Forecast reconciliation

1. Hierarchical time series & forecast reconciliation

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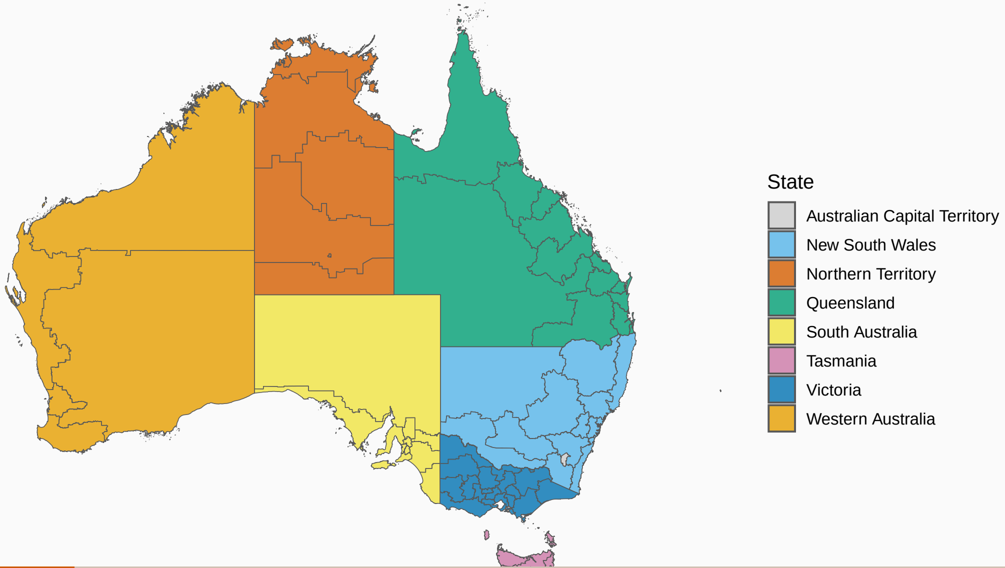
robjhyndman.com/fr2023

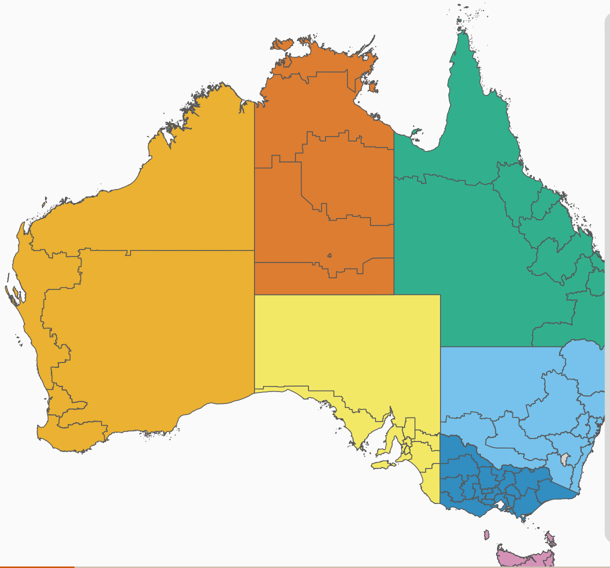
Outline

Outline

Australian tourism regions



Australian tourism regions



- Monthly data on visitor night from 1998 – 2017
- From *National Visitor Survey*, annual interviews of 120,000 Australians aged 15+.
- Geographical hierarchy split by
  - 7 states
  - 27 zones
  - 75 regions

