

Structural bioinformatics

A comprehensive benchmark of RNA–RNA interaction prediction tools for all domains of life

Sinan Uğur Umu^{1,2,*} and Paul P. Gardner^{1,2,3}¹School of Biological Sciences, ²Biomolecular Interaction Centre and ³Bio-Protection Research Centre, University of Canterbury, Christchurch, New Zealand

*To whom correspondence should be addressed.

Associate Editor: Cenk Sahinalp

Received on January 20, 2016; revised on October 21, 2016; editorial decision November 13, 2016; accepted on November 13, 2016

Abstract

Motivation: The aim of this study is to assess the performance of RNA–RNA interaction prediction tools for all domains of life.**Results:** Minimum free energy (MFE) and alignment methods constitute most of the current RNA interaction prediction algorithms. The MFE tools that include accessibility (i.e. RNAup, IntaRNA and RNAplex) to the final predicted binding energy have better true positive rates (TPRs) with a high positive predictive values (PPVs) in all datasets than other methods. They can also differentiate almost half of the native interactions from background. The algorithms that include effects of internal binding energies to their model and alignment methods seem to have high TPR but relatively low associated PPV compared to accessibility based methods.**Availability and Implementation:** We shared our wrapper scripts and datasets at Github (github.com/UCanCompBio/RNA_Interactions_Benchmark). All parameters are documented for personal use.**Contact:** sinan.umu@pg.canterbury.ac.nz**Supplementary information:** [Supplementary data](#) are available at *Bioinformatics* online.

1 Introduction

RNA biology has become more prominent after the discovery of non-coding RNAs (ncRNAs) and their versatile functions (Ambros, 2004; Barquist and Vogel, 2015; Kidner and Martienssen, 2005; Mattick, 2004; Mattick, 2009; Storz *et al.*, 2011; Waters and Storz, 2009). The versatility of RNA molecules has led to the idea of an ‘RNA world’ where RNA formed the first primitive life forms (Gilbert, 1986). The importance of RNA biology is highlighted by the relatively small fraction of protein-coding regions of most eukaryotic genomes (Mattick, 2004, 2009). For example, 1.2% of the human genome contain protein coding genes, while 76% is transcribed into RNA (Pennisi, 2012). Likewise, prokaryotic cells contain various ncRNAs genes (Gottesman, 2004; Holmqvist and Vogel, 2013; Thébault *et al.*, 2014; Vogel, 2009) and have also been shown to have transcriptional complexity like eukaryotes (Barquist and Vogel, 2015; Cohen *et al.*,

2016; Güell *et al.*, 2011, 2009; Lindgreen *et al.*, 2014). ncRNA molecules often utilize RNA–RNA base pairing such as bacterial/archaeal small RNAs (sRNAs) (Prasse *et al.*, 2013; Storz *et al.*, 2011), small interfering RNAs (siRNAs) (Carthew and Sontheimer, 2009), microRNAs (miRNAs) (Carthew and Sontheimer, 2009; Cuperus *et al.*, 2011), spliceosomal small nuclear RNAs (snRNAs) (Karijovich and Yu, 2010), small nucleolar RNAs (snoRNAs) (Brown *et al.*, 2001; Gardner *et al.*, 2010; Kiss, 2002; Omer *et al.*, 2000), cajal-body specific small nuclear RNAs (scaRNAs) (Darzacq *et al.*, 2002), clustered regularly-interspaced short palindromic repeats (CRISPR) RNA (Bhaya *et al.*, 2011) and piwi-interacting RNAs (piRNAs) (Brennecke *et al.*, 2007; Klattenhoff and Theurkauf, 2008). It seems some long-noncoding RNAs (lncRNAs) may also engage into RNA–RNA interactions (Kung *et al.*, 2013), which are quite abundant in eukaryotes (Zhao *et al.*, 2016).

In addition to endogenous ncRNAs genes, many experimental techniques take advantage of RNA–RNA interactions such as gene silencing (i.e. knock-out) by artificial siRNAs (Deleavey and Damha, 2012; Reynolds *et al.*, 2004) and designing oligonucleotides for ribosomal RNA (rRNA) depletion in RNA-seq experiments (O’Neil *et al.*, 2013).

Different clades of life utilize regulatory RNA–RNA interactions with different constraints: various mediator proteins (Carthew and Sontheimer, 2009; Vogel and Luisi, 2011), binding regions preference and distinct complementarity requirements (Ameres and Zamore, 2013; Millar and Waterhouse, 2005). Thus, many different tools have been developed to predict stable interactions. Some algorithms solve RNA–RNA interaction as an alignment problem using local alignment approaches (Hodas and Aalberts, 2004; Wenzel *et al.*, 2012). Most of these use dynamic programming and minimum free energy methods (MFE) (Backofen and Hess, 2010; Dieterich and Stadler, 2012; Lorenz *et al.*, 2011), which are also widely used methods for RNA secondary structure predictions (Markham and Zuker, 2008; McCaskill, 1990; Nussinov and Jacobson, 1980; Zuker, 2000; Zuker and Sankoff, 1984; Zuker and Stiegler, 1981). In bacteria, comparative methods are becoming popular (Kery *et al.*, 2014; Pain *et al.*, 2015; Wright *et al.*, 2013), but they are restricted to conserved sRNAs, which are quite rare (Barquist and Vogel, 2015; Lindgreen *et al.*, 2014).

RNA target detection is still a challenging task but it is vital to understand more about RNA–RNA interactions for functional annotation of unknown transcripts while making computationally feasible and biologically relevant prediction. In this study, we assessed the performance of available RNA–RNA interaction prediction tools on trusted, verified datasets from all domains of life. We evaluated their ability to recover established RNA–RNA pairs in eukaryotic, bacterial and archaeal systems. We also assessed how successfully they predict binding scores and reported the significance of these predictions.

2 Materials and methods

All RNA interaction prediction algorithms are freely available and cited in the manuscript. We used Python, R, Bash for the scripts and wrappers, which are shared in our Github repository (github.com/UCanCompBio/RNA_Interactions_Benchmark). A parser script (or a wrapper script) has been written for each of the tools benchmarked here. All the parameters and command line arguments are also accessible.

2.1 Benchmark datasets

We manually confirmed the correct interaction regions (which contain the binding base-pairs) for all dataset items and used entire target regions (i.e. UTRs, coding regions or target RNA) to make our benchmark as realistic as possible. We also manually confirmed that the true binding regions on target RNAs are consecutive with only few mismatches.

The eukaryotic benchmark dataset consisted of miRNAs from human, *Arabidopsis*, *Caenorhabditis elegans* (*C. elegans*) (Chou *et al.*, 2015; Kozomara and Griffiths-Jones, 2013); C/D and H/ACA box snoRNAs from human, *Arabidopsis*, *C. elegans*, yeast (Brown *et al.*, 2001; Lestrade and Weber, 2006; Piekna-Przybylska *et al.*, 2007; Yoshihama *et al.*, 2013); human and yeast U6/U2 snRNAs (Will and Lührmann, 2011); endogenous siRNAs from *Arabidopsis* (Addo-Quaye *et al.*, 2008) and piRNAs from mouse (Gou *et al.*, 2015). Experimentally verified miRNA/siRNA/piRNA-target

mRNAs and snoRNA/snRNA-target RNAs were selected from different ncRNA families as much as possible (in total 88 pairs) (Supplementary Table S1).

We compiled a bacterial sRNA and target mRNA dataset from *Salmonella*, *Escherichia coli* (*E. coli*) and *Listeria monocytogenes* (*L. monocytogenes*) that consists of 60 verified sRNA-mRNA pairs (Cao *et al.*, 2010; Lai and Meyer, 2015; Peer and Margalit, 2011). The target regions of bacterial sRNAs lie either in 5’UTR or downstream of start codon (Richter and Backofen, 2012; Storz *et al.*, 2011). We selected regions 200 nucleotides (nts) upstream to 100 nts downstream of the start codons (i.e. 5’end mRNA) which contain verified binding regions. We extracted both sRNAs and target 5’end mRNAs from their associated genome sequences (Acces. AE006468.1, AL591824.1 and U00096.3) (Supplementary Table S1).

