

# Kernel Selection Methods

Fergus Simpson

# Overview

## What is a kernel?

- Primitive kernels

- How to combine kernels

## Searching for the right kernel

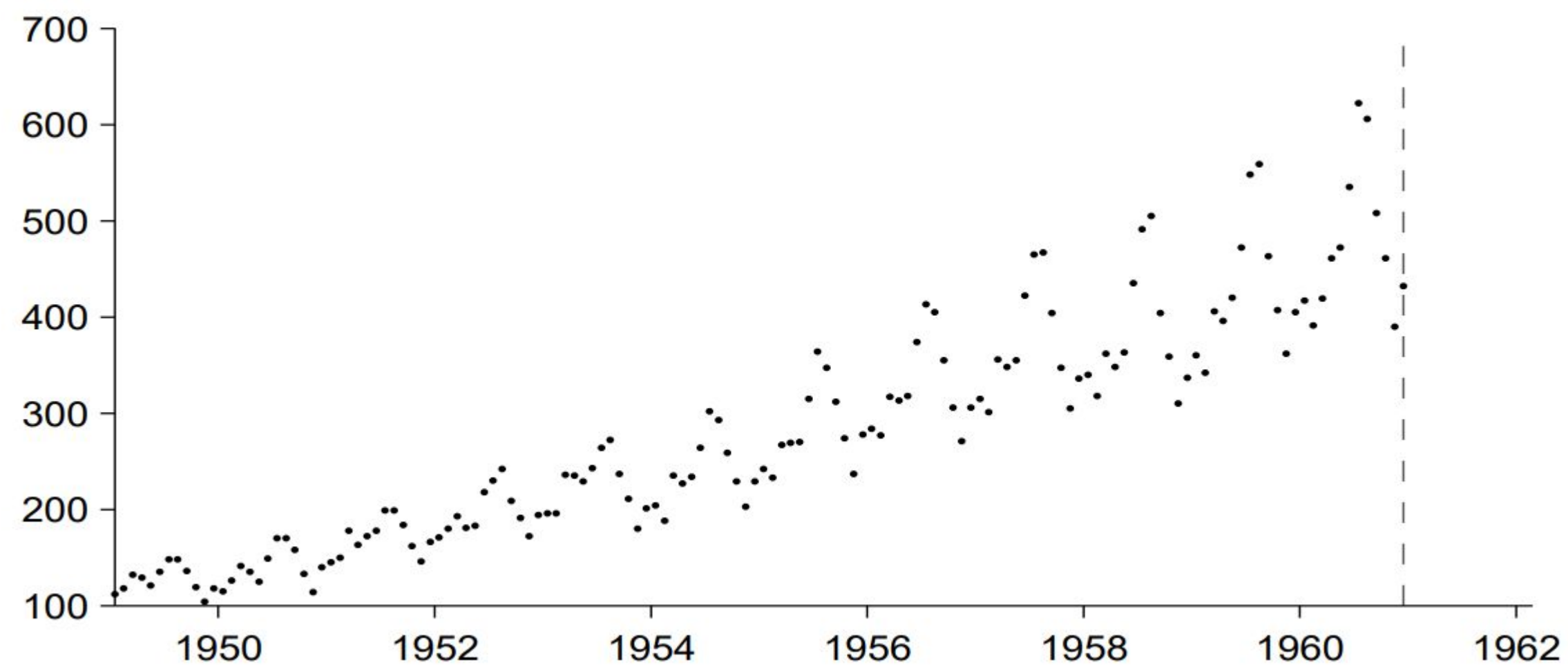
- Hand crafting

- The Automatic Statistician

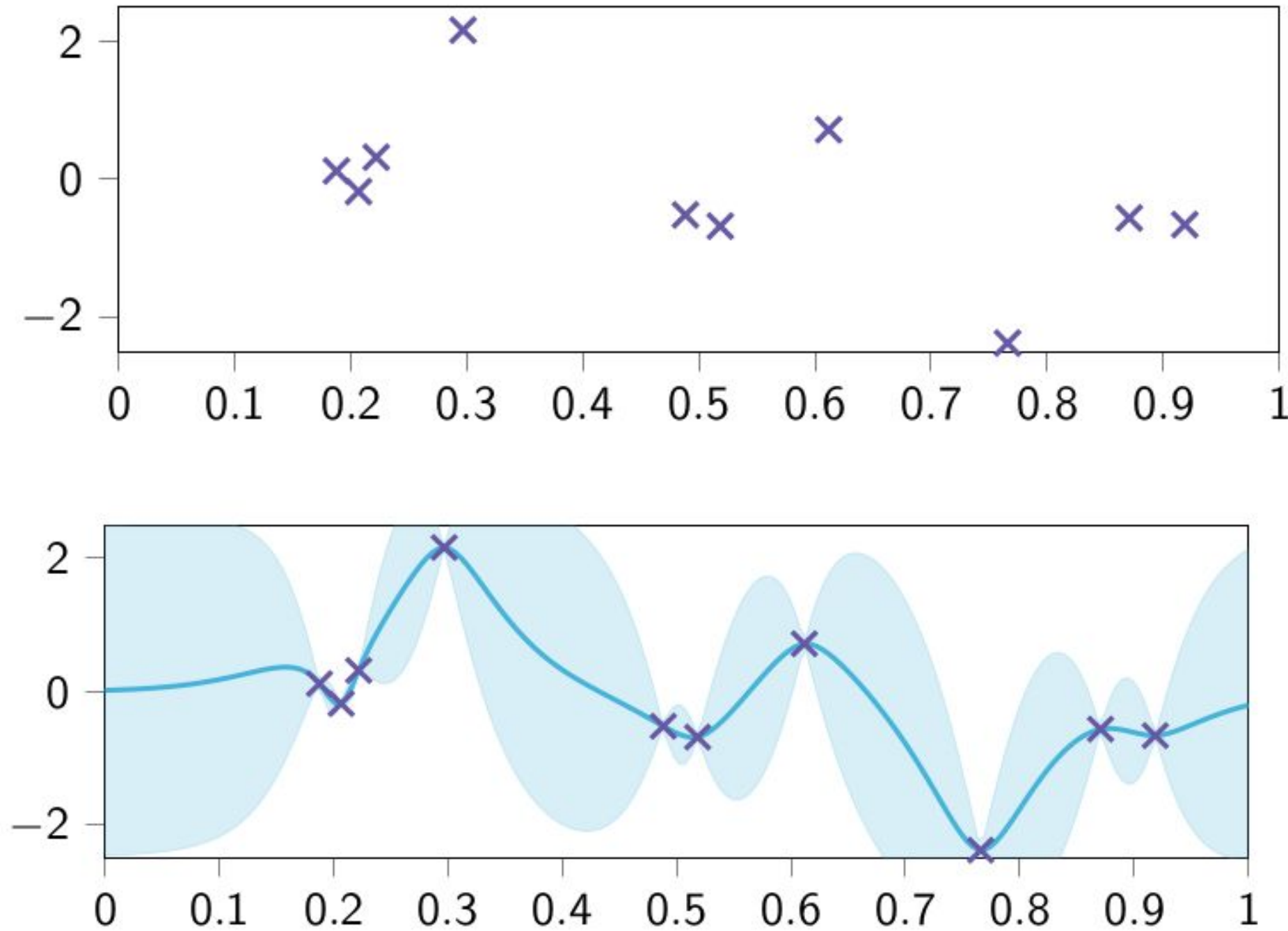
- Spectral Kernels

- The Neural Kernel Network

# Objective



# Gaussian Process Regression



$$p(f(\cdot)|\mathcal{D}) = \frac{p(\mathcal{D}|f(\cdot))p(f(\cdot))}{\int p(\mathcal{D}|f(\cdot))p(f(\cdot))}$$



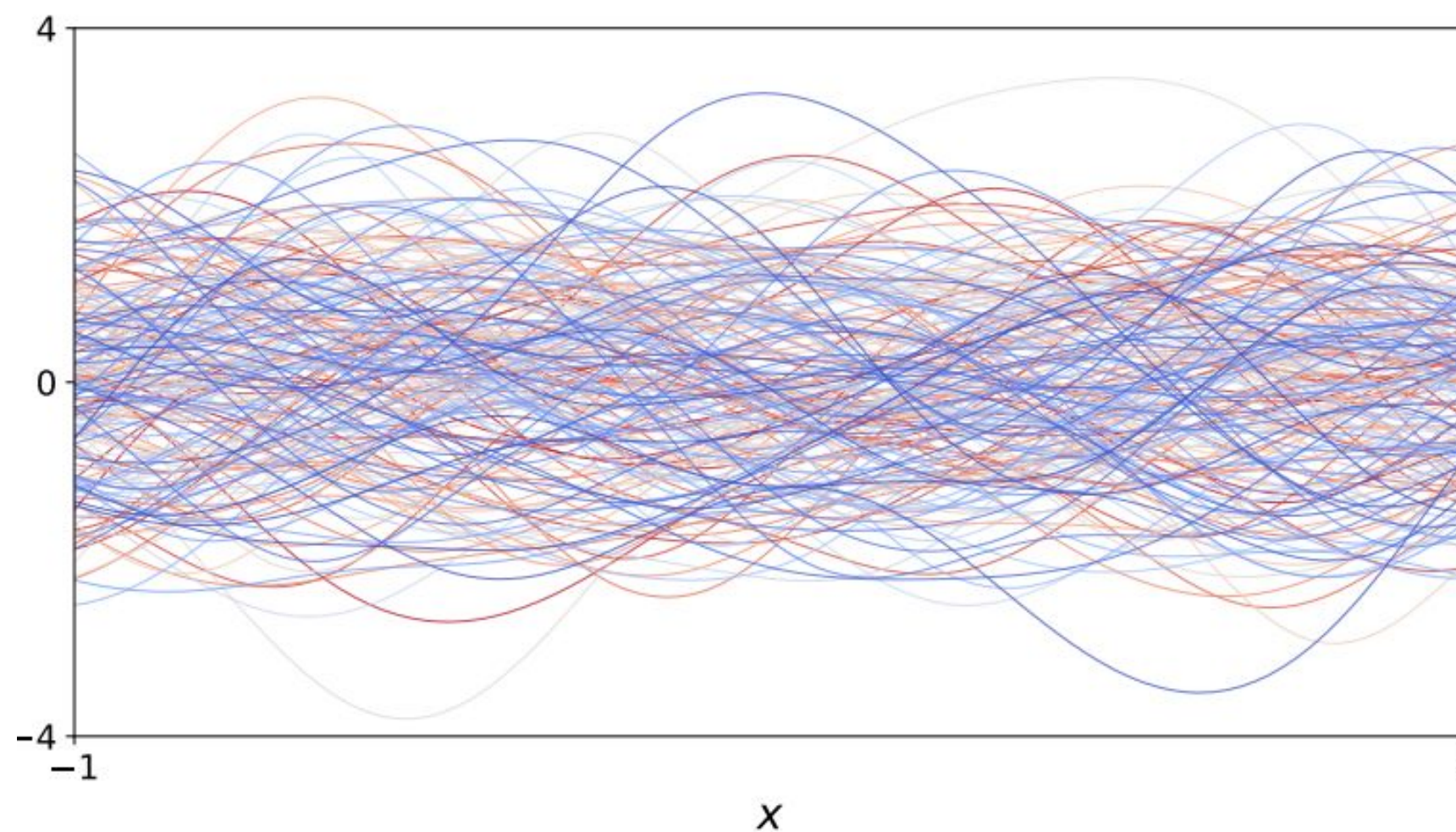


What is a kernel?

# What is a kernel?

The distribution of a GP is fully characterised by:

- its mean function  $m$  defined over  $D$
- its covariance function (or kernel)  $k$  defined over  $D \times D$ :  
 $k(x, x') = \text{cov}(f(x), f(x'))$



# Limitations of kernels

A kernel satisfies the following properties:

- It is symmetric:  $k(x, x') = k(x', x)$

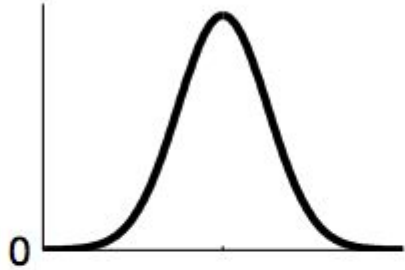
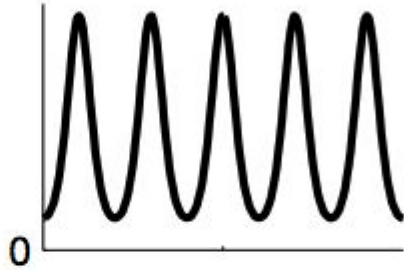
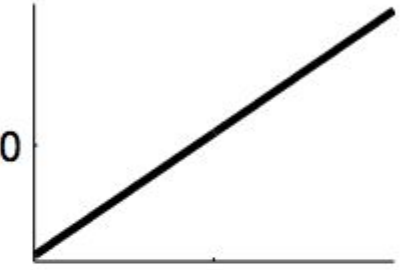
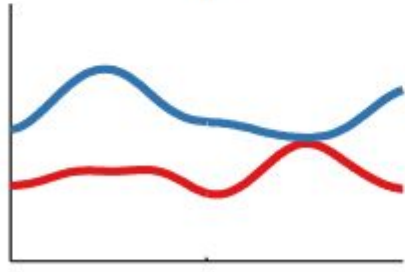
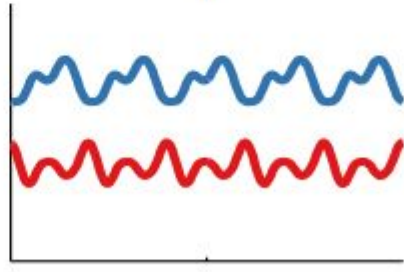
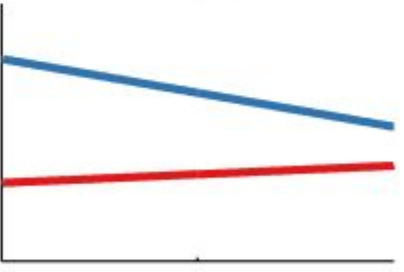
- It is positive semi-definite (psd): 
$$\sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j k(x_i, x_j) \geq 0$$

