Demand Forecasting Models for Contraceptive Supply Chain

An introduction to time series forecasting

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Assumptions

- You should be comfortable with R and Python coding.
- This is not a theory-based course—we will not derive formulas or mathematical proofs.
- Our focus is on practical time series forecasting: understanding when and how to use different tools effectively.

What we will cover

- Data wrangling and basic feature engineering
- Time series visualizations
- Traditional forecasting models
- Advanced forecasting models
- Performance evaluation

What we will not cover

- Handling missing values
- Advanced feature engineering
- Time series cross-validation
- Hyperparameter tuning

Materials

You can find the workshop materials here.

Note: These materials are based on F4SG: Africast training and F4SG Learning Labs trainings.

Recommended readings:

- Demand forecasting for executives and professionals by Bahman Rostami-Tabar, Enno Siemsen, and Stephan Kolassa.
- Forecasting: Principles and Practice (3rd ed) by Rob J Hyndman and George Athanasopoulos.
- Forecasting and Analytics with the Augmented Dynamic Adaptive Model (ADAM) by Ivan Svetunkov.

Outline

- What is forecasting?
- Prepare your data
- Explore your data
- Forecast modelling
- Evaluating the model performances
- Advance forecasting models
- Other forecasting models in family planning supply chains

What is forecasting?

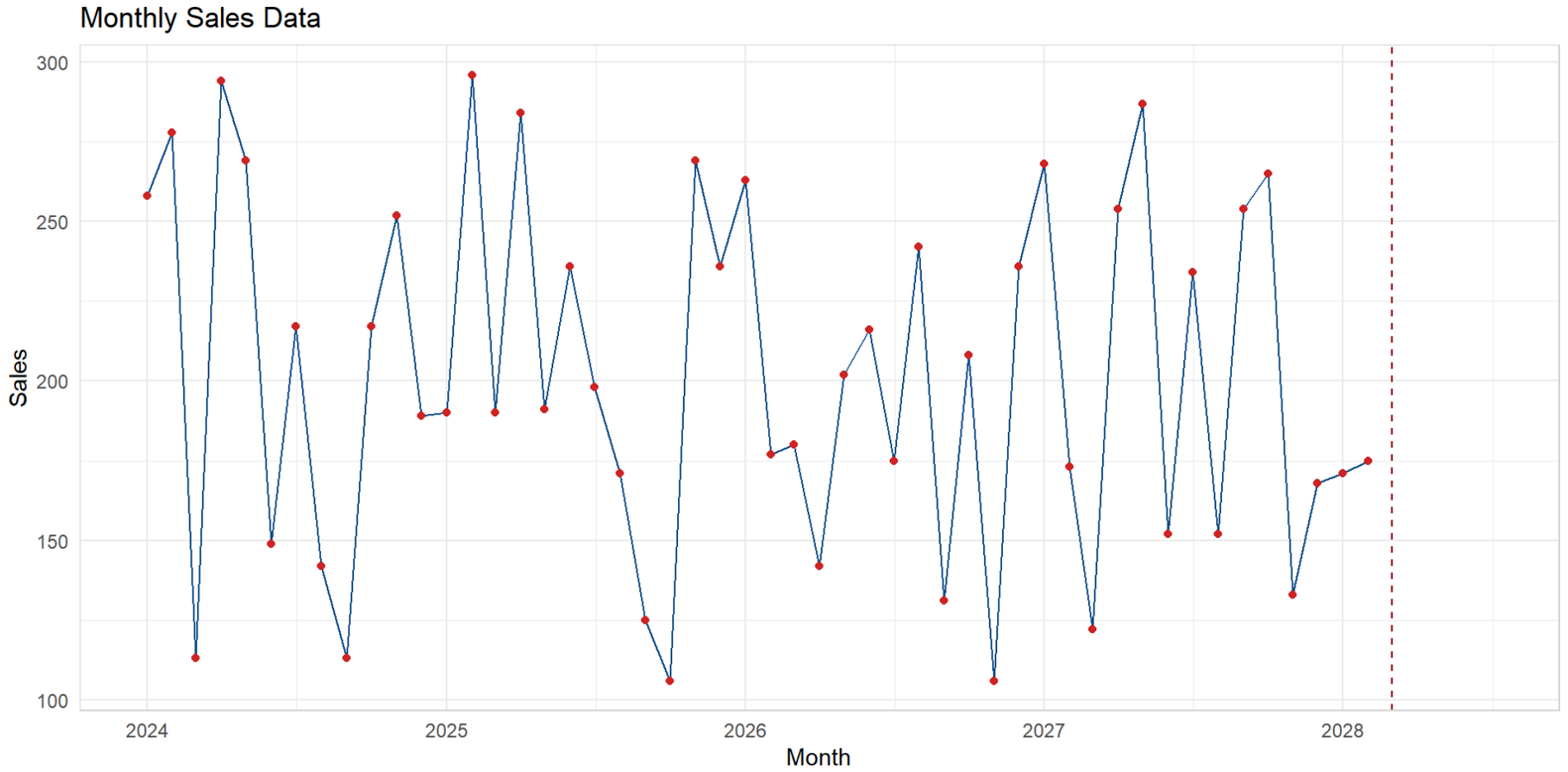
What is a FORECAST?

An estimation of the future based on all of the information available at the time when we generate the forecast;

- historical data,
- knowledge of any future events that might impact the forecasts.

What is time series data?

- Time series consist of sequences of observations collected over time.
- Time series forecasting is estimating how the sequence of observations will continue into the future.



What to FORECAST?

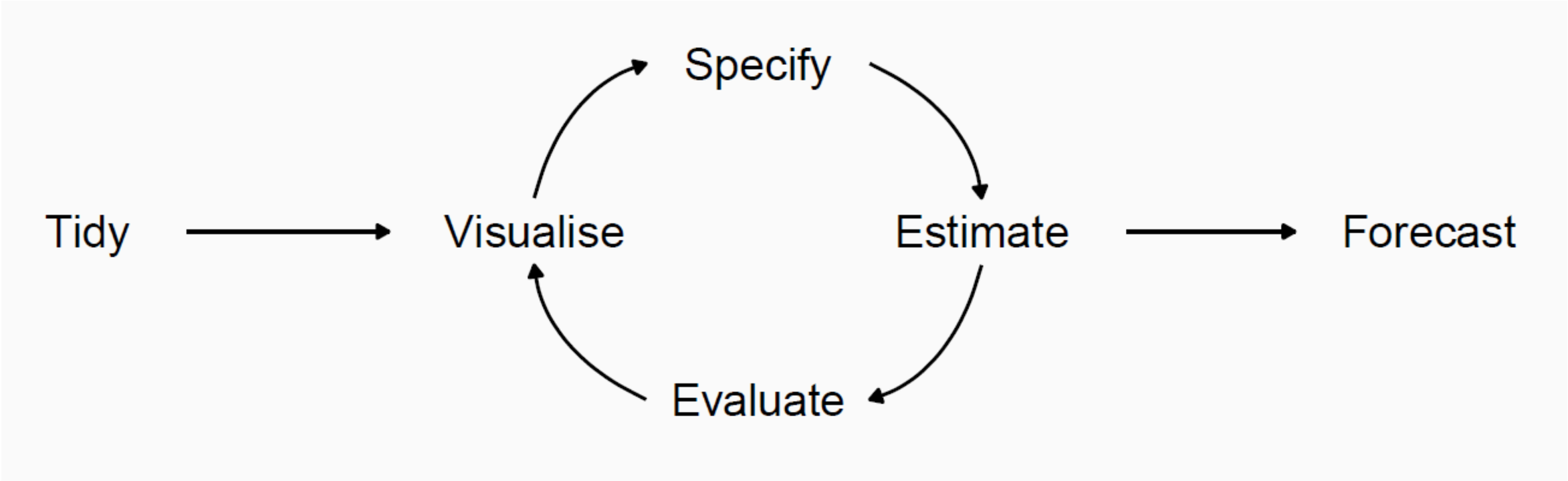
Understanding needs! Identify decisions that need forecasting support!

- Forecast variable/s
- Time granularity
- Forecast horizon
- Frequency
- Structure/hierarchy

Forecasting workflow

- *Step 1:* Problem definition
- *Step 2:* Gathering information
- *Step 3:* Preliminary (exploratory) analysis
- *Step 4:* Choosing and fitting models
- *Step 5:* Evaluating and using a forecasting model

Tidy forecasting workflow



Read more at Demand forecasting for executives and professionals by Bahman Rostami-Tabar, Enno Siemsen, and Stephan Kolassa.

Forecasting using R

Loading libraries

We use the `fpp3` package in this workshop, which provides all the necessary packages for data manipulation, plotting, and forecasting.

```r
# Define required packages
packages <- c("tidyverse", "fable", "tsibble", "feasts", 'zoo')

# Install missing packages
missing_packages <- packages[!(packages %in% installed.packages()[,"Package"])]
if(length(missing_packages)) {
  suppressWarnings(suppressMessages(install.packages(missing_packages)))
}

# Load libraries quietly
suppressWarnings(suppressMessages({
  library(tidyverse) # Data manipulation and plotting functions
  library(fable) # Time series manipulation
  library(tsibble) # Forecasting functions
  library(feasts) # Time series graphics and statistics
}))
```

Read more at Forecasting: Principles and Practice (3rd ed) by Rob J Hyndman and George Athanasopoulos.

Preparing the data

In this workshop, we are using `tsibble` objects. They provide a data infrastructure for tidy temporal data with wrangling tools, adapting the tidy data principles.

In `tsibble`:

- **Index:** time information about the observation
- **Measured variable(s):** numbers of interest
- **Key variable(s):** set of variables that define observational units over time
- It works with tidyverse functions.

Read `csv` file

```
1 med_qty <- read.csv('data/med_qty.csv')
2 med_qty |> head(10)
```

```
       date hub_id product_id quantity_issued
1  2017 Jul  hub_4  product_1              60
2  2017 Jul  hub_4  product_6            5200
3  2017 Jul  hub_7  product_1               8
4  2017 Jul  hub_7  product_5             120
5  2017 Jul  hub_8  product_7              10
6  2017 Jul hub_10  product_1             343
7  2017 Jul hub_10  product_2              53
8  2017 Jul hub_10  product_3              26
9  2017 Jul hub_10  product_4            1710
10 2017 Jul hub_10  product_5            1340
```

Do you think the `med_qty` data set is a tidy data?

Check for NA and duplicates

```r
# check NAs

anyNA(med_qty)
```

```
[1] FALSE
```

```r
#check duplicates

med_qty |>
  duplicated() |>
  sum()
```

```
[1] 0
```

Create tsibble

```
med_tsb <- med_qty |>
  mutate(date = yearmonth(date)) |>  # convert chr to date format
  as_tsibble(index = date, key = c(hub_id, product_id))

med_tsb
```

```
# A tsibble: 6,745 x 4 [1M]
# Key:       hub_id, product_id [133]
       date hub_id product_id quantity_issued
      <mth> <chr>  <chr>                <dbl>
 1 2017 Aug hub_1  product_1              721
 2 2017 Sep hub_1  product_1              795
 3 2017 Oct hub_1  product_1             1720
 4 2017 Nov hub_1  product_1              911
 5 2017 Dec hub_1  product_1              314
 6 2018 Jan hub_1  product_1             6913
 7 2018 Feb hub_1  product_1             2988
 8 2018 Mar hub_1  product_1             7120
 9 2018 Apr hub_1  product_1             3122
10 2018 May hub_1  product_1            11737
# ℹ 6,735 more rows
```

- What is the temporal granularity of `med_tsb`?
- How many time series do we have in `med_tsb`?

Check temporal gaps (implicit missing values)

```
1 has_gaps(med_tsb) |> head(3) #check gaps
```

```
# A tibble: 3 × 3
  hub_id product_id .gaps
  <chr>  <chr>      <lgl>
1 hub_1  product_1  TRUE
2 hub_1  product_2  TRUE
3 hub_1  product_3  TRUE
```

```
1 scan_gaps(med_tsb) |> head(3) # show gaps
```

```
# A tsibble: 3 x 3 [1M]
# Key:       hub_id, product_id [1]
  hub_id product_id     date
  <chr>  <chr>         <mth>
1 hub_1  product_1  2018 Jul
2 hub_1  product_1  2018 Aug
3 hub_1  product_1  2018 Sep
```

```
1 count_gaps(med_tsb) |> head(3) # count gaps
```

```
# A tibble: 3 × 5
  hub_id product_id    .from      .to    .n
  <chr>  <chr>         <mth>    <mth> <int>
1 hub_1  product_1  2018 Jul 2021 Feb    32
2 hub_1  product_1  2021 Jul 2022 Sep    15
3 hub_1  product_2  2018 Sep 2018 Sep     1
```

Check temporal gaps (implicit missing values)

If there is any gap, then we fill it.

```
med_tsb |> fill_gaps(quantity_issued=0L) # we can fill it with zero
```

```
# A tsibble: 8,795 x 4 [1M]
# Key:       hub_id, product_id [133]
       date hub_id product_id quantity_issued
      <mth> <chr>  <chr>                <dbl>
 1 2017 Aug hub_1  product_1              721
 2 2017 Sep hub_1  product_1              795
 3 2017 Oct hub_1  product_1             1720
 4 2017 Nov hub_1  product_1              911
 5 2017 Dec hub_1  product_1              314
 6 2018 Jan hub_1  product_1             6913
 7 2018 Feb hub_1  product_1             2988
 8 2018 Mar hub_1  product_1             7120
 9 2018 Apr hub_1  product_1             3122
10 2018 May hub_1  product_1            11737
# ℹ 8,785 more rows
```

Check temporal gaps (implicit missing values)

Note: Since the main focus of this study is to provide foundational knowledge on forecasting, we will filter out time series with many missing values and then fill the remaining gaps using `na.interp()` function (Read more).

```r
item_ids <- med_tsb |>
  count_gaps() |>
  group_by(hub_id, product_id) |>
  summarise(.n = max(.n), .groups = 'drop') |>
  filter(.n  < 2) |>
  mutate(id = paste0(hub_id,'-',product_id)) |>
  pull(id) # filtering the item ids

med_tsb_filter <- med_tsb |>
  mutate(id = paste0(hub_id,'-',product_id)) |>
  group_by(hub_id, product_id) |>
  mutate(num_observations = n()) |>
  filter(id %in% item_ids & num_observations >59) |>   # we have cold starts and discontinuations.
  fill_gaps(quantity_issued = 1e-6, .full = TRUE) |>   # Replace NAs with a small value
  select(-id, -num_observations) |>
  mutate(quantity_issued = if_else(is.na(quantity_issued),
                                   exp(
                                     forecast::na.interp(
                                     ts(log(quantity_issued), frequency = 12))),
```

Data wrangaling using `tsibble`

We can use the `filter()` function to select rows.

```
1 med_tsb |>
2   filter(hub_id == 'hub_10')
```

```
# A tsibble: 417 x 4 [1M]
# Key:       hub_id, product_id [7]
       date hub_id product_id quantity_issued
      <mth> <chr>  <chr>                 <dbl>
 1 2017 Jul hub_10 product_1               343
 2 2017 Aug hub_10 product_1                67
 3 2017 Sep hub_10 product_1               127
 4 2017 Oct hub_10 product_1               287
 5 2017 Nov hub_10 product_1               759
 6 2017 Dec hub_10 product_1               181
 7 2018 Jan hub_10 product_1              7015
 8 2018 Feb hub_10 product_1               840
 9 2018 Mar hub_10 product_1              4111
10 2018 Apr hub_10 product_1              1910
# ℹ 407 more rows
```

Data wrangaling using `tsibble`

We can use the `select()` function to select columns.

```
med_tsb |>
  filter(hub_id == 'hub_10') |>
  select(date, product_id, quantity_issued)
```

```
# A tsibble: 417 x 3 [1M]
# Key:       product_id [7]
       date product_id quantity_issued
      <mth> <chr>                <dbl>
 1 2017 Jul product_1              343
 2 2017 Aug product_1               67
 3 2017 Sep product_1              127
 4 2017 Oct product_1              287
 5 2017 Nov product_1              759
 6 2017 Dec product_1              181
 7 2018 Jan product_1             7015
 8 2018 Feb product_1              840
 9 2018 Mar product_1             4111
10 2018 Apr product_1             1910
# ℹ 407 more rows
```

Data wrangaling using `tsibble`

We can use `group_by()` function to group over keys. We can use the `summarise()` function to summarise over keys.

```
med_tsb |>
  group_by(product_id) |>
  summarise(total_quantity_issued = sum(quantity_issued), .groups = 'drop')
```

```
# A tsibble: 471 x 3 [1M]
# Key:       product_id [7]
   product_id     date total_quantity_issued
   <chr>         <mth>                 <dbl>
 1 product_1  2017 Jul                   691
 2 product_1  2017 Aug                 18855
 3 product_1  2017 Sep                 21654
 4 product_1  2017 Oct                 16456
 5 product_1  2017 Nov                 19694
 6 product_1  2017 Dec                 63107
 7 product_1  2018 Jan                 66703
 8 product_1  2018 Feb                 53012
 9 product_1  2018 Mar                 82566
10 product_1  2018 Apr                 56913
# ℹ 461 more rows
```

Data wrangaling using `tsibble`

We can use the `mutate()` function to create new variables.

```
1 med_tsb |>
2   mutate(quarter = yearquarter(date))
```

```
# A tsibble: 6,745 x 5 [1M]
# Key:       hub_id, product_id [133]
       date hub_id product_id quantity_issued quarter
      <mth> <chr>  <chr>                <dbl>   <qtr>
 1 2017 Aug hub_1  product_1              721 2017 Q3
 2 2017 Sep hub_1  product_1              795 2017 Q3
 3 2017 Oct hub_1  product_1             1720 2017 Q4
 4 2017 Nov hub_1  product_1              911 2017 Q4
 5 2017 Dec hub_1  product_1              314 2017 Q4
 6 2018 Jan hub_1  product_1             6913 2018 Q1
 7 2018 Feb hub_1  product_1             2988 2018 Q1
 8 2018 Mar hub_1  product_1             7120 2018 Q1
 9 2018 Apr hub_1  product_1             3122 2018 Q2
10 2018 May hub_1  product_1            11737 2018 Q2
# ℹ 6,735 more rows
```

Data wrangaling using `tsibble`

We can use `index_by()` function to group over index We can use the `summarise()` function to summarise over index.

```
1 med_tsb |>
2   mutate(quarter = yearquarter(date)) |>
3   index_by(quarter) |>
4   summarise(total_quantity_issues = sum(quantity_issued))
```

```
# A tsibble: 24 x 2 [1Q]
   quarter total_quantity_issues
     <qtr>                 <dbl>
 1 2017 Q3               2103843
 2 2017 Q4               2811202
 3 2018 Q1               2511488
 4 2018 Q2               3433726
 5 2018 Q3               1738860
 6 2018 Q4               2934886
 7 2019 Q1               2452192
 8 2019 Q2               1640048
 9 2019 Q3               2170015
10 2019 Q4               3045525
# ℹ 14 more rows
```

Now it is your `turn`.