We gathered a set of archaeal C/D box snoRNAs consisting of 5 snoRNAs and their ribosomal RNA targets (Omer *et al.*, 2000). We also added a member of less studied archaeal sRNA (from *Methanosarcina mazei*) (Jäger *et al.*, 2012). Selected genes and targets were obtained from their associated archaeal genomes (AE008384.1) or Genbank (Supplementary Table S1).

2.2 Accuracy measures for binding site predictions

We calculated TPR (sensitivity) and PPV (precision) scores of each algorithm based on prediction of RNA–RNA binding regions for 154 manually curated interactions from the scientific literature. They include functionally characterized RNA–RNA interactions from Archaea, Bacteria and Eukaryotes. Verified binding regions between ncRNAs and target RNAs are annotated with published base-pairing interactions. These interactions can be used to assess overlaps between predicted and true binding regions on target RNAs. In this work, true positives (TPs) are the number of nucleotides on a correctly predicted binding region, false positive (FPs) are the number of nucleotides in a falsely predicted binding region (i.e. a predicted target that is not part of the curated set of interactions), and false negatives (FNs) are the number of nucleotides in a binding region where interactions are not predicted (Supplementary Fig. S1). True negatives (TNs) are generally not used for the treatment of RNA structure as the number of true negatives grows exponentially with sequence length while TP, FP and FN grow linearly (Wenzel *et al.*, 2012). We can calculate an approximation to the Matthews correlation coefficient (MCC) (Matthews, 1975) by using the geometric mean of TPR and PPV (Gorodkin *et al.*, 2001; Wenzel *et al.*, 2012). These can be defined as:

$$TPR(\text{sensitivity}) = TP / (TP + FN) \quad (1)$$

$$PPV(\text{precision}) = TP / (TP + FP) \quad (2)$$

$$MCC \approx \sqrt{TPR \cdot PPV} \quad (3)$$

2.3 A significance test for prediction scores

Besides these well-known accuracy measures, we also assessed the scores generated by the algorithms, which usually show the stability of interaction (e.g. a binding MFE). For each true and verified target (positive control), we created 200 dinucleotide shuffled sequences (negative controls) using the esl-shuffle tool (Eddy, 2011) to prevent possible biases caused by the nearest-neighbour energy model of structure prediction (Workman and Krogh, 1999). To determine the significance of native interactions, we fitted the binding energies shuffled interactions (as a background) into both normal and

Gumbel distributions (using negative energies) (Gumbel, 1958), since MFE values mostly follow an extreme value distribution (Rehmsmeier *et al.*, 2004; Tjaden, 2008). In short, we assessed significance of positive controls using a set of negative controls. A similar methodology showed an avoidance of crosstalk RNA–RNA interactions in prokaryotes which can be measured as a binding energy shift (Umu *et al.*, 2016). We applied this approach only to bacterial dataset due to time constraints, and the uniform distribution of bacterial targets (i.e. identical 300 nucleotides long target mRNAs).

We selected the best scoring interaction as the native interaction if an algorithm produces more than one interaction, which is also true for all our analyses.

3 Results and discussion

3.1 RNA–RNA interaction prediction tools

The RNA–RNA interaction prediction methods are divided mainly into three groups: alignment like methods, MFE methods and comparative (homology) methods. We can also further divide the MFE methods into three different sub-classes based on whether their approach considers intramolecular base-pairs (internal structure), neglects intramolecular structure or measures the accessibility of the binding region. There are also other machine learning algorithms (Oğul *et al.*, 2011; Yang *et al.*, 2008), and probabilistic approaches like RactIP (Kato *et al.*, 2010), which uses the CONTRAfold model (Do *et al.*, 2006) for RNA interaction prediction.

RIsearch (Wenzel *et al.*, 2012), Bindigo (Hodas and Aalberts, 2004) and Google (Gerlach and Giegerich, 2006) are examples of alignment-like methods. The RIsearch algorithm was mainly developed for rapidly searching genomes to detect RNA–RNA pairs from genome sequencing data by combining the Smith-Waterman-Gotoh algorithm with a nearest-neighbor energy model (Wenzel *et al.*, 2012), while Bindigo adopts an optimized Smith-Waterman to find optimal oligonucleotide-RNA pairs (Hodas and Aalberts, 2004). Google uses suffix arrays to seek RNA targets based on RNA helix rules that allow G-U pairs (Gerlach and Giegerich, 2006).

Besides these alignment based methods, tools like BLAST (Altschul *et al.*, 1990), Blat (Kent, 2002), ssearch (Pearson and Lipman, 1988) or other local alignment implementations can be used to rapidly collect long (reverse) complementary regions by including G-U pairs (C-U or G-A for the reverse complement) in the scoring matrix (Gerlach and Giegerich, 2006; Thébault *et al.*, 2014; Wenzel *et al.*, 2012).

MFE methods form the majority of the RNA–RNA interaction prediction tools (Backofen and Hess, 2010; Dieterich and Stadler, 2012; Lorenz *et al.*, 2011). Many secondary structure prediction tools also utilize MFE methods (Lorenz *et al.*, 2011; Markham and Zuker, 2008; Mathews and Turner, 2006; Zuker and Sankoff, 1984). Some MFE methods including RNAhybrid (Rehmsmeier *et al.*, 2004), RNAduplex (Lorenz *et al.*, 2011), DuplexFold (Reuter and Mathews, 2010) and TargetRNA (Tjaden, 2008) neglect intramolecular structures for the sake of algorithmic speed. Algorithms like Pairfold (Andronescu *et al.*, 2005), RNAcifold (Bernhart *et al.*, 2006) and bifold (Reuter and Mathews, 2010) take intramolecular base-pairing into account. RNAup (Mückstein *et al.*, 2006), RNApplex (Tafer and Hofacker, 2008) and IntaRNA (Busch *et al.*, 2008) compute the accessibility of binding regions to report the final MFE of the RNA duplex, which is considered more realistic biophysically (Richter and Backofen, 2012). AccessFold includes accessibility using a method defined as pseudo-energy minimization

(DiChiacchio *et al.*, 2015). BistaRNA also includes accessibility and can predict multiple binding sites (Poolsap *et al.*, 2011). Lastly, tools like TargetRNA2 (Kery *et al.*, 2014), CopraRNA (Wright *et al.*, 2013), miRanda (John *et al.*, 2004), TargetScan (Lewis *et al.*, 2005), PETcofold (Seemann *et al.*, 2011) and DIANA-microT (Kiriakidou *et al.*, 2004) exploit homology and evolutionary conservation to predict interactions

Some RNA–RNA interaction prediction tools are developed to achieve a specific task or to predict very specific group of interactions. For example, PLEXY is designed for C/D snoRNAs (Kehr *et al.*, 2011), RNAsnoop (Tafer *et al.*, 2010) for H/ACA snoRNAs and TargetRNA (Tjaden, 2008) for bacterial sRNAs (*E. coli* and *Salmonella*). In this study, we tried to assess the versatility of prediction tools on different datasets as well as their prediction power where applicable. We excluded tools designed for specific RNA families such as specialized miRNA algorithms (reviewed in Witkos *et al.*, 2011), specialized snoRNA target prediction algorithms and comparative bacterial sRNA prediction methods (reviewed in Backofen and Hess, 2010; Pain *et al.*, 2015). We also excluded inteRNA (Alkan *et al.*, 2006), IRIS (Pervouchine, 2004), piRNA (Chitsaz *et al.*, 2009b) and biRNA (Chitsaz *et al.*, 2009a), as they are either no longer supported or obsolete.

