

SubVis: An interactive R package for exploring the effects of multiple substitution matrices on pairwise sequence alignment

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Understanding how proteins mutate is critical to solving a host of biological problems. Mutations occur when an amino acid is substituted for another in a protein sequence. The set of likelihoods for amino acid substitutions is stored in a matrix and input to alignment algorithms. The quality of the resulting alignment is used to assess the similarity of two or more sequences and can vary according to assumptions modeled by the substitution matrix. Substitution strategies with minor parameter variations are often grouped together in families. For example, the BLOSUM and PAM matrix families are commonly used because they provide a standard, predefined way of modeling substitutions. However, researchers often do not know if a given matrix family or any individual matrix within a family is the most suitable. Furthermore, predefined matrix families may inaccurately reflect a particular hypothesis that a researcher wishes to model or otherwise result in unsatisfactory alignments. In these cases, the ability to compare the effects of one or more custom matrices may be needed. This laborious process is often performed manually because the ability to simultaneously load multiple matrices and then compare their effects on alignments is not readily available in current software tools. This paper presents SubVis, an interactive R package for loading and applying multiple substitution matrices to pairwise alignments. Users can simultaneously explore alignments resulting from multiple predefined and custom substitution matrices. SubVis utilizes several of the alignment functions found in R, a common language among protein scientists. Functions are tied together with the Shiny platform which allows the modification of input parameters. Information regarding alignment quality and individual amino acid substitutions is displayed with the JavaScript language which provides interactive visualizations for revealing both high-level and low-level alignment information.

1 SubVis: An Interactive R Package for 2 Exploring the Effects of Multiple 3 Substitution Matrices on Pairwise 4 Sequence Alignment

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11 ABSTRACT

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13 when an amino acid is substituted for another in a protein sequence. The set of likelihoods for amino acid
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25 loading and applying multiple substitution matrices to pairwise alignments. Users can simultaneously
26 explore alignments resulting from multiple predefined and custom substitution matrices. SubVis utilizes
27 several of the alignment functions found in R, a common language among protein scientists. Functions
28 are tied together with the Shiny platform which allows the modification of input parameters. Information
29 regarding alignment quality and individual amino acid substitutions is displayed with the JavaScript
30 language which provides interactive visualizations for revealing both high-level and low-level alignment
31 information.

32 INTRODUCTION

33 Prediction of protein similarity through sequence alignment is an important tool for a number of biological
34 applications including the understanding of evolutionary divergence, identification of active/conserved
35 regions in proteins, and identification of key structural motifs in proteins. Identification of similarities
36 among protein families, individual proteins, or even short segments of a protein chain can give scientists
37 insights as to how an amino acid insertion or mutation may alter the active regions within the putative
38 protein. Accurate alignment of two or more proteins being compared is an important first step in evaluating
39 similarity and many algorithms exist that use a wide range of criteria to find the best alignment (Ma and
40 Wang, 2014; Haque et al., 2009; Gotoh, 1999; Li and Homer, 2010).

41 Alignments are highly dependent on algorithm parameters, such as gap penalties and scoring type
42 (local or global). One of the parameters influencing alignment scores is the chosen substitution matrix
43 capturing the likelihood of amino acid substitutions (Altschul, 1991). Substitution matrices capture
44 the likelihood of amino acid substitutions by reporting the log-odds ratio of each possible substitution
45 calculated by

$$s_{ij} = \frac{\ln \frac{q_{ij}}{p_i p_j}}{\lambda} \quad (1)$$

46 where, for amino acid i and amino acid j , s is the substitution score, q is the set of observed frequencies,
47 p is the probability of random appearance, and λ is a positive scaling constant allowing for the use of
48 different logarithm bases without changing observed frequencies. Conservative substitutions have a
49 positive score and non-conservative substitutions have a negative score (Pearson, 2013). Standard,
50 predefined matrices offer a quick way to model substitutions and those matrices that differ only by
51 variations of selected parameters can be grouped into families. Two well-known matrix families are
52 the PAM (Dayhoff et al., 1978; Schwartz and Dayhoff, 1978) and BLOSUM (Henikoff and Henikoff,
53 1992) matrices. A summary of both matrix families is given by Pearson (2013). Although both PAM and
54 BLOSUM find the log-odds ratios for matrix values, each family has different methods to calculate the
55 likelihood of substitution. PAM matrices are based on the mutation frequency of closely related proteins
56 which is then extrapolated to more distant evolutionary lines. Instead of extrapolation of highly related
57 proteins, BLOSUM matrices calculate frequencies by locating conserved blocks and then use a threshold
58 to exclude closely and moderately related proteins (for a more detailed discussion on how PAM and
59 BLOSUM matrices affect alignments we direct the reader to (Mount, 2008; Altschul, 1991; Pearson,
60 2013). Other matrix families exist (Müller et al., 2002; Benner et al., 1994) and the development and
61 analysis of additional families is a subject of ongoing research.

62 Predefined matrices may not adequately model substitutions for a variety of reasons. New substitution
63 strategies may be required and result in the modification of existing matrices (Yu and Altschul, 2005)
64 or the construction of entirely new ones. Reasons why predefined matrices may not accurately model
65 substitutions include the following scenarios: application-specific alignments (States et al., 1991; Paila
66 et al., 2008), matrix optimization (Saigo et al., 2006), compensating for non-conventional amino acid
67 composition (Jimenez-Morales et al., 2008), aligning distantly related sequences (Prlić et al., 2000),
68 accounting for site specific dynamics in phylogenetic models (Wang et al., 2008), and incorporating
69 structural information (Vilim et al., 2004; Teodorescu et al., 2004; Goonesekere and Lee, 2008), [for
70 another survey of custom substitution matrices see Yamada and Tomii (2014)]. While alignment of
71 sequences is central to phylogenetic studies, these investigations are commonly performed at the nucleotide
72 or codon level. In the case of protein-level phylogenetic studies, specialized, standardized matrices are
73 vital for assessing evolutionary heterogeneity (Wang et al., 2008, 2014; Rokas and Carroll, 2008; Dean
74 et al., 2002; Echave et al., 2016). Examples of phylogenetic-specific matrices include JTT (Jones et al.,
75 1992) and WAG (Whelan and Goldman, 2001). Despite the sophistication of phylogenetic models,
76 these matrices were not built for use in protein alignment with customizable matrices and to visualize
77 structure/function predictions (Whelan and Goldman, 2001; Wang et al., 2008, 2014).

