# Model-Based Approaches to Rejecting Confuser Targets


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# Outline

Approaches to ATR based on statistical models for observations
Desired result stated explicitly in terms of the model
Detection and recognition often stated in Neyman-Pearson or Bayes terms
How can the problem of confuser rejection be stated?

1. Notation
2. Forced Decisions
3. Rejection via Successive Decisions
4. Rejection via Joint Decisions
5. Conclusions

# Notation

Let $X \sim p(x;\theta)$ denote a random observation for $\theta \in \Omega$.
$\theta$ may denote a distribution family as well as parameters.

A model consists of assumptions about $p(x;\theta)$ and/or $\Omega$.
A hypothesis is a statement about $\theta$ such as $\theta \in \omega \subset \Omega$

Let target class $i \in \{1, 2, ..., M\}$ result in observations with $\theta \in \omega_i$.
$\theta$ varies in $\omega_i$ with pose, articulation, configuration, damage, etc.

- Denote by $H_i$ an assertion that $\theta \in \omega_i$
- Denote by $H_i^c$ an assertion that $\theta \notin \omega_i$
- Denote by $H_A$ an assertion that $\theta \in \omega_A = \Omega - \cup\, \omega_i$

Sets $\omega_i$ may be approximated from training data. Zhao and Principe* synthesize elements of $\omega_A$ close to $\omega_i$

*"Incorporating Virtual Negative Examples to Improve SAR ATR," SPIE 2000

# Forced Decisions

## Estimation: Given H$_i$ is true, estimate $\theta \in \omega_i$

- Maximum Likelihood: maximize $p(X;\theta)$ over $\omega_i$
- Bayesian: minimize expected cost using $p(\theta \mid \omega_i)$

## Classification: Given H$_i$ is true for some $i$, determine $i$

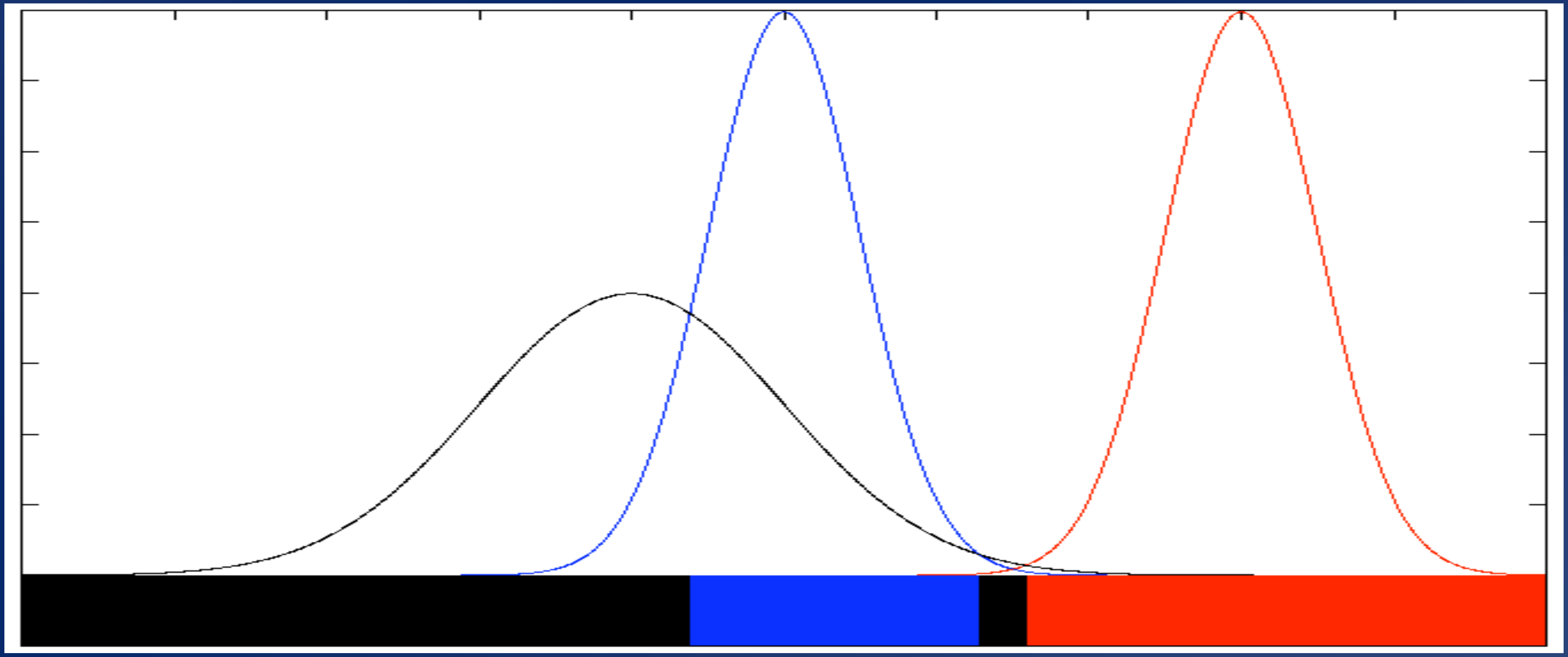
- Generalized-Likelihood: maximize $p(X;\theta)$ over $\omega_i$ for all $i$
- Bayesian: minimize expected cost using $p(X,\theta)$ and $p(\omega_i)$

