Inferring Models of cis-Regulatory Modules using Information Theory

BMI/CS 776

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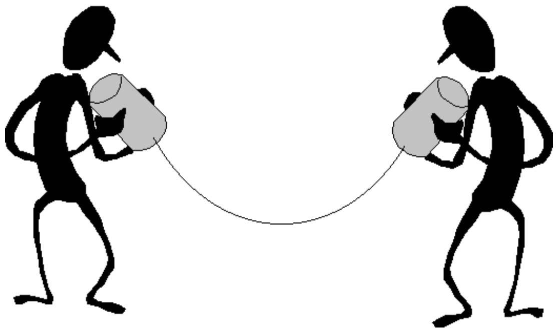
Goals for Lecture

the key concepts to understand are the following

- entropy
- mutual information
- motif logos
- using MI to identify CRM elements

Information Theory Background

- consider a problem in which you are using a code to communicate information to a receiver
- example: as bikes go past, you are communicating the manufacturer of each bike



Information Theory Background

- suppose there are only four types of bikes
- we could use the following code

type	code
Trek	11
Specialized	10
Cervelo	01
Serrota	00

- expected number of bits we have to communicate: 2 bits/bike

Information Theory Background

- we can do better if the bike types aren't equiprobable
- optimal code uses $-\log_2 P(c)$ bits for event with probability $P(c)$

Type/probability	# bits	code
$P(\text{Trek}) = 0.5$	1	1
$P(\text{Specialized}) = 0.25$	2	01
$P(\text{Cervelo}) = 0.125$	3	001
$P(\text{Serrota}) = 0.125$	3	000

- expected number of bits we have to communicate: 1.75 bits/bike

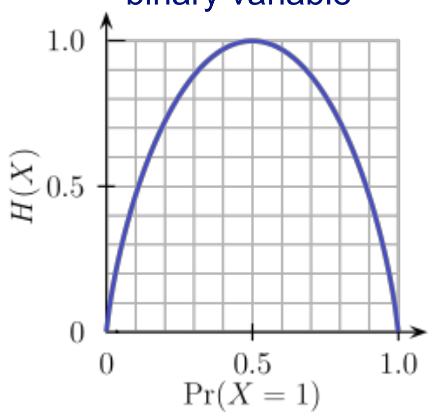
$$-\sum_{c=1}^{|C|} P(c)\log_2 P(c)$$

Entropy

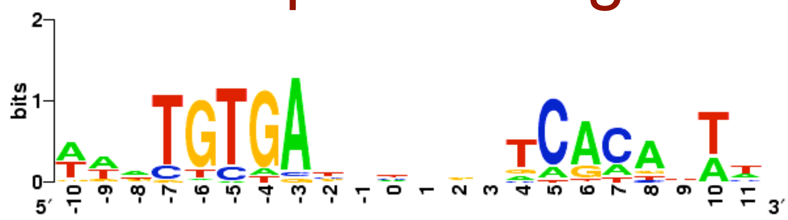
- entropy is a measure of uncertainty associated with a random variable
- defined as the expected number of bits required to communicate the value of the variable

$$H(C) = -\sum_{c=1}^{|C|} P(c)\log_2 P(c)$$

entropy function for binary variable



Sequence Logos



- based on entropy (H) of a random variable (C) representing distribution of character states at each position

- height of logo at a given position determined by decrease in entropy (from maximum possible)

$$H_{\max} - H(C) = -\log_2\left(\frac{1}{N}\right) - \left(-\sum_c P(c)\log_2 P(c)\right)$$

