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# Predicting Drug Synergy and Antagonism from Genetic Interaction Neighborhoods

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## Abstract

Although drug combinations have proven efficacious in a variety of diseases, the design of such regimens often involves extensive experimental screening due to the myriad choice of drugs and doses. To address these challenges, we utilize the budding yeast *Saccharomyces cerevisiae* as a model organism to evaluate whether drug synergy or antagonism is mediated through genetic interactions between their target genes. Specifically, we hypothesize that if the inhibition targets of one chemical compound are in close proximity to those of a second compound in a genetic interaction network, then the compound pair will exhibit synergy or antagonism. Graph metrics are employed to make precise the notion of proximity in a network. Knowledge of genetic interactions and small-molecule targets are compiled through literature sources and curated databases, with predictions validated according to experimentally determined gold standards. Finally, we test whether genetic interactions propagate through networks according to a “guilt-by-association” framework. Our results suggest that close proximity between the target genes of one drug and those of another drug does not strongly predict synergy or antagonism. In addition, we find that the extent to which the growth of a double gene mutant deviates from expectation is moderately anti-correlated with their distance in a genetic interaction network.

**Keywords**— Drug interactions, Synergy, Antagonism, Yeast

## Introduction

Drug combinations have an established history in treating disease, dating to the MOPP regimen for Hodgkin’s lymphoma in the 1960s to highly active antiretroviral therapy (HAART) for HIV in the 1990s [Hammer et al., 1997, DeVita and Chu, 2008]. In combating antibiotic resistance, combination regimens have proven effective and are actively under continued development [Worthington and Melander, 2013]. Yet in designing combination therapies, it is not immediately clear which drugs and doses to group together; there are simply a myriad of possible choices and the combinatorial space quickly grows unwieldy. As a result, any computational technique to either guide readily testable candidates or reliably predict the effect of drug combinations would be desirable. In this

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28 study, using the budding yeast *Saccharomyces cerevisiae* as a test platform, we determine whether  
29 the effect of drug pairs can be predicted from genetic interactions between their target genes.

30 The effect of a drug combination can be classified as synergistic, antagonistic, or additive.  
31 Two drugs are synergistic if they cause a significantly greater growth defect than expected, based  
32 on the effect of each drug individually. Antagonism is similar, although the effect is far more  
33 pronounced growth than expected. Drug additivity implies that no interaction exists between the  
34 agents, and the resulting phenotype is the sum of each drug's individual effect. There is more than  
35 one choice of a null model that defines the "expected effect" - commonly used models include  
36 Loewe additivity and Bliss independence [Loewe, 1953, Bliss, 1939, Yeh et al., 2009].

37 Previous studies to uncover genetic interactions as a mechanism underlying drug combi-  
38 nations have involved exhaustive screening of a number of small-molecule chemical compounds.  
39 An examination of 200 compound pairs administered in *Saccharomyces cerevisiae* found 38 of  
40 them to be synergistic, but genetic interactions were determined to be responsible for only 14 of  
41 those 38 [Cokol et al., 2011]. Another study screened all possible pairs of 128 compounds from a  
42 chemically diverse library to experimentally deduce synergy and antagonism, thereby establishing  
43 a validation set. Moreover, a model based directly on chemical-genetic and genetic interactions had  
44 low predictive power for synergy or antagonism, but combining naive Bayes and random forests  
45 trained on additional features led to successful predictions [Wildenhain et al., 2015].

46 We hypothesized that the proximity in a genetic interaction network between one drug's  
47 target genes and another drug's targets controls the degree to which the drug pair is synergistic  
48 or antagonistic. In particular, rather than considering only direct interactions between genes, our  
49 approach factored in whether a gene is within a neighborhood of (though not necessarily adjacent  
50 to) some other gene in the network. We leveraged knowledge of known small-molecule inhibition  
51 targets in *S. cerevisiae* from the Search Tool for Interactions of Chemicals (STITCH) database

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52 [Kuhn et al., 2013] and experimentally determined negative and positive genetic interactions  
53 [Costanzo et al., 2010]. Finally, predictions of synergy or antagonism were validated against gold  
54 standards assembled from the literature.

