

CrispRdesignR: A Versatile Guide RNA Design Package in R for CRISPR/Cas9 Applications

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1 **Abstract**

2 The success of CRISPR/Cas9 gene editing applications relies on the efficiency of the
3 single guide RNA (sgRNA) used in conjunction with the Cas9 protein. Current sgRNA design
4 software vary in the details they provide on sgRNA sequence efficiency and are almost
5 exclusively restricted to model organisms. The *crispRdesignR* package aims to address these
6 limitations by providing comprehensive sequence features of the generated sgRNAs in a single
7 program, which allows users to predict sgRNA efficiency and design sgRNA sequences for
8 systems that currently do not have optimized efficiency scoring methods. *crispRdesignR* reports
9 extensive information on all designed sgRNA sequences with robust off-target calling and
10 annotation and can be run in a user-friendly graphical interface. The *crispRdesignR* package is
11 implemented in R and has fully editable code for specialized purposes including sgRNA design
12 in user-provided genomes. The package is platform independent and extendable, with its source
13 code and documentation freely available at <https://github.com/dylanbeeber/crispRdesignR>.

15 **Introduction**

16 The CRISPR/Cas9 system has attracted attention in recent years for its ability to edit and
17 regulate DNA in a wide variety of organisms and cell types. Using a strand of single guide RNA
18 (sgRNA), the Cas9 protein is able to search a cellular genome and induce double stranded breaks
19 at a target sequence complementary to the sgRNA that can then be modified¹. However, several
20 sequence features of the sgRNA and surrounding DNA sequence can influence the enzymatic
21 activity of Cas9². Crucially, the genomic DNA must contain a protospacer adjacent motif (PAM)
22 in the region immediately following the 3' end of the target DNA for Cas9 to recognize the
23 sequence¹. Other sgRNA sequence features like nucleotide composition, presence of
24 homopolymers, and self-complementarity can affect the activity of the sgRNA².

25 The efficiency of the sgRNA is a major factor in the success of Cas9 gene editing
26 applications². To predict the efficiency of sgRNA sequences, scoring methods have been
27 developed by applying machine learning techniques to CRISPR/Cas9 experimental data^{3,4,5}.
28 These efficiency scoring methods are accurate within the parameters of the experiments they
29 were based on. However, the predictions are not necessarily generalizable to Cas9 applications in
30 all cell types, organisms, and PAMs not included in the efficiency scoring experimental data. At
31 their most predictive, scoring methods have been shown to only explain about 40% of the

32 variation in efficiency for most guides⁶. Known sequence features that decrease sgRNA
33 efficiency are not always considered by scoring models^{3,4}, which could result in suggesting
34 inactive sgRNAs. The predictive power of these machine learning models may be improved by
35 considering their predictions along with the known effects of sequence features in the genome.

36 Potential sgRNA sequences that contain a sequence feature not conducive to Cas9
37 enzymatic activity can be scored highly by efficiency scoring methods that have not been trained
38 on that feature. In order to generate the most active sgRNA, sequence features must be
39 considered alongside efficiency scoring, however current programs designed to identify suitable
40 sgRNAs often do not report all sequence features relevant to sgRNA efficiency. This forces users
41 to run multiple programs to obtain all pertinent information. Features like sgRNA self-
42 complementarity, presence of homopolymers, and potential off-target effects can drastically
43 affect experimental outcomes and are often not considered by scoring models^{3,4}. sgRNA
44 sequences that are able to form hairpins with themselves or with other regions of the RNA
45 backbone have been shown to either reduce or increase activity in separate situations^{7,8}.
46 Homopolymers that contain 4 or more consecutive identical base pairs (e.g. GGGG) can
47 decrease cutting activity, and a homopolymer with 4 consecutive T's will be terminated
48 prematurely in systems that utilize RNA polymerase III to create the sgRNA⁷. It is possible for
49 Cas9 to target and cleave DNA sequences with multiple mismatches to the guide RNA resulting
50 in off-target effects³. While often problematic for those working with Cas9, these off-target
51 sequences as well as hairpins and homopolymers can be predicted from the sequence features of
52 the guide RNA. Such features are expected to affect activity more consistently across different
53 cell types, organisms and PAMs than specific nucleotide position features².

