

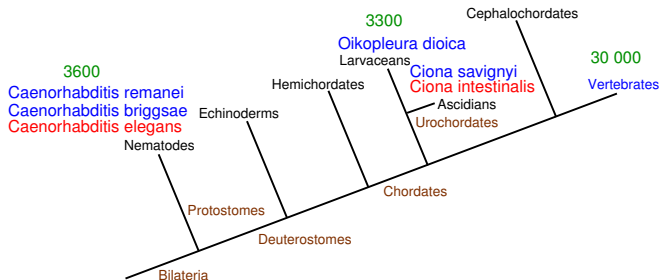
# RNAstrand : Reading direction of structured RNAs in multiple sequence alignments

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Bioinformatics Group, Department of Computer Science  
University of Leipzig

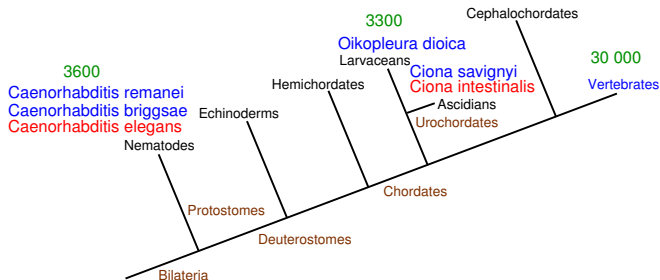
Bled 2007

# Why strand predictor of structured RNAs?



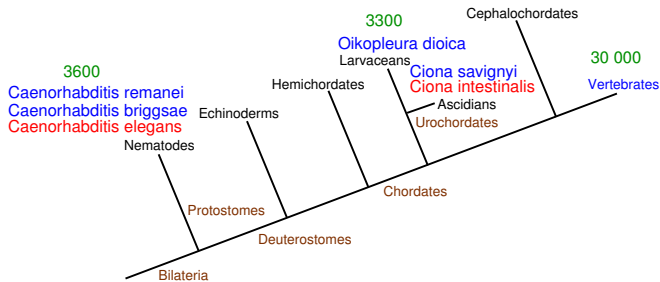
- Genome wide prediction of structured non-coding RNAs (RNAz , EvoFold )
- Annotation is next challenge:
  - RNAs with homologous secondary structures (LocARNA )
  - Detect specific RNA families (RNAmicro , snoReport )
  - intronic, intergenic or non-translated exon (RNAstrand )

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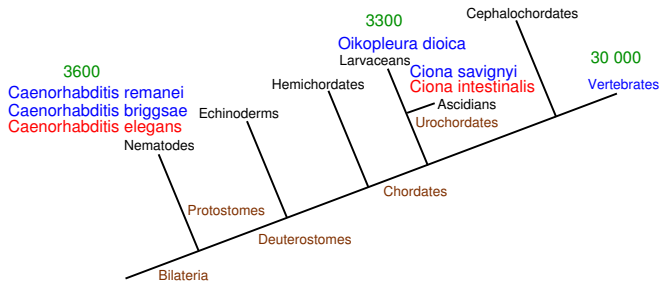
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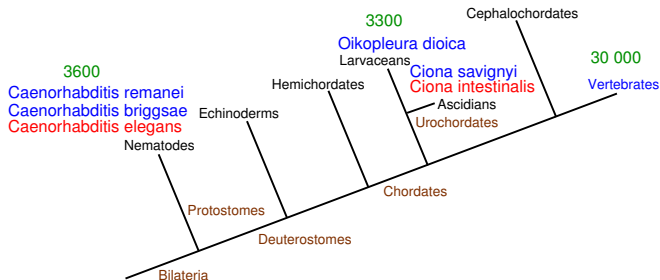
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- Naïve approach: Take strand which has higher `RNAz` probability or `EvoFold` score
- Problem: `RNAz` and `EvoFold` are not trained for strand prediction of RNA
- Accuracy: `RNAz` on miRNAs: 0.14, `EvoFold` on miRNAs: 0.84
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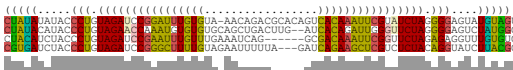
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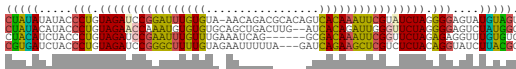
# Task

