

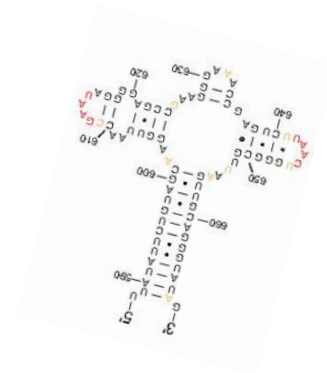
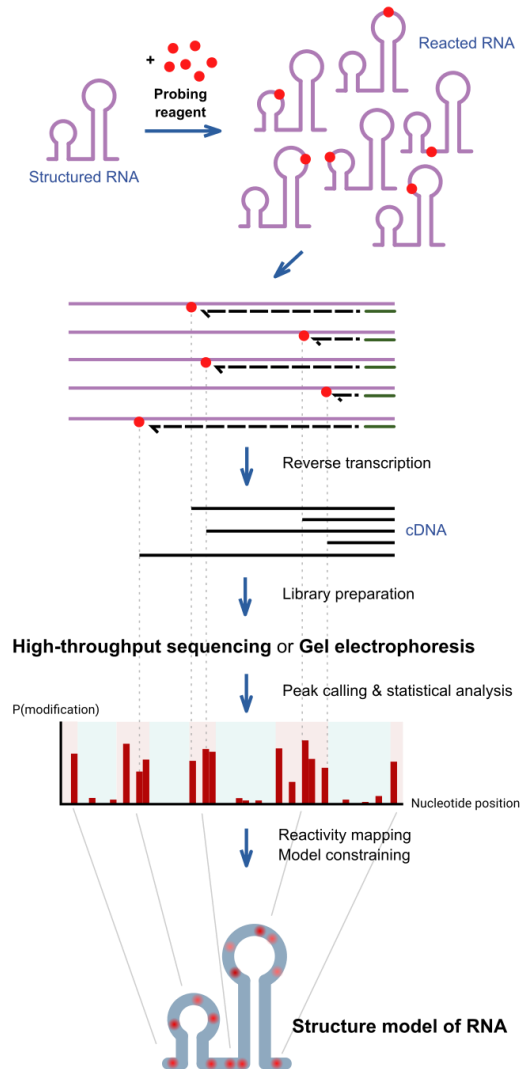
## IPANEMAP

# Integrative **P**robing **A**nalysis of **N**ucleic Acids **E**mpowered by **M**ultiple **A**ccessibility **P**rofiles

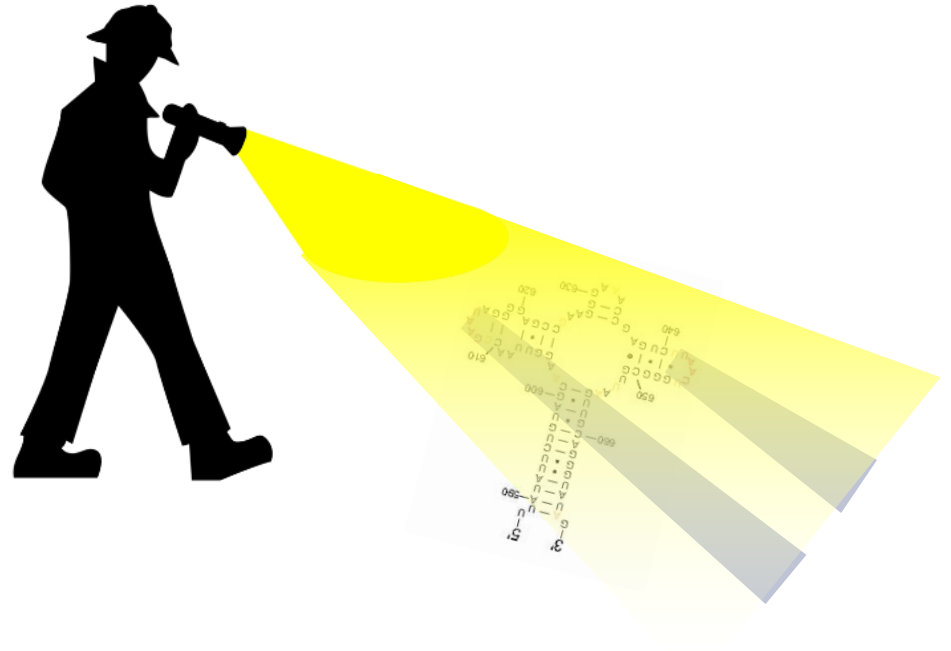
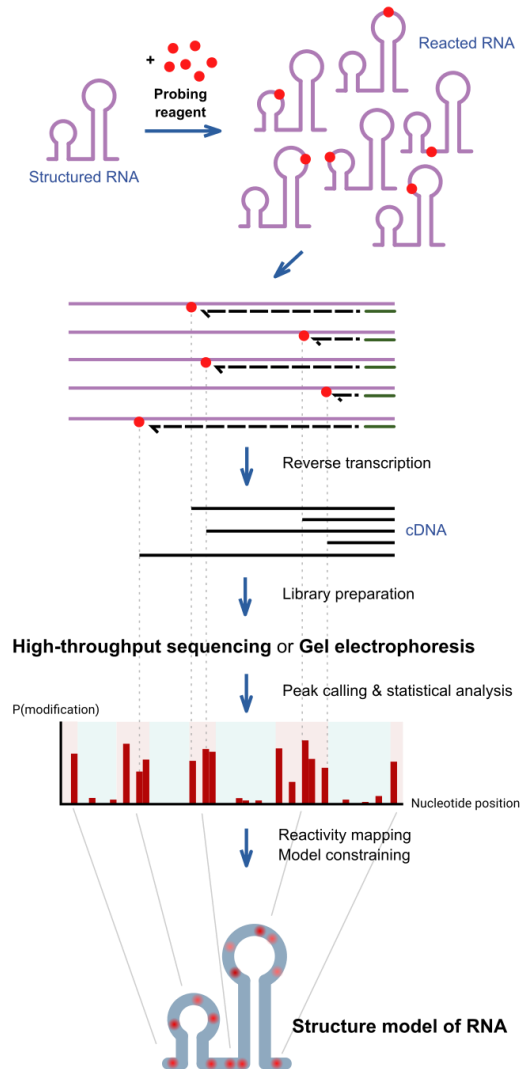
Afaf SAAIDI & Yann PONTY  
CNRS/Ecole Polytechnique

Bruno SARGUEIL & Delphine ALLOUCHE  
Univ. Paris Descartes

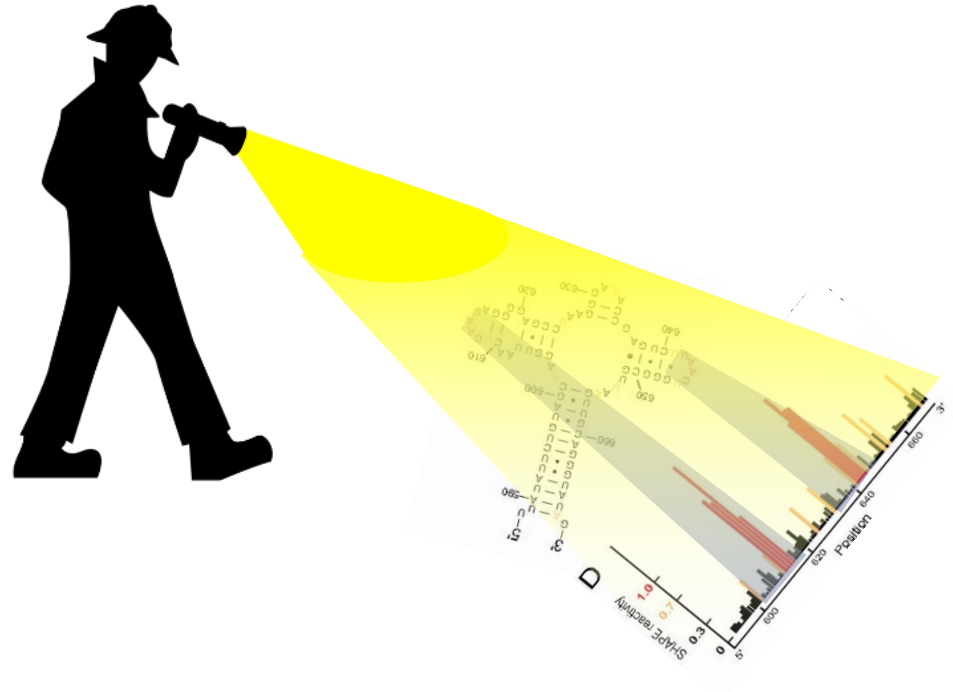
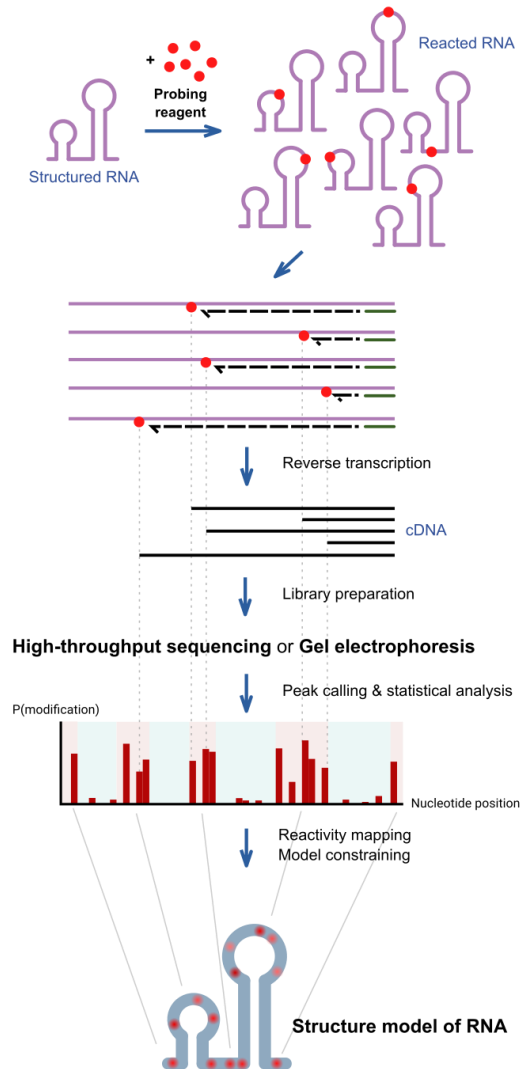
# Structure probing in a nutshell



