Machine Learning (CSE 446): Practical Issues

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scary words

Outline of CSE 446

We've already covered stuff in blue!

- Problem formulations: classification, regression
- Supervised techniques: decision trees, nearest neighbors, perceptron, linear models, probabilistic models, neural networks, kernel methods
- Unsupervised techniques: clustering, linear dimensionality reduction
- "Meta-techniques": ensembles, expectation-maximization
- Understanding ML: limits of learning, practical issues, bias & fairness
- Recurring themes: (stochastic) gradient descent, bullshit detection

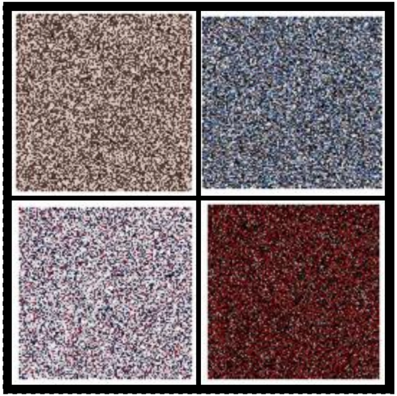
Today: (More) Best Practices

You already know:

- Separating training and test data
- Hyperparameter tuning on development data

Understanding machine learning is partly about knowing algorithms and partly about the art of mapping abstract problems to learning tasks.

Features Matter



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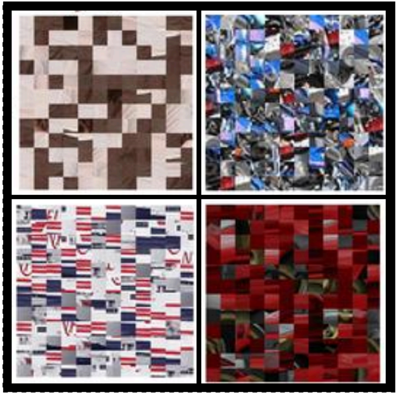

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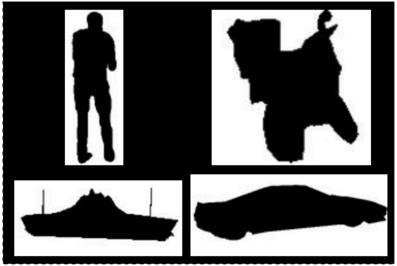

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What about *redundant* features ϕ_j and $\phi_{j'}$ such that $\phi_j \approx \phi_{j'}$?

Technique: Feature Pruning

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Generalization: if a feature has variance (in D) **lower** than some threshhold value, remove it.
Note: in lecture, I mistakenly said to remove high-variance features. Mea culpa.

$$\text{sample\_mean}(\phi; D) = \frac{1}{N} \sum_{n=1}^{N} \phi(x_n) \qquad \text{(call it “}\bar{\phi}\text{”)}$$

$$\text{sample\_variance}(\phi; D) = \frac{1}{N-1} \sum_{n=1}^{N} \left(\phi(x_n) - \bar{\phi}\right)^2 \qquad \text{(call it “Var}(\phi)\text{”)}$$

Technique: Feature Normalization

Center a feature:

$$\phi(x) \to \phi(x) - \bar{\phi}$$

(This was a required step for principal components analysis!)

Scale a feature. Two choices:

$$\phi(x) \to \frac{\phi(x)}{\sqrt{\mathsf{Var}(\phi)}} \qquad \text{“variance scaling”}$$

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Remember that you'll need to normalize test data before you test!

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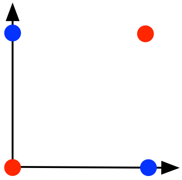

The classic "xor" problem: these points are *not* linearly separable.

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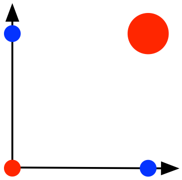

Define $\mathbf{x}[3] = \mathbf{x}[1] \wedge \mathbf{x}[2]$.

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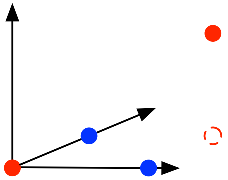

Rotating the view.

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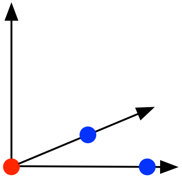

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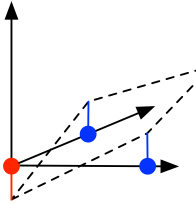

$$2 \cdot \mathbf{x}[1] + 2 \cdot \mathbf{x}[2] - 4 \cdot \mathbf{x}[3] - 1 = 0$$

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   This is one view of what decision trees are doing!
   - Every leaf's path (from root) is a conjunction feature.
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3. Transformations on features can be useful. For example,

$$\phi(x) \rightarrow \text{sign}(\phi(x)) \cdot \log\left(1 + |\phi(x)|\right)$$

   Example: $\phi(x)$ is the count of the word *cool* in document x.

Evaluation

Accuracy:

$$\begin{aligned} \mathrm{A}(f) &= \sum_{x} \mathcal{D}(x, f(x)) \\ &= \sum_{x,y} \mathcal{D}(x, y) \cdot \begin{cases} 1 & \text{if } f(x) = y \\ 0 & \text{otherwise} \end{cases} \\ &= \sum_{x,y} \mathcal{D}(x, y) \cdot [\![f(x) = y]\!] \end{aligned}$$

where $\mathcal{D}$ is the *true* distribution over data. Error is $1 - \mathrm{A}$; earlier we denoted error "$\epsilon(f)$."

This is *estimated* using a test dataset $\langle x_1, y_2 \rangle, \ldots, \langle x_{N'}, y_{N'} \rangle$:

$$\hat{\mathrm{A}}(f) = \frac{1}{N'} \sum_{i=1}^{N'} [\![f(x_i) = y_i]\!]$$

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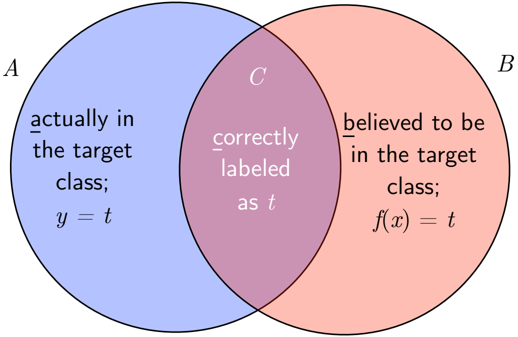
- Relative importance of classes or cost of error types.
- Variance due to the test data.

Evaluation in the Two-Class Case

Suppose we have two classes, and one of them, t, is a "target."

- E.g., given a query, find relevant documents.

Precision and **recall** encode the goals of returning a "pure" set of targeted instances and capturing *all* of them.



$$\hat{\mathrm{P}}(f) = \frac{|C|}{|B|} = \frac{|A \cap B|}{|B|}$$

$$\hat{\mathrm{R}}(f) = \frac{|C|}{|A|} = \frac{|A \cap B|}{|A|}$$

$$\hat{F}_1(f) = 2 \cdot \frac{\hat{\mathrm{P}} \cdot \hat{\mathrm{R}}}{\hat{\mathrm{P}} + \hat{\mathrm{R}}}$$

Another View: Contingency Table

	$y = t$	$y \neq t$	
$f(x) = t$	C (true positives)	$B \setminus C$ (false positives)	B
$f(x) \neq t$	$A \setminus C$ (false negatives)	(true negatives)	
	A		