

# Transfer String Kernel for Cross-Context Sequence Specific DNA-Protein Binding Prediction

by

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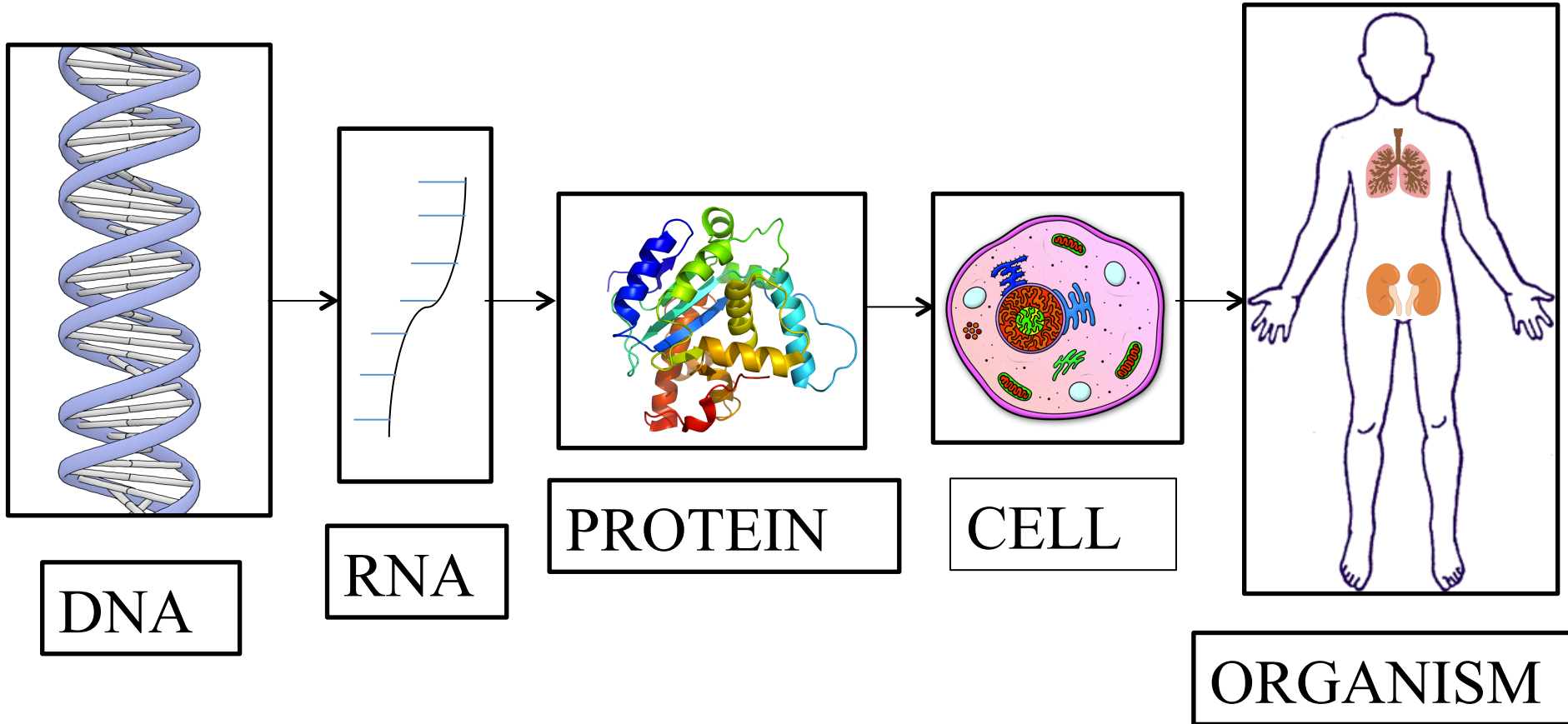
June 10, 2016



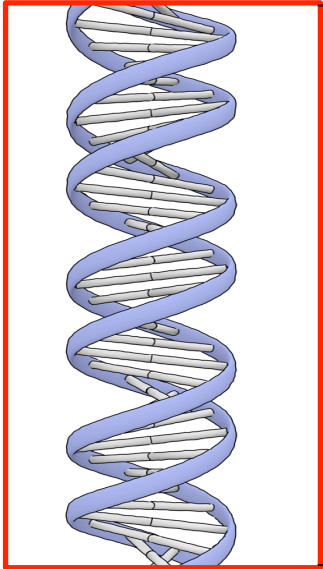
**Computer Science**  
*at the* UNIVERSITY of VIRGINIA



# Biology in a Slide



# DNA and Diseases

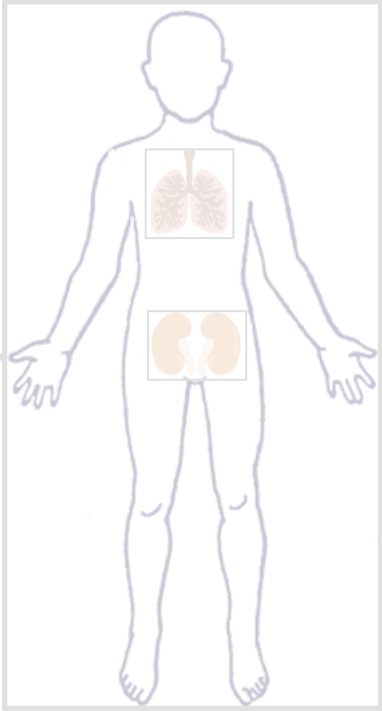


DNA

- Down Syndrome
- Parkinson's Disease
- Autism
- Muscular Atrophy
- Sickle Cell Disease
- .....
- .....

