Flowering date prediction for bulbous perennials

Dániel Nagy[1],
Imre M. Jánosi[2]

[1]Institute for Physics, Eötvös Loránd University, H-1117, Pázmány Péter sétány 1/A. Budapest, Hungary
[2]Department of Physics of Complex Systems, Eötvös Loránd University, H-1117, Pázmány Péter sétány 1/A. Budapest, Hungary

November 26, 2019

Abstract

The goal of this project is to efficiently predict the first flowering date of bulbous perennials and to identify, which meteorological parameters affect the flowering dates. The LSCD model is briefly presented, and the hyperparameters of the simpler LSC model are fitted using Gaussian process optimization. A neural network approach for the prediction of flowering dates is presented.

Introduction

Many observations prove that plants have a complex sense of climate, and that many of them developed the ability to prevent premature flowering. In order to uncover the relationship between meteorological data and flowering time, a long-term data acquisition was needed. The data available to my project is a `csv` file that is containing the first flowering dates of 329 bulbous perennial plants in the period 1968-2001. Further meteorological data is downloaded from the internet. The most significant meteorological parameter is the temperature of the soil at a depth of around 10cm. The temperature data is shown on 1.

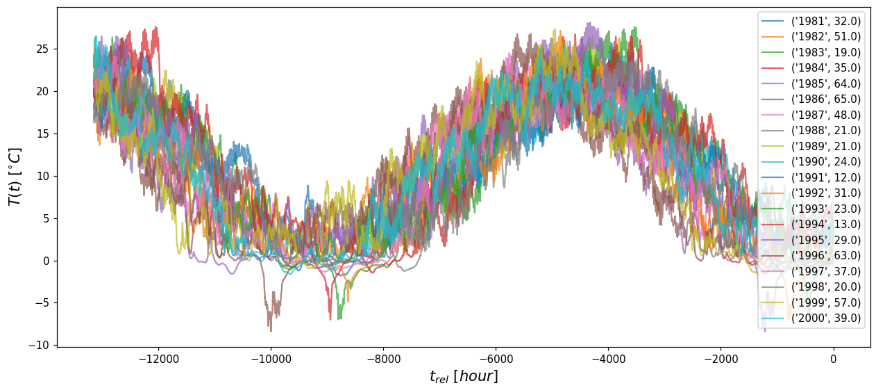


Figure 1: The soil temperature at 10cm depth across 22 years, plotted yearly at a 1-hour resolution. The x axis shows the hours before flowering date starting from 0.

The LSCD model

$$\frac{\mathrm{d}\nu}{\mathrm{d}t} = p_\nu(L, S, C, D) - s_\nu \nu \tag{1}$$

$$\frac{\mathrm{d}V}{\mathrm{d}t} = s_\nu \nu - d_V V \tag{2}$$

$p_\nu(L, S, C, D) = L \cdot S \cdot C \cdot D$ is the productive transcription, s_ν is the splicing rate, and d_V is the degradation rate of the spliced VIN3.

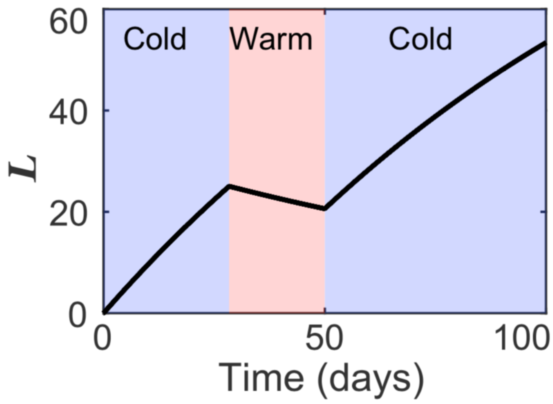
$$\frac{\mathrm{d}L}{\mathrm{d}t} = \begin{cases} 1 - d_L L & T < T_L \\ -d_L L & T \geq T_L \end{cases} \tag{3}$$

$$C(T) = \begin{cases} p_{c1} & T \leq T_{c1} \\ p_{c1} - p_{c2}\frac{T - T_{c1}}{T_{c2} - T_{c1}} & T_{c1} < T < T_{c2} \\ p_{c2} & T \geq T_{c2} \end{cases} \tag{4}$$

$$S(T_m) = \begin{cases} 1, & T < T_S \\ S_1, & T \geq T_S \end{cases} \tag{5}$$

$$D(t) = \left[p_D + \sin\left(2\pi\left(t - \frac{t_m - 1}{24}\right)\right)\right]^2 \tag{6}$$

T_m is the maximum temperature since the last resetting, which was chosen to occur each day at 4pm. t_m is the time at dawn.



