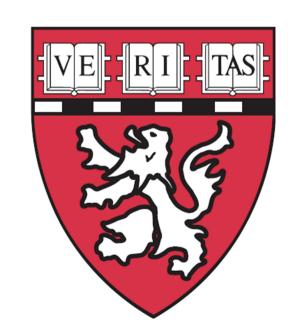
Mechanisms and models of distal enhancers of inducible gene expression

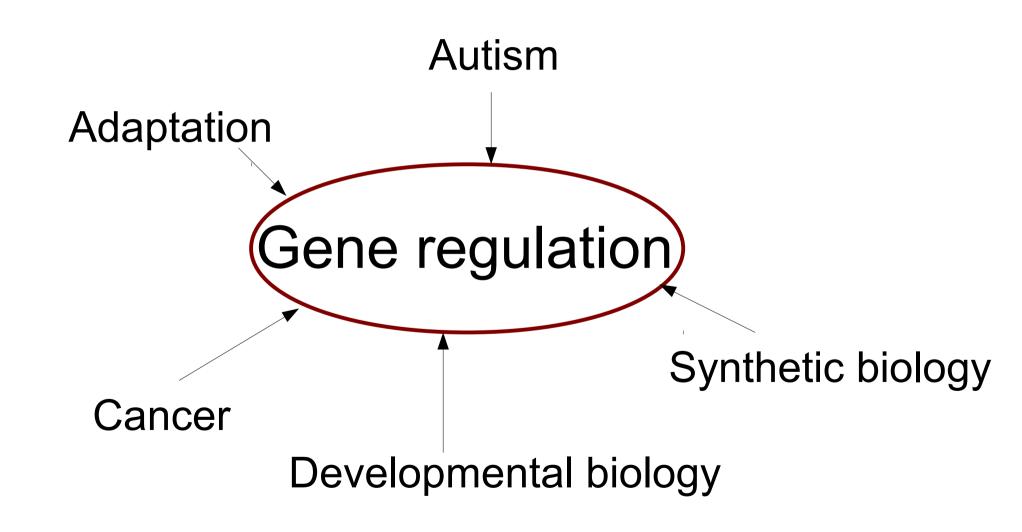
Martin Hemberg

UC Berkeley February 28, 2012

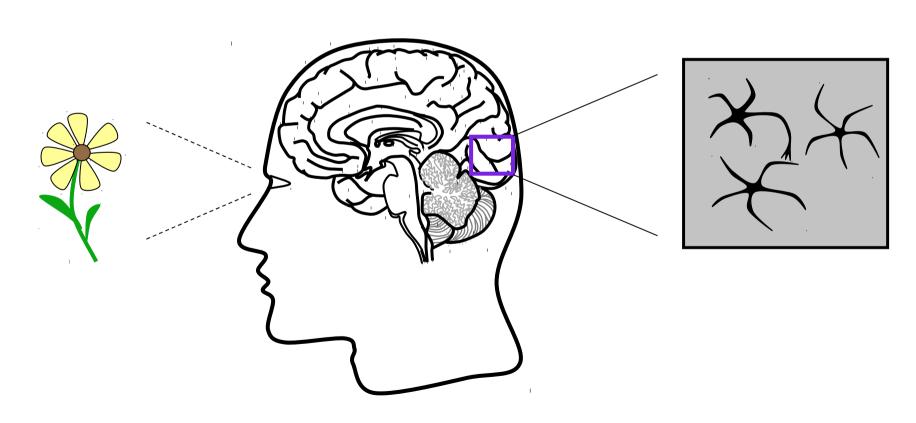




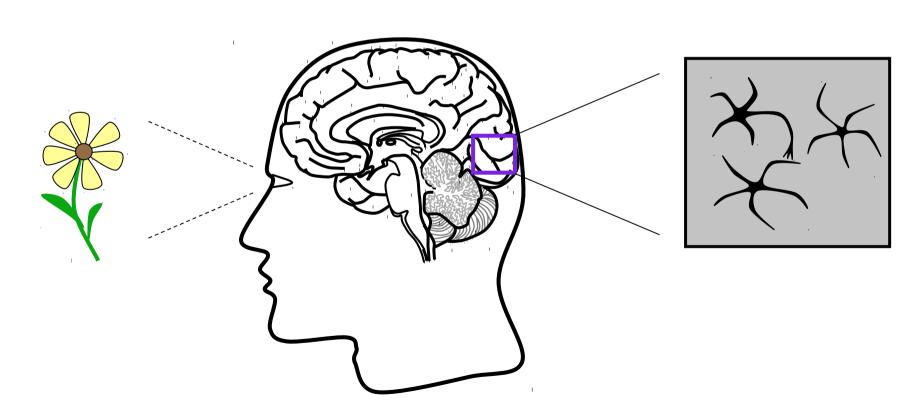
Why is gene regulation important?



Synapses change in response to external environmental stimuli



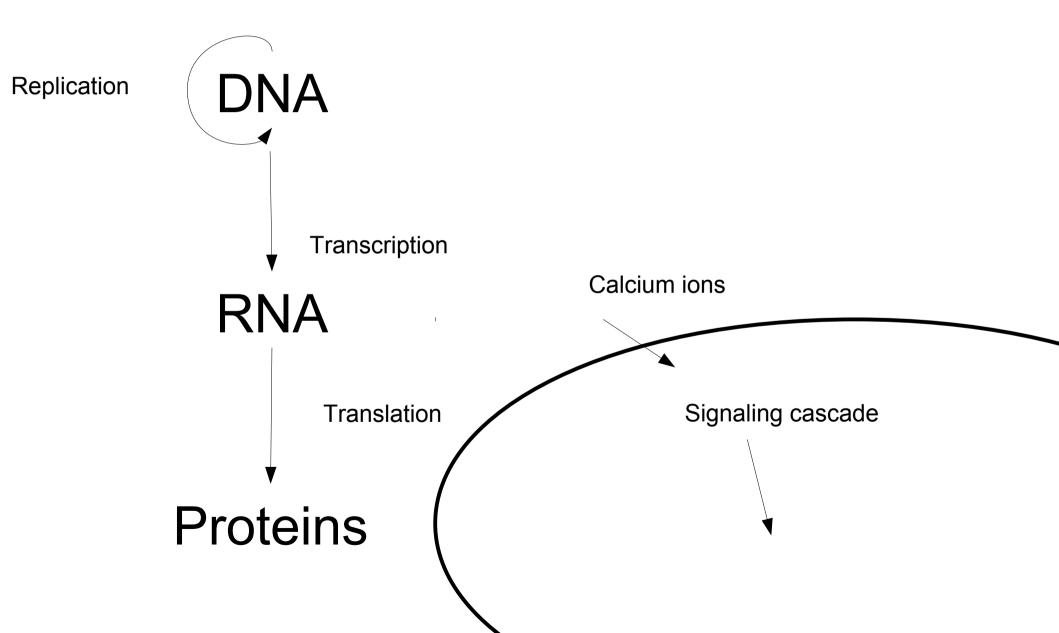
Changes in synapses are caused by changes in expression of ~1000 genes



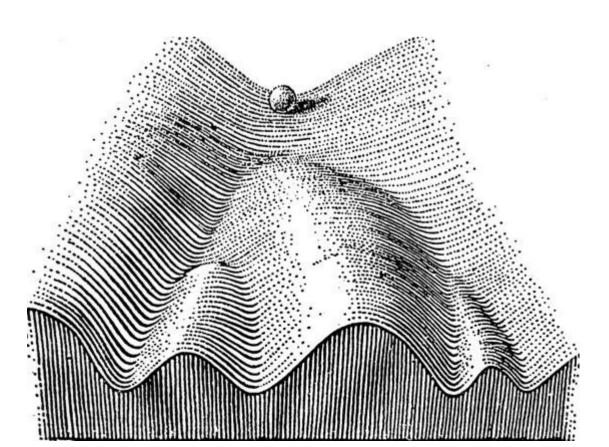
What is gene expression?

DNA Replication Transcription **RNA Translation Proteins**

Activity-dependent gene expression triggered by influx of Ca

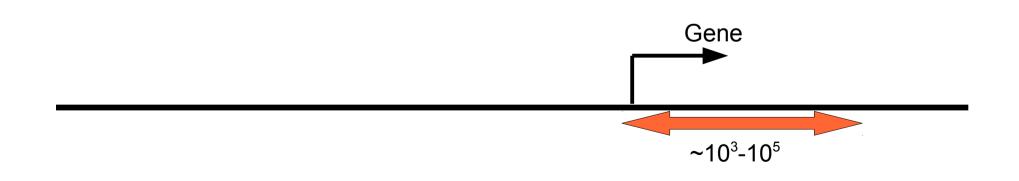


What is gene regulation?



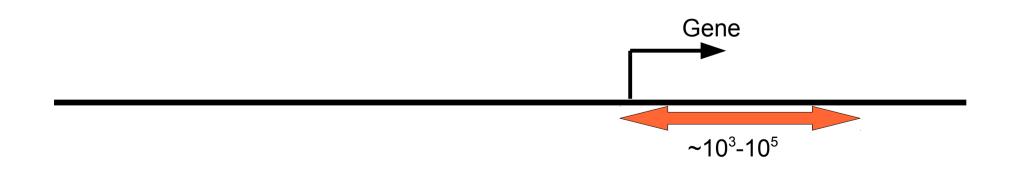
Mouse genome is large and has few genes

- ~25,000 genes
 - − ~2% of DNA



Mouse genome is large and has few genes

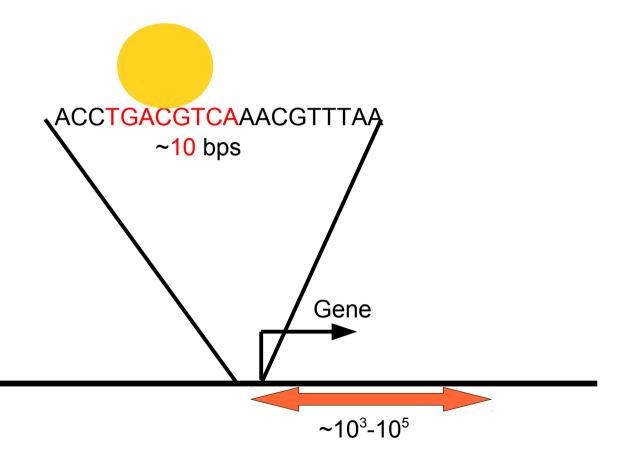
- ~25,000 genes
 - − ~2% of DNA
 - Bacteria ~10⁶ base pairs (bps)
 - 10³-10⁴ genes



Transcription Factors (**TF**s) bind to DNA motifs

• ~25,000 genes

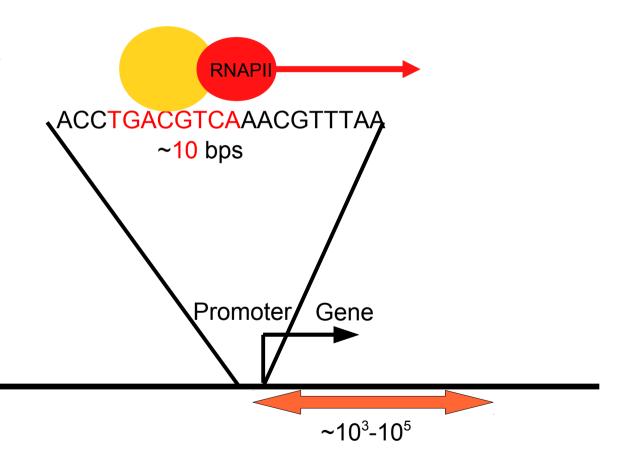
− ~2% of DNA



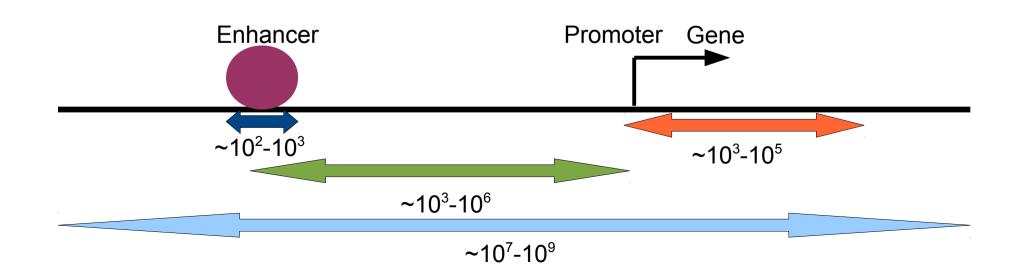
Transcription factors bind at promoter to recruit RNA Polymerase II (RNAPII)

• ~25,000 genes

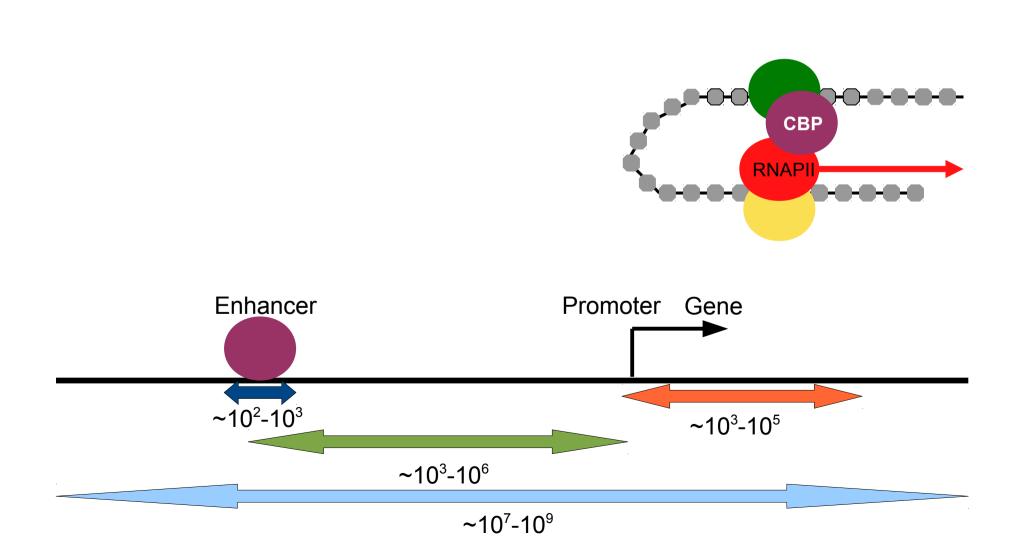
− ~2% of DNA



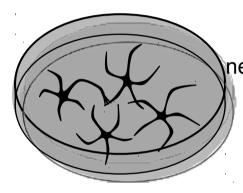
Enhancers are distal regulatory sequences



Enhancers characterized by CBP binding



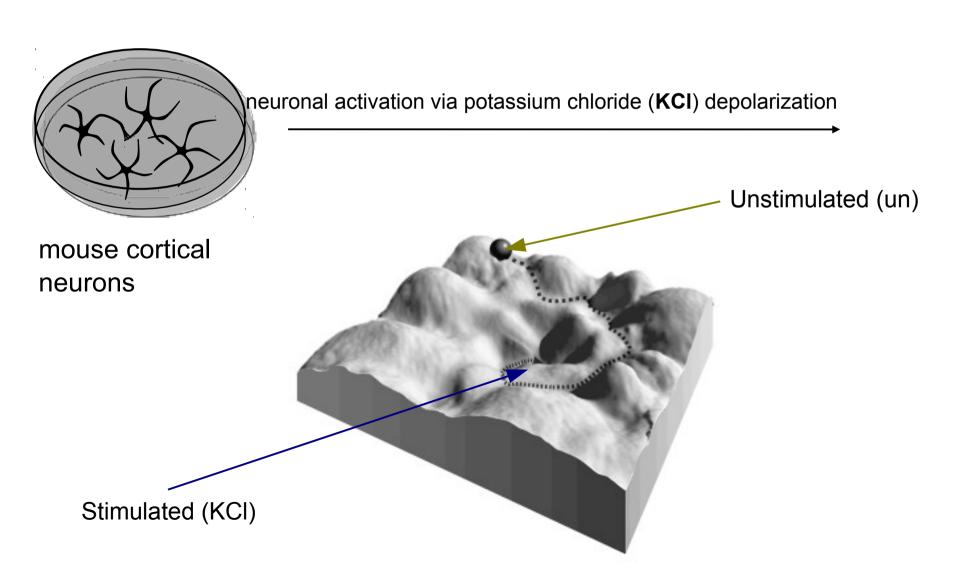
Cultured mouse cortical neurons for genome-wide study of activity dependent gene expression



