

Using Exponential Smoothing Models in Python

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Exponential Smoothing



The most common analytical tool for univariate time series besides ARIMA

Exponential smoothing models theory

Demo in Python with the nottem dataset

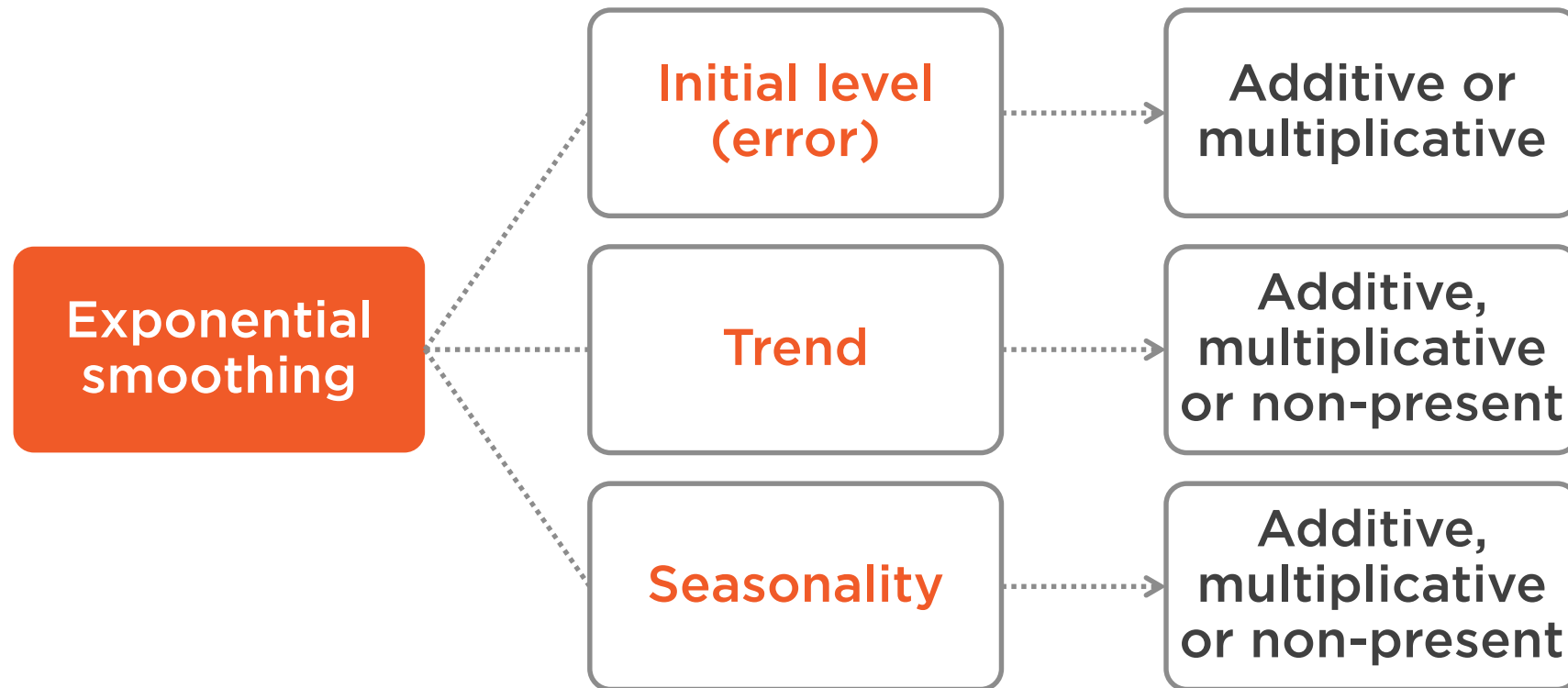
- Identifying the model parameters
- Modulating the trend component
- Forecasting



