

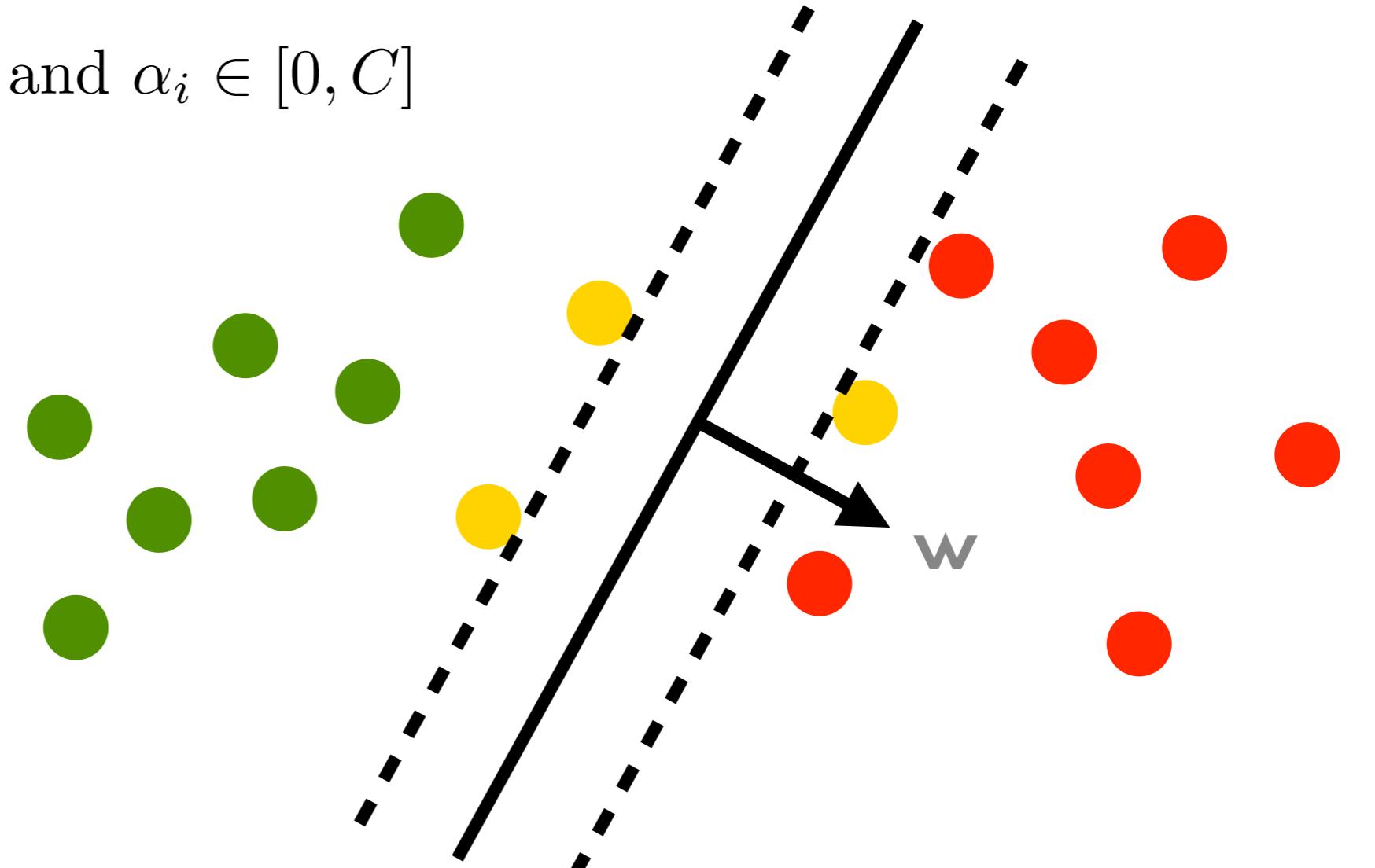
**6.867**

# **Nonlinear models,Kernels**

Fall 2016

$$\underset{\alpha}{\text{maximize}} -\frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle + \sum_i \alpha_i$$

subject to  $\sum_i \alpha_i y_i = 0$  and  $\alpha_i \in [0, C]$



$$w = \sum_i y_i \alpha_i x_i$$

$$\alpha_i [y_i [\langle w, x_i \rangle + b] + \xi_i - 1] = 0$$

$$\alpha_i = 0 \implies y_i [\langle w, x_i \rangle + b] \geq 1$$

$$\eta_i \xi_i = 0$$

$$0 < \alpha_i < C \implies y_i [\langle w, x_i \rangle + b] = 1$$

$$\alpha_i = C \implies y_i [\langle w, x_i \rangle + b] \leq 1$$

# The Kernel Trick

## Linear soft margin problem

$$\underset{w,b}{\text{minimize}} \quad \frac{1}{2} \|w\|^2 + C \sum_i \xi_i$$

subject to  $y_i [\langle w, x_i \rangle + b] \geq 1 - \xi_i$  and  $\xi_i \geq 0$

## Dual problem

$$\underset{\alpha}{\text{maximize}} \quad -\frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle + \sum_i \alpha_i$$

subject to  $\sum_i \alpha_i y_i = 0$  and  $\alpha_i \in [0, C]$

## Support vector expansion

$$f(x) = \sum_i \alpha_i y_i \langle x_i, x \rangle + b$$

# The Kernel Trick

Linear soft margin problem

$$\underset{w,b}{\text{minimize}} \quad \frac{1}{2} \|w\|^2 + C \sum_i \xi_i$$

subject to  $y_i [\langle w, \phi(x_i) \rangle + b] \geq 1 - \xi_i$  and  $\xi_i \geq 0$

Dual problem

$$\underset{\alpha}{\text{maximize}} \quad -\frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j k(x_i, x_j) + \sum_i \alpha_i$$

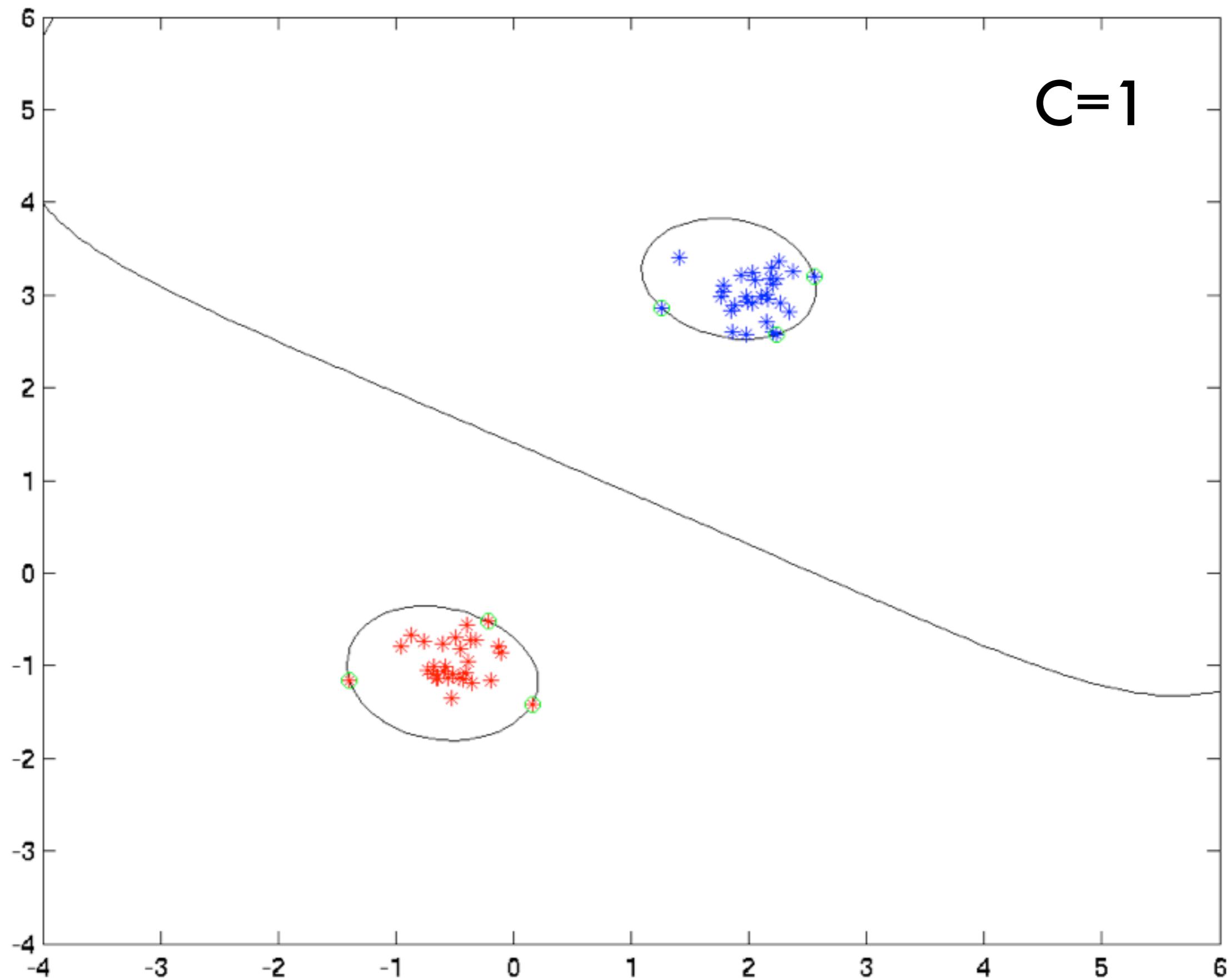
subject to  $\sum_i \alpha_i y_i = 0$  and  $\alpha_i \in [0, C]$

Support vector expansion

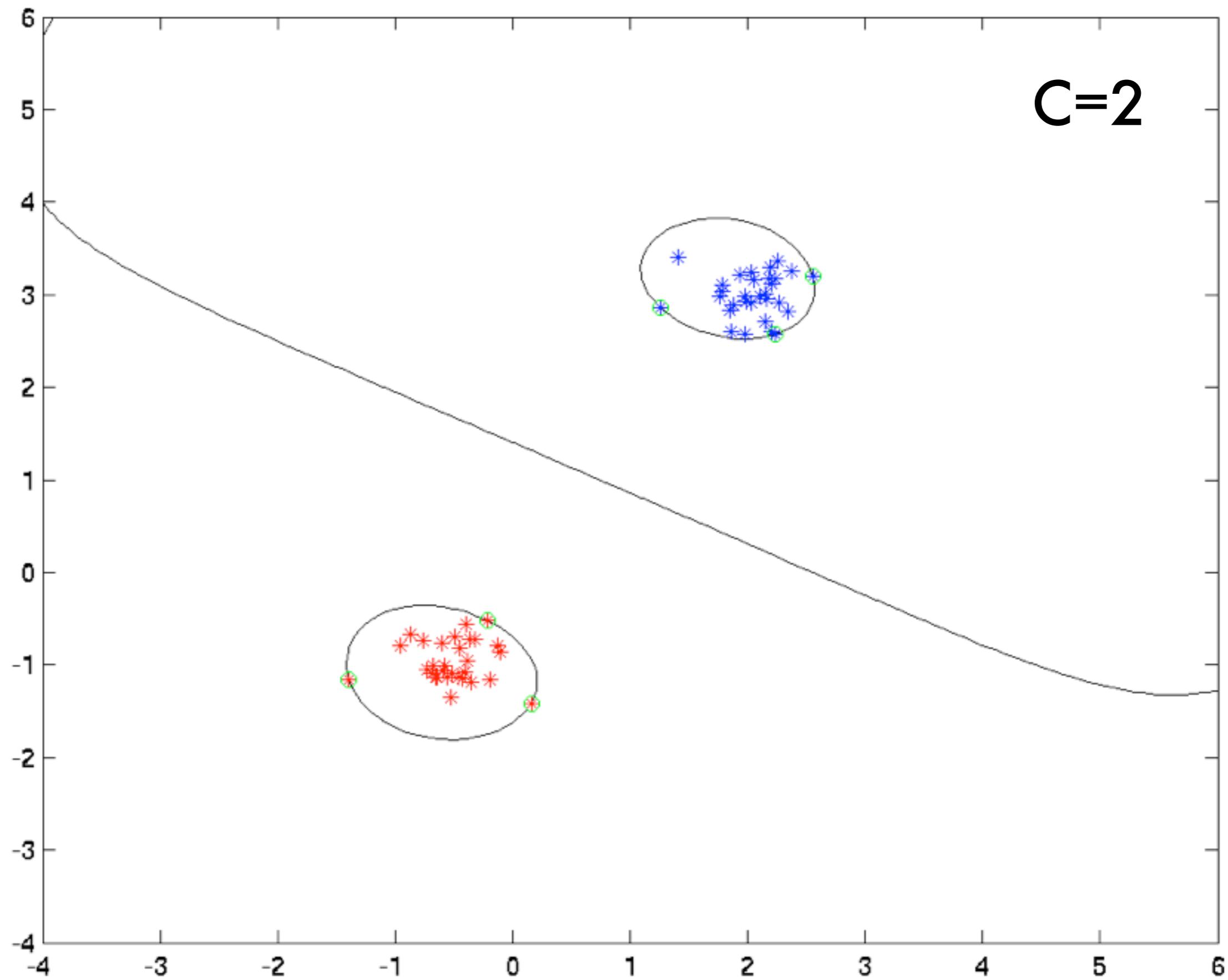
$$f(x) = \sum_i \alpha_i y_i k(x_i, x) + b$$

courtesy: A. Smola (CMU, 2013)