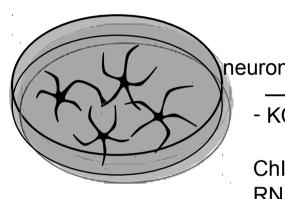
neuronal activation via potassium chloride (KCI) depolarization

mouse cortical neurons

Potassium chloride (**KCI**) stimulation induces cells to change state



Genome-wide data obtained using highthroughput sequencing



mouse cortical neurons

neuronal activation via potassium chloride (KCI) depolarization

- KCI + KCI

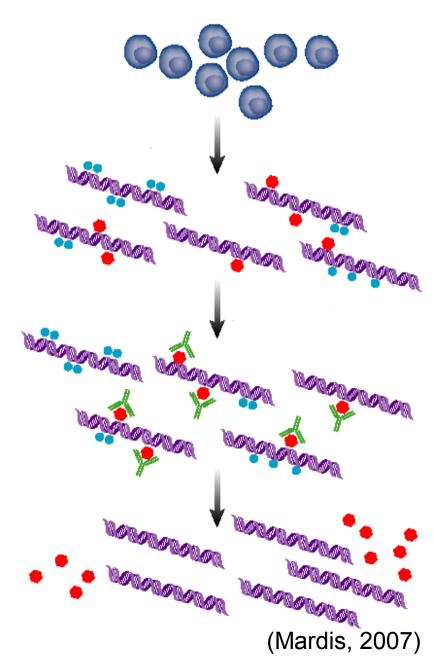
ChIP-Seq RNA-Seq

ChIP-Seq RNA-Seq

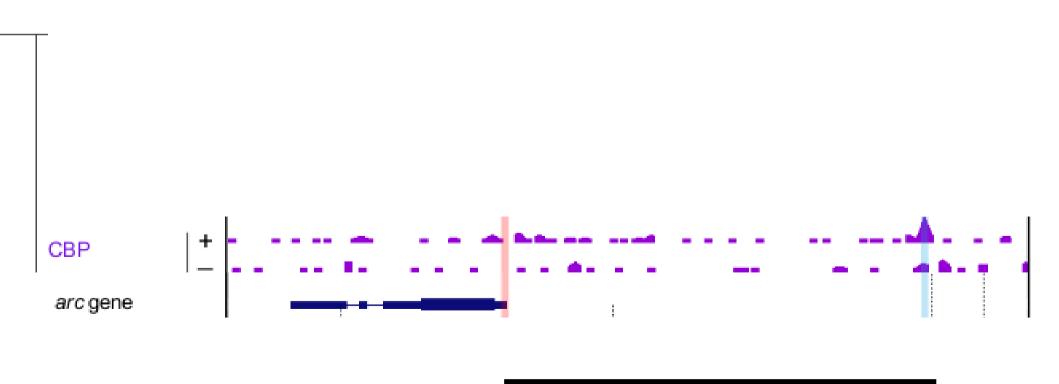


Jesse Gray Tae-Kyung Kim Greenberg Lab Chromatin immunoprecipitation and sequencing (**ChIP-Seq**) finds protein binding sites *in vivo*

- Short reads mapped to reference genome
- #reads ~ binding
- ~10 M reads
- Unbiased



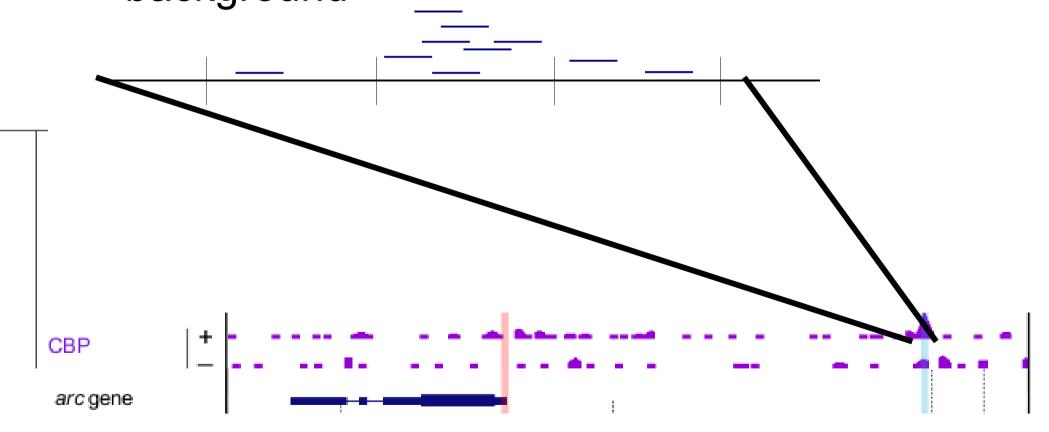
Inducible CBP binding at enhancers



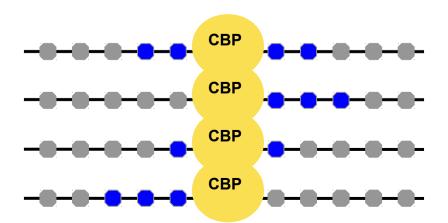
7 kb

Identifying ~28,000 CBP binding sites in two replicate experiments

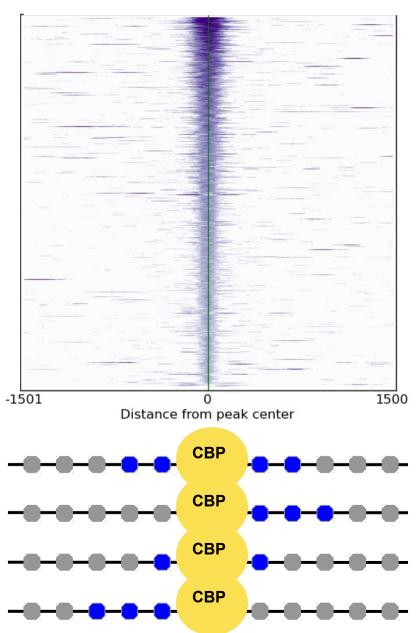
Regions that have significantly more CBP than background



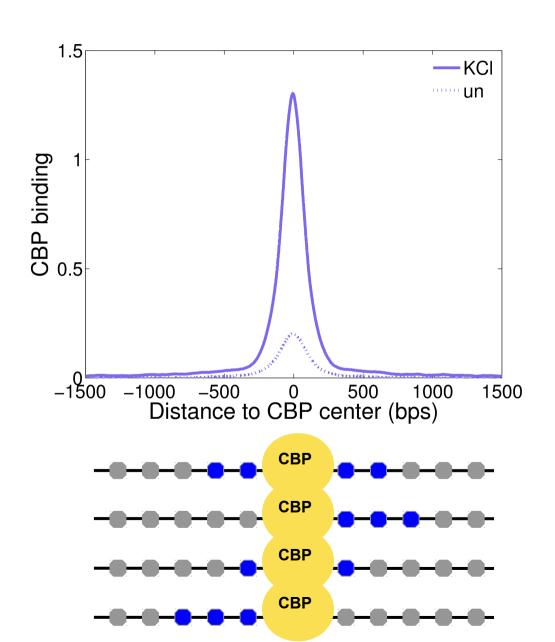
Aligning CBP peaks to calculate binding profiles



Aligning CBP peaks to calculate binding profiles



Average profile of CBP binding

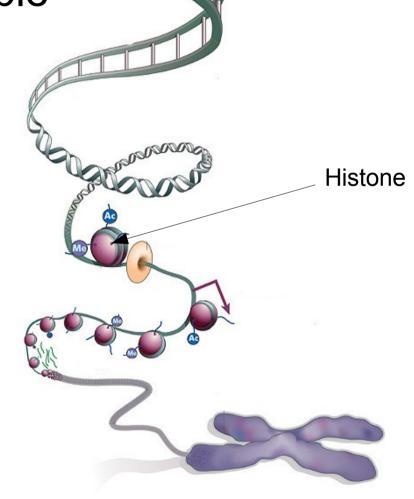


Histones prevent transcription factors from binding to DNA

~100 k loci or 1% accessible

Open chromatin

Cell-type specific



Post-translational modifications of histone tails correlate with function

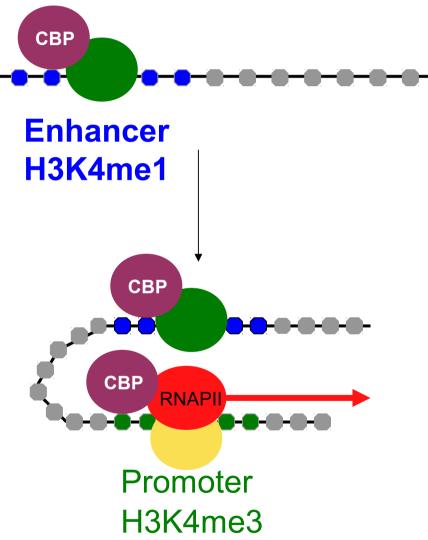
- ~100 k loci or 1% accessible
 - Open chromatin
 - Cell-type specific
- H3K4me1 open chromatin
- H3K4me3 active genes

Methyl group

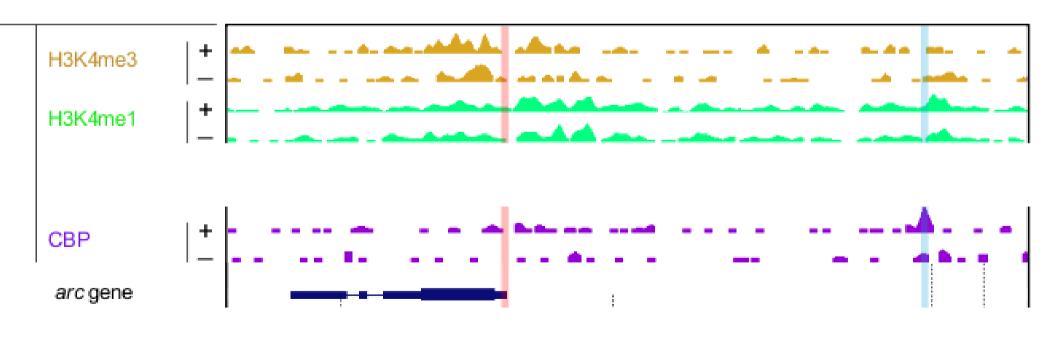
Histone

A combination of CBP and histone modifications identifies putative enhancers

- CBP binding
- H3K4me1 flanking
- H3K4me3 absent
 - Many unannotated promoters in the genome

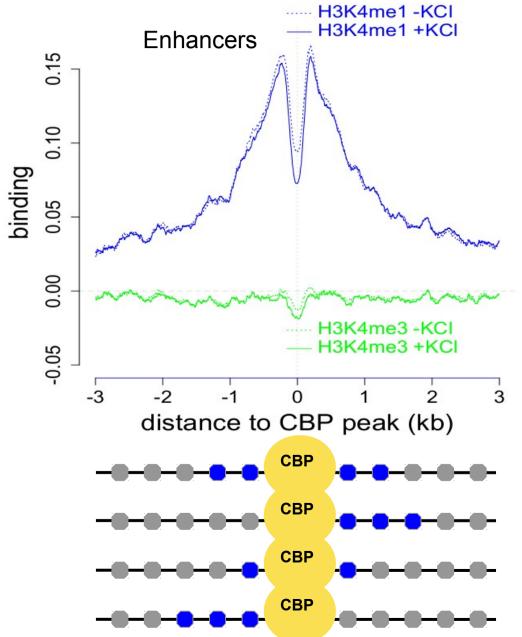


Distal CBP peaks have high levels of H3K4me1 and low levels of H3K4me3

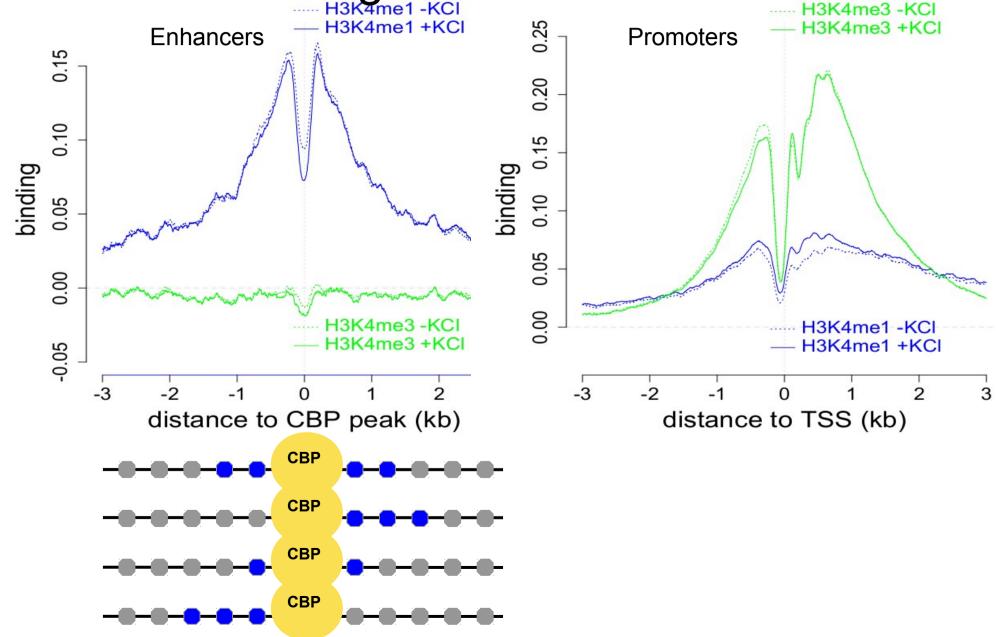


7 kb

Enhancers have high levels of H3K4me1 and low levels of H3K4me3

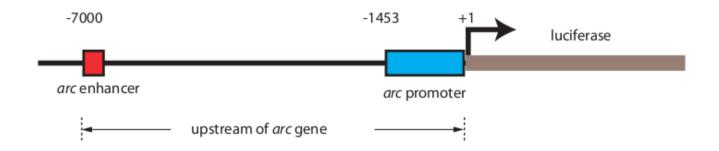


Transcription start sites have high levels of H3K4me1 and high levels of H3K4me3 -K



We identified ~12,000 activity-dependent enhancers throughout the genome

- CBP peak
- High levels of flanking H3K4me1
- Low levels of H3K4me3
 - 8/8 tested activity-dependent enhancers were validated using a luciferase assay



A quantitative model of distal enhancers



Enhancer H3K4me1

What TFs bind to enhancers?

TCGACGTAGCTAGCATGATCGATAGATC

CBP -

CREB Binding Protein

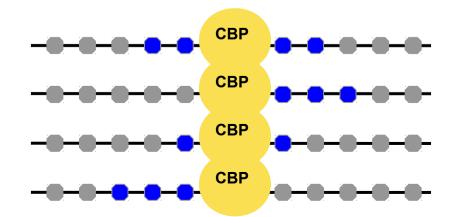
->50 partners

Enhancer H3K4me1

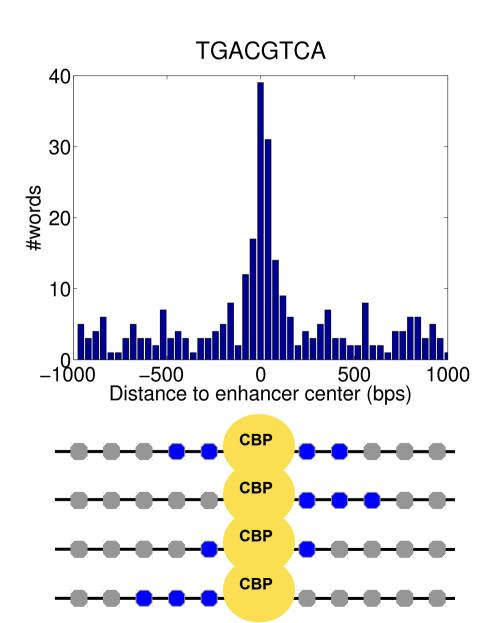
What motifs are enriched at enhancers?

