

ECGR 6114 Classifiers

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ECGR 6114

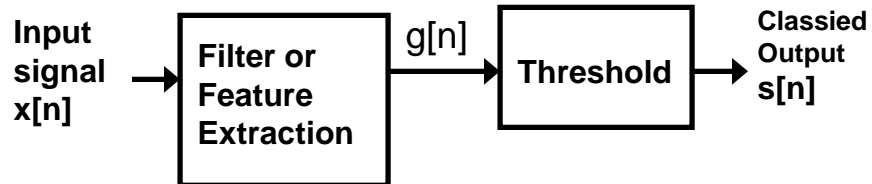
Classifiers

- Gaussian optimum threshold
- Multivariate Gaussian
- Bayesian Classifier
- Linear Discriminant Classifier
- K-Means Classifier
- K-Nearest Neighbor Classifier
- Minimum-Distance Classifier
- Supervised / Unsupervised

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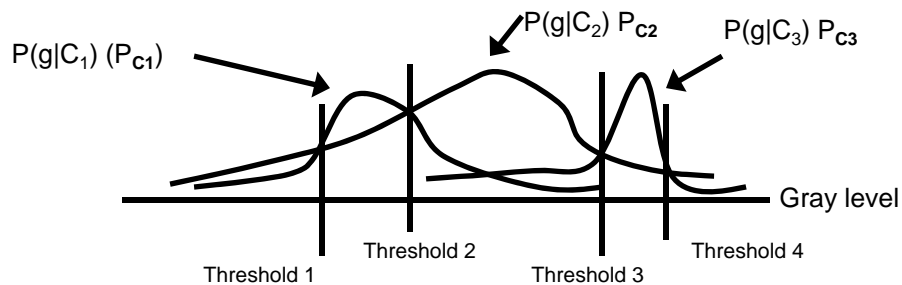
Single-Feature (Scalar) Threshold Classifier

- Suppose a signal processing system with 1 feature
- Scalar Feature g



Optimum Single-Feature Threshold

- Optimum Bayes classifier : use maximum likelihood ratio
 - $P(g|C_1)$ = probability density in region of class C_1
 - P_{C_1} = *a priori* probability of class C_1
 - g = observed scalar feature value
 - Choose class $s[n]=C_\alpha$ when
$$P(g|C_\alpha) P_{C_\alpha} \geq P(g|C_n) P_{C_n} \text{ for all } C_n \text{ (choose most likely)}$$



Gaussian pdf

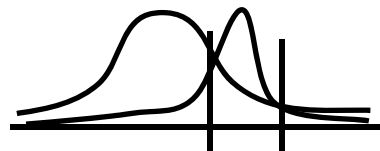
- Features are often well-modeled by Gaussian
- Gaussian pdf :

$$p(g | C_\alpha) = \frac{1}{\sigma_\alpha \sqrt{2\pi}} e^{-(g - \mu_\alpha)^2 / 2(\sigma_\alpha)^2}$$

- For class C_α with mean μ_α and standard deviation σ_α
- Bayes optimum classifier:
 - Choose class C_α when $P(g|C_\alpha) P_{C_\alpha} \geq P(g|C_n) P_{C_n}$ for all C_n (choose most likely)

