### Modern Discrete Probability

### I - Introduction

Stochastic processes on graphs: models and questions

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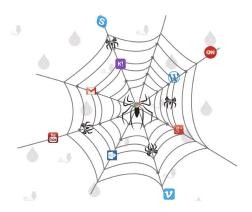
UW-Madison

Mathematics

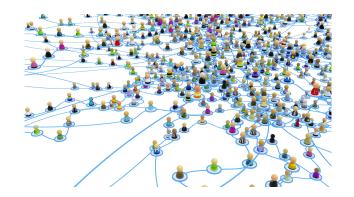
August 31, 2020



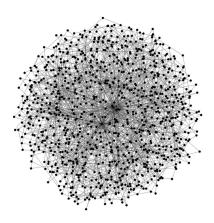
# **Exploring graphs**



## Processes on graphs



## Modeling complex graphs



Graph terminology

Basic examples of stochastic processes on graphs

### Graphs

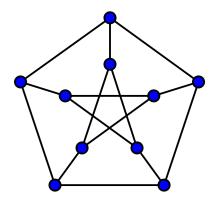
#### Definition

An *(undirected) graph* is a pair G = (V, E) where V is the set of *vertices* and

$$E \subseteq \{\{u, v\} : u, v \in V\},\$$

is the set of edges.

## An example: the Petersen graph



### **Basic definitions**

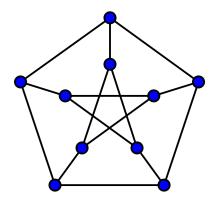
### Definition (Neighborhood)

Two vertices  $u, v \in V$  are *adjacent*, denoted by  $u \sim v$ , if  $\{u, v\} \in E$ . The set of adjacent vertices of v, denoted by N(v), is called the *neighborhood* of v and its size, i.e.  $\delta(v) := |N(v)|$ , is the *degree* of v. A vertex v with  $\delta(v) = 0$  is called *isolated*.

#### Example

All vertices in the Petersen graph have degree 3. In particular there is no isolated vertex.

## An example: the Petersen graph



### Paths and connectivity

### Definition (Paths)

A path in G is a sequence of vertices  $x_0 \sim x_1 \sim \cdots \sim x_k$ . The number of edges, k, is called the *length* of the path. If  $x_0 = x_k$ , we call it a *cycle*. We write  $u \leftrightarrow v$  if there is a path between u and v. The equivalence classes of  $\leftrightarrow$  are called *connected components*. The length of the shortest path between two vertices u, v is their *graph distance*, denoted  $d_G(u, v)$ .

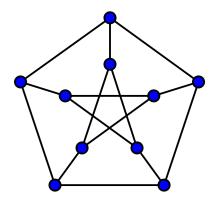
### **Definition (Connectivity)**

A graph is *connected* if any two vertices are linked by a path, i.e., if  $u \leftrightarrow v$  for all  $u, v \in V$ .

### Example

The Petersen graph is connected.

## An example: the Petersen graph



## Adjacency matrix

#### Definition

Let G = (V, E) be a graph with n = |V|. The *adjacency matrix* A of G is the  $n \times n$  matrix defined as  $A_{xy} = 1$  if  $\{x, y\} \in E$  and 0 otherwise.

### Example

The adjacency matrix of a *triangle* (i.e. 3 vertices with all edges) is

$$\begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}.$$

## Examples of finite graphs

- $K_n$ : clique with n vertices, i.e., graph with all edges present
- *C<sub>n</sub>*: cycle with *n* non-repeated vertices
- $\mathbb{H}^n$ : *n*-dimensional hypercube, i.e.,  $V = \{0, 1\}^n$  and  $u \sim v$  if u and v differ at one coordinate

Graph terminology

Basic examples of stochastic processes on graphs

## Random walk on a graph

#### Definition

Let G = (V, E) be a countable graph where every vertex has finite degree. Let  $c : E \to \mathbb{R}_+$  be a positive edge weight function on G. We call  $\mathcal{N} = (G, c)$  a *network*. Random walk on  $\mathcal{N}$  is the process on V, started at an arbitrary vertex, which at each time picks a neighbor of the current state proportionally to the weight of the corresponding edge.

#### Questions:

- How often does the walk return to its starting point?
- How long does it take to visit all vertices once or a particular subset of vertices for the first time?
- How fast does it approach equilibrium?



## Undirected graphical models I

#### Definition

Let S be a finite set and let G = (V, E) be a finite graph. Denote by  $\mathcal{K}$  the set of all cliques of G. A positive probability measure  $\mu$  on  $\mathcal{X} := S^V$  is called a *Gibbs random field* if there exist *clique potentials*  $\phi_K : S^K \to \mathbb{R}$ ,  $K \in \mathcal{K}$ , such that

$$\mu(\mathbf{X}) = \frac{1}{\mathcal{Z}} \exp \left( \sum_{\mathbf{K} \in \mathcal{K}} \phi_{\mathbf{K}}(\mathbf{X}_{\mathbf{K}}) \right),$$

where  $x_K$  is x restricted to the vertices of K and  $\mathcal{Z}$  is a normalizing constant.

