Lab #6: Tweaking Classifiers

Everything Data

CompSci 216 Spring 2015

DUKE
COMPUTER SCIENCE

Announcements (Mon. Feb. 23)

- **Project team formation** due tonight!
  - Submit `team.txt` to `proj-team`
  - Don't confuse it with submitting `team.txt` for this lab
- **Same team assignment** as last lab
  - Seating by project team assignment will begin next week
- **Sample solution to Homework #6** posted
- **Jun is moving office hours** to Fridays 3:30-4:45pm in LSRC D327

Winners from Lab #5

Team 9:

- Anthony Hagouel
- Dianwen Li
- Janvi Shah
- Alexander Shih

Format of this lab

- Introduction
- Two challenges
- Discussion

Introducing Lab #7

So you are not happy with your classifier (or any prediction algorithm in general); what can you do?

- *Try a different algorithm?*
- *Try different parameters of the algorithm?*
- *Get more training examples?*
- *Try fewer features?*
- *Try more features?*

Team challenge 1

- In Homework #6, we used hundreds of votes as features to predict party affiliation
- It turned out that 10 arbitrary votes were enough!
- But would any 10 work? Can you find 10 bad features to screw up Naïve Bayes?

5% extra credit if you get <70% accuracy

First to achieve the lowest accuracy wins!

Feature selection

Why?

- Faster, less prone to overfitting, easier to interpret model

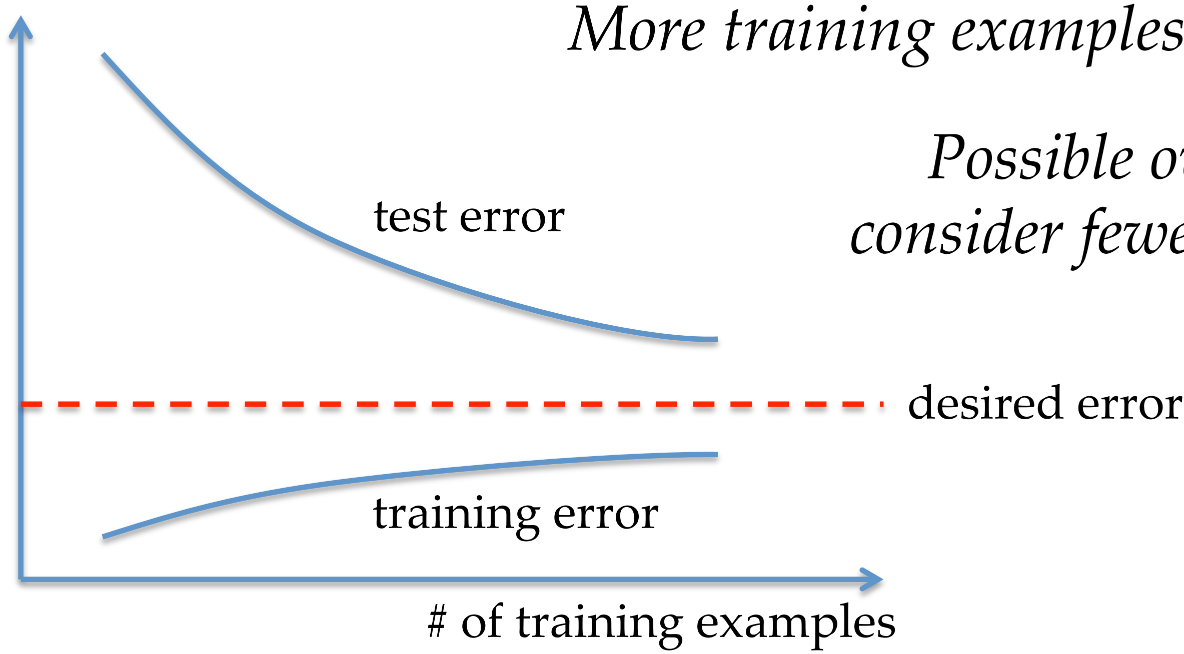
How?

