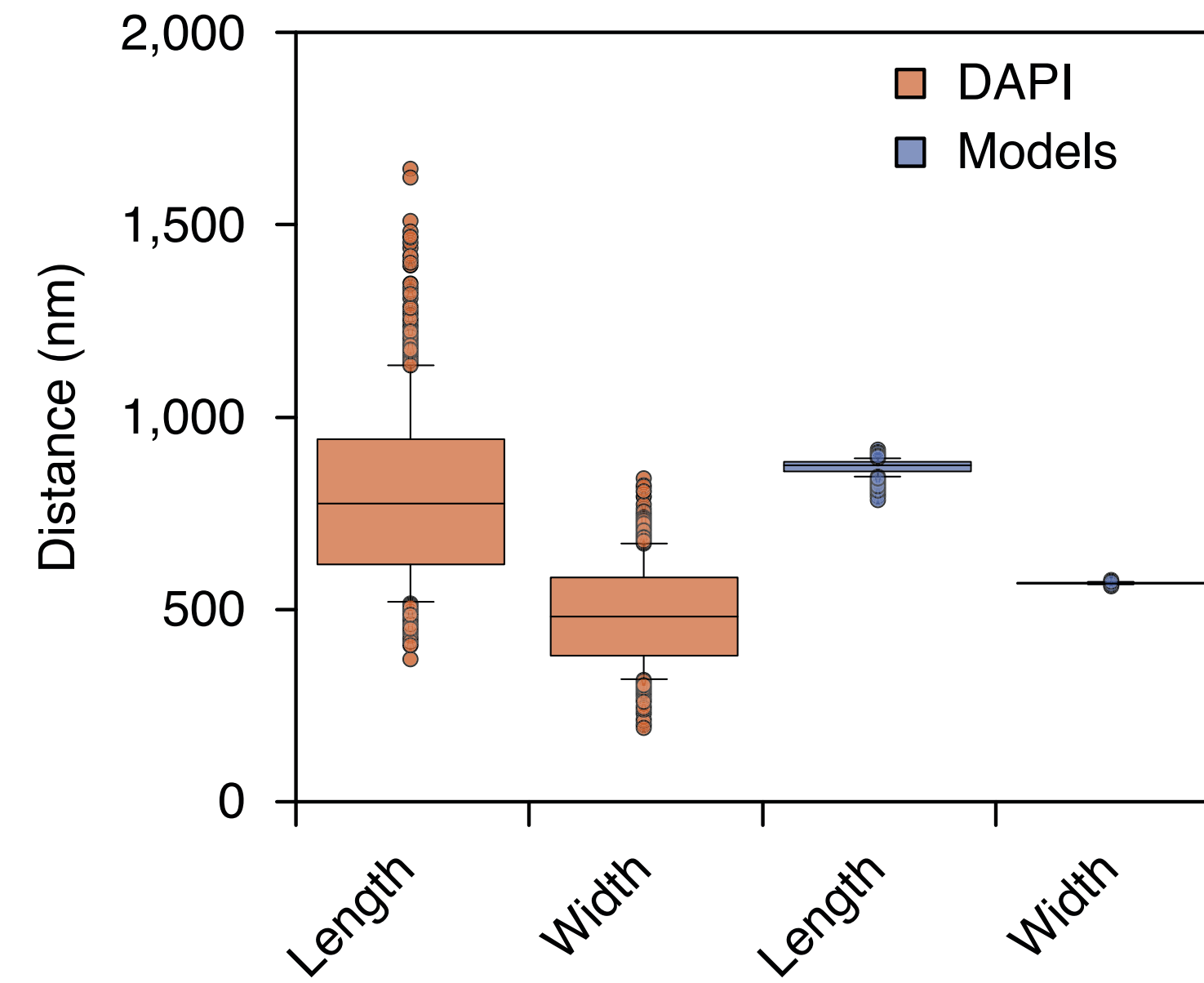
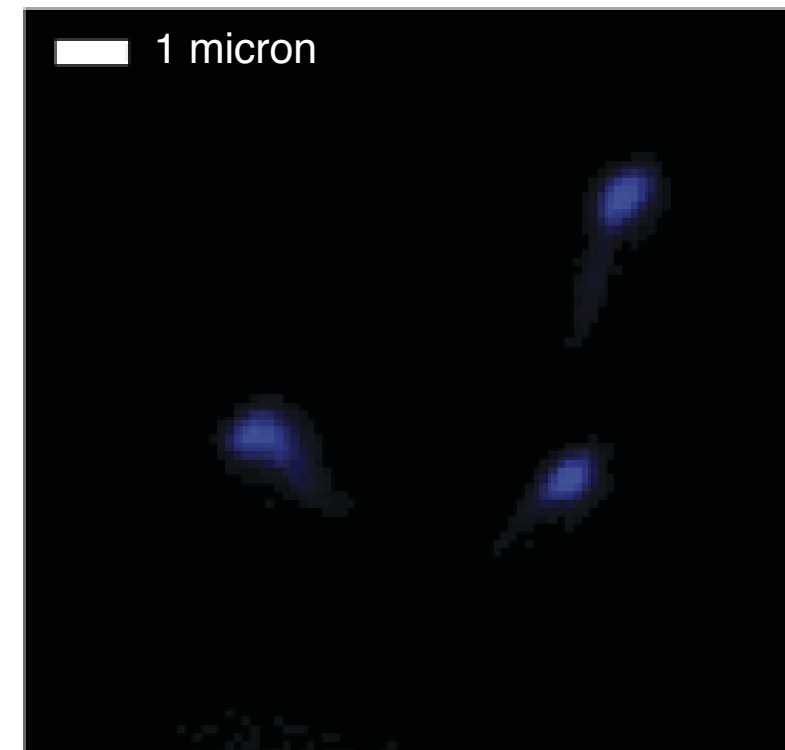
Can we build 3D models of *Mycoplasma*?



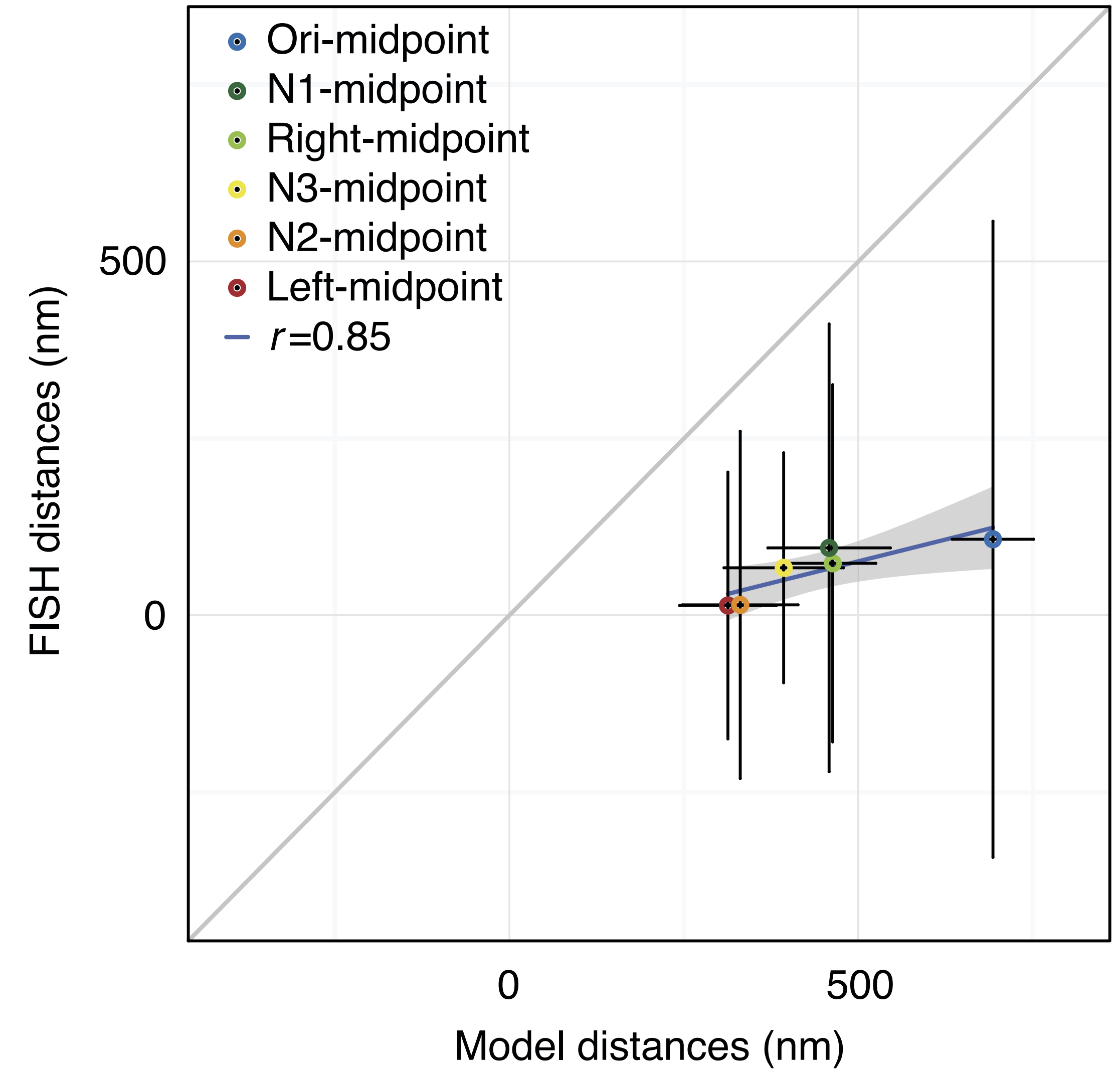
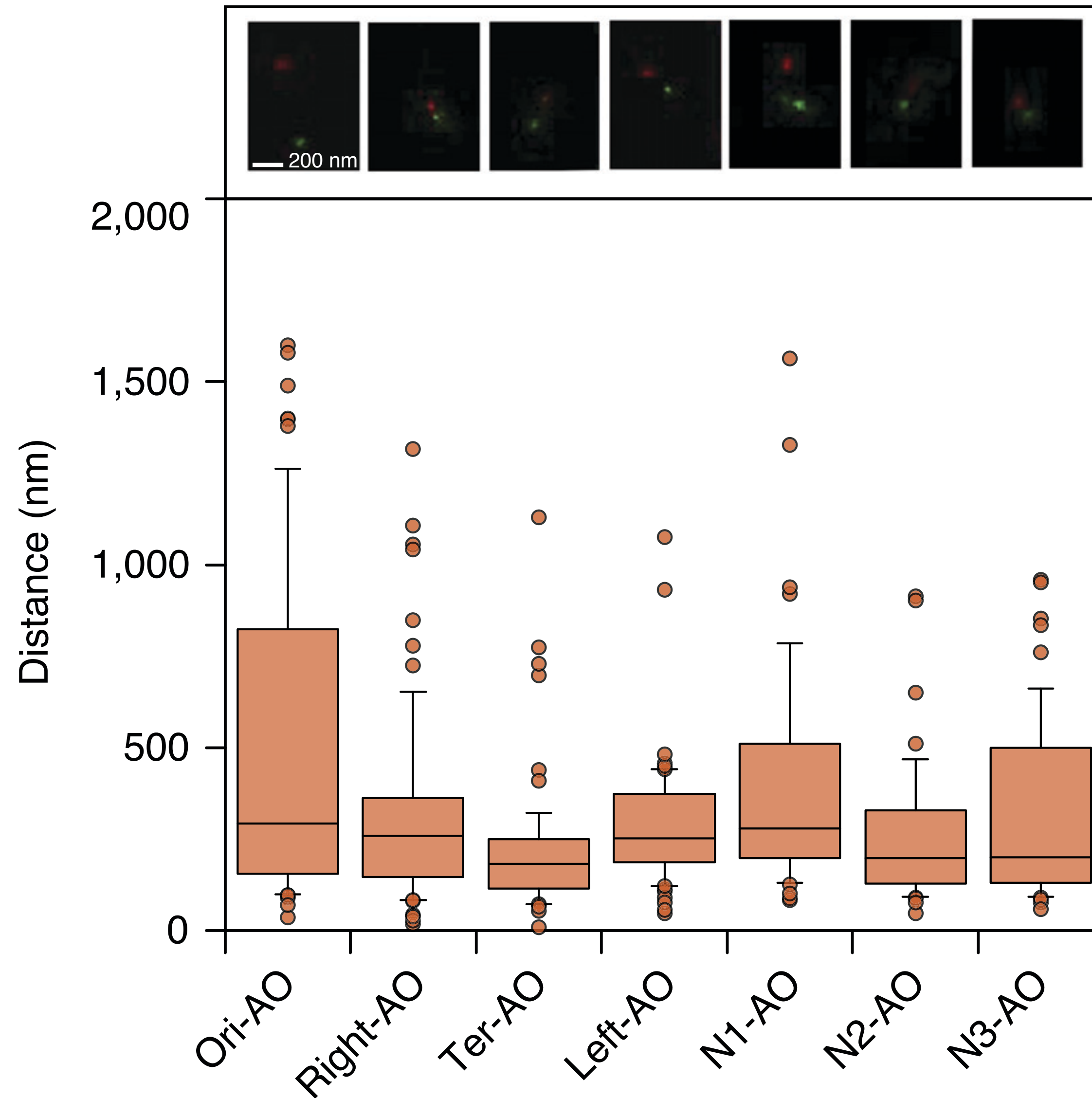
Can we build 3D models of *Mycoplasma*?



