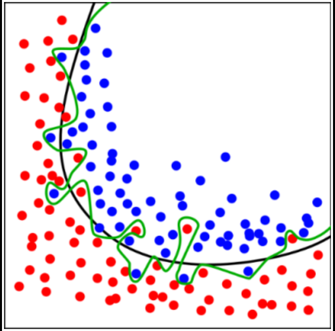
CS4495/6495
Introduction to Computer Vision

8C-L1 *Classification: Discriminative models*



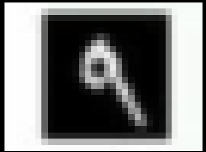
Remember: Supervised classification

Given a collection of *labeled* examples, come up with a function that will predict the labels of new examples.

Training examples

“four”

“nine”



?

Novel input

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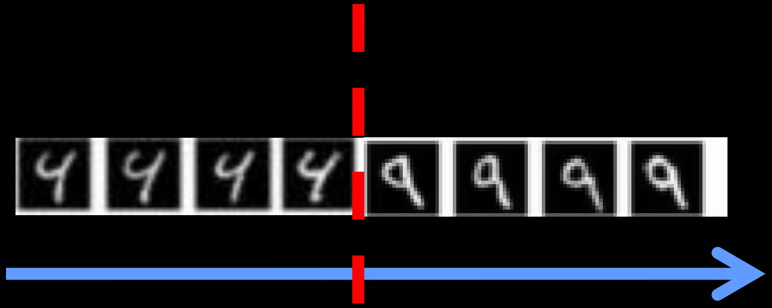
Supervised classification

Since we know the desired labels of training data, we want to *minimize the expected misclassification*

Two general strategies

- Generative – probabilistically model the classes
- Discriminative - probabilistically model the decision (the *boundaries*).

Generative classification & minimal risk



Feature value x

At best decision boundary, either choice of label yields same expected loss.

The best decision boundary is at point **x** where:

$$P(\text{class is } 9|\mathbf{x})\, L(9 \rightarrow 4) = \mathrm{P}(\text{class is } 4|\,\mathbf{x}) L(4 \rightarrow 9)$$

To classify a new point, choose class with lowest expected loss; i.e., choose “four” if:

$$P(4\,|\,\mathbf{x}) L(4 \rightarrow 9) > P(9\,|\,\mathbf{x}) L(9 \rightarrow 4)$$

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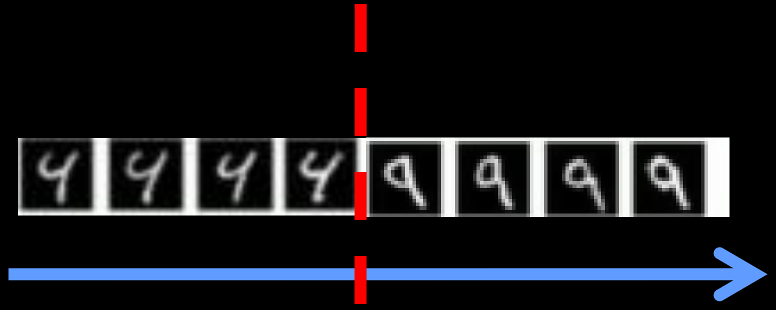
Generative classification & minimal risk



