

Machine Learning

MSE FTP MachLe

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In [1]: `%matplotlib inline`

Lab 9, A6: Gaussian process regression (GPR) with noise-level estimation

This example illustrates that GPR with a sum-kernel including a `WhiteKernel` can estimate the noise level of data.

```
In [2]: import numpy as np

from matplotlib import pyplot as plt
from matplotlib.colors import LogNorm

from sklearn.gaussian_process import GaussianProcessRegressor
from sklearn.gaussian_process import kernels

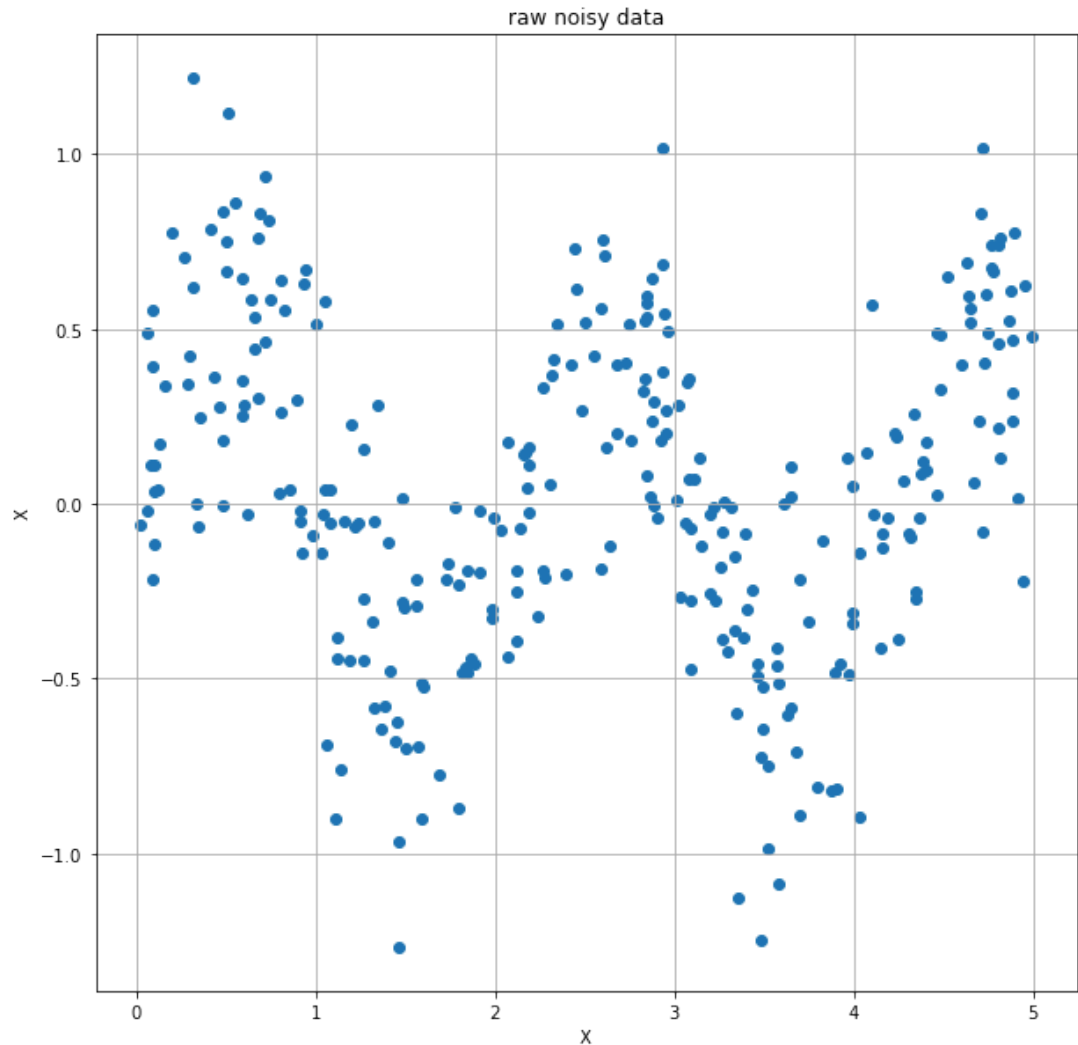
# Generate noisy sine wave
nSamples=300;
rng = np.random.RandomState(0)
X = rng.uniform(0, 5, nSamples)[: , np.newaxis]
y = 0.5 * np.sin(3 * X[: , 0]) + rng.normal(0, 0.3, X.shape[0])
```

(a) Inspect and interpret the data using a plot

Have a look at the data and make a good guess for the kernel to be selected.

```
In [3]: ▶ plt.figure(figsize=(10,10))
plt.scatter(X,y)
plt.grid(True)
plt.xlabel('x')
plt.ylabel('x')
plt.title('raw noisy data')
```

Out[3]: Text(0.5, 1.0, 'raw noisy data')



(b) Create a suitable kernel for the covariance function

The data shows a sin-like oscillation that is noisy. So it makes sense to select for the **oscillating part** of the covariance either

1. the sin-exponential kernel
2. the RBF-kernel

For the **noisy part**, we could either choose a white noise kernel (WhiteKernel). We start with the RBF-kernel and additive white noise.

