

The Composition of Dense Neural Networks and Formal Grammars for Secondary Structure Analysis

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- Different kinds of noise
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- Secondary structure
- 3D structure

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Probabilistic approach which can handle secondary structure information

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- Parsing is not for secondary structure modelling, but for features extraction
 - ▶ In the opposite to classical way of probabilistic CF grammars utilization

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- Parsing is not for secondary structure modelling, but for features extraction
 - ▶ In the opposite to classical way of probabilistic CF grammars utilization
- Formal grammars for secondary structure handling
- Parsing for features extraction
- Artificial neural network as probabilistic model for features processing
- Extracted features handling

Solution Structure

Grammar

Fixed formal grammar (not necessary context-free) describes features of secondary structure and can be tuned in order to increase result quality.

Sequences

Each sequence is treated as a text in $\{A, C, G, T\}$ alphabet.

Result of classification

Parser

Parser extracts features of given sequence secondary structure. Implementation of parsing algorithm is based on matrix multiplications (Valiant, Okhotin) and utilizes GPGPU.

Neural Network

Dense neural network with more than 10 dense layers. Aggressive dropout and batch normalization for learning process stabilization. Typical building block:

Dropout (75%)	input: 1024
	output: 1024

Dense	input: 1024
	output: 1024

BatchNormalization	input: 1024
	output: 1024

Activation (relu)	input: 1024
	output: 1024

Matrices

0	1	0	1
0	0	1	0
0	0	0	1
0	0	0	0

Parsing result is (0-1) matrix M which represents secondary structure features for sequence ω : $M.[i, j] = 1 \iff s_1 \rightarrow^* \omega.[i, j]$, and 0 in other case.

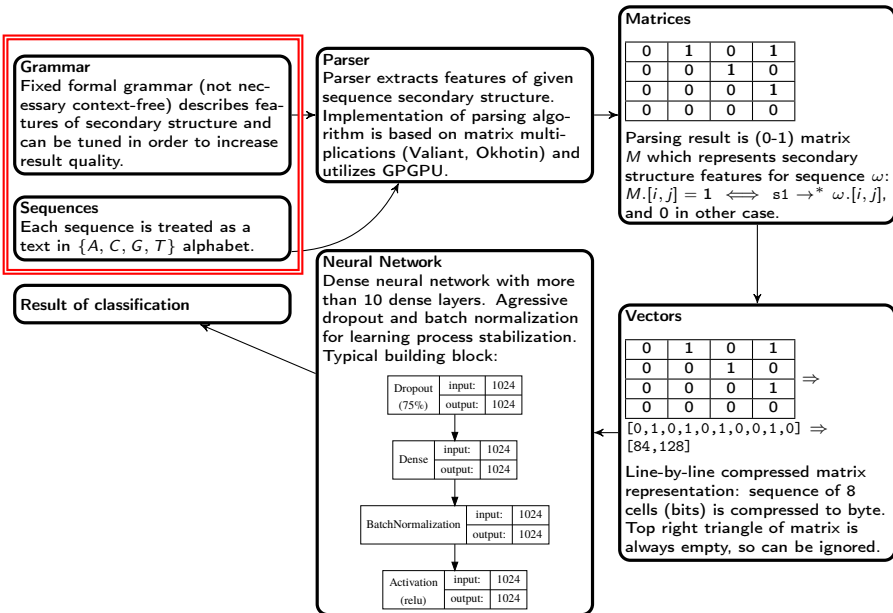
Vectors

0	1	0	1
0	0	1	0
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$[0, 1, 0, 1, 0, 1, 0, 0, 1, 0] \Rightarrow [84, 128]$

Line-by-line compressed matrix representation: sequence of 8 cells (bits) is compressed to byte. Top right triangle of matrix is always empty, so can be ignored.

