FORECASTING PRODUCT DEMAND IN R

Bottom-Up Hierarchical Forecasting

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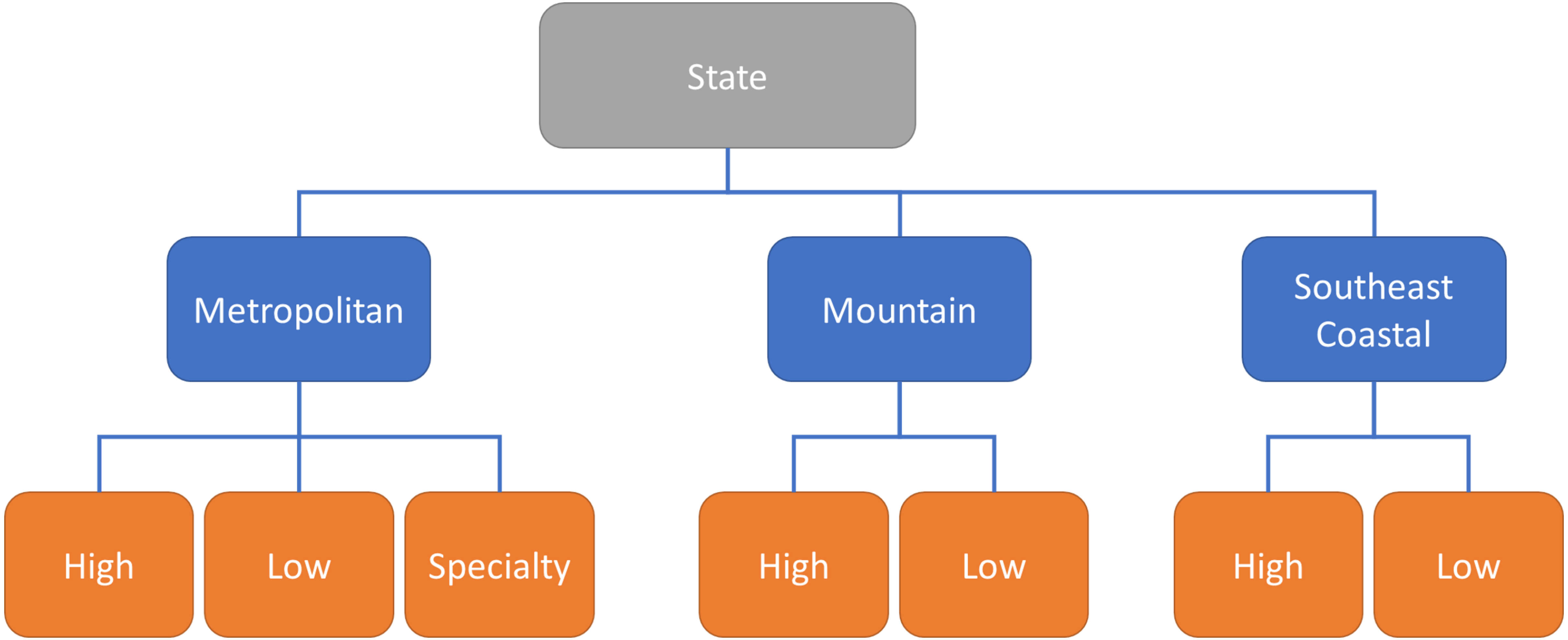
Hierarchical Forecasting

- **Hierarchical forecasting** can be used when different items that need to be forecasted can be arranged in a logical hierarchy
- Forecasts need to be **reconciled** up and down the hierarchy

