

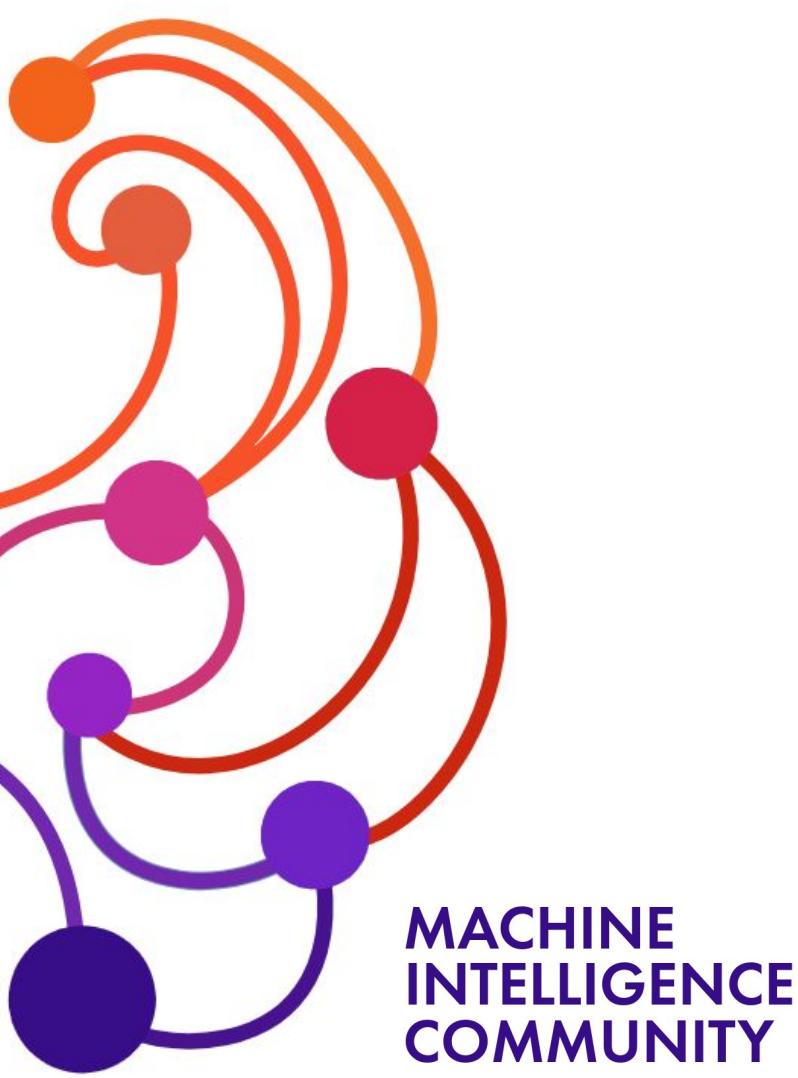
MACHINE
INTELLIGENCE
COMMUNITY

ML Series

Part 1

Sign-in Sheet with links to ML worksheet
bit.ly/bumicspring2019ws02

2/13/2019



MACHINE
INTELLIGENCE
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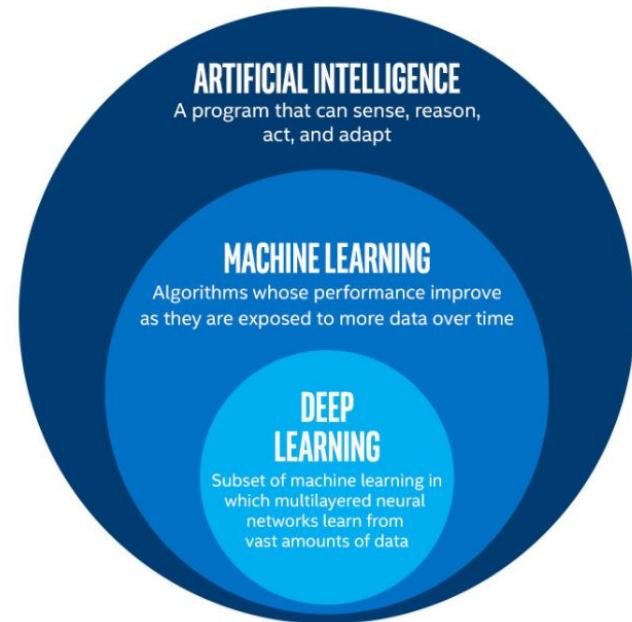
ML Series