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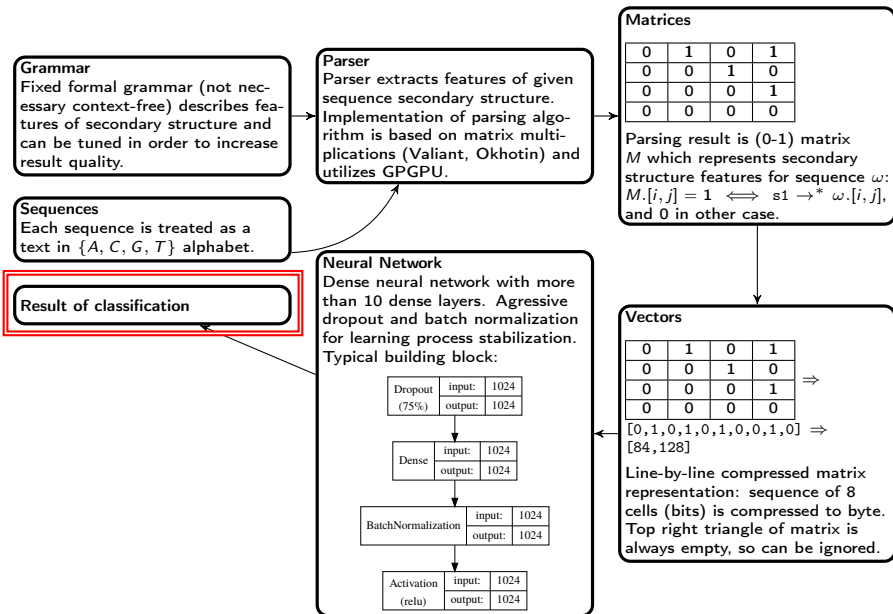
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```
s1: stem<s0>
any_str : any_smb*[2..10]
any_smb: A | T | C | G
s0: any_str | any_str stem<s0> s0
stem1<s>:                \\ stem of height exactly 1
    A s T | G s C | T s A | C s G
stem2<s>:                \\ stem of height exactly 2
    stem1< stem1<s> >
stem<s>:                \\ stem of height 3 or more
    A stem<s> T
    | T stem<s> A
    | C stem<s> G
    | G stem<s> C
    | stem1< stem2<s> >
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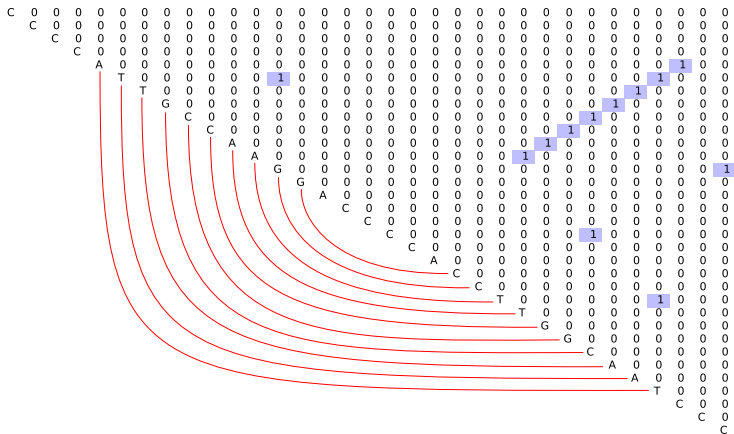
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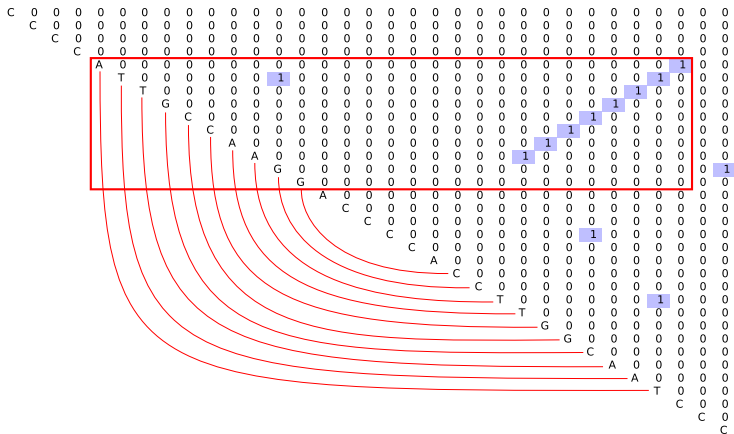
Example 1: Stem