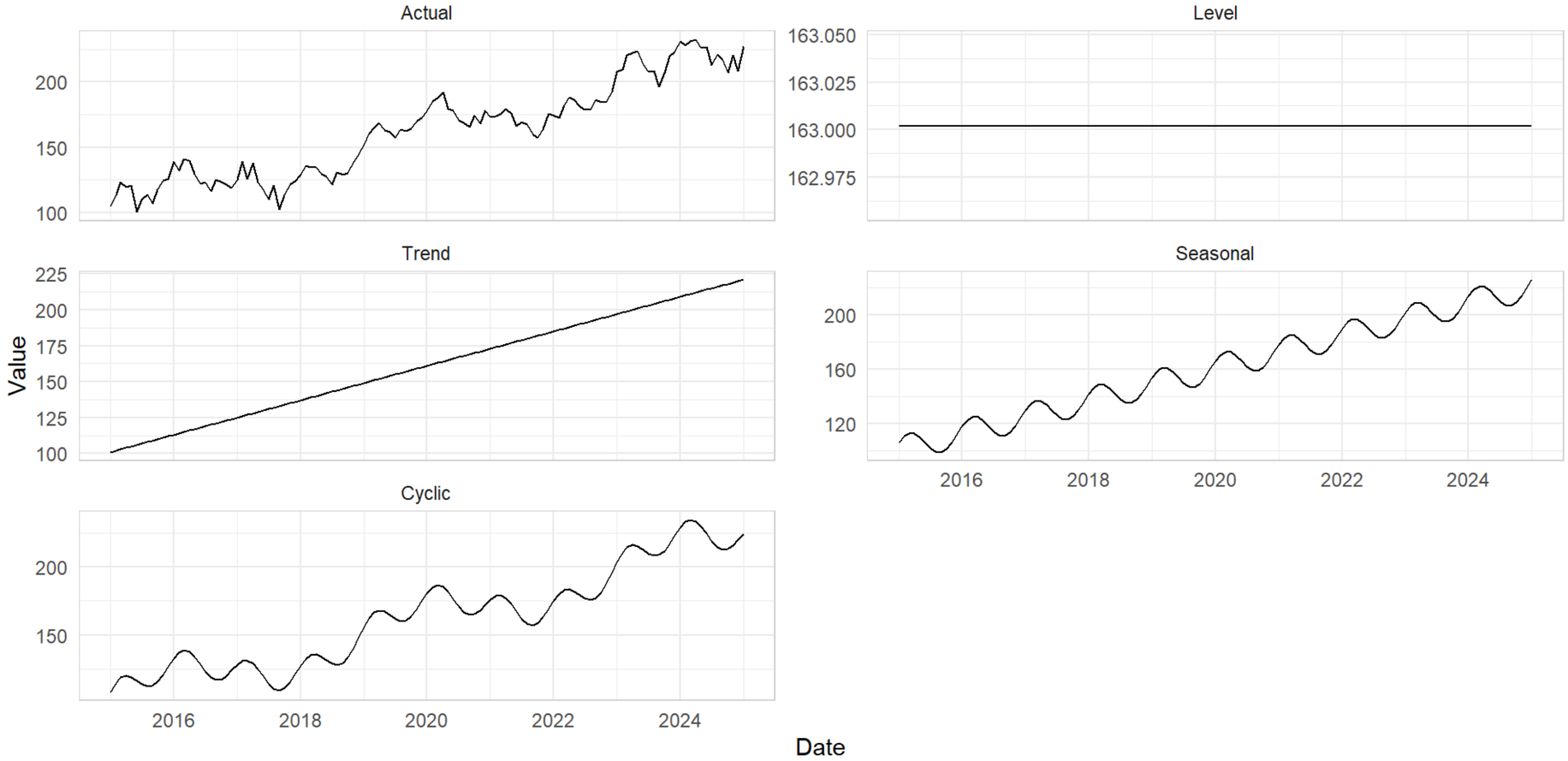
15:00

Explore your data

Time series patterns

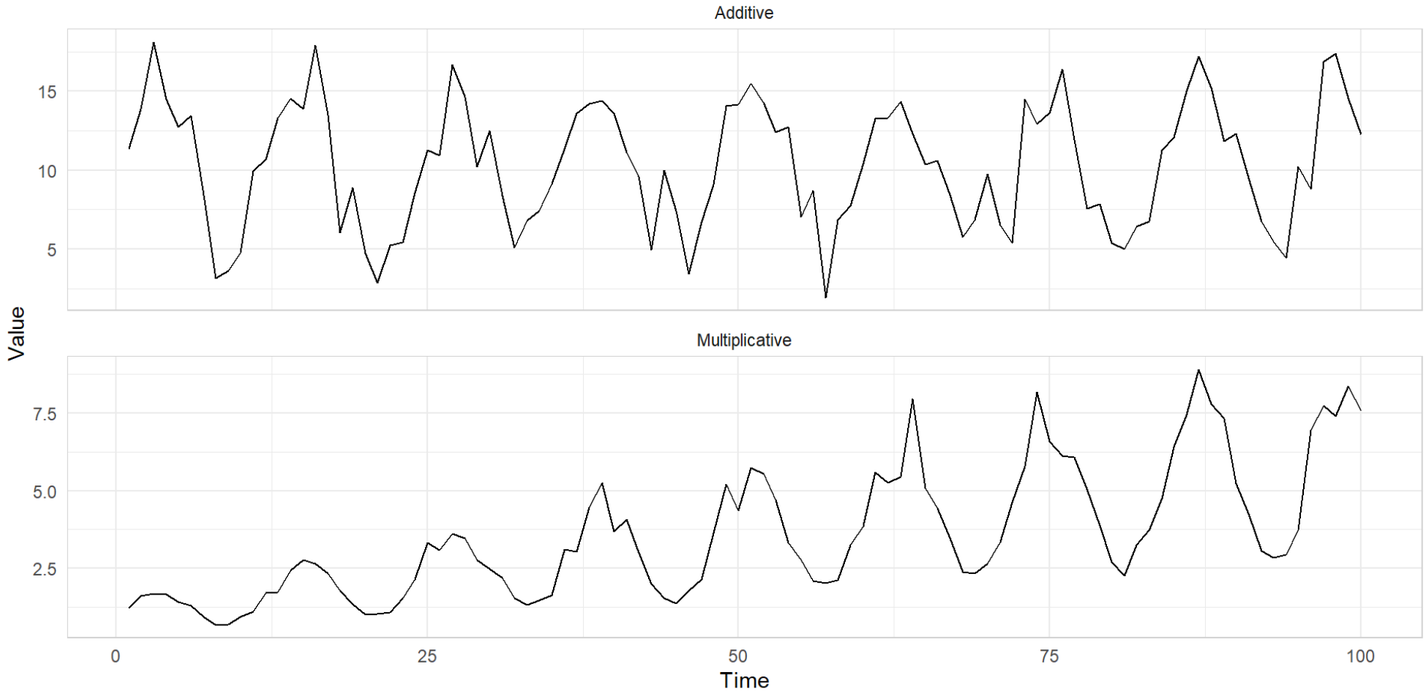
- `Level`: The level of a time series describes the center of the series.
- `Trend`: A trend describes predictable increases or decreases in the level of a series.
- `Seasonal`: Seasonality is a consistent pattern that repeats over a fixed cycle. pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week).
- `Cyclic`: A pattern exists when data exhibit rises and falls that are not of fixed period (duration usually of at least 2 years).

Time series patterns



Read more at Demand forecasting for executives and professionals by Bahman Rostami-Tabar, Enno Siemsen, and Stephan Kolassa.

Additive vs. multiplicative seasonality

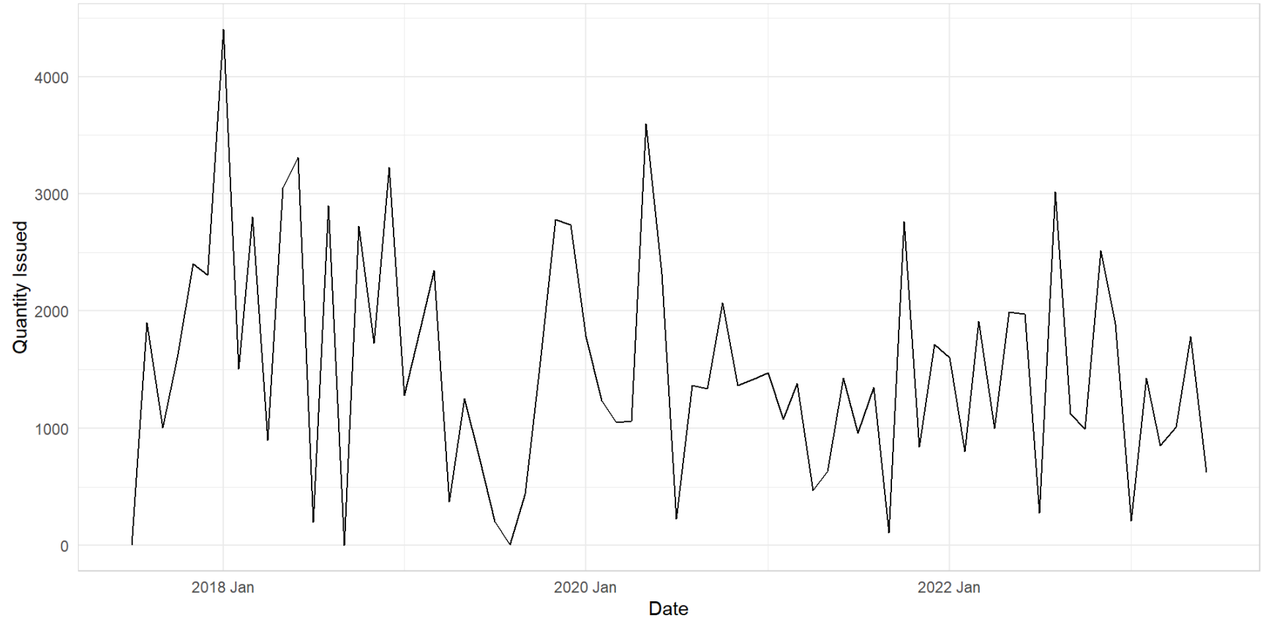


- When we have multiplicative seasonality, we can use transformations to convert multiplicative seasonality into additive seasonality.
- In this training, we are not discussing time series transformations. You can read more about it at Transformations and adjustments.

Time plots

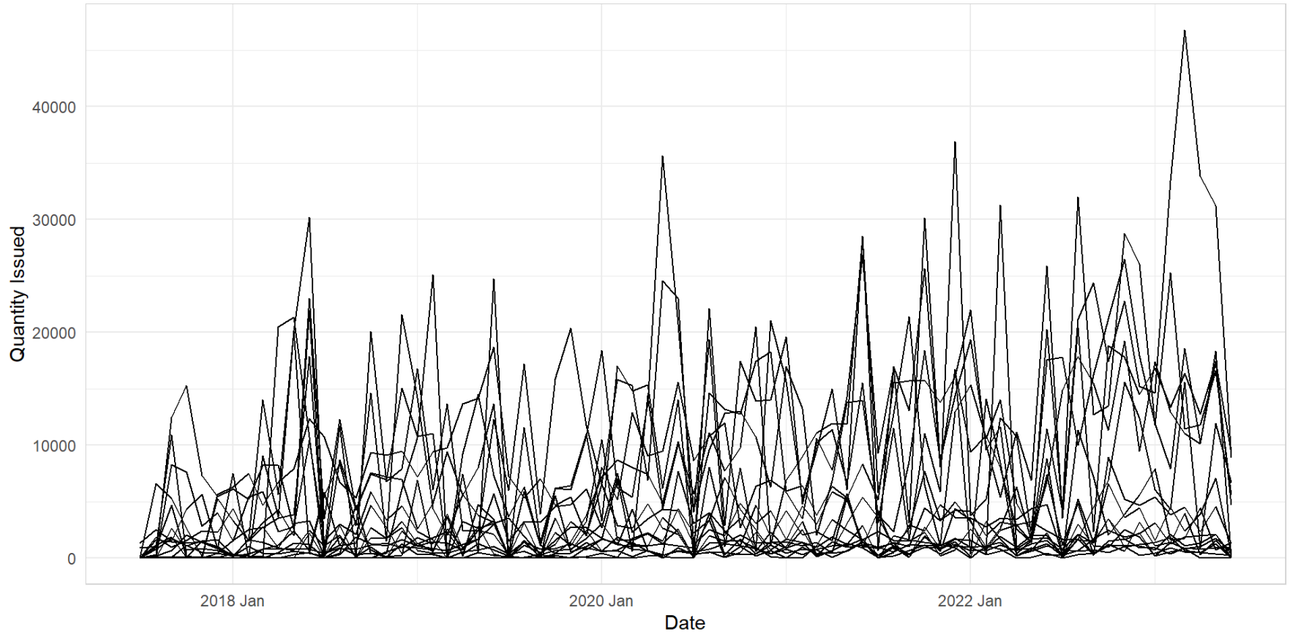
You can create time plot using `autoplot()` function.

```
med_tsb_filter |>
  filter(hub_id == 'hub_1' & product_id == 'product_2') |>
  autoplot(quantity_issued) +
  labs(
    x = "Date",
    y = "Quantity Issued"
  ) +
  theme_minimal() +
  theme(panel.border = element_rect(color = "lightgrey", fill = NA))
```



Are time plots best?

```
med_tsb_filter |>
  mutate(id = paste0(hub_id, product_id)) |>
  ggplot(aes(x = date, y = quantity_issued, group = id)) +
  geom_line() +
  labs(
    x = "Date",
    y = "Quantity Issued"
  ) +
  theme_minimal() +
  theme(legend.position = "none",
        panel.border = element_rect(color = "lightgrey", fill = NA))
```

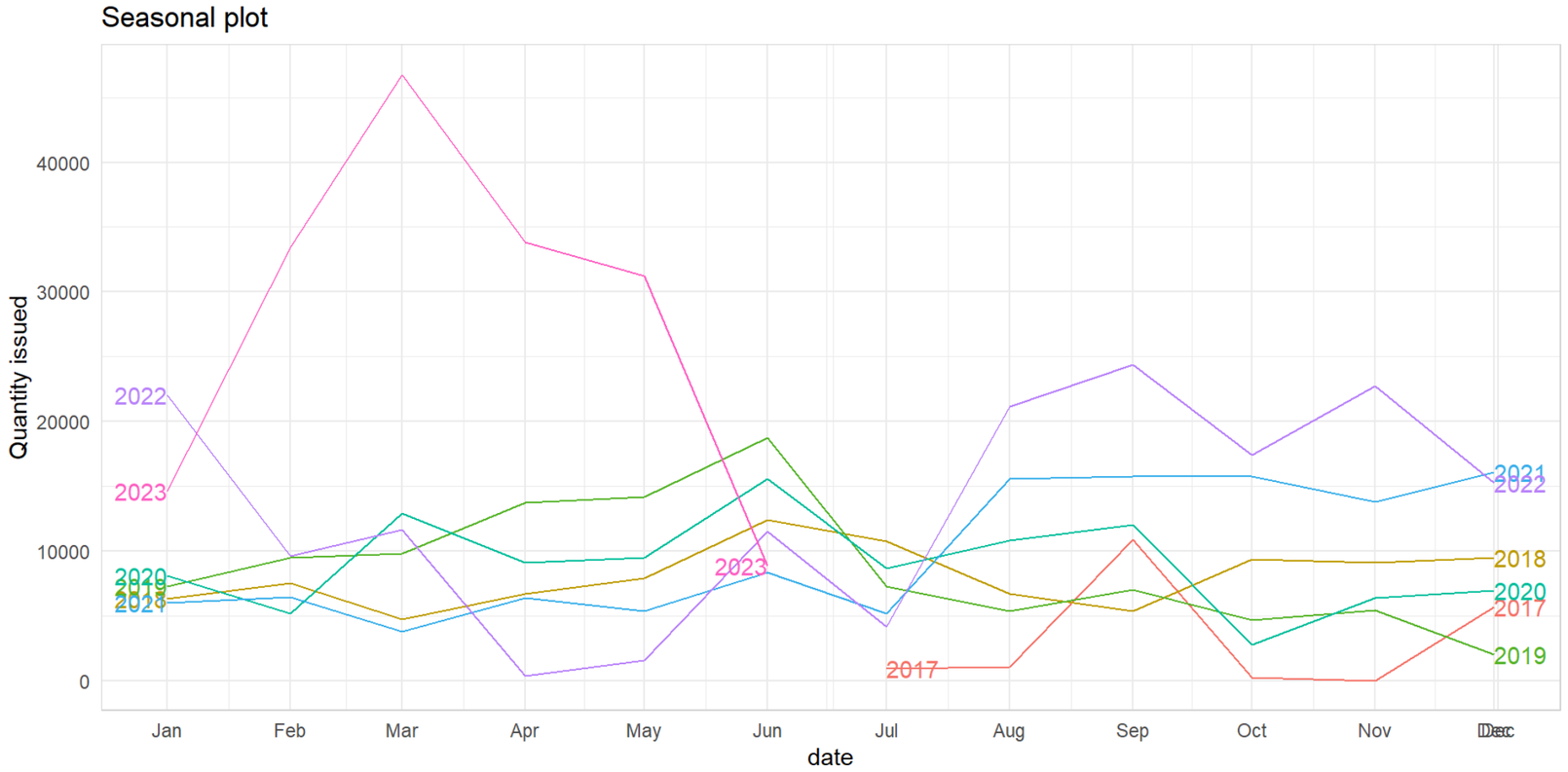


Seasonal plots

- Data plotted against the individual `seasons` in which the data were observed (In this case a “season” is a month).
- Enables the underlying seasonal pattern to be seen more clearly, and also allows any substantial departures from the seasonal pattern to be easily identified.
- You can create seasonal plots using `gg_season()` function.

Seasonal plots

```
med_tsb_filter |>
  filter(hub_id == 'hub_14' & product_id == 'product_5') |>
  gg_season(quantity_issued, labels = "both") +
  ylab("Quantity issued") +
  ggtitle("Seasonal plot") +
  theme_minimal() +
  theme(panel.border = element_rect(color = "lightgrey", fill = NA))
```

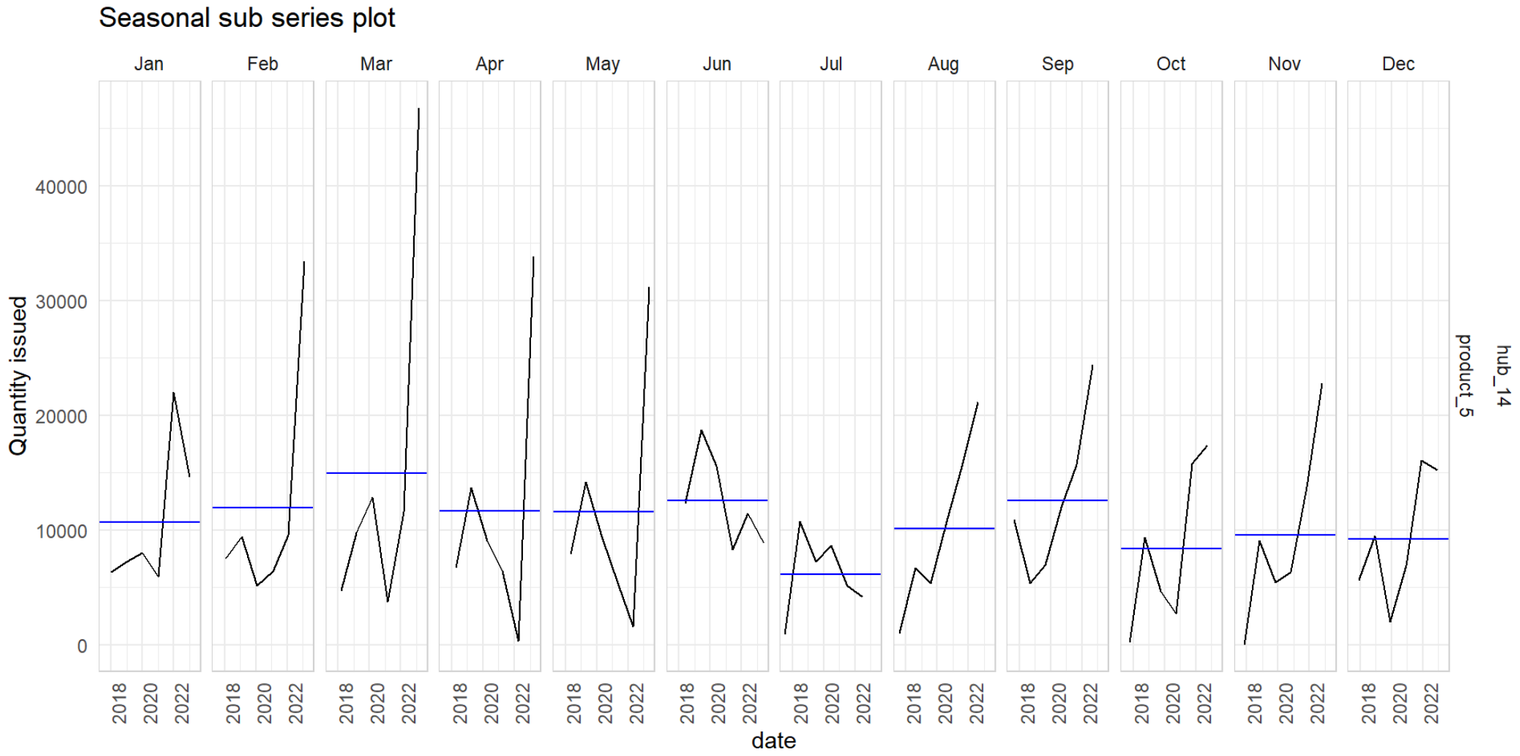


Seasonal sub series plots

- Data for each season collected together in time plot as separate time series.
- Enables the underlying seasonal pattern to be seen clearly, and changes in seasonality over time to be visualized.
- You can create seasonal sub series plots using `gg_subseries()` function.

Seasonal sub series plots

```
med_tsb_filter |>
  filter(hub_id == 'hub_14' & product_id == 'product_5') |>
  gg_subseries(quantity_issued) +
  ylab("Quantity issued") +
  ggtitle("Seasonal sub series plot") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1),
        panel.border = element_rect(color = "lightgrey", fill = NA))
```



Strength of seasonality and trend

- We used STL decomposition for additive decompositions.
- A multiplicative decomposition can be obtained by first taking logs of the data, then back-transforming the components.
- Decompositions that are between additive and multiplicative can be obtained using a Box-Cox transformation of the data.
- Read more at STL decomposition.

