

### **Computational Biology** (BIOSC 1540)

### Lecture 04A

Gene prediction

Foundations

Jan 28, 2025



### Announcements

Assignments

- Assignment P01C is due Saturday (Feb 1)
- Assignment P01D will be released on Saturday (Feb 1)

#### Quizzes

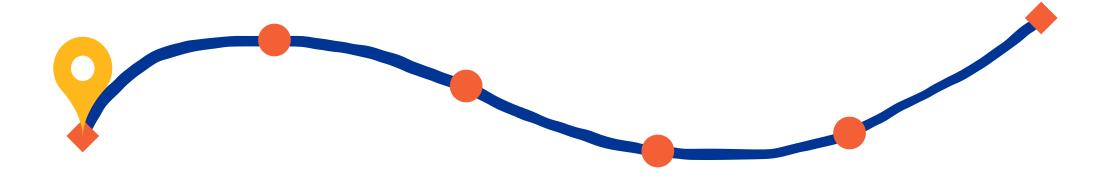
- Quiz 01 is today and will cover lectures 02A to 03B
- Quiz 02 is on Feb 18 and will cover lectures 04A to 06B

**CBytes** 

- CByte 01 is live and will expire on Feb 1
- CByte 02 is live and will expire on Feb 7
- CByte 03 will be released on Feb 8

**Next reward:** Checkpoint Submission Feedback

**ATP until the next reward:** 1,783



#### Quiz 01

Please put away all materials as we distribute the quiz

Sit with an empty seat between you and your neighbors for the quiz

Fill out the cover page, and do not start yet

### Quiz end at 9:50 am

https://www.clockfaceonline.co.uk/clocks/digital/

When you are finished, please hold on to your quiz and feel free to doodle, write anything, tell me a joke, etc. on the last page

The biological importance of gene prediction and genome annotation

## Genome assembly provides the sequence, but gene prediction and annotation assign meaning

In previous lectures, we explored the process of creating contiguous sequences with genome assembly

TACGATCGGATTACGCGTAGGCTAGCTTACGGACTCGATGTACGATCGGATTACG

DNA sequence (i.e., contig)

Gene prediction and genome annotation transform **raw sequence data into actionable biological insights**, identifying functional elements like genes, regulatory regions, etc.

### Gene prediction locates gene-containing regions and functional elements within a genome

Genes encode proteins, enzymes, and non-coding RNAs essential for cellular function

**Predicted genes** 

#### We often use Hidden Markov Models (HMMs) to

statistically predict gene locations

This is also called "structural annotation"

(Topic for L04B)

# Genome annotation links gene sequences to biological functions and processes

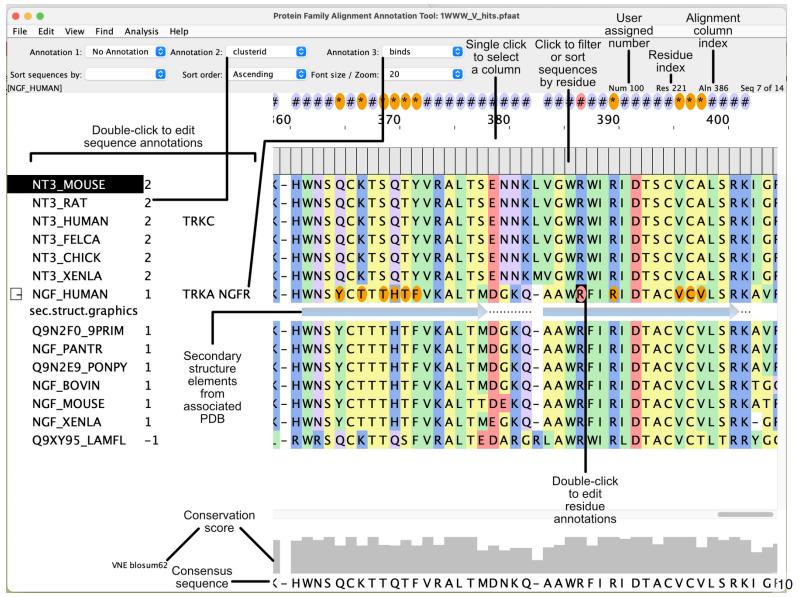
Annotation assigns putative functions to genes through experimental evidence, similarity to known genes, or *ab initio* predictions.

