

# Social-Network Analysis for Pain Medications: Influential physicians may not be high-volume prescribers

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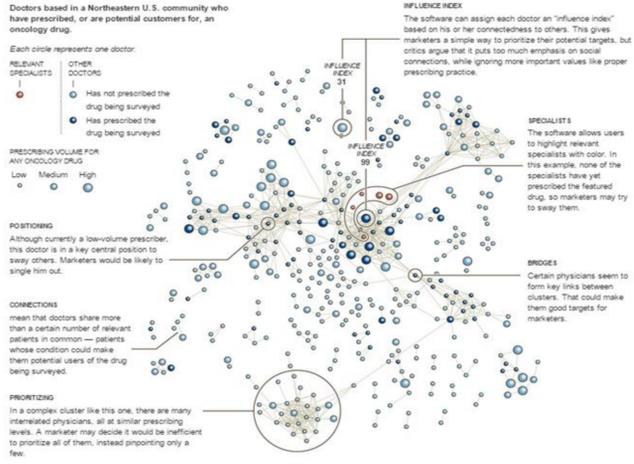
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Brain—Behavior  
Computation **ACSLAB**



## Introduction

### Social Network Analysis in Medical Domain



## Method

### Assumptions for building the social networks:

- Working in the same hospital
- Same specialty
- Same Specialty group (similar specialties are clustered into groups)

### Assumptions for creating the Directed Influence graph

- Pain medication prescription
- Time of adoption

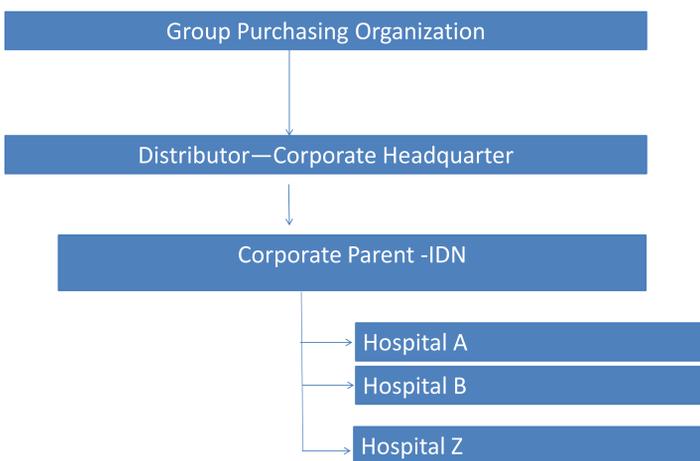


Fig. 2. Hierarchy of Hospitals in USA

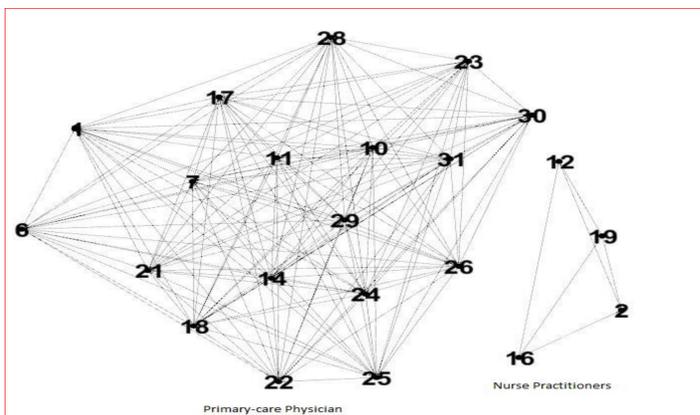


Fig. 3. Directed Influence graph between different prescribers of pain medication. The numbers associated with each node are the identification number of each physician. Two isolated clusters of specialty group (PCP and Nurse Practitioner) are visible

## Results

1. Physicians from specialty internal medicine and family medicine i.e. Primary care Providers had the highest in-degree centrality within the IDN
2. Neurology and nurse practitioners were the ones prescribing the highest volumes of medication within the IDN
3. Females physicians (mostly nurse-practitioners) were prescribing higher volume of scripts compared to male physicians

## Limitations

- Single Integrated Delivery Network (IDN) located in Massachusetts, USA
- One pain medication for creating the directed Influence graph
- In addition, we also assumed that a physician prescribing a pain medication before other physicians in their social network would influence these physicians in their social network with certainty

## Future Scope

- We plan to improve our assumptions by considering multitude of IDNs consisting of several physicians over several hospitals prescribing several pain medications
- Using referral patterns, author-coauthor relationship for creating the social network
- Furthermore, we also plan to improve our diffusion of innovation assumptions by parameterizing the diffusion process using a probability as well as by considering other data that indicates stronger diffusion possibilities in the network

