**BACHELOR THESIS**

**Analysis of autologous binding preferences**

**of RNA-binding proteins**

**RNA binding motifs reveal tendencies towards autologous binding**

submitted by

**Moritz Haderer**

in partial fulfillment of the requirements for the degree of

**Bachelor of Science (BSc)**

Vienna, 2022

**UA 033 630**

**Bachelor’s degree programme Biology**

**Univ.-Prof. Dr. Bojan Zagrovic, BA**

Degree programme code as it appears on the

student record sheet:

Degree programme as it appears on the

student record sheet:

Supervisor:

**Abstract**

The central dogma of molecular biology [1] is a proposed model for the passing down of genetic information in the cell. While it captures the essence of life on a molecular level, there are types of interactions that are difficult to understand when viewed from this perspective. Interactions between RNA-binding proteins (RBPs) and RNA count among them. They are integral parts of many cellular processes such as post-transcriptional regulation, RNA transport- and localization as well as post-transcriptional modification of RNA. As RBPs play a guiding role in these interactions, their availability needs to be tightly regulated so as to ensure proper cellular functioning. Autoregulatory feedback between RBPs and their own mRNAs [2] often lies at the heart of these regulations. The recently brought forward complementarity hypothesis helps understand how such interactions between proteins and their own mRNA can occur. As it is a relatively recent hypothesis, it suffers from a lack of experimental results. Given some new data in form of protein-RNA interaction profiles, I here show a possible systematic analysis of the theoretical binding behavior of RNA binding proteins. The results of the analysis show a general trend towards autologous interactions of RBPs with their own mRNAs. These interactions happen more readily when an RBP’s binding preferences are relatively unspecific. While protein-RNA interactions can happen highly specifically, these vaguer interaction profiles point towards the alignment of certain more low-level physicochemical properties of these biomolecules. As the central dogma states, information flows from RNA to protein. Perhaps, this flow of information includes properties that allow a protein to recognize its original mRNA in a global manner and, therefore, bind and regulate it.

Contents

[1. Introduction 5](#_Toc102645066)

[2. Materials and Methods 8](#_Toc102645067)

[2.1. Datasets 8](#_Toc102645068)

[2.1.1. RNAcompete [11] 8](#_Toc102645069)

[2.1.2. SELEX [11] 8](#_Toc102645070)

[2.1.1. HT-SELEX (2020) [16] 8](#_Toc102645071)

[2.1.2. MANE select (v0.95) transcriptome 9](#_Toc102645072)

[2.2. Methodology 9](#_Toc102645073)

[2.2.1. Motif occurrence null-model 9](#_Toc102645074)

[2.3. Extended introduction 10](#_Toc102645075)

[2.3.1. Position frequency matrix 10](#_Toc102645076)

[2.3.2. Position probability matrix 11](#_Toc102645077)

[2.3.3. Position-specific scoring matrix 11](#_Toc102645078)

[2.3.4. Scoring an occurrence 13](#_Toc102645079)

[2.3.5. Threshold setting 13](#_Toc102645080)

[2.3.6. Background distributions 14](#_Toc102645081)

[2.4. FIMO 15](#_Toc102645082)

[2.4.1. The MEME Suite 15](#_Toc102645083)

[2.4.2. What is FIMO 16](#_Toc102645084)

[2.4.3. FIMO Input preparation 16](#_Toc102645085)

[2.4.4. Statistical background 17](#_Toc102645086)

[2.4.5. Outputs 19](#_Toc102645087)

[3. Results 21](#_Toc102645088)

[3.1.1. Sequence motif search 21](#_Toc102645089)

[3.1.2. Sequence motif search – FIMO 21](#_Toc102645090)

[3.1.3. Position probability matrices 21](#_Toc102645091)

[4. Discussion 27](#_Toc102645092)

[5. References 28](#_Toc102645093)

[6. Acknowledgements 31](#_Toc102645094)

[7. Appendix 32](#_Toc102645095)

# Introduction

RNA binding proteins (RBPs) are a class of proteins that interact directly with RNA molecules [3]. These interactions have been found to involve very important cellular processes such as post-transcriptional modification and regulation of translation [4], RNA transport and localization as well as mRNA splicing [5]. Although being central to many cellular processes, the interactions between these important proteins and RNAs have not been studied to the extent they merit.

During evolution, RBPs got more and more specialized to recognize specific RNAs [5], developing binding regions that show affinity only to a specific type of recognition pattern of ribonucleic acids. These patterns are often called “motifs” and are one of the central topics of this thesis.

Recognition motifs could be structurally traced back to certain binding domains that exist within the 3D-structures of proteins. These domains have developed affinity for relatively specific sequences of ribonucleotides. While some domains prefer specific sequences of nucleotides, others bind to the phosphate backbone of RNA, being less nucleotide specific. Some domains bind linear RNA molecules, others bind complex structures or even unstructured RNAs. To have a more concrete idea of protein-RNA interactions, some knowledge of the most common RNA-binding domains is useful. Among those common domains are the RNA-Recognition Motif (RRM), the Double-stranded RNA-binding Motif (dsRBM), K-Homology domains, and RG/G repeats.

**The RNA-Recognition Motif** is found in 0.5%-1% of human genes and consists of a stretch of 90 amino acids. With conserved regions containing a handful of aromatic amino acids that bind the RNA in a base-unspecific manner, the composition of the surrounding β-sheets allows for nucleotide-specific binding.

**The Double-stranded RNA-binding motif** prefers to bind double-stranded RNAs. This also implies that these interactions are less specific, as the base-information is not as readily available as on a single-stranded nucleotide and the domain must resort to binding the phosphate-backbone. What these interactions lack in nucleotide-specificity, however, they make up in recognition of complex-structured RNA-molecules.

**K-Homology domains** are commonly able to bind a wide variety of four-nucleotide long sequences. As this alone would not suffice in efficient motif recognition, this domain has found ways of increasing its specificity. In some situations, a neighboring α-helix is integrated into its RNA recognition domain, thereby allowing efficient binding of six nucleotides. In other cases, KH-domains appear in repeats, which further increases specificity.

**RG/G (Arginine-Glycine/Glycine) repeats** are RNA-recognition domains that can interact with RNA molecules via their Arginine residue. They are usually found in intrinsically disordered protein regions and are hypothesized to play a role in protein phase-separation. As a single RGG region does not show enough specificity for efficient RNA binding, they are most often found in repeats, thereby increasing specificity.

