```
import os, sys
from google.colab import drive
drive.mount('/content/mnt', force_remount=True)
nb_path = '/content/notebooks'
os.symlink('/content/mnt/My Drive/Colab Notebooks/Librerias', nb_path)
#sys.path.insert(0, nb_path)  # or append(nb_path)
sys.path.append(nb_path)  # or append(nb_path)
```

```
Mounted at /content/mnt
```

```
import warnings
warnings.filterwarnings('ignore')
```

Predicción de Series Temporales

Bibliografía

- Hyndman, R. J., A. B. Koehler, J. K. Ord and R. D. Snyder (2008). Forecasting with exponential smoothing: the state space approach. Berlin: Springer-Verlag.

- Hydman, Rob y George Athanasopoulos (2015). "Forecasting: principles and practice". Otexts. *https://www.otexts.org/fpp*
- Gardner Jr, E. S. (1985). Exponential smoothing: The state of the art. Journal of Forecasting 4(1), 1–28.
- Gardner Jr, E. S. (2006). Exponential smoothing: The state of the art—Part II. International Journal of Forecasting 22(4), 637–666.

Una **serie temporal** es una sucesión de observaciones de una variable tomadas en varios instantes de tiempo:

- Interesa estudiar los cambios en esa variable con respeto al tiempo.
- Predecir sus valores futuros.

Problema:

Estas observaciones provienen de una distribución que puede ser diferente en cada instante del tiempo.

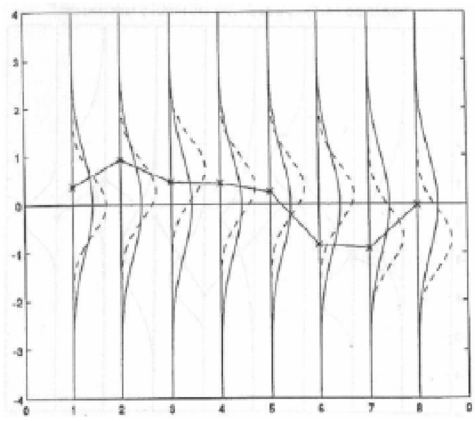
Estacionariedad:

- Una serie **es estacionaria** si la media y la variabilidad se mantienen constantes a lo largo del tiempo.

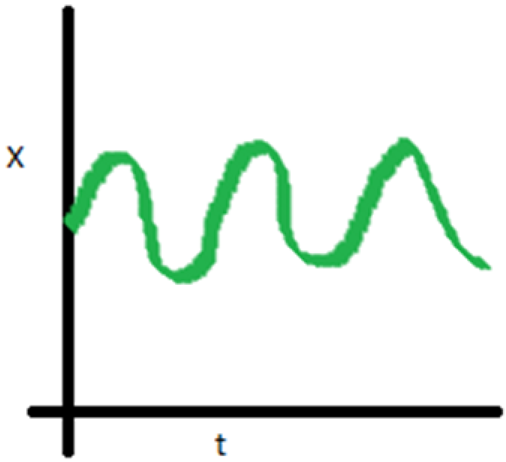
- Una serie **es no estacionaria** si la media y/o la variabilidad cambian a lo largo del tiempo.:
  - Series no estacionarias pueden mostrar cambios de varianza.
  - Series no estacionarias pueden mostrar una tendencia, es decir que la media crece o baja a lo largo del tiempo.
  - Además, pueden presentar efectos estacionales, es decir que el comportamiento de la serie es parecido en ciertos tiempos periódicos en el tiempo.

Definición 3. *Una serie temporal es* **estacionaria** *en sentido amplio si:*

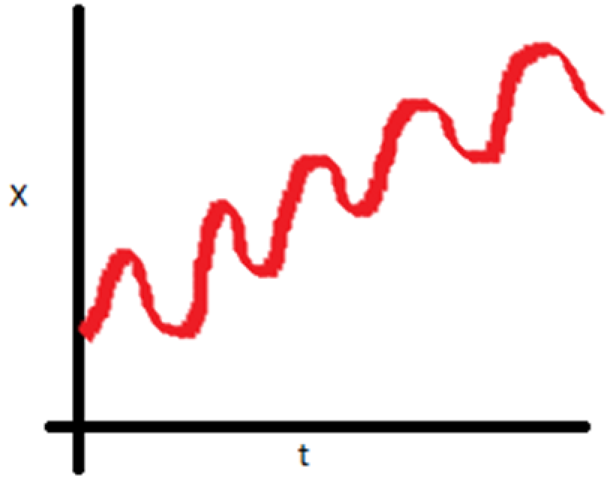
- $E[X_t] = \mu$ *para todo* t
- $Var(X_t) = \sigma^2$ *para todo* t.
- $Cov(X_t, X_{t+k}) = \gamma_k$ *para todo* t *y* k.



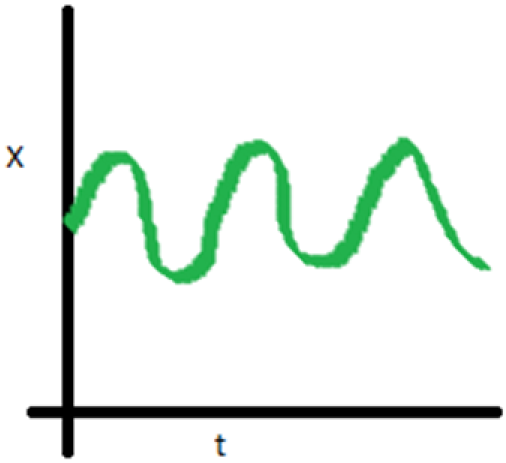
El ejemplo más simple es el RUIDO BLANCO, cuando la media y la covarianza son siempre cero.