54 We have developed the R package *crispRdesignR* to improve upon current sgRNA design
55 software for CRISPR/Cas9 applications by providing all guides that match a customizable PAM
56 sequence within a target region of any genome using the advanced Doench Rule Set 2 predictive
57 model³, and by reporting sequence features often missing from other available programs but
58 important in the CRISPR/Cas9 system including the GC content, self-complementarity, presence
59 of homopolymers, and potential off-target effects for each candidate sgRNA. This is especially
60 useful for working with non-standard Cas9 applications where the efficiency score may not be
61 reliable. An optional table can be generated that displays supplementary information on where
62 the potential off-target effects occur in a user-selected genome. The *crispRdesignR* package can

63 also be utilized with a graphical user interface for easier accessibility to non-bioinformaticians.
64 In addition, the flexibility of this R package allows users to design sgRNAs in non-model
65 organisms by inputting custom genomes and annotation files for analysis, highlighting the
66 versatility of *crispRdesignR*.

67

68 **Materials and Methods**

69 **Model Features**

70 The predictive sgRNA efficiency scoring model used in *crispRdesignR* examines the
71 same features as the Doench model³ except for the cut site within the resulting protein, because
72 not every Cas9 target site is located in a protein encoding region. Our program employs a
73 gradient boosted regression model trained on the FC and RES data set used in Doench Rule Set
74 2. The FC and RES data sets³ contain about 5000 sgRNA sites plus context sequence (30-mer)
75 for a variety of different genes. Ranks for each sgRNA site are calculated from read counts and
76 normalized between 0 and 1, which is used by the gradient boosting algorithm *gbm*¹⁵ to predict
77 sgRNA activity. The Doench 2016 scoring method is trained on guide RNA utilizing the
78 5'NGG3' PAM sequence. When designing guides for custom PAM sequences, *crispRdesignR*
79 does not change the scoring method as many of the sequence features considered by Doench
80 2016³ are unrelated to the PAM sequence. It is however important to note that the accuracy score
81 provided is expected to be less accurate when designing sgRNA sequences with custom PAMs.

82 The presence of specific nucleotides at certain positions in an sgRNA target site can
83 influence the activity of that site. *crispRdesignR* will consider the single and dinucleotides at
84 each position and convert them into features that our machine learning model uses to predict
85 activity. In accordance with the Doench Rule Set 2³, our model accounts for the presence of
86 position-dependent single nucleotides, position-dependent dinucleotides, single nucleotide count,
87 dinucleotide count, GC count, nucleotides that bookend the PAM sequence, and thermodynamic
88 features of the target sequence plus context region (30-mer). As in Doench Rule Set 2, nucleotide
89 features are one-hot encoded, meaning that the presence of a nucleotide in a position is either
90 “off” (0) or “on” (1). This leads to four features for each single nucleotide position (A, C, T, or
91 G) and sixteen features for each dinucleotide position (AA, AC, AG, AT, etc.). One-hot
92 encoding of these features is crucial for accurate machine learning predictions and is made
93 possible by the *vtreat* package⁹. A position-independent total count of single and dinucleotides is

94 also used. This is simply the number of each specific nucleotide and dinucleotide combination in
95 the 30-mer. Four features counting each single nucleotide and sixteen features counting each
96 dinucleotide are recorded.

97 The GC count of the target site (20-mer) is taken and converted into a single feature (a
98 number between 0 and 20). However, two additional GC features are taken, one binary variable
99 for if the GC count is above 10 and another for if the GC count is below 10. The two nucleotides
100 that bookend the “GG” of the PAM site are one-hot encoded as a dinucleotide feature. These are
101 the nucleotides at position 25 and 28 of the 30-mer. As with the position-dependent dinucleotide
102 features, these two nucleotides are converted into 16 binary features, one for each possible
103 dinucleotide combination.

