



vital: Tidy data analysis for demography

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9 July 2024

Demographic data structures in R packages

Package	Data class
demography	demogdata
StMoMo	StMoMoData (created by converting a demogdata object)
StanMoMo	Lists of matrices
lifecontingencies	data.frame
BayesMortalityPlus	tibble (that needs to be converted to a matrix for fitting)
MortalityLaws	individual vectors
HMDHFDplus	data.frame



Australian Deaths 1901–2020

A tibble: 145,440 x 7

	Year	Age	Sex	State	Mortality	Exposure	Deaths
	<int>	<int>	<chr>	<chr>	<dbl>	<dbl>	<dbl>
1	1901	0	female	WA	0.129	2511	325
2	1901	0	male	WA	0.158	2634	416
3	1901	1	female	WA	0.0275	2219	61
4	1901	1	male	WA	0.0391	2175	85
5	1901	2	female	WA	0.00688	2180	15
6	1901	2	male	WA	0.0131	2208	29
7	1901	3	female	WA	0.00584	1884	11
8	1901	3	male	WA	0.00503	1988	10
9	1901	4	female	WA	0.00290	1722	5
10	1901	4	male	WA	0.00287	1743	5

i 145,430 more rows



Australian Deaths 1901–2020

```
# A tsibble: 145,440 x 7 [1Y]
```

```
# Key:      Age, Sex, State [1,212]
```

	Year	Age	Sex	State	Mortality	Exposure	Deaths
	<int>	<int>	<chr>	<chr>	<dbl>	<dbl>	<dbl>
1	1901	0	female	WA	0.129	2511	325
2	1901	0	male	WA	0.158	2634	416
3	1901	1	female	WA	0.0275	2219	61
4	1901	1	male	WA	0.0391	2175	85
5	1901	2	female	WA	0.00688	2180	15
6	1901	2	male	WA	0.0131	2208	29
7	1901	3	female	WA	0.00584	1884	11
8	1901	3	male	WA	0.00503	1988	10
9	1901	4	female	WA	0.00290	1722	5
10	1901	4	male	WA	0.00287	1743	5

```
# i 145,430 more rows
```

Variables

Index:

■ Year

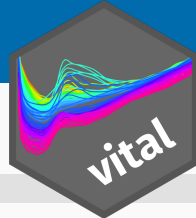
Keys:

■ Age

■ Sex

■ State

Every row must have a unique combination of Index and Keys



Australian Deaths 1901–2020

aus

```
# A vital: 145,440 x 7 [1Y]
```

```
# Key:      Age x (Sex, State) [101 x 12]
```

	Year	Age	Sex	State	Mortality	Exposure	Deaths
	<int>	<int>	<chr>	<chr>	<dbl>	<dbl>	<dbl>
1	1901	0	female	WA	0.129	2511	325
2	1901	0	male	WA	0.158	2634	416
3	1901	1	female	WA	0.0275	2219	61
4	1901	1	male	WA	0.0391	2175	85
5	1901	2	female	WA	0.00688	2180	15
6	1901	2	male	WA	0.0131	2208	29
7	1901	3	female	WA	0.00584	1884	11
8	1901	3	male	WA	0.00503	1988	10
9	1901	4	female	WA	0.00290	1722	5
10	1901	4	male	WA	0.00287	1743	5

```
# i 145,430 more rows
```

Variables

Index:

■ Year

Keys:

■ Age

■ Sex

■ State

Every row must have a unique combination of Index and Keys

Variables denoting age, sex, deaths, births and population can also be specified as attributes.

vital objects

```
index_var(aus)
```

```
[1] "Year"
```

```
key_vars(aus)
```

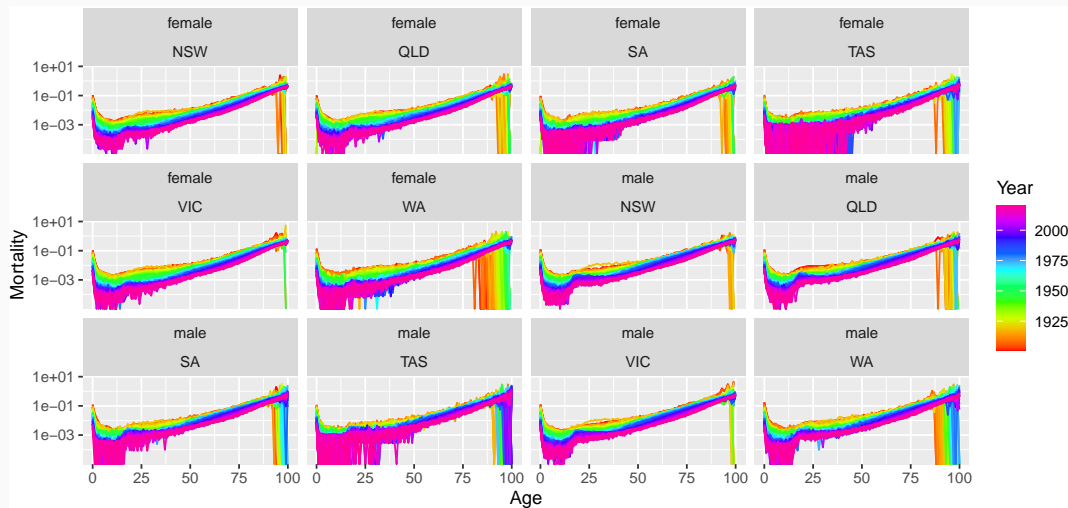
```
[1] "Age"  "Sex"  "State"
```

```
vital_vars(aus)
```

age	sex	deaths	population
"Age"	"Sex"	"Deaths"	"Exposure"