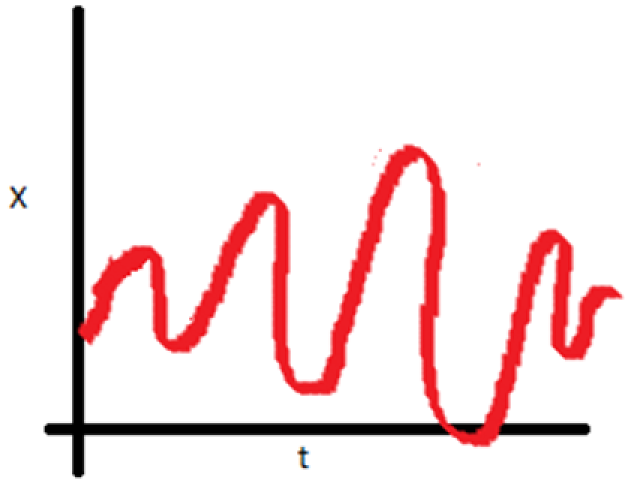
Stationary series



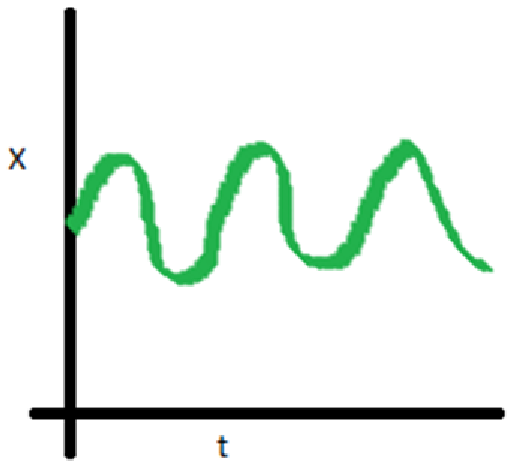
Non-Stationary series



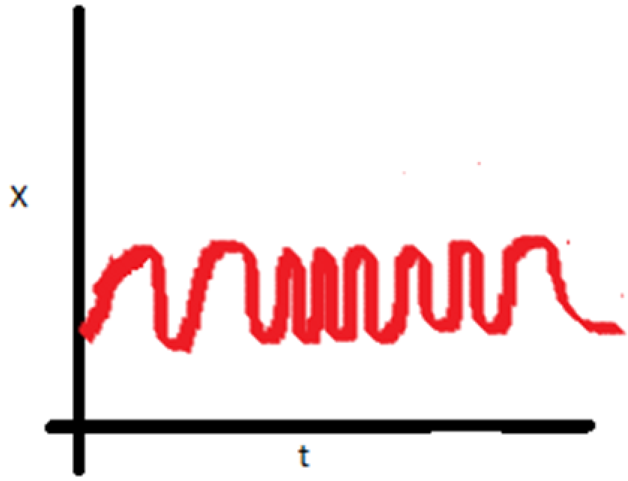
Stationary series



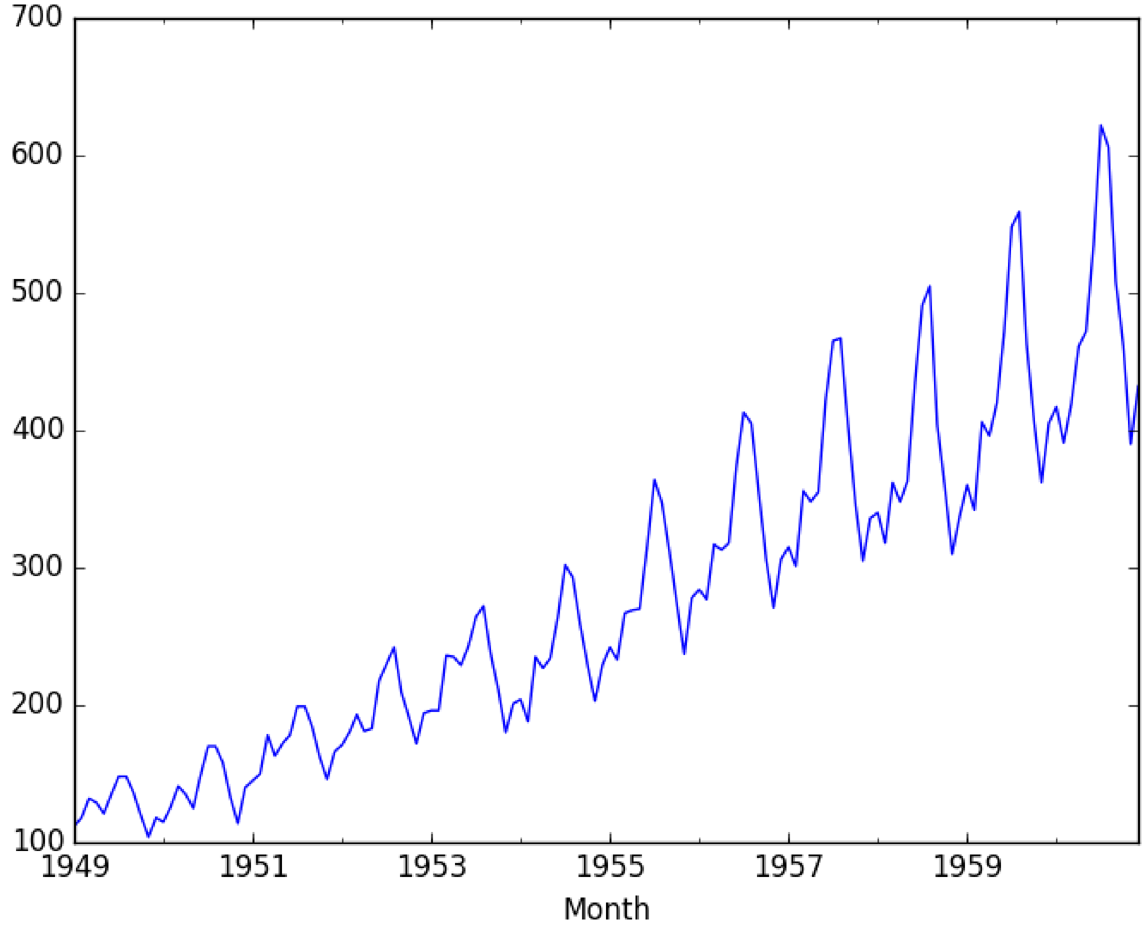
Non-Stationary series



Stationary series



Non-Stationary series



Series Temporales

¿Por qué es bueno que las series sean estacionarias?

- Con series estacionarias podemos obtener predicciones fácilmente.
- Como la media es constante, podemos estimarla con todos los datos, y utilizar este valor para predecir una nueva observación.
- También se pueden obtener intervalos de predicción (confianza) para las predicciones asumiendo que X_t sigue una distribución conocida, por ejemplo, normal.

Series temporales: Componentes

Componentes de una serie temporal

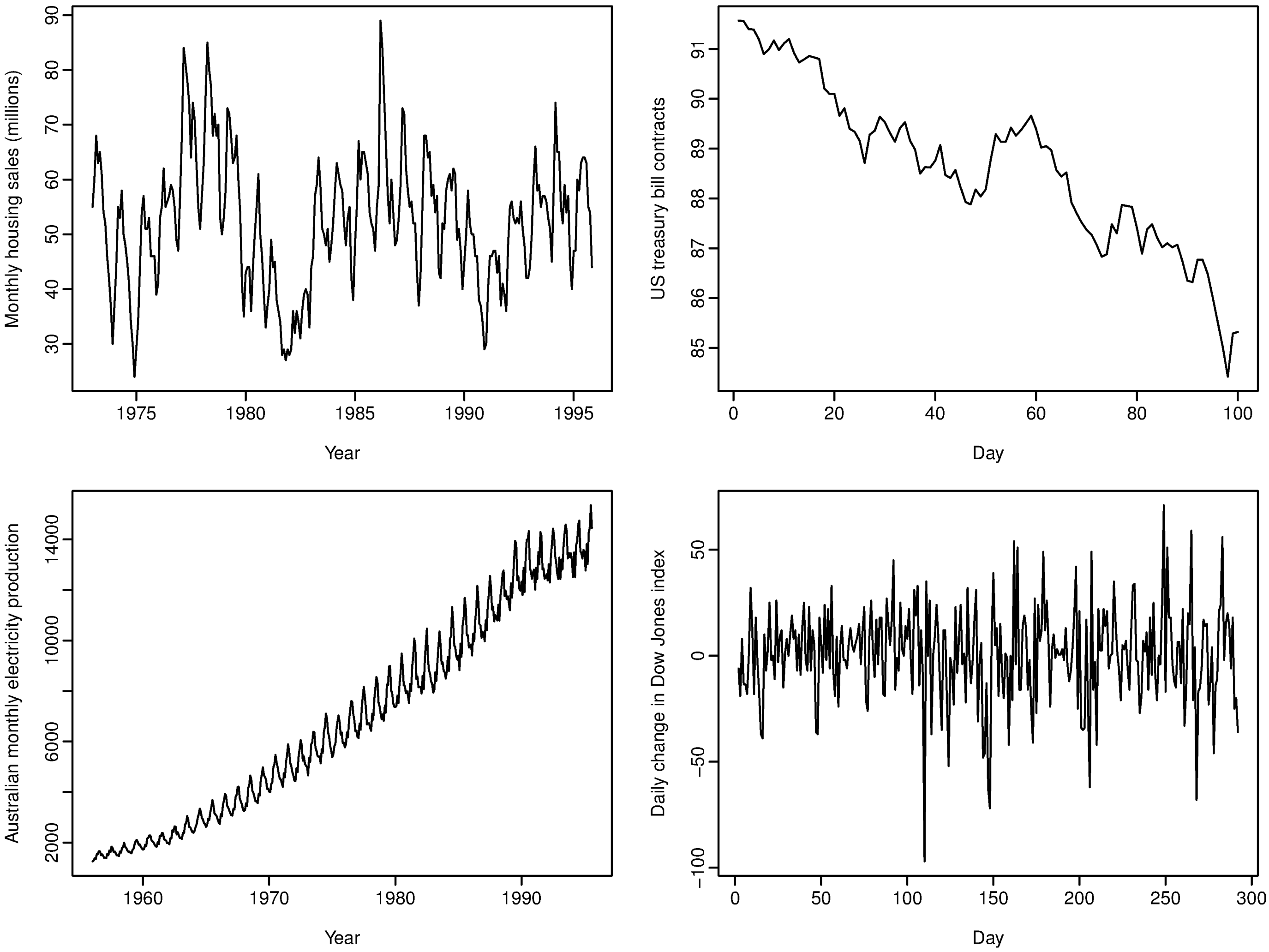
- En muchos casos, se supone que la serie temporal es la suma de varias componentes:

$$Y_t = T_t + S_t + E_t$$

Valor observado = Tendencia + Estacionalidad + Irregular

- **Tendencia:** comportamiento o movimiento suave de la serie a largo plazo. Puede ser creciente o decreciente y no tiene por que ser lineal. A veces incluye el ciclo (tendencia_ciclo).
- **Estacionalidad:** movimientos de oscilación dentro del año (trimestral, mensual, diario). La estacionalidad siempre es de un periodo fijo y conocido. No confundir con los ciclos que no tienen duración fija y como mínimo son de dos años.
- **Irregular:** variaciones aleatorias alrededor de los componentes anteriores.

