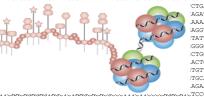
CBS MiniHack - MPRA Challenge Kickoff Talk

Jason Ernst
Professor
University of California, Los Angeles



From the epigenomic data can identify tens of thousands of

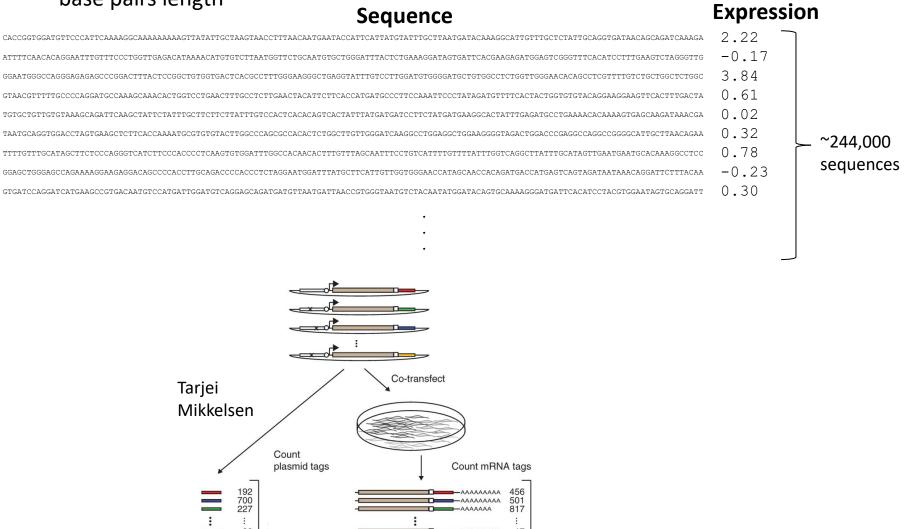
candidate regulatory regions in a single cell type



From the epigenomic data can identify tens of thousands of candidate regulatory regions in a single cell type A next challenge: test these regions and map at high resolution AGTCTGAA CTCAGATI activating and repressive nucleotides within them

Massively Parallel Reporter Assay (MPRA)

 Massively parallel reporter assay enables obtaining a quantitative readout of the ability to activate or repress gene expression for 244,000 user specified DNA sequences of 145 base pairs length



Melnikov et al, Nature Biotech 2012; Ernst et al, Nature Biotech 2016

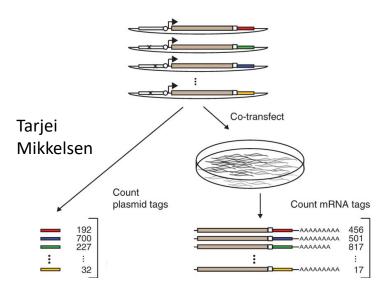
Massively Parallel Reporter Assay (MPRA)

Massively parallel reporter assay enables obtaining a quantitative readout of the ability to activate or repress gene expression for 244,000 user specified DNA sequences of 145 base pairs length
 Sequence

Expression

Problem: Leverage MPRA to map at close to nucleotide resolution activating and repressive bases for thousands of regions and not knowing the precise 145 base pairs to test.