## 55 **Methods**

### 56 **Negative and positive genetic interaction network**

57 Negative and positive genetic interactions were compiled from a high-throughput yeast synthetic  
58 genetic array (SGA) screening dataset [Costanzo et al., 2010]. The intermediate cutoff for the  
59 genetic interaction score  $\epsilon$  was chosen as the threshold for interacting versus non-interacting gene  
60 pairs. For the purposes of data processing, the suffixes “\_tsq” and “\_damp” were removed from  
61 gene symbols. Both unweighted and weighted versions of each of the negative and positive genetic  
62 interaction networks were assembled. Nodes in the networks correspond to genes and two genes  
63 are connected by an edge if they interact according to the intermediate cutoff  $\epsilon$ . Because a larger  
64 magnitude of  $\epsilon$  indicated stronger genetic interaction, in the weighted networks the edge weights  
65 were assigned by reversing the  $\epsilon$  values. For instance, the strongest genetically interacting pair was  
66 assigned an edge weight with the smallest  $\epsilon$  instead. All edge weights were set to be non-negative.

### 67 **Chemical compound targets and gold standards for synergy and antagonism**

68 Two literature sources were used as the gold standard to validate chemical synergy and antagonism  
69 predictions [Cokol et al., 2011, Wildenhain et al., 2015]. The inhibition targets in *S. cerevisiae*  
70 of chemical compounds identified by CID were assembled from STITCH version 4 [Kuhn et al.,  
71 2013]. Only chemical names were available from the Cokol et al. dataset; these were converted to

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72 CIDs with PubChemPy <https://pypi.python.org/pypi/PubChemPy>. SMILES strings from  
73 the Wildenhain et al. dataset were also converted to CIDs. Prediction performance was assessed  
74 with receiver operating characteristic (ROC) analysis as implemented in scikit-learn [Pedregosa  
75 et al., 2011].

### 76 Distances in networks

77 Distances between all pairs of nodes in unweighted and weighted versions of both the negative and  
78 positive genetic network were computed using Dijkstra's algorithm as implemented in NetworkX  
79 [Schult and Swart, 2008]. The distance between two sets  $A$  and  $B$  of nodes in an unweighted  
80 network was calculated using the earth mover's metric (EMD) [Rubner et al., 2000]. Here in  
81 the 1-dimensional special case, the EMD reduces to differences between cumulative distribution  
82 functions [Cohen, 1999]. For the purpose of measuring the distance between two sets of nodes,  
83  $\text{EMD}(A, B) = \sum_{i \in \mathbb{N}_0} |F_{X_{\text{ref}}}(i) - F_X(i)|$ , where  $F_{X_{\text{ref}}}$  and  $F_X$  are the cumulative distribution functions  
84 (CDFs) of a reference distribution  $X_{\text{ref}}$  and a random variable  $X$ . The reference distribution is  
85 intended to represent the scenario where every node in  $A$  is adjacent to some node of  $B$ . In an  
86 unweighted network, the reference probability mass function (pmf) of  $F_{X_{\text{ref}}}$  is defined as

$$P(X_{\text{ref}} = k) := \begin{cases} 1 & \text{if } k = 1 \\ 0 & \text{if } k \neq 1, k \in \mathbb{N} \end{cases}$$

87 and the pmf for  $X$  is constructed from the frequencies of all possible node pair distances between  
88  $A$  and  $B$  as found from Dijkstra's algorithm.

89 In a weighted network, we have

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$$\begin{aligned}\text{EMD}(A, B) &= \int_0^{+\infty} |F_{X_{\text{ref}}}(t) - F_X(t)| dt \\ &= \sum_{i=1} (x_i - x_{i-1})(F_{X_{\text{ref}}}(x_{i-1}) - F_X(x_{i-1})) \\ &= \sum_{i=1} (x_i - x_{i-1})(1 - F_X(x_{i-1})) \\ &= (x_1 - x_0) + \sum_{i=2} (x_i - x_{i-1})(1 - F_X(x_{i-1}))\end{aligned}$$

90 where by choosing  $x_0$  to be the minimum edge weight  $P(X_{\text{ref}} = x_0) := 1$  and 0 elsewhere, and  
91  $P(X)$  is non-zero only for the node pair distances  $x_1, x_2, \dots$  with  $x_0 \leq x_1 < x_2 < \dots$ .

### 92 **Software availability**

93 Computational analyses were performed with Python version 3.4; scripts and Jupyter notebooks are  
94 available under the BSD license at [https://bitbucket.org/youngjh/yeast\\_chem\\_synergy](https://bitbucket.org/youngjh/yeast_chem_synergy).  
95 All plots were created with Matplotlib and Seaborn [Hunter et al., 2007].

