CS 171: Intro to ML and DM

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UC Riverside

Slide Set 9: Nearest Neighbor II

Slides from CS 171

- From UC Riverside
  - CS 171: Introduction to Machine Learning and Data Mining
  - Professor Christian Shelton
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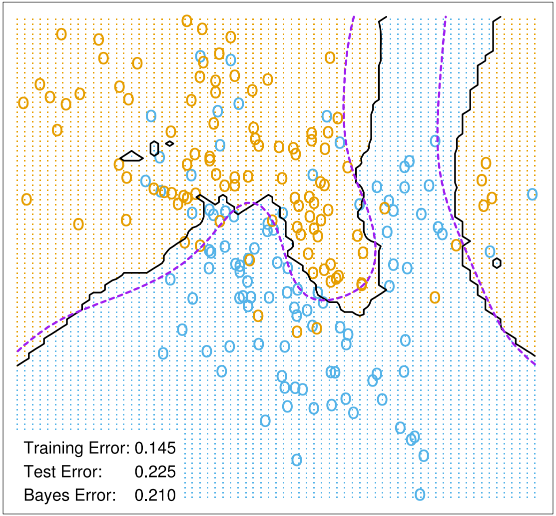
    - Elements of Statistical Learning (Hastie, et al.)
    - Pattern Recognition and Machine Learning (Bishop)
    - An Introduction to Machine Learning (Kubat)
    - Machine Learning: A Probabilistic Perspective (Murphy)
  - For use only by enrolled students in the course

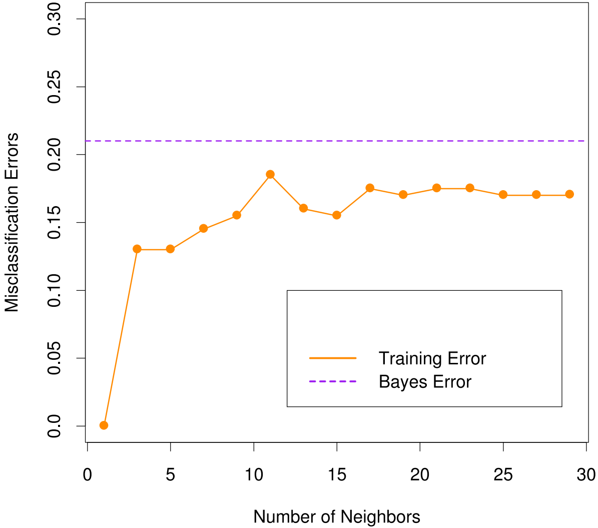
k-Nearest Neighbor Practical Considerations

- How to pick k
- How to pick distance measure (and scaling)
- How to reduce computational costs

Selection of k



Selection of k



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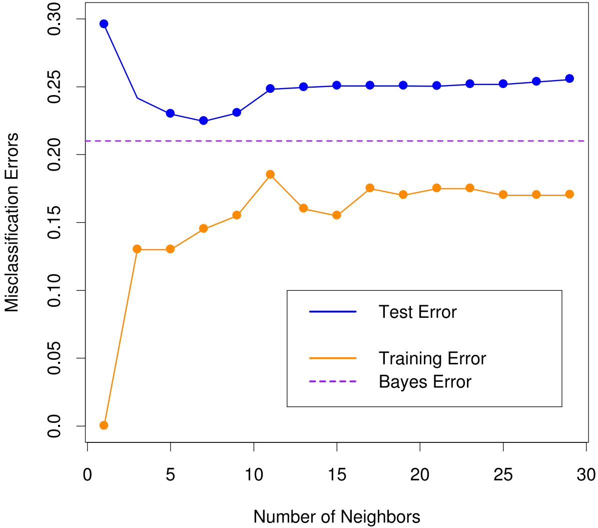
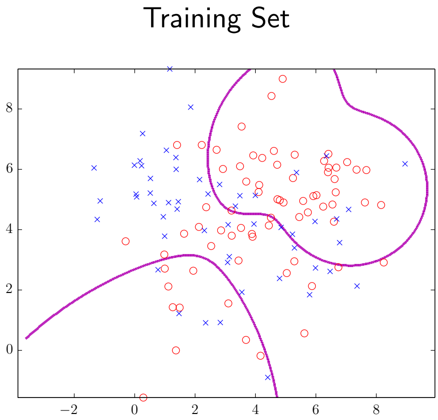
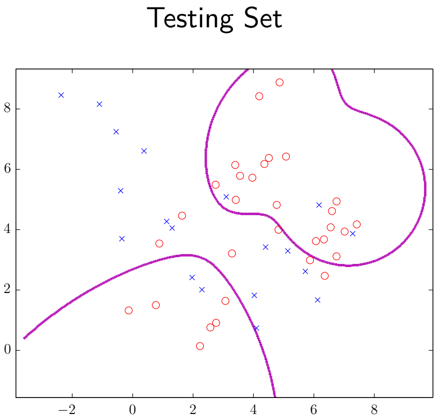


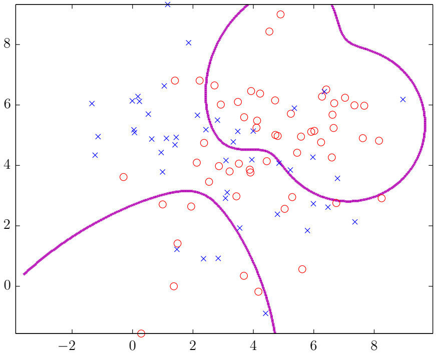
Cross Validation Example



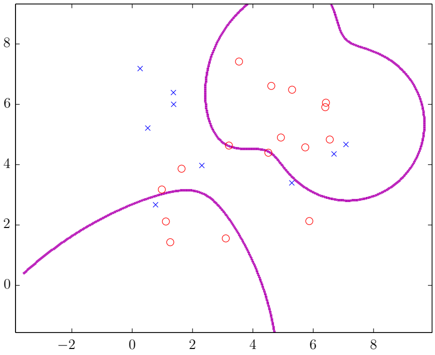


Cross Validation Example

Training Set

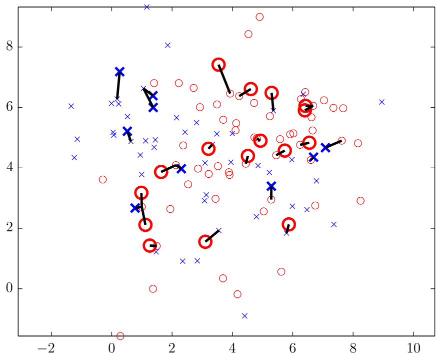


Validation Set

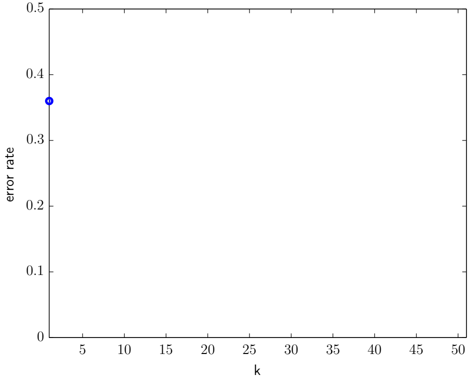


Cross Validation Example

$k = 1$



CV error rate



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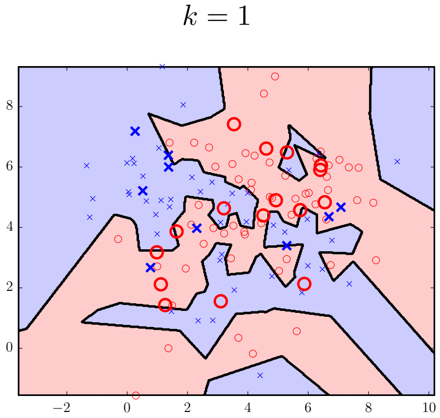

