Lecture 18

Models for areal data

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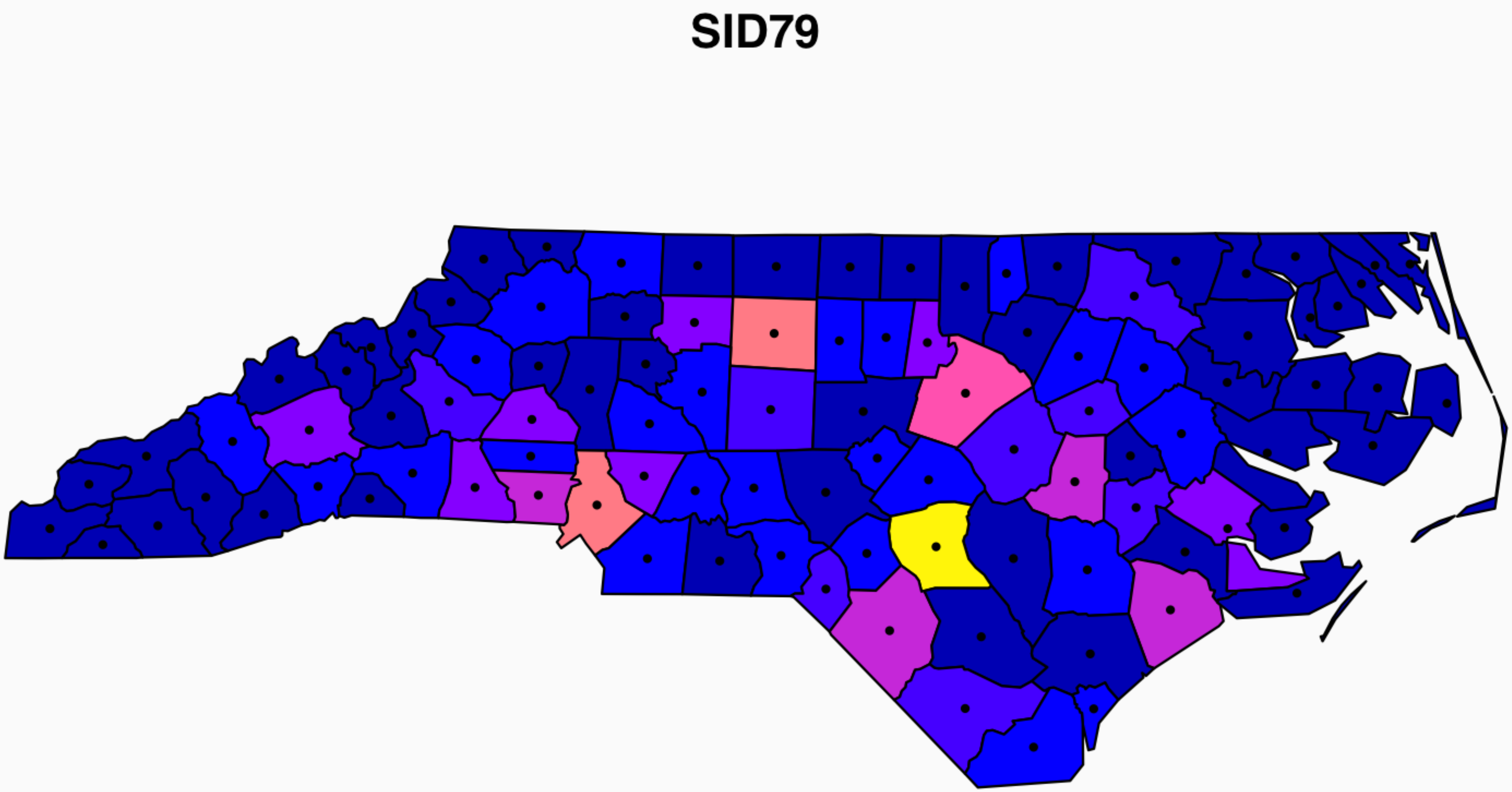
03/22/2017

areal / lattice data

Example - NC SIDS



EDA - Moran's I

If we have observations at n spatial locations $(s_1, \ldots s_n)$

$$I = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n w_{ij}} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \big(y(s_i) - \bar{y}\big)\big(y(s_j) - \bar{y}\big)}{\sum_{i=1}^n \big(y(s_i) - \bar{y}\big)^2}$$

where $\boldsymbol{w}$ is a spatial weights matrix.

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where $\boldsymbol{w}$ is a spatial weights matrix.

Some properties of Moran's I (when there is no spatial autocorrelation):

- $E(I) = -1/(n-1)$
- $Var(I) = E(I^2) - E(I)^2 =$ Something ugly but closed form
- Asymptotically, $\frac{I - E(I)}{\sqrt{Var(I)}} \sim \mathcal{N}(0,1)$

Lets start by using an adjacency matrix for w (shared county borders).

```
morans_I = function(y, w)
{
  n = length(y)
  y_bar = mean(y)
  num = sum(w * (y-y_bar) %*% t(y-y_bar))
  denom = sum( (y-y_bar)^2 )
  (n/sum(w)) * (num/denom)
}

morans_I(y = nc$SID74, w = 1*st_touches(nc, sparse=FALSE))
## [1] 0.119089
```

```
library(ape)
Moran.I(nc$SID74, weight = 1*st_touches(nc, sparse=FALSE)) %>% str()
## List of 4
##  $ observed: num 0.148
##  $ expected: num -0.0101
##  $ sd      : num 0.0627
##  $ p.value : num 0.0118
```

Like Moran's I, if we have observations at n spatial locations $(s_1, \ldots s_n)$

$$C = \frac{n-1}{2\sum_{i=1}^n \sum_{j=1}^n w_{ij}} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij}\big(y(s_i) - y(s_j)\big)^2}{\sum_{i=1}^n \big(y(s_i) - \bar{y}\big)^2}$$

where $\boldsymbol{w}$ is a spatial weights matrix.