## Input alignment containing structured ncRNA

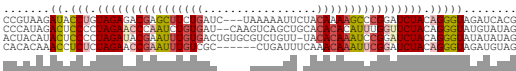
AL645782.2/32556-32631  
AY303232.1/800-874  
AF321227.1/48039-48109  
AF321227.1/86918-86845



Structured ncRNA on reading direction of input alignment?



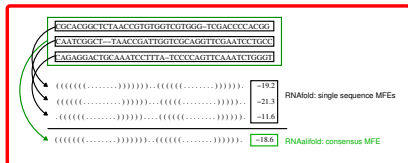
Structured ncRNA on reverse complement of input alignment?



# Approach

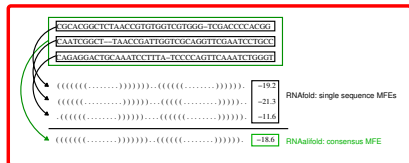
# Approach

## Reading direction of input alignment



# Approach

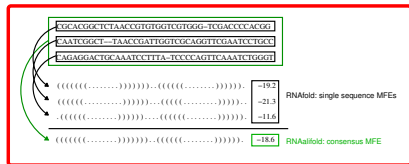
## Reading direction of input alignment



$$\text{meanz} = \frac{\sum \text{single sequence z-score}}{N}$$

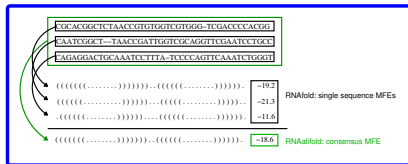
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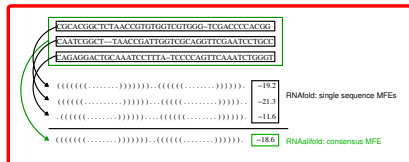
## Realigned reverse complement



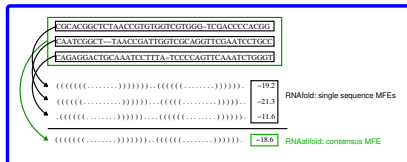
$$\text{meanz}$$

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## Reading direction of input alignment



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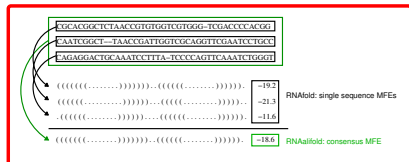
$$\text{meanmfe} = \frac{\sum \text{single sequence MFE}}{N}$$

meanz

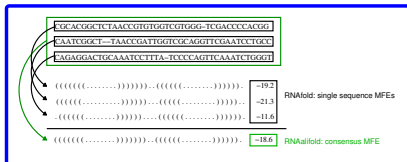


# Approach

## Reading direction of input alignment



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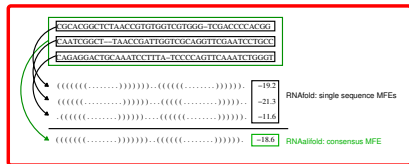
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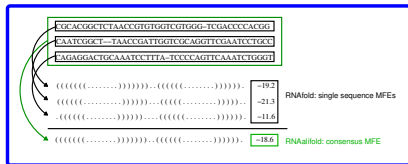
meanmfe