~244,000 sequences



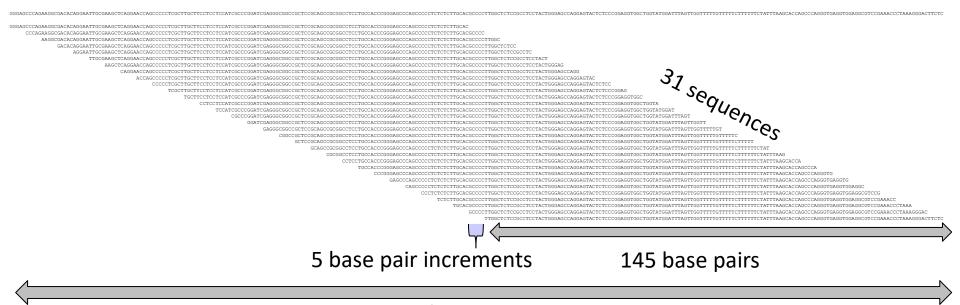
TGTGC

TTTTG

GGAGC

Melnikov et al, Nature Biotech 2012; Ernst et al, Nature Biotech 2016

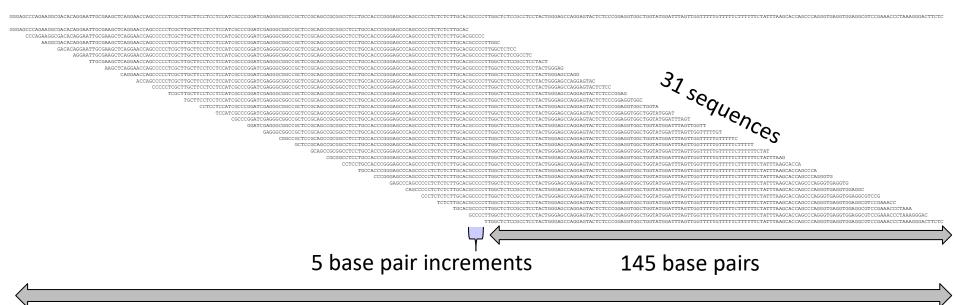
Tiling Strategy



295 base pairs

- ~8,000 regions can be tested in a single experiment
- Coverage of 295 base pairs for each regulatory region tested
- Information available to recover at high resolution activating and repressive bases