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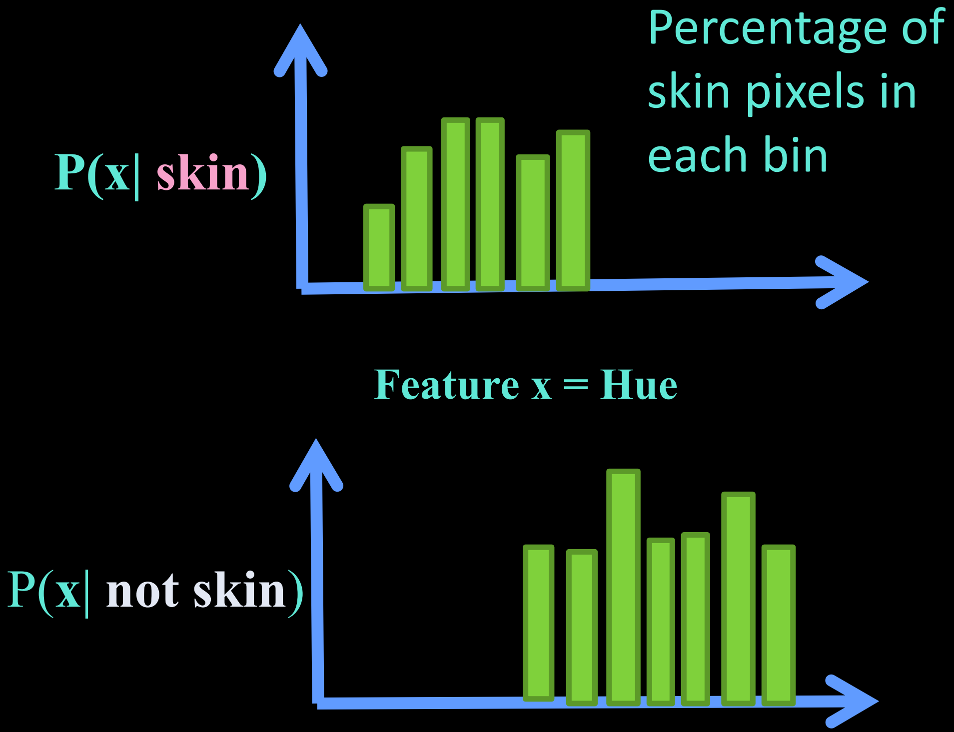
Example: learning skin colors



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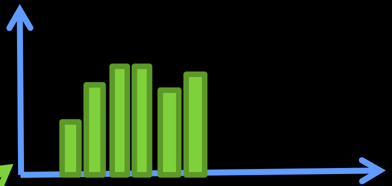
Bayes rule

P(x| skin)



$$\overbrace{P(\text{skin} \mid x)}^{\text{posterior}} = \frac{\overbrace{P(x \mid \text{skin})}^{\text{likelihood}} \; \overbrace{P(\text{skin})}^{\text{prior}}}{P(x)}$$

$$P(\text{skin} \mid x) \propto P(x \mid \text{skin}) \, \boxed{P(\text{skin})}$$

Where does the prior come from?

Example: Classifying skin pixels

Now for every pixel in a new image, we can estimate probability that it is generated by skin:

If $p(skin|x) > \theta$ classify as skin; otherwise not

Brighter pixels are higher probability of being skin

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Some challenges for generative models

Generative approaches were some of the first methods in *pattern recognition.*

- Easy to model analytically and could be done with modest amounts of moderate dimensional data.

Some challenges for generative models

But for the modern world there are some liabilities:

- Many signals are *high-dimensional* and *representing the complete density of class is data-hard*.

Some challenges for generative models

But for the modern world there are some liabilities:

- In some sense, we don't care about modeling the classes, *we only care about making the right decisions*.
  - *Model the hard cases- the ones near the boundaries!!*

Some challenges for generative models

But for the modern world there are some liabilities:

- We don’t typically know which features of instances actually *discriminate* between classes.

Discriminative classification: Assumptions

Going forward we’re gong to make some assumptions

- There are a fixed number of known classes.
- Ample number of training examples of each class.

Discriminative classification: Assumptions

Going forward we’re gong to make some assumptions

- Equal cost of making mistakes - what matters is getting the label right.
- Need to construct a representation of the instance but we don’t know a priori what features are diagnostic of the class label.

Generic category recognition: Basic framework

Train

- Build an object model – a *representation*

  Describe training instances (here images)

