Script R - Parte 2 - Thiago Menezes (ajuste para estilo do python)

1) Importação do conjunto de dados “dataset_st” no RStudio.

```
library(readxl)

dados <- read_excel("dataset_st.xlsx")
head(dados)
```

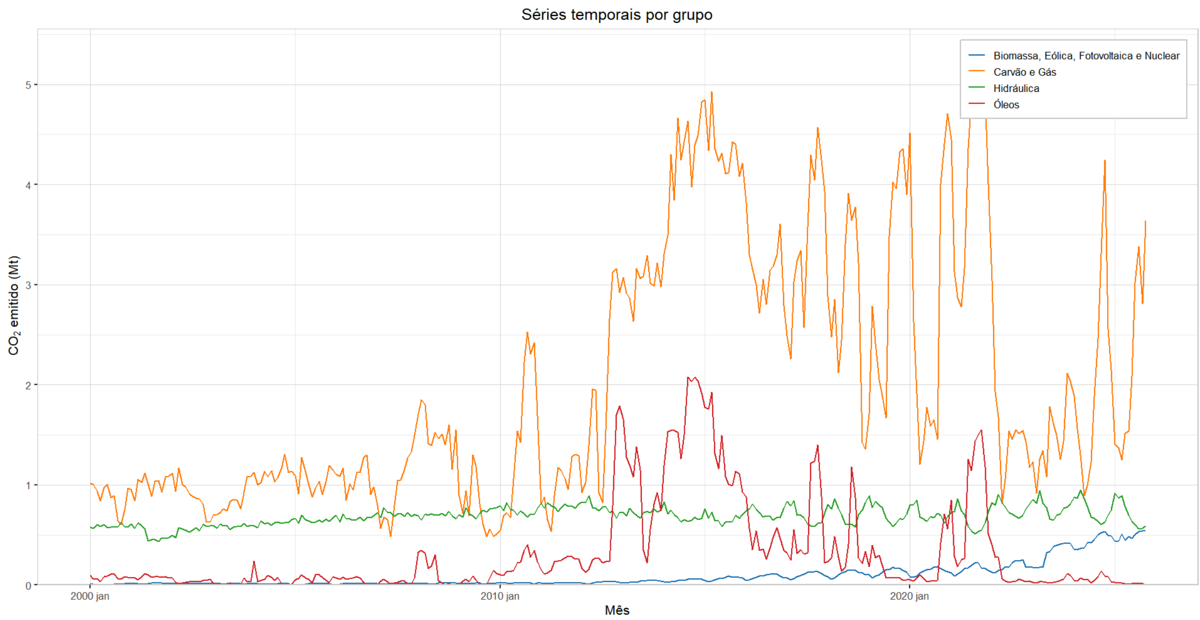
2) Conversão dos dados para em um objeto tsibble:

```
install.packages("dplyr")
install.packages("tsibble")
install.packages("fabletools")
install.packages("ggplot2")

library(dplyr)
library(tsibble)
library(fabletools)
library(ggplot2)

dataset_st <- dataset_st |>
  mutate(mes = yearmonth(mes)) |>
  as_tsibble(index = mes)

dataset_st
```

3) Geração das séries temporais por grupos:

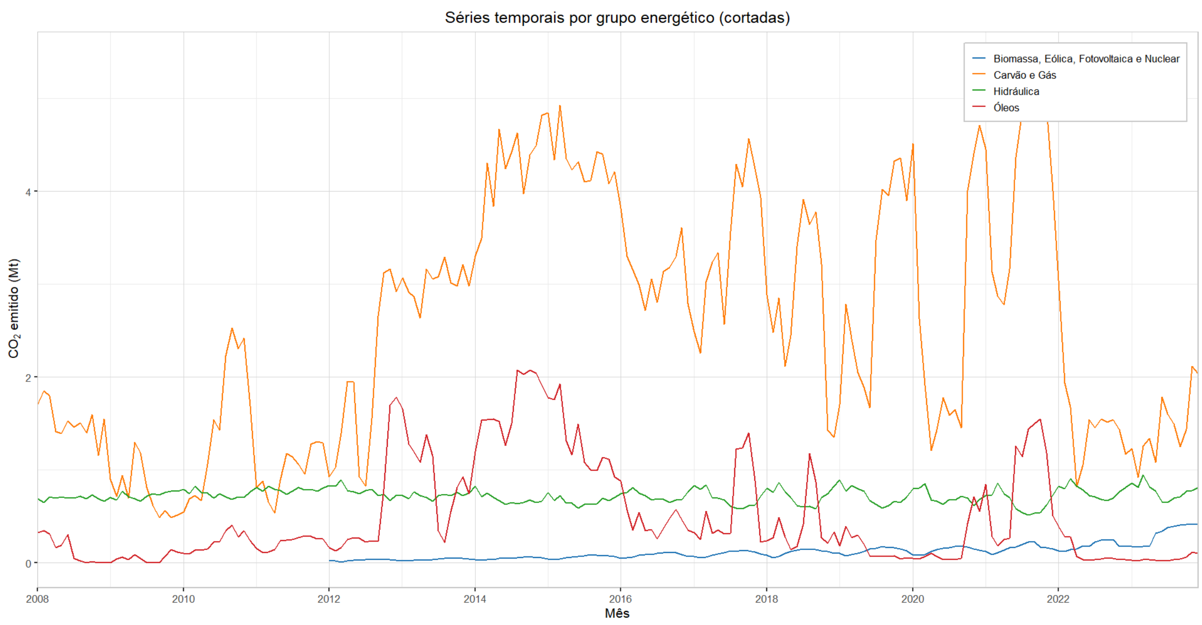
```
library(dplyr)
library(tidyr)
library(ggplot2)

# Paleta "tab10" do Matplotlib
tab10 <- c(
  "#1f77b4", "#ff7f0e", "#2ca02c", "#d62728",
  "#9467bd", "#8c564b", "#e377c2", "#7f7f7f",
  "#bcbd22", "#17becf"
)

theme_python <- function(base_size = 14) {
  theme_bw(base_size = base_size) +
    theme(
      panel.background = element_rect(fill = "white"),
      panel.grid.major = element_line(colour = "grey85", linewidth = 0.4),
      panel.grid.minor = element_line(colour = "grey92", linewidth = 0.2),
      panel.border     = element_rect(colour = "grey80", fill = NA),
      plot.title       = element_text(hjust = 0.5),
```

```r
    legend.title     = element_blank()
  )
}

# Tema global
theme_set(theme_python())


dataset_st %>%
  select(mes, grupo_befn, grupo_cg, grupo_hidraulica, grupo_o) %>%
  pivot_longer(-mes, names_to = "grupo", values_to = "valor") %>%
  mutate(
    grupo = recode(
      grupo,
      grupo_befn       = "Biomassa, Eólica, Fotovoltaica e Nuclear",
      grupo_cg         = "Carvão e Gás",
      grupo_hidraulica = "Hidráulica",
      grupo_o          = "Óleos"
    )
  ) %>%
  ggplot(aes(x = mes, y = valor, colour = grupo)) +
  geom_line(linewidth = 0.9) +
  scale_colour_manual(values = tab10[1:4]) +
  labs(
    y = expression("CO"[2] * " emitido (Mt)"),
    x = "Mês",
    title = "Séries temporais por grupo"
  ) +
  scale_y_continuous(expand = expansion(mult = c(0, 0.02))) +
  theme(
    legend.position      = c(0.99, 0.98),   # dentro do gráfico, canto sup. dir.
    legend.justification = c(1, 1),
    legend.background    = element_rect(fill = "white", colour = "grey80"),
    legend.key.width     = unit(1.5, "lines")
  )
```




```
## 4) Séries temporais por grupos cortadas:

library(dplyr)
library(tidyr)
library(ggplot2)
library(lubridate)
library(tsibble)

# --- manter apenas TREINO (até 2023 Dez) ---
train_only <- dataset_st %>%
  filter(mes <= yearmonth("2023 Dec"))

# --- aplicar cortes ANTES de plotar ---
train_only_cut <- train_only %>%
  mutate(
    grupo_befn       = if_else(mes < yearmonth("2012 Jan"), NA_real_, grupo_befn),
    grupo_cg         = if_else(mes < yearmonth("2008 Jan"), NA_real_, grupo_cg),
    grupo_hidraulica = if_else(mes < yearmonth("2008 Jan"), NA_real_, grupo_hidraulica),
    grupo_o          = if_else(mes < yearmonth("2008 Jan"), NA_real_, grupo_o)
  )

# --- GRÁFICO (somente treinamento, séries cortadas) ---
train_only_cut %>%
  filter(mes >= yearmonth("2005 Jan")) %>%    # começa no ano desejado
  select(mes, grupo_befn, grupo_cg, grupo_hidraulica, grupo_o) %>%
  pivot_longer(-mes, names_to = "grupo", values_to = "valor") %>%
  mutate(
    grupo = recode(
      grupo,
      grupo_befn       = "Biomassa, Eólica, Fotovoltaica e Nuclear",
```

```
    grupo_cg         = "Carvão e Gás",
    grupo_hidraulica = "Hidráulica",
    grupo_o          = "Óleos"
  ),
  date = as.Date(mes)
) %>%
ggplot(aes(x = date, y = valor, colour = grupo)) +
geom_line(linewidth = 0.9, na.rm = TRUE) +
scale_colour_manual(values = tab10[1:4]) +
labs(
  title = "Séries temporais por grupo energético (cortadas)",
  x = "Mês",
  y = expression("CO"[2] * " emitido (Mt)")
) +
scale_x_date(
  limits = c(as.Date(yearmonth("2008 Jan")), max(as.Date(train_only_cut$mes))),
  expand = c(0, 0),
  date_breaks = "2 years",
  date_labels = "%Y"
) +
theme(
  legend.position      = c(0.99, 0.98),   # canto superior direito, dentro
  legend.justification = c(1, 1),
  legend.background    = element_rect(fill = "white", colour = "grey80"),
  legend.title         = element_blank()
)
```



5) Divisão dos dados em treinamento e teste:

```
# --- Treino: 2008–2023 ---
hidraulica_treino_2008_2023 <- dataset_st |>
  select(mes, grupo_hidraulica) |>
  filter_index("2008 Jan" ~ "2023 Dec")

# --- Teste: 2024–2025 ---
hidraulica_teste_2024_25 <- dataset_st |>
  select(mes, grupo_hidraulica) |>
  filter_index("2024 Jan" ~ "2025 Oct")

oleos_treino_2008_2023 <- dataset_st |>
  select(mes, grupo_o) |>
  filter_index("2008 Jan" ~ "2023 Dec")

oleos_teste_2024_25 <- dataset_st |>
  select(mes, grupo_o) |>
  filter_index("2024 Jan" ~ "2025 Oct")

cg_treino_2008_2023 <- dataset_st |>
  select(mes, grupo_cg) |>
  filter_index("2008 Jan" ~ "2023 Dec")

cg_teste_2024_25 <- dataset_st |>
  select(mes, grupo_cg) |>
  filter_index("2024 Jan" ~ "2025 Oct")

befn_treino_2012_2023 <- dataset_st |>
  select(mes, grupo_befn) |>
  filter_index("2012 Jan" ~ "2023 Dec")

befn_teste_2024_25 <- dataset_st |>
  select(mes, grupo_befn) |>
  filter_index("2024 Jan" ~ "2025 Oct")
```