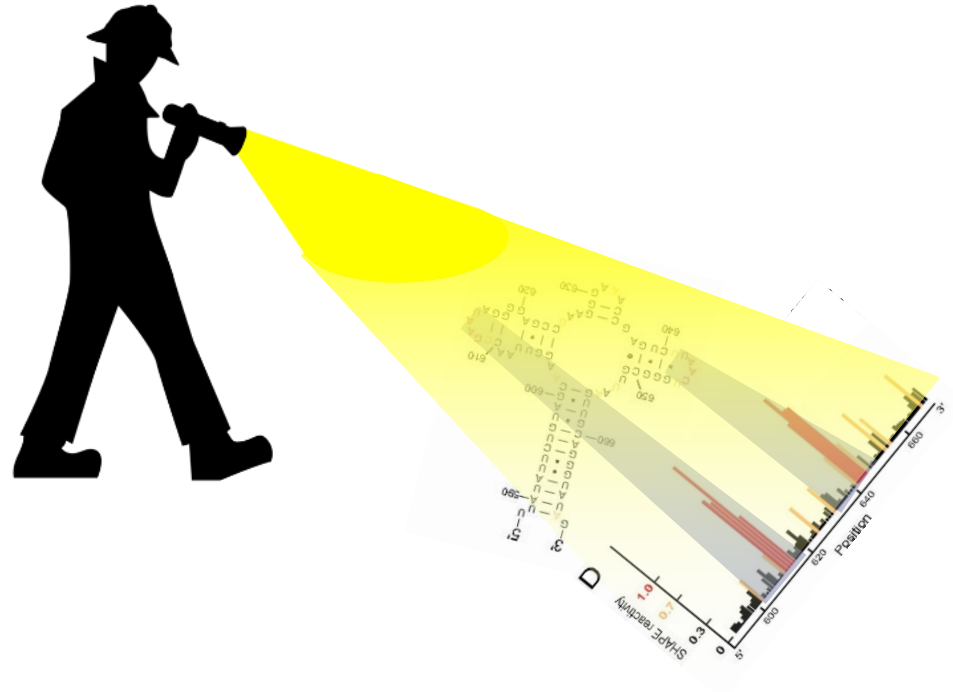
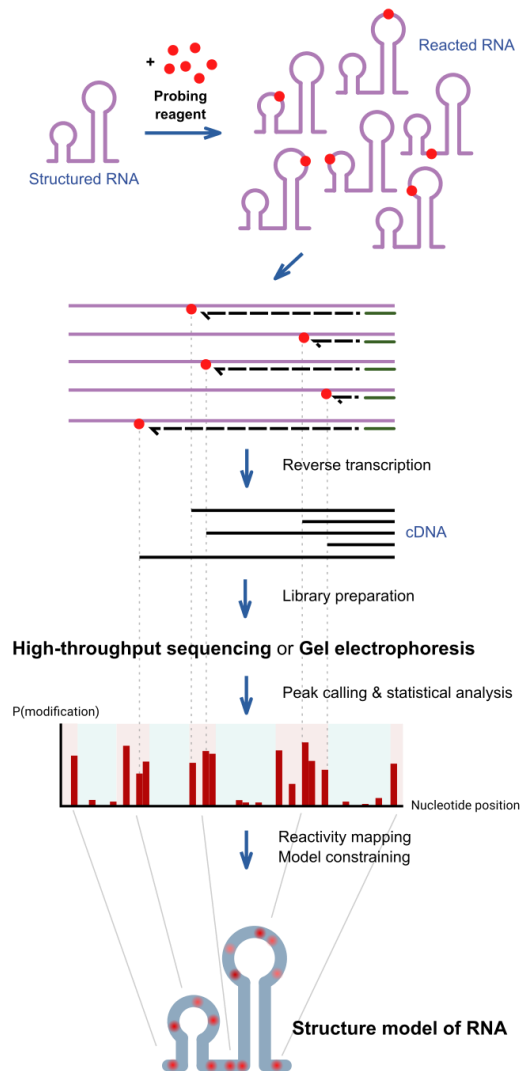
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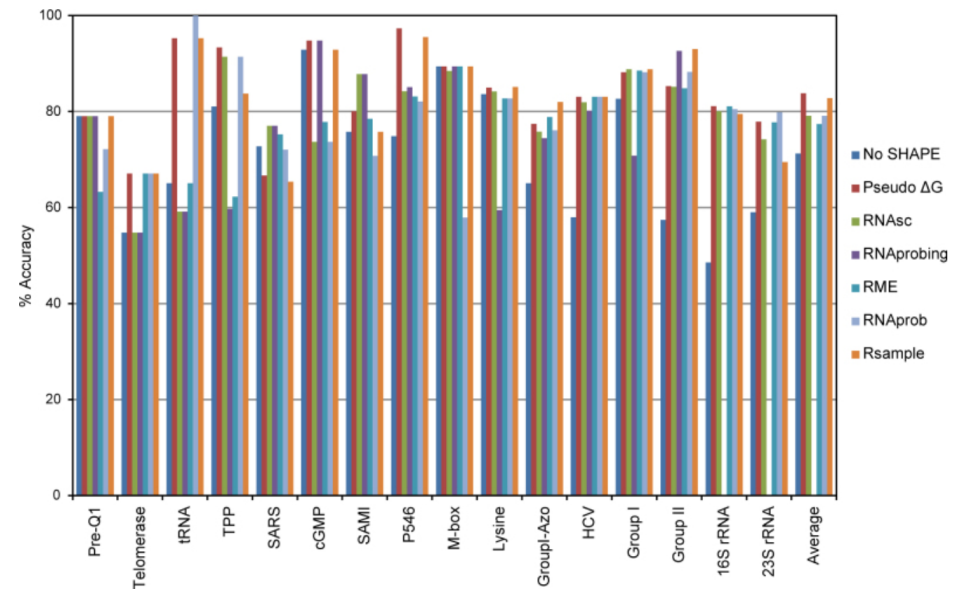


# The SHAPE wars: 100% accuracy and beyond...

Now, wait a minute  
guys...!



David H Mathews



Spasic *et al*, NAR 2018

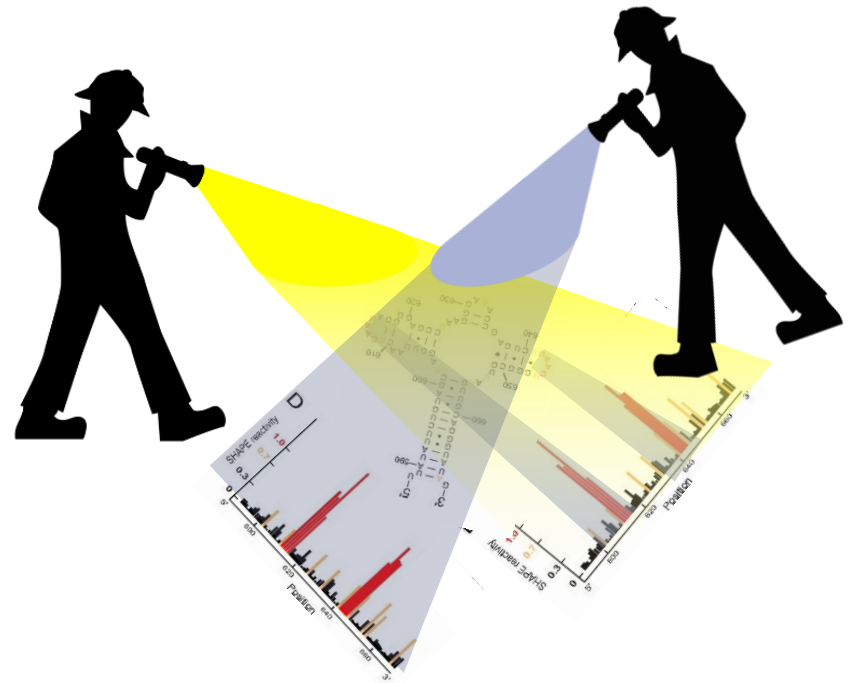
# The practice of RNA modeling



Bruno Sargueil

Probing is tricky to perform and interpret.

Beyond RNAPuzzle, modelers usually try different techniques and reagents, but integration is no gimme...

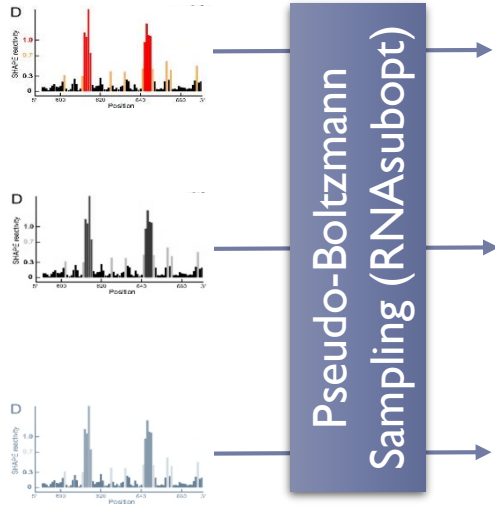


## How to integrate multiple probing profiles?

# A KISS approach

- ▶ Reactivity profiles uniformly captured as pseudo potentials in prediction methods (RNAsubopt + Soft constraints)
- ▶ Native structure should be represented in each of the pseudo-Boltzmann ensemble (maybe not at the top)

ACGAUGAUCGACUACGAUCGA  
UCGACUAGCUACGUACUGACU  
CGGCUAGAUUAGCUUAUGA...

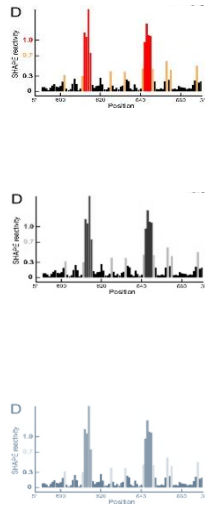




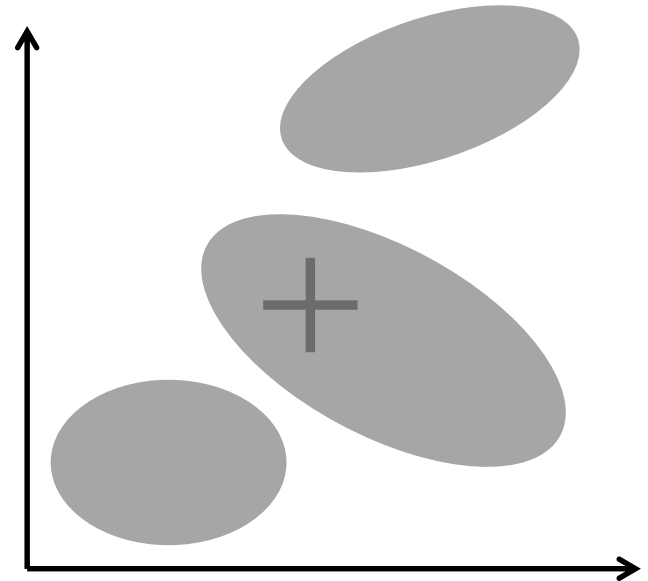
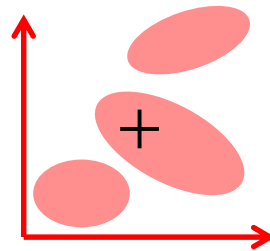
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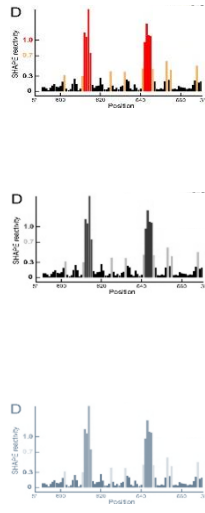
Pseudo-Boltzmann  
Sampling (RNAsubopt)