For example

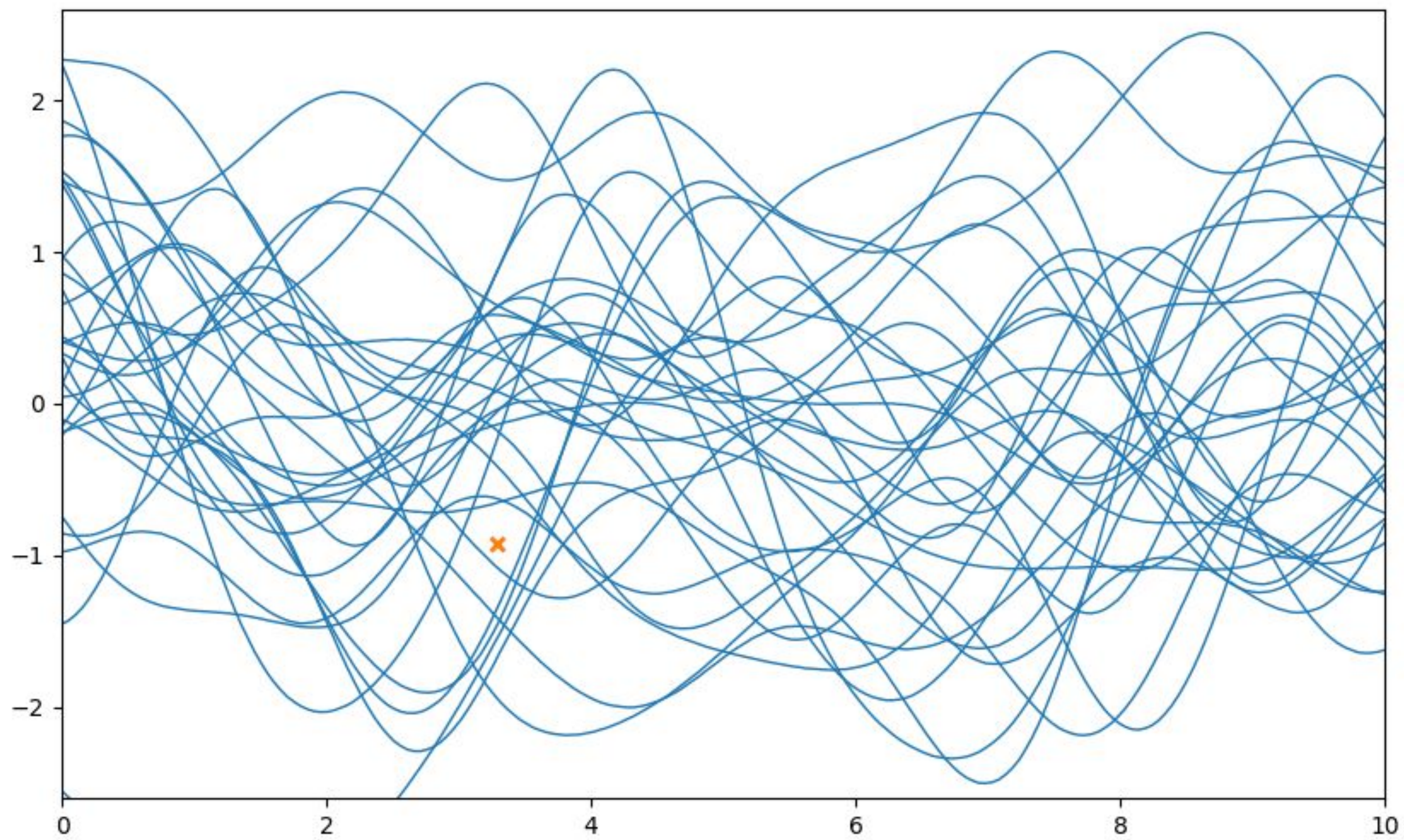
$$k(x_1, x_1) \geq 0$$

$$|k(x_1, x_2)|^2 \leq k(x_1, x_1) k(x_2, x_2)$$



|   |   |   |   |
|---|---|---|---|
| Kernel name:                                  | Squared-exp (SE)  | Periodic (Per)  | Linear (Lin)  |
| $k(x, x') =$                                  | $\sigma_f^2 \exp\left(-\frac{(x-x')^2}{2\ell^2}\right)$                               | $\sigma_f^2 \exp\left(-\frac{2}{\ell^2} \sin^2\left(\pi \frac{x-x'}{p}\right)\right)$ | $\sigma_f^2(x-c)(x'-c)$   |
| Plot of $k(x, x')$ :                          |   |   |   |
|   | $x - x'$<br>↓   | $x - x'$<br>↓   | $x$ (with $x' = 1$ )<br>↓   |
| Functions $f(x)$<br>sampled from<br>GP prior: |  |  |  |
|   | $x$   | $x$   | $x$   |
| Type of structure:                            | local variation   | repeating structure   | linear functions  |







# Gaussian Processes

## Examples of kernels

constant  $k(x, x') = \sigma^2$

white noise  $k(x, x') = \sigma^2 \delta_{x, x'}$

Brownian  $k(x, x') = \sigma^2 \min(x, x')$

exponential  $k(x, x') = \sigma^2 \exp(-|x - x'|/\theta)$

Matérn 3/2  $k(x, x') = \sigma^2 (1 + |x - x'|) \exp(-|x - x'|/\theta)$

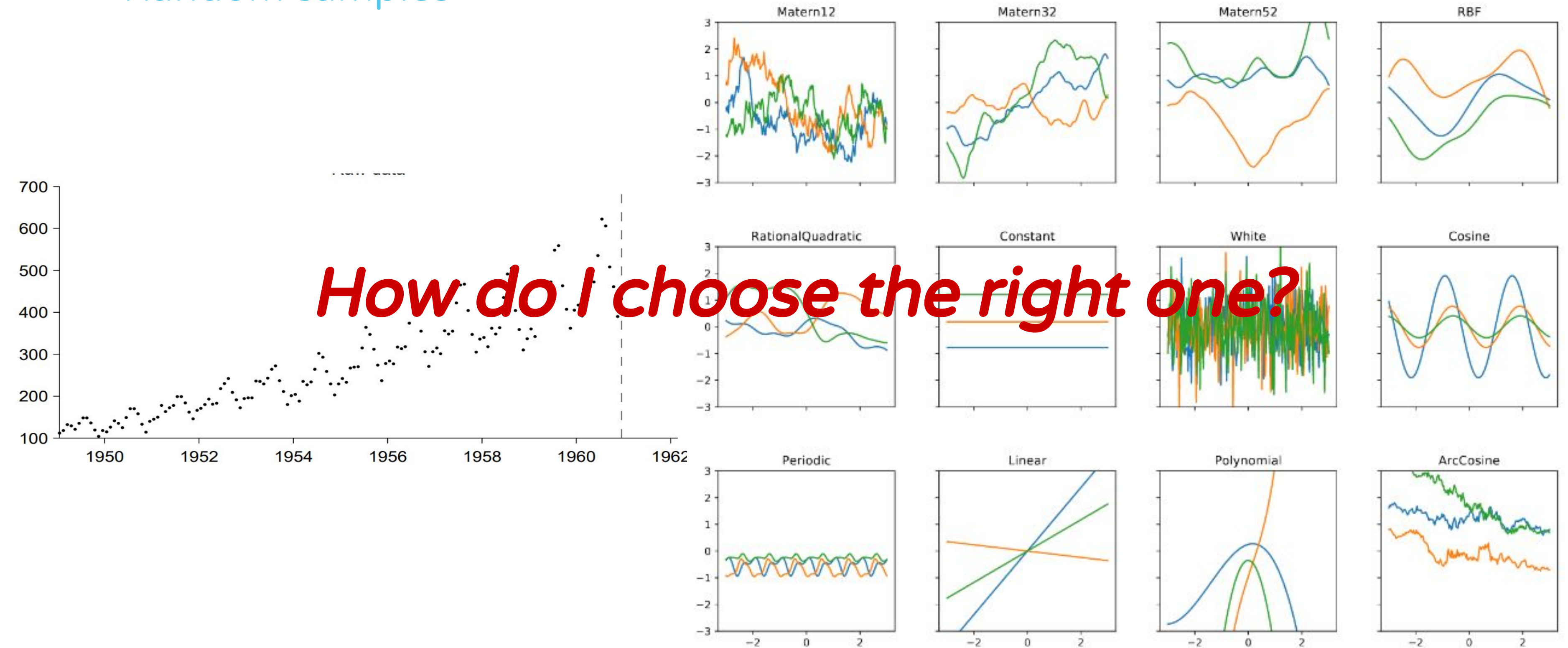
Matérn 5/2  $k(x, x') = \sigma^2 (1 + |x - x'|/\theta + 1/3|x - x'|^2/\theta^2) \exp(-|x - x'|/\theta)$