In summary, our final list of selected tools used for further analyses consisted of RIsearch (Wenzel *et al.*, 2012), IntaRNA (Busch *et al.*, 2008), RNAcifold (Bernhart *et al.*, 2006), RNAhybrid (Rehmsmeier *et al.*, 2004), RNAduplex (Lorenz *et al.*, 2011), RNApplex (Tafer and Hofacker, 2008), RNAup (Mückstein *et al.*, 2006), pairfold (Andronescu *et al.*, 2005), bifold (Reuter and Mathews, 2010), DuplexFold (Reuter and Mathews, 2010), ssearch (Pearson, 1991), RactIP (Kato *et al.*, 2010), bistaRNA (Poolsap *et al.*, 2011), AccessFold (DiChiacchio *et al.*, 2015) and NUPACK (Dirks *et al.*, 2007) (Supplementary Table S2).

3.2 Overall prediction performances

Our analyses of the overall performances of RNA interaction prediction algorithms show that three accessibility based algorithms (RNAup, IntaRNA and RNApplex) scored highest for sensitivity and precision. RNAup was highly precise compared to other tools (Fig. 1 and Table 1). IntaRNA was the second algorithm (almost identical to RNAup) with a reasonable running time. RNApplex was comparable to both algorithms. RNAduplex had the best overall TPR score, but it was not as precise as IntaRNA. Table 1 summarizes the 'cumulative' TPR, PPV and MCC scores, while Figure 1 shows their distribution for all interactions ($n = 154$) on all domains of life.

RIsearch and ssearch were the fastest methods, but they were not very sensitive or precise (Table 1). AccessFold and bifold had the longest run time, which appeared to increase for long RNA sequences like ribosomal RNAs or large target UTR regions. RIsearch and bifold gave inconsistent results, with combined MCCs of 0.33 and 0.40 respectively (Table 1). However, if we use a distribution of results as in Figure 1, the median MCCs appear to be zero for these algorithms. As bifold frequently returned no duplex structures for some RNA pairs (e.g. *C. elegans* miRNAs lin-4, lsy-6-3p, etc.), and RIsearch produced many unsuccessful predictions for bacterial sRNAs, which produced to zero MCC scores for both.

3.3 The significance test results of bacterial dataset

The MFE values produced by the algorithms are not very explicit, so it is common to use negative controls to determine the significance

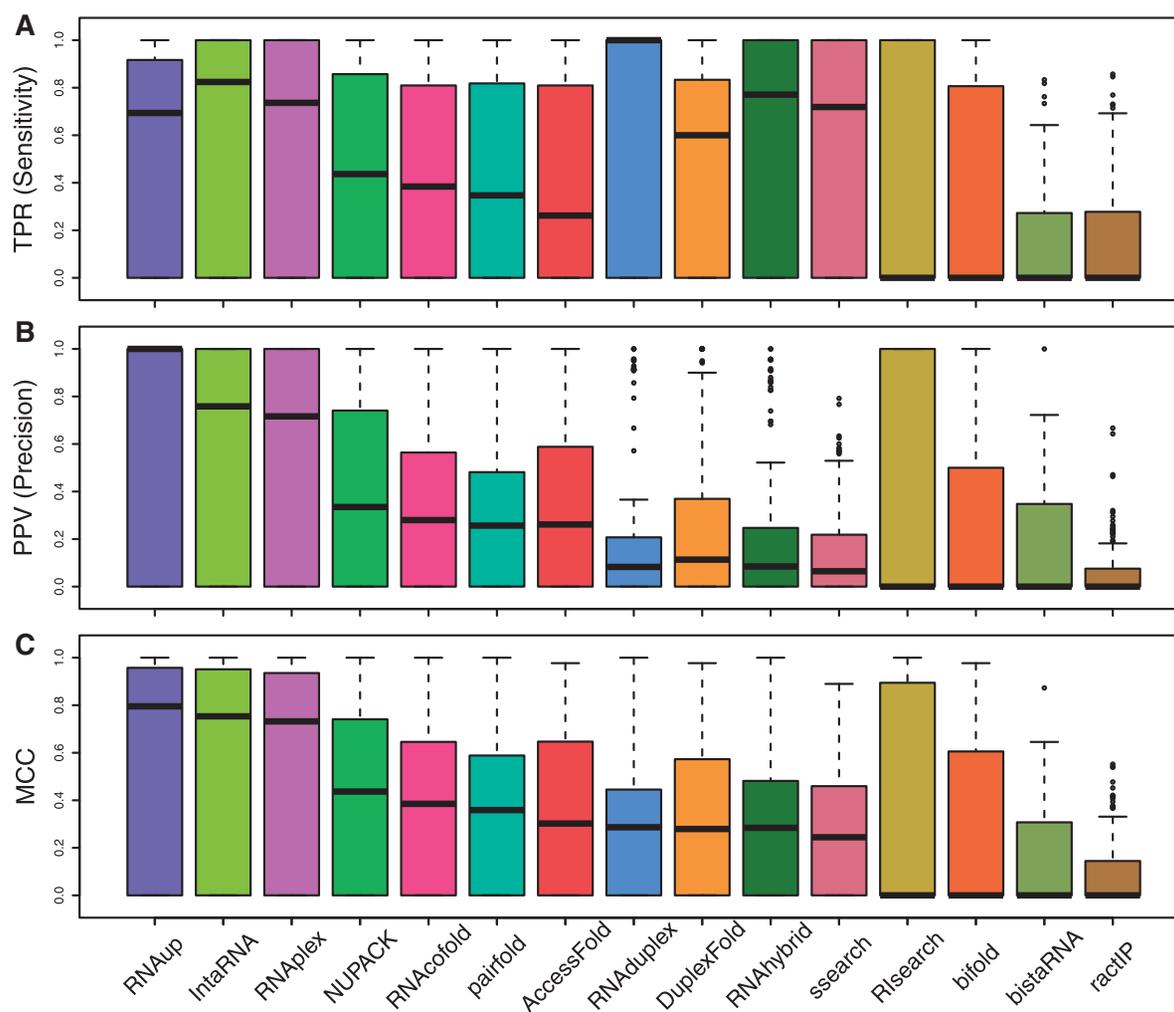


Fig. 1. The distribution of scores for RNA–RNA interaction prediction algorithms. (A) RNAduplex gave the highest median TPR (sensitivity) followed by IntaRNA. (B) RNAup was the most precise algorithm based on PPV score followed by the other accessibility based methods IntaRNA and RNAplex. (C) RNAup was the best prediction algorithm based on median MCC score, with IntaRNA and RNAplex giving similar scores. RactIP produced the worst overall MCC (Color version of this figure is available at *Bioinformatics* online.)

Table 1. Total run time of algorithms, and the cumulative TPR, PPV and MCC scores

Algorithm	Total run time (s) on selected files ($n = 50$)	TPR (Sensitivity)	PPV (Precision)	MCC
AccessFold	596.44	0.38	0.31	0.35
bifold	404.63	0.37	0.31	0.34
bistaRNA	102.29	0.15	0.16	0.15
DuplexFold	5.33	0.48	0.17	0.29
IntaRNA	24.44	0.59	0.56	0.58
NUPACK	794.2	0.42	0.42	0.42
pairfold	90.24	0.39	0.29	0.34
ractIP	87.62	0.16	0.06	0.1
Rlsearch	4.16	0.36	0.45	0.40
RNAcofold	15.28	0.41	0.32	0.36
RNAduplex	6.45	0.66	0.12	0.27
RNAhybrid	32.84	0.56	0.12	0.26
RNAplex	17.19	0.55	0.57	0.56
RNAup	137.48	0.51	0.69	0.60
ssearch	4.69	0.56	0.1	0.23

The cumulative scores (i.e. TPR, PPV, MCC) are calculated by adding individual TP, FP and FN values for all predictions.

of predicted energy values (Rehmsmeier *et al.*, 2004), especially for structure predictions (Workman and Krogh, 1999). As described in materials and methods, we created a set of negative controls for each native RNA–RNA interaction. Some algorithms were excluded from this assessment, because either they do not produce a score (i.e. RactIP, bistaRNA and ssearch) or are biased towards internal structures (i.e. pairfold, RNAcofold, bifold and NUPACK). Thus, the test of significance includes only 8 prediction algorithms (Table 2).