## Detection: Choose between man-made object or natural clutter

- Neyman-Pearson: Fix probability of misclassifying each target $i$ as clutter and maximize probability of correctly classifying clutter (Lehmann 1986)
- Rephrase as a two-class problem and apply generalized-likelihood or Bayesian methods

# Confuser Rejection

Confuser rejection complicated by difficulty of characterizing $\omega_A$
May be difficult to even define $P_A$
Power of rejection test (hence Pcc-Pfa curves) depend on confuser vehicles chosen
Handle $\omega_A$ either explicitly (i.e. direct evidence) or implicitly (i.e. relative to other hypotheses)



# Rejection via Successive Decisions

Successive decisions implemented in two steps:

1. Choose the best $H_i$ in a forced classification decision
2. Choose between $H_i$ and $H_i^c$

Examples of what it might mean to be a confuser:

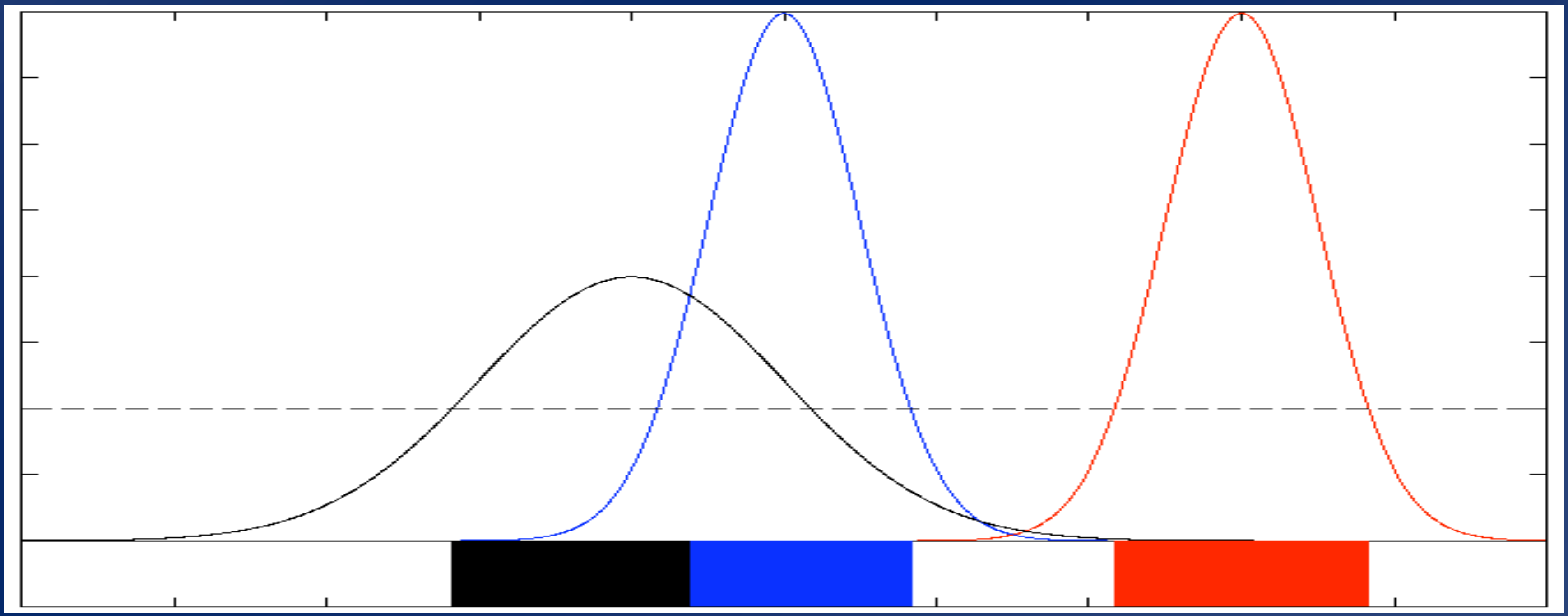
1. Low likelihood of being a known target
2. Low (conditional) probability observation
3. Estimated $\theta$ not close to $\omega_i$
4. High conditional probability of error