78 Multiple substitution matrices can be compared to find the most appropriate one (Altschul, 1991). Rios
79 et al. (2015) and Agrawal and Huang (2009) illustrate the importance of comparing pairwise alignments
80 produced by varying substitution matrices. However, this can be a difficult task. Comparison often
81 includes analysis of both alignment quality and behavior at individual amino acid positions. If using
82 predefined matrices, it may not be known which matrix family most accurately reflects the likelihood of
83 individual substitutions among the proteins being studied. Even within a family, one matrix may be more
84 suitable than others given a specific application (Altschul, 1991). Furthermore, none of the predefined
85 matrix families may adequately represent a scientist's knowledge about a particular set of proteins. In the
86 latter case, custom matrices are required to achieve accurate alignments which often need to be compared
87 to other widely used or custom matrices.

88 There are few tools for addressing the complex problem of choosing the most appropriate substitution
89 matrix for protein sequence alignments. Because of these needs, we have developed SubVis, a highly
90 interactive R (R Core Team, 2013) package that allows the simultaneous visual exploration of how varying
91 substitution matrices affect alignment results. To address the shortcomings of previous tools, SubVis

- 92 • Allows the uploading or text entry of FASTA (Pearson and Lipman, 1988) sequences.
- 93 • Utilizes widely-known R functions from the Biostrings package (Pages et al., 2016).
- 94 • Permits the application of several widely-used substitution matrices and multiple custom matrices.

- 95 • Provides intuitive and interactive visualizations to facilitate simultaneous exploration of protein
96 alignments produced by multiple substitution matrices. Detail information, such as the log-odds
97 score for each substitution, is available through mouse interaction.
- 98 • Employs the Shiny package (Chang et al., 2016) and JavaScript for web-based parameter loading
99 and visualization, respectively.

100 In this paper, we present background information including the difficulties associated with choosing a
101 substitution matrix and previous attempts using visualization to help understand the effect of substitution
102 matrices. We describe the organization and implementation of SubVis. Finally, we provide a case study
103 illustrating the utility of SubVis.

104 BACKGROUND

105 Alignment Quality

106 Performing quality pairwise sequence alignments is a critical first step in protein analyses such as the
107 formation of multiple sequence alignments and phylogenetic tree construction (Agrawal and Huang, 2009).
108 As described in detail by Landan and Graur (2008), alignments are subject to a host of errors, such as
109 the lack of parameters accurately reflecting true conditions before analysis is performed. This lack of *a*
110 *priori* information makes the seriousness of the error difficult to judge and contributes to uncertainty that
111 obfuscates biological insight.

112 Summary statistics can be useful for eliminating poor alignments from analysis during the initial
113 investigation. However, summary statistics can be problematic if they are not supplemented by detailed
114 exploration. For example, percent identity is a simple, popular metric but suffers from several deficiencies,
115 including high uncertainty and important calculation variations that are mostly ignored (Raghava and
116 Barton, 2006). Another aggregate quality metric is the alignment score which accounts for substitution
117 scores and gap penalties (Henikoff, 1996). However, many different alignments can result in the same
118 score (Landan and Graur, 2008). Furthermore, scoring functions can be suboptimal and result in an
119 alignment with a higher error being assigned a higher score. Edgar and Sjölander (2004) illustrate some of
120 the problems associated with assigning scores by analyzing three quality measures. Each presented score
121 has drawbacks that include not compensating for over-alignment, under-alignment, alignments offset
122 from the reference alignment, and a scoring function that itself requires decisions regarding parameter
123 input. Statistical significance represented by a P-value is often used to judge assigned alignment scores
124 (Mitrophanov and Borodovsky, 2006). However, this descriptor can suffer from assumptions about the
125 model of randomness used and from the fact that multiple P-value methods may be needed when varying
126 either the alignment parameters or the alignment algorithm.

127 The choice of substitution matrix is critical to defining and producing a quality alignment. This
128 choice becomes more important as alignment uncertainty increases (Henikoff, 1996). However, evaluating
129 substitution matrices can be a difficult task. Complex relationships among variables that affect protein
130 mutations are often simplified with model assumptions which may not be correct (Crooks et al., 2005).
131 Furthermore, substitution matrix evaluation can depend on some of the same factors described above,
132 including alignment scope (local or global) and whether gap penalties are applied (Henikoff, 1996).
133 Agrawal and Huang (2009) illustrate the type of analysis that is made difficult with the range and
134 variability of substitution matrix choice. Their work evaluates 15 substitution matrices with a range of
135 parameter sets. For each of the matrices, several alignment quality measures are compared. Although
136 substitution matrix evaluation is crucial in producing quality alignments, there is a shortage of tools that
137 can accommodate variability in parameters, are able to scale to a large number of matrices, and allow
138 exploration beyond summary quality measures.

139 Visual Approaches

140 Interactive visualization can be useful when comparing alignments resulting from the application of multi-
141 ple substitution matrices and varying parameter sets. Furthermore, a tool that allows visual exploration can
142 help uncover the details hidden in summary statistics. However, there have been few approaches applying
143 interactive visualization to the analysis of substitution matrices. Bulka et al. (2006) extends the work of
144 Nakai et al. (1988) and the work of Tomii and Kanehisa (1996) to present a web-based tool. The tool uses
145 a color-coded minimum spanning tree to visualize the similarities of amino acid indices to a substitution

146 matrix. Although these provide insight into the substitution similarity, the visual display does not reflect
147 the spatial context inherent in typical two- or three-dimensional alignment representations. Additionally,
148 the tool is limited in the amount of detail available through interactions. Eyal et al. (2007) presents another
149 web-based platform that performs multiple sequence alignment based on pair-to-pair substitution matrices.
150 However, it is designed for a specific custom matrix type, does not provide standard matrices, and lacks
151 features that facilitate comparison among different matrices. CRASP (Afionnikov and Kolchanov, 2004) is
152 a web-accessible tool that takes protein family sequence alignments, a phylogenetic tree or other weights,
153 physicochemical characteristics, and conservation filters as input. The output consists of a correlation
154 matrix, hierarchical clustering diagram, positional frequency statistics, and physicochemical descriptors.
155 Additional output includes statistical estimators of coordinated substitution contributions. Their approach
156 is limited to cases where the substitutions are thought to be highly correlated with one another and using a
157 matrix or proteins which do not reflect this assumption could lead to inaccurate alignments. Much of the
158 output is visualized as text with limited interactions.