104 Four thermodynamic features are recorded, one for the predicted melting temperature
105 (T_m) of the sgRNA plus context sequence (30-mer), one for the T_m of the five nucleotides
106 upstream from the PAM (positions 20-24), one for the T_m of the eight nucleotides upstream
107 from the previous 5-mer (positions 12-19) and one for the T_m of the five nucleotides upstream
108 from the 8-mer (positions 7-11). The Doench Rule Set 2 uses the T_m_staluc function from
109 biopython to calculate the T_m of these regions, so the function employed by *crispRdesignR*
110 mirrors the T_m_staluc function using thermodynamic data from Allawi and SantaLucia¹⁰.

111

112 **Model Predictions**

113 The model features were used to train a gradient boosted regression model with the R
114 package *gbm*¹¹ on the FC and RES data used by the Doench Rule Set 2. Position-dependent
115 features that contained no variation due to the restrictive PAM site were removed. Other features
116 that showed no impact on the predictive power of the model were also removed. To predict the
117 efficiency of package-generated sgRNA target sequences, the same features collected to design
118 the model are collected for each possible target site. The generated data are then run through the
119 *gbm* package and return a number from 0 to 1 for each target site, with 0 indicating less activity
120 and 1 indicating greater activity.

121

122 **Off-Target Annotation**

123 Users may search any genome that is provided through the BSgenome package¹².
124 BSgenome also allows users to import custom genomes and DNA sequences from FASTA files

125 (using the *forgeBSgenomeDataPkg* command on a seed file that describes the paths to the raw
126 sequence data in FASTA format; more information can be found in the BSgenome
127 documentation). Genome annotation files (.gtf) can be acquired through the Ensembl and
128 BioMart databases or users can upload their own. Larger genomes should be loaded as a
129 compressed .gtf file (.gtf.gz) due to size limitations.

130 When off-target searching is on, each sgRNA sequence is checked for the presence of
131 possible off-target sequences with up to four mismatches in the 20-mer. Off-target sequences
132 must match the rules of the PAM site or be included in the list of possible 5'NGG3' PAM
133 mismatches made available by Doench *et al.*³. Off-target sequences that contain 4 mismatches
134 and do not directly match the PAM sequence are not reported by *crispRdesignR* as they are
135 highly unlikely to be active³. The *matchPattern()* function available in the package *BioStrings*¹³
136 is used to collect data on each possible off-target sequence. *matchPattern()* searches the target
137 genome for matching patterns with between 1 and 4 mismatches. Indels are not considered when
138 searching for matches. When searching genomes with many base pairs (e.g. over 1 billion) it is
139 recommended to keep the DNA query sequence under 500 base pairs to keep the search time to
140 several minutes. While the *matchPattern()* function is slower than other match finding methods
141 because it does not require the genome to be pre-indexed, which itself takes additional time, this
142 method allows users to easily search uploaded custom genomes without prior processing.

143 The locations of the possible off-target sequences are cross referenced with a user
144 supplied genome annotation file (.gtf) and reports an off-target information table listing each
145 possible off-target along with the sgRNA target site that it matches. *crispRdesignR* reports
146 sgRNA target sequences and other perfect genomic matches in the off-target annotation table so
147 that the user may verify their target location within the genome. The off-target information table
148 lists the sequence type of the off-target, as well as the gene ID, gene name, and exon number. A
149 cutting frequency determinant (CFD) score for each off-target is also listed in the off-target
150 annotation table, which is calculated using data from Doench *et al.*³ to estimate the likelihood of
151 Cas9 targeting this sequence. Each mismatch position is assigned a value based on the change
152 from one specific nucleotide to another and the values are multiplied, producing a number
153 between 1 and 0, with 1 being more likely to be targeted and zero being less likely.
154 *crispRdesignR* does not consider the position of the query target DNA sequence when finding

155 possible off-targets so that the user may verify the location of their sgRNA target sequences
156 within the genome in the off-target annotation table.

157

158 **Functions**

159 All data is generated with a single function in R¹³: `sgRNA_design(userseq, genomename,`
160 `gtfname, userPAM, calloffs = TRUE, annotateoffs = TRUE)`.