Part 1

Darcy, Duy, Zack

Traditional machine learning

- Traditional machine learning offer an alternative to the data-and computation-hungry deep learning.
- Traditional machine learning can offer a more interpretable model.





k Nearest Neighbor (kNN)

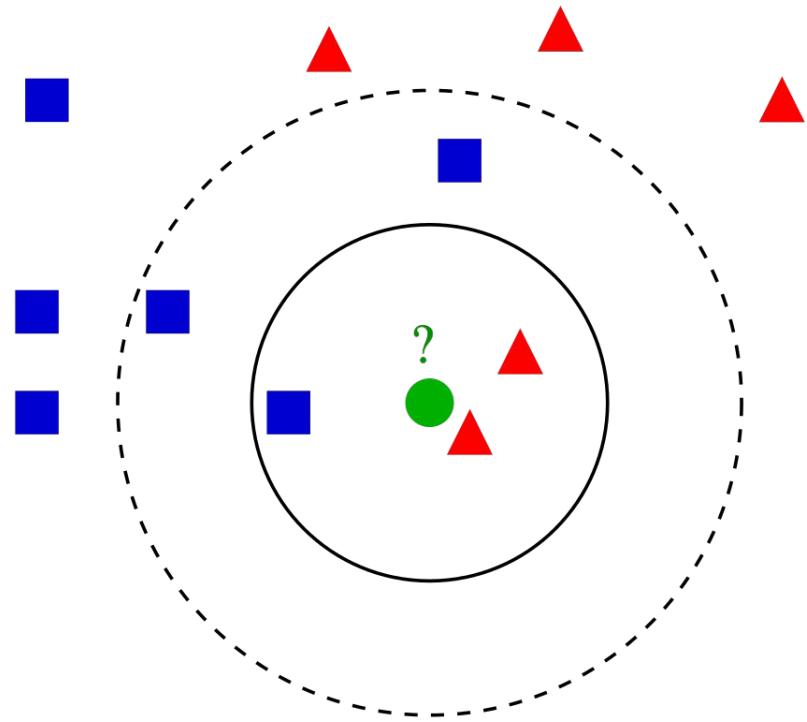
What's kNN

- Classify based on the k-nearest neighbor to the value in question.
- K-nearest neighbor doesn't really need "training", the classification is left until the value in question need to be classify.
- kNN is parametrized by k (the number of neighbor we need to consider for each value).
 - The smaller k is, the more prone to overfitting.
 - The larger k is, the more smoothing.



kNN in action

- k number of neighboring data point around is selected.
- These k-nearest neighbors vote on the class of the data point being classify.