159 Despite these attempts, much of the comparison and other analysis is still either performed manually
160 or with tools that lack the flexibility provided by combining standard substitution matrices, custom
161 substitution matrices, visualization, and robust interactions. We are not aware of any tool explicitly
162 designed for integrating alignment algorithms and interactive comparison across a range of substitution
163 matrices.

164 SubVis addresses many of the limitations to currently available platforms. SubVis allows scientists
165 to load a pair of proteins to be aligned, choose basic parameters (such as alignment score type and
166 gap penalties), and apply multiple substitution matrices. Applied matrices can include PAM matrices,
167 BLOSUM matrices, or custom matrices. After performing the alignment, options exist for the high-level
168 exploration of percent identities and alignment pair scores. Interactions also exist for the low-level
169 exploration of individual amino acids across selected substitution matrices by position in the aligned
170 sequence, properties (hydrophobic, physicochemical properties, volume, conserved or not, etc.), pattern
171 matching, and locations of insertions and deletions (indels).

172 IMPLEMENTATION

173 SubVis consists of three functional units: interface and parameter management, alignment processing, and
174 visualization. Interface and parameter management controls the capture of alignment parameters, including
175 selected substitution matrices. It also allows the user to choose the visualization (overview, detail view,
176 or search view) and options for selecting and searching displayed items. Alignment processing accepts
177 alignment parameters captured from the interface and includes those in the construction of alignments.
178 The visualization component displays the alignments after each of the selected parameters (including the
179 substitution matrix) has been applied and provides detailed information with mouse interaction.

180 Interface and Parameter Management with Shiny

181 Shiny is a recently developed R package for building web applications and was chosen for this system
182 because of the GUI widgets available and its integration with R. The first screen shown when starting
183 SubVis is the parameter view under the “Options” tab which captures alignment input such as the proteins
184 to be aligned, the predefined and custom matrices to be applied, gap penalties, and scoring type. Users are
185 allowed to load (and change) the following parameters:

- 186 • **Protein sequences.** Two protein sequences in FASTA (Pearson and Lipman, 1988) format can be
187 loaded by selecting the sequence file from the local computer or entering the sequences into text
188 boxes manually, including with copy and paste. If sequences are entered into the text boxes, FASTA
189 files are created in the package directory structure for future reference. One sequence represents the
190 *pattern* and the other represents the *subject*. (Sequences are referred to as the *pattern* or *subject* to
191 be consistent with the Biostrings package where they are defined in context of the functions utilized
192 in the SubVis implementation.)
- 193 • **Predefined substitution matrices.** Multiple PAM and BLOSUM matrices can be selected by
194 checking the corresponding boxes. Individual gap penalties can be entered for each predefined
195 matrix. Predefined PAM matrices included in SubVis are PAM30, PAM40, PAM70, PAM120,
196 and PAM250. Predefined BLOSUM matrices included in SubVis are BLOSUM45, BLOSUM50,
197 BLOSUM62, BLOSUM80, and BLOSUM100.

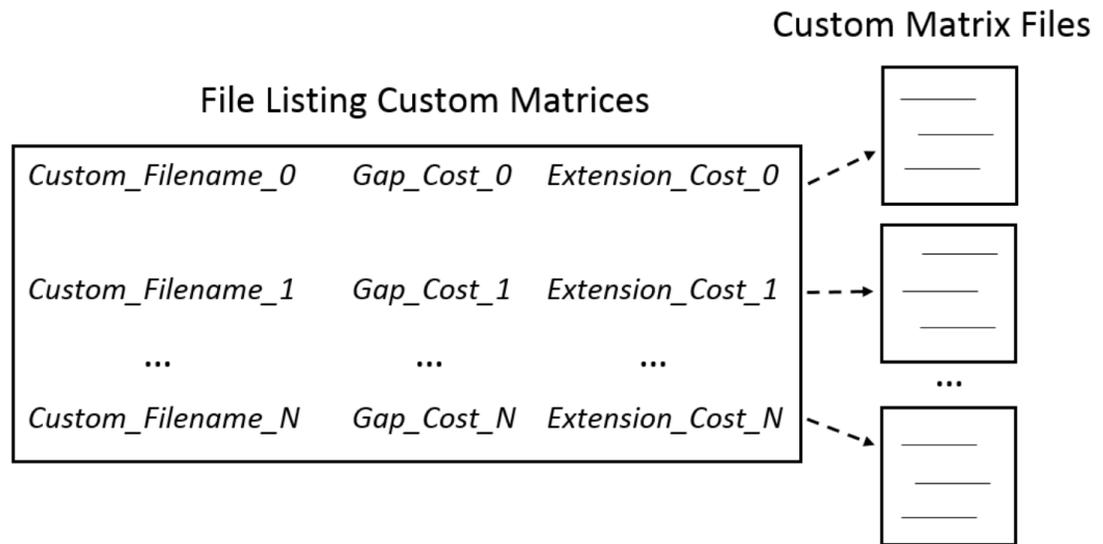


Figure 1. Loading custom matrices. Multiple custom matrices can be loaded by creating a master file listing the filenames and penalties associated with each matrix. In the master file, each line consists of the filename followed by the gap and extension penalties associated with individual matrices. Specific requirements for formatting the custom matrix master file can be found in the help contents. Several example custom matrices and master files are included in the software package.

