EECS 545: Machine Learning

Lecture 4. Classification

Honglak Lee and Michał Dereziński

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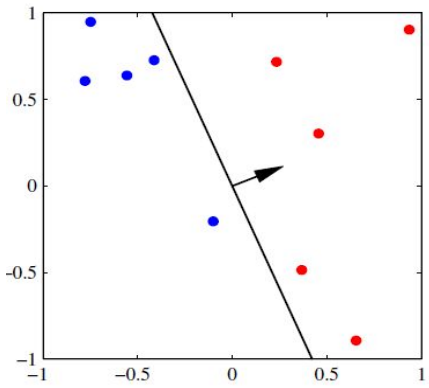
Outline

- Logistic regression
- Newton’s method
- K-nearest neighbors (KNN)

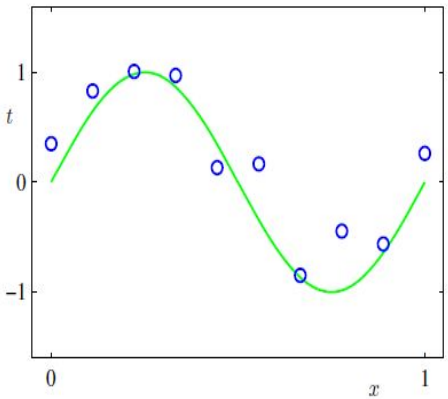
Supervised learning: classification

Supervised learning

- Goal:
  - Given data X in feature space and labels Y…
  - …learn to predict Y from X
- Labels could be discrete or continuous
  - Discrete-valued labels: classification (today's topic)
  - Continuous-valued labels: regression



classification



regression

Classification problem

- The task of classification:
  - Given an input vector **x**, assign it to one of K distinct classes C_k where k = 1, … K
- Representing the assignment:
  - For K=2:
    - y=1 means that **x** is in C_1
    - y=0 means that **x** is in C_2.
      - (Sometimes, y=-1 can be used depending on algorithms)
- For K>2:
  - Use 1-of-K coding
  - e.g., $\mathbf{y} = (0, 1, 0, 0, 0)^T$ means that **x** is in C_2.
    - (This works for K=2 as well)

Classification problem

- Training: train a classifier *h*(**x**) from training data
  - Training data

- Testing (evaluation):
  - testing data: $\left\{\left(x^{(1)}, y^{(1)}\right), \left(x^{(2)}, y^{(2)}\right), \ldots, \left(x^{(N)}, y^{(N)}\right)\right\}$
  - The learning algorithm produces predictions

$$h\left(x_{\text{test}}^{(1)}\right), h\left(x_{\text{test}}^{(2)}\right), \ldots, h\left(x_{\text{test}}^{(N)}\right)$$

  - 0-1 loss:

$$\text{classification error} = \frac{1}{N}\sum_{j=1}^{N} \mathbf{1}[h(x_{test}^{(j)}) \neq y_{test}^{(j)}]$$