Exponential Smoothing



Describing an Exponential Smoothing Model



Exponential Smoothing Model Types

Additive

Components are
summed up

Multiplicative

Components are
multiplied

Non-present

Components are
omitted

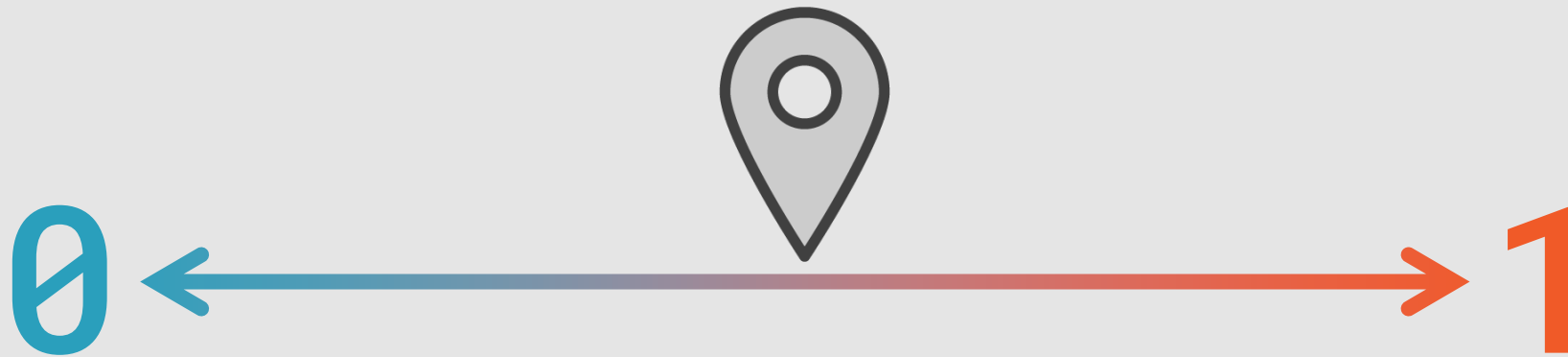


Exponential smoothing:

A model for univariate time series where fluctuations are smoothed out by weights which decrease exponentially over time.



Smoothing Coefficients Determine the Importance of a Time Lag



Smooth model

Reactive model



Smoothing Coefficients

Alpha: Initial level

Beta: Trend

Gamma: Seasonality

Phi: Damping parameter



Damping Parameter (φ)

Trend must be present, but it is not constant (e.g. Holt-Winters trend model)

Parameter phi defines the degree of trend damping

- $\varphi \approx 1$: Constant trend model
- $\varphi \approx 0$: Flattened trend curve
- **$0.8 < \varphi < 0.98$**



Python Tools for Exponential Smoothing

`statsmodels.tsa.holtwinters`

`SimpleExpSmoothing`
 (α)

`ExponentialSmoothing`
 $(\alpha, \beta, \gamma + \varphi)$





In [2]: `help(ExponentialSmoothing)`

Help on class ExponentialSmoothing in module statsmodels.tsa.holtwinters:

```
class ExponentialSmoothing(statsmodels.tsa.base.tsa_model.TimeSeriesModel)
    Holt Winter's Exponential Smoothing

    Parameters
    -----
    endog : array-like
        Time series
    trend : {"add", "mul", "additive", "multiplicative", None}, optional
        Type of trend component.
    damped : bool, optional
        Should the trend component be damped.
    seasonal : {"add", "mul", "additive", "multiplicative", None}, optional
        Type of seasonal component.
    seasonal_periods : int, optional
        The number of seasons to consider for the holt winters.

    Returns
    -----
    results : ExponentialSmoothing class
```





In [2]: `help(ExponentialSmoothing)`

```
fit(self, smoothing_level=None, smoothing_slope=None, smoothing_seasonal=None, damping_slope=None, optimized=True, use_boxcox=False, remove_bias=False, use_basinhopping=False)
```

fit Holt Winter's Exponential Smoothing

Parameters

`smoothing_level` : float, optional

The alpha value of the simple exponential smoothing, if the value is set then this value will be used as the value.