161 • *userseq*: The target sequence with which to generate sgRNA guides. Can either be a character
162 sequence containing DNA bases (A,C,T,G) or the name of a FASTA or text file in the
163 working directory.

164 • *genomename*: The name of a genome (in BSgenome format) to check for off-targets and
165 provide locations for sgRNA guides. These genomes can be downloaded through BSgenome
166 or compiled by the user.

167 • *gtfname*: The name of a genome annotation file (.gtf) in the working directory to annotate
168 sgRNAs and off-target sequences.

169 • *userPAM*: An optional argument used to set a custom PAM for the sgRNA. If not set, the
170 function will default to the "NGG" PAM. Warning: the accuracy of Doench efficiency scores
171 has only been tested for the "NGG" PAM.

172 • *calloffs*: If TRUE, the function will search for off-targets in the genome chosen specified by
173 the genomename argument. If FALSE, off-target calling will be skipped.

174 • *annotateoffs*: If TRUE, the function will provide annotations for the off-targets called using
175 the genome annotation file specified by the gtfname argument. If FALSE, off-target
176 annotation will be skipped.

177 • *getsgRNAdata(x)*: This command is used to retrieve the data on the generated sgRNA
178 sequences, where x is the raw data generated by `sgRNA_design()`.

179 • *getofftargetdata(x)*: This command is used to retrieve the additional off-target data, where x is
180 the raw data generated by `sgRNA_design()`.

181 `crispRdesignR` makes use of the R packages `vtreat`⁹, `gbm`¹¹, `Bsgenome`¹², `BioStrings`¹⁴,
182 `shiny`¹⁵, and `stringr`¹⁶. Sequence homology features are calculated based on the gRNA
183 interaction screen reported in Thyme *et. al.*¹⁷.

184

185 **Results**

186 The *crispRdesignR* tool is built entirely in the R programming language, utilizing various
187 packages to assist with different aspects of the program (see Materials and Methods). The
188 program can be run on the command line or through a graphical user interface (GUI). Guide
189 RNAs are designed based on a 23 base pair sequence from a user-input DNA sequence or
190 FASTA file that ends with the PAM. The only hard limitation on DNA regions that can be used
191 as guide RNA is the presence of the PAM site, 5'NGG3' in the case of spCas9, the most
192 commonly used Cas9 enzyme. In order to effectively provide a score for the experimentally-
193 supported scoring method used in *crispRdesignR*, flanking sequence is also collected; this
194 flanking sequence includes the four base pairs before the 5' end of the sgRNA and three base
195 pairs after the 3' end of the PAM sequence. In total, a region of 30 bases pairs is collected for
196 each possible sgRNA. The R package searches for sgRNAs from the input and returns a table
197 listing candidate sgRNAs and their sequence features, and optionally returns annotated off-target
198 information in a user-chosen genome (Figure 1). The GC content of each target sequence is
199 calculated excluding the PAM site, as the GC content of the PAM does not affect binding to the
200 target region³. The self-complementarity score provided by *crispRdesignR* includes possible
201 regions of self-complementarity within both the sgRNA target sequence and the region on the
202 sgRNA backbone that is prone to forming hairpins. Homopolymers are detected by searching for
203 strings of 4 or more consecutive base pairs.

204

205 **Featurization**

206 *crispRdesignR* has adopted the efficiency scoring method developed in Doench *et al.*
207 (2016), employing a gradient boosted regression model trained on the FC and RES data set used
208 in Doench Rule Set 2. In accordance with the Doench Rule Set 2, our model accounts for the
209 presence of position-dependent single nucleotides, position-dependent dinucleotides, single
210 nucleotide count, dinucleotide count, GC count, nucleotides that bookend the PAM sequence,
211 and thermodynamic features of the target sequence plus context region (30-mer). The presence of
212 specific nucleotides at certain positions in an sgRNA target site can influence the activity of that
213 site. *crispRdesignR* considers the single and dinucleotides at each position and converts them
214 into features that the machine learning model uses to predict activity.