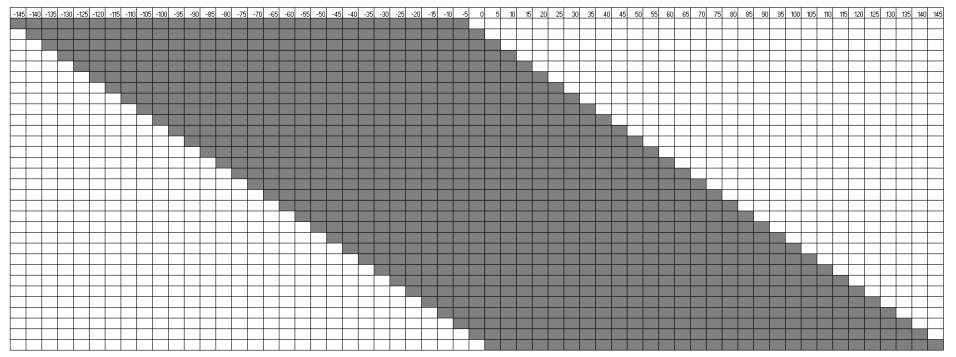
Tiling Strategy

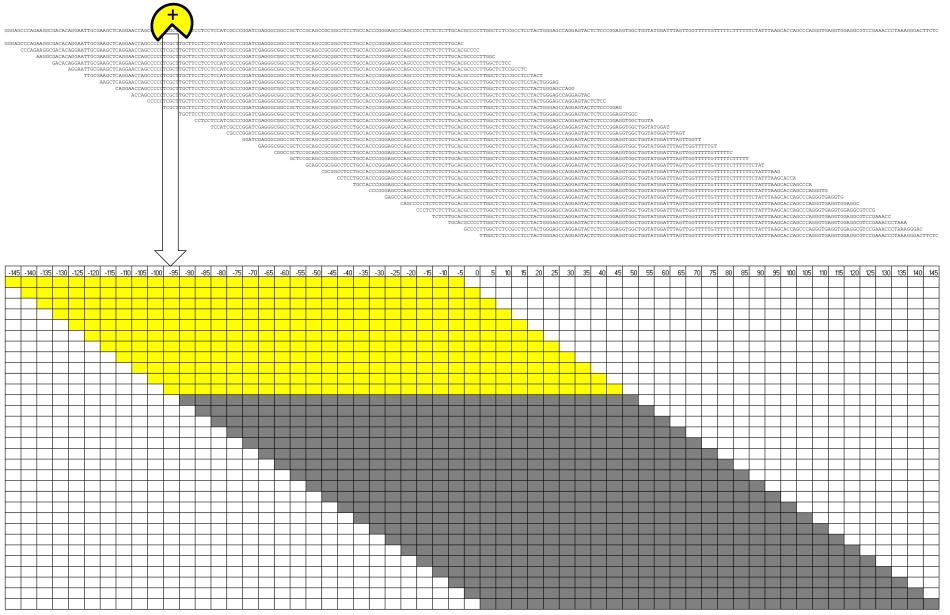


295 base pairs

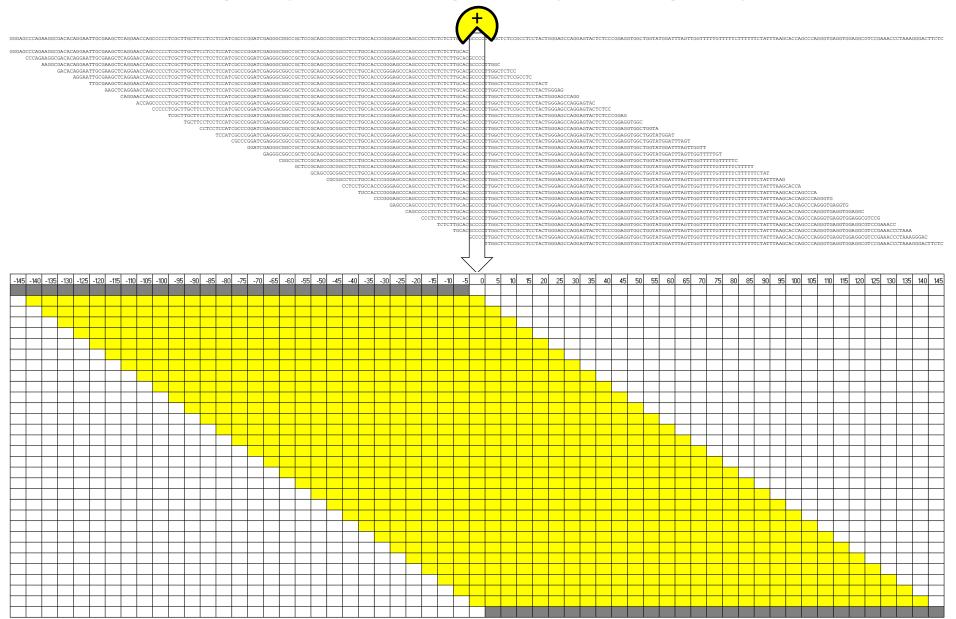
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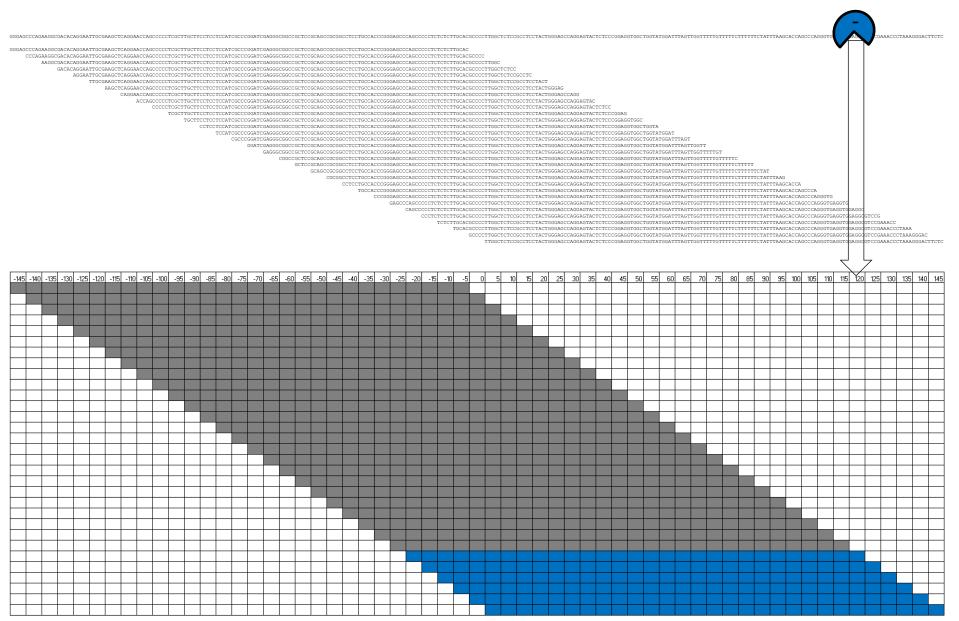