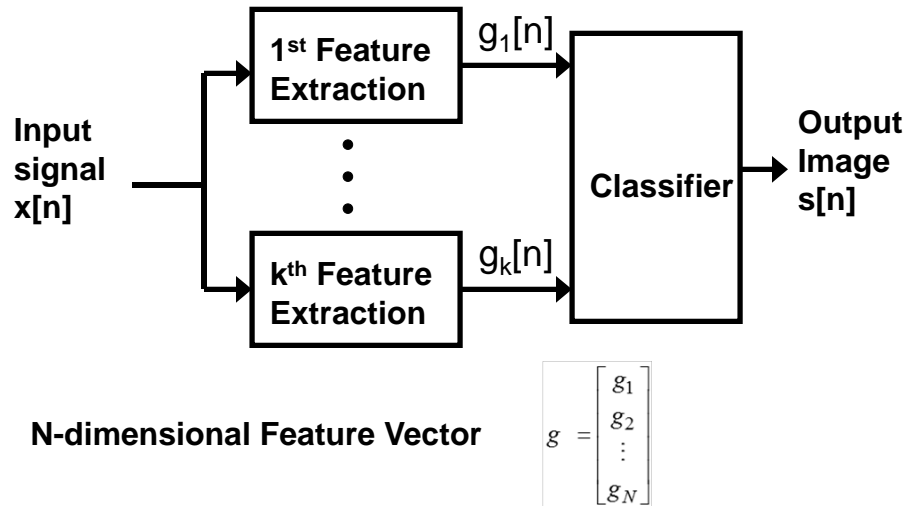
Gaussian Optimal Threshold

- For a single-feature system, the output $g[n]$ is a scalar
- Note that for Gaussian pdf:
 - If $\ln(P_{C_\alpha}/\sigma_\alpha) - (g - \mu_\alpha)^2/2(\sigma_\alpha)^2 \geq \ln(P_{C_n}/\sigma_n) - (g - \mu_n)^2/2(\sigma_n)^2$
 - Then $P(g|C_\alpha) P_{C_\alpha} \geq P(g|C_n) P_{C_n}$
- So, can classify based on exponent
- 2-class Bayes optimum Gaussian scalar classifier, solve:
 - $\ln(P_{C_1}/\sigma_1) - (g - \mu_1)^2/2(\sigma_1)^2 = \ln(P_{C_2}/\sigma_2) - (g - \mu_2)^2/2(\sigma_2)^2$
- Quadratic, so 2 solutions = 2 thresholds



Vector-Classifer

- Suppose a signal processing system with k features



Optimum Vector-Feature “Threshold”

- Optimum Bayes classifier : use maximum likelihood ratio again,
 - $P(\mathbf{g}|C_1)$ = probability density in region of class C_1
 - P_{C_1} = probability of class C_1
 - \mathbf{g} = observed N-dimensional feature vector value
 - Choose class C_α when
$$P(\mathbf{g}|C_\alpha) P_{C_\alpha} \geq P(\mathbf{g}|C_n) P_{C_n}$$
 for all C_n (choose most likely)
- Same form as before, except feature is a feature vector
- For 2-features, thresholds are closed curves (circle, ellipse)
- For 3 features Etc.

Multivariate Gaussian pdf

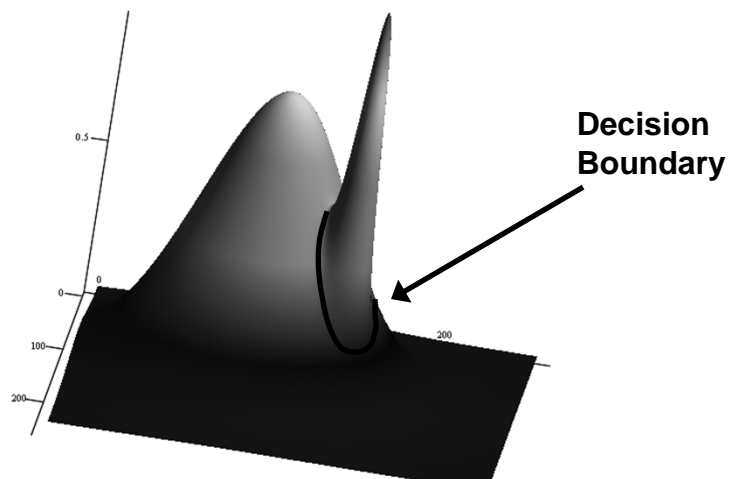
- Features are often well-modeled by multivariate Gaussian for output vector \mathbf{g} of dimension N
- Multivariate Gaussian pdf

$$p(\mathbf{g} | C_\alpha) = \frac{1}{|\Sigma_\alpha|^{1/2} (2\pi)^{N/2}} e^{-(\mathbf{g} - \mu_\alpha)^T (\Sigma_\alpha)^{-1} (\mathbf{g} - \mu_\alpha) / 2}$$