- One simple approach: rank all features by some utility measure, and use only the top k
  - A popular utility measure is χ^2
    - A high χ^2 means it's unlikely that the feature value and the class label are independent
- *When does this fail?*

Tweaking classifiers: Scenario 1

If you increase # training examples and see

- Test error continues to decrease
- Gap between test and training errors remains big



More training examples will help

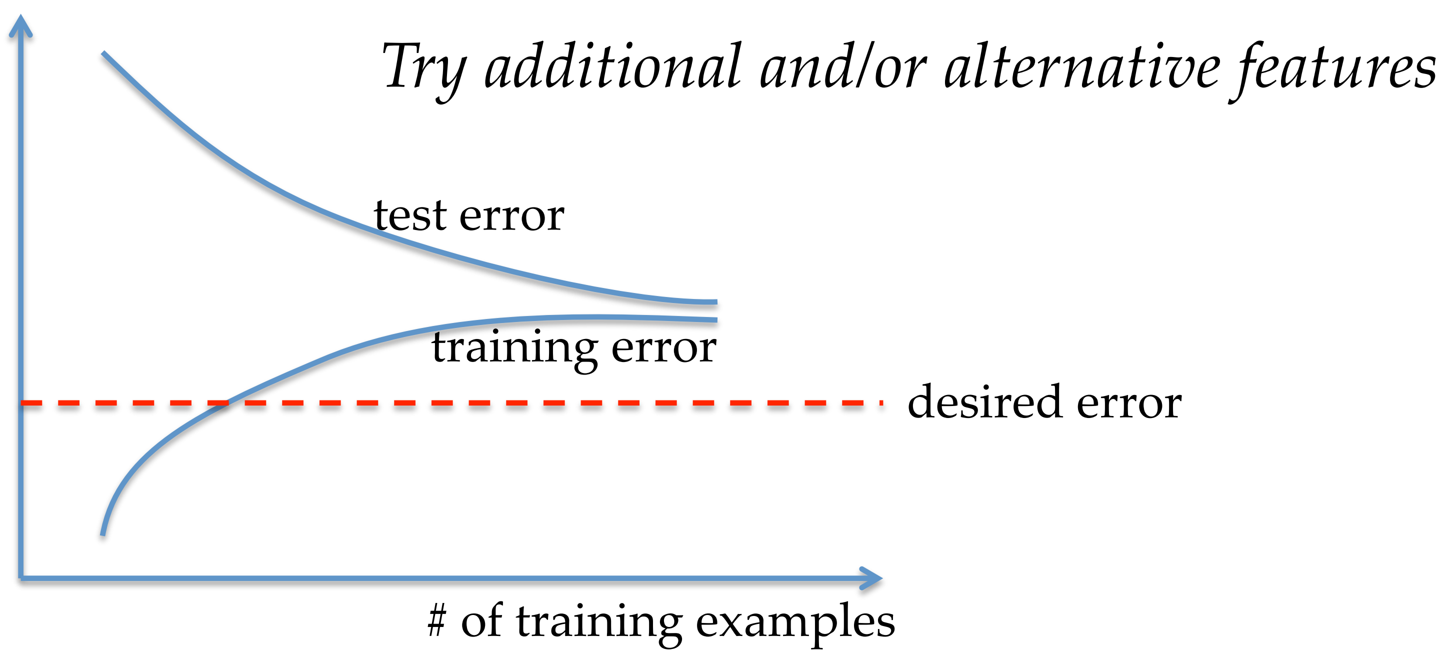
Possible overfitting, consider fewer features

From Andrew Ng: http://see.stanford.edu/materials/aimlcs229/ML-advice.pdf

Tweaking classifiers: Scenario 2

But if

- Even training error is unacceptably high
- Gap between test and training error is narrow