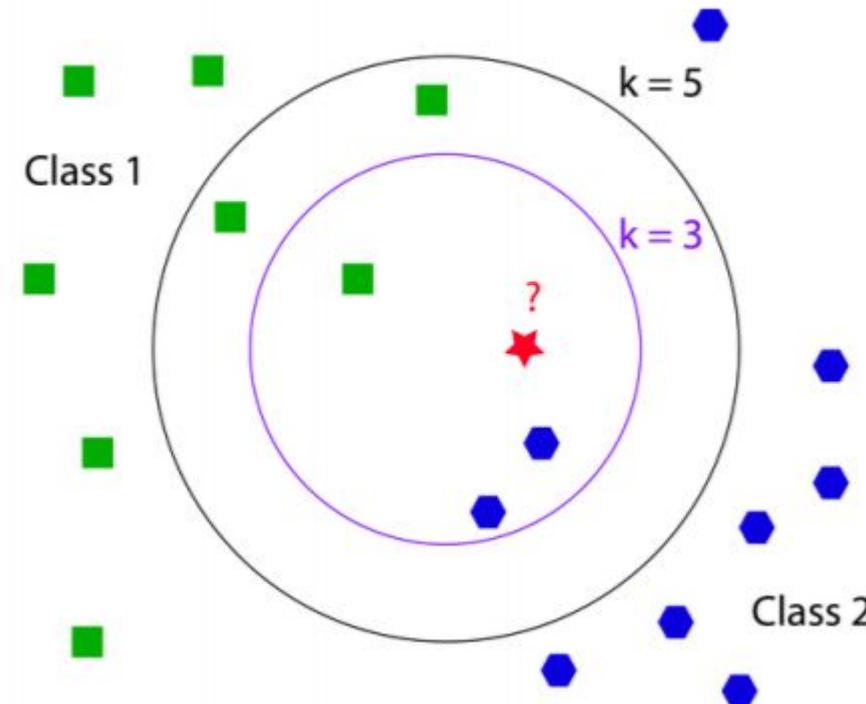


Distance metrics

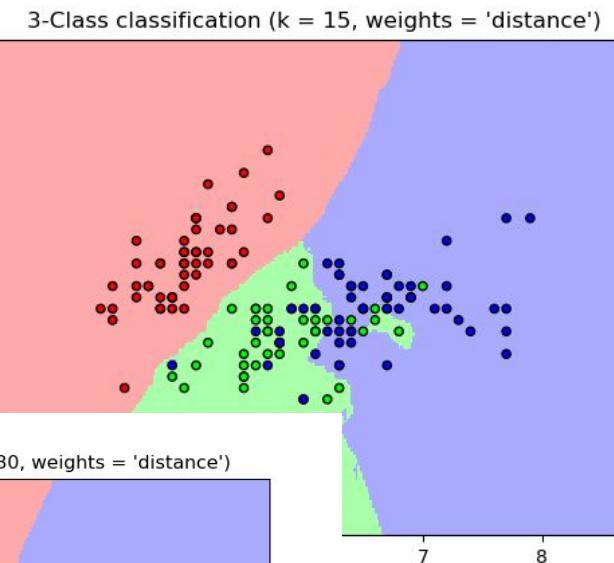
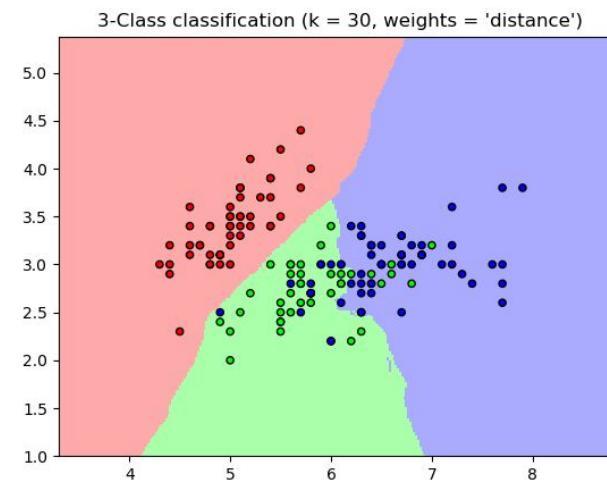
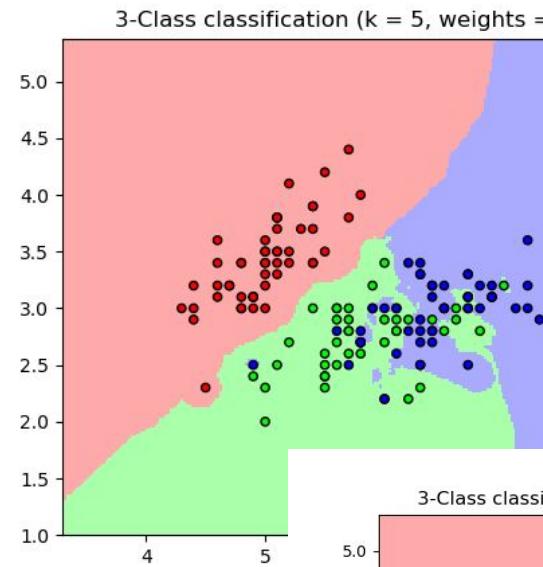
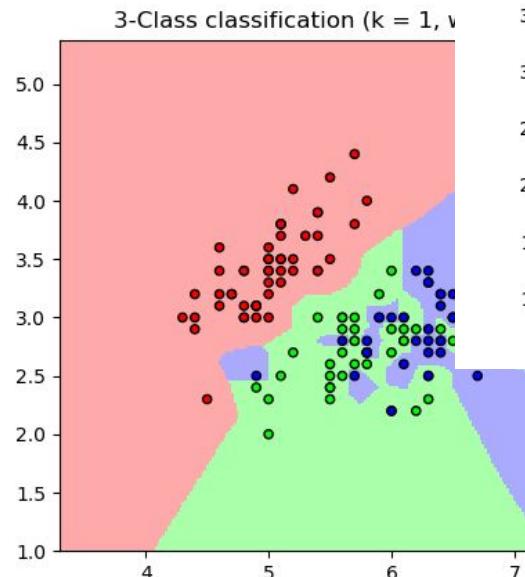
- Minkowski (L^p) $D(\mathbf{x}, \mathbf{y}) = \left(\sum_{i=1}^n |x_i - y_i|^p \right)^{\frac{1}{p}}$
- Manhattan ($L1$) $D(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^n |x_i - y_i|$
- Euclidian ($L2$) $D(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$
- Cosine $D(\mathbf{x}, \mathbf{y}) = ||\mathbf{x}|| ||\mathbf{y}|| \cos(\theta)$
$$\cos(\theta) = \frac{\mathbf{x} \cdot \mathbf{y}}{||\mathbf{x}|| ||\mathbf{y}||}$$