EDA - Geary's C

Like Moran's I, if we have observations at n spatial locations $(s_1, \ldots s_n)$

$$C = \frac{n-1}{2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\big(y(s_i) - y(s_j)\big)^2}{\sum_{i=1}^{n}\big(y(s_i) - \bar{y}\big)}$$

where $\boldsymbol{w}$ is a spatial weights matrix.

Some properties of Geary's C:

- $0 < C < 2$
  - If $C \approx 1$ then no spatial autocorrelation
  - If $C > 1$ then negative spatial autocorrelation
  - If $C < 1$ then positive spatial autocorrelation
- Geary's C is inversely related to Moran's I

NC SIDS & Geary's C

Again using an adjacency matrix for *w* (shared county borders).

```
gearys_C = function(y, w)
{
  n = length(y)
  y_bar = mean(y)
  y_i = y %*% t(rep(1,n))
  y_j = t(y_i)
  num = sum(w * (y_i-y_j)^2)
  denom = sum( (y-y_bar)^2 )
  ((n-1)/(2*sum(w))) * (num/denom)
}

gearys_C(y = nc$SID74, w = 1*st_touches(nc, sparse=FALSE))
## [1] 0.8898868
```

Spatial Correlogram

```r
d = nc %>% st_centroid() %>% st_distance() %>% strip_class()
breaks = seq(0, max(d), length.out = 21)
d_cut = cut(d, breaks)

adj_mats = map(
  levels(d_cut),
  function(l)
  {
    (d_cut == l) %>%
      matrix(ncol=100) %>%
      `diag<-`(0)
  }
)

d = data_frame(
  dist   = breaks[-1],
  morans = map_dbl(adj_mats, morans_I, y = nc$SID74),
  gearys = map_dbl(adj_mats, gearys_C, y = nc$SID74)
)
```

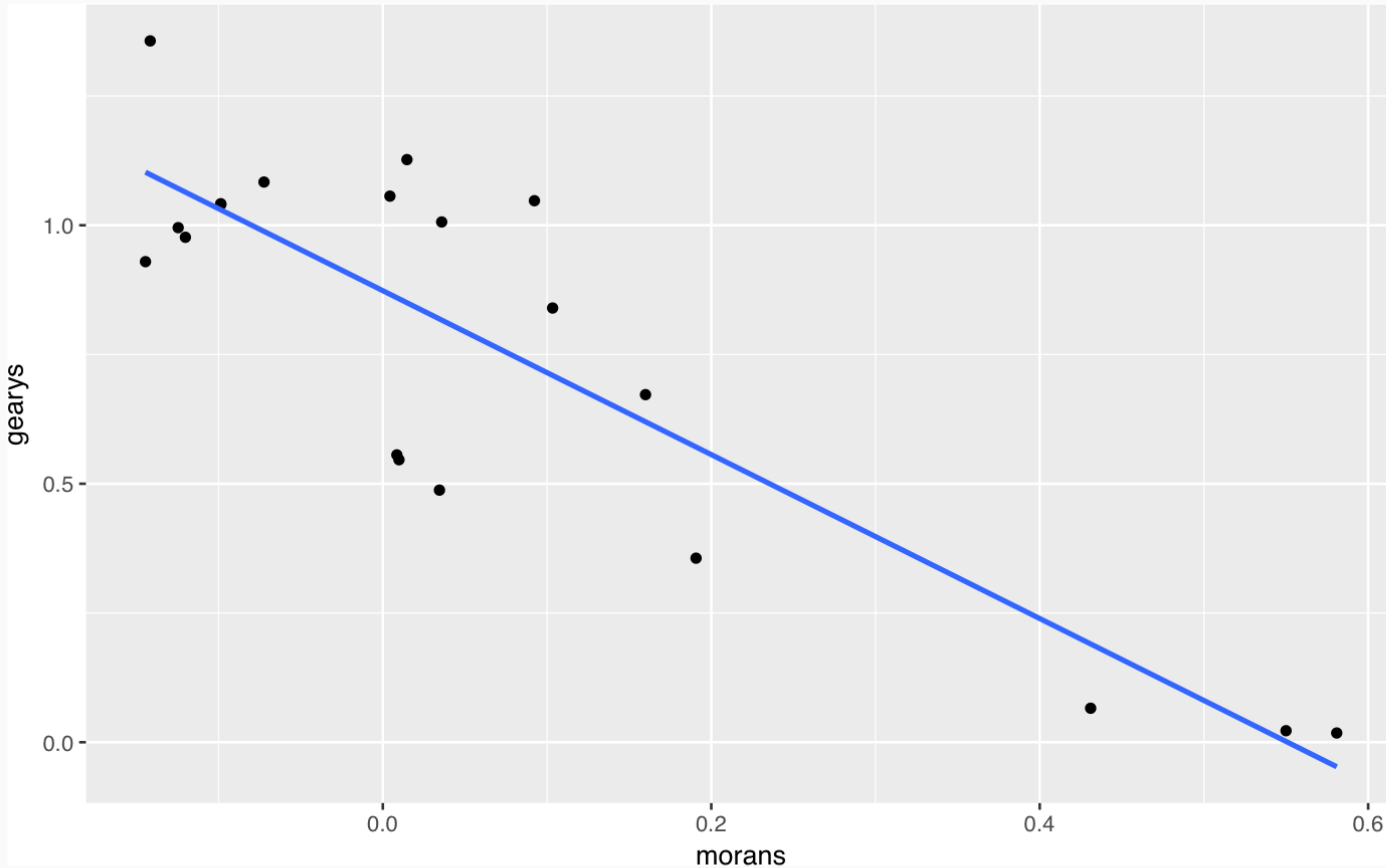
(0-1]