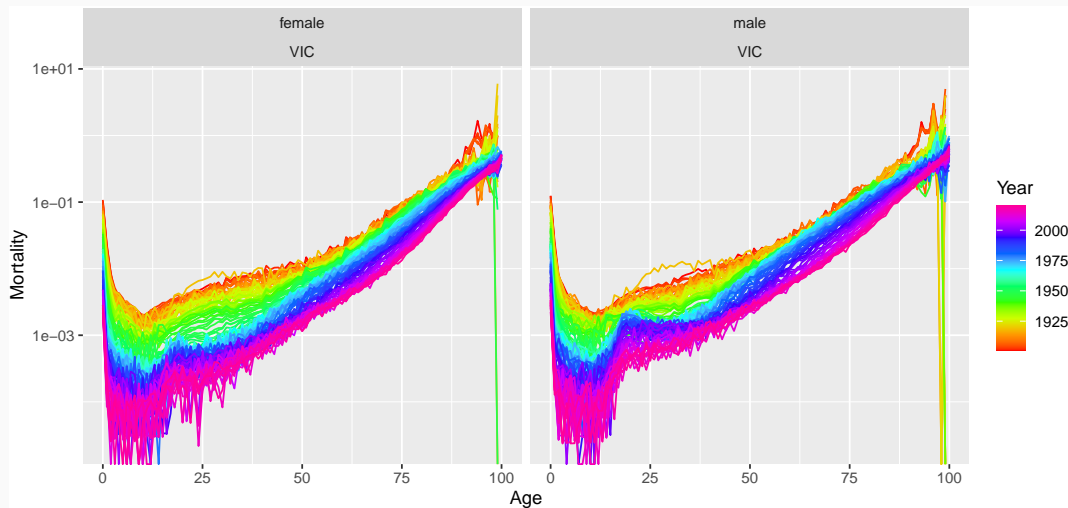
Rainbow plots

```
aus > autoplot(Mortality) + scale_y_log10()
```



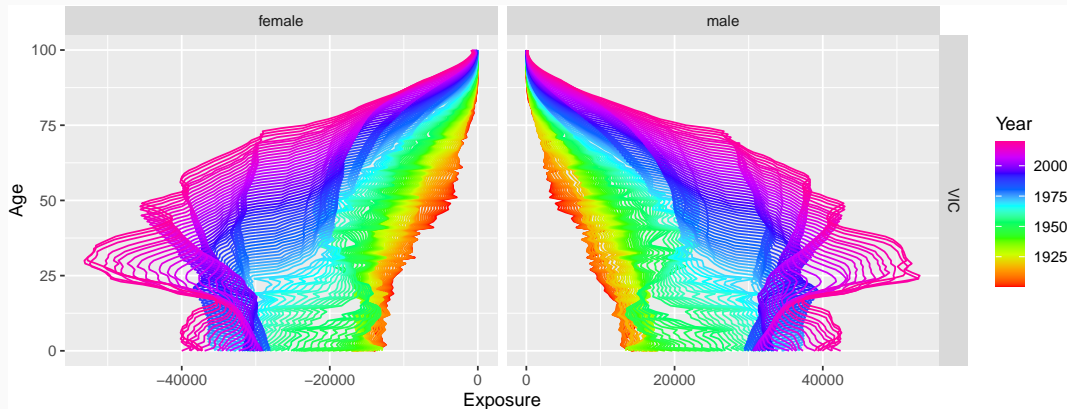
Rainbow plots

```
aus > filter(State == "VIC") > autoplot(Mortality) + scale_y_log10()
```



Rainbow plots

```
aus > filter(State == "VIC") >  
  mutate(Exposure = if_else(Sex == "female", -Exposure, Exposure)) >  
  autoplot(Exposure) +  
  facet_grid(State ~ Sex, scales = "free_x") + coord_flip()
```



Smoothing

```
sm_aus ← aus ► smooth_mortality(Mortality)
sm_aus
```

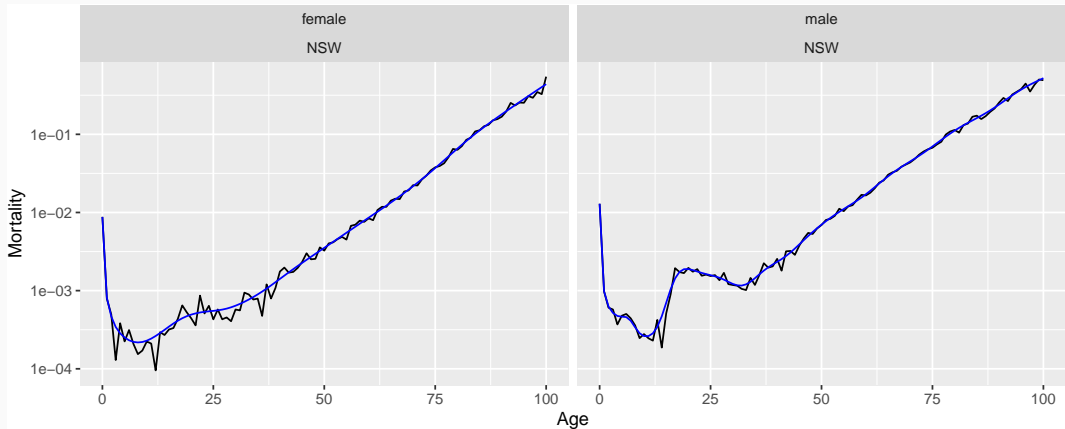
```
# A vital: 145,440 x 9 [1Y]
```

```
# Key:      Age x (Sex, State) [101 x 12]
```