Calculate enrichment relative to flanks

TCAGGCTGATGACGTCAAACCGTCGTTA ACCTTTTGACGTCAAATTTACGCTAGTAT TCGACGTAGCTAGCATGATCGATAGATC CGTGACGTCAGTGCTCGTAAATCATAAG

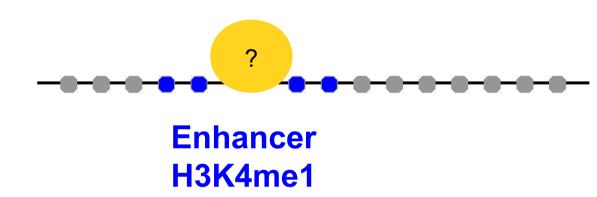


~100 enriched motifs found at enhancers

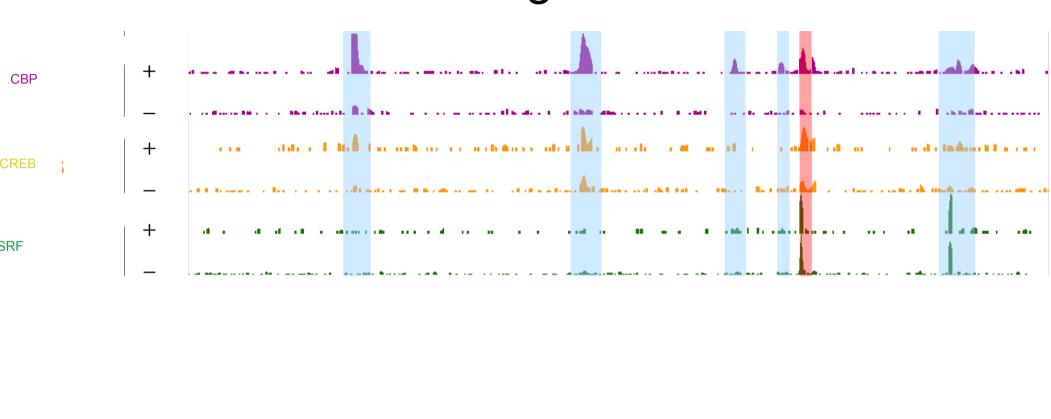


What TFs are bound at enhancers?

Enriched for ~100 sequence motifs



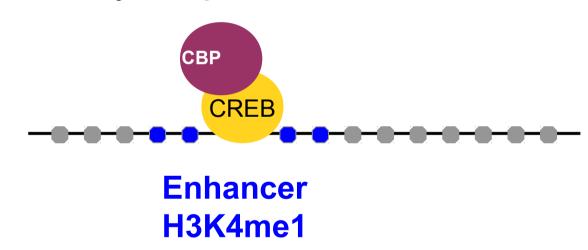
SRF and CREB binding at Fos enhancers



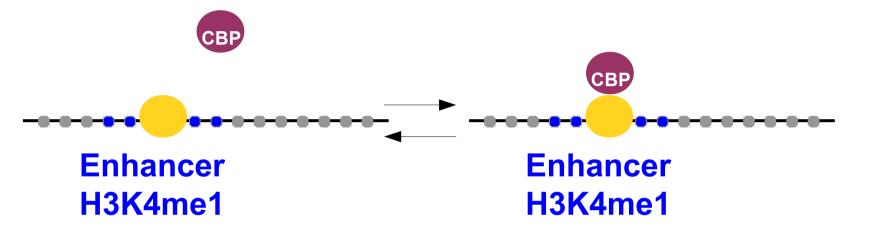


Is CBP binding determined by other TFs?

- Enriched for ~100 sequence motifs
- ChIP-seq reads predicted by sequence

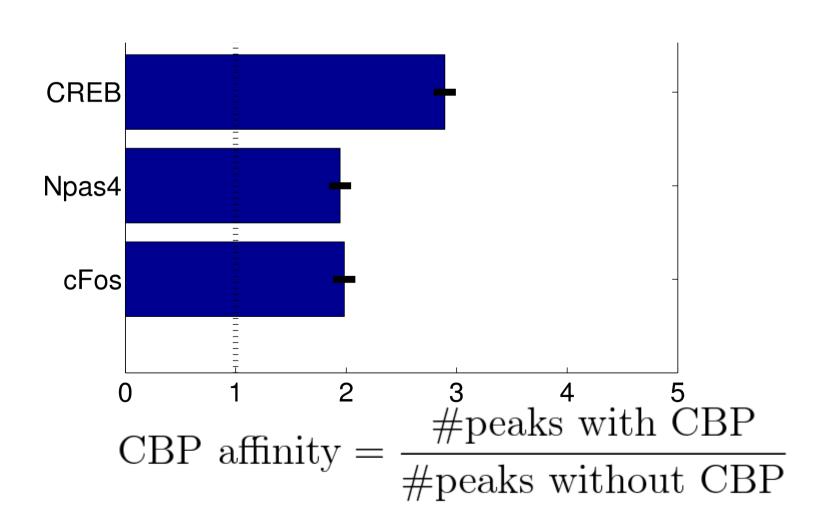


TFs compete for CBP

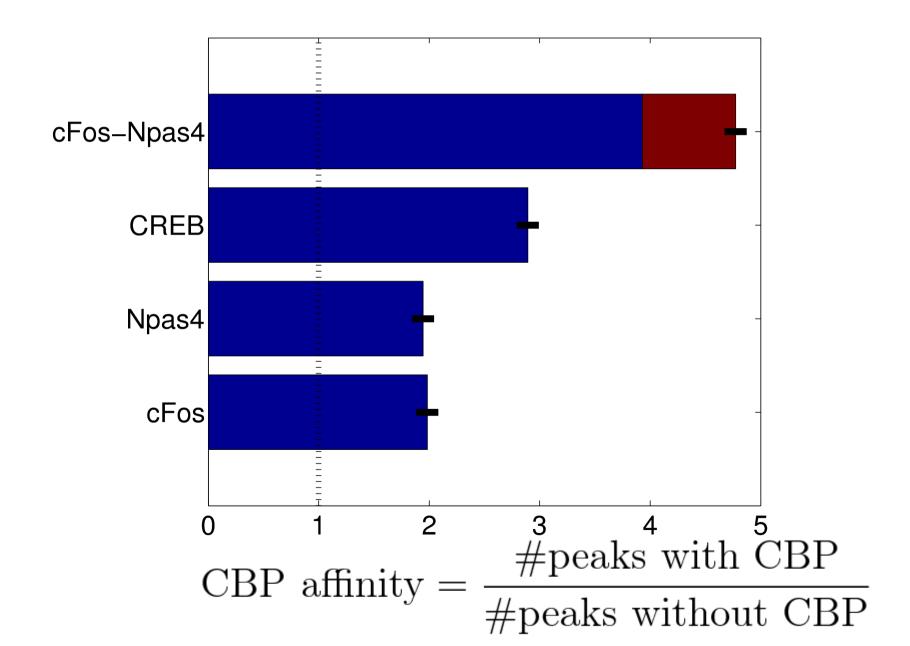


$$CBP affinity = \frac{\text{\#peaks with CBP}}{\text{\#peaks without CBP}}$$

CBP binding determined by affinity of TF

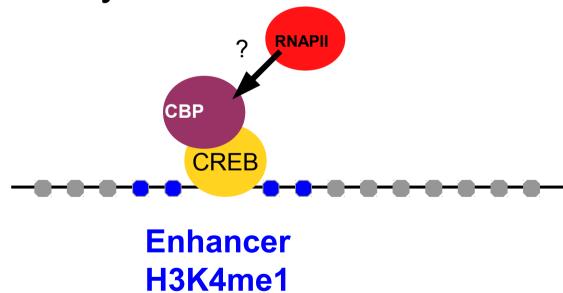


Synergistic effects for combinations of TFs

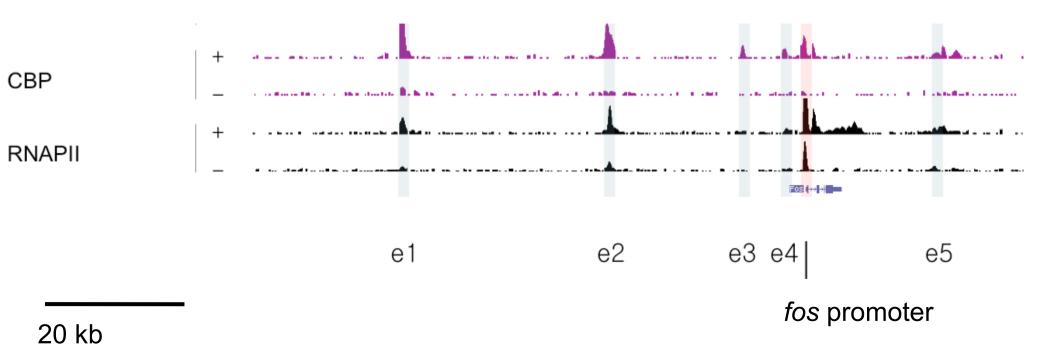


What is the function of CBP at enhancers?

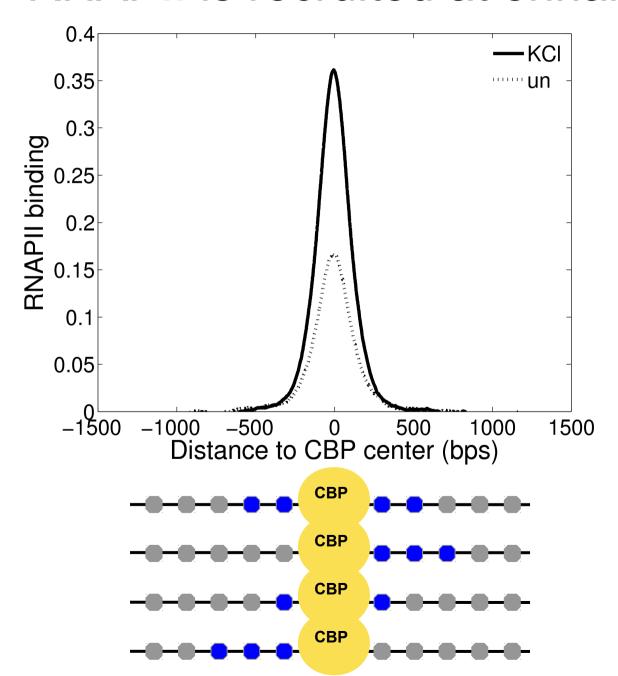
- Enriched for ~100 sequence motifs
- ChIP-seq reads predicted by sequence
- CBP binding determined by other TFs



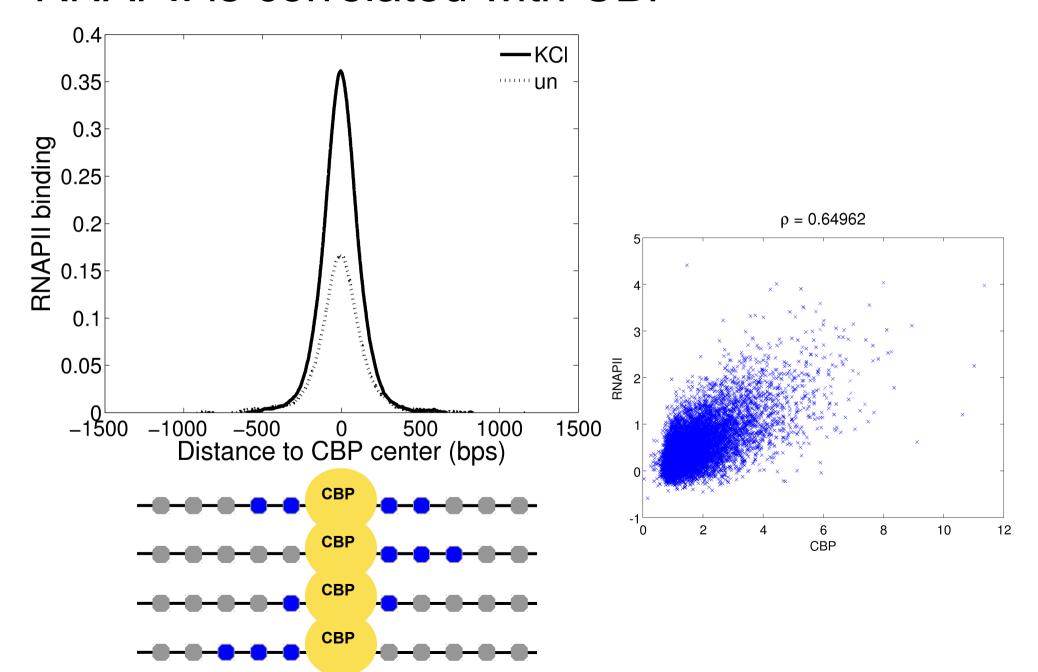
RNAPII is recruited to CBP binding sites at the *fos* locus



RNAPII is recruited at enhancers

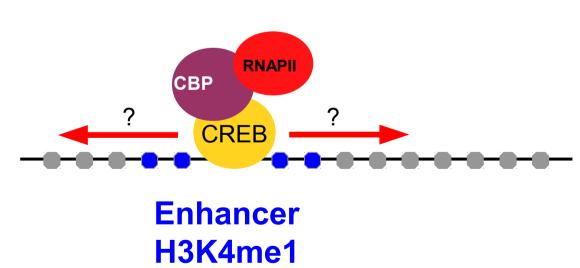


RNAPII is correlated with CBP



What is the function of RNAPII at enhancers?

- Enriched for ~100 sequence motifs
- ChIP-seq reads predicted by sequence
- CBP binding determined by other TFs
- CBP recruits RNAPII



RNA-Seq finds transcribed parts of the

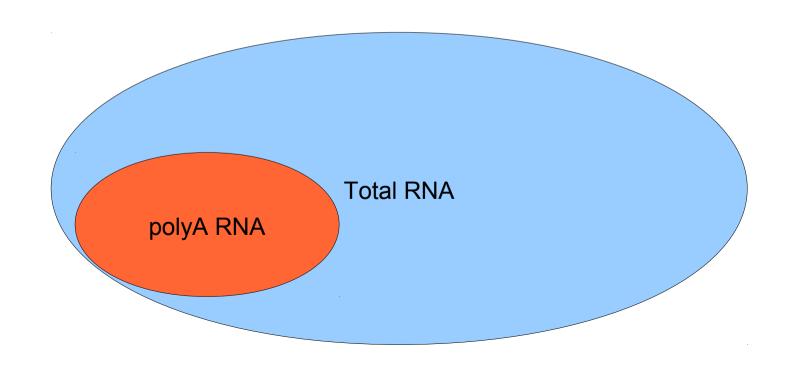
genome

 Short reads mapped to reference genome

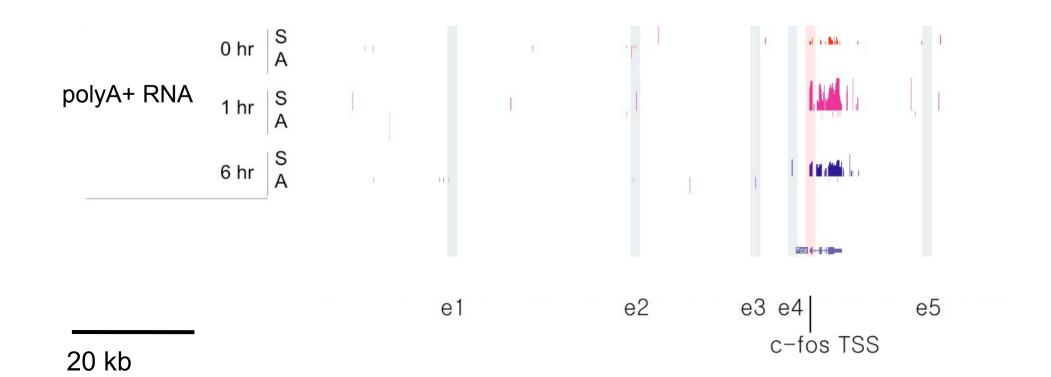
#reads ~ RNA



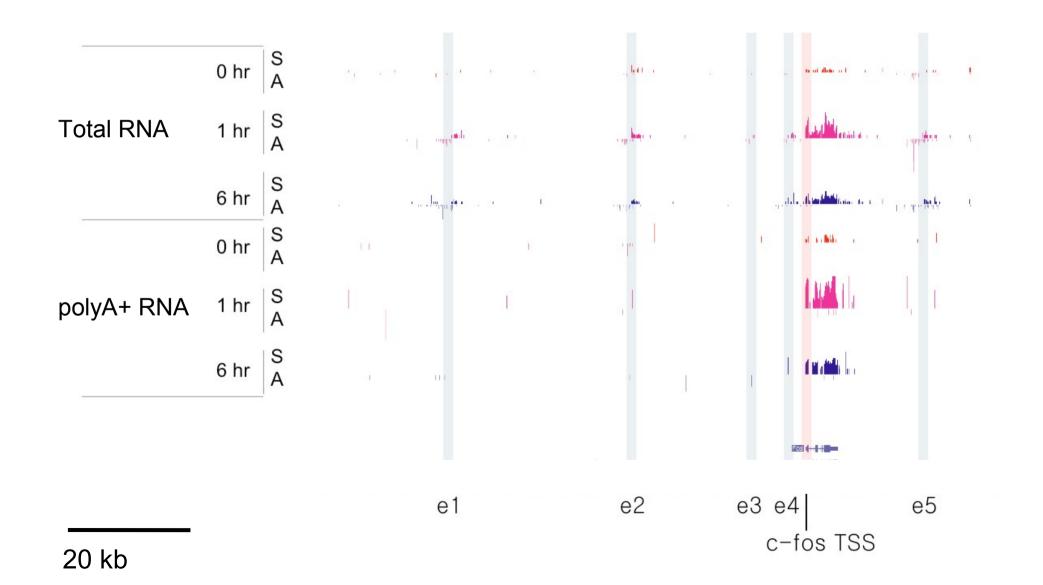
polyA tail is added to messenger RNAs (mRNAs)