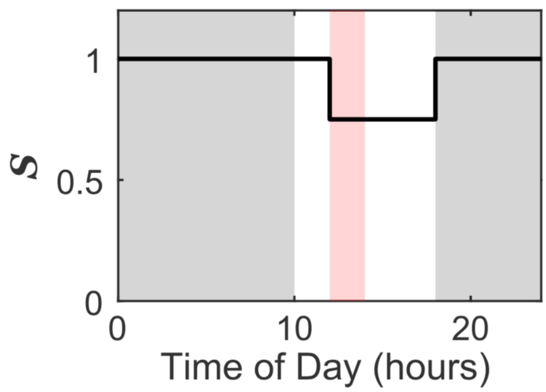
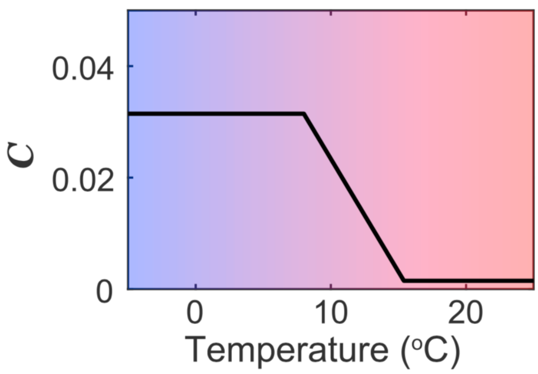
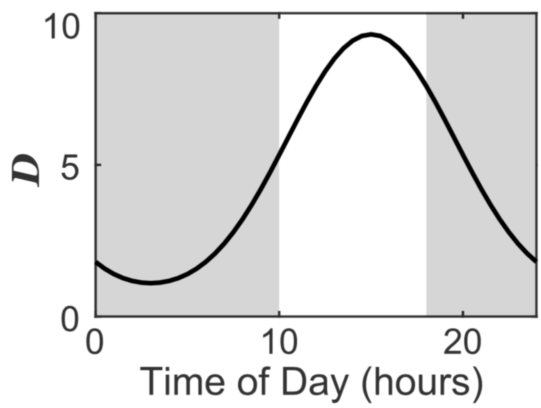
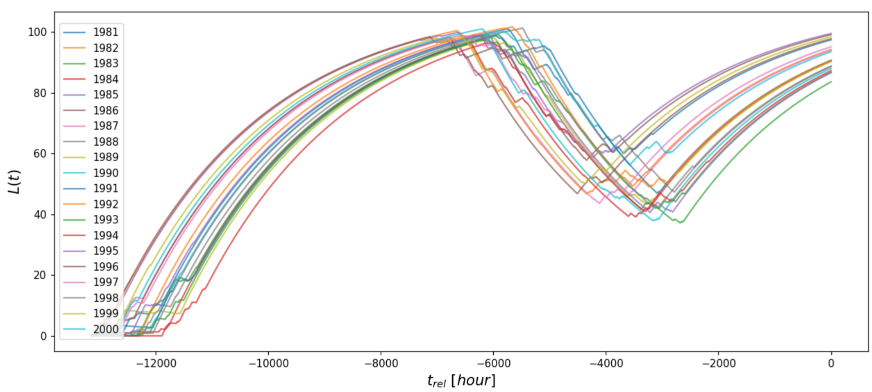