Gray – basal gene expression; Yellow – higher gene expression



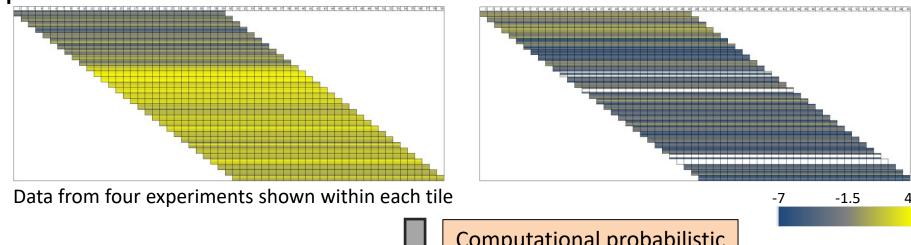
Gray – basal gene expression; Yellow – higher gene expression



Gray – basal gene expression; Blue – lower gene expression

Example Input Data and Regulatory Activity Inferences

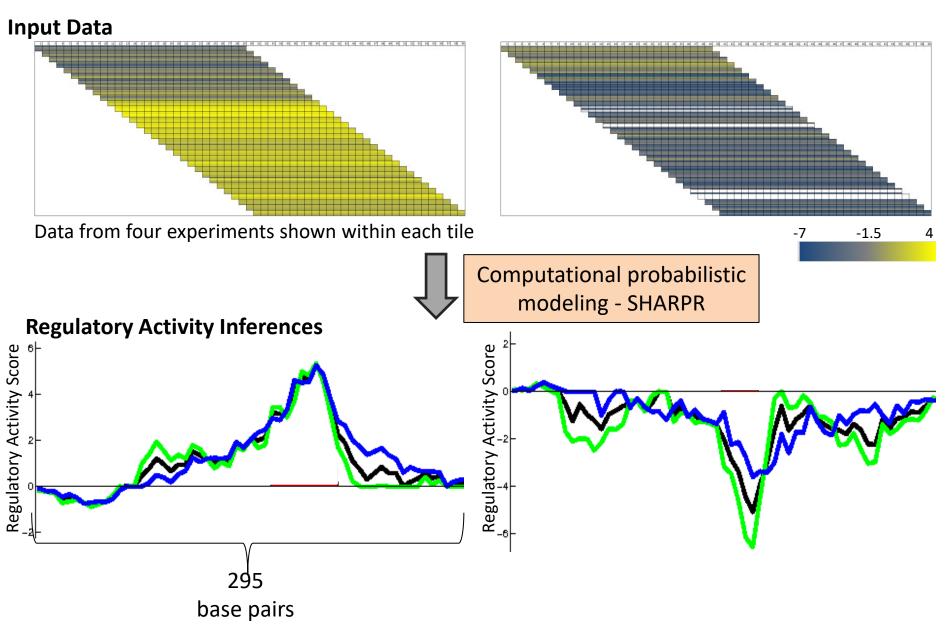






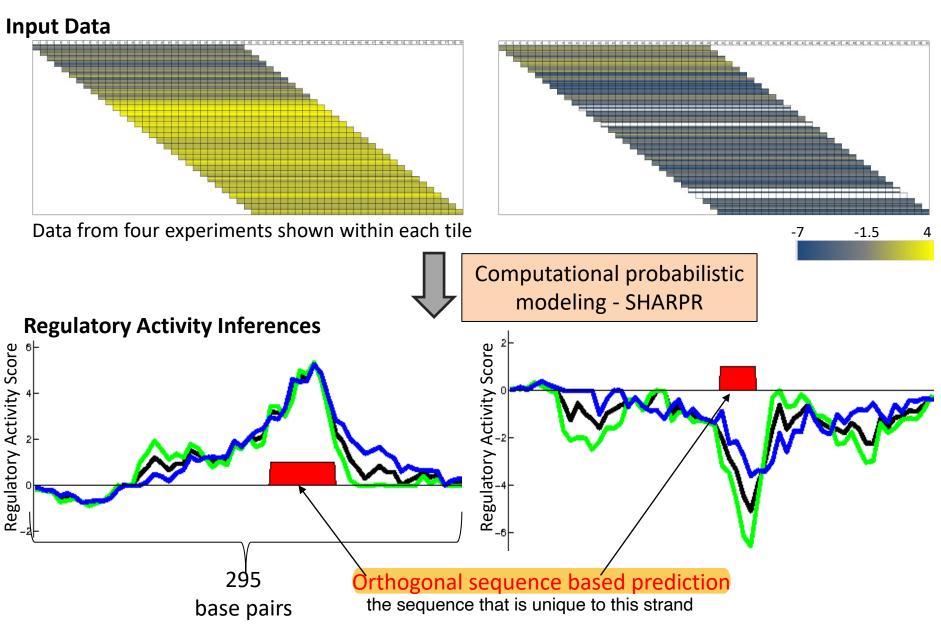
Computational probabilistic modeling - SHARPR