Componentes



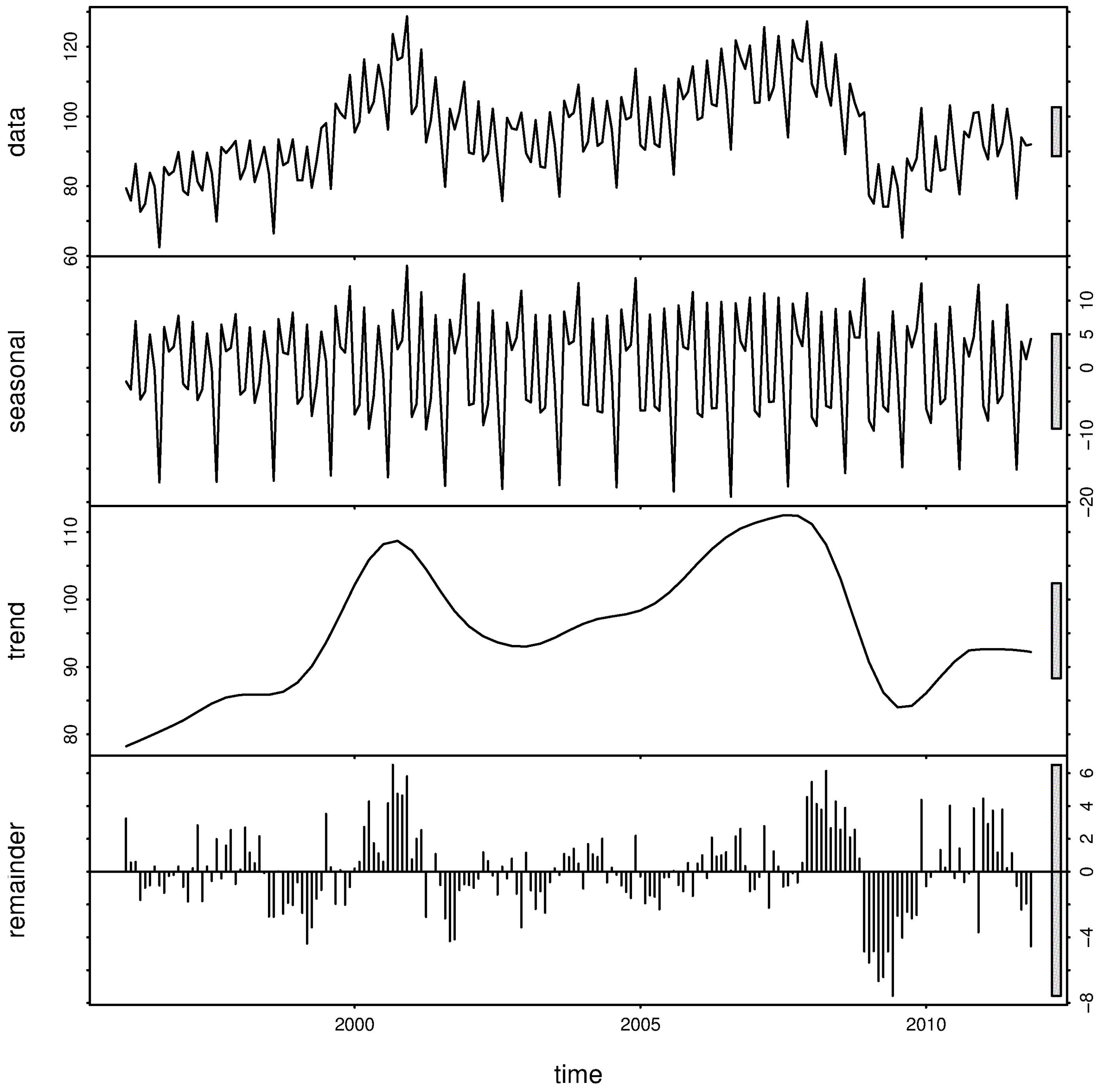
- Las ventas de casas muestra un componente estacional y uno cíclico. No parece que exista tendencia.
- Los t-bill no son estacionales pero tiene tendencia decreciente.
- La producción de electricidad tiene una fuerte tendencia y una fuerte estacionalidad.
- Los rendimientos del Dow Jones no tiene ni tendencia ni componentes estacional.

Modelo Multiplicativo

- El modelo también se puede expresar en forma multiplicativa cuando las variaciones alrededor de la tendencia son proporcionales al nivel de la serie temporal.
- Para ello se debe realizar una transformación logarítmica para que la variación de la serie sea estable:

$$Y_t = T_t \times S_t \times E_t$$
$$lnY_t = lnT_t + lnS_t + lnE_t$$

Ejemplo Descomposición:



Suavizado Exponencial

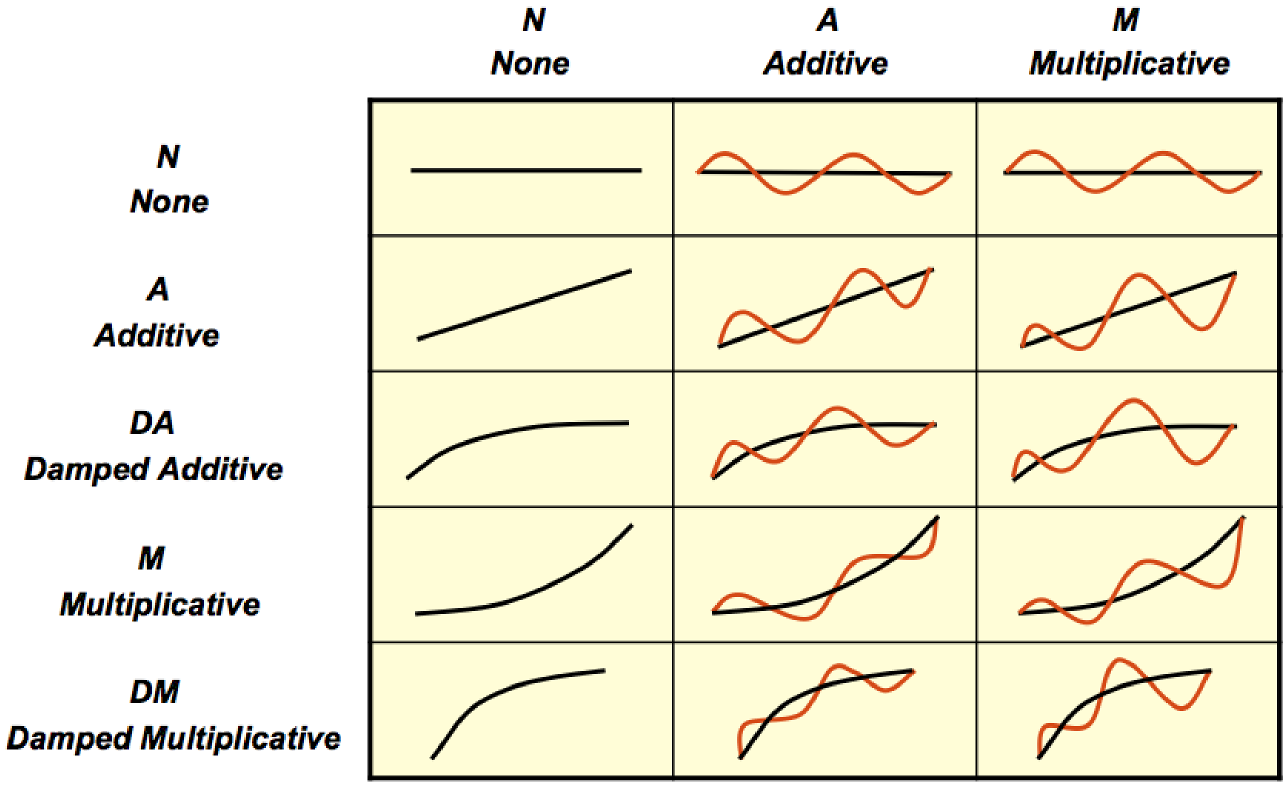
Modelos de Suavizado Exponencial

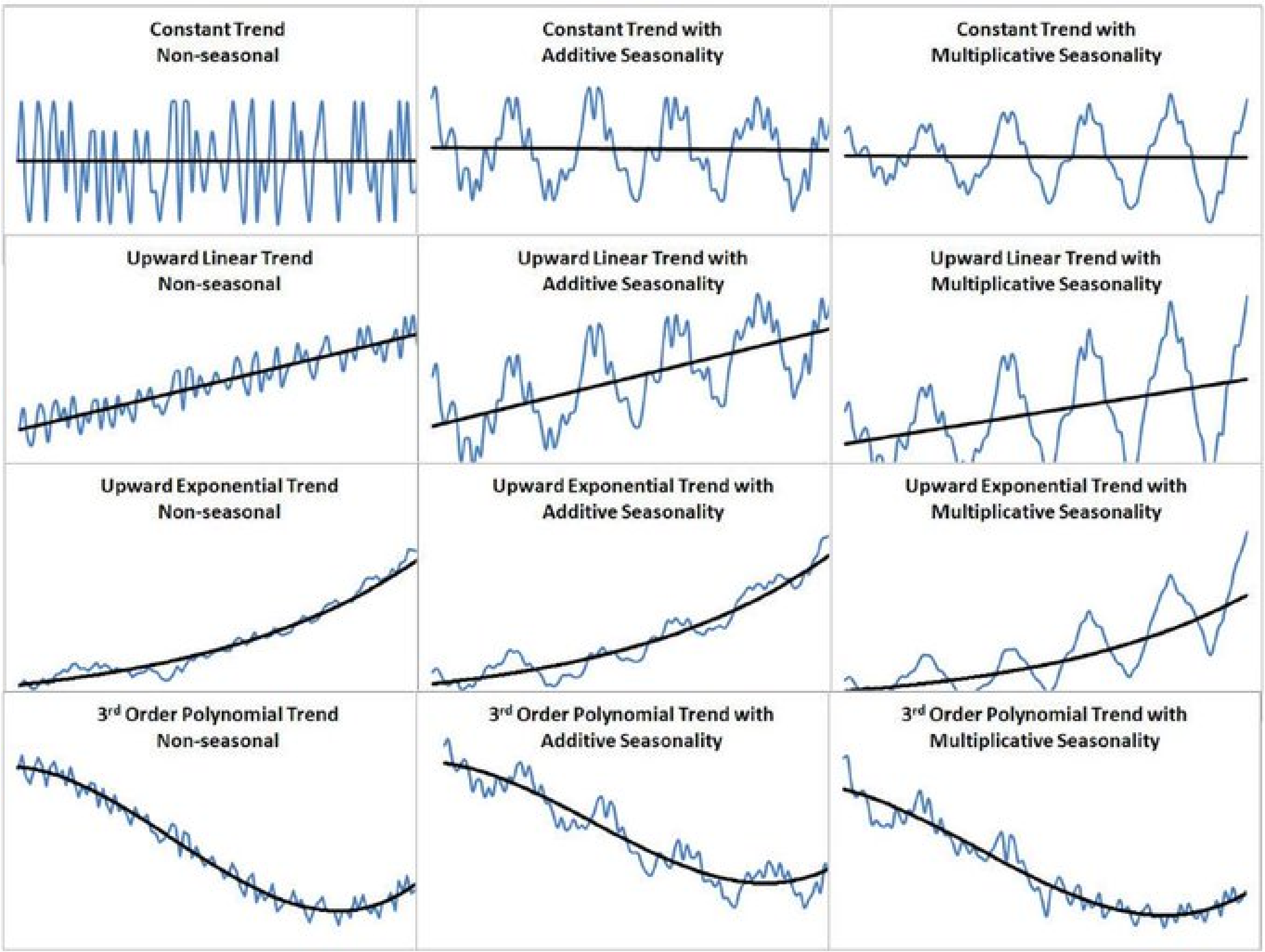
- Se emplean fundamentalmente para predecir nuevos valores de la serie.
- Se basan en modelos paramétricos deterministas que se ajustan a la evolución de la serie.
- Las observaciones más recientes tienen más peso en la predicción que las más alejadas.
- Se resuelven por métodos recursivos.

Modelos ETS

$$Y_t = T_t + S_t + E_t \quad \rightarrow \quad \text{Modelo Aditivo}$$
$$Y_t = T_t \times S_t \times E_t \quad \rightarrow \quad \text{Modelo Multiplicativo}$$

Trend Component		Seasonal Component N (None)	A (Additive)	M (Multiplicative)
N	(None)	N,N	N,A	N,M
A	(Additive)	A,N	A,A	A,M
A_d	(Additive damped)	A_d,N	A_d,A	A_d,M
M	(Multiplicative)	M,N	M,A	M,M
M_d	(Multiplicative damped)	M_d,N	M_d,A	M_d,M


N
None
A
Additive
M
Multiplicative
N
None
A
Additive
DA
Damped Additive
M
Multiplicative
DM
Damped Multiplicative


Constant Trend
Non-seasonal
Constant Trend with
Additive Seasonality
Constant Trend with
Multiplicative Seasonality
Upward Linear Trend
Non-seasonal
Upward Linear Trend with
Additive Seasonality
Upward Linear Trend with
Multiplicative Seasonality
Upward Exponential Trend
Non-seasonal
Upward Exponential Trend with
Additive Seasonality
Upward Exponential Trend with
Multiplicative Seasonality
3rd Order Polynomial Trend
Non-seasonal
3rd Order Polynomial Trend with
Additive Seasonality
3rd Order Polynomial Trend with
Multiplicative Seasonality

(N,N)	=	simple exponential smoothing
(A,N)	=	Holts linear method
(M,N)	=	Exponential trend method
(A_d,N)	=	additive damped trend method
(M_d,N)	=	multiplicative damped trend method
(A,A)	=	additive Holt-Winters method
(A,M)	=	multiplicative Holt-Winters method
(A_d,M)	=	Holt-Winters damped method

Selección de Modelos

¿Cómo seleccionar un modelo de entre varios candidatos?

- Utilizando los **Criterios de Información (IC)**:
    - Cuantifican la información residual. Cuanto más información tienen los residuos del modelo mayor es el IC, por lo tanto peor es el modelo.
    - Suponemos que tenemos k modelos alternativos, $M_1, M_2, \cdots,M_j,\cdots,M_k$, Se elige el j que **minimice**:

      $$IC(j)=ln\hat \sigma_j^2+\frac{C(T)}{T}$$

      donde $\hat \sigma_j^2$ es la varianza residual del modelo, T es el tamaño muestral y $C(T)$ es el término de penalización (penalty).
    - AIC (Akaike Information Criterium): $C(T)=2$
    - BIC (Bayesian Information Criterium): $C(T)=lnT$
    - HQ (Hannan-Quin Information Criterium): $C(T)=2\cdot ln(lnT)$

Precisión de las Predicciones

Precisión de las Predicciones

- Error de predicción:

$$e_t = y_t - \hat{y}_t \quad t = 1 \cdots h$$

- Medidas Absolutas (dependen de las unidades de medida):
    - Mean absolute error (MAE) = $\sum \frac{|e_t|}{h}$
    - Mean squared error (MSE) = $\sum \frac{e_t^2}{h}$
    - Root mean squared error (RMSE) = $\sqrt{MSE}$

Precisión de las Predicciones

- Medidas Relativas (expresadas en %, y no dependen de las unidades de medida)
  - Porcentaje de error: $p_t = 100\frac{e_t}{y_t}$
  - Mean absolute percentage error (MAPE) = $\sum \frac{|p_t|}{h}$

Precisión de las Predicciones

- Medidas Escaladas (se escalan los errores con respecto al modelo naïve)
  - Modelo naïve: $\hat{y}_t = y_{t-1}$
  - Error modelo naïve: $n_t = y_t - y_{t-1}$
  - Scaled error: $q_t = \frac{e_t}{\sum \frac{|n_t|}{h}}$
  - Mean absolute scaled error (MASE): $\sum \frac{|q_t|}{h}$

CP 01: Predicción Ingresos Coca-Cola (KO)

Introducción

- El objetivo es predecir las ventas de Coca-Cola.
- Se realizan diferentes predicciones de las ventas de Coca-Cola.
- Se tienen datos trimestrales desde 1991-1T hasta 2021-2T.
- Se dejan fuera de la estimación los ocho últimos trimestres para seleccionar el mejor modelo.
- Se prueban todos los modelos de suavizados exponencial.

```
# Packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
# Read Data
ko_df = pd.read_csv('/content/mnt/My Drive/Colab Notebooks/Series Temporales/S01/ko
ko_df['Fecha'] = pd.to_datetime(ko_df['Fecha'],format="%Y%m%d")
ko_df = ko_df.set_index('Fecha')
```

```
ko_df.head()
```

