

# Network-based approach for drug repurposing using drug signature and disease phenotype

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# Summary

- Introduction
- The data
- Principle of the method
- Implementation
- Results

# Introduction

- Drug repurposing consists of the investigation of already used drugs, to see if they can be used for treating other diseases.
- Interesting because it is a fast and cost-effective strategy for drug discovery and launching.
- Drug–disease associations prediction method based on a recommendation system (bipartite graph) where the studied features are the drug signatures and diseases phenotypes.

# The data

Drug signatures  
and disease phenotypes

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# Gene expression profiles

- **Disease phenotype:**

A list of genes that are up or down-regulated when compared to healthy controls.

48 diseases and 11,393 genes.

- **Drug signature:**

Gene expression response within cells when they are stimulated with a drug.

617 drugs and 12,717 genes.

	GSK-3-inhibitor-II	idelalisib	Salermide
RNF14	0.013539515	0.002370315	1.60E-05
UBE2Q1	-0.003986923	0.002493697	-0.005188018
RNF17	-0.013635419	-0.007685559	0.000911763
RNF10	-0.01313385	0.022245417	0.005333798
RNF11	0.005126541	0.000776593	0.012249535
C6ORF123	-0.002572781	-0.005962765	-0.003951608
RNF13	0.006363582	-0.000873812	0.001708042

# Drug-disease associations table

Table referencing some approved drug-disease associations.

- 7325 matches of 1543 distinct drugs and 1465 distinct diseases.
- 48/48 diseases of the phenotypes tables are in the association table.
- 45/617 of the drugs in the signatures are in the association table.

In total: 2115 distinct drugs and 1465 distinct diseases.

Drug	Disease	Status
Cetuximab	Malignant tumor of colon	Approved
Dornase alfa	Cystic Fibrosis	Approved
Denileukin diftitox	Lymphoma, T-Cell, Cutaneous	Approved
Etanercept	Rheumatoid Arthritis	Approved
Leuprolide	Endometriosis	Approved
Peginterferon alfa-2a	Hepatitis C, Chronic	Approved
Alteplase	Acute myocardial infarction	Approved
Sermorelin	Pituitary dwarfism	Approved
Urokinase	Pulmonary Embolism	Approved

# Principle of the method

Similarity metrics and  
recommendation systems

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# Statistically Significant Connectivity Map (ssCMap)

Connectivity between two drugs or two diseases with a signature of  $N$  genes?

The  $i^{\text{th}}$  most important gene effect will be assigned the rank  $(N-i+1)$  if it is upregulated and  $-(N-i+1)$  if it is downregulated.

ssCMap connectivity score with  $R_1$  and  $R_2$  the ranks :

$$C(R_1, R_2) = \frac{\sum_{i=1}^N R_1(g_i) R_2(g_i)}{\sum_{i=1}^N (N - i + 1)^2}$$



# Recommendation systems

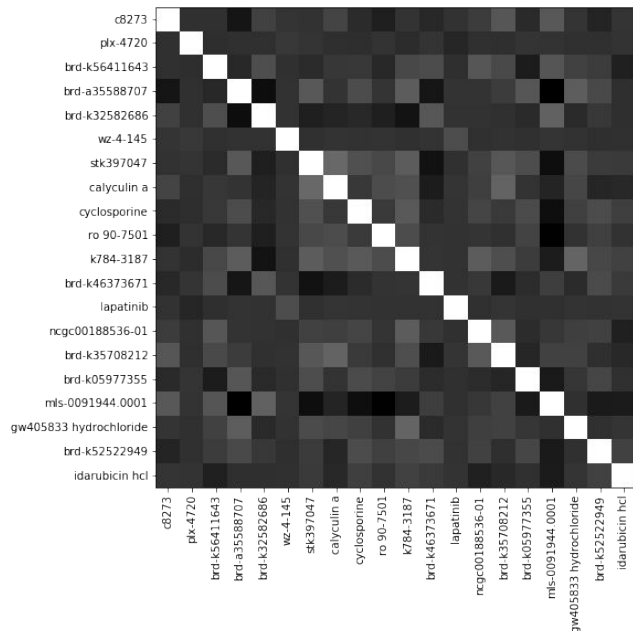
# Implementation

Computation of the matrices,  
choice of parameters

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# $S^{\text{drug}}$ and $S^{\text{disease}}$ the drug-drug and disease-disease similarity matrices