squared exponential  $k(x, x') = \sigma^2 \exp(-(x - x')^2/\theta^2)$

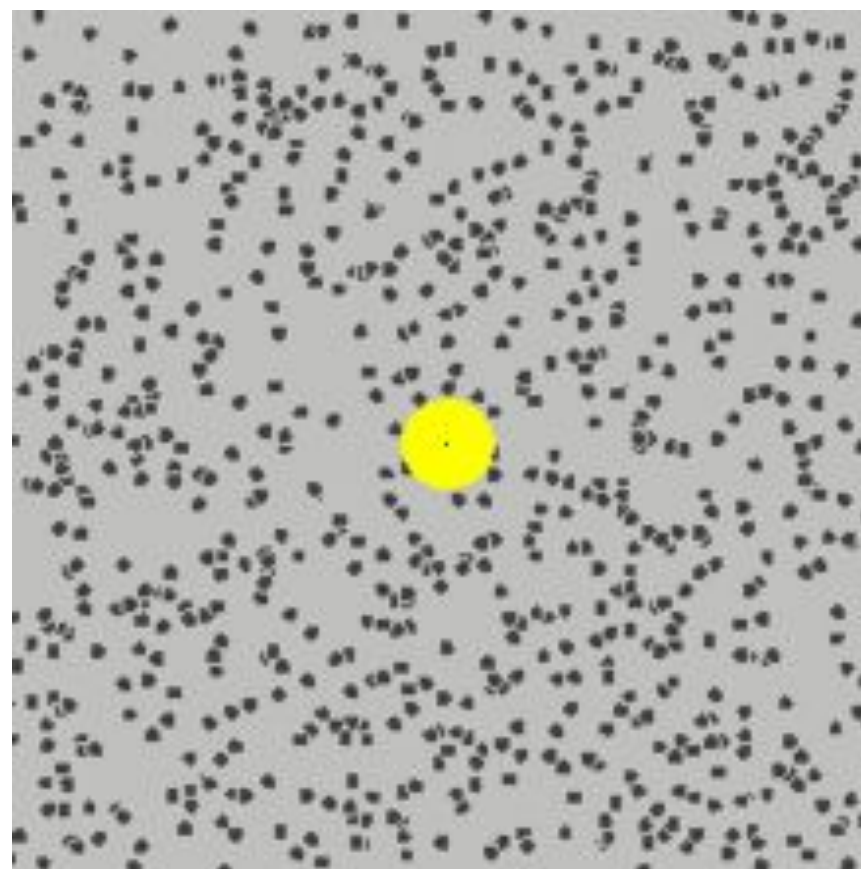
linear  $k(x, x') = \sigma^2 xy$

# Gaussian Processes

Random samples

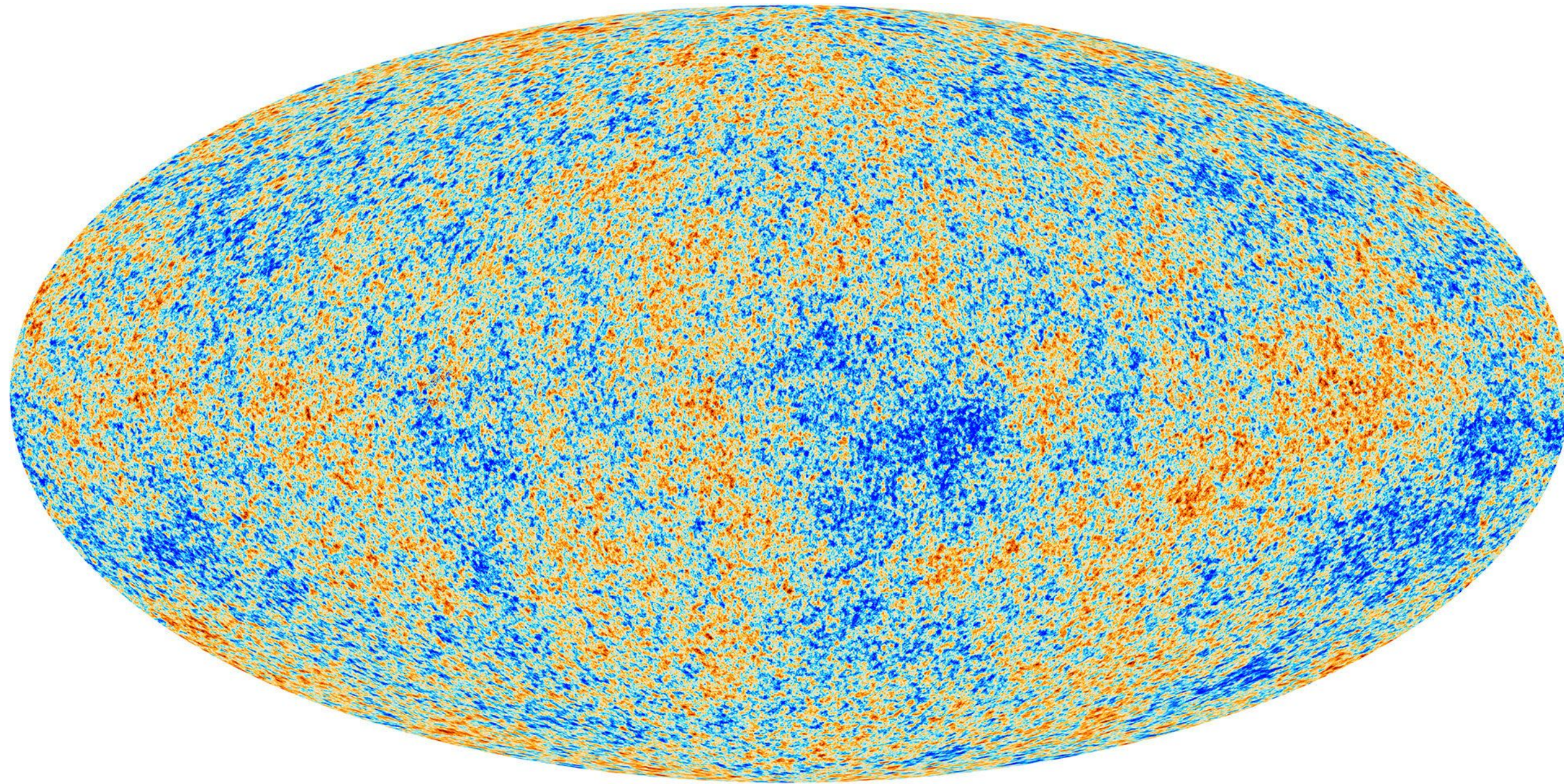


# Physically motivated kernels





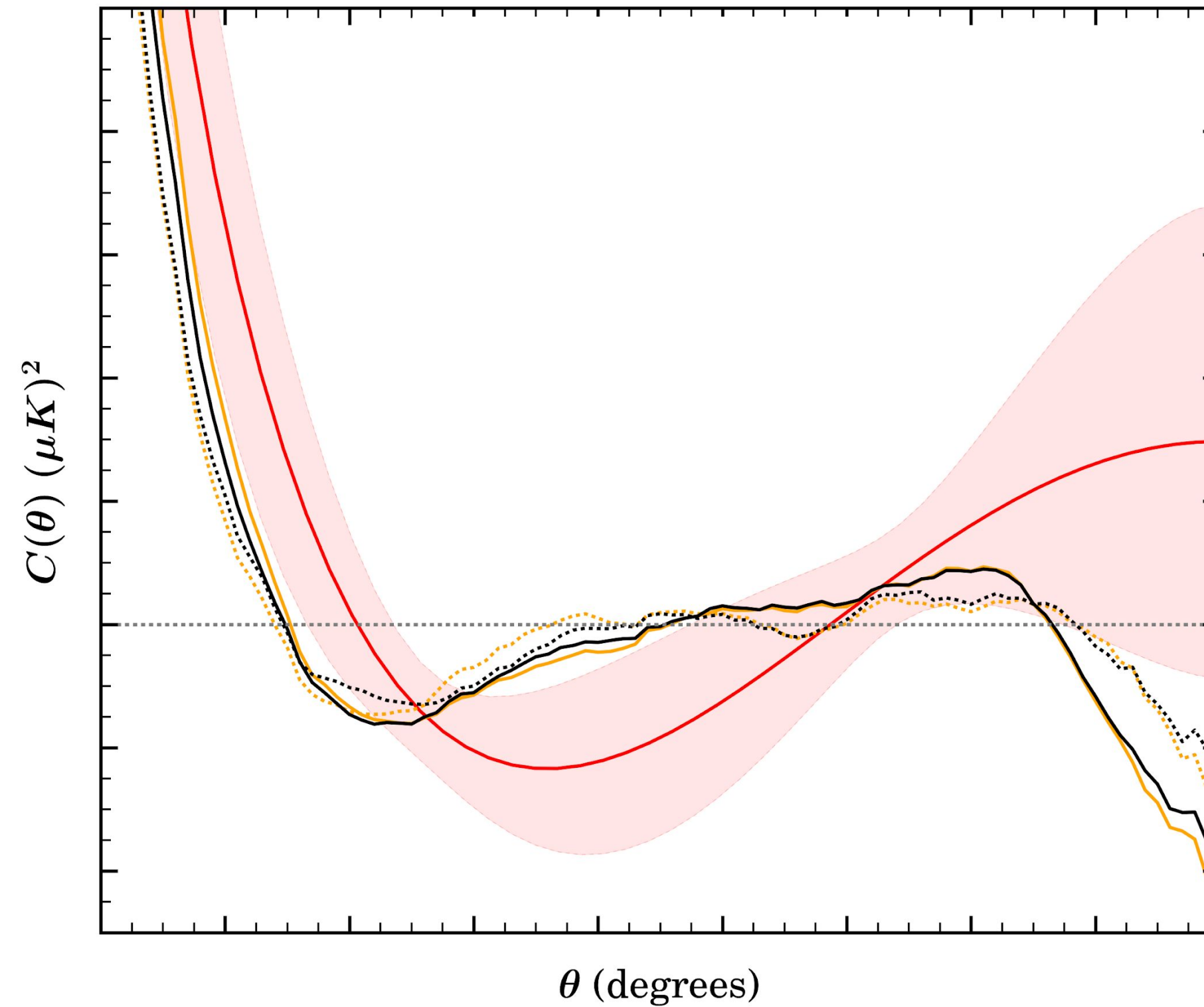
# Physically motivated kernels



ESA and the Planck Collaboration



# Physically motivated kernels



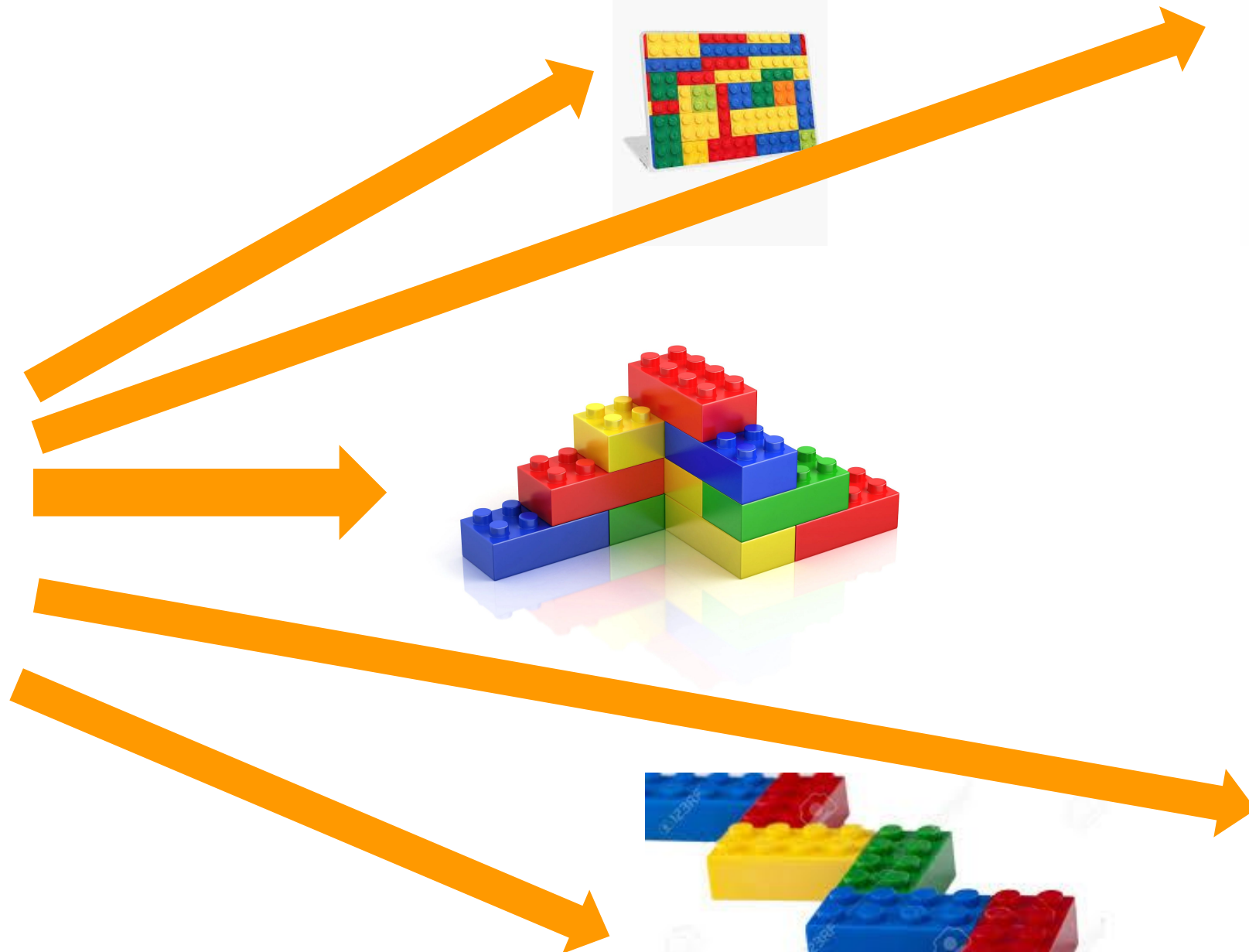
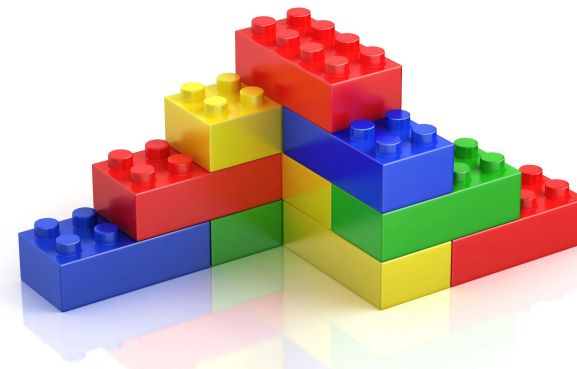


Hand crafted kernels

# Forming new kernels

Composite kernels

Primitive kernels





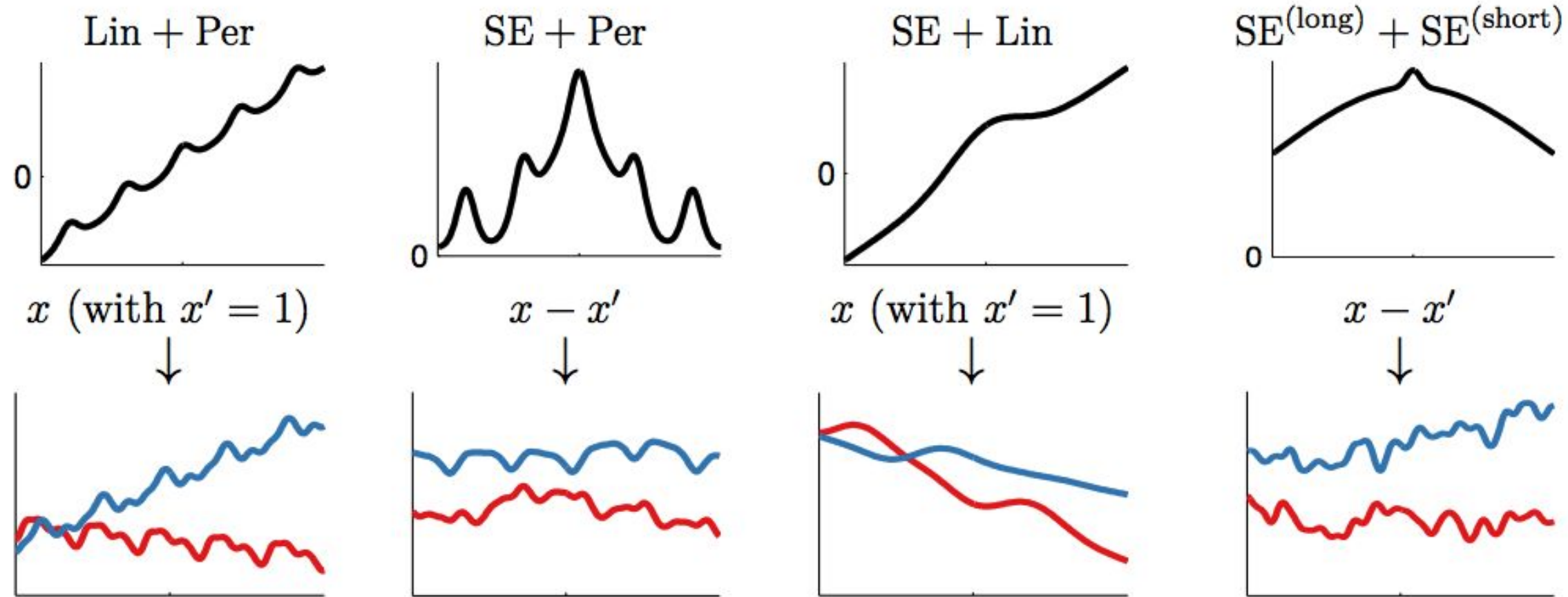
# Forming new kernels

## Kernel addition

Adding two kernels generates a new kernel

# Forming new kernels

## Kernel addition



Duvenaud (2014)