From Andrew Ng: http://see.stanford.edu/materials/aimlcs229/ML-advice.pdf

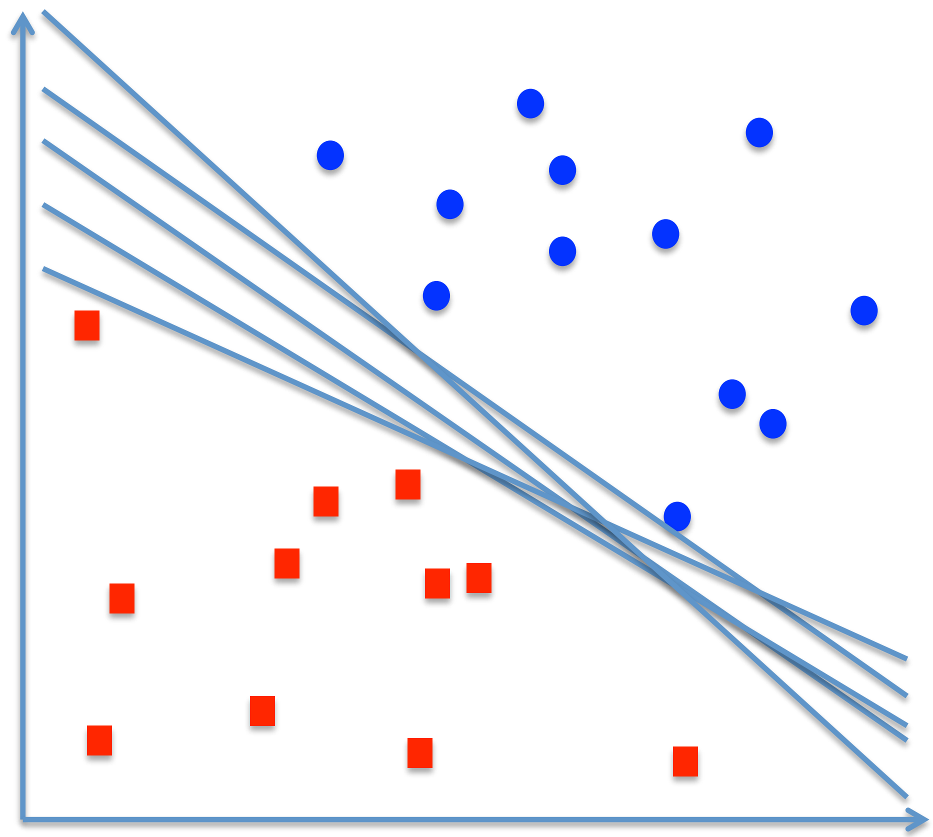
Tuning algorithm parameters

- Systematic search of parameter space
  - You don't get to see test data, yet
  - Use cross-validation on training data
- Understanding of how algorithms (and parameters) work will help
  - E.g., if you observe overfitting, try increasing k in the kNN classifier