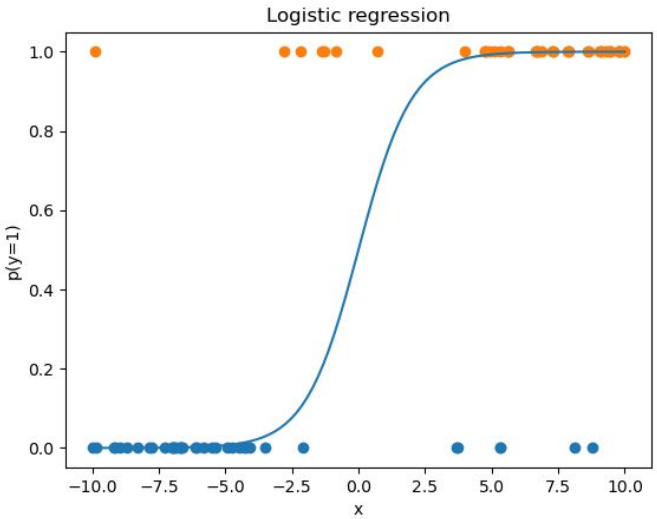
Logistic regression

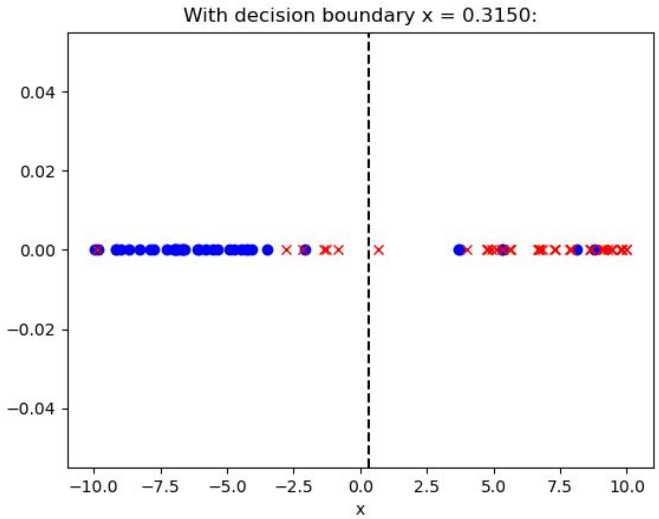
Probabilistic discriminative models

- Model decision boundary as a function of input **x**
  - Learn $P(C_k|\mathbf{x})$ over data (e.g., maximum likelihood)
  - Directly predict class labels from inputs

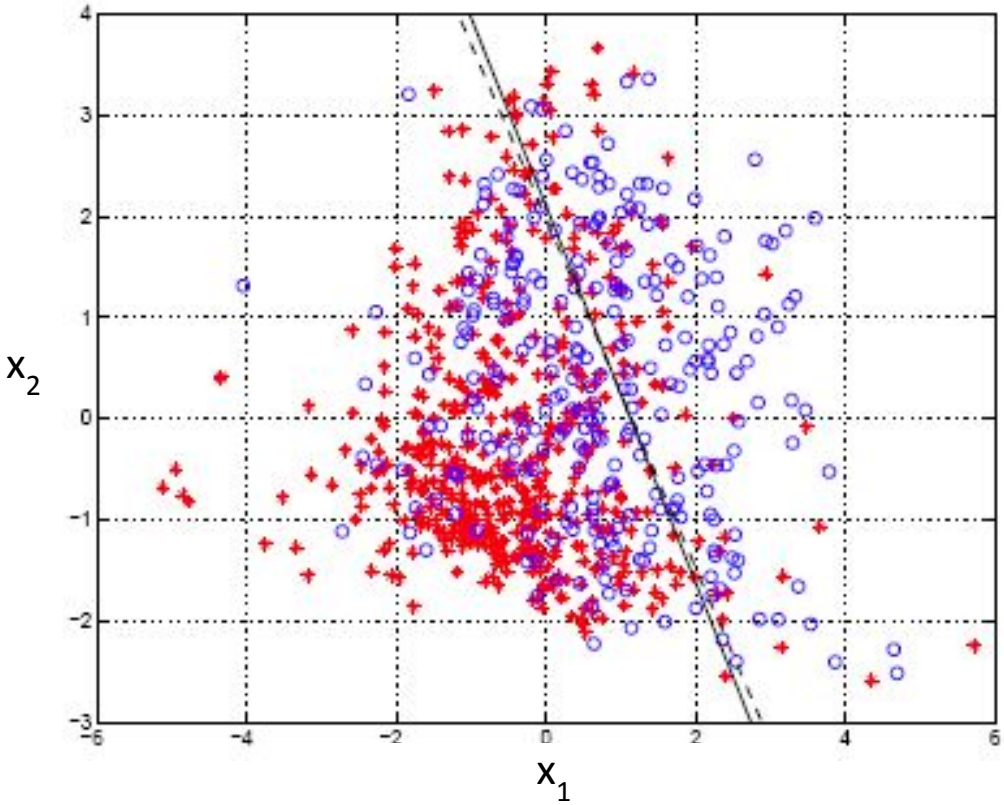
- Next class: we will cover probabilistic generative models
  - Learn $P(C_k, \mathbf{x})$ over data (maximum likelihood) and then use Bayes' rule to predict $P(C_k|\mathbf{x})$

Example (1-dim. case)





Example (2-dim. case)



Logistic regression

- Models the class posterior using a sigmoid applied to a linear function of the feature vector:

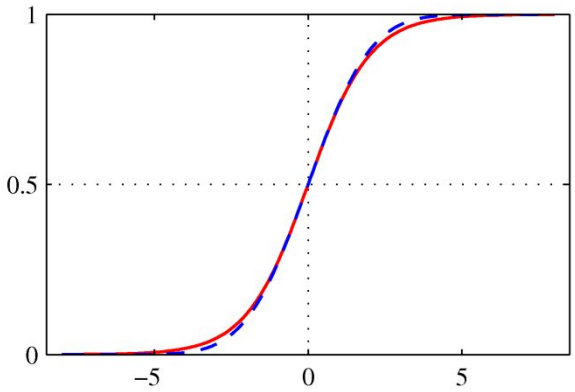
$$p(C_1|\phi) = h(\phi) = \sigma(\mathbf{w}^T \phi(\mathbf{x}))$$

- We can solve the parameter **w** by maximizing the likelihood of the training data

Sigmoid and logit functions

- The *logistic sigmoid* function is:

$$\sigma(a) = \frac{1}{1 + \exp(-a)}$$



- Its inverse is the *logit* function (aka log odds ratio):

$$a = \ln\left(\frac{\sigma}{1 - \sigma}\right)$$

- Generalizes to *normalized exponential*, or *softmax*

$$p_i = \frac{\exp(q_i)}{\sum_j \exp(q_j)}$$

Likelihood function

- Depending on the label *y*, the likelihood of **x** is defined as:

$$P(y = 1|\mathbf{x}, \mathbf{w}) = \sigma(\mathbf{w}^T \phi(\mathbf{x}))$$

$$P(y = 0|\mathbf{x}, \mathbf{w}) = 1 - \sigma(\mathbf{w}^T \phi(\mathbf{x}))$$

- Therefore:

$$P(y|\mathbf{x}, \mathbf{w}) = \sigma(\mathbf{w}^T \phi(\mathbf{x}))^y (1 - \sigma(\mathbf{w}^T \phi(\mathbf{x})))^{(1-y)}$$

Logistic regression

- For a data set $\{(\phi(\mathbf{x}^{(n)}), y^{(n)})\}, \text{ where } y^{(n)} \in \{0, 1\}$ the likelihood function is

$$p(\mathbf{y}|\mathbf{w}) = \prod_{n=1}^{N} (h^{(n)})^{y^{(n)}} (1 - h^{(n)})^{1-y^{(n)}}$$

where

$$h^{(n)} = p(C_1|\phi(\mathbf{x}^{(n)})) = \sigma(\mathbf{w}^T \phi(\mathbf{x}^{(n)}))$$

note: *h*(**x**) is the hypothesis function, σ(**x**) is the specific hypothesis for logistic regression

- Define a loss function
  - Minimizing *E*(**w**) maximizes likelihood

$$E(\mathbf{w}) = -\log p(\mathbf{y}|\mathbf{w})$$

Derivation

- $$\log P(\mathbf{y}|\mathbf{w}) = \sum_{n=1}^{N} y^{(n)} \log h^{(n)} + (1 - y^{(n)}) \log(1 - h^{(n)})$$
- Gradient (matrix calculus)

$$\nabla_{\mathbf{w}} \log P(\mathbf{y}|\mathbf{x}^{(1)}, ...\mathbf{x}^{(N)}, \mathbf{w})$$
$$= \sum_{n=1}^{N} \nabla_{\mathbf{w}} \left(y^{(n)} \log h(\mathbf{x}^{(n)}, \mathbf{w}) + (1 - y^{(n)}) \log(1 - h(\mathbf{x}^{(n)}, \mathbf{w})) \right)$$

Derivation

- $$\log P(\mathbf{y}|\mathbf{w}) = \sum_{n=1}^{N} y^{(n)} \log h^{(n)} + (1 - y^{(n)}) \log(1 - h^{(n)})$$

$$h(\mathbf{x}^{(n)}, \mathbf{w}) \triangleq \sigma\left(\mathbf{w}^T \phi(\mathbf{x}^{(n)})\right) \triangleq \sigma^{(n)}$$

- Gradient (matrix calculus)

$$\nabla_{\mathbf{w}} \log P(\mathbf{y}|\mathbf{x}^{(1)}, \ldots \mathbf{x}^{(N)}, \mathbf{w})$$
$$= \sum_{n=1}^{N} \nabla_{\mathbf{w}} \left(y^{(n)} \log h(\mathbf{x}^{(n)}, \mathbf{w}) + (1 - y^{(n)}) \log(1 - h(\mathbf{x}^{(n)}, \mathbf{w})) \right)$$

