Chromatin Conformation Prediction from ChIPseq Signal

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CSI-Meeting

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Contents

Chromatin Conformation Prediction

- **Main Question**: Can we use transcription factor (TF)-ChIPseq to predict protein complexes (direct and indirect bindings) on chromatin?

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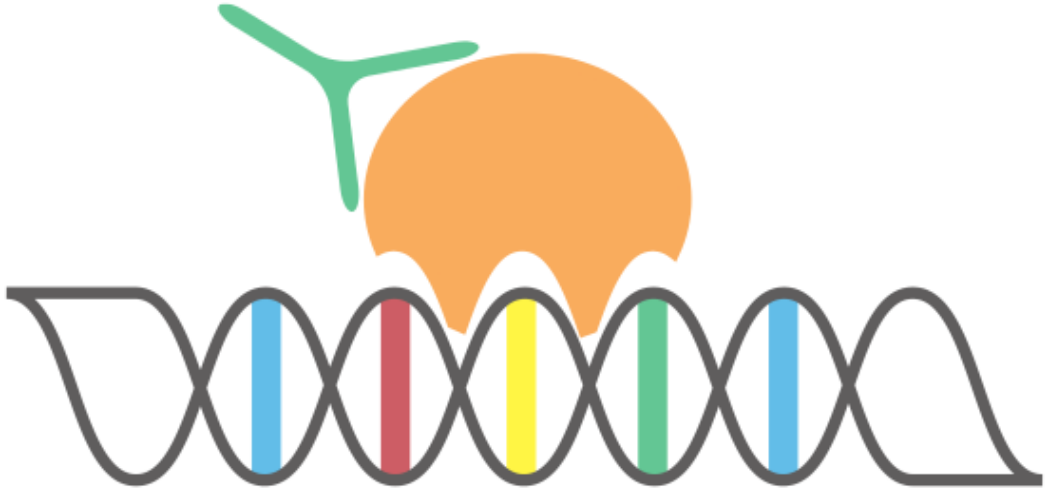
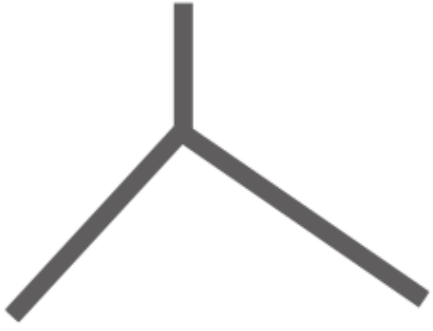
- **Main Question**: Can we use transcription factor (TF)-ChIPseq to predict protein complexes (direct and indirect bindings) on chromatin?
- **Strategy**: Model ChIPseq signal using Mixture Models to cluster the direct and indirect bindings.

What is ChIPseq?

