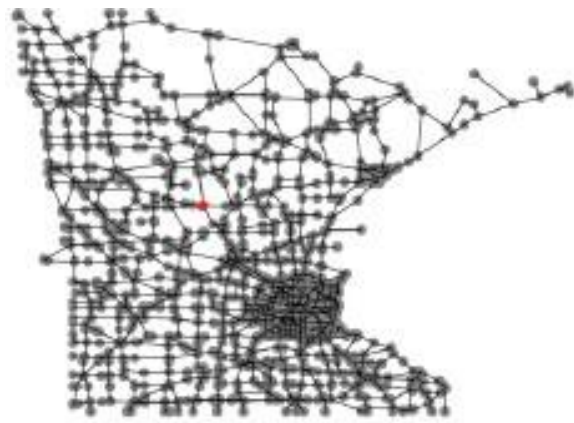


# Recent advances in learning with graphs

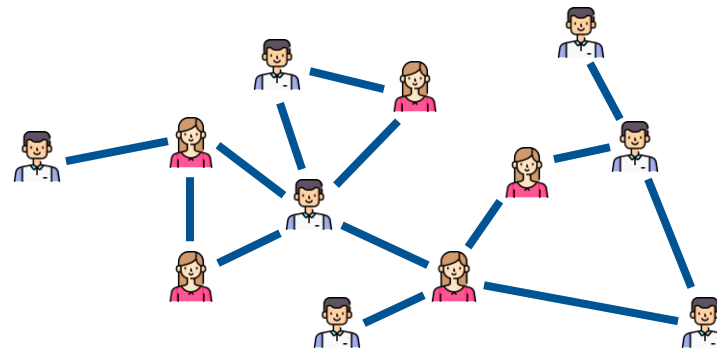
**Xiaowen Dong**

Department of Engineering Science  
University of Oxford

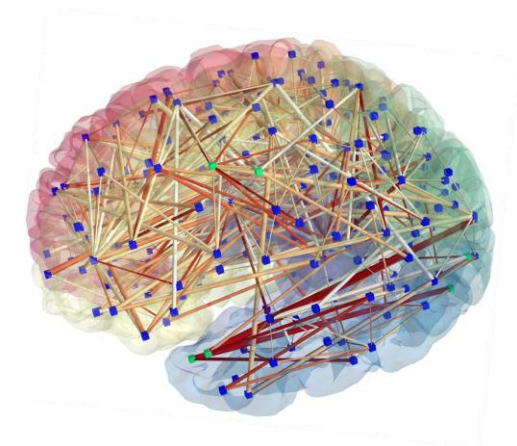
# Networks are pervasive



traffic network



social network



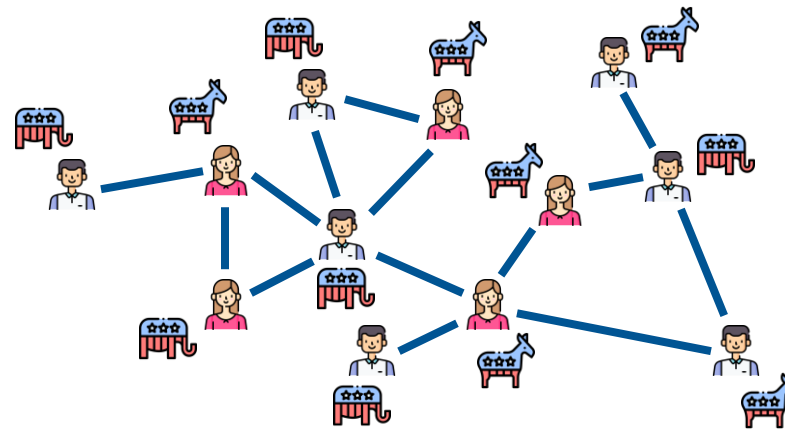
brain network

**networks** are mathematically represented by **graphs**

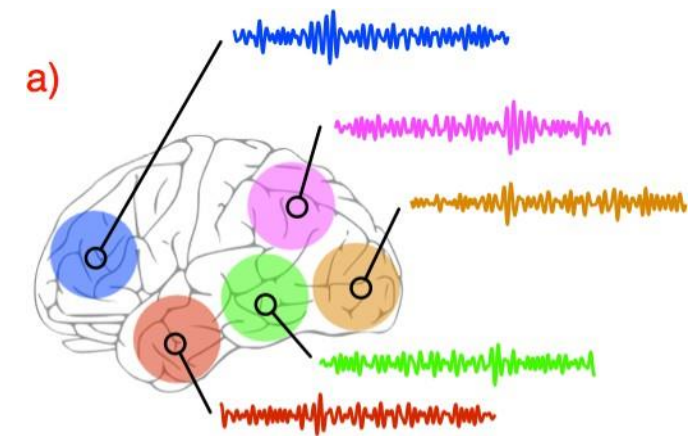
# Data collected in networks are pervasive



