

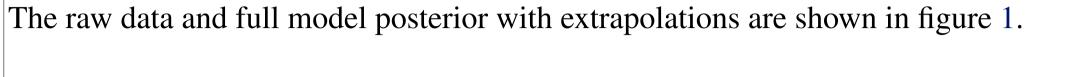
Automatic construction and description of nonparametric models

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This analysis was automatically generated



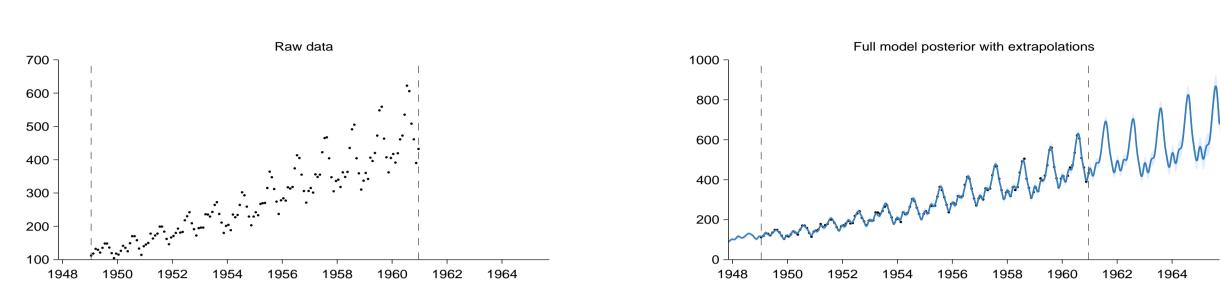


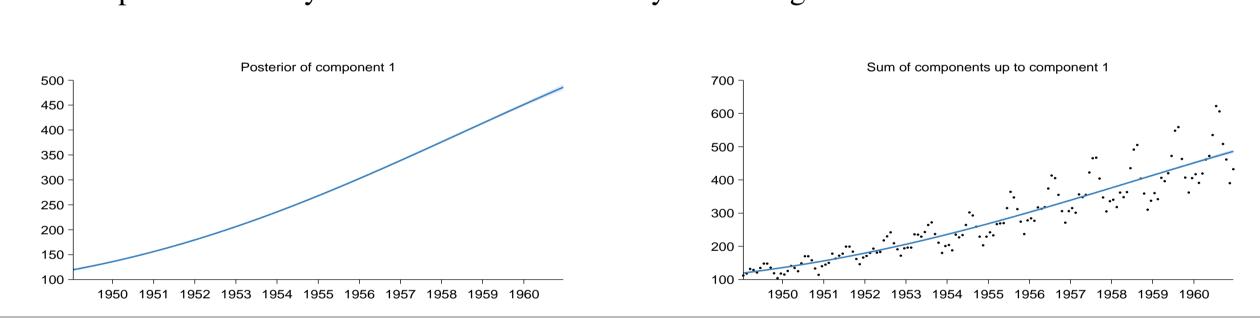
Figure 1: Raw data (left) and model posterior with extrapolation (right)

The structure search algorithm has identified four additive components in the data:

- A very smooth monotonically increasing function.
- An approximately periodic function with a period of 1.0 years and with approximately linearly increasing amplitude.
- An exactly periodic function with a period of 4.3 years but with linearly increasing amplitude.
- Uncorrelated noise with linearly increasing standard deviation.

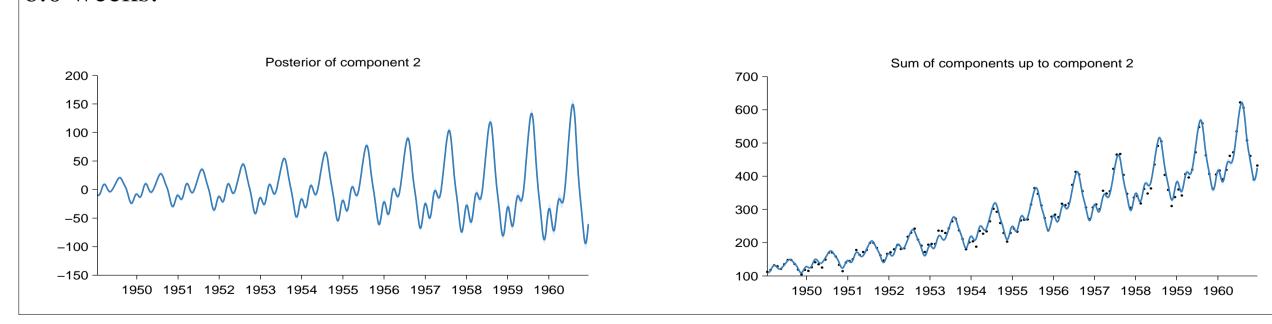
2.1 Component 1

This component is a very smooth and monotonically increasing function.