	Year	Age	Sex	State	Mortality	Exposure	Deaths	.smooth	.smooth_se
	<int>	<dbl>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl[1d]>	<dbl[1d]>
1	1901	0	female	NSW	0.107	17143	1833	0.107	0.00295
2	1901	1	female	NSW	0.0247	15071	373	0.0237	0.00141
3	1901	2	female	NSW	0.00686	15461	106	0.00804	0.000670
4	1901	3	female	NSW	0.00441	15629	69	0.00461	0.000405
5	1901	4	female	NSW	0.00374	15762	59	0.00341	0.000305
6	1901	5	female	NSW	0.00274	16030	44	0.00275	0.000251
7	1901	6	female	NSW	0.00252	16289	41	0.00230	0.000215
8	1901	7	female	NSW	0.00216	16639	36	0.00197	0.000189
9	1901	8	female	NSW	0.00169	16554	28	0.00175	0.000173
10	1901	9	female	NSW	0.00109	16468	18	0.00162	0.000163

Smoothing

```
sm_aus <- aus > smooth_mortality(Mortality)
sm_aus > filter(State == "NSW", Year == 1980) > autoplot(Mortality) +
  geom_line(aes(y = .smooth), col = "blue") + scale_y_log10()
```



Life tables

```
life_table(aus)
```

```
# A vital: 145,440 x 14 [1Y]
```

```
# Key:      Age x (Sex, State) [101 x 12]
```

	Year	Age	Sex	State	mx	qx	lx	dx	Lx	Tx	ex	rx
	<int>	<int>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	1901	0	fema~	NSW	0.107	0.100	1	1.00e-1	0.935	56.2	56.2	0.935
2	1901	1	fema~	NSW	0.0247	0.0244	0.900	2.20e-2	0.889	55.3	61.5	0.951
3	1901	2	fema~	NSW	0.00686	0.00683	0.878	6.00e-3	0.875	54.4	62.0	0.984
4	1901	3	fema~	NSW	0.00441	0.00441	0.872	3.84e-3	0.870	53.5	61.4	0.994
5	1901	4	fema~	NSW	0.00374	0.00374	0.868	3.24e-3	0.867	52.7	60.7	0.996
6	1901	5	fema~	NSW	0.00274	0.00274	0.865	2.37e-3	0.864	51.8	59.9	0.997
7	1901	6	fema~	NSW	0.00252	0.00251	0.863	2.17e-3	0.861	50.9	59.1	0.997
8	1901	7	fema~	NSW	0.00216	0.00216	0.860	1.86e-3	0.859	50.1	58.2	0.998
9	1901	8	fema~	NSW	0.00169	0.00169	0.859	1.45e-3	0.858	49.2	57.3	0.998
10	1901	9	fema~	NSW	0.00109	0.00109	0.857	9.36e-4	0.857	48.4	56.4	0.999

```
# i 145,430 more rows
```

Life expectancy

```
life_expectancy(aus)
```

```
# A vital: 1,440 x 8 [1Y]
```

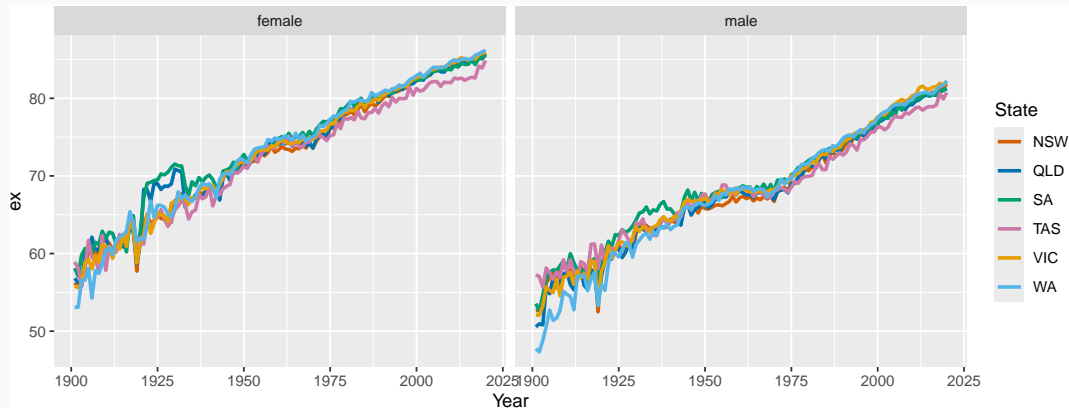
```
# Key:      Age x (Sex, State) [1 x 12]
```