Functional annotation helps classify genes into pathways (e.g., KEGG), ontologies (e.g., GO terms), and systems (e.g., metabolic networks).

Your search is limited to records that exclude: Homo sapiens (taxid:9606), models (XM/XP) Full Entrez Query			
Job Title	NM_001275:Homo sapiens chromogranin A (CHGA),	Filter Results	
RID	M3JFFUAU010 Search expires on 08-02 01:03 am Download All ▼	Organism only top 20 will appear exclude	
Program	BLASTN ? <u>Citation</u> ~		
Database	refseq_rna <u>See details</u> ✓	Type common name, binomial, taxid or group name	
Query ID	<u>NM_001275.4</u>	+ Add organism	
Description	Homo sapiens chromogranin A (CHGA), transcript variant 1, mRNA	Percent Identity E value	
Molecule type	nucleic acid	to	
Query Length	1985		
Other reports	Distance tree of results MSA viewer ?	Filter         Reset	
Descriptions       Graphic Summary       Alignments       Taxonomy         Sequences producing significant alignments       Download ×       Manage Columns ×       Show       100 ×       ©			
Select all 7 sequences selected GenBank Graphics Distance tree of result			
	Description	MaxTotalQueryEPer.ScoreScoreCovervalueIdent	
Macaca mu	latta chromogranin A.(CHGA), mRNA	3081 3081 99% 0.0 94.77% <u>NM 001278450.1</u>	
Macaca fascicularis chromogranin A (CHGA), mRNA		3075 3075 99% 0.0 94.72% <u>NM 001319389.1</u>	
Equus caballus chromogranin A (CHGA), mRNA		1628 1628 93% 0.0 83.08% <u>NM 001081814.2</u>	
	chromogranin A (CHGA), mRNA	1548 1548 95% 0.0 81.91% <u>NM 181005.2</u>	
Sus scrofa chromogranin A (CHGA), mRNA		1415 1415 80% 0.0 83.08% <u>NM 001164005.2</u>	
Rattus norvegicus chromogranin A (Chga), mRNA		278 278 20% 4e-72 80.34% <u>NM 021655.2</u>	
Mus musculus chromogranin A (Chga), mRNA 176 176 11% 2e-41 81.61% NM 007693.2			

# Gene prediction and annotation provides the starting point for downstream analyses and discoveries

All downstream (i.e., after) analyses are often genespecific, so any errors here will propogate



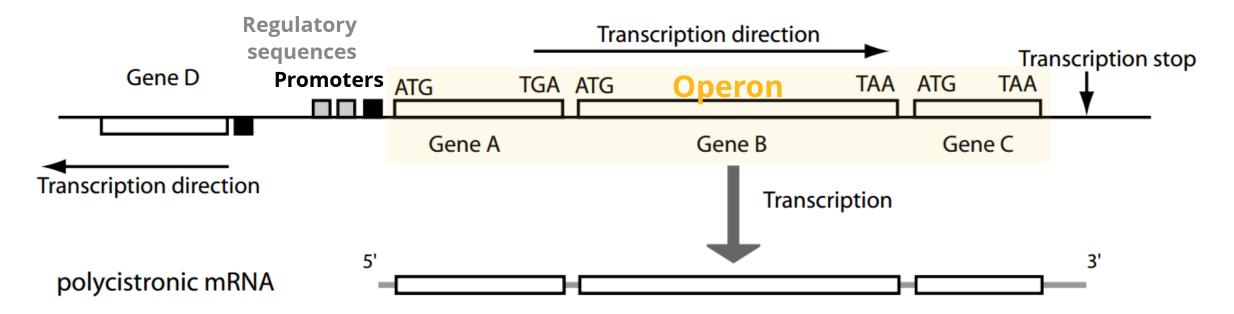


## Key differences and challenges of prokaryotic and eukaryotic gene prediction

**Prokaryotes** 

# Prokaryotic genomes are relatively straightforward due to their compact structure

Most genes are organized in **operons**—clusters of co-transcribed genes under a single promoter.