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- Gradient (matrix calculus)

$$\begin{aligned}
&\nabla_{\mathbf{w}} \log P(\mathbf{y}|\mathbf{x}^{(1)}, \ldots \mathbf{x}^{(N)}, \mathbf{w}) \\
&= \sum_{n=1}^{N} \nabla_{\mathbf{w}} \left(y^{(n)} \log h(\mathbf{x}^{(n)}, \mathbf{w}) + (1 - y^{(n)}) \log(1 - h(\mathbf{x}^{(n)}, \mathbf{w})) \right) \\
&= \sum_{n=1}^{N} \left(y^{(n)} \frac{\sigma^{(n)}(1 - \sigma^{(n)})}{\sigma^{(n)}} - (1 - y^{(n)}) \frac{\sigma^{(n)}(1 - \sigma^{(n)})}{1 - \sigma^{(n)}} \right) \nabla_{\mathbf{w}} (\mathbf{w}^T \phi(\mathbf{x}^{(n)}))
\end{aligned}$$

$$\boxed{\frac{\partial}{\partial s} \sigma(s) = \frac{\partial}{\partial s} \left(\frac{1}{1 + \exp(-s)} \right) = \sigma(s)(1 - \sigma(s))}$$

Derivation

- $$\log P(\mathbf{y}|\mathbf{w}) = \sum_{n=1}^{N} y^{(n)} \log h^{(n)} + (1 - y^{(n)}) \log(1 - h^{(n)})$$

$$h(\mathbf{x}^{(n)}, \mathbf{w}) \triangleq \sigma\left(\mathbf{w}^T \phi(\mathbf{x}^{(n)})\right) \triangleq \sigma^{(n)}$$

- Gradient (matrix calculus)

$$\begin{aligned}
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&= \sum_{n=1}^{N} \left(y^{(n)} \frac{\sigma^{(n)}(1 - \sigma^{(n)})}{\sigma^{(n)}} - (1 - y^{(n)}) \frac{\sigma^{(n)}(1 - \sigma^{(n)})}{1 - \sigma^{(n)}} \right) \nabla_{\mathbf{w}}(\mathbf{w}^T \phi(\mathbf{x}^{(n)})) \\
&= \sum_{n=1}^{N} \left(y^{(n)}(1 - \sigma^{(n)}) - (1 - y^{(n)})\sigma^{(n)} \right) \nabla_{\mathbf{w}}(\mathbf{w}^T \phi(\mathbf{x}^{(n)}))
\end{aligned}$$

Derivation

- $$\log P(\mathbf{y}|\mathbf{w}) = \sum_{n=1}^{N} y^{(n)} \log h^{(n)} + (1 - y^{(n)}) \log(1 - h^{(n)})$$

$$h(\mathbf{x}^{(n)}, \mathbf{w}) \triangleq \sigma\left(\mathbf{w}^T \phi(\mathbf{x}^{(n)})\right) \triangleq \sigma^{(n)}$$

- Gradient (matrix calculus)

$$\begin{aligned}
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&= \sum_{n=1}^{N} \left(y^{(n)} \frac{\sigma^{(n)}(1 - \sigma^{(n)})}{\sigma^{(n)}} - (1 - y^{(n)}) \frac{\sigma^{(n)}(1 - \sigma^{(n)})}{1 - \sigma^{(n)}} \right) \nabla_{\mathbf{w}} (\mathbf{w}^T \phi(\mathbf{x}^{(n)})) \\
&= \sum_{n=1}^{N} \left(y^{(n)}(1 - \sigma^{(n)}) - (1 - y^{(n)})\sigma^{(n)} \right) \nabla_{\mathbf{w}} (\mathbf{w}^T \phi(\mathbf{x}^{(n)})) \\
&= \sum_{n=1}^{N} \left(y^{(n)} - \sigma^{(n)} \right) \phi(\mathbf{x}^{(n)})
\end{aligned}$$

Logistic regression: gradient descent

recall: $E(\mathbf{w}) = -\log p(\mathbf{y}|\mathbf{w})$

- Taking the gradient of *E*(w) gives us

$$\nabla \mathbf{E}(\mathbf{w}) = \sum_{n=1}^{N} (h^{(n)} - y^{(n)}) \phi(\mathbf{x}^{(n)})$$

- Recall

$$h^{(n)} = p(C_1 | \phi(\mathbf{x}^{(n)})) = \sigma(\mathbf{w}^T \phi(\mathbf{x}^{(n)}))$$