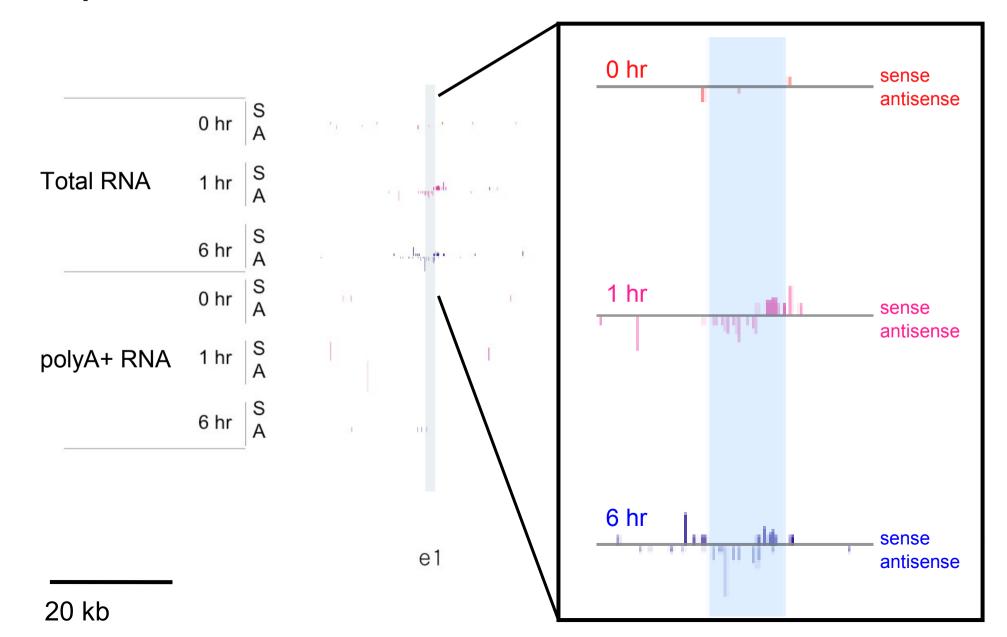
Transcription of mRNA at the fos locus



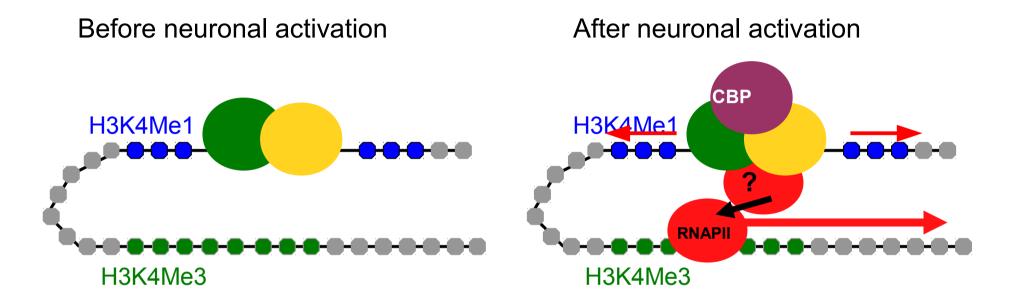
Transcription of total RNA at the fos locus



Transcription at enhancers is activity-dependent

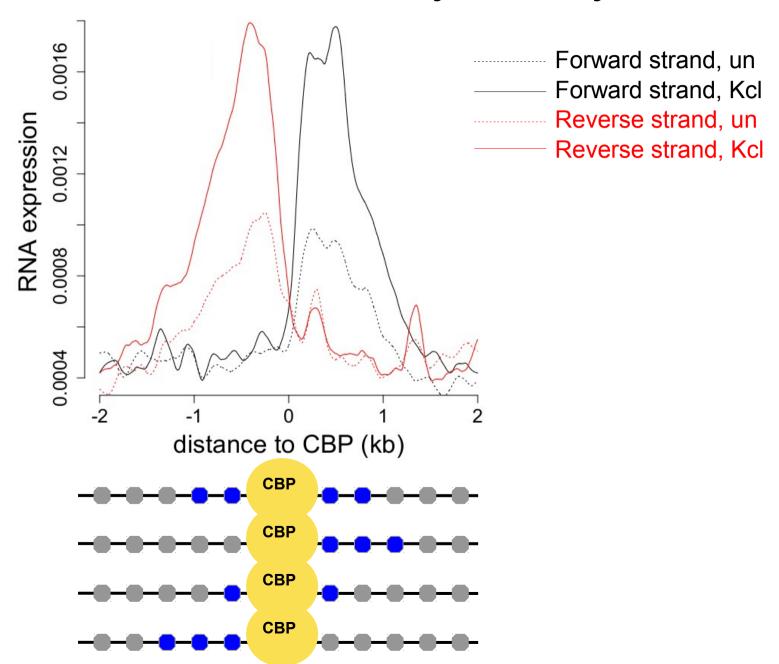


Enhancer RNAs (eRNAs) novel species

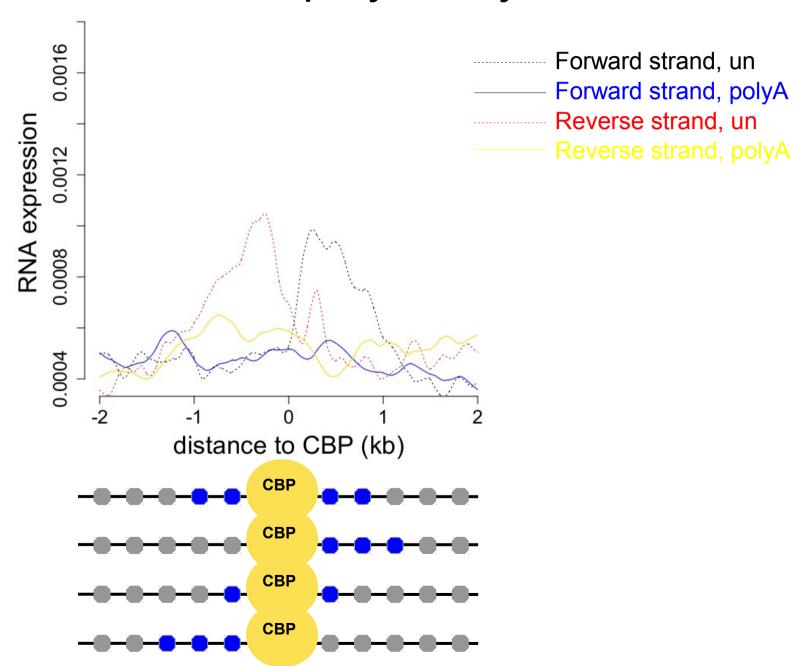


 mRNA, rRNA, tRNA, miRNA, snRNA, snoRNA, siRNA, piRNA, IncRNA, ... ?

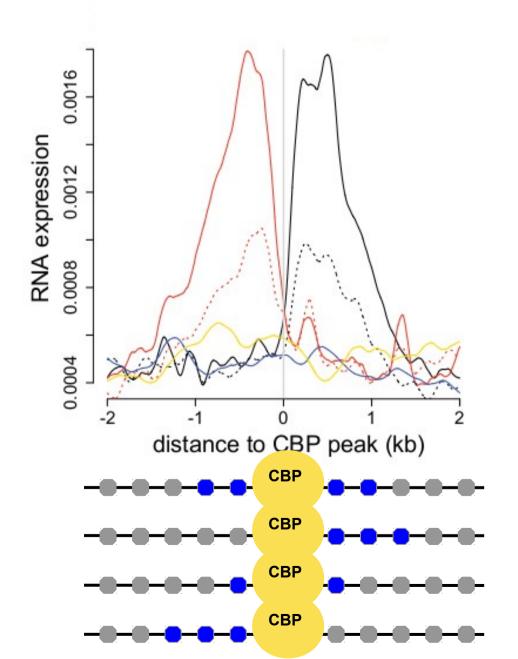
eRNAs are induced by activity



eRNAs are not polyadenylated



eRNAs are 100-fold lower than mRNAs



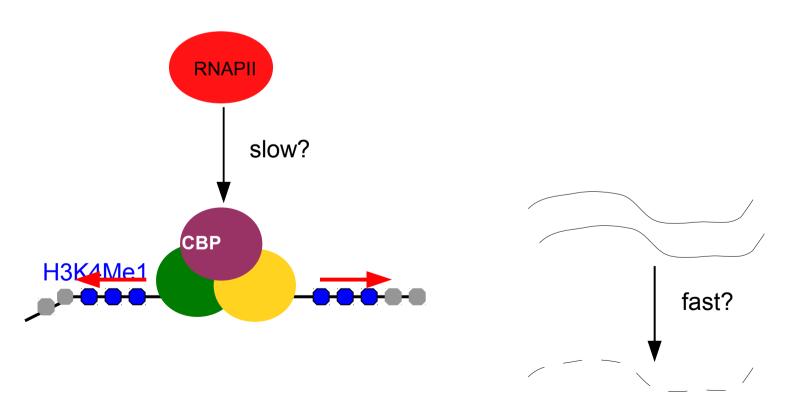
- 1 in 10k reads eRNA
- Inducible
- ~1 kb
- Bidirectional
- No polyA-tail
- Not protein-coding

Why do eRNAs have such low abundance?

- Enriched for ~100 sequence motifs
- ChIP-seq reads predicted by sequence
- CBP binding determined by other TFs
- CBP recruits RNAPII
- RNAPII synthesizes eRNAs

Why do eRNAs have such low abundance?

- eRNA production much slower than mRNA
- eRNA decay much faster than mRNA



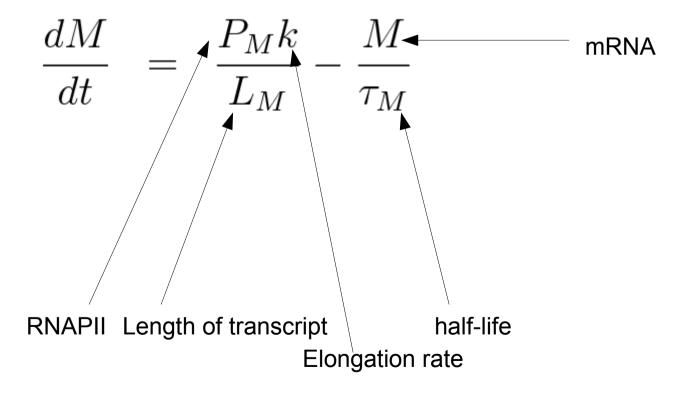
A simple model of transcription

- eRNA production much slower than mRNA
- eRNA decay much faster than mRNA

$$rac{dM}{dt} = rac{P_M k}{L_M} - rac{M}{ au_M}$$
 production decay

Parameters are straightforward to estimate

- eRNA production much slower than mRNA
- eRNA decay much faster than mRNA



Similar expression for eRNA levels

- eRNA production much slower than mRNA
- eRNA decay much faster than mRNA

$$\frac{dM}{dt} = \frac{P_M k}{L_M} - \frac{M}{\tau_M}
\frac{dE}{dt} = \frac{P_E k}{L_E} - \frac{E}{\tau_E}$$

Half life of eRNAs relative to mRNAs

- eRNA production much slower than mRNA
- eRNA decay much faster than mRNA

$$\frac{dM}{dt} = \frac{P_M k}{L_M} - \frac{M}{\tau_M}$$

$$\frac{dE}{dt} = \frac{P_E k}{L_E} - \frac{E}{\tau_E}$$

$$\frac{\tau_E}{\tau_M} = \frac{E^*}{M^*} \frac{L_E}{L_M} \frac{P_M}{P_E}$$

eRNAs half life is less than half an hour

- eRNA production much slower than mRNA
- eRNA decay much faster than mRNA

$$\frac{dM}{dt} = \frac{P_M k}{L_M} - \frac{M}{\tau_M}
\frac{dE}{dt} = \frac{P_E k}{L_E} - \frac{E}{\tau_E}$$

$$\frac{\tau_E}{\tau_M} = \frac{E^*}{M^*} \frac{L_E}{L_M} \frac{P_M}{P_E}$$

$$\tau_E \sim 10^{-2} \times 1 \times 2 \times \tau_M \sim 2 \times 10^{-2} \times 600 \text{min} = 12 \text{min}$$

Estimate consistent with experiments

- eRNA production much slower than mRNA
- eRNA decay much faster than mRNA

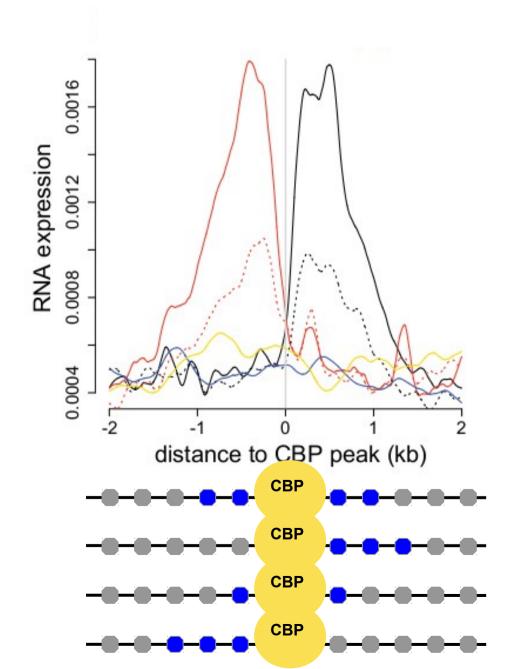
$$\frac{dM}{dt} = \frac{P_M k}{L_M} - \frac{M}{\tau_M}
\frac{dE}{dt} = \frac{P_E k}{L_E} - \frac{E}{\tau_E}$$

$$\frac{\tau_E}{\tau_M} = \frac{E^*}{M^*} \frac{L_E}{L_M} \frac{P_M}{P_E}$$

Finally we measured the stability of these transcripts using an actinomycinD chase. In comparison to both the mRNAs generated by the associated protein-coding genes and some known lncRNAs (like Xist and Neat), the upstream non-coding transcripts were very unstable, being reduced by 80% to 90% after a 30 min actinomycinD treatment (indicating a half-life lower than 7.5 min) (Figure 3D and Figure S3). High instability of a subset of lncRNAs both in yeast and mammals mainly depends on degradation by the nuclear exosome [39,40] and often results in the generation of more stable short RNA products [41], which in principle might be responsible for downstream functional effects.