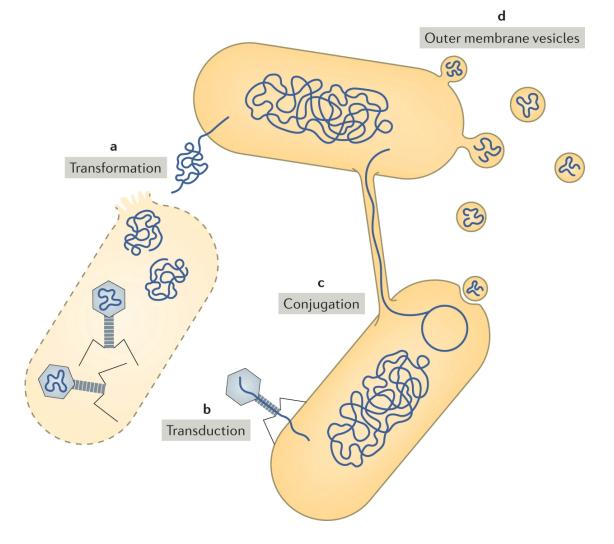
**Polycistronic**: coding sequences for two or more polypeptide chains that are transcribed in succession from the same promoter

Most genes are readily identifiable by open reading frame (ORF) detection.

# While prokaryotic genomes are simpler, challenges still exist

**Horizontal gene transfer**: Foreign genes may lack organism-specific sequence patterns, complicating detection.

**Short genes**: Genes shorter than 150 bp are harder to distinguish from random ORFs.



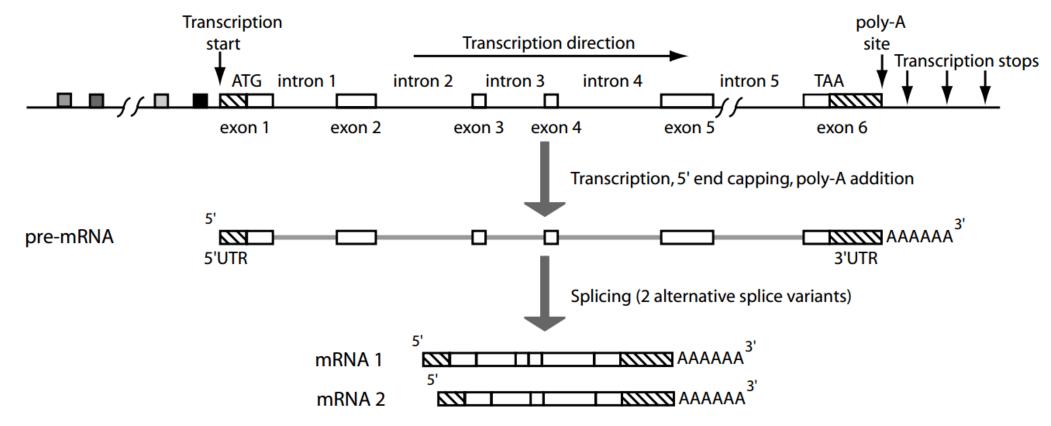


## Key differences and challenges of prokaryotic and eukaryotic gene prediction

**Eukaryotes** 

### Eukaryotic genomes are more complex due to noncoding regions and regulatory sequences

Genes contain **introns** (non-coding regions) and **exons** (coding regions), requiring splicing for expression



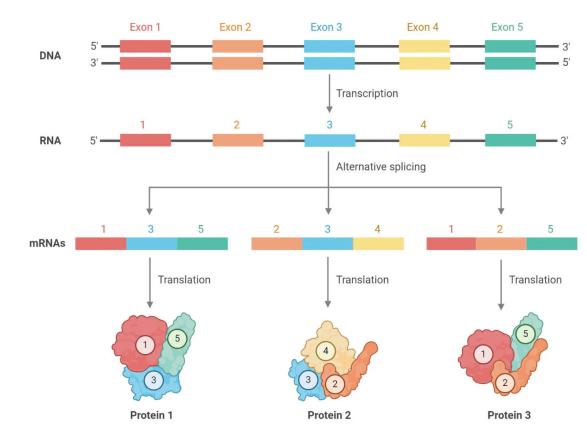
Intergenic (i.e., between genes) regions are large and often contain regulatory elements (e.g., enhancers, silencers).