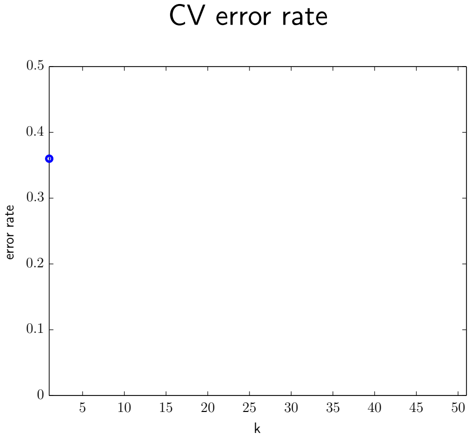

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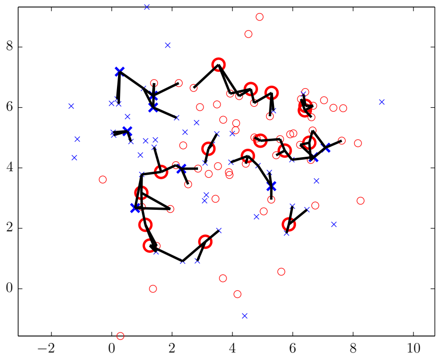

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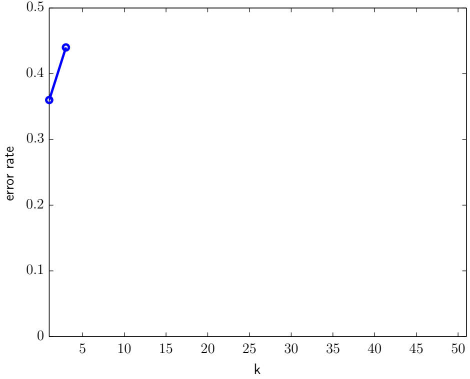

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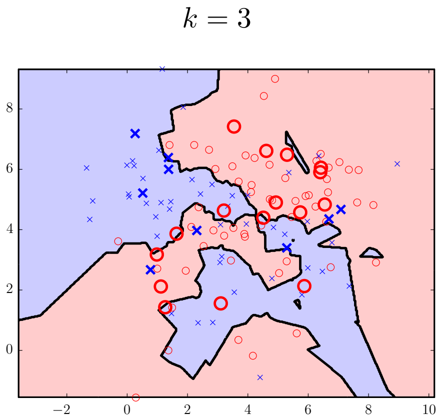
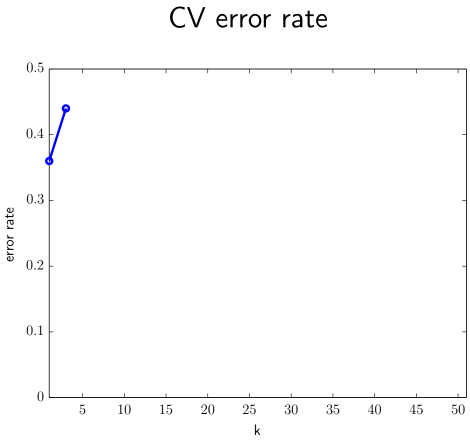
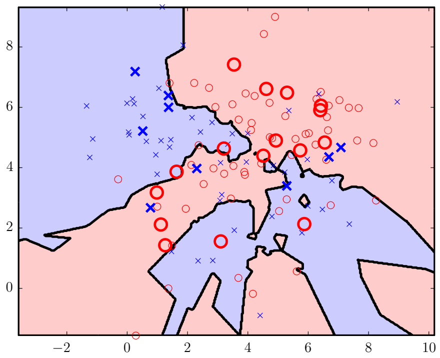




Cross Validation Example

$k = 5$



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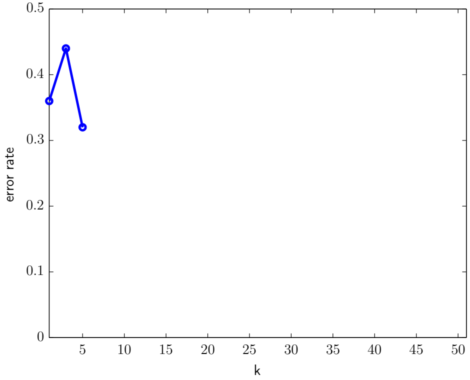

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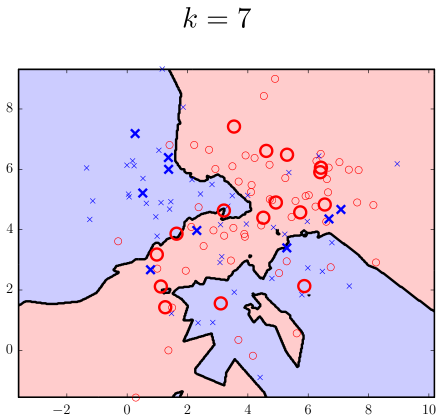

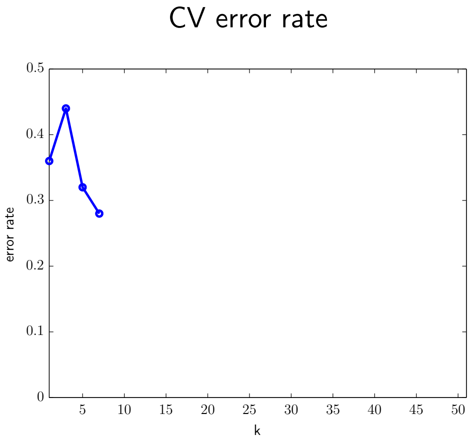

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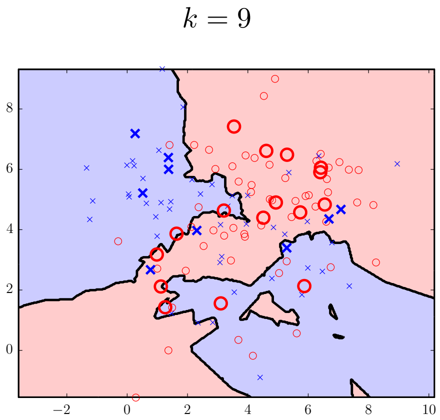
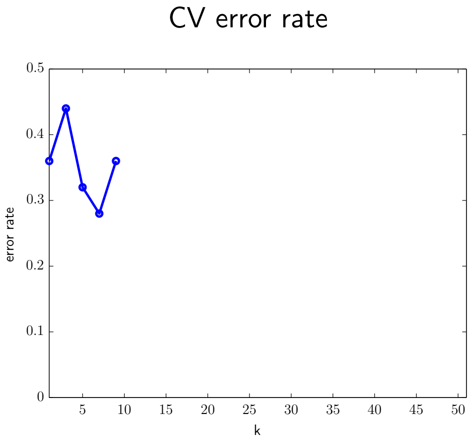
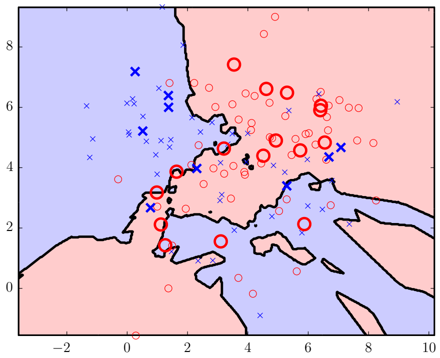


