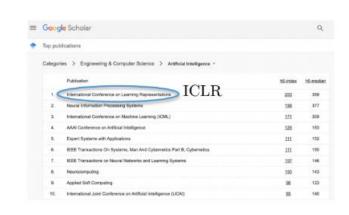
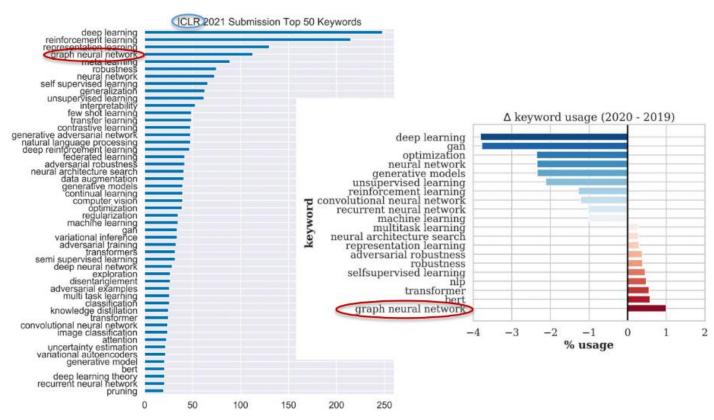
❤ 应用领域

❷ 学术圈子里那是越来越火,热度一个劲往上升



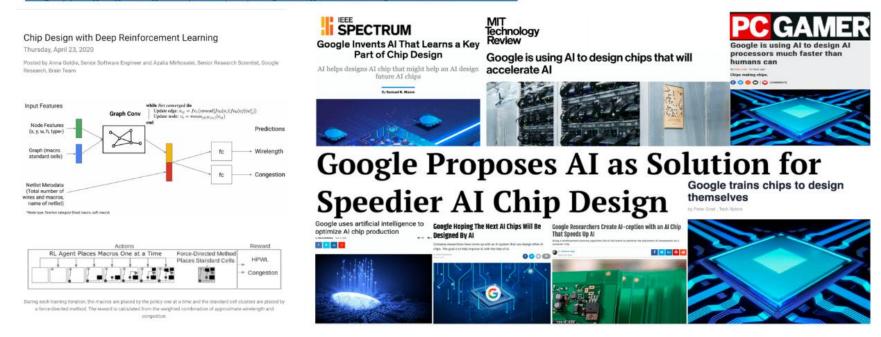


✅ 应用领域

❷ 先往大的层面整,芯片设计



https://ai.googleblog.com/2020/04/chip-design-with-deep-reinforcement.html



❤ 应用领域

∅ 场景分析与问题推理:

Questions in CLEVR test various aspects of visual reasoning including attribute identification, counting, comparison, spatial relationships, and logical operations.

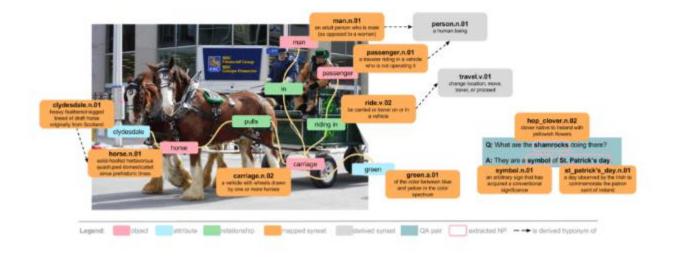


Q: Are there an equal number of large things and metal spheres?

Q: What size is the cylinder that is left of the brown metal thing that is left of the big sphere?

Q: There is a sphere with the same size as the metal cube; is it made of the same material as the small red sphere?

Q: How many objects are either small cylinders or red things?