	Year	Age	Sex	State	ex	rx	nx	ax
	<int>	<int>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
1	1901	0	female	NSW	56.2	0.935	1	0.352
2	1901	0	female	QLD	56.8	0.937	1	0.338
3	1901	0	female	SA	58.1	0.939	1	0.324
4	1901	0	female	TAS	58.9	0.946	1	0.275
5	1901	0	female	VIC	55.8	0.937	1	0.334
6	1901	0	female	WA	53.1	0.922	1	0.35
7	1901	0	male	NSW	52.6	0.925	1	0.33
8	1901	0	male	QLD	50.6	0.924	1	0.33
9	1901	0	male	SA	53.5	0.922	1	0.33
10	1901	0	male	TAS	57.3	0.930	1	0.33

```
# i 1,430 more rows
```

Life expectancy

```
life_expectancy(aus) ▷  
  ggplot(aes(x = Year, y = ex, colour = State)) +  
  geom_line(linewidth = 1) +  
  facet_grid(. ~ Sex)
```



Mortality models

$m_{x,t}$ = mortality rate at age x in year t .

Naive:
$$m_{x,t} = m_{x,t-1} + \varepsilon_{x,t}$$

Lee-Carter:
$$\log(m_{x,t}) = a_x + k_t b_x + \varepsilon_{x,t}$$

$\varepsilon_{x,t}$ = noise term with variance σ_x^2 .

Mortality models

$m_{x,t}$ = mortality rate at age x in year t .

Naive: $m_{x,t} = m_{x,t-1} + \varepsilon_{x,t}$

Lee-Carter: $\log(m_{x,t}) = a_x + k_t b_x + \varepsilon_{x,t}$

$\varepsilon_{x,t}$ = noise term with variance σ_x^2 .

```
fit ← aus ▷  
  model(  
    naive = FNAIVE(Mortality),  
    lc = LC(log(Mortality))  
  )
```


Mortality models

$m_{x,t}$ = mortality rate at age x in year t .

Naive: $m_{x,t} = m_{x,t-1} + \varepsilon_{x,t}$

Lee-Carter: $\log(m_{x,t}) = a_x + k_t b_x + \varepsilon_{x,t}$

$\varepsilon_{x,t}$ = noise term with variance σ_x^2 .

```
fit ← aus ▷
```

```
model(  
  naive = FNAIVE(Mortality),  
  lc = LC(log(Mortality))  
)
```

```
fit
```

```
# A mable: 12 x 4
```

```
# Key:      Sex, State [12]
```

	Sex	State	naive	lc
	<chr>	<chr>	<model>	<model>
1	female	NSW	<FNAIVE>	<LC>
2	female	QLD	<FNAIVE>	<LC>
3	female	SA	<FNAIVE>	<LC>
4	female	TAS	<FNAIVE>	<LC>
5	female	VIC	<FNAIVE>	<LC>
6	female	WA	<FNAIVE>	<LC>
7	male	NSW	<FNAIVE>	<LC>
8	male	QLD	<FNAIVE>	<LC>
9	male	SA	<FNAIVE>	<LC>
10	male	TAS	<FNAIVE>	<LC>
11	male	VIC	<FNAIVE>	<LC>
12	male	WA	<FNAIVE>	<LC>

$$\log(m_{x,t}) = a_x + k_t b_x + \varepsilon_{x,t}$$

```
fit ▷  
  filter(Sex == "female",  
         State == "NSW") ▷  
  select(lc) ▷  
  report()
```

Series: Mortality

Model: LC

Transformation: log(Mortality)

Options:

Adjust method: dt

Jump choice: fit

Age functions

A tibble: 101 × 3

	Age	ax	bx
	<int>	<dbl>	<dbl>
1	0	-4.07	0.0155
2	1	-6.20	0.0221
3	2	-6.89	0.0199

i 98 more rows

Time coefficients

A tsibble: 120 × 2 [1Y]

	Year	kt
	<int>	<dbl>
1	1901	109.
2	1902	111.
3	1903	108.

i 117 more rows

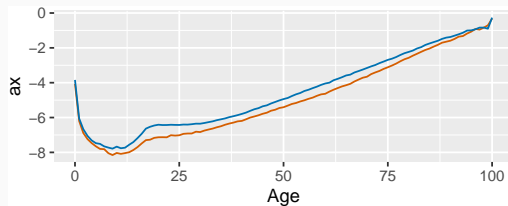
Time series model: RW w/ drift

Variance explained: 86.61%

Lee-Carter models

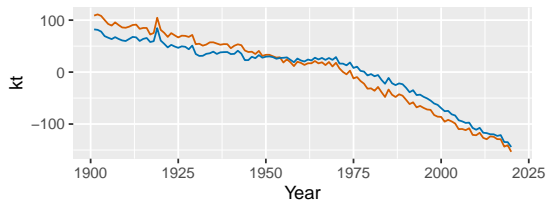
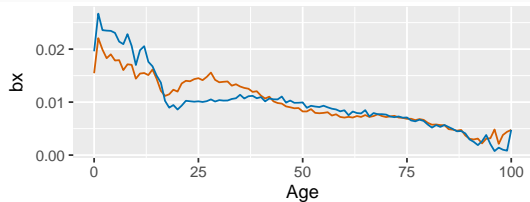
$$\log(m_{x,t}) = a_x + k_t b_x + \varepsilon_{x,t}$$

```
fit ▷  
  filter(State == "NSW") ▷  
  select(lc) ▷  
  autoplot()
```