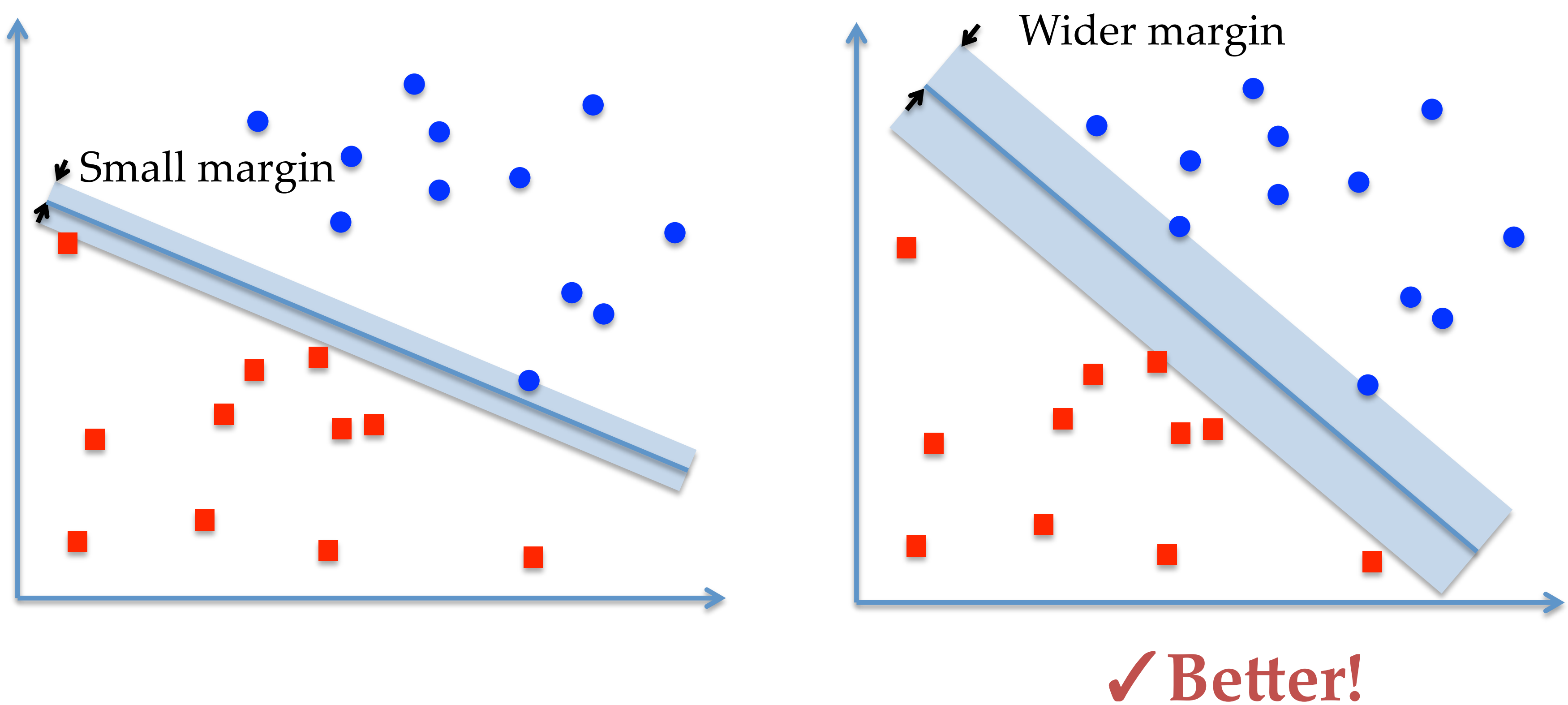
Intuition behind linear SVM

- Points labeled with two classes
- Find a hyperplane separating the two classes

But which one would you pick?



Max-margin classifier

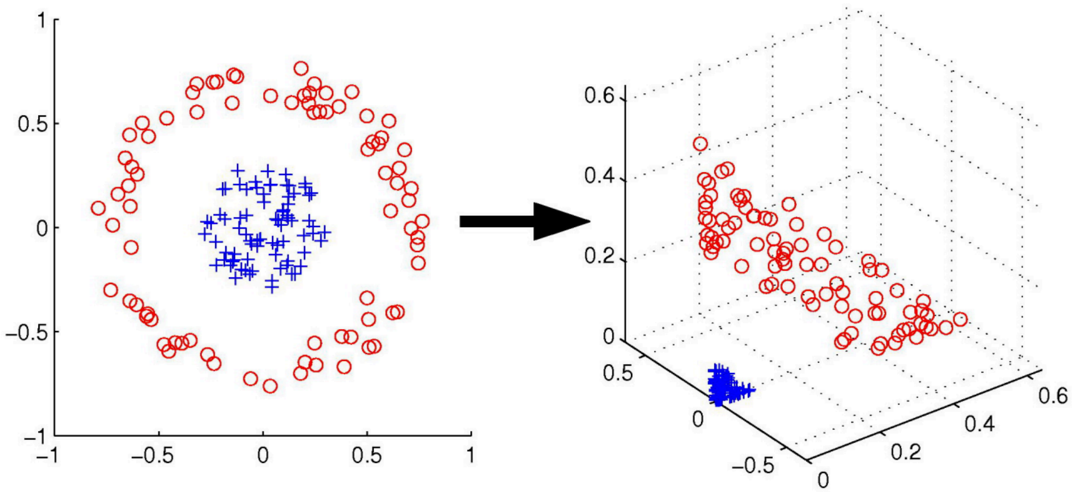


☞*Pick the hyperplane with the widest margin*

– Turns out this problem can be solved efficiently

Not linearly separable?

- Transform data to make it separable, e.g.:



$$(x_1, x_2) \mapsto (x_1^2, \sqrt{2}x_1x_2, x_2^2)$$

Instead of really transforming data, pick a distance metric (kernel), and the "kernel trick" will keep SVM efficient!

- In other cases, you can make the SVM "soft"
  - Allow misclassified points but pay a penalty

Image from http://www.cs.berkeley.edu/~jordan/courses/281B-spring04/lectures/lec3.pdf

Team challenge 2

- Classify articles into 6 newsgroups
- Naïve Bayes vs. *k*NN vs. SVM
- Various tweaking can be done by modifying `lab.py` and supplying additional command-line arguments

5% extra credit if you get >0.79 F-measure

First to achieve the highest accuracy wins!

Lessons learned

- Getting started should be easy; getting really good results is hard
- So many tools and knobs, so little time!
  - Automatic searches through feature and parameter spaces can help
  - Better understanding of the tools/knobs helps
- *"Careful design"* vs. *"build-and-fix"*
  - Andrew Ng

Image: http://drno-effects.com/products/black-magic/

Finally

- Remember to submit lab `team.txt` **under** `lab06` **by midnight**
- And also project `team.txt` **under** `proj-team`
- Slides on and sample solutions to Lab #6 will be posted by tonight