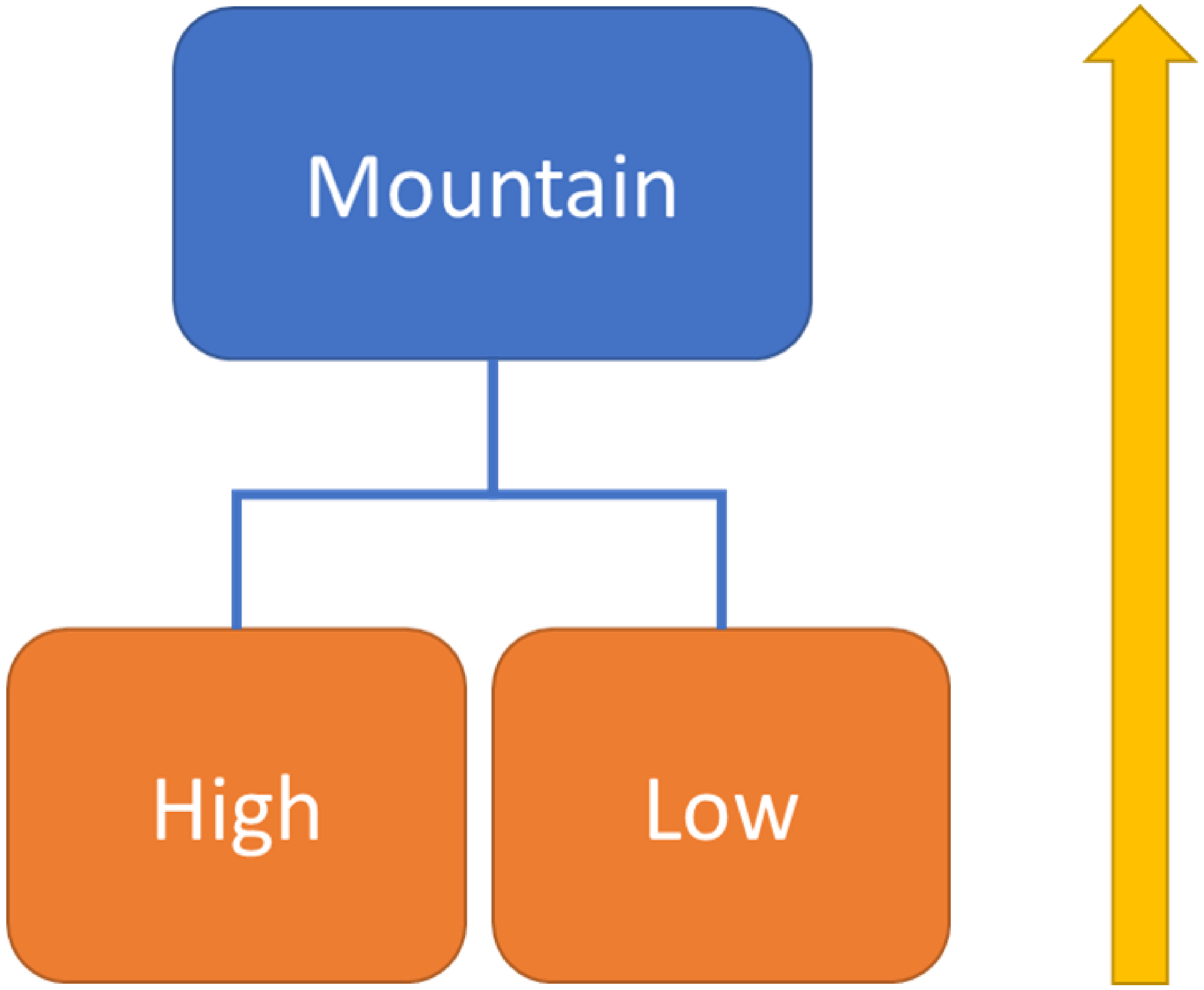
Hierarchical Structure



Types of Hierarchical Forecasting

- Three Types of Hierarchical Forecasting
  1. Bottom-up Forecasting
  2. Top-down Forecasting
  3. Middle-out Forecasting

Bottom-up Forecasting



Bottom-up Forecasting Example

```
for_M_total <- pred_M_hi_xts + pred_M_lo_xts

M_t_v <- bev_xts_valid[,"M.hi"] + bev_xts_valid[,"M.lo"]

MAPE <- 100*mean(abs((for_M_total - M_t_v)/M_t_v))
print(MAPE)
[1] 7.599677
```

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Let's practice!

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Top-Down Hierarchical Forecasting