215 To find off-target hits for the sgRNA, the genome from a user-selected species is loaded
216 into the program through the Bsgenome¹² package in R, and each guide RNA is then searched

217 through the genome for up to 4 mismatches. Once a complete list of matching sequences with
218 genomic locations has been collected, the program then cross-references the matching locations
219 with gene information provided in a user-input gene annotation file (.gtf). If the sgRNA matches
220 a position in a gene, *crispRdesignR* reports the gene name as well as whether the match lies in a
221 coding region.

222 Running *crispRdesignR* will output two results tables (Figure 2). The first table contains
223 the information on each individual sgRNA, including the sequence, PAM, location, direction
224 relative to the target sequence, GC content, homopolymer presence, self-complementarity, off-
225 target matches, and predicted efficiency score. The second table contains the information about
226 each off-target match, including the original sgRNA, off-target sequence, chromosome, location,
227 direction relative to the target sequence, number of mismatches, gene ID, gene name, type of
228 DNA, and exon number. These tables can be sorted and searched through the GUI or
229 downloaded as .csv files for further analysis. The location of the original sgRNA target sequence
230 in the genome can be found in the off-target information section for identity verification. If no
231 genome is provided or off-target searching is skipped, no data will be provided in the off-target
232 matches column or the off-target information table.

233

234 **Benchmarking**

235 Programs used to design sgRNA sequences often rely on predictive models but fail to
236 report other sequence features that impact Cas9 enzymatic activity. In other cases, the
237 information reported is calculated without excluding the PAM site, which is a recognition site for
238 the protein and is not found in the sgRNA sequence. For example, CHOPCHOP v2^{18,19} is one of
239 the few applications that will provide the GC content of each sgRNA sequence, but it provides
240 the GC content of both the target sequence plus the PAM site, instead of the target site alone
241 (however, this has been corrected in the newer version of CHOPCHOP (v3)²⁰).

242 The *crispRdesignR* software excludes the PAM site from the sequence information
243 reported and provides more sequence features to the user than other prominent free sgRNA
244 design programs (Table 1). Its ability to search custom genomes and annotation files is essential
245 when designing targets for non-model organisms and non-standard cell types. The ability to use
246 customized PAMs in *crispRdesignR* permits the design of sgRNAs for uncommon Cas9 proteins.
247 Another R-based program, CRISPRseek²¹, also allows users to design sgRNA in custom

248 genomes with non-standard PAMs, but lacks a GUI and does not report several important
249 sequence features such as hairpins, GC content, and homopolymers.

250 251 **Speed Comparisons**

252 *crispRdesignR* has relatively fast runtimes to discover sgRNA sequences compared to
253 other tools, although using custom genomes that are not pre-indexed leads to increased runtimes
254 when choosing to call and annotate off-targets (Table 2). Most other web-based programs have
255 pre-indexed genomes for fast off-target calling, but indexing can take several hours to perform
256 and as such is not always ideal for users uploading custom genomes or for few queries. On a
257 desktop with 3.4 GHz CPU and 8.00 GB RAM, the run time for a 128 bp sequence (“DAK1
258 short”, provided with the program) in *S. cerevisiae* averages out to 8 seconds in *crispRdesignR*
259 when calling off-targets (3 seconds without off-target calling) compared to 7 seconds in
260 *CRISPOR*²² and 5 seconds in *CHOPCHOP* v2¹⁹. GuideScan²³ has some of the shortest runtimes
261 when genomic coordinates are known beforehand and provided (2-3 seconds in *H. sapiens* and *S.*
262 *cerevisiae*), but the web application can take over a minute if provided a FASTA file when
263 searching the human genome. *crispRdesignR* and *CRISPRseek*²³ are comparable in terms of
264 speed, with *crispRdesignR* gaining a speed advantage when searching smaller genomes and
265 *CRISPRseek* gaining an advantage in larger genomes. When performing off-target searches in
266 the human genome, each additional sgRNA generated by *crispRdesignR* will add about 1 minute
267 of run time. To reduce run-time when searching for off-targets, it is recommended that users
268 keep DNA query sequences under 250 bases pairs when searching against a genome containing
269 over a billion base pairs.