The recently proposed “complementarity hypothesis” creates a framework for understanding these protein-RNA interactions in a general sense. According to this framework, whenever genetic information flows from mRNA to protein, the physicochemical properties of the mRNA sequence are translated to the physicochemical properties of the protein. Hence, the stretch of mRNA that codes for a given RNA-binding domain transfers a certain affinity towards itself. The complementarity hypothesis therefore states that RNA-binding domains have general affinity towards the mRNA they originated from. This flow of information is what constitutes the genetic code, being a dictionary for mRNA-to-protein translation. In fact, it has been found that translation does not simply go from base to amino acid, but rather involves passing down physicochemical properties. This phenomenon yields fascinating insight into affinity of proteins to their cognate mRNAs [6].

As experimental results for the complementarity hypothesis are scarce, we resort to in-silico analysis of protein-RNA interaction data for insight. The emergence of high-precision technologies like RNAcompete and SELEX, being methods that enable the determination of the exact nucleotide motifs a given RBP can recognize, facilitates this type of analysis a great deal.

Diagram

Description automatically generated

Figure 1: Description of experimental techniques for RBP binding preference determination [7]

**RNAcompete** [8] is an in-vitro experimental technique where a Glutathione-S-Transferase-tag is added to an RBP of interest. The modified RBP is then incubated in a large pool of RNAs (~ 250 000 molecules) that has been designed to cover all combinatorically possible sequences of up to 9 bases. After incubation of the RBP in an environment holding an excess of RNA, a pull-down assay is performed, eluting all RNA sequences that have been bound by the tagged RBP. The bound sequences are then separated from the RBP and hybridized against a microarray. As this assay is carried out in a large excess of RNA, the relative abundance of bound sequences indicates relative binding affinity.

**SELEX** [9], or “systematic evolution of ligands by exponential enrichment”, is another in-vitro technique for finding consensus motifs for RBPs. A SELEX run begins with a pool of DNA sequences of equal length, covering all combinatorically possible sequences. The DNA is in-vitro transcribed and an RBP is incubated in the resulting pool of RNA. Once incubation is finished, the unbound RNA sequences are washed out, whereas the bound targets are separated from the RBPs and reverse-transcribed to cDNA, which is then amplified via PCR and serves as the new starting point for the next SELEX run. After a certain number of runs, the resulting “winner” sequences are sequenced.

**High-throughput SELEX** [7] differs from SELEX in that a sample of all bound RNAs is sequenced using high-throughput methods after every run, thus allowing for the estimation of possible alternative binders.

In the context of the complementarity hypothesis and using datasets consisting of RBP-RNA binding motifs, I attempt to investigate theoretical binding affinity of RNA binding proteins towards their own mRNAs. I explore the availability of RNA-binding motifs that are bound by RBPs in every mRNA sequence of the human transcriptome, including the autologous mRNA of each RBP used in the analysis. If RBP motifs are indeed enriched in their own mRNAs, this can point to enrichment in binding affinity between a given RBP and the mRNA coding for it. To determine the binding affinity between an RBP and a given mRNA, the occurrence of RNA-binding motifs within the RNA sequences is investigated using the tool FIMO by MEME Suite [10].

* Short section on results once the final graphs arrive
* Section on how those results are relevant to the scientific community, what to they want to inspire

# Materials and Methods

## Datasets

### RNAcompete [11]

The ATtRACT database by Giudice et al. (downloaded at [ATtRACT-database](https://attract.cnic.es/download)) contains RNAcompete results for 194 RBPs in 24 different organisms. For each RBP, at least one consensus sequence is provided as well as information on the protein domain involved in binding and a quality score, being a numerical representation of binding affinity. RBPs are labelled by their gene-IDs according to Ensembl [12], Xenbase [13]or the European Nucleotide Archive [14]and gene names as provided in UniProt [15].

The data was filtered to include only human RBPs. As each RBP bound different motifs with varying consistency, only the motifs showing the highest quality score were used as a further filtering step. The resulting entries each contained a matrix ID referencing a position-probability matrix, yielding a total of 96 matrices for 77 proteins.

### SELEX [11]

The ATtRACT database also contains SELEX results for 41 RBPs in nine different organisms. As for RNAcompete, SELEX data was filtered to only include human entries of the highest quality scores. . After filtering, 26 RBPs remained, yielding a total of 46 PPMs to be used in the analysis.

### HT-SELEX (2020) [16]

Jolma et al. carried out a large High-throughput RNA-SELEX study with the goal of discovering and validating RNA binding motifs of human RNA binding proteins. The resulting data can be downloaded from the [European Nucleotide Archive](https://www.ebi.ac.uk/ena/browser/view/PRJEB25907?show=reads). It includes known RBPs, isolated RBP-binding domains as well as proteins that have been observed to bind RNA but are not among the canonical class of RBPs. All in all, this study yielded 145 binding models for 86 proteins. The database contains information on the structural preferences of specific proteins, indicating whether they bound to linear RNA rather than folded RNA. Furthermore, some RBPs have been found to bind RNA as dimers.

As the goal of this analysis is to explore motif coverage over linear RNA sequences of single RBPs, all dimeric binders and RBPs with structural preferences were excluded from the dataset. Additionally, one protein was not available in the MANE select database (as described below) For each protein, at least one position probability matrix was provided, in the end resulting in 49 proteins yielding 69 matrices.

### MANE select (v0.95) transcriptome

MANE, or “Matched Annotation from NCBI and EMBL-EBI“, is a large-scale collaboration between the National Center for Biotechnology Information and the European Bioinformatics institute as a Branch of the European Molecular Biology Laboratory. The database is available for download on [the NCBI homepage](https://www.ncbi.nlm.nih.gov/refseq/MANE/).

Its goal was to create a clearly annotated and matching database for human transcriptome data. It now covers over 18.000 transcripts with detailed information on each protein-coding gene’s location, function, 3’-UTR, 5’-UTR and coding sequence (CDS) length. The MANE database represents the transcriptome with equal weight per gene, rather than weighting by the number of transcript variants. Due to this weighting, only the best supported transcript for each gene is included.

## Methodology

### Motif occurrence null model

To assess enrichment in autologous binding, a distribution of binding affinities serving as a null hypothesis is necessary. The MANE select database, being a large repository for almost 98 % of the human transcriptome, adeptly fit this purpose. As this analysis explores the binding affinity of RNA binding proteins to their autologous mRNAs, the average affinities of RBPs to mRNAs must be established. With a null-model of RBP-mRNA-compatibility in place, p-values for autologous interactions can be derived.

