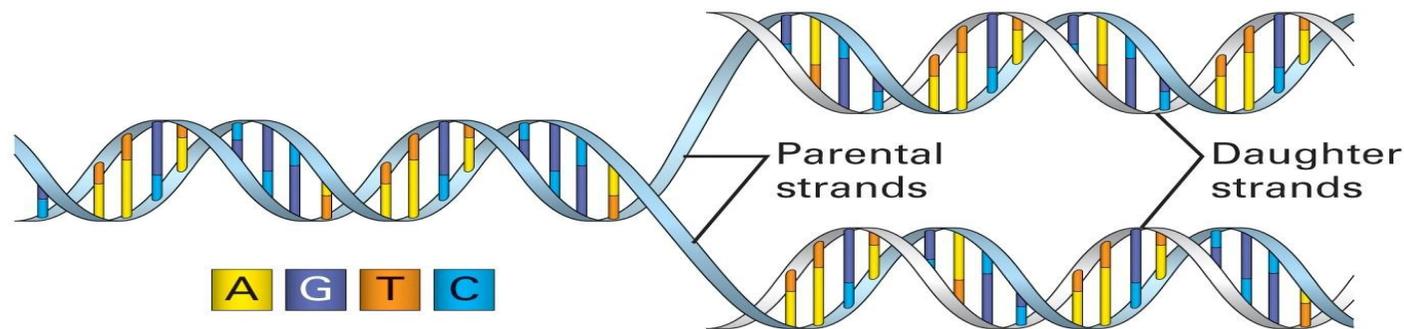


BASICS ON BASES: A-G-T-C AS WORDS



- The bases Adenine, Guanine, Thymine, and Cytosine form chemical pairs A-T and C-G → DNA double helix

- This lecture approaches the DNA-world by considering *words*, short strings of letters drawn from an alphabet, which in the case DNA is the set of letters A-G-T-C forming *k-words* or *k-tuples* (*k* is the word length).
 - DNA sequences from different regions of a genome differ by their *k-tuple* content and different organisms differ as well.
 - We take a look at computational issues on words, how to count words and how words can be located along a string.
 - Word distribution description includes probabilistic modelling.
 - Some statistics used to describe word frequencies.
-
- Next week lectures:
 - The biological perspective on DNA-world and A-G-T-C.
 - Flow of biological information, DNA, RNA, proteins
 - Next week also Biology for methodological scientists: The reading group in Meilahti campus starts (Wednesday, see the calendar and course list).
 - In the the *wet-lab* biology course, Measurement techniques, you extract DNA from yourselves in Wednesday 23. September.

A cell of an organism contains DNA-molecules, organized into chromosomes

| Organism | #base pairs | #chromosomes |
|---|--------------------|--------------|
| <i>Escherichia coli</i> (bacterium) | 4×10^6 | 1 |
| <i>Saccharomyces cerevisiae</i> (yeast) | 1.35×10^7 | 17 |
| <i>Drosophila melanogaster</i> (insect) | 1.65×10^8 | 4 |
| <i>Homo sapiens</i> (human) | 2.9×10^9 | 23 |
| <i>Zea mays</i> (corn / maize) | 5.0×10^9 | 10 |

DNA codes for proteins

- The DNA-code A-G-T-C through RNA-code, A-G-U-C, codes for 20 different amino acids.
- Trinucleotides (triplets) allow $4^3 = 64$ possible trinucleotides.
- Triplets are also called *codons*.

| | | Second letter | | | | |
|--------------|-----------------------------|-------------------|-------------------|-------------------|--------------|----------------------------------|
| | | U | C | A | G | |
| First letter | U | UUU Phenylalanine | UCU Serine | UAU Tyrosine | UGU Cysteine | Third letter U C A G |
| | | UUC Phenylalanine | UCC Serine | UAC Tyrosine | UGC Cysteine | |
| | UUA Leucine | UCA Serine | UAA Stop codon | UGA Stop codon | | |
| | UUG Leucine | UCG Serine | UAG Stop codon | UGG Tryptophan | | |
| C | CUU Leucine | CCU Proline | CAU Histidine | CGU Arginine | | |
| | | CUC Leucine | CCC Proline | CAC Histidine | CGC Arginine | |
| | CUA Leucine | CCA Proline | CAA Glutamine | CGA Arginine | | |
| | CUG Leucine | CCG Proline | CAG Glutamine | CGG Arginine | | |
| A | AUU Isoleucine | ACU Threonine | AAU Asparagine | AGU Serine | | |
| | | AUC Isoleucine | ACC Threonine | AAC Asparagine | AGC Serine | |
| | AUA Isoleucine | ACA Threonine | AAA Lysine | AGA Arginine | | |
| | AUG Methionine; start codon | ACG Threonine | AAG Lysine | AGG Arginine | | |
| G | GUU Valine | GCU Alanine | GAU Aspartic acid | GGU Glycine | | |
| | | GUC Valine | GCC Alanine | GAC Aspartic acid | GGC Glycine | |
| | GUA Valine | GCA Alanine | GAA Glutamic acid | GGA Glycine | | |
| | GUG Valine | GCG Alanine | GAG Glutamic acid | GGG Glycine | | |

DNA makes new copies of itself, replicates

- In this process, mistakes can occur.
- The cell repair machinery may, or may not, correct the mistakes.
- Mistakes can be moved on as mutations.
- This is one (simple) mechanism that generates differences to DNA-differences between organisms.
- This can be considered as *a string manipulation issue*

Biological string manipulation

- One type of a mutation is *deletion*: removal of one or more contiguous bases (substring)
 - ...TT**G**ATCA... => ...TTTCA...
- Another type is and *insertion*: insertion of a substring
 - ...GGCTAG... => ...GG**TCAAC**TAG...
- Point mutation: substitution of a base
 - ...ACG**G**CT... => ...ACG**C**CT...