- 198 • **Custom substitution matrices.** Multiple space delimited text files each containing a custom matrix
199 can be loaded. Users can load custom multiple matrices by selecting a master file that lists the
200 filename of each matrix. In the master file listing the custom matrices, each filename is on a separate
201 line. Following each filename on the same line are space delimited gap penalties for each custom
202 matrix. In addition to exploring different matrices, users can explore the effects of penalties by
203 repeating the same matrix file name with variations in gap and extension penalties. Figure 1 shows
204 the relationship between the master file and the custom matrices.
- 205 • **Alignment score type.** Users can choose from local, global, overlap, local-global, and global-local
206 scoring.
- 207 • **View choice.** Clicking the “GO” button in the parameter capture view performs the alignment and
208 automatically switches to the “VIZ” tab where users can choose from three visualization views. The
209 overview provides quality information by sorting and displaying four percent identity variations
210 (May, 2004; Raghava and Barton, 2006) and the overall alignment score. Based on this information,
211 matrices can be excluded or included in the detail view. The detail view shows individual amino
212 acids as either color-coded boxes or the single letter abbreviation, the classification of amino acid
213 properties, and the log-odds score for each substitution. This view also allows alignment navigation.
214 The search view allows searching by amino acid position in the aligned sequence, matching sections
215 in the alignment pair, indel location, and subsequence matching. The overview, detail view, and
216 search view can provide information that aids in the analysis of which substitution model is the
217 most suitable for a given scenario. Users can change views simply by clicking on the desired tab or
218 selecting the appropriate visualization from a drop-down menu. Features available for each view
219 are listed in Table 1 and will be discussed in detail later.

220 Sequence Processing with R

221 After capturing input with Shiny, SubVis reports the parameters to the alignment processing component and
222 utilizes functions from the Biostrings package to perform sequence alignment, calculate alignment scores,
223 capture indel locations, perform any other necessary alignment/string manipulations, and communicates
224 input changes to the visualization component. The primary functions used by SubVis are described below
225 (more detailed information can be found in the Biostrings documentation):

Table 1. Views available in SubVis. Beside each view is a list of interactions and information available for capturing parameters and visualization (overview, detail view, and search view).

Parameter Capture	Overview
Input protein sequences Select predefined matrices Load custom matrices Input penalties per matrix Select scoring type	Matrices sorted by percent identity Matrices sorted by overall alignment score Individual matrix scores Individual matrix percent identity
Detail View	Search View
Pairwise alignments per matrix Amino acid names and positions Amino acid substitution scores Multiple amino acid classifications One letter amino acid abbreviations Alignment navigation Subject/pattern filtering	Search by amino acid position Search for indels Search for matches in alignment pairs Search for input sequences

- 226 • **pairwiseAlignment.** Accepts the two protein sequences (*pattern* and *subject*), gap costs, alignment
227 score type, and substitution matrices entered as parameters. Alignment choices include local
228 alignments using the Smith-Waterman algorithm (Smith and Waterman, 1981), global alignments
229 with the Needleman-Wunsch algorithm (Needleman and Wunsch, 1970), and overlap algorithms
230 with an ends free algorithm. There are also two mixed scoring types: local-global scoring and
231 global-local scoring. All other parameters are left at default values. SubVis invokes this function
232 once for each substitution matrix. Because SubVis is open source, users can implement other
233 alignment algorithms or substitute alignments produced by other tools.
- 234 • **matchPattern.** Finds all occurrences of an input pattern. The output is the starting and ending
235 points of matches.
- 236 • **indel.** Finds gaps in the alignment resulting from insertions and deletions in the aligned sequences.
- 237 • **pid.** Calculates four percent identity types as reported by May (2004) and evaluated by Raghava and
238 Barton (2006) where differences in denominator calculation reflect variations in defining sequence
239 length. Parameters to this function indicate if the denominator should be defined as aligned positions
240 plus internal gap positions (PID 1), aligned positions (PID 2), the length of the shorter sequence
241 (PID 3), or the average of the two sequences (PID 4). For each selected matrix, SubVis sorts and
242 then displays the four unique percent identities in a color-coded row.

243 Before parameters are passed to alignment functions, they are checked for values and formats that may
244 cause system errors. Tailored error messages include those for missing sequence files, missing penalties,
245 and identical sequences. An error is also produced if the custom matrix option is enabled but a file listing
246 the matrices has not been selected. SubVis generates a general error message if the *pairwiseAlignment*
247 function defined by the Biostrings package fails. Possible causes of this error are poorly constructed
248 sequences or custom matrices.

249 Visualization with JavaScript

250 After constructing alignments based on user input, the alignments and supporting information are dis-
251 played. The interactive visualization component consists of an overview, a detail view, and a search view
252 developed in JavaScript with information passed to it from R.

253 Overview

254 Despite the problems associated with summary statistics, they can be useful in preliminary analysis to
255 help narrow the number of alignments being explored in detail. Percent identity is a commonly used
256 measure in sequence alignment but variations in how it is calculated are not typically reported even though
257 these differences can affect alignment assessment (Raghava and Barton, 2006). The overview in SubVis
258 provides a high-level perspective of the alignments by sorting and then displaying the four variations of