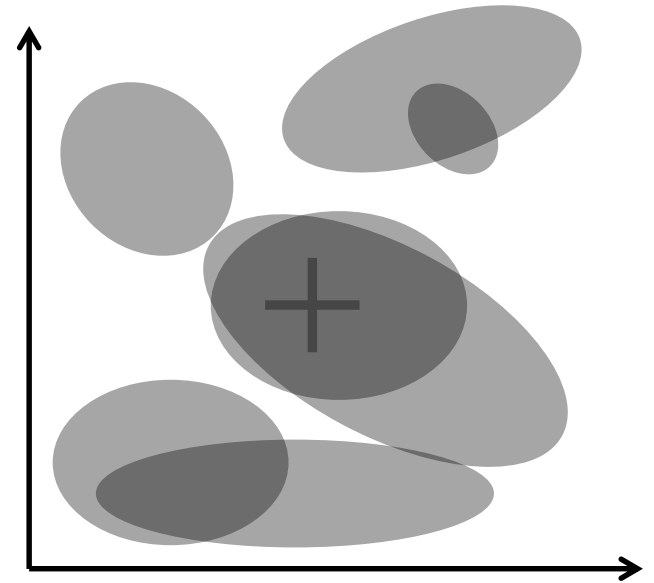
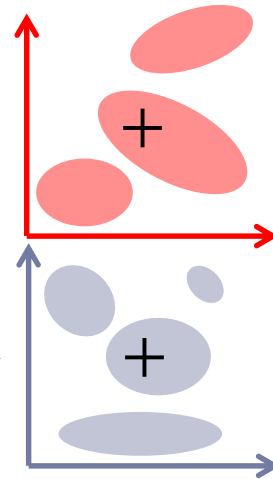
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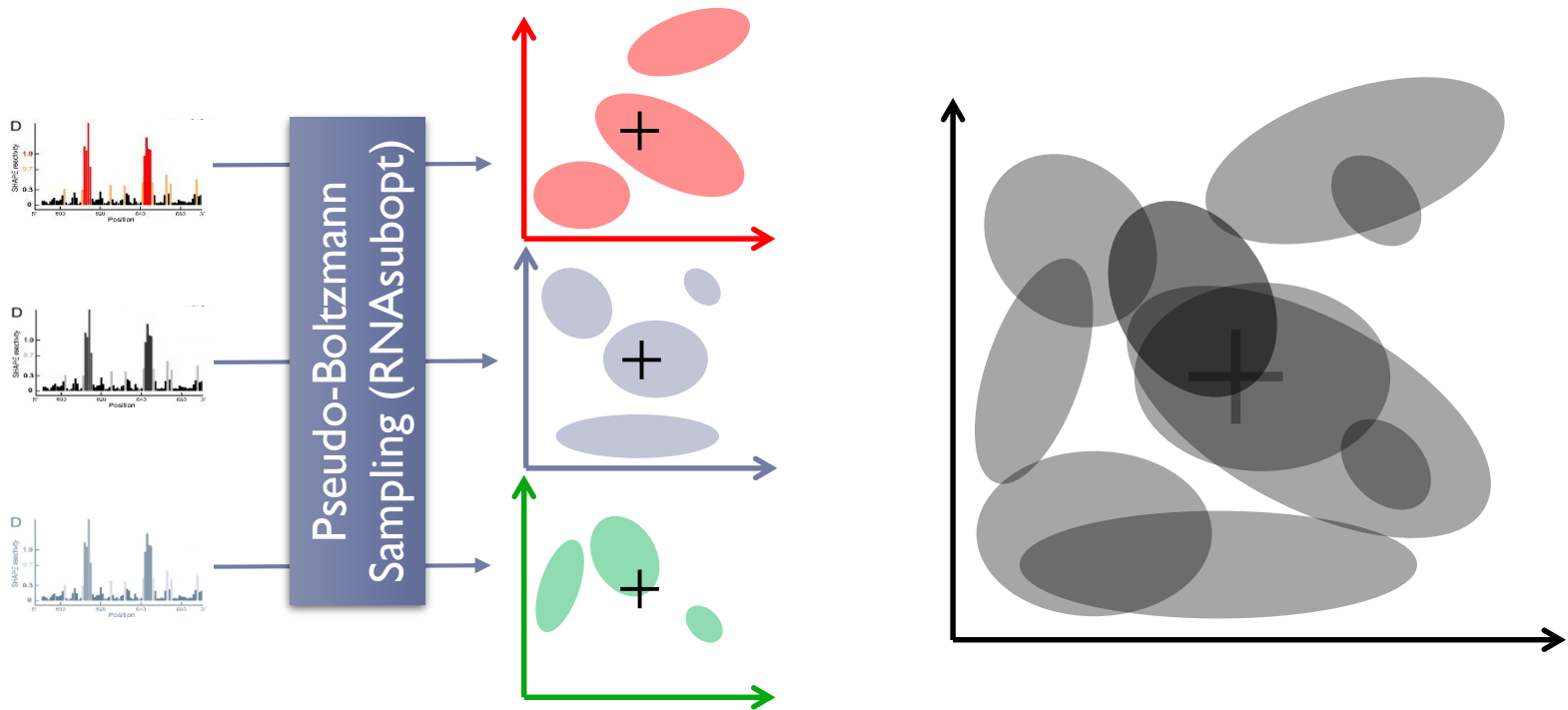
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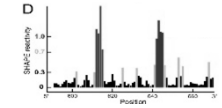
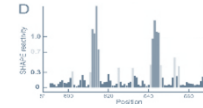
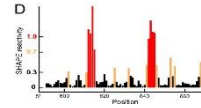
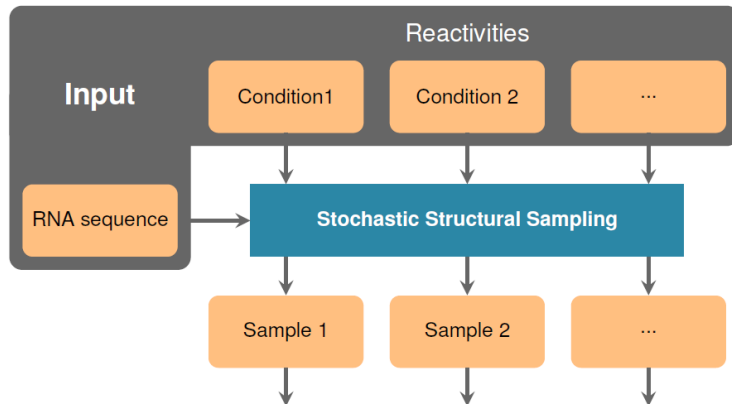
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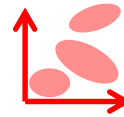
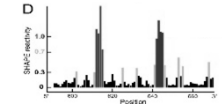
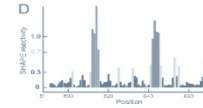
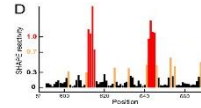
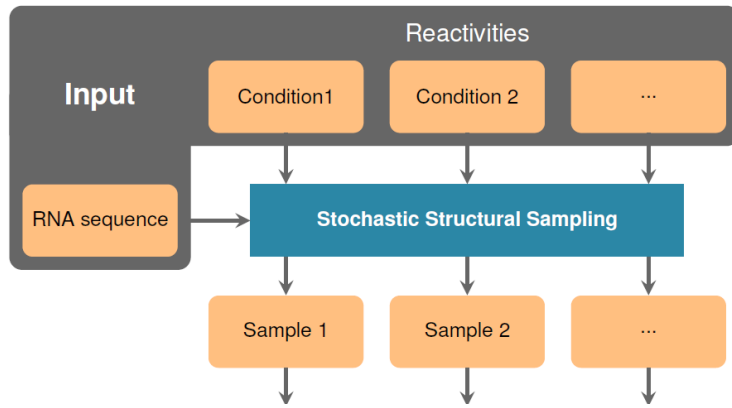
ACGAUGAUCGACUACGAUCGA  
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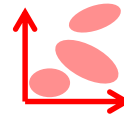
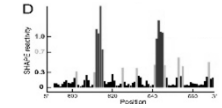
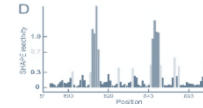
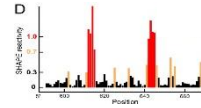
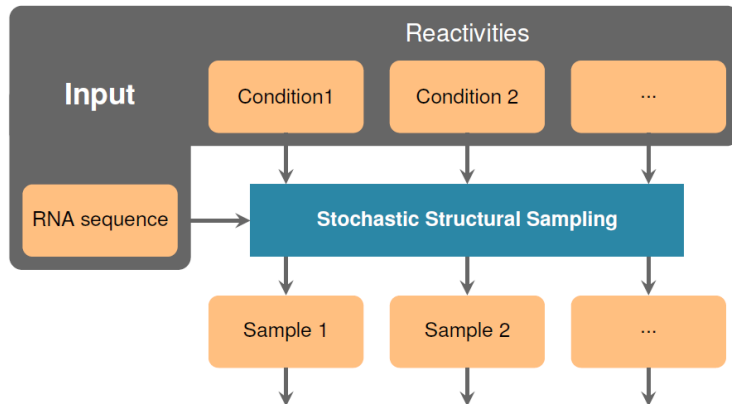
# IPANEMAP Pipeline



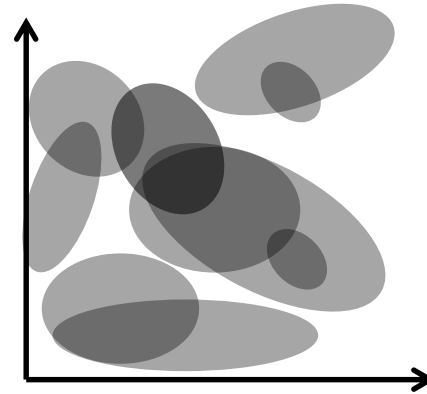
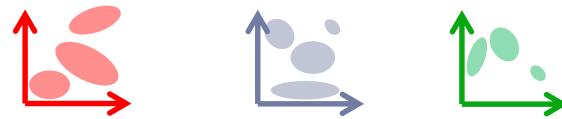
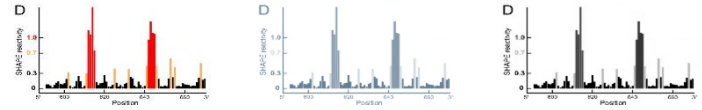
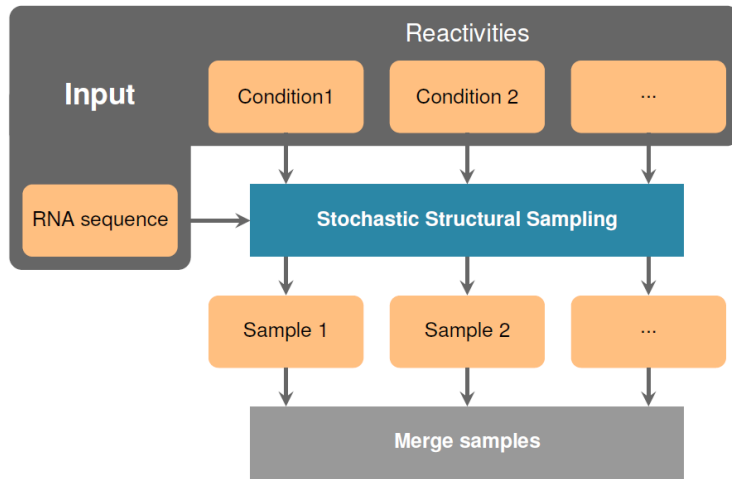
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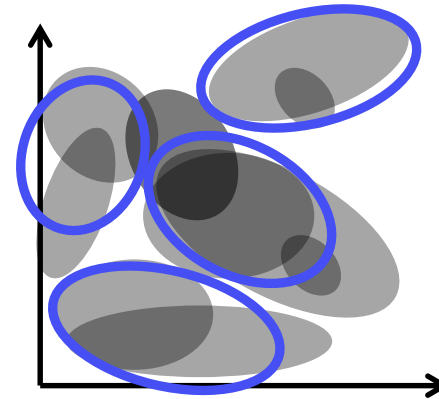
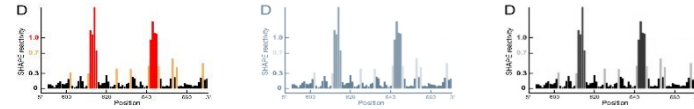
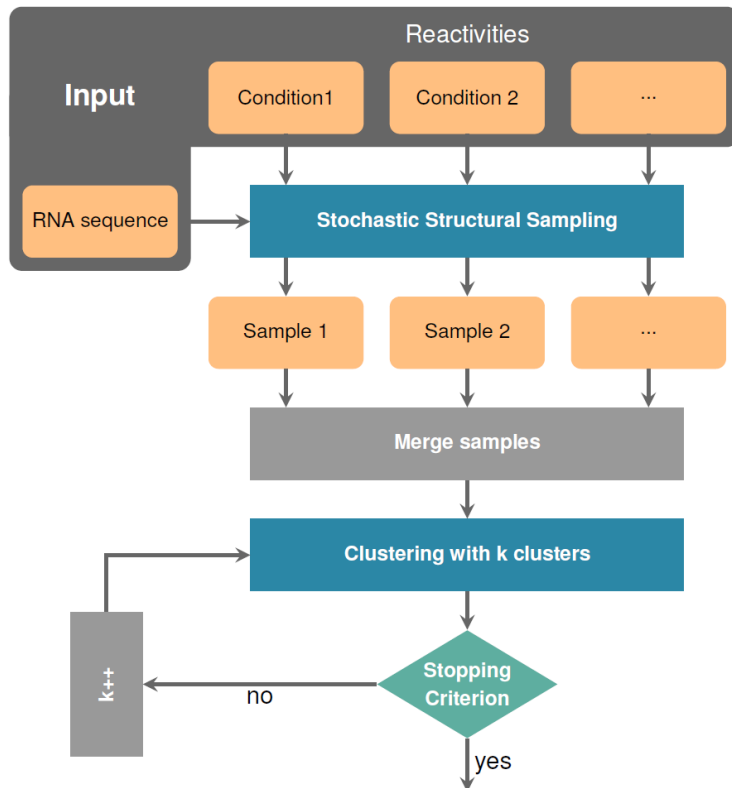
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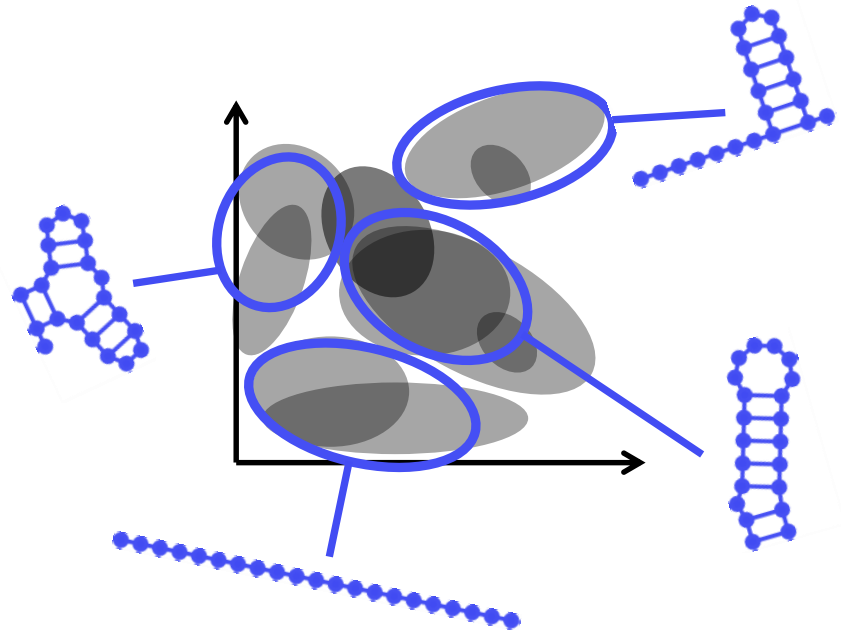
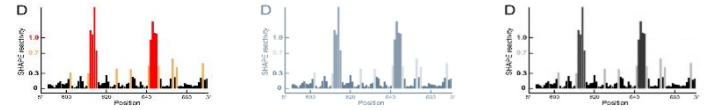
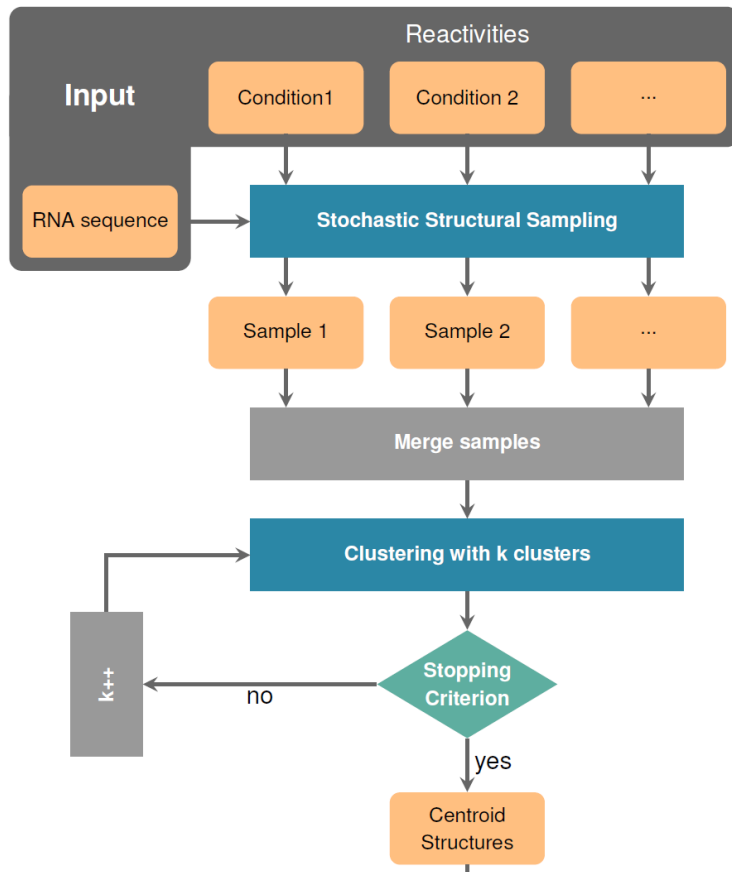