$$\begin{bmatrix} 0 & 5 & 3 \\ 5 & 0 & 1 \\ 3 & 1 & 0 \end{bmatrix} \to \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

(2-3]

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

morans
gearys
0.6
0.4
0.2
0.0
1.0
0.5
0.0
2e+05
4e+05
6e+05
2e+05
4e+05
6e+05
value
dist
var
morans
gearys


gearys
1.0
0.5
0.0
0.0
0.2
0.4
0.6
morans

Autoregressive Models

AR Models - Time

Lets just focus on the simplest case, an $AR(1)$ process

$$y_t = \delta + \phi\, y_{t-1} + w_t$$

where $w_t \sim \mathcal{N}(0, \sigma^2)$ and $|\phi| < 1$, then

$$E(y_t) = \frac{\delta}{1 - \phi}$$
$$Var(y_t) = \frac{\sigma^2}{1 - \phi}$$

AR Models - Time - Joint Distribution

Previously we saw that an $AR(1)$ model can be represented using a multivariate normal distribution

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \sim \mathcal{N}\left(\frac{\delta}{1-\phi} \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix},\ \frac{\sigma^2}{1-\phi} \begin{pmatrix} 1 & \phi & \cdots & \phi^{n-1} \\ \phi & 1 & \cdots & \phi^{n-2} \\ \vdots & \vdots & \ddots & \vdots \\ \phi^{n-1} & \phi^{n-2} & \cdots & 1 \end{pmatrix} \right)$$

AR Models - Time - Joint Distribution

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$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \sim \mathcal{N}\left(\frac{\delta}{1-\phi} \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix},\ \frac{\sigma^2}{1-\phi} \begin{pmatrix} 1 & \phi & \cdots & \phi^{n-1} \\ \phi & 1 & \cdots & \phi^{n-2} \\ \vdots & \vdots & \ddots & \vdots \\ \phi^{n-1} & \phi^{n-2} & \cdots & 1 \end{pmatrix} \right)$$

In writing down the likelihood we also saw that an $AR(1)$ is 1st order Markovian,

$f(y_t \mid y_{t-1}) \sim N(\delta + \phi y_{t-1}, \sigma^2)$

$$\begin{aligned} f(y_1,\ldots,y_n) &= f(y_1)\, f(y_2|y_1)\, f(y_3|y_2,y_1) \cdots f(y_n|y_{n-1},y_{n-2},\ldots,y_1) \\ &= f(y_1)\, f(y_2|y_1)\, f(y_3|y_2) \cdots f(y_n|y_{n-1}) \end{aligned}$$

Competing Definitions for y_t

$$y_t = \delta + \phi\, y_{t-1} + w_t$$

vs.

$$y_t | y_{t-1} \sim \mathcal{N}(\delta + \phi\, y_{t-1},\ \sigma^2)$$

Competing Definitions for y_t

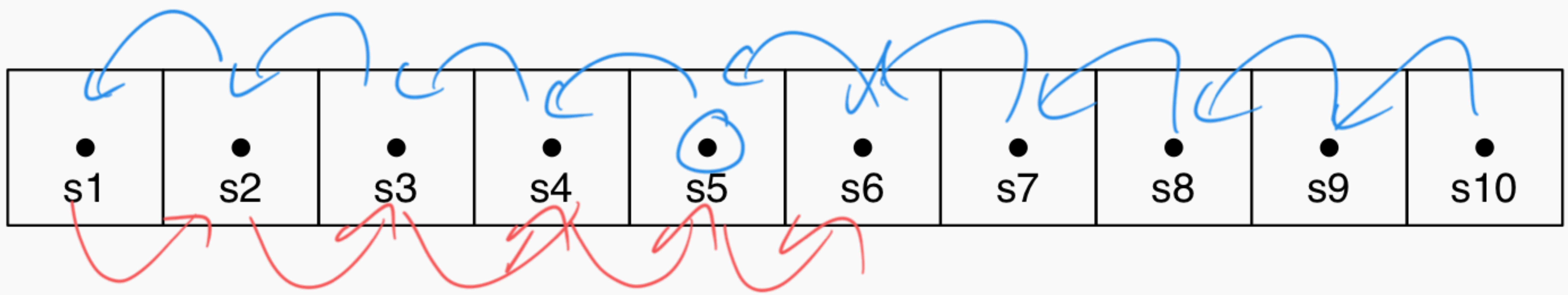
$$y_t = \delta + \phi\, y_{t-1} + w_t$$

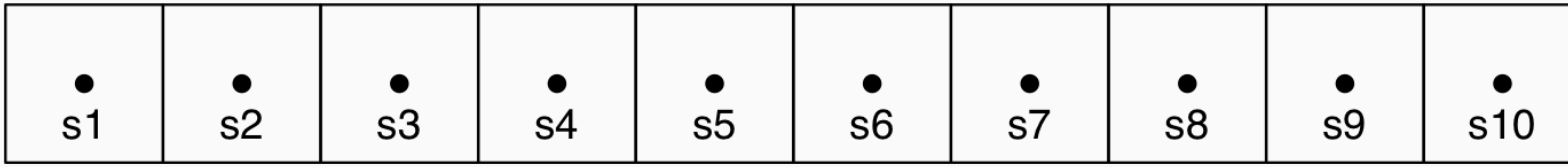
vs.