CHIP-SEQ

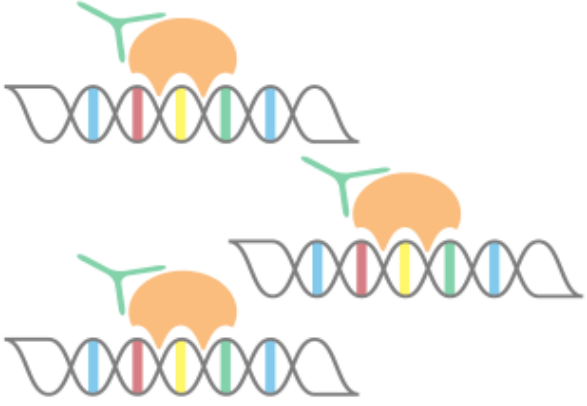


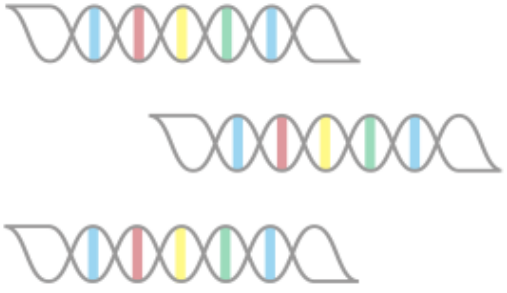
Chromatin Immunoprecipitation



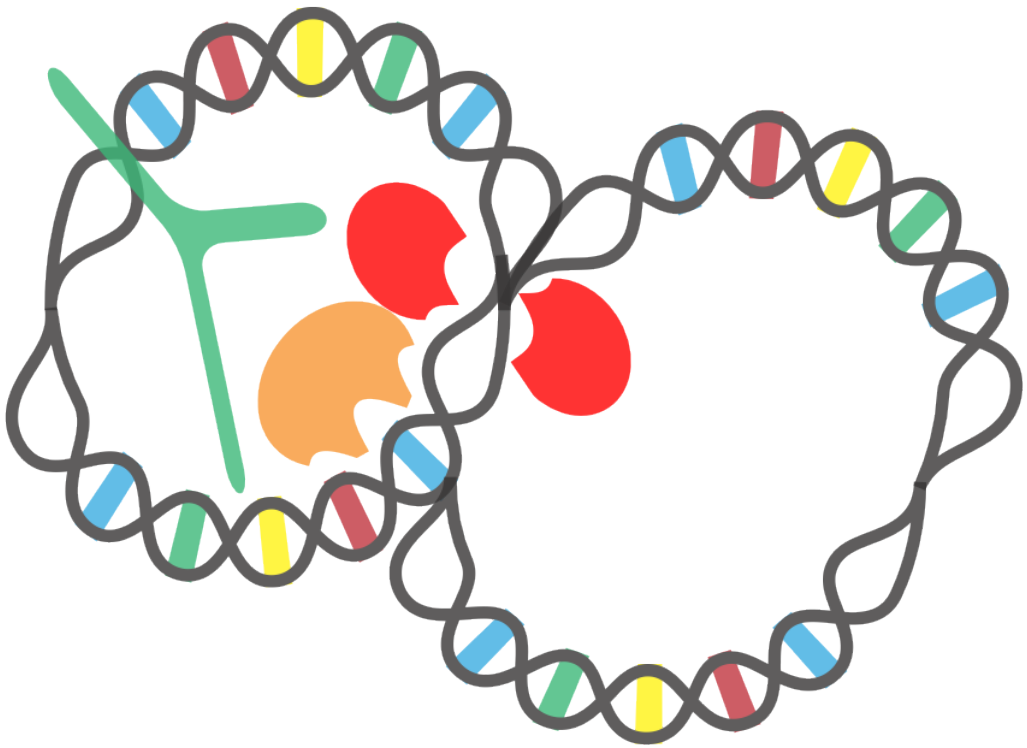
Sequencing

CAGTTACGCTAAGCCA

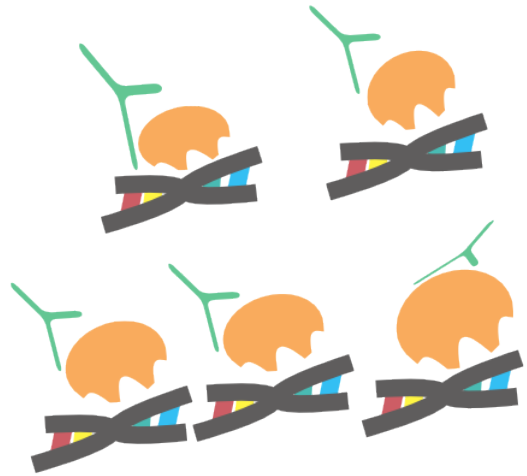




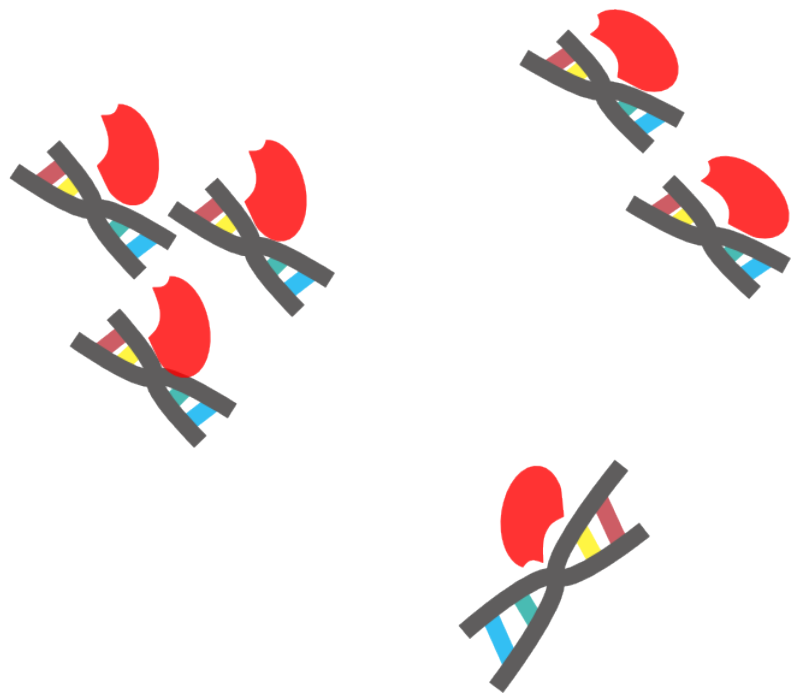
Chromatin Conformation



DIRECT BINDING SITES

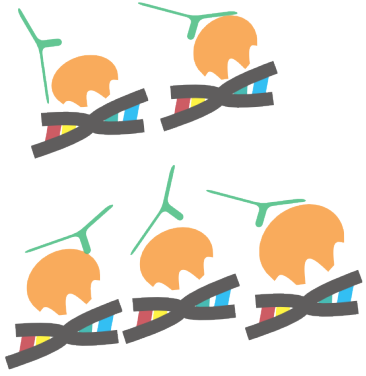


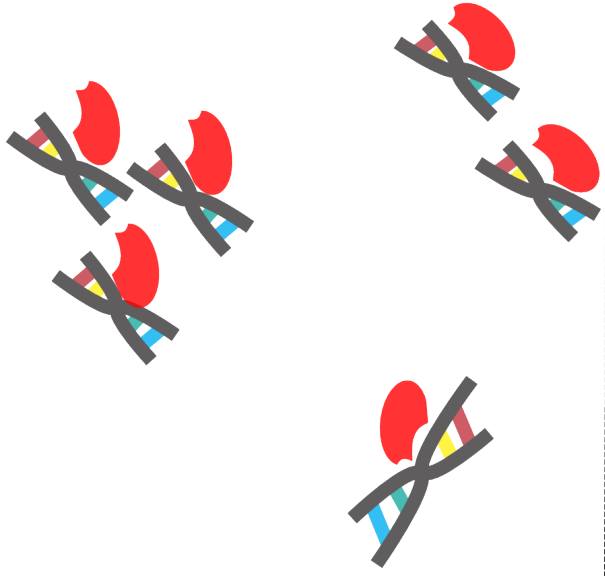
INDIRECT BINDING SITES

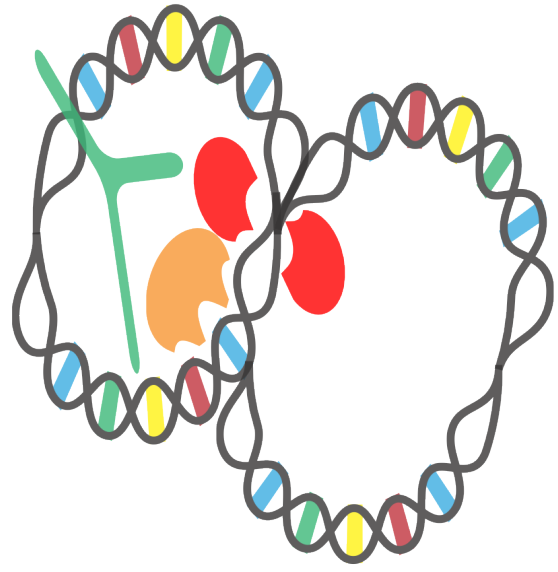


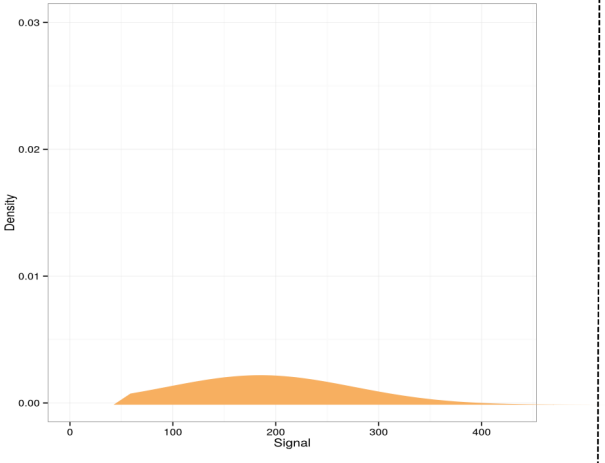
DIRECT BINDING SITES

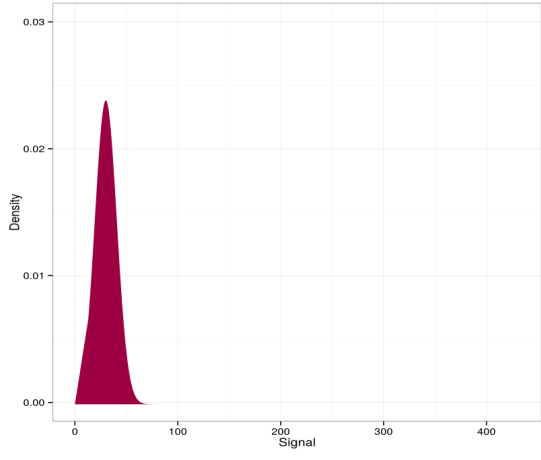
INDIRECT BINDING SITES

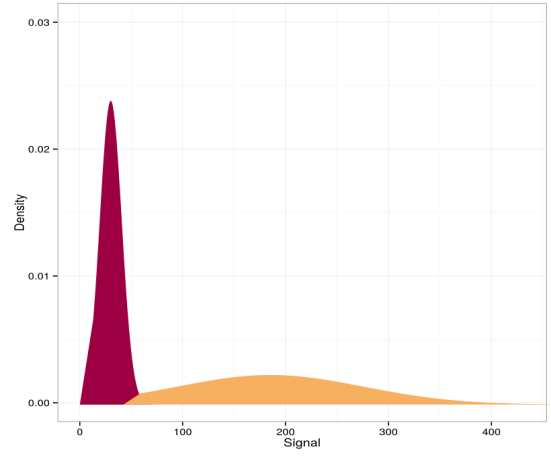












What is Mixture Model (MM)?

Mixture Model: Revisited

Types of clustering methods:

- Hard clustering: non-overlapping clusters
- Soft clustering: overlapping clusters

Mixture Model: Revisited

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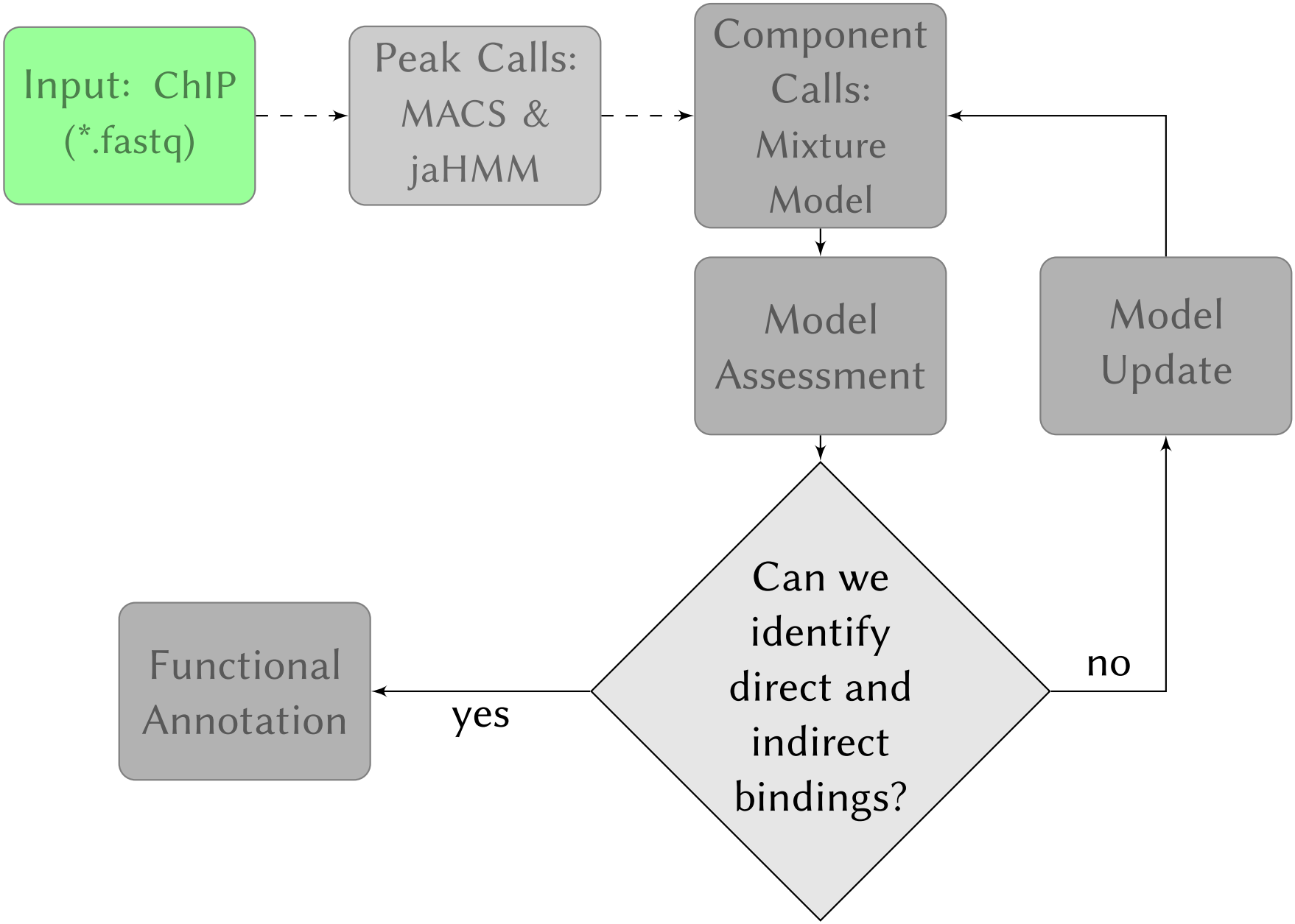
Mixture model is a probabilistic way of soft clustering. Each cluster is a generative mixture model with its parameters.

Gaussian Mixture Model

Key Assumption:

- ChIP-seq signals are drawn from a finite set of gaussian distributions.
- ChIPseq signals are fit with gaussian mixture models, with mixing λ parameter.
- Each gaussian corresponds to a cluster of signals with μ and σ parameters.


Input: ChIP (*.fastq)
Peak Calls: MACS & jaHMM
Component Calls: Mixture Model
Model Assessment
Model Update
Can we identify direct and indirect bindings?
yes
no
Functional Annotation

Input: ChIP-seq of Cebpϵ from Koeffler-BM

```
##FastQC 0.10.1
>>Basic Statistics pass
#Measure Value
Encoding Illumina 1.5
Total Sequences 41586141
Sequence length 40
#Summary
PASS  Basic Statistics
PASS  Per base sequence quality
PASS  Per sequence quality scores
WARN  Per base sequence content
PASS  Per base GC content
PASS  Per sequence GC content
PASS  Per base N content
PASS  Sequence Length Distribution
PASS  Sequence Duplication Levels
PASS  Overrepresented sequences
WARN  Kmer Content
```

Peak Calls: MACS2 vs jaHMM

[1] Zhang et al. Model-based Analysis of ChIP-Seq (MACS). Genome Biol (2008) vol. 9 (9) pp. R137

[2] Filion et al. jahmm: A tool for discretizing multiple ChIP seq profiles. arXiv (2014)

Peak Calls: MACS2 vs jaHMM

- **MACS2**: *poisson* model-based analysis of Peak calls [1]

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Peak Calls: MACS2 vs jaHMM

- **MACS2**: *poisson* model-based analysis of Peak calls [1]
- **jaHMM**: *negative binomial* model-based analysis of Peak calls [2]