# Eukaryotic gene prediction faces additional challenges due to complexity

Eukaryotic genes undergo splicing which will remove introns and then join exons to form mature mRNA

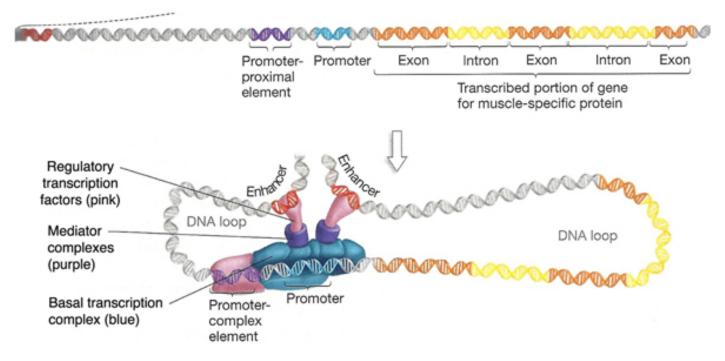
Gene prediction has to predict intron boundaries, which are often much longer than exons and not always consistent

Furthermore, eukaryotes use alternative splicing to join different exons of the same gene to form multiple different proteins



# Regulatory elements are critical for expression but are hard to predict

Promoters, enhancers, and silencers regulate transcription but are often far from the gene they control.



These elements lack a universal sequence pattern, making them difficult to identify.

# Eukaryotic gene prediction faces additional challenges due to complexity

**Repetitive sequences:** Large portions of eukaryotic genomes are repetitive, often confusing prediction algorithms.

## The principles behind *ab initio* and homology-based gene prediction approaches

Ab initio

## *Ab initio* gene prediction identifies genes based on intrinsic sequence features

Detects genes without requiring prior knowledge or reference sequences.

Relies on patterns like:

- Start and stop codons.
- Coding sequence biases (e.g., codon usage, GC content).
- Splice sites and promoter regions (in eukaryotes).

We use HMMs to detect these

1 ACCAGGCTTTATAATGTGGGAGAGCCTCCGGGGGGGGTTCATAATGCGATG 3 ATATAAGCCAGGGAGGCTGAAAGAGATCCGGTTACTATACTCTTTAT 4 AAGGGATGATGTCTCTCTGCGGTGATTCGGCGACTGGTTTAACCACAATA 5 ATAATGACGCAAACGTACAAACGGATCCTCCGGTCACGTTAAGGCGAGAT 6 AAAAGGGCACTGCTGGAGTACGTCACGTAGTTCCCCGATAAGATTAAGCCA 7 CAGTCCCTGGGCTGATAATGGTCATCGCATACCGGGGTCCAGATATTAGC 8 ACGGCTGCTCAGGAGCAGGTGGGAGCCACTGCTGCCATGATTCGCAAAAA 9 ATAACCTATGAACGGACTCCACTTCTAATGGCCCTGAGCATCTGGAGCCG 10 GAGCTAATGCGCAATAGTATGATAATGCGGTGGTCTACCCTAGAACTCGA 12 GGAGCTGGGTTACTGCAGTCCCCATATAAGTCGAGCTGTGGTAATGCGCG 13 CTCATCGAGCAGGTTAGGAAGGAACGCAAGATGATGGGGGCTATCTAGCAT 14 CAAATAAGGCGCTTCTGATCCCAACGCGTGGTGACCGTTAAGTAATAATG 15 AGGATCAAAAACAGCAAATGGTAGTGACCGAGCGTCGACCGAACATCGAC 16 TGATAATGCTGACGGAGGGGGGGGGGGGGGCGGTCGTCACATAAAAGTAGCGATGTATCT 17 TAAGGCGCGCCGAGGTTGATGATGGAGAGGTGGATCTGATGAGGCATTTG 18 ACTCCCTCGTGATGATGCTGATCTCTCAAGTTGCTTCATTGAATTATATA 19AGAGCCTGGTCAGGTAGTGCGATACTAGGGACGTTCAATAAATGATAATG 20 AAAAGCACGTACTGGCAAGAGTCAAGTAGTACGTGGATAAAAGGAGTCGG 21 CGGCTGCTGGGTCCAGCTCTGCTGCCATGATTCGGCCGCGGCCACTAAAA 22 ATCCAAATAATGCCATTCGAGGTCAAAATCGTCAAGGACAGTTAAAAAAT 23 ATAAGAGGGCTACGATTGCCGTCACTTCGTTGCATACACCCCTTAAAAGT 24 TTGCAACGCTGTACCTGACGACGTCATCAAGGAGGTCTTAATGAGCATGC 25 AAACGCGACAGATACTCTGCTATGATTATGGTCCTGACGAAATACTGATG 26 AGCCGCTGTGATTGTCTGCTGTATTGCACTGACGATGCCATACTTATCAA 27 TTCGTCACTGATATAAGCACTCGCATCTAGGCGACGGTACACGGCAGGTT 28 AATGCGCAGTGTCATTAATAATGTGGGAGAAAGATTAGTGCGCTGACCTT 29 ATGATTTCTATGCAAAGTTCTCATGATGCGACATTACTGGAGGTAGGGCG