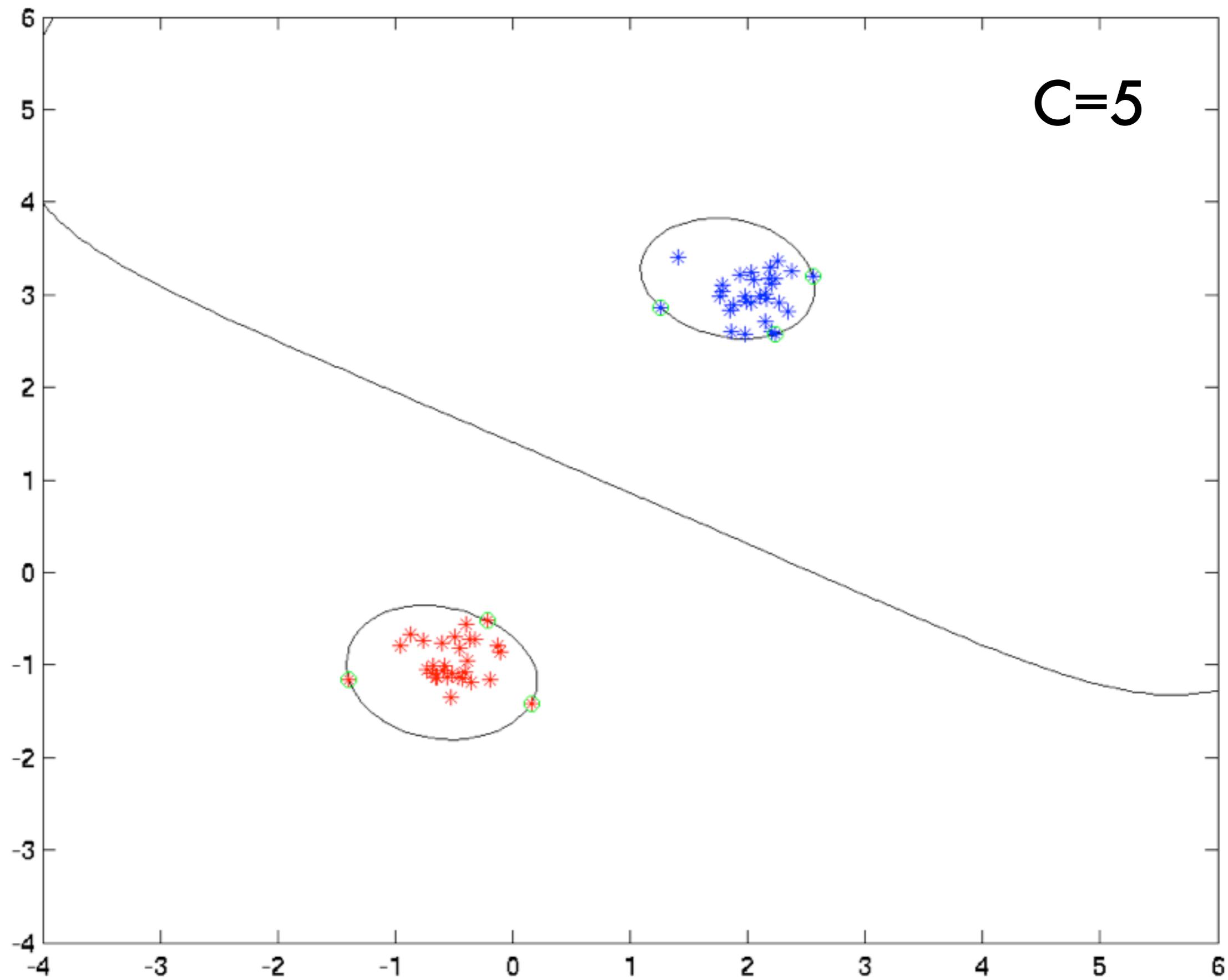
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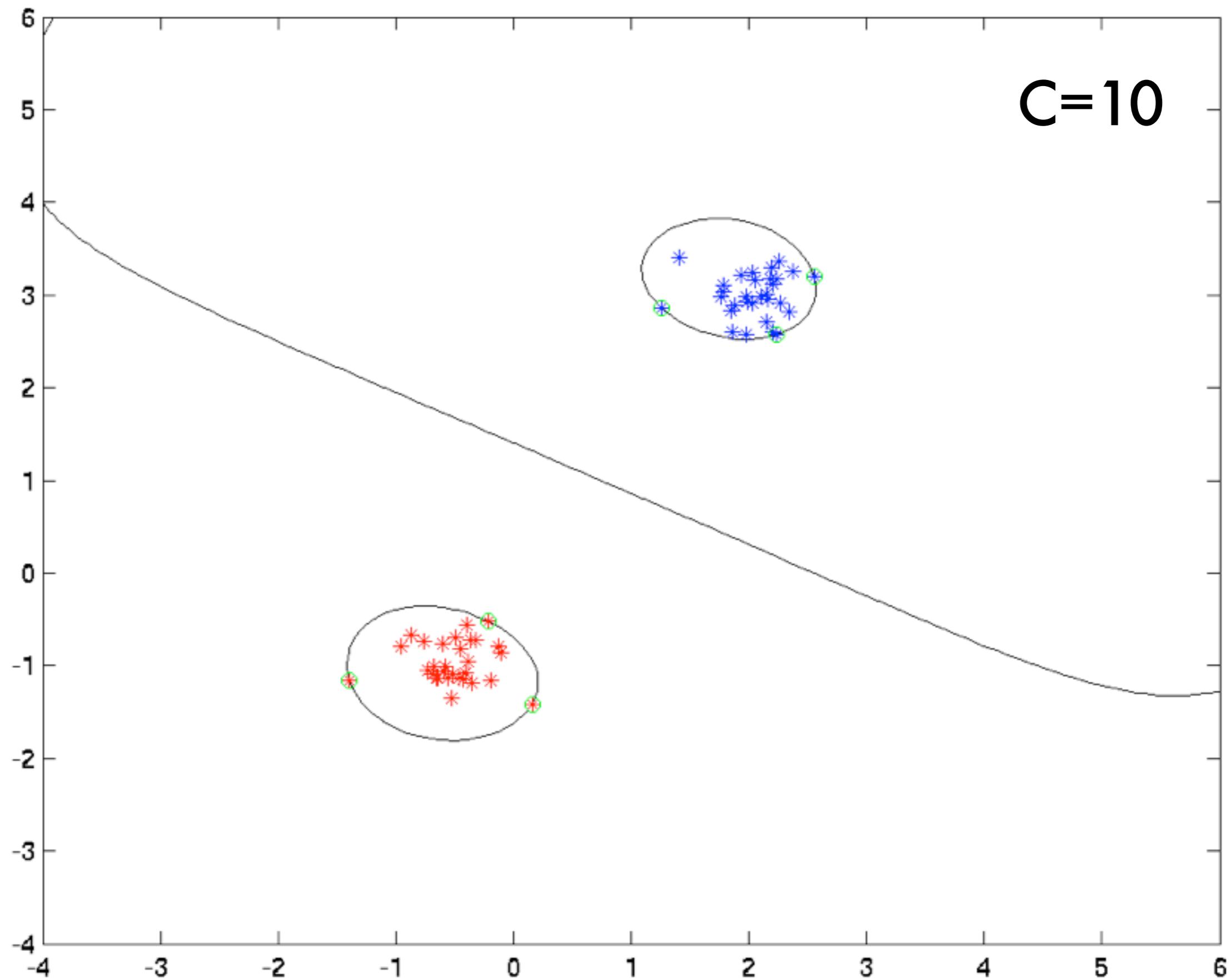
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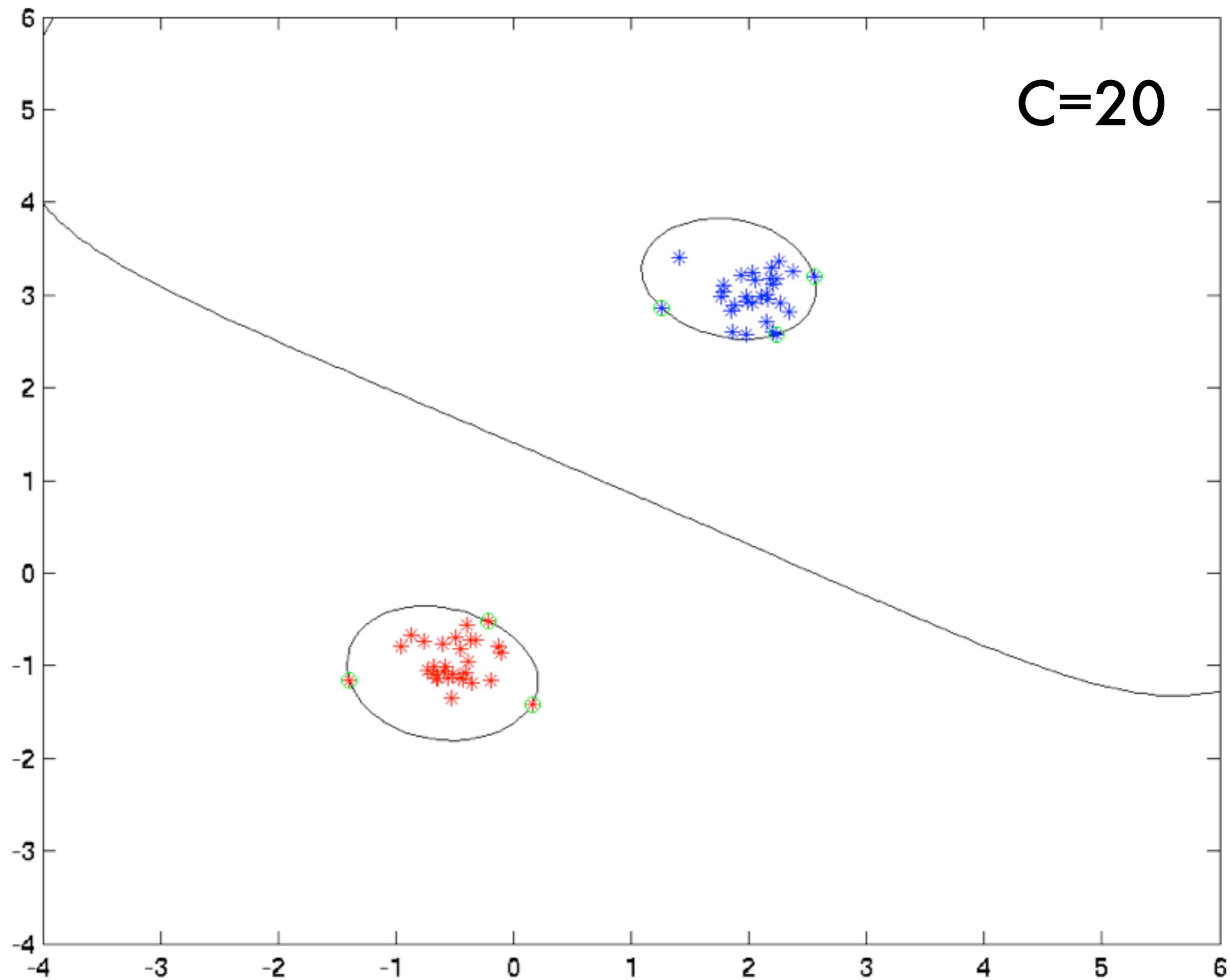
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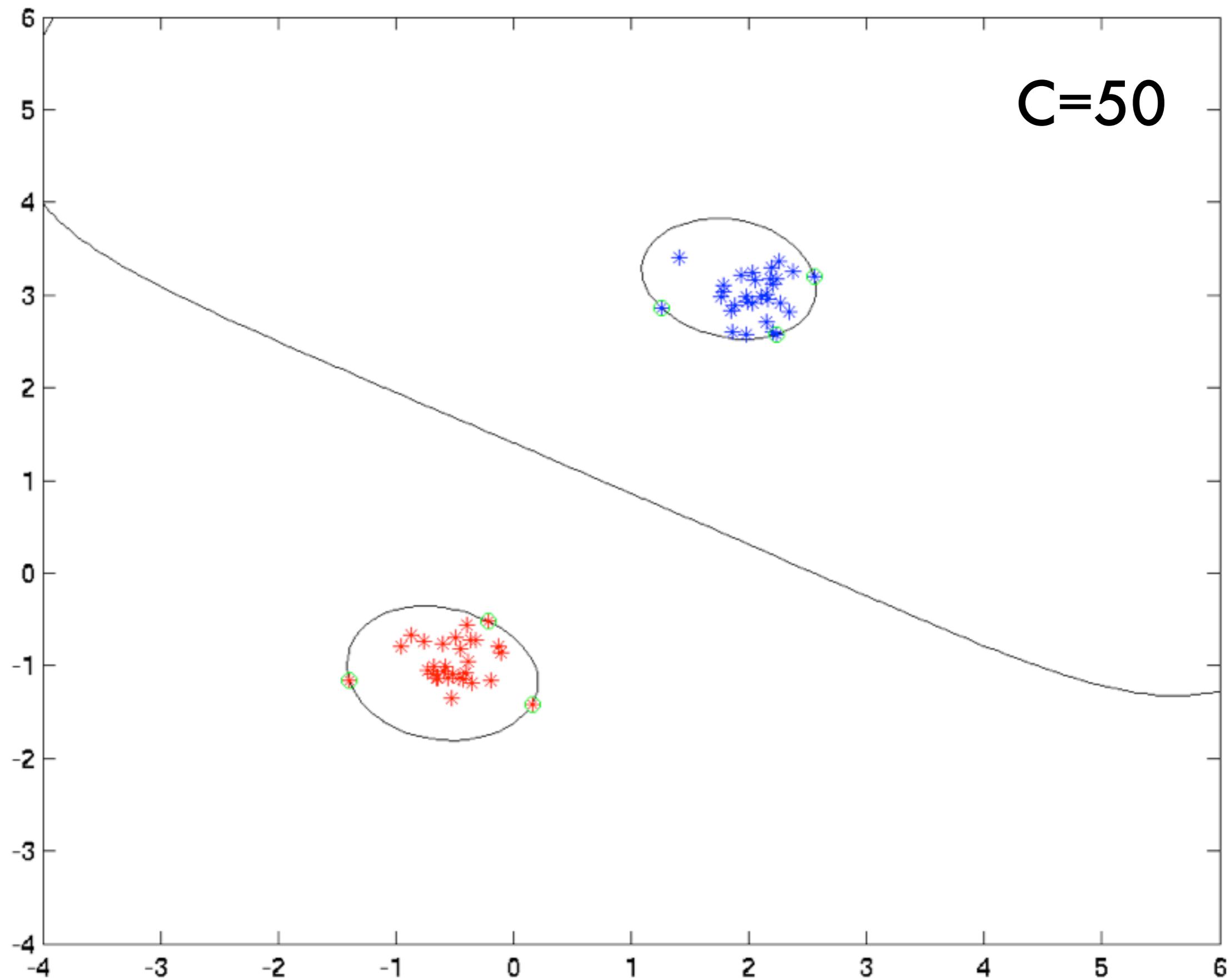
