SCIE2100 | BINF6000 Bioinformatics

Genome Analysis II

Atefeh Taherian Fard, PhD

Australian Institute for Bioengineering and Nanotechnology a.taherianfard@uq.edu.au

Outline

Lecture 1:

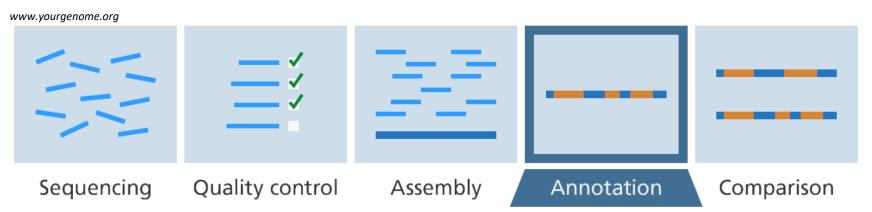
- Overview genome sequencing and sequencing technologies
- Genome re-sequencing
- De-novo genome assembly

Lecture 2:

- Gene features in prokaryotes
- Gene features in eukaryotes
- Computational approaches for gene prediction
- Functional genome annotation

Gene finding Approaches

- Physical, genetic or other *experimental approaches*
 - e.g. Genetic knockouts
- Computational approaches
- 1) Identity search
- 2) Similarity search Homology based
- 3) Ab initio approaches

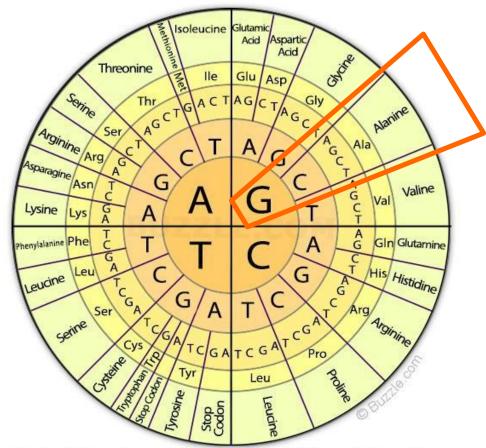


Using computational methods, find all genes (or other elements) in a long, unannotated string of nucleotides.

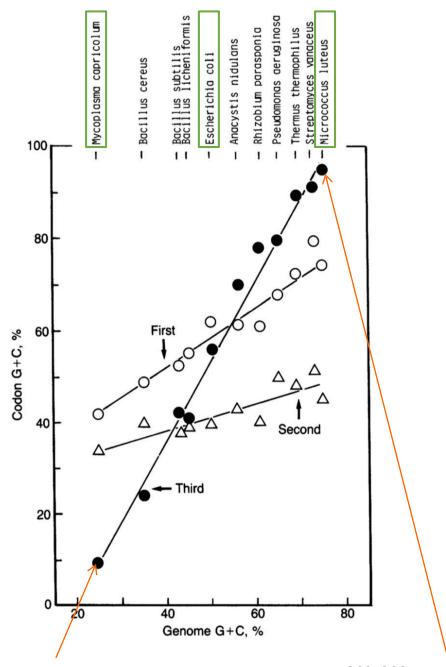
Aim: To identify transcriptional unit What do we know? Know only approximately what they look like How? Find their locations and boundaries as accurately as possible, overlook as few as possible, and report as few non-genes as possible.

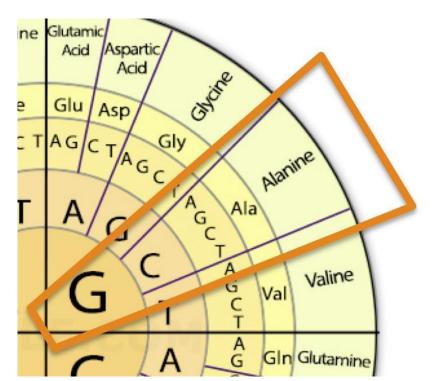
Codon bias

- 61 codons encoding 20 amino acids, genetic code is redundant
- Codon bias: Each organism seems to prefer a different set of codons over others



- This redundancy is mainly at the 3rd codon position
- Example 1: The codons for alanine can have ANY base in the 3rd position
- Examples 2: Leu is encoded by 6 codons. But human in nuclear genes it's most frequently coded by CTG, and only rarely by TTA or CTA