## Ab initio methods are powerful but limited by genome complexity

**Prokaryotes:** Compact genomes make ORF detection easier, but short genes and overlapping genes can still pose challenges.

#### **Eukaryotes:**

- Accurate prediction requires identifying introns, exons, and splice sites.
- Alternative splicing and non-coding regions can confound predictions.

False positives and false negatives are common, especially in large, complex genomes.

## The principles behind *ab initio* and homology-based gene prediction approaches

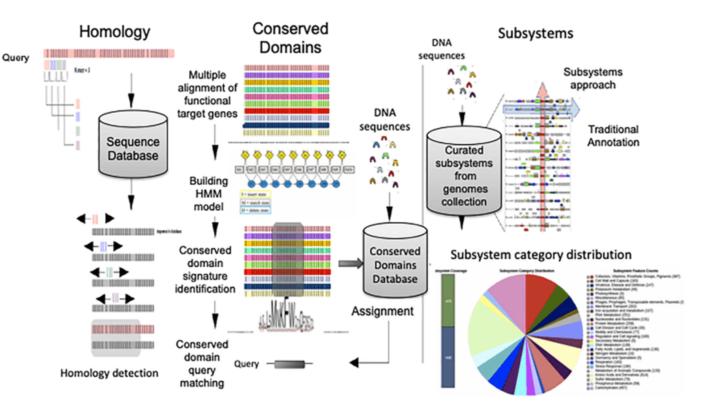
Homology

### Homology-based gene prediction identifies genes by comparing sequences to known databases

Searches for regions of similarity between the query genome and annotated sequences in databases.

Assumes genes are evolutionarily conserved across species.

Tools often use sequence alignment methods (e.g., BLAST, HMMER) to detect homologous genes.



# Homology-based methods depend on accurate and complete reference data

**Advantages:** High accuracy for conserved genes with reliable reference sequences.

### Limitations:

- Cannot predict novel genes or those without significant similarity to database entries.
- Errors in reference annotations propagate into predictions.
- Divergence and mutation can obscure homology signals.

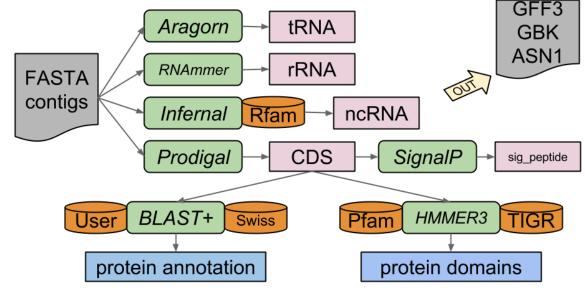
# Combining *ab initio* and homology-based methods improves gene prediction accuracy

*Ab initio* methods can detect novel genes, filling gaps left by homology-based methods.