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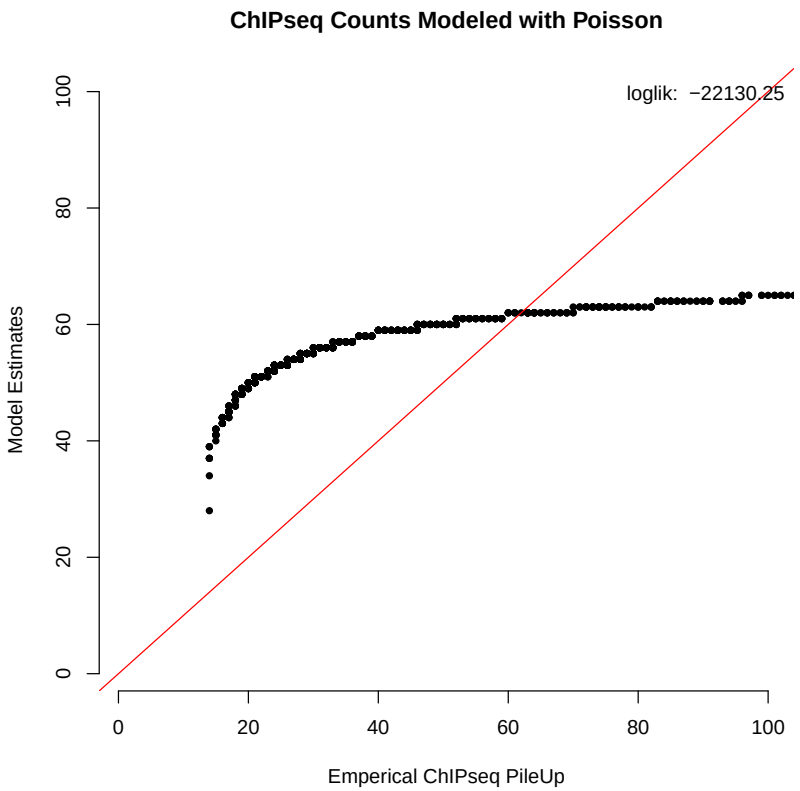
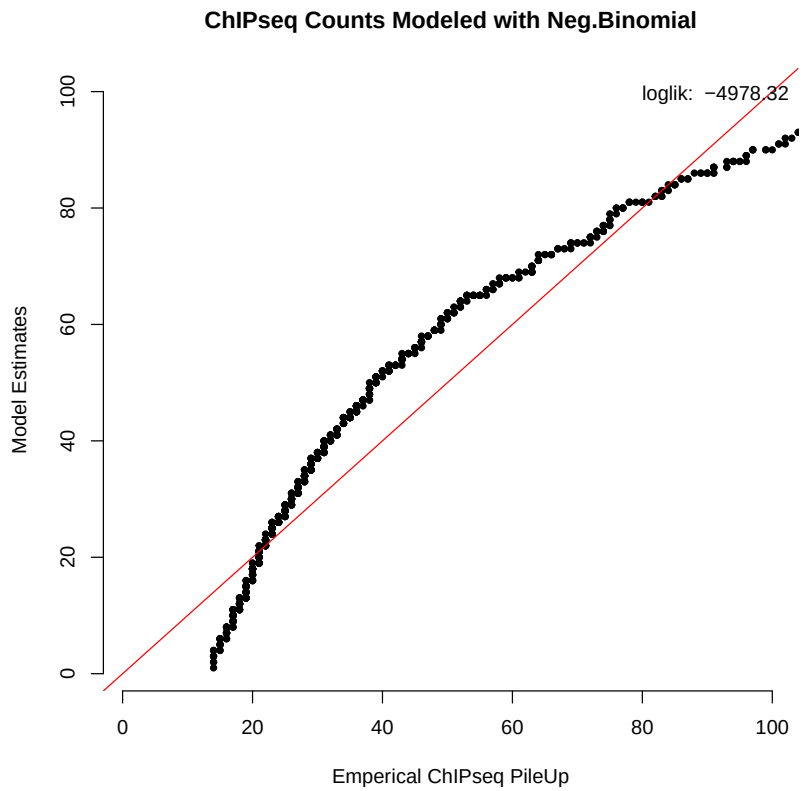
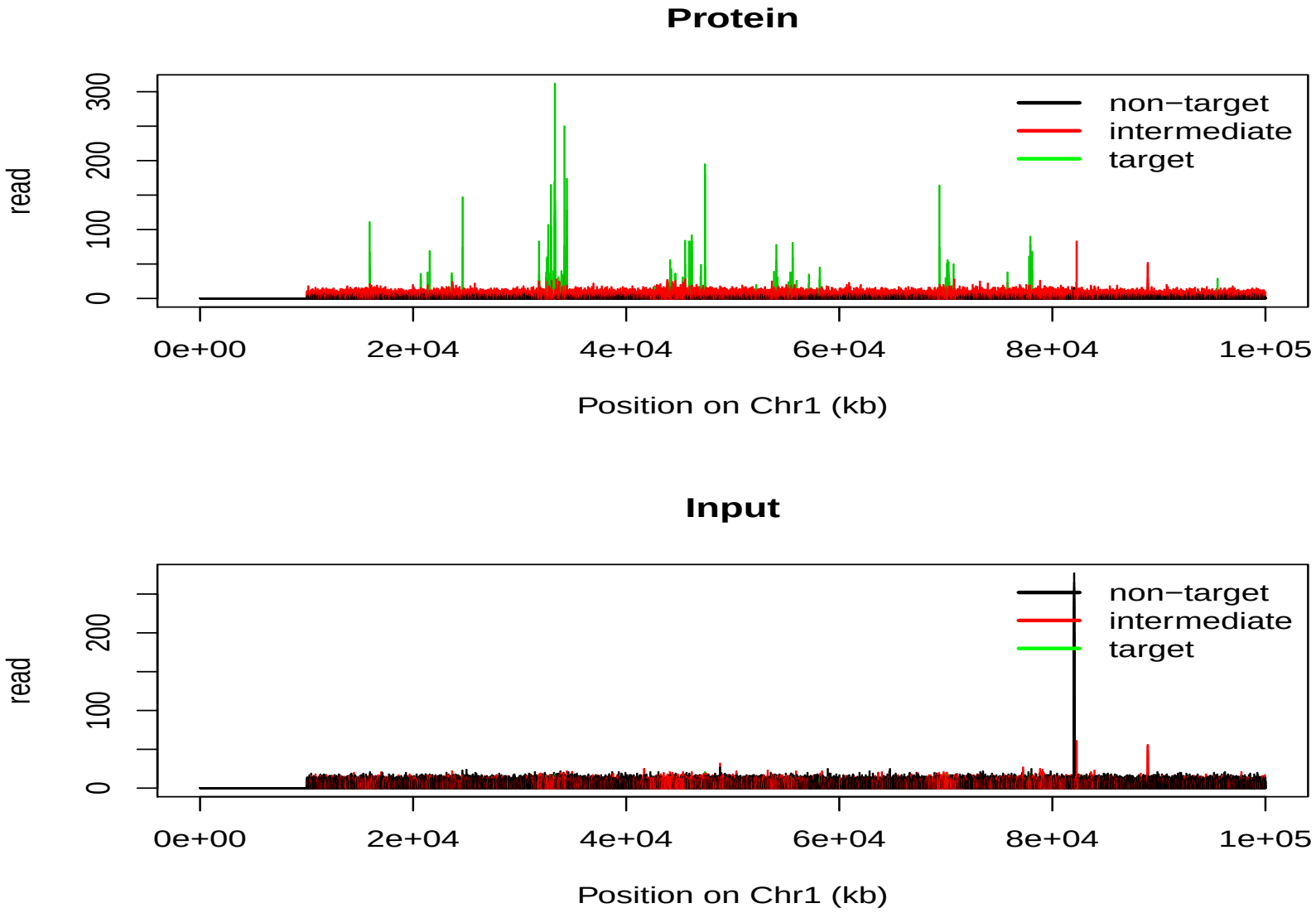
jaHMM fits ChIPseq Signals better than MACS2

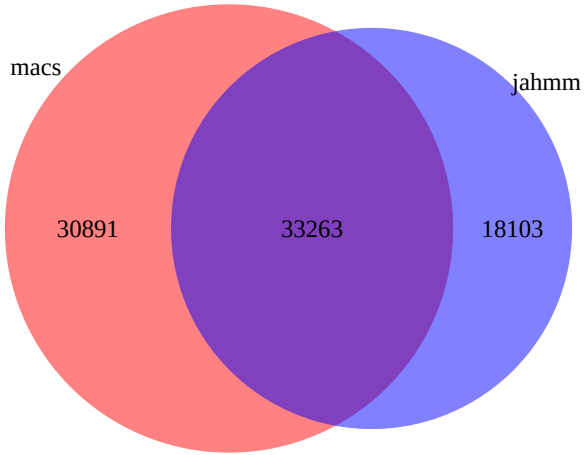


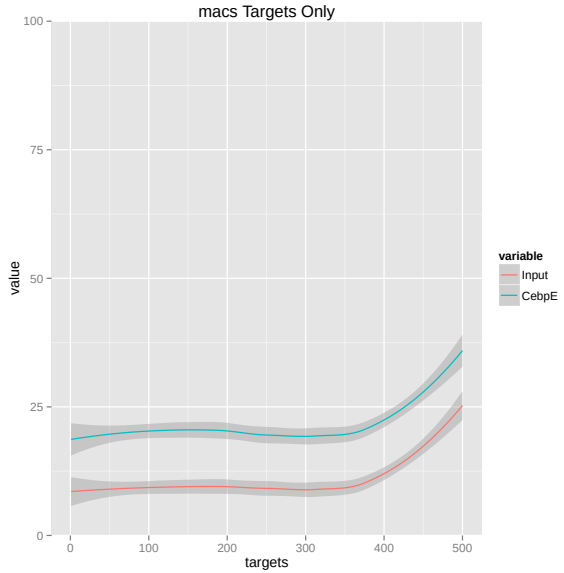


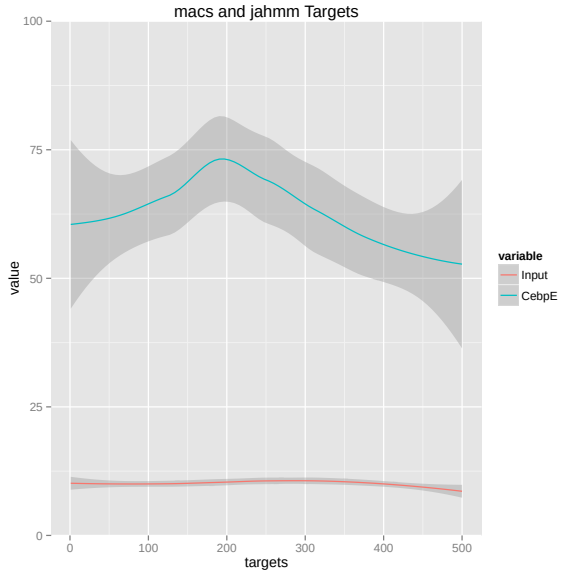
Peaks Called by jahmm

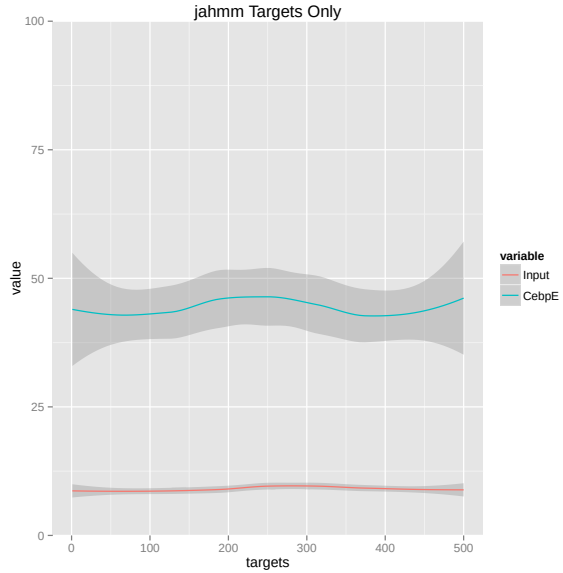


Peaks Called by MACS2 vs jahmm









Summary: Peak Calls

- Given our dataset, MACS2 is able to call peaks however, the estimated scores are less fit than JAHMM

