

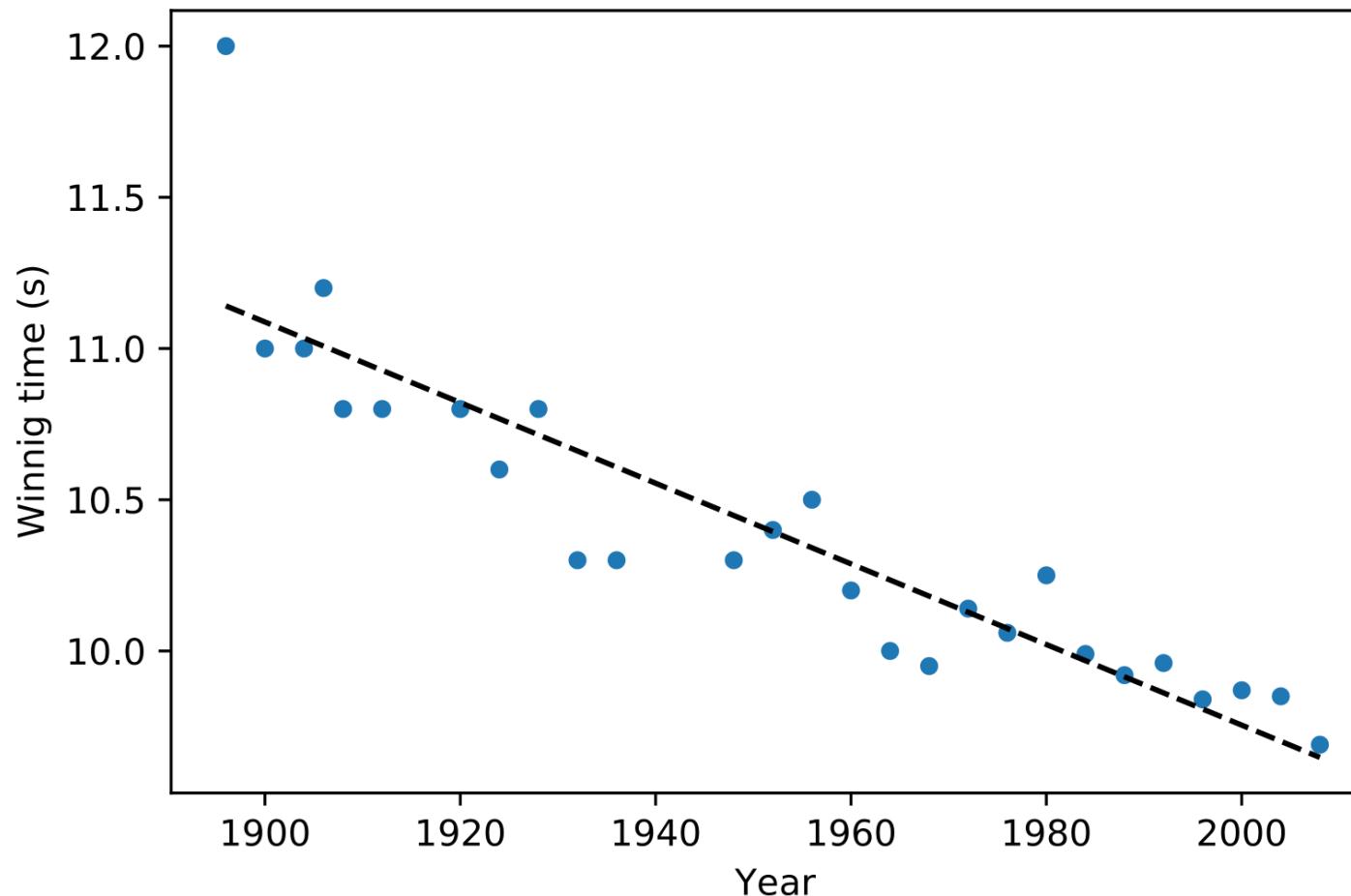
# Linear regression

Polynomial regression and basis functions

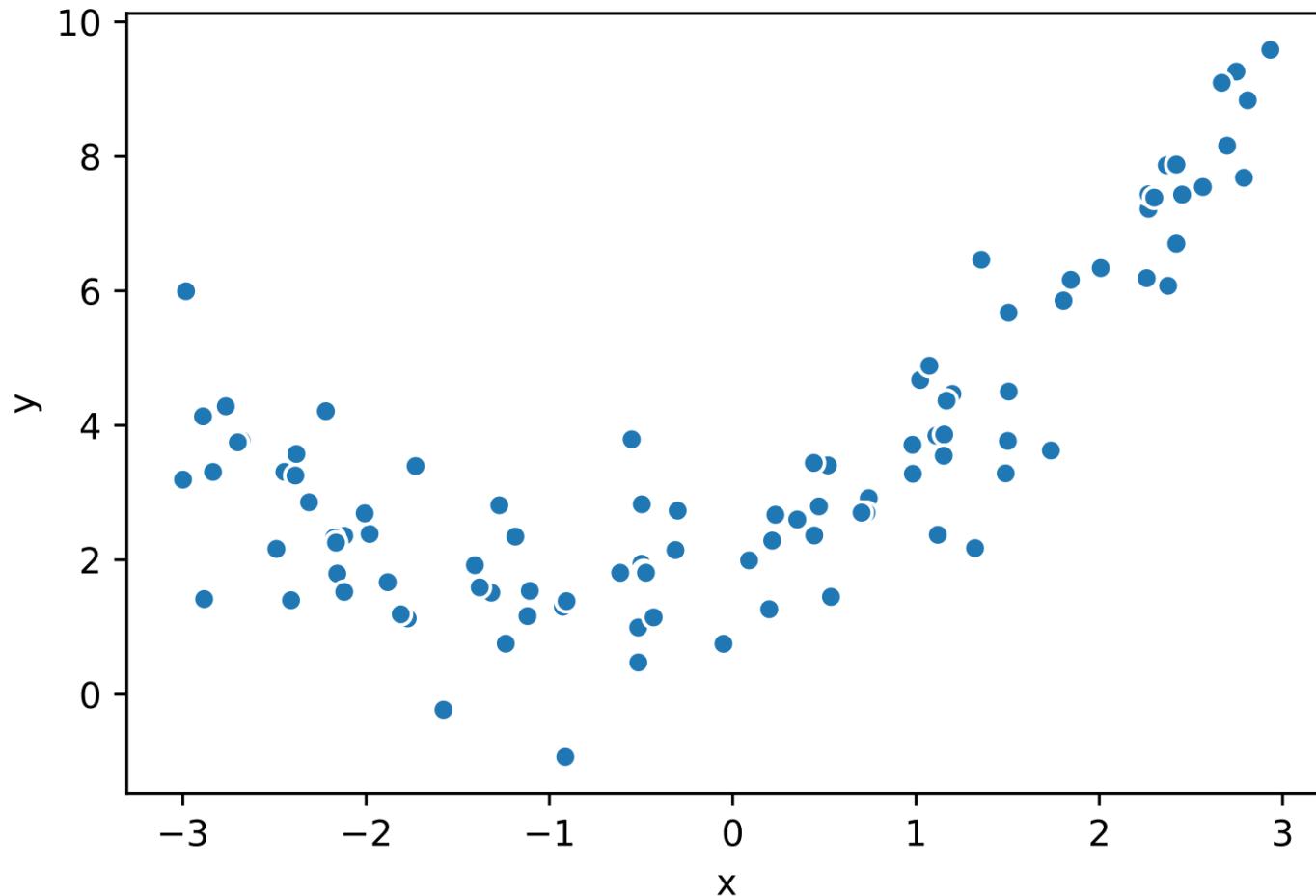
Herman Kamper

<http://www.kamperh.com/>

# Linear regression



# Non-linear relationship



## Polynomial regression

### Multiple linear regression recap:

$$f(\underline{x}; \underline{w}) = w_0 + w_1 x_1 + \dots + w_D x_D = \underline{w}^T \underline{x}$$