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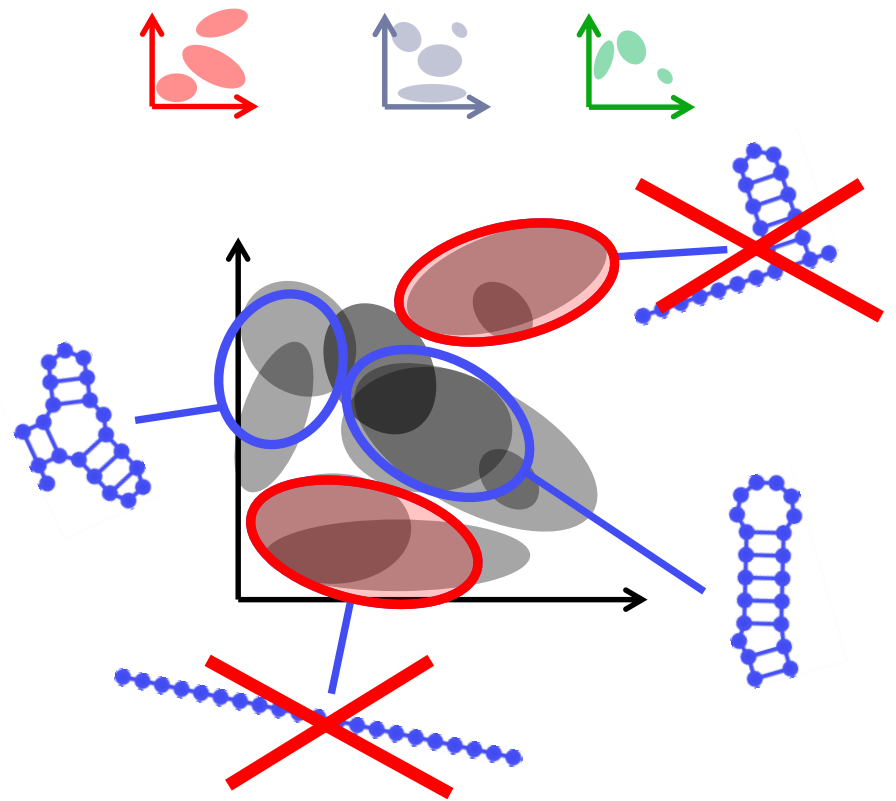
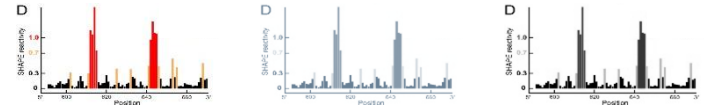
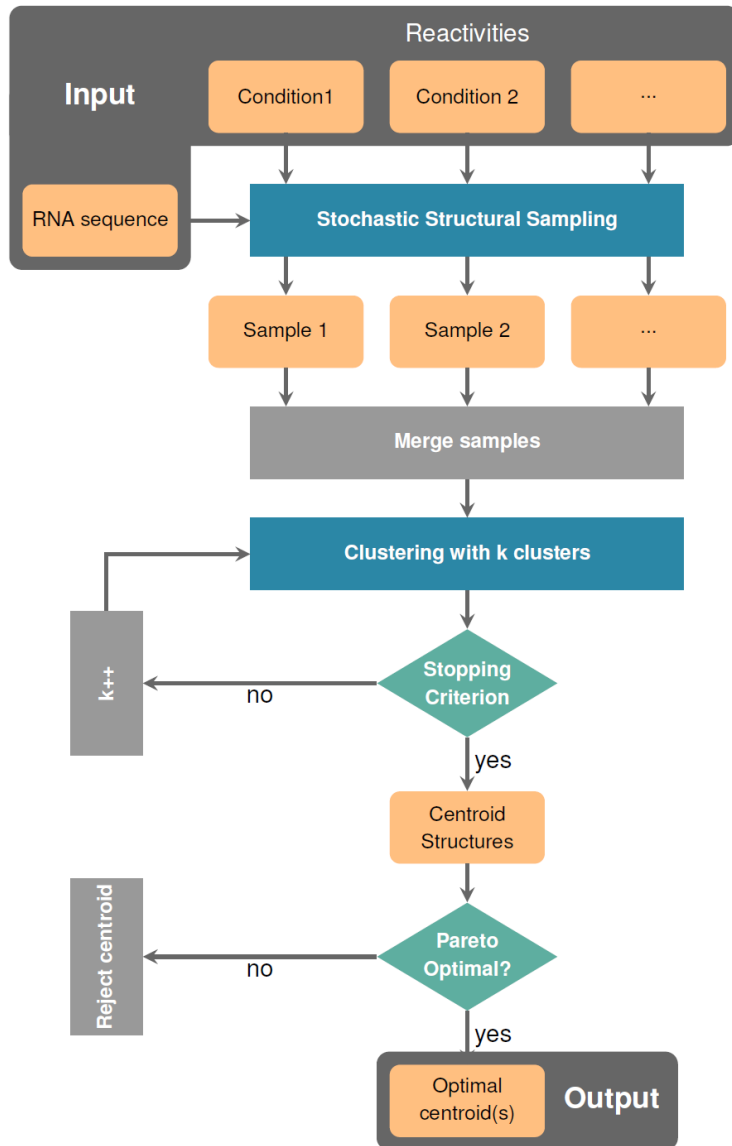




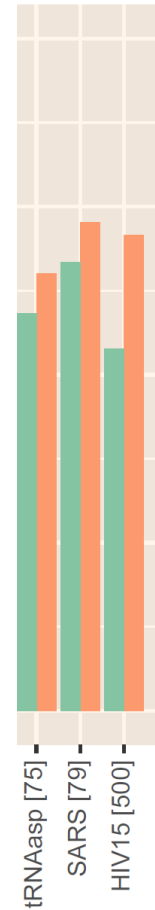
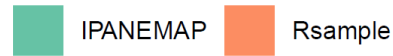
# IPANEMAP Pipeline



# IPANEMAP Pipeline



# Single condition/single structure dataset



▶ IPANEMAP vs Rsample  
[Spasic *et al*, NAR 2018]

▶ Hajdin *et al* dataset  
SHAPE IM7  
50-500nts RNAs

RNAs

**Geometric Mean**  $GM(S | R) = \sqrt{\text{Sens}(S | R) \times \text{PPV}(S | R)}$

# Single condition/single structure dataset

IPANEMAP Rsample



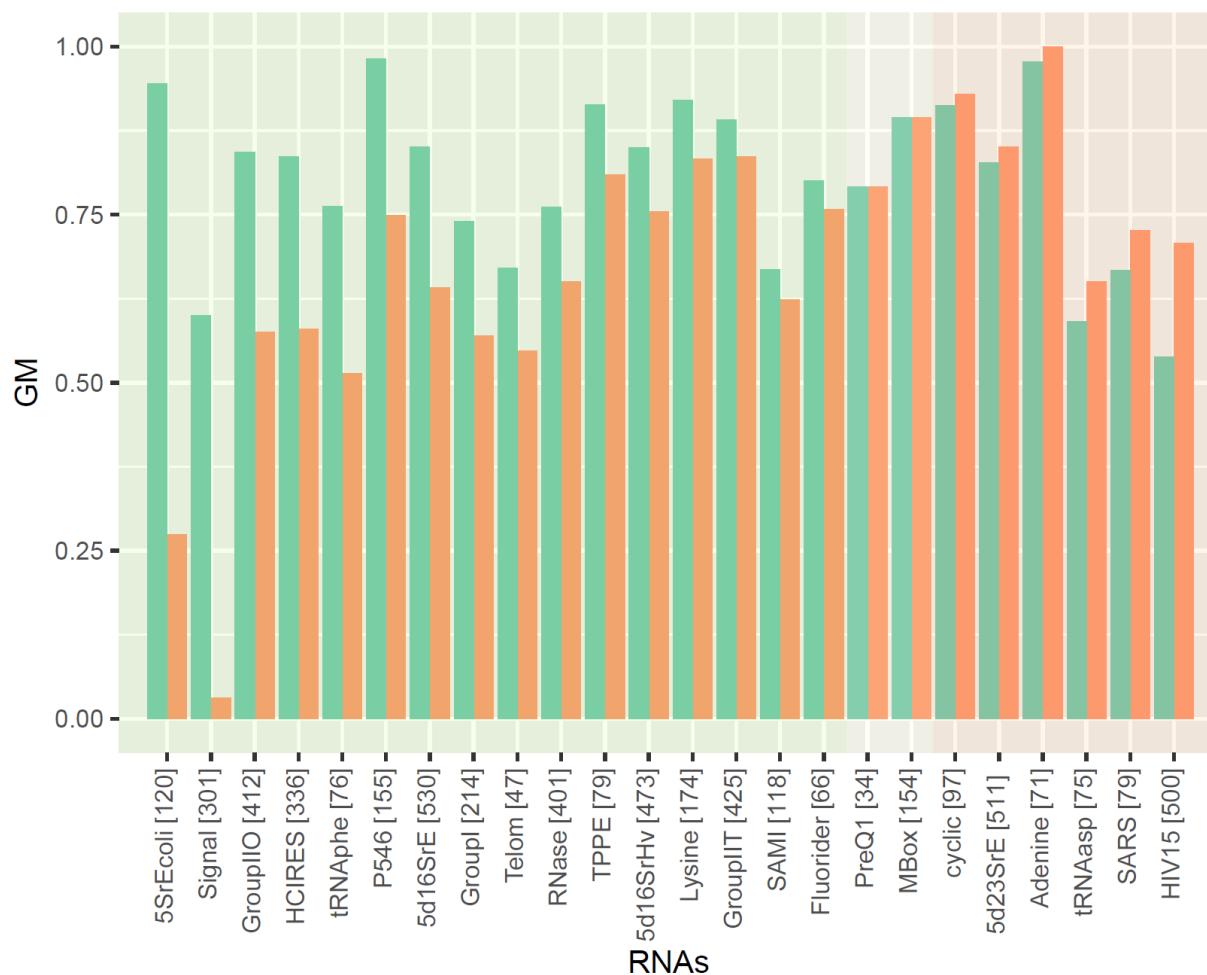
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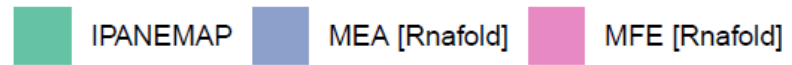
- ▶ IPANEMAP vs Rsample  
[Spasic *et al*, NAR 2018]
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SHAPE IM7  
50-500nts RNAs
- ▶ 80% GM IPANEMAP  
vs 63% GM for Rsample
- ▶ Reason: Rsample  $\approx$  MEA