Australian tourism data

```
# A tsibble: 18,000 x 5 [1M]
# Key:       state, zone, region [75]
      month state zone      region visitors
      <mth> <chr> <chr>     <chr>     <dbl>
 1 1998 Jan NSW   Metro NSW Sydney     926.
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```
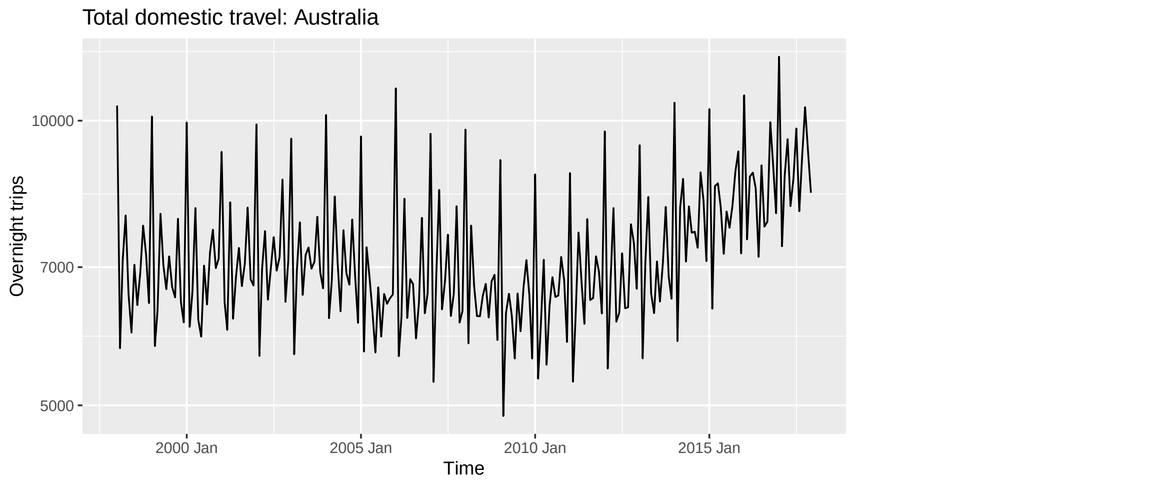
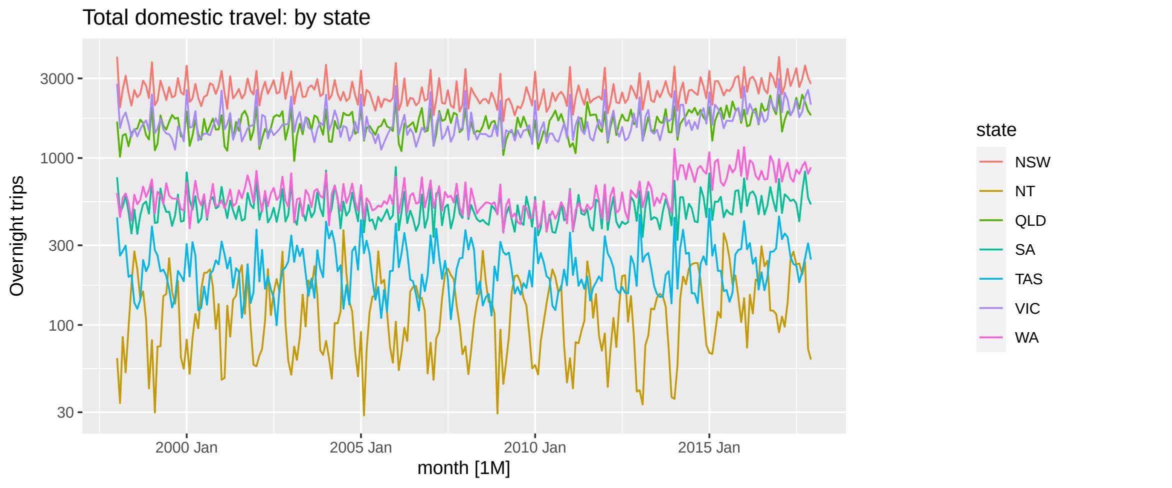

Australian tourism data



Australian tourism data



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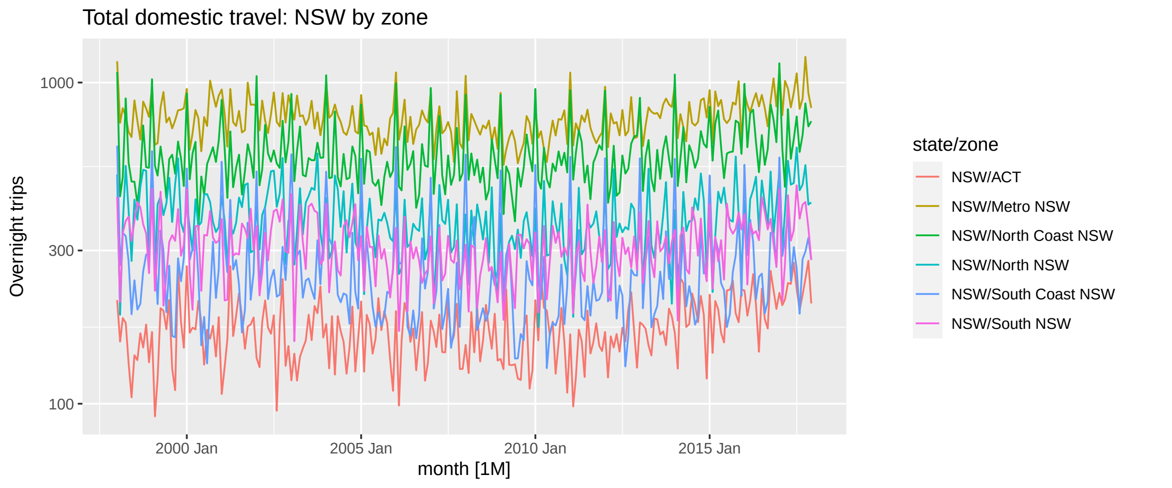

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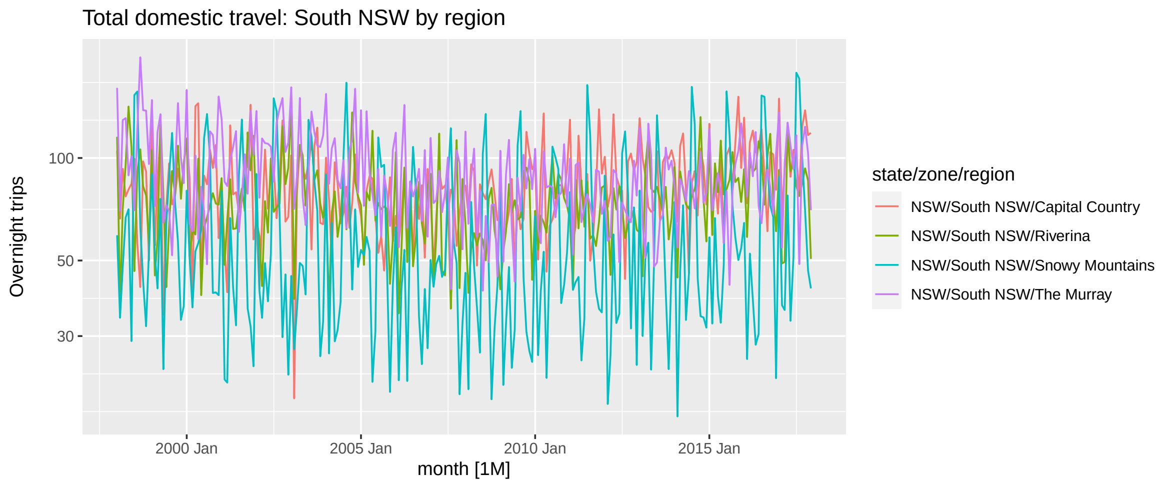
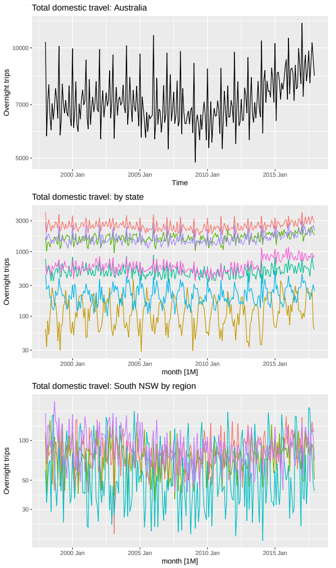
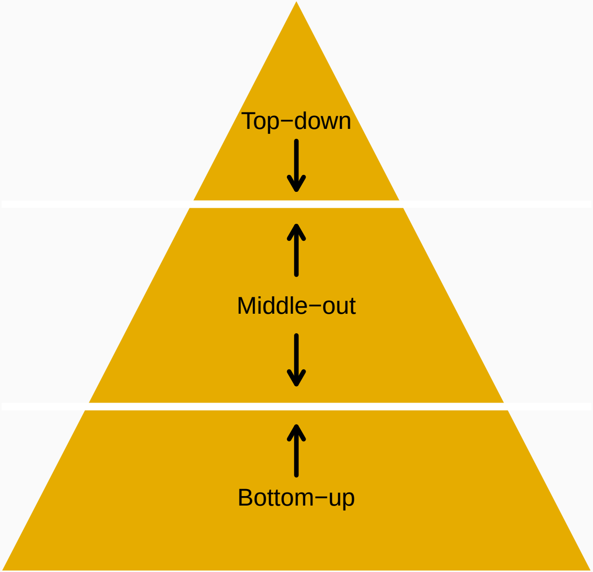


Hierarchical forecasting 20 years ago





Forecast reconciliation

- Forecast all series at all levels of aggregation.
- Reconcile forecasts using least squares optimization.

History

2001: Idea to use all available series to forecast Australia's labour market by occupation.

2004: PhD student Roman Ahmed begins, co-supervised with George Athanasopoulos.

2006: Presentation at ISF, Santander.

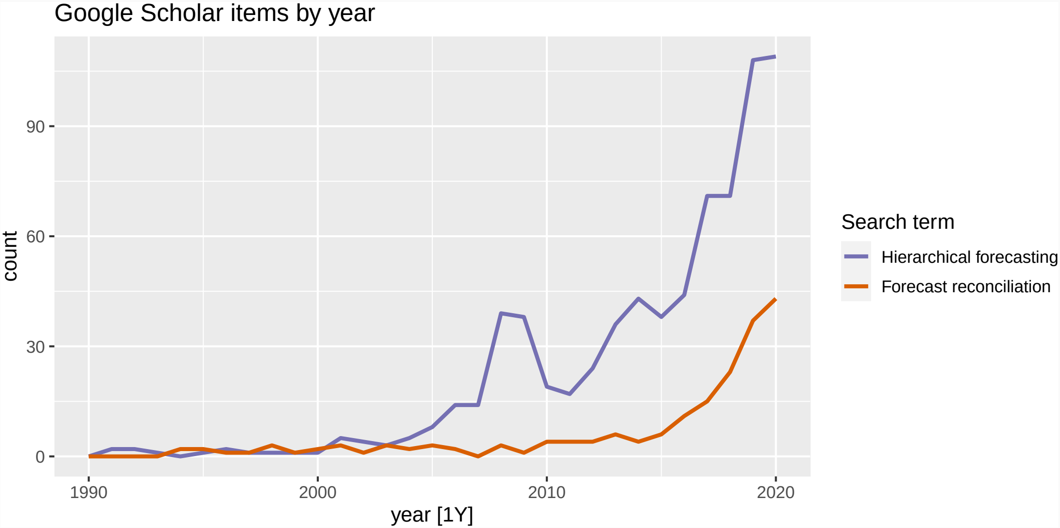
2007: Pre-print of "Optimal combination

2009: Application to Australian tourism published in IJF.

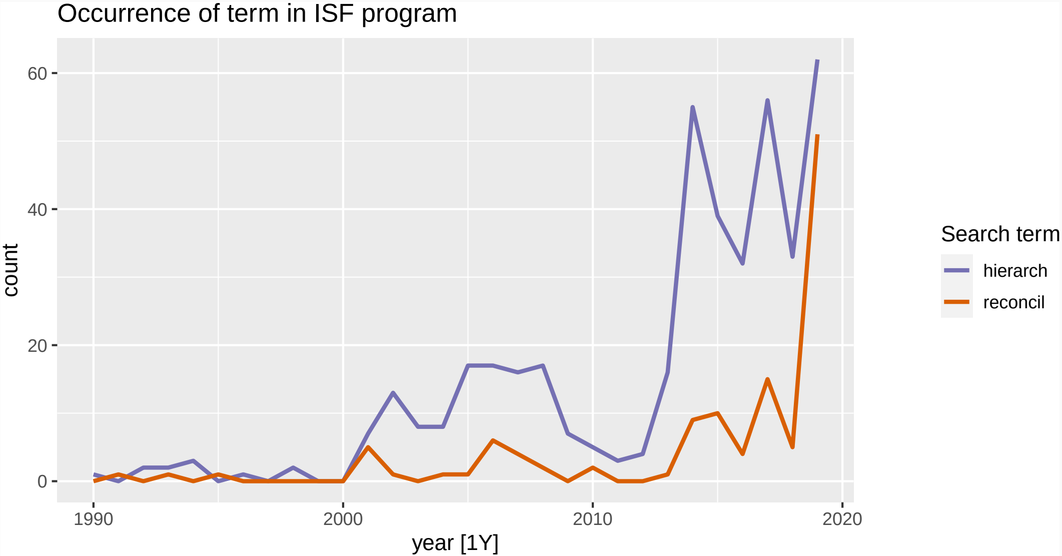
2010: First version of hts package on CRAN.

2011: "Optimal combination forecasts for hierarchical time series" appears in CSDA.

Forecast reconciliation research



Forecast reconciliation research



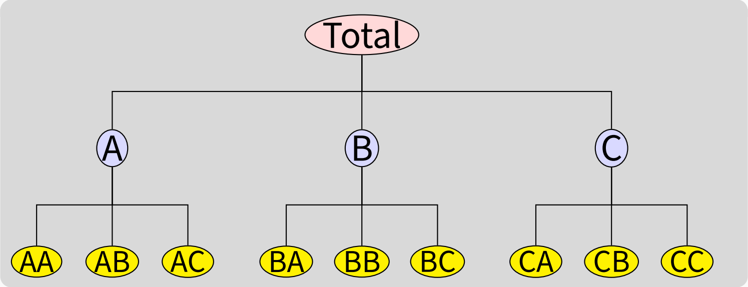
Outline

Point forecast reconciliation papers

- Hyndman, Ahmed, Athanasopoulos, Shang (2011 *CSDA*) Optimal combination forecasts for hierarchical time series.
- Hyndman, Lee, Wang (2016 *CSDA*) Fast computation of reconciled forecasts for hierarchical and grouped time series.
- Wickramasuriya, Athanasopoulos, Hyndman (2019 *JASA*) Optimal forecast reconciliation for hierarchical and grouped time series through trace minimization.
- Panagiotelis, Gamakumara, Athanasopoulos, Hyndman (2020 *IJF*) Forecast reconciliation: A geometric view with new insights on bias correction.

