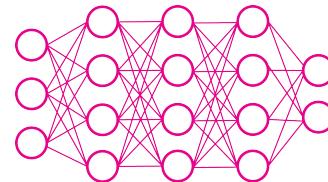


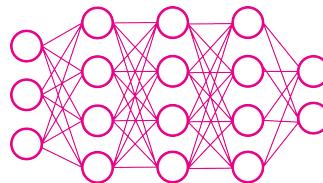
Deep Motif Dashboard: Visualizing and Understanding Genomic Sequences Using Deep Neural Networks

Jack Lanchantin, Ritambhara Singh, Beilun Wang, Yanjun Qi
University of Virginia, Department of Computer Science





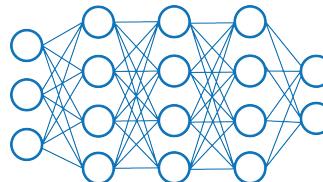
“Dog”

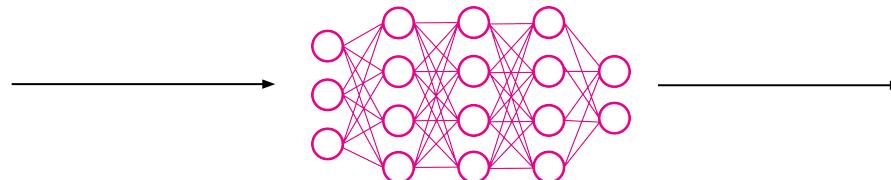


“Dog”

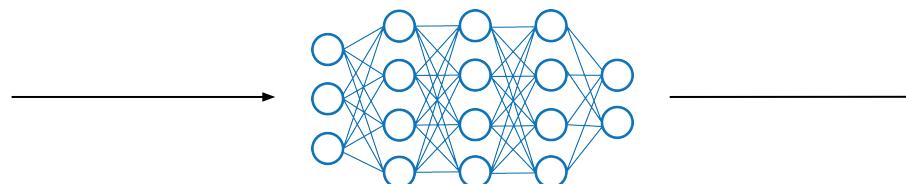
Can get overly sentimental at times, but Gus Van Sant's sensitive direction... and his excellent use of the city make it a hugely entertaining and effective film.

[Full Review...](#) | May 25, 2006

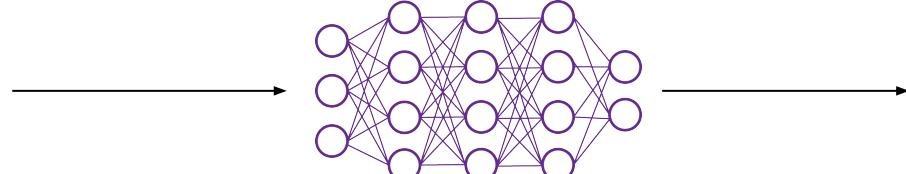




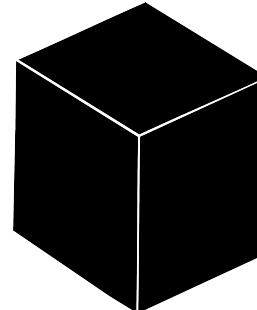
“Dog”



ATGCGATCAAGTCTG



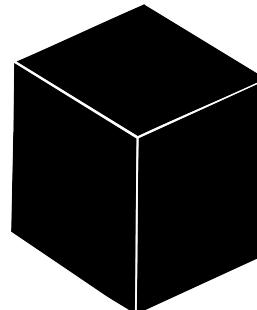
“Protein Binding Site”



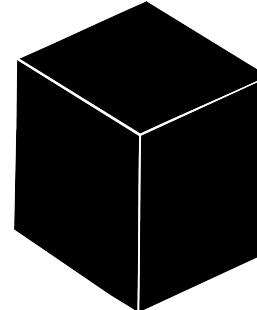
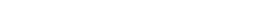
“Dog”

Can get overly sentimental at times, but Gus Van Sant's sensitive direction... and his excellent use of the city make it a hugely entertaining and effective film.