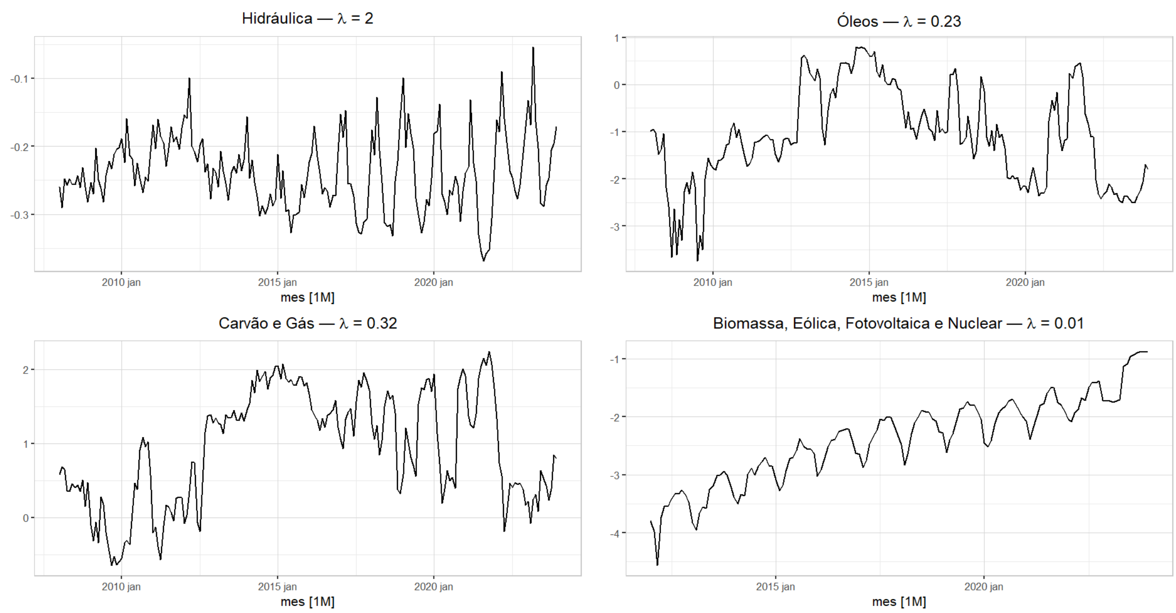
6) Transformações Box-cox:

```
library(ggplot2)
library(fabletools)
library(feasts)
library(latex2exp)
library(patchwork)

# ------------------------
# Hidráulica
# ------------------------
lambda_hid <- hidraulica_treino_2008_2023 |>
```

```
  features(grupo_hidraulica, features = guerrero) |>
  pull(lambda_guerrero)

p_hid <- hidraulica_treino_2008_2023 |>
  autoplot(box_cox(grupo_hidraulica, lambda_hid)) +
  labs(y = "",
       title = latex2exp::TeX(paste0(
         "Hidráulica — $\\lambda$ = ", round(lambda_hid,2)))) +
  theme_minimal(14)


# ------------------------
# Óleos
# ------------------------
lambda_ole <- oleos_treino_2008_2023 |>
  features(grupo_o, features = guerrero) |>
  pull(lambda_guerrero)

p_ole <- oleos_treino_2008_2023 |>
  autoplot(box_cox(grupo_o, lambda_ole)) +
  labs(y = "",
       title = latex2exp::TeX(paste0(
         "Óleos — $\\lambda$ = ", round(lambda_ole,2)))) +
  theme_minimal(14)


# ------------------------
# Carvão & Gás
# ------------------------
lambda_cg <- cg_treino_2008_2023 |>
  features(grupo_cg, features = guerrero) |>
  pull(lambda_guerrero)

p_cg <- cg_treino_2008_2023 |>
  autoplot(box_cox(grupo_cg, lambda_cg)) +
  labs(y = "",
       title = latex2exp::TeX(paste0(
         "Carvão e Gás — $\\lambda$ = ", round(lambda_cg,2)))) +
  theme_minimal(14)


# ------------------------
# Renováveis (BEFN)
# ------------------------
lambda_befn <- befn_treino_2012_2023 |>
  features(grupo_befn, features = guerrero) |>
  pull(lambda_guerrero)
```

```
p_befn <- befn_treino_2012_2023 |>
  autoplot(box_cox(grupo_befn, lambda_befn)) +
  labs(y = "",
       title = latex2exp::TeX(paste0(
          "Biomassa, Eólica, Fotovoltaica e Nuclear — $\\lambda$ = ", round(lambda_befn,2))))
+
  theme_minimal(14)


# ------------------------
# 2 x 2
# ------------------------

(p_hid | p_ole) /
(p_cg  | p_befn)


p_hid <- hidraulica_treino_2008_2023 |>
  autoplot(box_cox(grupo_hidraulica, lambda_hid)) +
  scale_colour_manual(values = tab10[1]) +
  labs(
    y = "",
    title = latex2exp::TeX(
      paste0("Hidráulica — $\\lambda$ = ", round(lambda_hid,2))
    )
  ) +
  theme(
    plot.title = element_text(hjust = 0.5),
    legend.position = "none"
  )

p_ole <- oleos_treino_2008_2023 |>
  autoplot(box_cox(grupo_o, lambda_ole)) +
  scale_colour_manual(values = tab10[2]) +
  labs(
    y = "",
    title = latex2exp::TeX(
      paste0("Óleos — $\\lambda$ = ", round(lambda_ole,2))
    )
  ) +
  theme(
    plot.title = element_text(hjust = 0.5),
    legend.position = "none"
  )

p_cg <- cg_treino_2008_2023 |>
  autoplot(box_cox(grupo_cg, lambda_cg)) +
  scale_colour_manual(values = tab10[3]) +
```

```
  labs(
    y = "",
    title = latex2exp::TeX(
      paste0("Carvão e Gás — $\\lambda$ = ", round(lambda_cg,2))
    )
  ) +
  theme(
    plot.title = element_text(hjust = 0.5),
    legend.position = "none"
  )

p_befn <- befn_treino_2012_2023 |>
  autoplot(box_cox(grupo_befn, lambda_befn)) +
  scale_colour_manual(values = tab10[4]) +
  labs(
    y = "",
    title = latex2exp::TeX(
      paste0("Biomassa, Eólica, Fotovoltaica e Nuclear — $\\lambda$ = ",
round(lambda_befn,2))
    )
  ) +
  theme(
    plot.title = element_text(hjust = 0.5),
    legend.position = "none"
  )

(p_hid | p_ole) /
(p_cg  | p_befn)
```



