

Decoding sequence syntax of gene regulation and functional genetic variation

Kundaje lab

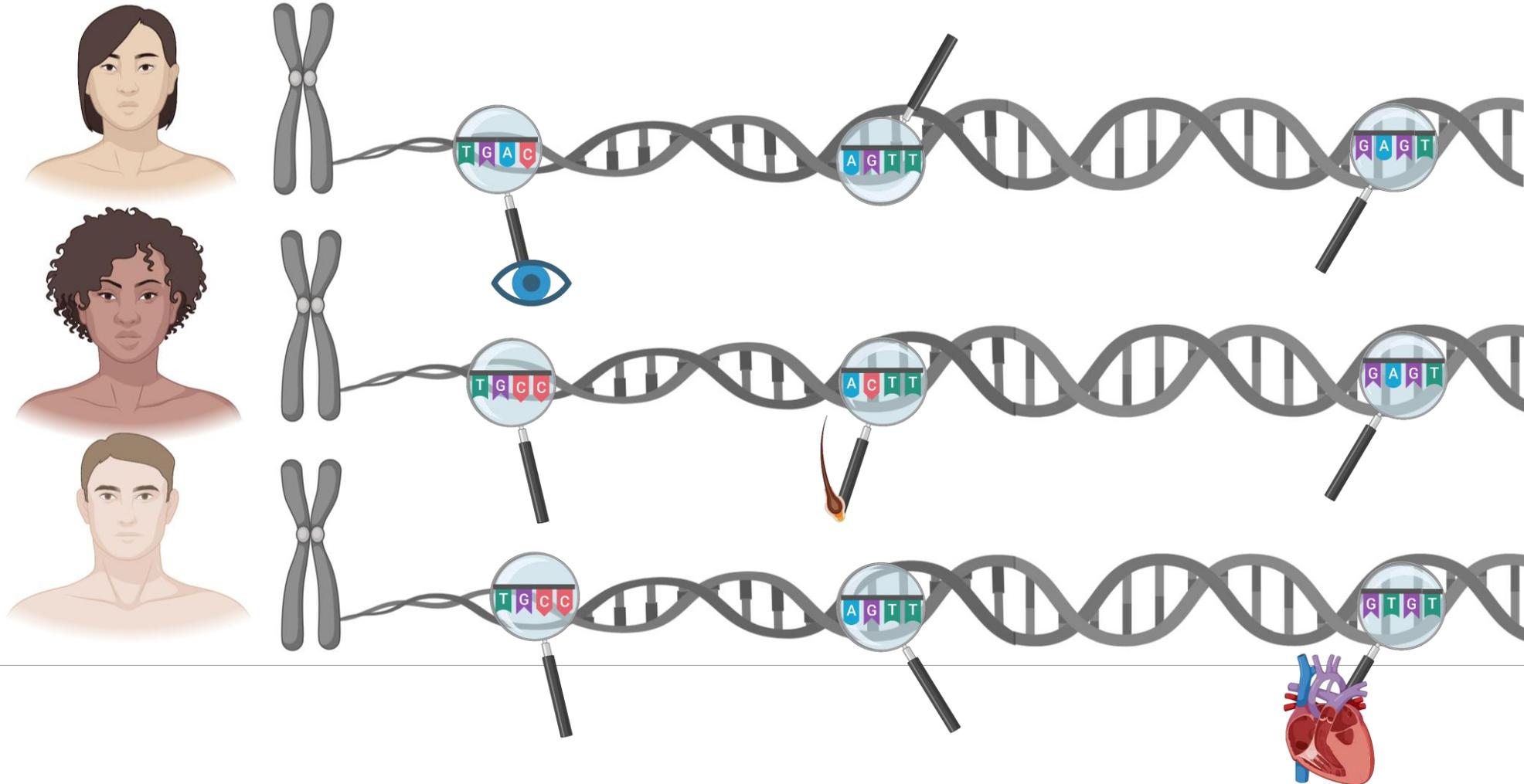
Twitter: @anshulkundaje

Website: <http://anshul.kundaje.net>

Genetic variants associated with traits and diseases

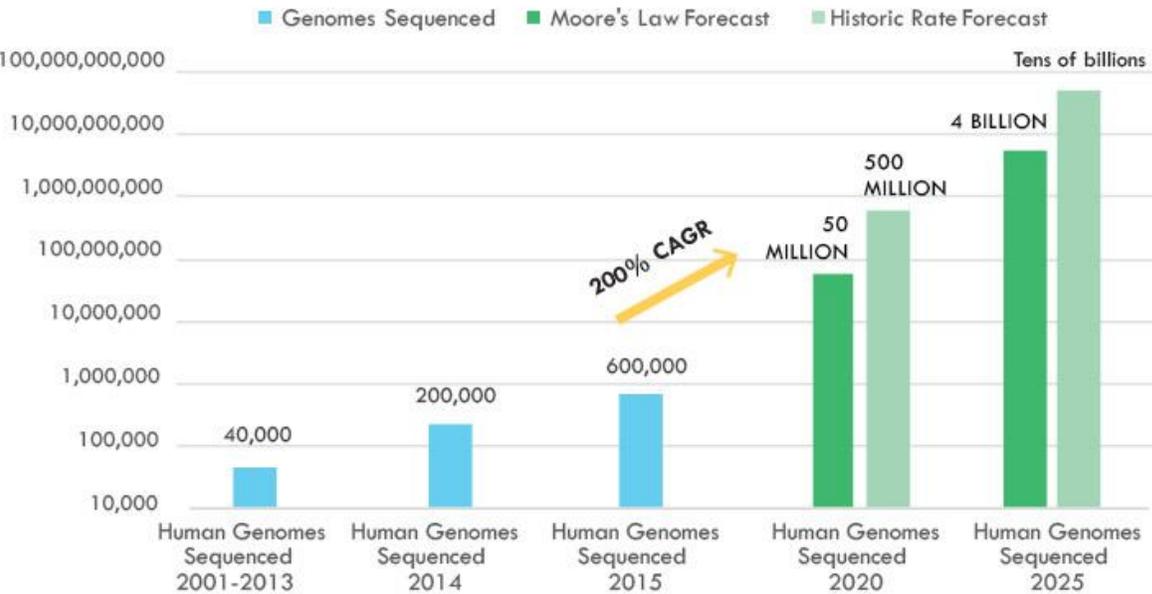


Genetic variants associated with traits and diseases



Population sequencing to identify disease-associated genetic variants

The Number of Human Genomes Sequenced (log scale)



Source: National Human Genome Research Institute (NHGRI), ARK Investment Management LLC



GA II
1.6 billion bp per day
(2008)



GA IIX
5 billion bp per day
(2009)



HiSeq 2500
60 billion bp per day
(2012)



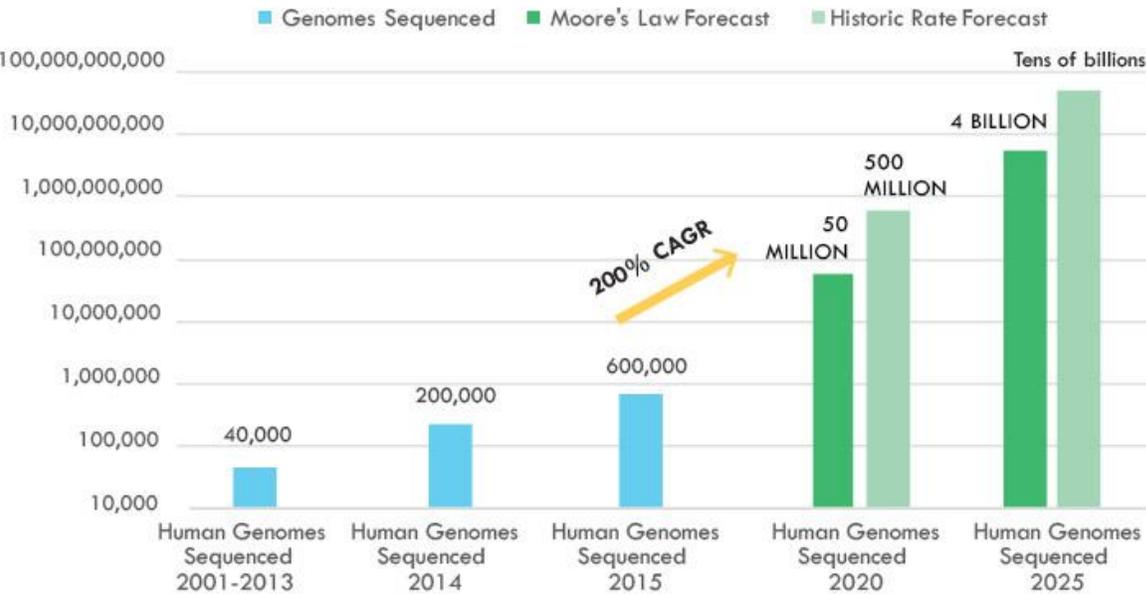
Oxford Nanopore
technology

Images: www.illumina.com/systems
Numbers: www.politgenomics.com/next-generation-sequencing-informatics
Dates: Illumina press releases

Millions of common and rare genetic variants found in human population

Population sequencing to identify disease-associated genetic variants

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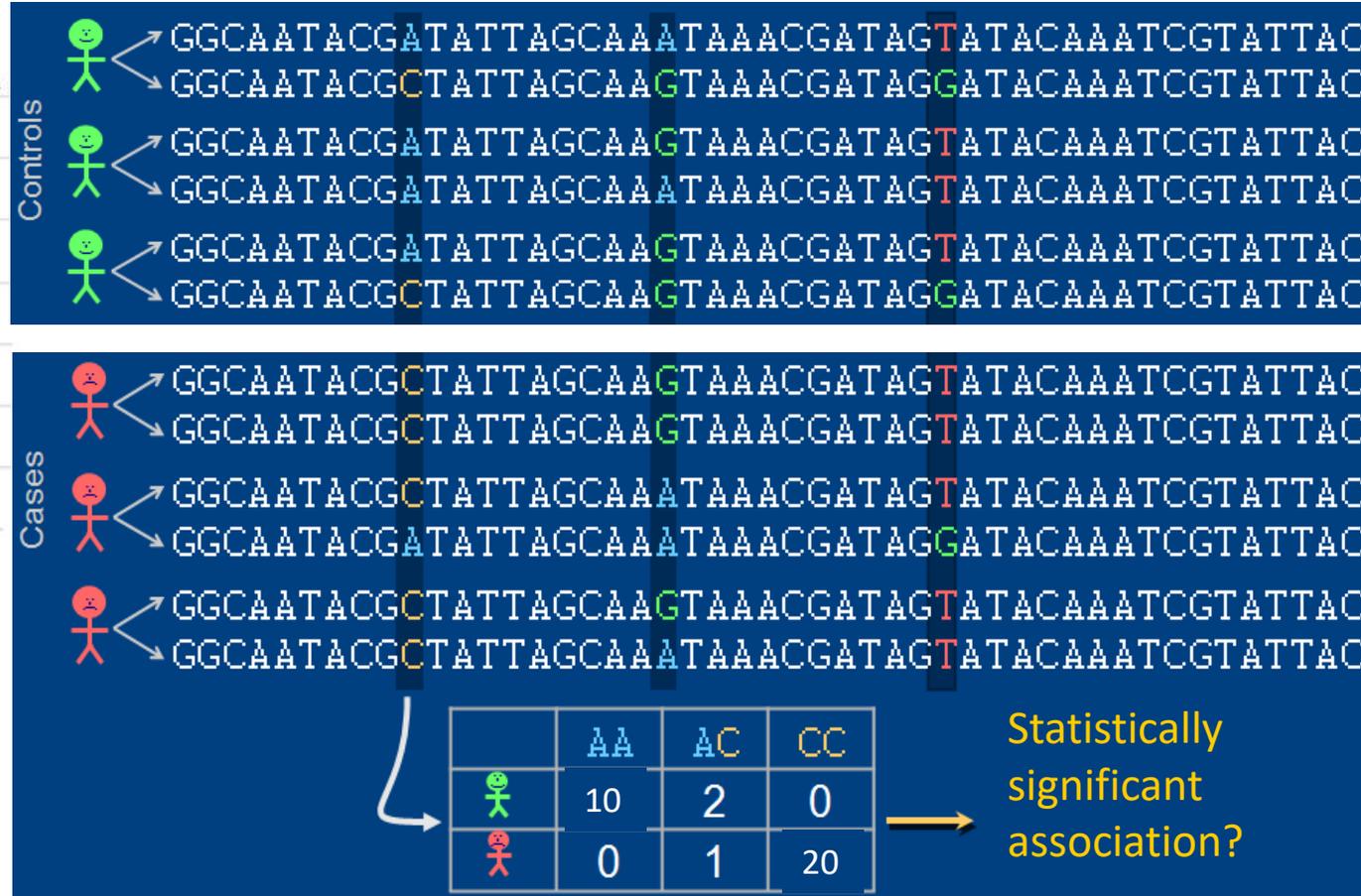


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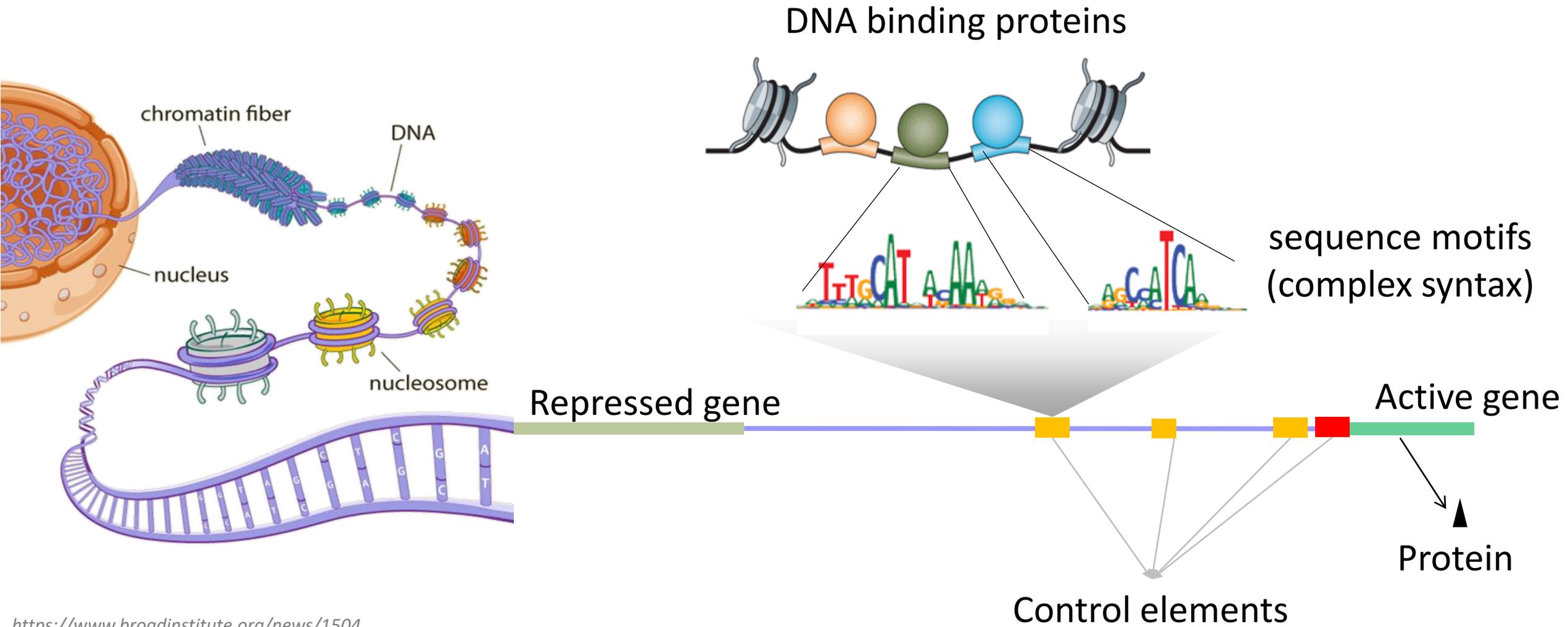


Millions of common and rare genetic variants found in human population

TGCCAAGCAGCAAAGTTTTGCTGCTGTTTATTTTTGTAGCTCTTACTATATTCT
ACTTTTACCATTGAAAATATTGAGGAAGTTATTTATATTTCTATTTTTTATATAT
TATATATTTTATGTATTTAATATACTATTACACATAATTATTTTTTATATATATGA
AGTACCAATGACTTCCTTTTCCAAGCAATAATGAAATTTACAGTATGAAA
ATGGAAGAAATCAATAAAATTATACGTGACCTGTGGCGAAGTACCTATCGTG
GACAAGGTGAGTACCATGGTGTATCA^AAAATGCTCTTTCCAAAGCCCTCTCC
GCAGCTCTTCCCCTTATGACCTCTCATCATGCCAGCATTACCTCCCTGGACCC
CTTTCTAAGCATGTCTTTGAGATTTTCTAAGAATTCTTATCTTGGCAACATCTT
GTAGCAAGAAAATGTAAAGTTTTCTGTTCCAGAGCCTAACAGGACTTACATA
TTTGACTGCAGTAGGCATTATATTTAGCTGATGACATAATAGGTTCTGTCATA
GTGTAGATAGGGATAAGCCAAAATGCAATAAGAAAAACCATCCAGAGGAA
ACTCTTTTTTTTTTCTTTTTCTTTTTTTTTTTTTCCAGATGGAGTCTCGCACTTC
TCTGTCACCCGGGCTGGAGCGCAGTGGTGCAATCTTGGCTCACTGCAACCT
CCACCTCCTGGGTTTCAGGTGATTCTCCACCTCAGCCTCCCGAGTAGTAGCT
GGAATTACAGGTGCGCGCTCCACACCTGGCTAATTTTTTGTATTCTTAGTA
GAGATGGGGTTTCACCATGTTGGCCAGGCTGGTCTCAAACCTCCTGCCCTCA
GGTGATCTGCCACCTTGGCCTCCAGTGTTGGGTTTACAGGCGTGAGCCA
CCGCGCCTGGCCTGGAGGAACTCTAACAGGGGAACTAAGAAAGAGTTG
AGGCTGAGGAACTGGGGCATCTGGGTTGCTTCTGGCCAGACCACCAGGCT
CTTGAATCCTCCCAGCCAGAGAAAGAGTTTCCACACCAGCCATTGTTTTCT
CTGGTAATGTCAGCCTCATCTGTTGTTCTAGGCTTACTTGATATGTTTGTA
ATGACAAAAGGCTACAGAGCATAGGTTCTCTAAAATATTCTTCTTCTGTGT
CAGATATTGAATACATAGAAATACGGTCTGATGCCGATGAAAATGTATCAGCT
TCTGATAAAAGGCGGAATTATAACTACCGAGTGGTGATGCTGAAGGGAGAC
ACAGCCTTGGATATGCGAGGACGATGCAGTGCTGGACAAAAGGCAGGTAT
CTCAAAGCCTGGGGAGCCAACCTACCCAAGTAACTGAAAGAGAGAAACA
AACATCAGTGCAGTGGAAAGCACCCAAGGCTACACCTGAATGGTGGGAAGC
TCTTTGCTGCTATATAAAATGAATCAGGCTCAGCTACTATTATT

What is the functional
consequence of genetic
variants?

Functional components of the human genome



>95% of disease variants are not disrupting protein coding gene regions

Benign

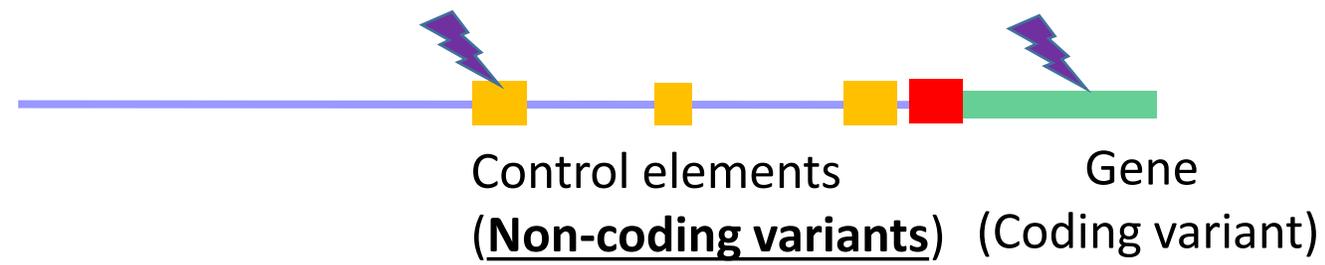
.....ACTGATCG**C**AATCG.....



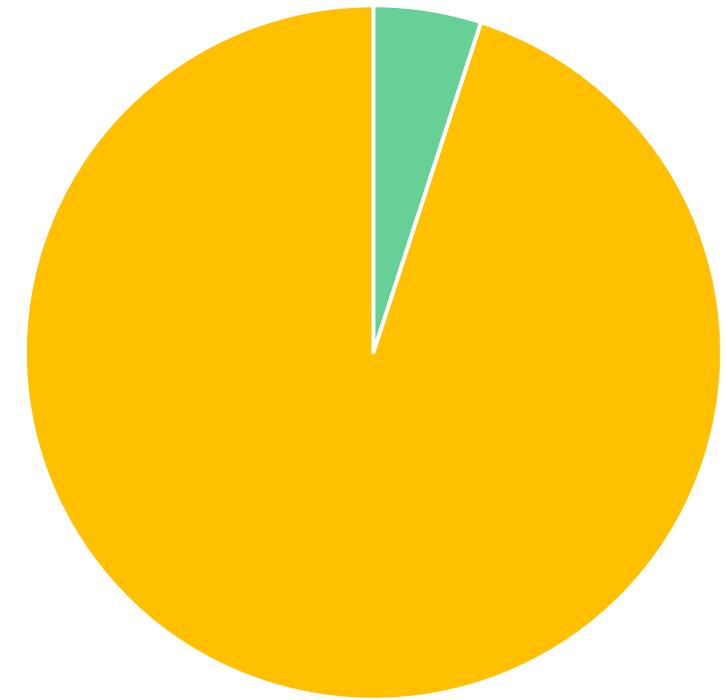
.....ACTGATCG**G**AATCG.....

Risk

>95% of disease variants are not disrupting protein coding gene regions

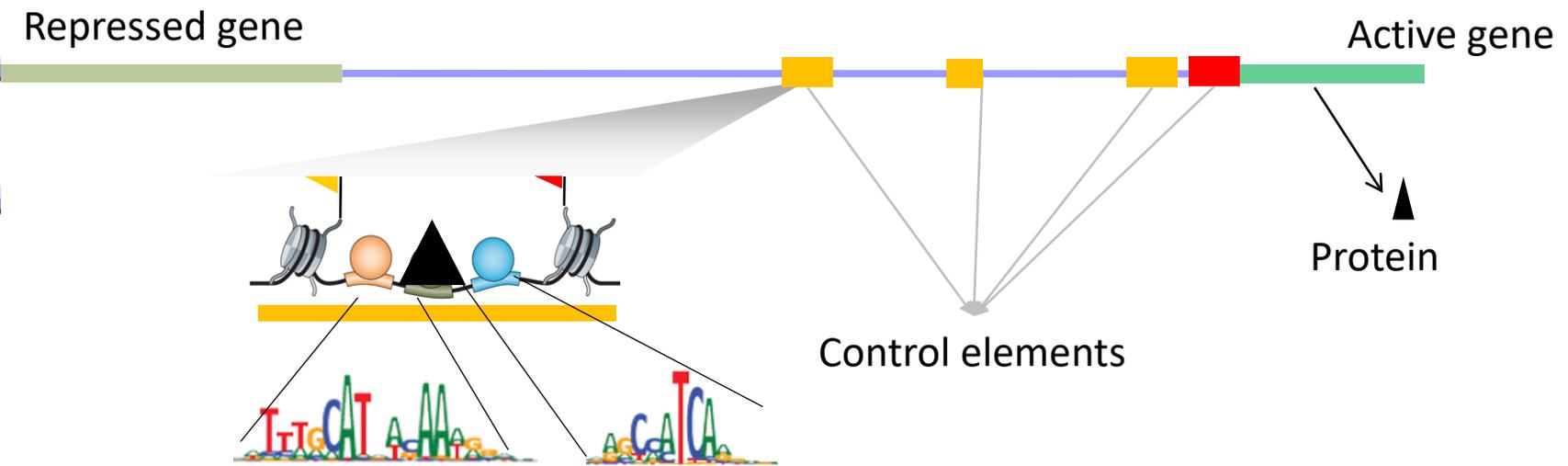
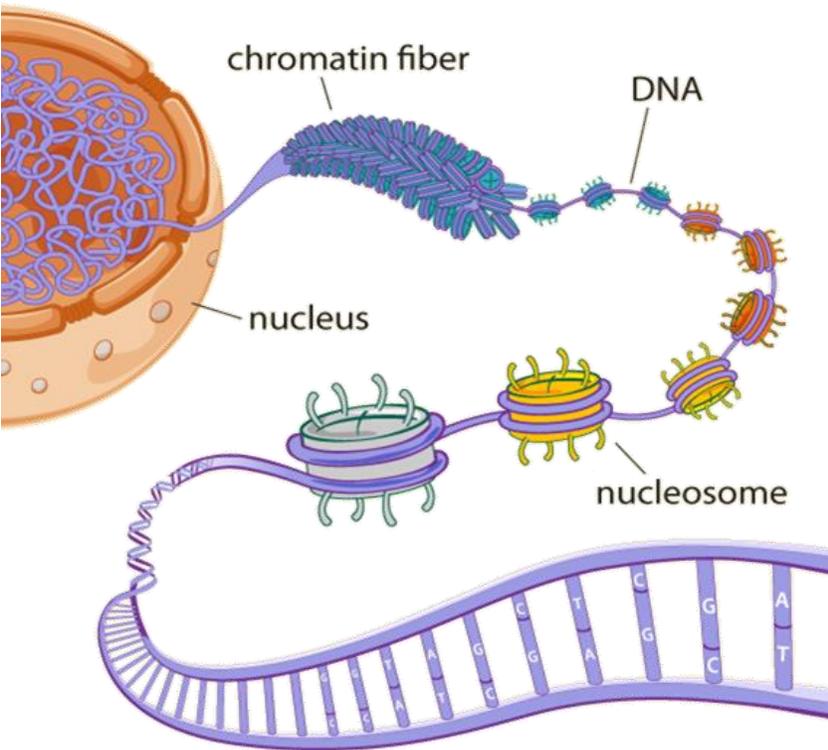


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Risk



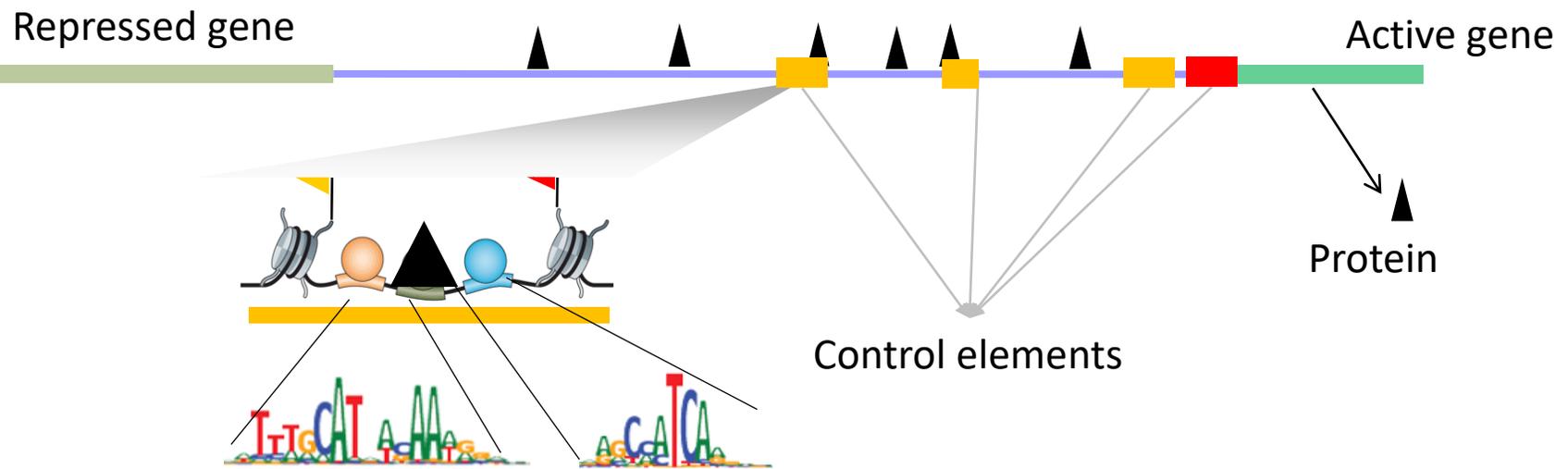
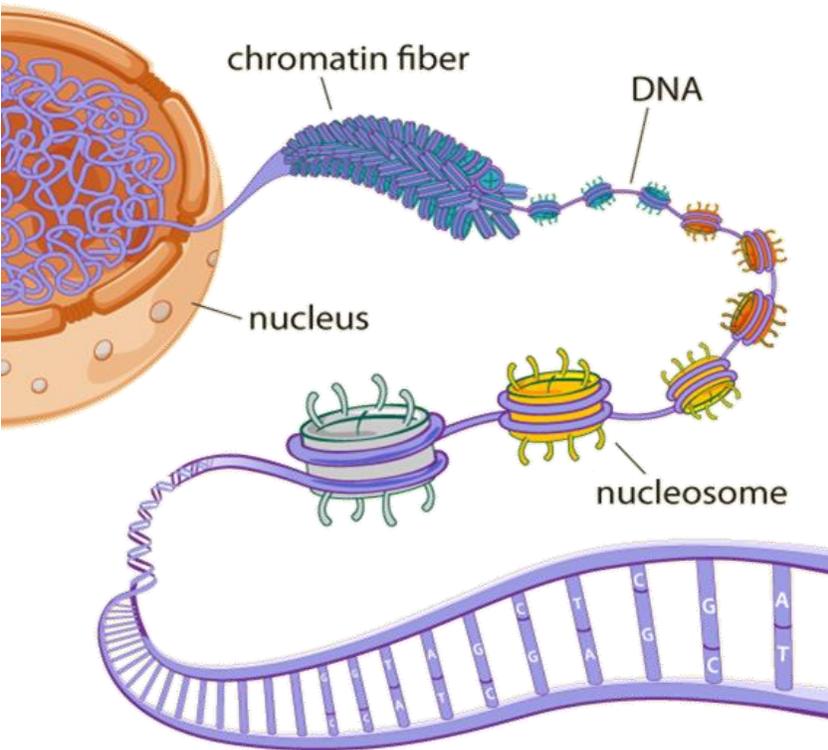
■ Coding ■ Non-coding