- This is essentially the same gradient expression that appeared in linear regression with least-squares.
- Note the error term between model prediction and target value:
  - Logistic regression: $h^{(n)} - y^{(n)} = \sigma(\mathbf{w}^T \phi(x^{(n)})) - y^{(n)}$
  - Cf. Linear regression: $h^{(n)} - y^{(n)} = \mathbf{w}^T \phi(x^{(n)}) - y^{(n)}$

Newton's method

- Goal: Minimizing a general function $E(\mathbf{w})$ (one-dimensional case)
  - Approach: solve for

$$f(\mathbf{w}) = \frac{\partial E(\mathbf{w})}{\partial \mathbf{w}} = 0$$

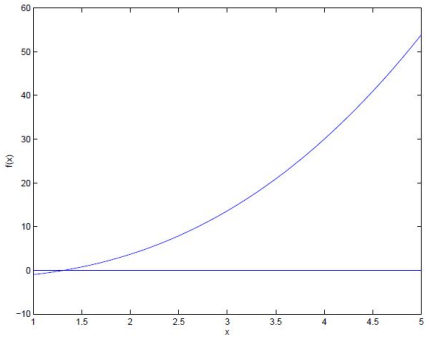
  - So, how to solve this problem?
- Newton's method (aka Newton-Raphson method)
  - Repeat until convergence:

$$\mathbf{w} := \mathbf{w} - \frac{f(\mathbf{w})}{f'(\mathbf{w})}$$

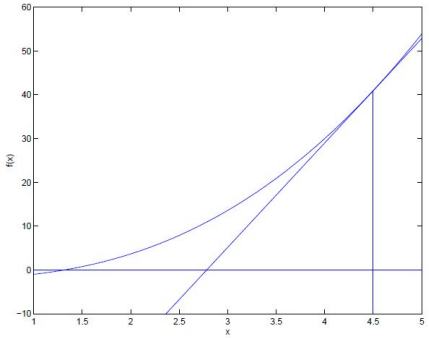
Newton's method

- Interactively solve until we get $f(\mathbf{w}) = 0$.

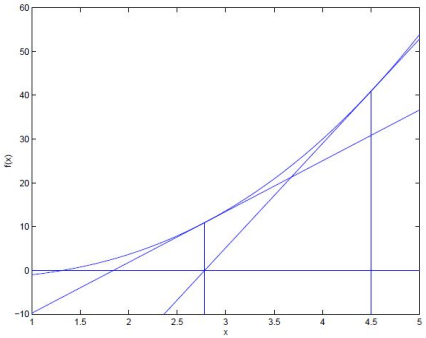
$f(\mathbf{w})$



w



w (new)



w (old)

- Geometric intuition:

$$\mathbf{w} := \mathbf{w} - \frac{f(\mathbf{w})}{f'(\mathbf{w})}$$

Current value

"Slope"

Newton's method

- Now we want to minimize $E(\mathbf{w})$
  - Convert $E'(\mathbf{w}) = f(\mathbf{w})$
  - Repeat until convergence

$$\mathbf{w} := \mathbf{w} - \frac{E'(\mathbf{w})}{E''(\mathbf{w})}$$

Newton update when w is a scalar

Newton's method

- Now we want to minimize $E(\mathbf{w})$
  - Convert $E'(\mathbf{w}) = f(\mathbf{w})$
  - Repeat until convergence

$$\mathbf{w} := \mathbf{w} - \frac{E'(\mathbf{w})}{E''(\mathbf{w})}$$

Newton update when w is a scalar

- This method can be extended to the multivariate case:

$$\mathbf{w} := \mathbf{w} - H^{-1}\nabla_{\mathbf{w}}E$$

Newton update when w is a vector

where **H** is a Hessian matrix evaluated at **w**

$$H_{ij}(\mathbf{w}) = \frac{\partial^2 E(\mathbf{w})}{\partial \mathbf{w}_i \partial \mathbf{w}_j}$$

- Note: for linear regression, the Hessian is $\Phi^T\Phi$

Logistic regression

- Recall: for linear regression, least-squares has a closed-form solution:

$$\mathbf{w}_{ML} = (\mathbf{\Phi}^T\mathbf{\Phi})^{-1}\mathbf{\Phi}^T\mathbf{y}$$

- This generalizes to weighted-least-squares with an NxN diagonal weight matrix **R**.

$$\mathbf{w}_{WLS} = (\mathbf{\Phi}^T\mathbf{R}\mathbf{\Phi})^{-1}\mathbf{\Phi}^T\mathbf{R}\mathbf{y}$$

- For logistic regression, however, *h*(**x**, **w**) is non-linear, and there is no closed-form solution. Must iterate (i.e. repeatedly apply Newton steps).