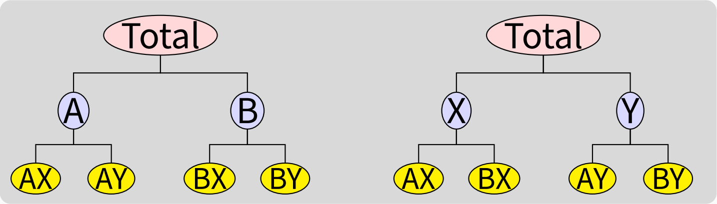
Hierarchical time series

A **hierarchical time series** is a collection of several time series that are linked together in a hierarchical structure.



Grouped time series

A **grouped time series** is a collection of time series that can be grouped together in a number of non-hierarchical ways.



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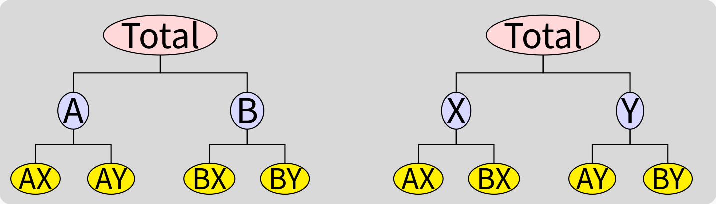
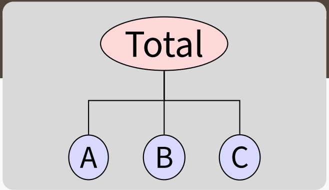


Examples

- Tourism by state and purpose of travel
- Retail sales by product groups/sub groups, and by countries/regions

Hierarchical and grouped time series



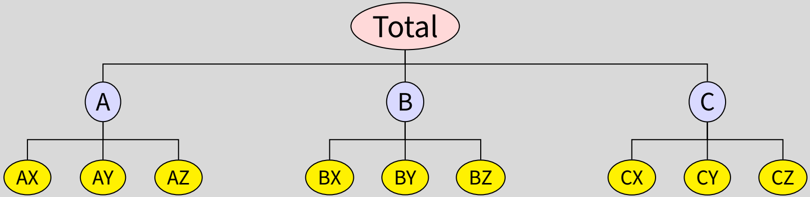
Every collection of time series with linear constraints can be written as

$$\boldsymbol{y}_t = \boldsymbol{S}\boldsymbol{b}_t$$

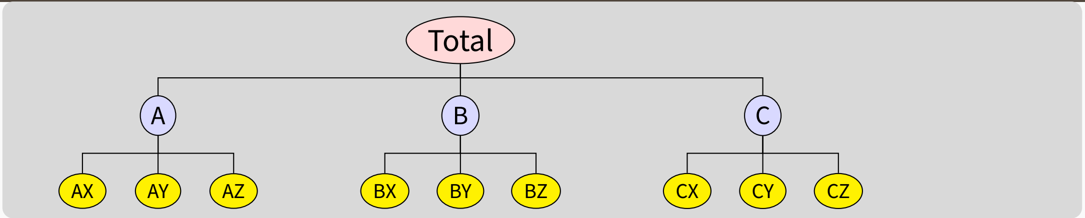
- $\boldsymbol{y}_t$ = vector of all series at time t
- y_t = aggregate of all series at time t.
- $y_{X,t}$ = value of series X at time t.
- $\boldsymbol{b}_t$ = vector of most disaggregated series at time t
- $\boldsymbol{S}$ = "summing matrix" containing the linear constraints.

$$\boldsymbol{y}_t = \begin{pmatrix} y_t \\ y_{A,t} \\ y_{B,t} \\ y_{C,t} \end{pmatrix} = \underbrace{\begin{pmatrix} 1 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}}_{\boldsymbol{S}} \underbrace{\begin{pmatrix} y_{A,t} \\ y_{B,t} \\ y_{C,t} \end{pmatrix}}_{\boldsymbol{b}_t}$$

Hierarchical time series



Hierarchical time series



$$\boldsymbol{y}_t = \begin{pmatrix} y_t \\ y_{A,t} \\ y_{B,t} \\ y_{C,t} \\ y_{AX,t} \\ y_{AY,t} \\ y_{AZ,t} \\ y_{BX,t} \\ y_{BY,t} \\ y_{BZ,t} \\ y_{CX,t} \\ y_{CY,t} \\ y_{CZ,t} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} y_{AX,t} \\ y_{AY,t} \\ y_{AZ,t} \\ y_{BX,t} \\ y_{BY,t} \\ y_{BZ,t} \\ y_{CX,t} \\ y_{CY,t} \\ y_{CZ,t} \end{pmatrix}$$

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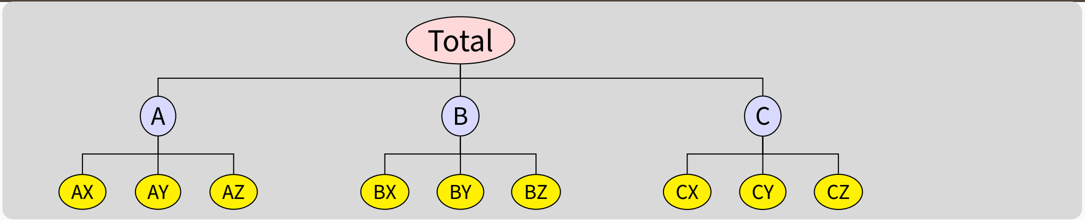

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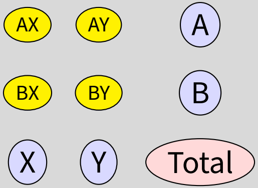