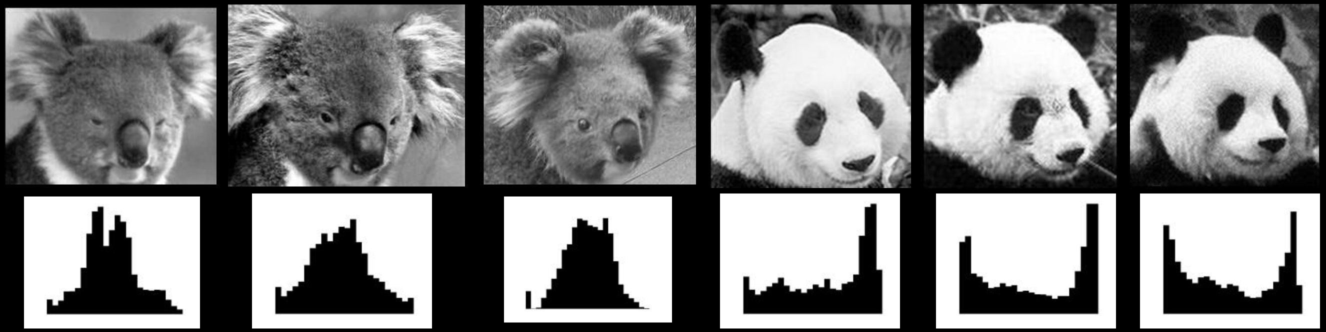
- Learn/train a *classifier*

Generic category recognition: Basic framework

Test

- Generate candidates in new image
- *Score* the candidates

Window-based models



Simple holistic descriptions of image content

- grayscale / color histogram

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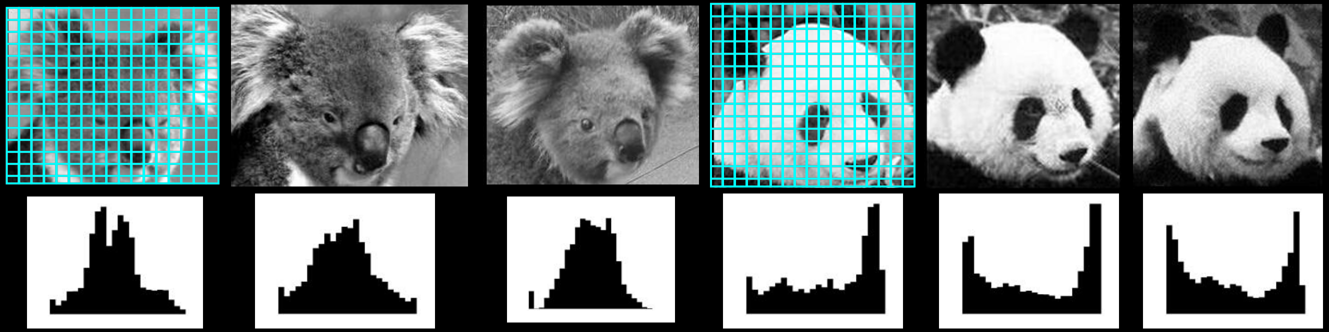
Window-based models



Simple holistic descriptions of image content

- grayscale / color histogram
- vector of pixel intensities

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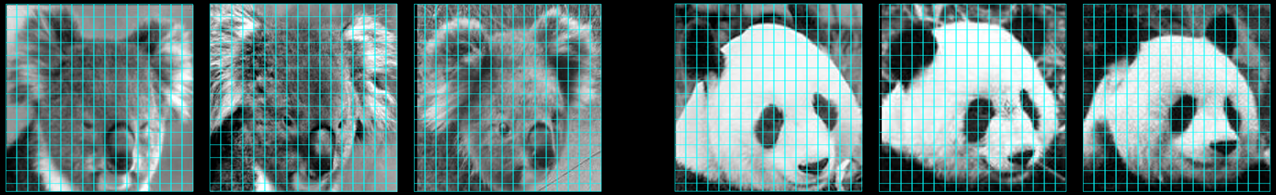
Window-based models

- Pixel-based representations sensitive to small shifts



- Color or grayscale-based description can be sensitive to illumination and intra-class appearance variation