$$y_t | y_{t-1} \sim \mathcal{N}(\delta + \phi\, y_{t-1},\ \sigma^2)$$

In the case of time, both of these definitions result in the same multivariate distribution for $\boldsymbol{y}$.

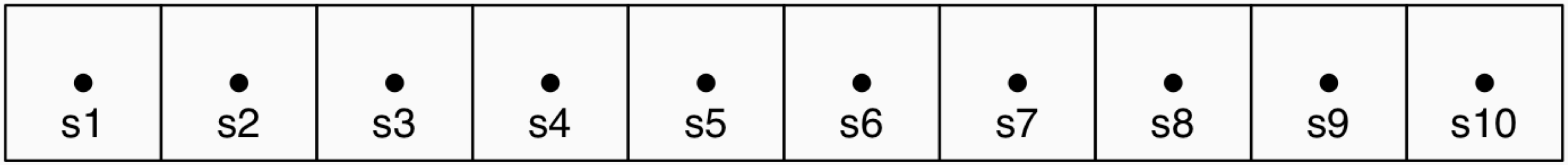
AR in Space





Even in the simplest spatial case there is no clear / unique ordering,

$$\begin{aligned}
f\Big(y(s_1),\ldots,y(s_{10})\Big) &= f\Big(y(s_1)\Big)\, f\Big(y(s_2)|y(s_1)\Big)\ \cdots\ f\Big(y(s_{10}|y(s_9),y(s_8),\ldots,y(s_1)\Big) \\
&= f\Big(y(s_{10})\Big)\, f\Big(y(s_9)|y(s_{10})\Big)\ \cdots\ f\Big(y(s_1|y(s_2),y(s_3),\ldots,y(s_{10})\Big) \\
&= ?
\end{aligned}$$



Even in the simplest spatial case there is no clear / unique ordering,

$$\begin{aligned} f\Big(y(s_1), \ldots, y(s_{10})\Big) &= f\Big(y(s_1)\Big)\, f\Big(y(s_2)|y(s_1)\Big) \;\cdots\; f\Big(y(s_{10}|y(s_9), y(s_8), \ldots, y(s_1)\Big) \\ &= f\Big(y(s_{10})\Big)\, f\Big(y(s_9)|y(s_{10})\Big) \;\cdots\; f\Big(y(s_1|y(s_2), y(s_3), \ldots, y(s_{10})\Big) \\ &= ? \end{aligned}$$

Instead we need to think about things in terms of their neighbors / neighborhoods. We will define $N(s_i)$ to be the set of neighbors of location s_i.

- If we define the neighborhood based on "touching" then $N(s_3) = \{s_2, s_4\}$
- If we use distance within 2 units then $N(s_3) = \{s_1, s_2, s_3, s_4\}$
  5
- etc.

Defining the Spatial AR model

Here we will consider a simple average of neighboring observations, just like with the temporal AR model we have two options in terms of defining the autoregressive process,

- Simultaneous Autogressve (SAR)

$$y(s) = \delta + \phi \frac{1}{|N(s)|} \sum_{s' \in N(s)} y(s') + \mathcal{N}(0, \sigma^2)$$

- Conditional Autoregressive (CAR)

$$y(s)|\boldsymbol{y}_{-s} \sim \mathcal{N}\left(\delta + \phi \frac{1}{|N(s)|} \sum_{s' \in N(s)} y(s'),\ \sigma^2\right)$$

Simultaneous Autogressve (SAR)

Using

$$y(s) = \delta + \phi \frac{1}{|N(s)|} \sum_{s' \in N(s)} y(s') + \mathcal{N}(0, \sigma^2)$$

we want to find the distribution of $\boldsymbol{y} = \Big(y(s_1),\, y(s_2),\, \ldots,\, y(s_n)\Big)^t$.

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we want to find the distribution of $\boldsymbol{y} = \Big(y(s_1),\, y(s_2),\, \ldots,\, y(s_n)\Big)^t$.

First we need to define a weight matrix $\boldsymbol{W}$ where

$$\{\boldsymbol{W}\}_{ij} = \begin{cases} 1/|N(s_i)| & \text{if } j \in N(s_i) \\ 0 & \text{otherwise} \end{cases}$$

Simultaneous Autogressve (SAR)

Using

$$y(s) = \delta + \phi \frac{1}{|N(s)|} \sum_{s' \in N(s)} y(s') + \mathcal{N}(0, \sigma^2)$$

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First we need to define a weight matrix $\boldsymbol{W}$ where

$$\{\boldsymbol{W}\}_{ij} = \begin{cases} 1/|N(s_i)| & \text{if } j \in N(s_i) \\ 0 & \text{otherwise} \end{cases}$$

