

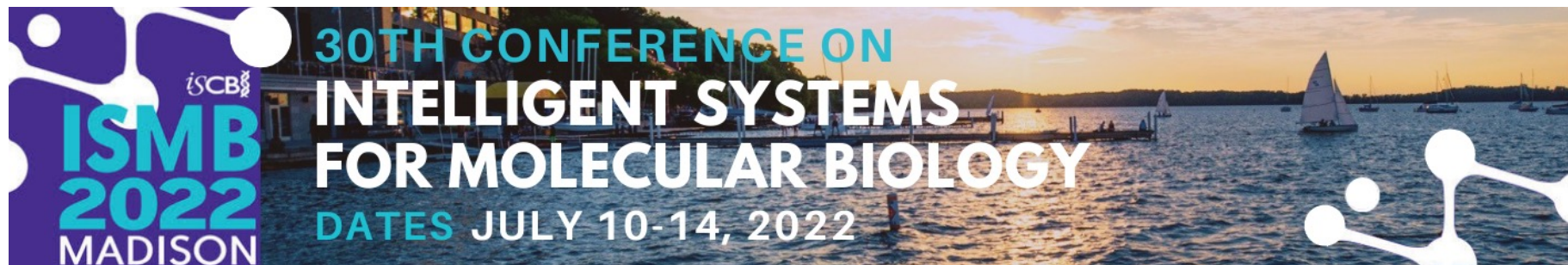
# Towards Precision Medicine with Graph Representation Learning

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[zitniklab.hms.harvard.edu/biomedgraphml](http://zitniklab.hms.harvard.edu/biomedgraphml)