$\omega_1 = \text{CCCCATTGCCAAGGACCCCACCTTGGCAATCCC}$



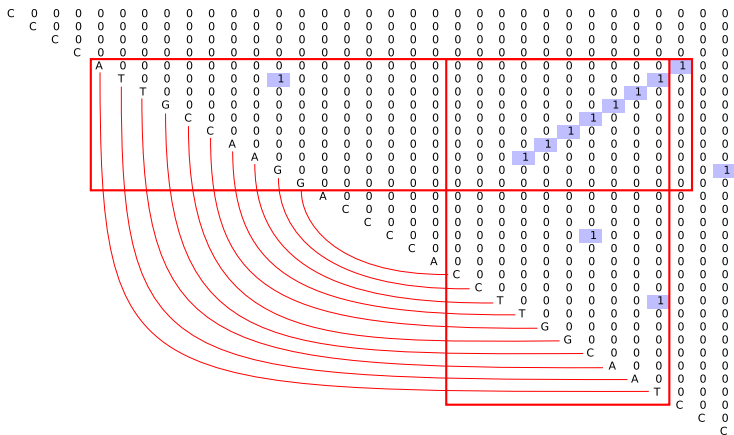
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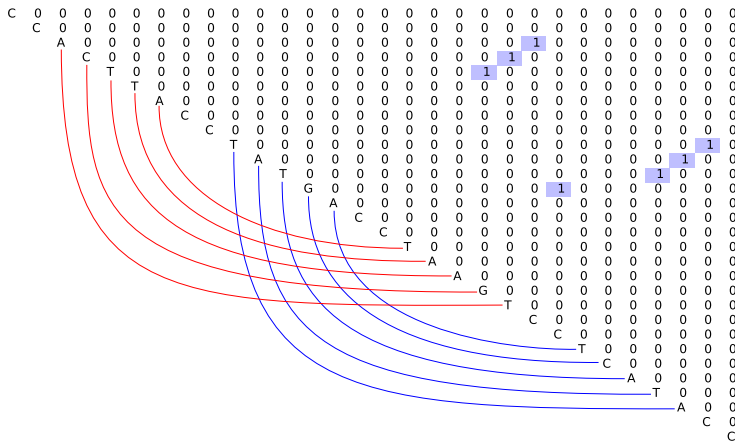
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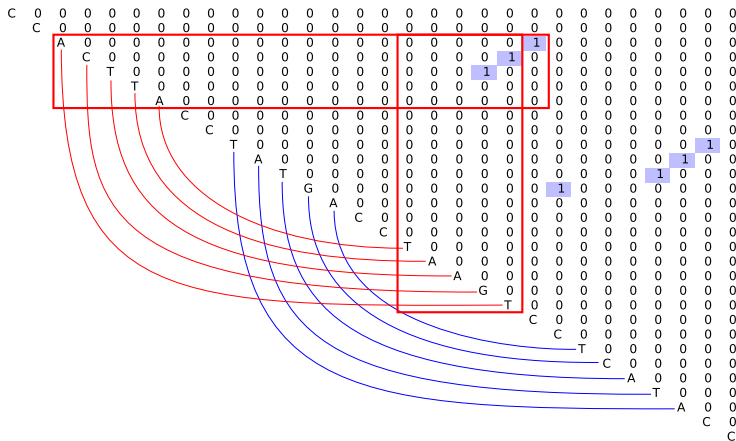
Example 2: Pseudoknot