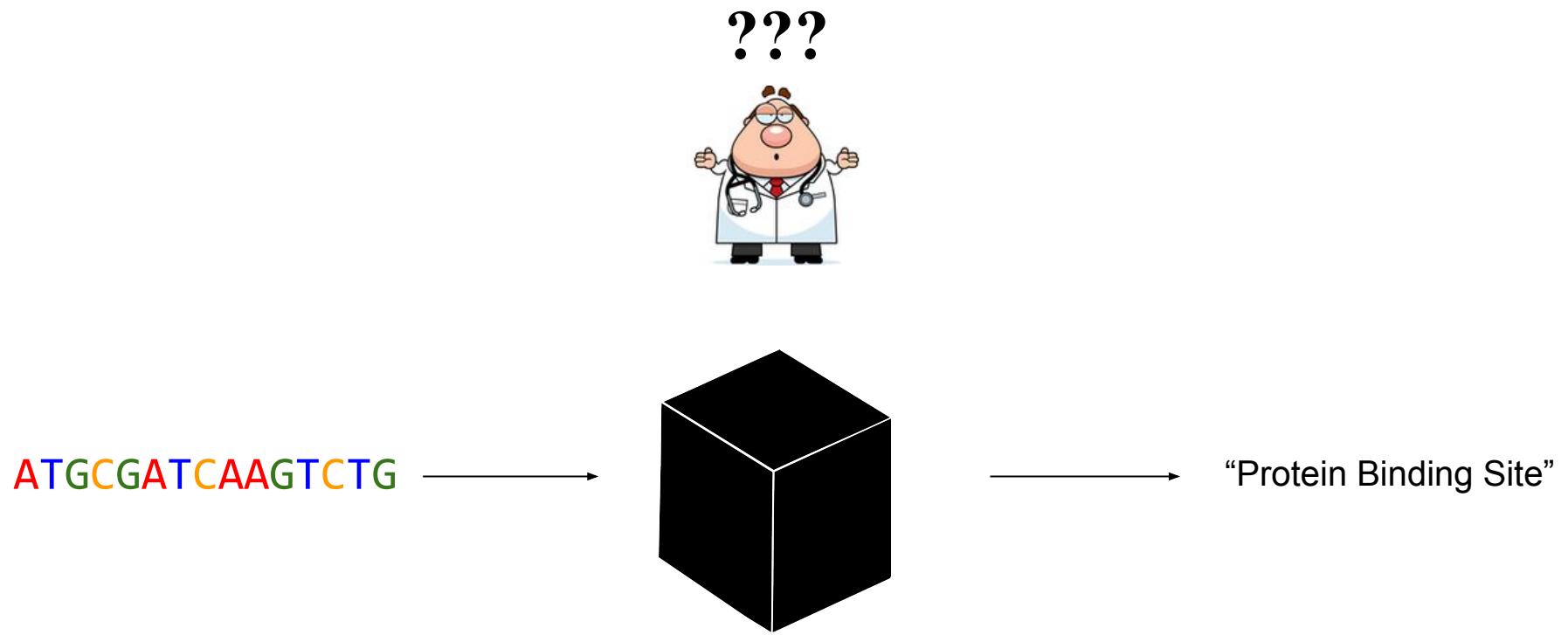
[Full Review...](#) | May 25, 2006



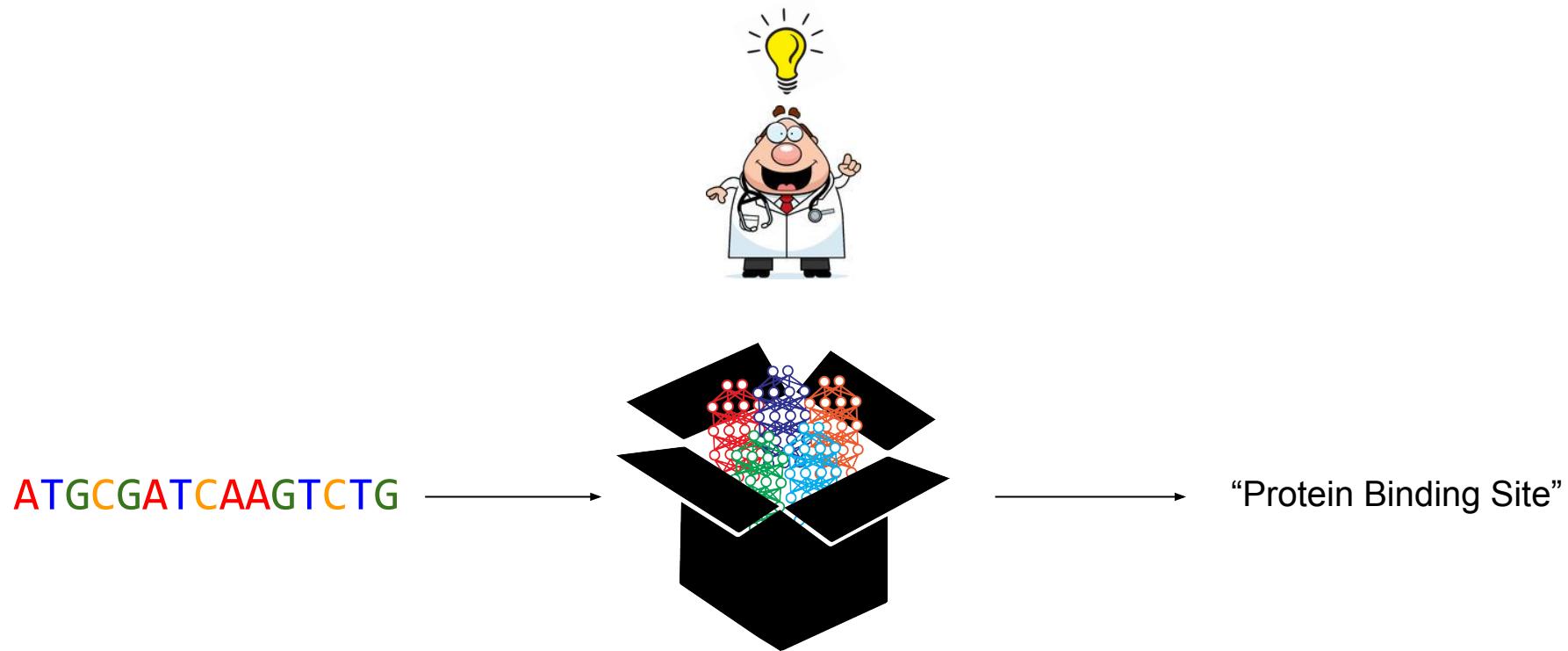
ATGCGATCAAGTCTG



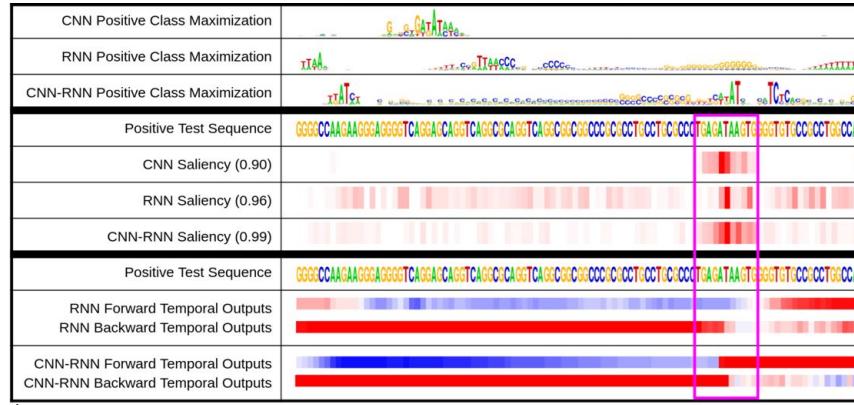
“Protein Binding Site”