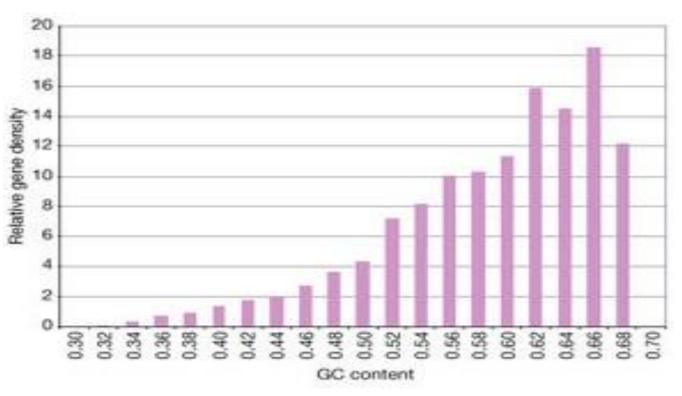


Very high correlation between **genomic** GC content and **3rd codon position GC** usage

=> Codons in GC-rich genomes will have higher frequency of GC at 3rd position

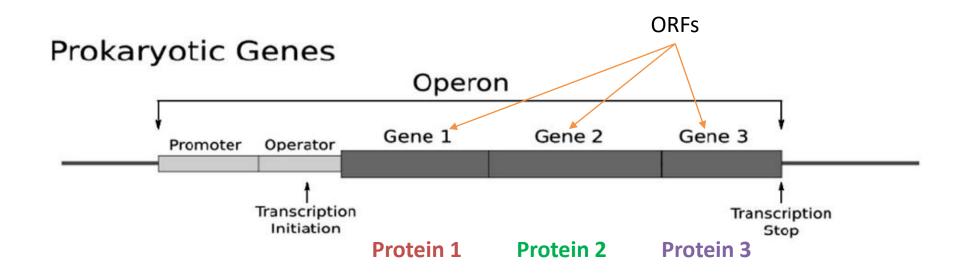
CpG islands, (G+C)-rich regions and genes

- For slightly more than half of human genes, transcriptional start site occurs in a CpG-rich region
- This is particularly true for "housekeeping" genes: the first coding exon usually occurs in a CpG island
- Mammalian genomes show elevated gene density in (G+C)-rich regions



Brown, Genomes 2

Gene features in Prokaryotes

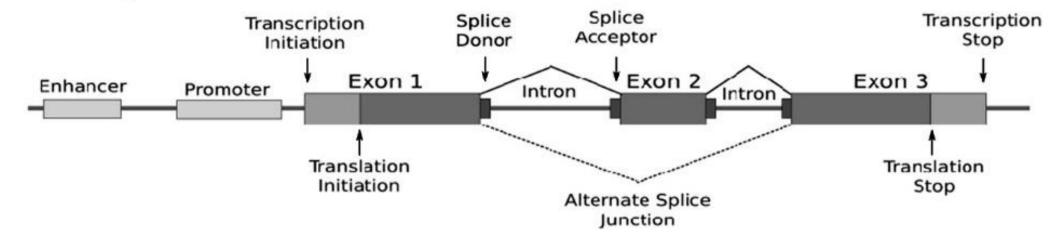


Protein coding genes in prokaryotes:

- Are open reading frames (ORFs)
- Begin with start codon (usually ATG for Methionine)
- End with stop codon
- No in-frame stop-codon

Gene features in Eukaryotes

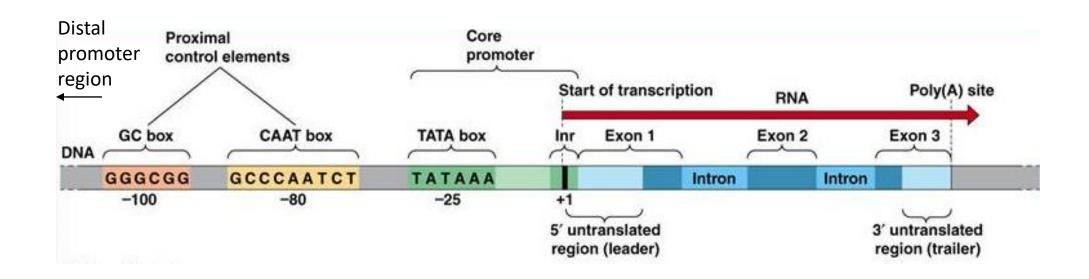
Eukaryotic Gene



Protein coding genes in Eukaryotes:

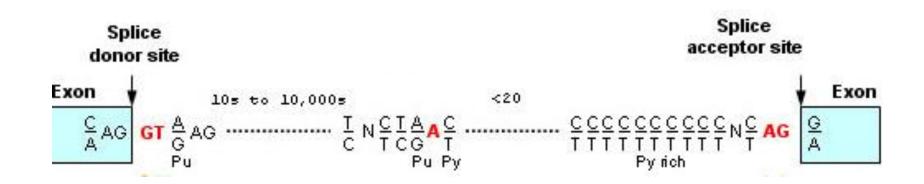
- Exons and introns
- Regulatory sequences (promoter and enhancer)
- Splice donor and accepter sides
- 5' Cap and 3' PolyA tail

Regulatory promoter regions in Eukaryotic genes



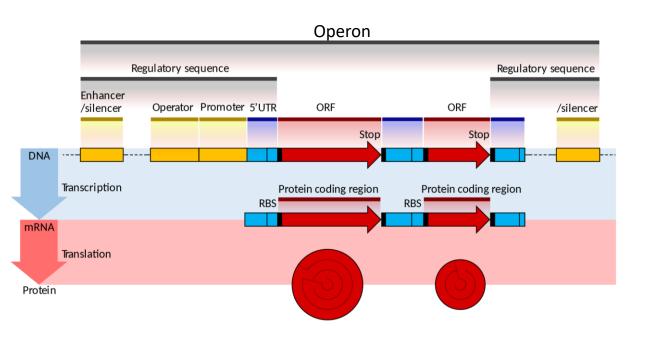
- Regulatory sequences have distinct features, recognised by DNA-binding proteins to regulate gene expression
- Sequence motifs, may be conserved
- In each species, different sets of genes have different motifs

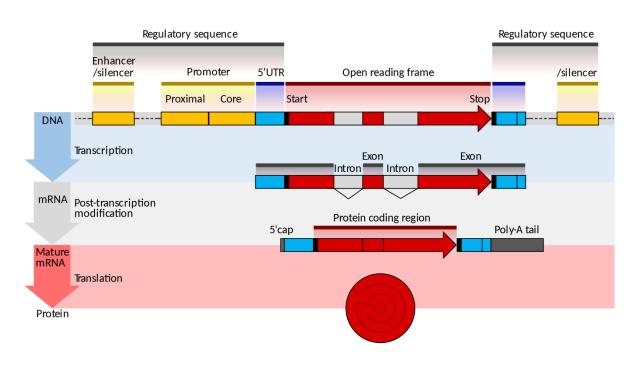
Intron-exon splice sites



- The GT-AG rule
- Numbers indicate the number of nucleotide bases between each conserved region
- Pu: Purines (A and G)
- Py: Pyrimidines (C and T)
- N: Any nucleotide

Summary: Gene features in Prokaryotics vs Eukaryotes





- Codon bias and GC rich regions
- Transcriptional start and stop sites
- ORFs: Start and stop codons
- 5' UTR: Ribosomal Binding Sequence site
- 3'UTR

- Codon bias and GC rich regions
- Promoter regions
- Intro and Exon splice site
- ORFs: Start and Stop codons
- 5' UTR: 5' Cap (G cap site)
- 3' UTR: PolyAs

Gene finding Approaches

Computational approaches

1) Identity search

Looks for exact match the query and target sequence!

