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Dynamic Healthcare Embeddings for Improving Patient Care

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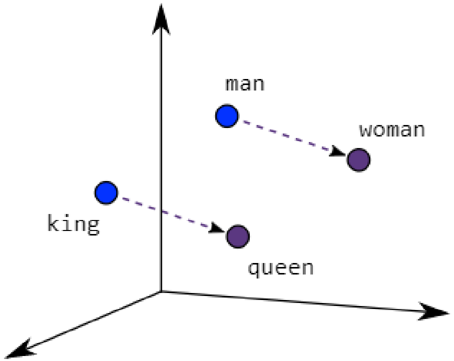
Contents

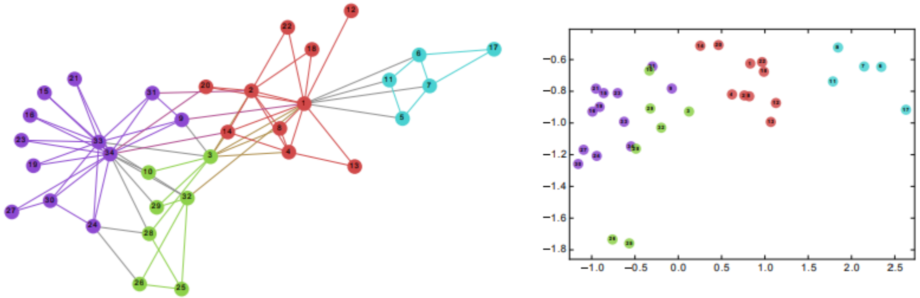
Background on learning embeddings

What are embeddings?

Embedding is a vector representation of an entity (words, nodes, etc)



Word embedding



(a) Input: Karate Graph

(b) Output: Representation

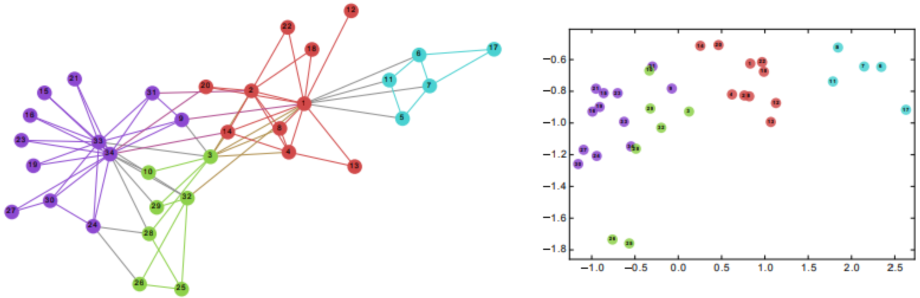
Node embedding

(http://www.perozzi.net/)

Background on learning embeddings

Why learn embeddings?

We can use the learned embeddings in various downstream ML tasks



(a) Input: Karate Graph (b) Output: Representation

- **Node classification** on partially labelled graph

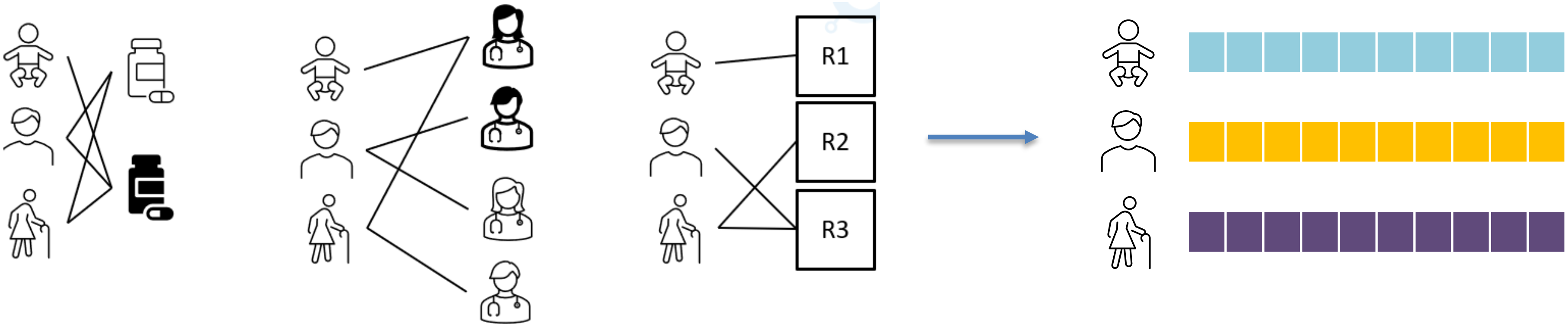
- **Link prediction** on unobserved or future links