Iterative solution

- Apply Newton-Raphson method to iterate to a solution
- This involves least-squares with weights **R**:

$$\nabla E(\mathbf{w}) = 0$$

- Since **R** depends on **w** (and vice versa), we get *iterative reweighted least squares* (IRLS)

$$R_{nn} = h^{(n)}(1 - h^{(n)})$$

where

$$\mathbf{w}^{(new)} = (\mathbf{\Phi}^T \mathbf{R} \mathbf{\Phi})^{-1} \mathbf{\Phi}^T \mathbf{R} \mathbf{z}$$

$$\mathbf{z} = \mathbf{\Phi} \mathbf{w}^{(old)} - \mathbf{R}^{-1}(\mathbf{h} - \mathbf{y})$$

K-nearest neighbor classification

K-nearest neighbors

- Training method:
  - Save the training examples (no sophisticated learning)
- At prediction (testing) time:
  - Given a test (query) example **x**, find the *K* training examples that are *closest* to **x**.

$$kNN(x) = \left\{ \left(x^{(1)'}, y^{(1)'} \right), \left(x^{(2)'}, y^{(2)'} \right), \ldots, \left(x^{(k)'}, y^{(k)'} \right) \right\}$$

- Predict the most frequent class among all *y*'s from *kNN*(**x**).

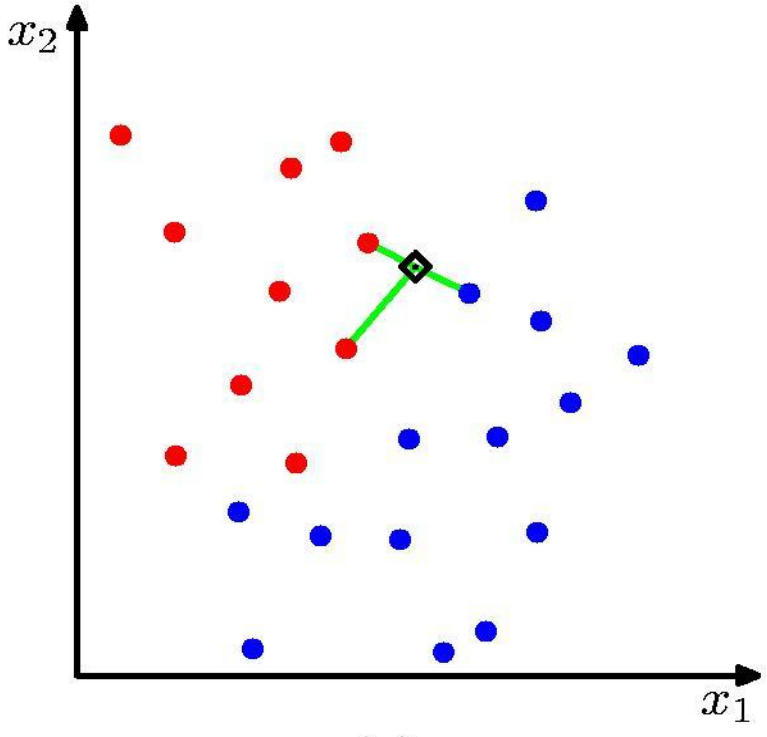
$$h(x) = \operatorname*{argmax}_{y} \sum_{(\mathbf{x}', y') \in kNN(\mathbf{x})} 1[y' = y]$$