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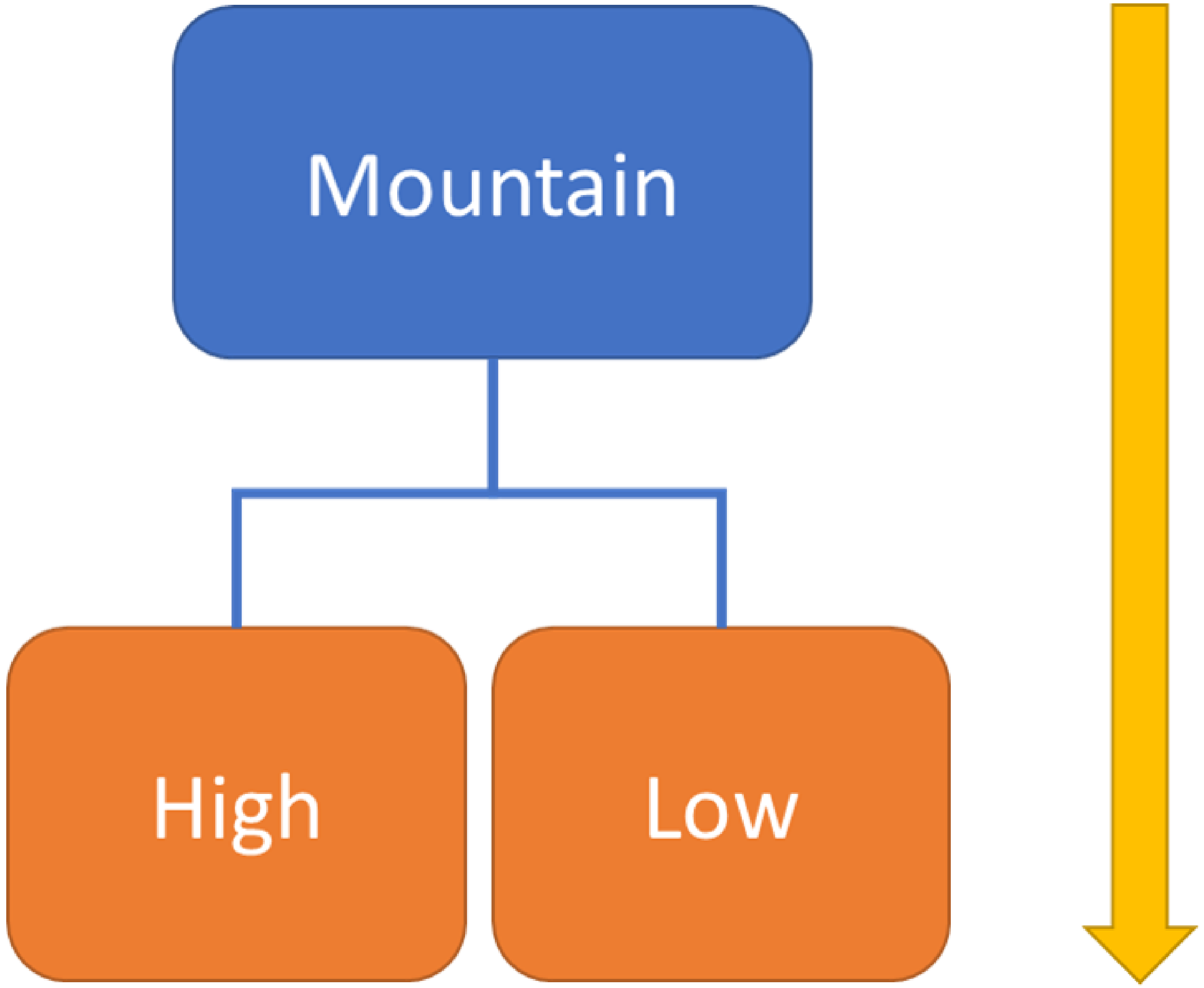
Top-down Forecasting



Top-down Reconciliation

- Two Techniques
    1. Average of historical proportions
    2. Proportion of historical averages
- Reconciled forecasts at lower level not as accurate as directly forecasting

Forecast Regional Total Sales

```
M_total <- M_hi + M_lo

M_t_model_arima <- auto.arima(M_total)
summary(M_t_model_arima)

Series: M_total
ARIMA(4,0,1) with non-zero mean

Coefficients:
         ar1      ar2     ar3     ar4      ma1       mean
      1.3158  -0.5841  0.1546  0.0290  -0.6285  2037.5977
s.e.  0.3199   0.2562  0.1534  0.1165   0.3089    87.5028

sigma^2 estimated as 67471:  log likelihood=-1072.02
AIC=2158.05   AICc=2158.81   BIC=2179.31
```

Forecast Regional Total Sales

```
for_M_t <- forecast(M_t_model_arima, h = 22)

dates_valid <- seq(as.Date("2017-01-01"), length = 22, by = "weeks")
for_M_t_xts <- xts(for_M_t$mean, order.by = dates_valid)

M_t_v <- bev_xts_valid[,"M.hi"] + bev_xts_valid[,"M.lo"]

MAPE <- 100*mean(abs((for_M_t_xts - M_t_v)/M_t_v))
print(MAPE)
[1] 9.576247
```

Average of Historical Proportions

```
head(M_hi, n = 5)
           M.hi
2014-01-19  458
2014-01-26  477
2014-02-02  539
2014-02-09  687
2014-02-16  389

head(M_total, n = 5)
           M.t
2014-01-19 1913
2014-01-26 2233
2014-02-02 2835
2014-02-09 3927
2014-02-16 2641

head(M_hi/M_total, n = 5)
                M.hi
2014-01-19 0.2394145
2014-01-26 0.2136140
2014-02-02 0.1901235
2014-02-09 0.1749427
2014-02-16 0.1472927
```

Average of Historical Proportions

```
prop_hi <- mean(M_hi/M_total)
print(prop_hi)
[1] 0.2317795

prop_lo <- mean(M_lo/M_total)
print(prop_lo)
[1] 0.7682205

for_prop_hi <- prop_hi*for_M_t_xts
for_prop_lo <- prop_lo*for_M_t_xts

MAPE_hi <- 100*mean(abs((for_prop_hi - M_hi_v)/M_hi_v))
MAPE_lo <- 100*mean(abs((for_prop_lo - M_lo_v)/M_lo_v))

print(MAPE_hi)
[1] 15.01613

print(MAPE_lo)
[1] 11.94092
```