Molecular mapping of functional components of the genome



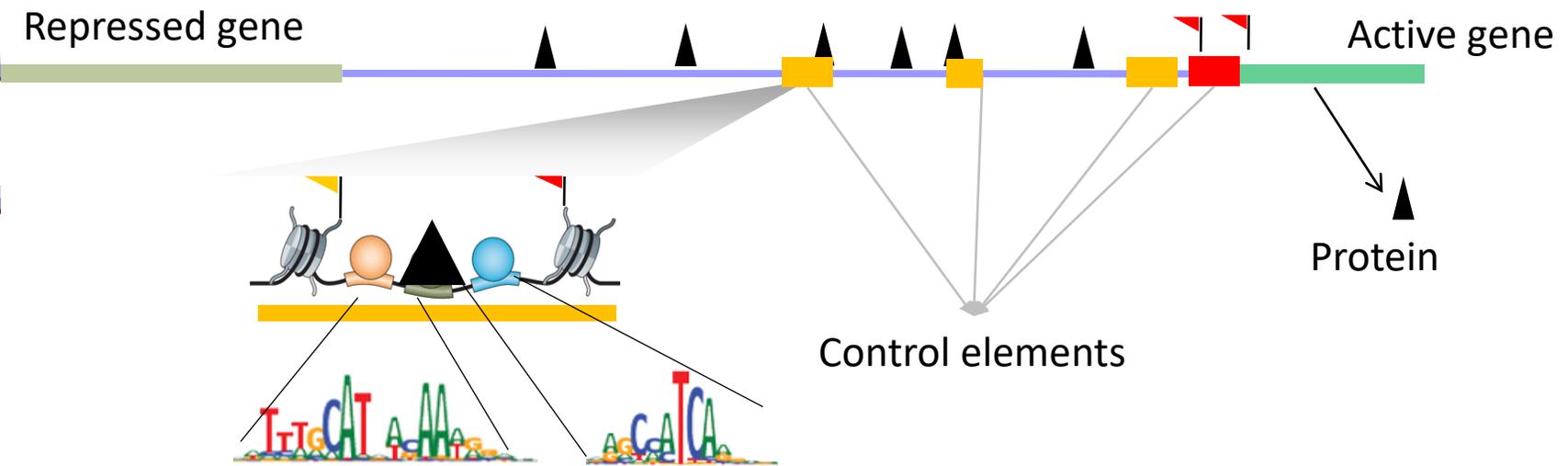
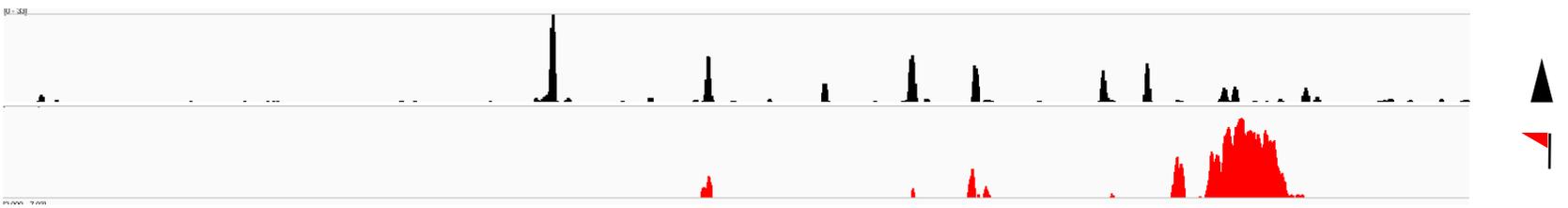
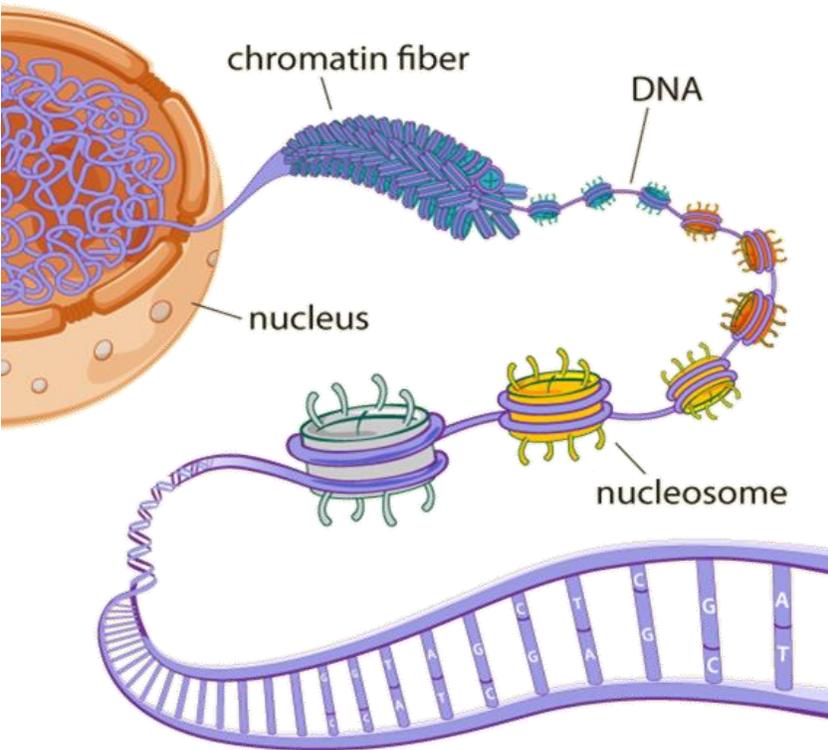
<https://www.broadinstitute.org/news/1504>

Molecular mapping of functional components of the genome



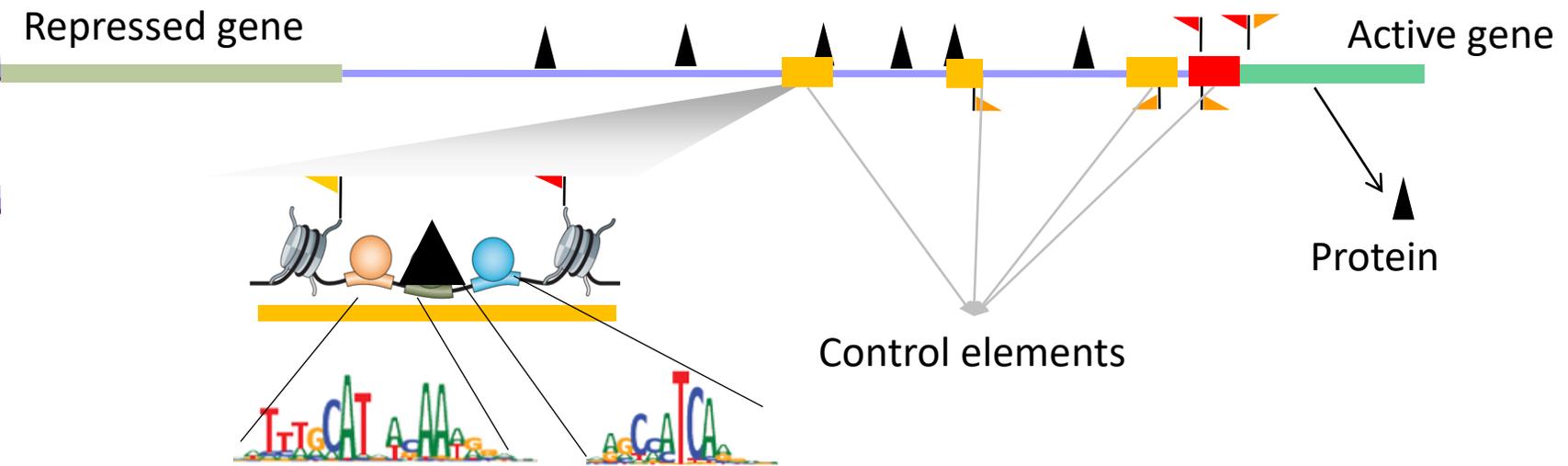
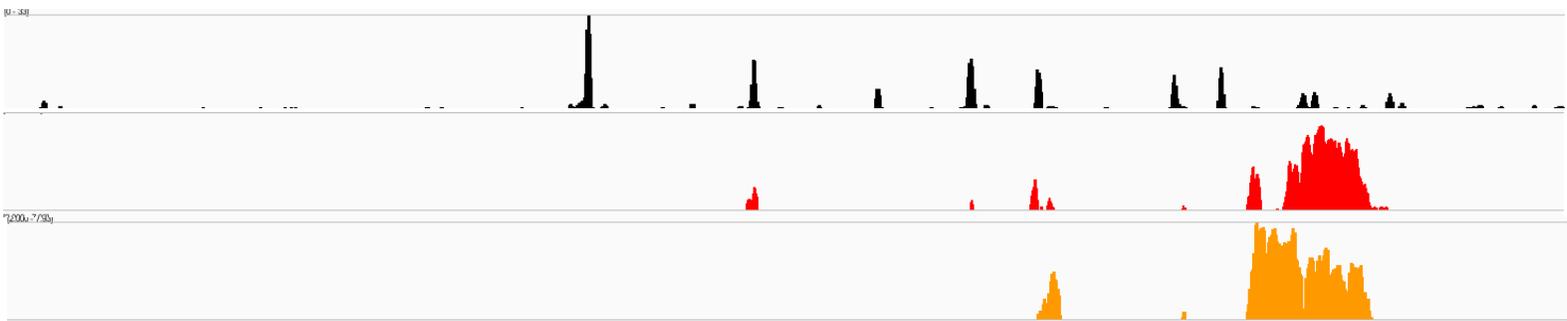
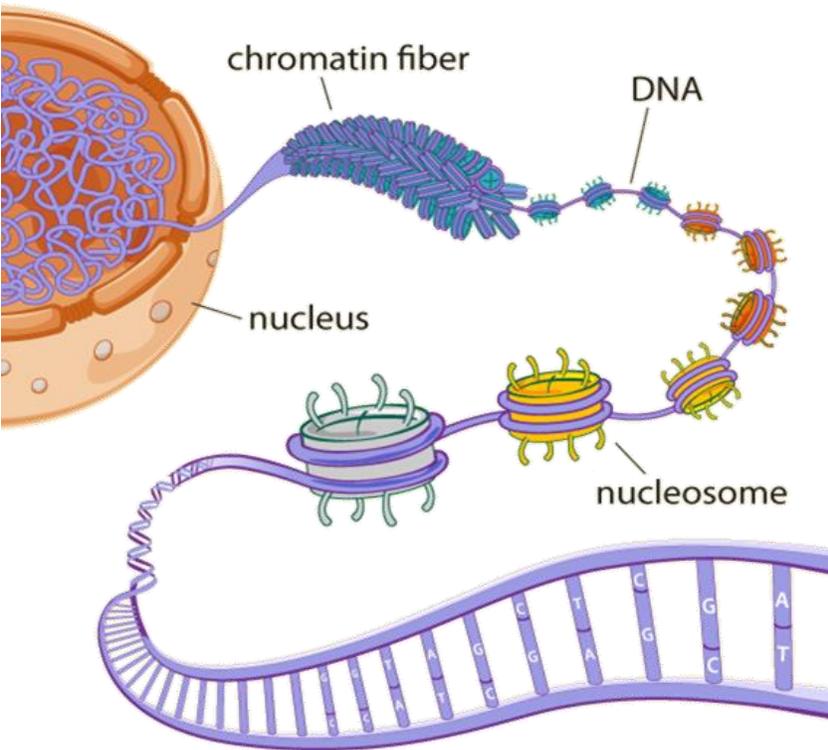
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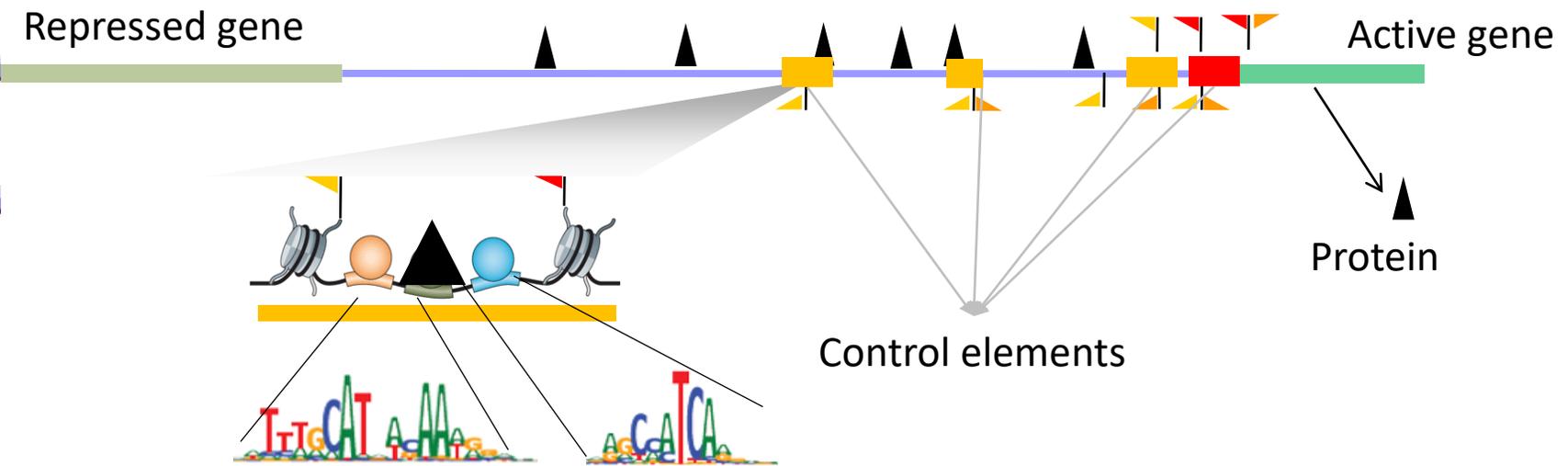
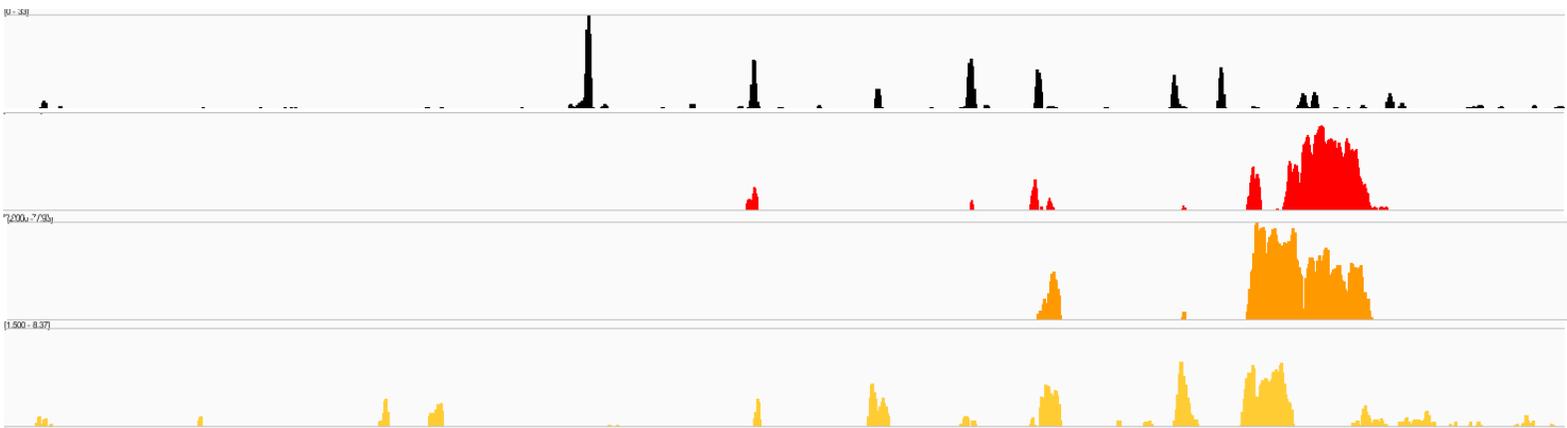
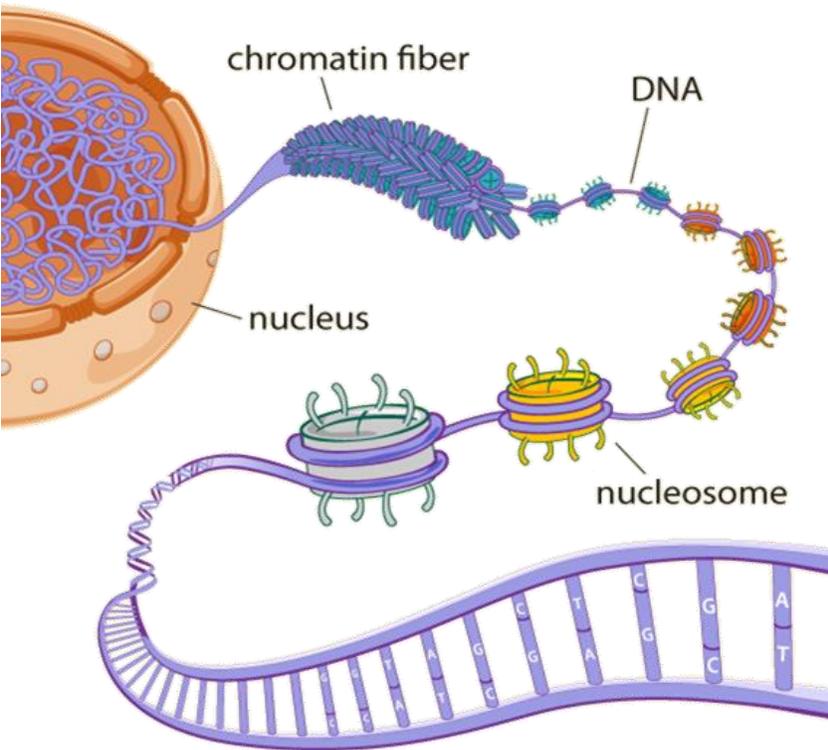
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Molecular mapping of functional components of the genome



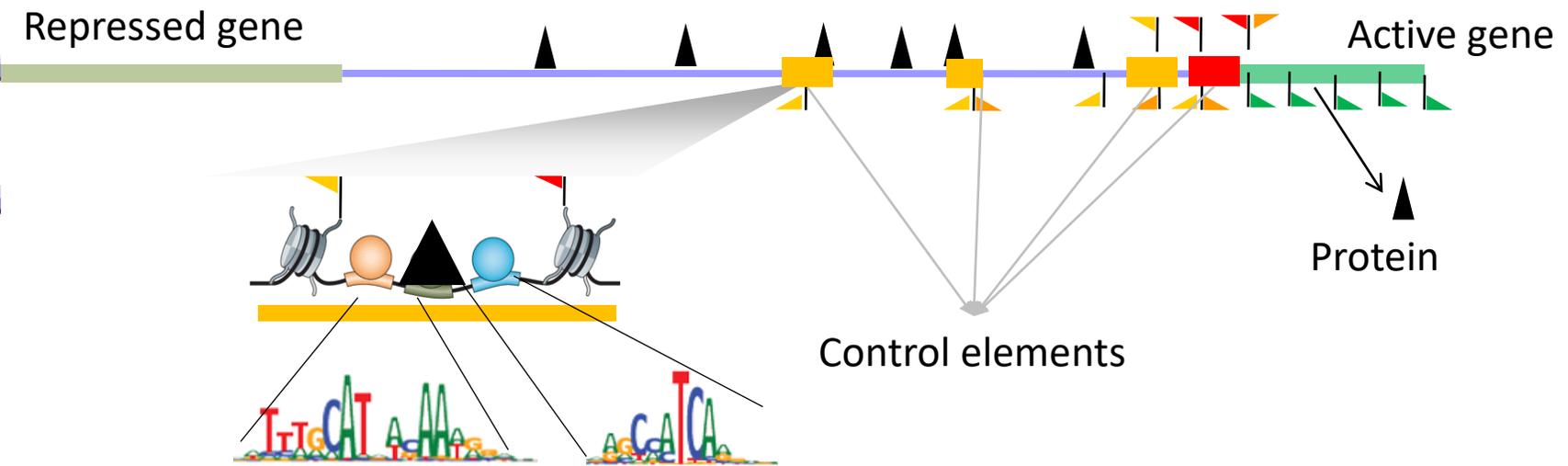
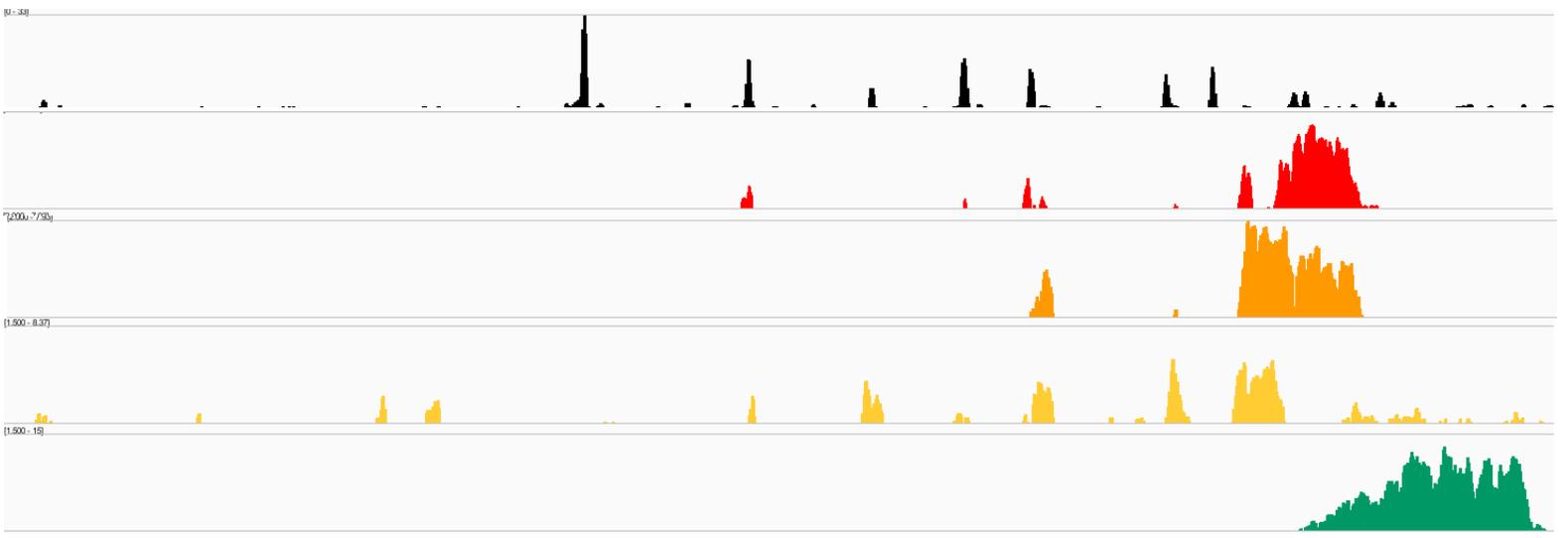
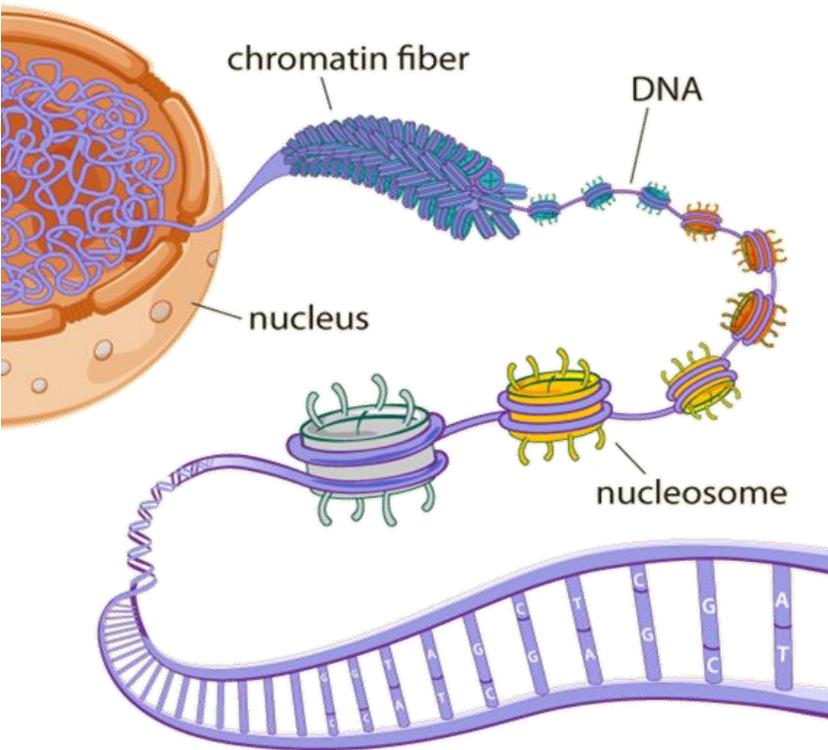
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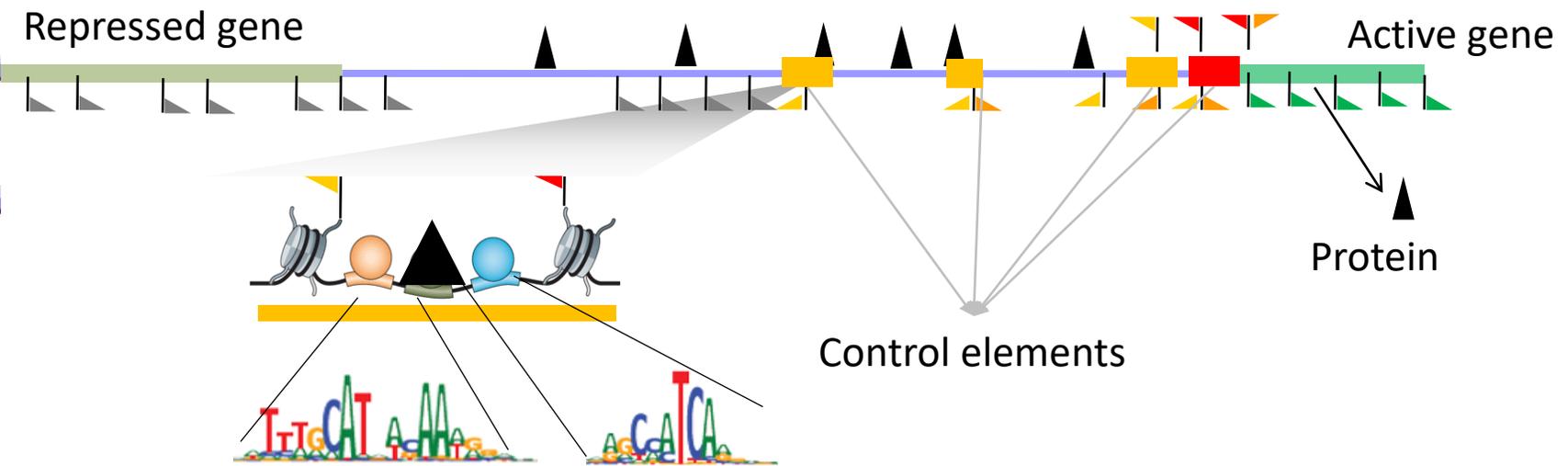
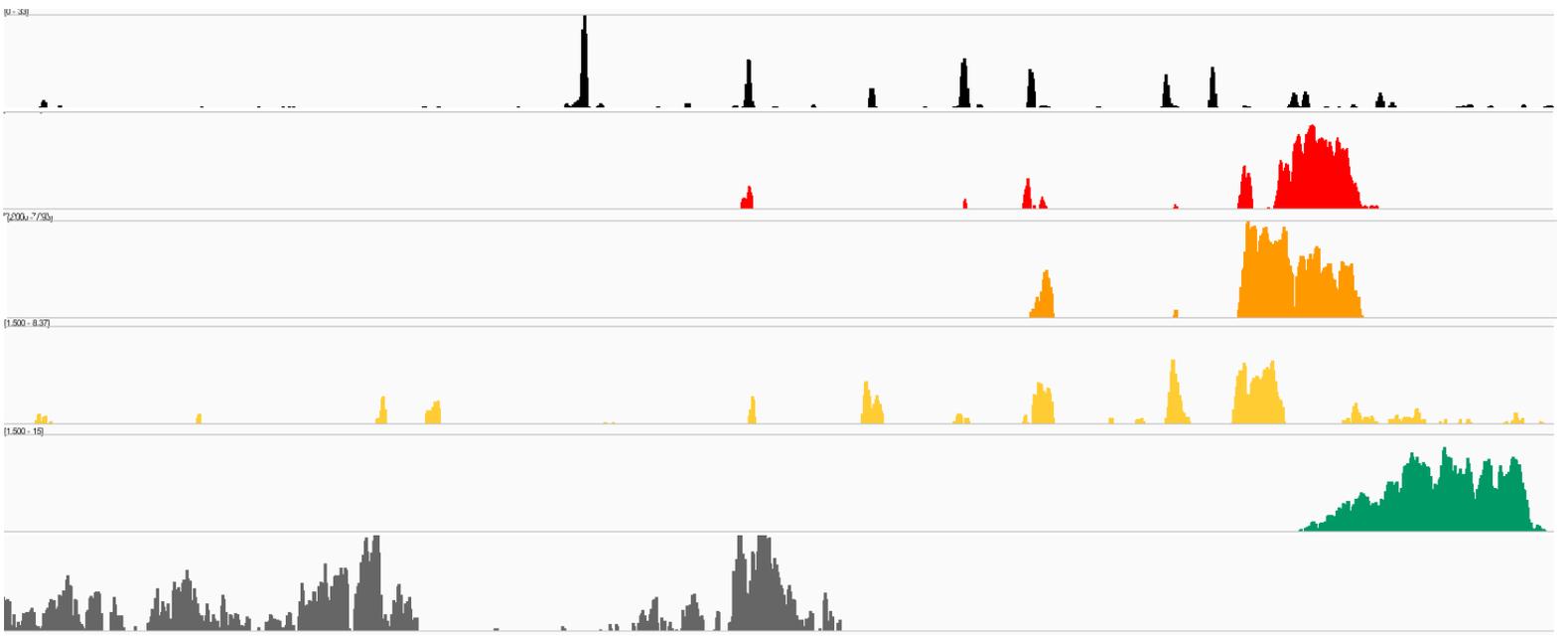
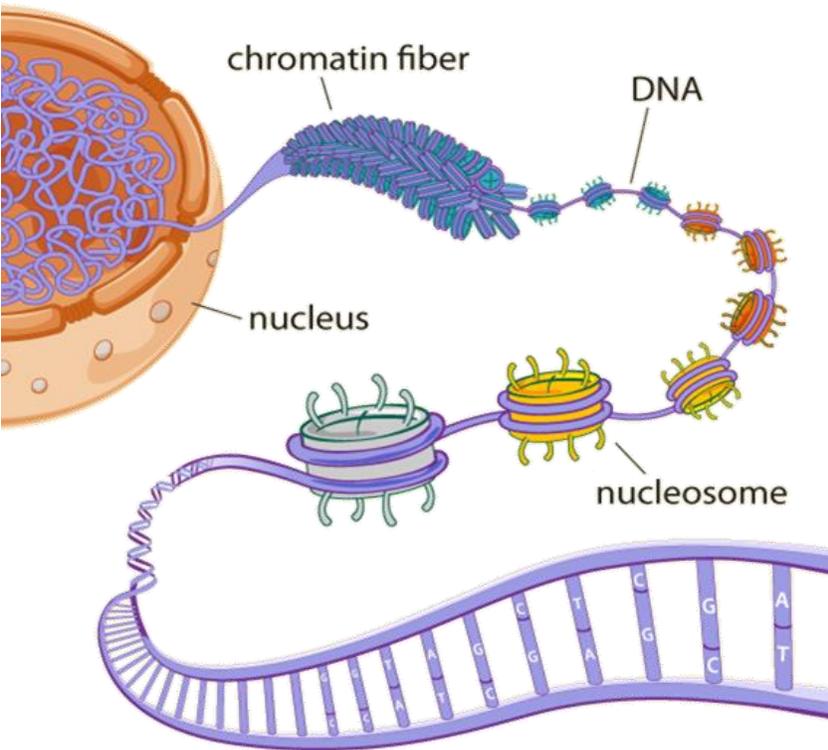
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Molecular mapping of functional components of the genome