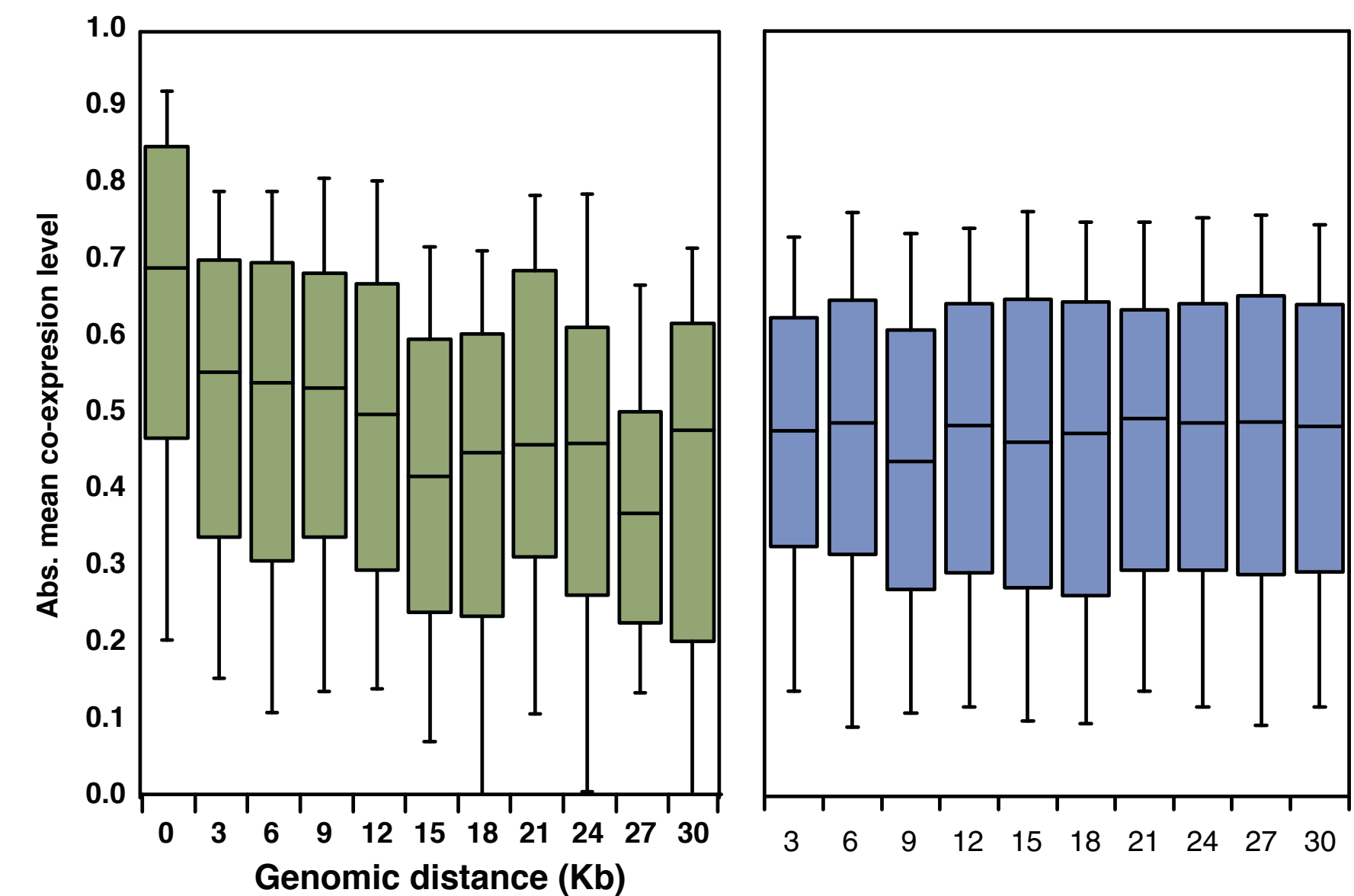
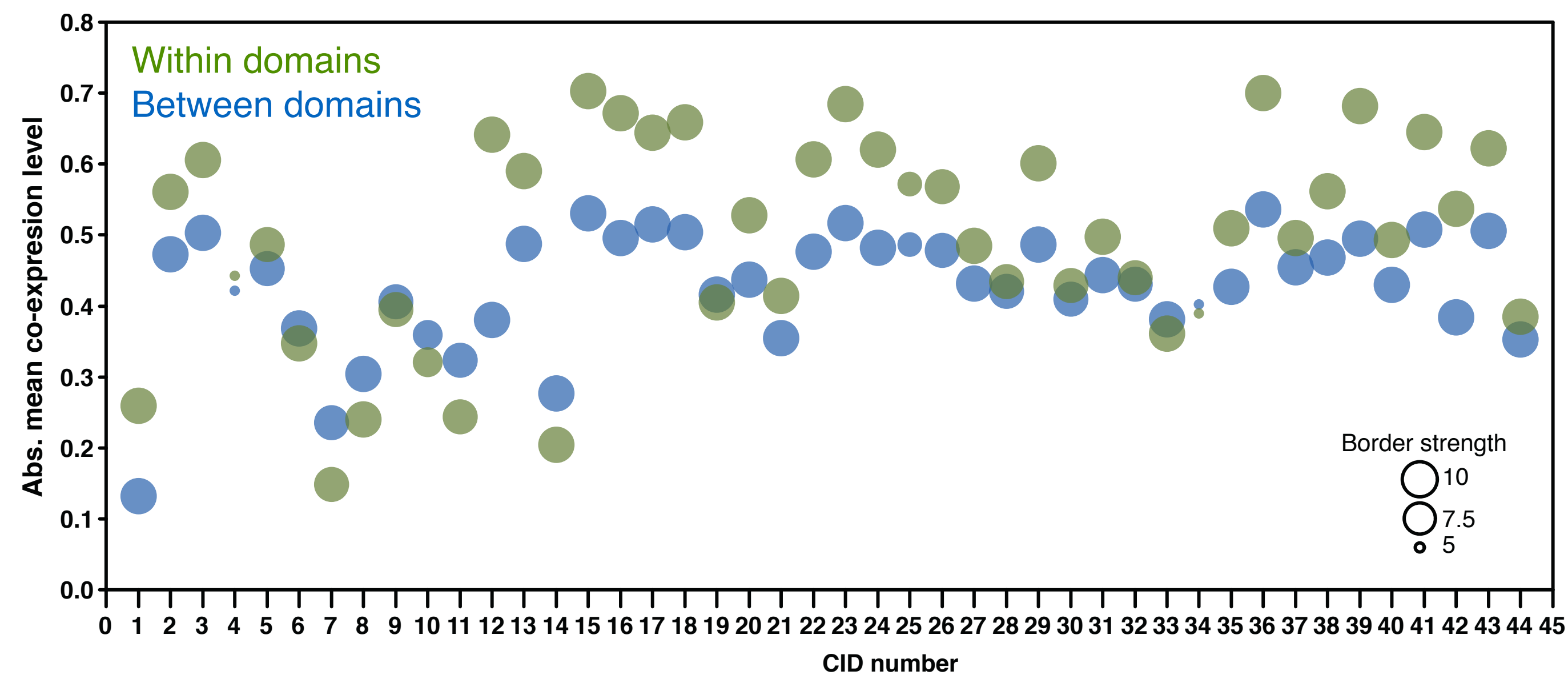
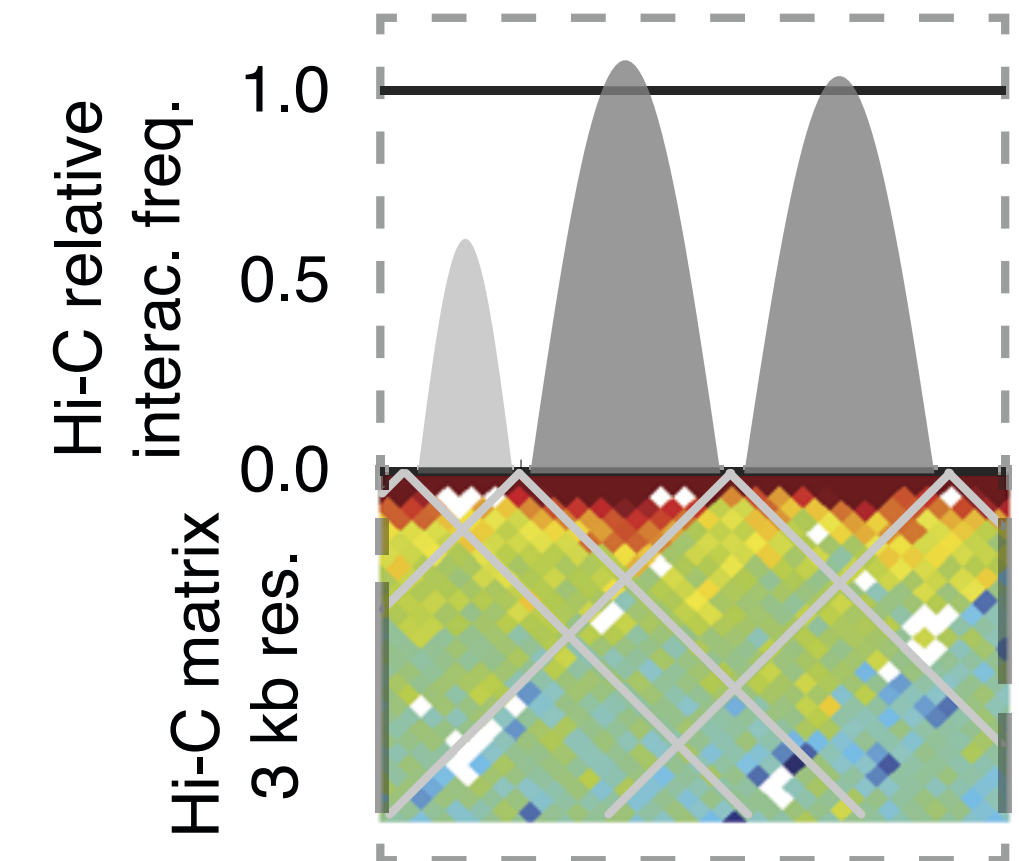
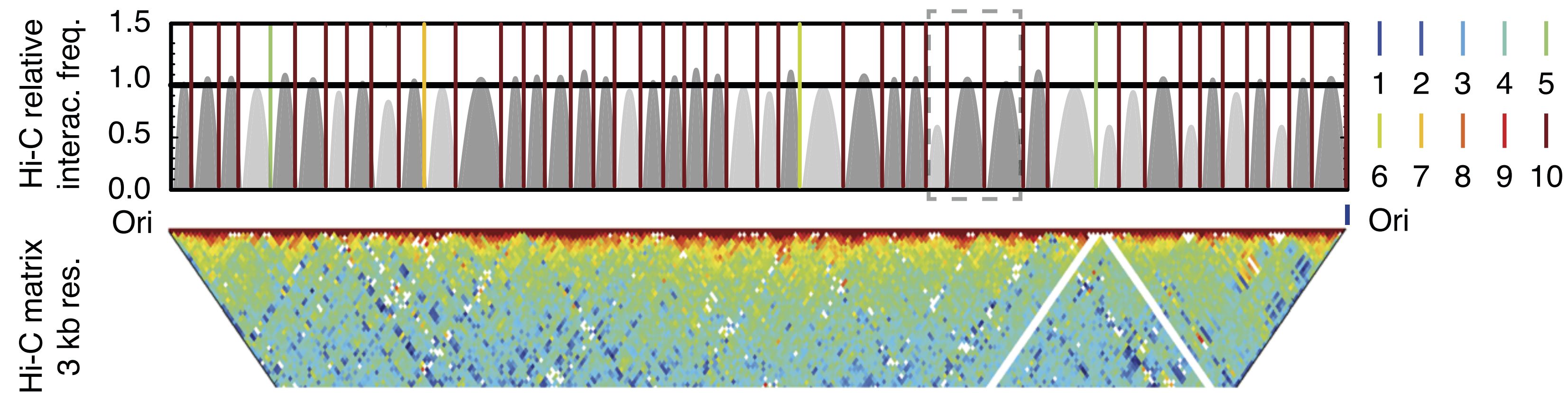
Is the overall 3D model accurate?



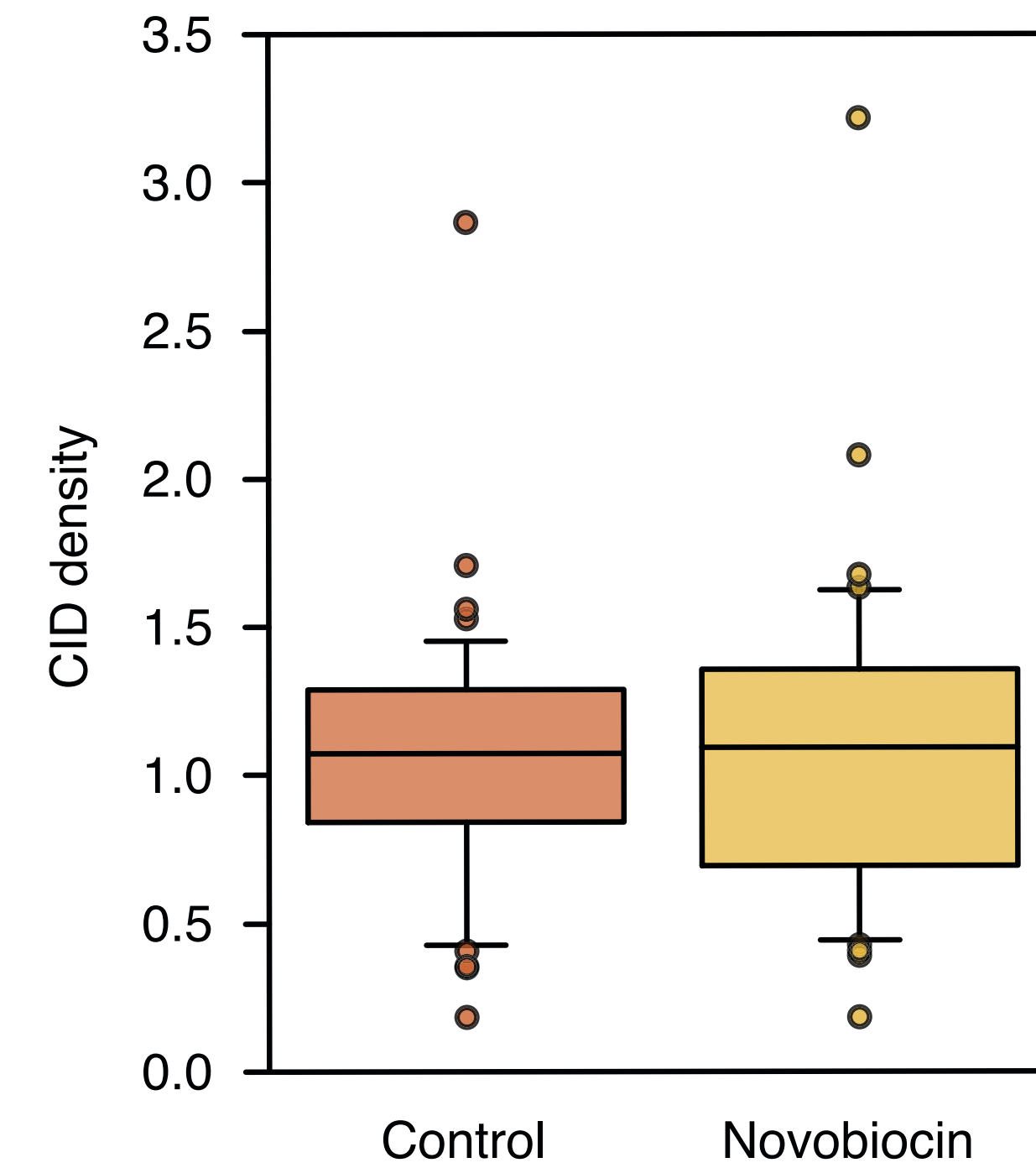
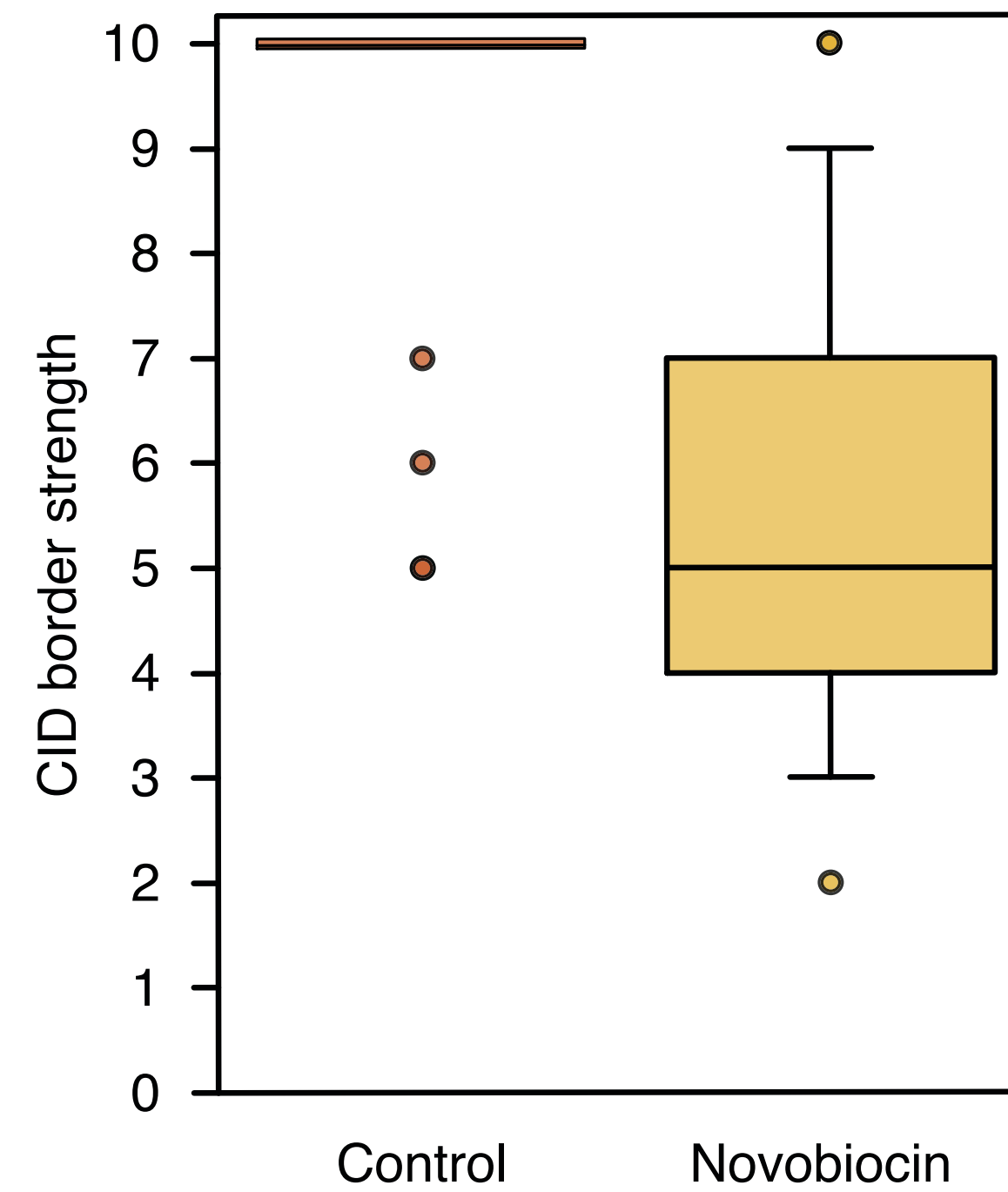
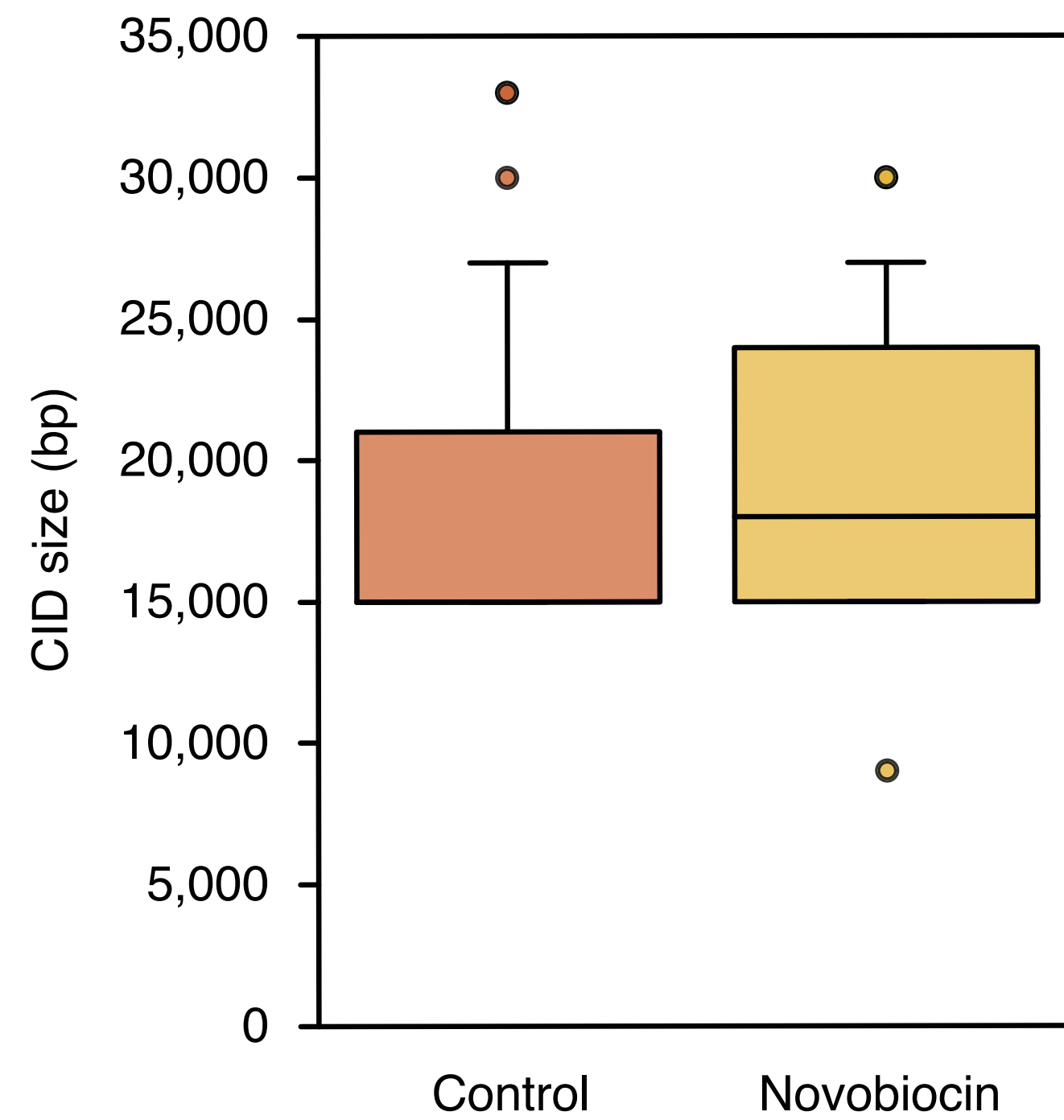
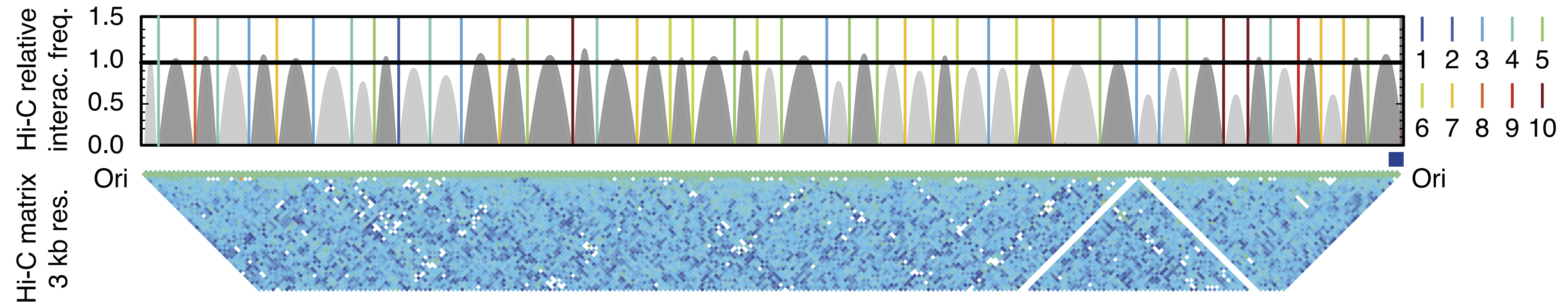
Are the details of the 3D model accurate?