In [4]: ▶

```
# First run: using the RBF kernel and white noise
```

```
kernel = 1.0 * kernels.RBF(length_scale=1.0, length_scale_bounds=(1e-2,  
    + kernels.WhiteKernel(noise_level=1e-5, noise_level_bounds=(1e-10,  
gp1 = GaussianProcessRegressor(kernel=kernel, alpha=1e-5).fit(X, y)
```

```

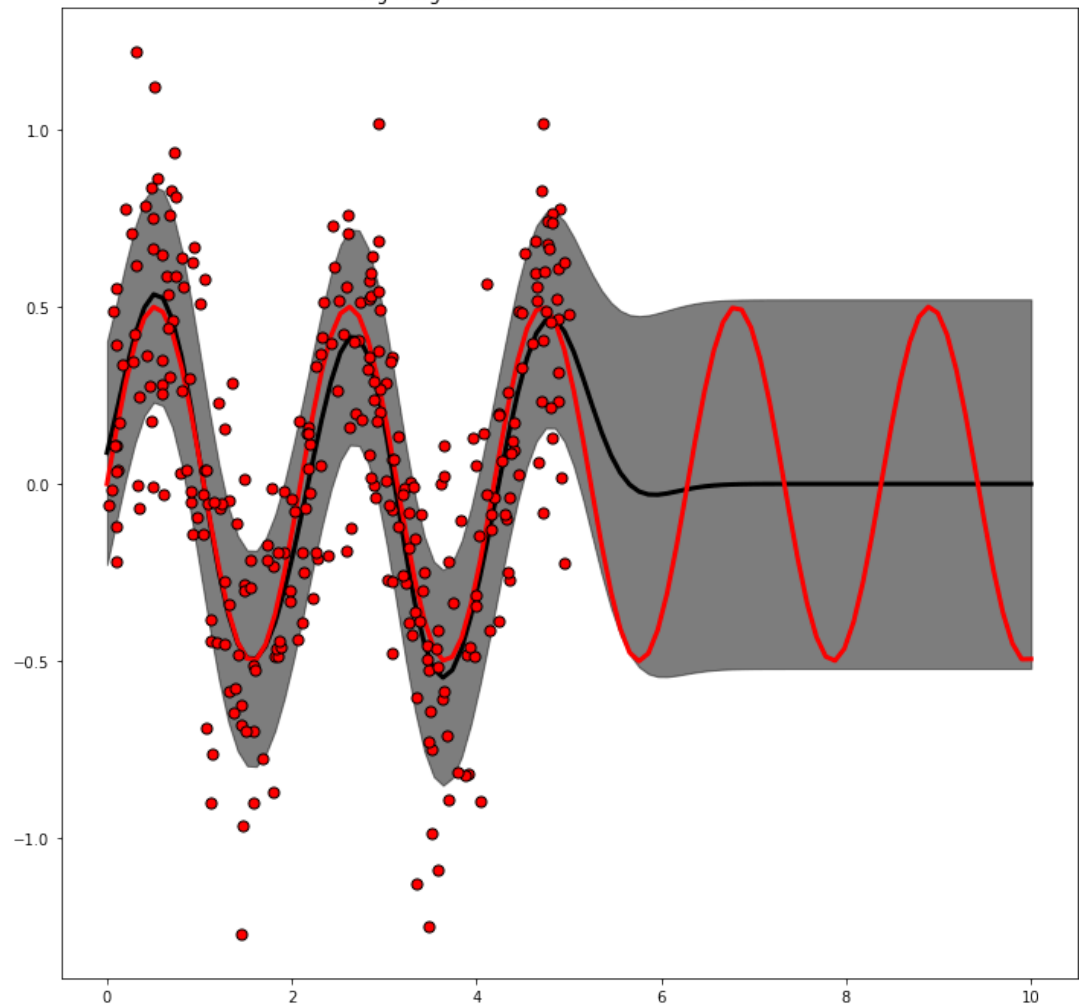
In [5]: X_ = np.linspace(0, 10, 100)
y_mean, y_cov = gp1.predict(X_[ :, np.newaxis], return_cov=True)

plt.figure(figsize=(10,10))
plt.plot(X_, y_mean, 'k', lw=3, zorder=9)
plt.fill_between(X_, y_mean - np.sqrt(np.diag(y_cov)),
                 y_mean + np.sqrt(np.diag(y_cov)),
                 alpha=0.5, color='k')
plt.plot(X_, 0.5*np.sin(3*X_), 'r', lw=3, zorder=9)
plt.scatter(X[:, 0], y, c='r', s=50, zorder=10, edgecolors=(0, 0, 0))
plt.title("Initial: %s\nOptimum: %s\nLog-Marginal-Likelihood: %s"
          % (kernel, gp1.kernel_,
             gp1.log_marginal_likelihood(gp1.kernel_.theta)))
plt.tight_layout()
y_cov.shape

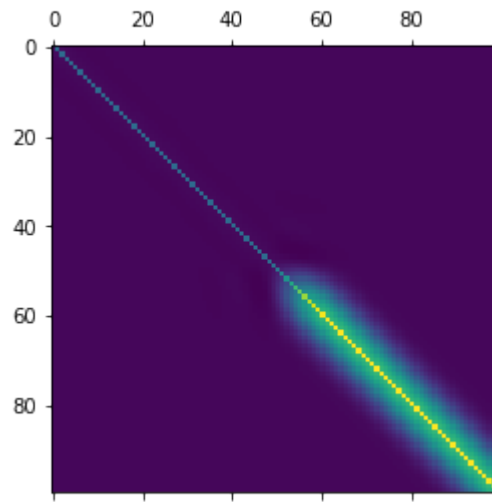
plt.figure()
plt.matshow(y_cov)
plt.show()