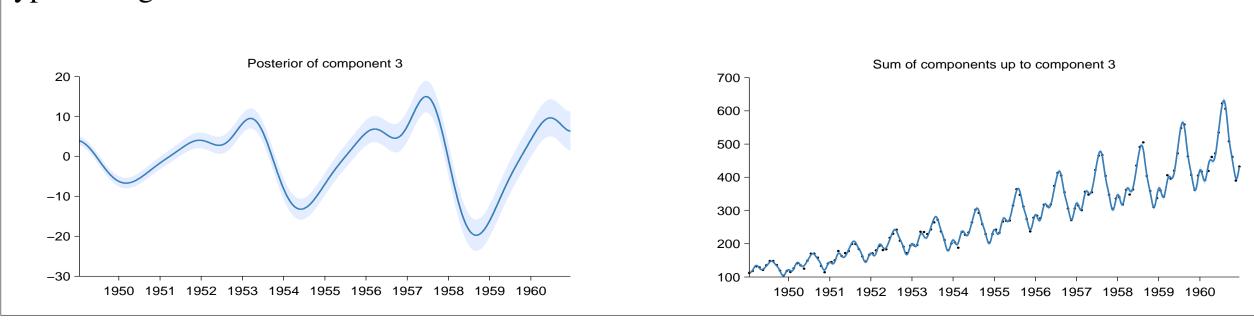
2.2 Component 2

This component is approximately periodic with a period of 1.0 years and varying amplitude. Across periods the shape of this function varies very smoothly. The amplitude of the function increases approximately linearly. The shape of this function within each period has a typical lengthscale of 6.0 weeks.



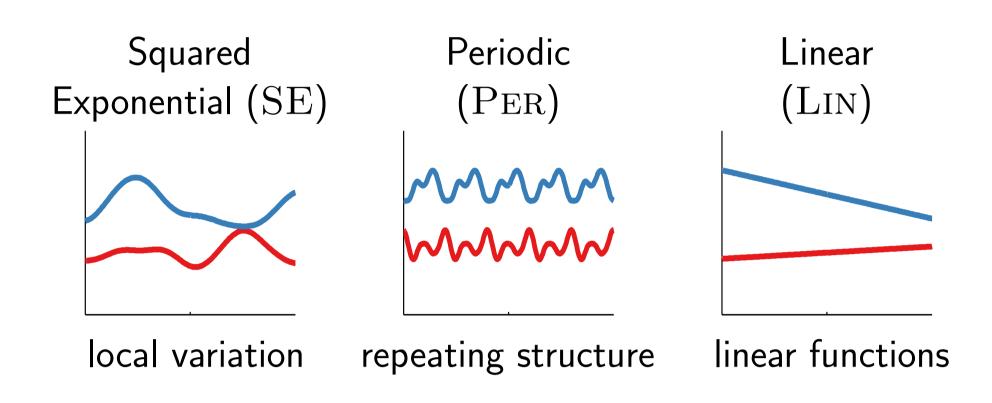
2.3 Component 3

This component is exactly periodic with a period of 4.3 years but with varying amplitude. The amplitude of the function increases linearly. The shape of this function within each period has a typical lengthscale of 7.4 months.