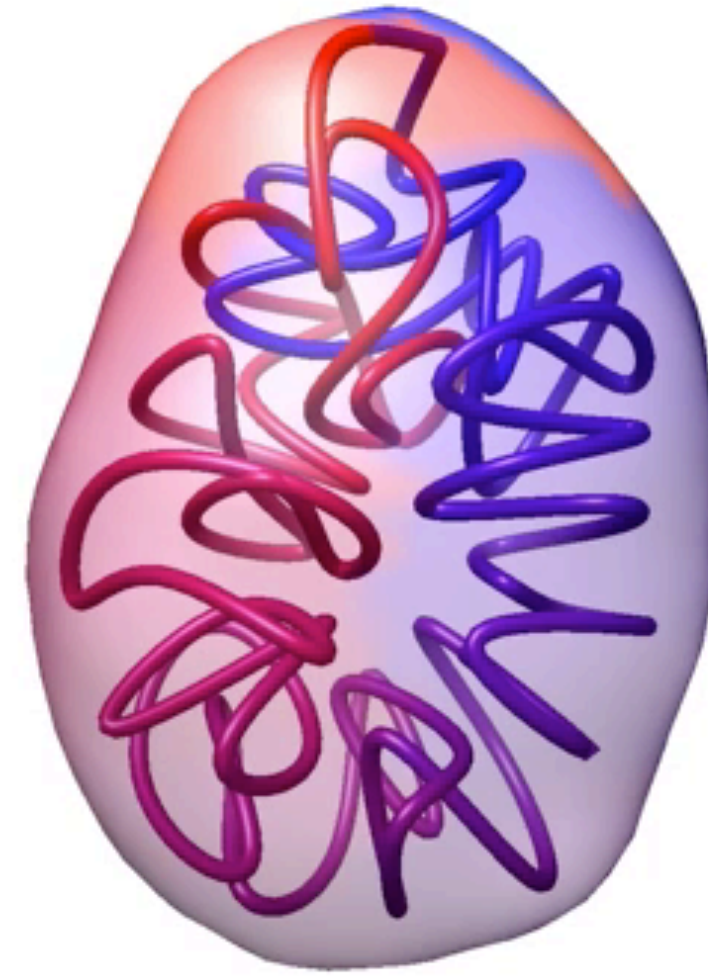


Mycoplasma genome is partitioned into co-regulated CIDs



Inhibiting supercoiling decreases the sharpness of domain borders





Mycoplasma reduced-genome has a “3D structure”

Similar to Caulobacter, Mycoplasma has a double diagonal intersecting near the centre of the genome

Mycoplasma has CIDs (TADs)

CIDs contain co-regulated genes.

Inhibition of supercoiling by novobiocin significantly reduced the sharpness of CID borders.

Very few factors may be necessary to define a 3D structure

Other elements like supercoiling could regulate these domain boundaries.



Marie Trussart
Davide Baù

Gireesh K. Bogu
David Castillo
Yasmina Cuartero
Irene Farabella
Silvia Galan
Mike Goodstadt
Julen Mendieta
François Serra
Paula Soler
Yannick Spill
Marco di Stefano

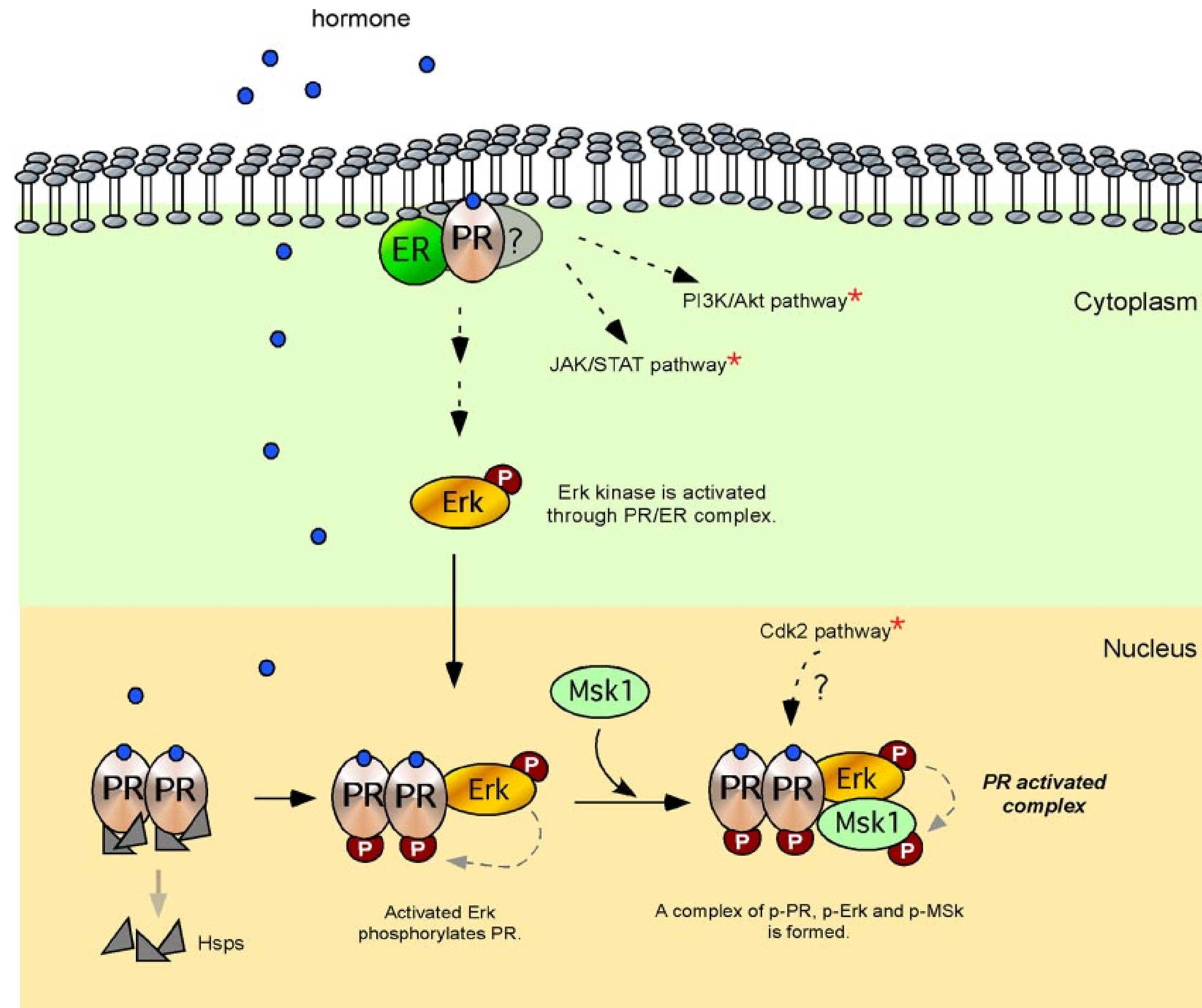
in collaboration with Ivan Junier (Université Joseph Fourier) & Luís Serrano (CRG)

<http://marciuslab.org>
<http://3DGenomes.org>
<http://cnag.crg.eu>



Progesterone-regulated transcription in breast cancer

Le Dily, F. et al. *Genes & Dev* (2014)

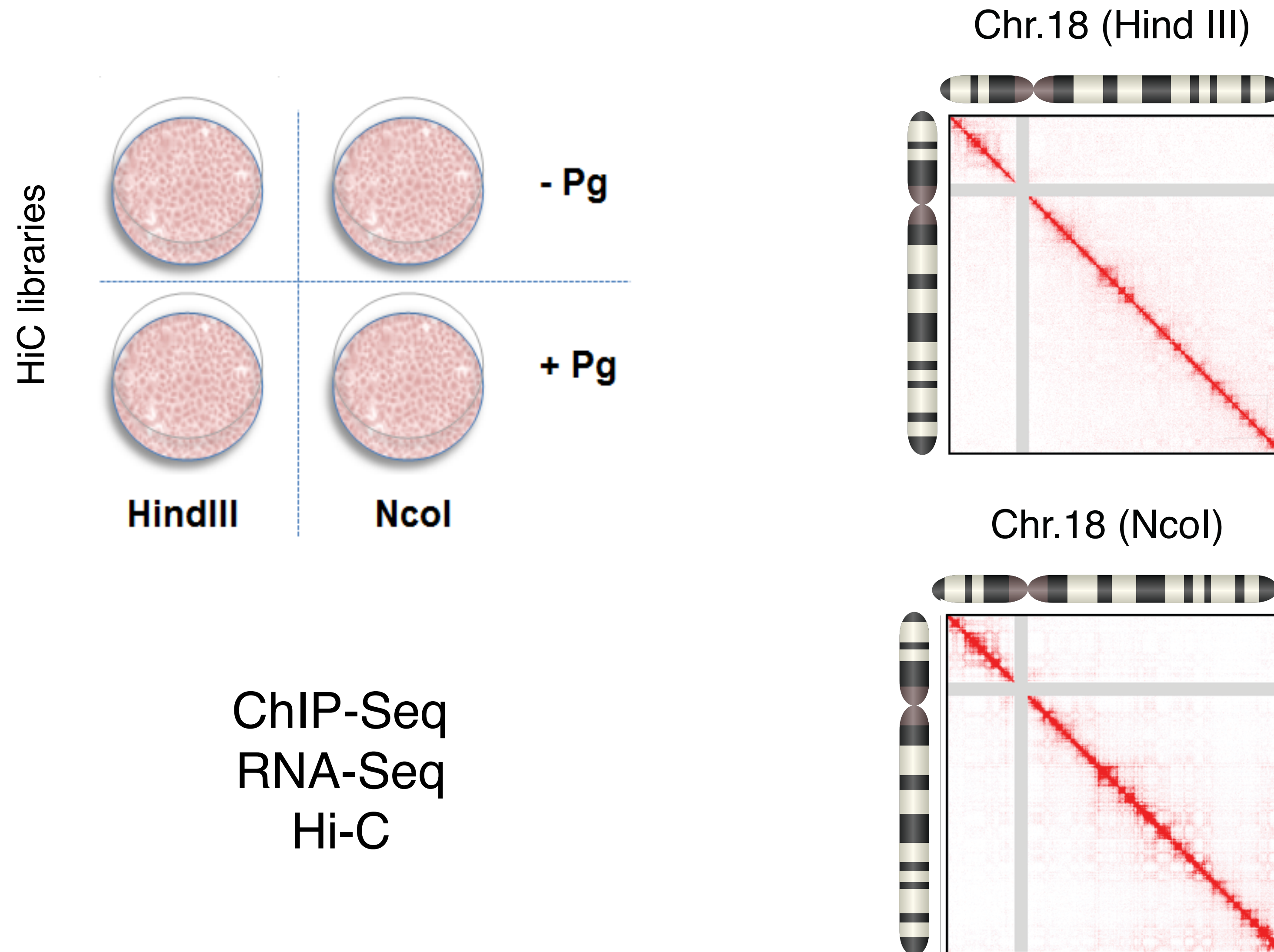


> 2,000 genes **Up-regulated**
> 2,000 genes **Down-regulated**

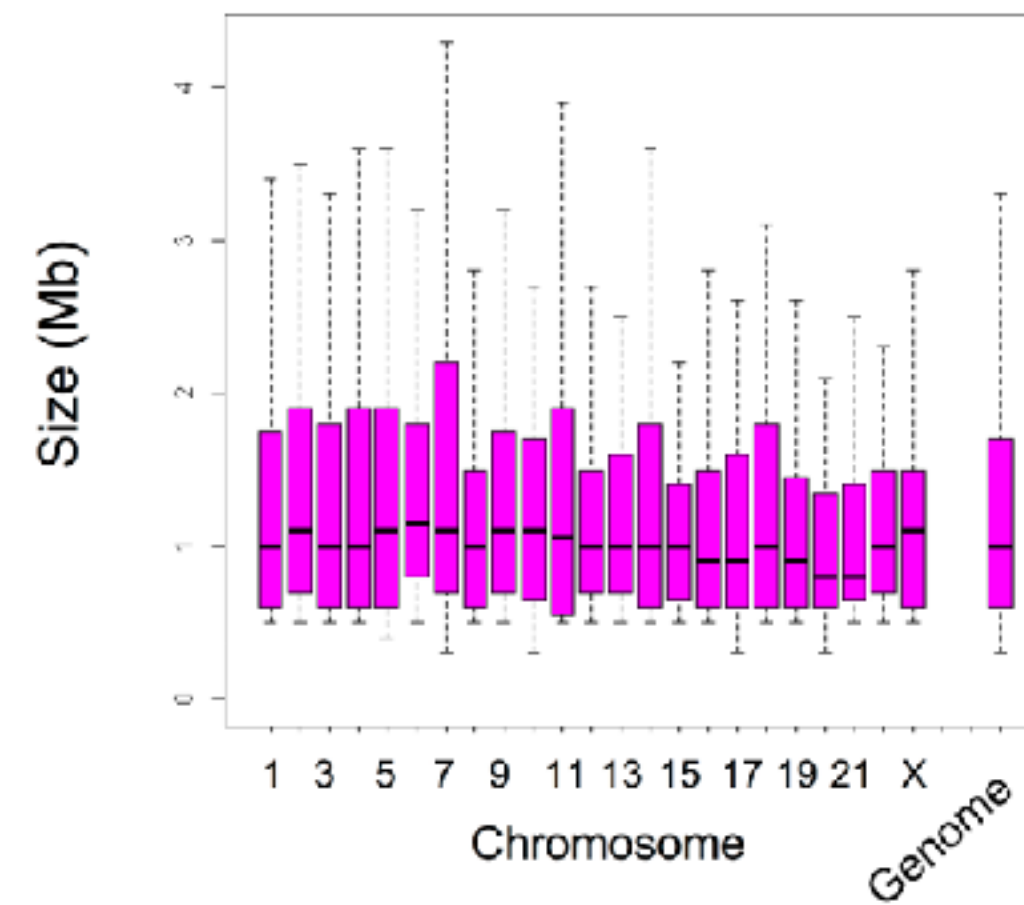
Regulation in 3D?