Strength of seasonality and trend

STL Decomposition

$$y_t = T_t + S_t + R_t$$

Seasonal Strength

$$\max\left(0, 1 - \frac{\mathrm{Var}(R_t)}{\mathrm{Var}(S_t + R_t)}\right)$$

Trend Strength

$$\max\left(0, 1 - \frac{\mathrm{Var}(R_t)}{\mathrm{Var}(T_t + R_t)}\right)$$

Feature extraction and statistics

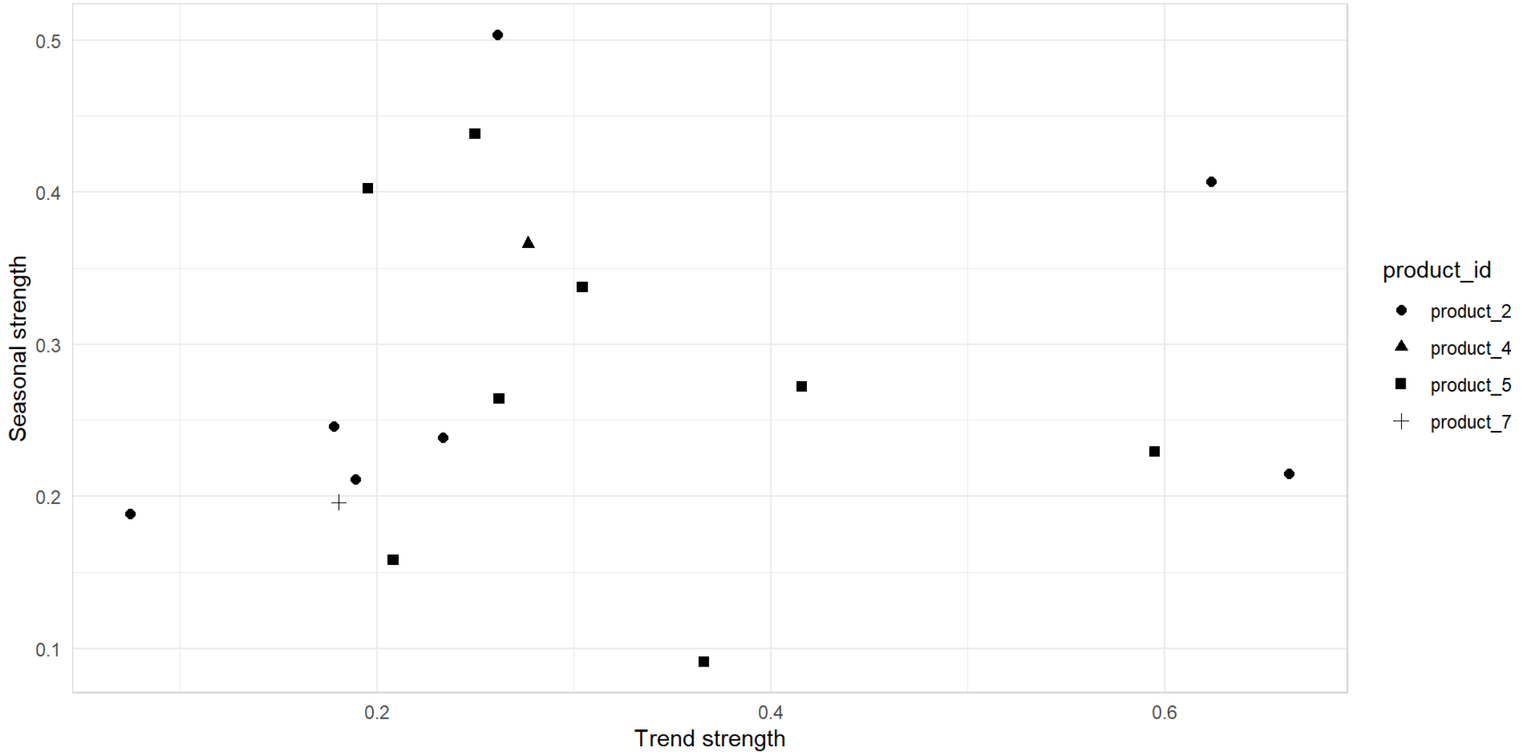
We can use `features()` function to extract the strength of trend and seasonality.

```
1 med_tsb_filter |>
2   features(quantity_issued, feat_stl)
```

```
# A tibble: 17 × 11
   hub_id product_id trend_strength seasonal_strength_year seasonal_peak_year
   <chr>  <chr>               <dbl>                  <dbl>              <dbl>
 1 hub_1  product_2           0.261                  0.503                  6
 2 hub_1  product_5           0.250                  0.438                  0
 3 hub_10 product_5           0.366                  0.0911                 0
 4 hub_11 product_2           0.624                  0.407                 11
 5 hub_11 product_7           0.181                  0.196                  7
 6 hub_13 product_5           0.196                  0.402                  0
 7 hub_14 product_5           0.595                  0.229                  9
 8 hub_16 product_2           0.233                  0.238                  7
 9 hub_16 product_5           0.416                  0.272                  0
10 hub_2  product_2           0.178                  0.246                  9
11 hub_2  product_5           0.262                  0.264                  6
12 hub_3  product_2           0.663                  0.215                  4
```

Feature extraction and statistics

```
med_tsb_filter |>
  features(quantity_issued, feat_stl) |>
  ggplot(aes(x = trend_strength, y = seasonal_strength_year, shape = product_id)) +
  geom_point(size = 2) +
  ylab("Seasonal strength") +
  xlab("Trend strength") +
  theme_minimal() +
  theme(panel.border = element_rect(color = "lightgrey", fill = NA))
```



Lag plots and autocorrelation

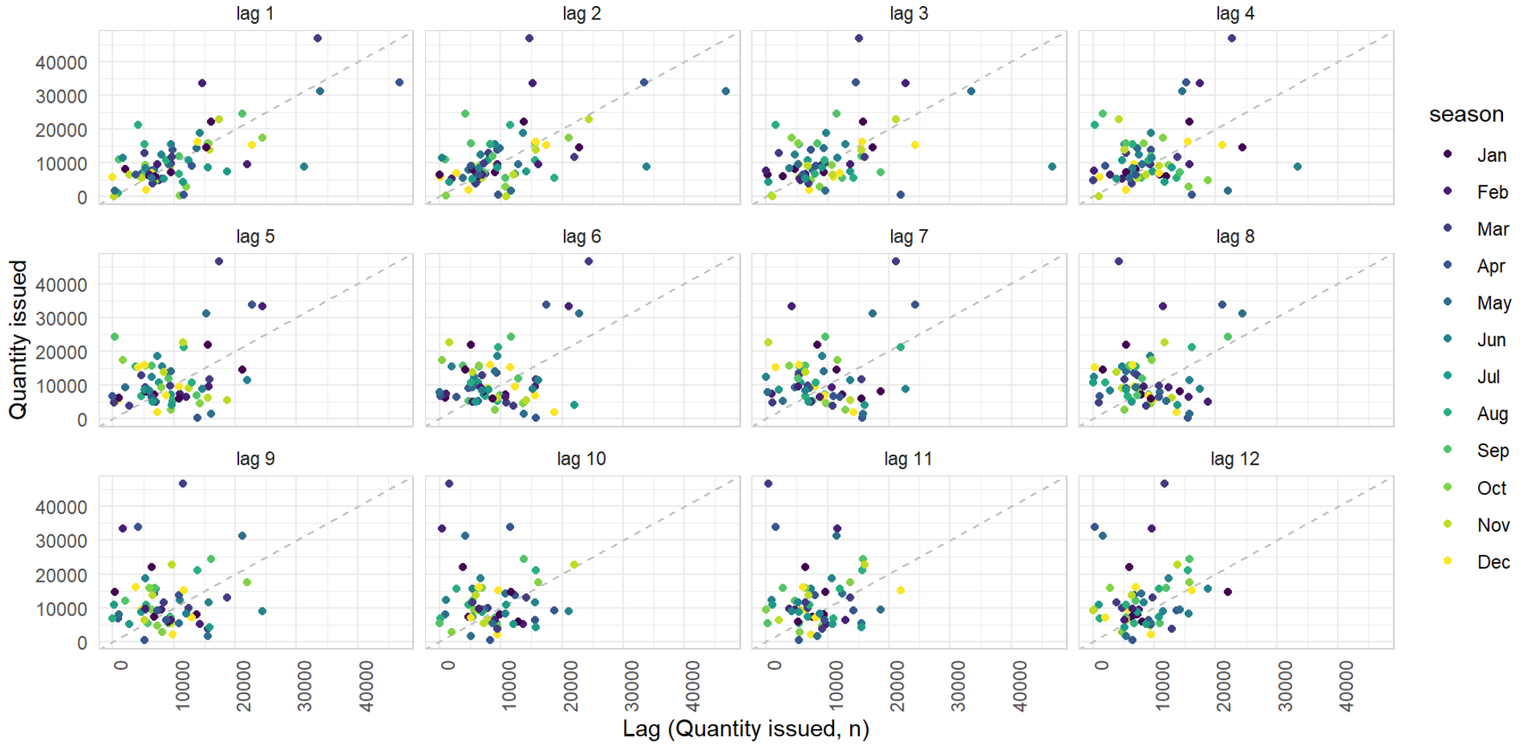
- Each graph shows plotted against for different values of .
- The `autocorrelations` are the correlations associated with these scatterplots:
- You can create lag plots using `gglag()` function.
- These values indicate the relationship between current and past observations in a time series.

y_t k

$$\text{Corr}(y_t, y_{t-k})$$

Lag plots and autocorrelation

```
med_tsb_filter |>
  filter(hub_id == 'hub_14' & product_id == 'product_5') |>
  gg_lag(quantity_issued, lags = 1:12, geom='point') +
  ylab("Quantity issued") +
  xlab("Lag (Quantity issued, n)") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1),
        panel.border = element_rect(color = "lightgrey", fill = NA))
```



Autocorrelation

- Autocovariance and autocorrelation: measure linear relationship between lagged values of a time series y.
- We denote the sample autocovariance at lag k by c_k and the sample autocorrelation at lag k by r_k. Then, we define:

$$c_k = \frac{1}{T}\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})$$

$$r_k = \frac{c_k}{c_0}$$

where c_0 is the variance of the time series.

- r_1 indicates how successive values of y relate to each other.
- r_2 indicates how values two periods apart relate to each other.
- r_k is almost the same as the sample correlation between y_t and y_{t-k}.

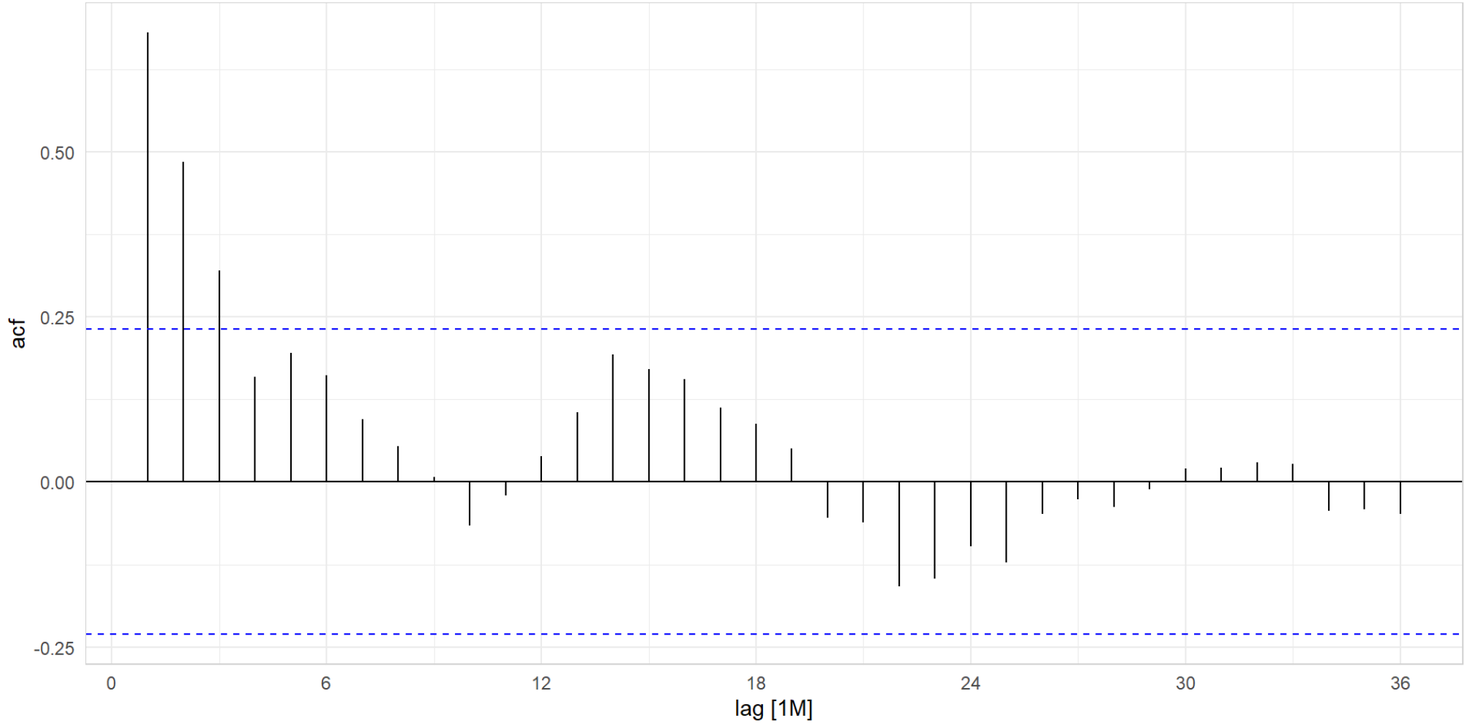
Autocorrelation

```
 1 med_tsb_filter |>
 2   filter(hub_id == 'hub_14' & product_id == 'product_5') |>
 3   ACF(quantity_issued, lag_max = 24)
```

```
# A tsibble: 24 x 4 [1M]
# Key:       hub_id, product_id [1]
   hub_id product_id      lag      acf
   <chr>  <chr>       <cf_lag>    <dbl>
 1 hub_14 product_5         1M  0.681
 2 hub_14 product_5         2M  0.485
 3 hub_14 product_5         3M  0.320
 4 hub_14 product_5         4M  0.160
 5 hub_14 product_5         5M  0.195
 6 hub_14 product_5         6M  0.162
 7 hub_14 product_5         7M  0.0956
 8 hub_14 product_5         8M  0.0540
 9 hub_14 product_5         9M  0.00739
10 hub_14 product_5        10M -0.0665
# ℹ 14 more rows
```

Autocorrelation

```
med_tsb_filter |>
  filter(hub_id == 'hub_14' & product_id == 'product_5') |>
  ACF(quantity_issued, lag_max = 36) |>
  autoplot() +
  theme_minimal() +
  theme(panel.border = element_rect(color = "lightgrey", fill = NA))
```



What autocorrelation will tell us? Which key features could be highlighted by ACF?

Autocorrelation

- When data have a trend, the autocorrelations for small lags tend to be large and positive.
- When data are seasonal, the autocorrelations will be larger at the seasonal lags (i.e., at multiples of the seasonal frequency)
- When data are trended and seasonal, you see a combination of these effects.

Now it is your `turn`.

15:00

Forecast modelling

Naive

Simplest forecasting method using last observation as forecast.

$$\hat{y}_{t+1|t} = y_t$$

Assumptions

- No systematic pattern in data
- Recent observations are most relevant

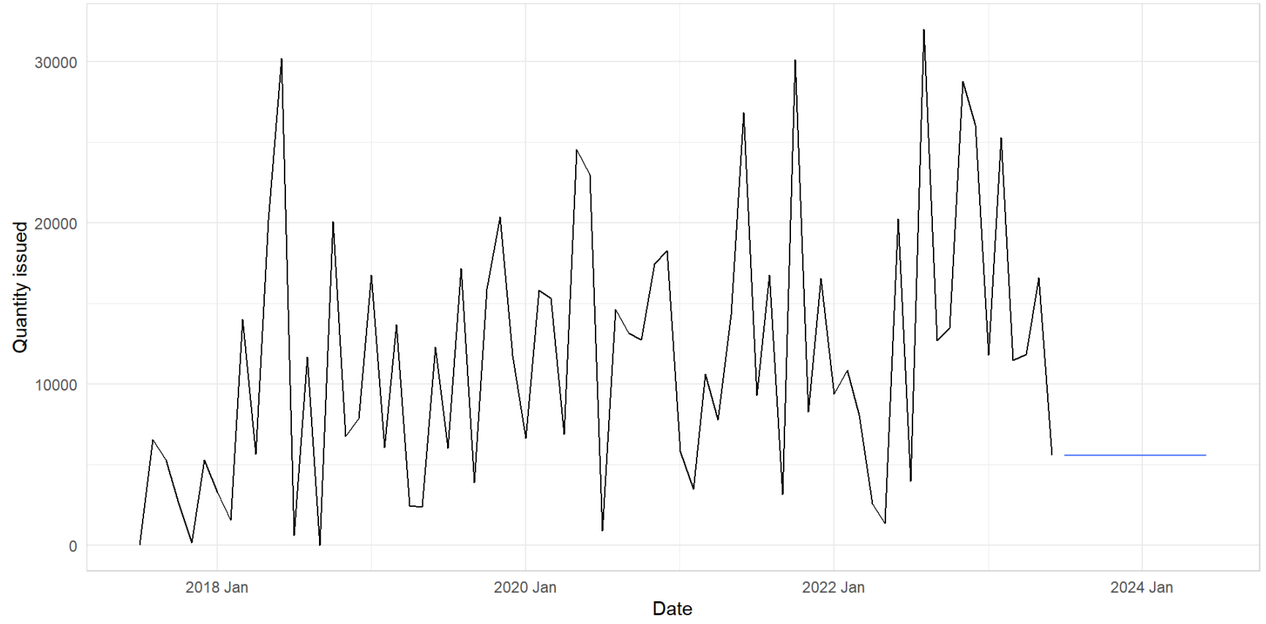
Strengths & Weaknesses

✓ Simple benchmark model
✓ Requires no computation
✗ Ignores all patterns
✗ Poor for trending/seasonal data

Naive

We use `NAIVE()` function and `model()` function to build the Naive model.

```
med_tsb_filter |>
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  model(naive = NAIVE(quantity_issued)) |>
  forecast(h = 12) |>
  autoplot(med_tsb_filter |>
             filter(hub_id == 'hub_1' & product_id == 'product_5'), level = NULL) +
  labs(y = "Quantity issued", x = "Date") +
  theme_minimal() +
  theme(panel.border = element_rect(color = "lightgrey", fill = NA))
```



Seasonal NAIVE (sNAIVE)

$$\hat{y}_{t+h|t} = y_{t+h-m(k+1)}$$

Where: m = seasonal period and $k = \lfloor \frac{h-1}{m} \rfloor$

Assumptions

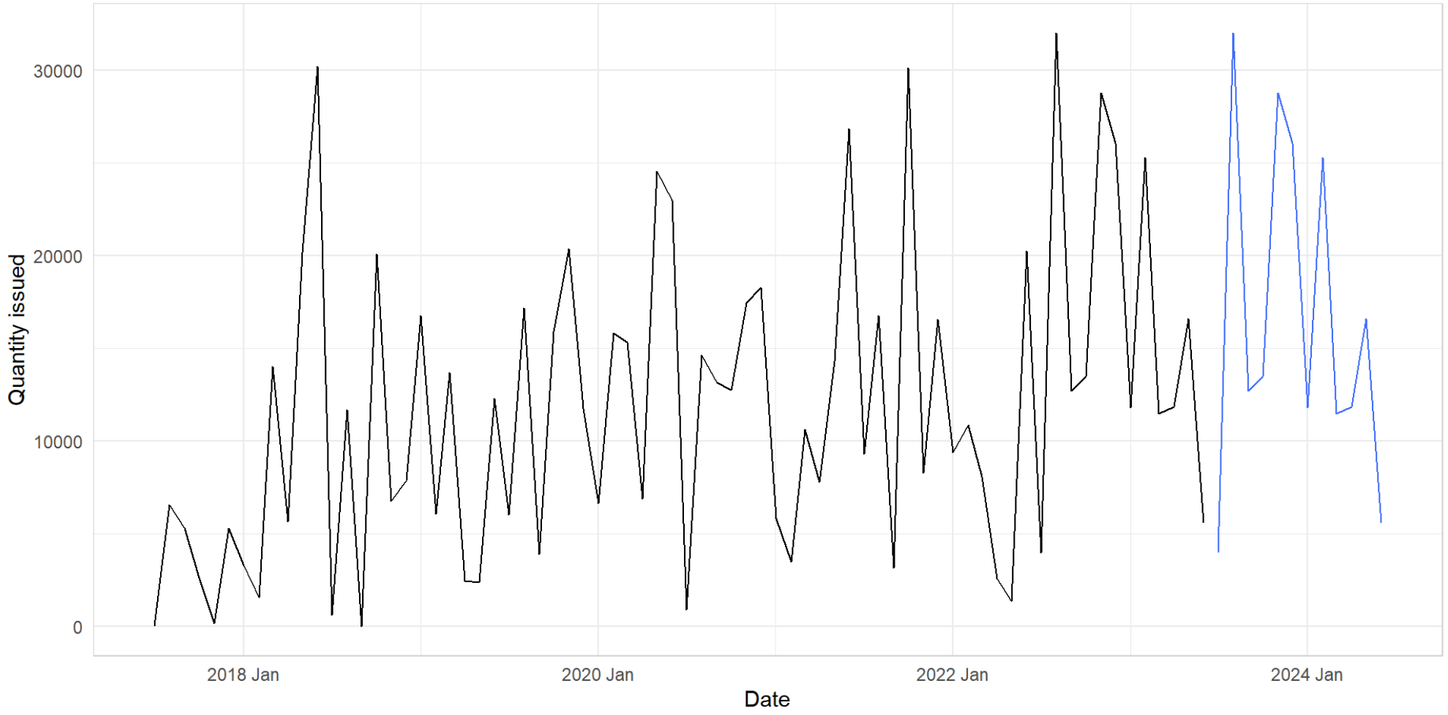
- Seasonal pattern is stable
- No trend present

Strengths & Weaknesses

✓ Handles strong seasonality
✓ Simple interpretation
✗ Fails with changing seasonality
✗ Ignores non-seasonal patterns

sNaive

```
med_tsb_filter |>
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  model(snaive = SNAIVE(quantity_issued ~ lag("year"))) |>
  forecast(h = 12) |>
  autoplot(med_tsb_filter |>
             filter(hub_id == 'hub_1' & product_id == 'product_5'), level = NULL) +
  labs(y = "Quantity issued", x = "Date") +
  theme_minimal() +
  theme(panel.border = element_rect(color = "lightgrey", fill = NA))
```



Mean

Uses the historical average of all observations as forecast.

$$\hat{y}_{t+h|t} = \bar{y} = \frac{1}{t}\sum_{i=1}^{t} y_i$$

Where: t is the number of past observations used for the forecast.

