Multiple imputation for lifecourse data

Brendan Halpin, Dept of Sociology, University of Limerick

Royal Statistical Society/SLLS June 9 2015

MICT: Gap-filling MI for lifecourse data

- Multiple imputation for categorical time series
- Particularly appropriate for life course history data
  - Spells in states, occasional transitions
  - Where missingness also tends to be consecutive
- More longitudinally coherent than MICE
- More appropriate to categorical time-series than approaches like Amelia
- Easy to use Stata add-on, computationally efficient
- Integrated with Stata's MI framework
  - uses its imputation engine
  - uses Stata's post-imputation estimation framework

Update

- This work updates work previously presented in 2012/3 (Halpin, 2012, 2013)
- Today I present new tests of performance using simulated and real data
- Now covers initial and terminal gaps as well as internal gaps
- Uses Stata's imputation engine rather than home-brewed version
- Integrates with Stata's MI infrastructure for post-imputation estimation
- Packaged as an easy-to-use Stata add-on

Missingness is endemic in longitudinal data

- Ever increasing availability of longitudinal data such as labour market, fertility, family formation, or residential histories
- But very subject to missingness, more than cross-sectional data
  - Repeated collection: attrition, contradiction
  - Demands of retrospection, etc

Some methods more affected than others

- Some methods can deal with missingness well
  - e.g. duration models can "censor" data from the first occurrence of missing onwards,
- Others require full data
- And throwing away data is wasteful, even where it does not introduce bias

Missingness is not random in lifecourse data

- Volatile life courses will be more prone to missingness
  - more likely to miss data collection point
  - less redundancy in the data (gap less likely to be papered over)
- Very often the information loss due to missingness is trivial
  - in practice lots of redundancy
  - a shame to throw the data away
- Hence we impute!

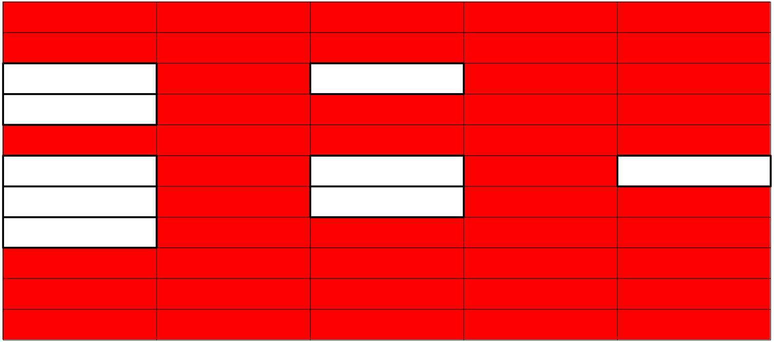
Multiple imputation now standard practice

- Rubin established the notion (1987)
  - Draw several imputations from the predictive distribution of the imputation model
  - Analyse each separately
  - Combine the results according to "Rubin's Rules"

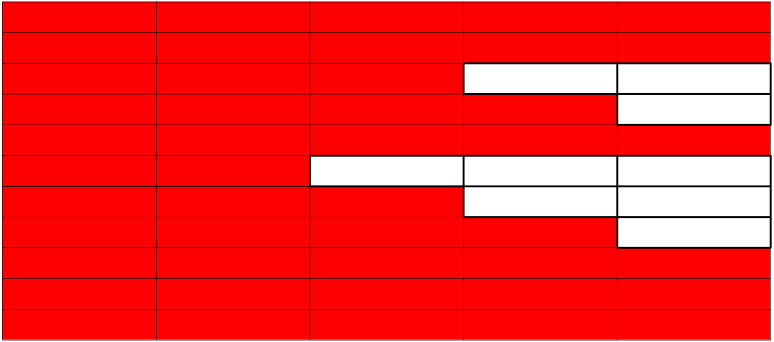
Multiple imputation with missingness in multiple variables

- Straightforward with single variable to impute
- A bit more complicated if there are multiple incomplete variables
- If missingness is monotone, a sequence of single imputations is possible

