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# Graph Representation Learning

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# Message Passing

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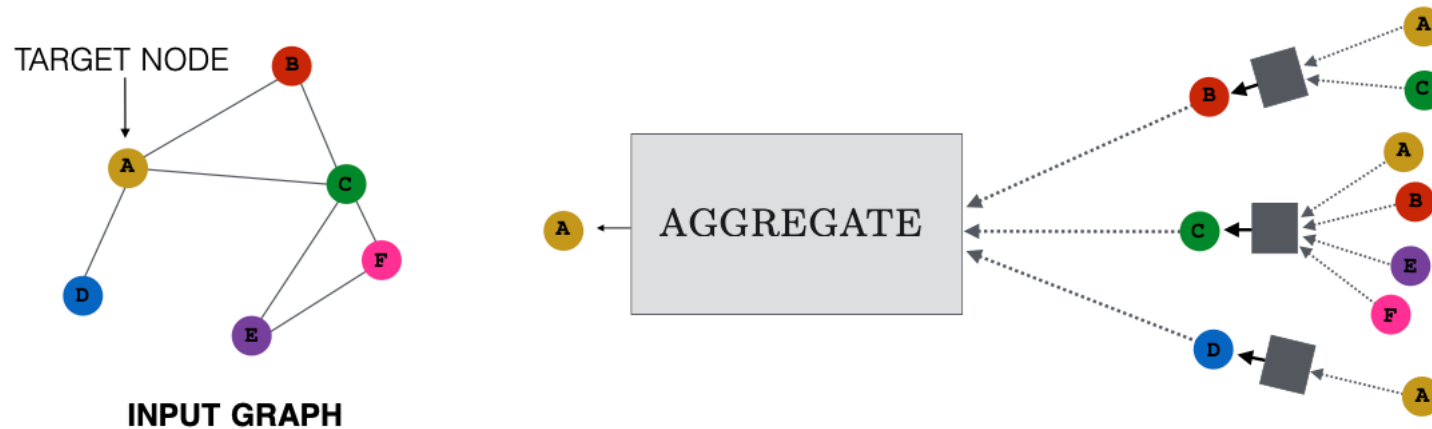
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# Message Passing

- The defining feature of a GNN is that it uses a form of *neural message passing* in which vector messages are exchanged between nodes and updated using neural networks [Gilmer et al., 2017].

## 5.1. NEURAL MESSAGE PASSING

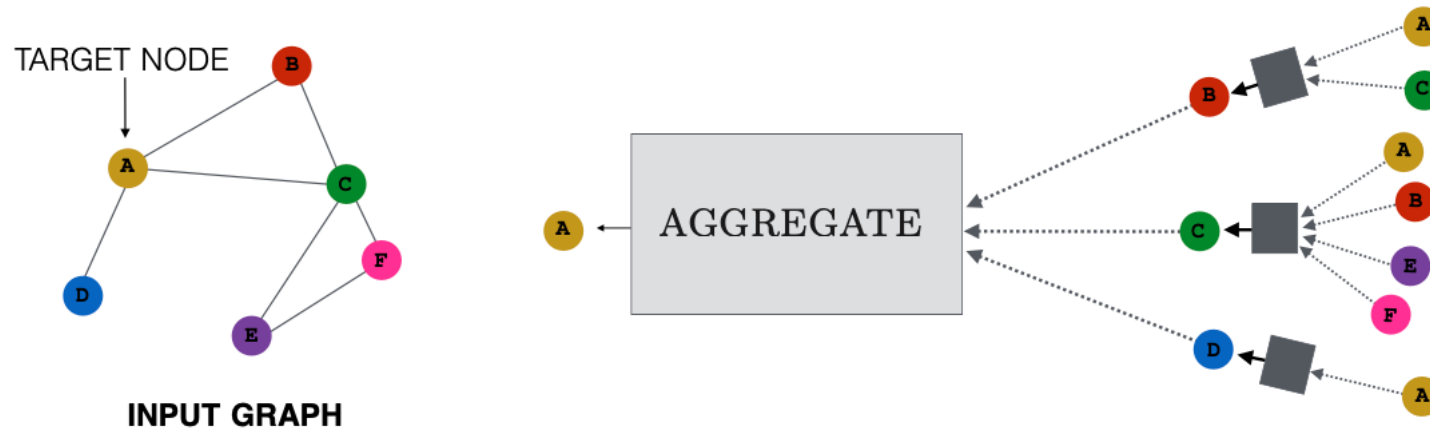
49



# Message Passing

## 5.1. NEURAL MESSAGE PASSING

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❑ Message = information(e.g., node features)

❑ Message Passing : aggregate message.

❑ 오른쪽 그림은 2layer 예시. Target A의 이웃은 B,C,D

- B는 또 A,C로부터 C는 A,B,E,F로부터, D는 A로부터 aggregate message.

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# Negative sampling

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# Negative sampling

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## □ Why?

- 계산의 효율성

## □ How?

- Parameter update시 중요한 것만 뽑아서 update.(모든 파라미터를 업데이트할 필요 없음)

## □ In gnn: target노드의 이웃 노드 parameter만 update.

- 한 100 홉의 이웃 노드 parameter를 업데이트 할 필요는 없다.

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# SOTA model for recommend system

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# SOTA model

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- ❑ **Graph4Rec: A Universal Toolkit with Graph Neural Networks for Recommender Systems(2019)**
  - **Dataset: RetailRocket3 , Rec154 , Tmall5 and UB6 . RetailRocket**
  
- ❑ **Improving Training Stability for Multitask Ranking Models in Recommender Systems(2023)**
  - **Dataset: Conducted on a YouTube production dataset**
  
- ❑ **Mixed Dimension Embeddings with Application to Memory-Efficient Recommendation Systems**
  - **Dataset: MovieLens dataset, Criteo Kaggle dataset(2019)**
  
- ❑ **Compositional Embeddings Using Complementary Partitions for Memory-Efficient Recommendation Systems(2019)**
  - **Dataset: Criteo Ad Kaggle Competition dataset**