Drug Side-Effects Predictions with Random Walk with Restart

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ABSTRACT

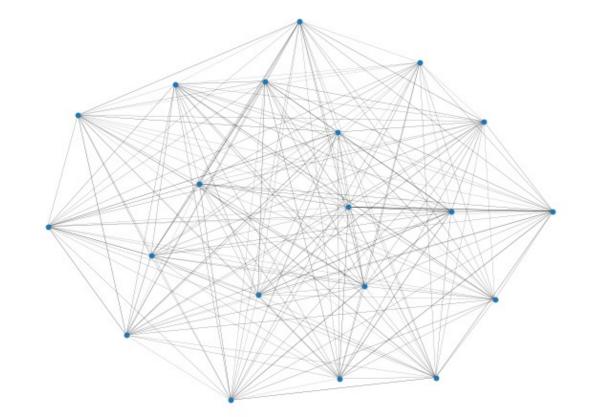
- Heterogeneous network of drug and side-effects is constructed based on side-effect similarity, drug chemical structures, and drug protein targets similarity.
- Random walk with restart is applied to the heterogeneous network of drug and side-effects to get the ranking of possible side-effect candidates of a drug from the steadystate probability distribution.

INTRODUCTION

- Side effects are considered as disturbances in the form of molecular intercommunication such as protein-protein communication or signal pathways.
- Predicting drug side effects then requires **network information** on the drug compounds, protein targets, and the side effects.
- Random walk is the state of the art network analysis method that relies on 'guilt by association' principle: molecules that are closer in the network tend to have similar properties.
- Random walk with restart introduces the restart
 probability of walking back to the seed nodes at each
 timestep to capture the local neighborhood of the seed
 nodes as well as the network global structure.

METHOD

Side-Effect Network:



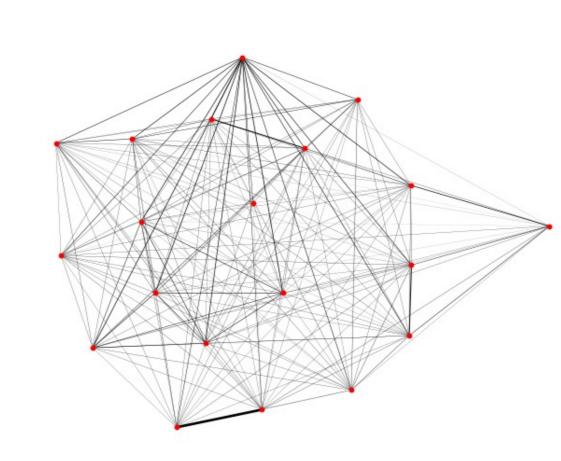
Similarity Matrix:

$$S_s(i,j) = rac{|\Gamma_d(i) \cap \Gamma_d(j)|}{|\Gamma_d(i) \cup \Gamma_d(j)|}$$
 $ar{S}_s = D_s^{-rac{1}{2}} S_s D_s^{-rac{1}{2}}$

Transition Matrix:

$$M_{ss}(i,j) = p(s_j|s_i) = \frac{(1-\lambda)\bar{S}_s(i,j)}{\sum_k \bar{S}_s(i,k)}$$

Drug Network:



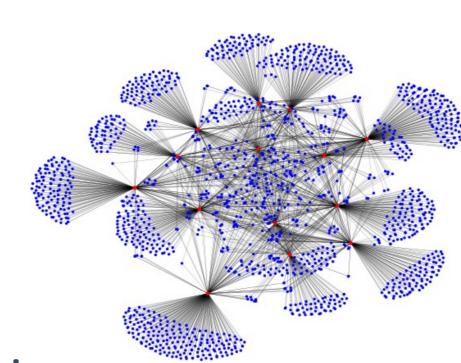
Similarity Matrix:

$$S_d^t(i,j) = rac{|\Gamma_t(i) \cap \Gamma_t(j)|}{|\Gamma_t(i) \cup \Gamma_t(j)|}$$
 $S_d^c(i,j) = ext{DiceSimilarity}(i,j)$
 $S_{dd} = w_d ar{S}_d^c + (1 - w_d) ar{S}_d^t$

Transition Matrix:

$$M_{dd}(i,j) = p(d_{j}|d_{i}) = \begin{cases} \frac{S_{dd}(i,j)}{\sum_{k} S_{dd}(i,k)}, & \text{if } \sum_{k} A_{dd}(i,k) = 0 \\ \frac{(1-\lambda)S_{dd}(i,j)}{\sum_{k} S_{dd}(i,k)}, & \text{otherwise} \end{cases}$$

Drug-Side Effect Network:



Transition Matrix:

$$M_{sd}(i,j) = p(d_j|s_i) = \begin{cases} \frac{\lambda A_{sd}(j,i)}{\sum_k A_{sd}(k,i)}, & \text{if } \sum_k A_{sd}(k,i) \neq 0\\ 0, & \text{otherwise} \end{cases}$$

$$M_{ds}(i,j) = p(s_j|d_i) = \begin{cases} \frac{\lambda A_{ds}(i,j)}{\sum_k A_{ds}(i,k)}, & \text{if } \sum_k A_{ds}(i,k) \neq 0\\ 0, & \text{otherwise} \end{cases}$$

Transition matrix of the heterogeneous network:

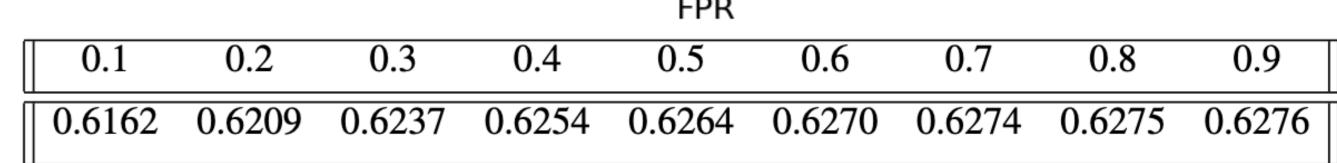
$$M = \begin{bmatrix} M_{ss} & M_{sd} \\ M_{ds} & M_{dd} \end{bmatrix}$$

Random Walk with Restart:

Iterative Update:
$$p_{t+1} = (1-\alpha)M^T p_t + \alpha p_0$$

Analytical Solution:
$$p=lpha(I-(1-lpha)M^T)^{-1}p_0$$

RESULTS 1.0 0.8 0.0 RWR RWR (with 10% of known side-effects as seed nodes) Random Ranking Rank Cutoff 1.0 0.8



RWR (with 10% of known side-effects as seed nodes), AUC=0.6226

RWR, AUC=0.6209

AUC of different restart probability values

CONCLUSION

- We integrate multiple network information to construct a heterogeneous network and apply the random walk with restart starting from the query drug.
- The side-effect ranking obtained is better than the random ranking, showing the potential of using biological network data for side-effect prediction.
- Performance could be improved by obtaining more relevant biological network information to better define the transition matrix.

REFERENCES

[1] S. R. Atias N, "An algorithmic framework for predicting side effects of drugs," J Comput Biol, vol. 18, p. 207, 2011.

[2] X. Chen, M. Liu, and G. Yan, "Drug-target interaction prediction by random walk on the heterogeneous network," Molecular bioSystems, vol. 8, pp. 1970–8, 04 2012.