## 96 **Results**

### 97 **Close proximity between drug target genes in the genetic interaction network** 98 **does not strongly predict synergy or antagonism**

99 We hypothesized that if two chemical compounds are synergistic, then the inhibition target genes  
100 of one compound would be close to those of the second compound in a negative genetic interaction  
101 network. Similarly, antagonistic compound pairs would have their respective targets near one

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102 another in a positive genetic network. Proximity between target genes were assessed in both  
103 unweighted and weighted genetic interaction networks. An experimental screen in *S. cerevisiae*  
104 provided the gold standard benchmark for testing the synergy hypothesis [Wildenhain et al., 2015].  
105 In this dataset, all possible pairs of 128 chemical compounds were screened, but only 7 compounds  
106 had inhibition target genes found in both the negative genetic network and the Search Tool for  
107 Interactions of Chemicals (STITCH) database. Thus, there were 21 possible pairs available for  
108 validation, three of which exhibited synergy from the screening results. None of the antagonistic  
109 compounds in this dataset contained targets listed in STITCH. As shown in Table 1, close proximity  
110 of the target genes were only weakly predictive of synergy, according to the area under the curve  
111 (AUC) from the receiver operating characteristic (ROC) analysis. The AUC from the unweighted  
112 network was reasonably consistent with that from the weighted network.

113 For the antagonism case, the gold standard was constructed from another experimental screen  
114 [Cokol et al., 2011]. Of the 200 pairs screened from 33 compounds, only 10 pairs had compounds  
115 whose inhibition targets were both listed in STITCH and in the positive genetic network. Of these  
116 10, 8 were experimentally determined to show antagonism. None of the synergistic compounds  
117 in this dataset contained targets listed in STITCH. No evidence was found to suggest that close  
118 proximity of target genes was predictive of antagonism (Table 1). In fact, the results suggest that  
119 the farther apart one set of target inhibition genes is from those of a second compound in the  
120 positive genetic network, the more likely the compound pairs are to be antagonistic. Strikingly,  
121 in contrast to the synergy case above, the AUC value from the unweighted network was quite far  
122 apart from that of the weighted network.

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### 123 **Genetic interaction strength is moderately correlated with network distance**

124 One assumption underlying our hypothesis was that any two genes that were not adjacent in the  
125 genetic interaction network but within a sufficiently small neighborhood of one another would still  
126 express some degree of interaction. Conversely, if the genes were located very far apart, they would  
127 essentially not interact at all. To examine the validity of this assumption, we sought to determine  
128 the correlation, if any, between a gene pair's distance in the network and its corresponding strength  
129 of genetic interaction. The interaction strength was simply the magnitude of the genetic interaction  
130 score  $|\epsilon|$  from the raw results of the synthetic genetic array (SGA) screening [Costanzo et al., 2010].  
131 The network distance of a gene pair was once again the distance computed from Dijkstra's algorithm  
132 as described above, such that smaller distances implied stronger interaction and consequently larger  
133  $|\epsilon|$ . Therefore, we expected to observe negative correlations for both negative and positive genetic.  
134 As shown in Figure 1, indeed the Spearman's rank correlation correlation is in fact moderately  
135 negative and statistically significant.

### 136 **Discussion**

137 Our results suggest that there is no evidence to support the claim that synergy or antagonism arises  
138 when the target genes of one chemical compound are close in a genetic interaction network to  
139 those of another compound. We confirmed previous results that such drug interactions are not  
140 directly mediated through genetic interactions [Cokol et al., 2011, Wildenhain et al., 2015], and also  
141 showed that neighborhoods of genetic interactions are neither a contributing factor as well. In the  
142 process, we presented an application of distance measures satisfying the mathematical definition  
143 of a metric to quantify proximity between sets of nodes in gene networks. Prediction performance  
144 was measured through AUC due to its robustness to unbalanced data in positive versus negative

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145 class labels [Jeni et al., 2013].