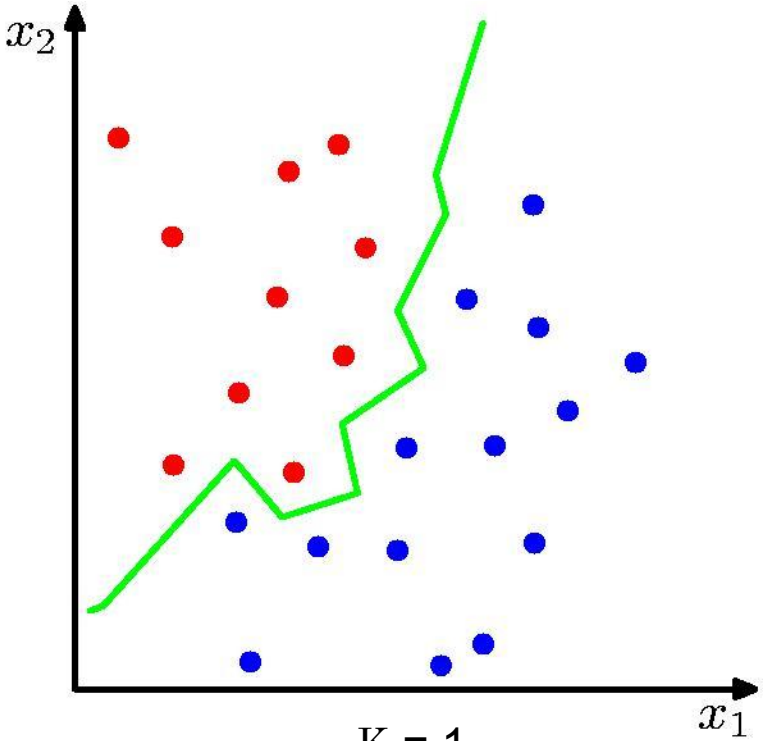
"majority vote"

- <u>Note: this function can be applied to regression!</u>

Slide credit: William Cohen

K-nearest neighbors for classification

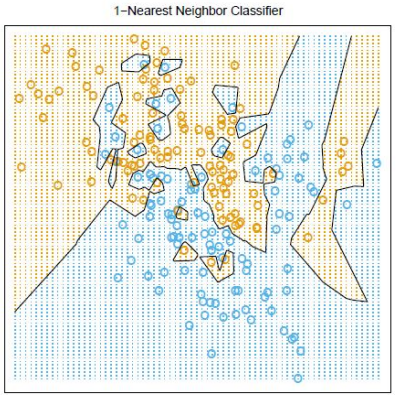


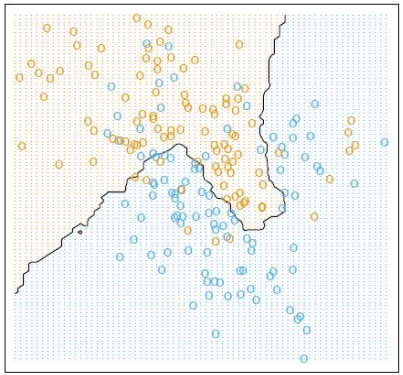


K = 1

Slide credit: Ben Kuipers

K-nearest neighbors for classification





- Larger *K* leads to a smoother decision boundary (bias-variance trade-off)
- Classification performance generally improves as *N* (training set size) increases
- For $N \Rightarrow \infty$, the error rate of the 1-nearest-neighbor classifier is never more than twice the optimal error (obtained from the true conditional class distributions). See ESL CH 13.3.

Slide credit: Ben Kuipers

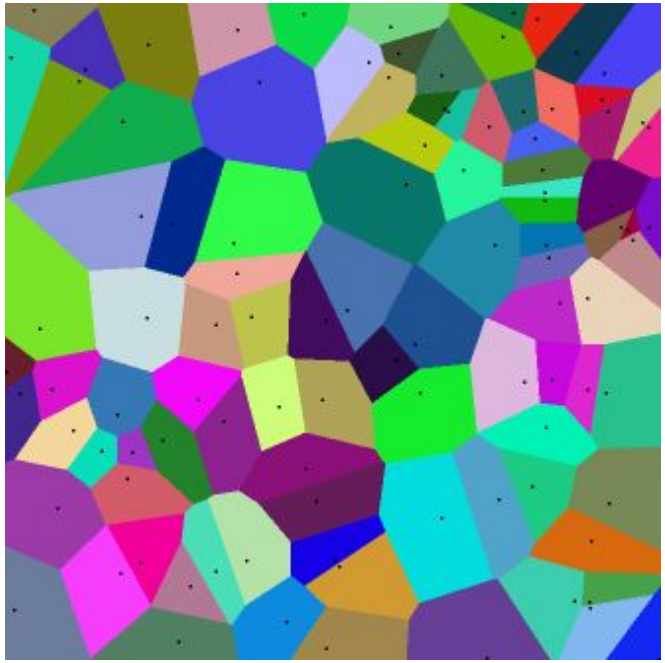
Factors (hyperparameters) affecting kNN

- Distance metric $D(\mathbf{x}, \mathbf{x'})$
  - How to define distance between two examples **x** and **x'**?