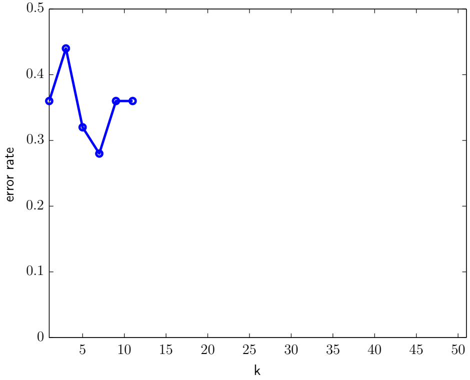


Cross Validation Example

$k = 11$

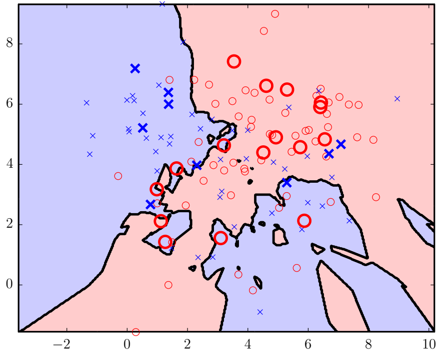


CV error rate

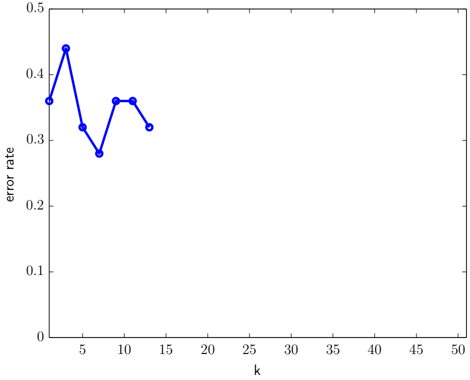


Cross Validation Example

$k = 13$



CV error rate



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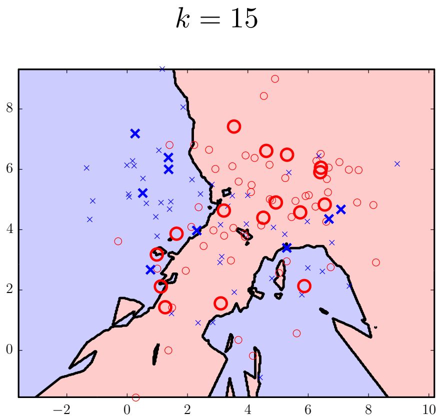
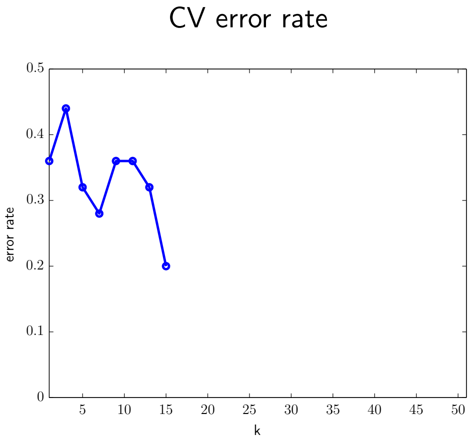
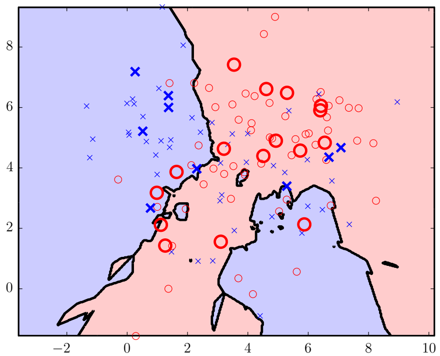


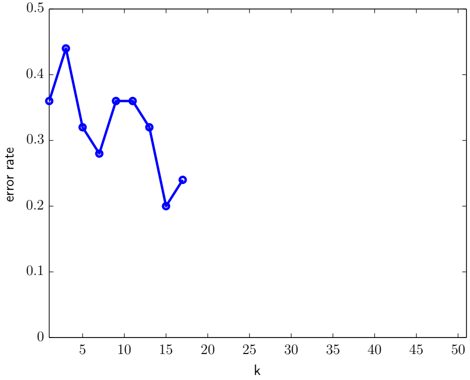


Cross Validation Example

$k = 17$



CV error rate



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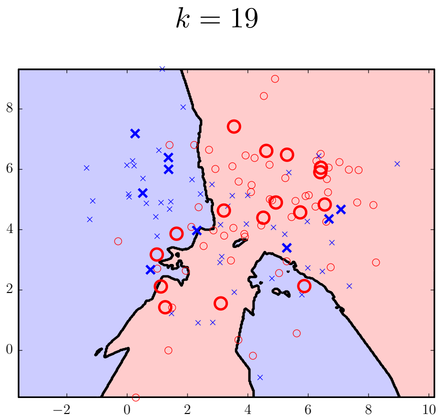
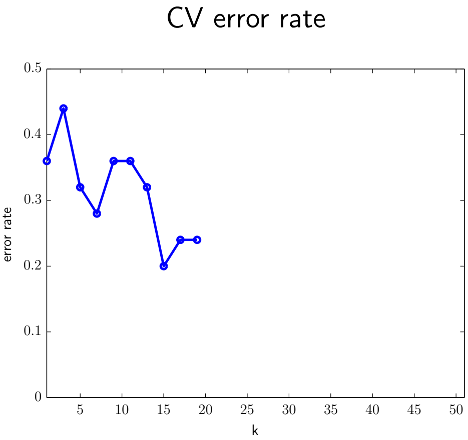
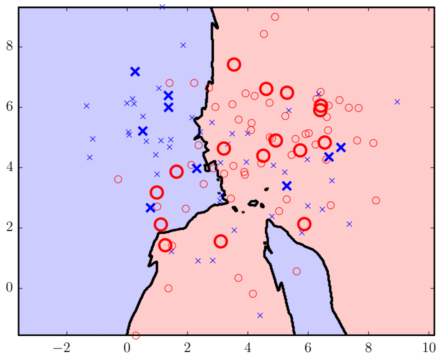


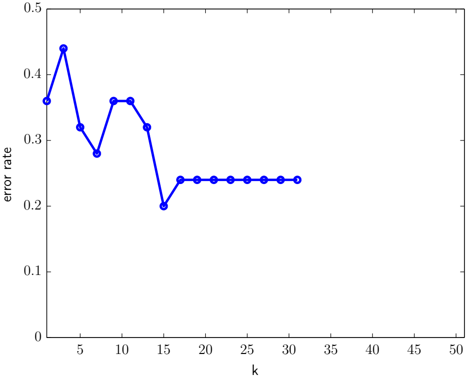


Cross Validation Example

$k = 31$



CV error rate



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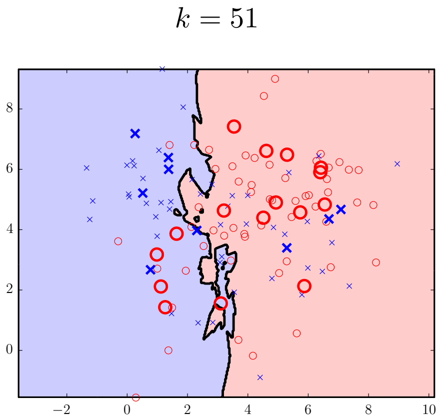
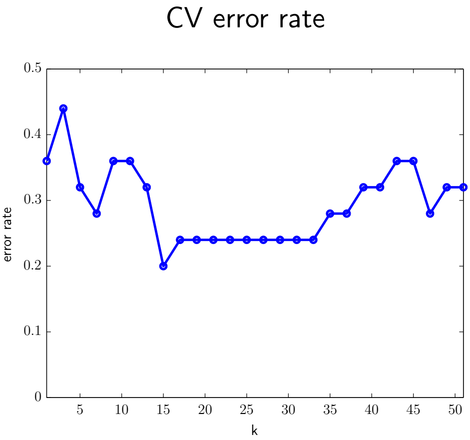
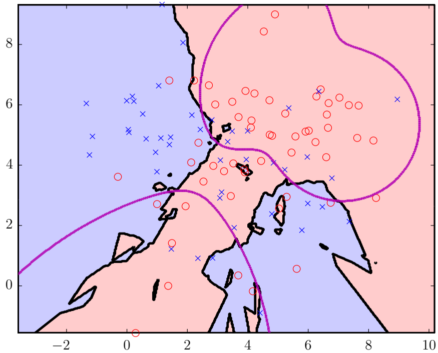




Cross Validation Example

$k = 15$



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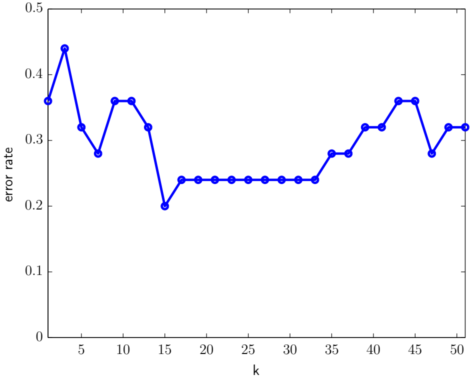