These results show that RNAplex and RNAup reported almost half of the native energies as significant if they are fitted to normal distributions. It seems the Gumbel fitting of scores is more conservative which likely decreases the risk of FP predictions on high-throughput predictions. RNAup results were almost identical for both distributions. IntaRNA performed slightly worse than these two algorithms. The last column of Table 2 shows the median rank of native interactions. If a prediction score of a native interaction has the highest score (e.g. lowest MFE), it is ranked 1 out of 201. Therefore, the median ranks in the last column can be interpreted as the expected number of FPs introduced by the algorithms before predicting the native interaction.

Table 2. The test of significance results of selected algorithms on bacterial sRNAs.

Algorithm	Total # of significant ($P < 0.05$) correct predictions for Gumbel dist. ($n = 60$)	Total # of significant ($P < 0.05$) correct predictions for normal dist. ($n = 60$)	Median rank of native interactions
AccessFold	15	17	41.75
DuplexFold	2	8	63.5
IntaRNA	23	26	19
RIsearch	13	14	52.25
RNA duplex	8	11	54.25
RNAhybrid	5	6	76
RNAplex	23	30	10.5
RNAup	28	29	13.5

Higher is better for the second and third columns. Lower is better for the fourth column.

3.4 A summary of RNA–RNA interactions and algorithm performances for all domains of life

Eukaryotic RNA interactions mostly focus on RNA interference (RNAi) (i.e. miRNAs and siRNAs) (Ambros, 2004; Carthew and Sontheimer, 2009; Chen, 2008). In animal RNAi, miRNAs (~20 nts long) prefer perfect complementarity in the seed region and have overall lower complementarity than plant counterparts (Ameres and Zamore, 2013; Axtell *et al.*, 2011). In plants, high complementary target regions may lie in coding region as well as UTRs rather than only 3'UTRs (Ameres and Zamore, 2013; Axtell *et al.*, 2011; Millar and Waterhouse, 2005). It is possible for a miRNA to target more than one region, especially in animals, which is known to increase efficiency of target gene downregulation (Millar and Waterhouse, 2005). However, in our benchmark we preferred to select miRNA targets containing a single designated binding region. Piwi associated piRNAs are also small endogenous RNAs (24–30 nts long) (Klattenhoff and Theurkauf, 2008; Zhang *et al.*, 2015), some of which use antisense binding to regulate target RNAs (Gou *et al.*, 2015) like miRNA and siRNA. H/ACA and C/D snoRNAs have roles in rRNA and snRNA maturation (Brown *et al.*, 2001; Gardner *et al.*, 2010; Kiss, 2002). These interactions differ in that C/D snoRNAs prefer a binding region on target RNA with consecutive nts around 7–20 bases long with a few mismatches (Gardner *et al.*, 2010; Kehr *et al.*, 2011), while H/ACA snoRNAs contain a stem loop within the binding region, which complicates target prediction (Gardner *et al.*, 2010; Kiss *et al.*, 2004; Tafer *et al.*, 2010). Spliceosomal snRNAs form ribonucleoprotein (RNP) complexes with other snRNAs (Karijolich and Yu, 2010), and they are also targeted by snoRNAs (termed scaRNAs) (Darzacq *et al.*, 2002). We included examples of both snRNA–snRNA and scaRNA–snRNA interactions to our dataset. It is also known that some lncRNAs use RNA–RNA interactions (Kung *et al.*, 2013) but these were not included in our benchmark.

We found that in the eukaryotic dataset, accessibility based methods performed best based on the average MCC scores (except AccessFold and bistaRNA) (Fig. 2). IntaRNA (av. MCC: 0.51) slightly outperformed RNAup (av. MCC: 0.49) and produced a higher PPV than the other tools benchmarked. RNAplex (av. MCC: 0.48) and RIsearch (av. MCC: 0.48) (an alignment-like method) were also comparable with these two algorithms for eukaryotic datasets. Supplementary Table S3 explicitly shows the prediction scores for all 88 eukaryotic interactions.

Bacterial small RNAs can be divided into three major types: antisense binding sRNAs, *Hfq* dependent sRNAs and *csrA* binding

sRNAs (Storz *et al.*, 2011; Vogel, 2009). However, in this study, bacterial sRNAs refer to either antisense or *Hfq* dependent sRNAs, which achieve their role via RNA–RNA base-pairing interactions. Bacterial sRNAs (50–200 nts long) prefer short binding regions relative to their size (Storz *et al.*, 2011; Vogel, 2009). This was also true for our dataset, with an average binding region size of 23 nts, with the smallest just 7 nts long (Supplementary Table S1). Model bacterial organisms like *E. coli* or *Salmonella* contain hundreds of different sRNAs which points to a complex regulatory system in prokaryotic organisms (Waters and Storz, 2009). Moreover, increasing number of RNA-seq studies (Cohen *et al.*, 2016; Sharma and Vogel, 2014; Sharma *et al.*, 2010) reveal that there are novel regulatory ncRNAs are spanning in prokaryotes than previously anticipated (Barquist and Vogel, 2015; Chen *et al.*, 2016; Lindgreen *et al.*, 2014).

We found that in the bacterial dataset, accessibility based methods performed better than the others based on the average MCC scores, as with the eukaryotic dataset. RNAup (av. MCC: 0.68) slightly outperformed IntaRNA (av. MCC: 0.65) in bacterial sRNA interactions. RNAplex (av. MCC: 0.61) was comparable with the other two algorithms. In bacterial dataset, RIsearch (av. MCC: 0.31) did not perform as well as on the eukaryotic dataset, which decreased the overall performance (Fig. 2).

RNA interactions in archaea are not well characterized. Recent studies have shown that archaeal genomes contain a large number of ncRNA repositories similar to bacterial genomes (Lindgreen *et al.*, 2014). Unfortunately, there are not many verified RNA interactions available in archaea, except archaeal snoRNAs. Archaeal genomes mostly contain C/D box snoRNAs; thus, we added 5 C/D box snoRNAs (Omer *et al.*, 2000) and one archaeal sRNA (Jäger *et al.*, 2012) as an archaeal benchmark dataset. The archaeal sRNA targets a bicistronic gene and trans-regulates expression of two protein coding genes concurrently (Jäger *et al.*, 2012) (Figs 1 and 2 and Supplementary Table S3).

We found that in the archaeal dataset, RNAplex (av. 0.65) performed better than the other algorithms, followed by IntaRNA (av. MCC: 0.61). These two algorithms were followed by RNAup (av. MCC: 0.53) and RIsearch (av. MCC: 0.40). RIsearch was better on snoRNA predictions than the single archeal sRNA, which reduced the average overall performance. RNAplex recovered the binding region with a perfect MCC score, followed by IntaRNA.

3.5 Limitations of RNA–RNA interaction predictions algorithms

Unfortunately, 15 out of 154 RNA interaction pairs in our benchmark dataset could not be correctly predicted by any of the algorithms (i.e. an MCC score of 0 for all algorithms) (Fig. 2 and Supplementary Table S3) including 6 human miRNAs, and snoRNAs from yeast, human and archaea. The mouse piRNA results were also unsatisfactory, and one (piR-013474) could not be detected by any of the algorithms. The algorithms benchmarked performed best on *Arabidopsis* miRNAs, siRNAs and bacterial sRNAs (Fig. 2).