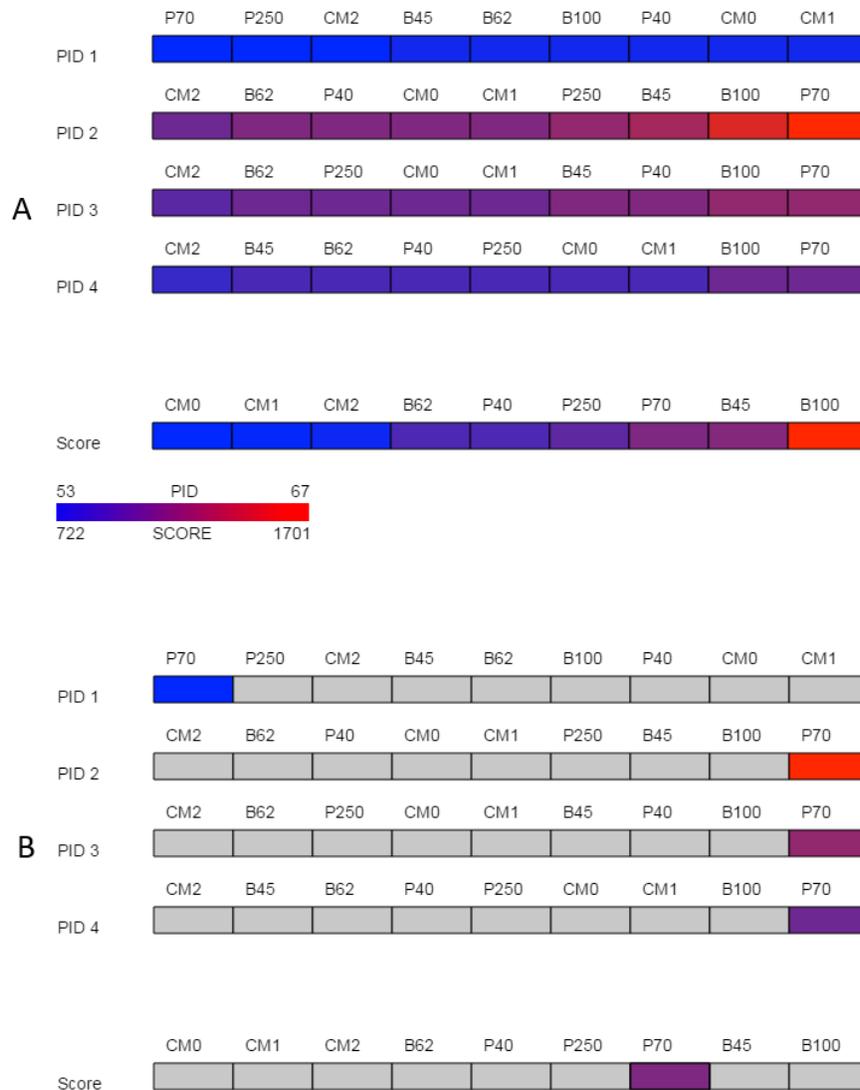


Figure 2. Overview. The overview provided by SubVis allows investigation of four unique percent identity calculations and the alignment score per substitution matrix. The display before interaction is shown in (A) and the highlighted substitution matrix selected with mouse movement is shown in (B). Custom matrices begin with the prefix “CM” followed by their position in the master file. A legend in the bottom-left corner lists how the maximum and minimum alignment score and PID correspond to color. In this example, the PAM70 matrix has a relatively high alignment score and PID except for PID 1 for which PAM70 is the lowest. The sequences used for this figure are *G-protein coupled receptor 6 isoform b* and *G-protein coupled receptor 12* from the rhodopsin family analyzed by Fredriksson et al. (2003). The custom matrix file lists a single matrix with varying, user-defined penalties and was developed for studying the transmembrane region of G protein-coupled receptors from the rhodopsin family (Rios et al., 2015). The same sequences and parameters are used in Figure 3 and Figure 4.

259 percent identities provided by the *pid* function in the Biostrings package. The sorted percent identities for
 260 each matrix type are shown in a color-coded bar (Figure 2(A)) normalized and colored from blue (lowest
 261 percent identity) to red (highest percent identity). Under the set of PID rows is a normalized, color-coded
 262 bar of all matrix types sorted by alignment score. A legend in the bottom-left corner illustrates how colors
 263 correspond to the PID and score range. When the mouse moves over either a matrix’s percent identity
 264 or alignment score, the same matrix is selected in the other rows (Figure 2(B)) to ease comparison. At

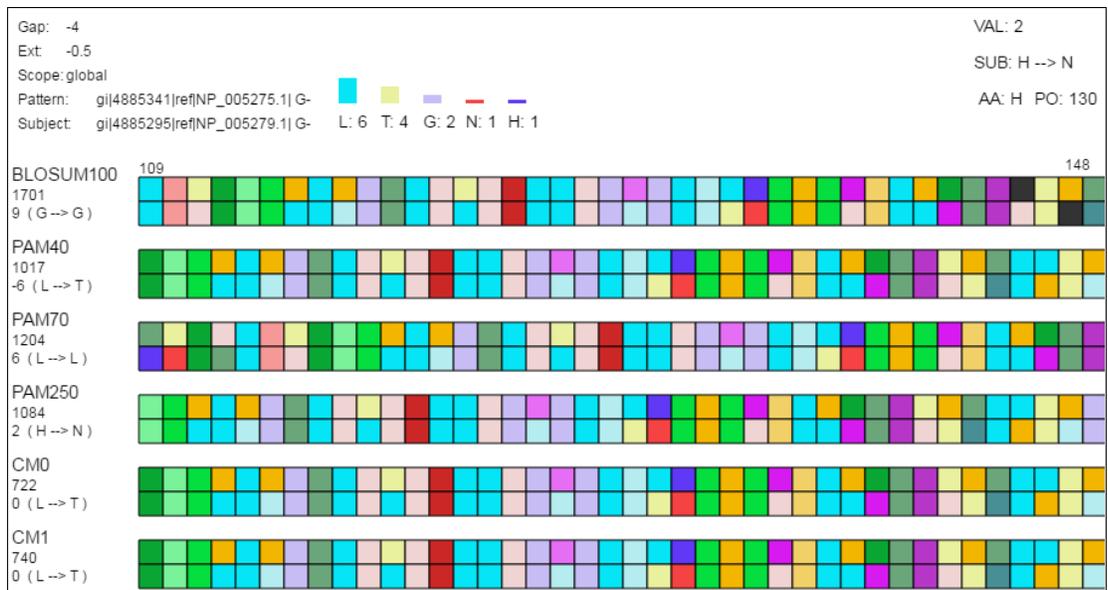


Figure 3. Detail view. The detail view allows investigation of individual amino acids. Aligned sequences are shown as *pattern-subject* pairs in the center using color-coded boxes (as shown) or one letter abbreviations to represent individual amino acids. When the mouse moves over an individual amino acid 1) the specific amino acid substitution occurring for that position in the aligned sequences and the corresponding log-odds score are shown under the alignment score for each pair along the left side of the display; 2) the top-left displays the gap cost, extension cost, and the score type; 3) a histogram is shown above the set of alignment pairs displaying the frequency of each amino acid in the selected column for all pairs; and 4) the log-odds score (“VAL”), the specific amino acid substitution (“SUB”), the current amino acid (“AA”), and the position in the aligned sequence (“PO”) are displayed in the top-right.