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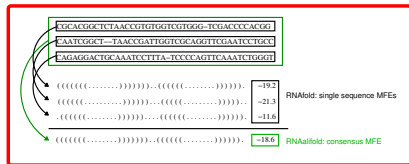
$$\text{sci} = \frac{\text{consmfe}}{\text{meanmfe}}$$

meanz

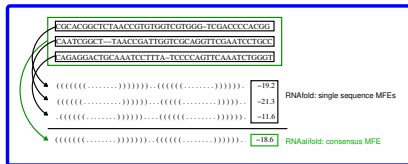
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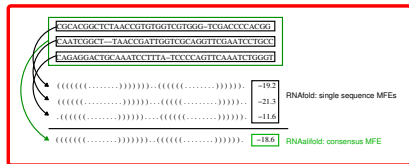
meanz

meanmfe

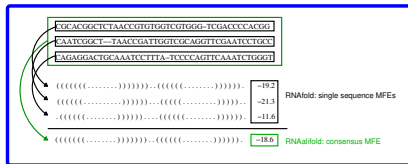
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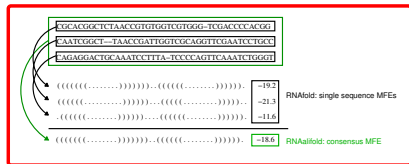
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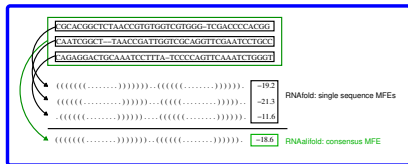
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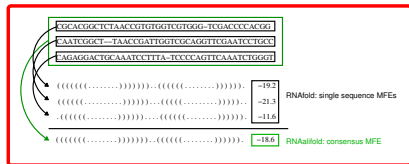
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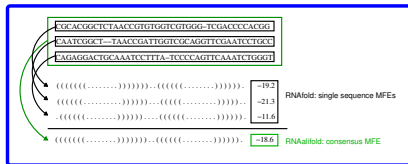
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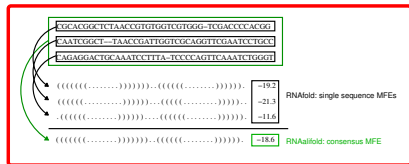
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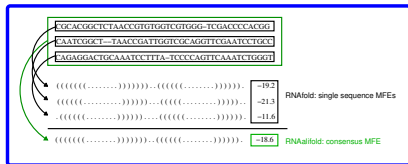
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Classification via support vector machine (SVM)