congestion in road  
junctions



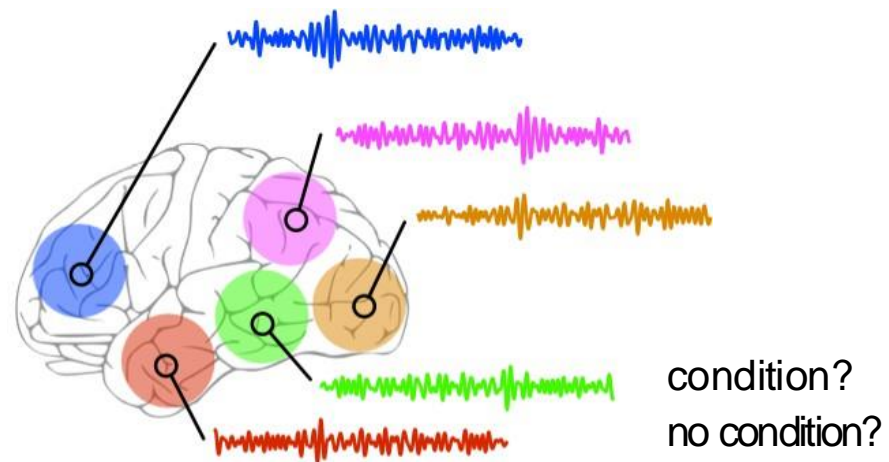
preferences of  
individuals



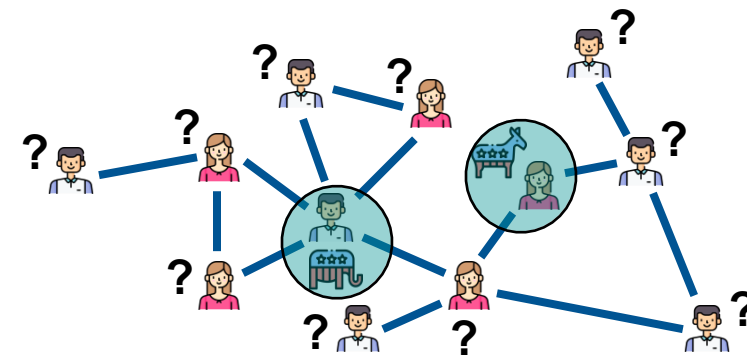
activities in brain  
regions

from **graphs** to **graph-structured data**

# Learning with graph-structured data



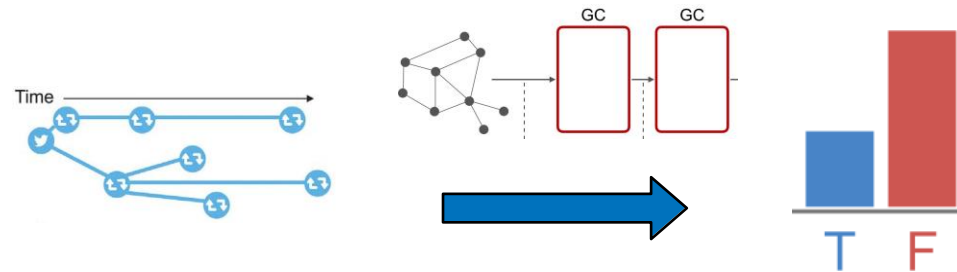
**graph-level classification  
(supervised)**



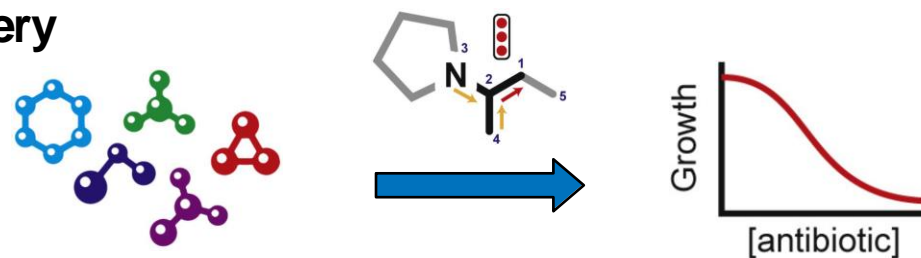
**node-level classification  
(semi-supervised)**

# Exciting possibilities enabled by graph ML

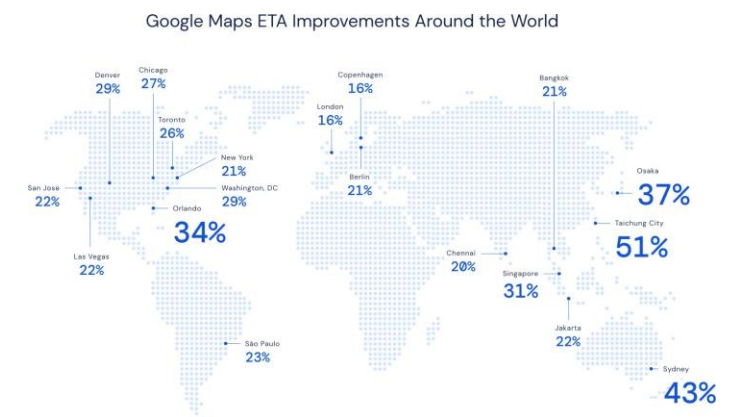
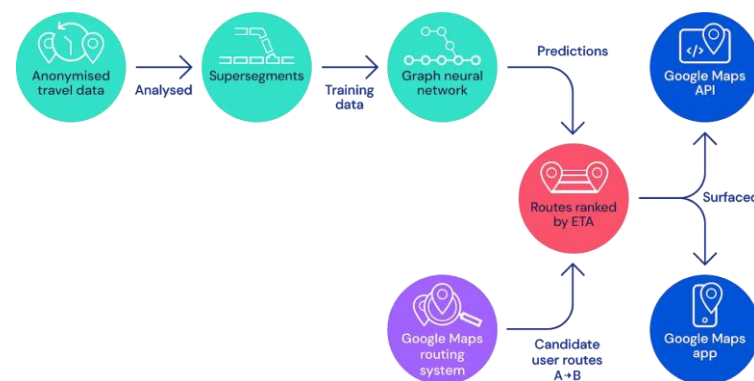
## fake news detection