Node embedding
(http://www.perozzi.net/)

Patient embedding

What are patient embeddings?

Vector representation of patients that captures **medical history** of patients

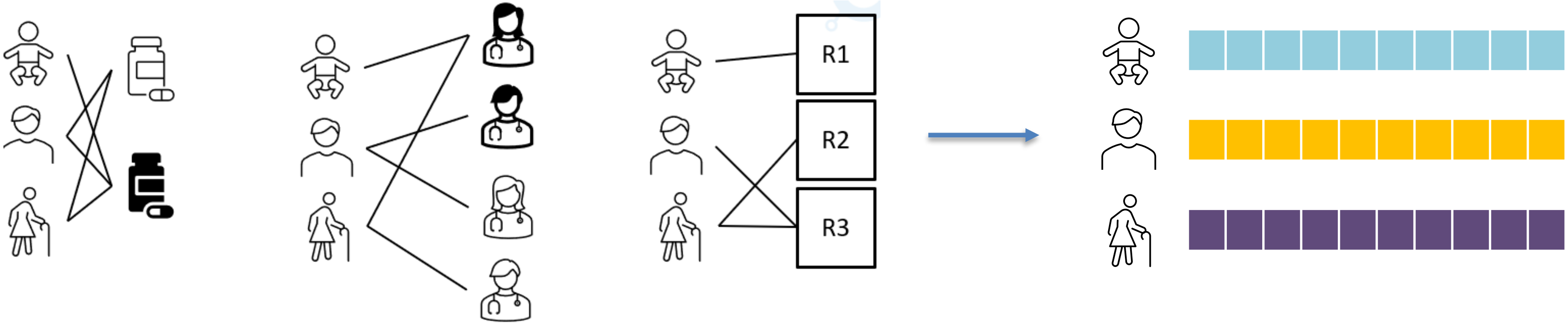


Patient embedding

Why learn patient embeddings?

We can use patient embeddings in various prediction tasks in healthcare

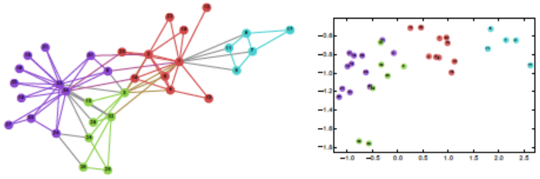
- sudden ICU transfer, infectious disease infection, length of stay at hospital, etc



Before we dive in to patient embedding methods, let's go over different **types** of **network embedding**

Network embedding methods

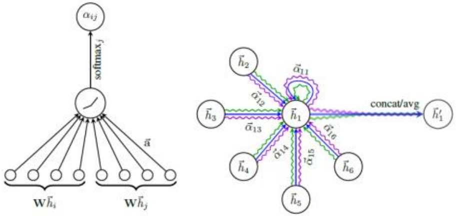
Unsupervised embedding



(a) Input: Karate Graph (b) Output: Representation

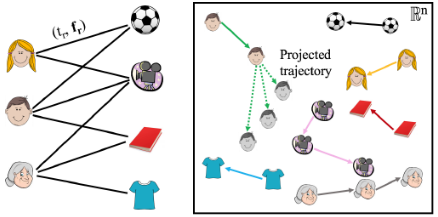
DeepWalk [+]: ***node embedding*** is learned by maximizing the likelihood of observing nearby nodes
Variation: ***walk***