Given a DNA sequence, we might ask a number of questions

```
1 atgagccaag ttccgaacaa ggattcgcgg ggaggataga tcagcgcgccg agaggggtga
61 gtcggtaaag agcattggaa cgtcggagat acaactccca agaaggaaaa aagagaaagc
121 aagaagcggg tgaatttccc cataacgcca gtgaaactct aggaagggga aagaggggaa
181 ctggaagaga aggaaggggg cgtcccatc ggagggggac gggggccang tttggaggag
241 actccggccc gaaggggttg gagtacccca gagggaggaa gccacacgga gtagaacaga
301 gaaatcacct ccagaggacc ccttcagcga acagagagcg catcgcgaga gggagtagac
361 catagcgata ggaggggatg ctaggagtgt ggggagaccg aagcgaggag gaaagcaaag
421 agagcagcgg ggctagcagg tgggtgttcc gcccccgag aggggacgag tgaggcttat
481 cccggggaac tcgacttata gtccccacat agcagactcc cggaccccct ttcaaagtga
541 ccgagggggg tgactttgaa cattggggac cagtggagcc atgggatgct cctcccgatt
```

What sort of statistics should be used to describe the sequence?

What sort of organism did this sequence come from?

```
601 cctcccgagg tctctcagc cctcccgagg cctcccgagg cctcccgagg cctcccgagg
661 tccgcgttcc atcctttctt acctgatggc cggcatggtc ccagcctcct cgctggcgcc
721 ggctgggcaa cattccgagg ggaccgtccc ctcggtaatg gcgaatggga cccacaaatc
781 tctctagctt cccagagaga agcagagaga aagtggctct cccttagcca tccgagtgga
841 cgtgcgtcct ccttcggatg cccaggtcgg accgcgagga ggtggagatg ccatgccgac
901 ccgaagagga aagaaggacg cgagacgcaa acctgcgagt ggaaaccgcg tttattcact
961 ggggtcgaca actccgagga cctcccgagg cctcccgagg cctcccgagg cctcccgagg
```

Does the description of this sequence differ from the description of other DNA in the organism?

```
1021 atccctggct tccccctat tccccctat tccccctat tccccctat tccccctat
1081 ctcttgcat gctggggacg aagccgcccc cgggcgctcc cctcgttcca ccttcgaggg
1141 ggttcacacc cccaacctgc gggccggcta ttcttcttcc ccttctctcg tcttcctcgg
1201 tcaacctcct aagtctctct tctctctcct tgctgaggtt ctttcccccc gccgatagct
1261 gctttctctt gttctcgagg gccttccttc gtcggtgate ctgcctctcc ttgtcggatg
1321 atcctcccct ggaaggcctc ttcttaggtc cggagtctac ttccatctgg tccgttcggg
```

What sort of sequence is this? What does it do?

```
1441 tgtttcccag ccagggatgt tcatcctcaa gtttcttgat tttcttctta accttccgga
1501 ggtctctctc gagttcctct aacttcttcc ttccgctcac ccaactgctc agaacctctt
1561 ctctccccc gcggttttcc cttccttcgg gccggctcat ctctgactag aggcgacggt
1621 cctcagtact ctactcttt tctgtaaaga ggagactgct ggccctgtcg cccaagtctc
```

Biological words

- We can try to answer questions like these by considering the *words* in a sequence
- A *k*-word (or a *k*-tuple) is a string of length *k* drawn from some alphabet
- A DNA *k*-word is a string of length *k* that consists of letters A, C, G, T
 - 1-words: individual nucleotides (bases)
 - 2-words: dinucleotides (AA, AC, AG, AT, CA, ...)
 - 3-words: codons (AAA, AAC, ...)
 - 4-words and beyond

1-words: base composition

- Typically DNA exists as *duplex* molecule (two complementary strands)

5' -GGATCGAAGCTAAGGGCT-3'
3' -CCTAGCTTCGATTCCCGA-5'

Top strand: 7 G, 3 C, 5 A, 3 T
Bottom strand: 3 G, 7 C, 3 A, 5 T
Duplex molecule: 10 G, 10 C, 8 A, 8 T
Base frequencies: 10/36 10/36 8/36 8/36

These are something
we can determine
experimentally.



$$\text{fr}(G + C) = 20/36, \text{fr}(A + T) = 1 - \text{fr}(G + C) = 16/36$$

G+C content

- $\text{fr}(G + C)$, or *G+C content* is a simple statistics for describing genomes
- Notice that one value is enough characterise $\text{fr}(A)$, $\text{fr}(C)$, $\text{fr}(G)$ and $\text{fr}(T)$ for duplex DNA
- Is G+C content (= base composition) able to tell the difference between genomes of different organisms?
 - Simple computational experiment, if we have the genome sequences under study (-> exercises)

G+C content for various organisms

Bacteria

- *Mycoplasma genitalium* 31.6%
- *Escherichia coli* K-12 50.7%
- *Pseudomonas aeruginosa* PAO1 66.4%
- *Pyrococcus abyssi* 44.6%
- *Thermoplasma volcanium* 39.9%