Fecha	Ingresos
2021-06-03	10129
2021-03-03	9020
2020-12-31	8611
2020-09-26	8652
2020-06-27	7150

Convertimos los datos en trimestrales

```
ko_ts=ko_df.resample("q").last()
#ko_ts=ko_df['Ingresos'].astype('float64').to_period('Q')
ko_ts.tail()
```

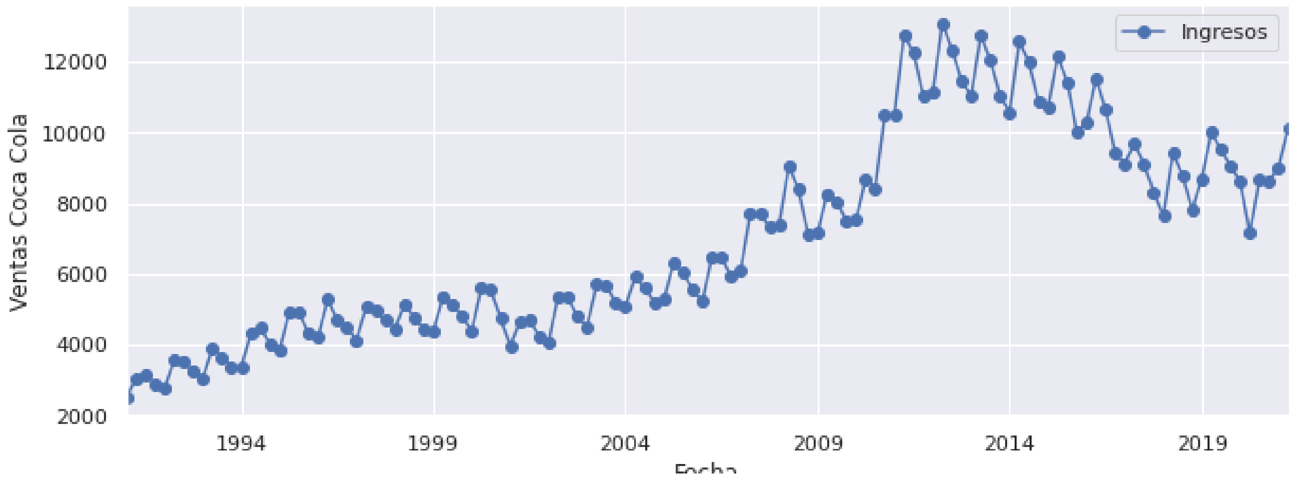
Fecha	Ingresos
2020-06-30	7150
2020-09-30	8652
2020-12-31	8611
2021-03-31	9020
2021-06-30	10129

Solución

Graficar los Ingresos

- Tendencia - Componente Estacional - Varianza no constante

```
import seaborn as sns
# Use seaborn style defaults and set the default figure size
sns.set(rc={'figure.figsize':(11, 4)})
ax = ko_ts.plot(marker='o', linestyle='-')
ax.set_ylabel('Ventas Coca Cola');
```



Analizamos la estacinalidad

- Componente estacional
- Las Ventas dependen del trimestre
- Más ventas en el 2T y en el 3T
- El Componente estacional no es estacionario

```
import statsmodels.api as sm
```

```
ax = plt.gca()
sm.graphics.tsa.quarter_plot(ko_ts['Ingresos'],ax=ax)
ax.set_title('Comportamiento Estacional')
```

```
Text(0.5, 1.0, 'Comportamiento Estacional')
```

Modelos de Suavizado Exponencial

Vamos a separar la muestra en la parte de estiamción (Training) y la parte de predicción/Verificación (Testing). Quitamos 8 trimestres.

Vamos a predecir 4 periodos (un año) (h=4)

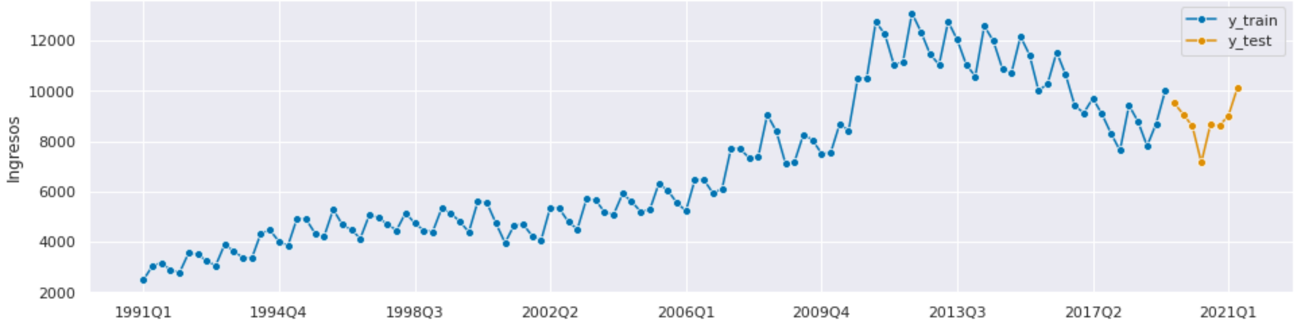
```
from sktime.forecasting.base import ForecastingHorizon
from sktime.utils.plotting import plot_series
from sktime.forecasting.model_selection import temporal_train_test_split
```

```
ko_ts['Ingresos'].astype('float64').to_period('Q')
```

```
Fecha
1991Q1     2480.0
1991Q2     3039.0
1991Q3     3172.0
1991Q4     2879.0
1992Q1     2772.0
             ...
2020Q2     7150.0
2020Q3     8652.0
2020Q4     8611.0
2021Q1     9020.0
2021Q2    10129.0
Freq: Q-DEC, Name: Ingresos, Length: 122, dtype: float64
```

```
y_train, y_test = temporal_train_test_split(y = ko_ts['Ingresos'].astype('float64')
# we will try to forecast y_test from y_train
# plotting for illustration
plot_series(y_train, y_test, labels=["y_train", "y_test"])
print(y_train.shape[0], y_test.shape[0])
```

```
114 8
```



Se observa la necesidad de incluir componente estacional.

```
from sktime.forecasting.ets import AutoETS
```

```
# step 2: specifying forecasting horizon
fh = np.arange(1, 17)

# step 3: specifying the forecasting algorithm
ko_auto_model = AutoETS(auto=True, sp=4, n_jobs=-1)
```

```
ko_auto_model.fit(y_train)
```

```
    AutoETS(auto=True, n_jobs=-1, sp=4)
```

```
print(ko_auto_model.summary())
```

```
                                 ETS Results
    ==============================================================================
    Dep. Variable:              Ingresos   No. Observations:                   114
    Model:                      ETS(MAM)   Log Likelihood                 -828.866
    Date:               Sun, 25 Sep 2022   AIC                            1677.731
    Time:                       11:46:31   BIC                            1705.093
    Sample:                   03-31-1991   HQIC                           1688.836
                            - 06-30-2019   Scale                             0.003
    Covariance Type:              approx
    ==============================================================================
                             coef    std err          z      P>|z|      [0.025
    ------------------------------------------------------------------------------
    smoothing_level        0.9999      0.121      8.246      0.000       0.762
    smoothing_trend     9.999e-05        nan        nan        nan         nan
    smoothing_seasonal  4.239e-05        nan        nan        nan         nan
    initial_level       2902.6074        nan        nan        nan         nan
    initial_trend         73.3890        nan        nan        nan         nan
    initial_seasonal.0     1.0390        nan        nan        nan         nan
    initial_seasonal.1     1.1352        nan        nan        nan         nan
    initial_seasonal.2     1.1936        nan        nan        nan         nan
    initial_seasonal.3     1.0000        nan        nan        nan         nan
    ==============================================================================
    Ljung-Box (Q):                        4.90   Jarque-Bera (JB):               9
    Prob(Q):                              0.77   Prob(JB):
    Heteroskedasticity (H):               2.36   Skew:
    Prob(H) (two-sided):                  0.01   Kurtosis:
    ==============================================================================

    Warnings:
    [1] Covariance matrix calculated using numerical (complex-step) differentiatic
```

```
# step 5: querying predictions
ko_pred = ko_auto_model.predict(fh)
print(ko_pred)
```

```
    2019Q3     9591.389872
    2019Q4     8853.969701
    2020Q1     8594.952101
```