\# of characters in alphabet

- height of each character c is proportional to $P(c)$

Mutual Information

- *mutual information* quantifies how much knowing the value of one variable tells about the value of another

entropy of M

entropy of M conditioned on C

$$I(M;C) = H(M) - H(M \mid C)$$

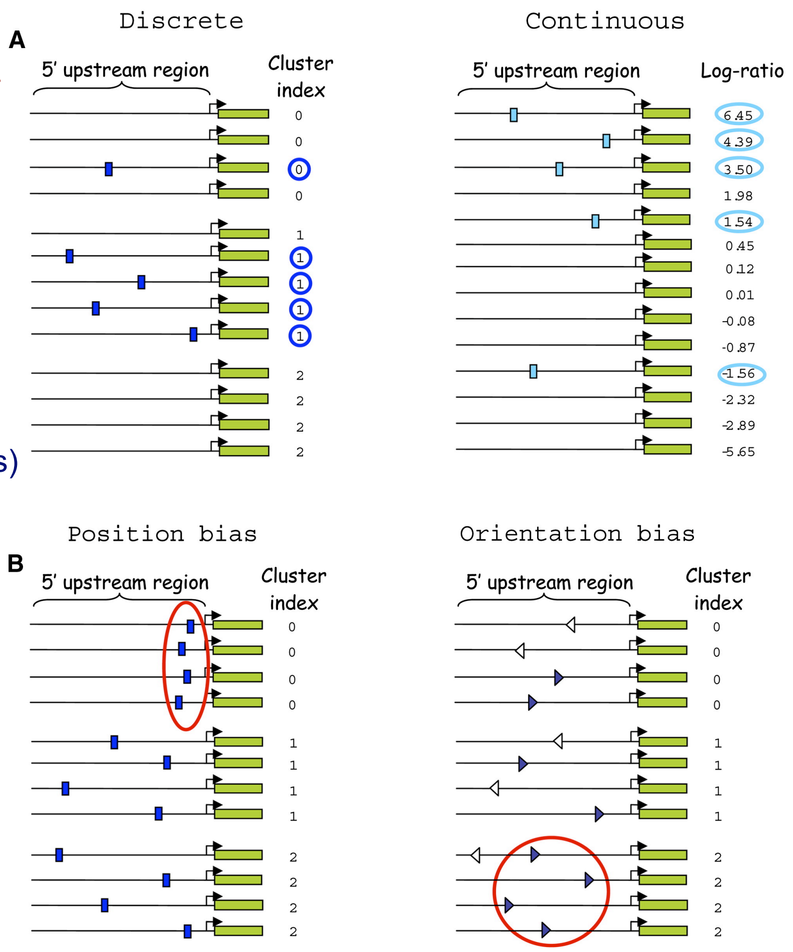
$$= \sum_m \sum_c P(m,c)\log_2\left(\frac{P(m,c)}{P(m)P(c)}\right)$$

FIRE

Elemento et al., *Molecular Cell* 2007

- **Given** a set of sequences grouped into clusters
- **Find** motifs, and relationships, that have high *mutual information* with the clusters

- (also can do this when sequences have continuous values instead of cluster labels)



Mutual Information in FIRE

- we can compute the mutual information between a motif and the clusters as follows

$$I(M;C)=\sum_{m=0}^{1}\sum_{c=1}^{|C|}P(m,c)\log_2\frac{P(m,c)}{P(m)P(c)}$$

$m=0, 1$ represent absence/presence of motif

c ranges over the cluster labels

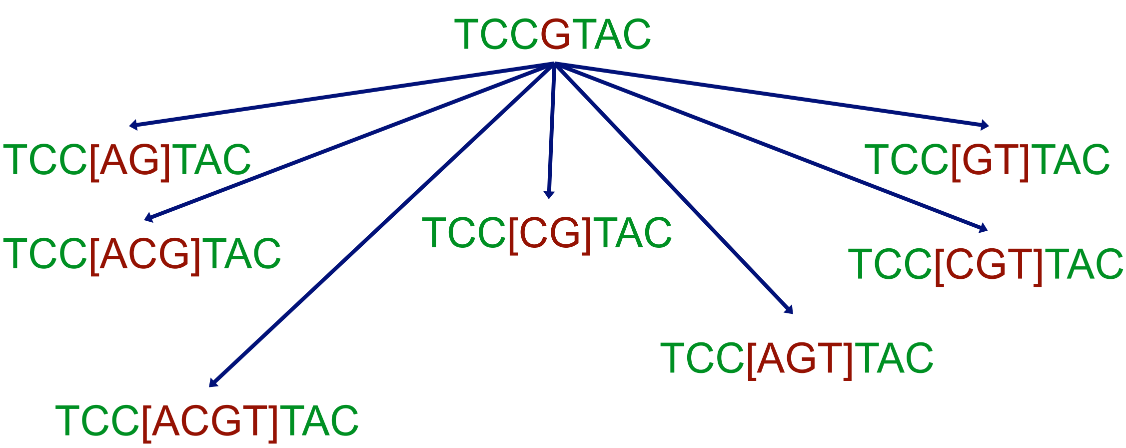
Finding Motifs in FIRE

- motifs are represented by regular expressions; initially each motif is represented by a strict *k*-mer (e.g. TCCGTAC)