7) Ajuste dos modelos ARIMA (automático) para cada grupo:

```
# HIDRÁULICA
hidraulica_bc <- hidraulica_treino_2008_2023 %>%
  mutate(co2_bc = box_cox(grupo_hidraulica, lambda_hid))

# ÓLEOS
oleos_bc <- oleos_treino_2008_2023 %>%
  mutate(co2_bc = box_cox(grupo_o, lambda_ole))

# CARVÃO & GÁS
cg_bc <- cg_treino_2008_2023 %>%
  mutate(co2_bc = box_cox(grupo_cg, lambda_cg))

# BEFN (Renováveis)
befn_bc <- befn_treino_2012_2023 %>%
  mutate(co2_bc = box_cox(grupo_befn, lambda_befn))



library(fable)
library(fabletools)

# HIDRÁULICA
fit_hid_arima <- hidraulica_bc %>%
  model(
    arima = ARIMA(co2_bc, stepwise = FALSE, approx = FALSE)
  )

# ÓLEOS
fit_ole_arima <- oleos_bc %>%
  model(
    arima = ARIMA(co2_bc, stepwise = FALSE, approx = FALSE)
  )

# CARVÃO & GÁS
fit_cg_arima <- cg_bc %>%
  model(
    arima = ARIMA(co2_bc, stepwise = FALSE, approx = FALSE)
  )

# RENOVÁVEIS + NUCLEAR (BEFN)
fit_befn_arima <- befn_bc %>%
  model(
    arima = ARIMA(co2_bc, stepwise = FALSE, approx = FALSE)
  )
```

report(fit_hid_arima)
report(fit_ole_arima)
report(fit_cg_arima)
report(fit_befn_arima)

```
> report(fit_hid_arima)
Series: co2_bc
Model: ARIMA(2,0,0)(2,1,1)[12]

Coefficients:
         ar1      ar2     sar1     sar2     sma1
      0.9866  -0.1879  -0.0819  -0.2388  -0.6082
s.e.  0.0747   0.0762   0.1134   0.0902   0.1018

sigma^2 estimated as 0.0005725:  log likelihood=413.37
AIC=-814.73   AICc=-814.25   BIC=-795.58
> report(fit_ole_arima)
Series: co2_bc
Model: ARIMA(0,1,4)(2,0,0)[12]

Coefficients:
         ma1     ma2      ma3      ma4    sar1     sar2
      -0.021  0.0503  -0.2379  -0.1198  0.0836  -0.1573
s.e.   0.073  0.0711   0.0828   0.0756  0.0788   0.0831

sigma^2 estimated as 0.1702:  log likelihood=-99.3
AIC=212.6   AICc=213.21   BIC=235.36
> report(fit_cg_arima)
Series: co2_bc
Model: ARIMA(0,1,4)(2,0,0)[12]

Coefficients:
         ma1      ma2      ma3      ma4    sar1    sar2
      0.0971  -0.0947  -0.1529  -0.3150  0.0457  0.1613
s.e.  0.0710   0.0717   0.0759   0.0827  0.0723  0.0759

sigma^2 estimated as 0.08146:  log likelihood=-29.07
AIC=72.15   AICc=72.76   BIC=94.91
> report(fit_befn_arima)
Series: co2_bc
Model: ARIMA(3,0,1)(0,1,1)[12] w/ drift

Coefficients:
         ar1      ar2     ar3      ma1     sma1  constant
      0.8309  -0.1311  0.2660  -0.4601  -0.8708    0.0077
s.e.  0.1913   0.1307  0.1322   0.1838   0.1624    0.0011

sigma^2 estimated as 0.01429:  log likelihood=88
AIC=-162   AICc=-161.1   BIC=-141.82
```

8) Ajuste do e ETS com Box–Cox para cada grupo:

```
library(fable)

# HIDRÁULICA
fit_hid_ets <- hidraulica_bc %>%
  model(
    ets = ETS(co2_bc)
  )

# ÓLEOS
fit_ole_ets <- oleos_bc %>%
  model(
    ets = ETS(co2_bc)
  )

# CARVÃO & GÁS
fit_cg_ets <- cg_bc %>%
  model(
    ets = ETS(co2_bc)
  )

# BEFN
fit_befn_ets <- befn_bc %>%
  model(
    ets = ETS(co2_bc)
  )

fit_hid_ets
fit_ole_ets
fit_cg_ets
fit_befn_ets


report(fit_hid_ets)
report(fit_ole_ets)
report(fit_cg_ets)
report(fit_befn_ets)
```

```
> report(fit_hid_ets)
Series: co2_bc
Model: ETS(A,N,A)
  Smoothing parameters:
    alpha = 0.8386846
    gamma = 0.1578135

  Initial states:
        l[0]        s[0]       s[-1]        s[-2]        s[-3]          s[-4]
s[-5]       s[-6]       s[-7]
```

```
  -0.3380537  0.04870997  0.01194264  0.001345753  -0.03386021  -0.007175918
-0.03963994 -0.07013598 -0.02834456
        s[-8]      s[-9]      s[-10]     s[-11]
 -0.009038573 0.05204129 0.007170066 0.06698545

  sigma^2:  8e-04

      AIC      AICc       BIC
-348.3707 -345.6434 -299.5082
> report(fit_ole_ets)
Series: co2_bc
Model: ETS(A,N,N)
  Smoothing parameters:
    alpha = 0.9906681

  Initial states:
       l[0]
 -0.9838421

  sigma^2:  0.1844

     AIC     AICc      BIC
688.7740 688.9016 698.5464
> report(fit_cg_ets)
Series: co2_bc
Model: ETS(A,N,N)
  Smoothing parameters:
    alpha = 0.9998999

  Initial states:
     l[0]
 0.581717

  sigma^2:  0.0898

     AIC     AICc      BIC
550.7614 550.8891 560.5339
> report(fit_befn_ets)
Series: co2_bc
Model: ETS(A,A,A)
  Smoothing parameters:
    alpha = 0.276589
    beta  = 0.03029959
    gamma = 0.0001002197

  Initial states:
       l[0]        b[0]         s[0]       s[-1]      s[-2]      s[-3]     s[-4]
s[-5]      s[-6]      s[-7]
  -3.683144  0.02525095  -0.05123652  0.08197678  0.2111572  0.2626876  0.282074
0.1891946 0.1274097 0.04237296
      s[-8]      s[-9]     s[-10]     s[-11]
 -0.1369123 -0.3295867 -0.4228454 -0.256292
```

```
  sigma^2:  0.0135

     AIC      AICc       BIC 
113.0455 117.9027 163.5323
```