Al General Engineering

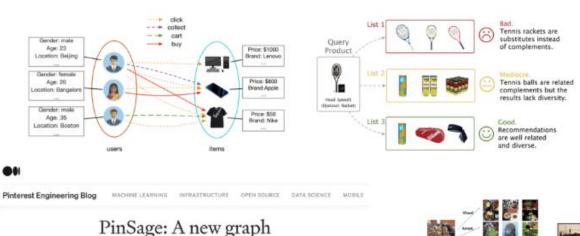
✅ 应用领域

❷ 推荐系统相关,那肯定得图了:

Food Discovery with Uber Eats: Using Graph Learning to Power Recommendations Ankit Jain, Issac Liu, Ankur Sarda, and Piero Molino. December 4, 2019 Graph learning for dish and restaurant recommendation at Ubo < 142 ¥ 139 0 0 The Uber Eats app serves as a portal to more than 320,000 restaurant-partners in over 500 cities globally across 36 countries. In order to make the user experience more seamless and easy-tonavigate, we show users the dishes, restaurants, and cuisines they might like up front. To this end, we previously developed ML models to better understand queries and for multi-objective optimization in Uber Eats search and recommender system in Uber Eats searches and surfaced Pinterest food options.

AliGraph: A Comprehensive Graph Neural Network Platform

Rong Zhu, Kun Zhao, Hongxia Yang, Wei Lin, Chang Zhou, Baole Ai, Yong Li, Jingren Zhou



A E E E --

PinSage: A new graph convolutional neural network for web-scale recommender systems



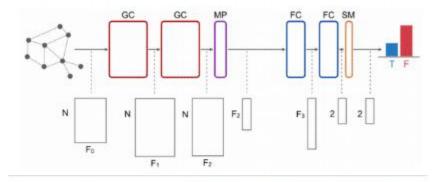


Figure 3: Ecomples of pins recommended by different algorithms. The image to the left in the query pin. Recommended items to the right are computed using Visual embeddings. Annotation embeddings, Pinic Southly graph beard mitted, and PiniSeps.

❤ 应用领域

❷ 欺诈检测,风控相关:





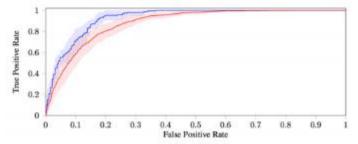
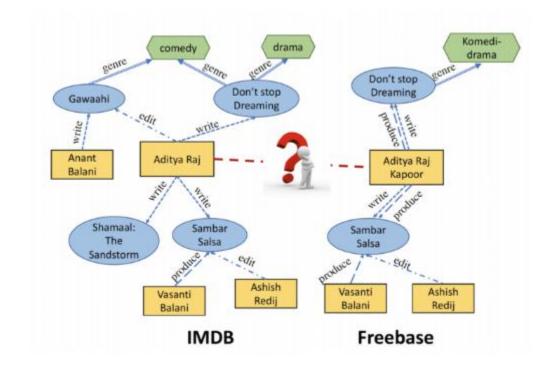
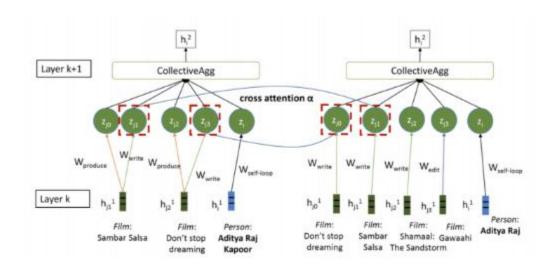


Figure 6: Performance of URL-wise (blue) and cascade-wise (red) fake news detection using 24hrlong diffusion time. Shown are ROC curves averaged on five folds (the shaded areas represent the standard deviations). ROC AUC is 92.70 ± 1.80% for URL-wise classification and 88.30 ± 2.74% for cascade-wise classification, respectively. Only cascades with at least 6 tweets were considered for cascade-wise classification.