Assumptions

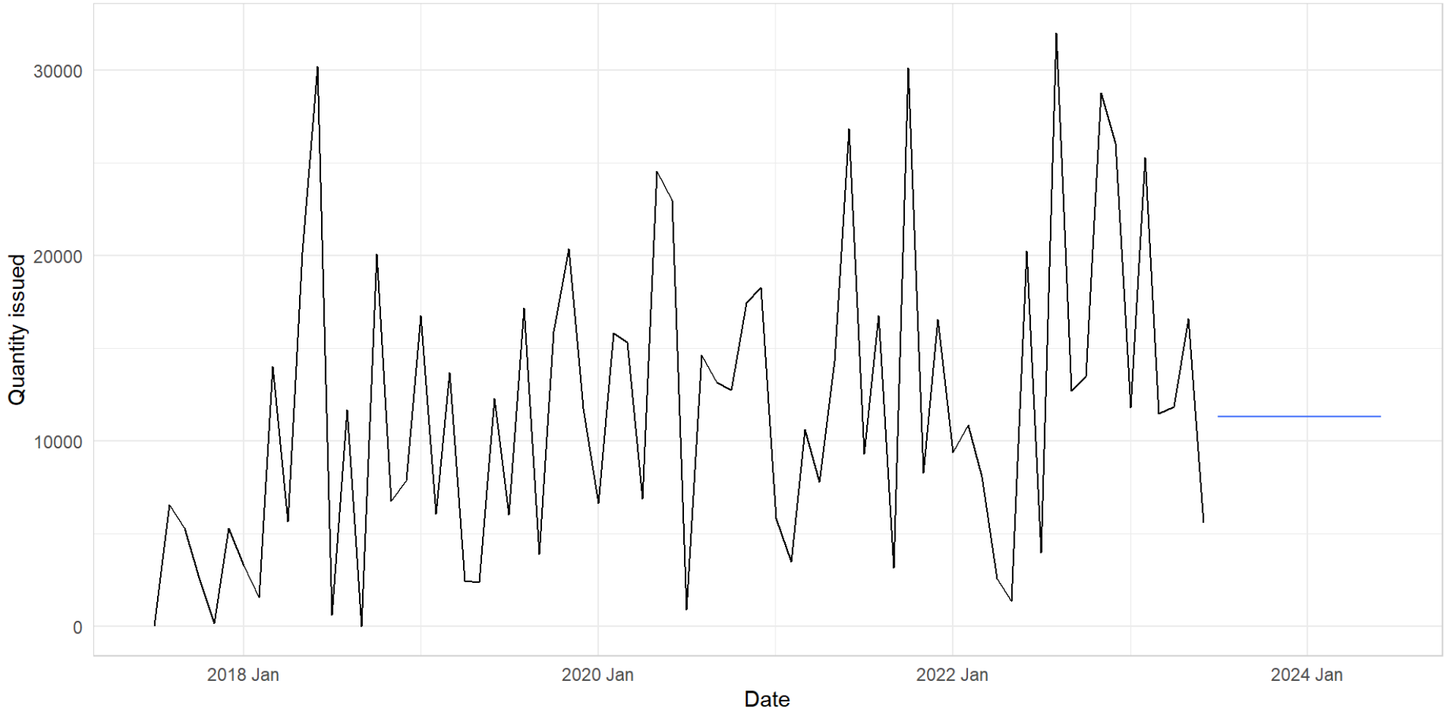
- Series is stationary
- Short-term fluctuations are noise

Strengths & Weaknesses

✓ Effective noise reduction
✓ Simple to implement
✗ Ignores all patterns
✗ Lags behind trends

Mean

```
med_tsb_filter |>
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  model(MEAN(quantity_issued ~ window(size = 3))) |>
  forecast(h = 12) |>
  autoplot(med_tsb_filter |>
             filter(hub_id == 'hub_1' & product_id == 'product_5'), level = NULL) +
  labs(y = "Quantity issued", x = "Date") +
  theme_minimal() +
  theme(panel.border = element_rect(color = "lightgrey", fill = NA))
```



ARIMA

Combines Autoregressive (AR) and Moving Average (MA) components with differencing.

- `AR`: autoregressive (lagged observations as inputs)
- `I`: integrated (differencing to make series stationary)
- `MA`: moving average (lagged errors as inputs)

The ARIMA model is given by:

$$(1 - \phi_1 B - \cdots - \phi_p B^p)(1 - B)^d y_t = c + (1 + \theta_1 B + \cdots + \theta_q B^q)\epsilon_t$$

Where: B: Backshift operator, ϕ: AR coefficients, θ: MA coefficients, d: Differencing order, p: AR order, q: MA order and ϵ_t: White noise

ARIMA

Assumptions

- Series is stationary
- Linear relationship between past values and errors
- White noise errors
- No missing values in series

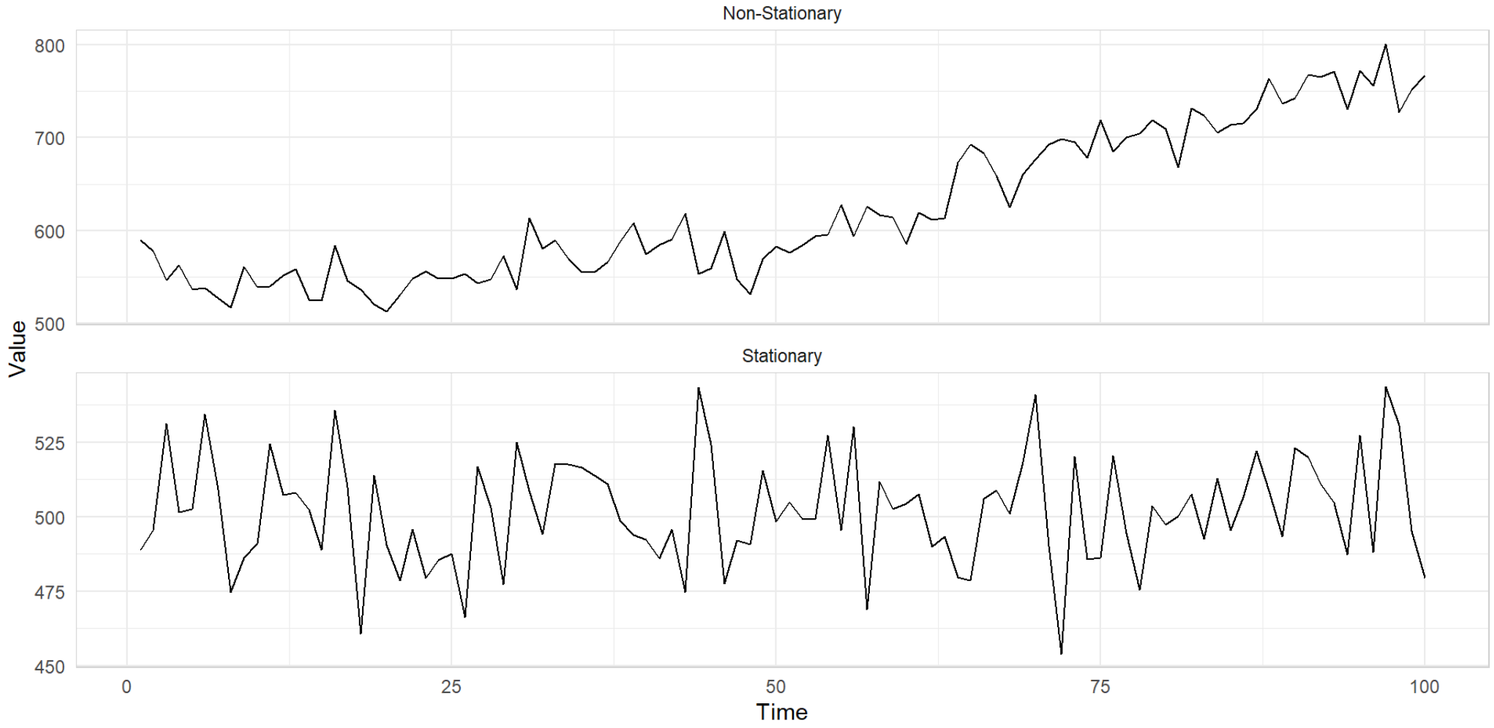
Strengths & Weaknesses

✓ Flexible for various time series patterns
✓ Perform well for short term horizons
✗ Requires stationarity for optimal performance
✗ The parameters are often not easily interpretable in terms of trend or seasonality

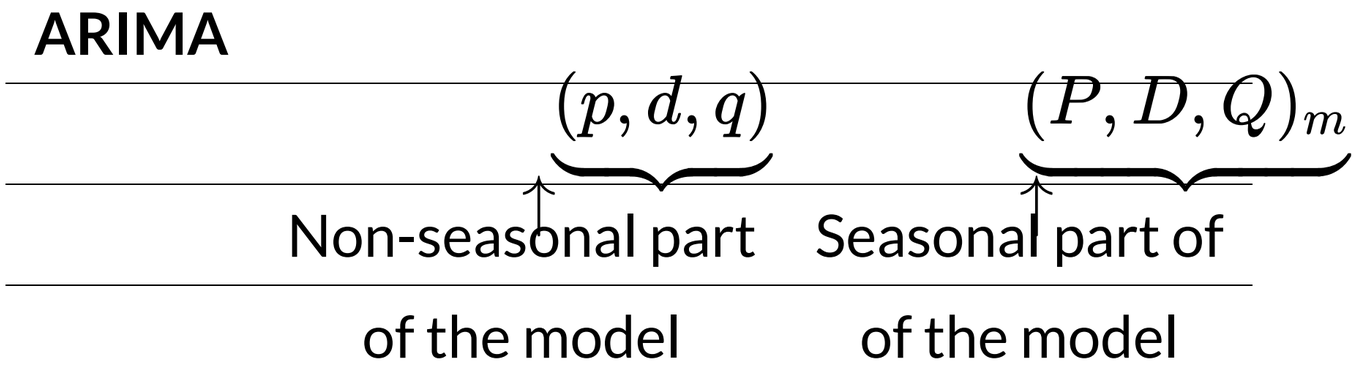
ARIMA

A `stationary series` is:

- roughly horizontal
- constant variance
- no patterns predictable in the long-term



Seasonal ARIMA models



- : number of observations per year.
- : first differences, : seasonal differences
- : AR lags, : MA lags
- : seasonal AR lags, : seasonal MA lags

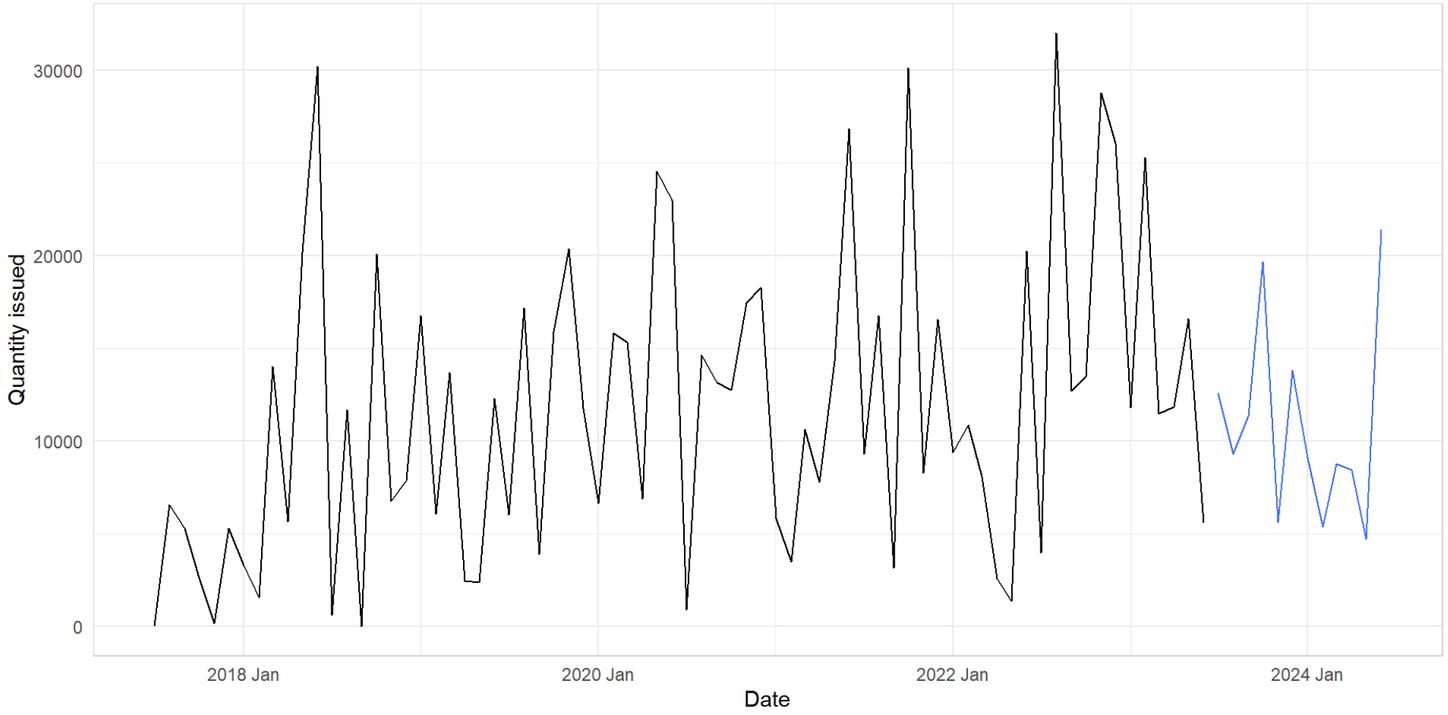
Seasonal and non-seasonal terms combine multiplicatively.

ARIMA automatic modelling

- Plot the data. Identify any unusual observations.
- If necessary, transform the data (e.g., Box-Cox transformation) to stabilize the variance.
- Use `ARIMA()` to automatically select a model.
- Check the residuals from your chosen model and if they do not look like white noise, try a modified model.
- Once the residuals look like white noise, calculate forecasts.

ARIMA automatic modelling

```
med_tsb_filter |>
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  model(ARIMA(quantity_issued)) |>
  forecast(h = 12) |>
  autoplot(med_tsb_filter |>
             filter(hub_id == 'hub_1' & product_id == 'product_5'), level = NULL) +
  labs(y = "Quantity issued", x = "Date") +
  theme_minimal() +
  theme(panel.border = element_rect(color = "lightgrey", fill = NA))
```



ETS

ETS stands for Exponential Smoothing and is based on a state space framework that decomposes a time series into three components:

General Notation	E T S	ExponenTial Smoothing
	↗ ↑ ↖	
	Error Trend	Season

- Error: Additive (`"A"`) or multiplicative (`"M"`)
- Trend: None (`"N"`), additive (`"A"`), multiplicative (`"M"`), or damped (`"Ad"` or `"Md"`).
- Seasonality: None (`"N"`), additive (`"A"`) or multiplicative (`"M"`)

For example, `ETS(A,N,N)` is the simple exponential smoothing model (no trend or seasonality) with additive errors.

ETS

How do we combine these elements?

`Additively`?

$$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$$

`Multiplicatively`?

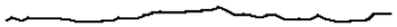
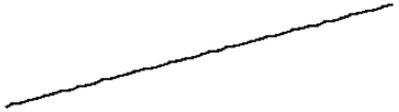
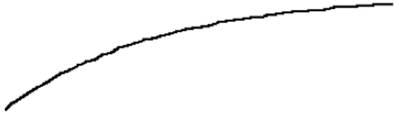
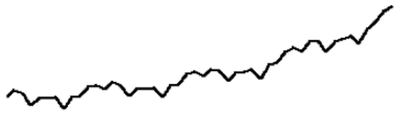
$$y_t = \ell_{t-1} b_{t-1} s_{t-m} (1 + \varepsilon_t)$$

Perhaps `a mix of both`?

$$y_t = (\ell_{t-1} + b_{t-1}) s_{t-m} + \varepsilon_t$$

ETS

How do the level, trend and seasonal components evolve over time?

Trend	Seasonality		
	None	Additive	Multiplicative
None			
Additive			
Additive Damped			
Multiplicative			
Multiplicative Damped			

ETS

Assumptions

- Decomposable patterns
- Recent observations more important
- Consistent error structure (additive/multiplicative)

Strengths & Weaknesses

✓ They can be adapted to various data characteristics with different error, trend, and seasonal formulations

✓ Often very effective when the underlying components are stable

✗ Parameter estimates (including smoothing parameters and initial states) can affect the forecasts

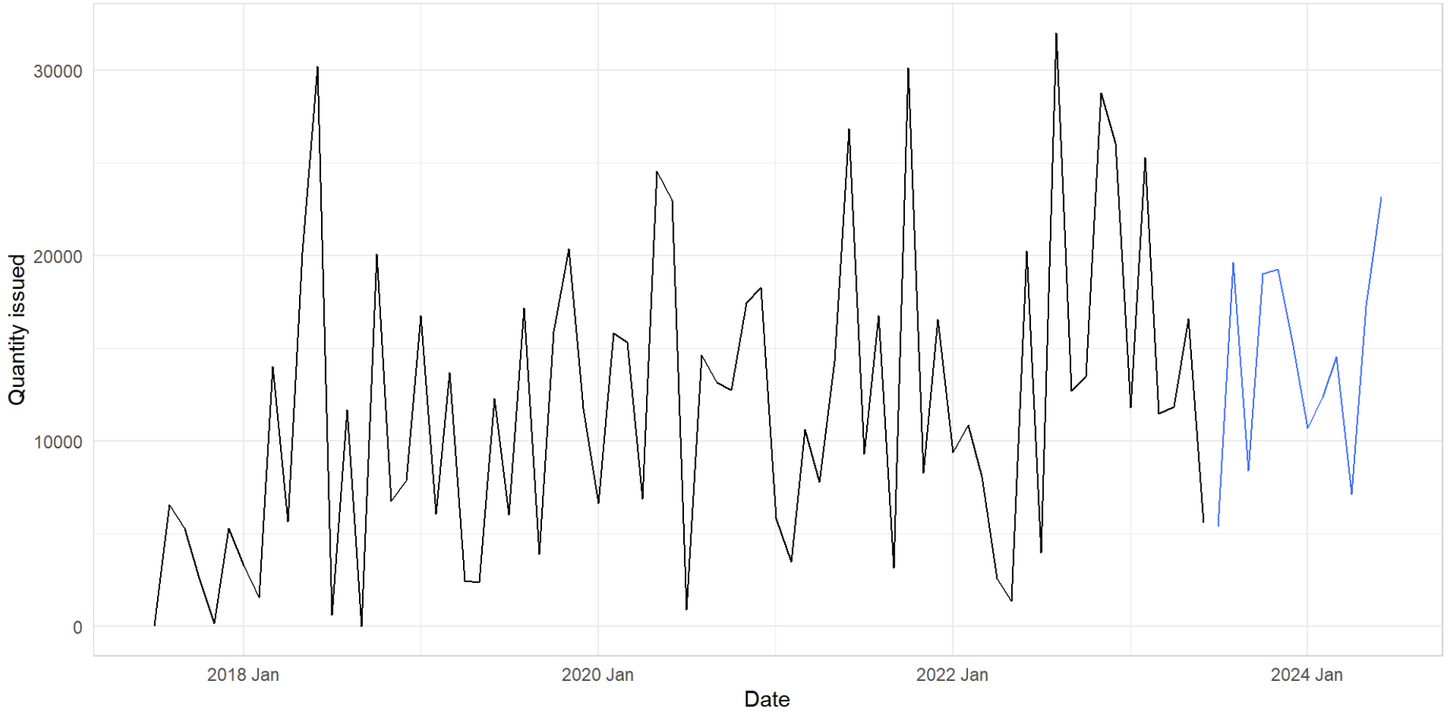
✗ SMay struggle to capture sudden shifts or non-standard patterns if the smoothing parameters are constant

ETS automatic modelling

- Apply each model that is appropriate to the data.
- Optimize parameters and initial values using MLE (or some other criterion).
- Select best method using AICc.
- Use `ETS()` to automatically select a model.
- Produce forecasts using best method.

