

Cocke-Kasami-Younger Parser

Suppose all rules of form $A \rightarrow BC$ or $A \rightarrow a$
 (by mechanically transforming grammar)

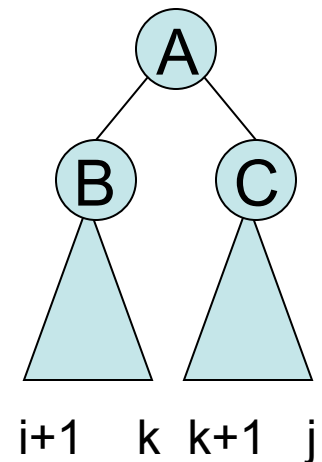
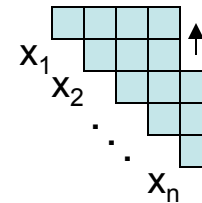
Given $x = x_1 \dots x_n$, want $M^A_{i,j} = \{1 \text{ if } (A \Rightarrow^* x_{i+1} \dots x_j) \text{ else } 0\}$

For $j=2$ to n

$M^A[j-1,j] = \{1 \text{ if } (A \rightarrow x_j \text{ is a rule) else } 0\}$

for $i = j-1$ down to 1

$$M^A[i,j] = \bigvee_{A \rightarrow BC, i < k < j} M^B[i,k] \wedge M^C[k,j]$$

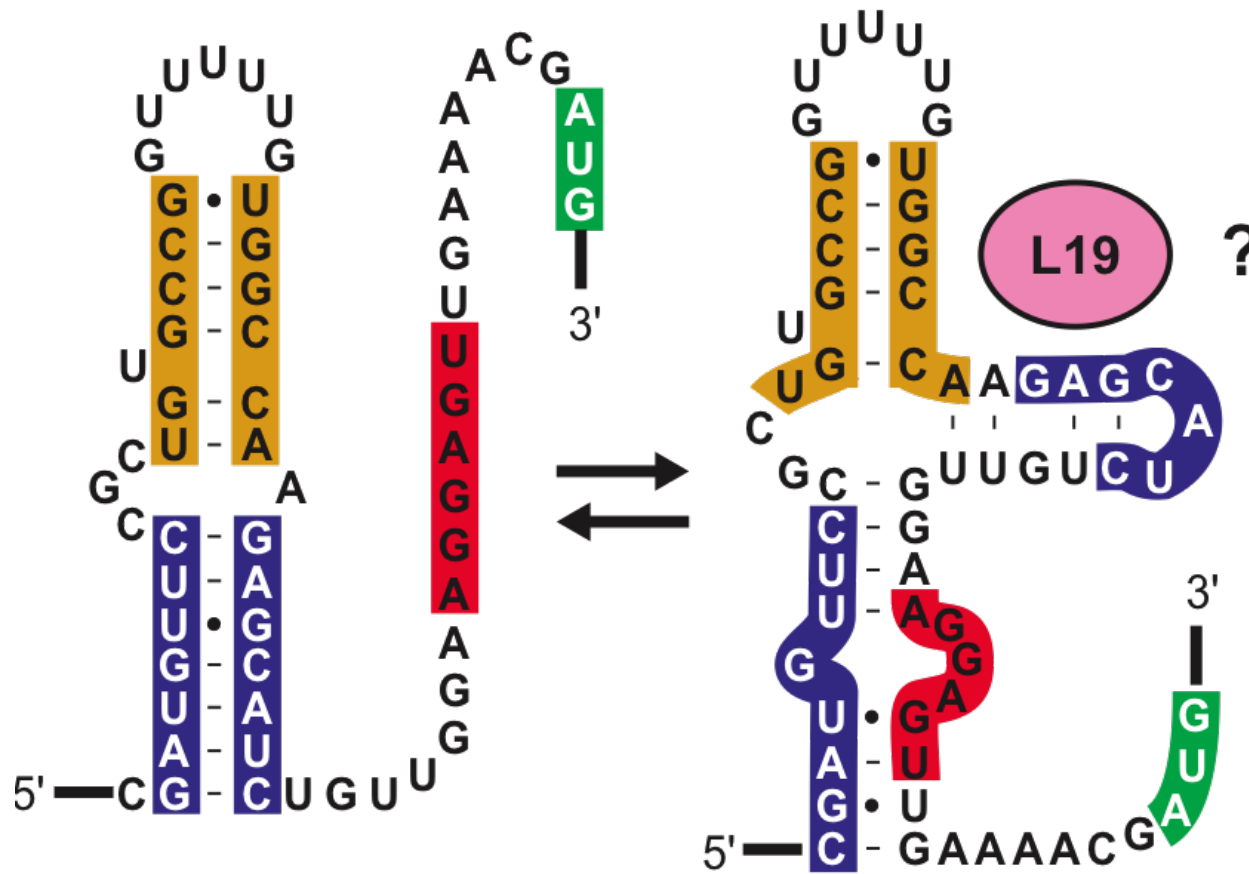


Time: $O(n^3)$

*And now for something
completely different ...*

CFGs beyond compilers

An RNA Computer! Sensor & On/Off Switch



L19 absent: Gene On

L19 present: Gene Off

A CFG for RNA

$S \rightarrow LS \mid L$

$L \rightarrow \text{"dFd"} \mid s$

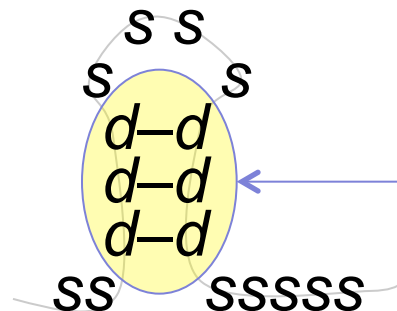
$F \rightarrow \text{"dFd"} \mid LS$

“s” means unpaired;

“dFd” means paired
(Watson–Crick:

$aFu \mid uFa \mid gFc \mid cFg$
paren-like nesting)

$S \Rightarrow LS \Rightarrow^* LLLLLLLS$
 $\Rightarrow LLLLLLLL$
 $\Rightarrow^* ssLsssss$
 $\Rightarrow ssdFds$
 $\Rightarrow ssddFdds$