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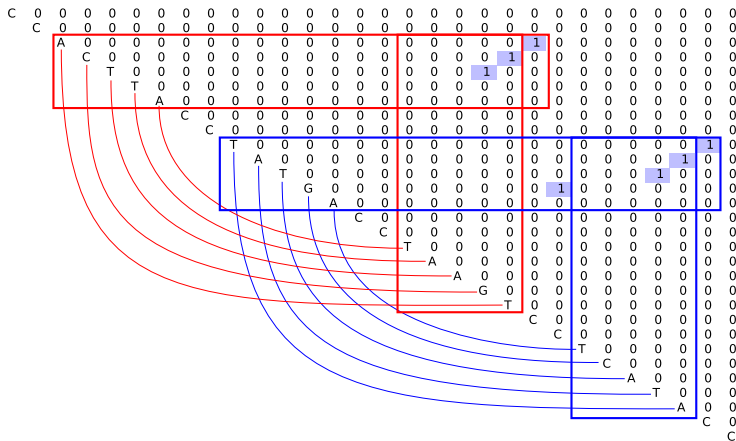
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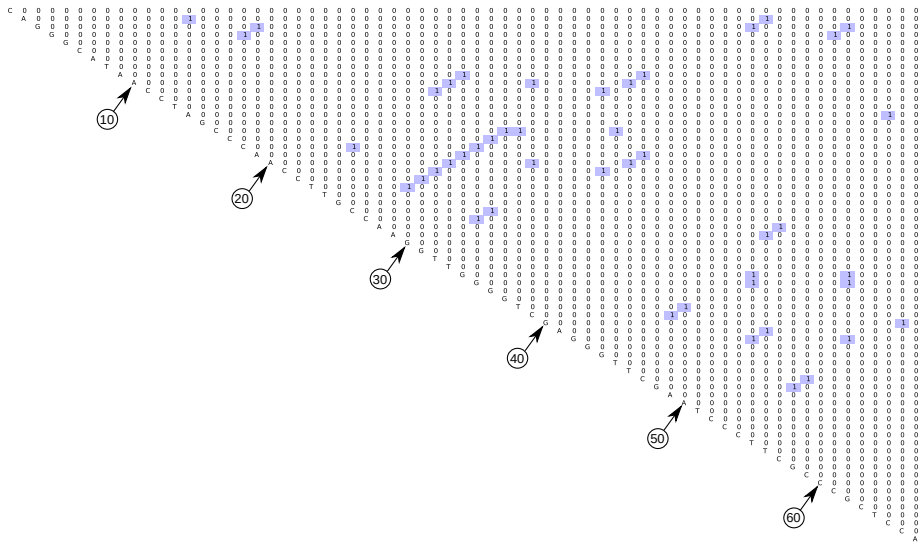


Example 3: real tRNA

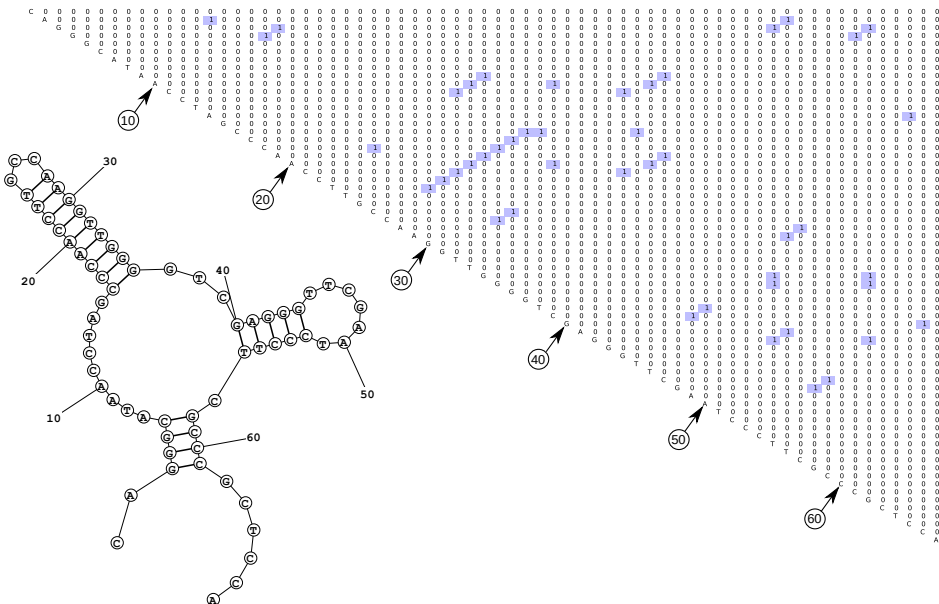
$\omega_3 =$ CAGGGCATAACCTAGCCCAACCTTGCCAAGG
TTGGGGTCGAGGGTTCGAATCCCTTCGCCCCTCCA

