Mixed Integer Linear Programming based machine learning approach identifies *regulators* **of telomerase in yeast**

Alexandra Poos^{1,2,3}, André Maicher^{4,5}, Anna Dieckmann^{2,3}, Marcus Oswald^{1,2}, Roland Eils^{3,6}, Martin Kupiec⁵, Brian Luke^{4,7} and Rainer König^{1,2,3,*}

¹ Integrated Research and Treatment Center, Center for Sepsis Control and Care (CSCC), Jena

University Hospital, D-07747 Jena, Erlanger Allee 101, Germany

² Network Modeling, Leibniz Institute for Natural Product Research and Infection Biology - Hans Knöll

Institute (HKI) Jena, Beutenbergstrasse 11a, 07745 Je

Institute (HKI) Jena, Bioinformatics, German Cancer Research Center (DKFZ), Im Neuenheimer Feld 580,
69120 Heidelberg, Germany
⁴ Center for Molecular Biology at Heidelberg University (ZMRH), Cerman Cancer Bessersh Center

Center for Molecular Biology at Heidelberg University (ZMBH), German Cancer Research Center (DKFZ)-ZMBH-Alliance, Im Neuenheimer Feld 282, 69120 Heidelberg, Germany

⁵ Department of Molecular Microbiology and Biotechnology, Tel Aviv University, Ramat Aviv 69978,

Israel.

⁶ Department of Bioinformatics and Functional Genomics, Institute of Pharmacy and Molecular Biotechnology, and Bioquant, University of Heidelberg, Im Neuenheimer Feld 267, 69120 Heidelberg, Germany

 7 Telomere Biology Group, Institute of Molecular Biology (IMB), Ackermannweg 4, 55128 Mainz, Germany.

* To whom correspondence should be addressed. Tel: 004936415321189; Fax: 004936415320800; Email: rainer.koenig@uni-jena.de

Supplementary Material

Text S1. Model performances

To elucidate if rather small models or the larger models show a better performance, we assembled the performance results (Pearson correlation between prediction and measured expression value) of all cross-validation runs for each model size (from 1 until 10 regulators). The results are given in Figure S6, showing a quite homogenous performance with a tendency that the smaller models yielded the better results. Furthermore, Figure S7 shows a scatterplot of the predicted versus the experimental expression of *EST1* for the short *tlm* (red) and the control dataset (black) with a correlation of PCC r=0.51.

As typically, a standard (L2 based) linear regression coupled with analysis of Variance is employed for such a bottom up or top down approach to get models with different optimized sets of parameters, we calculated the adjusted R² for the complete short *tlm* dataset (Figure S8). We found increasing adjusted R^2 values until 11 regulators, after which a large decline occurred. This is in line with our approach of selecting models below 11 regulators. To relate the model results with the correlation analysis, we compared the beta values (median over all cross-validations) with the correlation between the regulator activities and *EST1* expression. We expected that a positive correlation between the regulator activities and *EST1* expression is positively correlated with the beta values for this regulator. Indeed, 10 out of the 12 significant regulators of *EST1* in the short *tlm* dataset showed this behavior (see Table S9 for all values). For the controls, this was much less (3 out of 12) reflecting the property of the selected TFs to better explain the dataset we foccused on (short *tlm* mutants). We further investigated how often each regulator was chosen over the cross-validation runs in the short *tlm* and the control datasets (Figure S3) as well as how often the regulator was chosen in models with one to 10 regulators (Table S10 and S11). For *EST1*, Sum1 and Hst1 were selected most often for the short *tlm* dataset and comparably unfrequently for the control dataset. This confirms that Sum1 and Hst1 were the most important regulators explaining *EST1* expression. These frequencies further showed that Sum1 and Hst1 were used mutually exclusive, in particular for the smaller models (1-5 regulators, see Table S12).

Text S2. Correlation analysis

If the activity of a regulator was very similar to the activity of another regulator in each of the investigated samples, the model may have difficulties distinguishing between them and may neglect one of these regulators causing false negatives. To identify such false negatives due to collinearity of the regulators' activity values, we (i) performed a correlation analysis between the activity values of each pair of the different regulators, (ii) calculated the correlations between the regulators' activitiy values and the gene expression of the putatively targeting *EST* genes, and (iii) simulated *in silico* knockouts to identify mutually exclusive regulators.