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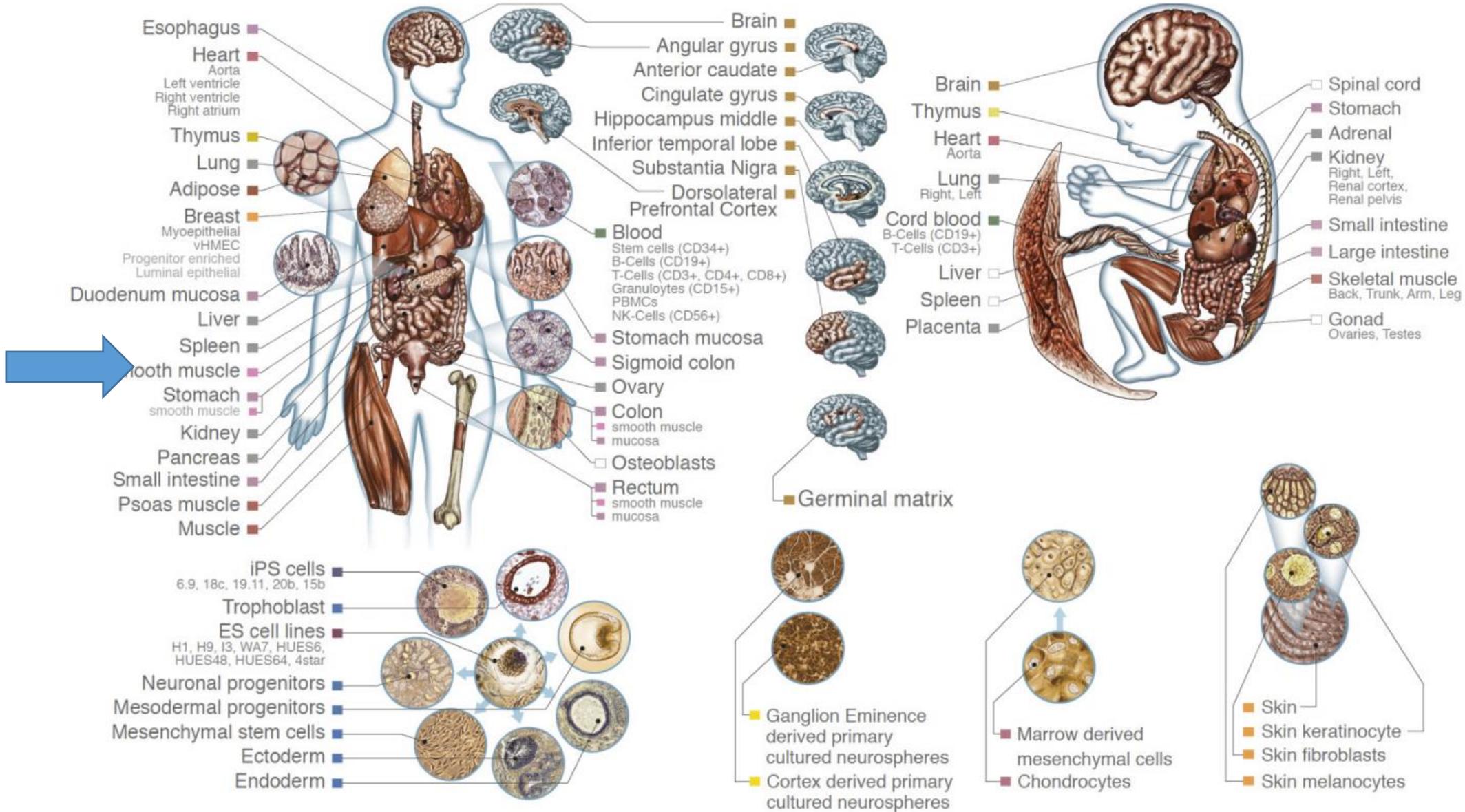
Molecular mapping of functional components of the genome

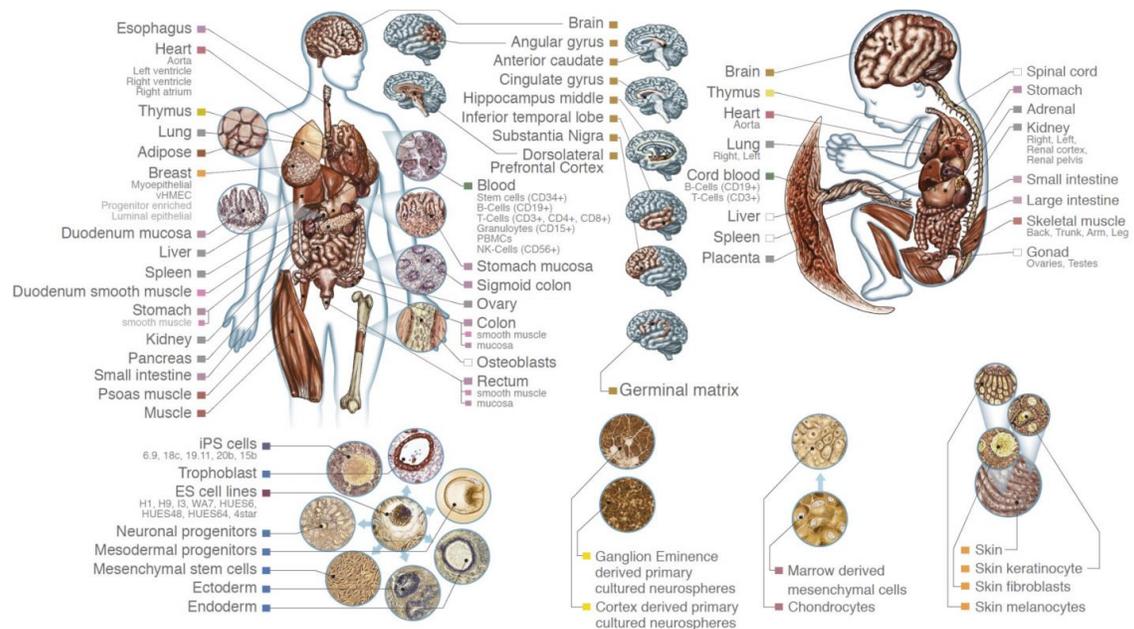
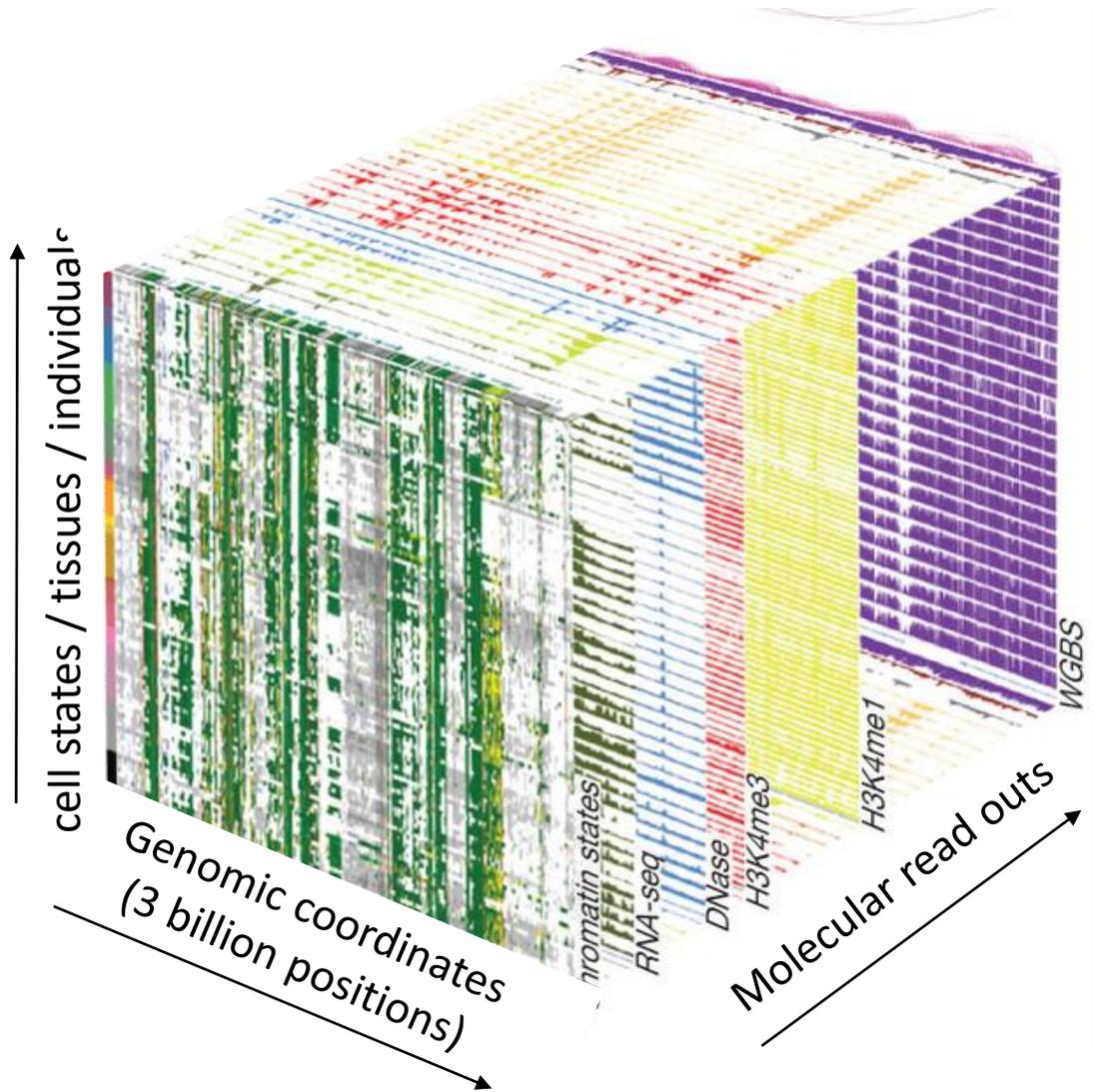
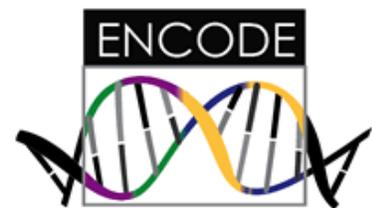


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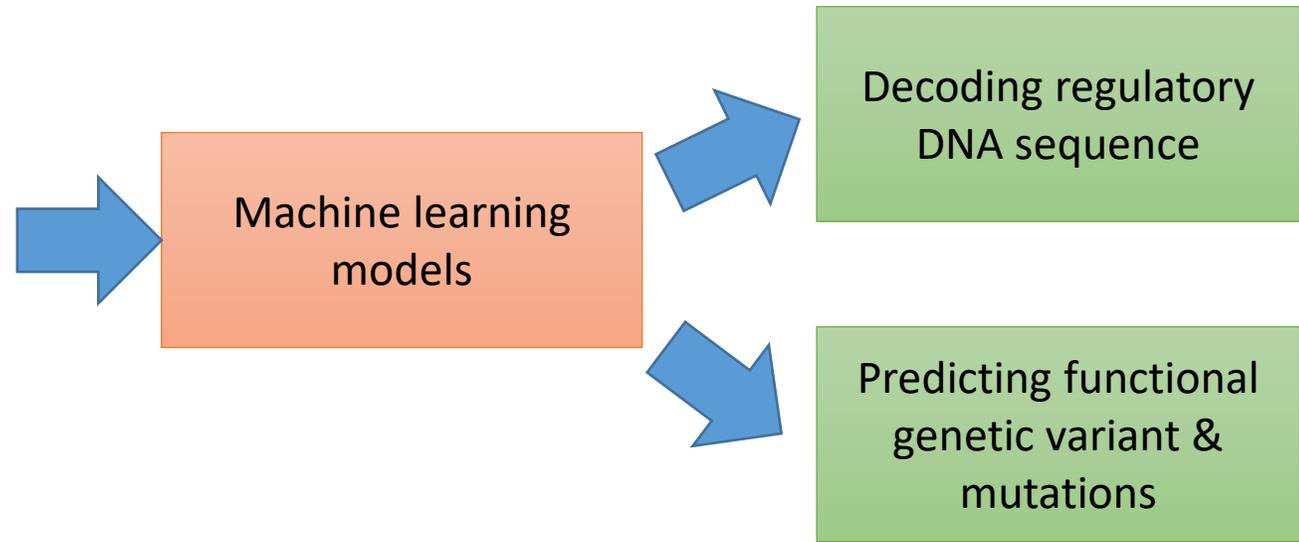
One genome ⇔ many cell types

ACCAGTTACGACGG
 TCAGGGTACTGATA
 CCCCAAACCGTTGA
 CCGCATTTACAGAC
 GGGGTTTGGGTTTT
 GCCCCACACAGGTA
 CGTTAGCTACTGGT
 TTAGCAATTTACCG
 TTACAACGTTTACA
 GGGTTACGGTTGGG
 ATTTGAAAAAAGT
 TTGAGTTGGTTTTT
 TCACGGTAGAACGT
 ACCTTACAAA.....





100s of Cell-Types/Tissues

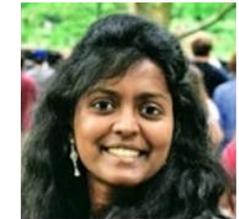


Dunham, Kundaje et al. 2012 Nature
Kundaje et al. 2015 Nature

Deep learning framework for decoding regulatory DNA



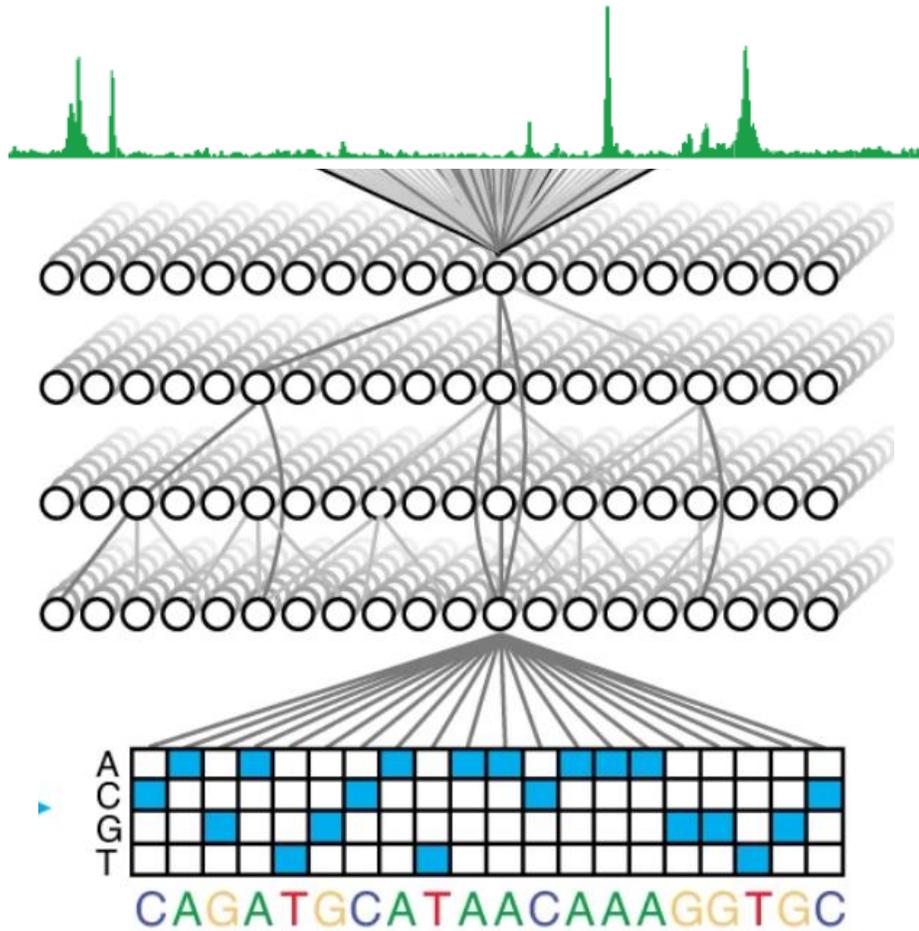
Ziga Avsec



Anusri Pampari



Anna Shcherbina



Avanti Shrikumar



Alex Tseng



Surag Nair



Jacob Schreiber

BPNet

(maps sequence to base-resolution profiles)

One model for every expt.

Avsec et al. 2021, Nature Genetics

Shrikumar et al. 2017, ICML

Tseng et al. 2020, NeurIPS

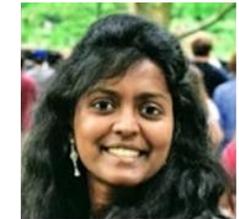
Nair et al, 2022, Bioinformatics

Schreiber et al. 2022, Biorxiv

Deep learning framework for decoding regulatory DNA



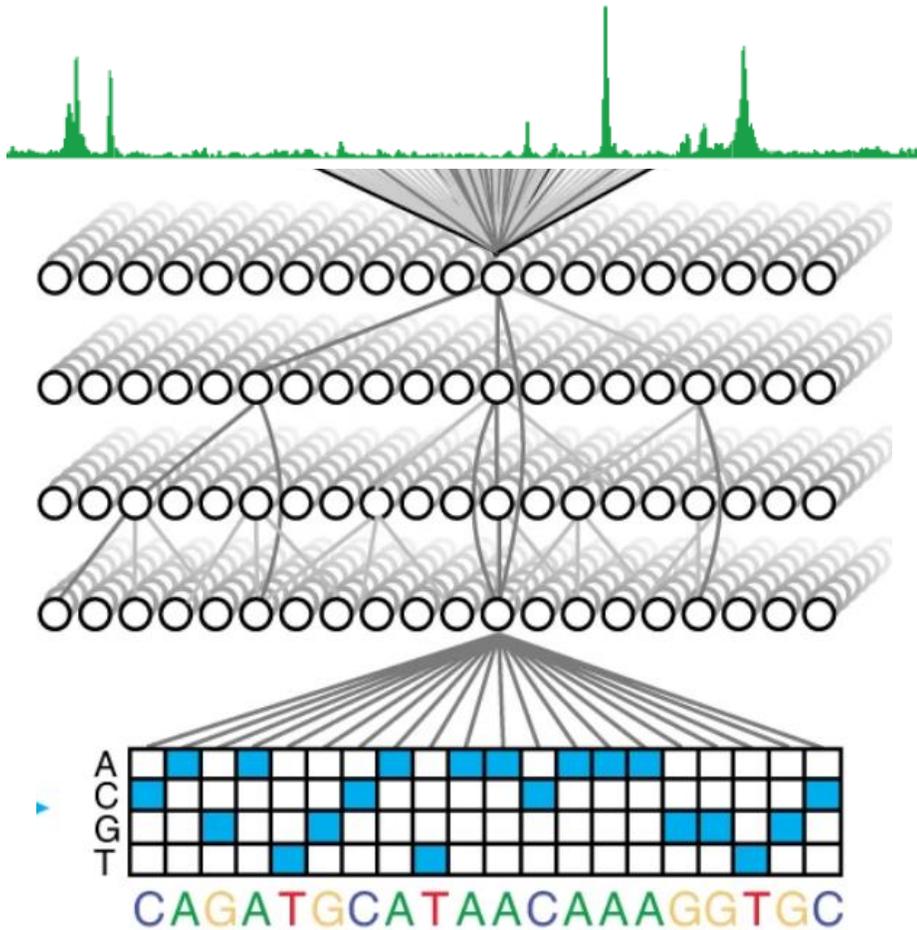
Ziga Avsec



Anusri Pampari



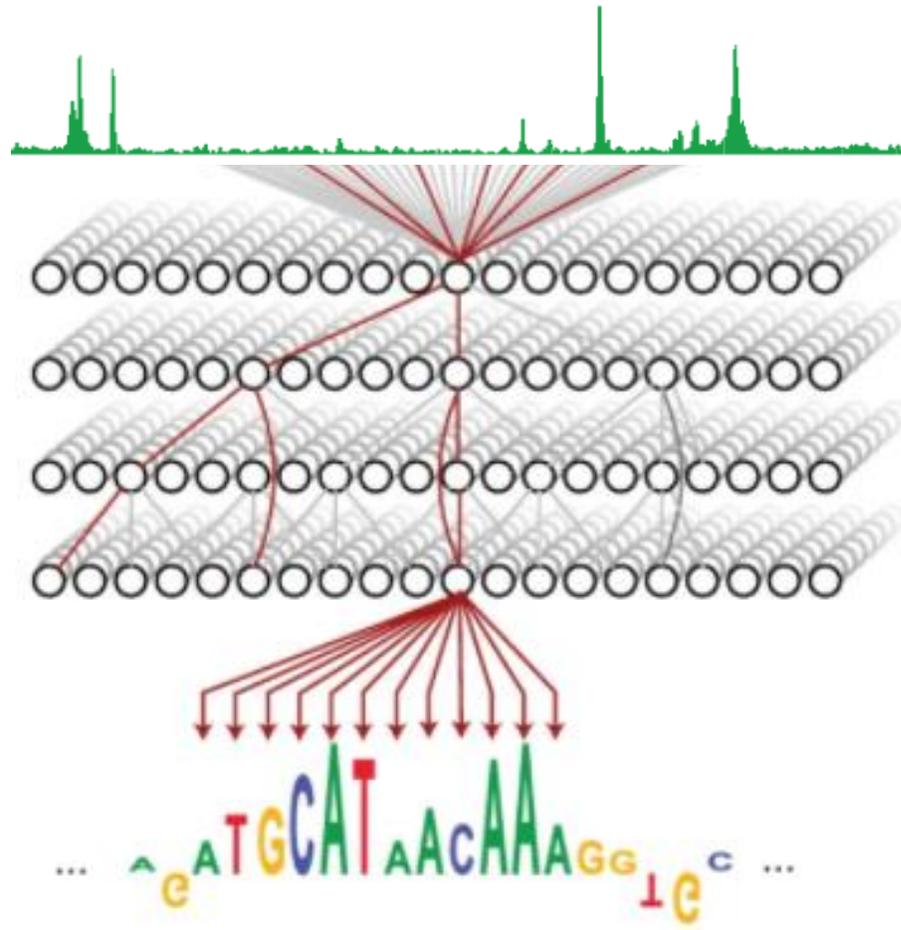
Anna Shcherbina



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Avsec et al. 2021, Nature Genetics
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Tseng et al. 2020, NeurIPS
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Schreiber et al. 2022, Biorxiv



DeepLIFT, FastISM, Yuzu, MoDISCo

(infers contribution of every base in each control sequence thru lens of model)



Avanti Shrikumar



Alex Tseng

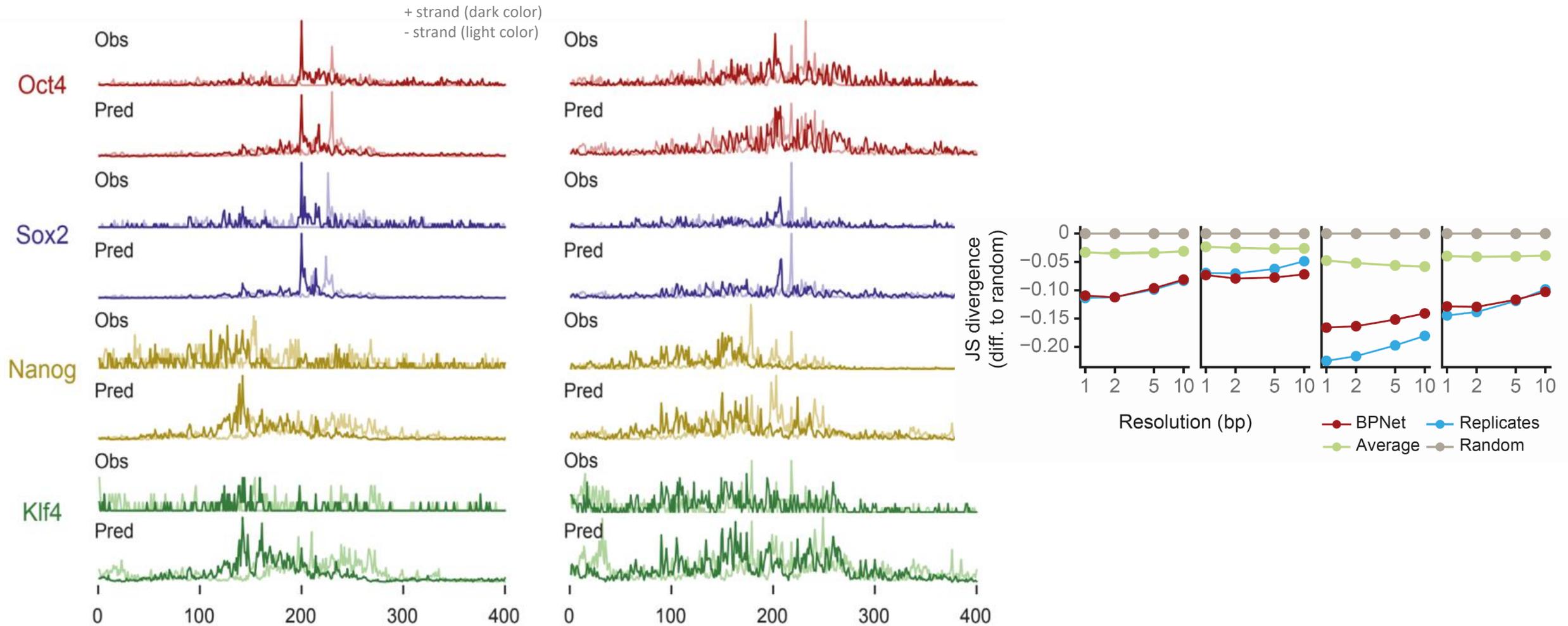


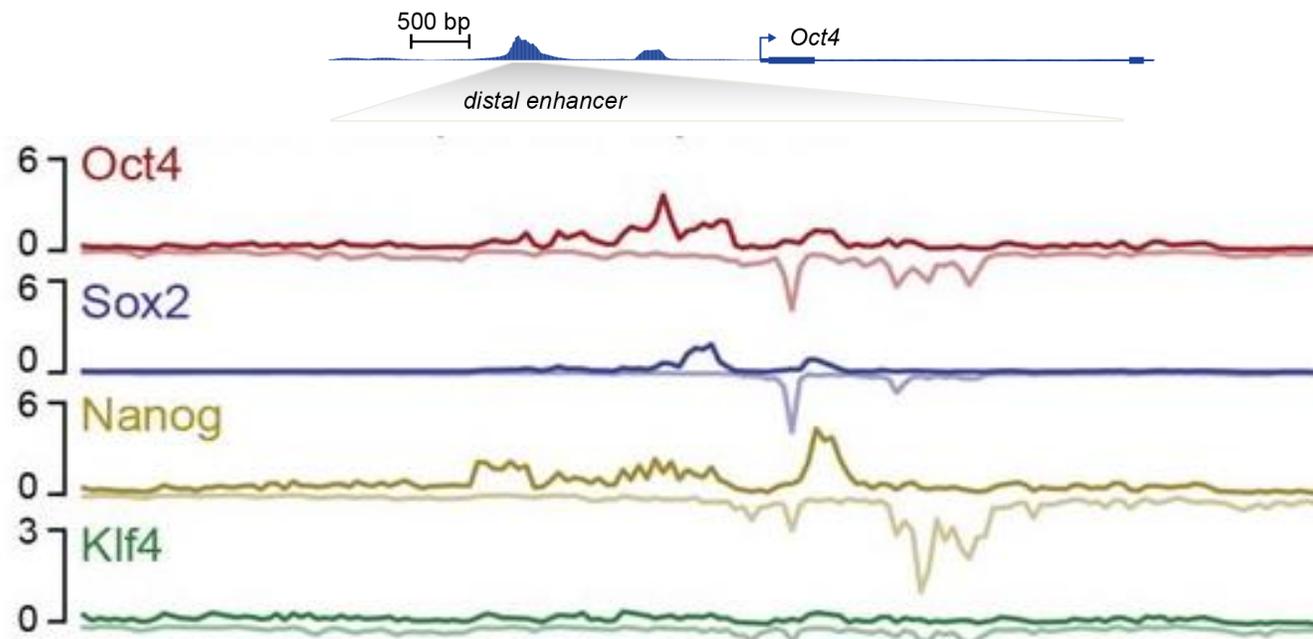
Surag Nair



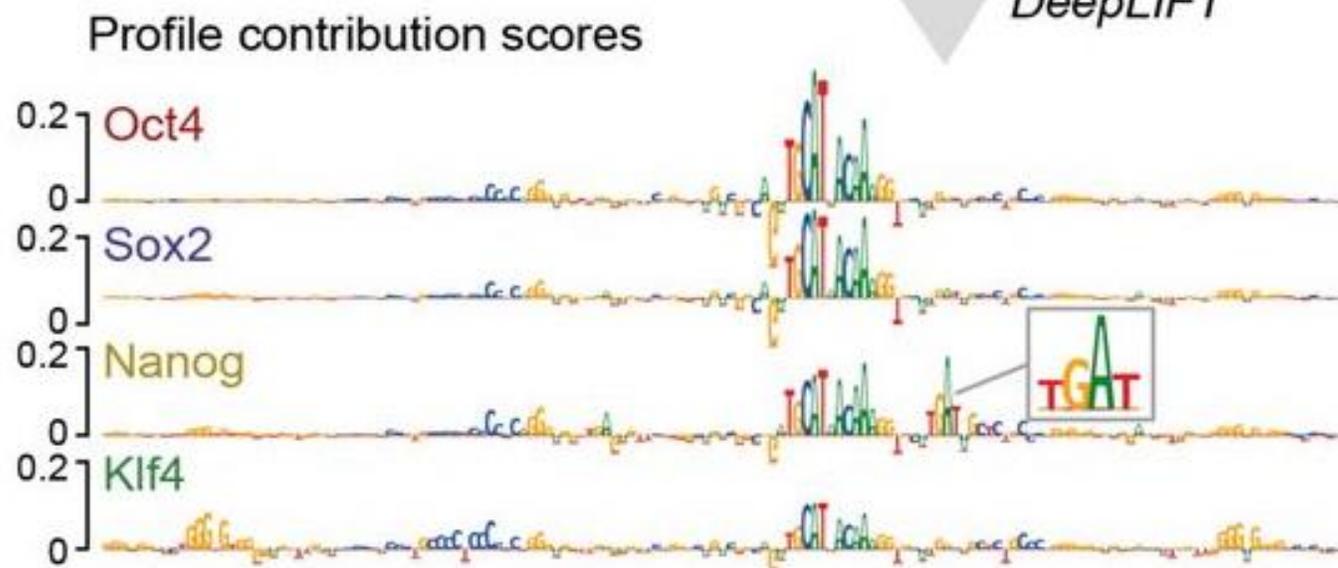
Jacob Schreiber

BpNet maps DNA sequence to base-resolution molecular profiles with unprecedented accuracy (on par with concordance between replicate experiments)