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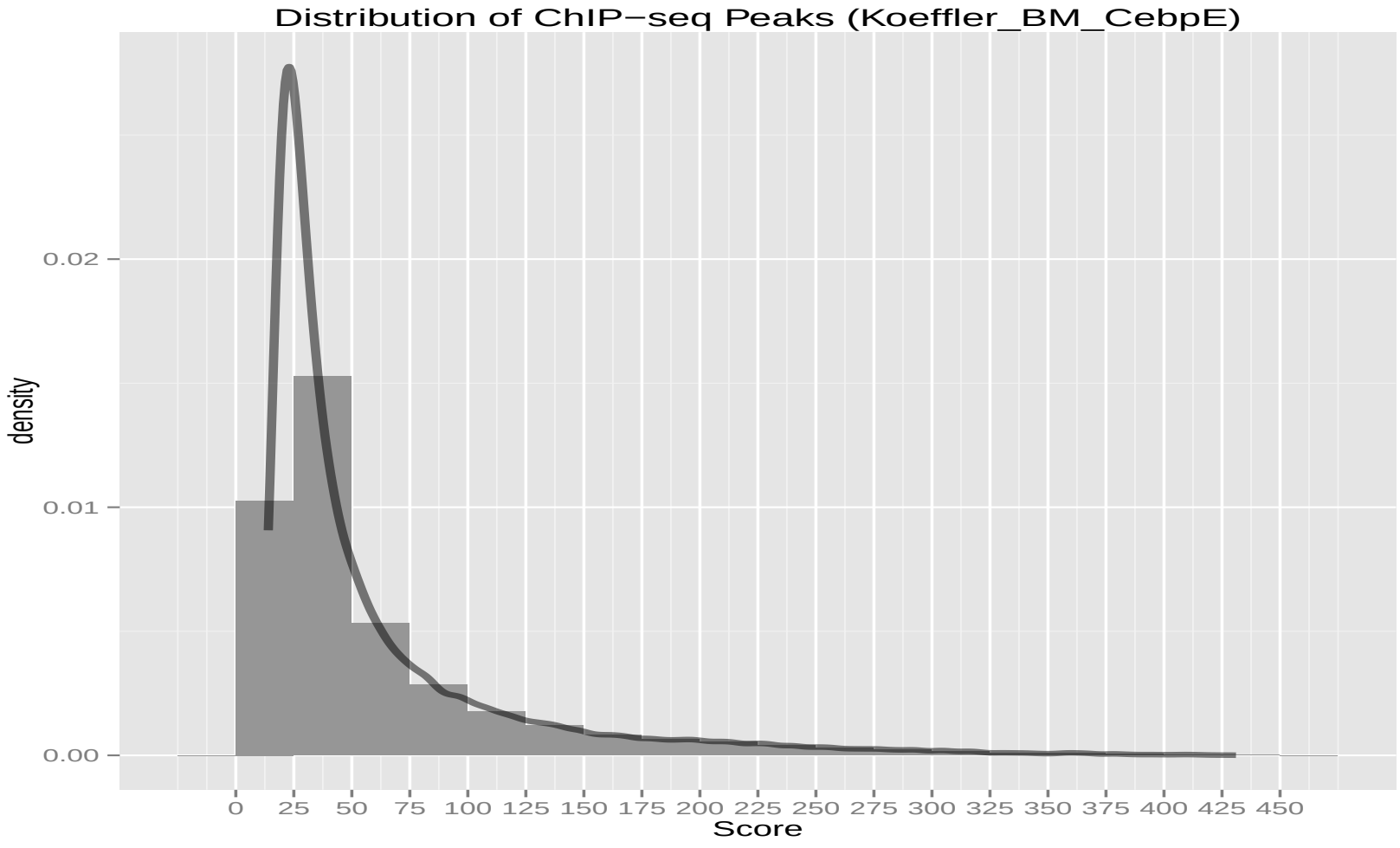
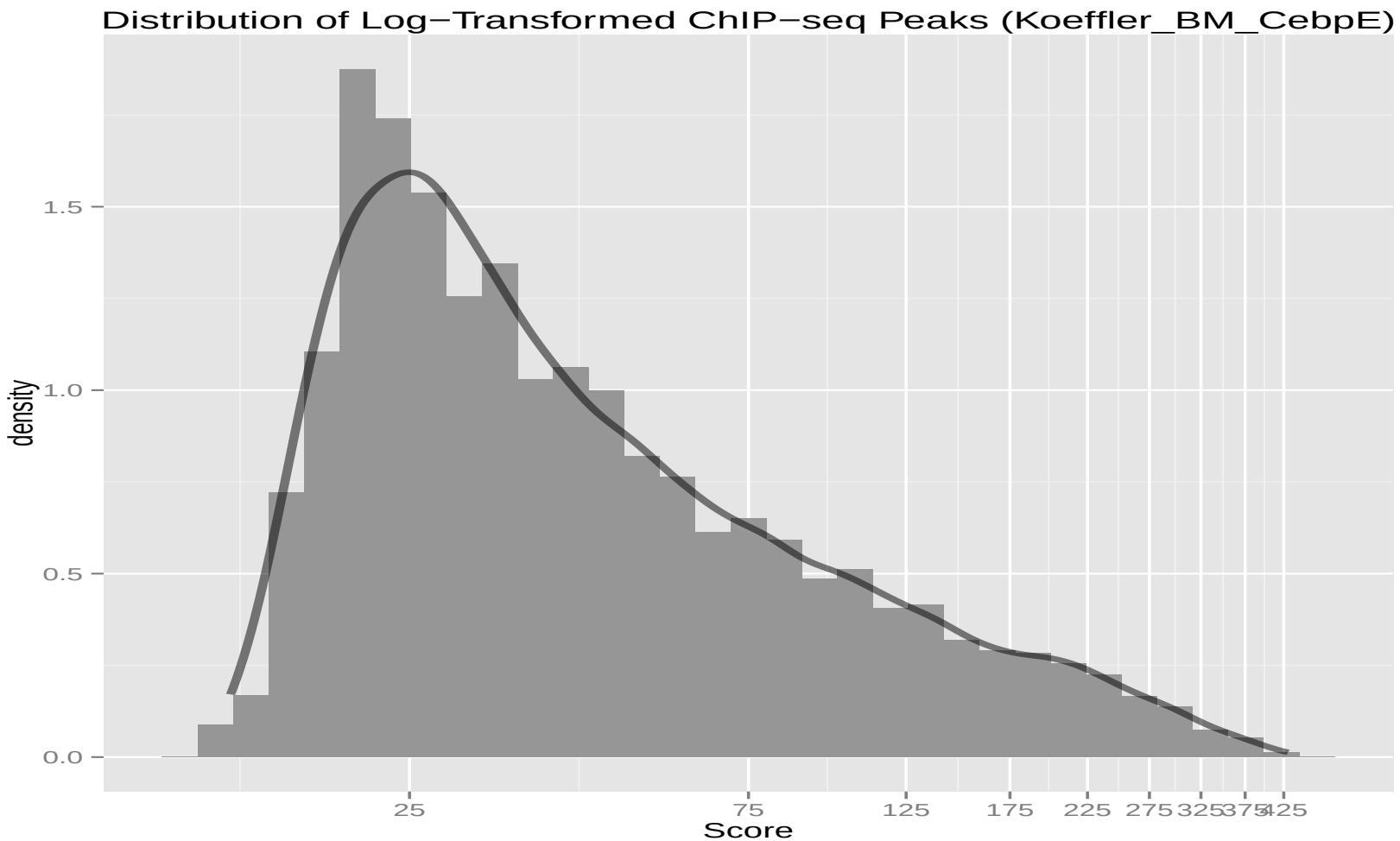
- Given our dataset, MACS2 is able to call peaks however, the estimated scores are less fit than JAHMM
- Peaks identified solely by jaHMM have scores higher with respect to their input (higher ratio) than solely by MACS2

Can we model ChIPseq using components of MMs?

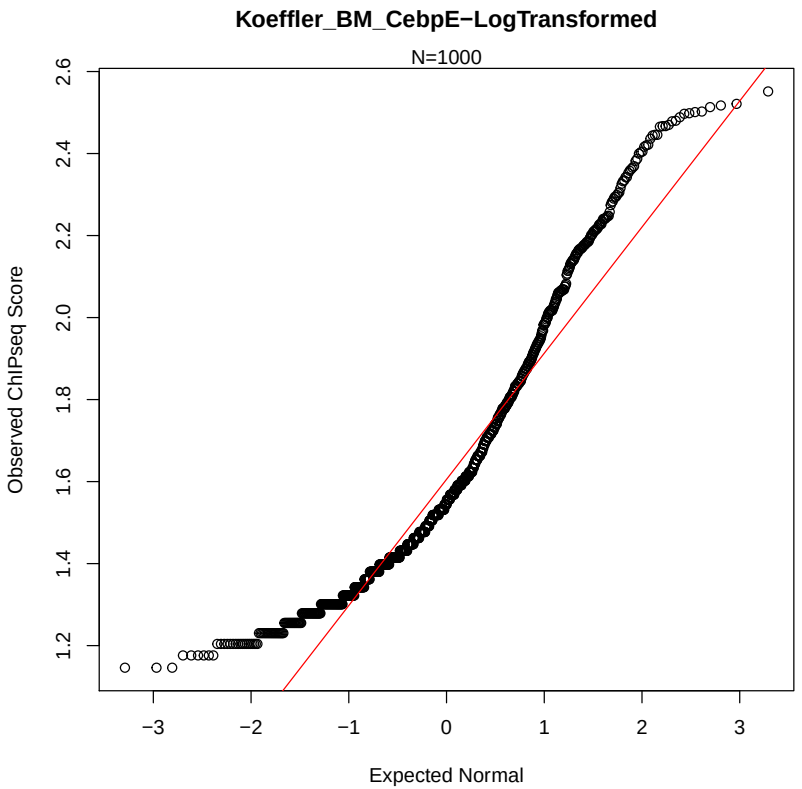
Input: ChIP-seq of Cebpϵ from Koeffler-BM