`smoothing_slope` : float, optional

The beta value of the holts trend method, if the value is set then this value will be used as the value.

`smoothing_seasonal` : float, optional

The gamma value of the holt winters seasonal method, if the value is set then this value will be used as the value.

`damping_slope` : float, optional

The phi value of the damped method, if the value is set then this value will be used as the value.

`optimized` : bool, optional

Should the values that have not been set above be optimized



Exponential Smoothing Model Variations

SES

Deducts the present observation by the last few observations

Holt

Initial level (α) and trend (β) with optional damping (φ)

Holt-Winters

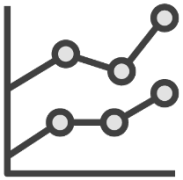
A Holt model with seasonality (γ)



Drawbacks of Exponential Smoothing Models



Sensitivity towards outliers



Cannot handle multiple trends



Changes in the intercept cannot be handled accurately

Demo



Modeling the nottem seasonal dataset

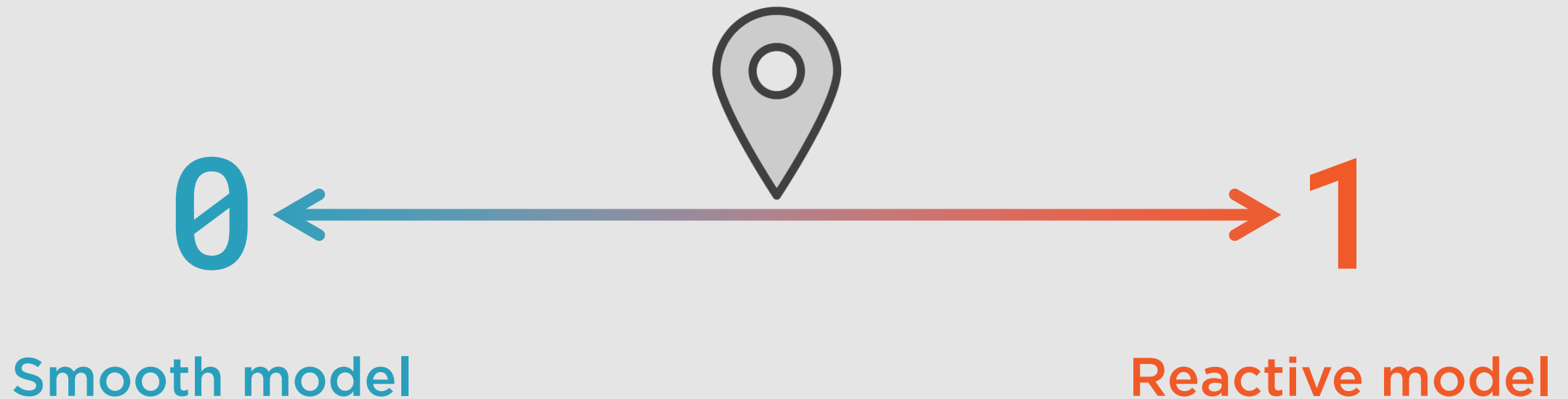
- No trend and constant seasonality

Model: Holt-Winters(A,N,A)