Homology-based methods provide functional validation for predictions from *ab initio*.

Integrated pipelines (e.g., Prokka, AUGUSTUS) use both approaches to produce more reliable results.

#### Prokka pipeline (simplified)



### Practical examples of gene prediction tools and how to interpret their outputs

Prokka

# Gene prediction tools apply computational principles to real-world problems

Selecting the right tool depends on the organism, genome complexity, and research goals.

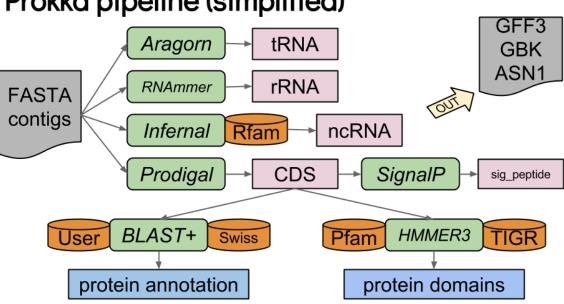
## Prokka is a popular tool for prokaryotic genome annotation

Combines *ab initio* and homology-based methods for prokaryotic genomes.

Annotates coding sequences, tRNAs, rRNAs, and regulatory regions.

#### Outputs:

- GenBank files for visualization.
- FASTA files of predicted genes/proteins.
- Summary statistics of genome features.



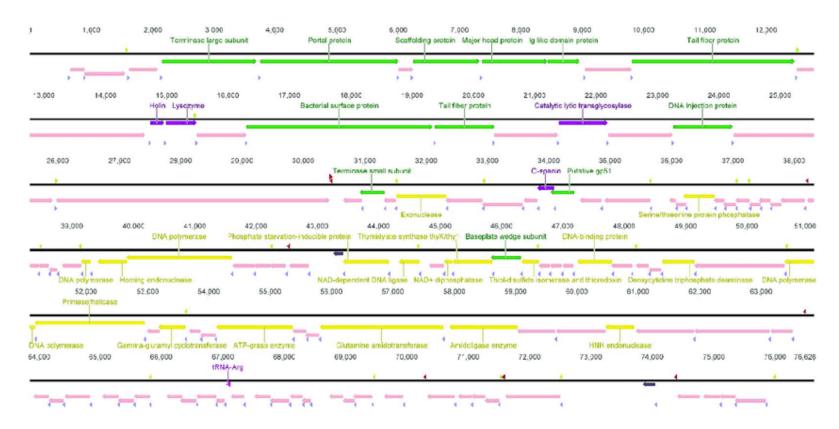
#### Prokka pipeline (simplified)

# Prokka provides an efficient workflow for bacterial genome annotation

**Inputs:** Assembled genome in FASTA format.

Outputs:

- A list of coding sequences (CDSs) with predicted functions.
- Identification of antibiotic resistance genes (e.g., beta-lactamases).



### Prokka output files example

>ECNNONJI\_02637 Dihydrofolate reductase MTLSILVAHDLQRVIGFENQLPWHLPNDLKHVKKLSTGHTLVMGRKTFESIGKPLPNRRN VVLTSDTSFNVEGVDVIHSIEDIYQLPGHVFIFGGQTLFEEMIDKVDDMYITVIEGKFRG DTFFPPYTFEDWEVASSVEGKLDEKNTIPHTFLHLIRKK

Extension	Description	
.gff	This is the master annotation in GFF3 format, containing both sequences and annotations. It can be viewed directly in Artemis or IGV.	
.gbk	This is a standard Genbank file derived from the master .gff. If the input to prokka was a multi-FASTA, then this will be a multi-Genbank, with one record for each sequence.	
.fna	Nucleotide FASTA file of the input contig sequences.	
.faa	Protein FASTA file of the translated CDS sequences.	
.ffn	Nucleotide FASTA file of all the prediction transcripts (CDS, rRNA, tRNA, tmRNA, misc_RNA)	
.sqn	An ASN1 format "Sequin" file for submission to Genbank. It needs to be edited to set the correct taxonomy, authors, related publication etc.	
.fsa	Nucleotide FASTA file of the input contig sequences, used by "tbl2asn" to create the .sqn file. It is mostly the same as the .fna file, but with extra Sequin tags in the sequence description lines.	
.tbl	Feature Table file, used by "tbl2asn" to create the .sqn file.	
.err	Unacceptable annotations - the NCBI discrepancy report.	
.log	Contains all the output that Prokka produced during its run. This is a record of what settings you used, even if thequiet option was enabled.	
.txt	Statistics relating to the annotated features found.	
.tsv	Tab-separated file of all features: locus_tag,ftype,len_bp,gene,EC_number,COG,product	