 $\Rightarrow ssdddFddd$
 $\Rightarrow \dots$



Actually, a Stochastic CFG

Associate *probabilities* with rules, e.g.:

$$S \rightarrow LS \quad (p = 0.87)$$

$$S \rightarrow L \quad (p = 0.13)$$

...

Now we can ask, not only

“Does S generate w?”

But also

“How likely is it?”

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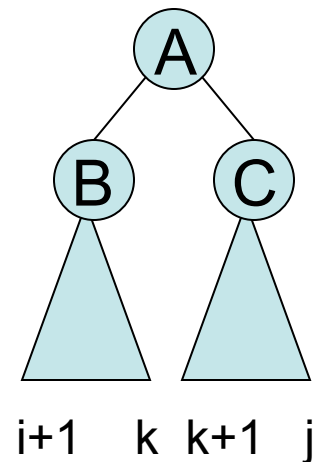
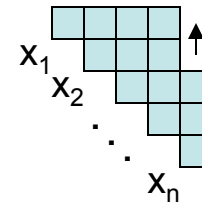
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Time: $O(n^3)$

“Inside” Algorithm for SCFG

Suppose all rules of form $A \rightarrow BC$ or $A \rightarrow a$
 (by mechanically transforming grammar)

Given $x = x_1 \dots x_n$, want $M^A_{i,j} = p(A \Rightarrow^* x_{i+1} \dots x_j)$

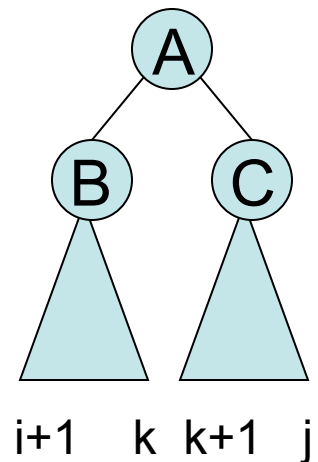
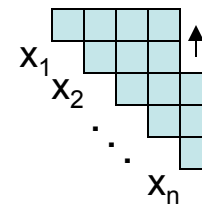
For $j=2$ to n

$$M^A[j-1, j] = p(\text{rule } A \rightarrow x_j)$$

for $i = j-1$ down to 1

$$M^A[i, j] = \sum_{A \rightarrow BC, i < k < j} M^B[i, k] \times M^C[k, j] \times p(A \rightarrow BC)$$

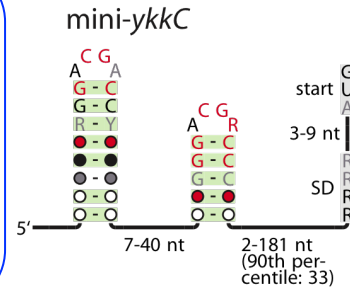
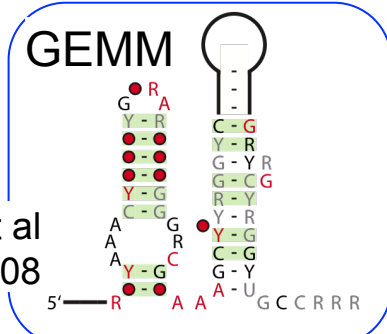
I.e., *probability* of A in $M[i, j]$, instead of its *possibility*