2) Similarity search- Homology based

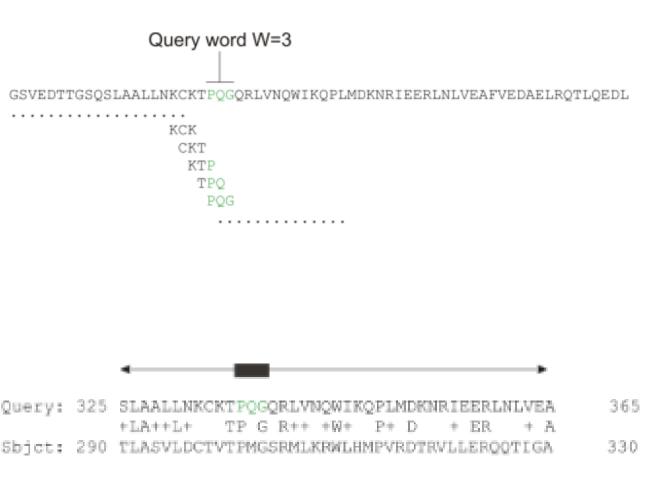
- Translate genome in all 6 reading frames, map translated sequence to known proteins (e.g. using BLAST)
- Only identifies known genes
- Species specific
- Unknown genes and evolved genes with low sequence identity are missed
- Compare genome to close relative organism and identify conserved regions

3) Ab initio approaches

- Evaluate *specific sequence properties of genes* to distinguish between non-coding and coding regions
- Identifies also new genes, but may produce many false predictions

Similarity search (e.g. BLAST)

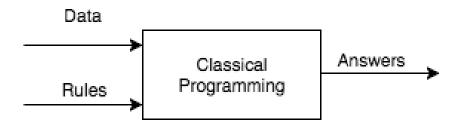
- BLAST identifies homologous sequences using a heuristic method which initially finds short matches between two sequences.
- When finding a match between a query sequence and a hit sequence, the starting point is the *words* that the two sequences have in common.
- After initial finding of words (seeding), the BLAST algorithm will extend the (only 3 residues long) alignment in both directions.
- Each time the alignment is extended, an alignment score is increases/decreased.
- When the alignment score drops below a predefined threshold, the extension of the alignment stops.
- If the obtained alignment receives a score above a certain threshold, it will be included in the final BLAST result.

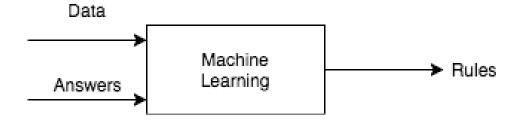


Machine learning approach to ab initio gene finding

- A branch of artificial intelligence
- Enabling computers make successful predictions using past experiences
- Based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention

Machine Learning vs Traditional programming





Machine learning approach to ab initio gene finding

Features of known protein-coding genes:

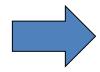
Presence of one or more ORF
ORFs in G+C islands

Promoter-element motif scores & positions
Transcriptional start site in CpG island
Codon bias & correspondence with ORF
Splice-site motif scores & positions
Poly(A) signal motif scores & positions

(...)

(...



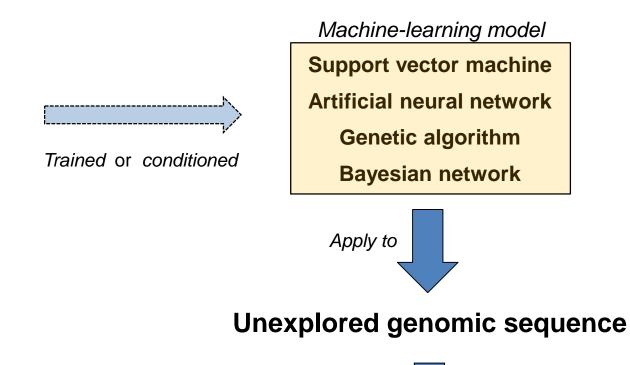


Support vector machine
Artificial neural network
Genetic algorithm
Bayesian network

Machine-learning model

Training or conditioning

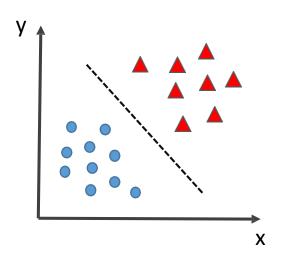
Machine learning approach to ab initio gene finding



With the result that...

Genes are found!

