TimeSeries_NaiveForecasting

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[ ]:
```
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```

1 Naive forecasting

Run in Google Colab

View source on GitHub

1.1 Setup

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
```

[2]:
```
def plot_series(time, series, format="-", start=0, end=None, label=None):
    plt.plot(time[start:end], series[start:end], format, label=label)
    plt.xlabel("Time")
    plt.ylabel("Value")
    if label:
        plt.legend(fontsize=14)
    plt.grid(True)

def trend(time, slope=0):
    return slope * time

def seasonal_pattern(season_time):
    """Just an arbitrary pattern, you can change it if you wish"""
    return np.where(season_time < 0.4,
```

```
                    np.cos(season_time * 2 * np.pi),
                    1 / np.exp(3 * season_time))

def seasonality(time, period, amplitude=1, phase=0):
    """Repeats the same pattern at each period"""
    season_time = ((time + phase) % period) / period
    return amplitude * seasonal_pattern(season_time)

def white_noise(time, noise_level=1, seed=None):
    rnd = np.random.RandomState(seed)
    return rnd.randn(len(time)) * noise_level
```

1.2 Trend and Seasonality

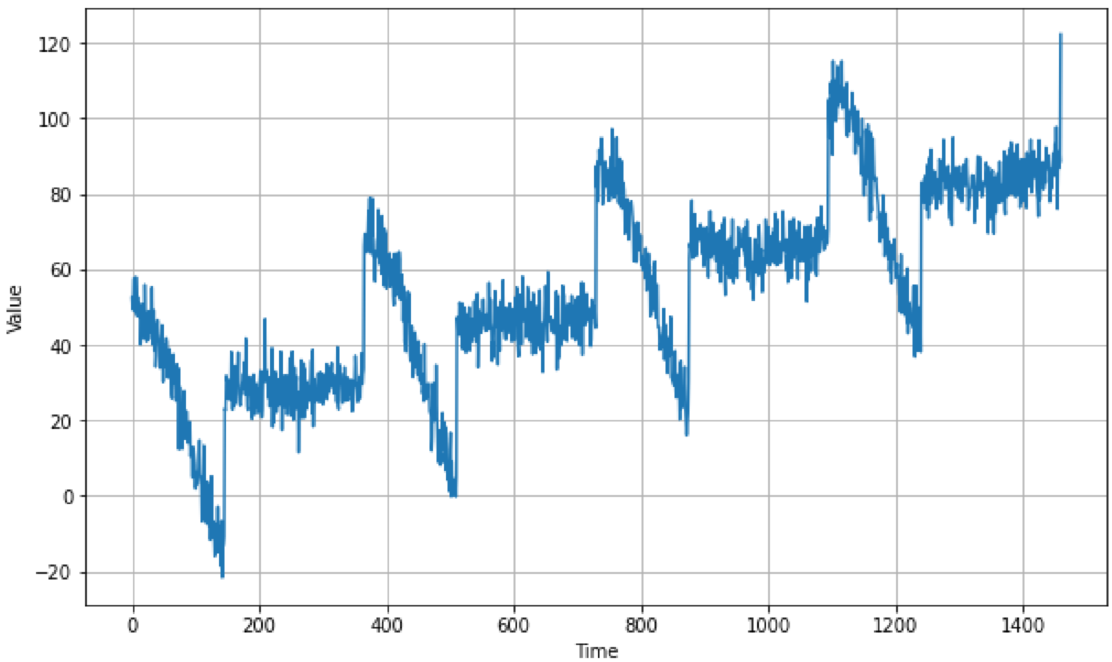
[3]:
```
time = np.arange(4 * 365 + 1)

slope = 0.05
baseline = 10
amplitude = 40
series = baseline + trend(time, slope) + seasonality(time, period=365,␣
 ↪amplitude=amplitude)

noise_level = 5
noise = white_noise(time, noise_level, seed=42)

series += noise

plt.figure(figsize=(10, 6))
plot_series(time, series)
plt.show()
```