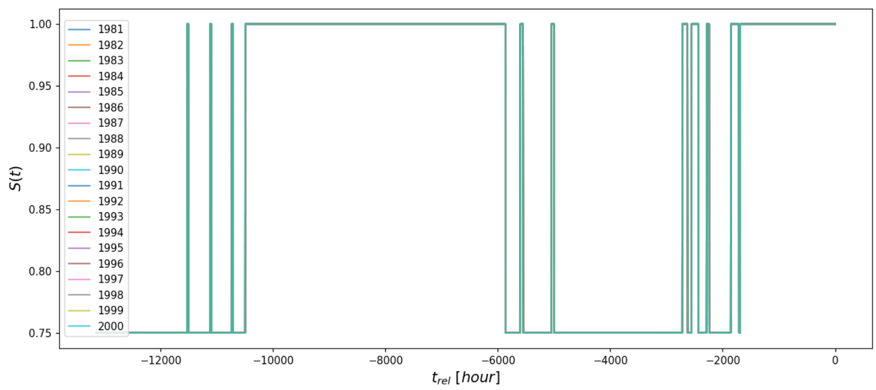
Figure 2: L intermediator for a



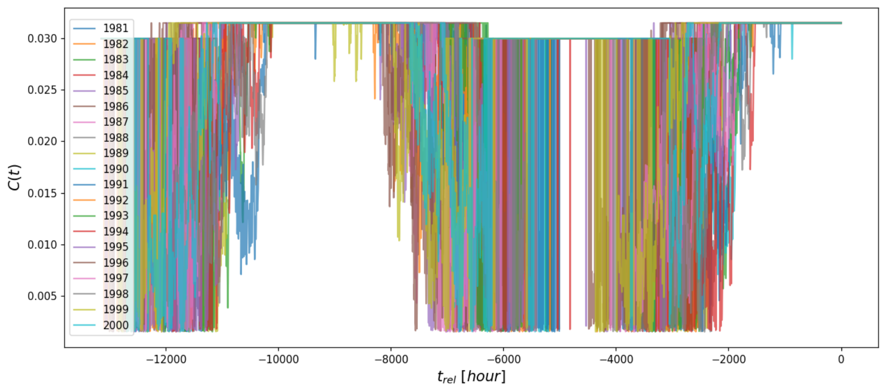


Results with the LSCD model