Sex/State

- female/NSW
- male/NSW



Lee-Carter models

$$\log(m_{x,t}) = a_x + k_t b_x + \varepsilon_{x,t}$$

```
fit > select(lc) > age_components()
```

```
# A tibble: 1,212 x 5
```

	Sex	State	Age	ax	bx
	<chr>	<chr>	<int>	<dbl>	<dbl>
1	female	NSW	0	-4.07	0.0155
2	female	NSW	1	-6.20	0.0221
3	female	NSW	2	-6.89	0.0199
4	female	NSW	3	-7.24	0.0183
5	female	NSW	4	-7.47	0.0190
6	female	NSW	5	-7.65	0.0178
7	female	NSW	6	-7.80	0.0179
8	female	NSW	7	-7.81	0.0160
9	female	NSW	8	-8.05	0.0171
10	female	NSW	9	-8.15	0.0170

```
# i 1,202 more rows
```

```
fit > select(lc) > time_components()
```

```
# A tsibble: 1,440 x 4 [1Y]
```

# Key:	Sex	State	Year	kt
	<chr>	<chr>	<int>	<dbl>
1	female	NSW	1901	109.
2	female	NSW	1902	111.
3	female	NSW	1903	108.
4	female	NSW	1904	100.
5	female	NSW	1905	92.7
6	female	NSW	1906	89.5
7	female	NSW	1907	95.7
8	female	NSW	1908	90.5
9	female	NSW	1909	85.9
10	female	NSW	1910	85.4

```
# i 1,430 more rows
```

Forecasts

```
fc ← fit ▷ forecast(h = 20)
fc
```

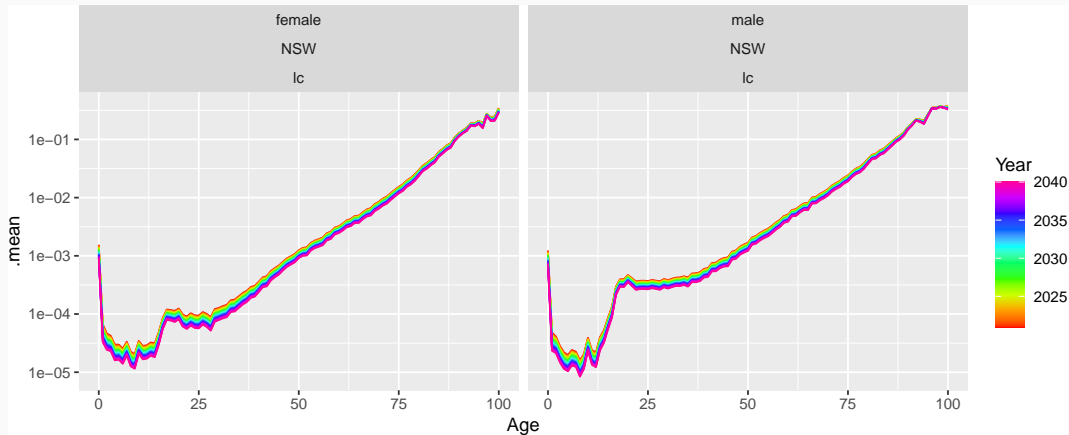
```
# A vital fable: 48,480 x 7 [1Y]
```

```
# Key:           Age x (Sex, State, .model) [101 x 24]
```

	Sex	State	.model	Year	Age	Mortality	.mean
	<chr>	<chr>	<chr>	<dbl>	<int>	<dist>	<dbl>
1	female	NSW	naive	2021	0	N(0.0027, 1.8e-05)	0.00270
2	female	NSW	naive	2022	0	N(0.0027, 3.6e-05)	0.00270
3	female	NSW	naive	2023	0	N(0.0027, 5.4e-05)	0.00270
4	female	NSW	naive	2024	0	N(0.0027, 7.2e-05)	0.00270
5	female	NSW	naive	2025	0	N(0.0027, 9e-05)	0.00270
6	female	NSW	naive	2026	0	N(0.0027, 0.00011)	0.00270
7	female	NSW	naive	2027	0	N(0.0027, 0.00013)	0.00270
8	female	NSW	naive	2028	0	N(0.0027, 0.00014)	0.00270
9	female	NSW	naive	2029	0	N(0.0027, 0.00016)	0.00270
10	female	NSW	naive	2030	0	N(0.0027, 0.00018)	0.00270

NSW forecasts using Lee-Carter method

```
fc > filter(State == "NSW", .model == "lc") >  
  autoplot() + scale_y_log10()
```



Functional data models

Let $m_{x,t}$ be the mortality rate at age x in year t .

$$\log(m_{t,x}) = s_t(x) + \sigma_t(x)\varepsilon_{t,x}$$

$$s_t(x) = \mu(x) + \sum_{j=1}^J \beta_{t,j} \phi_j(x) + e_t(x)$$

- $s_t(x)$ = smoothed version of $y_t(x)$
- $\mu(x)$ = mean $s_t(x)$ across years.
- $\phi_j(x)$ and $\beta_{t,j}$ estimated using principal component analysis.
- $\beta_{1,j}, \dots, \beta_{T,j}$ modelled with ARIMA or ARFIMA processes.