We applied the significance test to some of these failed eukaryotic interactions (e.g. mouse piRNAs, human miRNAs), aiming to see whether the predicted scores enabled the detection of true interactions (and separate scores for native interactions from background) rather than using correctly predicted binding regions. The comparison of two methods revealed consistent results as expected. For example, the native interaction of piR-013474 cannot be differentiated from background by any algorithm. This is also similar for

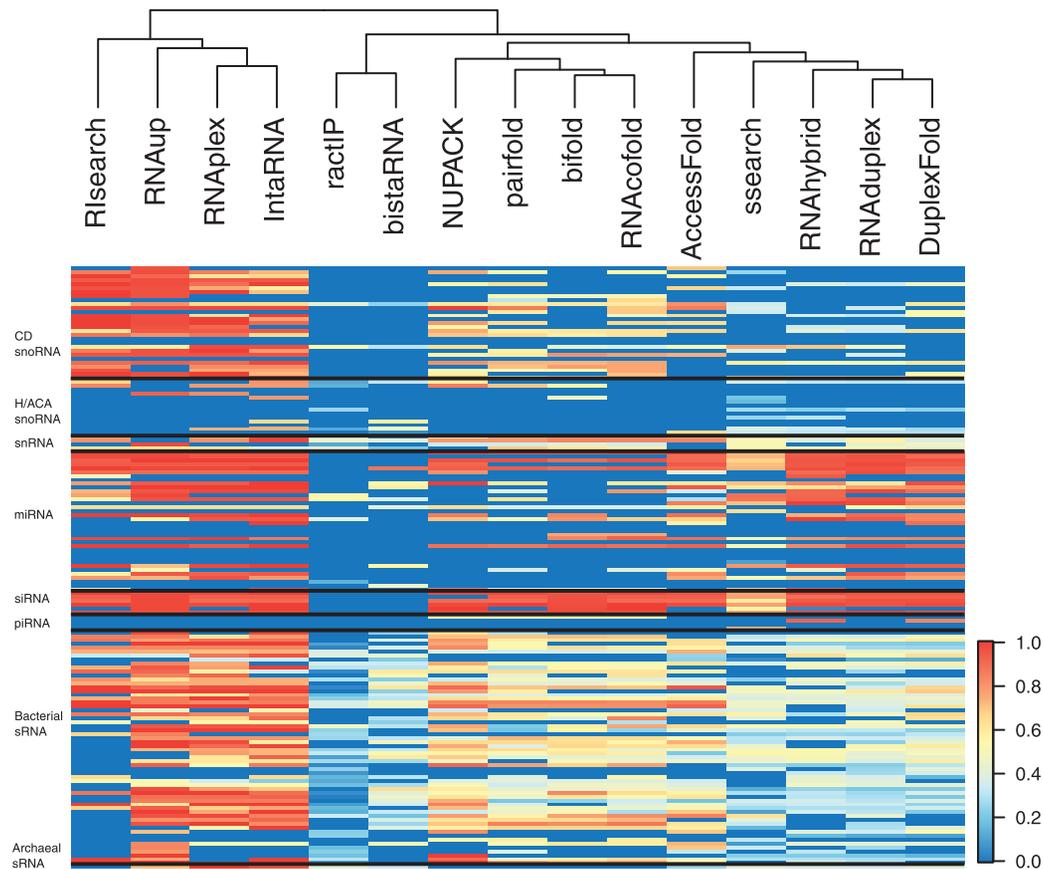


Fig. 2. This heatmap shows MCC values of each tool for entire dataset. The red cells display a higher MCC value denoting a better prediction. Similar methods are mostly clustered together based on these predictions (dendrogram at top). Row labels show the type of interactions. Predictions for the single archaeal sRNA are on the last row. An in depth examination of these results show that the algorithms are poor at predicting human miRNA–mRNA interactions (av. MCC: 0.22), snoRNAs (weaker for H/ACA as expected, av. MCC: 0.09), mouse piRNAs (av. MCC: 0.07). Conversely, they perform best on *Arabidopsis* miRNAs (av. MCC: 0.72), siRNAs (av. MCC: 0.71) and bacterial sRNAs (av. MCC: 0.40), which is most likely an effect of high complementarity in binding regions for these

other piRNAs and human miRNAs, where all algorithms consistently failed.

The lengths of target RNA regions (which include binding regions) seem to influence prediction quality (also discussed by Lai and Meyer, 2015). The average length of a eukaryotic target RNA is 1690 nts long in our dataset. However, this rises to around 2400 nts for those miRNAs which did not give prediction scores, and longer in piRNAs. As described in materials and methods, we did not truncate the targets (e.g. UTRs) that contained binding regions. We found a significant reverse correlation (Pearson's $r = -0.28$, $p < 0.05$) between the lengths of target RNAs and average MCCs (i.e. overall performances). However, some of the algorithms (RNAup, RNApIex, RIssearch, RNAcofold and NUPACK) are less prone to this length bias ($p > 0.05$) (Supplementary Table S4), making them ideal for use on untruncated targets.

Another explanation for inadequate prediction may be the quality of the dataset. Not all experimental protocols are equally strong at detecting correct binding regions, functional characterization or identifying new targets (Chou *et al.*, 2015; Kuhn *et al.*, 2008; Thomson *et al.*, 2011; Vogel and Wagner, 2007). However, the incorrectly predicted human miRNAs (hsa-miR-21-5p, hsa-miR-29b-3p, etc.) were validated by relatively strong evidence (Chou *et al.*, 2015), which could rule out this explanation.

RNA structure prediction (and also RNA–RNA interaction prediction) algorithms are based on biophysical assumptions where the

influence of tertiary interactions and other factors are neglected (Mathews, 2006; Mathews and Turner, 2006; Wuchty *et al.*, 1999). RNA structures with the lowest free energy may not be the biologically active form, which may have multiple different conformations with different MFEs (Mathews, 2006; Mathews and Turner, 2006). Many algorithms ignore computationally expensive RNA structures (e.g. pseudoknots) (Do *et al.*, 2006; Hofacker *et al.*, 1994; Lorenz *et al.*, 2011). MFE methods also become inaccurate with longer RNA sequences (Lai and Meyer, 2015; Lange *et al.*, 2012; Mathews and Turner, 2006; Meyer, 2008). RNA interaction prediction algorithms generally do not consider multiple binding regions—only a few of which such as bistaRNA and ractIP, include multiple binding positions in their model (Kato *et al.*, 2010; Poolsap *et al.*, 2011). Cellular dynamics (i.e. interaction with other molecules, ion concentrations, etc.) can influence RNA structures (Onoa and Tinoco, 2004) and RNA interactions (Meyer, 2008; Mückstein *et al.*, 2006), which is hard to factor into prediction models.

The ssearch tool uses the Smith-Waterman algorithm (Pearson and Lipman, 1988) and is the only pure alignment tool in our benchmark, although it is possible to use similar tools, such as BLAST or Blat, to extract complementary regions for high-throughput predictions. Once the gap penalty and scoring matrix parameters were tweaked to make it more suitable for RNA–RNA interaction prediction, ssearch was quite successful and even comparable with some MFE methods (e.g. RNAhybrid and DuplexFold) (Fig. 1).

Those MFE methods that include internal structures (e.g. pairfold, RNAcofold, bifold, NUPACK) are biased towards internal structures as many ncRNAs have stable internal structures (Clote *et al.*, 2005). Therefore, using negative controls may lead to false significant predictions due to internal structures of interacting partners, giving misleading MFE scores. We also observed this effect in our predictions (data not shown), and so excluded those algorithms from the significance test. They also have relatively slow running times, and some have problems utilizing memory (e.g. bifold). NUPACK is the best among this type of prediction methods and RNAcofold is the fastest (Table 1).

It is apparent that the algorithms do not necessarily perform equally for all types of RNA–RNA interactions, and it is better to select algorithms appropriate to the input dataset. For example, Rsearch is fast and accurate for eukaryotic datasets, and would be suitable for high throughput predictions which can be combined with statistical significance testing of the predicted scores. IntaRNA and RNAplex seem to be reliable and relatively fast for all datasets. RNAup is precise and less prone to length bias (Supplementary Table S4).