DeepLIFT

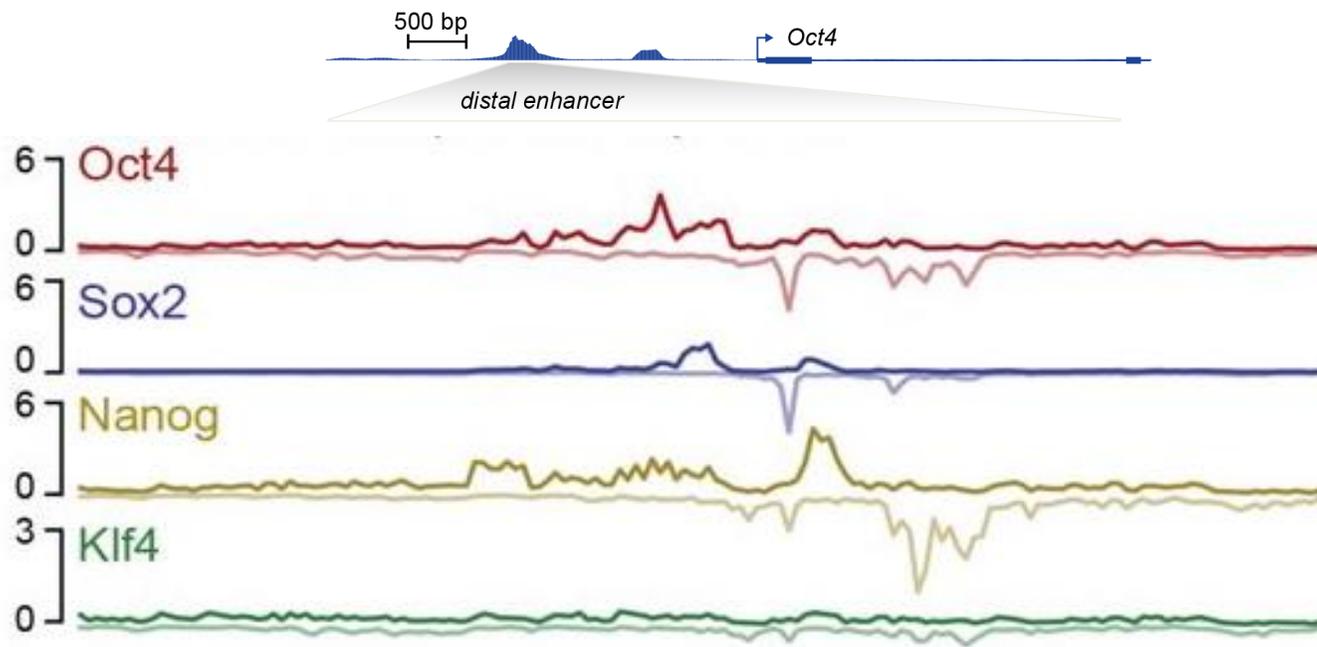


Avanti Shrikumar



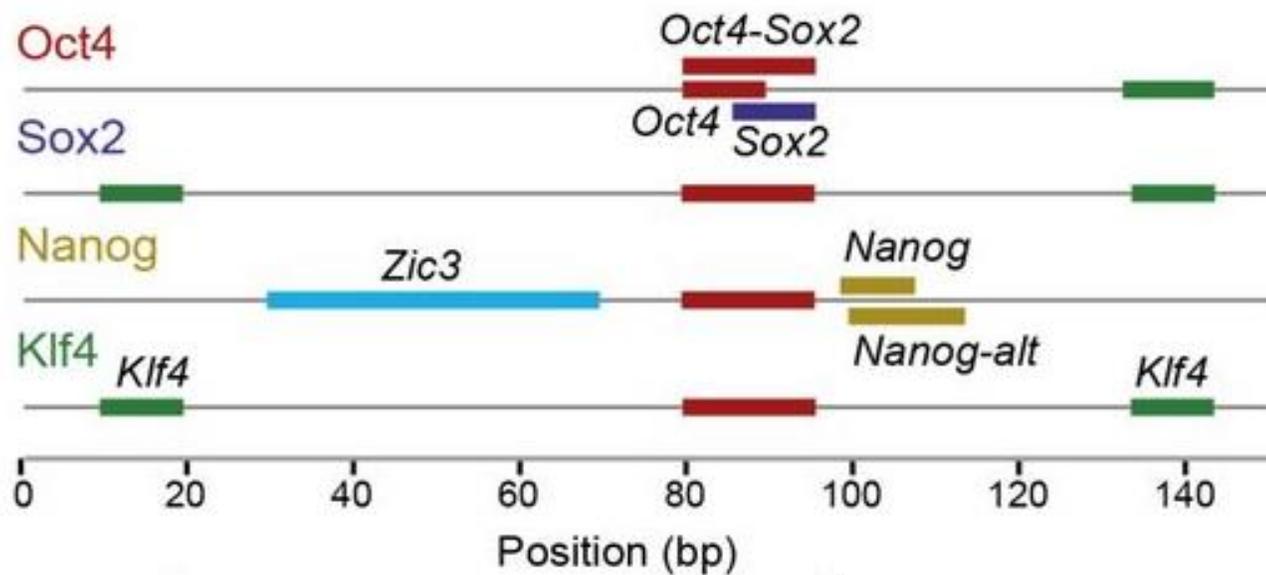
Alex Tseng

Shrikumar et al. 2017 ICML
 Shrikumar et al. 2019 ISMB
 Tseng et al. 2020 NeurIPS
 Greenside et al. 2018, ECCB



Profile contribution scores

DeepLIFT



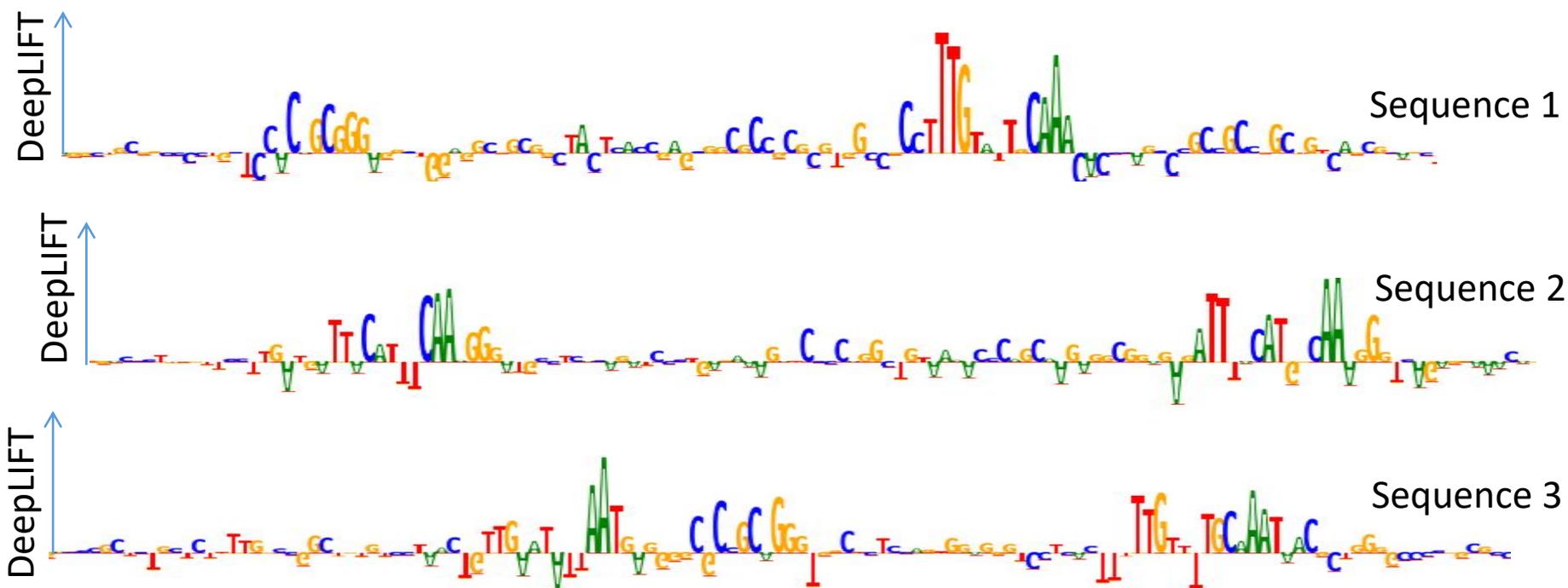
Avanti Shrikumar



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TF-MoDISCO: Consolidate predictive subsequences into non-redundant motif representations

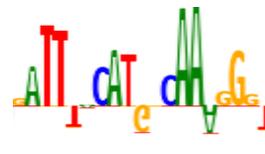
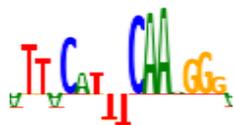
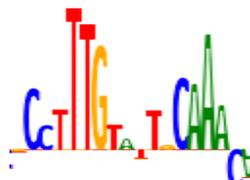


Avanti Shrikumar



Alex Tseng

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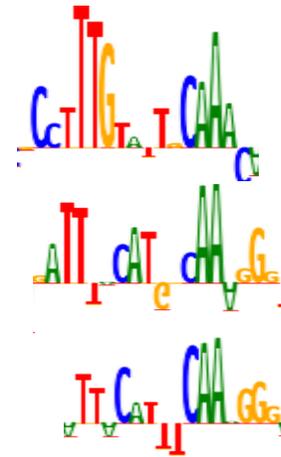
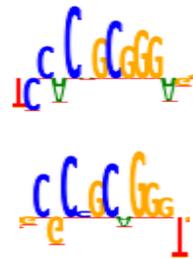


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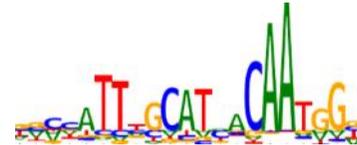


Avanti Shrikumar



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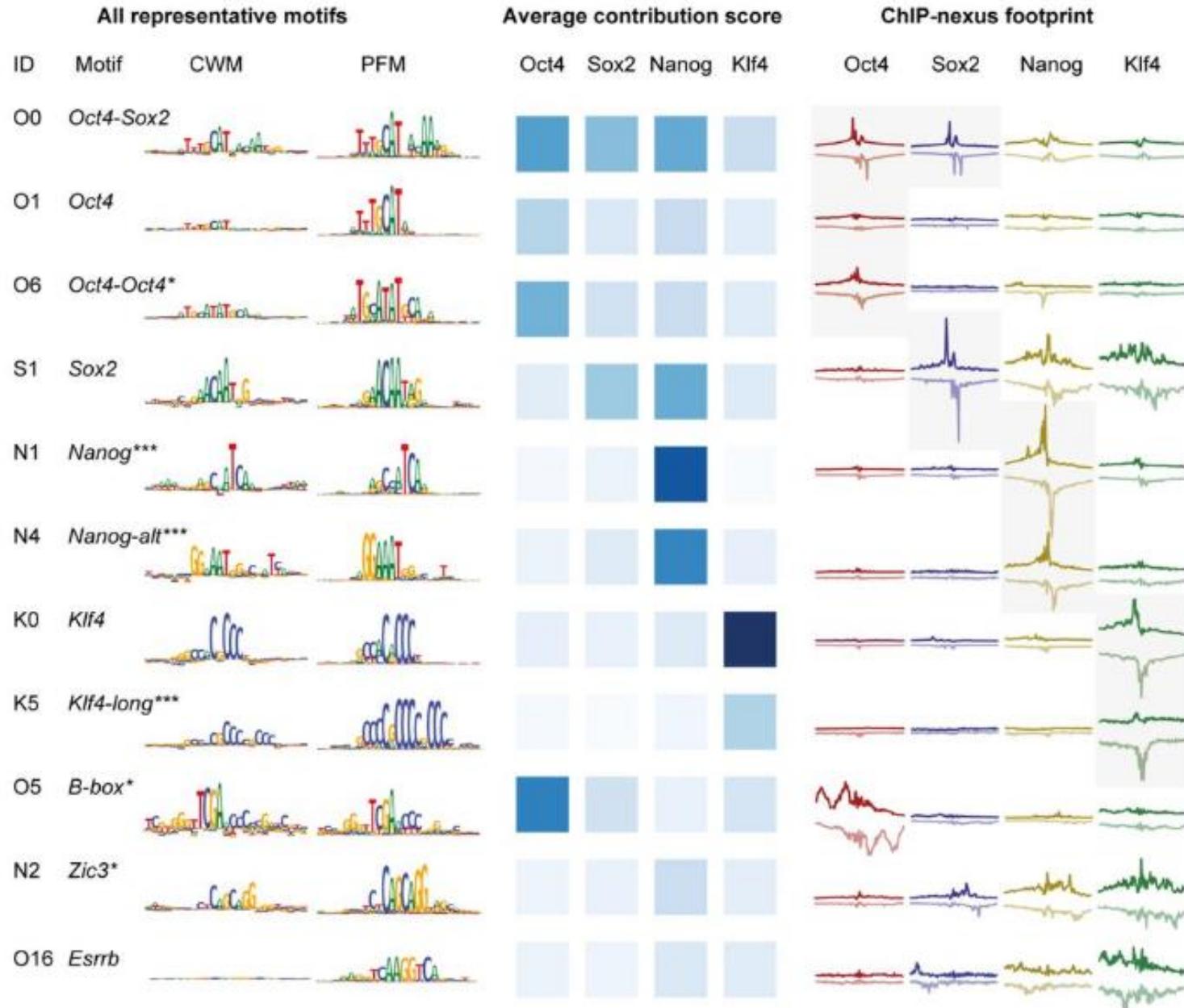


Avanti Shrikumar



Alex Tseng

Complex repertoire of motifs due to cooperative binding



50 motifs for 4 proteins!

Syntax discovery using *in-silico* perturbations

Use BpNet model as in-silico oracle to perform perturbation experiments



- 1) On synthetic sequences

Syntax discovery using *in-silico* perturbations

Use BpNet model as in-silico oracle to perform perturbation experiments



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Syntax discovery using *in-silico* perturbations

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1) On synthetic sequences



2) By mutating genomic sequences

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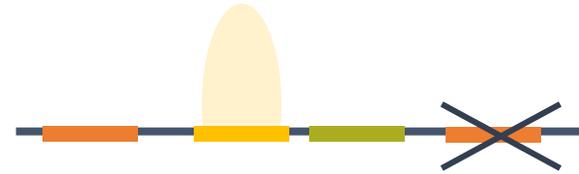
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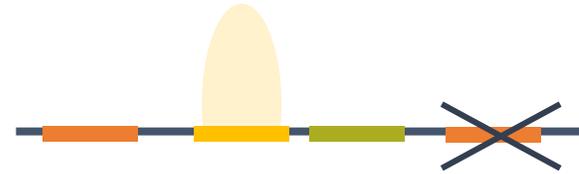
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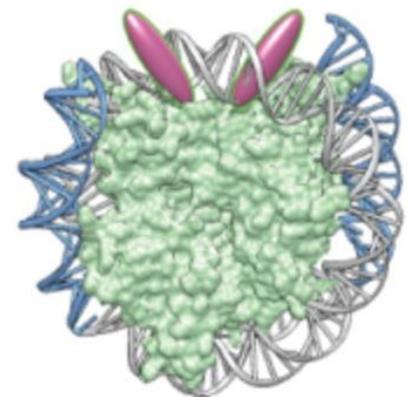
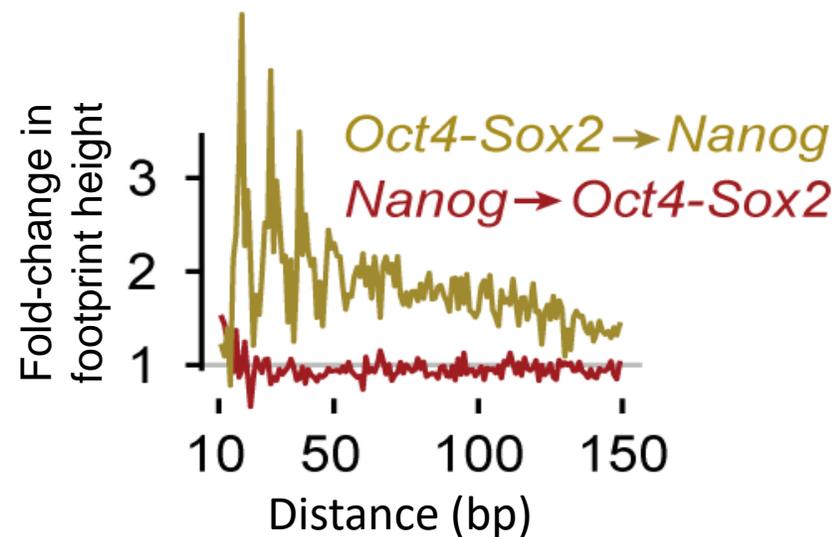
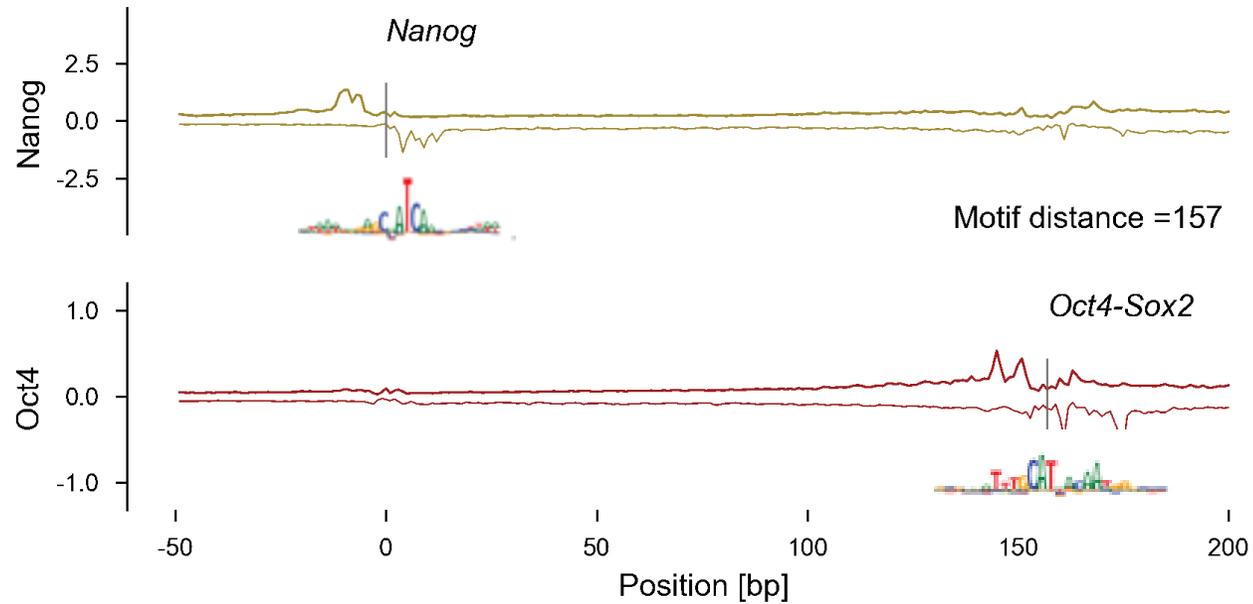
In silico biochemistry



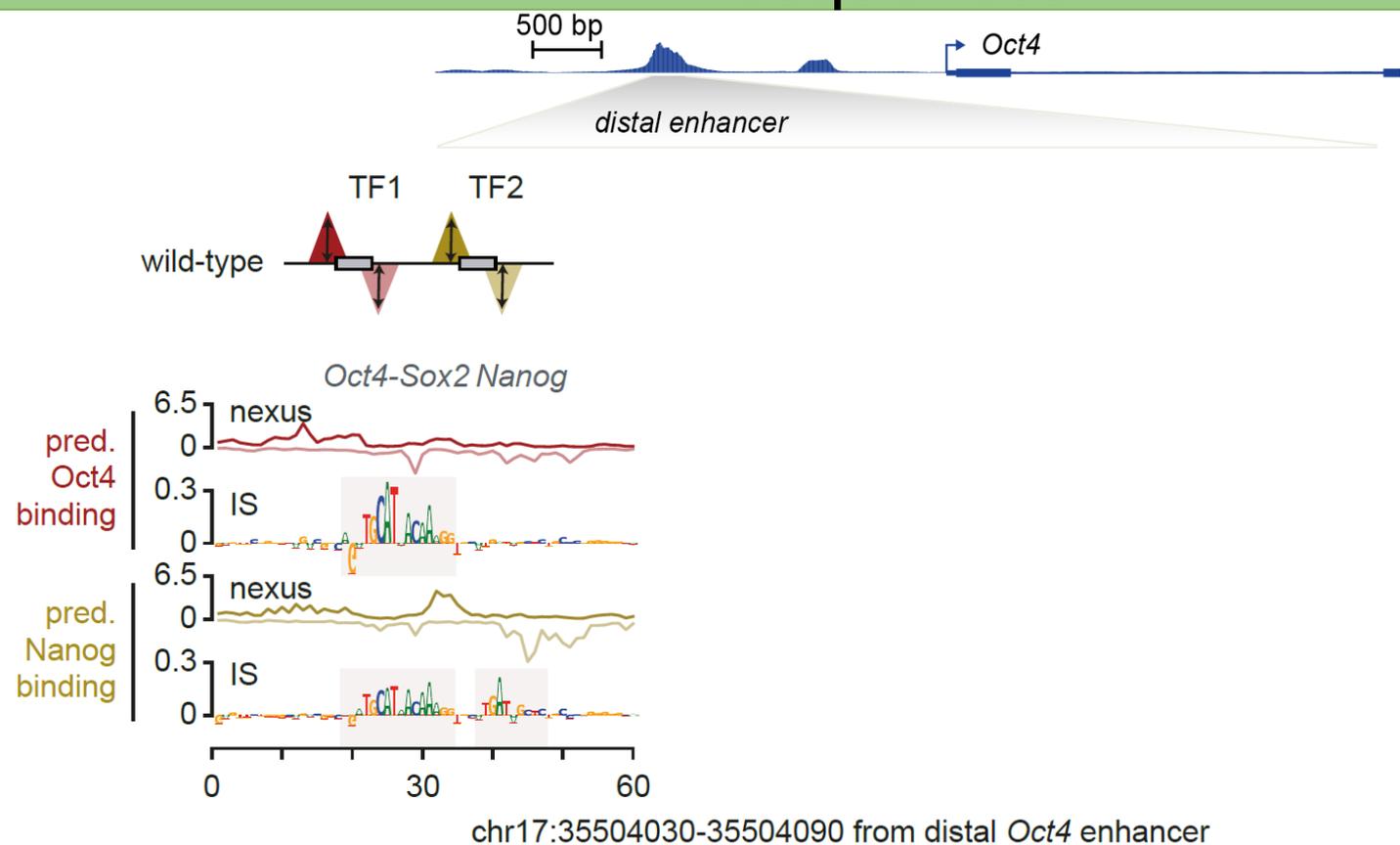
2) By mutating genomic sequences

In silico genetics

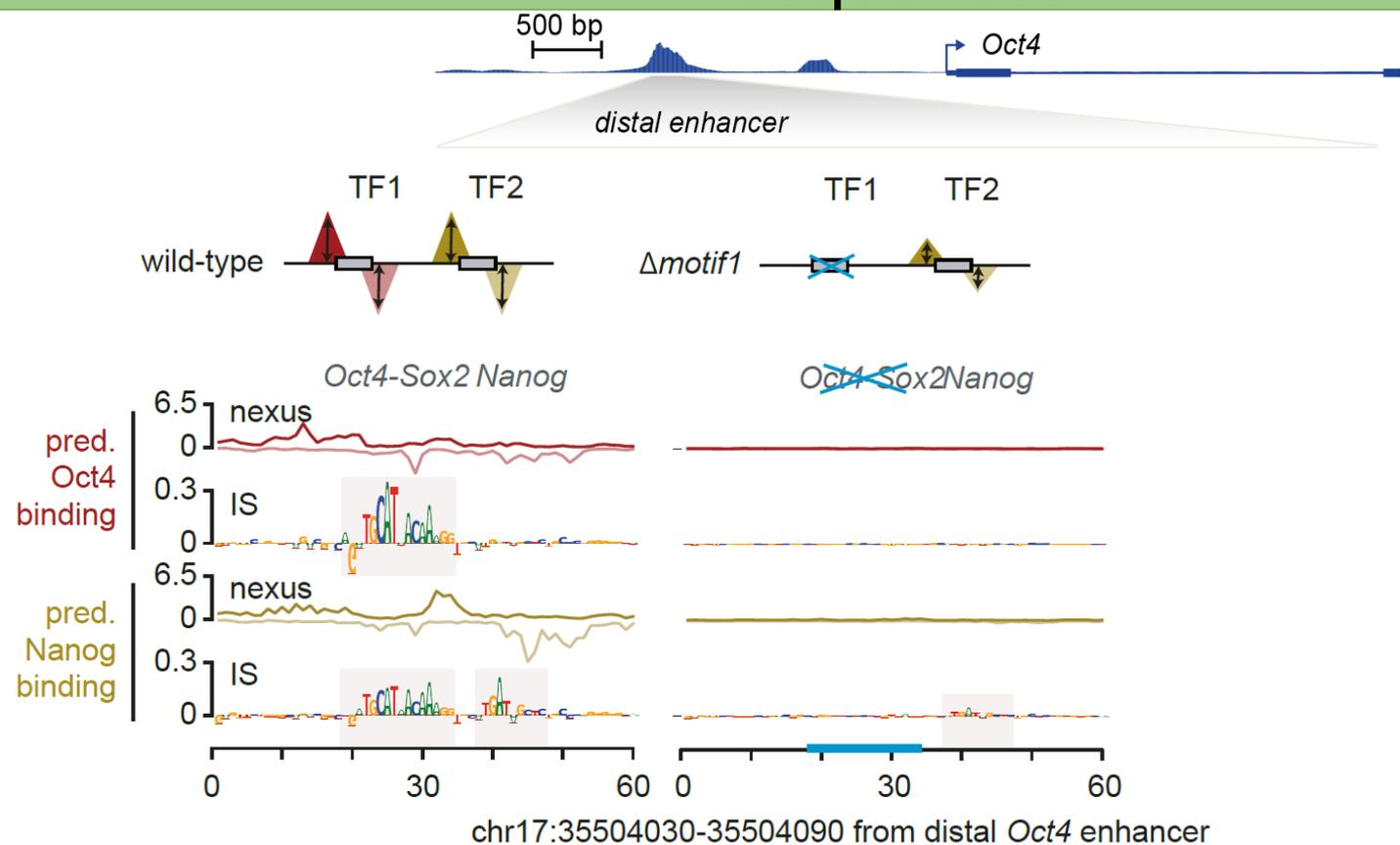
In-silico reporters: Designing synthetic sequences to query models to reveal syntax



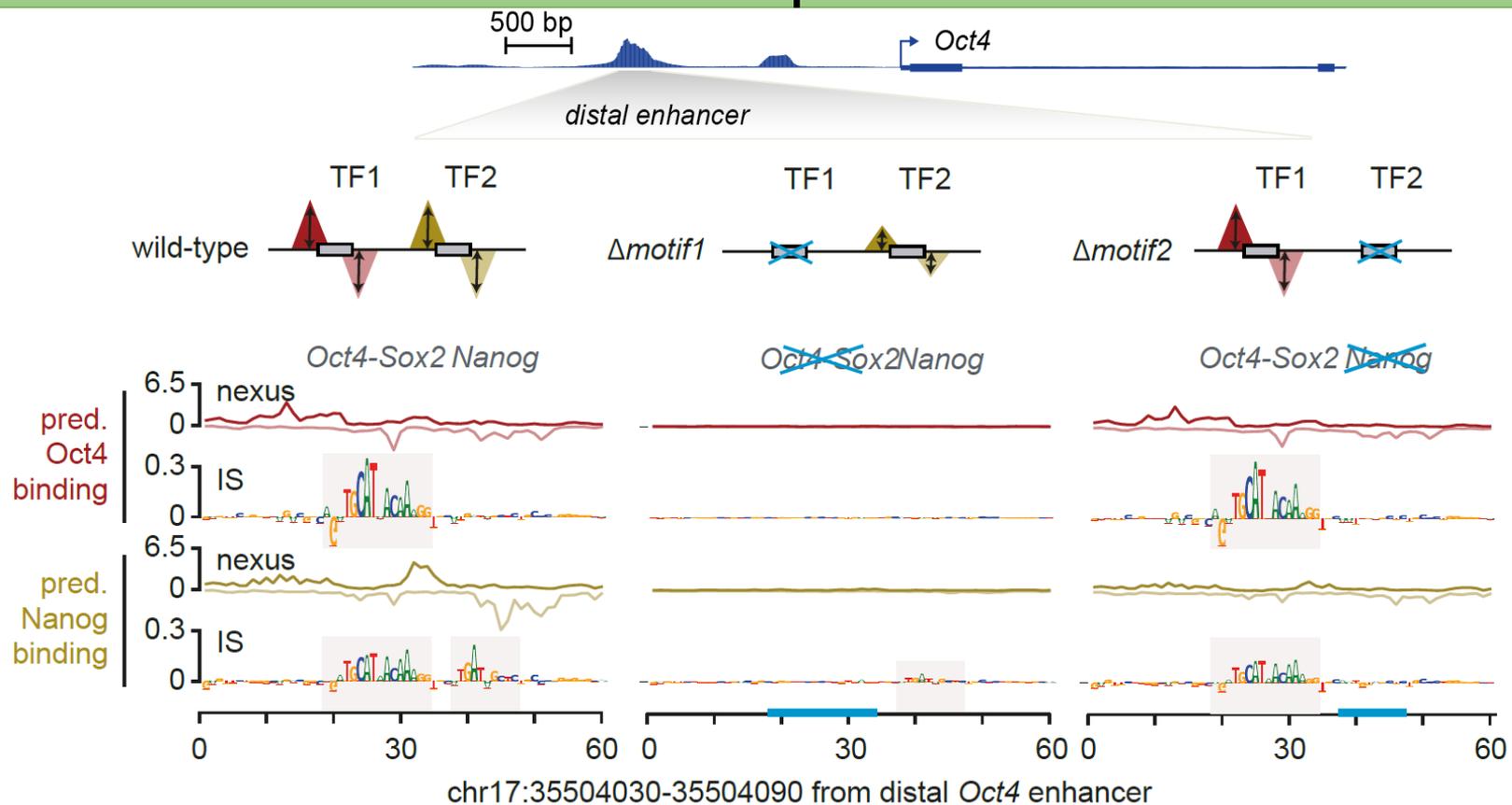
in-silico genome editing: Deciphering syntax by perturbing genomic sequences