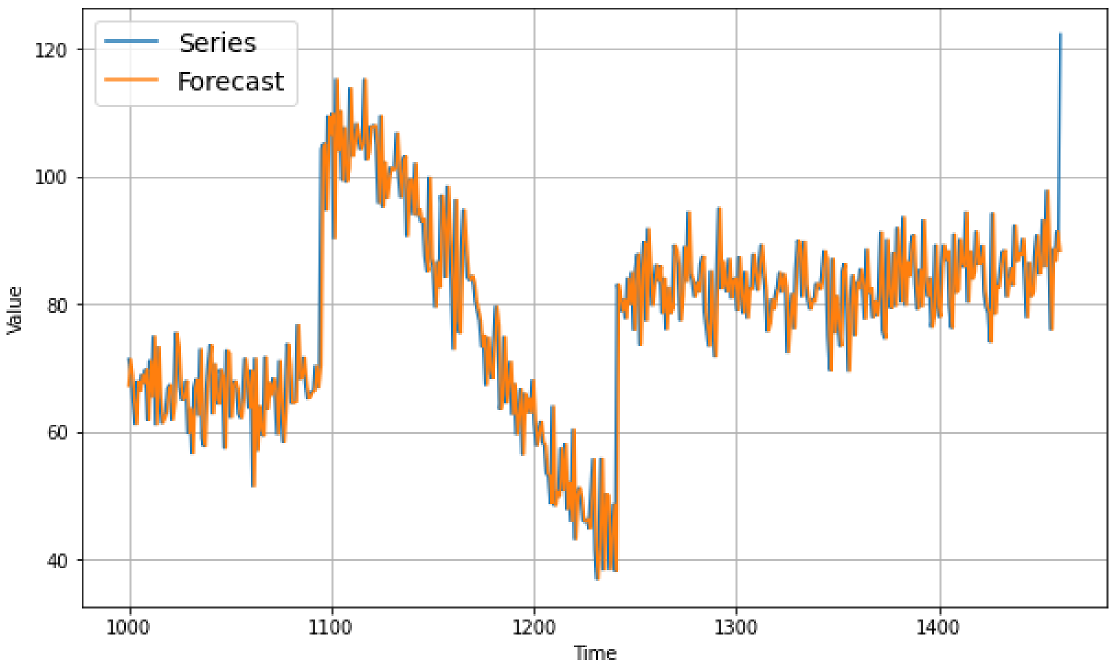
All right, this looks realistic enough for now. Let's try to forecast it. We will split it into two periods: the training period and the validation period (in many cases, you would also want to have a test period). The split will be at time step 1000.

[4]:
```
split_time = 1000
time_train = time[:split_time]
x_train = series[:split_time]
time_valid = time[split_time:]
x_valid = series[split_time:]
```

1.3 Naive Forecast

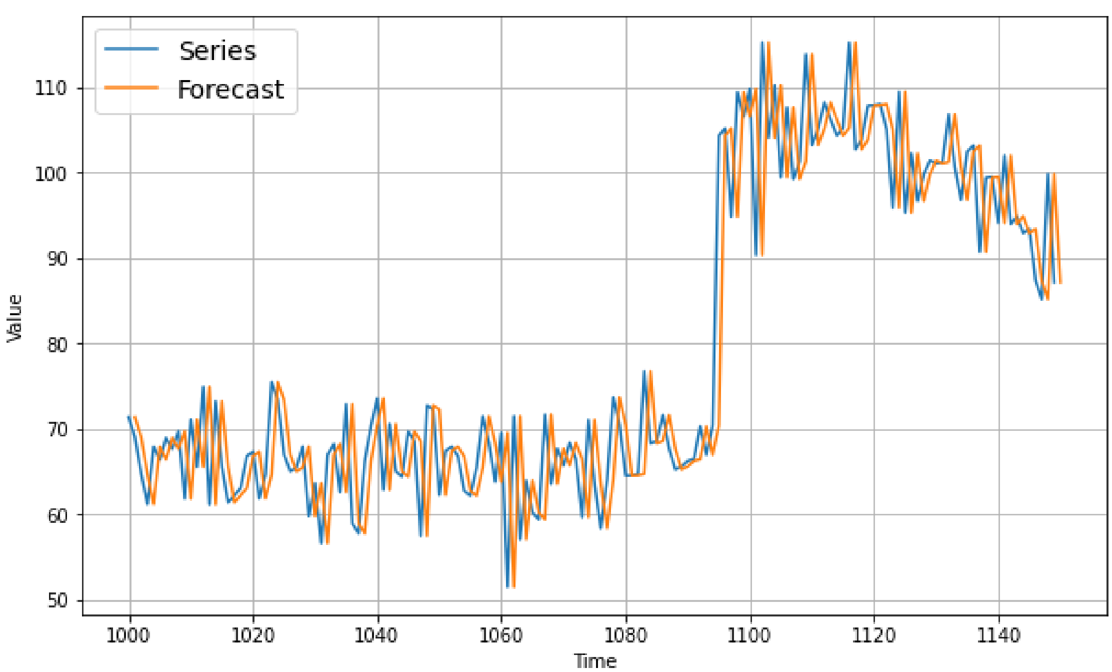
[5]:
```
naive_forecast = series[split_time - 1:-1]
```

[6]:
```
plt.figure(figsize=(10, 6))
plot_series(time_valid, x_valid, label="Series")
plot_series(time_valid, naive_forecast, label="Forecast")
```



Let’s zoom in on the start of the validation period:

[7]:
```
plt.figure(figsize=(10, 6))
plot_series(time_valid, x_valid, start=0, end=150, label="Series")
plot_series(time_valid, naive_forecast, start=1, end=151, label="Forecast")
```



You can see that the naive forecast lags 1 step behind the time series.

Now let's compute the mean absolute error between the forecasts and the predictions in the validation period:

[8]:
```
errors = naive_forecast - x_valid
abs_errors = np.abs(errors)
mae = abs_errors.mean()
mae
```

[8]:
```
5.9379085153216735
```

That's our baseline, now let's try a moving average.