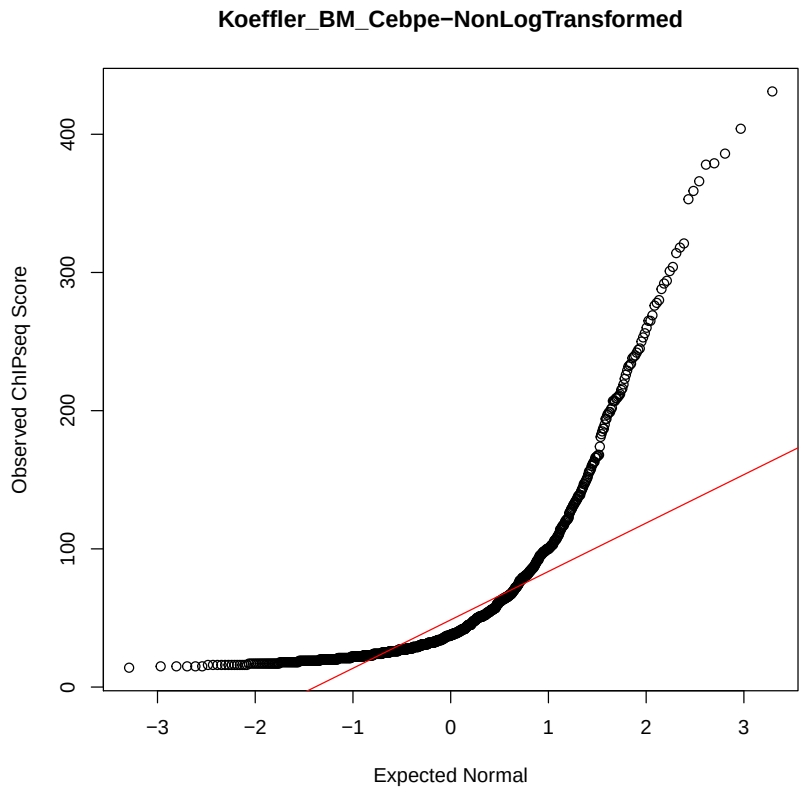


Log Transformation of ChIP-seq Input

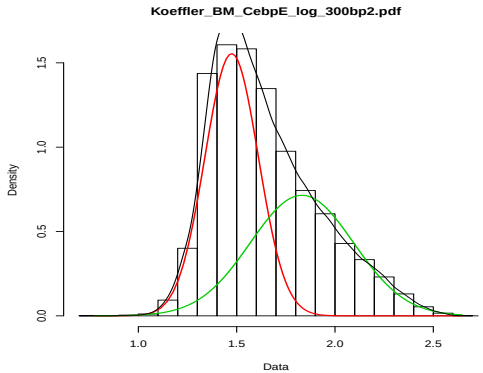


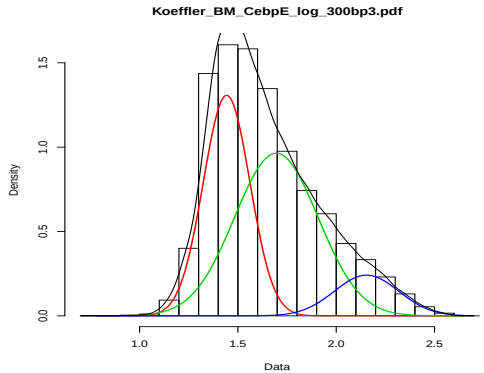
Check the Gaussian Normality

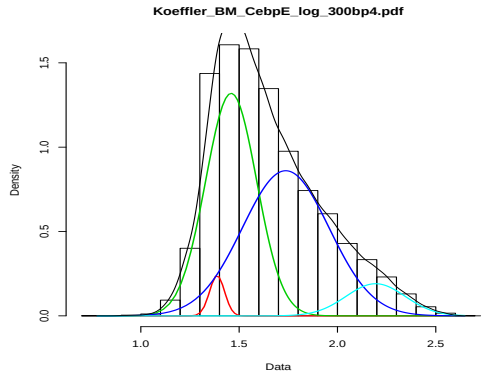


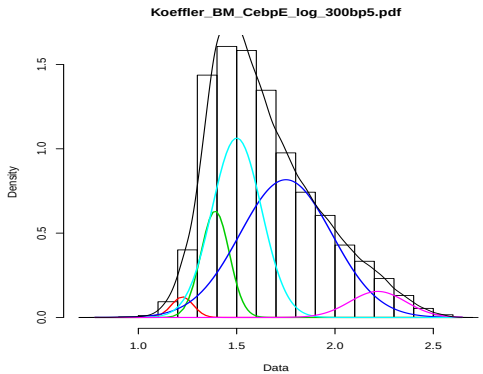


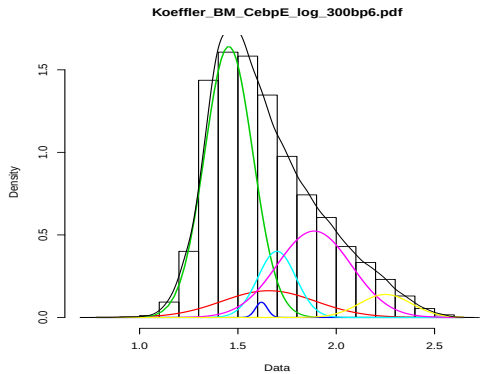
ComponentCalls: Fit ChIPseq Peaks with GMMs