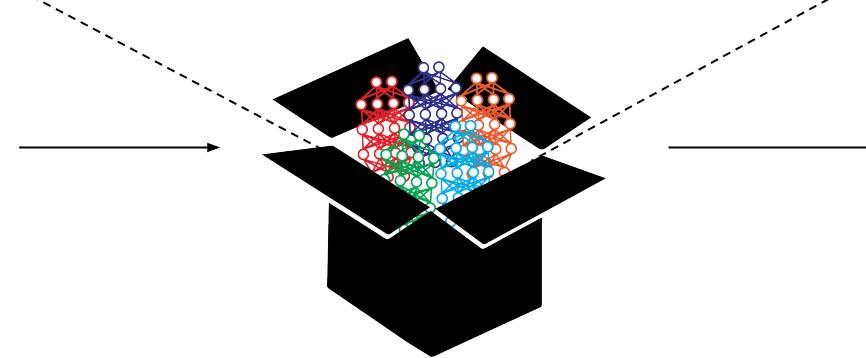
Deep Motif Dashboard: Opening the black box for deep-learning based genomic sequence classifications



Deep Motif Dashboard: Opening the black box for deep-learning based genomic sequence classifications



ATGCGATCAAGTCTG



“Protein Binding Site”

Introduction

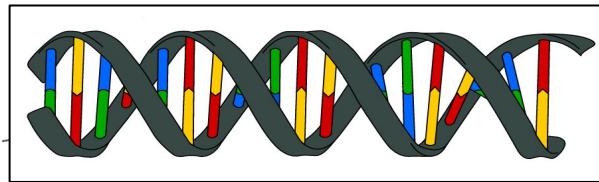
TFBS Classification Task

Neural Models

Visualization Methods

Evaluation and Results

Transcription Factor Binding Sites (TFBSs)



TF1 TF2 TF3
...**GCGACGAATCG...** **AACGATATGCT...** **CATATCATTTC...** **TGTCAAG...** **CTCGAGTC...** **TATCAAAGCTG...**

TFBS Classification Datasets

TF1 (◊)

G	C	G	A	◊	A	A	T	C	G
C	T	C	G	A	G	T	C	T	C
C	G	A	T	A	T	G	C	T	C
A	A	G	A	◊	A	C	T	T	A

TF2 (◊)

A	A	C	G	A	T	A	T	G	C
T	G	T	C	A	A	G	C	A	G
A	T	A	T	C	◊	A	T	A	T
A	G	C	A	T	◊	T	G	C	G

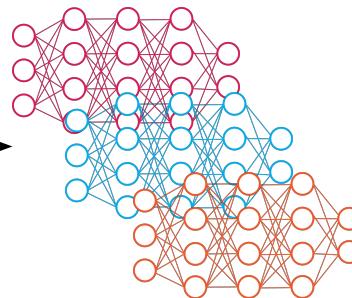
TF3 (◊)

C	A	T	A	T	C	A	T	T	C
T	A	T	C	A	◊	G	C	T	G
C	G	A	A	T	G	C	A	T	A
A	C	G	A	C	◊	T	T	A	T

Deep Motif (DeMo) Dashboard Approach

1.

GAAGCTTGTACGCTATGGA
CTCGATCGAATCGCATGTC
ATGAGATCATGCTTCATCT
CTCGATCGAATCGCATATG
TGTCAACTATGCTCTCGAA



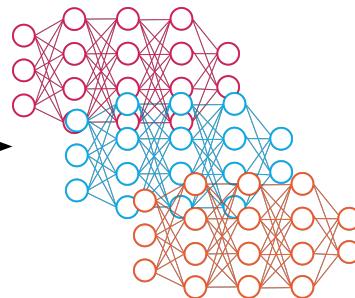
TFBS
NO TFBS
TFBS
TFBS
NO TFBS



Deep Motif (DeMo) Dashboard Approach

1.

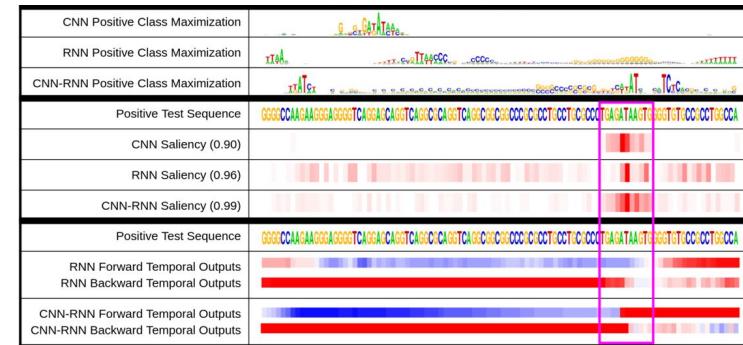
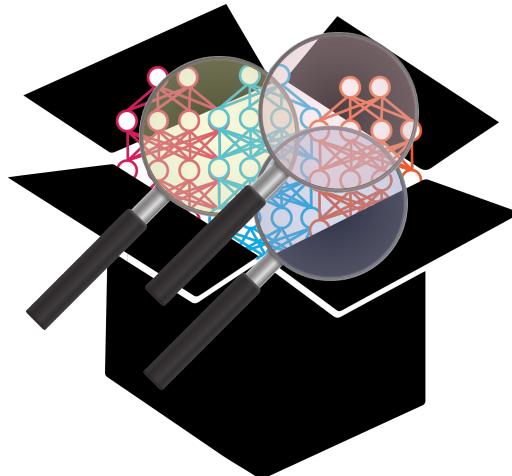
GAAGCTTGTACGCTATGGA
CTCGATCGAATCGCATGTC
ATGAGATCATGCTTCATCT
CTCGATCGAATCGCATATG
TGTCAACTATGCTCTCGAA



TFBS
NO TFBS
TFBS
TFBS
NO TFBS



2.