❤ 应用领域

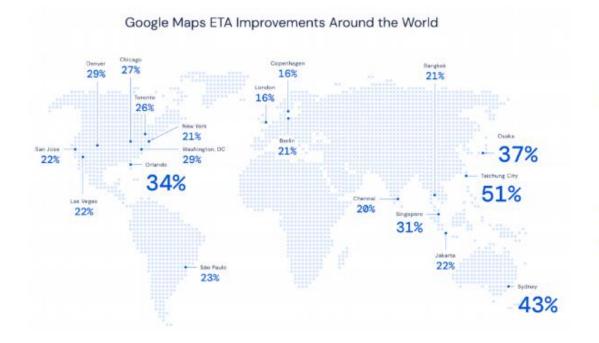
知识图谱本身也是个图模型





❤ 应用领域

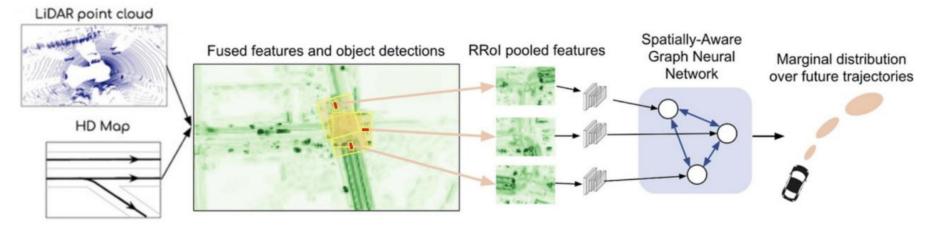
❷ 道路交通,动态流量预测





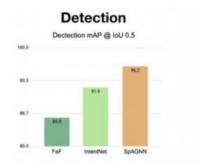
❤ 应用领域

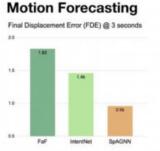
❷ 自动驾驶,无人机等场景

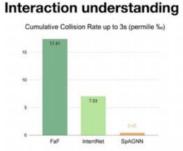




https://slideslive.com/38930570/graphneural-networks-for-selfdriving







❤ 应用领域

❷ 化学,医疗等场景

AlphaFold: a solution to a 50-year-old grand challenge in biology



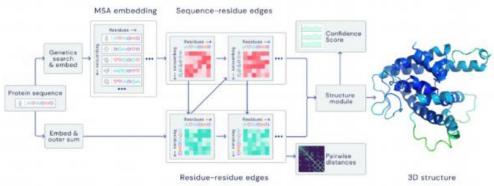
SHARE

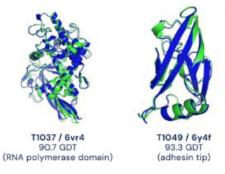
of in

AUTHORS

TAt The AlphaFold team

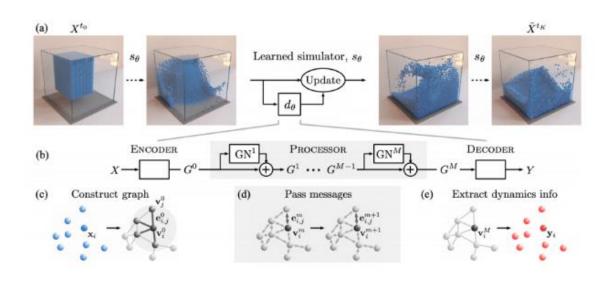
Proteins are essential to life, supporting practically all its functions. They are large complex molecules, made up of chains of amino acids, and what a protein does largely depends on its unique 3D structure. Figuring out what shapes proteins fold into is known as the "protein folding problem", and has stood as a grand challenge in biology for the past 50 years. In a major scientific advance, the latest version of our AI system AlphaFold has been recognised as a solution to this grand challenge by the organisers of the biennial Critical Assessment of protein Structure Prediction (CASP). This breakthrough demonstrates the impact AI can have on scientific discovery and its potential to dramatically accelerate progress in some of the most fundamental fields that explain and shape our world.