Functional data models

```
sm_aus ← aus ▷ smooth_mortality(Mortality)
sm_aus
```

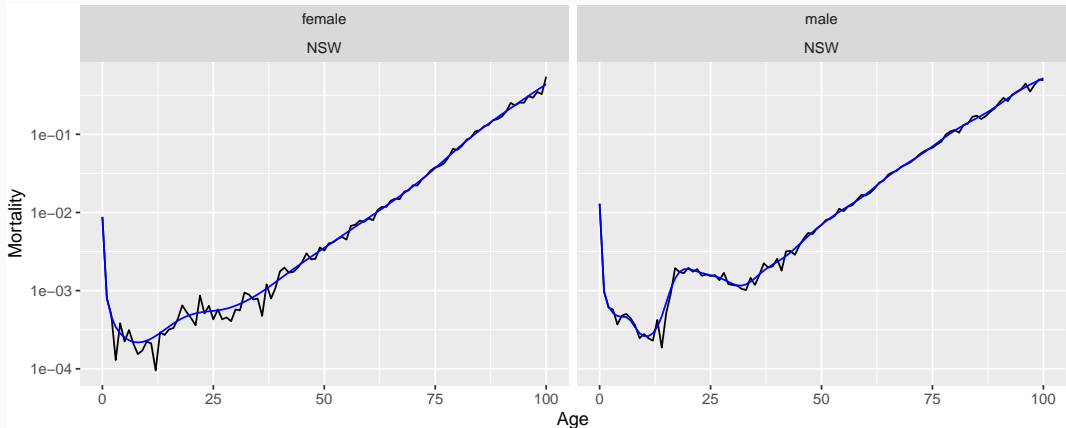
```
# A vital: 145,440 x 9 [1Y]
```

```
# Key:      Age x (Sex, State) [101 x 12]
```

	Year	Age	Sex	State	Mortality	Exposure	Deaths	.smooth	.smooth_se
	<int>	<dbl>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl[1d]>	<dbl[1d]>
1	1901	0	female	NSW	0.107	17143	1833	0.107	0.00295
2	1901	1	female	NSW	0.0247	15071	373	0.0237	0.00141
3	1901	2	female	NSW	0.00686	15461	106	0.00804	0.000670
4	1901	3	female	NSW	0.00441	15629	69	0.00461	0.000405
5	1901	4	female	NSW	0.00374	15762	59	0.00341	0.000305
6	1901	5	female	NSW	0.00274	16030	44	0.00275	0.000251
7	1901	6	female	NSW	0.00252	16289	41	0.00230	0.000215
8	1901	7	female	NSW	0.00216	16639	36	0.00197	0.000189
9	1901	8	female	NSW	0.00169	16554	28	0.00175	0.000173
10	1901	9	female	NSW	0.00109	16468	18	0.00162	0.000163

Functional data models

```
sm_aus <- aus > smooth_mortality(Mortality)
sm_aus > filter(State == "NSW", Year == 1980) > autoplot(Mortality) +
  geom_line(aes(y = .smooth), col = "blue") + scale_y_log10()
```



Functional data models

```
fit ← sm_aus ▷ model(hu = FDM(log(.smooth)))  
fit
```

```
# A mable: 12 x 3
```

```
# Key:      Sex, State [12]
```

	Sex	State	hu
	<chr>	<chr>	<model>
1	female	NSW	<FDM>
2	female	QLD	<FDM>
3	female	SA	<FDM>
4	female	TAS	<FDM>
5	female	VIC	<FDM>
6	female	WA	<FDM>
7	male	NSW	<FDM>
8	male	QLD	<FDM>
9	male	SA	<FDM>
10	male	TAS	<FDM>

Functional data models

```
fit ▷  
  filter(Sex == "female", State == "NSW") ▷  
  select(hu) ▷  
  report()
```

Series: .smooth

Model: FDM

Transformation: log(.smooth)

Basis functions

A tibble: 101 x 8

	Age	mean	phi1	phi2	phi3	phi4	phi5	phi6
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	0	-4.07	0.147	0.0625	-0.0270	0.0986	0.0112	-0.0624
2	1	-6.16	0.200	-0.0609	-0.194	0.116	0.0383	-0.238
3	2	-6.82	0.182	-0.0483	-0.157	0.0924	0.0443	-0.264
4	3	-7.17	0.170	-0.0368	-0.130	0.0362	0.000338	-0.321
5	4	-7.40	0.164	-0.0165	-0.114	-0.0154	-0.0303	-0.374

i 96 more rows

Functional data models

Coefficients

```
# A tsibble: 120 x 8 [1Y]
  Year mean beta1 beta2 beta3 beta4 beta5 beta6
  <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1  1901     1  11.1 -0.522 -0.0553  0.207  0.358  0.0305
2  1902     1  11.8 -0.649  0.399  0.856  0.0319  0.422
3  1903     1  11.5 -0.930 -0.485  0.398  0.399 -0.376
4  1904     1  11.1 -0.827 -0.214 -0.000305 0.00125 -0.0783
5  1905     1  10.2 -0.563 -0.105  0.324  0.122  0.0478
# i 115 more rows
# i Use 'print(n = ...)' to see more rows
```