$$\boldsymbol{y}_t = \boldsymbol{S}\boldsymbol{b}_t$$

Grouped data



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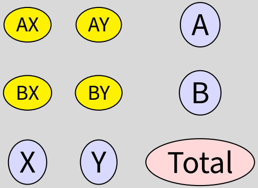

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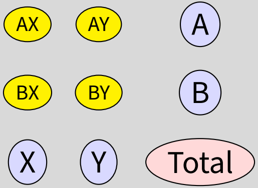

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Definitions

Coherent subspace

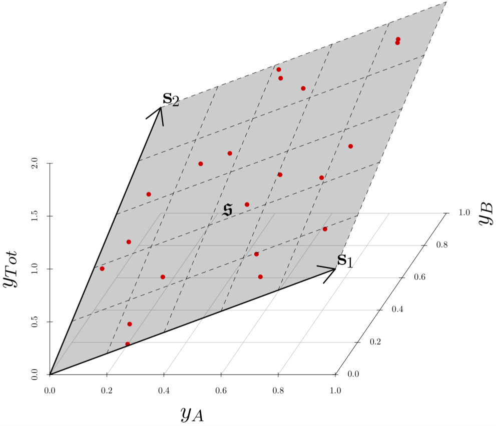
m-dimensional linear subspace $\mathfrak{s} \subset \mathbb{R}^n$ for which linear constraints hold for all $\boldsymbol{y} \in \mathfrak{s}$.

Hierarchical time series

An n-dimensional multivariate time series such that $\boldsymbol{y}_t \in \mathfrak{s} \quad \forall t$.

Coherent point forecasts

$\tilde{\boldsymbol{y}}_{t+h|t}$ is *coherent* if $\tilde{\boldsymbol{y}}_{t+h|t} \in \mathfrak{s}$.



$$y_{Tot} = y_A + y_B$$

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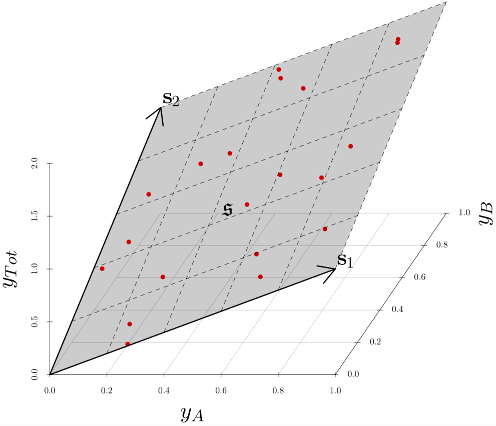
Base forecasts

Let $\hat{\boldsymbol{y}}_{t+h|t}$ be vector of *incoherent* initial h-step forecasts.



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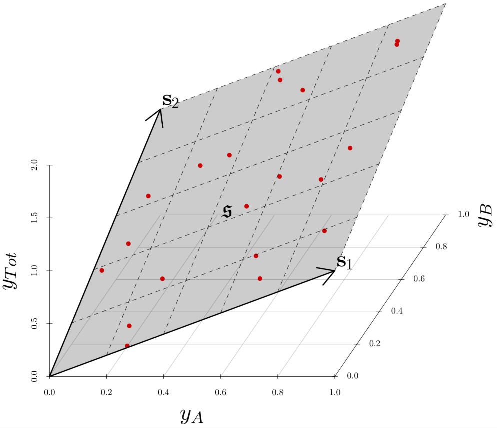

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Reconciled forecasts

Let ψ be a mapping, $\psi : \mathbb{R}^n \to \mathfrak{s}$. $\tilde{\boldsymbol{y}}_{t+h|t} = \psi(\hat{\boldsymbol{y}}_{t+h|t})$ “reconciles” $\hat{\boldsymbol{y}}_{t+h|t}$.

Linear reconciliation

If ψ is a linear function, then
$\tilde{\boldsymbol{y}}_{t+h|t} = \boldsymbol{S}\boldsymbol{G}\hat{\boldsymbol{y}}_{t+h|t}$

- $\boldsymbol{G}$ combines base forecasts $\hat{\boldsymbol{y}}_{T+h|T}$ to get bottom-level forecasts.
- $\boldsymbol{S}$ creates linear combinations.

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Mean

$$\mathrm{E}[\tilde{\boldsymbol{y}}_{T+h|T} \mid \boldsymbol{y}_1, \dots, \boldsymbol{y}_n] = \mathrm{E}[\boldsymbol{y}_{T+h|T} \mid \boldsymbol{y}_1, \dots, \boldsymbol{y}_n]$$

provided $\boldsymbol{S}\boldsymbol{G}\boldsymbol{S}' = \boldsymbol{S}$ and

$$\mathrm{E}[\hat{\boldsymbol{y}}_{T+h|T} \mid \boldsymbol{y}_1, \dots, \boldsymbol{y}_n] = \mathrm{E}[\boldsymbol{y}_{T+h|T} \mid \boldsymbol{y}_1, \dots, \boldsymbol{y}_n]$$

