Gene Finding by Computational Analysis

Limsoon Wong 13 September 2006



Lecture Plan



- Gene structure basics
- Gene finding overview
- GRAIL
- Indel & frame-shift in coding regions
- Histone promoters: A cautionary case study

Gene Structure Basics

Some slides here are "borrowed" from Ken Sung







- Our body consists of a number of organs
- Each organ composes of a number of tissues
- Each tissue composes of cells of the same type





- Performs two types of function
 - Chemical reactions necessary to maintain our life
 - Pass info for maintaining life to next generation
- In particular
 - Protein performs chemical reactions
 - DNA stores & passes info
 - RNA is intermediate between DNA & proteins

DNA



- DNA stores instruction needed by the cell to perform daily life function
- Consists of two strands interwoven together and form a double helix
- Each strand is a chain of some small molecules called nucleotides



Francis Crick shows James Watson the model of DNA in their room number 103 of the Austin Wing at the Cavendish Laboratories, Cambridge



Chromosome

- DNA is usually tightly wound around histone proteins and forms a chromosome
- The total info stored in all chromosomes constitutes a genome
- In most multi-cell organisms, every cell contains the same complete set of chromosomes

 May have some small different due to mutation
- Human genome has 3G base pairs, organized in 23 pairs of chromosomes





- A gene is a sequence of DNA that encodes a protein or an RNA molecule
- About 30,000 35,000 (protein-coding) genes in human genome
- For gene that encodes protein
 - In Prokaryotic genome, one gene corresponds to one protein
 - In Eukaryotic genome, one gene can corresponds to more than one protein because of the process "alternative splicing"



Complexity of Organism vs. Genome Size

- Human Genome: 3G base
 pairs
- Amoeba dubia (a single cell organism): 600G base pairs
- ⇒ Genome size has no relationship with the complexity of the organism

Number of Genes vs. Genome Size

- Prokaryotic genome (e.g., *E. coli*)
 - No. of base pairs: 5M
 - Number of genes: 4k
 - Average length of a gene: 1000 bp
- Eukaryotic genome (e.g., human)
 - No. of base pairs: 3G
 - Estimated number of genes: 30k – 35k
 - Estimated average length of a gene: 1000-2000 bp

- ~ 90% of *E. coli* genome are of coding regions
- < 3% of human genome is believed to be coding regions
- ⇒ Genome size has no relationship with the number of genes!

Mutation

- Mutation is a sudden change of genome
- Basis of evolution
- Cause of cancer
- Can occur in DNA, RNA, & Protein



Chromosome 4



Central Dogma

- Gene expression consists of two steps
 - − Transcription
 DNA → mRNA
 - − Translation
 mRNA → Protein





Genetic Code

• Start codon: ATG (code for M)

• Stop codon: TAA, TAG, TGA

			Second Pos	sition of Codon	Codon G G TGT Cys [C] T rr [Y] TGT Cys [C] C rr [Y] TGC Cys [C] C r [end] TGA Ter [end] A									
		Т	С	A	G									
F i r s t	т	TTT Phe [F] TTC Phe [F] TTA Leu [L] TTG Leu [L] CTT Leu [L] CTC Leu [L] CTA Leu [L]	TCT Ser [S] TCC Ser [S] TCA Ser [S] TCG Ser [S] CCT Pro [P] CCC Pro [P] CCA Pro [P]	TAT Tyr [Y] TAC Tyr [Y] TAA Ter [end] TAG Ter [end] CAT His [H] CAC His [H] CAA Gln [Q]	TGT Cys [C] TGC Cys [C] TGA Ter [end] TGG Trp [W] CGT Arg [R] CGC Arg [R] CGA Arg [R]	T C A G T C A C	T h i r d							
P o s i t i	A	ATT Ile [I] ATC Ile [I] ATA Ile [I] ATG Met [M]	ACT Thr [T] ACC Thr [T] ACA Thr [T] ACG Thr [T]	AAT Asn [N] AAC Asn [N] AAA Lys [K] AAG Lys [K]	AGT Ser [S] AGC Ser [S] AGA Arg [R] AGG Arg [R]	T C A G	P o s i t i							
o n	G	GTT Val [V] GTC Val [V] GTA Val [V] GTG Val [V]	GCT Ala [A] GCC Ala [A] GCA Ala [A] GCG Ala [A]	GAT Asp [D] GAC Asp [D] GAA Glu [E] GAG Glu [E]	GGT Gly [G] GGC Gly [G] GGA Gly [G] GGG Gly [G]	T C A G	o n							



Introns and exons

- Eukaryotic genes contain introns & exons
 - Introns are seq that are ultimately spliced out of mRNA
 - Introns normally satisfy
 GT-AG rule, viz. begin w/
 GT & end w/ AG
 - Each gene can have many introns & each intron can have thousands bases

- Introns can be very long
- An extreme example is a gene associated with cystic fibrosis in human:
 - Length of 24 introns
 ~1Mb
 - Length of exons ~1kb