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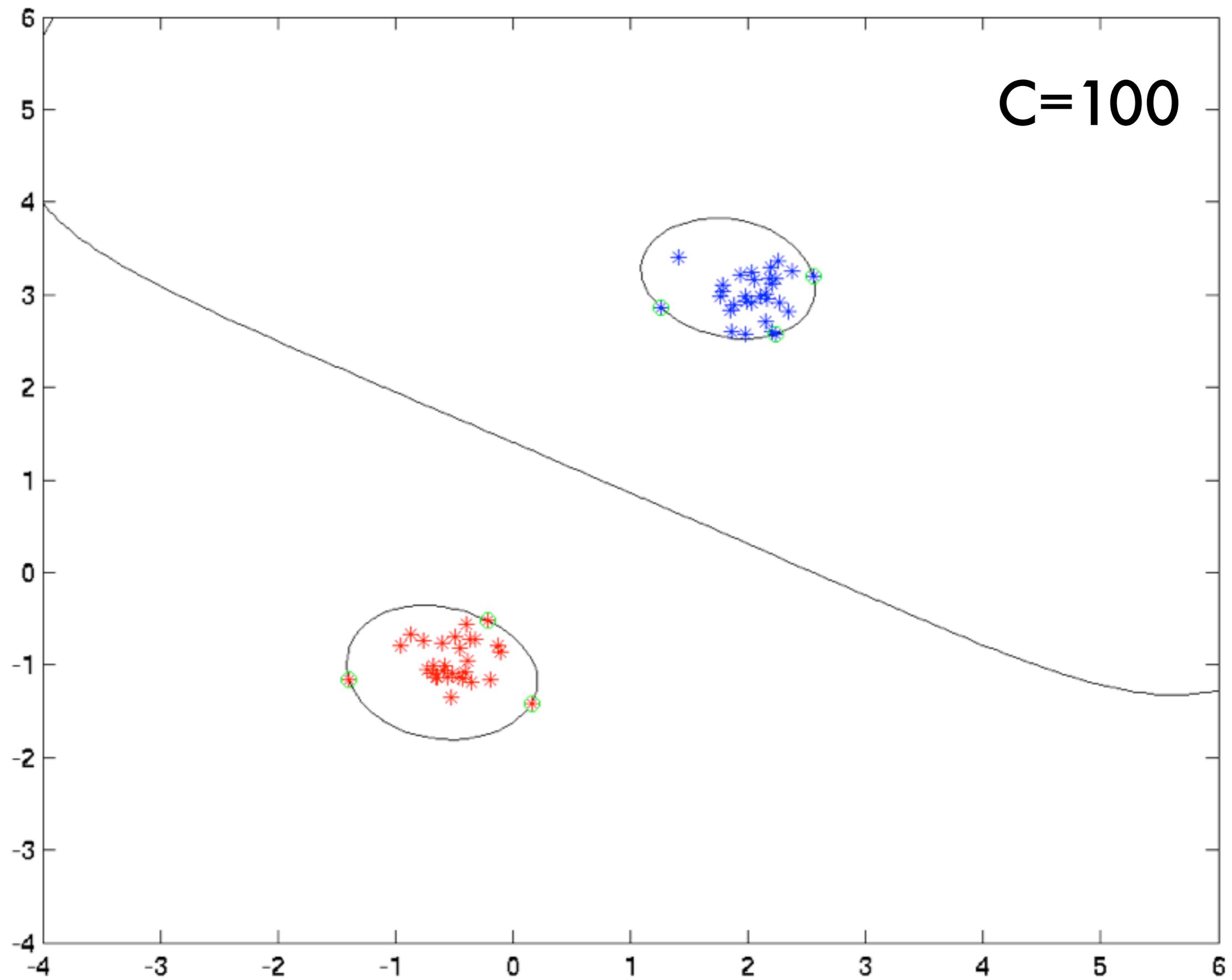
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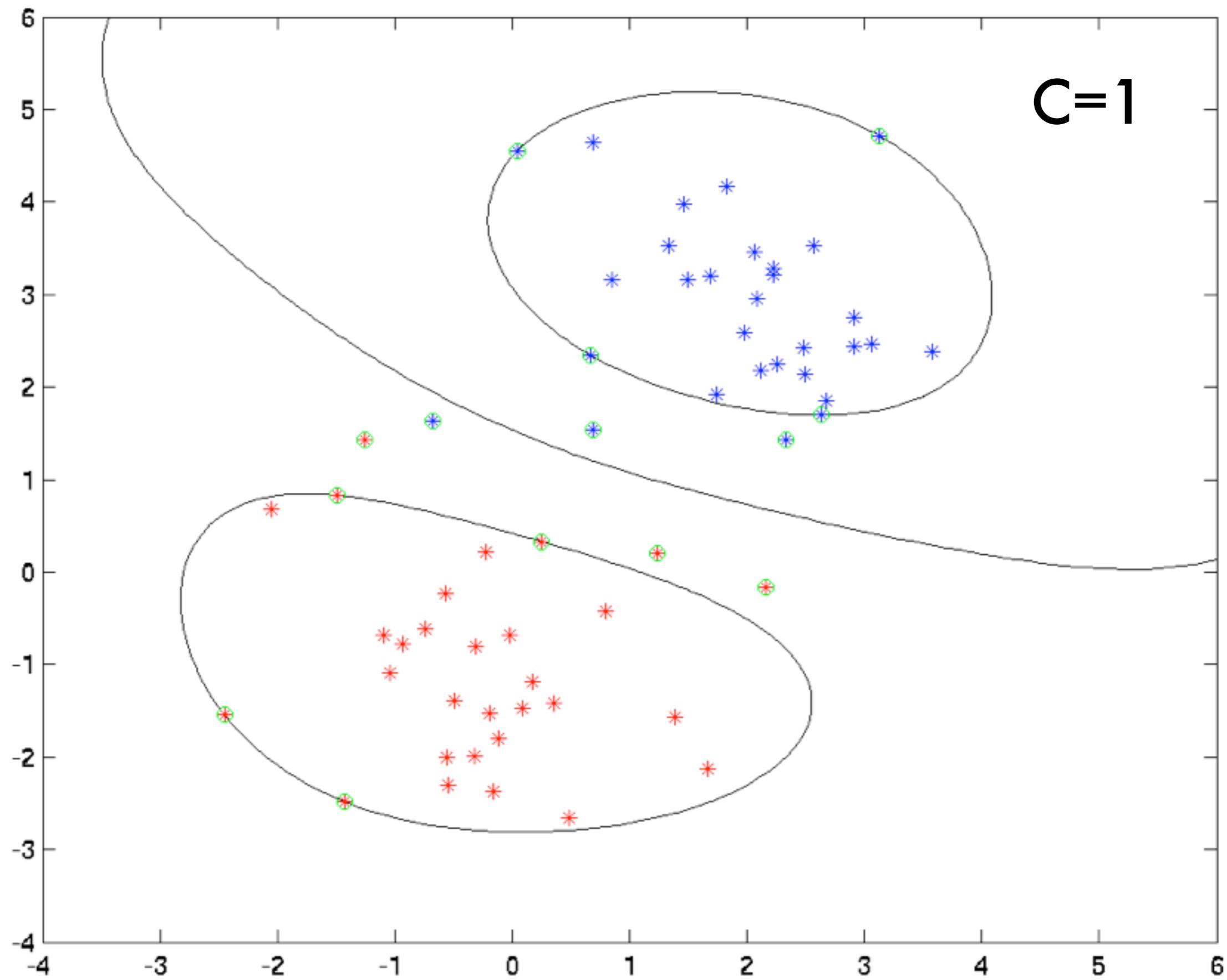
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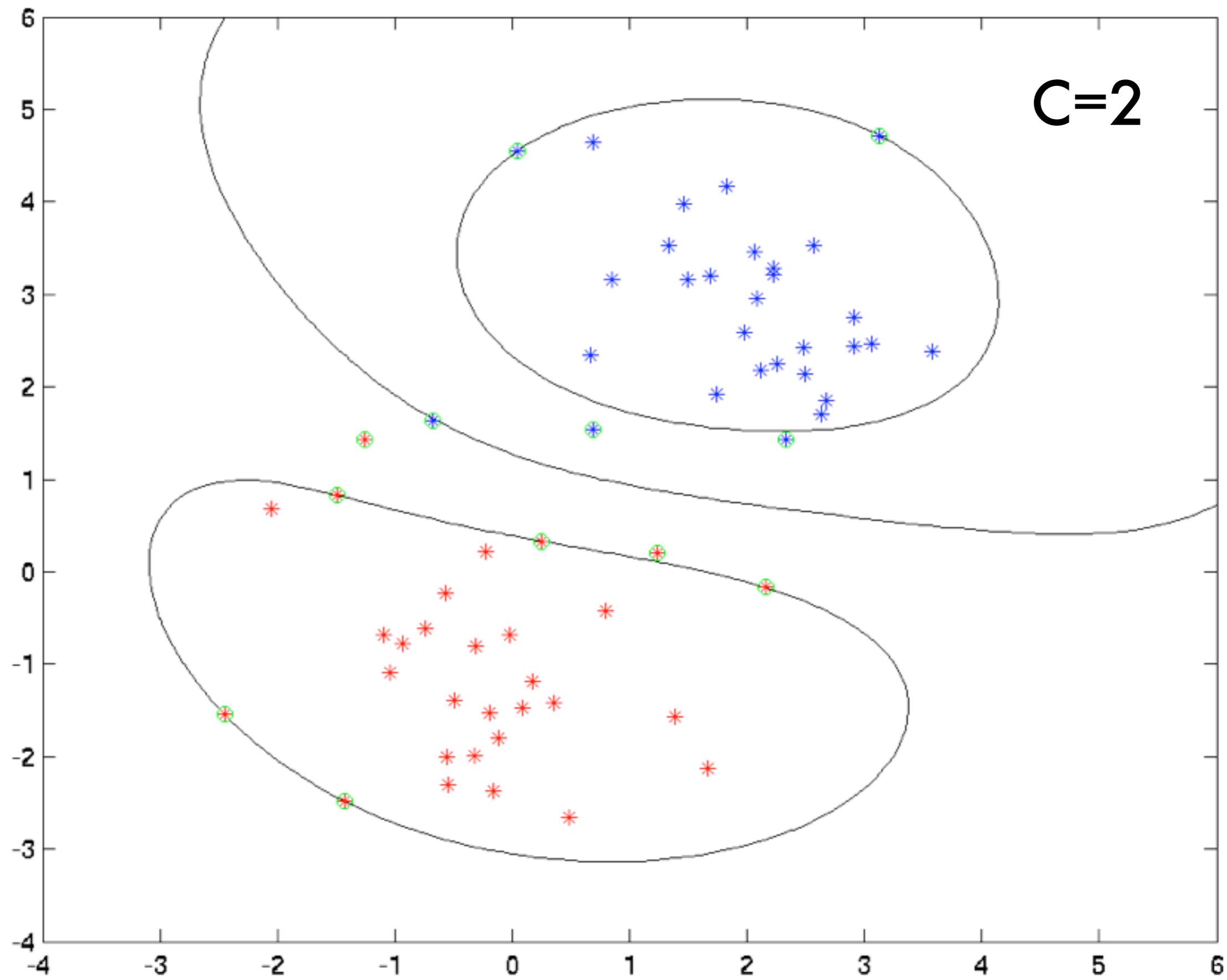
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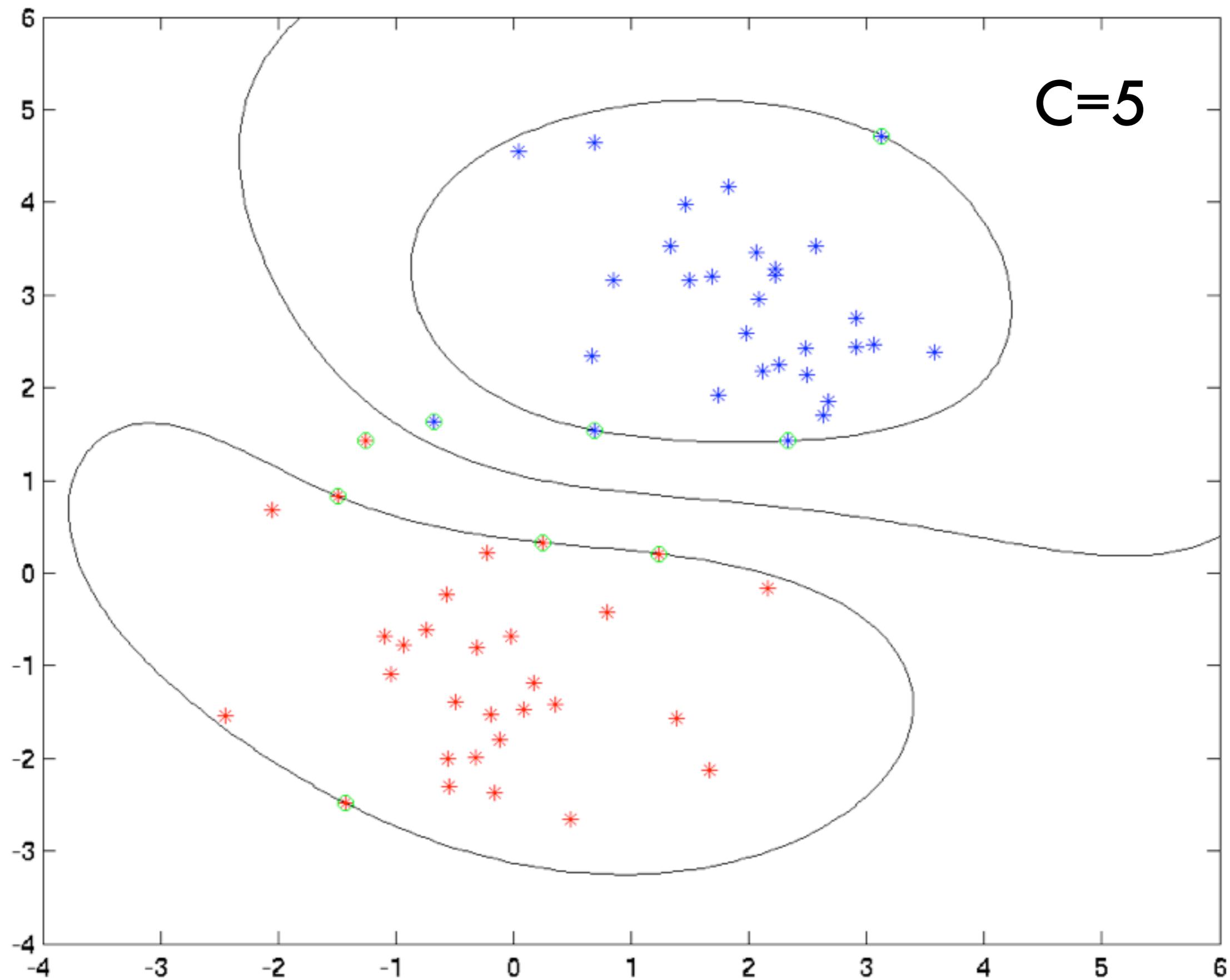