### Sequence motif search

In a sequence motif search procedure, an alignment of RNA-binding motifs to every subsequence along a transcript is attempted and exact matches reported. From a probabilistic perspective, motif length plays a big role in an exact matching procedure. Since only the exact alignment of a motif to the scanned RNA stretch will count as a match, shorter motifs would be represented considerably more often in any random sequence than longer motifs would. To remedy this bias, motifs were fragmented to a specified size. Whenever a motif exceeded the desired length, every possible subsequence of this motif was used to determine a combined coverage value. The matches of individual motif fragments would finally be combined, showing matches per complete motif.

### Sequence motif search – FIMO [10]

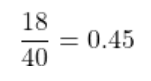
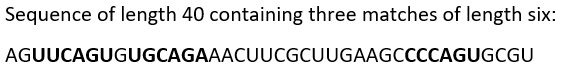
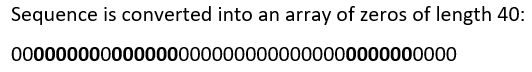
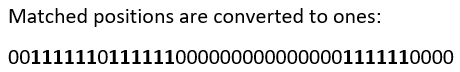
Probability matrices offer a probabilistic approach to the sequence motif match finding problem. Matrices are created from experimentally determined motifs. As RBPs can bind motifs with a certain degree of variability, the probability of a certain nucleotide appearing at any position can be calculated and combined to form a position probability matrix. When a matrix is placed against the sequence to test, a score is calculated by adding up/multiplying the values in the matrix that correspond to the sequence of letters. How exactly this scoring procedure happens is explained in detail in the extended introduction.

FIMO performs sequence motif search over a set of sequences using the position probability matrices provided. Every matrix is run over every sequence, yielding a score for every position the matrix is compared against as well as a p-value corresponding to the score. A match is reported whenever the calculated p-value is lower than the p-value cutoff specified by the user.

The motif data coming from RNAcompete, SELEX and HT-SELEX experiments as well as the MANE select database were written to text files according to the format specifications FIMO uses and motif search was performed for a variety of p-value cutoffs. As FIMO uses PSSMs rather than PPMs (a detailed explanation of matrix types can be found in the Extended introduction), a nucleotide background distribution of the scanned transcripts should be provided. This background distribution was chosen to be a zero-order Markov model based on the entire MANE select transcriptome data. Finally, FIMO returns a list of matches where each entry contains all necessary identifiers, the p-value of the score and the start and stop indices of the match in the transcript

### Evaluation of motif-occurrence enrichment

Sequence motif search was carried out for every transcript found in the MANE transcriptome database. Any significant motif-sequence alignments were reported as matches, which were then combined to a coverage value. Coverage indicates how often a given motif is present on a transcript sequence and is calculated as portrayed by the following example:



The given sequence has a coverage value of 0.45 or, in other words, 45 % of the sequence contain matches to the matrix. In a real-life example, the sequence would be significantly longer, and the coverage value would be expected to be several magnitudes lower.

Enrichment in motif-occurrence is evaluated by comparing the coverage value of each transcript to the mean coverage a motif achieves. To this end, a z-score for every transcript is calculated. The z-score is determined using Equation 1, where *covtranscript* is the coverage value of a given transcript, *covµ* is the mean coverage over all transcripts and *covσ* is the standard deviation over all coverage values.

Text

Description automatically generated

Equation 1: Z-score calculation

## Extended introduction

### Position frequency matrix

Experiments for finding new motifs of RNA binding proteins will yield a number of motifs that have been bound by the RBP. These motifs will often be similar in length and composition. To account for non-similarities between bound motifs, the Position Frequency Matrix helps visualize the number of times a given nucleotide was found at position P of the motif. As the name suggests, it indicates the frequency of nucleotides at a position.

A list of ten motifs bound by a given RBP in an experiment might look like this:

Table

Description automatically generated

Figure 2: Example for experimental sequences used to construct PFM

Counting the number of times a nucleotide is observed in a given position, a PMF of the following structure can be constructed:

A picture containing text, clock

Description automatically generated

Figure 3: Position frequency matrix (PFM)

### Position probability matrix

In a similar fashion to the position frequency matrix, the position probability matrix (or PPM) gives clear insight into the proportions of nucleotides bound at a given position. The main difference between the PFM and the PPM is a count-normalization to probability values (ranging from 0 to 1). This is done by dividing the frequency by the number of bound motifs. Continuing with the example from above, the corresponding PPM would be created by dividing each frequency count by ten:

Table

Description automatically generated

Figure 4: Position probability matrix (PPM)

In practice, the position probability matrix can be used to give a probability score to a novel motif by multiplying the letters’ corresponding probabilities over all positions. In a programmatical context, one usually deals with rather long/a large number of motifs to assign a score to. Potential downsides of this type of matrix are 1) multiplication is a more expensive computation than, e. g., addition. Once the sequences to be scored exceed a certain length, this is noticeable in the duration of computations. Another downside is that multiplication of very long matrices can lead to underflowwhen computing the score of a motif. When multiplying many small numbers, floating point precision can be thought of as a resource. This effect might skew the scoring and, consequently, determination of sufficiency of a score.

### Position-specific scoring matrix

To remedy both downsides of the PPM, a third type of matrix can be employed. The position-specific scoring matrix (PSSM), also called position weight matrix, can be derived from the PPM. It incorporates the background distribution of nucleotides of the target sequences. By computing the log-likelihood ratio of a nucleotide’s probability given the background distribution, the matrix’ entries can now be both positive and negative. The reason behind the alternative name “position weight matrix” is given by the interpretation of what these resulting values express: a positive value puts strong weight on a given nucleotide, while a negative value indicates, that this nucleotide should occur less often at that given position than the background distribution should suggest, thus reducing the weight.

An example calculation is easily done. First, let’s assume a uniform background distribution of 0.25 per nucleotide. Now, each value can be plugged into the equation:

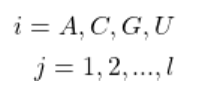
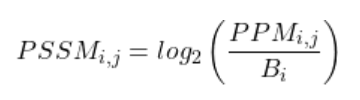


Figure 5: Constructing a Position-specific scoring matrix by taking the binary logarithm of the likelihood-ratio

The log-likelihood ratio *L* is given by the binary logarithm of the probability of nucleotide *i* at position *j,* divided by the probability of a nucleotide as given by the background   
distribution *B*.