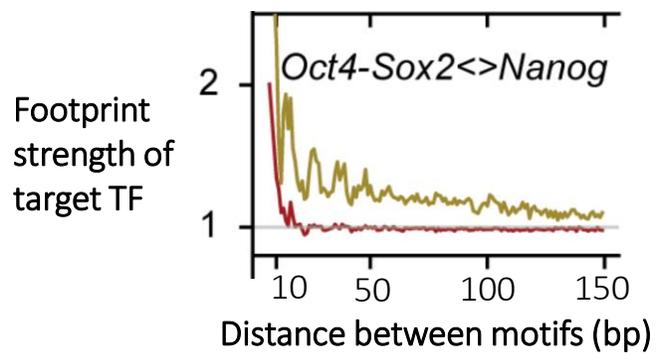
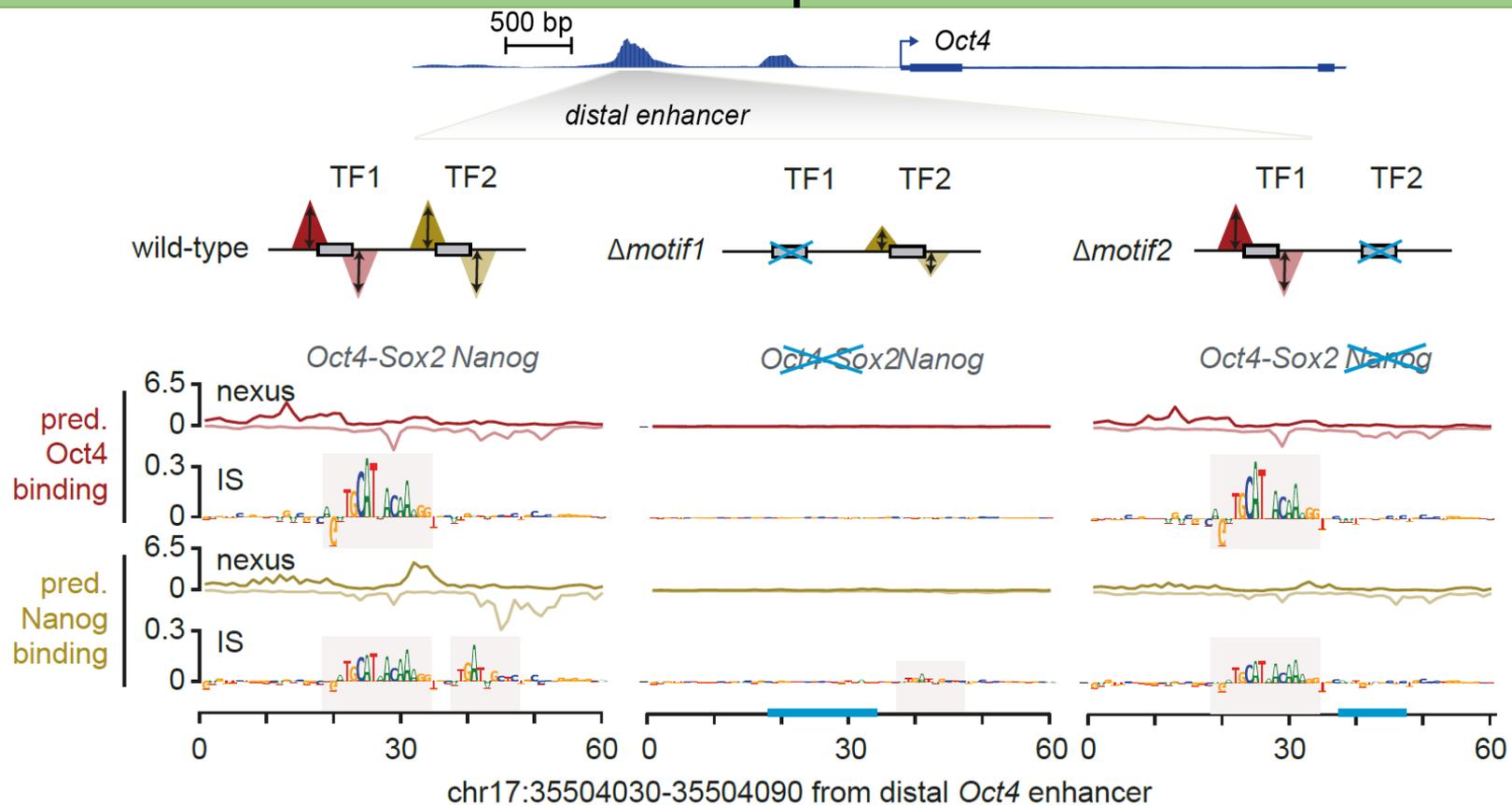
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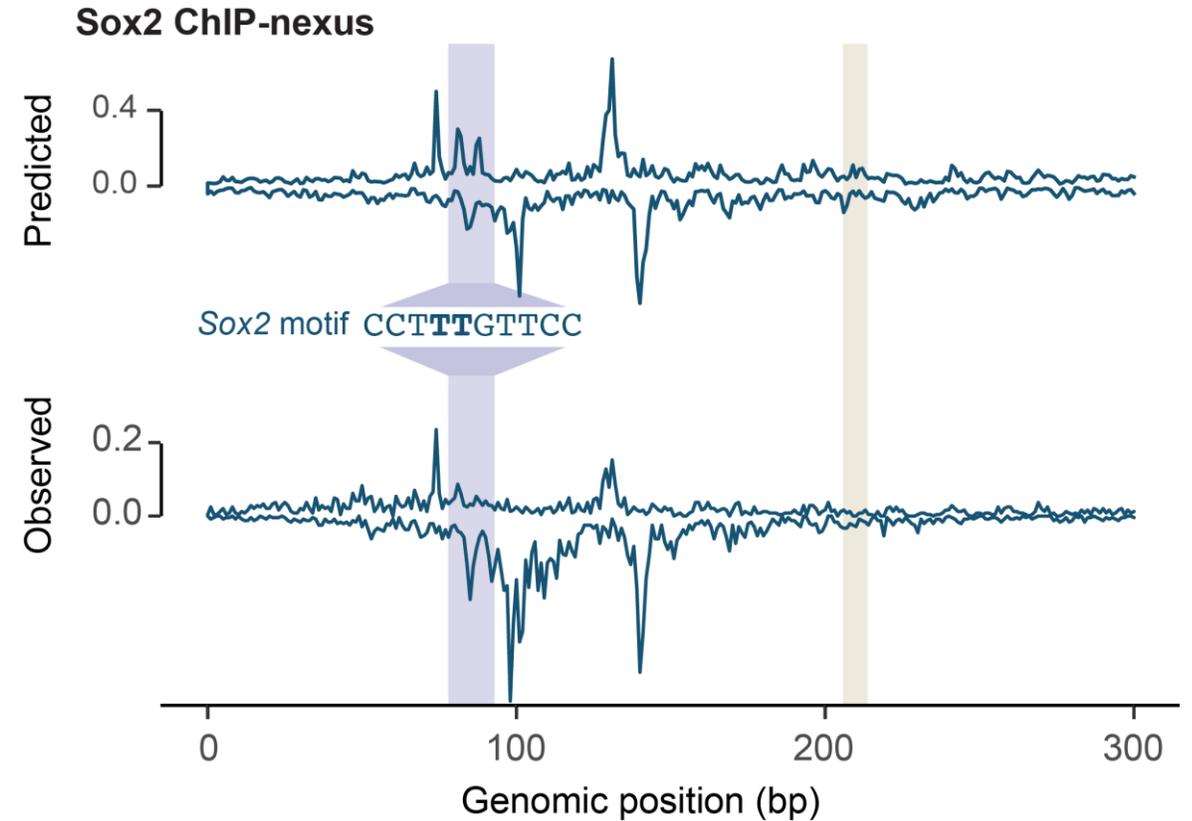
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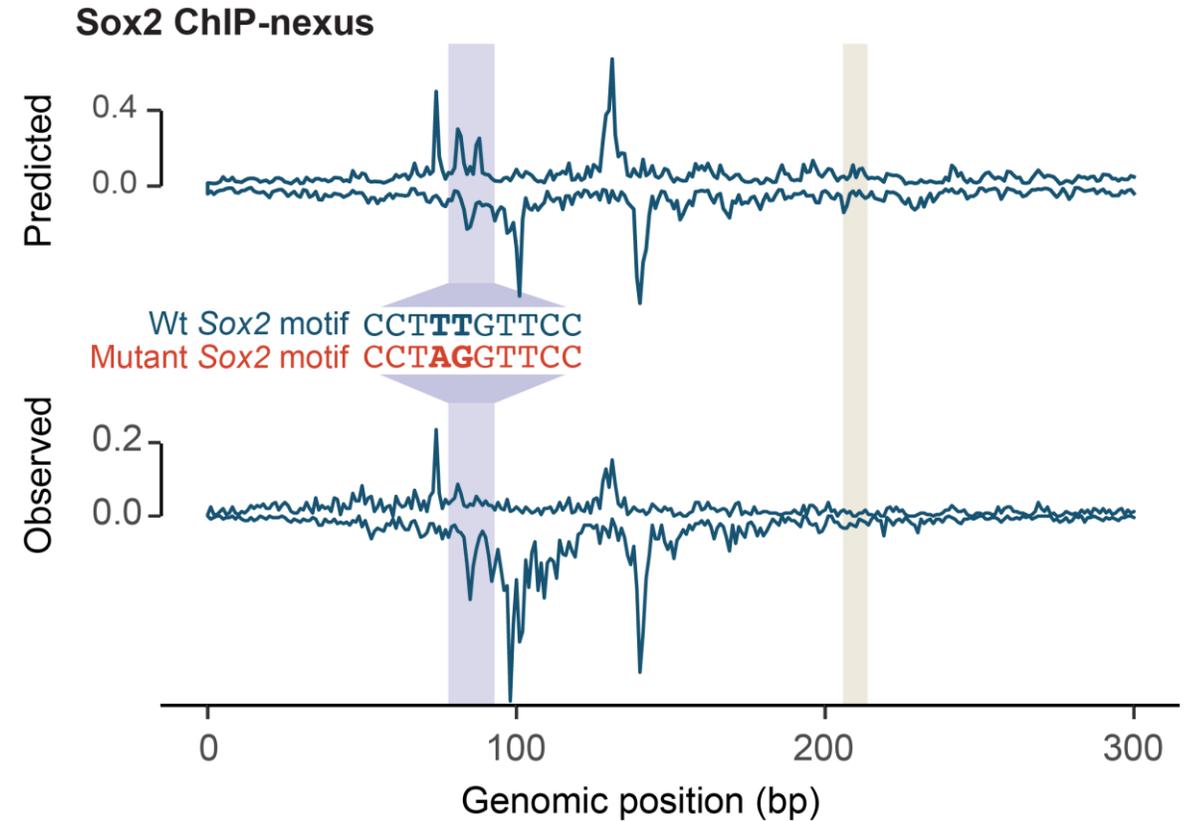


Designing CRISPR experiments to validate motif syntax



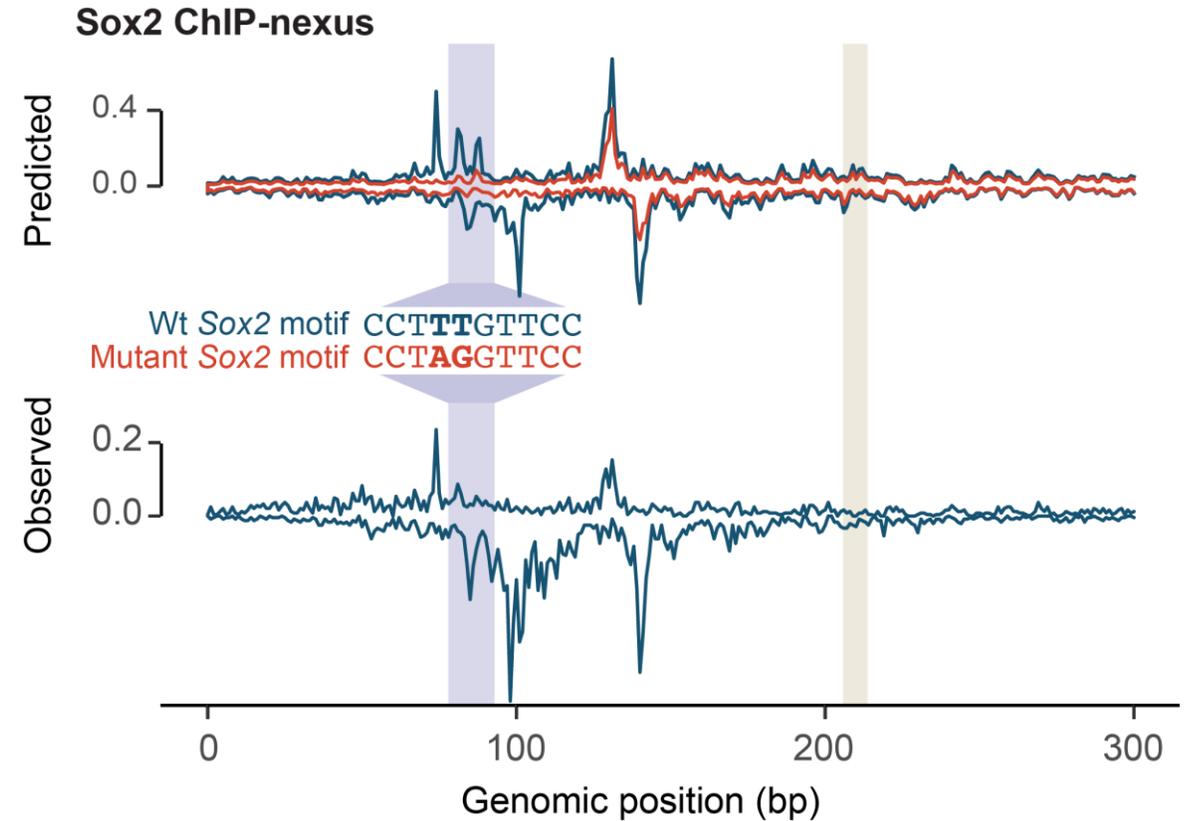
Julia Zeitlinger, Sabrina Krueger, Melanie Weilert

Designing CRISPR experiments to validate motif syntax



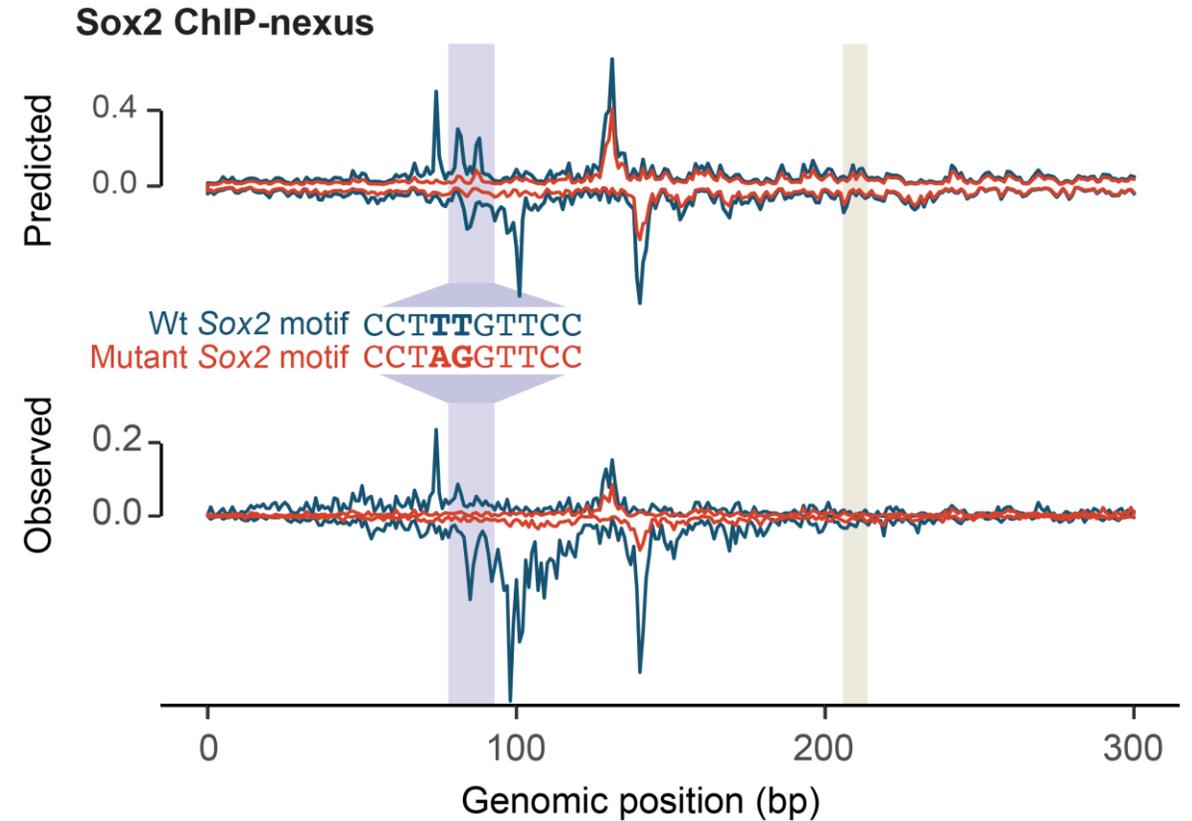
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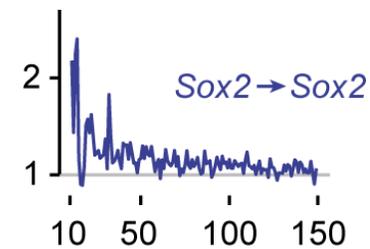
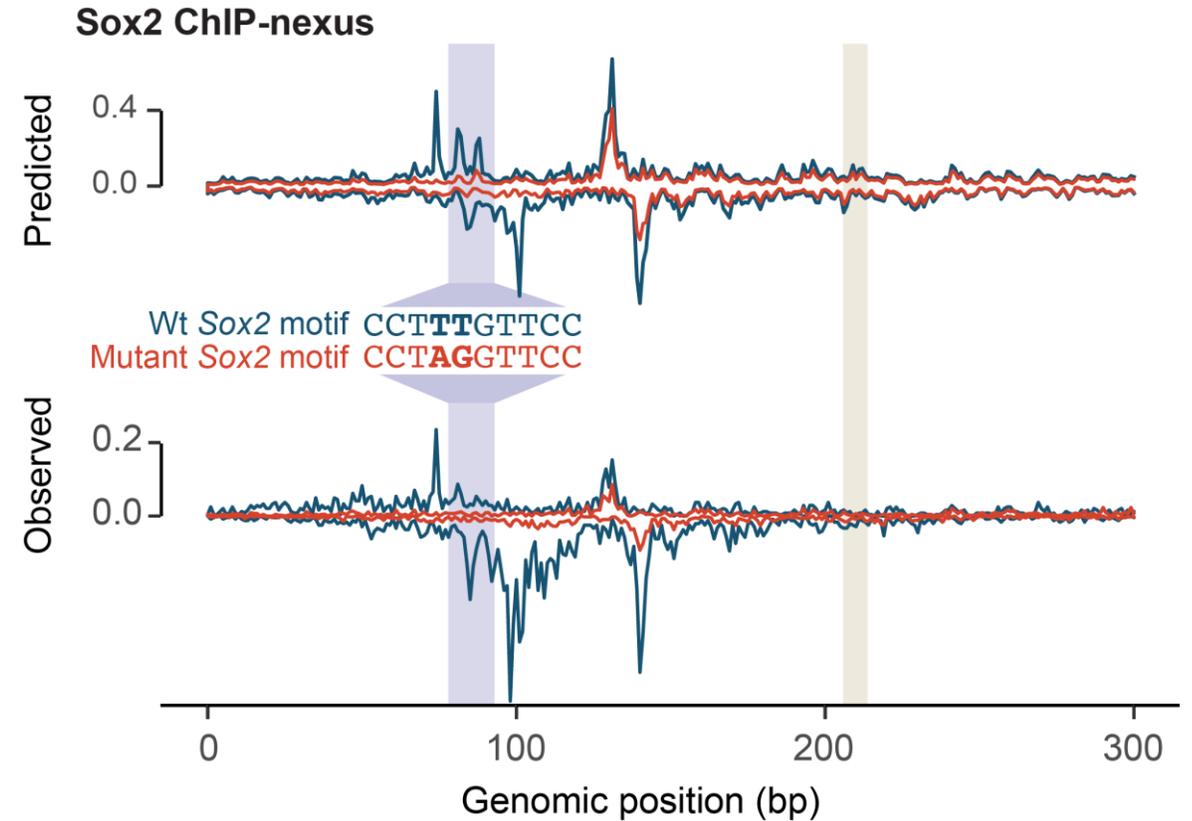
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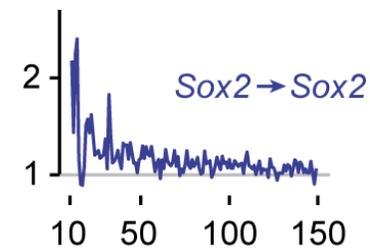
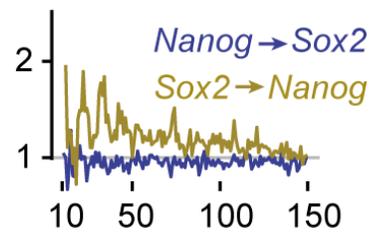
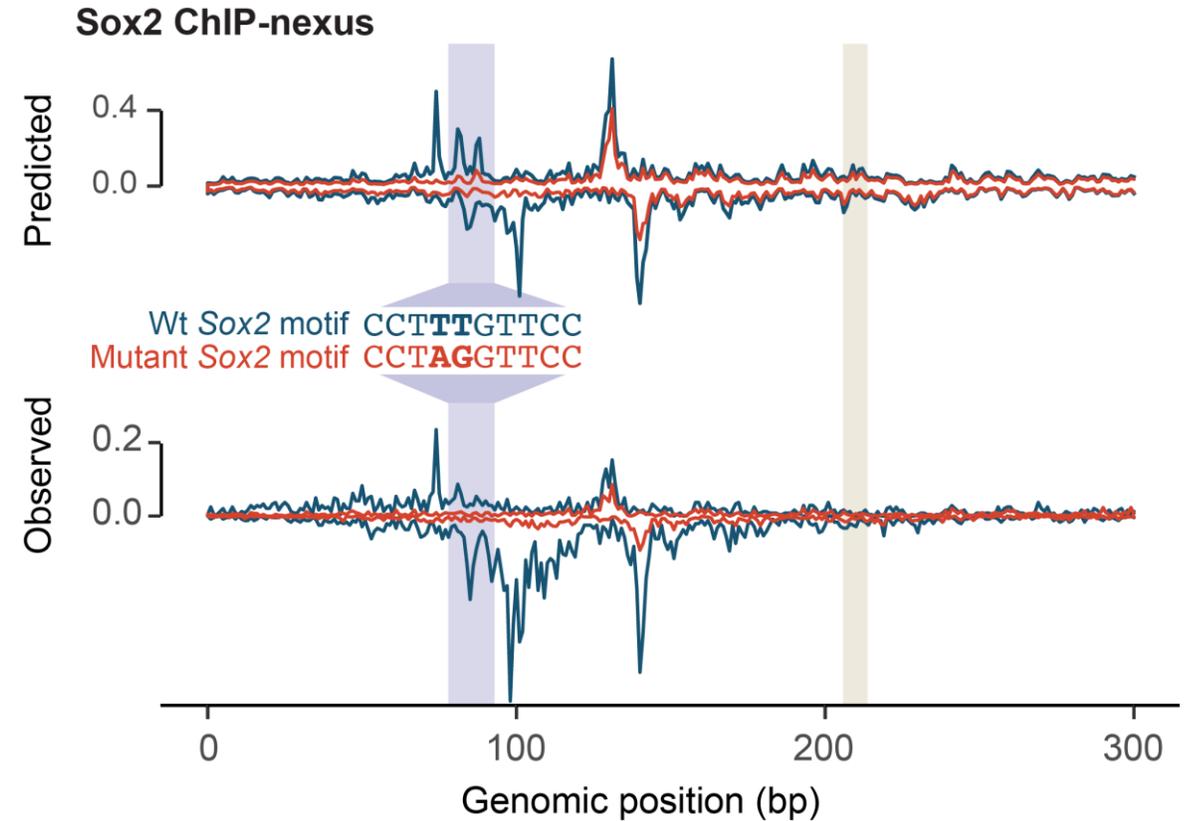


Julia Zeitlinger, Sabrina Krueger, Melanie Weilert

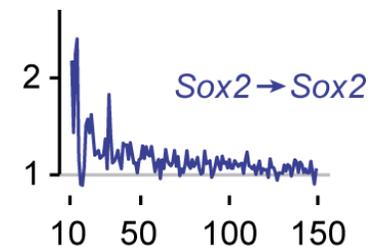
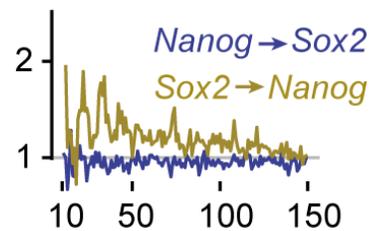
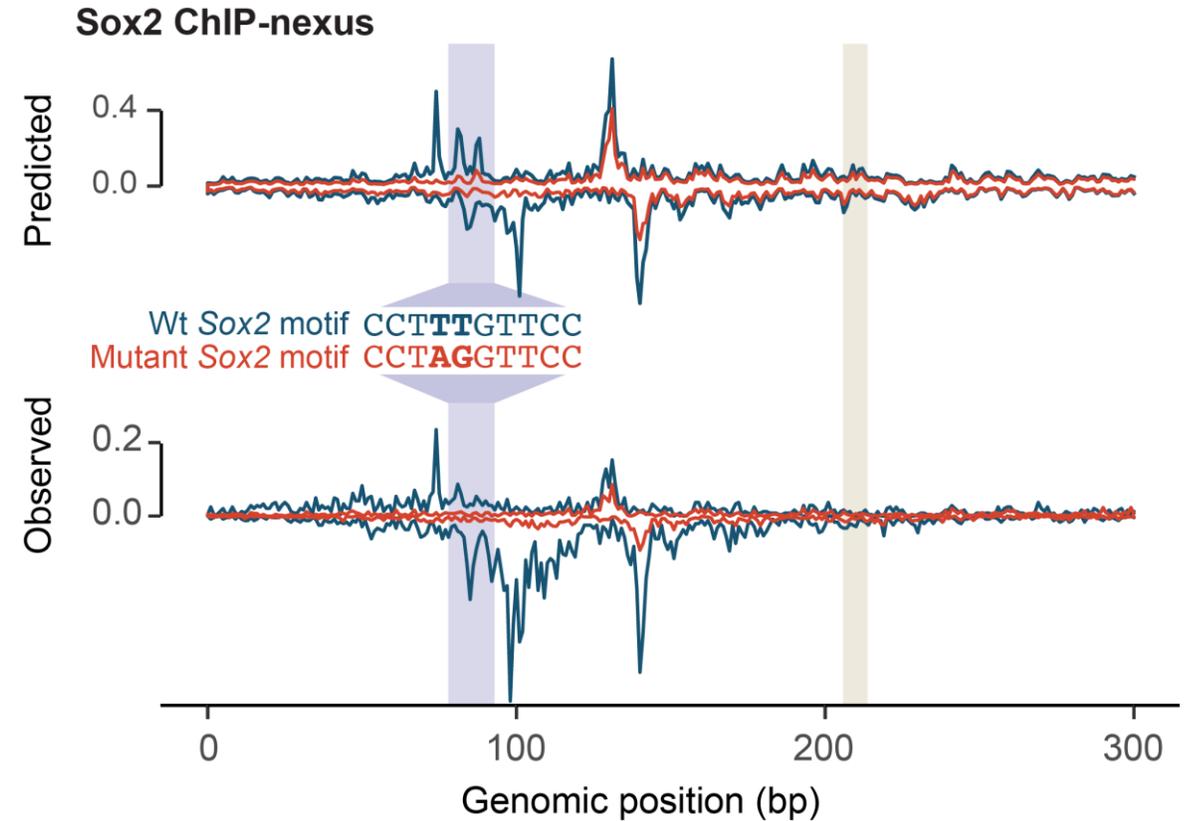
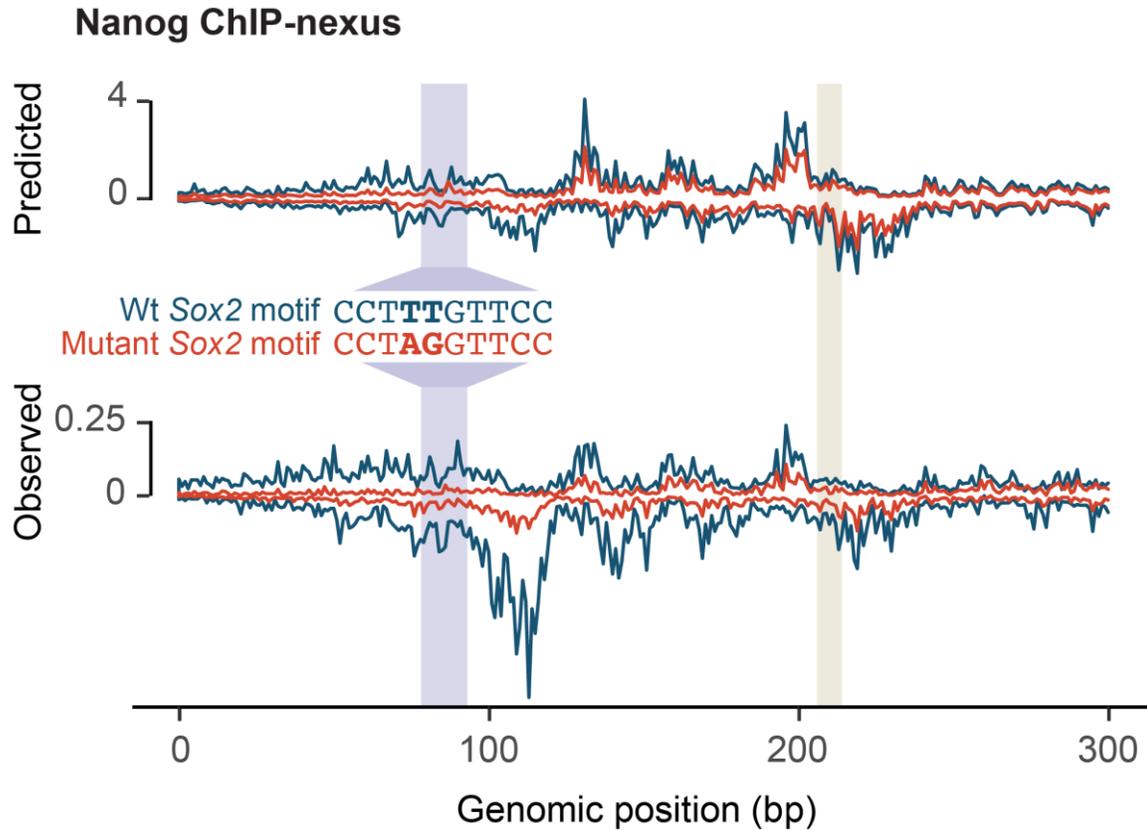
Designing CRISPR experiments to validate motif syntax