worm

- *Caenorhabditis elegans* 36%

plant

- *Arabidopsis thaliana* 35%

human

- *Homo sapiens* 41%

Base frequencies in duplex molecules

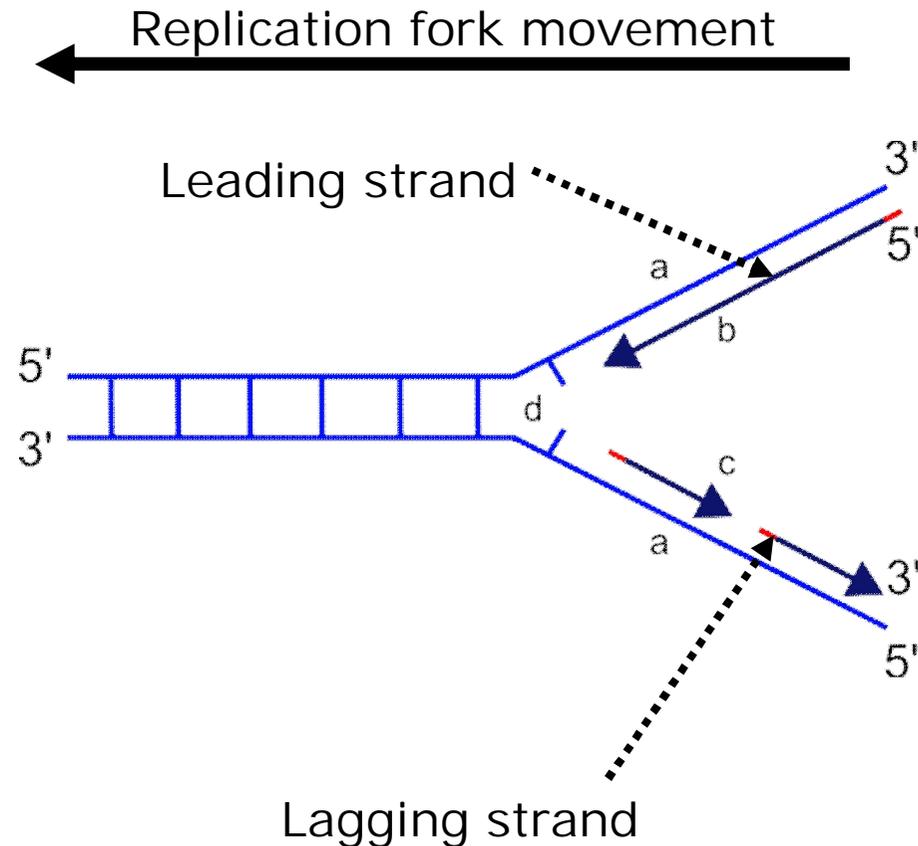
- Consider a DNA sequence generated randomly, with probability of each letter being independent of position in sequence
- You could expect to find a uniform distribution of bases in genomes...

5' - . . . GGATCGAAGCTAAGGGCT . . . - 3'
3' - . . . CCTAGCTTTCGATTCCCGA . . . - 5'

- This is not, however, the case in genomes, especially in bacteria
 - This phenomenon is called *GC skew*

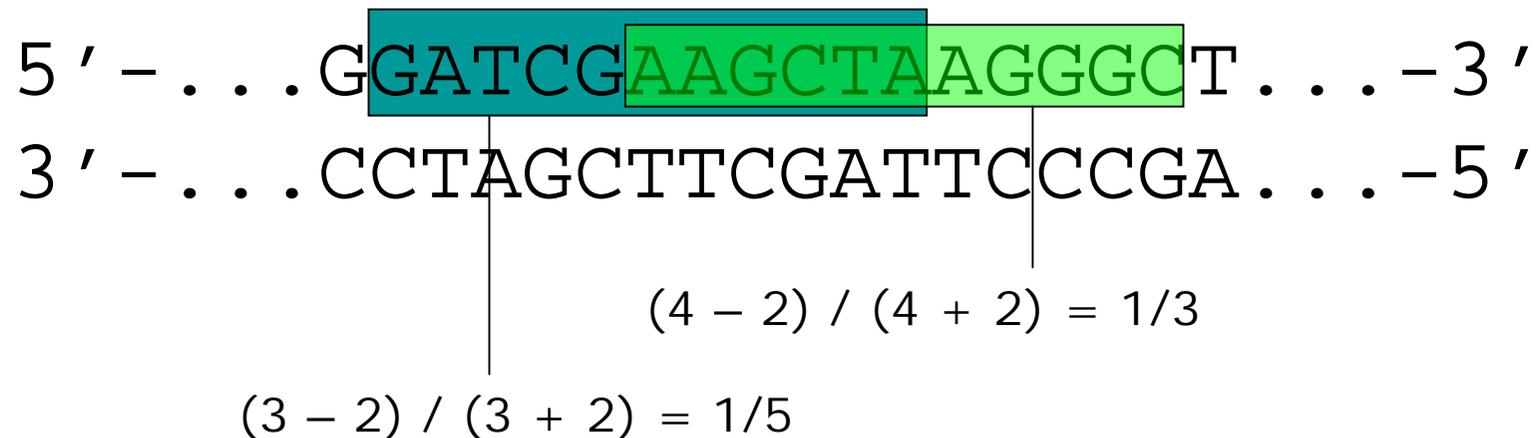
DNA replication fork

- When DNA is replicated, the molecule takes the *replication fork* form
- New complementary DNA is synthesised at both strands of the "fork"
- New strand in 5'-3' direction corresponding to replication fork movement is called *leading strand* and the other *lagging strand*
- This process has specific starting points in genome (*origins of replication*)
- Observation: Leading strands have an excess of G over C
- This can be described by *GC skew* statistics