For (i) and (ii), the correlations were calculated for the short *tlm* mutants and the controls seperately. Then, the largest differences (between short *tlm* mutants and controls) were selected to obtain short *tlm* mutant specific regulators. A complete list of all positively correlating regulators with a difference in activity correlation larger or equal to 0.1 is shown in Table S8, some results are pointed out in the

following. For *EST1,* the correlation differences of regulator pairs were quite low, we found the highest activity correlation difference between Sum1 and Hst1 activities (correlation difference between short *tlm* mutants and the controls: PCC r=0.17). This is in agreement with the results from our modeling analysis (Table 1 in the main text). For *EST2* and *EST3* the differences were larger. The largest difference for *EST2* was r=0.45 for the pair Rtg3 and Rgt1, and for *EST3* it was r=0.37 for the pair Dig1 and Gln3. Our modeling approach found Rtg3 but not Rgt1 for *EST2* and Dig1 but not Gln3 hinting at Rgt1 and Gln3 being potential further candidates regulating *EST2* and *EST3*, respectively. We then analyzed the correlation between activity of the regulators and the expression of the putative target genes (*EST*s). Again, we calculated the difference in correlation between short *tlm* mutants and controls. The results are given in Table S5, S6 and S7 for *EST1*, *EST2* and *EST3*, respectively. For *EST1* we found Hst1 and Sum1 with the highest correlation difference (Hst1-Est1: r=0.51, Sum1-Est1: r=0.62, Table S5) confirming our modelling results that these regulators are involved in *EST1* regulation. For *EST2*, we found Arg81, Nrg1, Tec1, Nrg2, Msn4 and Pdr3 with the highest correlation difference of which all were predicted by our model except of Nrg1. For *EST3*, Ume6 had the highest absolute correlation difference, in agreement to our modeling results. In summary, the results of the correlation analysis confirmed the modeling results, in particular for *EST1* and our most promising regulators of the modelling analysis, Hst1 and Sum1. We note that this analysis may serve the purpose of adding potential other candidates to the regulatos that we selected from our modeling analysis. (iii) Further, we simulated a knockout of a specific regulator if we found this regulator's activity to correlate highly with another regulator. As a case study, we investigated *EST1* as the target gene and the pair of Sum1 and Hst1 as regulators. Indeed, when Sum1 was knocked out, Hst1 took over Sum1's function explaining the gene expression of *EST1* and was used distinctively more often by the models when compared to the non knockout models (P=5.49 E-30, Table S13). In turn, knocking out Hst1, Sum1 was used instead (P=2.55 E-40, Table S14). This is consistent with the literature, it was reported that Sum1 and Hst1 together with Rfm1 form a complex repressing genes through histone deacetylation (1-4). Hence, we suggest that Sum1 and Hst1 act synergistically also for the expression of the telomerase gene *EST1*. To further confirm this computationally, we followed up on this complex and built models with the combination Sum1-Hst1 (we multiplied the activities and used the square root of the product as activity of the complex) instead of the single regulators Sum1 and Hst1. In this case the combination Sum1-Hst1 was used instead of the single regulators (P=4.51 E-32, Table S15).

Text S3. Modeling a complex of Sum1 and Hst1

We further built models with only the regulators Sum1 and Hst1 as well as with a combination of both mimicking cooperative activity [as suggested by (5)]. We used the data of the short *tlm* mutants and estimated the performance using a ten-times sixfold cross-validation (as described in the main text, see section The machine learning approach). We investigated the new model starting with one parameter for the smallest possible model (only beta 0 and one of the three possibilities of Sum1, Hst and Sum1-Hst1). The results are shown in Table S16. For the smallest models, Hst1 was most often selected (43 out of 60). Restricted to two β-parameters (either two single regulators, or one single and one Sum1-Hst1 combined) the optimizer chose the combination of Sum1-Hst1 together with Sum1 most often supporting the suggestion of a combined regulation of Sum1 and Hst1.

Regulator	One regulator model	Two regulator model	Three regulator model
Hst1	43	28	60
Sum1		46	60
Hst1-Sum1		46	60

Table S16. Modeling results of the Sum1-Hst1 combined model

* Number of selections by the model out of 60 runs.

Figure S1. The regulatory model. The *EST* genes are regulated by regulators $R_1 - R_n$.

Figure S2. Overlaps between the TLM genelist (orange, data was taken from (6-10)), the yeast deletion strains of regulators of which we used the expression data (blue, data was taken from (11)), and regulators with know binding (taken from YEASTRACT) to at least one of the *EST* genes (*EST1, EST2, EST3*).

Figure S3. Regulator frequencies (of all 10 runs of each cross-validation) for the short *tlm* (red) and the control dataset (blue) over all cross-validation runs. a) *EST1*, b) *EST2*, c) *EST3.*

Figure S4. EST1-3 expression (log-fold change) over all observed 269 regulator knockouts, ranked according to the expression levels of the corresponding EST gene; a) EST1, b) EST2 and c) EST3 (red: short tlm, blue: long tlm and black: control sample).

Figure S5. Incoherent feed forward loop, where Sum1/Hst1 and *EST1* positively regulate telomeres and Sum1/Hst1 negatively regulate *EST1*.