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Variance

$$\begin{aligned}\boldsymbol{V}_h &= \mathrm{Var}[\boldsymbol{y}_{T+h} - \tilde{\boldsymbol{y}}_{T+h|T} \mid \boldsymbol{y}_1, \dots, \boldsymbol{y}_n] \\ &= \boldsymbol{S}\boldsymbol{G}\boldsymbol{W}_h\boldsymbol{G}'\boldsymbol{S}'\end{aligned}$$

where
$\boldsymbol{W}_h = \mathrm{Var}[\boldsymbol{y}_{T+h} - \hat{\boldsymbol{y}}_{T+h|T} \mid \boldsymbol{y}_1, \dots, \boldsymbol{y}_n]$

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where
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Minimum trace (MinT) reconciliation

If $\boldsymbol{S}\boldsymbol{G}$ is a projection, then the trace of $\boldsymbol{V}_h$ is minimized when

$$\boldsymbol{G} = (\boldsymbol{S}'\boldsymbol{W}_h^{-1}\boldsymbol{S})^{-1}\boldsymbol{S}'\boldsymbol{W}_h^{-1}$$

Linear projections

$$\tilde{\boldsymbol{y}}_{T+h|T} = \boldsymbol{S}\boldsymbol{G}\hat{\boldsymbol{y}}_{T+h|T}$$

Reconciliation method	$\boldsymbol{G}$
OLS	$(\boldsymbol{S}'\boldsymbol{S})^{-1}\boldsymbol{S}'$
WLS(var)	$(\boldsymbol{S}'\Lambda_v\boldsymbol{S})^{-1}\boldsymbol{S}'\Lambda_v$
WLS(struct)	$(\boldsymbol{S}'\Lambda_s\boldsymbol{S})^{-1}\boldsymbol{S}'\Lambda_s$
MinT(sample)	$(\boldsymbol{S}'\hat{\boldsymbol{W}}_{\text{sam}}^{-1}\boldsymbol{S})^{-1}\boldsymbol{S}'\hat{\boldsymbol{W}}_{\text{sam}}^{-1}$
MinT(shrink)	$(\boldsymbol{S}'\hat{\boldsymbol{W}}_{\text{shr}}^{-1}\boldsymbol{S})^{-1}\boldsymbol{S}'\hat{\boldsymbol{W}}_{\text{shr}}^{-1}$

These approximate MinT by assuming $\boldsymbol{W}_h = k_h\boldsymbol{W}_1$.

- $\Lambda_v = \text{diag}(\boldsymbol{W}_1)^{-1}$
- $\Lambda_s = \text{diag}(\boldsymbol{S}\boldsymbol{1})^{-1}$
- $\hat{\boldsymbol{W}}_{\text{sam}}$ is sample estimate of the residual covariance matrix
- $\hat{\boldsymbol{W}}_{\text{shr}}$ is shrinkage estimator $\tau\text{diag}(\hat{\boldsymbol{W}}_{\text{sam}}) + (1-\tau)\hat{\boldsymbol{W}}_{\text{sam}}$ where τ selected optimally.

Outline

Example: Australian tourism