```

Initial: 1**2 * RBF(length_scale=1) + WhiteKernel(noise_level=1e-05)
 Optimum: 0.426**2 * RBF(length_scale=0.53) + WhiteKernel(noise_level=0.0896)
 Log-Marginal-Likelihood: -81.99142323092914



<Figure size 432x288 with 0 Axes>



In [6]: `#Get out the hyperparameters
gp1.kernel_`

Out[6]: `0.426**2 * RBF(length_scale=0.53) + WhiteKernel(noise_level=0.0896)`

(c) using the ExpSineSquared kernel

```

In [7]: ▶ # Second run: using the sin-exponential kernel and white noise
kernel = 0.5 * kernels.ExpSineSquared(length_scale=4.0, periodicity=1,
                                     length_scale_bounds=(1e-1, 1e3),
                                     periodicity_bounds=(1e-1, 4)) \
    + kernels.WhiteKernel(noise_level=1e-6, noise_level_bounds=(1e-10, 1e-5))
gp = GaussianProcessRegressor(kernel=kernel, alpha=1E-5).fit(X, y)

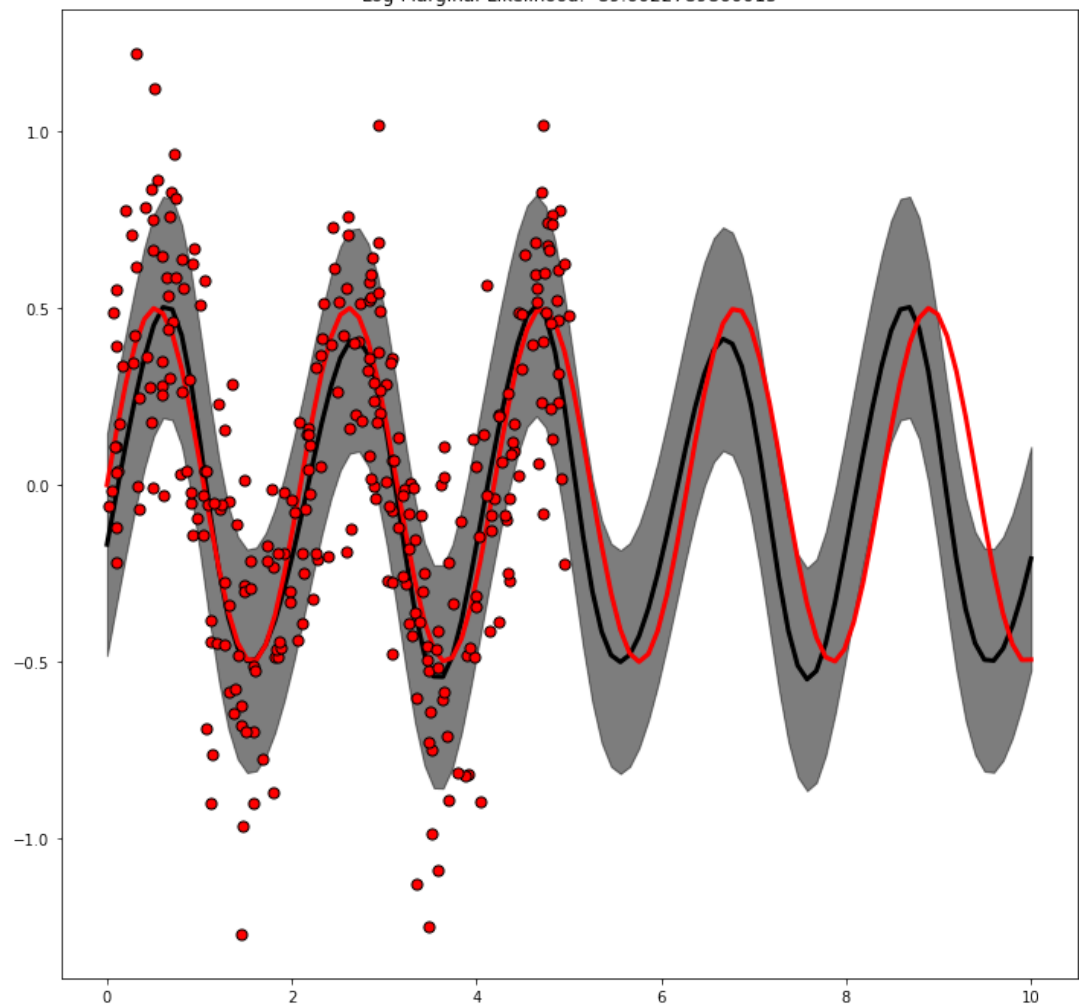
X_ = np.linspace(0, 10, 100)
y_mean, y_cov = gp.predict(X[:, np.newaxis], return_cov=True)

plt.figure(figsize=(10,10))
plt.plot(X_, y_mean, 'k', lw=3, zorder=9)
plt.fill_between(X_, y_mean - np.sqrt(np.diag(y_cov)),
                y_mean + np.sqrt(np.diag(y_cov)),