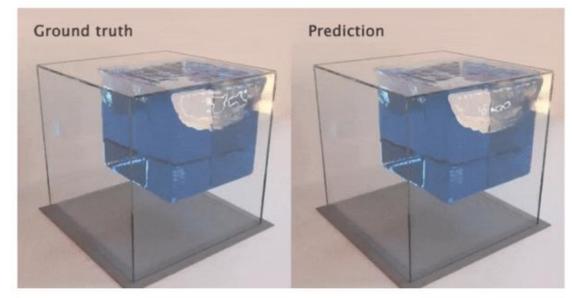




❤ 应用领域

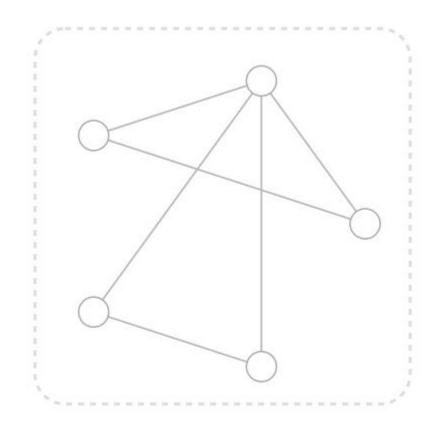
∅ 物理模型相关





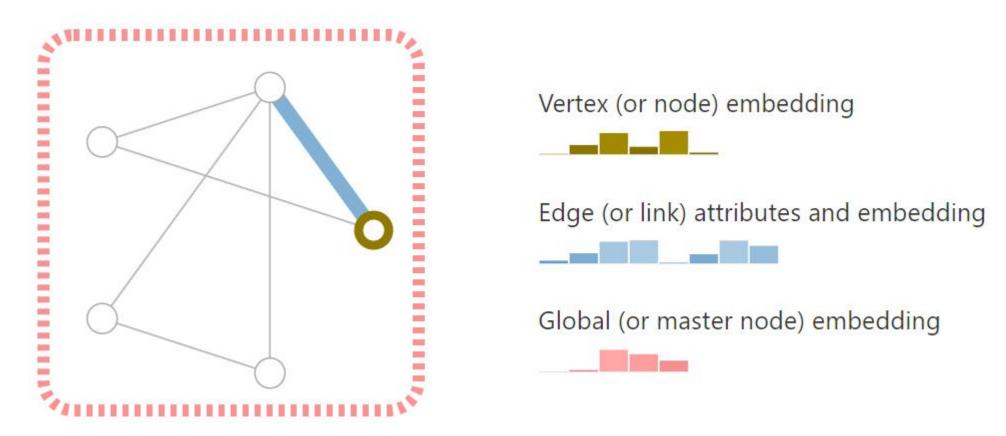
❤ 图的基本组成

❷ 跟大家想的一样,还是这点东西,我们要做的就是提取特征而已



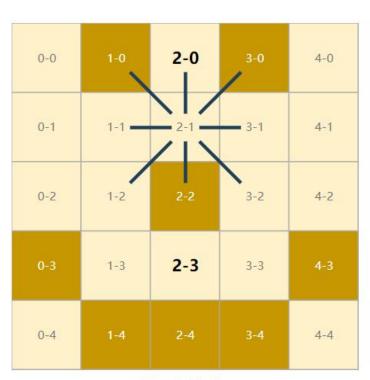
- Vertex (or node) attributes
 e.g., node identity, number of neighbors
- E Edge (or link) attributes and directions e.g., edge identity, edge weight
- U Global (or master node) attributes e.g., number of nodes, longest path

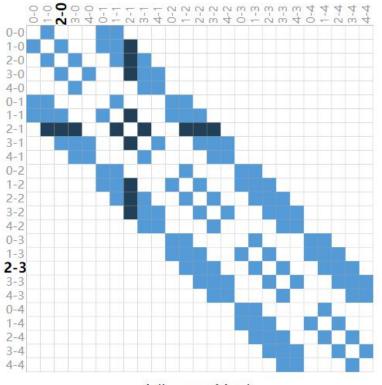
✓ 图神经网络要做啥



❤ 图的邻接矩阵

Ø 以图像为例子,每个像素点周围都有邻居,A就表示邻居之间的关系





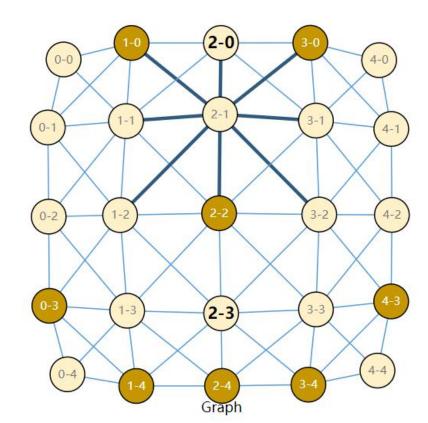
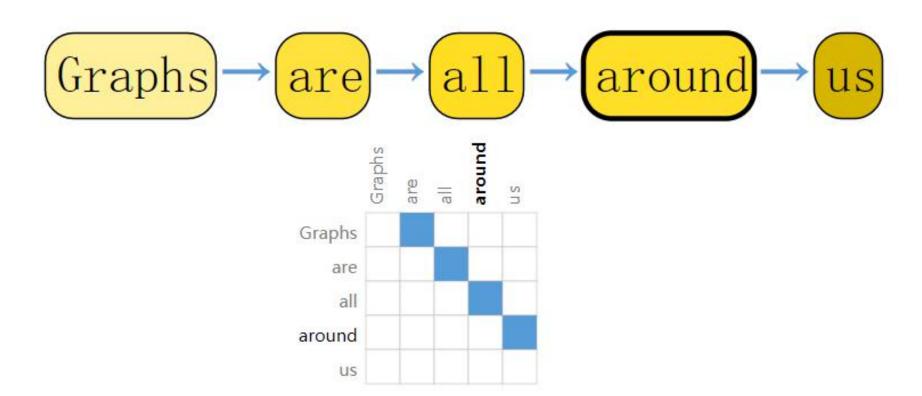