# Which descriptors are the best?

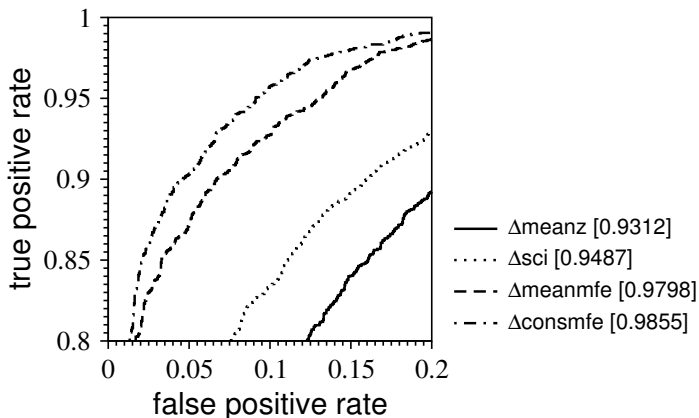


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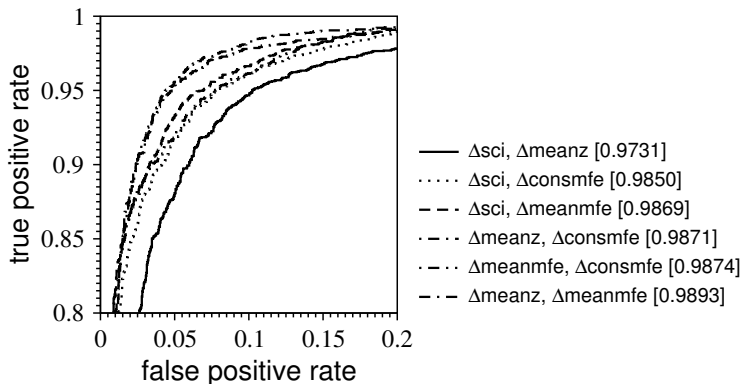
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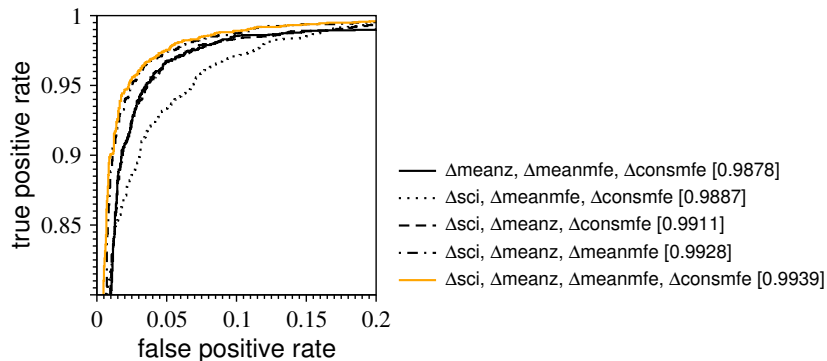
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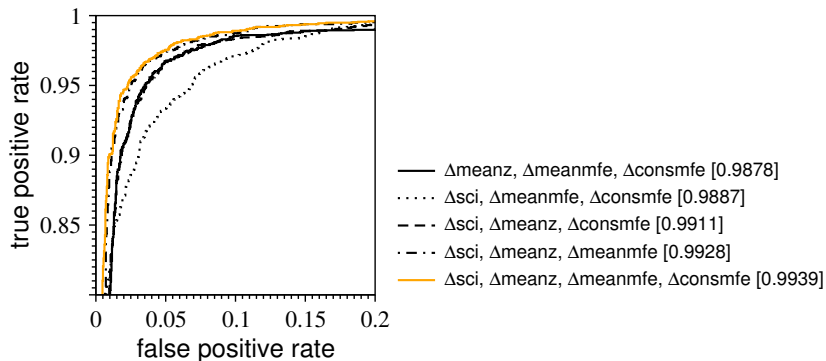
# Combination of two



# Combination of at least three



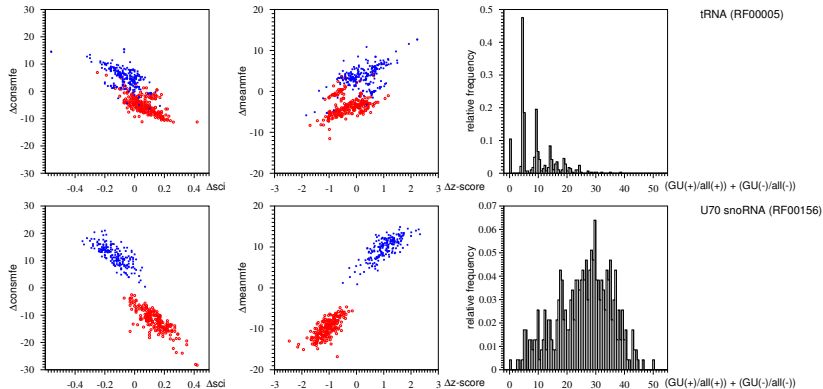
# Combination of at least three



Maximal area under the curve (99.39%) if all four descriptors are taken

# Additional descriptors

$\Delta meanmfe$  ,  $\Delta consmfe$  ,  $\Delta meanz$  ,  $\Delta sci$  depend on fraction of GU base pairs:



# Final set of descriptors

Strand differences are captured by:

- Differences in stability
  - $\Delta meanz$
  - $\Delta meanmfe$
- Differences in structure conservation
  - $\Delta sci$
  - $\Delta consmfe$
- $\frac{\text{GU pairs in consensus}}{\text{all pairs in consensus}} + \frac{\text{GU pairs in consensus}}{\text{all pairs in consensus}}$
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- SVM library `libsvm`
- Radial basis function kernel:  $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$
- Attributes are scaled to  $-1$  and  $1$
- Optimal parameters: penalty of error term  $C = 128$ ,  $\gamma = 0.5$
- Probability estimates  $P$  that alignment contains ncRNA in same reading direction
- RNAstrand score:  $D = 2 * P - 1$ ,  $D \in [-1, 1]$
- Different cutoffs  $c$  of score provide different prediction reliabilities:
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# SVM specifications

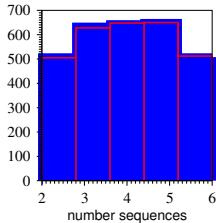
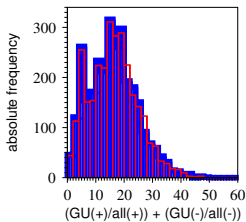
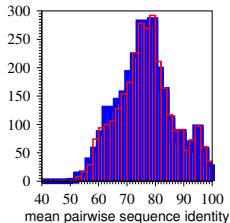
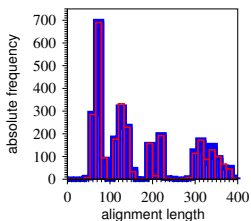
- SVM library `libsvm`
- Radial basis function kernel:  $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$
- Attributes are scaled to  $-1$  and  $1$
- Optimal parameters: penalty of error term  $C = 128$ ,  $\gamma = 0.5$
- Probability estimates  $P$  that alignment contains ncRNA in same reading direction
- `RNAstrand` score:  $D = 2 * P - 1$ ,  $D \in [-1, 1]$
- Different cutoffs  $c$  of score provide different prediction reliabilities:
  - $D > +c$ : ncRNA in reading direction of input alignment
  - $D < -c$ : ncRNA is reverse complement of input alignment
  - $-c \leq D \leq +c$ : No decision

# Training of RNAstrand

5886 training alignments including representatives of rRNAs, snRNAs, snoRNAs, tRNAs, miRNAs, nuclear RNase P and SRP RNA

# Training of RNAstrand

5886 training alignments including representatives of rRNAs, snRNAs, snoRNAs, tRNAs, miRNAs, nuclear RNase P and SRP RNA

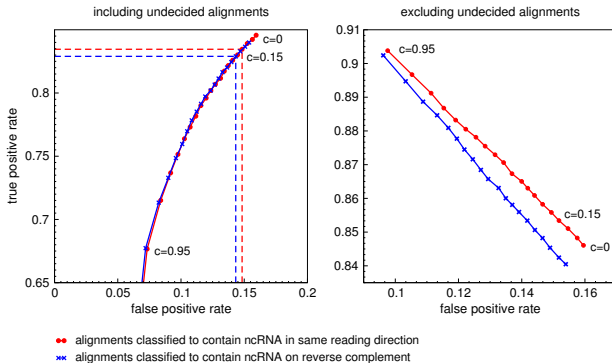


# Validation of RNAstrand

Validate RNAstrand with 35766 automatically created ClustalW alignments of 313 non-coding RNA families found in RFAM 7.0