Computed with the previous formula + normalization between 0 and 1. Extract:



$S^{dd}$  the disease-disease similarity matrix based on the interactions with similar drugs in the network

If two diseases  $i$  and  $j$  are linked by many highly similar drugs then  $s_{ij}^{dd}$  will be high. It is computed with:

$$s_{ij}^{dd} = \frac{\sum_{k=1}^{N_{\text{drug}}} \sum_{l=1}^{N_{\text{drug}}} (a_{il} a_{jk} s_{lk}^{\text{drug}})}{\sum_{k=1}^{N_{\text{drug}}} \sum_{l=1}^{N_{\text{drug}}} (a_{il} a_{jk})}$$

# Final disease-disease similarity matrix S

Combination of  $S^{\text{dd}}$  and  $S^{\text{disease}}$  :

$$s_{ij} = \alpha s_{ij}^{\text{disease}} + (1 - \alpha) s_{ij}^{\text{dd}}$$

$\alpha$  is a parameter to choose to get the best results.

To do that, we computed S for different values of  $\alpha$ , with cross-validation.

# Weight matrix $W$

Matrix of weights (corresponding to objection-projection of the bipartite graph) such that the reco can be computed with  $R = W \times A$ .

$$w_{ij} = \frac{s_{ij}}{k(t_i)^{1-\lambda} k(t_j)^\lambda} \sum_{l=1}^{N_{\text{drug}}} \frac{a_{il} a_{jl}}{k(d_l)}$$

$\lambda$  is a parameter to choose to get the best results.

To do that, we computed  $W$  for different values of  $\lambda$ , with cross-validation.

# Cross-validation

- 10 folds
- Each time removing 20% of the associations from the A table
- Testing each fold with 81 W matrices with combinations of parameters  $\lambda$  and  $\alpha$
- Total: 810 W matrices
- Best recovery of missing associations with  $\lambda=0.1$  and  $\alpha=0.1$

# Results

Examples of interesting  
results

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ind_id	abdominal actinomycosis	previous reco
benzylpenicillin	1.000000	1
phenoxymethylpenicillin	0.845747	0
procaine benzylpenicillin	0.727375	0
cefixime	0.540433	0
cefradine	0.537274	0
cefprozil	0.529992	0
cefaclor	0.529436	0
cyclacillin	0.354836	0
cephalexin	0.328189	0
antipyrine	0.303486	0

ind_id	addison disease	previous reco
fludrocortisone	0.131250	1
hydrocortisone	0.097084	1
cortisone acetate	0.097005	1
prednisone	0.085866	1
dalfampridine	0.081788	0
glatiramer acetate	0.081788	0
betamethasone	0.079831	1
dexamethasone	0.079320	1
triamcinolone	0.074891	1
prednisolone	0.072578	1

ind_id	alcohol withdrawal delirium	previous reco
chlordiazepoxide	1.000000	1
oxazepam	1.000000	1
diazepam	1.000000	1
clorazepate	0.554800	0
etizolam	0.442906	0
halazepam	0.442906	0
chlormezanone	0.442906	0
ethyl loflazepate	0.442906	0
meprobamate	0.442906	0
trifluoperazine	0.442906	0

ind_id	hypersomatotropic gigantism	previous reco
lanreotide	1.000000	1
pegvisomant	0.772644	0
lisuride	0.381525	0
bromocriptine	0.211878	0
octreotide	0.132879	0
abacavir	0.000000	0
olsalazine	0.000000	0
oritavancin	0.000000	0
orciprenaline	0.000000	0
oprelvekin	0.000000	0