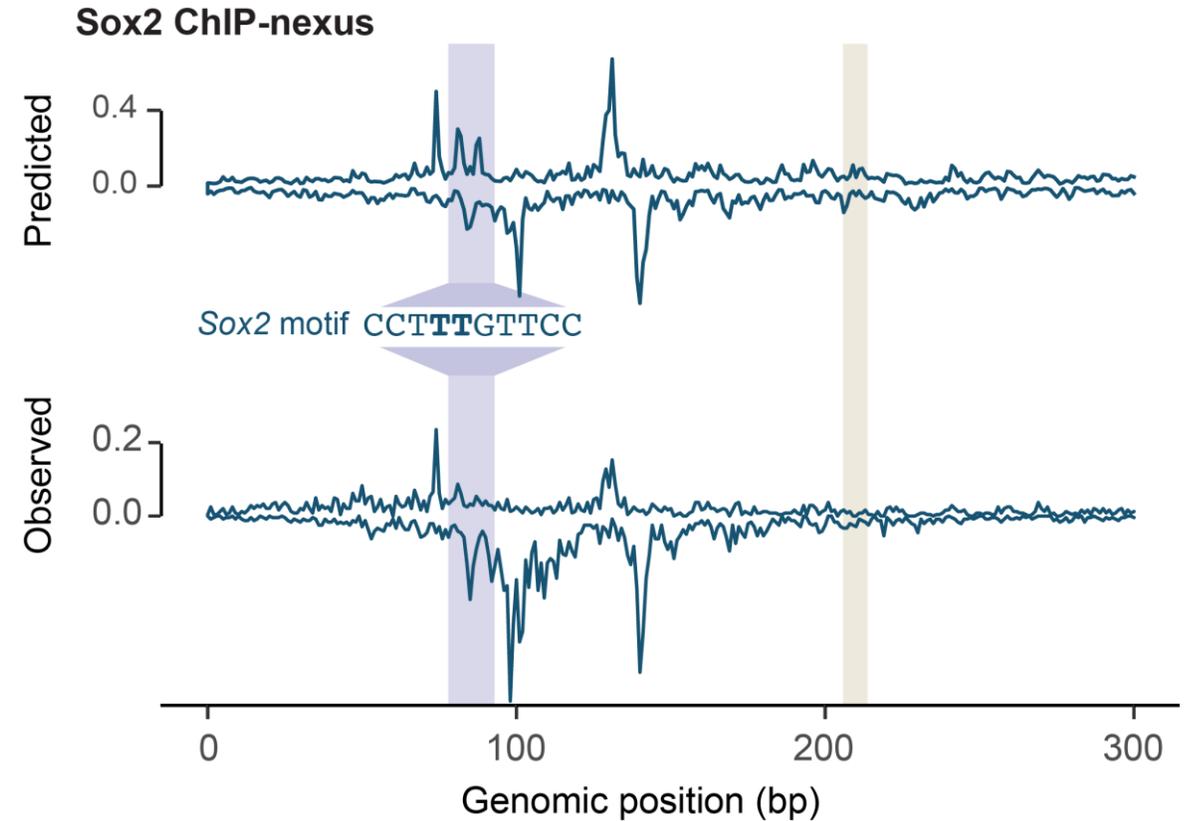
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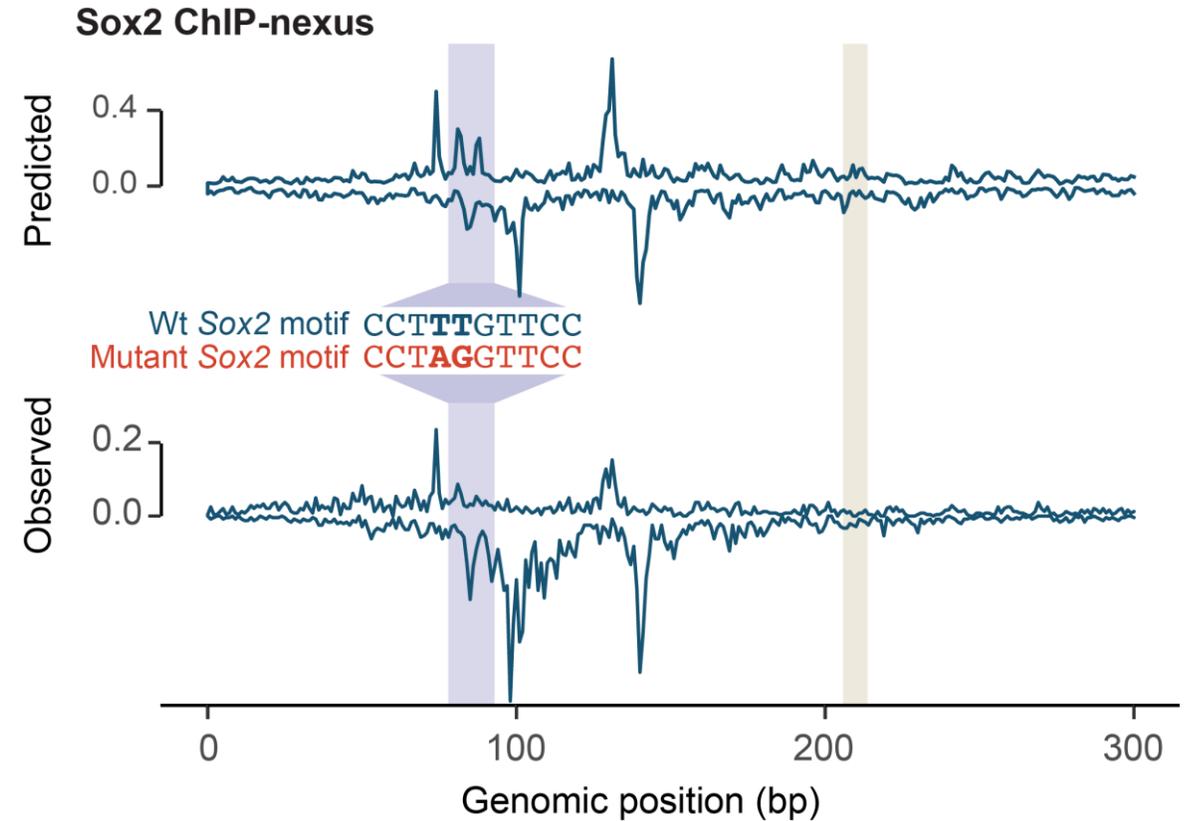


Designing CRISPR experiments to validate motif syntax



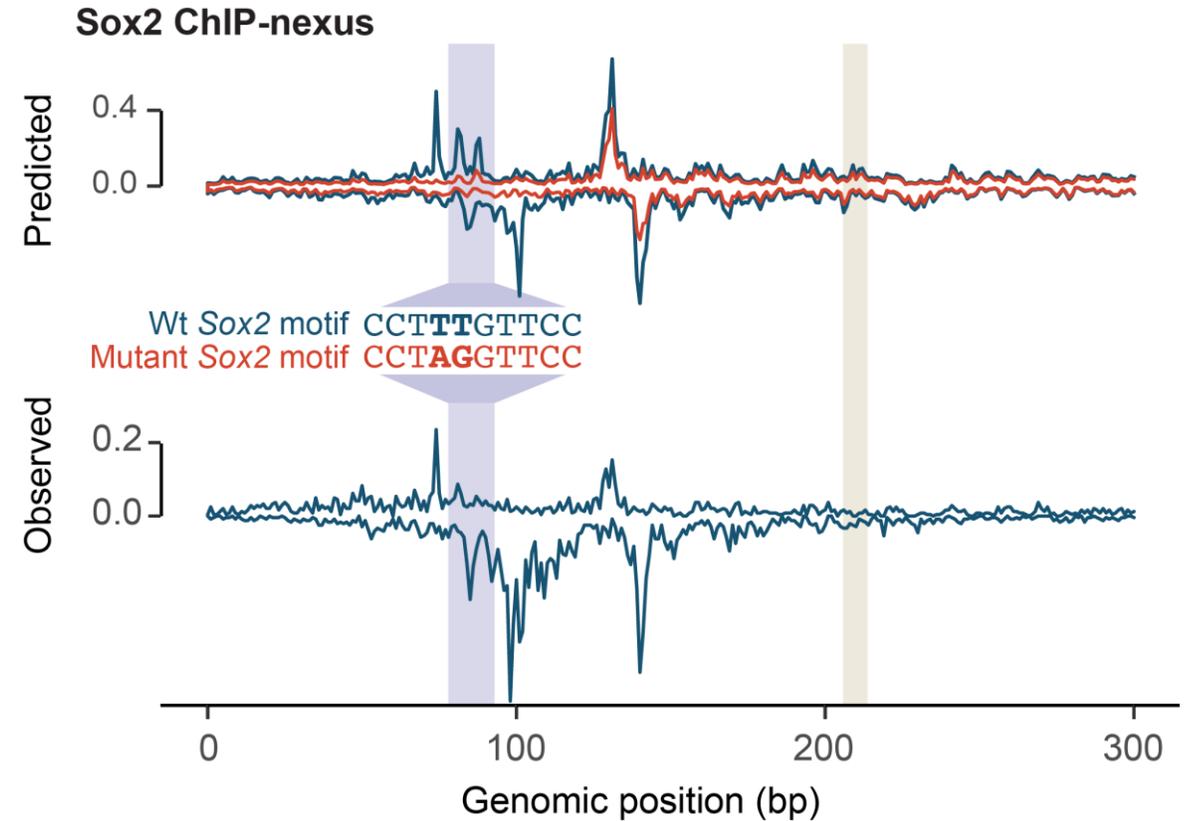
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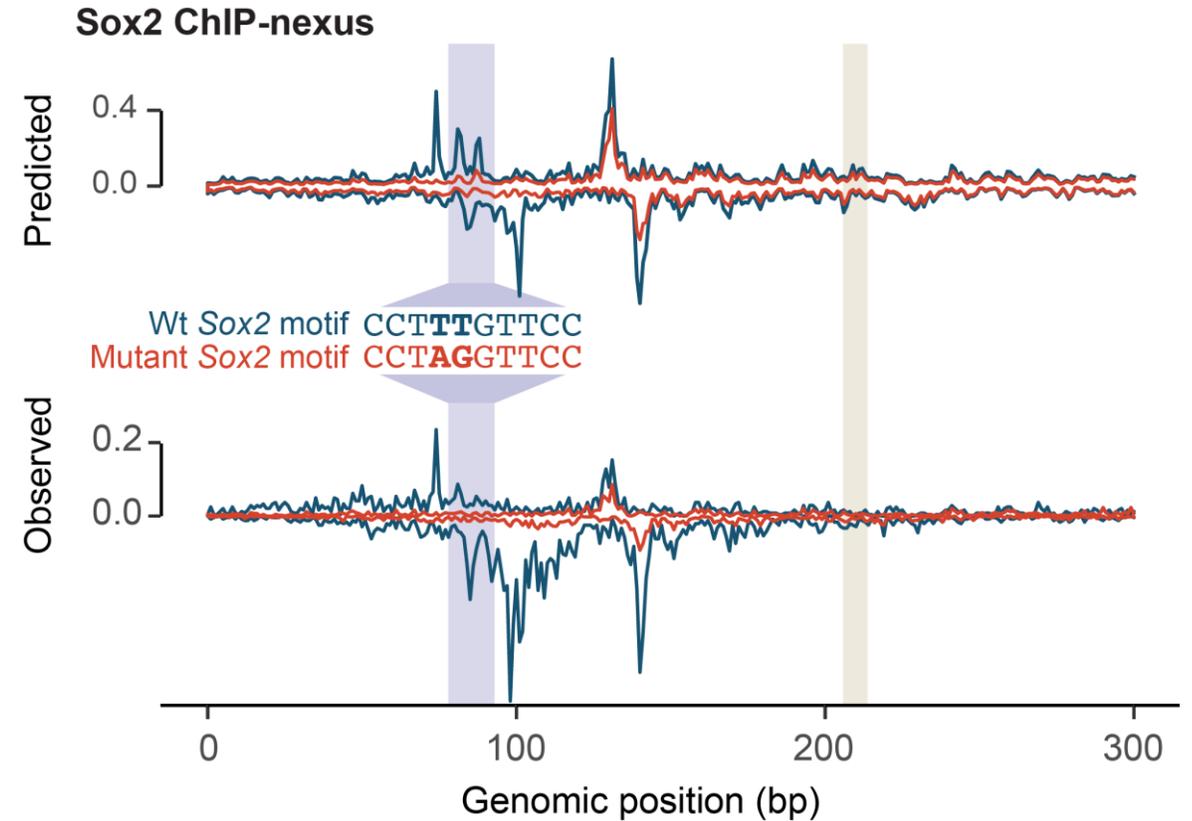


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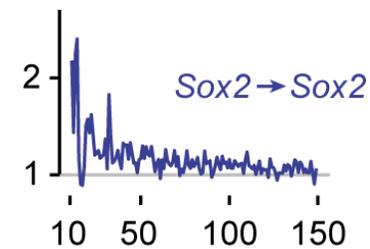
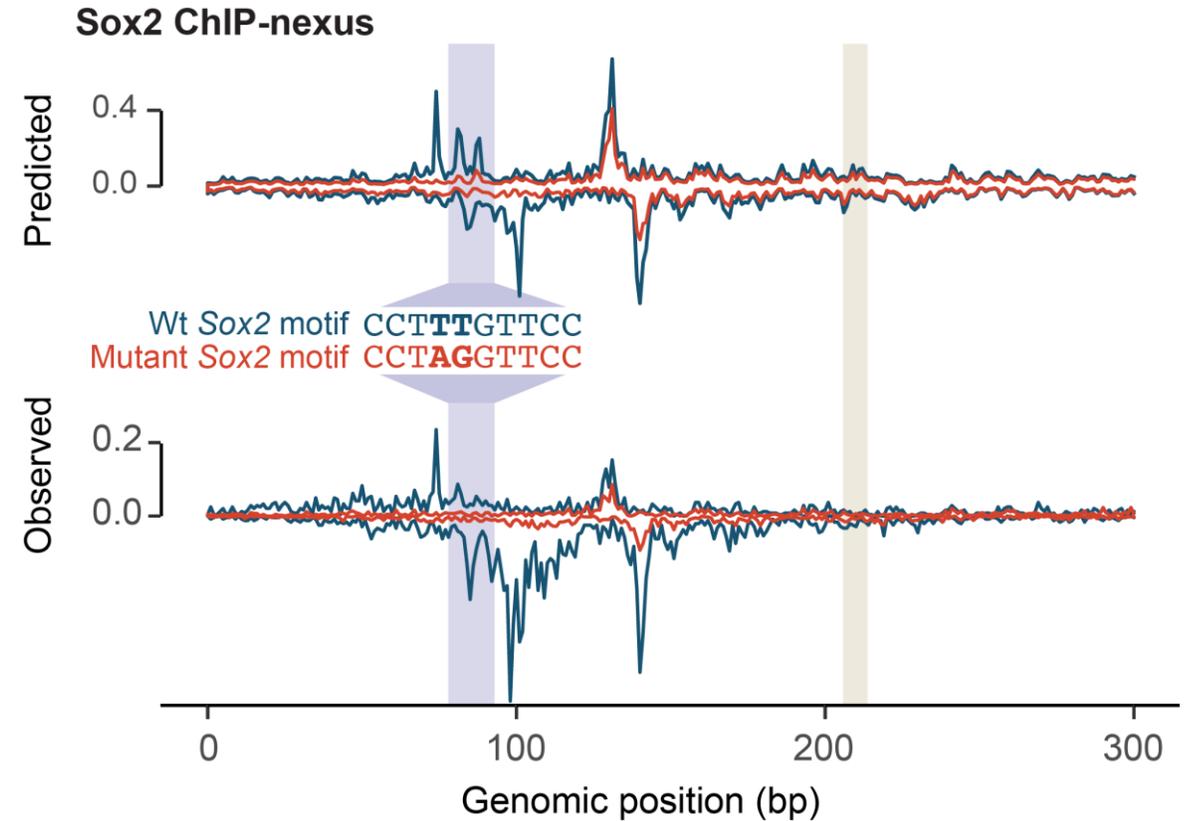


Designing CRISPR experiments to validate motif syntax

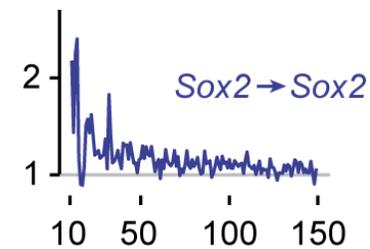
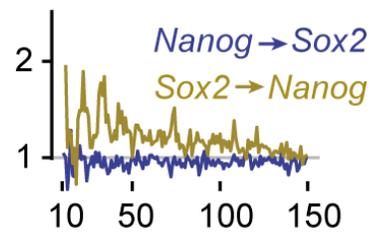
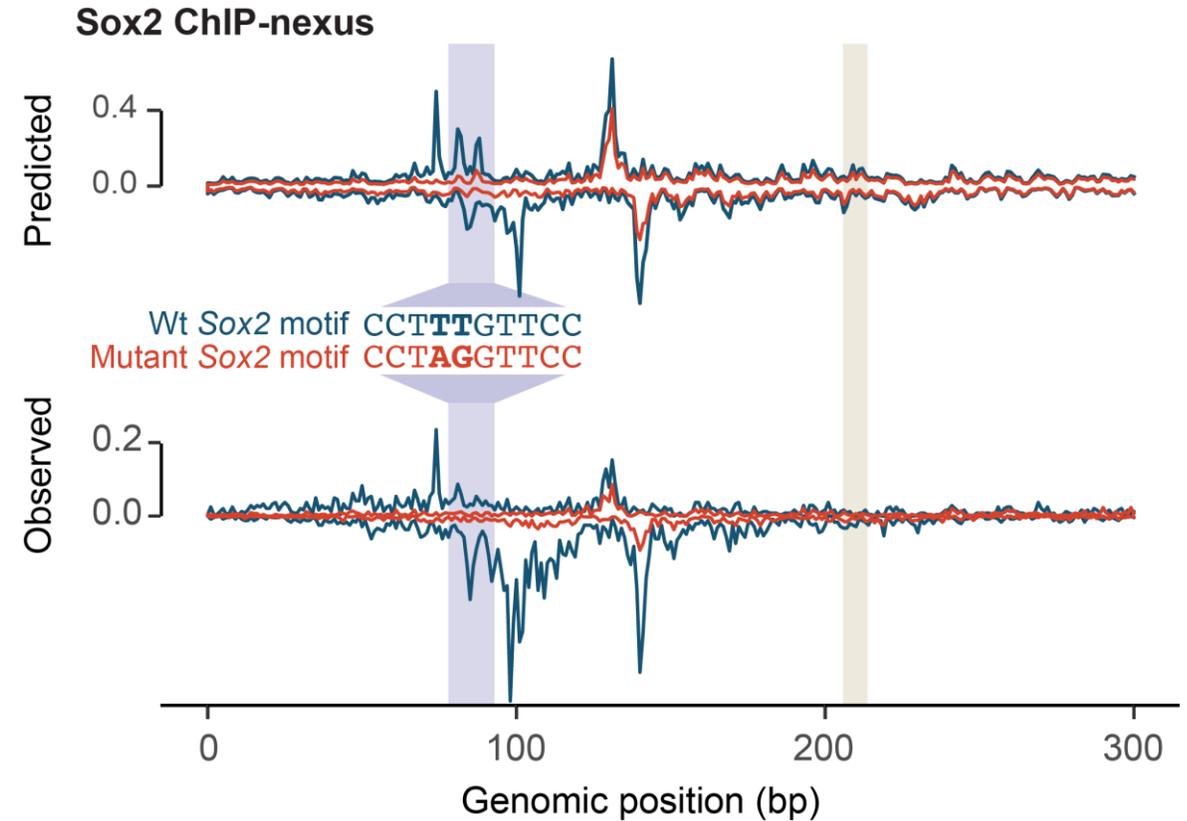


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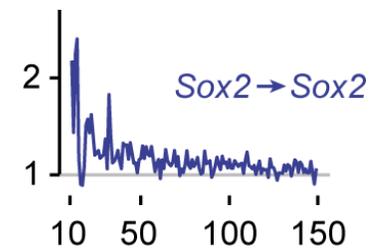
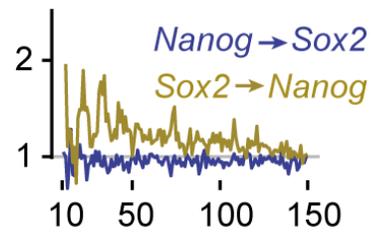
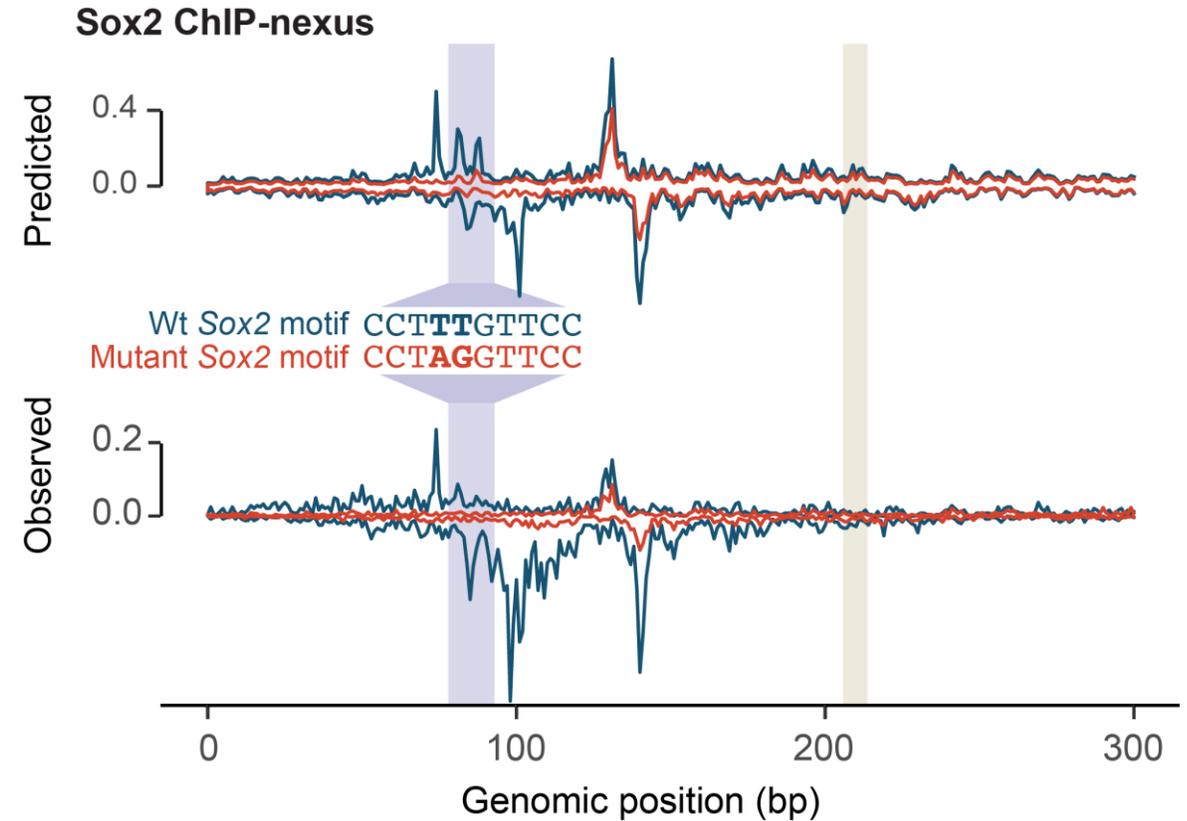
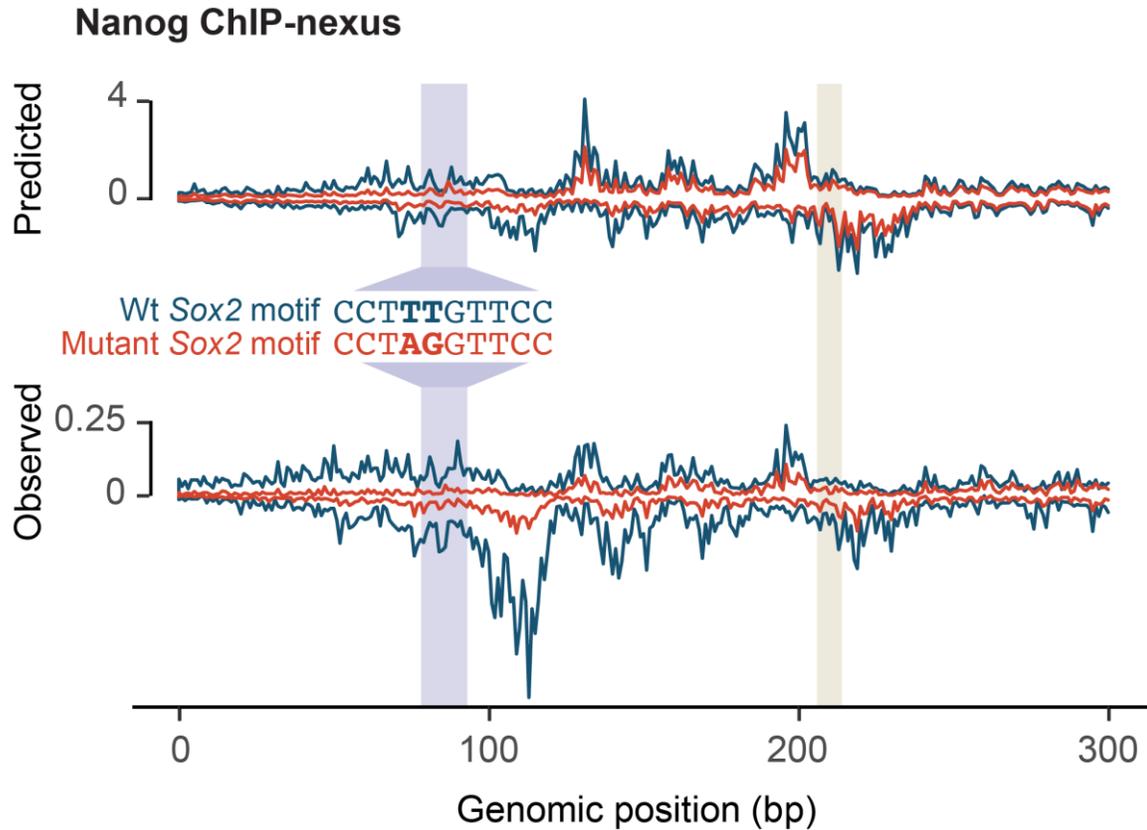
Designing CRISPR experiments to validate motif syntax



Designing CRISPR experiments to validate motif syntax

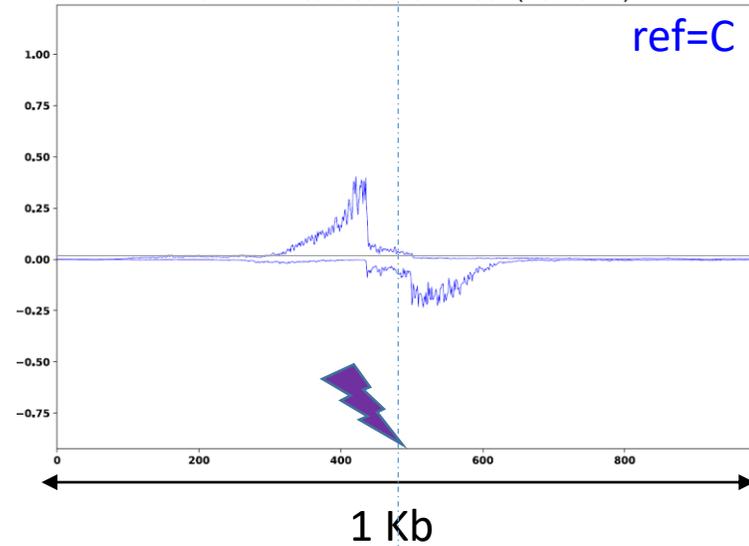


Designing CRISPR experiments to validate motif syntax

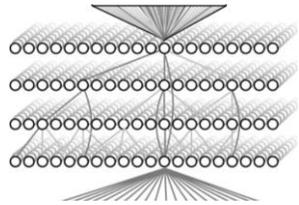


In-silico mutagenesis: Predict effect of genetic variant on molecular activity

Predicted molecular profile of protein-DNA binding



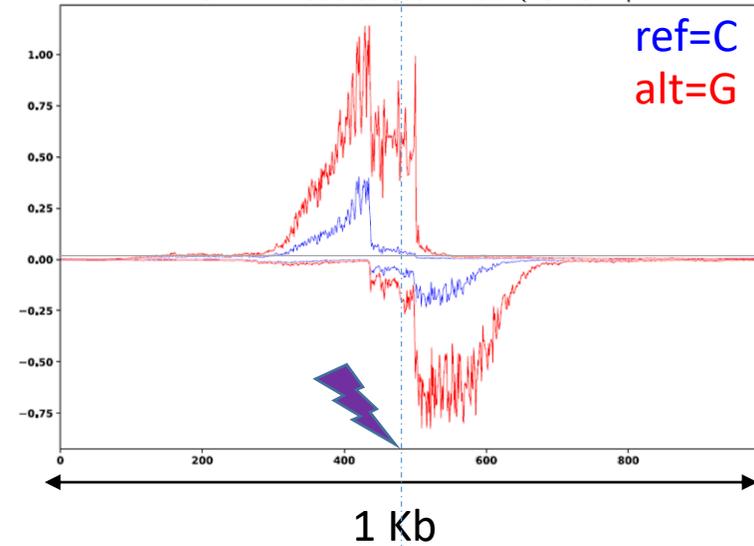
PredictedSignal



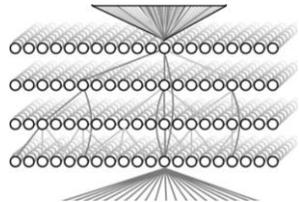
.....ACTGAT **C**GCAATCG.....

In-silico mutagenesis: Predict effect of genetic variant on molecular activity

Predicted molecular profile of protein-DNA binding



Δ PredictedSignal

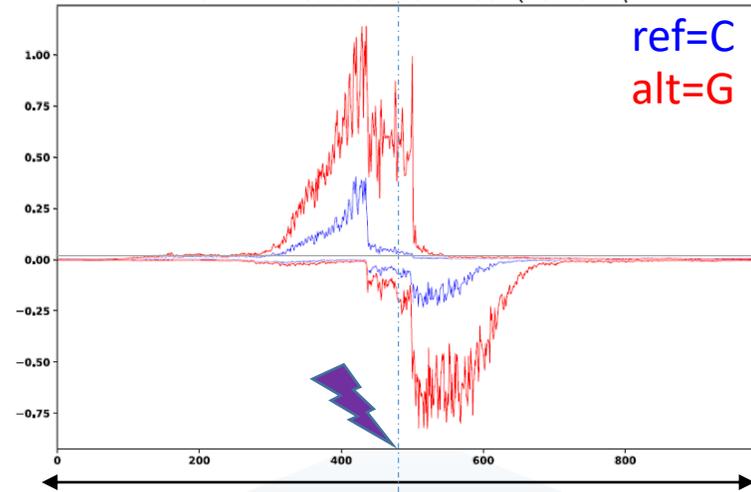


.....ACTGAT **C** GCAATCG.....

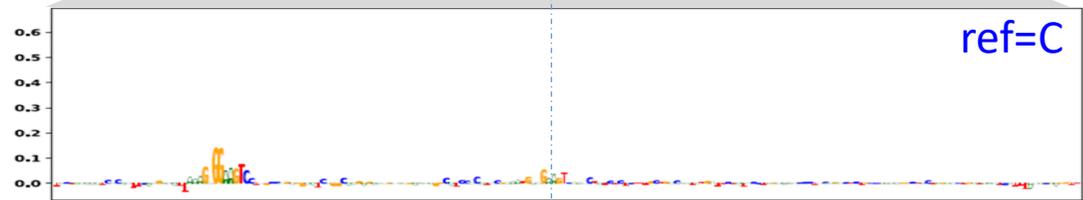
.....ACTGAT **G** GCAATCG.....