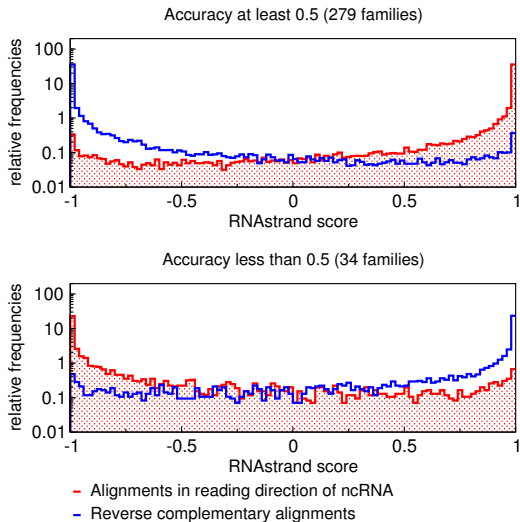
ncRNA type	<i>N</i>	<i>O</i>	<i>c</i> = 0			<i>c</i> = 0.5		<i>c</i> = 0.9		
			<i>A</i> <sub>+</sub>	<i>A</i> <sub>-</sub>	<i>A</i>	1- <i>A</i> - <i>u</i>	<i>u</i>	<i>A</i>	1- <i>A</i> - <i>u</i>	<i>u</i>
5S rRNA	860	12.6%	0.98	0.98	0.98	0.00	0.01	0.95	0.00	0.03
5.8S rRNA	146	-	0.93	0.93	0.89	0.05	0.05	0.73	0.02	0.24
tRNA	294	0.9%	0.94	0.94	0.88	0.01	0.09	0.62	0.00	0.36
miRNA	2496	4.5%	0.98	0.97	0.96	0.00	0.02	0.89	0.00	0.10
snoRNA (C/D)	204	9.9%	0.59	0.57	0.48	0.32	0.18	0.29	0.18	0.52
snoRNA (H/ACA)	1340	1.2%	0.98	0.98	0.97	0.01	0.01	0.94	0.00	0.05
spliceos. RNA	2878	35.0%	0.92	0.92	0.88	0.05	0.06	0.77	0.02	0.19
euk. SRP RNA	1000	8.1%	0.99	0.99	0.99	0.00	0.00	0.97	0.00	0.02
nucl. RNaseP	260	41.9%	0.93	0.93	0.92	0.04	0.03	0.85	0.01	0.12
RNase MRP	140	-	0.98	1.00	0.98	0.00	0.01	0.96	0.00	0.03
SECIS	76	-	0.65	0.64	0.51	0.25	0.22	0.32	0.19	0.48
7SK	184	-	0.04	0.03	0.02	0.91	0.05	0.01	0.80	0.18

# Best cutoff $c$

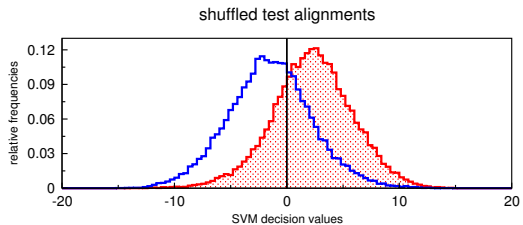
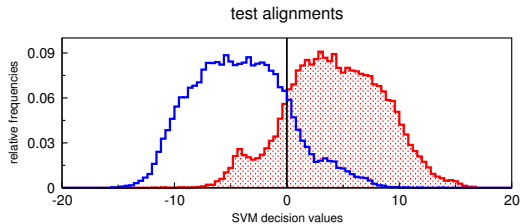


Maximal Youden index of 0.75 with cutoff  $c = 0.15$

# Distribution of RNAstrand scores



# Distribution of SVM decision values



# Are we better than naïve approach? (RNAz )

ncRNA type	<i>N</i>	Accuracy (RNAstrand: <i>c</i> = 0)	
		<i>A</i> (RNAstrand)	<i>A</i> (RNAz)
5S rRNA	860	0.98	0.97
5.8S rRNA	146	0.93	0.90
tRNA	294	0.94	0.53
miRNA	2496	0.97	0.14
snoRNA (C/D)	204	0.58	0.46
snoRNA (H/ACA)	1340	0.98	0.94
spliceos. RNA	2878	0.92	0.82
euk. SRP RNA	1000	0.99	0.84
nucl. RNaseP	260	0.93	0.82
RNase MRP	140	0.99	0.50
SECIS	76	0.65	0.48
7SK	184	0.04	0.03