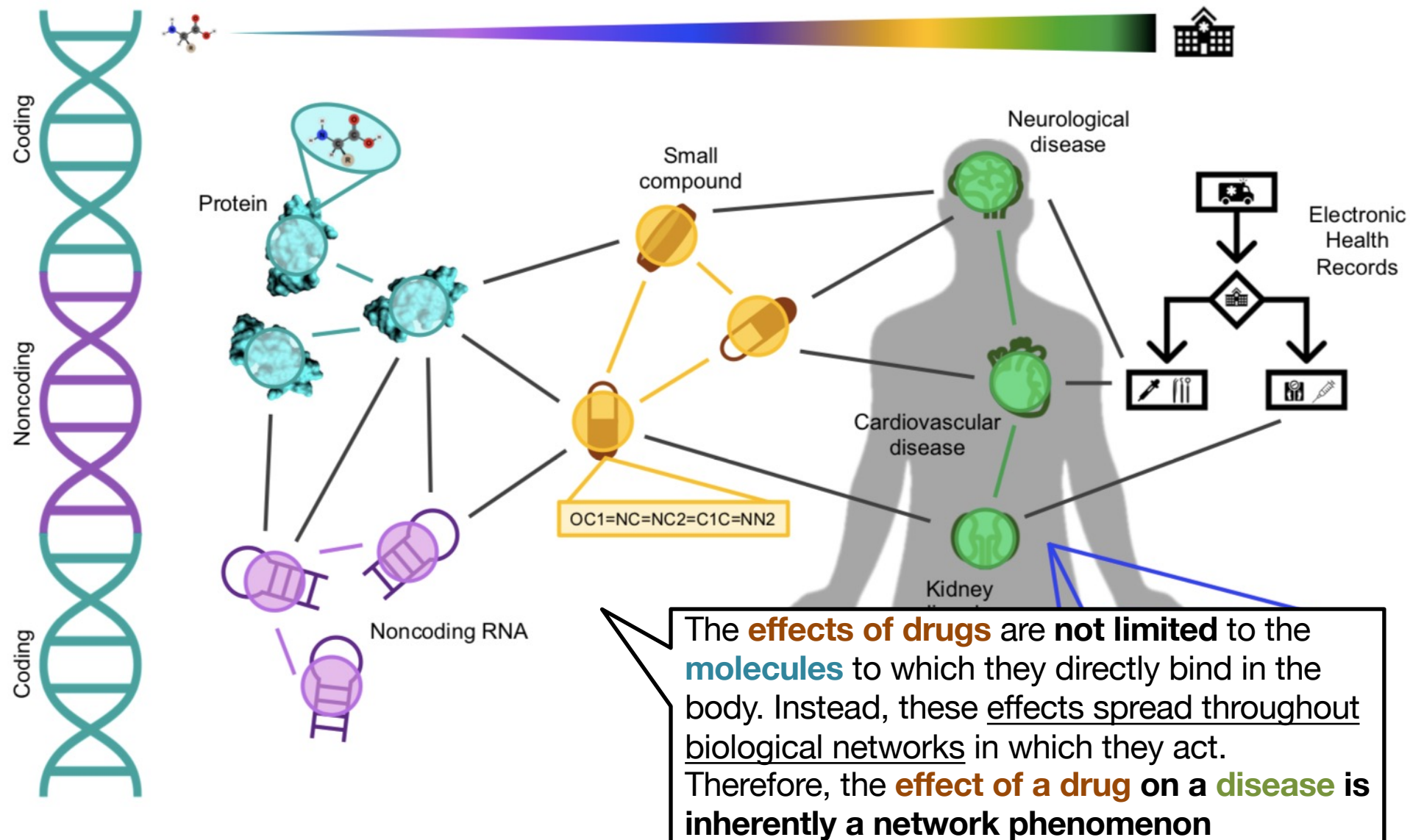
## Tutorial VT4

July 7, 2022 at 9am – 1pm CDT

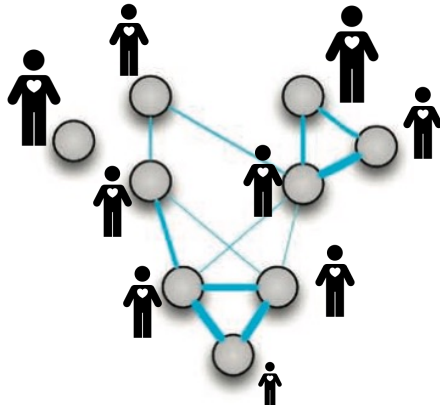


All tutorial materials are available at  
[zitniklab.hms.harvard.edu/biomedgraphml](https://zitniklab.hms.harvard.edu/biomedgraphml)

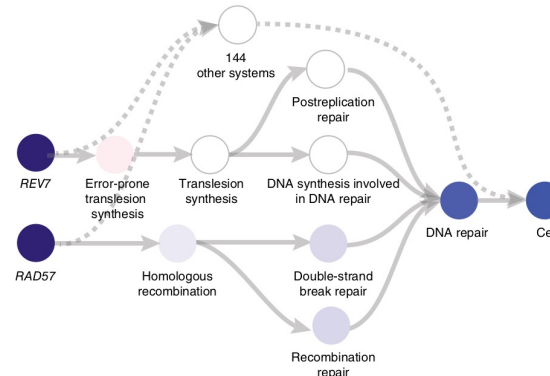
# Biology is interconnected



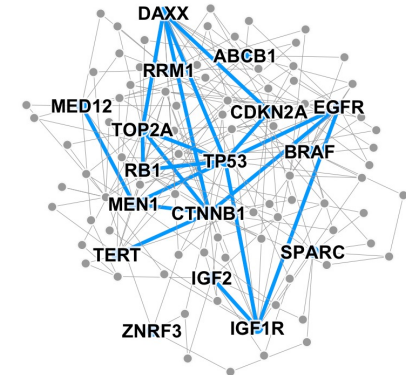
# Networks are a general language for describing and modeling complex systems