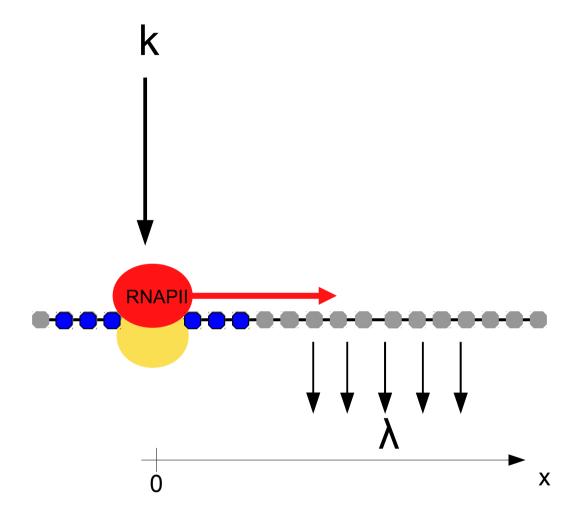
$$\tau_E \sim 10^{-2} \times 1 \times 2 \times \tau_M \sim 2 \times 10^{-2} \times 600 \text{min} = 12 \text{min}$$

A mechanistic model of eRNA levels



RNAPII binds and falls of at a constant rate

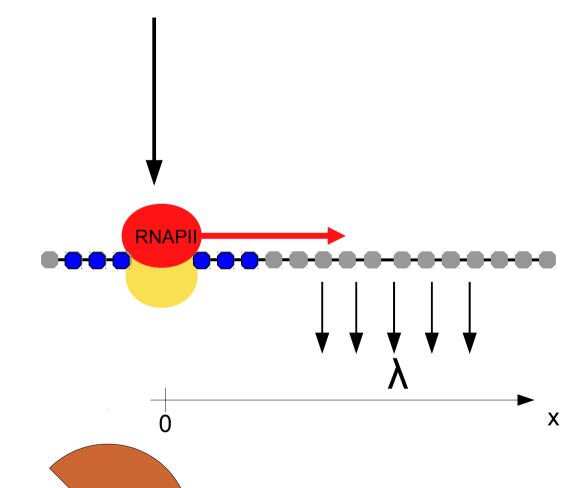
$$\frac{dP}{dx} = k - \lambda P$$



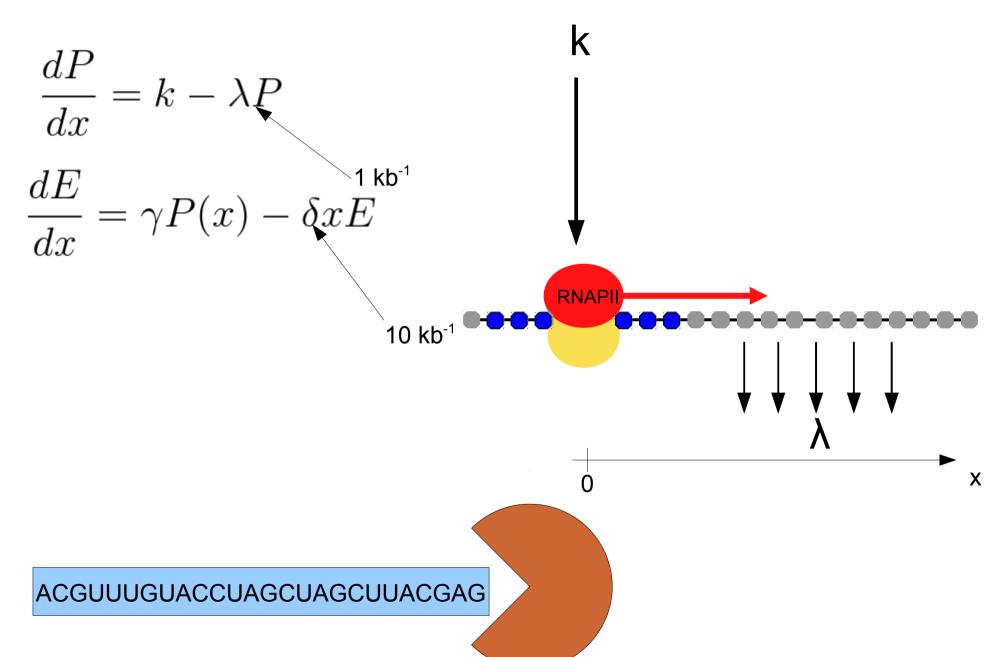
eRNA production proportional to RNAPII

$$\frac{dP}{dx} = k - \lambda P$$

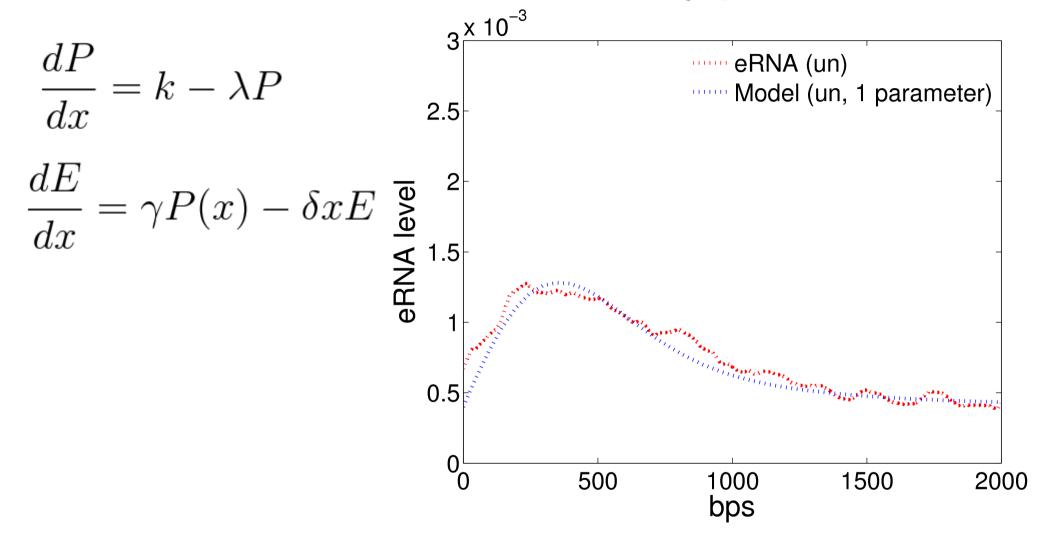
$$\frac{dE}{dx} = \gamma P(x) - \delta x E$$



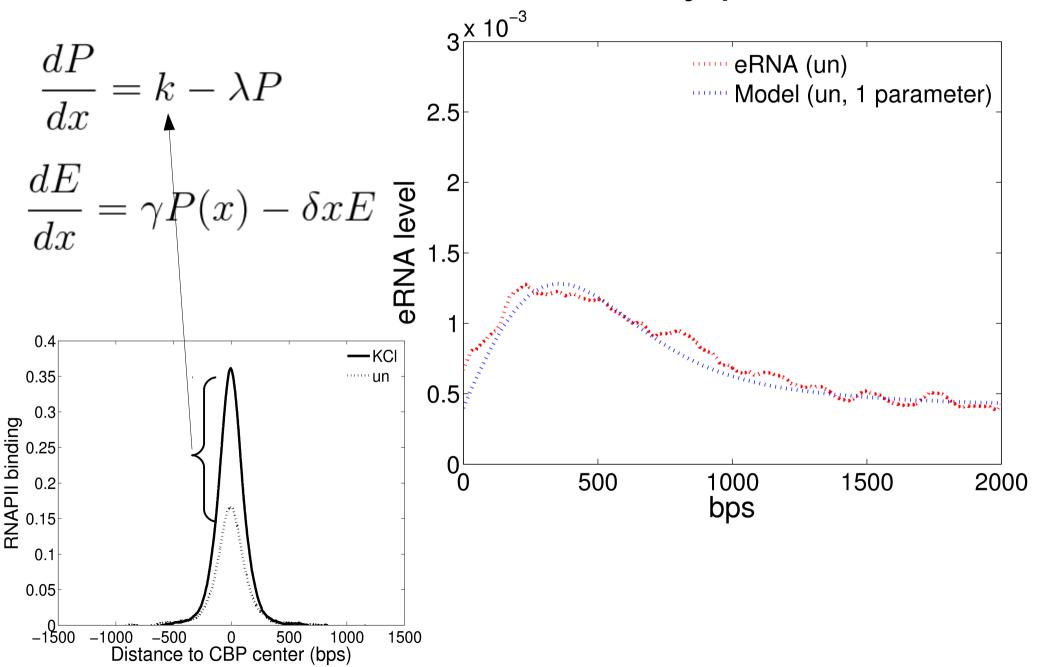
Parameters can be estimated from literature



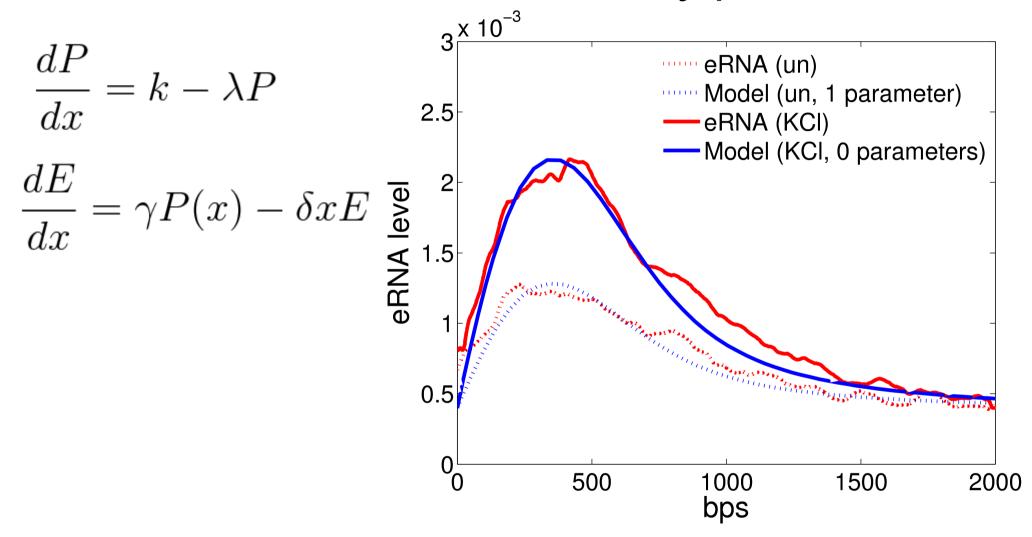
eRNA levels can be accurately predicted



eRNA levels can be accurately predicted



eRNA levels can be accurately predicted



A PDE for eRNA levels

$$\frac{\partial P}{\partial x} + \frac{\partial P}{\partial t} = k(x, t) - \lambda_x P - \lambda_t P$$

$$\frac{\partial E}{\partial x} + \frac{\partial E}{\partial t} = \gamma P(x,t) - \delta_x x E - \delta_t t$$

$$0.02$$

$$0.015$$

$$0.005$$

$$0.005$$

$$0.0005$$

$$0.000$$

$$0.0005$$

$$0.000$$

$$0.0000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

$$0.000$$

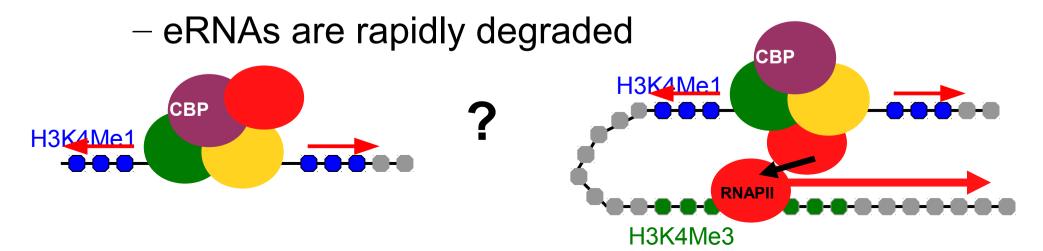
CBP distance (bps)

2500

time (min)

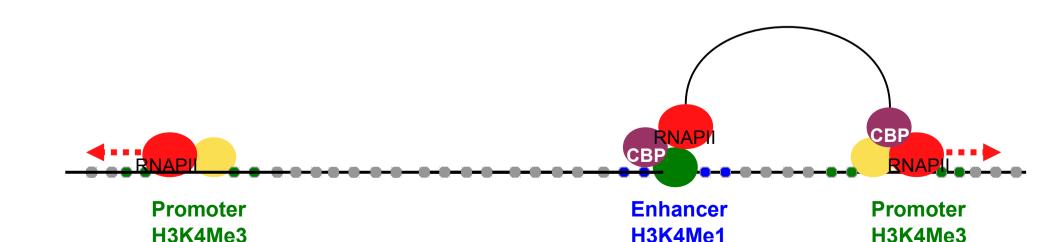
Enhancers bind RNAPII and produce eRNA, but do they require the promoter?

- Enriched for ~100 sequence motifs
- ChIP-seq reads predicted by sequence
- CBP binding determined by other TFs
- CBP recruits RNAPII
- RNAPII synthesizes eRNAs



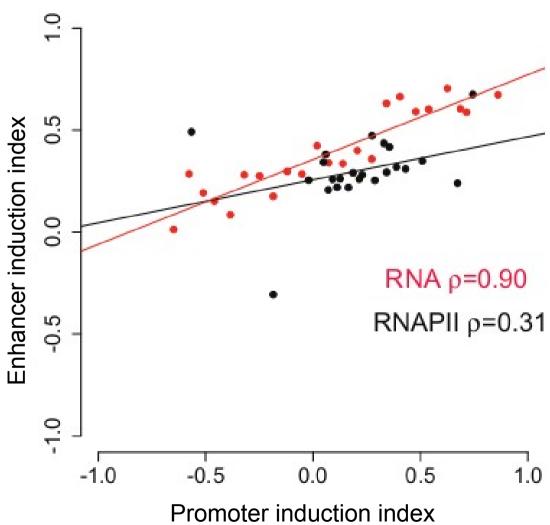
Pair each enhancer with nearest promoter and compare RNAPII and RNA

$$induction\ index = \frac{KCl - un}{KCl + un}$$

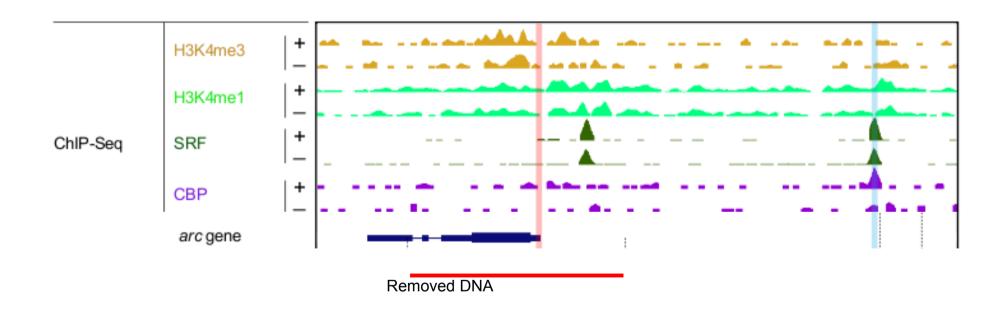


eRNA induction is correlated with induction of nearby mRNAs but not RNAPII

$$induction\ index = \frac{KCl - un}{KCl + un}$$



Deletion of the Arc-promoter confirms that RNAPII recruitment is independent but eRNA transcription is not.

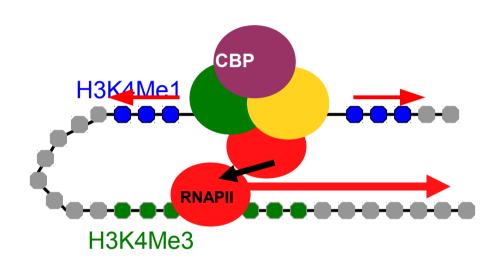


Properties of activity-dependent enhancers

- Enriched for ~100 sequence motifs
- ChIP-seq reads predicted by sequence
- CBP binding determined by other TFs
- CBP recruits RNAPII
- RNAPII synthesizes eRNAs
 - eRNAs are rapidly degraded
 - eRNA induction correlated with mRNA induction
 - RNAPII recruitment independent of promoter

What is the function of RNAPII at enhancers?