Choosing k

- k is a parameter that we need to tune.
- In the example, the example to be classified could be either a blue hexagon or a green square depends on how large k is.



Choosing k



Adapted from [scikit-learn example](#)

Pros/Cons of kNN

- Intuitive and simple to understand
- Doesn't require training
- Easy to build online classifier: we can just classify new data as it comes
- Computationally intensive for large number of data points: fast for
- Sensitive to outliers
- Sensitive to un-balance dataset





Linear Classification

Linear Classification is not Linear Regression

Linear Classification: Given a training example, decide which of a finite number of classes it belongs to

- e.g. is this a dog, a cat, or a bird?

Linear Regression: Given a training example, estimate some continuous value

- e.g. what is the price of this house?

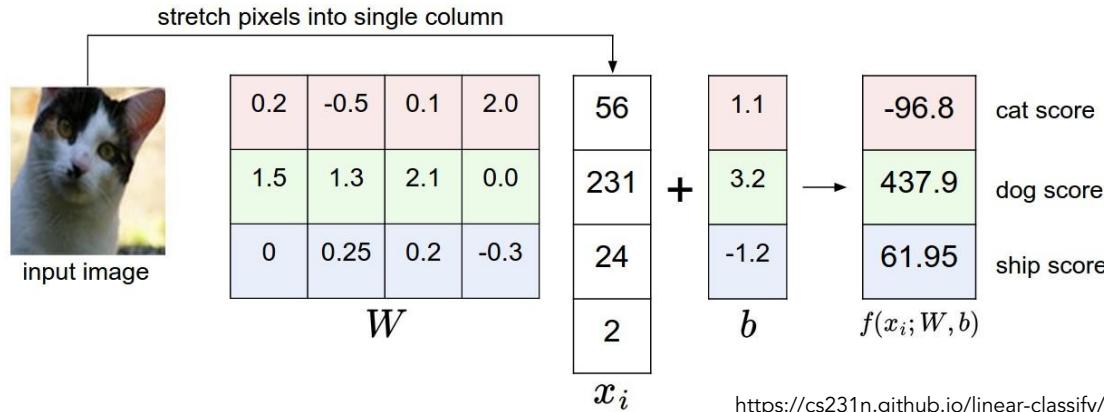
Linear Classification

1. Input training data
 2. Make predictions
 3. Compute loss
 4. Update the model parameters
2. Make predictions
- $f(x_i, W, b) = Wx_i + b$



Linear Classification

- Represent input as a vector
- Matrix multiply to get class scores -- highest score wins



- W and b must be trained



Support Vector Machine (SVM)

(Multiclass) SVM = a loss function

Measures incorrectness of the prediction

1. Input training data
 2. Make predictions
 3. Compute loss
 4. Update the model parameters
3. Compute loss
- $$L = \frac{1}{N} \sum_i \sum_{j \neq y_i} [\max(0, f(x_i; W)_j - f(x_i; W)_{y_i} + \Delta)]$$