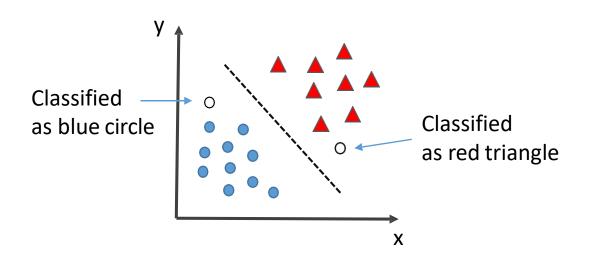
Support Vector Machines (SVMs)



Training:

 Given a training set of items from two classes a SVM learns a hyperplane that separates the items from both classes

Support Vector Machines (SVMs)



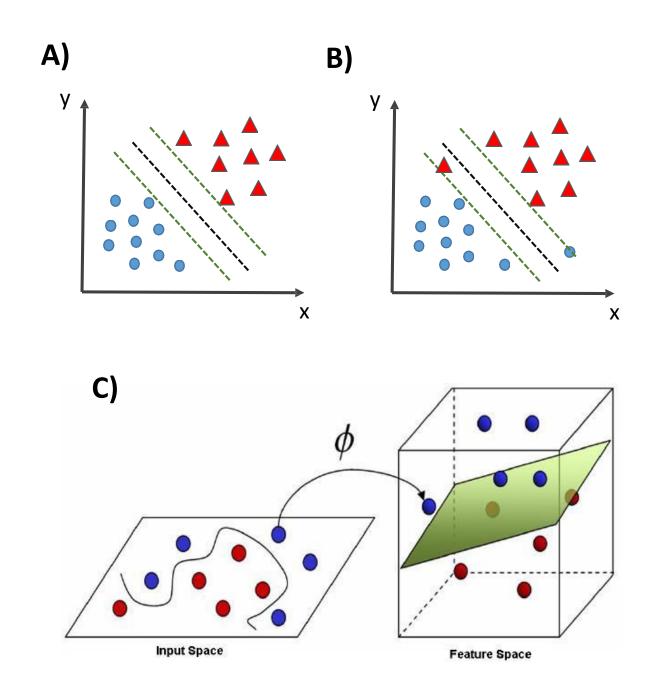
Training:

 Given a training set of items from two classes a SVM learns a hyperplane that separates the items from both classes

Classification:

 New items with unknown class affiliation classified depending on the side of the hyperplane

- a) SVMs learn hyperplanes with maximal margins to improve generalization ability
- b) Over fitting avoided by allowing misclassification of outliers of training set (called softmargin hyperplane)
- c) Non-linear classifier achieved by mapping data to higher dimensional feature space via non-linear mapping function (kernel). By learning hyperplane in feature space, non-linear classifier achieved in input space



SVMs for Gene Identification

• SVMs can be used to classify ORFs into coding and non-coding (e.g. Krause et al. NAR 2008)

Training:

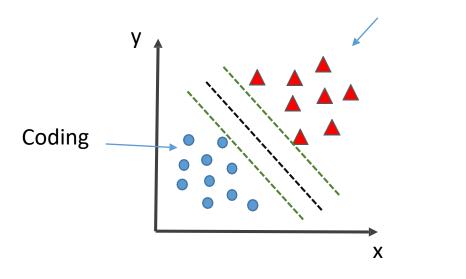
- Generate training set of ORFs known to be coding (positive training set) and ORFs known to be non-coding (negative training set)
- For each ORF, count codon frequencies
- Represent each ORF as 61 dimensional vector of codon frequencies
- Train SVM to distinguish between to sets of ORFs

ORF: ATGGCTATCGACGAAAACAAACAGAA...

Our **ORF** has the frequencies:

ATG = 0.1 GCT = 0.02 ATC = 0.001 GAC = 0.02

Non-coding



SVMs for Gene Identification

Classification (gene prediction):

- Extract all ORFs of genome
- Represent each ORF as 61 dimensional vector of codon frequencies
- Apply trained SVM to classify all ORFs into coding and non-coding depending on side of hyperplane
- scikit-learn library in Python
 - sklearn.svm

ORF: ATGGCTATCGACGAAAACAAACAGAA...

Codons:

GCT

GAC

GAC

etc.

Our **ORF** has the frequencies:

ATG = 0.1 GCT = 0.02 ATC = 0.001 GAC = 0.02

Classified as non-coding
Classified as Coding



Hidden Markov Models

The dishonest casino:

Known information:

- Casino has 2 die, fair dice, loaded dice
- Casino player switches back & forth between dies
- Once either of the dice is used, it will continue to be used for a while

Observations:

• Sequence of roles:

3531363644162...