Vicent *et al* 2011, Wright *et al* 2012, Ballare *et al* 2012

Experimental design

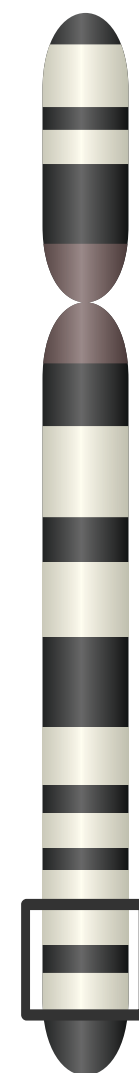


Are there TADs? how robust?

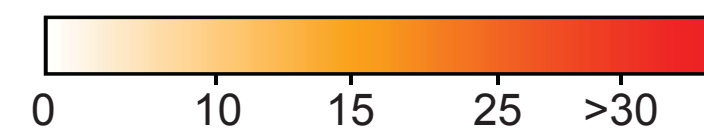
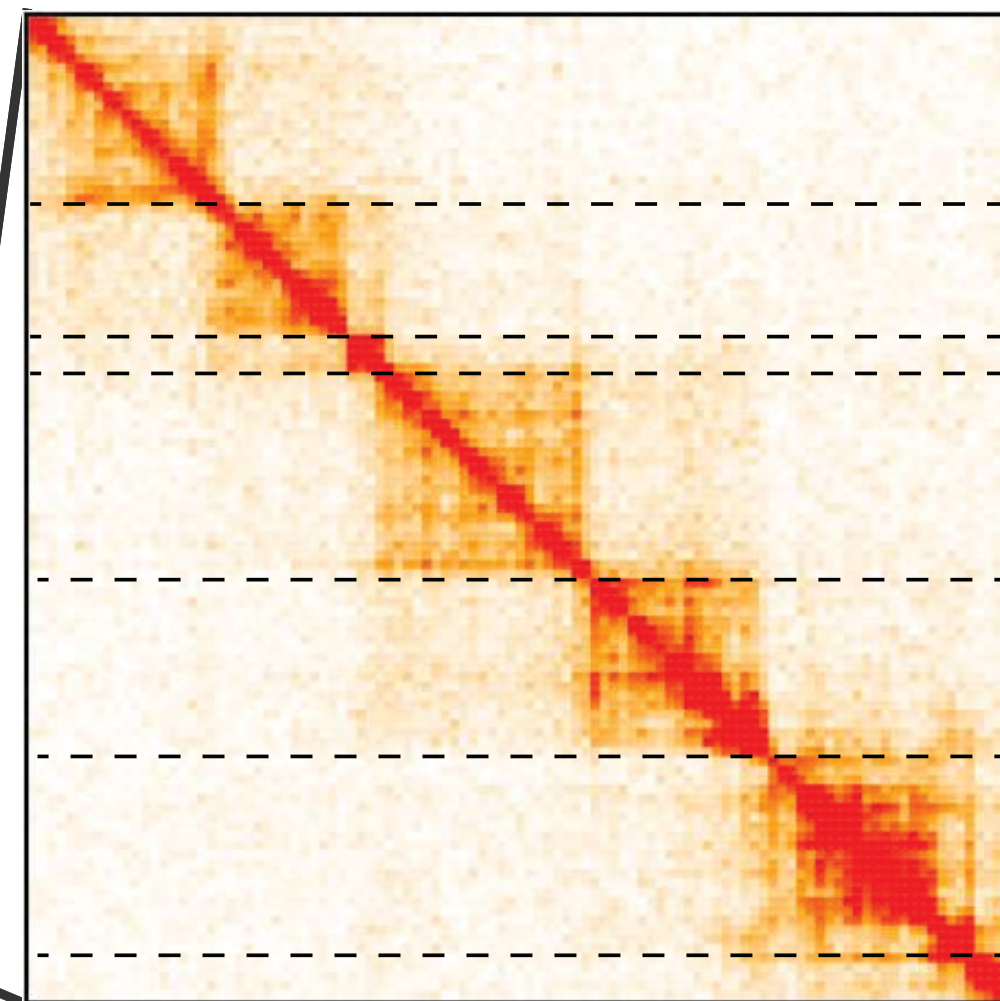


>2,000 detected TADs

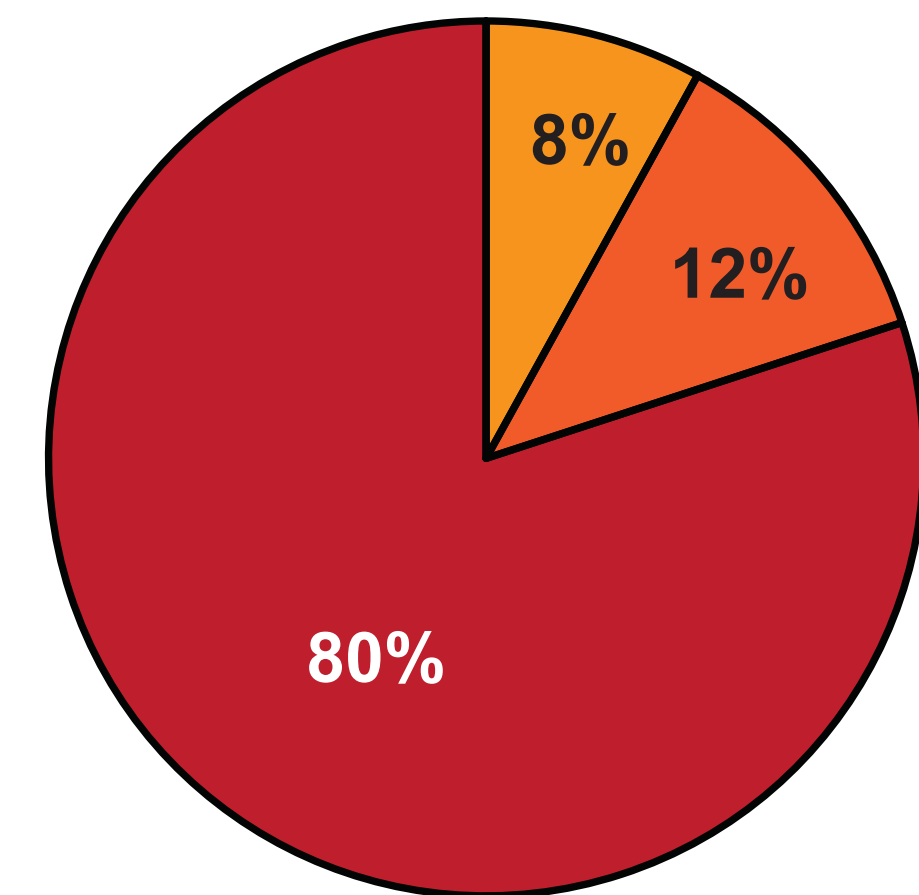
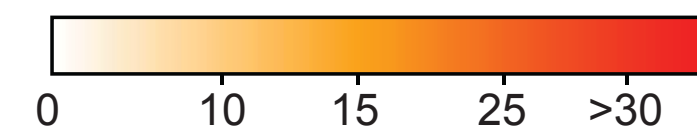
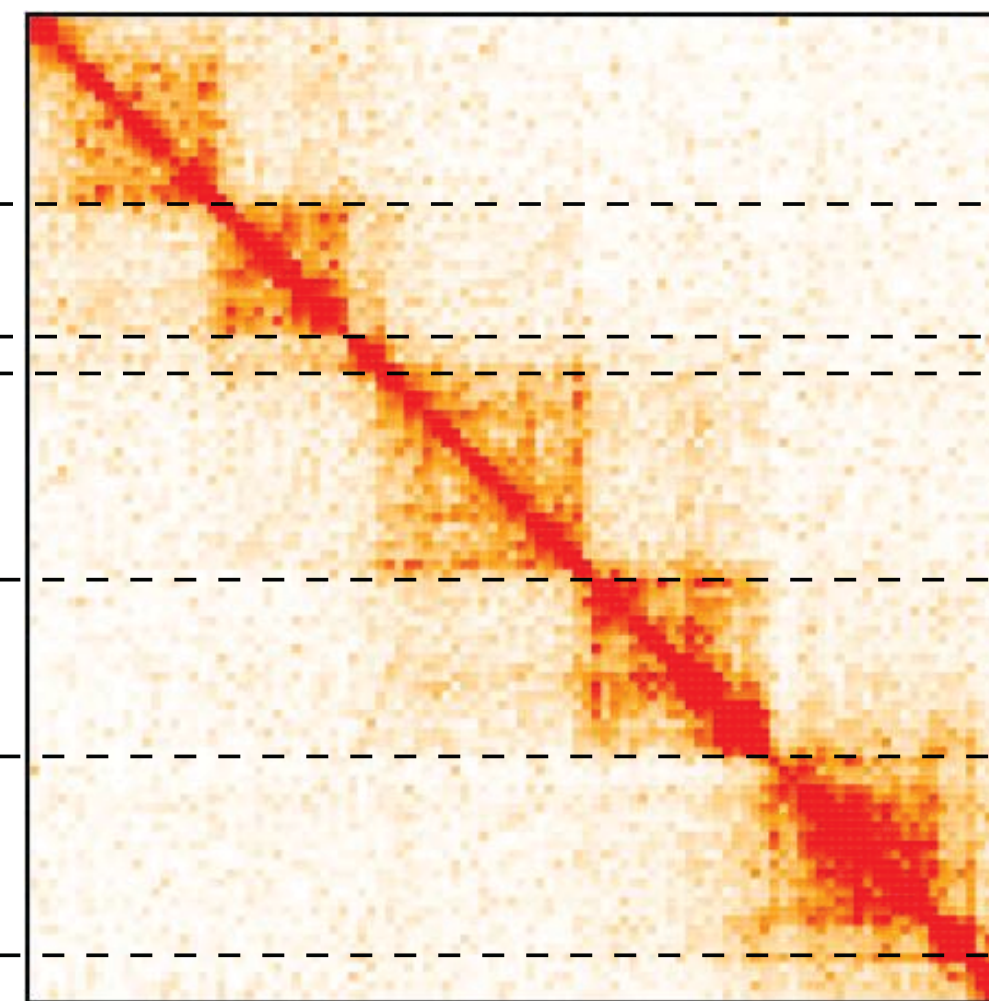
Chr.18