# Forming new kernels

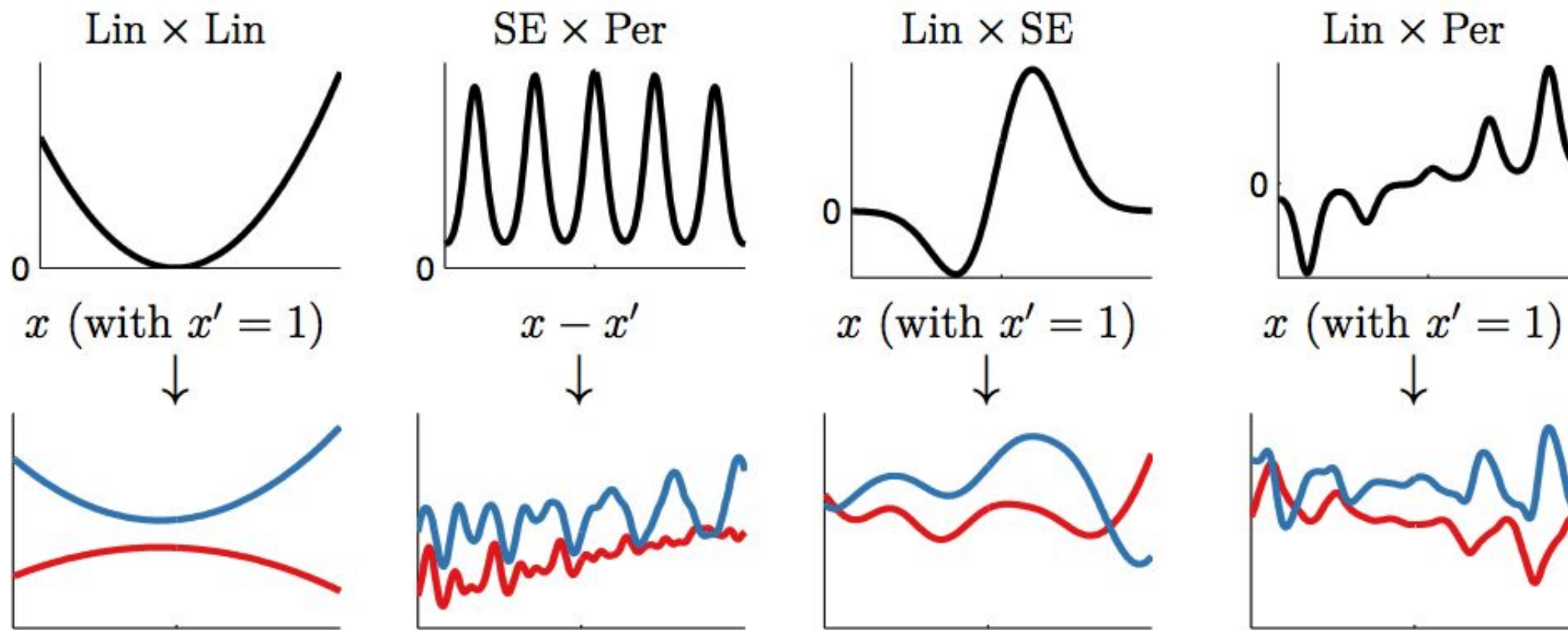
## Kernel products

**Adding two kernels generates a new kernel**

**Multiplying two kernels generates a new kernel**

# Forming new kernels

## Kernel products



Duvenaud (2014)



# Forming new kernels

## Kernel changepoints

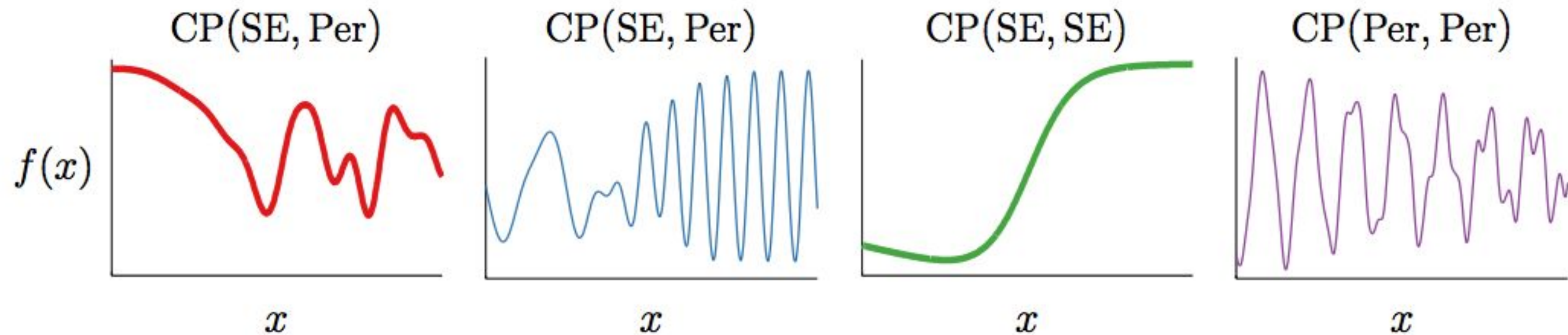
**Adding two kernels generates a new kernel**

Multiplying two kernels generates a new kernel

Stitching two kernels together generates a new kernel

# Forming new kernels

## Kernel changepoints



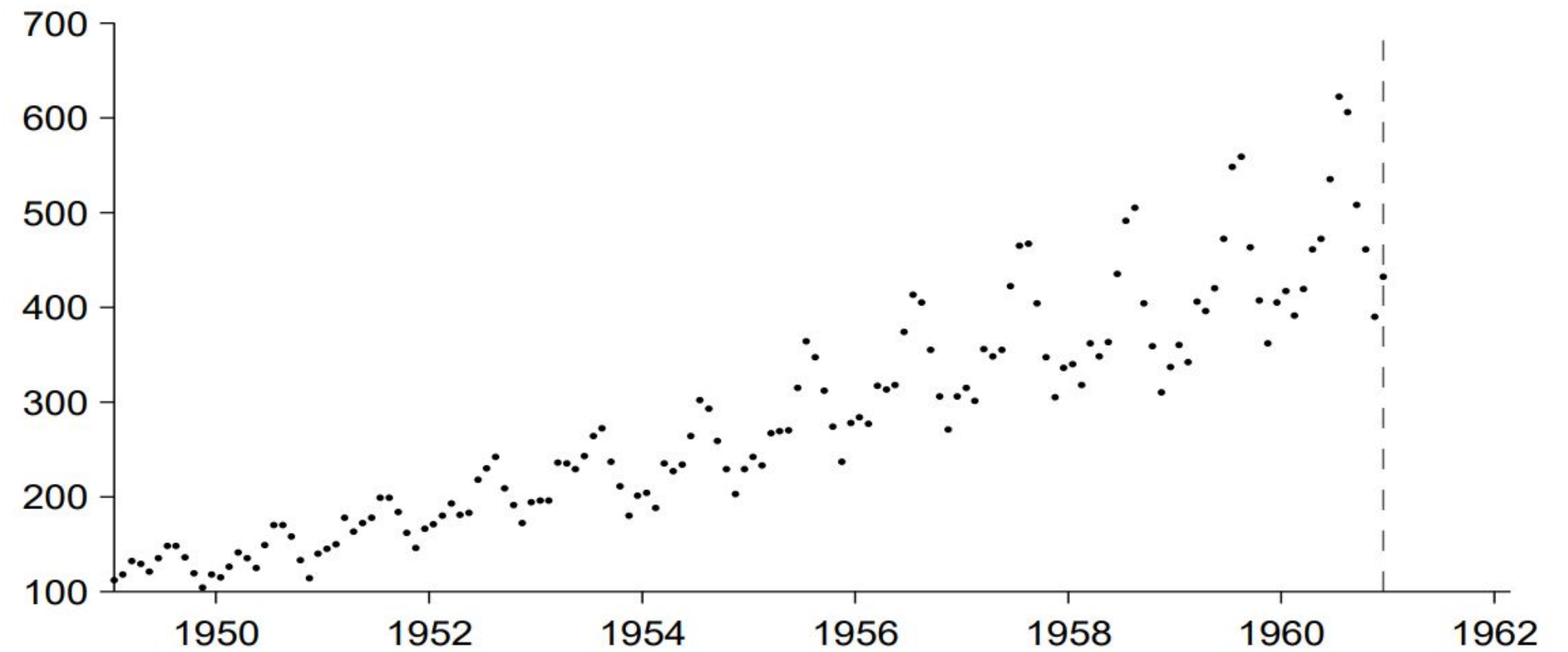
$$\text{CP}(k_1, k_2) = k_1 \times \boldsymbol{\sigma} + k_2 \times \bar{\boldsymbol{\sigma}}$$

where  $\boldsymbol{\sigma} = \sigma(x)\sigma(x')$  and  $\bar{\boldsymbol{\sigma}} = (1 - \sigma(x))(1 - \sigma(x'))$ .

Duvenaud (2014)

# Manual approach

- 1) Try  $k_{SE}$
- 2) Try  $k_{SE} \times k_{Per} + k_{SE} + k_{Noise}$
- 3) Try  $k_{SE} + k_{SE} \times k_{Per} + k_{RQ} + k_{SE} + k_{Noise}$
- 4) Try ....



Building bespoke models by hand is very time-consuming



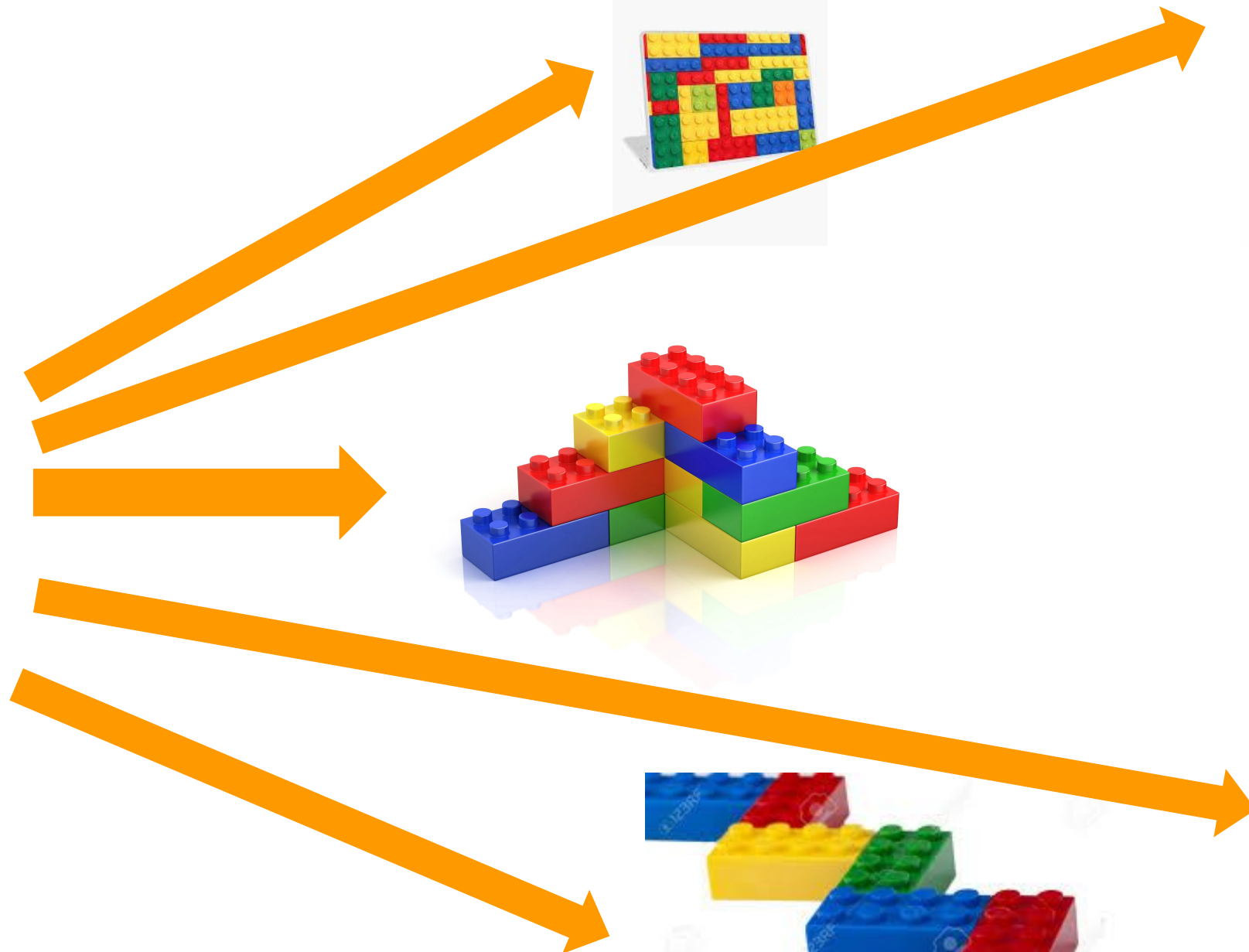
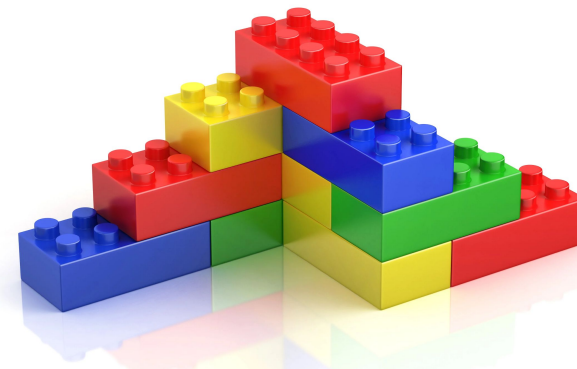
# The Automatic Statistician