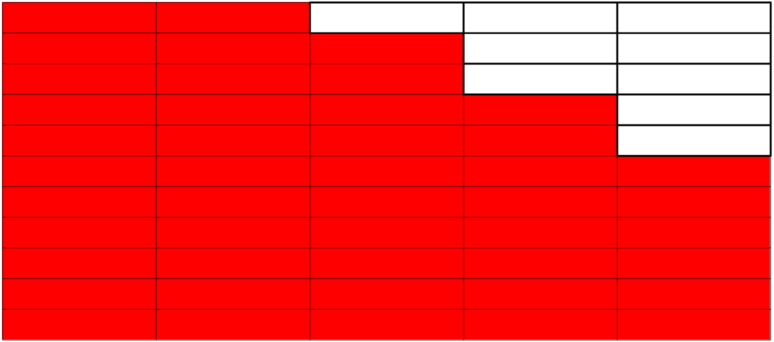
Monotone missing



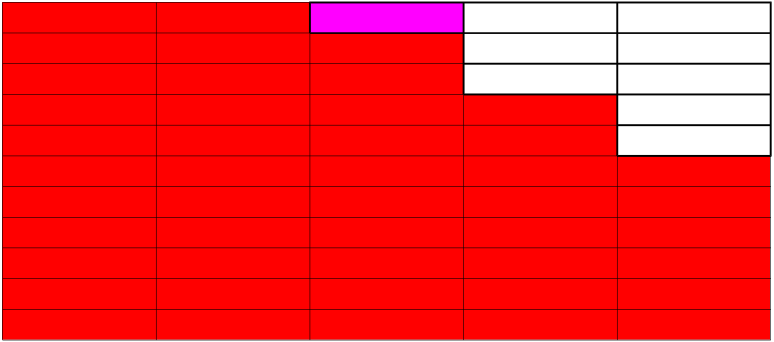
Monotone missing



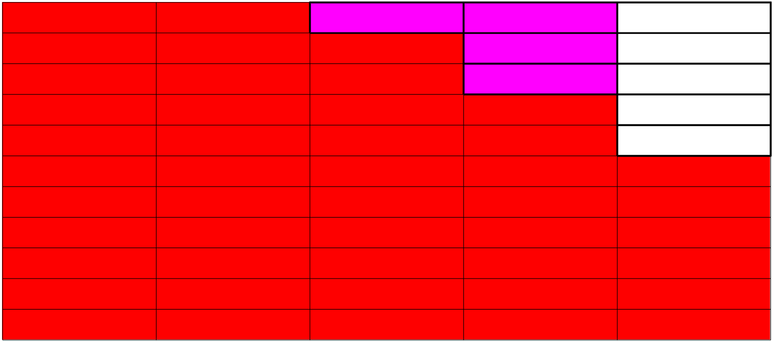
Monotone missing



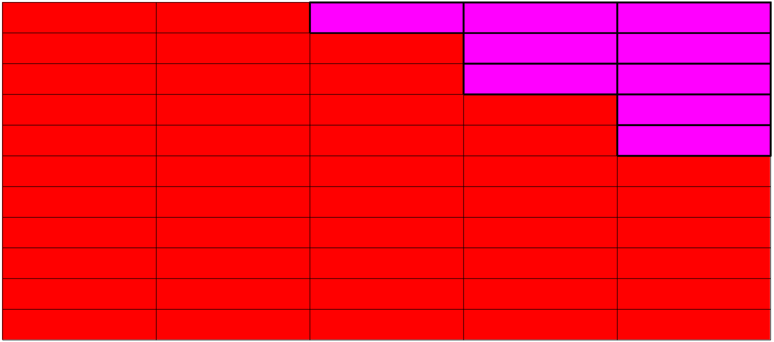
Monotone missing



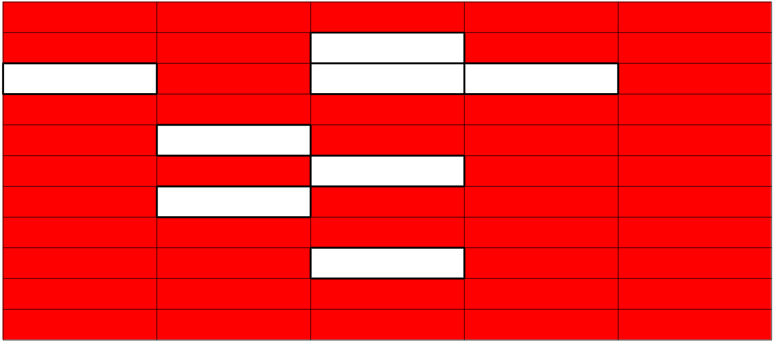
Monotone missing



Monotone missing

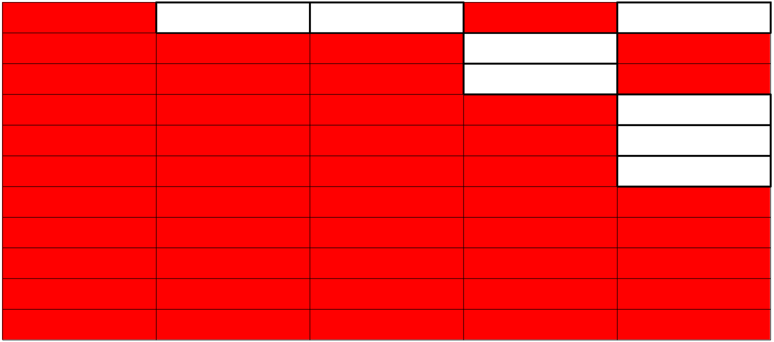


Non-Monotone missing



Non-Monotone missing

Non-Monotone missing



Two approaches: Joint Modelling and MICE

- If non-monotonic, two approaches
  - "Joint Modelling" (i.e., model the joint distribution P(Y,X,R))
  - MI by chained equations (van Buuren, 2007; van Buuren and Groothuis-Oudshoorn, 2011; Royston, 2009; White et al., 2011)
- The former has better theoretical foundations, but has substantial difficulties if some variables are categorical
- The latter is less well theorised but is flexible and experience says it works well, including for categorical variables.

MICE

- A separate equation for each imputed variable
- Thus allows logit, ordinal logit, multinomial logit as appropriate
- Deals with the joint nature of imputation by an iterative chain:
  - First, cheaply impute all missing observations (e.g., hot-deck)
  - Then re-impute using earlier imputations and observed data
  - Repeat until convergence occurs (often quite soon)
- While the theoretical base is not fully established, it works well
- It improves on joint modelling particularly for categorical variables (van Buuren, 2007; Allison, 2005)

MICE not for time-series

- Existing implementations of MICE are not adapted for time-series
- As yet, no mechanisms for treating lags and leads as "passively imputed"
- Currently difficult to express models that take longitudinality properly into account
