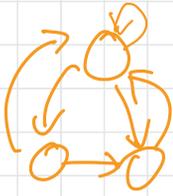


# Review:

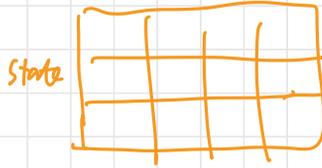
## ① HMM



transition

$$T[p, p']$$

Symbols



emission

$$E[p, s]$$



$$D[i, p] = \max_{p'} D[i-1, p'] \times T[p', p] \times E[p, s_i]$$

## ② Gene

prokaryotes v.s. eukaryotes

genetic code, start, stop, codons,

open reading frame.

codon bias.

# <http://www.kazusa.or.jp/codon/>

*Escherichia coli* O157:H7 EDL933 [gbbct]: 5347 CDS's (1611503 codons)

fields: [triplet] [frequency: per thousand] ([number])

UUU 22.2 ( 35846)	UCU 8.7 ( 14013)	UAU 16.5 ( 26648)	UGU 5.2 ( 8458)
UUC 15.9 ( 25565)	UCC 8.9 ( 14420)	UAC 12.3 ( 19766)	UGC 6.4 ( 10285)
UUA 13.8 ( 22316)	UCA 8.1 ( 13117)	UAA 2.0 ( 3163)	UGA 1.1 ( 1751)
UUG 13.0 ( 20904)	UCG 8.8 ( 14220)	UAG 0.3 ( 435)	UGG 15.3 ( 24656)
CUU 11.4 ( 18366)	CCU 7.2 ( 11657)	CAU 12.8 ( 20631)	CGU 20.2 ( 32590)
CUC 10.5 ( 16869)	CCC 5.6 ( 8961)	CAC 9.4 ( 15116)	CGC 20.8 ( 33547)
CUA 3.9 ( 6257)	CCA 8.4 ( 13507)	CAA 14.7 ( 23703)	CGA 3.8 ( 6166)
CUG 51.1 ( 82300)	CCG 22.4 ( 36178)	CAG 29.4 ( 47324)	CGG 6.2 ( 9955)
AUU 29.7 ( 47838)	ACU 9.1 ( 14639)	AAU 19.2 ( 30864)	AGU 9.4 ( 15123)
AUC 23.9 ( 38504)	ACC 22.8 ( 36724)	AAC 21.7 ( 34907)	AGC 16.0 ( 25800)
AUA 5.5 ( 8835)	ACA 8.1 ( 13030)	AAA 34.0 ( 54723)	AGA 2.9 ( 4656)
AUG 27.2 ( 43846)	ACG 15.0 ( 24122)	AAG 11.0 ( 17729)	AGG 1.8 ( 2915)
GUU 18.1 ( 29200)	GCU 15.4 ( 24855)	GAU 32.8 ( 52914)	GGU 24.2 ( 38983)
GUC 14.8 ( 23870)	GCC 25.2 ( 40571)	GAC 19.2 ( 30953)	GGC 28.1 ( 45226)
GUA 10.9 ( 17561)	GCA 20.7 ( 33343)	GAA 39.3 ( 63339)	GGA 8.9 ( 14286)
GUG 26.2 ( 42261)	GCG 32.3 ( 52091)	GAG 18.7 ( 30158)	GGG 11.8 ( 18947)

Coding GC 51.50% 1st letter GC 58.44% 2nd letter GC 40.88% 3rd letter GC 55.17%

$$\frac{\text{Pr}(\text{seq} | \text{gene})}{\text{Pr}(\text{seq} | \text{random})}$$