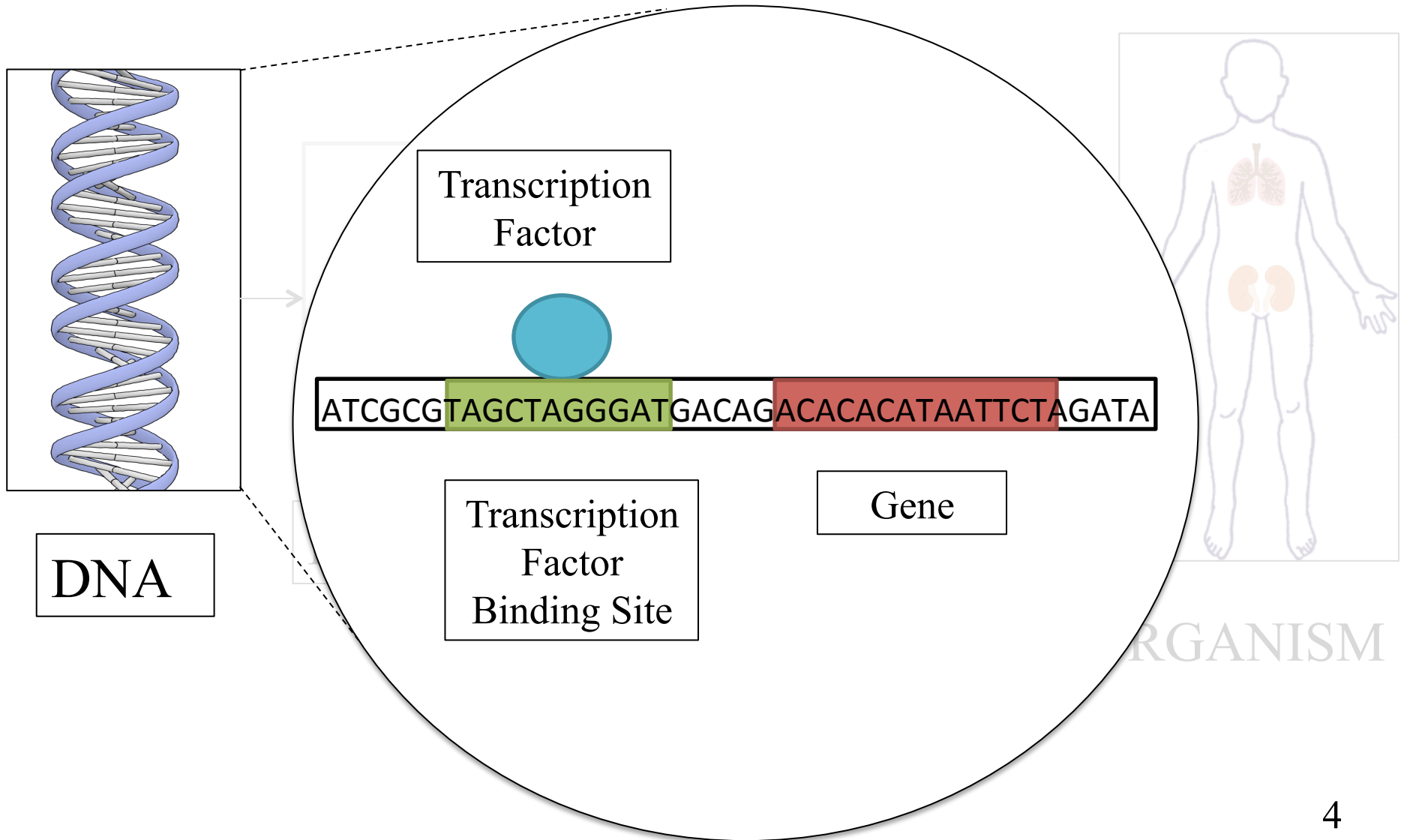


CELL

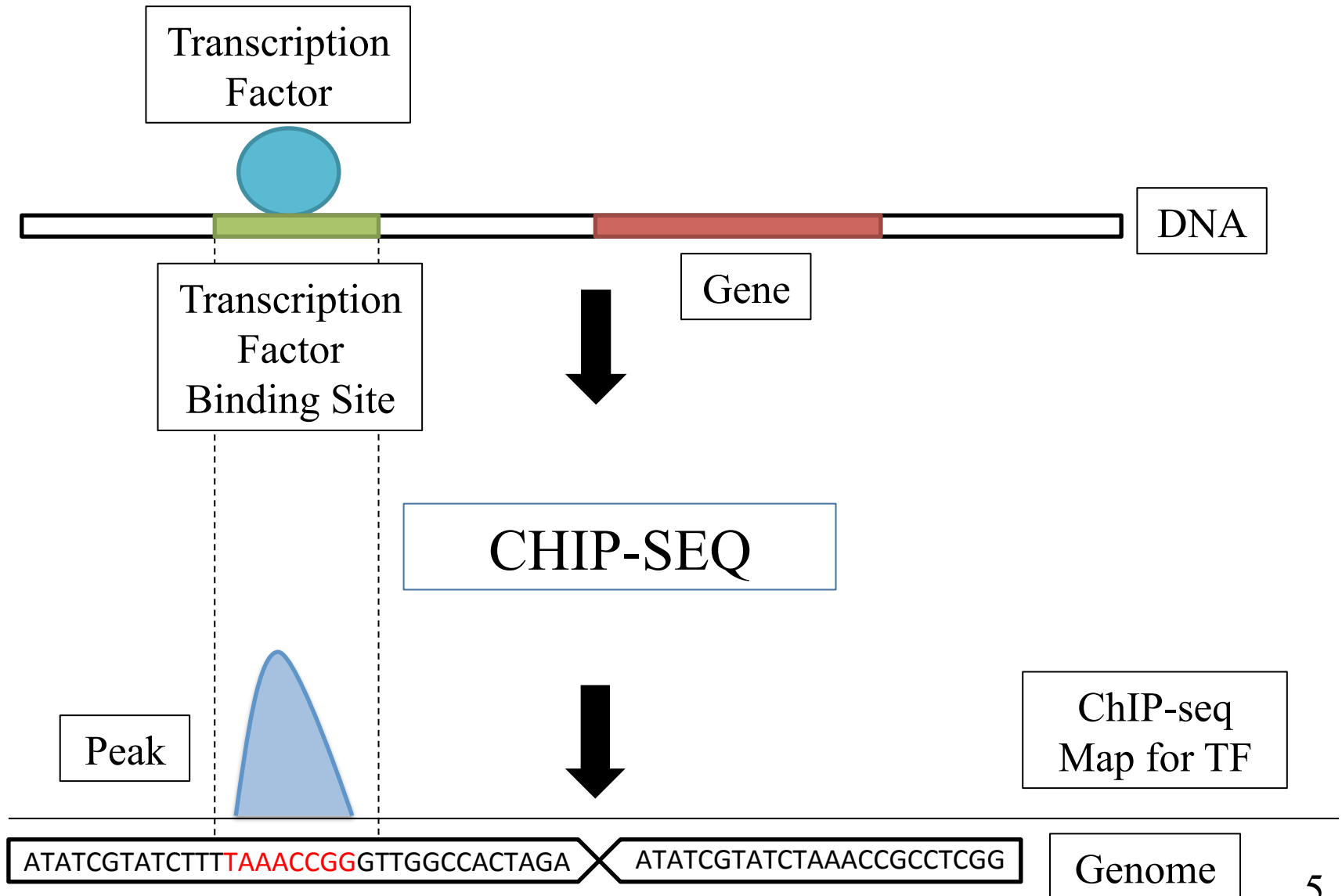


ORGANISM

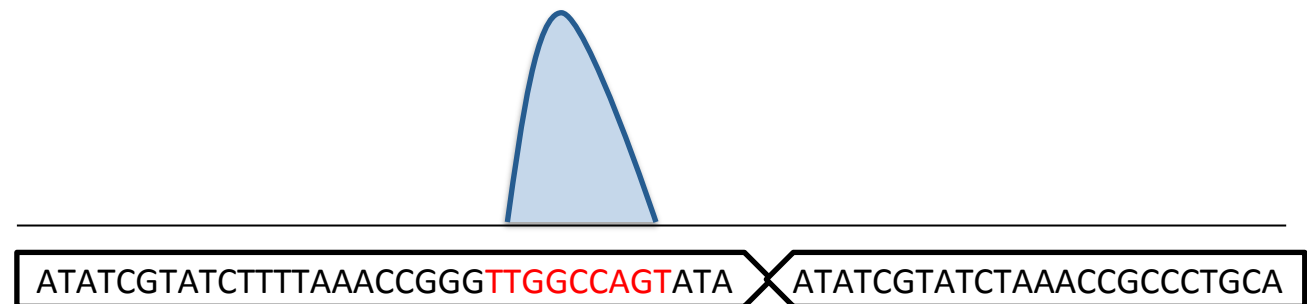
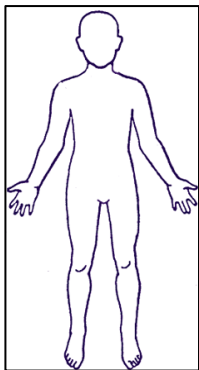
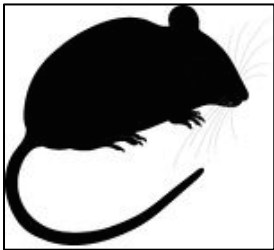
# Transcription Factors



# ChIP-seq Maps TF binding



# TF Binding Differs Across Contexts

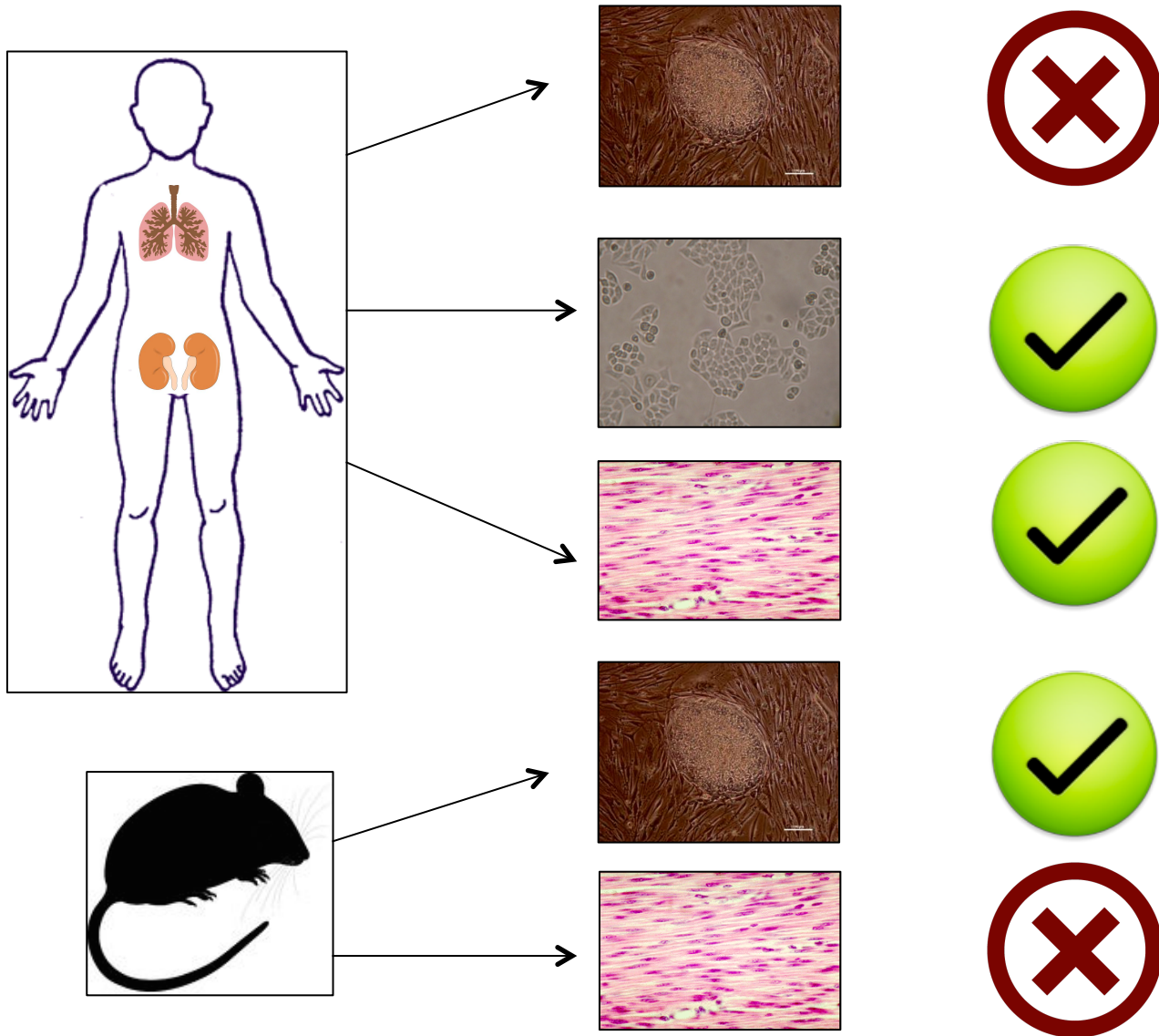


# Current Challenge: ENCODE Data Gap

Cell Types		Transcription Factor																		
		ARID3A	ATF1	ATF2	ATF3	BACH1	BATF	BCL11A	BCL3	BCLAF1	BDP1	BHLHE40	BRCA1	BRF1	BRF2	CBX2	CBX3	CBX8	CCNT2	CEBPB
<b>Tier 1</b>																				
GM12878	(Blood Cell)			■	■		■	■	■	■		■	■							■
H1-hESC	(Stem Cell)			■	■	■		■					■							■
K562	(Leukemia)	■	■		■	■			■	■	■	■		■	■	■	■	■	■	■
<b>Tier 2</b>																				
A549	(Lung Cancer)				■				■			■								■
CD20+	(Immunity related)																			
CD20+_RO01778					?										?					
CD20+_RO01794																				
H1-neurons	(Nerve Cell)										■		■	■	■					■
HeLa-S3	(Cervical Cancer)	■			■							■	■							■