Example Input Data and Regulatory Activity Inferences



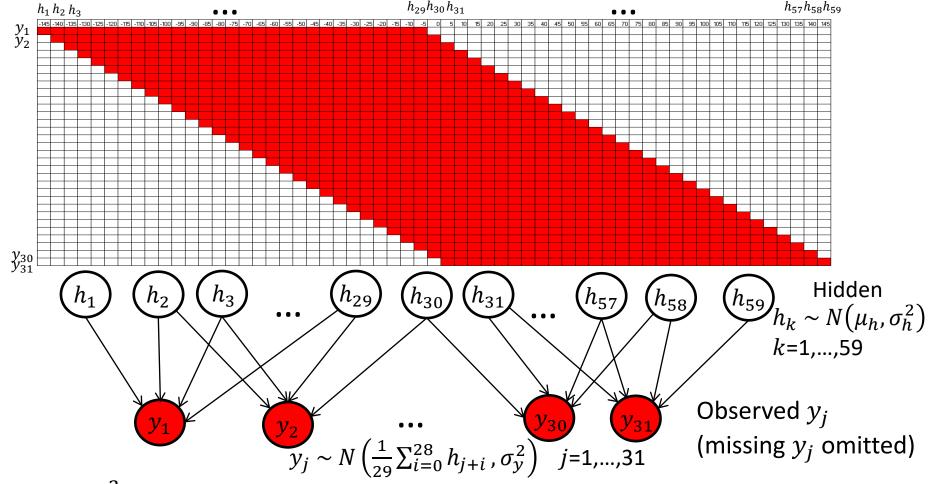
Regulatory Activity Inferences: Green - SV40 promoter only; Blue - minimal promoter only; Black combined

Example Input Data and Regulatory Activity Inferences



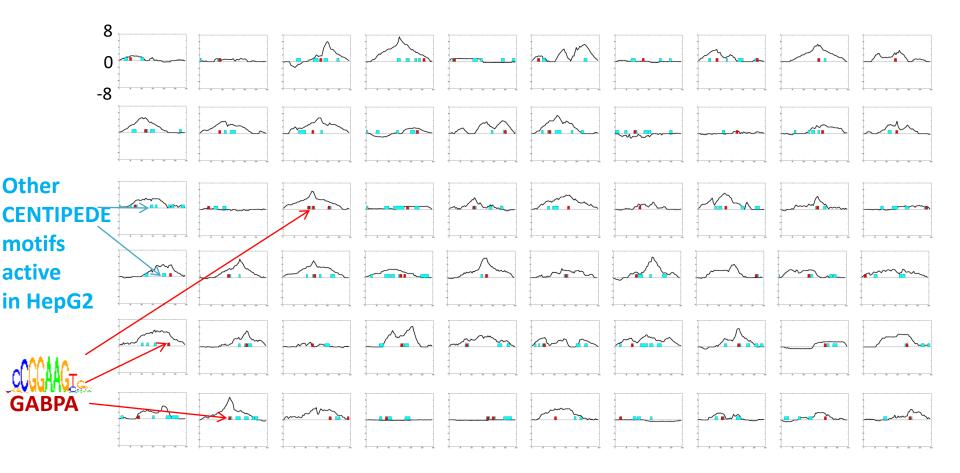
Regulatory Activity Inferences: Green – SV40 promoter only; Blue – minimal promoter only; Black combined Sequence based predictions from CENTIPEDE (Pique-Regi, et al, 2011)