## drug discovery

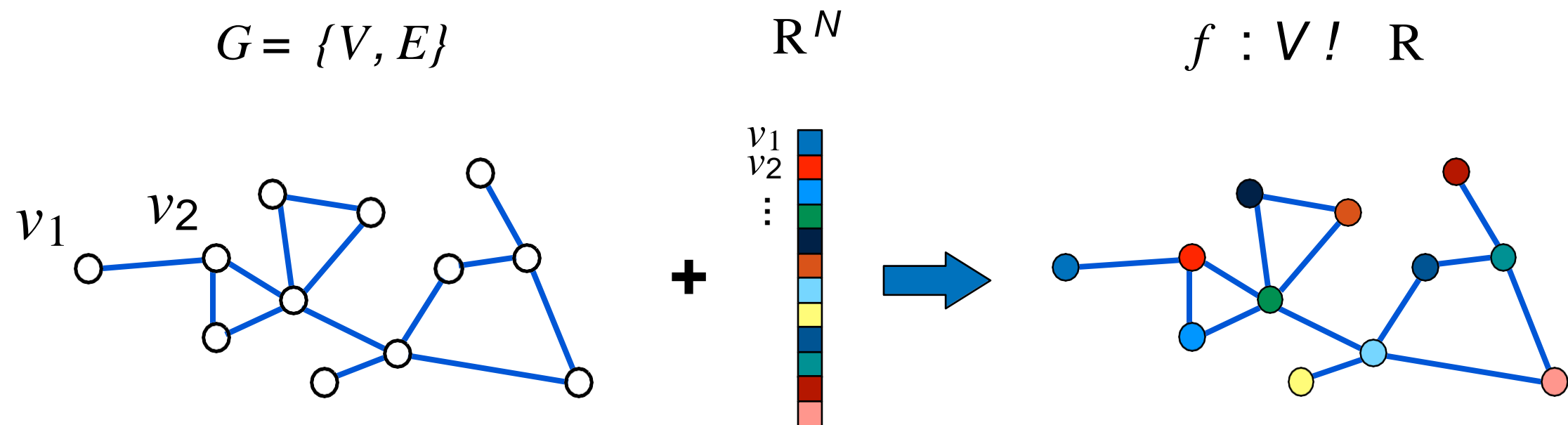


## traffic prediction



# Graph signal processing

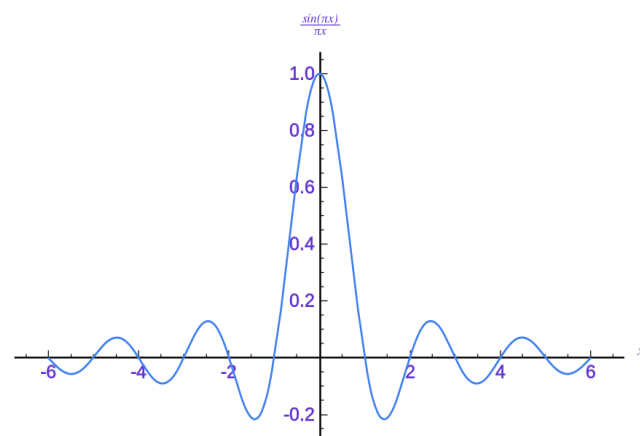
- Graph-structured data can be represented by graph signals



takes into account both **structure (edges)** and **data (values at nodes)**

# Graph signal processing

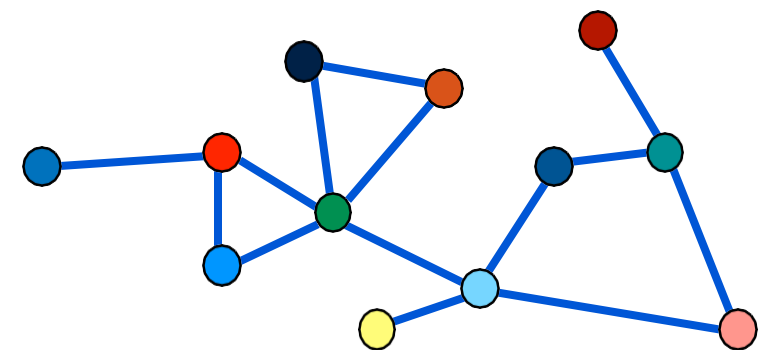
1D signal



2D signal



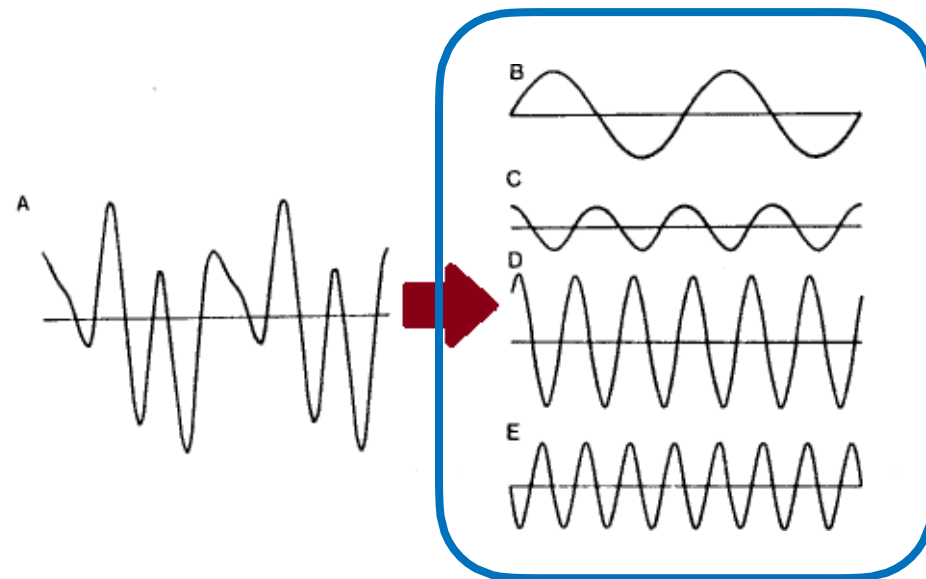
$$f : V \rightarrow \mathbb{R}$$



how to generalise **classical** signal processing tools on  
irregular domains such as **graphs**?



