

CUAI GNN 스터디

2022.03.22

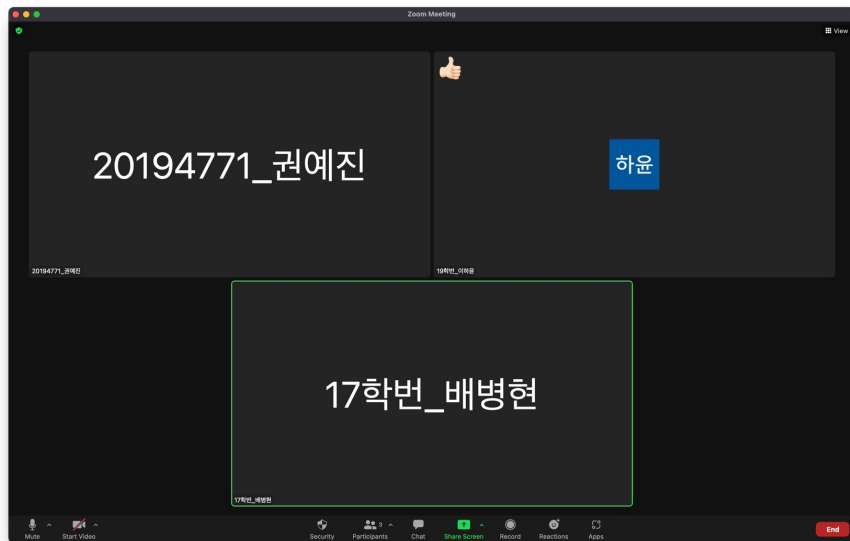
발표자 : 이하윤

목차

1. 스터디 소개 및 만남 인증
2. Node Embedding 소개

스터디원 소개 및 만남 인증

첫번째 미팅: 22.03.10 ZOOM



스터디원 1 : 권예진

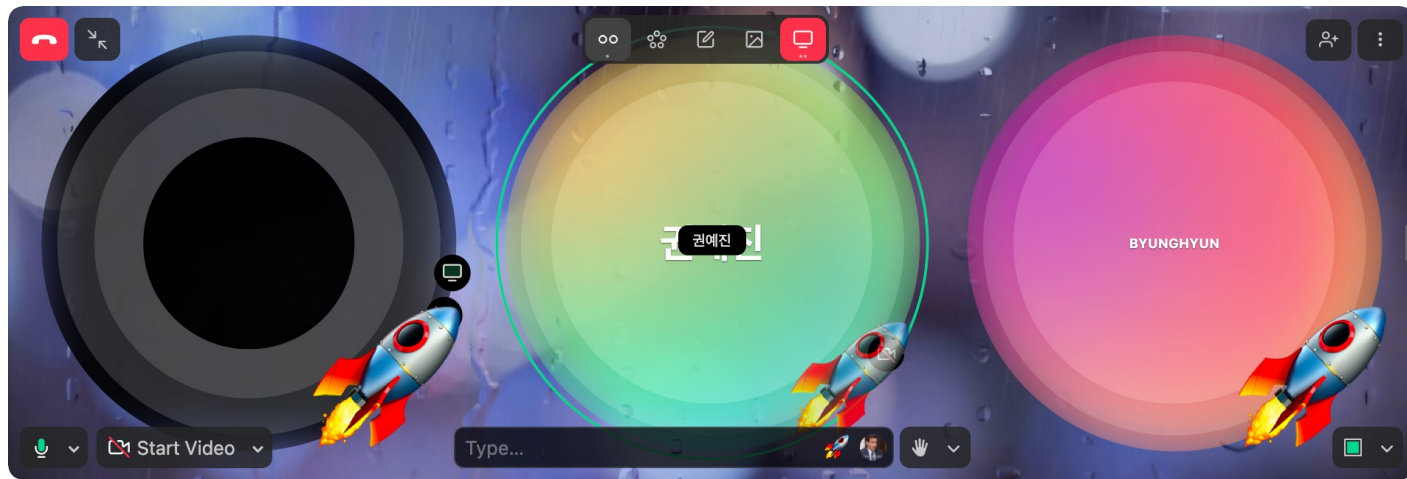
스터디원 2 : 이하윤

스터디원 3 : 배병현

- 스터디 규칙 및 진도 정하기

스터디원 소개 및 만남 인증

두번째 미팅: 22.03.17 Around



1. Introduction; Machine Learning for Graphs
2. Traditional Methods for ML on Graphs
3. Node Embeddings

스터디원 소개 및 만남 인증

두번째 미팅: 22.03.17 Around

The screenshot shows a presentation slide titled "Learn Walk Embeddings" with handwritten notes in pink and blue. The slide content includes:

- Run T different random walks from u each of length l :
 $N_R(u) = \{w_1^u, w_2^u \dots w_T^u\}$ (Handwritten: \hookrightarrow Neighbors)
- Learn to predict walks that co-occur in Δ -size window
- Estimate embedding z_i of anonymous walk w_i . Let η be number of all possible walk embeddings

Objective:
$$\max_{z, \Delta} \frac{1}{T} \sum_{t=\Delta}^{T-\Delta} \log P(w_t | \{w_{t-\Delta}, \dots, w_{t+\Delta}, z_G\})$$

$$P(w_t | \{w_{t-\Delta}, \dots, w_{t+\Delta}, z_G\}) = \frac{\exp(y(w_t))}{\sum_{i=1}^{\eta} \exp(y(w_i))}$$
 (Handwritten: $\sum_{w \in N_R(u)} P(N_R(u) | z_u$)
All possible walks (require negative sampling)

- $y(w_t) = b + U \cdot \left(\text{cat}(\frac{1}{2\Delta} \sum_{i=-\Delta}^{\Delta} z_i, z_G) \right)$
 - $\text{cat}(\frac{1}{2\Delta} \sum_{i=-\Delta}^{\Delta} z_i, z_G)$ means an average of anonymous walk embeddings in window, concatenated with the graph embedding z_G
 - $b \in \mathbb{R}, U \in \mathbb{R}^D$ are learnable parameters. This represents a linear layer.

Anonymous Walk Embeddings, ICLR 2018 <https://arxiv.org/pdf/1805.11921.pdf>
Jure Leskovec, Stanford CS224W: Machine Learning with Graphs, <http://cs224w.stanford.edu>

3 / 50

Unmute Start Video Type... Productivity Stop Chillhop

THOI

두번째 미팅: 22.03.17 Around

Graph Representation Learning

Graph Representation Learning alleviates the need to do feature engineering **every single time**.