Applying these manipulations to the PPM in the previous section, we get the following matrix:

A screenshot of a computer

Description automatically generated with low confidence

Figure 6: Position-specific scoring matrix (PSSM)

#### Pseudocounts

Since the logarithm is not defined at zero, the resulting matrix contains placeholders for an undefined value – often in form of negative infinity. A simple method to alleviate this issue is adding “pseudocounts” to the probability values in the PPM. In most practical applications, a pseudocount value of 0.1 is added to each entry in the position probability matrix. Doing this for the above PPM leads to the following PSSM:

Table

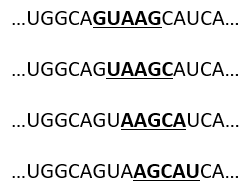
Description automatically generated

Figure 7: Position-specific scoring matrix (PSSM) with pseudocounts

### Scoring an occurrence

Every matrix encodes the affinity of an RBP for a certain motif. While exact motifs can be derived from the matrix, the probabilistic view of affinity is what makes this approach so popular. Instead of looking for an exact overlap between a “best” motif in a sequence, a matrix is “slid” over the sequence and a score is calculated at every position by adding up the value of the respective nucleotide in the matrix. Using the PSSM from above, the following scores can be assigned to the bold-marked sequence positions below:

Figure 8: Scoring procedure for a sequence given a PSSM

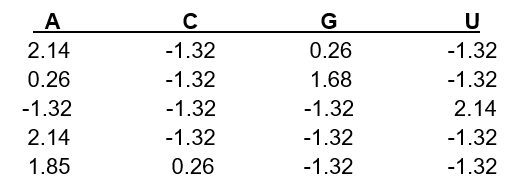


0.26 + (-1.32) + (-1.32) + 2.14 + (-1.32) = **-1.56**

(-1.32) + 0.26 + (-1.32) + (-1,32) + 0.26 = **-3.44**

2.14 + 0.26 + (-1.32) + (-1.32) + 1.85 = **1.61**

2.14 + 1.68 + (-1.32) + 2.14 + (-1.32) = **3.32**



Having calculated the corresponding scores, it is hard to say whether each score represents a “strong” or a “weak” match of a protein to a motif. To set the threshold where a score is deemed sufficient, certain statistical methods are necessary.

### Threshold setting

Chart, line chart

Description automatically generatedA motif of length five contains 45 computable scores. This arises from the fact that each nucleotide can come at any position. By computing all possible scores a matrix can yield, a score distribution is created. The PSSM from the example above leads to the distribution in Figure 9. When a percentile significance threshold is chosen, for sake of example let this be 0.05, then all scores that lie within the top 5 % of the distribution will be considered sufficient.

Figure 9: Score distribution of PSSM.

While this approach is statistically sound, creating the entire distribution of scores poses a computational problem as the length of the matrix increases. With a matrix of length 15, 415, so more than a billion, scores would have to be computed. To deal with this computational constraint, an approximation of the matrix-specific threshold can be computed by randomly sampling the possible nucleotide arrangements. As Pan and Phan [17] state in their paper, determining score thresholds by using random sampling rather than computing a full distribution was “verified to be technically identical” to creating the full distribution, if sampling size was larger than 410

## FIMO [10]

FIMO is a tool offering discovery of motif occurrences in sequences as a part of the MEME Suite package [18]. It is used for the scanning of sequences with a set of motif matrices and returns all significant matches that may occur. A significance threshold can be set by the user.

### FIMO Input

#### Motifs

FIMO takes as an input tab-separated-value files containing position probability matrices with headers containing an identifier, additional information, the matrix length and width and more optional data. At the top of the file, some information on the MEME Suite version used as well as the alphabet the motifs are coding for.

These files are appropriately output by some of the MEME Suites software tools but can also be created from scratch by following the simple formatting layout provided by FIMO. Alternatively, FIMO offers a variety of conversion tools for common file types encountered in the space of motif analysis.

#### Sequences

The sequences must be handed to FIMO in “.fasta” or, alternatively, “.fna”-format. Files of this format contain a unique identifier, such as a gene ID, and the sequence in question.

#### Background nucleotide frequency distribution

As the distribution of nucleotide frequencies determines the PSSM, it has a large impact on the entire analysis. Whenever the background frequency is greater than probability of a nucleotide as given by the matrix, the value yielded by the conversion from PPM to PSSM would be a negative one. Therefore, whenever a nucleotide has high frequency in the background, tendentially more values in the PSSM would be negative. This effect is discussed further in the result section.

### FIMO output

Using the commands as they are elaborated upon in the appendix, one file per analysis is output by FIMO. Each file contains a header and all information on a single significant match in one line. This includes information on identification:

* **the matrix used for scoring**
* **the experiment the matrix originates from**
* **the transcript the match occurred in**

as well as information on the details the match:

* **the position in the full sequence the match started at (start) and ended at (stop)**
* **the strand direction the motif was found in**
* **the exact score achieved by the scored subsequence**
* **the p-value of the score**
* **an empty column for q-values (not computed in this example) and**
* **the exact subsequence matched by the motif**

Table

Description automatically generated

# Results

## Enriched occurrence of motif sequences in RBP’s autologous transcripts

The hypothesis that proteins have affinity towards their own coding sequences, the complementarity hypothesis, not only predicts, but reveals the significance of autologous feedback in post-transcriptional regulation of RNA-binding protein-coding genes. To test this hypothesis, the enrichment of RBP affinity motifs in autologous mRNA sequences was analyzed. The ATtRACT database [11] as well as the HT-SELEX experiment of Jolma et al. [16] offer some of the most comprehensive sources for RBP motif data, while the MANE select database serves as a null-model for motif enrichment in the entire transcriptome.

An enrichment of motif occurrences in autologous transcripts was indeed observed for p-value cutoffs 0.01 and 0.05, which only include motif-sequence match-scores within the top 1 % or 5 %, respectively.

The vertical axis of the following plots shows the distribution of z-scores, while the horizontal axis is separated into the three datasets that were used in the analysis (RNAcompete, SELEX, HT-SELEX). The left side of each part of the triplet visualizes the z-scores of autologous matches in their respective sequence (1. UTR3, 2. CDS, 3. UTR5, 4. full transcript) as well as the mean of these z-scores in the respective color. The right side describes the distribution of z-scores over the entire background, with the mean fixed at zero.

Below each plot, the number of matrices which found matches in the transcriptome is shown contrasted to the total of matrices available in the dataset. The p-values below these numbers stem from a one-tailed z-test describing the probability that the autologous matches’ z-scores came from the same distribution as the null-model z-scores.

Diagram

Description automatically generated

Diagram

Description automatically generated

## Reproducibility using exact motif-sequence matches

## Dataset analysis

Chart

Description automatically generated

Figure 11: Distribution of matrix lengths for a given experiment

Chart, bar chart, histogram

Description automatically generated

Figure 12: Some proteins bound significantly different motifs, resulting in the creation of multiple probability matrices per protein.