Typical Eukaryotic Gene Structure



 Unlike eukaryotic genes, a prokaryotic gene typically consists of only one contiguous coding region

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Reading Frame

Each DNA segment has six possible reading frames

Forward strand:	ÁTGGCTTÁCGCTTG	À
Reading frame #1	Reading frame #2	Reading frame #3
ATG	TGG	GGC
GCT	CTT	TTA
TAC	ACG	CGC
GCT	CTT	TTG
TGC	GA.	A
Reverse strand:	TCAAGCGTAAGCCAT	<u> </u>
Reading frame #4	Reading frame #5	Reading frame #6
TCA	CAA	AAG
AGC	GCG	CGT
GTA	ТАА	AAG
AGC	GCC	CCA
CAT	AT.	Т

Open Reading Frame (ORF)



• ORF is a segment of DNA with two in-frame stop codons at the two ends and no in-frame stop codon in the middle





Coding Region

- Each coding region (exon or whole gene) has a fixed translation frame
- A coding region always sits inside an ORF of same reading frame
- All exons of a gene are on the same strand
- Neighboring exons of a gene could have different reading frames



Frame Consistency

 Neighbouring exons of a gene should be frameconsistent



Overview of Gene Finding

Some slides here are "borrowed" from Mark Craven





What is Gene Finding?

- Find all coding regions from a stretch of DNA sequence, and construct gene structures from the identified exons
- Can be decomposed into
 - Find coding potential of a region in a frame
 - Find boundaries betw coding & non-coding regions

atgaacagacgcgatcttcttttacaagaaatgggcatttcccagtgggaattatatcgc cccgaggtactgcaggttcagtaggaattagtgtggcagagaatattcgcctta gtttccgatgaaaatatcagtagctcgcctttgttggctgatgtgctgttaagccttaat cttaabaaagaaaattgtttatgtttgaattacgatcaaatccagcatatggaatgtaaa (agcctattcgltattggttactatcagaaaatagcgaccaaattgaccgcactttgcca tttgcaagcaggctgagcaggtttatcgctcgccaagttggcagcaatttcaatctaat catcaaccaagcaggctgagcaggtttatcgctcgccaagttggcagcaatttcaatctaat

Image credit: Xu

Approaches



- Search-by-signal: find genes by identifying the sequence signals involved in gene expression
- Search-by-content: find genes by statistical properties that distinguish protein coding DNA from non-coding DNA
- Search-by-homology: find genes by homology (after translation) to proteins
- State-of-the-art systems for gene finding usually combine these two strategies

Relevant Signals for Search-by-Signals



of Singapore



How Search-by-Signal Works

• There are 2 impt regions in a promoter seq

-10 region, ~10bp before TSS

- -35 region, ~35bp before TSS
- Consensus for–10 region in *E. coli* is **TATAAT**, but few promoters actually have this seq

\Rightarrow Recognize promoters by

- weight matrices
- probabilistic models
- neural networks, ...



How Search-by-Content Works

- Encoding a protein affects stats properties of a DNA seq
 - some amino acids used more frequently
 - diff number of codons for diff amino acids
 - for given protein, usually one codon is used more frequently than others
- ⇒ Estimate prob that a given region of seq was "caused by" its being a coding seq

Codon Pro	eference	in E. Coli
AA	codon	/1000
Gly	GGG	1.89
Gly	GGA	0.44
Gly	GGU	52.99
Gly	GGC	34.55
Glu	GAG	15. <u>6</u> 8
Glu	GAA	57.20
Asp	GAU	21.63
Asp	GAC	43.26

Image credit: Craven



How Search-by-Homology Works

- Translate DNA seq in all reading frames
- Search against protein db
- High-scoring matches suggest presence of homologous genes in DNA
- \Rightarrow You can use BLASTX for this



Search-by-Content Example: Codon Usage Method

- Staden & McLachlan, 1982
- Process a seq w/ "window" of length L
- Assume seq falls into one of 7 categories, viz.
 - Coding in frame 0, frame 1, ..., frame 5
 - Non-coding
- Use Bayes' rule to determine prob of each category
- Assign seq to category w/ max prob





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Search-by-Homology Example: Geventsity Finding Using BLAST

- High seq similarity typically implies homologous genes
- \Rightarrow Search for genes in yeast seq using BLAST
- \Rightarrow Extract Feature for gene identification







 Searching all ORFs against known genes in nr db helps identify an initial set of (possibly incomplete) genes







- A (yeast) gene starts w/ ATG and ends w/ a stop codon, in same reading frame of ORF
- Have "strong" coding potentials, measured by, preference models, Markov chain model, ...
- Have "strong" translation start signal, measured by weight matrix model, ...
- Have distributions wrt length, G+C composition,
- Have special seq signals in flanking regions, ...