**Geometric Mean**  $GM(S | R) = \sqrt{\text{Sens}(S | R) \times \text{PPV}(S | R)}$

# Multiple conditions improve predictions?

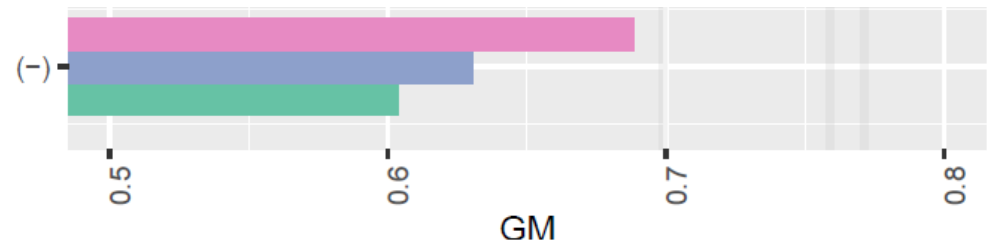
## ▶ 6 RMDB RNAs

- ▶ 5s RNA *E. coli*
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*F. Nucleatum*
- ▶ cidGMP riboswitch  
*V. Cholerae*
- ▶ P4 - P6 domain  
Tetrahymena ribozyme
- ▶ *add* Adenine Riboswitch
- ▶ tRNA phenylalanine yeast



## ▶ 3 conditions

- ▶ SHAPE (NMIA)
- ▶ DMS
- ▶ CMCT



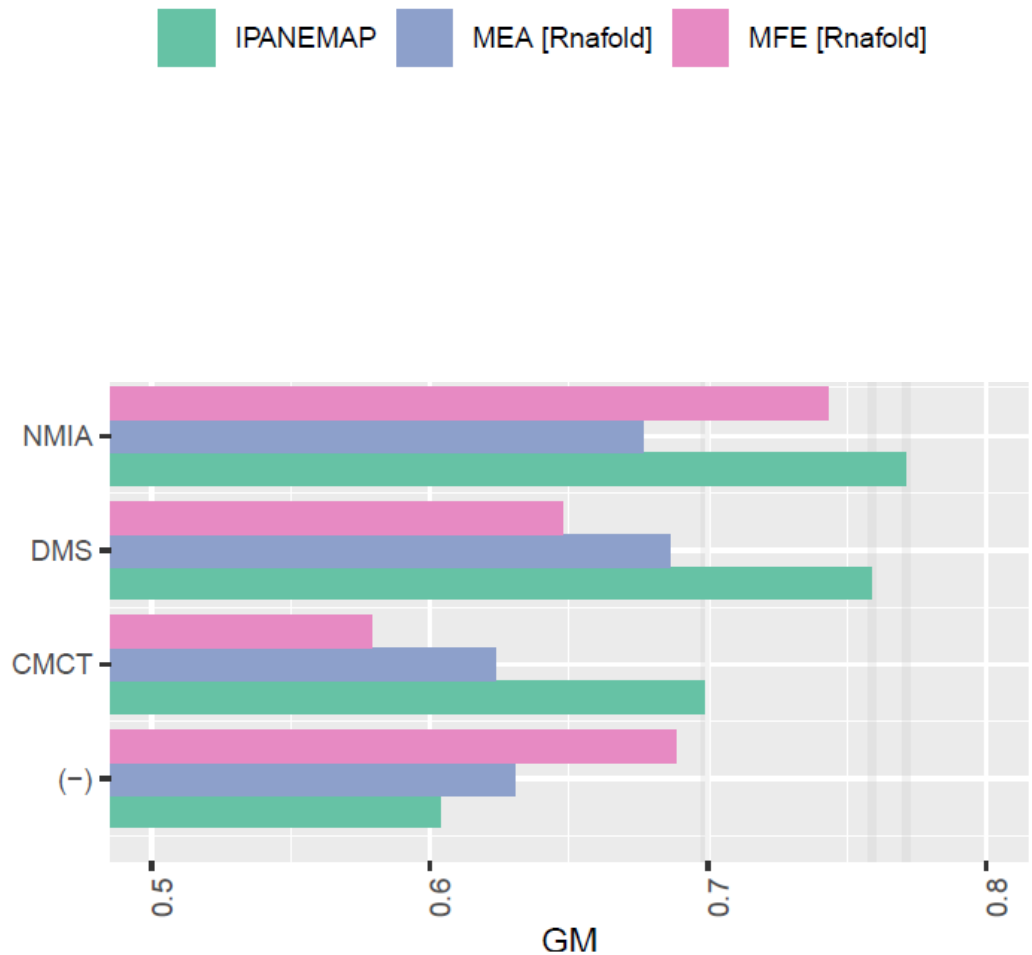
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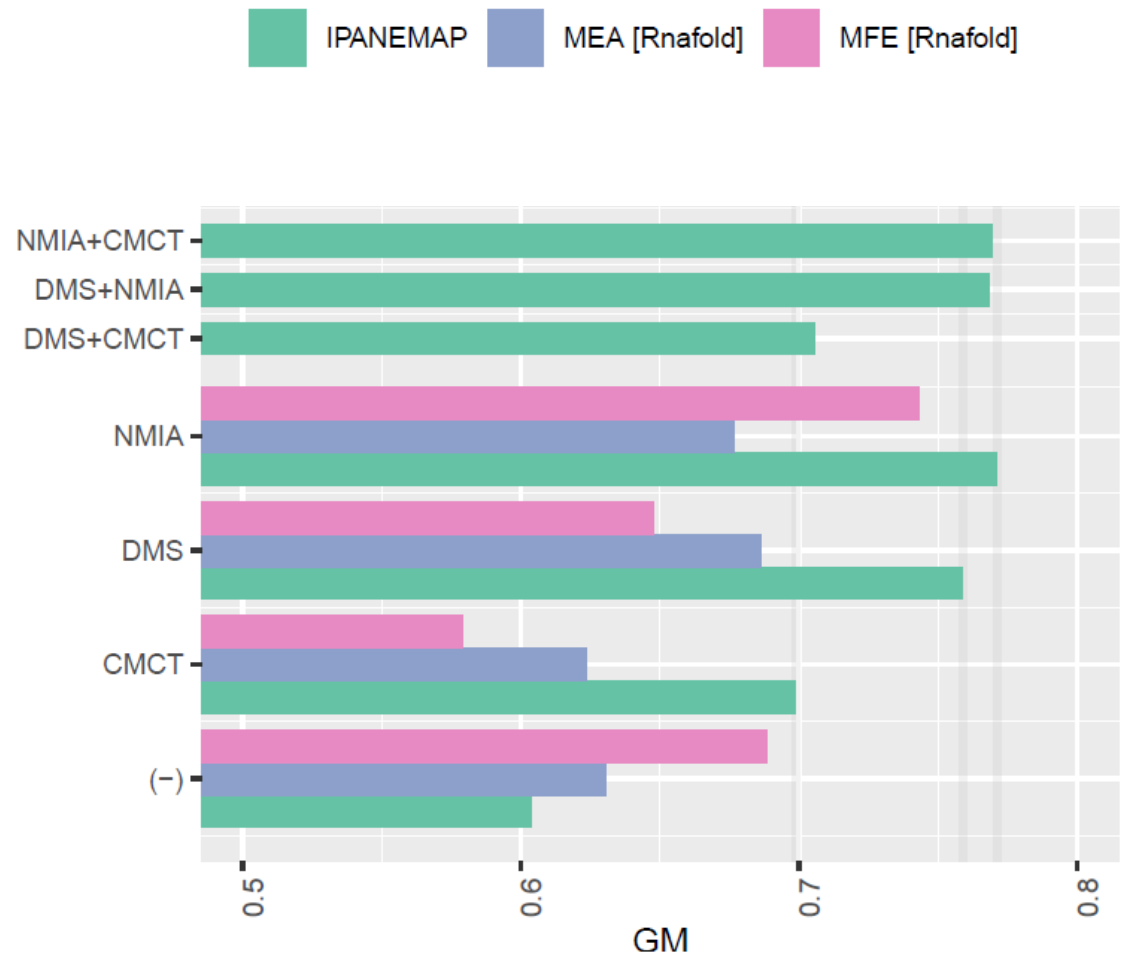
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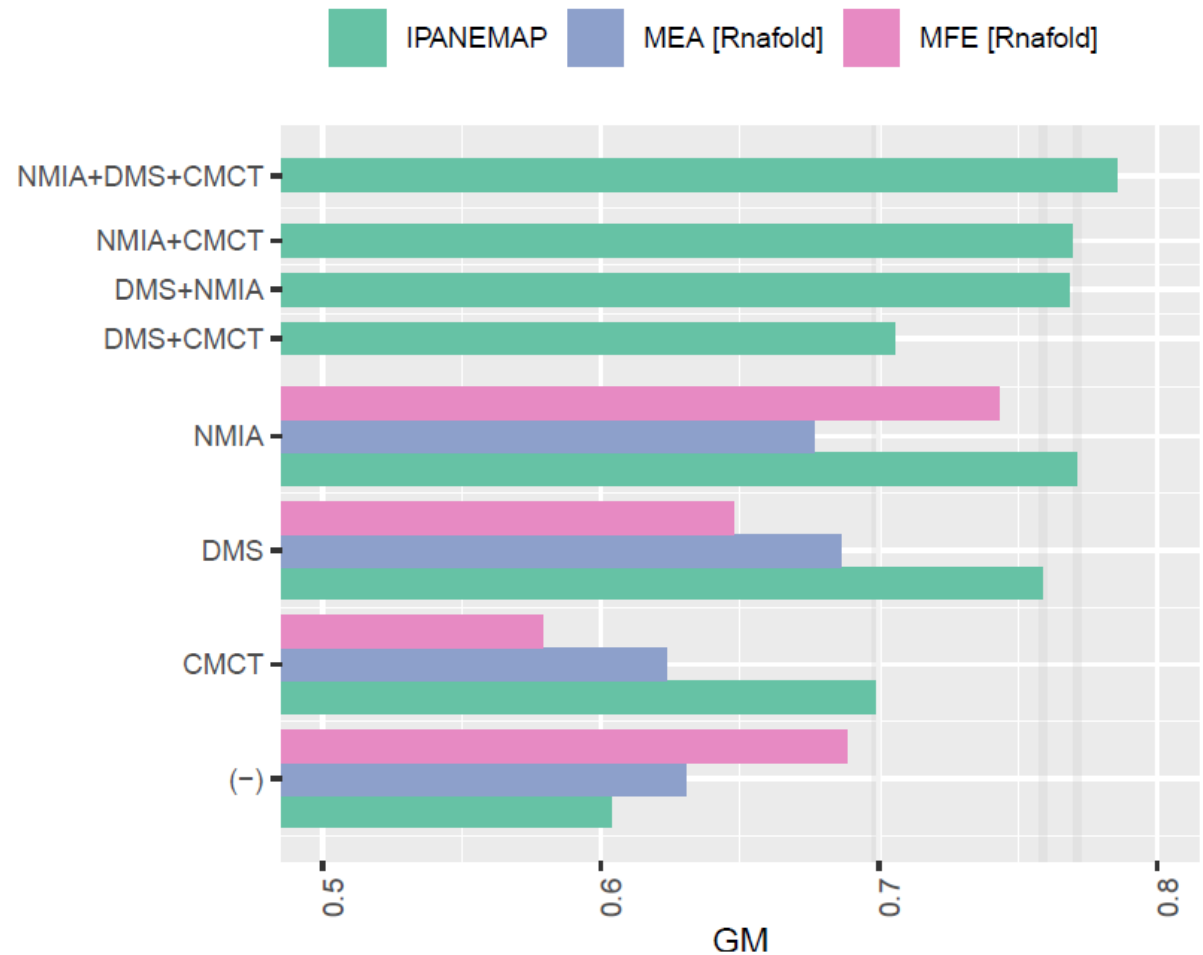
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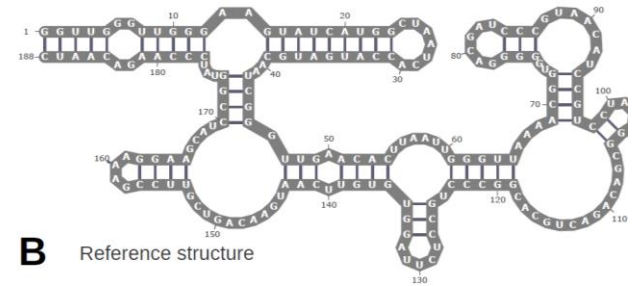
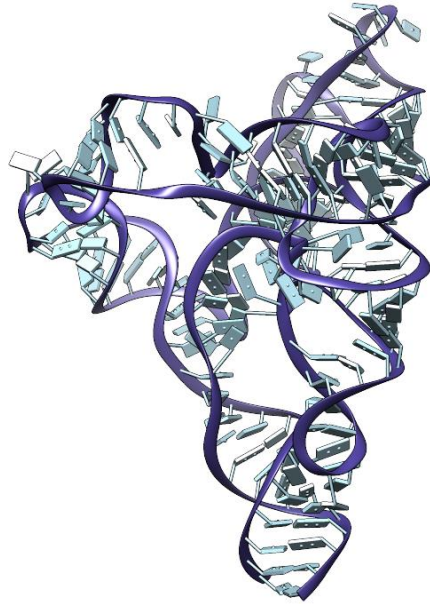
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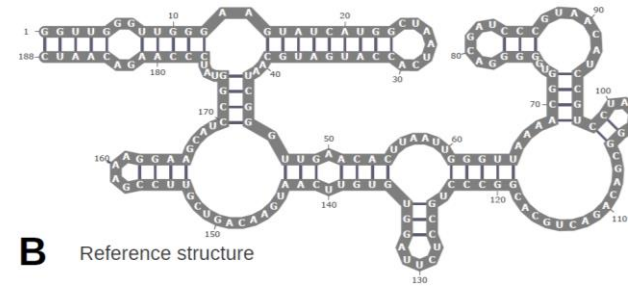
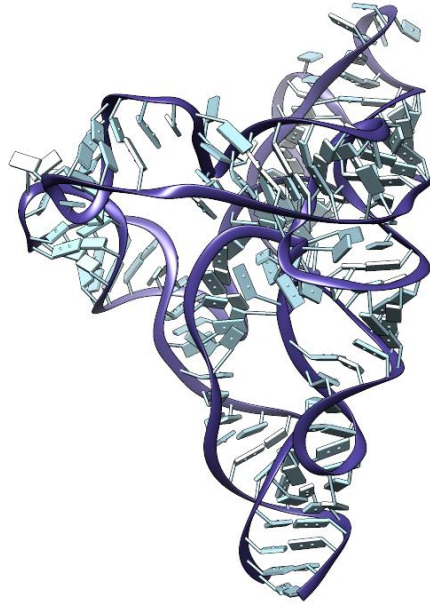