9) Ajuste dos modelos BENCHMARKS:

```
library(dplyr)
library(fable)
library(fabletools)
library(tsibble)

# ============================================================
#  Função correta para inversa Box–Cox
# ============================================================
# Agora shift tem valor padrão = 0  → NÃO OCORRE MAIS O ERRO
inv_box_cox <- function(y_bc, lambda, shift = 0) {
  if (abs(lambda) < 1e-8) {
    exp(y_bc) - shift
  } else {
    (lambda * y_bc + 1)^(1 / lambda) - shift
  }
}

# ============================================================
#  Utilitária para aplicar inverse BC nas colunas previstas
# ============================================================
inv_bc_across <- function(fc_tbl, lambda, cols = c(".mean", ".lower", ".upper")) {
  for (col in cols) {
    if (col %in% names(fc_tbl)) {
      fc_tbl[[col]] <- inv_box_cox(fc_tbl[[col]], lambda)
    }
  }
  fc_tbl
}

# ============================================================
#  HORIZONTES (número de períodos do teste)
# ============================================================
h_hid  <- nrow(hidraulica_teste_2024_25)
h_ole  <- nrow(oleos_teste_2024_25)
h_cg   <- nrow(cg_teste_2024_25)
h_befn <- nrow(befn_teste_2024_25)

# ============================================================
#  1) Ajustar benchmarks (na série transformada co2_bc)
# ============================================================
```

```
fit_hid_bench <- hidraulica_bc %>%
  model(
    naive  = NAIVE(co2_bc),
    snaive = SNAIVE(co2_bc),
    mean   = MEAN(co2_bc),
    drift  = RW(co2_bc ~ drift())
  )

fit_ole_bench <- oleos_bc %>%
  model(
    naive  = NAIVE(co2_bc),
    snaive = SNAIVE(co2_bc),
    mean   = MEAN(co2_bc),
    drift  = RW(co2_bc ~ drift())
  )

fit_cg_bench <- cg_bc %>%
  model(
    naive  = NAIVE(co2_bc),
    snaive = SNAIVE(co2_bc),
    mean   = MEAN(co2_bc),
    drift  = RW(co2_bc ~ drift())
  )

fit_befn_bench <- befn_bc %>%
  model(
    naive  = NAIVE(co2_bc),
    snaive = SNAIVE(co2_bc),
    mean   = MEAN(co2_bc),
    drift  = RW(co2_bc ~ drift())
  )

# ============================================================
#  2) Forecasts (escala transformada), bias_adjust = TRUE
# ============================================================
fc_hid_raw  <- forecast(fit_hid_bench,  h = h_hid,  bias_adjust = TRUE)
fc_ole_raw  <- forecast(fit_ole_bench,  h = h_ole,  bias_adjust = TRUE)
fc_cg_raw   <- forecast(fit_cg_bench,   h = h_cg,   bias_adjust = TRUE)
fc_befn_raw <- forecast(fit_befn_bench, h = h_befn, bias_adjust = TRUE)

# ============================================================
#  3) Inversão da Box–Cox (.mean / .lower / .upper)
# ============================================================
fc_hid  <- inv_bc_across(as_tibble(fc_hid_raw),  lambda_hid)
fc_ole  <- inv_bc_across(as_tibble(fc_ole_raw),  lambda_ole)
fc_cg   <- inv_bc_across(as_tibble(fc_cg_raw),   lambda_cg)
fc_befn <- inv_bc_across(as_tibble(fc_befn_raw), lambda_befn)
```

```
# ============================================================
#  4) Preparar dataframes finais (observado + previsão)
# ============================================================
fc_hid_df  <- fc_hid  %>% select(mes, .model, pred = .mean)
fc_ole_df  <- fc_ole  %>% select(mes, .model, pred = .mean)
fc_cg_df   <- fc_cg   %>% select(mes, .model, pred = .mean)
fc_befn_df <- fc_befn %>% select(mes, .model, pred = .mean)

hid_join <- hidraulica_teste_2024_25 %>%
  as_tibble() %>%
  select(mes, obs = grupo_hidraulica) %>%
  left_join(fc_hid_df, by = "mes")

ole_join <- oleos_teste_2024_25 %>%
  as_tibble() %>%
  select(mes, obs = grupo_o) %>%
  left_join(fc_ole_df, by = "mes")

cg_join <- cg_teste_2024_25 %>%
  as_tibble() %>%
  select(mes, obs = grupo_cg) %>%
  left_join(fc_cg_df, by = "mes")

befn_join <- befn_teste_2024_25 %>%
  as_tibble() %>%
  select(mes, obs = grupo_befn) %>%
  left_join(fc_befn_df, by = "mes")
```