GRAIL, A Pioneer Gene Finding Program

Signals assoc w/ coding regions Models for coding regions Signals assoc w/ boundaries Models for boundaries Other factors & information fusion

Some slides here are "borrowed" from Ying Xu





Coding Signal

- Freq distribution of dimers in protein sequence
- E.g., Shewanella
 - Ave freq is 5%
 - Some amino acids prefer to be next to each other
 - Some amino acids prefer to be not nex to each other

Name	ala	arg	asn	asp	cys	glu	gln	gly	his	ile	leu	lys	met	phe	pro	ser	thr	trp	tyr	val
ala	9.5	4.1	4.3	5.3	1.2	6	4.8	6.5	2	6.5	11.5	6	2.6	3.7	3.5	6.2	5	1.1	2.7	6.5
arg	7.9	5.5	3.9	5.3	1.1	6	5.5	5.9	2.6	6.5	11.4	5	2.2	4.7	3.6	5.5	4.4	1.4	4	6.6
asn	9.6	4.9	4.2	4.9	1	5.3	5.6	7.4	2.3	6	10	4.9	2	3.5	5.1	6.1	5.5	1.5	3.1	6.1
asp	9.3	4	4.7	5.1	1	6.7	2.9	7	1.8	7.1	9.6	6.3	2.3	4.3	3.9	5.9	5.1	1.6	3.6	6.6
cys	8.4	4.8	3.3	5.4	1.7	5.6	5.2	8.1	4.3	5.4	10.2	3.8	1.8	4.1	4.5	6.3	4.3	1.6	3.4	6.8
glu	9.4	5.8	3.6	4.5	0.8	4.9	7	5.8	2.6	5.9	12.7	5	2.4	4	3.5	5.4	5	1.1	2.8	6.8
gln	10.3	4.9	3	4.4	0.9	4.5	6.8	7	2.7	5.5	12.8	4.1	2	3.9	3.8	5.8	5.3	1.4	3	6.9
gly	8.1	4.8	3.9	5.1	1.2	6	4.6	6.4	2.4	6.8	10.5	5.8	2.7	4.8	2.4	5.8	5.1	1.4	3.7	7.5
his	7.3	4.7	4	4.8	1.5	4.9	5.6	6.9	3	6.2	10.8	4.8	1.6	5	5.2	6.8	4.9	1.7	4.2	5.1
ile	11	4.7	4.9	6.5	1.1	6.9	3.6	7.2	2.1	5.3	8.6	5.3	1.8	3.2	4.2	7	5.6	0.9	2.9	6.1
leu	10.4	4.2	4.3	5.2	1.1	5.2	3.7	6.8	2	5.6	10.6	5.3	2.3	3.8	4.5	7.4	6.2	1	2.6	6.6
lys	10.6	5.2	3.8	5.2	0.5	5.3	5.9	6.6	2.6	5.2	11.3	4.7	1.9	2.8	4.6	6	5.5	1.2	2.6	7.6
met	10.8	4.8	3.8	4.6	0.7	4.6	4.9	7	1.7	4.7	11.4	5.2	2.8	3.3	5.1	7.4	6.3	0.9	2	6.8
phe	9.6	3.7	5.2	6.5	1.2	6.4	2.7	7 <i>.</i> 9	1.9	6.7	7.4	5	2.5	3.9	3.6	8	5.8	1.3	3.3	6.3
pro	8.4	3.6	4.6	5.4	0.7	7.6	5.2	5.4	2.3	6.1	11.2	5.5	2.4	4.2	2.8	6.5	5.4	1.4	2.9	7.5
ser	9.1	4.6	3.7	5	1	5.4	5.2	7.2	2.6	6	11.6	4.5	2.2	4.1	4.1	6.5	5	1.2	3.2	6.8
thr	9.1	4.2	3.7	5.6	0.9	5.7	5.7	7.5	2.2	5.5	12	4.2	2	3.5	5.5	6.2	5.3	1.1	2.6	6.7
trp	7.1	6.3	3.2	4.8	1.3	3.9	8.5	6.6	3.6	5	14.2	3.2	2.4	4.6	3.9	5.8	4.3	1.3	3	6.1
tyr	7.9	6.5	3.6	4.9	1.2	4.5	7	7.1	2.6	5	11.7	4	1.6	4.7	4.9	6.4	4.6	1.5	3.4	5.7
val	9.6	4.1	4.4	5.9	1	6.2	3.4	6.4	1.8	6.5	10.2	5.2	2.5	3.7	3.8	7.2	6.1	1.1	2.7	7.1

Image credit: Xu

Exercise: What is shewanella?


- Dimer preference implies dicodon (6-mers like AAA TTT) bias in coding vs non-coding regions
- Relative freq of a di-codon in coding vs non-coding
 - Freq of dicodon X (e.g, AAA AAA) in coding region, total number of occurrences of X divided by total number of dicocon occurrences
 - Freq of dicodon X (e.g, AAA AAA) in noncoding region, total number of occurrences of X divided by total number of dicodon occurrences
- Exercise: In human genome, freq of dicodon "AAA AAA" is ~1% in coding region vs ~5% in non-coding region. If you see a region with many "AAA AAA", would you guess it is a coding or non-coding region?