Chart

Description automatically generated with medium confidence

Figure 10: Distribution of nucleotide frequencies among subsequences of the MANE select database.

## Results without using multiple motifs per protein

Chart

Description automatically generatedChart

Description automatically generated

My analysis is based on previous work by Arthur Theuer, who’s investigation is, in turn, derived from Thomas Kapral’s excellent groundwork. Arthur Theuer established several frameworks for investigating this question. In his analysis, he attempted to investigate binding behavior of RBPs by finding exact matches of protein motifs in transcript, he employed in-silico translation and worked with probability matrices to explore his hypothesis.

By using the same datasets as Arthur Theuer, I extended his analysis by an in-depth view of how theoretical protein-RNA binding behavior can be investigated using probability matrices, which offer a probabilistic view on binding affinity.

*Instead of using the transcriptome sequences as they are, in one approach, they were randomly shuffled around to exclude compositional biases. In another approach, only transcripts of equal or higher length than the autologous mRNA were considered and, in turn, randomly shuffled around so as to avoid length and compositional biases. In a third approach, random sequences of equal length to the autologous mRNA of each RBP were created using the di-nucleotide frequency distribution of the MANE database.*

Chart, diagram

Description automatically generated

Figure 13: The distribution of z-scores over autologous transcripts (left of each section) and the background (right of each section). Exact matching was used to obtain these results. Significant enrichment of autologous binding was observed in most transcript subsequences.

**P-value cutoff of 1e-4**

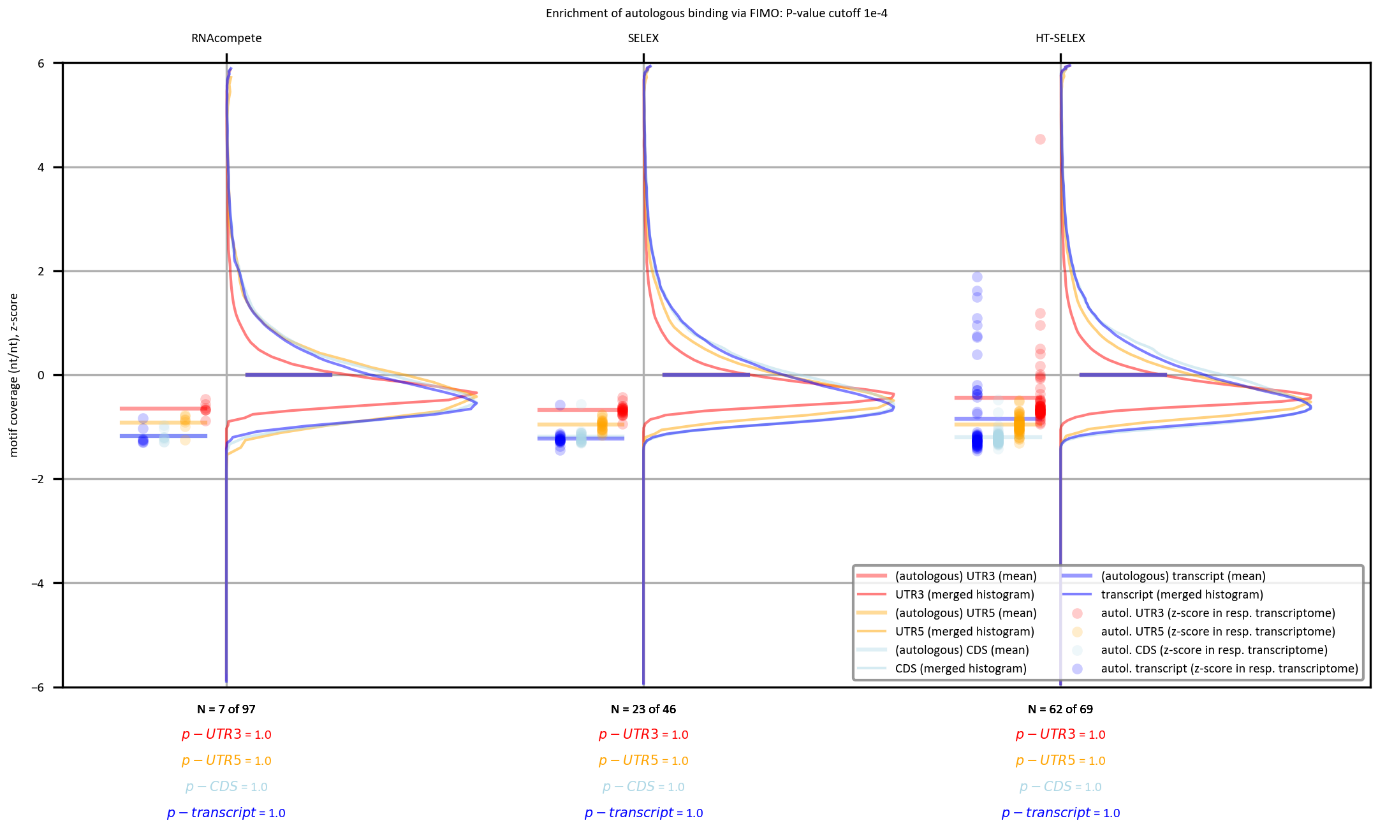


Figure 14: P-value cutoff of 1e-4

The above plotted data originates from a FIMO analysis, in which 96, 46 and 69 matrices from RNAcompete, SELEX and HT-SELEX were used, respectively. The nucleotide frequency distribution provided to FIMO was chosen according to the absolute nucleotide frequencies in the entire transcriptome dataset (MANE select dataset). As a p-value cutoff, FIMO’s default cutoff of 1e-4 was selected.

In RNAcompete and SELEX, all autologous transcripts show lower-than-average coverage in all subsequences, leading largely insignificant p-values. Matrices from HT-SELEX show the same trend, but the coverage of several autologous transcripts exceeded the background-mean, especially in the full-transcript searches.

As given below the figure, the number of matrices that found significant matches in any sequence varies considerably. While in RNAcompete only seven of 97 matrices found matches at all, in SELEX almost half of them did. In HT-SELEX matrices, almost all of them got at least one match.

(Preliminary plots; 5e-2 and 1e-2 analyses that include multiple matrices per protein will follow)

Background distribution nucleotides

#### Background nucleotide frequency distribution in log-likelihood ratio

As previously described, a nucleotide frequency distribution *B* is necessary to compute the log-likelihood ratios that constitute a PSSM.

