

General idea: we have
 n distinct locations z_1, \dots, z_n
 $(z_w = (lat, long) \text{ eg})$

page 3
 rec 5

the goal is to
 define a model for the partitioning
 of z_i into $k_m(t)$ groups

so we define $p_m = \{s_1, \dots, s_{k_m(t)}\}$ the clusters
 solution, i.e. $w \in s_a \Leftrightarrow$ location z_i is
 in cluster a .

(in symmetric) let c_1, \dots, c_m with
 $c_w = a$ w/ ecc.

then the prior for p_m is

$$\varphi_m(p) = P(p = p_m) \propto \prod_{w=1}^{k_m} C(s_w, c_w^p)$$

no model for us w/ will become $C(s_w, t)$?

s_w will be like
 $C\{z_1, \dots, z_n, a\}$
 arbit

this makes the
 clustering process
 location dependent

we call this
 model / law as
 oPPM (optimal
 project parti-
 tion model)

this is a
 cohesion function:
 measures how likely
 these selected
 values of s_w would be
 clustered together
 or near

the set of locations
 that $\in s_w$ for
 like if $s_w = \{z_1, z_3, z_5\}$ then
 $c_w^p = \{z_1, z_3, z_5\}$

then the idea is to set to each s_i for $w=1 \rightarrow m$ a
 low / likelihood which is cluster dependent

$$\gamma_i = \gamma(z_i) | z_i, c_i \sim \frac{1}{\sigma^2} f(c_i^p) \text{ for } w=1 \rightarrow m$$

$$\frac{1}{\sigma^2} \sim \gamma_0 \text{ for } l=1 \rightarrow k_m$$

no actually later
 we show $\gamma_m(t)$ $\rightarrow k_m = |p_m(t)|$

$$\{c_i\}_{i=1}^m \sim \text{oPPM}$$

for example $c_i^p = (\gamma_i | \sigma^2)$
 and we set $f(\dots) = N(\dots)$

page 3
 rec 46

and we can include covariates with

let $\gamma_w(t)$ the values shared (gamma is covariates)

let $z_w(t)$ the covariate set

let $\beta_1^p, \dots, \beta_{k_m(t)}^p$ the cluster specific regression terms

the c_i^p of
 these
 (most, low can we have
 a non-zero value for $\gamma_i(t)$?
 ie, low will the extra influence
 work then? if the $\#k_m$ varies
 then the β_0 one time or not
 the have "model"

$$\gamma_i = \gamma(z_i) | z_w(t), c_i(t), \beta^p, \sigma^2 \sim N(z_i^T \beta_{c_i}^p, \sigma^2)$$

(all this temporal extension
 test makes me won)

there are more examples of models.
 note that we have $\{c_i\}_{i=1}^m \sim \text{oPPM}$, but that's
 equivalent to $p_m \sim \text{oPPM}$, so for the p_m we
 can transform to get the c_i .

$$p_m = \{s_1, \dots, s_{k_m}\}$$

$$\text{eg } \begin{pmatrix} 2 \\ 3 \\ 4 \end{pmatrix} \begin{pmatrix} 4 \\ 2 \\ 1 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

$$k_m = 4$$

for w from $1:m$
 $| c_i = \text{which } i \text{ from } s_j \text{ for } i=1:k_m$
 and

page 3
 rec 22

Oh, no!, now we can understand better the model of an un. (tes) most relevant topic, the topic 4.

Here the slow move the time extension!
at first alone

As the set $\omega = 4 \rightarrow m$ the units, ok, then model the partition so $P_t = \{S_1(t), \dots, S_{k_t}(t)\} \Rightarrow$ NICE
or again $S_t = (c_1(t), \dots, c_m(t))$ as before.