Why Dicodon (6-mer)?

- Codon (3-mer)-based models are not as info rich as dicodon-based models
- Tricodon (9-mer)-based models need too many data points

There are $4^3 = 64$ codons $4^6 = 4096$ dicodons $4^9 = 262144$ tricodons

- To make stats reliable, need ~15 occurrences of each X-mer
- ⇒ For tricodon-based models, need at least 15*262144 = 3932160 coding bases in our training data, which is probably not going to be available for most genomes



- Most dicodons show bias towards either coding or non-coding regions
- ⇒ Foundation for coding region identification

Regions consisting of dicodons that mostly tend to be in coding regions are probably coding regions; otherwise non-coding regions

⇒ Dicodon freq are key signal used for coding region detection; all gene finding programs use this info



Dicodon freq in coding vs non-coding are genome-dependent

Image credit: Xu



Shewanella

Bovine



 In-frame vs any-frame dicodons • In-frame dicodon freq provide a more sensitive measure than any-frame dicodon freq





Dicodon Preference Model

• The preference value *P(X)* of a dicodon *X* is defined as

 $P(X) = \log FC(X)/FN(X)$

where

FC(X) is freq of X in coding regions
FN(X) is freq of X in non-coding regions

Dicodon Preference Model's Property Stational University

- P(X) = 0 if X has same freq in coding and noncoding regions
- P(X) > 0 if X has higher freq in coding than in noncoding region; the larger the diff, the more positive the score is
- P(X) < 0 if X has higher freq in non-coding than in coding region; the larger the diff, the more negative the score is



Dicodon Preference Model Example

• Suppose AAA ATT, AAA GAC, AAA TAG have the following freq:

FC(AAA ATT) = 1.4%FN(AAA ATT) = 5.2%

FC(AAA GAC) = 1.9%FN(AAA GAC) = 4.8%

FC(AAA TAG) = 0.0%FN(AAA TAG) = 6.3% Then P(AAA ATT) = -0.57 P(AAA GAC) = -0.40 $P(AAA TAG) = -\infty$, treating STOP codons differently

⇒ A region consisting of only these dicodons is probably a non-coding region



Coding Region Preference Model

Frame-Insensitive

A frame-insensitive coding preference S_{is}(R) of a region R can be defined as

 $S_{is}(R) = \Sigma_{X \text{ is a dicodon in } R} P(X)$

R is predicted as coding region if S_{is}(*R*) > 0

• NB. This model is not commonly used

In-Frame



Dicodon Preference Model

- The *in-frame* + *i* preference value P_i(X) of a dicodon X is defined as
 P_i(X) = log FC_i(X)/FN(X)
- where

FC_i(X) is freq of X in coding regions
 at in-frame + i positions
FN(X) is freq of X in non-coding regions



In-Frame



Coding Region Preference Model

 The *in-frame* + *i* preference S_i(R) of a region R can be defined as

 $S_i(R) = \Sigma_{X \text{ is a dicodon at in-frame + i position in } R} P_i(X)$

• *R* is predicted as coding if $\sum_{i=0,1,2} S_i(R)/|R| > 0$

• NB. This coding preference model is commonly used

Coding Region Prediction: An Example of Singapore Procedure

- Calculate all ORFs of a DNA segment
- For each ORF
 - Slide thru ORF w/ increment of 10bp
 - Calculate in-frame coding region preference score, in same frame as ORF, within window of 60bp
 - Assign score to center of window
- E.g., forward strand in a particular frame...



Problem with Coding Region Boundaries

 Making the call: coding or non-coding and where the boundaries are



⇒ Need training set with known coding and noncoding regions to select threshold that includes as many known coding regions as possible, and at the same time excludes as many known noncoding regions as possible



Types of Coding Region Boundaries

- Knowing boundaries of coding regions helps identify them more accurately
- Possible boundaries of an exon

{ translation start, acceptor site } { translation stop, donor site }

Image credit: Xu

- Splice junctions:
 - Donor site: coding region | GT
 - Acceptor site: CAG | TAG | coding region
- Translation start
 - in-frame ATG



- Splice junction sites and translation starts have certain distribution profiles
- For example, ...



Acceptor Site (Human Genome)

• If we align all known acceptor sites (with their splice junction site aligned), we have the following nucleotide distribution

	-14	-13	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	1
A	11.1	12.7	3.2	4.8	12.7	8.7	16.7	16.7	12.7	9.5	26.2	6.3	100	0.0	21.4
с	36.5	30.9	19.1	23.0	34.9	39.7	34.9	40.5	40.5	36.5	33.3	68.2	0.0	0.0	7.9
G	9.5	10.3	15.1	12.7	8.7	9.5	16.7	4.8	2.4	6.3	13.5	0.0	0.0 🕻	100	62.7
ប	38.9	41.3	58.7	55.6	42.1	40.5	30.9	37.3	44.4	47.6	27.0	25.4	0.0	0.0	7.9

Image credit: Xu

• Acceptor site: CAG | TAG | coding region



Donor Site (Human Genome)

• If we align all known donor sites (with their splice junction site aligned), we have the following nucleotide distribution

	-3	-2	-1	1	2	3	4	5	6
A	34.0	60.4	9.2	0.0	0.0	52.6	71.3	7.1	16.0
С	36.3	12.9	3.3	0.0	0.0	2.8	7.6	5.5	16.5
G	18.3	12.5	80.3	100	0.0	41.9	11.8	81.4	20.9
ប	11.4	14.2	7.3	0.0	100	2.5	9.3	5.9	46.2

Image credit: Xu

• Donor site: coding region | GT



What Positions Have "High" Information Content?