146 It is particularly notable that the gold standard for synergy produced results different than  
147 those from the antagonism gold standard. One potential contributing factor is that the benchmark  
148 derived from Cokol et al. used the Loewe additivity model [Loewe, 1953, Tallarida, 2006] to  
149 determine synergy and antagonism, while Wildenhain et al. instead utilized Bliss independence  
150 [Bliss, 1939]. The Bliss theory is closer to the multiplicative fitness model employed in calling  
151 negative and positive genetic interactions, which was defined as  $\epsilon_{ij} = f_{ij} - f_i f_j$  with  $f_{ij}$  equal to  
152 the double mutant fitness and  $f_i, f_j$  as the single mutant fitness scores [Costanzo et al., 2010].

153 The moderate correlation between genetic interaction strength and network distance goes  
154 some way towards supporting the results from the synergy gold standard, where AUCs of 0.57  
155 and 0.61 were attained. In any case, the weak correlation implies that genetic interactions cannot  
156 be reliably identified through “guilt-by-association” in the network. It should be noted that both  
157 datasets used to benchmark prediction performance were highly imbalanced, thus reflecting the  
158 need for even more data on which chemical compounds are synergistic or antagonistic, and  
159 which genes are inhibited by the compounds of interest. Yet despite the relatively limited data  
160 available to construct gold standards, our results and those of others indicate that a more nuanced  
161 mechanism beyond genetic interactions of target genes is responsible for explaining effects of  
162 chemical compound interactions.

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### 167 **References**

- 168 CI Bliss. The toxicity of poisons applied jointly. *Annals of Applied Biology*, 26(3):585--615, 1939.
- 169 Scott Cohen. *Finding color and shape patterns in images*. PhD thesis, Stanford University, 1999.
- 170 Murat Cokol, Hon Nian Chua, Murat Tasan, Beste Mutlu, Zohar B Weinstein, Yo Suzuki, Mehmet E  
171 Nergiz, Michael Costanzo, Anastasia Baryshnikova, Guri Giaever, et al. Systematic exploration  
172 of synergistic drug pairs. *Molecular Systems Biology*, 7(1):544, 2011.
- 173 Michael Costanzo, Anastasia Baryshnikova, Jeremy Bellay, Yungil Kim, Eric D Spear, Carolyn S  
174 Sevier, Huiming Ding, Judice LY Koh, Kiana Toufighi, Sara Mostafavi, et al. The genetic  
175 landscape of a cell. *Science*, 327(5964):425--431, 2010.
- 176 Vincent T DeVita and Edward Chu. A history of cancer chemotherapy. *Cancer Research*, 68(21):  
177 8643--8653, 2008.
- 178 Scott M Hammer, Kathleen E Squires, Michael D Hughes, Janet M Grimes, Lisa M Demeter,  
179 Judith S Currier, Joseph J Eron Jr, Judith E Feinberg, Henry H Balfour Jr, Lawrence R Deyton,  
180 et al. A controlled trial of two nucleoside analogues plus indinavir in persons with human  
181 immunodeficiency virus infection and cd4 cell counts of 200 per cubic millimeter or less. *New*  
182 *England Journal of Medicine*, 337(11):725--733, 1997.
- 183 John D Hunter et al. Matplotlib: A 2d graphics environment. *Computing in Science and Engineering*,  
184 9(3):90--95, 2007.
- 185 László A Jeni, Jeffrey F Cohn, and Fernando De La Torre. Facing imbalanced data--recommen-  
186 dations for the use of performance metrics. In *Affective Computing and Intelligent Interaction*  
187 *(ACII), 2013 Humaine Association Conference on*, pages 245--251. IEEE, 2013.
- 188 Michael Kuhn, Damian Szklarczyk, Sune Pletscher-Frankild, Thomas H Blicher, Christian von  
189 Mering, Lars J Jensen, and Peer Bork. Stitch 4: integration of protein--chemical interactions  
190 with user data. *Nucleic Acids Research*, page gkt1207, 2013.
- 191 S Loewe. The problem of synergism and antagonism of combined drugs. *Arzneimittel-Forschung*,  
192 3(6):285, 1953.
- 193 Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier  
194 Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. Scikit-learn:  
195 Machine learning in python. *The Journal of Machine Learning Research*, 12:2825--2830, 2011.
- 196 Yossi Rubner, Carlo Tomasi, and Leonidas J Guibas. The earth mover's distance as a metric for  
197 image retrieval. *International Journal of Computer Vision*, 40(2):99--121, 2000.