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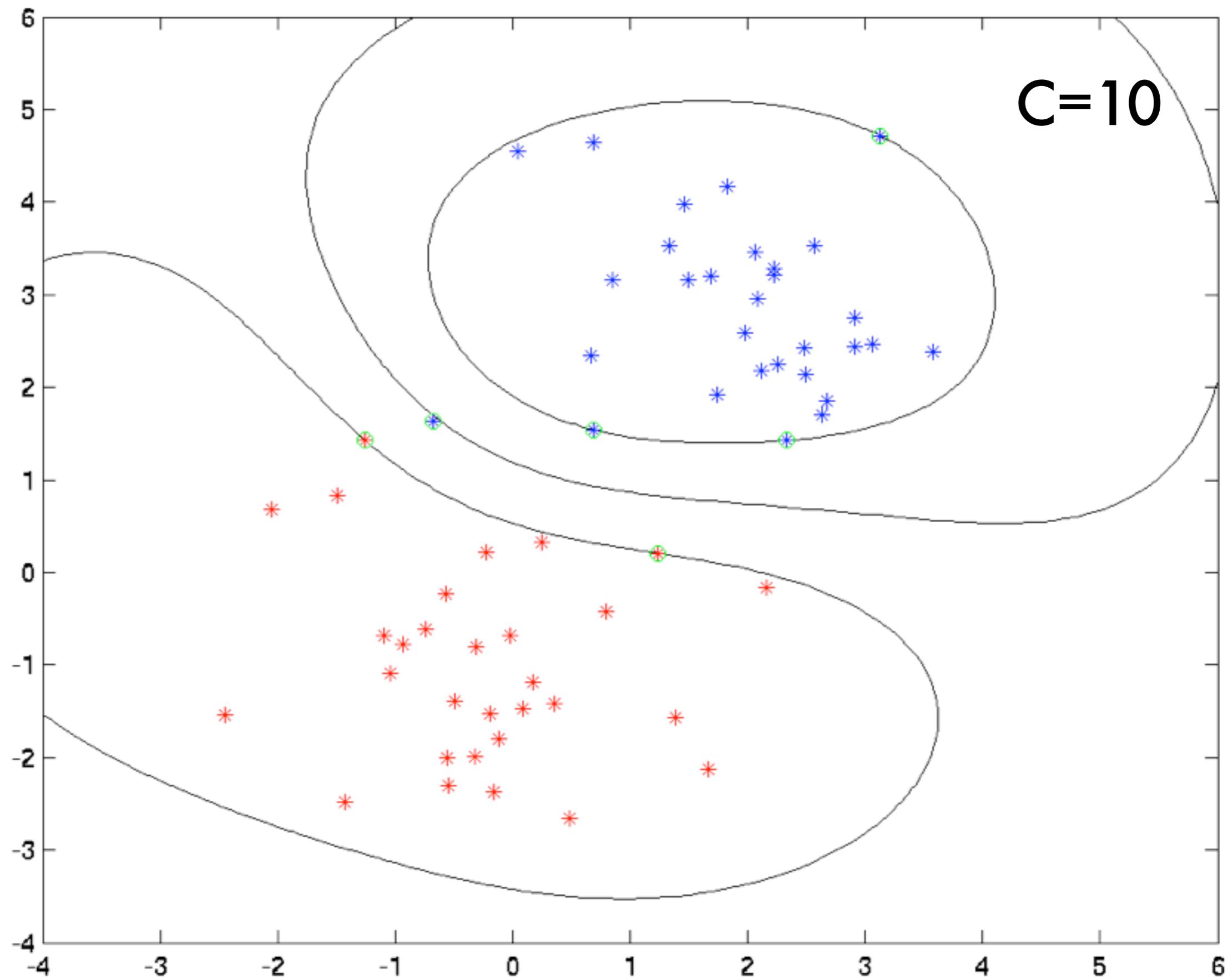
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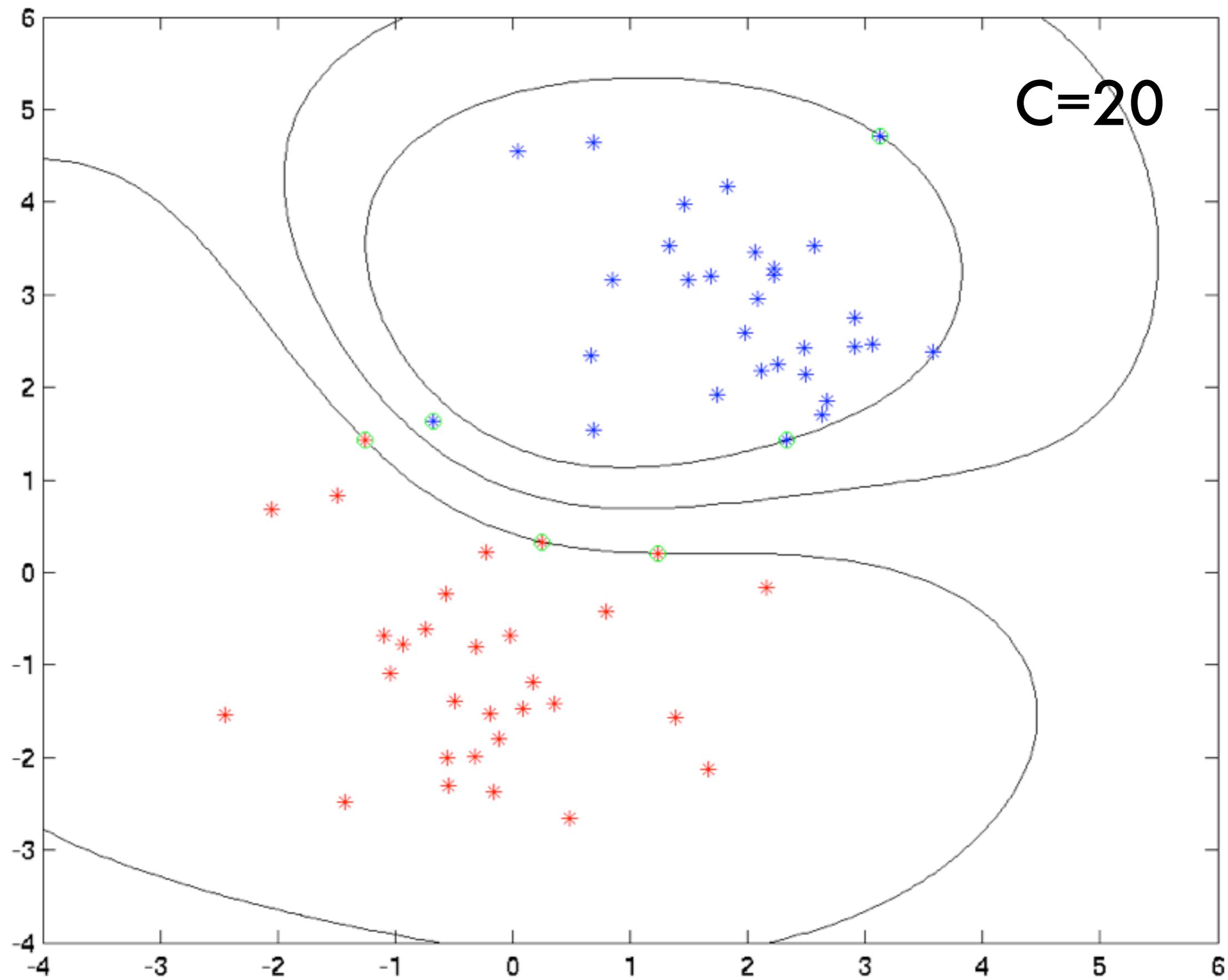
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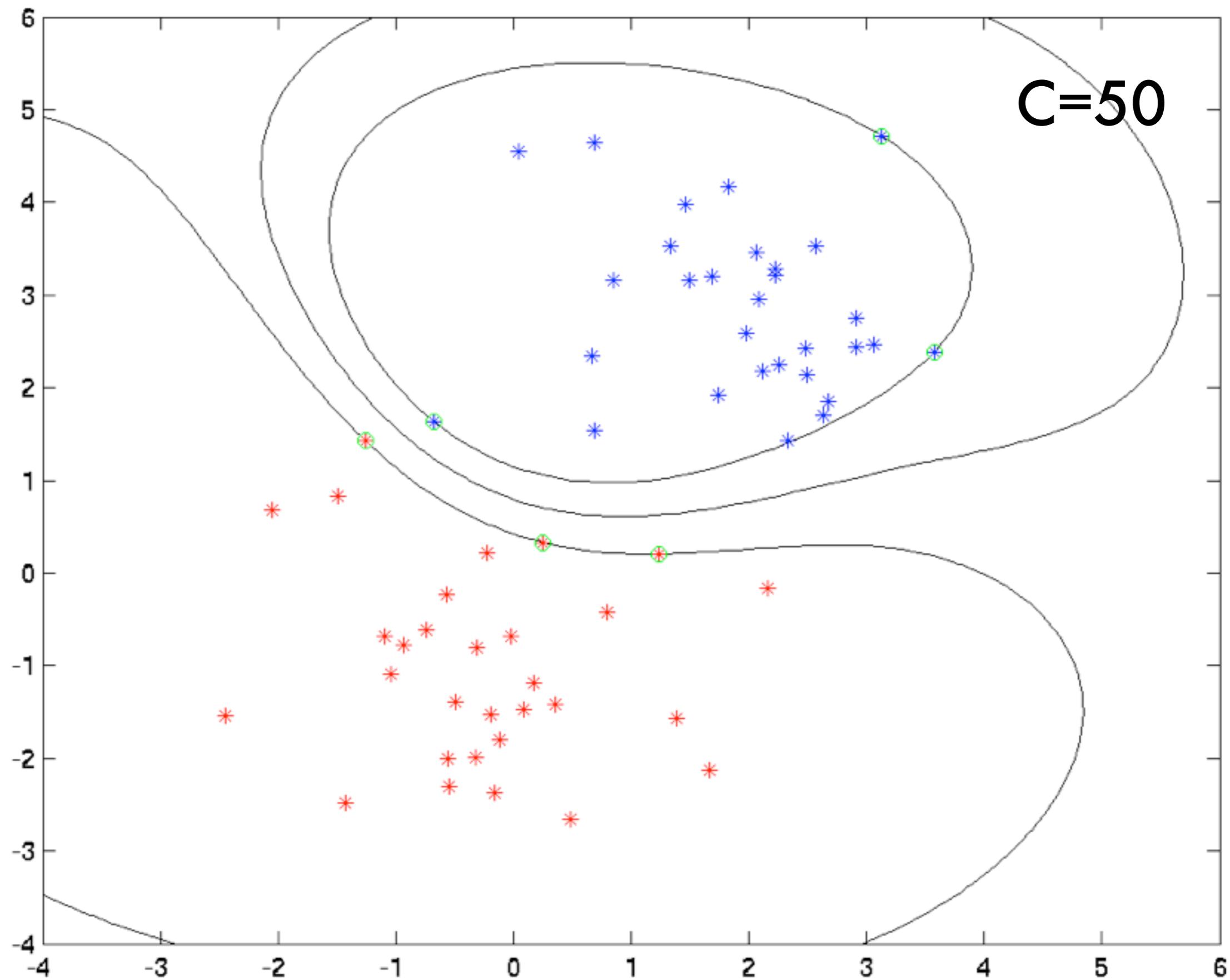