- For class C_α with mean vector $\mu_\alpha = \mathbf{E}\{\mathbf{g}\}$ and covariance matrix $\Sigma_\alpha = \mathbf{E}\{(\mathbf{g}_\alpha - \mu_\alpha)(\mathbf{g}_\alpha - \mu_\alpha)^T\}$
- Bayes optimum classifier:
 - Choose class C_α when $P(\mathbf{g}|C_\alpha) P_{C_\alpha} \geq P(\mathbf{g}|C_n) P_{C_n}$ for all C_n (choose most likely)
- In similar fashion, can use logarithmic form for classifier

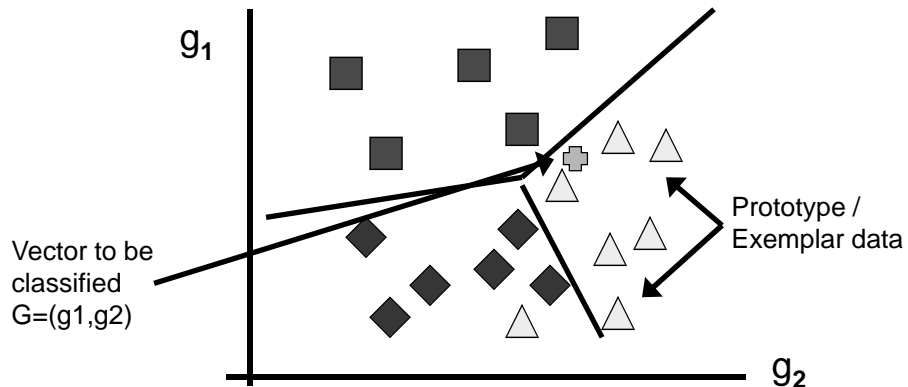
Multivariate Gaussian Example

- $N=2$ dimensional vector, 2 classes shown



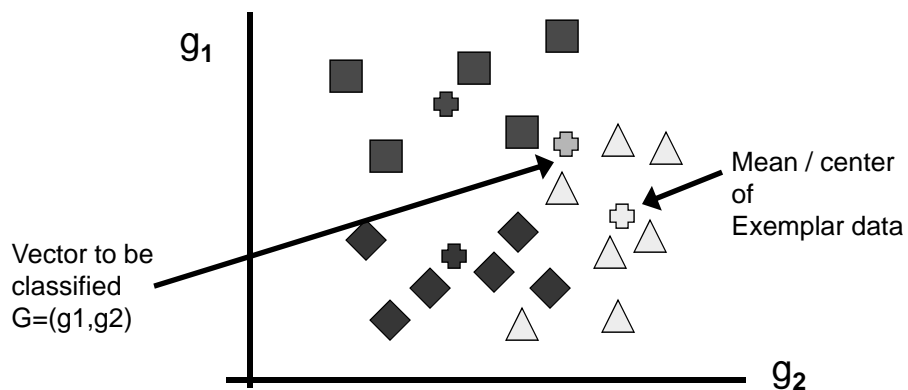
Linear Discriminant Classifier

- Simple clustering: Linear boundary (line or hyperplane)
- Distribution-free (non-parametric) method