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---

- 198 Daniel A Schult and P Swart. Exploring network structure, dynamics, and function using networkx.  
199 In *Proceedings of the 7th Python in Science Conferences (SciPy 2008)*, volume 2008, pages  
200 11--16, 2008.
- 201 Ronald J Tallarida. An overview of drug combination analysis with isobolograms. *Journal of*  
202 *Pharmacology and Experimental Therapeutics*, 319(1):1--7, 2006.
- 203 Jan Wildenhain, Michaela Spitzer, Sonam Dolma, Nick Jarvik, Rachel White, Marcia Roy, Emma  
204 Griffiths, David S Bellows, Gerard D Wright, and Mike Tyers. Prediction of synergism from  
205 chemical-genetic interactions by machine learning. *Cell Systems*, 1(6):383--395, 2015.
- 206 Roberta J Worthington and Christian Melander. Combination approaches to combat multidrug-re-  
207 sistant bacteria. *Trends in Biotechnology*, 31(3):177--184, 2013.
- 208 Pamela J Yeh, Matthew J Hegreness, Aviva Presser Aiden, and Roy Kishony. Drug interactions  
209 and the evolution of antibiotic resistance. *Nature Reviews Microbiology*, 7(6):460--466, 2009.

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### 210 **Tables**

	Synergy	Antagonism
Unweighted network	0.61	0.41
Weighted network	0.57	0.19

Synergy and antagonism prediction performance assessed by AUC, the area under the receiver operating characteristic (ROC) curve.

Table 1: Chemical compound pairs were scored and ranked for synergy or antagonism by the distance between their inhibition targets in a genetic interaction network. The predictions were validated through receiver operating characteristic (ROC) analysis with true interactions labeled according to gold standards for synergy and antagonism. In the synergy case, target gene proximity is only marginally more predictive than random for chemical synergy or antagonism.

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### 211 Figures

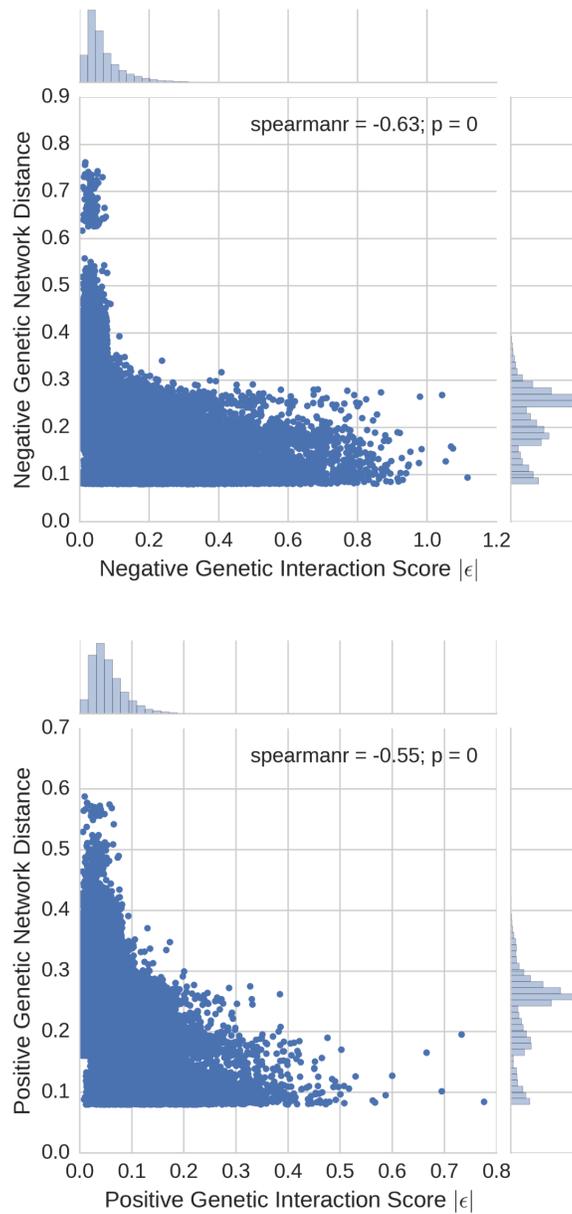


Figure 1: The magnitude of the genetic interaction score  $\epsilon$  is moderately anti-correlated with gene network distance. Thus, the greater the growth deviation from expectation of a double mutant, the closer the two genes are in the genetic interaction network.