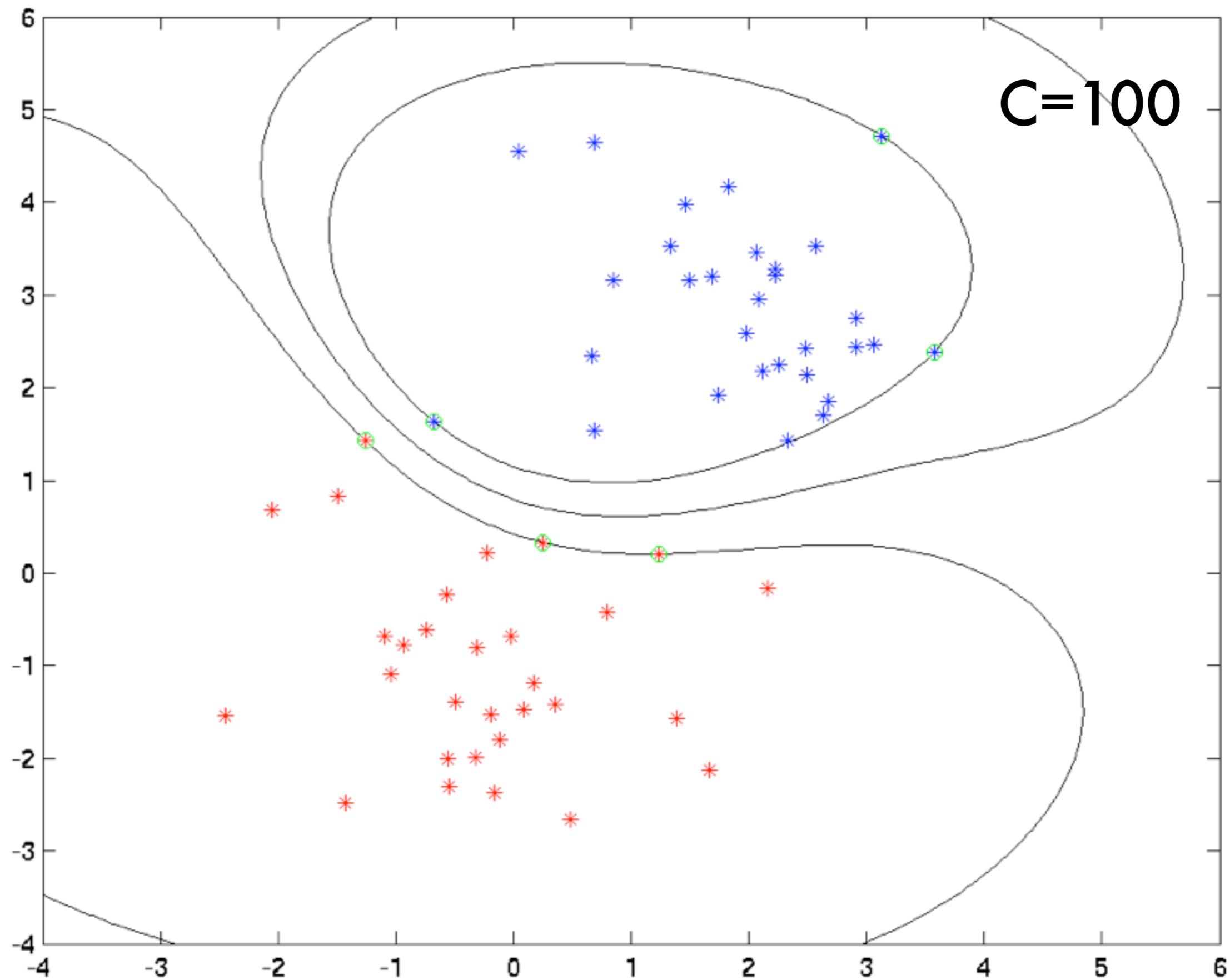
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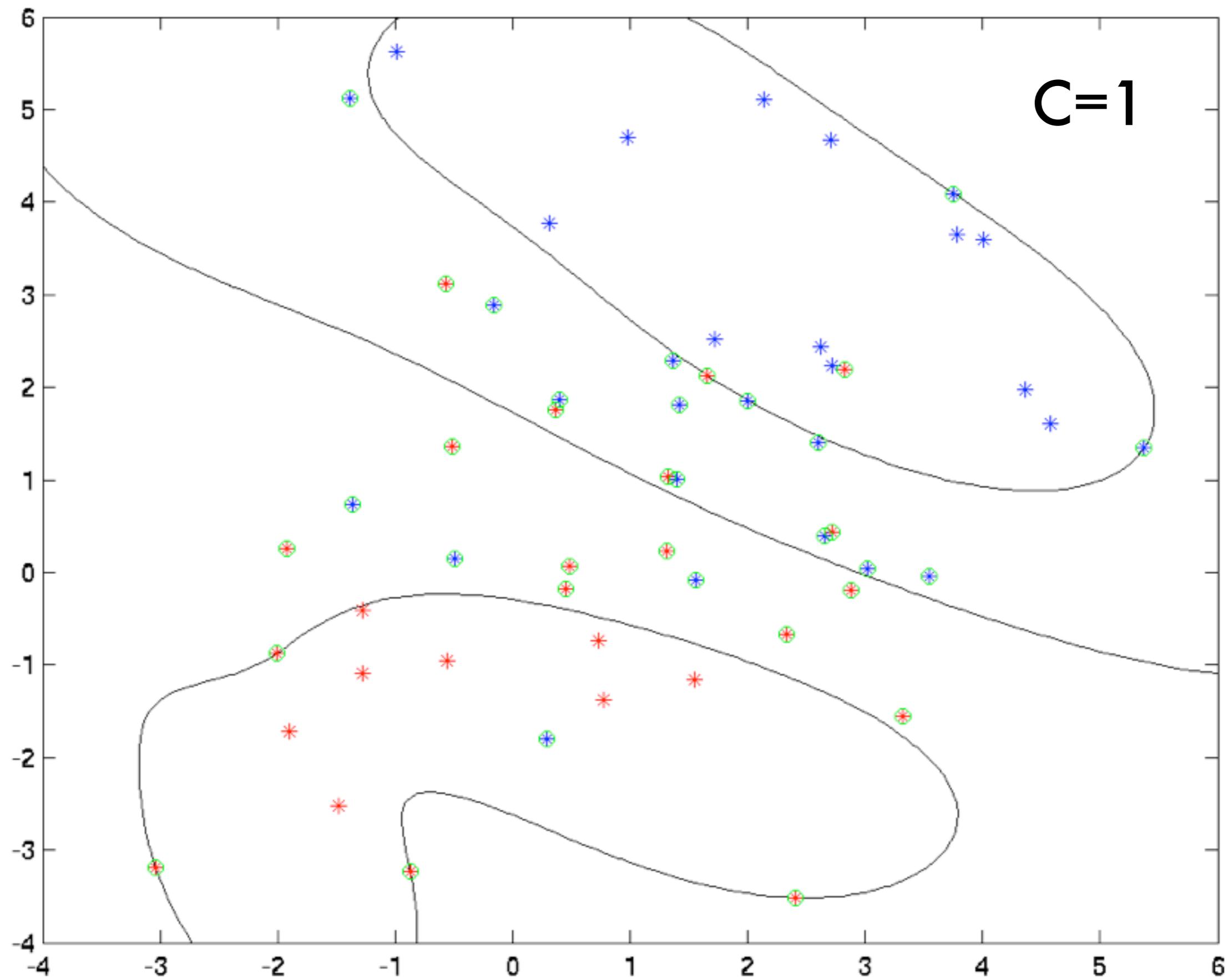
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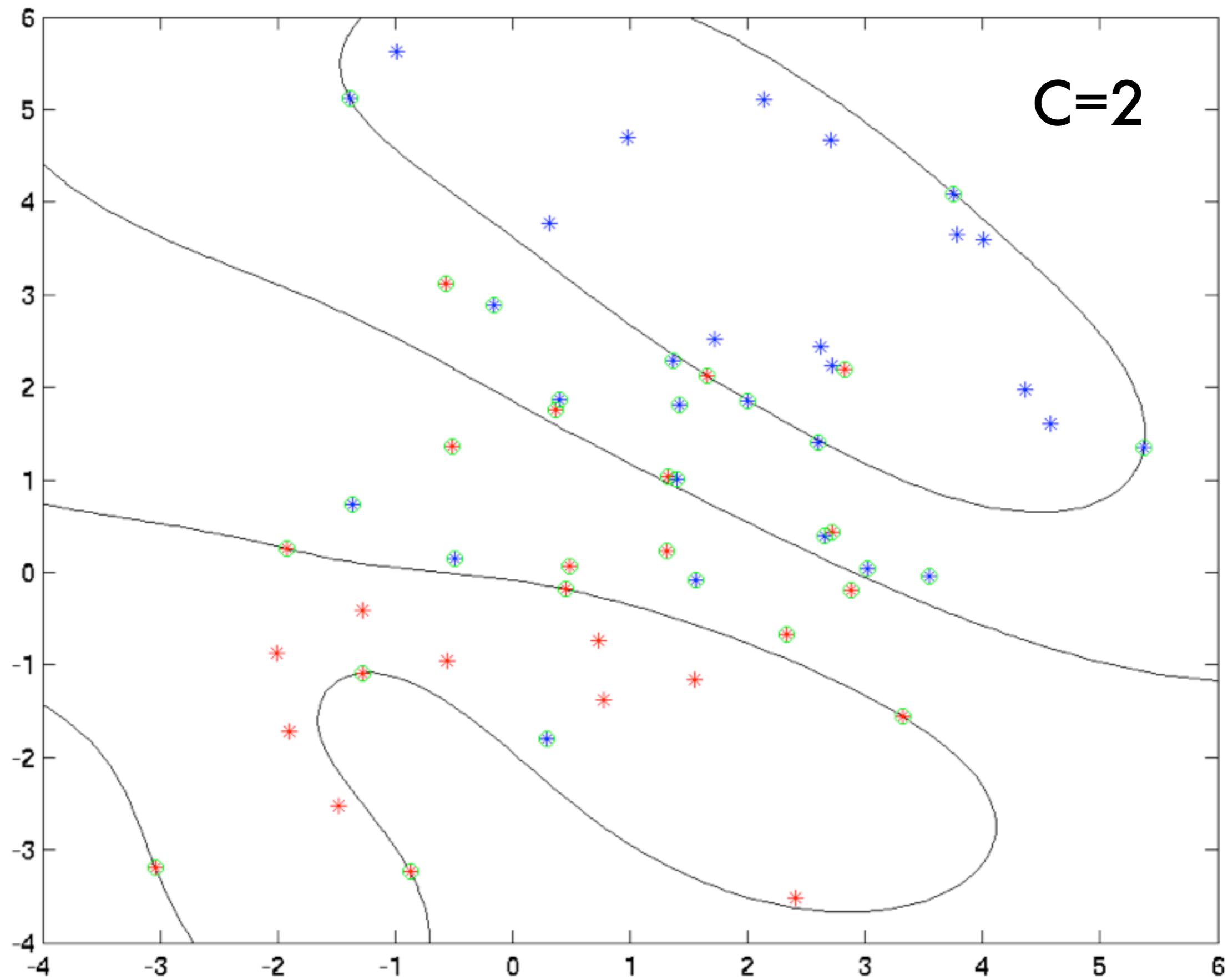