- *Novosphingobium aromaticivorans* DSM 12444
chr.trna57-GlyGCC(268150-268084) Gly (GCC) 67 bp Sc: 22.9, from GtRNAdb
- Predicted secondary structures are given by using the Fold Web Server with default settings

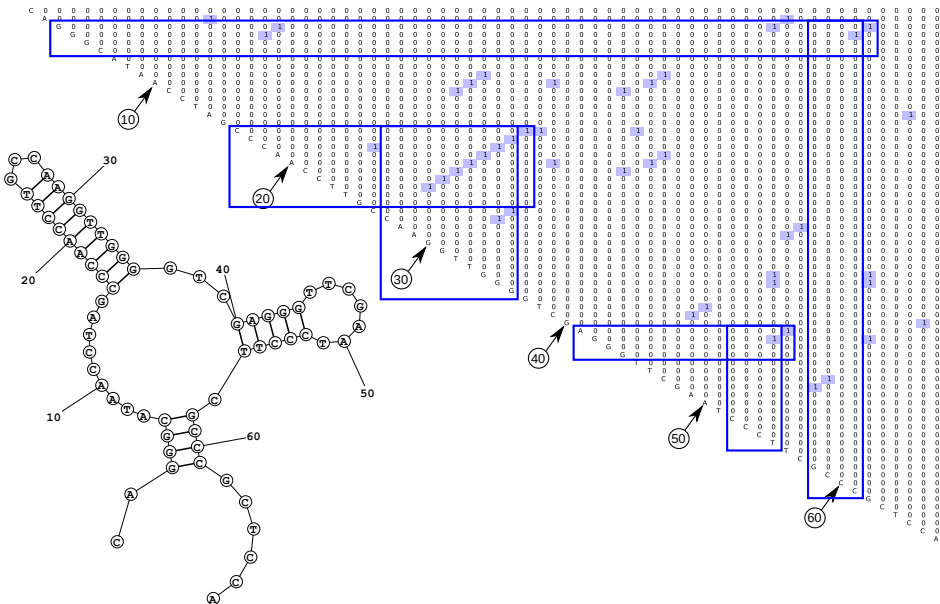
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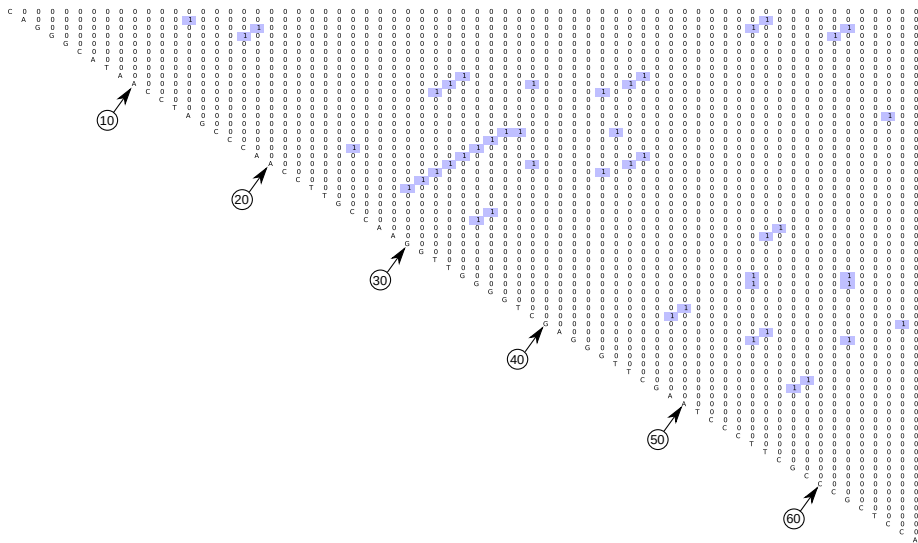