-Pg

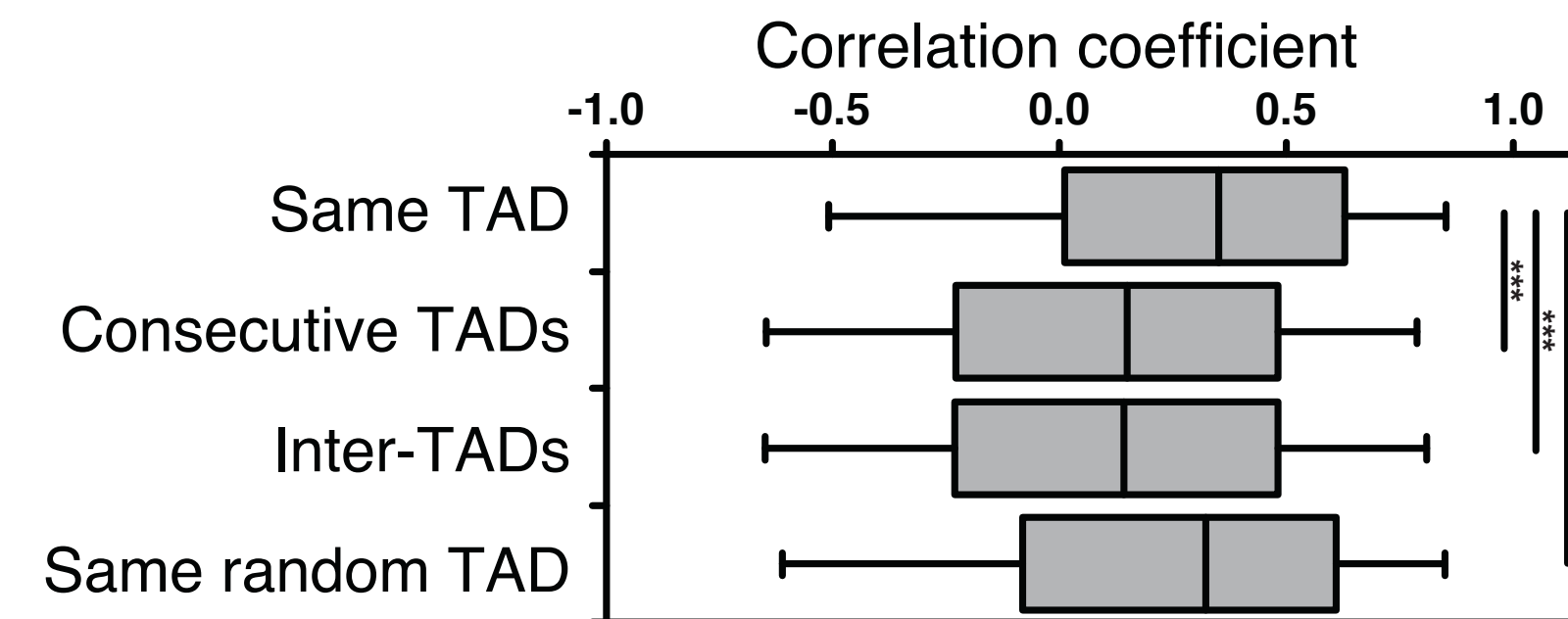
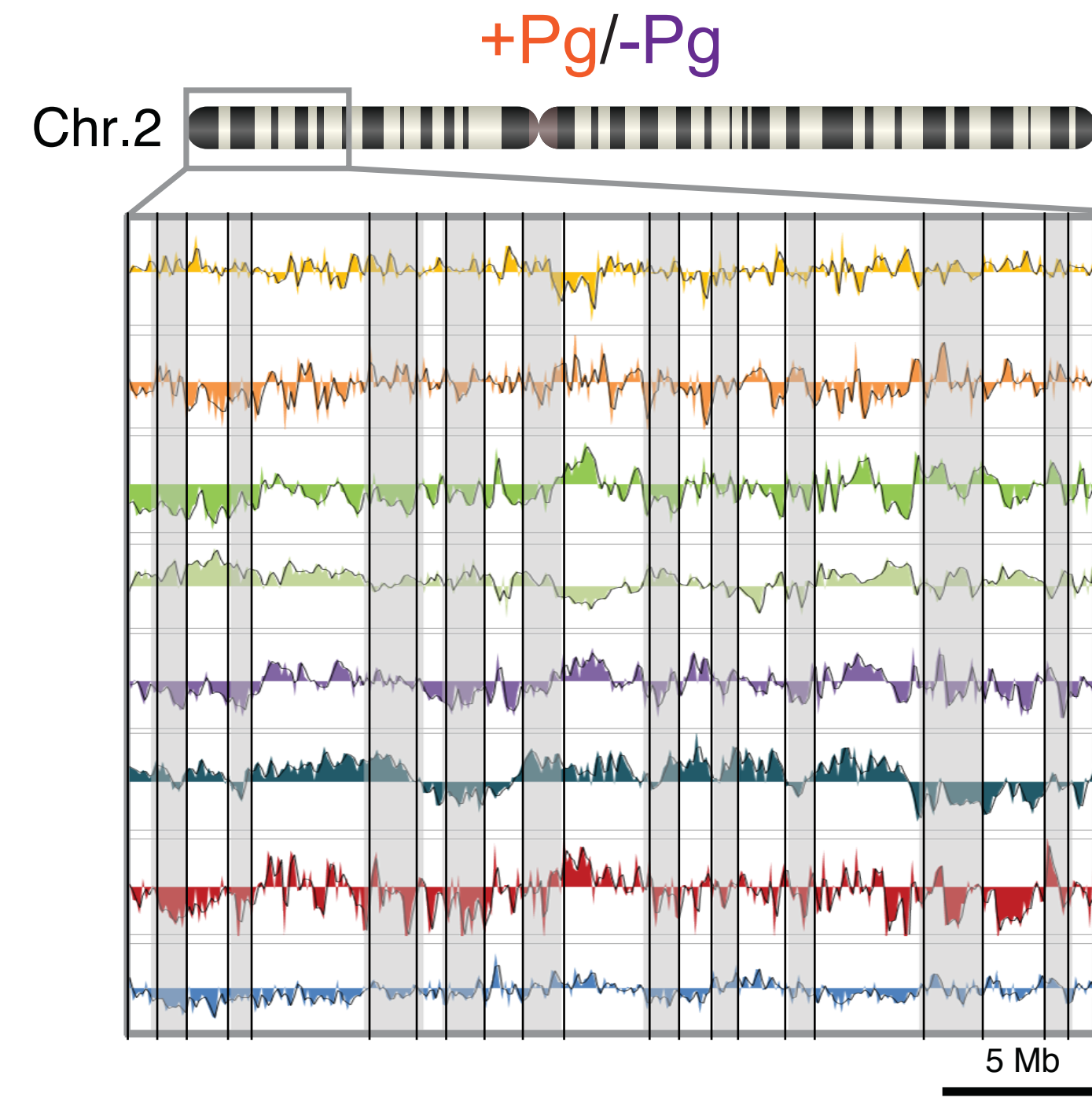
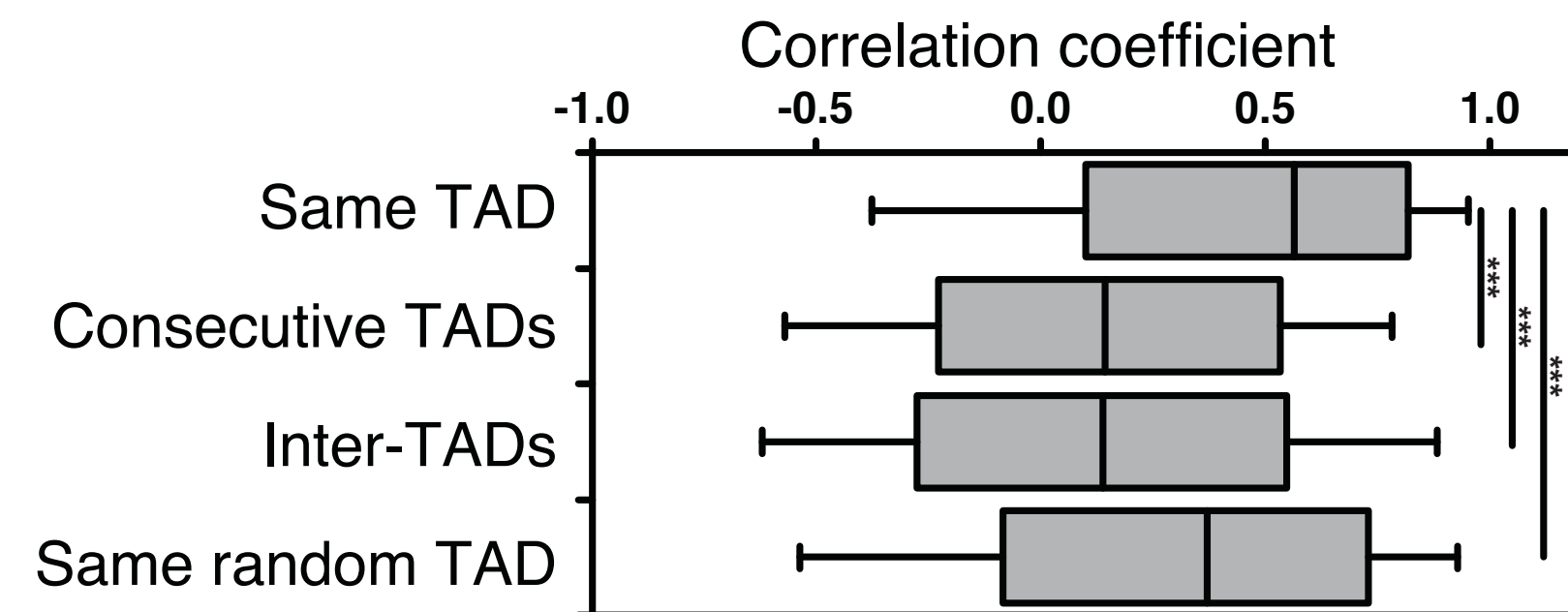
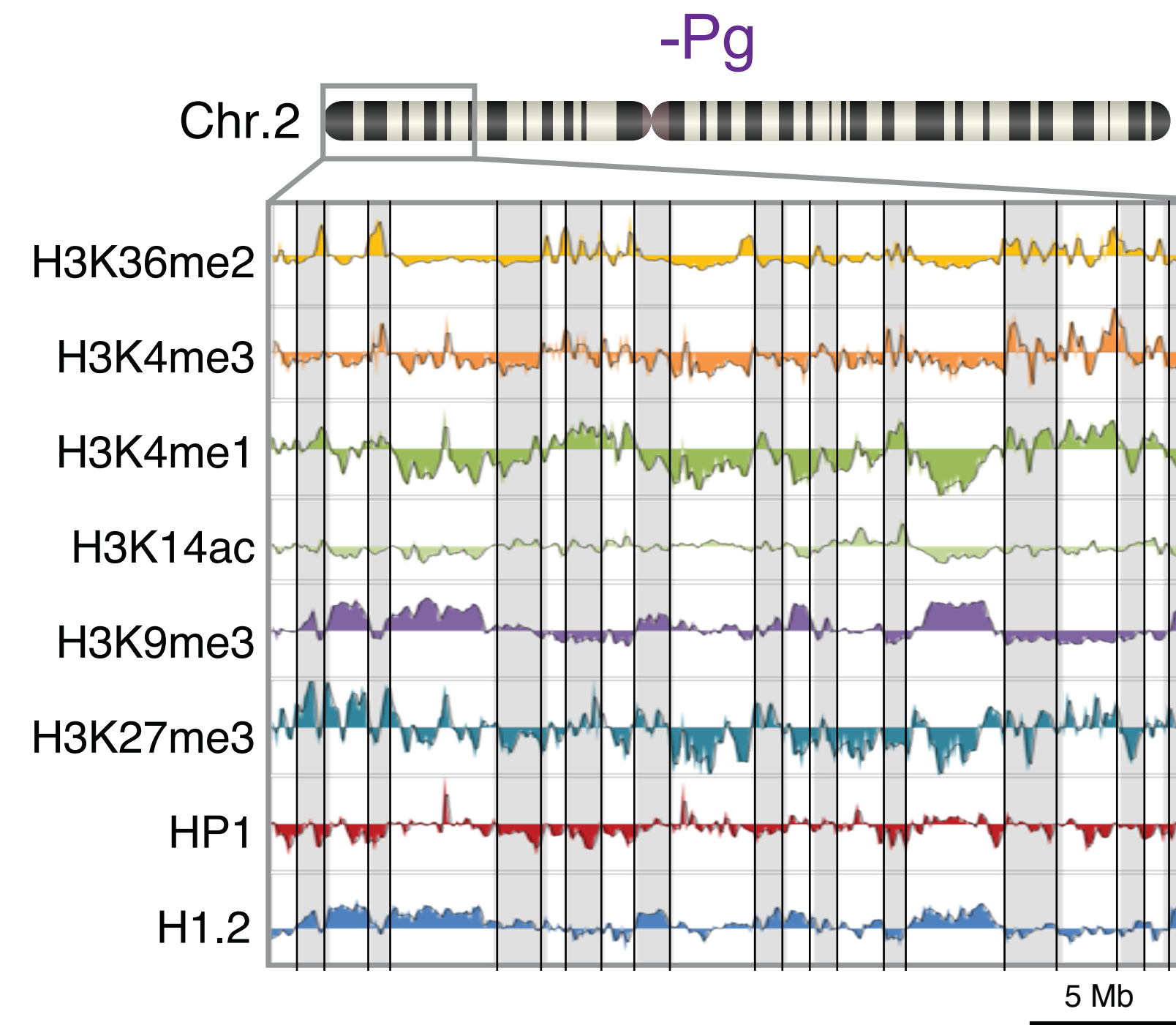


+Pg

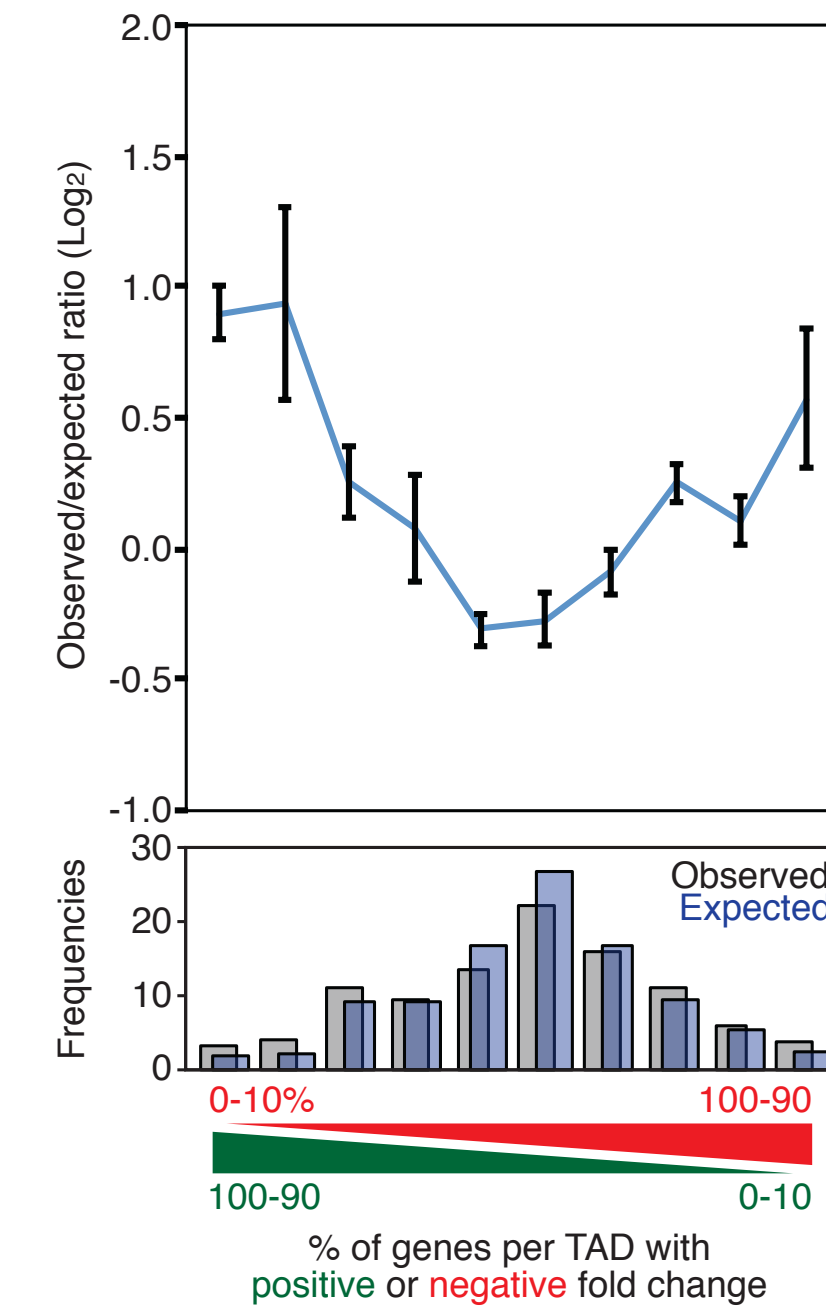
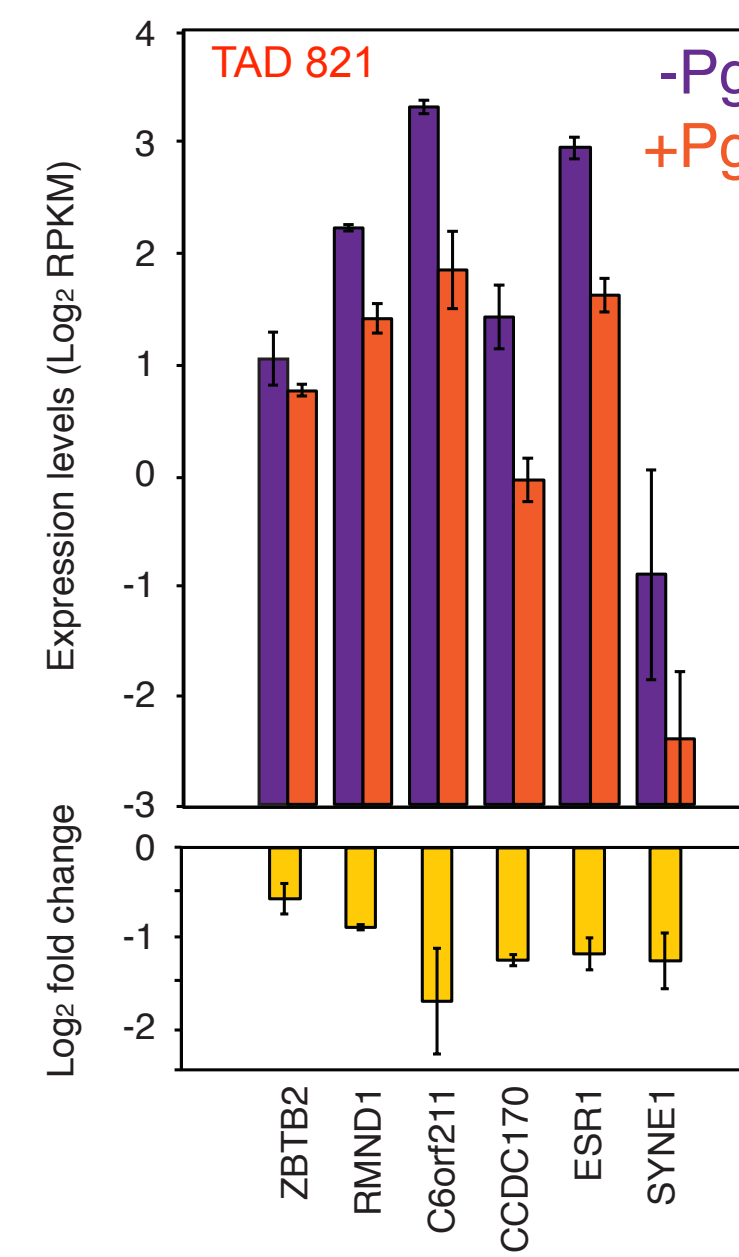
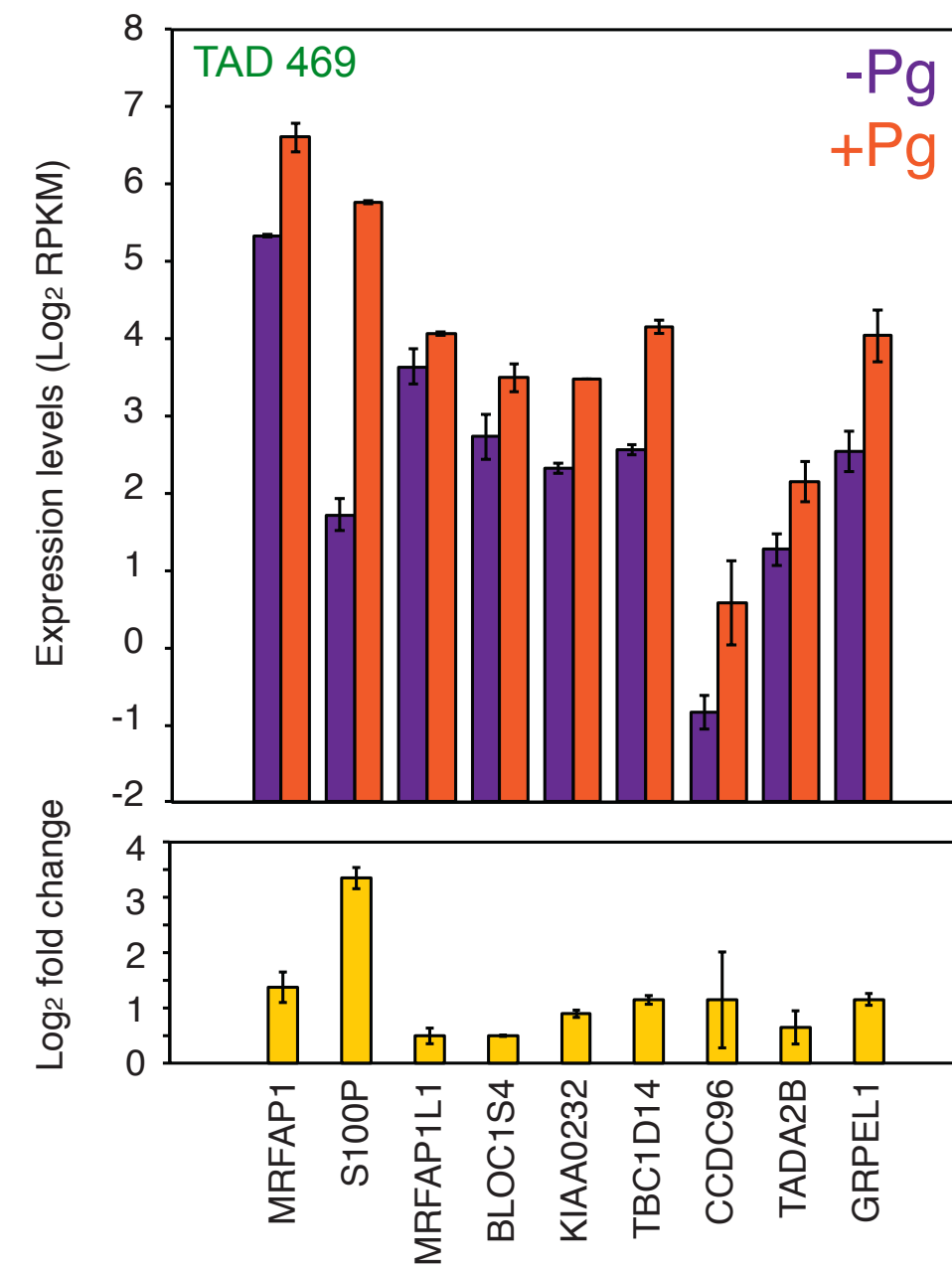