Time series models

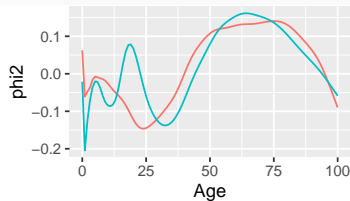
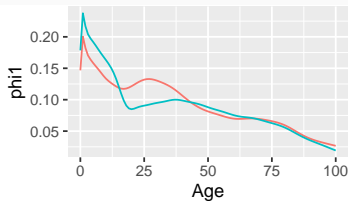
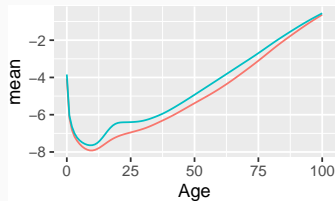
```
beta1 : ARIMA(0,1,1) w/ drift
beta2 : ARIMA(0,2,2)
beta3 : ARIMA(1,0,1)
beta4 : ARIMA(0,0,2)
beta5 : ARIMA(0,0,0)
beta6 : ARIMA(2,0,2)
```

Variance explained

$91.38 + 1.81 + 0.58 + 0.49 + 0.42 + 0.39 = 95.06\%$

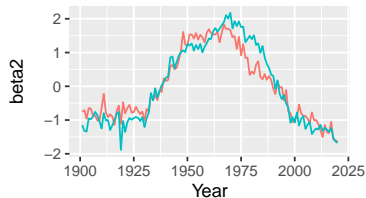
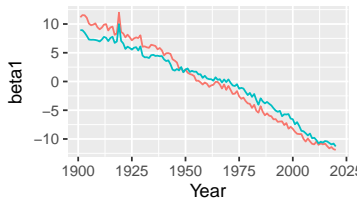
Functional data models

```
fit ▷  
  filter(State == "NSW") ▷  
  select(hu) ▷  
  autoplot()
```



Sex/State

— female/NSW
— male/NSW



Functional data models

```
fit > select(hu) > age_components()
```

```
# A tibble: 1,212 x 10
```

	Sex	State	Age	mean	phi1	phi2	phi3	phi4	phi5	phi6
	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	female	NSW	0	-4.07	0.147	0.0625	-0.0270	0.0986	0.0112	-0.0624
2	female	NSW	1	-6.16	0.200	-0.0609	-0.194	0.116	0.0383	-0.238
3	female	NSW	2	-6.82	0.182	-0.0483	-0.157	0.0924	0.0443	-0.264
4	female	NSW	3	-7.17	0.170	-0.0368	-0.130	0.0362	0.000338	-0.321
5	female	NSW	4	-7.40	0.164	-0.0165	-0.114	-0.0154	-0.0303	-0.374
6	female	NSW	5	-7.57	0.158	-0.00759	-0.121	-0.0564	0.0247	-0.315
7	female	NSW	6	-7.71	0.153	-0.00942	-0.133	-0.0976	0.112	-0.197
8	female	NSW	7	-7.81	0.149	-0.0121	-0.143	-0.143	0.175	-0.0863
9	female	NSW	8	-7.88	0.143	-0.0141	-0.148	-0.181	0.211	0.0131
10	female	NSW	9	-7.92	0.138	-0.0185	-0.142	-0.196	0.236	0.101

```
# i 1,202 more rows
```

Functional data models

```
fit > select(hu) > time_components()
```

```
# A tsibble: 1,440 x 10 [1Y]
```

```
# Key:           Sex, State [12]
```

	Sex	State	Year	mean	beta1	beta2	beta3	beta4	beta5	beta6
	<chr>	<chr>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	female	NSW	1901	1	11.2	-0.756	-0.0301	0.269	-0.155	0.409
2	female	NSW	1902	1	11.6	-0.708	0.0899	0.207	0.0282	0.507
3	female	NSW	1903	1	11.5	-0.962	0.169	-0.103	0.366	0.323
4	female	NSW	1904	1	11.1	-0.648	0.0985	-0.433	0.131	0.270
5	female	NSW	1905	1	10.1	-0.660	0.342	-0.0910	0.0862	0.612
6	female	NSW	1906	1	9.78	-0.865	0.496	-0.147	-0.101	0.306
7	female	NSW	1907	1	9.90	-0.861	0.0530	1.33	0.278	0.181
8	female	NSW	1908	1	10.1	-1.01	0.554	-0.0198	-0.00428	0.578
9	female	NSW	1909	1	9.42	-1.02	0.293	-0.365	-0.149	0.353
10	female	NSW	1910	1	9.08	-0.650	0.172	-0.559	-0.253	0.0110

```
# i 1,430 more rows
```

Coherent functional models

$$y_t(x) = s_t(x) + \sigma_t(x)\varepsilon_{t,x}$$

$$s_t(x) = \mu(x) + \sum_{j=1}^J \beta_{t,j} \phi_j(x) + e_t(x)$$

- $y_t(x) = \log(m_{x,t}^M m_{x,t}^F)$ and $\log(m_{x,t}^M / m_{x,t}^F)$
- $s_t(x)$ = smoothed version of $y_t(x)$
- $\mu(x)$ = mean $s_t(x)$ across years.
- $\phi_j(x)$ and $\beta_{t,j}$ estimated using principal component analysis.
- $\beta_{1,j}, \dots, \beta_{T,j}$ modelled with ARIMA for products and ARMA for ratios (to ensure stationary sex-ratios)