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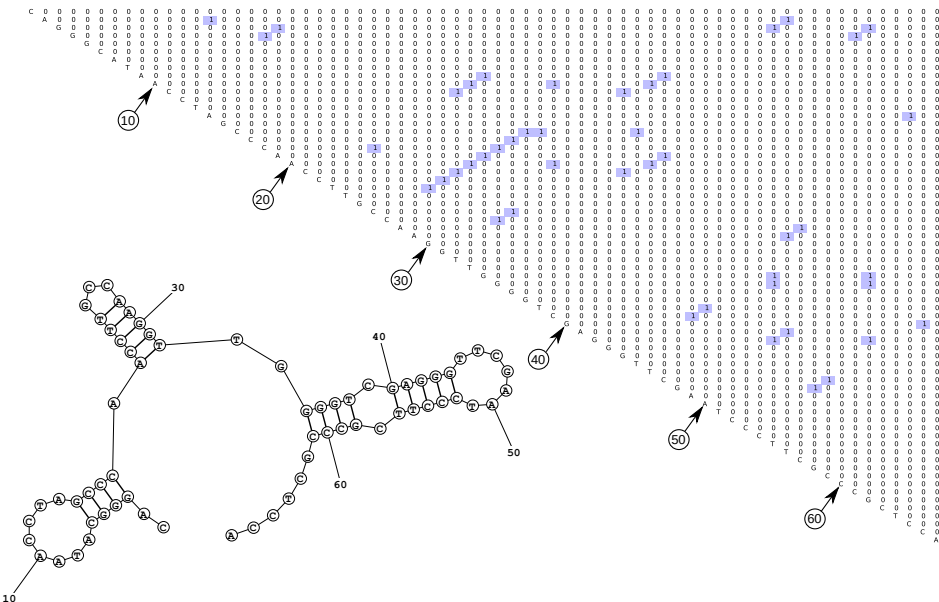
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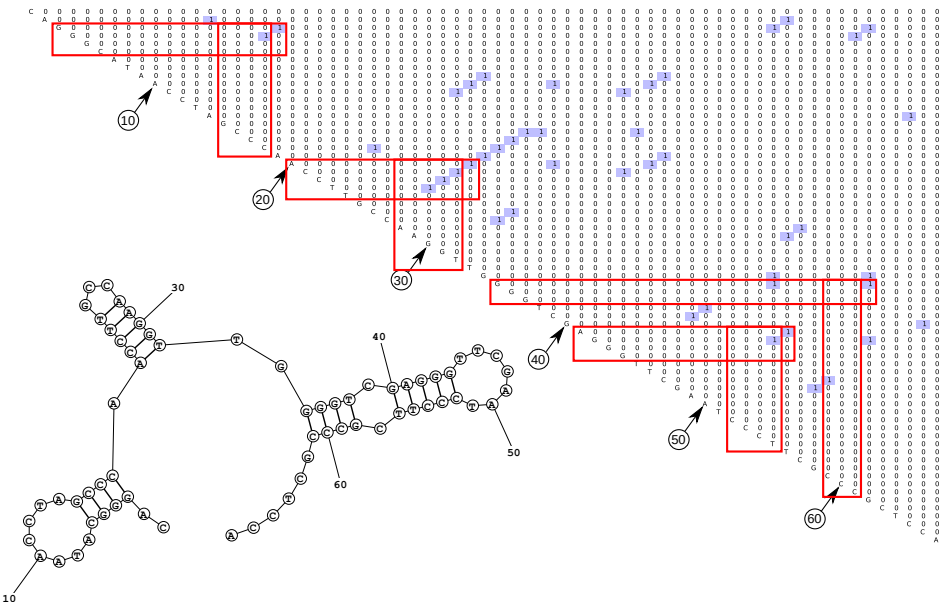
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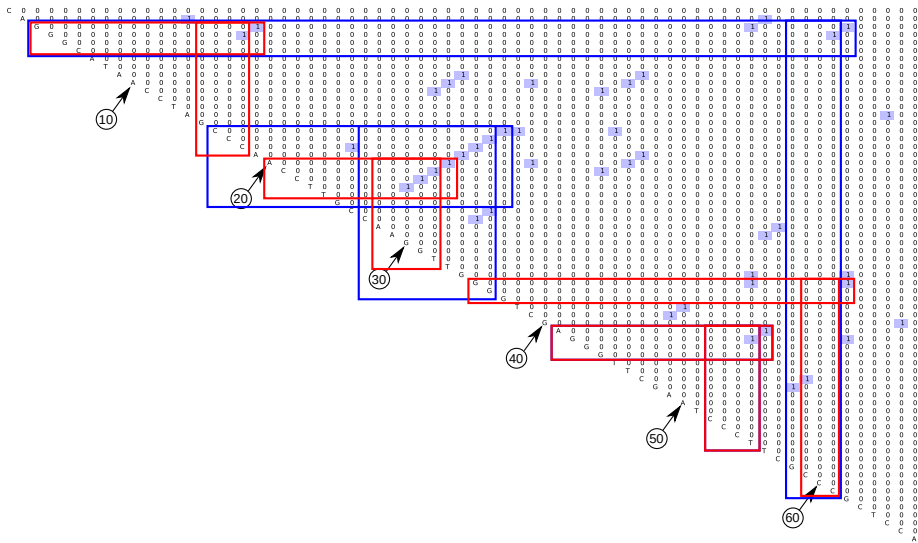
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Summary