Input Graph → Structured Features → Learning Algorithm → Prediction

~~Feature Engineering~~

Representation Learning -- Automatically learn the features

Downstream prediction task

Stanford University

Stanford CS224W: Machine Learning with Graphs

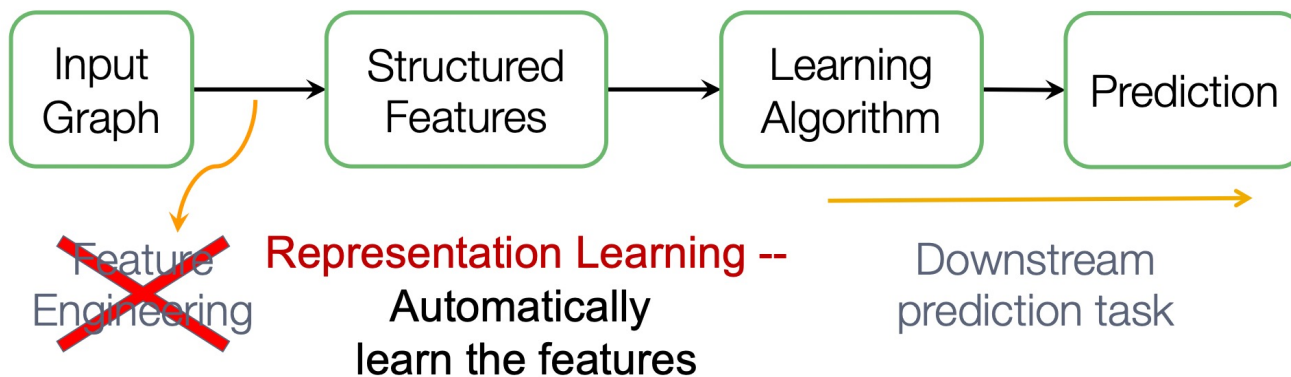
Instructor: Prof. Jure Leskovec

Lecture 3.1: Node Embeddings

3 / 50

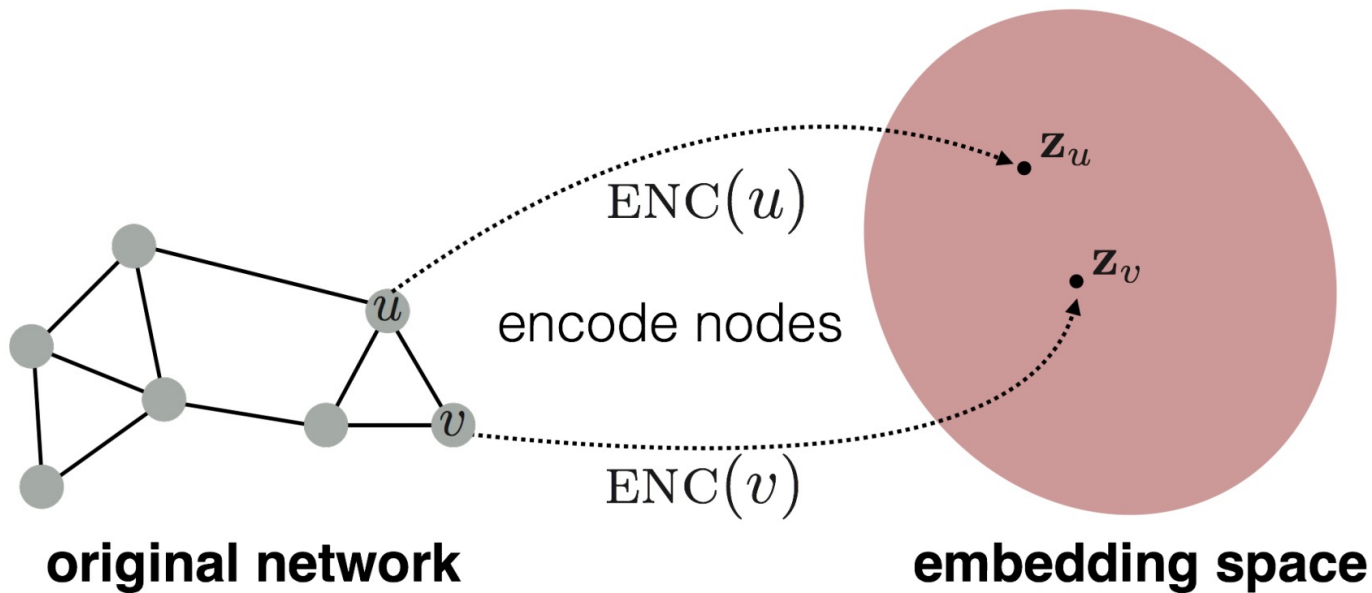
Node Embedding

Machine learning in graph



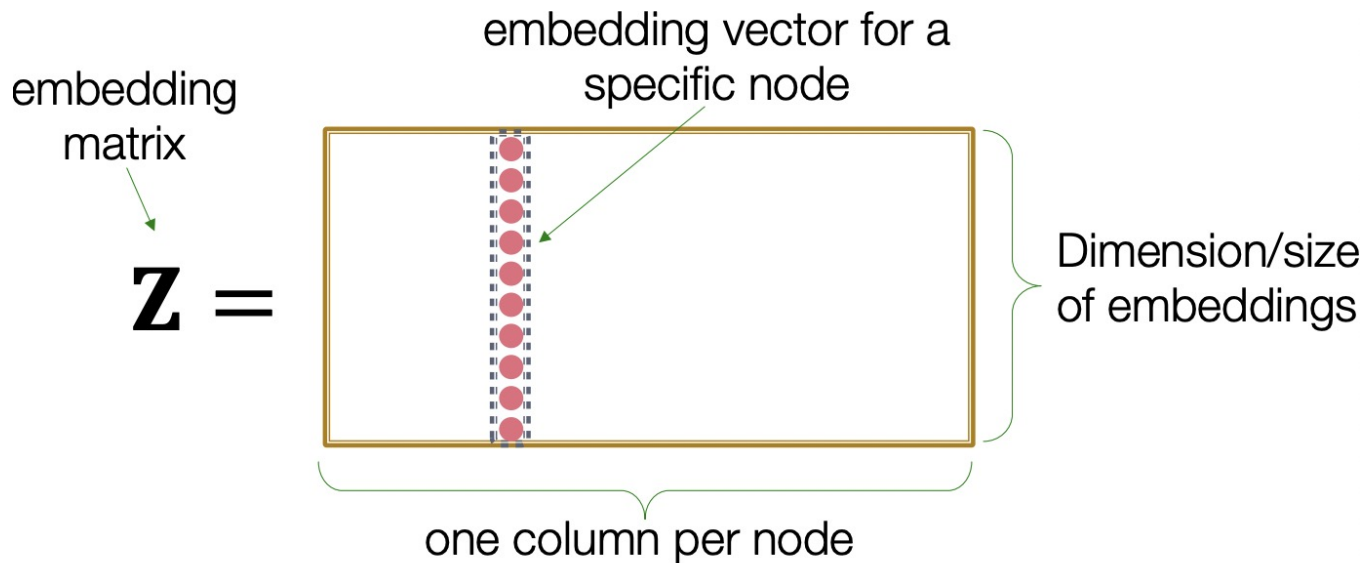
Node Embedding

Goal



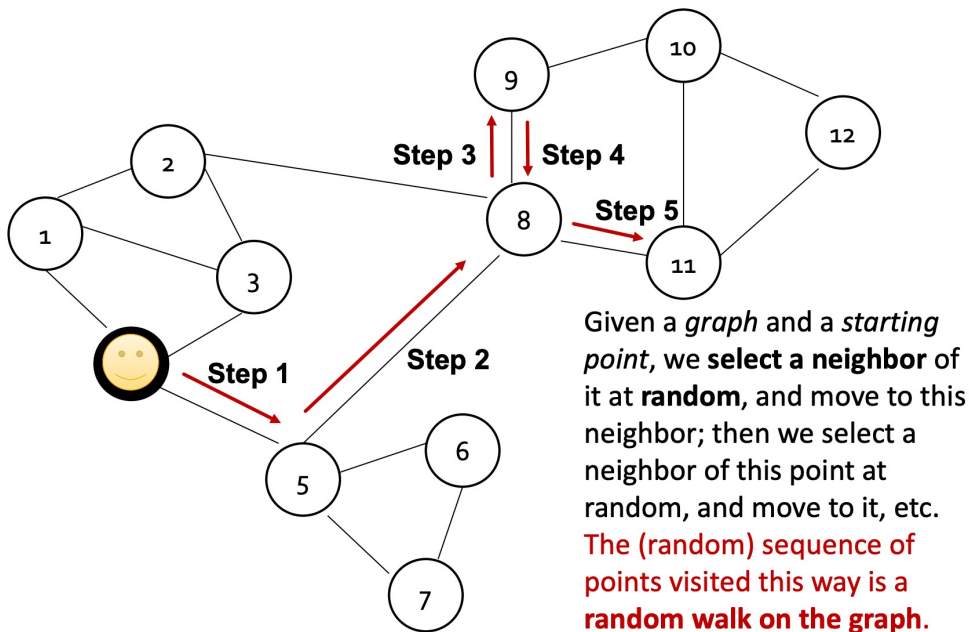
Node Embedding

