#### PREDICTING IN VIVO RNA SECONDARY STRUCTURE

by

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#### Abstract

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## Introduction

- 1.1 RNA secondary structure
- 1.2 High throughput probing of RNS secondary structure
- 1.3 Deep neural network

#### Yeast Model

To model in vivo RNA secondary structure, we compiled training data from [1]. In this study, yeast strain was treated with dimethyl sulphate (DMS), which reacts with unpaired adenine and cytosine bases. The pool of modified RNAs were fragmented and sequenced. Since DMS modification blocks reverse transcription, number of reads (TODO stops?) at each position is indicative of relative accessibility of that site.

The authors aligned 25nt of each read to a non-redundant set of RefSeq transcripts, where each gene is represented by its longest protein-coding transcript. Only uniquely mapped reads with less than 2 mismatches were retained, and the authors further filtered out aligned reads whose RT stop is not A/C. The count at each position represents the combined number of RT stops at that site, across 4 biological replicates.

To construct training dataset, Saccharomyces cerevisiae assembly R61 (secCer2) RefSeq gene annotation was used to extract mRNA sequences. For each transcript, we first extract the raw read count for all adenine (A) and cytosine (C) bases (A/C positions with no RT stop coverage were set to a count of 0), and applied 90% Winsorization to remove outliers. Specifically, for each non-overlapping window of 100 A/C bases, values above the 95% percentile was set to the 95% percentile, and values below the 5% percentile was set to the 5% percentile. Then, all values within this window were divided by the max, to obtain values between 0 and 1.

We used the poly-A selected yeast data to compile training dataset consists of mRNAs. 5-fold CV, chromosomes soft label cross entropy missing value, loss/gradient masking TODO RT stop / total coverage TODO 4 reps

# Mouse Model

# **Human Model**

## Conclusion and future work

one dataset that has multiple mods per sequence, so we can reconstruct collection of structures joint learning of accessibility and other data, e.g. chip-seq peaks

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