Figure S6. Pearson correlation of our modeling predictions with the measured expression values, shown for different sizes of the model, left: only one regulator, right, the maximal number of 10 regulators (shown for *EST1* regulators, short *tlm* mutants and control).

Figure S7. Actual vs. model predicted performance of EST1 for the short tlm (red) and the control dataset over all cross-validation runs (cor (actual GE, predicted GE) = 0.51).

Figure S8. Adjusted R^2 calculation for all short *tim* samples (similar to ANOVA)

Table S2. Putative regulators of the *EST* genes (taken from YEASTRACT).

	Regulator	Z-score*	Significance (P)**	Number of targets
EST ₁	Sum1***	6.85	3.76 E-30	579
	Hst1 ^{**}	3.61	2.51 E-28	219
	Rfx1	-0.45	5.71 E-22	660
	Mig1	0.14	1.56 E-17	423
	Srb2 ^{***}	2.08	5.23 E-10	785
	Sfp1	3.24	6.56 E-9	4199
	Ste12	**** -	8.89 E-6	3673
	Cup ₂	-0.30	2.09 E-2	548
EST ₂	Nrg ₂		6.11 E-23	331
	Pdr1	0.31	1.28 E-17	1318
	Gcn4	-0.22	1.77 E-16	2712
	Rtg3	0.16	5.33 E-9	646
	$Cdc73$ ***	-3.79	2.23 E-8	757
	Yrm1	$\mathcal{L}_{\mathcal{A}}$	6.11 E-6	2509
	Tec1	-0.22	$1.05E - 5$	3669
	Msn2	0.05	2.83 E-5	3260
	Arg81	0.42	9.24 E-5	335
	Ste12	÷,	$1.12E - 2$	3673
	Sfp1	-0.06	1.43 E-2	4199
	Gln3	-2.67	1.57 E-2	981
	Ace2	-1.70	1.63 E-2	4683
	Rme1	-0.31	3.22 E-2	399
	Abf1	-0.29	4.38 E-2	2715
	Pdr3	-0.44	4.38 E-2	929
	Nrg1	0.07	4.48 E-2	686
	Msn4	-1.17	4.83 E-2	2483
EST ₃	Digit	-1.87	1.15 E-36	334
	Sok2	0.28	4.39 E-23	2160
	Cin5	1.81	1.03 E-21	2062
	$Sin3$ ^{***}	-3.11	1.41 E-20	1759
	Ste12		9.37 E-14	3673
	Sin4	2.31	1.58 E-10	2144
	Msn2	-0.46	2.72 E-6	3260
	Spt10	-2.37	1.46 E-5	1691
	Msn4	0.62	3.19 E-4	2483
	$Srb2$ ^{**}	-2.38	9.73 E-4	785
	Gln3	-1.50	4.05 E-2	978

Table S3. Significant regulators of EST genes comparing tlms (short + long) vs. control samples

* Effect of the knockout of the regulator on the expression of the EST genes (positive z-score = upregulation of the corresponding EST gene; negative z-score = downregulation of the corresponding *EST* gene); ** Multiple testing corrected (Benjamini-Hochberg); *** red: short *tlm* mutant, blue: long *tlm* mutant; **** For some genes, no expression data was available

Table S4 is in a separate file of the Supplementary Material and includes the correlation between all regulator activities**.**

Table S5. Correlations between *EST1* expression and the correpsonding regulator activities in the short *tlm* dataset and the control dataset (non-*TLM* dataset)

Table S6. Correlations between *EST2* expression and the corresponding regulator activities in the short *tlm* dataset and the control dataset (non-*TLM* dataset)

Table S7. Correlations between *EST3* expression and the corresponding regulator activities in the short *tlm* dataset and the control dataset (non-*TLM* dataset)

Table S8: Positive correlation differences (diff ≥ 0.1) of regulator activities between the short *tlm* and the control dataset; the correlation differences between significant hits of the corresponding *EST* gene are marked in bold.

Table S9. Median beta values of short *tlm* and control models, and Pearson correlation between regulator activities and *EST1* expression

*red: short *tlm* mutant, blue: long *tlm* mutant

Table S10. Frequency of the regulators in the models for the short *tlm* models, from 1 (left) to 10 regulators (right)

Table S12. Frequency of the regulators Sum1 and Hst1 individually or combined (Hst & Sum1) in the short *tlm* models, from 1 (left) to 10 regulators (right)

Table S13. Significant regulators of *EST1* after a simulated *SUM1* knockout

* Effect of the knockout of the regulator on the expression of the *EST* genes (positive z-score = upregulation of the corresponding *EST* gene; negative z-score = downregulation of the corresponding *EST* gene); ** Multiple testing corrected (Benjamini-Hochberg); *** red: short *tlm* mutant, blue: long *tlm* mutant