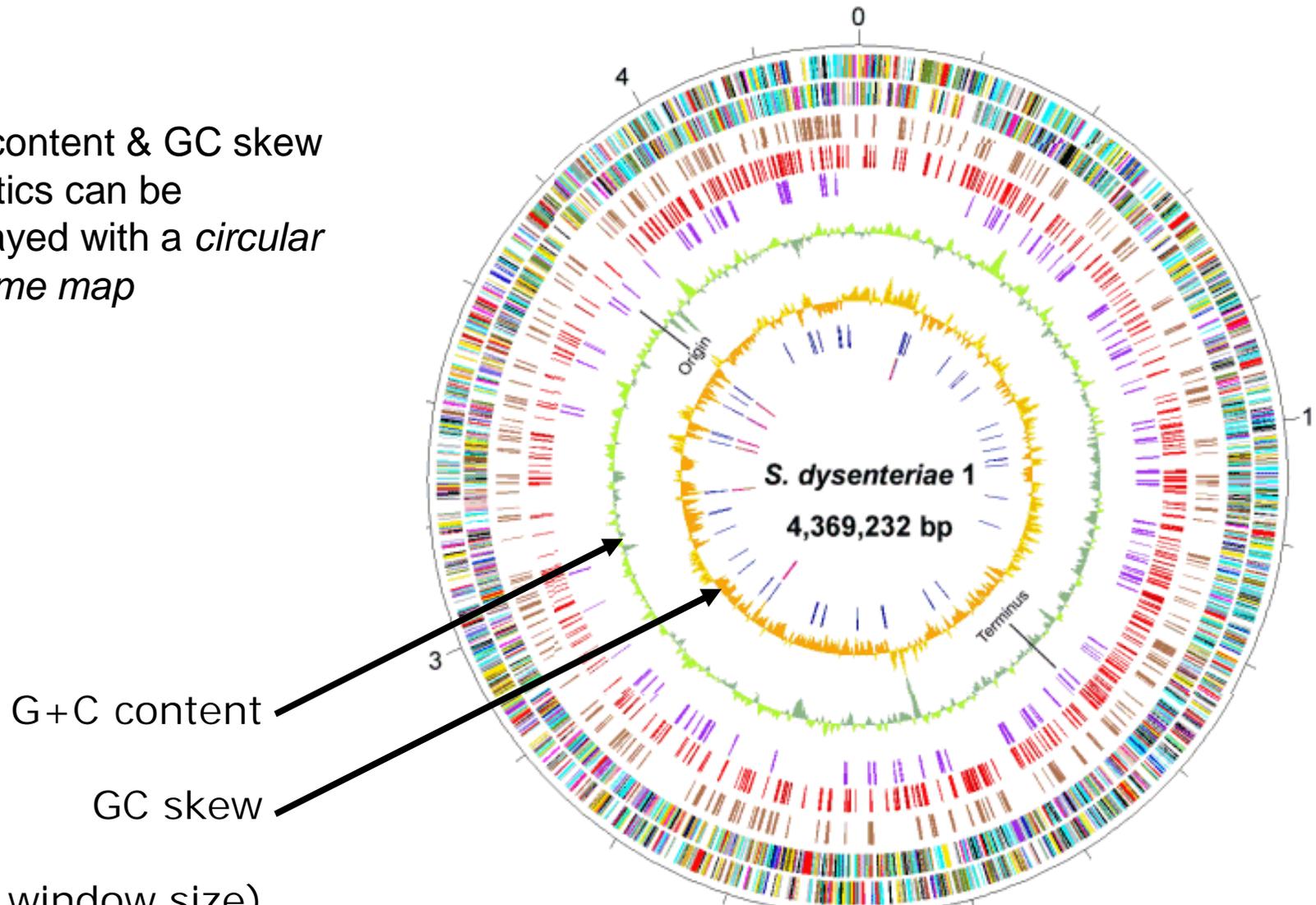
GC skew

- GC skew is defined as $(\#G - \#C) / (\#G + \#C)$
- It is calculated at successive positions in intervals (windows) of specific width



G-C content & GC skew

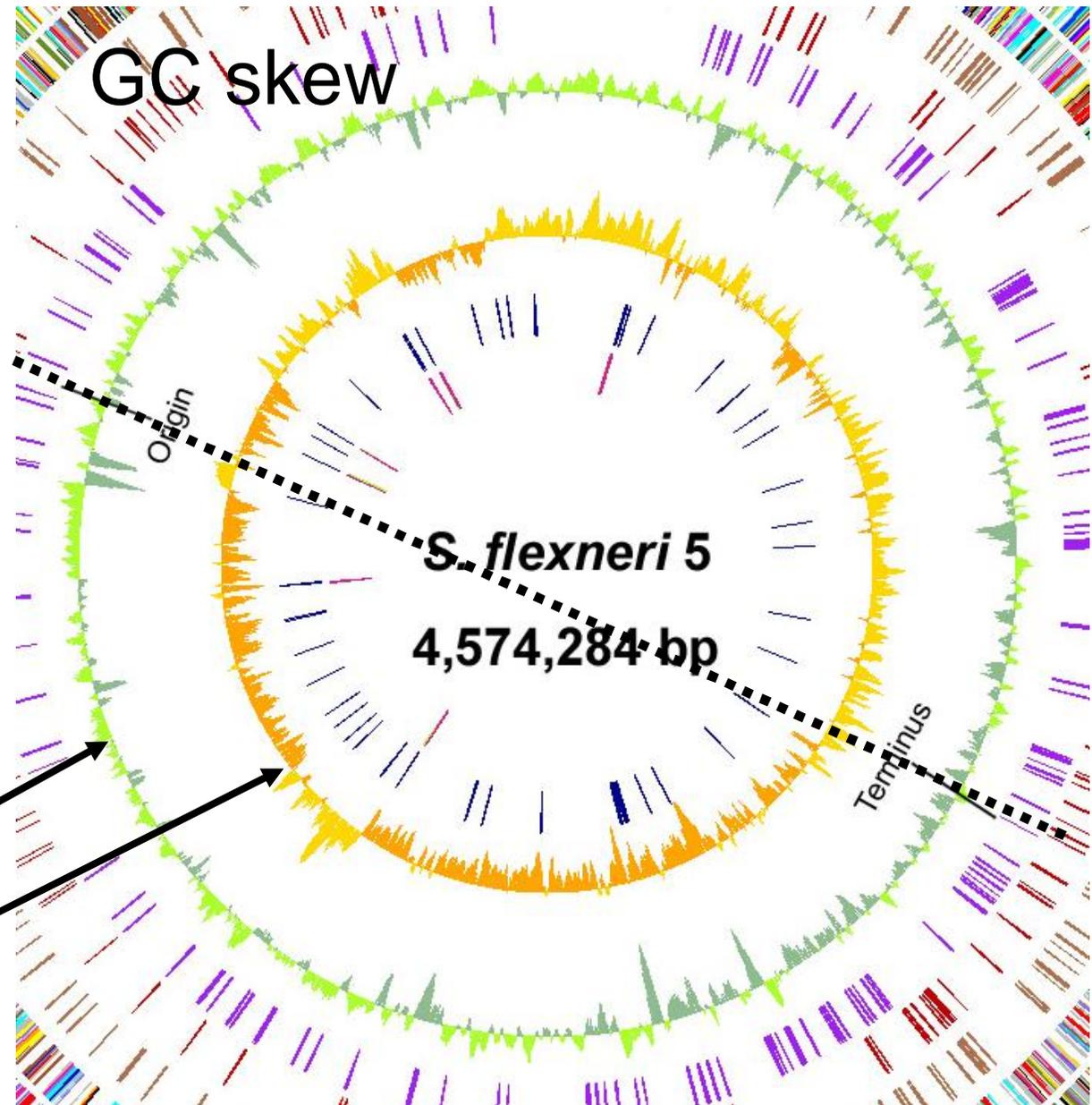
- G-C content & GC skew statistics can be displayed with a *circular genome map*