265 the same time, the numerical value of the percent identity and alignment score are displayed in the lower
 266 right corner. After exploring the overview, substitution matrices can be removed or added by revisiting
 267 the “Options” tab.

268 **Detail View**

269 After investigating alignments based on percent identities and alignment score, alignments and individual
 270 amino acids can be explored in the detail view (Figure 3). If the mouse is not over an amino acid,
 271 only basic information such as protein chain names, the matrix type per alignment pair, the score per
 272 alignment pair, and the amino acid position range after alignment is displayed. By default, amino acids
 273 are represented by colored boxes where an amino acid corresponds to a single color and gaps are black.

274 If the mouse moves over a single amino acid, additional details appear. In the top-right corner,
 275 additional information includes the log-odds score, the substitution that occurred, the name of the selected
 276 amino acid, and the aligned position. (For amino acid - gap pairs, SubVis reports the log-odds score
 277 as undefined.) In the top-left corner, the gap penalties for that alignment are displayed along with the
 278 selected score type. Beneath the alignment score for each matrix type along the left side, the log-odds
 279 score and the substitution that occurred are displayed for amino acids appearing in the same column as
 280 the one selected. Above the set of alignments is a histogram that shows the type and number of the amino
 281 acids (and gaps) occurring in that column.

282 Classifying amino acids according to their properties is an important part of protein research (Biro,
 283 2006; Koshi and Goldstein, 1997; Pommié et al., 2004; Bulka et al., 2006; Aftabuddin and Kundu, 2007).
 284 SubVis allows amino acids in the aligned sequences to be classified into groups based on the physical
 285 and chemical properties of interest by selecting that group from a drop-down box (Figure 4). Groups
 286 are color-coded where a color corresponds to a single group. This simplifies alignment analysis by
 287 allowing groups of amino acids sharing common characteristics to be compared instead of individual
 288 amino acids. We use the classification scheme presented by Pommié et al. (2004). Table 2 shows the
 289 classes and subgroups. A legend of the grouping is shown at the top of the display and the histogram is

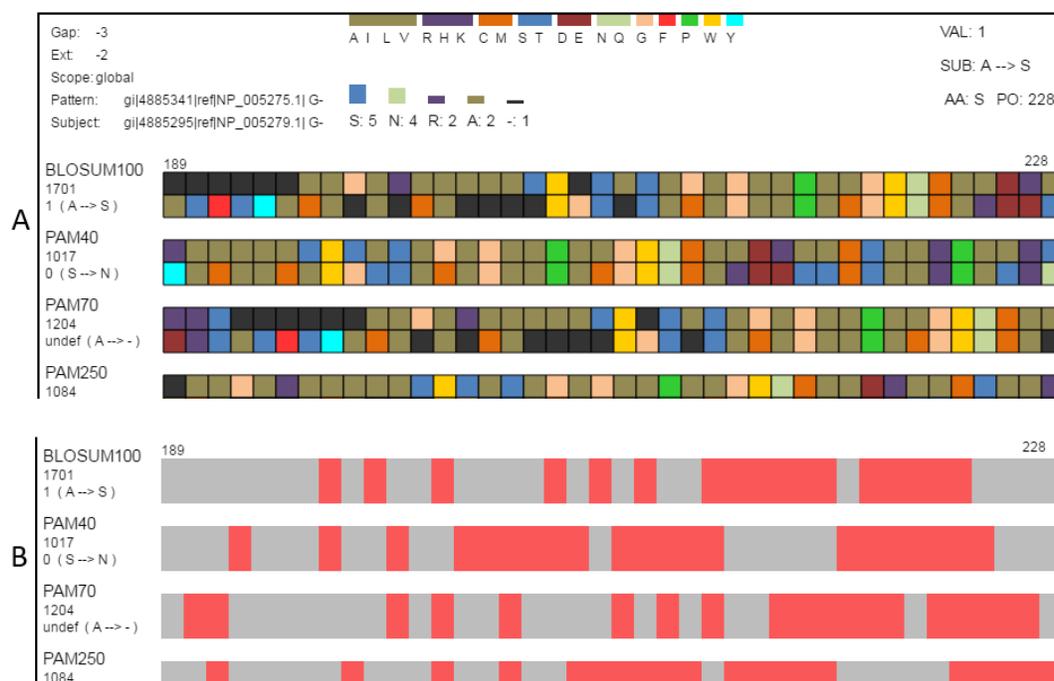


Figure 4. Classification and searching. (A) Amino acids can be grouped according to the seven classifications (Table 2) reported by Pommié et al. (2004). When a classification is selected, a legend showing how amino acid colors correspond to classification groups is displayed in the top-center and the histogram is recolored to match subgroups. Amino acids can also be grouped as conservative or non-conservative. The physicochemical classification is shown here. (B) The same region in the search view where matches to one of the search criteria are colored in red. This figure shows locations in the view where the alignment pairs match.

290 also colored by group. Additionally, substitution pairs can be grouped as conservative (log-odds score
291 > 0) or non-conservative (log-odds score < 0) (Pearson, 2013).

Table 2. Amino acid classification groups per the scheme found in Pommié et al. (2004).

Hydropathy	Volume	Chemical	Charge	Hydrogen Don/Acc	Polarity	Physicochemical
Hydrophobic	Very Small	Aliphatic	Positive	Donor	Polar	Aliphatic
Neutral	Small	Aromatic	Negative	Acceptor	Nonpolar	Basic
Hydrophilic	Medium	Sulfur	Uncharged	Both		Sulfur
	Large	Hydroxyl		None		Hydroxyl
	Very Large	Basic				Acidic
		Acidic				Amide
		Amide				G
						F
						P
						W
						Y

292 There are many additional interactions to ease alignment navigation. Instead of colored boxes, the
293 single letter amino acid abbreviation can be displayed. The default layout shows both the *pattern* and
294 *subject* for each pair. Alignment sequences can be navigated forward and backward by clicking a button.
295 To maintain positional context, incrementally moving forward or backward only shifts the alignment
296 one-half of the number of amino acids currently displayed. SubVis also has an option for showing only

297 the *pattern* or only the *subject*.