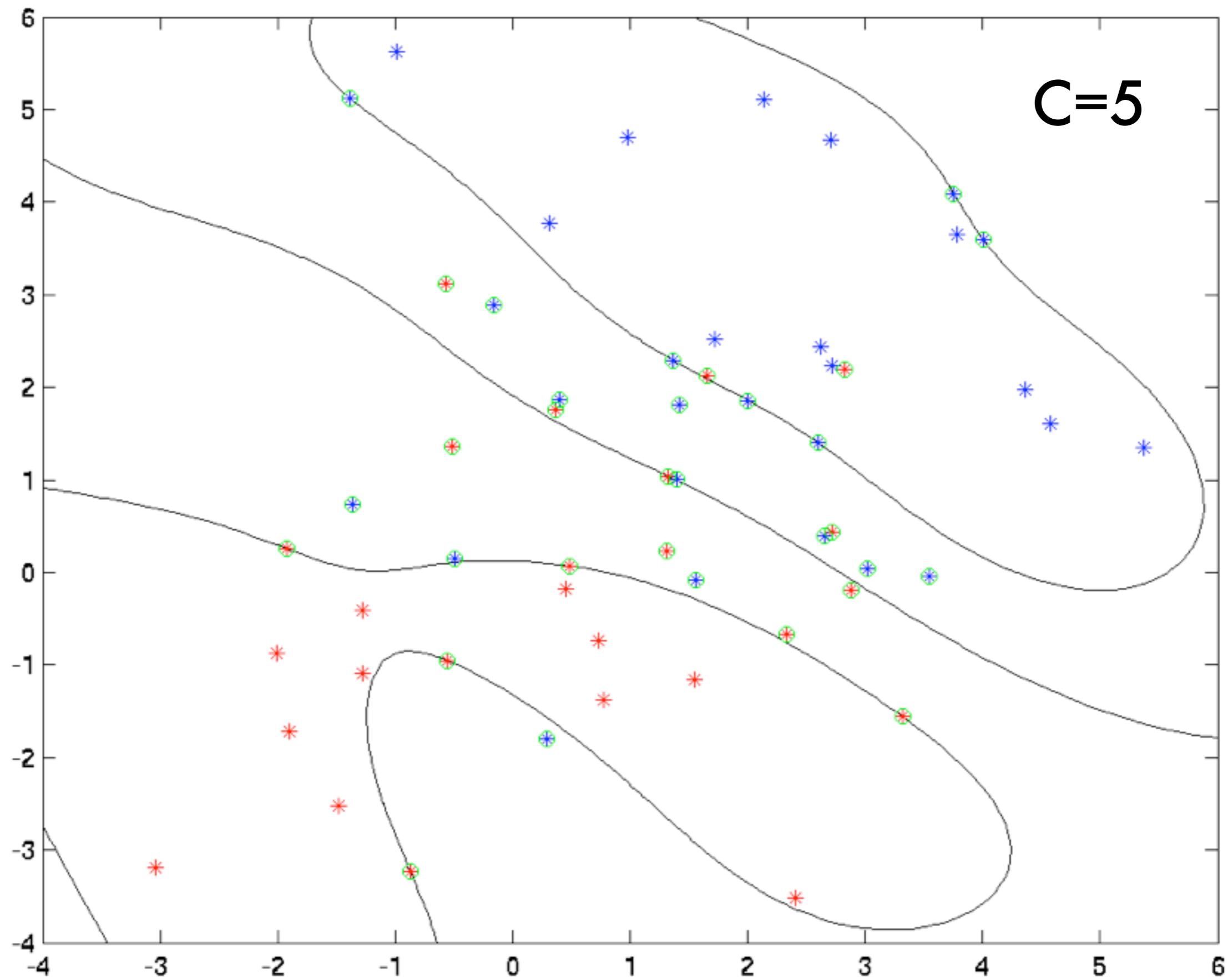
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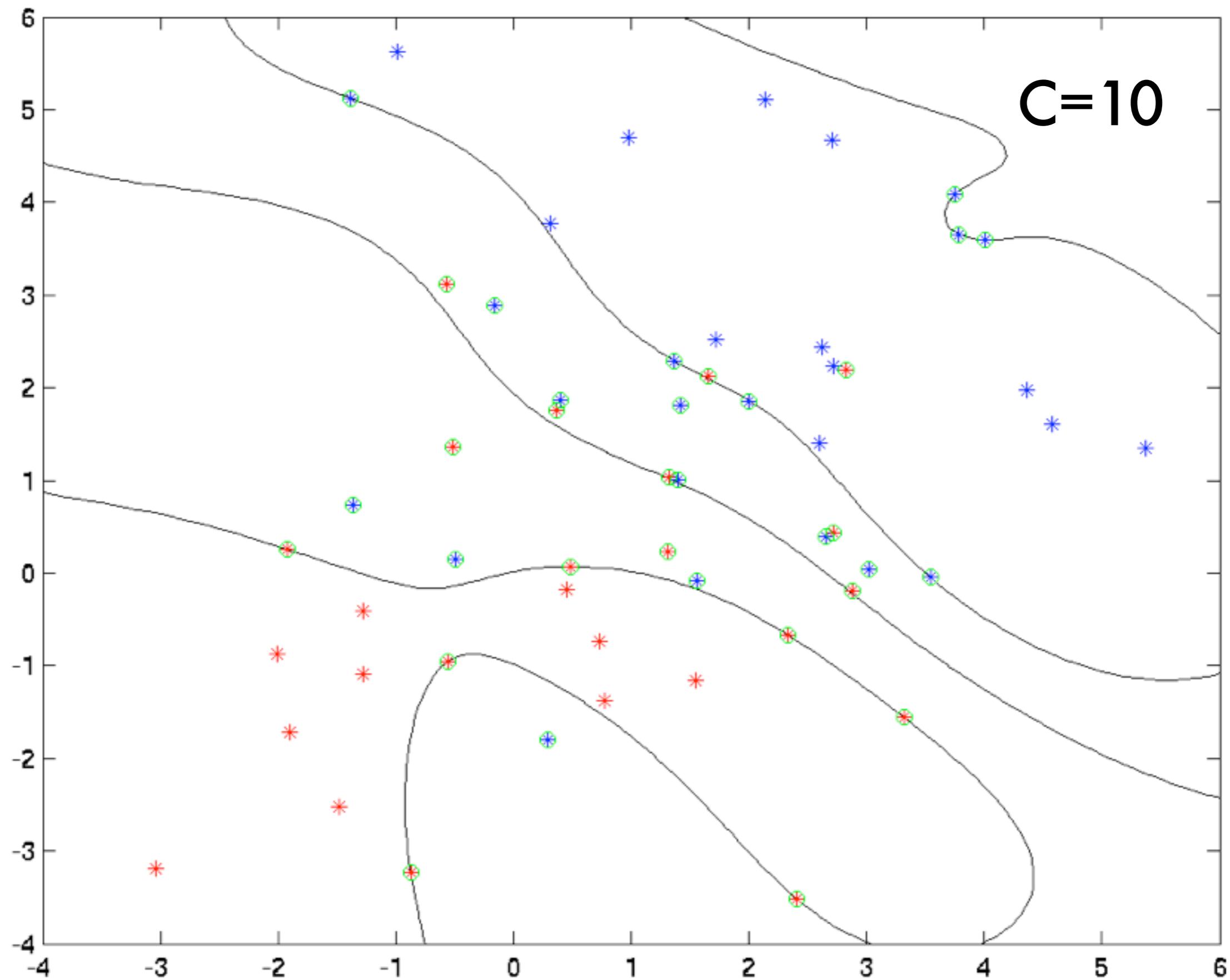
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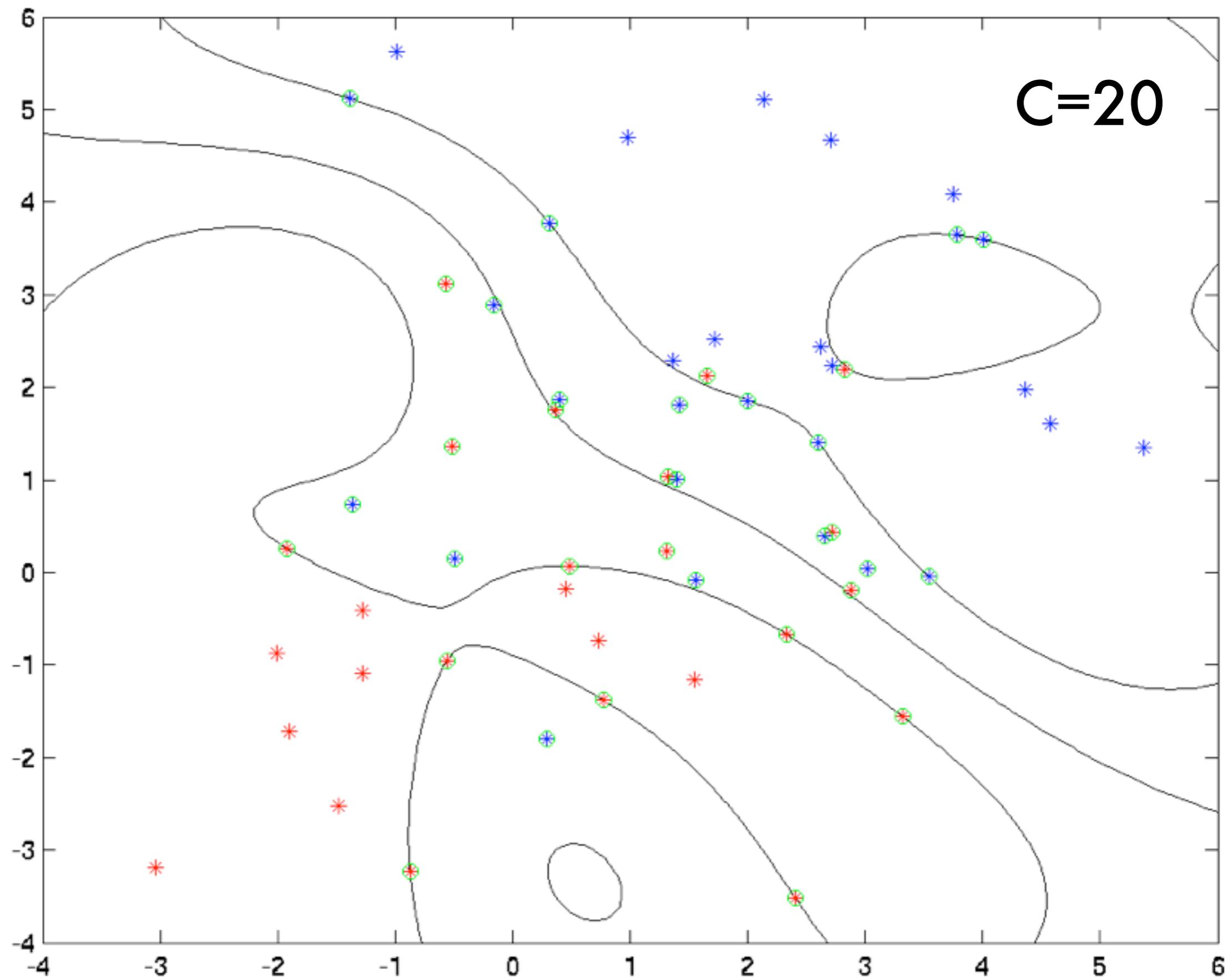
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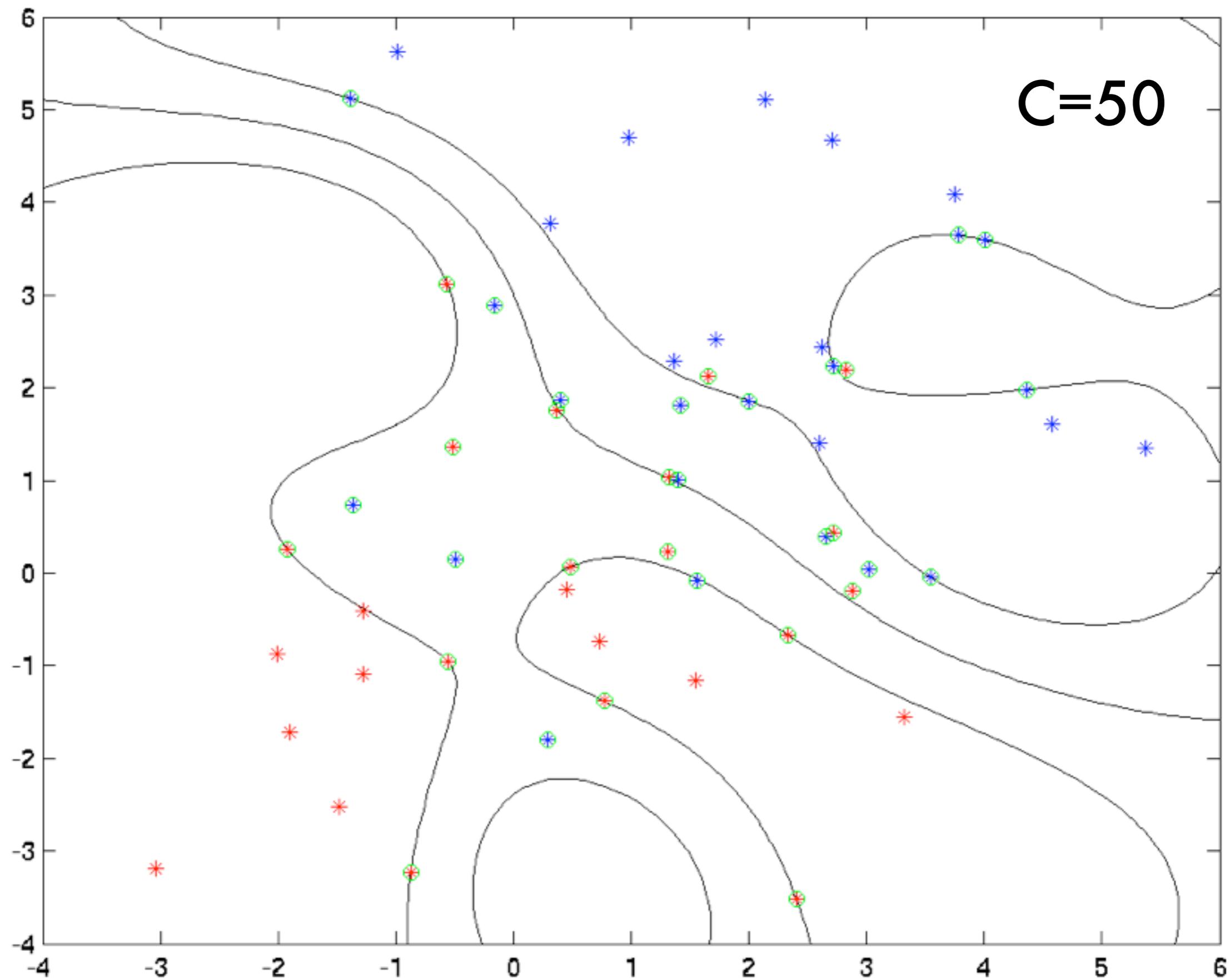
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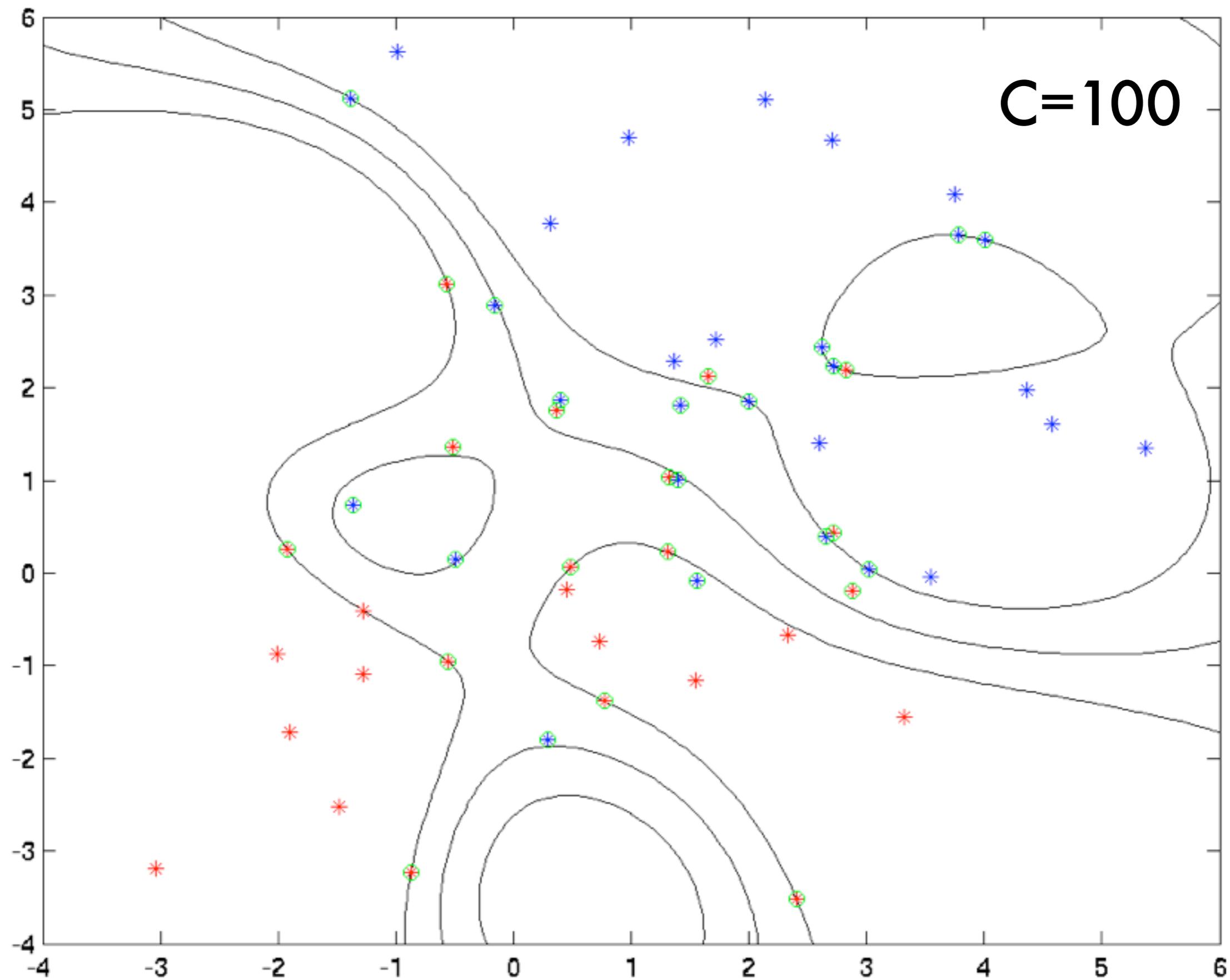
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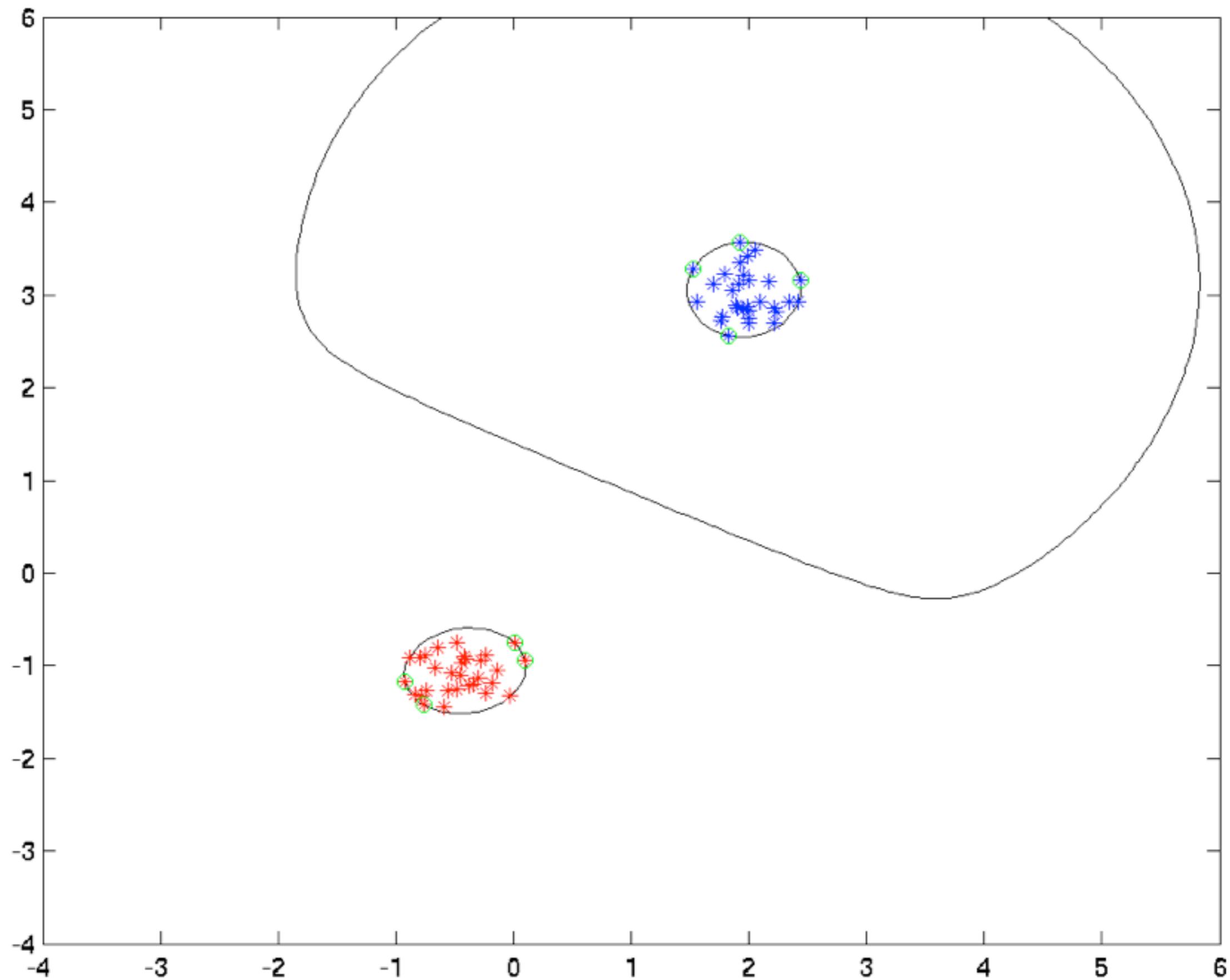
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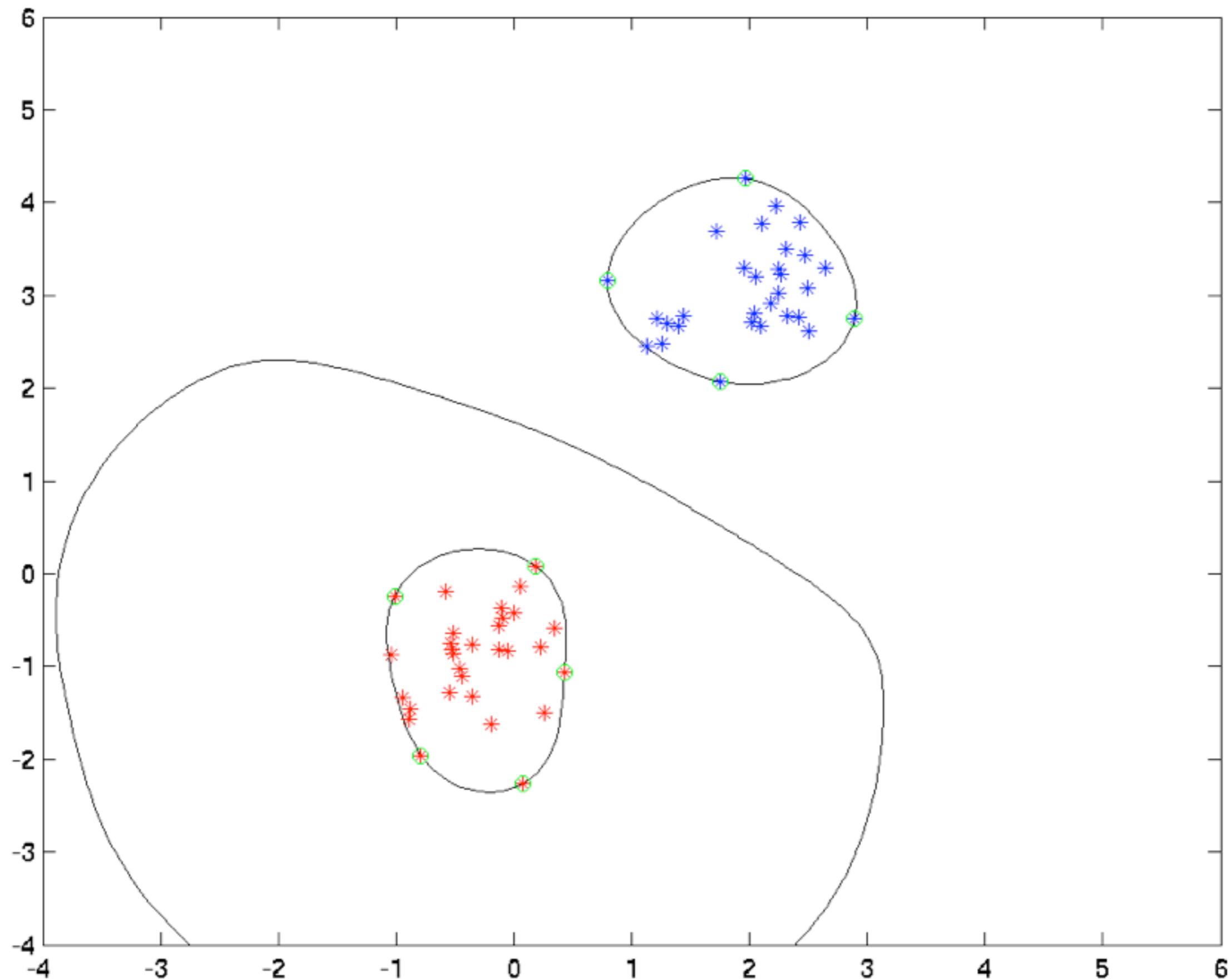