270 271 **Discussion**

272 When utilizing other web-based sgRNA design programs, a user is often limited by a list
273 of preinstalled genomes. *crispRdesignR* sets itself apart by allowing the user to import a custom
274 genome and/or genome annotation file to search for sgRNAs and off-target effects. Allowing
275 custom genomes and providing extensive target sequence information makes *crispRdesignR*
276 particularly useful when working with non-model organisms, non-standard cell types and
277 uncommon PAMs. The *crispRdesignR* software provides comprehensive sequence features to the
278 user that are often omitted from other prominent free sgRNA design programs. The complete

279 sequence feature information provided by *crispRdesignR* is very well-suited to applications
280 where efficiency scores are of limited use. When using efficiency scoring methods with
281 conditions that they have not been trained on (for example different organisms, cell types, and
282 PAMs), the efficiency predictions will be less accurate. However, the predictive power of the
283 model may not be completely lost if efficiency scoring methods are used in addition to known
284 effects of various sequence features on activity to eliminate inactive sgRNA³.

285 The open source nature of *crispRdesignR* allows user to build on the features of the
286 software for their specific uses. The gradient boosted regression model that *crispRdesignR* uses
287 for efficiency scoring can be trained on other experimental data sets that contain the sgRNA
288 sequence plus context (30-mer) and guide rankings assigned scores between 0 and 1. This allows
289 for user-generated efficiency scoring models trained on data relevant to that user's needs.
290 However, for this to be a strongly predictive model, activity data must be available and
291 normalized for thousands of sgRNA sequences in that relevant context³. The accessibility of the
292 output tables as .csv files generated by *crispRdesignR* also allow a user to easily isolate the
293 sgRNA sequences and run them through other scoring applications that are more appropriate for
294 a specific application but that lack the sequence features, off-target annotation, or genome
295 customization of *crispRdesignR*.

296 The flexibility and detail that is provided by the robust off-target annotation system used
297 by *crispRdesignR* currently limits the speed of the program. While other programs may allow a
298 user to index genomes for quicker searching, the process of indexing a custom genome can be
299 hardware intensive and overall slower than a few searches on an unindexed genome for off-
300 targets, particularly for design applications in a small target region. For applications that require
301 sgRNA design in a large target region (over 1000 base pairs) within a large genome (over 1
302 billion base pairs), the user can turn off off-target calling in *crispRdesignR* to prevent long run
303 times. Although web-based programs that access pre-indexed genomes offer superior speed, we
304 show that they often report less sequence feature information, fewer off-targets, and they are
305 limited to the genomes that can be searched to a pre-defined list.

306 Another R package, CRISPRseek²³, uses similar methods of efficiency scoring and off-
307 target calling, allowing for searching custom genomes and annotation files. However, it lacks the
308 graphical user interface and several sequence features provided by *crispRdesignR*. The two
309 programs both take longer to run than many of their web-based counterparts due to the ability to

310 use non-indexed genomes, although *crispRdesignR* has a speed advantage when searching
311 smaller genomes while *CRISPRseek* is faster when searching larger genomes. Although both
312 programs use the same efficiency scoring method, *CRISPRseek* requires the user to add python
313 packages in order to obtain the scores based on Doench Rule Set 2³. *crispRdesignR* is able to
314 provide scores based on Rule Set 2 completely within R. Each program contains exclusive
315 features that the other lacks that may be useful in different settings. For example, *CRISPRseek*
316 has the ability to filter sgRNA based on restriction enzyme cutting sites, while *crispRdesignR*
317 detects possible self-complementary sgRNA sequences.

318 The R package *crispRdesignR* sets itself apart by allowing the user to import a custom
319 genome and/or genome annotation file to search for sgRNAs and off-target effects, while
320 providing extensive target sequence information and the option of an accessible GUI. These
321 unique features make *crispRdesignR* particularly useful for non-bioinformaticians working with
322 non-model organisms, non-standard cell types, and uncommon PAMs. Accessible source code
323 further adds to the versatility of *crispRdesignR* and lends itself to integration with different
324 analysis pipelines and efficiency scoring methods as future technological improvements are
325 made.