Image Pixels

Adjacency Matrix

❤ 图的邻接矩阵

文本数据也可以表示图的形式,邻接矩阵表示的连接关系

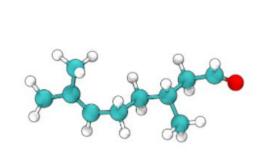


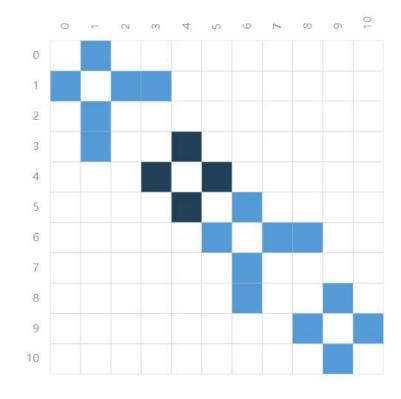
❤ 但是啊但是

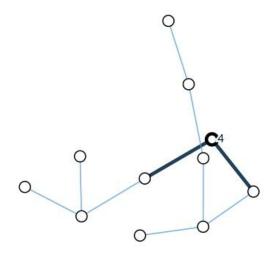
- ❷ 图像和文本任务中, 你用过图相关的模型吗? 好像木有吧
- ❷ 为啥呢?因为图像和文本数据的格式都贼固定,想─想咱们的预处理

- 文本固定长度和词向量大小,然后也是这么个事,不需要特殊的邻接矩阵

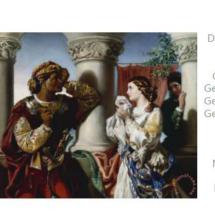
✓ 想想这些数据是固定格式吗?