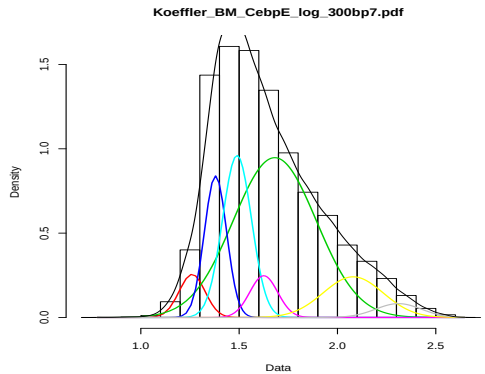


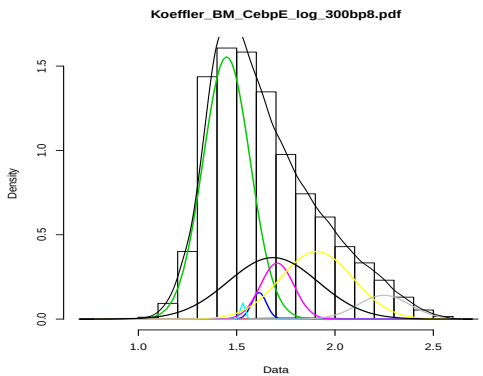


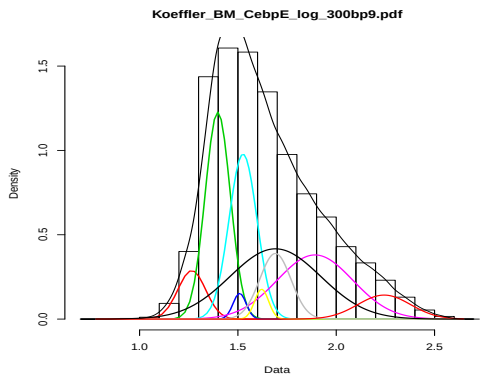


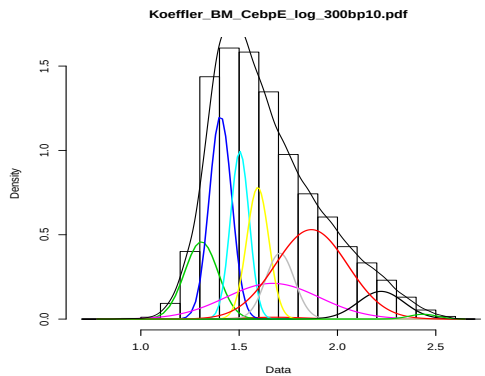




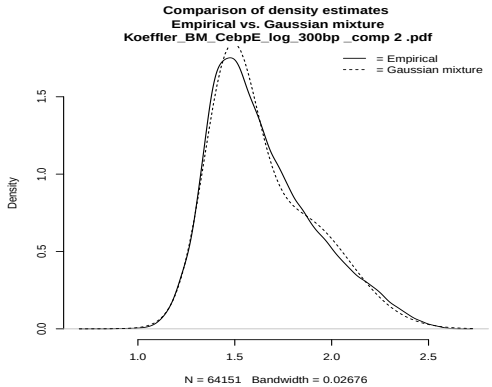


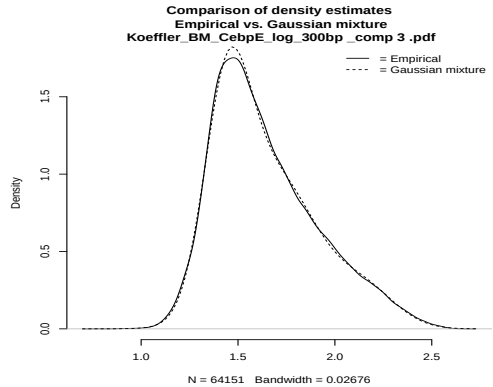


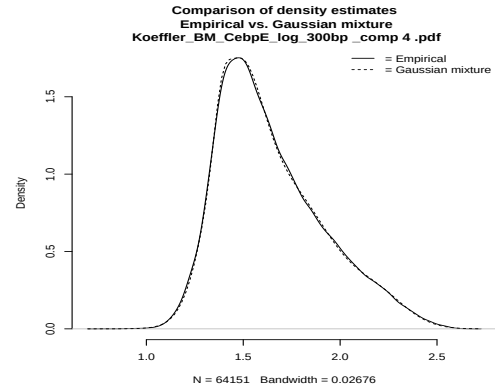


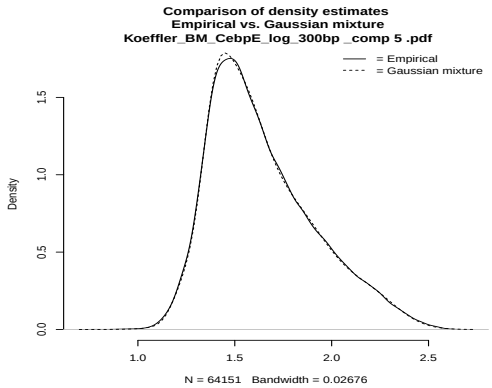


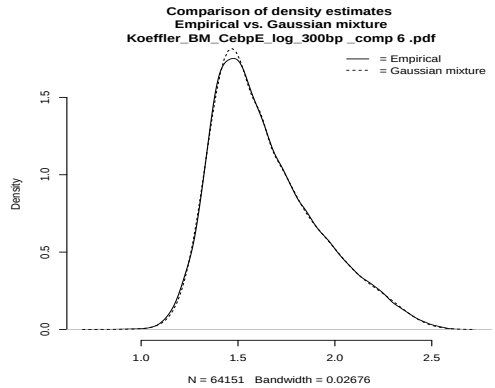
GMM-ModelAssessment: Overfit

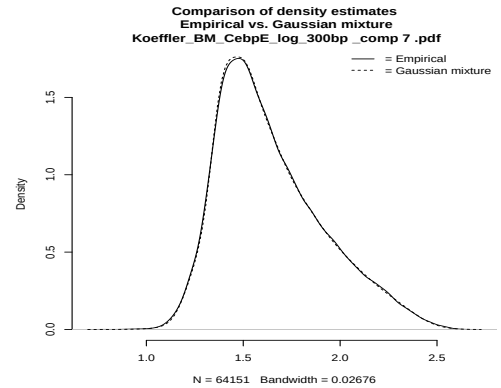


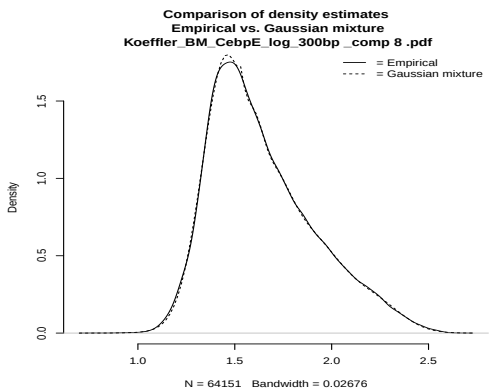


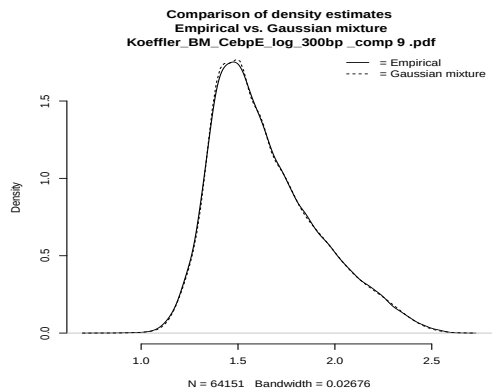


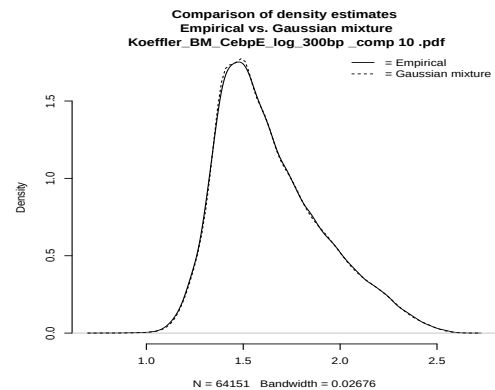










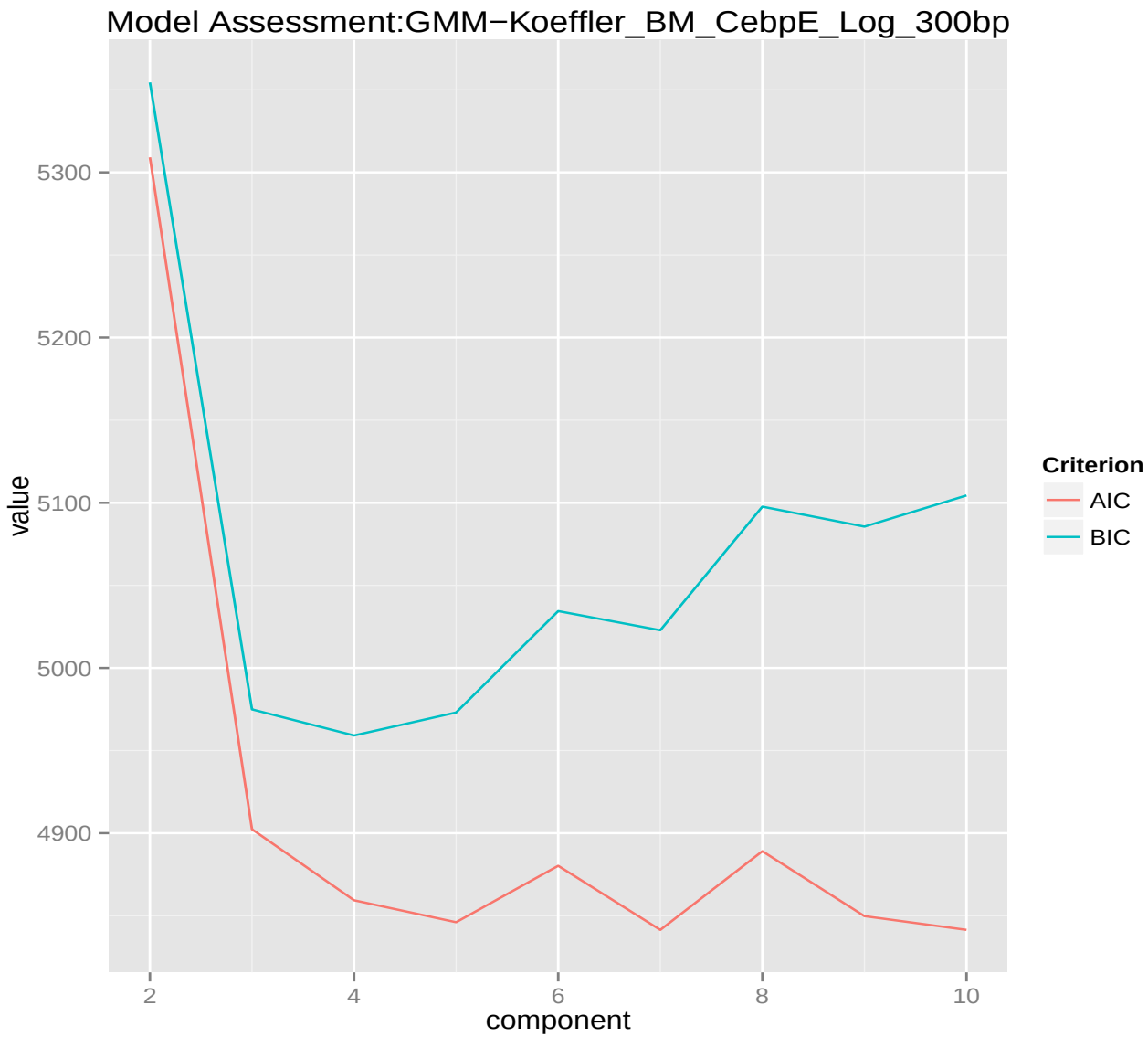


Model Assessment: BIC-AIC

AIC and BIC is based on Occam's razor principle, i.e, the simplest the better.

$\text{AIC} = -2 \times \log L + 2 * P$
$\text{BIC} = -2 \times \log L + \log(n) * P$
L is likelihood
P is the number of parameters

Model Assessment: BIC-AIC



Summary: Gaussian Mixture Models (GMMs)

- **Can we model ChIPseq using several components of MMs?**
  Yes, our ChIPseq Peaks identified by jaHMM can be fit with GMMs.

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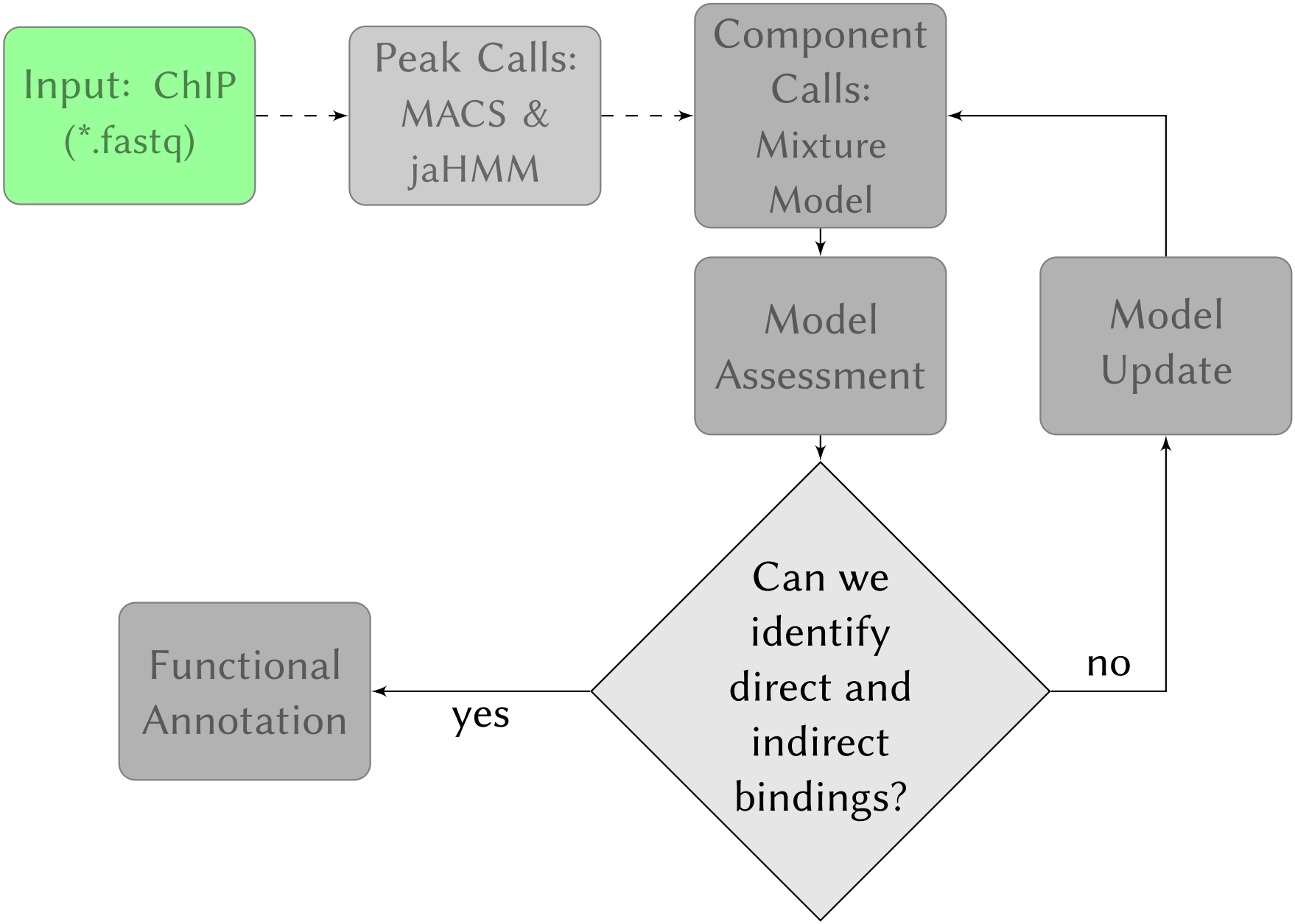
- **Can we model ChIPseq using several components of MMs?**
  Yes, our ChIPseq Peaks identified by jaHMM can be fit with GMMs.
- **How many components are required?**
  From AIC-BIC model assessment, 3 components are sufficient to fit ChIPseq signals.
  Note: the lower the AIC and BIC values, the better the fitting.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Component Calls: Mixture Model
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Model Update
Can we identify direct and indirect bindings?
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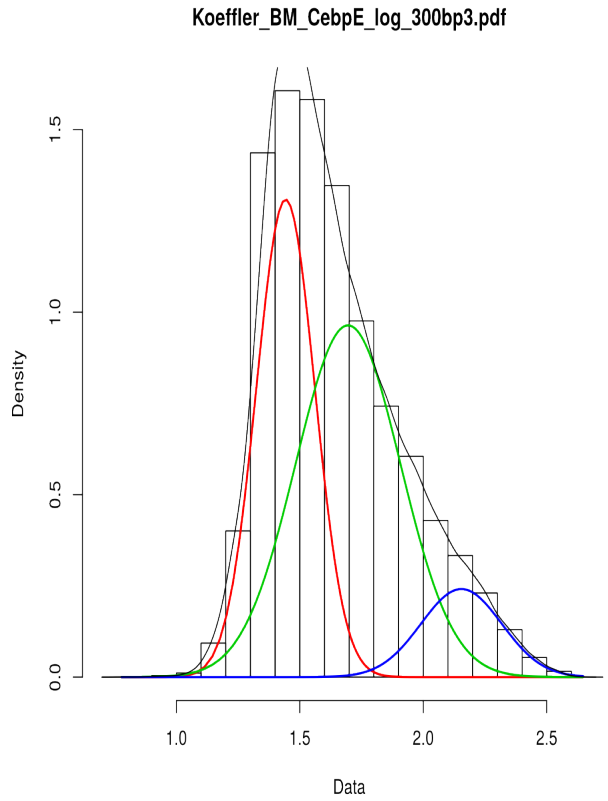
Functional Annotation

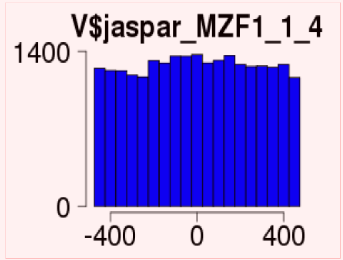
Motif Calls using Centdist [1]

[1] Zhang et al. CENTDIST: discovery of co-associated factors by motif distribution. Nucleic Acids (2011)

Group1: low peak score (29559 peaks)