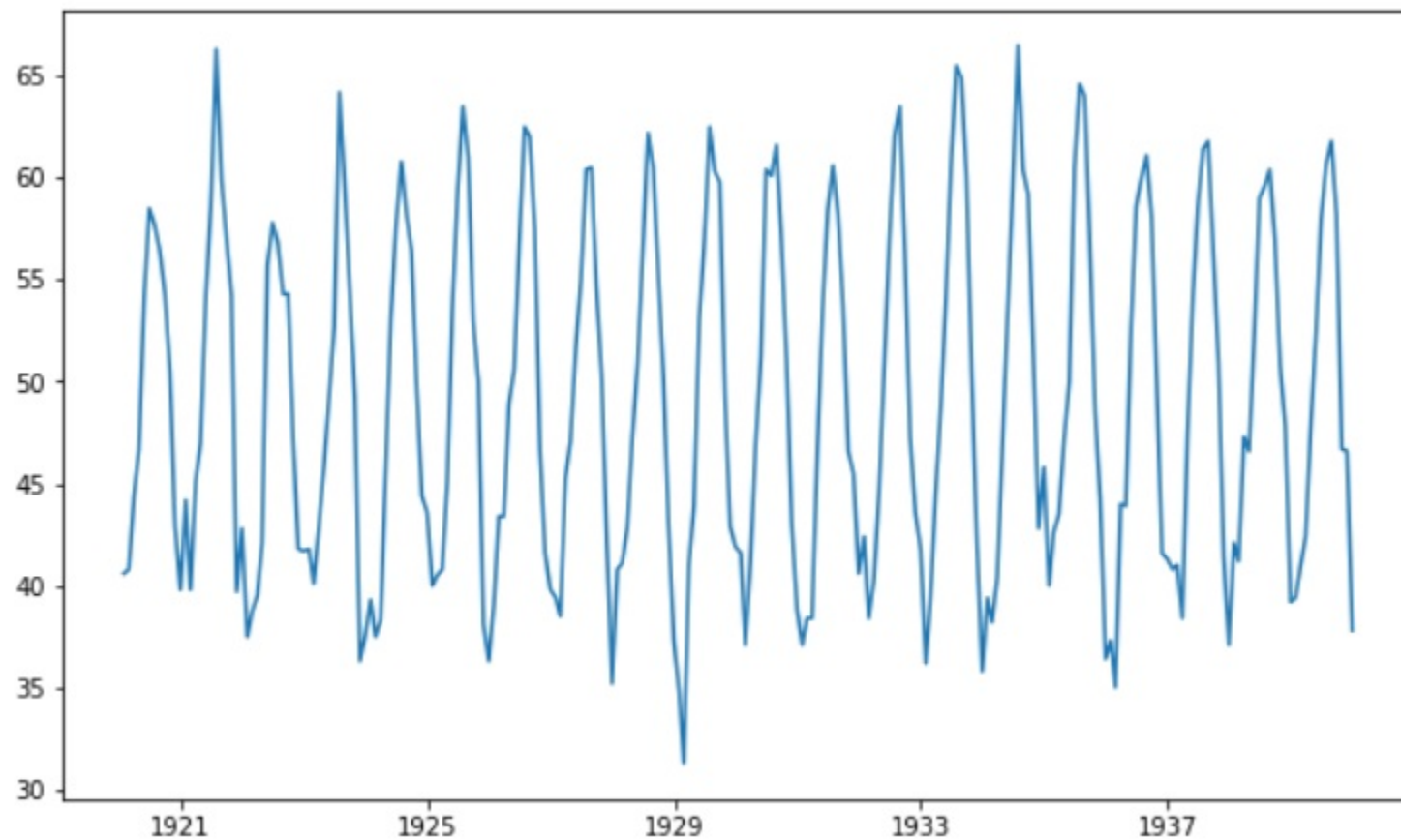
- Additive level, no trend, additive seasonality



Smoothing Coefficients Determine the Importance of a Time Lag



The Nottm Dataset



```
expsfcast = model.predict(start = 240, end = 251)
```

or

```
expsfcast = model.forecast(steps = 12)
```

Choosing a Forecast Method

StatsModels offers two tools for predictive modeling

- Method 'predict'
- Method 'forecast'



Exponential Smoothing Model



Model setup: `ExponentialSmoothing()`



Fitting the model: `model.fit()`



Prediction with the fitted model:
`model.predict(start = , end =)`



Exponential Smoothing



Exponential smoothing implements trend, seasonality and the initial level

Demo on a non-trending seasonal dataset

Smoothing coefficients: alpha, beta and gamma

- Determine the number of lags to be included in the model
- Additional trend dampening parameter ϕ