- Brute force approaches fail: high numbers of highly collinear variables
- As I show below, it tends to impute data with too little longitudinal stability (transition rates too high)

Other MI software

- MI for time-series does exist
- In particular, Amelia (for R and Stata) (Honaker and King, 2010)
- However, this depends on joint imputation based on a MVN joint distribution
- As mentioned above, this is poor for categorical data (van Buuren, 2007; Allison, 2005)

Hence MICT: filling gaps with nearest info

- Treat explicitly as a time-series, use lags and leads to predict
- Focus on gaps rather than variables to orient sequence of imputation
- Effectively monotone missingness in this framework
- One model per unit of length of longest gap, not one per incomplete variable

Chained gap-healing

- Begin with longest gap, predict first (or last) element
- Then predict last (or first) of next shortest gap length (including longer gaps already reduced)
- Until no gaps remain
- Important to begin fill from edges
    - Least distance from observed data
    - But each gap has two edges: to begin pick one at random and impute
    - Then the other edge (of the newly shortened gap) has better data than the former, so alternate

Sketching gap closure

- Five unit gap Three unit gap
- `XXX.....XXX` `XXX...XXXXX`

Sketching gap closure

• Five unit gap	Three unit gap
• `XXX.....XXX`	`XXX...XXXXX`
• `XXX....iXXX`	`XXX...XXXXX`

Sketching gap closure

Five unit gap	Three unit gap
`XXX.....XXX`	`XXX...XXXXX`
`XXX....iXXX`	`XXX...XXXXX`
`XXXi...IXXX`	`XXX...XXXXX`

Sketching gap closure

- Five unit gap   Three unit gap
- `XXX.....XXX`   `XXX...XXXXX`
- `XXX....iXXX`   `XXX...XXXXX`
- `XXXi...IXXX`   `XXX...XXXXX`
- `XXXI..iIXXX`   `XXX..iXXXXX`

