Symbol Recognition in Sketch-Based Interfaces

Lecture #9: Symbol Recognition
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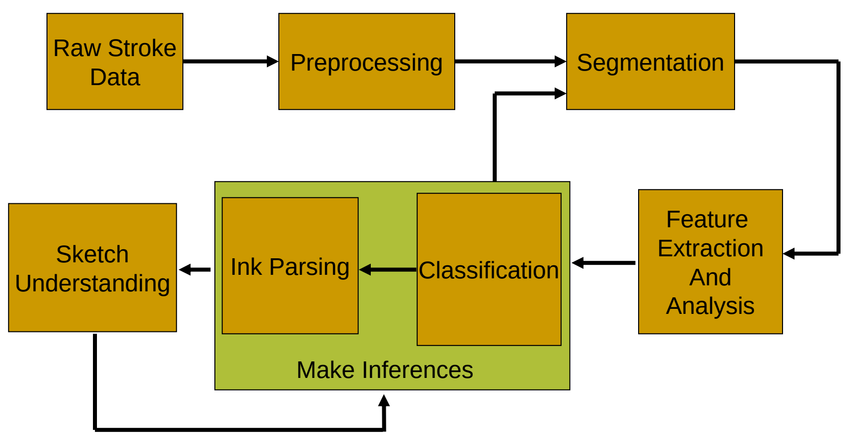
Recall Pen-Based Interface Dataflow



Symbol Recognition

- Want to recognize handwritten symbols
  - characters
  - shapes
  - gestures
- Use machine learning approach
- Which algorithm?
  - depends on number of symbols in alphabet
  - complexity (i.e., similarity of symbols)
  - distribution assumptions

Recognition Algorithms

- Many different approaches
- Machine learning techniques (classification)
  - linear classifiers
  - k-means classifiers
  - neural networks
  - Hidden Markov Models
  - template matching
  - support vector machines
  - AdaBoost
- Curve matching
  - elastic matching
- Primitive decomposition

Rubine's Gesture Recognition Algorithm (Rubine 1991)

- Simple linear classifier
- Utilizes rejection metrics
- Assumes normality for features
- Simple to implement
- Does not need a lot of training samples

Recall Rubine's Feature Set

- Cosine and sine of initial angle
- Length and angle of bounding box diagonal
- Distance between first and last point
- Cosine and sine of angle between first and last point
- Total gesture length
- Total angle traversed
- Sum of absolute value of the angle at each point
- Sum of squared values of the angle at each point
- Maximum speed
- Stroke duration

Rubine Classifier

$$v_{\hat{c}} = w_{\hat{c}0} + \sum_{i=1}^{F} w_{\hat{c}i} f_i \quad 0 \le c < C$$

where F is the number of features,

$w_{\hat{c}}$ is the weights, and the classification

of symbol g is the c that maximizes $v_{\hat{c}}$

- Evaluate each gesture *0 ≤ c < C*.
- $v_{\hat{c}}$ = value = goodness of fit for that gesture c.

Rubine Classifier Training

- Collect *E* samples for each symbol class
- Calculate feature vector for each sample for each class
  - $f_{\hat{c}ei}$ = the feature value of the i^{th} feature for the e^{th} sample of the c^{th} symbol
- For each symbol calculate the mean value for each feature

$$\overline{f_{\hat{c}i}} = \frac{1}{E_{\hat{c}}} \sum_{e=0}^{E_{\hat{c}}-1} f_{\hat{c}ei} \quad \text{where } 0 \le e < E_{\hat{c}}$$

and $E_{\hat{c}}$ is the number of training samples per class

Rubine Classifier – Computing Weights

- We first need the covariance matrix of each class *c*

$$\Sigma_{\hat{c}ij} = \frac{1}{E_{\hat{c}} - 1} \sum_{e=0}^{E_{\hat{c}}-1} \left(f_{\hat{c}ei} - \overline{f_{\hat{c}i}}\right)\left(f_{\hat{c}ej} - \overline{f_{\hat{c}j}}\right)$$

Rubine Classifier – Computing Weights (2)

- Using the covariance matrices from each class, find the common covariance matrix
  - numerator = non-normalize total covariance
  - denominator = normalization factor = total number of examples – total number of shapes

$$\Sigma_{ij} = \frac{\sum_{c=0}^{C-1} \Sigma_{\hat{c}ij}}{-C + \sum_{c=0}^{C-1} E_{\hat{c}}}$$

Rubine Classifier – Computing Weights (3)