Successive decisions allow classification and rejection algorithms (models) to be chosen independently

# Successive Decisions: Likelihood Threshold

**Small likelihood values taken to indicate poor fit**
**Reject an observation if: max $p(x \mid H_i) < \gamma$**

**Equivalent to commonly used MSE thresholding (cf. Novak, *et al.*)[*]**
**in Gaussian, equal variance models**



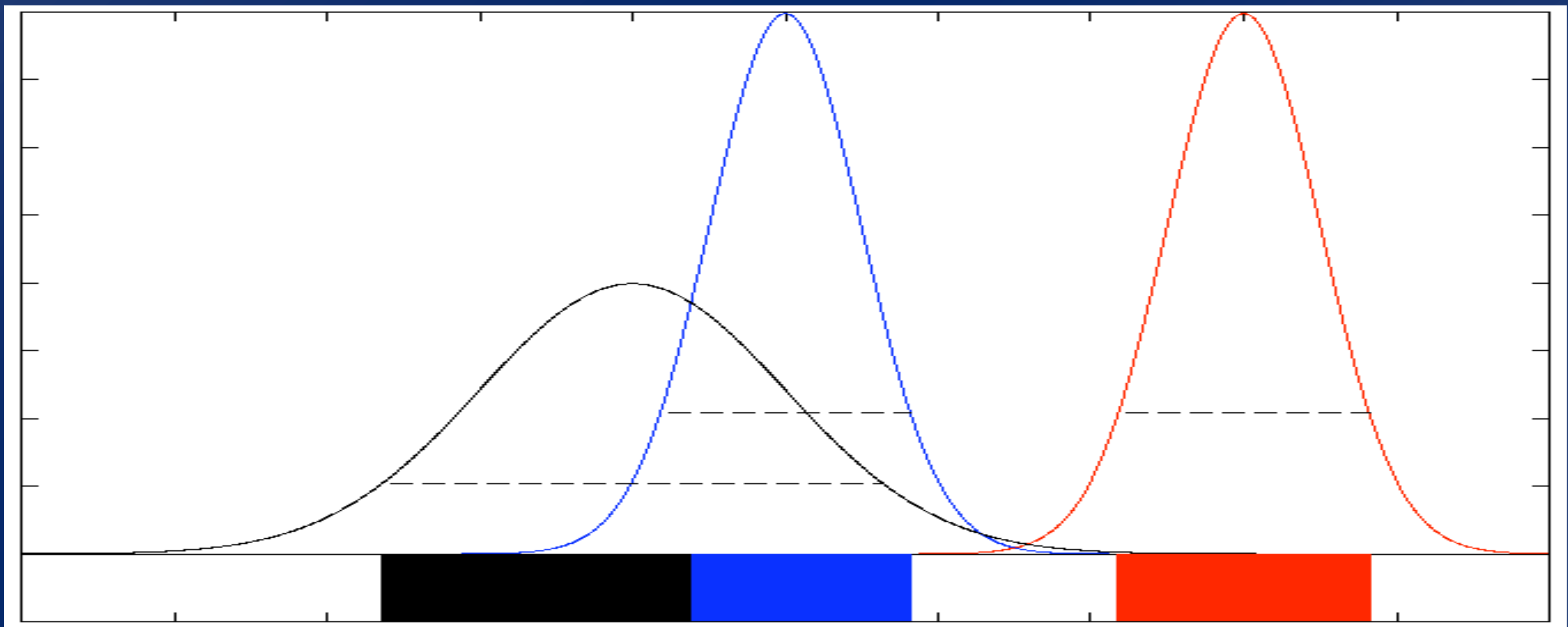
[*]"Performance of 10- and 20-Target MSE Classifiers," Trans. AES 2000