Introduction

TFBS Classification Task

Neural Models

Visualization Methods

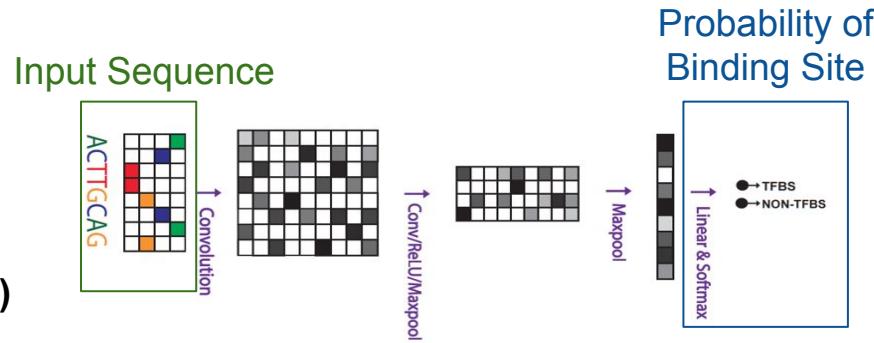
Evaluation and Results

Neural Network Models

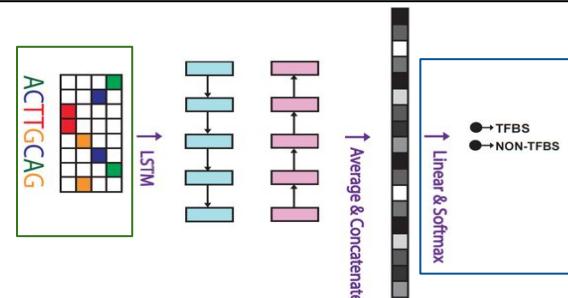
1. Convolutional (CNN)
2. Recurrent (RNN)
3. Convolutional-Recurrent (CNN-RNN)

3 Neural Models

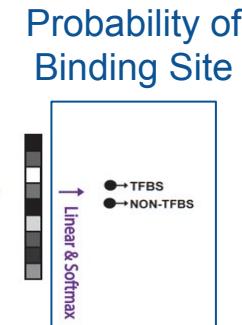
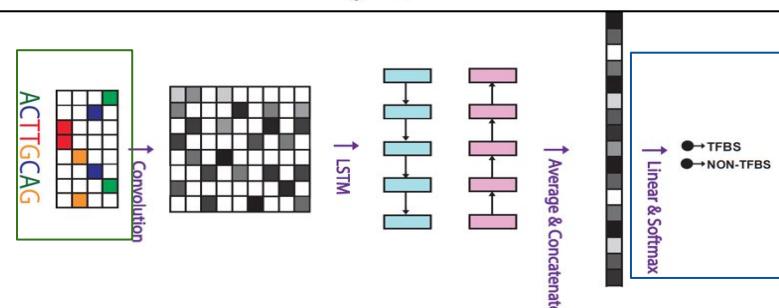
1. Convolutional (CNN) (short local patterns, or motifs)



2. Recurrent (RNN) (long term dependencies)



3. Convolutional- Recurrent (CNN-RNN) (long term dependencies among motifs)



Introduction

TFBS Classification Task

Neural Models

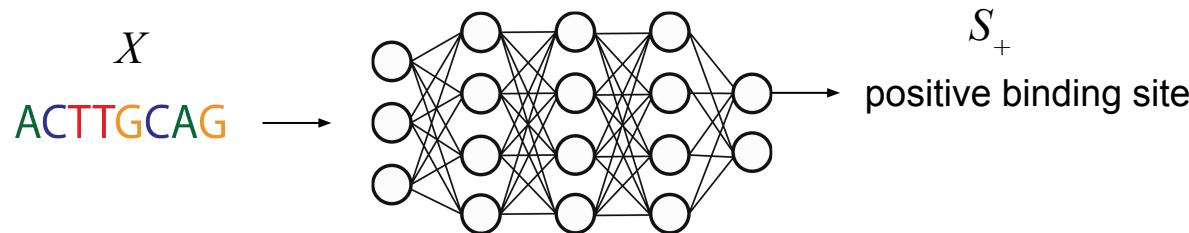
Visualization Methods

Evaluation and Results

Visualization Methods

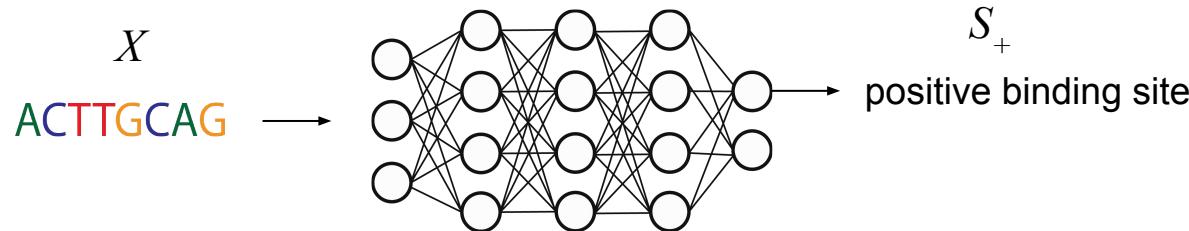
1. Saliency Maps
2. Temporal Output Values
3. Class Optimization

1. Saliency Map



Which nucleotides are most important for classification?