# Graph signal processing

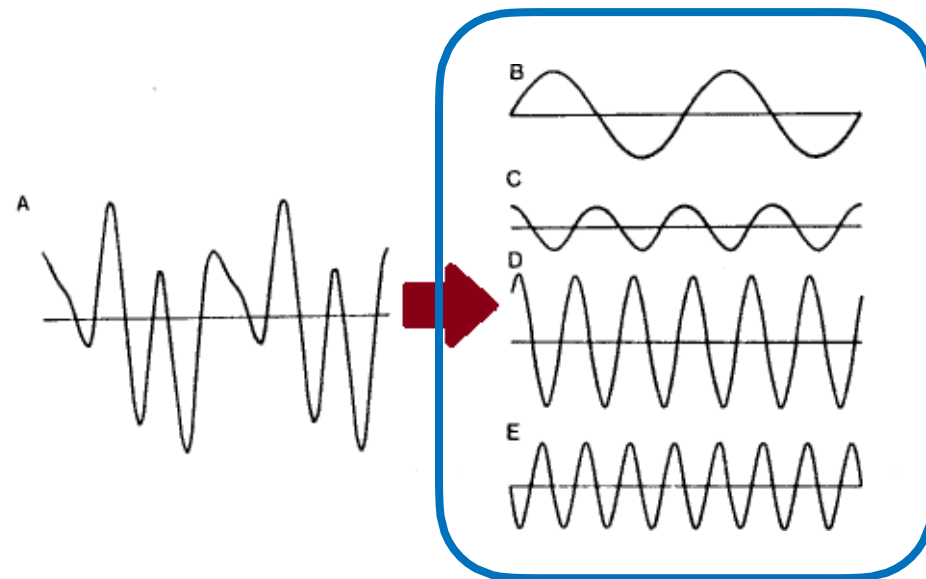


classical signal processing

- complex exponentials provide “building blocks” of 1D signal (different oscillations or frequencies)
- leads to **Fourier transform**
- enables frequency filtering (equivalent to convolution)

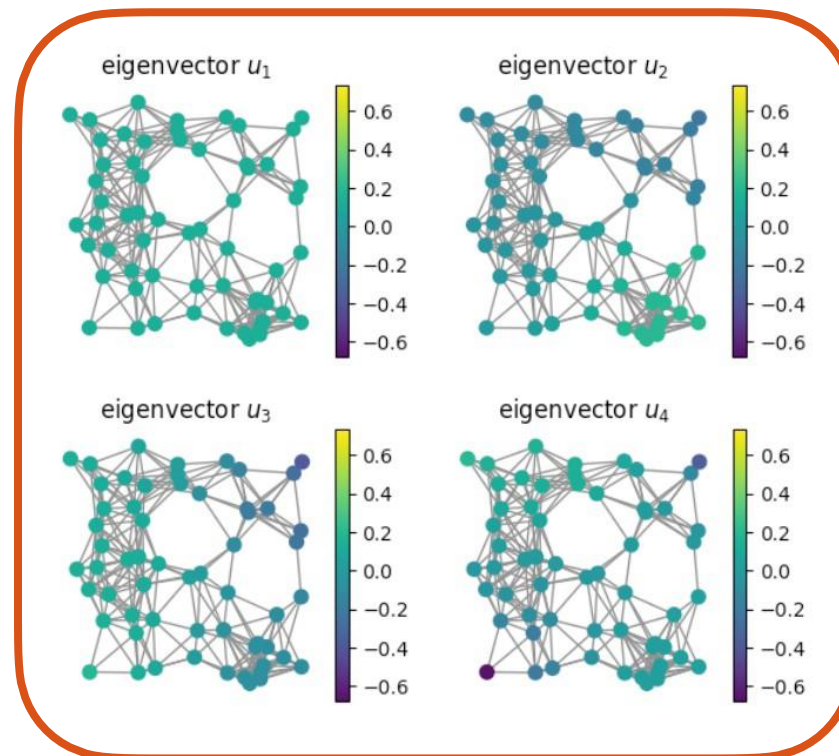
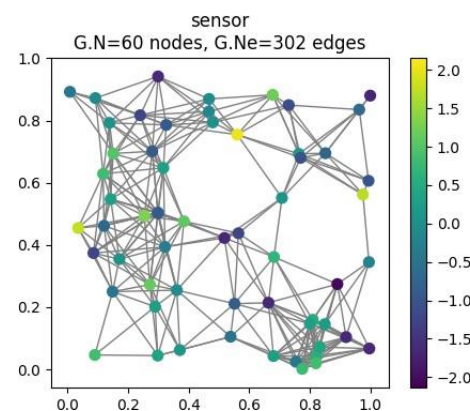


# Graph signal processing



## classical signal processing

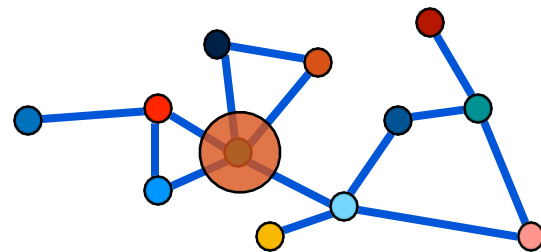
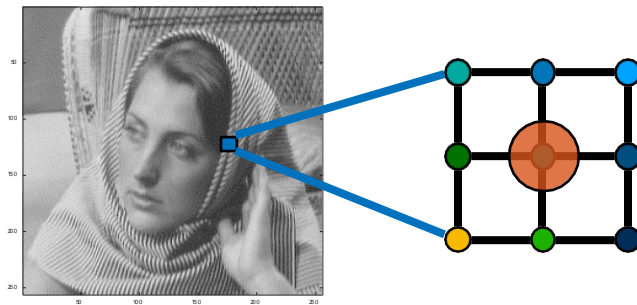
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- enables frequency filtering (equivalent to convolution)