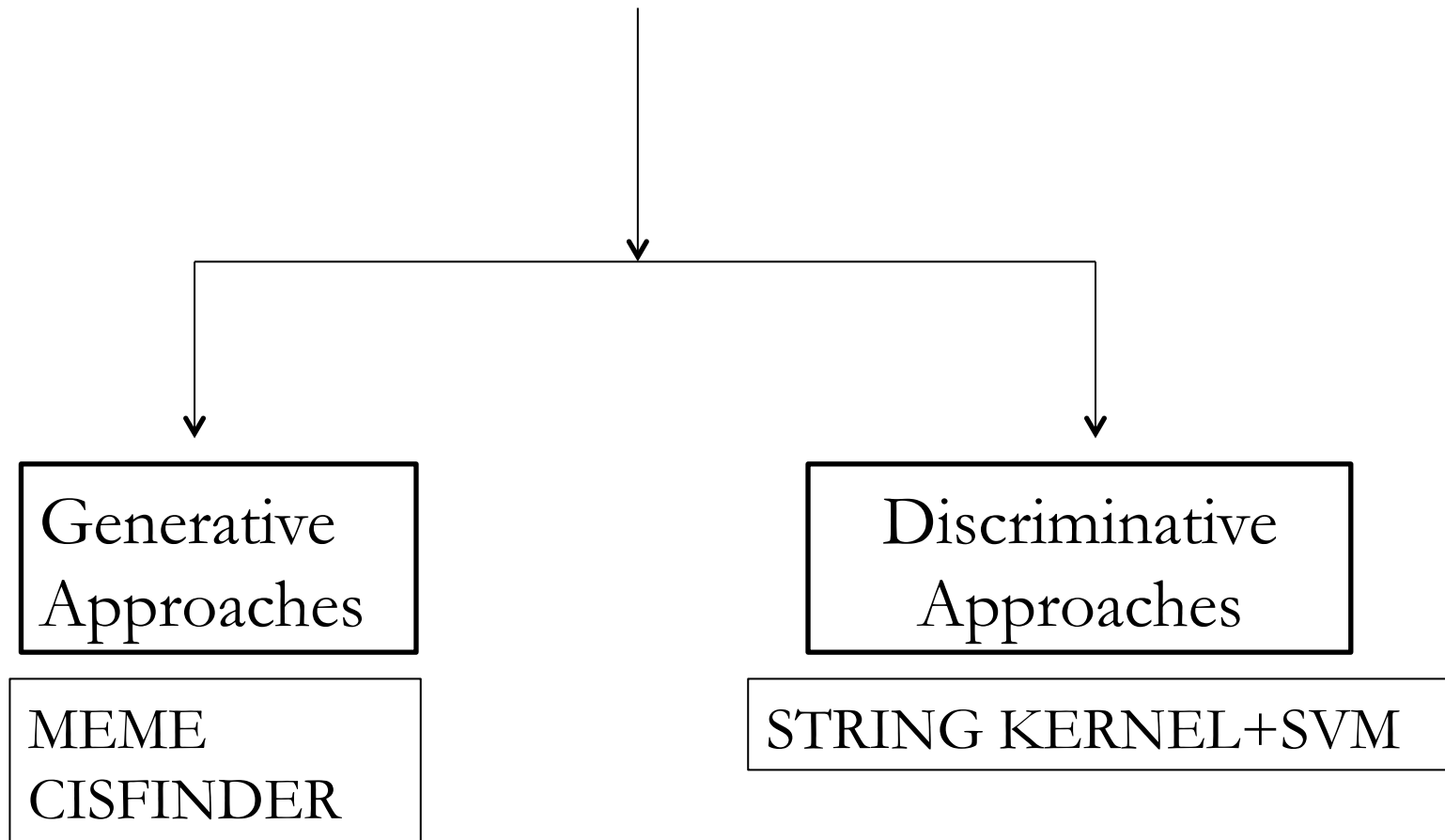
Source : <http://genome.ucsc.edu/ENCODE/dataMatrix/encodeChipMatrixHuman.html>

# Case for Computational Tools

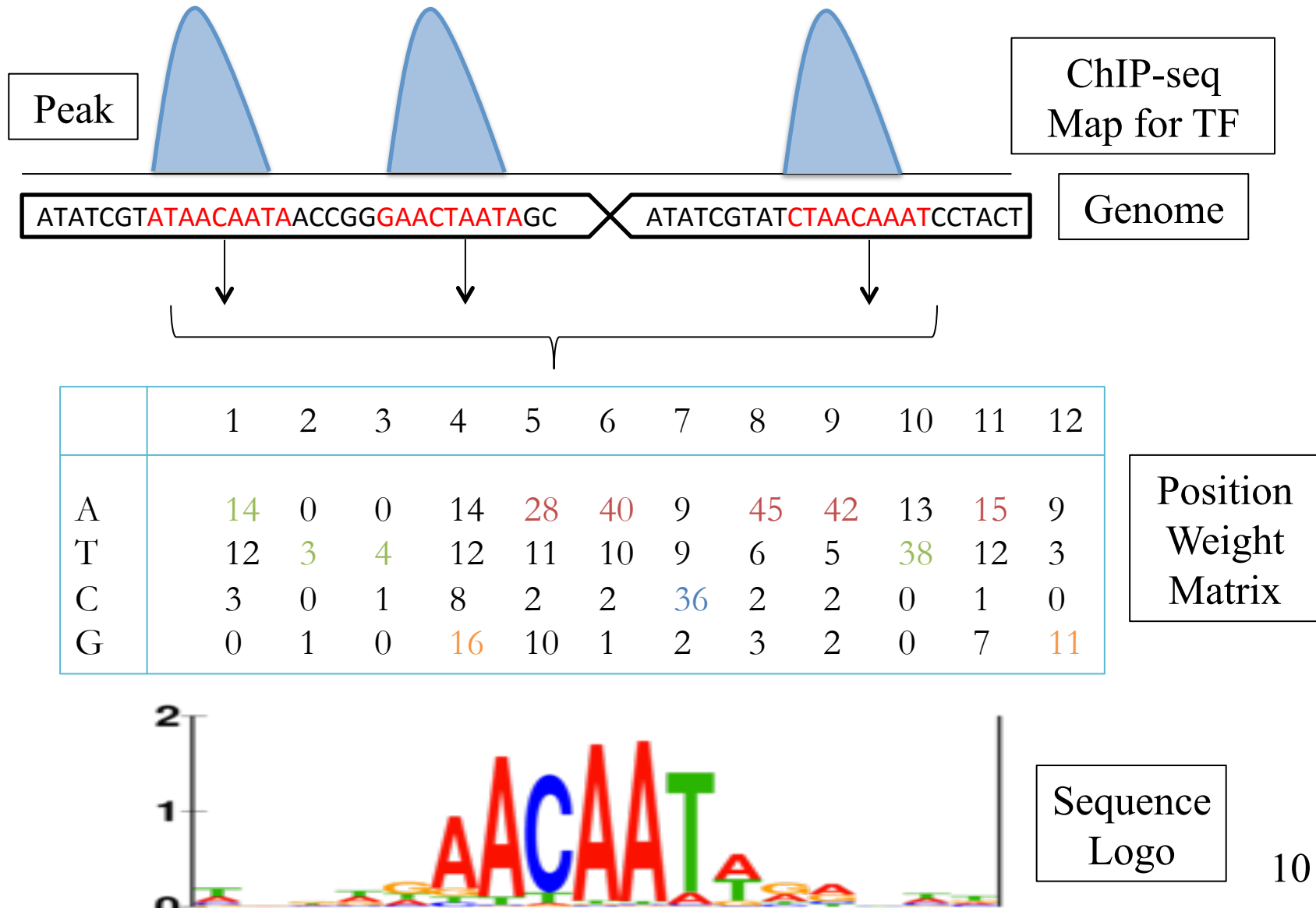




# Existing Computational Tools



# Generative : PWM Based approach



# Generative Approach : Output

?

?