298 **Search View**

299 The search view includes several options for locating a desired alignment region. Users can search
300 alignments by amino acid position in the aligned sequence by entering the position number into a text
301 box. Searches can also locate indels, regions where the pattern and subject of an alignment pair match,
302 and sections that match an input sequence. Indel locations and areas that fulfill match criteria are shown
303 as red with the remainder of the sequence in gray.

304 **CASE STUDY**

305 We now present an example of how SubVis can aid in the exploration of alignment sequences produced
306 by multiple matrices and their associated penalties. Intrinsically disordered proteins (Wright and Dyson,
307 1999; Dunker et al., 2002; Dyson and Wright, 2005) contain functional regions associated with ill-defined
308 fold structures. Although intrinsically disordered proteins are thought to participate in important functions
309 such as network signaling and regulation, their lack of a stable, predictable structure makes designing
310 effective analysis tools difficult. For example, Radivojac et al. (2011) attempted to construct a substitution
311 matrix for disordered proteins. They tested their matrix, called DISORDER, on a wide range of disordered
312 proteins and found that it did not produce a notable cumulative score improvement over BLOSUM62.

313 Radivojac et al. (2011) notes that evaluating the performance of new matrices is more difficult than
314 their construction. SubVis allows detailed exploration of the effect of substitution matrices and eases the
315 alignment analysis for a given set of proteins, especially for insights about specific regions that may be
316 hidden in aggregate scores. For example, we desired to test the hypothesis that the DISORDER matrix
317 would perform better than the BLOSUM62 matrix when applied to the disordered DDX4 human and
318 *Xenopus laevis* proteins. The BLOSUM62 and DISORDER matrices were both loaded into SubVis as
319 custom matrices using a subset of the associated gap/extension costs reported by Radivojac et al. (Note
320 that although the entire set of matrices could have been loaded for any pair of proteins, a smaller set
321 makes our example more concise.) Specifically, the subset included the following custom matrices listed
322 by label and matrix type followed by (*gap cost, extension cost*):

323
324 **CM0:** DISORDER (-3.2, -0.1)
325 **CM1:** DISORDER (-10, -0.6)
326 **CM2:** DISORDER (-7.5, -0.9)
327 **CM3:** BLOSUM62 (-3.2, -0.1)
328 **CM4:** BLOSUM62 (-10, -0.6)
329 **CM5:** BLOSUM62 (-7.5, -0.9)

330
331 The overview produced by SubVis (Figure 5(A)) shows that the BLOSUM62 matrix generally per-
332 forms better. For instance, the top three alignment scores are BLOSUM62 matrices and the bottom three
333 alignment scores are DISORDER (Radivojac et al., 2011) matrices. Furthermore, all percent identities
334 except for PID 2 have BLOSUM62 matrices as three out of the four highest percent identities. Evident
335 from the color distribution, PID 2 results in the highest percent identities (72 max, 64 min) but has a
336 similar ordering as the others except for a shuffling at the lower end. The two consistently best PID
337 performers are DISORDER (CM0) and BLOSUM62 (CM3), both of which were produced with gap and
338 extension costs of -3.2 and -0.1, respectively. For these two matrices, the maximum difference across all
339 PID types is only one percent. Because the PID for CM0 and CM3 are similar but their alignment scores
340 are less similar, we decided to explore those alignments in more detail.

341 The search view and detail view in SubVis allowed us to learn more about the similarities and
342 differences between CM0 and CM3. In the search view, individual regions were visually scanned by
343 incrementally advancing the alignments from beginning to end. The region outlined with solid black
344 rectangles in Figure 5(B) shows aligned regions that have similar match patterns in CM0 and CM3.
345 Examining the single letter abbreviations in the detail view shows that the alignments are identical except
346 for a single column offset (Figure 5(C)). The percent identity is the same for both regions but we wanted
347 to find more detail about the substitution scores. Simple mouse interaction in SubVis allowed us to find
348 where there are substitution scores in that region that differ between matrices. For example, CM0 scores
349 the substitution of glutamic acid (E) to glutamine (Q) as 0. However, CM3 scores this substitution as 2