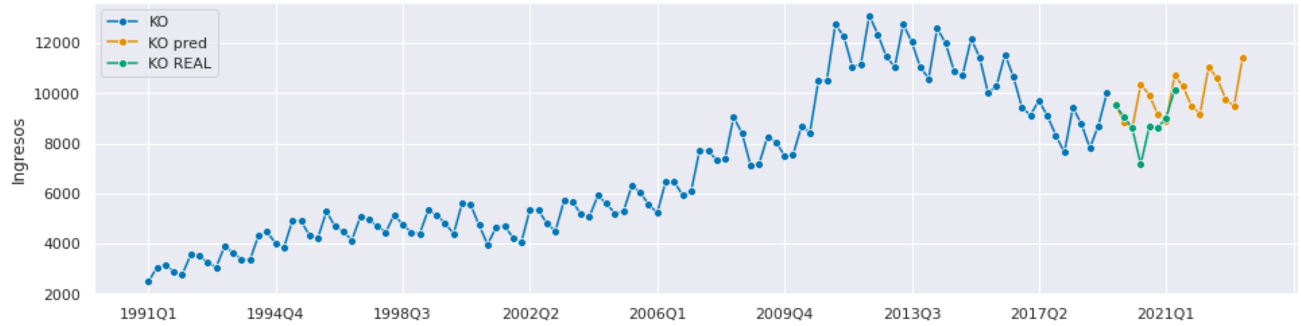
```
2020Q2    10346.028127
2020Q3     9923.333013
2020Q4     9157.763414
2021Q1     8887.350349
2021Q2    10695.029335
2021Q3    10255.276153
2021Q4     9461.557128
2022Q1     9179.748597
2022Q2    11044.030543
2022Q3    10587.219293
2022Q4     9765.350841
2023Q1     9472.146845
2023Q2    11393.031750
Freq: Q-DEC, dtype: float64
```

```
ko_pred_ints = ko_auto_model.predict_interval(fh, coverage=0.9)
ko_pred_ints
```

	Coverage	
	0.9	
	lower	upper
2019Q3	8705.280749	10436.243032
2019Q4	7697.298211	9946.818797
2020Q1	7247.372905	9958.127255
2020Q2	8510.784281	12288.077361
2020Q3	8071.813201	12093.502643
2020Q4	7283.716351	11190.941105
2021Q1	6904.223998	11125.933896
2021Q2	8292.387636	13555.588992
2021Q3	7735.655883	13124.229589
2021Q4	7041.407272	12265.083426
2022Q1	6739.015208	12033.671137
2022Q2	8010.033674	14609.324064
2022Q3	7597.340071	14415.696275
2022Q4	6897.289484	13241.737406
2023Q1	6511.050275	13029.030958
2023Q2	7895.518157	15941.590043

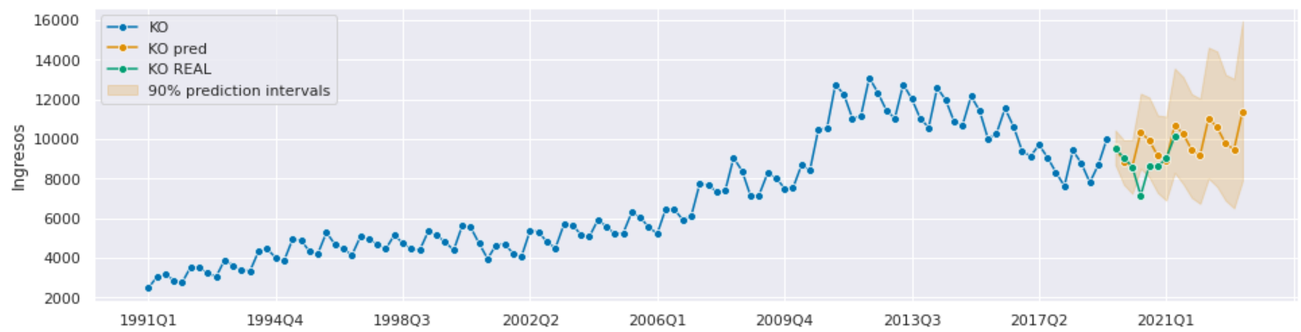
```
# optional: plotting predictions and past data
plot_series(y_train, ko_pred,y_test, labels=["KO", "KO pred", "KO REAL"])
```

```
(<Figure size 1152x288 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f5e711fd410>)
```



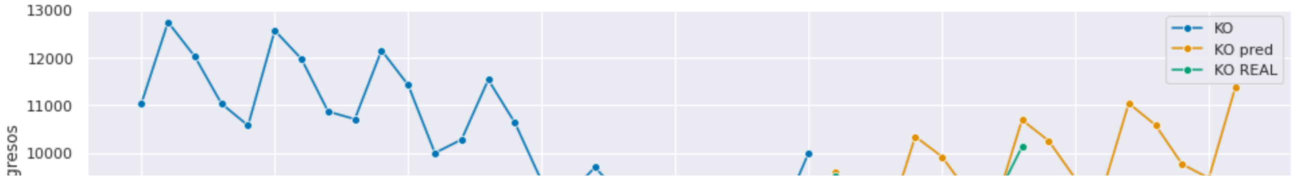

```
fig, ax = plot_series(y_train, ko_pred, y_test, labels=["KO", "KO pred", "KO REAL"]
ax.fill_between(
    ax.get_lines()[-2].get_xdata(),
    ko_pred_ints[('Coverage', 0.9, 'lower')],
    ko_pred_ints[('Coverage', 0.9, 'upper')],
    alpha=0.2,
    color=ax.get_lines()[-2].get_c(),
    label=f"90% prediction intervals",
)
ax.legend(loc='upper left')
```

```
<matplotlib.legend.Legend at 0x7f5e6d5c2850>
```

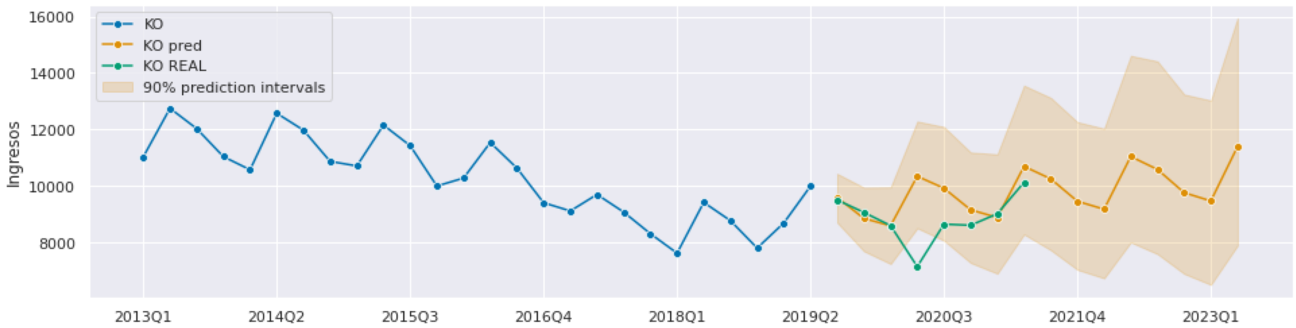



```
plot_series(y_train["2013":], ko_pred,y_test, labels=["KO", "KO pred", "KO REAL"])
```

```
(<Figure size 1152x288 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f5e708d4290>)
```




```
fig, ax = plot_series(y_train["2013":], ko_pred, y_test, labels=["KO", "KO pred", "
ax.fill_between(
    ax.get_lines()[-2].get_xdata(),
    ko_pred_ints[('Coverage', 0.9, 'lower')],
    ko_pred_ints[('Coverage', 0.9, 'upper')],
    alpha=0.2,
    color=ax.get_lines()[-2].get_c(),
    label=f"90% prediction intervals",
)
ax.legend(loc='upper left');
```



Comprobemos la precisión de las predicciones

```
from sktime.performance_metrics.forecasting import mean_absolute_percentage_error
# option 1: using the lean function interface
mean_absolute_percentage_error(y_test, ko_pred[0:8])
```

```
0.0951505761366288
```

```
from sktime.performance_metrics.forecasting import MeanSquaredError
mse = MeanSquaredError()
mse(y_test, ko_pred[0:8])
```

```
1565098.2481350685
```

```
rmse = MeanSquaredError(square_root=True)
rmse(y_test, ko_pred[0:8])
```

```
1251.038867555708
```