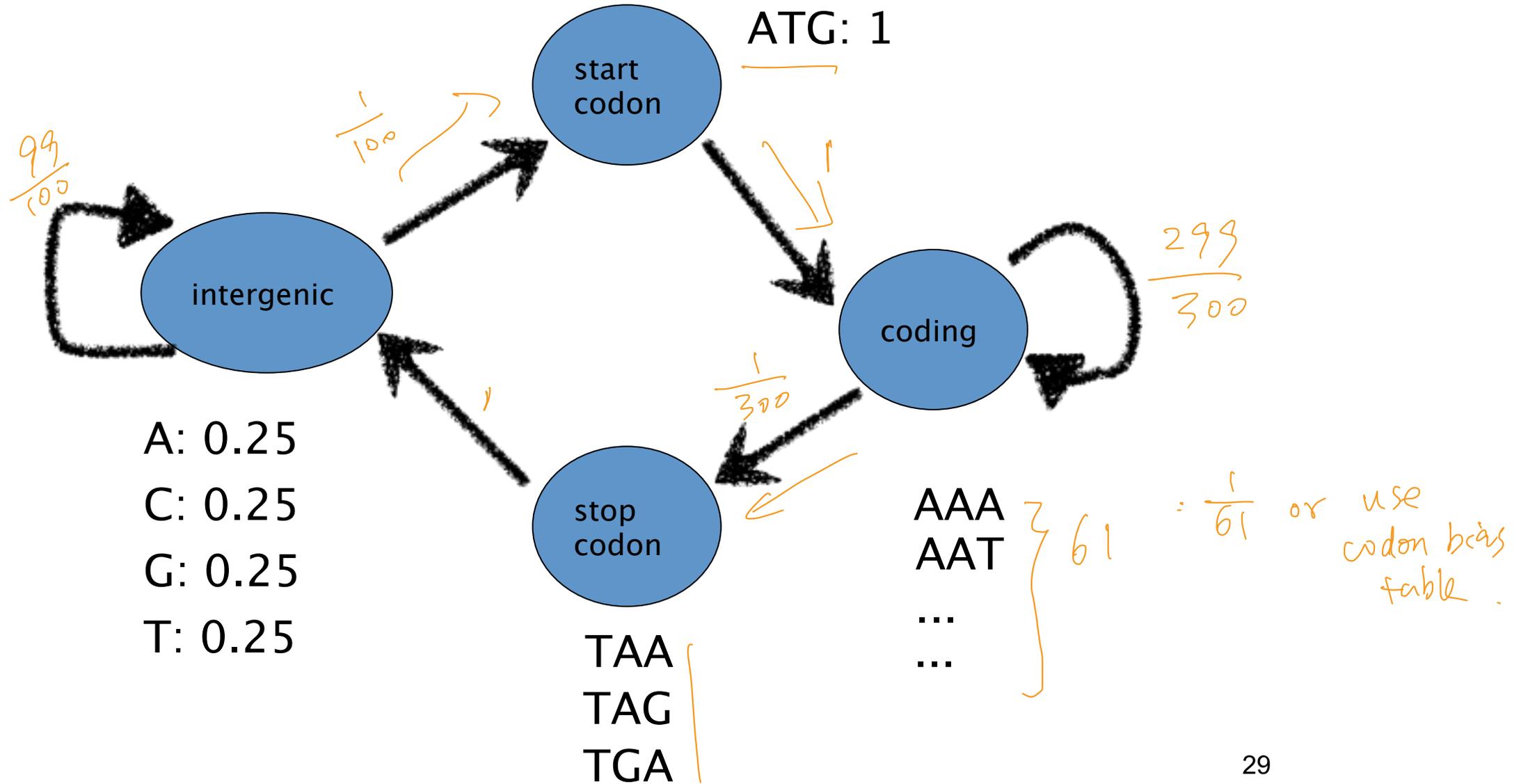
# A Better Gene Finder

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- We can use the log likelihood ratio score to evaluate each ORF. Each codon XYZ contributes score
- $\log \frac{P(XYZ)}{P(X)P(Y)P(Z)}$
- An ORF is predicted as a gene if the sum of codon score is above a threshold.
- This is better. But it does not catch the correlation between adjacent codons.



# Prokaryote gene finding HMM



# Gene Prediction as HMM

---

Symbols:     A T A A T G A A A T A A C C A  
                  ↑ ↑ ↑     ↑            ↑            ↑            ↑ ↑ ↑  
State path:   *i* → *i* → *i* → *s* → *c* → *t* → *i* → *i* → *i*

*s* start codon  
*c* coding  
*i* intergenic  
*t* stop codon

- Annotated the sequence with most probable path of states. This provides a reasonable answer to gene prediction.
- A difference here: emission is not fixed length. But this does not forbid us from solving it with dynamic programming.