1. test all *k*-mers (*k*=7 by default) to see which have significant mutual information with the cluster label
2. filter *k*-mers using a significance test
3. generalize each *k*-mer into a motif
4. filter motifs using a significance test

Key Step in Generalizing a Motif in FIRE

- randomly pick a position in the motif
- generalize in all ways consistent with current value at position
- score each by computing mutual information
- retain the best generalization



Generalizing a Motif in FIRE

```
given: k-mer, n

best ← null
repeat n times
    motif ← k-mer
    repeat
        motif ← GeneralizePosition(motif)    // shown on previous slide
    until convergence (no improvement at any position)
    if score(motif) > score(best)
        best ← motif

return: best
```

Generalizing a Motif in FIRE: Example

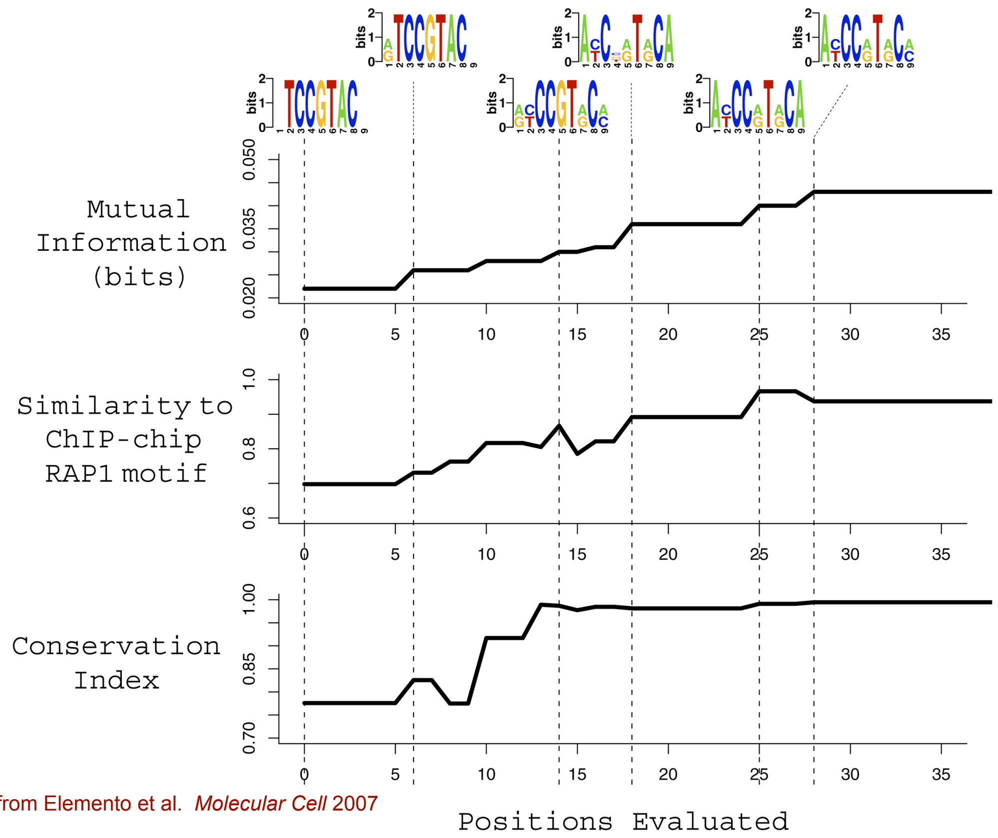


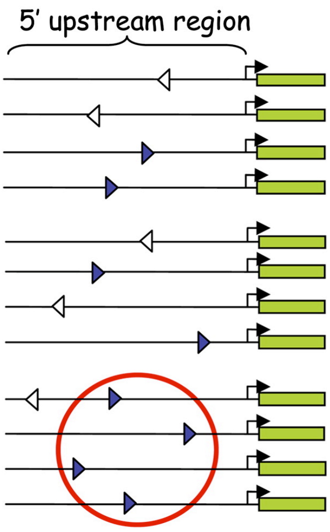
Figure from Elemento et al. *Molecular Cell* 2007