ATATCGTATCTTTAAACCGGGTTGGCCAATAGC ATATCGTATCTAAACCGCCCTACT

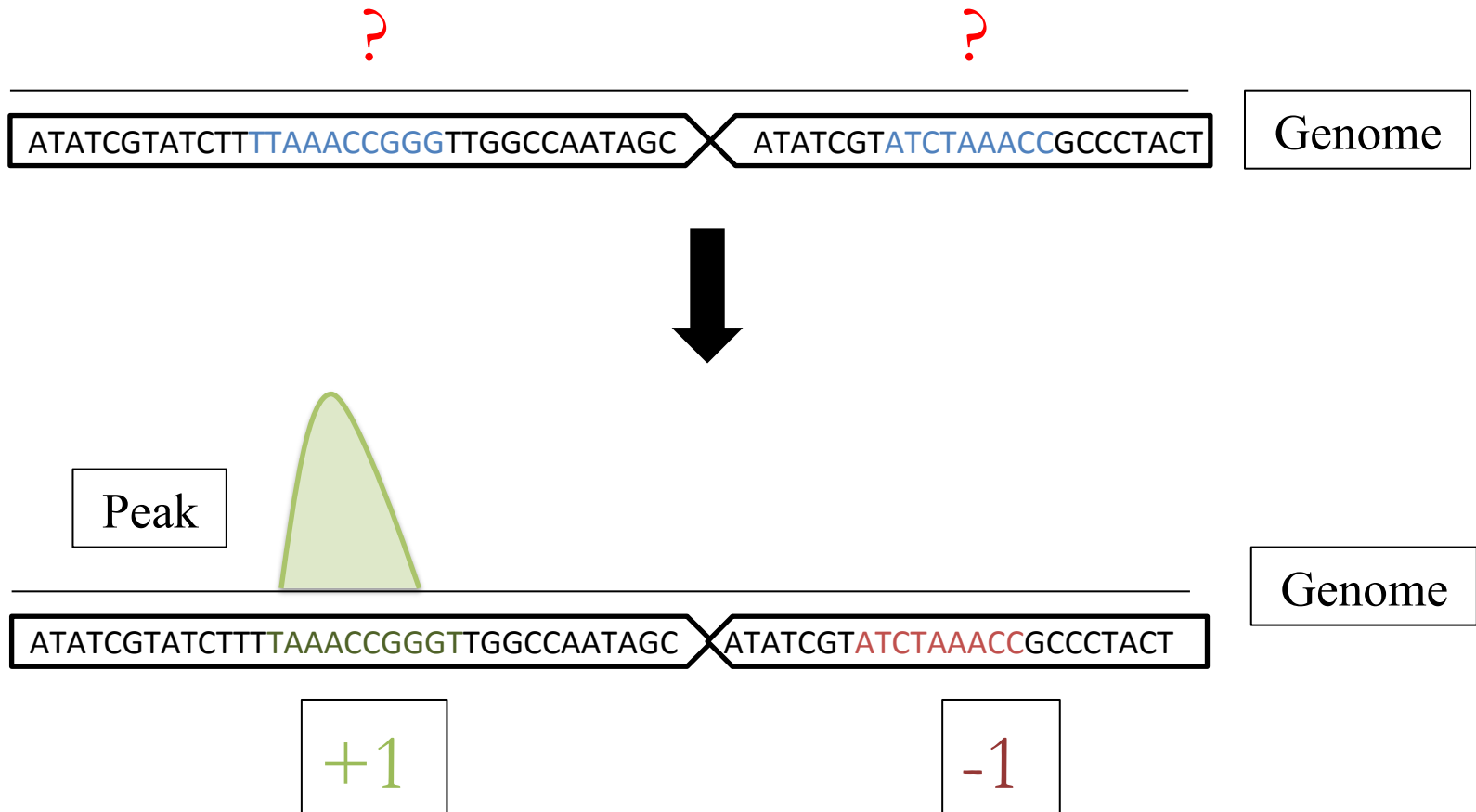
Genome



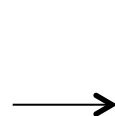
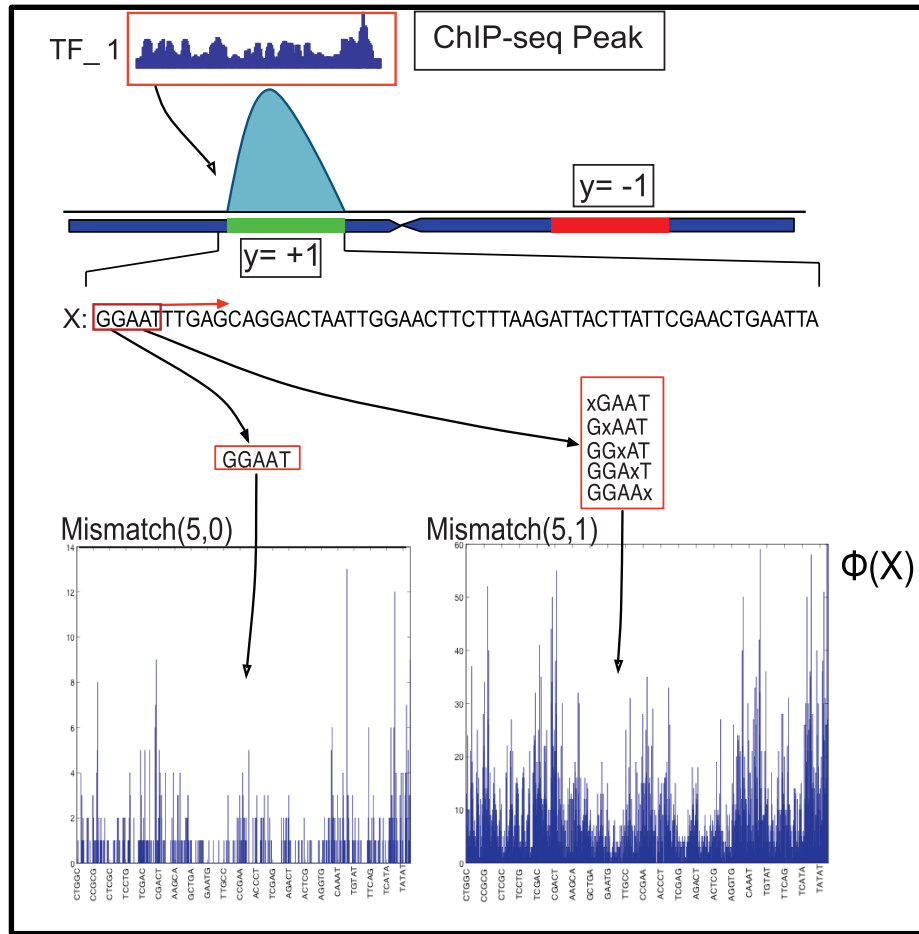
# Generative Approach: Limitations

- Output: **Long list** of potential TFs
- Work well for only **well preserved motifs or large training datasets**
- PWMs for all  $\sim 2000$  TFs **not available**
- **Lower** prediction performance than discriminative approaches

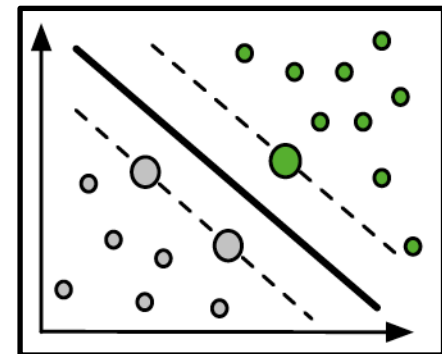
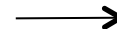
# Discriminative Approach : Output



# Discriminative : String Kernel Approach



Support Vector Machine



# Discriminative Approach : Limitation

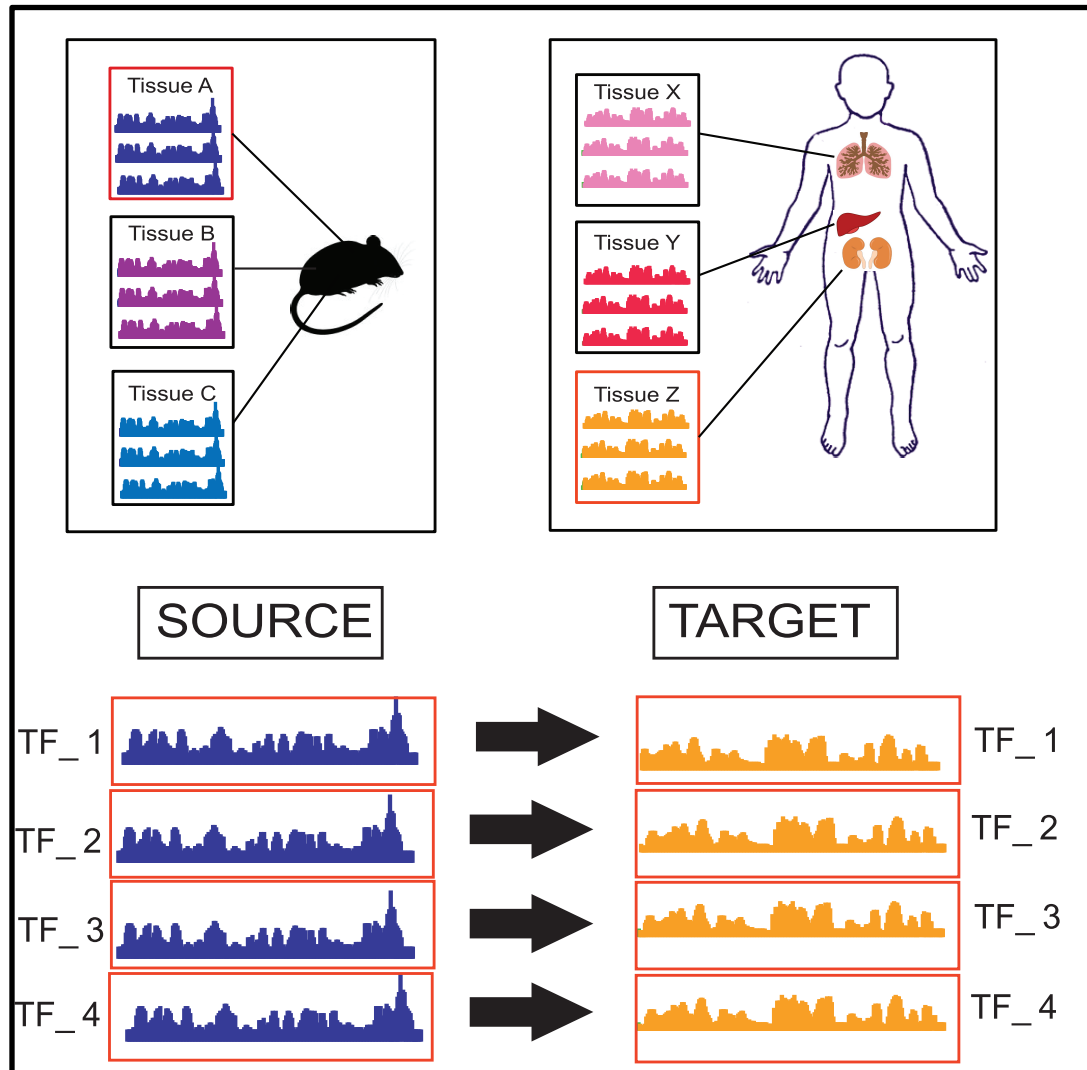
Assumption: Training/test data follow **same distribution regardless of context.**