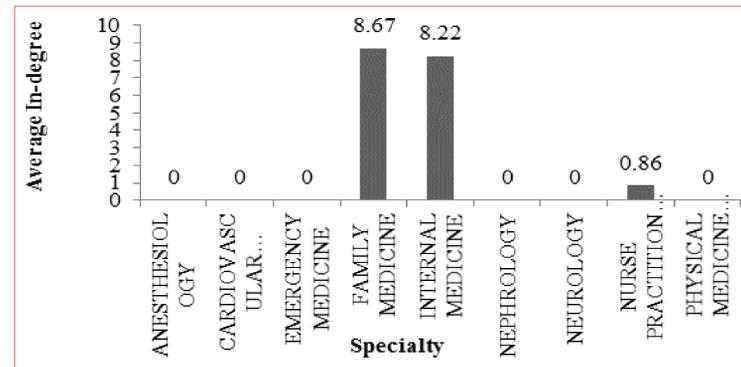


Fig. 4. Average In-degree for different specialties

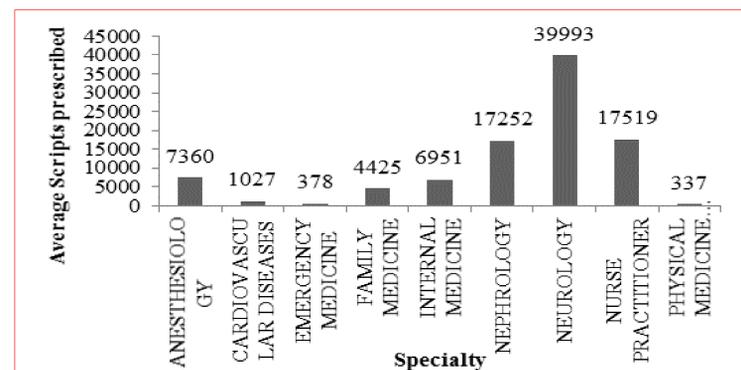


Fig. 5. Average number of scripts prescribed for different specialty

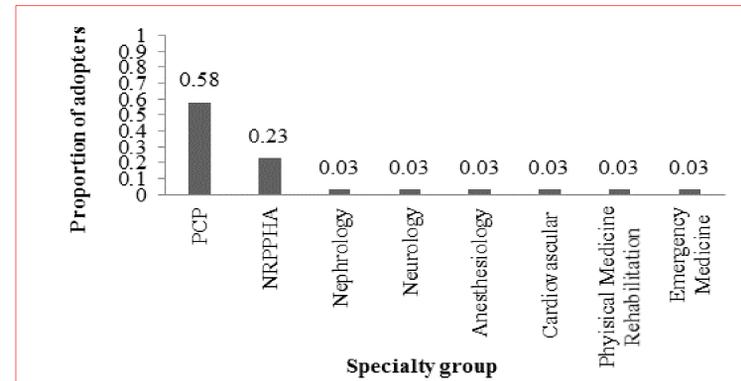


Fig. 6. Proportion of physicians adopting medicine M from different specialty group

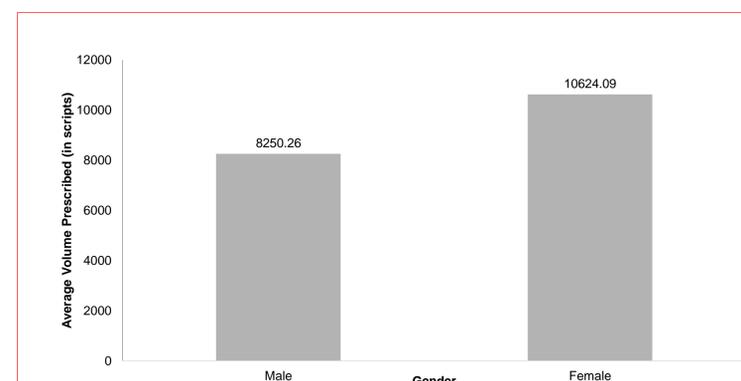


Fig. 7. Average number of scripts prescribed for different gender

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## Data

### Health Database

- Physician's dataset (80,000+): contains physician's geographical data, specialty etc.
- Prescription and sales dataset (1 billion): contains every physician's prescription history

### Affiliation Database

- Business dataset (1 million): contains hospital affiliation and hierarchy data
- Physician's affiliation dataset (3.2 million): contains data regarding affiliation of physicians' to different Health center's

Medication Duration: January-2011-March 2016