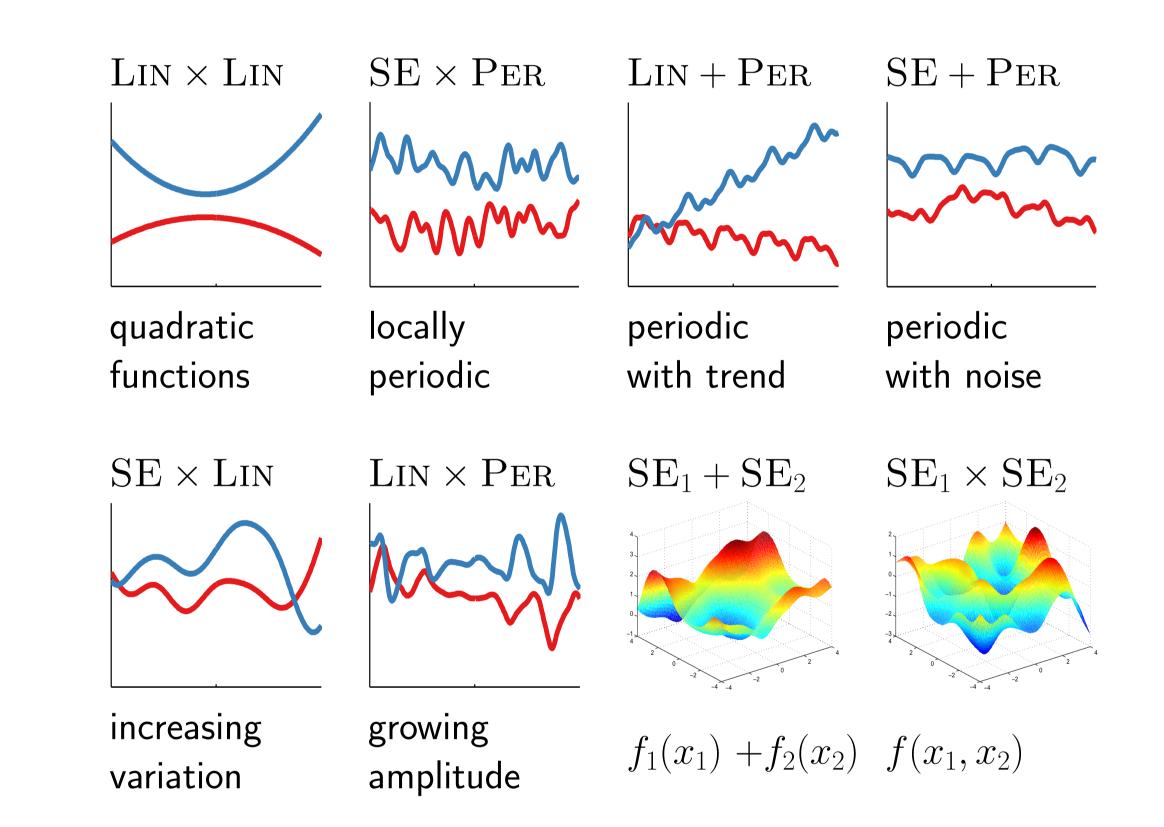


Gaussian processes model structure through kernels

• The kernel specifies which structures are likely under the GP prior - which determines the generalization properties of the model.