# Successive Decisions: Probability Threshold

**For two classes, C. R. Rao* suggests rejecting observations not occurring in a high probability region for the most likely hypothesis *i***

**For *M* classes, reject *x* if $F(l(x) \mid H_i) < \alpha$ (reject $100\alpha\%$ of actual images)**

**Likelihood threshold is a special case for equal scale**



*"The Utilization of Multiple Measurements in Problems of Biological Classification," JRSS-B 1948

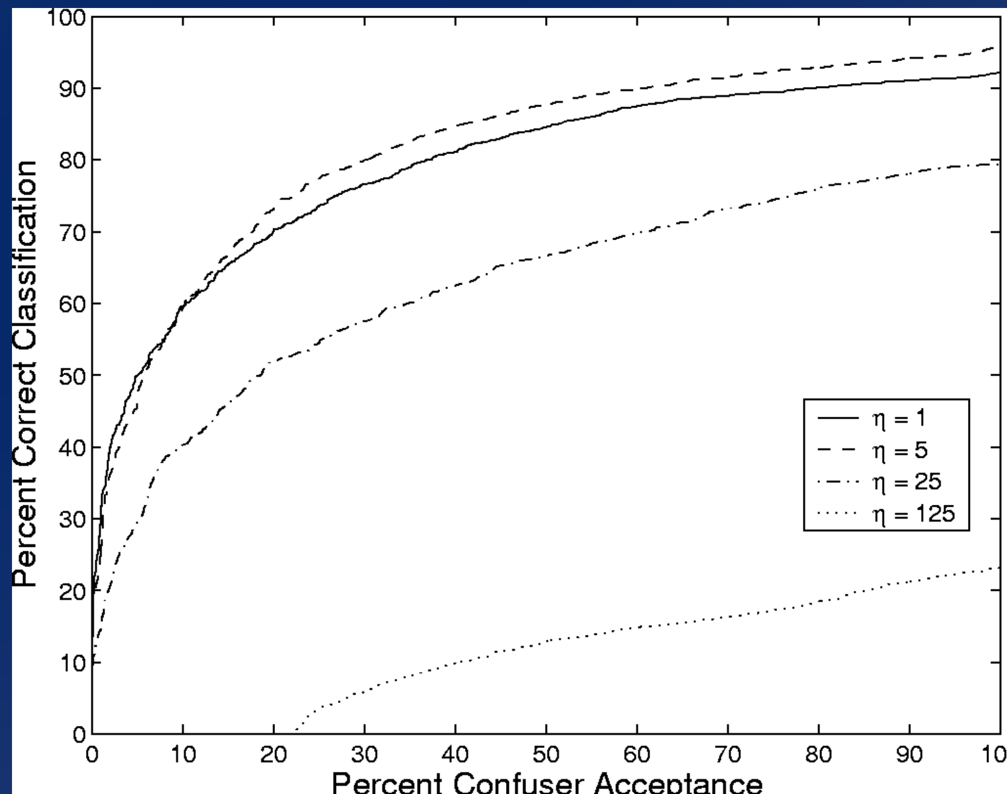
# Successive Decisions: Parameter Estimates