Chromosome map of *S. dysenteriae*, the nine rings describe different properties of the genome

- GC skew often changes sign at origins and termini of replication

(10kb window size)



2-words: dinucleotides

- Let's consider a sequence L_1, L_2, \dots, L_n where each letter L_i is drawn from the DNA alphabet $\{A, C, G, T\}$
- We have 16 possible dinucleotides $L_i L_{i+1}$: AA, AC, AG, ..., TG, TT.

i.i.d. model for nucleotides

- Assume that bases
 - occur independently of each other
 - bases at each position are **identically distributed**
- Probability of the base A, C, G, T occurring is p_A, p_C, p_G, p_T , respectively
 - For example, we could use $p_A=p_C=p_G=p_T=0.25$ or estimate the values from known genome data
- Probability of $I_i|I_{i+1}$ is then $P_{ii}P_{ii+1}$
 - For example, $P(TG) = p_T p_G$

What is i.i.d ?

In probability theory and statistics a sequence or other collection of random variables is

independent and identically distributed (i.i.d.) if each random variable has the same probability distribution as the others and all are mutually independent.

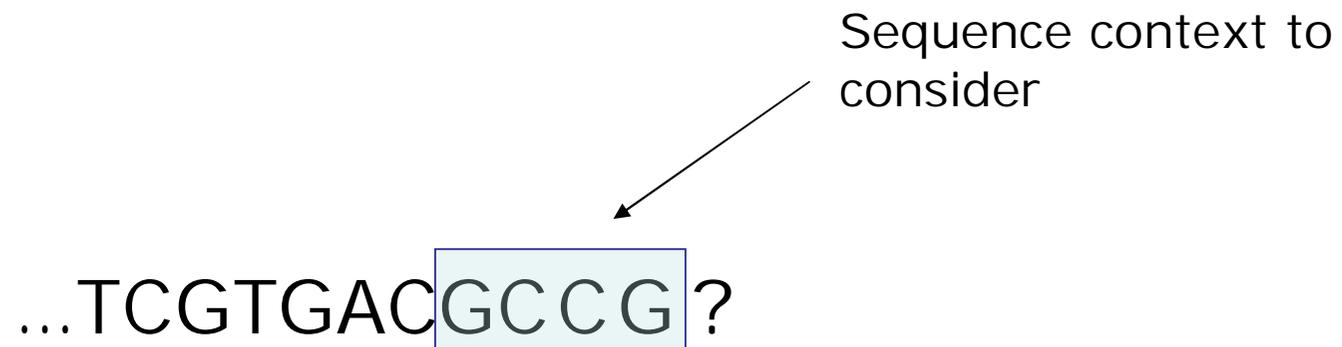
2-words: is what we see surprising?

- We can test whether a sequence is "unexpected", for example, with a χ^2 test
- Test statistic for a particular dinucleotide r_1r_2 is $\chi^2 = (O - E)^2 / E$ where
 - O is the observed number of dinucleotide r_1r_2
 - E is the expected number of dinucleotide r_1r_2
 - $E = (n - 1)p_{r_1}p_{r_2}$ under i.i.d. model
- Basic idea: high values of χ^2 indicate deviation from the model
 - Actual procedure is more detailed -> basic statistics courses

Refining the i.i.d. model

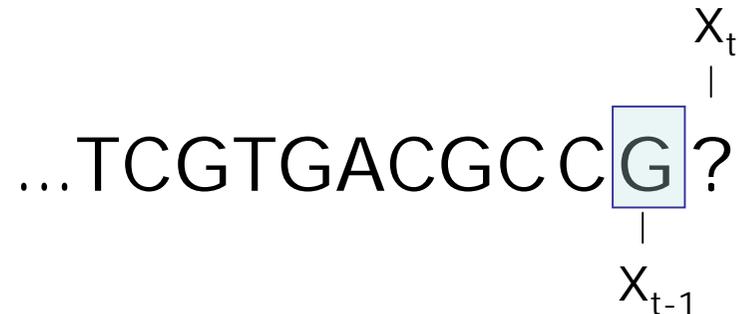
- i.i.d. model describes some organisms well but fails to characterise many others
- We can refine the model by having the DNA letter at some position depend on letters at preceding positions

Sequence context to consider



The diagram illustrates the concept of sequence context. It shows a DNA sequence: "...TCGTGACGCCG?". The last five nucleotides, "GCCG?", are enclosed in a light blue rectangular box. An arrow points from the text "Sequence context to consider" to this box, indicating that the probability of the next nucleotide (the question mark) depends on the preceding sequence.