Supervised embedding



GCN [-]: Learn ***node embedding*** by ***end-to-end*** node classification task
Variation: ***feature aggregation***

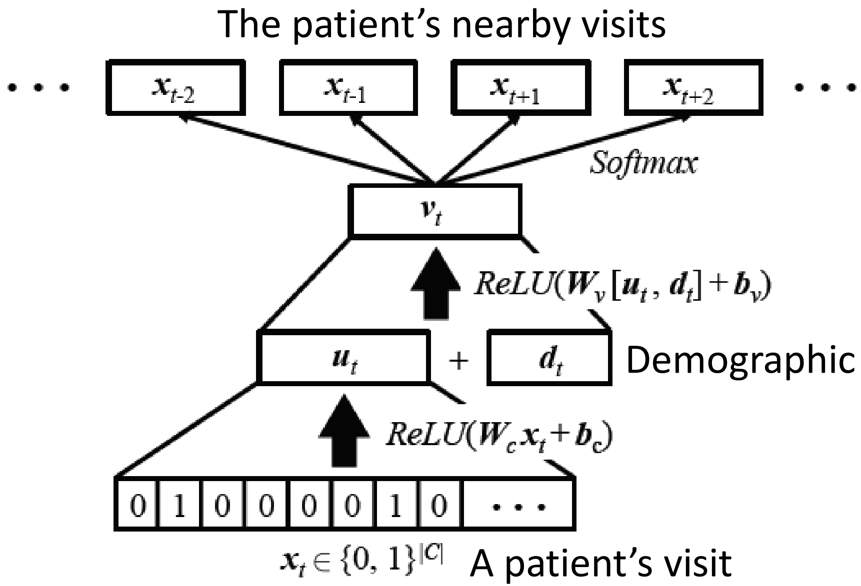
Dynamic embedding



JODIE [*]: Learns ***user embedding*** and ***item embedding over time*** based on interactions by predicting future interaction

[+] B. Perozzi et al., "DeepWalk: online learning of social representations," KDD 14
[-] T. N. Kipf and M. Welling, "Semi-Supervised Classification with Graph Convolutional Networks," ICLR 17
[*] S. Kumar, X. Zhang, and J. Leskovec, "Predicting dynamic embedding trajectory in temporal interaction networks,", KDD 19

Patient embedding (unsupervised)

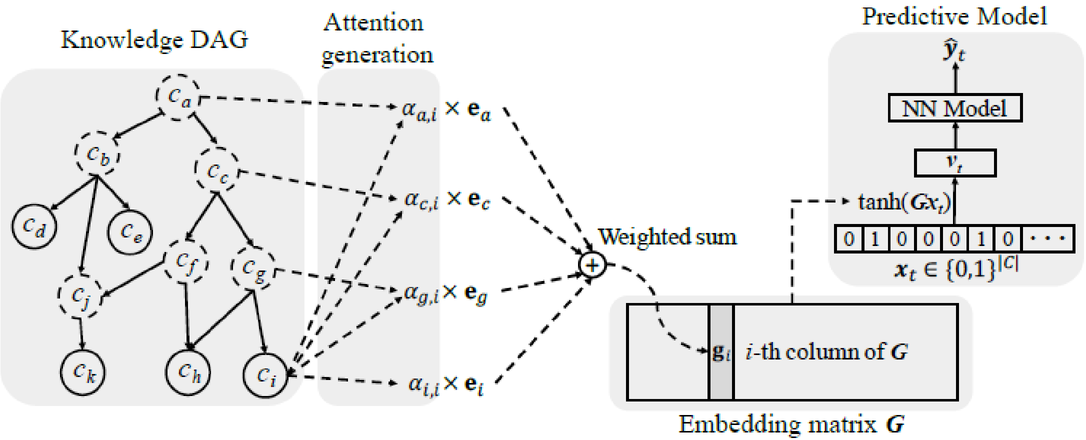


Med2Vec: ***patient visit embedding*** is learned by maximizing the likelihood of observing nearby visits