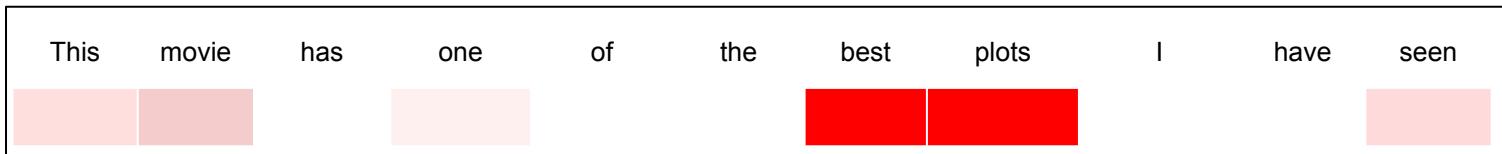
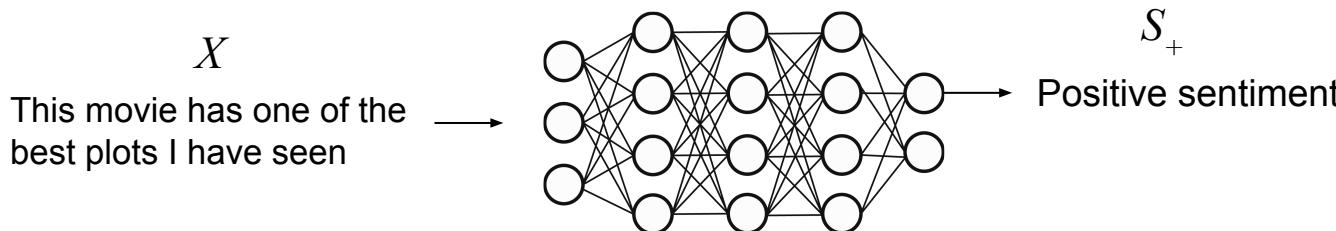
1. Saliency Map



$$S_+(X) \approx w^T X + b = \sum_{i=1}^{|X|} w_i x_i$$

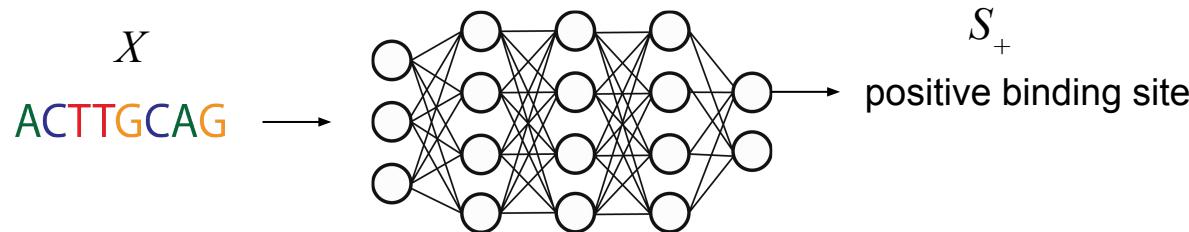
$$w = \frac{\partial S_+}{\partial X} \Big|_{X_0} = \text{"saliency map"}$$

1. Saliency Map



█ = important for classification

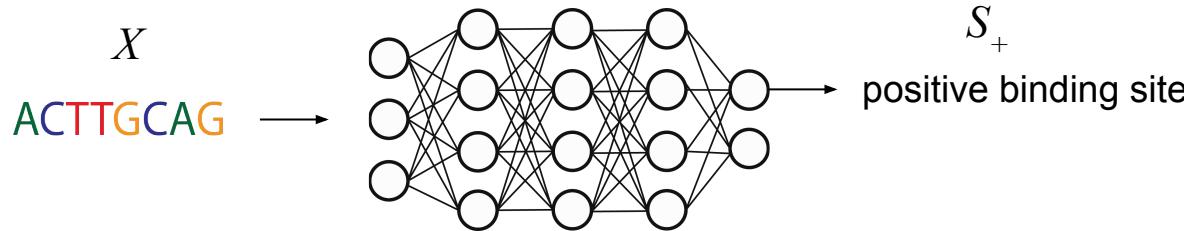
1. Saliency Map



Positive Test Sequence	TGCTCGCATCCTATTGGCCACCGTTAGTCACATGGCCCCACCTGGCTGCCAAGCACCGCTGGAAACGTTAGTCCTTCTT
Saliency Map	A horizontal bar divided into 20 segments, corresponding to the nucleotides in the sequence. The segments are colored in a gradient from light pink to dark red. The segment at position 13 (the 14th nucleotide) is the darkest red, indicating it is the most important for the prediction.