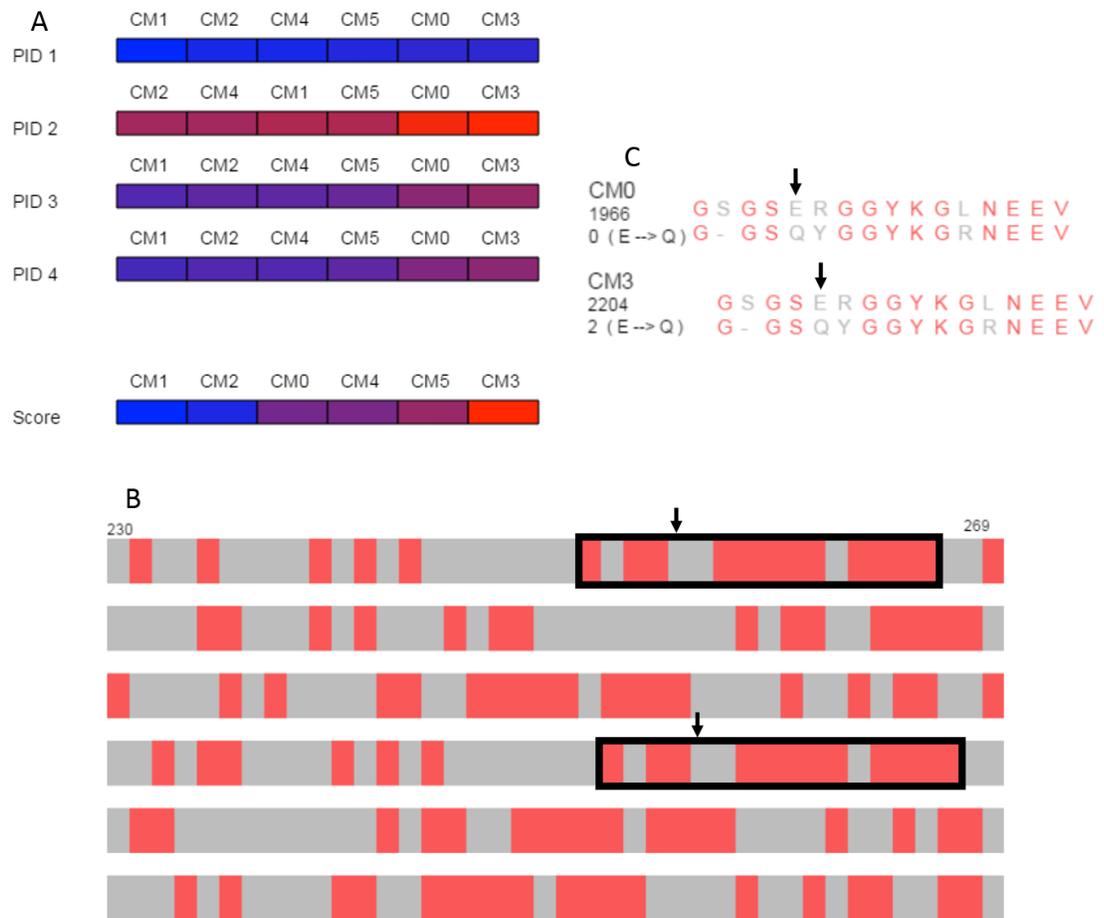


Figure 5. Case study. (A) Overview of PID and alignment score calculations show that BLOSUM62 generally outperforms DISORDER (Radivojac et al., 2011) for the DDX4 human and *Xenopus laevis* proteins. CM0 (DISORDER) and CM3 (BLOSUM62) have similar penalties and PID results but relatively different alignment scores. (B) Browsing the alignments in the search view shows similar patterns for CM0 and CM3 that are marked with black rectangles in the figure. Black arrows indicate the location of the glutamic acid to glutamine substitution. (C) The single letter amino acid abbreviation with the substitution and substitution score that appear when the mouse moves over the amino acid pair marked with arrows. The figure above was produced with a local alignment but a global alignment produced similar results for both the overview and for the outlined regions.

350 (Figure 5(C)). Classifying the properties of the amino acids indicates why this substitution score is low
 351 for both matrices by showing that they share the same group for only hydrophathy, volume, and polarity.
 352 Furthermore, CM3 has substitution scores that are greater than or equal to the corresponding substitution
 353 in CM0, except for the single tyrosine (Y) match. In that case, the substitution has a higher value in
 354 CM0. In cases where the region of interest is longer and expands across a larger, more varied range of
 355 substitution matrices, manually comparing the substitution values for even a limited set of substitutions
 356 can become cumbersome. SubVis can aid analysis even in these more complex cases by making the
 357 classification of amino acids and the score for a substitution quickly available.

358 RESULTS AND DISCUSSION

359 SubVis allows scientists to load protein sequences and visually explore alignment differences that result
 360 from varying predefined and custom substitution matrices. This platform allows scientists to view
 361 coarse-grain and fine-grain information ranging from summary alignment scoring to specific amino acid
 362 substitution details. Additional interactions include searching multiple alignment pairs and classifying

363 amino acids according to a selected property. The ability to load sequences, apply desired alignment
364 parameters (including substitution matrices), search alignments, classify amino acids, and access detailed
365 substitution scores facilitate the comparison of established substitution matrices and the evaluation of
366 matrices being developed for specific purposes.

367 SubVis utilizes general R programming constructs and the Biostrings package, both of which are
368 well-known in the bioinformatics community. SubVis is available as an R package on CRAN. The
369 package contains the data sets and custom matrices used to produce the presented figures. There is also
370 a detailed vignette included in the package and demonstration videos located on GitHub. The SubVis
371 package allows users to access the vignette through a “Help” tab persistent in all views. The help content
372 includes (but is not limited to) descriptions of interactions, specific error messages, and the specific
373 format of the file listing custom matrices and their associated penalties. The help section also explains
374 the location of created files (sequence files created by text box entry and custom matrices) and when
375 read/write permissions for those locations may be needed. The help content is organized by subject and
376 can be accessed quickly by clicking on corresponding links at the top of the page.

377 CONCLUSIONS AND FUTURE WORK

378 Substitution matrices are crucial to alignment algorithms but current tools do not allow the simultaneous
379 exploration of alignments resulting from multiple matrices. This work presents SubVis, an interactive R
380 package for visually exploring the effects of substitution matrices on protein sequence alignment. Widely
381 used matrices and multiple user-defined custom matrices can be applied to alignments. SubVis utilizes
382 Shiny for capturing parameters, R to process alignments, and JavaScript to visualize overview and detail
383 results. Users can easily transition from overall metrics, such as percent identity and alignment score, to
384 detailed information for individual amino acids and vice versa. Many interactions allow the display of
385 desired information including log-odds ratios, pattern matches, and amino acid classification by property.

386 There are many opportunities for future work. For example, we plan to extend SubVis from pairwise
387 sequence alignments to multiple sequence alignments and include more descriptors of alignment quality.
388 We would also like to include the ability to dynamically build or modify individual substitution matrices
389 and then immediately investigate the effects of changes on the alignment. Other avenues include the
390 addition of automatic recommendation of substitution matrices so that the researcher can quickly narrow
391 the number of matrices to be evaluated and the incorporation of visual alignment clustering to make
392 comparison more intuitive to users.

393 AVAILABILITY OF DATA AND MATERIALS

394 **Project name:** SubVis

395 **Project home page - Package:** <https://cran.r-project.org/web/packages/SubVis/>

396 **Project home page - Demo videos:** <https://github.com/sabarlowe/SubVis>

397 **Operating system(s):** Platform independent

398 **Tested browsers:** Mozilla Firefox and Google Chrome

399 **Programming languages:** R and JavaScript

400 **Other requirements:** R (> 3.3.0), Shiny (R package), Biostrings (R package), and a web browser

401 **License:** GNU GPL > 3

402 **Data:** The FASTA sequences for *G-protein coupled receptor 6 isoform b* (NP_005275.1), *G-protein*
403 *coupled receptor 12* (NP_005279.1), *DDX4 Homo sapiens* (AAH47455.1), *DDX4 Xenopus laevis*
404 (NP_001081728.1), and supplemental sequences were downloaded from the Protein database at the
405 National Center for Biotechnology Information (Coordinators, 2016). The data used in the manuscript,
406 supplemental sequences, and supplemental custom matrices are provided as part of the software package.

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