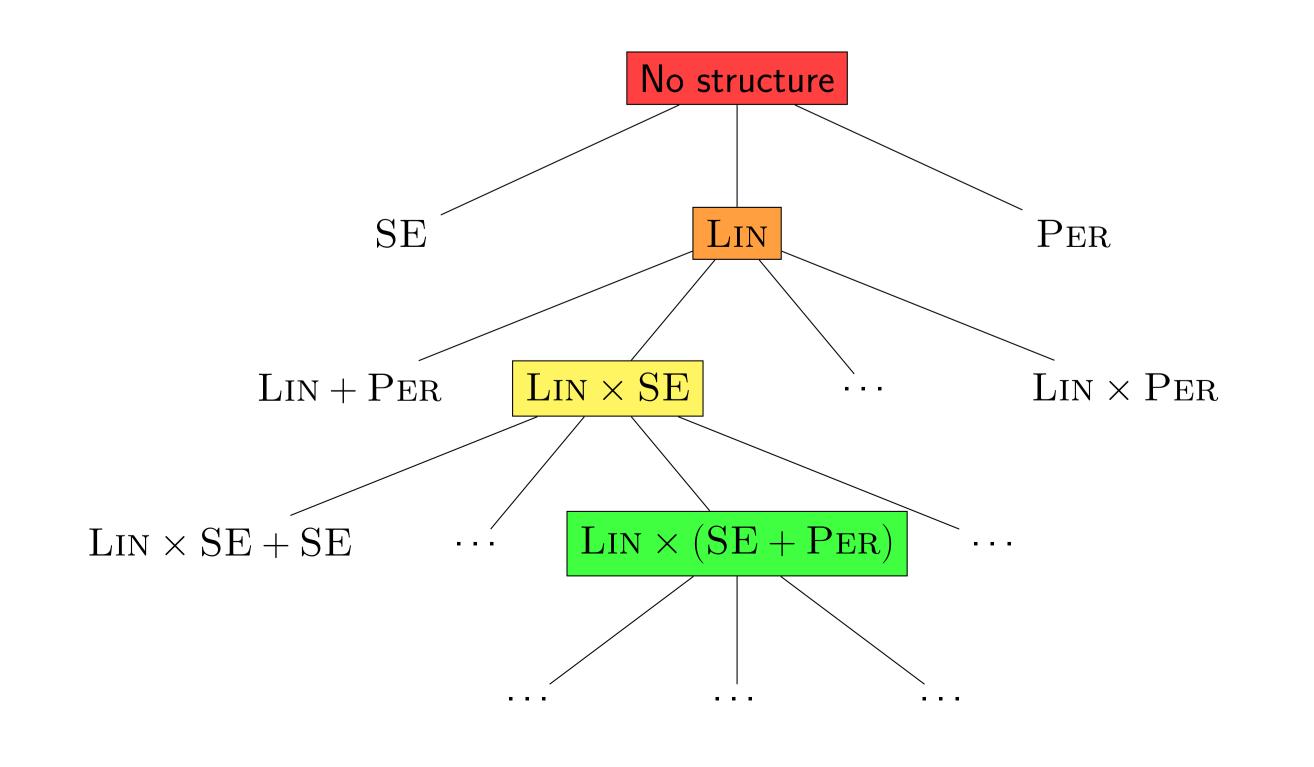


• Composite kernels can express many types of structure



Building composite kernels previously required human expertise

We can build models by greedy search



Automatically describing model properties

How to automatically describe arbitrarily complex kernels:

- 1. Break each kernel into a sum of products.
- 2. For each product, look up the properties of each kernel in that product.
- 3. Combine the properties into one sentence.
- 4. Plot contribution of this compoenent to the model.

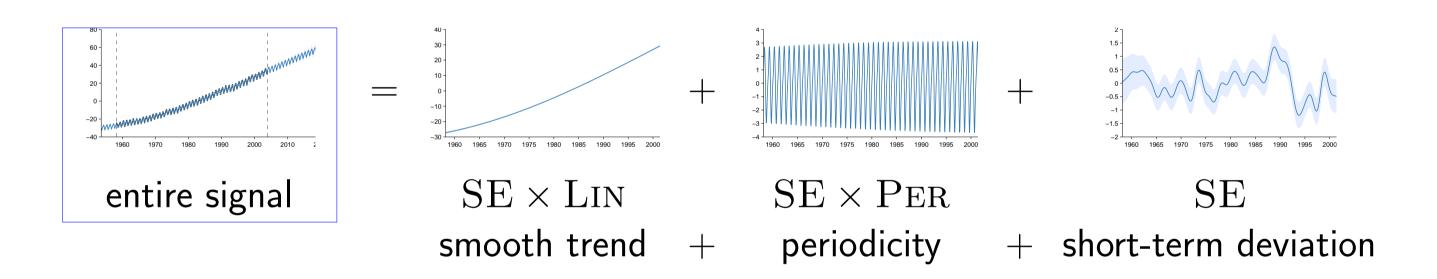
Kernels can be distributed into a sum of products

$$SE \times (LIN + PER + SE)$$

becomes

$$(SE \times LIN) + (SE \times PER) + (SE).$$

Sums of kernels correspond to sums of functions



If $f_1(x) \sim \text{GP}(0, k_1)$ and $f_2(x) \sim \text{GP}(0, k_2)$ then $f_1(x) + f_2(x) \sim \text{GP}(0, k_1 + k_2)$. Therefore, a sum of kernels can be described as a sum of independent functions.

Each kernel in a product roughly corresponds to an adjective

Kernel How it modifies the prior

SE functions change smoothly

PER | functions repeat

LIN amplitude increases linearly

On its own, each kernel simply modifyies the constant function f(x) = c.

Example short descriptions

Product of Kernels Description

Per			An exactly periodic function
Per	\times SE		An approximately periodic function
D	α	T	

 $ext{Per} imes ext{SE} imes ext{Lin}$ An approximately periodic function with linearly varying amplitude

LIN A linear function $LIN \times LIN$ A quadratic function

 $ext{Per} imes ext{Lin} imes ext{Lin}$ An exactly periodic function with quadratically varying amplitude

Code available at github.com/jamesrobertlloyd/gpss-research