conserved
100 kb
±200 kb or more

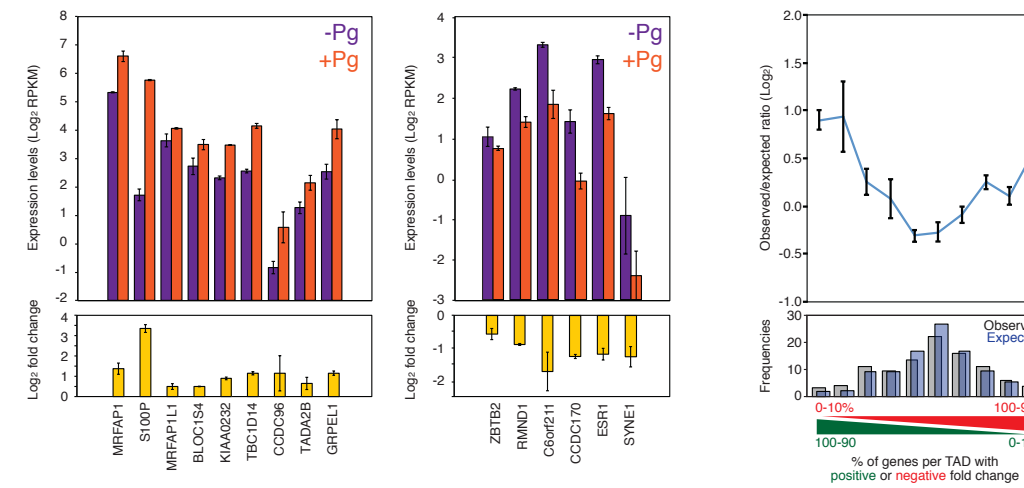
Are TADs homogeneous?



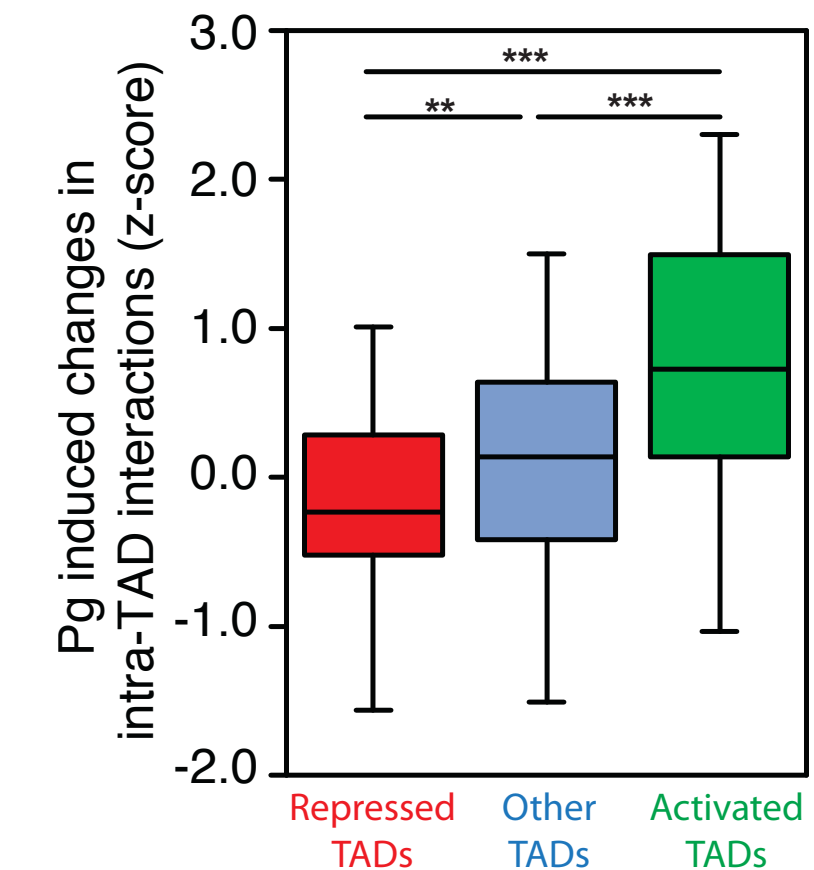
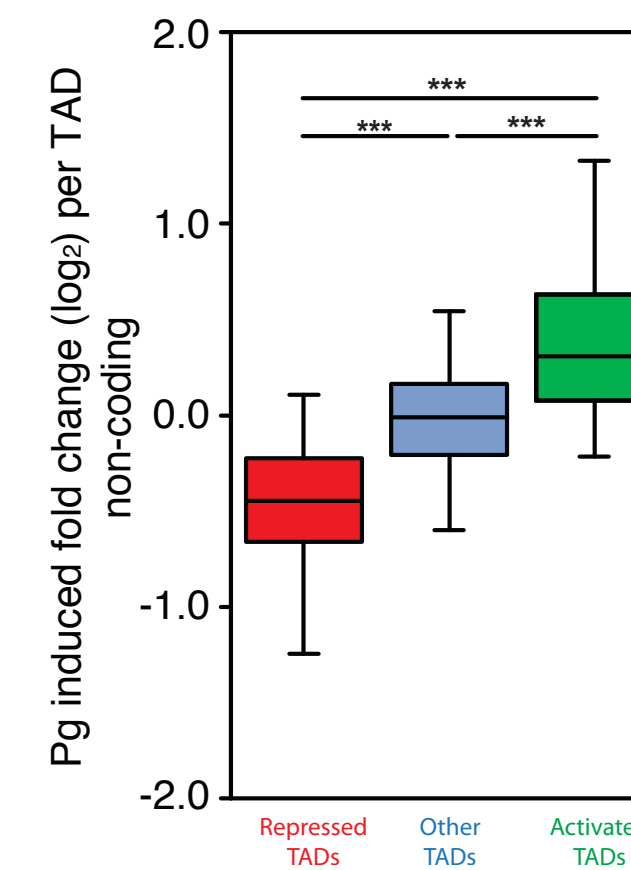
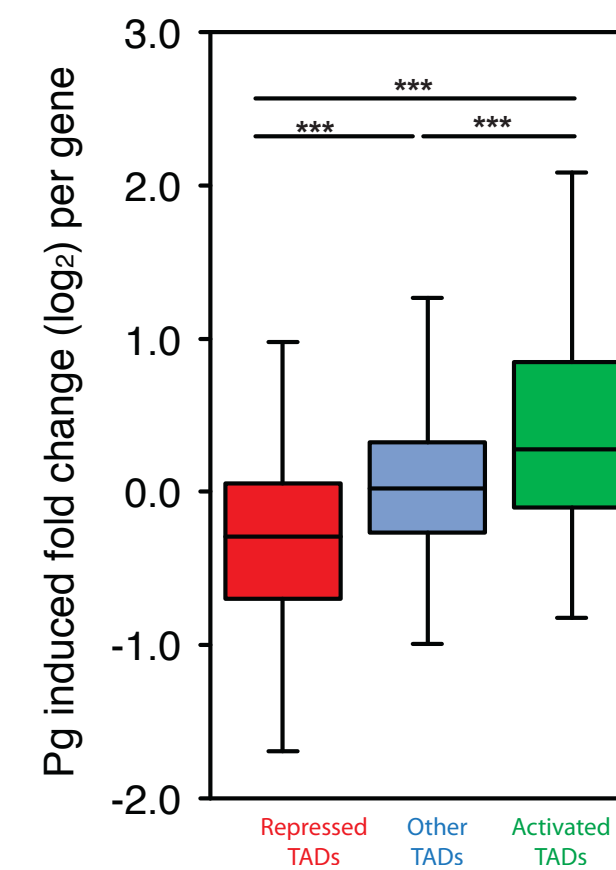
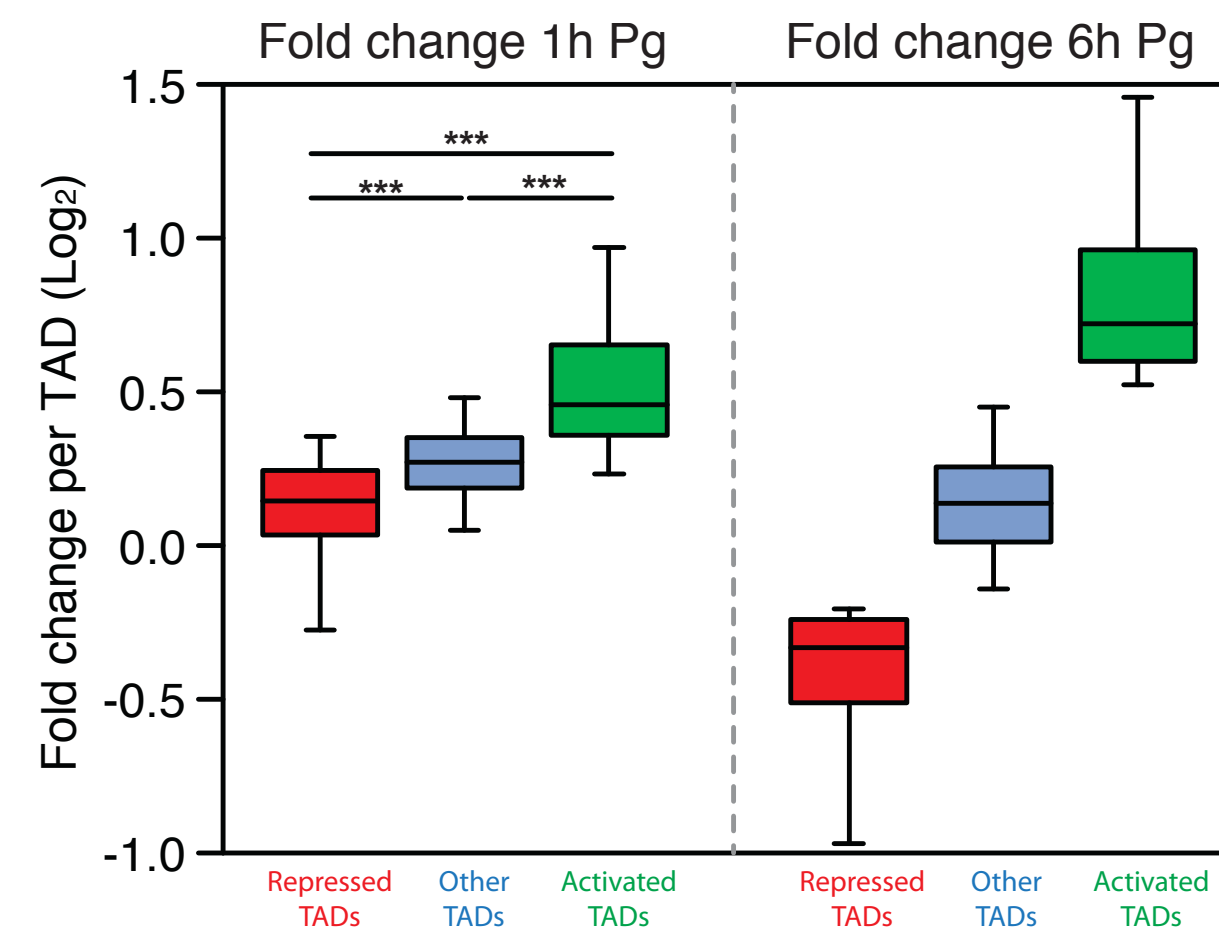
Do TADs respond differently to Pg treatment?



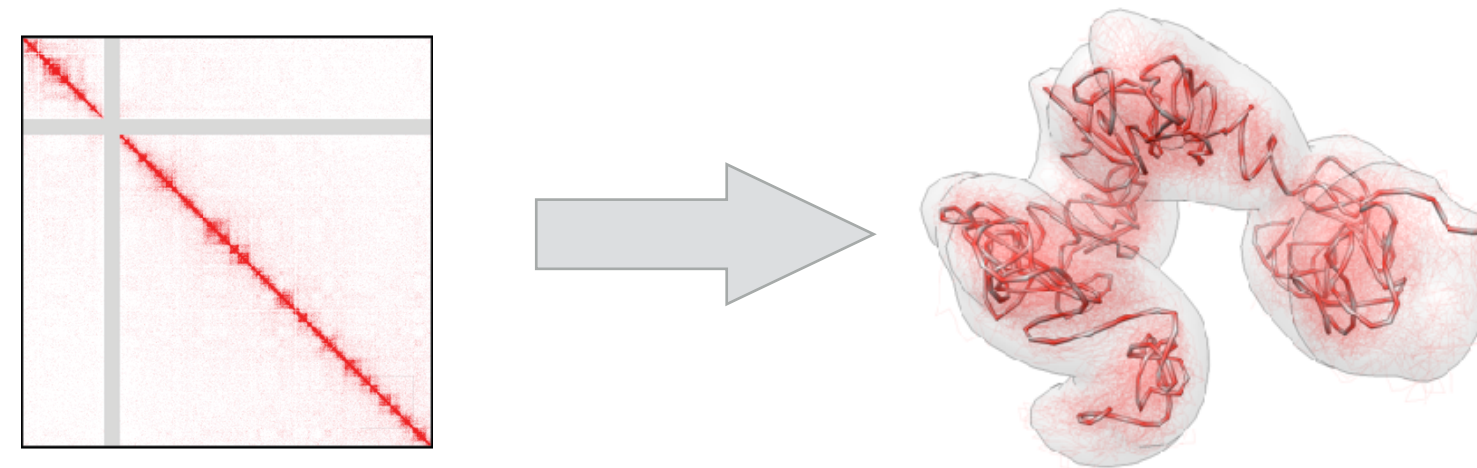
Do TADs respond differently to Pg treatment?