Coherent functional models

```
pr <- sm_aus > make_pr(.smooth)
pr
```

```
# A vital: 218,160 x 9 [1Y]
```

```
# Key:      Age x (Sex, State) [101 x 18]
```

	Year	Age	Sex	State	Mortality	Exposure	Deaths	.smooth	.smooth_se
	<int>	<dbl>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl[1d]>	<dbl[1d]>
1	1901	0	female	NSW	0.107	17143	1833	0.939	0.00295
2	1901	1	female	NSW	0.0247	15071	373	1.03	0.00141
3	1901	2	female	NSW	0.00686	15461	106	0.965	0.000670
4	1901	3	female	NSW	0.00441	15629	69	0.982	0.000405
5	1901	4	female	NSW	0.00374	15762	59	1.02	0.000305
6	1901	5	female	NSW	0.00274	16030	44	1.04	0.000251
7	1901	6	female	NSW	0.00252	16289	41	1.04	0.000215
8	1901	7	female	NSW	0.00216	16639	36	1.01	0.000189
9	1901	8	female	NSW	0.00169	16554	28	0.972	0.000173
10	1901	9	female	NSW	0.00109	16468	18	0.938	0.000163

Coherent functional models

```
pr <- sm_aus > make_pr(.smooth)
fit <- pr > model(hby = FDM(log(.smooth), coherent = TRUE))
fit
```

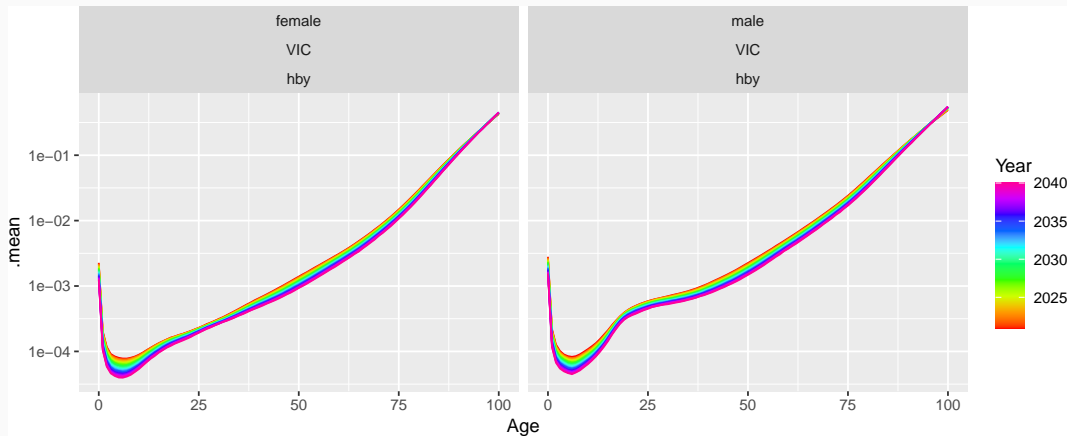
A mable: 18 x 3

Key: Sex, State [18]

	Sex	State	hby
	<chr>	<chr>	<model>
1	female	NSW	<FDM>
2	female	QLD	<FDM>
3	female	SA	<FDM>
4	female	TAS	<FDM>
5	female	VIC	<FDM>
6	female	WA	<FDM>
7	geometric_mean	NSW	<FDM>
8	geometric_mean	QLD	<FDM>
9	geometric_mean	SA	<FDM>

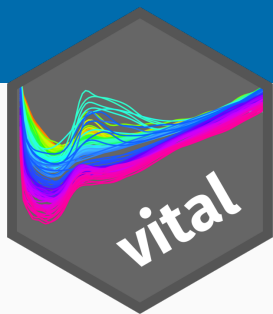
Coherent functional models

```
fc <- fit ▷ forecast(h = 20) ▷ undo_pr(.smooth)  
fc ▷ filter(State == "VIC") ▷ autoplot() + scale_y_log10()
```



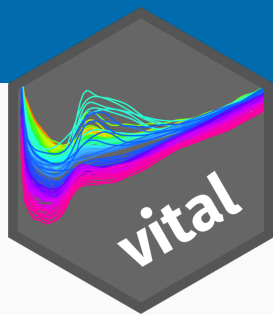
Other functionality

- Import data from Human Mortality Database and Human Fertility Database
- Convert demogdata, tsibble & data.frame objects to vital.
- Compute net migration from population, births and deaths.
- Compute total fertility rates from age-specific fertility rates.
- Various smoothing functions
- Other mortality models including functional data models, and coherent functional data models.



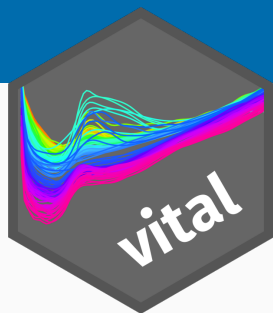
Future plans

- Remaining tools from the demography package
- Stochastic population forecasting (as per Hyndman-Booth, IJF, 2008)
- All models handled by StMoMo package
- All methods from MortalityLaws package
- Suggestions from users



Future plans

- Remaining tools from the demography package
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- **Slides:** robjhyndman.com/user2024
- **Package:** pkg.robjhyndman.com/vital/