Digit Recognition

with Support Vector Machines

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Outline

- 1. Introduction to Our Data Set
- 2. Our Approach
- 3. Sequential Minimal Optimization (SMO)
- 4. Multi-Class Classification
- 5. Results & Conclusions

Introduction to Our Data Set

Main Goal: train algorithm to recognize handwritten digits

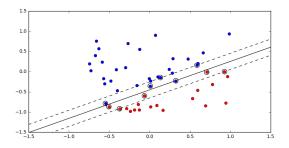


Data:

- ▶ 42,000 greyscale images
- 28 by 28 pixels each
- partitioned into ten classes

Our Approach

We want to use the concept of SVMs.



- ▶ **Problem I:** SVMs are binary classifiers
- Problem II: Need to solve optimization problem

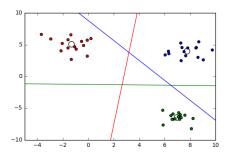
Our Approach

- 1. Implement solver for our QP
 - ▶ 3 versions
- 2. Implement basic SVM algorithm
 - linear kernel / Gaussian kernel
 - Parameter optimization
- 3. Combine individual SVMs in different ways
 - ▶ 3 versions
- 4. Validate and compare results

Sequential Minimal Optimization (SMO)

Multi-Class Classification

- Choose k groups of the classes
- ► Train *k* SVMs that separate each group from the rest
- ▶ Compare outcome to what would arise for each digit.
- Problem: Points may not be classified uniquely.
- ► Handle overlappings by minimizing distance to barycenters



Multi-Class Classification

1. One-vs-All

Idea: For each $i \in \{0, 1, ..., 9\}$, train an SVM that separates class i from the rest

Class	f_0	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9
0	-1	1	1	1	1	1	1	1	1	1
1	1	-1	1	1	1	1	1	1	1	1
2	1	1	-1	1	1	1	1	1	1	1
3	1	1	1	-1	1	1	1	1	1	1
4	1	1	1	1	-1	1	1	1	1	1
5	1	1	1	1	1	-1	1	1	1	1
6	1	1	1	1	1	1	-1	1	1	1
7	1	1	1	1	1	1	1	-1	1	1
8	1	1	1	1	1	1	1	1	-1	1
9	1	1	1	1	1	1	1	1	1	-1

Multi-Class Classification

2. Error Correcting Output Codes

Idea: Relabeling with large Hamming distance according to:

Class	f_0	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}
0	1	1	-1	-1	-1	-1	1	-1	1	-1	-1	1	1	-1	1
1	-1	-1	1	1	1	1	-1	1	-1	1	1	-1	-1	1	-1
2	1	-1	-1	1	-1	-1	-1	1	1	1	1	-1	1	-1	1
3	-1	-1	1	1	-1	1	1	1	-1	-1	-1	-1	1	-1	1
4	1	1	1	-1	1	-1	1	1	-1	-1	1	1	-1	-1	1
5	-1	1	-1	-1	1	1	-1	-1	1	1	-1	-1	-1	-1	1
6	1	-1	1	1	1	-1	-1	-1	-1	1	-1	1	-1	-1	1
7	-1	-1	-1	1	1	1	1	-1	1	-1	1	1	-1	-1	1
8	1	1	-1	1	-1	1	1	-1	-1	1	-1	-1	-1	1	1
9	-1	1	1	1	-1	-1	-1	-1	1	-1	1	-1	-1	1	1

Results & Conclusions

# training points	One-vs-All uniquely classfied, linear	One-vs-All with bary- centers, linear	One-vs-All uniquely classfied, Gaussian	One-vs-All with bary- centers, Gaussian	ECOC, linear	ECOC, Gaussian
500						
1000						
2000						
5000						
10000						

Table: Correctly Classified Digits

Results & Conclusions

# training points	One-vs-All uniquely classfied, linear	One-vs-All with bary- centers, linear	One-vs-All uniquely classfied, Gaussian	One-vs-All with bary- centers, Gaussian	ECOC, linear	ECOC, Gaussian
500	65.9%	74.1%	75.4%	83.3%	74.2%	87.4%
1000	68.2%	75.0%	84.3%	89.0%	78.0%	92.7%
2000	70.2%	76.4%	89.8%	91.9%	77.8%	94.3%
5000	70.0%	73.8%	88.9%	91.6%	82.0%	95.2%
10000	64.6%	67.5%	88.0%	90.6%	82.5%	95.4%

Table: Correctly Classified Digits

Results & Conclusions



Figure: Visualizing very illegible digits