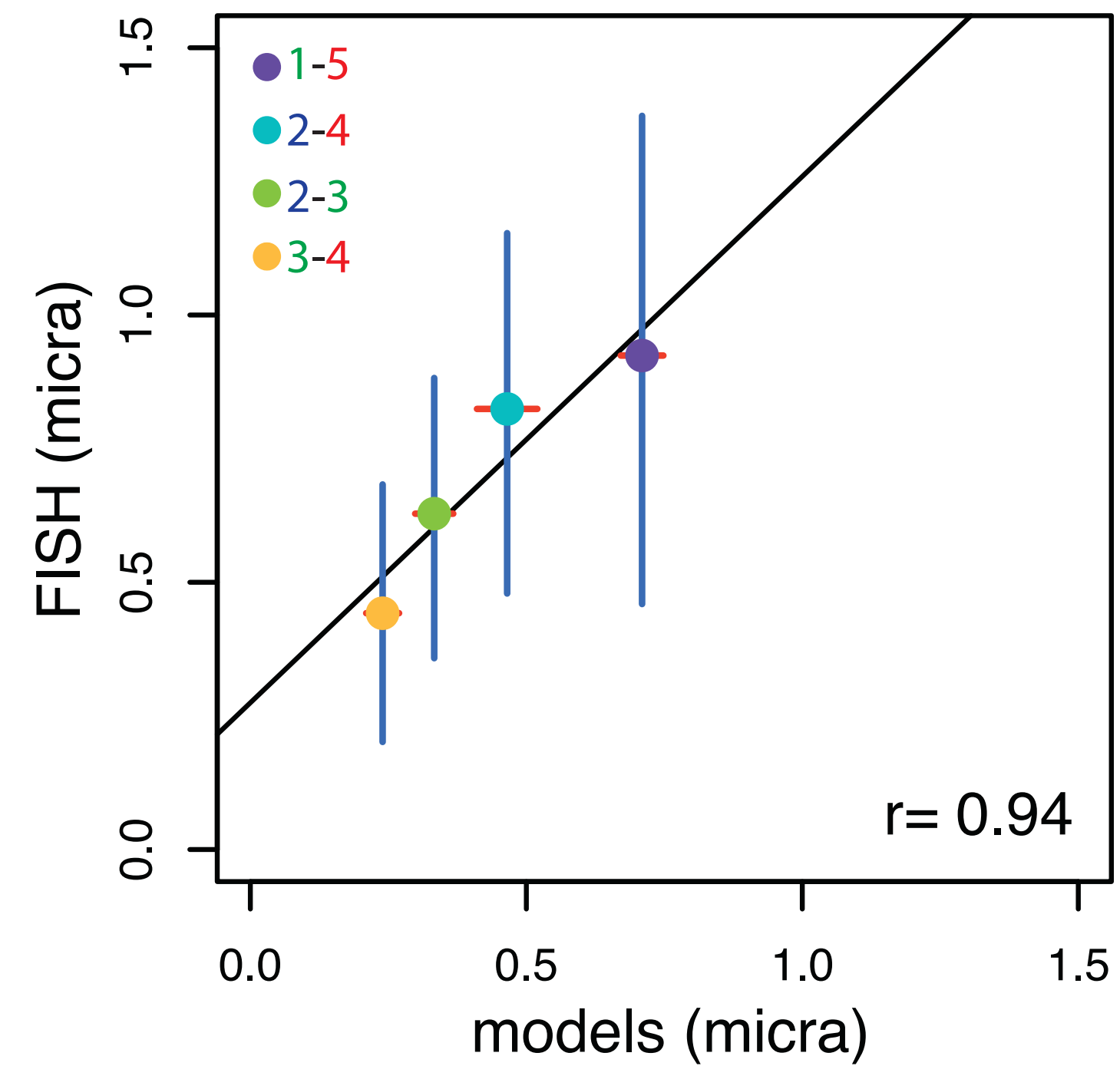
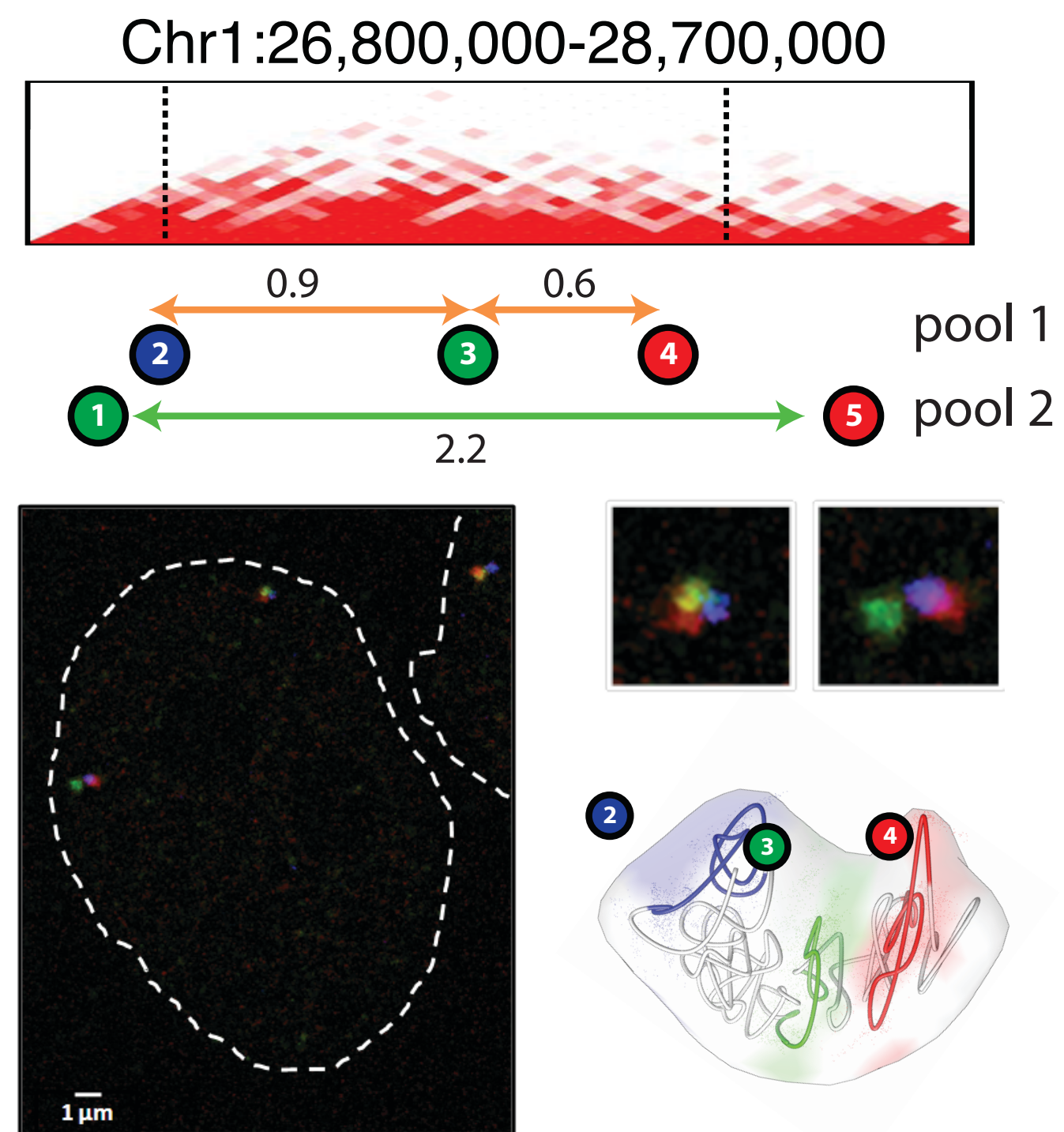
Pg induced fold change per TAD (6h)



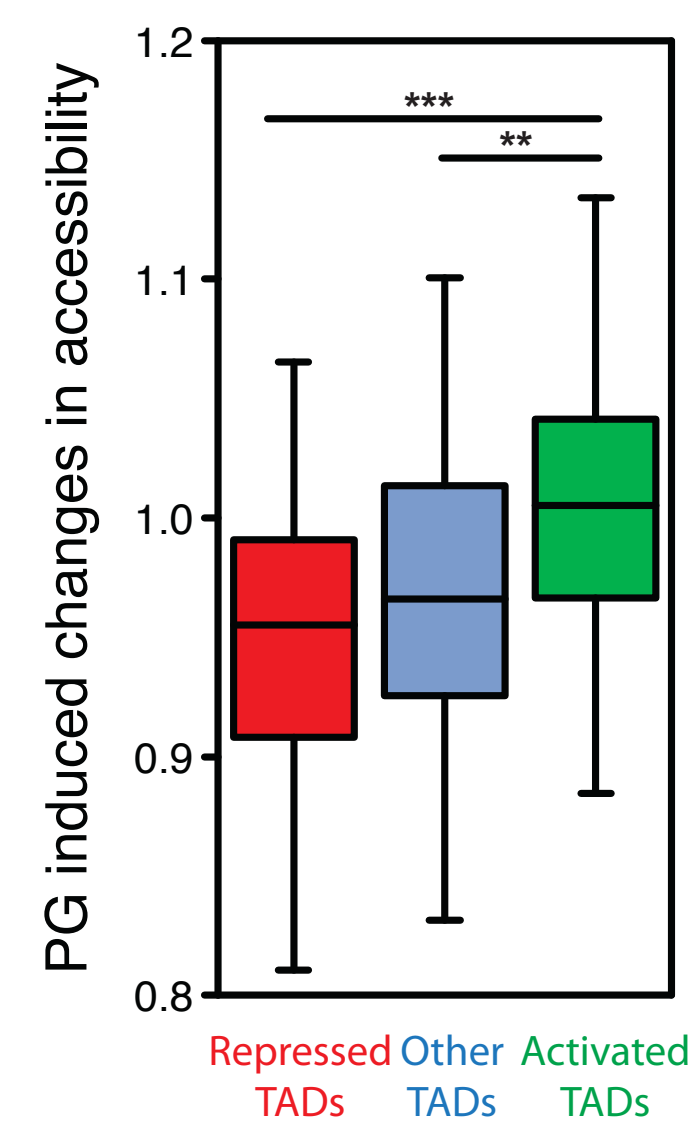
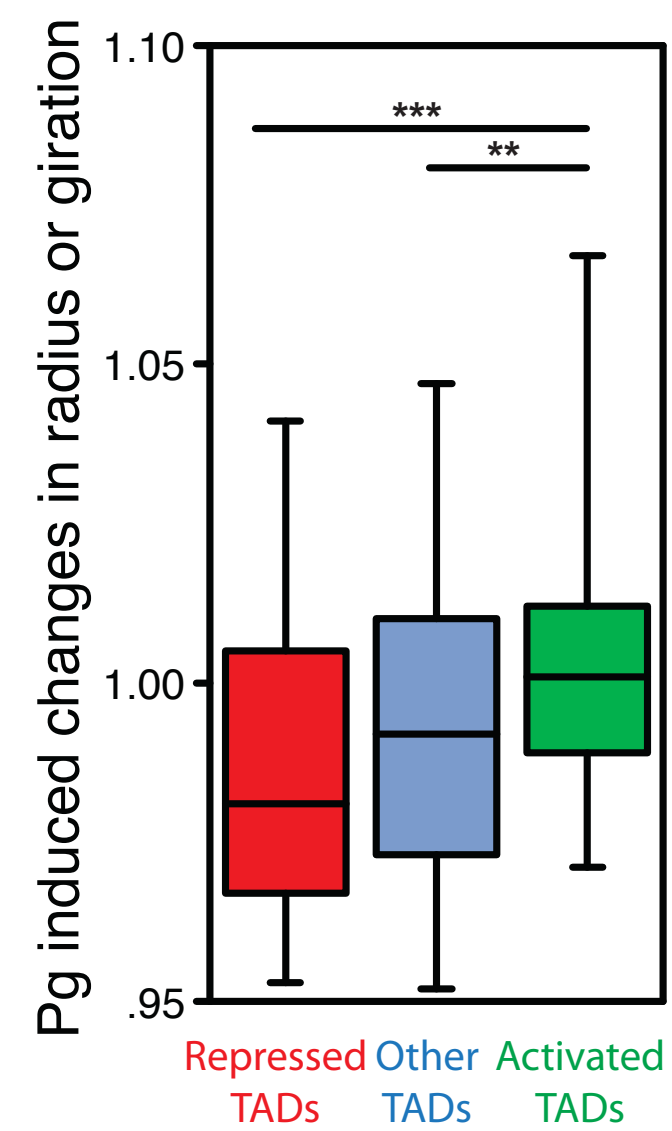
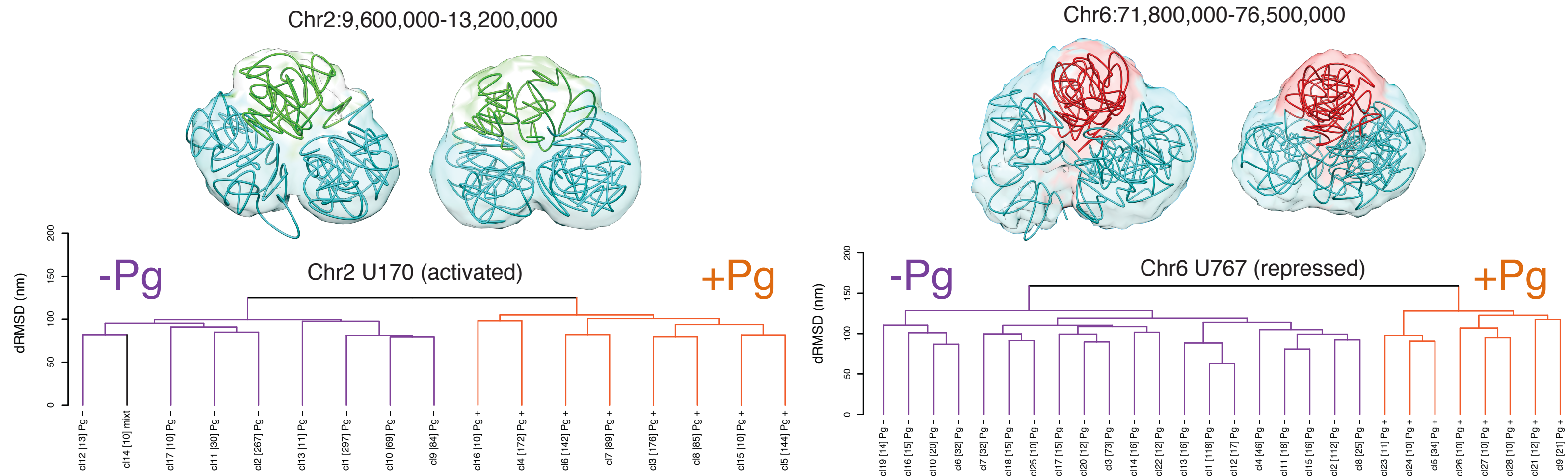
Modeling 3D TADs



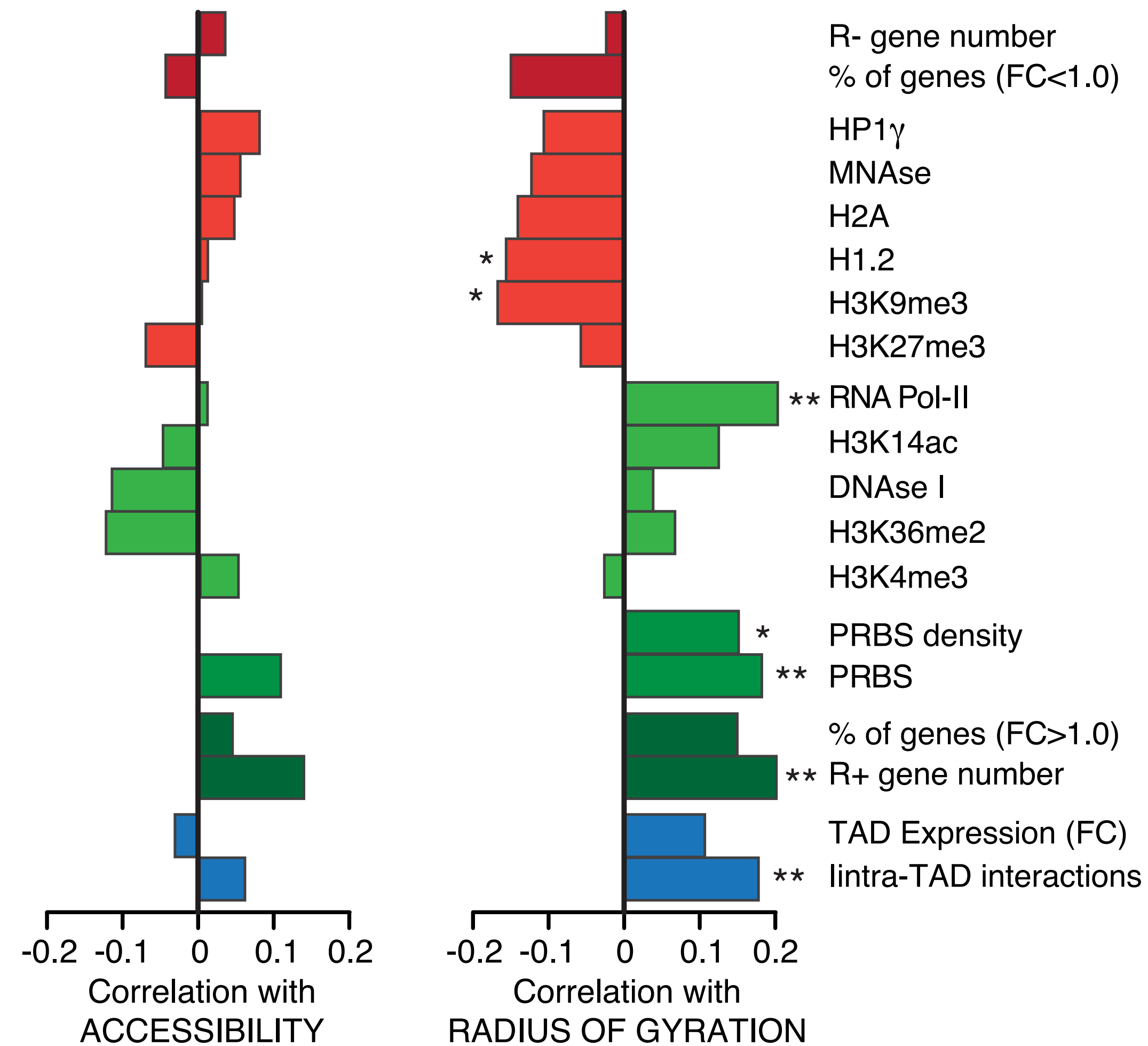
61 genomic regions containing 209 TADs covering 267Mb