                alpha=0.5, color='k')
plt.plot(X_, 0.5*np.sin(3*X_), 'r', lw=3, zorder=9)
plt.scatter(X[:, 0], y, c='r', s=50, zorder=10, edgecolors=(0, 0, 0))
plt.title("Initial: %s\nOptimum: %s\nLog-Marginal-Likelihood: %s"
          % (kernel, gp.kernel_,
             gp.log_marginal_likelihood(gp.kernel_.theta)))
plt.tight_layout()

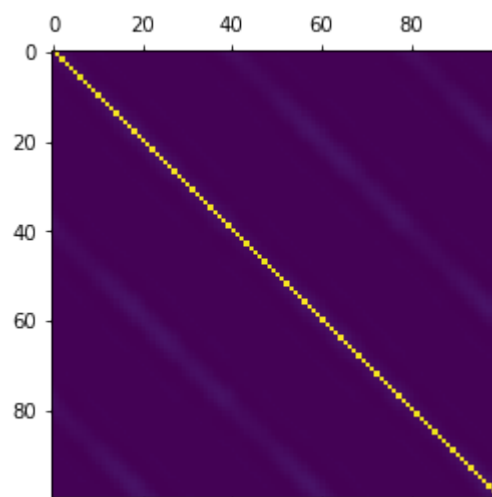
plt.figure()
plt.matshow(y_cov)
plt.show()

```

Initial: $0.707 \times 2 * \text{ExpSineSquared}(\text{length_scale}=4, \text{periodicity}=1) + \text{WhiteKernel}(\text{noise_level}=1\text{e-}06)$
 Optimum: $0.44 \times 2 * \text{ExpSineSquared}(\text{length_scale}=0.769, \text{periodicity}=4) + \text{WhiteKernel}(\text{noise_level}=0.0958)$
 Log-Marginal-Likelihood: -89.6022789860015



<Figure size 432x288 with 0 Axes>



In [8]: `#Get out the hyperparameters
gp.kernel_`

Out[8]: $0.44 \times 2 * \text{ExpSineSquared}(\text{length_scale}=0.769, \text{periodicity}=4) + \text{WhiteKernel}(\text{noise_level}=0.0958)$

References

[1] Jan Hendrik Metzen jhm@informatik.uni-bremen.de (<mailto:jhm@informatik.uni-bremen.de>).

In []: ▶

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