ETS automatic modelling

```
med_tsb_filter |>
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  model(ETS(quantity_issued)) |>
  forecast(h = 12) |>
  autoplot(med_tsb_filter |>
             filter(hub_id == 'hub_1' & product_id == 'product_5'), level = NULL) +
  labs(y = "Quantity issued", x = "Date") +
  theme_minimal() +
  theme(panel.border = element_rect(color = "lightgrey", fill = NA))
```



Model fitting in `Fable`

- The `model()` function trains models on data.
- It returns a `mable` object.
- A `mable` is a model table, each cell corresponds to a fitted model.

```
# Fit the models

fit_all <- med_tsb_filter |>
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  model(
    naive = NAIVE(quantity_issued),
    snaive = SNAIVE(quantity_issued ~ lag('year')),
    mean = MEAN(quantity_issued ~ window(size = 3)),
    arima = ARIMA(quantity_issued),
    ets = ETS(quantity_issued)
    )

fit_all
```

```
# A mable: 1 x 7
# Key:     hub_id, product_id [1]
  hub_id product_id   naive   snaive    mean                       arima
  <chr>  <chr>      <model>  <model> <model>                     <model>
1 hub_1  product_5  <NAIVE> <SNAIVE>  <MEAN> <ARIMA(0,1,1)(0,0,2)[12]>
# ℹ 1 more variable: ets <model>
```

Extract information from `mable`

```
fit_all  |>  select(snaive) |>  report()
fit_all |>  tidy()
fit_all  |>  glance()
```

- The `report()` function gives a formatted model-specific display.
- The `tidy()` function is used to extract the coefficients from the models.
- We can extract information about some specific model using the `filter()` and `select()`functions.

Producing forecasts

- The `forecast()` function is used to produce forecasts from estimated models.
- `h` can be specified with:
  - a number (the number of future observations)
  - natural language (the length of time to predict)
  - provide a dataset of future time periods

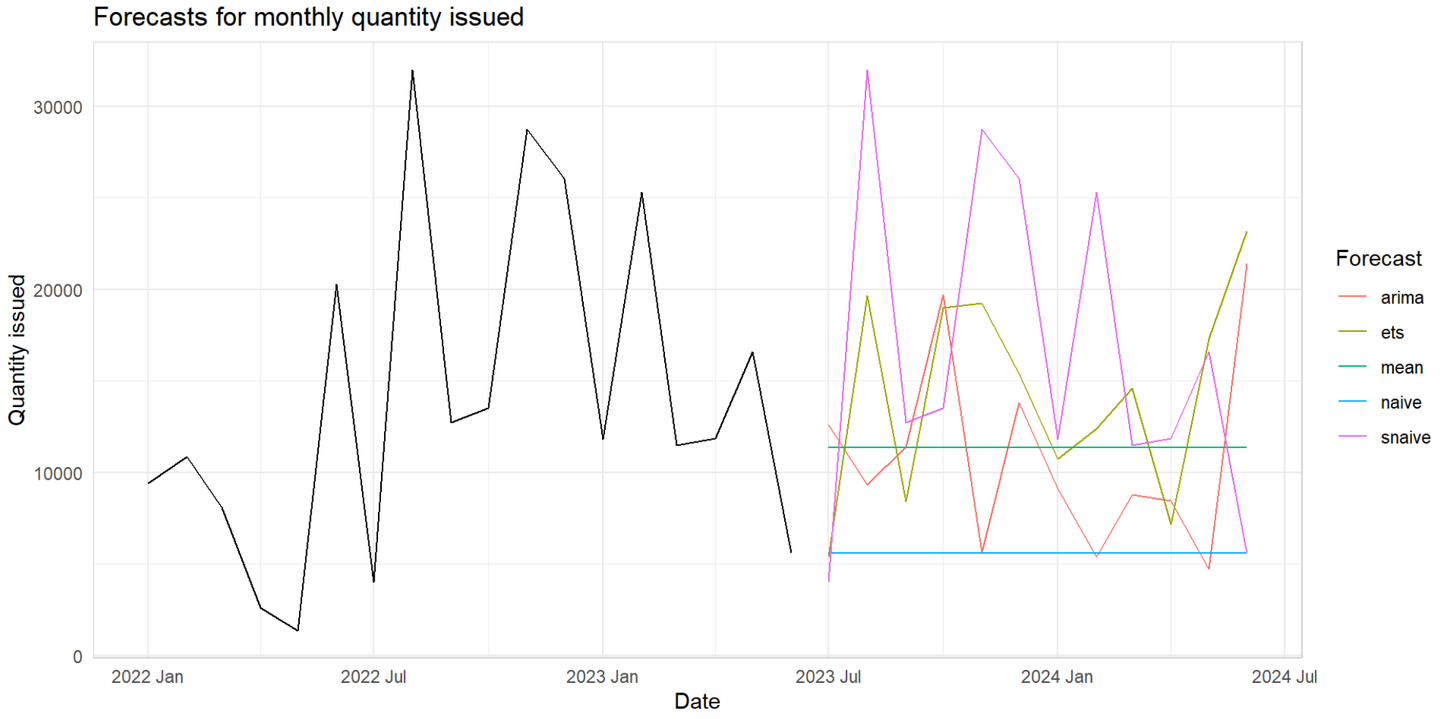
Producing forecasts

```r
fit_all_fc <- fit_all |>
  forecast(h = 'year')

#h = "year" is equivalent to setting h = 12.

fit_all_fc
```

```
# A fable: 60 x 6 [1M]
# Key:     hub_id, product_id, .model [5]
   hub_id product_id .model     date  quantity_issued .mean
   <chr>  <chr>      <chr>     <mth>           <dist> <dbl>
 1 hub_1  product_5  naive  2023 Jul N(5568, 1.4e+08)  5568
 2 hub_1  product_5  naive  2023 Aug N(5568, 2.7e+08)  5568
 3 hub_1  product_5  naive  2023 Sep N(5568, 4.1e+08)  5568
 4 hub_1  product_5  naive  2023 Oct N(5568, 5.4e+08)  5568
 5 hub_1  product_5  naive  2023 Nov N(5568, 6.8e+08)  5568
 6 hub_1  product_5  naive  2023 Dec N(5568, 8.2e+08)  5568
 7 hub_1  product_5  naive  2024 Jan N(5568, 9.5e+08)  5568
 8 hub_1  product_5  naive  2024 Feb N(5568, 1.1e+09)  5568
 9 hub_1  product_5  naive  2024 Mar N(5568, 1.2e+09)  5568
10 hub_1  product_5  naive  2024 Apr N(5568, 1.4e+09)  5568
# ℹ 50 more rows
```

Visualising forecasts

```
fit_all_fc |>
  autoplot(level = NULL) +
  autolayer(med_tsb_filter |>
              filter_index("2022 JAn" ~ .) |>
              filter(hub_id == 'hub_1' & product_id == 'product_5'), color = 'black') +
  labs(title = "Forecasts for monthly quantity issued", y = "Quantity issued", x = "Date") +
  theme_minimal() +
  theme(panel.border = element_rect(color = "lightgrey", fill = NA)) +
  guides(colour=guide_legend(title="Forecast"))
```



Now it is your `turn`.

15:00

What is wrong with point forecasts?

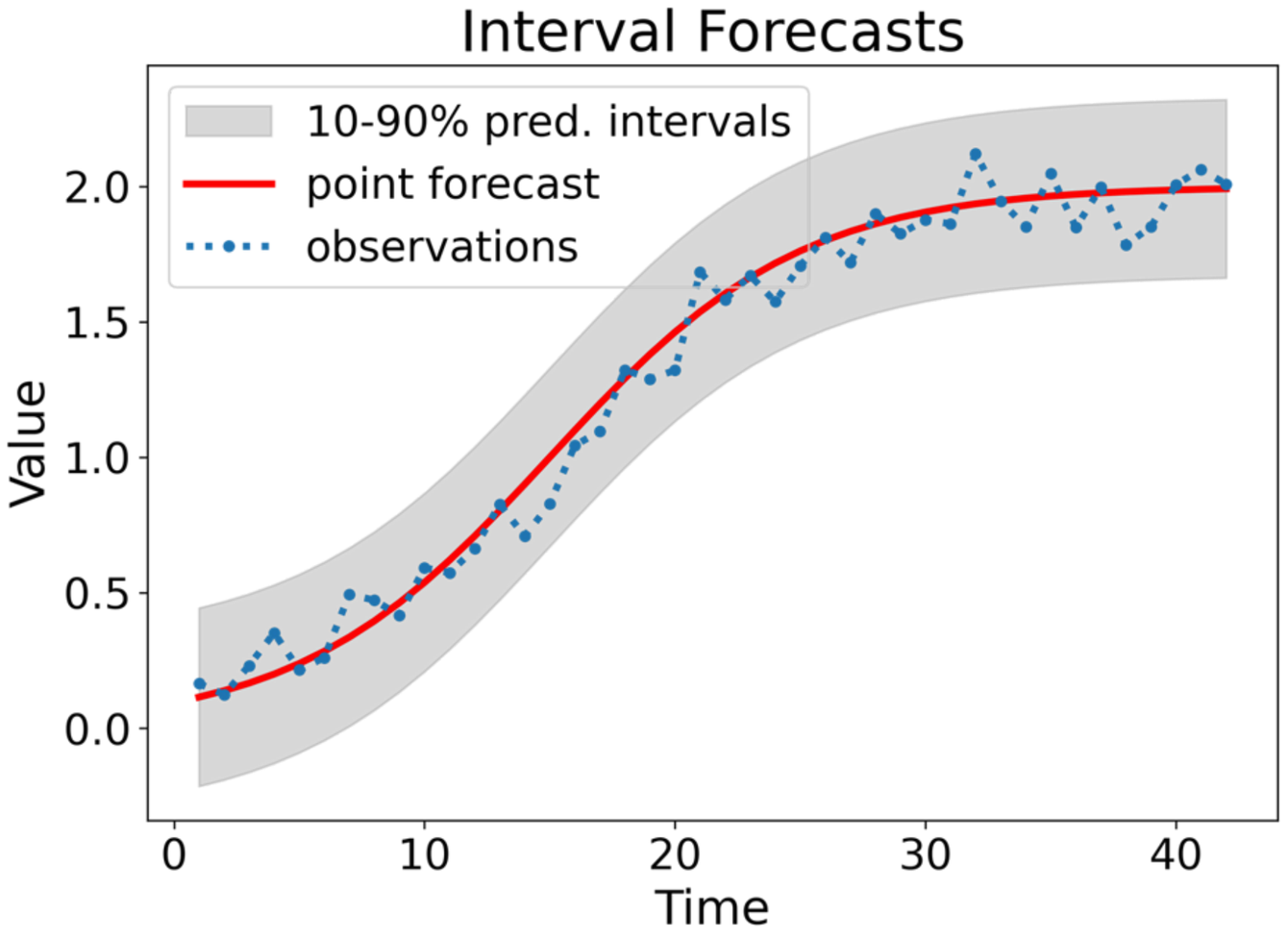
A point forecast is a single-value prediction representing the most likely future outcome, based on current data and models.

The disadvantage of point forecast;

✗ It ignores additional information in future.
✗ It does not explain uncertainties around future.
✗ It can not deal with assymmetric.

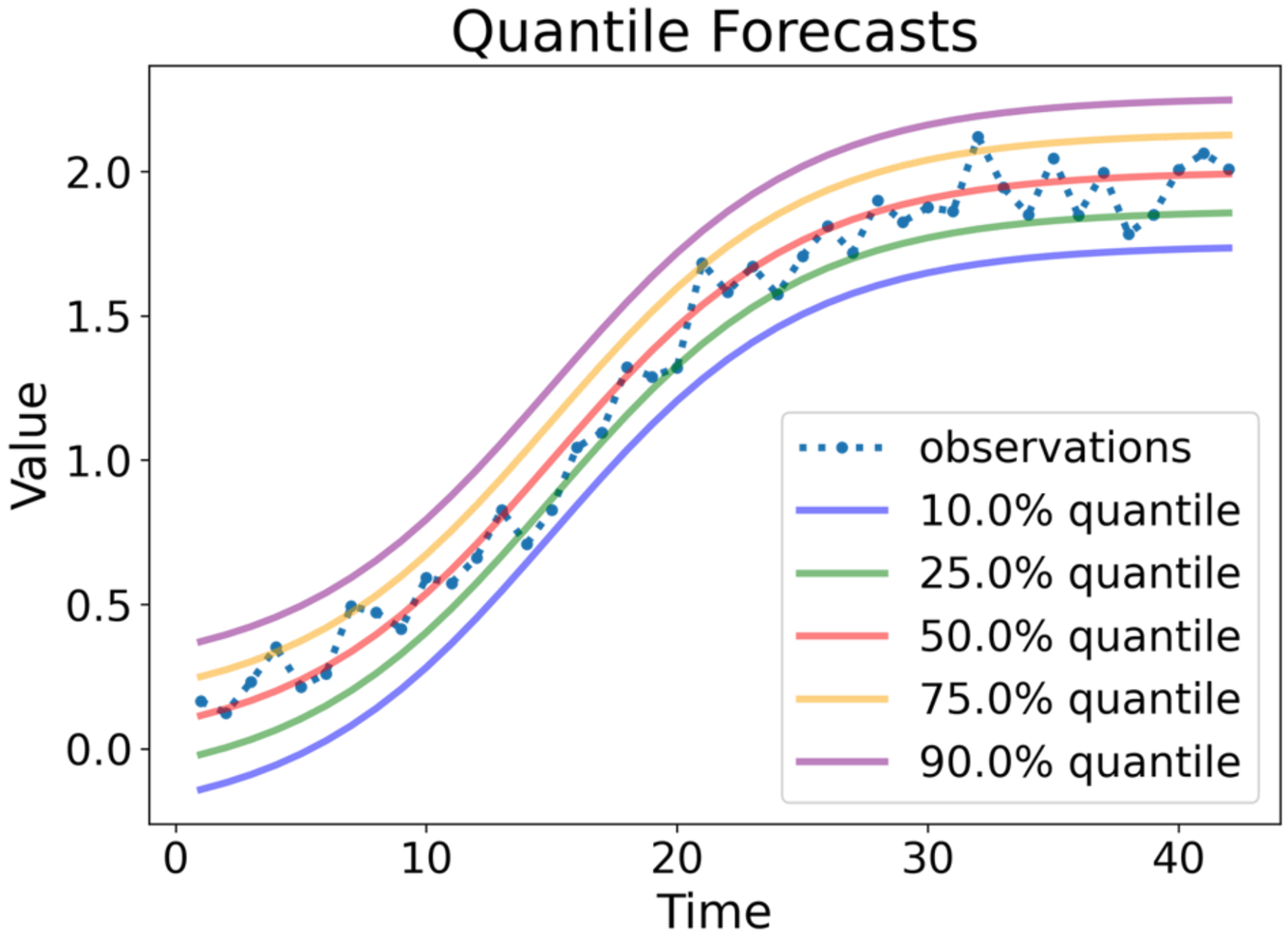
Types of probabilistic forecasts

`Interval forecasts`: A prediction interval is an interval within which power generation may lie, with a certain probability.



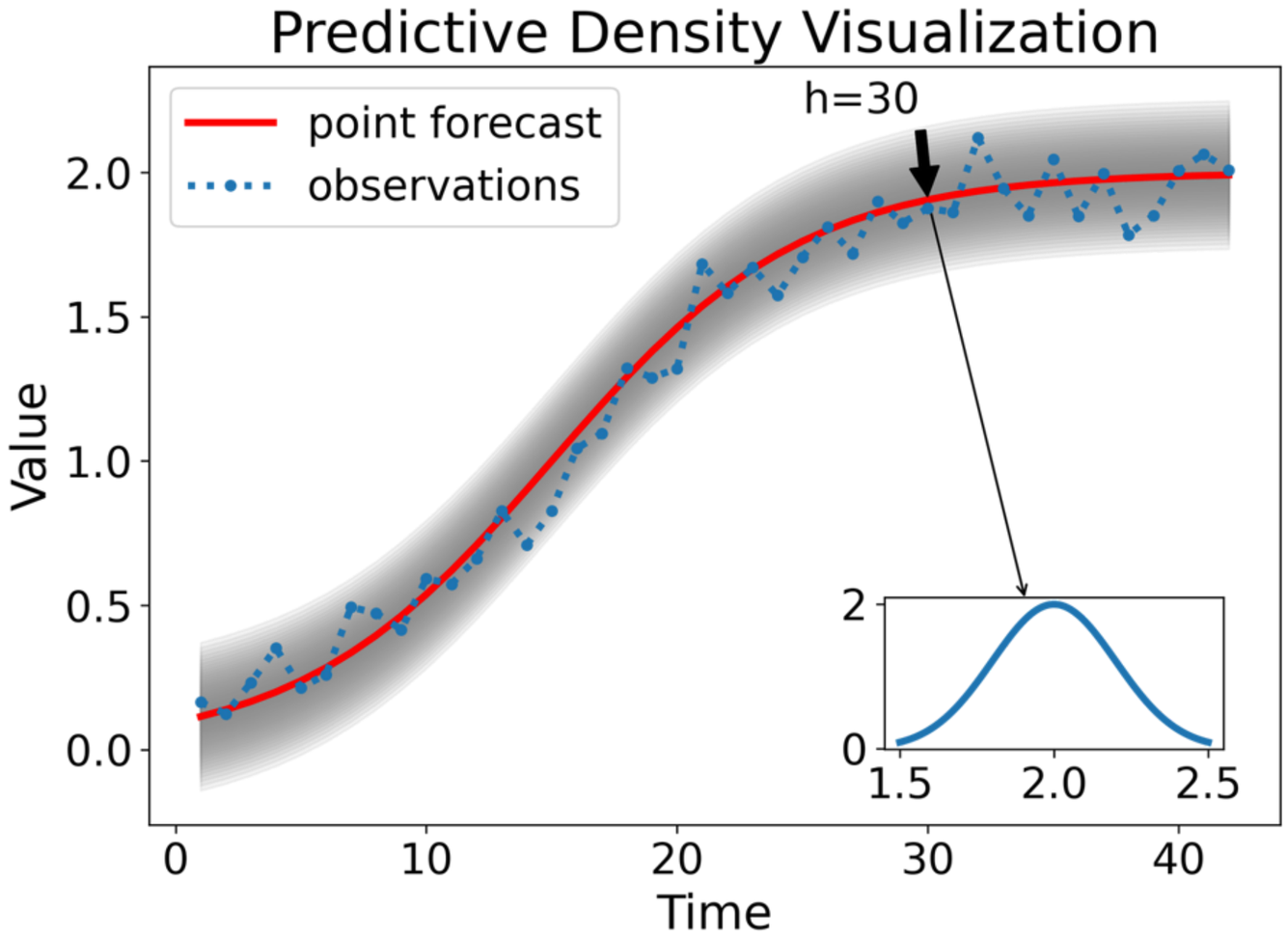
Types of probabilistic forecasts

`Quantile forecasts`: A quantile forecast provides a value that the future observation is expected to be below with a specified probability.