First-order Markov chains



- Lets assume that in sequence X the letter at position t , X_t , depends only on the previous letter X_{t-1} (*first-order markov chain*)
- Probability of letter j occurring at position t given $X_{t-1} = i$: $p_{ij} = P(X_t = j \mid X_{t-1} = i)$
- We consider *homogeneous* Markov chains: probability p_{ij} is independent of position t

Estimating p_{ij}

- We can estimate probabilities p_{ij} ("the probability that j follows i ") from observed dinucleotide frequencies

| | A | C | G | T | |
|---|-------------------------------------|----------|----------|----------|--|
| A | p_{AA} | p_{AC} | p_{AG} | p_{AT} | ← Frequency of dinucleotide AT in sequence |
| C | $p_{CA} + p_{CC} + p_{CG} + p_{CT}$ | | | | ← Base frequency $fr(C)$ |
| G | p_{GA} | p_{GC} | p_{GG} | p_{GT} | |
| T | p_{TA} | p_{TC} | p_{TG} | p_{TT} | |

...the values $p_{AA}, p_{AC}, \dots, p_{TG}, p_{TT}$ sum to 1

Estimating p_{ij}

Dinucleotide frequency

$$p_{ij} = P(X_t = j \mid X_{t-1} = i) = \frac{P(X_t = j, X_{t-1} = i)}{P(X_{t-1} = i)}$$

Probability of transition $i \rightarrow j$

Base frequency of nucleotide i , $fr(i)$

$$0.052 / 0.345 \approx 0.151$$

| | A | C | G | T |
|---|-------|-------|-------|-------|
| A | 0.146 | 0.052 | 0.058 | 0.089 |
| C | 0.063 | 0.029 | 0.010 | 0.056 |
| G | 0.050 | 0.030 | 0.028 | 0.051 |
| T | 0.086 | 0.047 | 0.063 | 0.140 |

$$P(X_t = j, X_{t-1} = i)$$

| | A | C | G | T |
|---|-------|-------|-------|-------|
| A | 0.423 | 0.151 | 0.168 | 0.258 |
| C | 0.399 | 0.184 | 0.063 | 0.354 |
| G | 0.314 | 0.189 | 0.176 | 0.321 |
| T | 0.258 | 0.138 | 0.187 | 0.415 |

$$P(X_t = j \mid X_{t-1} = i)$$

Simulating a DNA sequence

- From a transition matrix, it is easy to generate a DNA sequence of length n :
 - First, choose the starting base randomly according to the base frequency distribution
 - Then, choose next base according to the distribution $P(x_t | x_{t-1})$ until n bases have been chosen

T T C T T C A A

| | A | C | G | T |
|---|-------|-------|-------|-------|
| A | 0.423 | 0.151 | 0.168 | 0.258 |
| C | 0.399 | 0.184 | 0.063 | 0.354 |
| G | 0.314 | 0.189 | 0.176 | 0.321 |
| T | 0.258 | 0.138 | 0.187 | 0.415 |

$$P(X_t = j | X_{t-1} = i)$$

Now we can quickly generate sequences of arbitrary length...

.

```

ttcttcaaaataaggatagtgattccttattggcttaaggataacaatttagatctttttcatgaatcatgtatgtcaacgttaaagttgaactgcaataagttc
ttacacacgattgttatctgctgcaagcatttcactacatttgccgatgcagccaaaagtatttaacatttggtaaacaaattgacttaaatcgcgacttaga
gtttgacgtttcatagttgatgctgtctaaacaattacttttagtttttaaatgctgttctacaatcattaatcagctctggaaaaacattaatgcatttaac
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taaaagaaaaaggagattaaaaaacctgcggtgccacatttttgttacgggcatttaaggttgcagtggtgagcaattgaaacctacaactcaataagtcag
ttaagtcacttctttgaaaaaaaaaagaccctttaagcaagctc

```

Results from simulating a DNA sequence

| Dinucleotide frequencies | | |
|--------------------------|-----------|----------|
| | Simulated | Observed |
| aa | 0.145 | 0.146 |
| ac | 0.050 | 0.052 |
| ag | 0.055 | 0.058 |
| at | 0.092 | 0.089 |
| ca | 0.065 | 0.063 |
| cc | 0.028 | 0.029 |
| cg | 0.011 | 0.010 |
| ct | 0.058 | 0.056 |
| ga | 0.048 | 0.050 |
| gc | 0.032 | 0.030 |
| gg | 0.029 | 0.028 |
| gt | 0.050 | 0.051 |
| ta | 0.084 | 0.086 |
| tc | 0.052 | 0.047 |
| tg | 0.064 | 0.063 |
| tt | 0.138 | 0.0140 |

n = 10000

Simulating a DNA sequence

- The model is able to generate correct proportions of 1- and 2-words in genomes...
- ...but fails with $k=3$ and beyond.