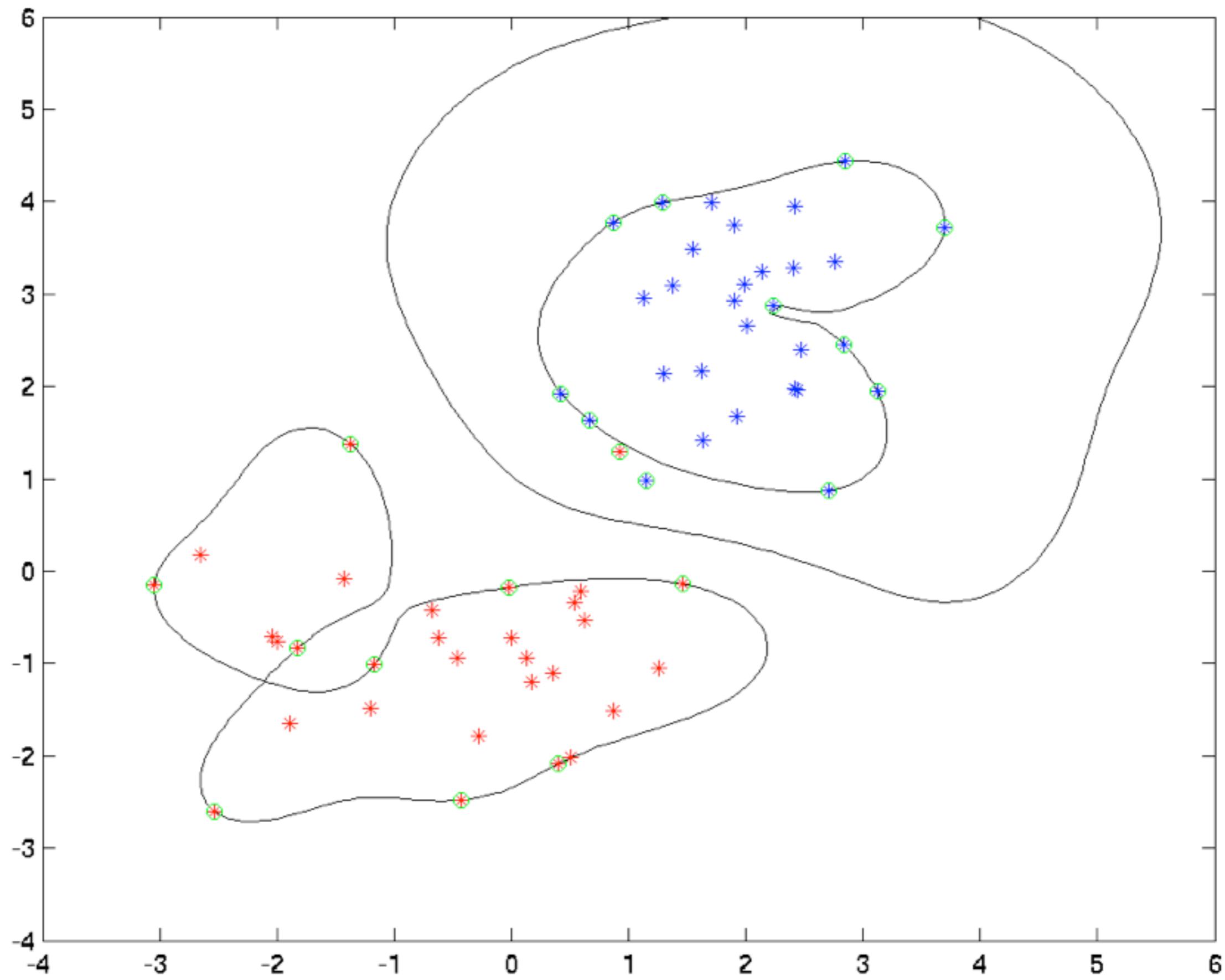
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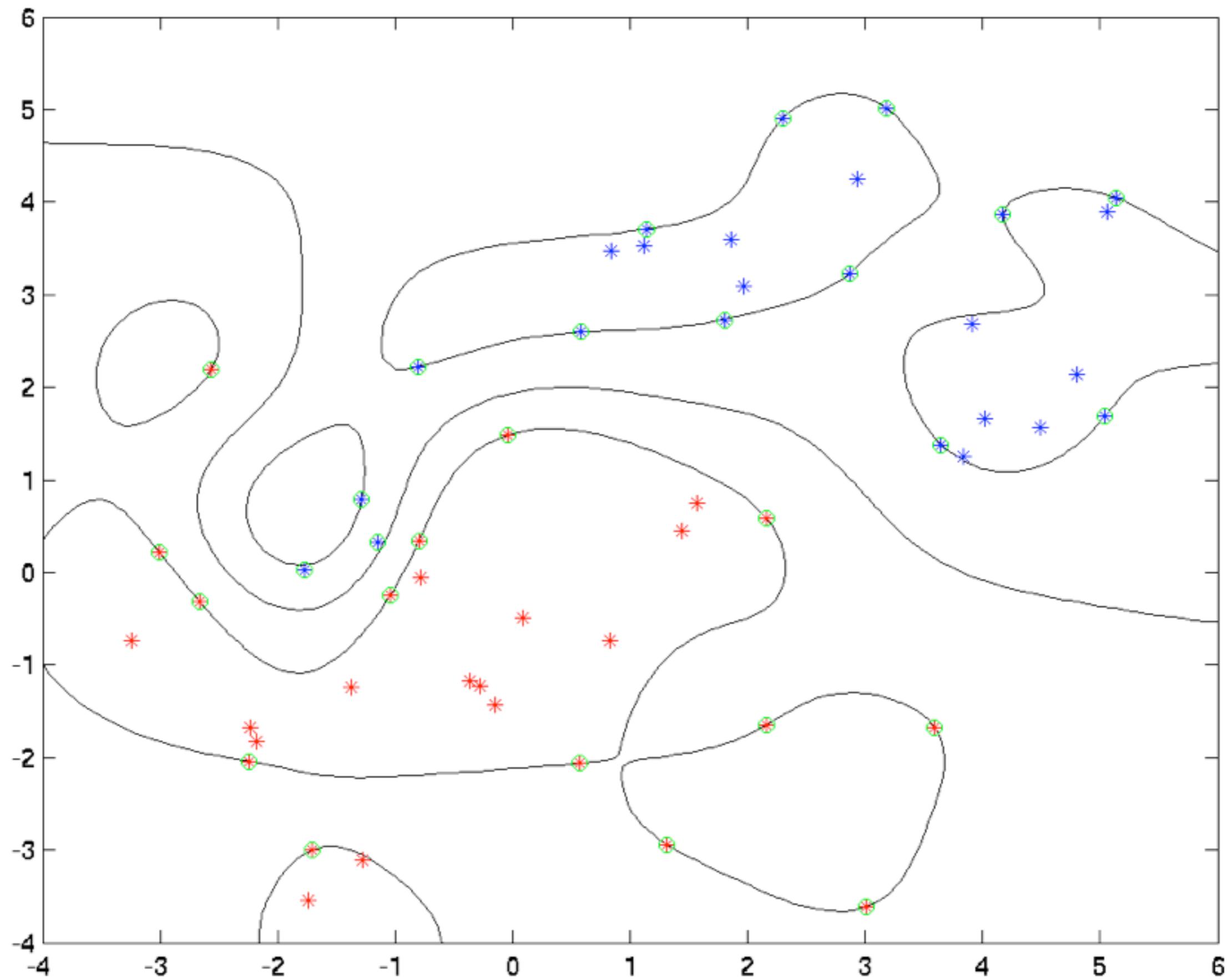