Question:

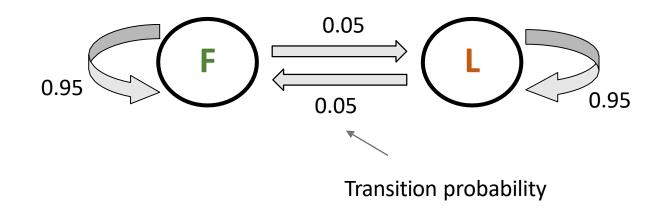
Which dice used for each role?

	Probability	
Number	Fair	Loaded
1	1/6	1/10
2	1/6	1/10
3	1/6	1/10
4	1/6	1/10
5	1/6	1/10
6	1/6	1/2



Dishonest Casino Example

	Probability	
Number	Fair	Loaded
1	1/6	1/10
2	1/6	1/10
3	1/6	1/10
4	1/6	1/10
5	1/6	1/10
6	1/6	1/2



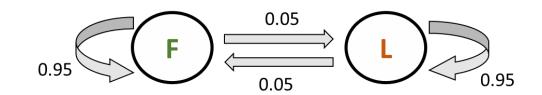


Dishonest Casino Example

Observation:

Sequence of roles:

Obs: 316252313636646626 ...



Hidden information:

Sequence of states, e.g.

S1: FFFFFFFFLLLLLLLL....

S2: FFFFFFFFFFFFF....

S3: LLLFFFFFFLLLLLLLLLL.....

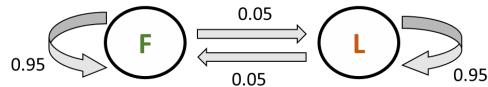
Probability		
Number	Fair	Loaded
1	1/6	1/10
2	1/6	1/10
3	1/6	1/10
4	1/6	1/10
5	1/6	1/10
6	1/6	1/2



Dishonest Casino Example

Obs: 3 1 6 2 5 2 3 1 3 6 3 6 6 4 6 6 2 6

S1: FFFFFFFFLLLLLLLLL



Transition to L state



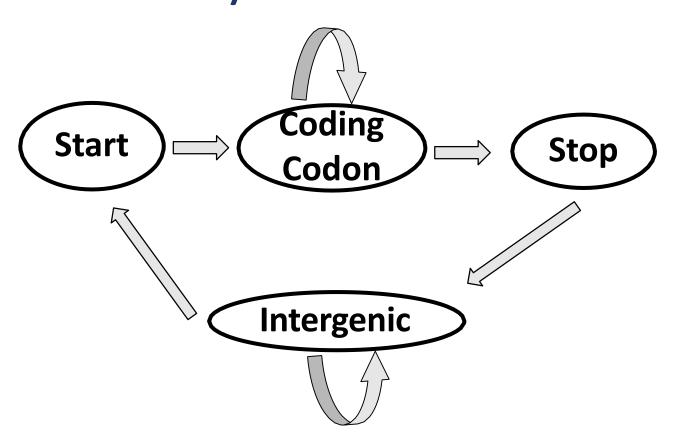
$$P(Obs|S2) = 4.1e-15$$

• • • • •

Aim: Identify most likely path through model, which is S1 in this case, 9 roles fair dice, 9 roles loaded dice

	Probabilit	
Namelogi	У	
Number	Fair	Loaded
1	1/6	1/10
2	1/6	1/10
3	1/6	1/10
4	1/6	1/10
5	1/6	1/10
6	1/6	1/2

Simple HMM for Gene Identification in Prokaryotes

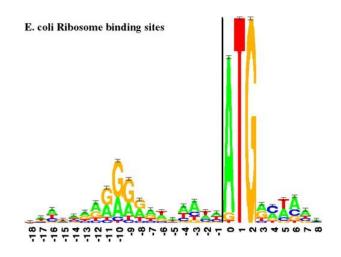


Training: Train model to learn codon frequencies of coding and non-coding sequences