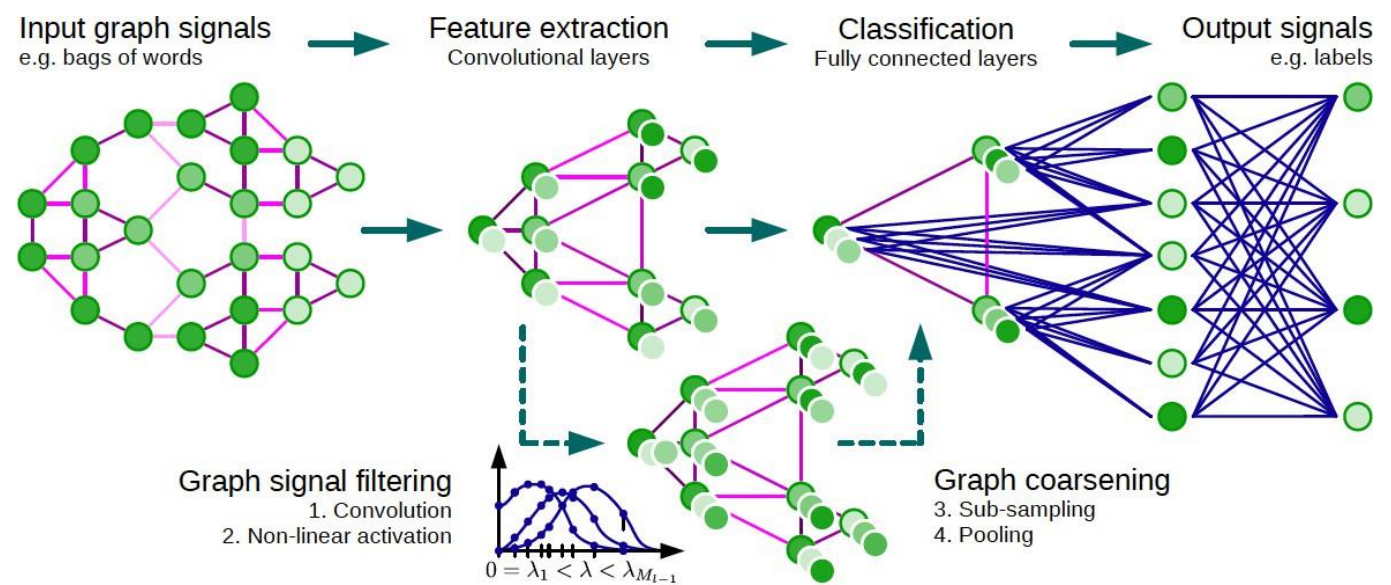
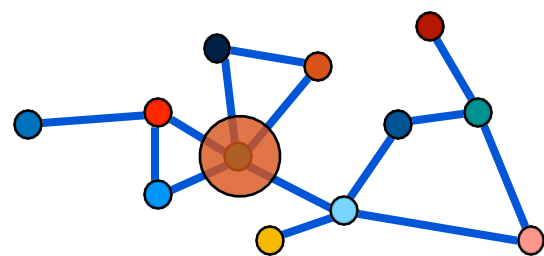
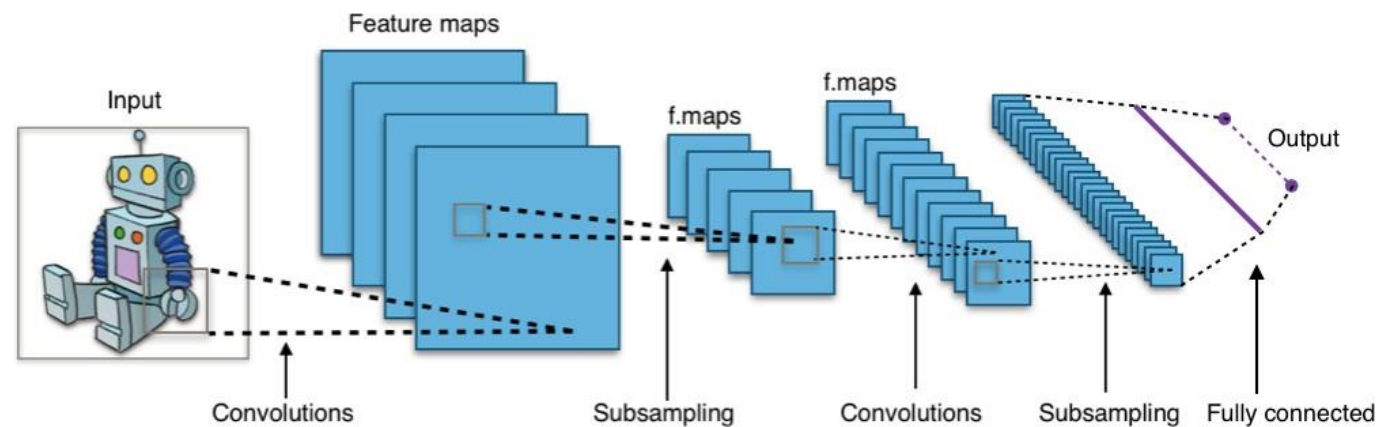
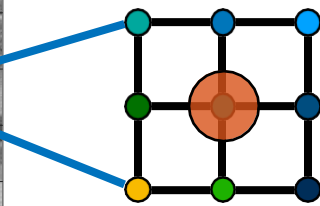
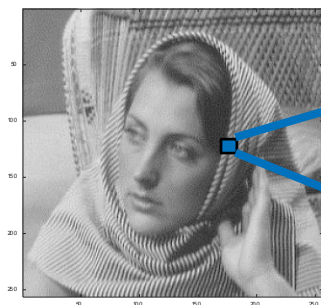
## graph signal processing

- Laplacian eigenvectors provide “building blocks” of graph signal (different oscillation or frequencies)
- leads to **graph Fourier transform**
- enables **convolution** and **filtering** on graphs