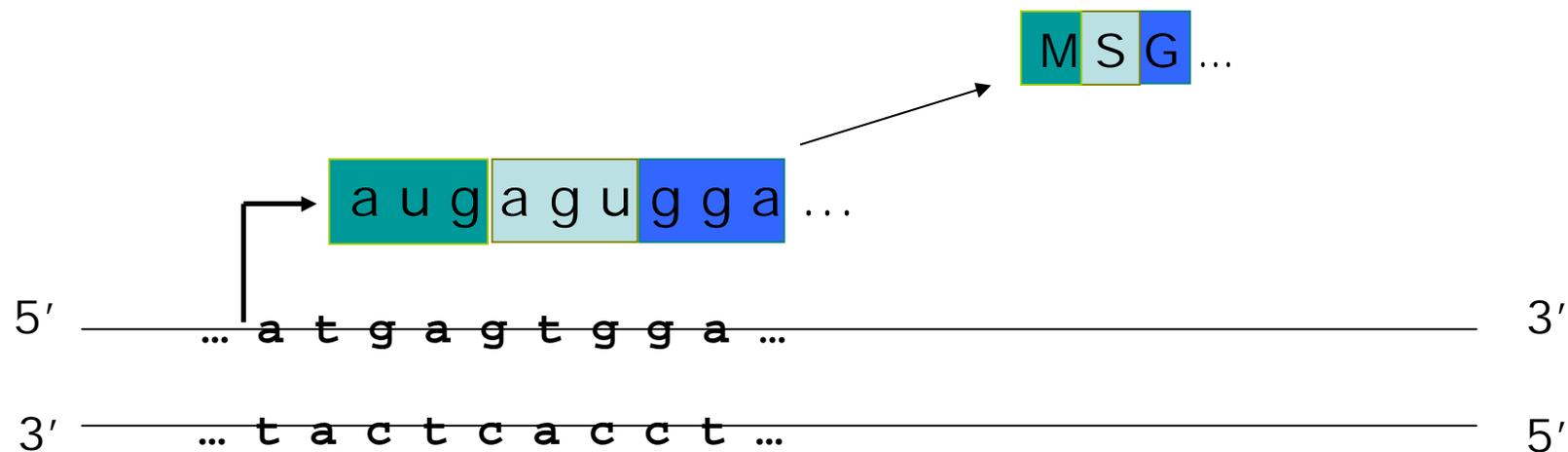
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ttcttcaaaataaggatagtgattccttattggcttaaggataacaatttagatctttttcatgaatcatgtatgtcaacgttaaagttgaactgcaataagttc
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ttaagtcacttctttgaaaaaaaaaagaccctttaagcaagctc

```

3-words: codons

- We can extend the previous method to 3-words
- $k=3$ is an important case in study of DNA sequences because of genetic code



3-word probabilities

- Let's again assume a sequence L of independent bases
- Probability of 3-word $r_1 r_2 r_3$ at position $i, i+1, i+2$ in sequence L is

$$P(L_i = r_1, L_{i+1} = r_2, L_{i+2} = r_3) =$$

$$P(L_i = r_1)P(L_{i+1} = r_2)P(L_{i+2} = r_3)$$

3-words in Escherichia coli genome

| Word | Count | Observed | Expected | Word | Count | Observed | Expected |
|------|--------|----------------|----------------|------|--------|----------------|----------------|
| AAA | 108924 | 0.02348 | 0.01492 | CAA | 76614 | 0.01651 | 0.01541 |
| AAC | 82582 | 0.01780 | 0.01541 | CAC | 66751 | 0.01439 | 0.01591 |
| AAG | 63369 | 0.01366 | 0.01537 | CAG | 104799 | 0.02259 | 0.01588 |
| AAT | 82995 | 0.01789 | 0.01490 | CAT | 76985 | 0.01659 | 0.01539 |
| ACA | 58637 | 0.01264 | 0.01541 | CCA | 86436 | 0.01863 | 0.01591 |
| ACC | 74897 | 0.01614 | 0.01591 | CCC | 47775 | 0.01030 | 0.01643 |
| ACG | 73263 | 0.01579 | 0.01588 | CCG | 87036 | 0.01876 | 0.01640 |
| ACT | 49865 | 0.01075 | 0.01539 | CCT | 50426 | 0.01087 | 0.01589 |
| AGA | 56621 | 0.01220 | 0.01537 | CGA | 70938 | 0.01529 | 0.01588 |
| AGC | 80860 | 0.01743 | 0.01588 | CGC | 115695 | 0.02494 | 0.01640 |
| AGG | 50624 | 0.01091 | 0.01584 | CGG | 86877 | 0.01872 | 0.01636 |
| AGT | 49772 | 0.01073 | 0.01536 | CGT | 73160 | 0.01577 | 0.01586 |
| ATA | 63697 | 0.01373 | 0.01490 | CTA | 26764 | 0.00577 | 0.01539 |
| ATC | 86486 | 0.01864 | 0.01539 | CTC | 42733 | 0.00921 | 0.01589 |
| ATG | 76238 | 0.01643 | 0.01536 | CTG | 102909 | 0.02218 | 0.01586 |
| ATT | 83398 | 0.01797 | 0.01489 | CTT | 63655 | 0.01372 | 0.01537 |

2nd order Markov Chains

- Markov chains readily generalise to higher orders
- In 2nd order markov chain, position t depends on positions t-1 and t-2
- Transition matrix:

| | A | C | G | T |
|-----|---|---|---|---|
| AA | | | | |
| AC | | | | |
| AG | | | | |
| AT | | | | |
| CA | | | | |
| ... | | | | |

Codon Adaptation Index (CAI)

- Observation: cells prefer certain codons over others in highly expressed genes
 - Gene expression: DNA is transcribed into RNA (and possibly translated into protein)
- CAI is a statistic used to compare the distribution of codons **observed** with the **preferred** codons for highly expressed genes

| Amino acid | Codon | Predicted | Gene class I | Gene class II | Moderately expressed |
|------------|-------|-----------|--------------|---------------|----------------------|
| Phe | TTT | 0.493 | 0.551 | 0.291 | Highly expressed |
| | TTC | 0.507 | 0.449 | 0.709 | |
| Ala | GCT | 0.246 | 0.145 | 0.275 | Highly expressed |
| | GCC | 0.254 | 0.276 | 0.164 | |
| | GCA | 0.246 | 0.196 | 0.240 | |
| | GCG | 0.254 | 0.382 | 0.323 | |
| Asn | AAT | 0.493 | 0.409 | 0.172 | Highly expressed |
| | AAC | 0.507 | 0.591 | 0.828 | |

Codon frequencies for some genes in E. coli

Codon Adaptation Index (CAI)

- Consider an amino acid sequence $X = x_1x_2 \dots x_n$
- Let p_k be the probability that codon k is used in highly expressed genes
- Let q_k be the highest probability that a codon coding for the same amino acid as codon k has
 - For example, if codon k is "GCC", the corresponding amino acid is Alanine (see genetic code table; also GCT, GCA, GCG code for Alanine)
 - Assume that $p_{GCC} = 0.164$, $p_{GCT} = 0.275$, $p_{GCA} = 0.240$, $p_{GCG} = \mathbf{0.323}$
 - Now $q_{GCC} = q_{GCT} = q_{GCA} = q_{GCG} = \mathbf{0.323}$

Codon Adaptation Index (CAI)

- CAI is defined as

$$CAI = \left(\prod_{k=1}^n p_k / q_k \right)^{1/n}$$

- CAI can be given also in *log-odds* form:

$$\log(CAI) = (1/n) \sum_{k=1}^n \log(p_k / q_k)$$

CAI: example with an E. coli gene

q_k
 p_k

| M | A | L | T | K | A | E | M | S | E | Y | L | ... |
|--|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-----|
| ATG | GCG | CTT | ACA | AAA | GCT | GAA | ATG | TCA | GAA | TAT | CTG | |
| 1.00 | 0.47 | 0.02 | 0.45 | 0.80 | 0.47 | 0.79 | 1.00 | 0.43 | 0.79 | 0.19 | 0.02 | |
| | 0.06 | 0.02 | 0.47 | 0.20 | 0.06 | 0.21 | | 0.32 | 0.21 | 0.81 | 0.02 | |
| | 0.28 | 0.04 | 0.04 | | 0.28 | | | 0.03 | | | 0.04 | |
| | 0.20 | 0.03 | 0.05 | | 0.20 | | | 0.01 | | | 0.03 | |
| | | 0.01 | | | | | | 0.04 | | | 0.01 | |
| | | 0.89 | | | | | | 0.18 | | | 0.89 | |
| ATG | GCT | TTA | ACT | AAA | GCT | GAA | ATG | TCT | GAA | TAT | TTA | |
| | GCC | TTG | ACC | AAG | GCC | GAG | | TCC | GAG | TAC | TTG | |
| | GCA | CTT | ACA | | GCA | | | TCA | | | CTT | |
| | GCG | CTC | ACG | | GCG | | | TCG | | | CTC | |
| | | CTA | | | | | | AGT | | | CTA | |
| | | CTG | | | | | | AGC | | | CTG | |
| | | | | | | | | | | | | |
| $\left[\begin{array}{cccccccccccc} 1.00 & 0.20 & 0.04 & 0.04 & 0.80 & 0.47 & 0.79 & 1.00 & 0.03 & 0.79 & 0.19 & 0.89\dots \\ 1.00 & 0.47 & 0.89 & 0.47 & 0.80 & 0.47 & 0.79 & 1.00 & 0.43 & 0.79 & 0.81 & 0.89 \end{array} \right]^{1/n}$ | | | | | | | | | | | | |

Biological words: summary

- Simple 1-, 2- and 3-word models can describe interesting properties of DNA sequences
 - GC skew can identify DNA replication origins
 - It can also reveal *genome rearrangement* events and *lateral transfer* of DNA
 - GC content can be used to locate genes: human genes are comparably GC-rich
 - CAI predicts high gene expression levels
 - $k=3$ models can help to identify correct *reading frames* :
 - Reading frame starts from a start codon and stops in a stop codon
 - Consider what happens when a single extra base is introduced in a reading frame

Note on programming languages

- Working with probability distributions is straightforward with R.
- You can use R in Computer science classrooms Linux systems
- Python works too!

Example Python code for generating DNA sequences with first-order Markov chains.