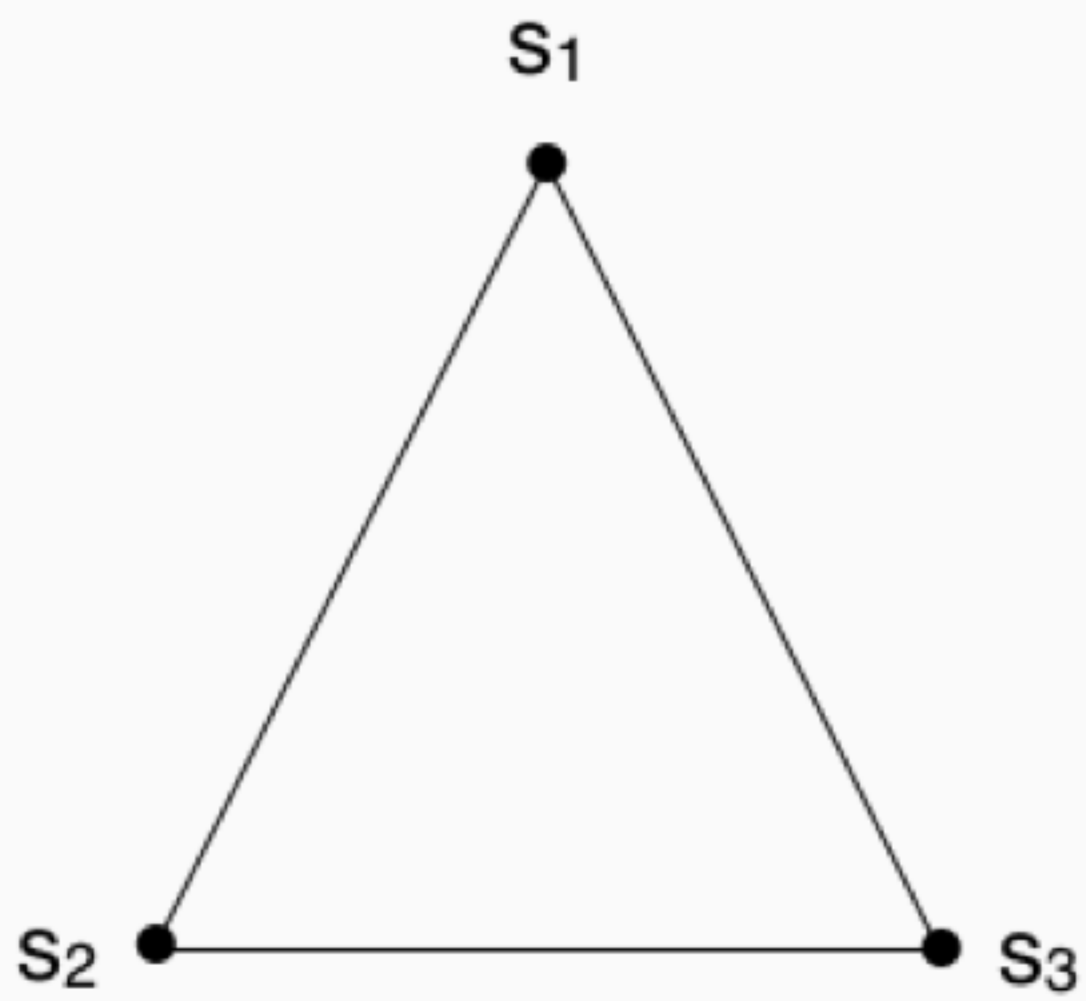
then we can write $\boldsymbol{y}$ as follows,

$$\boldsymbol{y} = \boldsymbol{\delta} + \boxed{\phi\, \boldsymbol{W}\, \boldsymbol{y}} + \boldsymbol{\epsilon}$$

where

$$\boldsymbol{\epsilon} \sim \mathcal{N}(0, \sigma^2\, \boldsymbol{I})$$

A toy example



$$\phi W y = \phi \begin{bmatrix} 0 & 1/2 & 1/2 \\ 1/2 & 0 & 1/2 \\ 1/2 & 1/2 & 0 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

$$\phi\left(\frac{y_2}{2} + \frac{y_3}{2}\right)$$

$$\phi\left(\frac{y_1}{2} + \frac{y_3}{2}\right)$$

$$\phi\left(\frac{y_2}{2} + \frac{y_1}{2}\right)$$

$$W = \begin{bmatrix} 0 & 1/2 & 1/2 \\ 1/2 & 0 & 1/2 \\ 1/2 & 1/2 & 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 1/|N(s_i)| & \frac{1}{|N(s_i)|} \\ & & \\ & & \end{bmatrix}$$

Back to SAR

$$\underset{(n\times 1)}{\boldsymbol{y}} = \underset{(n\times 1)}{\boldsymbol{\delta}} + \underset{(1\times 1)}{\phi}\,\underset{(n\times n)}{\boldsymbol{W}}\,\underset{(n\times 1)}{\boldsymbol{y}} + \underset{(n\times 1)}{\boldsymbol{\epsilon}}$$

$$(y - \phi W y) = \delta + \varepsilon$$

$$(\underset{(n\times n)}{I} - \phi W)\,y = \delta + \varepsilon$$

$$(n\times n)$$

$$y = (I - \phi W)^{-1}(\delta + \varepsilon)$$

$$= (I - \phi W)^{-1}\delta + (I - \phi W)^{-1}\varepsilon$$

$$Y = (I - \phi V)^{-1}\delta + (I - \phi W)^{-1}\varepsilon$$

$$\varepsilon \sim MVN\Big(\underset{(n\times 1)}{0},\ \underset{(n\times n)}{\operatorname{diag}(\sigma^2)}\Big)$$

$$E(Y) = (I - \phi V)^{-1}\delta$$

$$Var(Y) = (I - \phi V)^{-1}\, \underbrace{Var(\varepsilon)}_{\operatorname{diag}(\sigma^2) = I\sigma^2}\, \left((I - \phi W)^{-1}\right)^t$$

$$= \sigma^2 (I - \phi V)^{-1}\left((I - \phi V)^{-1}\right)^t$$

$$\underline{Y} \sim MVN\left((I - \phi V)^{-1}\delta,\ \Sigma = \right)$$

Conditional Autogressve (CAR)