# Back to the lab for even more data



- ▶ Lariat Capping Ribozyme (PDB 4P8Z) from *Didymium iridis*

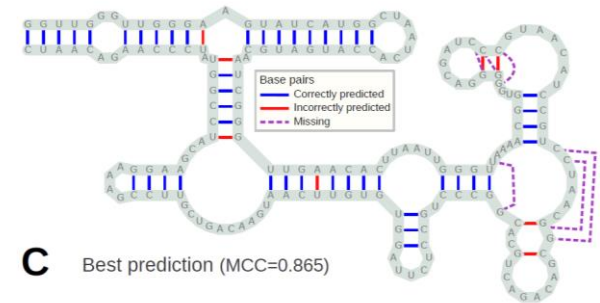
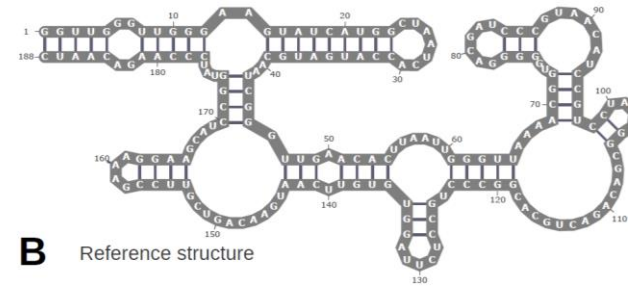
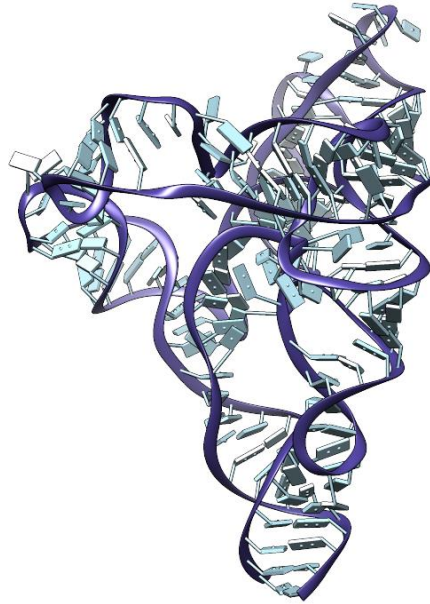
# Back to the lab for even more data



- ▶ Lariat Capping Ribozyme (PDB 4P8Z) from *Didymium iridis*
- ▶ Probed under 14 different conditions:
  - ▶ Technique: SHAPE, DMS, CMCT
  - ▶ Reagents: IM7, NMIA, DMS, CMCT, NAI, BzCN
  - ▶ Stop based and Mutation based readouts
  - ▶ Presence/absence Magnesium



# Back to the lab for even more data



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# Mono probing analysis

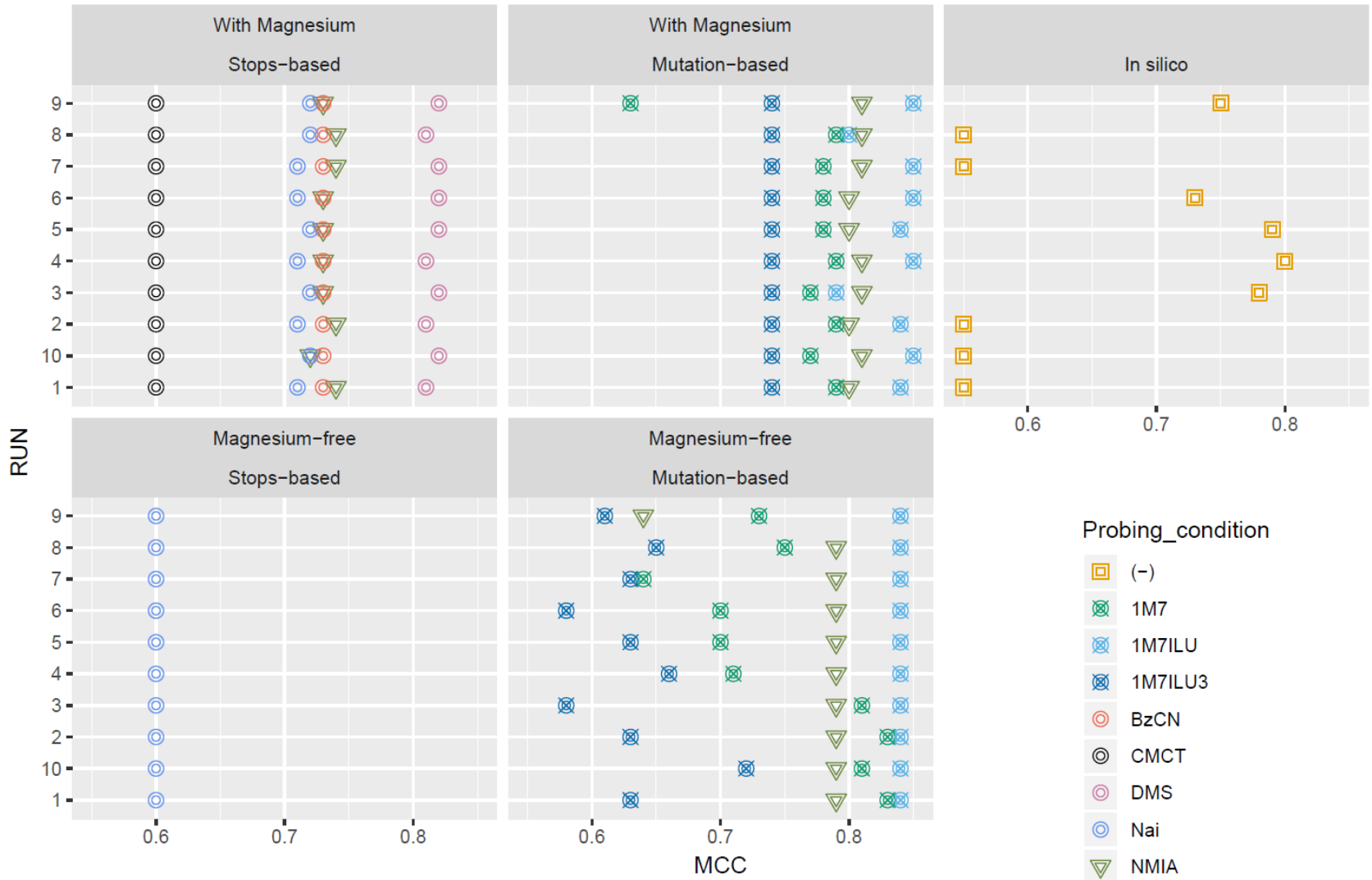
Condition name	Tech.	+/- Mg <sup>2+</sup>	MCC		
			IPANEMAP	MFE	MEA
1M7ILU	Mut	○	.84	.82	.85
1M7ILUMg	Mut	●	.83	.82	.8
DMSMg	Stop	●	.82	.41	.86
NMIAMg	Mut	●	.81	.8	.8
1M7ILU3Mg	Mut	●	.77	.75	.76
NMIAMgCE	Stop	●	.77	.675	.74
1M7Mg	Mut	●	.74	.735	.64
BzCNMg	Stop	●	.74	.72	.73
NMIA	Mut	○	.73	.69	.71
NaiMg	Stop	●	.73	.65	.71
1M7	Mut	○	.71	.51	.56
1M7ILU3	Mut	○	.62	.59	.67
CMCTMg	Stop	●	.6	.58	.59
Nai	Stop	○	.6	.59	.6
Avg Technology	Mut	–	.76	.71	.72
	Stop	–	.71	.61	.71
Avg +/- Mg <sup>2+</sup>	–	○	.76	.68	.74
	–	●	.70	.64	.68
<b>Average overall</b>	–	–	.74	.67	.72

- ▶ Different performances
- ▶ No clear factor
- ▶ Some outliers  
(NAI & CMCTMg)

MCC:

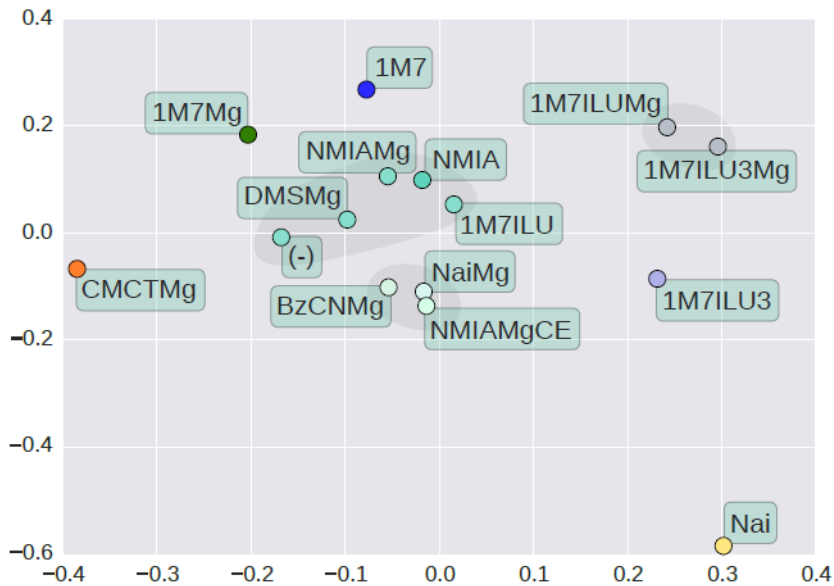
$$\frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