# Aim

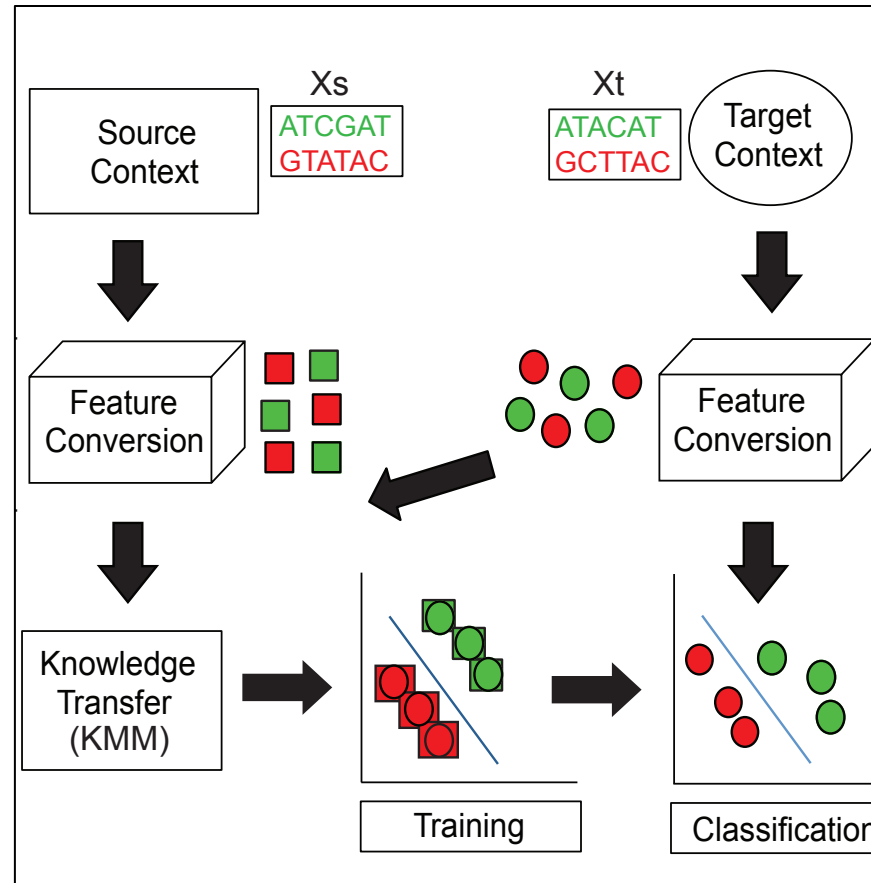
- **Improve** prediction of Transcription Factor Binding sites across contexts using knowledge transfer.



# Proposed Solution : Cross-Context Knowledge Transfer



# Transfer String Kernel : Overview



# Outline

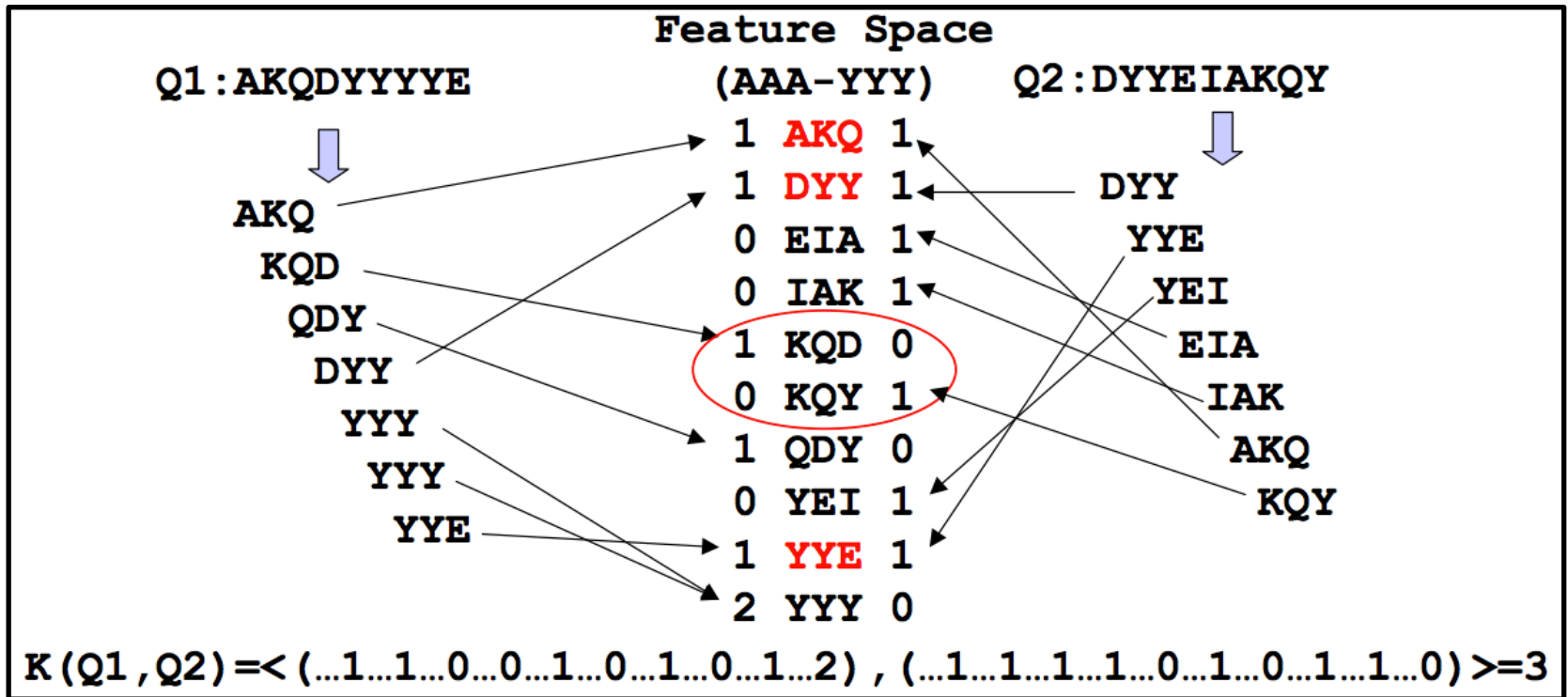
- Method
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  - Support Vector Machine
  - Transfer Learning (KMM)
  - Importance re-weighting
  - Transfer String Kernel
- Evaluation
  - Experimental Setup
  - Cross-context TFBS prediction
  - Cross-context Protein Binding prediction

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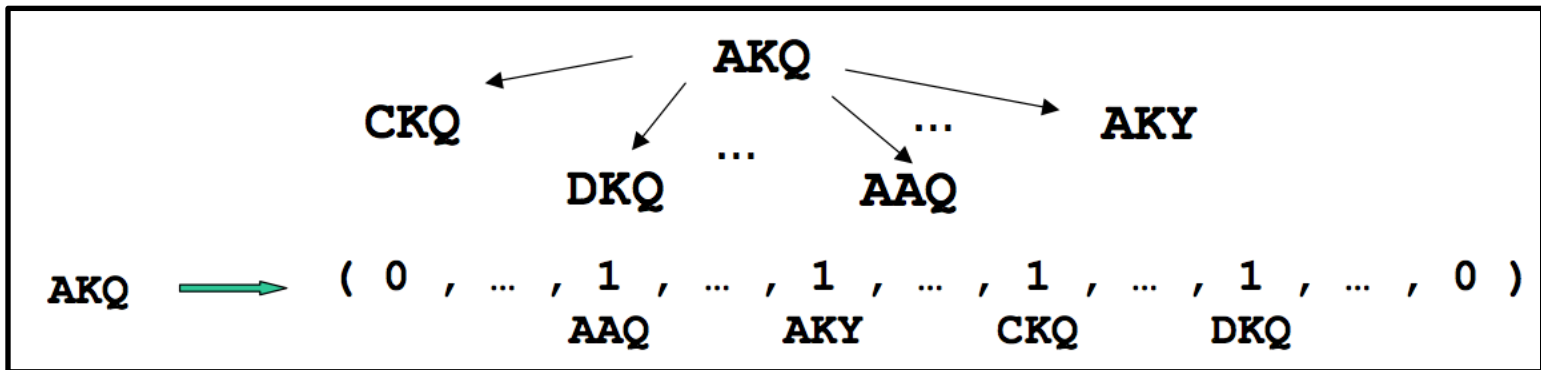
# String Kernel : Spectrum Kernel

