

Statistical Detection

A. Tsanakas, Prof. Ioannis Pitas Aristotle University of Thessaloniki pitas@csd.auth.gr www.aiia.csd.auth.gr Version 3.0





- Introduction
- Signal or Noise Decision
- Cost Function
- Likelihood Ratio Test
- MAP Detector
- Neyman-Pearson Hypothesis Testing



Introduction



Signal detection theory is a means to measure the ability to differentiate between information-bearing patterns and random patterns that distract from the information.



Introduction



• **Example:** A bit, 0 or 1, is sent through a noisy channel of a communication channel. The noise is modeled as a realization of a N(0,1) random variable The receiver gets the bit plus noise. Assume that $P_0 = P_1 = \frac{1}{2}$. We must decide between two hypotheses, when the *x* received:

 $H_0: X \sim N(0,1)$ $H_1: X \sim N(1,1)$





- Introduction
- Signal or Noise Decision
- Cost Function
- Likelihood Ratio Test
- MAP Detector
- Neyman-Pearson Hypothesis Testing





• A *noisy signal* x has the following representation:

x = s + n,

• where s is the clean signal and n is the noise.

• The problem we want to deal with is how we can decode the signal *s* from *x*.

Artificial Intelligence & Information Analysis Lab



• If noise is white:

- The received noisy signal will distribute as a normal distribution
- 2. The mean of this distribution would reflect the signal



7





Decision can be made based on the information from two distribution. A simple criterion to make decisions is the following:

If x < C: The received signal is noise.
If x > C: The original signal is received.



С



 Sensitivity (Discriminability) is a measure of how close are signal and noise. We can estimate the Sensitivity d' as the difference between means of s and n by the following type:

9

$$d' = \mu_s - \mu_n.$$







Different combinations of stimuli and responses.







Figure: Distribution of the decision variable across noise and signal trials.

Artificial Intelligence & Information Analysis Lab

11



- Introduction
- Signal or Noise Decision
- Cost Function
- Likelihood Ratio Test
- MAP Detector
- Neyman-Pearson Hypothesis Testing



Cost Function



• We want to design a decision rule $\hat{H}(x)$. For this purpose, we create two disjoint regions:

$$\mathcal{R}_0 = \left\{ x : \widehat{H}(x) = H_0 \right\}$$
$$\mathcal{R}_1 = \left\{ x : \widehat{H}(x) = H_1 \right\}$$

 To optimize the choice of decision regions, we can specify a cost for decisions.



Cost Function



• The expected Bayes Cost defined as:

$$C = \sum_{i,j=0}^{1} c_{ij} P(decided H_i, H_j is true)$$

= $\sum_{i,j=0}^{1} c_{ij} \pi_j P(decided H_i | H_j is true)$

where π_i is the probability the hypothesis H_i is true.





- Introduction
- Signal or Noise Decision
- Cost Function
- Likelihood Ratio Test
- MAP Detector
- Neyman-Pearson Hypothesis Testing



Likelihood Ratio Test



- Therefore, the *optimal test* takes the following Likelihood Ratio form:
- For H_1 :

$$L(x) = \frac{p_1(x)}{p_0(x)} > \frac{\pi_0 (c_{10} - c_{00})}{\pi_1 (c_{01} - c_{11})},$$

and for H_0 :

$$L(x) = \frac{p_1(x)}{p_0(x)} < \frac{\pi_0 (c_{10} - c_{00})}{\pi_1 (c_{01} - c_{11})}$$





- Introduction
- Signal or Noise Decision
- Cost Function
- Likelihood Ratio Test
- MAP Detector
- Neyman-Pearson Hypothesis Testing



MAP Detector



Finally, the MAP detector has the following form:

• For H_1 :

$$P(H = H_1|x) > P(H = H_0|x),$$

and for H_0 :

$$P(H = H_1|x) < P(H = H_0|x).$$

• This is also called Maximum a Posteriori (MAP) Detector.





- Introduction
- Signal or Noise Decision
- Cost Function
- Likelihood Ratio Test
- MAP Detector
- Neyman-Pearson Hypothesis Testing



Neyman-Pearson Hypothesis Testing

We defined the following probabilities:

- *Hit* probability: $P(\hat{H} = H_1 | H_1).$
- **Correct Rejection** probability: $P(\hat{H} = H_0 | H_0)$.
- **False Alarm** probability: $P_{FA} = P(\hat{H} = H_1 | H_0) = \int_{\mathcal{R}_1} p_0(x) dx$.
- *Mis-detection* probability: $P_{MD} = P(\hat{H} = H_0 | H_1) = \int_{\mathcal{R}_0} p_1(x) dx$.

$$P_{MD} = 1 - P_D$$



(VML

Neyman-Pearson Hypothesis **(VML** Testing

The Neyman-Pearson criterion is defined as follows.

• Minimize the probability $P_{MD} = P(\hat{H} = H_0 | H_1)$ subject to:

 $P_{FA} < a$.

 The main advantage of this minimization criterion is that it does not require prior probabilities nor cost assignments.

Artificial Intelligence & Information Analysis Lab

Neyman-Pearson Hypothesis **VML** Testing

To *minimize* the probability P_{MD} , we rely on the following *theorem*: To *maximize* P_D with a given $P_{FA} < a$, decide H_1 if

$$L \doteq \frac{p(x|H_1)}{p(x|H_0)} \ge \lambda$$

where λ found from

$$P_{FA} = \int_{x:L(x)>\lambda} p(x|H_0)dx = a$$





Bibliography

[STN99] S. Harold, N. Todorov, "Calculation of signal detection theory measures", Behavior research methods, instruments, & computers, 31.1 (1999): 137-149.

[HOP89] I.Y. Hoballah, P. K. Varshney, "Distributed Bayesian signal detection", IEEE Transactions on Information Theory 35.5 (1989): 995-1000.

[WIC02] T.D. Wickens, "Elementary signal detection theory", Oxford University Press, USA, 2002.

[KIN89] G. King, Gary (1989). "Unifying Political Methodology: The Likelihood Theory of Statistical Inference. Cambridge University Press", p. 84, 1989.

[STE] S. Glen, "Neyman-Pearson Lemma: Definition", https://www.statisticshowto.com/neyman-pearsonlemma/

[SCR05] S. Clayton, R. Nowak, "A Neyman-Pearson approach to statistical learning", IEEE Transactions on Information Theory 51.11 (2005): 3806-3819.

[NP33] J. Neyman, E.S. Pearson, "On the problem of the most efficient tests of statistical hypotheses", Philosophical Transactions of the Royal Society of London, Series A Containing Papers of a Mathematical or Physical Character, 231(694-706), 289-337, 1933.







Thank you very much for your attention!

More material in http://icarus.csd.auth.gr/cvml-web-lecture-series/

Contact: Prof. I. Pitas pitas@csd.auth.gr