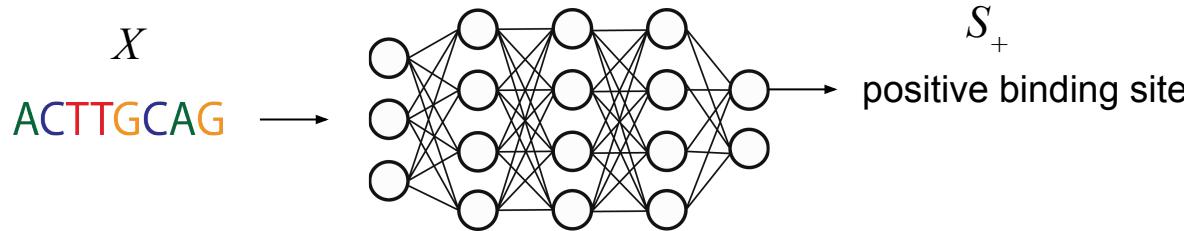
■ = important nucleotide for prediction

2. Temporal Output Values



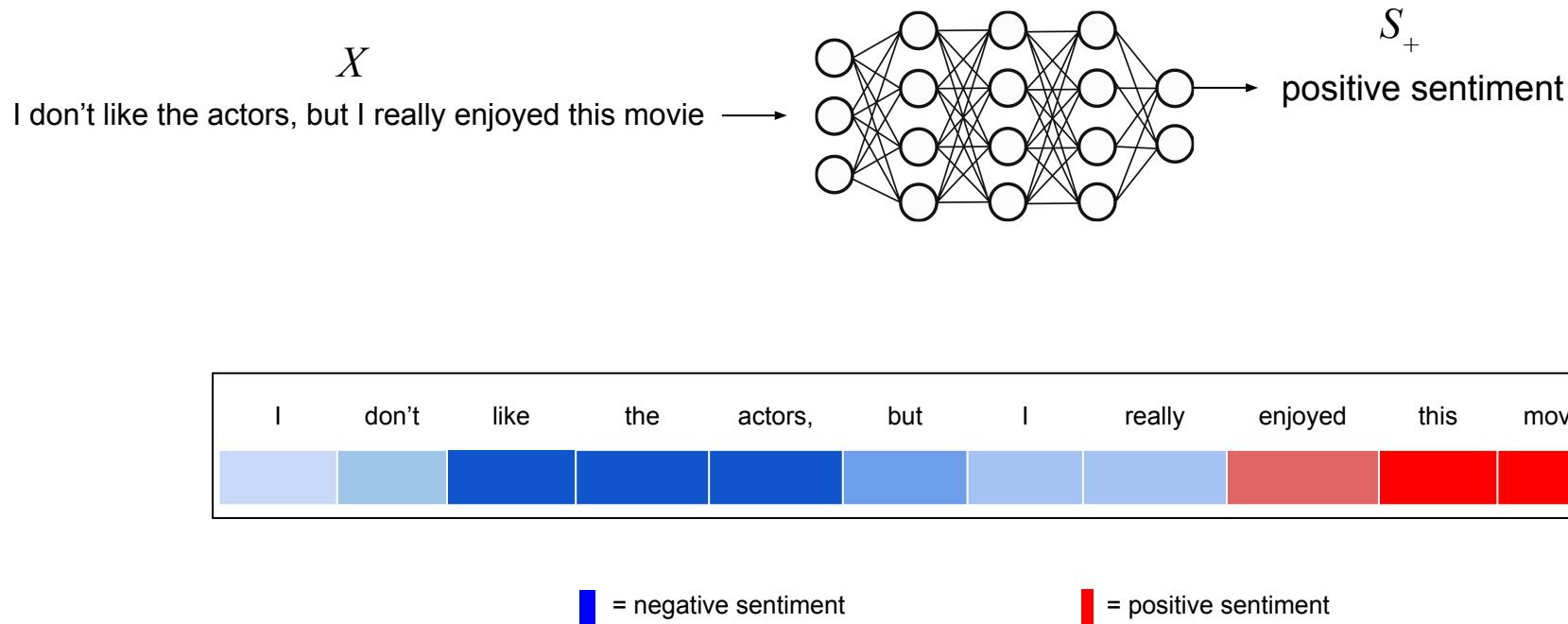
What are the model's predictions at each timestep of the DNA sequence?

2. Temporal Output Values

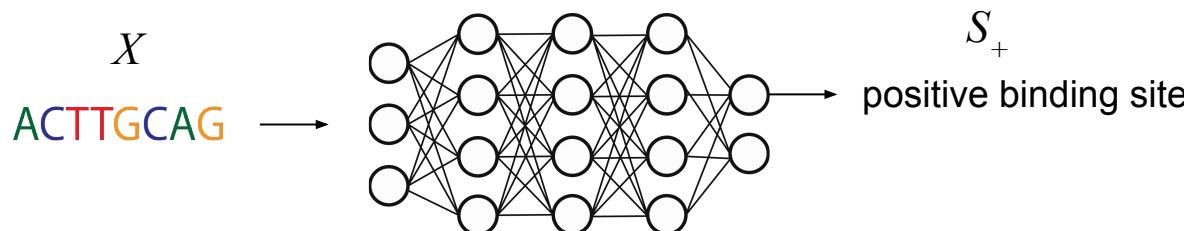


Check the RNN's prediction scores when we vary the input of the RNN starting from the beginning to the end of a sequence.

2. Temporal Output Values



2. Temporal Output Values



Positive Test Sequence	CTTCTGCTCGCATCCTATTGGCCACGTTAGTCACATGGCCCCACCTGGCTGCAAAGCACGCTGGGAAACGTAGTCTTCTT
RNN Forward Output	
RNN Backward Output	