## Undirected graphical models II

### Example

For  $\beta > 0$ , the ferromagnetic Ising model with inverse temperature  $\beta$  is the Gibbs random field with  $S := \{-1, +1\}$ ,  $\phi_{\{i,j\}}(\sigma_{\{i,j\}}) = \beta \sigma_i \sigma_j$  and  $\phi_K \equiv 0$  if  $|K| \neq 2$ . The function  $\mathcal{H}(\sigma) := -\sum_{\{i,j\} \in E} \sigma_i \sigma_j$  is known as the Hamiltonian. The normalizing constant  $\mathcal{Z} := \mathcal{Z}(\beta)$  is called the partition function. The states  $(\sigma_i)_{i \in V}$  are referred to as *spins*.

#### Questions:

- How fast is correlation decaying?
- How to sample efficiently?
- How to reconstruct the graph from samples?



### Erdös-Rényi random graph

#### Definition

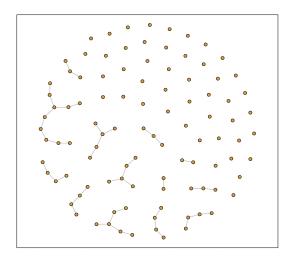
Let V = [n] and  $p \in [0, 1]$ . The *Erdös-Rényi graph* G = (V, E) on n vertices with density p is defined as follows: for each pair  $x \neq y$  in V, the edge  $\{x, y\}$  is in E with probability p independently of all other edges. We write  $G \sim \mathbb{G}_{n,p}$  and we denote the corresponding measure by  $\mathbb{P}_{n,p}$ .

#### Questions:

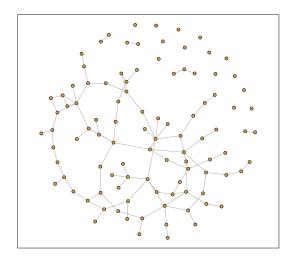
- What is the probability of observing a triangle?
- Is G connected?
- What is the typical chromatic number (i.e., the smallest number of colors needed to color the vertices so that no two adjacent vertices share the same color)?



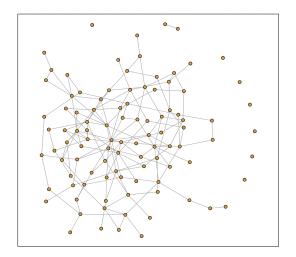
### Erdös-Rényi with n = 100 and $p_n = 1/100$



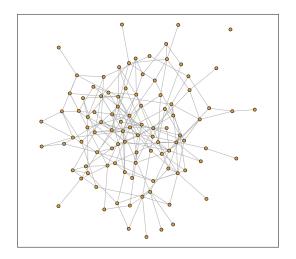
### Erdös-Rényi with n = 100 and $p_n = 2/100$



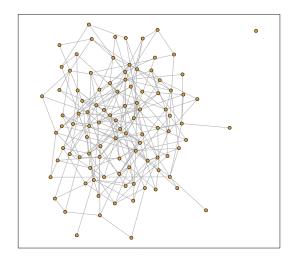
### Erdös-Rényi with n = 100 and $p_n = 3/100$



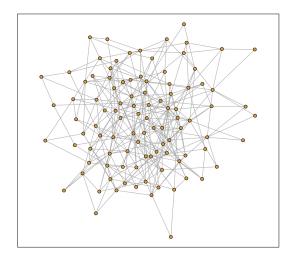
### Erdös-Rényi with n = 100 and $p_n = 4/100$



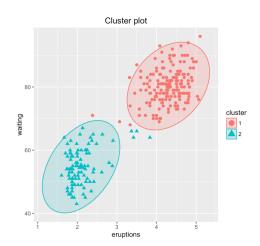
## Erdös-Rényi with n = 100 and $p_n = 5/100$



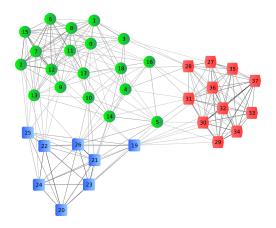
### Erdös-Rényi with n = 100 and $p_n = 6/100$



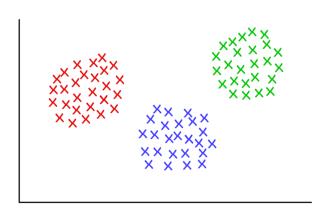
### Clustering in Euclidean space



# Clustering in graphs



### Reducing the second problem to the first one



### Go deeper

#### More details at:

http://www.math.wisc.edu/~roch/mdp/