## **Supplementary Information**

## **Genome-wide functional screens enable the prediction of high activity CRISPR-Cas9 and -Cas12a guides in** *Yarrowia lipolytica*

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Supplementary Table 11: Parameters for bioinformatics tools used in analysis of NGS reads. Supplementary Table 12: Correlation of SRA files names to demultiplexing information.



**Supplementary Figure 1.** Design and validation of Cas12a and Cas9 sgRNA library for *Y. lipolytica* PO1f. (a) An 8-fold redundant sgRNA library was designed to target 7,919 protein coding genes in the *Y. lipolytica* CLIB89 strain, the parent strain of PO1f. Coding sequences were confirmed to be present in the PO1f genome sequence. Over 80% of the genes had 8 sgRNAs and over 91% of the genes had at least 5 sgRNAs. (b) A library consisting of 58,421 sgRNAs was synthesized by Agilent, cloned in-house and characterized by next generation sequencing. The library exhibited a tight normal distribution with nearly equal mean and median signifying minimal skew. The average representation of sgRNAs was ~100-fold (at 5.84 million reads which is 100 times the library size, we can calculate the mean representation of sgRNAs to be 5.84\*17.31 = 101.09). **Note**: The Cas9 library design was previously reported in ref. 1 (see Figure S1). Additional details of this library are also provided in the materials and methods section of this manuscript.



**Supplementary Figure 2.** Replicate correlation graphs at Day 4 of the growth screen for Cas12a experiments. The column on the left shows pairwise correlations for the control strain while the column on the right shows the same for sample strain.

**Supplementary Table 1.** Replicate correlations for the genome-wide growth screens in *Y. lipolytica* with the Cas9 and Cas[1](https://paperpile.com/c/xDRB90/Or5P5)2a endonucleases. Cas9 data was previously reported in ref.<sup>1</sup> Note: Work conducted in ref. 1 uses PO1f with functional KU70 as the control strain.





**Supplementary Table 2.** The twelve layers in the convolutional auto-encoder (first network in DeepGuide); the autoencoder is composed by an encoder (layers 1-6) and a decoder (layers 7- 12).



**Supplementary Table 3.** The eleven layers in the second network in DeepGuide, composed of an encoder (layers 1-6) and a fully connected network (layers 7-11).



**Supplementary Table 4.** Ablation analysis on Cas12a dataset; green row (row 1) show the performance of the encoder (followed by a flatten layer) using random weights (no pre-training or backpropagation); purple row (row 2) show the performance of the encoder (followed by a flatten layer) using random weights and then performing back-propagation only on the flatten layer; blue rows (3-7) show the performance after pre-training the encoder and then running back-propagation only layers downstream of the encoder; pink rows (8-12) show the performance after pre-training and then running back-propagation on the whole network (including the encoder); correlation coefficients in bold corresponds to the best performance; fc  $=$  fully connected layer; pool  $=$  pooling layer; flatten  $=$  flatten layer; mult  $=$  multiplication layer (see Table S5 for the list of layers)



**Supplementary Table 5.** Ablation analysis on Cas9 dataset; dataset; green row (row 1) show the performance of the encoder (followed by a flatten layer) using random weights (no pre-training or backpropagation); purple row (row 2) show the performance of the encoder (followed by a flatten layer) using random weights and then performing back-propagation only on the flatten layer; blue rows (3-7) show the performance after pre-training the encoder and then running back-propagation only layers downstream of the encoder; pink rows (8-12) show the performance after pre-training and then running back-propagation on the whole network (including the encoder); correlation coefficients in bold corresponds to the best performance; fc  $=$  fully connected layer; pool  $=$  pooling layer; flatten  $=$  flatten layer; mult  $=$  multiplication layer (see Table S5 for the list of layers)







**Supplementary Figure 3.** Genes selected for experimental validation of DeepGuide and the observed phenotype of the null mutants. MGA1 and RAS2 are implicated in the pseudohyphal and filamentous growth, and their null mutants show smooth colonies as shown in the picture on the left. CAN1 disruption confers resistance to L-Canavanine which is a toxic analog of Arginine. This leads to growth on plates supplemented with canavanine, as shown in the middle picture. MFE1 disruption renders *Y. lipolytica* unable to utilize oleic acid as a carbon source, and null mutants do not grow on plates with oleic acid as the sole carbon source as shown in the right-most picture.