```r
tourism
```

```
# A tsibble: 18,000 x 5 [1M]
# Key:       state, zone, region [75]
      month state zone      region visitors
      <mth> <chr> <chr>     <chr>     <dbl>
 1 1998 Jan NSW   Metro NSW Sydney     926.
 2 1998 Feb NSW   Metro NSW Sydney     647.
 3 1998 Mar NSW   Metro NSW Sydney     716.
 4 1998 Apr NSW   Metro NSW Sydney     621.
 5 1998 May NSW   Metro NSW Sydney     598.
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10 1998 Oct NSW   Metro NSW Sydney     771.
# i 17,990 more rows
```

Example: Australian tourism

```r
tourism_agg <- tourism %>%
  aggregate_key(state/zone/region, visitors = sum(visitors))
```

```
# A tsibble: 26,400 x 5 [1M]
# Key:       state, zone, region [110]
      month state        zone         region       visitors
      <mth> <chr*>       <chr*>       <chr*>          <dbl>
 1 1998 Jan <aggregated> <aggregated> <aggregated>   10376.
 2 1998 Feb <aggregated> <aggregated> <aggregated>    5746.
 3 1998 Mar <aggregated> <aggregated> <aggregated>    7129.
 4 1998 Apr <aggregated> <aggregated> <aggregated>    7939.
 5 1998 May <aggregated> <aggregated> <aggregated>    6552.
 6 1998 Jun <aggregated> <aggregated> <aggregated>    5969.
 7 1998 Jul <aggregated> <aggregated> <aggregated>    7041.
 8 1998 Aug <aggregated> <aggregated> <aggregated>    6382.
 9 1998 Sep <aggregated> <aggregated> <aggregated>    6907.
10 1998 Oct <aggregated> <aggregated> <aggregated>    7744.
```

Example: Australian tourism

```
fit <- tourism_agg %>%
  filter(year(month) <= 2015) %>%
  model(ets = ETS(visitors))
```

```
# A mable: 110 x 4
# Key:     state, zone, region [110]
   state  zone            region                    ets
   <chr*> <chr*>          <chr*>                <model>
 1 NSW    ACT             Canberra         <ETS(M,N,A)>
 2 NSW    ACT             <aggregated>     <ETS(M,N,A)>
 3 NSW    Metro NSW       Central Coast    <ETS(M,N,M)>
 4 NSW    Metro NSW       Sydney           <ETS(M,N,A)>
 5 NSW    Metro NSW       <aggregated>     <ETS(M,N,A)>
 6 NSW    North Coast NSW Hunter           <ETS(M,N,M)>
 7 NSW    North Coast NSW North Coast NSW  <ETS(M,N,M)>
 8 NSW    North Coast NSW <aggregated>     <ETS(M,N,M)>
 9 NSW    North NSW       Blue Mountains   <ETS(M,N,A)>
```

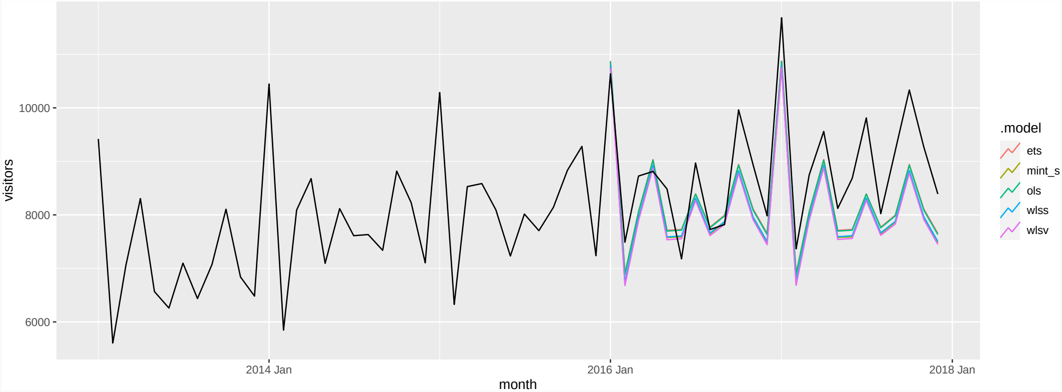
Example: Australian tourism