* Uniform distribution: 0.25 per nucleotide; why not appropriate? di-nucleotide frequency
* Interpretation of log-likelihood in light of background distribution

0 = identical to background

negative = less likely than background would suggest; large negative value would imply that, considering the background, this position should not be as likely as it is.

Is this anything worth considering? If a position scores a large negative value, a two-sided test would yield a significant p-value, even though the protein has an extremely low theoretical affinity

positive = the motif diverges from what the background would suggest; It stands out and may be considered “conserved”, if one only considered the background nucleotide frequency distribution of the scanned sequence.

a high value implies strong theoretical affinity to this position by the protein

# Discussion

What is obvious from these results is that no enrichment in motif coverage could be observed in autologous transcripts as opposed to the entire transcriptome when the p-value cutoff was too stringent (i. e. 1e-4). This is not surprising, since only a relatively low number of matches was observed in the first place. This is due to fact that a large part of matrices, especially in RNAcompete, had a length covering six nucleotides or less. A matrix of length six can only achieve 4^6 (or 4096) different scores. Since the p-value is calculated via the probability that a certain score occurs in the distribution of all possible scores, this probability being 1/4096, the p-value cutoff of 1/10 000 can never be satisfied. As matrices get longer than seven nucleotides (4^7 = 16 384), surpassing this threshold becomes possible. Remembering the graph that showed the distribution of matrix length per dataset, RNAcompete stayed very much on the shorter side, while SELEX and HT-SELEX proteins recognized longer motifs.

As the p-value threshold became less stringent, more enrichment in autologous binding could be observed.

# References

|  |  |
| --- | --- |
| [1] | F. Crick, "Central Dogma of Molecular Biology," *Nature,* vol. 227, pp. 561-563, 1970. |
| [2] | M. Müller-McNicoll, O. Rossbach, J. Hui and J. Medenbach, "Auto-regulatory feedback by RNA-binding proteins," *Journal of Molecular Cell Biology,* vol. 11, no. 10, p. 930–939, 2019. |
| [3] | M. Corley, M. C. Burns and G. W. Yeo, "How RNA-Binding Proteins Interact with RNA: Molecules and Mechanisms," *Molecular Cell,* vol. 78, no. 1, pp. 9-29, 2020. |
| [4] | R. E. Halbeisen, A. Galgano, T. Scherrer and A. P. Gerber, "Post-transcriptional gene regulation: From genome-wide studies to principles," *Cellular and Molecular Life Sciences,* vol. 65, no. 5, pp. 798-813, 2008. |
| [5] | G. T, B. JL, Y. J and D. G, "RNA-binding proteins and post-transcriptional gene regulation," *Journal of the Federation of European Biochemical Societies,* vol. 582, no. 14, pp. 1977-1986, 2008. |
| [6] | A. A. Polyansky and B. Zagrovic, "Evidence of direct complementary interactions between messenger RNAs and their cognate proteins," *Nucleic acids research,* vol. 41, pp. 8434-8443, 2013. |
| [7] | C. KB, H. TR and M. QD, "High-throughput characterization of protein-RNA interactions," *Brief Funct Genomics,* vol. 14, no. 1, pp. 74-89, 2015. |
| [8] | R. D, H. KCH, N. K, Z. H, H. TR and M. QD., "RNAcompete methodology and application to determine sequence preferences of unconventional RNA-binding proteins," *Methods,* pp. 118-119, 2017. |
| [9] | F. Yasmeen, H. Seo, N. Javaid, M. S. Kim and S. Choi, "Therapeutic Interventions into Innate Immune Diseases by Means of Aptamers," *Pharmaceutics,* vol. 12, no. 10, p. 955, 2020. |
| [10] | C. E. Grant, T. L. Bailey and W. S. Noble, "FIMO: scanning for occurrences of a given motif," *Bioinformatics,* vol. 27, no. 7, pp. 1017-1018, 2011. |
| [11] | G. G, S.-C. F, T. C and L.-P. E, "ATtRACT-a database of RNA-binding proteins and associated motifs," *Database (Oxford),* 2016. |
| [12] | P. Flicek, M. Amode, D. Barrell, K. Beal, K. Billis, S. Brent, D. Carvalho-Silva, P. Clapham, G. Coates, S. Fitzgerald, L. Gil, C. Girón, L. Gordon, T. Hourlier, S. Hunt, N. Johnson, T. Juettemann, A. Kähäri, S. Keenan, E. Kulesha, F. Martin, T. Maurel, W. McLaren, D. Murphy, R. Nag, B. Overduin, M. Pignatelli, B. Pritchard, E. Pritchard, H. Riat, M. Ruffier, D. Sheppard, K. Taylor, A. Thormann, S. Trevanion, A. Vullo, S. Wilder, M. Wilson, A. Zadissa, B. Aken, E. Birney, F. Cunningham, J. Harrow, J. Herrero, T. Hubbard, R. Kinsella, M. Muffato, A. Parker, G. Spudich, A. Yates, D. Zerbino and S. Searle, "Ensembl 2014," *Nucleic Acids Research,* no. 42, pp. 749-755, 2014. |
| [13] | K. JB, F. JD, B. KA, J.-Z. C, P. VG, L. J, K. K, Z. AM and V. PD, "Xenbase, the Xenopus model organism database; new virtualized system, data types and genomes," *Nucleic Acids Research,* no. 43, pp. 756-763, 2015. |
| [14] | S. N, A. B, A. C, C.-T. A, C. I, G. R, G. N, T. H. P, K. S, L. R, L. W, L. X, L. R, P. N, P. S, P. S, R. R, R. M, S. A, S. D, T. AL, V. D, V. Zalunin and G. Cochrane, "Content discovery and retrieval services at the European Nucleotide Archive," *Nucleic Acids Research,* no. 43, pp. 23-29, 2015. |
| [15] | U. Consortium, "UniProt: a hub for protein information," *Nucleic Acids Research,* no. 43, pp. 204-212, 2015. |
| [16] | A. Jolma, J. Zhang, E. Mondragón, E. Morgunova, T. Kivioja, K. U. Laverty, Y. Yin, F. Zhu, G. Bourenkov, Q. Morris, T. R. Hughes, L. J. 3. Maher and J. Taipale, "Binding specificities of human RNA-binding proteins toward structures and linear RNA sequences," *Genome Research,* vol. 30, no. 7, pp. 962-973, 2020. |
| [17] | Y. Pan and S. Phan, "Guide to Threshold Selection for Motif Prediction Using Positional Weight Matrix," *Proceedings of the International MultiConference of Engineers and Computer Scientists,* vol. 1, pp. 19-21, 2008. |
| [18] | T. L. Bailey, J. Johnson, C. E. Grant and W. S. Noble, "The MEME Suite," *Nucleic Acids Research,* vol. 43, no. 1, pp. 39-49, 2015. |
| [19] | A. Theuer, "Analysis of autologous binding preferences of RNA-binding proteins," *Bachelor Thesis,* 2022. |
| [20] | B. Zagrovic, L. Bartonek and A. A. Polyansky, "RNA-protein interactions in an unstructured context," *FEBS letters,* vol. 592, pp. 2901-2916, 2018. |
| [21] | M. Hlevnjak, A. A. Polyansky and B. Zagrovic, "Sequence signatures of direct complementarity between mRNAs and cognate proteins on multiple levels," *Nucleic acids research,* vol. 40, pp. 8874-8882, 2012. |
| [22] | A. A. Polyansky, M. Hlevnjak and B. Zagrovic, "Proteome-wide analysis reveals clues of complementary interactions between mRNAs and their cognate proteins as the physicochemical foundation of the genetic code," *RNA biology,* vol. 10, pp. 1248-1254, 2013. |
| [23] | D. D, F. P, A. MS, S. A, H. M, P. T, B. C, L. NJ, V. N. EL, P. GA, Y. GW, G. BR and B. CB, "Sequence, Structure, and Context Preferences of Human RNA Binding Proteins," *Mol Cell,* vol. 70, no. 5, pp. 854-867, 2018. |
| [24] | J. Zhang, B. Jiang, M. Li, J. Tromp, X. Zhang and M. Q. Zhang, "Computing exact P-values for DNA motifs," *Bioinformatics,* vol. 23, no. 5, p. 531–537, 2007. |
| [25] | A. C. Allain and F. H.-T., "From Structure to Function of RNA Binding Domains," in *Madame Curie Bioscience Database [Internet]*, Austin (TX), Landes Bioscience, 2000-2013. |
| [26] | P. A. Chong, R. M. Vernon and J. D. Forman-Kay, "RGG/RG Motif Regions in RNA Binding and Phase Separation," *Journal of Molecular Biology,* vol. 430, no. 23, pp. 4650-5685, 2018. |