**now with a narrower kernel**

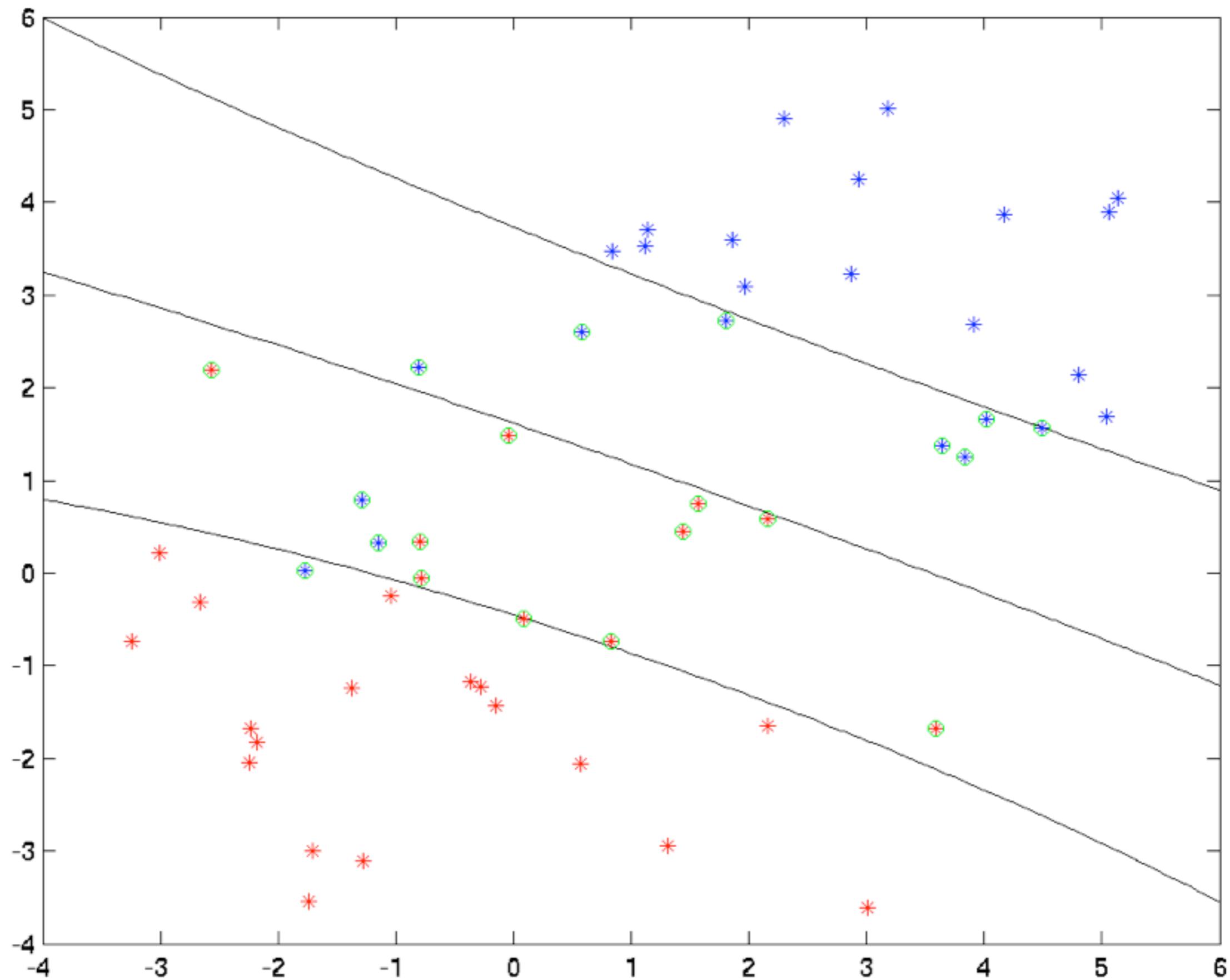




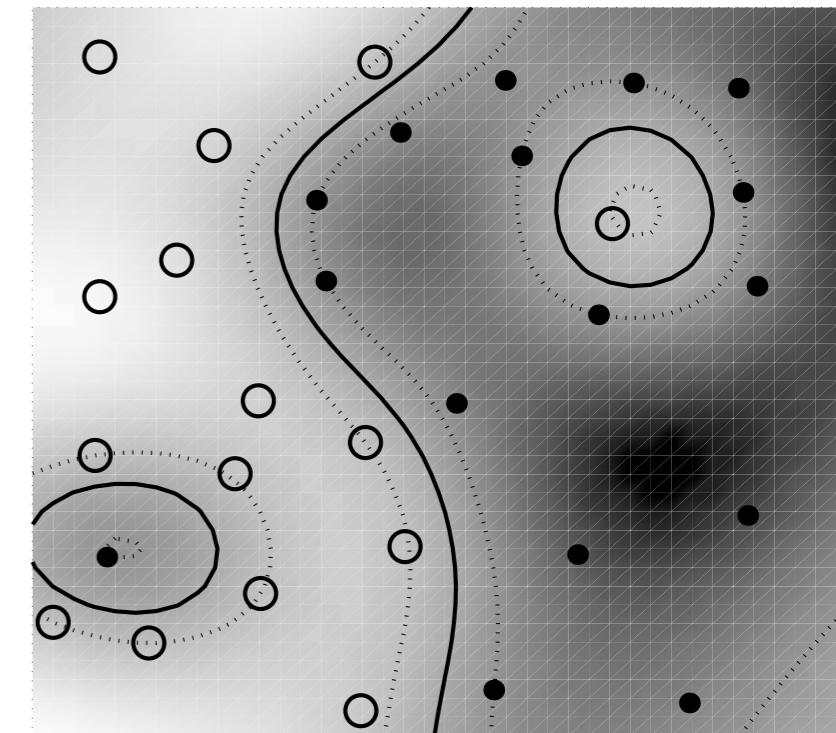
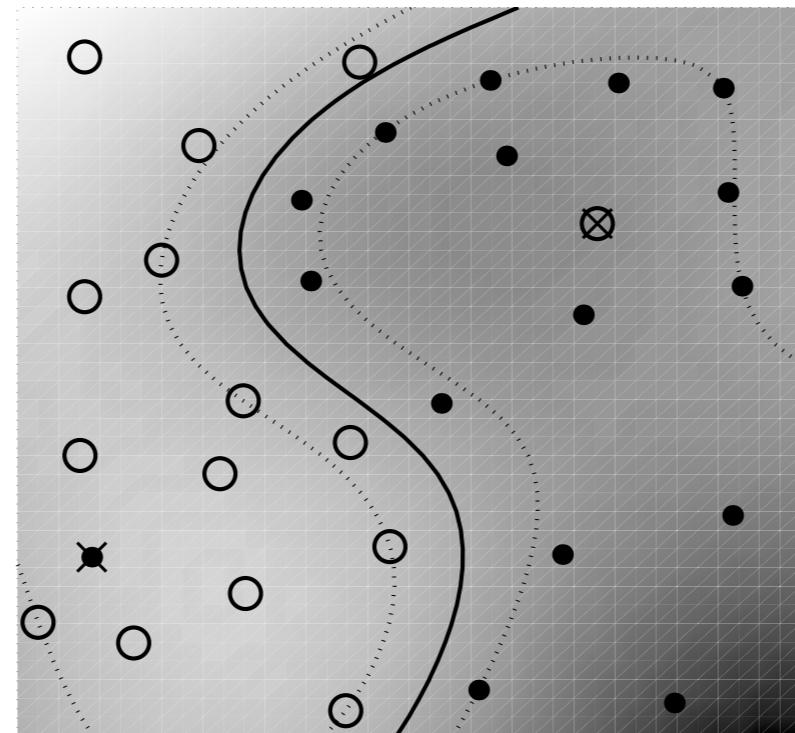
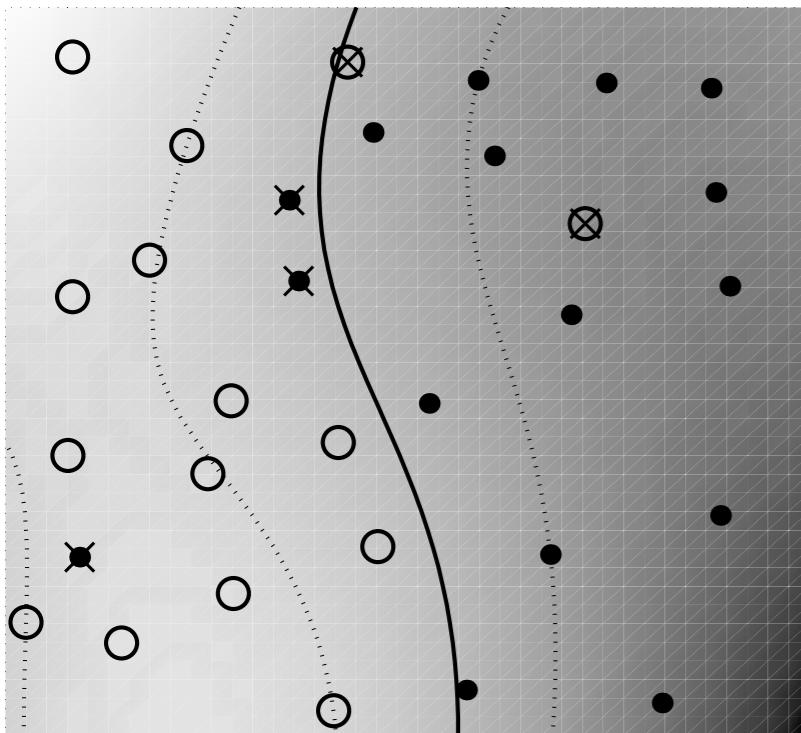




**now with a very wide kernel**



# Nonlinear separation



- Increasing C allows for more nonlinearities
- Decreases number of errors
- SV boundary need not be contiguous
- Kernel width adjusts function class