```r
fc <- fit %>%
  reconcile(
    ols = min_trace(ets, method="ols"),
    wlsv = min_trace(ets, method="wls_var"),
    wlss = min_trace(ets, method="wls_struct"),
    #mint_c = min_trace(ets, method="mint_cov"),
    mint_s = min_trace(ets, method="mint_shrink"),
  ) %>%
  forecast(h = "2 years")
```

```
# A fable: 13,200 x 7 [1M]
# Key:     state, zone, region, .model [550]
   state  zone   region   .model    month      visitors .mean
   <chr*> <chr*> <chr*>   <chr>     <mth>        <dist> <dbl>
 1 NSW    ACT    Canberra ets    2016 Jan N(202, 1437)   202.
 2 NSW    ACT    Canberra ets    2016 Feb  N(160, 912)   160.
 3 NSW    ACT    Canberra ets    2016 Mar N(204, 1489)   204.
```

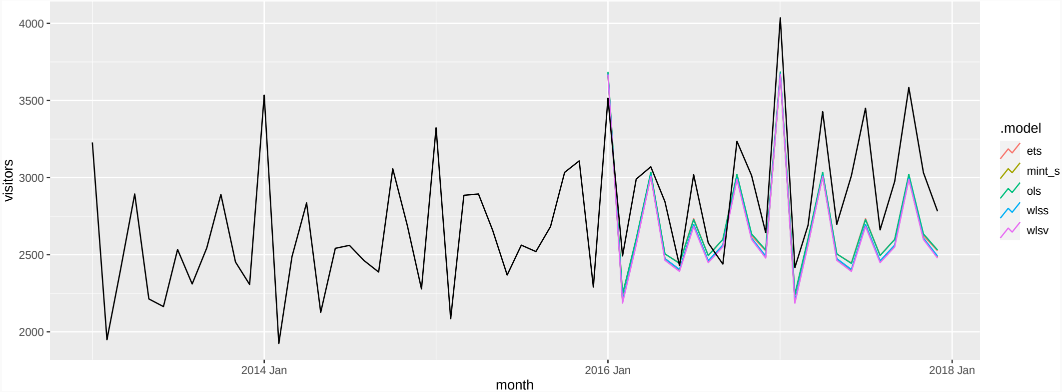
Example: Australian tourism

```
fc %>%
  filter(is_aggregated(state)) %>%
  autoplot(filter(tourism_agg, year(month) > 2012), level = NULL)
```



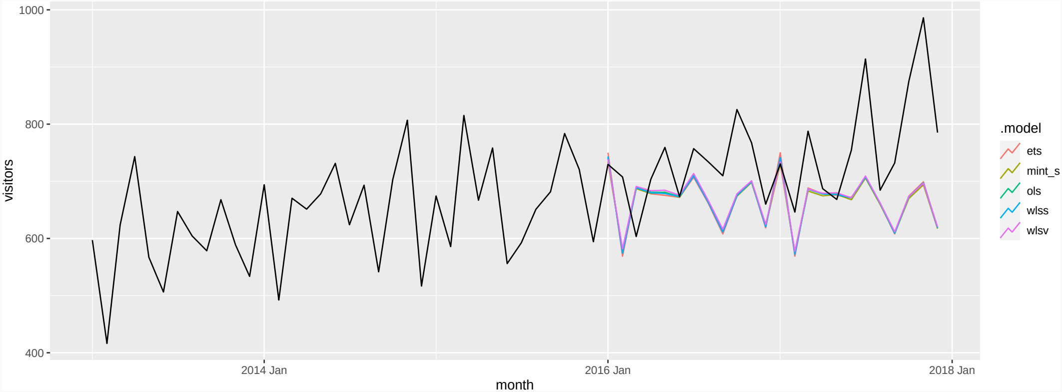
Example: Australian tourism

```r
fc %>%
  filter(state == "NSW" & is_aggregated(zone)) %>%
  autoplot(filter(tourism_agg, year(month) > 2012), level = NULL)
```



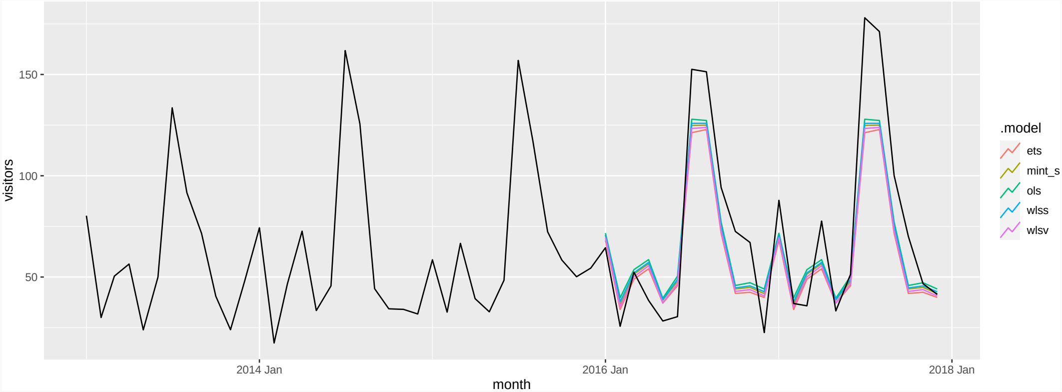
Example: Australian tourism