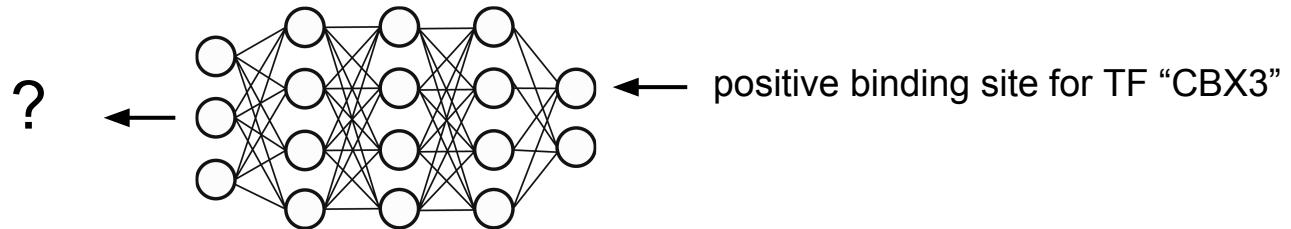
■ = negative binding site prediction

■ = positive binding site prediction

Visualization Methods

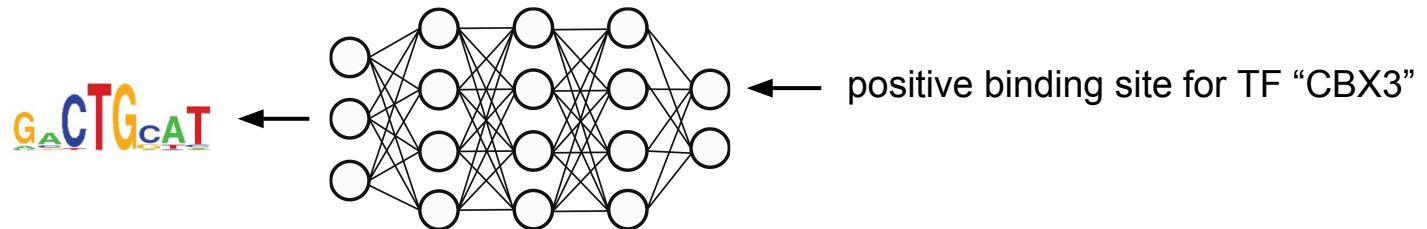
- Sequence Specific {
 - 1. Saliency Maps
 - 2. Temporal Output Values
- TF Specific {
 - 3. Class Optimization

3. Class Optimization



For a particular TF, what does the optimal binding site sequence look like?

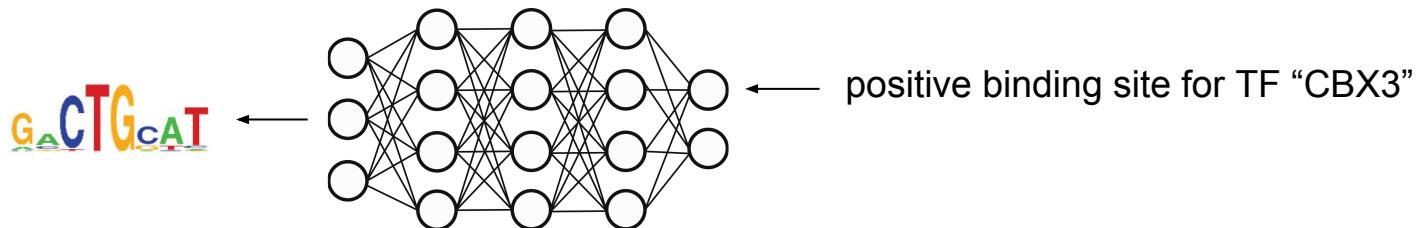
3. Class Optimization



$$\arg \max_X S_+(X) + \lambda \|X\|_2^2$$

Where X is the input sequence and the score S_+ is probability of sequence X being a positive binding site

3. Class Optimization



positive binding site for TF "CBX3"

Optimal binding site
for TF "CBX3"



Introduction

TFBS Classification Task

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Experimental Setup

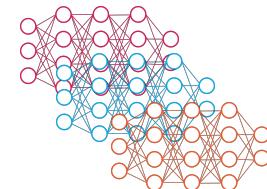
Dataset

- Alipanahi et al. “*Predicting the sequence specificities of DNA- and RNA-binding proteins by deep learning*”. Nature Biotechnology 2015.
- 108 cancer cell TFs (train separate model for each TF)
- Each sequence is 101-length centered around ChIP-seq peak

TF1 (♀)	GCGAC A TTCG CTCGAG T CTCA CGATAT G TTC AAGAA A ATTA
TF2 (♀)	AACGATAT G CT TGTCAAG C AG ATAT A TATA AGCAT T GCGA
TF3 (♂)	CATAT C ATTTC TAT C A S CTGG CGAAT G CATAC ACGAC D TTAT

Models

- Test several variations of 3 different models (CNN, RNN, CNN-RNN)