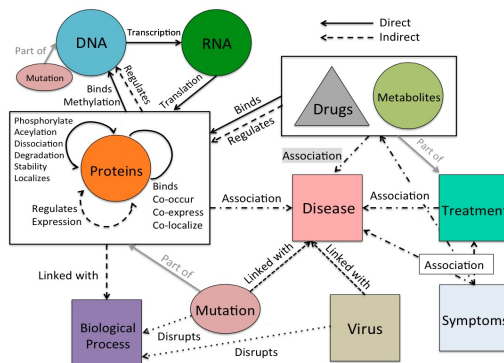
Patient networks



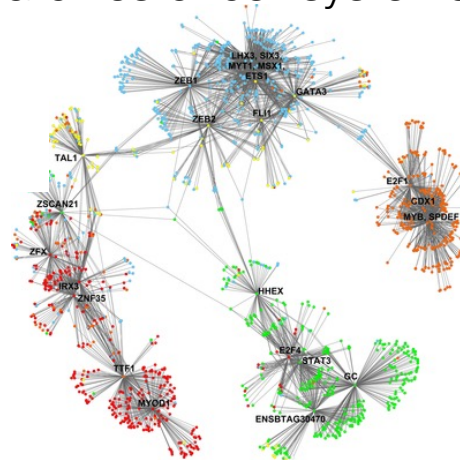
Hierarchies of cell systems



Disease pathways



Biomedical knowledge graphs



Gene interaction networks

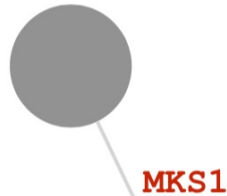


Cell-cell similarity networks

Graph Representation Learning for Biomedicine, *Nature Biomedical Engineering* (in press), 2022, arXiv:2104.04883

Machine learning for integrating data in biology and medicine: Principles, practice, and opportunities, *Information Fusion* 2019

# Why networks in biology?



## Long-standing paradigm: “local hypothesis”

Proteins involved in the same disease have an increased tendency to interact with each other

## Corollary of the local hypothesis

Mutations in interacting proteins often lead to similar diseases

Network medicine: a network-based approach to human disease, *Nature Reviews Genetics*, 2011



Known disease proteins

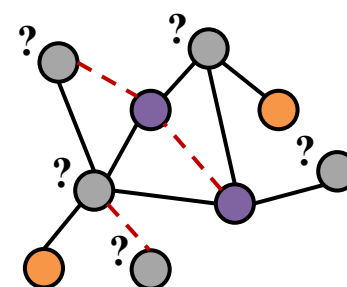
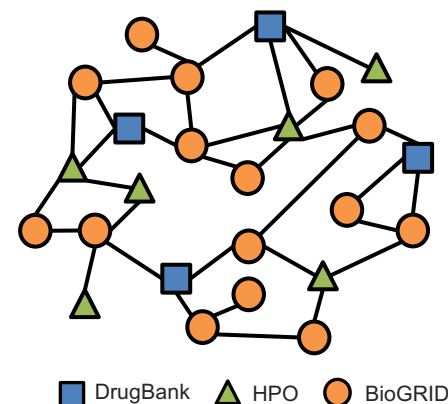
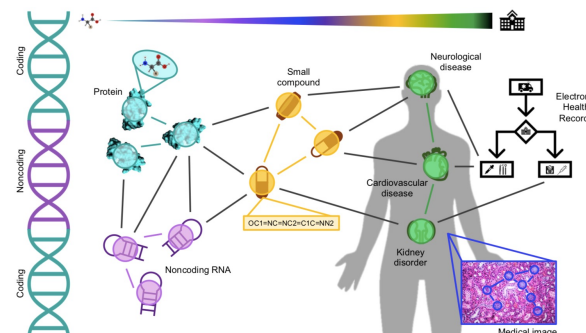