- Transcribe eRNAs
- Speed up recruitment of RNAPII at promoter



A simple model of RNAPII recruitment

- Transcribe eRNAs
- Speed up recruitment of RNAPII at promoter

$$\frac{dP_M}{dt} = k_p + Nk_ec - \frac{P_M}{\tau}$$
 Binding rate decay

P – polymerase levels

 k_{p} – binding rate at promoter

 k_e – binding rate at enhancer

N – number of enhancers

c – contact probability

tau - RNAPII half life

Steady state level of RNAPII is increased

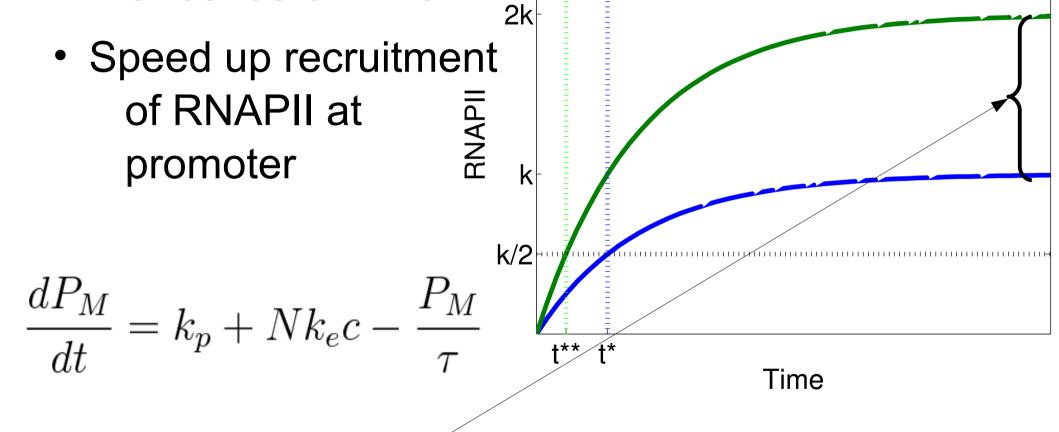
- Transcribe eRNAs
- Speed up recruitment of RNAPII at promoter

$$\frac{dP_M}{dt} = k_p + Nk_ec - \frac{P_M}{\tau}$$

$$P_M(t) = \underbrace{(k_p + Nk_e c)}_{\text{Steady state level}} (1 - e^{-t/\tau})$$

Steady state level of RNAPII is increased

Transcribe eRNAs

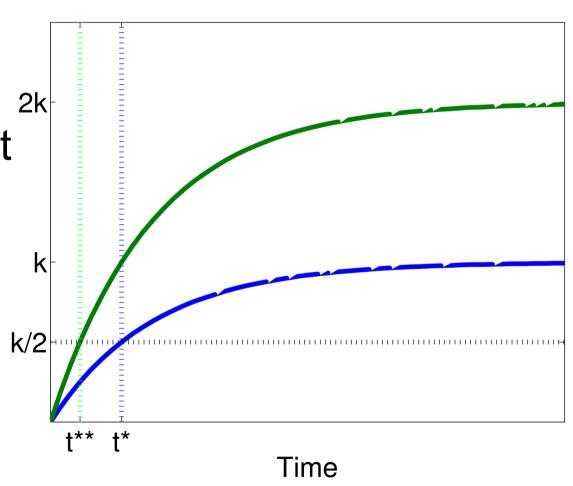


$$P_M(t) = (k_p + Nk_e c)(1 - e^{-t/\tau})$$

Rise time is reduced

- Transcribe eRNAs
- Speed up recruitment of RNAPII at promoter

$$\frac{dP_M}{dt} = k_p + Nk_ec - \frac{P_M}{\tau}$$



$$P_M(t) = (k_p + Nk_e c)(1 - e^{-t/\tau})$$

Significant speed-up with ~5 enhancers

Transcribe eRNAs

• Speed up recruitment of RNAPII at promoter
$$\frac{dP_M}{dt} = k_p + Nk_ec - \frac{P_M}{\tau} = \sum_{\substack{0.2 \ \text{mediate} \\ 0.2 \ \text{mediate}}} \sum_{\substack{0.2 \ \text{mediate} \\ 0.2 \ \text{mediate}}} \sum_{\substack{0.2 \ \text{mediate} \\ \text{mediate}}} \sum_{\substack{0.2 \ \text{mediate}}}}$$

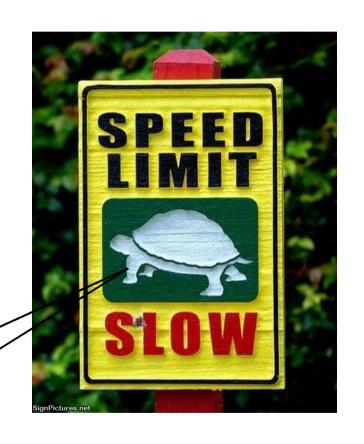
$$P_M(t) = (k_p + Nk_e c)(1 - e^{-t/\tau})$$

Recruitment of RNAPII is diffusion limited

- Transcribe eRNAs
- Speed up recruitment of RNAPII at promoter

$$\frac{dP_M}{dt} = k_p + Nk_ec - \frac{P_M}{\tau}$$

$$P_M(t) = (k_p + Nk_e c)(1 - e^{-t/\tau})$$



Enhancers may reduce the noise in RNAPII

- Transcribe eRNAs
- Speed up recruitment of RNAPII at promoter

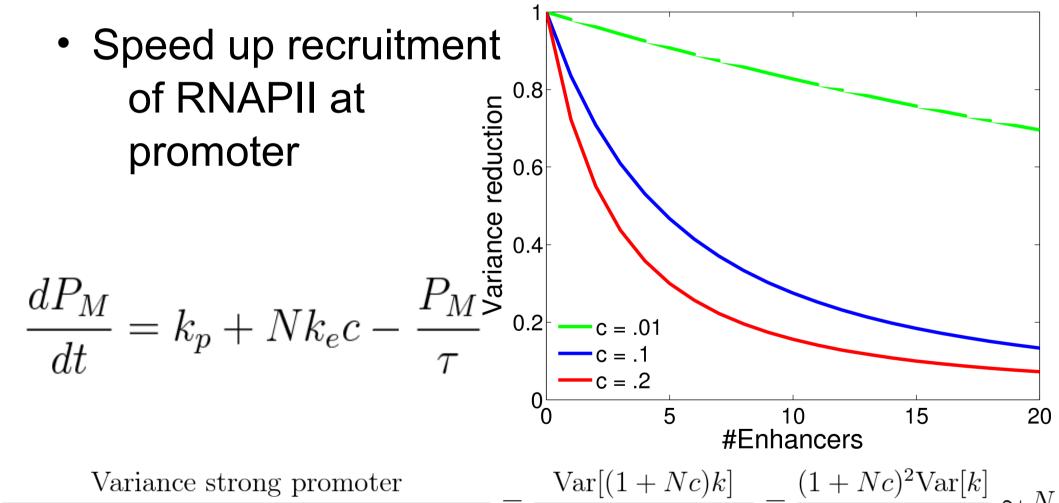
$$\frac{dP_M}{dt} = k_p + N_k k_e c - \frac{P_M}{\tau}$$
 $\Gamma(\alpha, \beta)$

RNAPII noise reduction proportional to number of enhancers

Transcribe eRNAs

Speed up recruitment

$$\frac{dP_M}{dt} = k_p + Nk_e c - \frac{P_M}{\tau}$$



$$= \frac{\operatorname{Var}[(1+Nc)k]}{\operatorname{Var}[k] + N\operatorname{Var}[ck]} = \frac{(1+Nc)^{2}\operatorname{Var}[k]}{(1+Nc^{2})\operatorname{Var}[k]} \sim N$$

What is the function of eRNAs?

- What is the function of RNAPII at enhancers?
 - Increase rate of RNAPII recruitment
 - Possibly faster than diffusion limit
 - Faster rise-time
 - Reduced noise
- What is the function of eRNAs?
 - Noise
 - Transcription establishes histone modifications
 - Transcript has function

Establishing H3K4me1 levels at enhancers

$$\frac{dP}{dx} = k - \lambda P$$

$$\frac{dH}{dx} = \kappa P(x) - \mu H$$

Establishing H3K4me1 levels at enhancers

$$\frac{dP}{dx} = k - \lambda P$$

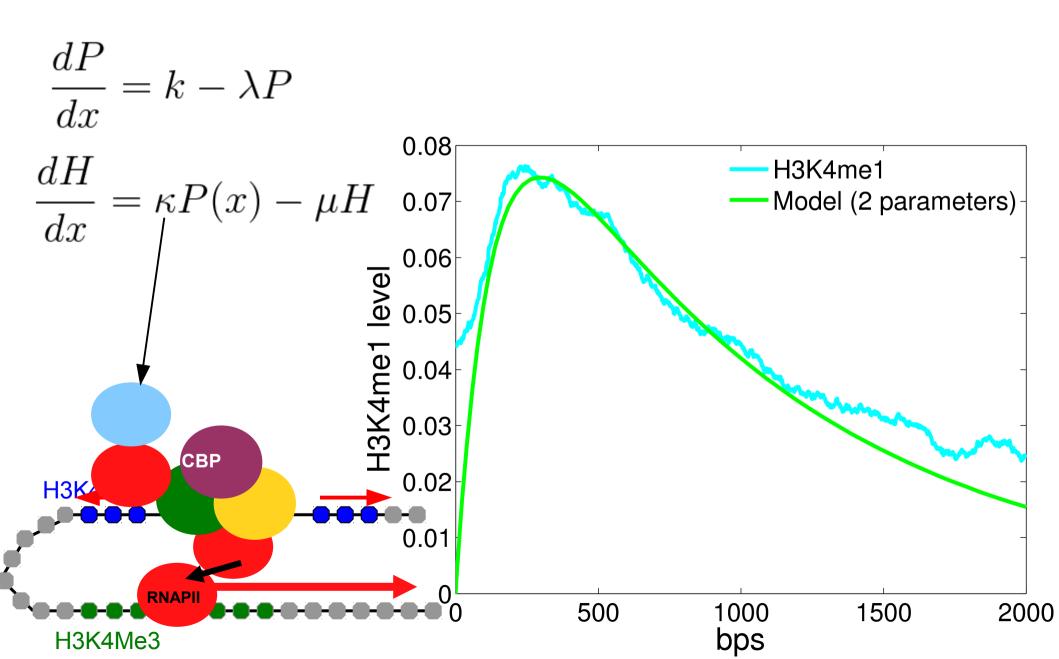
$$\frac{dH}{dx} = \kappa P(x) - \mu H = 0.07$$

$$\frac{\partial}{\partial \theta} = 0.06$$

$$\frac{\partial}{\partial \theta} = 0.04$$

$$\frac{\partial}{\partial \theta} =$$

Establishing H3K4me1 levels at enhancers



eRNAs have been found in other cell types

loi:10.1038/nature09033

nature

ARTICLES

Widespread transcription at neuronal activity-regulated enhancers

Tae-Kyung Kim¹*†, Martin Hemberg²*, Jesse M. Gray¹*, Allen M. Costa¹, Daniel M. Bear¹, Jing Wu³, David A. Harmin^{1,4}, Mike Laptewicz¹, Kellie Barbara-Haley⁵, Scott Kuersten⁶, Eirene Markenscoff-Papadimitriou¹†, Dietmar Kuhl⁷, Haruhiko Bito⁸, Paul F. Worley³, Gabriel Kreiman² & Michael E. Greenberg¹

Histone H3K27ac separates active from poised enhancers and predicts developmental state

Menno P. Creyghton^{a,1}, Albert W. Cheng^{a,b,1}, G. Grant Welstead^a, Tristan Kooistra^{c,d}, Bryce W. Carey^{a,e}, Eveline J. Steine^{a,e}, Jacob Hanna^a, Michael A. Lodato^{a,e}, Garrett M. Frampton^{a,e}, Phillip A. Sharp^{d,e}, Laurie A. Boyer^e, Richard A. Young^{a,e}, and Rudolf Jaenisch^{a,e,2}

OPEN & ACCESS Freely available online

PLOS BIOLOGY

A Large Fraction of Extragenic RNA Pol II Transcription Sites Overlap Enhancers

Francesca De Santa^{1,9}, Iros Barozzi^{1,9}, Flore Mietton^{1,9}, Serena Ghisletti¹, Sara Polletti¹, Betsabeh Khoramian Tusi¹, Heiko Muller¹, Jiannis Ragoussis², Chia-Lin Wei³, Gioacchino Natoli^{1,8}



doi:10.1038/nature09692

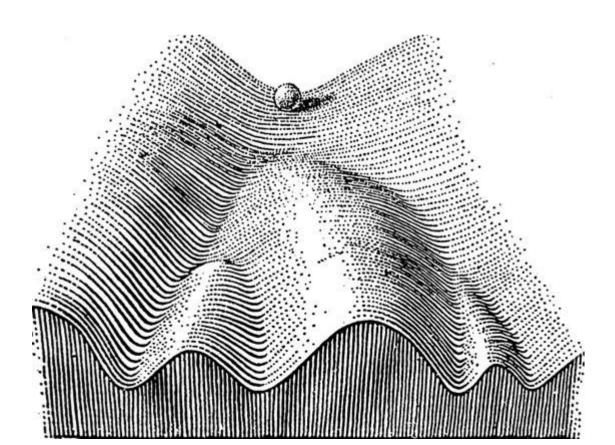
A unique chromatin signature uncovers early developmental enhancers in humans

Summary

- Identified ~12k activity-dependent enhancers
- Discovered and quantified novel mechanisms
 - Identified enriched motifs and bound TFs
 - Combinatorial code for CBP affinity
 - Recruitment of RNAPII at enhancers
 - Transcription at enhancers
 - Properties of eRNA
 - Model of RNAPII and eRNA levels
 - Interaction with promoter necessary
 - Function of RNAPII and eRNA

Stochastic models of gene expression

- Transitions between stable states
- Noise



Master Equation (ME) description

$$\frac{dP_{j}}{dt} = \sum_{i} W_{ij} P_{i}(t) - W_{ji} P_{j}(t)$$

 P_j - **Probability** of having j molecules W_{ij} - **Transition rate** from i to j

MCMC required for solving ME

$$\frac{dP_{j}}{dt} = \sum_{i} W_{ij} P_{i}(t) - W_{ji} P_{j}(t)$$

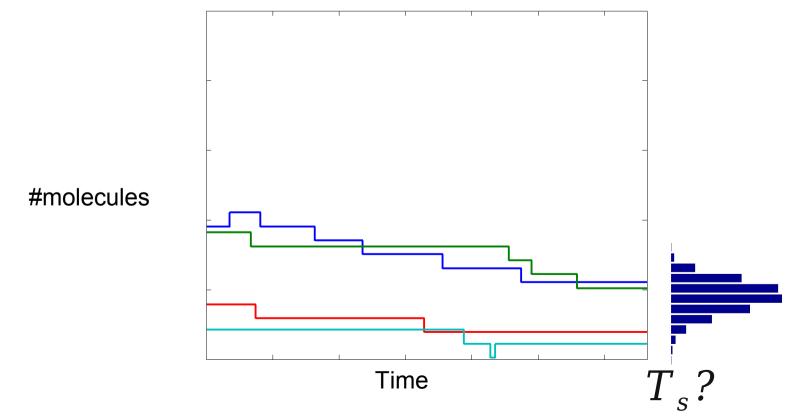
- P_j **Probability** of having j molecules
- W_{ij} Transition rate from i to j
- Use Markov Chain Monte Carlo (MCMC)
 - Gillespie's Stochastic Simulation Algorithm (SSA)

How long do we need to run MCMC?

$$\frac{dP_{j}}{dt} = \sum_{i} W_{ij} P_{i}(t) - W_{ji} P_{j}(t)$$

 P_i - **Probability** of having j molecules

 W_{ii} - Transition rate from i to j



Perfect sampling guarantees stationarity

$$\frac{dP_{j}}{dt} = \sum_{i} W_{ij} P_{i}(t) - W_{ji} P_{j}(t)$$

- P_{j} **Probability** of having j molecules
- W_{ii} Transition rate from i to j
- Dominated Coupling From The Past SSA proven to reach stationary distribution