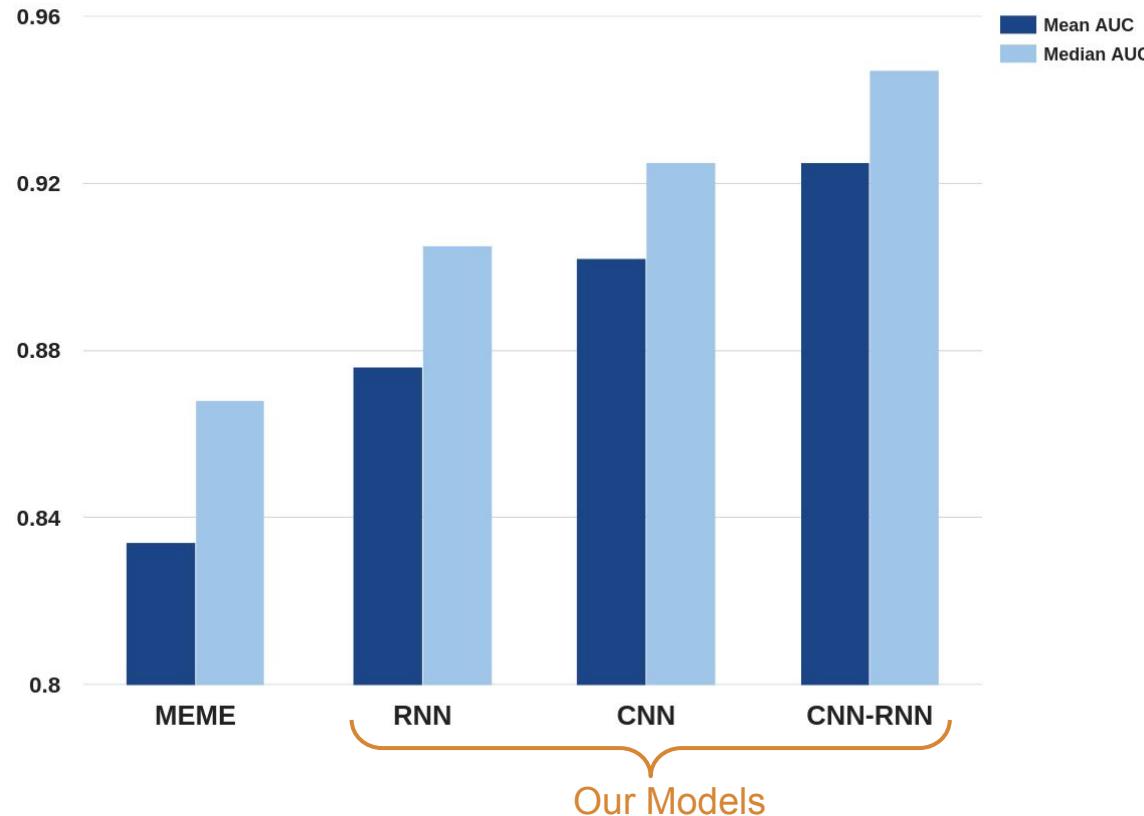


Evaluation

- Compare models using AUC scores on test set
- Evaluate visualization methods manually and by motif matching

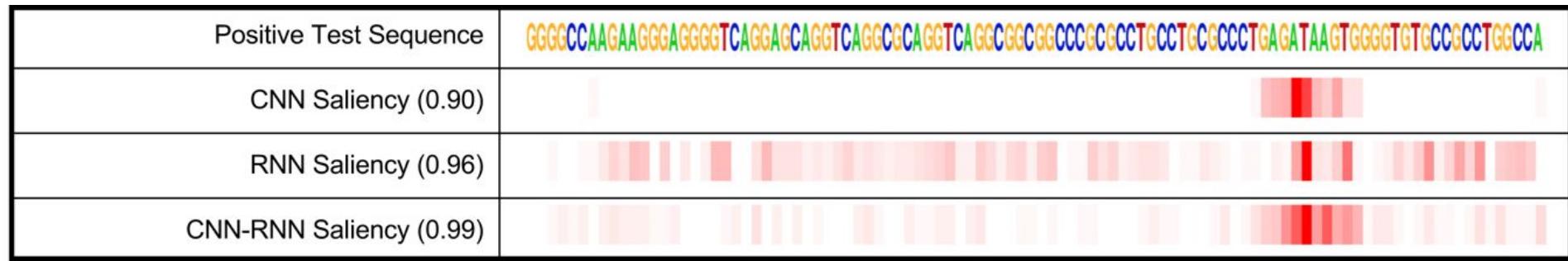


Model Accuracy (AUC Scores)



1. Saliency Maps

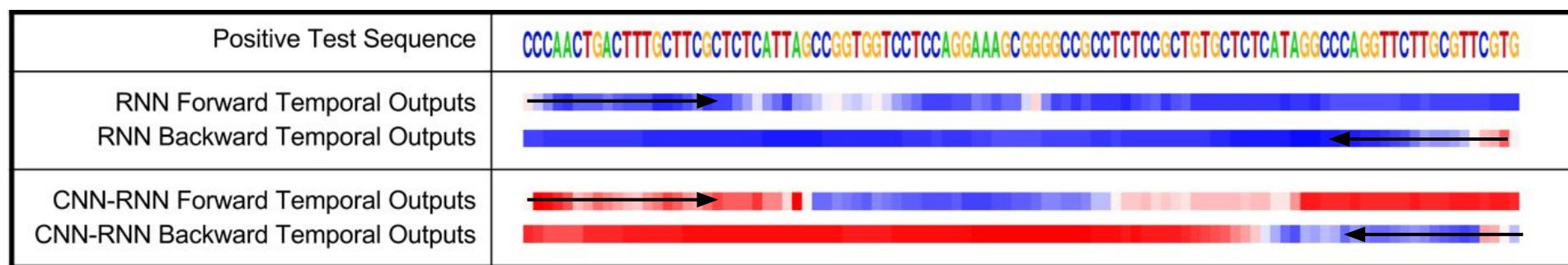
GATA1



█ = important nucleotide for prediction

2. Temporal Output Values

NFYB



■ = negative binding site prediction

■ = positive binding site prediction

Saliency Map AND Temporal Output Values

NFYB

Positive Test Sequence	
CNN Saliency (0.30)	
RNN Saliency (0.12)	
CNN-RNN Saliency (0.91)	
Positive Test Sequence	
RNN Forward Temporal Outputs RNN Backward Temporal Outputs	
CNN-RNN Forward Temporal Outputs CNN-RNN Backward Temporal Outputs	

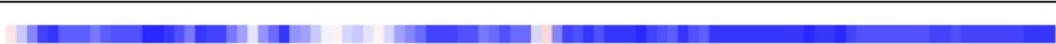
3. Class Optimization

GATA1

CNN Positive Class Maximization	
RNN Positive Class Maximization	
CNN-RNN Positive Class Maximization	

DeMo Dashboard

NFYB

JASPAR Motifs	Forward: 	Backward: 
CNN Positive Class Maximization		
RNN Positive Class Maximization		
CNN-RNN Positive Class Maximization		
Positive Test Sequence		
CNN Saliency (0.30)		
RNN Saliency (0.12)		
CNN-RNN Saliency (0.91)		
Positive Test Sequence		
RNN Forward Temporal Outputs		
RNN Backward Temporal Outputs		
CNN-RNN Forward Temporal Outputs		
CNN-RNN Backward Temporal Outputs		

Deep Motif (DeMo) Dashboard Contributions and Results

1. Comparative analysis of 3 different neural models on TFBS task
 - CNN-RNNs perform the best

2. Presented 3 different visualization techniques to understand the predictions of neural models
 - Although TFBSs are influenced by motifs, the interactions among motifs are also important

Thank You!

code available at: deepmotif.org



Ritambhara Singh



Beilun Wang



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UVA Machine Learning and Biomedicine Group