Predicted disease proteins



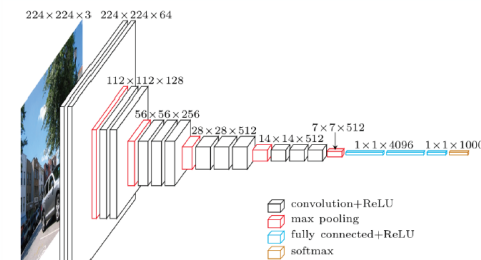
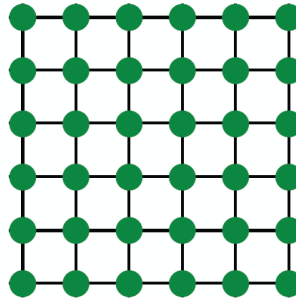
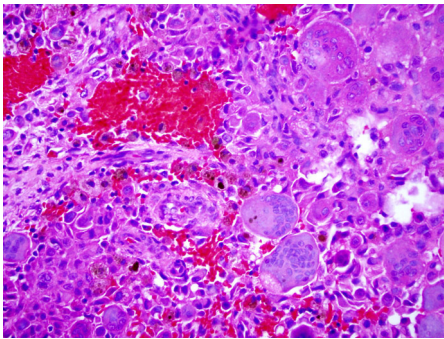
# Why are biological networks challenging?

- **Heterogeneous interactions** that span from molecules to whole populations
  - **Challenge:** Computationally operationalize these data & make them amenable to ML
- **Requires data from diverse sources**, including experimental readouts, curated annotations, metadata
  - **Challenge:** Capture all factors necessary to understand a phenomenon (e.g. disease)
- **Noisy** due to inherent natural variations & limitations of measurement platforms
  - **Challenge:** Handle missing data, repeated measurements, and contradictory observations

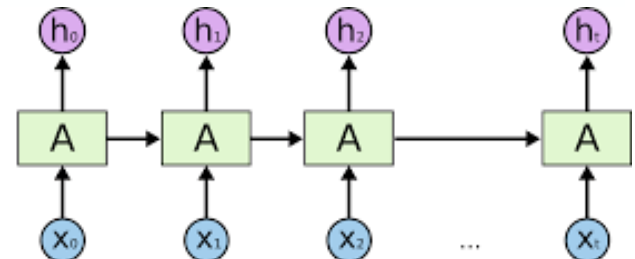


# Classic deep learning

- Primarily designed for **grids** or **simple sequences**:
  - CNNs for fixed-size images/grids...

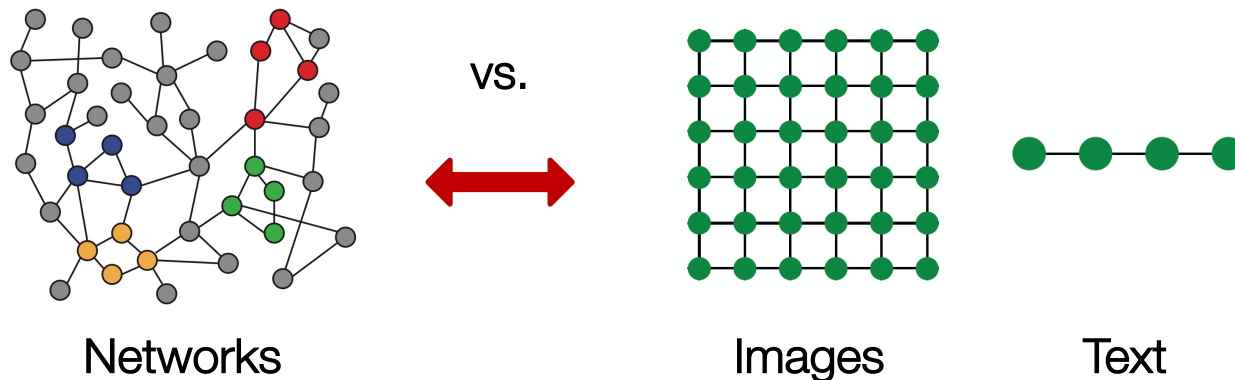


- RNNs for text and sequences...