So we want to study the IP of getting a certain combination of partitions. So, suppose a MC random structure, we let our target be

$$p(p_1, \dots, p_T) = P(\underbrace{p_1(t) = p_1, \dots}_{\text{monotone}}) = p(p_T | p_{T-1}) \dots p(p_2 | p_1) \cdot p(p_1)$$

Then the we as you be the partition structure this

$$Pr(p|M) = \varphi_{p|M}(p|M) = P(p_M = p|M) = \frac{M^k}{\prod_{\omega=1}^m (M+\omega-1)} \frac{k}{\prod_{\omega=1}^k (1+\omega-1)}!$$

the constant monodirectional count the $\prod(1/\omega!)$ told in the previous topic

we call this low CRP(M).
But that low gives low we want to model the combination more p_{t-1} and p_t .

$p \sim \text{CRP}(M)$

So we introduce

$\alpha_t = \begin{cases} 1 & \text{unit } \omega \text{ stays in the same cluster from } t-1 \text{ to } t \\ 0 & \text{otherwise} \end{cases}$
we set $\alpha_t \sim \text{Ber}(\alpha_t)$ $\begin{cases} \alpha_t = 0: p_t \perp p_{t-1} \\ \alpha_t = 1: p_t = p_{t-1} \end{cases}$

Then as better into everything we introduce random $\mathcal{I}_t = (\mu_1(t), \dots, \mu_m(t))$ where $\mu_i(t) \in \{0, 1, 2\}$, to us) which values we set can be $\text{Ber}(\alpha_t)$ on the α_t we introduced alone.

we call this model tRPM(α, M), and that is what we will find in the model, about S_t , is equivalent, or the p_t .

$$\begin{aligned} Y_{it} | \mu_t^*, \sigma_t^{2*}, c_t &\stackrel{\text{ind}}{\sim} N(\mu_{c_{it}}^*, \sigma_{c_{it}}^{2*}), i = 1, \dots, m \text{ and } t = 1, \dots, T, \\ (\mu_{jt}^*, \sigma_{jt}^{2*}) | \theta_t, \tau_t^2 &\stackrel{\text{ind}}{\sim} N(\theta_t, \tau_t^2) \times \text{UN}(0, A_\sigma), j = 1, \dots, k_t, \\ (\theta_t, \tau_t) &\stackrel{\text{iid}}{\sim} N(\phi_0, \lambda^2) \times \text{UN}(0, A_\tau), t = 1, \dots, T, \\ (\phi_0, \lambda) &\sim N(m_0, s_0^2) \times \text{UN}(0, A_\lambda), \\ \checkmark \{c_t, \dots, c_T\} &\sim \text{tRPM}(\alpha, M), \text{ with } \alpha_t \stackrel{\text{iid}}{\sim} \text{Beta}(a_\alpha, b_\alpha), \end{aligned} \quad (5)$$

The effect of this \mathcal{I}_t on the low of p is just that it reduces the support, in now

$$P(p_t = \lambda | \mathcal{I}_t, p_{t-1}) = \begin{cases} 0 & \text{if } p_{t-1} \text{ and } p_t \text{ are not compatible with } \mathcal{I}_t \\ \dots & \text{otherwise} \end{cases}$$

now with gets more complex, less clear

topic 4
page 9

Or, we can see there was a data generation mechanism, so we could use it to make yet of our own new models.

paper 3
sec 23

$$y(cu) = \hat{y}_u = \gamma_{cu}^{\#}(cu) + \Delta u^T \beta_{cu} + \theta(cu) + \Delta u^T \beta$$

spatial effect
cluster + label
specific

concrete effect
cluster + label
specific

$$y_u(t) | y_u(t-1), \dots, s_t \sim \mathcal{N}(\gamma_{cu}^{\#}(t) + w_u y_u(t-1), \dots)$$

to introduce an
AR(1) effect

but by having just \hat{y}_u (we ^{and} ~~can~~ use all the models as mixture models)

or

$$y_u(t) | w_t, y_a \sim \text{ind} \quad f_y(y) = \sum_{a=1}^{k(t)} w_a(t) \cdot f_a(y)$$

where $w_a(t) = P(cu(t) = a | w)$

or

$$y_u(t) | s_t, \dots \sim \text{ind} \dots$$

where $s_t \sim \dots$

paper 4
sec 40

introduction
TA 2