• For a weight matrix, information content of each column is calculated as

 $-\Sigma_{X \in \{A,C,G,T\}} F(X) * log (F(X)/0.25)$

- ⇒ When a column has evenly distributed nucleotides, its information content is lowest
- ⇒ Only need to look at positions having high information content



Information Content Around Donor Sites in Human Genome

	-3	-2	-1	1	2	3	4	5	6
A	34.0	60.4	9.2	0.0	0.0	52.6	71.3	7.1	16.0
С	36.3	12.9	3.3	0.0	0.0	2.8	7.6	5.5	16.5
G	18.3	12.5	80.3	100	0.0	41.9	11.8	81.4	20.9
ប	11.4	14.2	7.3	0.0	100	2.5	9.3	5.9	46.2

Image credit: Xu

Information content

 $\begin{aligned} \text{column} &-3 = -.34*\log(.34/.25) - .363*\log(.363/.25) \\ &-.183*\log(.183/.25) - .114*\log(.114/.25) = 0.04 \\ \text{column} &-1 = -.092*\log(.92/.25) - .03*\log(.033/.25) \\ &-.803*\log(.803/.25) - .073*\log(.73/.25) = 0.30 \end{aligned}$

Weight Matrix Model for Splice Site NUS

Weight matrix model

- build a weight matrix for donor, acceptor, translation start site, respectively
- use positions of high information content

	-3	-2	-1	1	2	3	4	5	6
A	34.0	60.4	9.2	0.0	0.0	52.6	71.3	7.1	16.0
С	36.3	12.9	3.3	0.0	0.0	2.8	7.6	5.5	16.5
G	18.3	12.5	80.3	100	0.0	41.9	11.8	81.4	20.9
ប	11.4	14.2	7.3	0.0	100	2.5	9.3	5.9	46.2

Image credit: Xu



Just to make sure you know what I mean?...

- Give me 3 DNA seq of length 10:
 - Seq₁ = ACCGAGTTCT
 - Seq₂ = AGTGTACCTG
 - Seq₃ = AGTTCGTATG
- Then the weight matrix is ...

1-mer	pos1	pos2	pos3	pos4	pos5	pos6	pos7	pos8	pos9	pos10
A	3/3	0/3	0/3							
C	0/3	1/3	1/3		Exerc	ise: Fil	l in the	rest of t	he table	
G	0/3	2/3	0/3							
Т	0/3	0/3	2/3							



Splice Site Prediction: A Procedure

	-3	-2	-1	1	2	3	4	5	6
A	34.0	60.4	9.2	0.0	0.0	52.6	71.3	7.1	16.0
С	36.3	12.9	3.3	0.0	0.0	2.8	7.6	5.5	16.5
G	18.3	12.5	80.3	100	0.0	41.9	11.8	81.4	20.9
ប	11.4	14.2	7.3	0.0	100	2.5	9.3	5.9	46.2

Image credit: Xu

• Add up freq of corr letter in corr positions:

AAGGTAAGT: .34 + .60 + .80 +1.0 + 1.0 + .52 + .71 + .81 + .46 = 6.24

TGTGTCTCA: .11 + .12 + .03 +1.0 + 1.0 + .02 + .07 + .05 + .16 = 2.56

 Make prediction on splice site based on some threshold

Other Factors Considered by GRA

- G+C composition affects dicodon distributions
- Length of exons follows certain distribution
- Other signals associated with coding regions
 - periodicity
 - structure information
- Pseudo genes

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•



Info Fusion by ANN in GRAIL

Exon Candidate Parameters



DNA	Predictions								
# Exons	TP	%	FP	%					
229	171	74.7	39	18.6					
600	575	95.8	30	4.9					
829	746	90.0	69	8.5					
# Bases									
134814	122885	91.2	13048	9.6					

Image credit: Xu

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Remaining Challenges in GRAIL

• Initial exon

- R. V. Davuluri et al., "Computational identification of promoters and first exons in the human genome", *Nat. Genet.*, 29:412--417, 2001
- H. Liu et al., "Data Mining Tools for Biological Sequences", *JBCB*, 1:139--168, 2003
- V. B. Bajic et al., "Dragon Gene Start Finder: An advanced system for finding approximate locations of the start of gene transcriptional units", *Genome Research*, 13:1923--1929, 2003