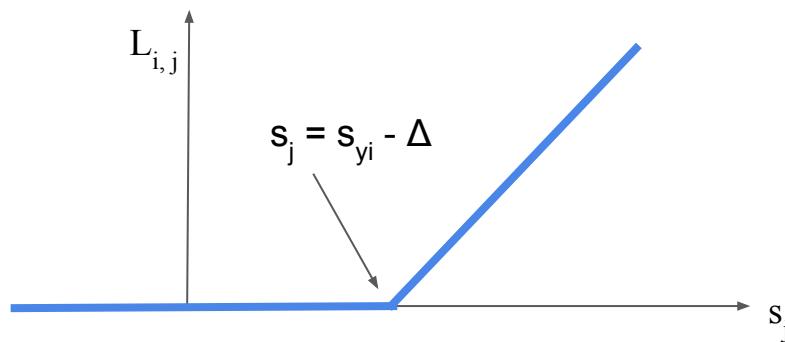


Multiclass SVM

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + \Delta)$$

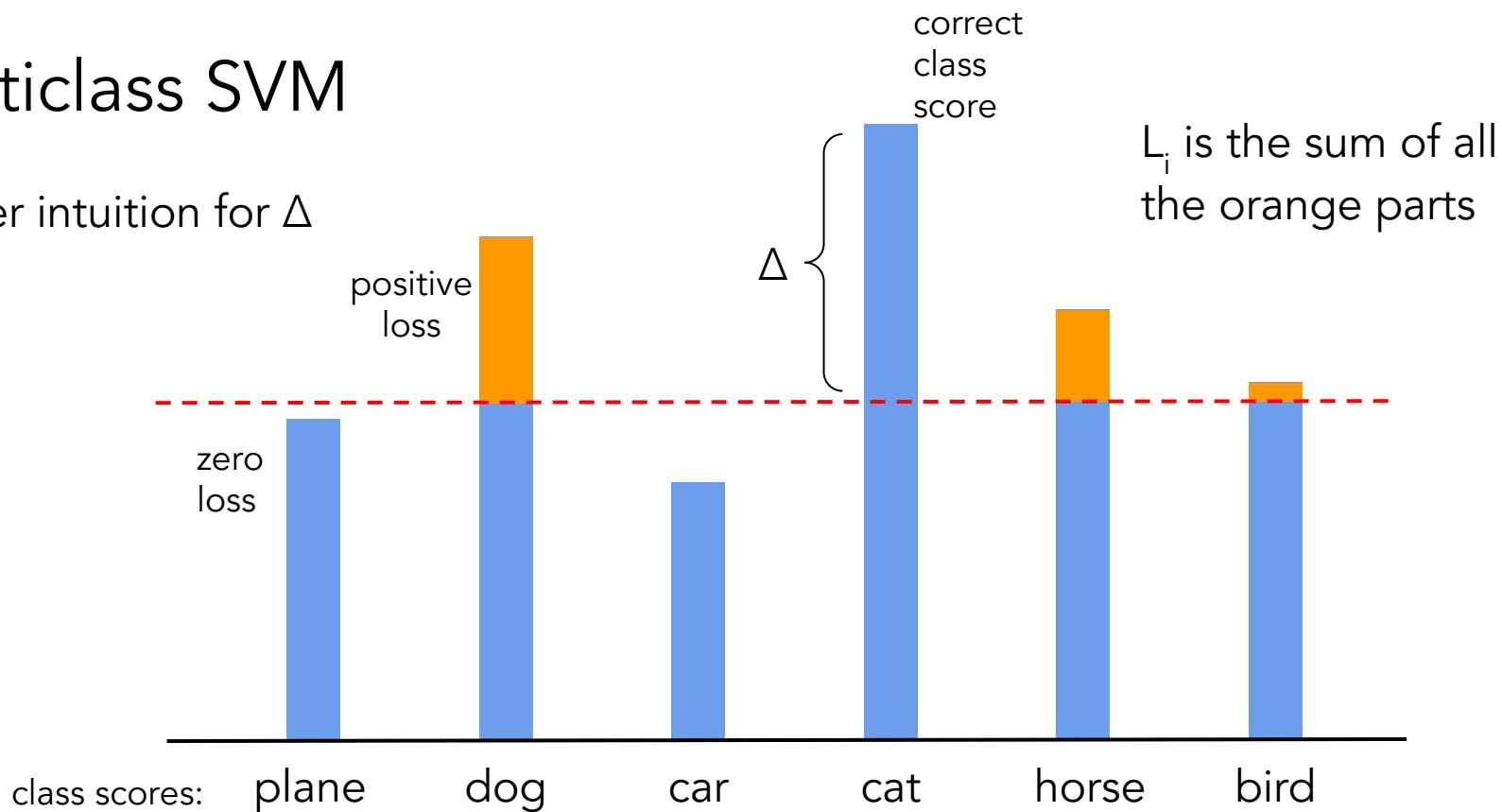
Annotations for the equation:

- Loss for example i → points to the first term L_i
- All classes j except the class of this example i → points to the summand $\sum_{j \neq y_i}$
- Score for class j → points to s_j
- Score for true class y_i of example i → points to s_{y_i}
- "Delta" → points to the term Δ