Sketching gap closure

Five unit gap	Three unit gap
`XXX.....XXX`	`XXX...XXXXX`
`XXX....iXXX`	`XXX...XXXXX`
`XXXi...IXXX`	`XXX...XXXXX`
`XXXI..iIXXX`	`XXX..iXXXXX`
`XXXIi.IIXXX`	`XXXi.IXXXXX`

Sketching gap closure

Five unit gap	Three unit gap
`XXX.....XXX`	`XXX...XXXXX`
`XXX....iXXX`	`XXX...XXXXX`
`XXXi...IXXX`	`XXX...XXXXX`
`XXXI..iIXXX`	`XXX..iXXXXX`
`XXXIi.IIXXX`	`XXXi.IXXXXX`
`XXXIIiIIXXX`	`XXXIiIXXXXX`

MICT for Stata

- Implemented as a Stata add-on: Multiple Imputation for Categorical Time-series (MICT: soon available in SSC)
- Key added value is handling the updating of lag and lead vars, defining the sequence of operations
- Predictive model: at least prior and subsequent states, but can be more sophisticated
  - summaries of prior and subsequent histories
  - time-varying effects
  - fixed individual-level variables
  - other time-dependent variables (fully observed or simply imputed)
- Analogous models for initial and terminal gaps

Examples

- Some demonstrations
  1. Real data with simulated missing: compare imputed with observed
  2. Simulated data with simulated missing: compare MICT and MICE using very simple data
  3. Real data with real gaps, using a fairly complex model
  4. Real data with real gaps, using more complex model that takes data collection context into account

Real data with simulated missing

- Data (McVicar and Anyadike-Danes, 2002):
  - 6 years of monthly data
  - Labour market histories of Northern Irish youth
- Insertion of missingness at random
  - Each month has a 1.25% chance of being missing, but
  - But 67% chance if the previous month is missing
- $\Rightarrow$ consecutive runs of missingness, MCAR wrt observed data

Default imputation model

```
mi impute mlogit _mct_state i._mct_next i._mct_last . . .
```

- where `_mct_state` is the internal copy of the state variable
- `_mct_last` and `_mct_next` are respectively the most recent and nearest future observation
- Initial and terminal gaps are imputed using only respectively subsequent and prior information.

```
use mvadmar
mict_prep state, id(id)
mict_impute
```

Defining better imputation models

- Default imputation model is very simple:
  $Y = f(X_{t-lag}, X_{t+lead})$
- Implicitly assumes a zero-order Markov process with time-constant transition rates
- We can over-ride the built-in models by redefining the programs
  - `mict_model_gap`
  - `mict_model_initial`, and
  - `mict_model_terminal`

Over-ride internal gap model

```
capture program drop mict_model_gap
program define mict_model_gap
mi impute mlogit _mct_state                                   ///
      i._mct_next##c._mct_t i._mct_last##c._mct_t  ///
      _mct_before* _mct_after*,                               ///
   add(1) force augment
end
```

Built-in variables

- Variables `_mct_before1` to `_mct_beforeC` and `_mct_after1` to `_mct_afterC` are built-in
- The proportion of time before and after the gap spent in each of the `C` categories of the state variable
- ⇒ incorporate history beyond zero-order in a simple way
- Interactions `i._mct_next##c._mct_t` `i._mct_last##c._mct_t` allow for time-varying transition rates
- Other variables can also be entered
  - fixed individual variables
  - variables indicating time-dependent state in other domains

Three cases, with 10 imputations

Examining the imputations

- Four cases of gaps embedded in a single state:
  - nearly always filled with that state
  - one example of it being filled with another plausible state
- Two examples of gaps between two different states
  - Imputations mostly randomise the point of transition
  - A few imputations interpolate spells in other states
- One gap spans a complete spell: this is very unlikely to be imputed

Good enough?

- A good if not perfect performance: lots of redundancy in lifecourse histories
- One particular worry: spells that are entirely missing are not recovered
  - It may be that the process generating missingness is related to spell structure
- Below I consider a way of partially addressing this

Comparing MICT with MICE

- Very difficult to fit a model like this with the conventional `MICE` framework
- Models with "everything in" will fail computationally
  - too many variables
  - much too collinear
- Models with more refined prediction equations are very hard to express
- Neither `mi impute` nor `ice` are adapted for lags and leads, etc.