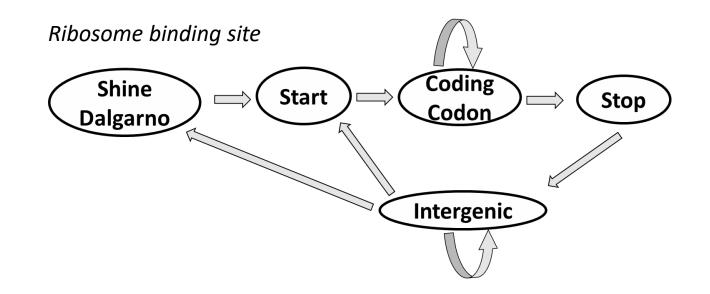
Classification: Given observed DNA sequence, find most likely path through model to divide sequence into coding and non-coding regions

More Complex HMM for Gene Identification in Prokaryotes

Include signal for ribosomal binding site

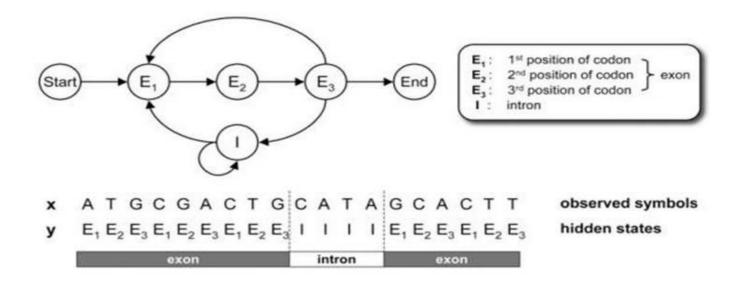


A/G-rich region about 10 bases upstream of the start codon Helps recruit ribosome to mRNA

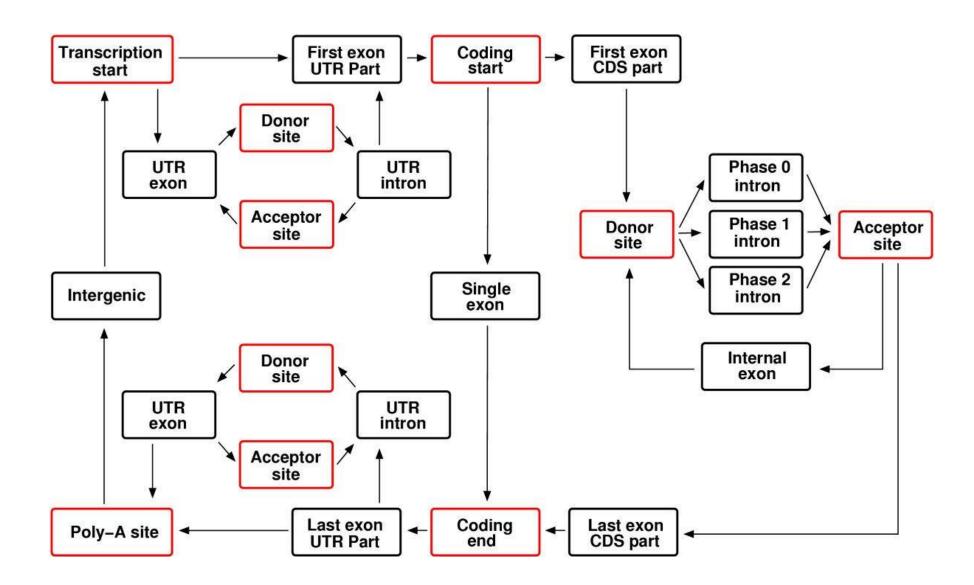


Gene Prediction in Eukaryotic Genomes

 A Simple HMM for Modeling Eukaryotic Genes



• hmmlearn() Python package. https://github.com/hmmlearn/hmmlearn

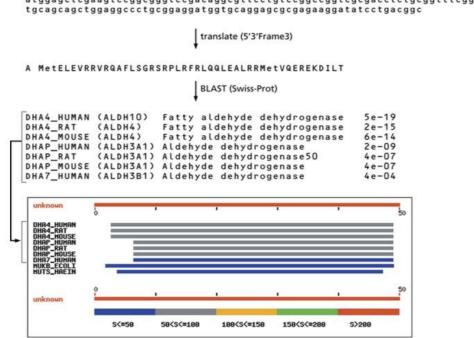


Overview Characteristics that Can be Incorporated into HMM

- Coding regions begin with start codon and end with stop codon
- Coding regions do not contain stop codons
- Motifs of splice sites
- Sequence characteristics of UTRs
- Sequence characteristics of promoter regions
- Length distribution of coding regions, exons and introns
- polyA site