# Many possible combinations

Composite kernels

Primitive kernels

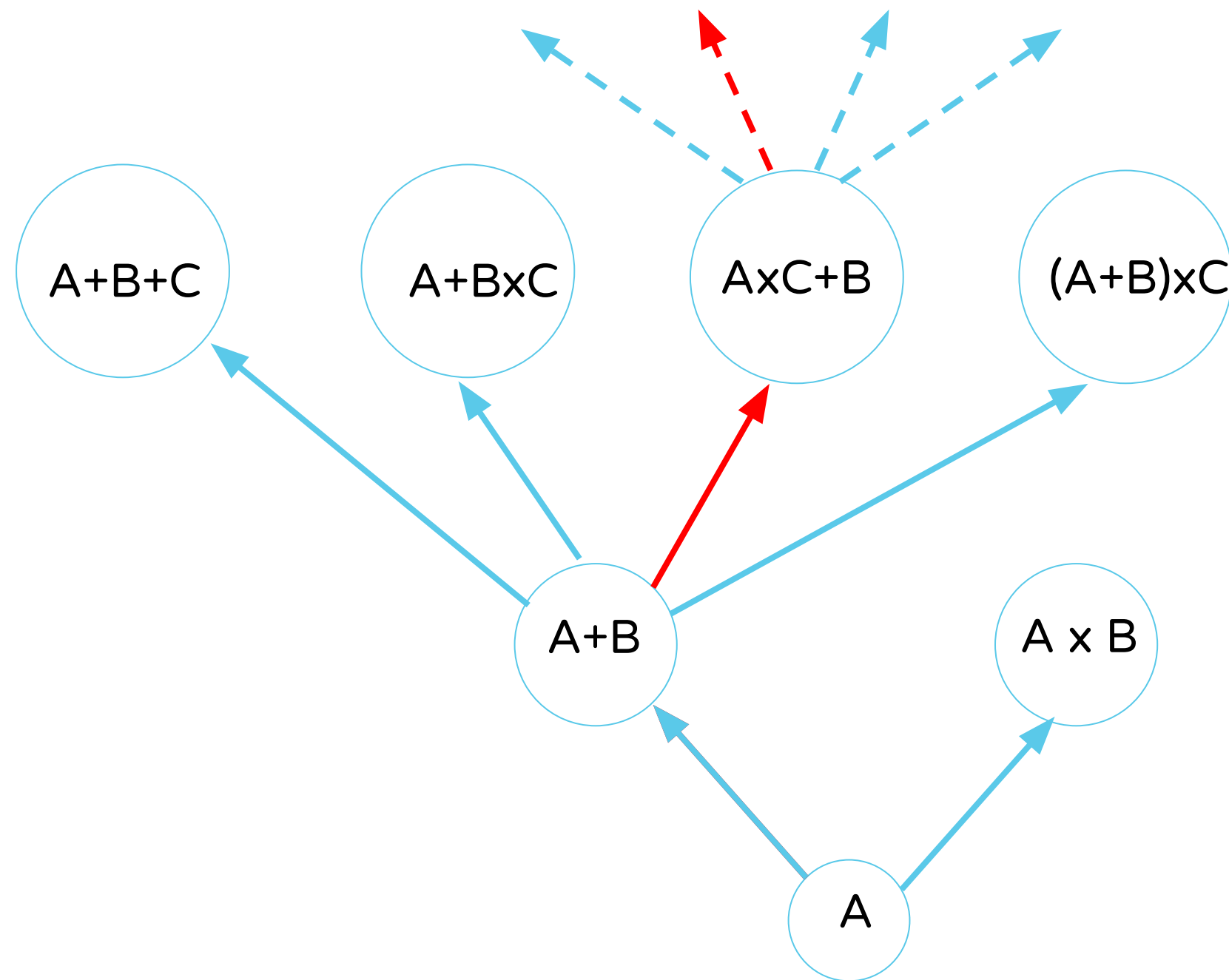








# Tree of kernels

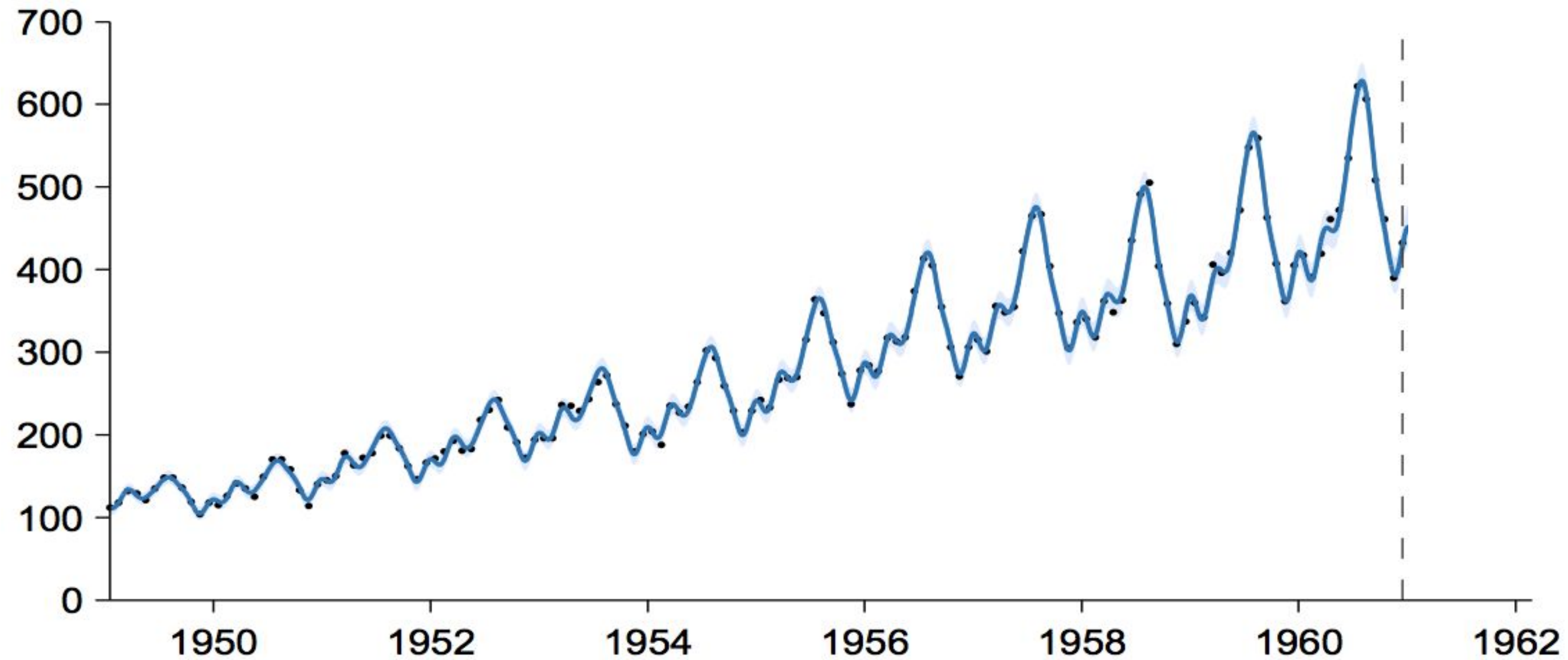


where B can be:

Linear  
Periodic  
Squared exponential  
Constant  
Noise

# Does it work?

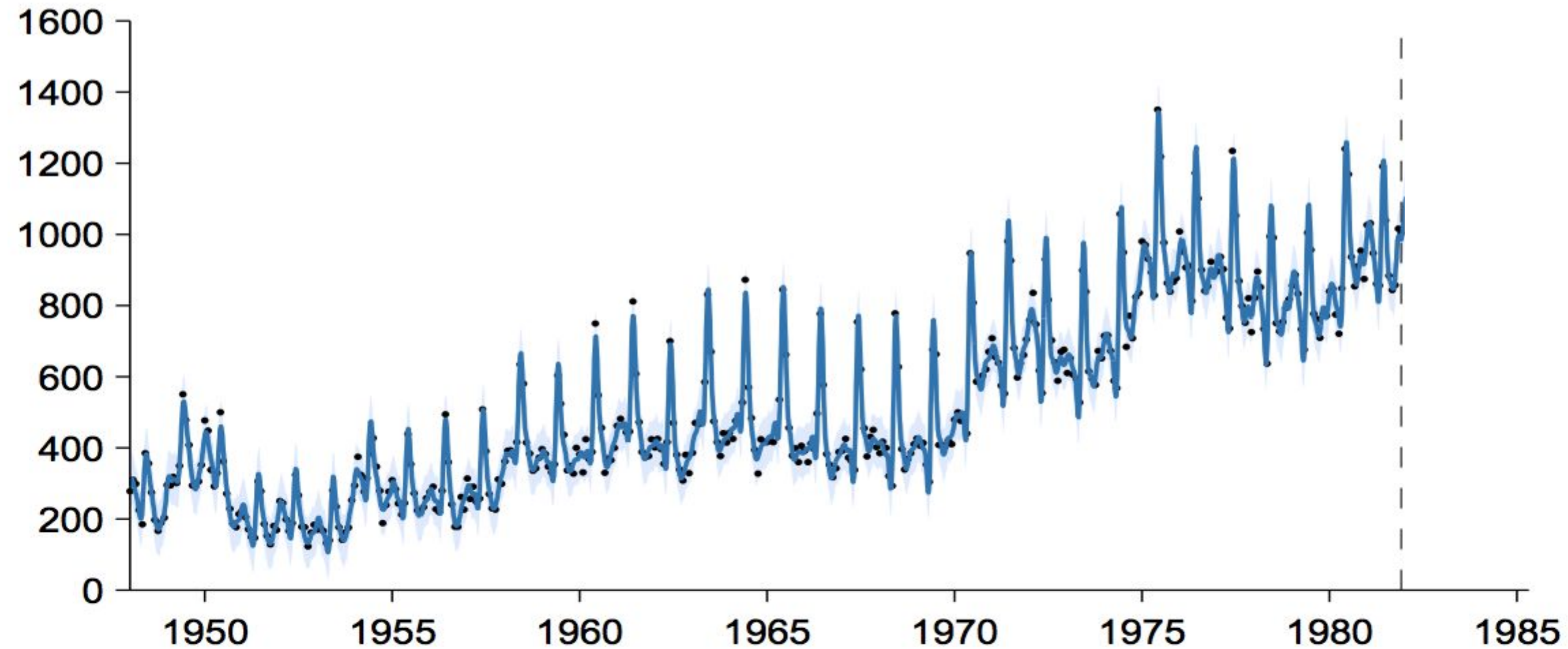
## Predicting airline passengers



From [www.automaticstatistician.com](http://www.automaticstatistician.com)

# Does it work?

## Forecasting unemployment levels

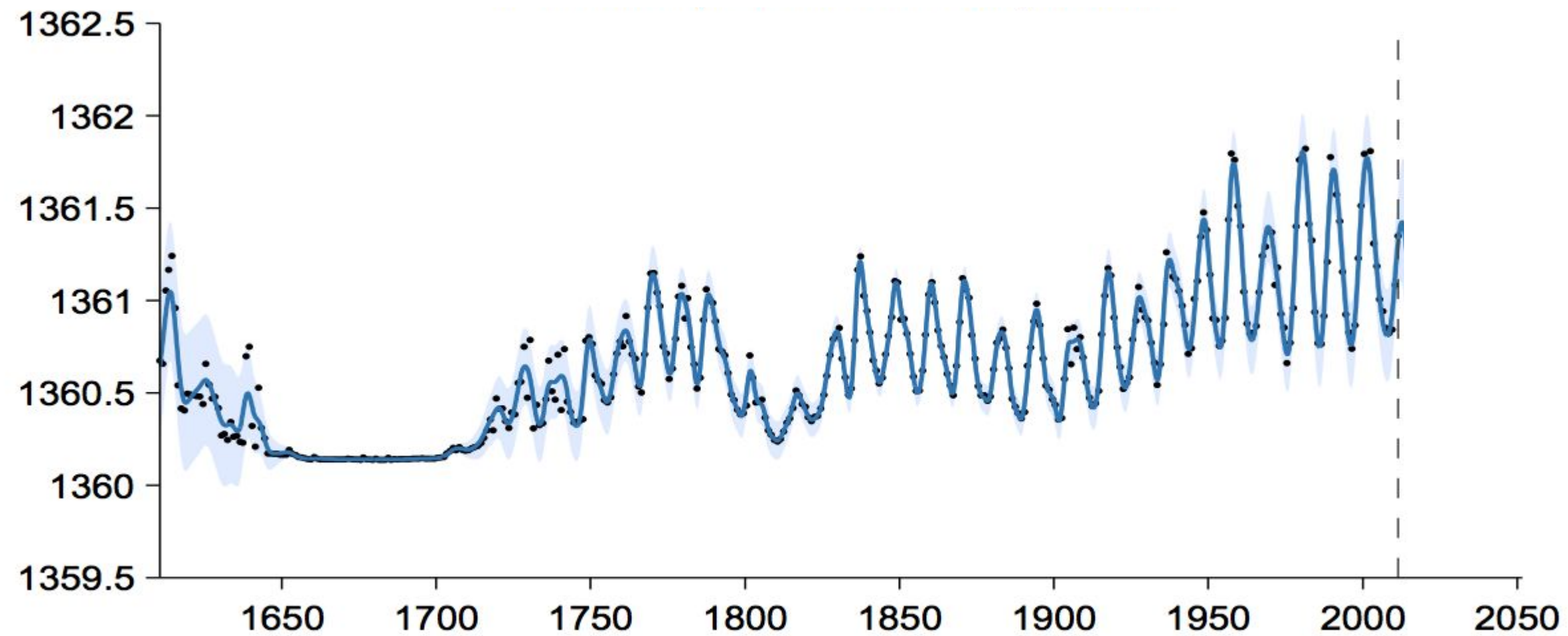


From [www.automaticstatistician.com](http://www.automaticstatistician.com)



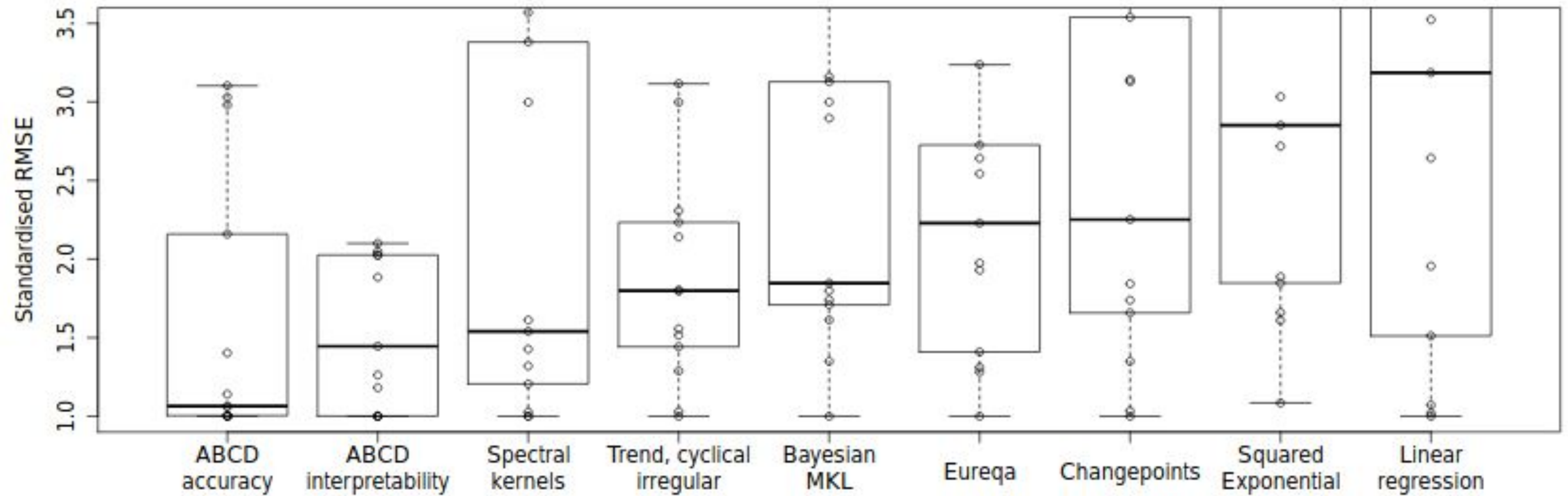
# Does it work?