Strategy: Compare performance on very simple data

- Generate simple simulated data where a very simple model is correct
- To wit, 36-element long, 4-categories, with fixed transition rates and a zero-order Markov process
- MCAR runs of missingness
- Zero-order ⇒ only adjacent last and next observations carry information with which to impute
- MICT uses only `_mct_last` and `_mct_next` as predictors
- MICE uses only immediately adjactents states, $X_{t\text{-}1}$ and X_{t+1}

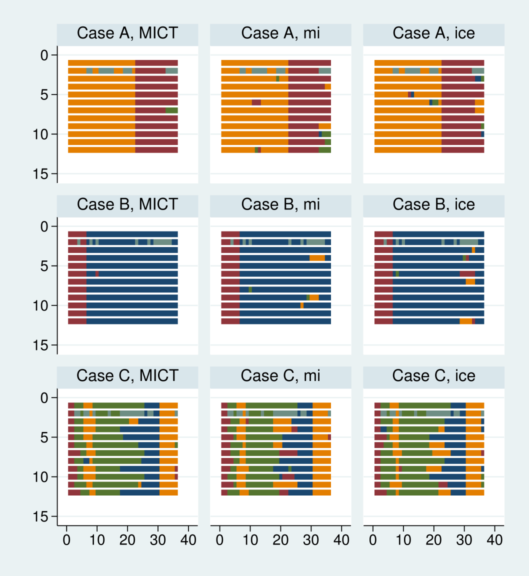
Royston's ICE

```
ice m.m1 m.m2 m.m3 m.m4 m.m5 m.m6 m.m7 m.m8 m.m9 m.m10 ///
    m.m11 m.m12 m.m13 m.m14 m.m15 m.m16 m.m17 m.m18    ///
    m.m19 m.m20 m.m21 m.m22 m.m23 m.m24 m.m25 m.m26    ///
    m.m27 m.m28 m.m29 m.m30 m.m31 m.m32 m.m33 m.m34    ///
    m.m35 m.m36, ///
    saving(ice, replace) persist m(10) cycles(10) ///
  eq(m1:     i.m2        ,  ///
     m36:  i.m35         ,  ///
     m2:     i.m1   i.m3,   ///
     m3:     i.m2   i.m4,   ///
 [ ... ]
     m35:  i.m34 i.m36)
```

Stata's mi impute chained

```
mi set flong
mi register imputed m*
mi impute chained ///
 (mlogit, omit(          i.m3 i.m4 [...] i.m34 i.m35 i.m36 )) m1 ///
 (mlogit, omit(               i.m4 [...] i.m34 i.m35 i.m36 )) m2 ///
 (mlogit, omit(i.m1                [...] i.m34 i.m35 i.m36 )) m3 ///
 (mlogit, omit(i.m1 i.m2           [...] i.m34 i.m35 i.m36 )) m4 ///
 (mlogit, omit(i.m1 i.m2 i.m3      [...] i.m34 i.m35 i.m36 )) m5 ///
[...]
 (mlogit, omit(i.m1 i.m2 i.m3 i.m4 [...]                   )) m35 ///
 (mlogit, omit(i.m1 i.m2 i.m3 i.m4 [...] i.m34             )) m36 ///
 , add(10) force augment
```

Some imputations, MICT and MICE



Too many transitions

- Inspection suggests that `mi impute` and `ice` are more prone to interpolating spells in other states
- Is this a systematic feature?
- Calculate the difference between the observed and impute number of spells for each case
- Use `mi estimate` to carry out a t-test using Rubin's rules

$$H_0 : N_{obs} = N_{imp}$$

Method	Difference	Std. Err.	t	p
MICT	-.0058	.0326	-0.18	0.859
`mi impute`	.2733	.0305	8.95	0.000
`ice`	.3962	.0434	9.14	0.000