• Final exon

- J. E. Tabaska et al., "Identifying the 3'-terminal exon in human DNA", *Bioinformatics*, 17:602--607, 2001
- J. E. Tabaska et al., "Detection of polyadenylation signals in human DNA sequences", *Gene*, 23:77--86, 1999
- H. Liu et al., "An in-silico method for prediction of polyadenylation signals in human sequences", *GIW*, 14:84--93, 2003
- Indels & frame shifts

Indel & Frame-Shift in Coding Regions

Problem definition Indel & frameshift identification Indel correction An iterative strategy

Some slides here are "borrowed" from Ying Xu



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Indels in Coding Regions

- Indel = insertion or deletion in coding region
- Indels are usually caused by seq errors



Effects of Indels on Exon Prediction Singapore

 Indels may cause shifts in reading frames & affect prediction algos for coding regions



Image credit: Xu



Key Idea for Detecting Frame-Shift

- Preferred reading frame is reading frame w/ highest coding score
- Diff DNA segments may have diff preferred reading frames



- ⇒ Segment a coding sequence into regions w/ consistent preferred reading frames corr well w/ indel positions
- ⇒ Indel identification problem can be solved as a sequence segmentation problem!



Frame-Shift Detection by Sequence Segmentation

- Partition seq into segs so that
 - Chosen frames of adjacent segs are diff
 - Each segment has >30 bps to avoid small fluctuations
 - Sum of coding scores in the chosen frames over all segments is maximized

This can be solved as a dynamic programming problem ...



Frame-Shift Detection: A Simplified Treatment

- Given DNA sequence $a_1 \dots a_n$
- Define key quantities

C(i, r) = max score on a₁ ... a_i, w/ the last segment in frame r

• Then

$max_{r \in \{0, 1, 2\}}C(n, r)$ is optimal solution

Frame-Shift Detection: *C(i,r)*



- To calculate *C(i,r)*, there are 3 possible cases for each position *i*:
 - Case 1: no indel occurred at position i
 - Case 2: a_i is an inserted base
 - Case 3: a base has been deleted in front of a_i
- \Rightarrow C(i, r) = max { Case 1, Case 2, Case 3 }



Frame-Shift Detection: Case 1

• No indel occurs at position *i*. Then

 $C(i,r) = C(i-1, r') + P_r(a_{i-5}...a_i)$





Frame-Shift Detection: Case 2

• *a_{i-1}* is an inserted base. Then

$$C(i,r) = C(i-2, r') + P_r(a_{i-6}...a_{i-2}a_i)$$



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Frame-Shift Detection: Case 3

• A base has been deleted in front of *a_i*. Then

$$C(i, r) = C(i-1, r'') + P_{r'}(a_{i-5}..., a_{i-1}C) + P_{r}(a_{i-4}..., a_{i-1}Ca_{i})$$



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Frame-Shift Detection: Initiation

• Initial conditions,

 $C(k, r) = -\infty, k < 6$ $C(6, r) = P_r(a_1 \dots a_6)$

• This is a dynamic programming (DP) algorithm; the equations are DP recurrences

Exercise: How to modified the recurrence so that each fragment is at least 30bp?


Frame-Shift Detection: Step 3

- Calculation of max_{r∈{0, 1, 2}}C(i, r) gives an optimal segmentation of a DNA sequence
- Tracing back the transition points---viz. case 2 & case 3---gives the segmentation results



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Frame-Shift Detection: Determine Coding Regions



• For given H_1 and H_2 (e.g., = 0.25 for noncoding and 0.75 for coding), partition a DNA seq into segs so that each seg has >30 bases & coding values of each seg are consistently closer to one of H_1 or H_2 than the other



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Frame-Shift Detection: Step 5

 Overlay "preferred reading-frame segs" & "coding segs" gives coding region predictions regions w/ indels

actual exon	
predicted exons	
actual indels-	(B)
predicted_ indels	(C)
predicted exon ⊮/ frameshift correction	(D)
	Image credit: Xu

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Frame-Shift Detection: Step 6

• We still need to correct the identified indels...

If an "insertion" is detected, delete the base at the transition point

 If a "deletion" is detected, add a neutral base "C" at transition point



What Happens When Indels Are Close Together?

- Our procedure works well when indels are not too close together (i.e., >30 bases apart)
- When indels are too close together, they will be missed...