Feature map indexed by all k-length subsequences (“k-mers”) from alphabet  $\Sigma$  of amino acids,  $|\Sigma|=20$



# String Kernel : Mismatch Kernel

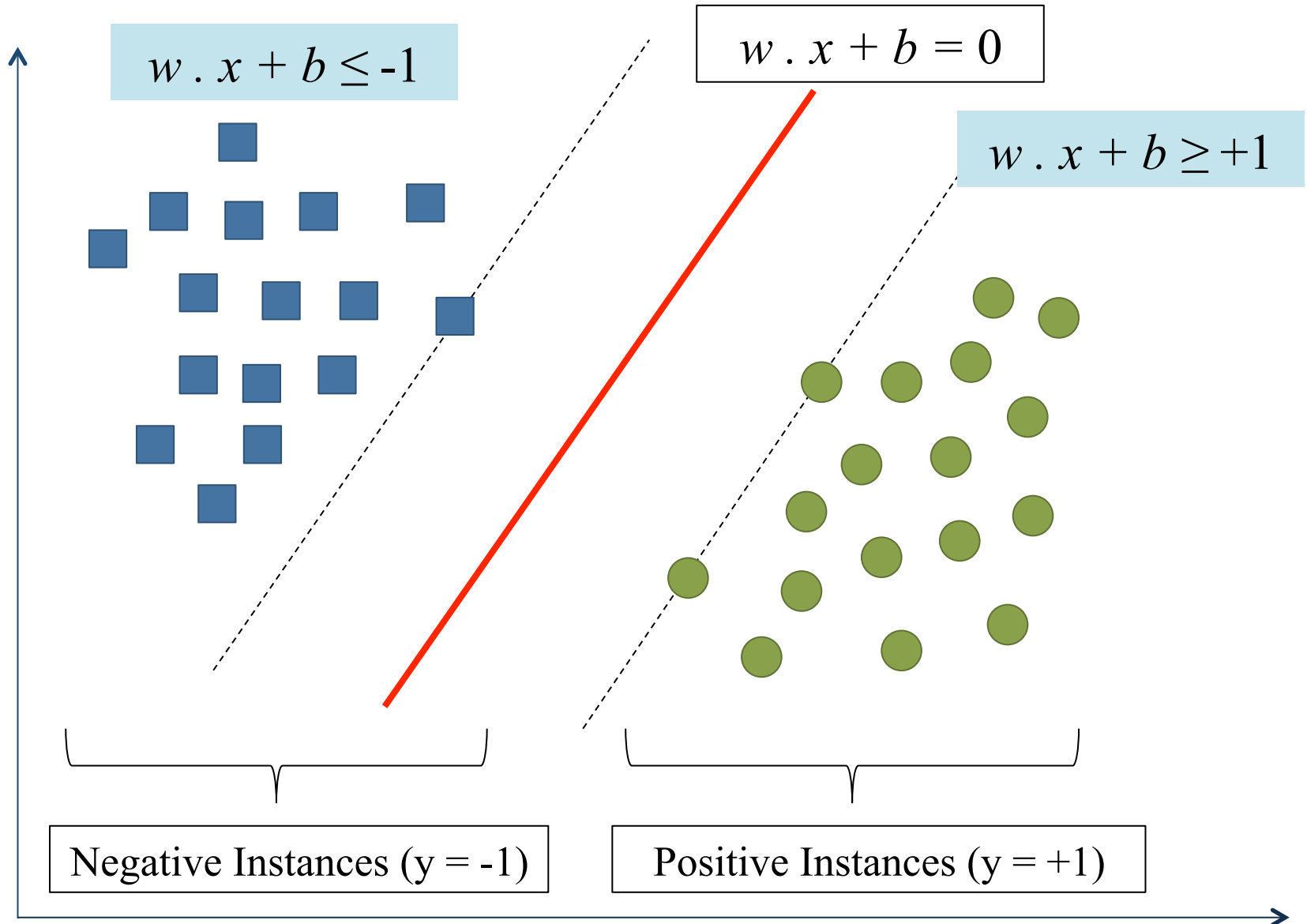
For k-mer  $s$ , the **mismatch neighborhood**  $N_{(k,m)}(s)$  is the set of all k-mers  $t$  within  $m$  mismatches from  $s$ .



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# Support Vector Machine

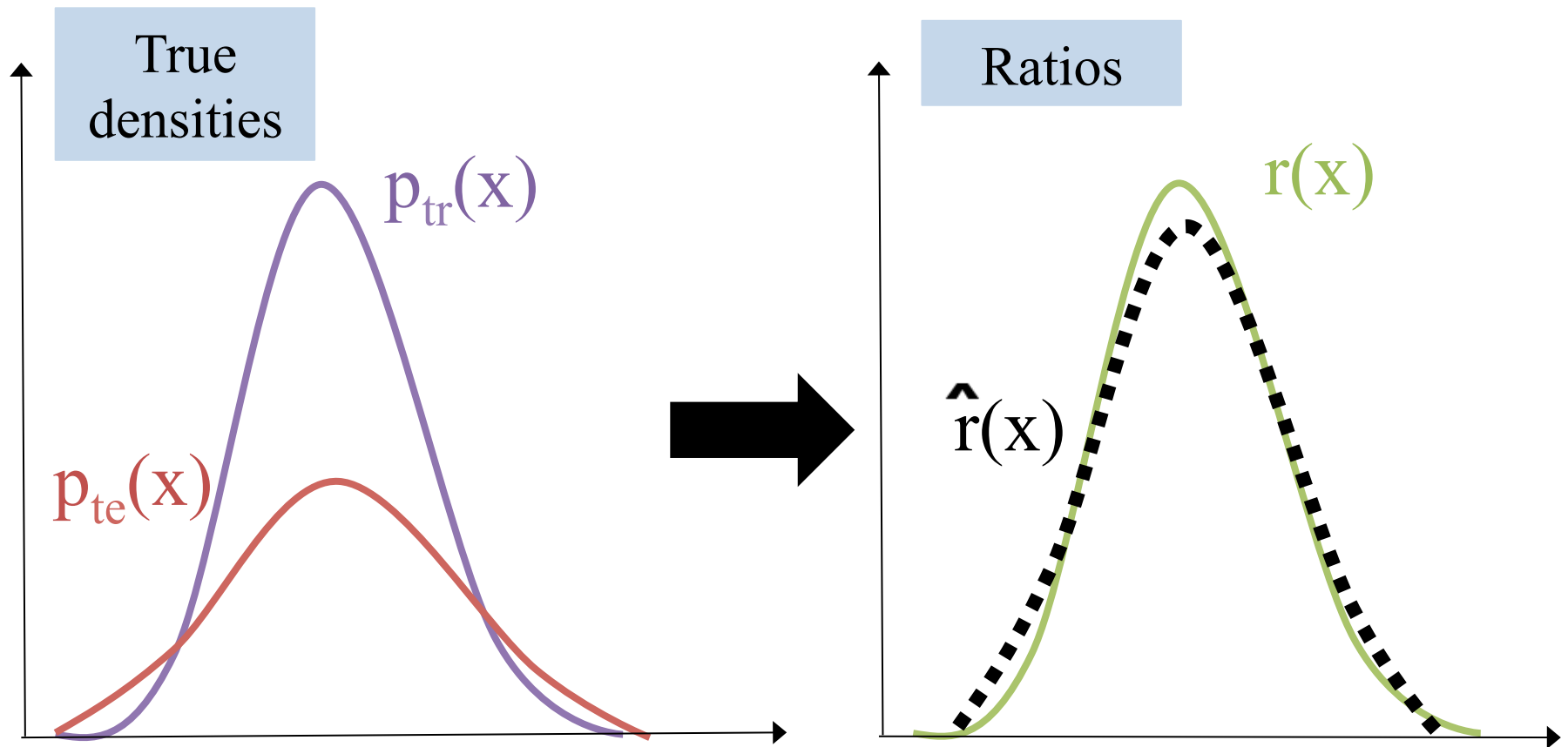




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# Transfer Learning (KMM)