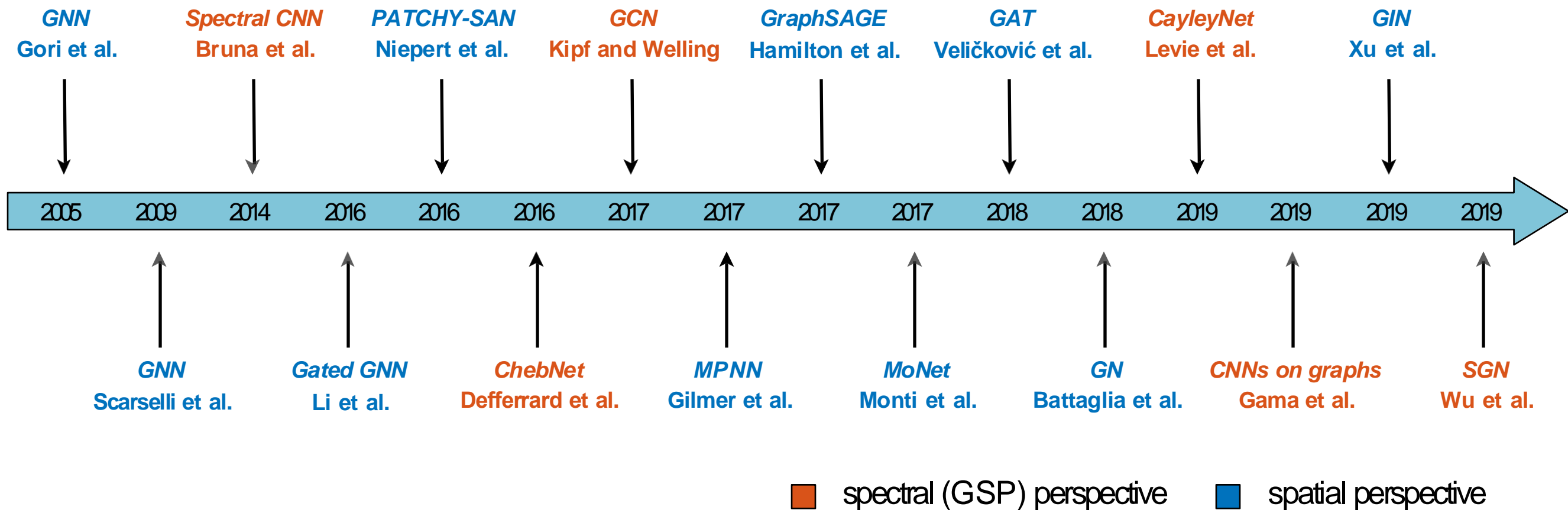
# Convolutional neural networks on graphs



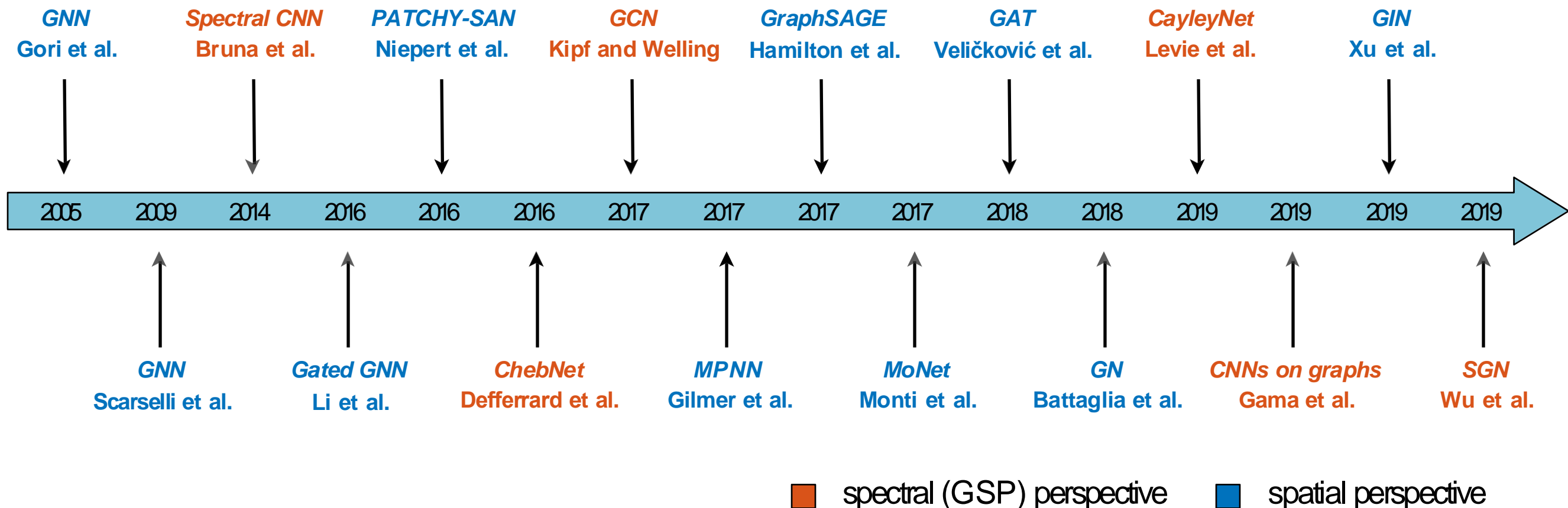
# Convolutional neural networks on graphs