Interpret disrupted predictive sequence syntax

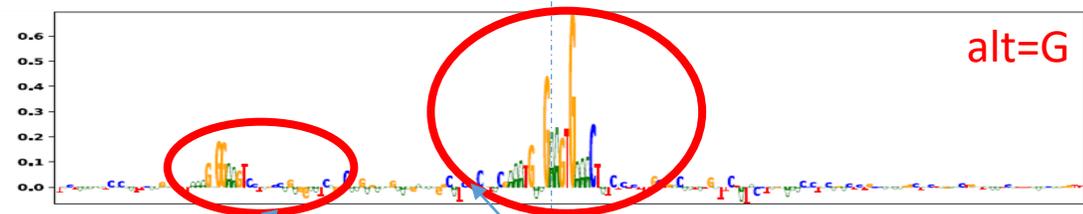
Predicted molecular profile of protein-DNA binding



1 Kb



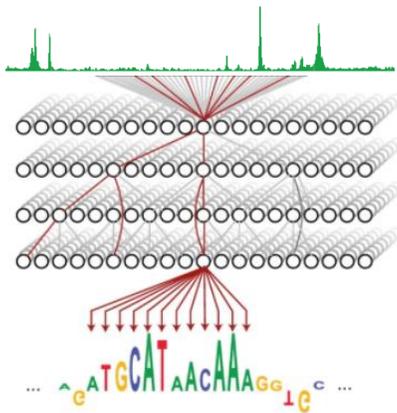
ref=C



alt=G

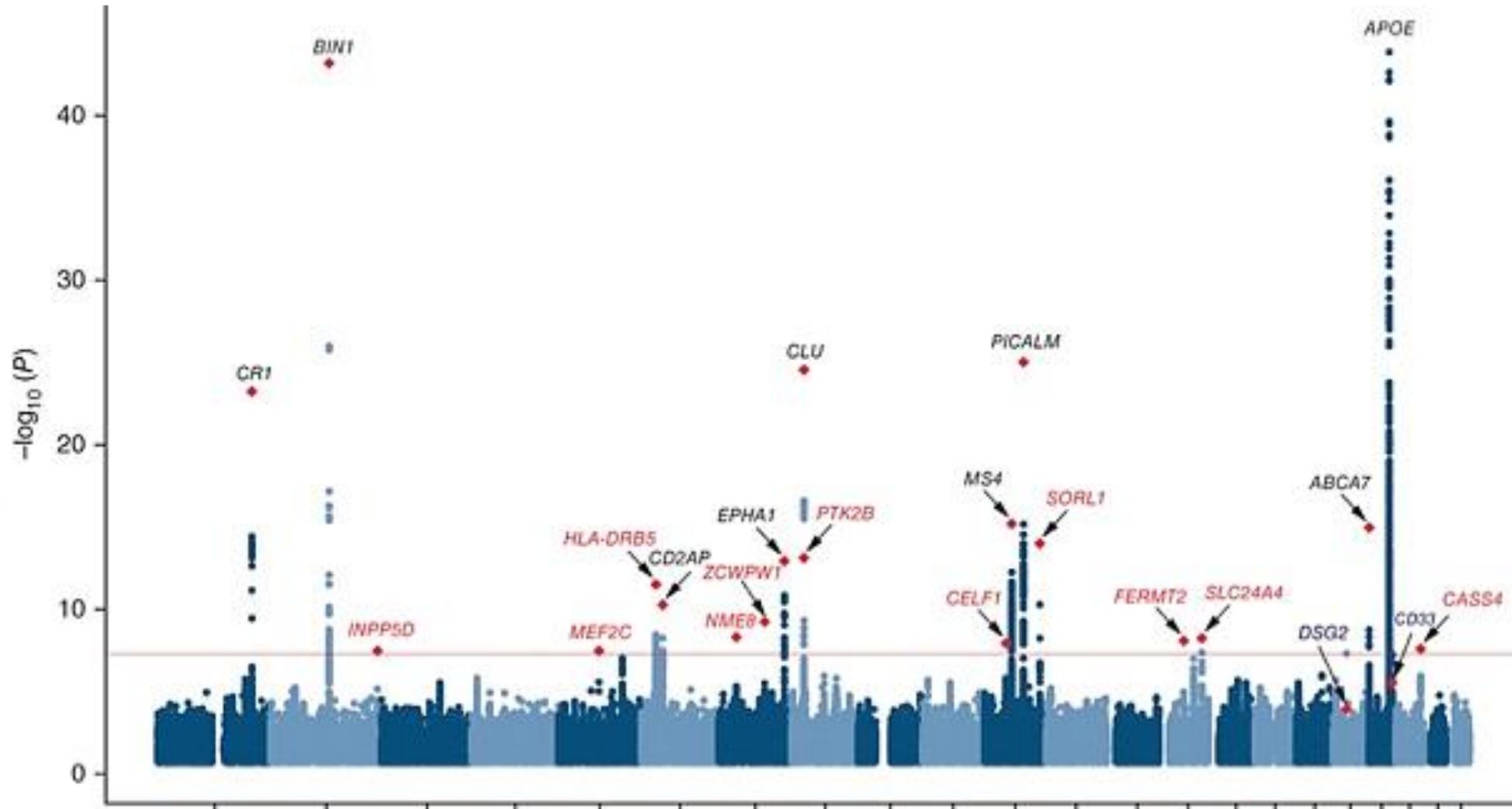
200 bp

Sequence binding motifs of SPI1 DNA binding protein



Genetic loci associated with Alzheimer's disease

Statistical significance of association



(Lambert et al., Nat. Genet., 2013)

Genomic position →

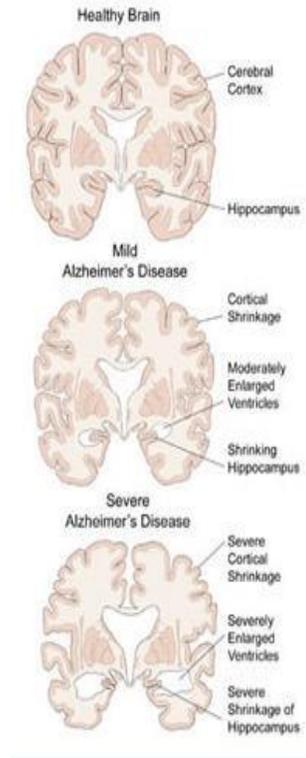
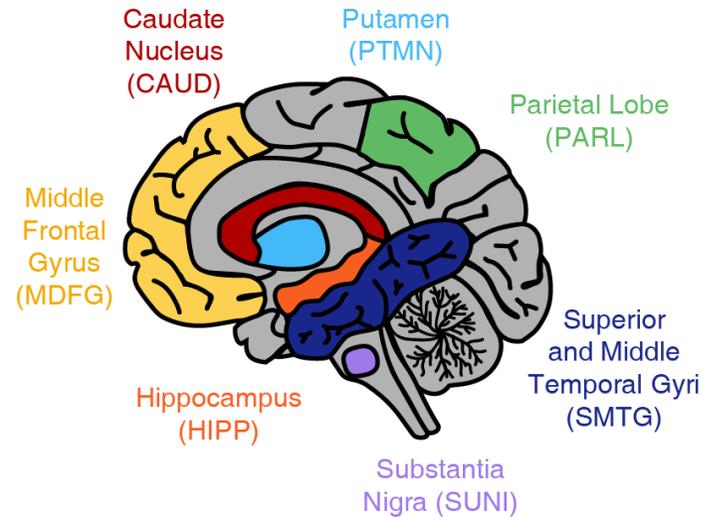


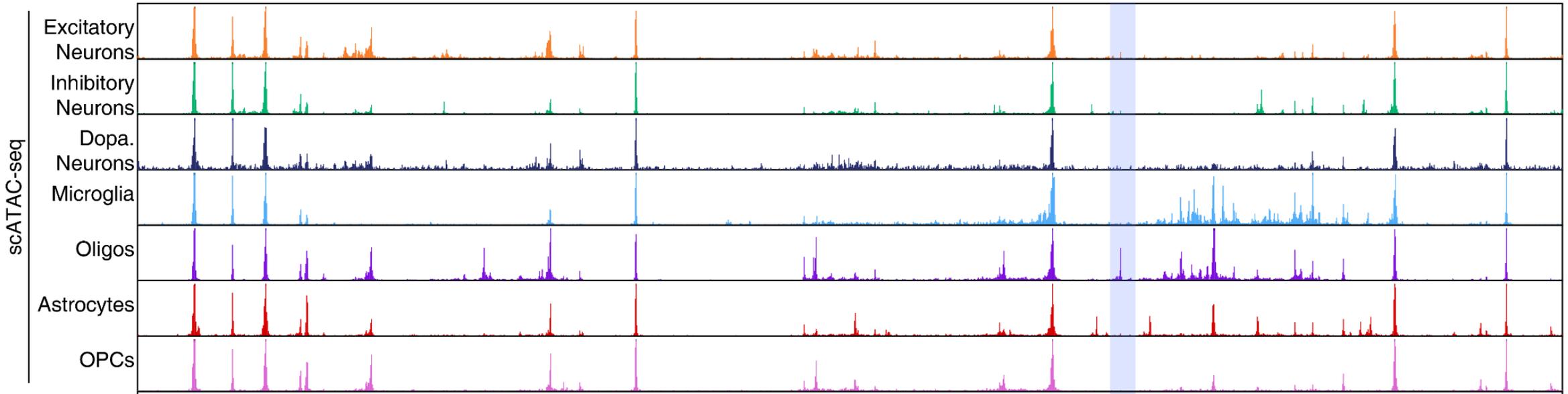
Illustration by Bob Morreale, American Health Assistance Foundation

Molecular profiling of cell types in the brain

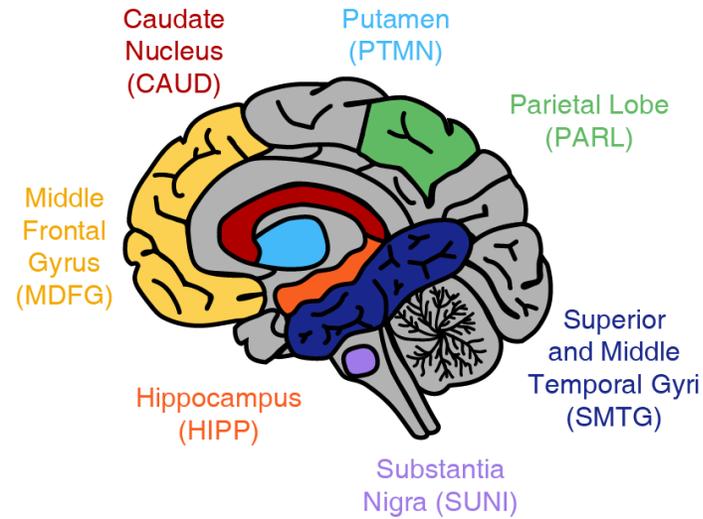


Corces et al. 2020, Nature Genetics

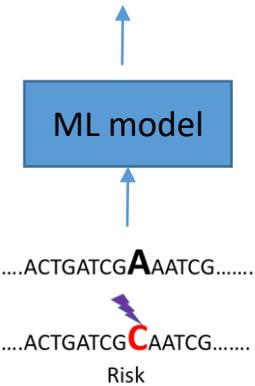
chr11:85599000-86331000 - Alzheimer's Disease rs1237999 - PICALM Locus



Molecular profiling of cell types in the brain

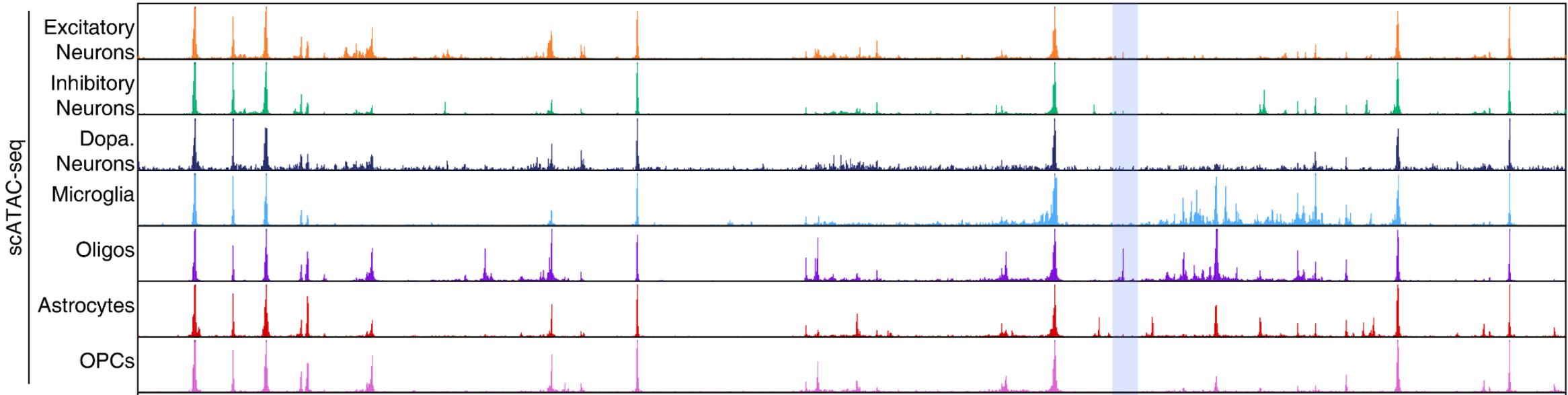


Δ Predicted signal



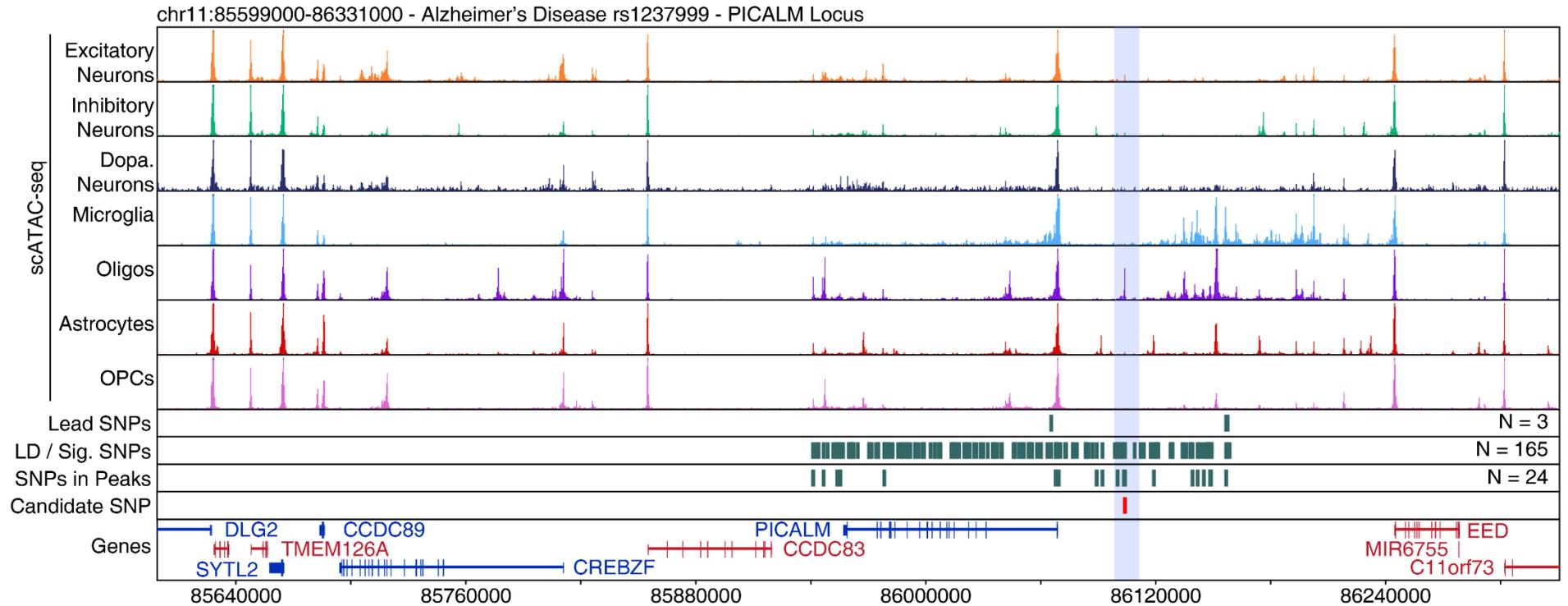
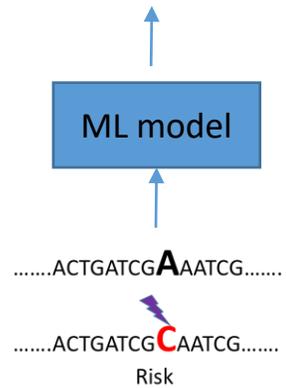
Corces et al. 2020, Nature Genetics

chr11:85599000-86331000 - Alzheimer's Disease rs1237999 - PICALM Locus



Predicting and interpreting causal AD variants

Δ Predicted signal



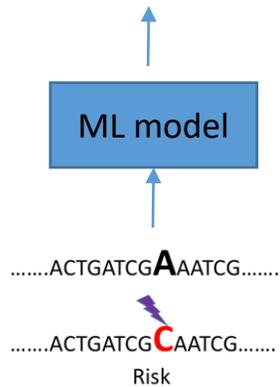
Anna Shcherbina



Soumya Kundu

Predicting and interpreting causal AD variants

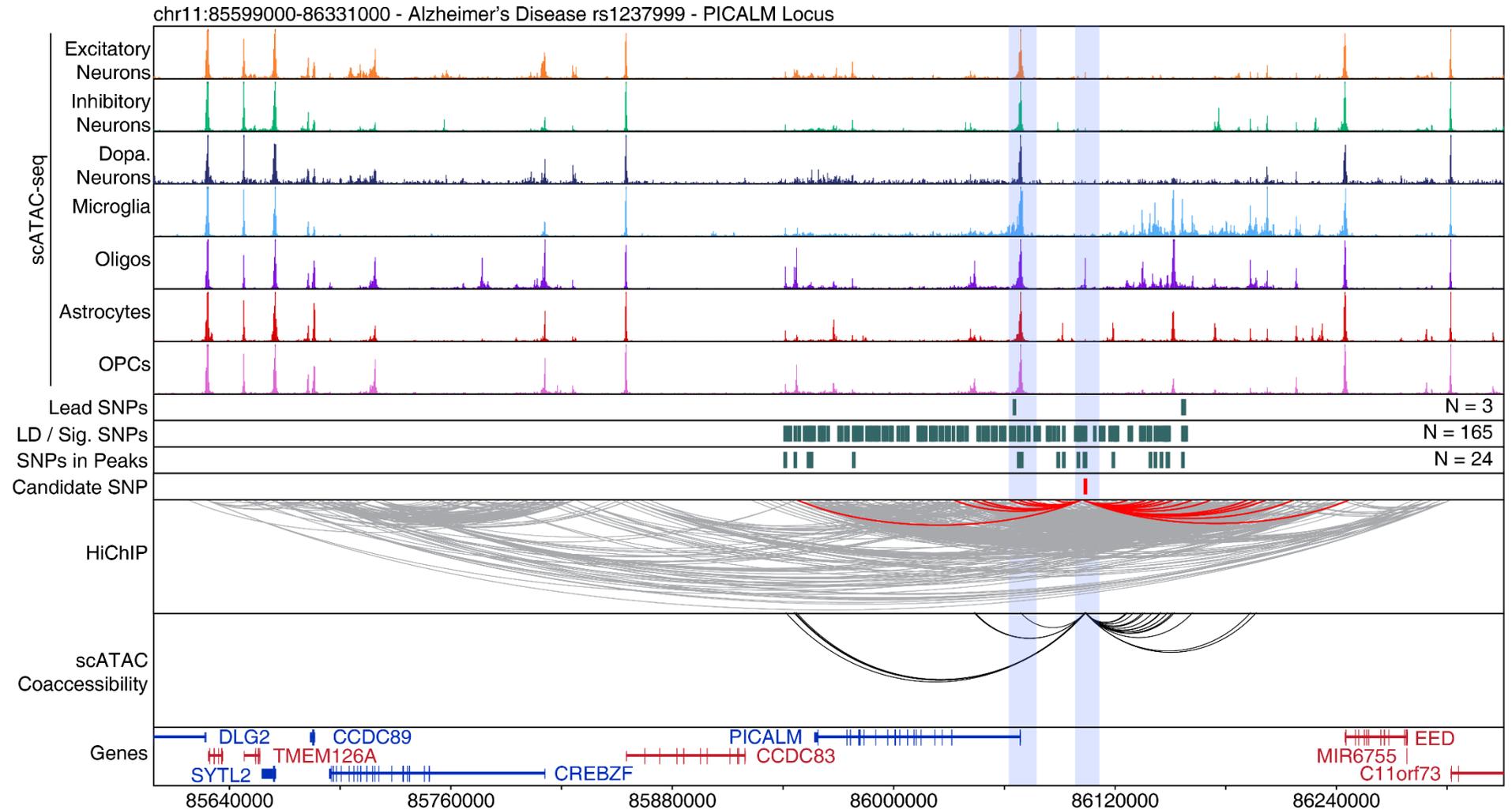
Δ Predicted signal



Anna Shcherbina

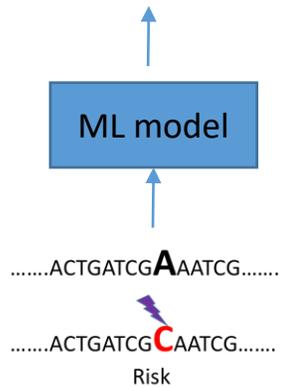


Soumya Kundu



Predicting and interpreting causal AD variants

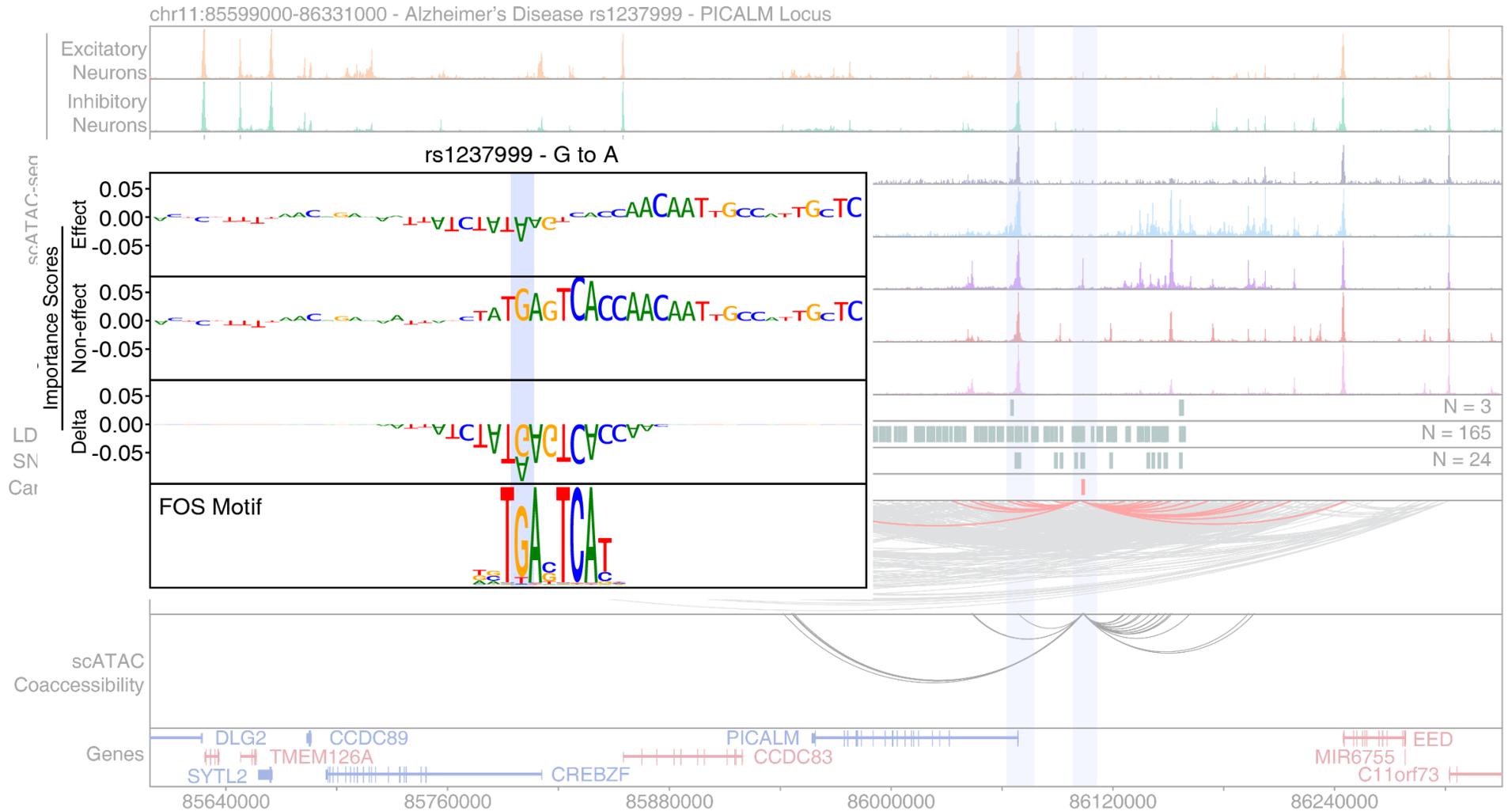
Δ Predicted signal



Anna Shcherbina

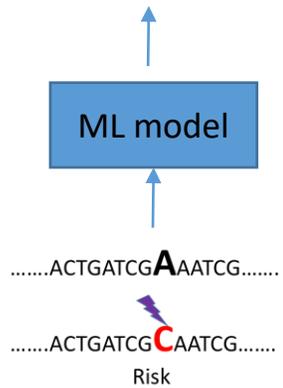


Soumya Kundu



Predicting and interpreting causal AD variants

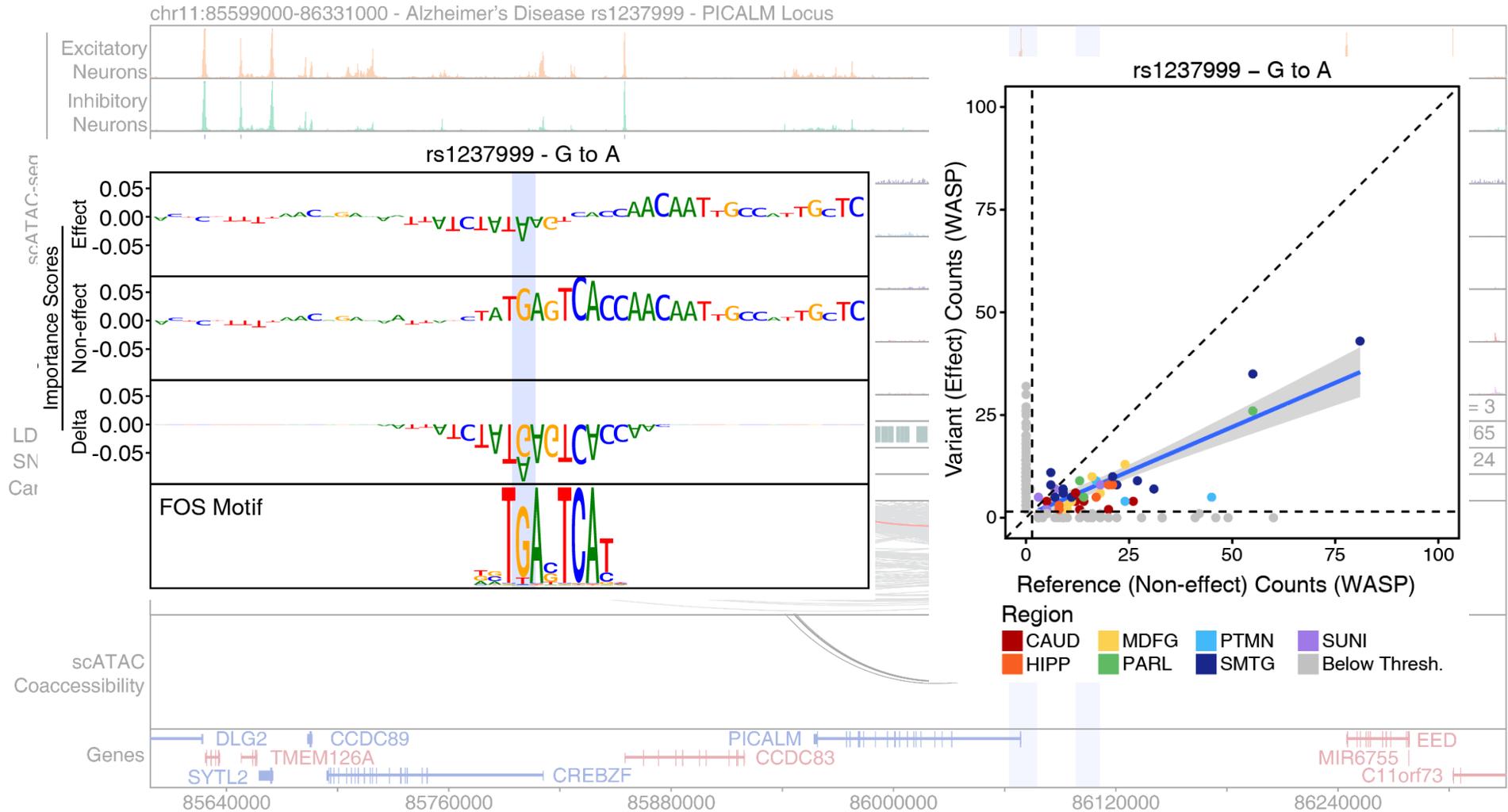
Δ Predicted signal



Anna Shcherbina



Soumya Kundu



Predicting and interpreting causal AD variants

Δ Predicted signal

ML model

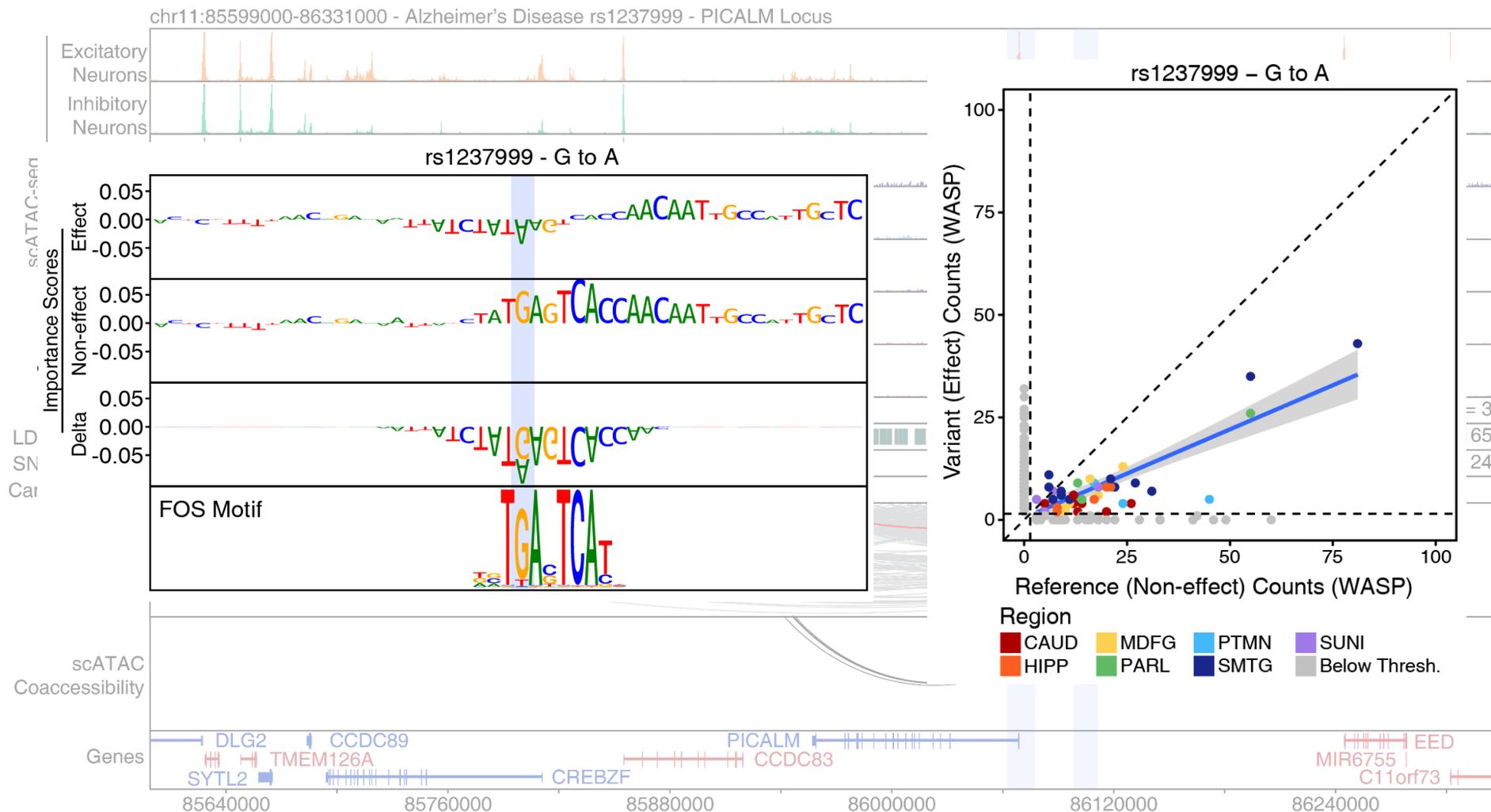
.....ACTGATCG**A**AATCG.....
ACTGATCG**C**AATCG.....
 Risk