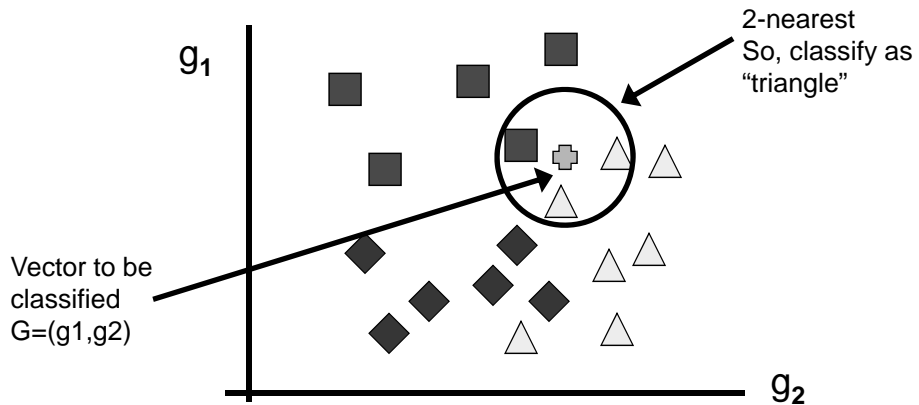
K-Means Classifier

- K-means clustering (minimum mean distance classifier): compute cluster centers, classifier assigns to class with closest center (mean)



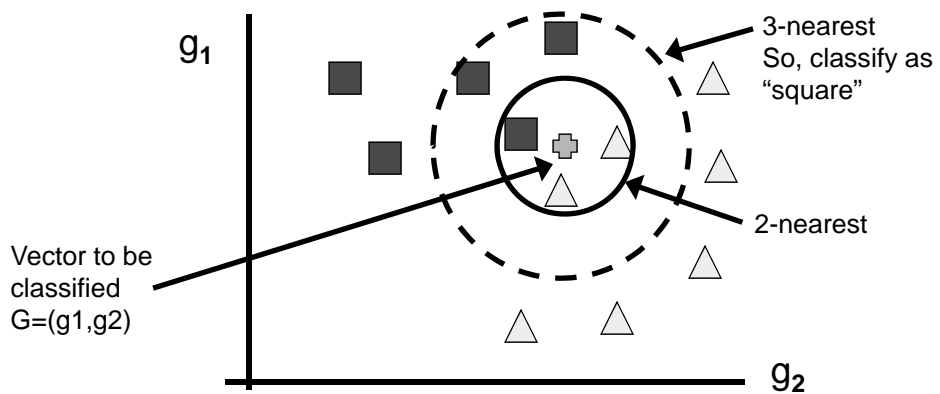
K-Nearest Neighbor Classifier

- K-nearest neighbor: find the k nearest neighbors of the vector G, assigns to majority class of the k neighbors



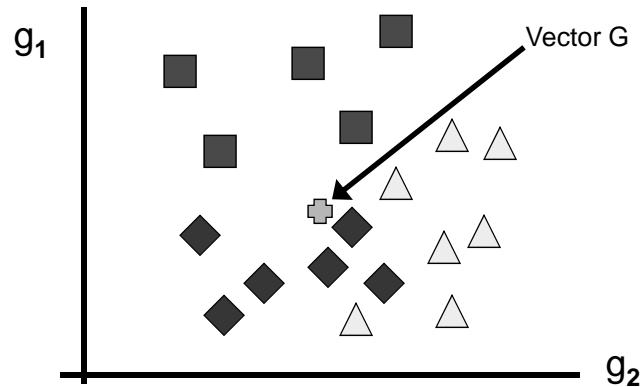
K-Nearest Neighbor Classifier

- K-nearest neighbor: find the k nearest neighbors of the vector G, assigns to majority class of the k neighbors



Minimum-Distance Classifier

- Minimum-distance Classifier: (1-nearest neighbor)
find the nearest neighbor of the vector G , and
assign to that class



Supervised/Unsupervised Classifiers

- Supervised Classification:
 - A set of examples/prototype/exemplar data from each class are used to design the classifier
- Unsupervised Classification:
 - No set of examples/prototype/exemplar
 - Typically look for clusters/concentrations in feature space

Unsupervised Classifier

- As a first step, an unsupervised classifier would look at the data and organize it into a number of classes based on “clumping” of points in feature space
- Then, any of the prior methods, such as nearest neighbor, could be used to assign a vector to a class