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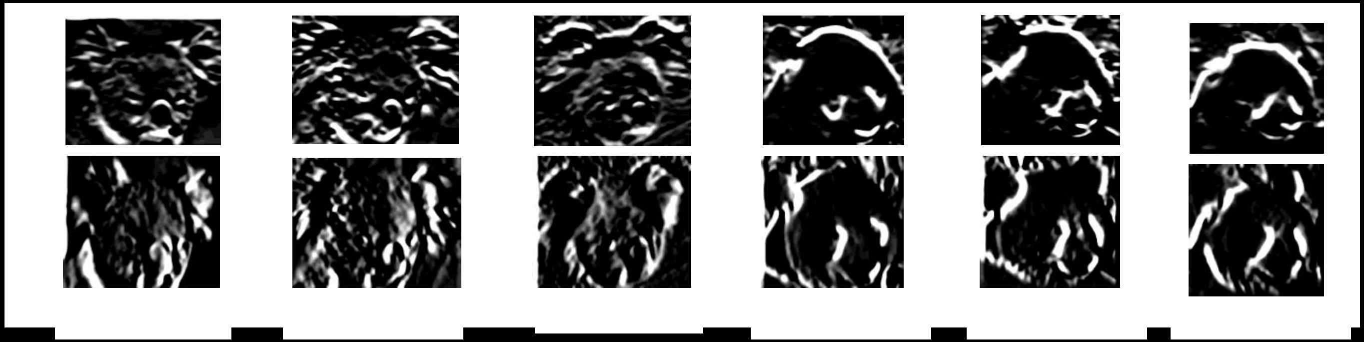
Window-based models

- Consider edges, contours, and (oriented) intensity gradients



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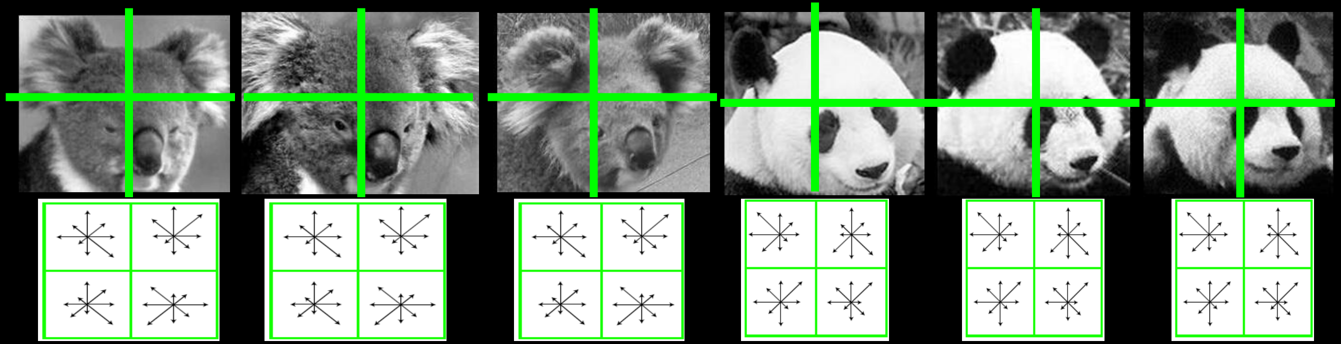
Window-based models

- Consider edges, contours, and (oriented) intensity gradients



- Summarize local distribution of gradients with histogram
  - Locally orderless: offers invariance to small shifts and rotations
  - Contrast-normalization: try to correct for variable illumination

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Generic category recognition: basic framework

Train

- Build an object model – a *representation*

  Describe training instances (here images)

- Learn/train a *classifier*

Window-based models

Given the representation, train a *binary classifier*

Car/non-car Classifier

Yes, car.

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Window-based models

Given the representation, train a *binary classifier*

Car/non-car Classifier

No, not a car.

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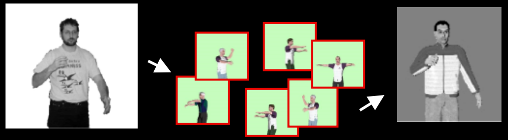
Discriminative classifier construction

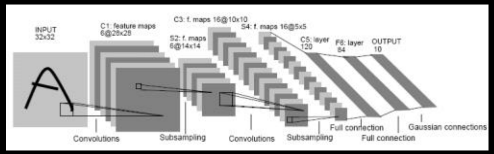
Nearest neighbor



10^6 examples

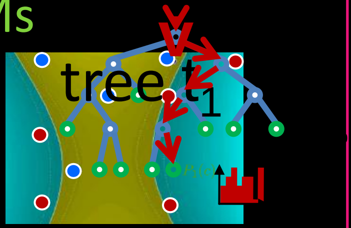
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005 …