## Forecasting solar irradiance



Lloyd et al (2014)

# Does it work?



Lloyd et al 2014

# But...

Searching deep into the tree is slow

Difficult to decide when to stop

Ad hoc selection of primitive kernels



| Group<br>Period | 1        | 2        | 3             | 4              | 5         | 6         | 7         | 8         | 9         | 10        | 11        | 12        | 13        | 14        | 15        | 16        | 17        | 18        |
|-----------------|----------|----------|---------------|----------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| 1               | 1<br>H   |          |               |                |           |           |           |           |           |           |           |           |           |           |           |           |           | 2<br>He   |
| 2               | 3<br>Li  | 4<br>Be  |               |                |           |           |           |           |           |           |           |           | 5<br>B    | 6<br>C    | 7<br>N    | 8<br>O    | 9<br>F    | 10<br>Ne  |
| 3               | 11<br>Na | 12<br>Mg |               |                |           |           |           |           |           |           |           |           | 13<br>Al  | 14<br>Si  | 15<br>P   | 16<br>S   | 17<br>Cl  | 18<br>Ar  |
| 4               | 19<br>K  | 20<br>Ca | 21<br>Sc      | 22<br>Ti       | 23<br>V   | 24<br>Cr  | 25<br>Mn  | 26<br>Fe  | 27<br>Co  | 28<br>Ni  | 29<br>Cu  | 30<br>Zn  | 31<br>Ga  | 32<br>Ge  | 33<br>As  | 34<br>Se  | 35<br>Br  | 36<br>Kr  |
| 5               | 37<br>Rb | 38<br>Sr | 39<br>Y       | 40<br>Zr       | 41<br>Nb  | 42<br>Mo  | 43<br>Tc  | 44<br>Ru  | 45<br>Rh  | 46<br>Pd  | 47<br>Ag  | 48<br>Cd  | 49<br>In  | 50<br>Sn  | 51<br>Sb  | 52<br>Te  | 53<br>I   | 54<br>Xe  |
| 6               | 55<br>Cs | 56<br>Ba | 57<br>La      | *<br>72<br>Hf  | 73<br>Ta  | 74<br>W   | 75<br>Re  | 76<br>Os  | 77<br>Ir  | 78<br>Pt  | 79<br>Au  | 80<br>Hg  | 81<br>Tl  | 82<br>Pb  | 83<br>Bi  | 84<br>Po  | 85<br>At  | 86<br>Rn  |
| 7               | 87<br>Fr | 88<br>Ra | 89<br>Ac      | *<br>104<br>Rf | 105<br>Db | 106<br>Sg | 107<br>Bh | 108<br>Hs | 109<br>Mt | 110<br>Ds | 111<br>Rg | 112<br>Cn | 113<br>Nh | 114<br>Fl | 115<br>Mc | 116<br>Lv | 117<br>Ts | 118<br>Og |
|                 |          |          | *<br>58<br>Ce | 59<br>Pr       | 60<br>Nd  | 61<br>Pm  | 62<br>Sm  | 63<br>Eu  | 64<br>Gd  | 65<br>Tb  | 66<br>Dy  | 67<br>Ho  | 68<br>Er  | 69<br>Tm  | 70<br>Yb  | 71<br>Lu  |           |           |
|                 |          |          | *<br>90<br>Th | 91<br>Pa       | 92<br>U   | 93<br>Np  | 94<br>Pu  | 95<br>Am  | 96<br>Cm  | 97<br>Bk  | 98<br>Cf  | 99<br>Es  | 100<br>Fm | 101<br>Md | 102<br>No | 103<br>Lr |           |           |





# Spectral Kernels







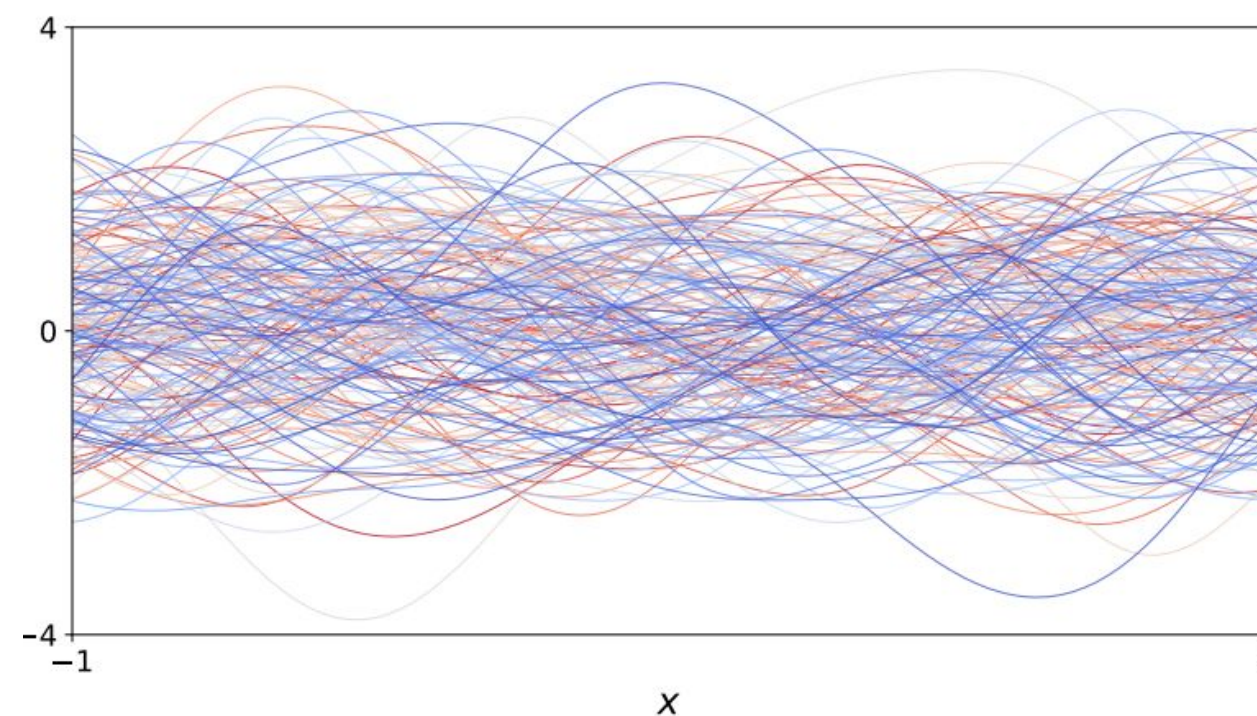
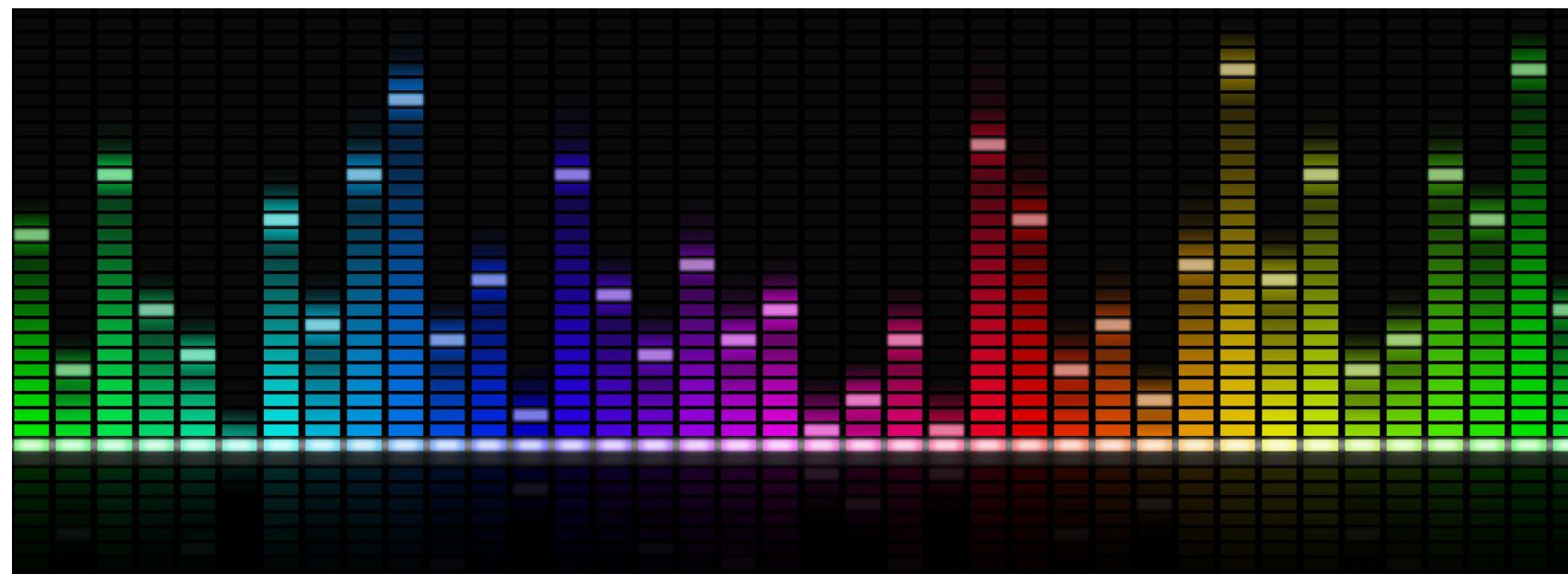
# Spectral Kernel