326

327 **Data Availability**

328 The source code and example data for the *crispRdesignR* package is available at:
329 <https://github.com/dylanbeeber/crispRdesignR>.

330

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334

335 **Competing Interests**

336 The authors declare no competing interests.

337

338 **Contributions**

339 D.B. conceived the project. D.B. and F.C. designed and structured the R package. D.B. wrote the
340 code for *crispRdesignR* and performed the analyses. D.B. and F.C. wrote the manuscript.

341

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- 392

393

Software name	CHOPCHOP v2 ^{18,19}	CRISPR Design ³	CRISPRseek ²¹	CRISPOR ²²	GuideScan ²³	crispRdesignR
Providing entity	Harvard	Broad Institute	UMASS Medical	Tefor	MSKCC	UML
All targets	Yes	No	Yes	Yes	Yes	Yes
Scoring method	Customizable	Doench	Doench	Doench & M.-Mateos	Doench	Doench
Hairpins	Yes	No	No	No	No	Yes
GC content	Yes	No	No	No	No	Yes
Homopolymers	No	No	No	No	No	Yes
Max no. of mismatches	3	4	4	4	3	4
PAM	Customizable	NGG, NNGRR	Customizable	Customizable	NGG, TTTN	Customizable
Off-target Annotation	No	Limited	Yes	Yes	No	Yes

394 **Table 1.** Feature comparisons between several prominent free sgRNA design programs
 395 CHOPCHOP v2^{18,19}, CRISPR Design³, CRISPRseek²¹, CRISPOR²², and GuideScan²³. Features
 396 reported include whether all targets that match the PAM are output (All targets), the scoring
 397 method from Doench³, Moreno-Mateos⁴, or customizable), self-complementarity through hairpin
 398 detection, GC content, homopolymer filtering, the maximum number of mismatches permitted
 399 between the guide sequence and reference, the available PAM sequence, and whether off-target
 400 sequences are reported and annotated.

401

Test Sequence	Genome	CHOP-CHOP ¹⁹	CRISPR Design ³	CRISPRseek ²³	CRISPOR ²²	Guide Scan ²³	crispRdesignR (no off-targets)	crispRdesignR (with off-target calling)
DAK1 short	<i>S. cerevisiae</i> (yeast)	0:05	N/A	2:10	0:07	0:02	0:03	0:08
DAK1	<i>S. cerevisiae</i> (yeast)	0:18	N/A	4:24	0:19	0:02	0:14	1:47
MYBPC3 deletion	<i>H. sapiens</i> (human)	0:06	0:15	6:50	0:10	0:03	0:03	7:36
Partial ADRB1	<i>H. sapiens</i> (human)	0:34	0:26	14:35	0:15	0:03	0:05	15:42

402 **Table 2.** Runtime comparisons for example sequences in each program analyzed. Run times
 403 (minutes:seconds) were averaged over three trials on a desktop PC with 3.4 GHz CPU and 8.00
 404 GB RAM. Some programs offered a limited list of available genomes that prevented analysis
 405 (indicated by N/A). The DAK1 short example sequence can be found on the *crispRdesignR*
 406 github site; it is 128 bp long and generates 13 target sequences, with 35 off-targets. The DAK1
 407 sequence contains 1780 bp and generates 170 target sequences, with 495 off-targets. The
 408 MYBPC3 deletion sequence contains 57 bp and generates 6 target sequences, with 2,219 off-
 409 targets. The Partial ADRB1 sequence contains 70 bp and generates 11 target sequences, with
 410 9,200 off-targets.

411 **Figure 1.** A screen capture from the *crispRdesignR* GUI demonstrating the target sequence,
412 genome selection, and genome annotation file inputs. Partial sgRNA results and off-target
413 annotations are also shown.