4 Conclusion

Here we present one of the most comprehensive benchmarks of RNA–RNA interaction prediction methods that covers almost all RNA–RNA interactions in RNA biology. We extended the previous work (Lai and Meyer, 2015; Pain *et al.*, 2015) by including all types of RNA–RNA interactions and the latest algorithms (DiChiaccchio *et al.*, 2015) in the RNA interaction prediction field. We have included a test to determine the statistical significance of the predicted scores by each algorithm. We have also reported that increasing length of target RNAs which contain binding regions also negatively influences overall prediction quality (Supplementary Table S4).

Three accessibility based algorithms, RNAup, IntaRNA and RNAplex, performed best for all types of interactions. We found that the accessibility based MFE methods could also differentiate almost half of the native interactions from background in our bacterial dataset (Table 2). Therefore, carefully designed negative controls (e.g. dinucleotide shuffling) allow for the use of predicted MFE values and separate scores for native interactions from the background. This makes the accessibility algorithms ideal tools for *de novo* predictions, especially those with smaller run-times such as IntaRNA and RNAplex, since candidate target RNAs can be thousands of nts long. RNAplex is also effective on detecting correct interaction regions buried in larger RNA targets (Results and Supplementary Table S4).

RNA interaction prediction is still an expanding field. Advances in sequencing technology has unveiled a vast number of novel uncharacterized ncRNA transcripts in different clades of life. These methods are also showing that many ncRNAs utilize RNA–RNA interactions (Kudla *et al.*, 2011; Lu *et al.*, 2016; Sharma *et al.*, 2016) which makes RNA target prediction an important asset to determine functions of novel genes. Comparative methods are becoming popular (Lai and Meyer, 2015; Pain *et al.*, 2015; Seemann *et al.*, 2011; Wright *et al.*, 2013), and may increase the prediction accuracy (Pain *et al.*, 2015; Wright *et al.*, 2013). However, some other results suggest that there is little to be gained from comparative approaches for predicting interactions (Lai and Meyer, 2015; Richter and Backofen, 2012) due to low conservation of many ncRNAs (Lindgreen *et al.*, 2014). Unfortunately, most of the verified interactions in the RNA

literature still belong to model species (human, *C. elegans*, *Arabidopsis* and *E. coli*, etc.) which also raises the risk of overfitting results to a modest numbers of known interactions. Weak prediction rates for piRNAs may suggest inadequacy of prediction methods for novel regulatory RNAs, but even well-known miRNA interaction predictions have failed to be detected by any of the algorithms benchmarked (Fig. 2). Archaeal regulatory systems are also not well studied, and only a handful of archaeal sRNAs have been identified. Therefore, non-comparative methods are still a robust way to produce *ab initio* interaction predictions. Our benchmark will help researchers to find an appropriate algorithm for functional annotation of unknown transcripts or a basis from which to improve or develop new methods. Our scripts and datasets are publicly available at Github (github.com/UCanCompBio/RNA_Interactions_Benchmark).

Funding

SUU is supported by a Biomolecular Interaction Centre and UC HPC (Bluefern) joint PhD Scholarship from the University of Canterbury. PPG is supported by Rutherford Discovery Fellowships, administered by the Royal Society of New Zealand.

Acknowledgments

We also thank Lars Barquist for valuable discussions and comments. We also thank Bethany Jose for extensive comments and proofreading.

Conflict of Interest: none declared.

References

- Addo-Quaye, C. *et al.* (2008) Endogenous siRNA and miRNA targets identified by sequencing of the Arabidopsis degradome. *Curr. Biol.*, **18**, 758–762.
- Alkan, C. *et al.* (2006) RNA–RNA interaction prediction and antisense RNA target search. *J. Comput. Biol.*, **13**, 267–282.
- Altschul, S.F. *et al.* (1990) Basic local alignment search tool. *J. Mol. Biol.*, **215**, 403–410.
- Ambros, V. (2004) The functions of animal microRNAs. *Nature*, **431**, 350–355.
- Ameres, S.L. and Zamore, P.D. (2013) Diversifying microRNA sequence and function. *Nat. Rev. Mol. Cell Biol.*, **14**, 475–488.
- Andronescu, M. *et al.* (2005) Secondary structure prediction of interacting RNA molecules. *J. Mol. Biol.*, **345**, 987–1001.
- Axtell, M.J. *et al.* (2011) Vive la différence: biogenesis and evolution of microRNAs in plants and animals. *Genome Biol.*, **12**, 221.
- Backofen, R. and Hess, W.R. (2010) Computational prediction of sRNAs and their targets in bacteria. *RNA Biol.*, **7**, 33–42.
- Barquist, L. and Vogel, J. (2015) Accelerating discovery and functional analysis of small RNAs with new technologies. *Annu. Rev. Genet.*, **49**, 367–394.
- Bernhart, S.H. *et al.* (2006) Partition function and base pairing probabilities of RNA heterodimers. *Algorithms Mol. Biol.*, **1**, 3.
- Bhaya, D. *et al.* (2011) CRISPR–Cas systems in bacteria and archaea: versatile small RNAs for adaptive defense and regulation. *Annu. Rev. Genet.*, **45**, 273–297.
- Brennecke, J. *et al.* (2007) Discrete small RNA-generating loci as master regulators of transposon activity in drosophila. *Cell*, **128**, 1089–1103.
- Brown, J.W. *et al.* (2001) Multiple snoRNA gene clusters from Arabidopsis. *RNA*, **7**, 1817–1832.
- Busch, A. *et al.* (2008) IntaRNA: efficient prediction of bacterial sRNA targets incorporating target site accessibility and seed regions. *Bioinformatics*, **24**, 2849–2856.
- Cao, Y. *et al.* (2010) sRNATarBase: a comprehensive database of bacterial sRNA targets verified by experiments. *RNA*, **16**, 2051–2057.