- We can estimate $\theta$ and reject $x$ if $d(\theta,\omega_i) > \gamma$ for some $d$
- MSE threshold is a special case for fixed scale
- May require multiple observations

For SAR imagery, DeVore and O'Sullivan* reject if empirical relative entropy is large

$$D(p(\bullet|\theta(x)) \,||\, p(\bullet|\omega_i)) > \gamma$$

For zero-mean Gaussian model, $\theta$ is an estimate of $\sigma^2$



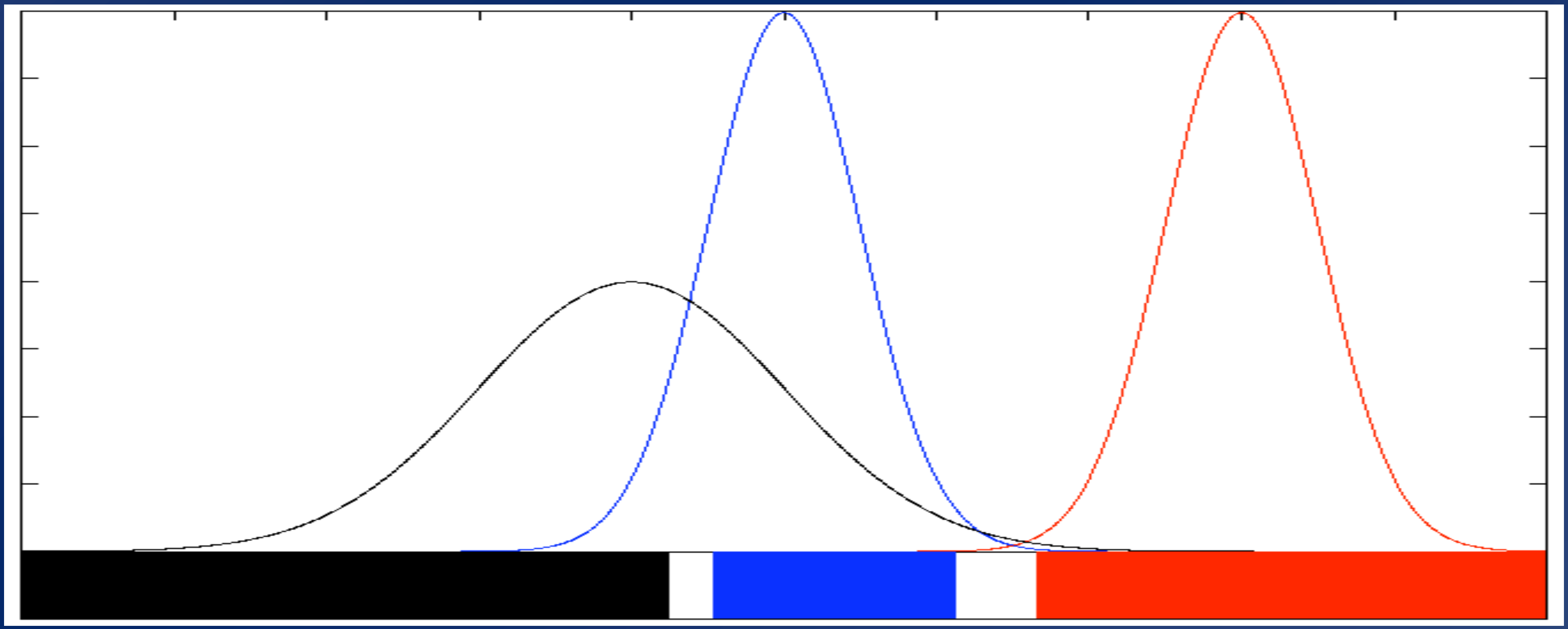

*"Target-Centered Models and Information Theoretic Segmentation for ATR," SPIE 2001

# Successive Decisions: Conditional Error Threshold

**Fukunaga* rejects when the conditional probability of error is large**
**Conditional probability mass $P(\omega_i \mid x)$ found from Bayes' rule**