10) Previsões e geração dos gráficos

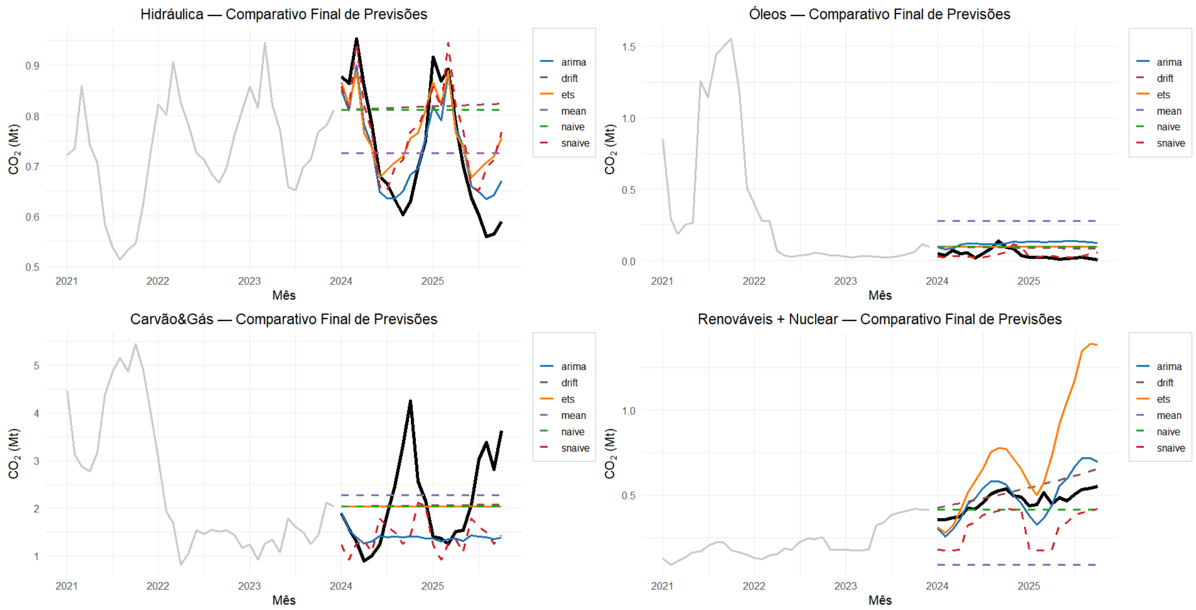
```
library(dplyr)
library(tsibble)
library(fable)
library(fabletools)
library(feasts)
library(ggplot2)
library(patchwork)

#--------------------------------------------------
# 1) Função genérica para gerar forecast + intervalos
#--------------------------------------------------
fc_models <- function(fit, h, lambda) {
  fit |>
    forecast(h = h, bias_adjust = TRUE) |>
    hilo(level = 95) |>
    unpack_hilo(`95%`) |>
    rename(
```

```
    .lower = `95%_lower`,
    .upper = `95%_upper`
  ) |>
  as_tibble() |>
  mutate(
    .mean  = inv_box_cox(.mean,  lambda),
    .lower = inv_box_cox(.lower, lambda),
    .upper = inv_box_cox(.upper, lambda)
  )
}

#--------------------------------------------------
# 2) Configuração dos grupos
#--------------------------------------------------
groups <- list(
  list(grupo = "Hidráulica",
       lambda = lambda_hid,
       train = hidraulica_treino_2008_2023,
       test  = hidraulica_teste_2024_25,
       fits = list(
         arima = fit_hid_arima,
         ets   = fit_hid_ets,
         bench = fit_hid_bench
       )),

  list(grupo = "Óleos",
       lambda = lambda_ole,
       train = oleos_treino_2008_2023,
       test  = oleos_teste_2024_25,
       fits = list(
         arima = fit_ole_arima,
         ets   = fit_ole_ets,
         bench = fit_ole_bench
       )),

  list(grupo = "Carvão&Gás",
       lambda = lambda_cg,
       train = cg_treino_2008_2023,
       test  = cg_teste_2024_25,
       fits = list(
         arima = fit_cg_arima,
         ets   = fit_cg_ets,
         bench = fit_cg_bench
       )),

  list(grupo = "Renováveis + Nuclear",
       lambda = lambda_befn,
       train = befn_treino_2012_2023,
```

```
    test  = befn_teste_2024_25,
    fits = list(
      arima = fit_befn_arima,
      ets   = fit_befn_ets,
      bench = fit_befn_bench
    ))
)

#--------------------------------------------------
# 3) Cores (tab10) igual ao Python
#--------------------------------------------------
model_colors <- c(
  "arima"  = "#1f77b4",  # azul
  "ets"    = "#ff7f0e",  # laranja
  "naive"  = "#2ca02c",  # verde
  "snaive" = "#d62728",  # vermelho
  "mean"   = "#9467bd",  # roxo
  "drift"  = "#8c564b"   # marrom
)

# Linhas: modelos principais = sólida, benchmarks = tracejada
model_linetype <- c(
  "arima"  = "solid",
  "ets"    = "solid",
  "naive"  = "dashed",
  "snaive" = "dashed",
  "mean"   = "dashed",
  "drift"  = "dashed"
)

# helper simples pra pegar a coluna do grupo como 'obs'
get_grupo_obs <- function(df) {
  col <- grep("grupo", names(df), value = TRUE)
  if (length(col) == 0) {
    stop("Nenhuma coluna contendo 'grupo' encontrada.")
  }
  df[[col[1]]]
}

plots <- list()

#--------------------------------------------------
# 4) Loop para gerar gráficos no estilo Python final
#--------------------------------------------------
for (g in groups) {

  grupo   <- g$grupo
  lambda  <- g$lambda
```

```r
train   <- g$train
test    <- g$test
fits    <- g$fits
h       <- nrow(test)

# Forecasts de cada modelo
fc_arima <- fc_models(fits$arima, h, lambda)
fc_ets   <- fc_models(fits$ets,   h, lambda)
fc_bench <- fc_models(fits$bench, h, lambda)

fc_all <- bind_rows(fc_arima, fc_ets, fc_bench) |>
  mutate(
    mes    = as.Date(mes),
    .model = as.character(.model)   # garante compatível com escalas manuais
  )

# Histórico (últimos 36 meses do treino)
hist_obs <- train |>
  mutate(
    mes = as.Date(mes),
    obs = get_grupo_obs(cur_data_all())
  ) |>
  dplyr::slice_tail(n = 36)

# Série real (teste)
real_obs <- test |>
  mutate(
    mes = as.Date(mes),
    obs = get_grupo_obs(cur_data_all())
  )

# --------------------------
#  Gráfico Estilo Python
# --------------------------
p <- ggplot() +

  # Histórico em cinza
  geom_line(
    data   = hist_obs,
    aes(x = mes, y = obs),
    colour = "grey75",
    linewidth = 1.2,
    alpha  = 0.8
  ) +

  # Série REAL (preto grosso)
  geom_line(
    data   = real_obs,
```

```
    aes(x = mes, y = obs),
    colour = "black",
    linewidth = 1.6
  ) +

  # Previsões (todas)
  geom_line(
    data = fc_all,
    aes(x = mes, y = .mean, colour = .model, linetype = .model),
    linewidth = 1.1
  ) +

  scale_colour_manual(values = model_colors) +
  scale_linetype_manual(values = model_linetype) +

  labs(
    title    = paste0(grupo, " — Comparativo Final de Previsões"),
    x        = "Mês",
    y        = expression("CO"[2] * " (Mt)"),
    colour   = "",
    linetype = ""
  ) +

  theme_minimal(base_size = 13) +
  theme(
    legend.position      = c(1.02, 1),
    legend.justification = c(0, 1),
    legend.background    = element_rect(fill = "white", colour = "grey80"),
    plot.margin          = margin(5.5, 80, 5.5, 5.5),
    plot.title           = element_text(hjust = 0.5)
  )

 # guarda usando o nome do grupo
 plots[[grupo]] <- p
}

#---------------------------------------------------
# 5) Exibir tudo em 2x2
#---------------------------------------------------
(p1 <- plots[[1]] | plots[[2]])
(p2 <- plots[[3]] | plots[[4]])
p1 / p2
```