**Supplementary Figure 4.** Clustering of high and poor activity guides used to validate DeepGuide. Predicted CS values and experimental disruption efficiencies for both the Cas12a and Cas9 were plotted on an XY scatter plot and a gaussian mixture model was used to cluster the sgRNA into two clusters (high and low activity). The high activity clusters are indicated in green, while the low activity clusters are indicated in red. Dark green and red points correspond to cluster centroids. Data point shape indicates whether the guide was predicted to be of high or low activity (circles are high activity, diamonds are low activity). Three predicted high activity guides cluster with low activity guides for Cas12a. For Cas9, three guides in the high activity cluster have a significantly higher euclidean distance from the cluster centroid and appear to be outliers (marked with empty circles).



**Supplementary Figure 5.** ROC plots and AUROC values for DeepGuide, DeepCpf1 (original and retrained), DeepCRISPR (original and retrained), sgRNA Scorer, SSC, and CRISPRater for the prediction of sgRNA activity on the Cas12a dataset (left) and the Cas9 dataset (right). DeepGuide had higher AUROC values than all other guide activity prediction algorithms. Guides with  $CS > 1.67$  for Cas12a and  $CS > 4.91$  for Cas9 were classified as active, and guides with a CS value below this threshold were classified as inactive. DeepGuide (w/o pt) indicates that no pre-training was carried out.



**Supplementary Figure 6.** Training and validation loss for DeepGuide without pre-training (left) and with pre-training (right) as a function of the number of training epochs. These curves show that pre-training improves the architecture's generalization.



**Supplementary Figure 7.** Evaluation of DeepGuide's ability to predict guide activity in other species. DeepGuide was tested on four non-Yarrowia datasets, including a CRISPR-Cas9 activity profile in *E. coli*<sup>[2](https://paperpile.com/c/xDRB90/9xLp)</sup> and three CRISPR-Cas9 datasets in mammalian cell lines <sup>[3](https://paperpile.com/c/xDRB90/HR9C)</sup>. These datasets were selected from the 44 publicly available sets listed in ref. [4,](https://paperpile.com/c/xDRB90/JjLj) because they were the only ones having a size comparable to our *Y. lipolytica* datasets (*i.e.*, they contained at least 30,000 data points; see Figure 4 of main text, DeepGuide requires at least this many data points for high accuracy predictions). DeepGuide, before and after retraining, was compared to DeepCpf1 $<sup>5</sup>$  $<sup>5</sup>$  $<sup>5</sup>$  (also before</sup> and after retraining) on all four datasets, as well as to the method originally developed for the respective datasets. DeepCpf1 was chosen because of its strong performance on our *Y. lipolytica*  datasets. The data show that (i) retraining is necessary for DeepGuide and DeepCpf1 to achieve a reasonable predictive performance, (ii) when retrained, DeepGuide achieves a slightly higher predictive performance than DeepCpf1. We note that the Spearman coefficient reported on the *E. coli* dataset using the method proposed in ref. [2,](https://paperpile.com/c/xDRB90/9xLp) which is based on gradient boosting regression trees, was 0.542. This matches the performance of DeepGuide, showing that our method is able to capture CRISPR-Cas9 activity in *E. coli*. DeepGuide was not able to capture guide activity measured in mammalian cell lines, thus demonstrating the importance of architecture optimization for broad cross-species prediction abilities.

**Supplementary Table 6.** Yeast strains used in this study.



**Supplementary Table 7.** Plasmids used for genome wide CRISPR screens.



**Supplementary Table 8.** Sequences of primers used in this study.











**Supplementary Table 9.** Transformation efficiencies measured as  $x10^6$  transformants, for all replicates in the control and treatment strains.





**Supplementary Table 10.** Primers used for NGS fragment amplification





**Supplementary Figure 8.** Schematic and sequence information of Cas9 (top) and Cas12a (bottom) amplicons for NGS. Amplicons contain (i) P5 and P7 sequences (light blue) that are necessary for binding with the flow cell in Illumina sequencers, (ii) TruSeq adapter (brown) for binding of the sequencing primer, (iii) a portion of  $tRNA<sup>gly</sup>$  (black) expressing the sgRNA, (iv) Cas9 or Cas12 spacer (green) (v) Cas12a associated direct repeats or a portion of the Cas9 tracrRNA sequence (red), (vi) Universal 8 bp Illumina barcodes (blue), (vii) Index read 1 sequence for the binding of primers to sequence the Illumina barcodes, and (viii) 4-9 nt pseudobarcodes (orange) at the 5' end between the TruSeq and tRNA<sup>gly</sup> which help demultiplex replicates that contain the same illumine barcode.



**Supplementary Table 11.** Parameters for bioinformatics tools used in analysis of NGS reads

Note: All parameters other than those mentioned here are kept at default values.



**Supplementary Table 12.** Correlation of SRA files names to demultiplexing information





\*\* The symbol '^' before the barcode sequence represents that it is anchored, i.e the read begins with the barcode sequence from the 5' end. This information is needed for demultiplexing with CutAdapt.

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