	Regulator	Z-score*	Significance (P)**	Number of targets
EST ₁	Sum1"**	6.85	2.59 E-40	579
	Rfx1	-0.45	1.22 E-15	660
	Gcn4	-0.13	3.40 E-12	2712
	Srb2 ^{***}	2.08	$1.02 E-9$	785
	Msn4	-0.63	2.71 E-8	2483
	$Sin3$ ^{**}	2.01	$2.13 E - 7$	1759
	Mig1	0.14	5.35 E-7	423
	Mbp1	0.76	5.74 E-6	665
	Sfp1	3.24	7.06 E-6	4199
	Ste ₁₂		$6.43E - 5$	3673

Table S14. Significant regulators of *EST1* after a simulated *HST1* knockout

* Effect of the knockout of the regulator on the expression of the *EST* genes (positive z-score = upregulation of the corresponding *EST* gene; negative z-score = downregulation of the corresponding *EST* gene); ** Multiple testing corrected (Benjamini-Hochberg); *** red: short *tlm* mutant, blue: long *tlm* mutant

Table S15. Significant regulators of *EST1* using the regulator complex Sum1-Hst1 instead of the single regulators Sum1 and Hst1

* Effect of the knockout of the regulator on the expression of the *EST* genes (positive z-score = upregulation of the corresponding *EST* gene; negative z-score = downregulation of the corresponding *EST* gene); ** Multiple testing corrected (Benjamini-Hochberg); *** red: short *tlm* mutant, blue: long *tlm* mutant

References

- 1. Li, M., Valsakumar, V., Poorey, K., Bekiranov, S. and Smith, J.S. (2013) Genome-wide analysis of functional sirtuin chromatin targets in yeast. *Genome biology*, **14**, R48.
- 2. Bedalov, A., Hirao, M., Posakony, J., Nelson, M. and Simon, J.A. (2003) NAD+-dependent deacetylase Hst1p controls biosynthesis and cellular NAD+ levels in Saccharomyces cerevisiae. *Molecular and cellular biology*, **23**, 7044-7054.
- 3. McCord, R., Pierce, M., Xie, J., Wonkatal, S., Mickel, C. and Vershon, A.K. (2003) Rfm1, a novel tethering factor required to recruit the Hst1 histone deacetylase for repression of middle sporulation genes. *Molecular and cellular biology*, **23**, 2009-2016.
- 4. Zill, O.A. and Rine, J. (2008) Interspecies variation reveals a conserved repressor of alphaspecific genes in Saccharomyces yeasts. *Genes Dev*, **22**, 1704-1716.
- 5. Lai, X., Schmitz, U., Gupta, S.K., Bhattacharya, A., Kunz, M., Wolkenhauer, O. and Vera, J. (2012) Computational analysis of target hub gene repression regulated by multiple and cooperative miRNAs. *Nucleic acids research*, **40**, 8818-8834.
- 6. Askree, S.H., Yehuda, T., Smolikov, S., Gurevich, R., Hawk, J., Coker, C., Krauskopf, A., Kupiec, M. and McEachern, M.J. (2004) A genome-wide screen for Saccharomyces cerevisiae deletion mutants that affect telomere length. *Proceedings of the National Academy of Sciences of the United States of America*, **101**, 8658-8663.
- 7. Ben-Shitrit, T., Yosef, N., Shemesh, K., Sharan, R., Ruppin, E. and Kupiec, M. (2012) Systematic identification of gene annotation errors in the widely used yeast mutation collections. *Nature methods*, **9**, 373-378.
- 8. Gatbonton, T., Imbesi, M., Nelson, M., Akey, J.M., Ruderfer, D.M., Kruglyak, L., Simon, J.A. and Bedalov, A. (2006) Telomere length as a quantitative trait: genome-wide survey and genetic mapping of telomere length-control genes in yeast. *PLoS Genet*, **2**, e35.
- 9. Shachar, R., Ungar, L., Kupiec, M., Ruppin, E. and Sharan, R. (2008) A systems-level approach to mapping the telomere length maintenance gene circuitry. *Molecular systems biology*, **4**, 172.
- 10. Ungar, L., Yosef, N., Sela, Y., Sharan, R., Ruppin, E. and Kupiec, M. (2009) A genome-wide screen for essential yeast genes that affect telomere length maintenance. *Nucleic acids research*, **37**, 3840-3849.
- 11. Reimand, J., Vaquerizas, J.M., Todd, A.E., Vilo, J. and Luscombe, N.M. (2010) Comprehensive reanalysis of transcription factor knockout expression data in Saccharomyces cerevisiae reveals many new targets. *Nucleic acids research*, **38**, 4768-4777.