Time: $O(n^3)$

Examples: 7 typical motifs

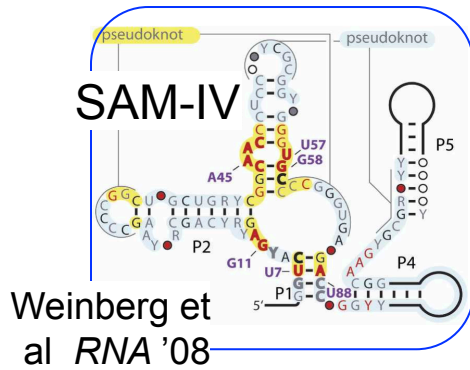
Sudarsan, et al
Science, 2008



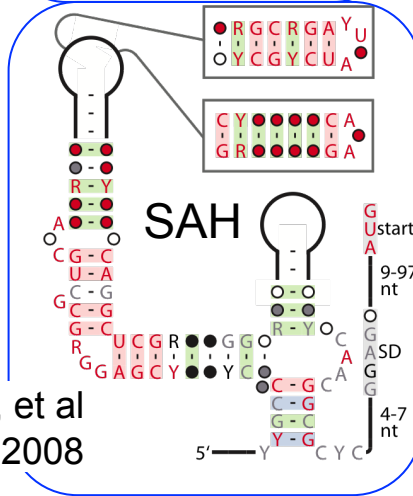
Legend nucleotides, SD: Shine-Dalgarno
start: start codon, R: A/G, Y: C/U

nucleotide identity	base pair annotations
N 97%	- has covarying mutations
N 90%	- has compatible mutations
N 75%	- no mutations observed

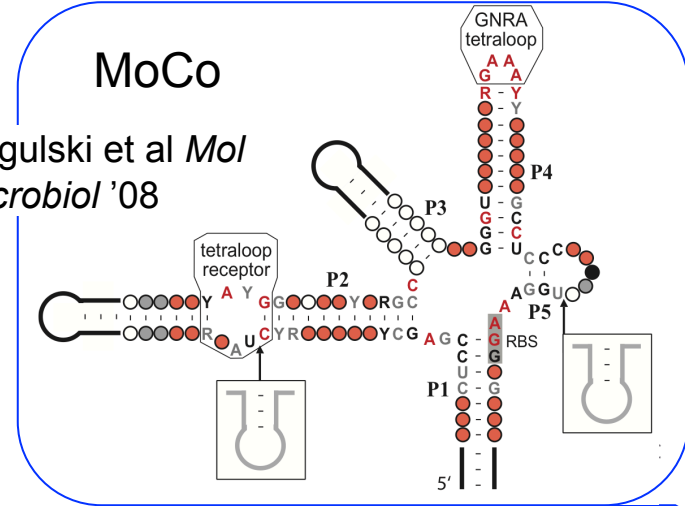
nucleotide present	variable hairpin
● 97%	○ variable loop
● 90%	□ modular structure
● 75%	
○ 50%	



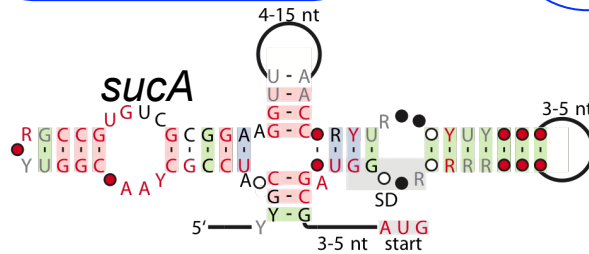
Wang, et al
Mol Cell, 2008



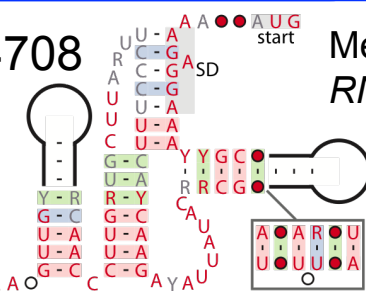
MoCo
Regulski et al *Mol Microbiol* '08



boxed =
confirmed
riboswitch



COG4708



Meyer, et al
RNA, 2008

Weinberg, Barrick, Yao, Roth, Kim, Gore, Wang, Lee, Block, Sudarsan, Neph, Tompa, Ruzzo, Breaker. Identification of 22 candidate structured RNAs in bacteria using the CMfinder comparative genomics pipeline. *Nucl. Acids Res.*, July 2007 35: 4809-4819.

Bottom Line

CFG technology is a *key tool* for RNA description, discovery and search

A *very active* research area

(Some call RNA the “dark matter” of the genome.)

Huge *compute hog*: results above represent hundreds of CPU-years; smart algorithms have a big impact

(Recall the $O(n^3)$...)

More?

Check out CSE 427/428: “Comp Bio”