Neural networks



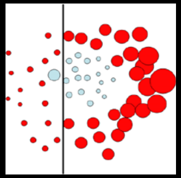
LeCun, Bottou, Bengio, Haffner 1998
Rowley, Baluja, Kanade 1998 …

SVMs



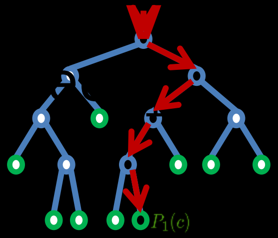
Guyon, Vapnik, Heisele,
Serre, Poggio, 2001, …

Boosting



Viola, Jones 2001,
Torralba et al. 2004,
Opelt et al. 2006,…

Random Forests



Breiman, 1984
Shotton, et al CVPR 2008

Slide adapted from Antonio Torralba

Discriminative classifier construction

Nearest neighbor

10^6 examples

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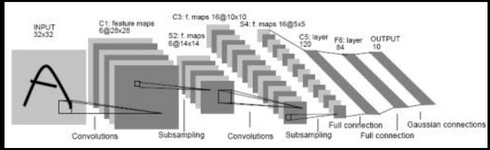

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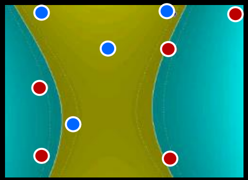
SVMs



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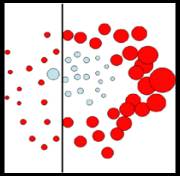

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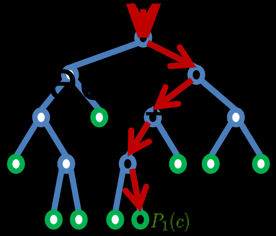

Breiman, 1984
Shotton, et al CVPR 2008

Slide adapted from Antonio Torralba

Generic category recognition: basic framework

Test

- Generate candidates in new image
- *Score* the candidates

Window-based models: Generating and scoring candidates

Car/non-car Classifier

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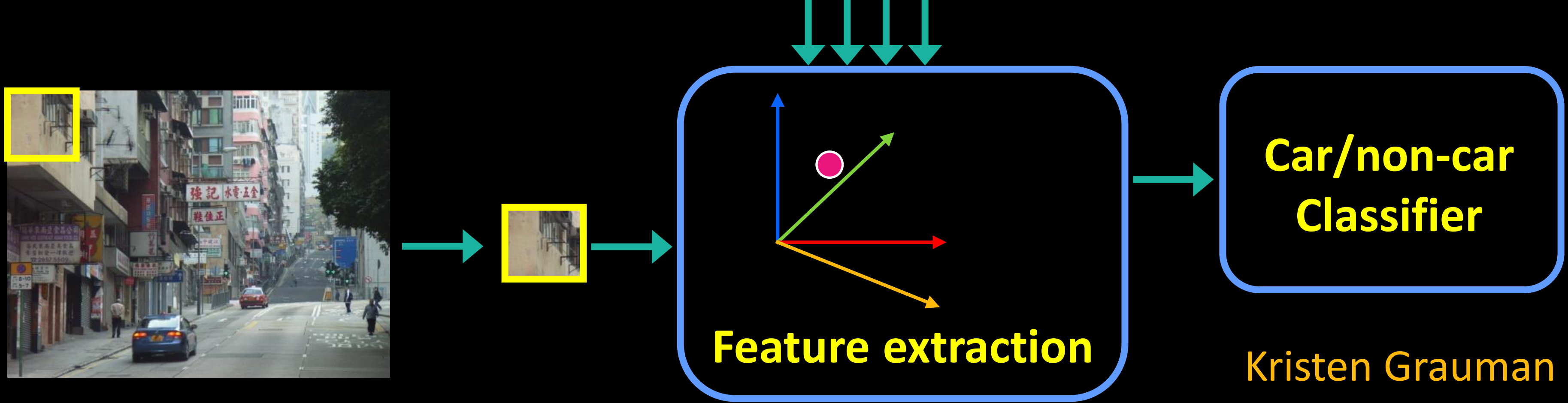
Window-based object detection: Recap

Training:

1. Obtain training data
2. Define features
3. Train classifier



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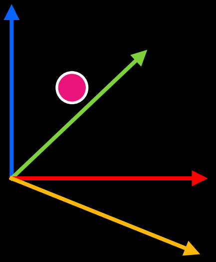
Window-based object detection: Recap

Given new image:

1. Slide window
2. Score by classifier

Cars Training examples non-Cars



Feature extraction

Car/non-car Classifier

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Discriminative classification methods

Discriminative classifiers – find a division (surface) in feature space that separates the classes

Several methods

- Nearest neighbors
- Boosting
- Support Vector Machines

Discriminative classification methods

Discriminative classifiers – find a division (surface) in feature space that separates the classes

Several methods

- Nearest neighbors
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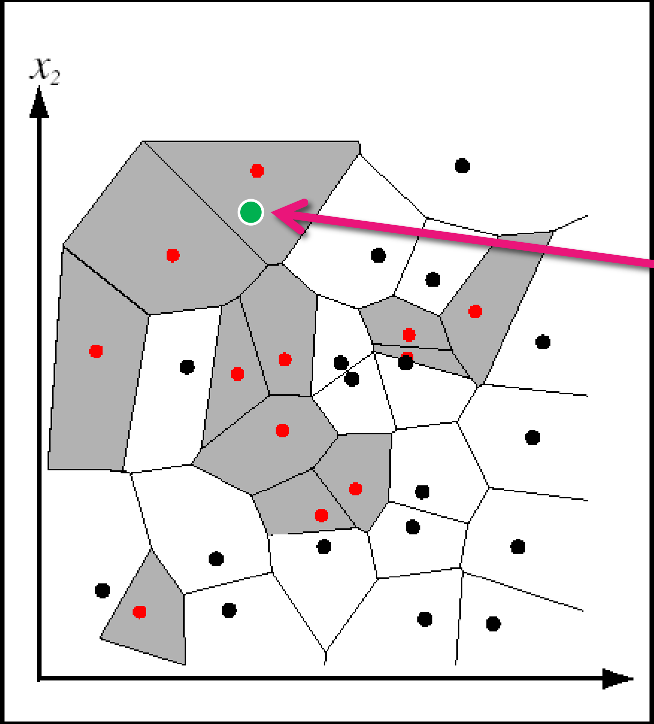
Nearest Neighbor classification

Choose label of nearest training data point

Black = negative

Red = positive

Voronoi partitioning of feature space for 2-category 2D data



Novel test example

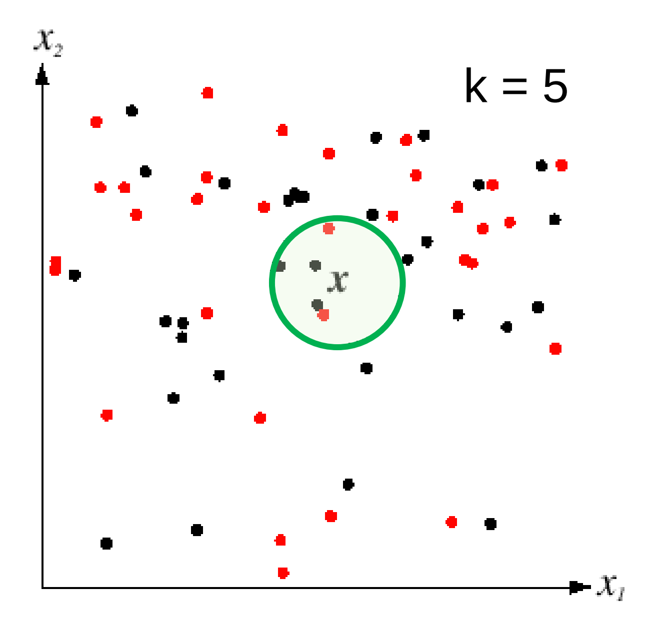
Duda et al.

K-Nearest Neighbors classification

- For a new point, find the k closest points from training data
- Labels of the k points "vote" to classify

Black = negative

Red = positive



If query lands here, the 5 NN consist of 3 negatives and 2 positives, so we classify it as **negative**

D. Lowe