# Reproducibility





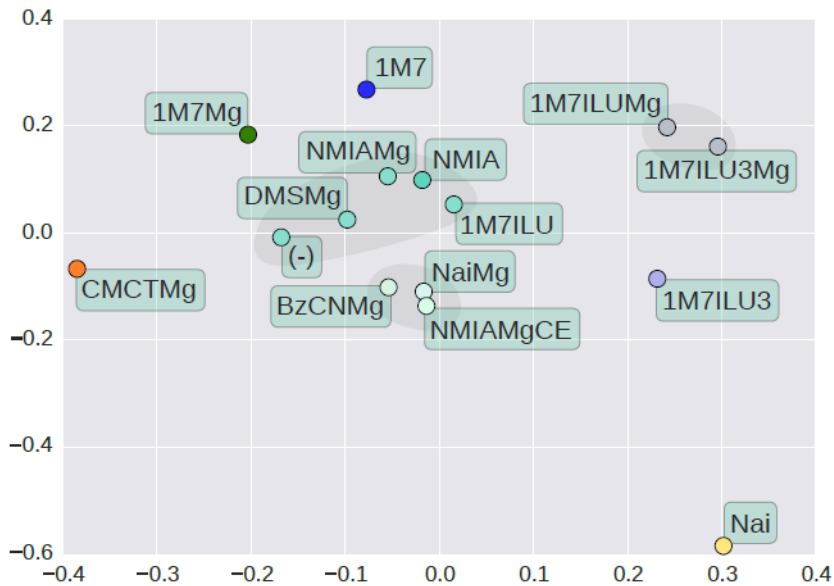
# More mono probing analysis



(Squared) Euclidian distance  
between conditions

$$\text{Dist}(d, d') = \sum_{i=1}^n \sum_{j=x+1}^n (\mathbb{P}(i, j | d) - \mathbb{P}(i, j | d'))^2$$

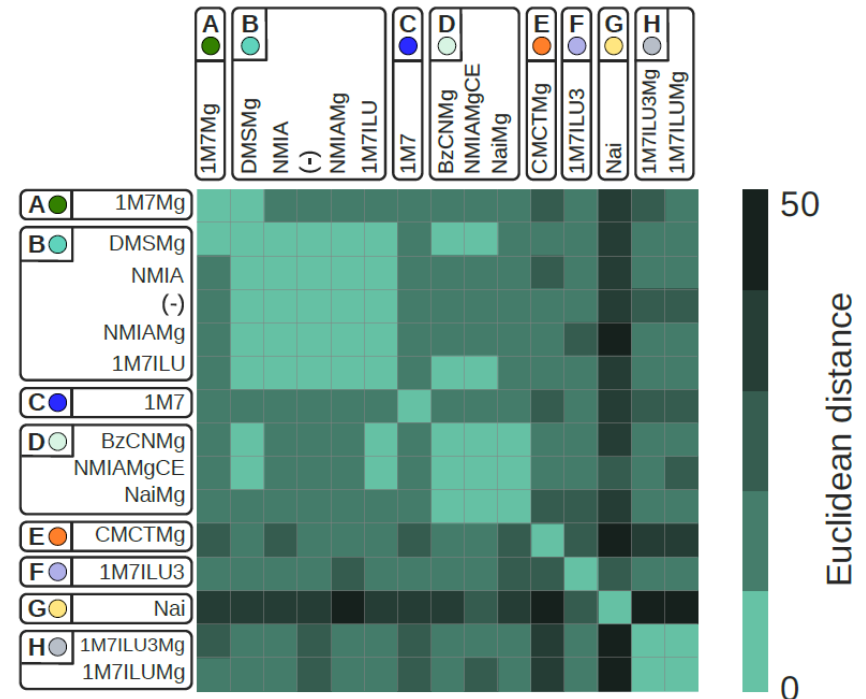
# More mono probing analysis



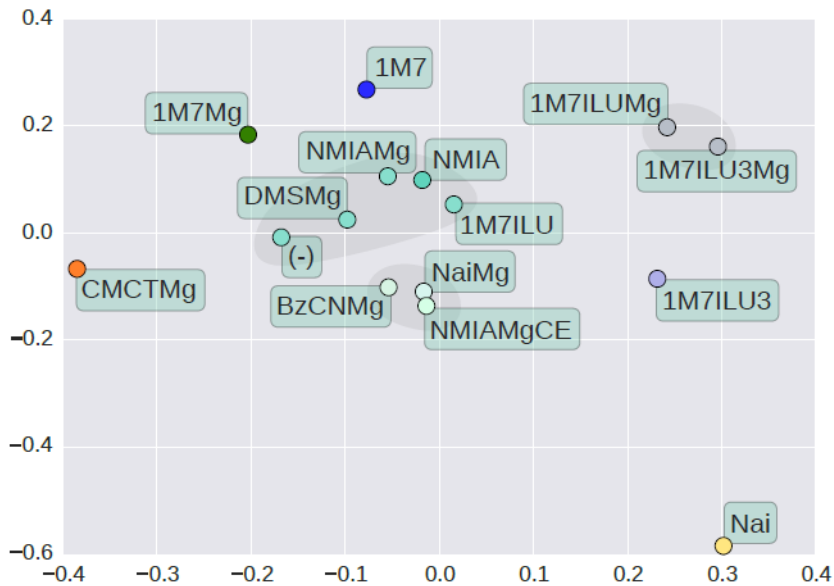
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$$\text{Dist}(d, d') = \sum_{i=1}^n \sum_{j=x+1}^n (\mathbb{P}(i, j | d) - \mathbb{P}(i, j | d'))^2$$

► 14 conditions + no-probing (-)



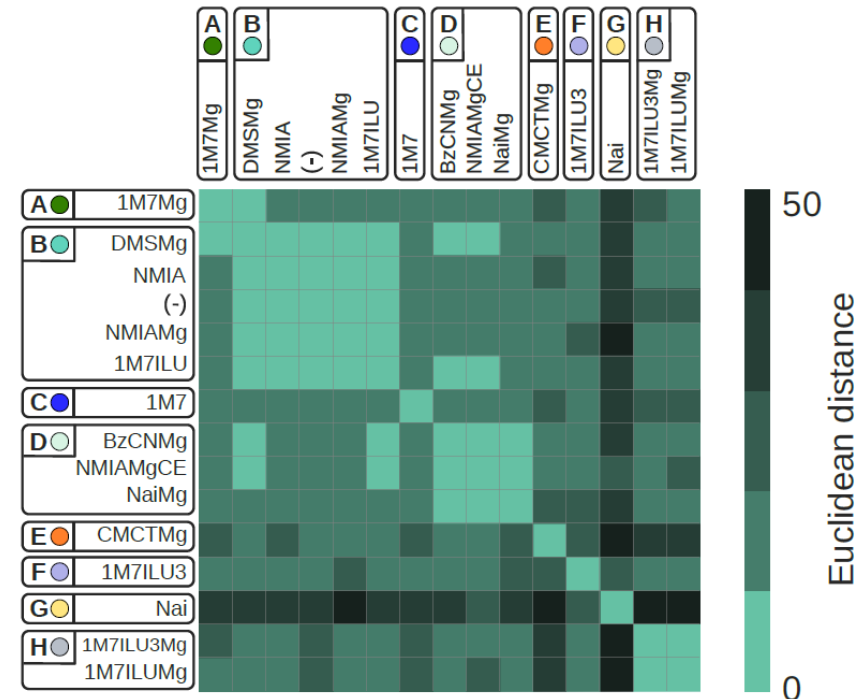
# More mono probing analysis



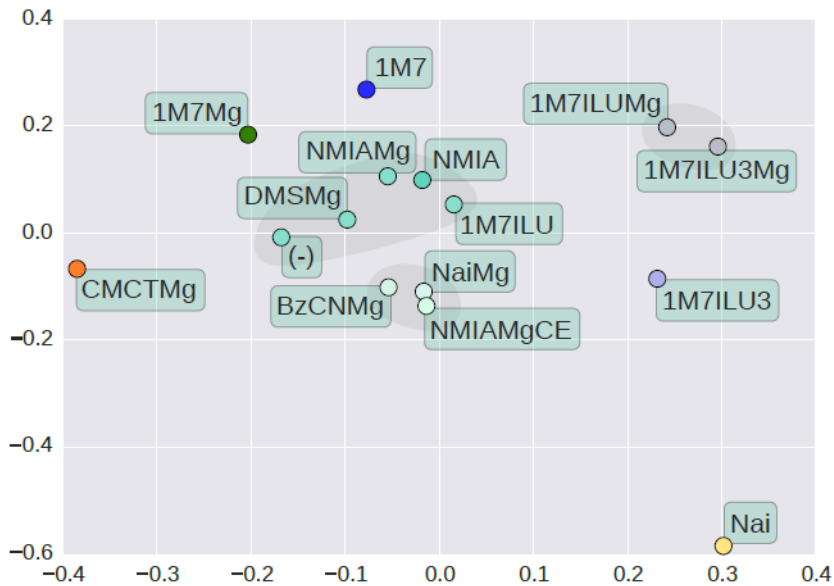
(Squared) Euclidian distance  
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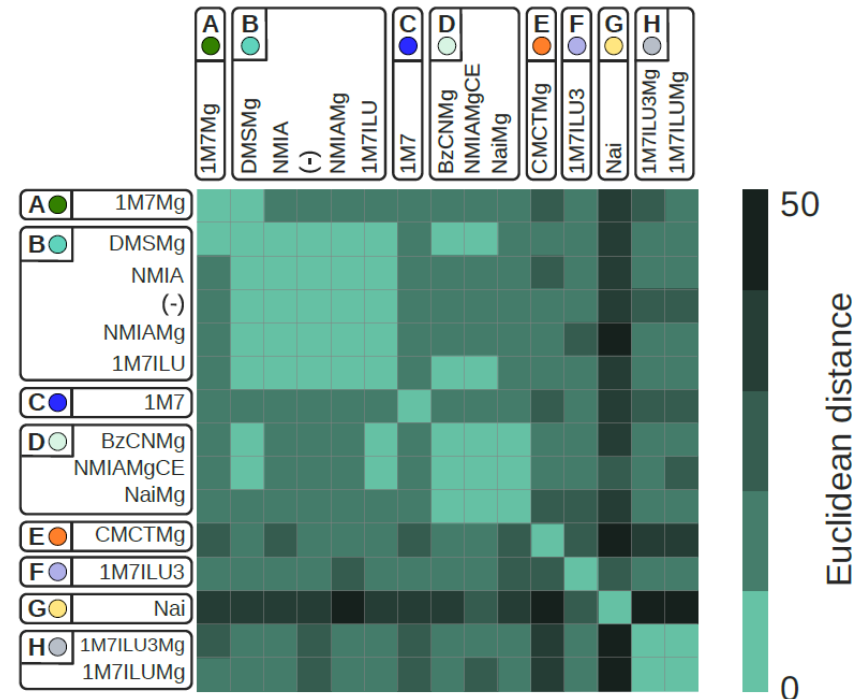
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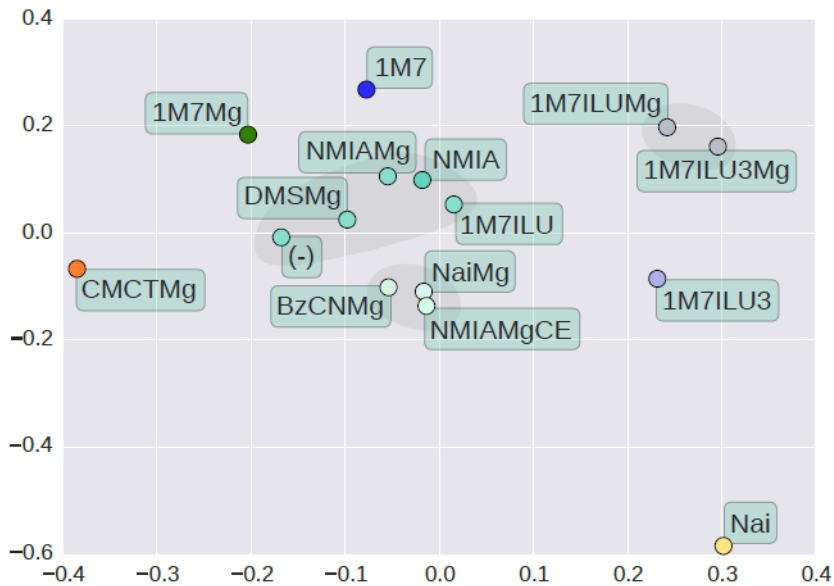
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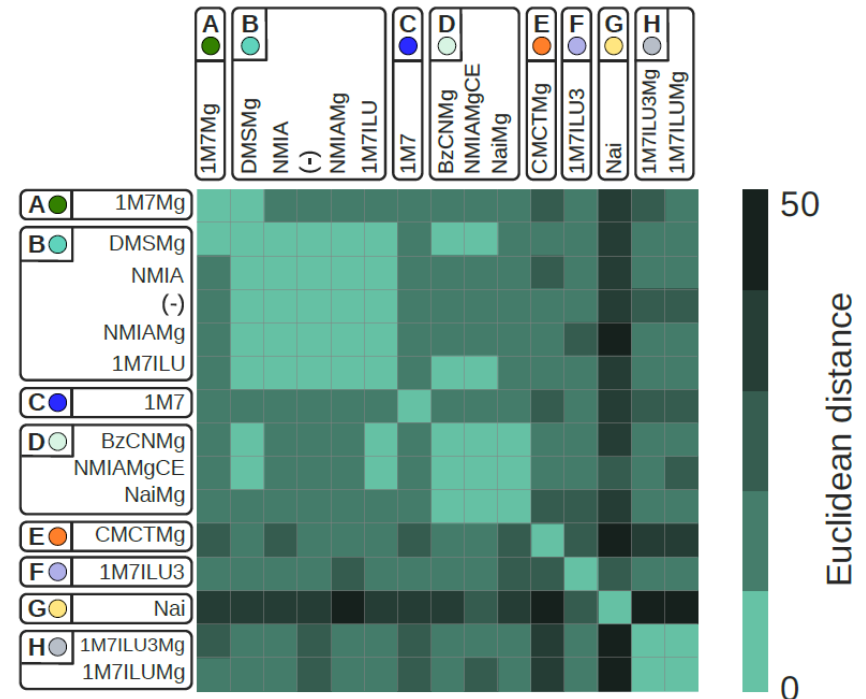
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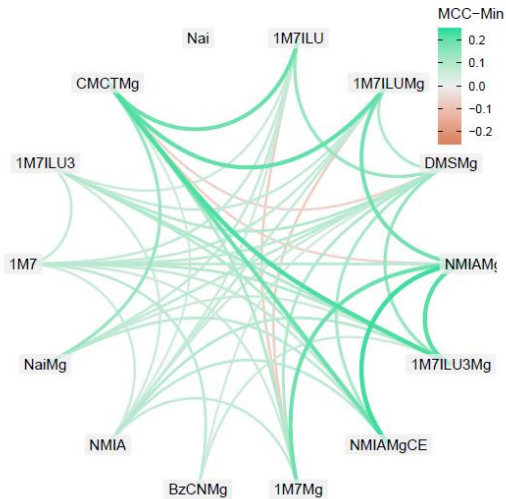
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- ▶ Outliers confirmed: NAI & CMCTM<sub>g</sub>