Characterizing Predicted Motifs in FIRE

- mutual information is also used to assess various properties of found motifs
  - orientation bias
  - position bias
  - interaction with another motif

Using MI to Determine Orientation Bias

$I(S;C)$ C indicates cluster
$S=1$ indicates motif present on transcribed strand
$S=0$ otherwise (not present or not on transcribed strand)

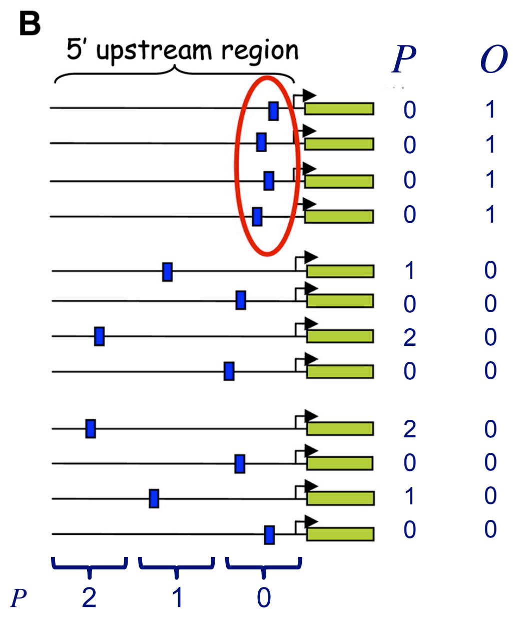


C	S
0	0
0	0
0	1
0	1
1	0
1	1
1	0
1	1
2	1
2	1
2	1
2	1

also compute MI where S=1 indicates motif present on complementary strand

Using MI to Determine Position Bias

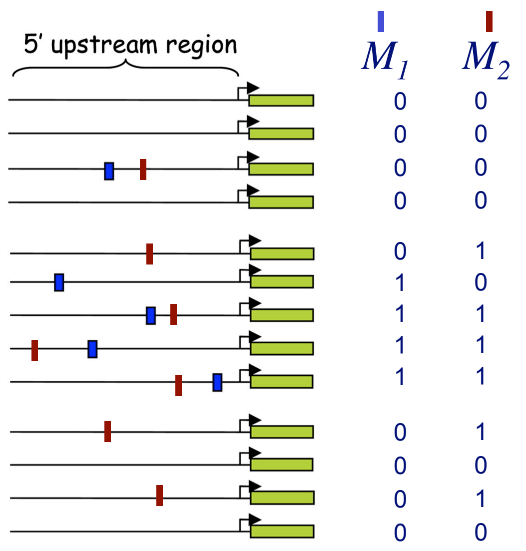
$I(P;O)$ P ranges over position bins
O=0, 1 indicates clusters in which the motif is overrepresented or not



only sequences containing the motif are considered for this calculation

Using MI to Determine Motif Interactions

$I(M_1;M_2)$ M_1=0, 1 indicates clusters in which motif 1 is overrepresented or not; similarly for M_2



Discussion of CRM Finding Methods

- Noto & Craven
  - HMM structure search to find CRM model
  - search operators apply to compact, logical representation instead of directly to HMM
  - employs generalized (a.k.a. semi-Markov) HMM approach to model *background* sequence lengths

- FIRE
  - mutual information used to identify motifs and relationships among them
  - motif search is based on generalizing informative *k*-mers

- in contrast to many motif-finding approaches, both CRM methods take advantage of *negative* sequences

- FIRE returns all informative motifs/relationships found, whereas the Noto & Craven approach returns single discriminative model