# (More generally) Graph neural networks



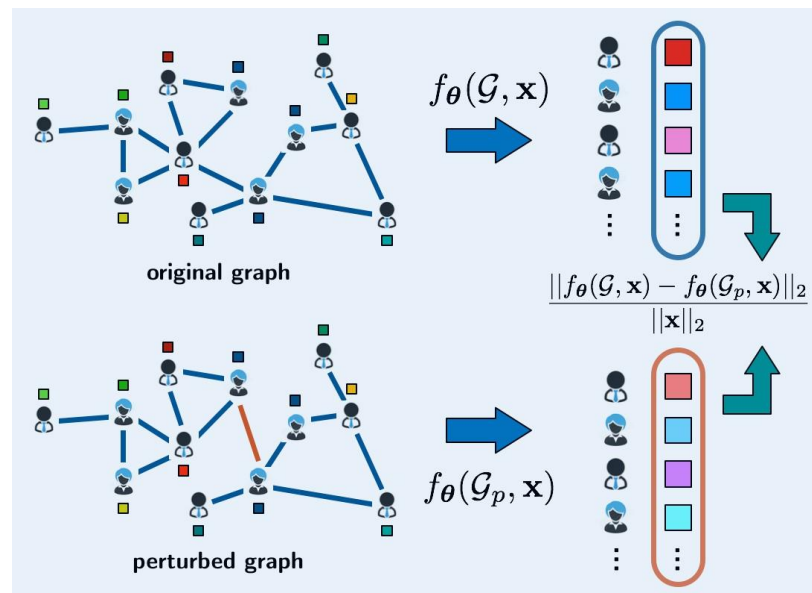
# (More generally) Graph neural networks



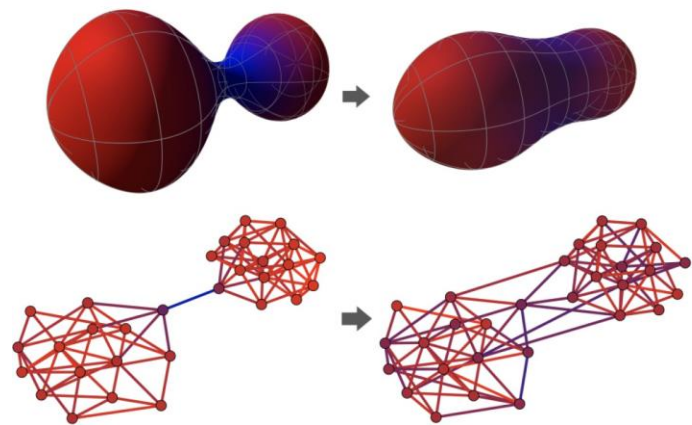
more recently: graph transformers and LLM-powered models



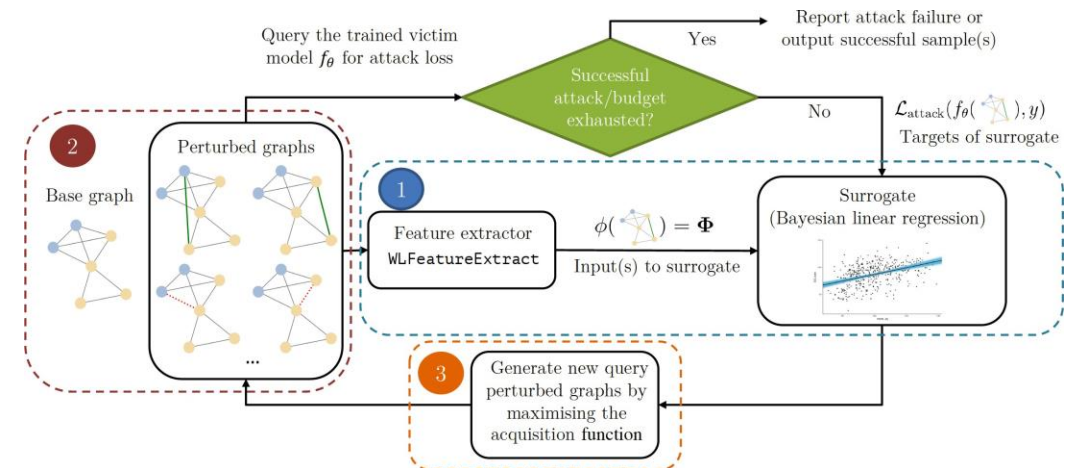
# Our research - Theoretical investigation