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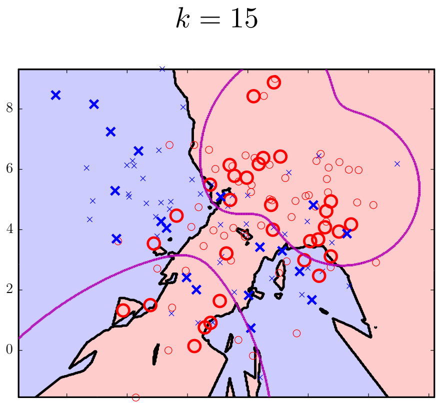

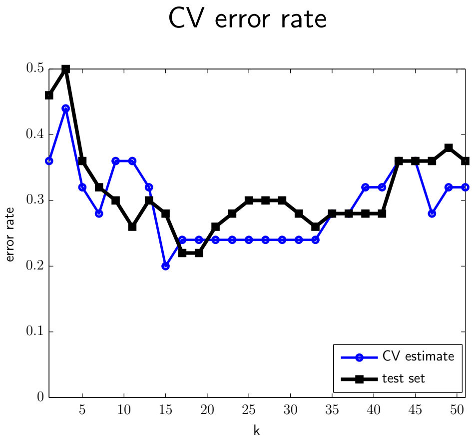

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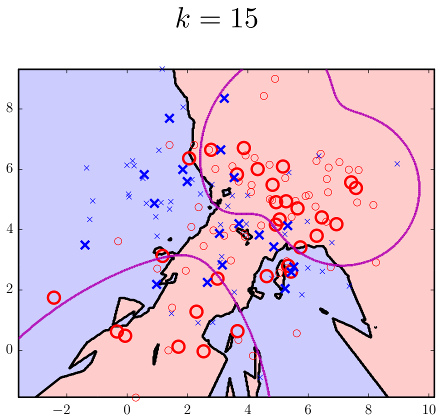

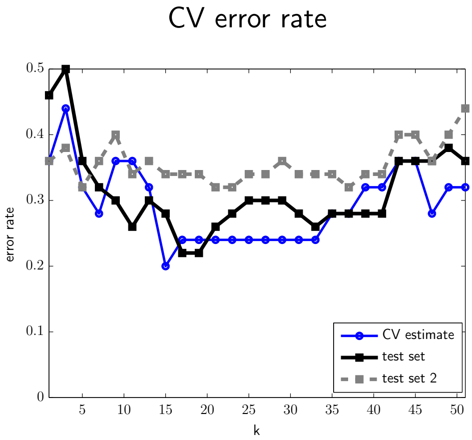

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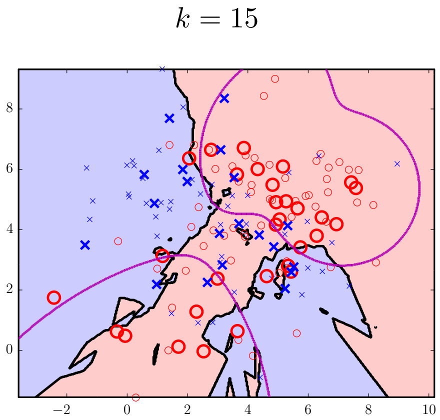

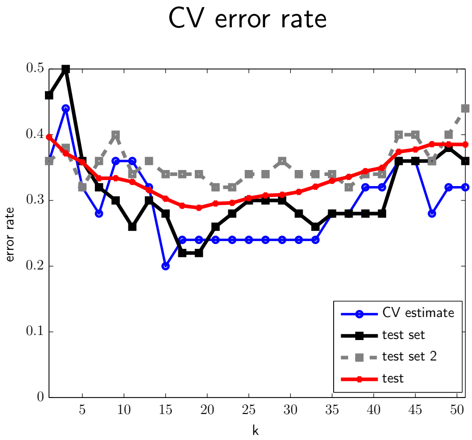

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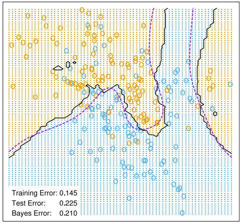

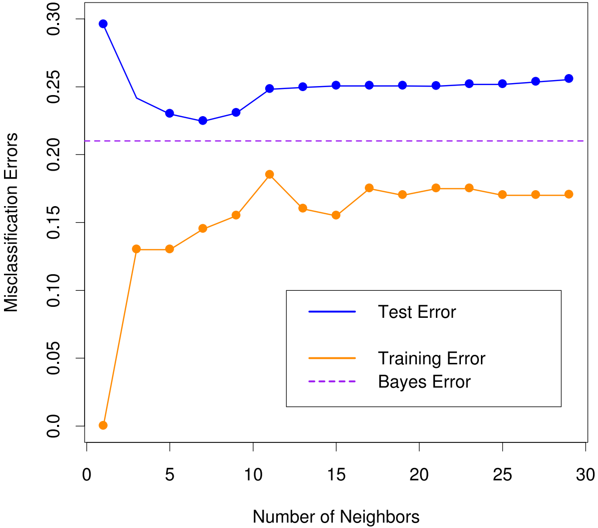

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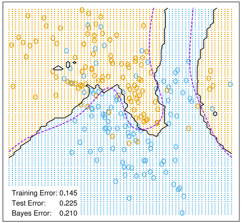

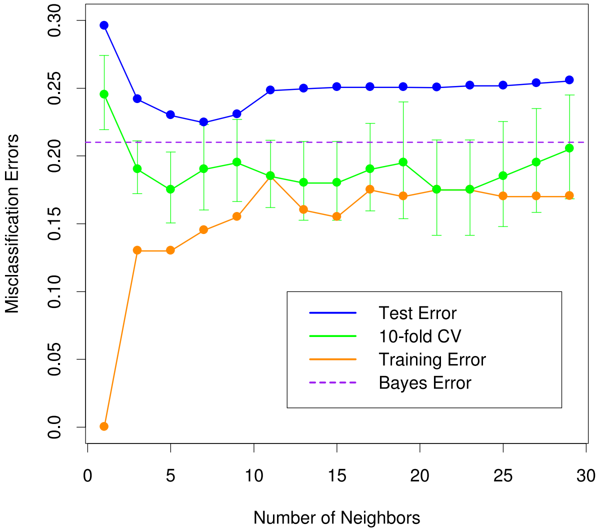

Selection of Distance Metric

- Use cross validation

Selection of Distance Metric

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- Fine unless you have lots of distance metrics to try (overfitting to the validation set!)
- If distance metric also includes axis scaling, need something else

Attribute Scaling

- Distance metric learning algorithms (beyond the scope of this course)

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  - Scale and translate so that the min is 0 and the max is 1:

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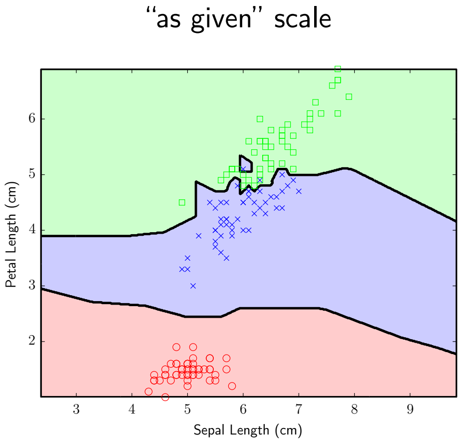
  - Scale and translate so that the mean is 0 and the standard deviation is 1 (z-normalization and many other names)