BMC Systems Biology



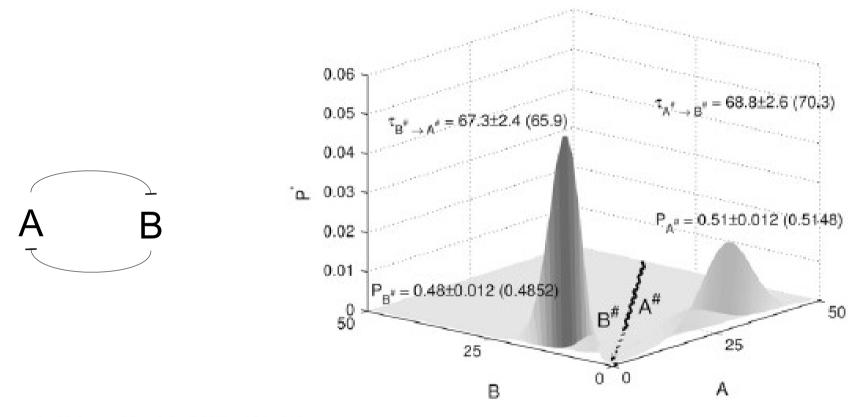
Methodology article

Open Access

A Dominated Coupling From The Past algorithm for the stochastic simulation of networks of biochemical reactions

Martin Hemberg¹ and Mauricio Barahona* 1,2

Perfect sampling of transitions between steady states



Biophysical Journal Volume 93 July 2007 401-410

Perfect Sampling of the Master Equation for Gene Regulatory Networks

401

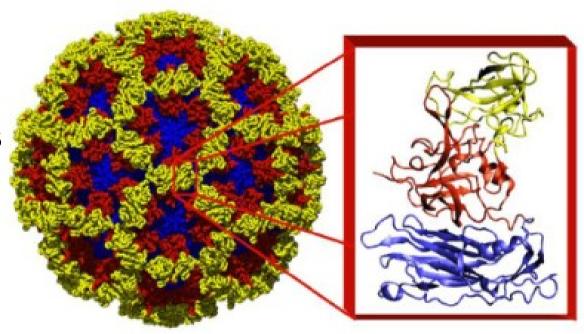
Martin Hemberg and Mauricio Barahona

Department of Bioengineering and Institute for Mathematical Sciences, Imperial College London, London, United Kingdom

Assembly of viral capsids

- Protect viral genome
 - Self-assembly
 - Identical subunits
 - Icosahedral symmetry

Biophysical Journal Volume 90 May 2006 3029-304:

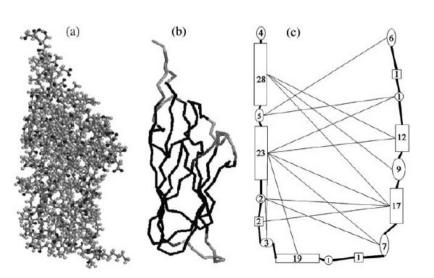


Stochastic Kinetics of Viral Capsid Assembly Based on Detailed Protein Structures

Martin Hemberg,* Sophia N. Yaliraki,[†] and Mauricio Barahona*
*Department of Bioengineering and [†]Department of Chemistry, Imperial College London, London, United Kingdom

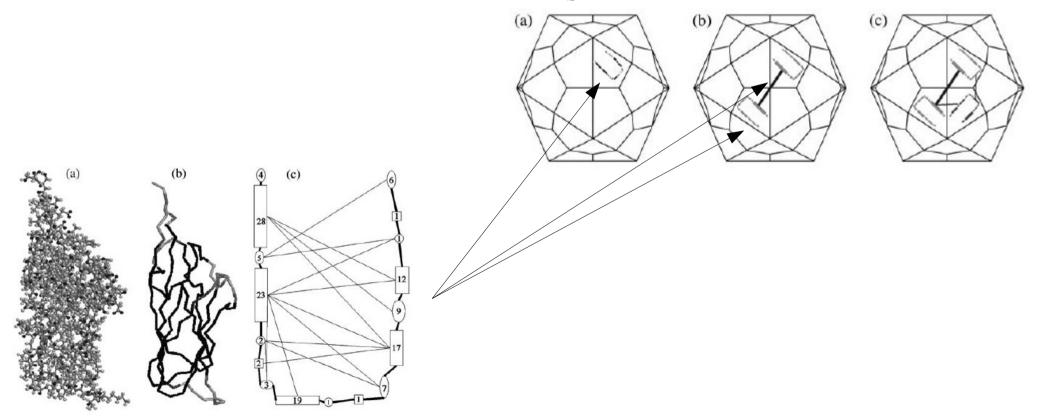
Coarse-grained protein model

- Atomic-structure
- FIRST calculates rigidity of amino acids
- Identify ~20 rigid blocks



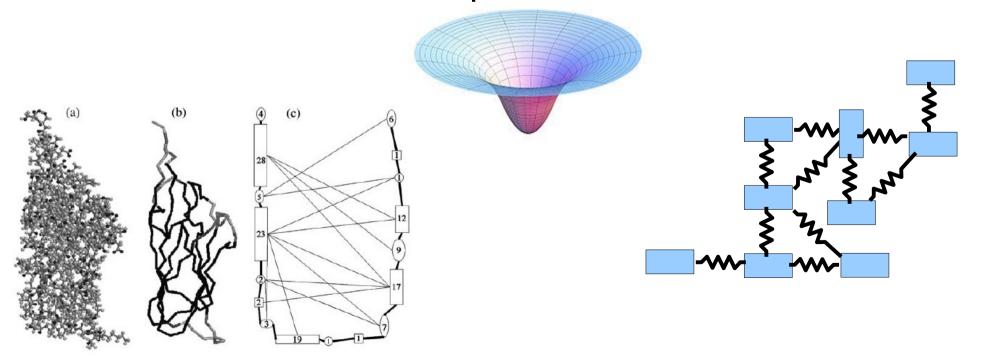
Use reduced representation for aggregates

- Atomic-structure, identify rigid blocks
- Oligomer association and dissociation rates
 - Association restricted by diffusion



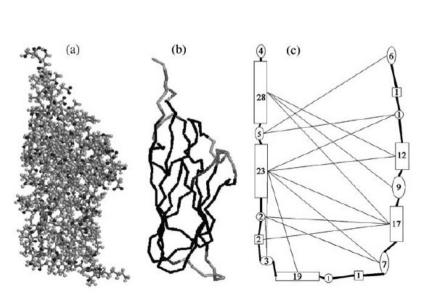
Aggregates modeled as mass-spring graph

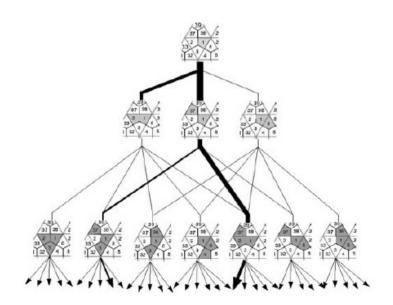
- Atomic-structure, identify rigid blocks
- Oligomer association and dissociation rates
 - Association restricted by diffusion
 - Dissociation escape from multi-dimensional well



All reactions cannot be enumerated

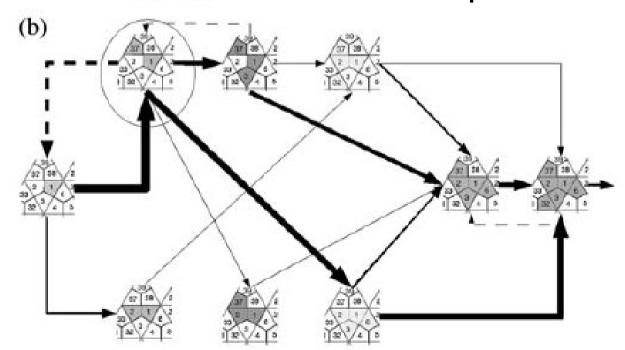
- Atomic-structure, identify rigid blocks
- Oligomer association and dissociation rates
 - Association restricted by diffusion
 - Dissociation escape from multi-dimensional well





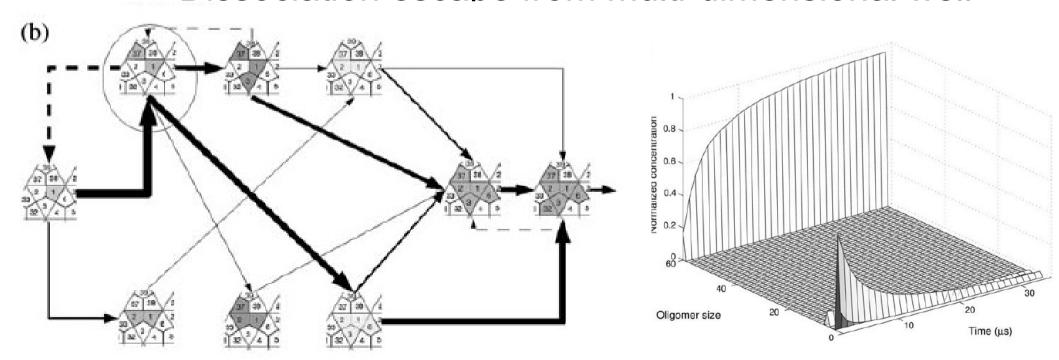
Probabilistic sampling of assembly paths

- Atomic-structure, identify rigid blocks
- Oligomer association and dissociation rates
 - Association restricted by diffusion
 - Dissociation escape from multi-dimensional well



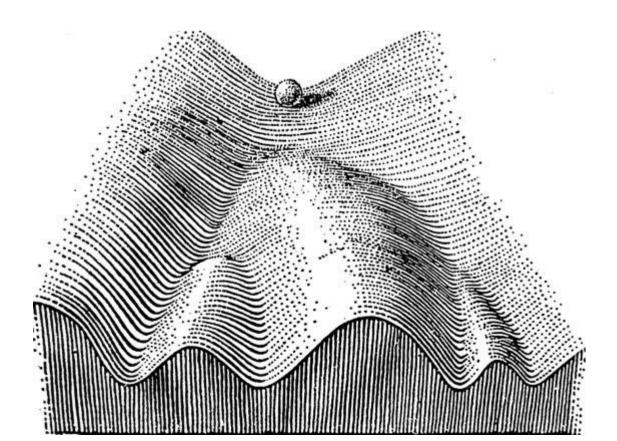
Identify stable intermediaries

- Atomic-structure, identify rigid blocks
- Oligomer association and dissociation rates
 - Association restricted by diffusion
 - Dissociation escape from multi-dimensional well



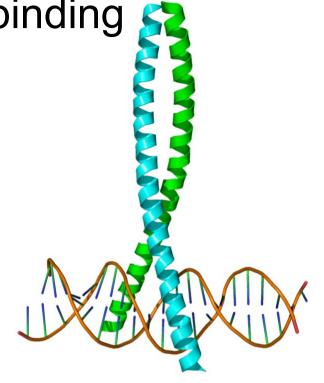
Future Work: Organizing principles of the genome

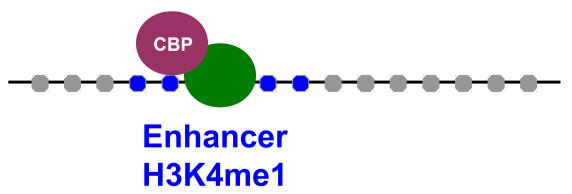
 Use genome-wide data to develop systems biology and biophysical models of gene regulation and gene expression



Develop biophysical models of TF binding

- Use ChIP-Seq for biophysical models of TF binding
- Relate looping to biophysical properties of DNA



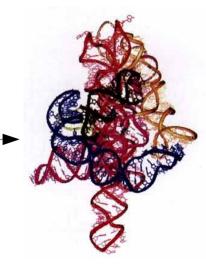


Model stochastic gene expression for entire transcriptome

- Analytical models of gene expression noise
 - Parametric robustness
- Apply to genome-wide single-cell RNA-Seq

Determine structure of RNAs

- Other species of novel non-coding RNAs
 - Identify structural motifs
- High-throughput sequencing of structure
 - PARS
 - SHAPE-Seq



Acknowledgements

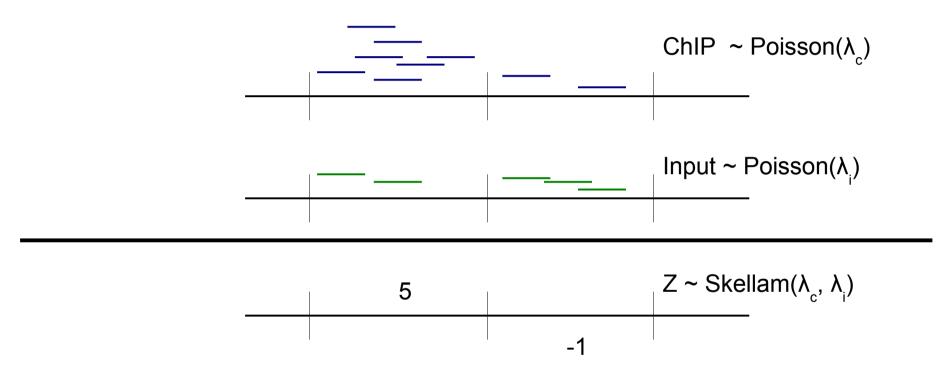
- Gabriel Kreiman
- Jesse Gray
- Tae-Kyung Kim
- Michael Greenberg
- Mauricio Barahona

Thank You

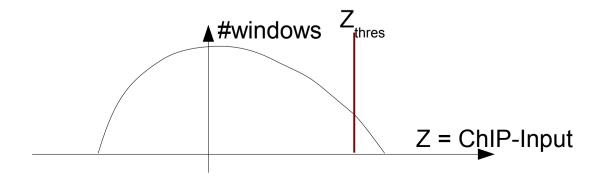




Identifying regions with larger than expected number of ChIP-Seq reads



False Detection Rate (FDR) determine threshold



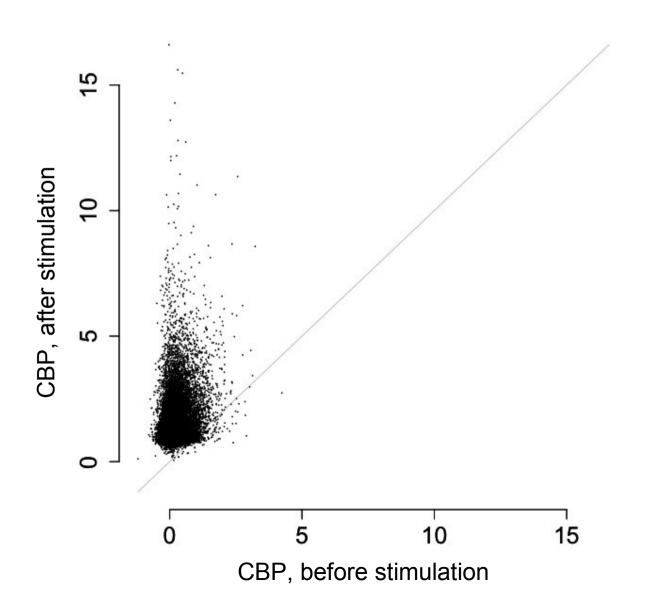
Use False Detection Ratio (FDR) to correct for multiple hypotheses

- Z_i = #ChIP reads #input reads in window i
- ~1 read/100 bp
 - Assume #reads in window P(k) = $\lambda^k \exp(-\lambda)/k!$
 - Difference between two Poisson random variables
 - Z_i ~ Skellam(z, λ_1 , λ_2)

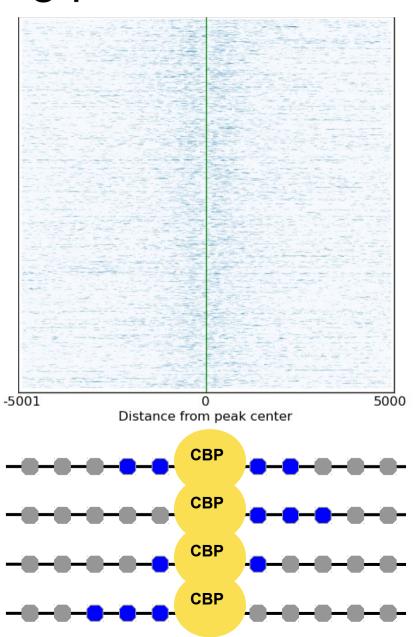
$$p(x) = e^{-(\lambda_1 + \lambda_2)} (\lambda_1 / \lambda_2)^{x/2} I_x (2\sqrt{\lambda_1 \lambda_2})$$

- Millions of windows need to be tested
 - FDR expected fraction of false positives