# Acknowledgements

# Appendix

**Setting path for FIMO executable in command line**

export PATH=$HOME/meme/bin:$HOME/meme/libexec/meme-5.4.1:$PATH

To save space, the “—text” option in the FIMO command enables us to write the tab-separated data directly to the appropriate file.

First, make sure to create a .tsv file for each FIMO command you will run, e. g. for each output file you expect to have. In my case, this would be 12 files, each called “experiment\_subsequence.tsv”. The commands to create these files are best executed from the “DATA” folder in my hierarchy, which is the main branching point for all the data FIMO needs. You can use the following commands to create the files:

cd DATA/FIMO\_OUT

mkdir pval5e-2

touch pval5e-2/rnacompete\_UTR3.tsv

Once the directories and files are in place, the FIMO commands are used as such:

fimo

--text

--max-stored-scores 2,147,483,646

--thresh 5e-2

--bfile FIMO\_input/background\_file.txt

FIMO\_input/motifs/motif\_file.txt

FIMO\_input/sequences/transcript\_file.txt

> FIMO\_OUT/ target\_file.tsv

Let’s break down each part of this command:

--text: reduces the output to “tsv” output sent to the standard-output, i. e. to the command line itself. This argument allows us to redirect the outputs to the appropriate file using the “>” operator.

--max-stored-scores: for score significance to be calculated, a certain number of matches will have to be held in memory. This argument is especially important when working with Q-values instead of P-values. The large number after the command is the maximum number of stored scores FIMO allows for.

--thresh: sets the custom P-value cutoff. The default cutoff lies at 1e-4.

--bfile: after this argument, a file containing the nucleotide frequency distribution of the background is added – in my example called “background\_file.txt”. This file can be created using the “fasta-get-markov” command, which is distributed together with MEME Suite. More on this command below. The background file contains a zero-order Markov model of the background distribution. No higher order models are allowed as input to FIMO. If a higher order model is entered, FIMO will only consider the zero-order part.

The penultimate argument hands the input motif file to FIMO, while the last one enters the sequence file.

The “>”-operator: In Linux, this operator is often used to write the output of a command to a file. Additionally, this operator overwrites the contents of the file, if they exist.

For each experiment-subsequence combination (e. g. RNAcompete+CDS, SELEX+UTR3 etc.) such a command must be constructed. The choice of background file and P-value threshold is left up to the user. To chain up multiple of these commands, one can place a semicolon “;” or an “and”-operator “&&” in between. While for the “and”-operator, the preceding command must have been completed successfully, the semicolon chains up commands without requiring successful completion.

Here are all FIMO commands I used, chained up by semicolons:

cd ~; cd Moritz\_BSc/BSc\_enriched\_autologous\_RBP/DATA/

Creation of file containing background nucleotide frequencies:

fasta-get-markov sequences/fimo\_transcriptome\_full.txt

folder system by cutoff:

pval5e-2

pval1e-2

pval1e-3

pval1e-4

cd FIMO\_OUT

mkdir pval5e-2

touch pval5e-2/rnacompete\_UTR3.tsv

touch pval5e-2/rnacompete\_CDS.tsv

touch pval5e-2/rnacompete\_UTR5.tsv

touch pval5e-2/rnacompete\_full.tsv

touch pval5e-2/selex\_UTR3.tsv

touch pval5e-2/selex\_CDS.tsv

touch pval5e-2/selex\_UTR5.tsv

touch pval5e-2/selex\_full.tsv

touch pval5e-2/htselex\_UTR3.tsv

touch pval5e-2/htselex\_CDS.tsv

touch pval5e-2/htselex\_UTR5.tsv

touch pval5e-2/htselex\_full.tsv

mkdir pval1e-2

touch pval1e-2/rnacompete\_UTR3.tsv

touch pval1e-2/rnacompete\_CDS.tsv

touch pval1e-2/rnacompete\_UTR5.tsv

touch pval1e-2/rnacompete\_full.tsv

touch pval1e-2/selex\_UTR3.tsv

touch pval1e-2/selex\_CDS.tsv

touch pval1e-2/selex\_UTR5.tsv

touch pval1e-2/selex\_full.tsv

touch pval1e-2/htselex\_UTR3.tsv

touch pval1e-2/htselex\_CDS.tsv

touch pval1e-2/htselex\_UTR5.tsv

touch pval1e-2/htselex\_full.tsv

mkdir pval1e-3

touch pval1e-3/rnacompete\_UTR3.tsv

touch pval1e-3/rnacompete\_CDS.tsv

touch pval1e-3/rnacompete\_UTR5.tsv

touch pval1e-3/rnacompete\_full.tsv

touch pval1e-3/selex\_UTR3.tsv

touch pval1e-3/selex\_CDS.tsv

touch pval1e-3/selex\_UTR5.tsv

touch pval1e-3/selex\_full.tsv

touch pval1e-3/htselex\_UTR3.tsv

touch pval1e-3/htselex\_CDS.tsv

touch pval1e-3/htselex\_UTR5.tsv

touch pval1e-3/htselex\_full.tsv

mkdir pval1e-4

touch pval1e-4/rnacompete\_UTR3.tsv

touch pval1e-4/rnacompete\_CDS.tsv

touch pval1e-4/rnacompete\_UTR5.tsv

touch pval1e-4/rnacompete\_full.tsv

touch pval1e-4/selex\_UTR3.tsv

touch pval1e-4/selex\_CDS.tsv

touch pval1e-4/selex\_UTR5.tsv

touch pval1e-4/selex\_full.tsv

touch pval1e-4/htselex\_UTR3.tsv

touch pval1e-4/htselex\_CDS.tsv

touch pval1e-4/htselex\_UTR5.tsv

touch pval1e-4/htselex\_full.tsv

**Pvalue: 1e-4**

**ATtRACT - SELEX**

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval1e-4/selex\_UTR5.tsv;

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval1e-4/selex\_CDS.tsv;

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval1e-4/selex\_UTR3.tsv;

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval1e-4/selex\_full.tsv

**ATtRACT - RNAcompete**

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval1e-4/rnacompete\_UTR5.tsv;

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval1e-4/rnacompete\_CDS.tsv;

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval1e-4/rnacompete\_UTR3.tsv;

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval1e-4/rnacompete\_full.tsv

**HT-SELEX**

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval1e-4/htselex\_UTR5.tsv;

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval1e-4/htselex\_CDS.tsv;

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval1e-4/htselex\_UTR3.tsv;

fimo --text --max-stored-scores 21474836466 --thresh 1e-4 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval1e-4/htselex\_full.tsv

**Pvalue: 1e-3**

**ATtRACT - SELEX**

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval1e-3/selex\_UTR5.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval1e-3/selex\_CDS.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval1e-3/selex\_UTR3.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval1e-3/selex\_full.tsv

**ATtRACT - RNAcompete**

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval1e-3/rnacompete\_UTR5.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval1e-3/rnacompete\_CDS.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval1e-3/rnacompete\_UTR3.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval1e-3/rnacompete\_full.tsv

**HT-SELEX**

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval1e-3/htselex\_UTR5.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval1e-3/htselex\_CDS.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval1e-3/htselex\_UTR3.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-3 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval1e-3/htselex\_full.tsv

**Pvalue: 1e-2**

**ATtRACT - SELEX**

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval1e-2/selex\_UTR5.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval1e-2/selex\_CDS.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval1e-2/selex\_UTR3.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval1e-2/selex\_full.tsv

**ATtRACT - RNAcompete**

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval1e-2/rnacompete\_UTR5.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval1e-2/rnacompete\_CDS.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval1e-2/rnacompete\_UTR3.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval1e-2/rnacompete\_full.tsv;

**HT-SELEX**

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval1e-2/htselex\_UTR5.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval1e-2/htselex\_CDS.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval1e-2/htselex\_UTR3.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 1e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval1e-2/htselex\_full.tsv

**Pvalue 5e-2**

**ATtRACT - SELEX**

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval5e-2/selex\_UTR5.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval5e-2/selex\_CDS.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval5e-2/selex\_UTR3.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_selex.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval5e-2/selex\_full.tsv

**ATtRACT - RNAcompete**

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval5e-2/rnacompete\_UTR5.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval5e-2/rnacompete\_CDS.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval5e-2/rnacompete\_UTR3.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_attract\_rnacomp.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval5e-2/rnacompete\_full.tsv

**HT-SELEX**

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_5utr.txt > FIMO\_OUT/pval5e-2/htselex\_UTR5.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_cds.txt > FIMO\_OUT/pval5e-2/htselex\_CDS.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_3utr.txt > FIMO\_OUT/pval5e-2/htselex\_UTR3.tsv;

fimo --text --max-stored-scores 2147483646 --thresh 5e-2 --bfile FIMO\_input/markov\_full.txt FIMO\_input/motifs/fimo\_htselex.txt FIMO\_input/sequences/fimo\_transcriptome\_full.txt > FIMO\_OUT/pval5e-2/htselex\_full.tsv

**EXTRA WRITTEN STUFF**

**Do RBPs bind their own mRNAs more than the average mRNA?**

**Autologous binding and how to analyze it**

RNA-binding proteins carry out a multitude of functions in the cell. It is their interactions with mRNA, the carrier sequence for genetic information, that makes them so important. Despite their importance, there exist only a handful of datasets pinpointing the mRNA sequence profiles those RNA-binding proteins (RBPs) like to bind to. In a set of experiments, around 170 such binding-profiles, or motifs, were discovered and reconfirmed.

The complementarity hypothesis states that a protein will have a larger affinity towards the coding sequence (CDS) of its own mRNA. Applying this hypothesis to the world of RBPs, a set of proteins that are known to bind mRNA in the first place, we would like to affirm that an RBP has a higher propensity to bind to its own coding region than to any other mRNA sequence and subsequence.

The MANE transcriptome dataset serves as a control dataset for our analysis. It’s a dataset of 200k~ mRNAs (the whole human transcriptome), including a number of RNA binding proteins.

In order to test the complementarity hypothesis, the RNA binding motifs of our RBPs are checked against every single sequence in the MANE transcriptome dataset.

A motif consists of a probability value that any of the four nucleotides would appear at a given position in the motif. When a sequence is similar enough to the motif, then the added up probabilities surpass a set threshold score (usually set via p-values and including a background distribution of nucleotides in the sequence considered in order to eliminate bias). According to the complementarity hypothesis, the score of a given RNA binding protein’s motif when it is run over its own mRNA should be significantly higher than the average score it would reach when running over any other mRNA. Additionally, scoring the coding sequence of its own (autologous) mRNA would reach a higher score than any other subsequences.

In practice, every sequence in the MANE transcriptome is handed to every single RNA binding motif and a score is calculated.

FIMO decides the cutoff score depending on the likelihood of getting the scanned subsequence with a given distribution of nucleotides.

The files FIMO outputs give the exact position and score of a motif that matched a sequence. In theory, following the complementarity hypothesis, a motif would match its own mRNA more often than a motif would match any other sequence.