Fit on data  $\{(x^{(n)}, y^{(n)})\}_{n=1}^N$ , using:

$$\begin{aligned} J(\underline{w}) &= \sum_{n=1}^N (y^{(n)} - f(x^{(n)}; \underline{w}))^2 \\ &= (\underline{y} - \underline{X}\underline{w})^T (\underline{y} - \underline{X}\underline{w}), \text{ with} \\ \underline{X} &= \begin{bmatrix} -(\underline{x}^{(1)})^T & - \\ -(\underline{x}^{(2)})^T & - \\ \vdots & \\ -(\underline{x}^{(N)})^T & - \end{bmatrix} ; \quad \underline{y} = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(N)} \end{bmatrix} \end{aligned}$$

↑ Design matrix

Solution:  $\hat{\underline{w}} = (\underline{X}^T \underline{X})^{-1} \underline{X}^T \underline{y}$  Normal equations

## Polynomial regression:

What do we do if we want to fit  $f(x; w_0, w_1, w_2) = w_0 + w_1 x + w_2 x^2$ ?

Let's define

$$\underline{\phi}(x) = \begin{bmatrix} 1 \\ x \\ x^2 \end{bmatrix} \quad "w^T x"$$

We can then write  $f(x; \underline{w}) = \underline{w}^T \underline{\phi}(x)$

Now we can solve the problem exactly as for multiple linear regression by "pretending" that  $\underline{\phi}(x)$  is  $\underline{x}$ .

Our design matrix would now become:

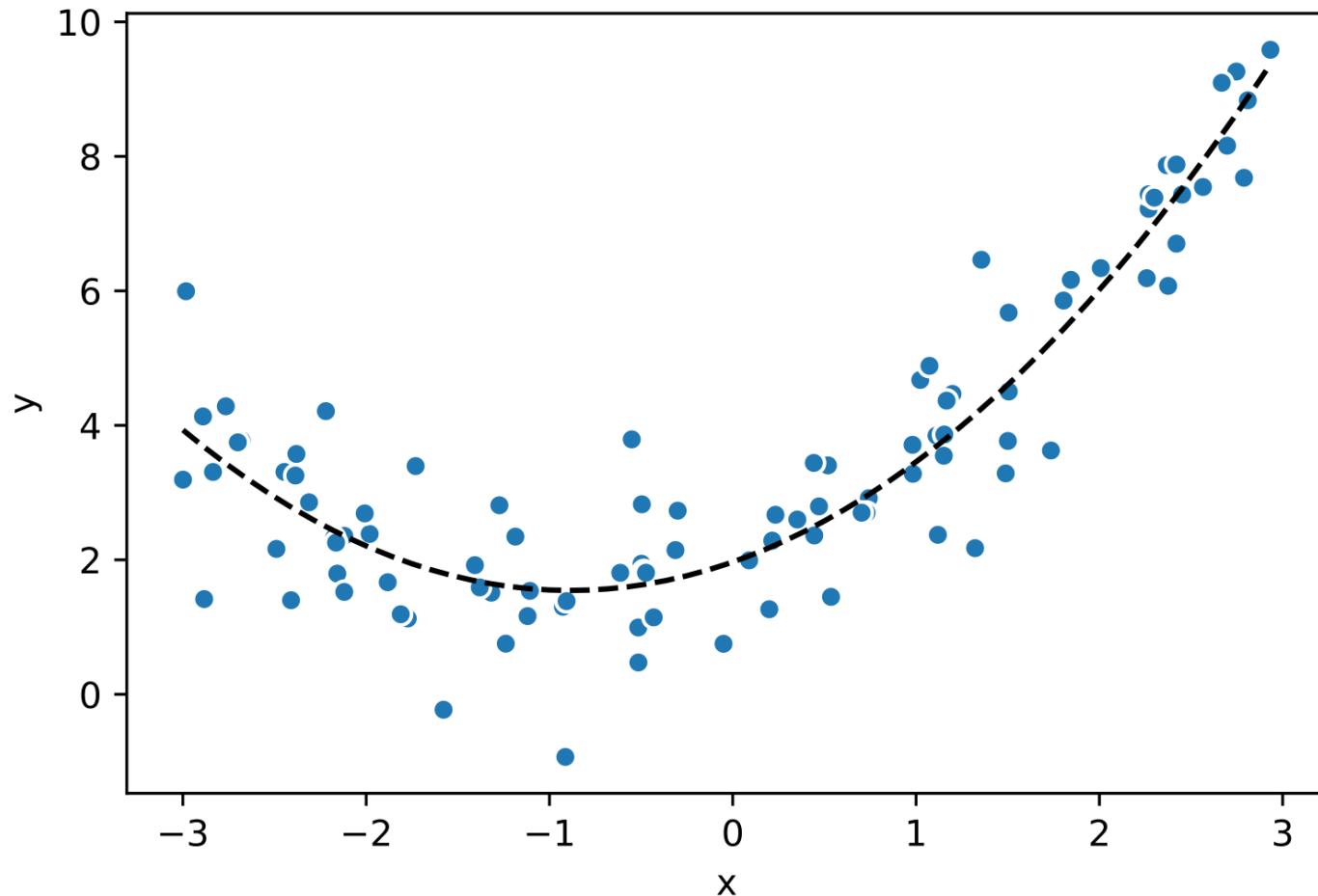
$$\underline{\Phi} = \begin{bmatrix} -\underline{\phi}(x^{(1)})^T & - \\ -\underline{\phi}(x^{(2)})^T & - \\ \vdots & \\ -\underline{\phi}(x^{(N)})^T & - \end{bmatrix} = \begin{bmatrix} 1 & x^{(1)} & (x^{(1)})^2 \\ 1 & x^{(2)} & (x^{(2)})^2 \\ \vdots & & \\ 1 & x^{(N)} & (x^{(N)})^2 \end{bmatrix}$$

Other example:

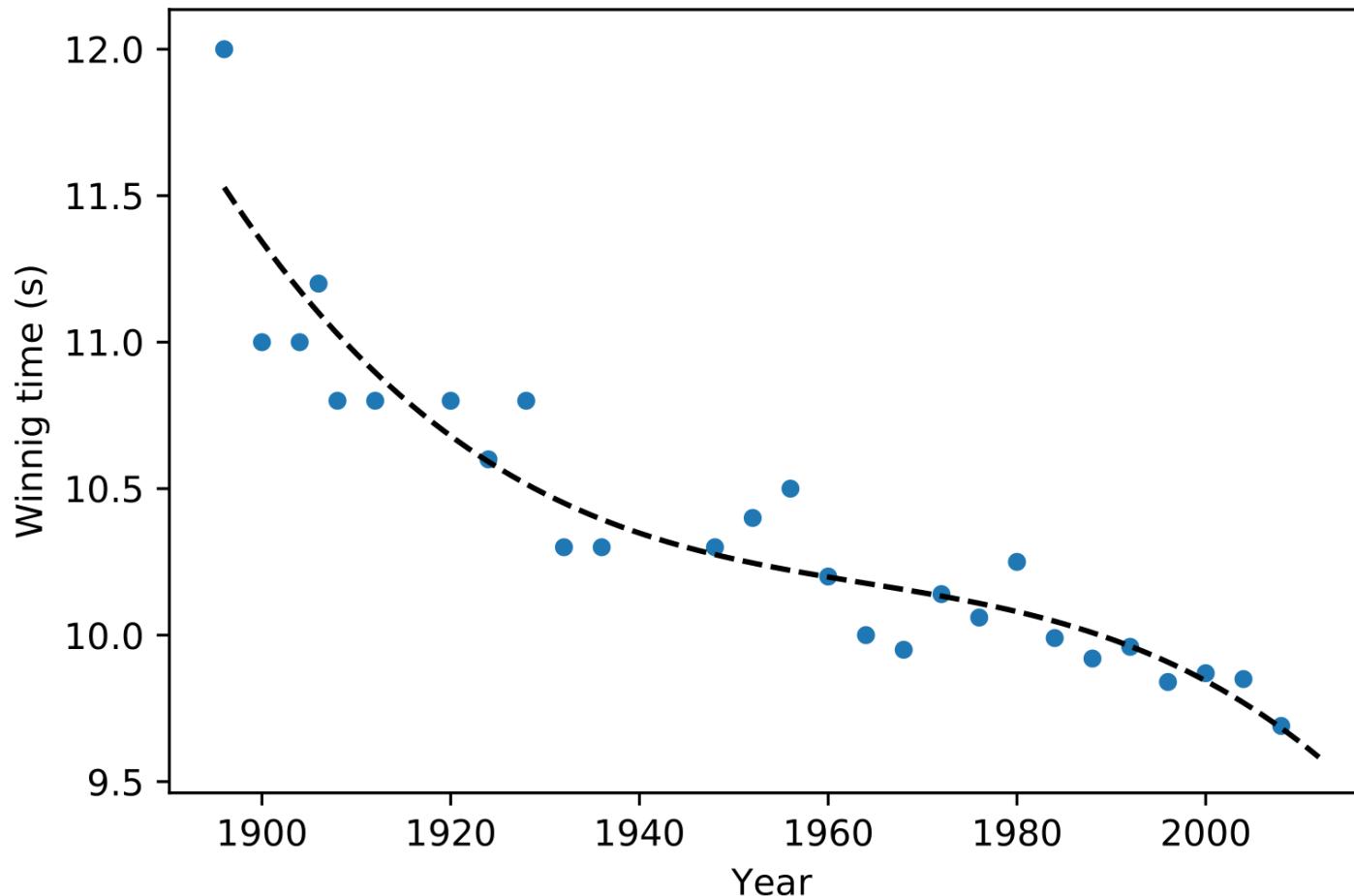
$$f(\underline{x}; \underline{w}) = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_1 x_2 + w_4 x_1^2 + w_5 x_2^2$$

with  $\underline{\phi}(x) = [1 \ x_1 \ x_2 \ x_1 x_2 \ x_1^2 \ x_2^2]^T$

# Polynomial regression



# 3<sup>rd</sup>-order polynomial regression



## Basis functions

Instead of just polynomials, we can actually put any function in

$$\phi(\underline{x}) = [\phi_1(\underline{x}) \ \phi_2(\underline{x}) \ \dots \ \phi_K(\underline{x})]^T$$

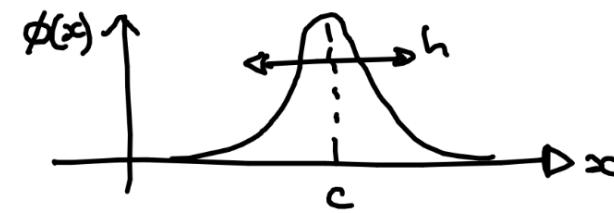
e.g. sin, cos, log, exp, FFT, etc.

This can be quite useful if we have some inside domain knowledge of the data and problem.