- Carthew,R.W. and Sontheimer,E.J. (2009) Origins and mechanisms of miRNAs and siRNAs. *Cell*, **136**, 642–655.
- Chen,W.H. *et al.* (2016) Integration of multi-omics data of a genome-reduced bacterium: Prevalence of post-transcriptional regulation and its correlation with protein abundances. *Nucleic Acids Res.*, **44**, 1192–1202.
- Chen,X. (2008) MicroRNA metabolism in plants. *Curr. Top. Microbiol. Immunol.*, **320**, 117–136.
- Chitsaz,H. *et al.* (2009a). biRNA: fast RNA–RNA binding sites prediction. In: Salzberg,S.L. and Warnow,T. (eds.) *Algorithms in Bioinformatics, Lecture Notes in Computer Science*, pages 25–36. Springer, Berlin, Heidelberg.
- Chitsaz,H. *et al.* (2009b) A partition function algorithm for interacting nucleic acid strands. *Bioinformatics*, **25**, i365–i373.
- Chou,C.H. *et al.* (2015) miRTarBase 2016: updates to the experimentally validated miRNA–target interactions database. *Nucleic Acids Res.*, **44**, D239–D247.
- Cohen,O. *et al.* (2016) Comparative transcriptomics across the prokaryotic tree of life. *Nucleic Acids Res.*, **44**, W46–W53.
- Clote,P. *et al.* (2005) Structural RNA has lower folding energy than random RNA of the same dinucleotide frequency. *RNA*, **11**, 578–591.
- Cuperus,J.T. *et al.* (2011) Evolution and functional diversification of MIRNA genes. *Plant Cell*, **23**, 431–442.
- Darzacq,X. *et al.* (2002) Cajal body-specific small nuclear RNAs: a novel class of 2'-o-methylation and pseudouridylation guide RNAs. *EMBO J.*, **21**, 2746–2756.
- Deleavey,G.F. and Damha,M.J. (2012) Designing chemically modified oligonucleotides for targeted gene silencing. *Chem. Biol.*, **19**, 937–954.
- DiChiacchio,L. *et al.* (2015) AccessFold: predicting RNA–RNA interactions with consideration for competing Self-Structure. *Bioinformatics*, **32**, 1033–1039.
- Dieterich,C. and Stadler,P.F. (2012) *Computational Biology of RNA Interactions. Wiley Interdiscip. Rev. RNA*, **4**, 107–120.
- Dirks,R.M. *et al.* (2007) Thermodynamic analysis of interacting nucleic acid strands. *SIAM Rev.*, **49**, 65–88.
- Do,C.B. *et al.* (2006) CONTRAfold: RNA secondary structure prediction without physics-based models. *Bioinformatics*, **22**, e90–e98.
- Eddy,S.R. (2011) Accelerated profile HMM searches. *PLoS Comput. Biol.*, **7**, e1002195.
- Gardner,P.P. *et al.* (2010) SnoPatrol: how many snoRNA genes are there?. *J. Biol.*, **9**, 4.
- Gerlach,W. and Giegerich,R. (2006) GUUGle: a utility for fast exact matching under RNA complementary rules including G–U base pairing. *Bioinformatics*, **22**, 762–764.
- Gilbert,W. (1986) Origin of life: The RNA world. *Nature*, **319**, 618.
- Gorodkin,J. *et al.* (2001) Discovering common stem–loop motifs in unaligned RNA sequences. *Nucleic Acids Res.*, **29**, 2135–2144.
- Gottesman,S. (2004) The small RNA regulators of *Escherichia coli*: roles and mechanisms*. *Annu. Rev. Microbiol.*, **58**, 303–328.
- Gou,L.T. *et al.* (2015) Pachytene piRNAs instruct massive mRNA elimination during late spermiogenesis. *Cell Res.*, **25**, 266.
- Güell,M. *et al.* (2009) Transcriptome complexity in a genome-reduced bacterium. *Science*, **326**, 1268–1271.
- Güell,M. *et al.* (2011) Bacterial transcriptomics: what is beyond the RNA horizon?. *Nat. Rev. Microbiol.*, **9**, 658–669.
- Gumbel,E.J. (1958). *Statistics of Extremes*. 1958. Columbia Univ. Press, New York.
- Hodas,N.O. and Aalberts,D.P. (2004) Efficient computation of optimal oligo-RNA binding. *Nucleic Acids Res.*, **32**, 6636–6642.
- Hofacker,I.L. *et al.* (1994) Fast folding and comparison of RNA secondary structures. *Monatsh. Chem.*, **125**, 167–188.
- Holmqvist,E. and Vogel,J. (2013) A small RNA serving both the hfq and CsrA regulons. *Genes Dev.*, **27**, 1073–1078.
- Jäger,D. *et al.* (2012) An archaeal sRNA targeting cis- and trans-encoded mRNAs via two distinct domains. *Nucleic Acids Res.*, **40**, 10964–10979.
- John,B. *et al.* (2004) Human MicroRNA targets. *PLoS Biol.*, **2**, e363.
- Karijolich,J. and Yu,Y.T. (2010) Spliceosomal snRNA modifications and their function. *RNA Biol.*, **7**, 192–204.
- Kato,Y. *et al.* (2010) RactIP: fast and accurate prediction of RNA–RNA interaction using integer programming. *Bioinformatics*, **26**, i460–i466.
- Kehr,S. *et al.* (2011) PLEXY: efficient target prediction for box C/D snoRNAs. *Bioinformatics*, **27**, 279–280.
- Kent,W.J. (2002) BLAT—the BLAST-like alignment tool. *Genome Res.*, **12**, 656–664.
- Kery,M.B. *et al.* (2014) TargetRNA2: identifying targets of small regulatory RNAs in bacteria. *Nucleic Acids Res.*, **42**, W124–W129.
- Kidner,C.A. and Martienssen,R.A. (2005) The developmental role of microRNA in plants. *Curr. Opin. Plant Biol.*, **8**, 38–44.
- Kiriakidou,M. *et al.* (2004) A combined computational-experimental approach predicts human microRNA targets. *Genes Dev.*, **18**, 1165–1178.
- Kiss,A.M. *et al.* (2004) Human box H/ACA pseudouridylation guide RNA machinery. *Mol. Cell Biol.*, **24**, 5797–5807.
- Kiss,T. (2002) Small nucleolar RNAs. *Cell*, **109**, 145–148.
- Klattenhoff,C. and Theurkauf,W. (2008) Biogenesis and germline functions of piRNAs. *Development*, **135**, 3–9.
- Kozomara,A. and Griffiths-Jones,S. (2013) miRBase: annotating high confidence microRNAs using deep sequencing data. *Nucleic Acids Res.*, **41**, gkt1181.
- Kudla,G. *et al.* (2011) Cross-linking, ligation, and sequencing of hybrids reveals RNA–RNA interactions in yeast. *Proc. Natl. Acad. Sci. U. S. A.*, **108**, 10010–10015.
- Kuhn,D.E. *et al.* (2008) Experimental validation of miRNA targets. *Methods*, **44**, 47–54.
- Kung,J.T.Y. *et al.* (2013) Long noncoding RNAs: past, present, and future. *Genetics*, **193**, 651–669.
- Lai,D. and Meyer,I.M. (2015) A comprehensive comparison of general RNA–RNA interaction prediction methods. *Nucleic Acids Res.*, **44**, e61.
- Lange,S.J. *et al.* (2012) Global or local? Predicting secondary structure and accessibility in mRNAs. *Nucleic Acids Res.*, **40**, 5215–5226.
- Lestrade,L. and Weber,M.J. (2006) snoRNA-LBME-db, a comprehensive database of human H/ACA and C/D box snoRNAs. *Nucleic Acids Res.*, **34**, D158–D162.
- Lewis,B.P. *et al.* (2005) Conserved seed pairing, often flanked by adenosines, indicates that thousands of human genes are microRNA targets. *Cell*, **120**, 15–20.
- Lindgreen,S. *et al.* (2014) Robust identification of noncoding RNA from transcriptomes requires phylogenetically-informed sampling. *PLoS Comput. Biol.*, **10**, e1003907.
- Lorenz,R. *et al.* (2011) ViennaRNA package 2.0. *Algorithms Mol. Biol.*, **6**, 26.
- Lu,Z. *et al.* (2016) RNA duplex map in living cells reveals Higher-Order transcriptome structure. *Cell*, **165**, 1267–1279.
- Markham,N.R. and Zuker,M. (2008) UNAFold: software for nucleic acid folding and hybridization. *Methods Mol. Biol.*, **453**, 3–31.
- Mathews,D.H. (2006) Revolutions in RNA secondary structure prediction. *J. Mol. Biol.*, **359**, 526–532.
- Mathews,D.H. and Turner,D.H. (2006) Prediction of RNA secondary structure by free energy minimization. *Curr. Opin. Struct. Biol.*, **16**, 270–278.
- Matthews,B.W. (1975) Comparison of the predicted and observed secondary structure of T4 phage lysozyme. *Biochim. Biophys. Acta*, **405**, 442–451.
- Mattick,J.S. (2004) RNA regulation: a new genetics?. *Nat. Rev. Genet.*, **5**, 316–323.
- Mattick,J.S. (2009) The genetic signatures of noncoding RNAs. *PLoS Genet.*, **5**, e1000459.
- McCaskill,J.S. (1990) The equilibrium partition function and base pair binding probabilities for RNA secondary structure. *Biopolymers*, **29**, 1105–1119.
- Meyer,I.M. (2008) Predicting novel RNA–RNA interactions. *Curr. Opin. Struct. Biol.*, **18**, 387–393.
- Millar,A.A. and Waterhouse,P.M. (2005) Plant and animal microRNAs: similarities and differences. *Funct. Integr. Genomics*, **5**, 129–135.
- Mückstein,U. *et al.* (2006) Thermodynamics of RNA–RNA binding. *Bioinformatics*, **22**, 1177–1182.
- Nussinov,R. and Jacobson,A.B. (1980) Fast algorithm for predicting the secondary structure of single-stranded RNA. *Proc. Natl. Acad. Sci. U. S. A.*, **77**, 6309–6313.
- Omer,A.D. *et al.* (2000) Homologs of small nucleolar RNAs in archaea. *Science*, **288**, 517–522.