$$A = k_{SE} \times k_{COS}$$

$$K = A + A + A + A + A + A + A + A + A + A$$

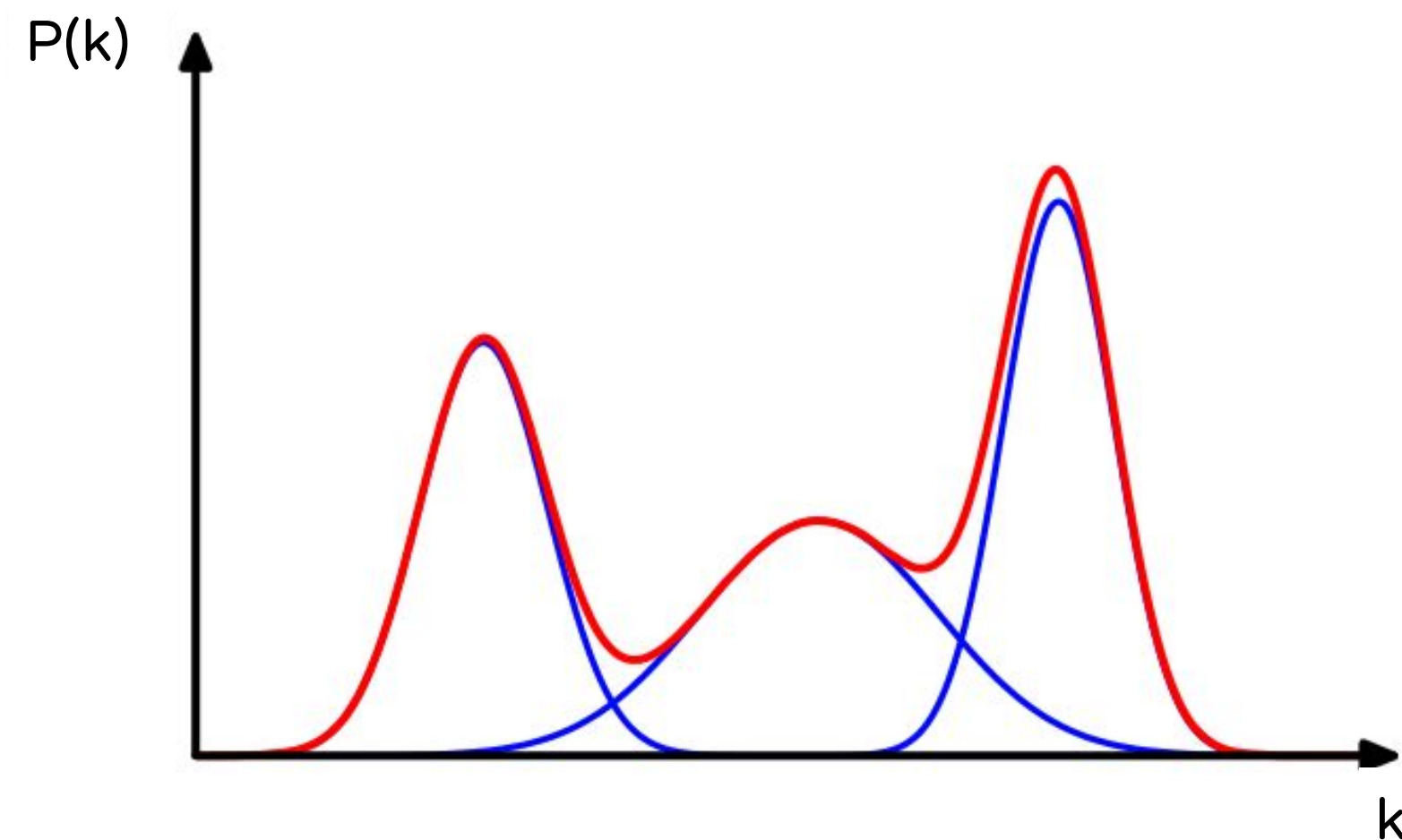
# Spectral representation

Any stationary kernel can be represented by a spectral density



# Spectral Mixture Kernel

A mixture of Gaussians can approximate any stationary Gaussian process





# Spectral Mixture Kernel

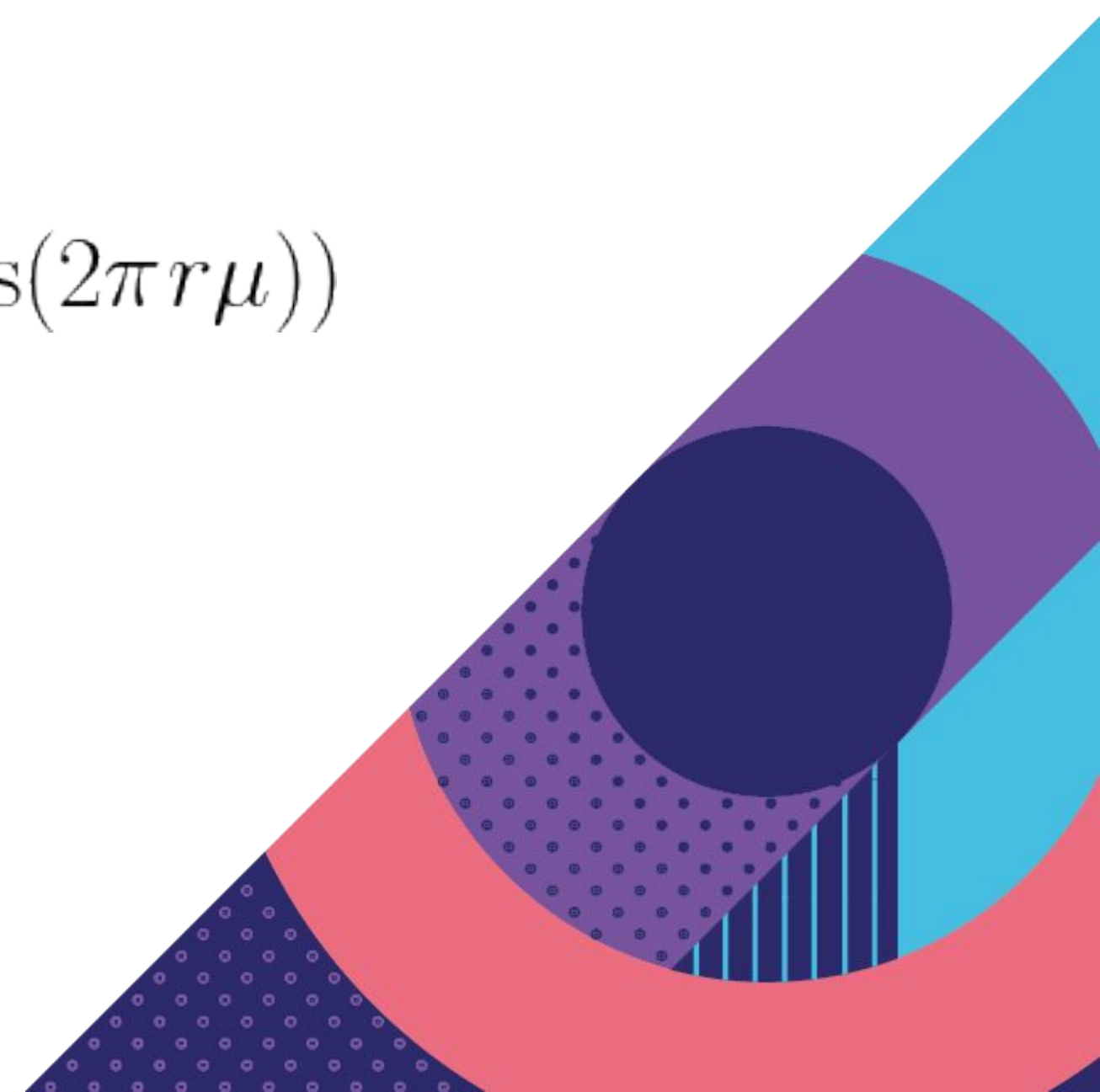
Power spectrum described by a single Gaussian:

$$P(k) = G(\mu, \sigma^2)$$

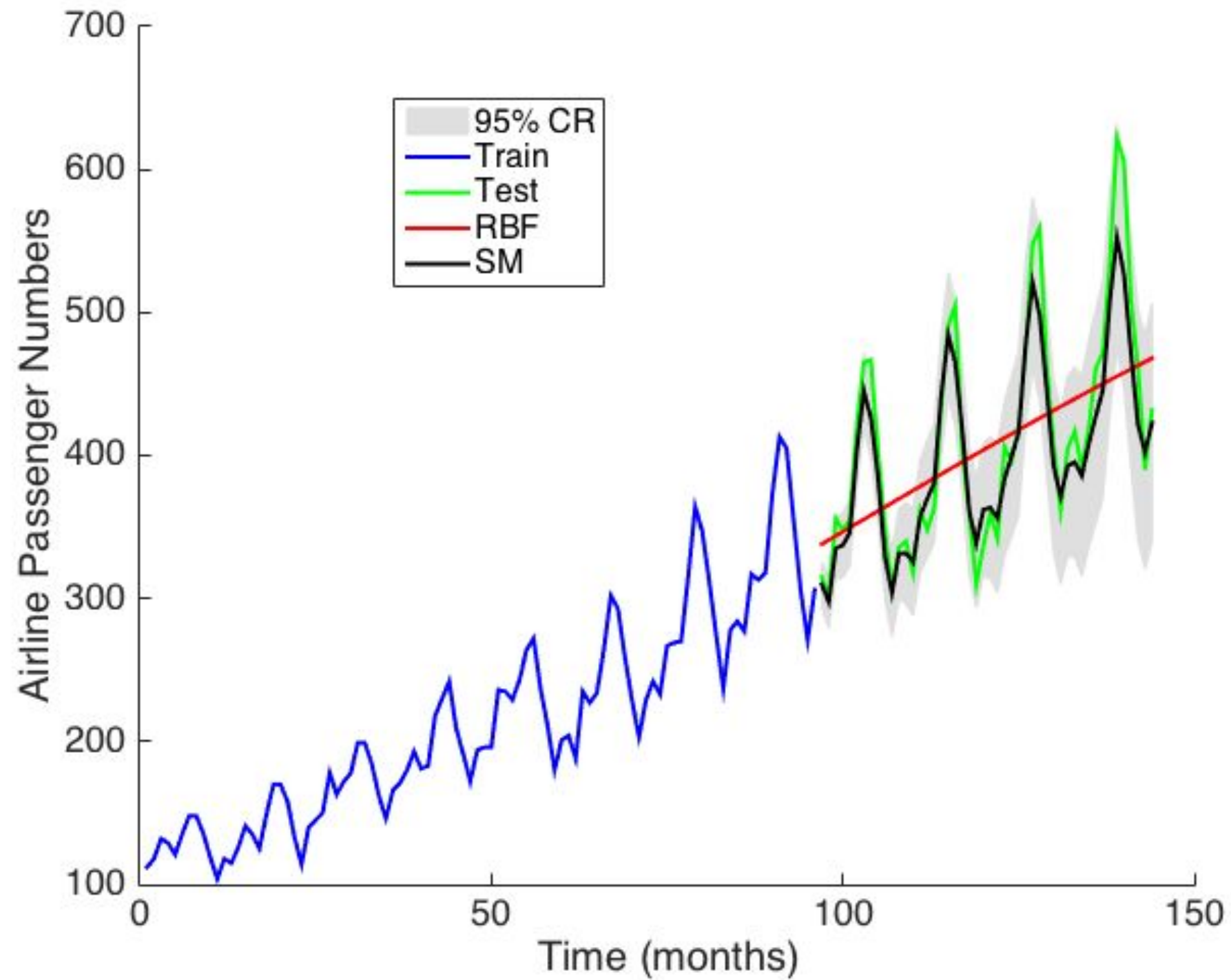
$$K(r) = \exp(-2\pi^2 r^2 \sigma^2) \cos(2\pi r \mu)$$

A mixture of Gaussians can approximate **any** stationary Gaussian process:

$$K(r) = \sum_i w_i K_i(r)$$



# Does it work?



Wilson & Adams (2013)