**Reject if $1 - P(\omega_i \mid x) > \gamma$**

**Rejection decision depends upon likelihood of all hypotheses**



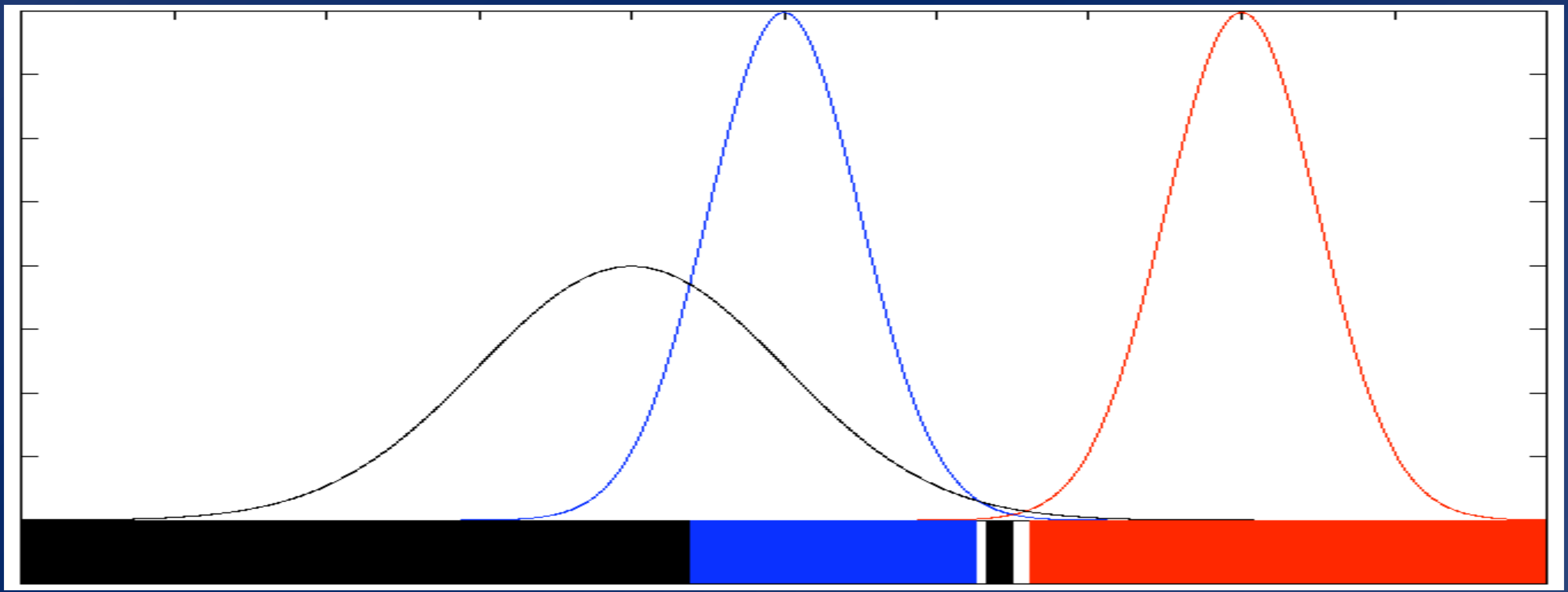
*"Statistical Pattern Recognition," 1990

# Rejection via Joint Decisions

## Joint decisions involve choosing between $H_A$, $H_1$, $H_2$, …, $H_M$

Bayes risk formulation*:

- Assign costs to each combination of true and chosen hypotheses
- Assume conditional prior probabilities $P_1$, $P_2$, …, $P_M$
- Minimize expected cost



*DeVore, DSc Dissertation 2001

# Conclusions

- Model-based approaches allow a precise problem statement
- Rejection algorithm depends on statement of what constitutes a confuser target
- Power of a confuser rejection test depends on the set of confuser targets employed
- Many statements of confuser targets allow independent selection of classification and rejection tests

- An understanding of what should and should not belong to a class would be useful.
- What alterations can a target undergo and still be of the same class?