Handling Indels That Are Close Together

 Employ an iterative process, viz
Find one set of indels and correct them & then iterate until no more indels can be found



Modeling & Recognition of Histone Promoters

Some slides here are "borrowed" from Rajesh Chowdhary



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- Form a major part of chromosomal proteins
- Help in packaging DNA in the chromatin complex
- Five types, namely H1, H2A, H2B, H3 and H4
- Highly conserved across species
 - H1 least conserved, H3 & H4 most conserved



chromosomal processes

- gene transcription, regulation,
- chromosome condensation, recombination & replication



Histone Transcription



- TFs bound in core, proximal, distal promoter & enhancer regions
- TFIID binds to TATA box & identifies TSS with help of TAFs & TBP
- RNA Pol-II supplemented by GTFs (A,B,D,E,F,H) recruited to core promoter to form Preinitiation complex
 - **Transcription initiated**
 - Basal/Activated, depending on space & time



Histone Promoter Modeling



- Three promoter types: Core, proximal and distal
- Characterised by the presence of specific TFBSs
 - CAAT box, TATA Box, Inr, & DPE
 - Order and mutual distance of TFBS modules is specific & determine function



INACTIVE Histone H1t PROMOTER





- One gene can express in diff ways in diff cells
- Same binding site can have diff functions in diff cells

Why Model Histone promoters



- To understand histone's regulatory mechanism
 - To characterise regulatory features from known promoters
 - To identify promoter from uncharacterised genomic sequence (promoter recognition)
 - To find other genes with similar regulatory behaviour and gene-products
 - To define potential gene regulatory networks

Difficulties of Histone Promoter Modeling

- Not a plain sequence alignment problem
- Not all features are common among different groups
- Not only TFBSs' presence, but their location, order, mutual distance and orientation are critical to promoter function
- Not all TFs & TFBSs have been characterized yet



Tools for Promoter Modeling

- Genomic signals in promoter v/s non-promoter
 - Core promoter (TATA Box, Inr, DPE) and/or few TFBS outside core promoter
 - Entire promoter (core, proximal & distal) with whole ensemble of TFBS
- Genomic content in promoter v/s non-promoter
 - CpG islands, GC content

- 2D-3D DNA structural features
- Model with a scoring system based on training data (good data not always available)
 - Input seq scanned for desired patterns & those whose scores above certain threshold are reported



Promoter Recognition Programs

"GENERAL PROMOTERS"							
First Generation							
Name	Scoring Technique used	Search by content/signal	Features used				
NNPP	Time delay NN	Signal	TATA box, Inr				
Promoter 2	NN	Signal	TATA box, Inr, CAAT box, GC Box				
PromFind	Discriminative count	Content	Hexamer frequency				
PromoterScan	Discriminative count	Signal	TATA box, TFBS				
TSSG/TSSW	Linear discriminant Content + analysis signal		TATA box, TSS, hexamer frequency upstream TSS, TFBS				
Second Generation	n						
DGSF	NN	Content + signal	CpG island, TSS, DPF output				
DPF	NN	Content + signal	Promoter, exon, intron, TSS				
Eponine	SVM variant	Content + signal	TATA box, GC rich content, TSS				
FirstEF	Quadratic discriminant analysis	Content + signal	First exon, CpG islands				
Mcpromoter	NN & Interpolated markov models	Content + signal	TATA box, CAAT box, GC box, nucleosome position				
PromoterInspector	Discriminative counts	Content	Oligonuleotides, Exon, Intron, 3'UTR, Promoter genomic context				
CpG Promoter	Quadratic discriminant analysis	Content + signal	CpG island, TSS				
CpGProD	Generalised linear model	Content	CpG island, AT/GC content				
"SUB-CLASS OF F	ROMOTERS"						
Muscle family	Discriminative counts	Signal	TFBS, relative distance				
Globin family	Logical operators AND, OR and NOT	Signal	TFBS, relative distance				

- Programs have different objectives
- Use various combinations of genomic signals and content
- Typically analyse 5' region [-1000,+500]
- Due to low accuracy, programs developed for sub-classes of promoters

Image credit: Rajesh

Steps for Building Histone Promotive Steps for Building Histore Promotive Steps for B

• Exercise: What do you think these steps are?





- MEME is a powerful and good method for finding motifs from biological sequences
- T. L. Bailey & C. Elkan, "Fitting a mixture model by expectation maximization to discover motifs in biopolymers", *ISMB*, 2:28--36, 1994

Motifs Discovered by MEME in History NUS Gene 5' Region [-1000,+500]



Image credit: Rajesh

H2A

Motifs Discovered by MEME in Hist Gene 5' Region [-1000,+500]



H₂B



Are These Really Motifs of H2A and Promoters?

- One could use the motifs discovered by MEME to detect H2A & H2B promoters
- But....it is strange that the motifs for H2A and H2B are generally the same, but in opposite orientation
- Exercise: Suggest a possible explanation





Image credit: Rajesh

The Real Common Promoter Regio H2A & H2B is at [-250,-1]!