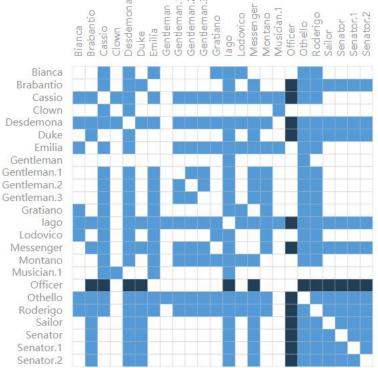


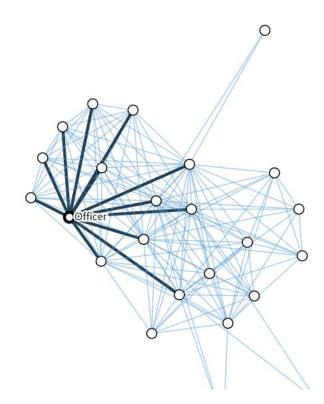




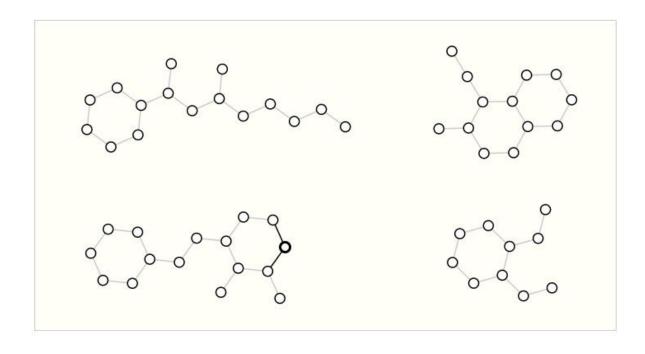
社交网络中各个人物的关系,这种邻接矩阵会比较庞大

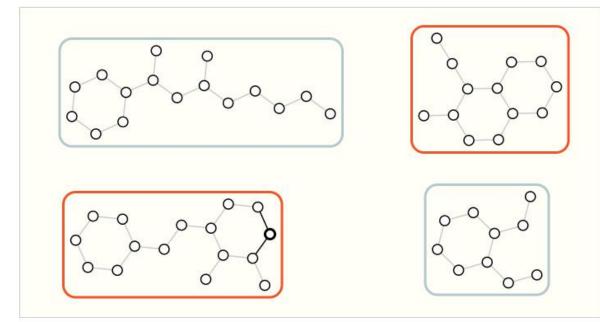






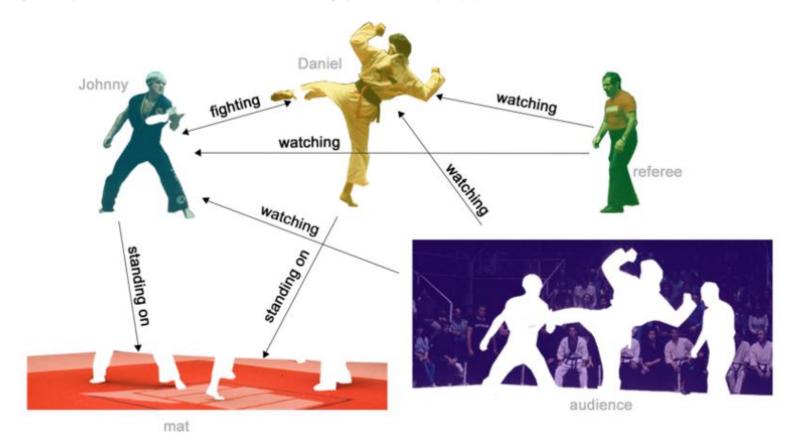
✓ Graph级别任务





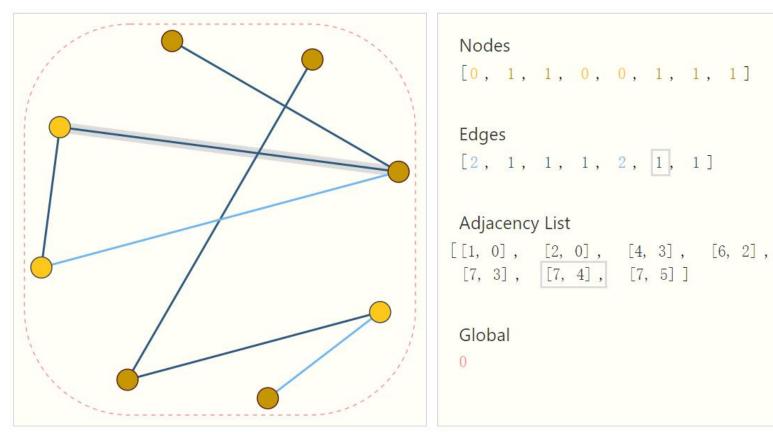
✓ Node与Edge级别任务

∅ 预测这个点是谁呢? 这条边在做什么动作等



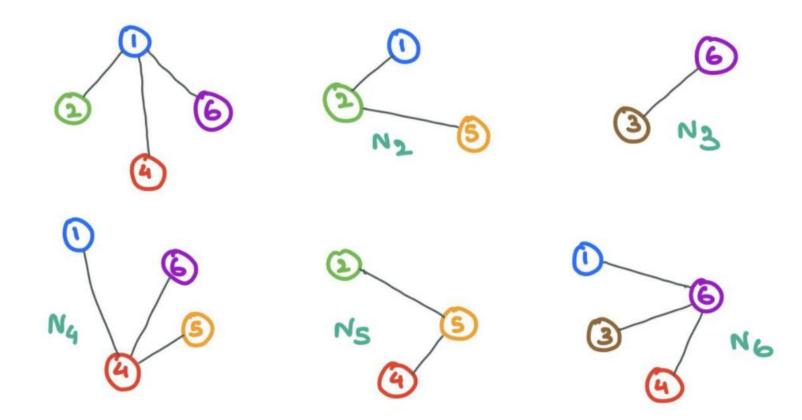
❤ 邻接矩阵

❷ 一般邻接矩阵表达形式如下,并不是一个N*N的矩阵,而是保存source,target



message passing neural network