Proportion of Historical Averages

```
prop_hi_2 <- mean(M_hi)/mean(M_total)
prop_lo_2 <- mean(M_lo)/mean(M_total)

print(prop_hi_2)
0.2275504

print(prop_lo_2)
0.7724496

for_prop_hi_2 <- prop_hi_2*for_M_t_xts
for_prop_lo_2 <- prop_lo_2*for_M_t_xts

MAPE_hi <- 100*mean(abs((for_prop_hi_2 - M_hi_v)/M_hi_v))
MAPE_lo <- 100*mean(abs((for_prop_lo_2 - M_lo_v)/M_lo_v))

print(MAPE_hi)
[1] 14.31853

print(MAPE_lo)
[1] 12.01166
```

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Middle-Out Forecasting

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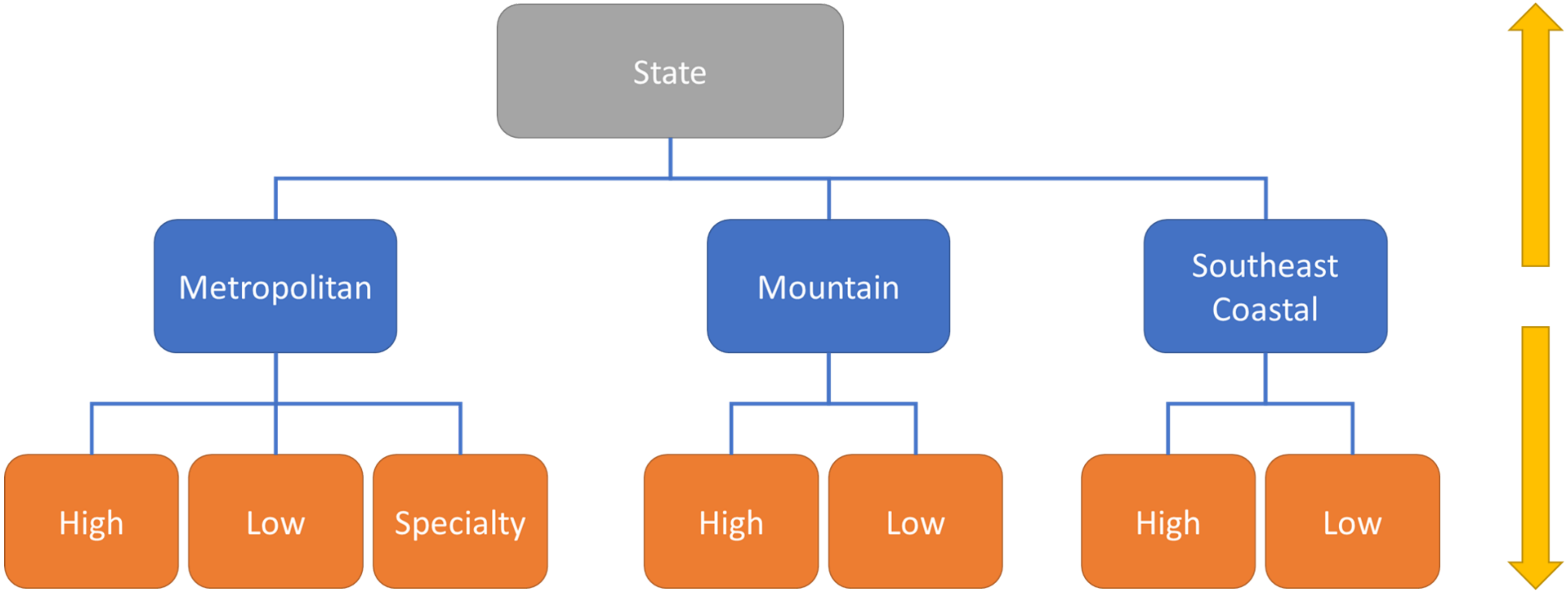
Review of bottom-up and top-down forecasting

- Bottom-up forecasting
  - Time consuming
- Top-down forecasting
  - Not as accurate

Middle-out Forecasting



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Let's practice!

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Congratulations!

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What Did You Learn?

- Chapter 1: *Using time series to forecast demand*
- Chapter 2: *Incorporating external factors in demand forecast*
- Chapter 3: *Blending time series and regression approaches*
- Chapter 4: *Hierarchical forecasting*

What Next?

- **Extensions to Demand Forecasting**
  - More external factors to demand - cross-elasticities
  - Forecast future proportions in hierarchies
  - More time series techniques than ARIMA
- **Further Learning**
  - Time series techniques and modeling
  - Linear regression techniques

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See You Next Time!