# Spectral kernels

## Pros:

- Spans all stationary kernels

- Avoids complex search

## Cons:

- Challenging to optimize

- Conventional approach cannot generate non-stationary kernels

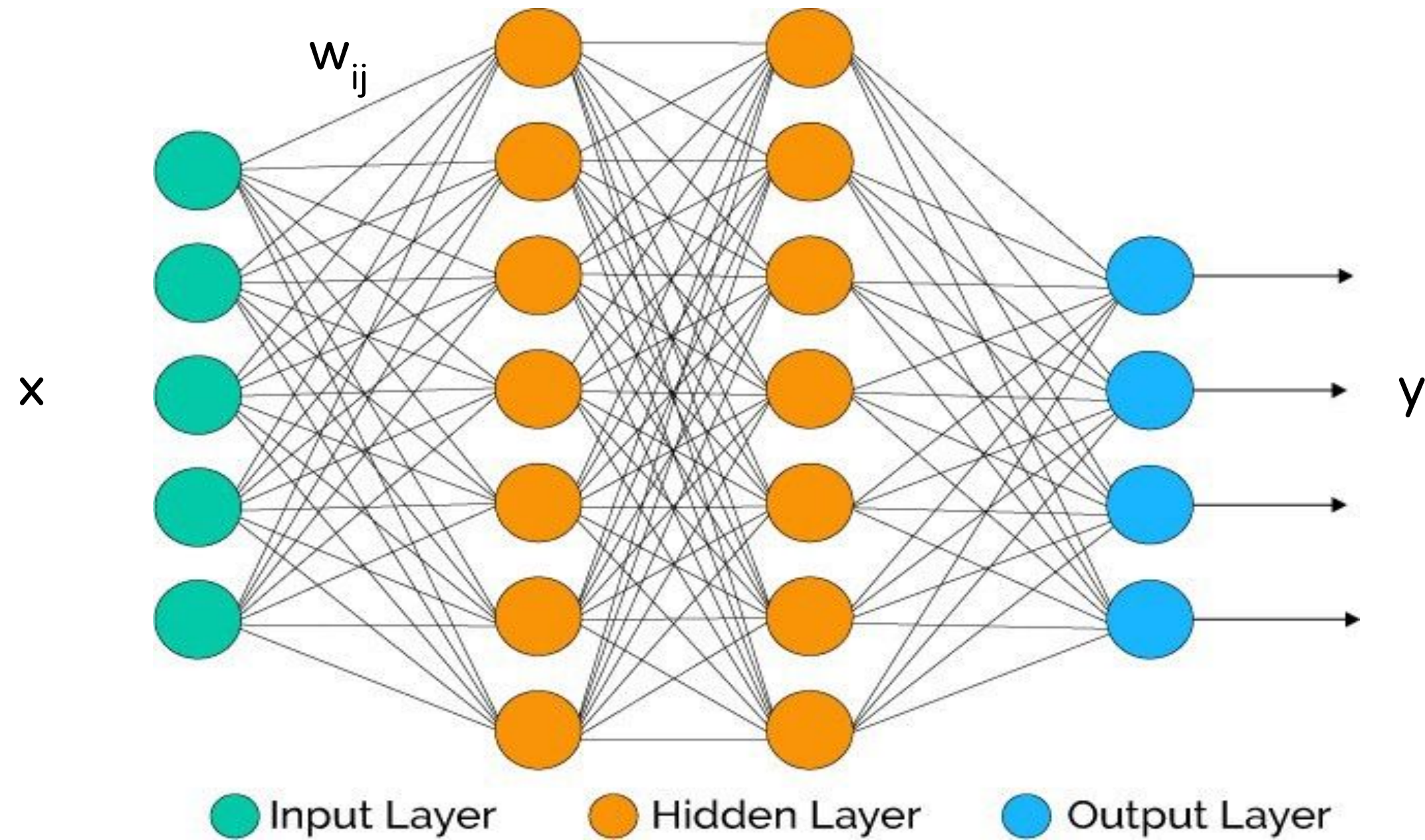






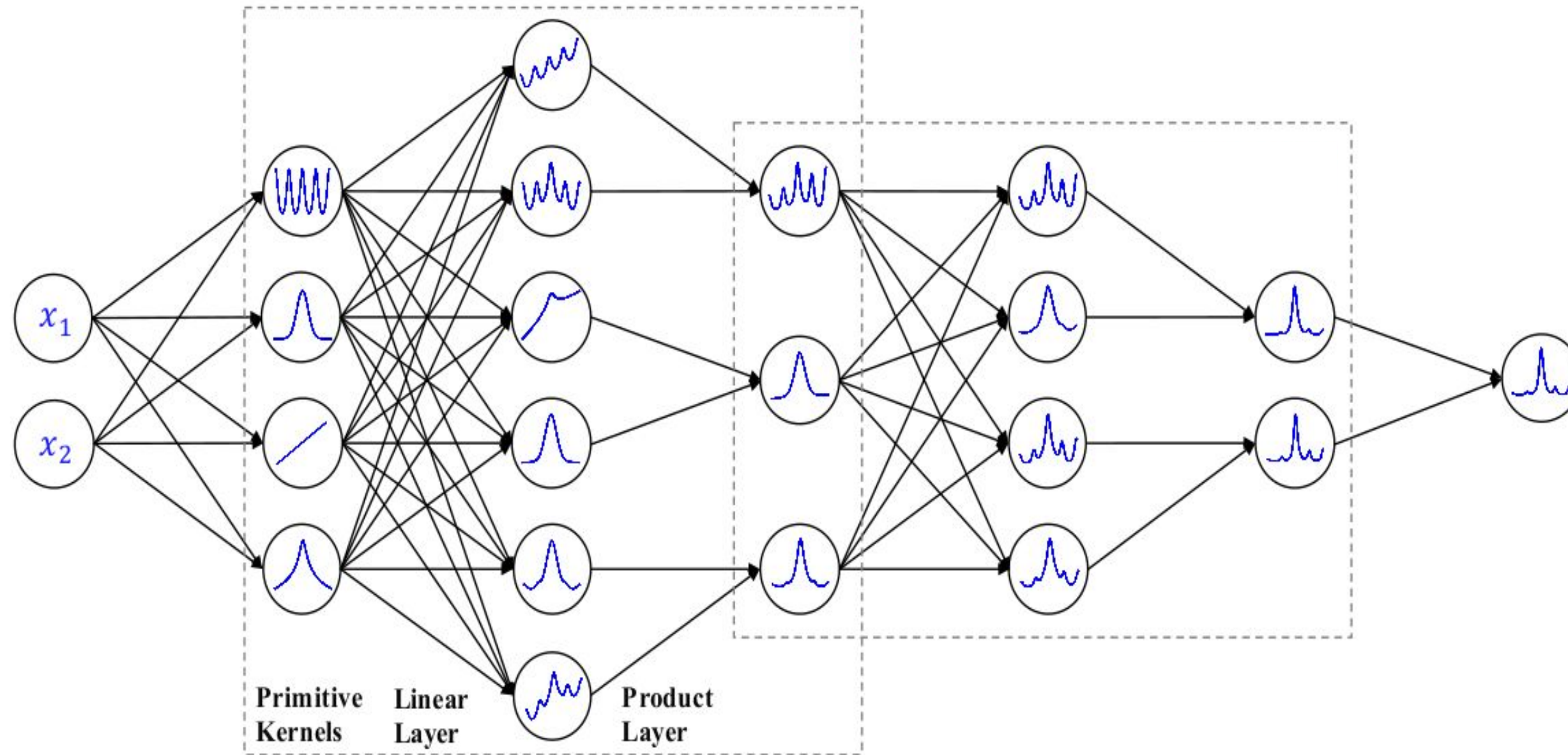
# Neural Kernel Network

# Neural Network





# Neural Kernel Network

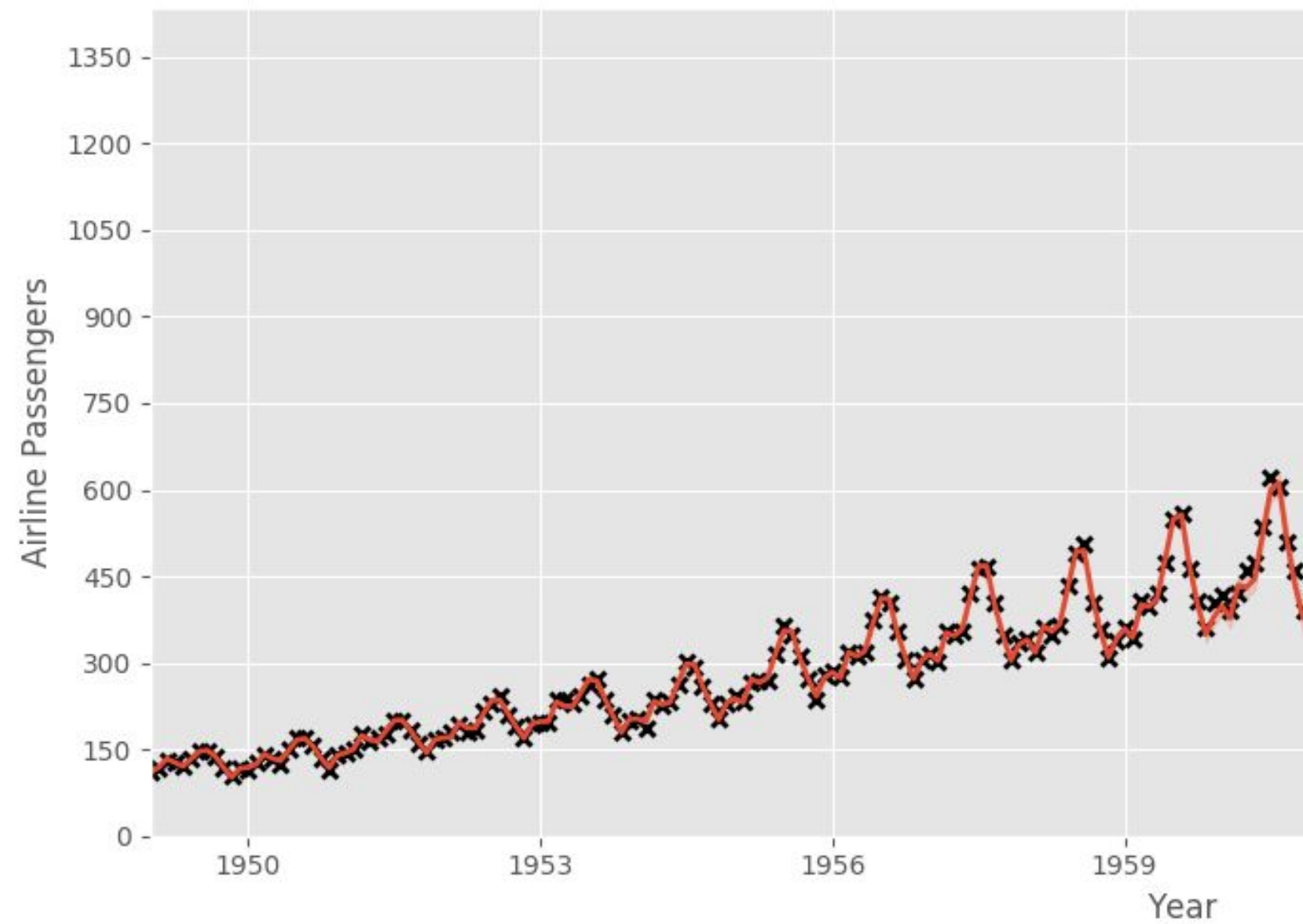


Sun et al (2018)



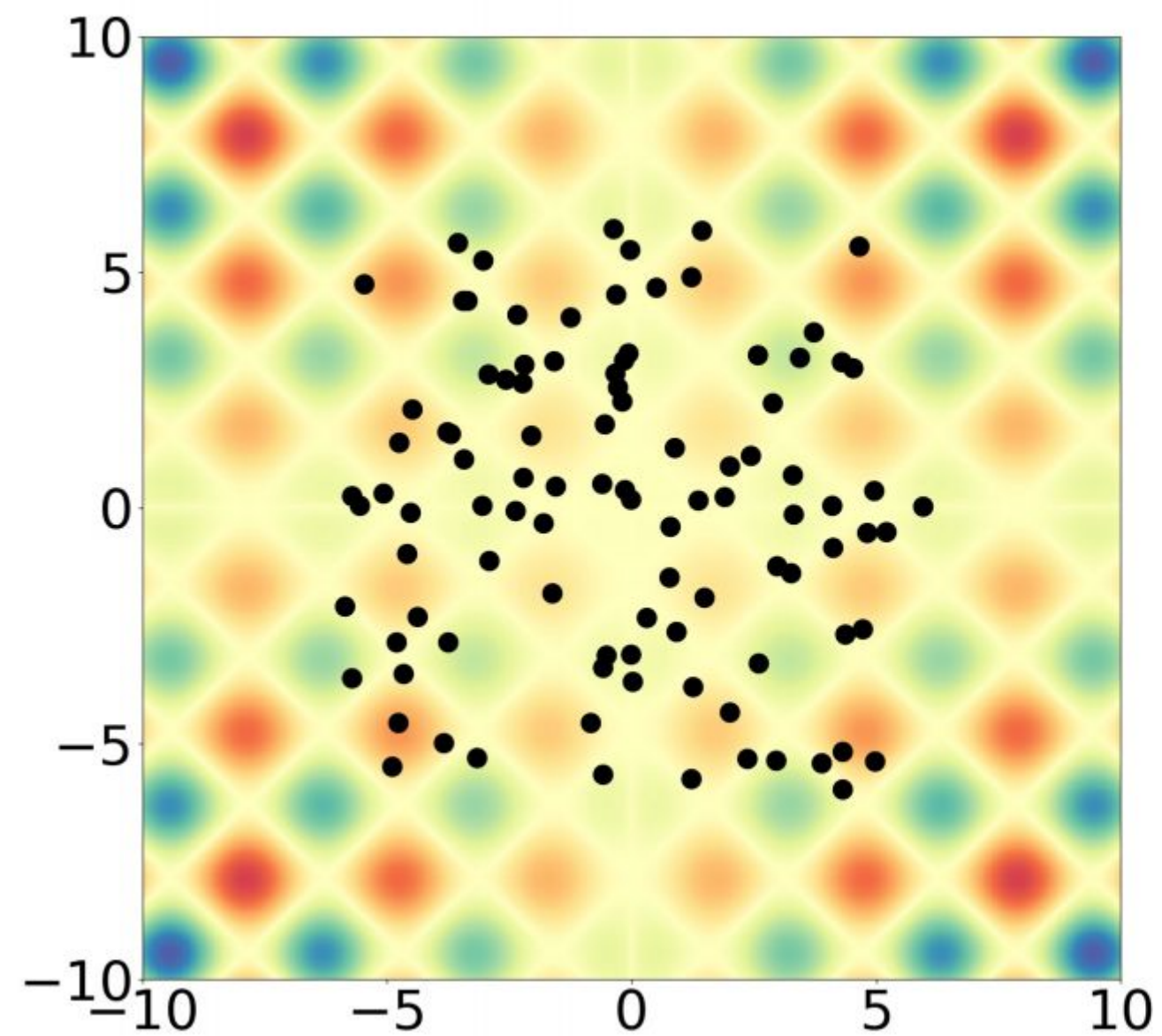
# Does it work?

## Predicting airline passengers



# Does it work?

## Extrapolating patterns



Sun et al (2018)

# Summary

## Kernel Selection Methods

### Automatic Statistician

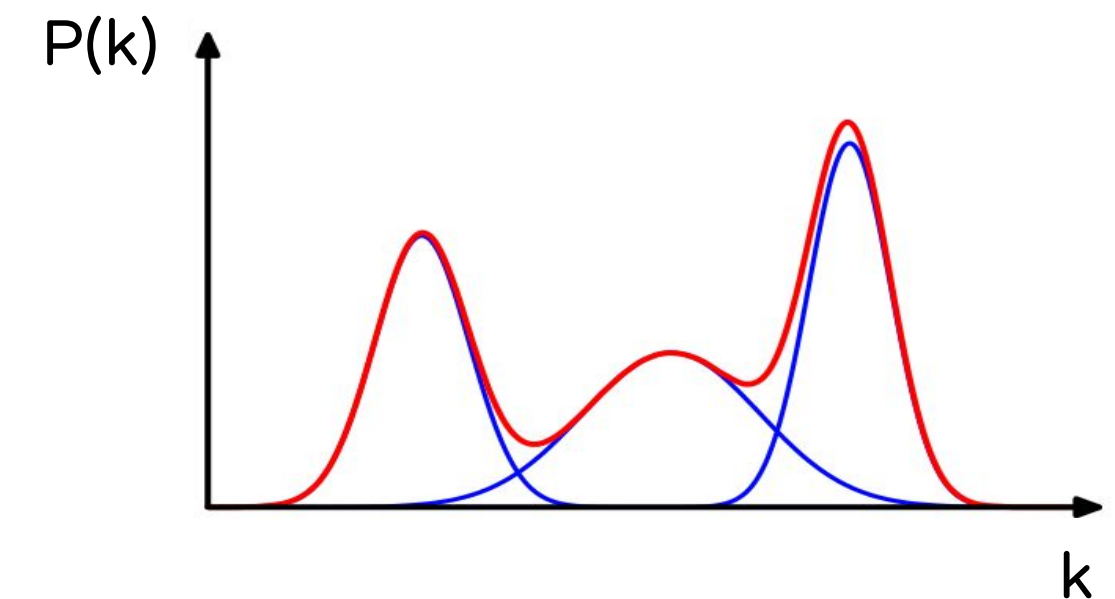
[www.automaticstatistician.com](http://www.automaticstatistician.com)



### Spectral Kernels

Generalised Spectral Mixture <https://github.com/sremes/nssm-gp>

Multi-output <https://github.com/GAMES-UChile/mogptk>



### Neural Kernel Network

Sun et al 2018: <https://arxiv.org/abs/1806.04326>

GPflow implementation [https://github.com/frgsimpson/kernel\\_learning](https://github.com/frgsimpson/kernel_learning)