SHARPR - Probabilistic Model



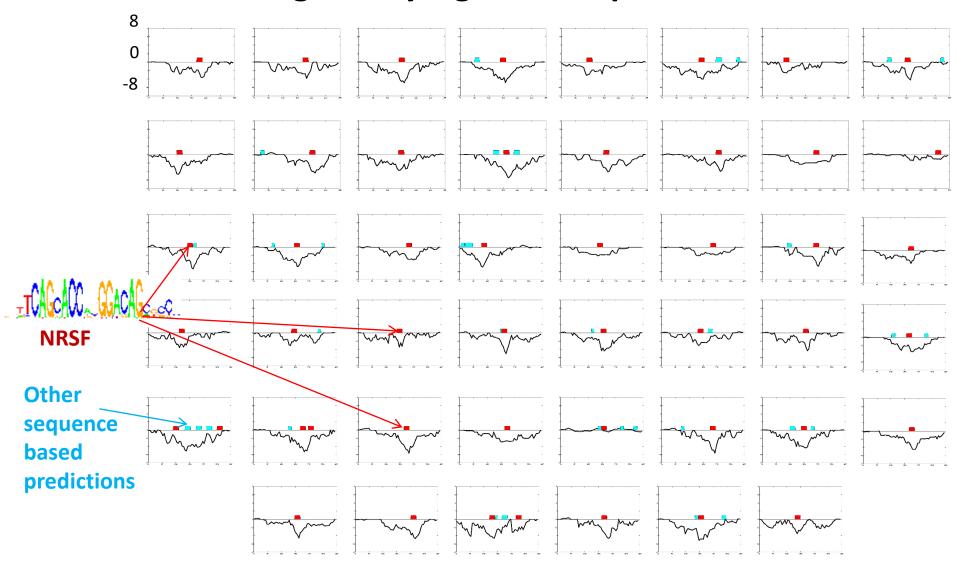
- μ_h and σ_y^2 empirical mean and variances of y_j
- Hidden variables can be inferred exactly and efficiently using multivariate gaussians
- Z-score transformation on inferred hidden values, four experiments averaged
- σ_h^2 was set to both of 1 and 50, and more conservative final output was used
- Piecewise linear interpolation for base resolution predictions

Inferred regulatory signal vs. activator motif



60 sites containing GABPA HepG2 motifs predicted by CENTIPEDE

Inferred regulatory signal vs. repressor motif



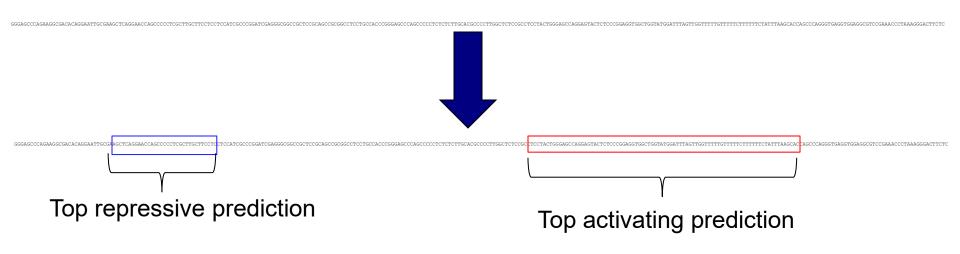
All sites tested containing NRSF motif based predictions in HepG2



Mini-Hackathon CBS



- In collaboration with Computational Biologist's Society (CBS) at UCLA
- Task is to predict from DNA sequence highly activating and repressive nucleotides annotated by Sharpr-MPRA





Why predict from DNA sequence?

- Do not have experimental data across every loci
- Not feasible to experimentally map in every individual
- If we have an effective predictive model of regulatory activity from DNA sequence, can use it to make predictions of regulatory impact of sequence variants in specific cell types

e.g. what is predicted impact of mutating an A to T?



Provided File 1

- train_MPRA.txt contains 8000 sequences.
- One sequence per line
- For each sequence, a sequence ID, 295-bp sequence, followed by 295 columns of activity values corresponding to nucleotides in order

```
train1
train2
```

AGCTCACGGGGACTAGGGCAGGGAGGCTGCGGGGATGGAAAGATC...
ACTCTCATCCCACAGAATGAGCTTTACAGTAACTTGGATCTCTAC...

0.019

0.019

0.019 -0.113

0.018... -0.113...