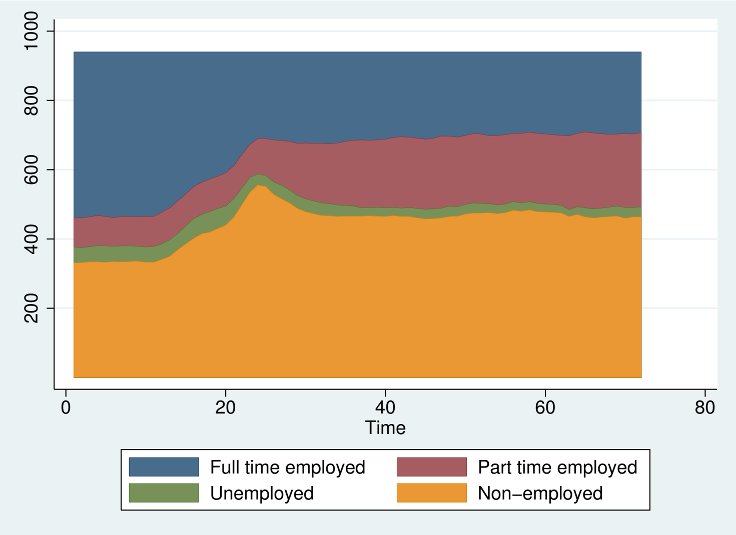
MICT has greater longitudinal consistency

- 10 imputations, 2000 sequences, 3 methods
- With a very simple data set, MICT outperforms MICE in terms of longitudinal consistency

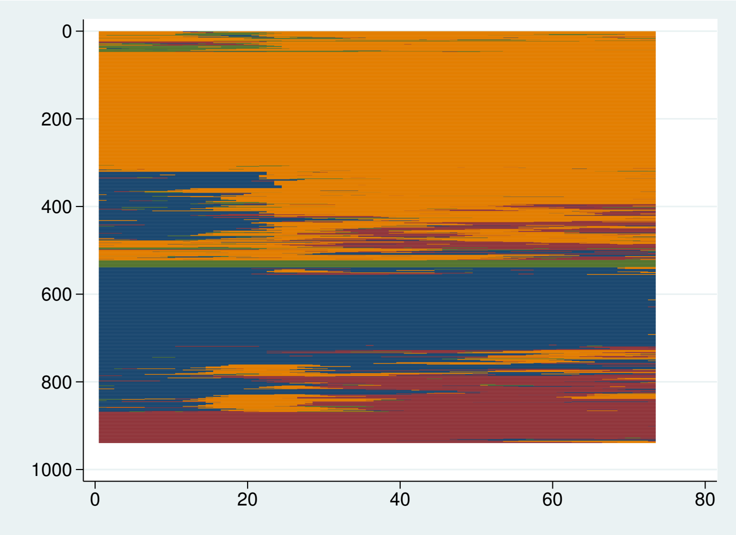
From simulation to a real example

- The first example used real data with simulated missing
- The second example used simulated data with simulated missing
- Now an example with real missing data from BHPS
  - 6 years of monthly data, women who have a birth at end year 2
    - Employed full-time
    - Employed part-time
    - Unemployed
    - Not in the labour market
  - 706 fully observed sequences, 194 with gaps under 12 months, c400 with bigger gaps but with data that can be used for prediction

State distribution: Mothers' labour market history



Indexplot: Mothers' labour market history

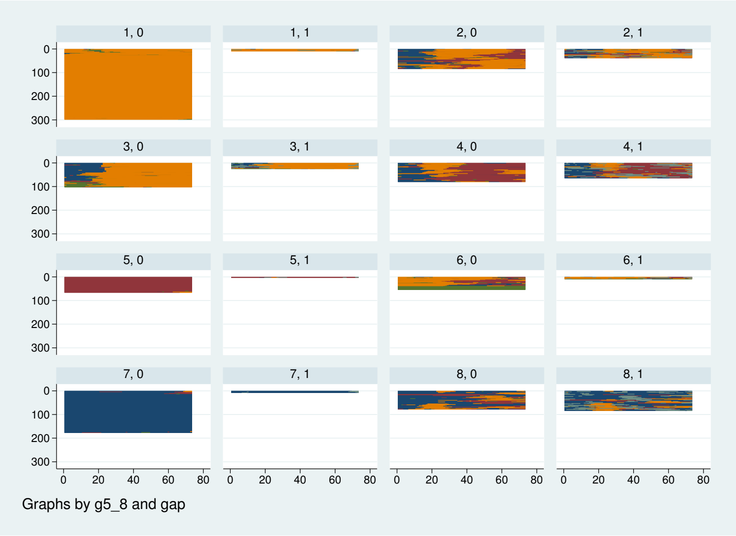


Predictive model

```
mi impute mlogit _mct_state              ///
     i._mct_next##c._mct_t##c._mct_t ///
     i._mct_last##c._mct_t##c._mct_t ///
     _mct_before*                    ///
     _mct_after*
```