# Are we better than naïve approach? (RNA<sub>z</sub>)

RNAstrand	correct		incorrect	
correct	21536	21425	8711	8639
incorrect	1618	1729	3901	3973

2-fold reduction of misclassification rate

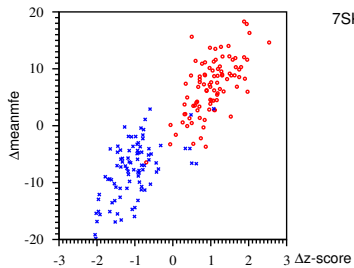
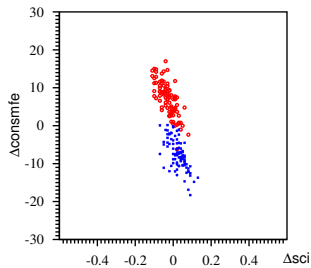
# Are we better than naïve approach? (EvoFold)

RNAstrand(fwd)	correct	incorrect		
correct	104	8	15	0
incorrect	16	0	7	2
RNAstrand(rev)	correct	incorrect		
correct	102	8	11	0
incorrect	18	0	11	2

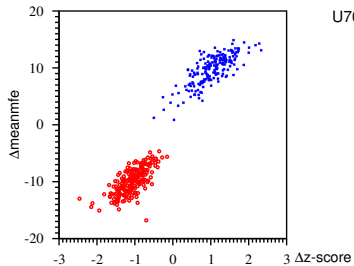
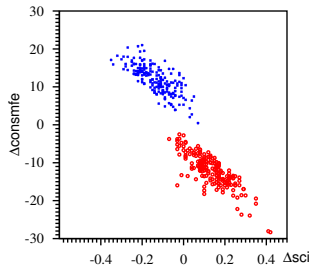
Strand prediction of EvoFold comparable to RNAstrand.



# Backup Slide - Classification of 7SK RNAs

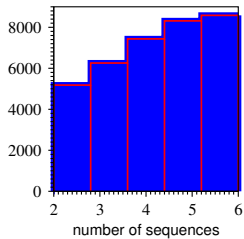
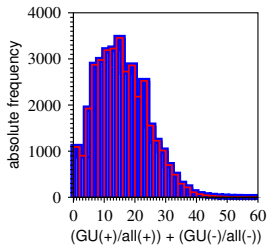
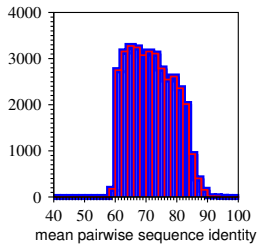
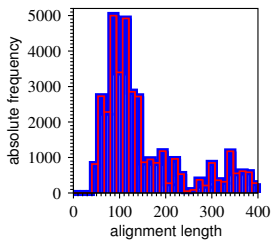


7SK (RF00100)



U70 snoRNA (RF00156)

# Backup Slide - Test alignments



# Backup Slide - Standard deviations

ncRNA class	$N$	$c = 0$		$c = 0.5$			$c = 0.9$		
		$A_+$	$A_-$	$A$	$1-A-u$	$u$	$A$	$1-A-u$	$u$
rRNA	2	0.02	0.02	0.04	0.02	0.01	0.11	0.01	0.10
miRNA	36	0.15	0.13	0.18	0.05	0.13	0.31	0.00	0.31
snoRNA (C/D)	23	0.38	0.40	0.38	0.36	0.15	0.37	0.28	0.35
snoRNA (H/ACA)	26	0.17	0.17	0.22	0.11	0.15	0.32	0.05	0.30
spliceos. RNA	6	0.24	0.25	0.29	0.20	0.08	0.29	0.12	0.17

# Backup Slide - GU base pair fraction