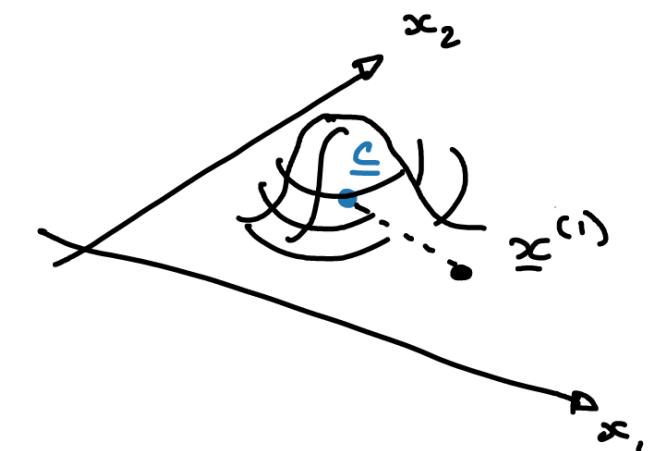
One possible choice as a basis function is the radial basis function (RBF):

$$\phi(\underline{x}) = \exp \left\{ -\frac{(\underline{x} - \underline{c})^T (\underline{x} - \underline{c})}{h^2} \right\}$$

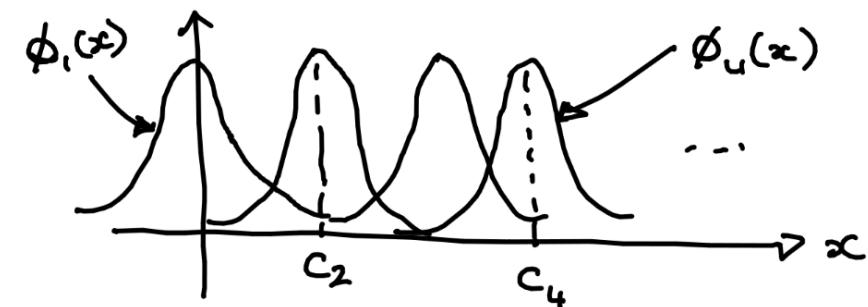
In the 1-D case:



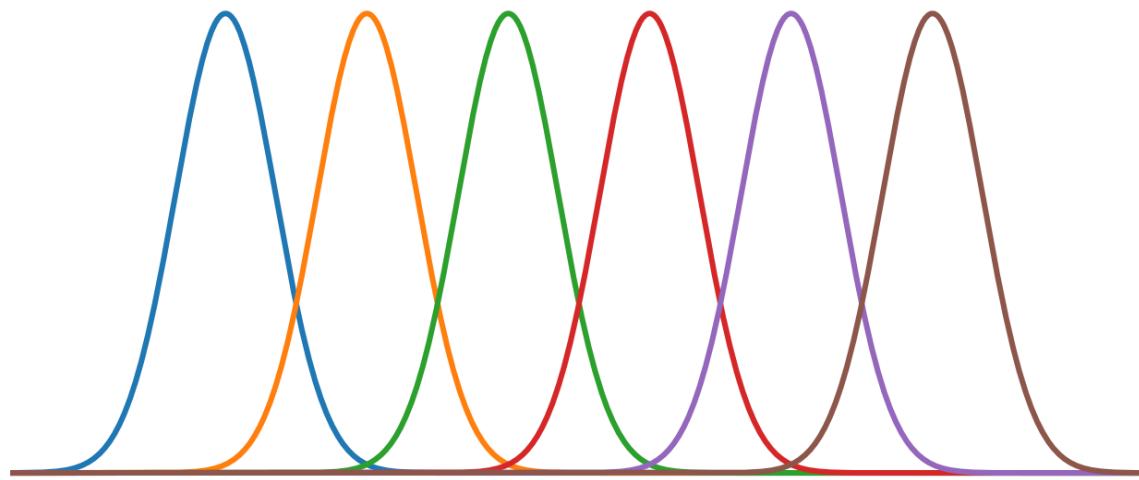
RBF in 2 dimensions:



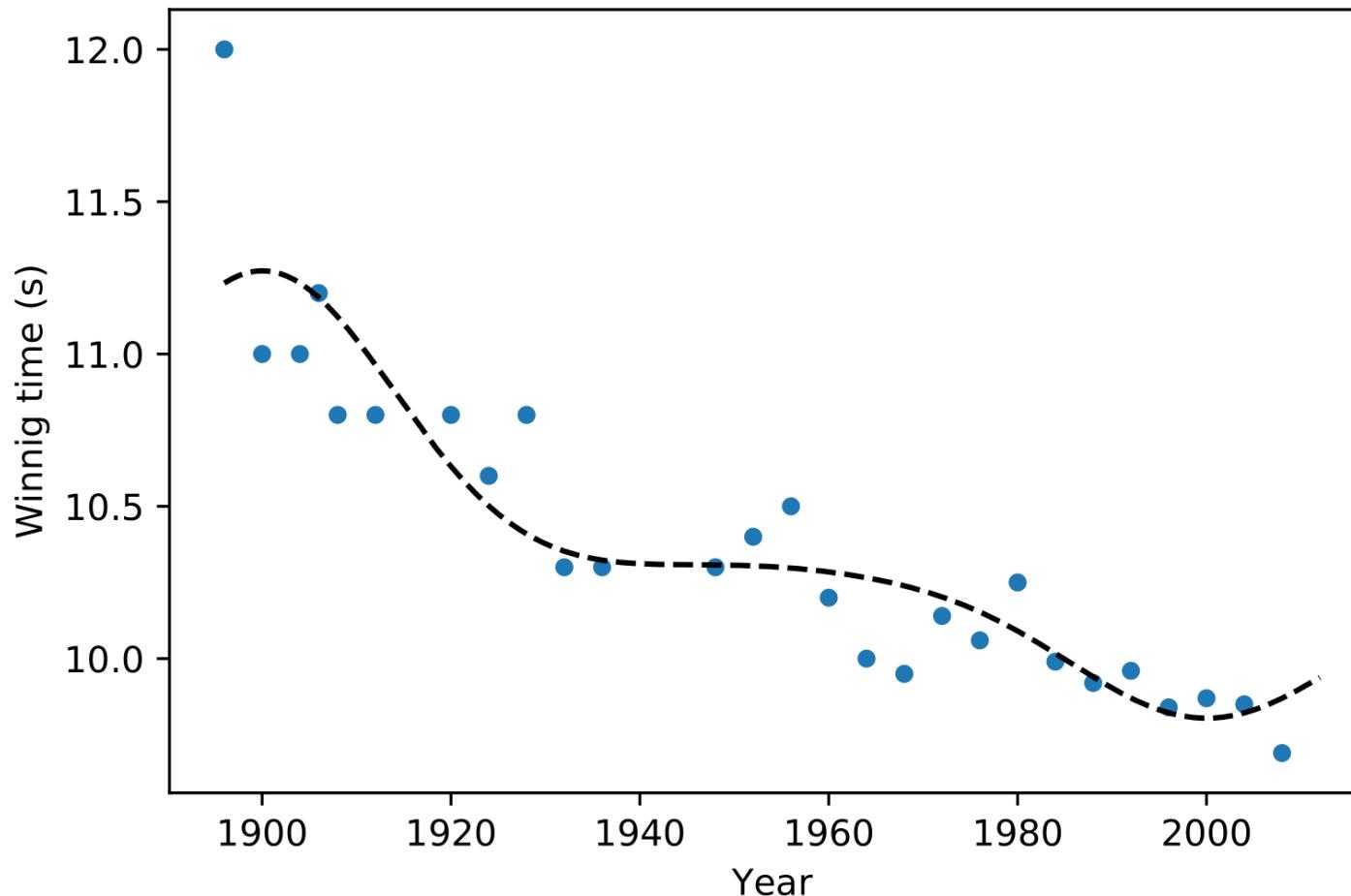
Can even have a family of RBFs:



# Basis functions: RBF



RBF with  $c = [1900, 1950, 2000]$  and  $h = 20$



RBF with  $c = [1900, 1910, \dots, 2000]$  and  $h = 10$