11) Identificação dos melhores modelos para cada série temporal por grupo:

```
calc_metrics <- function(df) {
  df %>%
    summarise(
      RMSE = sqrt(mean((obs - pred)^2, na.rm = TRUE)),
      MAE  = mean(abs(obs - pred), na.rm = TRUE),
      MAPE = mean(abs((obs - pred) / obs), na.rm = TRUE) * 100
    )
}

metrics_list <- list()

for(g in groups) {

  grupo   <- g$grupo
  lambda  <- g$lambda
  train   <- g$train
  test    <- g$test
  fits    <- g$fits
  h       <- nrow(test)

  # forecasts já transformados para a escala original
  fc_arima <- fc_models(fits$arima, h, lambda)
  fc_ets   <- fc_models(fits$ets,   h, lambda)
  fc_bench <- fc_models(fits$bench, h, lambda)

  fc_all <- bind_rows(fc_arima, fc_ets, fc_bench) %>%
    mutate(mes = as.Date(mes))
```

```
  # Observado (apenas teste)
  obs_test <- test %>%
    mutate(
      mes = as.Date(mes),
      obs = dplyr::coalesce(
        across(contains("grupo")) |> unlist()
      )
    ) %>%
    select(mes, obs)

  # juntar previsões x observados
  joined <- fc_all %>%
    left_join(obs_test, by = "mes") %>%
    rename(pred = .mean)

  # calcular métricas por modelo
  metrics <- joined %>%
    group_by(.model) %>%
    calc_metrics() %>%
    mutate(grupo = grupo) %>%
    select(grupo, modelo = .model, RMSE, MAE, MAPE)

  metrics_list[[grupo]] <- metrics
}

# resultado final
metrics_all <- bind_rows(metrics_list) %>%
  arrange(grupo, RMSE)

print(metrics_all)
```

```
> print(metrics_all)
# A tibble: 24 × 5
   grupo       modelo   RMSE    MAE  MAPE
   <chr>       <chr>   <dbl>  <dbl> <dbl>
 1 Carvão&Gás  drift  0.917  0.764  41.3
 2 Carvão&Gás  ets    0.923  0.768  41.1
 3 Carvão&Gás  naive  0.923  0.768  41.1
 4 Carvão&Gás  mean   0.934  0.818  48.3
 5 Carvão&Gás  snaive 1.13   0.805  32.2
 6 Carvão&Gás  arima  1.16   0.808  30.4
 7 Hidráulica  arima  0.0521 0.0439  6.20
 8 Hidráulica  snaive 0.0803 0.0648  9.82
 9 Hidráulica  ets    0.0828 0.0678 10.3
10 Hidráulica  mean   0.124  0.111  15.3
```

```
best_models <- metrics_all %>%
```

```
  group_by(grupo) %>%
  slice_min(RMSE, n = 1, with_ties = FALSE)

print(best_models)
```

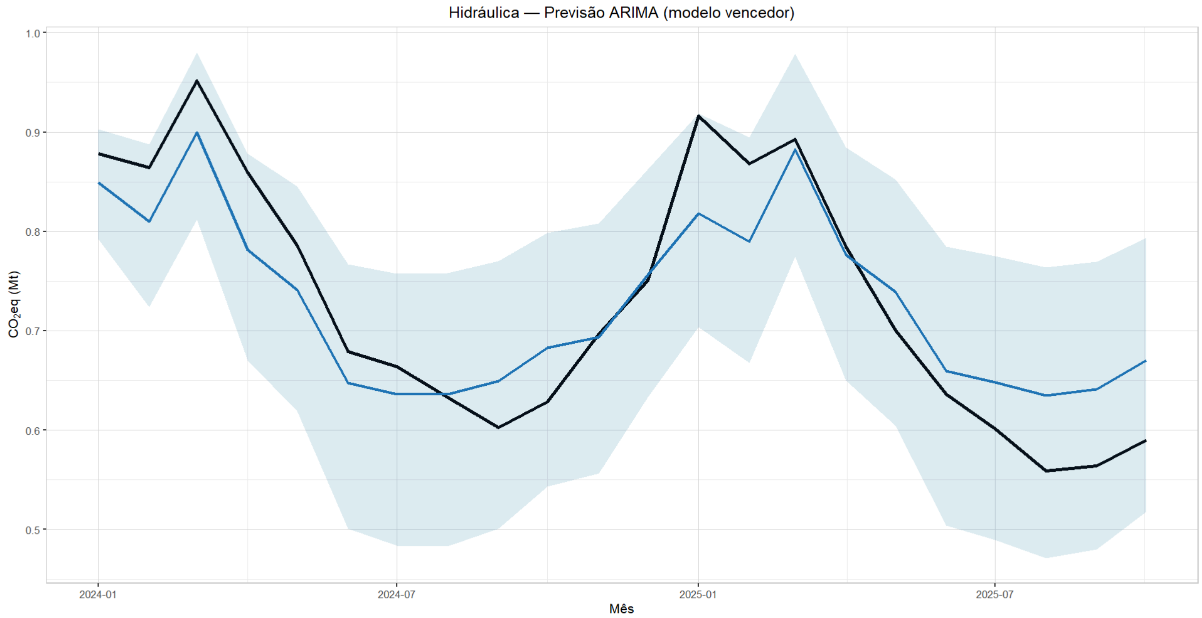
```
> print(best_models)
# A tibble: 4 × 5
# Groups:   grupo [4]
  grupo                modelo   RMSE    MAE   MAPE
  <chr>                <chr>   <dbl>  <dbl>  <dbl>
1 Carvão&Gás           drift  0.917  0.764   41.3
2 Hidráulica           arima  0.0521 0.0439   6.20
3 Renováveis + Nuclear naive  0.0781 0.0682  14.2
4 Óleos                snaive 0.0348 0.0265 108.
```