414
415 **Figure 2.** The output tables of *crispRdesignR* using a partial version of the DAK1 gene
416 sequence, which is provided with the package download. Not all off-target matches are shown in
417 the screenshot. Columns in the sgRNA table include sgRNA sequence, PAM, direction, start,
418 end, GC content, presence of homopolymers, possible self-complementary sequences, efficiency
419 score³, and number of matches in the user-provided genome with between 0 and 4 mismatches
420 (MM). The Off-target information table includes the original sgRNA sequence, chromosome,
421 start, end, number of mismatches, strand, CFD scores, matched sequence, gene ID, gene name,
422 sequence type, and exon number.
423

424 **Figure 1**

sgRNA Designer

Target Sequence

ATGTCCGCTAAATCGTTTGAAGTC

Use FASTA or txt file as target sequence

Select Genome

Saccharomyces cerevisiae (UCSC.sacCer2)

Choose genome annotation file (.gff)

Browse... Saccharomyces_cerev

Upload complete

Additional Options

Find sgRNA

sgRNA Table

Download sgRNA

Show 25 entries Search:

sgRNA sequence	PAM sequence	Direction	Start	End	GC content
CCAGTCAATTCAAGTCTCAA	AGG	+	31	53	0.40
CAGTCAATTCAAGTCTCAA	GGG	+	32	54	0.35
TGTGACTTCAAACGATTTAG	CGG	-	34	56	0.35
CCTTTGAGACTTGAATTGAC	TGG	-	60	82	0.40

sgRNA sequence PAM sequen Direction Start End GC conte

Showing 1 to 4 of 4 entries Previous 1 Next

Off-target Information

Note: this program may report sequences in the target region as potential off-target sequences

Download Off-Targets

Show 25 entries Search:

sgRNA sequence	Chromosome	Start	End	Mismatches
CCAGTCAATTCAAGTCTCAAAGG	chrII	65493	65515	4

425

426

427 **Figure 2**

sgRNA Table

Download sgRNA

Show 25 entries

Search:

sgRNA sequence	PAM sequence	Direction	Start	End	GC content	Homopolymer	Self Complementary	Efficiency Score	MM0	MM1	MM2	MM3	MM4
GGACATGAACCTACACACGC	CGG	+	7	29	0.55	FALSE	1	0.7110890	1	0	0	0	1
CCAATGAAACCGCGTGTGT	AGG	-	45	67	0.55	FALSE	0	0.6094593	1	0	0	0	1
CATACCTTACCAATGAAAC	CGG	-	55	77	0.40	FALSE	0	0.5584608	1	0	0	0	1
ATTGGTAAGGTATGTTGAG	TGG	+	34	56	0.40	FALSE	0	0.5584598	1	0	0	0	0
CACGCCGTTTCATTGGTAA	GGG	+	22	44	0.50	FALSE	0	0.5026394	1	0	0	0	2
ACAGCCGTTTCATTGGTA	AGG	+	21	43	0.50	FALSE	0	0.4909957	1	0	0	0	1
CCTACACAGCCGTTTCAT	TGG	+	16	38	0.55	FALSE	0	0.4308757	1	0	0	0	0

sgRNA sequence PAM sequen Direction Start End GC conten Homopolymer Self Complementa Efficiency Sc MM0 MM1 MM2 MM3 MM4

Showing 1 to 7 of 7 entries

Previous 1 Next

Off-target Information

Note: this program may report sequences in the target region as potential off-target sequences

Download Off-Targets

Show 25 entries

Search:

sgRNA sequence	Chromosome	Start	End	Mismatches	Direction	CFD Scores	Off-target sequence	Gene ID	Gene Name	Sequence Type	Exon Number
CACGCCGTTTCATTGGTAAGG	chrVI	23615	23637	4	+	0.091	CATGCCGTTTGTGGTGAAGG	YFL053W	DAK2	gene, transcript, exon, CDS	1
CCAATGAAACCGCGTGTAGG	chrVI	23609	23631	4	-	0.403	CCAACAAAACCGCATGCGTTGG	NA	NA	NA	NA
CACGCCGTTTCATTGGTAAGG	chrVII	287767	287789	4	+	0.000	CACGCCGTTTCGTTTCTAATGG	NA	NA	NA	NA
ACAGCCGTTTCATTGGTAAGG	chrVIII	247448	247470	4	+	0.065	TCACTCTGTTTCATGGGTACGG	YHR074W	QNS1	gene, transcript,	1

428