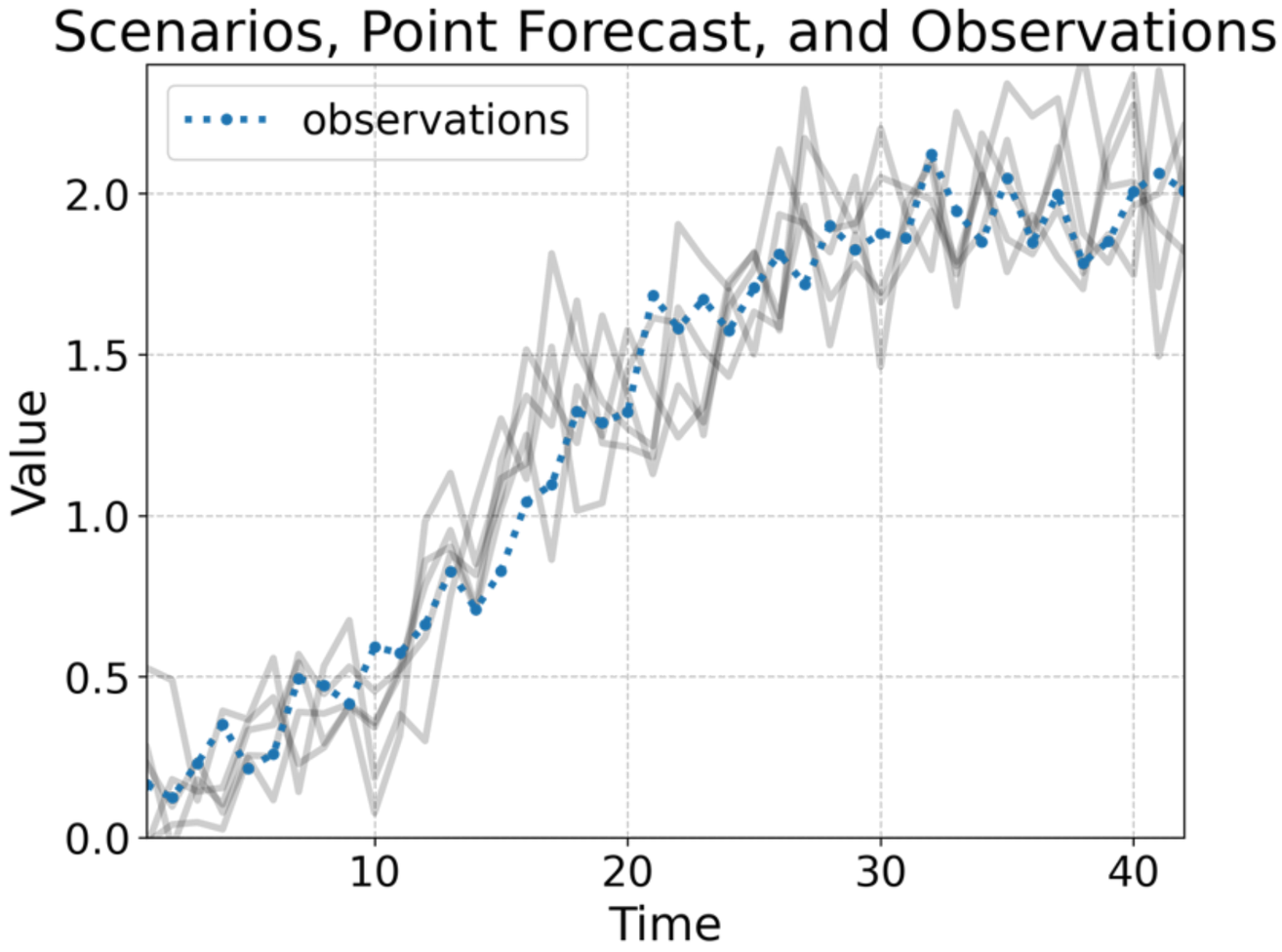
Types of probabilistic forecasts

`Distribution forecasts`: A comprehensive probabilistic forecast capturing the full range of potential outcomes across all time horizons.



Types of probabilistic forecasts

`Scenario forecasts`: A spectrum of potential futures derived from probabilistic modeling to inform decision- making under uncertainty.



Forecast distributions from `bootstrapping`

When a normal distribution for the residuals is an unreasonable assumption, one alternative is to use `bootstrapping`, which only assumes that the residuals are uncorrelated with constant variance.

- A one-step forecast error is defined as

,

$e_t = y_t - \hat{y}_{t|t-1}$

$y_t = \hat{y}_{t|t-1} + e_t$

- So we can simulate the next observation of a time series using

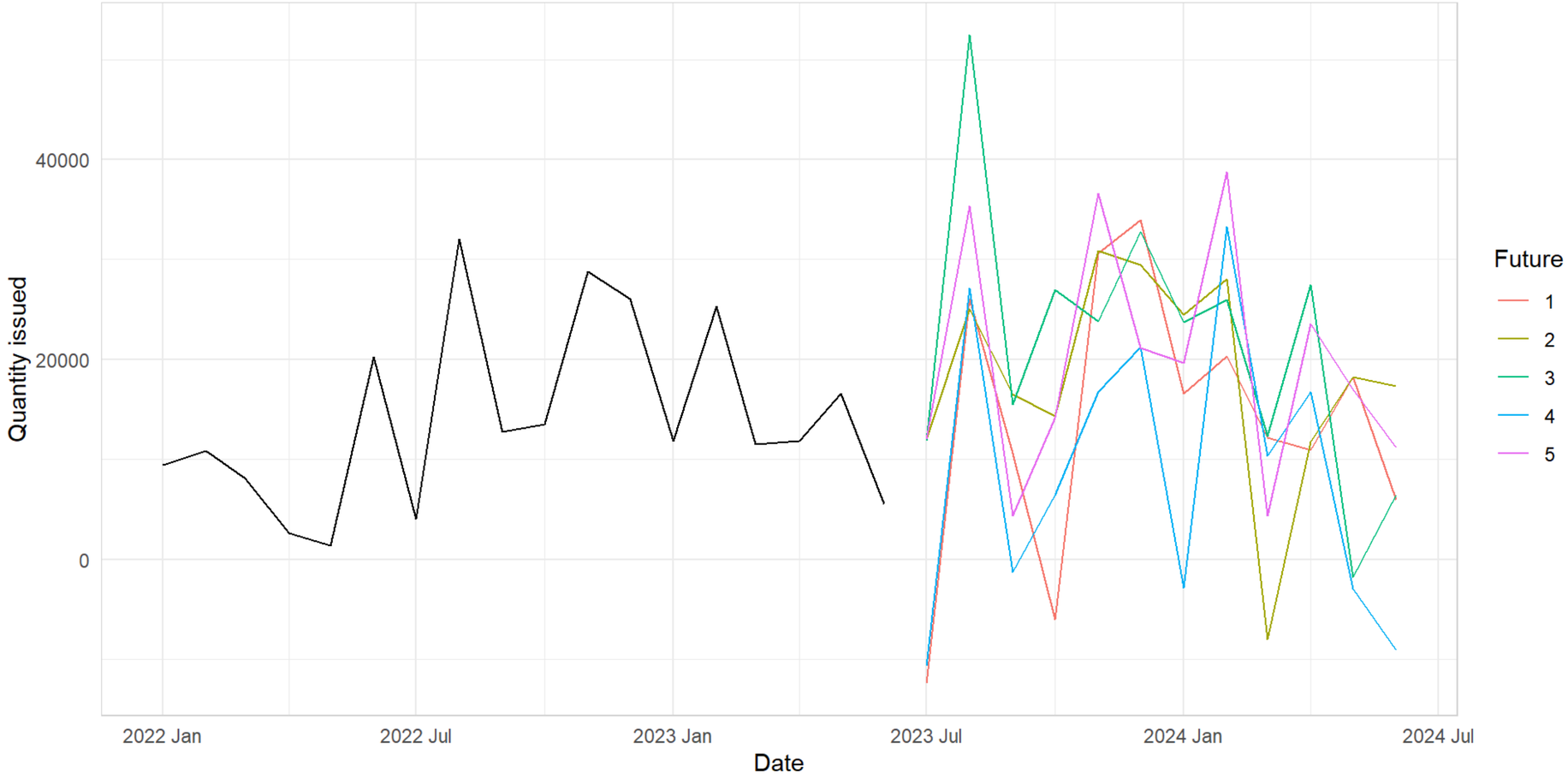
$$y_{T+1} = \hat{y}_{T+1|T} + e_{T+1}$$

- Adding the new simulated observation to our data set, we can repeat the process to obtain

$$y_{T+2} = \hat{y}_{T+2|T+1} + e_{T+2}$$

Generate different futures forecast

```
med_tsb_filter |>
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  model(snaive = SNAIVE(quantity_issued ~ lag("year"))) |>
  generate(h = 12, bootstrap = TRUE, times = 5)
```



Generate probabilistic forecast

```
med_tsb_filter |>
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  model(snaive = SNAIVE(quantity_issued ~ lag("year"))) |>
  forecast(h = 12, bootstrap = TRUE, times = 1000)
```

```
# A fable: 12 x 6 [1M]
# Key:     hub_id, product_id, .model [1]
   hub_id product_id .model     date quantity_issued  .mean
   <chr>  <chr>      <chr>     <mth>          <dist>  <dbl>
 1 hub_1  product_5  snaive 2023 Jul    sample[1000]  3790.
 2 hub_1  product_5  snaive 2023 Aug    sample[1000] 32090.
 3 hub_1  product_5  snaive 2023 Sep    sample[1000] 13039.
 4 hub_1  product_5  snaive 2023 Oct    sample[1000] 13203.
 5 hub_1  product_5  snaive 2023 Nov    sample[1000] 28567.
 6 hub_1  product_5  snaive 2023 Dec    sample[1000] 26470.
 7 hub_1  product_5  snaive 2024 Jan    sample[1000] 11766.
 8 hub_1  product_5  snaive 2024 Feb    sample[1000] 25393.
 9 hub_1  product_5  snaive 2024 Mar    sample[1000] 11540.
10 hub_1  product_5  snaive 2024 Apr    sample[1000] 11942.
11 hub_1  product_5  snaive 2024 May    sample[1000] 16975.
```

Prediction intervals

Forecast intervals can be extracted using the `hilo()` function.

```
med_tsb_filter |>
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  model(snaive = SNAIVE(quantity_issued ~ lag("year"))) |>
  forecast(h = 12, bootstrap = TRUE, times = 1000) |>
  hilo(level = 75) |>
  unpack_hilo("75%")
```

```
# A tsibble: 12 x 8 [1M]
# Key:       hub_id, product_id, .model [1]
   hub_id product_id .model     date quantity_issued  .mean `75%_lower`
   <chr>  <chr>      <chr>     <mth>          <dist>  <dbl>       <dbl>
 1 hub_1  product_5  snaive 2023 Jul    sample[1000]  3509.      -8015.
 2 hub_1  product_5  snaive 2023 Aug    sample[1000] 32690.      20230.
 3 hub_1  product_5  snaive 2023 Sep    sample[1000] 12713.        850.
 4 hub_1  product_5  snaive 2023 Oct    sample[1000] 13433.       1624.
 5 hub_1  product_5  snaive 2023 Nov    sample[1000] 29074.      16981.
 6 hub_1  product_5  snaive 2023 Dec    sample[1000] 25767.      14190.
 7 hub_1  product_5  snaive 2024 Jan    sample[1000] 11377.        -48.1
 8 hub_1  product_5  snaive 2024 Feb    sample[1000] 25310.      13406.
 9 hub_1  product_5  snaive 2024 Mar    sample[1000] 11876.       -410.
10 hub_1  product_5  snaive 2024 Apr    sample[1000] 12137.        -44.1
11 hub_1  product_5  snaive 2024 May    sample[1000] 16901.       4829.
12 hub_1  product_5  snaive 2024 Jun    sample[1000]  5407.       6449.
```

Now it is your `turn`.

15:00

Evaluating the model performances

Forecast accuracy evaluation using test sets

- We mimic the real life situation
- We pretend we don’t know some part of data (new data)
- It must not be used for any aspect of model training
- Forecast accuracy is computed only based on the test set

`Training and test sets`

Evaluating `point forecast` accuracy

- In order to evaluate the performance of a forecasting model, we compute its forecast accuracy.
- Forecast accuracy is compared by measuring errors based on the test set.
- Ideally it should allow comparing benefits from improved accuracy with the cost of obtaining the improvement.

Evaluating `point forecast` accuracy

Forecast Error

$$e_{T+h} = y_{T+h} - \hat{y}_{T+h|T}$$

where

- y_{T+h} is the $(T+h)^{\text{th}}$ observation, $(h = 1, \ldots, H)$, and
- $\hat{y}_{T+h|T}$ is the forecast based on data up to time T.

Read more on How to choose appropriate error measure by Ivan Svetunkov.

Evaluating `point forecast` accuracy

Measure	Formula	Notes
MAE (Mean Absolute Error)	$\text{MAE} = \text{mean}(\lvert e_{T+h} \rvert)$	Scale dependent
MSE (Mean Squared Error)	$\text{MSE} = \text{mean}(e_{T+h}^2)$	Scale dependent
MAPE (Mean Absolute Percentage Error)	$\text{MAPE} = 100\,\text{mean}(\lvert e_{T+h} \rvert / \lvert y_{T+h} \rvert)$	Scale independent; use when $y_t \gg 0$ has a natural zero
RMSE (Root Mean Squared Error)	$\text{RMSE} = \sqrt{\text{mean}(e_{T+h}^2)}$	Scale dependent

Evaluating `point forecast` accuracy

Measure	Formula	Notes
MASE (Mean Absolute Scaled Error)	$\text{MASE} = \text{mean}(\lvert e_{T+h} \rvert / Q)$	**Non-seasonal:** $Q = \frac{1}{T-1}\sum_{t=}^{T}$ **Seasonal:** , where is the seasonal frequency $Q = \frac{1}{T-m}\sum_{t=m+}$
RMSSE (Root Mean Squared Scaled Error)	$\text{RMSSE} = \sqrt{\text{mean}(e_{T+h}^2 / Q)}$	**Non-seasonal:** $Q = \frac{1}{T-1}\sum_{t=}^{T}$ **Seasonal:** , where is the seasonal frequency $Q = \frac{1}{T-m}\sum_{t=m+}$

Evaluating `point forecast` accuracy

Create train and test sets.

```
f_horizon <- 12 # forecast horizon

train <- med_tsb_filter |> # create train set
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  filter_index(. ~ '2022 June')

fit_all <- train |> # model fitting
  filter(hub_id == 'hub_1' & product_id == 'product_5') |>
  model(
    naive = NAIVE(quantity_issued),
    snaive = SNAIVE(quantity_issued ~ lag('year')),
    mean = MEAN(quantity_issued ~ window(size = 3)),
    arima = ARIMA(quantity_issued),
    ets = ETS(quantity_issued)
    )

fit_all_fc <- fit_all |> # forecasting
  forecast(h = f_horizon)
```

Evaluating point forecast accuracy

```
fit_all_fc |>
  accuracy(med_tsb_filter |>
             filter(hub_id == 'hub_1' & product_id == 'product_5'),
           measures = list(point_accuracy_measures))
```

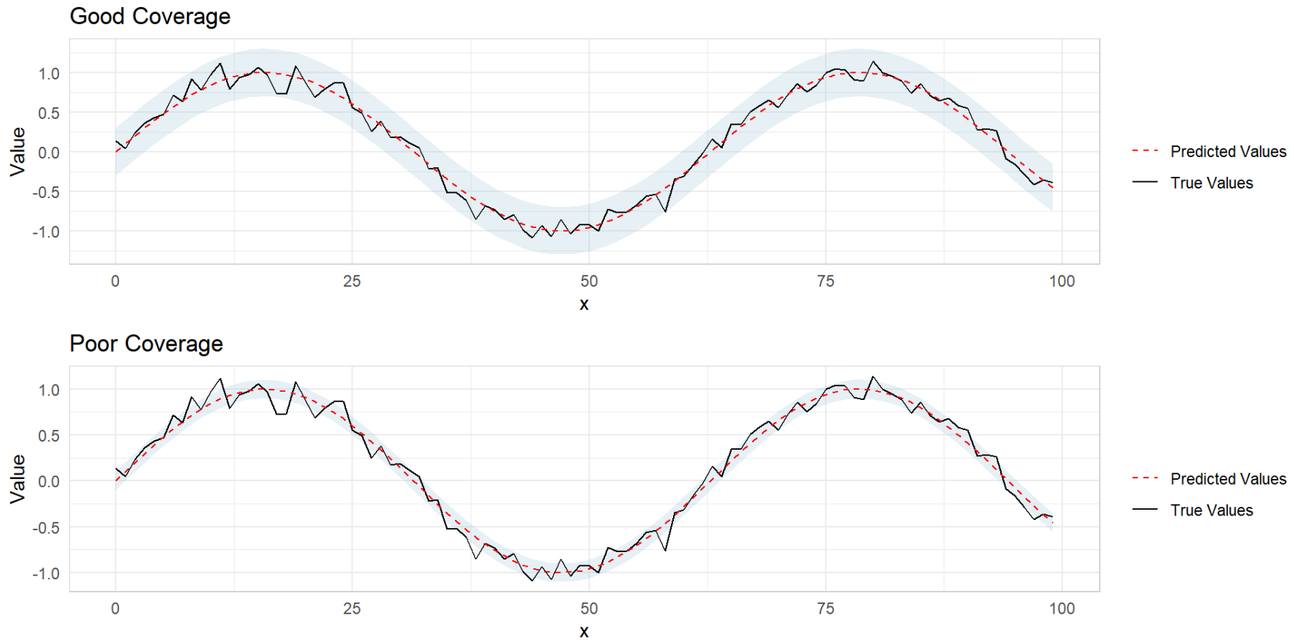
```
# A tibble: 5 × 12
  .model hub_id product_id .type     ME   RMSE    MAE    MPE  MAPE  MASE RMSSE
  <chr>  <chr>  <chr>      <chr>  <dbl>  <dbl>  <dbl>  <dbl> <dbl> <dbl> <dbl>
1 arima  hub_1  product_5  Test   5787. 10679.  8732.   5.08  59.3  1.23  1.21
2 ets    hub_1  product_5  Test   5400. 11163.  8681.   5.33  57.0  1.23  1.27
3 mean   hub_1  product_5  Test   8568. 12274.  9664.  29.9   54.3  1.37  1.39
4 naive  hub_1  product_5  Test  -3627.  9508.  8803. -76.1   94.1  1.24  1.08
5 snaive hub_1  product_5  Test   5237. 12571. 11346.  -1.06  85.6  1.60  1.43
# ℹ 1 more variable: ACF1 <dbl>
```

Evaluating probabilistic forecast accuracy

Coverage

- Measures how often the true value falls within a prediction interval
- Typically assessed for specific confidence levels (e.g., 95% interval)

Example: A 95% prediction interval should contain the true value 95% of the time.

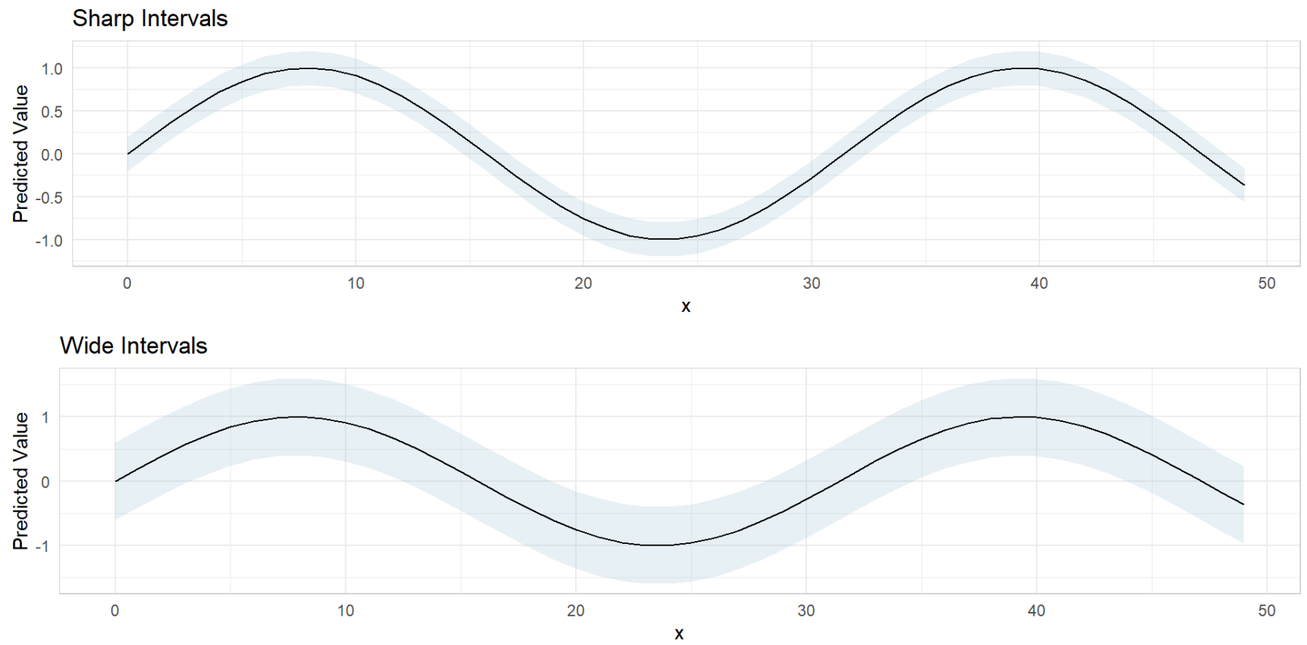


Evaluating probabilistic forecast accuracy

Sharpness

- Refers to the width of prediction intervals
- Measures how precise or focused the forecast is

Example: A forecast predicting monthly sales qty between 2500-5000 is sharper than 500-10000.