❷ 每个点的特征该如何更新呢? 肯定得考虑他们邻居的

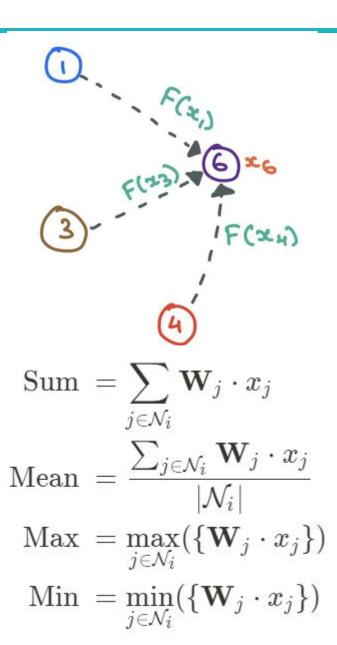


message passing neural network

❷ 但是更新的方法有很多,可以自己设置

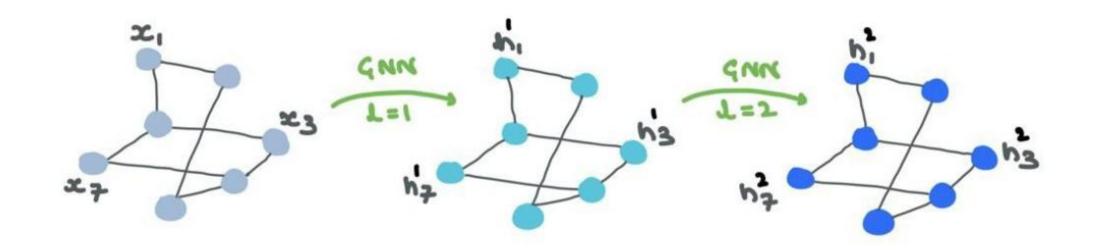
 \mathscr{O} 结合邻居与自身信息: $\bar{m}_i = G(\{\mathbf{W}_j \cdot x_j : j \in \mathcal{N}_i\})$

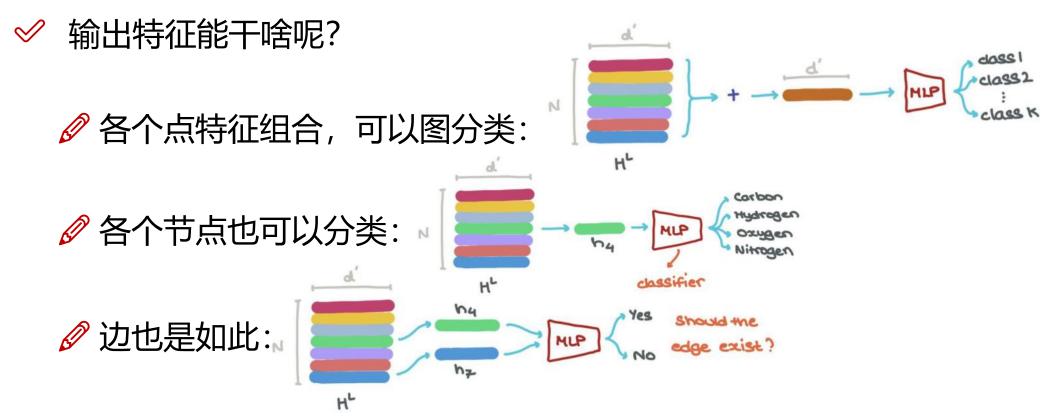
グ 汇总:
$$h_i = \sigma(W_1 \cdot h_i + \sum_{j \in \mathcal{N}_i} \mathbf{W}_2 \cdot h_j)$$



✓ GNN也可以有多层

∅ 其中輸入是特征,輸出也是特征,邻接矩阵也不会变的





∅ 其实只是利用图结构得到特征,最终要做什么还是我们自己定