Image credit: Rajesh

Motifs Discovered by MEME in History NUS Promoter 5' Region [-250,-1]

MOTIF	MOTIF		TRANSFAC
NO.	DEFINITION	TFBS AND ASSOCIATED FACTORS	SITE NUMBER
		CCAAT-box: H1TF2 (La Bella et al.	
		1989; Martinelli and Heintz 1994;	
		Gailinan et al. 1989), HINF-B (Van Milinan et al. 1989a b), NE V	
		(Mantovani 1988a,D), NE-1 (Mantovani 1990), HiNE D (van Minon	
1		et al 1996: Grimes et al. 2003)	R00660
		Oct-1: Octamer transcription factor 1	
2	ATGCAAATGAGG	(OTF-1) (Fletcher et al. 1987)	R00662
		TATA-box: TBP, TFIID (Nakajima et al.	
3		1988)	R00770
		E2F-binding site: E2F-1 factor (Oswald	
4	TTTTCGCGCCCA	et al. 1996)	R09798
_		H4TF2 binding site: H4TF2 (La Bella	
5	CAATCAGGTCCG	and Heintz 1991)	R00681
		AC-DOX: H11F1 (La Bella et al. 1989), - HiNE A (van \Atinon at al. 1089h)	
		HiNE-A (vari vvijnen et al. 19000), HiNE-D (van Wiinen et al. 1996:	
6		Grimes et al. 2003)	R00658
		CCAAT-box: H1TF1 (La Bella et al.	
		1989), HiNF-B (van Wijnen et al.	
		1988a,b), NF-Y (Mantovani 1999),	
		HiNF-D (van Wijnen et al. 1996;	
		Grimes et al. 2003), H1TF2 (La Bella	000050
7		et al. 1989; Martinelli and Heiniz 1994; Gallinari et al. 1989)	R00659, P00660
<u> </u>		CCAAT-box: H1TE2 (La Bella et al	
		1989: Martinelli and Heintz 1994:	
		Gallinari et al. 1989), HiNF-B (van	
		Wijnen et al. 1988a,b), NF-Y	
		(Mantovani 1999), HiNF-D (van Wijnen	
8	<u>CCATTGGTTAAA</u>	et al. 1996; Grimes et al. 2003)	R00660
		GC-box: HiNF-C (van Wijnen et al.	
		(1989), Sp1 (Courey and Lian 1988),	
0		ърз (вітрацт егаі, 1995; Hagen et ы. 1004)	000694
2	pulleulle	(al. 1994)	R00004

- Discovered 9 motifs among all 127 histone promoters
- All 9 motifs are experimentally proven TFBSs (TRANSFAC)

Image credit: Rajesh



Deriving Histone Promoter Models

Histone H1 genes	Name	Motifs					
Model 1: H1.1-H1.5 (cell cyc	le depende	nt)					
Human H1 3024 - 6	H1.1	-	-	-6	-9	-1	+3
Mouse H1 80838 + 13	H1.1	-	-	-	-9	-1	+3
Human H1 3006 - 6	н1.2	-	-	+6	-	-1	+3
Mouse H1 50708 + 13	н1.2	-	-	+6	-	-1	+3
Human H1 3007 - 6	н1.3	+4	-	+6	-	-1	+3
Mouse H1 14957 + 13	н1.3	+4	-	+6	-	-1	+3
Human H1 3008 + 6	н1.4	-	-	+6	-	-1	+3
Mouse H1 50709 - 13	н1.4	-	-	+6	-	-1	+3
Human H1 3009 - 6	н1.5	+4	+8	+6	-	-1	-3
Mouse H1 56702 - 13	н1.5	-	-	+6	-	-1	+3
Consensus Model 1		+4	+8	+6	<mark>-9</mark>	-1	+3
Model 2: H1f0/H1(zero) (cell	cycle ind	epender	nt/rep	lacemen	nt)		
Rat H1 24437 + 7	H1FO	-	-	-	-	-	-
Human H1 3005 + 22	H1FO	-4	-9	+6	+5	-	-
Mouse H1 14958 + 15	H1FO	-	-	+6	+5	-	-
Consensus Model 2		<mark>-4</mark>	<mark>-9</mark>	+6	+5	-	-
Model 3: H1X (alike cell cyc	le indepen	dent hi	istone	genes))		
Human H1 8971 - 3	HIX	-	-	+6	-5	-	+3
Consensus Model 3		-	-	+6	-5	-	<mark>+3</mark>
Model 4: Hlfo (ovary-specifi	.c)						
Human H1 132243 + 3	H1FO	-	-	+7	-	+1	+3
Mouse H1 171506 + 6	H1FO	-	-	-7	-	+8	+3
Consensus Model 4		-	-	+7/-7	-	+1/+8	<mark>+3</mark>
Model 5: Hlt (testis-specifi	.c)						
Mouse H1 107970 + 13	H1T	-	-	+6	-9	-1	+3
Rat H1 24438 + 17	ніт	-	-	+6	-9	-1	+3
Human H1 3010 - 6	ніт	-	-	+6	-9	-1	+3
Consensus Model 5		-	-	+6	<mark>-9</mark>	-1	<mark>+3</mark>
Overall Consensus model for	H1			_			
histone group		+4	- 1	+6	<mark>-9</mark>	-1	+3

- Divide H1 seqs into 5 subgroups
- Aligned seqs within each subgroup
- Consensus alignment matches biologically known H1 subgroup models
- ⇒ Can apply same approach to find promoter models for H2A, H2B, H3, H4...

Image credit: Rajesh



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