Note: do not have to use all the training data available

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Provided File 2

- trainsolutions.txt
- Sample output data file that would receive a perfect score

```
R train1310 168
R train1310 169
R train1310 167
...
A train2219 193
A train2219 194
A train2219 195
```

Note because of ties not a unique such solution

Provided File 3

- test MPRA.txt
- test1 CTCCGGACAGGTGGGTTTGACAACATCTATTTTGGTCATGCCTGGGCAGTTCTGGCTTATCCATCTACACTAGTCTCAAATGATCCTGGGATTTGCTCTTGGGTA
 test2 CTGTCCCAGCCTACAGTCAGCTCACGCGCCTCTTCCTGTGTGTACCTGCAGGCCCCACCTGGGCTGGAATGCTGCCTTCTTCACCACACAGAGGCGGC
- test3 TCAAATCTCTTGAACTTCTCTCCAACACCAGCTGGAGAAAGAGGCTCTCATTTTGAAGGGCCCCTGTGATTAGATTGCAACCATTTGAATAGTCTTTTTTGA
- First column is ID
- Second column is 295 bp sequence
- In total 7720 sequences

Provided File 4

JASPAR2024_CORE_vertebrates_nonredundant_pfms_jaspar.txt

contains a library of positional weight matrices (PWMs) from JASPAR database

Optional to use

```
>MA0004.1 Arnt

A [ 4 19 0 0 0 0 0 0 ]

C [ 16 0 20 0 0 0 0 20 ]

G [ 0 1 0 20 0 20 0 20 ]

T [ 0 0 0 0 0 20 0 0 ]

>MA0069.1 PAX6

A [ 2 2 4 39 3 1 1 21 1 2 36 11 1 1 1]

C [ 4 2 26 2 34 0 37 2 4 14 0 11 5 0 ]

G [ 4 0 1 1 1 1 41 4 2 1 25 6 13 3 17]

T [ 33 39 12 1 5 1 1 18 37 2 1 8 34 25]
```





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Output

Text file which contains your top 100,000 activating and top 50,000 repressive predictions for test sequences. One per line.

```
R test1310 168
R test1310 169
A test2084 45
A test5261 221
```

- First column 'A' for activating; 'R' for repressive
- Second column IDs from testing sequence
- Third column is nucleotide position in sequence where positions are indexed starting from 1
- Columns can be tab, space, or comma delimited



Competition Scoring

■ The final score will be the sum of the number of top 100,000 activating base predictions that are in the top 100,000 activating bases and the number of top 50,000 repressive predictions in the top 50,000 repressive bases

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Competition Rules

- Winners will be determined based on status of leaderboard on Friday, January 10th at 5pm
- May only use provided data files. No use of external data is allowed.
- Use of standard machine learning libraries is allowed but using existing software specifically designed for predicting from DNA sequence is not allowed
- Winning team(s) will be asked to give presentation and may be asked to submit code



Online system

- Will use CodaLab which provides leaderboard scoring
- CodaLab link:
 https://compmed.codalab.click/competitions/192?secret_key=409a5
 b0d-cfd6-4076-84aa-da6bffd958ed
- File link:

https://ucla.box.com/s/3dpi45n9fslao5uygqyjngkhval15soi

- Data files and competition system will be released with kickoff event on Monday
- Must be on UCLA network (including VPN) to access
- Will need to create a CodaLab account to submit
- Access/login issues https://uclahs.fyi/codalab-support goes to Clifford Kravit
- Follow slack for updates/clarification

Submission instructions

a. Once you have your answers written in your text editor, save the file as predictions.csv (Required). Alternatively, convert your existing .txt file containing the answers to .csv by running the following command:

\$ mv ./FILE.txt ./predictions.csv

b. Then run the following command to zip the predictions.csv into a .zip file (any name allowed)

\$ zip -r predictions.zip predictions.csv

c. To submit your .zip file, go to the competition page and navigate to the Participate tab, then click on Submit / View Results. When you click the Submit button a file explorer will open up for you to select a file to upload. Then you are done. You may have to refresh the page manually after a minute for the grader's output to be calculated and tabulated on the Results tab/section below the submit button.



Some possible strategies

- Simple baseline approaches
- Explicit features to standard supervised classification or regression methods
- Deep learning methods directly from DNA sequences



Some possible strategies

- Simple baseline approaches
- Explicit features to standard supervised classification or regression methods
- Deep learning methods directly from DNA sequences



Simple baseline approach – GC content

- Count the number of G's or C's in a sequence and rank sequences in increasing or decreasing counts. Could either be the same or different choice between the two for activating and repressive.
- All bases within a sequence would be equivalently ranked.