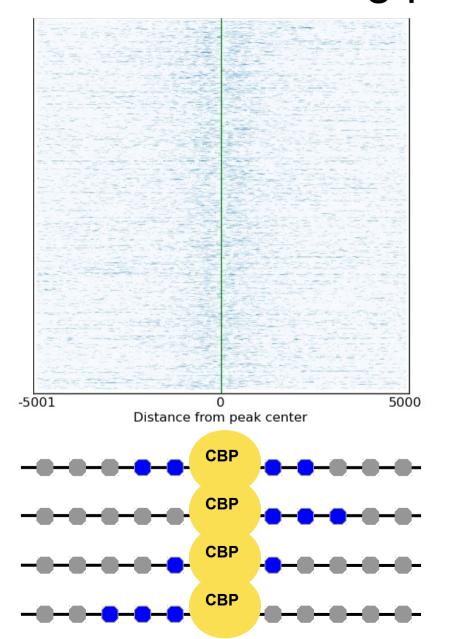
CBP binds in an activity regulated manner to ~28,000 sites throughout the genome

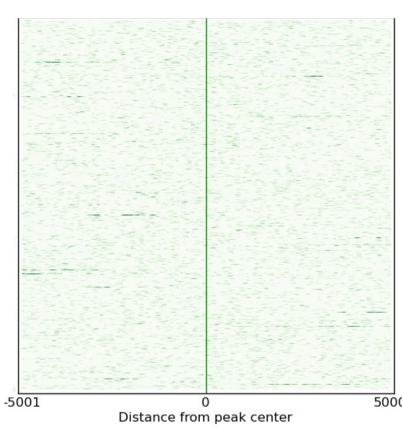


Aligning CBP peaks to calculate H3K4me1 binding profiles

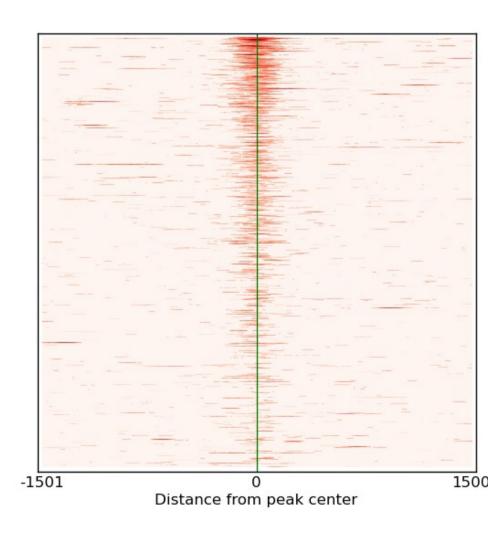


Aligning CBP peaks to calculate H3K4me1 and H3K4me3 binding profiles

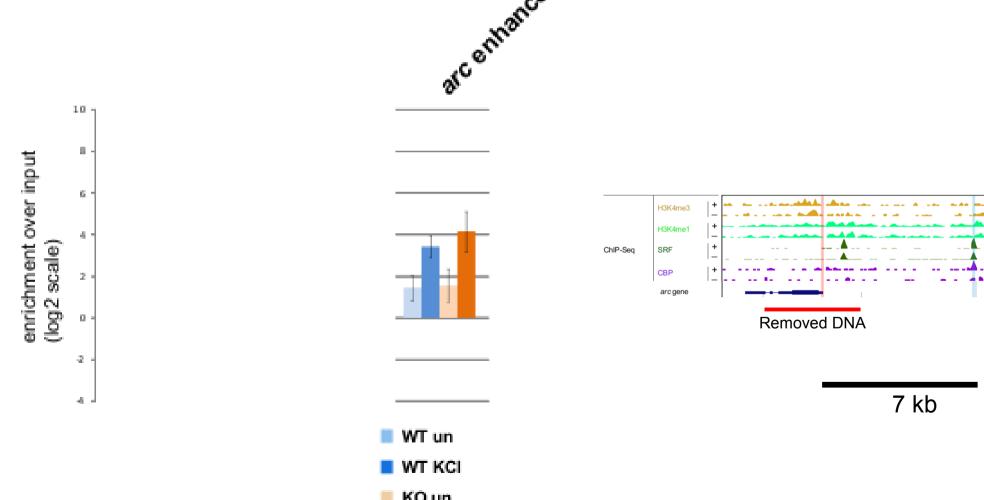




RNAPII binds at activity-dependent enhancers

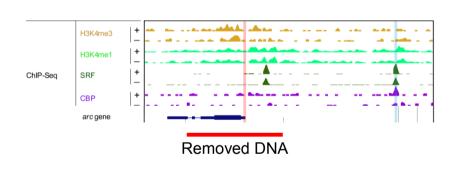


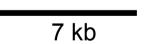
RNAPII levels are unchanged at the enhancer in the mutant before and after KCI

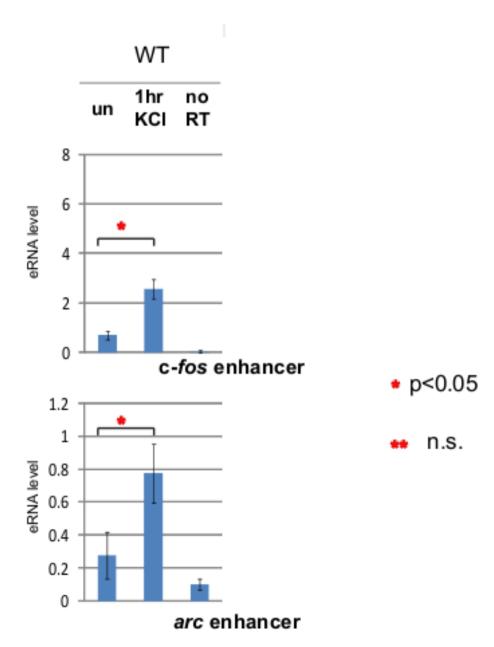


KO KCI

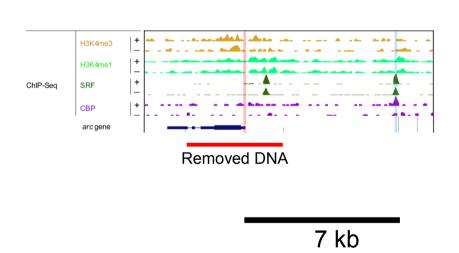
Transcription at the Fos and Arc enhancers

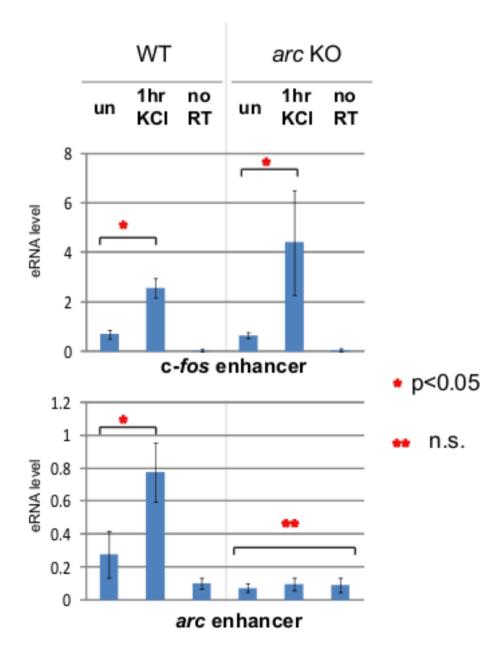






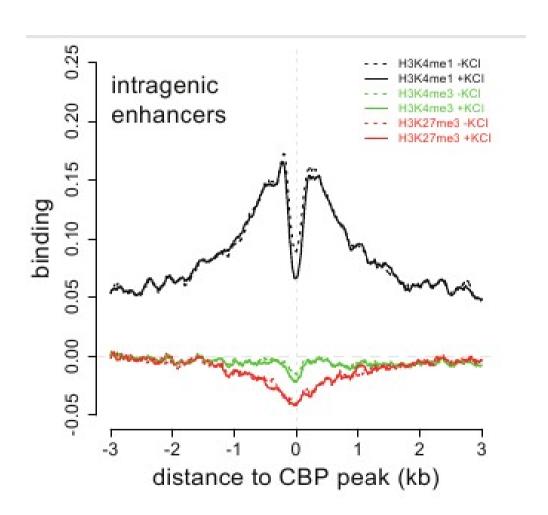
No transcription at Arc enhancer in mutant





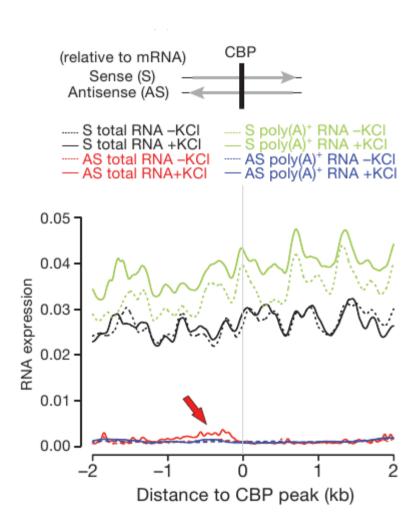
Intragenic enhancers

- ~7,000 enhancers overlapping introns
 - H3K4me1, but noH3K4me3



Intragenic enhancers are also transcribed

- ~7,000 enhancers
 overlapping introns
 - No signal detectable on sense strand
 - Significant anti-sense transcription



~100 enriched motifs are found

Word	Enrichment	Known TF
TGASTCA	4.74	Fos/Jun
TGACGTCA	6.41	Creb
CTAWWWATA	3.34	Srf
TCGTG	1.56	Npas4
CTGCCAAA	3.34	?

How abundant are eRNAs compared to mRNAs?

- Identify all transcripts in the genome
 - Wavelet-based algorithm for de novo detection of transcribed regions accounts for 99.8% of reads
 - Annotated RNAs ~ 98.3%
 - eRNAs ~ 0.02%
 - 1 in 10,000 reads is an eRNA read
 - mRNAs ~100 times more abundant

Estimating the production rate of eRNAs

$$\frac{dE}{dt} = kN - \frac{E}{\tau_E}$$

$$k = \frac{E^*}{N\tau_E} \sim \frac{10^3}{10^4 \times 10^{-1} \text{h}} = 1\text{h}^{-1}$$

Parameters for the eRNA fit

$$\lambda = \frac{k_{drop} \text{ s}^{-1}}{k_{elong} \text{ bp}^{-1} \text{s}^{-1}} \sim \frac{2 \times 10^{-2}}{20} \text{ bp}^{-1} = 10^{-3} \text{ bp}^{-1}$$

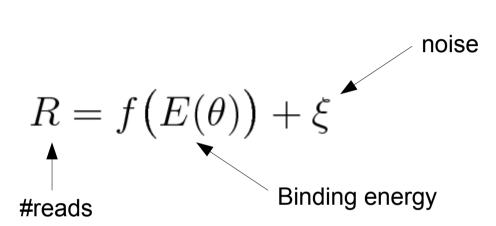
$$\tau_{decay} = \tau_{find} + \tau_{bp}L$$

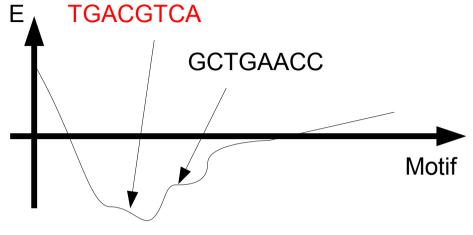
$$H(x,t) = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$E(x) = \sqrt{\frac{\pi}{2\lambda}} \frac{\gamma k}{\lambda} e^{-\delta^2/2\lambda - \lambda x^2/2} i \left[\operatorname{erf}\left(\frac{\delta i - \lambda i x}{\sqrt{2\pi}}\right) - \operatorname{erf}\left(\frac{\delta i}{\sqrt{2\lambda}}\right) \right]$$

Can the read count be predicted from

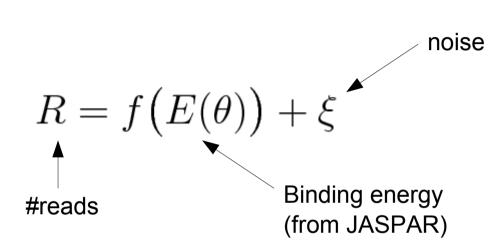
sequence motifs?



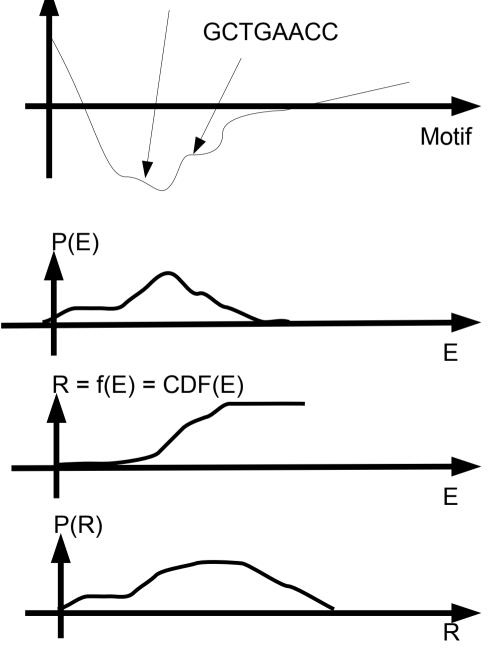


Assume transfer function maximizes mutual

information

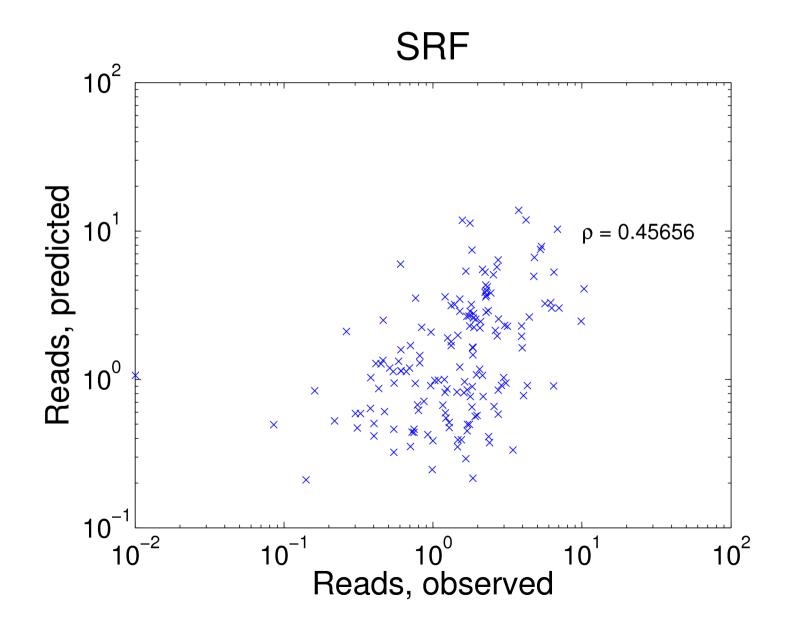


- f monotone
- max *I(R; E)*
- Noise small and gaussian



TGACGTCA

Number of reads can be predicted by binding energy



A PDE for histone levels

$$\frac{\partial H}{\partial x} + \frac{\partial H}{\partial t} = \kappa P(x,t) - \mu_x H - \mu_t H$$

$$H(x,t) = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial x} + \frac{\partial H}{\partial t} = \kappa P(x,t) - \mu_x H - \mu_t H$$

$$H(x,t) = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\mu_x x}) \times e^{-\mu_t t}$$

$$\frac{\partial H}{\partial t} = \frac{k\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\lambda x}) (e^{-\lambda x} - e^{-\lambda x})$$

$$\frac{\partial H}{\partial t} = \frac{\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\lambda x}) (e^{-\lambda x} - e^{-\lambda x})$$

$$\frac{\partial H}{\partial t} = \frac{\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\lambda x})$$

$$\frac{\partial H}{\partial t} = \frac{\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\lambda x})$$

$$\frac{\partial H}{\partial t} = \frac{\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\lambda x})$$

$$\frac{\partial H}{\partial t} = \frac{\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\lambda x})$$

$$\frac{\partial H}{\partial t} = \frac{\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda x} - e^{-\lambda x})$$

$$\frac{\partial H}{\partial t} = \frac{\kappa}{\mu_x(\mu_x - \lambda)} (e^{-\lambda$$