Anna Shcherbina

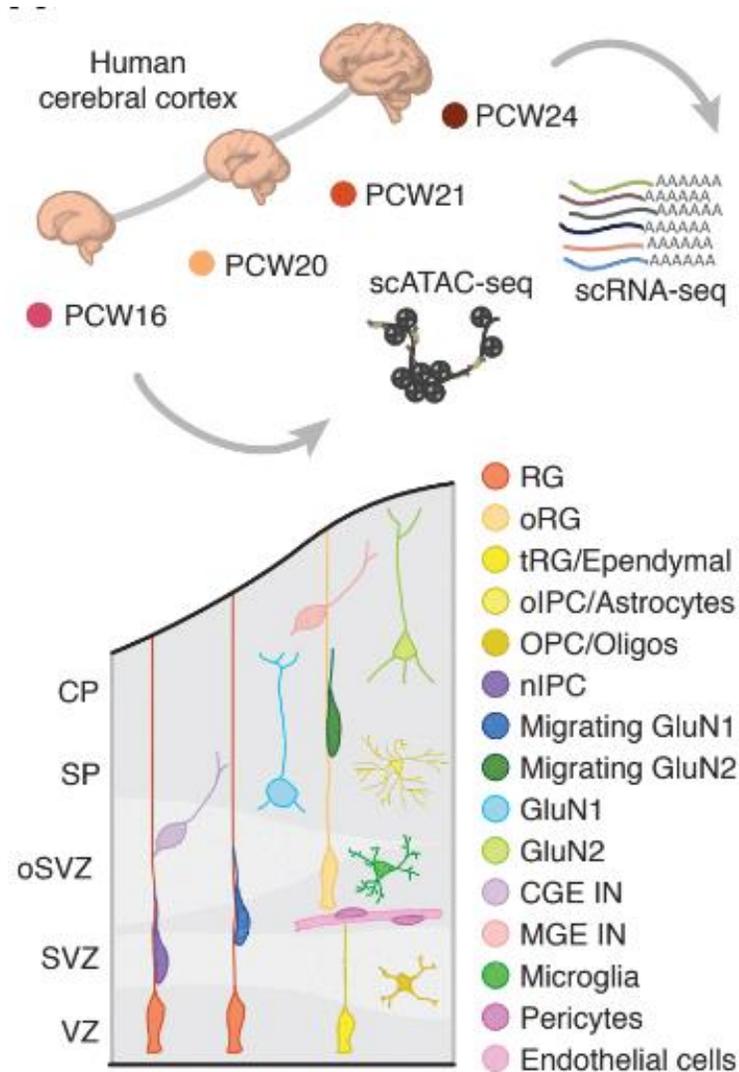


Soumya Kundu



Genetic variant rs1237999 disrupts a sequence motif of the FOS protein in a control element of the PICALM gene in oligodendrocyte cells in the brain

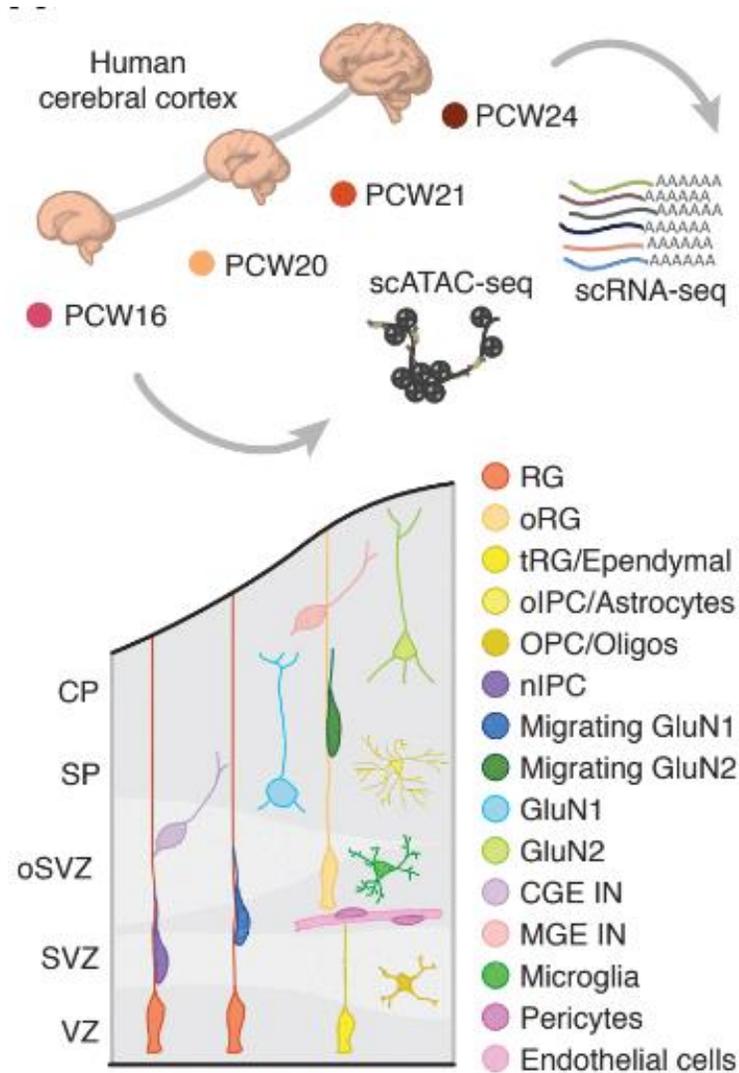
Predicting *de-novo* mutations in Autism



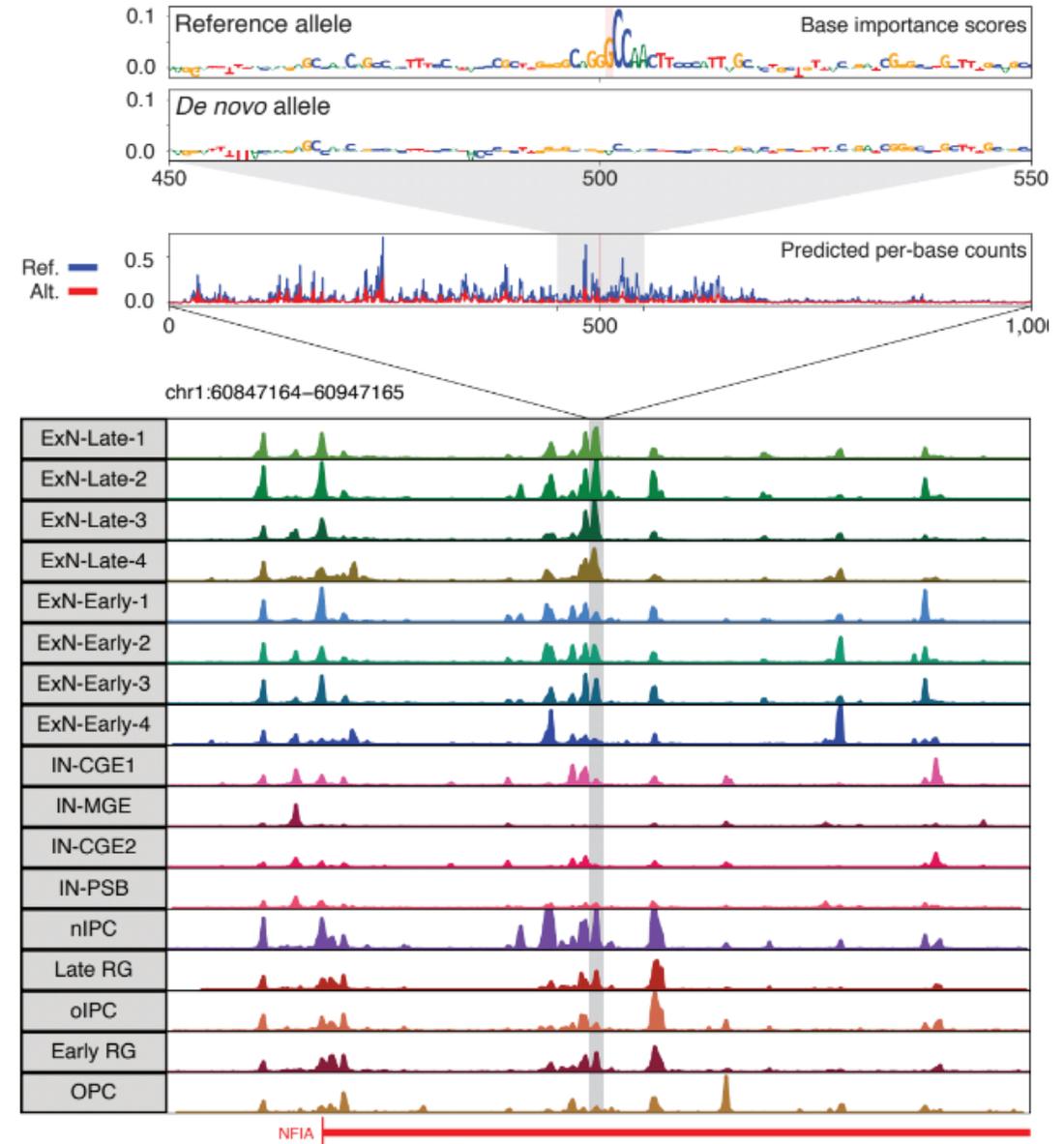
Lakshman Sundaram

Prediction: Mutation disrupts NFIA motif in control element of NFIA gene in glutamatergic neurons

Predicting *de-novo* mutations in Autism

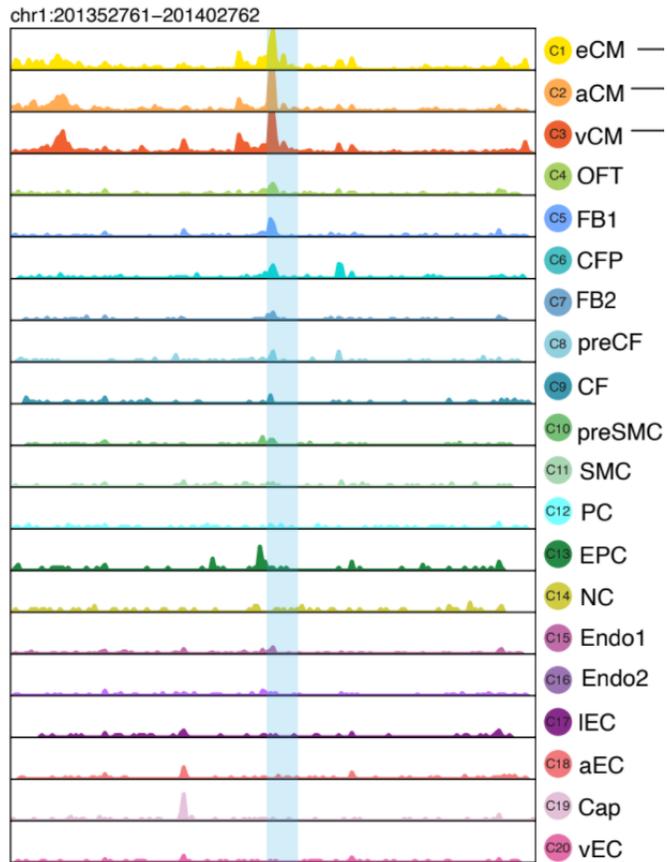
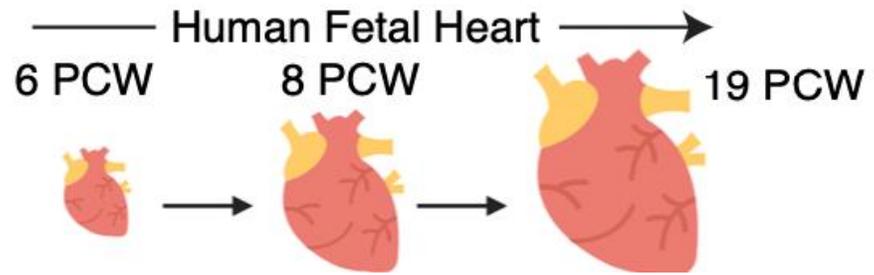


Lakshman Sundaram



Prediction: Mutation disrupts NFIA motif in control element of NFIA gene in glutamatergic neurons

Predicting *de-novo* mutations in congenital heart disease

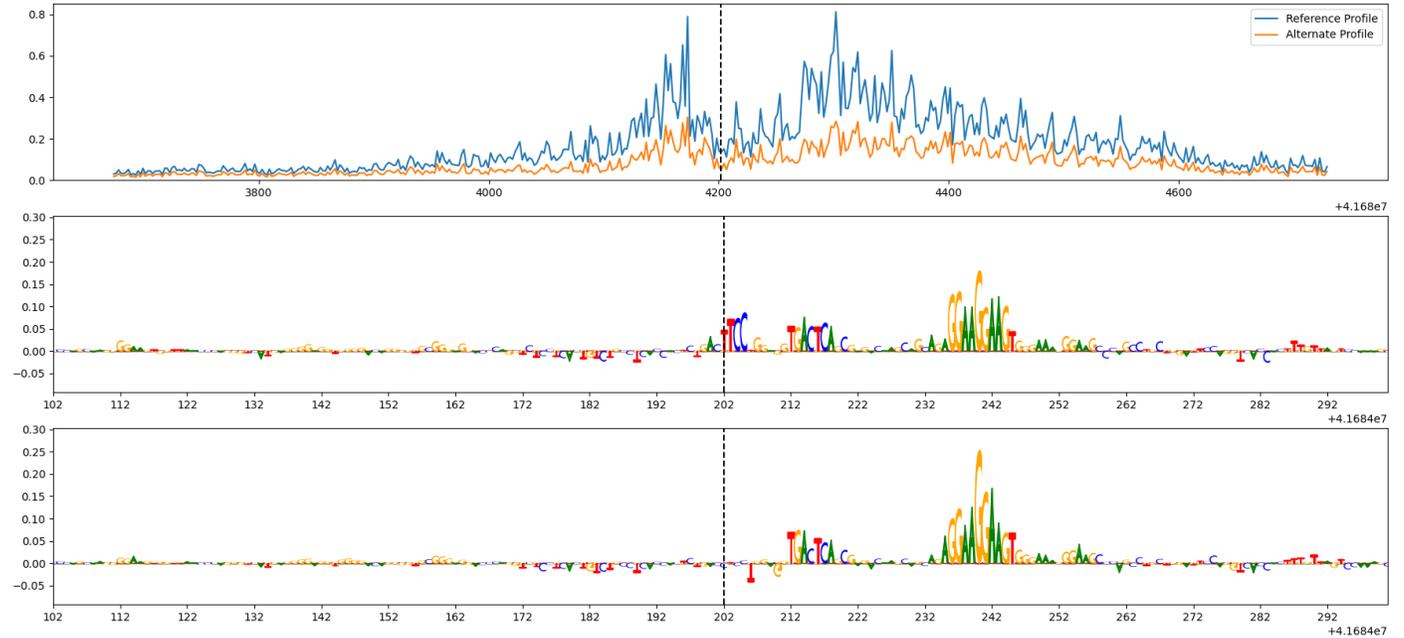
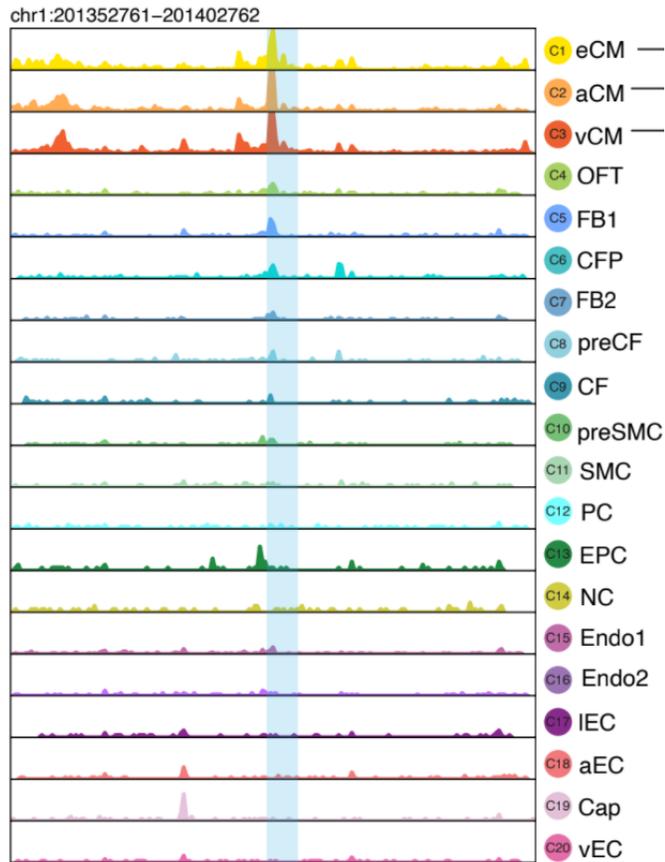
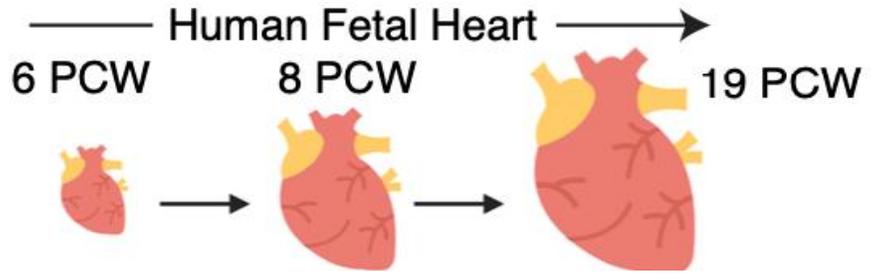


Lakshman
Sundaram



Mo Ameen

Predicting *de-novo* mutations in congenital heart disease



Prediction: Mutation disrupts ETV motif in control element active in arterial endothelial cells

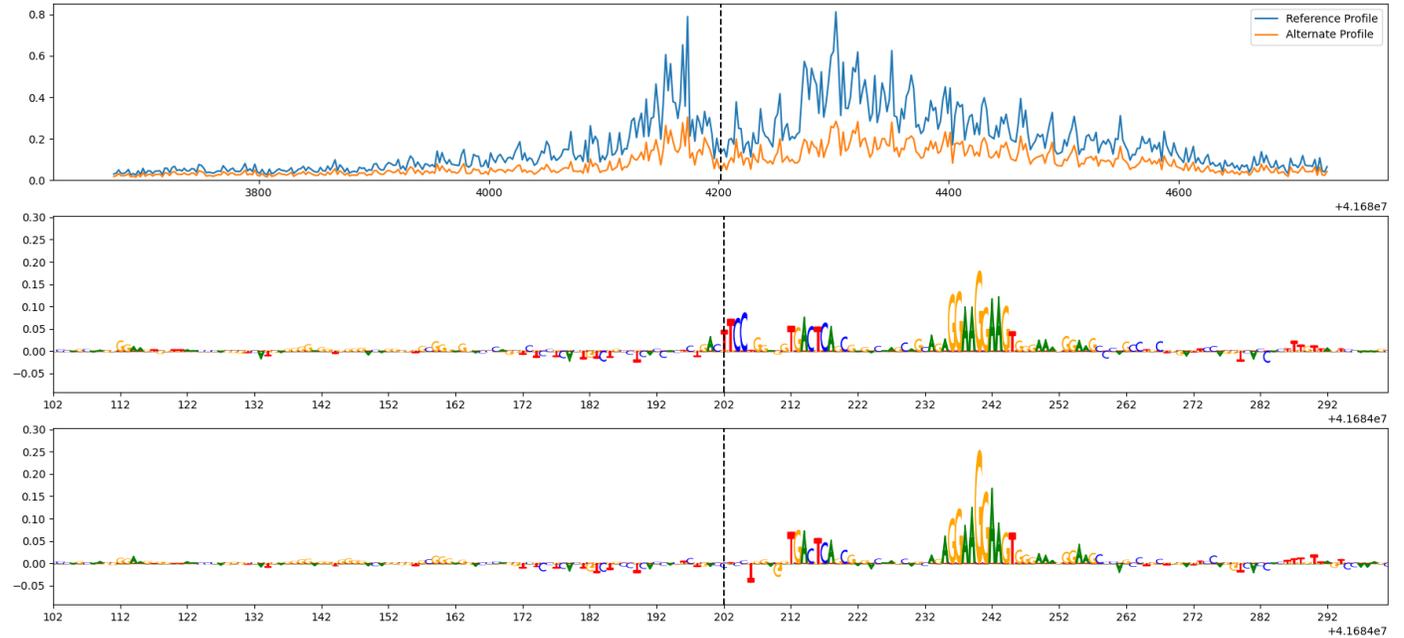
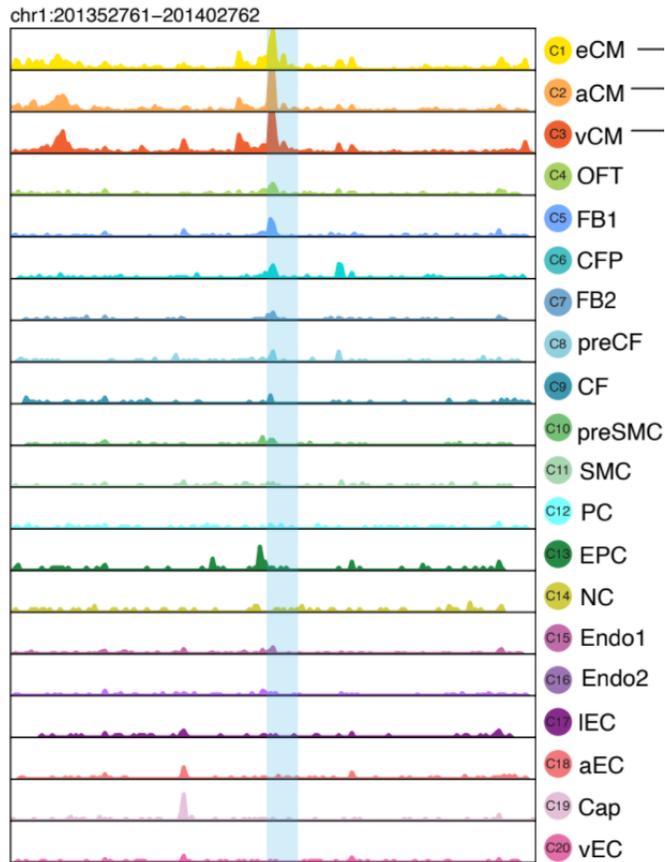
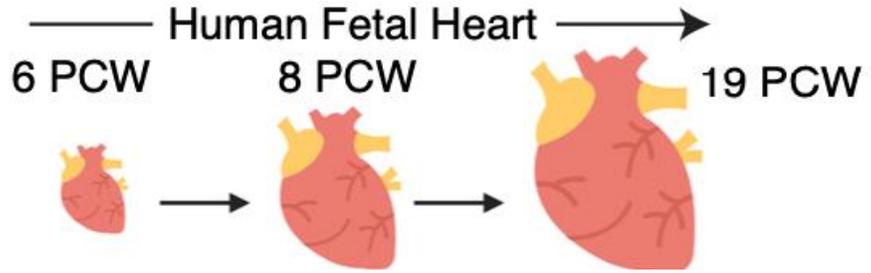


Lakshman Sundaram



Mo Ameen

Predicting *de-novo* mutations in congenital heart disease

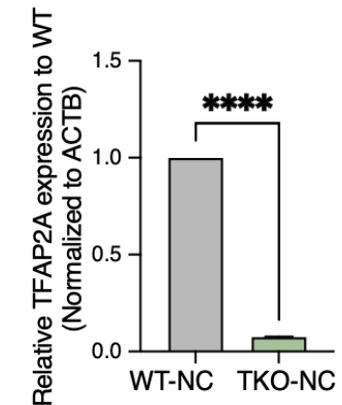
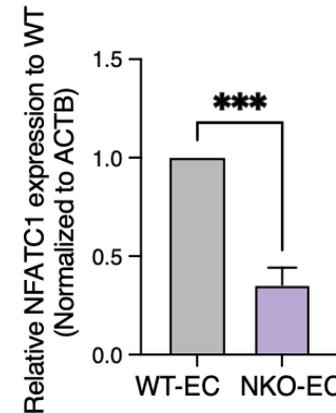
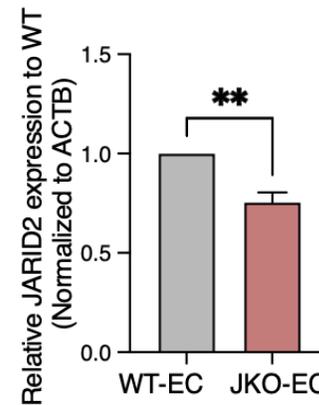


Lakshman Sundaram



Mo Ameen

Prediction: Mutation disrupts ETV motif in control element active in arterial endothelial cells

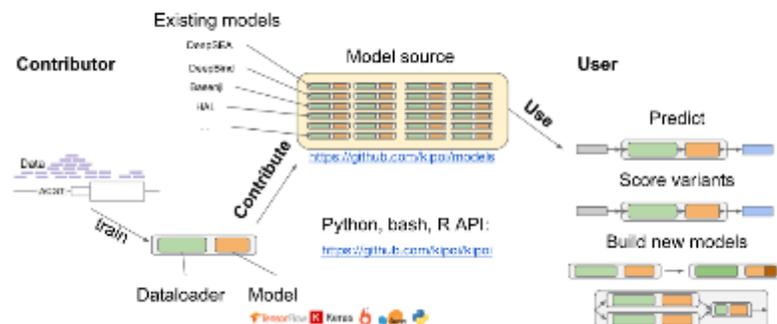


CRISPR/Cas9 experiments validate downstream target genes

Democratizing ML for genomics: <http://kipoi.org/>



Kipoi: Model zoo for genomics



Kipoi (pronounce: kípi; from the Greek κήποι: gardens) is an **API** and a **repository** of ready-to-use trained models for regulatory genomics. It currently contains 1709 different models, covering canonical predictive tasks in transcriptional and post-transcriptional gene regulation. Kipoi's API is implemented as a python package (github.com/kipoi/kipoi) and it is also accessible from the command line or R.

Numbers

of models: 1709

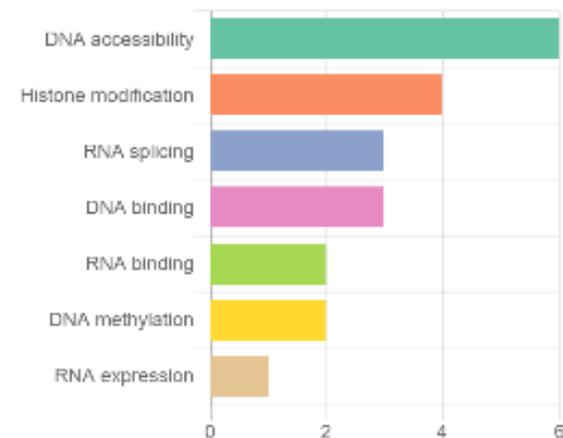
of model groups: 16

of contributors: 6

of model groups supporting postprocessing:

- Variant effect prediction: 11/16

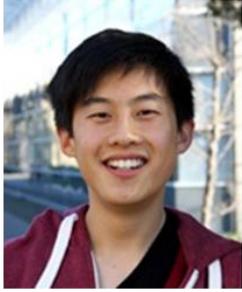
Model groups by tag



Summary

- Large-scale molecular profiling datasets => decipher genome function
- Neural networks can map DNA sequence to molecular profiles with unprecedented accuracy
- Models can be interpreted to decipher functional DNA letters, words and syntax
- Models can be used to decipher disease-associated mutations
- Predictions are validated by genome editing experiments
- Predictions can provide clues for therapeutic interventions

Kundaje lab



Daniel Kim (BMI)



Kelly Cochran (CS)



Soumya Kundu (CS)



Surag Nair (CS)



Maxim Zaslavsky (CS)



Vivek Ramalingam (Postdoc)



Caleb Lareau (Postdoc)



Akshay Balsubramani (Postdoc)



Georgi Marinov (Postdoc)



Alex Tseng (CS)



Amr Alexandari (CS)



Abhimanyu Banerjee (Physics)



Lakshman Sundaram (CS)



Anusri Pampari (CS)



Kristy Mualim (Bioinformatician)



Jacob Schreiber (Postdoc)



Mahfuza Sharmin (Postdoc)



Eran Kotler (Postdoc)



Zahoor Zafrulla (ML engineer)

Collaborators



Funding



1R01HG009674

1U01HG009431

1U24HG009446



R01ES02500902

1DP2OD022870