# Dual probing analysis

**A** – Bi-probing MCC vs Min MCC of mono-probing

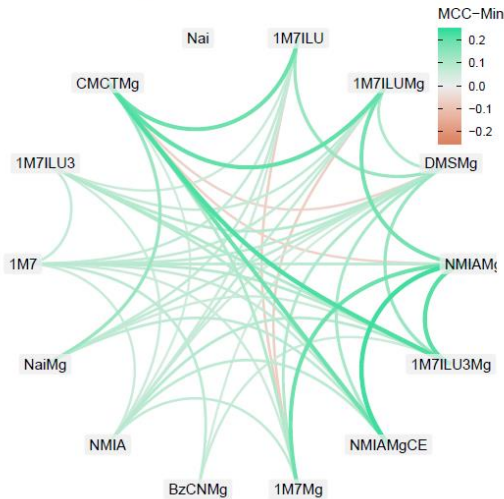


Pairs of conditions do not improve predictions (+.2% MCC) but:

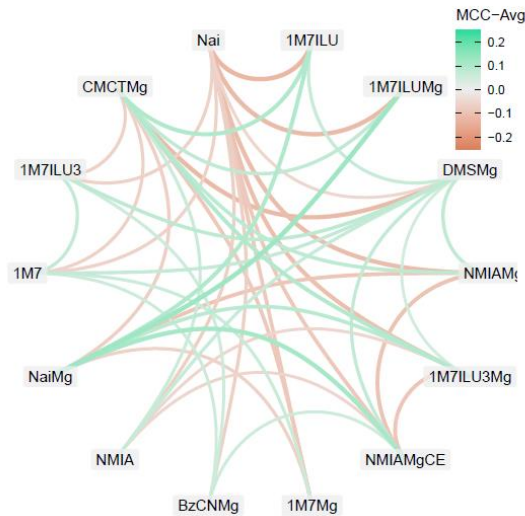
- ▶ Mitigates the risk of poor conditions:  
+5% MCC on average against worst condition

# Dual probing analysis

**A** – Bi-probing MCC vs Min MCC of mono-probing



**B** – Bi-probing MCC vs Average MCC of mono-probing

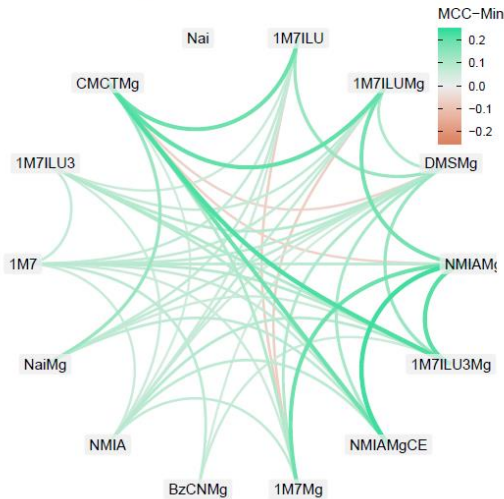


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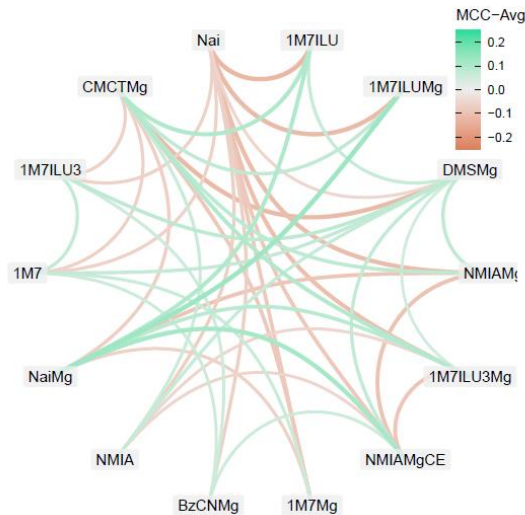
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- ▶ Slightly increases expectation:  
+0.2% against mean MCC, +1% w/o NAI

# Dual probing analysis

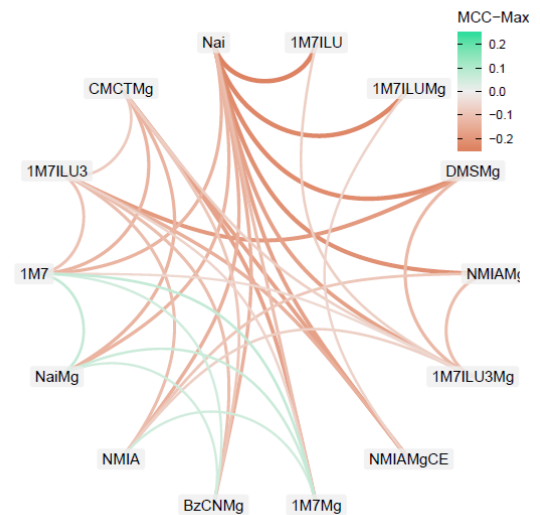
**A** – Bi-probing MCC vs Min MCC of mono-probing



**B** – Bi-probing MCC vs Average MCC of mono-probing



**C** – Bi-probing MCC vs Max MCC of mono-probing



Pairs of conditions do not improve predictions (+.2% MCC) but:

- ▶ Mitigates the risk of poor conditions:  
+5% MCC on average against worst condition
- ▶ Slightly increases expectation:  
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- ▶ Sensitive to contamination:  
-4.4% against best, -1.5% w/o NAI & CMCTMg



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- ▶ Degrades by 4% over best MCC of triplet (2% median)
- ▶ Some triplets improve overall best MCCs
  - ▶ IM7ILUM<sub>g</sub> + NMIAM<sub>g</sub>CE + IM7ILU3
  - ▶ IM7ILUM<sub>g</sub> + IM7 + BzCNM<sub>g</sub> → 85.3%MCC
  - ▶ IM7ILUM<sub>g</sub> + IM7ILU3 + IM7

Beyond three conditions?

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- ▶ All 14 conditions: 80% MCC (vs 73% Avg)
- ▶ Within clustered conditions: Limited info/improvement

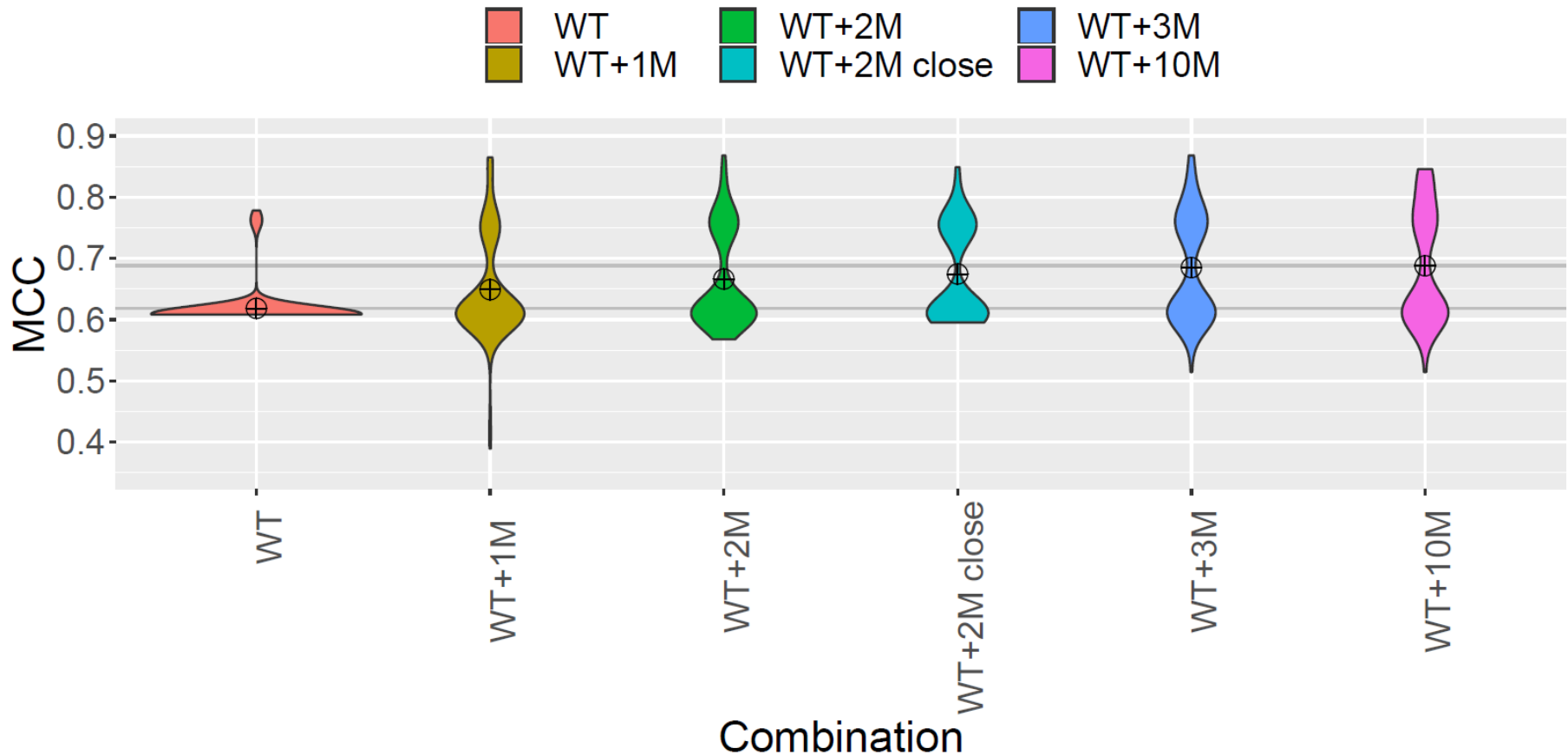






# Preliminary: Treating mutants as conditions

- ▶ Mutate-And-Map profiles produced by Das lab
- ▶ Systematic single-point mutants, usually similar structure



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- ▶ Test on multi-stable RNAs
- ▶ Optimal/iterative design of probing experiments
- ▶ More data to build mechanical understanding of SHAPE

# Thank you!



**Afaf Saaidi**  
Postdoc?



Bruno Sargueil



Delphine Allouche

**Ronny** (*da main man*) for modular extensions to Vienna package



**Soft constraints** × **Sampling** = **Awesomeness**

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