# Classic deep learning

- Networks are far more complex!
  - Arbitrary size and complex topological structure (i.e., no spatial locality like grids)



- No fixed node ordering or reference point
- Often dynamic and have multimodal features

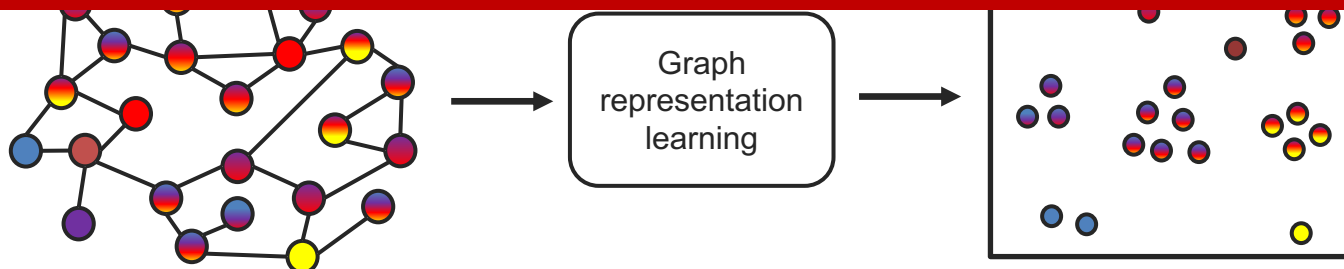


# Graph representation learning realizes key network principles for data-rich biomedicine

Cellular components associated with a specific disease (phenotype) show a tendency to cluster in the same network neighborhood



Deep graph representation learning methods are well-suited for the analysis of biological networks



# This Tutorial

1. Methods: Network diffusion, shallow network embeddings, graph neural networks, equivariant neural networks
2. Applications: Fundamental biological discoveries and precision medicine
3. Hands-on exercises: Demos, implementation details, tools, and tips

# Resources

- Books & survey papers

- William Hamilton, *Graph Representation Learning*  
([morganclaypool.com/doi/abs/10.2200/S01045ED1V01Y202009AIM046](https://morganclaypool.com/doi/abs/10.2200/S01045ED1V01Y202009AIM046))
- Li et al., Graph Representation Learning for Biomedicine  
([arxiv.org/abs/2104.04883](https://arxiv.org/abs/2104.04883))

- Keynotes

- Michael Bronstein, “Geometric Deep Learning: The Erlangen Programme of ML” (ICLR 2021 keynote)  
([youtube.com/watch?v=w6Pw4MOzMuo](https://youtube.com/watch?v=w6Pw4MOzMuo))

- Software & packages

- PyTorch Geometric
- NetworkX
- Stanford Network Analysis Platform (SNAP)

# Resources

- **Conferences & summer schools**
  - London Geometry and Machine Learning Summer School ([logml.ai](https://logml.ai))
  - Learning on Graphs Conference ([logconference.github.io](https://logconference.github.io))
- **Tutorials & code bases**
  - Pytorch Geometric Colab Notebooks ([pytorch-geometric.readthedocs.io/en/latest/notes/colabs.html](https://pytorch-geometric.readthedocs.io/en/latest/notes/colabs.html))
  - Zitnik Lab Graph ML Tutorials ([github.com/mims-harvard/graphml-tutorials](https://github.com/mims-harvard/graphml-tutorials))
  - Stanford University's CS224 ([web.stanford.edu/class/cs224w](https://web.stanford.edu/class/cs224w))
- **Datasets**
  - Precision Medicine Oriented Knowledge Graph (PrimeKG) ([zitniklab.hms.harvard.edu/projects/PrimeKG](https://zitniklab.hms.harvard.edu/projects/PrimeKG))
  - Therapeutic Data Commons (TDC) ([tdcommons.ai](https://tdcommons.ai))
  - BioSNAP ([snap.stanford.edu/biodata/](https://snap.stanford.edu/biodata/))
  - Open Graph Benchmark (OGB) ([ogb.stanford.edu](https://ogb.stanford.edu))