Prediccion para final de año 2021 y 2022

```
# step 2: specifying forecasting horizon
fh = np.arange(1, 7)

# step 3: specifying the forecasting algorithm
ko_auto_model = AutoETS(auto=True, sp=4, n_jobs=-1)

y = ko_ts['Ingresos'].astype('float64').to_period('Q')

ko_auto_model.fit(y)

print(ko_auto_model.summary())
```

```
                                 ETS Results
==============================================================================
Dep. Variable:                 Ingresos   No. Observations:                 122
Model:                         ETS(MAM)   Log Likelihood                 -905.927
Date:                  Sun, 25 Sep 2022   AIC                            1831.853
Time:                          11:42:36   BIC                            1859.893
Sample:                      03-31-1991   HQIC                           1843.242
                           - 06-30-2021   Scale                             0.004
Covariance Type:                 approx
==============================================================================
                         coef    std err          z      P>|z|      [0.025
------------------------------------------------------------------------------
smoothing_level        0.8438      0.087      9.652      0.000       0.672
smoothing_trend     8.438e-05        nan        nan        nan         nan
smoothing_seasonal     0.1179      0.046      2.567      0.010       0.028
initial_level       2892.1665        nan        nan        nan         nan
initial_trend         53.4918     18.626      2.872      0.004      16.985
initial_seasonal.0     1.0491        nan        nan        nan         nan
initial_seasonal.1     1.1644        nan        nan        nan         nan
initial_seasonal.2     1.1958        nan        nan        nan         nan
initial_seasonal.3     1.0000        nan        nan        nan         nan
==============================================================================
Ljung-Box (Q):                        4.02   Jarque-Bera (JB):               6
Prob(Q):                              0.86   Prob(JB):
Heteroskedasticity (H):               2.15   Skew:
Prob(H) (two-sided):                  0.02   Kurtosis:
==============================================================================

Warnings:
[1] Covariance matrix calculated using numerical (complex-step) differentiatic
```

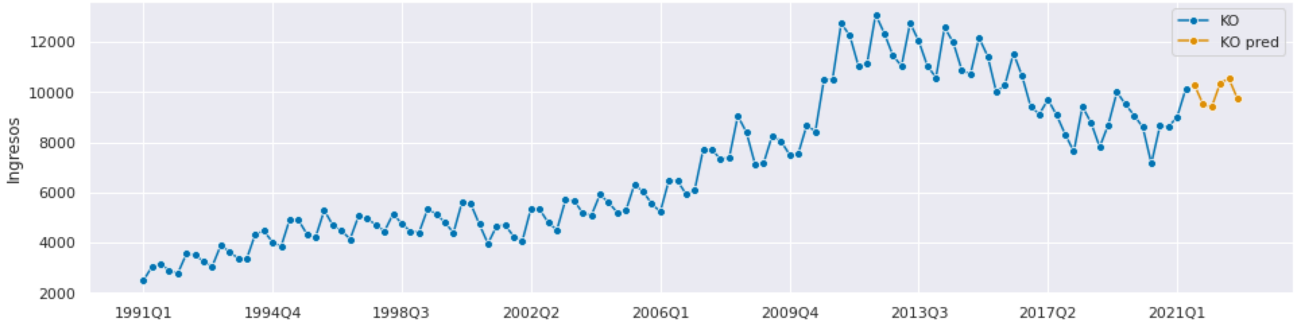
```
# step 5: querying predictions
ko_pred = ko_auto_model.predict(fh)
print(ko_pred)
```

```
2021Q3    10282.769738
2021Q4     9506.523609
2022Q1     9401.106815
2022Q2    10361.900677
2022Q3    10527.174373
```

```
2022Q4     9731.143430
Freq: Q-DEC, dtype: float64
```

```
plot_series(y, ko_pred, labels=["KO", "KO pred"])
```

```
(<Figure size 1152x288 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f5e6de44c50>)
```



Estimemos el modelo de forma manual

```
from sktime.forecasting.exp_smoothing import ExponentialSmoothing
forecaster = ExponentialSmoothing(trend='additive', seasonal='multiplicative', sp=4
forecaster.fit(y)
```

```
ExponentialSmoothing(seasonal='multiplicative', sp=4, trend='additive')
```

```
y_pred = forecaster.predict(fh)
y_pred
```

```
2021Q3    10223.765652
2021Q4     9456.334854
2022Q1     9373.310362
2022Q2    10430.163683
2022Q3    10535.227084
2022Q4     9742.239445
Freq: Q-DEC, Name: Ingresos, dtype: float64
```

```
print(forecaster._fitted_forecaster.summary())
```

```
                        ExponentialSmoothing Model Results
==============================================================================
Dep. Variable:                 Ingresos   No. Observations:                  1
Model:             ExponentialSmoothing   SSE                      29538439.8
Optimized:                         True   AIC                          1528.4
Trend:                         Additive   BIC                          1550.8
```

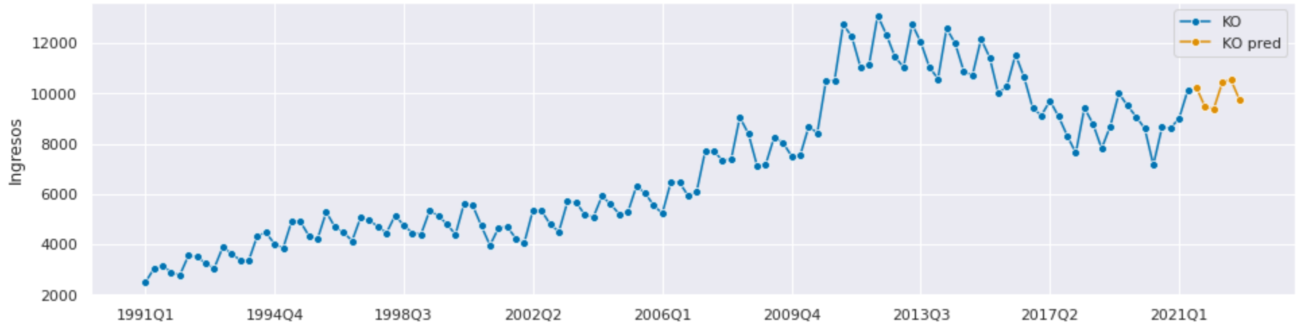
```
Seasonal:                Multiplicative   AICC                        1530.4
Seasonal Periods:                     4   Date:                 Sun, 25 Sep 20
Box-Cox:                          False   Time:                       11:43:
Box-Cox Coeff.:                    None
==============================================================================
                          coeff                 code              optimized
------------------------------------------------------------------------------
smoothing_level               0.8889286                alpha                 T
smoothing_trend               0.0001000                 beta                 T
smoothing_seasonal            0.1110714                gamma                 T
initial_level                 2902.6083                  l.0                 T
initial_trend                 73.389214                  b.0                 T
initial_seasons.0             0.9139023                  s.0                 T
initial_seasons.1             1.1063511                  s.1                 T
initial_seasons.2             1.0795056                  s.2                 T
initial_seasons.3             0.9970990                  s.3                 T
------------------------------------------------------------------------------
```

```
forecaster.get_fitted_params()
```

```
{'initial_level': 2902.6083250886268,
 'initial_slope': None,
 'initial_seasons': array([0.91390226, 1.10635106, 1.07950563, 0.99709896]),
 'aic': 1528.4562007472675,
 'bic': 1550.8883691051335,
 'aicc': 1530.4381827292495}
```

```
plot_series(y, y_pred, labels=["KO", "KO pred"])
```

```
(<Figure size 1152x288 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f5e6dee1550>)
```



Estimemos el modelo de forma manual sin componente estacional

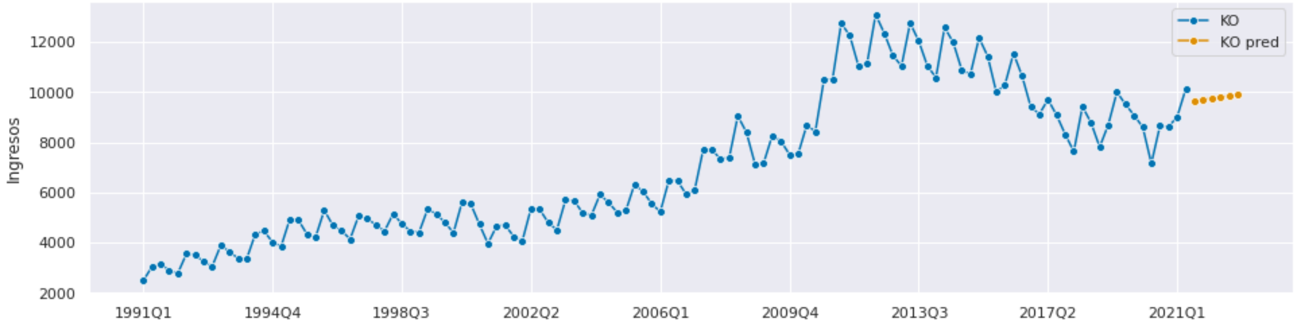
```
forecaster = ExponentialSmoothing(trend='additive',seasonal=None, sp=4)
forecaster.fit(y)
```

```
ExponentialSmoothing(sp=4, trend='additive')
```

```
y_pred = forecaster.predict(fh)
```

```
plot_series(y, y_pred, labels=["KO", "KO pred"])
```

