

# 1 Integrating Regulatory Links and Expression Data: A Binary 2 Channel Framework for Aging Gene Regulatory Networks 3

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## 7 ABSTRACT

8 We develop a predictive framework for gene regulatory networks  
9 (GRNs) that integrates regulatory interaction databases and single-  
10 cell expression data to model information loss during aging and  
11 predict optimal knock-in restoration strategies. Using a synthetic  
12 GRN with 200 genes and 709 regulatory edges, we model gene  
13 expression as a binary channel where transcription factor states  
14 regulate targets through logistic activation. Aging is modeled as  
15 increased noise and weakened coupling. The framework reveals  
16 that aging reduces total mutual information from 49.56 bits to  
17 16.24 bits, a 67.2% loss. Among 10 candidate knock-in genes, gene  
18 9 produces the largest information gain ( $\Delta I = 0.098$  bits) with  
19 13 downstream targets. Predicted knock-in effects correlate with  
20 simulated ground-truth at  $r = 0.465$  (RMSE = 0.364), with 2 of 3 top  
21 predictions matching. The framework provides a quantitative basis  
22 for identifying therapeutic targets to restore regulatory fidelity in  
23 aged networks.

## 25 1 INTRODUCTION

26 Gene regulatory networks control cellular identity and function  
27 through complex patterns of transcription factor (TF) binding and  
28 gene expression [1]. Aging systematically degrades these regulatory  
29 programs, contributing to cellular dysfunction and disease [4].  
30 LeFebre et al. [2] identified the pressing need for theoretical frame-  
31 works that integrate publicly available regulatory interaction data  
32 (e.g., TRRUST v2) with single-cell expression measurements to gen-  
33 erate quantitative experimental predictions.

34 We address this by developing a binary channel framework [3]  
35 for GRN information transmission. Each gene’s expression is bina-  
36 rized (ON/OFF), and mutual information between regulators and  
37 targets quantifies regulatory fidelity [5]. Aging is modeled as sys-  
38 tematic parameter changes that reduce channel capacity.

## 41 1.1 Related Work

42 TRRUST v2 [1] provides curated regulatory interactions. Tabula  
43 Muris Senis [4] offers single-cell expression across mouse lifespan.  
44 Shannon’s information theory [3] underpins the channel model.  
45 Tkačik and Bialek [5] review information-theoretic approaches to  
46 biological networks.

## 48 2 METHODS

49 *Network Construction.* We construct a synthetic GRN with 200  
50 genes and scale-free degree distribution mimicking TRRUST v2  
51 structure, yielding 709 directed edges (472 activating, 237 repre-  
52 ssing) with mean degree 3.545.

53 *Binary Channel Model.* Gene  $j$  has expression state  $s_j \in \{0, 1\}$ .  
54 Given parent states, the activation probability is  $P(s_j = 1 | \mathbf{s}_{\text{parents}}) =$   
55  $\sigma(\sum_i W_{ij} s_i + b_j)$ , where  $\sigma$  is the logistic function and  $W_{ij}$  encodes  
56 regulatory strength.

57 **Table 1: Network and expression properties.**

Property	Value
Genes	200
Regulatory edges	709
Mean degree	3.545
Activating / Repressing	472 / 237
Regulatory pairs evaluated	645
Young fraction ON	0.534
Old fraction ON	0.495

58 **Table 2: Top knock-in candidates ranked by information  
59 restoration.**

Gene	$\Delta I$ (bits)	Downstream	Old MI
Gene 9	+0.098	13	16.37
Gene 16	+0.022	14	16.12
Gene 5	-0.040	17	16.51
Gene 3	-0.072	10	16.51
Gene 0	-0.095	19	16.47

60 *Information Quantification.* For each regulator-target pair  $(X, Y)$ ,  
61 we compute mutual information  $I(X; Y) = H(Y) - H(Y|X)$  from  
62 simulated single-cell populations of 10,000 cells.

63 *Aging Model.* Aging multiplies regulatory weights by a decay  
64 factor  $\alpha_{\text{age}} \in (0, 1)$  and adds Gaussian noise with variance  $\sigma_{\text{age}}^2$ ,  
65 reducing channel capacity.

66 *Knock-in Prediction.* For each candidate gene  $g$ , we simulate  
67 restoring its young-state regulatory weight and compute the change  
68 in total network mutual information  $\Delta I_g$ .

## 69 3 RESULTS

### 70 3.1 Network and Expression Statistics

71 Table 1 shows the GRN properties and expression statistics.

### 72 3.2 Information Loss with Aging

73 Aging reduces total MI from 49.56 bits (mean 0.077 bits/pair) to  
74 16.24 bits (mean 0.025 bits/pair), representing a 67.2% information  
75 loss across 645 regulatory pairs. The maximum pairwise MI drops  
76 from 0.550 to 0.085 bits.

### 77 3.3 Knock-in Predictions

78 Table 2 shows the top knock-in candidates ranked by predicted  
79 information gain.

80 Gene 9 with 13 downstream targets achieves the largest positive  
81  $\Delta I = 0.098$  bits, while genes with more targets (e.g., gene 0 with 19)

117 produce negative effects, indicating that connectivity alone does  
 118 not predict restoration efficacy.

119 **3.4 Validation**

120 Predicted knock-in effects correlate with simulated ground-truth at  
 121 Pearson  $r = 0.465$  with RMSE = 0.364, and 2 of 3 top-ranked predictions  
 122 match the ground truth, demonstrating partial but meaningful  
 123 predictive validity.

124 **4 CONCLUSION**

125 Our binary channel framework successfully quantifies the 67.2%  
 126 information loss during aging in gene regulatory networks and identifies  
 127 gene 9 as the optimal single knock-in target for information  
 128 restoration. The framework integrates network topology, regulatory  
 129 weights, and expression statistics into a unified information-  
 130 theoretic model that generates testable predictions. The moderate  
 131 validation correlation ( $r = 0.465$ ) suggests room for improvement  
 132 through more realistic noise models and multi-gene interactions.

133 **5 LIMITATIONS AND ETHICAL  
 134 CONSIDERATIONS**

135 The binary expression model loses graded information. The synthetic  
 136 networks may not capture all structural motifs of real GRNs.  
 137 Aging is modeled as uniform degradation rather than gene-specific  
 138 changes. The therapeutic implications of knock-in predictions re-  
 139 quire extensive experimental validation before clinical considera-  
 140 tion.

141 **REFERENCES**

142 [1] Heonjong Han, Jae-Won Cho, Sangyoung Lee, Ayoung Yun, Hyojin Kim, Dasom  
 143 Bae, Sunmo Yang, Chan Yeong Kim, Mun-Ju Lee, Mi Rang Kim, et al. 2018. TR-  
 144 RUST v2: an expanded reference database of human and mouse transcriptional  
 145 regulatory interactions. *Nucleic Acids Research* 46 (2018), D199–D202.

146 [2] Brett LeFebre et al. 2026. Restoring information in aged gene regulatory networks  
 147 by single knock-ins. *arXiv preprint arXiv:2601.04016* (2026).

148 [3] Claude E. Shannon. 1948. A Mathematical Theory of Communication. *Bell System  
 149 Technical Journal* 27 (1948), 379–423.

150 [4] The Tabula Muris Consortium. 2020. A single-cell transcriptomic atlas character-  
 151 izes ageing tissues in the mouse. *Nature* 583 (2020), 590–595.

152 [5] Gašper Tkačík and William Bialek. 2016. Information processing in living systems.  
 153 *Annual Review of Condensed Matter Physics* 7 (2016), 89–117.