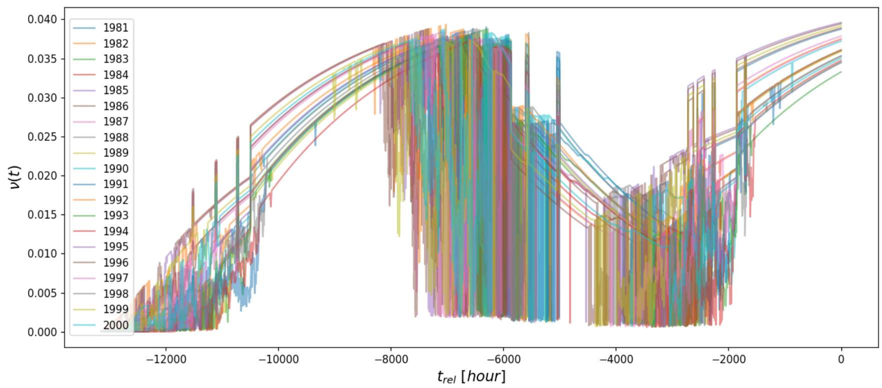




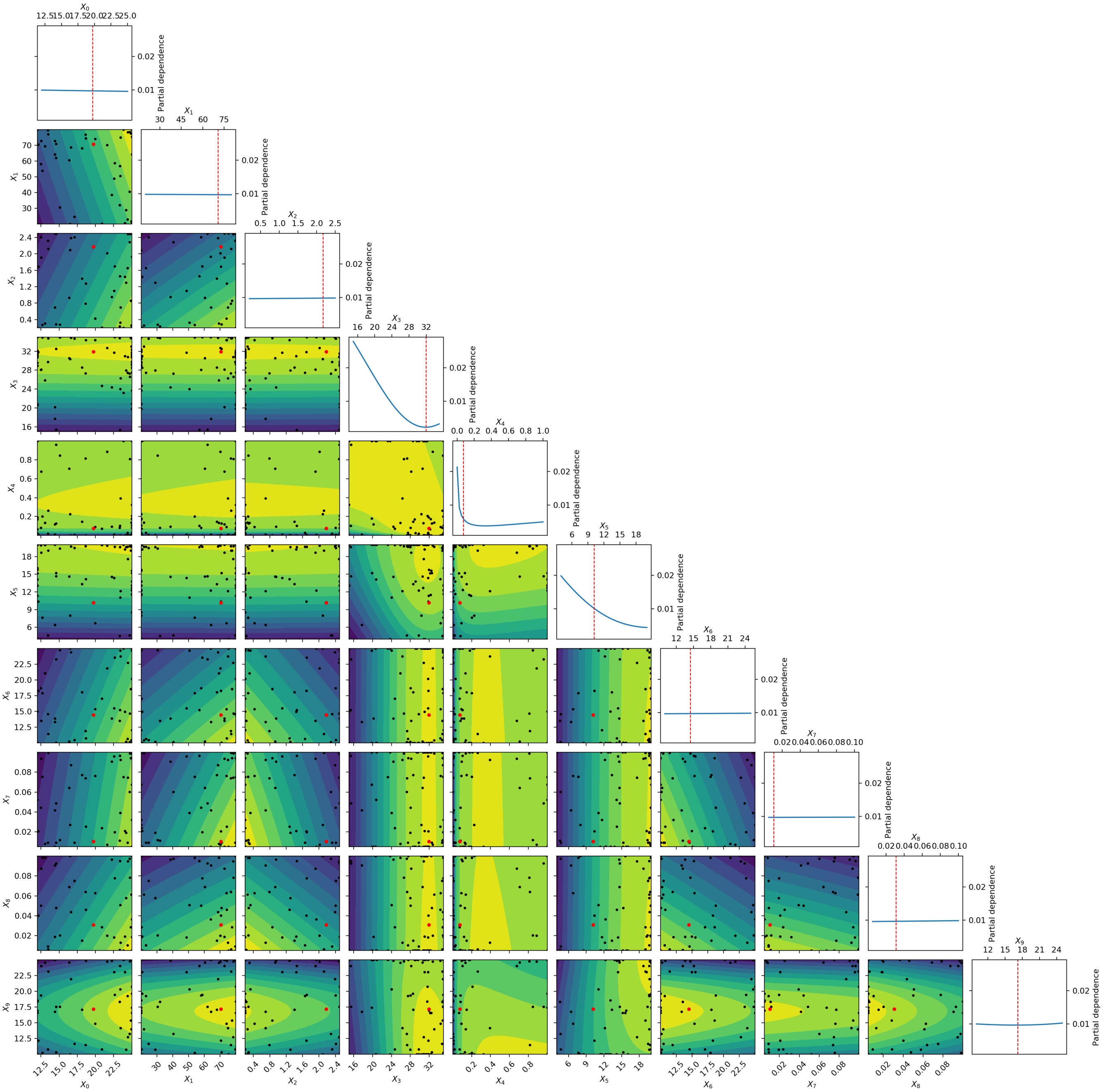
S(t)
t_{rel} [hour]
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000