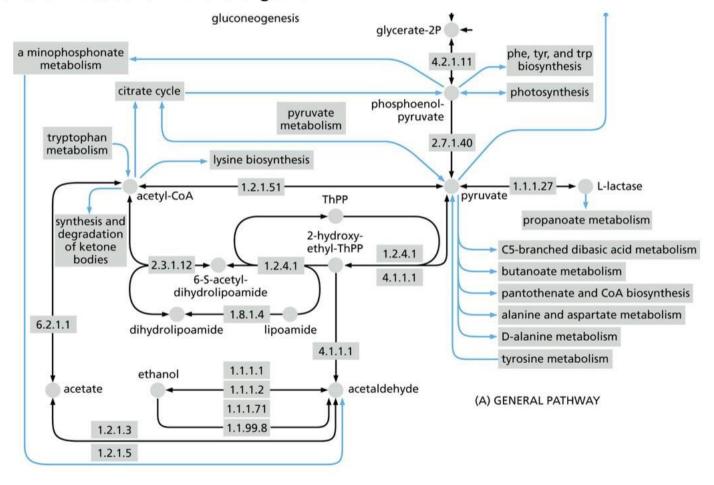
Genome annotation

- Once you have identified bona fide genes, what do you do with them?
- Use homology searchers (e.g. BLAST) to identify putative functions for genes, as well as identify other genetic elements such as functional RNAs and repeats
- Gene ontology provides a standard vocabulary to describe gene functions
- Annotations can be done for a whole genome/set of genomes using online services (e.g. IMG-M, KAAS)



Pathway analysis

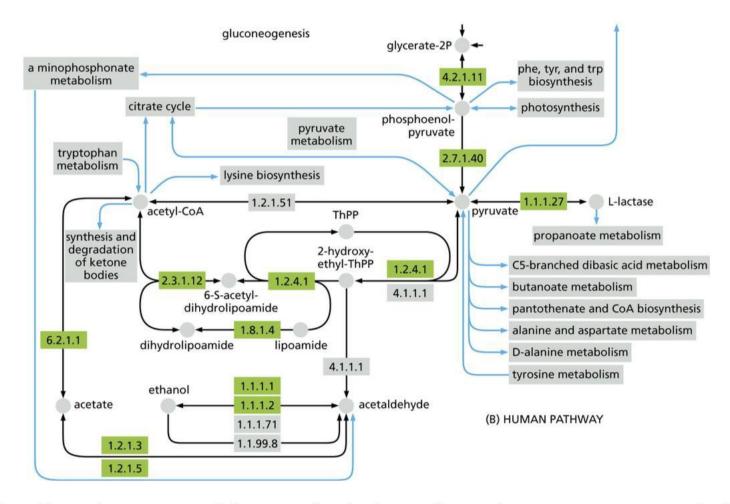
Once genes have been annotated, they are then fit into metabolic pathways to try and decipher the metabolism of the organism



Each gray box with a number represents an enzyme/protein in the pathway

Pathway analysis

We can color in the boxes based on which proteins we find in the organism



Also, if you have most of the proteins in the pathway, but one or two are missing, it suggests functions for some of your "unknown"/hypothetical proteins

Pathway Databases

 KEGG: Kyoto Encyclopedia of Genes and Genomes (https://www.genome.jp/kegg/)

Reactome (https://reactome.org/)

GO: Gene Ontology (http://geneontology.org/)

Take-Home points

- Eukaryotic gene-finding is more difficult because of the presence of introns and exons, and also because exons are short and some exons may have no coding sequence
- Exon finding can be aided by using transcriptional signals and splice sites
- Determining correct starting positions and length of exons is essential as all predicted exons must eventually be linked together to form a total coding sequence
- Once you have found genes, they can be annotated and used to infer metabolism
- Practical things you might want to know:
 - How to identify ORFs
 - Differences between prokaryotic and eukaryotic genes, and
 - Bioinformatics strategies for eukaryotic gene finding
 - How to read pathway maps