- Using the common covariance matrix and the mean feature vectors from each class, we can compute the weights

$$w_{\hat{c}j} = \sum_{i=1}^{F} \left(\Sigma^{-1}\right)_{ij} \overline{f_{\hat{c}i}}, \; 1 \le j \le F$$

$$w_{\hat{c}0} = -\frac{1}{2} \sum_{i=1}^{F} w_{\hat{c}i} \overline{f_{\hat{c}i}}$$

Rubine Classifier – Rejection Measures

- Linear classifier always will classify a symbol as one of the *C* classes
  - want to try to reject outliers and ambiguous symbols
  - two approaches
    - probabilistic
    - distance measure

Rubine Classifier – Probabilistic Rejection Measure

- Given a symbol *g* with feature vector **f** classified as class *i* $(v_i > v_j, \forall j \neq i)$

$$\tilde{P}(i \mid g) = \frac{1}{\sum_{j=0}^{C-1} e^{(v_j - v_i)}}$$

$$\text{Reject symbols with } \tilde{P}(i \mid g) < 0.95$$

Rubine Classifier – Rejection based on Distance

- Mahalanobis distance – the number of standard deviations a symbol *g* is away from the mean of its chosen class *i*

$$\delta^2 = \sum_{j=1}^{F} \sum_{k=1}^{F} \left(\Sigma^{-1}\right)_{jk} \left(f_j - \overline{f_{ij}}\right)\left(f_k - \overline{f_{ik}}\right)$$

$$\text{Rejecting symbols for which } \delta^2 > \frac{1}{2} F^2$$

- May need to be careful not to reject too many good symbols (a simple alternate list to correct mistakes will be helpful)

AdaBoost (Schapire 1997)

- Not really a classification algorithm – more like a framework
- Can use many different classification algorithms within AdaBoost framework
- Works with series of weak (base) classifiers
  - Want to increase the importance of incorrectly classified examples
    - series of weak hypotheses and weights form a strong hypothesis
    - need to ensure weak learners output either 1 or -1
- Many different variants (M1,M2, etc…)

AdaBoost Algorithm

Given $(x_1, y_1),\ldots,(x_m, y_m)$ where $x_i \in X$, $y_i \in Y = \{-1,+1\}$

Initialize $D_1(i) = 1/m$

For $t = 1 \ldots T$

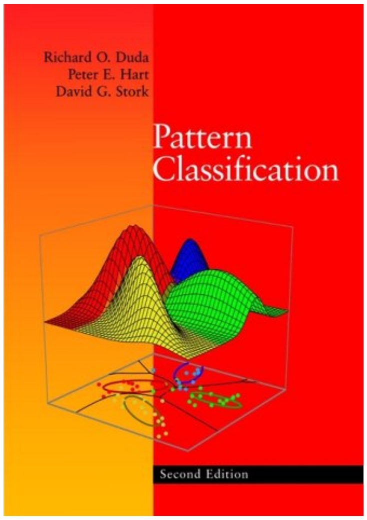
- Train weak learner using distribution D_t
- Get weak hypothesis $h_t : X \to \{-1,+1\}$ with error

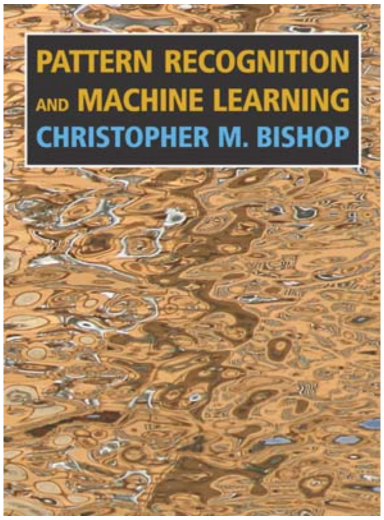
$$\varepsilon_t = \Pr_{i \sim D_t}[h_t(x_i) \neq y_i] = \sum_{i:h_t(x_i) \neq y_i} D_t(i)$$

- Compute $\alpha_t = \frac{1}{2}\ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$
- Update $D_{t+1}(i) = \frac{D_t(i)e^{-\alpha_t y_i h_t(x_i)}}{Z_t}$

Final hypothesis is $H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$

More Information on Machine Learning





Readings

- LaViola, J., and Zeleznik, R. A Practical Approach to Writer-Dependent Symbol Recognition Using a Writer-Independent Recognizer, IEEE Transactions on Pattern Analysis and Machine Intelligence, November 2007.
- Patel, R., B. Plimmer, J. Grundy, and R. Ihaka. Ink Features for Diagram Recognition, Proccedings of the 2007 Eurographics Workshop on Sketch-based Interfaces and Modeling, August, 2007.
- Connell, Scott D. and Anil K. Jain. Template-Based On-Line Character Recognition. Pattern Recognition, 34(1):1-14, January 2000.