12) Geração dos gráfico com a série temporal hidráulica com o melhor modelo ajustado (ARIMA):

```
library(dplyr)
library(tsibble)
library(fable)
library(fabletools)
library(feasts)
library(ggplot2)

# h = tamanho do conjunto de teste
h_hid <- nrow(hidraulica_teste_2024_25)

# ------------------------------------------------
# 1) Forecast ARIMA vencedor + IC 95% (escala original)
# ------------------------------------------------
fc_hid <- fit_hid_arima |>
  forecast(h = h_hid, bias_adjust = TRUE) |>
  hilo(95) |>
  unpack_hilo(`95%`) |>
  rename(
    .lower = `95%_lower`,
    .upper = `95%_upper`
  ) |>
  as_tibble() |>
  mutate(
    .mean  = inv_box_cox(.mean,  lambda_hid),
    .lower = inv_box_cox(.lower, lambda_hid),
    .upper = inv_box_cox(.upper, lambda_hid),
    mes    = as.Date(mes)
  )
```

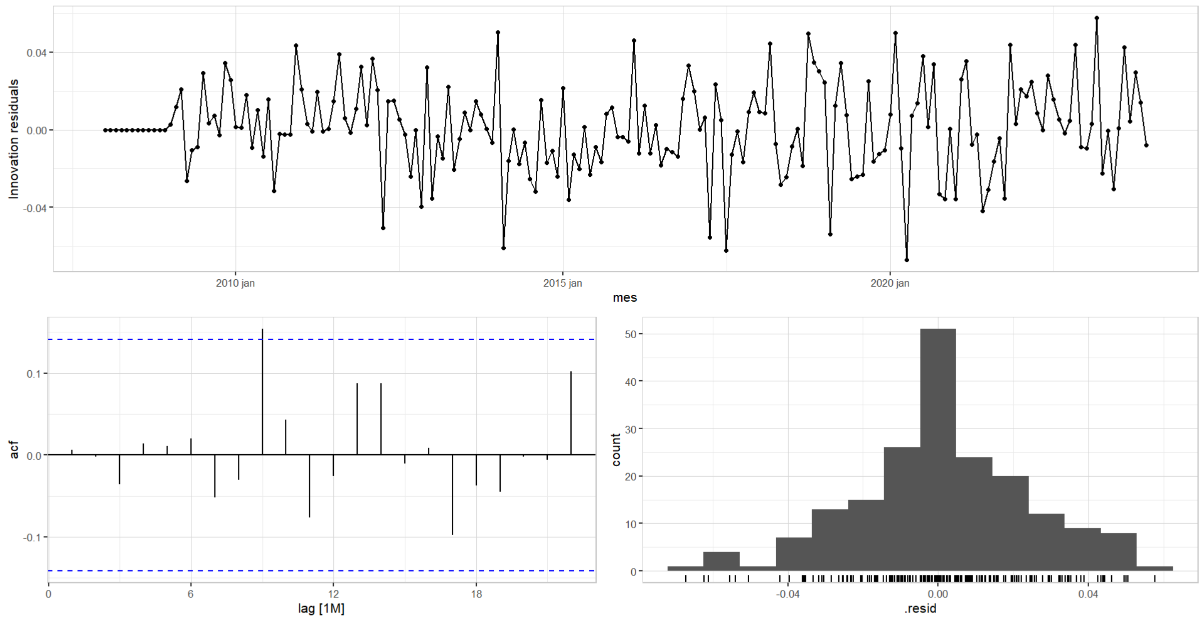
```
# --------------------------------------------------
# 2) Séries observadas (treino + teste)
# --------------------------------------------------
obs_full <- dataset_st |>
  select(mes, obs = grupo_hidraulica) |>
  mutate(mes = as.Date(mes))

obs_test <- hidraulica_teste_2024_25 |>
  select(mes, obs = grupo_hidraulica) |>
  mutate(mes = as.Date(mes))

# --------------------------------------------------
# FILTRO PARA PLOTAR APENAS A PARTIR DE 2024-01-01
# --------------------------------------------------
obs_full <- obs_full %>% filter(mes >= as.Date("2024-01-01"))
obs_test <- obs_test %>% filter(mes >= as.Date("2024-01-01"))
fc_hid   <- fc_hid   %>% filter(mes >= as.Date("2024-01-01"))

# --------------------------------------------------
# 3) Gráfico Estilo Python (igual ao notebook)
# --------------------------------------------------
p_hid <- ggplot() +

  # Histórico em cinza claro
  geom_line(
    data = obs_full,
    aes(x = mes, y = obs),
    colour   = "grey75",
    linewidth = 1.2,
    alpha     = 0.8
  ) +

  # Série REAL de teste (preto grosso)
  geom_line(
    data = obs_test,
    aes(x = mes, y = obs),
    colour   = "black",
    linewidth = 1.6
  ) +

  # Faixa do IC (em azul claro = tab10 azul com alta transparência)
  geom_ribbon(
    data = fc_hid,
    aes(x = mes, ymin = .lower, ymax = .upper),
    fill  = tab10[1],
    alpha = 0.15
  ) +
```

```
# Linha de previsão em azul (tab10)
geom_line(
  data = fc_hid,
  aes(x = mes, y = .mean),
  colour    = tab10[1],
  linewidth = 1.3
) +

labs(
  title     = "Hidráulica — Previsão ARIMA (modelo vencedor)",
  x = "Mês",
  y = expression("CO"[2] * "eq (Mt)"),
  colour    = ""
) +

theme(
  plot.title  = element_text(hjust = 0.5),
  plot.subtitle = element_text(hjust = 0.5),
  legend.position      = "none",     # igual ao Python
  panel.grid.minor     = element_line(colour = "grey92", linewidth = 0.25),
  panel.grid.major     = element_line(colour = "grey85", linewidth = 0.40)
)

print(p_hid)
```



13) Diagnóstico dos resíduos e teste Ljung Box

```
fit_hid_arima |> gg_tsresiduals()

fit_hid_arima |>
  augment() |>
  features(.innov, ljung_box, lag = 24)
```




```
+     features(.innov, ljung_box, lag = 24)
# A tibble: 1 × 3
  .model lb_stat lb_pvalue
  <chr>    <dbl>     <dbl>
1 arima     23.2     0.507
```