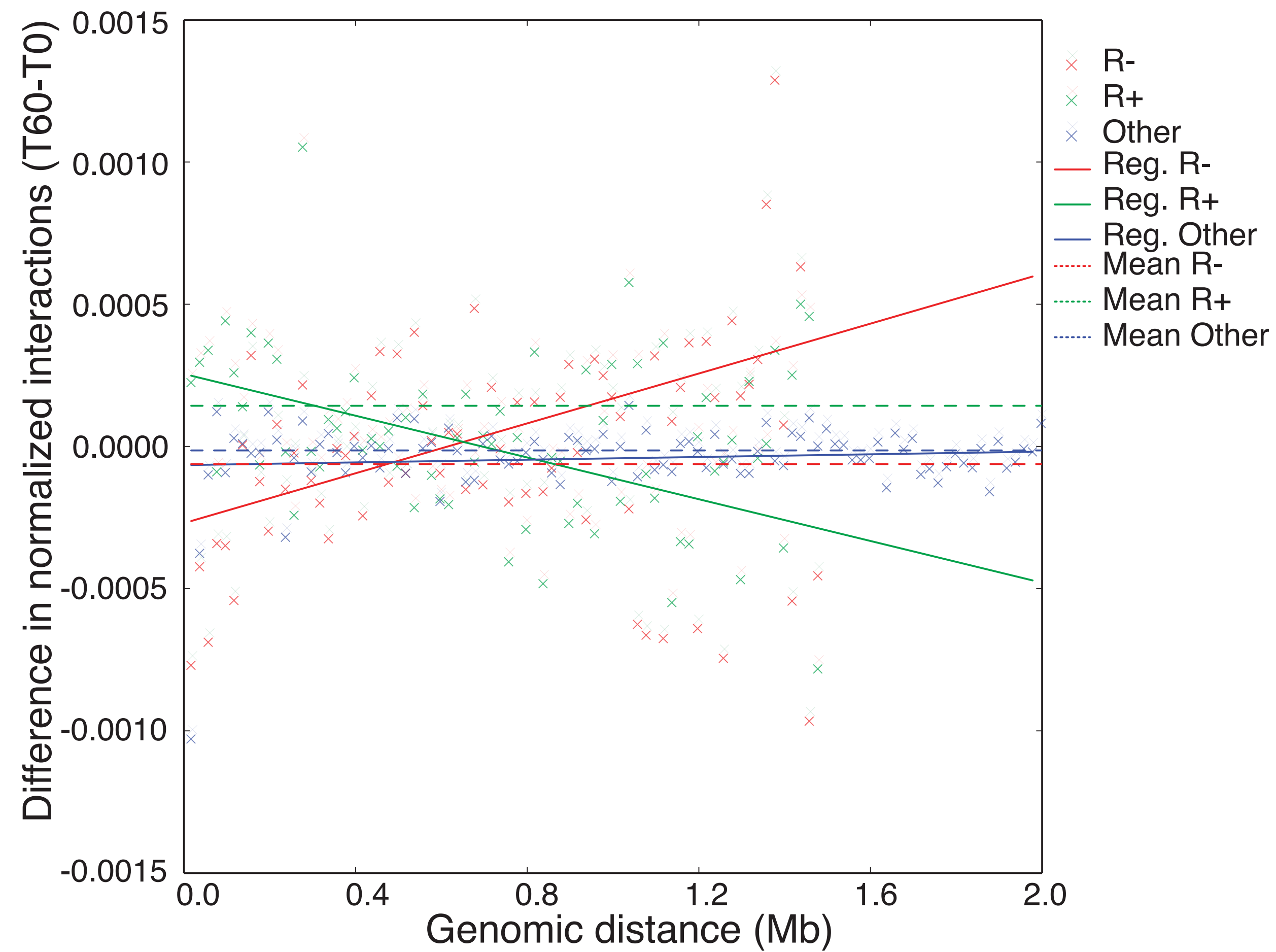
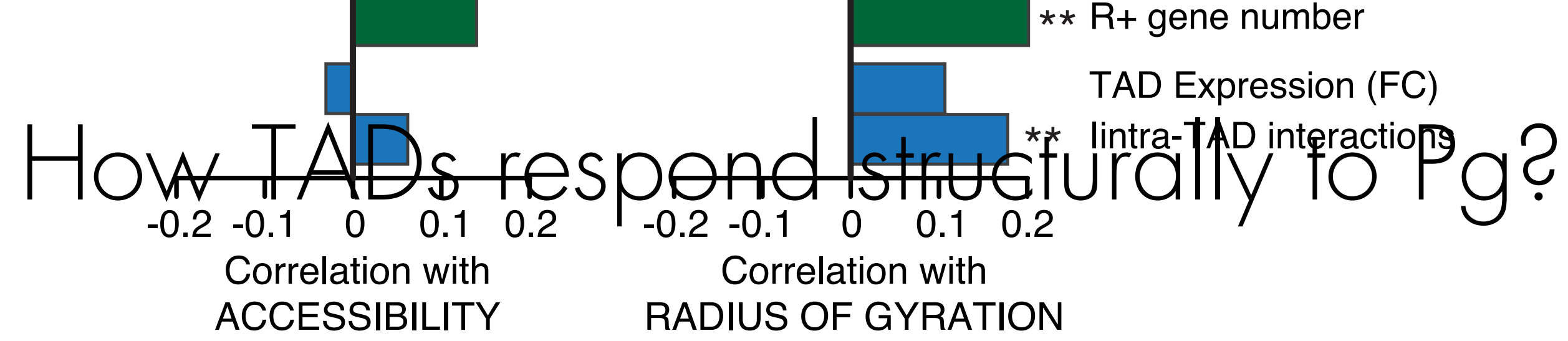


How TADs respond structurally to Pg?



How TADs respond structurally to Pg?

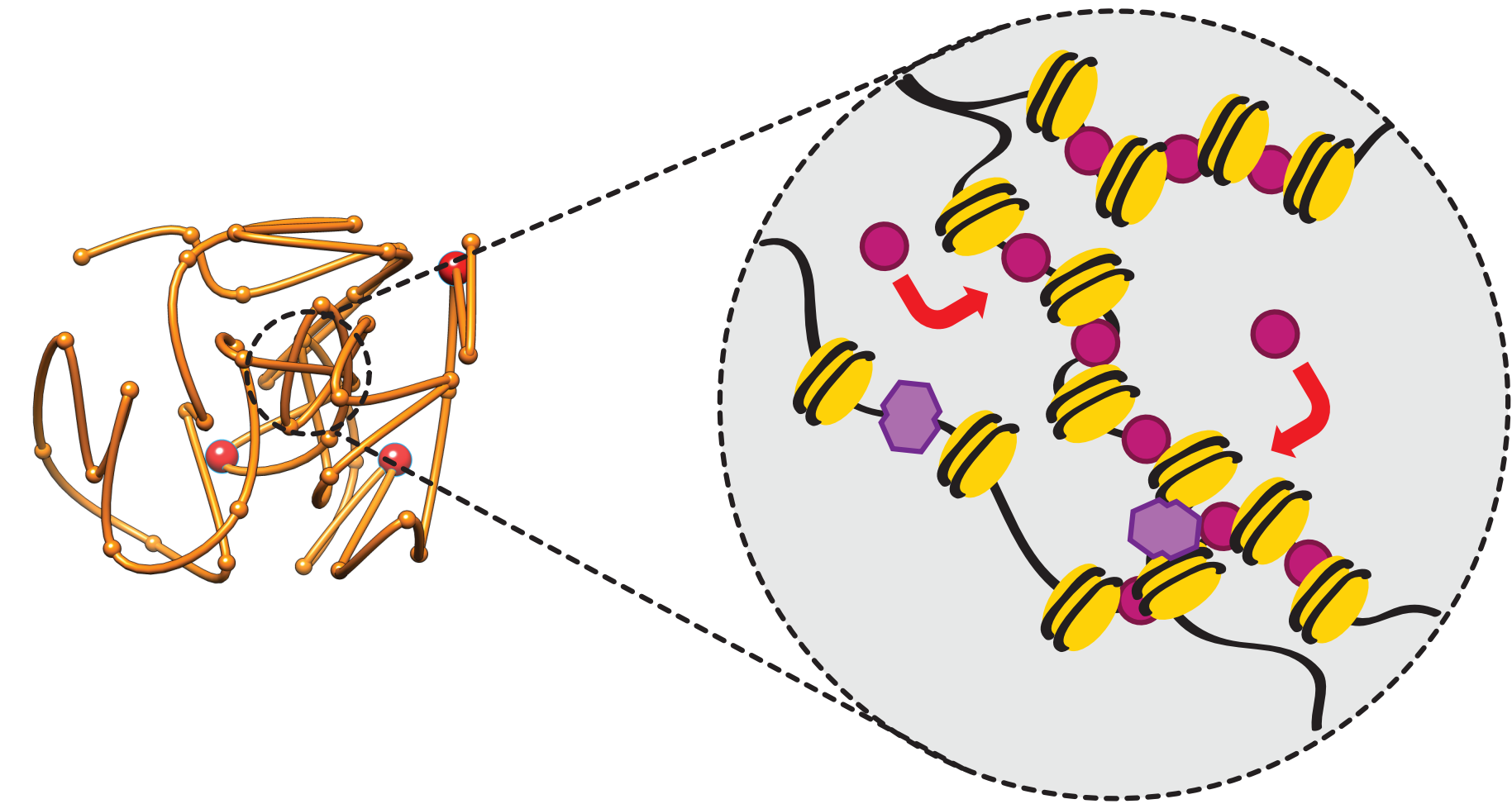
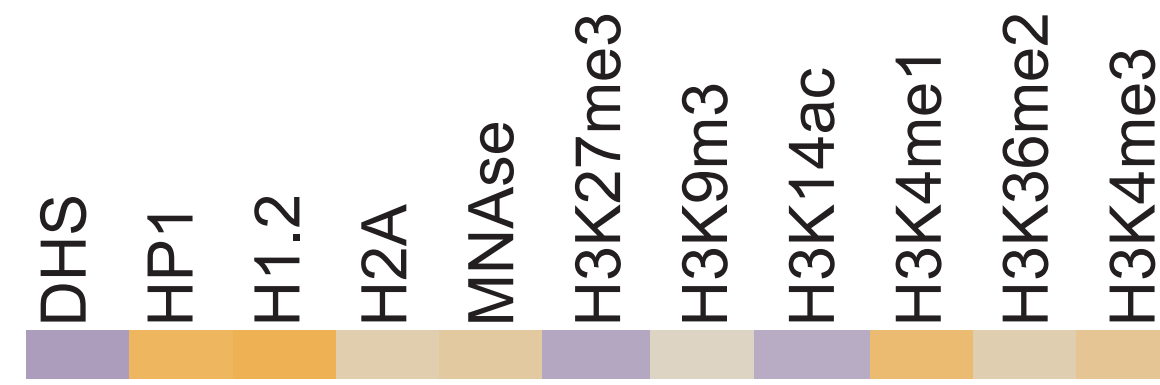
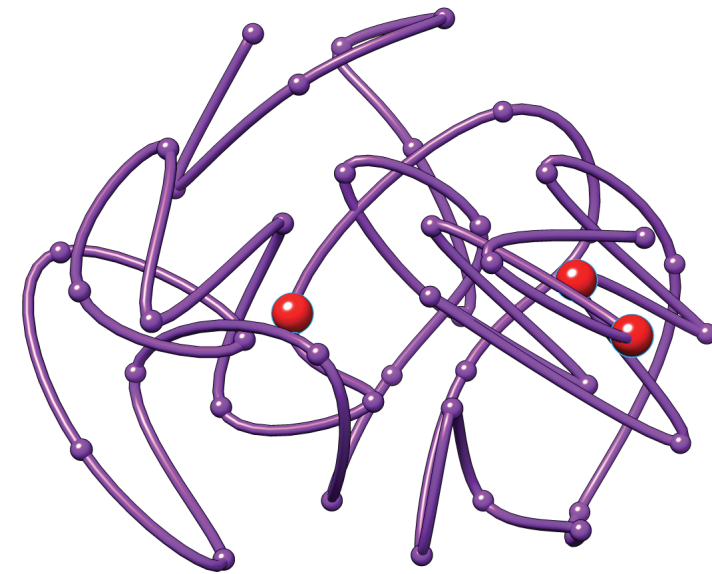




Model for TAD regulation

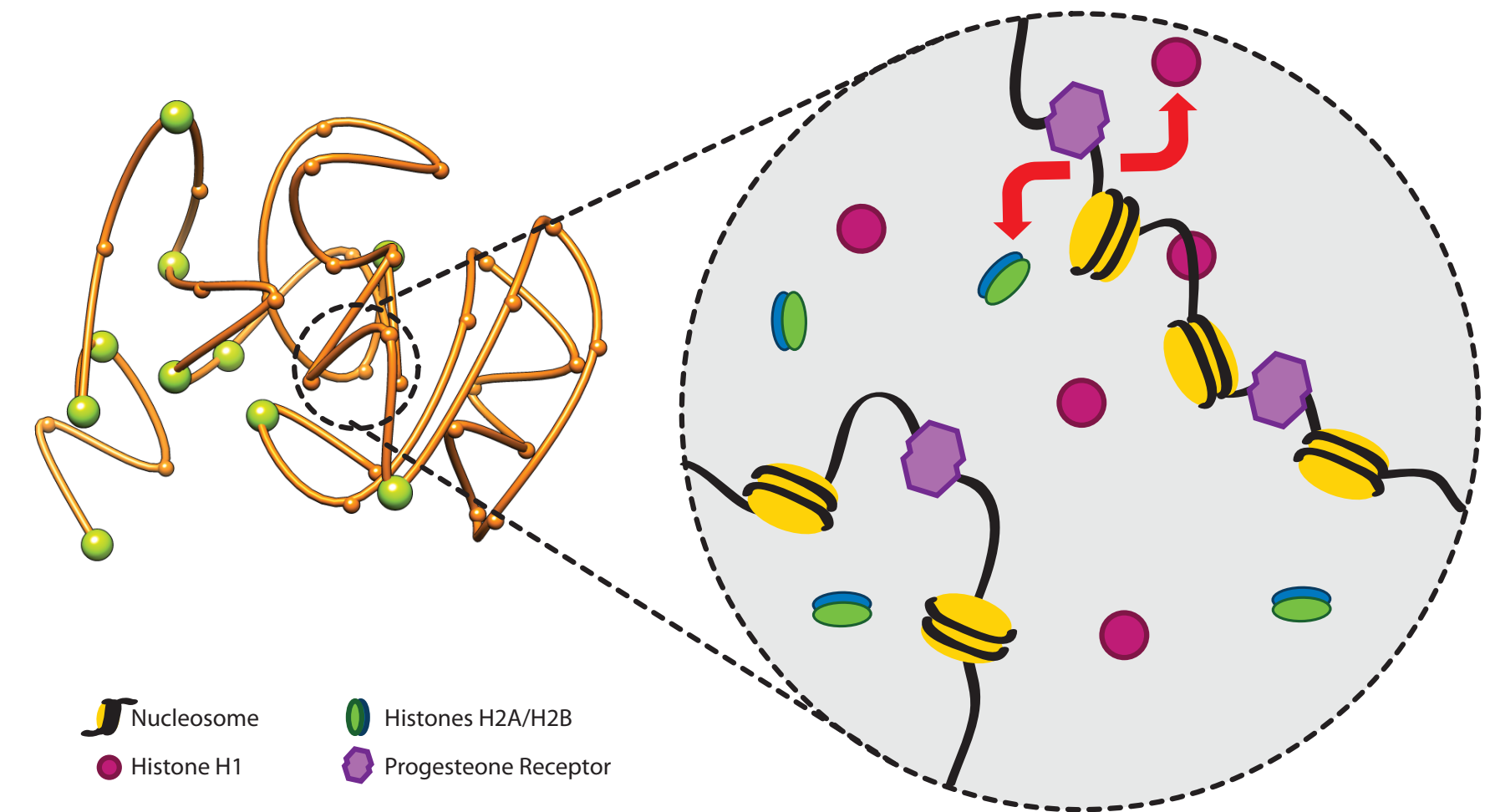
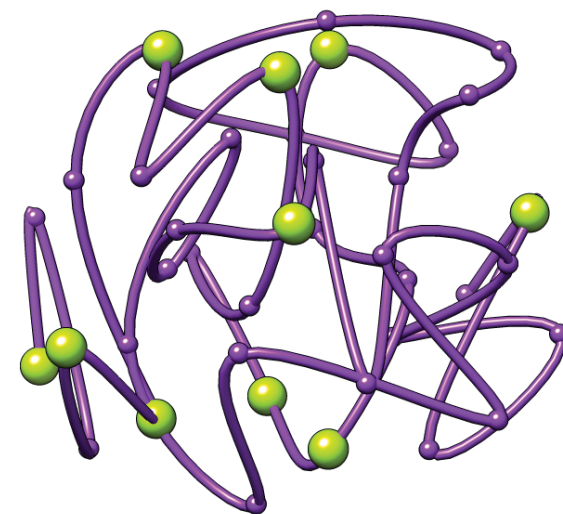
Repressed TAD

chr1 U41



Activated TAD

chr2 U207



Nucleosome
Histone H1
Histones H2A/H2B
Progesterone Receptor



Marie Trussart
Davide Baù

Gireesh K. Bogu
David Castillo
Yasmina Cuartero
Irene Farabella
Silvia Galan
Mike Goodstadt
Julen Mendieta
François Serra
Paula Soler
Yannick Spill
Marco di Stefano

in collaboration with Ivan Junier (Université Joseph Fourier) & Luís Serrano (CRG)

<http://marciuslab.org>
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