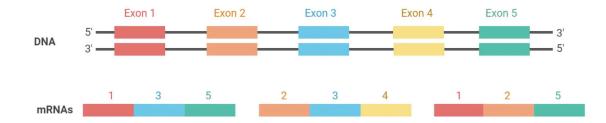
### Practical examples of gene prediction tools and how to interpret their outputs

AGUSTUS

# AUGUSTUS excels at predicting genes in eukaryotic genomes

Focuses on *ab initio* gene prediction but integrates hints like RNA-seq data for improved accuracy

Suitable for genomes with limited or no reference annotations



#### Outputs:

- Predicted gene structures, including exons, introns, and UTRs.
- GFF3 files for integration with genome browsers.

### Practical examples of gene prediction tools and how to interpret their outputs

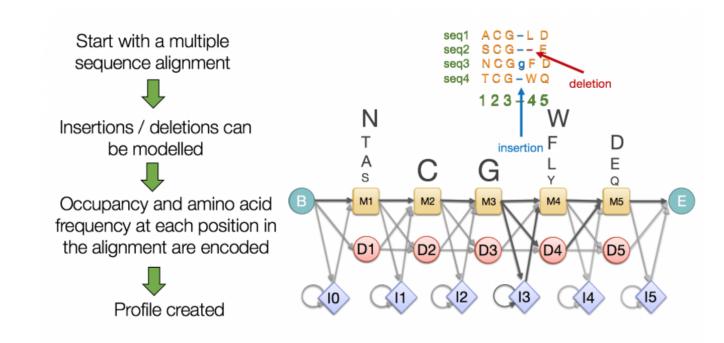
## HMMER uses Hidden Markov Models (HMMs) for detecting homologous genes

Aligns query sequences to profiles of known genes/proteins in curated databases like Pfam.

Identifies genes based on conserved domains or motifs.

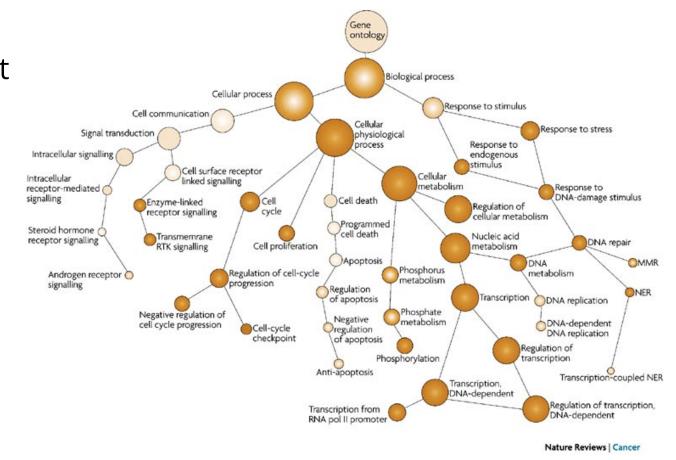
Outputs:

- Alignment scores for detected homologs.
- Functional annotations from database hits.



# Interpreting outputs requires understanding key metrics and visualizations

- Gene locations: Coordinates of start and stop codons or exon-intron boundaries.
- Scores: Confidence values for predictions, such as e-values in HMMER or reliability scores in AUGUSTUS.
- Functional annotations: Gene ontology (GO) terms, protein domains, or pathway mappings.



### Before the next class, you should

## Lecture 04A: Lecture 04B: Gene prediction -Foundations Methodology Today Thursday

- Start P01C (due Jan 31)
- Work on CByte 01 and CByte 02