- O'Neil,D. *et al.* (2013) Ribosomal RNA depletion for efficient use of RNA-Seq capacity. *Curr. Protoc. Mol. Biol.*, DOI: 10.1002/0471142727.mb0419s103.
- Onoa,B. and Tinoco,I. Jr. (2004) RNA folding and unfolding. *Curr. Opin. Struct. Biol.*, **14**, 374–379.
- Oğul,H. *et al.* (2011) A probabilistic approach to microRNA-target binding. *Biochem. Biophys. Res. Commun.*, **413**, 111–115.
- Pain,A. *et al.* (2015) An assessment of bacterial small RNA target prediction programs. *RNA Biol.*, **12**, 509–513.
- Pearson,W.R. (1991) Searching protein sequence libraries: comparison of the sensitivity and selectivity of the Smith-Waterman and FASTA algorithms. *Genomics*, **11**, 635–650.
- Pearson,W.R. and Lipman,D.J. (1988) Improved tools for biological sequence comparison. *Proc. Natl. Acad. Sci. U. S. A.*, **85**, 2444–2448.
- Peer,A. and Margalit,H. (2011) Accessibility and evolutionary conservation mark bacterial small-rna target-binding regions. *J. Bacteriol.*, **193**, 1690–1701.
- Pennisi,E. (2012) Genomics. ENCODE project writes eulogy for junk DNA. *Science*, **337**, 1159, 1161.
- Pervouchine,D.D. (2004) IRIS: intermolecular RNA interaction search. *Genome Inform.*, **15**, 92–101.
- Piekna-Przybylska,D. *et al.* (2007) New bioinformatic tools for analysis of nucleotide modifications in eukaryotic rRNA. *RNA*, **13**, 305–312.
- Poolsap,U. *et al.* (2011) Using binding profiles to predict binding sites of target RNAs. *J. Bioinform. Comput. Biol.*, **9**, 697–713.
- Prasse,D. *et al.* (2013) Regulatory RNAs in archaea: first target identification in methanoarchaea. *Biochem. Soc. Trans.*, **41**, 344–349.
- Rehmsmeier,M. *et al.* (2004) Fast and effective prediction of microRNA/target duplexes. *RNA*, **10**, 1507–1517.
- Reuter,J.S. and Mathews,D.H. (2010) RNAstructure: software for RNA secondary structure prediction and analysis. *BMC Bioinform.*, **11**, 129.
- Reynolds,A. *et al.* (2004) Rational siRNA design for RNA interference. *Nat. Biotechnol.*, **22**, 326–330.
- Richter,A.S. and Backofen,R. (2012) Accessibility and conservation: General features of bacterial small RNA-mRNA interactions?. *RNA Biol.*, **9**, 954–965.
- Seemann,S.E. *et al.* (2011) PETcofold: predicting conserved interactions and structures of two multiple alignments of RNA sequences. *Bioinformatics*, **27**, 211–219.
- Sharma,C.M. and Vogel,J. (2014) Differential RNA-seq: the approach behind and the biological insight gained. *Curr. Opin. Microbiol.*, **19**, 97–105.
- Sharma,C.M. *et al.* (2010) The primary transcriptome of the major human pathogen helicobacter pylori. *Nature*, **464**, 250–255.
- Sharma,E. *et al.* (2016) Global mapping of human RNA–RNA interactions. *Mol. Cell*, **62**, 618–626.
- Storz,G. *et al.* (2011) Regulation by small RNAs in bacteria: expanding frontiers. *Mol. Cell*, **43**, 880–891.
- Tafer,H. and Hofacker,J.L. (2008) RNAplex: a fast tool for RNA–RNA interaction search. *Bioinformatics*, **24**, 2657–2663.
- Tafer,H. *et al.* (2010) RNAsnoop: efficient target prediction for H/ACA snoRNAs. *Bioinformatics*, **26**, 610–616.
- Thébault,P. *et al.* (2014) Advantages of mixing bioinformatics and visualization approaches for analyzing sRNA-mediated regulatory bacterial networks. *Brief. Bioinform.*, **16**, 795–805.
- Thomson,D.W. *et al.* (2011) Experimental strategies for microRNA target identification. *Nucleic Acids Res.*, **39**, 6845–6853.
- Tjaden,B. (2008) TargetRNA: a tool for predicting targets of small RNA action in bacteria. *Nucleic Acids Res.*, **36**, W109–W113.
- Umu,S.U. *et al.* (2016) Avoidance of stochastic RNA interactions can be harnessed to control protein expression levels in bacteria and archaea. *Elife*, **5**, e13479.
- Vogel,J. (2009) A rough guide to the non-coding RNA world of salmonella. *Mol. Microbiol.*, **71**, 1–11.
- Vogel,J. and Luisi,B.F. (2011) Hfq and its constellation of RNA. *Nat. Rev. Microbiol.*, **9**, 578–589.
- Vogel,J. and Wagner,E.G.H. (2007) Target identification of small noncoding RNAs in bacteria. *Curr. Opin. Microbiol.*, **10**, 262–270.
- Waters,L.S. and Storz,G. (2009) Regulatory RNAs in bacteria. *Cell*, **136**, 615–628.
- Wenzel,A. *et al.* (2012) Rlsearch: fast RNA–RNA interaction search using a simplified nearest-neighbor energy model. *Bioinformatics*, **28**, 2738–2746.
- Will,C.L. and Lührmann,R. (2011) Spliceosome structure and function. *Cold Spring Harb. Perspect. Biol.*, **3**.
- Witkos,T.M. *et al.* (2011) Practical aspects of microRNA target prediction. *Curr. Mol. Med.*, **11**, 93–109.
- Workman,C. and Krogh,A. (1999) No evidence that mRNAs have lower folding free energies than random sequences with the same dinucleotide distribution. *Nucleic Acids Res.*, **27**, 4816–4822.
- Wright,P.R. *et al.* (2013) Comparative genomics boosts target prediction for bacterial small RNAs. *Proc. Natl. Acad. Sci. U. S. A.*, **110**, E3487–E3496.
- Wuchty,S. *et al.* (1999) Complete suboptimal folding of RNA and the stability of secondary structures. *Biopolymers*, **49**, 145–165.
- Yang,Y. *et al.* (2008) MiRTif: a support vector machine-based microRNA target interaction filter. *BMC Bioinform.*, **9**, S4.
- Yoshihama,M. *et al.* (2013) snOPY: a small nucleolar RNA orthological gene database. *BMC Res. Notes*, **6**, 426.
- Zhang,P. *et al.* (2015) MIWI and piRNA-mediated cleavage of messenger RNAs in mouse testes. *Cell Res.*, **25**, 193–207.
- Zhao,Y. *et al.* (2016) NONCODE 2016: an informative and valuable data source of long non-coding RNAs. *Nucleic Acids Res.*, **44**, D203–D208.
- Zuker,M. (2000) Calculating nucleic acid secondary structure. *Curr. Opin. Struct. Biol.*, **10**, 303–310.
- Zuker,M. and Sankoff,D. (1984) RNA secondary structures and their prediction. *Bltm. Mathcal. Biol.*, **46**, 591–621.
- Zuker,M. and Stiegler,P. (1981) Optimal computer folding of large RNA sequences using thermodynamics and auxiliary information. *Nucleic Acids Res.*, **9**, 133–148.