# Caclulation

## 1 Calculation

We calculate what the covariance matrix looks like after a single partition/local complementation operation. We assume that the partition is sampled according to the stochastic block model. So the graph is partitioned in to subgraphs  $V_1$  and  $V_2$  and an edge between two vertices in  $V_i$  exists with probability p, while an edge between a vertex in  $V_1$  and a vertex in  $V_2$  exists with probability q. We assume  $|V_1| = |V_2|$ .

### 1.1 Edge Exists

First calculate P(edge e exists after partition/complement operation). Let e connect vertices i and j. This equals

 $P(\text{e exists after complementing}|(i \text{ and } j \in V_1)) \cdot P(i \text{ and } j \in V_1)$ 

 $+P(\text{e exists after complementing}|(i \text{ and } j \in V_2)) \cdot P(i \text{ and } j \in V_2)$ 

 $+P(e \text{ exists after complementing } | i \in V_1, j \in V_2) \cdot P(i \in V_1, j \in V_2)$ 

 $+P(e \text{ exists after complementing } | i \in V_2, j \in V_1) \cdot P(i \in V_2, j \in V_1).$ 

When vertices i and j are in the same partition after a complement, the probability the edge exists after the complement is 1-p. Complements don't affect edges which go across partitions, so the probability of that edge existing after the complement is still q. So the above equals

$$(1-p) \cdot \frac{1}{4} + (1-p) \cdot 14 + q \cdot \frac{1}{4} + q \cdot \frac{1}{4}.$$
$$= \frac{1-p+q}{2}.$$

#### 1.2 Variance

Let  $X_{e_i}$  denote the random variable where  $X_{e_i} = 1$  if the edge  $e_i$  exists and 0 otherwise. So the covariance matrix we want to calculate looks like

$$\begin{bmatrix} Var(X_{e_1}) & Cov(X_{e_1}, X_{e_{n^2}}) \\ Cov(X_{e_2}, X_{e_1}) & Var(X_{e_2}) \\ & \cdot & \cdot \\ \\ Cov(X_{e_{n^2}}, X_{e_1}) & Var(X_{e_{n^2}}) \end{bmatrix}$$

We first calculate the diagonal elements (i.e. the variances). By definition,  $Var(X_{e_i}) = E(X_{e_i}^2) - E(X_{e_i})^2$ .  $E(X_{e_i})$  is just the probability that the edge  $e_i$  exists, which we already calculated.

Consider the random variable  $Y_{e_i} = x_{e_i}^2$ . Then  $Y_{e_i}$  is 1 when the edge  $e_i$  exists after the complement and zero otherwise. That is, it has the exact same distribution as  $X_{e_i}$ . Therefore,

$$Var(X_{e_i}) = E(Y_i) - E(X_{e_i})^2$$
  
=  $\left(\frac{1-p+q}{2}\right) - \left(\frac{(1-p+q)^2}{4}\right)$ .

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#### 1.3 Covariance

We calculate  $Cov(X_{e_i}, X_{e_i})$ . By definition,

$$Cov(X_{e_i}, X_{e_j}) = E(X_{e_i} - \mu_{X_{e_i}})(X_{e_j} - \mu_{X_{e_j}})$$
$$= E(X_{e_i}X_{e_j} - X_{e_i}\mu_{X_{e_i}} - X_{e_j}\mu_{X_{e_i}} + \mu_{X_{e_i}}\mu_{X_{e_j}}).$$

We just need to calculate the product term. Then we can use the linearity to get the whole thing. See that  $X_{e_i}X_{e_j}$  is the random variable which takes the value 1 if both edges  $e_i$  and  $e_j$  exist after complementing and zero otherwise. So  $E(X_{e_i}X_{e_j}) = P(X_{e_i} = 1 \text{ and } X_{e_j} = 1)$ . Let  $e_i$  connect vertices i, j and  $e_j$  connect vertices (i', j'). This is

$$P(X_{e_{i}=1} \land X_{e_{j}=1} | (i,j), (i',j') \in V_{1}) \cdot P((i,j), (i',j') \in V_{1})$$

$$+P(X_{e_{i}=1} \land X_{e_{j}=1} | (i,j), (i',j') \in V_{2}) \cdot P((i,j), (i',j') \in V_{2})$$

$$+P(X_{e_{i}=1} \land X_{e_{j}=1} | (i,j) \in V_{1}, (i',j') \in V_{2}) \cdot P((i,j) \in V_{1}, (i',j') \in V_{2})$$

$$+P(X_{e_{i}=1} \land X_{e_{j}=1} | (i,j) \in V_{2}, (i',j') \in V_{1}) \cdot P((i,j) \in V_{2}, (i',j') \in V_{1}).$$

$$= (1-p)^{2} \cdot 1/4 + (1-p)^{2} \cdot 1/4 + (1-p)q \cdot 1/4 + (1-p)q \cdot 1/4$$

$$= \frac{(1-p)((1-p)+q)}{2}.$$

So the covariance is equal to  $\frac{(1-p)((1-p)+q)}{2}$  plus the (expectation of) the other terms. These values and the variance values give us all entries in the covariance matrix after a single partition/complementing operation.