Evaluating `probabilistic forecast` accuracy

`Quantile score/ Pin ball loss`

- Assesses entire prediction interval, not just point forecast
- Penalizes too narrow and too wide intervals
- Interpretation: Lower values indicate better calibrated intervals

$$Q_{p,t} = \begin{cases} 2(1-p)(f_{p,t} - y_t), & \text{if } y_t < f_{p,t}, \\ 2p(y_t - f_{p,t}), & \text{if } y_t \geq f_{p,t}. \end{cases}$$

Evaluating probabilistic forecast accuracy

CRPS (Continuous Ranked Probability Score)

- Proper scoring rule
- Measures accuracy of full predictive distribution
- Generalizes absolute error to probabilistic forecasts
- Interpretation: Lower CRPS = better forecast
- Advantage: Sensitive to distance, rewards sharp and calibrated forecasts

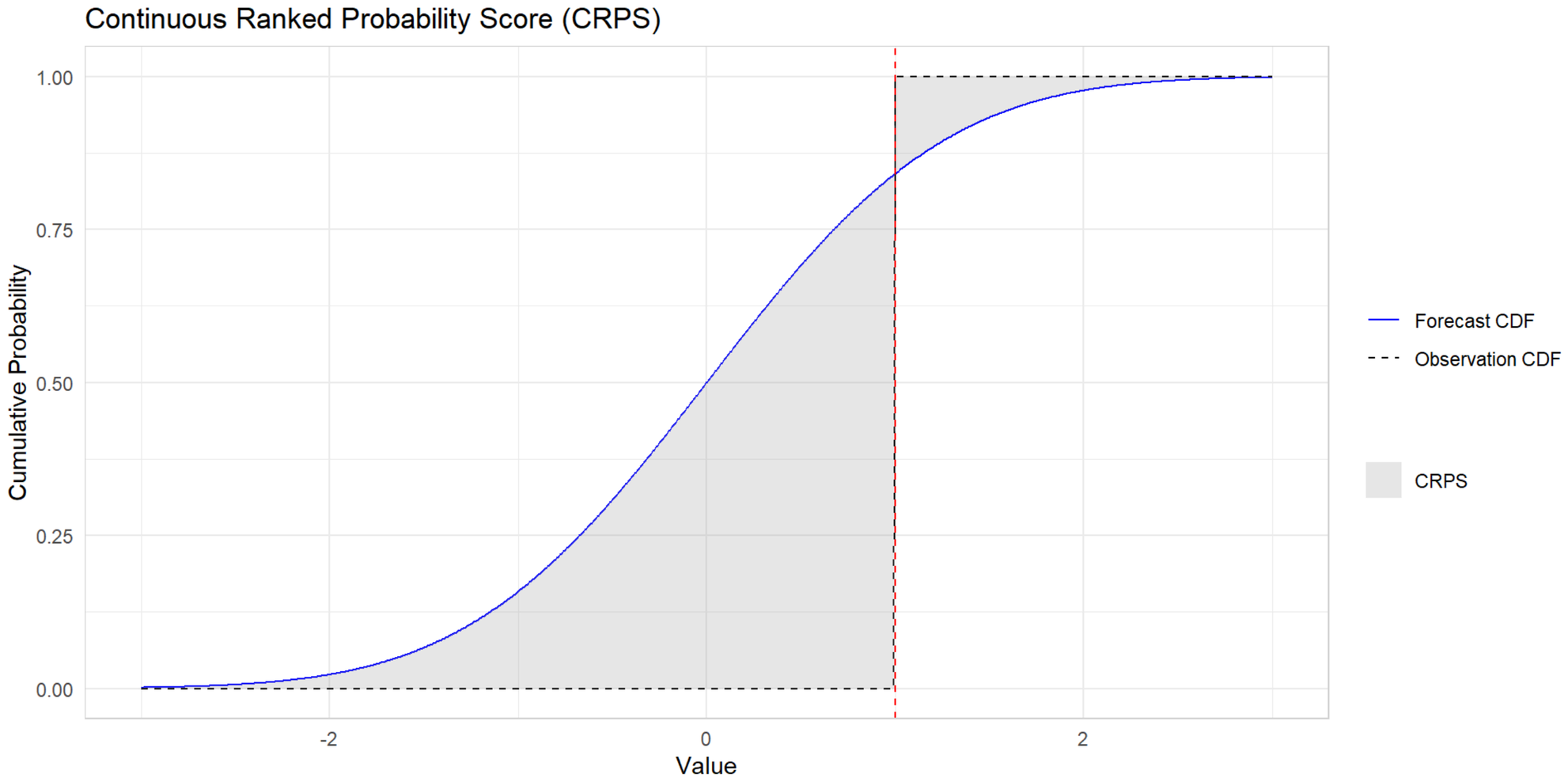
$$\text{CRPS} = \text{mean}(p_j),$$

where

$$p_j = \int_{-\infty}^{\infty} \left(G_j(x) - F_j(x)\right)^2 dx,$$

Evaluating probabilistic forecast accuracy

CRPS (Continuous Ranked Probability Score)



Evaluating probabilistic forecast accuracy

```
fit_all_fc |>
  accuracy(med_tsb_filter |>
             filter(hub_id == 'hub_1' & product_id == 'product_5'),
           measures = list(distribution_accuracy_measures)) |>
  select(-percentile)
```

```
# A tibble: 5 × 5
  .model hub_id product_id .type  CRPS
  <chr>  <chr>  <chr>      <chr> <dbl>
1 arima  hub_1  product_5  Test  6311.
2 ets    hub_1  product_5  Test  6648.
3 mean   hub_1  product_5  Test  7081.
4 naive  hub_1  product_5  Test  8034.
5 snaive hub_1  product_5  Test  7823.
```

Now it is your `turn`.

15:00

Advance forecasting models

Feature engineering

In this training, we only do a basic feature engineering.

```
# Load data
from google.colab import files
uploaded = files.upload()
df = pd.read_csv('med_tsb_filter.csv')

# Make the yearmonth as date format
df['date'] = pd.to_datetime(df['date']) + pd.offsets.MonthEnd(0)

# Feature Engineering
df['month'] = df['date'].dt.month  # create month feature

# categorical encoding
enc = OrdinalEncoder()
df[['hub_id_cat', 'product_id_cat']] = enc.fit_transform(df[['hub_id', 'product_id']])

# Create unique identifier for series
df['unique_id'] = df['hub_id'] + '_' + df['product_id']
```

Feature engineering

```
# Create series and exogenous data
series = df[['date', 'unique_id', 'quantity_issued']]
exog = df[['date', 'unique_id', 'month', 'hub_id_cat', 'product_id_cat']]

# Transform series and exog to dictionaries

series_dict = series_long_to_dict(
    data      = series,
    series_id = 'unique_id',
    index     = 'date',
    values    = 'quantity_issued',
    freq      = 'M'
)

exog_dict = exog_long_to_dict(
    data      = exog,
    series_id = 'unique_id',
    index     = 'date',
    freq      = 'M'
```

Feature engineering

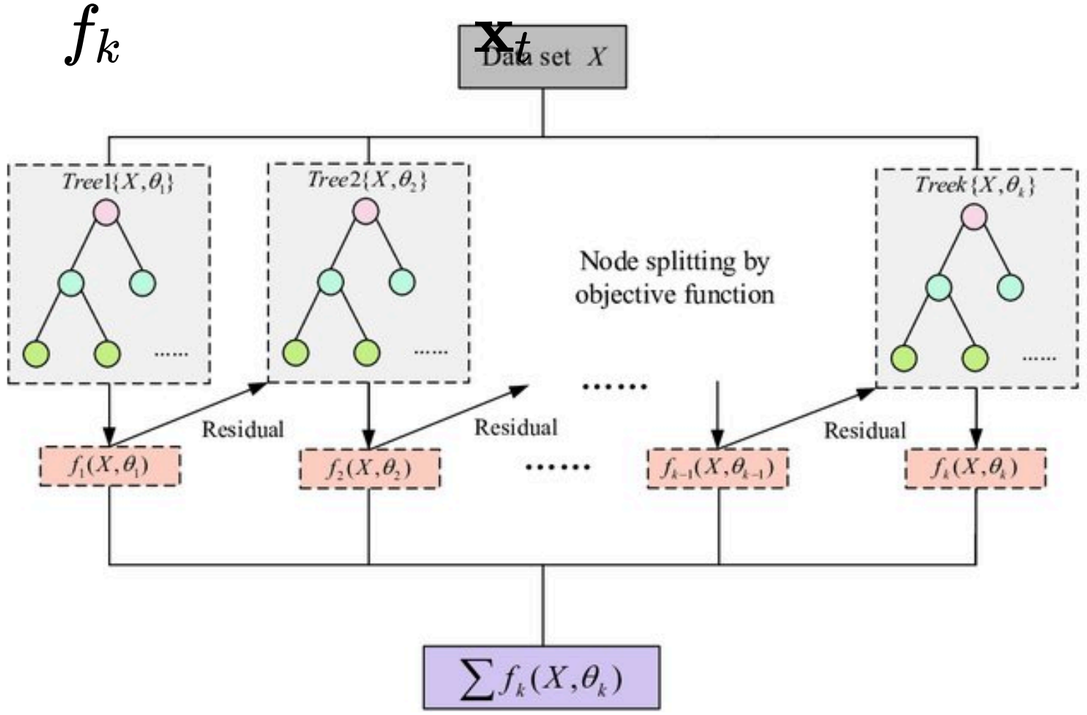
```
# Partition data in train and test
end_train = '2022-06-30'
start_test = pd.to_datetime(end_train) + pd.DateOffset(months=1)  # Add 1 month

series_dict_train = {k: v.loc[:end_train] for k, v in series_dict.items()}
exog_dict_train = {k: v.loc[:end_train] for k, v in exog_dict.items()}
series_dict_test = {k: v.loc[start_test:] for k, v in series_dict.items()}
exog_dict_test = {k: v.loc[start_test:] for k, v in exog_dict.items()}
```

XGBoost

Extreme Gradient Boosting (XGBoost) is a scalable tree-based gradient boosting machine learning algorithm.

$$\hat{y}_{t+1|t} = \sum_{k=1}^{K} f_k(\mathbf{x}_t), \quad f_k \in \mathcal{F}$$

Where: K = number of trees, f_k = tree function, $\mathbf{x}_t$ = feature vector (lags, calendar features, etc.)



source: Rui Guo et al.

XGBoost

Assumptions

- Predictive patterns can be captured through feature engineering
- Relationships between features and target are stable
- No strong temporal dependencies beyond engineered features

Strengths & Weaknesses

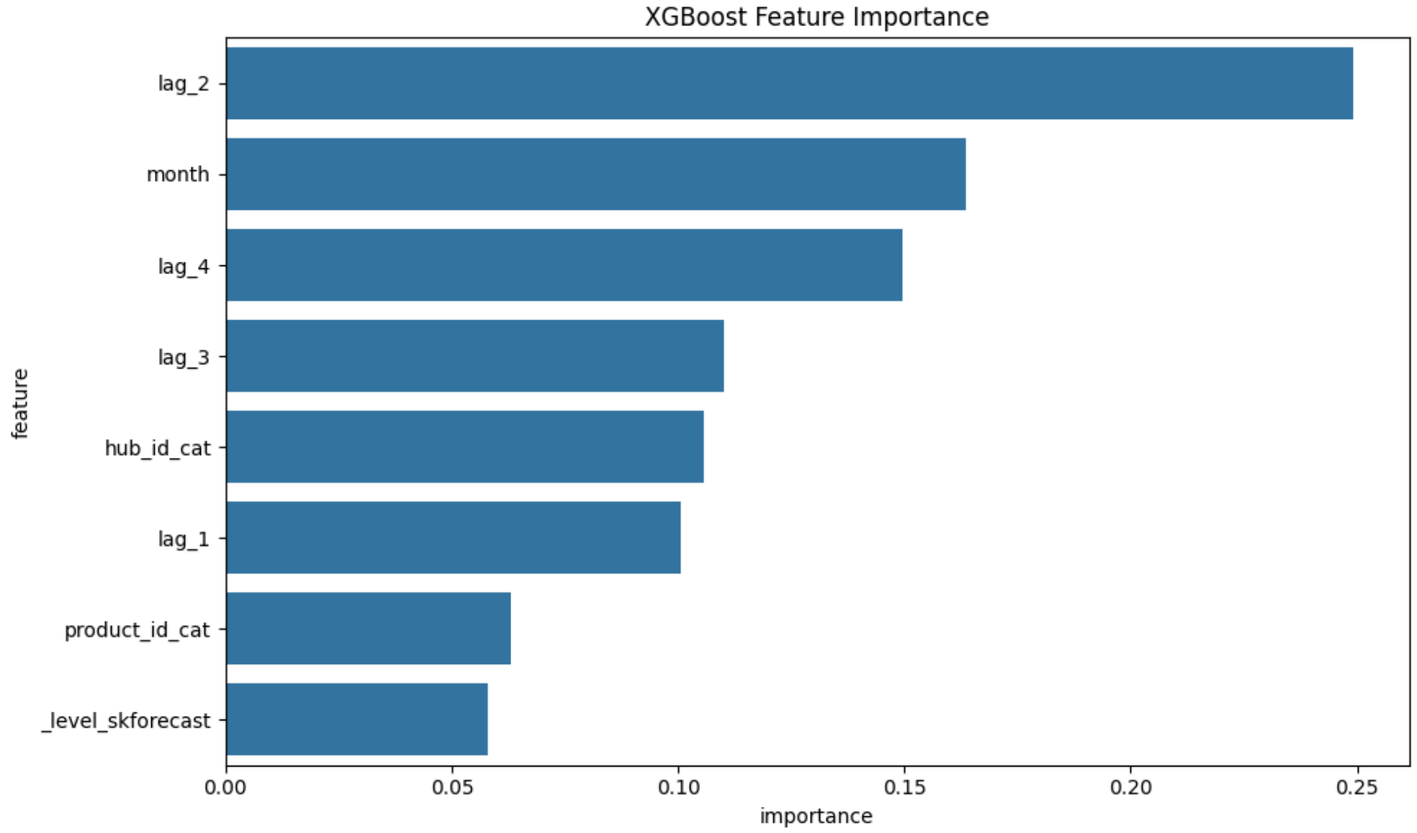
✓ Handles non-linear relationships well
✓ Provides feature importance metrics
✗ Requires careful parameter tuning
✗ Less interpretable than linear models

XGBoost

```
# Fit xgboost forecaster
regressor_xgb = XGBRegressor(tree_method = 'hist',
                             enable_categorical = True)

forecaster_xgb = ForecasterRecursiveMultiSeries(
                 regressor          = regressor_xgb,
                 transformer_series = None,
                 lags               = 4,
                 dropna_from_series = False
             )

forecaster_xgb.fit(series=series_dict_train, exog=exog_dict_train, suppress_warnings=True)

forecaster_xgb
```

XGBoost

```
# Feature importance plot for XGB
plt.figure(figsize=(10, 6))
feat_xgb = forecaster_xgb.get_feature_importances()
sns.barplot(x='importance', y='feature', data=feat_xgb.sort_values('importance', ascending=False).head(10))
plt.title('XGBoost Feature Importance')
plt.tight_layout()
plt.show()
```

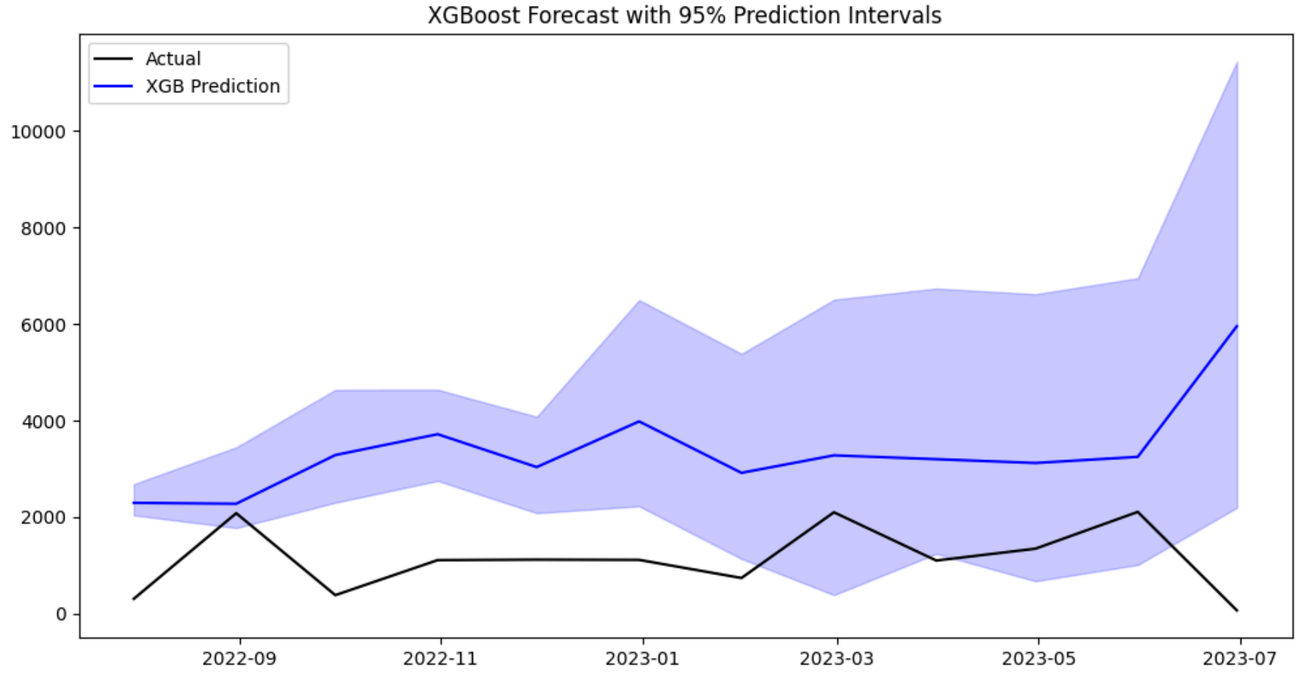


XGBoost

```
# XGB predictions and plot
boot = 100
predictions_xgb = forecaster_xgb.predict_bootstrapping(steps=12, exog=exog_dict_test, n_boot=boot)

# Create prediction DF and plot example series
example_series = list(series_dict_test.keys())[2]
xgb_pred_test = predictions_xgb[example_series].copy()

# Calculate statistics
mean_pred = xgb_pred_test.mean(axis=1)
lower_pred = xgb_pred_test.quantile(0.025, axis=1)
upper_pred = xgb_pred_test.quantile(0.975, axis=1)
```

XGBoost

```
# Plotting
plt.figure(figsize=(12, 6))
plt.plot(series_dict_test[example_series], label='Actual', color='black')
plt.plot(mean_pred, label='XGB Prediction', color='blue')
plt.fill_between(mean_pred.index,
                 lower_pred,
                 upper_pred,
                 color='blue', alpha=0.2)
plt.title('XGBoost Forecast with 95% Prediction Intervals')
plt.legend()
plt.show()
```

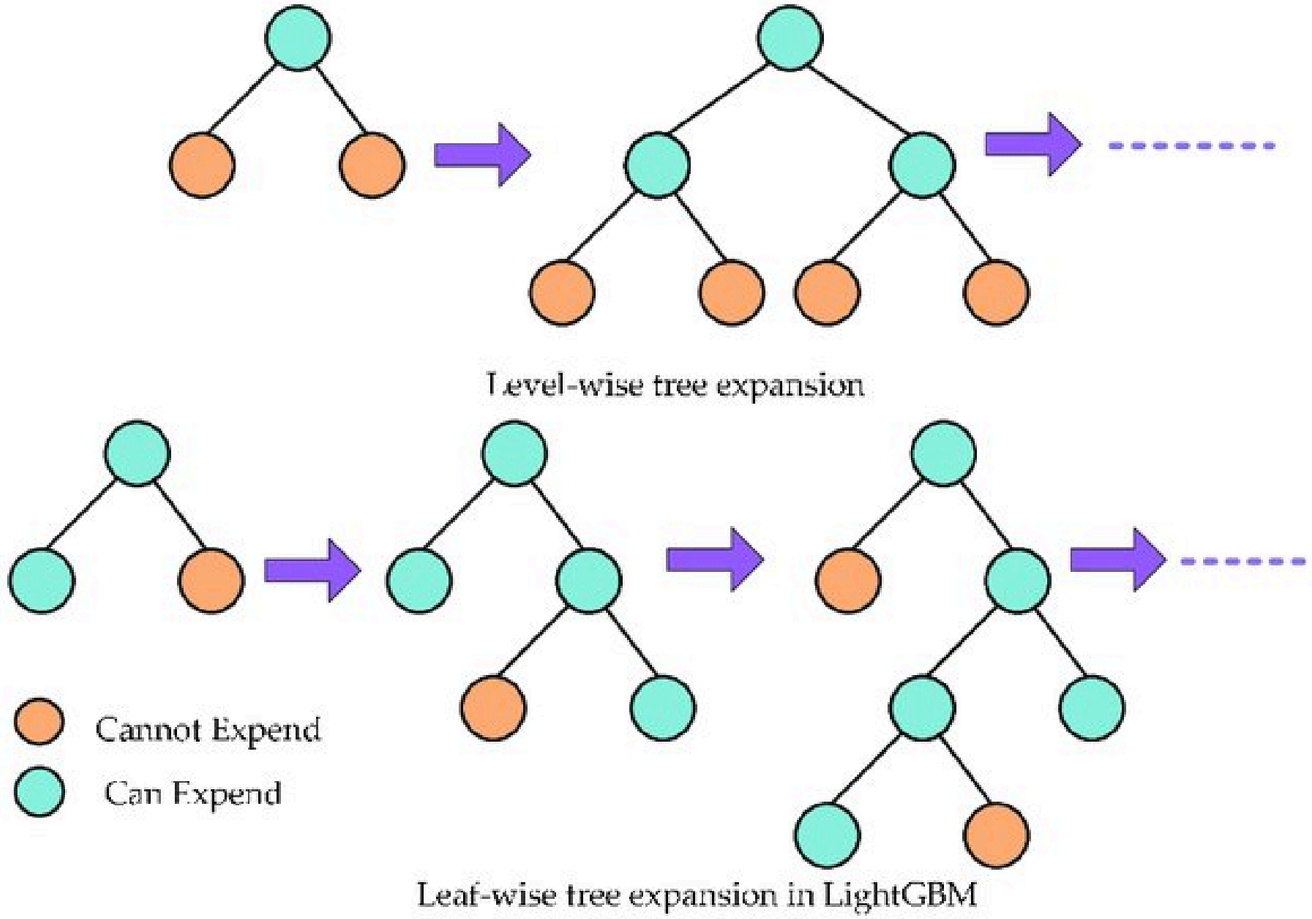


XGBoost

```
# Create prediciton df

pred_id = list(predictions_xgb.keys())

# Create an empty DataFrame
xgb_pred = pd.DataFrame(columns=['date', 'unique_id', 'model'] + [f'X_{i}' for i in range(boot)])

for i in pred_id:
    xgb_pred_test = predictions_xgb[i]
    xgb_pred_test = xgb_pred_test.reset_index()
    xgb_pred_test.columns = ['date'] + [f'X_{i}' for i in range(boot)]
    xgb_pred_test['unique_id'] = i
    xgb_pred_test['model'] = 'xgb'
    xgb_pred = pd.concat([xgb_pred, xgb_pred_test])

xgb_pred.head()
```

LightGBM

Light Gradient Boosting Machine (LightGBM) uses leaf-wise tree growth for efficiency whereas other boosting methods divide the tree level-wise.



source: Sheng Dong et al.