This is a bit trickier, in the case of the temporal AR process we actually went from joint distribution $\longrightarrow$ conditional distributions (which we were then able to simplify).

Since we don't have a natural ordering we can't get away with this (at least not easily).

Going the other way, conditional distributions $\longrightarrow$ joint distribution is difficult because it is possible to specify conditional distributions that lead to an improper joint distribution.

Brook's Lemma

For sets of observations $\boldsymbol{x}$ and $\boldsymbol{y}$ where $p(x) > 0 \;\; \forall \, x \in \boldsymbol{x}$ and $p(y) > 0 \;\; \forall \, y \in \boldsymbol{y}$ then

$$
\begin{aligned}
\frac{p(\boldsymbol{y})}{p(\boldsymbol{x})} &= \prod_{i=1}^{n} \frac{p(y_i \mid y_1, \ldots, y_{i-1}, x_{i+1}, \ldots, x_n)}{p(x_i \mid \cancel{x_1, \ldots, x_{i-1}, y_{i+1}, \ldots, y_n})} \\
&= \prod_{i=1}^{n} \frac{p(y_i \mid x_1, \ldots, x_{i-1}, y_{i+1}, \ldots, y_n)}{p(x_i \mid \cancel{y_1, \ldots, y_{i-1}, x_{i+1}, \ldots, x_n})}
\end{aligned}
$$

A simplified example

Let $\boldsymbol{y} = (y_1, y_2)$ and $\boldsymbol{x} = (x_1, x_2)$ then we can derive Brook's Lemma for this case,

$$
\begin{aligned}
p(y_1, y_2) &= p(y_1|y_2)p(y_2) \\
&= p(y_1|y_2)\frac{p(y_2|x_1)\, p(x_1)}{p(x_1|y_2)} = \frac{p(y_1|y_2)}{p(x_1|y_2)}p(y_2|x_1)\, p(x_1) \\
&= \frac{p(y_1|y_2)}{p(x_1|y_2)}p(y_2|x_1)\, p(x_1)\left(\frac{p(x_2|x_1)}{p(x_2|x_1)}\right) \\
&= \frac{p(y_1|y_2)}{p(x_1|y_2)}\,\frac{p(y_2|x_1)}{p(x_2|x_1)}\, p(x_1, x_2)
\end{aligned}
$$

$$
\frac{p(y_1, y_2)}{p(x_1, x_2)} = \frac{p(y_1|y_2)}{p(x_1|y_2)}\,\frac{p(y_2|x_1)}{p(x_2|x_1)}
$$

Utility?

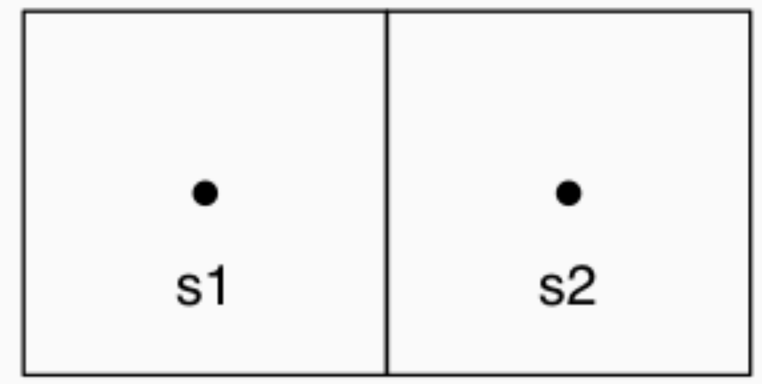
Lets repeat that last example but consider the case where $\boldsymbol{y} = (y_1, y_2)$ but now we let $\boldsymbol{x} = (y_1 = 0, y_2 = 0)$

$$\frac{p(y_1, y_2)}{p(x_1, x_2)} = \frac{p(y_1, y_2)}{p(y_1 = 0, y_2 = 0)}$$

$$p(y_1, y_2) = \frac{p(y_1|y_2)}{p(y_1 = 0|y_2)} \frac{p(y_2|y_1 = 0)}{p(y_2 = 0|y_1 = 0)} \, p(y_1 = 0, y_2 = 0)$$

$$\begin{aligned} p(y_1, y_2) &\propto \frac{p(y_1|y_2) \, p(y_2|y_1 = 0)}{p(y_1 = 0|y_2)} \\ &\propto \frac{p(y_2|y_1) \, p(y_1|y_2 = 0)}{p(y_2 = 0|y_1)} \end{aligned}$$