# Dynamic Programming

---

Symbols:     A T A A T G A A A T A A C C A  
                  ↑   ↑   ↑        ↑            ↑            ↑            ↑   ↑   ↑  
State path:   *i* → *i* → *i* → *s* → *c* → *t* → *i* → *i* → *i*

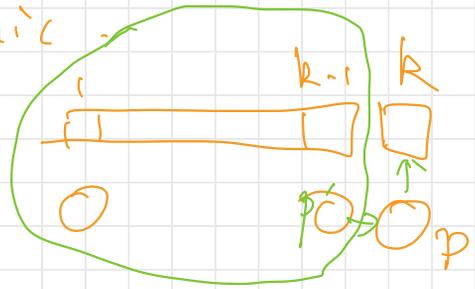
*s* start codon  
*c* coding  
*i* intergenic  
*t* stop codon

- Define  $D[k,p]$  be the max probability achieved by first  $k$  symbols for a path with the last state being  $p$ .



$$D[k, p]$$

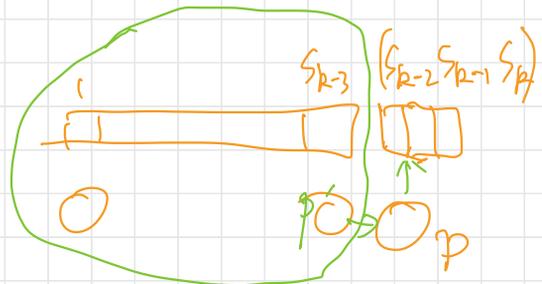
Case 1:  $p = \text{intergenic}$



$$D[k, p] = \max_{p'} D[k-1, p'] \times T[p', p] \times E[p, s_k]$$

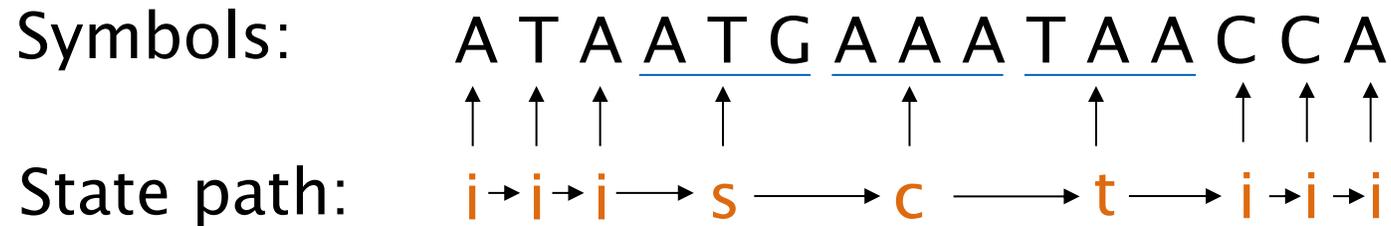
Case 2:  $p \neq \text{intergenic}$

$$D[k, p] = \max_{p'} D[k-3, p'] \times T[p', p] \times E[p, s_{k-2} s_{k-1} s_k]$$



# Recurrence Relation

---



**s** start codon  
**c** coding  
**i** intergenic  
**t** stop codon

For  $p = \text{intergenic}$

$$D[k, p] = \max_{p'} \{ D[k-1, p'] \Pr(p|p') \Pr(S_k|p) \}$$

For  $p = \text{start, coding, or stop}$

$$D[k, p] = \max_{p'} \{ D[k-3, p'] \Pr(p|p') \Pr(S_{k-2}S_{k-1}S_k|p) \}$$

# Dynamic Programming

---

- Once the recurrence relation is obtained. It is straightforward to work out a dynamic programming algorithm.

# Easy enough to implement?

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- This is very easy to implement.
- If desired, one can also use a higher-order HMM.
- Parameter training must be done carefully.





# PSWM

## Positional Specific Weight Matrix

	1	2	3	4	5	6
A	0.1	0.76	0.1	0.61	0.56	0.1
C	0.1	0.1	0.1	0.1	0.1	0.04
G	0.03	0.1	0.2	0.1	0.2	0.04
T	0.77	0.04	0.6	0.17	0.14	0.82

$$p_i(a)$$

$$q(a) = \frac{1}{4}$$

$$\text{score}(s_1 \dots s_6) = \log \frac{\text{Pr}(s_1 \dots s_6 | \text{promoter})}{\text{Pr}(s_1 \dots s_6 | \text{random})}$$

$$= \log \frac{\prod_{i=1}^6 p_i(s_i)}{\prod_{i=1}^6 q(s_i)}$$

$$= \log \prod_{i=1}^6 \frac{p_i(s_i)}{q(s_i)}$$

$$= \sum_{i=1}^6 \log \frac{p_i(s_i)}{q(s_i)}$$

# Summary

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- HMM is a general model to predict some hidden states by examining emitted symbols.
- HMM can be used in gene prediction to harvest the codon bias and adjacent codon correlation.
- Gene prediction can use more information about the gene structure than codon bias.
- We only talked about prokaryote gene prediction. Eukaryote gene prediction is harder because of introns.