```
#!/usr/bin/env python
```

```
import sys, random
```

```
n = int(sys.argv[1])
```

} Initialisation: use packages 'sys' and 'random', read sequence length from input.

```
tm = {'a': {'a': 0.423, 'c': 0.151, 'g': 0.168, 't': 0.258},
      'c': {'a': 0.399, 'c': 0.184, 'g': 0.063, 't': 0.354},
      'g': {'a': 0.314, 'c': 0.189, 'g': 0.176, 't': 0.321},
      't': {'a': 0.258, 'c': 0.138, 'g': 0.187, 't': 0.415}}
```

} Transition matrix tm and initial distribution pi.

```
pi = {'a': 0.345, 'c': 0.158, 'g': 0.159, 't': 0.337}
```

```
def choose(dist):
    r = random.random()
    sum = 0.0
    keys = dist.keys()
    for k in keys:
        sum += dist[k]
        if sum > r:
            return k
    return keys[-1]
```

} Function choose(), returns a key (here 'a', 'c', 'g' or 't') of the dictionary 'dist' chosen randomly according to probabilities in dictionary values.

```
c = choose(pi)
for i in range(n - 1):
    sys.stdout.write(c)
    c = choose(tm[c])
sys.stdout.write(c)
sys.stdout.write("\n")
```

} Choose the first letter, then choose next letter according to $P(x_t | x_{t-1})$.

BASICS ON BIOLOGICAL DATABASES

- Storage of information
- Sources of data
- Go to: <http://www.ncbi.nlm.nih.gov/>
 - Have a look, what kind of databases
 - Familiarize yourself, at least, with PubMed, visit also OMIM

FASTA format

the basic format – and an important practical concept

```
>Hepatitis delta virus, complete genome
```

Header line,
begins with >

```
atgagccaagttccgaacaaggattcgcggggaggatagatcagcgcgccgagaggggtga  
gtcggtaaagagcattggaacgtcggagatacaactccaagaaggaaaaaagagaaagc  
aagaagcggatgaatttccccataacgccagtgaaactctaggaaggggaaagaggggaag  
gtggaagagaaggaggcgggcctcccgatccgagggggcccggcggccaagtttgaggagac  
actccggcccgaagggttgagagtaccccagagggaggaagccacacggagtagaacaga  
gaaatcacctccagaggacccttcagcgaacagagagcgcacgcgagaggggagtagac  
catagcgataggaggggatgctaggagtggggggagaccgaagcagaggaggaaagcaaag  
agagcagcggggctagcaggtgggtgttccgccccccgagagggggacgagtgaggcttat  
cccggggaactcgacttatcgtccccacatagcagactcccggaccccccttcaaagtga
```

...