Encoder : Just an embedding-lookup



Node Embedding

Node/vector 간의 similarity를 어떻게 정의하는가; Random Walk



Why Random Walk?

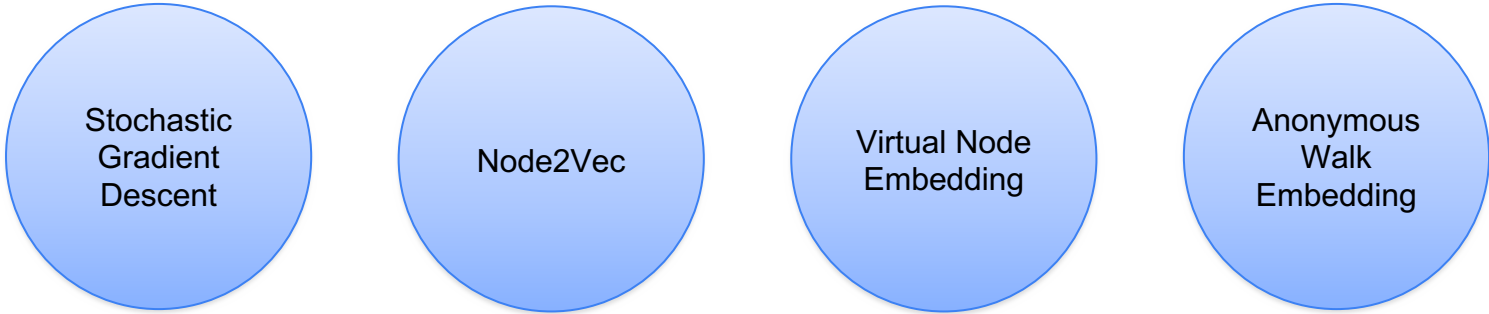
- Expressivity
- Efficiency

Node Embedding

Negative Sampling : K 개를 샘플링하는 것으로 모든 노드 V 를 대체

- Sample k negative nodes each with prob. proportional to its degree
- Two considerations for k (# negative samples):
 1. Higher k gives more robust estimates
 2. Higher k corresponds to higher bias on negative eventsIn practice $k = 5-20$

Node Embedding



Stochastic
Gradient
Descent

Node2Vec

Virtual Node
Embedding

Anonymous
Walk
Embedding