DeepWalk	**Med2Vec**
Node	Patient visit
Nodes in Random walk	Nearby visit

E. Choi et al., "Multi-layer representation learning for medical concepts," KDD '16

Patient embedding (supervised)



GRAM: Learn ***patient embedding*** by ***end-to-end*** classification task on the onset of a disease

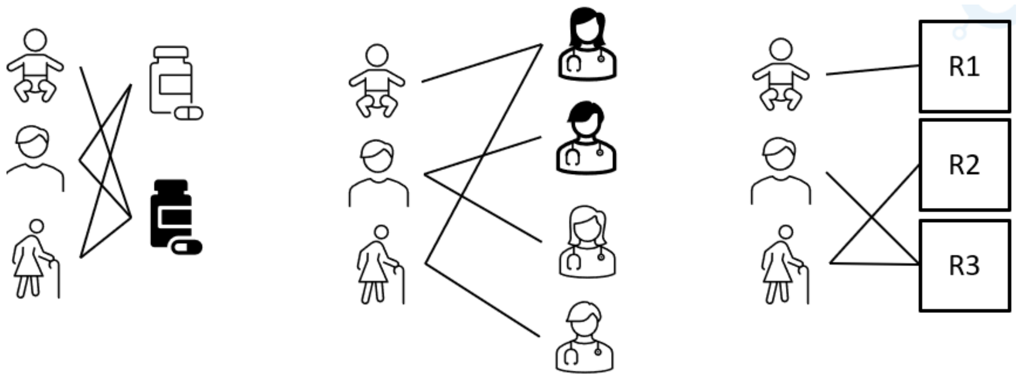
$$\begin{aligned} \mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_t &= \tanh(\mathbf{G}[\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_t]), \\ \mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_t &= \mathrm{RNN}(\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_t, \theta_r), \\ \widehat{\mathbf{y}}_t = \widehat{\mathbf{x}}_{t+1} &= \mathrm{Softmax}(\mathbf{W}\mathbf{h}_t + \mathbf{b}), \end{aligned}$$

Learn ***medical concept embedding*** during training

$$\alpha_{ij} = \frac{\exp(f(\mathbf{e}_i, \mathbf{e}_j))}{\sum_{k \in \mathcal{A}(i)} \exp(f(\mathbf{e}_i, \mathbf{e}_k))} \qquad f(\mathbf{e}_i, \mathbf{e}_j) = \mathbf{u}_a^\top \tanh(\mathbf{W}_a \begin{bmatrix} \mathbf{e}_i \\ \mathbf{e}_j \end{bmatrix} + \mathbf{b}_a)$$

E. Choi et al., "Gram: graph-based attention model for healthcare representation learning," KDD 2017

Patient embedding (dynamic)



DECEnt: Learns patient embedding and {doctor, medication, room} embedding over time