As applied to a simple CAR



$$W = \begin{bmatrix} 0 & w_{12} \\ w_{21} & 0 \end{bmatrix}$$

$$y(s_1)|y(s_2) \sim \mathcal{N}(\phi W_{12}\, y(s_2), \sigma^2)$$
$$y(s_2)|y(s_1) \sim \mathcal{N}(\phi W_{21}\, y(s_1), \sigma^2)$$

$$y(s_1)|y(s_2) \sim \mathcal{N}(\phi W_{12}\, y(s_2), \sigma^2)$$
$$y(s_2)|y(s_1) \sim \mathcal{N}(\phi W_{21}\, y(s_1), \sigma^2)$$

$$
\begin{aligned}
p\Big(y(s_1), y(s_2)\Big) &\propto \frac{p\Big(y(s_1)|y(s_2)\Big)\; p\Big(y(s_2)|y(s_1) = 0\Big)}{p\Big(y(s_1) = 0|y(s_2)\Big)} \\
&\propto \frac{\exp\Big(-\frac{1}{2\sigma^2}\,(y(s_1) - \phi\, W_{12}\, y(s_2))^2\Big)\, \exp\Big(-\frac{1}{2\sigma^2}\,(y(s_2) - \phi\, W_{21}\, 0)^2\Big)}{\exp\Big(-\frac{1}{2\sigma^2}\,(0 - \phi W_{12} y(s_2))^2\Big)} \\
&\propto \exp\left(-\frac{1}{2\sigma^2}\Big((y(s_1) - \phi\, W_{12}\, y(s_2))^2 + y(s_2)^2 - (\phi W_{12} y(s_2))^2\Big)\right) \\
&\propto \exp\left(-\frac{1}{2\sigma^2}\Big(y(s_1)^2 - 2\phi\, W_{12}\, y(s_1)\, y(s_2) + y(s_2)^2\Big)\right) \\
&\propto \exp\left(-\frac{1}{2\sigma^2}(\boldsymbol{y} - 0)\begin{pmatrix} 1 & -\phi W_{12} \\ -\phi W_{12} & 1 \end{pmatrix}(\boldsymbol{y} - 0)^t\right)
\end{aligned}
$$

Σ^{-1}

μ

$\mathcal{N}$

Implicatiomns for y

$$\boldsymbol{\mu} = 0$$

$$\begin{aligned}\boldsymbol{\Sigma}^{-1} &= \frac{1}{\sigma^2}\begin{pmatrix} 1 & -\phi W_{12} \\ -\phi W_{12} & 1 \end{pmatrix} \\ &= \frac{1}{\sigma^2}(I - \phi W)\end{aligned}$$

assume $W_{12} = W_{21}$

$$\Sigma = \sigma^2 (I - \phi W)^{-1}$$

Implicatiomns for y

$$\boldsymbol{\mu} = 0$$

$$\begin{aligned} \boldsymbol{\Sigma}^{-1} &= \frac{1}{\sigma^2} \begin{pmatrix} 1 & -\phi W_{12} \\ -\phi W_{12} & 1 \end{pmatrix} \\ &= \frac{1}{\sigma^2} (\boldsymbol{I} - \phi\, \boldsymbol{W}) \end{aligned}$$

$$\Sigma = \sigma^2 (\boldsymbol{I} - \phi\, \boldsymbol{W})^{-1}$$

we can then conclude that for $\boldsymbol{y} = \big(y(s_1),\ y(s_2)\big)^t$,

$$\boldsymbol{y} \sim \mathcal{N}\left(\boldsymbol{0},\ \sigma^2 (\boldsymbol{I} - \phi\, \boldsymbol{W})^{-1}\right)$$

which generalizes for all mean 0 CAR models.

General Proof

Let $\mathbf{y} = (y(s_1), \ldots, y(s_n))$ and $\mathbf{0} = (y(s_1) = 0, \ldots, y(s_n) = 0)$ then by Brook's lemma,

$$
\begin{aligned}
\frac{p(\mathbf{y})}{p(\mathbf{0})} &= \prod_{i=1}^{n} \frac{p(y_i|y_1, \ldots, y_{i-1}, 0_{i+1}, \ldots, 0_n)}{p(0_i|y_1, \ldots, y_{i-1}, 0_{i+1}, \ldots, 0_n)} \\
&= \prod_{i=1}^{n} \frac{\exp\left(-\frac{1}{2\sigma^2}\left(y_i - \phi \sum_{j<i} W_{ij}\, y_j - \cancel{\phi \sum_{j>i} 0_j}\right)^2\right)}{\exp\left(-\frac{1}{2\sigma^2}\left(\cancel{0_i} - \phi \sum_{j<i} W_{ij}\, y_j - \cancel{\phi \sum_{j>i} 0_j}\right)^2\right)} \\
&= \exp\left(-\frac{1}{2\sigma^2}\sum_{i=1}^{n}\left(y_i - \phi \sum_{j<i} W_{ij}\, y_j\right)^2 + \frac{1}{2\sigma^2}\sum_{i=1}^{n}\left(\phi \sum_{j<i} W_{ij}\, y_j\right)^2\right) \\
&= \exp\left(-\frac{1}{2\sigma^2}\sum_{i=1}^{n} y_i^2 - 2\phi y_i \sum_{j<i} W_{ij}\, y_j\right) \\
&= \exp\left(-\frac{1}{2\sigma^2}\sum_{i=1}^{n} y_i^2 - \phi \sum_{i=1}^{n}\sum_{j=1}^{n} y_i\, W_{ij}\, y_j\right) \quad (\text{if } W_{ij} = W_{ji}) \\
&= \exp\left(-\frac{1}{2\sigma^2}\mathbf{y}^t(I - \phi W)\mathbf{y}\right)
\end{aligned}
$$