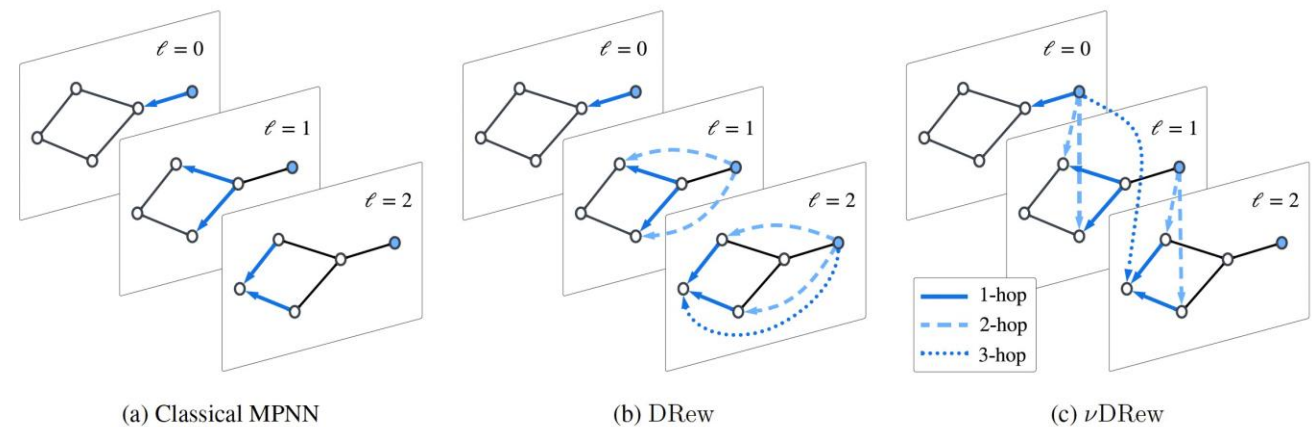
filter stability



understanding/mitigating over-squashing

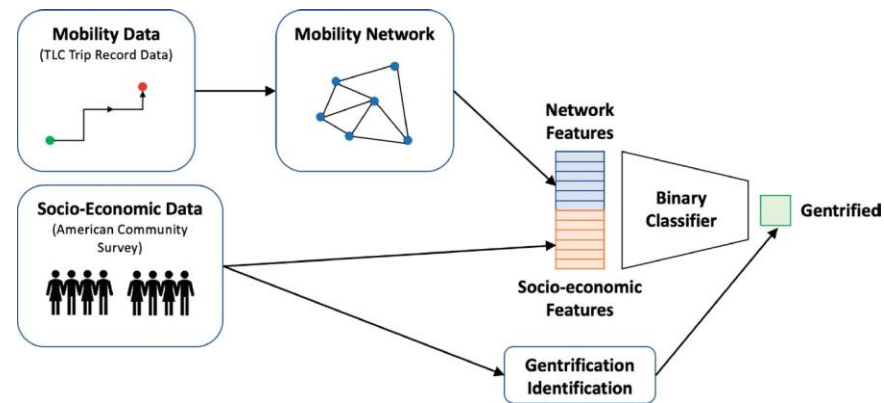


adversarial attacks

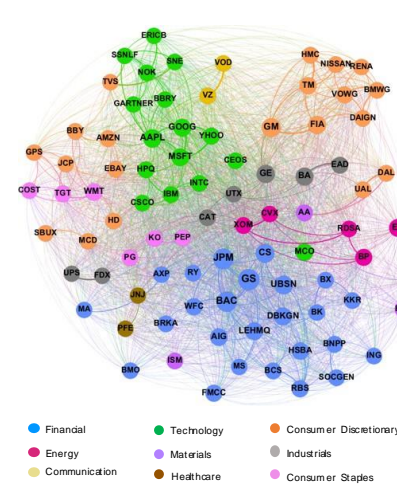


dynamic message passing with delay

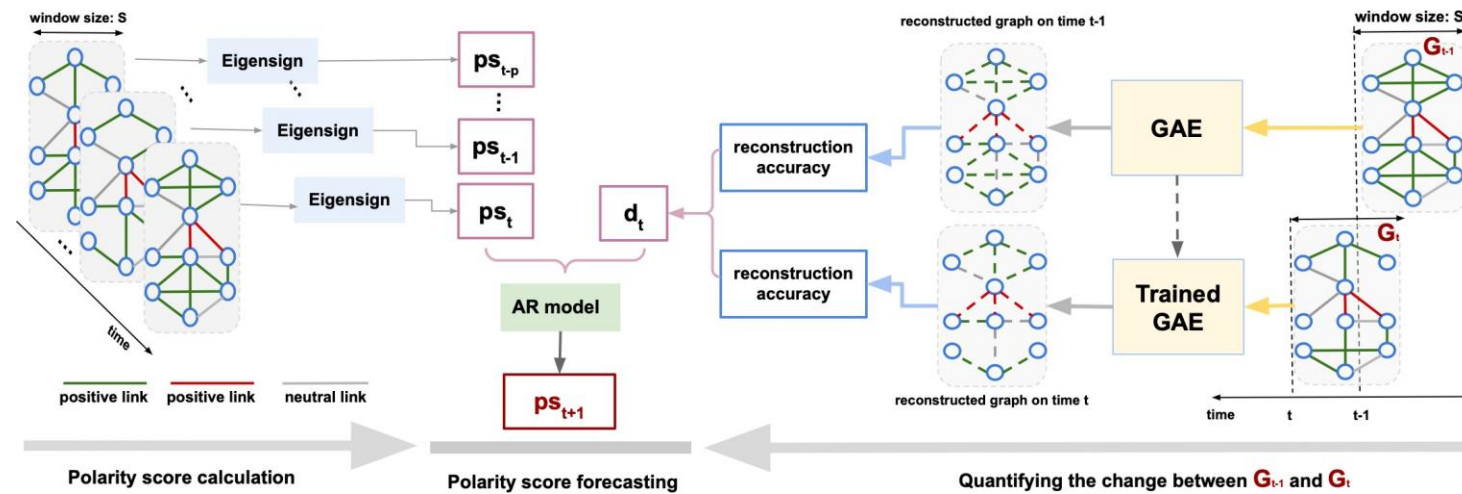
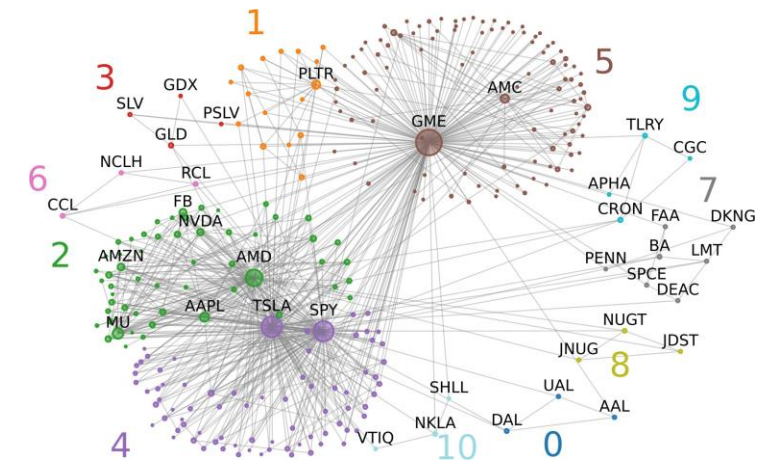
# Our research - Applications



urban gentrification



financial market analysis



social network polarisation



# Why we need JADE



- Graph-structured datasets are typically very large
  - millions of nodes and billions of edges
  - rich features associated with nodes/edges
- Graph ML models can be computationally costly to train
  - on large graphs (even with linear complexity)
  - for graph transformers (in theory quadratic complexity)
- Graph ML tasks take diverse forms
  - graph-level tasks
  - node/edge-level tasks
  - dynamic/online settings

**Thank  
you!**

contact: [xdong@robots.ox.ac.uk](mailto:xdong@robots.ox.ac.uk)