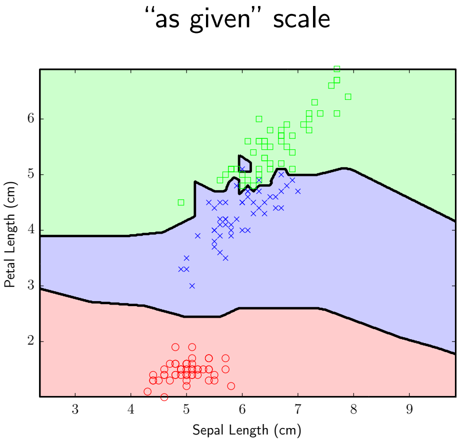
$$\mathsf{mean}_j = \frac{1}{m}\sum_i x_{i,j}$$

$$\mathsf{std}_j = \sqrt{\frac{1}{m}\sum_i (x_{i,j} - \mathsf{mean}_j)^2}$$

$$x_{i,j} \leftarrow \frac{x_{i,j} - \mathsf{mean}_j}{\mathsf{std}_j}$$

Iris Scaling





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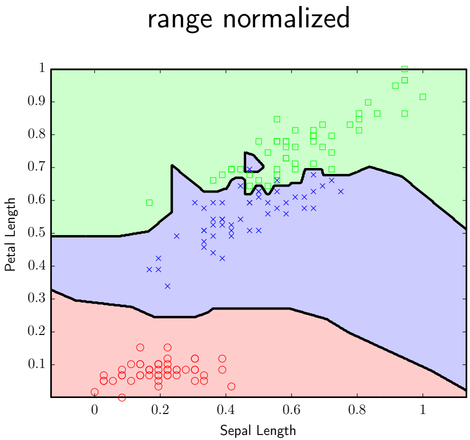

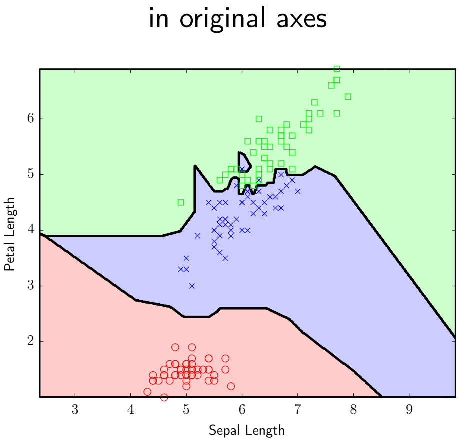

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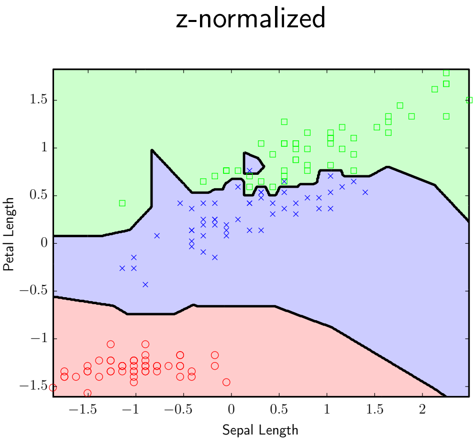

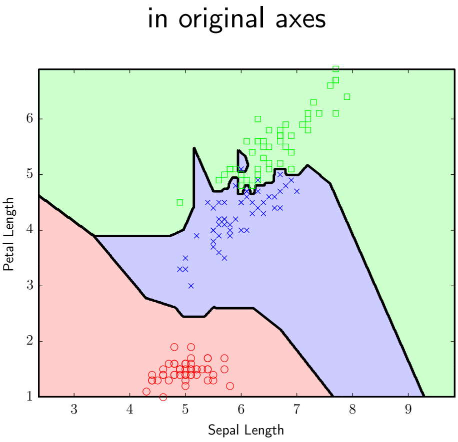

Example Problem

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- Each pixel corresponds to an area on the Earth.
- Observations are the intensity from four different spectral bands (two visible spectrum, two infrared)
- 7 different classes: red soil, cotton, vegetation stubble, mixture, gray soil, damp gray soil, very damp gray soil

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Problem specification: to classify land use from satelite imagery.

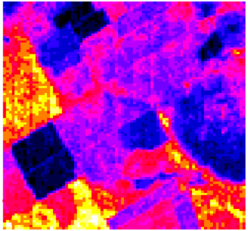
- Each pixel corresponds to an area on the Earth.
- Observations are the intensity from four different spectral bands (two visible spectrum, two infrared)
- 7 different classes: red soil, cotton, vegetation stubble, mixture, gray soil, damp gray soil, very damp gray soil

Attributes: the four values from the pixel in question,
plus the four values from each of the neighboring eight pixels.
(total 36 attributes)

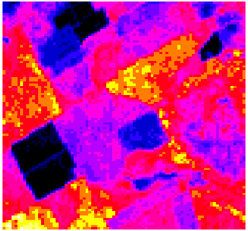
Example Problem

Using $k = 5$, performance is better than any other tried method (error rate of 9.5%).

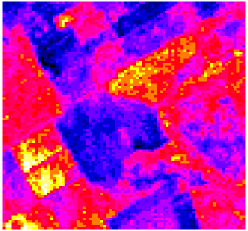
Spectral Band 1



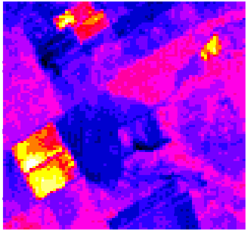
Spectral Band 2



Spectral Band 3



Spectral Band 4



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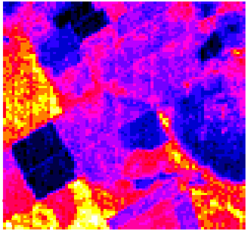
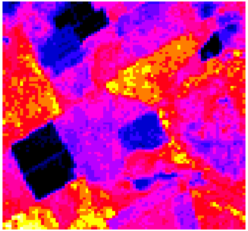
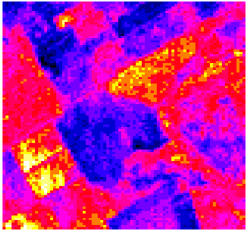


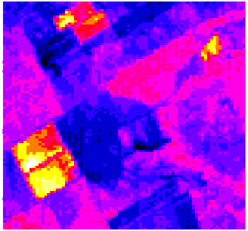
Spectral Band 2



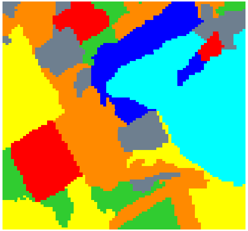
Spectral Band 3



Spectral Band 4



Land Usage



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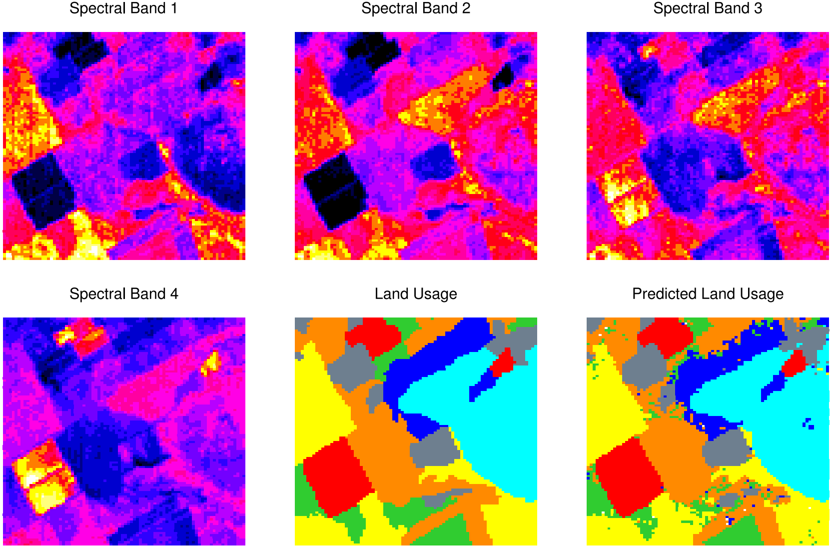

Computational Concerns

The time to test a single point is $O(m)$ (linear in the size of the training data).

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This is a problem for large datasets.

We can try to prune the dataset.

There are many ways...