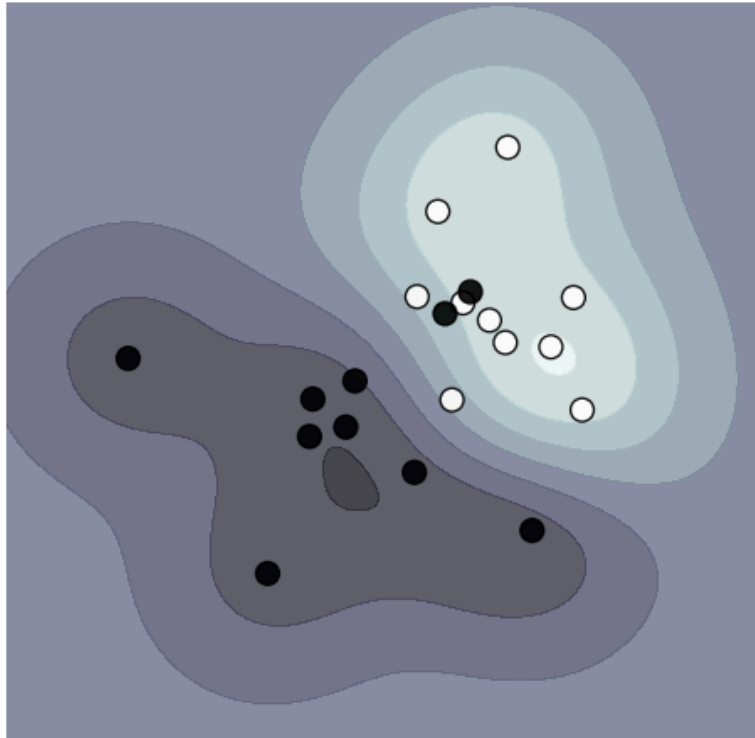


# Outline

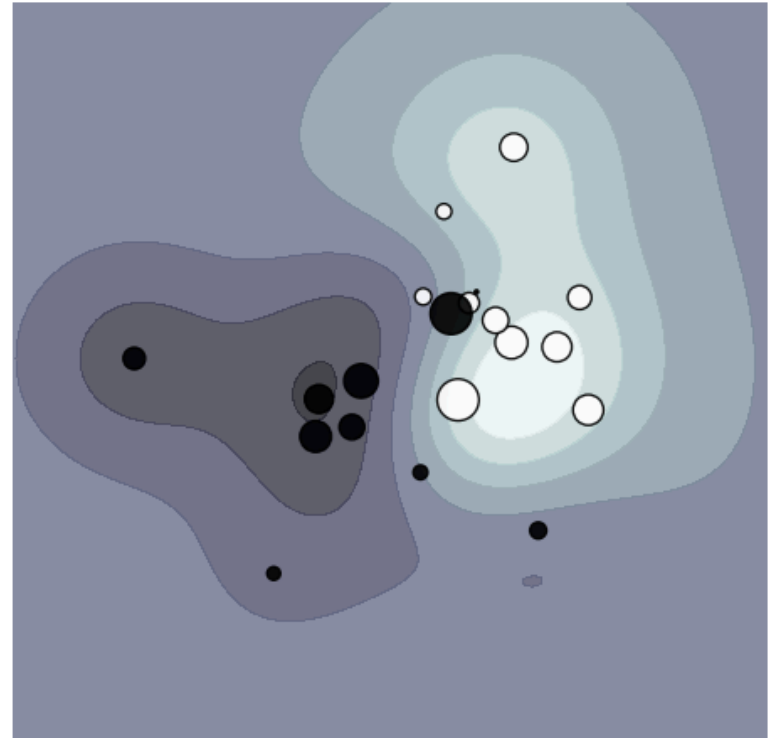
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# Importance Re-weighting

Original Weights



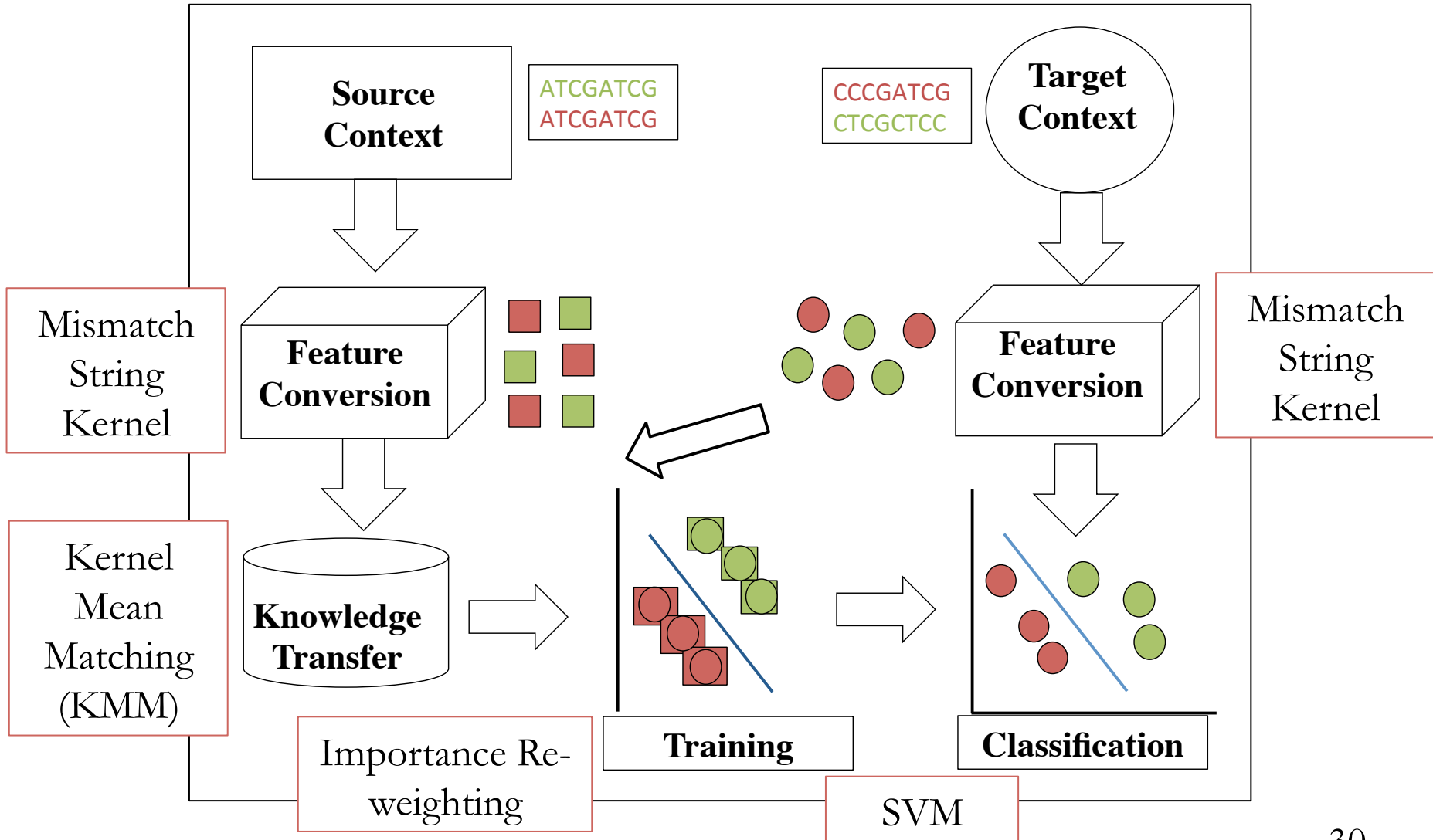
KMM Weights



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# Transfer String Kernel (TSK)



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# Experimental Setup

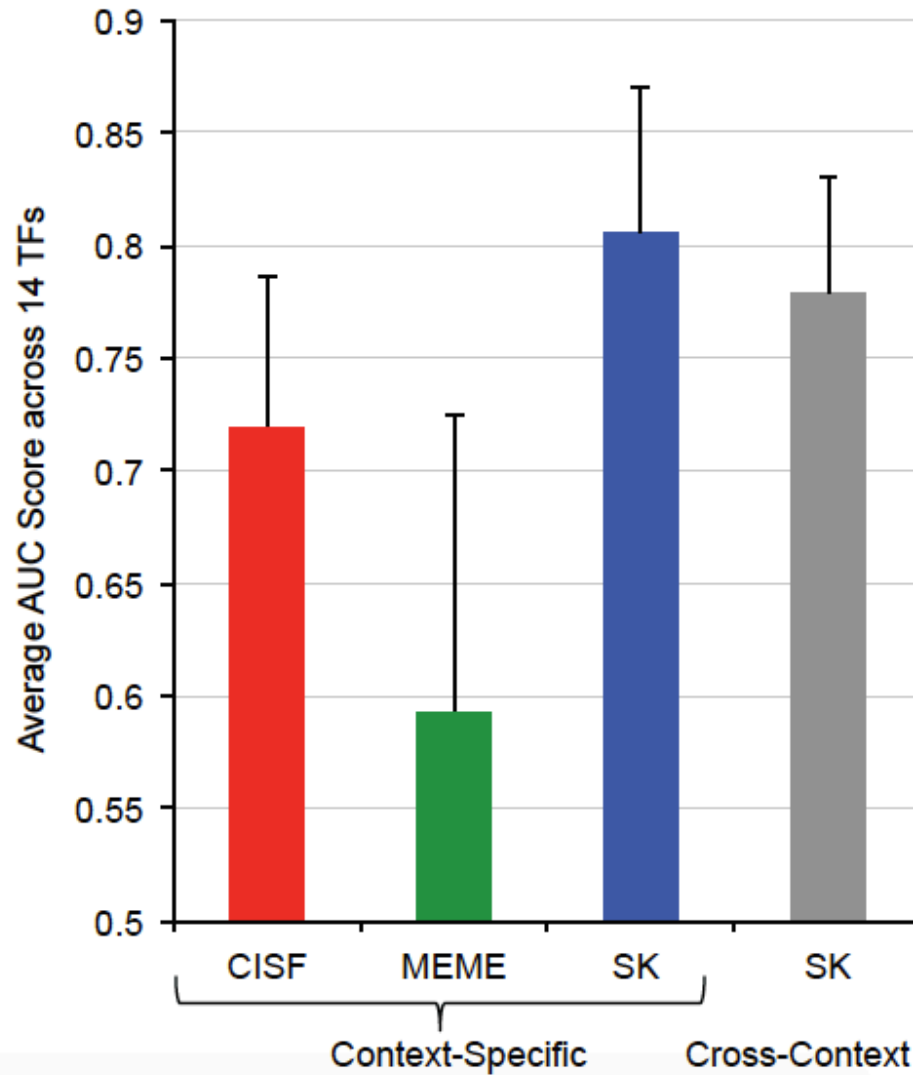
- 14 Transcription Factors (ENCODE ChIP-seq)
- Top 1000 positive sequences (500 training and 500 testing)
- 1000 random negative sequences
- Hyper-parameter tuning for  $k=(8,10,12)$  and  $m=(1,2,3)$
- Dictionary size = 4 {A,T,C,G}