Σ^{-1}

CAR vs SAR

- Simultaneous Autogressve (SAR)

$$y(s) = \phi \sum_{s'} \frac{W_{s\,s'}}{W_{s\,\cdot}} y(s') + \epsilon$$

$$\boldsymbol{y} \sim \mathcal{N}(0,\; \sigma^2 \left((\boldsymbol{I} - \phi \boldsymbol{W})^{-1} \right) \left((\boldsymbol{I} - \phi \boldsymbol{W})^{-1} \right)^t)$$

- Conditional Autoregressive (CAR)

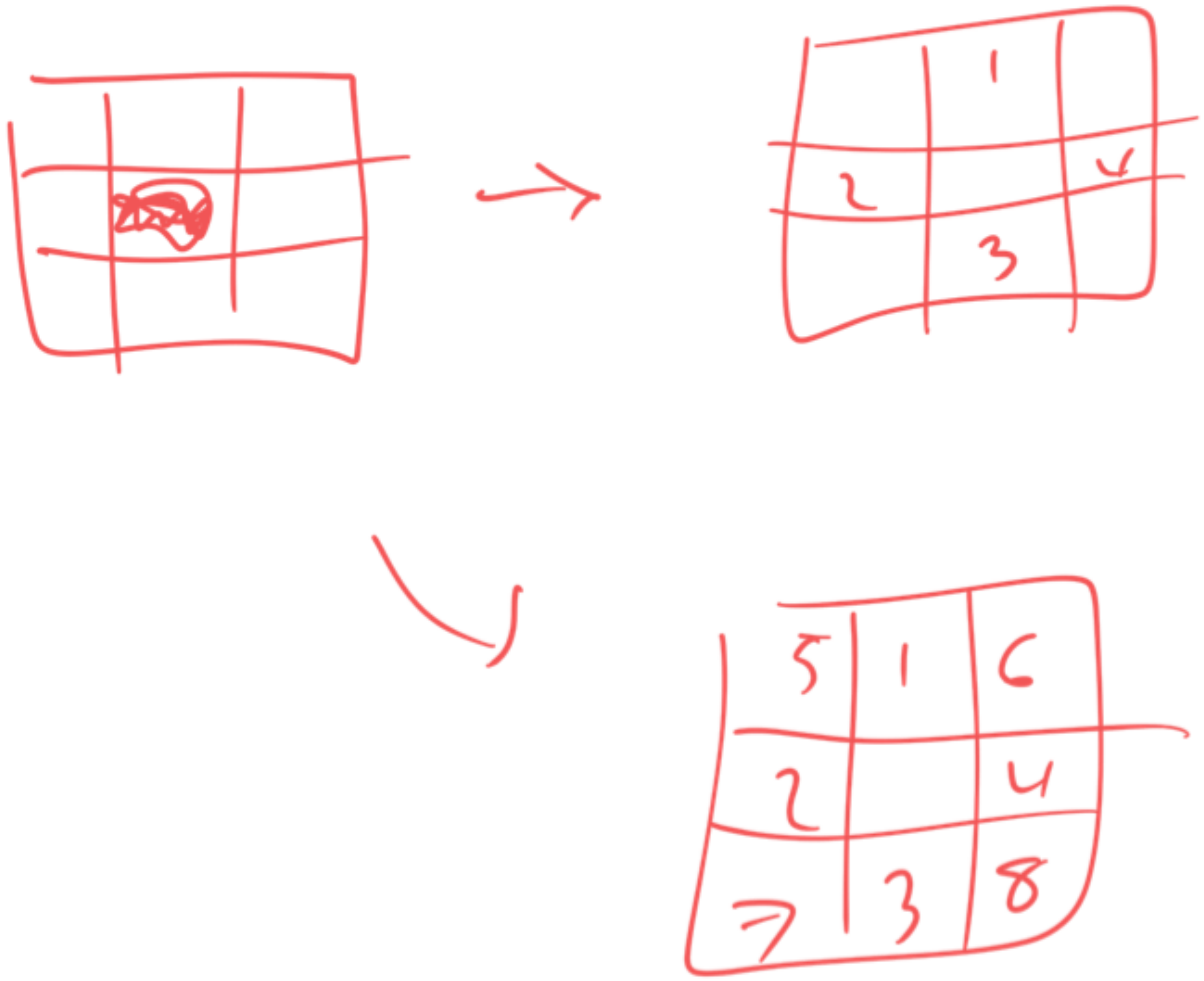
$$y(s) | \boldsymbol{y}_{-s} \sim \mathcal{N} \left(\sum_{s'} \frac{W_{s\,s'}}{W_{s\,\cdot}} y(s'),\; \sigma^2 \right)$$

$$\boldsymbol{y} \sim \mathcal{N}(0,\; \sigma^2 \left(\boldsymbol{I} - \phi \boldsymbol{W} \right)^{-1})$$

Assumes
$w = w^t$

Generalization

- Adopting different weight matrices, W
  - Between SAR and CAR model we move to a generic weight matrix definition (beyond average of nearest neighbors)
  - In time we varied p in the $AR(p)$ model, in space we adjust the weight matrix.
  - In general having a symmetric W is helpful, but not required
- More complex Variance (beyond $\sigma^2 I$)
  - σ^2 can be a vector (differences between areal locations)
  - E.g. since areal data tends to be aggregated - adjust variance based on sample size


1
2
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