Condensing

1. Add a single random point to the current point set
2. In random order:
    1. Take a point and classify it according to the current point set
    2. If it is incorrectly classified, add it to the current point set

Condensing

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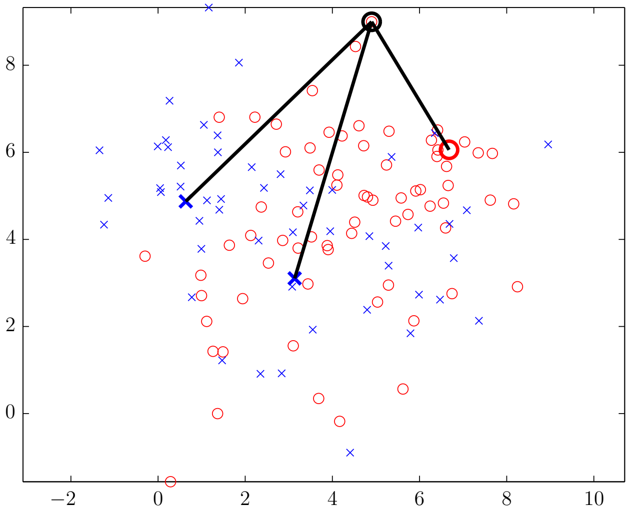
May need to be repeated to find consistent set

Condensing



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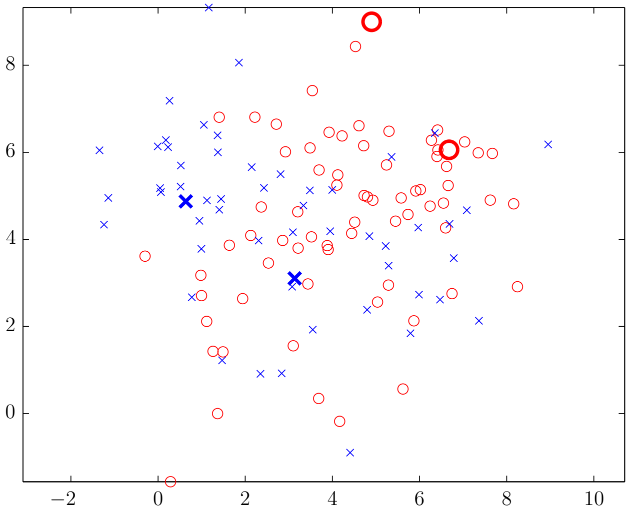

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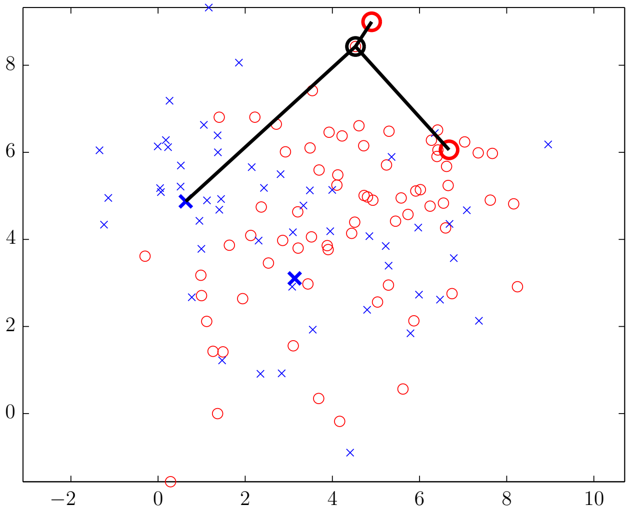

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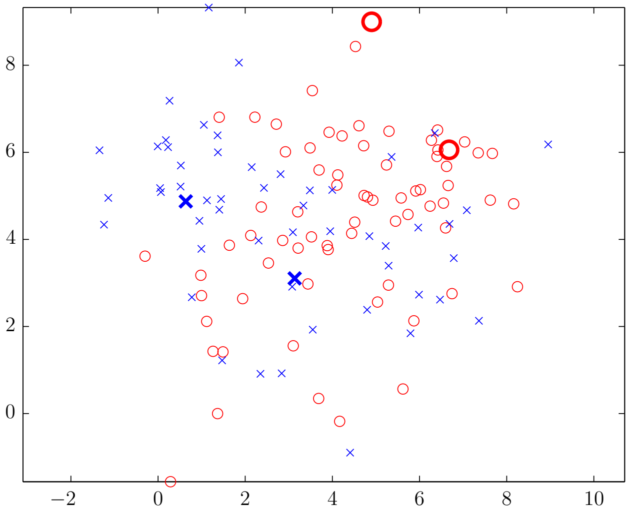

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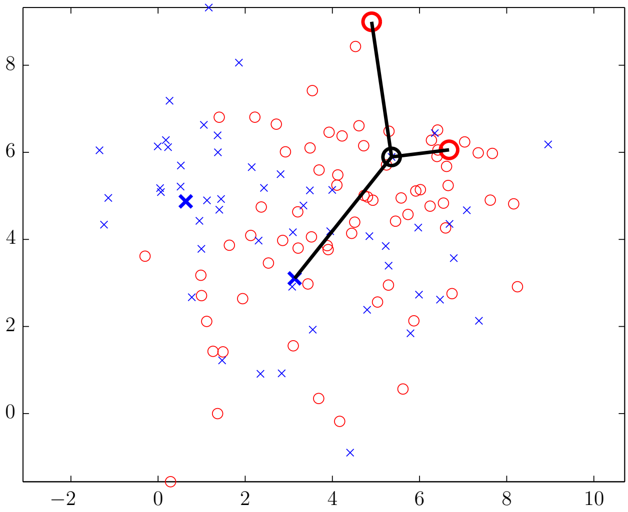

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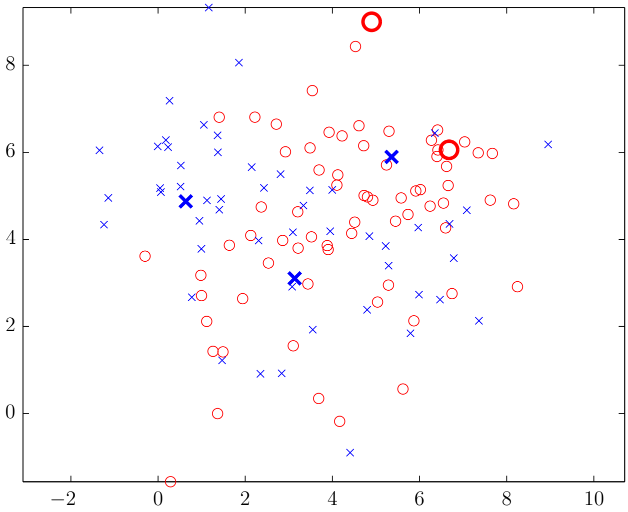

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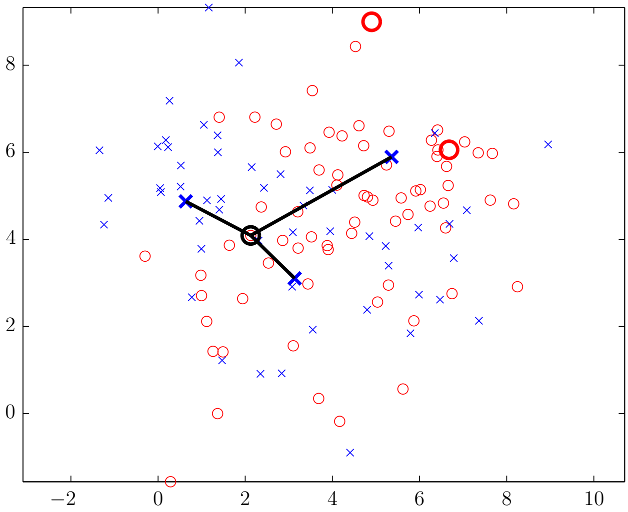