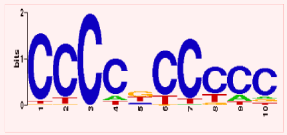


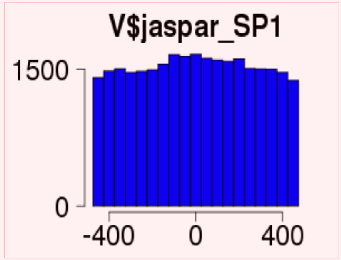
MZF



7.79e-13

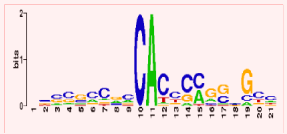
SP1

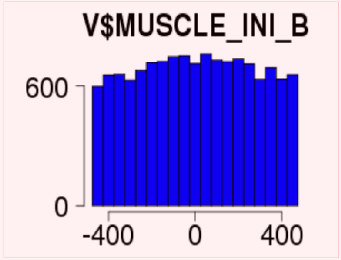




2.0e-11

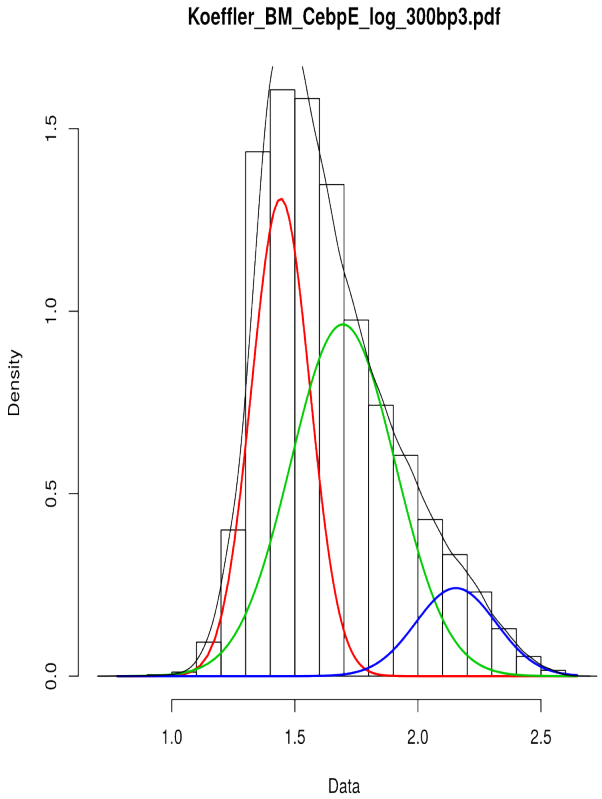
MIN1



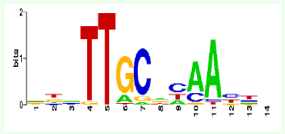


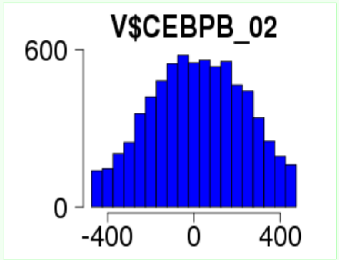
3.53e-8

Group2: intermediate peak score (28851 peaks)



CEBP





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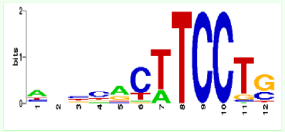
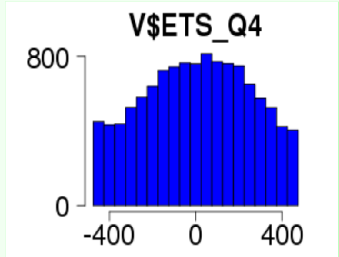
ETS





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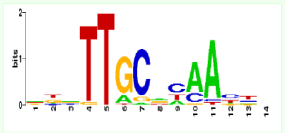
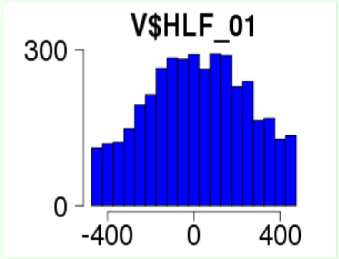
CREB





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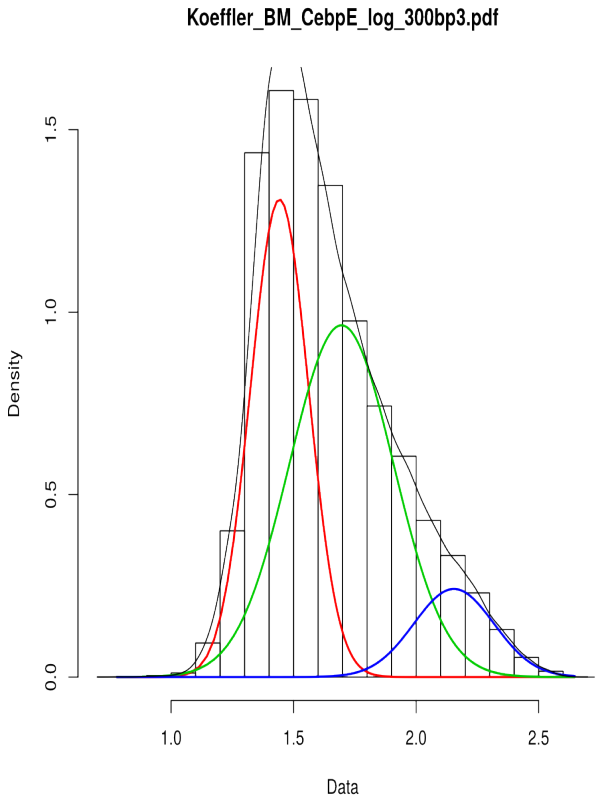
Group3: high peak score (5741 peaks)



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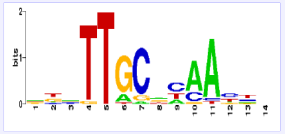

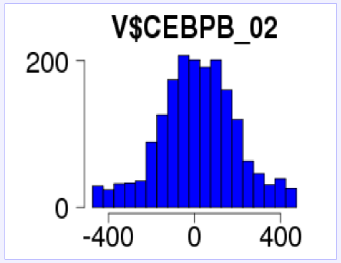

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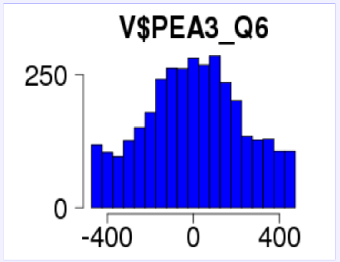
ETS



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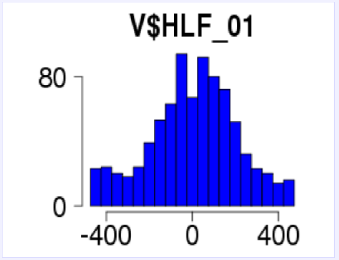

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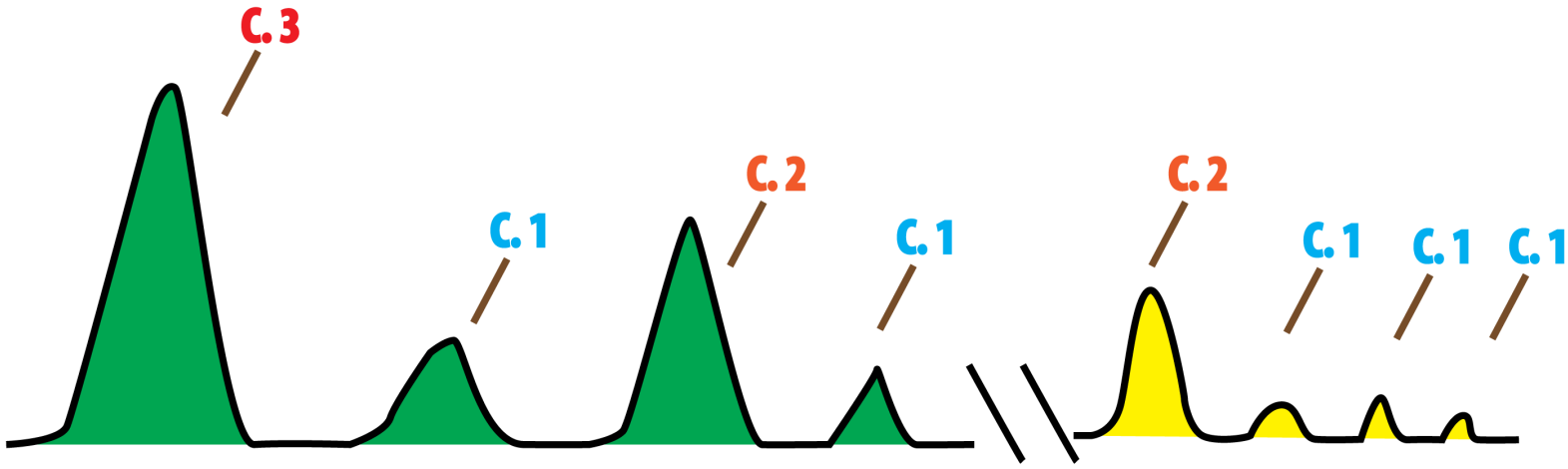
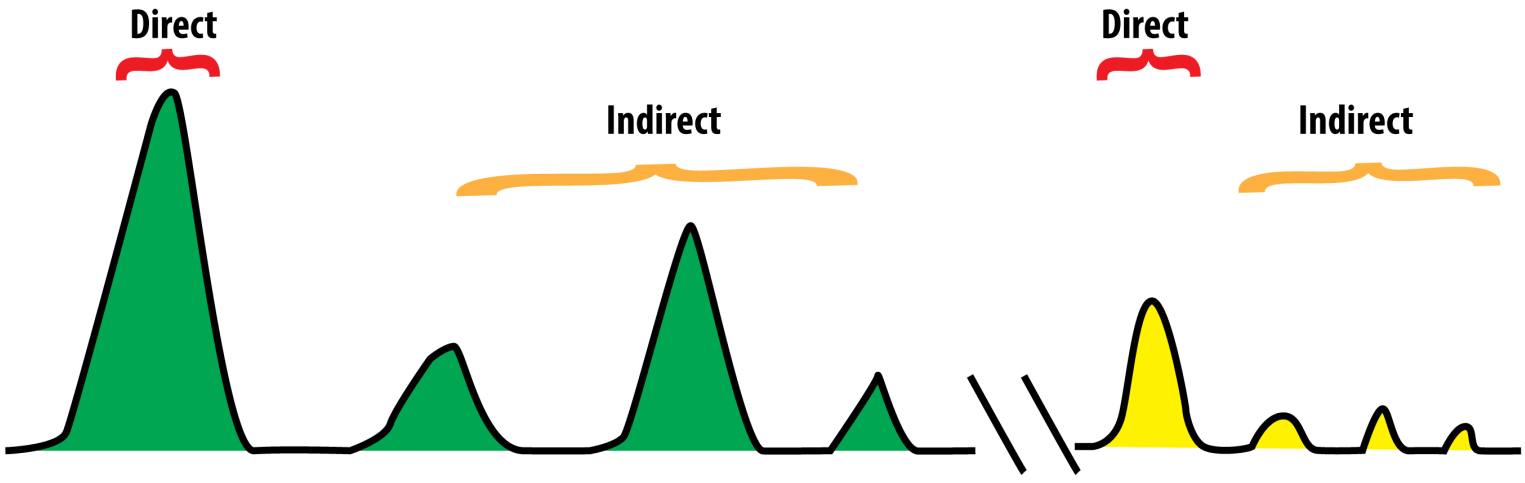
- Cebp motif is found in group 2 and 3 in 3-component GMMS using centdist

- Cebp motif is found in group 2 and 3 in 3-component GMMS using centdist
- Next, can we further segregate these groups into direct and indirect bindings?