- The value of K
  - K determines how much we “smooth out” the prediction

What is the decision boundary?

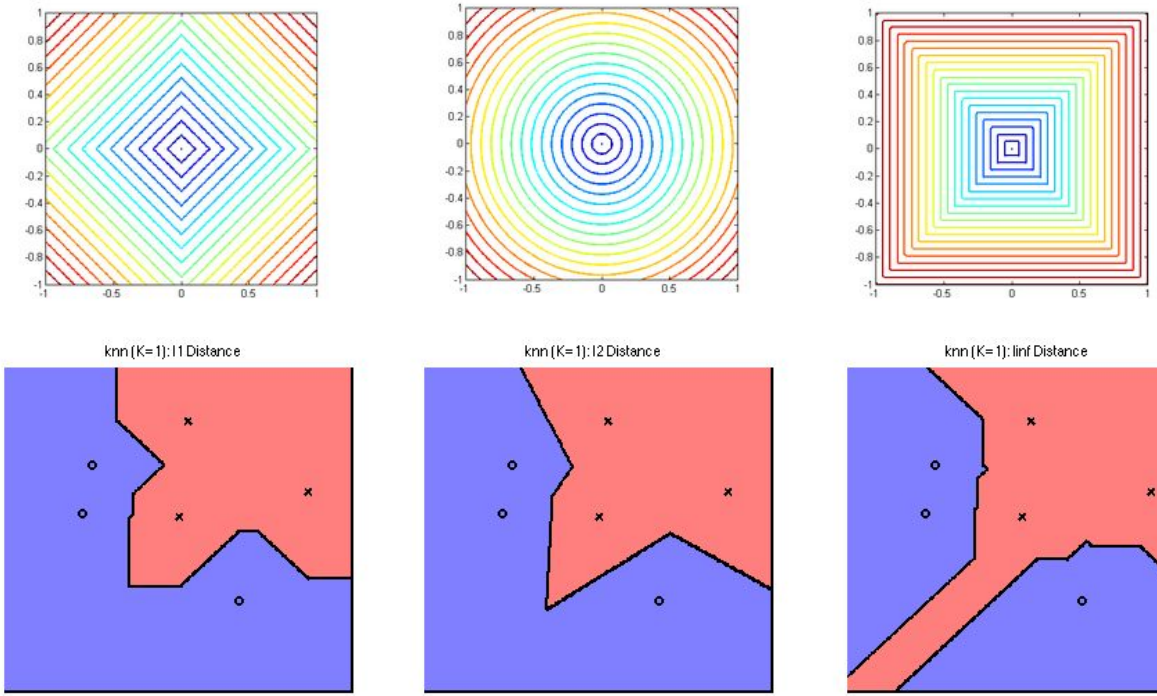
Voronoi diagram: Euclidean (L_2) distance



Slide credit: William Cohen

Dependence on distance metric (L^q norm)

Distance between i-th and j-th example: $\sqrt[q]{\sum_l \left(x_l^{(i)} - x_l^{(j)}\right)^q}$



Slide credit: Ben Taskar

kNN: classification vs regression

- We can formulate kNN into regression/classification
- For classification, where the label *y* is categorical, we take the “majority vote” over target labels.

$$h(x) = \operatorname*{argmax}_{y} \sum_{(\mathbf{x}',y') \in kNN(\mathbf{x})} 1[y' = y]$$

- For regression, where the label *y* is real-valued numbers, we take “average” over target labels.

$$h(x) = \frac{1}{k} \sum_{(\mathbf{x}',y') \in kNN(\mathbf{x})} y'$$

Advantage/disadvantages of kNN methods

- Advantage:
  - Very simple and flexible (no assumption on distribution)
  - Effective (e.g. for low dimensional inputs)
- Disadvantages:
  - Expensive: need to remember (store) and search through all the training data for every prediction
  - Curse of dimensionality: in high dimensions, all points are far
  - Not robust to irrelevant features: if **x** has irrelevant/noisy features, then distance function does not reflect similarity between examples

Concept check

- How are labels represented in multiclass classification problems?
- What is the motivation for using Newton's method for optimization in logistic regression?
- What does increasing K do for the results from kNN?

- Google Forms quiz at https://tinyurl.com/eecs545-4
  - Requires UM authentication
- We'll have ungraded quizzes at the end of lectures from this point forward