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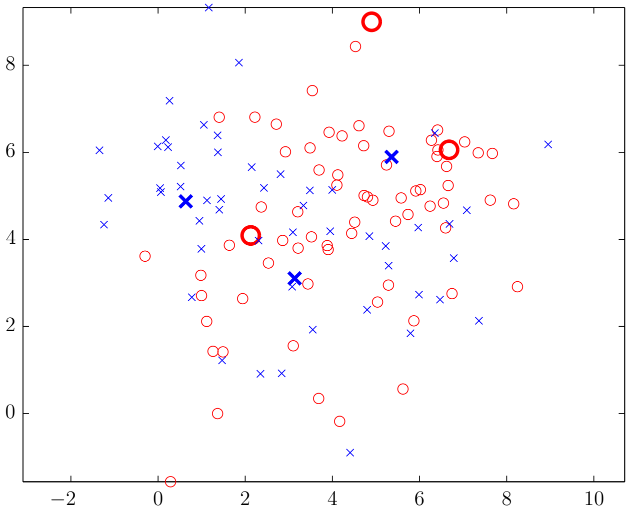

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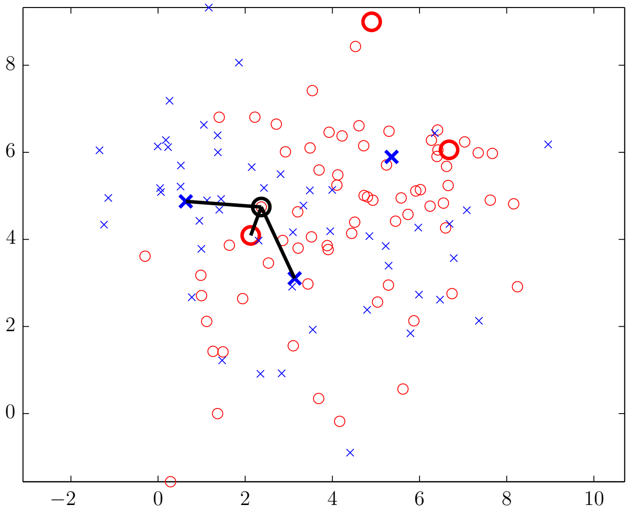

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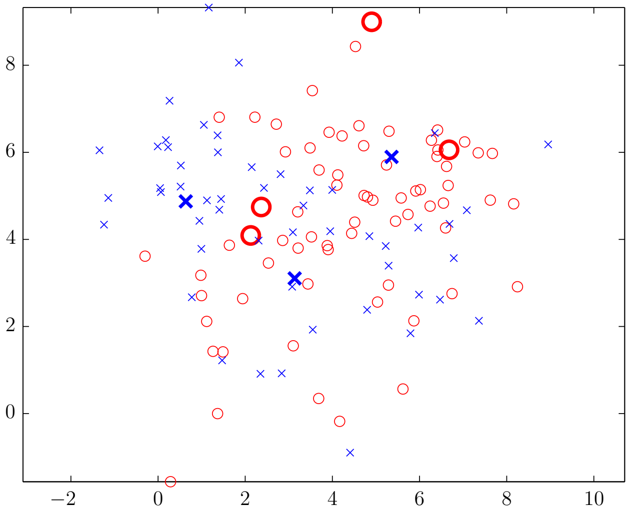

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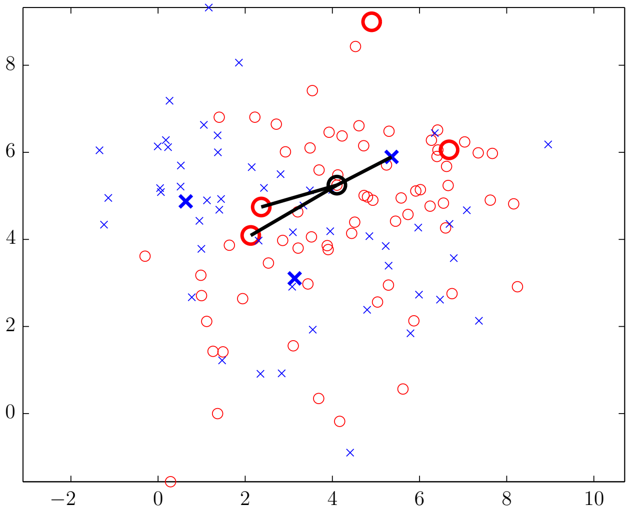

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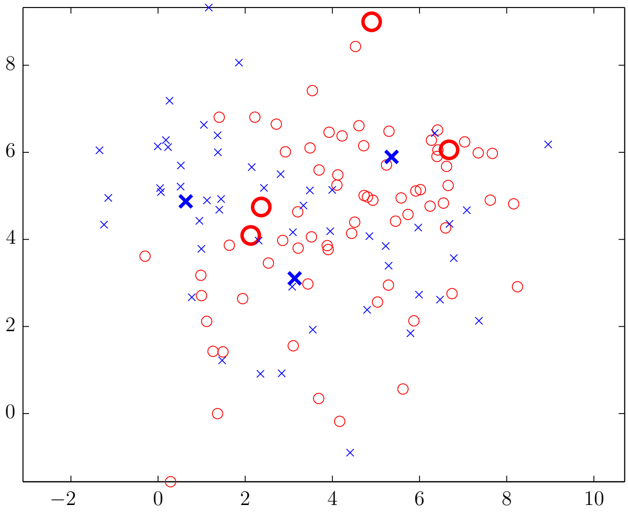

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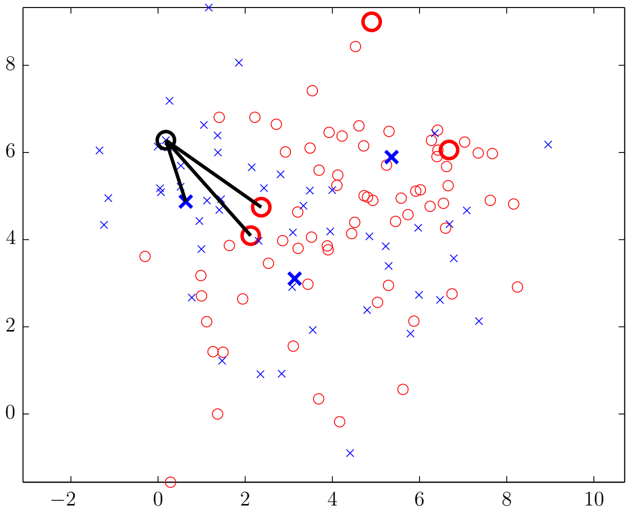

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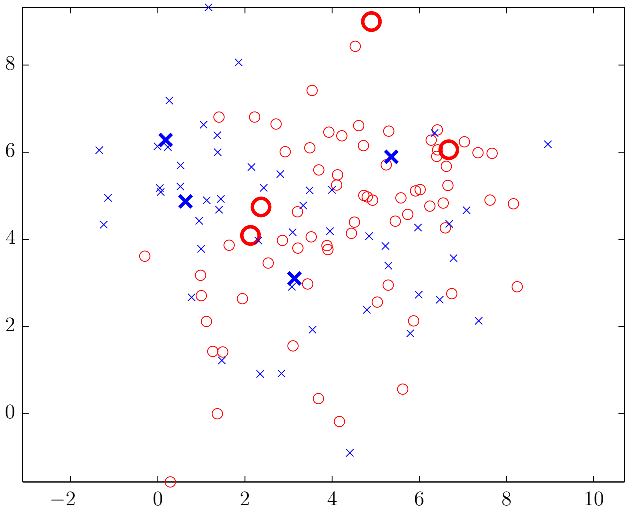

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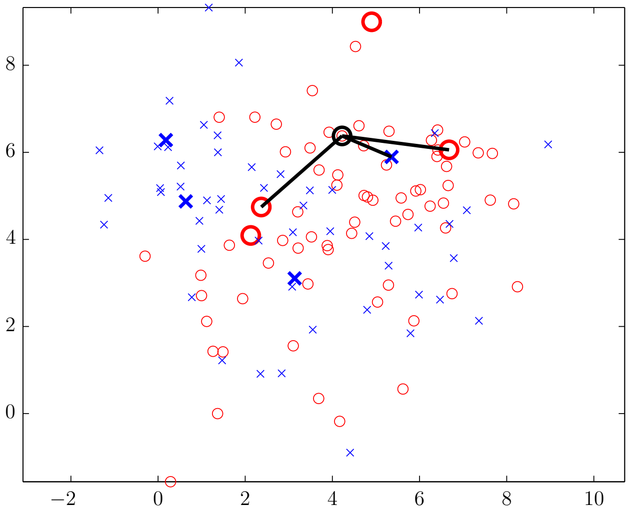