- Implies transition pattern that varies in a non-linear fashion
- Uses history and future distribution of states

Gappy sequences are differently distributed: cluster analysis



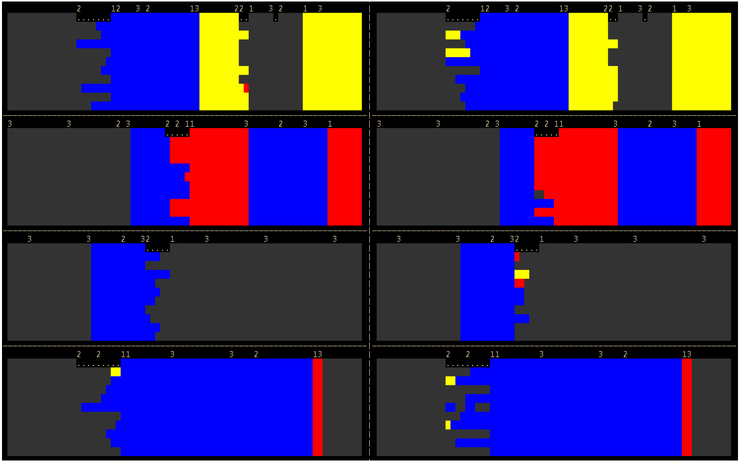
Information from data collection structure

- In the initial simulation, I noted that if a gap spans a complete spell it will be lost
  - no redundancy in this case
- If missingness is related to spells this can be a systematic feature $\Rightarrow$ bias
- In the BHPS, missingness (and transition patterns) is correlated with data collection structure (Halpin, 1998):
  - Month of interview disproportionately likely to be followed by gap, or transition
  - 1st month of a reported spell likely to follow a gap/transition

Time-dependent observations

- Can bring this to bear on the imputation, improving the imputation of transition points
- A monthly observation:
  - Nothing special
  - Reported start of spell current at interview
  - Reported start of a spell in the inter-wave job history
  - Date of interview
- Improves the fit of the model, improves the timing of predicted transitions

Selected imputatations without (L) and without data collection info (R)



Conclusions

- MICT creates realistic imputations of gap-prone lifecourse data
- It respects longitudinal continuity better than MICE
- It is easy to define good prediction models with MICT
- It is reasonably stable in computational terms
- Longitudinal data is often missing, and not at random: needs imputation
- Important to pay attention to the processes generating gaps too

References

Allison, P. D. (2005). Imputation of categorical variables with PROC MI. In *SUGI 30 Proceedings 2005*, pages 1–14.

Halpin, B. (1998). Unified BHPS work-life histories: Combining multiple sources into a user-friendly format. *Bulletin de Méthodologie Sociologique*, (60).

Halpin, B. (2012). Multiple imputation for lifecourse sequence data. Working Paper WP2012-01, Dept of Sociology, University of Limerick, Ireland.

Halpin, B. (2013). Imputing sequence data: Extensions to initial and terminal gaps, stata's `mi`. Working Paper WP2013-01, Dept of Sociology, University of Limerick, Ireland.

Honaker, J. and King, G. (2010). What to do about missing values in time-series cross-section data. *American Journal of Political Science*, 54(2):561–581.

McVicar, D. and Anyadike-Danes, M. (2002). Predicting successful and unsuccessful transitions from school to work using sequence methods. *Journal of the Royal Statistical Society (Series A)*, 165:317–334.

Royston, P. (2009). Multiple imputation of missing values: Further update of ice, with an emphasis on categorical variables. *Stata Journal*, 9(3):466–477(12).

Rubin, D. (1987). *Multiple imputation for non-response in surveys*. John Wiley and Sons, New York.

van Buuren, S. (2007). Multiple imputation of discrete and continuous data by fully conditional specification. *Statistical Methods in Medical Research*, 16(3):219–242.

van Buuren, S. and Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in r. *Journal of Statistical Software*, 45(3):1–67.

White, I. R., Royston, P., and Wood, A. M. (2011). Multiple imputation using chained equations: Issues and guidance for practice. *Statistics in Medicine*, 30(4):377–399.