- Parser is a features extractor, not a way to model secondary structure of full sequence
- Parsing result contains all possible foldings (w.r.t. grammar) including practically unreal foldings
- Grammar is a variable parameter: one can add G-T pair, change minimal height of stem, etc
- It is possible to detect features which is not expressable in language class which in use

Artificial Neural Networks

- Dense neural network
 - ▶ About 10 dense layers
 - ▶ ReLU activation function
- Problem: size of input is fixed, but length of sequences is variable

ACACAC		ACACAC\$\$
CGTACGCT	\Rightarrow	CGTACGCT
GCT		GCT\$\$\$\$\$

- Aggressive dropout (up to 90% after each layer) and batch normalization (after each layer) for learning stabilization

Evaluation: 16s rRNA detection

- Training data
 - ▶ All sequences have the length of 512 symbols
 - ▶ Totally up to 310000 sequences
 - ▶ Positive: random subsequences of 16s rRNA sequences from the Green Genes database
 - ▶ Negative: random subsequences of full genes from the NCBI database
- Validation set: up to 81000 sequences
- After training, accuracy is 90%

Evaluation: tRNA classification

- Training data: 50000 sequences from GtRNADB
- Input data normalization
 - ▶ Set the upper bound of sequence length to 220
 - ▶ First k symbols of the input are tRNA and the rest $220 - k$ symbols are filled by a special symbol
- Validation set: 217984 sequences for prokaryotes and 62656 sequences for eukaryotes from tRNADB-CE 3
- After training, accuracy is 97%
 - ▶ 3276 of eukaryotes (5.23% of all eukaryotes in the validation set) are classified as prokaryotes
 - ▶ 4373 of prokaryotes (2.01% of all prokaryotes in the validation set) are classified as eukaryotes

- DNN without parsing
 - ▶ Create a training set of matrices using parsing
 - ▶ Train the network NN_1 which can handle vectorized matrices
 - ▶ Create network NN_2 by extending NN_1 with a set of layers which convert the sequence to input for NN_1
 - ▶ Train NN_2 , weights of layers from NN_1 are fixed
- Other types of neural networks: bitwise networks, convolutional networks
- More evaluation
- Comparison with other tools

- We propose the approach to handle secondary structure of sequences
- This approach can be applied for real data processing
- This approach can be extended to more expressive formal languages classes
 - ▶ Conjunctive and boolean grammars
 - ▶ Multiple context-free grammars

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- Polind Lunina:
 - ▶ lunina_polina@mail.ru
- Trained models:

Thanks!