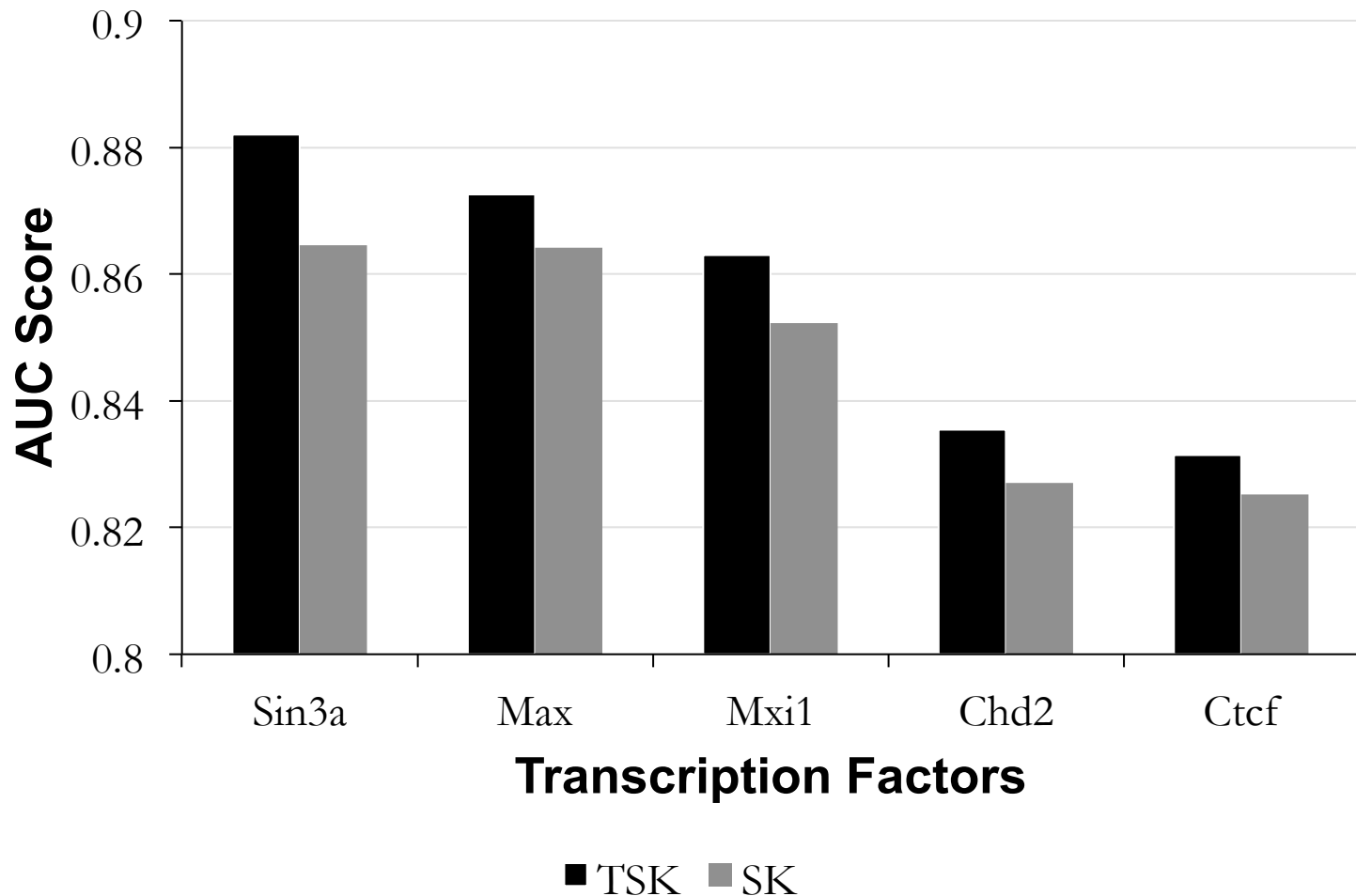
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# Results



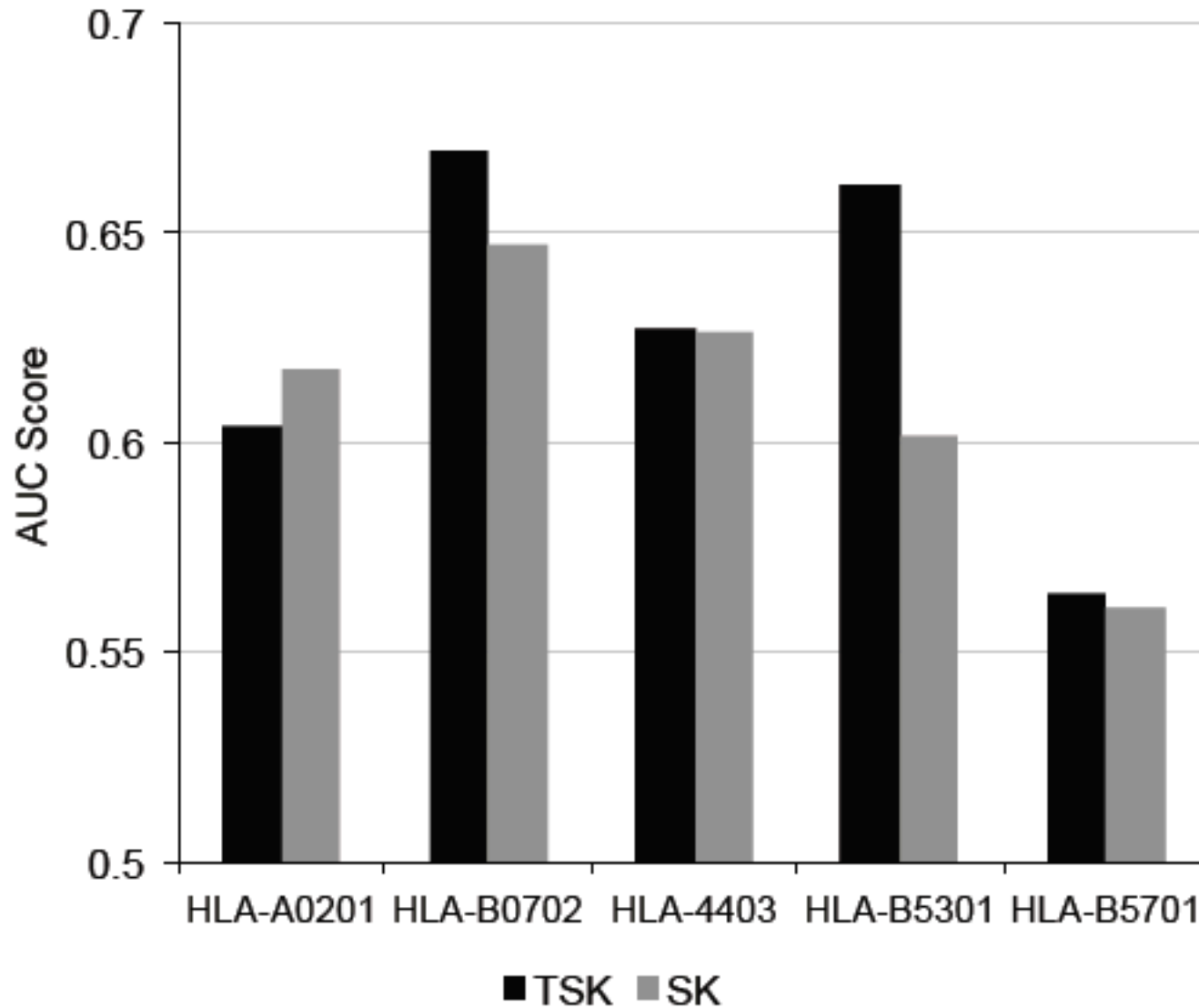
# Results – Cross Context



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# Results – Cross context



# Summary

- TSK overall improves the cross-context TFBS predictions;
- String kernel based approaches perform better than the state-of-the-art Position Weight/Frequency Matrix based TFBS tools;
- TSK approach is generalizable for performance improvement of any cross-context sequence prediction task.

# Acknowledgements

**Dr. Mazhar Adli**

Adli Lab : Department of Biochemistry and  
Molecular Genetics @Uva

**Nipun Batra**

IIIT-Delhi

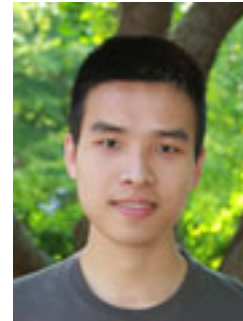
# Machine Learning Lab @ UVa



**Dr. Yanjun Qi**  
(Advisor)



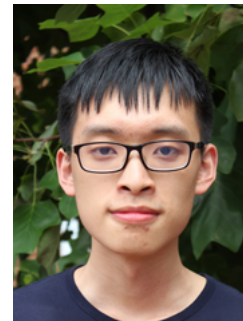
Beilun Wang



Weilin Xu



**Jack Lanchantin**



Ji Gao



# Future Directions

- Deep Learning :
  - Gene expression prediction using histone modification data (ECCB 2016)
  - Improving TFBS prediction using DNA sequences (ICLR Workshop 2016, ICML Workshop 2016)
- String Kernels: Improving efficiency!! (on-going work)

# Thank You