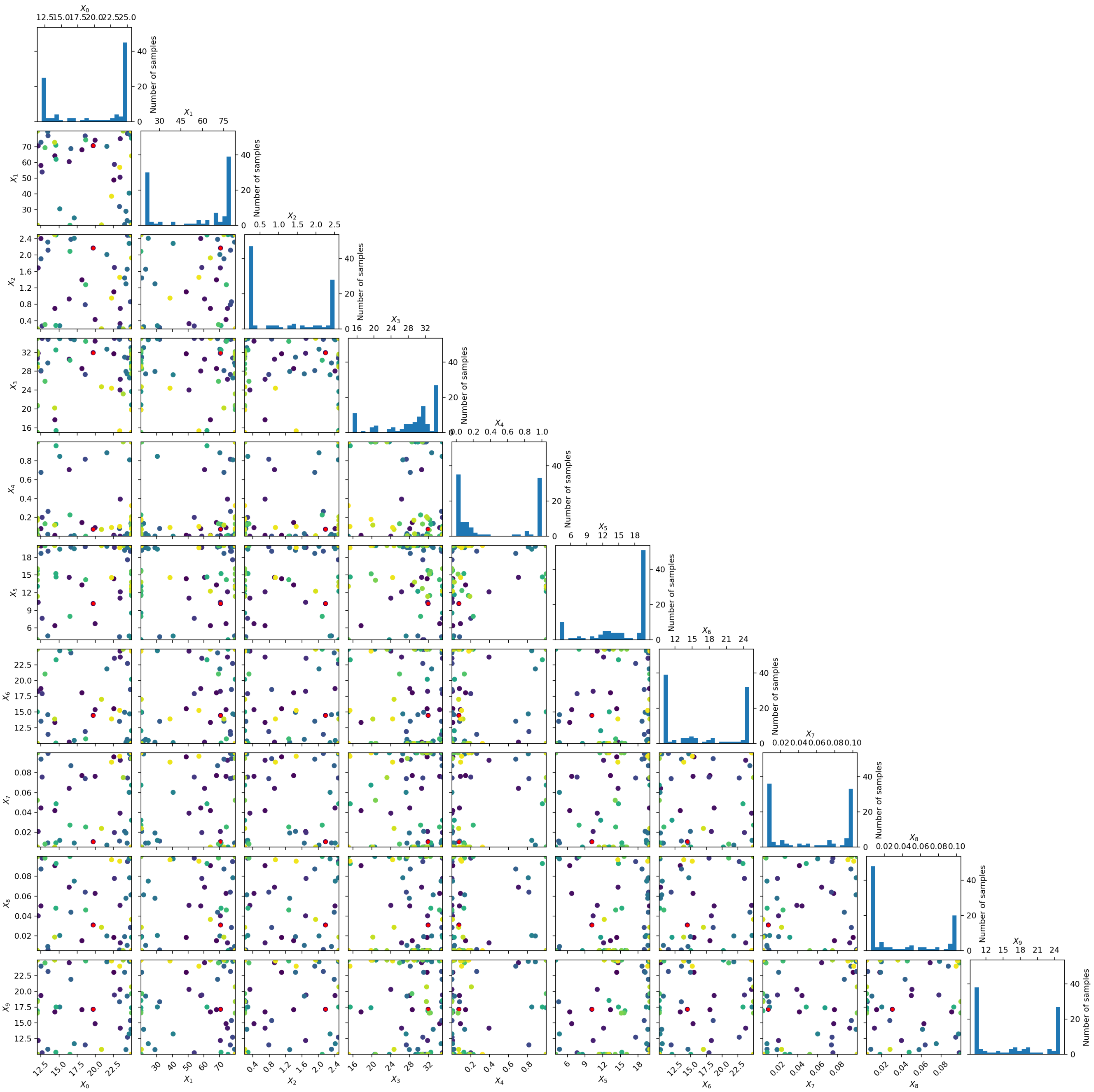


C(t)
t_{rel} [hour]
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000



ν(t)
t_{rel} [hour]
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000





Neural network approach

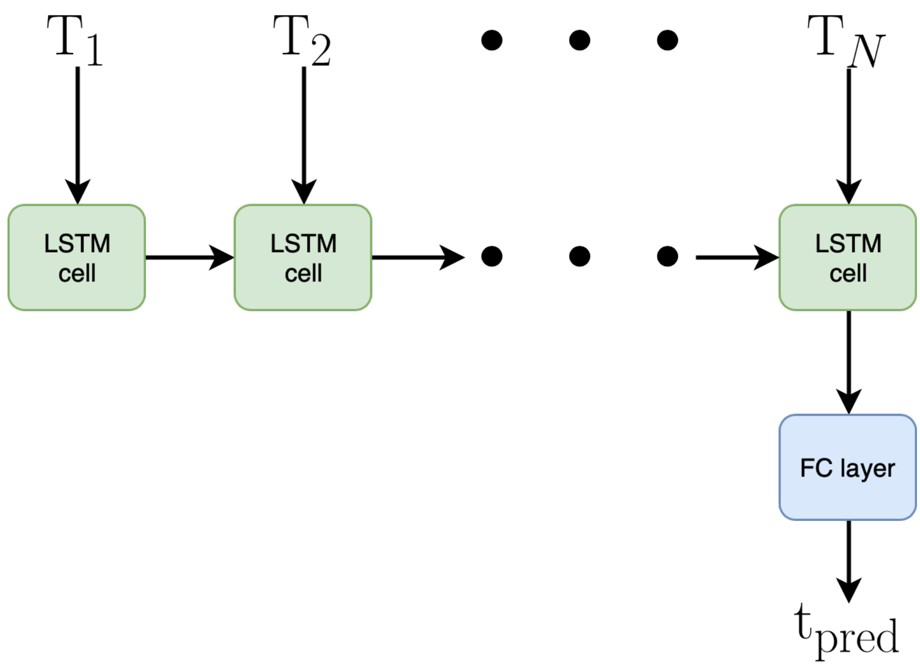


Figure 3: LSTM architecture for predicting flowering time from temperature measurement series.

Results of the neural network approach