Multiclass SVM

Further intuition for Δ



Multiclass SVM

$$L = \frac{1}{N} \sum_i L_i$$

Total loss is average loss over all training examples

Multiclass SVM

4. Updating the model parameters...

- Update the parameters such that the loss is minimized

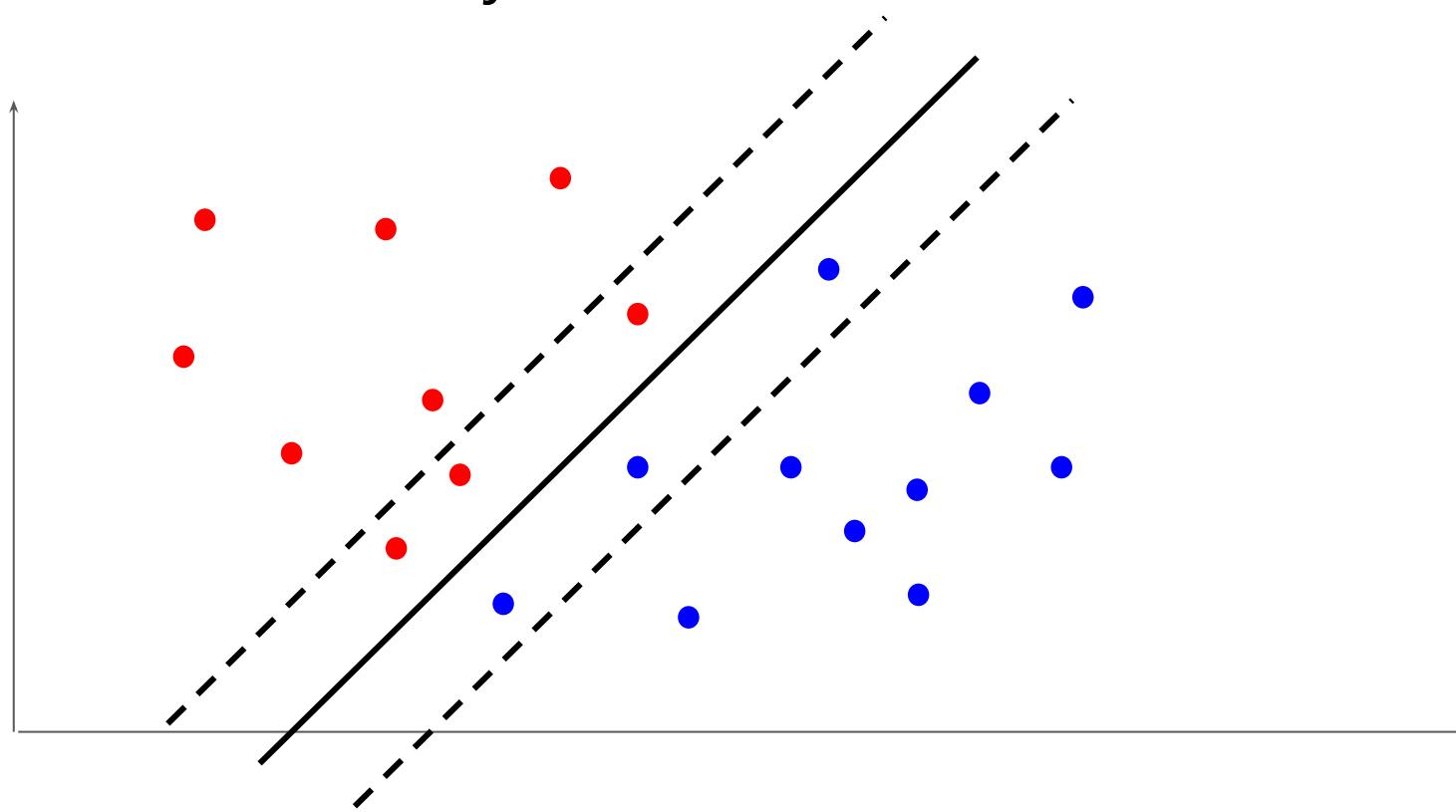
For weights of correct class:

$$\nabla_{w_{y_i}} L_i = - \left(\sum_{j \neq y_i} \mathbb{1}(w_j^T x_i - w_{y_i}^T x_i + \Delta > 0) \right) x_i$$

For weights of incorrect classes:

$$\nabla_{w_j} L_i = \mathbb{1}(w_j^T x_i - w_{y_i}^T x_i + \Delta > 0) x_i$$

Decision boundary



Pros/Cons of SVM

- Classification is fast
- Simple to implement
- Training is slow
- Is not sensitive to more complex relationships between variables



Upcoming Events

- Society and MI Discussion
 - Wed, February 20, 7pm – 8pm, MCS
- First Paper Discussion
 - Tue, February 19, TBD



Scaffolded kNN Exercise

http://bit.ly/scaffolded_kNN_example

Complete kNN:

http://bit.ly/complete_kNN_example

Regression Example Using SVM:

http://bit.ly/complete_SVM_example_2

1. You can choose to implement the algorithms with a scaffolded version or study the complete version of the code.
2. You would have access to both kNN and SVM solutions.
3. Challenge: extend the code into using one-versus-one multiclass SVM.