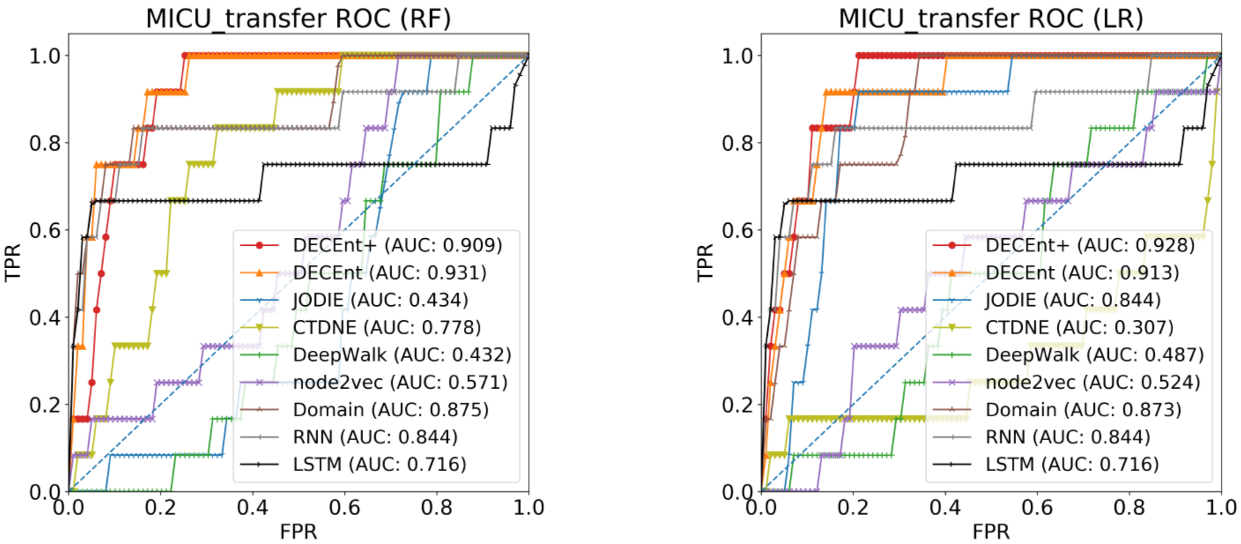
Architecture: Auto-encoding heterogeneous co-evolving dynamic neural network

Optimize on reconstructing current interaction item

For each interaction (e.g., patient-doctor) DECEnt reconstructs **current interaction item** (e.g., doctor) via auto-encoder

H. Jang, S. Lee, H. Hasan, S. Pemmaraju, B. Adhikari, "Dynamic Healthcare Embeddings for Improving Patient Care", ***in submission***

Patient embedding (dynamic) – results



Detecting patients who will get transferred to medical ICU a day before the event

H. Jang, S. Lee, H. Hasan, S. Pemmaraju, B. Adhikari, "Dynamic Healthcare Embeddings for Improving Patient Care", ***in submission***

Patient embedding (dynamic) – results

Method	AUC		
RNN	0.56 (0.119)		
LSTM	0.585 (0.103)		
-	LR	RF	MLP
Domain	0.655 (0.123)	0.709 (0.104)	0.582 (0.137)
DeepWalk	0.494 (0.087)	0.487 (0.093)	0.492 (0.103)
Node2Vec	0.453 (0.098)	0.43 (0.106)	0.478 (0.1)
CTDNE	0.463 (0.101)	0.528 (0.079)	0.483 (0.116)
JODIE	0.552 (0.192)	0.377 (0.177)	0.469 (0.176)
DECEnt	0.732 (0.069)	0.711 (0.08)	0.668 (0.082)
DECEnt +	**0.736 (0.064)**	0.717 (0.078)	0.664 (0.091)

[a]The value in bold denotes best performance

Detecting patients who will get CDI 3 days prior to the event

H. Jang, S. Lee, H. Hasan, S. Pemmaraju, B. Adhikari, "Dynamic Healthcare Embeddings for Improving Patient Care", ***in submission***

Patient embedding (dynamic) – results

Method	**Mortality**	**Severity**
RNN	0.276 (0.039)	0.31 (0.032)
LSTM	0.289 (0.033)	0.308 (0.026)
Domain	0.22 (0.017)	0.258 (0.007)
DeepWalk	0.172 (0.034)	0.192 (0.019)
Node2Vec	0.172 (0.02)	0.196 (0.009)
CTDNE	0.184 (0.019)	0.199 (0.007)
JODIE	0.143 (0.039)	0.193 (0.014)
DECEnt	0.421 (0.027)	0.34 (0.014)
DECEnt+	**0.428 (0.022)**	**0.349 (0.015)**

[a]The value in bold denotes best performance

Average F1 Macro scores on predictive tasks of mortality and severity risk of a patient

H. Jang, S. Lee, H. Hasan, S. Pemmaraju, B. Adhikari, "Dynamic Healthcare Embeddings for Improving Patient Care", ***in submission***

Thank you!