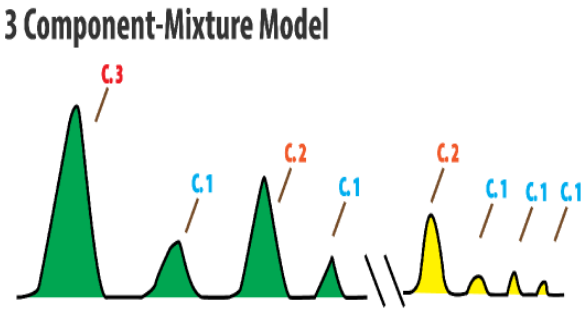
3 Component-Mixture Model



Local Clustering



Direct: 24948 peaks



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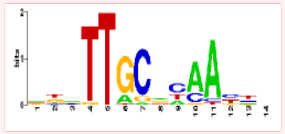

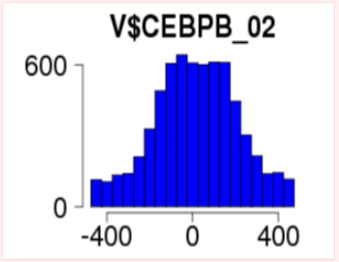

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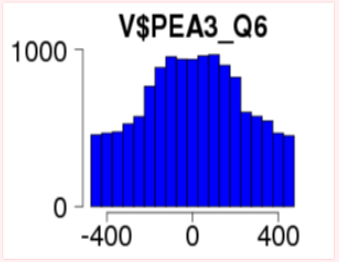
ETS



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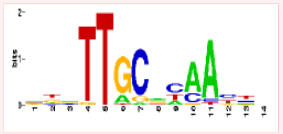
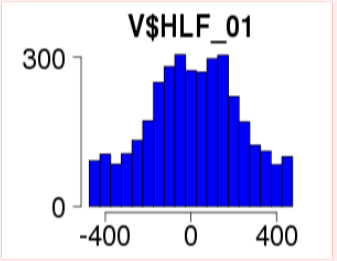
CREB





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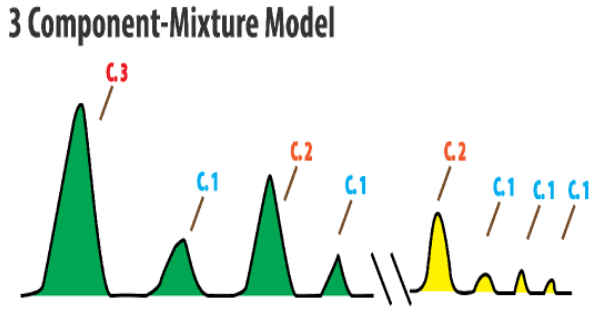
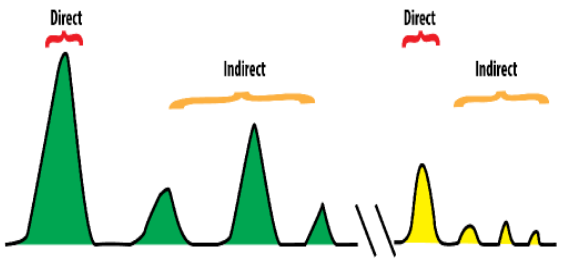
Indirect: 26547 peaks





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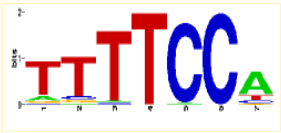

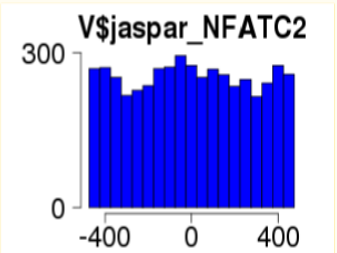

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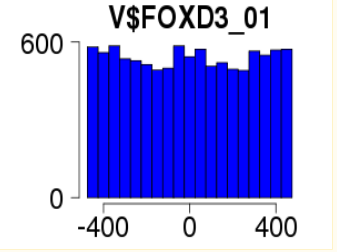
FOX



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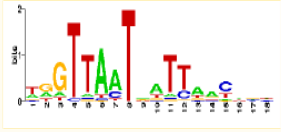
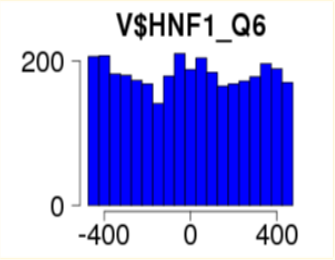
HNF1



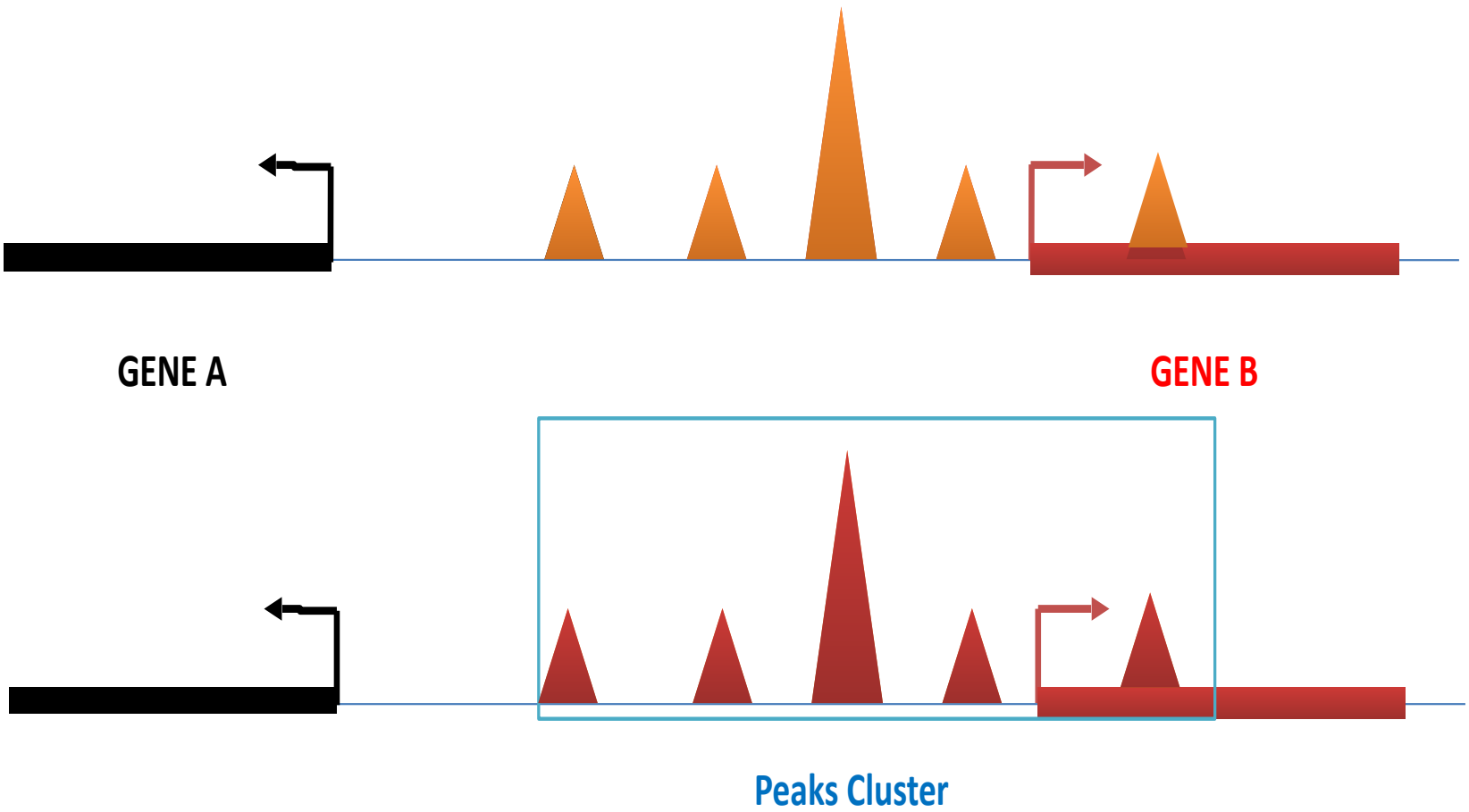


0.00266

- Our current method could separate direct and indirect bindings

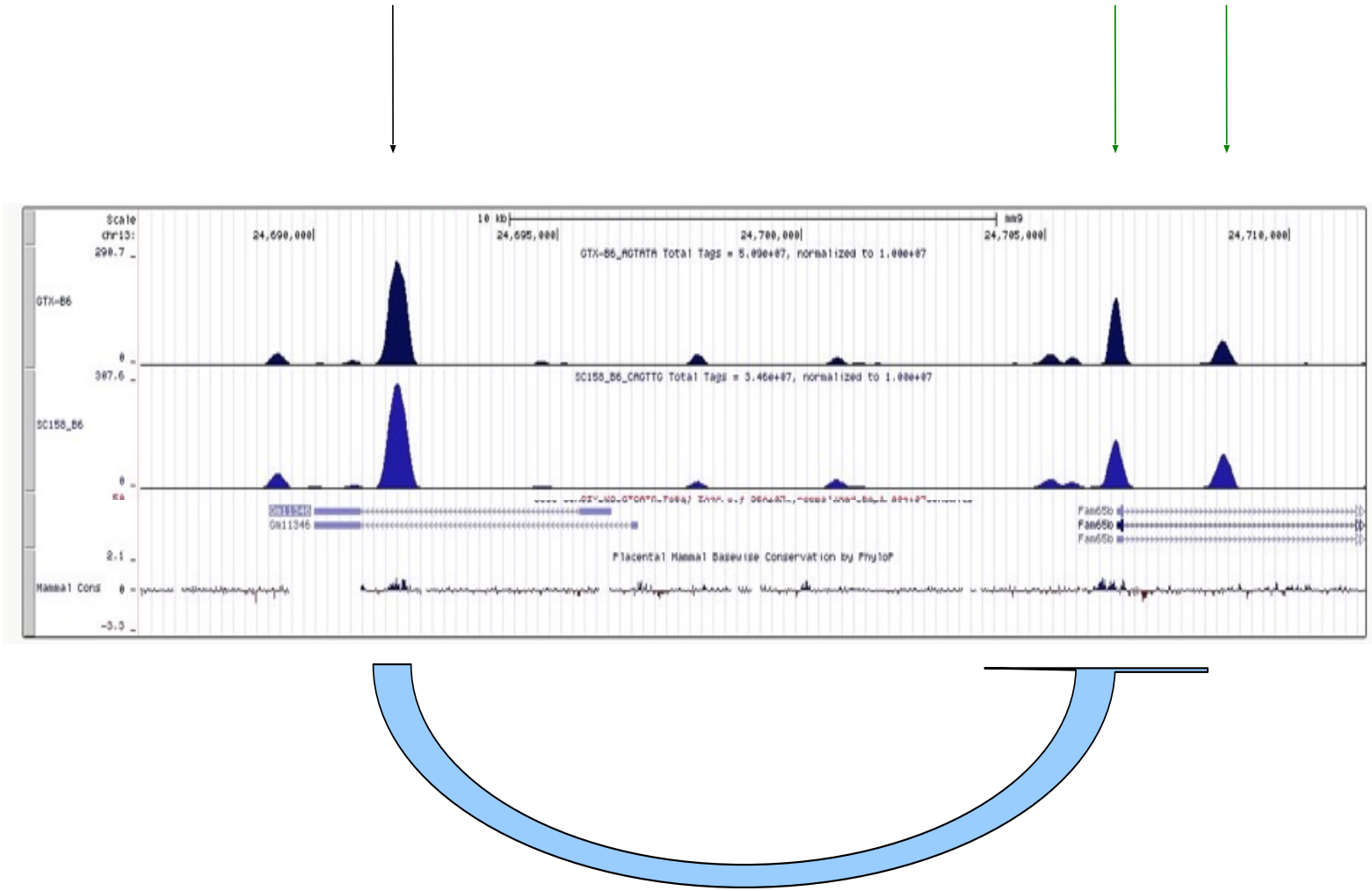
- Our current method could separate direct and indirect bindings
- Next, can we further using peak clusters increase functional annotation?

Find the targeted genes



What problems the invention solves and advantages over existing methods?

An Example:



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- Phillip Koeffler (CSI-NUS)