LightGBM

Assumptions

- Similar to XGBoost but more efficient with large datasets
- Handles categorical features natively

Strengths & Weaknesses

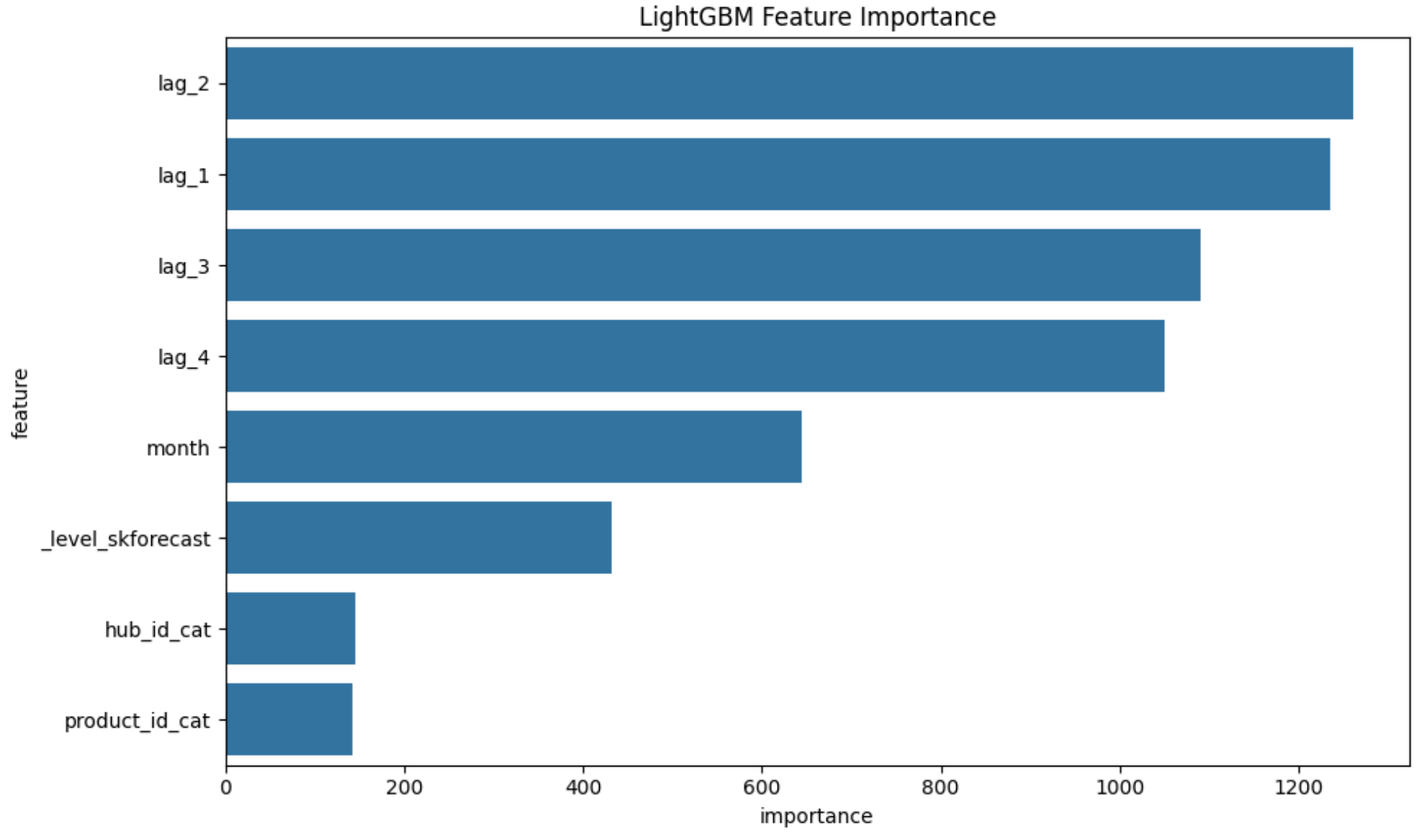
✓ Faster training speed
✓ Lower memory usage
✗ Sensitive to small datasets
✗ May overfit with noisy data

LightGBM

```
# Fit lightgbm forecaster

regressor_lgbm = LGBMRegressor(
                 boosting_type = 'gbdt',
                 metric = 'mae',
                 learning_rate = 0.1,
                 num_iterations = 200,
                 n_estimators = 100,
                 objective = 'poisson')

forecaster_lgbm = ForecasterRecursiveMultiSeries(
                  regressor          = regressor_lgbm,
                  transformer_series = None,
                  lags               = 4,
                  dropna_from_series = False
              )

forecaster_lgbm.fit(series=series_dict_train, exog=exog_dict_train, suppress_warnings=True)
```

LightGBM

```
# Feature importance plot for LGBM
plt.figure(figsize=(10, 6))
feat_lgbm = forecaster_lgbm.get_feature_importances()
sns.barplot(x='importance', y='feature', data=feat_lgbm.sort_values('importance', ascending=False).head(10))
plt.title('LightGBM Feature Importance')
plt.tight_layout()
plt.show()
```

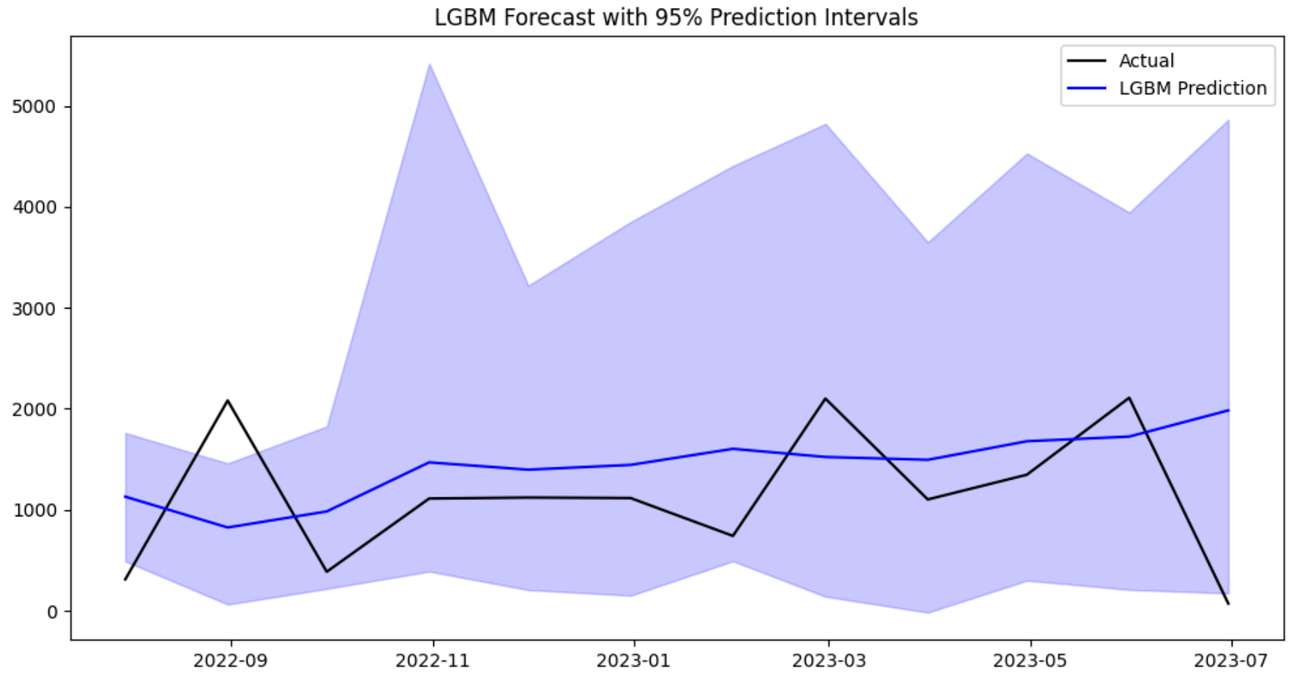


LightGBM

```
# LGBM predictions and plot
boot = 100
predictions_lgbm = forecaster_lgbm.predict_bootstrapping(steps=12, exog=exog_dict_test, n_boot=boot)

# Create prediction DF and plot example series
example_series = list(series_dict_test.keys())[2]
lgbm_pred_test = predictions_lgbm[example_series].copy()

# Calculate statistics
mean_pred = lgbm_pred_test.mean(axis=1)
lower_pred = lgbm_pred_test.quantile(0.025, axis=1)
upper_pred = lgbm_pred_test.quantile(0.975, axis=1)
```

LightGBM

```
# Plotting
plt.figure(figsize=(12, 6))
plt.plot(series_dict_test[example_series], label='Actual', color='black')
plt.plot(mean_pred, label='LGBM Prediction', color='blue')
plt.fill_between(mean_pred.index,
                 lower_pred,
                 upper_pred,
                 color='blue', alpha=0.2)
plt.title('LGBM Forecast with 95% Prediction Intervals')
plt.legend()
plt.show()
```



LightGBM

```python
# Create prediciton df

pred_id = list(predictions_lgbm.keys())

# Create an empty DataFrame
lgbm_pred = pd.DataFrame(columns=['date', 'unique_id', 'model'] + [f'X_{i}' for i in range(boot)])

for i in pred_id:
    lgbm_pred_test = predictions_lgbm[i]
    lgbm_pred_test = lgbm_pred_test.reset_index()
    lgbm_pred_test.columns = ['date'] + [f'X_{i}' for i in range(boot)]
    lgbm_pred_test['unique_id'] = i
    lgbm_pred_test['model'] = 'lgbm'
    lgbm_pred = pd.concat([lgbm_pred, lgbm_pred_test])

lgbm_pred.head()
```

Model evaluation

```
# Calculate metrics for both models
xgb_mase, xgb_rmse, xgb_qs, xgb_crps = calculate_metrics(predictions_xgb, series_dict_test, series_dict_train)
lgbm_mase, lgbm_rmse, lgbm_qs, lgbm_crps = calculate_metrics(predictions_lgbm, series_dict_test, series_dict_train)
```

Model	Average MASE	Average RMSE	Average Quantile Score	Average CRPS
XGBoost	1.218	4878.992	1151.738	3548.056
LightGBM	1.061	4953.944	310.234	3498.346

Note: We can improve the performance of XGBoost and LightGBM through better feature engineering and hyperparameter tuning.

TimeGPT

Foundational time series model for time series forecasting by Nixtla (Read more).

Assumptions

- No strict stationarity requirements
- Automatically handles multiple series

Strengths & Weaknesses

✓ Zero configuration needed
✓ Handles complex patterns
✗ Requires API access
✗ Black-box model

TimeGPT

Get API key from Nixtla

1. Visit https://nixtla.io/
2. Sign up for free account
3. Navigate to API Keys section
4. Create new key and copy it

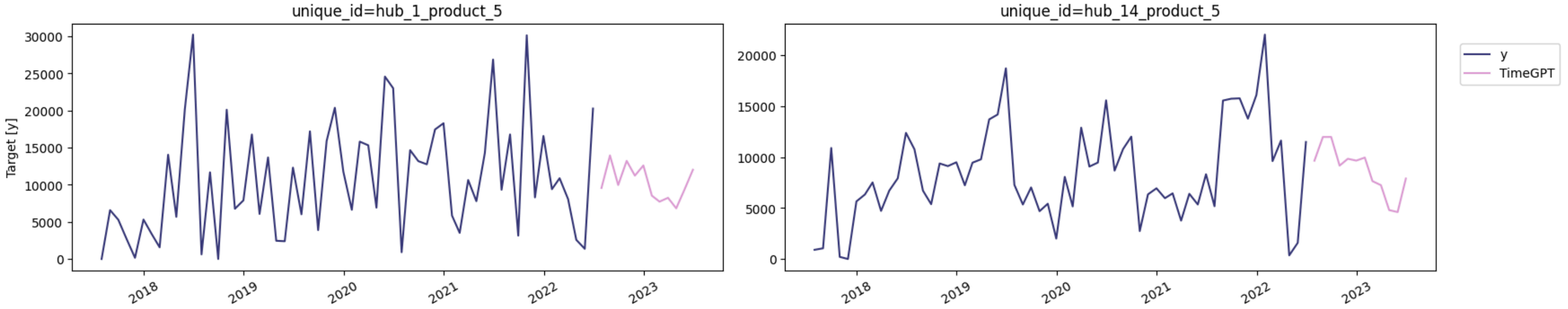
```
!pip install nixtla

# Load libraries
from nixtla import NixtlaClient

# Initialize Nixtla client
nixtla_client = NixtlaClient(api_key='your_api_key_here')
```

TimeGPT

```
# Since we already have done the feature engineering, we dont need to do it again
# Create unique identifier and rename columns for TimeGPT
df_timegpt = df.rename(columns={'date': 'ds', 'quantity_issued': 'y'}).drop(columns=['hub_id', 'product_id'])

# Split data into train-test
end_train = '2022-06-30'
train_df = df_timegpt[df_timegpt['ds'] <= end_train]
test_df = df_timegpt[df_timegpt['ds'] > end_train]
```

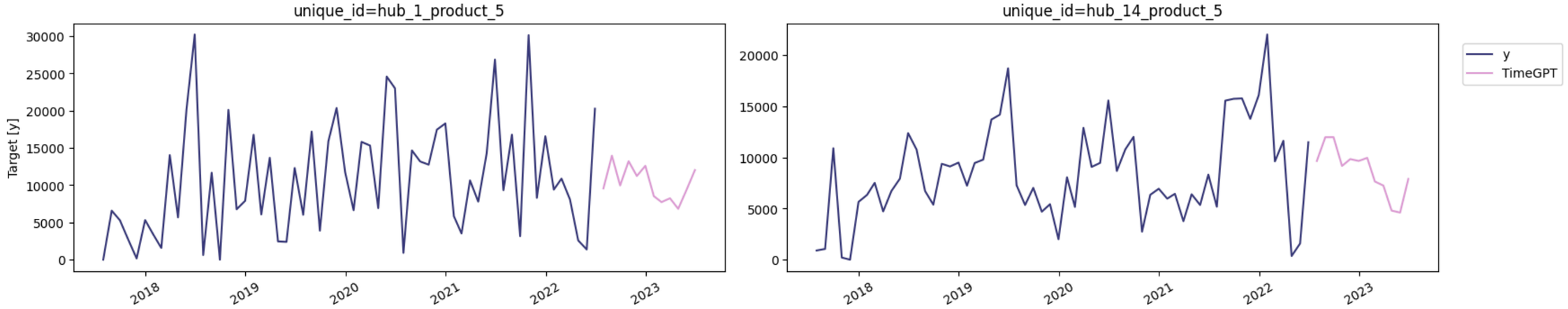
TimeGPT

```python
# TimeGPT Base Model
timegpt_fcst =  nixtla_client.forecast(
    df=train_df,
    h=len(test_df['ds'].unique()),
    freq='M',
    level=[90, 95]  # 90% and 95% prediction intervals
)

nixtla_client.plot(train_df, timegpt_fcst, time_col='ds', target_col='y')
```



TimeGPT

```python
# TimeGPT with Exogenous Variables

# Prepare exogenous data
exog_features = ['month', 'hub_id_cat', 'product_id_cat']

# Future exogenous variables (from your test set)
future_exog = test_df[['unique_id', 'ds'] + exog_features]

timegpt_reg_fcst = nixtla_client.forecast(
    df=train_df,
    X_df=future_exog,
    h=len(test_df['ds'].unique()),
    freq='M',
    level=[90, 95]
)

nixtla_client.plot(train_df, timegpt_reg_fcst, time_col='ds', target_col='y')
```



Model evaluation

```
# Calculate metrics for both models
xgb_mase, xgb_rmse, xgb_qs, xgb_crps = calculate_metrics(predictions_xgb, series_dict_test, series_dict_train)
lgbm_mase, lgbm_rmse, lgbm_qs, lgbm_crps = calculate_metrics(predictions_lgbm, series_dict_test, series_dict_train)

# Calculate metrics for base model
base_metrics = calculate_metrics(timegpt_fcst, test_df, train_df)

# Calculate metrics for regressor model
reg_metrics = calculate_metrics(timegpt_reg_fcst, test_df, train_df)
```

Model	Average MASE	Average RMSE	Average Quantile Score
TimeGPT Base Model	1.019	4261.135	41.892
TimeGPT Regressor Model	1.125	5016.053	57.571

Other Models

Demographic forecasting method (FPSC Context)

A population-based contraceptive needs estimation model combining:

- Population dynamics
- Family planning indicators
- Method/brand distribution factors

Demographic forecasting method (FPSC Context)

$$y_{i,t} = \left(\sum_{j=15}^{50} \text{mCPR}_{t,j} \times \text{WomenPopulation}_{t,j} \right. \\ \left. \times \text{MethodMix}_{t,i} \times \text{CYP}_{t,i} \times \text{BrandMi} \right.$$

- i: Contraceptive product
- t: Time period (year)
- mCPR: Modern Contraceptive Prevalence Rate (%)
- WomenPopulation: Women aged 15-49
- MethodMix: Contraceptive method distribution
- CYP: Couple-Years of Protection factor
- BrandMix: Brand preference distribution
- SourceShare: Provider type distribution

Demographic forecasting method (FPSC Context)

Assumptions

1. Stable demographic patterns during forecast period
2. Consistent reporting of family planning indicators
3. Accurate CYP values for different methods
4. Historical brand/source mixes remain valid
5. Linear relationship between population and needs
6. Proper spatial distribution via site coordinates
7. Valid monthly weight distribution

Demographic forecasting method (FPSC Context)

Strengths & Weaknesses

✓ Directly ties to population dynamics
✓ Incorporates multiple programmatic factors
✓ Enables spatial allocation to health sites
✓ Aligns with public health planning frameworks
✗ Sensitive to input data quality
✗ Static assumptions about behavior patterns
✗ Limited responsiveness to sudden changes
✗ Provides national level need

Next steps and further learning

- Forecasting for social good learning labs
- Forecasting: Principles and Practice
- Forecasting and Analytics with the Augmented Dynamic Adaptive Model (ADAM)
- Nixtla
- SKTIME
- skforecast

Any Q/As?

Thank you!

Scan the QR Code and follow us on LinkedIn…