Simple baseline approach – Center position

Predict the most center bases in every sequence

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Some possible strategies

- Simple baseline approaches
- Explicit features to standard supervised classification or regression methods
- Deep learning methods directly from DNA sequences

K-mer features

ACACCATTAGACCA

Example with k=2

2-mers	count
AA	0
AC	3
AG	1
AT	1
CA	3
CC	2
CG	0
CT	0
GA	1
GC	0
GG	0
GT	0
TA	1
TC	0
TG	0
TT	1

K-mer features



Example with *k*=2

2-mers	count
AA	0
AC	3
AG	1
AT	1
CA	3
CC	2
CG	0
СТ	0
GA	1
GC	0
GG	0
GT	0
TA	1
TC	0
TG	0
TT	1

Positional Weight Matrix

PWM scanning

	1	2	3	4	5	6	7
Α	3/5	0	0	2/5	1	1/5	1
С	2/5	1	0	0	0	1/5	0
G	0	0	4/5	0	0	1/5	0
Т	0	0	1/5	3/5	0	2/5	0

Scoring agreement of a sequence with the PWM

CCGTATA

$$\frac{2}{5} \times 1 \times \frac{4}{5} \times \frac{3}{5} \times 1 \times \frac{2}{5} \times 1 = \frac{48}{625}$$

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PWM features

- May want to represent as log-ratio relative to background model e.g. probability ¼ of each nucleotide
- May want to truncate score (e.g. set to 0, logratio values less than 0)
- Different ways to aggregate over region (e.g. maximum or average)
- Can also consider scanning reverse
 complement (swap A's and T's; C's and G's; then scan in the reverse direction)



Positional information

- Could have features corresponding to where base being predicted is along the sequence and its distance to the center or ends
- Could have sequence features be the same for the entire sequence or specific to each position

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Prediction task

- Could either model task as regression or classification after discretizing
- With classification could either be model as separate classification problems for activation or repression or three -way classification
- With regression could either be modeled as single regression problem or separate regression problems for activation and repression, where low and high values are truncated respectively
- Many standard methods for regression or classification (e.g. linear/logistic regression, tree based, SVM based etc)



Some possible strategies

- Simple baseline approaches
- Explicit features to standard supervised classification or regression methods
- Deep learning methods directly from DNA sequences

Deep learning modeling of sequences

ANALYSIS

Predicting the sequence specificities of DNA- and RNA-binding proteins by deep learning

Babak Alipanahi^{1,2,6}, Andrew Delong^{1,6}, Matthew T Weirauch³⁻⁵ & Brendan J Frey¹⁻³

Nature Biotechnology, 2015

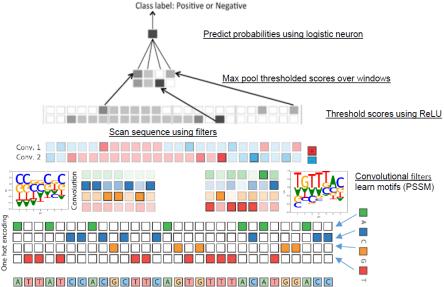


Image from Anshul Kundaje

- Often give state of the art results for prediction tasks from DNA sequence
- Connection between convolutional filters and PWMs
- Could be applied de novo or could try to integrate PWM library

Final remarks

Be creative and have fun!

 Contact: Slack or Jason Ernst (jason.ernst@ucla.edu)

Prof. Eskin and I will be teaching "Algorithms in Computational Genomics" C122 in Winter 2025

MiniHack Timeline of Events

- Kickoff event November 25th Franz Hall Room 1260 from 6-7PM
- Zoom office hours Dec 5th 5pm
- Submission deadline Jan 10th 5pm
- Presentations of winning teams TBD (likely week of Jan 13th)



Questions?

CodaLab link:

https://compmed.codalab.click/competitions/ s/192?secret_key=409a5b0d-cfd6-4076-84aa-da6bffd958ed

■ Files link:

https://ucla.box.com/s/3dpi45n9fslao5uygqyjngkhval15soi