```
fc %>%
  filter(region == "Melbourne") %>%
  autoplot(filter(tourism_agg, year(month) > 2012), level = NULL)
```



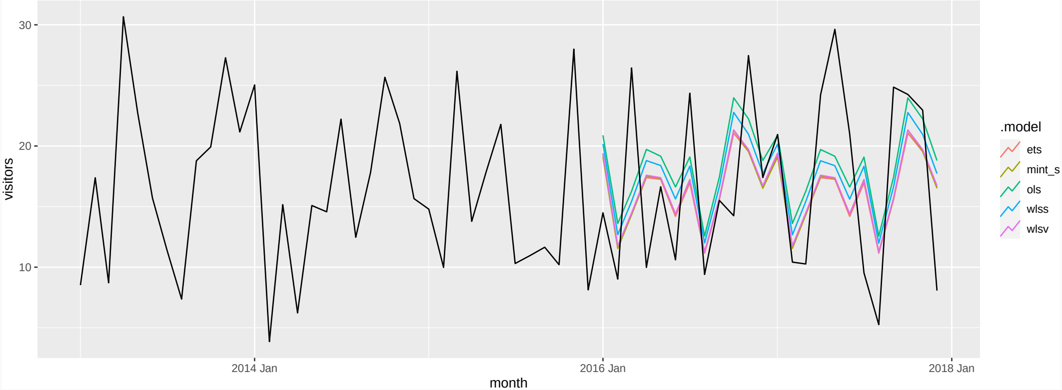
Example: Australian tourism

```r
fc %>%
  filter(region == "Snowy Mountains") %>%
  autoplot(filter(tourism_agg, year(month) > 2012), level = NULL)
```



Example: Australian tourism

```r
fc %>%
  filter(region == "Barossa") %>%
  autoplot(filter(tourism_agg, year(month) > 2012), level = NULL)
```



Example: Australian tourism

```
fc %>%
  accuracy(data = tourism_agg,
           measures = list(rmsse = RMSSE))
```

```
# A tibble: 550 x 6
   .model state  zone             region           .type rmsse
   <chr>  <chr*> <chr*>           <chr*>           <chr> <dbl>
 1 ets    NSW    ACT              Canberra         Test  0.835
 2 ets    NSW    ACT              <aggregated>     Test  0.835
 3 ets    NSW    Metro NSW        Central Coast    Test  0.747
 4 ets    NSW    Metro NSW        Sydney           Test  1.16
 5 ets    NSW    Metro NSW        <aggregated>     Test  1.18
 6 ets    NSW    North Coast NSW Hunter           Test  1.21
 7 ets    NSW    North Coast NSW North Coast NSW Test  0.884
 8 ets    NSW    North Coast NSW <aggregated>     Test  1.02
 9 ets    NSW    North NSW        Blue Mountains   Test  1.02
10 ets    NSW    North NSW        Central NSW      Test  1.18
```

Example: Australian tourism

```r
fc %>%
  accuracy(tourism_agg,
           measures = list(mase = MASE, rmsse = RMSSE)) %>%
  group_by(.model) %>%
  summarise(mase = mean(mase), rmsse = sqrt(mean(rmsse^2))) %>%
  arrange(rmsse)
```

```
# A tibble: 5 x 3
  .model  mase rmsse
  <chr>  <dbl> <dbl>
1 ols    0.930 0.926
2 wlss   0.949 0.948
3 mint_s 0.953 0.954
4 wlsv   0.964 0.965
5 ets    0.968 0.968
```

Example: Australian tourism

```r
fc %>%
  accuracy(tourism_agg,
           measures = list(mase = MASE, rmsse = RMSSE)) %>%
  group_by(.model) %>%
  summarise(mase = mean(mase), rmsse = sqrt(mean(rmsse^2))) %>%
  arrange(rmsse)
```

```
# A tibble: 5 x 3
  .model  mase rmsse
  <chr>  <dbl> <dbl>
1 ols    0.930 0.926
2 wlss   0.949 0.948
3 mint_s 0.953 0.954
4 wlsv   0.964 0.965
5 ets    0.968 0.968
```

- Overall, every reconciliation method is better than the base ETS forecasts.

Example: Australian tourism

```
# A tibble: 20 x 4
# Groups:   .model [5]
   .model level     mase rmsse
   <chr>  <fct>    <dbl> <dbl>
 1 ets    National 1.44  1.27 
 2 ols    National 1.46  1.29 
 3 wlss   National 1.61  1.43 
 4 mint_s National 1.64  1.45 
 5 wlsv   National 1.69  1.49 
 6 ols    State    1.07  1.08 
 7 ets    State    1.10  1.11 
 8 wlss   State    1.13  1.14 
 9 mint_s State    1.15  1.15 
10 wlsv   State    1.18  1.17 
11 ols    Zone     0.954 0.948
12 wlss   Zone     0.987 0.980
13 mint_s Zone     0.995 0.988
14 ets    Zone     1.01  0.999
15 wlsv   Zone     1.01  1.00 
16 ols    Region   0.901 0.895
17 wlss   Region   0.910 0.907
18 mint_s Region   0.911 0.911
19 wlsv   Region   0.917 0.919
20 ets    Region   0.935 0.938
```

Example: Australian tourism

```
# A tibble: 20 x 4
# Groups:   .model [5]
   .model level     mase rmsse
   <chr>  <fct>    <dbl> <dbl>
 1 ets    National 1.44  1.27
 2 ols    National 1.46  1.29
 3 wlss   National 1.61  1.43
 4 mint_s National 1.64  1.45
 5 wlsv   National 1.69  1.49
 6 ols    State    1.07  1.08
 7 ets    State    1.10  1.11
 8 wlss   State    1.13  1.14
 9 mint_s State    1.15  1.15
10 wlsv   State    1.18  1.17
11 ols    Zone     0.954 0.948
12 wlss   Zone     0.987 0.980
13 mint_s Zone     0.995 0.988
14 ets    Zone     1.01  0.999
15 wlsv   Zone     1.01  1.00
16 ols    Region   0.901 0.895
17 wlss   Region   0.910 0.907
18 mint_s Region   0.911 0.911
19 wlsv   Region   0.917 0.919
20 ets    Region   0.935 0.938
```

- OLS is best for all levels except national.
- Improvements due to reconciliation are greater at lower levels.