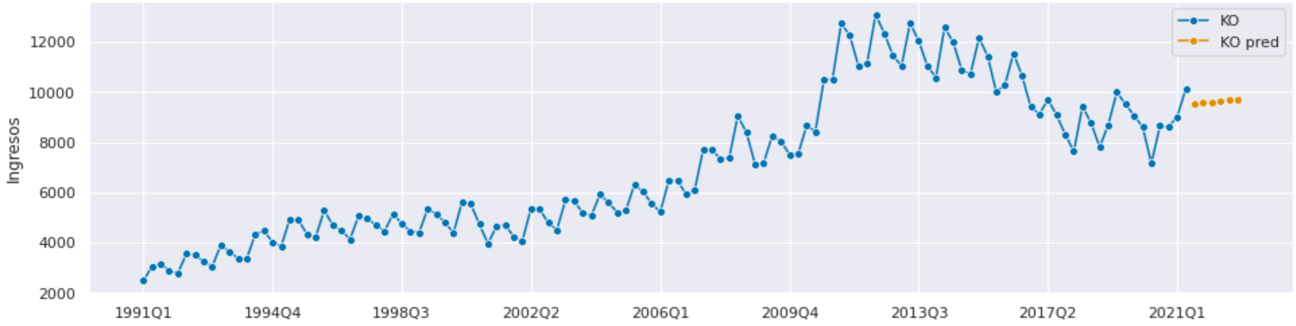
```
(<Figure size 1152x288 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f5e708592d0>)
```



Estimemos el modelo de forma manual sin componente estacional y tendencia multiplicativa

```
forecaster = ExponentialSmoothing(trend='mul',seasonal=None, sp=4)
forecaster.fit(y)
y_pred = forecaster.predict(fh)
plot_series(y, y_pred, labels=["KO", "KO pred"])
```

```
(<Figure size 1152x288 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f5e6de0e090>)
```

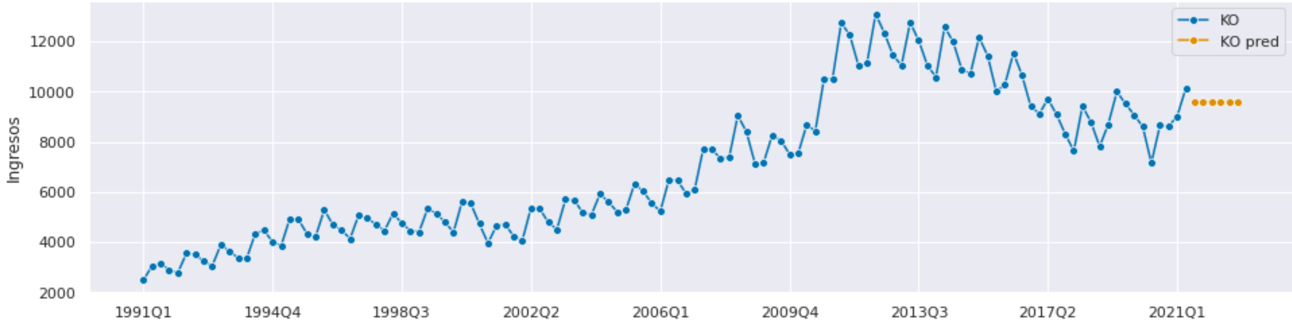


Estimemos el modelo de forma manual sin componente estacional y sin tendencia

```
forecaster = ExponentialSmoothing(trend=None,seasonal=None, sp=4)
forecaster.fit(y)
```

```
y_pred = forecaster.predict(fh)
plot_series(y, y_pred, labels=["KO", "KO pred"])
```

```
(<Figure size 1152x288 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f5e6dc99310>)
```

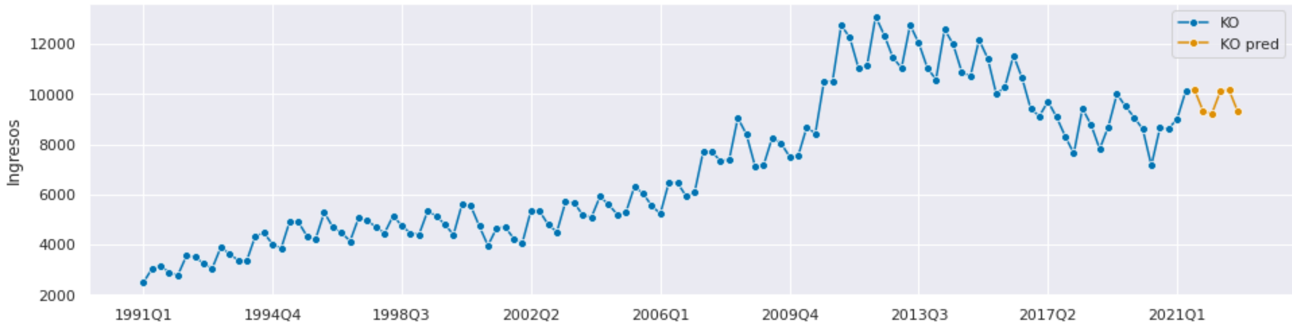


Estimemos el modelo de forma manual sin tendencia

```
Componente estacional multiplicativo
```

```
forecaster = ExponentialSmoothing(trend=None,seasonal="mul", sp=4)
forecaster.fit(y)
y_pred = forecaster.predict(fh)
plot_series(y, y_pred, labels=["KO", "KO pred"])
```

```
(<Figure size 1152x288 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f5e6dc3cb90>)
```



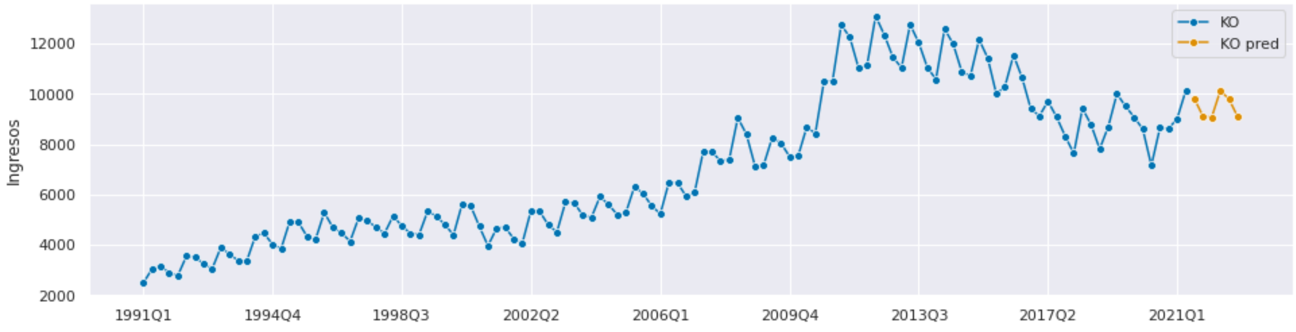
Estimemos el modelo de forma manual sin tendencia

Componente estacional aditivo

```
forecaster = ExponentialSmoothing(trend=None,seasonal="add", sp=4)
forecaster.fit(y)
```

```
y_pred = forecaster.predict(fh)
plot_series(y, y_pred, labels=["KO", "KO pred"])
```

```
(<Figure size 1152x288 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f5e6dc7f910>)
```



Comparar modelo con tendencia aditiva con y sin dumped

Componente estacional aditivo

```
forecaster = ExponentialSmoothing(trend="add",seasonal="add",damped_trend=False, sp
forecaster.fit(y)
y_pred = forecaster.predict(fh)

forecaster = ExponentialSmoothing(trend="add",seasonal="add",damped_trend=True, sp=
forecaster.fit(y)
y_pred_dump = forecaster.predict(fh)
plot_series(y["2009":], y_pred, y_pred_dump,labels=["KO", "KO pred","KO Pred Dumped
```

```
(<Figure size 1152x288 with 1 Axes>,
 <matplotlib.axes._subplots.AxesSubplot at 0x7f5e6db40910>)
```