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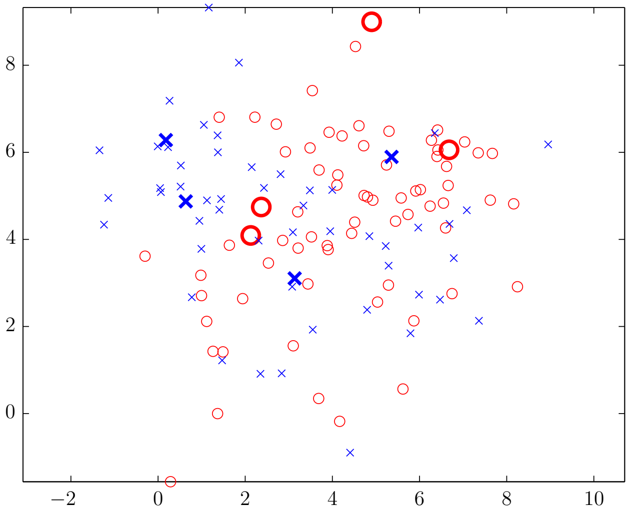

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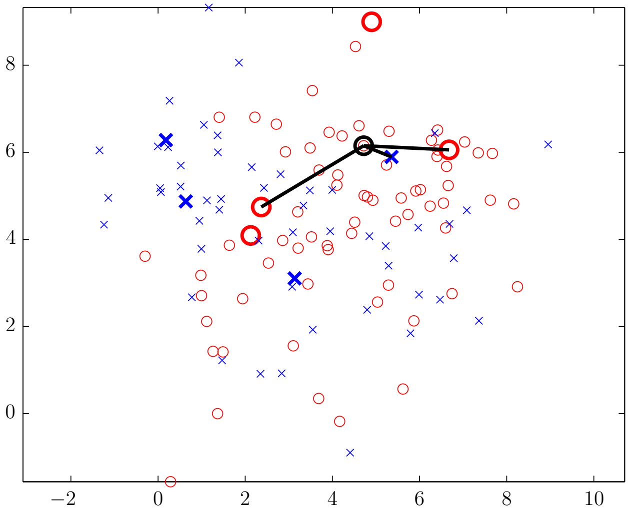

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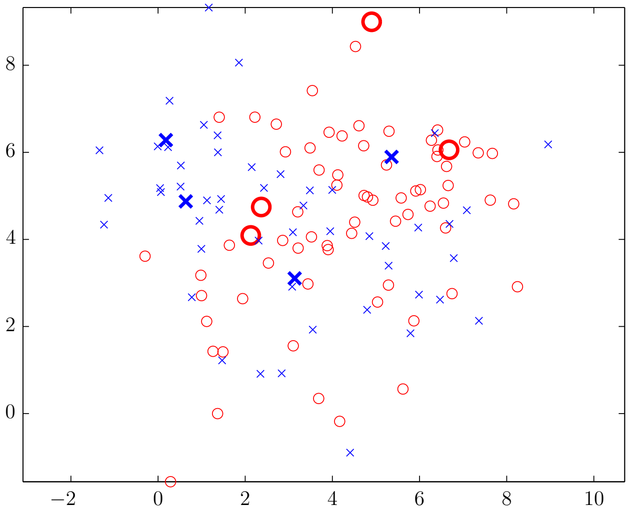

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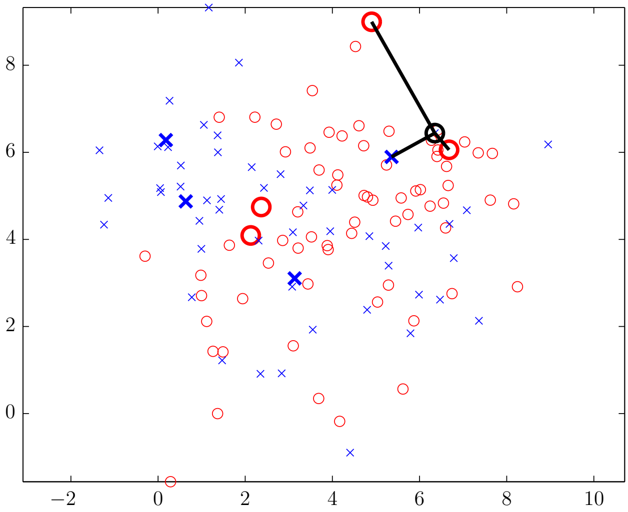

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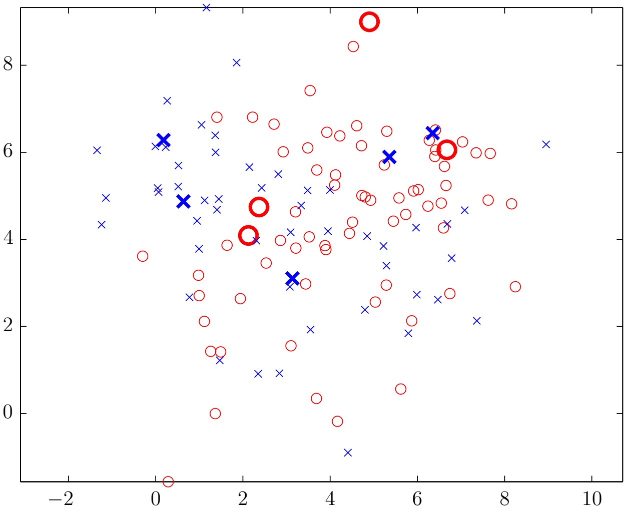

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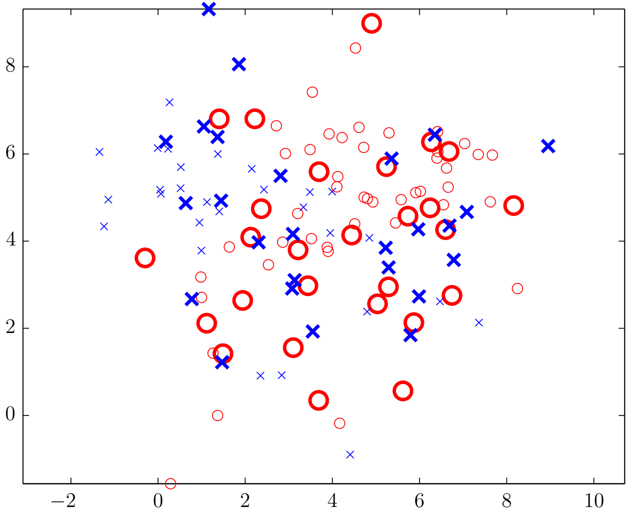

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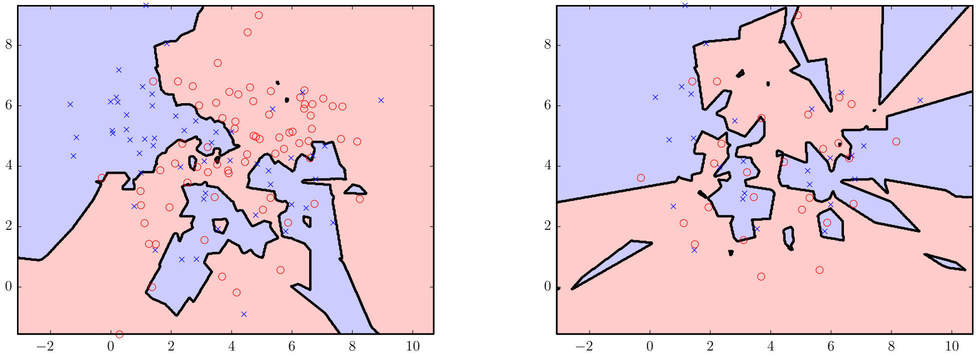

k-Nearest Neighbor

When is it good?

- Low-dimensional space
- Lots of data
- Lots of computational power
- Highly irregular decision surface